Special Issue Paper

Environmetrics

Received: 05 February 2013, Revised: 19 October 2013, Accepted: 05 December 2013, Published online in Wiley Online Library: 23 January 2014

(wileyonlinelibrary.com) DOI: 10.1002/env.2257

County-level analysis of the impact of temperature and population increases on California wildfire data

M. Baltar[a], J. E. Keeley[b,c] and F. P. Schoenberg[a]*

The extent to which the apparent increase in wildfire incidence and burn area in California from 1990 to 2006 is affected by population and temperature increases is examined. Using generalized linear models with random effects, we focus on the estimated impacts of increases in mean daily temperatures and populations in different counties on wildfire in those counties, after essentially controlling for the overall differences between counties in their overall mean temperatures and populations. We find that temperature increase appears to have a significant positive impact on both total burn area and number of observed wildfires. Population growth appears to have a much less pronounced impact on total burn area than do annual temperature increases, and population growth appears to be negatively correlated with the total number of observed wildfires. These effects are especially pronounced in the winter season and in Southern California counties.

Keywords: generalized linear models; poisson regression; random effects models; spatial-temporal statistics; wildfire

1. INTRODUCTION

The Western USA in general, and California in particular, has exhibited a noticeable increase in both wildfire frequency and total annual area burned over the past several decades (Arno and Allison-Bunnell, 2002; Westerling *et al*., 2003; Stephens, 2005; Westerling *et al*., 2006; Miller *et al*., 2009). A possible explanation for these increases is climate change, as increased temperatures may cause wildfires to ignite more easily and become more difficult to extinguish and also cause land to become increasingly arid and its vegetation flammable. In addition, as the vast majority of these wildfires are ignited as a result of human activity (Keeley, 1982), the observed increase in wildfire may in part be attributed to human population increases in California over this same time period. The goal of this paper is to determine and quantify the extent of the role played by human population and temperature increase in affecting fire frequency and area burned. To this end, we employ spatial-temporal wildfire, population, and mean temperature data in California for the 17 years spanning from 1 January 1990 to 31 December 2006, using California counties as the spatial units of analysis, and examine the estimated coefficients in generalized linear models (GLMs) in order to discern the relative impacts attributable to population and temperature change.

2. DATA

The wildfire data in this analysis were cataloged and compiled by the US Geological Survey, Western Ecological Research Center, and were provided to us by CalFire. They consist of wildfire occurrences on CalFire protected areas from 1 January 1990 to 31 December 2006. The dataset consists of several thousand wildfires and represents an accumulation of a wealth of wildfire data collected from an assortment of different sources. The wildfire dataset is perhaps exceptional in its completeness and is believed to be at least approximately complete for wildfires down to 10 ha, since 1990. Keeley (1982) analyzed historical wildfire activity in this region and estimated that 16.2% of wildfires (or 13.1% of the area burned) in this region were caused by lightning, and the remainder of the ignitions were attributable to human activities.

Wildfire burn areas appear often to be roughly Pareto or tapered Pareto distributed (Cumming, 2001; Malamud *et al*., 2005), and hence, the completeness of a wildfire dataset may be assessed by observing the extent to which the survivor function of the areas burned appears to be approximated by the tapered Pareto distribution as suggested in Schoenberg *et al*. (2003). Figure 1 shows that the wildfire sizes are well approximated by a tapered Pareto law for fires above approximately 5 ha; such fires account for over 98% of the total area burned in our time frame. The data are organized by county; for each of the 58 counties in California, we have records of all observed wildfires on CalFire protected areas occurring during the selected time period, as well as population estimates by year, and daily high temperature. Daily high

* *Correspondence to: F. Schoenberg, Department of Statistics, UCLA, Los Angeles, CA, U.S.A. frederic@stat.ucla.edu*

a *Department of Statistics, UCLA, Los Angeles, CA, U.S.A.*

b *Sequoia-Kings Canyon National Parks, US Geological Survey Western Ecological Research Center, Three Rivers, CA, U.S.A.*

c *Department of Ecology and Evolutionary Biology, UCLA, Los Angeles, CA, U.S.A.*

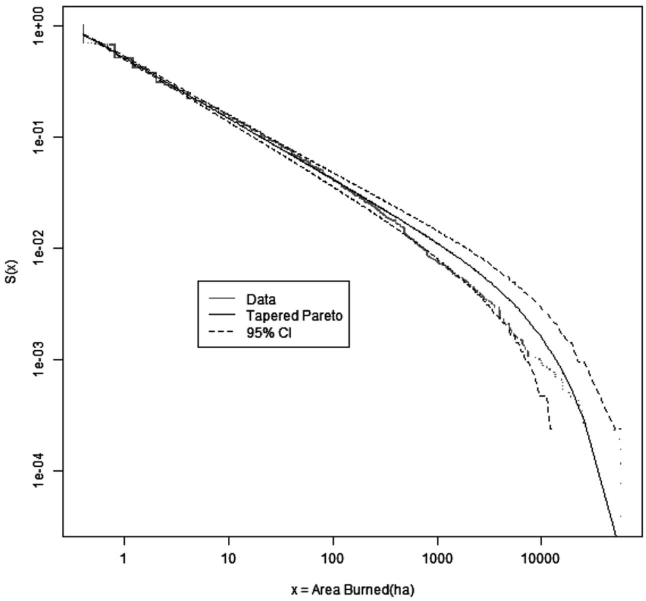

Figure 1. Observed survivor function of the areas burned in California wildfires from 1/1/1990–12/31/2006, along with the survivor function (1 – F(x)) corresponding to the tapered Pareto distribution fit by maximum likelihood

