Fire Risk in San Diego County, California: A Weighted Bayesian Model Approach

Crystal A. Kolden
Clark Graduate School of Geography, Worcester, MA
Timothy J. Weigel
University of Nevada, Reno

Abstract

Fire risk models are widely utilized to mitigate wildfire hazards, but models are often based on expert opinions of less understood fire-ignition and spread processes. In this study, we used an empirically derived weights-of-evidence model to assess what factors produce fire ignitions east of San Diego, California. We created and validated a dynamic model of fire-ignition risk based on land characteristics and existing fire-ignition history data, and predicted ignition risk for a future urbanization scenario. We then combined our empirical ignition-risk model with a fuzzy fire behavior-risk model developed by wildfire experts to create a hybrid model of overall fire risk. We found that roads influence fire ignitions and that future growth will increase risk in new rural development areas. We conclude that empirically derived risk models and hybrid models offer an alternative method to assess current and future fire risk based on management actions.

Introduction

THE DANGERS POSED by wildland fires, particularly in areas where the urban interfaces the rural, have led to numerous methodologies for mapping wildfire risk over the past two decades (Chuvieco 2003). Mapping wildfire risk requires not only an understanding of what factors contribute to the existence of a wildfire, but also a designation of the values actually at risk. Usually, this encompasses humans, human infrastructure, and human-valued ecosystems and ecosystem services. Given this human-oriented definition of risk, maps and mathematical models of fire risk fall primarily into two categories: the probability of an initial ignition; and, given that an ignition occurs, the potential for fire behavior conducive to fire spread. In both cases, Geographic Information Systems (GIS) and remotely sensed data have contributed significantly not only to spatially mapping fire risk, but also to understanding the relationships between con-

tributing factors (such as the weather, vegetation composition and condition, and topography) and wildfire occurrence and behavior at variable spatiotemporal scales (Chuvieco 2003). These relationships are often difficult to quantify as inputs to the models used to produce fire risk maps and, given this lack of existing empirical knowledge about fire risk, there is considerable room to explore new approaches to mapping fire risk and modeling the factors that contribute to fire risk.

This study focuses on mapping the probability of current and future risk of wildfire ignition in one of the most fire-prone regions of the U.S.: San Diego County in southern California. Compared to the number of models developed for mapping risk of fire spread, models of fire-ignition risk have been fewer in number. This stems primarily from the difficulty of predicting atmospheric conditions conducive to lightning strikes, which start fires that eventually become the majority of large fires in the U.S. In urban southern California, however, fewer than five percent of wildfires are ignited by lightning, with most large wildfires ignited by human activities (Keeley, Fotheringham, and Morais 1999). Understanding how humans ignite fires in this region, then, is critical to fire management personnel who are responsible for mitigating this risk. Additionally, this understanding must be flexible enough to accommodate the changing human footprint on the landscape in the rapidly growing region.

Two types of models are generally developed for mapping wildfire-ignition risk. The deterministic, or "fuzzy," model relies on expert opinion to determine which factors contribute to the process being modeled, and then assigns a weight to each of those factors within the model. A static map, predicting a set of outcomes, is then produced. This is the most common type of model currently used to map wildfire risk, as weights can be adjusted to produce the outcome expected by model developers based on their knowledge and the intended use for the resulting map. For example, Radke (1995) created a GIS model of fire hazard in the East Bay Hills of California, with arbitrarily chosen inputs of vegetative fuels and structural fuels, which were differentially weighted based on expert opinions obtained in interviews of experienced fire experts. Burgan, Klaver, and Klaver (1998) used estimated fuel moisture in the linearly weighted National Fire Danger Rating System to produce a Fire Potential Index for the continental U.S.

The second method for mapping fire-ignition risk relies on statistical modeling to empirically derive relationships between causal factors and the resulting ignition of a wildfire. Since these models rely on a training data set of fire occurrences, they can be revised as additional training data is acquired, and, more importantly, can be validated using some portion of the training data not used for model creation. In wildfire-ignition risk, these models use previous fire occurrences as the data for training the model, and often assess potential for ignition based on either the availability of the surface fuel to burn (Hardy and Burgan 1998) or the development of atmospheric conditions conducive to dry lightning (Rorig et al. 2003). The most frequent critique of these models is that they are based on only limited data and don't necessarily represent local conditions, as there is no place for expert knowledge in pure empirical models (Martin et al. 2005). However, empirical models define relationships and describe a process when little is known pertaining to how causal factors produce an outcome. This is often the case with wildfire risk, as the contributing factors to wildfire ignitions are often poorly understood, and therefore difficult to predict.

Since both types of models offer both benefits and drawbacks, it is critical to understand the purpose of the model when choosing a type; in this case it is the mitigation of wildfire ignitions by fire management and public planners. Farris, Pezeshki, and Neuenschwander (1999) reviewed the inputs, decision-making process, and accuracy levels of both deterministic and empirical methods of modeling wildfire risk, and concluded that none of the models tested was "ideal" for fire management. They suggested that a hybrid model incorporating both expert knowledge and empirical, non-biased methods may provide the desired answers. The southern California region has been the focus of many wildfire risk studies (Yool et al. 1985; Chou et al.1993; Keeley, Fotheringham, and Morais 1999), largely because it is densely populated and has experienced numerous catastrophic wildfires in the past century, including the 2003 Cedar Fire east of San Diego, the largest wildfire ever recorded in California at just over 113,000 ha (Keeley, Fotheringham, and Moritz 2004). Since previous studies in the region have been primarily deterministic, using expertly weighted models to produce static maps, this study produced an empirical model as an alternative approach for mapping wildfire-ignition risk (e.g., Dickson et al. 2006). The model was used to mask both current fire-ignition risk and future potential fire-ignition risk, based on a predicted urban growth scenario (Steinitz et al. 1997). The hybridization approach

advocated by Farris, Pezeshki, and Neuenschwander (1999) was then used to combine the wildfire-ignition probability map with a deterministically produced map of wildfire-spread risk from the California Department of Forestry and Fire Protection (CDF) to create an overall wildfire risk map for the region.

