Building Loss to Wildfires in the Wildland Urban Interface in the U.S.

By

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Overview

Wildfires are a natural element of many ecosystems and have a great impact on society by destroying property and sometimes even by taking lives. In the United States alone, thousands of individual fires occur every year and the number of both burned hectares and destroyed buildings are higher than ever since recorded fire history. In 2013 alone, a total of 2135 buildings (residences, out-buildings and commercial buildings) were destroyed (NICC 2013). Although the problem of burned buildings is not new, the impact of wildland fires is expected to increase due to the expansion of the wildland urban interface (WUI) (Hammer et al. 2007; Maranghides and Mell 2012) combined with climate change that is projected to increase the occurrence and intensity of forest fires (Dale et al. 2001). Given that billions of dollars are being allocated to fuel management and fire suppression and that the main fire suppression goal is to protect people and property, it is necessary to obtain a clear picture and understanding of WUI losses and WUI recovery. Therefore, the goal in my dissertation was to understand the major factors that contribute to building loss to wildfire in the WUI in the United States. To achieve my main goal, I divided my research in four chapters where I asked the following questions related to wildfires and buildings: 1) what are the key variables among vegetation, terrain and spatial arrangement of buildings and their location that explain why buildings burn in wildfires? 2) does the role of vegetation, terrain, location and the spatial arrangement of buildings regarding the probability that individual buildings will burn in a wildfire differ among ecoregions across the conterminous

United States? 3) what is the spatial distribution of the vulnerability of buildings to burning when wildfires occur, across the United States? and, 4) what are the patterns of rebuilding and new development after wildfires?

Many people want to live “closer to nature”. With increasing and broad access to better communication and transportation technology, what was once wild and isolated is now easily accessible (Theobald 2005). Forestlands, in particular, are very attractive as residential building sites because they provide positive externalities such as scenic views, wildlife and bird watching opportunities, shade, screening from neighbors and easy access to forest-based recreation opportunities (Tyrvainen and Hannu 1998). Consequently, in many parts of the US there is increasing pressure from residential housing development on both public and private forested lands (Radeloff et al. 2010, Hammer et al. 2009). These areas, where houses meet or intermingle with undeveloped wildland vegetation, are called the wildland-urban interface (WUI) (Radeloff et al. 2005). The WUI is a pivotal area for human-environment conflicts, such as habitat fragmentation, introduction of exotic species, and biodiversity decline and loss, and the destruction of buildings by wildfires (Radeloff et al. 2005; Gonzalez-Abraham et al. 2007; Bar-Massada et al. 2014).

Fire policies have explicitly considered the WUI since at least 1960 (USDI and USDA 1995), as firefighting resources in the WUI are typically focused on defending buildings rather than containing fires (Hammer et al. 2007). Consequently, fire in the WUI is intimately connected to housing growth patterns and any decisions related to fire management in the WUI have potentially substantial political, social, and economic impacts (Hammer et al. 2007).

Six of the 10 fires with the largest losses of lives and homes of the 20th century occurred in the WUI, and all of them occurred within the last 20 years (NFPA 2008). WUI fires have economic consequences and public costs, as federal resources for suppression and wildland fuel treatments are allocated preferentially in WUI areas (Mell et al. 2010). The annual costs are growing, increasing from US$1.3 billion annually from 1996 to 2000, to US$3.1 billion annually from 2001 to 2005 (GAO 2007). The increase in fire related costs raises the question how to curtail these costs and minimize fire risk.

The problem of WUI and wildfires is not exclusive of the United States. Other countries feel it as well and some research has been done in this area with particular attention and concern in the southern European countries where every year people are killed by wildland fires (Lampin-Maillet et al. 2010a). However, the WUI, as a defined problem, became present in the forest fire environment in Europe more recently and only since 2000 (Lampin-Maillet et al. 2010b). Wildfires in WUI areas are a serious threat to communities because they can be very destructive as was the case in California 2003, Portugal 2003, Greece 2007, and Australia 2009, and can produce damages in the billions of dollars (Haynes et al. 2010; Mell et al. 2010; Lampin-Maillet et al. 2011). WUIs represent serious problems for risk management in the context of high urban pressure (Davis 1990;

Cohen 2000; Lampin-Maillet et al. 2010a), because it involves two major fire risk components in terms of threatening inhabited areas: hazard (fire ignitions caused by human activities), and vulnerability, (Hardy 2005; Jappiot et al. 2009).

There is a relationship between human settlement patterns and vulnerability to natural disasters. Land use changes and housing growth not only create stresses on natural ecosystems, they also increase society's vulnerability to natural hazards (Liu et al. 2007b). Human communities are both a source of, and a victim of, natural hazards (Alig et al. 2008), particularly when it comes to wildfires. Exurban development causes increased vulnerability to wildfire in two ways. First, isolated communities, and especially unincorporated areas, have less infrastructure (e.g., roads and water supply systems) and fewer resources for providing protection services (e.g., police and fire departments). Second, wildland fire is a threat to homes in the WUI, the same area where housing growth has been highest (Alig et al. 2008). Lastly, people are also contributing to the increase in the probability of fire occurrence because they are themselves a source of ignitions.

In terms of the annual burned area, wildland fires burned 70% more area from 2000 to 2005 than in the 1990s (Mell et al. 2010), despite increases in federal funding for suppression and wildland fuel treatments. A large proportion of these costs is redirected to protect private property and communities from wildfires (USDA et al. 2009). Two major trends and political choices have grown in parallel contributing to increased fire intensity and increased WUI growth and susceptibility. Those are: management choices made decades ago (fire suppression in particular), and many people in the U.S. rapidly moving into the countryside because they are fleeing from negative aspects of urbanization toward the positive externalities of the countryside (Colburn 2008).

The policy of wildfire exclusion started at the time of the origin of the U.S. Forest Services, in the 1910s (Cohen 2008). Although several foresters and researchers promoted the benefits of wildland burning, public land management policy saw fires as unwanted, thus to be prevented and suppressed (fire exclusion). The political (reflected in policies) recognition that wildfire is an ecological factor only happened in the late 1960s and early 1970s (Pyne 2004). However, even today and nationwide, the total number of fires suppressed dominates the fire occurrence statistics suggesting that the exclusion approach largely continues (Cohen 2008). These policies have significantly contributed to fire reduction in most areas of the U.S, while at the same time having changed vegetation fuel structure, leading to fire food (fuel) accumulation and vegetation arrangements that enhance, in some systems, the potential for extensive areas of high intensity wildland fires like those experienced during the last decade (Scheller et al. 2005; Cohen 2008). The argument that fire suppression is one of the culprits for more frequent and more intense fires is true for forest types that can sustain crown fires and where tree composition contains species that are fire dependent or fire resistant, such as Jack Pine forests (Scheller et al. 2005). However, crown fires rarely consume the entire forest, creating therefore a mosaic like landscape that provides spatial heterogeneity which can be desirable for the system's resilience (Turner and Romme 1994; Schoennagel et al. 2008).

Despite the fact that crown fires can cause damage to buildings, ground fires, grassland fires, shrub fires, all have the potential to cause damage to human property. Building loss to wildfires occurs in different regions, with different fire regimes and vegetation types, suggesting that there are more factors contributing to building loss than simply vegetation and fire occurrence. Building loss to wildfire in the WUI is partly caused by the occurrence of housing, as people are often a source of ignitions (Bar-Massada et al. 2011b), and, buildings that are located at intermediate distances to other buildings or cluster of buildings, are more likely to be lost to wildfires (Syphard, 2012). Other factors contributing to building loss include the landscape context of the surrounding vegetation, topography, and spatial arrangement of buildings (Syphard, 2012). Buildings located at higher elevations, or steeper slopes, or with difficult road access, are more susceptible to fire conditions that can ignite a building. While many efforts have focused on reducing vegetation and fuel load in the WUI, it was not clear how much the surrounding vegetation was in fact contributing to building losses to wildfires, nor *where* in the United States vegetation may play a more determinant role than terrain or the spatial arrangement of buildings. My thesis addresses these questions and provides an insight to how these factors interact, and whether there are regional differences in these relationships.

Another aspect I considered in my research regarding wildfires in the WUI is disaster recovery, with rebuilding as the main focus. For political reasons, local governments are usually quick in announcing financial or other types of aid for those who have lost their homes in natural disasters (Nakazato and Murao 2007). Because homes are one of the fundamental investments of families, rebuilding them is of paramount importance to the families who live there. Wildfires, however, affect communities in a semi-random way. One building may burn while the building next to it is unaffected. This apparent randomness in fire effects makes rebuilding a case by case situation, in which homeowners find themselves dealing with their insurance companies and local authorities individually. Rebuilding, however, provides an interesting insight on how people react and adapt to wildfire, because they are aware of the fire, but they still make the choice to rebuild. Rebuilding is an important part of the recovery process, but little is known about rebuilding patterns and rates across the United States.

My objectives for this dissertation were to identify the factors related to vegetation, terrain and spatial arrangement that contribute to building loss from wildfires, and examine nationwide spatial patterns of vulnerability and rebuilding. In my ***first chapter***, I looked at two fires that burned more than 100 buildings, one in California and another in Colorado and learned that each community was unique in what contributed to building loss. In Boulder, Colorado, topography was one of the most important factors influencing building loss, while in California, spatial arrangement and in some cases topography and how connected the vegetation around buildings is, were significant factors. This paper was published in the Journal of Landscape Ecology. In my ***second chapter***, I expanded the analysis to the conterminous United States and looked at all the fires that occurred between 2000 and 2010. I divided the analysis into ecoregions and the general trend that was captured in chapter one was present in this chapter as well. Overall, variables related to topography and the spatial arrangement of buildings were more frequently present in the best 20 regression models than vegetation-related variables. This chapter has been submitted to the journal Ecological Applications. In ***chapter three*** I used the information obtained from the previous chapter and used MaxEnt to provide a vulnerability map for the conterminous United States. This chapter is not yet submitted. Finally, in ***chapter four*** I characterized rebuilding and new development patterns after wildfires that occurred between 2000 and 2005. This paper is published in the International Journal of Wildland Fire.

In the following pages I will provide short synopsis for each paper/chapter.

Chapter 1 Summary

Wildfires destroy thousands of buildings every year in the Wildland Urban Interface. However, fire typically only destroys a fraction of the buildings within a given fire perimeter, suggesting more could be done to mitigate risk if we understood how to configure residential landscapes so that both people and buildings could survive fire.

The goal was to understand the relative importance of vegetation, topography and spatial arrangement of buildings on building loss, within the fire's landscape context.

I analyzed two fires: one in Boulder CO and another in San Diego, CA. We used Google Earth historical imagery to digitize buildings exposed to the fires, a geographic information system to measure some of the explanatory variables, and FRAGSTATS to quantify landscape metrics. Using logistic regression we conducted an exhaustive model search to select the best models.

The type of variables that were important varied among communities. We found complex spatial effects and no single model explained building loss everywhere, but topography and the spatial arrangement of buildings explained most of the variability in building losses. Vegetation connectivity was more important than vegetation type.

Location and spatial arrangement of buildings affect which buildings burn in a wildfire, which is important for urban planning, building siting, landscape design of future development, and to target fire prevention, fuel reduction, and homeowner education efforts in existing communities. Landscape context of buildings and communities is an important aspect of building loss, and if taken into consideration, could help communities adapt to fire.

Resulting paper: **Alexandre, Patricia M.,** Susan I. Stewart, Miranda H. Mockrin, Nicholas S. Keuler Alexandra D. Syphard, Avi Bar-Massada, Murray K. Clayton, Volker C. Radeloff, 2015, *The relative impacts of vegetation, topography and spatial arrangement on building loss to wildfires in case studies of California and Colorado,* Landscape Ecology, DOI: 10.1007/s10980-015-0257-6.

Chapter 2 Summary

Wildfire is globally an important ecological disturbance affecting biochemical cycles, and vegetation composition, but also puts peoples and their homes at risk. Suppressing wildfires has detrimental ecological effects and can promote larger and more intense wildfires when fuels accumulate, which increases the threat to buildings in the Wildland Urban Interface (WUI). Yet, when wildfires occur, typically only a small proportion of the buildings within the fire perimeter are lost, and the question is what determines which buildings burn.

The goal was to examine which factors are related to building loss when a wildfire occurs throughout the United States. I was particularly interested in the relative roles of vegetation, topography, and the spatial arrangement of buildings, and how their respective roles vary among ecoregions.

I analyzed all fires that occurred within the conterminous U.S. from 2000 to 2010 and digitized which buildings were lost and which survived according to Google Earth historical imagery. I modeled the occurrence as well as the percentage of buildings lost within clusters using logistic and linear regression. Overall, variables related to topography and the spatial arrangement of buildings were more frequently present in the best 20 regression models than vegetation related variables. In other words, specific locations in the landscape have inherently a higher fire risk, and certain development patterns can exacerbate that risk.

Fire policies and prevention efforts focused on vegetation management are important, but insufficient to solve current wildfire problems. Furthermore, the factors associated with building loss varied considerably among ecoregions suggesting that fire policy applied uniformly across the US will not work equally well in all regions, and that efforts to adapt communities to wildfires must be regionally tailored.

Resulting paper: **Alexandre, Patricia M.,** Susan I. Stewart, Nicholas S. Keuler, Murray K. Clayton, Miranda H. Mockrin, Avi Bar-Massada, Alexandra D. Syphard, Volker C. Radeloff, 2015, "*Factors related to building loss due to wildfires in the conterminous United States*", Ecological Applications, in review.

Chapter 3 Summary

Housing growth is predicted to increase and, consequently, the WUI will increase as well. Housing development alters fire size and distribution around the WUI due to a potential increase in ignitions. Every ignition has the potential to become a large fire, and when it does, the potential loss is high. For these reasons it is important to understand how buildings are affected by fire and how vulnerable they can be in case of fire occurrence. The goal was thus to produce a map of building vulnerability if a wildfire occurs for the conterminous United States.

I analyzed Google Earth's historical imagery to assess building loss due to wildfires in all fire perimeters in the conterminous United States between 2000 and 2010 recorded in the Monitoring Trends in Burn Severity (MTBS) dataset. I digitized all the buildings that were lost (building present before the fire date, but not after). I digitized a total of 9,233 burned buildings. I used Omernik's Level II ecoregions to sub-divide the conterminous U.S. into regions that share ecological traits. To project the potential distribution of building loss likelihood given the occurrence of a wildfire, I used the maximum entropy model MaxEnt, a map-based modeling software built and used primarily for species distribution modeling.

The Maxent models presented good discrimination, with all AUC values between 0.80 – 0.98, meaning that the model can at least be considered useful, and some of them highly accurate, in their predictive performance. Even though we divided the conterminous in ecoregions, there is a clear difference between the west and the east. The western part of the US presents higher vulnerability in clustered patterns that are more closely related to either topography and/or land cover, while the eastern US presents a reticulate pattern that relates closely to populated areas (land use).

My analysis allowed, for the first time, to use real data from buildings lost to wildfires, related the occurrence of a lost building to the building's surroundings, and then used this information to identify areas with similar characteristics. Thus my maps are of major importance for local government agencies aiming to plan ahead of time and allocate resources before the hazard occurs in order to reduce vulnerability. Furthermore, having access to a map of vulnerability may inform individuals' decision of where to buy or build their primary residence or second home.

Resulting paper: **Alexandre, Patricia M.**; Anthony To; Susan I. Stewart; Murray K. Clayton; Brooke Bateman-Plumb; Avi Bar-Massada; Alexandra D. Syphard; Miranda H. Mockrin; Volker C. Radeloff, 2015, *Building vulnerability to wildfires across the US*, International Journal of Wildland Fire, not submitted yet.

Chapter 4 Summary

Despite protection efforts, many WUI buildings are lost every year to wildfires, and these losses entail considerable social, economic and emotional costs. Between 1999 and 2011, an average of 1,354 residences were lost to wildfire each year in the U.S. (NIFC 2011a), and on average two billion dollars were spent annually to suppress wildfires (NIFC 2011a; USDA 2011a; NIFC 2012). However, little is known to how much of the lost buildings is being rebuilt.

The goal was to characterize the pattern of buildings destroyed by wildfire, and the rebuilding and new development patterns across the conterminous United States for all fires that occurred from 2000 to 2005. Specific objectives were to: Assess rebuilding rates across the conterminous U.S., at the fire/county, the state, and the ecoregion levels; Compare rebuilding rates to rates of new development at each of the three levels of analysis; Compare the rate of new housing development within fire perimeters to the rate of new housing development in the surrounding county.

I identified all burned and rebuilt buildings within 2000-2005 fire perimeters from the Monitoring Trends in Burn Severity (MTBS, www.mtbs.gov) dataset, across the conterminous U.S., using Google Earth imagery.

Overall, the percentage of burned buildings relative to all buildings within fire perimeters was low, and so were rebuilding percentages. Over the six-year study period, the percentage of burned buildings within fire perimeters ranged from 0.4% to 20.4% per year (average of 5.9%). For each fire year, the percentage of buildings rebuilt within five years varied from 6.2% to 63.8% (average of 25.3%). The percentage of new buildings within fire perimeters also varied among years from 1.4% to 10.3% (average of 4.4%). Inter-annual variation was very high partly because 2003 was a severe fire year with exceptional large number of fires. The number of burned buildings in 2003 was an order of magnitude larger than for all other years combined (20.4% of burned buildings), and had the highest rebuilding rate (63.8%).

The fact that we found generally low rebuilding rates may thus indicate that people are adapting to fire by choosing not to rebuild. However, high rates of new development suggest the opposite and support the notion that homeowners are not aware of fire risk, or that amenities and other considerations outweigh the risk.

Resulting paper: **Alexandre, P.M.**, Mockrin, M., Stewart, S., Hammer, R., Radeloff, V., 2015, *Rebuilding and new housing development after wildfire*, International Journal of Wildland Fire, 24(1).

Significance

Current demographic processes and trends point to an increasing number of people who will migrate and redistribute into wildland areas and continue to affect and profoundly change landscapes and ecosystems across the United States (Hammer et al. 2009b). Housing has become increasingly dispersed, particularly in rural areas where land is more affordable, which leads to low-density development in wildlands (Gude et al. 2008). In the Western states only 14% of the potential WUI has been developed, which means that there is a potential for substantially more housing development (Gude et al. 2008; McDaniel 2009). Assuming that population, income increase and technological changes will continue, the expectation is that WUI fires will continue to be a serious and costly issue in the US (Radeloff et al. 2010). Given the magnitude and significance of wildfires in the WUI, my research contributes to decreasing the gap within several domains, such as scientific, methodological, and management.

Scientific contribution

The WUI represents a system where humans are interacting with a natural system (forests, shrub lands, or grasslands), causing relationships that are complex and not well understood (Liu et al. 2007b). The WUI is an example of a coupled human and natural system (CHANS), in which people interact with natural components (Liu et al. 2007a). This particular human-natural system presents reciprocal effects on both human and natural sides of the system (Liu et al. 2007b). My research is an example of an interdisciplinary project that integrates ecological and social science and shares the four major features that Liu, 2007 enumerated: 1) “it explicitly addresses complex interactions and feedback between human and natural systems". I explicitly included anthropogenic variables that represent human activities and human decisions, such as building placement and road infrastructure. 2) "the team is interdisciplinary, engaging both ecological and social scientists around common questions". My collaborators included fire experts, statisticians and social scientists. 3) "integrate various tools and techniques from ecological and social sciences as well as other disciplines such as remote sensing and geographic information sciences for data collection, management, analysis, modeling and integration". I used remote sensing and GIS tools to acquire my data and use advanced statistical techniques to model the data. 4) "simultaneously context specific and longitudinal over periods of time long enough to elucidate temporal dynamics". I collected my data for an eleven year period (2000-2010) for the conterminous U.S., but performed my analysis within ecoregions that are context specific. I have also divided the analysis into administrative boundaries instead of ecological, which accounts for the social aspect of the WUI since building regulations follow administrative boundaries and not ecological.

The WUI is not only an example of a CHANS, it is also an example of a novel ecosystem with emergent properties (of both landscape and people). Due to climate change and faster-than-ever environmental and social changes, ecosystems are now facing new anthropogenic stressors, such as pollution, habitat fragmentation, land-use change, invasive plants, animals and pathogens, and altered fire regimes (Millar et al. 2007). The increase in climate variability together with anthropogenic stressors creates novel environmental conditions that are completely new to ecosystems (Millar et al.

2007; Radeloff et al. 2015). Although my research focus was related to how people are affected by and adapt to wildfires, the area where human settlement adjoins or is intermingled with natural landscapes is much larger than the *fire* WUI (Bar-Massada et al. 2014). There are biotic and abiotic interactions occurring in the WUI that can give place to the creation of novel ecosystems that science is starting to identify and study. Examples of biotic interactions include exotic species introduction and spread, wildlife subsidization, disease transfer, landcover conversion, fragmentation, and habitat loss (Bar-Massada et al. 2014). Examples of abiotic factors would be wildfire ignitions and spread (Bar-Massada et al. 2014), and I would add building/property loss, which is where my contribution lies.

My scientific contribution is a better understanding of how the coupled human-natural system of the WUI is affected by wildfires and how people are adapting to it. The decision whether or not to rebuild after a wildfire can been seen as a form of adaptation. In chapter four, my results showed that not everyone rebuilds within five years of the fire, which could be an indication of fire adaptation. On the other hand, rebuilding suggests that other non-ecological factors, such as local regulations or incentives, personal experience, regional cultures, and even insurance policies might be more important determinants for people's response to wildfires. In parallel, new development occurred at higher rates than rebuilding, suggesting that homeowners are either not aware of the fire risk, or amenities and other considerations outweigh the risk.

My research supports previous research on how building location affects the probability of a building being lost to wildfires. Chapter one's major findings were that variables describing the landscape, such as vegetation/fuel connectivity, topography, and the spatial arrangement of buildings were present more frequently in the models than variables measuring more common targets of fire risk mitigation. While chapter two highlights that fire policy should be regionally tailored because drivers of building loss differ across ecoregions.

Methodological contribution

From the methodological point of view, the development of new measuring techniques using free satellite imagery (Google Earth) is of major importance for quick data access and data collection. I used a freely available tool to collect all my data at a broad scale. The use of freely available data sources together with providing free access to both my data and my scripts, allows for time efficiency for future studies since these methods are easily reproducible in new regions of the world. I also combined methodologies from different fields of science, such as landscape ecology and GIS to calculate my variables of interest. I combined different statistical techniques, such as logistic regression with General Linear Models (GLM) and semi-likelihood generalized models that account for spatial autocorrelations. I used large computational processing methods available at UW campus in collaboration with computer science students and researchers.

The characterization of post-wildfire rebuilding patterns had not been done before at this scale due to difficulty in accessing data. My methodological approach overcomes this obstacle providing the opportunity to depict patterns and identify for the first time what is in fact happening after wildfires. The location and type of one's home is a directly observable and almost universal human behavior that affects biodiversity conservation directly and it is potentially the most pervasive and direct link between human attitudes and intention (Peterson et al. 2008). The understanding of the why people are rebuilding, or not, after wildfires can only be pursued after the pattern has been clearly identified and characterized.

Management contribution

My major contribution, however, is related to management and policy making. By providing a relative importance of vegetation, terrain and spatial arrangement for different regions in the United States, my research allows for better planning and resource allocation. It also allows homeowners to focus on the most relevant factors in their own regions. It provides a customized approach to land management and urban planning. For example, in my second chapter, results show that vegetation is not as significant in Mountain areas, and topography is more strongly related to building loss. Different ecoregions should focus on the aspects that are most relevant in their ecological region, and funding for fuel treatments should be channeled to those areas where vegetation does have a major contribution to building loss. These results have major consequences for community planning, zoning officials, policy and decision makers all across the United States. My results can help inform future policy and land use decisions, as well as being useful to potential future homeowners. In particular, my vulnerability maps provide a better understanding of where housing development is more vulnerable to wildfires, but also, where prevention measures can be done to minimize vulnerability. Maps are also great to help prioritize management actions and create a hierarchy of prevention measures according to the regions vulnerability "hotspots".

In sum, fire, people and housing create a complex system with economic, social, and environmental considerations. The WUI has unique dynamics at both the environmental and social levels in each instance. To analyze WUI communities individually is helpful at a very local management scale. However, in order to have a broad understanding of the phenomenon and the similarities and differences among communities, my analysis was necessary because it provided a broader scale and looked at the phenomenon as a whole.

Summary and remarks

Housing growth in the WUI is likely to continue (Hammer et al. 2007; Radeloff et al. 2010). Land use changes and housing growth not only create stresses on natural ecosystems, they also increase society's vulnerability to natural hazard (Liu et al. 2007). Human communities are both a source of, and a victim of, natural hazards (Alig et al. 2008).

It seems prudent, in the WUI context, to focus more on prevention, planning and community preparedness and adaptation. However, when losses to human communities are substantial, the outcome is often new policy, reallocation of public spending, and regulation (Alig et al. 2008). People's decision on whether or not to rebuild after a wildfire or to develop on areas that were affected by fires are a combination of complex factors that vary across social and ecological gradients. The scientific community agrees that there is no single solution nor any single factor that is most important in managing wildland fire (Moritz et al. 2014). My research builds on this premise and examines what the combination of factors is when buildings are lost. Generally, factors other than vegetation are more strongly related to building loss. Although some of the factors are not manageable, such as topography and the spatial arrangement of building that are already in place, the awareness that these are influencing the outcomes of a wildfire that hits a community is important to both government agencies, local authorities, but mainly homeowners.

There are three possible approaches to reduce building loss risk in the WUI: 1. Federal and local governments intervene every time a wildfire occurs to protect lives and property; 2. The government (either local or federal) imposes regulations to homeowners through regulation such as zoning and building codes; 3. Provide homeowners with science based information on how to protect a building from wildfires (example: Firewise program) and let the homeowners decide and bare the risks and not actively fight wildfires. There are precedents for all the listed options. Europe is heavy on regulations and laws are in place that mandate homeowners that live in high fire risk zones to clear the area around buildings. In the U.S. the approach is to fight and priority is given to protect property, and some communities have adopted the Firewise program. Argentina, for example, has neither regulations nor a mandate to protect property. Either to adopt one or a combination of these alternatives, it is something that society as a whole, or communities locally, will have to decide on which approach works best for them.

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Chapter 1

The relative impacts of vegetation, topography and spatial arrangement on building loss to wildfires in case studies of California and Colorado.

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Abstract

Wildfires destroy thousands of buildings every year in the Wildland Urban Interface. However, fire typically only destroys a fraction of the buildings within a given fire perimeter, suggesting more could be done to mitigate risk if we understood how to configure residential landscapes so that both people and buildings could survive fire. Our goal was to understand the relative importance of vegetation, topography and spatial arrangement of buildings on building loss, within the fire's landscape context. Methods. We analyzed two fires: one in Boulder CO and another in San Diego, CA. We analyzed Google Earth historical imagery to digitize buildings exposed to the fires, a geographic information system to measure some of the explanatory variables, and FRAGSTATS to quantify landscape metrics. Using logistic regression we conducted an exhaustive model search to select the best models. The type of variables that were important varied across communities. We found complex spatial effects and no single model explained building loss everywhere, but topography and the spatial arrangement of buildings explained most of the variability in building losses. Vegetation connectivity was more important than vegetation type. Location and spatial arrangement of buildings affect which buildings burn in a wildfire, which is important for urban planning, building siting, landscape design of future development, and to target fire prevention, fuel reduction, and homeowner education efforts in existing communities. Landscape context of buildings and communities is an important aspect of building loss, and if taken into consideration, could help communities adapt to fire.

Keywords: WUI, Building loss, Wildfires, FRAGSTATS, Connectivity, Logistic and Linear Regression, Modeling, best-subsets.

Introduction

Wildfires are an integral part of many terrestrial ecosystems (Pausas and Keeley 2009), but in a changing climate, wildfires are becoming more frequent, extensive, and destructive (Pechony and Shindell 2010; Brotons et al. 2013). As houses are built in or near wildlands, and the Wildland Urban Interface (WUI) continues to grow (Radeloff et al. 2005; Hammer et al. 2009b), future wildfires may cause catastrophic losses of property, and sometimes life (Karter 2010). However, when fire occurs, typically not all houses burn, raising the question, what determines which houses burn? In most cases, there will be multiple factors at play, ranging from building materials to the surroundings of a house. What is not clear though is the relative importance of factors such as vegetation, topography, and the spatial arrangement of buildings.

Several recent pieces of legislation, including the National Fire Plan and the Healthy Forest Restoration Act, were at least partly motivated by the goal to reduce fire risk in the WUI (Radeloff et al 2005; Stewart et al 2007, 2009; Hammer et al 2009a). The need to reduce fire risk arises because the social, economic, and ecological losses from wildfire were and still are mounting, despite major fire prevention and suppression efforts (Syphard et al. 2008). This is why the protection of homes and lives is a main objective of wildland fire agencies across the United States, with widespread efforts to treat fuels, and some examples of programs to raise community awareness and preparedness.

Landscape context and the location and spatial arrangement of buildings may be other important factors to consider though when aiming to reduce fire risk, especially when new housing developments are planned, and our study was designed to investigate how important these factors are.

