



Development and application of a probabilistic method for wildfire suppression cost modeling



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ABSTRACT

Wildfire activity and escalating suppression costs continue to threaten the financial health of federal land management agencies. In order to minimize and effectively manage the cost of financial risk, agencies need the ability to quantify that risk. A fundamental aim of this research effort, therefore, is to develop a process for generating risk-based metrics for annual suppression costs. Our modeling process borrows from actuarial science and the process of assigning insurance premiums based on distributions for the frequency and magnitude of claims, generating parameterized probability distributions for fire occurrence and fire cost. A compound model of annual suppression costs is built from the coupling of a wildfire simulation model and a suppression cost model. We present cost modeling results for a set of high cost National Forests, with results indicating variation in expected costs due to variation in factors driving financial risk. We describe how our probabilistic cost models can be used for a variety of applications, in the process furthering the Forest Service's movement towards increased adoption of risk management principles for wildfire management. We review potential strengths and limitations of the cost modeling process, and conclude by discussing policy implications and research needs.

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1. Introduction

Wildfire activity and escalating suppression costs continue to threaten the financial health of federal land management agencies, in particular the U.S. Department of Agriculture Forest Service (Forest Service). Again in 2013 the Forest Service faced emergency budget funding transfers to allow the agency to continue to suppress fires because fire suppression funds were exhausted. Transferring funds from multiple critical budgets (timber, recreation, research, etc.) can be highly disruptive (U.S. Government Accountability Office, 2004; U.S. Government Accountability Office, 2007; Peterson et al., 2008), even for fire-related programs such as hazardous fuels management (Stephens and Ruth, 2005). High inter-annual variability in large fire suppression costs leads to reliance on the use of a 10-year rolling average for budgetary purposes, and increasing suppression expenditures have led to decreasing budgets for non-fire programs. In both 2012 and 2013 the proportion of the Forest Service's budget associated with wildfire has approached 50% of total discretionary funds; whereas in 2000 allocation

represented less than 20% (Abt et al., 2009a; U.S. Department of Agriculture, 2009). Including emergency budget transfers, in 2012 and 2013 wildfire suppression expenditures exceeded 50% of the Forest Service's total budget. Collectively these financial impacts constrain the ability of the Forest Service to achieve land and resource management objectives.

The high variability of annual suppression costs and associated impacts to program budgets creates financial risk for the Forest Service. In order to minimize and effectively manage the cost of that financial risk, the agency needs the ability to quantify that risk. A fundamental aim of this research effort, therefore, is to develop a process for generating risk-based metrics for annual suppression costs. With risk monetized, it becomes possible to better monitor fire manager performance and to put incentives in place that encourage sound risk management. Our process is also intended to provide an improved ability to understand variation in factors driving financial risk, in order to identify efficient risk mitigation and cost containment actions.

Our work builds from research aimed at better understanding suppression expenditures, as well as better understanding how various wildfire management activities may affect future suppression costs (Taylor et al., 2013; Thompson et al., 2013d). A growing body of work attempts to use mid-range climate forecasts to project fire season costs, and thereby improve predictive power relative to a 10-year

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moving average (Prestemon et al., 2008; Abt et al., 2009b; Preisler et al., 2011). However, these models have a limited ability to compare projected costs against actual fire workload, and do not have the spatial resolution to estimate costs of specific fires in specific geographic areas. By contrast, most of the existing work has more refined spatial resolution but limits the focus to understanding factors affecting the costs of individual incidents (Gebert et al., 2007; Liang et al., 2008; Yoder and Gebert, 2012; Gude et al., 2013). Econometric analyses of historical per-fire suppression costs have identified a number of environmental and socioeconomic factors that influence suppression costs, principal among which are final fire size, ownership, and the presence of populated areas proximal to the fire. However, the fire-by-fire nature of these cost analyses provides only a limited ability to assess the cumulative impacts of fire management decisions and associated suppression costs across multiple fires and across multiple fire seasons.

In this paper, we review major developments and improvements in suppression cost estimation based on actuarial science principles. Our modeling process is built from the coupling of a wildfire simulation model and a suppression cost model, and is based on recent work estimating suppression costs on National Forest System lands (Thompson et al., 2013a; Thompson et al., 2013d). Relative to earlier work, the key advancement here is the generation of parameterized probability distributions for fire occurrence and fire cost, leading to a compound model of annual suppression costs. This approach leverages advancements in spatial, stochastic wildfire simulation to better capture geographic variation in wildfire ignition probability and growth potential, and further to better account for current landscape conditions resulting from past management activities and disturbances (insect outbreak, wildfire, etc.). This latter component allows for an extension of the cost analysis framework to consider not just suppression response alone but rather the entire spectrum of land and fire management activities (e.g., fuel treatment), and thus periodic re-estimation of suppression cost distributions could reflect expected cost reductions due to past investments in risk-mitigation activities. Similarly, the framework could account for changes in factors likely to increase suppression costs, such as expanded residential development in fire-prone areas or increased fire spread potential due to accumulation of fuels. Combined with a suppression cost model that incorporates geographic information such as ownership at ignition, fuel type, topography, and proximal values-at-risk, this new modeling approach can generate annual forecasts of suppression expenditures while capturing fine-scale spatial variation in factors influencing fire growth and suppression costs, all within a probabilistic framework.

As a demonstration of our novel, actuarially-based annual suppression cost estimation process we present cost modeling results — expected values and compound probability distributions — for a set of identified high cost National Forests. To clarify, this is not a retrospective analysis of historical costs, but rather a forward-looking forecast based on current conditions, using models parameterized from historical data. We describe how our probabilistic cost models can be used for a variety of applications, in the process furthering the Forest Service's movement towards increased adoption of risk management principles for wildfire management. We review potential strengths and limitations of the cost modeling process, and conclude by discussing policy implications and research needs.

2. Development of a probabilistic model for annual suppression costs

In this section we develop a compound model of aggregate suppression cost for annual large fire suppression costs. The compound model is based on the joint estimation of the distribution of the number of escaped large wildfires per year, and the distribution of the per-fire suppression cost. Application of the model is premised on the geographic delineation of a land management unit of interest and their respective areas of responsibility for managing ignitions. In effect this model is

identical to a compound model of aggregate loss used by actuaries to develop insurance premiums, for instance in the health insurance arena actuaries estimate distributions for the annual number of claims and the amount per claim to derive a distribution for the total annual claim amount.