The objectives of our study were to (1) determine the process by which recent wildfires have ignited in eastern San Diego County, California, by developing and validating an empirical model for fire-ignition risk; (2) apply the risk model to a future growth scenario to assess future fire-ignition risk; and (3) combine the weights-of-evidence model with a knowledge-driven fire-risk model to create a hybrid overall fire-risk model.

Study Area

In this study, we focus on the eastern part of San Diego County, primarily because it is the area that will likely see the most wildland-urban interface (WUI) expansion over the next few decades (Steinetz et al. 1997). A 378,720 ha portion of San Diego County, California, was chosen as the study area (Figure 1) based on the availability of the most accurate and extensive fire-ignition data to train the statistical model. The area lies to the east of the San Diego metropolitan area and contains the city of Ramona and portions of the Cleveland National Forest and Anza-Borrego Desert State Park. Mediterranean vegetation types dominate the region, with most of the study area covered in chamise (*Adenostoma* spp.), chaparral (*Ceanothus* spp.), and manzanita (*Arctostaphylos* spp.). At higher elevations, oak (*Quercus* spp.) forms a broadleaf deciduous forest adjacent to coniferous forest consisting of mountain mahogany (*Cercocarpus betuloides*), pine (*Pinus* spp.), and fir (both *Abies concolor* and *Pseudotsuga macrocarpa*) (Wells 2004). The mostly shrub vegetation is both fire-dependent and fire-prone: its waxy leaves burn easily and intensely, and it resprouts quickly after a fire. This makes the region prone to frequent fires and to less-frequent but highly catastrophic large fires driven by fall Santa Ana weather patterns (Keeley, Fotheringham, and Morais 1999; Keeley and Fotheringham 2001).

Methods and Data

To assess wildfire-ignition risk in the study area, we used a Bayesian weights-of-evidence model in a GIS environment. This was the same approach taken by Dickson et al. (2006) in their assessment of fire-ignition risk in Arizona. Arc Spatial Data Modeler (ArcSDM)

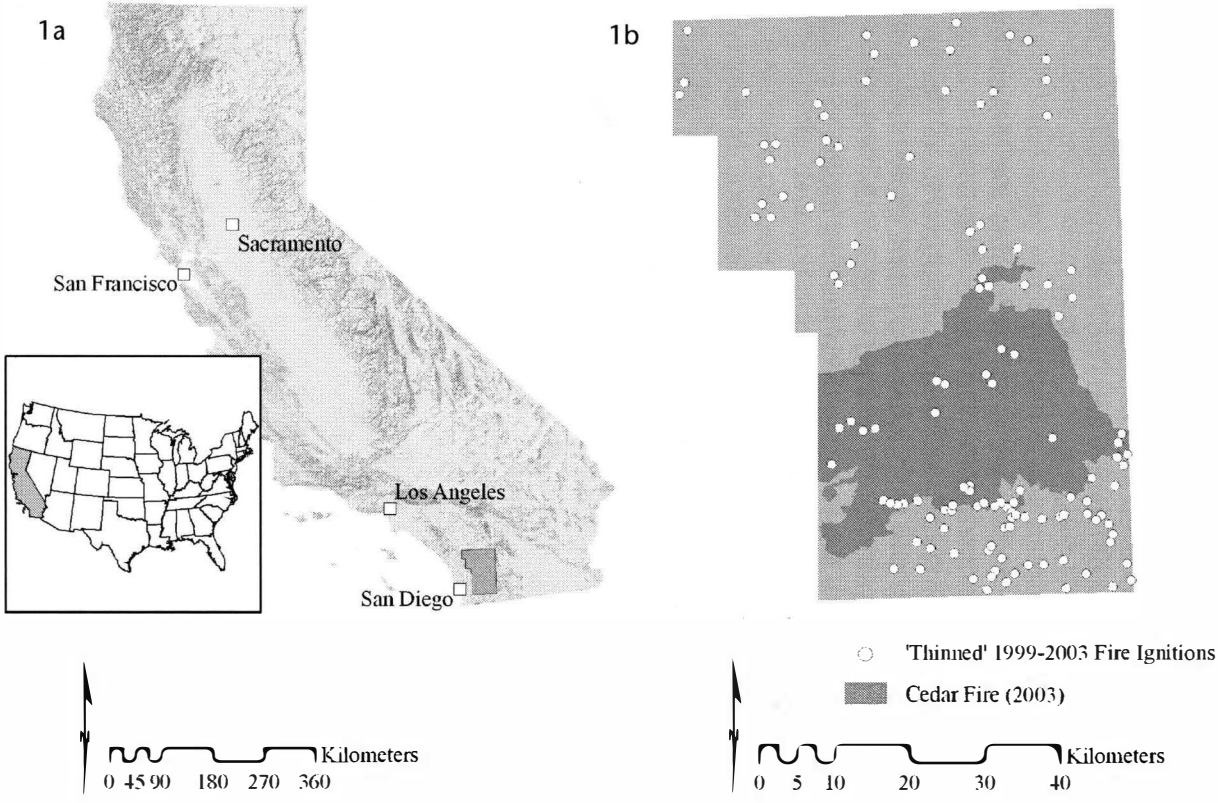


Figure 1a.—The project location in the southwestern corner of California, near the San Diego metropolitan area. Fire ignition data was obtained from the California Department of Forestry for this region. 1b.—The 378,720 ha study area used during weights calculation. The fire ignition distribution (n = 128) is for the period 1999–2003. 110,600 ha of the study area was impacted by the 2003 Cedar fire.