Vegetation greatly affects wildfire behavior and is thus a main focus of wildfire prevention efforts (Andreu et al. 2013; Stevens et al. 2014; Kennedy and Johnson 2014). In addition to vegetation, topography influences the spatial variability of fuels and the biophysical conditions that determine fire spread, intensity and duration (Dillon et al. 2011). Topography influences fire behavior as well as vegetation distribution and productivity (Barbour et al. 1999), by affecting energy and water balances that control vegetation development, and hence the amount of biomass that fuels fires when sufficiently dry (Dillon et al. 2011). Elevation, aspect, latitude, and topographic position all influence microclimatic conditions, such as temperature, precipitation, direct solar radiation, wind exposure, etc., which in turn influence the moisture content of fuel (Dillon et al. 2011). Type, spatial pattern and distribution of vegetation determine the probability of fire ignition, fire spread rate and intensity, and ultimately, the type of vegetation that will regenerate after the fire (Marlon et al. 2012). Indirectly, topography can affect ignition probability because steep slopes, ridge tops, and south-facing slopes are all characterized by drier fuel conditions (Haire and McGarigal 2009). Weather conditions can strongly affect fire behavior. Humidity and temperature determine the rate at which fuels dry (Westerling et al. 2006; Finney et al. 2010), and wind also dries fuels, provides the fire with oxygen, and governs fire direction and spread rate (Bessie and Johnson 1995). However, neither fire spread data nor weather data was available at scales fine enough to determine the weather condition of a given building at the exact time it was hit by a fire, making it ill-suited to the scale of our analysis.

While vegetation, topography, and weather influence fire occurrence and behavior, these factors are not the only reason why some buildings burn within the perimeters of a fire and others do not. Factors related to the building themselves are also important, including building location and the spatial arrangement of buildings (Gibbons et al. 2012; Syphard et al. 2012). The probability that a building is lost is highest in small, isolated building clusters with low to intermediate building density and few roads (Bar-Massada et al. 2009; Syphard et al. 2012; Maranghides et al. 2013). What is unclear though is the relative importance of vegetation and building location to the probability that a building will be lost when a wildfire occurs, and how much this relative importance varies by setting.

There are several reasons why it is important to understand which buildings are likely to be lost if a fire occurs, and especially which roles the location and the spatial patterns of buildings play. First, understanding where buildings are more likely to be lost is important when planning future development (Syphard et al. 2013). If there are ways to place new buildings so that the chances of loss to fire are reduced, then that could be one important step towards more fire-adapted communities. Knowing where buildings are most likely to burn is also important for established communities because this information can inform mitigation efforts. For example, a building in a higher-risk location may require a larger defensible space than one in a lower-risk area.

Ultimately, all mitigation strategies have strengths and weaknesses, and no single mitigation strategy will suffice to stem the rise in the number of buildings lost to wildfire. Vegetation management aimed at removing biomass to reduce fire intensity and risk (Agee and Skinner 2005) can be highly effective in the short run, but requires large and recurring investments of time and money. Furthermore, vegetation management can have negative ecological impacts, and may not be effective in some ecosystem types, or for fires that occur under severe weather conditions (Merriam et al. 2006; Syphard et al. 2011; Moritz et al. 2014). Nonetheless, the U.S. National Fire Plan (NFP), which aims to reduce the risks of catastrophic wildland fire to communities (USDA 2007), is focusing resources on fuel reduction efforts, especially in the WUI (Husari et al. 2006; Schoennagel et al. 2009).

In addition to fuel reduction efforts, mitigation actions available to homeowners and legislators (for new construction) include the use of fire resistant building materials to limit fire spread and building ignitions (Cohen and Butler 1998; Cohen 2000; Nowicki and Schulke 2002; Gude et al. 2008). The combination of the buildings' exterior materials with its exposure to flames and firebrands ultimately determines its likelihood of ignition (Cohen 2000). Wildfire cannot ignite buildings unless their surroundings supply the necessary heat from flames of adjacent burning materials, such as firewood piles, vegetation, neighboring buildings, or firebrands (Cohen 2000; Nowicki and Schulke 2002). Building materials are also important. As an extreme example, a concrete bunker would not ignite during a wildfire, while a building with a wooden roof could ignite without any flames in its vicinity due to firebrands (Cohen

2000; Quarles et al. 2010). In sum, a building's ignition potential during a wildfire is determined by the characteristics of its exterior materials, the characteristics of the surroundings within 30 m (i.e.,the home ignition zone (Cohen 2008; Syphard et al. 2014), and the occurrence of firebrands, which can travel up to 2500 m (Cohen 2000). This means that a variety of actions to manage vegetation and building materials is necessary to reduce fire risk.

In addition to vegetation and building materials, current wildfire policy recommendations, are urging work at the level of homeowners and throughout a community to enact multiple mitigation strategies and create fire-adapted communities (e.g., Schwab and Meck, 2005), and such efforts may hold promise over the long term. However, choosing among potential management actions, requires knowledge of which factors determine building loss and how their relative importance might vary with site characteristics.

Our goal was to understand the effects of vegetation, topography and spatial patterns of buildings on the probability of building loss when a wildfire occurs. Furthermore, we were interested to see how much the relative importance of these variables differs among landscapes and communities.

Methods

Study areas

We analyzed two fires from two ecoregions in the US where fires are frequent and building losses have been high in recent years: the Cedar fire, which occurred in San

Diego County, California in October 2003, and the Fourmile Canyon fire, which occurred in Boulder County, Colorado in September 2010.

Most of California has a Mediterranean climate, and major metropolitan areas are juxtaposed with highly flammable ecosystems (Syphard et al. 2009). The dominant vegetation types are coastal sage scrub, chaparral, oak woodland and oak forest, and at higher elevations, pine forest (CDF 2003). The WUI fire problem is particularly critical in southern California, where the highest losses of property and life from wildfires in the US occur, and 400 buildings are lost every year on average (Calfire 2000; Alexandre et al. 2015a). San Diego is a major, growing city in a particularly fire prone area. Its Mediterranean climate of cool, wet winters and long, dry summers creates dry fuels, and the autumnal, adiabatic Santa Ana wind can result in severe fire weather. The Cedar fire started near San Diego in the afternoon of October 25th 2003 when a lost hunter set a fire to signal for help (CDF 2003). It burned for 10 days, during which time it covered 110,579 ha, claimed the lives of 13 civilians and one firefighter, injured 91 people, and destroyed more than 2500 buildings (Fig. **1**).

Fire regimes in Colorado are influenced by the El Niño-Southern Oscillation (ENSO), which drive year-to-year variability in moisture, with dry conditions linked to reduced amplitude of the ENSO (Kitzberger et al. 2001). In addition, the negative, cool phase of the Pacific Decadal Oscillation (PDO) is sometimes associated with increased drought in the southern Rockies when coupled with the positive (warm) phase of the Atlantic Multidecadal Oscillation (MDO) (Sibold and Veblen 2006). These broad-scale climate patterns can cause severe droughts resulting in conditions in which large fires can occur

(Sibold and Veblen 2006). Dominant vegetation types are ponderosa Pine (*Pinus ponderosa*), ponderosa pine/juniper (Juniperus spp.), and Douglas-fir (*Pseudotsuga menziesii*)/ponderosa pine forests (Graham et al. 2012). Between 2006 and 2011, Colorado lost 476 buildings to wildfire (Graham et al. 2012). Boulder, Colorado, is a medium sized city located in the Northern Colorado Front Range, where the Rocky Mountains meet the Great Plains. The Fourmile fire started on the morning of September 6th 2010 in the Rocky Mountain Front Range adjacent to Boulder under dry conditions and steady winds. It was active for 11 days, during which time it covered 2307 ha and destroyed 331 buildings, a statewide record number at that time (Fig. **2**).

Data

The probability of building loss due to wildfire is potentially affected by several predictor variables operating at different spatial scales. We measured all variables at one of three spatial scales:

1. The building scale, where we derived variables at the location of a building, or averaged within 30 m of each building (30 m is the distance from a heat source beyond which a building is not likely to ignite; (Cohen and Butler 1998; Cohen 2000; Nowicki and Schulke 2002; Gibbons et al. 2012);
2. The neighborhood scale, where we considered buildings within 200 m of each other as part of the same neighborhood (Syphard et al. 2007a); and
3. The landscape scale, defined as the area within 2500 m of each building, where we calculated landscape metrics. The 2500 m distance is the approximate distance up to which wind might carry an ember or fire brand during a fire event

(Cohen 2000). The exact distance will depend on wind conditions at the day of the fire.

Building data

We used Google Earth's historical imagery to collect spatially explicit data on building loss due to wildfires (Fig. **3**), where we distinguished buildings that were destroyed from those that did not burn. For the Cedar fire, we digitized all the buildings within the fire perimeter (USDA 2011b) from Google Earth imagery before and after the wildfires. We digitized a total of 15,543 buildings, of which 1,715 were destroyed. We considered a building to be destroyed when it burned to the ground and was no longer standing. We were not able to assess buildings that were damaged by the fire, for example by smoke damage or partial siding melt. We considered all buildings that were still standing after the fire as "surviving buildings."

All the buildings inside the Fourmile fire were digitized by Boulder County and are available online (Boulder County Colorado 2015). A total of 1,122 buildings were digitized, and 174 residential buildings plus 157 accessory buildings were destroyed by the fire.

Vegetation Data

We analyzed land cover data from the National Land Cover Dataset (NLCD 2006, 30-m spatial resolution, Fry et al. 2011) and reclassified the land cover types as highly flammable, flammable, or non-flammable (Appendix 1). The two most extensive NLCD classes inside both fire perimeters were Evergreen forests (42), and Shrub/Scrub (52). Evergreen forests and shrubs differ in terms of fire behavior, but both can support intense fires that can produce firebrands and ignitions far ahead of the fire front. Grassland areas tend to be highly flammable, especially in the dry season, and as such may exhibit fires that lead to building ignition (Knapp 1998; Mell et al. 2007). We therefore classified Evergreen Forest, Mixed forest, Shrub/Scrub, and Grassland/Herbaceous classes as highly flammable. Deciduous Forest, Pasture/Hay, and Crops are vegetation classes that can support fire spread in some seasons, but because hay and crop harvest occurs typically before moisture levels drop, and therefore are less likely to produce a fire that will ignite a building, we classified them as flammable. We classified the remaining NLCD classes as not flammable due to their lack of vegetation or because their moisture content is too high to sustain a fire.

At the landscape level, we calculated landscape metrics based on the reclassified NLCD and the program Fragstats (McGarigal et al. 2012). The landscape metrics provided a measure of fuel configuration and connectivity in the area surrounding each building, which are important factors for fire occurrence and spread in the vicinity of buildings. We calculated two landscape metrics within 2500 m from each building: the Contagion Index (CONTAG) and Connectance Index (CONNECT). In addition, we calculated the percentage of Land ($PLAND_i$) that each class occupied and the total number of patches for each class (NP_i - see Appendix 2 for definitions).

In addition to the NLCD, we collected the Existing Vegetation Type (EVT), and Fuel Characteristic Classification System Fuelbeds (FCCS), at the building level, from LANDFIRE version 1.0.5 (http://www.landfire.gov) as proxies for the flammable vegetation and fuels around each building. EVT represents vegetation conditions around the year 2001, i.e., before either fire occurred. EVT values are calculated using several sources of information, including field data, elevation, Landsat imagery, NLCD, and biophysical gradient data, and are widely used in several other LANDFIRE fuel models and fire behavior models (http://www.landfire.gov). FCCS define a fuelbeds as the inherent physical characteristics of fuel that contribute to fire behavior (Riccardi et al. 2007). Fuelbeds represent a wide range of fuel characteristics in six horizontal fuel layers called strata (Ottmar et al. 2007). Strata include canopy, shrub, non-woody vegetation, woody fuel, litter/lichen/moss, and ground fuel. Each stratum is further divided into 16 categories and 20 subcategories to represent the complexity of wildland and managed fuel (http://www.landfire.gov). We were interested in knowing which vegetation or fuel related variables were most strongly related to building loss, and thus most useful for future modeling of building loss to fire.

Topographic data

Topographic variables that affect fire behavior include elevation and aspect, which affect moisture gradients, and topographic features like narrow valleys or steep slopes, which influence fire spread. Topography also affects vegetation distribution and productivity (Barbour et al. 1999) because it affects energy and water balances (Dillon et al. 2011), and therefore precipitation, runoff, temperature, wind and solar radiation (Daly et al. 1994).

We included several topographic variables, including elevation, slope, topographic position index (TPI), and southwestness derived from aspect (Syphard et al. 2007b). Slope and elevation were acquired from LANDFIRE and are derived from the National

Elevation Dataset (NED, ned.usgs.gov, verified on 01/06/2015). LANDFIRE elevation data has a 30-m resolution and covers the entire United States. We also used the Digital Elevation Model (DEM) from LANDFIRE to calculate the topographic position index (TPI) using an algorithm that defines standardized threshold values for the difference between a cell elevation value and the average elevation of the cells around that cell measured in standard deviations from the mean (Jenness 2006). Topographic position is a categorical variable that refers to landscape position (i.e., valley, lower slope, gentle slope, steep slope, upper slope, ridges). The algorithm results in a categorical raster that contains values between 1 and 6 to represent the topographic position:

1 - Valley: TPI ≤ -1 SD

2 - Lower Slope: -1 SD < TPI ≤ -0.5 SD

3 - Flat Slope: -0.5 SD < TPI < 0.5 SD, Slope ≤ 5°

4 - Middle Slope: -0.5 SD < TPI < 0.5 SD, Slope > 5°

5 - Upper Slope: 0.5 SD < TPI ≤ 1 SD

6 - Ridge: TPI > 1 SD

While weather also affects fire behavior, we were not able to include weather data in our analysis because, neither fire spread data nor weather data was available at scales fine enough to determine the weather conditions of a given building at the exact time it was hit by a fire, making it ill-suited to the scale of our analysis.

Spatial arrangement of buildings

To quantify the spatial pattern of buildings, we analyzed spatial relationships among individual buildings and the arrangement of buildings within clusters. Clusters were created by placing a circular radius of 100 m around each building. Overlapping circles were merged to become part of the same cluster. Clusters defined the Neighborhood level of our analyses (Fig. **4**). For each cluster we calculated total area, total number of buildings, building dispersion (eq.1), and building density (eq.2).

(Equation 1)

$$Building\ dispersion = \frac{st\ dev\ of\ the\ dist.among\ buildings\ within\ a\ cluster}{mean\ dist.among\ buildings\ within\ a\ cluster}$$

(Equation 2)

$$Building\ density = \frac{number\ of\ buildings\ within\ a\ cluster}{cluster\ area\ (ha)}$$

We also calculated the distance to the edge of the nearest neighboring cluster and the closest building, and the distance from each individual building to the edge of the cluster (Fig. **4**), based on research indicating that buildings in the interior of a cluster are less susceptible to wildfire than those at its edge (Syphard et al. 2012; Maranghides et al. 2013). At the Building level we counted the number of buildings within 40 m of each building (Fig. **4**). For a complete list of all the variables used in the models, see Table 1.

Statistical analyses

We analyzed all data with the statistical software R (R Core Team 2014). We performed exploratory analysis of the data by plotting scatterplots and calculating summaries. Our response variable was whether a building was destroyed by fire or survived, and hence a binary variable. Thus, we selected logistic regression to model the relationships between the probability of building loss as a function of our predictor variables (Hosmer and Lemeshow 2000).

In our preliminary statistical analyses, we parameterized a model for the entire Cedar fire perimeter, based on all the buildings within the perimeter (total of 13,543 buildings). However, the semivariograms showed spatial patterns indicating the need to parameterize models for sub-regions in the Cedar fire. Similarly, when we mapped the residuals, there was strong evidence of spatial clustering. We therefore split the California study area into three separate communities within the perimeter of the Cedar fire: Crest, Julian, and Poway; and analyzed them separately (Fig. **1**). This left us with three separate models for which the autocorrelation conformed to a more typical and more easily modeled form that could be adequately handled with a generalized linear mixed models (GLMMs), using penalized quasi likelihood (PQL), and one model for the Fourmile fire as a whole.

We conducted model selection based on an exhaustive search of all possible combinations of predictor variables, selecting up to seven of them per model, and selected the best models based on the Bayesian Information Criterion (BIC) (Schwarz 1978), and the single best for each community. We conducted the search with the R packages *bestglm* (McLeod and Xu 2011) when possible, and *glmulti* (Calcagno 2013) when the number of explanatory variables was larger than 32. In this first set of variables, we did not account for spatial autocorrelation, and therefore we refer to these models as the 'non-spatial models.'

We checked for spatial autocorrelation in the residuals by plotting semivariograms (R package *geoR*, Ribeiro and Diggle, 2001) for the top model in each community (see supplementary material). Because we found evidence of spatial autocorrelation in the residuals of the models for all four communities, we used generalized linear mixed models (GLMMs), using penalized quasi likelihood (PQL), to account for spatial autocorrelation (R package *nlme*; (Pinheiro et al. 2014). Hereafter we shall refer to these as the 'spatial models.' Since the BIC cannot be used to assess the fit of a GLMM based on PQL, (PQL is not a true likelihood), we incorporated spatial autocorrelation only into the top non-spatial model for each community and applied backward selection to remove extraneous variables (p-values higher than 0.05 were excluded).

To measure the discriminatory ability of both the spatial and non-spatial models, we calculated the area under the curve (AUC) of the receiver operating characteristic (ROC) curve (R package *ROCR*, (Sander et al. 2005). In the case of the spatial models, we calculated the AUC based on the fixed effects coefficients, since there is no straightforward way to calculate the AUC for models with random effects. This means that the AUC values for the spatial models are only an approximation.

Results

Our initial list of variables included 23 potential explanatory variables and we were able to reduce it to eight variables for all four communities. Our goal was to understand the effect of vegetation, topography and spatial arrangement of buildings on the probability of building loss to wildfire. Hence we looked at each type of variable and their relative impact on building loss.

Vegetation variables

We included seven variables related to vegetation in our analysis: vegetation type[B], land cover class[B], fuel characteristic classification system fuelbeds[B], percentage of highly flammable vegetation within 2500 m[L], number of patches for each class within 2500 m[L], contagion index of the landscape within 2500 m[L], and connectivity of the landscape within 2500 m[L]. Vegetation-related variables were part of the best non-spatial and spatial models for three of the four communities.

Percentage of highly flammable land[L] was present in both spatial and non-spatial models in Boulder, and in the non-spatial model of the Crest community (Table 2). In both Boulder and Crest communities, the probability of building loss given a wildfire increased with higher percentages of highly flammable land surrounding the buildings.

Contagion[L] was present in the non-spatial model for Boulder, but not in the spatial model and it had negative signal, meaning that lower contagion values for the landscape around the building represent higher risk of building loss (Table 2)

Connectivity^{L} was present in both the best spatial and the best non-spatial models of the Julian community, with higher connectivity values representing higher risk of building loss (Table 2).

Number of patches of highly flammable land^{L} was in both the spatial and non-spatial models of the Poway community, with a smaller number of patches of highly flammable land^{L} representing higher risk for building loss (Table 2).

It is noteworthy that all the vegetation-related variables that were included in our best spatial models were landscape-level variables (Table 3).

Topography variables

We included four variables related to topography in our analysis: elevation^{B}, slope^{B}, topographic position^{B} and southwestness^{B}. Elevation^{B}, topographic position index^{B}, and slope^{B} were part of the best non-spatial models for three of four communities (Table 2). In the Cedar fire, elevation^{B} was important in non-spatial models of two of the three communities (Table 2 and 3). In the Crest community, the probability of building loss was higher for buildings located at higher elevations^{B} and on steeper slopes^{B}.

Spatial-arrangement of buildings

Spatial-arrangement variables were included in the final spatial models of two of the four communities analyzed (Table 3) We included in our analysis eight variables related to spatial arrangement of buildings, and six of those variables were present in the non-spatial models for all communities. Three out of the eight variables were present in the spatial models for two communities: number of buildings in the cluster^{C}, building density^{C}, and cluster size^{C}. However, the results varied from one community to another, and what was selected in the model for one community was typically not included in models for the other. These results highlighted the importance of spatial arrangement since it was the most prevalent group of variables in both spatial and non-spatial models. In the Julian community, the probability of building loss given a wildfire was greater when the cluster size^{C} was smaller and when there was a larger number of buildings within a cluster. In the Poway community, however, the probability of building loss was greater when building density^{C} was lower.

Discussion

When modeling which buildings burned within a fire perimeter, we found that variables describing the landscape – vegetation connectivity, topography, and the spatial arrangement of buildings – were present more frequently in the models than were the variables measuring more common targets of fire risk mitigation, such as vegetation type and vegetation cover.

We based our choice of variables in part on the work of Cohen and others whose investigation of building ignition and building loss to wildfires (Cohen and Butler 1998; Cohen 2000; Nowicki and Schulke 2002; Gibbons et al. 2012; Syphard et al. 2012) has strongly influenced recommendations made to homeowners and fire managers regarding structure protection and risk mitigation. This is why we included variables to represent the concepts these researchers found significant, and to assess their importance, in an effort to clarify which contribute the most to the risk of building loss, given a fire occurrence.

Vegetation

Vegetation was present in models for three communities. Interestingly, it was not the type of vegetation that was present, but rather the amount and the connectivity of this vegetation that mattered most. These results may be due to the fact that the vegetation type was fairly uniform, in particular in the Fourmile fire where the vegetation cover was either Evergreen forest or shrub/scrub. The degree to which communities were different in terms of the factors determining building loss further underlines the importance of landscape factors in the risk of building loss.

The vegetation-related measures that we included (e.g., land cover, fuel beds, and vegetation type), and their consistent relatively lower importance demonstrated that once a fire starts and there is adequate vegetation to carry the fire, other factors become more important determinants of building loss. Vegetation and fuel is related to fire probability and fire spread and therefore fire exposure (Whitlock et al. 2003; Marlon et al. 2006), but less to building loss. The presence of fuel near the building was not a strong predictor in our models of the likelihood that a building would be lost to the fire.

Topography

Across all locations and models, topographic characteristics such as elevation and slope, were selected in the model fitting. Topography can affect the outcome of a wildfire directly or indirectly. Directly, because topography influences fire spread and behavior. Steeper slopes decrease the angle between the flame and the new fuel source, drying fuels faster and therefore, moving up the hill faster (Dupuy 1995), and indirectly because buildings located at higher places are typically harder to access and therefore to defend (e.g. The Valparaiso fire in Chile, Associated Press, 2014). The combination of faster moving flames with difficult access often results in building loss and was likely the reason why elevation was an important variable in the Fourmile fire.

Spatial arrangement of buildings

Spatial arrangement of buildings, including cluster size, number of buildings in the cluster, and building density, was also consistently important in our models. For example, clusters with many buildings were associated with greater probability of loss in the case of the Julian community. This may be because burning buildings are themselves a source of firebrands that can be carried by the wind and ignite other buildings (Suzuki et al. 2014). Smaller clusters with more buildings will be denser, again increasing the probability of building-to-building ignition. However, the model for the Poway community showed higher risk in lower-density neighborhoods, perhaps reflecting an unmeasured covariate such as differences in the ease of accessibility for suppression or in the age and building materials of different neighborhoods. Fire-specific factors such as the time of day or sequence of the flame front's passage through the community could also be important and we were not able to consider them here (Maranghides et al. 2013).

Caveats

The relatively low AUC values suggest that factors not included in our models may also affect building loss. For example, construction materials (Cohen and Butler 1998; Cohen 2000), fire suppression efforts during the fire (Graham et al. 2012), weather conditions during the fire event, and vegetation in the home ignition zone (Cohen and Butler 1998; Nowicki and Schulke 2002; Cohen 2008) play a role in the outcome of wildfire events, including building loss. Due to the scale of our analysis and reliance on satellite imagery and remote sensing information to collect our data, it was not possible to include these factors in the models. We do acknowledge that wind influences how far a firebrand can reach, which may be why buildings closer to the edge are at greater risk under severe weather conditions. However, we did not account for weather because there was not enough variability in available weather data, particularly for the Cedar fire, which occurred under Santa Ana conditions. Furthermore, why including weather would be interesting from a scientific perspective, it is less relevant for community planning purposes, because weather conditions during future fires are unknown.

The most important variables in the Fourmile fire were more closely related to topography and flammability of the landscape surrounding the buildings, than in the communities in San Diego. The AUC values were the lowest of all four communities and we can only speculate that we missed some variables, such as building materials, suppression efforts and pre-fire mitigation efforts on the property by the owners.

Despite the fact that many other variables could have been added to our initial list, we began with a broad set of 24 variables and reduced it to a fairly small, focused, collection of explanatory variables that resulted in good AUC values. We see this as a modeling success. The statistical methods used in this study are cutting-edge when dealing with binary dependent variables and spatial autocorrelation. As in any modeling approach, there is always a possibility for Type II errors and for that reason we used AUC to assess the quality of the models by looking at both matches and mismatches in the model estimates.

We would like to emphasize that our goal was to understand the underlying drivers to building loss and that we had no data that allowed us to cross-validate the models in a different place. Therefore, we did not try to use the models to make prediction for areas outside our study area. We did try each model on all other three communities and the results were always a model with a poor performance, strengthening our finding that the drivers are location specific and may not apply in other WUI areas.

Management implications

The defense of buildings and the replacement of destroyed buildings constitute a substantial portion of the costs associated with wildland fires in the WUI (Gude et al. 2013). Knowing *where on the landscape* buildings face the most risk could focus both mitigation and suppression efforts and inform land use planning, urban planning, and WUI regulation. This knowledge could also be used to expand and improve the fire risk information available to homeowners, and to highlight more location-specific factors (i.e., lot-related risk in addition to building material- and landscaping-related risk). Our findings have implications for policy makers, urban planners and homeowners, reinforcing the growing awareness that landscape configuration, as modified through land use and urban planning, and WUI building regulations, is a crucial focus for creating fire-adapted communities.

Past land-use decision-making have led to many buildings in highly flammable areas resulting in high exposure and therefore, vulnerability to wildfires, of both buildings and people (Pincetl et al. 2008). Our results support other studies (Gibbons et al. 2012; Syphard et al. 2012) in highlighting that the location of a building on the landscape and in relation to other buildings matters greatly in terms of the probability that a building will burn when a fire occurs. This suggests that building placement could be given more weight when deciding which homeowners to focus on first in outreach efforts like Firewise. Owners of the highest-risk building locations, i.e, those at higher elevation, at the top of a ridge, in dense clusters of buildings, or at the periphery of a cluster, should be made aware that their building has a higher probability of loss than their neighborhood as a whole if a wildfire occurs, so that they can decide upon mitigation steps. Community outreach programs aimed at helping communities adapt to fire (Firewise and similar programs) could prioritize efforts to reach the owners of these higher-risk properties, and to enlist their cooperation. While targeting higher-risk properties is a standard practice for firefighters working with their community, our study reinforces the significance of building placement, and indicates that it is a major risk factor.

While it is rarely feasible to alter development patterns once houses have been built, it may be possible to reduce future fire risk by more carefully siting new development in high fire-risk landscapes, or steering development away from such areas entirely. In addition, rebuilding after a wildfire can be an opportunity to implement mitigation actions, incentives and even regulations that place more responsibility on the homeowner side (Alexandre et al. 2015a; Mockrin et al. 2015). In this regard, our findings are especially important for urban planners who want to take fire risk into account. Similarly, land-use regulations intended to minimize fire risk must address landscape-level factors, including building location and arrangement (Syphard et al. 2012), as well as promote defensible space (Syphard et al. 2014) if they are to be successful in reducing wildfire-related losses. Subdivision or planned unit development requirements are the local regulations that directly govern the configuration of newly-built landscapes, suggesting these particular rules could be targeted for change. Vegetation connectivity is the province of landscape architects as well as landscape maintenance services, two additional groups whose cooperation in fire adaptation would be beneficial. Our study suggests that there are opportunities to be proactive about future risk by considering building locations and vegetation connectivity when planning to new housing developments.

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Table 1 – Variables used in the models, their meaning and sources.

Response variable: Destroyed (1) vs Survived (0)

Level of analysis	Variable	Description	Source
Building level (40 m radius)	Vegetation type^B	Existing Vegetation Type, represents the species composition currently present at a given site.	Landfire EVT (http://www.landfire.gov/National ProductDescriptions21.php)
	Fuel Characteristic Classification System Fuelbeds^B	The Fuel Characteristic Classification System Fuelbeds (FCCS) layer describes the physical characteristics of a relatively uniform unit on a landscape that represents a distinct fire environment. FCCS provides standardized descriptions of fuelbeds and fire hazard.	LANDFIRE FCCS (http://www.landfire.gov/National ProductDescriptions25.php)
	Land Cover class^B	See Annex 1 for details on cover classes	NLCD 2006 or 2001
	Elevation^B	Digital Elevation Model, 30 meters resolution.	Landfire DEM (http://www.landfire.gov/National ProductDescriptions7.php)
	Slope^B	Slop calculated in degrees	Derived from DEM
	Topographic position^B	6 classes, extansion tool on ArcMap	Jenness 2006
	Southwestness^B	Create a new field and calculate the cosin(ASP) in ArcMap	Calculated by us
	Buildings within 40 m radius^B	Derived from digitized buildings	Calculated by us
Cluster level (groups of buildings that are within 100 m)	Building density^C	Number of buildings within a cluster divided by the cluster area.	Calculated by us
	Cluster size^C	Cluster area (m^2)	Calculated by us
	Building dispersion^C	Standard deviation of the distance among buildings within a cluster divided by the mean distance amog buildings within the cluster.	Calculated by us
	Number of buildings inside cluster^C	Derived from digitized buildings	Calculated by us
	Distance to edge of cluster^C	Derived from digitized buildings	Calculated by us
	Distance to nearest building^C	Derived from digitized buildings	Calculated by us
	Distance to nearest cluster^C	Derived from digitized buildings	Calculated by us
Landscape level (radius of 2500 m)	Percentage of land/class^L	See Appendix 2 for detailed description	FRAGSTATS
	Number of patches/class^L		FRAGSTATS
	Contagion Index^L		FRAGSTATS
	Connectance Index^L		FRAGSTATS

Note. Superscripts B = building, C= cluster and L=landscape are used with variable names throughout tables and text to denote the level of measurement.