Consider a given National Forest F , and let S represent the total annual suppression costs for F in a given fire season. Our ultimate aim is the identification of a probability distribution for S . Next, let N represent the number of escaped large wildfires in a given fire season, and X_k the total suppression expenditures for fire k in F . Eq. (1) presents derivation of S as a function of N and X . For our purposes here we assume independence between N and S , which may not strictly hold under rare circumstances where high synchronous fire load leads to scarcity of available firefighting resources. Turning to a probabilistic framework, the derivation of the expected value ($E(S)$) and variance ($Var(S)$) for total annual suppression expenditures are presented in Eqs. (2) and (3), respectively.

$$S = \sum_{k=1}^N X_k \quad (1)$$

$$E(S) = E(N)E(X) \quad (2)$$

$$Var(S) = E(N)Var(X) + [E(X)]^2Var(N) \quad (3)$$

To illustrate application of the suppression cost estimation process we identified a set of 25 high cost National Forests to study, all of which are located in the western United States, selected on the basis of mean annual suppression costs over the period 2000–2012. We obtained suppression cost information from the Foundation Financial Information System,² a system used by the Forest Service to track wildfire suppression expenditures. Table 1 provides summary information for each National Forest, including historical mean annual suppression costs ($\bar{S}_h$).

There are a number of compelling reasons to turn to a compound loss model rather than estimate the distribution of S directly from historical costs. From a practical perspective, the historical record has limited utility to directly estimate S due to prior cost accounting practices that made it difficult to comprehensively link suppression costs to specific fires (Gebert et al., 2007). Further, decoupling annual suppression expenditures (S) allows for a more refined ability to model spatiotemporal variation in the underlying factors driving fire occurrence (N) and cost (X). Fire occurrence patterns, for instance, can range from almost exclusively lightning-caused to strongly human-influenced. Landscape changes due to vegetative growth, previous wildfires, other disturbances (e.g., insect and disease), and land management activities (e.g., hazardous fuel reduction) can directly influence fire growth potential and area burned, key variables influencing suppression costs.

To generate frequency distributions for N we queried a historical (1992–2011) nationwide fire occurrence database (Short, 2013), filtering fires on the basis of size (≥ 300 acres, a “large” fire for cost accounting purposes), reporting unit (individual National Forest preparing the fire report), and owner (Forest Service, agency responsible for managing the land at the ignition location). We tested three parametric frequency distributions (Poisson, negative binomial, and geometric), and selected a model for each National Forest based upon the criterion of the lowest value of the χ^2 goodness-of-fit test statistic.

To generate severity distributions for X we combined a suppression cost model (Gebert et al., 2007) with FSim, a stochastic fire simulation system (Finney et al., 2011), using a similar process to that outlined in (Thompson et al., 2013a; Thompson et al., 2013d). The cost model is a statistical regression model based on historical costs, and provides

² The Foundational Financial Information System is being replaced by the Financial Management Modernization Initiative (FMMI), available at <http://info.fmmi.usda.gov/>.

Table 1

Top 25 high cost National Forests, according to mean annual suppression cost (2000–2012), ranked in order of Unit ID (the first digit of the Unit ID corresponds to the Forest Service Region number). None of the high cost forests come from the Rocky Mountain (R2), Southern (R8), Eastern (R9), or Alaska (R10) Regions.

Unit ID	National Forest	Forest Service Region	Annual suppression cost (2000–2012)	
			Mean	Standard deviation
103	Bitterroot	Northern	\$9,815,021	\$9,761,683
110	Flathead	Northern	\$14,466,436	\$27,477,686
116	Lolo	Northern	\$15,176,216	\$22,321,817
117	Nez Perce	Northern	\$10,052,874	\$8,758,009
301	Apache-Sitgreaves	Southwestern	\$13,975,932	\$23,550,251
305	Coronado	Southwestern	\$15,162,474	\$16,349,708
306	Gila	Southwestern	\$10,848,905	\$9,250,849
312	Tonto	Southwestern	\$12,119,432	\$9,171,445
402	Boise	Intermountain	\$17,419,745	\$19,253,090
412	Payette	Intermountain	\$11,151,025	\$13,030,689
413	Salmon-Challis	Intermountain	\$14,523,727	\$14,943,284
501	Angeles	Pacific Southwest	\$21,811,916	\$28,158,261
502	Cleveland	Pacific Southwest	\$11,002,495	\$9,970,965
505	Klamath	Pacific Southwest	\$17,521,434	\$19,887,857
507	Los Padres	Pacific Southwest	\$40,137,234	\$47,181,113
508	Mendocino	Pacific Southwest	\$12,693,959	\$13,568,109
510	Six Rivers	Pacific Southwest	\$11,869,254	\$18,263,222
511	Plumas	Pacific Southwest	\$17,748,051	\$20,501,882
512	San Bernardino	Pacific Southwest	\$19,826,445	\$14,955,394
513	Sequoia	Pacific Southwest	\$17,003,823	\$8,424,548
514	Shasta-Trinity	Pacific Southwest	\$25,177,222	\$36,784,348
601	Deschutes	Pacific Northwest	\$17,380,703	\$15,518,080
610	Rogue River-Siskiyou	Pacific Northwest	\$16,241,620	\$25,895,041
615	Umpqua	Pacific Northwest	\$12,674,818	\$16,904,775
617	Okanogan/Wenatchee	Pacific Northwest	\$29,372,811	\$27,056,507

estimates of the natural logarithm of cost-per-acre. Significant predictors of cost-per-acre include variables associated with the fire environment (e.g., fuel type), values-at-risk (e.g., total housing value within a given radius), and fire size. Operationally a transformed value of cost-per-acre is used by federal agencies for suppression cost analysis purposes, and the regression model is embedded within the Wildland Fire Decision Support System (WFDSS) for cost projection guidance on active wildfire incidents (Calkin et al., 2011b). Within WFDSS fire managers are presented with a range of potential final fire sizes along with cost-per-acre estimates; all else being equal, fires that are larger tend to cost less on a per-acre basis. Multiplying cost-per-acre by final fire size provides an estimate of total fire cost (Thompson et al., 2013a).

The suppression cost model is updated on an annual basis to account for more recent fires, and so the model that we actually employ in this analysis is slightly different than that originally published in 2007, and built from more recent suppression expenditure data. Note however that the model we used relies on Census data from the year 2000 to determine housing values, so that a historical snapshot rather than contemporaneous housing values is incorporated in the model. Reliance on Census data has the likely effect of under-predicting suppression expenditures in areas that have been developed since 2000.

The FSim fire modeling system provides fire-level characteristics (ignition location, size, and perimeter) and raster values summarizing burn probabilities and conditional fireline intensities, and is used for interagency planning purposes as well as landscape exposure and risk assessment (Thompson et al., 2011; Ager et al., 2012; Scott et al., 2012; Thompson et al., 2013b). A key output provided by FSim is the ignition location, which is determined probabilistically according to a historical ignition density grid. Based on the ignition location, variables required for the cost model can be identified, including the fire environment (slope, aspect, elevation, fuel type, and energy release component, a function of fuel moisture) as well as threatened resources and assets (distance to the nearest town, total housing value within 20 miles of ignition). To identify simulated fires to include in our estimation process

we filtered according to ignition location, including only fires that ignited within National Forest boundaries. We used FSim fire size outputs, calibrated to approximate geographically-specific historical fire size distributions. Combining these models enables fire suppression cost distributions (X) to be estimated, for which we tested the fit of the lognormal, Weibull, and exponential distributions. We selected a model for each National Forest based jointly on the lowest value of the Kolmogorov–Smirnov and χ^2 goodness-of-fit test statistics.