temperature records for each county were obtained from www.almanac.com/weather/history/CA, and in cases where more than one reporting station was available for a county, the average of records from those stations was used. Population data are publicly available from the California Department of Finance; see www.dof.ca.gov/research/demographic/reports/view.php. Counties with virtually no recorded wildfire activity, or containing Cal Fire lands but providing their own fire protection and thus not included in the dataset, were discarded from the analysis; these were the following nine counties: Alpine, Imperial, Los Angeles, Marin, Mono, San Francisco, Sierra, Sutter, and Ventura. The focus of this paper is on the remaining 49 counties with 9996 county-months for the analysis.

3. METHODS

Note that the results of a simple linear regression of area burned or number of fires on temperature and population would say little about the impact of temperature and population changes on wildfire, as most of the variation in the covariates would be due to overall differences in temperature and population between counties. The regression estimates would be dominated by the correlation between characteristics (average population and temperature) of the counties and wildfire activity in those counties, which is not our focus here. Instead, we seek to identify the extent to which *changes* in population and temperature, within a given county, appear to influence burn area and number of wildfires. Further, we do not wish to combine similar counties but instead leave each of the 49 counties as a separate entity so that spatial heterogeneity of the results may be investigated. We incorporate a random effects model to account for the fact that different counties will have different population sizes and mean temperatures and correspondingly quite different numbers of wildfires and area burned between them. We also include a random effect term for the month of the year to emphasize the temporal aspect of the analysis and to account for varying temperatures across seasons during the year.

A histogram of the total number of observed wildfires per county per month (Figure 2a) closely resembles the exponential distribution. Note also that observed wildfires per month must be non-negative, so a random effects regression model assuming roughly Gaussian error terms seems inappropriate. Instead, in consideration of Figure 2a, we propose the use of a random effects GLM with a log-link function, to model this response variable as a function of population growth and temperature increase. The fact that the number of observed wildfires in a county-month is count data suggests fitting a Poisson regression model in particular. The distribution of total area burned in each county-month (Figure 2b) appears similar to that of the wildfire frequency data, so we fit a Poisson GLM with a log-link when modeling the total area burned as the response variable as well. A log-link function for area burned seems appropriate considering Figure 3, where we see a roughly log-linear relationship between change in log-area burned from log-mean area burned in a county plotted against each of our two covariates, population, and temperature.

Overdispersion is frequently a concern when fitting data with Poisson models. The burn area data do exhibit this problem, having a variance considerably higher than the mean. To account for the overdispersion present in monthly burn area, we fit a model containing an observation-level random effect term (Elston *et al.*, 2001). These considerations suggest models of the form:

$$Yi_{jk} \sim \text{Poisson}\left(\exp\left\{\mu_{1i} + v_{1j} + \tau_{1ijk} + \alpha_1 P_{ij} + \beta_1 T_{ij}\right\}\right) \tag{1}$$

and

$$Z_{ijk} \sim \text{Poisson}\left(\exp\left\{\mu_{2i} + v_{2j} + \tau_{2ijk} + \alpha_2 P_{ij} + \beta_2 T_{ij}\right\}\right) \tag{2}$$

where Y and Z denote the total area burned and number of observed wildfires, respectively, index i represents the county, index j represents the month and k the year in consideration, P denotes population, and T is temperature. Parameters μ_{1i} and μ_{2i} represent the baseline for the mean

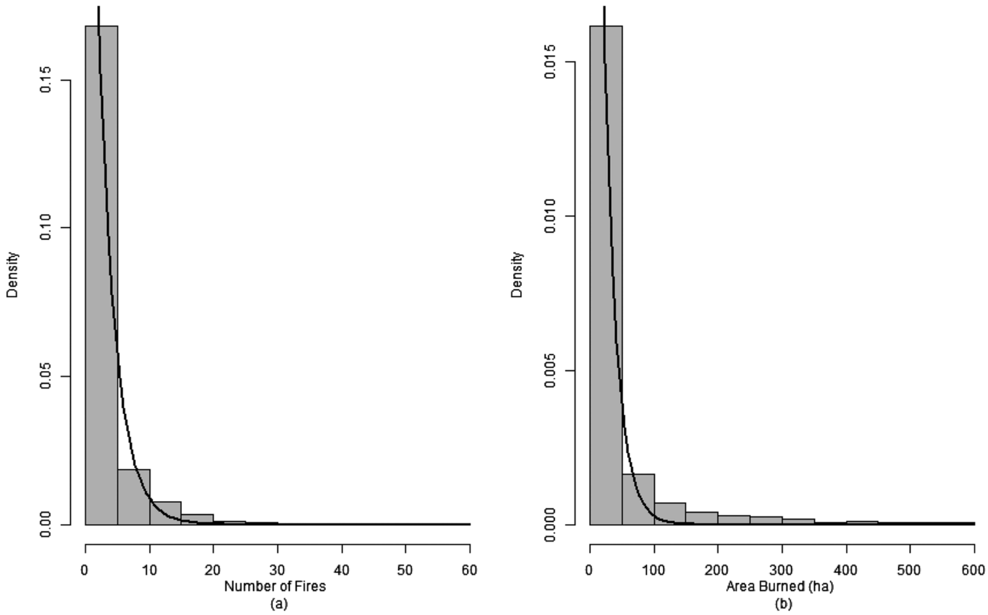

Figure 2. (a) Histogram of number of fires per county-month. An exponential density fit by maximum likelihood is shown; (b) Histogram of total area burned per county-month. An exponential density fit by maximum likelihood is shown

