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HUMAN INFLUENCE ON CALIFORNIA FIRE REGIMES

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Abstract. Periodic wildfire maintains the integrity and species composition of many ecosystems, including the mediterranean-climate shrublands of California. However, human activities alter natural fire regimes, which can lead to cascading ecological effects. Increased human ignitions at the wildland–urban interface (WUI) have recently gained attention, but fire activity and risk are typically estimated using only biophysical variables. Our goal was to determine how humans influence fire in California and to examine whether this influence was linear, by relating contemporary (2000) and historic (1960–2000) fire data to both human and biophysical variables. Data for the human variables included fine-resolution maps of the WUI produced using housing density and land cover data. Interface WUI, where development abuts wildland vegetation, was differentiated from intermix WUI, where development intermingles with wildland vegetation. Additional explanatory variables included distance to WUI, population density, road density, vegetation type, and ecoregion. All data were summarized at the county level and analyzed using bivariate and multiple regression methods. We found highly significant relationships between humans and fire on the contemporary landscape, and our models explained fire frequency ($R^2 = 0.72$) better than area burned ($R^2 = 0.50$). Population density, intermix WUI, and distance to WUI explained the most variability in fire frequency, suggesting that the spatial pattern of development may be an important variable to consider when estimating fire risk. We found nonlinear effects such that fire frequency and area burned were highest at intermediate levels of human activity, but declined beyond certain thresholds. Human activities also explained change in fire frequency and area burned (1960–2000), but our models had greater explanatory power during the years 1960–1980, when there was more dramatic change in fire frequency. Understanding wildfire as a function of the spatial arrangement of ignitions and fuels on the landscape, in addition to nonlinear relationships, will be important to fire managers and conservation planners because fire risk may be related to specific levels of housing density that can be accounted for in land use planning. With more fires occurring in close proximity to human infrastructure, there may also be devastating ecological impacts if development continues to grow farther into wildland vegetation.

Key words: California, USA; fire; fire history; housing density; nonlinear effects; regression; wildland–urban interface.

Introduction

Fire is a natural process in many biomes and has played an important role shaping the ecology and evolution of species (Pyne et al. 1996, Bond and Keeley 2005). Periodic wildfire maintains the integrity and species composition of many ecosystems, particularly those in which taxa have developed strategic adaptations to fire (Pyne et al. 1996, Savage et al. 2000, Pausas et al. 2004). Despite the important ecosystem role played by fire, human activities have altered natural fire regimes relative to their historic range of variability. To develop effective conservation and fire management strategies to deal with altered fire regimes, it is necessary to understand the causes underlying altered fire behavior and their human relationships (DellaSalla et al. 2004). Nowhere is this more critical in the United States than in California, which is the most populous state in the nation, with roughly 35×10^6 people. Most of the population lives in lower elevations dominated by hazardous chaparral shrublands susceptible to frequent high-intensity crown fires.

In California, as elsewhere, the two primary mechanisms altering fire regimes are fire suppression, resulting in fire exclusion, and increased anthropogenic ignitions, resulting in abnormally high fire frequencies (Keeley and

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Fotheringham 2003), though climate change, vegetation manipulation, and other indirect factors may also play a role (Lenihan et al. 2003, Sturtevant et al. 2004). For most of the 20th century, fire suppression effectively excluded fire from many western U.S. forest ecosystems, such as ponderosa pine. In these ecosystems, fire exclusion contributed to unnatural fuel accumulation and increased tree density (Veblen et al. 2000, Allen et al. 2002, Gray et al. 2005). Recently, when wildfires have hit many of these forests, hazardous fuel loads have contributed to high-intensity crown fires that are considered outside the historical range of variability (Stephens 1998). While these patterns are widely applicable to many forested landscapes in the western United States, California chaparral shrublands have experienced such substantial human population growth and urban expansion that the increase in ignitions, coupled with the most severe fire weather in the country (Schroeder et al. 1964), have acted to offset the effects of suppression to the point that fire frequency exceeds the historic range of variability (Keeley et al. 1999). Because anthropogenic ignitions tend to be concentrated near human infrastructure, more fires now occur at the urban fringe than in the backcountry (Pyne 2001, Keeley et al. 2004). Profound impacts on land cover condition and community dynamics are possible if a disturbance regime exceeds its natural range of variability, and altered fire regimes can lead to cascading ecological effects (Landres et al. 1999, Dale et al. 2000). For example, too-frequent fire can result in habitat loss and fragmentation, shifting forest composition, reduction of small-mammal populations, and accompanying loss of predator species (Barro and Conard 1991, DellaSalla et al. 2004).

Landscape-level interactions between human activities and natural dynamics tend to be spatially concentrated at the wildland–urban interface (WUI; see Plate 1), which is the contact zone in which human development intermingles with undeveloped vegetation (Radeloff et al. 2005). The WUI has received national attention because housing developments and human lives are vulnerable to fire in these locations and because anthropogenic ignitions are believed to be most common there (Rundel and King 2001, USDA and USDI 2001). The majority of WUI fire research has focused on strategies to protect lives and structures (e.g., Cohen 2000, Winter and Fried 2000, Winter et al. 2002, Shindler and Toman 2003) or on the assessment of fire risk using biophysical or climate variables that influence fire behavior (Bradstock et al. 1998, Fried et al. 1999, Haight et al. 2004). However, it is also important to understand how the WUI itself (or other indicators of human activity) affects fire and to quantify the spatial relationships between human activities and fire (Duncan and Schmalzer 2004).

The influence of proximity to the WUI and other human infrastructure appears to vary markedly with region. In the northern Great Lakes states, areas with higher population density, higher road density, and lower distance to nonforest were positively correlated with fire (Cardille et al. 2001). Also, in southern California, a strong positive correlation between population density and fire frequency was reported (Keeley et al. 1999). However, no relationship between housing count and fire was found in northern Florida counties (Prestemon et al. 2002); population density and unemployment were positively related, and housing density and unemployment were negatively related to fire in a different analysis of Florida counties (Mercer and Prestemon 2005). A negative relationship between housing density and fire was also found in the Sierra Nevada Mountains of California (CAFRAP 2001).

In addition to potential regional differences, it is also difficult to draw general conclusions from these studies because they used different indicators of human activities, their data sets differed in spatial and temporal scale, and they were conducted in small areas where ranges of variability in both fire frequency and level of development were limited. Human–fire relationships may also vary based on factors that were not accounted for, such as pattern of development. Another explanation for the discrepancy is that relationships between human activities and fire may be nonlinear in that humans may affect fire occurrence positively or negatively, depending on the level of influence. These nonlinear effects were apparent in data from a recent study in the San Francisco Bay region, where population growth was positively related to fire frequency over time up to a point, but then fire frequency leveled off as population continued to increase (Keeley 2005).

