Human-fire interactions and their influence on patterns of fire and fire risk to housing development in the United States

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The interaction between wildfire and human development is one example of a coupled human natural system where human activities affect patterns of fire occurrence and fire presents risks to society. The questions addressed by this research were (1) how does human development interact with fire? and (2) where is housing at risk from fires? I used active fire detections made by the Terra and Aqua Moderate Resolution Imaging Spectroradiometer (MODIS) satellite sensors collected between 2000 and 2006. First, I quantified detection rates of the MODIS fire data with a set of reference fire perimeters. Second, I used the MODIS fires to quantify patterns of fire occurrence. Third, I used the MODIS fires in logistic regression models to evaluate the influence of weather, vegetation, topography, and human variables on fire occurrence. Finally, the predicted fire occurrence models were used to quantify risk to housing units across the U.S. The MODIS active fire data captured most reference fires, especially large fires that are relevant for understanding fire occurrence and risk. Between 2003 and 2006, 1.24% of the area of the U.S. and 1 million housing units experienced MODIS fires each year. Shrublands and evergreen forests, vegetation with the most intense fire behavior, experienced 39% of all MODIS fires but contained only 57,000 housing units in MODIS fires per year. Logistic regressions showed that human variables played an important role determining patterns of fire occurrence, but their influence was minor compared to weather, vegetation, and topographic variables. When predicted fire occurrence was used to estimate risk, I found that nearly 3.2 million houses were located in areas with moderate to high fire risk, but they were dispersed over 19% of the U.S. Human development introduces novel disturbance processes to ecosystems and acts as an external driver of change. However, fires have reciprocal effects on adjacent development and present a significant hazard to human values. Human development and fire are inextricably linked, and development in fire-prone landscapes will likely continue. Ecosystem and fire management will be continually challenged by housing development and solutions are needed that better integrate human communities with ecosystem dynamics.

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Introduction

Problem statement

The overarching goals of my dissertation research were to first, increase our understanding of the interactive relationships between human development and fire, and second to use that understanding to identify locations in the U.S. where human development is placed at risk by fires.

Most ecosystems in the U.S. are embedded in human dominated landscapes. How human activities affect ecosystems and the reciprocal effects of ecosystem processes on society are not fully understood. The interaction between wildfire and human development in the wildland-urban interface is one example of a coupled human-natural system. The wildland-urban interface (WUI) is the zone where housing development and wildland vegetation co-occur or abut one another (Radeloff et al. 2005). Development in the WUI creates a context where patterns of fire occurrence are affected by human actions and fire management decisions are dominated by human values. However, the outcomes of those actions and decisions shape adjacent ecosystems and the processes occurring within them. In turn, ecosystem processes have reciprocal effects on society, especially disturbances such as fire which often times place human values at risk.

Many fire management decisions aim to limit risk, especially to human lives and homes. However, the location and relative magnitude of fire risk in the U.S. has not been well quantified (U.S. Department of Agriculture and U.S. Department of Interior 2001, U.S. General Accounting Office 2003). The main objective of my dissertation, and its primary outcome, was thus to quantify wildfire risk to houses across the conterminous U.S. We know where development is (Radeloff et al. 2005), and we have a pretty good idea about how fires behave (Rothermel 1972), but we have less information about where fires are most likely occur. Consequently, our understanding of fire risk in the WUI is limited. To quantify risk, we need to also describe the relationships between people and the environment. Therefore, examining fire risk in a coupled natural human systems framework has the practical value of helping identifying risk, but also contributes to our scientific understanding of the interactions between people and ecosystems.

Risk modeling considers the joint probability that an event will occur with the probability that an event will inflict damage on something of value (Bachman and Allgöwer 1999, Finney 2005). Using this framework, fire risk in the WUI can be quantified using probabilities of fire occurrence, potential fire behavior, and housing locations. To examine risk, I developed consistent models across the U.S. that quantified the potential for fire occurrence and its spatial variability. Predictive fire models require a thorough understanding of the underlying the human and biophysical drivers influencing fire occurrence. The different influences of biophysical variables have been well documented, but our knowledge of the human impacts on fire remains limited to regional studies. The results of these studies suggest that human development has an antagonistic relationship with fire, increasing ignition rates through arson and accidents, but also limiting the area burned by fragmenting fuels and suppressing fires (Cardille et al. 2001, Syphard et al. 2007b). However, the magnitude, direction, and variability of human influences on fire are poorly understood at the national scale. A greater understanding of variability in human influences on fire is needed because human influences on fire occurrence have both ecological and social implications.

Testing the relative importance of the drivers of fire occurrence necessitates a good sense of what has burned. However, basic information about the patterns of fire occurrence in the U.S. is lacking. Fire and ecosystem management efforts are mostly directed to public lands, but risk to housing mostly occurs primarily on private lands in the WUI. This is why I quantified the extent to which fire occurs across different land ownership and property types. Questions such as "how often do fires occur in the WUI?" and "how many houses are actually exposed to fire?" had not been previously answered. These are important questions because they address where human-fire interactions exist and the current extent of risk in the U.S.

One of the reasons for our limited understanding of fire occurrence at the national scale is due to the lack of good fire data. The federal fire occurrence database is virtually the only national information source. It is based on records from the ground; however, the spatial accuracy of the records are often questionable and therefore they are of limited use for examining fine-scale fire occurrence patterns (Brown et al. 2002). Additionally, federal fire data may under-represent fires on private lands, and this is especially important in a risk context, because almost all houses are on private lands. Satellite observations of fires offer a viable alternative to federal and state fire databases for modeling fire occurrence and risk. I used the MODIS active fire data (Justice et al. 2002a, Giglio et al. 2003a) to assess patterns of fire occurrence in the U.S. In comparison to federal and state fire databases, satellite fire detections span all ownerships and property types, can monitor the extent of fire activity (not just ignition locations), and have more consistent spatial detail. The ability of satellite fire detections to track spatial and temporal patterns of fire has been well documented at regional and continental scales (Li et al. 1997, Giglio et al. 2003b, Pu et al. 2007), as well as the entire globe (Dwyer et al. 2000, Csiszar et al. 2005, Giglio et al. 2006a). However, whether or not satellite detections capture fires and patterns of fire occurrence at a scale relevant to fire management has not been fully explored. This is why I assessed the accuracy of the MODIS active fire data.

In summary, there were two primary research questions that my research aimed to address; (1) what are the interactions between human development and fire, and (2) where do fires present a risk to houses? My dissertation research filled several substantial knowledge gaps in order to answer these two questions. First, ***uncertainty remains about the quality of satellite fire observations***. Satellite fire detections offer a promising data source, but the types of fires they do and do not detect are not well documented. Second, ***the geography of fire is poorly described*** and we need to both determine if satellite fire observations capture relevant patterns of fire occurrence, and to understand the current extent of human-fire interactions. Third, ***the driving variables behind fire occurrence and how their influence varies across the country are not fully understood***. Finally, ***where human development is at risk from fires is not known***. Each of these four knowledge gaps was addressed individually in the chapters of my dissertation.

Key findings

Chapter 1 of my dissertation quantified uncertainty in the detection capabilities of MODIS satellite fire observations. Satellite fire detections could provide an extremely useful dataset for examining patterns of fire occurrence, but uncertainty in their detection rates could be problematic for interpreting results. I evaluated the active fire data collected by the MODIS (moderate resolution imaging spectroradiometer) sensors part of NASA Earth Observation System Terra and Aqua satellites (Justice et al. 2002a). Using a set of reference fire perimeters mapped from Landsat imagery, I examined how cloud cover and reference fire size affected MODIS detection rates. I also examined how detection rates varied across the U.S.

Overall, the MODIS active fire data captured fires well and successfully detected 82% of the reference fires. Detection rates were generally lower on cloudy days and fire size also mattered. Fires that were 105 ha in size only had a 50% chance of being found by MODIS. Detection rates varied across the U.S. and were greatest in the West and lowest in the East. Based on these findings, the MODIS active fire data may under-represent small fires and eastern fires. However, the MODIS active fires data do capture large fires that account for most of the area burned in the U.S. and are most relevant from a risk perspective.

Chapter 2 examined the geography of fire in the U.S. Using MODIS active fire data collected between 2003 and 2006, I compared the number of MODIS fires and number of houses in MODIS fires (i.e., a 1x1 km pixel with an active fire) among 4 property types (the wildland-urban interface, federal lands, Wilderness Areas, and everything else) and among eight landcover categories representing different vegetation types (developed, agriculture, wetlands, grasslands, shrublands, and evergreen, mixed, and deciduous forests). I also quantified the how the number of fire pixels and number of houses in MODIS fires varied according to the total size of contiguous clusters of MODIS fire pixels.

Between 2003 and 2006, approximately 1.24% of the U.S. and more than 1 million housing units were in MODIS fires each year. Most MODIS fires occurred outside of federal lands and the WUI (71% of all MODIS fires), and only 33% of MODIS fires were in developed and agriculture land covers. Approximately 39% of all fires occurred in shrubland and evergreen forest vegetation types but only 57,000 housing units were found in MODIS shrubland and evergreen forest fires. Across the country, fires were common in the Southeast and localized in parts of the West. More houses were exposed to fires in the East than in the West. However, fire sizes were considerably larger and more variable in the West than in the East. The results of this chapter demonstrated that the MODIS fire data do capture patterns of fire that vary spatially across the country and among land cover and property types. These patterns are relevant to understanding the interactions between humans and fire as well as for addressing fire management and fire risk.

Chapter 3 focused on explaining the strength of human influences on fire occurrence throughout the U.S. National-scale models of fire occurrence are needed to both understand the driving factors behind fires and to identify areas where there is high potential for fires. I used the MODIS active fire data as observations in a series of logistic regression models that tested the relative importance of weather, vegetation, topography, and human variables for predicting fire occurrence. I then used my models of fire occurrence to identify areas that had high fire potential but did not necessarily burn during the time period of the analysis (2000 – 2006).

In general, the human variables I used (distance from roads and housing density) were influential in our models but the strength of their importance was relatively small compared to the combined effects of weather, vegetation, and topography. Most of the time, fire occurrence increased over low housing unit densities and short distance to roads, but the trend switched and fire also had a negative relationship at higher housing unit densities and greater distances from roads. However, the shape and strength of the relationships varied among years and regions of the U.S. Predictions largely followed observed patterns and fires occurrence was most likely in the Southeast, western mountain regions, and Mediterranean California. However, there was much more variability in predictions in the West among years than in the East.

Chapter 4 investigated patterns of fire risk to houses. National-scale assessments are needed to prioritize federal fire management efforts to reduce risk in the WUI as well as determine where fires can be allowed to burn for their ecological benefits. I defined risk as the combined probability of fire occurrence and housing across the U.S. I combined existing housing data with the models of fire occurrence developed in chapter

3 to map and quantify risk. Fire intensity may vary among vegetation types and present different types of risk, so I also stratified the analysis between two vegetation groups: shrubland and evergreen forests and all other vegetation types. Finally, I quantified risk at the national scale and made comparisons of risk among different ecoregions.

The results of my risk analysis showed that fire risk to houses in shrublands and evergreen forests was twice as high as in other vegetation types. Across the country, 2.8% of all housing units were located in shrublands and evergreen forests with ≥2% chance of fire per year. Those housing units were dispersed over 19% of the U.S. Regionally, risk was high in the Southeast, following patterns of both fire occurrence and housing. However, in the West, risk locations were isolated and matched the clustered patterns of development.

Significance

The results of my research are significant from technological, social, economic, and scientific perspectives and have important implications for fire management in the United States. **Technologically**, my research demonstrated that satellite fire observations provide useful information that overcomes some of the limitations of existing state and federal fire databases. We found that the MODIS active fire data did not locate all fires, but they did identify most large fires and those fires are of primary concern for risk management and landscape change analysis. We also found that the MODIS fire detection rates varied across the country and this could be important when satellite fire data are used to summarize patterns of fire occurrence because the satellite data might underestimate true fire occurrence in some regions, especially the eastern U.S. However, the influence of missing fires should not be problematic in statistical modeling if the detected fires are a representative sample of all fires, or at least the fires of greatest interest for risk analysis and fire management.

From a societal and policy perspective, my research quantified past fire occurrence and the extent to which fires directly impacted housing development across the U.S. As far as I know this has not been done before. A small proportion of housing units occurred in locations where MODIS detected fires, only 1.24% of the 115 million housing units in the U.S. What I found surprising was that only 57,000 housing units were found in MODIS fires in shrublands and evergreen forests, the vegetation types most prone to extreme fire behavior. However, when predictive models of fire occurrence were combined with housing locations, the total number of houses with at least a 2% chance per year of experiencing a fire totaled 3.2 million. Those houses were distributed across 19% of the U.S. Because protection of property is a primary goal of fire management, there is a lot of ground to cover.

Landscape-level fuel treatments to reduce fire intensity are one strategy that is being pursued to reduce fire risk. Treatments are placed in or near the WUI or other values at risk from fire. The cost of treatments can be high and the duration of their effects can be short (Berry and Hesseln 2004, U.S. Department of Agriculture 2006). Other approaches to reducing risk are worth pursuing, such as placing more responsibility on individual land owners to reduce fire risk on their property (Fried et al. 1999, Cohen

2000) and implementing fire-safe building codes so that housing can serve as a shelter in place1.

Housing growth in the WUI is greater than the national average (Hammer et al. 2007). Whether or not future housing development will also be at risk from fire remains to be seen, but things don't look promising given the current patterns of development. Greater thought needs to be paid about where future development will occur, how to limit the impacts of development to ecosystems, and how to avoid the negative impacts of ecosystem processes to humans.

Scientifically, my dissertation research provides a national view of one aspect of coupled human-natural systems: how development and fires interact. My research compared the relative effects of weather, vegetation, topography and human development on fire occurrence across the U.S. Not surprisingly, I found that variables representing weather, vegetation, and topography had the most predictive power for explaining fire occurrence, and that human variables such as distance from road and housing density did matter too, but with less predictive strength. We may be in less control of fire than we would like to believe!

Previous, studies in the Upper Great Lakes and California found positive relationships between development and fire at short distances from roads and low housing densities, but a negative relationship at long distances from roads and high

[1] http://www.firewise.org/

housing densities (Cardille et al. 2001, Syphard et al. 2007b). My results confirmed that those same general patterns exist in vary degrees among ecoregions of the U.S. My results also demonstrated that the relationships between humans and fire often vary from year to year. The only other variables in my analysis that varied temporally were weather variables and this suggests that inter-annual variability in weather might have moderated the interactions between humans and fire. The temporal variability in human-fire interactions has rarely been studied. This is an avenue of research that could warrant further investigation especially because ecological and societal implications of climate change will depend to some extent on the coupling of humans and natural systems.

Human development affects fire regimes through increasing ignitions (Cardille et al. 2001, Syphard et al. 2007b) and decreasing area burned through active suppression and by fragmenting fuels (Turner et al. 1989, Finney 2001). Thus human development can impose novel patterns of fire occurrence that do not necessarily match natural, lightning-caused patterns. Human-induced changes in fire occurrence can push ecosystem disturbance regimes outside their historic range of variability, which is often considered a benchmark for conservation success (Hunter 1993, Landres et al. 1999). Today, few ecosystems have fire regimes within historic range of variability (Rollins et al. 2001, Cleland et al. 2004) and as a consequence their composition, structure, and function are changing (Baker 1992, Covington and Moore 1994, Foster et al. 1998, Abrams 2003).

My research identified places across the country where fires pose a risk to housing development. The ecological benefit of knowing where fire risk is greatest is that it also highlights where development will be less likely to limit the use of fire to maintain historic range of variability. Federal fire management in the U.S. is embracing policies that allow fires to burn for their ecological benefit, but the extent to which it is possible to implement those policies across the country has been largely unknown, until now.

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Chapter 1: Detection rates of the MODIS active fire product in the United States

Abstract

MODIS active fire data offer new information about global fire patterns. However, uncertainties in detection rates can render satellite-derived fire statistics difficult to interpret. We evaluated the MODIS 1 km daily active fire product to quantify detection rates for both Terra and Aqua MODIS sensors, examined how cloud cover and fire size affected detection rates, and estimated how detection rates varied across the United States. MODIS active fire detections were compared to 361 reference fires (≥18 ha) that had been delineated using pre- and post-fire Landsat imagery. Reference fires were considered detected if at least one MODIS active fire pixel occurred within 1 km of the edge of the fire. When active fire data from both Aqua and Terra were combined, 82% of all reference fires were found, but detection rates were less for Aqua and Terra individually (73% and 66% respectively). Fires not detected generally had more cloudy days, but not when the Aqua data were considered exclusively. MODIS detection rates decreased with fire size, and the size at which 50% of all fires were detected was 105 ha when combining Aqua and Terra (195 ha for Aqua and 334 ha for Terra alone). Across the United States, detection rates were greatest in the West, lower in the Great Plains, and lowest in the East. The MODIS active fire product captures large fires in the U.S. well,

but may under-represent fires in areas with frequent cloud cover or rapidly burning, small, and low-intensity fires. We recommend that users of the MODIS active fire data perform individual validations to ensure that all relevant fires are included.

Introduction

Satellite sensors can monitor global fire patterns (Dwyer et al. 1998, Dwyer et al. 2000, Csiszar et al. 2005) and have increased our understanding of fire emissions (Seiler and Crutzen 1980, Kaufman et al. 1992), land-use/land-cover change (Eva and Lambin 2000), and fire risk (Chuvieco and Congalton 1989). Satellite fire data offer clear advantages over other fire data sources. In the U.S., many public agencies keep fire occurrence records, but may not include fires occurring on private lands (Brown et al. 2002). Collecting fire data in the field is time consuming, expensive and difficult, especially in remote areas. Satellite fire observations thus offer a reliable source of fire occurrence data that may overcome some of the limitations of traditional fire monitoring (Flannigan and Vonder Haar 1986, Eva and Lambin 1998a, Csiszar et al. 2005, Korontzi et al. 2006). However, although satellite fire data offer valuable information, uncertainty in their detection rates can make interpretation difficult (Congalton and Green 1999).

A variety of sensors have been used to detect and map fires. Global to continental coverage has been derived from the Advanced Very High Resolution Radiometer (Flannigan and Vonder Haar 1986, Li et al. 1997), and MODIS onboard the EOS Terra and Aqua satellites (Justice et al. 2002a). Other moderate to coarse resolution sensors used for fire monitoring include Geostationary Operational Environmental Satellite (Prins and Menzel 1992), Along Track Scanning Radiometer (Eva and Lambin 1998a), Defense Meteorological Satellite Program-Operational Linescan System (Elvidge et al. 1996, Fuller and Fulk 2000), Visible and Infrared Scanner (Giglio et al. 2000), and SPOT VEGETATION (Fraser et al. 2000). For regional fire mapping, finer-resolution sensors, such as Landsat (Minnich 1983, Chuvieco and Congalton 1989, Pereira and Setzer 1993), Advanced Wide Field Sensor (Chand et al. 2006) and Advanced Spaceborne Thermal Emission and Reflection Radiometer (Morisette et al. 2005a, Morisette et al. 2005b, Csiszar et al. 2006) have been used.

Regardless of the sensor, two general approaches to fire mapping have been taken; burn scar mapping and active fire detection. Burn scar mapping involves identifying the area affected by fire after the event has occurred (Chuvieco and Congalton 1988, Kasischke et al. 1993, Pereira and Setzer 1993). In contrast to burn scar delineation, active fire detection maps the flaming front of fires at the time of satellite overpass (Matson and Dozier 1981, Flannigan and Vonder Haar 1986, Flasse and Ceccato 1996). In this paper, we focused on MODIS active fire detections because they represent the state-of-the-art in global fire mapping and can be used as a basis for other fire products, for instance to distinguish burned areas from other disturbances (Giglio et al. 2006b, Loboda et al. 2007).

Active fire detection is possible because radiant energy increases with temperature, producing a high contrast fire pixel relative to cool surrounding non-fire pixels. Small increases in an object's temperature result in large increases in radiance in the mid-IR range (3-5 μm) and slight increases in the thermal-IR range (5-12 μm) and because of this, even sub-pixel size fires can be detected (Dozier 1981, Matson and Dozier 1981). In practice, active fire detection algorithms either evaluate individual pixel values relative to a threshold (Matson and Dozier 1981, Flannigan and Vonder Haar 1986); compare a pixel's temperature contextually to its neighboring pixels (Flasse and Ceccato 1996, Giglio et al. 2003a); or track temporal changes in temperature (Cuomo et al. 2001, Lasaponara et al. 2003).

Errors of commission in active fire mapping can be caused by non-fire surfaces that are highly reflective such as urban areas, senescent vegetation, bare soil, water, or clouds (Flannigan and Vonder Haar 1986, Setzer and Verstraete 1994, Giglio et al. 2003a). Contextual algorithms sometimes exhibit commission errors where there is sharp radiometric contrast, for example, between desert and vegetation (Giglio et al. 2003a). Errors of omission may occur, if there is a difference between the time of fire occurrence and satellite overpass, and these errors are particularly common when satellite overpass does not coincide with peak daily fire activity (Prins et al. 1998, Cardoso et al. 2005, Giglio 2007). Clouds and thick smoke can also obscure fire activity (Flannigan and Vonder Haar 1986). Theoretically, small fires should be identifiable by even moderate resolution sensors such as AVHRR or MODIS (Dozier 1981, Matson and Dozier 1981, Giglio et al. 1999), but in practice, they may lack the intensity needed to trigger detection thresholds and will remain undetected especially at large scan angles where the amount of energy reaching the satellite is limited (Giglio et al. 1999, Giglio et al. 2003a, Schroeder et al. 2005). Contextual algorithms are more likely to miss fires in heterogeneous land cover, which complicates the selection of an appropriate background temperature (Lasaponara et al. 2003, Schroeder et al. 2005, Wang et al. 2007).

The MODIS active fire products are produced using a contextual algorithm for the MODIS sensors on NASA's two Earth Observing System (EOS) satellites: Terra and Aqua. Interested readers should refer to Giglio et al. (2003) for details about the algorithm. The two satellites are in sun-synchronous orbits with different local overpass times; 1:30 and 13:30 for Aqua, and 10:30 and 22:30 for Terra (Lillesand and Kiefer 1999). Aqua generally detects more fires than Terra because its afternoon overpass time is closer to daily peak fire activity in many regions (Justice et al. 2002a).

Several approaches have been taken to quantify errors in fire data, including simulation models, comparison with independent but simultaneously collected satellite data, and comparison with field data. Simulation models predict that commission errors of MODIS and other satellites' fire detections are very low (Giglio et al. 1999, Giglio et al. 2003a). However, errors of omission are likely and simulations show that MODIS has a 50% probability of detecting a 100 m^2 flaming fire (~ 1,000 K) or a 1,000-2,000 m^2 smoldering fire (~ 600 K; Kaufman et al. 1998, Giglio et al. 2003a). Detection limits are generally similar among biomes, but somewhat lower for dry tropical savannas (Giglio et al. 1999, Giglio et al. 2003a). These simulation results suggest that small fires can be detected under ideal conditions, but validations with real fire data are needed to fully understand the detection capabilities of MODIS.

Quantifying fire activity on the ground at satellite overpass times is logistically difficult (Roy et al. 2005). One approach is to use data collected by the ASTER sensor, also onboard the Terra satellite with MODIS. ASTER senses energy in the 0.5 to 10 μm wavelengths, has finer spatial resolution (15-90 m) than MODIS, and its simultaneous but independent observations of fire events can validate MODIS active fire products (Justice et al. 2002b, Morisette et al. 2005a, Morisette et al. 2005b, Csiszar et al. 2006). Comparisons with ASTER suggest commission errors in the MODIS active fire data are rare (0.01% in Brazil (Morisette et al. 2005b) and 0.002% in northern Eurasia (Csiszar et al. 2006). Errors of omission are more common, especially for small fires. For instance, MODIS has a 50% detection rate when fire activity spanned clusters of 47 or more ASTER pixels (30-m resolution each) in Brazil (Morisette et al. 2005b), 25-34 ASTER pixels in southern Africa (Morisette et al. 2005a) and ~60 ASTER pixels in northern Eurasia (Csiszar et al. 2006). When aggregated to MODIS resolutions, the actual fires mapped by ASTER can be composed of many individual fire components and each fire component potentially has a different temperature. In contrast, the theoretical simulations of MODIS fire detection capabilities ignore the heterogeneity of individual fire components and are based on one temperature describing the entire active fire area. It is impossible to know what portion of each ASTER pixel was actively burning at the time of image capture, but results from ASTER validation studies suggest the actual MODIS 50% detection threshold could be considerable larger than theoretical predictions (Giglio et al. 2003a).

The true fire size detection threshold of MODIS may be even lower because the ASTER imagery is restricted to a portion of the MODIS viewing area. The MODIS sensors collect data over a 2,330 km wide swath. In comparison, ASTER collects SWIR and TIR data in 60 x 60 km segments within ±116 km of the center of MODIS Terra's path (Yamaguchi et al. 1998). Results from validation studies based on ASTER data are limited to that range and may overestimate MODIS detection rates because detection capabilities are reduced at the periphery of MODIS' swath (Schroeder et al., 2005). Furthermore, ASTER provides no information about fire activity occurring at times different from MODIS Terra overpass (10:30 / 22:30; Morisette et al. 2005a, Morisette et al. 2005b, Csiszar et al. 2006).

Validation efforts based on independently collected fire data are thus important. Ground-based validations can include small fires and fires that are not actively burning during satellite overpass. Unfortunately, only few ground-based studies have validated the MODIS active fire product. In one study examining MODIS fire detection rates in Brazil (Cardoso et al. 2005), errors of commission were high with only 33% of MODIS active fires confirmed on the ground. Errors of omission were even greater; only 0.7% of all the fires observed on the ground were identified by MODIS. The Cardoso et al. (2005) covered only a small study area, and was limited to one biome, but it raises the question what proportion of fires is captured by the MODIS active fire product. Simulation studies and ASTER validations alone can not answer this question, and additional ground-based accuracy assessments are needed to interpret the MODIS fire data.

Our objective was to determine how well the MODIS active fire products capture broad-scale patterns of fire activity. We took an approach different from prior MODIS active fire validation efforts and used a set of fire perimeters spanning a wide range of environmental conditions across the United States as reference data. The specific questions we sought to answer were:

1. What proportion of fires is detected by the MODIS active fire product?
2. Do detection rates change if lower confidence MODIS active fires are excluded?
3. Are there differences in cloud cover between detected and undetected fires?
4. Are there differences in size between detected and undetected fires?
5. Are there regional differences in fire detection rates?

Our goal was to provide information that will enhance the interpretation of MODIS fire data in national-level assessments of fire activity, fire risk modeling, disturbance ecology, and biogeochemical cycling.

Methods

Reference fires

We selected reference fire polygons from the U.S. Geological Survey (USGS) / U.S. National Park Service (NPS) Burn Severity Mapping program and the USGS / U.S. Forest Service (USFS) Monitoring Trends in Burn Severity program. These polygons represent fire perimeters of burn scars, manually interpreted from pre and post-fire Landsat images close to the peak of the growing season. The fires mapped by these projects were selected from existing fire databases, such as the federal incident reports. Small fire perimeters exist in the data but mapping priority was given to fires large enough to leave visible scars in Landsat imagery (≥ 202 hectares in the East and ≥ 404 hectares in the West). We selected these fire polygons as reference data because there was little spatial uncertainty in the location of fires, unlike other fire data sources such as the Federal Fire Occurrence Database (Brown et al. 2002).

We only used reference fire perimeters after 2003, the date at which both MODIS Terra and Aqua were operational. Reference data included perimeters of 38 fires from 2003, 31 from 2004, and 16 from 2005 from the NPS / USGS National Burn Severity Mapping project[2] and 276 fires from 2004 from the USGS / USFS Monitoring Trends in Burn Severity project[3]. These were all the fires available through the two burn severity mapping projects at the time this study was performed. The size of reference fires ranged from 18 ha to 48,360 ha (Figure 1.1).

We converted the reference fire polygons to raster images with the same spatial resolution as the MODIS active fire data (1 km). Although MODIS georeferencing errors are reported as being low (approximately 0.1 pixels; Wolfe et al. 2002), we expanded the reference fire perimeters by a 1-km buffer to account for potential georeferencing errors and pixel overlap (Figure 1.2).

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[2] http://burnseverity.cr.usgs.gov/

[3] http://svinetfc4.fs.fed.us/mtbs/index.html

MODIS active fire data

We compared the reference fire data to MODIS Terra and Aqua daily active fire data (MOD14a1 and MYD14a1, Collection 04). MODIS data were acquired from the Land Processes Distributed Active Archive Center[4]. For each day, the MOD14a1 or MYD14a1 files were mosaicked and reprojected to Albers Equal Area with the 1983 North American Datum using the MODIS Land Data Operational Product Evaluation tools[5].

Data analysis

To compare fire detection rates between the two sensors, we determined the proportion of reference fires detected for three different combinations of the MODIS Aqua and Terra active fire products: (1) Aqua only, (2) Terra only, and (3) Aqua and Terra combined. In the combined MODIS data, pixels were flagged as having an active fire if either Aqua or Terra detected a fire. A reference fire was considered detected if it was within 1 km of at least one MODIS active fire pixel from either satellite during the year the reference fire was reported (Figure 1.2). For this analysis, we included all MODIS active fires of low confidence or greater.

We also assessed how many reference fires were detected by the MODIS active fire product when lower confidence MODIS fires were excluded. We used the same three data combinations as in the detection rates between MODIS sensors (Aqua only,

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[4] LPDAAC, http://edcdaac.usgs.gov/modis/dataproducts.asp

[5] LDOPE; http://edcdaac.usgs.gov/landdaac/tools/ldope/

Terra only, and Aqua or Terra). When the Aqua and Terra data were combined, we retained the highest confidence level for detected fires.