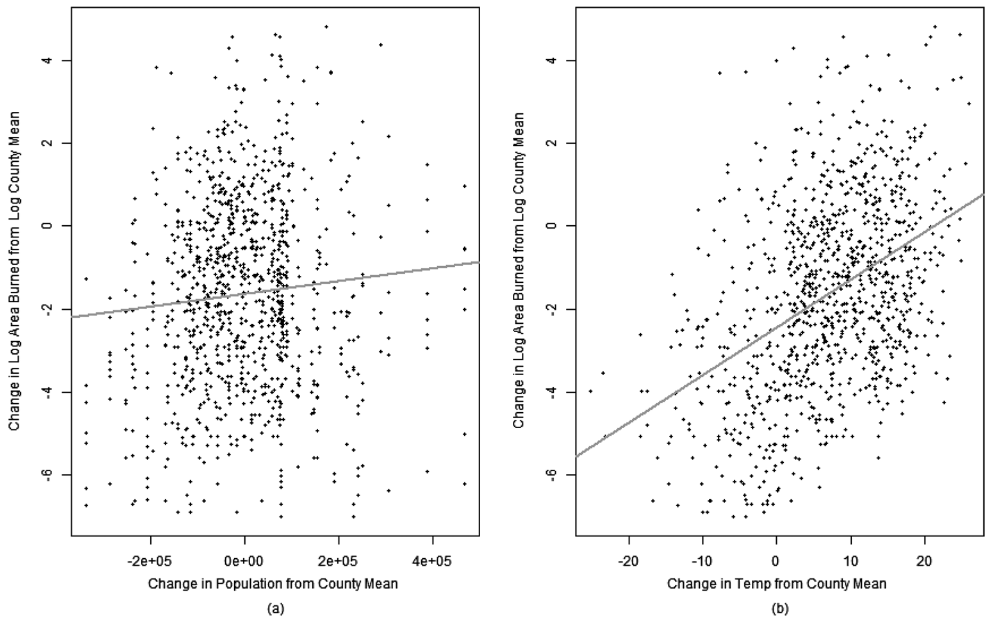

Figure 3. (a) Change in population from county-mean population versus change in log burn area minus log county-mean burn area; (b) Change in temperature from county-mean temperature versus change in log burn area minus log county-mean burn area. Least squares lines overlaid

number of wildfires and total area burned for county i across all months, respectively, parameters v_{1j} and v_{2j} represent the baseline for the mean number of wildfires and total area burned for month j, α_1 and α_2 denote the estimated coefficients for population increase, and β_1 and β_2 the estimated coefficients corresponding to temperature increases. The observation-level random effect term given to each data point is denoted τ.

Models (1) and (2) allow us to focus on temperature increases and population growth within each county and the effect of these changes on wildfire incidence and total area burned, while essentially controlling for the differences in overall population and mean temperature between counties and months.

Models (1) and (2) were initially fit using data from all seasons, for each county-year, leaving out the random effects for months. However, a problem with this is that a particularly cold winter could average out an exceptionally hot summer in a given county and thus the effects of temperature changes on our response variables would be masked. To account for this, we added random effect terms for month, v_{1j} and v_{2j}, and fit the models (1) and (2) to all the county-months as well as separately after splitting the data temporally into fire seasons delineated as suggested in Nichols *et al*. (2011). The first season, the most active season and covering the summer months, extends from 25 May to 26 September. This is followed by an intense fall season characterized by fewer but larger fires. This season begins 27 September and continues until 7 November. The remaining months, 8 November to 24 May cover the mostly dormant, winter season. This seasonal splitting allows us to investigate whether the overall trends are present in these shorter time periods, which have more consistent weather throughout them.

Each county-month has its own background rate of total area burned or number of fires estimated in the models. The parameters α_1, α_2, β_1, and β_2, which are constrained to be the same across all counties, are influenced then by *changes* in population and temperature within a county. After both population and temperature have been standardized (converted to z-scores), the parameters are also in standard units. Table 1 shows the root mean square (RMS) of the county-wide month-to-month variations in the covariates in each subset of the data being analyzed. Thus, for instance, the size of a *typical* increase in population from one year to the next is 11,644 for the southern counties and roughly 2000 for the coastal and inland counties. The population data for each county are annual, and thus, the RMS of the population changes from 1 year to another is identical to 3813 for each of the seasonal subsets. We fit all of our models by Laplace approximation using R software (2013).