Whether positive or negative, the significance of the relationships between human activities and fire that were detected in previous studies stresses the importance of further exploring links between anthropogenic and environmental factors and their relative influence on wildfire patterns across space and time. Therefore, our research objective was to quantify relationships between human activities and fire in California counties using temporally and spatially rich data sets and regression models. Although fire regimes encompass multiple characteristics, including seasonality, intensity, severity, and predictability, we restricted our analysis to questions about fire frequency and area burned to determine: (1) what the contemporary relationship between human activities and fire is; (2) how human activities have influenced change in fire over the last 40 years; and (3) whether fire frequency and area burned vary nonlinearly in response to human influence.

Humans are responsible for igniting the fires that burn the majority of area in California (Keeley 1982); therefore, we expected our anthropogenic explanatory variables to significantly explain fire activity on the current landscape and over time. In addition to population density (which simply quantifies the number of people in an area), we expected the spatial pattern of human development (indicated by housing density and

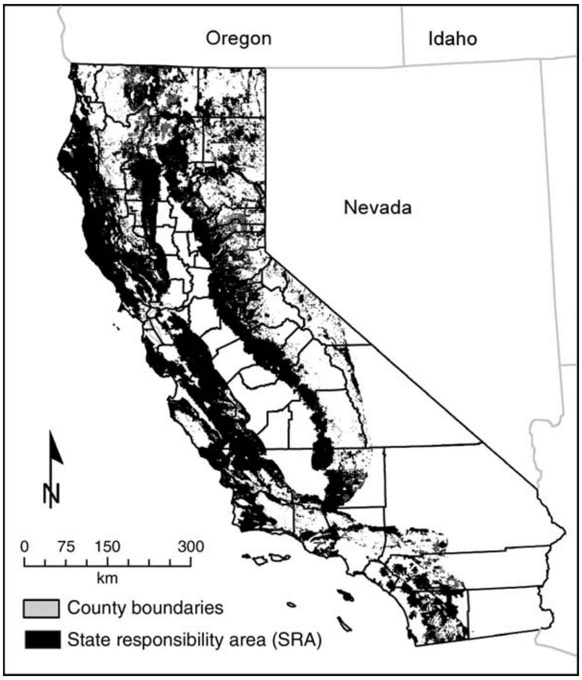

FIG. 1. Map of California Department of Forestry and Fire Protection (CDF) state responsibility areas (SRAs) within county boundaries of California, USA.

land cover combinations and distance variables) to be an important influence on fire because we assumed that anthropogenic ignitions are most likely to occur where human presence is greatest. We also expected that the relationships between human activities and fire would be both positive and negative because humans ignite fires, but development patterns affect fuel continuity and the accessibility of fire suppression resources. Finally, we included several environmental variables in the analysis because we expected the human relationships to be mediated by these other biophysical variables that shape the pattern and frequency of fire (Wells et al. 2004).

METHODS

Study area

California is the second largest state in the continental United States and is the most populous and physically diverse. Most of the state has a mediterranean climate, which, along with a heterogeneous landscape, contributes to tremendous biodiversity (Wilson 1992). Because the state contains a large proportion of the country's endangered species, it is considered a "hotspot" of threatened biodiversity (Dobson et al. 1997). There is extensive spatial variation in human population density: large areas in the north are among the most sparsely populated in the country, but metropolitan regions in the south are growing at unprecedented rates (Landis and Reilly 2004). Much of the landscape is highly fire-prone, but fire regimes vary, and fire management is divided among many institutions. Humans have altered California's fire regimes, and its fire-related financial losses are among the highest in the country (Halsey 2005).

Data

Dependent variables: fire statistics.—We assembled our fire statistics from the California Department of Forestry and Fire Protection (CDF; Sacramento, California, USA) annual printed records, which included information on all fires for which the CDF took action between 1931 and 2004. For all state responsibility areas (SRA; Fig. 1), fire statistics are recorded by county and include numbers by size class, total area burned, vegetation type, and cause. Because the statistics did not include spatially explicit information on individual fires, we weighted the data by the area within the SRA in each county by calculating proportions to use as our dependent variables. These fire statistics were substantially more comprehensive than the readily available electronic Statewide Fire History Database, which excludes most fires <40 ha, which in many counties represents >90% of the fires. Although both anthropogenic and lightning ignitions would be important to consider for fully understanding fire patterns in other regions (e.g., Marsden 1982), humans were responsible for ~95% of both the number of fires and area burned in California in the last century. We restricted our analysis to these anthropogenic fires because our focus was on human relationships with fire. Although the fire statistics were not spatially explicit, we developed GIS grids at 100-m resolution to derive data for all of the explanatory variables. The data for these explanatory variables were only extracted and averaged from within the SRA boundaries corresponding to the fire data.

Out of the 58 counties in California, we had fire statistics for 54 of them for the year 2000. Therefore, to assess the contemporary relationship between fire and human activities (hereafter referred to as the "contemporary analysis"), we analyzed the data from these counties using the annual number of fires and area burned as our dependent variables (Table 1).

Based on a preliminary exploration of the fire history data (averaged across all counties), we observed two distinct trends during the last 50 years. First, the number of fires substantially increased until 1980 and then decreased until 2000; and second, the average area burned changed inversely to the number of fires, but the differences over time were less dramatic and not statistically significant (Fig. 2). Considering these trends, we broke the historic analysis into two equal time periods (1960–1980 and 1980–2000) to compare the relative influence of the explanatory variables on both the increase (i.e., from 1960 to 1980) and decrease (from 1980 to 2000) in fire activity. The year 1980 is used to compute differences for both time periods because the census data that formed the basis for many of our explanatory variables were only available by decade. We averaged the number of fires and the area burned for 10-

TABLE 1. Variables analyzed in the regression models.

Variable	Source	Processing
2000 data		
Dependent variables		
Number of fires	CDF	proportion in SRA, square-root transformed
Area burned	CDF	proportion in SRA, square-root transformed
Explanatory variables		
Human		
Intermix WUI	SILVIS	proportion in SRA
Interface WUI	SILVIS	proportion in SRA
Low-density housing	SILVIS	proportion in SRA
Distance to intermix WUI	SILVIS	mean Euclidean distance in SRA
Distance to interface WUI	SILVIS	mean Euclidean distance in SRA
Population density	SILVIS	proportion in SRA
Road density	TIGER	mean km/km^2 in SRA
Distance to road	TIGER	mean Euclidean distance in SRA
Biophysical		
Ecoregion	CDF	discrete class
Vegetation type	CDF	area burned in vegetation type/area burned in SRA
Historic data, 1960–1980 and 1980–2000		
Dependent variables		
Change in number of fires	CDF	difference between decadal averages, proportion in SRA, square-root transformed
Change in area burned	CDF	difference between decadal averages, proportion in SRA, square-root transformed
Explanatory variables		
Human		
Change in housing density	SILVIS	difference between decades
Change in distance to low-density housing	SILVIS	difference between mean Euclidean distance in SRA
Initial housing density	SILVIS	mean housing density in either 1960 or 1980
Initial distance to low-density housing	SILVIS	mean Euclidean distance in SRA in either 1960 or 1980
Biophysical		
Ecoregion	CDF	discrete class
Vegetation type	CDF	mean area burned in vegetation type/area burned in SRA over time period

Notes: Key to abbreviations: WUI, wildland–urban interface; SRA, state responsibility area. Sources are as follows: CDF, California Department of Forestry and Fire Protection, Sacramento, California, USA, *unpublished data*; SILVIS, Radeloff et al. (2005); TIGER, U.S. Census Bureau (2000).

year time periods that bracketed the dates of the census data (e.g., 1955–1964 [1960], 1975–1984 [1980], 1995–2004 [2000]) and then calculated the difference in averages from the 1960–1980 and 1980–2000 periods for our dependent variables (Table 1). By averaging the fire data, we smoothed some of the annual variability that may have occurred due to stochastic factors such as weather.