To examine the effects of cloud cover on MODIS active fire detection rates, we compared the number of cloudy days between detected and undetected reference fires. The MODIS active fire product implements a simple mask to exclude areas covered by optically thick clouds from processing (Giglio et al. 2003a). Optically thin clouds might also be present but are generally considered to have negligible effects on fire detection and are not identified by the masking algorithm. We assumed that the presence of any cloud pixels within the reference fire perimeters was indicative of cloud or smoke cover that might have obscured fire activity.

For each reference fire, we calculated the number of days with cloud cover between the fire's start date and 14 days after the start date. End dates were not reported for many fires. However, visual examination of the MODIS data showed that most fire activity occurred within two weeks of the reported start date, so we constrained our cloud cover analysis to that time span. We used two-sided t-tests assuming unequal variance to determine whether there was a statistically significant difference in the number of days with cloud cover between detected and undetected fires.

In order to assess the effects of fire size on detection rates, we related reference fire size (x) to the proportion of reference fires not detected by MODIS (P) using a logistic regression with the logit-link function (Agresti 1996).

$P = \frac{e^{\pi}}{1+e^{\pi}}$, where $\pi = \beta_0 + \beta_1 x + \varepsilon$ (Equation 1; β_0 = intercept; β_1 = slope).

We calculated the size at which 50% of the reference fires were not detected as

$x_{50\%} = \beta_0 / \beta_1$ (Equation 2; Agresti 1996).

To make regional comparisons of MODIS active fire detection rates, we subdivided the United States into three areas by grouping Omernik Level 1 ecoregions (Omernik 1987). The West included Omernik's Northwestern Forested Mountains, Marine West Coast Forest, North American Deserts, Mediterranean California, Southern Semi-arid Highlands, and Temperate Sierras. The East included Omernik's Northern Forests, Eastern Temperate Forests, and Tropical Wet Forests. The Great Plains was composed solely of Omernik's Great Plains ecoregion. Within each region, we calculated the proportion of reference fires detected by each sensor individually and combined.

Results

When active fire data from both MODIS satellites were combined, 82% of the reference fires were detected. The combined detection rate was greater than when either of the MODIS sensors were considered individually (73% for Aqua and 66% for Terra). Excluding low-confidence MODIS active fire detections had little effect on detection rates, decreasing the total number of fires detected by 1 for Aqua and 2 for Terra. However, excluding nominal-confidence MODIS active fire detections had a greater effect, decreasing the number of fires detected by 12% and 14% for Aqua and Terra respectively.

The number of cloudy days during the first two weeks of fire activity was generally low, but reference fires not detected by MODIS had more cloudy days (Table 1.1). The difference was statistically significant (p-values < 0.05) for the combined MODIS Aqua and Terra data when all fires across the U.S. were considered, as well as in the East and in the West. When Aqua and Terra were treated individually, the pattern of more cloudy days for undetected fires persisted, but was only significant when all fires across the U.S. were considered. At regional levels (East, Great Plains, and West), cloud cover effects on Aqua or Terra fire detections were most pronounced in the East.

There were significant differences in the size of fires detected and undetected by MODIS for Terra and Aqua. The smallest reference fire detected by Aqua was 17.6 ha versus 27.8 ha for Terra. Mean fire sizes of detections were 915 and 1,044 ha for Aqua and Terra respectively, while mean fire sizes of non-detections were 364 and 346 ha for Aqua and Terra. The largest fire not detected by Aqua was 2,638 ha and 2,484 for Terra.

The proportion of reference fires detected increased with reference fire size (Figure 1.3, Table 1.2). The models including both Aqua and Terra sensors and the model based on Aqua alone generally exhibited greater detection rates relative to fire size than the model based on Terra alone. This is demonstrated by the threshold at which > 50% of fires were detected: 105 ha (combined Aqua and Terra), 195 ha (Aqua only), and 334 ha (Terra only).

MODIS fire detection rates also varied regionally across the United States (Figure 1.4). When the Aqua and Terra sensors were combined, overall detection rates were greatest in the West (89%), slightly lower in the Great Plains (80%), and lowest in the East (60%). When the sensors were considered individually, Aqua and Terra performed equally well in the West, where both sensors detected 81% of the reference fires. However, we found different detection rates between sensors in the Great Plains, where detection rates were 69% for Aqua and 60% for Terra, and in the East where detection rates were 58% for Aqua and 39% for Terra (Figure 1.5).

Discussion

Overall, we found that the MODIS active fire products detected the majority of our reference fires. Detection rates were greatest when the active fire product data from both MODIS Aqua and Terra were used together, and individually Aqua outperformed Terra. The difference in the detection rates between the two MODIS sensors is most likely related to their overpass timing. Fire activity follows a diurnal cycle, often peaking in the afternoon, when weather conditions are most favorable for burning (Prins et al. 1998, Giglio 2007). Aqua's early afternoon (13:30) overpass is closest to this peak and is the most likely reason for Aqua's higher detection rates. The daily data for Terra did detect a small number of fires not found by Aqua, about 9% of 361 total fires. These additional fires represent early morning or late evening fires that were not active at Aqua's overpass times (1:30 and 13:30). Unless there is specific interest in diurnal variability in fire activity, we recommend combining the Aqua and Terra active fire observations to obtain the greatest detection rates.

Almost no additional reference fires were detected when low confidence MODIS active fire pixels were included in the analysis. Low-confidence fire pixels tended to occur at the periphery of clusters of high and nominal confidence active fire pixels, and these reference fires would have been detected by the nominal and high confidence active fire pixels alone. Including low-confidence fire pixels might be desirable for other applications such as mapping clusters of fire activity (Loboda and Csiszar 2007) or approximating burned area (Giglio et al. 2006b); however, low-confidence fire pixels did not improve detection rates for our analysis of large fires.

Clouds are a confounding factor affecting estimates of fire activity by reducing satellite fire detection rates (Flannigan and Vonder Haar 1986). We observed a significantly greater number of days with cloud cover for undetected reference fires. This pattern was strongest in the Eastern U.S., where the spring and fall fire seasons may coincide with higher cloud cover. However, in most cases the difference in the number of cloudy days was small. We had little information on when and where fires were active within our reference fire perimeters. Because of this, we assumed the presence of at least one MODIS cloud pixel within the reference fire perimeter represented clouds or smoke that could obscure fire activity. This assumption might have overestimated the influence of clouds on MODIS detection rates. However, cloud cover is clearly an important factor affecting MODIS detection rates and satellite fire detections will underestimate true fire activity in regions with persistent cloud cover.

MODIS active fire detection rates decreased as the size of reference fires decreased. There are several reasons why this might have occurred. First, the duration a fire burns might decline with total fire size. Shorter duration fires have fewer chances of being detected at MODIS overpass. It was not possible to test this because of the limited temporal information associated with our reference fires; however our reference fires were typically large fires that likely burned for multiple days. Another possible explanation for the decline in detection rate with fire size is that small reference fires lacked the energy output needed to trigger the thresholds of the MODIS active fire product algorithms (Giglio et al. 2003a). For instance, a small surface fire burning leaf litter under a deciduous forest canopy might not have generated temperatures high enough for MODIS detection.

Even though detection rates increased with fire size, the MODIS active fire products failed to detect two large fires (>2,000 ha, Figure 1.4). One of these was a shrub fire in west-central Washington and the other was a grassland fire in southern Florida. The number of days with cloud cover for both fires was between 3 and 4, but there were no days where the view of both satellites was entirely obscured by clouds. Fires in flashy fuels such as shrubs and grasses can burn rapidly and often lack large fuels that would continue to burn after the fire front has passed. It is possible that these two large fires, and other reference fires, were not detected by the MODIS active fire products because they had rapidly moving flaming fronts that were extinguished before, and left little residual heat at MODIS overpass time. This is a plausible explanation, but to fully address this question, detailed information about the location of the fire front at the time of MODIS overpass would be needed. Unfortunately, this information was not available and we were not able to perform such an analysis.

Across the United States, MODIS active fire detection rates were lowest in the East and greatest in the West. Fire sizes tended to be smaller in the East than in the Great Plains and West (Figure 1.5). However, we believe the different detection rates were primarily caused by differences in forest types, landscape pattern, fuel loadings, and fire behavior. The majority of fires in the Great Plains and eastern U.S. occurred in grasslands and deciduous forests that typically experience surface fires. Fuels in these ecosystems experience limited post-frontal combustion and if fires are not active during MODIS overpass there will be little chance of detection. In contrast, many forests in the Western U.S. are coniferous and experience a variety of fire behavior including intense crown fires (Agee 1993). Heavy fuels in western fires may continue to combust after the fire front has passed. The increased energy output of active western fires and their remaining residual heat makes them more likely to be detected by the MODIS active fire products.

Most of our reference fires occurred on state and federal lands. As a consequence, our results may not be valid for substantially different vegetation types and fuel loadings. For instance, agricultural lands in the United States experience frequent fire activity that is clearly visible in the MODIS imagery (Korontzi et al. 2006, McCarty et al. 2007). Fuel loadings in forests and grasslands are quite different than those found in agricultural fields where fires tend to be small and short in duration (McCarty et al.

2007). Hence, we would expect detection rates for agricultural fires to be slightly less than those we observed for wildland fires.

If all fire activity is considered, there are many small fires (<1 ha; Brown et al. 2002). However, our reference fires were burn scars mapped from Landsat imagery. Using these data limited our analysis to fires that were large enough to make a visible burn scar in 30 m Landsat imagery; the smallest reference fire we included was 18 ha. Data for small fires, 1 ha or less, with the necessary spatial accuracy were not available for analysis. For that reason, our results tell us little about MODIS active fire detection rates for such small fires. However, given that the size threshold at which 50% of the reference fires were detected was 105 ha, we believe it is safe to assume that most small fires remain undetected by the MODIS active fire products.

How can we improve efforts to monitor global fire activity in the future? Our results highlighted that the size detection threshold above which fires on the ground are likely detected by the MODIS active fire product is fairly large (105 ha). However, these results are specific to the United States and differed depending on ecoregion. More studies in other biomes are needed to understand the spatial variability of the detection threshold and field-based studies on errors of commission are needed to interpret the MODIS active fire data fully. The primary limitation of the fire detection capabilities of the MODIS sensors appears to be the temporal gaps between satellite overpasses. During these gaps, it is not possible to monitor small fires or rapidly burning fires that extinguish before the next overpass. More frequent observations offered by geostationary systems, i.e., GOES (Prins et al., 1998; Prins & Menzel, 1992) and multi-sensor approaches (Eva and Lambin 1998b, Giglio 2007) offer promise to fill the gaps between MODIS overpasses and provide a more comprehensive record of fire occurrence.

Small and low intensity fires are less likely to be detected by the MODIS active fire products. Increased sensor resolution might help to detect small, low temperature fires, but simulations and ASTER validation studies suggest that these fires are quite visible if active during MODIS overpass (Giglio et al. 1999, Giglio et al. 2003a, Morisette et al. 2005a, Morisette et al. 2005b, Csiszar et al. 2006). Detection is heavily dependent on fire intensity, which varies with fuel loads, moisture levels, and weather; regional fire detection algorithms, tuned to local variability in fuels and fire behavior might offer greater fire detection than global algorithms (Loboda et al. 2007, Wang et al. 2007).

Our results have consequences for the use of the MODIS active fire product in fire management. Fire fighting is most effective when fires are detected before they become large, but the MODIS active fire products may be of limited value as an early-warning system because small fires are often undetected. The use of MODIS active fire data to differentiate burn scars from other disturbances may be questionable, because small fires are less likely to have an active fire detect, and burned area estimates would be downwardly biased. The accuracy of the MODIS active fire product also has consequences for estimating the effects of fires. For instance, wildfire aerosol and trace gas emission estimates relying on the MODIS active fire data (Kaufman et al. 2003) may be low because not all fires are included. However, since the undetected fires are likely to be small, they should have a relatively small effect on total emissions. The active fire data are quite useful for tracking large fires and since large fires account for the majority of area burned, the MODIS active fire products should be useful to quantify relative differences in fire activity among regions with similar biophysical characteristics. In summary, the MODIS active fire product provides important data for fire management, but the interpretation of the data needs to take the detection size threshold into account to avoid false conclusions.

Conclusions

MODIS active fire products provide a valuable source of data about fire activity that capture spatial and temporal patterns not represented in other fire data. Based on our analysis, overall detection rates of fires by the MODIS active fire products were high (82%) when data from both the Aqua and Terra sensors were combined. However, small fires were less likely to be detected than large fires. MODIS fire detection rates varied across the country, being greatest in the West and lowest in the East. We suggest that the MODIS active fire data are appropriate for applications where relatively large and intense fires are of primary interest. We recommend that users of the MODIS active fire data perform an individual quality assessment to ensure that fires relevant to their application are represented.

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Table 1.1. Mean number of cloudy days for reference fires that were detected and undetected by the MODIS active fire products. P-values indicate significance for two-sided t-test of difference in mean number of cloudy days assuming equal variance.

		Entire US	East	Great Plains	West
	Degrees of freedom	359	109	63	183
Combined	Detected	0.45	0.75	0.81	0.21
	Undetected	1.20	1.42	1.15	0.75
	p-value	< 0.0001	0.0032	0.2996	0.0006
Aqua	Detected	3.14	3.68	4.62	2.49
	Undetected	4.08	4.65	4.65	2.87
	p-value	0.0036	0.0645	0.9666	0.4430
Terra	Detected	2.88	3.36	4.59	2.31
	Undetected	4.00	4.21	4.69	2.97
	p-value	0.0001	0.0883	0.8754	0.1749

Table 1.2. Logistic regression parameters, standard errors and z and p-values for proportion of references fires that were not detected by the MODIS active fire products from 2003 to 2005. β_0 = Intercept, β_1 = Slope, sample size = 361 fires.

	Coefficient	Estimate	Standard error	z-value	*p*-value
Aqua or Terra combined	β_0	13.0267	3.1901	4.083	< 0.0001
	β_1	-0.9379	0.2094	-4.478	< 0.0001
Aqua	β_0	12.2055	2.7944	4.368	< 0.0001
	β_1	-0.8433	0.1819	-4.637	< 0.0001
Terra	β_0	13.8224	2.7396	5.045	< 0.0001
	β_1	-0.922	0.1775	-5.196	< 0.0001

Figure 1.1. Histogram of the fire size distribution of the reference fires used for comparison with the MODIS active fire products. X-axis increments follow a log scale.

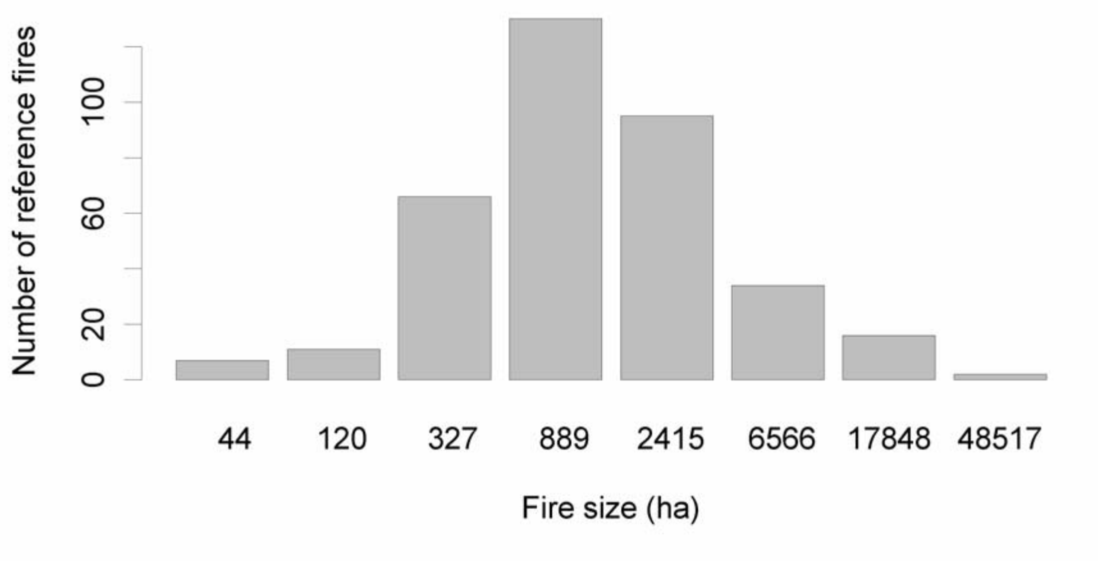


Figure 1.2. Example of fire comparison methods used to determine MODIS active fire detection rates. Data are shown for the Balcony House Fire in Wyoming, 2003. Reported start date was Julian date 196 (July 15). Reported stop date was Julian date 221 (August 9); however, no MODIS fire pixels occurred within the perimeter after Julian day 197 (July 16).

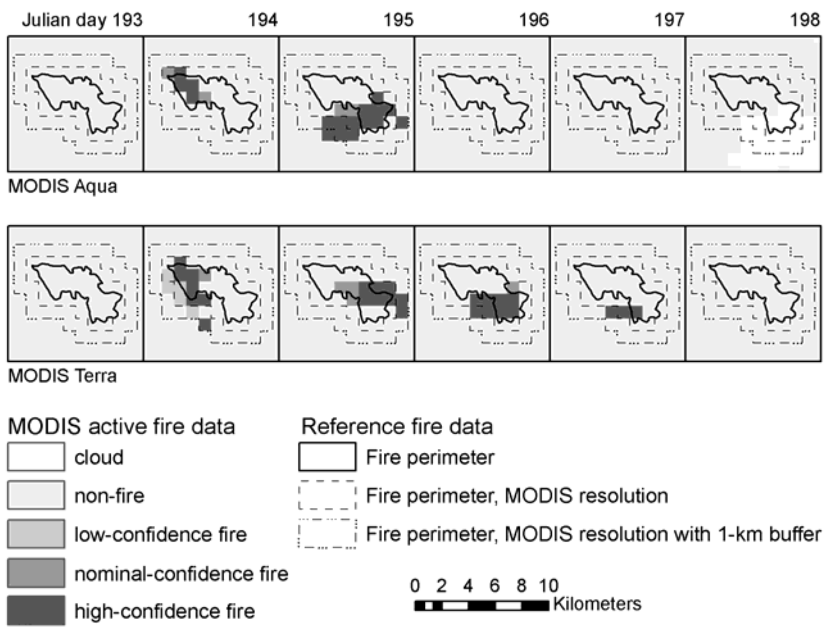


Figure 1.3. MODIS active fire product detection status in relation to reference fire size for (a) Aqua or Terra combined, (b) Aqua only, and (c) Terra only. X-axis increments follow a log scale. Black lines show the fitted logistic regression curve for the proportion of fires not being detected by MODIS against log(fire size).

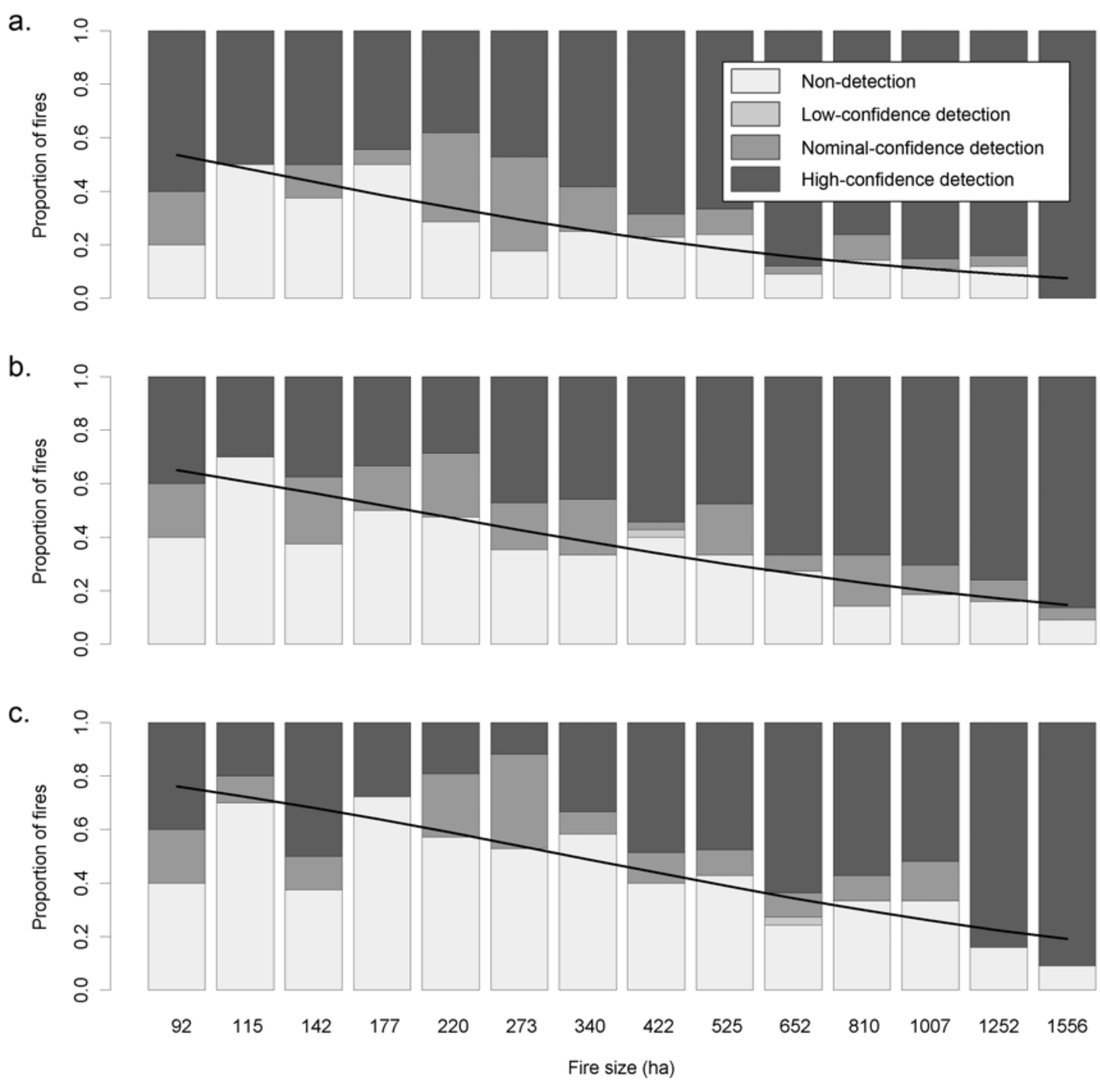


Figure 1.4. Geographic distribution of reference fires detected and not detected by the MODIS active fire product between 2003 and 2005. Total number of reference fires was 361.

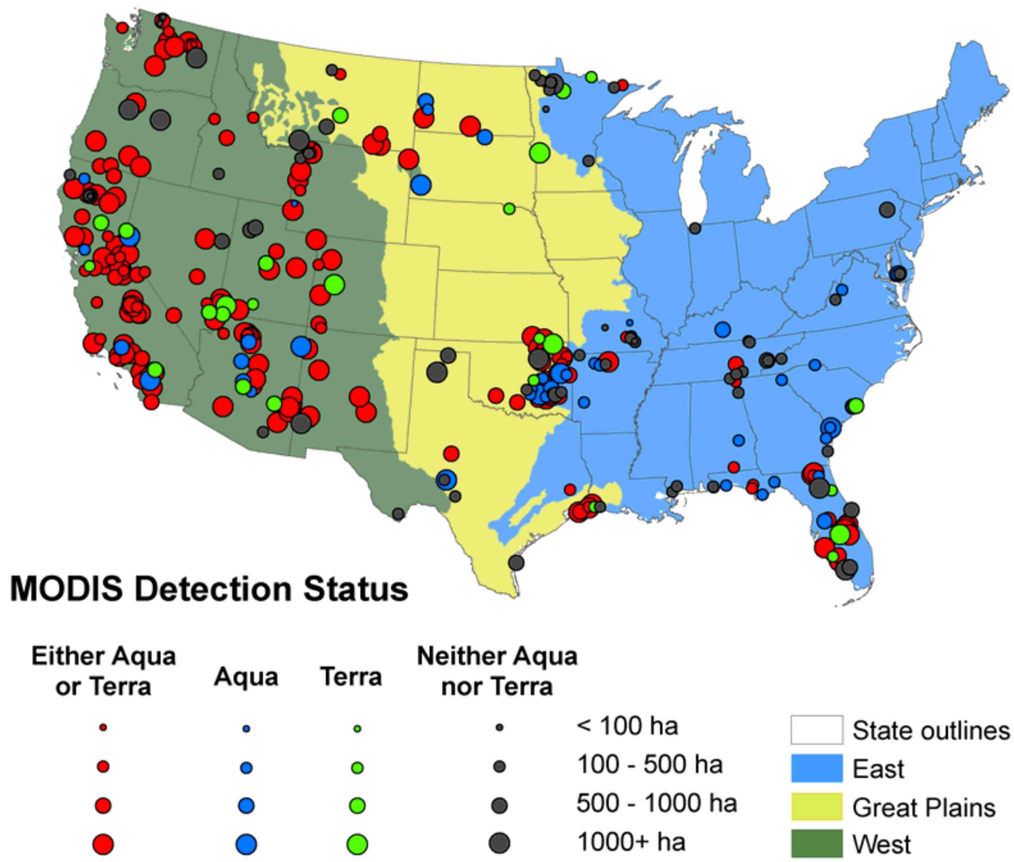
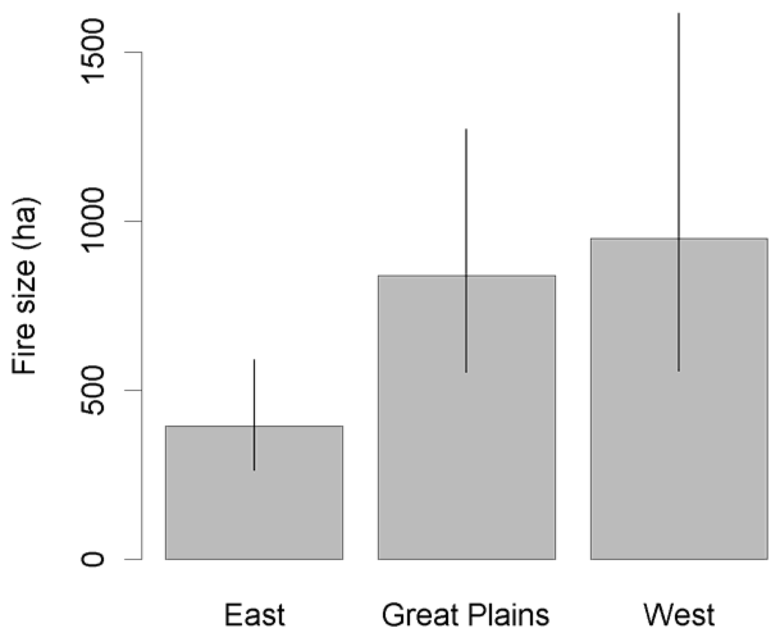


Figure 1.5. Mean size of reference fires among regions of the U.S. Error bars show ± 95% confidence levels. Fires were significantly smaller in the East compared to the U.S. (ANOVA difference of means p-value < 0.0001).



Chapter 2: Patterns of fire occurrence among land cover and property types of the United States

Abstract

Understanding the geography of fire is important for determining the ecological effects of fire disturbances, assessing risk, and prioritizing funds for fire management. Basic questions regarding the geographic distribution of fire in the United States remain largely unanswered, especially beyond the boundaries of public lands. Our objective was to quantify where fires occurred and where houses were in close proximity to fires across the United States. We used active fire observations collected between 2003 and 2006 from the Moderate Resolution Imaging Spectroradiometer (MODIS) satellite sensors with 1 km resolution. First, we compared fire occurrence among four property types (wildland-urban interface, federal lands, wilderness areas, and all other lands) and 8 land-cover categories (developed, agriculture, wetlands, grasslands, shrublands, and evergreen, deciduous, and mixed forests). Second, we identified spatially and temporally contiguous clusters of MODIS active fire pixels and examined how the number of MODIS fires and houses in MODIS fires varied relative to the size of MODIS fire clusters. On average, MODIS fires were observed for 1.24% of the U.S. per year and over 1 million houses were located in MODIS fires. Approximately 6% of all MODIS fires occurred in the wildland-urban interface (WUI) and 23% on federal lands. Fifty eight percent of all

shrubland and evergreen forest MODIS fires were in the West compared to 38% in the East, but the number houses in those fires was less in the West than in the East (28,100 vs. 37,300). Among ecoregions, the Southeastern U.S. and Mediterranean California had the greatest number of houses in shrubland and evergreen forest MODIS fires. Small fires predominated in the WUI and more than 50% of all the WUI fire pixels were found in fire clusters 4 pixels or less in size. Approximately 80% of all WUI houses in MODIS fires were found in clusters less than 12 pixels in size. However, in Mediterranean California, more than 50% of the WUI houses in MODIS fires were contained in 11 large fire clusters, each spanning more than 200 pixels. Our results highlight the regional variability in fire occurrence across property and land cover types and the different challenges they present to fire management. Recognizing these differences can be important when promoting the ecological benefits of fire while limiting its undesirable effects.

