Modeling Containment of Large Wildfires Using Generalized Linear Mixed-Model Analysis

Mark Finney, Isaac C. Grenfell, and Charles W. McHugh

Abstract: Billions of dollars are spent annually in the United States to contain large wildland fires, but the factors contributing to suppression success remain poorly understood. We used a regression model (generalized linear mixed-model) to model containment probability of individual fires, assuming that containment was a repeated-measures problem (fixed effect) and individual fires were random effects. Changes in daily fire size from 306 fires occurring in years 2001–2005 were processed to identify intervals of high spread from those of low spread. The model was tested against independent data from 140 fires in 2006. The analysis suggested that containment was positively related to the number of consecutive days during which the fire grew little and the number of previous intervals. Containment probability was negatively related to the length of intervals during which the fire exhibited high spread and the presence of timber fuel types, but fire size was not a significant predictor. Characterization of containment probability may be a useful component of cost-benefit analysis of large fire management and planning systems. FOR. SCI. 55(3):249–255.

Keywords: wildfire containment, large wildfires, fire suppression, generalized linear mixed models

THOUSANDS OF FIRES start annually in the wildlands of the United States, but most are contained by initial attack (IA) efforts. Studies suggest that only about 1–2% of wildland fires in the western United States grow beyond 100 ha (Neuenschwander et al. 2000, National Interagency Fire Center 2002). The largest 1% have been estimated to be responsible for 83–96% of the burned area (Strauss et al. 1989, Calkin et al. 2005) and elicit suppression responses that, in recent years, have exceeded about 1 billion dollars annually (Donovan and Brown 2005, Gebert et al. 2007). Nevertheless, the effectiveness of suppression efforts on the progress or containment of large fires has not been modeled or even characterized, and it is presently not known what or how different factors are related to successful containment. Understanding the factors contributing to containment success might make it possible to begin assessing the cost-effectiveness of suppression actions or consequences of alternative management strategies for the largest and most expensive fires.

Suppression of large fires is considerably more complex than the IA of small fires. Small fires exist in a more restricted fire environment (fuels, weather, and topography), with far fewer resources assigned to firefighting. Containment on small fires has been modeled geometrically by assuming a direct attack at the combustion edge (Mees 1985, Anderson 1989) or at some fixed distance from it (Fried and Fried 1996). With this kind of modeling, the fire line is anchored at a point on the fire's edge, and the line is constructed in opposite directions around an assumed elliptical fire perimeter until containment is achieved. For large fires, fire line construction typically occurs simultaneously along multiple sectors and may involve an indirect fire line (National Wildfire Coordinating Group 2006) constructed at a distance from the active fire edge and accompanied by burnout operations.

The main factors controlling IA success are often assumed to be deterministic (i.e., fire line production rates, fire behavior, and crew arrival time) (Dimitrakopolous and Omi 2003), but uncertainty in these factors (Haven et al. 1982, Smith 1986, Hirsch et al. 2004) has also led to consideration of stochastic simulations (Smith 1987, Fried and Gilless 1989, Mees et al. 1993, Gilless and Fried 1999, Fried et al. 2006). IA success probability in Canada was found to be strongly influenced by the starting fire size and an index of fire behavior for that day (Arienti et al. 2006). In contrast, large fires are characterized by heterogeneous fuels, vegetation, and weather over many days or weeks. This variability produces much more complicated perimeter growth and associated suppression tactics, prompting the use of probability for characterizing large fire containment (Flowers et al. 1983, Mills and Bratten 1988, Mees and Strauss 1992). Such variability and heterogeneity among the relatively few large wildfires presents many challenges for modeling. In this article, we applied a generalized linear mixed-model analysis (Breslow and Clayton 1993) to data derived from records of recent large fires in an attempt to understand what factors contribute to the probability of containment.

Methods

Our approach to modeling containment of large fires followed field-level experience that these efforts are essentially opportunistic: suppression success depends on having time periods of moderate weather lasting long enough for fire crews to complete containment lines before an extreme episode of weather recurs. For individual fires, the time

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series of daily fire sizes shows that increased growth occurs during intermittent episodes of extreme weather (Mees and Bednar 1989) with the interim periods promoting suppression progress (Flowers et al. 1983). These patterns of alternating containment opportunity suggested that containment probability may be modeled using the intervals of fire activity available from fire records. Modeling the probability of containment would then be a repeated-measurement problem for which the intervals constitute repeated measurements on each fire. Thus, the measurements taken at the intervals (high spread versus low spread, length of the interval, and number of previous low-spread intervals) would be considered fixed effects, and the fires themselves would be random effects (each fire having its unique identifier as a grouping variable).