Our analysis begins by exploring variation in distributions of fire occurrence (N) and cost (X) across the high cost National Forests. Using the formulation presented in Eqs. (1)–(3), we then estimate $E(S)$ and $Var(S)$ values. Lastly, through Monte Carlo simulation based upon parametric probability distributions obtained for N and X , we simulate annual suppression cost distributions and compare these distributions across a selected set of National Forests.

3. Model demonstration: a case study of high cost forests

Tables 2 and 3 summarize the models selected for each of the N and X distributions, respectively, for each of the National Forests identified in Table 1. Model selection for N was fairly uniform across the theoretical distributions, with 10 negative binomial distributions, 9 Poisson distributions, and 6 geometric distributions (Table 2). This could reflect variation in factors driving large fire occurrence, including ignition patterns and initial attack capacity, although further research would be necessary to make more conclusive statements. To the contrary, for the distribution of X the lognormal distribution provided the best fit in all cases (Table 3).

Fig. 1 displays a scatterplot of modeled $E(N)$ and $E(X)$ values for all 25 high cost National Forests. The product of these axes is $E(S)$, and isolines indicate a range of values for $E(S)$ — \$2.5M, \$5M, \$10M, \$15M, \$20M, \$25M, and \$30 M. The isolines help identify National Forests with similar expected annual costs, while use of the scatterplots helps identify variation in the underlying the factors driving cost estimates. For instance, Unit 110 (\$4.9M) and Unit 510 (\$5.4M) have similar $E(S)$ values but vary substantially in terms of the expected frequency (N) and cost (X) of large fires. For National Forests in Regions 1, 3, and 4, variation in $E(S)$ is driven more by variation in fire frequency. Relative

Table 2

Selected models for N , the distribution of the number of fires per year, ranked in order of Unit ID.

Unit ID	Selected Distribution	param 1	param 2	$E(N)$	Standard Deviation
103	Geometric	0.15		5.50	5.98
110	Negative binomial	0.61	0.17	3.05	4.28
116	Negative binomial	0.31	0.20	1.25	2.50
117	Negative binomial	1.27	0.21	4.75	4.74
301	Poisson	2.75		2.75	1.66
305	Geometric	0.16		5.40	5.88
306	Poisson	7.95		7.95	2.82
312	Negative binomial	1.65	0.27	4.40	4.02
402	Negative binomial	0.95	0.30	2.25	2.75
412	Poisson	4.15		4.15	2.04
413	Geometric	0.16		5.25	5.73
501	Poisson	1.75		1.75	1.32
502	Poisson	0.60		0.60	0.77
505	Negative binomial	0.86	0.40	1.30	1.81
507	Geometric	0.36		1.75	2.19
508	Negative binomial	0.46	0.29	1.15	2.00
510	Negative binomial	0.31	0.26	0.85	1.79
511	Negative binomial	0.35	0.20	1.45	2.72
512	Poisson	2.10		2.10	1.45
513	Poisson	2.40		2.40	1.55
514	Negative binomial	0.22	0.09	2.25	5.07
601	Poisson	1.60		1.60	1.26
610	Poisson	0.45		0.45	0.67
615	Geometric	0.47		1.15	1.57
617	Geometric	0.23		3.35	3.82

Table 3
Selected models for X, the distribution of per fire suppression cost, ranked in order of Unit ID.

Unit ID	Selected Distribution	mu	sigma	E(X)	Standard Deviation
103	Lognormal	13.70	1.36	\$2,245,612	\$5,179,528
110	Lognormal	13.45	1.30	\$1,613,078	\$3,392,451
116	Lognormal	13.85	1.06	\$1,810,039	\$2,591,114
117	Lognormal	12.42	1.39	\$650,125	\$1,584,743
301	Lognormal	13.54	1.07	\$1,352,017	\$1,992,512
305	Lognormal	13.58	1.02	\$1,338,222	\$1,820,035
306	Lognormal	12.99	1.16	\$860,241	\$1,460,362
312	Lognormal	13.71	1.05	\$1,559,193	\$2,218,377
402	Lognormal	13.73	1.19	\$1,873,693	\$3,315,993
412	Lognormal	12.91	1.41	\$1,086,634	\$2,714,014
413	Lognormal	13.35	1.34	\$1,527,245	\$3,404,493
501	Lognormal	16.02	1.15	\$17,572,368	\$28,994,967
502	Lognormal	16.01	1.13	\$17,073,989	\$27,508,889
505	Lognormal	15.19	1.10	\$7,230,676	\$11,117,172
507	Lognormal	15.17	1.13	\$7,362,598	\$11,827,704
508	Lognormal	15.10	1.08	\$6,487,892	\$9,631,038
510	Lognormal	15.16	1.00	\$6,358,860	\$8,347,673
511	Lognormal	15.59	0.98	\$9,584,825	\$12,195,588
512	Lognormal	15.90	1.07	\$14,204,153	\$20,683,363
513	Lognormal	15.56	1.05	\$10,003,667	\$14,279,788
514	Lognormal	15.49	1.02	\$9,041,688	\$12,293,284
601	Lognormal	14.96	0.95	\$4,900,379	\$5,886,607
610	Lognormal	15.02	1.00	\$5,511,940	\$7,263,572
615	Lognormal	14.91	0.94	\$4,651,320	\$5,569,859
617	Lognormal	15.20	1.09	\$7,282,826	\$11,055,866

to National Forests in Regions 5 and 6, these Forests have significantly lower per-fire costs (average \$1.4M) but significantly higher rates of large fire occurrence (4.25/year). Variation in $E(S)$ values for Forests in Region 6 is also driven more by variation in frequency than cost, although to a lesser degree. By contrast, variation in $E(S)$ estimates for National Forests in Region 5 is driven more by variation in cost, with expected per fire costs ranging from \$6.4M to \$17.6M. This figure cements the importance of sufficiently capturing the influences of both N and X on total annual suppression costs (S).

Fig. 2 depicts results from the aggregate compound loss model ($E(S)$), quantified relative to the highest cost National Forest (Unit 501). Annual suppression cost estimates for National Forests in Regions 5 (Pacific Southwest) and 6 (Pacific Northwest) were generally higher than those for Regions 1 (Northern), 3 (Southwestern), and 4 (Intermountain), which was expected given historical regional differences embedded in the construction of the cost model (Gebert et al., 2007). The figure also presents relative prediction errors (quantified as the difference between observed and simulated divided by observed), which ranged from 0.07 (Unit 502) to 0.85 (Unit 116). The correlation coefficient between the historical and simulated costs is 0.51, with a normalized root mean square error of 31.56%.