Table 2 – Coefficients, standard errors, and p-values for the top model, with

	GLM					glmmPQL			
	Coefficient	st. Error	p-value	BIC*	AUC	Coefficient	st. Error	p-value	AUC
Boulder, CO									
Intercept	-249.3	33.14	p < 0.001			-119.61	27.75	p < 0.001	
Elevation[B]	0.01	0	p < 0.001			0.01	0	p < 0.001	
Distance to edge cluster[C]	-0.02	0.01	0.002	1279	0.69	-	-	-	0.66
Contagion Index[L]	-0.54	0.12	p < 0.001			-	-	-	
Percentage of highly flammable land[L]	2.92	0.43	p < 0.001			1.09	0.26	p < 0.001	
Crest, San Diego, CA									
Intercept	-834.7	143	p < 0.001			-10.08	2.05	0	
Elevation[B]	0.01	0	p < 0.001			0.01	0	0	
Slope[B]	0.11	0.02	p < 0.001			0.07	0.02	0	
TPI - Top Ridges[B]	-0.68	0.17	p < 0.001			-	-	-	
Buildings within 40 m[B]	-0.39	0.11	p < 0.001	1075	0.79	-	-	-	0.73
Building density[C]	-1.1	0.32	p < 0.001			-	-	-	
Percentage of highly flammable land[L]	8.16	1.42	p < 0.001			-	-	-	
Percentage of non-flammable land[L]	8.44	1.47	p < 0.001			-	-	-	
Julian, San Diego, CA									
Intercept	-1.34	0.35	0.043			-2.64	0.43	p < 0.001	
Elevation[B]	0	0	p < 0.001			-	-	-	
Buildings within 40 m[B]	0.17	0.03	p < 0.001			-	-	-	
Cluster Size[C]	-0.01	0	p < 0.001	2623	0.75	-0.01	0	0.038	0.72
Number of buildings in the cluster[C]	0.01	0	p < 0.001			0	0	0.033	
Distance to nearest cluster[C]	0	0	0.009			-	-	-	
Connectance Index[L]	0.31	0.04	p < 0.001			0.25	0.06	p < 0.001	
Poway, San Diego, CA									
Intercept	-0.81	0.27	0.003			-0.81	0.26	0.002	
Building density[C]	-0.82	0.24	p < 0.001	294	0.78	-0.82	0.23	p < 0.001	0.78
Number of patches of highly flammable land[L]	-0.04	0.01	p < 0.001			-0.04	0.01	p < 0.001	

*-BIC values showed here are the absolute values and were used solely to rank the models and not for comparisons among models.

Table 3 - Variables present in the top models that account for spatial autocorrelation

Communitiy	Vegetation	Topography	Spatial Arrangement	AUC for glm	AUC for glmmPQL*
Boulder	Percentage of highly flammable land[L]	Elevation[B]		0.69	0.66
Crest		Elevation[B] Slope[B]		0.79	0.73
Julian	Connectance index[L]		Cluster size[C] Number of buildings in the cluster[C]	0.75	0.72
Poway	Number of patches of highly flammable land[L]		Building Density[C]	0.78	0.78

[*] - AUC for spatial models does not explicitly account for spatial autocorrelation.

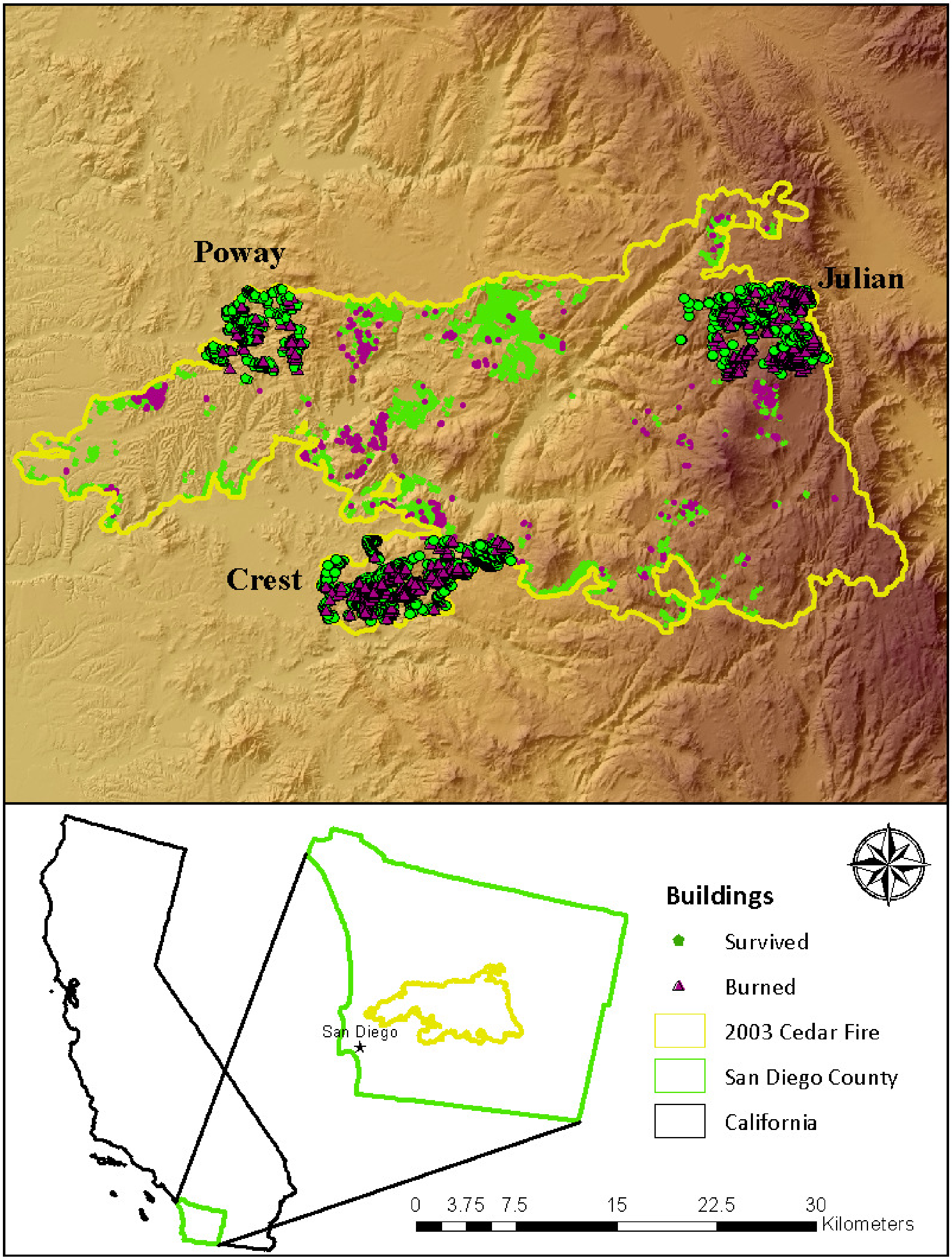


Fig. 1- Cedar Fire perimeter with the three communities, Crest, Julian and Poway, and their affected buildings in San Diego, California, 2003

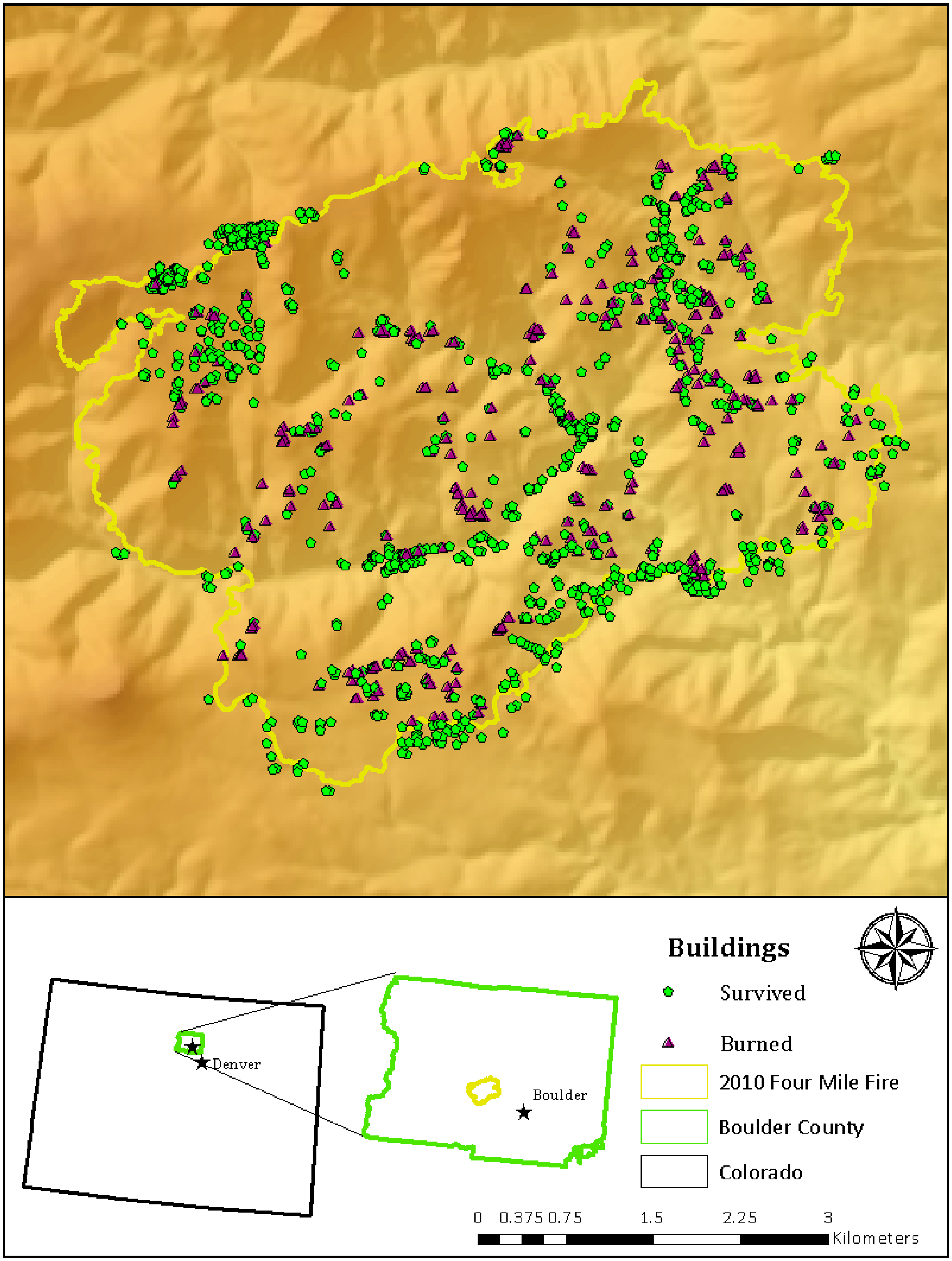


Fig. 2 - Fourmile Fire perimeter and affected buildings in Boulder, Colorado, 2010.

Fig. 3 - Example of Google Earth imagery before and after the Fourmile Fire in Colorado in 2010.

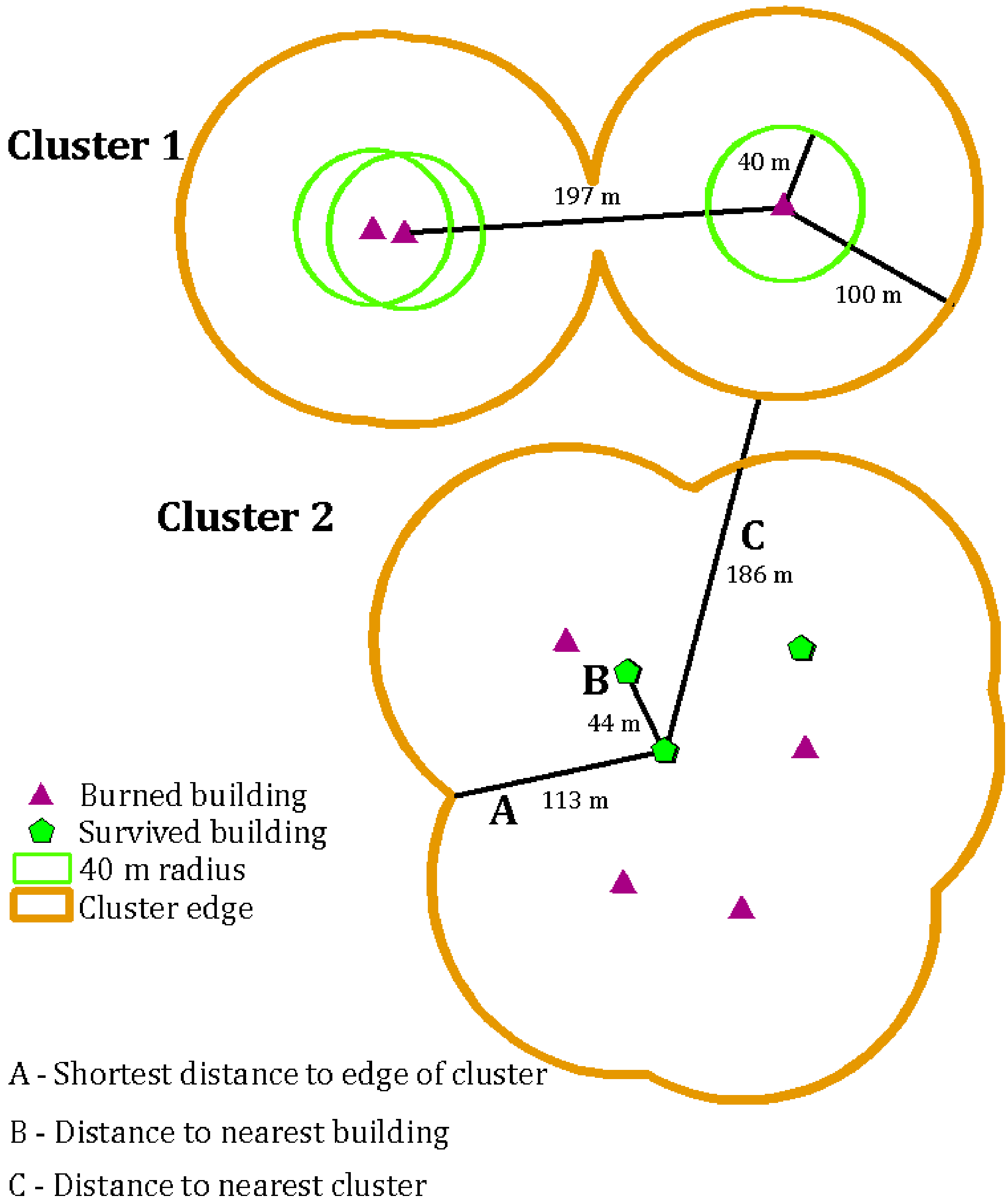


Fig. 4 - Example of clusters that were created using a radius of 100 m; Cluster 1: example of how the buildings within 40 m were calculated. The two buildings on the left would have one building within 40 m each, while the building on the right would have zero buildings. Cluster 2: examples of how distance to the edge of cluster, distance to the nearest building and distance to the nearest cluster were calculated.

Appendix 1 - Reclassification scheme of NLCD classes to use as input for FRAGSTATS.

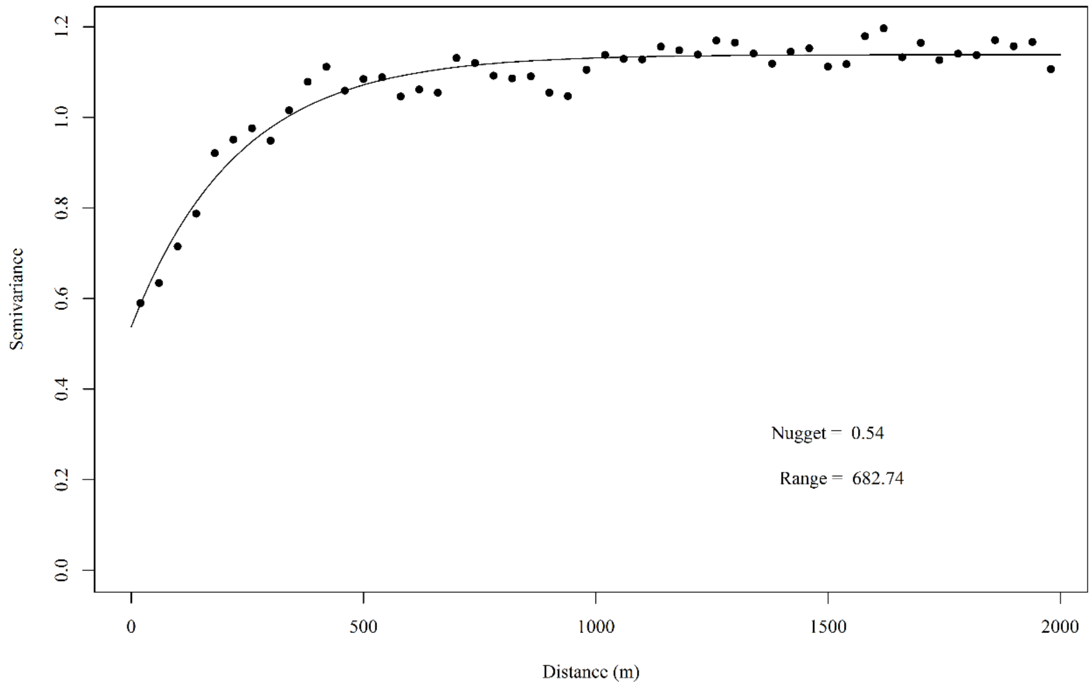
Classes:	Original NLCD class	New Class
42	Evergreen Forest	Highly flammable
43	Mixed Forest	
52	Shrub/Scrub	
71	Grassland/Herbaceous	
41	Deciduous Forest	Flammable
81	Pasture/Hay	
82	Crops	
21,22,23,24	Urban classes	Non-flammable
11	Open Water	
12	Perennial Ice/Snow	
31	Barren Land	
90,95	Wetlands	
No Data	No Data	999 - No data

Appendix 2 - Explanation of FRAGSTATS variables used in the models at the landscape level.

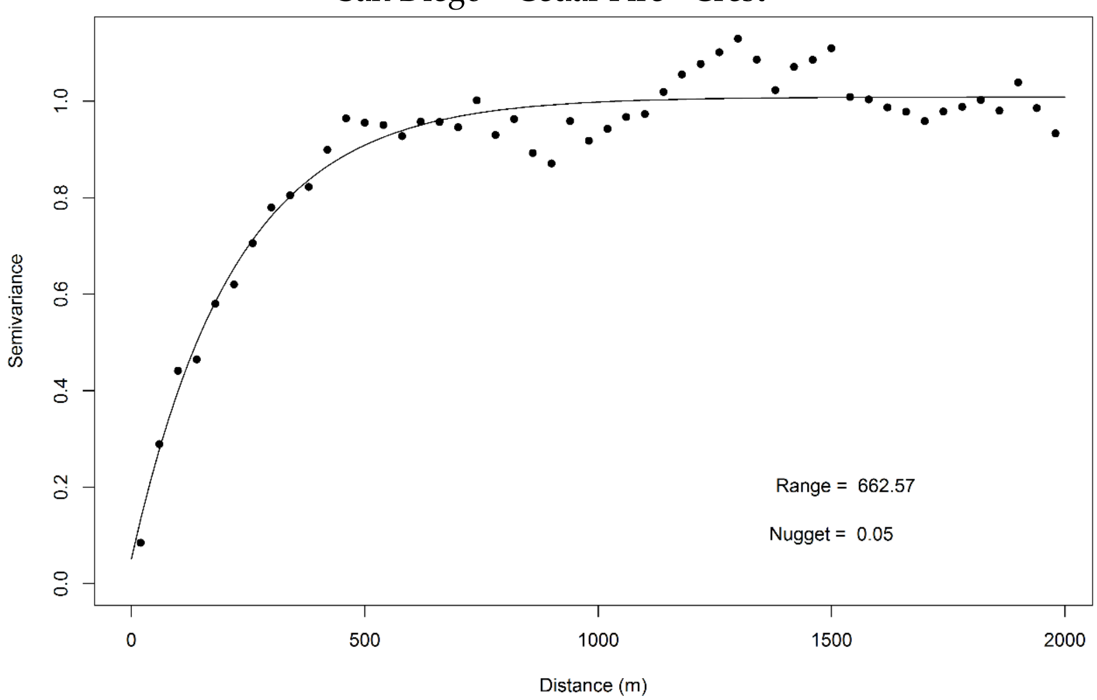
	Metric	Explanation
Class	PLAND	Percentage of Landscape (0 < PLAND ≤ 100) - equals the sum of the areas (m2) of all patches of the corresponding patch type, divided by total landscape area (m2), multiplied by 100 (to convert to a percentage); in other words, PLAND equals the percentage the landscape comprised of the corresponding patch type. Note, total landscape area (A) includes any internal background present. PLAND approaches 0 when the corresponding patch type (class) becomes increasingly rare in the landscape. PLAND = 100 when the entire landscape consists of a single patch type; that is, when the entire image is comprised of a single patch.
	NP	Number of Patches - equals the number of patches of the corresponding patch type (class).
Landscape	CONNECT	Connectance Index (0 ≤ CONNECT ≤ 100) - equals the number of functional joinings between all patches of the same patch type (sum of cijk where cijk = 0 if patch j and k are not within the specified distance of each other and cijk = 1 if patch j and k are within the specified distance), divided by the total number of possible joinings between all patches of the same type, multiplied by 100 to convert to a percentage. CONNECT = 0 when either the landscape consists of a single patch, or all classes consist of a single patch, or none of the patches in the landscape are "connected" (i.e., within the user-specified threshold distance of another patch of the same type). CONNECT = 100 when every patch in the landscape is "connected."
	CONTAG	Contagion Index (0 < CONTAG ≤ 100) - equals minus the sum of the proportional abundance of each patch type multiplied by the proportion of adjacencies between cells of that patch type and another patch type, multiplied by the logarithm of the same quantity, summed over each unique adjacency type and each patch type; divided by 2 times the logarithm of the number of patch types; multiplied by 100 (to convert to a percentage). In other words, the observed contagion over the maximum possible contagion for the given number of patch types. CONTAG approaches 0 when the patch types are maximally disaggregated (i.e., every cell is a different patch type) and interspersed (equal proportions of all pairwise adjacencies). CONTAG = 100 when all patch types are maximally aggregated; i.e., when the landscape consists of single patch. CONTAG is undefined and reported as "N/A" in the "basename".land file if the number of patch types is less than 2, or all classes consist of one cell patches adjacent to only background.

Supplementary Material - Semivariograms for the non-spatial models of each community.

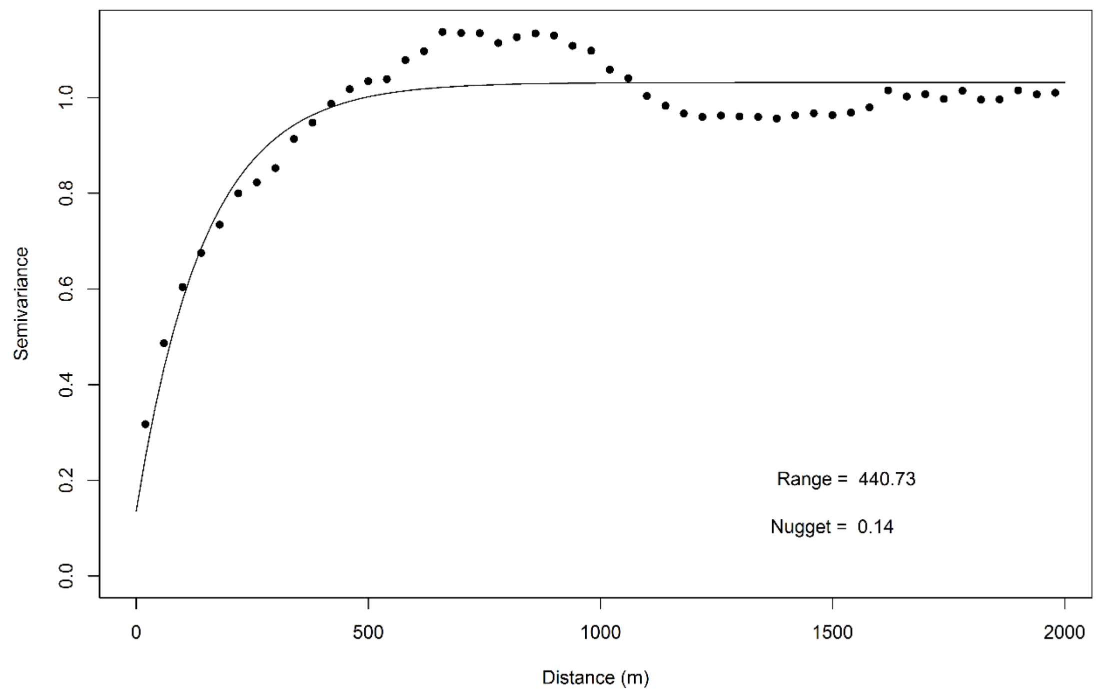
Boulder – Fourmile fire



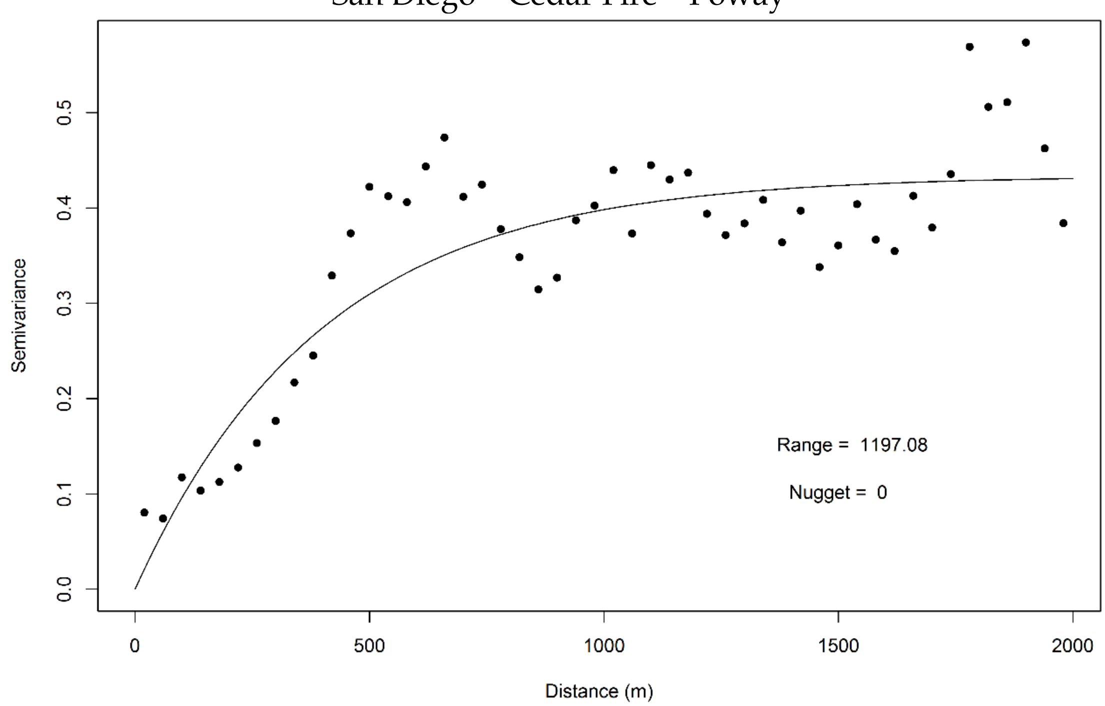
San Diego – Cedar Fire - Crest



San Diego – Cedar Fire - Julian



San Diego – Cedar Fire – Poway



Chapter 2

Factors related to building loss due to wildfires in the conterminous United States

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Abstract

Wildfire is globally an important ecological disturbance affecting biochemical cycles, and vegetation composition, but also puts people and their homes at risk. Suppressing wildfires has detrimental ecological effects and can promote larger and more intense wildfires when fuels accumulate, which increases the threat to buildings in the Wildland Urban Interface (WUI). Yet, when wildfires occur, typically only a small proportion of the buildings within the fire perimeter are lost, and the question is what determines which buildings burn. Our goal was to examine which factors are related to building loss when a wildfire occurs throughout the United States. We were particularly interested in the relative roles of vegetation, topography, and the spatial arrangement of buildings, and how their respective roles vary among ecoregions. We analyzed all fires that occurred within the conterminous U.S. from 2000 to 2010 and digitized which buildings were lost and which survived according to Google Earth historical imagery. We modeled the occurrence as well as the percentage of buildings lost within clusters using logistic and linear regression. Overall, variables related to topography and the spatial arrangement of buildings were more frequently present in the best 20 regression models than vegetation-related variables. In other words, specific locations in the landscape have a higher fire risk, and certain development patterns can exacerbate that risk. Fire policies and prevention efforts focused on vegetation management are important, but insufficient to solve current wildfire problems. Furthermore, the factors associated with building loss varied considerably among ecoregions suggesting that fire policy applied uniformly across the US will not work

equally well in all regions, and that efforts to adapt communities to wildfires must be regionally tailored.