We obtained data for this analysis from the Incident Status Summary ICS-209 reports required for fires administered by US Federal land management agencies. The ICS-209 program is a US National Fire and Aviation Management (2009) Web Application that Incident Management Teams use to report incident-specific information on more than 40 items such as acres burned, percent containment, number of personnel assigned, and costs to date (US Department of Agriculture-US Department of the Interior 2003). An ICS-209 form is completed for large wildfires, wildland fire use incidents, and any other significant events (e.g., hurricanes, volcanoes, and hazardous materials) on lands under US Federal protection or ownership. The ICS-209 is submitted daily for fire incidents and is used by the National Interagency Coordination Center to prepare the daily National Incident Management Situation Report. Fire incidents requiring an ICS-209 are those with sizes of 40 ha or larger in timber fuel types (100 ac) and 120 ha or larger in grass or brush fuel types (300 ac). Daily fire size is estimated by the local incident management organization using a variety of methods, including helicopter global positioning systems, fixed-wing infrared mapping, and ground-based reconnaissance.

From the ICS-209 reports, we used only the reporting date, daily fire size, and fuel types identified daily as involved in the fire in terms of fuel model (Anderson 1982). We categorized fuels by general vegetation type, with fuel models 1–3 as grass, 4–7 as brush, and 8, 9, or 10 designated as timber. We did not use data recorded for estimated costs because the estimates in the ICS-209 have been suspected of having substantial errors (Gebert et al. 2007). Records for assigned personnel were also not used because there are only ambiguous connections between these general figures and relevant firefighting tactics. That is, the tactical assignments of fire suppression resources (for holding, direct line construction, home defense, and others) are not knowable only from their reported association with a particular fire. Data used for model development were extracted for all fires in the database for years 2001–2005 (earlier records did not contain information on fuel types and were not available electronically). Fires were included for analysis if they met the criteria for being designated a suppression fire only (i.e., no modified suppression or wilderness fires managed for resource benefits) and lasted longer than 5 days. In our analysis we did not attempt to account for tactics or decisions using the various crew and equipment categories reported for the large fires because their actual uses on the fire could not be known. Instead, we reasoned that rates of change in fire size through time were reflective of fire behavior opportunities (or lack of them) as influenced by weather, topography, and fuels and ultimate suppression success.

For each fire, intervals of high and low fire growth were determined (Figure 1). These intervals are a collection of sequential days for which the rate of fire area growth was either greater or less than the average growth rate for the individual fire. A high-spread interval was defined as any sequence of days that remained above the daily average area change for the individual fire, whereas a low-spread interval exhibited daily growth that never exceeded the average area change for the individual fire (Figure 1). The average daily growth rates vary considerably among fires, owing to the local characteristics of fuel patterns, topography, weather, and suppression tactics, which are not knowable from the ICS-209 data. Thus, the distinction of days with high spread is relative and relevant only for an individual fire, which is consistent with our intention here to explore ex post facto the factors affecting containment rather than to forecast containment successes. Containment is officially defined as the "status of suppression action signifying that a control