Two significant trends are evident from the results in Fig. 2. First, relative cost and relative prediction error are inversely related, with a correlation coefficient of -0.53 . That is, model results perform better on higher cost National Forests. Prediction errors tend to be lowest in Region 5 (the highest cost Forests), and aggregated across the Region 5 Forests included in our analysis overall prediction error was 0.16. By contrast prediction errors tend to be highest in Region 1 Forests (the lowest cost Forests), with aggregate prediction error of 0.64. In terms of better identifying the Forests that present the greatest overall financial risk, these model results are encouraging.

Second, modeling results tend to perform better where National Forests have lower inter-annual variability (standard deviation column of Table 1). In particular the influence of singularly extreme high cost seasons is evident in degraded model performance, for instance Unit 110 (single season comprises 53% of cumulative 2000–2012 costs), Unit 301 (49%), and Unit 610 (47%). While many National Forests in Region 5 similarly experienced a high cost season in 2008, relative to other years the magnitude of suppression costs wasn't as high, and Forests in that region tended to have lower overall inter-annual variability.

To further explore inter-annual variability we quantified Gini coefficients as a measure of the dispersion of annual cost distributions. Although typically used to characterize inequality of income distributions, here we use the coefficients to characterize the degree of inequality across fire seasons. Values range from 0 to 1, with 0 indicating maximal

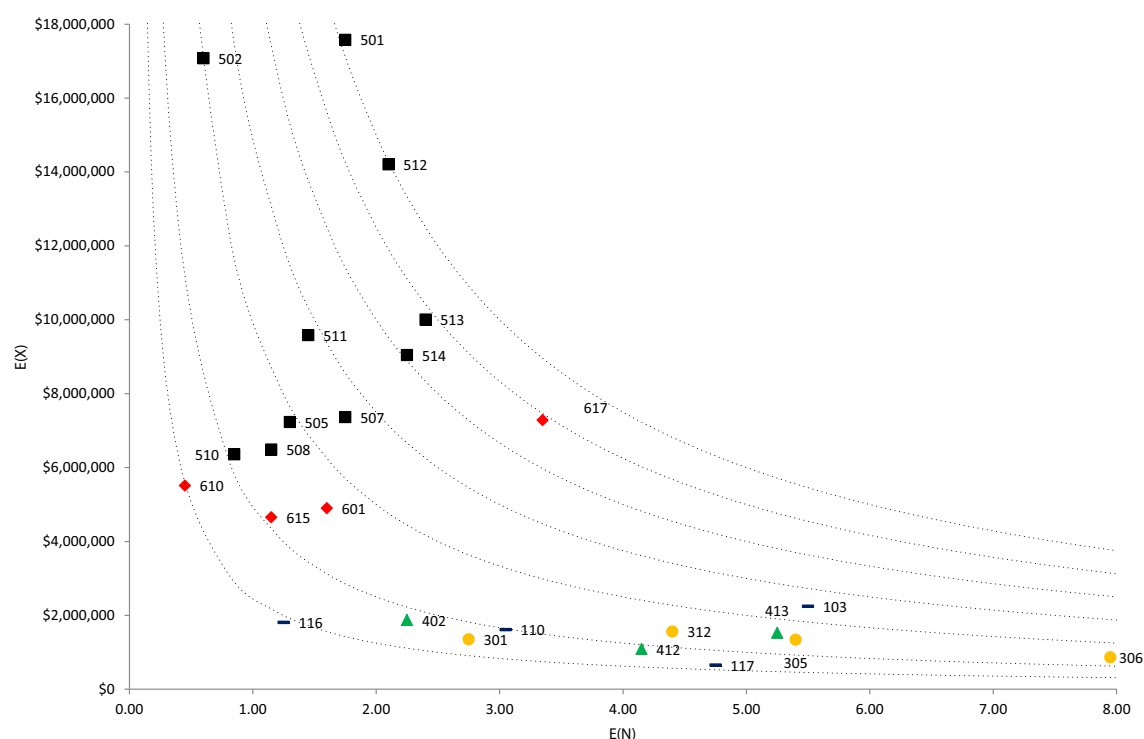


Fig. 1. Scatterplot of modeled $E(N)$ and $E(X)$ values, along with isolines for a range of $E(S)$ values. Unit (i.e., National Forest) identifiers vary according to Forest Service Region by color and shape.