is an extension developed for ESRI ArcGIS software that calculates weights based on raster dataset inputs and vector (point) training data (Sawatzky et al. 2004). The ArcSDM weights-of-evidence tool has previously been used to predict fire ignitions (Dickson et al. 2006), and also for predicting mineral deposits (Bonham-Carter, Agterberg, and Wright 1988; Raines 1999), ecological habitats (Aspinall 1992; Mensing et al. 2000), and landslide potential (Lee and Choi 2004). Bayesian weights-of-evidence modeling calculates "weighted" positive and negative coefficients for the classes in evidential raster layers, based on the spatial correlation with the classes. Evidential layers are generalized into binary maps, according to favorable and unfavorable correlation, and are then combined using Bayesian modeling to calculate the posterior probability that a fire ignition will occur in a given cell within the study area.

Data

During pre-processing, several data sets (designated "evidential layers" for purposes of modeling) were spatially correlated to the fire-ignition history set, to determine what characteristics of the study area contribute to ignition of wildfires. Aspect, slope, vegetation, and fuel model layers showed no significant correlation to past fire-ignition points. Land use/land cover (LULC), land ownership, roads, and elevation showed significant correlation to the fire-ignition training points; subsequently, these four evidential layers were utilized as inputs to the fire-ignition risk model. The LULC and land ownership data were provided from the continuation of a previous project (Steinitz et al. 1997), and since they were initially derived from Landsat data analysis, the spatial resolution of the data was 30 m. The elevation data was derived from the national elevation dataset (also 30 m resolution), and the roads were rasterized from a TIGER line file available at the California Geospatial Data Clearinghouse.

The fire-ignition occurrence data was derived from a 12-year fire-ignition history published by CDF (http://frap.cdf.ca.gov/projects/fire_data/fire_perimeters/). Due to the rapidly changing land cover in the study area, training points were selected for the years 1999–2003, allowing us to assess the fire-ignition process and predict future ignition risk for a five-year period. The 390 initial fire-ignition history points where "thinned" to remove all but one point per 30m raster cell, leaving 363 points for "training" the model. A 50 percent subset of the "thinned" training points was selected using

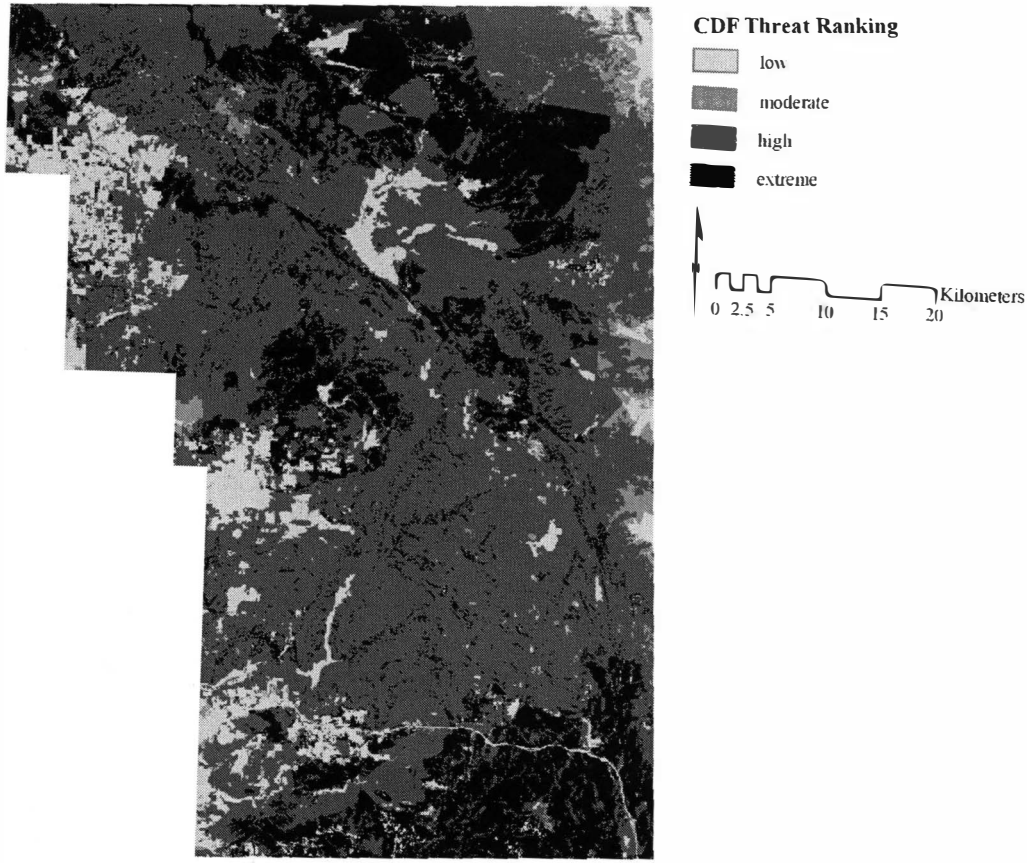
ArcSDM to randomly remove half of the set for validation, leaving 128 training points.