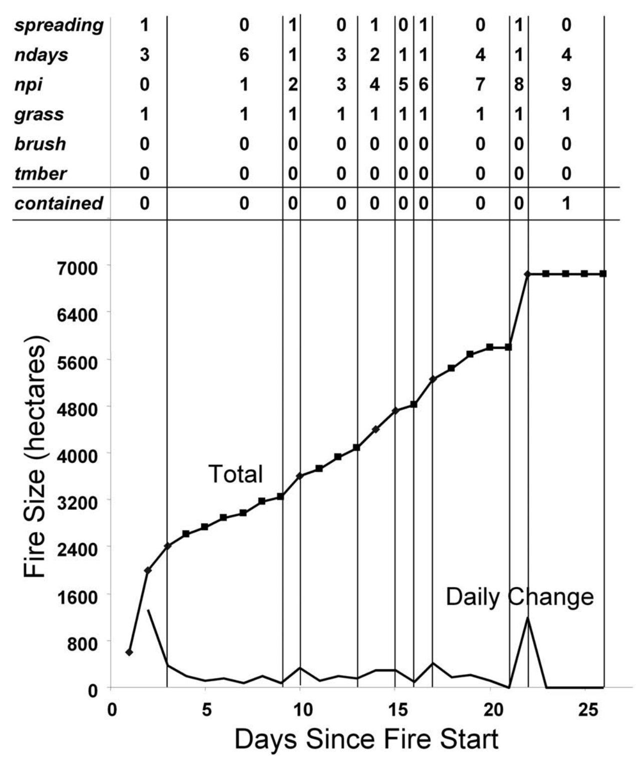

Figure 1. Graph showing how changes in daily fire size were converted into interval-based data for regression analysis. Vertical lines divide the daily fire sizes into intervals. Data at the top of the graph represent the independent variables by interval used to predict containment by the end of the interval (*spreading*, interval exhibiting high fire spread; *ndays*, number of days in an interval [both high-spread and low-spread]; *npi*, number of previous intervals; *grass*, presence of grass fuels, *brush*, presence of brush fuels; *tmber*, presence of timber fuels). This example is from the Apple fire that occurred in Oregon in 2002.

Table 1. Summary of ICS-209 data used formodeling of large wildland fire suppression probability

State	No. fires	Spread intervals: total, average/fire (min, max)	Duration of fires (days): average (min, max)	Fire size (ha): average (min, max)	Intervals with timber fuels (%)
2001–2005 data					
AZ	38	162, 4.3 (2, 9)	14.9 (6, 54)	15,529 (385, 189,732)	47
CA	36	147, 4.1 (1, 10)	11.4 (6, 39)	12,642 (526, 113,473)	64
CO	19	83, 4.4 (2, 7)	13.8 (7, 31)	6,097 (585, 55,773)	79
FL	3	12, 4.0 (1, 8)	17.7 (13, 21)	8,357 (587, 13,846)	33
HI	1	2, 2.0 (2, 2)	17.0 (17, 17)	824 (824, 824)	0
ID	27	145, 5.4 (2, 14)	17.1 (7, 56)	3,544 (289, 16,546)	96
LA	1	2, 2.0 (2, 2)	7.0 (7, 7)	1,433 (1,433, 1,433)	0
MN	1	6, 6.0 (6, 6)	15.0 (15, 15)	540 (540, 540)	100
MT	42	283, 6.7 (2, 20)	23.5 (6, 60)	7,428 (344, 53,007)	98
NM	20	109, 5.5 (1, 17)	13.8 (7, 38)	5,881 (451, 37,449)	95
NV	15	64, 4.3 (2, 8)	10.5 (7, 20)	23,414 (483, 205,972)	27
OK	1	2, 2.0 (2, 2)	11.0 (11, 11)	1,417 (1,417, 1,417)	100
OR	33	168, 5.1 (2, 23)	15.6 (6, 54)	8,331 (567, 48,617)	88
SC	1	2, 2.0 (2, 2)	7.0 (7, 7)	743 (743, 743)	0
SD	6	29, 4.8 (4, 6)	10.2 (6, 13)	6,543 (1,238, 19,433)	100
TX	1	3, 3.0 (3, 3)	1.0 (10, 10)	3,073 (3,073, 3,073)	0
UT	21	91, 4.3 (2, 8)	13.7 (6, 35)	6,963 (630, 38,267)	62
VA	1	7, 7.0 (7, 7)	15.0 (15, 15)	1,532 (1,532, 1,532)	100
WA	23	168, 7.3 (2, 22)	26.0 (6, 98)	4,765 (69, 32,932)	100
WY	16	70, 4.4 (2, 9)	16.3 (7, 55)	450 (486, 9,717)	94
Total	306	1,556, 5.1 (1, 23)	16.3 (6, 98)	8,870 (69, 205,972)	44
2006 data					
AR	2	7, 3.5 (3, 4)	9.0 (8, 10)	2,625 (1,893, 3,358)	50
AZ	9	38, 4.2 (2, 6)	12.9 (7, 19)	2,009 (606, 5,116)	67
CA	18	159, 8.8 (2, 41)	21.3 (7, 92)	9,693 (411, 68,705)	67
CO	1	3, 3.0 (3, 3)	10.0 (10, 10)	5,595 (5,595, 5,595)	100
FL	6	25, 4.2 (2, 6)	12.2 (8, 20)	2,785 (337, 11,842)	83
ID	21	155, 7.4 (2, 17)	23.3 (7, 49)	10,701 (406, 89,086)	90
MN	2	6, 3.0 (2, 4)	25.0 (15, 35)	7,646 (2,405, 12,887)	100
MT	18	106, 5.9 (2, 17)	19.1 (7, 47)	16,521 (429, 90,514)	89
NE	1	6, 6.0 (6, 6)	11.0 (11, 11)	19,757 (19,757, 19,757)	100
NM	6	21, 3.5 (2, 5)	11.3 (7, 16)	8,645 (1,296, 20,772)	100
NV	15	52, 3.5 (2, 7)	9.6 (7, 16)	22,556 (479, 96,542)	13
OK	2	6, 3.0 (2, 4)	7.5 (7, 8)	2,217 (1,194, 3,239)	50
OR	12	66, 5.5 (2, 12)	20.3 (8, 36)	8,073 (433, 44,300)	83
TX	6	19, 3.2 (2, 5)	9.3 (8, 12)	2,312 (526, 4,939)	0
UT	9	24, 2.7 (2, 4)	9.0 (7, 13)	4,798 (517, 17,640)	22
VA	1	6, 6.0 (6, 6)	7.0 (7, 7)	783 (783, 783)	100
WA	5	58, 11.6 (7, 18)	40.2 (28, 55)	13,962 (672, 44,292)	100
WY	6	24, 4.0 (2, 6)	17.5 (7, 37)	3,381 (409, 9,155)	83
Total	139	781, 5.6 (2, 41)	17.3 (7, 92)	10,119 (337, 96,542)	68