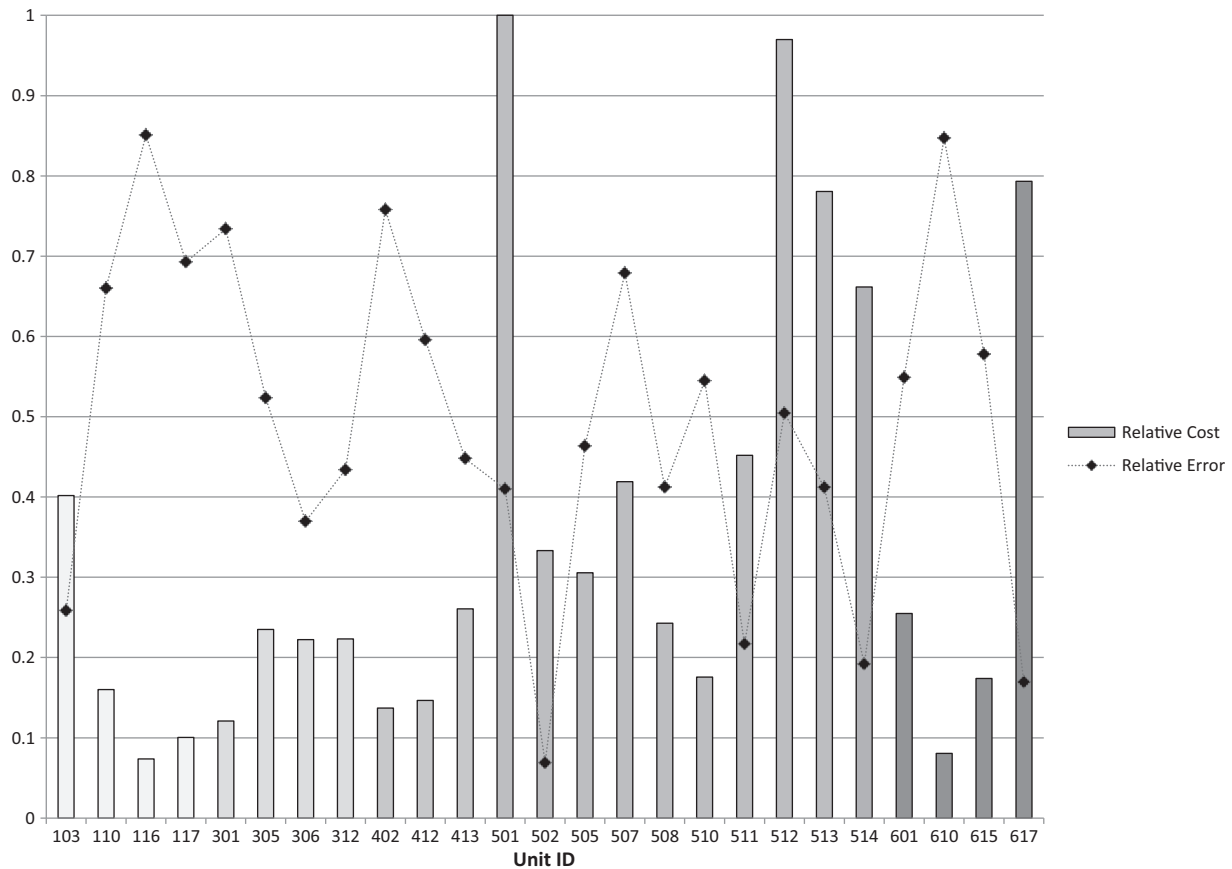


Fig. 2. Comparison of $E(S)$ estimates to historical values for years 2000–2012.

equality (i.e., all fire seasons cost the exact same), and 1 indicating maximal inequality (i.e., all costs were incurred during a single fire season). Across all units, coefficient values ranged from 0.44 (Unit 513) to 0.72 (Unit 110), with a mean of 0.58 and a median of 0.59, indicating a tendency towards inequality across seasons. Units in Region 1 tend to have the highest coefficients, consistent with earlier findings where a single season was particularly influential in raising the 2000–2012 average. Importantly, variation in patterns of N and X is a key driving factor in the inter-annual variability observed across National Forests. For instance, Unit 110 presents a case where significantly high fire load (N) in 2003 led to high costs (the same is true across other units in Region 1, particularly Unit 116). By contrast, Unit 610 experienced a single high cost event (X) in 2002 (Biscuit Fire).

Continuing with implications of variation across distributions of N and X , Fig. 3 compares histograms of simulation results for total annual suppression cost (S) for two National Forests — Unit 501 and Unit 306. The former has the highest expected per fire cost whereas the latter has the highest expected fire occurrence (see Fig. 1). These results stem from 1000 simulated fire seasons, in each of which first N and then X values are randomly generated from their respective probability distributions. Unit 501 has a greater frequency of years with little to no suppression costs incurred, due to the lower large fire occurrence rates. However, when a fire does occur in Unit 501, suppression costs can be much higher, and correspondingly the distribution of S has a longer right tail.

Fig. 4 displays fitted lognormal distributions for the same two National Forests, conditional on large fire occurrence and positive suppression expenditures. Out of 1000 simulated seasons, Unit 501 had at least one large fire 80.2% of the time, while Unit 306 had at least one large fire across all simulations. Consistent with the histogram in

Fig. 3, these distributions vary widely in terms of potential for extremely high cost fire seasons. Fig. 5 displays similar information but across two additional National Forests from Region 5 (Pacific Southwest): Unit 502 and Unit 510. These National Forests have similar conditional distributions for total annual suppression cost, although variation is still evident, with Unit 501 having the longest right hand tail. In addition, these Units vary in terms of number of simulated seasons actually experiencing at least one large fire. Unit 510 has the combination of fewer fires per year, each of which tends to be lower cost, leading to the lowest expected total annual suppression costs of the National Forests in Region 5 (Figs. 1 and 2). These results suggest that National Forest annual cost distributions may exhibit similarities to health care costs (Manning et al. 1987), with a spike at zero and a lognormal distribution for conditional expenses given wildfire does occur.

In summary, suppression cost modeling results indicate substantial variation in financial risk across 25 of the highest cost National Forests in the National Forest System. Forests with the highest expected annual costs tend to have the highest expected per fire costs, with fire occurrence playing less of a role. Geographic variation in Forest-level large fire occurrence, per-fire cost, and expected annual cost is evident not only across but also within Forest Service Regions. Our modeling results tend to do well in terms of identifying the high cost Forests, although estimated ($E(S)$) values tend to be lower than historical values. There are likely a number of reasons for this phenomenon. First, our results are likely to be conservative estimates since we included only ignitions occurring within National Forest boundaries, which could exclude fires (and their costs) that occur in other areas where the Forest Service has financial responsibility for lands falling within their fire protection responsibility. In these areas proximity to homes or other factors could be leading to higher cost structures, and further these areas may

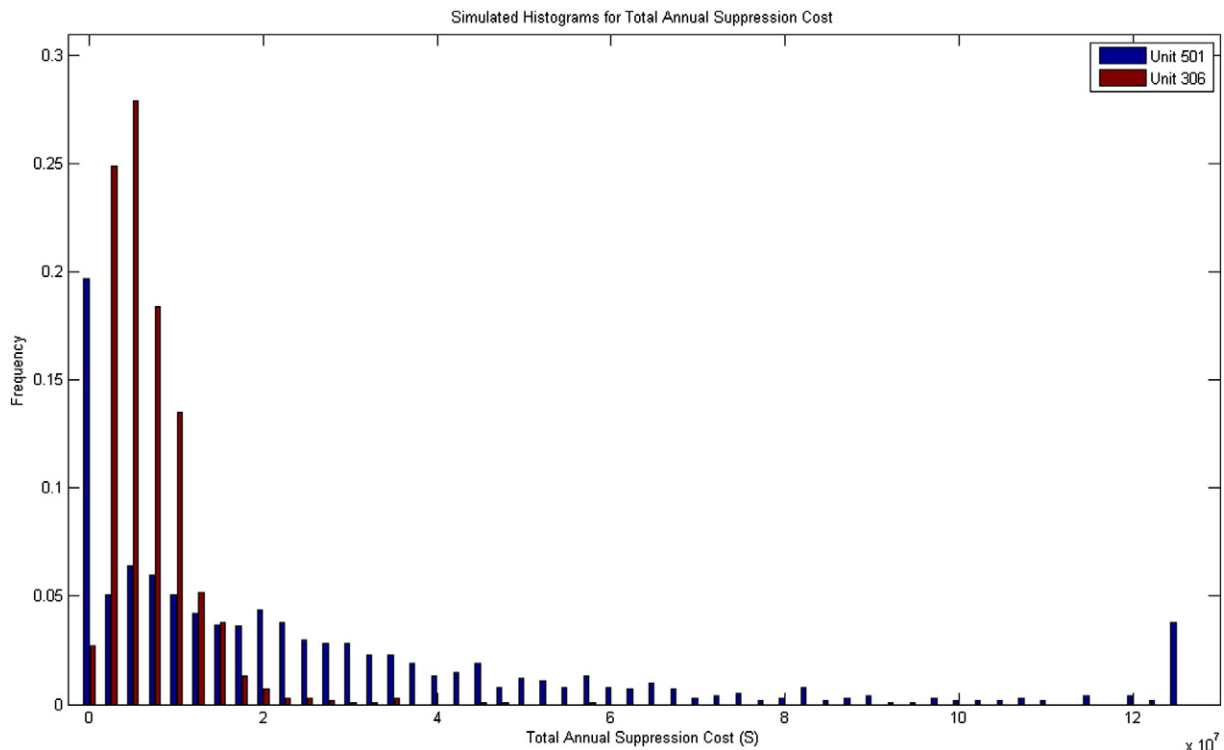


Fig. 3. Histogram of simulated total annual suppression costs (S_m) for Unit 501 and Unit 306, which vary widely in terms of $E(N)$ and $E(X)$.