The future-growth scenario input layer was based on changes estimated in the LULC evidential layer from a study performed using regional growth models (Steinitz et al. 1997). The premise of the regional growth models was that one million new residents would move into San Diego County under one of four potential development scenarios: rural, low-density growth; or high-density growth in either coastal regions, the northern portion of the county, or around three new "urban centers." Previous work by the lead author test-modeled all four scenarios, and the "three urban centers" scenario showed the most significant change in wildfire-ignition risk. This scenario was selected for the final model run and is presented here as the future growth evidence layer. Farris, Pezeshki, and Neuenschwander (1999) noted the importance of hybrid models in capitalizing on both expert knowledge and statistically derived quantification of a process. With this in mind, we found a deterministic, fuzzy model of wildfire risk for comparison to the weights-of-evidence model (Figure 2). CDF derived this predictive Fire Threat model from a potential fire-behavior map (based primarily on vegetative fuels) and a fire-history assessment based on large fire perimeters, where the input layers were weighted according to the modeler's expert knowledge of fire (http://frap.cdf.ca.gov/data/frapgisdata/select.asp).

Calculation of Probability

The prior probability of a wildfire ignition was calculated as the total number of ignition points in the training data set over the area of the study region, essentially describing the potential for an ignition point to occur in any cell by chance. Correlations between evidence layer classes and training points were calculated in ArcSDM to determine which classes were associated with the fire-ignition training points. The difference between positive and negative correlations was calculated as the contrast value, which measures the "strength" of the association between training points and classes within evidence layers (Bonham-Carter 1994). The contrast was then used to generalize evidence layers into binary maps (Figure 3), where positive contrast denoted the classes "inside" the pattern (meaning those classes were significantly associated with wildfire ignitions), while negative or null contrast denoted the classes "outside" the pattern (not associated with wildfire ignitions). The four generalized evidential layers were then combined to calculate a response theme representing posterior probability of an ignition based on binary

Figure 2.—CDF knowledge-driven model of fire threat, based upon historic fire extents and vegetation classification (adapted from CDF). Higher values indicate greater threat from fire events.



weights of evidence. The weights-of-evidence modeling process assumes that the evidence layers within the model are conditionally independent (CI) with respect to the training points. To test for the assumption of CI, a CI ratio and Agterberg and Cheng test were calculated using ArcSDM (Bonham-Carter 1994; Agterberg and Cheng 2002). The accuracy for the posterior probability map was validated by tallying the percentage of validation points that fell within the range of posterior probabilities that exceeded the prior probability.

The future-growth simulation model was created by generalizing the future-growth evidence layer into a binary map using contrast values derived from the current LULC contrast values, and a posterior probability map was calculated. Percent change between the current and future posterior probability maps was calculated to assess changes in wildfire-ignition risk based on future urban growth.

Finally, a hybrid model was created to incorporate the empirically derived Bayesian model with the expert knowledge integrated into fuzzy models. First, we compared the CDF expert threat model to our model using a Kappa coefficient statistic to determine the extent of spatial difference between the two assessments. We then combined our two models by assigning each risk level a numerical value (low = 1, extreme = 4) and creating a new overall fire risk map where the cell value equals the sum of the two model values. The final risk of fire based on whether a cell has a probability of igniting (empirical model) and then burning (deterministic model) was broken into four categories based on the final sums.

Results

Fire-ignition process

Since empirical models are often distrusted by fire managers and can be difficult to validate with a relatively infrequent occurrence such as a wildfire ignition, it is less meaningful to report probabilities of ignition than to report on and discuss the process by which fires ignite in the study region. The posterior probability maps produced by the weights-of-evidence model were reclassified into "Low," "Moderate," "High," and "Extreme" risk of ignition (Figure 4), based on the natural breaks above and below the prior probability of an ignition. The positive and negative correlation weights calculated for each evidence layer indicate that proximity to roads (C = 1.288) was the best predictor of where fire ignitions do occur (Table 1).