Key words: Building loss, ecoregions, linear and logistic regression, national analysis, wildfires, WUI.

Introduction

Severe wildfire is a growing threat to buildings in the Wildland Urban Interface (WUI), the area where houses meet or intermingle with undeveloped wildland vegetation (Radeloff et al., 2005). The number of buildings lost and the resources spent fighting fires (approximately two billion dollars per year for fuel management suppression (Colburn 2008; USDA 2014)) demonstrate how serious this problem has become in the U.S. Interestingly though, when wildfires occur, typically only a small proportion of the buildings within the fire perimeter are lost (Alexandre et al. 2015a), and one major gap in our knowledge of WUI fire is why some buildings burn and others do not. Building materials and vegetation characteristics are important (Cohen 2000; Cary et al. 2009; Quarles et al. 2010; Maranghides and Mell 2012). However, building materials and vegetative fuel alone do not explain why only some buildings are destroyed (Alexandre et al. 2015b). A few local studies conducted in California, Colorado and State of Victoria (south-eastern Australia), suggest that topography and the spatial arrangement of buildings are also key factors in building loss (Gibbons et al. 2012; Syphard et al. 2012; Alexandre et al. 2015b), but it is unclear if these findings apply in other ecoregions. Successful fire policy and mitigation must be based on understanding how human and ecological factors interactively determine which buildings burn when a fire occurs, and how their relative importance changes among ecoregions.

Globally, wildfire is an important ecological disturbance that affects biochemical cycles and vegetation composition (Thonicke et al. 2001), and maintains biodiversity in many areas (Pausas and Keeley 2009). Suppressing wildfires can have detrimental ecological effects in some dry forest types (Keeley et al. 1999), potentially promoting larger and more intense wildfires due to excess fuel accumulation and continuity (Covington and Moore 1994; Hessburg et al. 2007). However, too-frequent fire due to human-caused ignitions and invasive species can also threaten ecological functioning and biodiversity, especially in non-forested ecosystems (Brooks and Matchett 2006; Syphard et al. 2009). Deleterious ecological effects of changes in fire regimes are likely when broad-scale fire management strategies do not account for the inherent variation in natural fire regimes (Moritz et al. 2014).

National fire policy in the United States, which originated after several years of severe fires between 1910 and 1935 (e.g., the Great Fire in 1910 in Idaho, Montana, and Washington, and the Porcupine Fire, in 1911 Ontario - Egan, 2009, http://www.nwcg.gov) mandated fire suppression to contain all fires by 10 am of the following day. This policy was in effect until 1964 when the positive benefits of natural and prescribed fires were formally recognized in the Wilderness Act, after having been demonstrated by research (Busenberg 2004). Similarly, in 1968 the National Park Service changed its policy to recognize the natural role of fire (Busenberg 2004).

Even with less emphasis on suppression, wildfire-related expenditures have continued to increase, yet the average area burned nationally has not decreased (Westerling et al. 2006; NICC 2013; Ellison et al. 2015). Some argue that throughout the United States, the protection of buildings has now become the primary activity of wildland fire agencies because scattered development patterns place so many homes and other buildings at risk (Pincetl et al. 2008). Indeed, on average, 2,677 buildings (residences, outbuildings, and commercial) were lost to wildfires every year in the conterminous U.S from 1999 to 2003 (NICC 2013). However, this number is much lower than the number of buildings exposed to wildfires, i.e., those located within fire perimeters. When wildfires occur in the wildland-urban interface (WUI), typically only a small proportion of the buildings within the fire perimeter are lost (Alexandre et al. 2015a), raising the question why some buildings burn and others do not.

Because wildfires are shaped by climate, topography and vegetative fuel, and because vegetation is the only factor that can be directly managed (Husari et al. 2006), fuel manipulation is seen as the most effective way to influence future wildland fires (Husari et al. 2006). Thus in 2000, the US National Fire Plan (NFP) established "a long-term hazardous fuels reduction program to reduce the risks of catastrophic wildland fire to communities" (http://www.forestsandrangelands.gov/) and mandated to focus fuel management funds on the WUI (Husari et al. 2006). However, NFP's implementation resulted in only a small proportion of the hazardous fuel reduction treatments within WUI areas, and only 50% guided by Community Wildfire Protection Plans (CWPPs) (Schoennagel et al. 2009). This is unfortunate, because it matters greatly where WUI fuel treatments are located in relation to buildings (Bar-Massada et al. 2011a). Irrespective of the location of fuel treatment, focusing solely on fuels may be insufficient, because where buildings are located in relation to other buildings is more important in explaining building loss than are vegetation patterns (Syphard et al. 2012; Alexandre et al. 2015b). In fact, at the building level, the most effective actions are to reduce woody cover by up to 40% immediately adjacent to buildings and ensure that vegetation does not overhang or touch the building (Syphard et al. 2014). However, at the landscape level, building density and distance to major roads were the strongest explanatory variables of building loss (Syphard et al. 2014). Arrangement and location of buildings are key in determining susceptibility to wildfire in southern California, where property loss is highest at low to intermediate building densities and in areas with short fire return intervals (Syphard et al. 2012). In Australia, a greater proportion of the buildings lost were within 40 m of other buildings (Gibbons et al. 2012). And finally, in Southern California and Colorado, topography, the spatial arrangement of buildings, and vegetation connectivity explain a larger portion of the variability in building losses than does vegetation type (Alexandre et al. 2015b).

However, it is likely that the relationships and dynamics between fuel treatments, building placement, and landscape configuration differ among ecoregions of the U.S., in part because their fire regimes vary. Some forest types have historically burned infrequently but with high intensity (Agee 1993), while others have long dry seasons and easily combusted forest floors, burning more frequently but less intensely. For example, the dry Ponderosa Pine forests have short fire return intervals with frequent, low severity fire (Allen et al. 2002), while California's Chaparral and southern shrublands have longer fire return intervals, and periodic fires under severe weather conditions (Keeley et al. 2009). Because the drivers of fire occurrence and behavior differ in these two landscapes, they have different fire regimes. The two landscapes also have different building patterns, regulations and topography. It would be expected that the topography strongly affects building loss to wildfire in a landscape where topography is variable, while in flat areas dominated by grasslands building loss might be more strongly related to building materials or wind intensity. In Southern California, strong winds that pass through deep valleys generate extreme fire behavior resulting in a large number of buildings lost to wildfires, and likely affecting which buildings are lost. Similarly, in a crown fire regime versus a low intensity grassland fire regime, it is likely that vegetation affects building loss differently even if building loss is high in both situations. These examples highlight that there is a need to understand which factors are most important in determining if a building will be lost when a wildfire occurs.

In summary, our goal was to identify how vegetation, topography, and the spatial patterns of buildings relate to building loss when a wildfire occurs, and how the relative importance of these factors varies among ecoregions. Specifically, we asked:

1. What factors are related to whether any buildings are lost when a wildfire hits a cluster of buildings? and,
2. What factors are related to the proportion of buildings that are lost within a cluster when at least one building in the cluster is lost?

Methods

Study area and Data - Buildings and clusters

We used Google Earth's historical imagery to assess building loss due to wildfires in all fire perimeters in the conterminous United States between 2000 and 2010 recorded in the Monitoring Trends in Burn Severity (MTBS) dataset (http://www.mtbs.gov/ downloaded on 03/05/2012). Google Earth imagery comes from a variety of sources, such as satellites (Landsat, SPOT Image, GeoEye-1, and IKONOS), aerial photography and even kites and balloons, which means that the spatial and temporal resolution, as well as the number of available historical images, varies by location (http://www.gearthblog.com/blog/archives/2014/04/google-earth-imagery.html, assessed on Sep/2/2015)

Within each fire perimeter we digitized all the buildings that survived the fire (buildings present before and after the fire date), and all that were lost (buildings present before the fire date, but not after). We considered a building to be lost when it was completely removed in the post-fire image. This means that our estimates are conservative, and did not include partial damage or damage that was not visible from the top, such as smoke damage or partial siding melt. In total, we digitized 114,532 buildings, of which 9,236 were lost (Fig. **5**).

We conducted our analysis at the scale of clusters of buildings, because previous analysis (Alexandre, 2015) showed evidence of spatial autocorrelation when buildings were the unit of analysis. We considered buildings to be in the same cluster if 100-m buffers around each building were contiguous (Syphard et al. 2007a) (Fig. **6**). For each cluster we calculated our independent variables, derived from mapped data, at two scales: 1. within the cluster; and 2. within the surrounding landscape, defined as the area within 2500 m (because 2500 m is the approximate distance the wind might carry an ember (Cohen 2000)).

We examined only clusters that had at least eight buildings, because smaller cluster areas make analysis of the percentage of buildings lost less meaningful. For the logistic regression analysis, we examined only clusters with at least eight buildings. The reason was that in clusters with fewer buildings, over 75% lost no buildings due to fire, potentially biasing the logistic regressions (Appendix 3). In addition, we restricted our analyses to ecoregions that had at least 40 clusters and where at least 10% of clusters lost buildings (Table 4). In total, there were 16,595 clusters of buildings within fire perimeters, of which 2,029 contained at least eight buildings and these included 70% of all digitized buildings. We used 1,980 of these clusters for the logistic regression analysis, categorizing them according to whether any building was lost, or none of the buildings was lost, and used that binary variable as the response (we also ran our logistic regression models for all clusters with at least four buildings and results were very similar to those for clusters with at least eight buildings). For the linear regression, we used only those 547 clusters that had at least one building lost. The response variable for the linear regression was the proportion of buildings lost within the cluster (Table 4).

Ecoregions

We analyzed our data for Omernik level I ecoregions (http://www.epa.gov/wed/pages/ecoregions/na_eco.htm#Downloads, last accessed on 02/20/2015, Fig. **7**, (Omernik 1987)). We assigned clusters to ecoregions based on their location. However, only five ecoregions had enough clusters (> 40) for our logistic regression analysis, which accounted for 69% (78,961 buildings) of all the buildings that we digitized; and four ecoregions had enough for our linear regression analysis, which included 67% (77,170 buildings) of all buildings digitized (see Table 4 and Appendix 5 for total number of digitized buildings).

Vegetation Data

The 2006 National Land Cover Database (NLCD 2006, (Fry et al. 2011) is a land cover classification scheme that has been applied consistently across the conterminous U.S. at a spatial resolution of 30 m, based on Landsat satellite data of circa 2006. Since our study area was the conterminous U.S. and our fire data was from 2000 to 2010, we used NLCD 2006 data as a proxy for the horizontal distribution of fuels during that time period. Due to the categorical nature of this variable, and for effective statistical analysis, we reclassified the data for deriving fuels metrics at both the cluster level and landscape level analyses. For cluster level analyses, we reclassified land cover into four groups: Non-flammable, Forest, Shrubs/Scrubs, and Grassland/Pasture/Hay (Appendix 5). For landscape level analysis, we reclassified land cover into three groups: Highly-flammable, Flammable, and Non-flammable (Appendix 6). Shrublands can support intense fires that may produce firebrands, and grassland areas produce less intense fast moving fires. We therefore included Evergreen Forest, Mixed forest, Shrub/Scrub, and Grassland/Herbaceous classes in the Highly-flammable class. Deciduous Forest, Pasture/Hay, and Crops are vegetation types that can support fire spread in some seasons but are less likely to produce a fire that will ignite a building, so we classified them as Flammable. The remaining NLCD classes are not flammable due to their lack of vegetation or because their moisture content is too high to produce a fire and these were classified as Non-flammable (Appendix 6).

Landscape metrics provide a measure of fuel configuration and connectivity in the area surrounding a building, which are important to fire spread. We derived landscape metrics, based on the second reclassification of the NLCD, using Fragstats, a software for spatial analysis, (McGarigal et al. 2012) for the area within 2500 m from each cluster. We calculated one landscape-scale metric, contagion (Fragstats name: CONTAG), and two class-scale metrics; percentage of land for each class ($PLAND_i$), and connectivity ($CONNECT_i$) (see Appendix 7 for definitions).

Topographic data

In our statistical models we included elevation, slope, topographic position index (TPI), road density, and southwestness derived from aspect (Syphard et al. 2007b). Topography affects fire behavior due to the micro-weather conditions created by elevation and aspect (e.g., moisture gradients), and topographic features such as narrow valleys or steep slopes influence fire spread. Topography also affects fires indirectly by determining vegetation distribution and productivity (Barbour et al. 1999) because it affects energy and water balances (Dillon et al. 2011) and therefore precipitation, runoff, temperature, wind and solar radiation (Daly et al. 1994).

Slope and elevation are part of the LANDFIRE (http://landfire.cr.usgs.gov/viewer assessed on 03/05/2015, 30-m resolution) dataset and derived from the National Elevation Dataset (NED, ned.usgs.gov). Topographic position index is a categorical variable that refers to the position of a building on the landscape (valley, lower slope, gentle slope, steep slope, upper slope, ridge). We calculated the topographic position index from the LANDFIRE elevation data using an algorithm that defines standardized threshold values for the difference between a cell elevation value and the average elevation of the cells around that cell measured in standard deviations from the mean (Jenness 2006). The algorithm results in a categorical raster that contains values between 1 and 6 to represent the topographic position:

1 - Valley: TPI ≤ -1 SD

2 - Lower Slope: -1 SD < TPI ≤ -0.5 SD

3 - Flat Slope: -0.5 SD < TPI < 0.5 SD, Slope ≤ 5°

4 - Middle Slope: -0.5 SD < TPI < 0.5 SD, Slope > 5°

5 - Upper Slope: 0.5 SD < TPI ≤ 1 SD

6 - Ridge: TPI > 1 SD

Each building acquired the TPI value of the raster cell that intersected the building. Each cluster assumed the majority value of the buildings in the cluster. Due to a biased distribution of values towards ridges or valleys, we reclassified the remaining values to be either valleys or ridges, having a simple classification of two categorical values. Values 2 and 3 were reclassified to 1 (valley). Values 4 and 5 were reclassified to 6 (ridge).

Road density is a proxy for both human presence on the landscape and access to buildings. We downloaded road data from the U.S. Census Bureau website (www.census.gov downloaded on 04/14/2014) and calculated road density by dividing total road length within each cluster by cluster area.

Spatial arrangement of buildings

Because research suggests that buildings in the interior of a cluster are less susceptible to wildfire than those at its edge (Syphard et al. 2012; Maranghides et al. 2013), we calculated seven variables to quantify the spatial pattern of buildings within clusters. For each cluster we calculated a) the area, b) the number of buildings, c) building density (eq. 3), d) building dispersion (eq.4), e) the average distance to the edge of the cluster, f) the average distance to the nearest building, and g) average distance to the nearest cluster (Fig. **6**). We calculated building density and building dispersion using the following equations:

Equation 3

$$Building\ density = \frac{number\ of\ buildings\ within\ a\ cluster}{cluster\ area\ (ha)}$$

Equation 4

$$\boldsymbol{Building\ dispersion = \frac{st\ dev.\ of\ dist.\ among\ buildings\ within\ a\ cluster}{mean\ distance\ among\ buildings\ within\ a\ cluster}}$$

For a complete list of all the variables used in our analysis, see Table 5.

Statistical analysis

To answer our first question, i.e., what factors are related to whether any buildings are lost when a wildfire hits a cluster of buildings, we used logistic regression (Hosmer and Lemeshow 2000). We selected the best model based on an exhaustive search of all possible combinations of explanatory variables, and ranked models by their Bayesian Information Criterion (BIC) (Schwarz 1978), while allowing the maximum number of variables in the models to vary depending on the number of observations within a given ecoregion. We conducted the search with *bestglm* (McLeod and Xu 2011) in the statistical software R (R Core Team 2014) and examined the top 20 models in detail. For simplicity, we report the coefficients for the best model for each ecoregion in each group and how frequently each explanatory variable was present in the top 20 models, a more informative measure of variable importance than presence in the top model only. We checked for spatial autocorrelation in the residuals of the top model in each ecoregion using semivariograms (R package *geoR*, Ribeiro and Diggle, 2001), and found no significant spatial autocorrelation. In order to measure the discriminatory ability of the models, we calculated the area under the curve (AUC) of the receiver operating characteristic (ROC) curve (R package *ROCR*, (Sander et al. 2005). In addition, for each ecoregion, we performed cross-validation to test for robustness. We randomly removed 20% of the observations, performed model selection with the remaining 80%, and calculated AUC for the best model using the 20% data that was removed. We followed these steps 10 times for each ecoregion.

To answer our second question, i..e, what factors are related to the proportion of buildings that are lost within a cluster where at least one building is lost, we modeled the proportion of buildings lost within each cluster using multiple linear regression models (Freedman 2009). We conducted model selection based on an exhaustive search of all possible combinations of explanatory variables using the R package *bestglm* (McLeod and Xu 2011) and ranked models based on the Bayesian Information Criterion (BIC) (Schwarz 1978). We again observed how frequently each variable was selected in the top 20 models. We checked for spatial autocorrelation in the residuals of the top model in each ecoregion using semivariograms (R package *geoR*, Ribeiro and Diggle, 2001), and found no significant spatial autocorrelation. To measure the ability of the models to explain the variability in the data, we calculated the adjusted R^2 for the top model in each ecoregion.

Although we expected that there would be differences in the importance of variables among ecoregions, we conducted a preliminary analysis where we used all the observations regardless of the ecoregion to which they belonged (a 'national model'). In this national model, we found significant interactions between ecoregion and some variables (results shown in Appendix 8 and 9), indicating that the effect of these variables was different in different ecoregions, and because we were interested in these differences, we conducted our analysis at the ecoregion level.

Results

Likelihood of any wildfire losses - Logistic regression

Vegetation

We included seven variables related to vegetation and fuels in our analysis: land cover, contagion index, connectivity of the landscape, connectivity of highly flammable land and non-flammable land, and percentage of highly flammable land and non-flammable land. Overall, the frequency of vegetation-related variables in the top 20 models was low. The variable that appeared most frequently in the top 20 models was percentage of non-flammable land in the Mediterranean California ecoregion (Fig. **8**) with a negative effect, meaning that places with a higher percentage of urban area were less likely to be affected by wildfires (Table 6). Contagion index and connectivity of non-flammable land were the next most frequent vegetation variables and occurred in Eastern Temperate Forests and in the Northwestern Forested Mountains (Fig. **8**). In both ecoregions, the effect was negative, meaning that dispersed urban areas and fragmented landscapes were more likely to be associated with building losses to wildfires. For the remaining ecoregions, the frequency of vegetation related variables was always less than eight times out of 20.

Topography

We included five variables related to topography in our analysis: Elevation, slope, southwestness, topographic position index (TPI) and road density. Topographic position index, elevation and road density appeared more frequently in the models of Mediterranean California, Northwestern Forested Mountains, and Eastern Forested Mountains. Topography related variables were selected in the top models for Mediterranean California and Northwestern Forested Mountains, always with positive effects, meaning that clusters located at the tops of ridges, at higher elevations and with higher road density were more likely to be affected if a wildfire occurs. In the remaining ecoregions, Great Plains and North American Deserts, topography related variables were present in fewer than seven of the top 20 models.

Spatial-arrangement of buildings

Of the three types of variables, the spatial arrangement variables were most frequent in the top 20 models (Fig. **8**). We included seven variables related to spatial arrangement of buildings in our analysis: Cluster area, number of buildings in the cluster, average distance to the nearest building, average distance to the nearest cluster, average distance to cluster edge, building density, and building dispersion. Cluster area was the most frequently included variable (selected in all 20 top models) in the models of Mediterranean California and Great Plains, and was present in 18 of the 20 top models of the North American Deserts (Fig. **8**). All three coefficients had a positive sign meaning that larger clusters were more strongly associated with the loss of at least one building, mostly likely because more buildings are exposed (Table 6). The number of buildings in the cluster and average distance to the nearest building were the second most frequent variables and were present in the top model of Mediterranean California, Northwestern Forested Mountains and Easter Temperate Forests. In both Northwestern Forested Mountains and in Eastern Temperate Forest, the higher the number of buildings in the cluster, the more likely it was that at least one building was lost. In Mediterranean California, the average distance to the nearest building had a positive effect, meaning that the farther apart the buildings are, the more likely they are to be affected. In the Northwestern Forested Mountains the average distance to the nearest cluster had a negative sign meaning that clusters that are closer to other clusters are more likely to be affected by wildfires (Table 6). All other variables were present in fewer than seven of the 20 top models.

Extent of wildfire losses - Linear regression

Vegetation

The vegetation variables that occurred most frequently in all 20 top models were percentage of highly flammable land and connectivity of highly flammable land, followed by the contagion index (14 out of 20 top models). Vegetation variables were most frequently selected in two ecoregions: the Northwestern Forested Mountains and the Eastern Temperate Forests (Fig. **9**). In both ecoregions, clusters that were located in landscapes with higher percentage of flammable land but with lower connectivity, i.e., fragmented landscapes, were more likely to have a higher proportion of buildings lost

(Table 7). In Mediterranean California and the Great Plains ecoregions, vegetation related variables were present fewer than seven times in the 20 top models (Fig. **9**).

Topography

The most frequently included topography variables were elevation, topographic position index, and road density (Fig. **9**). In the Mediterranean California ecoregion, clusters located at higher elevations were more likely to have higher proportions of buildings lost (Table 7). In the Northwestern Forested mountains ecoregion, clusters with lower road density were more likely to have higher proportions of buildings lost (Table 7). In the Eastern Temperate Forest clusters on ridges were more likely to have higher proportions of buildings lost (Table 7). In the Great Plains, topography variables were less frequent in the top models, and all topography variables occurred fewer than seven of the top 20 models (Fig. **9**).

Spatial arrangement of buildings

Variables related to the spatial arrangement of buildings were present more frequently than topography or vegetation related variables in the top 20 models, and in all four studied ecoregions. Cluster area was the most frequent variable in the Eastern Temperate Forests, and the second-most frequent in the Great Plains. In both cases, smaller clusters were more likely to have a higher proportion of buildings lost (Table 7). Building dispersion was frequently present in the models for the Great Plains, where clusters with lower dispersion values were more likely to have a higher proportion of buildings lost. In the Northwestern Forested Mountains, building density was the most frequent spatial arrangement variable, and clusters with lower density had a higher proportion of buildings lost (Table 7). In Mediterranean California variable frequencies were less consistent among the top 20 models, but the number of buildings in the cluster was selected in 14 of the 20 top models (Fig. **9**), and clusters with fewer buildings were more likely to have a higher proportion of buildings lost (Table 7).

Model performance

The AUC values for the logistic regression for each top model in each ecoregion ranged from 0.66 to 0.88 (Table 6). For the linear regression the adjusted R^2 values were generally low, ranging from 0.20 to 0.67 (Table 7). Cross-validation for each ecoregion yielded averaged AUC values that were close to the ones obtained in the top model for each ecoregion (Table 6), indicating that our results were robust.

Discussion

As we expected, the role of vegetation, topography and the spatial arrangement of buildings differed greatly among ecoregions. However, for both questions, i.e., whether any building was lost, and what proportion of buildings was lost, topography and the spatial arrangement of buildings were more frequently selected than vegetation related variables.

People are moving near wildland vegetation and into landscapes where fire is a reality, even though fire frequency varies depending on the ecosystem (Nowak and Walton 2005; Hammer et al. 2007; Gude et al. 2008). More people means higher probability for human caused ignitions (Bar-Massada et al. 2009; Price and Bradstock 2014), creating a positive feedback cycle and thus a coupled human-natural system.

For both logistic and linear regressions, vegetation variables related to landscape metrics, such as connectivity and percentage of highly flammable land, were important. For example, the top model for the North American Deserts ecoregion identified cluster area and landscape connectivity as the two main drivers of wildfire effects on communities. Although fire behavior in grasslands is not as well studied as in other vegetation types, some studies in shrubland dominated areas, such as California, have shown us that crown fires in forests are not required for building loss to occur (Brooks and Matchett 2006; Syphard et al. 2011; Gray and Dickson 2015). Furthermore, invasive annual grasses in the desert are providing fuel connectivity to support fires where they had been absent historically, raising ecological concern (Gray and Dickson 2015).

Topography-related variables were present in the top logistic models of two ecoregions and the top linear models in three ecoregions. For both Mediterranean California and the Northwestern Forested Mountains, clusters located at higher elevations or on top of ridges were more likely to have lost buildings. That supports other studies done in California where topography was an important driver of extreme fire behavior (Flatley et al. 2011; Dillon et al. 2011; Syphard et al. 2012). The Northwestern Forested Mountains is a very diverse ecoregion. It contains the highest mountain of North America and the most diverse mosaic of ecosystem types, such as mountains and plateaus separated by valleys and lowlands. Topography is the common denominator for such diversity, and clusters in Northwestern Forested Mountains that were located at higher elevations or at the tops of ridges were more likely to be affected by wildfire.

High road density increased the probability that any building was lost in Mediterranean California, but it was negatively correlated with the proportion of buildings lost in the Northwestern Forested Mountains. Mediterranean landscapes are often heavily settled and roads are a proxy of human activity, which is linked to a higher probability of ignition (Syphard et al. 2007b; Bar-Massada et al. 2011b). In the Northwest Forested Mountains, however, lower road density makes areas harder to access when fighting fires, leading to a higher proportion of buildings lost.

The spatial arrangement of buildings was important in every top logistic or linear model. This is one of the most striking results, given the predominant focus in fire management on vegetation as a risk factor. Independent of the ecoregion's characteristics, the location of the cluster in relation to other clusters and how far buildings were from other buildings had a clear association with building loss in case of wildfire. The most prominent variable was cluster area, followed by the number of buildings in the cluster, but the signs of the coefficients for both variables varied depending on the type of analysis. When explaining if any building was lost, larger clusters with more buildings were more likely to be affected by a wildfire. However, when explaining what proportion of buildings was lost, smaller clusters with fewer buildings were more likely to lose a higher proportion. When building density is higher, there is a higher probability that once a wildfire hits one building, the fire will progress from building to building. Indeed, in Australia being close to other buildings increases a building's chance of being lost to wildfires (Gibbons et al. 2012). In addition, smaller clusters are more likely to contain buildings lost because they have more edge and thus more buildings directly exposed to wildland vegetation.

Finding that smaller, denser clusters are more likely to be affected by wildfires poses a land use dilemma because conservation strategies seek to cluster buildings in order to minimize the human footprint on the landscape (Theobald et al. 1997; Gonzalez-Abraham et al. 2007). Furthermore, it is cheaper to protect buildings in groups rather than each individually (Bar-Massada et al. 2011a). The question is what size a cluster should be in order to optimize both conservation and fire risk reduction goals. The relationships between building density and fire risk are non-linear and fire risk decreases rapidly above a building density threshold (Syphard et al. 2012), but at such high building density values, conservation options are limited because space for natural habitat is limited. At low to medium building densities, clustering would be advantageous for conservation, but appears to be problematic for fire risk reduction.

Both top models for the Great Plains ecoregion contained only variables related to the spatial arrangement of buildings, whereas topography, or vegetation, or both were also important in the other ecoregions. The potential natural vegetation of the Great Plains are grasslands, and the climate is dry and continental, characterized by short hot summers and long cold winters, high winds, and periodic, intense droughts and frosts.

High winds might be one explanation of why so many wildfires result in building loss in the Great Plains. Out of all ecoregions, the Great Plains had the highest proportion of clusters where at least one building was affected (122 out of 319). When modeling if any building was lost, only cluster area was significant and larger clusters were more likely to have at least one destroyed building in the event of a wildfire. The topography in the Great Plains generally consists of mild slopes, with a very low range of variation. Therefore, it is not surprising that topography was not present in the models. Similarly, vegetation, although certainly important to carry wildfires, was not variable enough to be included in the models. However, low AUC and adjusted R^2 values suggest that some important variables were missing. We speculate wind may play an important role, but one that we were not able to consider. Higher wind speeds will produce fast moving fires, which may catch homeowners by surprise. Firebrands from burning structures can be carried far enough to ignite another roof or a pile of wood stored close to a building. We suggest that management efforts could focus on building materials and defensible space and less on the larger surrounding landscape.

The linear regression analysis was designed to explain variation in the proportion of buildings lost within the cluster and although our models did explain substantial amounts of the variation, quite a bit of this variation remained unexplained, suggesting that some factors were missing from our models. The most obvious of these are building materials and firefighting effort, neither of which we could measure. Another issue is that the number of buildings lost that we identified is likely lower than the number actually lost, and some buildings may have been damaged but not lost. Because we used satellite imagery, we could only identify buildings that were completely lost.

Conclusions

The most important message from our results is that topography and building arrangements strongly affect which buildings are lost, but that the relative importance of variables varies considerably among ecoregions suggesting that policies and management efforts need to be regionally tailored, as the National Science analysis for the cohesive strategy strongly suggest in their report (**http://cohesivefire.nemac.org/option/6** assessed on October 10 2015).

Although vegetation may be the most obvious and manageable aspect of wildfire risk that managers can address, fuel treatments are only a partial and short-term solution, and insufficient to address the other sources of fire risk to buildings, as our models clearly show. The challenge is that factors such as topography and building patterns cannot be changed after buildings are in place, and need to be accounted for when urban planners make community-wide planning, subdivision layout, or building siting decisions. We suggest that a better understanding how different factors contribute to the risk that a building will be lost in a wildfire, as we present here, will allow policy makers, planners, and resource managers to develop long-term solutions to reduce fire risk to buildings and make communities more fire adapted.