have different underlying distributions for the number of large fires per year. Second, there could well be latent trends driving increases in fire activity and fire cost that our models built on historical data are not capturing; a changing climate and expanding ex-urban development in fire prone areas are two likely factors. Third, our estimated $E(S)$ values are effectively averaging out the inter-annual variability in distributions for fire occurrence, fire size, and fire cost, which as described earlier can be quite high for some Forests. Additionally, because of the limited historical record on unit-level expenditures, we have a limited ability to infer where observations fall with respect to the right tail of the actual underlying suppression cost distribution. That is, in many cases a single high cost season drove the 2000–2012 average, but with 13 years of data we are unable to determine the relative rarity of such an event. This challenge may be even more pronounced if in fact the underlying probability distributions are non-stationary.

We should emphasize that while comparisons to historical costs are informative and help with calibration efforts, the ultimate aim of our illustration here is not necessarily to closely match annual historical costs. For reasons just mentioned, the limited nature of historical records means that there is little reason to believe that the potential full range of variation is sufficiently captured, either for quiescent or extreme fire seasons. Further, wildfire potential and associated suppression costs are dynamic and may depend more on current environmental and socioeconomic conditions than on historical costs per se. Observed differences in simulated and historical values may therefore be telling us something about current landscape conditions as a result of historical disturbances and management activities, for instance treated fuels due to wildfire or prescribed fire leading to conditions with more limited potential for fire activity.

4. Potential applications

The derivation of probability distributions for annual suppression costs has a number of useful applications. The methods could be applied to different ownerships (e.g., other federal land management agencies)

or across different geographic scales (e.g., Forest Service Ranger Districts), and could be coupled with auxiliary analyses to see how increased wildfire activity (e.g., due to climate change) or increased asset density (e.g., expanded residential development) may affect future costs. The modeling techniques could also be used to enhance forecasts of within season expenditures and to identify potentially adverse budgetary situations based upon the observed or projected geographic distribution of the fire workload. At the incident level, improved estimations of likely cost trajectories could be coupled with additional information to help inform efficient allocations of suppression resources (Mendes, 2010; Mavsar et al., 2013).

By leveraging insights gained from our new modeling approaches it may be possible to begin to identify and implement wildfire management actions to control suppression costs. Efficiency gains are likely to be premised on targeted mitigation and prioritization on the basis of geographically relevant financial risk factors. As results indicated that it is not just the frequency with which large wildfires occur that drive variation in expected suppression expenditures, but also how individual large wildfires are managed.

A crucial step accompanying an improved understanding of factors driving high costs is the identification of factors that are within or outside the scope of management control. This could include, for instance, identifying whether most ignitions are human-caused, and if so, whether ignitions can be reduced through prevention programs (Prestemon et al., 2013). Other alternatives include enhancing response capacity to improve initial attack success, reducing hazardous fuel loads, and changing large wildfire response.

The distributions of N and X provide information about the marginal effect on suppression costs when fire management investments can affect the likelihood of large fire occurrence or per-fire costs. These results can directly support assessing tradeoffs and improving efficiencies. For a given level of total funding, an efficient allocation of investments would equate across all National Forest units the expected marginal reduction in suppression costs resulting from a marginal investment that reduces either the likelihood of large fire occurrence (N) or costs per fire (X). For

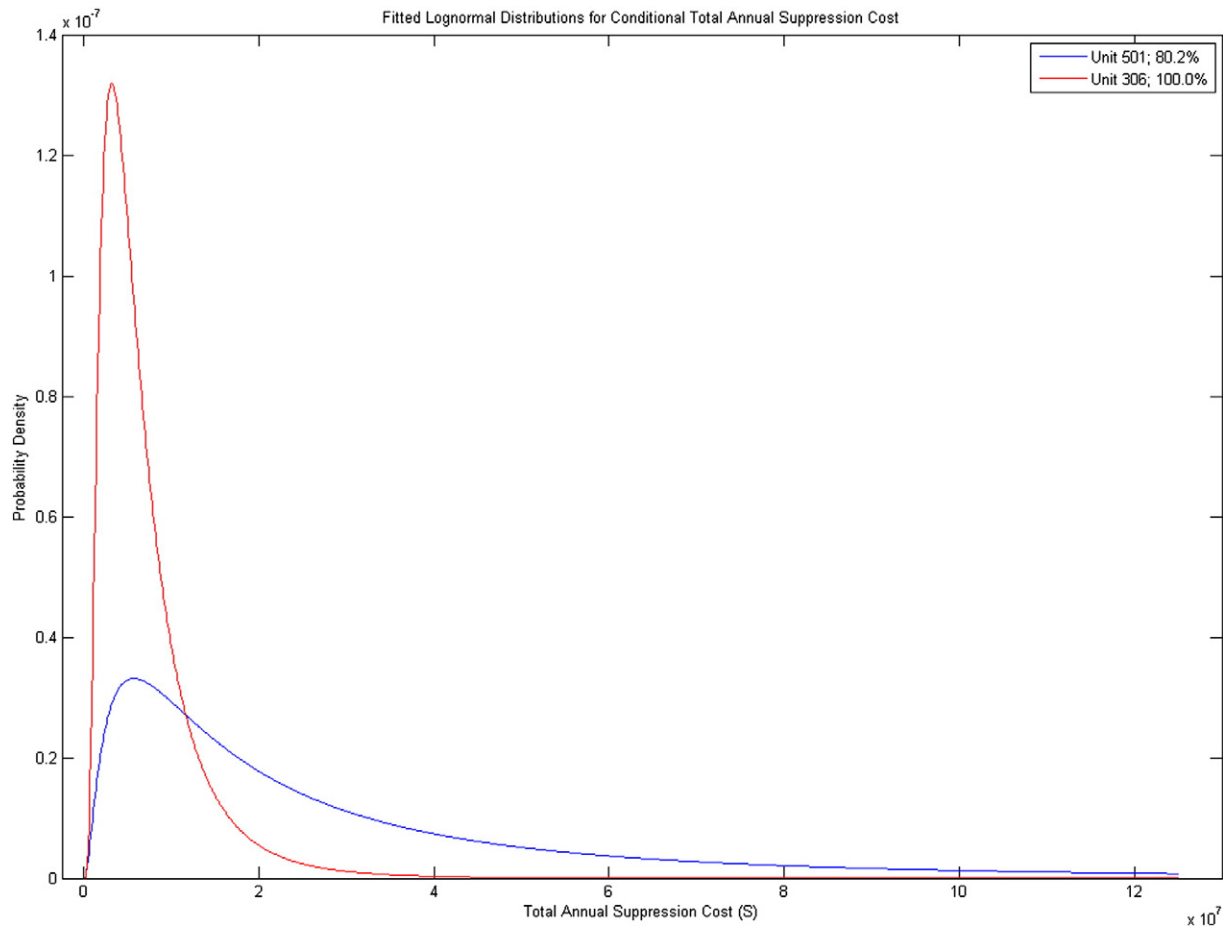


Fig. 4. Fitted lognormal distributions for conditional total annual large fire costs, i.e., total suppression expenditures given at least one large fire occurred in the simulated fire season. The curves fit the data shown in Fig. 3 for Unit 501 and Unit 306, with the legend indicating the percentage of simulated seasons with at least one large fire.