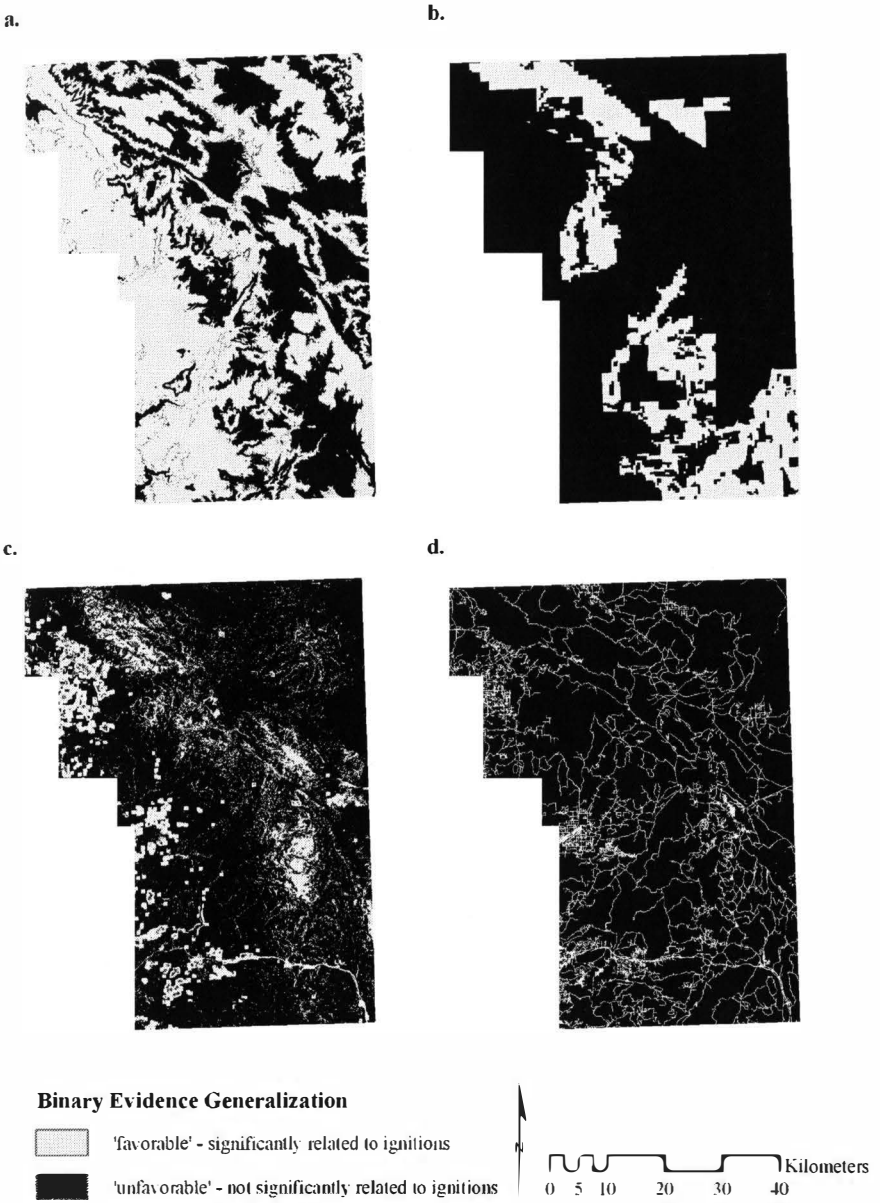


Figure 3.—Evidence layers generalized into "favorable" and "unfavorable" evidence, based upon maximized contrast values. a. Elevation, b. Ownership, c. Land Use Land Cover, d. Proximity to Roads. The binary patterns are then combined using Bayesian statistics to generate a posterior probability map, which indicates the unique combination of binary patterns and is the probability that a fire ignition will occur, given the presence of some favorable evidence.

Elevation was the worst predictor of fire-ignition occurrence (C = 0.069). In the validation assessment, 72 percent of the validation ignition points occurred in areas that were predicted at high or extreme ignition risk, the two classes where posterior probability values exceeded the prior probability.

Table 1. Weights, contrast, and confidence values for each evidential layer used in the weights-of-evidence model. The hypothesis of conditional independence can be accepted as expressed by a CI Ratio of 1.003 and an Agterberg & Cheng test of 48.3 percent. The contrast value indicates the strength of association between training points and evidence layers, with a high-contrast value indicating a strong predictive evidence layer. The confidence value is the StudC measure, which indicates the model's confidence that the contrast value is not zero. Confidence values $\geq$ 1.64 are operating at the 95 percent confidence interval (a = 0.05).

Training Points:	n = 128
Unit Area (Sq. m)	30
Prior Probability:	0.00003
Conditional Independence Ratio:	1.003
Agterberg & Cheng Test:	48.3%

Evidence	W^+	W^-	Contrast (C)	Confidence (StudC)
Proximity to Roads	1.0020	-0.2860	1.2882	6.9220
Land Use/Land Cover	0.4840	-0.1610	0.6442	3.3780
Ownership	0.41	-0.162	0.5718	3.0725
Elevation	0.0270	-0.0430	0.0690	0.3796

Future Growth Scenario Model

The percent change between the posterior probability maps for current fire-ignition risk and fire risk based on a future growth scenario indicated that 3 percent of the study area will see a decrease in fire-ignition risk, 87 percent will see no significant change in fire risk, and 10 percent will see an increase in fire-ignition risk (Figure 5). Development of high-density urban areas is associated with decreases in fire-ignition risk in this model, while development of

Figure 4.—Fire-ignition risk classified into four classes, based upon posterior probabilities for a fire ignition occurring given the presence of favorable evidence. Values classified as "High" or "Extreme" are most probabilistic for a fire ignition to occur. Values classified as "Low" or "Moderate" are less probabilistic for a fire ignition to occur.