Data are average (minimum, maximum) unless otherwise indicated. A total of 306 fires were used to develop the statistical model (2001–2005), and 139 fires from 2006 were used for testing the model performance.

line has been completed around the fire, and any associated spot fires which can reasonably be expected to stop the fire's spread" (National Wildfire Coordinating Group 2006). For this study, we interpreted containment at the fire size and date of the ICS-209 form filed as the last of a continuous sequence of reports. This excludes final dates that, for unknown reasons, are preceded by a hiatus in reporting of days or weeks with no change in fire size.

The number of days in each interval was recorded along with number of previous spread intervals (Figure 1). The end point of each interval was also identified as either the permanent end of fire growth (successful containment) or not (i.e., the fire gained in size in later periods) (Figure 1). This procedure assumed that each fire represented a history of opportunities for complete containment (little or no growth) as well as a record of the outcome of containment efforts (containment or not).

Statistical analysis of the derived containment data was performed using a generalized linear mixed model (GLMM) in the statistics program R (R Development Core Team 2008). Models of this type allow for explicit separation of terms for random and fixed effects (Schall 1991). Using the GLMM with the logit link for which the responses are assumed to follow a binomial family [with error term assumed Normal(0, σ^2)]. We considered all measured variables with first-order interactions. We then culled all insignificant interactions ($P > 0.05$) and lower-order terms based on the Akaike information criterion (AIC) (Sakamoto et al. 1986). The AIC reflects both an explanatory value of the predictors as well as penalties for model overspecification.

Table 2. Results of the generalized linear mixed model analysis showing the statistical model of large fire containment probability (logit)

	Coefficient	SE	z	Pr(>|Z|)
Intercept	−3.81414	0.53283	−7.158	8.17e−13
timber	0.81305	0.55562	1.463	0.143382
ndays	1.14347	0.19092	5.989	2.11e−09
npi	0.13592	0.02665	5.100	3.40e−07
spread	−1.21689	0.64623	−1.883	0.059694
timber:ndays	−0.74262	0.19348	−3.838	0.000124
ndays:spread	−0.95960	0.33478	−2.866	0.004152
Number of intervals	1,556			
Number of fires:	308			
Degrees of freedom:	1,241			
AIC	857.9			
Deviance	841.9			

The variables are *ndays,* number of days in an interval (both high-spread and low-spread); *npi,* number of previous intervals; *spread,* Boolean presence of high spread in interval; and *timber,* Boolean presence of timber fuels in interval.

The quality of the model predictions was assessed in two ways. First, we used a jackknife analysis (Zheng et al. 2005), in which one fire (and associated intervals) was removed from the sample, the remaining fires were used to fit the model (using the same independent variables), and the containment probability was predicted for the removed fire at each of its spread intervals. When done for all fires and all intervals, Pearson's product-moment correlation was used to examine the correlation of observed containment (binary) and predicted containment probability. These predicted probabilities were then used to obtain a receiver operating characteristic (ROC) plot, which summarizes the correct classification rate of the model as a function of the rates of false predictions (Hosmer and Lemeshow 2000). Second, we tested the regression model that was developed from the 2001–2005 data against independent data for 139 fires that occurred in 2006. We used these predicted probabilities to form another ROC curve. Also, for each data set, the percentage of actual containment was evaluated relative to the predicted rate by probability decile.