Explanatory variables: housing data.—Data for most of the anthropogenic variables were available through a nationwide mapping project that produced maps of the WUI in the conterminous United States using housing density data from the 1990 and 2000 U.S. Census (U.S. Census Bureau 2002) and land cover data from the USGS National Land Cover Dataset (Radeloff et al. 2005). The maps were produced at the finest demographic spatial scale possible, the 2000 decennial census blocks. The vegetation data were produced at 30-m resolution. These maps delineated two types of WUI in accordance with the Federal Register definition (USDA and USDI 2001). "Intermix WUI" is defined as the intermingling of development with wildland vegetation; the vegetation is continuous and occupies >50% of the area. "Interface WUI" is defined as the situation in which development abuts wildland vegetation; there is <50% vegetation in the WUI, but it is within 2.4 km of an area that has >75% vegetation. In both types of WUI communities, housing must meet or exceed a density of more than one structure per 16 ha (6.17 housing units/km^2). Interface WUI tends to occur in buffers surrounding higher-density housing, whereas intermix WUI is more dispersed across the landscape (Fig. 3A, B).

The WUI data were only produced for 1990 and 2000 due to the lack of historic land cover data, but housing density data were available from 1960 to 2000. Historic housing density distribution was estimated using back-casting methods to allocate historic county-level housing unit counts into partial block groups (as described in Hammer et al. 2004). We used both intermix and interface WUI as explanatory variables (proportions within the county SRAs) in the current analysis to evaluate how these different patterns of vegetation and housing density affected fire activity. We also used low-density housing (housing density $\geq$6.17 housing units/km^2 and <49.42 housing units/km^2) to determine whether it could act as a substitute for WUI as an explanatory variable in the historic analysis (Table 1).

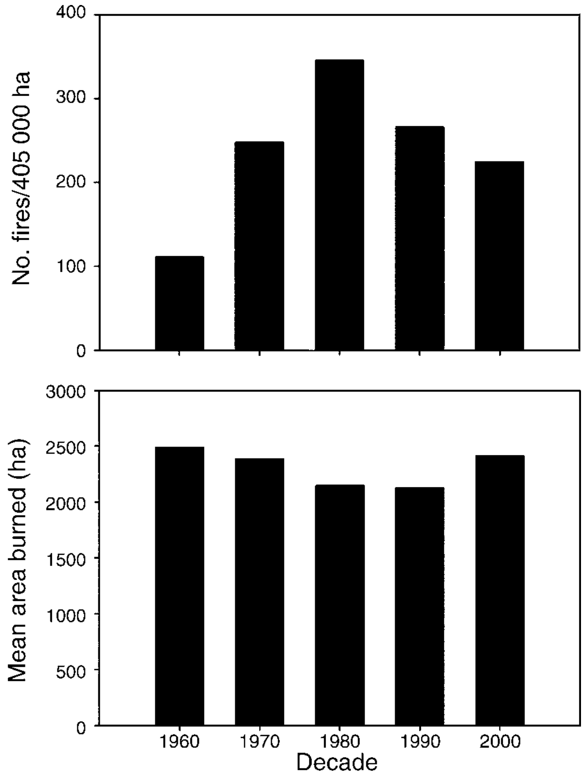

FIG. 2. Trends in number of fires and area burned for all land in the state responsibility areas (SRAs) in California from 1960 to 2000.

Looking at an overlay of fire perimeters from the electronic Statewide Fire History Database (from the last 25 years; *available online*)[7] on the WUI data, it was apparent that many fires occurred close to the WUI, but not necessarily within the WUI (Fig. 3C, D). Therefore, we calculated the mean distance to intermix and interface WUI to evaluate as explanatory variables (Table 1). These means were calculated by iteratively determining the Euclidean distances from every grid cell in the county SRA boundaries and then averaging the distances across all cells to determine means for the counties. We also included population density data from the 2000 Census.

For the historic analysis, we calculated changes in mean housing density and mean distance to low-density housing between the 1960–1980 and 1980–2000 periods to relate to change in the dependent variables. We excluded the proportion of low-density housing from our analysis because it was highly correlated with mean housing density ($r = 0.84$). Unlike the historical fire data that switched in their direction of change over time, housing density continued to increase while the mean distance to low-density housing continued to decline (Fig. 4). We included the initial values of these data (e.g., 1960 and 1980) to account for the fact that the same magnitude of change may have different effects on the dependent variables depending on the starting value of the explanatory variables (Table 1).

Explanatory variables: road data.—The quality of road data can vary according to data source (Hawbaker and Radeloff 2004), so we compared the U.S. Geological Survey digital line graph (DLG; U.S. Geological Survey 2002) and the US TIGER 2000 GIS (U.S. Census Bureau 2000) layers of roads to determine whether there were substantial differences that could affect the interpretation of the results. After calculating and summarizing road density by county, we found a strong positive correlation ($r = 0.97$). Therefore, we used the TIGER data because they were produced in 2000, the same year as the contemporary analysis. The more current TIGER data generally capture new development that might not be included in the DLG data. We evaluated mean road density and mean distance to roads in the current analysis (Table 1), but road data were unavailable for the historic analysis.

Explanatory variables: environmental.—In the absence of human influence, fire behavior is primarily a function of biophysical variables (Pyne et al. 1996, Rollins et al. 2002). These can vary widely across a county, but ecoregions capture broad differences by stratifying landscapes into unique combinations of physical and biological variables (ECOMAP 1993). Our ecoregion data were the geographic subdivisions of California defined for The Jepson Manual (Hickman 1993), designated through broadly defined vegetation types and geologic, topographic, and climatic variation (Fig. 5).

Because vegetation type influences the ignitability of fuel and the rate of fire spread (Bond and van Wilgen 1996, Pyne et al. 1996), we also evaluated the proportion of area burned within three broad vegetation types: shrubland, grassland, and woodland (Fig. 5). Differences in fire regimes between broadly defined vegetation types can be striking, particularly between shrubland and woodland in southern California (Wells et al. 2004). The CDF fire statistics included information on the proportion of area burned in these vegetation types. For the historic analysis, we averaged the proportion of fires burned within different vegetation types over the entire decade (Table 1).

