Montana Wildfire Cost Study
Technical Report

8-8-2008

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Executive Summary

Montana's "big sky" appeal, wealth of recreational opportunities, and growing economy have contributed to rapid population growth in the last few decades, particularly in the western portion of the state. Many of the new homes have been built in rural areas, outside existing cities and towns. Living in Montana's forests, however, is not a risk free nor a low-cost proposition. Most years, federal, state, tribal and county governments spend millions of dollars suppressing the state's inevitable wildfires to protect Montanan's homes in the woods.

To better understand the current and future implications for Montana's taxpayers, Headwaters Economics analyzed daily fire suppression costs across 18 large fires that burned in Montana during 2006 and 2007, systematically distilling out the portion of total fire suppression costs directly associated with housing – that is: the dramatically higher costs required to fight fires in the "Wildland Urban Interface."

Montana State University collaborated in the statistical analysis, identifying the fire characteristics that were most responsible for daily firefighting costs, including the size of the fire, the nature of the terrain the fire burned through, whether roads and other infrastructure aided or complicated suppression, and the extent of housing threatened by the fire. MSU helped determine the relative contribution of each characteristic to the total costs. Headwaters Economics then incorporated these main drivers of firefighting cost into a growth model that projects new development expected in Montana by 2025 based on the state's recent rate of growth and pattern of development. With these tools, it was possible to understand the increases in firefighting costs that Montana will likely see unless development changes significantly from its current pattern. Key findings of our research include:

- Firefighting costs are highly correlated with the number of homes threatened by a fire.
- The pattern of development (dense vs. spread out) is an important contributing factor.
- When large forest fires burn near homes, costs related to housing usually exceed $1 million per fire.
- As few as 150 additional homes threatened by fire can result in a $13 million increase in suppression costs in a single year.
- For all agencies involved in fire suppression in Montana, the estimated annual costs related to home protection for 2006 and 2007 were approximately $55 million and $36 million, respectively.
- If current development trends continue, fires seasons similar to 2006 and 2007 could cost $15 to $23 million more by 2025, bringing total fire suppression costs associated with homes to between $51 and $79 million dollars. Adjusted for inflation, future costs could be as high as $124 million in 2025.
- A conservative estimate is that 25% of all costs of protecting homes from wildfires within Montana are paid for by the state. Therefore, Montana's costs for home protection in 2006 and 2007 are estimated to have been $13.9 million and $9.2 million, respectively. By 2025, Montana's future costs, adjusted for inflation, could be as high as $31 million.

Decisions about how and where to fight fires, and where homes will be built in the future will have a major effect on the state's firefighting costs. Our research reported here was funded by the Montana State Legislature Fire Suppression Interim Committee.

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The objective of Headwaters Economics' analysis is to identify whether homes surrounding wildfires are related to changes in fire suppression costs, and if so, to what degree. We used a statistical approach to compare the daily fire suppression costs across 18 large fires in Montana, some of which burned in remote areas where few or no homes were threatened, and some of which burned through developed areas. This sample of fires allowed for a comparison between fires that threatened homes, and those that did not. We also investigated the importance of housing relative to the other factors that may affect suppression costs, including weather, vegetation, terrain, and other human factors including road access and threatened infrastructure.

This document explains the statistical methodology and provides some basic interpretations of the results. Section 1 describes the data, and a candidate set of models to account for non-independence of daily observations. Section 2 describes how we chose the best model among this candidate set. Section 3 uses model selection to arrive at a best set of predictors of average daily wildfire cost. Section 4 describes the results of a cross validation exercise on the best model from Section 3. Section 5 incorporates weighting of the residuals. Section 6 gives some basic interpretations of the coefficient estimates in the best model. Finally, in Section 7 we extrapolate from these results to answer two questions:

(1) How much is protecting homes from wildfires currently costing Montana?

(2) How will future home construction impact fire suppression costs?