Results

The ICS-209 forms for years 2001–2005 produced a total of 306 fires and data for 1,556 intervals (Table 1). Fires varied in size from 69 to 205,972 hectares and burned for time periods ranging from 6 to 98 days. Data from the year 2006 used for testing the model included 139 individual fires with sizes ranging from 337 to 96,542 hectares (Table 1).

The GLMM regression analysis produced predictions of containment probability on a logit scale (Table 2) and suggested that successful containment was positively related to the number of days in an interval (high-spread or low-spread) and the number of previous intervals (*npi*) (Figure 2). Probability of containment was much higher during low-spread intervals (Figure 2) than during high-spread intervals.

The regression model with the best AIC included significant two-way interactions of *timber* and *spread* with interval length (*ndays*) (Table 2). These interaction terms improved the model (lower AIC), but rendered the individual *timber* and *spread* terms not significant (these were retained in the final model because of the significant interactions). The individual terms (*timber*, *spread*) were shown to be significant in models without the interactions as well, with the same direction of influence on containment probability. When graphed, the *timber* and *spread* interactions suggest that containment probabilities in nontimber fuel types increased with the length of intervals (both high-spread and

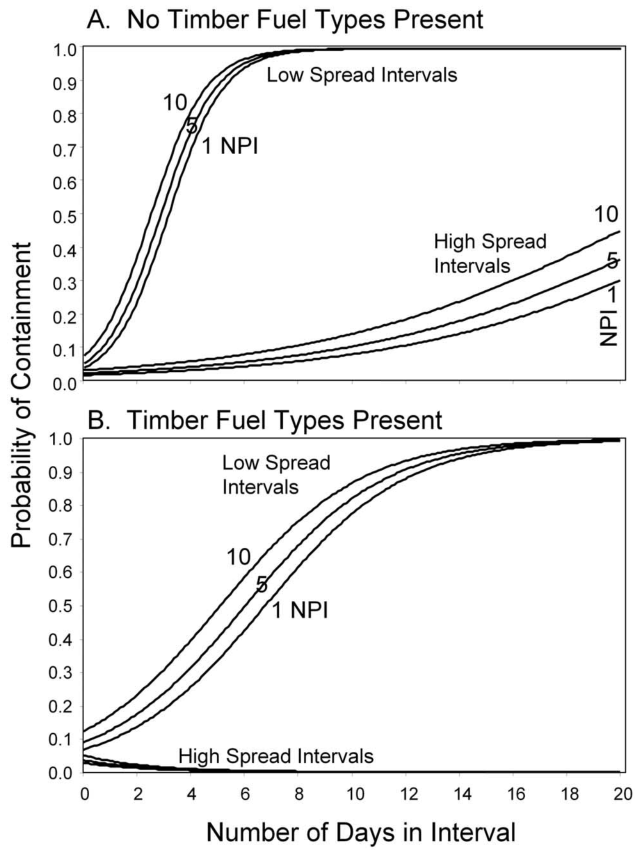

Figure 2. Graph showing the effects of the main variables on containment success (NPI, number of previous intervals). The comparison of (A) the low probability of containing fires during high-spread intervals compared with low-spread intervals in fuel types that do not include timber fuel types and (B) the lower probability of containing fires when timber fuel types are present is shown. The probability of containment during high-spread intervals increased when timber fuels were absent (A) but decreased when present (B).