Analytical methods

Diagnostics and data exploration.—Before developing regression models, we examined scatter plots for each variable. Nonlinear trends were apparent (e.g., Fig. 6), suggesting that we needed to include quadratic terms for the explanatory variables in the regressions. Unequal variances in the residual plots prompted us to apply a square-root transformation to the dependent variables. We also plotted semivariograms of the models' residuals (using centroids from the SRA boundaries) and found no evidence of spatial autocorrelation. To check for

[7] ⟨http://frap.cdf.ca.gov/data/frapgisdata/select.asp⟩

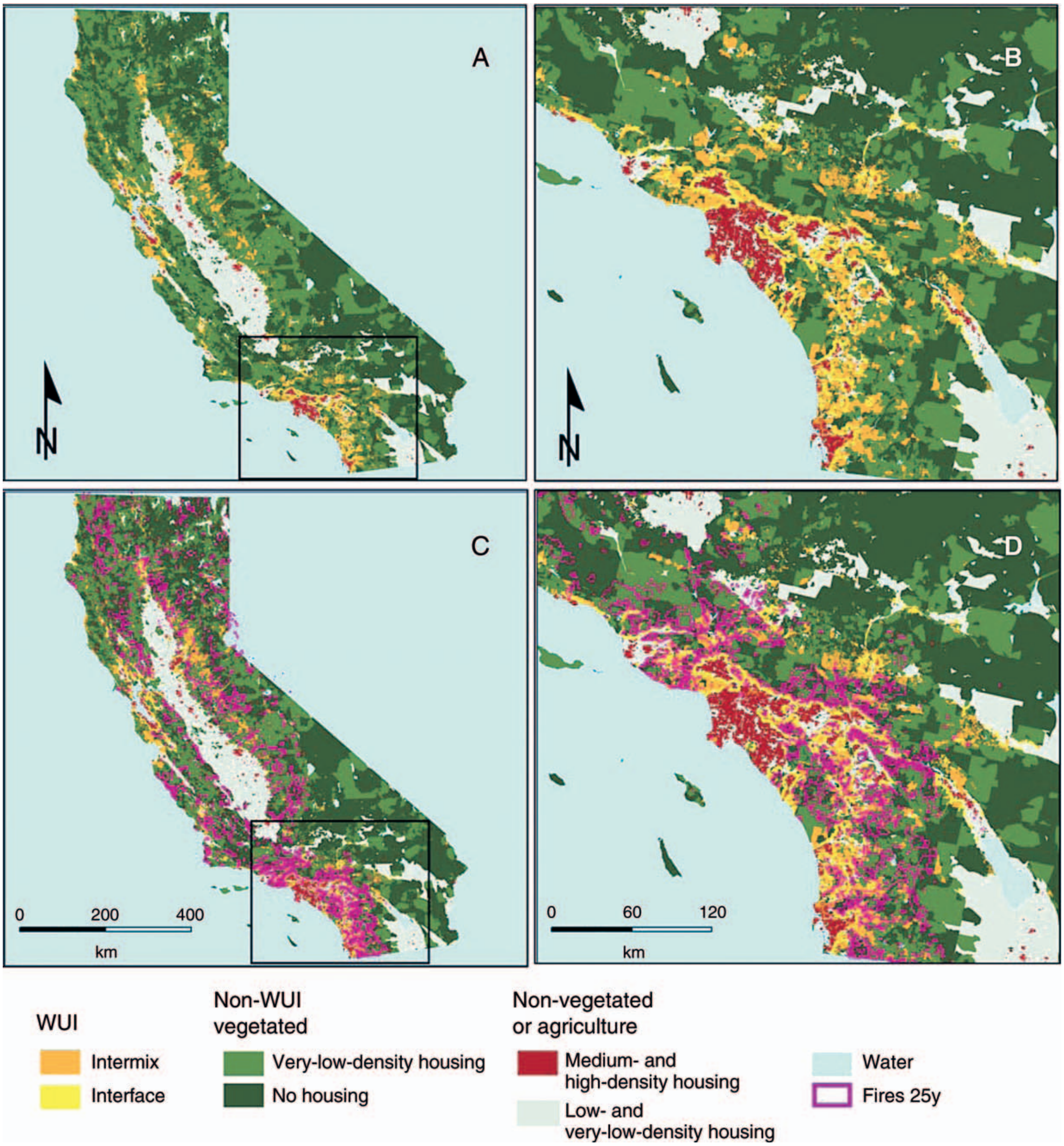

FIG. 3. The wildland–urban interface (WUI) in 2000 with and without fire perimeter overlays (from 1979 to 2004) in (A, C) California and (B, D) southern California. Housing density is defined as follows: very low, >0–6.17 housing units/km^2; low, 6.17–49.42 housing units/km^2; medium, 49.42–741.31 housing units/km^2; and high, >741.31 housing units/km^2 (USDA and USDI 2001). "Fires 25y" refers to 25 years of fire perimeters, from 1980 to 2005.

multicollinearity, we calculated the correlation coefficients between all of the explanatory variables and only included noncorrelated variables ($r \leq 0.7$) in the multiple regression models.

The areas of CDF jurisdiction for each county varied slightly over time. Therefore, we compared separate regressions from the full historic data set ($n = 37$) to a subset of the data excluding counties that experienced a greater than 20% change in area over time ($n = 23$). For both the 1960–1980 regressions and the 1980–2000 regressions, every one of the explanatory variables that was significant in the subset was also significant in the full data set, with very similar R^2 values; therefore, we felt confident proceeding with the full data set for the historic analysis because we had greater power with the larger sample size.

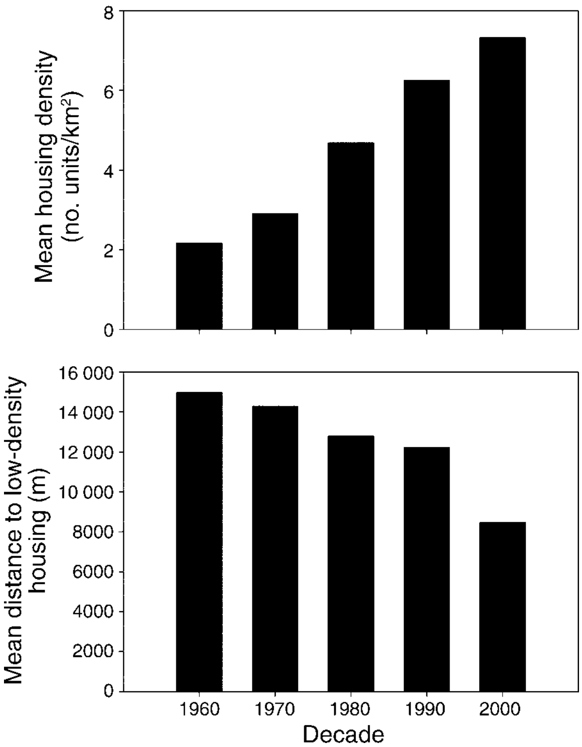

FIG. 4. Trends in housing density and distance to low-density housing (6.17–49.42 housing units/km^2) for all land in the state responsibility areas (SRAs) in California from 1960 to 2000.