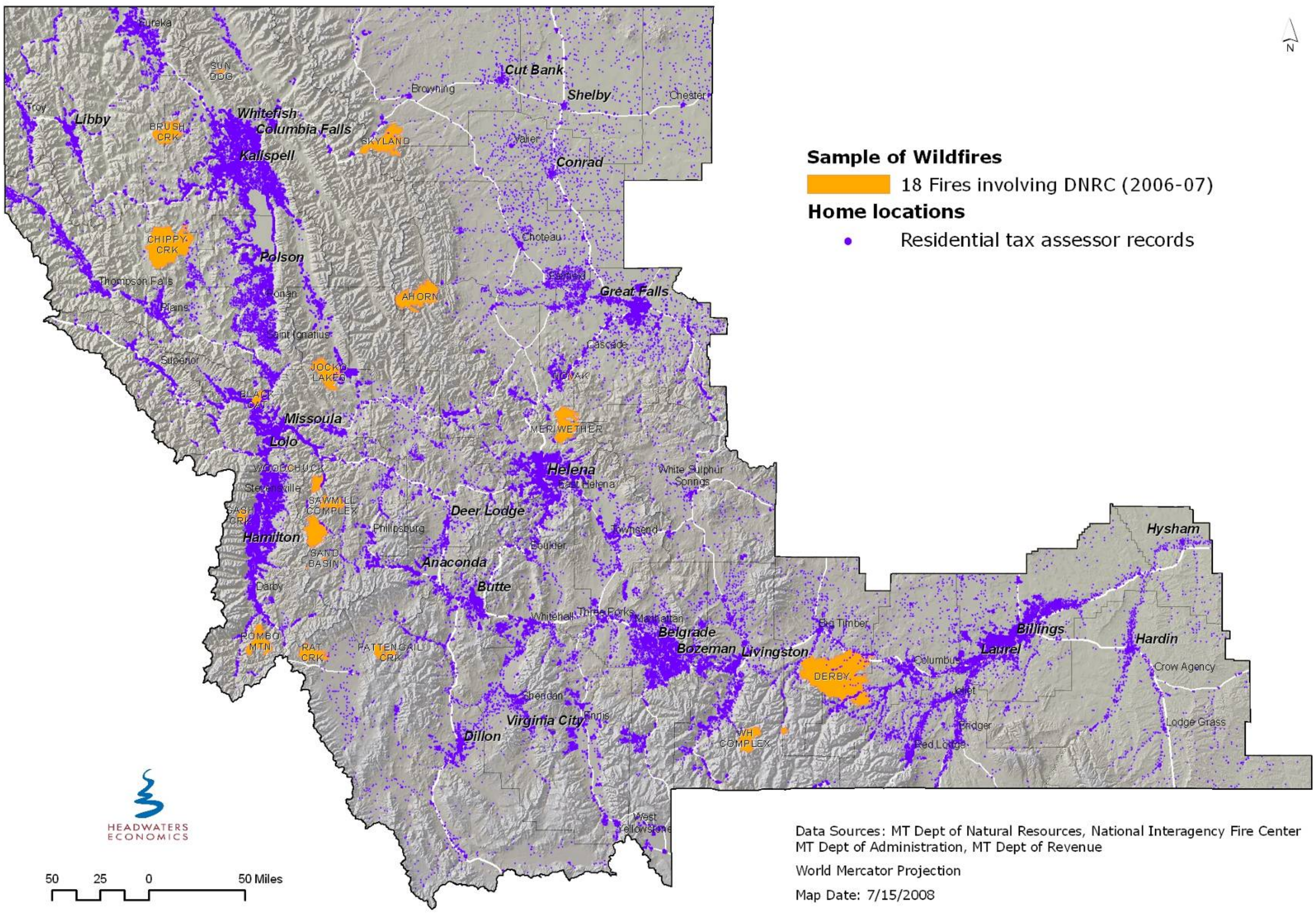
1 Data and Candidate Models

The wildfire data consist of 294 days of information on total suppression costs and wildfire characteristics, including size, surrounding development, weather, terrain, and surrounding infrastructure, which were collected for 18 wildfires in western Montana (Map 1). Much of data describing the wildfire costs and characteristics were pulled from a large body of documents, including ISUITE and 209 forms, recorded by federal and state agencies. The 18 fires were selected because they met several criteria, including:

(1) The state of Montana provided firefighting resources for the fire.

(2) The fire burned in either 2006 or 2007, which guaranteed the availability of daily cost data.

(3) The fire was large enough to guarantee the availability of daily Geographic Information System (GIS) data describing the fire (location, area, perimeter, etc.). These data are not consistently available for wildfire smaller than one square mile.



Map 1. Locations of the 18 fires included in this study are shown relative to housing in western Montana.

The 18 fires studied were Ahorn, Black Cat, Brush Creek, Chippy Creek, Jocko Lakes, Meriwether, Novak, Pattengail, Rat Creek, Rombo Mountain, Sawmill Complex, Skyland, and W H Complex from 2007, and Derby, Gash Creek, Sand Basin, Sun Dog, and Woodchuck from 2006. Data that were collected for each of these fires are listed, alongside their data sources and abbreviations that are used throughout this document, in Table 1.

Table 1: Data collected for each day of firefighting for each of the 18 wildfires studied.