A mapping of California wildfires (Figure 4) suggests a possible grouping of counties for an improved spatial analysis. We thus also re-fit models (1) and (2) using only subsets of the data, such as data from all counties but only in fall, or data from the entire year but only for coastal counties, and so on. Tables 2, 3, and 4 present the results of 14 fitted models, all of which follow either Equation (1) or (2), but differ in the data being used to fit the model, either spatially or temporally.

4. RESULTS

Figure 5 displays the random effects for our models. The estimated random effects for county show correlation between fire activity and total burn area, as we might expect. Southern California and Northern California both appear to have low and high activity counties, although the southernmost part of California is considerably active (Riverside and San Diego counties). The estimated monthly random effects reveal, not surprisingly, that the hot summer months tend to have both larger and more frequent fires. The curve for area burned has a spike in October, which is caused by the year 2003. In 2003, San Diego County had over 150,000 ha burned in what was called the 2003 Fire Siege.

Table 1. Root mean square of within-county differences, between 1 month and the next, of the covariates used to fit models (1) and (2), using various subsets of the dataset

	Entire year	Winter	Summer	Fall	Coastal	Inland	Southern
RMS of month-to-month temperature changes (^{o}F)	4.31	1.18	1.52	2.82	3.74	4.99	3.29
RMS of month-to-month population changes (people)	3813	3813	3813	3813	2205	1821	11644

RMS, root mean square.

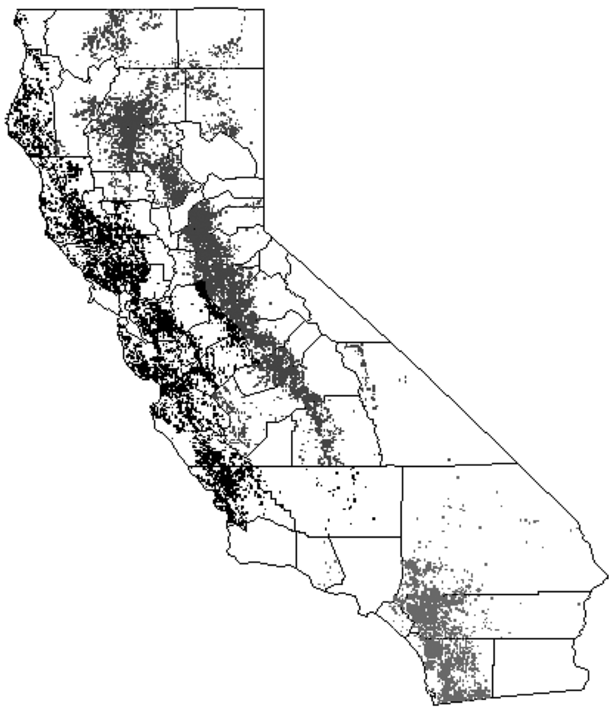

Figure 4. Map of California showing fire locations. Areas of different shades represent possible grouping of counties for spatial analysis

Table 2. Estimated coefficients in models (1) and (2), using data from all counties and months

Data from entire year	α	β
Model 1 {response = area burned (ha)}	**0.024 ha/100,000 increase in population (0.032)**	0.209 ha/°C (0.011)
Model 2 {response = no. of wildfires}	−0.040 wildfires/100,000 increase in population (0.013)	0.063 wildfires/°C (0.003)

Standard errors are in parentheses. Coefficients in bold are not significant at 0.10 level. All models in this paper fit using the "glmer" function in the "lme4" package in R.

Table 3. Estimated coefficients for population and temperature using temporally split data

Seasonal models		Summer	Winter	Fall
Model 1 {response = area burned (ha)}	α_1 (ha/100,000 increase in population)	0.204 (0.075)	**−0.018 (0.043)**	**0.056 (0.050)**
	β_1 (ha/°C)	0.210 (0.043)	0.368 (0.064)	0.226 (0.044)
Model 2 {response = number of fires}	α_2 (wildfires/100,000 increase in population)	**−0.013 (0.023)**	−0.043 (0.026)	**−0.038 (0.026)**
	β_2 (wildfires/°C)	0.047 (0.011)	0.182 (0.026)	0.065 (0.014)

Each model was fit using exclusively data from either summer or winter or fall. Standard errors are in parentheses. Coefficients in bold are not significant at 0.10 level.

Table 4. Coefficients for models fit using spatially split data

Regional models		Coastal	Inland	Southern
Model 1 {response = area burned (ha)}	α_1 (ha/100,000 increase in pop.)	**0.040 (0.053)**	**0.036 (0.047)**	**−0.072 (0.064)**
	β_1 (ha/°C)	0.290 (0.024)	0.562 (0.020)	0.405 (0.045)
Model 2 {response = number of fires}	α_2 (wildfires/100,000 increase in population)	**0.020 (0.025)**	**−0.017 (0.020)**	−0.07 (0.018)
	β_2 (wildfires/°C)	0.116 (0.008)	0.150 (0.010)	0.119 (0.013)

Divided into coastal, inland, and Southern California regions, as shown in Figure 4. Standard errors are in parentheses. Coefficients in bold are not significant at 0.10 level.