Statistical analysis

We used the same regression modeling approach for both the current and historic analyses. First, we developed bivariate regression models for all of the explanatory variables and their quadratic terms so that we could evaluate their independent influence on fire frequency and area burned. To account for the interactions between variables (and their quadratic terms), we also built multiple regression models using the R statistical package (R Development Core Team 2005). For all models, we first conducted a full stepwise selection analysis (both directions) using Akaike Information Criteria to identify the best combination of predictor variables (Burnham and Anderson 2002). Some of the models retained a quadratic term without including the lower-order variable. In these models, we added the lower-order term, rebuilt the model, and then proceeded with a backwards elimination process until all predictor variables in the model were significant with P values ≤ 0.05.

RESULTS

Current analysis

Bivariate regressions.—Many of the anthropogenic variables were highly significant in explaining the number of fires in 2000. The quadratic term for each of these variables was also significant, and the direction of influence was both positive and negative (Fig. 7). Compared to the other variables, population density explained the greatest amount of variability. The proportion of intermix WUI and low-density housing in the counties also explained significant variation in the number of fires; but the proportion of interface WUI was insignificant. The number of fires was significantly related to the mean distance to both types of WUI, but neither of the road variables was significant. All three vegetation types, particularly shrubland, significantly influenced the number of fires, but ecoregion was insignificant.

For the anthropogenic variables, the number of fires was highest at intermediate levels of population density (from ~35 to 45 people/km^2; Fig. 6), proportion of intermix WUI (~20–30% in the county), and proportion of low-density housing (~25–35% in the county). It was also highest at the shortest distances to intermix and interface WUI, but started to level off at ~9–10 km for intermix (Fig. 6) and 14–15 km for interface WUI.

Unlike the number of fires, none of the anthropogenic variables were significantly associated with the area burned in 2000. In fact, shrubland was the only variable that explained significant variation in area burned.

Multiple regression.—When all of the variables were modeled in the multiple regressions, the resulting model for number of fires in 2000 included population density, the proportion of intermix WUI and its quadratic term, grassland and its quadratic term, and shrubland (Table 2). The model was highly significant with an adjusted R^2 value of 0.72.

The multiple regression model for area burned in 2000 included distance to road, shrubland, and woodland, and all three variables had significant positive relationships (no quadratic terms were retained). This model was also highly significant with an adjusted R^2 of 0.50.

Historical analysis 1960–1980

Bivariate regressions.—Change in the number of fires (net increase) from 1960 to 1980 was significantly explained by each of the human-related variables except for change in the mean distance to low-density housing (Fig. 8). The quadratic term was also significant in the separate models, except for the initial distance to low-density housing (in 1960), which had a negative influence on the change in number of fires. Change in number of fires was also significantly related to ecoregion and shrubland vegetation.

The only three variables with significant influence on the change in area burned (net decrease) were the three vegetation types.

Multiple regression.—The explanatory variables that were retained in the multiple regression model for change in the number of fires from 1960 to 1980 included mean housing density in 1960 and its quadratic term, grassland vegetation, and ecoregion (Table 2). The adjusted R^2 value was highly significant at 0.72.

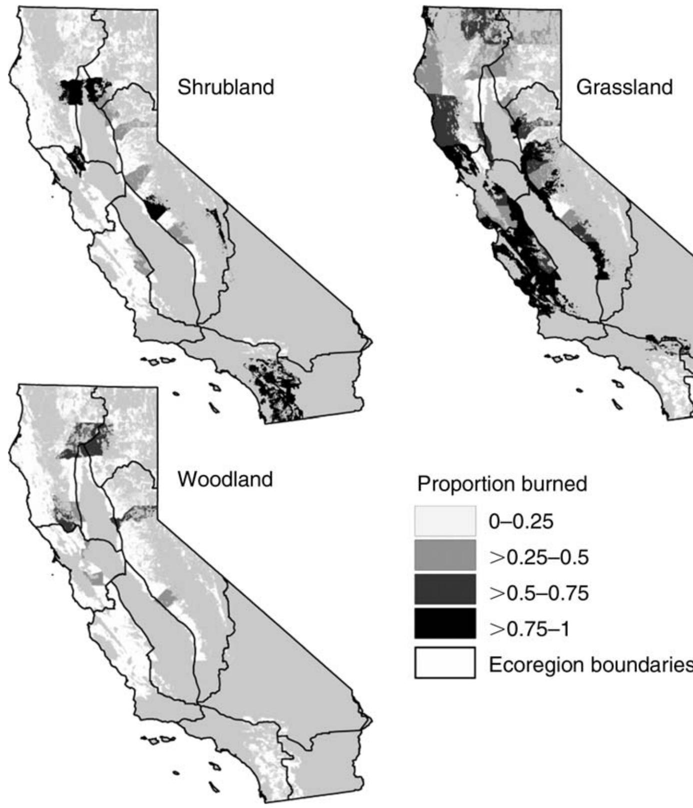

FIG. 5. Maps showing ecoregion boundaries and the proportion of area burned in shrubland, grassland, and woodland in 2000.

Mean housing density in 1960 was positively associated with change in area burned from 1960 to 1980, and the distance to low-density housing had first a positive, then a negative influence because the quadratic term was included. Other variables retained in the multiple regression model included shrubland and its quadratic term, grassland, woodland, and ecoregion.

Historical analysis 1980–2000

Bivariate regressions.—Initial housing density (in 1980) was the only significant explanatory variable explaining change in number of fires (net decrease) from 1980 to 2000 (Fig. 9). Woodland vegetation was the only significant variable out of the separate models explaining change in area burned from 1980 to 2000 (net increase). The quadratic terms were significant for both of these models.

Multiple regression.—The multiple regression model explaining change in number of fires from 1980 to 2000 included change in housing density, initial housing density (in 1980), and woodland vegetation; the quadratic term was also significant for these three variables (Table 2). Although the model was significant, the R^2 was substantially lower than the 1960–1980 model, at 0.26.

The multiple regression model explaining change in area burned included initial housing density (in 1980) and its quadratic term, initial distance to low-density

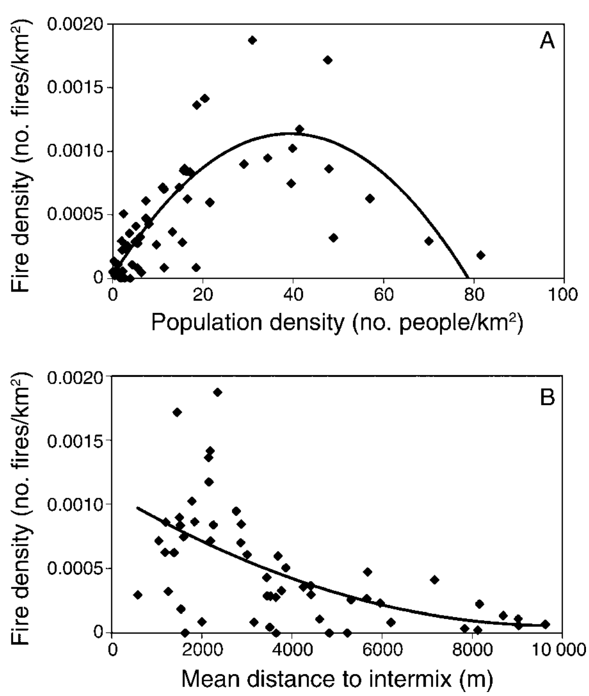

FIG. 6. The relationships between (A) the proportion of the number of fires and population density and (B) the proportion of the number of fires and mean distance to intermix wildland–urban interface (WUI).