Data	Abbreviation	Source
Total Daily Cost	Cost	ISUITE Forms
Size of Fire	Acres	GIS Perimeter Files
Rate of Spread	AcresGrowth	GIS Perimeter Files
Percent Contained	Pct	209 Forms
Wind Speed	Wind	209 Forms
Temp. taken by Fire Crews	Temp	209 Forms
Temp. Weather Station at 5 pm	Temp1700	Nearest Weather Station
Temp. Weather Station 24hr Low	TempL	Nearest Weather Station
Temp. Weather Station 24hr High	TempH	Nearest Weather Station
Relative Humidity	Humidity	209 Forms
Fire Growth Potential	GrPot	209 Forms
Terrain Difficulty	TerrDiff	209 Forms
Mean Vegetation Height	VegH	LANDFIRE
Mean Fire Severity Rating	Sev	LANDFIRE
Points of Road Access	AccPts	MT Dept. of Admin.
Length (mi) of Intersecting Roads	RdLen	MT Dept. of Admin.
Major Infrastructure Threatened	InfThreat	Global Energy/Penwell/MT Dept. of Admin.
Homes within 1 mi. of wildfire	Homes1	Tax Assessor Records
Homes within 2 mi. of wildfire	Homes2	Tax Assessor Records
Homes within 3 mi. of wildfire	Homes3	Tax Assessor Records
Homes within 4 mi. of wildfire	Homes4	Tax Assessor Records
Homes within 5 mi. of wildfire	Homes5	Tax Assessor Records
Homes within 6 mi. of wildfire	Homes6	Tax Assessor Records
Homes within 7 mi. of wildfire	Homes7	Tax Assessor Records
Homes within 8 mi. of wildfire	Homes8	Tax Assessor Records
Developed acres within 1 mi.	Acres1	Tax Assessor Records
Developed acres within 2 mi.	Acres2	Tax Assessor Records
Developed acres within 3 mi.	Acres3	Tax Assessor Records
Developed acres within 4 mi.	Acres4	Tax Assessor Records
Developed acres within 5 mi.	Acres5	Tax Assessor Records
Developed acres within 6 mi.	Acres6	Tax Assessor Records
Developed acres within 7 mi.	Acres7	Tax Assessor Records
Developed acres within 8 mi.	Acres8	Tax Assessor Records
Homes at Risk	HomesAtRisk	209 Forms
Evacutation in Progress (Y/N)	Evac	209 Forms

Within each wildfire, there were cases when data were missing for particular dates. Usually this was due to a lack of GIS perimeter data on individual dates when weather did not permit flying or the capture of satellite imagery for digitizing fire perimeters. This type of data is known as a time series with missing/unequally spaced observations, which was important in choosing the correct statistical method of analyzing the data. The response variable for the statistical analysis was the average daily wildfire cost since the last date with available data.

Depending on the nature of the correlation in the data, we considered four possible models to address the obvious non-independence in the daily observations within fire:

(1) A linear model that does not attempt to model correlation. This is no attempt to address the non-independence – a baseline case.

(2) A mixed model with random intercepts to account for the possibility that two observations within each fire share information not explained by the explanatory variables.

(3) A linear model that fits the residual autocorrelation with a continuous autoregressive (CAR) model.[1] This accounts for the possibility that observations close in time within each fire share information not explained by differences in the explanatory variables.

(4) A linear mixed model that allows for random intercepts and fits the residual autocorrelation with a CAR model.

Formally, this set of models can be expressed as:

$$
\begin{aligned}
&(1)\quad y_{ij} = \boldsymbol{X}_{ij}\,\beta + \varepsilon_{ij} \\
&(2)\quad y_{ij} = \boldsymbol{X}_{ij}\,\beta + b_i + \varepsilon_{ij} \\
&(3)\quad y_{ij} = \boldsymbol{X}_{ij}\,\beta + \nu_{ij} \\
&(4)\quad y_{ij} = \boldsymbol{X}_{ij}\,\beta + b_i + \nu_{ij}
\end{aligned}
$$

where $i = 1,2,\ldots,18$ indicates the wildfire on which the observation was made, $j = 1,2,\ldots,n_i$ indicates the day of the fire on which the observation was made, $\mathbf{X}_{ij}$ is a $1 \times p$ vector of observations on explanatory variables, β is a $p \times 1$ vector of regression coefficients, $b_i \sim N\left(0,\sigma_b^2\right)$ is a random intercept for the i^{th} wildfire (shows up in models (2) and (4)), $\varepsilon_{ij} \sim N\left(0,\sigma^2 I\right)$ is an *iid* normal error term (shows up in models (1) and (2)), and $\nu_{ij} \sim N\left(0,\sigma^2\,\Omega\right)$ is a more general error term where Ω is a block

[1] Continuous Autoregressive (CAR) models are an extension of autoregressive (AR) models for residual autocorrelation. CAR models are valid for unequally spaced time series, which is the type of data we have within each fire. Pinheiro and Bates's *Mixed-effects Models in S* (2000) describes the use of CAR models in the mixed model framework. Another good discussion of AR (and the more general ARMA) models is presented in Chapter 3 of Shumway and Stoffer's *Time Series Analysis and Its Applications with R Examples* (2006).

diagonal matrix with each block accounting for temporal correlation within each fire (shows up in models (3) and (4)).[2]

2 Comparison of AIC for Potential Models of Residual Autocorrelation[3]

In this section, we compare AIC from fits of the previous section's candidate set of models. We fit models (1) through (4) in `R Version 2.7.0`, using the `gls` and `lme` functions in R's `nlme` library. Table 1 presents AIC values for models (1) through (4), where a different of 2 units between models is considered large (Burnham and Anderson, 2002).