Table 2 shows the results for the models fit with data for all months and for all counties. Temperature has a positive slope in both models, meaning higher temperatures are associated with increasing total area burned and fire frequency. Area burned (model 1) increases along with population and temperature, but typical temperature variations appear to have a much stronger effect on area burned than do typical population increases. Indeed, one may interpret what the fitted model implies for a given county given a typical increase in population or temperature as indicated in Table 1: an increase of about 4.31 °C (1 RMS temperature increase) in a typical county would correspond to an expected increase of about 146% (±4.8%) in its monthly number of wildfires (because $\exp\{0.209 * 4.31\} \sim 2.461$) and an expected increase of about 31% (±1.3%) in its monthly number of observed wildfires ($\exp\{0.063 * 4.31\} \sim 1.312$). Meanwhile, a typical jump in population of 3813 people would correspond to an increase in a typical county's annual area burned of about 0.09% (±0.1%) ($0.024 * 3813/100{,}000\} \sim 1.00093$) and a decrease in its total annual number of observed wildfires of about 0.15% (±0.05%), ($\exp\{-0.040 * 3813/100{,}000\} \sim 0.9985$).

The fact that typical monthly temperature variations appear to outweigh population increases in influencing area burned and number of observed wildfires is hardly surprising, because wildfires are well known to be more prevalent and often larger during especially hot years (Pyne *et al*., 1996; Johnson and Miyanishi, 2001; Moritz *et al*., 2005).

The result of the fitted model (2) indicating that population increases tend on average to correlate with decreased fire frequency may seem curious. It is conceivable that as a county becomes more urbanized and developed, there is less burnable land remaining and thus decreased potential for a wildfire to ignite. Sonoma County is a prime example. From Figure 6, one sees that population has increased steadily in Sonoma County over the observed time interval studied here, while the number of observed wildfires has decreased sharply. The least-squares fit is shown and confirms the downward trend.

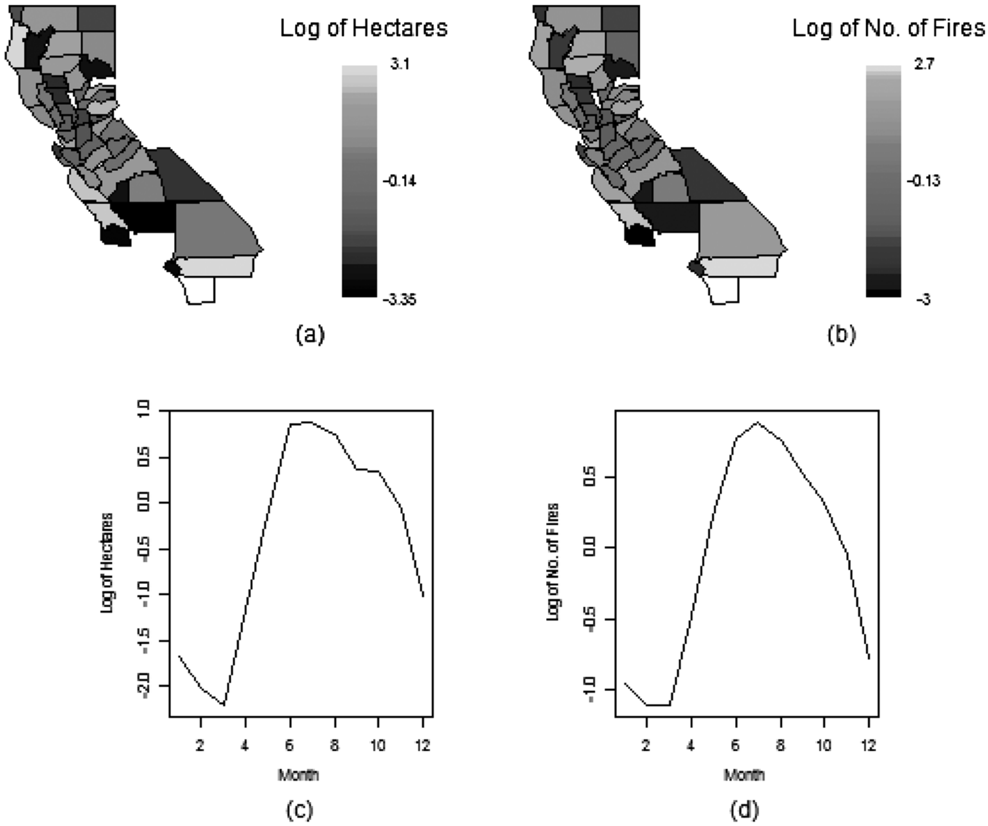

Figure 5. (a) Estimated random effect of county for area burned; (b) Estimated random effect of county for number of fires; (c) Estimated random effect of month for area burned; (d) Estimated random effect of month for number of fires