Introduction

Limiting fire risk to a growing number of houses in the wildland-urban interface and determining where fires should be allowed to burn in wildlands are primary questions in the debate about the role of fire in the U.S. The questions are not trivial; however, basic information is lacking about what proportion of the U.S. burns, where it burns, and how many houses are exposed to fire. Without such information, comparisons of where fires are most likely to occur, where houses are most at risk, and where fire use is feasible are difficult to address. Thus, because fires have ecological, social, and economic importance, a greater understanding of the patterns of fire occurrence at the national-scale is needed (Noss et al. 2006, U.S. Department of Agriculture 2006). In this paper we quantified the location and extent of fire in the U.S. among property types and vegetation categories at multiple scales and identified areas where houses were most exposed to fires.

Federal fire suppression expenditures have steadily increased, exceeding $1 billion in four of the seven years between 2000 and 2006 (U.S. Department of Agriculture 2006). As suppression costs have risen, so has the annual area burned (NIFC 2008) and escalating costs are in part related to increases in burned area (Calkin et al. 2005). However, the increasing expense of fire suppression has also been attributed to the large and growing number of houses in the wildland-urban interface (WUI), which is the zone where houses and wildland vegetation intermingle (U. S. Department of Agriculture and U. S. Department of Interior 2001). Nearly 39% of all houses in the U.S. were located in the WUI in 2000 (Radeloff et al. 2005) and housing growth rates in the WUI are considerably higher than in non-WUI areas (Hammer et al. 2007).

The opportunities to realize the ecological benefits of fires are becoming increasingly limited as development expands into the surrounding wildlands (Noss et al. 2006). People have an antagonistic relationship with fire, typically increasing fire ignitions but also decreasing the area burned through suppression efforts (Cardille et al. 2001, Syphard et al. 2007b). Many plant communities are adapted to and maintained by periodic fire disturbance (Keeley et a. 1998; Bond and Keeley 2005). Human-driven changes in fire regimes, whether caused by suppression or increased ignitions, can push ecosystems outside their historic range of variability and can cause shifts in species composition and ecosystem structure and function (Keeley et al. 1999, Lorimer and White 2003, Franklin et al. 2005, Syphard et al. 2006, Syphard et al. 2007a). Maintaining fire disturbance within the historic range of variability may be critical for the protection of many fire adapted ecosystems and that puts many conservation goals at odds with risk-reducing fire suppression and management activities.

The balance between managing the risks and the benefits of fire depend to a large extent on the property type and the landscape surrounding the property. Wilderness Areas are recognized as "an area where the earth and its community are untrammeled by man" (Wilderness Act of 1964) and lightning fires may be allowed to burn under certain conditions (USDA-USDI 2000). Wildland fire use (WFU) is increasing in both Wilderness Areas and other federal lands, but in practice, less than 30% of Wilderness Areas in the U.S. have a 'let burn' or WFU policy explicitly stated in their management plans and most natural fires are still extinguished (Miller 2006). In contrast, fire suppression efforts and fuel treatments are focused in the WUI and at the boundary of public and private lands to protect human life and property (Healthy Forests Restoration Act of 2003). Because of these different fire management objectives, there is a gradient of decreasing ecological benefit and increasing risk of fire moving from Wilderness Areas to the WUI.

The patterns of fire occurrence in different property types along the wilderness to WUI gradient is largely unknown and even less is known about where houses are in close proximity to fires. Such information is important because fire management is often focused on public lands but most houses and structures at risk from fire are on private lands in the WUI (Radeloff et al. 2005, Theobald and Romme 2007). Quantifying fire occurrence along the wilderness to WUI gradient could help to determine whether or not fire management goals and efforts are being focused in the most appropriate places.

In addition to property types, a variety of other variables can influence fire occurrence. Humans play a large role in fire ignition patterns, but total area burned typically has a stronger relationship with biophysical variables (Cardille et al. 2001, Syphard et al. 2007b). Among these variables are the three sides of the classic fire environment triangle: weather, fuels, and topography, which interact in complex ways to determine when and where fires occur and spread (Pyne et al. 1996). Fuels alone can be good indicators of potential fire behavior over long time periods and many fire risk assessments are based primarily on current or historic fuel type (Schmidt et al. 2002, Haight et al. 2004, Theobald and Romme 2007). Specifically shrublands and coniferous forests are important because these vegetation types are prone to intense crown fires under severe weather conditions (Agee 1993, Turner and Romme 1994, Keeley et al. 1999). Thus, in addition to quantifying fire occurrence among property types, including vegetation type can provide additional information about the expected intensity of fires and risks to society.

Fires can vary greatly in their frequency, size, and intensity. Small fires are most common; however, large fires present the most series challenges to fire managers because they are difficult to control and account for a disproportionate amount of burned area and economic damage (Strauss et al. 1989, Kasischke et al. 2002, Finney 2005). Because size is a good proxy measure for the management challenges presented by fires, it can provide additional information about the ecological and social significance of fires.

Vegetation type influences fire occurrence at local scales, but broad-scale variability in weather, climate, and culture can also matter (Pyne 1982, Swetnam and Betancourt 1990, Veblen et al. 2000, Rollins et al. 2002). Ecoregional boundaries are based largely on climate, soils, and vegetation gradients and could be useful for examining fire occurrence patterns at different spatial extents while controlling for broad-scale variability in the drivers of fire occurrence (Omernik 1987, Bailey et al. 1994). Multi-scale analyses of fire occurrence are important because policies are provided at a national scale, but how these policies are implemented locally varies depending on regional social and environmental context.

Poor fire data may limit national-scale analyses of fire occurrence. The federal fire occurrence database provides much information about fires on public lands. However, the federal fire data have questionable spatial accuracy, are often aggregated to the county-level, and fires outside of public lands may not always be included (Brown et al. 2002, Schmidt et al. 2002). Furthermore, the federal data typically include only point locations, not the entire fire perimeter, although efforts are underway to remedy this situation (i.e., the National Trends in Burn Severity Mapping program), it will be some time before they are complete.

In comparison to the federal fire occurrence database, satellite fire detections are useful for national-scale analyses because they span all ownerships and property types, can monitor the extent of fire activity (not just point locations), and have more consistent spatial detail. Several studies of fire occurrence have analyzed satellite fire observations across broad regions (Li et al. 1997, Giglio et al. 2003b, Pu et al. 2007) and the entire globe (Dwyer et al. 2000, Csiszar et al. 2005, Giglio et al. 2006a). Those studies demonstrated the ability of satellite fire detections to track important spatial and temporal patterns of fire. However, no study explicitly examined fire patterns across vegetation and property types, and the range of spatial scales relevant for fire management in the U.S.

Our objective was to determine the location of fires and their potential impacts to human communities. We addressed the direct impacts of fire on human communities and ecosystems by asking first "*what is burning where in the U.S.?"* and second, *"where are houses near fires in the U.S.?"* Our third and fourth research questions addressed management challenges posed by large fires and asked *"where are large fires and where do houses and large fires coincide?"*

Methods

When wildfires threaten communities, priority is given to protecting lives, homes, and other structures. We focused our analysis on homes because they are stationary (while people are evacuated), information on the number and approximate location of housing units are readily available, and housing units serve as a proxy measure of population.

Last but not least, the number of structures protected and lost is often considered used as a measure of fire fighting effectiveness.

Fire management decisions are made at a variety of scales but national-level analyses are particularly valuable for policy decisions. Most categorical data analyses quantify data as a proportion calculated for each group i.e., the proportion of fire pixels to forest pixels. We took a different approach, because we wished to quantify the total not relative impact of fires. Hence, we quantified the number of fires and houses in fires for the contiguous 48 states of the U.S.

MODIS Active Fire Detections

We used active fire observations collected by the MODIS sensors onboard the NASA Earth Observing System Aqua and Terra satellites (Justice et al. 2002b, Giglio et al. 2003a). These data are categorical and represent fires that were actively flaming at the time of satellite overpass, 1:30 and 13:30 for Aqua and 10:30 and 22:30 for Terra (Justice et al. 2002a). We restricted our analysis to the years for which both the Aqua and Terra data were complete, 2003 – 2006 (Figure 2.1). We combined the Terra and Aqua data and classified pixels as a “MODIS fire” if either sensor had detected a fire within any given year. The MODIS fires are assigned one of three categories depending on fire detection confidence. We retained high- and nominal-confidence fire detections but excluded low-confidence fire detections to avoid false positives and limit the analysis to fires intense enough to generate a thermal signature visible from space (Giglio et al. 2003a).

For the sake of simplicity, we refer to the MODIS active fire observations as MODIS fires throughout this paper. However, we urge readers to use caution when interpreting our results. The MODIS fires do not necessarily imply that the entire 1 km^2 pixel burned, only that there was fire activity somewhere within the pixel.

Property types

Polygon data for the WUI, federal lands, and Wilderness Areas were provided by the authors (Radeloff et al. 2005) and downloaded from the National Atlas[6] and converted to raster data with 1-km resolution. Commonly used polygon to grid conversion algorithms assign pixels the value of the polygon overlapping the pixel center. Our property type classification assigned each pixel a categorical value depending on which property types it intersected. Pixels were assigned only one property type and labeling priority was given to WUI first, federal land second, then wilderness (Figure 2.2a). If a pixel did not overlap any of those three property types, it was assigned to the 'other' category. With this methodology, pixels labeled as federal lands or wilderness were not necessarily entirely in federal ownership or designated Wilderness Areas, but contained some portion of those property types. Furthermore the 'other' category does not imply private land ownership and may have included land in state and county ownership. We refer to these data as property types because they reflect differences in both land ownership and management.

[6] www.nationalatlas.gov

Housing units

The WUI data are based in part on a housing density criteria, thus the data also included housing information (Radeloff et al. 2005, Stewart et al. 2007). Using these data, we quantified the number of housing units within each 1-km pixel for the entire U.S. by rasterizing the 2000 Census Data polygons using area-proportional allocation (Figure 2.2b). In the Census data, a housing unit is not necessarily an individual house, but could also be a duplex, apartment building, or other multi-unit dwelling that the Census Bureau classified as a housing unit.

Land cover

We expected variability in fire occurrence among different land cover types and we accounted for this variability using land cover data from the 2001 Multiple Resolution National Land Cover Database[7] (NLCD; Homer et al. 2004). The NLCD data were derived from Landsat imagery and have 30 meter resolution. We grouped NLCD classes to simplify the number of land cover types in the analysis and combined the 4 developed categories (developed - open space; developed - low intensity; developed - medium intensity; and developed - high intensity) into a single developed class. We also grouped the four woody wetland and four emergent herbaceous wetland NLCD classes into a single wetland category. NLCD pasture/hay and cultivated agriculture were combined into a single agriculture class. We grouped the open water, permanent snow/ice, and

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[7] http://www.mrlc.gov/mrlc2k_nlcd.asp

barren because they represented a very small fraction of pixels in the contiguous 48 states of the U.S. All other NLCD classes were retained. In total, we included eight land cover categories: developed, agriculture, wetland, grassland, shrubland, evergreen forest, deciduous forest, and mixed forest (Figure 2.2c). Finally, we aggregated the reclassified 30-m NLCD data to 1-km resolution using a majority rule.

Ecoregions

We used three scales of analysis to compare regional patterns of fire occurrence. The first scale examined national patterns of fire occurrence in the conterminous U.S. as a whole. The second scale we examined divided the conterminous U.S. into three broad geographic regions: the East, the Great Plains, and the West (Figure 2.2d). Our third scale of analysis was based on the 21 Omernik level II ecoregions (Figure 2.2d). At this scale the effects of climate, soils, and vegetation were assumed to be more homogenous within the ecoregion than among ecoregions (Omernik 1987).

Questions 1 and 2: What is burning where and where are houses near fires?

To answer our first question, we compared the average number of MODIS fires among property and land cover types for each year between 2003 and 2006. These quantities were intended to determine which property and land cover types experienced the most and least amount of fire activity. For reference, we also calculated the total number of MODIS pixels (fires and non-fires) for each vegetation and land cover type in the conterminous U.S. Thus, our results always summed across property types and land cover categories to equal the total number of MODIS pixels and MODIS fires in the U.S. (9,110,100 and 113,400 respectively).

We used a similar method to answer our second question, but summed the number of housing units in MODIS fires according to property and land cover types. We compared the total number of housing units in all MODIS pixels (115,183,100 housing units) and MODIS fire pixels (1,017,800 housing units) across the conterminous U.S. for each group. Because of the resolution of the MODIS fire data, it was impossible to know exactly how many housing units were directly affected by fires because fire activity could have occurred anywhere within the 1 km^2 MODIS pixels. Thus, our results should be interpreted as a relative comparison of where housing units were in close proximity to fires among property and land cover types.

We made comparisons among all land cover and property types at the national scale. At the regional scale, we also compared the number of MODIS fires and housing units in MODIS fires among shrublands and deciduous and evergreen forests. Among these three land cover types, shrublands and evergreen forests are most relevant to fire management because they are the vegetation types most likely to experience uncontrollable, high-intensity, stand-replacing fires (Agee 1993, Pyne et al. 1996). Finally, we compared the number of MODIS fires and housing units in MODIS fires by ecoregion, relative to U.S. totals. These comparisons were made first across all land covers and then in shrublands and evergreen forests.

Questions 3 and 4: Where are large fires and where are houses in large fires?

Large fires were visible as distinctive clusters of connected MODIS active fire pixels. To determine the variation of fire cluster size across the country, we developed an algorithm that identified individual fire clusters by tracking the spatial and temporal spread of MODIS active fires. Previous studies have used a similar approach with AVHRR (Chuvieco and Martin 1994) and MODIS active fire data (Loboda and Csiszar 2007). Our algorithm was based on user-specified distances defining the amount of spatial and temporal overlap required to label pixels as part of a contiguous fire cluster. Through visual comparison with known fire perimeters, we found that one pixel spatial and one day temporal overlap identified fire clusters while keeping different fire events separate.

We examined the cumulative proportion of MODIS fires in relation to the size of fire clusters that contained each MODIS fire pixel. We first compared the cumulative proportion of MODIS fires in relation to fire cluster size among property types at the national scale and then at the Omernik level 2 ecoregion scale. For these two analyses, we did not stratify among land cover types due to land cover heterogeneity within fire clusters.

Results

On average, 1.2% or 113,400 of the 9,110,100 MODIS pixels spanning the conterminous U.S. contained an active fire each year from 2003 to 2006. The number of MODIS fires in the U.S. varied among years, with 2006 having the most fires (128,600 pixels) and 2004 the least (90,500 pixels). The majority of fires occurred in the ‘other’ property type (on average 80,500 pixels in the U.S. or 71.0% of all fires). Federal lands had the second highest amount of fire activity with an average of 20,400 MODIS fires per year. The WUI and Wilderness Areas had the lowest number of fire activity (7,200 and 5,300 MODIS fires respectively) and less variability among years (Table 2.1). Differences in fire activity across property types were generally consistent over the four years we analyzed.

Distribution of MODIS fires

Anthropogenic land cover types (developed and agriculture) contained an average of 37,200 active fire pixels per year between 2003 and 2006; this represented 33% of all MODIS fires, but only 0.41% of the entire U.S. Almost all MODIS fires in anthropogenic land cover were located in the 'other' property type (Table 2.2). Grassland and wetland fires accounted for 22,100 MODIS fire pixels and were also mainly in the 'other' property type.

The average number of MODIS fires in shrubland pixels was 15,700, or 14% of all active fires per year. A few of these fires were located in the Great Plains and East and most of those were outside federal lands and the WUI (Table 2.2). The majority of shrubland fires, however, were in federal lands and the 'other' property type (approximately 5.5% and 6.5% of all fires respectively) and most of those were in the West. Only 0.7% of western shrubland pixels experienced MODIS fires even though the total shrubland area was extensive (1,636,900 pixels). In the East, the percent of fires in shrublands was relatively greater than in the West (3.3%) even though the total area in was small (only 48,900 pixels).

MODIS fires in pixels classified as forest were nearly as common as MODIS fires in anthropogenic land covers (33.2% of all fires; Table 2.2). MODIS fires in forest pixels were primarily in the ‘other’ and federal property types (18.2% and 9.9% of all MODIS fires in the U.S.) while only 2.4% of all MODIS fires were in both forest and the WUI. There were more eastern than western forests (16.7% vs. 9.7% of all pixels respectively), and only a few in the Great Plains (1.3% of all pixels). Similarly, there were more active fires in eastern than western forests (17.6% and 12.7% of all MODIS fires respectively) and very few fires in the forests of the Great Plains (2.9% of all MODIS fires). Forests and fire activity in the eastern U.S. were primarily outside of federal lands and in the WUI property type, while in the West, federal lands and wilderness accounted for the greatest number of forest pixels and active fires.

We also examined fire occurrence among different forest types. In the West, evergreen forests were more common than deciduous forests and accounted for a much greater area than the East (9.0% vs. 4.1% of the U.S.; Table 2.2). However, fire occurrence was only slightly greater in western than eastern evergreen forests (12.3% of all MODIS fires for the West vs. 10.9% of all MODIS fires for the East).

Distribution of housing units in MODIS fires

On average between 2003 and 2006, there were 1,017,800 housing units in MODIS fires each year. That represents less than 1% of the 115,183,100 housing units in the conterminous U.S. The majority of housing units and housing units in MODIS fires occurred in developed areas (81,004,000 and 730,500 respectively; Table 2.3). Most of these housing units were in the WUI and 'other' property types. The agriculture land cover pixels contained the next highest number of housing units in MODIS fires (117,700); this category also contained the second highest number of all housing units (13,181,300). Wetlands, grasslands, and mixed forests had the lowest percents of all housing units in the U.S. (1.8%, 1.4%, and 0.6% respectively) and represented the lowest numbers of housing units in MODIS fires (25,800; 20,300; and 4,000 respectively). Shrublands contained 1,932,300 of all U.S. housing units, but only 24,600 housing units were in shrublands with MODIS fires (17,300 of those housing units were in the West and 4,600 were in the East).

After the developed and agriculture land covers, deciduous and evergreen forests contained the third and fourth highest percentage of all housing units in the U.S. (8.3 and 2.4% respectively). A greater number of housing units were found in eastern forests compared to western forests (11.6 million vs. 1.0 million houses respectively). MODIS fires in eastern forests also contained a greater number of housing units than in western forests (70,900 vs. 11,400 houses respectively). When only housing units in evergreen forests were considered, 0.75% of all housing units were in western evergreen forests and 1.55% of all housing units were in eastern evergreen forests. From 2003 to 2006, the average number housing units that were in evergreen forests with fires was 32,700 per year (0.03% of all housing units) in the East and 10,800 per year (0.01% of all housing units) in the West. These housing units were predominantly in the WUI in the West and split between the WUI and 'other' property types in the East.

Ecoregion patterns of MODIS fires and housing units in MODIS fires

The ecoregions that contained the largest number of MODIS fires were the Southeastern Plains, South Central Semi-Arid Prairies, and Mississippi Alluvial and Southeast Coastal Plain (Figure 2.3a). These three were followed by the Western Cordillera, the Western Interior Basins and Ranges, and the Temperate Prairies. Ecoregions in the northeastern U.S. and the extreme southwestern U.S. contained the lowest number of MODIS fires.

Ecoregions with the greatest proportion of the nation's housing units in MODIS fires included the Southeastern Plains, Mississippi Alluvial and Southeast Coastal Plain, and the Ozark, Ouachita-Appalachian Forests (Figure 2.3b). These regions were closely followed by Mediterranean California, the Mixed Wood Plains, and the Central Plains. Because of the large number of agricultural and grassland fires, the Great Plains also stood out, whereas the Western Cordillera and Marine West Coast forests contained a relatively small number of housing units in MODIS fires.

We also examined which ecoregions had the greatest amount of land cover types with potential for high-severity fires, i.e., shrublands and evergreen forests. Ecoregions in the western U.S. contained the majority of these land cover types (Figure 2.3c). However, the number of housing units that were in these land cover types in western ecoregions was generally small. The top three ecoregions containing the greatest number of housing units in shrublands and evergreen forests were the Southeastern Plains, the

Western Cordillera, and the Sonoran and Mohave Desert. The Mississippi Alluvial and Southeast Coastal Plain, the Western Interior Basin and Ranges, and the South-Central Semi-Arid Prairies also had a high number of housing units in shrubland and evergreen forest cover types (Figure 2.3d).

Ranking ecoregions by the number of pixels with MODIS fires occurring in shrublands and evergreen forests did not follow the ranking by the number of pixels in those land cover types by ecoregion (Figure 2.3c & e). The Western Cordillera and Interior Basins and Ranges were in the top three with the Southeastern Plains. The Upper Gila Mountains, Mississippi Alluvial and Southeast Coastal Plan, and the South-Central Semi-Arid Prairies also had a high number of shrubland and evergreen MODIS fires.

Ecoregions with the greatest number of housing units in MODIS fires in shrublands and evergreen forests included the Southeastern Plains, Mediterranean California, and the Mississippi Alluvial and Southeast Coastal Plain (Figure 2.3f). Other ecoregions with a high number of houses in shrubland and evergreen forest MODIS fires also included the Western Cordillera, the Upper Gila Mountains, and the Western Interior Basins and Ranges. The South-Central Semi-Arid Prairies, the Sonoran and Mohave Deserts, and the Ozark, Ouachita-Appalachian Forests were also notable, but the northeastern and north-central U.S. did not have many housing units in MODIS fires in shrublands and evergreen forest.

Distribution of large fires

There were clear differences in spatial patterns of fire sizes (Figure 2.4). Most MODIS fires in federal lands were part of large fires; nearly 50% of all federal MODIS fires were part of fire clusters at least 17 pixels and 39 pixels in size for Wilderness Areas. In contrast, most MODIS fires in the WUI and 'other' property types were part of small fire clusters; nearly 50% of all WUI MODIS fires were part of clusters that were 4 pixels or less in size.

Western ecoregions had the greatest range of fire cluster sizes (Figure 2.5), reaching 1,280 pixels in Mediterranean California. Among ecoregions in the Great Plains and East, the largest fire clusters were found in the West-Central Semi-Arid Prairies (661 pixels), the South-Central Semi-Arid Prairies (281 pixels), and the Everglades (163 pixels). Across all ecoregions, the largest fire clusters occurred primarily in wilderness and federal lands. In most regions WUI fires were small; however, large fire clusters burning the WUI were observed in Mediterranean California.

Housing units in large fires

The cumulative proportion of housing units among fire cluster sizes followed similar trends as the cumulative proportion of fire pixels in fire cluster sizes (Figure 2.3b & Figure 2.6). Approximately 80% of all houses in WUI fires were in fire clusters of 12 of fewer pixels. A few large MODIS fire clusters of approximately 200 pixels and 950 pixels caused a large increase in the cumulative percent of WUI houses in fires. Because of the resolution of our analysis and private property inholdings, there were a few housing units in the federal lands and wilderness property types (1.98% and 0.03% of all housing units in the U.S. respectively). The proportion of housing units in MODIS fires in the federal property type followed a pattern similar to that of the WUI, but housing units in MODIS fires near wilderness were more erratic.

Ecoregional patterns of the proportion of housing units in relation to MODIS fire cluster size followed the national trend (Figure 2.6). However, the influence of large fires in the Western U.S. was especially apparent in Mediterranean California, the Western Sierra Madre Piedmont and the Sonoran and Mohave Deserts ecoregions. In these areas, large increases in the proportion of housing units in MODIS fires were caused by a few very large fires. For example, in Mediterranean California, 11 large fires contained for approximately 50% of all housing units in MODIS fires; these clusters of MODIS fires included the 2003 Cedar Fire (1,280 pixels), the Simi and Piru fires (955 pixels), the Padua, Grand Prix, and Old fires (943 pixels) and the 2006 School (962 pixels), and the Sawtooth and Millard complexes (525 pixels).

Discussion

A small proportion of the U.S. experienced fire (1.24% annually); however, the potential impacts of fires are great and approximately 1 million housing units each year were located within MODIS active fires. A large proportion of fire activity and housing units in fires were outside of federal lands. This pattern held true when all MODIS fires and only wildland vegetation fires were considered. Our results emphasize that fire management is not a challenge limited to public agencies and effective fire management strategies will require cooperation across a variety of land ownership and property types.

MODIS fires were relatively uncommon in the WUI with only 6.4% of all fires occurring there, even though the WUI covers 9% of the U.S. (Radeloff et al. 2005) Fire protection and suppression limit fire occurrence in the WUI but when fires do escape the risk is high because the WUI contains 34% of all houses in the U.S. The WUI represents the dangerous confluence of houses and wildland vegetation, especially in vegetation types where intense crown fires are possible. Nearly 53% of all housing units in MODIS fires in shrubland and evergreen forests were in the WUI. This demonstrates that the WUI is rightfully the focus of efforts to reduce risk of wildfire damage to houses. However, because approximately 37% of all housing units in MODIS fires in shrubland and evergreen forests were not in the WUI or federal lands, it may be worth considering extending fire management priorities beyond the current property type definitions used to prioritize fuel treatments.

Because fire prevention and suppression efforts are strong in the WUI, very few structures in the WUI are actually destroyed by fires but protecting these structures entails great effort and expense. One government report suggests that 50-95% of the costs of large wildfire are dues to homes and property protection in the WUI (USDA Forest Service 2006). Given the high growth rates in the WUI and rural areas (Hammer et al. 2007), greater efforts are needed reduce the risk to existing development and limit the impacts of future development in fire prone areas.

Patterns of fire occurrence varied across the U.S. and because fire occurrence is related to weather, climate, topography, and vegetation, as well as development, certain ecoregions were disproportionately prone to fire. The southeastern U.S. had a large number of MODIS fires in shrublands and evergreen forests. It is unlikely that all the fires observed by MODIS in the Southeast were wildfires because prescribed fire is commonly used in this region to reduce fire risk and understory vegetation (Cleaves et al. 2000, Haines et al. 2001, Lafon et al. 2005). In contrast, fire use is less common in the western U.S. (Pyne et al. 1996, Cleaves et al. 2000, Miller 2006) and wildfire activity is predominantly driven by extreme weather (Bessie and Johnson 1995, Keeley 2004) .

MODIS fire occurrence and fire size varied regionally and these differences require different fire management strategies. In the southeast, MODIS fires were common, but tended to be consistently small. In the West, there was greater variability in the size of MODIS fire clusters and large fires were more common. Although there are large contiguous blocks of forest in the Southeast, they are highly fragmented by development and roads, which can limit the spread fires (Turner et al. 1989, Duncan and Schmalzer 2004). The challenge in the southeastern U.S. is managing frequent fire in the presence of a large number of houses and across fragmented ownership patterns where the indirect impacts of fire are distributed across a large population.

When conditions are right for fires to reach such very large sizes, spread can occur quickly and direct attack is nearly impossible. The large fire clusters in Mediterranean California captured by the MODIS active fire data demonstrate the extreme end of this variability. The 2003 southern California fires alone destroyed 3,361 homes (Keeley et al. 2004) and again in October 2007, more than 1,500 homes were destroyed and 346,000 homes were evacuated in southern California[8]. The challenge in the West will continue to be confronting large conflagrations and limiting their impacts on communities. However, because housing development tends to be spatially concentrated and public lands are extensive in the West, the opportunities to use fire for its ecological benefits may remain.

Potential limitations

The MODIS active fire product does not detect all fires and previous research has shown detection rates to be greatest in the western U.S. and lowest in the eastern U.S. (Hawbaker et al. 2008). Detection rates are greatest for large fires and these fires tend to burn the majority of area and cause the most damage (Kasischke and French 1995, Neuenschwander et al. 2000, Finney 2005). Because the MODIS data do not include all fires, our results provide a conservative estimate of fire activity. However, the MODIS active fires do provide a national view of fire activity that spans all property types and has greater spatial resolution and certainty in fire locations than existing fire databases (Brown et al. 2002). Thus, even though satellites do not capture all fires, we suggest they have great utility for broad-scale fire assessments. Additionally, the MODIS active fire data used in this study represent a relatively short time-span; 2003 – 2006. These four

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[8] http://en.wikipedia.org/wiki/California_wildfires_of_October_2007#cite_note-AP_1024-6

years exhibited some of the most extensive fire activity in history; however, there has been an increasing trend in the amount of area burned (Calkin et al. 2005) and if this trend continues, our analysis may well estimate the impacts of fire for the near future.

Our observation units, MODIS active fire pixels, had 1 km spatial resolution. At this resolution, land cover, ownership, and housing counts can be highly heterogeneous within pixels. Thus, our findings should be interpreted with scale-dependence in mind and our findings might change if more detailed data were used. However, comparison with results from similar studies suggests the difference would be small. Previous estimates put the proportion of the U.S. in vegetation types with potential for high-severity fires at 36.7% based on 30 meter pixels (Theobald and Romme 2007) compared to our estimate of 35.6% based on 1 km pixels (Table 2.2). Thus, we believe our analysis is relatively robust in regards to the grain of resolution.

The spatial extent of the ecoregions we used might not fully capture the spatial heterogeneity of fire potential and occurrence. The Omernik level 2 ecoregions do not delineate fire prone areas such as the Jack Pine barrens of Michigan, Wisconsin, New Jersey, and the Boundary Waters of Minnesota. These areas historically experienced frequent stand-replacing fires and occasionally experience them now, such as the Mack Lake Fire in 1980 (Simard et al. 1983). More detailed ecoregion delineations might capture these patterns, but with a loss of generality. Thus, our results do not capture variability within the ecoregions we used and this should be kept in mind when interpreted our findings.