example, investments in preparedness that could assist in initial attack efforts may reduce the number of expected large fires on a National Forest in a given year. The distributions of N and X allow decision makers to compare the marginal benefits of investments across forest units in risk terms, e.g., the necessary reduction in the probability of a large fire occurring in two different forest units that would result in an equivalent dollar decrease in expected suppression expenditures.

To illustrate, suppose a \$1 million marginal investment in initial attack preparedness on the Los Padres National Forest (Unit 507) would reduce the expected number of large fires by 0.5 fires per year. Assuming that the per fire suppression cost distribution (X) is not affected by initial attack investment, this would result in an expected reduction of \$3.68 million in annual suppression expenditures. That is, the marginal benefit of the investment is: $MB_{507} = \Delta \text{ benefit} / \Delta \text{ cost} = 0.5 \times \$7.36 \text{ million} / \$1 \text{ million} = \3.68 . In the Bitterroot National Forest (Unit 103), achieving an equivalent expected marginal reduction in suppression expenditures would require that the same \$1 million marginal investment in initial attack preparedness yield a reduction in the expected number of large fires of about 1.64 fires per year; if this is the case, the marginal benefits of initial attack investments would be equalized between the two forests and no reallocation of initial attack investments would improve efficiency. If the marginal reduction in expected large fires per year in Unit 103 is greater (less) than 1.64, and given diminishing returns to initial attack investments, efficiency can be improved by allocating marginal initial attack investments to Unit 103 (Unit 507) until the marginal reduction in suppression costs is equalized between the units.

A similar application could be devised for investments that affect the expected behavior and growth of fires in the future. An important attribute in the model used to predict costs for simulated fires is final fire size. A given investment aimed at limiting the growth of future fires (e.g., fuel treatments) could be evaluated by comparing the marginal expected dollar reduction in suppression costs due to reduced expected fire size across forest units. If the costs of such investments are known, simulation-based assessments can provide an indication of marginal cost effectiveness (e.g., Thompson et al., 2013d).

The key is to jointly identify factors driving costs with factors that can be efficiently managed, and further to understand who is responsible for mitigating that loss. On the federal estate, on some landscapes it may be possible to support expanded use of unplanned ignitions to effectuate self-limiting fires (e.g., Unit 306), whereas on others fire exclusion will likely have to remain a prominent management objective due to a high density of at-risk assets (e.g., Unit 501). From a broader loss minimization perspective, in many cases the primary responsibility for loss reduction activities may lie with local governments or homeowners (Calkin et al., 2014).

Probabilistic cost modeling results could also inform broader policy and budgetary processes. The ability to measure and monetize the financial risk associated with wildfire suppression – provided by the development of the compound loss model – is critical for improved risk-based budgeting efforts. Improved modeling and monitoring of costs could help improve fire manager performance measurement, financial accountability, and ideally restructure the incentives facing fire managers and their decision processes (Donovan and Brown,

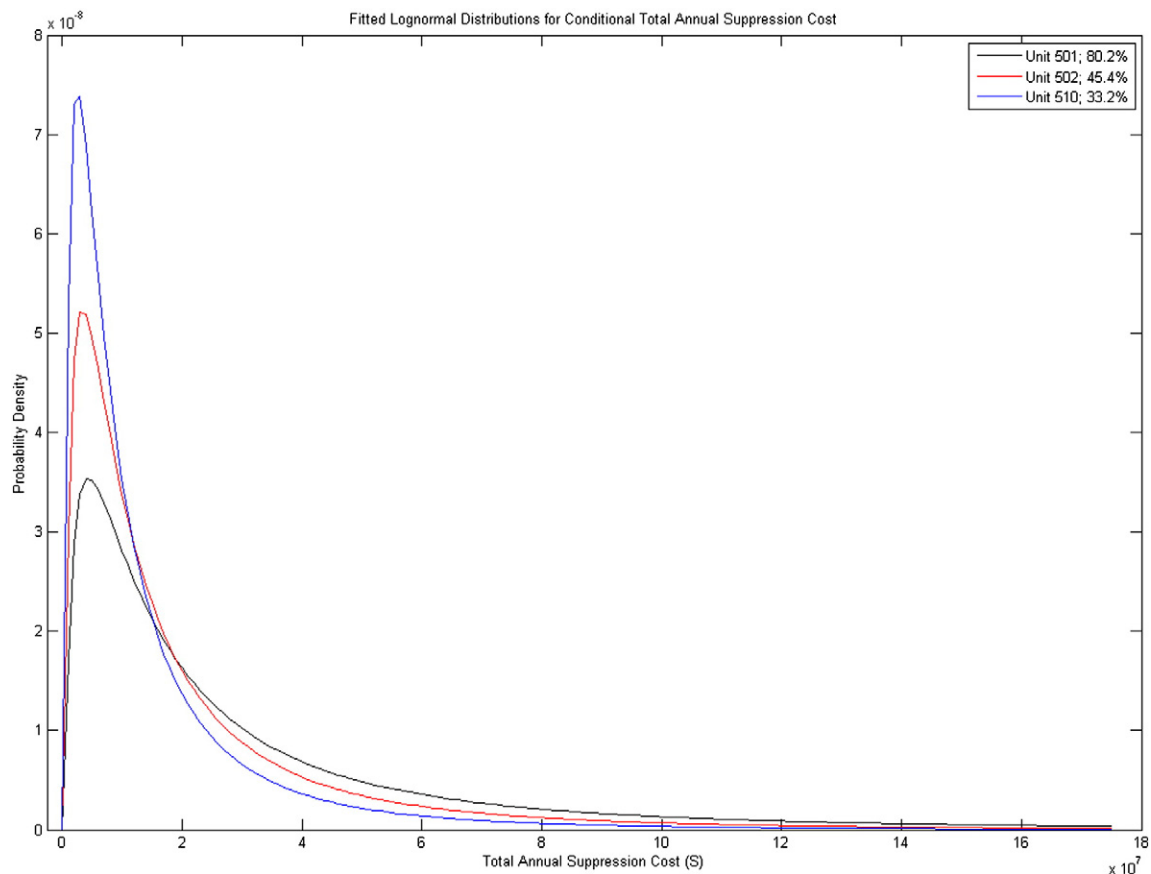


Fig. 5. Fitted lognormal distributions for conditional total annual large fire costs for Unit 501, Unit 502, and Unit 510, with the legend indicating the percentage of simulated seasons with at least one large fire.