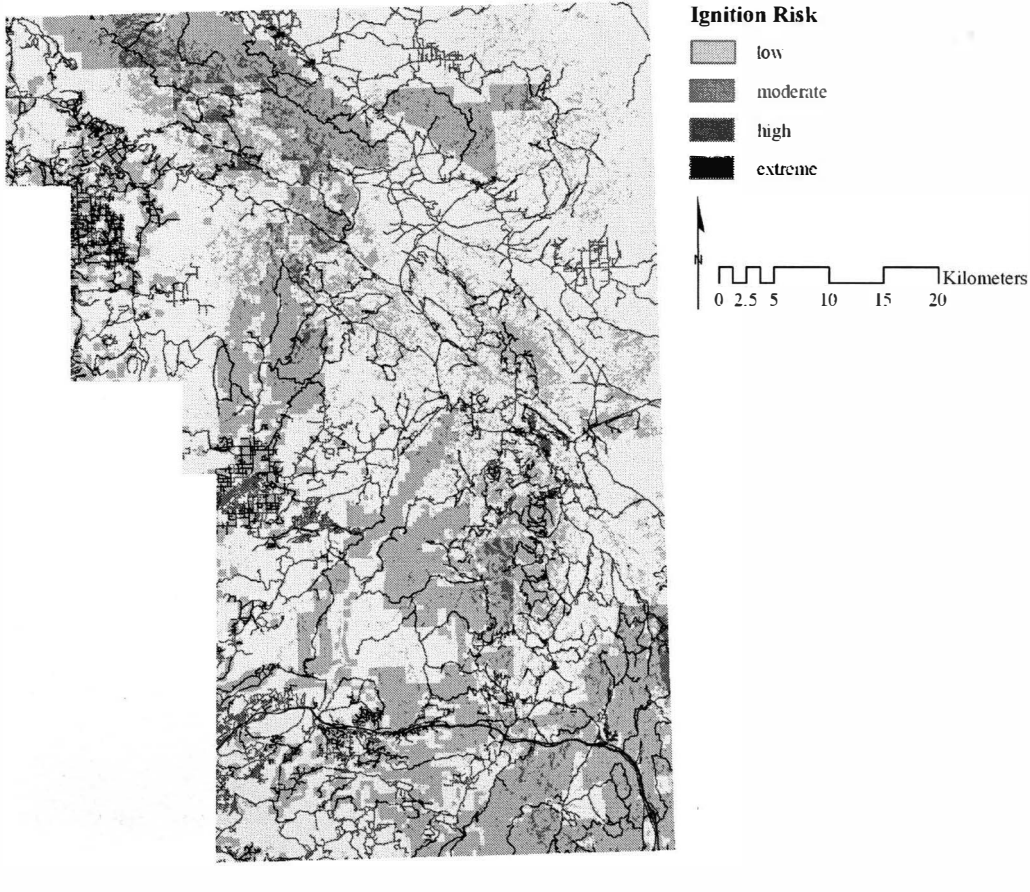
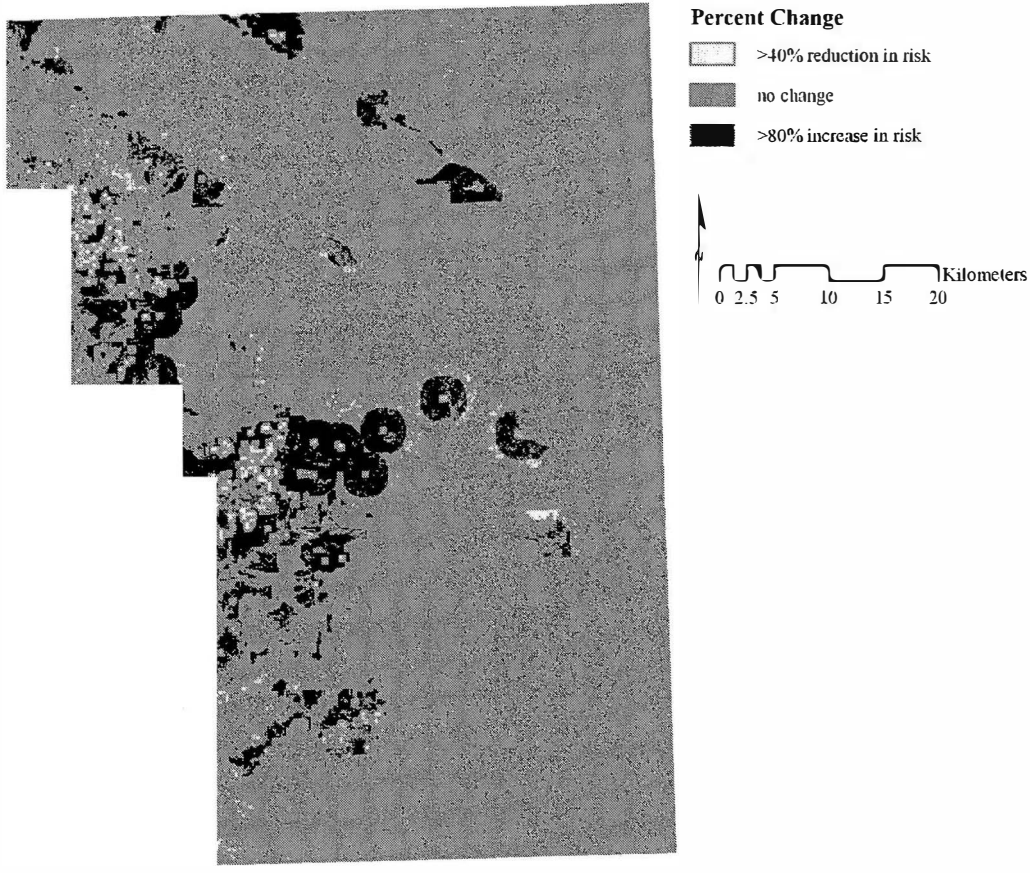


Figure 5.—Percent change in fire-ignition risk, based on a future growth scenario of 1 million new residents. Higher values indicate an increase in fire-ignition risk due to an expanding wildland urban interface. Lower values indicate a decrease in fire-ignition risk due to an increase in urbanization and unburnable areas.



rural residential areas (the WUI areas) is associated with increased probability of ignition.

Deterministic vs. Empirical Models

We found our two models to be significantly different (kappa = -0.029), which was to be expected given that CDF modeled fire threat was based primarily on potential fire behavior, while we modeled risk of ignition. Our hybrid approach, however, yielded a clearer picture of overall fire risk by taking into account both the likelihood of a fire ignition and the ability for the ignition to spread (Figure 6). For example, an area that was deemed high risk in the CDF threat model is not necessarily at high risk if there is no threat of an ignition occurring.