Implications for fire policy and management

Risk modeling calls for integrating probabilities of event occurrence with potential for damage caused by the event (Bachman and Allgöwer 1999). Risk analyses based on vegetation or fuel types alone can be misleading because they do not account for variability in fire occurrence within vegetation types. Our results highlight the importance of such a risk modeling approach. We examined the location of housing units in evergreen forests and shrublands; vegetation types with potential for intense wildfires. We also examined the extent of fires in those areas. Our results suggest that the location and extent of risk varies depending on how risk is assessed, especially whether or not fire occurrence is incorporated. Risk analyses based only on fire potential could overestimate the extent of risk and cause home owners, policy makers, and land managers to misinterpret fire risk in the places where it matters most.

Our analysis considered housing units as the only value at risk from wildfires; however the impacts of fire extend beyond just houses in the WUI. Other resources beyond houses are also impacted by fires, such as increased surface erosion and debris flows (Gresswell 1999, Wondzell and King 2003), or undesired impacts on wildlife and aquatic species (Rieman and Clayton 1997). However, fire risk to houses is one of the primary reasons for fire suppression (Parsons 2000). Thus, understanding where fire risk to houses is greatest is a necessary step in the process of determining where the benefits of fire can be realized. Until that risk is fully addressed the opportunities for the ecological benefits of fire will remain limited.

The default response of suppressing wildfires has become increasingly expensive as the area burned has grown in recent years (Calkin et al. 2005, U.S. Department of Agriculture 2006). Accommodating fire but limiting its negative effects by altering fuel arrangement and loadings is one strategy that may apply in certain ecosystems, such as southwestern ponderosa pine forests (Covington 2000, Allen et al. 2002). However, fuel treatments are not a universal solution because their effectiveness is short-lived and limited in ecosystems where fire occurrence and spread is controlled less by fuel load and more by extreme fire weather (e.g., chaparral shrublands or lodgepole pine forests; Agee 1993, Turner and Romme 1994, Keeley et al. 1999, Noss et al. 2006).

Approaches that limit the negative consequences of fire in these ecosystems are needed. A few potential approaches to reduce risk in landscapes where fires are driven by extreme weather include implementing fire-safe zones and building codes (Cohen 2000, 2004) and limiting additional housing growth into such areas (Hammer et al. 2007, Syphard et al. 2007b). The time to act is now, because the number of houses exposed to fire is likely to increase in the near future and the challenges of fire management in the WUI are unlikely to diminish. Housing growth has been high in rural areas (Brown et al. 2005), especially in the WUI (Hammer et al. 2007, Theobald and Romme 2007). New development will bring new risks (Syphard et al. 2007b) and fewer opportunities to realize the ecological benefits of fire. Managing fire in the face of ongoing housing development is destined to become more challenging and more expensive unless serious efforts are made to counteract new development in fire-prone ecosystems.

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Table 2.1. Annual number of MODIS active fire pixels by property type for the conterminous United States. Total number of pixels (fire and non-fire) for each property type is in parentheses.

Year	WUI (838,000)	Federal (1,857,500)	Wilderness (348,100)	Other (6,066,500)	Total (9,110,100)
2003	6,600	20,800	6,300	78,600	112,200
2004	5,900	15,000	2,200	67,400	90,500
2005	8,000	20,100	5,200	89,100	122,300
2006	8,500	25,700	7,500	86,900	128,600
Average	7,200	20,400	5,300	80,500	113,400

Table 2.2. The annual number of MODIS active fire pixels and total number pixels, grouped according to ownership and land-cover categories (2003 - 2006). Regional totals are shown in italics.

		WUI		Federal		Wilderness		Other		Total	
Land cover	**Region**	**MODIS fires**	**Total**	**MODIS fires**	**Total**	**MODIS fires**	**Total**	**MODIS fires**	**Total**	**MODIS fires**	**Total**
Developed	Total	1,300	105,600	0	2,900	0	100	2,100	167,000	3,500	275,600
Water, ice, or barren	Total	100	14,800	100	32,200	0	6,600	500	141,800	700	195,400
Agriculture	Total	1,500	182,300	600	32,000	0	500	31,600	2,225,900	33,700	2,440,700
Wetland	Total	600	47,000	1,100	40,300	200	8,500	6,500	280,200	8,400	376,100
Grassland	Total	400	31,800	1,200	190,700	200	23,000	11,800	1,063,300	13,700	1,308,800
Shrubland	*East*	200	7,400	100	1,800	0	100	1,400	39,600	1,600	48,900
	Great Plains	100	5,700	200	21,200	0	500	2,600	281,900	2,900	309,300
	West	400	25,800	6,000	832,100	1,600	163,200	3,300	615,800	11,200	1,636,900
	Subtotal	600	38,800	6,200	855,100	1,600	163,800	7,300	937,300	15,700	1,995,100
Evergreen forest	*East*	1,200	64,200	1,400	41,000	100	5,100	9,800	264,800	12,400	375,100
	Great Plains	100	3,600	300	11,300	0	900	1,100	36,500	1,500	52,300
	West	200	23,400	8,200	498,400	3,100	128,800	2,500	173,300	14,000	823,900
	Subtotal	1,500	91,200	9,900	550,700	3,200	134,700	13,400	474,600	27,900	1,251,300
Deciduous forest	*East*	1,000	290,900	1,000	117,200	0	7,600	4,800	636,000	6,800	1,051,700
	Great Plains	100	6,700	0	1,000	0	0	1,700	54,500	1,800	62,100
	West	0	1,400	100	25,600	0	2,200	0	12,200	200	41,500
	Subtotal	1,100	298,900	1,200	143,800	100	9,900	6,500	702,600	8,800	1,155,300
Mixed forest	*East*	100	24,000	100	5,900	0	500	600	65,400	800	95,800
	Great Plains	0	200	0	100	0	0	0	600	0	1,000
	West	0	3,200	100	3,600	0	500	100	7,700	200	15,000
	Subtotal	100	27,400	100	9,600	0	1,000	700	73,700	1,000	111,800
Grand Total		7,200	838,000	20,400	1,857,500	5,300	348,100	80,500	6,066,500	113,400	9,110,100

Table 2.3. The annual average number of houses in MODIS active fire pixels and total number of houses, grouped according to property type and land-cover categories (2003 - 2006). Regional totals are shown in italics.

		WUI		Federal		Wilderness		Other		Total	
Land cover	**Region**	**MODIS fires**	**Total**	**MODIS fires**	**Total**	**MODIS fires**	**Total**	**MODIS fires**	**Total**	**MODIS fires**	**Total**
Developed	Total	292,800	23,060,500	3,200	459,700	0	900	434,500	57,482,900	730,500	81,004,000
Water, ice, or barren	Total	3,100	608,700	200	153,400	0	2,700	7,300	1,516,300	10,600	2,281,100
Agriculture	Total	28,400	3,543,100	900	69,800	0	300	88,400	9,568,100	117,700	13,181,300
Wetland	Total	13,400	1,175,400	700	44,900	0	1,500	11,700	825,700	25,800	2,047,500
Grassland	Total	8,100	758,800	600	33,600	0	2,100	11,600	868,900	20,300	1,663,400
Shrubland	*East*	2,600	108,000	100	2,900	0	0	2,000	78,900	4,600	189,800
	Great Plains	1,100	147,800	0	2,100	0	0	1,600	152,900	2,700	302,900
	West	10,000	894,600	2,300	143,300	200	7,900	4,800	393,900	17,300	1,439,700
	Subtotal	13,700	1,150,500	2,400	148,300	200	7,900	8,400	625,600	24,600	1,932,300
Evergreen forest	*East*	16,100	1,124,700	1,400	49,700	0	1,300	15,200	604,900	32,700	1,780,600
	Great Plains	1,000	89,000	100	4,100	0	100	900	47,600	2,000	140,800
	West	6,100	528,500	3,000	158,200	300	13,100	1,400	165,300	10,800	865,000
	Subtotal	23,200	1,742,200	4,400	212,000	300	14,500	17,500	817,800	45,400	2,786,400
Deciduous forest	*East*	21,800	6,206,000	1,100	230,200	0	5,200	12,100	2,768,400	35,000	9,209,700
	Great Plains	1,400	123,400	0	2,600	0	0	2,400	181,100	3,700	307,100
	West	0	36,500	0	9,200	0	900	0	10,700	100	57,200
	Subtotal	23,200	6,365,800	1,200	241,900	0	6,200	14,500	2,960,100	38,900	9,574,000
Mixed forest	*East*	1,800	409,700	100	11,200	0	600	1,300	166,600	3,200	588,200
	Great Plains	100	5,500	0	100	0	0	100	3,200	200	8,900
	West	300	87,500	0	4,400	0	100	200	24,000	600	116,000
	Subtotal	2,200	502,800	100	15,700	0	700	1,700	193,800	4,000	713,000
Grand Total		408,000	38,907,600	13,700	1,379,300	500	36,800	595,600	74,859,300	1,017,800	115,183,100

Figure 2.1. MODIS active fire detections from the EOS-1 Terra and EOS-2 Aqua satellites, 2003 - 2006.

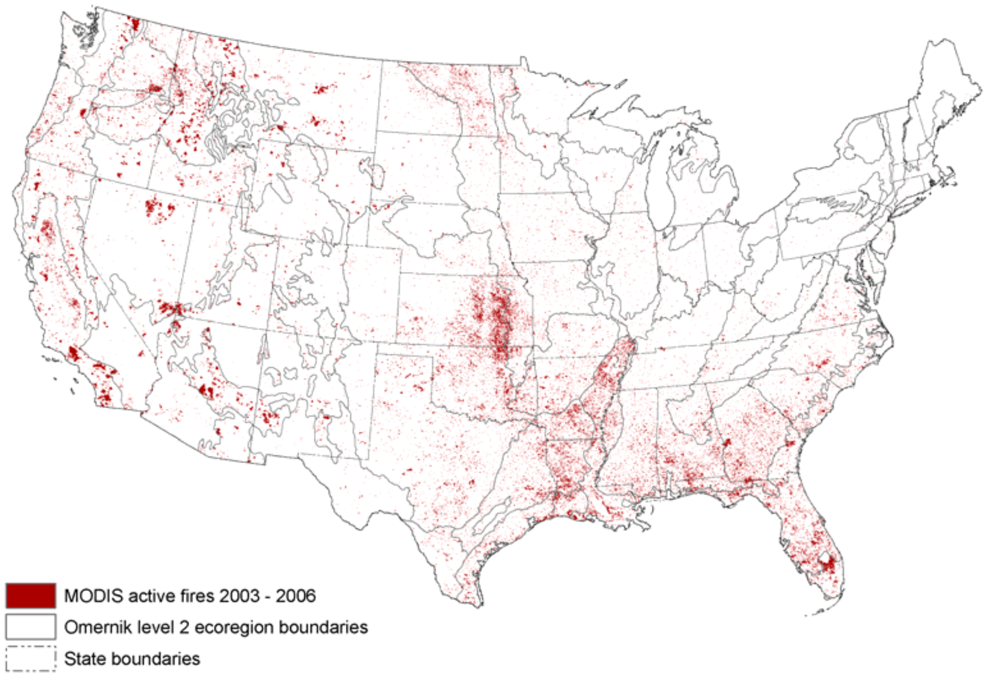


Figure 2.2. (a) Land type categories; (b) density of housing units in 2000 (housing units / km2); (c) land cover categories; (d) Omernik level 2 ecoregions.

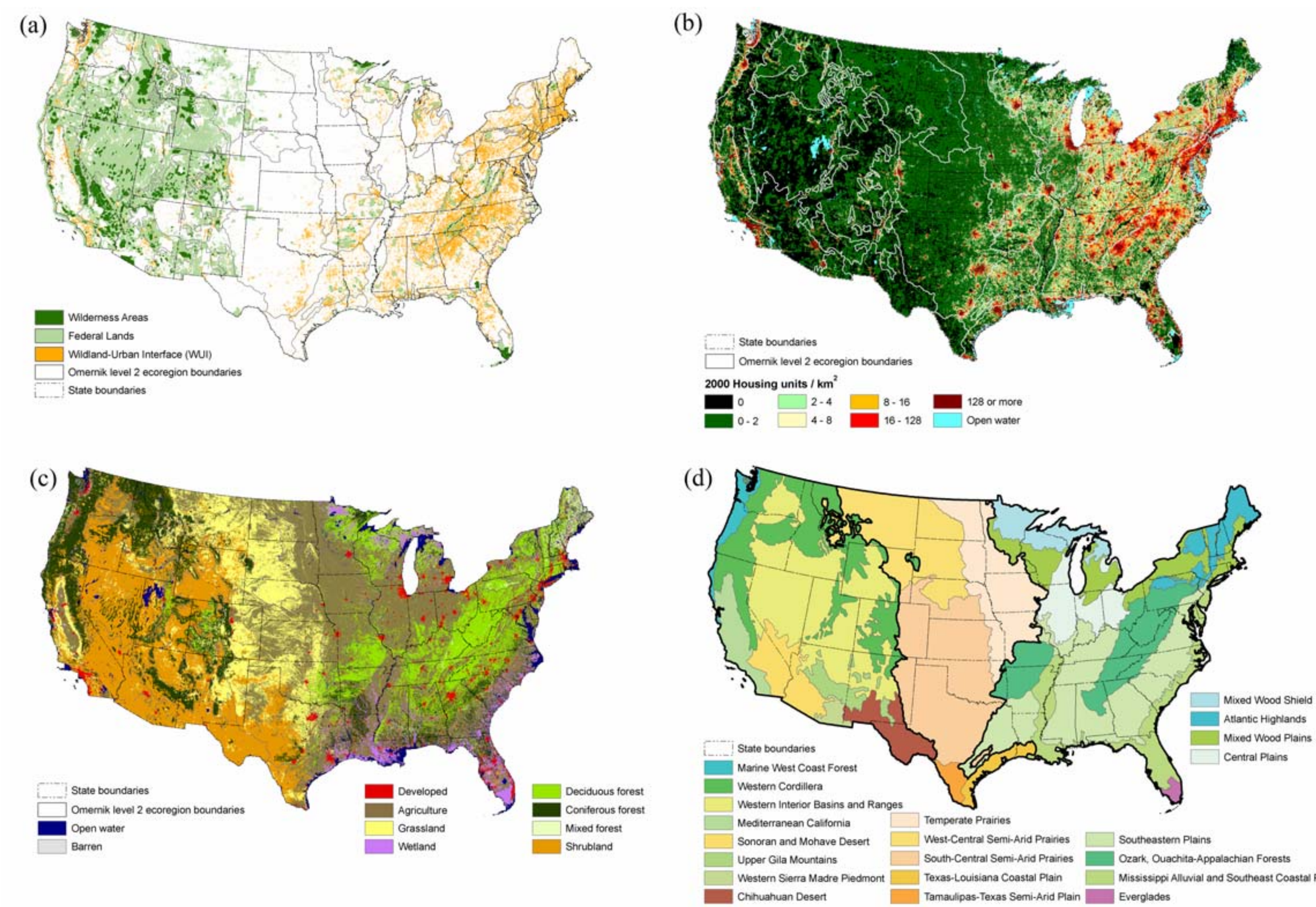


Figure 2.3. Omernik level 2 ecoregions ranked by (a) average number of pixels with active fires (ecoregion fire pixel count / total pixel count in US); (b) average number of houses in pixels with active fires (ecoregion count of housing units in active fire pixels / total housing unit count for US); (c) average number of pixels classified as shrubland and coniferous forest (ecoregion shrubland and coniferous forest pixel count / total pixel count in US) and (d) average number of houses in shrubland and coniferous forest pixels (ecoregion count of housing units in shrubland and coniferous forest pixels / total housing unit count for US); (e) proportion of pixels classified as shrubland and coniferous forest with active fires (ecoregion in shrubland and coniferous forest pixels with fires count / total pixel count in US); (f) proportion of houses in shrubland and coniferous forest pixels with active fires (ecoregion count of housing units in shrubland and coniferous forest pixels with fires / total housing unit count for US) for years 2003 – 2006.

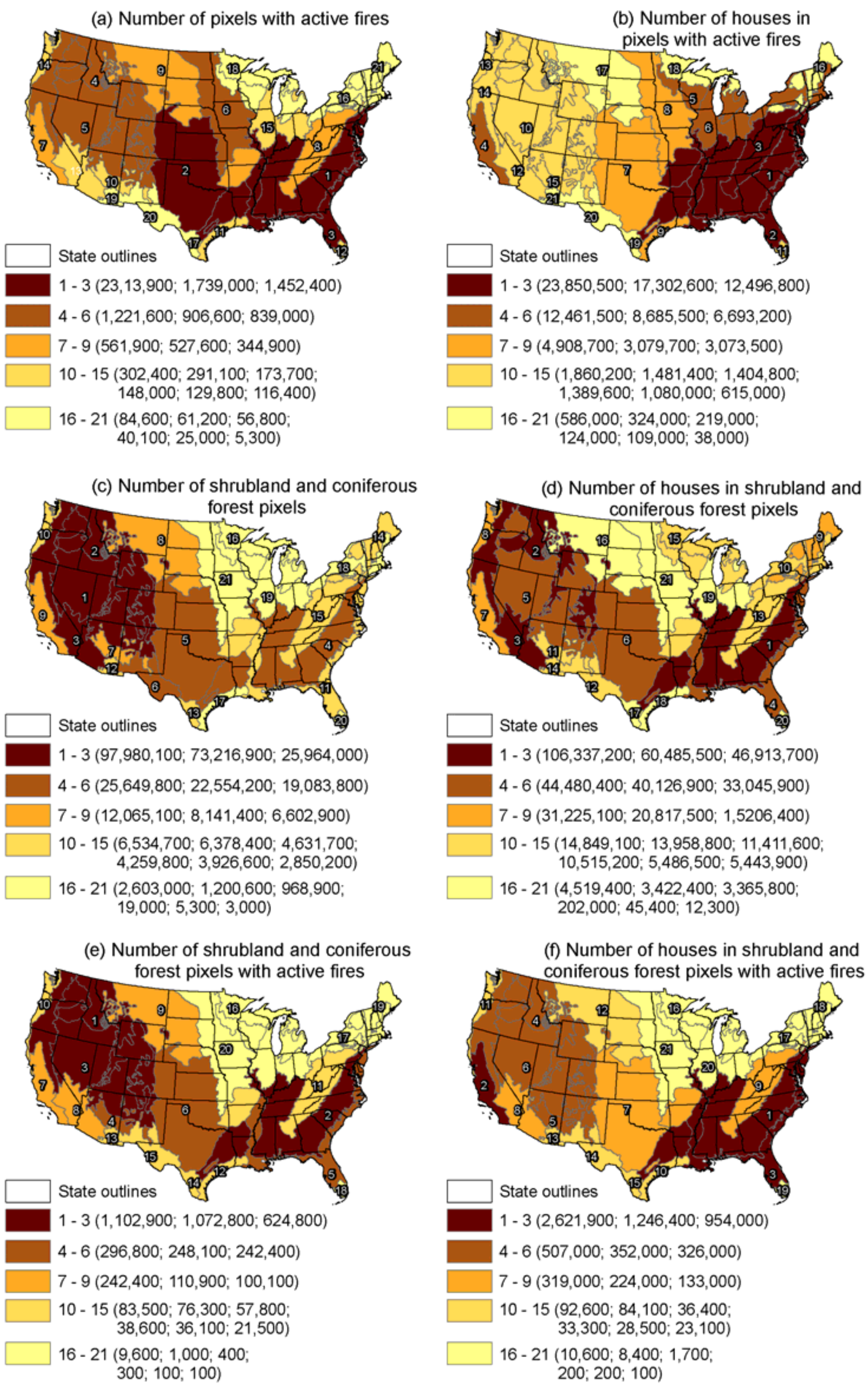

(a) Number of pixels with active fires
State outlines
1 - 3 (23,13,900; 1,739,000; 1,452,400)
4 - 6 (1,221,600; 906,600; 839,000)
7 - 9 (561,900; 527,600; 344,900)
10 - 15 (302,400; 291,100; 173,700; 148,000; 129,800; 116,400)
16 - 21 (84,600; 61,200; 56,800; 40,100; 25,000; 5,300)
(b) Number of houses in pixels with active fires
State outlines
1 - 3 (23,850,500; 17,302,600; 12,496,800)
4 - 6 (12,461,500; 8,685,500; 6,693,200)
7 - 9 (4,908,700; 3,079,700; 3,073,500)
10 - 15 (1,860,200; 1,481,400; 1,404,800; 1,389,600; 1,080,000; 615,000)
16 - 21 (586,000; 324,000; 219,000; 124,000; 109,000; 38,000)
(c) Number of shrubland and coniferous forest pixels
State outlines
1 - 3 (97,980,100; 73,216,900; 25,964,000)
4 - 6 (25,649,800; 22,554,200; 19,083,800)
7 - 9 (12,065,100; 8,141,400; 6,602,900)
10 - 15 (6,534,700; 6,378,400; 4,631,700; 4,259,800; 3,926,600; 2,850,200)
16 - 21 (2,603,000; 1,200,600; 968,900; 19,000; 5,300; 3,000)
(d) Number of houses in shrubland and coniferous forest pixels
State outlines
1 - 3 (106,337,200; 60,485,500; 46,913,700)
4 - 6 (44,480,400; 40,126,900; 33,045,900)
7 - 9 (31,225,100; 20,817,500; 1,5206,400)
10 - 15 (14,849,100; 13,958,800; 11,411,600; 10,515,200; 5,486,500; 5,443,900)
16 - 21 (4,519,400; 3,422,400; 3,365,800; 202,000; 45,400; 12,300)
(e) Number of shrubland and coniferous forest pixels with active fires
State outlines
1 - 3 (1,102,900; 1,072,800; 624,800)
4 - 6 (296,800; 248,100; 242,400)
7 - 9 (242,400; 110,900; 100,100)
10 - 15 (83,500; 76,300; 57,800; 38,600; 36,100; 21,500)
16 - 21 (9,600; 1,000; 400; 300; 100; 100)
(f) Number of houses in shrubland and coniferous forest pixels with active fires
State outlines
1 - 3 (2,621,900; 1,246,400; 954,000)
4 - 6 (507,000; 352,000; 326,000)
7 - 9 (319,000; 224,000; 133,000)
10 - 15 (92,600; 84,100; 36,400; 33,300; 28,500; 23,100)
16 - 21 (10,600; 8,400; 1,700; 200; 200; 100)

Figure 2.4. Cumulative proportion of (a) pixels and (b) houses by land type as a function of the size of contiguous clusters of active fire pixels.

(a) (b)

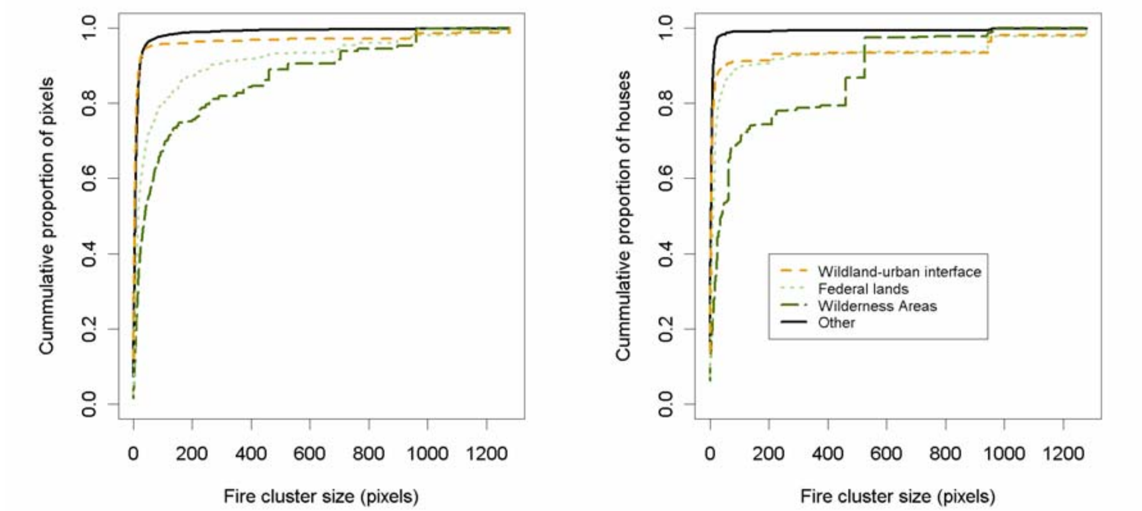


Figure 2.5. Cumulative proportion of active fire pixels as a function of the size of fire clusters by land type for Omernik Level 2 Ecoregions.

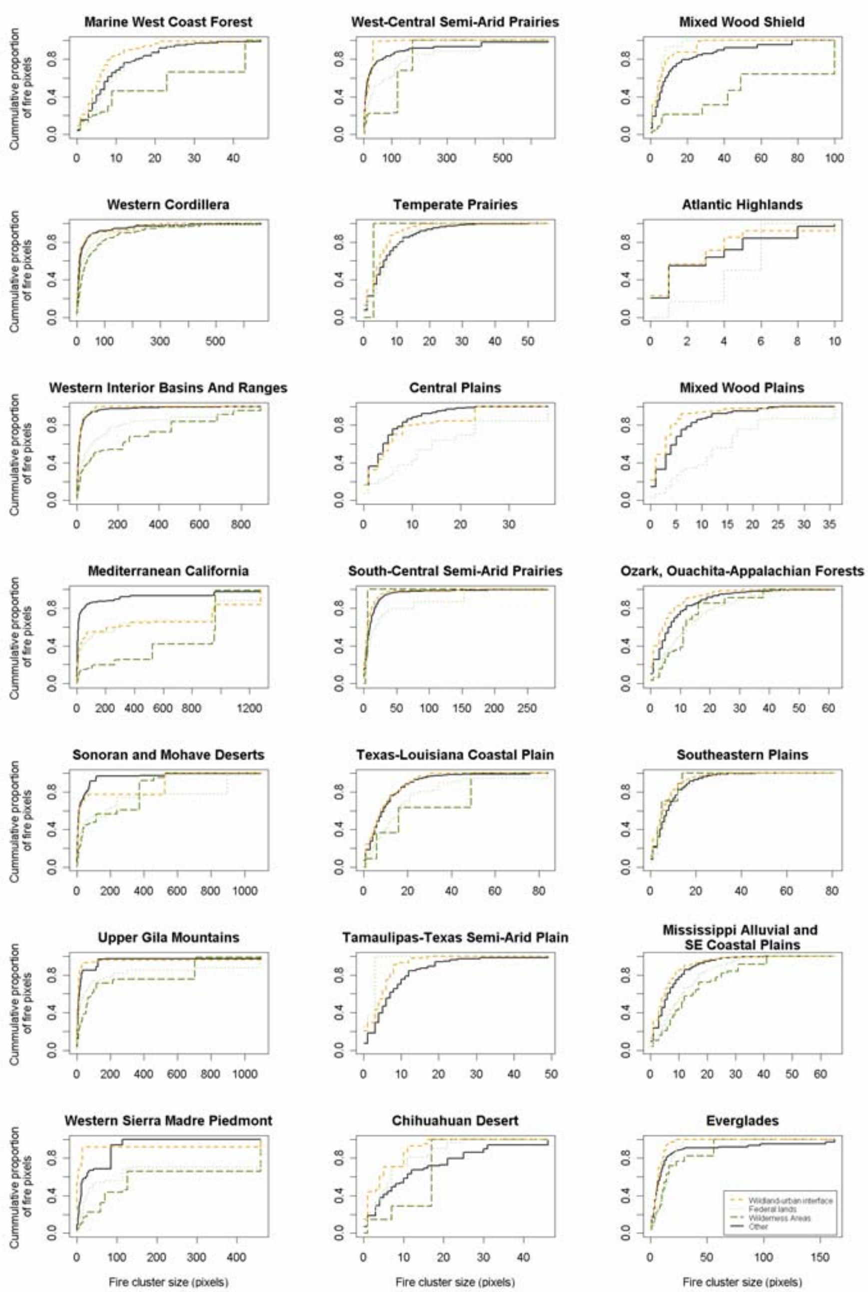
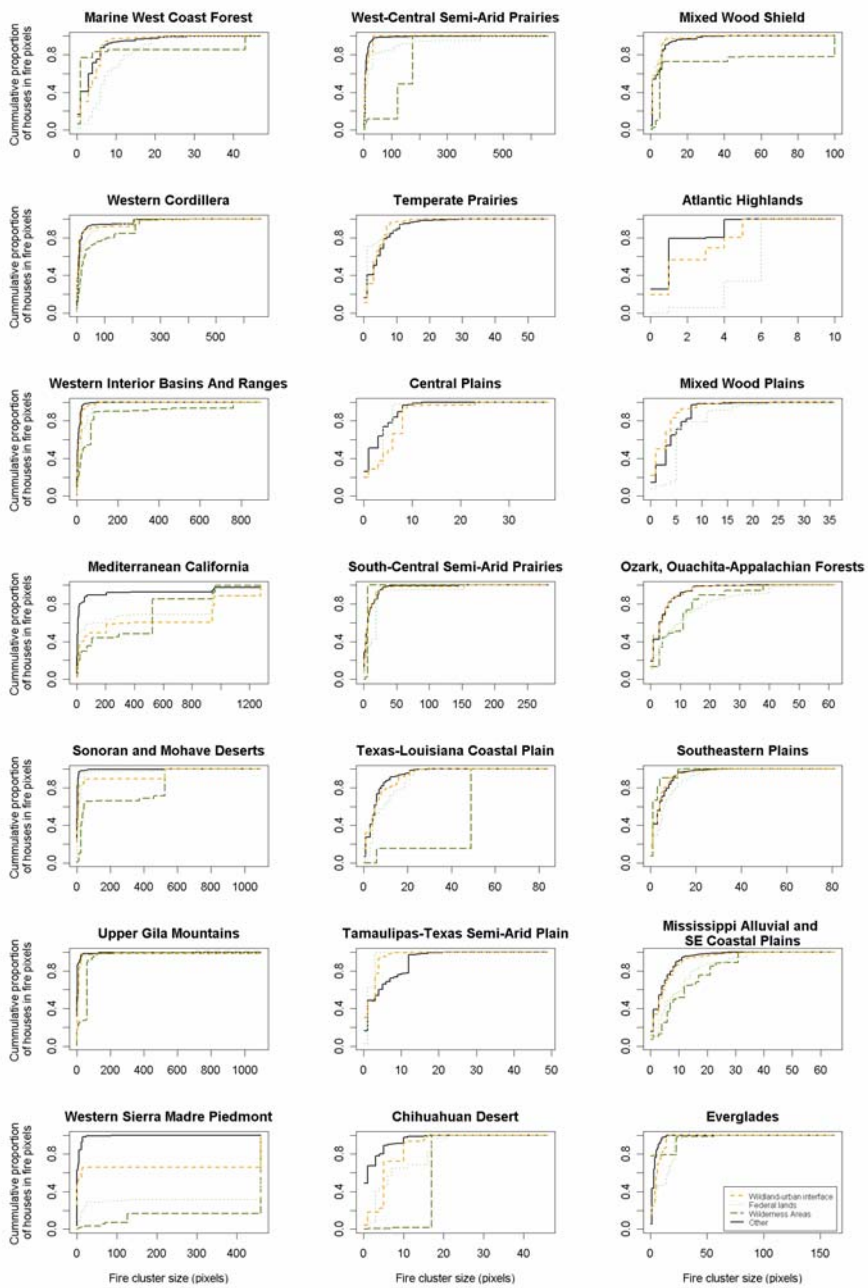


Figure 2.6. Cumulative proportion of houses in active fire pixels as a function of the size of fire clusters by land type for Omernik Level 2 Ecoregions.