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Table 4 - Total number of digitized buildings and total number of clusters with more than eight buildings within in each ecoregion.

	Total number of clusters	Clusters w/ at least one building lost	% of clusters w/ lost buildings	Buildings within fire perimeters	Buildings lost	% of buildings lost
Conterminous United States	2029	547	27%	80393	7171	9%
North American Deserts	92	17	18%	1791	64	4%
Mediterranean California	860	298	35%	53093	5301	10%
Southern Semiarid Highlands	8*	3	38%	328	160	49%
Temperate Sierras	20	1	5% *	632	4	0.6%
Tropical Wet Forests	4*	1	25%	152	2	1%
Northern Forests	13	1	8% *	274	1	0.4%
Northwestern Forested Mountains	163	49	30%	4504	800	18%
Marine West Coast Forest	4*	2	50%	46	23	50%
Eastern Temperate Forest	546	53	10%	12806	216	2%
Great Plains	319	122	38%	6767	600	9%

*Ecoregion not included in the regression analyses because either they had less than 40 clusters within fire perimeters, or less than 10% of the clusters lost at least one building.

Table 5 - The list of variables that we included in our logistic and linear regression models and their source.

Variable	Description	Source
Land Cover	See Appendices 1 and 2 for details on cover classes and their reclassification	NLCD 2006 (http://www.mrlc.gov/nlcd06_data.php)
Percentage of land/class	See Appendix **8** for detailed description	FRAGSTATS
Connectance/class		FRAGSTATS
Connectance		FRAGSTATS
Contagion Index		FRAGSTATS
Elevation	Digital Elevation Model, 30 m resolution.	Landfire DEM (http://www.landfire.gov)
Slope	Slope calculated in degrees	Derived from DEM
Topographic Position Index	6 classes, extension tool on ArcMap	Jenness 2006
Southwestness	Create a new field and calculate the cosin(ASP) in ArcMap	Calculated by us
Road density	Total length inside cluster/total area	2010 TIGER/Line Shapefiles (https://www.census.gov/cgi-bin/geo/shapefiles2010/file-download)
Cluster area	Cluster area (m^2)	Calculated by us
Number of buildings within cluster	Total number of buildings within the cluster	Calculated by us
Building density	Number of buildingss within a cluster divided by the cluster area.	Calculated by us
Building dispersion	Standard deviation of the distance among buildings within a cluster divided by the mean distance among buildings within the cluster.	Calculated by us
Average distance to cluster edge	Average distance from each building to the edge of the cluster	Calculated by us
Average distance to nearest building	Average distance to the nearest building	Calculated by us
Average distance to nearest cluster	Average distance to the nearest cluster	Calculated by us

Table 6 - Coefficients, standard errors, p-values and AUC values for 10-fold cross-validation for the top logistic model in each ecoregion.

	Coefficient	St. Error	Pr(>|z|)	AUC
North American Deserts				
Intercept	-3.56	0.74	$p < 0.001$	0.802 (0.56 to 0.88, 0.69 avg)
Cluster area	0.07	0.02	0.007	
Connectivity of the landscape	0.04	0.02	0.030	
Mediterranean California				
Intercept	-2.13	0.28	$p < 0.001$	0.766 (0.70 to 0.82, 0.76 avg)
Cluster area	0.03	0.00	$p < 0.001$	
Road density	9.94E-04	0.00	0.004	
Distance to nearest building	0.01	0.00	0.001	
Topographic Position Index - Top ridges	0.64	0.17	$p < 0.001$	
Percentage of non-flammable land	-0.02	0.01	$p < 0.001$	
Northwestern Forested Mountains				
Intercept	-2.97	0.73	$p < 0.001$	0.878 (0.70 to 0.93, 0.81 avg)
Number of buildings in the cluster	0.04	0.01	0.002	
Distance to nearest cluster	-1.52E-03	0.00	0.157	
Elevation	1.01E-03	0.00	0.004	
Topographic Position Index - Top ridges	1.33	0.46	0.004	
Connectivity Index of non-flammable class	-0.07	0.03	0.033	
Eastern Temperate Forests				
Intercept	-1.31	0.55	0.018	0.727 (0.68 to 0.84, 0.75 avg)
Number of buildings in the cluster	0.02	0.00	$p < 0.001$	
Contagion index	-0.03	0.01	0.005	
Great Plains				
Intercept	-1.30	0.21	$p < 0.001$	0.669 (0.62 to 0.75, 0.69 avg)
Cluster area	0.04	0.01	$p < 0.001$	

Table 7 - Coefficients, standard errors, and p-values for the top linear model in each ecoregion.

	Coefficient	St. Error	Pr(>|t|)	Adj R^2
Mediterranean California				
Intercept	3.24	0.27	$p < 0.001$	
Number of buildings in the cluster	-0.35	0.05	$p < 0.001$	0.20
Elevation	0.02	0.01	0.003	
Northwestern Forested Mountains				
Intercept	0.21	1.89	0.910	
Building density	-0.95	0.24	$p < 0.001$	
Road density	-0.10	0.03	0.004	0.34
Contagion index	-0.78	0.25	0.003	
Percentage of highly flammable land	1.05	0.35	0.005	
Eastern Temperate Forests				
Intercept	5.48	0.47	$p < 0.001$	
Cluster Area	-1.15	0.12	$p < 0.001$	
Topographic Position Index - Top ridges	0.83	0.25	0.002	0.67
Percentage of highly flammable land	0.33	0.09	0.001	
Connectivity of highly flammable class	-1.18	0.30	$p < 0.001$	
Great Plains				
Intercept	7.68	1.19	$p < 0.001$	
Cluster area	-0.60	0.09	$p < 0.001$	0.30
Building dispersion	-4.15	1.57	0.009	

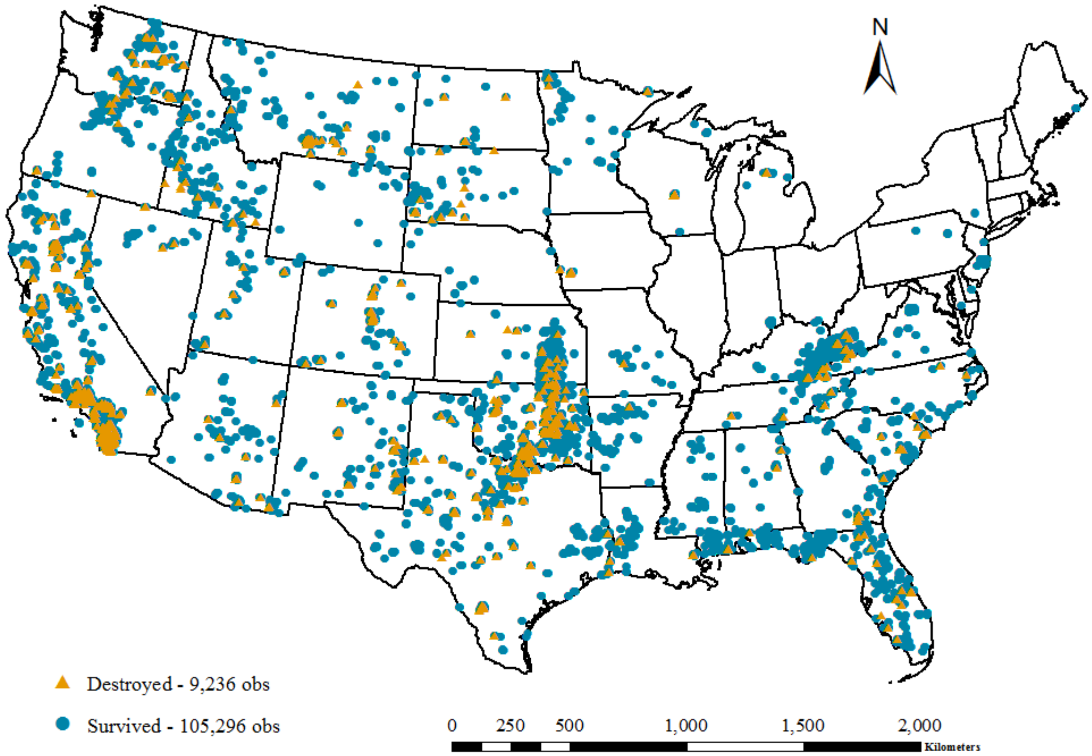

Fig. 5 – Distribution of all the digitized buildings (destroyed and survived) that were inside fire perimeters between 2000 and 2010 for the conterminous U.S.

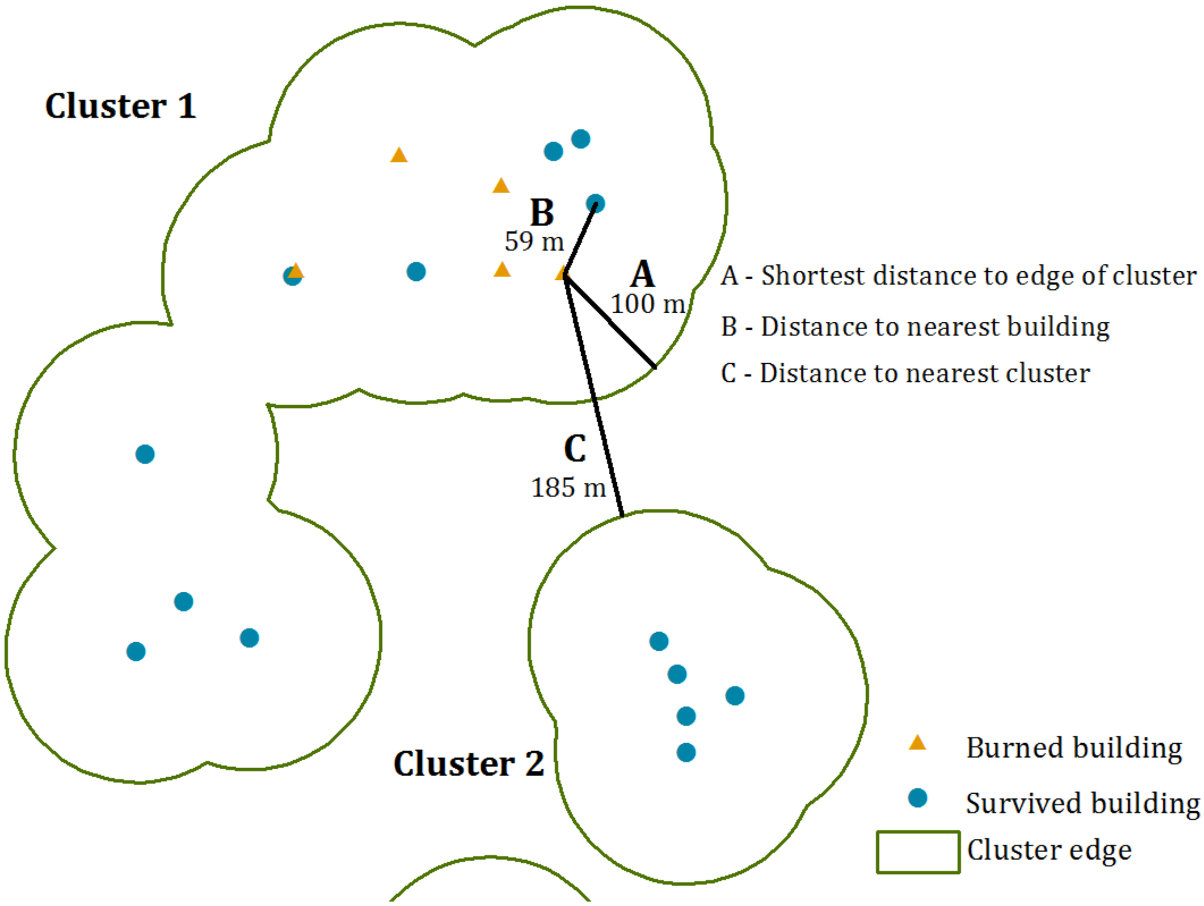

Fig. 6 - Example of clusters that were created using a radius of 100 m; Cluster 1 contains one example of how the shortest distance to the edge of cluster (A), shortest distance to the nearest building (B) and shortest distance to the nearest cluster (C) were calculated.

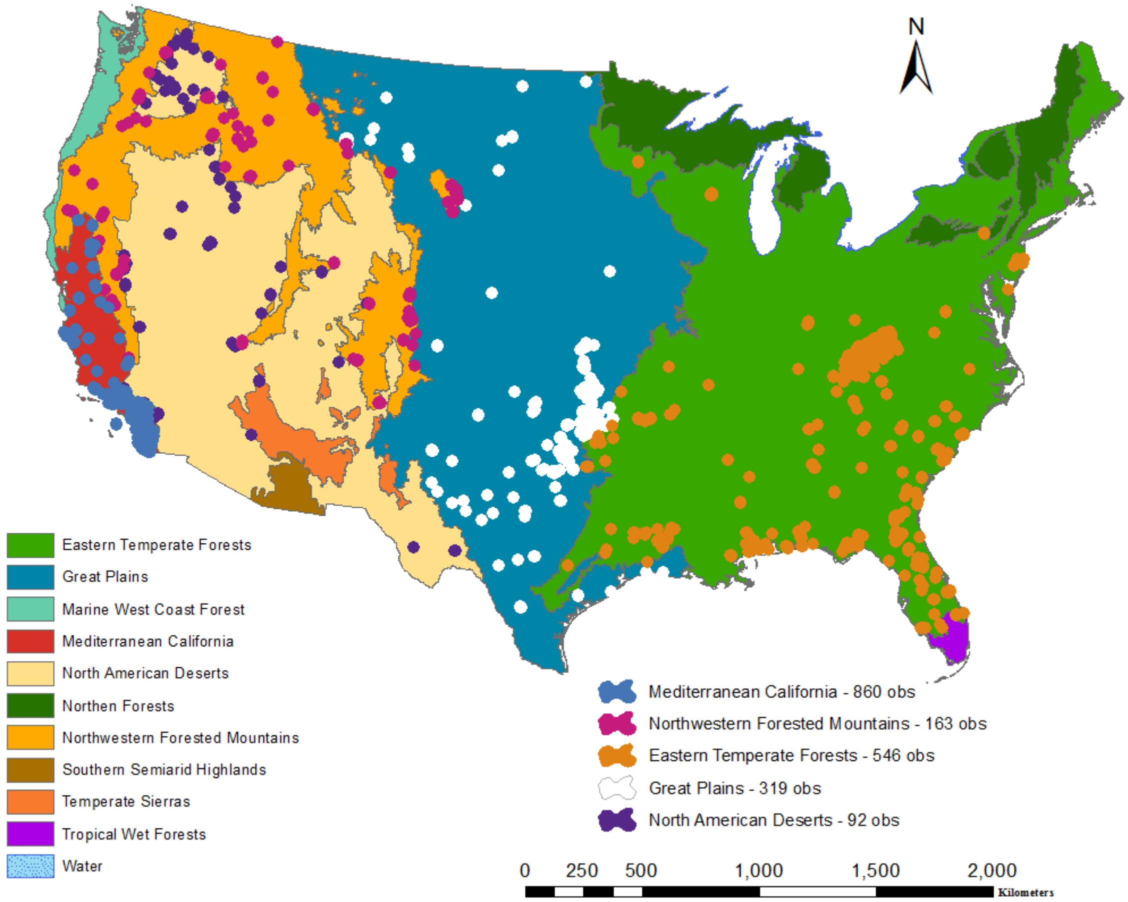

Fig. 7 – Divisions Level for Omernik Ecoregions for the conterminous U.S and clusters distribution per ecoregion.

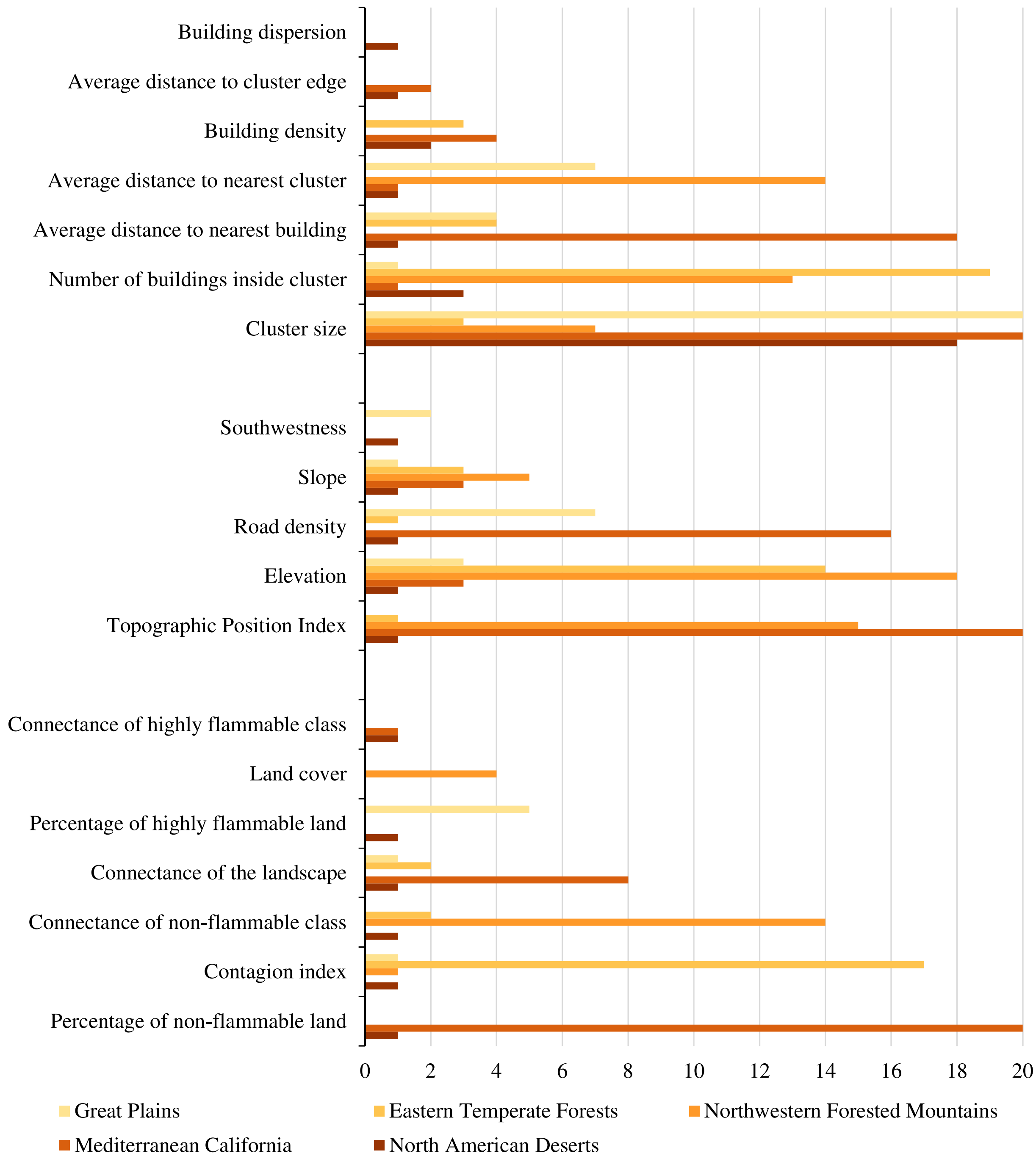

Fig. 8 - Frequency of variables in the top 20 models of our logistic regressions.

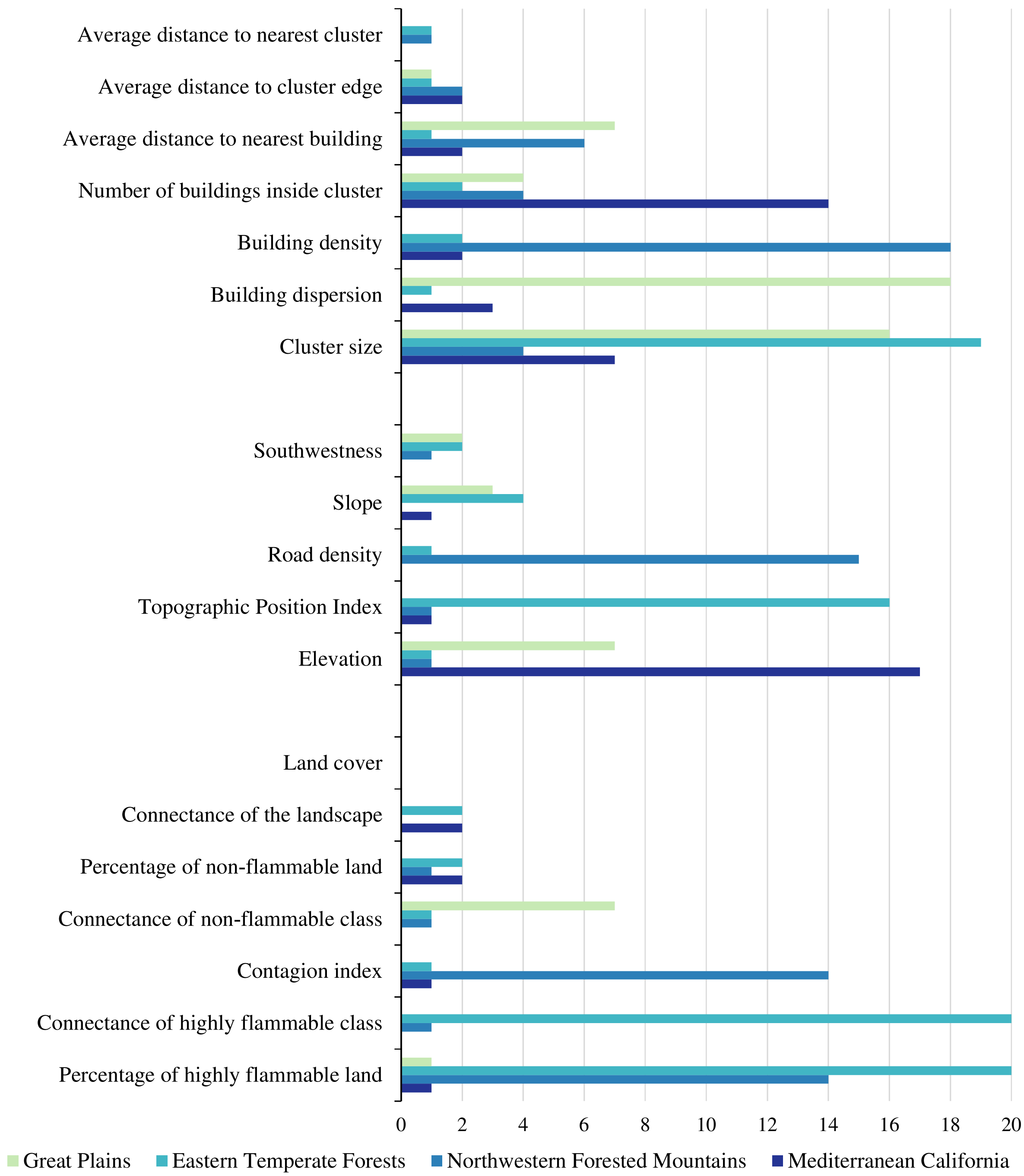

Fig. 9 - Frequency of variables in the top 20 models of our linear regressions

Appendix 3 - Total number of clusters depending on how many buildings are considered for analysis

Number of buildings within the cluster	Total number of clusters	Number of clusters with at least 1 building lost	%
Any	16595	1713	10.32
2	10571	1435	13.57
3	6980	1175	16.83
4	5019	987	19.67
5	3789	825	21.77
6	2960	691	23.34
7	2428	603	24.84
8	2029	547	26.96

Bar graph of number of clusters depending on the minimum number of buildings in the clusters.

Appendix 4 - Total number of digitized buildings and total number of clusters within in each ecoregion.

	of clusters	building lost	buildings	perimeters		lost
Conterminous United States	16595	1713	10%	114532	9236	8.10%
North American Deserts*	1189	88	7%*	4309	185	4.30%
Mediterranean California	4213	742	18%	61249	6085	9.90%
Southern Semiarid Highlands*	97	9	9%*	541	173	32.00%
Temperate Sierras*	177	11	6%*	1022	25	2.40%
Tropical Wet Forests*	43	1	2%*	243	2	0.80%
Northern Forests*	80	5	6%*	446	10	2.20%
Northwestern Forested Mountains	1419	175	12%	7314	1041	14.20%
Marine West Coast Forest*	39*	9	23%	129	33	25.60%
Eastern Temperate Forest	4169	137	3%*	21660	373	1.70%
Great Plains	5169	536	10%	17619	1309	7.40%

*Ecoregion not included in the regression analyses because either they had less than 40 clusters within fire perimeters, or less than 10% of the clusters lost at least one building.

Appendix 5 - NLCD reclassification scheme for statistical analysis

	Original Class	Frequency	New Class	Frequency
21	Developed - Open Space	113	I Non-flammable	212
22	Developed - low intensity	56		
23	Developed - Medium intensity	24		
31	Barren Land (Rock/Sand/Clay)	1		
82	Cultivated crops	10		
90	Woody wetland	6		
95	Emergent Herbaceous wetlands	2		
41	Deciduous Forest	13	II Forest	46
42	Evergreen Forest	31		
43	Mixed Forest	2		
52	Shrub/Scrub	96	III Shrubs/Scrubs	96
71	Grassland/Herbaceous	157	IV Grassland/Pasture, Hay	175
81	Pasture/Hay	18		

Appendix 6 - NLCD reclassification scheme for FRAGSTATS

Classes:	**Original NLCD class**	**New Class**
42	Evergreen Forest	Highly flammable
43	Mixed Forest	
52	Shrub/Scrub	
71	Grassland/Herbaceous	
41	Deciduous Forest	Flammable
81	Pasture/Hay	
82	Crops	
21,22,23,24	Urban classes	Non-flammable
11	Open Water	
12	Perennial Ice/Snow	
31	Barren Land	
90,95	Wetlands	
No Data	No Data	999 - No data

Appendix 7 – Fragstats metrics definitions

	Explanation
CONTAG (Landscape)	Contagion Index ($0 < \text{CONTAG} \leq 100$) - equals minus the sum of the proportional abundance of each patch type multiplied by the proportion of adjacencies between cells of that patch type and another patch type, multiplied by the logarithm of the same quantity, summed over each unique adjacency type and each patch type; divided by 2 times the logarithm of the number of patch types; multiplied by 100 (to convert to a percentage). In other words, the observed contagion over the maximum possible contagion for the given number of patch types. Note, CONTAG considers all patch types present on an image, including any present in the landscape border, if present, and considers like adjacencies (i.e., cells of a patch type adjacent to cells of the same type). All background edge segments are ignored, as are landscape boundary segments if a border is not provided, because adjacency information for these edge segments is not available and the intermixing of the classes with background is assumed to be irrelevant. Cell adjacencies are tallied using the double-count method in which pixel order is preserved, at least for all internal adjacencies (i.e., involving cells on the inside of the landscape). If a landscape border is present, adjacencies on the landscape boundary are counted only once as are all adjacencies with background. Note, Pi is based on the total landscape area (A) excluding any internal background present. CONTAG approaches 0 when the patch types are maximally disaggregated (i.e., every cell is a different patch type) and interspersed (equal proportions of all pairwise adjacencies). CONTAG = 100 when all patch types are maximally aggregated; i.e., when the landscape consists of single patch. CONTAG is undefined and reported as "N/A" in the "basename".land file if the number of patch types is less than 2, or all classes consist of one cell patches adjacent to only background.

PLAND (Class)	Percentage of Landscape (0 < PLAND ≤ 100) - equals the sum of the areas (m2) of all patches of the corresponding patch type, divided by total landscape area (m2), multiplied by 100 (to convert to a percentage); in other words, PLAND equals the percentage the landscape comprised of the corresponding patch type. Note, total landscape area (A) includes any internal background present. PLAND approaches 0 when the corresponding patch type (class) becomes increasingly rare in the landscape. PLAND = 100 when the entire landscape consists of a single patch type; that is, when the entire image is comprised of a single patch.
CONNECT (Class)	Connectance Index (0 ≤ CONNECT ≤ 100) - equals the number of functional joinings between all patches of the corresponding patch type (sum of cijk where cijk = 0 if patch j and k are not within the specified distance of each other and cijk = 1 if patch j and k are within the specified distance), divided by the total number of possible joinings between all patches of the corresponding patch type, multiplied by 100 to convert to a percentage. CONNECT = 0 when either the focal class consists of a single patch or none of the patches of the focal class are "connected" (i.e., within the user-specified threshold distance of another patch of the same type). CONNECT = 100 when every patch of the focal class is "connected."