Discussion

Our objective in modeling fire-ignition risk with a Bayesian weights-of-evidence model was to statistically assess the process by which wildfire ignites in the study area, particularly given the high frequency of human-ignited fires. Other fire-risk models (particularly deterministic models) have utilized slope, aspect, and vegetation, three variables that determine fire behavior in the standard fire behavior models (Rothermel 1983). For the study area, however, we did not find significant correlations between these variables and fire ignitions. Instead, we found significant correlations between the fire ignitions and roads, land use/land cover, elevation, and land ownership. While we report on only 5 years of fire-ignition data, we found the same significant correlations between the evidential layers and 10 years of fire-ignition data. This indicates that for the study area, the biophysical factors have less influence in wildfire ignitions than human-environment characteristics (e.g., roads, land ownership, and land use). While the human-environment factors can be manipulated through regulation, education, construction, and other avenues, the biophysical elements are more difficult to control. For fire managers, understanding what human factors they need to focus on managing is critical to lowering the incidence of fire, and this model provides this focus through the weights produced.

To someone familiar with the area, simply looking at a map of fire-ignition density may reveal to the observer that fire ignitions in the area are primarily along major roads. The empirical model, however, defines quantitatively the strength of the correlation between roads and ignitions, and tells us how much stronger the roads correlation

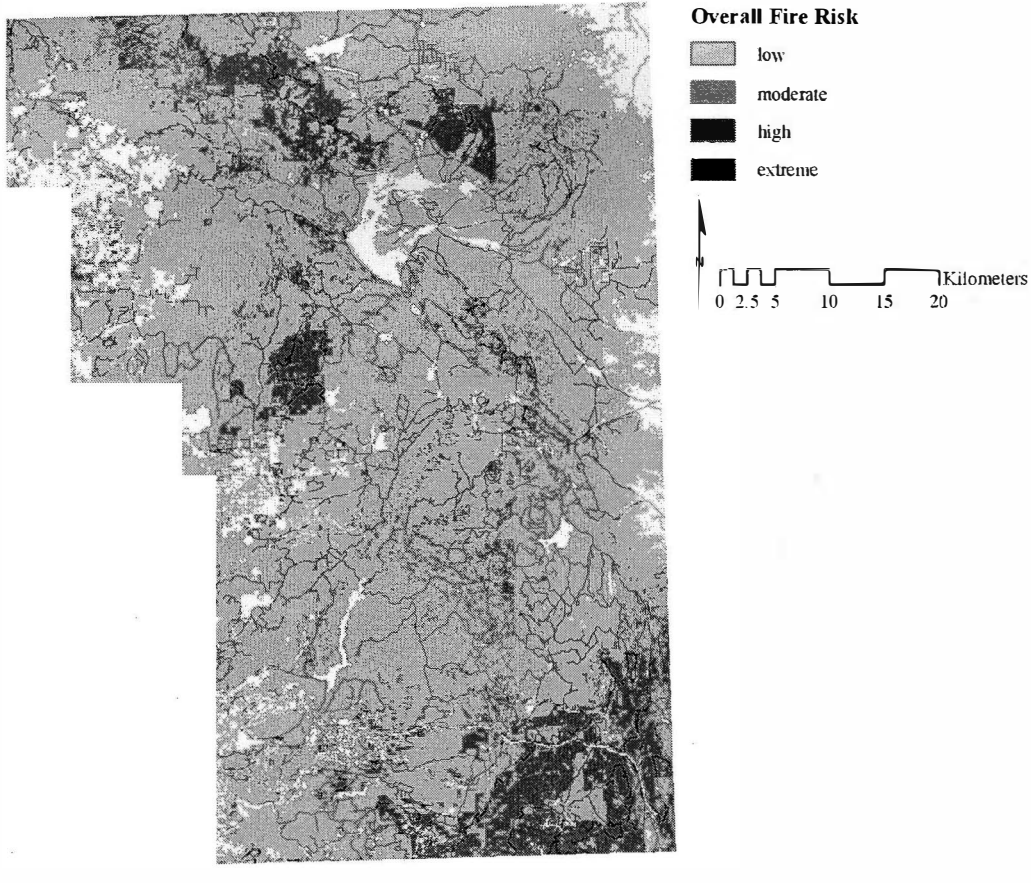


Figure 6.—Overall fire risk based on combining the expert CDF fire-threat model and the data-driven weights-of-evidence fire-ignition risk model. High values indicate areas that have a high probability of a fire ignition occurring and a high probability of a fire ignition spreading into a large fire. Low values indicate areas that have a low probability of a fire ignition occurring and a low probability of a fire ignition spreading into a large fire.

is than correlation to certain vegetation types, population densities, or elevations. Additionally, the posterior probabilities allow us to assess the percent changes in ignition risk associated with inevitable future development.

Beyond evaluating the risk for wildfire ignitions, the empirical model also allows us to assess the weaknesses of current methods for predicting wildfire hazard. Our training data set is one commonly used for fire research, but CDF still uses the somewhat-outdated method of locating ignitions in the exact center of a map section, making the dataset less accurate as a whole. We also questioned whether the reason so many ignitions occurred along roads was because GPS points or mile markers were taken at a fire truck sitting on the road somewhere near the actual fire.

Conclusion

Coupled with expert knowledge, weights-of-evidence and other empirical models can be an effective tool for fire-hazard management. Utilizing the weights-of-evidence tool within the Spatial Data Modeler extension for ArcGIS allows a user to create empirical models to evaluate and gain insight into processes that may not be fully understood, such as fire ignitions. For eastern San Diego County, the location of major roads was shown to be the primary determinant in fire-ignition occurrence. Limitations in weights-of-evidence models do occur and are dependent upon the data being used and the bias of the modeler. We were limited in our processing of these models by our training dataset obtained from the CDF.