Chapter 3: Human influences on fire occurrence and fire potential in the conterminous United States

Abstract

National scale models of fire occurrence are needed to prioritize fire management activities across the United States. However, national scale patterns and drivers of fire occurrence are not fully understood. We used satellite active fire detections collected by the moderate resolution imaging spectroradiometer (MODIS) Terra and Aqua sensors between 2000 and 2006 in logistic regression models to compare the relative strength of vegetation, physical, and human variables for predicting fire occurrence across the United States. Human variables were important in our models, but their strength was low relative to vegetation and physical variables, and fire in the U.S. is still largely driven by weather, vegetation and topography. We found positive relationships with fire at low housing unit densities and short distance to roads and negative relationships at high housing unit densities and distance from roads. However, the shape and strength of the relationships varied among years. Predicted potential for fire occurrence was high and localized in the western U.S. to mountainous regions and southern California, and high potential for fire occurrence was also widespread in the Southeast. The probability of fire occurrence is an important component to risk modeling and our results show that fire occurrence can be highly variably in both space and time. Uncertainty in fire risk models

could be minimized by incorporating probabilistic measures of fire occurrence in addition to vegetation type and potential fire behavior.

Introduction

Wildfire management in the United States has to balance the ecological benefits of fire with the risks wildfires pose to society. On one hand, fire suppression is necessary to limit the damage and expense of wildfires. On the other hand, fire is an important disturbance process in many ecosystems and its periodic occurrence is desirable. In the U.S., fire policies, management directives, and funding are national in scope (Stephens & Ruth 2005). In spite of national fire policies, national scale patterns and drivers of fire occurrence are not fully understood. National scale models of fire occurrence are needed to help prioritize fire management and fire use. In this paper, we compared the relative influence of human and biophysical drivers of fire occurrence and developed predictive models of where fires were most likely to occur in the conterminous United States.

The expense of fighting wildfires and the damage of uncontrolled wildfires to society can be great. In October 2007, more than 1,500 homes were destroyed and 346,000 homes were evacuated in southern California[9]. Much of southern California had also burned in 2003 when 3,361 houses were destroyed (Keeley 2004). Large fires are not limited to southern California though. In 2000, the Cerro Grande fire burned 235 homes in New Mexico (National Park Service 2006), and in 1998, 340 homes were

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[9] http://en.wikipedia.org/wiki/California_wildfires_of_October_2007#cite_note-AP_1024-6

destroyed in Florida wildfires (Butry et al. 2001). The recent history of houses lost to wildfires demonstrates that the problem is national in scope, but exhibits temporal and geographic variability.

Federal fire suppression expenditures exceeded $1 billion in four of the seven years between 2000 and 2006 (U.S. Department of Agriculture 2006). Wildfires also have indirect costs. By reducing timber supply, tourism, and increasing health care costs, the 1998 wildfires in Florida had a greater economic impact than expected by a category 2 hurricanes (Butry et al. 2001). Because the expense of fighting fires is large and the consequences of uncontrolled wildfires are great, there is a need to understand and predict fire occurrence across broad scales.

The expense of preventing and suppressing fires is stretching public agencies thin during a time when there are few resources for other management activities that could promote the ecological benefits of fire (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 & Keeley 2005). Active management can maintain fire regimes of ecosystems within their historic ranges of variability, which is often considered a benchmark for conservation success (Hunter 1993; Morgan et al. 1994; Landres et al. 1999).

Today, few ecosystems have fire regimes within their historic range of variability. In many cases fire return intervals have increased by an order of magnitude (Cowell 1998, Rollins et al. 2001, Cleland et al. 2004, Grissino-Mayer et al. 2004). Changes in fire regimes have ecological consequences. In some places, reductions in fire frequencies can allow changes to a more fire resistant state, as in many eastern U.S. forests where fire intolerant species, such as maple, are replacing fire adapted oak species (Foster et al. 1998, Abrams 2003). In other places, such as 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). Human development affects fire occurrence, and can push disturbance regimes beyond the historic range of variability.

Human development influences fire occurrence through two primary mechanisms: ignition and suppression. Human activities in wildlands, correlated with roads and housing, cause novel ignition patterns that do not necessarily match the patterns of natural, lightning-caused ignitions (Chuvieco and Congalton 1989, Cardille et al. 2001, Kasischke et al. 2002, Stephens 2005). Suppression often counteracts ignitions. Suppression occurs both through direct action, i.e. fuel treatments and fire fighting (Rideout and Omi 1990, Prestemon et al. 2002). The effects of suppression can be especially pronounced in the wildland-urban interface where the fire risk to houses and expense of uncontrolled fires is assumed to be greatest (Cohen 2000, Radeloff et al. 2005, Syphard et al. 2007b). Suppression can also occur indirectly through landscape-level alteration of the arrangement and type of fuels across which fires can spread (Turner et al. 1989, Finney 2001, Duncan and Schmalzer 2004). The impacts of human development on fire occurrence have not been examined at a national-scale. Understanding national-scale relationships between humans and fires is important because the magnitude and shape of the relationship between human development and fire has ecological, economic, and social implications.

Biophysical variables of weather, vegetation, and topography have a large effect on fire occurrence and constitute the three sides of the fire environment triangle (Pyne et al. 1996). Long-term precipitation and temperature patterns influence patterns of fuel type, loads and moisture (Neilson 1995, Rollins et al. 2004, Bond et al. 2005). Deviation from long term precipitation patterns can indicate drought and increased fire activity (Simard et al. 1985, Swetnam and Betancourt 1990, Veblen et al. 2000). Short-term weather changes in precipitation, temperature, humidity, and solar radiation cause changes in fuel moisture, while wind dominates fire spread (Rothermel 1972, Bessie and Johnson 1995). The effects of short-term weather controls are moderated by vegetation type and topographic influences on fire spread (Rothermel 1972, Rollins et al. 2004). Because biophysical variables have such strong relationships with fire occurrence, their effects need to be accounted for in order to untwine the human relationships.

In summary, fire occurrence in a given place is a function of human variables that influence ignition patterns and suppression efforts, as well as a suite of biophysical variables influencing spread rate, such as fuel type, fuel amount, fuel moisture, topography, and weather. Our primary research questions were: (1) how did the relative importance of human variables on fire occurrence differ among different ecoregions of the United States; and (2) how did the probability of fire occurrence vary within and among ecoregions in the conterminous United States? We developed a statistical approach that examined the human variables and their influence on fire occurrence, while controlling for the vegetation, weather, and topographic effects (question 1). Then, using our statistical model, we estimated the potential for fire occurrence, assuming that places on the landscape most likely to burn would be similar to places that did burn (question 2).

Methods

Data sources

Our understanding of national-scale patterns of fire occurrence has been limited by the lack of good fire data. The federal fire occurrence database is frequently used in broad-scale fire studies (Schmidt et al. 2002, Westerling et al. 2003, Stephens 2005), but it does not include fires across all land ownership, its spatial resolution is limited to the county level in many states, and the spatial locations of fires are often inaccurate (Brown et al. 2002).

Satellite fire observations of fire occurrence offer an alternative information source (Flannigan and Vonder Haar 1986, Giglio et al. 1999, Justice et al. 2002a). Satellite fire data should capture important patterns because they include some of the most extreme fire years in recent history (Calkin et al. 2005, U.S. Department of Agriculture 2006). Additionally, satellites observe fires with consistent methodology and effort across all ownerships and vegetation types. This is especially relevant for fire risk monitoring because most structures occur outside of public lands.

Fire Observations

We used observations of fire occurrence collected by the MODIS sensors onboard NASA's Earth Observing System Aqua and Terra satellites (Justice et al. 2002b, Giglio et al. 2003a; Figure 3.1). The MODIS fires capture actively flaming fires at satellite overpass, 1:30 and 13:30 for Aqua and 10:30 and 22:30 for Terra (Justice et al. 2002a). MODIS Terra was launched in December of 2000 and MODIS Aqua in April of 2002. Thus, we used MODIS Terra active fire observations for years 2000 – 2002 and combined MODIS Terra and Aqua fire observations for the years 2003 – 2006. Image mosaicking, reprojection, and conversion with the MODIS land data operational product evaluation software tools[10] resulted in 926 m resolution pixels. For all years, we removed low-confidence MODIS active fire detections to avoid false detections and limit the analysis to the most intense fires. The remaining nominal- and high-confidence MODIS fires were combined and labeled as fire if an active fire was observed by Terra or Aqua within a given year, otherwise pixels were labeled as no-fire.

Throughout this paper, we refer to the MODIS active fire observations as MODIS fires. However, we caution readers to interpret our results carefully. The MODIS fire detections only indicate that there was fire activity somewhere within the pixel, not that the entire pixel burned. Additionally, some fires may have been missed by MODIS, especially small and low intensity fires (Hawbaker et al. 2008)

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[10] ; http://lpdaac.usgs.gov/landdaac/tools/ldope/

Human variables

To represent the influence of human activity on ignitions and human development on landscape fragmentation, we selected housing unit density (housing units / km^2) and median distance to roads as variables to include in our models. Polygon-level housing unit density data, derived from the U.S. Census Bureau Decennial Census were acquired and converted to 1 km grids (Radeloff et al. 2005). Rasterizing polygon data can result in a loss of information when individual grid cells overlap multiple polygons. Typical polygon to grid conversion assigns grid cells the polygon value at the center of the grid cell or the majority of the cell. To avoid information loss, we used an area aggregation method that weighted the value of each polygon by the proportion of the grid cell area. Euclidian distances to road data were available at 30 meter 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 unit density and median distance to road data contained many small values and few large values, so both variables were ln (X+1) transformed prior to analysis. Additionally, past studies found that housing density best predicts fire occurrence at intermediate levels (Syphard et al. 2007b) so we included quadratic terms for both housing density and median distance to roads.

Land cover

Fire occurrence varies among vegetation types and we accounted for that variability using land cover classes from the 2001 Multiple Resolution National Land Cover Database[11], derived from 30 m resolution Landsat imagery (NLCD; Homer et al. 2004). We combined some of the NLCD classes to simplify the number of categories used in our models (Table 3.2). After combining classes, we had a modified land cover data set with eight unique land cover categories: developed, agriculture, wetland, grassland, shrubland, evergreen forest, deciduous forest, and mixed forest. These 8 land cover categories were aggregated to 1 km resolution with a majority rule.

Topography

We expected that fire occurrence would be more likely on south-facing slopes than north-facing slopes, on steeper slopes, and at lower elevations. We measured aspect, percent slope, and elevation using the GTOPO 30 global elevation dataset[12]. These data have a 30 arc second or approximately 1 km spatial resolution. Southerly or southwesterly facing slopes receive greater incident solar radiation and hence fuels dry more quickly on these slopes. Using equation 1 (Beers et al. 1966), we converted aspect, measured as degrees clockwise from north, to a southwesterly index increasing from -1 (northeast) to 1 (southwest).

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[11] http://www.mrlc.gov/mrlc2k_nlcd.asp

[12] http://edc.usgs.gov/products/elevation/gtopo30/gtopo30.html

$$southwestness = \cos(\text{aspect} + 135) \times \frac{\pi}{180} \qquad \text{Equation 1.}$$

Annual weather

Monthly summaries of temperature and precipitation data with 4 km spatial resolution were acquired from the PRISM Group at Oregon State University[13]. To represent inter-annual variability in weather, we averaged the monthly mean maximum temperature, summed the monthly precipitation over each year of our analysis, calculated the difference in annual precipitation between the current year and the previous year, and the difference in annual precipitation between the current year and precipitation averages from 1971-2000.

We expected that the probability of fire occurrence would have quadratic relationships and be greatest at intermediate temperature and precipitations because this allows for high fuel production. The extreme ends of the temperature and precipitation gradients represent places where fuel production is either too low to support fire spread, or places with high moisture levels where fires are rare. We also expected that the differences in precipitation between years would explain fire occurrence because dry years following wet years experience more fires (Swetnam and Betancourt 1990). We included both the difference in precipitation from the previous year and from long-term averages because the effects of long-term drought on fire occurrence might not be captured by a one year difference in precipitation.

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

Modeling approach

The total volume of our data (9,110,100 pixels per year) prevented us from building a single national model of fire occurrences. Instead, we used a divide and conquer modeling strategy. We were primarily interested in wildland fire occurrence, so we removed all fire observations in agriculture, developed, barren, permanent snow/ice, and open water. Second, we subdivided the remaining data according to Omernik level II ecoregions (Omernik 1987; Figure 3.2). These are well suited geographic units to subdivide data for fire modeling because weather, climate, soils, and vegetation can be assumed to be less variable within ecoregions than among ecoregions.

For each year of observations in the ecoregion subsets, we took the following modeling approach. A subset of fire and non-fire observations was systematically sampled from each ecoregion. Our systematic subsampling approach subdivided the ecoregion into 3x3 blocks of pixels. Within each block, one fire and one non-fire observation were randomly selected. If there were no fire observations within a block, then the non-fire observation was still retained. Likewise, if there were no non-fire observations within a block then the fire observation was kept. We generated 5 systematic subsample replicates for each year and ecoregion. Exploratory data analysis showed that averaging models across subset replicates and over years reduced the influence of spatial autocorrelation and provided estimates of variability in the regression coefficients both within years and among years.

The proportion of fire and non-fire observations in our samples was different from the proportion in the entire population of observations. These differences can bias logistic regression results and we applied a correction factor (Manly et al. 2002, Keating and Cherry 2004). The correction factor (equation 2) weighted the sampled proportion of fires (P_f) and sampled non-fires (P_n) relative to their prevalence in the entire population of fires and non-fires; B_i and X_i are the regression coefficients and predictor variables.

$$P(\text{fire}=1\,|\,\overline{X}) = \exp\left[\frac{\ln(P_n/P_f) + (B_0 + B_1X_1 + B_2X_2 + ... + B_iX_i)}{1+\ln(P_n/P_f) + (B_0 + B_1X_1 + B_2X_2 + ... + B_iX_i)}\right] \quad \text{Equation 2.}$$

Drivers of fire occurrence

To compare the importance of human variables to biophysical variables we considered four different models. For each ecoregion, we selected an initial model including all variables that explained probability of fire occurrence using a modeling approach described in more detail in the next section; we refer to this model as the full model. We compared the full model to three additional models, each using a subset of the variables included in the full model. The first model assumed that fire occurrence could be explained by vegetation type alone; we refer to this model as the vegetation model. The second model added human variables (housing unit density and distance to roads) to the vegetation model. The third model added the physical variables representing weather and topography to the vegetation model. The full model then included vegetation, physical, and human variables. These four models were used to compare the relative importance of human, vegetation and physical variables for explaining fire occurrence.

We fit the four models to the systematic subset replicates for each year and ecoregion. Step-wise selection was used to eliminate variables that had little influence on fire occurrence (Chatterjee et al. 2000). When step-wise selection included quadratic variables, the linear form of the variable was also included in the models. We pooled regression coefficients, their standard errors, and area-under curve (AUC) of receiver-operator plots (ROC) first across model replicates and then across years for each ecoregion. Pooling averaged regression coefficients, but accounted for within and among group differences when combining standard errors (Levy and Lemeshow 1991; page 320). The relative importance of variables for explaining fire occurrence was assessed by comparing the predictive ability of the four models, measured using AUC, a threshold-independent measure of classification success. AUC can be interpreted as the probability of correctly classifying a pair of random observations, given the knowledge that the pair contains one fire and one non-fire (Hanley and McNeil 1982).

Ecoregional variability in predicted fire occurrence

To examine variability in fire occurrence among ecoregions, we made predictive maps of the probability of fire occurrence. Using the ‘full model’ described in the previous section, predictions were made for each replicate dataset for each year. We averaged replicate predictions within a year, and then across years, and calculated the average, standard deviation, and maximum annual probability of fire occurrence. We also made comparisons of the probability of fire occurrence among and within ecoregions by summarizing the proportion of ecoregion area in different ranges of fire occurrence probabilities.

Results

Our models predicting the occurrence of fire performed well. The success of our best models, measured by area-under-curve ranged between 0.65 and 0.87 (Table 3.3). Among the subset data replicates our models provided consistent results with low variability in regression coefficients within years (Table 3.4). Our models were also generally consistent in their predictive ability among the different years, measured by low among-year variability in AUC. However, among-year variability in regression coefficients was often large.

Drivers of fire occurrence

In many regions, models including both vegetation and human variables had nearly the same predictive power as models including both vegetation and physical variables (Table 3.3). Ecoregions where the vegetation and human model performed nearly as well as the vegetation and physical model included the Southeast Plains, the Central Plains, Mediterranean California, and the Mixed Wood Shield. Ecoregions where the vegetation and physical models had greater AUC than the vegetation and human models included the South-Central Semi-Arid Prairies, Western Interior Basin and Ranges, and Temperate Prairies. The AUC of the full models was similar to that of the vegetation and physical models, but generally increased with inclusion of the human variables (Table 3.3). The exception was the Western Interior Basin and Ranges ecoregions, where human variables did not increase AUC when the vegetation and physical variables were also included in the model.

Effects of human variables

Interpreting individual regression coefficients in logistic regression models can be complicated because the relationships are not linear and the coefficient values depend on the presence of the other variables in the model (Gelman and Hill 2007). To help interpret the regression coefficients, we used scatter plots of the predicted values plotted against individual variables. We summarized the general trends from these plots and presented here a few noteworthy examples.

The probability of fire occurrence generally declined with increasing housing unit density, even though models for all ecoregions included both the quadratic and linear terms (Table 3.3). In a few ecoregions, predicted fire occurrence was more likely at intermediate housing unit densities. These were primarily in the Southwest and included The Sonoran and Mohave Deserts, the Chihuahuan Desert, Mediterranean California, and the Upper Gila Mountains (Figure 3.3).

The relationships between distance from roads and fire occurrence were more variable among ecoregions (Table 3.4). In general, fire occurrence decreased as distance to roads increased. This was especially true in the Mixed Wood Shield and the Atlantic Highlands (Figure 3.4a). However, in most ecoregions, the decrease in fire occurrence as distance to roads increased was preceded by a slight increase in fire occurrence, indicating a quadratic effect (Figure 3.4b). There were a few exceptions to these trends.

In the Western Cordillera and the Upper Gila Mountains, fire potential exhibited a U-shaped relationship with distance from roads, where fire was most likely near roads and far from roads and less likely at intermediate distances (Figure 3.4c).

Among years, there was a wide range of variability in the shape of the relationships both between fire occurrence and housing unit density and distance from roads (Table 3.4). Generally speaking, the replicate models within years produced consistent coefficient estimates, but the shape of the relationships changed among years.

Ecoregional variability in potential fire occurrence

There was wide strong ecoregional variability in potential fire occurrence across the United States (Figure 3.5a). Mediterranean California stood out as having both high mean and maximum potential for fire occurrence. Elsewhere in the West, isolated hotspots occurred in the Western Cordillera and Upper Gila Mountains, while broad regions with high fire potential occurred in the southern Great Plains and the Southeast. In contrast, much of the northeast, northern Great Plains, and Interior Basins and Ranges had low potential for fire occurrence.

In areas where the potential for fire occurrence was high, there was also considerable variability in the potential for fire occurrence among years (Figure 3.5b). The variability was especially noticeable in Mediterranean California, but also in the Southeastern, Western Cordillera, and Upper Gila Mountains. Maximum potential for fire occurrence generally followed the same patterns as mean potential for fire occurrence and variability in potential for fire occurrence (Figure 3.5c).

Within ecoregions, the mean potential for fire occurrence was often low and skewed to the right (Figure 3.6). This suggested that a small proportion of most ecoregions had a similar combination of predictor variables as places where MODIS fires occurred. A few ecoregions had less skewed distributions (Western Cordillera, Southeastern Plains, Mississippi Alluvial and SE Coastal Plain, Texas-Louisiana Coastal Plain, Mediterranean California, and Everglades). In these ecoregions, there was a greater range in potential for fire occurrence and a relatively smaller area of the ecoregion had low potential for fire occurrence.

Discussion

We found that human variables influenced fire in most ecoregions of the United States, but with varying strength among ecoregions. However, the magnitude of anthropogenic effects was small relative to the influence of vegetation and physical variables. Human development has had a large effect on shaping landscape structure and ecological processes (Turner et al. 1996, Foster et al. 1998, Hawbaker et al. 2006). However, fire remains a largely biophysical process, dominated by patterns of weather, vegetation, and topography. We found this to be especially true in many western ecoregions, where fire occurrence had high variability and the size of fire events was quite large (Chapter 2).

Our results showed that human variables exhibited both positive and negative influences on fire occurrence. Positive relationships between humans and patterns of fire ignitions have been shown by previous studies in many regions; however, many of these studies found measures of human development to have little explanatory power for large fire occurrence (Cardille et al. 2001; Sturtevant et al. 2007; Syphard et al. 2007). Given the limited predictive power of human variables in previous studies, our results were somewhat surprising, especially given the coarse resolution of our analysis, and that our fire data included both large and small fires.

Human variables improved models most in the Upper Great Lakes region and the southwestern deserts. It appears that the primary effect of development was to limit fire occurrence, whether through active fire management (Veblen et al. 2000) or indirect effects of landscape fragmentation (Miller and Urban 1999, Duncan and Schmalzer 2004). Many of our models also included quadratic relationships between human variables, indicating that the human effect was positive at low housing densities or close to roads, but negative at high densities and distant from roads. However, even within an ecoregion, the shape of the relationships between human variables and fire changed among years. Thus, relationships between people and fire developed from long-term fire data may capture long-term trends, but are likely to be dominated by time periods with high fire activity and may not fully represent year to year variability in patterns of fire occurrence.

Limitations of methods and approach

The grain of our fire observations was approximately 1 km. At this spatial resolution, fine-scale effects of predictor variables could have been masked by coarse-scale measures. For instance, within a square kilometer, topographic variability fragmenting fuels is not fully represented. Likewise, we assigned vegetation types to pixels using a majority rule. Using this approach, we assumed that MODIS fires occurred within the predominant vegetation type when in reality fires could have occurred in any of the vegetation types present in the pixel. Hence, one has to be careful when drawing strong conclusions about the drivers of fire occurrence from our results, because we examined coarse-scale relationships among our variables. However, our results suggest that there were general relationships among our predictor variables that held true with varying levels of strength across the country.

The MODIS satellite fire observations have a relatively short history with the first data collected in early 2000. Since that time, the U.S. has experienced several record years of fire activity (U.S. Department of Agriculture 2006). Because of the limited history of the MODIS fire data, extrapolating our results beyond the time period of our study (2000-2006) would require some important assumptions. Primarily, one would have to assume that future weather and climates are well represented by the annual weather summaries we used for 2000 – 2006. This is a difficult assumption to make given that the western U.S. has been in a drought for most of these years[14]. Furthermore, climate change scenarios suggest that future weather patterns will be different and patterns of fire occurrence will likely shift accordingly (Flannigan et al. 2000, Lenihan et al. 2003). Thus, our findings represent relative potential for fire occurrence over the years the data were collected and it would be questionable to extrapolate them beyond that time period.

[14] http://www.drought.unl.edu/DM/monitor.html

We built our models with the assumption that satellite observations of fire activity capture the fires most important from ecological and social perspectives. Our observations of fire occurrence were based on imperfect satellite data (Hawbaker et al. 2008). Because we used the MODIS fires as samples in logistic regression models, we believe that the effect of undetected fires on our results would be minimal as long as we can assume the fires detected by MODIS were representative of all fires. The MODIS fire data underrepresent small fires (Hawbaker et al. 2008), so our logistic regression models explain the occurrence of large fires which are most relevant for fire management.

Our analyses were performed individually for Omernik level 2 ecoregions. Because we used the same input data and modeling approaches, we believed our logistic regression results were comparable among ecoregions. However, the explanatory power of our models may have been limited by small sample sizes, especially the Northeast where fires events were rare.

Statistical models of fire occurrence do not fully represent the underlying processes of primary production, water balance, and weather that influence fuels, fuel moisture, and fire spread (Rollins et al. 2004). Our models used indirect measures of the biological and physical environment to describe ecological and climate processes. However, previous studies have shown that the indirect measures that we used are good predictors of ecological processes of primary production (Zaks et al. 2007) and fuel dynamics (Rollins et al. 2004). Our objectives were to estimate the human impacts on fire and to predict relative fire potential, and we operated with the assumption that our measures of weather, vegetation, and topography would control for patterns and processes relevant to fire occurrence and allow us to examine the effects of human variables.

Implications for ecosystem conservation and fire management

Our models showed that human variables influence fire occurrence across most of the U.S. Even though the relative strength of human compared to vegetation and physical variables for describing patterns of fire occurrence was low, the 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). Both types of change push disturbance regimes beyond their historic range of variability and have consequences for biodiversity and ecosystem function. These 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). As human development grows (Hammer et al. 2007, Syphard et al. 2007a), we can expect human impacts on fire to become more pronounced and present greater management challenges.

In our models, fire occurrence remained strongly tied to biophysical variables. When fires do occur, their spread and intensity are largely determined by weather and to a lesser extent by fuels and topography (Bessie and Johnson 1995, Keeley 2004). Human activities do have an influence on fire occurrence, but because their impact is small, we have less control over fire occurrence than we might like. Fires are natural events and development in fire-prone landscapes should adapt to reduce the losses caused fire's inevitable occurrence.

Even though our models did not include all components important for fire risk analysis, our results demonstrated some of the potential risks to U.S. society. 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, fire sizes in the West tended to be larger, more variable (chapter 2), and more localized. 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. On one hand, the limited footprint of human development could limit the area needing direct fire management. However, on the other hand, when large fires do occur in or near development, houses are also concentrated and loss can be great.

Potential for fire occurrence is an important component of fire risk modeling; however, the limitations of the federal fire database have constrained the use of national-scale fire probability maps in risk analyses. A common approach is to make assumptions about fire risk based on vegetation or potential fire behavior (Schmidt et al. 2002, Hessburg et al. 2007, Theobald and Romme 2007). However, both estimates of the probability of fire occurrence and the potential for fire damage are needed in a true risk-modeling framework (Bachman and Allgöwer 1999, Finney 2005). Our results showed that potential for fire occurrence varies within ecoregions and vegetation types and across the U.S. Because of this variability, risk models based on vegetation type or potential fire behavior alone may not fully estimate the spatial variability in fire risk.

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Table 3.1. Input variables and units for logistic regression models.

Variable name	Units	Source
Elevation	Meters	GTOPO 30, USGS
Slope	Percent	GTOPO 30, USGS
Southwestness	NA	GTOPO 30, USGS
Mean maximum temperature (TMAX)	°C	(PRISM Group 2004)
Annual precipitation (PPT)	Millimeters	(PRISM Group 2004)
Precipitation difference, 1 – year lag ($\Delta PPT_{1\ year}$)	Millimeters	(PRISM Group 2004)
Precipitation difference from long-term averages ($\Delta PPT30_{\ year\ averages}$)	Millimeters	(PRISM Group 2004)
Housing unit density*	Housing units / km^2	(Radeloff et al. 2005)
Median distance to road*	Meters	(Watts et al. 2007)
Land cover	8 categories: Developed, Water, barren, and ice, Agriculture, Wetlands, Grasslands, Shrublands, Evergreen forest, Mixed forest, Deciduous forest	(Homer et al. 2004)

* natural-log transformed

Table 3.2. 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 (4 classes)	Developed
Pasture / hay	Agriculture
Cultivated agriculture	Agriculture
Woody wetlands (4 classes)	Wetland
Emergent herbaceous wetlands (4 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

Table 3.3. Area-under-curve (AUC) and standard error for the four regression models for each ecoregion.