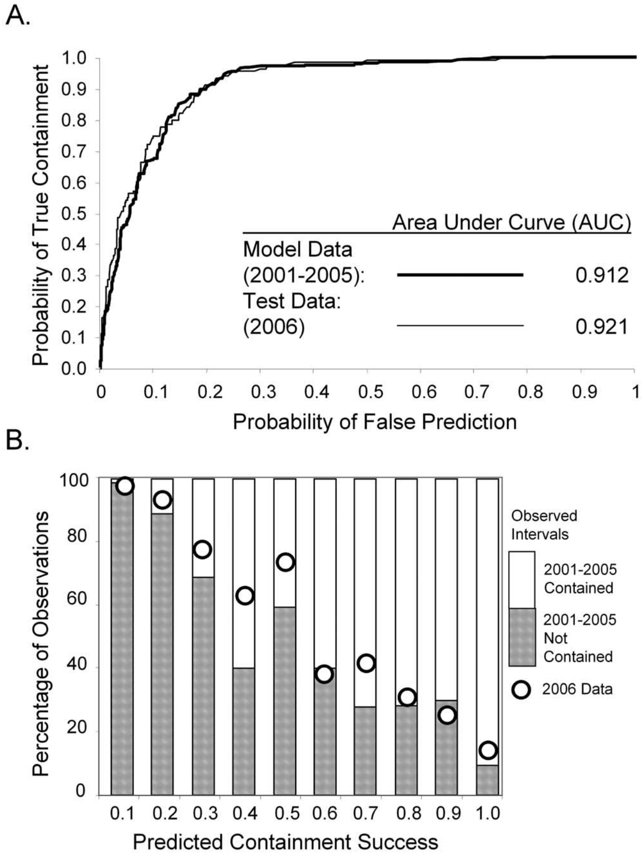

Figure 3. Model performance and behavior are depicted by (A) the ROC curve constructed using the 2001–2005 data from which the model was constructed and the 2006 independent data, and (B) containment rates compared with predicted containment probability deciles for both the 2001–2005 data set and the 2006 independent data sets.

low-spread), but probabilities decreased with longer high-spread intervals when timber fuels are present (Figure 2). Fire size was not significant in any of the regression models.

Pearson's product-moment correlation for the regression was 0.6913, suggesting that observed and predicted containment probabilities are highly correlated. The ROC plots (Figure 3a), with areas under the curve of 0.912 using the 2001–2005 data and 0.921 for the independent 2006 data, suggest that the model had a very high rate of discrimination of containment. Rates of observed containment of fires in both data sets (2001–2005, and 2006) were similar, and both appeared to be linearly related to the probability of containment by the model (Figure 3b).

Discussion

The statistical predictors of containment success seemed to support the intuition of firefighters that large fires are contained opportunistically. The opportunities for successful containment were significantly higher during periods of low fire spread (Table 2; Figure 2). Thus, the consequence of containment success is reflected in the area not burned during future periods of extreme weather. An increase in containment probability was also found on fires that had been burning longer (more previous intervals). This finding probably reflects the increased size and organization of the suppression response (management team, crews, and equipment) as well as the accumulation of partial perimeter containment achieved during earlier intervals (making ultimate containment easier). Surprisingly, fire size was not found by this analysis to be a significant predictor of containment. An explanation may involve similar time-dependent factors, namely the concomitant increases in suppression forces and accumulated perimeter containment that accompany fire growth. These factors are confounded with time and fire growth in these data and may be indirectly accounting for trends expected to suggest more difficult suppression of larger fires. However, this result raises important questions concerning the factual basis for presupposing that containment depends more on fire size than on opportunity.

Timber fuel types were associated with lower probability of containment success. This result may partly reflect fire occurrence in mountainous terrain in which access is more limited and the fact that heavier fuels are associated with slower line construction (Haven et al. 1982). It could also reflect a greater likelihood that timber fuels may be encompassed by fires as they become larger (and burn longer) or that fires burning in woody fuels can smolder and resume spreading after enduring many days of unfavorable weather (unlike grass fires). Such "holdover" fires and more difficult mop-up by fire crews offer more possibilities for escape during return episodes of extreme weather even after nominal containment is achieved. Spotting and crown fire present particular control problems in timber fuels and may be responsible for the regression trend showing longer intervals of high spread associated with decreasing containment probabilities but increasing probability of containment on fires without timber fuels (Figure 1). Perhaps these issues with containment difficulty underlie the recent finding that timber fuel types were associated with the highest suppression costs (Gebert et al. 2007).

Compared with the mechanistic approaches used for the IA (e.g., Anderson 1989, Fried and Fried 1996), our statistical model cannot be used to examine tradeoffs or sensitivity to the use of alternative mixtures of suppression resources. The data and model presented here assume implicitly the use of resources according to generic historic fire suppression strategies. We did not have data that would allow us to separate fires according to management strategy (e.g., full suppression versus modified or no suppression). These data also did not allow analysis of effects of resource scarcity on containment success (Bednar et al. 1990, Fried et al. 2006), although constraints of firefighting resources would be generally expected to diminish successful containment probability. Furthermore, our methods of distinguishing intervals of high versus low growth rely on having fire growth history for each fire individually, meaning that this analysis is not usable for prognosticating containment of active fires if data on past growth are absent and future daily growth cannot be estimated. The particular or unique situation contributing to the behavior of each fire is, thus, important to its containment.