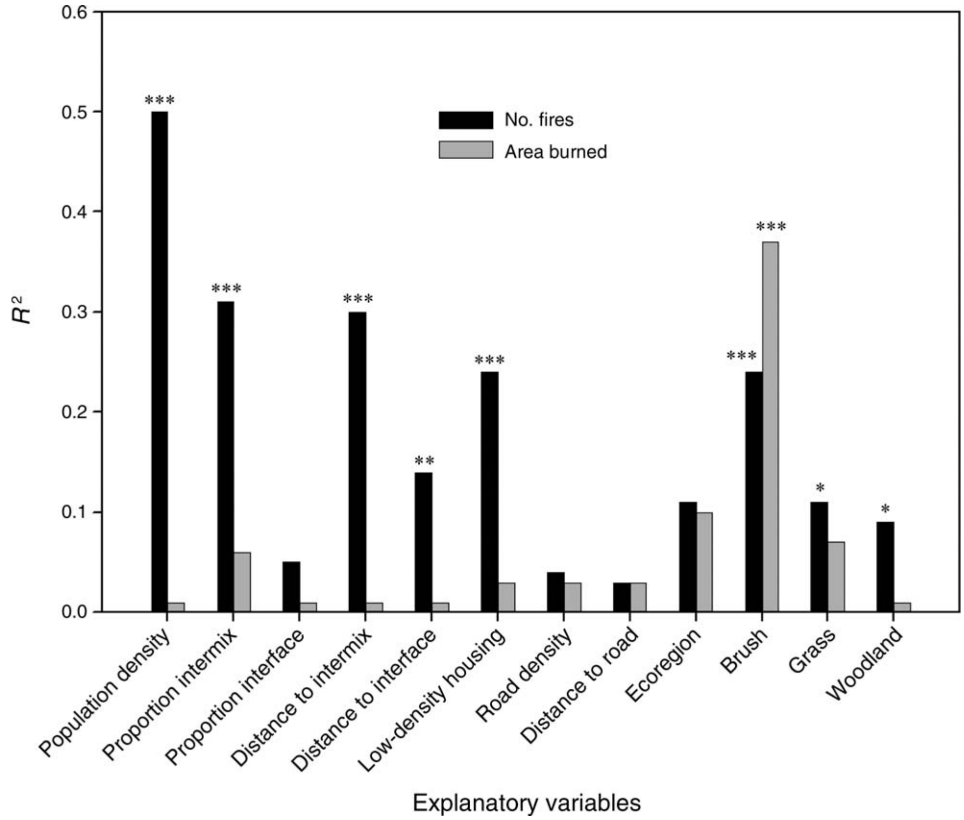

FIG. 7. R^2 values and significance levels for the explanatory variables in the bivariate regression models for number of fires and area burned in 2000.
* $P < 0.05$; ** $P < 0.01$; *** $P < 0.001$.

housing, woodland vegetation and its quadratic, and ecoregion. This model had better explanatory power than the number of fires model, with an R^2 of 0.41.

DISCUSSION

The expression of fire on a landscape is influenced by a combination of factors that vary across spatial and temporal scales and involve both physical and biological characteristics. Fire behavior has long been viewed as a largely physical phenomenon illustrated by the classic fire environment triangle that places fire as a function of weather, fuels, and topography (Countryman 1972), but clearly the human influence on modern fire regimes must also be understood to meet fire management needs (DellaSalla et al. 2004). We first asked what the current relationship is between human activities and fire in California and found that humans and their spatial distribution explained a tremendous proportion of the variability in the number of fires, but that area burned was more a function of vegetation type. Anthropogenic ignitions are the primary cause of fire in California and were the focus of our analysis, so we were not surprised by the strong human influence. Nevertheless, the high explanatory power of the models underscores the importance of using locally relevant anthropogenic factors as well as biophysical factors in fire risk assessments and mapping. The models also identify which indicators of human activity are most strongly associated with fire in California. For number of fires, the proportion of intermix WUI explained more variation than any other variable except for population density, suggesting that the spatial pattern of housing development and fuel are important risk factors for fire starts.

Human-caused ignitions frequently occur along transportation corridors (Keeley and Fotheringham 2003, Stephens 2005), so it was surprising that neither road density nor average distance to road were significant in explaining fire frequency. Although roads are important in local-scale ignition modeling, detecting their influence on fire ignitions may be difficult at an aggregated, county level since they are narrow, linear features. On the other hand, distance to roads was the only anthropogenic variable associated with area burned, having a positive influence when grassland and shrubland were also accounted for in the multiple regression model, which may reflect the difficulty of fire suppression access contributing to fire size.

Humans influence fire frequency more than area burned because anthropogenic ignitions are responsible

TABLE 2. Variables retained in the multiple regression models for the current and historic analyses.

Analysis and explanatory variable	Coefficient and intercept	P
Current		
2000		
No. fires		
Population density	0.0006	<0.01
Proportion intermix	0.0702	<0.01
(Proportion intermix)^2	−0.2629	<0.01
Grassland	0.0496	<0.01
(Grassland)^2	−0.0441	<0.01
Shrubland	0.0093	0.02
Overall model (adjusted R^2: 0.72)	0.0001	<0.01
Area burned		
Distance to road	0.00004	<0.01
Shrubland	0.0833	<0.01
Woodland	0.0559	<0.01
Overall model (adjusted R^2: 0.50)	−0.0052	<0.01
Historic		
1960–1980		
No. fires		
Initial housing	2.7649	<0.01
(Initial housing)^2	−0.1523	<0.01
Grassland	4.6311	0.05
Ecoregion	...†	<0.01
Overall model (adjusted R^2: 0.72)	0.6443	<0.01
Area burned		
Initial housing	0.0188	<0.01
Initial distance	0.00002	<0.01
(Initial distance)^2	-2×10^{-10}	<0.01
Shrubland	−0.3641	0.12
(Shrubland)^2	0.8778	0.01
Grassland	0.0371	<0.01
Woodland	0.0449	0.01
Ecoregion	...†	0.03
Overall model (adjusted R^2: 0.51)	−0.373	<0.01
1980–2000		
No. fires		
Change housing	3.0666	0.01
(Change housing)^2	−0.2661	0.01
Initial housing	−1.8269	0.01
(Initial housing)^2	0.0505	0.03
Woodland	38.1957	0.03
(Woodland)^2	−107.0112	0.02
Overall model (adjusted R^2: 0.26)	−1.894	0.01
Area burned		
Initial housing	−0.0114	0.01
(Initial housing)^2	0.0003	0.05
Initial distance	−0.000003	<0.01
Woodland	0.0292	0.18
(Woodland)^2	−1.2831	0.02
Ecoregion	...†	0.05
Overall model (adjusted R^2: 0.41)	0.0409	<0.01

† Coefficients are not listed for categorical variables.

for fire initiation, but fire spread and behavior is ultimately more a function of fuel availability and type (Bond and van Wilgen 1996, Pyne et al. 1996). Yet humans do have some control over fire size through suppression and, indirectly, through fuel connectivity (Sturtevant et al. 2004), although fires are extremely difficult to suppress in California shrublands under high-wind conditions that typify the most destructive fires (Keeley and Fotheringham 2003). Therefore, human effects on area burned may cancel one another out to some extent because fire suppression can minimize the increase in area burned that would result from increased ignitions, at least at the WUI. Fire suppression resources are more likely to be concentrated on structural protection in developed areas (Calkin et al. 2005), which would explain the positive relationship between area burned and distance to road. Roads can serve as firebreaks and can also provide access routes for firefighters.