	Vegetation		Vegetation & human		Vegetation & physical		Vegetation & physical & human	
Ecoregion	**mean**	**se**	**mean**	**se**	**mean**	**se**	**mean**	**se**
Mixed Wood Shield (5.2)	0.58	0.04	0.67	0.05	0.73	0.03	0.76	0.02
Atlantic Highlands (5.3)	0.60	0.07	0.74	0.12	0.85	0.06	0.87	0.07
Western Cordillera (6.2)	0.56	0.01	0.60	0.03	0.67	0.03	0.68	0.03
Marine West Coast Forest (7.1)	0.54	0.01	0.62	0.01	0.69	0.04	0.71	0.03
Mixed Wood Plains (8.1)	0.64	0.03	0.75	0.06	0.81	0.05	0.85	0.04
Central Plains (8.2)	0.54	0.04	0.69	0.05	0.71	0.03	0.77	0.04
Southeastern Plains (8.3)	0.64	0.01	0.67	0.02	0.69	0.01	0.70	0.02
Ozark, Ouachita-Appalachian Forests (8.4)	0.58	0.01	0.66	0.03	0.76	0.03	0.77	0.03
Mississippi Alluvial and SE Coastal Plains (8.5)	0.55	0.01	0.60	0.02	0.64	0.01	0.65	0.01
Temperate Prairies (9.2)	0.58	0.02	0.61	0.02	0.73	0.03	0.75	0.03
West-Central Semi-Arid Prairies (9.3)	0.61	0.05	0.64	0.04	0.69	0.04	0.70	0.04
South Central Semi-Arid Prairies (9.4)	0.59	0.02	0.62	0.02	0.76	0.05	0.77	0.05
Texas-Louisiana Coastal Plain (9.5)	0.59	0.03	0.62	0.03	0.70	0.06	0.71	0.06
Tamaulipas-Texas Semiarid Plain (9.6)	0.55	0.04	0.58	0.05	0.71	0.03	0.72	0.04
Western Interior Basins and Ranges (10.1)	0.57	0.04	0.61	0.06	0.75	0.01	0.75	0.01
Sonoran and Mohave Deserts (10.2)	0.56	0.05	0.73	0.11	0.79	0.08	0.82	0.08
Chihuahuan Desert (10.4)	0.54	0.02	0.63	0.06	0.72	0.03	0.76	0.03
Mediterranean California (11.1)	0.59	0.02	0.64	0.02	0.67	0.05	0.69	0.04
Western Sierra Madre Piedmont (12.1)	0.58	0.09	0.66	0.08	0.77	0.05	0.79	0.04
Upper Gila Mountains (13.1)	0.65	0.06	0.69	0.09	0.77	0.05	0.78	0.05
Everglades (15.4)	0.50	0.01	0.58	0.05	0.69	0.06	0.71	0.05

Table 3.4. Pooled regression coefficients and standard errors (in parentheses as within year; among years; and total) for full models.

Ecoregion	Mixed Wood Shield (5.2)	Atlantic Highlands (5.3)	Western Cordillera (6.2)
Area under curve (AUC)	0.76 (0.02)	0.87 (0.07)	0.68 (0.03)
n non-fires sampled	22,987 (37)	22,633 (41)	96,700 (192)
n fires sampled	133 (73)	20 (13)	2,968 (999)
Used vs. available correction	-1.36 (0.16)	-1.75 (0.12)	-0.93 (0.15)
Intercept	5.45 (12.30; 39.89; 41.74)	-47.22 (33.23; 36.49; 49.35)	-4.59 (0.60; 3.58; 3.63)
Grassland	1.68 (0.46; 0.65; 0.80)	3.89 (1.35; 2.16; 2.55)	0.67 (0.43; 1.31; 1.38)
Shrubland	-0.52 (0.62; 10.39; 10.41)	1.98 (NA; NA; NA)	0.52 (0.37; 0.42; 0.56)
Evergreen	0.66 (0.32; 0.25; 0.41)	-15.98 (938.98; 0.06; 938.98)	0.86 (0.37; 0.37; 0.52)
Mixed	-13.76 (441.83; NA; NA)	-0.25 (0.77; 2.27; 2.40)	-0.75 (0.58; 6.01; 6.04)
Deciduous	-0.01 (0.22; 0.76; 0.79)	0.78 (0.71; 1.14; 1.34)	0.03 (0.45; 1.06; 1.15)
PPT (cm)	-0.92 (0.20; 0.17; 0.26)	0.27 (0.28; 0.63; 0.69)	-0.04 (0.01; 0.04; 0.04)
PPT^2	-0.03 (0.01; 0.00; 0.01)	0.03 (0.02; NA; NA)	0.00 (0.00; 0.00; 0.00)
$\Delta PPT_{1\ year}$	-0.11 (0.17; 0.54; 0.57)	-0.15 (0.32; 0.75; 0.82)	-0.01 (0.02; 0.09; 0.10)
$\Delta PPT_{30\ year\ averages}$	0.86 (0.25; 0.48; 0.54)	-0.63 (0.30; 0.43; 0.53)	0.00 (0.01; 0.06; 0.06)
TMAX (°C)	-1.21 (2.13; 7.04; 7.36)	6.40 (5.45; 6.04; 8.14)	0.26 (0.05; 0.36; 0.36)
$TMAX^2$	0.07 (0.10; 0.34; 0.35)	-0.23 (0.22; 0.27; 0.35)	-0.01 (0.00; 0.01; 0.01)
Elevation (km)	12.48 (11.86; 14.40; 18.66)	-5.72 (2.86; 4.53; 5.36)	0.68 (0.16; 0.77; 0.79)
$Elevation^2$	-18.93 (15.93; 21.82; 27.02)	7.44 (3.60; 3.03; 4.71)	-0.37 (0.05; 0.28; 0.29)
Slope (%)	-0.57 (0.41; 0.92; 1.01)	-0.49 (0.34; 0.37; 0.51)	0.01 (0.01; 0.01; 0.01)
Southwestness	0.29 (0.13; 0.23; 0.27)	-0.79 (0.52; NA; NA)	0.07 (0.03; 0.02; 0.04)
ln(dist. from roads) (m)	0.35 (0.81; 1.05; 1.33)	0.52 (4.10; 3.62; 5.47)	-0.46 (0.11; 0.35; 0.37)
$\ln(\text{dist. from roads})^2$	-0.07 (0.08; 0.11; 0.13)	-0.34 (0.46; 0.41; 0.62)	0.04 (0.01; 0.03; 0.03)
ln(housing unit density) (units / km2)	-1.15 (0.35; 0.31; 0.47)	-0.33 (1.04; 1.23; 1.61)	-0.21 (0.09; 0.11; 0.14)
$\ln(\text{housing unit density})^2$	0.28 (0.11; 0.08; 0.13)	-0.02 (0.32; 0.45; 0.56)	0.07 (0.04; 0.03; 0.05)

Table 3.4 continued.

Ecoregion	Marine West Coast Forest (7.1)	Mixed Wood Plains (8.1)	Central Plains (8.2)
Area under curve (AUC)	0.71 (0.03)	0.85 (0.04)	0.77 (0.04)
n non-fires sampled	9,135 (31)	20,227 (85)	3,332 (43)
n fires sampled	338 (125)	75 (45)	55 (34)
Used vs. available correction	-1.34 (0.10)	-1.40 (0.11)	-1.46 (0.20)
Intercept	-32.98 (5.97; 7.90; 9.90)	0.55 (12.49; 22.64; 25.85)	-51.74 (23.71; 25.73; 34.99)
Grassland	1.26 (0.64; 0.61; 0.89)	-0.94 (0.52; 7.51; 7.53)	-2.66 (401.74; 9.18; 401.85)
Shrubland	1.03 (0.64; 0.33; 0.72)	-4.36 (NA; NA; NA)	
Evergreen	0.82 (0.63; 0.32; 0.71)	-0.17 (0.60; NA; NA)	2.02 (0.93; NA; NA)
Mixed	1.01 (0.62; 0.36; 0.71)	-10.74 (448.48; 7.24; 448.54)	
Deciduous	-13.02 (314.09; 0.65; 314.09)	-0.66 (0.33; 0.31; 0.46)	0.16 (0.59; 2.11; 2.20)
PPT (cm)	0.02 (0.01; 0.04; 0.04)	-0.44 (0.22; 0.43; 0.49)	0.68 (0.33; 0.43; 0.55)
PPT^2	0.01 (0.01; 0.00; 0.01)	-0.02 (0.01; 0.01; 0.01)	0.01 (0.02; 0.06; 0.06)
$\Delta PPT_{1\ year}$	0.02 (0.04; 0.19; 0.20)	-0.13 (0.17; 0.36; 0.40)	-0.01 (0.23; 0.52; 0.57)
$\Delta PPT_{30\ year\ averages}$	-0.06 (0.02; 0.04; 0.05)	0.63 (0.32; 0.22; 0.39)	-1.23 (0.45; 0.16; 0.47)
TMAX (°C)	3.25 (0.66; 1.10; 1.28)	-1.17 (1.99; 3.28; 3.84)	5.70 (2.80; 3.37; 4.39)
$TMAX^2$	-0.09 (0.02; 0.03; 0.04)	0.05 (0.06; 0.30; 0.31)	-0.19 (0.09; 0.11; 0.14)
Elevation (km)	-0.74 (0.92; 2.38; 2.55)	13.06 (15.44; 20.18; 25.41)	18.88 (52.05; 30.29; 60.22)
$Elevation^2$	0.84 (1.17; 3.42; 3.61)	-32.10 (28.77; 29.50; 41.21)	-70.15 (126.63; 65.33; 142.49)
Slope (%)	-0.03 (0.03; 0.07; 0.07)	-0.72 (0.50; 0.60; 0.79)	-1.04 (0.62; 0.34; 0.71)
Southwestness	0.09 (0.10; 0.19; 0.21)	-0.14 (0.15; 0.69; 0.71)	0.07 (0.26; NA; NA)
ln(dist. from roads) (m)	0.62 (0.72; 1.46; 1.62)	0.68 (1.17; 1.71; 2.07)	0.62 (3.17; 3.91; 5.03)
$\ln(\text{dist. from roads})^2$	-0.05 (0.06; 0.12; 0.14)	-0.10 (0.13; 0.21; 0.25)	-0.02 (0.38; 0.59; 0.70)
ln(housing unit density) (units / km2)	-0.41 (0.21; 0.15; 0.26)	-1.85 (0.35; 0.31; 0.47)	-1.38 (0.45; 0.47; 0.65)
$\ln(\text{housing unit density})^2$	-0.14 (0.10; 0.01; 0.10)	0.30 (0.07; 0.06; 0.10)	0.24 (0.09; 0.08; 0.12)

Table 3.4 continued.

Ecoregion	Southeastern Plains (8.3)	Ozark, Ouachita-Appalachian Forests (8.4)	Mississippi Alluvial and SE Coastal Plains (8.5)
Area under curve (AUC)	0.70 (0.02)	0.77 (0.03)	0.65 (0.01)
n non-fires sampled	74,554 (134)	49,448 (82)	24,118 (54)
n fires sampled	5,736 (1,828)	1,360 (517)	2,041 (903)
Used vs. available correction	-1.23 (0.02)	-1.34 (0.05)	-1.22 (0.02)
Intercept	-26.94 (2.54; 10.67; 10.97)	-22.44 (95.50; 5.84; 95.68)	-6.34 (2.42; 7.12; 7.52)
Grassland	0.65 (0.09; 0.24; 0.26)	4.44 (95.44; 5.08; 95.57)	0.36 (0.13; 0.29; 0.31)
Shrubland	0.33 (0.07; 0.21; 0.23)	4.92 (122.60; 7.16; 122.81)	0.55 (0.14; 0.21; 0.26)
Evergreen	0.44 (0.04; 0.07; 0.08)	3.68 (103.08; 5.47; 103.23)	0.21 (0.06; 0.15; 0.16)
Mixed	0.19 (0.09; 0.06; 0.11)	5.03 (134.08; 8.00; 134.32)	-4.80 (98.30; 8.50; 98.67)
Deciduous	0.03 (NA; NA; NA)	5.31 (139.48; 8.72; 139.76)	-0.67 (0.35; 0.38; 0.52)
PPT (cm)	0.04 (0.01; 0.06; 0.06)	-0.02 (0.03; 0.11; 0.11)	0.05 (0.03; 0.07; 0.08)
PPT^2	0.00 (0.00; 0.00; 0.00)	0.00 (0.00; NA; NA)	0.00 (0.00; 0.01; 0.01)
$\Delta PPT_{1\ year}$	-0.01 (0.01; 0.13; 0.13)	0.07 (0.03; 0.12; 0.12)	0.00 (0.02; 0.11; 0.11)
$\Delta PPT_{30\ year\ averages}$	-0.13 (0.02; 0.16; 0.16)	-0.09 (0.04; 0.06; 0.08)	-0.14 (0.03; 0.04; 0.05)
TMAX (°C)	1.96 (0.22; 0.95; 0.98)	1.02 (0.32; 0.41; 0.52)	0.06 (0.19; 0.61; 0.64)
$TMAX^2$	-0.04 (0.00; 0.02; 0.02)	-0.02 (0.01; 0.01; 0.01)	0.00 (0.00; 0.01; 0.02)
Elevation (km)	1.85 (0.97; 3.15; 3.29)	2.73 (0.77; 1.80; 1.96)	10.43 (3.92; 16.73; 17.19)
$Elevation^2$	-13.82 (3.43; 10.45; 11.00)	-2.69 (0.75; 1.24; 1.45)	-223.56 (85.74; 380.97; 390.50)
Slope (%)	-0.22 (0.06; 0.06; 0.08)	-0.05 (0.02; 0.08; 0.08)	-0.32 (0.30; 0.75; 0.81)
Southwestness	0.03 (0.02; 0.04; 0.05)	0.10 (0.05; 0.02; 0.06)	0.10 (0.04; 0.04; 0.05)
ln(dist. from roads) (m)	-0.10 (0.10; 0.11; 0.15)	0.56 (0.40; 0.52; 0.66)	0.05 (0.17; 0.25; 0.30)
$ln(dist.\ from\ roads)^2$	0.01 (0.01; 0.03; 0.03)	-0.06 (0.04; 0.04; 0.06)	-0.01 (0.01; 0.03; 0.03)
ln(housing unit density) (units / km2)	-0.51 (0.05; 0.15; 0.15)	-0.61 (0.08; 0.27; 0.28)	-0.28 (0.07; 0.12; 0.14)
$ln(housing\ unit\ density)^2$	0.07 (0.02; 0.03; 0.03)	0.12 (0.02; 0.05; 0.06)	0.03 (0.02; 0.04; 0.04)

Table 3.4 continued.

Ecoregion	Temperate Prairies (9.2)	West-Central Semi-Arid Prairies (9.3)	South Central Semi-Arid Prairies (9.4)
Area under curve (AUC)	0.75 (0.03)	0.70 (0.04)	0.77 (0.05)
n non-fires sampled	8,451 (63)	65,174 (91)	82,180 (119)
n fires sampled	503 (312)	601 (376)	2,961 (1,911)
Used vs. available correction	-1.35 (0.14)	-1.09 (0.17)	-1.28 (0.13)
Intercept	-0.81 (2.39; 4.06; 4.71)	0.35 (2.90; 8.61; 9.09)	-9.02 (2.03; 5.90; 6.25)
Grassland	0.16 (0.23; 0.57; 0.61)	-0.70 (0.16; 0.33; 0.37)	-0.21 (0.17; 0.54; 0.56)
Shrubland		0.69 (0.18; 0.40; 0.43)	-0.03 (0.32; 0.43; 0.53)
Evergreen		1.11 (0.34; 0.30; 0.45)	0.60 (0.20; 0.31; 0.37)
Mixed		1.96 (0.84; NA; NA)	-2.71 (75.25; 7.45; 75.62)
Deciduous	-0.60 (0.20; 0.15; 0.25)	-2.95 (130.56; 13.22; 131.23)	-0.24 (0.25; 0.65; 0.70)
PPT (cm)	0.19 (0.09; 0.08; 0.12)	-0.14 (0.06; 0.16; 0.17)	0.50 (0.04; 0.15; 0.15)
PPT^2	0.00 (0.00; 0.01; 0.01)	0.00 (0.00; 0.01; 0.01)	0.00 (0.00; 0.01; 0.01)
$\Delta PPT_{1\ year}$	0.02 (0.07; 0.29; 0.30)	-0.30 (0.08; 0.17; 0.19)	-0.13 (0.02; 0.15; 0.15)
$\Delta PPT_{30\ year\ averages}$	-0.24 (0.12; 0.20; 0.24)	0.15 (0.06; 0.66; 0.66)	-0.29 (0.05; 0.25; 0.26)
TMAX (°C)	-0.92 (0.21; 0.36; 0.42)	-1.05 (0.28; 1.09; 1.12)	0.30 (0.19; 0.63; 0.66)
$TMAX^2$	0.03 (0.01; 0.01; 0.01)	0.06 (0.01; 0.02; 0.03)	-0.01 (0.00; 0.02; 0.02)
Elevation (km)	20.89 (4.54; 8.72; 9.83)	3.29 (0.91; 2.78; 2.93)	1.35 (0.55; 1.23; 1.34)
$Elevation^2$	-29.36 (6.05; 10.98; 12.54)	-1.96 (0.41; 0.98; 1.06)	-1.07 (0.24; 0.44; 0.50)
Slope (%)	-0.25 (0.19; 0.31; 0.36)	0.08 (0.03; 0.10; 0.11)	0.27 (0.05; 0.07; 0.09)
Southwestness	0.05 (0.07; 0.15; 0.17)	0.10 (0.07; 0.14; 0.16)	-0.04 (0.03; 0.09; 0.10)
ln(dist. from roads) (m)	0.19 (0.60; 1.14; 1.29)	0.88 (0.72; 1.08; 1.30)	-0.28 (0.21; 0.19; 0.28)
$ln(dist.\ from\ roads)^2$	-0.03 (0.06; 0.12; 0.13)	-0.09 (0.06; 0.08; 0.10)	0.03 (0.02; 0.02; 0.03)
ln(housing unit density) (units / km2)	-0.82 (0.25; 0.16; 0.30)	0.51 (0.39; 0.64; 0.75)	-0.45 (0.11; 0.18; 0.21)
$ln(housing\ unit\ density)^2$	0.13 (0.06; 0.02; 0.06)	-0.26 (0.26; 0.40; 0.48)	0.07 (0.03; 0.04; 0.05)

Table 3.4 continued.

Ecoregion	Texas-Louisiana Coastal Plain (9.5)	Tamaulipas-Texas Semiarid Plain (9.6)	Western Interior Basins and Ranges (10.1)
Area under curve (AUC)	0.71 (0.06)	0.72 (0.04)	0.75 (0.01)
n non-fires sampled	4,278 (29)	5,882 (23)	125,254 (123)
n fires sampled	483 (199)	137 (110)	1,610 (755)
Used vs. available correction	-1.11 (0.10)	-1.42 (0.15)	-0.92 (0.09)
Intercept	112 (38; 34; 51)	163 (243; 268; 361)	-7.60 (1.30; 7.26; 7.37)
Grassland	0.54 (0.21; 0.18; 0.27)	-1.50 (0.62; 0.79; 1.00)	-0.58 (0.30; 0.78; 0.83)
Shrubland	0.47 (0.24; 0.16; 0.29)	-1.45 (0.52; 0.57; 0.77)	-0.50 (0.16; 1.04; 1.05)
Evergreen	0.42 (0.17; 0.11; 0.21)		0.04 (0.37; 0.57; 0.68)
Mixed	-9.22 (244; 6.36; 244)		-4.27 (NA; NA; NA)
Deciduous	-7.13 (190; 10; 190)	-13.88 (419; 0.91; 419)	-1.47 (0.60; 0.84; 1.03)
PPT (cm)	0.14 (0.05; 0.07; 0.09)	-0.59 (0.44; 1.06; 1.14)	0.28 (0.03; 0.06; 0.07)
PPT^2	-0.01 (0.00; NA; NA)	-0.01 (0.01; 0.02; 0.02)	0.01 (0.00; 0.01; 0.01)
$\Delta PPT_{1\ year}$	-0.08 (0.07; 0.20; 0.21)	0.01 (0.27; 0.66; 0.71)	-0.20 (0.05; 0.40; 0.40)
$\Delta PPT_{30\ year\ averages}$	-0.14 (0.09; 0.18; 0.20)	0.16 (0.61; 2.13; 2.22)	-0.05 (0.04; 0.18; 0.18)
TMAX (°C)	-8.41 (2.74; 2.58; 3.76)	-12.51 (17.47; 19.23; 25.98)	0.61 (0.11; 0.83; 0.83)
$TMAX^2$	0.15 (0.05; 0.05; 0.07)	0.34 (0.32; 0.42; 0.52)	-0.02 (0.00; 0.03; 0.03)
Elevation (km)	21.75 (12.61; 23.50; 26.67)	-2.34 (9.45; 17.21; 19.63)	-1.08 (0.23; 0.99; 1.02)
$Elevation^2$	-539 (256; 363; 445)	-29.42 (34.82; 68.19; 76.56)	0.03 (0.08; 0.40; 0.40)
Slope (%)	-0.46 (0.82; 2.01; 2.17)	-0.03 (0.57; 1.45; 1.56)	0.05 (0.01; 0.04; 0.04)
Southwestness	0.13 (0.11; 0.27; 0.29)	-0.31 (0.26; NA; NA)	-0.05 (0.05; 0.15; 0.15)
ln(dist. from roads) (m)	0.31 (0.45; 0.73; 0.86)	0.65 (1.23; 1.29; 1.78)	-0.10 (0.27; 0.55; 0.61)
$ln(dist.\ from\ roads)^2$	-0.03 (0.03; 0.06; 0.07)	-0.06 (0.11; 0.13; 0.17)	0.01 (0.02; 0.05; 0.06)
ln(housing unit density) (units / km2)	-0.48 (0.15; 0.24; 0.28)	0.41 (0.83; 0.86; 1.20)	0.07 (0.15; 0.66; 0.67)
$ln(housing\ unit\ density)^2$	0.07 (0.05; 0.09; 0.10)	-0.31 (0.62; 0.55; 0.83)	0.05 (0.05; 0.17; 0.18)

Table 3.4 continued.

Ecoregion	Sonoran and Mohave Deserts (10.2)	Chihuahuan Desert (10.4)	Mediterranean California (11.1)
Area under curve (AUC)	0.82 (0.08)	0.76 (0.03)	0.69 (0.04)
n non-fires sampled	29,714 (50)	22,702 (12)	14,443 (115)
n fires sampled	199 (278)	83 (42)	612 (345)
Used vs. available correction	-1.11 (0.24)	-1.33 (0.20)	-0.93 (0.23)
Intercept	3.17 (79.76; 18.33; 81.84)	4.06 (16.69; 28.04; 32.63)	-11.87 (4.13; 7.99; 8.99)
Grassland	-3.46 (0.74; 6.84; 6.88)	-3.47 (1.47; 1.17; 1.88)	-1.20 (0.30; 0.49; 0.57)
Shrubland	-1.10 (95.79; 3.34; 95.85)	-2.36 (1.68; 1.64; 2.35)	-0.89 (0.29; 0.33; 0.43)
Evergreen	1.23 (1.19; 9.27; 9.34)	-5.93 (95.13; 8.60; 95.52)	-1.06 (0.36; 0.59; 0.69)
Mixed	-14.34 (NA; NA; NA)		-1.30 (0.58; 0.61; 0.84)
Deciduous	14.39 (NA; NA; NA)	-3.46 (2,237.47; NA; NA)	-3.80 (113.22; 5.59; 113.36)
PPT (cm)	0.57 (0.39; 0.86; 0.95)	0.60 (0.32; 0.84; 0.90)	-0.04 (0.02; 0.12; 0.12)
PPT^2	-0.09 (0.06; 0.45; 0.45)	-0.01 (0.04; 0.07; 0.08)	0.00 (0.00; 0.01; 0.01)
$\Delta PPT_{1\ year}$	-0.48 (0.20; 0.80; 0.83)	-0.43 (0.30; 0.70; 0.76)	0.05 (0.06; 0.55; 0.55)
$\Delta PPT_{30\ year\ averages}$	-0.16 (0.29; 1.00; 1.04)	-0.76 (0.24; 0.26; 0.35)	-0.09 (0.05; 0.28; 0.28)
TMAX (°C)	-0.50 (0.61; 1.36; 1.49)	-1.35 (1.37; 2.05; 2.47)	0.86 (0.33; 0.78; 0.85)
$TMAX^2$	0.01 (0.01; 0.02; 0.03)	0.04 (0.03; 0.05; 0.06)	-0.03 (0.01; 0.01; 0.01)
Elevation (km)	-4.76 (1.32; 4.62; 4.80)	4.64 (3.54; 8.59; 9.29)	0.00 (0.36; 0.72; 0.81)
$Elevation^2$	1.36 (0.52; 0.71; 0.88)	-1.58 (1.54; 3.72; 4.03)	-0.01 (0.19; 0.56; 0.59)
Slope (%)	0.01 (0.06; 0.13; 0.14)	-0.06 (0.13; 0.25; 0.28)	0.00 (0.02; 0.05; 0.05)
Southwestness	0.13 (0.19; 0.57; 0.60)	-0.41 (0.18; 0.21; 0.27)	0.02 (0.05; NA; NA)
ln(dist. from roads) (m)	1.16 (0.99; 1.27; 1.61)	0.00 (0.52; 0.38; 0.64)	0.02 (0.48; 1.15; 1.25)
$\ln(\text{dist. from roads})^2$	-0.12 (0.09; 0.13; 0.16)	-0.06 (0.05; 0.09; 0.11)	-0.02 (0.04; 0.11; 0.12)
ln(housing unit density) (units / km2)	0.88 (0.41; 0.77; 0.87)	1.31 (0.82; 1.28; 1.52)	0.34 (0.13; 0.29; 0.32)
$\ln(\text{housing unit density})^2$	-0.18 (0.11; 0.16; 0.20)	-0.36 (0.39; 0.58; 0.70)	-0.12 (0.04; 0.07; 0.08)

Table 3.4 continued.

Ecoregion	Western Sierra Madre Piedmont (12.1)	Upper Gila Mountains (13.1)	Everglades (15.4)
Area under curve (AUC)	0.79 (0.04)	0.78 (0.05)	0.71 (0.05)
n non-fires sampled	5,492 (17)	14,619 (67)	1,891 (11)
n fires sampled	78 (49)	570 (289)	140 (83)
Used vs. available correction	-0.97 (0.39)	-0.78 (0.22)	-1.08 (0.13)
Intercept	-1.10 (216; 43.2; 220)	-8.72 (3.03; 13.70; 14.03)	-1,179 (552; 781; 957)
Grassland	2.61 (1.18; NA; NA)	0.95 (0.42; 0.46; 0.62)	
Shrubland	7.31 (346; 6.80; 346)	0.57 (NA; NA; NA)	
Evergreen	9.99 (401; 8.42; 401)	1.17 (0.27; 0.40; 0.48)	1.84 (0.91; 0.42; 1.00)
Mixed			
Deciduous			
PPT (cm)	0.22 (0.34; 0.99; 1.04)	0.43 (0.07; 0.12; 0.14)	0.07 (0.18; 0.36; 0.41)
PPT^2	0.01 (0.02; 0.04; 0.04)	-0.01 (0.00; 0.01; 0.01)	0.00 (0.01; 0.03; 0.03)
$\Delta PPT_{1\ year}$	-0.20 (0.43; 1.03; 1.11)	-0.36 (0.15; 0.26; 0.30)	-0.04 (0.14; 0.78; 0.79)
$\Delta PPT_{30\ year\ averages}$	-0.04 (0.14; 0.69; 0.70)	-0.30 (0.10; 0.17; 0.20)	-0.60 (0.33; 0.53; 0.63)
TMAX (°C)	-0.67 (1.57; 3.44; 3.78)	0.43 (0.30; 2.13; 2.15)	93.90 (40.81; 42.53; 58.94)
$TMAX^2$	0.02 (0.04; 0.08; 0.09)	-0.01 (0.01; 0.07; 0.07)	-1.67 (0.66; 0.65; 0.92)
Elevation (km)	3.40 (3.96; 7.97; 8.90)	3.30 (1.95; 4.69; 5.08)	795 (310; 752; 813)
$Elevation^2$	-0.57 (1.21; 2.08; 2.41)	-0.89 (0.49; 1.28; 1.37)	-146,794 (61,879; 109,949; 126,166)
Slope (%)	0.00 (0.05; 0.19; 0.19)	0.00 (0.02; 0.10; 0.10)	-13.08 (11.26; 56.99; 58.09)
Southwestness	-0.30 (0.17; 0.79; 0.81)	-0.15 (0.08; 0.06; 0.10)	0.28 (0.25; 0.86; 0.89)
ln(dist. from roads) (m)	-0.24 (0.72; 0.59; 0.94)	-1.00 (0.45; 1.21; 1.29)	0.06 (0.71; 1.41; 1.58)
$ln(dist.\ from\ roads)^2$	0.03 (0.06; 0.06; 0.09)	0.07 (0.04; 0.11; 0.11)	-0.01 (0.05; 0.11; 0.12)
ln(housing unit density) (units / km2)	0.81 (1.42; 1.10; 1.80)	0.33 (0.25; 0.19; 0.31)	0.22 (0.59; 0.78; 0.98)
$ln(housing\ unit\ density)^2$	-0.89 (2.74; 1.56; 3.15)	-0.11 (0.11; 0.09; 0.14)	-0.17 (0.37; 0.52; 0.64)

Figure 3.1. MODIS active fires from both the Terra and Aqua sensors from 2000 to 2006.