Notwithstanding these limitations, statistical models of containment success might be useful for fire planning and budgeting. Given the assumption of the historic suppression response, a probability model such as the one reported here could be used to assess containment of active fires provided a weather forecast is available. If the forecast could be interpreted to suggest the lengths and sequences of quiescent and active periods, the containment probability could be anticipated by using other attributes of the fire known to date (e.g., number of previous low-spread intervals). By combining the probability of containment with predictions of fire growth, two fire progression scenarios (with and without suppression) could contribute to cost-benefit analysis when combined with values at risk. Further analysis may reveal improved statistical modeling from directly considering fire behavior or some measure of firefighting effort (e.g., numbers of crews involved in line construction).

Cost-benefit analysis could also be applied to past fires as a metric to explore effects of alternative fire management strategies as well as questions regarding the role of 20th century suppression policies in altering burning rates and fire size distributions. The latter subject is controversial because large fires exhibit episodes of uncontrollable behavior (Miyanishi and Johnson 2001). However, this study suggests that intervals of moderate behavior are conducive to control, perhaps contributing to the decreases in burned area (Ward et al. 2001) and escape frequencies (Cumming 2005) coincident with implementation of modern suppression organizations.

Conclusions

The generalized linear mixed-model analysis performed using data on size changes in historic large fires lends support for the idea that suppression effects are opportunistic and dependent on the duration of moderate fire behavior. This modeling is a first step in trying to understand how suppression efforts and large fire containment are related. Better models are needed to describe large fire responses to resources and budget variables but must await the availability of better data.

Literature Cited

ANDERSON, D.H. 1989. A mathematical model for fire containment. *Can. J. For. Res.* 19:997–1003.

ANDERSON, H.E. 1982. *Aids to determining fuel models for estimating fire behaviour.* US For. Serv. Intermountain Forest and Range Exp. Stn., Ogden, UT, Gen. Tech. Rep. INT-GTR-122.

ARIENTI, M.C., S.G. CUMMING, AND S. BOUTIN. 2006. Empirical models of forest fire initial attack success probabilities: The effects of fuels, anthropogenic linear features, fire weather, and management. *Can. J. For. Res.* 36:3155–3166.

BEDNAR, L.F., R. MEES, AND D. STRAUSS. 1990. Fire suppression effectiveness for simultaneous fires: An examination of fire histories. *West. J. Appl. For.* 5(1):16–19.

BRESLOW, N.E., AND D.G. CLAYTON. 1993. Approximate inference in generalized linear mixed models. *J. Am. Statist. Assoc.* 88:9–25.

CALKIN, D.E., K. M. GEBERT, J. G. JONES, AND R. P. NEILSON. 2005. Forest service large fire area burned and suppression expenditure trends 1970–2002. *J. For.* 103(4):179–183.

CUMMING, S.G. 2005. Effective fire suppression in Boreal Forests. *Can. J. For. Res.* 35(4):772–786.

DIMITRAKOPOLOUS, A.P., AND P.N. OMI. 2003. Evaluation of the fire simulation processes of the national fire management system's initial attack analysis processor. *Environ. Manag.* 31(1): 147–156.

DONOVAN, G.H., AND T.C. BROWN. 2005. An alternative incentive structure for wildfire management on National Forest land. *For. Sci.* 51(5):387–395.

FLOWERS, P.J., T. P. HUNTER, AND T. J. MILLS. 1983. Design of a model to simulate large-fire suppression effectiveness. P. 168–173 in *Proc. 7th Conf. on Fire and Forest Meteorology.* American Meteorological Society, Boston, MA.

FRIED, J.S., AND B.D. FRIED. 1996. Simulating wildfire containment with realistic tactics. *For. Sci.* 42(3):267–281.

FRIED, J.S., AND J.K. GILLESS. 1989. Expert opinion estimation of fireline production rates. *For. Sci.* 35(3):870–877.

FRIED, J.S., J.K. GILLESS, AND J. SPERO. 2006. Analyzing initial attack on wildland fires using stochastic simulation. *Int. J. Wildl. Fire* 15:137–146.

GEBERT, K.M., D.E. CALKIN, AND J. YODER. 2007. Estimating suppression expenditures for individual large wildland fires. *West. J. Appl. For.* 22(3):188–196.