The inclusion of vegetation type in the multiple regression models illustrates that, despite the strong influence of humans, fire occurrence remains a function

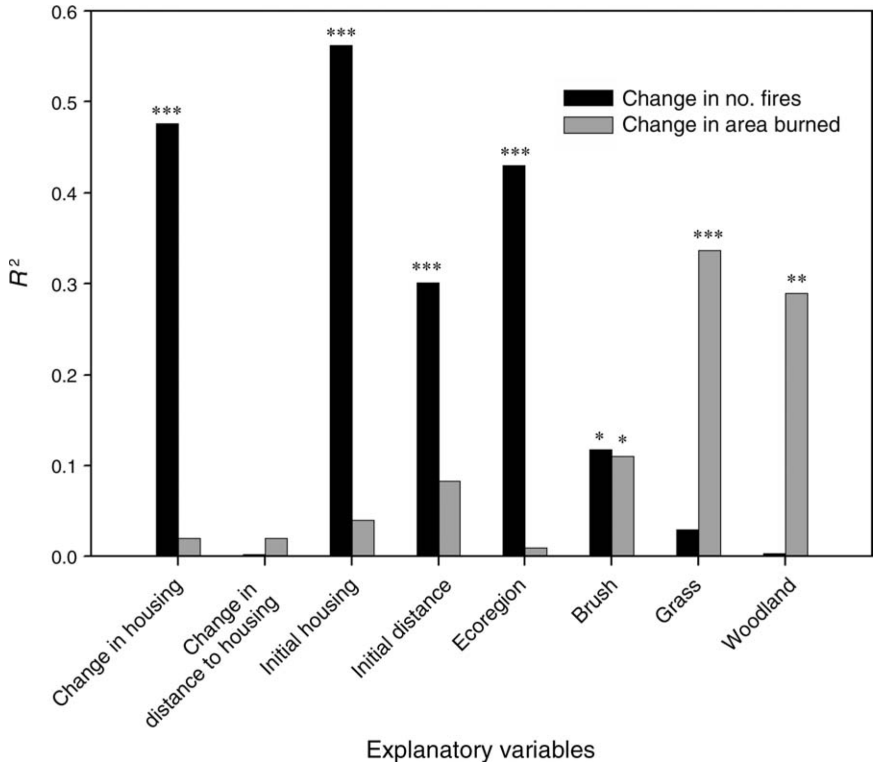

FIG. 8. R^2 values and significance levels for the explanatory variables in the bivariate regression models for number of fires and area burned from 1960 to 1980.
* $P < 0.05$; ** $P < 0.01$; *** $P < 0.001$.

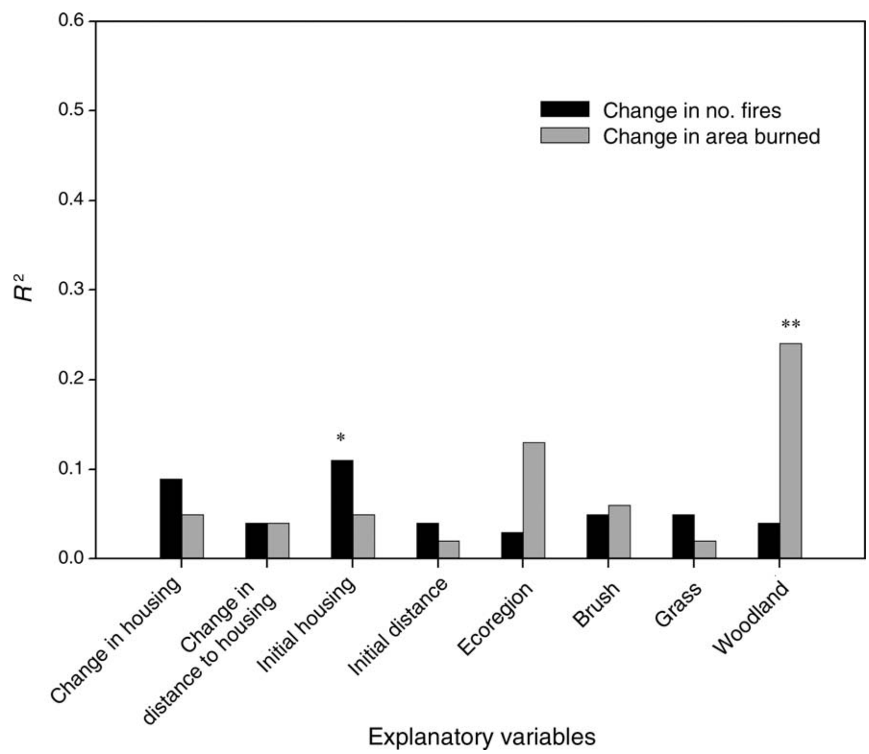

FIG. 9. R^2 values and significance levels for the explanatory variables in the bivariate regression models for number of fires and area burned from 1980 to 2000.
* $P < 0.05$; ** $P < 0.01$; *** $P < 0.001$.

PLATE 1. (Left) Wildland–urban interface (WUI) and (right) burned-over fuel break, both at the eastern end of Scripps Ranch (San Diego County, California, USA) after the autumn 2003 Cedar Fire (largest fire in California since the beginning of the 20th century). Photo credits: J. E. Keeley.

of multiple interacting social and environmental variables. For number of fires and area burned, shrubland had the strongest explanatory power of the vegetation types. Chaparral and coastal sage scrub are both extremely fire-prone vegetation types and high human population density tends to be distributed in these types; other studies have shown that they have experienced a higher rate of burning than other vegetation types in the southern part of the state in the last century (Keeley et al. 1999, Keeley 2000, Wells et al. 2004). Increased ignitions in highly flammable vegetation types can lead to very hazardous conditions (Halsey 2005).

The second question we asked was "How do human activities relate to change in fire?" In the last 40 years, the most substantial change was the increase in number of fires from 1960 to 1980. The decrease in number of fires was less dramatic between 1980 and 2000; and the change in area burned was relatively small in both time periods. Housing development patterns were most influential when change was greatest, from 1960 to 1980, and for trends in fire frequency (vs. area burned).