Empirical models give us a way to assess future risk and help us to understand processes and mechanisms driving risk. They do not replace expert knowledge and deterministic models, and it would not be recommended to conduct modeling without insights from those individuals who understand the process best. Combining a fuzzy model with an empirical model in a hybrid fashion is an alternative way to infuse expert knowledge into the risk-modeling process. Overall, continued efforts to model the processes that produce fire risk in the first place can serve only to assist the fire-management community whose goal is to mitigate that risk.

Acknowledgments

We thank Dr. John Rogan for helpful comments on an earlier draft of this work. Insight from Dr. Jill Heaton and Dr. Gary Raines im-

proved the paper immensely. We also thank Gene Lohrmeyer for assistance with early analysis.

References

Agterberg, F. P. and Q. Cheng. 2002. "Conditional independence test for weights-of-evidence modeling." *Natural Resources Research* 11 (4):249–255.

Aspinall, R. J. 1992. "An inductive modeling procedure based on Bayes' theorem for analysis of pattern in spatial data." *International Journal of Geographical Information Systems* 6 (2):105–121.

Bonham-Carter, G. F. 1994. *Geographic Information Systems for Geoscientists: Modelling with GIS*. Pergamon Press.

Bonham-Carter, G. F., F. P. Agterberg, and D. F. Wright. 1988. "Integration of geological datasets for gold exploration in Nova Scotia." *Photogrammetric Engineering and Remote Sensing* 54:1585–1592.

Burgan, R. E., R. W. Klaver, and J. M. Klaver. 1998. "Fuel models and fire potential from satellite and surface observations." *International Journal of Wildland Fire* 8 (3):159–170.

Chou, Y. H., R. A. Minnich, and R.A . Chase. 1993. "Mapping probability of fire occurrence in the San Jacinto Mountains." *Environmental Management* 17:129–140.

Chuvieco, E. 2003. *Wildland fire danger estimation and mapping: the role of remote sensing data*. World Scientific Publishing Company.

Dickson, B. G., J. W. Prather, Y. Xu, H. M. Hampton, E. N. Aumack, and T. Sisk. 2006. "Mapping the probability of large fire occurrence in northern Arizona, USA." *Landscape Ecology* 21:747–761.

Farris, C. A., C. Pezeshki, and L. F. Neuenschwander. 1999. "A comparison of fire probability maps derived from GIS modeling and direct simulation techniques." In *Proceedings from the Joint Fire Science Conference and Workshop Vol. I. June 15–17, 1999*, pp. 131–138. University of Idaho and the International Association of Wildland Fire.

Hardy, C. C. and R. E. Burgan. 1998. "Evaluation of NDVI for monitoring live moisture in three vegetation types of the western U.S." *Photogrammetric Engineering and Remote Sensing* 65 (5):603–610.

Keeley, J. E., C. J. Fotheringham, and M. Morais. 1999. "Reexamining fire suppression impacts on brushland fire regimes." *Science* 284:1829–1832.

Keeley, J. E. and C. J. Fotheringham. 2001. "Historical fire regime in southern California shrublands." *Conservation Biology* 15 (6):1536–1548.

Keeley, J. E., C. J. Fotheringham, and M. A. Moritz. 2004. "Lessons from the October 2003 wildfires in southern California." *Journal of Forestry* 102 (7):26–31.

Lee, S. and J. Choi. 2004. "Landslide susceptibility mapping using GIS and the weight-of-evidence model." *International Journal of Geographical Information Science* 18:789–814.

Martin, T. G., P. M. Kuhnert, K. Mengersen, and H. P. Possingham. 2005. "The power of expert opinion in ecological models using Bayesian methods: Impact of grazing on birds." *Ecological Applications* 15 (1):266–280.

Mensing, S. A., R. G. Elston Jr., G. L. Raines, R. J. Tausch, and C. L. Nowak. 2000. "A GIS model to predict the location of fossil packrat (*Neotoma*) middens in central Nevada." *Western North American Naturalist* 60:111–120.

Radke, J. 1995. "Modeling urban/wildland interface fire hazards within a Geographic Information System." *Geographic Information Science* 1:7–20.

Raines, G. L. 1999. "Evaluation of weights-of-evidence to predict epithermal gold deposits in the Great Basin of the western United States." *Natural Resources Research* 8:257–76.

Rorig M., S. J. McKay, S. A. Ferguson, and P. Werth. 2003. "Model-generated predictions of dry-lightning risk—Initial results." *Proceedings of the Joint Sixth Symposium on Fire and Forest Meteorology and the Interior West Fire Council Conference, Canmore, Alberta, October 24–28, 2005.*

Rothermel, R. 1983. *How to predict the spread and intensity of forest and range fires.* USDA Forest Service, Intermountain Research Station General Technical Report INT-143.

Sawatzky, D. L., G. L. Raines, G. F. Bonham-Carter, and C. G. Looney. 2004. *ARCSDM3.1: ArcMap extension for spatial data modelling using weights of evidence, logistic regression, fuzzy logic and nerual network analysis.* Available at: http://www.ige.unicamp.br/sdm.ArcSDM31/. *Accessed 21 May 2006.*

Steinitz, C., C. Adams, L. Alexander, J. DeNormandie, R. Durant, L. Eberhart, J. Felkner, K. Hickey, A. Mellinger, R. Narita, T. Slattery, C. Viellard, Y. Wang, and E. M. Wright. 1997. *Biodiversity and Landscape Planning: Alternative Futures for the Region of Camp Pendleton California.* Harvard University, Graduate School of Design.

Yool, S. R., D. W. Eckhardt, J. E. Estes, and M. J. Cosentino. 1985. "Describing the brushfire hazard in southern California." *Annals of the Association of American Geographers* 75:417–430.