GILLESS, J.K., AND J.S. FRIED. 1999. Stochastic representation of fire behavior in a wildland fire protection planning model for California. *For. Sci.* 45(4):492–499.

HAVEN, L., T. P. HUNTER, AND T.G. STOREY. 1982. Production rates for crews using hand tools on firelines. US For. Serv. Pacific Southwest Forest and Range Exp. Stn. Gen. Tech. Rep. PSW-62. 8 p.

HIRSCH, K.G., J.J. PODUR, R.F. JANSER, RS. MCALPINE, AND D.L. MARTELL. 2004. Productivity of Ontario initial-attack fire crews: Results of an expert-judgment elicitation study. *Can. J. For. Res.* 34:705–715.

HOSMER, D.W., AND S. LEMESHOW. 2000. *Applied logistic regression*. 2nd ed. John Wiley and Sons, New York, NY, p. 160–164.

MEES, R.M. 1985. Simulating initial attack with two fire containment models. US For. Serv. Res. Note PSW-378. 7 p.

MEES, R.M., AND L. BEDNAR. 1989. The use of fire weather indices in the prediction of extreme fire loads. *West. J. Appl. For.* 4(2):46–48.

MEES, R.M., AND D. STRAUSS. 1992. Allocating resources to large wildland fires: A model with stochastic production rates. *For. Sci.* 38(4):882–853.

MEES, R.M., D. STRAUSS, AND R. CHASE. 1993. Modeling wildland fire containment with uncertain flame length and fireline width. *Intl. J. Wildl. Fire.* 3(3):179–185.

MILLS, T.J., AND F.W. BRATTEN. 1988. Economic efficiency and risk character of fire management programs, Northern Rocky Mountains. US For. Serv. Pacific Southwest Forest and Range Exp. Stn. Res. Pap. PSW-192.

MIYANISHI, K., AND E.A. JOHNSON. 2001. Comment—A reexamination of the effects of fire suppression in the boreal forest. *Can. J. For. Res.* 31:1462–1466.

NATIONAL FIRE AND AVIATION MANAGEMENT. 2009. FAMWEB. Available online at fam.nwcg.gov/fam-web/; last accessed Apr. 22, 2009.

NATIONAL INTERAGENCY FIRE CENTER. 2002. *Highlights for the 2002 wildland fire season*. Available online at www.nifc.gov/fire-info/fire_summaries/summary_2002; last accessed Apr. 22, 2009.

NATIONAL WILDFIRE COORDINATING GROUP. 2006. *Glossary of wildland fire terminology.* Publ. PMS 205, NFES#1832. National Interagency Fire Center, Great Basin Cache Supply Office, Boise, ID.

NEUENSCHWANDER, L.F., J.P. MENAKIS, K.M. MILLER, R.N. SAMPSON, C. HARDY, B. AVERAILL, AND R. MASK. 2000.

Indexing Colorado watersheds to risk of wildfire. *J. Sustain. For.* 11(1/2):35–55.

R Development Core Team. (2008). *R: A language and environment for statistical computing.* R Foundation for Statistical Computing, Vienna, Austria. Available online at www.r-project.org/; last accessed Apr. 22, 2009.

Sakamoto, Y., M. Ishiguro, and G. Kitagawa. 1986. *Akaike information criterion statistics.* KTK Scientific Publishers, Tokyo, Japan, p. 56–85.

Schall, R. 1991. Estimation in generalized linear models with random effects. *Biometrika* 78:719–727.

Smith, E.L. 1986. Sensitivity of fire size to fireline construction rates in a simulation model. *Fire Technol.* 22(2):136–147.

Smith, E.L. 1987. A fire management simulation model using stochastic arrival times. US For. Serv. Pacific Southwest Forest and Range Exp. Stn. Res. Pap. PSW-189. 9 p.

Strauss, D., L. Bednar, and R. Mees. 1989. Do one percent of forest fires cause ninety-nine percent of the damage? *For. Sci.* 35(2):319–328.

US Forest Service-US Department of Interior. 2003. *Interagency situation report user's guide*. 158 p.

Ward, P.C., A.G. Tithecott, and B.M. Wotton. 2001. Reply—A re-examination of the effects of fire suppression in the boreal forest. *Can. J. For. Res.* 31:1467–1480.

Zheng, B., D.P. Chakraborty, H.E. Rockette, G.S. Maitz, and D. Gur. 2005. A comparison of two data analyses from two observer performance studies using jackknife ROC and JAFROC. *Med. Phys.* 32(4):1031–1034.