Although anthropogenic influence was partially responsible for the change in area burned, the apparent inverse relationship between change in fire frequency and change in area burned may be spurious. In other words, the explanation for a decrease in number of fires may be independent of the concurrent increase in area burned. Trends in area burned are naturally cyclic due to broad-scale factors such as climate. Recent research has shown that change in climate was a major factor driving fire activity in the western United States in the last several decades (Westerling et al. 2006); however, that research was restricted to large montane fire events on federally owned land above 1370 m. Therefore, while climate change may have played some role in our observed change in area burned, we cannot extend those results to our analysis because we included fires of all sizes under multiple land ownership classes, and historical fire patterns in the lower elevations do not correspond to patterns in montane forests (Halsey 2005).

Fire both constrains and is constrained by the fuel patterns it creates, resulting in cycles of fire activity and temporal autocorrelation in area burned, in part because young fuels are often less likely to burn (Malamud et al. 2005). Temporal autocorrelation effects vary with ecosystem, fuel type, and the area of analysis; but in all vegetation types, temporal dependence diminishes over time due to post-fire recovery. Therefore, we assumed that the effects would be low in our study because we were looking at change over 20-year time periods. Furthermore, the chaparral vegetation that dominates much of California recovers very quickly following fire, meaning that the effect of temporal autocorrelation in this vegetation type would last for only brief periods of time. Also, under extreme weather conditions, young age classes are capable of carrying fires in the southern portions of California (Moritz 1997, Moritz et al. 2004).

In general, the anthropogenic influence on fire frequency and extent was complicated through the combination of positive and negative effects, which helps to answer our third question: "Do fire frequency and area burned vary nonlinearly in response to human influence?" Nonlinear effects were evident in the scatter plots and confirmed by the significance of quadratic terms in most of the models. The regression models indicate that humans were responsible for first increasing and then decreasing fire frequency and area burned. These dual influences may explain why prior studies presented conflicting results, because a positive or negative response was dependent on the level of human presence. Aside from the fact that we intentionally tested hypotheses regarding nonlinear relationships, our data also contained a wide range of human presence due to the large extent and diversity of the state of California.

The scatter plots illustrate how these human–fire relationships occurred. For both the number of fires and area burned, and in the current and historic analyses, the maximum fire values occurred at intermediate levels of human presence (as in Fig. 6A); and when human activity was either lower or higher, fire activity was lower. Initial increase in fire occurrence with increasing population is reasonable since human presence results in more ignitions. However, it appears that when human population density and development reach a certain threshold density, ignitions decline, and this is likely the result of diminished and highly fragmented open space with fuels insufficient to sustain fire. In addition, above a certain population threshold, fire suppression resources are likely to be more concentrated in the WUI. Inverse relationships were evident in the scatter plots of distance (Fig. 6B). In these, fire frequency and area burned were greatest at short distances to WUI; and at longer distances, the trend lines leveled off. These distance relationships indicate that more fires would be expected in close proximity to settled areas where ignitions are likely to occur.

The inclusion of quadratic terms in the multiple regression models supports the concept that fire frequency and area burned were dependent on the level of human activity. Initial housing density was important in all four historic multiple regression models, and initial distance to low-density housing was important in both of the historic area-burned models. The change in number of fires for both periods was also related to change in housing density, in bivariate regression models for the earlier period and in the multiple regression model for the later period (1980–2000). These results further emphasize that fire activity was a function of a certain level of human presence. In addition to the strong influence of human presence, ecoregion and vegetation types were also highly significant in the multiple regression models, suggesting that the particular level of human activity that was most influential in explaining fire activity was dependent upon biophysical context.

The primary value of the multiple regression models was to identify the most influential variables and their direction of influence when accounting for other factors. While they explained how fire activity varied according to context-dependent interactions, their purpose was not to provide a formula for determining fire risk at a landscape scale. Environmental and social conditions differ from region to region, and processes such as fire and succession are controlled by a hierarchy of factors, with different variables important at different scales (Turner et al. 1997). Nevertheless, these models provide strong evidence about the strength and nature of human–fire relationships. That these relationships are significant across a state as diverse as California suggests that human influence is increasingly overriding the biophysical template; yet, managers must account for the interactions with ecoregion and vegetation type when making management decisions. Determining the conditions (e.g., thresholds) for nonlinear anthropogenic relationships will be important to understand how fire risk is distributed across the landscape.

At the coarse scale of our analysis, we can estimate these thresholds based on the nonlinear relationships in our scatter plots (as in Fig. 6) and suggest that fire frequency is likely to be highest when population density is between 35 and 45 people/km^2, proportion of intermix WUI is ~20–30%, proportion of low-density housing is ~25–35%, the mean distance to intermix WUI is $<$9 km, and the mean distance to interface WUI is $<$14 km. Our next step is to more precisely define these relationships at scales finer than the county level (where management decisions often occur) and to understand the conditions under which human activities positively or negatively influence fire.

These results imply that fire managers must consider human influence, together with biophysical characteristics such as those represented in the LANDFIRE database, when making decisions regarding the allocation of suppression and hazard mitigation resources. If human presence is not explicitly included in decision making, inefficiencies may result, because fire occurrence is related to human presence on the landscape. In particular, we identify an intermediate level of housing density and distance from the WUI at which the effects of human presence seem to be especially damaging, i.e., a point at which enough people are present to ignite fires, but development has not yet removed or fragmented the wildland vegetation enough to disrupt fire spread. This intermediate level of development is one that large areas of the lower 48 states, particularly in the West and Southwest, will achieve in the coming decade. Hence, the WUI's location, extent, and dynamics will continue to be essential information for wildland fire management.

Conclusion

In addition to the risk to human lives and structures, changing fire regimes may have substantial ecological impacts, and the results in this analysis support the hypothesis that humans are altering both the spatial and temporal pattern of the fire regime. Although the overall area burned has not changed substantially, the distribution of fires across the landscape is shifting so that the majority of fires are burning closer to developed areas, and more remote forests are no longer burning at their historic range of variability (Pyne 2001). In either case, the ecological impacts may be devastating. Due to lack of dendrochronological information, historic reference conditions are difficult to determine in stand-replacing chaparral shrublands. Although chaparral is adapted to periodic wildfire, there is substantial evidence that fires are burning at unprecedented frequencies, and this repeated burning (at intervals closer than 15–20 years apart) exceeds many species' resilience and has already resulted in numerous extirpations (Zedler et al. 1983, Haidinger and Keeley 1993, Halsey 2005).

If present trends continue in California, the population may increase to 90×10^6 residents in the next 100 years. Recent trends in housing development patterns also indicate that growth in area and number of houses in intermix WUI has far outpaced the growth in interface WUI (Radeloff et al. 2005; Hammer et al., *in press*). Our results showing that fire frequency and area burned tend to be highest at intermediate levels of development (more typical of intermix than interface) suggest that fire risk is a function of the spatial arrangement of housing development and fuels. Therefore, in addition to more people in the region that could ignite fires, future conditions that include continued growth of intermix WUI may also contribute to greater fire risk. Land use planning that encourages compact development has been advocated to lessen the general impacts of growth on natural resources (Landis and Reilly 2004), and we suggest that reducing sprawling development patterns will also be important to the control of wildfires in California.

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