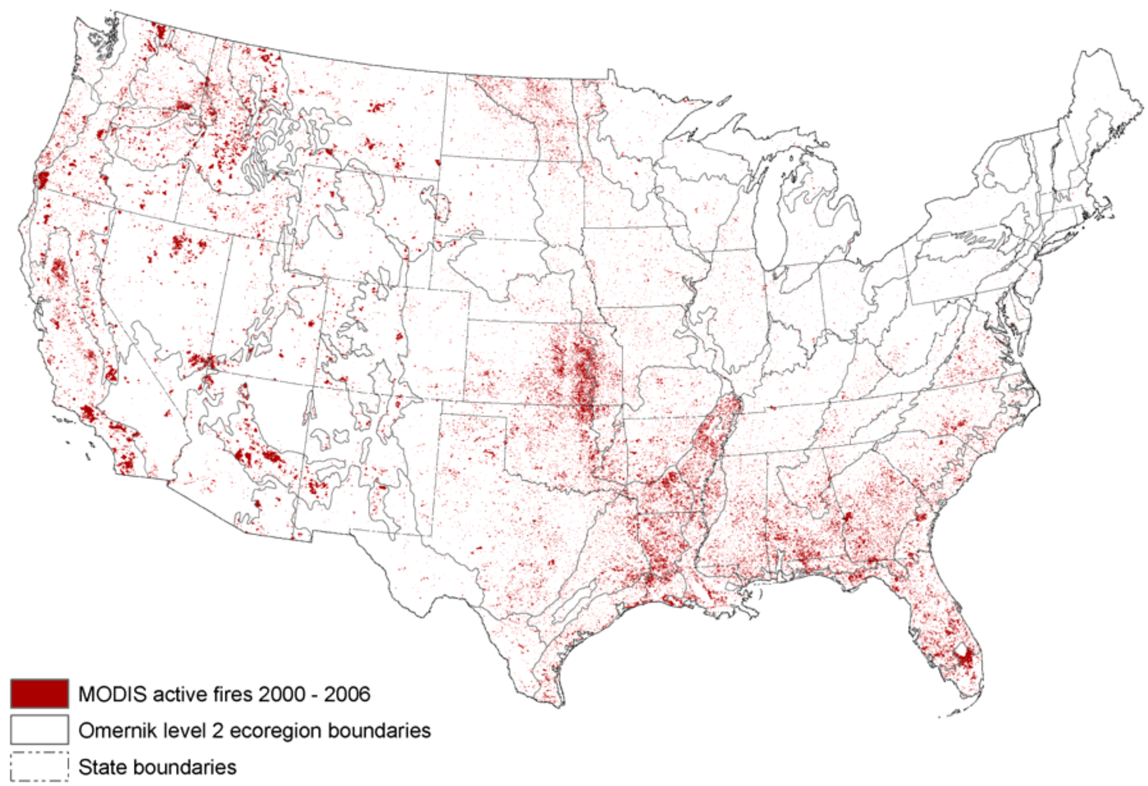


Figure 3.2. Omernik level II ecoregions.

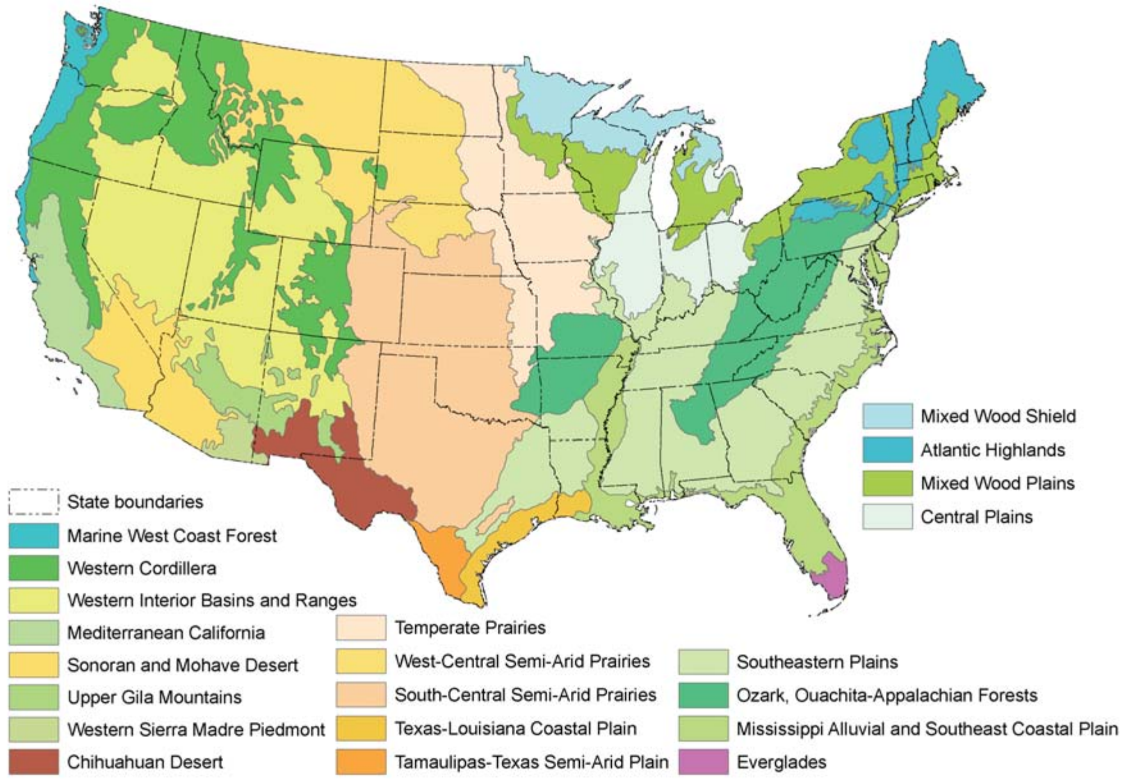


Figure 3.3. Fitted potential for fire occurrence against housing unit density gradient for Mediterranean California, 2001. Black dots show individual fitted values. Red dots show fitted values at the mean value of all other variables in the model.

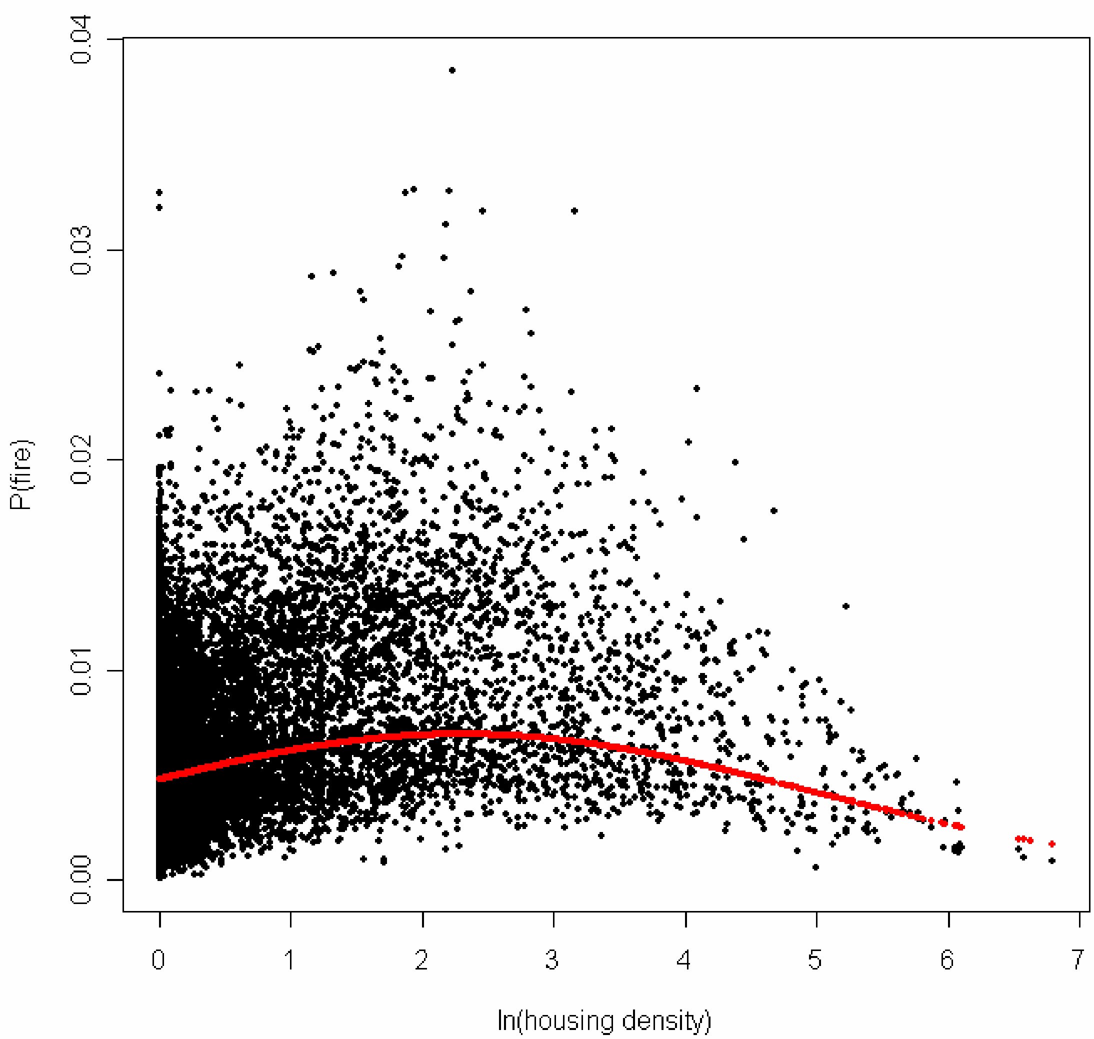


Figure 3.4. Fitted potential for fire occurrence against distance from road gradient for (a) Mixed Wood Shield 2001, (b) West-Central Semi-Arid Prairies 2006, and (c) Upper Gila Mountains 2003. Black dots show individual fitted values. Red dots show fitted values at the mean value of all other variables in the model.

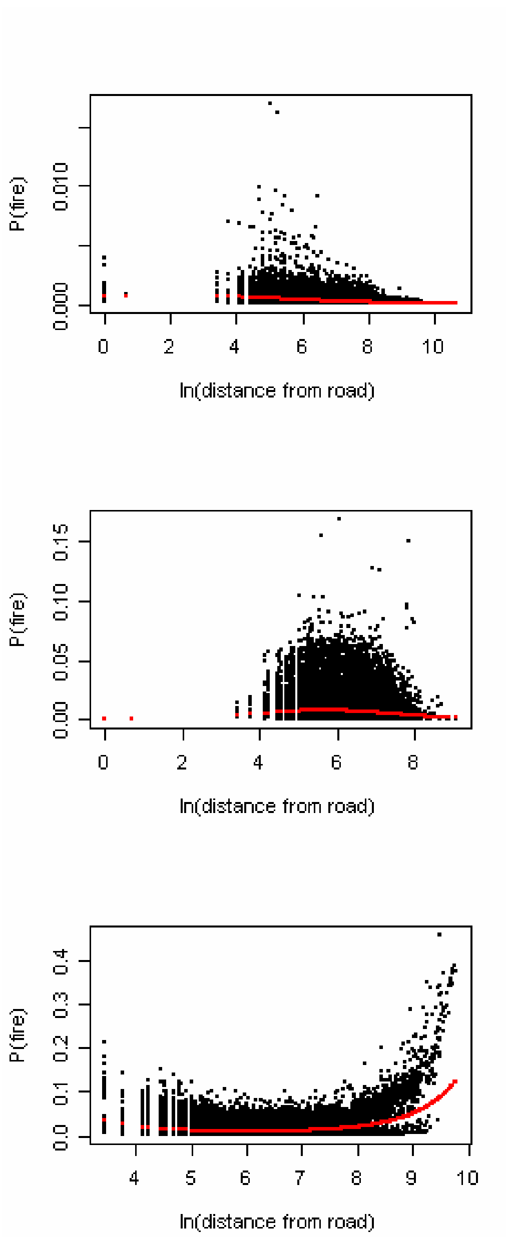


Figure 3.5. Mean potential for fire occurrence (a), standard deviation in potential for fire occurrence (b), and maximum potential for fire occurrence (c) for years 2000 – 2006.

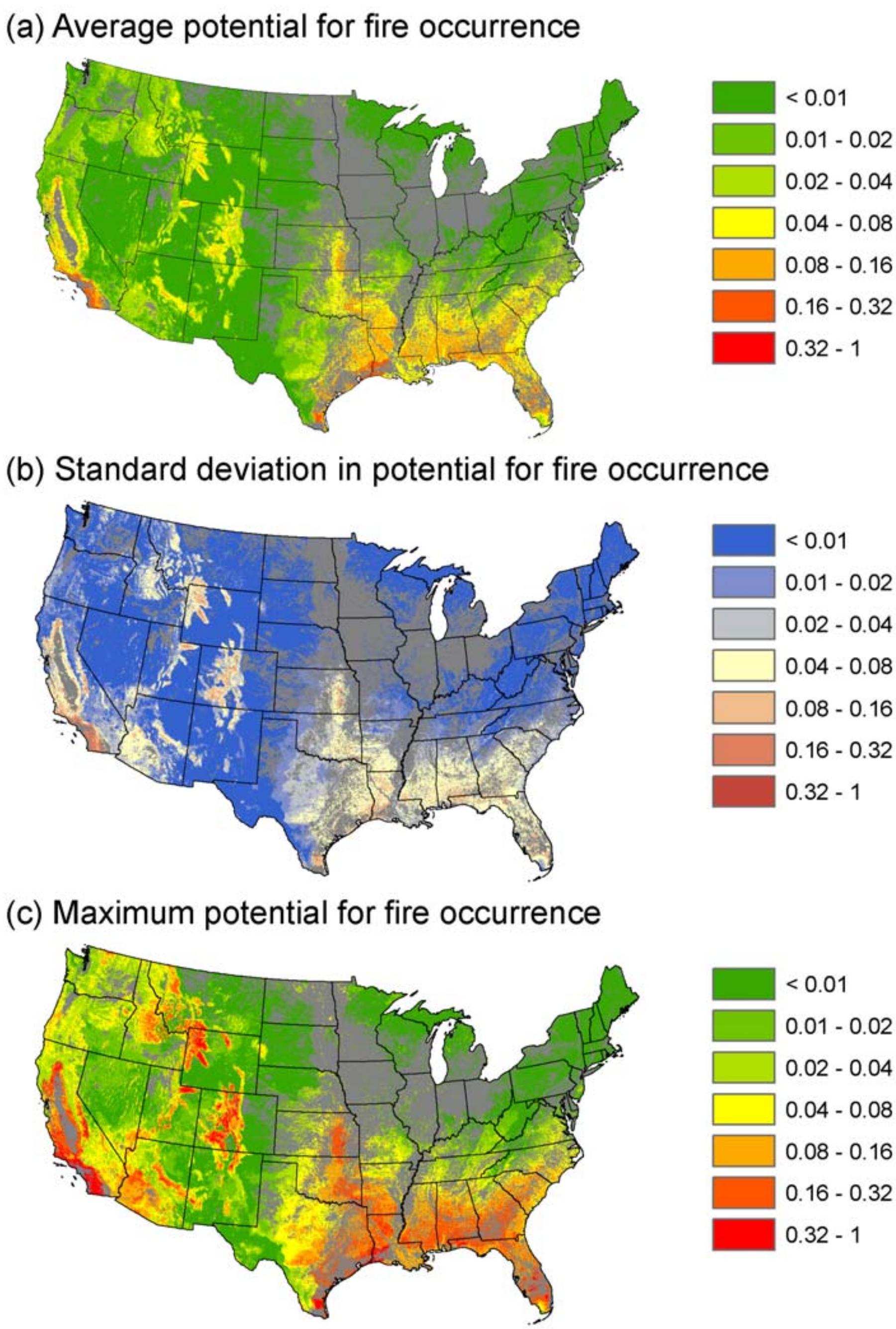
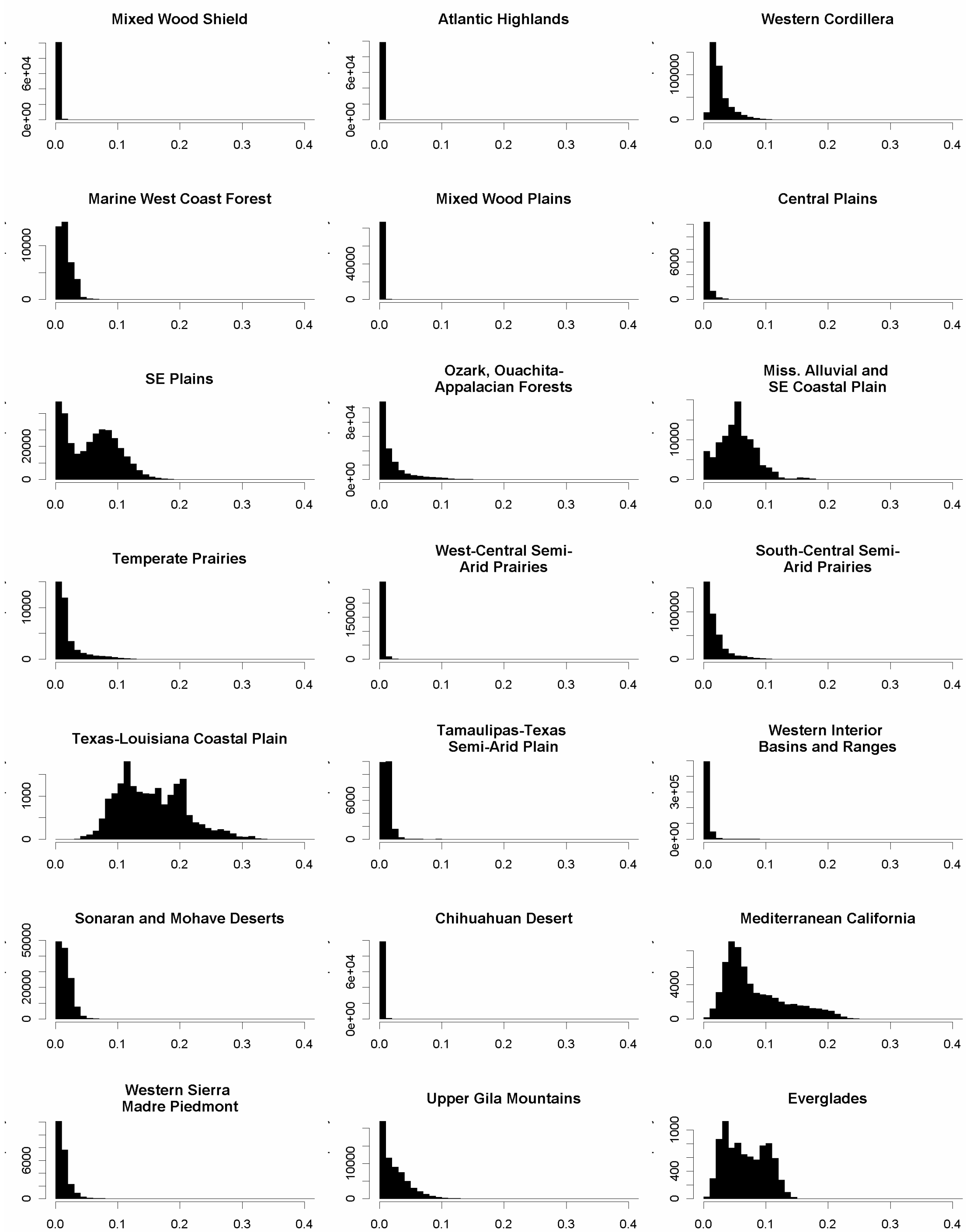


Figure 3.6. Histograms of the count of MODIS pixels (on y-axis) by ecoregion according to potential for mean fire occurrence from 2000 to 2006.



Chapter 4: National and ecoregional patterns of fire risk to housing units in the conterminous United States

Abstract

Protection of lives and property is a primary goal of fire management, and much is known about national patterns of human development. Less is known about national patterns of fire risk. Our goal here was to conduct a national-scale assessment of wildfire risk to houses developed with consistent methods to help fire planning, budgeting, and management efforts. We defined risk as a function of the probability of fire occurrence and housing locations across the U.S. We compared risk among vegetation types based on their potential for severe fire behavior. We also examined the relative contribution of housing numbers and fire potential to risk and then compared ecoregional differences in fire risk to houses. Our measure of risk did not differentiate areas with low housing density and high fire probability from areas with high housing density and low fire probabilities. However, it did provide an aggregate estimate of the exposure of houses to fires. Risk to houses in shrublands and evergreen forest was twice as high as risk in other vegetation types. We found that 3.2 million housing units (2.8% of all housing units) were located in shrublands and evergreen forests with ≥ 2% chance of fire per year. However, those housing units were scattered over 19% of the area of the U.S. Regionally, risk was highest in the Southeast, the mountains and some deserts of the West, and Mediterranean California. The scattering of a large number of housing units at

risk from fire over a large area may make broad-scale fire risk reduction methods difficult to implement. The results of our analysis demonstrate that national-scale risk analysis useful for fire planning are possible and could be used as a guide to where fire risk needs to be addressed most in the U.S.

Introduction

National scale risk assessments are needed to help prioritize management efforts to reduce the threats wildland fires present to communities. Formally defined, risk incorporates both the probability that an event will occur and the potential for that event to cause change or damage something of value (Bachman and Allgöwer 1999, Finney 2005). For fire risk assessments, human life and property are the primary value of concern (U.S. Department of Agriculture and U.S. Department of Interior 2001), although watershed and ecosystem health are also considered important (Healthy Forests Restoration Act of 2003). However, because protecting structures in the wildland-urban interface (WUI) is a primary goal of federal fire policy, many risk analyses focus on fire risk to housing units.

Measuring risk as a function of the number of housing units accounts for direct effects of fire, such as the destruction of structures. Housing units are highly correlated with population, and even when fires do not directly threaten structures, housing units represent a measure of the indirect effects and additional costs generated by wildfires. For instance, increased health care needs (Butry et al. 2001). Because housing can represent both direct and indirect types of fire risk, they are a good metric for estimating the potential impact of fires on society.

The responsibility to identify communities at risk has largely been placed on state agencies (U.S. Department of Agriculture and U.S. Department of Interior 2001) and the National Association of State Foresters (NASF) assists states with that task (National Association of State Foresters 2003). Even though the process is evolving, it allows a wide range of interpretations of what constitutes a community at risk (U.S. General Accounting Office 2003). Consequently, individual state fire risk assessments are variable in their input data, methods, and outcomes.

Previous state and regional studies have incorporated a variety of methods and data sources to quantify fire risk. Most use probabilistic function to determine the likelihood of fire occurrence (Chou et al. 1993, Neuenschwander et al. 2000). Fire occurrence is typically is coupled with estimates of fire intensity from probabilistic models based on historic fire behavior (Neuenschwander et al. 2000), potential fire intensity (Florida Division of 2002), historic fire regimes (Haight et al. 2004), or weighted overlays and expert opinion (Arizona Interagency Coordinating Group 2004). The final step in risk estimation is completed by combining fire probability and behavior with housing units or population determined from housing point locations (Arizona Interagency Coordinating 2004), urban night time lights (Cova et al. 2004), or U.S. Census Bureau data (Haight et al. 2004).

Different risk assessment methodologies can produce substantially different results for the same region (Farris et al. 1999), therefore comparisons among the varying regional and state-level risk assessments is difficult because of the varying methodologies and data used to generate them. We're not brash enough to claim that state-level risk assessments are not without value. They have their advantages and make use of the best available local data and knowledge. However, because many fire policies and fire funding are national in scope, national-scale risk assessments are needed to compare the relative amount and extent of risk across the U.S.

Few national-scale studies of fire risk in the WUI have incorporated fine-scale probabilistic measures of fire occurrence, most rely on assumed fire potential and behavior based on vegetation types alone (Theobald and Romme 2007) or potential fire activity from historic weather patterns (Schmidt et al. 2002). These studies did not account for spatial heterogeneity in the probability of fire occurrence. Our past research has shown that the probability of fire occurrence can be quite variable, even within homogenous vegetation types (Chapter 3). Therefore, probabilistic measures of fire occurrence could help inform national fire risk assessments when used in combination with housing locations.

Information about the location of the wildland-urban interface (WUI) is well defined at the national level (Radeloff et al. 2005) and is often used as a starting point for state-level analyses and fire planning analysis[15] by federal agencies. The SILVIS WUI data were based on U.S. Census Bureau Housing data in combination with vegetation from the National Landcover Database. Therefore, the SILVIS WUI data identify places where housing and vegetation coincide, but because they do not incorporate measures of fire probability or behavior, additional information is needed to determine risk.

In this paper, we examined national patterns of fire risk by combining housing locations from the SILVIS WUI data (Radeloff et al. 2005) with probabilistic models of fire occurrence based on MODIS active fire observations, and spatial gradients of precipitation, temperature, vegetation, topography, and human development (Chapter 3). The questions we sought to answer were (1) What is the fire risk to housing units in the U.S.? (2) Does the risk vary among vegetation types? Because risk to housing units can vary based on either housing or fire potential, we also asked (3) what was the relative contribution of probability of fire occurrence and number of housing units to risk? Finally, we examined regional patterns and asked (4) how does fire risk to housing units vary among ecoregions of the U.S.?

Methods

We used previously developed predictive models of fire occurrence (Chapter 3) to determine where housing units were at risk from wildland fires. Our models of potential

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[15] http://www.fpa.nifc.gov/

for fire occurrence were based on active fire observations from the Moderate Resolution Imaging Spectroradiometer (MODIS) satellite sensors, Terra and Aqua (Justice et al. 2002a, Giglio et al. 2003a). The MODIS fires were used as observations in logistic regression models with precipitation, temperature, topography, vegetation, housing density, and distance to roads as predictor variables. Models of fire potential were constructed for each year between 2000 and 2006.

The locations of housing units were derived from 2000 U.S. Census Bureau TIGER data (Radeloff et al. 2005). The finest spatial resolution of these data is block-level polygons, which have an average of 10.1 ha and standard deviation of 1,082 ha in size (Stewart et al. 2007). We converted the polygon housing data to a raster with the same resolution as the MODIS fire potential models (~ 1 km) using an area-weighted allocation method.

Fire risk to houses varies among vegetation types because of differences in potential fire intensity and severity. Fires pose the greatest danger in shrublands and evergreen forests where extreme fire behavior can result in crown fires that are nearly impossible to control, generate high amounts of radiative heat, and can shower adjacent areas with firebrands (Rothermel 1972, Pyne et al. 1996). These fires are of concern because they present the greatest risk to structures and houses (Cohen 2000, 2004). Fires in other vegetation types can also put structures and houses at risk; but fire behavior is generally less extreme and fires take considerably less effort to control. Accordingly, we calculated risk to houses for both shrublands and evergreen forests separately from all other wildland vegetation types (grasslands, wetlands, deciduous, and mixed forests).

We defined vegetation types using the land cover classes from the 2001 Multiple Resolution National Land Cover Database (NLCD)[16], derived from 30 m resolution Landsat imagery (Homer et al. 2004). We combined some of the NLCD categories to eight unique land cover categories: developed, agriculture, wetland, grassland, shrubland, evergreen forest, deciduous forest, and mixed forest. These eight land cover categories were aggregated to 1 km resolution with a majority rule. Developed and agriculture pixels were excluded from this analysis. We considered all the other remaining vegetation types to be wildland vegetation. Of our vegetation groups, all wildland vegetation represented 68.0% of the land area and 16.2% of all housing units in the U.S., and shrubland and evergreen forest vegetation alone represented 35.6% of the land area and 4.1% of all houses in the U.S. (Chapter 2).

We considered fire risk to be a function of the number of housing units and the potential for fire occurrence. Risk was calculated per pixel as the product of the number of housing units and the average potential for fire occurrence between 2000 and 2006, normalized by the total number of housing units in the United States (Equation 1). Thus risk can be interpreted as the probability that a housing unit was exposed to fires under average conditions during the years for which our fire potential models were constructed (2000-2006).

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[16] http://www.mrlc.gov/mrlc2k_nlcd.asp

$$\frac{\sum_{i=1}^{\text{n pixels}}(\text{Average fire potential} \times \text{Housing units})}{\sum_{i=1}^{\text{n pixels}}\text{Housing units}} \qquad \text{Equation 1.}$$

To answer our first question, what is the fire risk to housing units in the U.S., we solved equation 1 for all housing units in all wildland vegetation types in the U.S. The same approach was taken to answer question 2, except that we limited the risk calculation to only housing units occurring in shrubland and evergreen forests.

For our third question, we examined the relative contribution of fire potential and housing units to risk across the country. We subdivided the potential for fire occurrence data into seven categories representing a range from very unlikely to almost certain. We also subdivided the housing density data into seven categories representing a potential loss gradient. When combined, these 49 categories represented a two-dimensional feature space from fires unlikely, to fires certain and minimal to high housing loss. We calculated the number of pixels and number of housing units in each category to evaluate their contribution to risk. We performed this analysis for all pixels that were wildland vegetation (grassland, wetland, shrubland, forest) and for pixels whose vegetation was predominantly shrubland or evergreen forest.

To answer our third question, in which regions of the U.S. are houses most at risk, we used Omernik level 2 ecoregions to subdivide our data (Figure 4.1). Risk was calculated in each ecoregion, but normalized by the total number of housing units in an ecoregion instead of the U.S. Comparison of risk between ecoregions gives a measure of the relative risk, or the increased or decreased chance that a house will experience a fire in one ecoregion over another.