Source:

http://www.umass.edu/landeco/research/fragstats/documents/fragstats.help.4.2.pdf

Appendix 8 - Logistic regression – National model interactions with Ecoregion

National model - glm	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-5.19	2.64	-1.96	0.05
Cluster area	0.07	0.03	2.22	0.03
Mediterranean California	5.94	2.85	2.08	0.04
Southern Semiarid Highlands	-74.60	39200.00	0.00	1.00
Temperate Sierras	-2810.00	266000.00	-0.01	0.99
Tropical Wet Forests	-9.87	3220.00	0.00	1.00
Northern Forests	-109.00	51300.00	0.00	1.00
Northwestern Forested Mountains	3.48	3.86	0.90	0.37
Marine West Coast Forest	-27.20	11200.00	0.00	1.00
Eastern Temperate Forests	2.12	2.86	0.74	0.46
Great Plains	3.91	2.71	1.44	0.15
Road density	-0.02	0.01	-2.06	0.04
Elevation	0.00	0.00	1.22	0.22
Topographic Position Index	-0.28	1.15	-0.24	0.81
Contagion Index	0.00	0.03	0.01	0.99
Percentage of highly flammable land	0.03	0.03	0.95	0.34
Percentage of non-flammable land	-0.03	0.04	-0.83	0.41
Cluster area:Mediterranean California	-0.05	0.03	-1.37	0.17
Cluster area:Southern Semiarid Highlands	1.14	72.30	0.02	0.99
Cluster area:Temperate Sierras	-0.09	57.30	0.00	1.00
Cluster area:Tropical Wet Forests	0.14	22.20	0.01	0.99
Cluster area:Northern Forests	-0.16	127.00	0.00	1.00
Cluster area:Northwestern Forested Mountains	-0.02	0.04	-0.57	0.57
Cluster area:Marine West Coast Forest	0.45	348.00	0.00	1.00

Cluster area:Eastern Temperate Forests	-0.05	0.03	-1.43	0.15
Cluster area:Great Plains	-0.03	0.03	-0.76	0.45
Mediterranean California:Road density	0.02	0.01	2.18	0.03
Southern Semiarid Highlands:Road density	-1.50	132.00	-0.01	0.99
Temperate Sierras:Road density	0.01	6.44	0.00	1.00
Tropical Wet Forests:Road density	0.02	5.50	0.00	1.00
Northern Forests:Road density	0.00	16.40	0.00	1.00
Northwestern Forested Mountains:Road density	0.01	0.01	1.87	0.06
Marine West Coast Forest:Road density	-0.04	65.60	0.00	1.00
Eastern Temperate Forests:Road density	0.01	0.01	1.91	0.06
Great Plains:Road density	0.02	0.01	2.26	0.02
Mediterranean California:Elevation	0.00	0.00	-0.37	0.71
Southern Semiarid Highlands:Elevation	0.04	6.63	0.01	0.99
Temperate Sierras:Elevation	0.00	1.83	0.00	1.00
Tropical Wet Forests:Elevation	-0.38	1080.00	0.00	1.00
Northern Forests:Elevation	0.12	52.90	0.00	1.00
Northwestern Forested Mountains:Elevation	0.00	0.00	0.30	0.77
Marine West Coast Forest:Elevation	0.05	18.30	0.00	1.00
Eastern Temperate Forests:Elevation	0.00	0.00	2.39	0.02
Great Plains:Elevation	0.00	0.00	-0.18	0.86
Mediterranean California:Top-ridges	0.93	1.16	0.80	0.42
Southern Semiarid Highlands:Top-ridges	-63.50	7000.00	-0.01	0.99
Temperate Sierras:Top-ridges	31.60	2550.00	0.01	0.99
Tropical Wet Forests:Top-ridges	NA	NA	NA	NA
Northern Forests:Top-ridges	21.60	1850.00	0.01	0.99

Northwestern Forested Mountains:Top-ridges	2.04	1.25	1.63	0.10
Marine West Coast Forest:Top-ridges	NA	NA	NA	NA
Eastern Temperate Forests:Top-ridges	0.29	1.23	0.23	0.82
Great Plains:Top-ridges	0.06	1.18	0.05	0.96
Mediterranean California:Contagion Index	0.01	0.03	0.24	0.81
Southern Semiarid Highlands:Contagion Index	-0.55	73.40	-0.01	0.99
Temperate Sierras:Contagion Index	0.00	30.30	0.00	1.00
Tropical Wet Forests:Contagion Index	NA	NA	NA	NA
Northern Forests:Contagion Index	0.98	738.00	0.00	1.00
Northwestern Forested Mountains:Contagion Index	0.08	0.05	1.82	0.07
Marine West Coast Forest:Contagion Index	NA	NA	NA	NA
Eastern Temperate Forests:Contagion Index	-0.03	0.03	-1.02	0.31
Great Plains:Contagion Index	-0.03	0.03	-0.91	0.36
Mediterranean California:Percentage of highly flammable land	-0.06	0.04	-1.76	0.08
Southern Semiarid Highlands:Percentage of highly flammable land	1.59	460.00	0.00	1.00
Temperate Sierras:Percentage of highly flammable land	28.00	2650.00	0.01	0.99
Tropical Wet Forests:Percentage of highly flammable land	NA	NA	NA	NA
Northern Forests:Percentage of highly flammable land	-0.35	78.80	0.00	1.00

Northwestern Forested Mountains:Percentage of highly flammable land	-0.14	0.06	-2.26	0.02
Marine West Coast Forest:Percentage of highly flammable land	NA	NA	NA	NA
Eastern Temperate Forests:Percentage of highly flammable land	-0.02	0.04	-0.60	0.55
Great Plains:Percentage of highly flammable land	-0.02	0.04	-0.50	0.62
Mediterranean California:Percentage of non-flammable land	-0.01	0.04	-0.33	0.74
Southern Semiarid Highlands:Percentage of non-flammable land	NA	NA	NA	NA
Temperate Sierras:Percentage of non-flammable land	28.10	2620.00	0.01	0.99
Tropical Wet Forests:Percentage of non-flammable land	NA	NA	NA	NA
Northern Forests:Percentage of non-flammable land	0.80	72.00	0.01	0.99
Northwestern Forested Mountains:Percentage of non-flammable land	0.03	0.06	0.56	0.57
Marine West Coast Forest:Percentage of non-flammable land	NA	NA	NA	NA
Eastern Temperate Forests:Percentage of non-flammable land	0.05	0.04	1.25	0.21
Great Plains:Percentage of non-flammable land	0.03	0.04	0.69	0.49

Appendix 9 - Linear regression – National model interactions with Ecoregion

National model - lm	Estimate	Std. Error	t-value	Pr (>|t|)
(Intercept)	8.35	7.13	1.17	0.24
Cluster area	-0.38	0.29	-1.34	0.18
Mediterranean California	-2.39	7.23	-0.33	0.74
Southern Semiarid Highlands	-0.24	3.50	-0.07	0.95
Temperate Sierras	0.06	1.26	0.05	0.96
Tropical Wet Forests	0.43	2.48	0.17	0.86
Northern Forests	-0.92	1.36	-0.68	0.50
Northwestern Forested Mountains	-6.13	7.79	-0.79	0.43
Marine West Coast Forest	-1.96	3.76	-0.52	0.60
Eastern Temperate Forests	-2.40	7.65	-0.31	0.75
Great Plains	-2.03	7.32	-0.28	0.78
Forest	0.82	0.59	1.37	0.17
Shrubs/Scrubs	0.32	0.66	0.48	0.63
Grasslands/Pasture	-0.10	0.72	-0.14	0.89
Building dispersion	-9.13	8.17	-1.12	0.26
Percentage of highly flammable land	0.26	0.32	0.81	0.42
Cluster area:Mediterranean California	-0.06	0.29	-0.22	0.83
Cluster area:Southern Semiarid Highlands	-0.29	1.09	-0.26	0.79
Cluster area:Temperate Sierras	NA	NA	NA	NA
Cluster area:Tropical Wet Forests	NA	NA	NA	NA
Cluster area:Northern Forests	NA	NA	NA	NA
Cluster area:Northwestern Forested Mountains	0.44	0.34	1.27	0.20
Cluster area:Marine West Coast Forest	1.15	1.28	0.90	0.37
Cluster area:Eastern Temperate Forests	-0.50	0.33	-1.53	0.13

Cluster area:Great Plains	-0.13	0.31	-0.40	0.69
Mediterranean California:Forest	0.02	0.66	0.02	0.98
Southern Semiarid Highlands:Forest	2.85	2.31	1.24	0.22
Temperate Sierras:Forest	NA	NA	NA	NA
Tropical Wet Forests:Forest	NA	NA	NA	NA
Northern Forests:Forest	NA	NA	NA	NA
Northwestern Forested Mountains:Forest	0.09	0.72	0.12	0.90
Marine West Coast Forest:Forest	NA	NA	NA	NA
Eastern Temperate Forests:Forest	-0.65	0.72	-0.89	0.37
Great Plains:Forest	NA	NA	NA	NA
Mediterranean California:Shrubs/Scrubs	-0.31	0.68	-0.47	0.64
Southern Semiarid Highlands:Shrubs/Scrubs	NA	NA	NA	NA
Temperate Sierras:Shrubs/Scrubs	NA	NA	NA	NA
Tropical Wet Forests:Shrubs/Scrubs	NA	NA	NA	NA
Northern Forests:Shrubs/Scrubs	NA	NA	NA	NA
Northwestern Forested Mountains:Shrubs/Scrubs	0.30	0.85	0.35	0.72
Marine West Coast Forest:Shrubs/Scrubs	NA	NA	NA	NA
Eastern Temperate Forests:Shrubs/Scrubs	-0.27	0.86	-0.31	0.76
Great Plains:Shrubs/Scrubs	-0.10	0.80	-0.13	0.90
Mediterranean California:Grasslands/Pasture	0.01	0.73	0.01	0.99
Southern Semiarid Highlands:Grasslands/Pasture	NA	NA	NA	NA
Temperate Sierras:Grasslands/Pasture	NA	NA	NA	NA
Tropical Wet Forests:Grasslands/Pasture	NA	NA	NA	NA
Northern Forests:Grasslands/Pasture	NA	NA	NA	NA

Northwestern Forested Mountains:Grasslands/Pasture	0.19	1.04	0.18	0.86
Marine West Coast Forest:Grasslands/Pasture	NA	NA	NA	NA
Eastern Temperate Forests:Grasslands/Pasture	0.13	0.80	0.17	0.87
Great Plains:Grasslands/Pasture	0.51	0.75	0.69	0.49
Mediterranean California:Building dispersion	5.86	8.27	0.71	0.48
Southern Semiarid Highlands:Building dispersion	NA	NA	NA	NA
Temperate Sierras:Building dispersion	NA	NA	NA	NA
Tropical Wet Forests:Building dispersion	NA	NA	NA	NA
Northern Forests:Building dispersion	NA	NA	NA	NA
Northwestern Forested Mountains:Building dispersion	7.36	8.70	0.85	0.40
Marine West Coast Forest:Building dispersion	NA	NA	NA	NA
Eastern Temperate Forests:Building dispersion	7.42	8.77	0.85	0.40
Great Plains:Building dispersion	5.58	8.40	0.66	0.51
Mediterranean California:Percentage of highly flammable land	-0.19	0.32	-0.58	0.56
Southern Semiarid Highlands:Percentage of highly flammable land	NA	NA	NA	NA
Temperate Sierras:Percentage of highly flammable land	NA	NA	NA	NA

Tropical Wet Forests:Percentage of highly flammable land	NA	NA	NA	NA
Northern Forests:Percentage of highly flammable land	NA	NA	NA	NA
Northwestern Forested Mountains:Percentage of highly flammable land	-0.10	0.40	-0.26	0.80
Marine West Coast Forest:Percentage of highly flammable land	NA	NA	NA	NA
Eastern Temperate Forests:Percentage of highly flammable land	-0.16	0.33	-0.50	0.62
Great Plains:Percentage of highly flammable land	-0.21	0.32	-0.65	0.51

Chapter 3

Building vulnerability to wildfires across the US

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Abstract

The wildland Urban Interface is the area where buildings are most frequently lost to wildfires. However, where buildings are most vulnerable if a wildfire occurs is unknown. Our goal was to create building vulnerability maps across the conterminous United States that capture the probability of a building being lost if a wildfire occurs based on environmental characteristics. We collected data on all visibly destroyed buildings within fire perimeters that occurred between 2000 and 2010 across the US using Google Earth, and used these data as presence observations in a species distribution model (MaxEnt). We parameterized the models for each Omernik level II ecoregion to account for regional differences in building loss patterns. We generated one vulnerability map and one map depicting the certainty of the predictions (both with 30-m resolution) for each ecoregion that contained enough lost buildings. Results were consistent across ecoregions, with land cover, elevation and distance to urban areas being the most frequent variables in the predictive models. Our maps showed a clear difference between west and east, with vulnerable areas more clustered in the west and more reticulate in the east. Overall, our maps had good performances with AUC values ranging between 0.8 and 0.98. We were able to cover 90% of the conterminous U.S. and we created for the first time a large scale and high resolution vulnerability map based on lost buildings observations.

Keywords: Building loss, Ecoregions, Maximum Entropy, Maxent, Predictive models, WUI.

Introduction

The areas where houses intermix or intermingle with natural vegetation are called the Wildland Urban Interface (WUI), and represent an area of human-environment conflict (Radeloff et al 2005), and where buildings are most frequently destroyed by wildfires.

Housing growth is predicted to increase and, consequently, the WUI will increase as well (Nowak and Walton 2005; Theobald and Romme 2007; Bar-Massada et al 2009). Simultaneously, housing development alters fire size and distribution around the WUI due to a potential increase in ignitions, although most fires are quickly extinguished and thus fire sizes remain small (Spyratos et al 2007). However, every ignition has the potential to become a large fire (Bar-Massada et al 2009), and when it does, the potential loss can be high. For these reasons it is important to assess the vulnerability of building loss to wildfire across the United States.

The risk of a building being destroyed by wildfire depends on two likelihoods, first the likelihood that a fire will occur, and second the likelihood that a building will actually burn if it is within a wildfire. Most fire risk and probability assessments focus on the likelihood that a fire will occur based on biophysical and climate variables (e.g. Bradstock et al. 1998; Fried et al. 1999; Diaz-Avalos et al. 2001; Rollins et al. 2002; Preisler et al. 2004). These models consider fire only as a physical phenomenon function of weather, fuels, and topography (Countryman 1972). Other models are used to predict fire behavior within different fuel types and weather condition inputs (Burgan and Rothermel 1984; Forestry Canada 1992).

Another approach to model fire risk or fire occurrence, is to model ignitions. Fire occurrence is a function of suitable environmental conditions and the occurrence of ignitions (Parisien and Moritz 2009). The most common approach to ignition modeling is to use past ignitions locations (Sturtevant and Cleland 2007; Syphard et al 2008; Bar-Massada et al 2011). Ignitions can be caused by lightning or by humans. In human-dominated landscapes, anthropogenic ignitions surpass natural ignitions, thus making human accessibility and population density good predictors of ignition risk (Dickson et al 2006; Yang et al 2007; Bar-Massada et al 2013b). For example, in southern California, a human-dominated landscape, fire ignition patterns are strongly influenced by variables related to human activities (roads, trails, and housing development), and fire history (Syphard et al 2008).

It is equally important to understand how buildings are affected by fire and how vulnerable they can be in case of fire occurrence (Pyne 2001; DellaSalla et al 2004; Haight et al 2004). Factors such as topography and spatial arrangement of buildings are important when explaining building loss (Gibbons et al 2012; Syphard et al 2012; Alexandre et al 2015b). However, since we did not have information on the location of all existing buildings in the U.S., we could not measure the spatial arrangement of buildings. Therefore, we had to use proxy variables based on land use cover, such as distance to urban areas and distance to roads.

Models are useful tools in several fields of science and they can be either explanatory or predictive. Explanatory models test hypotheses that specify how and why certain empirical phenomena occur, while predictive models are aimed at predicting the future or new observations with high accuracy (Shmueli 2010). In other words, the primary goal of explanatory models is to depict relationships between an observed pattern and its causal factors. In contrast, for predictive models, the relationships are not as important as the accuracy of the prediction (Elith and Leathwick 2009). When using explanatory models, the statistical techniques (e.g. linear regression) are somewhat intuitive and it is easier to understand the relationship between the response phenomenon and the explanatory variable because both the signal and the magnitude of the relationships are available in the form of coefficients, p-values and confidence intervals. However, many assumptions have to be met in order to apply statistical modeling (e.g., normality, and independence of data). When prediction is the main objective, other techniques, such as machine learning, neural networks, maximum entropy, generalized linear models (GLM), or support vector regression, can produce very good predictions and are less demanding in terms of data requirements (e.g. no requirement of normality - Culbert, 2012).

Species distribution models (SDMs) are a special type of model, that estimate the probability of a certain species occurring in sites outside the observed sites by comparing the environmental variables that are relevant to habitat suitability in sites of occurrence with sites where the species was not seen. This approach is widely used in ecology, biogeography, biology and conservation to determine species distribution. In formal biological surveys, it is possible to determine presence and absence or abundance of a certain species at each site and therefore, models such as generalized linear or additive models (GLMs or GAMs) or regression trees are used. However, because systematic surveys are often sparse or inexistent, and in many cases data records capture presence only, new SDM methods were developed that can interpret presence-only data. MaxEnt is one such method and the one used in this study, which estimates a distribution across geographic space (Phillips et al 2006). A presence-only modeling approach is particularly useful when predicting where buildings are most vulnerable to wildfires because it is difficult to ascertain which buildings can burn if a wildfire occurs. Even buildings that did not burn during a wildfire would not represent true absence points, because it may be actions by firefighters that prevented them from burning, but knowing if that was the case would be difficult for large areas.

Predictive models are powerful for decision making, because they result in maps, and maps are a pragmatic and powerful visual policy tool (Stewart et al 2009) and WUI maps in particular are important for wildfire management (Radeloff et al 2005; Wilmer and Aplet 2005; Theobald and Romme 2007; Bar-Massada et al 2013a). However, WUI maps only depict where houses meet or intermingle with wildland vegetation, not where fire vulnerability is highest at a national scale, but that is needed to improve the efficiency of prevention actions (Lampin-Maillet et al 2010).

I would like to distinguish between vulnerability and risk. Vulnerability is the ability of, or susceptible to, being wounded or hurt, and risk is the exposure to the chance of injury or loss, or the degree of probability of such loss. The maps that we created are a measure of the ability to be "hurt" by a hazard, in this specific case, wildfire. It is important to make this distinction because of the different implications vulnerability versus risk have on the type of data they demand. A fire risk map requires information on variables that are related to the likelihood of fire itself, which include ignitions, fire behavior and fire spread. Our models and maps do not depict fire risk. Instead they are based on the assumption that a wildfire will occur at some point in time and they predict how vulnerable buildings are to that particular hazard.

Our goal was thus to produce a map of the vulnerability of buildings if a wildfire occurs for the conterminous United States.

Methods

Data

We analyzed Google Earth's historical imagery to assess building loss due to wildfires in all fire perimeters in the conterminous United States between 2000 and 2010 recorded in the Monitoring Trends in Burn Severity (MTBS) dataset (http://www.mtbs.gov/ downloaded on 03/05/2012).

Within each fire perimeter we digitized all the buildings that were lost (building present before the fire date, but not after). We considered a building to be lost when it was completely removed in the post fire image. This means that our estimates are conservative, and did not include damage caused by the fire, such as smoke damage or partial siding melt. We digitized a total of 9,233 burned buildings (Fig. **10**).

Ecoregions

We parameterize models for Omernik level II ecoregions (http://www.epa.gov/wed/pages/ecoregions/na_eco.htm#Downloads assessed on

02/20/2015, (Omernik 1987). We assigned buildings to ecoregions based on their location. Fourteen ecoregions had enough buildings (> 25) for our analysis (Table 8).

Vegetation Data

The National Land Cover Database - NLCD 2006 (Fry et al 2011), is a 30-m land cover class classification based on Landsat satellite data of circa 2006 covering the conterminous U.S. We used NLCD 2006 data as a proxy for the distribution of fuels.

Topographic data

We included elevation, slope, and southwestness derived from aspect (Syphard et al 2007) as explanatory variables. Topographical variables that affect fire behavior include micro weather conditions created by elevation and aspect (e.g., moisture gradients), and topographic features such as narrow valleys or steep slopes that influence fire spread. Topography also affects vegetation distribution and productivity (Barbour et al 1999) because it affects energy and water balances (Dillon et al 2011), and therefore precipitation, runoff, temperature, wind and solar radiation (Daly et al 1994).

Slope, elevation and aspect are part of the LANDFIRE (http://landfire.cr.usgs.gov/viewer assessed on 03/05/2015, 30-m resolution) dataset and are derived from the National Elevation Dataset (NED, ned.usgs.gov).

Human related data

There are two sources of wildfire ignitions, natural and human. Both natural and human ignitions are non-random and their spatial distribution can be predicted based on social and biophysical data (Bar-Massada et al 2011). We used distance to roads and distance to urban areas as proxies for human presence and therefore higher probability for ignitions sources. Road data was available through the United States Census bureau (www.census.gov), TIGER products, and we downloaded a file that contained all the roads in the conterminous US in 2010. We selected all the roads that were classified as primary road, secondary road, local neighborhood road, rural road or city streets.

Lastly, we measured distance of each pixel to urban areas, defined as the classes in the NLCD data set that are classified as developed (Developed, Open Space (21), Developed, Low Intensity (22), Developed, Medium Intensity (23), and Developed High Intensity (24)).

GUIDOS/ MSPA

Landscape context, especially the connectivity of the fuels around the buildings, also affects the probability of building loss to wildfire (Alexandre et al 2015b). Based on the national land cover dataset, we reclassified areas into two categories: forest and non-forest. We then used the Graphical User Interface for the Description of Image Objects (GUIDOS) toolbox, which contains a wide variety of generic processing routines to process geospatial data. GUIDOS represents Morphological Spatial Pattern Analysis (MSPA), which is a customized sequence of mathematical operators targeted to measure the connectivity of the image components (http://forest.jrc.ec.europa.eu/download/software/guidos/ assessed on 02/12/2015). MSPA can be used at any scale to any kind of binary image. The output image has a new value for each pixel indicating if the pixel is one of the eight classes: Core, islet, loop, bridge, perforation, edge, branch, and non-forest (http://forest.jrc.ec.europa.eu/download/software/guidos/mspa/ assessed on 02/12/2015). We simplified the original MSPA classification system into six classes:

0 = non-forest

1 = other mspa-class forest (loop, branch and bridge)

2 = perforation forest

3 = islet forest

4 = edge forest

5 = core forest

Modeling

To project the potential distribution of building loss likelihood given the occurrence of a wildfire, we used the maximum entropy model MaxEnt (Phillips et al 2006; Elith et al 2011), a map-based modeling software built and used primarily for species distribution modeling (Elith et al 2011). The dependent variable was the location of buildings destroyed by fire between 2000 and 2010. The MaxEnt software uses a machine-learning algorithm that iteratively evaluates contrasts among values of predictor values at locations where buildings burned versus values distributed across the entire study area. MaxEnt assumes that the best approximation of an unknown distribution (in this case destroyed buildings) is the one with maximum entropy. The output is an exponential function that assigns a probability to every cell in the map, in our case the probability of a building being destroyed if a fire occurs.

We parameterized MaxEnt with default settings (Phillips and Dudík 2008) but removed threshold and hinge features (for details, see Phillips et al 2006), to assure more ecologically realistic response curves (Austin 2007; Bateman et al 2012).. We selected the jackknife variable importance option to assess the relative importance of the environmental predictors in the models. Ten-thousand background points were selected at random from each ecoregion. Model validation was based on the area under the curve (AUC) of the receiver operating characteristics (ROC) curve (Fielding and Bell, 1997; Phillips et al., 2006; Wiley et al., 2003). AUC values above 0.5 are better than random predictions, with those above 0.7 being considered useful (Elith et al 2006) and those above 0.9 highly accurate (Guisan et al 2007).

Maxent calculates several measures of variable importance: (1) relative gain contribution per variable (a goodness-of-fit measure similar to deviance, Phillips et al. (2006)), (2) variable response curves for single-variable models, and (3) a jackknife procedure to assess AUC/gain changes when excluding a variable. We analyzed all of them to assure that our models were ecologically reasonable.

Fire vulnerability maps were calculated by applying Maxent models to all cells in the study region, using a logistic link function to yield a habitat suitability index (HSI) between zero and one (Phillips and Dudik, 2008). We mapped each ecoregion separately, and then combined maps for a broad scale depiction.

Due to the high resolution of our explanatory variables (environmental variables in MaxEnt), we used UW Madison's High Throughput Computing System (HTCS), called HTCondor (https://research.cs.wisc.edu/htcondor, assessed on 10/12/2015). This system allowed us to access high memory machines needed to analyze our largest MaxEnt jobs. Specifically, we were allotted 370 GB of RAM on dedicated servers for the Great Plains, Eastern Temperate Forest, and Northwestern Forested Mountains Level I ecoregions. For the remaining ecoregions (Southern Semi-Arid Highlands, Mediterranean California, Marine West Coast, and North American Deserts), we used the servers owned by SILVIS lab which have 260 GB of RAM.

Results

The Maxent models had good discrimination, with all AUC values between 0.80 – 0.98, meaning that our model can at least be considered useful, and some of them highly accurate, in their predictive performance (Elith et al 2006; Guisan et al 2007). Even though we divided the conterminous U.S. into ecoregions, there is a clear difference between the west and the east. The western part of the US presents higher vulnerability in clustered patterns that are more closely related to topography and/or land cover, while the eastern US presents a reticulate pattern that relates closely to populated areas (land use) (Fig. **11**).

We used eight variables that are available for the conterminous United States and that have been shown to be related to building loss in previous studies (Alexandre et al 2015a; Alexandre et al 2015b). Interestingly, the variables that contributed the most to the predictive ability of models were overal similar for the different ecoregions. Indeed, the top three variables that most consistently contributed to the models were land cover, elevation, and distance to urban areas (Table 9).

Discussion

Our goal was to produce a map depicting the vulnerability of buildings if a wildfire occurs that was both accurate and useful for managers, policy makers and homeowners. We successfully achieved our goal, our models had good predictive power, and resulted in 30-m spatial resolution maps showing the probability of a building to be lost to wildfire across the conterminous U.S., but specific to each ecoregion.

We used species distribution models (SDMs) to identify the probability of losing a building to wildfire. We treated buildings that had been destroyed by wildfire essentially as a species where each burnt building location is an occurrence (or presence). SDM have been used in the context of wildfire to map fire hazard using burned structures in Southern California (Syphard et al 2012; Syphard et al 2013), and to map ignitions distribution (Parisien and Moritz 2009; Bar-Massada et al 2013b), but never at such broad scale (conterminous U.S.) and at the spatial resolution (30-m) used here. Our results provided interesting and exciting information including a very detailed visualization of the locations that have higher vulnerability.

We acknowledge that our maps could be improved if information on the spatial arrangement of buildings was available, but at this scale it was not possible to calculate such variables because we do not have information on where all buildings on all the U.S. are located.

Our maps can greatly facilitate decision processes by providing managers, land planners and the general public information about burning vulnerability. For example, fire risk maps are used in the decision process in California, where they are available online to the public via the California Department of Forestry and Fire protection (http://www.fire.ca.gov). However, Syphard et al. (2012) showed that California's maps are not good predictors of where people and their homes are vulnerable. Similarly, at a National scale, what is readily available is current fires and smoke maps, such as the NOAA Satellite and Information Service (http://www.osdpd.noaa.gov), the NASA active fire data (http://earthdata.nasa.gov), or the current fuels and fire behavior advisory map made by the National Interagency Coordination Center (http://www.predictiveservices.nifc.gov). These maps are useful for disaster management and short-term prevention in situations where the hazard is already ongoing and people within the affected area can use the information to make decisions about whether or not to stay. However, maps of vulnerability have been lacking so far.

Existing fire risk maps are most useful if they properly identify areas where property loss is most likely to occur. In order to evaluate the effectiveness of such maps they must be analyzed against empirical data. Our analysis allowed, for the first time, the use of real data from buildings lost to wildfires, related the occurrence of a lost building to the building's surroundings, and then used this information to identify areas with similar characteristics. Thus our maps are of major importance for local government agencies aiming to plan ahead of time and allocate resources before the hazard occurs in order to reduce vulnerability. Furthermore, having access to a map of vulnerability may inform individuals' decision of where to buy or build their primary residence or second home.

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Table 8: Omernik ecoregions that contained more than 25 observations

Ecoregion	Observations	
Eastern Temperate Forests	373	
Central USA Plains*		0
Mississippi Alluvial and Southeast USA Coastal Plains		133
Mixed Wood Plains		48
Ozark/Quachita-Appalachian Forests		124
South Eastern USA Plains		68
Great Plains	1309	
South Central Semiarid Prairies		1134
Tamaulipas-Texas Semiarid Plain*		13
Temperate Prairies		37
Texas Louisiana Coastal Plain*		3
West Central Semiarid Prairies		122
Marine West Coast	41	
Mediterranean California	6074	
North American Deserts	186	
Cold Deserts		159
Warm Deserts		27
Northern Forests*	10	
Northwest Forested Mountains	1040	
Southern Semiarid Highlands	173	
Temperate Sierras	25	
Tropical Wet Forests*	2	
Total		9233

* Ecoregion not used in the analysis because the number of observations was below 25.

Table 9 – Maxent output: mean AUC, standard deviation values (10 fold cross-validation); variable contribution (%) and permutation importance for each ecoregion.