2005; Thompson et al., 2013a). The ability to update model results based upon current conditions could reflect the longer-term impacts of past management choices and create a feedback loop where risk-informed land and fire management activities across fire seasons are rewarded. Transparently sharing results could help identify what have been in effect cross-subsidies where low cost Forest are financially burdened by high cost Forests, and could improve the ability of fire managers to monitor and potentially exert pressure on other fire managers.

There exist multiple options for additional analyses to identify other socioeconomic, environmental, and institutional factors associated with high or low cost Forests. Ultimately the management of wildfire incidents and associated suppression costs tie back to decisions, hence an increasing focus on human factors and their role in influencing incident decision-making (Maguire and Albright, 2005; Wilson et al., 2011; Wibbenmeyer et al., 2013; Thompson, 2014). Another critical factor to consider is the degree to which existing land and fire management plans themselves may limit incident response flexibility (Steelman and McCaffrey, 2011). Spatial delineation of fire management areas according to established fire management objectives (Thompson et al., 2013c) could help directly quantify managerial influences on geographic variation in expected costs. Collectively these analyses could help with improved estimation of likely suppression costs and could also help target Forests where opportunities exist to measurably reduce future costs.

5. Discussion

Wildfire management organizations are challenged to efficiently mitigate short-term and long-term threats under considerable uncertainty and complexity, and with only partial control of factors driving wildfire risk. For federal land management agencies like the Forest

Service, another major challenge is to limit the negative financial impacts associated with the escalating suppression expenditures. Recognition of these challenges underscores the need for a strategic, risk-based approach to wildfire management and loss mitigation.

In support of improved financial risk management, we developed a probabilistic modeling approach to estimate annual suppression costs, based upon the generation of parametric probability distributions for fire occurrence and per-fire cost. With risk monetized, fire managers would be better able to make decisions to reduce the costs of risk. This compound model approach to quantifying financial risk is similar to landscape risk analyses that decompose potential wildfire consequences into component factors including fire likelihood, fire intensity, and the relative degree of resource or asset susceptibility to loss (Ager et al., 2012; Scott et al., 2012; Scott et al., 2013). Our modeling approach can help policymakers better understand variation in factors driving costs, better monitor fire manager performance, potentially modify fire manager incentives, and ideally direct efficient investments in wildfire risk mitigation and cost containment.

A great strength of this approach is the flexibility afforded by separately modeling distributions for frequency, N , and severity, X , and the opportunity to incorporate how current landscape conditions may affect either of these distributions. As mentioned earlier, the use of stochastic fire simulation can evaluate how events like fuel treatments and wildfires could change fire sizes and associated cost distributions. Very large fire events, such as the Wallow Fire (2011) could also influence distributions for N , and thereby limit the utility of historical fire occurrence data for fire modeling purposes. However, current fire activity is a product of the historical landscape structure so the effects of new large fires may have similar effects as previous large fires, and near-term changes to fuel conditions may be less important for long-term actuarial assessment and planning. Where impacts are thought to be

significant and long-lasting, techniques such as Bayesian updating and expert opinion are available for changing distributions for N . Expanded modeling could also explore how the distribution of N changes in response to other factors such as enhanced initial attack capacity or ignition prevention planning.

Caution is warranted when interpreting results for policy decisions, and other factors not accounted for in the component models should be considered. Due to the nature of wildfires, modeling efforts can only go so far in loss prediction. Actuarial models are not able to predict precisely the amount of loss in any particular Forest in any particular year. Nevertheless, over time and with increasing amounts of data as time passes, the prediction models will become more refined.

Future work is likely to proceed in a number of areas, beginning with the cost estimation process itself. Updated estimates could include other distributions (e.g., Pareto) or could investigate the applicability of non-parametric distributions as well. The compilation of comprehensive and up-to-date fire history databases (Short, 2013), and calibration of fire modeling systems on the basis of fire occurrence and area burned (Finney et al., 2011), should improve our ability to more fully capture the likely geographic extent and underlying probability distribution of large fire occurrence. Suppression cost modeling for other land owners, in particular non-federal agencies, could improve the ability to characterize fires spanning multiple jurisdictions or areas of protection responsibility.

Suppression cost modeling efforts could explore opportunities to better capture the full extent of human development proximal to wildfires and to be reflective of values-at-risk present during the management of the incident. The use of historical and decadal Census data as a proxy essentially amounts to a form of measurement error, and in response researchers could explore the predictive performance of other data sources, for instance the locations of individual homes or structures (Calkin et al., 2011a; Gude et al., 2013). Given the significant potential for increased development in fire-prone areas and subsequent demand for suppression, (Gude et al., 2008; Mann et al., 2014) research efforts could project suppression expenditures through time in areas likely to experience development.

Suppression cost distributions can also be refined in the future using more spatially descriptive data to generate cost models (Hand et al., 2014). Current models used to generate cost distributions rely on fire characteristics determined at the ignition point of each fire. Yet fire characteristics associated with costs — such as fuels composition and proximity to human development — may be significantly different over the extent of the final burned area than at the ignition point. Spatially descriptive data has been used on a limited scale to model suppression costs (Liang et al., 2008), and ongoing cost modeling efforts use a similar approach to model costs in the Western United States.

Accounting for spatial heterogeneity in cost models may serve multiple purposes. First, using spatially descriptive data can reduce measurement error and improve predictive power of cost models. Second, spatially descriptive models may mitigate bias due to geographic aggregation and the use of multiple geographic scales. Finally, spatially descriptive data may be able to accommodate landscape-scale changes that affect how fires are managed. For example, fuel treatments may alter where and under what conditions a fire burns for a given ignition point; to the extent that suppression costs are related to such conditions, a spatially descriptive model may be able to indicate how fuel treatments alter the suppression cost distribution.

Lastly, returning to the incident decision making context could yield additional insights for understanding and managing suppression costs. Capturing the impacts of past fire scars on future suppression costs may affect current incident decisions and costs (Houtman et al., 2013). So too is capturing how fire managers make decisions under uncertainty and perceive risks, which could lead to development of strategies for reframing decisions and encouraging more risk-informed and cost-effective use of suppression resources (Wilson et al., 2011; Wibbenmeyer et al., 2013). Ultimately, continued research will need to

look at not only suppression costs, but to consider what the fire management expenditures are actually achieving in terms of reduced loss and enhanced ecosystem health.

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