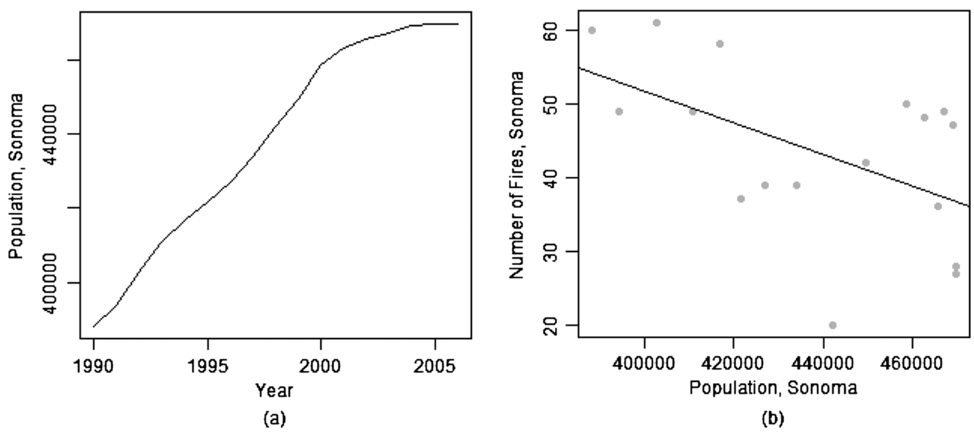

Figure 6. (a) Sonoma County's population over time; (b) Sonoma County's annual number of observed wildfires versus Sonoma County's population, with a least squares line overlaid

Table 3 shows the coefficients for our models fitting the data split according to wildfire seasons. These models do not contain the monthly random effect term seen in models (1) and (2) and instead are of the form:

$$Y_{ijk} \sim \text{Poisson}\left(\exp\left\{\mu_{1i} + \tau_{1ijk} + \alpha_1 P_{ij} + \beta_1 T_{ij}\right\}\right) \quad (3)$$

and

$$Z_{ijk} \sim \text{Poisson}\left(\exp\left\{\mu_{2i} + \tau_{2ijk} + \alpha_2 P_{ij} + \beta_2 T_{ij}\right\}\right) \quad (4)$$

where parameters μ, τ, α, and β are defined as in models (1) and (2). With this temporally focused analysis, we see that as in the entire-year fits of models (1) and (2) from Table 2, temperature increases are associated with increases in both total area burned and fire frequency. Population increases, however, are associated with decreases in the number of observed wildfires in a county. Our discussion thus shifts to the seasonal variation in effect size between temperature and population.

The fits for model (1) in Table 3 show that the increases in total area burned attributable to population increases are most evident in the active summer season, less so in the intense fall season and considerably less substantial in the dormant winter season. Somewhat surprisingly, it is the warm summer season's total area burned and number of wildfires that appears to be least affected by changes in temperature. In the fit for summer, one sees a 37.6% increase in burn area corresponding to a 1 RMS (1.52 °C) increase in temperature, which is considerably lower than the 54.4% and 89.2% increases in burn area corresponding to comparable temperature changes in winter and fall, respectively. In terms of wildfire activity, this same 1 RMS increase in temperature is associated with a 7.5% increase in number of fires, which is again less than is seen in winter and fall, with changes of 23.9% and 20.0%, respectively.

It is worthwhile to note that fall has the highest variability in temperature of the three seasons (1 RMS is 2.82 °C); if instead of a 1 RMS increase, we consider a 1 °C increase in temperature for each season, the fitted seasonal model parameters from Table 3 suggest that winter