Region	Mean AUC	Std. Dev.	Variable	Percent contribution	Permutation importance
Eastern Temperate Forests					
Mississippi Alluvial and Southeast USA Coastal Plains	0.825	0.058	Land cover	53.7	32.6
			Distance to vegetation	13.3	18.9
			MSPA	11.5	15.5
			Elevation	7.8	18
			Southwestness	4.7	4.6
			Slope	4.2	3.1
			Distance to roads	2.6	4.6
			Distance to urban areas	2.2	2.7
Mixed Wood Plains	0.973	0.044	Land cover	43	9.5
			Elevation	19.5	49.4
			Slope	14.4	13.2
			Distance to urban areas	13.2	17.2
			MSPA	6.4	2
			Distance to roads	2.5	1.2
			Distance to vegetation	0.5	7.1
			Southwestness	0.4	0.3
Ozark/Quachita-Appalachian Forests	0.898	0.058	Land cover	46.1	31.4
			MSPA	28.7	24.3
			Elevation	10.4	20.4
			Distance to vegetation	5.1	9.4
			Distance to urban areas	4.5	6.4
			Slope	4.1	5.4
			Distance to roads	0.9	2.2
			Southwestness	0.2	0.5
South Eastern USA Plains	0.811	0.055	Land cover	40.6	32.7
			Distance to urban areas	32.8	32.9
			MSPA	16.1	7
			Distance to vegetation	4.1	12.5
			Elevation	2.5	7.3
			Distance to roads	1.5	3.3
			Southwestness	1.4	0.8
			Slope	1.1	3.5

Great Plains					
South Central Semiarid Prairies	0.853	0.019	Land cover	40.7	26.8
			Elevation	39.3	23.5
			Distance to urban areas	11.4	32.9
			Distance to roads	5.4	7.9
			Distance to vegetation	2	6.3
			MSPA	0.7	0.2
			Slope	0.6	2.2
			Southwestness	0	0.1
Temperate Prairies	0.896	0.06	Land cover	25.1	4.4
			Elevation	20.3	2.4
			Distance to urban areas	19.4	15.8
			Distance to roads	16.7	15.5
			Distance to vegetation	13.5	52.1
			MSPA	2.5	0.8
			Southwestness	1.8	6
			Slope	0.8	3.2
West Central Semiarid Prairies	0.819	0.059	Land cover	41.8	24.4
			Distance to roads	36.1	45.4
			Distance to urban areas	7.1	6.6
			Southwestness	6.2	6.2
			Slope	4.4	8.9
			Elevation	3.1	5.3
			Distance to vegetation	0.8	2.5
			MSPA	0.5	0.6
Marine West Coast	0.976	0.022	Elevation	48.1	84.9
			Land cover	21.8	5.6
			Distance to urban areas	12.1	1.9
			Slope	6.8	1.1
			Distance to roads	5.4	5.9
			MSPA	5	0.1
			Southwestness	0.7	0.4
			Distance to vegetation	0	0.1
Mediterranean California	0.795	0.007	Land cover	53.7	25.2
			Distance to urban areas	17.2	25.2
			Distance to roads	9.3	22.1
			Elevation	6.2	8.1
			Distance to vegetation	5.3	9.6
			Slope	4.2	7.1

			MSPA	4.1	2.6
			Southwestness	0.1	0
North American Deserts					
Cold Deserts	0.88	0.029	Distance to urban areas	34.6	41.3
			Elevation	32.5	24.7
			Land cover	15.3	4.1
			Distance to roads	8.1	4.7
			Slope	4.5	17.3
			MSPA	2.7	3
			Distance to vegetation	1.7	3.5
			Southwestness	0.7	1.5
Warm Deserts	0.961	0.022	Distance to roads	51.5	81.7
			Elevation	15.5	9.9
			Land cover	15.1	2
			MSPA	9.8	2.8
			Southwestness	3.8	1.9
			Slope	2	1
			Distance to vegetation	1.6	0.2
			Distance to urban areas	0.6	0.4
Northwest Forested Mountains	0.888	0.012	Elevation	29	4.4
			Distance to roads	25.2	59.6
			Land cover	22.7	6
			Slope	12.9	16.9
			Distance to urban areas	5.1	11.5
			MSPA	4.4	0.8
			Southwestness	0.4	0.4
			Distance to vegetation	0.3	0.3
Southern Semiarid Highlands	0.963	0.031	Land cover	40.3	2.2
			Elevation	39.8	39.8
			Distance to urban areas	9.8	33.8
			Distance to roads	5.5	17.2
			Slope	2.3	6.4
			MSPA	2.1	0
			Southwestness	0.3	0.5
			Distance to vegetation	0	0
Temperate Sierras	0.926	0.063	Distance to roads	27.8	63.5
			Elevation	25.3	4.8
			MSPA	23.2	19.5
			Land cover	16.4	5.5

Distance to urban areas	4.6	3.3
Distance to vegetation	1.6	0.2
Southwestness	0.7	3.1
Slope	0.4	0.1

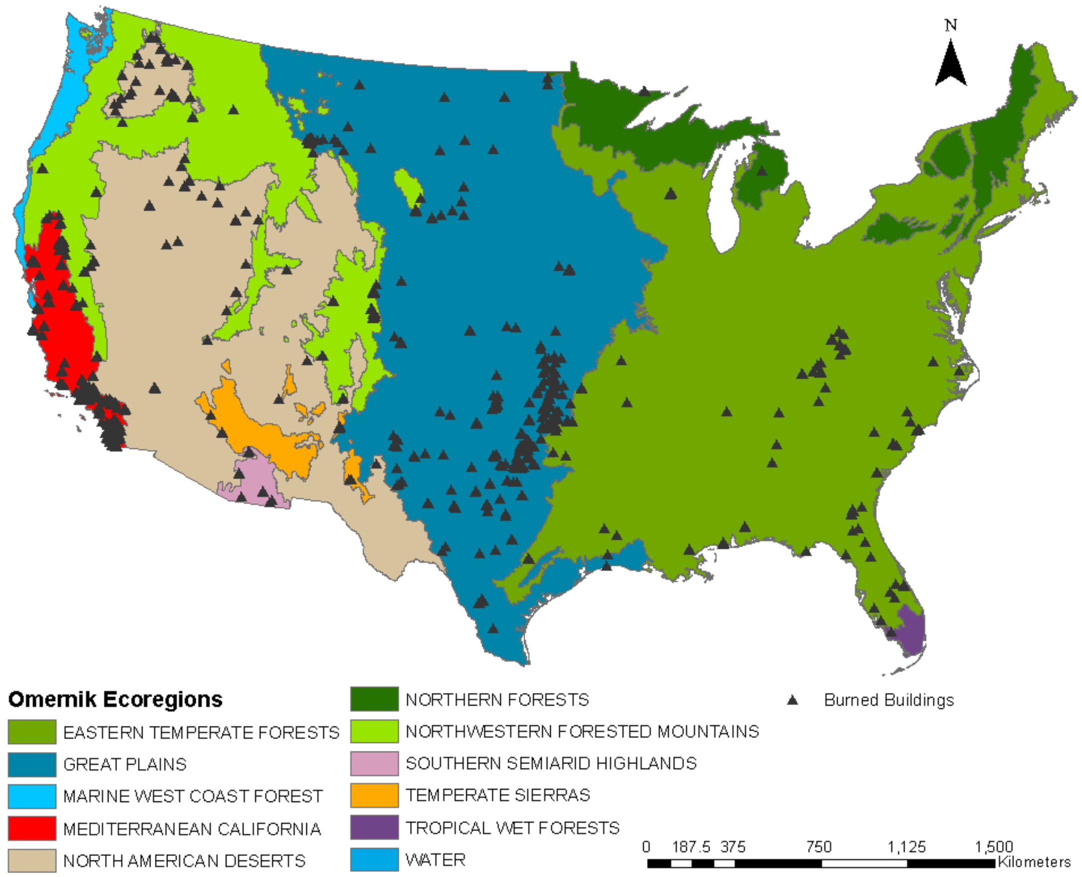

Fig. 10 – Burned buildings distribution across the U.S. between 2000 and 2010, and Omernick Ecoregions levels I and II.

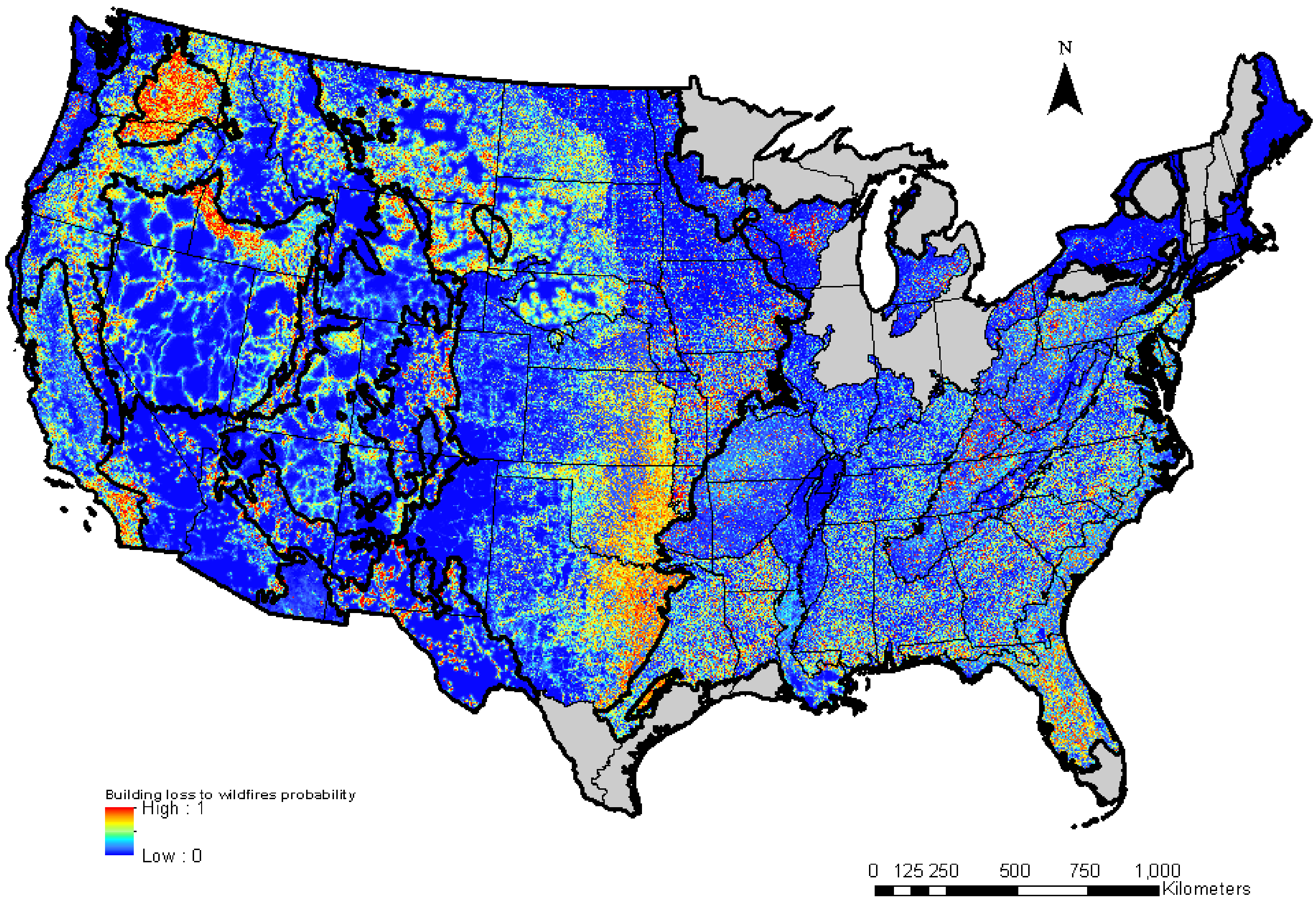

Fig. 11 – Predictive maps of building loss probability output of Maxent software. Warmer colors indicate regions with high probability, while cooler colors suggest lower probability.

Chapter 4

Rebuilding and new housing development after wildfire

Suggested running head: Rebuilding after wildfire

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Abstract

The number of communities exposed to and affected by wildfire, particularly in the Wildland Urban Interface, is increasing, and both losses from and prevention of wildfires entail substantial economic costs. However, little is known about post-wildfire response by homeowners and communities after buildings are lost. Our goal was to characterize patterns and rates of rebuilding and new development after wildfires across the conterminous United States. We analyzed all wildfires that occurred in the conterminous U.S. from 2000 to 2005. We mapped a total of 42,724 buildings, of which 34,836 were present before the fire and survived, 3,604 were burned, 2,403 were post-fire new development, and 1,881 burned and were rebuilt. The total pre-fire number of buildings within fire perimeters was 38,440 (surviving plus burned). Within five years after the fires there were 39,120 buildings (surviving, rebuilt, and new development). Nationally, rebuilding rates were low; only 25% of burned buildings were rebuilt within five years, but rates were higher in the West, the South, and in Kansas. New development rates inside fire perimeters were similar to development rates outside of fire perimeters. The finding that the number of buildings within the fire perimeters was higher within 5 years of the fire than before, indicated that people want to live in wildland areas and are either willing to face wildfire risks, or are unaware of them, or that the economic incentives to rebuild in the same place are stronger than any considerations of risk.

Summary:

Our goal was to assess rates of rebuilding and new development after wildfires destroy buildings. Across the U.S., rebuilding rates were low (about 25%), but new development within burned areas was common and new-development rates similar to surrounding non-burned areas, suggesting that knowledge, awareness, or concern about wildfire risk was limited or people chose to maintain their home in fire prone area regardless of the risks, even after a fire occurred.

Additional keywords: Wildland Urban Interface, Rebuilding patterns, Wildfires, Housing development.

Introduction

Wildfires are common in many parts of the United States. Every year, large areas burn and substantial efforts are made to prevent and suppress wildfire (Gorte 2011; NIFC 2011a; NIFC 2011b). Although unpopulated wildlands account for the majority of the burned area, fire prevention and firefighting focus on areas where human assets and lives are in danger (Hammer et al. 2009c). These areas of housing development intermingled with - or adjacent to - vegetated areas are called the Wildland Urban Interface (WUI, Radeloff et al., 2005). Despite protection efforts, many WUI buildings are lost every year to wildfires, and these losses entail considerable social, economic and emotional costs.

Between 1999 and 2011, an average of 1,354 residences were lost to wildfire each year in the U.S. (NIFC 2011b), and on average two billion dollars were spent annually to suppress wildfires (NIFC 2011a; USDA 2011a; NIFC 2012). In the future, residential development is expected to further increase in rural wildland areas (Brown et al. 2005), and wildfires may become even more common due to climate change (Dale et al. 2000; Dale et al. 2001; Westerling et al. 2006), increasing the threat posed by wildfire to buildings in the WUI.

Given the high cost of protecting buildings and the likelihood of increasing wildfires in the future, homeowners and local authorities face challenging questions after a fire occurs: should buildings lost to wildfire be rebuilt? If so, should they be rebuilt in the same location? Which materials and vegetation treatments should homeowners use? A heightened perception of fire risk after a fire has occurred may discourage rebuilding, but WUI homeowners have in general widely varying attitudes, behaviors, and perceptions regarding fire, making it difficult to predict how fire occurrence may affect them. Instead, the combination of a person's previous experience with fire, aesthetic preferences, and knowledge and beliefs about fire behavior will influence the decision to rebuild (Cohn et al. 2008; McCaffrey et al. 2011). Social and economic characteristics of a WUI community also shape the homeowner's receptiveness to changing the characteristics of their buildings and surrounding landscape, their ability to carry out mitigation work, and their perceptions of risk (Collins and Bolin 2009). Hence, many factors encourage homeowners to rebuild, though rebuilding rates depend on the social and economic characteristics of the region affected (Lyons et al. 2010; Daly and Brassard 2011; Fillmore et al. 2011; Fujimi and Tatano 2012).

Rebuilding after wildfires is problematic, because the fact that a building has burned indicates that the site is prone to future fire risk once vegetation has regenerated (Syphard et al. 2012). Firewise and similar programs have worked with residents and community leaders to mitigate fire risk by managing vegetation and structural characteristics. However, the placement of a building on the landscape also affects risk, and factors such as slope and terrain are important contributors to property loss (Bar-Massada et al. 2009; Syphard et al. 2012). For example, in the Witch and Guejito Fires in southern California, buildings near the edges of subdivisions were more likely to be destroyed by fire than those in the center, even when Firewise practices were used, and more than half of the buildings on properties with slopes greater than 20% were destroyed or damaged (Maranghides et al. 2013). Unfortunately, while building materials and landscaping can make the rebuilt building more defensible and less likely to burn, its position on the landscape is not easily altered once a building is in place, and even when rebuilding, the possibility to build in a less fire prone location within the lot is limited to those homeowners who have larger lots. This is why it is important to understand how building location affects risk, since the fire risk related to location (e.g. slope and elevation) cannot be changed after a building is built.

Wildfire is not the only disaster that destroys buildings, and rebuilding patterns after other natural disasters suggests that homeowners commonly rebuild (Ingram et al. 2006; Fillmore et al. 2011). Prior research on post-disaster rebuilding has focused on hurricanes and earthquakes that destroy extensive areas and multiple neighborhoods. Studies show recovery follows a process, where typically: 1) rebuilding occurs on the same site; 2) the availability of large external sources, innovative leadership, existence of prior plans, community consensus and wide dissemination of information speeds rebuilding; 3) ongoing urban trends (eg., housing growth) accelerate after the disaster; 4) the recovery process is not egalitarian; and 5) comprehensive re-planning is rare (Haas et al. 1977; Olshansky 2005).

Rebuilding after fire may share some of these characteristics. Homeowners who are attached to their lot, lifestyle, and community are motivated to rebuild in the same location (Norris et al. 2008; Cutter et al. 2008; Mockrin et al. 2015). Various federal loans and grants are available to help communities rebuild or repair essential services and facilities (e.g., water, sewage treatment, communications), and while homeowners bear the burden for rebuilding private residences, they may receive insurance payments to cover much of the cost. In addition, local governments may facilitate the permitting process (Mockrin et al. 2015) and ease regulations both to assist homeowners, and to re-establish their property tax base (Becker 2009). Local governments lose tax revenues if homeowners move and their lot is not rebuilt (Becker 2009), which is why local governments are inclined to assist homeowners to rebuild (Mockrin et al. 2015).

The broader post-disaster recovery literature provides a basis for our research, but fires are somewhat unique, in that they typically tend to destroy only a small fraction of all the buildings within a fire perimeter. However, in a given neighborhood a large portion of buildings can burn as was the case in Majestic Drive and Courtney Court communities within the Waldo Canyon fire in Colorado, 2012. More information about post-fire rebuilding is needed though, as Federal and local fire managers shift emphasis away from expectations of fire suppression, towards communities becoming more fire adapted (see www.fireadapted.org). Understanding the rebuilding process can help clarify what role local and state governments play in wildfire regulation and policy, specifically regarding residential construction and reconstruction. Information on rebuilding patterns needs to be region-specific though, given ecological and economic differences (Agee 1993; Busenberg 2004), but also because different states, counties and municipalities have different building codes, some of which were changed after major fire events. For example, in Boulder Colorado new building codes were adopted after the Black Tiger fire (1989, 850 ha), to reduce wildfire damage (Mockrin et al. 2015).

In terms of the ecological differences in fire regimes, they are strongly related to landscape characteristics (vegetation, fuel load, topography), climate, and weather conditions (Flatley et al. 2011). Ecoregions encompass areas with similar characteristics with regard to geology, physiography, vegetation, climate, soils, land use, wildfire and hydrology, and are critical for structuring and implementing ecosystem management strategies (Omernik 1987; McMahon et al. 2001). Ecoregions also represent the ecological environment to which homeowners or their communities must adapt. Examining patterns of loss and rebuilding across ecoregions can reveal variations in post-fire adaptive response; regions with fire intervals of one hundred years or more, such as Northern Hardwoods in Maine (Lorimer 1977) or the Great Lakes Region

(Cardille and Ventura 2001; Sturtevant and Cleland 2007), may exhibit very different patterns than regions with short fire-return intervals where future risk is higher. Similarly, social institutions vary markedly by state and county, including regulations regarding development before and after wildfires. Such social factors can eclipse the effects of ecological patterns, and if that is the case, then rebuilding patterns will be strongly related to political boundaries. For this reason, we examined rebuilding rates also at the state and county levels. Because information on buildings' presence, absence, loss, and reconstruction is not part of fire (or any other public) records, it has not been possible to analyze post-fire recovery. We turned to a new resource, satellite images compiled by Google, to fill this information gap, developing protocols to extract and analyze these data.

Our goal was to characterize the pattern of buildings destroyed by wildfire, and the rebuilding and new development patterns across the conterminous United States for all fires that occurred from 2000 to 2005. Our specific objectives were to:

- Assess rebuilding rates across the conterminous U.S., at the fire/county, the state, and the ecoregion levels.
- Compare rebuilding rates to rates of new development at each of the three levels of analysis.
- Compare the rate of new housing development within fire perimeters to the rate of new housing development in the surrounding county.

By answering these questions we identify when and where homeowners decide to rebuild or build new houses in areas that suffered a wildfire. We provide the information on rebuilding and new construction after wildfires for the years 2000 to 2010, and this information can assist national fire policy development, and local land use planning, since future rates of rebuilding and new development within fire perimeters are likely to be similar to those in the first decade of the 2000s.

Methods

Data collection

We identified all burned and rebuilt buildings within 2000-2005 fire perimeters from the Monitoring Trends in Burn Severity (MTBS, www.mtbs.gov) dataset, across the conterminous U.S., using Google Earth imagery. We chose the 2000-2005 time frame because it contains the housing boom peak (Weller 2006; Haughwout et al. 2012), and because satellite imagery from this period that was available from Google Earth was of high enough resolution to assess whether or not a building was burned by fire. The MTBS project provides consistent, 30-m resolution burn-severity data and fire perimeters (USDA Forest Service 2011b). We used the National MTBS Burned Area Boundaries, downloaded in September 2011 using the ESRI Shapefile/Metadata option. We analyzed the fire perimeters in a geographic information system (ArcGIS 10 - ESRI, 2011) and intersected them with 2010 U.S. decennial census block-level housing density data (www.silvis.forest.wisc.edu), adjusted for public land boundaries (Radeloff et al. 2010), to exclude fires that did not contain any buildings within their perimeters. Out of a total of 4,078 fire perimeters from 2000 to 2005, 2,318 had a housing density greater than zero.

We use the term “building” (instead of ‘home’ or ‘house’) because we could not distinguish between houses, barns, and sheds in the Google Earth images. However, we were able to distinguish buildings from other structures such as roads, antennas, bridges, etc., and that is why we did not use the more generic term ‘structures’.

For each fire perimeter, we digitized: 1) each building within the fire perimeter that was present prior to the fire, and that was not burned to the ground i.e., a surviving building, 2) each building burned to the ground, 3) each building rebuilt within five years after the fire, 4) new buildings built within five years after the fire, and 5) buildings present in the images, but for which either the time between images in Google Earth was too long, or the resolution of the images too coarse to determine the origin or fate of the building (called unknown). We could not distinguish damaged from undamaged buildings using satellite images, except when the building burns to the ground, (2), see Fig. **12**). Hereafter, “burned building” refers to those that burned to the ground, and we acknowledge that some surviving buildings may have sustained damage in the fire.

Data were collected between September 2011 and December 2012 by four people. The lead author conducted training and frequently checked for errors, both visually, and by comparison with ancillary data. Google Earth imagery came from different sources (e.g. LANDSAT, SPOT Image, GeoEye-1, IKONOS, etc.) and presented several challenges.

When using the historical imagery tool and going backward and forward in time, there were spatial shifts in the images of up to several meters. To overcome this problem, we analyzed images in a chronosequence with the fire-year period as the central point of reference. Depending on the best image available after the fire, we always digitized on the same image to avoid spatial shifts. To determine if a building was rebuilt, we analyzed all the available images up to five years after the fire event and we assumed that the building was rebuilt in the earliest year for which it was present in imagery. For example: a fire destroyed a building, and then there was a new building in the same location depicted in an image from 2004. In this case, we labeled the building as "rebuilt", because it was rebuilt within five years. However, if the first images in which a new building is present dated from 2008, then we did not digitize the new building, because more than five years had passed.

Another issue that we encountered was that there was sometimes a gap of several years between images. For example, for some of the earlier fires (in 2000 and 2001), the pre-fire image was recorded as early as 1992 or 1994, and the post-fire image was from 2003 or later. If a building occurred only in the 2003 images, then we digitized the buildings, and labeled it as 'unknown' because the image dates made it impossible to discern if the building had been built before the fire (and survived it), or if it represented new development. In total, these 'unknown' buildings represented only 7% of all the buildings we digitized (3,185). Furthermore, this problem disappeared from 2002 on since the image records in Google Earth were much more complete thereafter.

Data analysis

We used the total number of surviving plus burned buildings as the denominator when calculating the percentage of both burned and new buildings, because this is the total number of buildings that were within the fire perimeter at the time of the fire (eq. 1 and 2). To calculate percentage rebuilt, we divided the number of rebuilt buildings by the number of burned buildings within the fire (eq. 3).

1) $\% \; Burned = \frac{Burned \; buildings}{Surviving + Burned}$

2) $\% \; New = \frac{New \; buildings}{Surviving + Burned}$

3) $\% \; Rebuilt = \frac{Rebuilt \; buildinss}{Burned \; Structures}$

In order to compare the new development rates inside and outside fire perimeters we compared post-fire development rates to county-level data on housing growth from the 2000 and 2010 U.S. decennial census (United States Census Bureau 2001; United States Census Bureau 2011). For each fire where we recorded new development, we calculated an annual development rate based on the total number of new buildings inside the fire perimeter, divided first by the fire area, and second by the number of years that had elapsed since the fire, resulting in the number of buildings built/year/km^2. When a fire spanned multiple counties, then we compared the within-fire perimeter development rate to the development rate for the county that contained the majority of the fire's area. The county's development rate was based on the difference between the total number of housing units in 2000 and 2010, minus the number of buildings inside fire perimeter, divided by the county area and by 10 years. We then compared annual development rates inside and outside the fire perimeters, to determine the difference. Differences $\geq |0.1|$ (new buildings/km^2) were considered different rates of development. Because we analyzed all the fires that occurred during our time frame (a complete enumeration and not a sample), we did not test for statistical significance in differences.

Results

Of the selected 2,318 fires that occurred between 2000 and 2005 across the 48 contiguous states, 931 contained buildings, and 106 contained buildings that burned to the ground. We analyzed a total of 42,724 buildings, of which 3,604 were burned, 1,881 were rebuilt within 5 years of the fire, and 34,836 survived (Table 10). Concomitantly, 2,403 new buildings were built inside the fire perimeters within 5 years of the fire. This means that there were more buildings within fire perimeters five years after the fire than before, and that by the five year post-fire anniversary, the number of new buildings within the fire perimeters was greater than the number of rebuilt buildings (Table 10).

Among the fires for which Census data indicated a potential presence of buildings (2,318), 40% contained buildings within their perimeters (931 of 2,318). Among the fires with buildings, 11% (106 of 931) contained buildings that burned ground, and 4% (39) contained buildings that were rebuilt (Table 11). However, post-fire new development was more common, occurring in 14% (130) of fires (Table 11). We found a moderate correlation (Spearman's correlation r = 0.514) between fire size and the number of buildings lost.

Overall, the percentage of burned buildings relative to all buildings within fire perimeters was low, and so were rebuilding percentages. Over the six-year study period, the percentage of burned buildings within fire perimeters ranged from 0.4% to 20.4% per year (average of 5.9%, Table 12). For each fire year, the percentage of buildings rebuilt within five years varied from 6.2% to 63.8% (average of 25.3%, Table 12). The percentage of new buildings within fire perimeters also varied among years from 1.4% to 10.3% (average of 4.4%, Table 12). Inter-annual variation was very high partly because 2003 was a severe fire year with exceptional large number of fires. The number of burned buildings in 2003 was an order of magnitude larger than for all other years combined (20.4% of burned buildings), and had the highest rebuilding rate (63.8%) (Table 12).

Analyzing our data at the level of individual fires, there were only 10 fires that burned all of the buildings within their perimeter during the six-year period that we studied, and those fires contained only two to five buildings each. For each fire year, the rate of rebuilding varied considerably, with 2003 being a unique year, especially in California, in that rebuilding rates were very high. However, even in 2003 there was not one fire perimeter in California within which all buildings were rebuilt. Only Colorado, Kansas, Louisiana, and Arizona had fire perimeters within which all buildings were rebuilt, but in those four fires the total number of burned buildings ranged from one to four. Indeed, only 11.3% of all fires that burned buildings, had a rebuilding rate > 50% (12 out of 106 fires).

Buildings lost to wildfires were concentrated in the Western and Central states (Fig. **13**a). However, fires that burned more than 25% of the buildings within their perimeters occurred mainly in the Central Great Plains, Pacific Northwest, and Southwestern states (Fig. **13**a). High rebuilding rates often coincided with high percentages of burned buildings, and such fires were concentrated in California, Texas and Oklahoma (Fig. **13**b). Rates of new development inside the fire perimeters had no particular geographic patterns (Fig. **13**c).

Summarizing data by state, California was the top-ranked state in terms of the number of buildings within fire perimeters, and of burned, rebuilt and new buildings (Fig. **14**a,c,e,g). After California, Texas, Arizona and Washington had the highest number of burned buildings (Fig. **14**a). However, California, Arizona, and Wisconsin had the highest percentages of burned buildings (Fig. **14**b). Rebuilding rates were low in general (less than 40% in 10 states) but highest in Kansas followed by California, Nevada, and Wisconsin (Fig. **14**d). The greatest numbers of rebuilt buildings were in California and Arizona (Fig. **14**c). Finally, the greatest number of new buildings were built in California, Oklahoma, and Texas (Fig. **14**e), but rates of new housing development were highest in Michigan, followed by California, Missouri, Georgia, and Alabama (Fig. **14**f). Oklahoma, Kentucky, and West Virginia also had a high total number of buildings (surviving plus burned buildings) within fire perimeters (Fig. **14**g).