Results

Risk at the national scale

We quantified risk as the probability that a housing unit was exposed to fires under average conditions during the years for which our fire potential models were constructed (2000 – 2006). By this measure, the risk to housing units in all wildland vegetation in the U.S. was 0.020. We performed that same calculation for only housing units occurring in shrublands and evergreen forests. In those vegetation types, risk was greater at 0.035.

Influence of fire potential and housing units

The majority of the area with wildland vegetation (35.6% of the U.S.) had low potential for fire occurrence (< 0.01; Figure 4.2). However, nearly an equivalent area had moderate to high potential for fire occurrence (≥ 0.01). Across the range of fire potential in wildland vegetation, more than 89% of the area had between 0 and 4 housing units per square kilometer. However, in the remaining 11% of wildland vegetation pixels, housing density was higher and there were more than 8.6 million housing units in areas with a moderate to high potential for fire ≥ 0.01 (Figure 4.3).

The amount of land and housing units in shrublands and evergreen forests was much less compared to all wildland vegetation (16% of the U.S. and 4.1% of all housing units). In shrubland and evergreen forest vegetation types, 53% of the area (Figure 4.4) and 3.2 million housing units (Figure 4.5) were located in moderate to high fire potential zones (≥ 0.01). Housing units in moderate to high fire potential areas had a more uniform distribution in shrubland and evergreen forests and a greater proportion of high-density housing (Figure 4.6) than all wildland vegetation (Figure 4.3).

Risk among ecoregions

Ecoregions in the southeastern U.S. contained a large number of housing units (Figure 4.8a) and also had a high potential for fire (chapter 3), which resulted in high risk when all vegetation types were considered (Figure 4.8b). The Texas-Louisiana Coastal Plain and the Everglades had remarkably high risk when compared to the other ecoregions. Risk levels were also high in Mediterranean California, especially in 2003. Among the other western ecoregions, risk was greatest in the Western Cordillera, the Sonoran and Mohave Deserts and the Upper Gila Mountains. However, risk in theses regions was still relatively low compared to Mediterranean California and the Southeast. Not surprisingly, risk was low in the northeastern U.S. where few fires were observed by the MODIS sensors (Chapter 2).

The total number of housing units in all ecoregions was substantially less when only shrublands and evergreen forests were considered (Figure 4.9a). However, patterns of risk paralleled those found in all wildland vegetation. Risk remained high in the Southeast, especially in the Southeastern Plains ecoregion (Figure 4.9b). Risk also remained high in Mediterranean California, especially in 2003, and also in the Western Cordillera ecoregion (Figure 4.9b).

When only shrublands and evergreen forests were analyzed, risk was remarkably high in the Everglades and Texas-Louisiana Coastal Plain again. These results were unexpected and we examine potential reasons later in the discussion. Other ecoregions with relatively high risk levels in shrublands and evergreen forests included the Southeast and parts of the West: Western Cordillera, Sonoran and Mohave Deserts, Mediterranean California, and the Upper Gila Mountains (Figure 5b).

Discussion

We used a formal risk framework to evaluate the risk of housing units from fire for the entire U.S. and among ecoregions in the U.S. We defined risk as the probability that a housing unit was exposed to fires under average conditions during the years for which our fire potential models were constructed (2000 – 2006). Approximately 4.7 million housing units were located in areas predominantly covered by shrubland and evergreen forest vegetation. Both of these vegetation types can experience extreme fire behavior under certain weather conditions present the greatest concern to fire managers. Our analysis found that relatively more houses were in high fire potential zones in shrubland and evergreen forests than other vegetation types. As a result, fire risk in shrubland and evergreen forests was nearly twice as high as it was for all other wildland vegetation. The good news is that the 4.7 million housing units in risky vegetation types represent only a small fraction of all the houses in the U.S. (4.1%). The bad new is that they are scattered across nearly 22% of the U.S. land area. If the management strategy is to reduce risk by mechanical fuel treatments and prescribed fires, then there is a lot of ground to cover.

With our definition, the spatial patterns of risk followed patterns of fire occurrence and the distribution of housing, and risk was greatest where both high fire occurrence probabilities and housing development overlapped. In the West, this resulted in a few concentrated hotspots of risk. In the Southeast, risk was more evenly distributed because both fire potential and housing development were consistently high across a large area. In most parts of the U.S. our results matched our expectations; however, in a couple of cases, our risk metric produced some unexpected results.

The Texas-Louisiana Coastal Plain and the Everglades both had high risk when all vegetation types and when only shrublands and evergreen forests were considered. We expected risk to be high in both ecoregions, but not to the magnitude we observed. Both ecoregions had average fire potential that was normally distributed with a mean greater than zero, whereas most other ecoregions had skewed distributions with most of their area having fire potential near zero (Chapter 3; Figure 3.6). Both ecoregions also had large urban centers at the periphery of wildland vegetation. Scatter plots (not shown) of housing units and fire potential did not reveal any outliers. In the Texas-Louisiana Coastal Plain, risk was concentrated at the periphery of Houston, TX, along Interstate 10, and near Corpus Christi, TX. This matched the Texas Forest Service description of where fire risk in the WUI is greatest in this region (Gray 2008). Therefore, the high risk levels we observed in these two ecoregions may be valid and appear to be primarily related to our predicted high potential for fire occurrence.

Our analysis was based on 1 km resolution satellite data and at this scale of observation what risk actually represents can be uncertain. The specific location of houses, their juxtaposition to fuels, and the potential behavior of fires are not exactly known, so evaluating the exact type of risk is difficult. From a worst-case scenario, areas we identified as risky represent places where extreme fire behavior could present a direct threat to human lives and destroy structures (Cohen 2000, 2004). Under less extreme fire behavior, our measure of risk represents the potential for indirect impacts of fire, for instance, changes in water and air quality (Wondzell and King 2003, McMeeking et al. 2006, Wiedinmyer et al. 2006). The type and magnitude of fire impacts on society at the national scale could be distinguished with more detailed models differentiating these types of risk. However, our risk model provided a simple index of where conflicts between development and fire were most likely to occur. These places could be good starting points for more detailed, local analyses about the different aspects of fire risk. Additionally, the locations we identified could be used with existing information about the wildland-urban interface (Radeloff et al. 2005) to consistently rank communities at risk (National Association of State Foresters 2003).

Housing growth in rural areas and the wildland urban interface is high (Brown et al. 2005, Hammer et al. 2007, Theobald and Romme 2007) and the challenges of managing fire risk are likely to increase. What can be done to limit the risk to housing in fire prone landscapes? Structural ignitions in wildfires are primarily caused by two mechanisms; direct heat transfer and firebrands (Cohen 2000, 2004). Potential for ignition by direct heat transfer is high when houses are surrounded by flammable vegetation capable of generating enough heat to ignite building materials. Firebrands, flaming particles of wood or debris that can be carried aloft for several miles before falling can also cause structural ignitions. Establishment of fire-safe zones by clearing brush and reducing flammable vegetation is a simple and effective way to protect most structures from ignition by direct heat transfer (Cohen 2000, 2004). To reduce the risks posed by firebrands, fuel treatments to limit the extreme fire behavior that produces firebrands in the vicinity of development are also a possibility (Agee and Skinner 2005). However, fuel treatments are expensive to implement across large spatial extents and their effects can be short-lived (Rideout and Omi 1995, Berry and Hesseln 2004). In contrast, fire-safe building standards can limit the ignition potential from both firebrands and nearby fires (Cohen 2000, 2004). Most importantly, we should be smart about where new development occurs (Hammer et al. 2007, Syphard et al. 2007b) and avoid ecologically sensitive areas with high fire potential.

Fortunately, land owners in the wildland-urban interface are often aware of fire risk and are willing to engage in risk reduction activities on their property when they perceive a benefit. Enthusiasm for funding risk-reduction activities on public lands is low in comparison (Fried et al. 1999). Thus, the most promising prospects of reducing fire risk to housing fall largely in the hands of private homeowners at the edge or outside of public lands. Our risk assessment provides a gradient in which people can evaluate their relative risk and take risk reduction actions on their property accordingly.

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Figure 4.1. Omernik level 2 ecoregions (Omernik 1987).

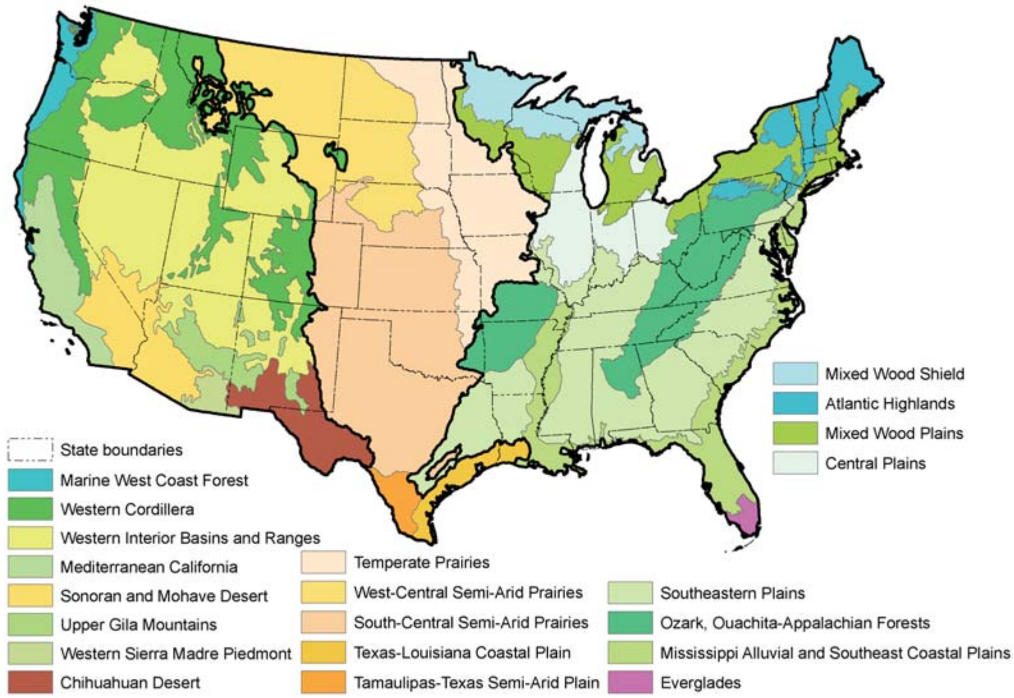

Figure 4.2 Average potential for fire occurrence (2000 – 2006), grouped by housing density categories (# housing units / km^2) for all wildland vegetation pixels.

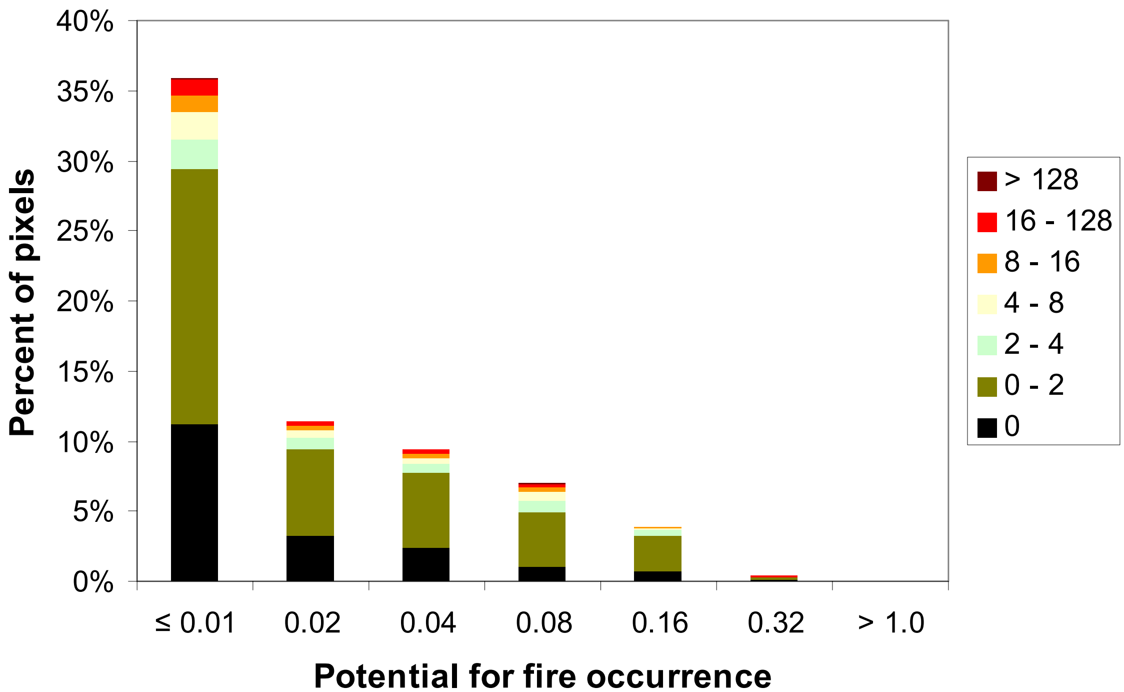

Figure 4.3. Number of housing units according to average potential for fire occurrence (2000 – 2006), grouped according to housing density categories (# housing units / km^2) for all wildland vegetation pixels.

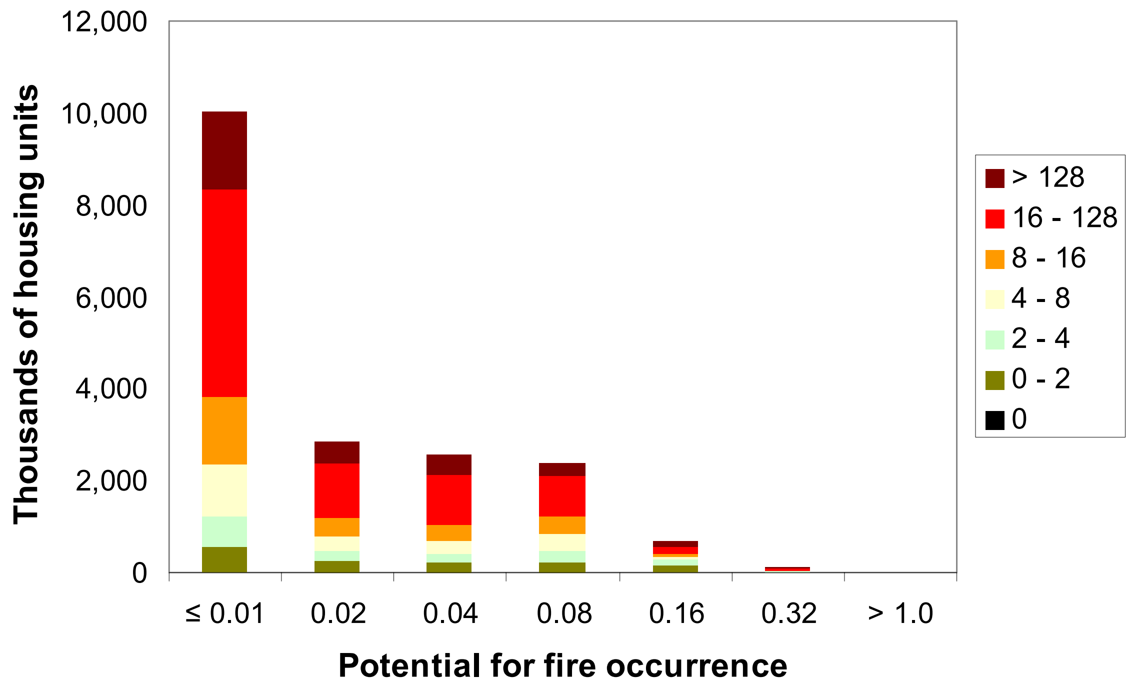

Figure 4.4. Risk according to average potential for fire occurrence (2000 – 2006), grouped according to housing density categories (# housing units / km^2) for all wildland vegetation pixels.

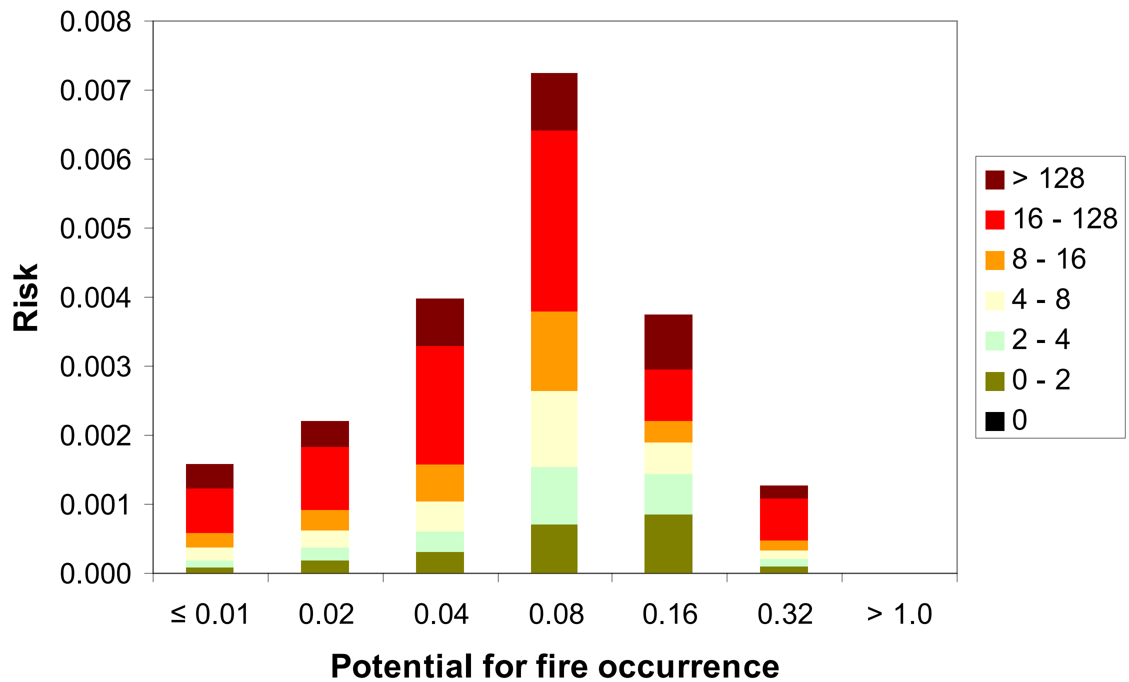

Figure 4.5. Average potential for fire occurrence (2000 – 2006), grouped by housing density categories (# housing units / km^2) for shrubland and evergreen forest vegetation pixels.

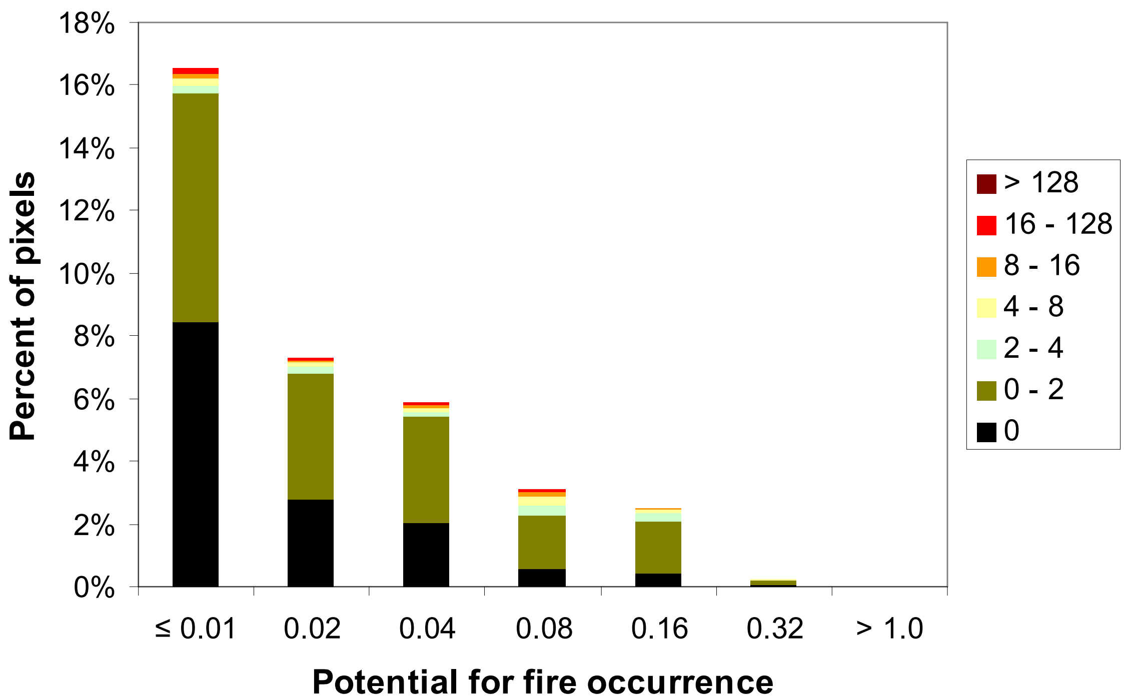

Figure 4.6. Number of housing units according to average potential for fire occurrence (2000 – 2006), grouped according to housing density categories (# housing units / km^2) for all shrubland and evergreen forest vegetation pixels.

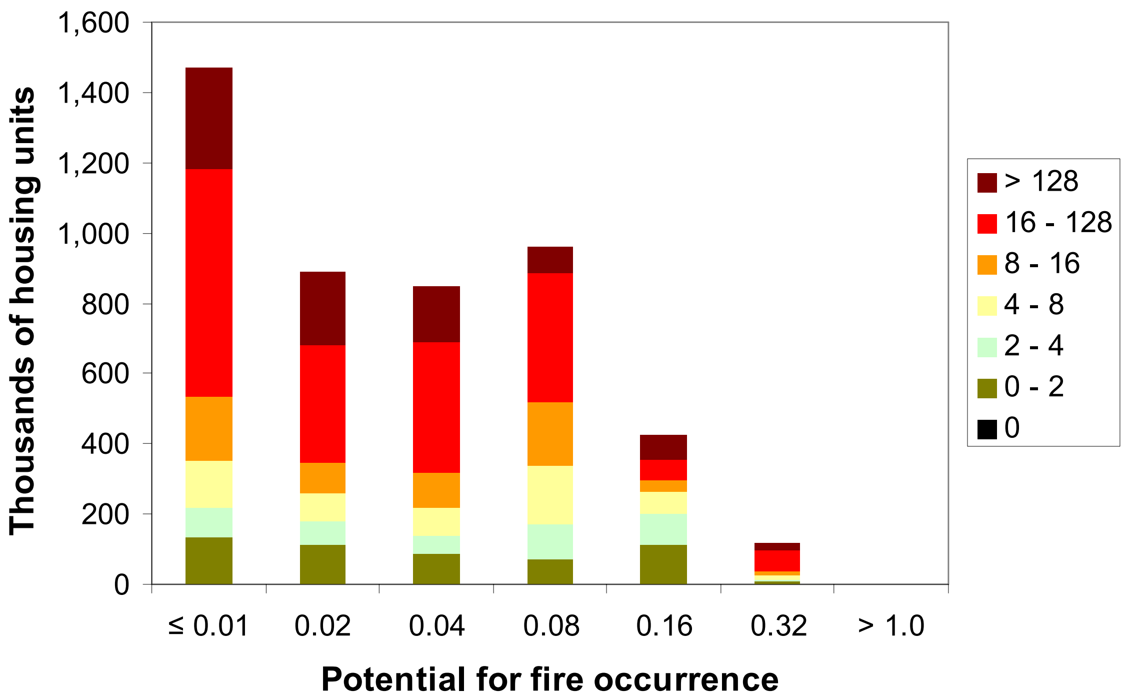

Figure 4.7. Risk according to average potential for fire occurrence (2000 – 2006), grouped according to housing density categories (# housing units / km^2) for all shrubland and evergreen forest vegetation pixels.

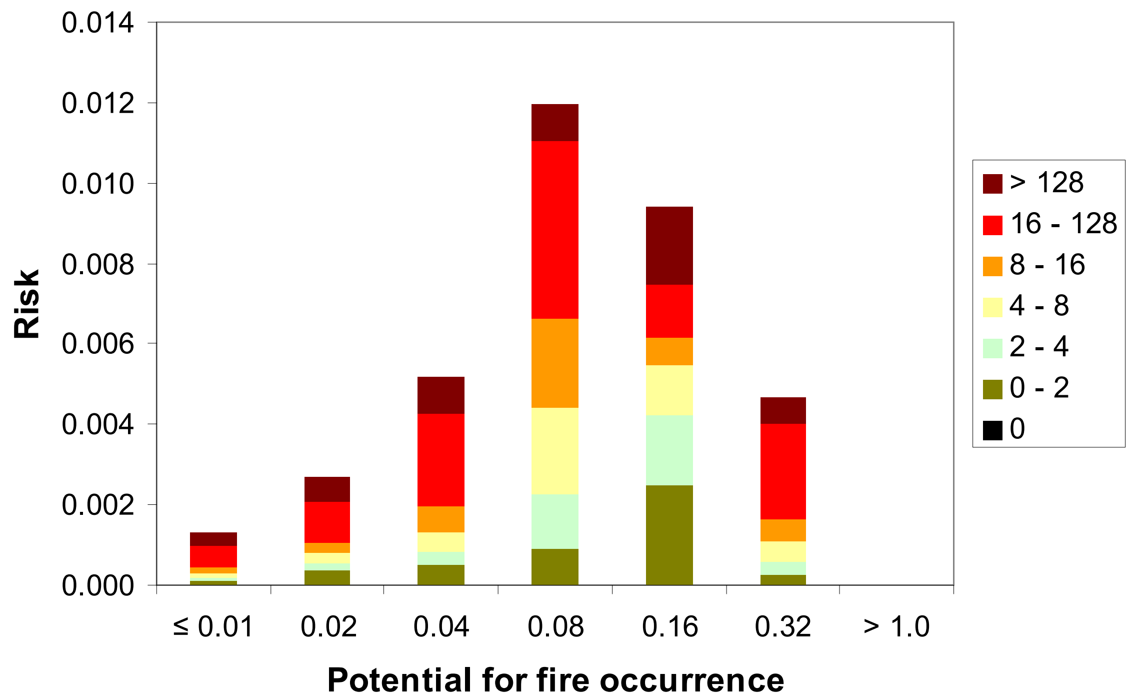

Figure 4.8. (a) Housing units and (b) average risk by ecoregion for all vegetation types. Vertical bars show range between maximum and minimum yearly risk observed between 2000 and 2006.

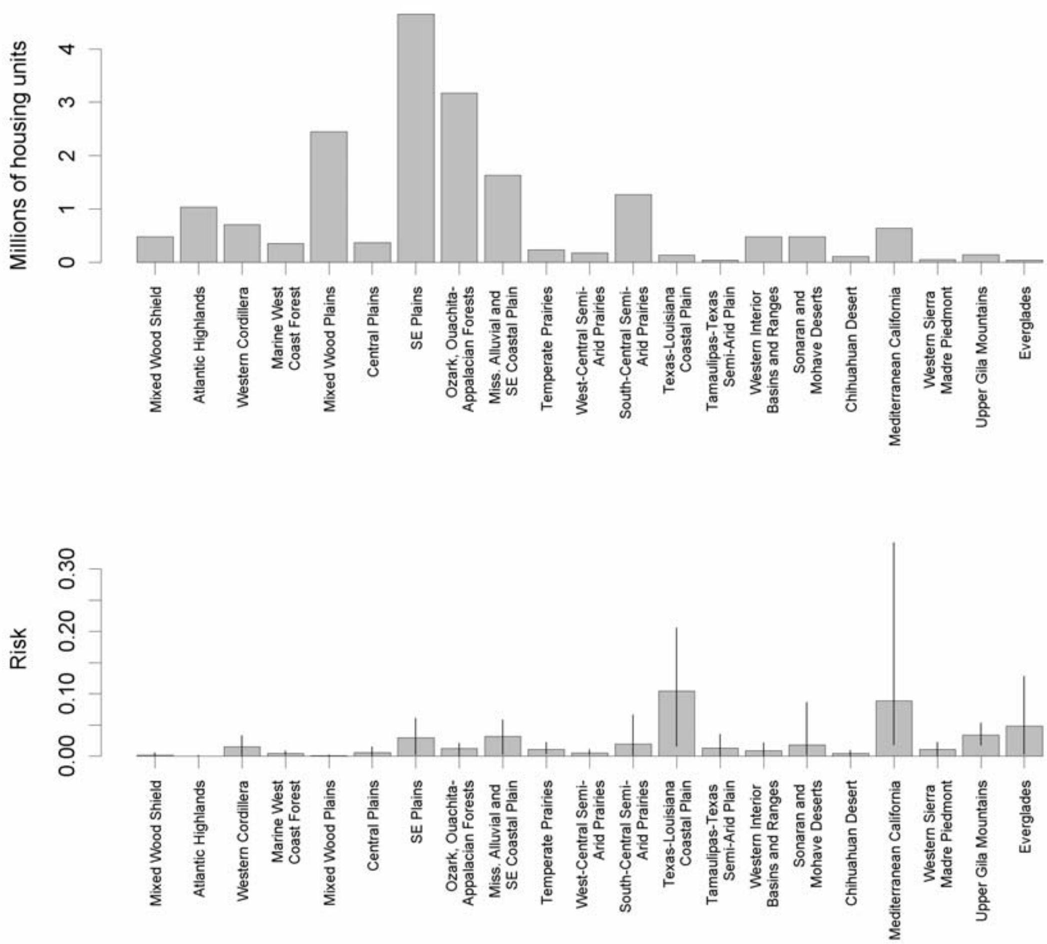

Figure 4.9. (a) Housing units and (b) average risk by ecoregion for shrubland and evergreen vegetation types. Vertical bars show range between maximum and minimum yearly risk observed between 2000 and 2006.