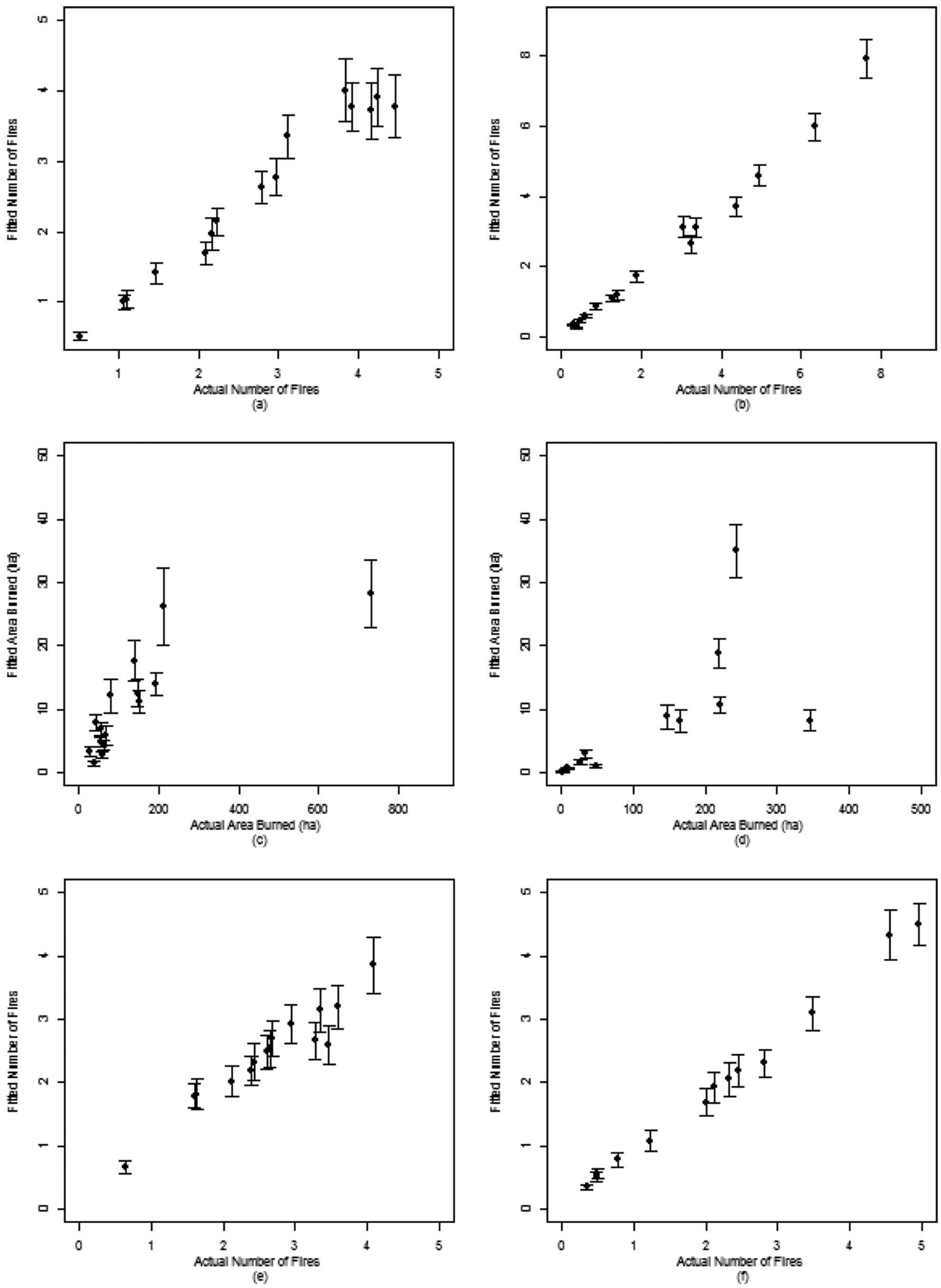

Figure 7. Binned plots comparing observed monthly number of wildfires with fitted monthly number of wildfires (a,b), binned by population and temperature, respectively; observed monthly total area burned with fitted monthly total area burned (c,d), binned by population and temperature, respectively; and observed monthly number of wildfires with fitted monthly number of wildfires (e,f), binned by changes in population and changes in temperature, respectively. The bin sizes were determined so that each bin has the same number of points, resulting in different ranges for each bin. Fifteen bins were used for each plot. Ninety-five percent confidence intervals shown for each point

would have a 44% increase in monthly burn area, whereas fall and summer would have increases of only about 25%. Note that the fall season includes the most area burned for any single county-year in the dataset; this is partially attributable to the 2003 Fire Siege in San Diego County. The fall season accounts for 30% of all area burned in the data yet represents only 11% of the total number of fires.

Considering now changes in population, total area burned in summer and number of fires in winter are the most significantly affected. The effect of population is not as pronounced as that of temperature, but is present, and appears to follow a pattern qualitatively similar to that for the entire year; population increases are associated with increases in area burned, but a decrease in fires ignited. In summer, a 1 RMS change in population corresponds to a 0.8% increase in total burn area yet a not statistically significant 0.04% decrease in number of fires. The same population increase (3813 people) in winter corresponds to a 0.2% decrease in wildfire activity.

Figure 4 displays a map of California wildfire locations in the 49 counties used in our analysis. Three very distinct clusters are visible: fires in coastal counties, counties with fires east of the San Joaquin and Sacramento Valleys and west of the Sierra Nevada mountain range, and counties in southern California. We divide the data spatially referring to the darkest shaded cluster as the coastal region, the medium gray shaded area as the inland region, and the lightest shaded as the southern region.

Coefficients for the spatially grouped data can be seen in Table 4. The fits to model (1) indicate that population increases have their strongest effect in the southern region, where a typical population change of 11,644 people results in a 0.85% decrease in both total monthly area burned and number of wildfires. Population's effect is only significant in the southern region and then only for number of fires. As in the entire-state analysis (Table 2) and the temporally divided analysis (Table 3), population increases appear to be associated with decreases in observed wildfire frequency, while temperature increases are associated with increases in fire activity in all three regions.

Temperature increases, meanwhile, are significant across all regions and for both burn area and wildfire frequency. Temperature's effect is most strongly seen in the inland region, where a 1 RMS increase in temperature is associated with a 111% increase in wildfire activity, whereas a comparable change in the southern and coastal regions produces 48% and 54% increases, respectively. A similar trend is seen for total area burned, where comparable temperature changes affect the inland region approximately four times as much as either the coastal or southern regions.

It is important to assess how well these models actually fit the data. The standard deviation of the monthly number of observed wildfires across all county-years in the dataset is 4.84 fires. This may be compared with the standard deviation of the residuals for model (2) of 2.92 fires; the model (2) explains nearly 40% of the variation observed. Correspondingly, the standard deviation of annual total area burned across all county-months is 1959 ha, whereas the residual standard deviation for model (1) is 1954 ha; model (1) accounts for only 0.3% of the observed variation in monthly burn area changes. This percentage is small because of the effect of the outlier San Diego, 2003, having a large residual. When we remove this point from the data, model (1) accounts for 14% of the variation in monthly burn area changes.

Figure 7 shows binned plots comparing observed responses with fitted responses. From Figure 7a and 7b, one sees that the model (2) predicts number of fires very accurately; we see a clear linear relationship between actual and fitted number of fires, whether we bin by population or temperature. Figure 7c also shows a closely linear relationship between observed and fitted annual burn areas, although from Figure 7d, when binned by temperature, the relationship shows some mild departures from linearity. The outlier seen in Figure 7c contains San Diego County, 2003.