Variability among ecoregions was also high (Fig. **15**a). The ecoregions with the most buildings within fire perimeters (surviving plus burned) were the Ozark/Quachita-

Appalachian Forests, and Mediterranean California (Fig. **15**h). Mediterranean California had the most burned buildings, followed by the South Central Semiarid Prairies, and the Western Cordillera (Fig. **15**b). In terms of percentage of burned buildings, Mediterranean California was highest, followed by Western Sierra Madre Piedmont and the Mixed Wood Plains (Fig. **15**c). While rebuilding numbers were low, Mediterranean California had the most rebuilt buildings (Fig. **15**d), and together with the Mixed Wood Plains the highest rebuilding rates (Fig. **15**e). The most new buildings were in Mediterranean California and the Ozark/Ouachita-Appalachian Forests (Fig. **15**f). Mediterranean California had the highest rate of new development within fire perimeters (25% new buildings on average within five years after a fire, Fig. **15**g).

We compared annualized rates of housing growth for our study period (2000-2005) within the fire perimeters to the housing growth rates within the counties where fires occurred from 2000-2010 (Census count of housing units in 2010 - housing units in 2000, divided by 10). We found that fire and county growth rates were similar (Fig. **16**), and only very few counties experienced a decrease in total housing units. Of all the fire perimeters, 29% had higher development rates and 25% had lower development rates than the surrounding county. The majority of fires (46%) had similar housing development rates to their surrounding county (difference between inside and outside rates between -0.1 and 0.1). In Kentucky and West Virginia, even though the surrounding counties experienced housing declines, the number of buildings within those fire perimeters increased. By contrast, California, Arizona, Colorado, Wisconsin, and most of Utah experienced lower development rates within fires than in their surrounding counties (Fig. **16**).

Discussion

The main goal of our study was to characterize rebuilding and new development patterns after wildfire across the conterminous United States. The fact that buildings are frequently located in fire-prone areas is a key aspect of the U.S. wildfire problem (Syphard et al. 2009), partly because there is a positive feedback loop in that building ignitions increase as more people build near wildland vegetation (Syphard et al. 2012). The homeowners' response to losing their home, and whether they decide to move, rebuild, or even preferentially build new buildings in burned areas, is thus an important question for fire policy and management. One current national-level policy emphasis is on creating fire-adapted communities, where fire is expected to occur and communities are configured to survive fire (Winter et al. 2009; McCaffrey et al. 2012). If communities are to become "adapted" to fire, they must respond to the occurrence of fire, and choosing not to rebuild a burned building is one possible adaptive response. Our results showed that rebuilding was limited, and we found more new development than rebuilding.

One emphasis of current national-level fire policy is to create more fire-adapted communities, where fires are expected to occur and communities are configured to survive these fires (Winter et al. 2009; McCaffrey et al. 2012). Concomitant to these national-level efforts are local-level changes in building codes that have often been adopted in response to major wildfires. Examples of fires that prompted communities to adopted their fire-related building codes include the Black Tiger Fire in Colorado in 1989 (DORA 2010); and the Cedar Fire in San Diego, California in 2003, which resulted in further refining of the existing codes (http://www.amlegal.com/sandiego_county_ca/). Changes in the codes included both building construction requirements, such as the use of non-combustible, ignition-resistant materials in exterior wall, and fuel modification requirements, such as keeping the area located within 15 m (50 feet) of any structure cleared or planted with fire-resistant plants, and reducing fuels within at least 30 m (100 feet) distance from buildings (http://www.sdcounty.ca.gov/pds/docs/pds664.pdf). However, none of the building codes are retroactive, meaning that the buildings already in place would remain at risk to be lost in a wildfire.

Ecoregions provide a proxy for vegetation, soils and climate (Bailey 2004), which in turn influence fire regimes (Bond and Keeley 2005). In our analysis, the Mediterranean ecoregion stood out as the area where a particularly large number of buildings were lost, and fires were frequent. The Mediterranean ecoregion contains unique ecosystems because of the combination of dry summers (typical of this climate), strong winds, and heat waves, together with a high human development pressure that contributes to a higher ignition probability (Vannière et al. 2010). Vegetation in the Mediterranean ecoregion evolved together with fire to a point where it is now fire dependent (Keeley and Fotheringham 2003; Montenegro et al. 2004; Goforth and Minnich 2007). However, the Mediterranean ecoregion is also the region where past housing and population growth have been particularly rapid, growth is projected to continue in coming decades (Hammer et al. 2009c; United States Census Bureau 2011), and fire is projected to increase both in frequency and intensity due to climate change (Dale et al. 2000; Dale et al. 2001; Running 2006). A high demand for residential building sites to house a growing population provides incentive for rebuilding and for new development, but the risk of another loss due to fire is a disincentive. Despites this disincentive, our results showed that the occurrence of fire did not depress housing construction, and: both rebuilding and new development rates within the fire perimeters were highest in the Mediterranean ecoregion. This suggests that either homeowners were not aware of fire risk, or that a combination of non-ecological factors such as local regulations, personal experience, regional cultures, and insurance policies were more important determinants for people's response to wildfires that the fire patterns themselves.

Our results highlighted the importance of understanding fire damage and rebuilding in grassland/prairie ecoregions. In the Great Plains and Prairies (e.g., Oklahoma, Texas) a high number of buildings were burned. Similarly, in California a large percentage of structures lost to wildfires are in low fuel-volume grassland areas, which tend to burn quickly and then carry fire into shrublands or woodlands (Syphard et al. 2012). These shrublands and woodlands, turn, have a higher ability to produce embers and firebrands, which are a major cause of structure ignition (Cohen 2000; Blanchi et al. 2011; Graham et al. 2012). A common perception of surface fires is that they do not pose as large a danger as crown fires. However, buildings are often lost to surface fires and therefore, risk from surface fire should be taken into consideration when developing land use policies or helping communities adapt to fire in the Great Plains and Prairies. Indeed, the number of new buildings built after fires within their perimeters was high (between 100 and 500) in the Plains states. This may indicate that people are underestimating the risk of wildfire, maybe perceiving low risk since the vegetation was burned and there is no fuel for a subsequent fire in the short-term (Rowe and Wright 2001; Brewer et al. 2004; Champ et al. 2013).

Our use of Google Earth imagery to map rebuilding patterns was a novel approach but it was not without limitations. First, the number of available images varied from region to region and there were gaps of one or more years between available images in some areas. This meant that in some situations it was not possible to determine a precise date of rebuilding. Second, we were only able to identify buildings that burned to the ground. Our count of buildings lost to fire excludes the many buildings that are partially damaged by the fire itself, or by smoke. Nonetheless, the dataset that we derived from Google Earth images is unique, and our mapping approach could be useful for other studies as well.

Another caveat of our study is that the new development needs to be interpreted in the context of the housing construction boom, which peaked in 2005 (Weller 2006; Haughwout et al. 2012), the last year of our study. Housing construction started to decline after 2005, but many buildings were still being built in subsequent years. Our image analysis covered up to five years after a fire (i.e., new development up to 2010).

However, even during this period of rapid housing growth, we saw low to moderate rebuilding rates, and across the U.S., the rate of development inside fire perimeters was similar to housing development in the county at large (Fig. **16**). The base rate of development also differed substantially across the country. In California development rates were generally very high, whereas the border area of Kentucky, Virginia and West Virginia witnessed little to no growth in housing. In summary, there were no clear patterns for new development after wildfires across the U.S. Patterns differed by fire, and some mix of local, social, ecological, and political characteristics appeared to have determined the outcome.

Conclusions

The combination of housing growth in the WUI (Stewart et al. 2007; Radeloff et al. 2010) and climate change, particularly a hotter and drier climate, is likely to increase the frequency and intensity of wildfires in many WUI areas. This means that despite fire prevention and suppression efforts, the rate at which buildings will be destroyed by wildfire will probably rise. Information on rebuilding and new development is important in order to anticipate future needs for fire management in the WUI, and to gain a deeper understanding of homeowner attitudes towards fire and perceptions of risk.

Although community adaptation to wildfire is widely discussed, few suggestions have been put forward to evaluate such adaptations, in part because adaptation can take many forms. For example, rebuilding with fire resistant materials, following defensible space and/or Firewise directives, and keeping the home ignition zone clean, is one form of adaptation, while not rebuilding in the same place would be another type of adaptation since building location greatly affects fire risk (Gibbons et al. 2012; Syphard et al. 2012). The fact that we found generally low rebuilding rates may thus indicate that people are adapting to fire by choosing not to rebuild. However, high rates of new development suggest the opposite and support the notion that homeowners are not aware of fire risk, or that amenities and other considerations outweigh the risk (Donovan et al, 2007).

Although overall rebuilding rates were low, regional variability was high, suggesting that it is difficult to predict rebuilding responses to any individual fire. In general, we found little evidence though that homeowners or communities adapted to fire by changing the locations of buildings, or by lowering rates of new development after the fire. Given how much a home's position on the landscape determines its fire risk (Gibbons et al. 2012; Syphard et al. 2012), rebuilding in the same location may expose the building to future fire risk once the vegetation has recovered. Rebuilding in the same location thus represents a missed opportunity to adapt to wildfire.

Clarifying where and how much rebuilding occurs provides essential information for all of those involved with planning for future fires, and suggests that people will continue living in that area despite the occurrence of fire events. The insights that our study provides regarding new development within fire perimeters is important for WUI communities considering fire-specific planning, zoning, codes, and infrastructures. The prevalence of new development inside fire perimeters within five years of a fire suggests that a proactive approach to fire policy is essential, because while the community is recovering from fire, development pressure will continue and may exacerbate future fire problems.

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Table 10 - Buildings digitized using Google Earth, by type and by fire[1].

Year	2000	2001	2002	2003	2004	2005	Total
Total buildings before fire	3309	5896	3560	13240	2482	9953	38440
Surviving buildings	3212	5870	3457	10536	2415	9346	34836
Burned buildings	97	26	103	2704	67	607	3604
Rebuilt buildings[2]	6	2	26	1726	22	99	1881
New buildings	46	38	69	1131	91	1028	2403
Total buildings after fire	3264	5910	3552	13393	2528	10473	39120
Housing types by fire (n=106):							
New buildings	4	0	32	1112	19	618	1785
Surviving buildings	747	346	1365	9035	976	6194	18663
% of burned buildings	46.50%	32.00%	16.10%	33.20%	23.60%	13.50%	23.60%
% of rebuilt buildings	2.90%	5.00%	25.00%	34.80%	19.90%	10.20%	14.70%
% new buildings	3.90%	0.00%	0.90%	6.30%	5.50%	10.80%	6.90%
Total Area (ha)	127519	6343	179396	315079.92	36740	438853	1103930

[1] Only the106 fires which contained at least one building were included in this analysis.

[2] Buildings rebuilt within five years after the fire occurred, i.e., for a 2001 fire, by 2006; for a 2004 fire, by 2009.

Table 11 - Number of fires that contained buildings by year and type of building.

	Year	2000	2001	2002	2003	2004	2005	Total
Number of fire perimeters		573	375	306	345	245	474	2318
Building type	Any	228	168	119	114	93	209	931
	Surviving	195	160	114	109	87	205	870
	Burned	17	5	12	13	13	46	106
	Rebuilt	2	1	4	9	6	17	39
	New	6	4	3	8	16	93	130
Mean Fire Area (ha)		6858	2136	7898	6906	2148	6201	5527
Max fire Area (ha)		132357	31099	198297	116845	17320	128586	198297

Table 12 - Summary of buildings within fire perimeters by fire year.

	2000	2001	2002	2003	2004	2005	Total
Percent of fires with buildings within its perimeter	39.80%	44.80%	38.90%	33.00%	38.00%	44.10%	40.20%
Percent of burned buildings	2.90%	0.40%	2.90%	20.40%	2.70%	6.10%	5.90%
Percent of rebuilt buildings	6.20%	7.70%	25.20%	63.80%	32.80%	16.30%	25.30%
Percent of buildings newly built	1.40%	0.60%	1.90%	8.50%	3.70%	10.30%	4.40%

(percentages were calculated using the totals for each year, example: number of fire perimeters in 2000 = 573, fire perimeters that had any kind of buildings in 2000 = 228, percentage = 39.8%. Percent rebuilt was calculated using the number of rebuilt buildings in a year divided by the number of burned buildings in that year. Percent new was calculated using the number of new buildings in a year divided by the sum of surviving and burned buildings. Percent unknown was calculated using the number of new buildings in a year divided by the sum of surviving and burned buildings.

Fig. 12- Example of a rebuilt building after a fire in 2003 in Colorado (from left to right: 2000, 2003, 2005).

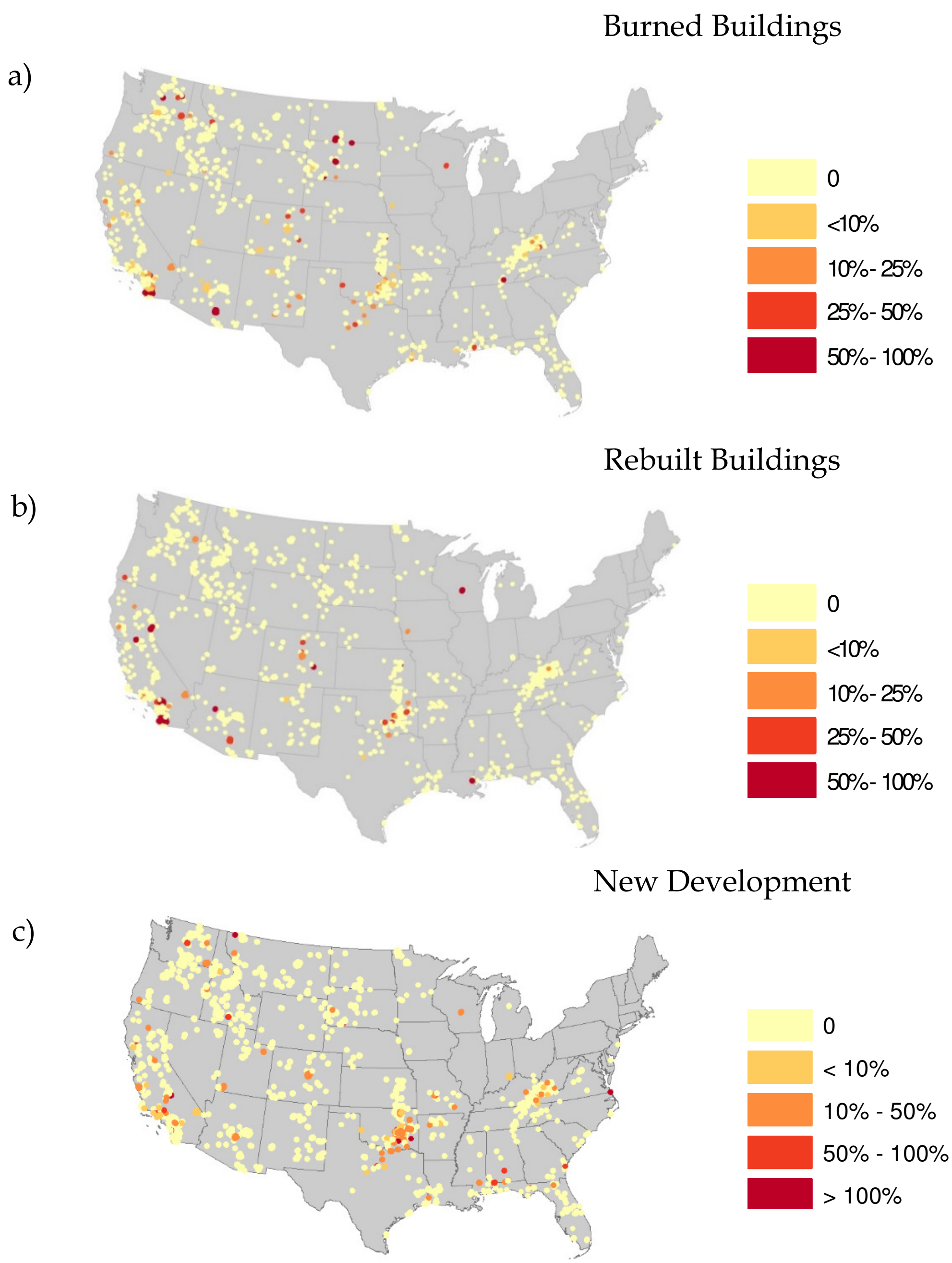

Fig. 13 - Fires that occurred between 2000 and 2005 and the respective percentages of a) burned buildings, b) rebuilt buildings, and c) new development within the fire perimeters.

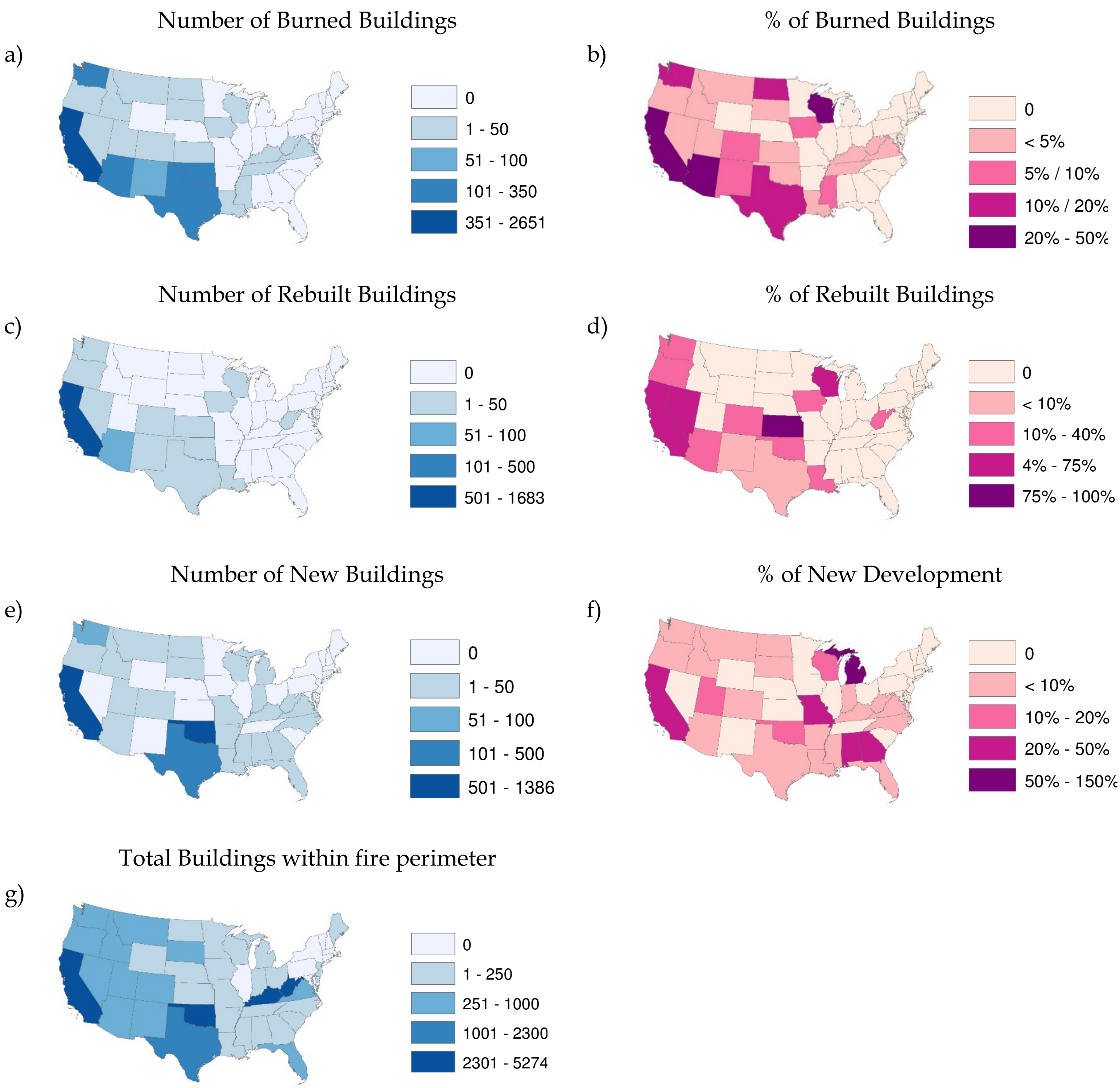

Fig. 14 - Summary data for fires that occurred between 2000 and 2005 of a) burned buildings, b) % of burned buildings, c) rebuilt buildings, d) % of rebuilt buildings, e) New buildings, f) % of new buildings, and g) total number of buildings within states.

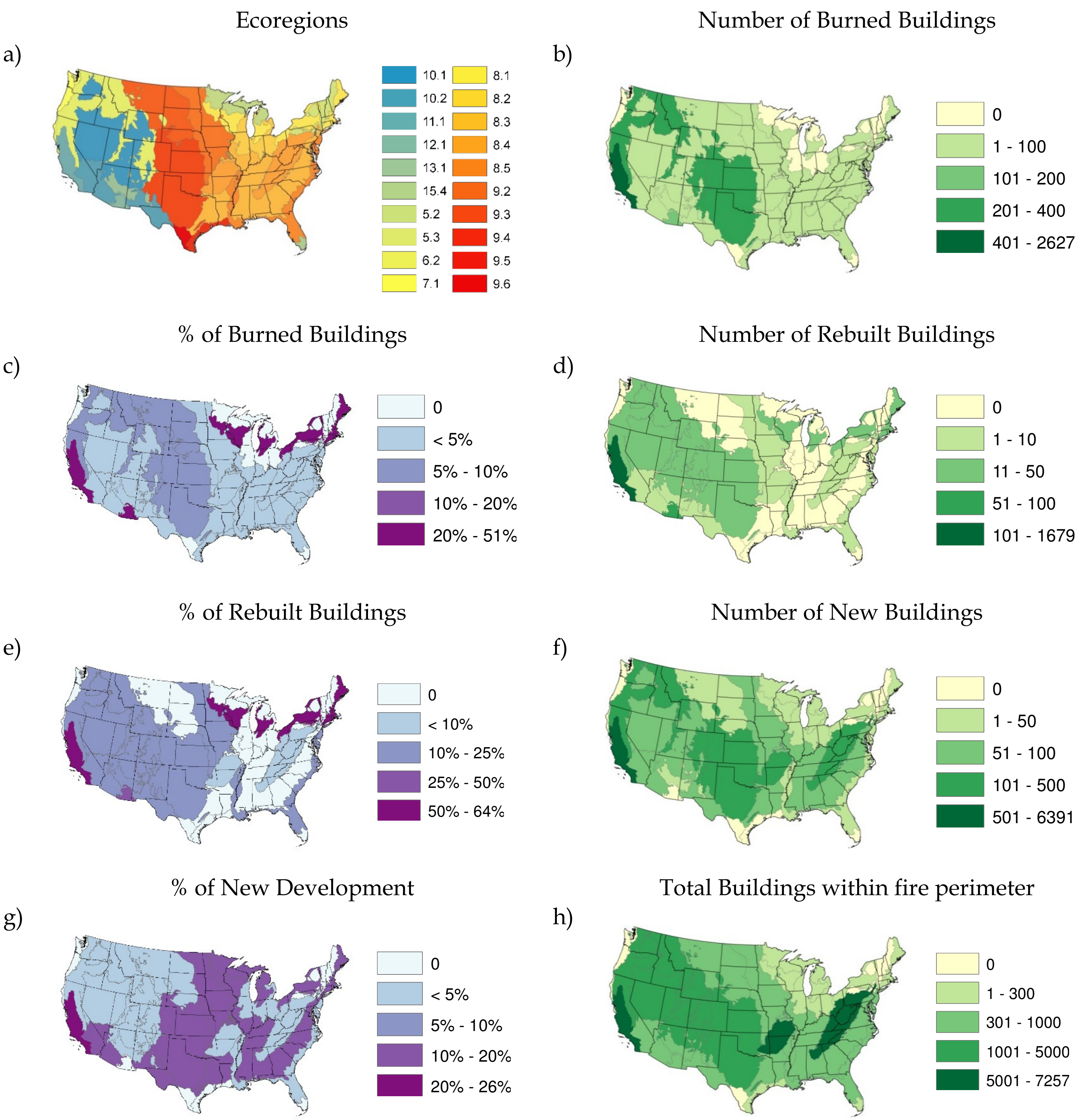

Fig. 15 - a) Map of Bailey's Ecoregions for the U.S. (legend:10.1 Cold Deserts; 10.2 Warm Deserts; 11.1 Mediterranean California; 12.1 Western Sierra Madre Piedmont; 13.1 Upper Gila Mountains; 15.4 Everglades; 5.2 Mixed Wood Shield; 5.3 Atlantic Highlands; 6.2 Western Cordillera; 7.1 Marine West Coast Forest; 8.1 Mixed Wood Plains; 8.2 Central USA Plains; 8.3 Southeastern USA Plains; 8.4

Ozark/Ouachita-Appalachian Forests; 8.5 Mississippi Alluvial and Souteast USA Coastal Plains; 9.2 Temperate Prairies; 9.3 West-Central Semiarid Prairies; 9.4 South Central Semiarid Prairies; 9.5 Texas-Louisiana Coastal Plain; 9.6 Tamaulipas-Texas Semiarid Plain), and summary data for fires that occurred between 2000 and 2005 of b) burned buildings, c) % of burned buildings, d) rebuilt buildings, e) % of rebuilt buildings, f) new buildings, g) % of new buildings, and h) total number of buildings within ecoregions.

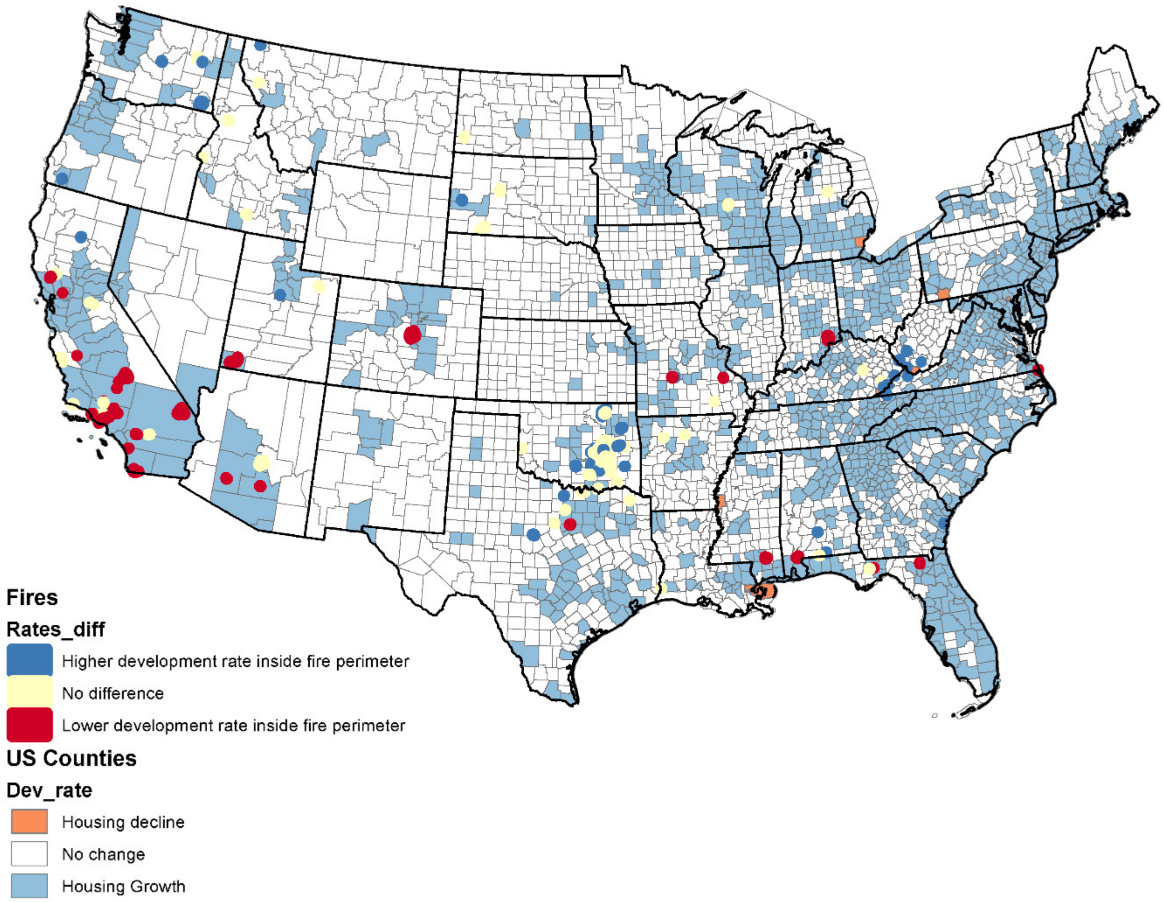

Fig. 16 - Development rates within and outside fire perimeters 2000-2005, and housing growth by county for the whole U.S., 2000 - 2010. Bar plot shows States where fires occurred and if the average development rate was higher or lower inside the fire perimeters for that state