As discussed earlier, the coefficients in the models are influenced by changes in population and temperature. Thus, we can also check the model with binned plot where we are not simply binning by temperature or population, but by the change in each of those variables from the year 1990 to any given year. Figure 7e and 7f shows these plots, and in both cases, we do see a linear structure indicating rather satisfactory fit overall.

5. DISCUSSION

The random effect Poisson regression models for total area burned and total number of observed wildfires as functions of county-wide temperature increases and population increases suggest that temperature increases are positively associated with both total area burned and number of observed wildfires, which is not surprising. The models suggest that far more of the variation in area burned and number of wildfires may be attributable to changes in temperature than to changes in population, especially in the coastal and inland counties. The variability in these effects between spatial locations is extremely pronounced. This is most clearly seen in differences between the fitted models for the coastal and Southern California regions, where population growth and temperature appear to exhibit nearly opposite effects on total burn area and fire frequency.

It is important to note that the observations here are only for the time span 1/1/1990 to 31/12/2006 and are only for wildfires on CalFire protected lands; so further investigation may be necessary to confirm these results more generally. Of course, wildfire ecology is extremely complex (Pyne *et al*., 1996; Johnson and Miyanishi, 2001; Moritz *et al*., 2005), and several important covariates, such as windspeed, precipitation, drought indices, bark beetle populations, cloud cover, and so on, may act as confounding factors in our analysis. Future work may include the use of Burning Index (BI) and/or the variables determining the BI as covariates, although some previous analyses have shown the BI not to be an accurate predictor of wildfire incidence or area burned in Southern California (Schoenberg *et al*., 2007; Schoenberg *et al*., 2009; Xu and Schoenberg, 2011). In addition, the model with total area burned as the response had highly skewed residuals and several highly influential observations. Further, while the completeness of this dataset is thought to be rather exceptional, some missing observations may have influenced the results here. The results here should be tested and confirmed in the future with other datasets and for other spatial-temporal regions.

REFERENCES

Arno SF, Allison-Bunnell S. 2002. Flames in Our Forest: Disaster or Renewal? Island Press: Washington, D.C.
Cumming S. 2001. A parametric model of the fire-size distribution. Canadian Journal of Forest Research 31: 1297–1303.
Elston DA, Moss R, Boulinier T, Arrowsmith C, Lambin X. 2001. Analysis of aggregation, a worked example: numbers of ticks on red grouse chicks. Parasitology 122(5): 563–569.

Johnson EA, Miyanishi K. 2001. Forest Fires: Behavior and Ecological Effects. Academic Press: San Diego.
Keeley JE. 1982. Distribution of lightning- and man-caused wildfires in California. In Proceedings of the Symposium on Dynamics and Management of Mediterranean-type Ecosystems, CE Conrad, WC Oechel (eds), USDA Forest Service: Pacific Southwest Forest and Range Experiment Station, General Technical Report PSW-58; 431–437.
Malamud BD, Millington JDA, Perry GLW. 2005. Characterizing wildfire regimes in the United States. Proceedings of the National Academy of Sciences of the USA 102(13): 4694–4699.
Miller JD, Safford HD, Crimmins MA, Thode AE. 2009. Quantitative evidence for increasing forest fire severity in the Sierra Nevada and Southern Cascade Mountains, California and Nevada, USA. Ecosystems 12: 16–32.
Moritz MA, Morais ME, Summerell LA, Doyle J. 2005. Wildfires, complexity, and highly optimized tolerance. Proceedings of the National Academy of Sciences of the USA 102: 17912–17917.
Nichols K, Schoenberg FP, Keeley J, Diez D. 2011. The application of prototype point processes for the summary and description of California wildfires. Journal of Time Series Analysis 32(4): 420–429.
Pyne S, Andrews P, Laren R. 1996. Introduction to Wildland Fire. Wiley: New York.
Schoenberg FP, Peng R, Woods J. 2003. On the distribution of wildfire sizes. Environmetrics 14(6): 583–592.
Schoenberg FP, Chang C, Keeley J, Pompa J, Woods J, Xu H. 2007. A critical assessment of the burning index in Los Angeles County, California. International Journal of Wildland Fire 16(4): 473–483.
Schoenberg FP, Pompa JL, Chang C. 2009. A note on non-parametric and semi-parametric modeling of wildfire hazard in Los Angeles County, California. Environmental and Ecological Statistics 16(2): 251–269.
Stephens SL. 2005. Forest fire causes and extent on United States Forest Service lands. International Journal of Wildland Fire 14: 213–222.
Westerling AL, Brown TJ, Gershunuov DR, Cayan D, Dettinger MD. 2003. Climate and wildfire in the Western United States. Bulletin of the American Meteorological Society 84: 595–604.
Westerling AL, Hidalgo HG, Craven DR, Swetnam TW. 2006. Warming and earlier spring increase Western U.S. forest wildfire activity. Science 313: 940–943.
Xu H, Schoenberg FP. 2011. Point process modeling of wildfire hazard in Los Angeles County, California. Annals of Applied Statistics 5(2a): 684–704