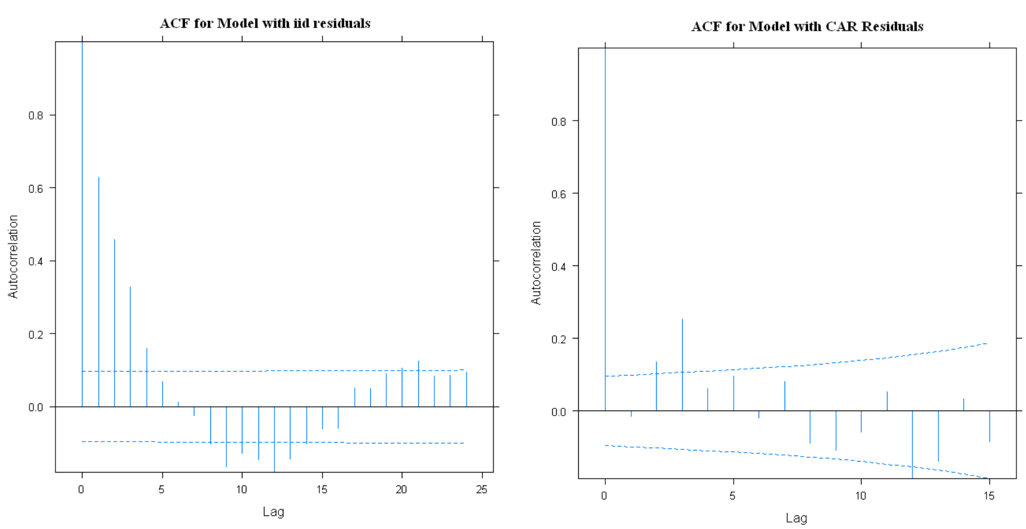
Table 2: AIC comparison of Competing models for Residual Autocorrelation.

Model	*AIC*
(1) iid errors	7747
(2) random intercepts	7721
(3) CAR residuals	7542
(4) random intercepts and CAR residuals	7544

Note: Each model was fit with the entire set of predictors in the dataset.

Clearly, the model that does not account for any non-independence in the residuals performs poorly. Models (2) through (4) are substantially better. The model that accounts for a CAR process in the residuals within each fire outperforms a pure random intercepts mixed model by nearly 200 AIC units. It also appears that random intercepts do not improve on the model that already accounts for the CAR process in the residuals. Therefore, we use the CAR model that does not have random intercepts.

Figure 1: ACF Plots



[2] After the model selection for the fixed effects, we will also consider weighting of the residuals to account for possible heteroskedasticity.
[3] A good discussion of the use of AIC and alternative model selection criteria is presented on pages 356 and 357 of Ramsey and Schafer's *The Statistical Sleuth: A Course in Methods of Data Analysis* (2002).

Additionally, as Figure 1 demonstrates, the autocorrelation function (ACF) for the CAR model looks much better than the ACF for model 1 in that there is no apparent pattern in the residuals. It appears that the CAR model does an adequate job of accounting for non-independent observations.

3 Selection of Model with the Best Set of Explanatory Variables

Because there are many combinations of the explanatory variables that could be considered, we use a stepwise procedure for selecting the best set of explanatory variables. At each step in the model selection process, the computer fits all models with one fewer predictor than the current model and all models that have one more predictor than the current model (within the set of variables considered). We take the model with lowest AIC, and then repeat the process in the next step. The model selection terminates when the lowest AIC model is the current model. The `stepAIC` command in R's `MASS` library automatically goes through this stepwise procedure for selecting the best model.

To allow for ease of interpretation, we only allow one housing/ development variable enter the model for any given stepwise selection. There are 17 separate housing / development variables in the data set (eight GIS housing, eight GIS developed acres, and one self reported houses at risk variable). Therefore, we ran the stepwise process 17 separate times to select the best model.

In model selection, housing variables were always included in the best model. Excluding the Acres1 model, the models with developed acres did not perform as well. Nearly all of the selected models also had `Acres`, `AcresGrowth`, `AccPts`, and `TerrDiff` as the other predictors in these models. This suggests that these variables are important to include in the final model. Of these selected models, the model that included `Homes6` had the lowest AIC.

Table 3: AIC values for the Selected Models when only one development variable is allowed

Development Variable	***AIC***
Homes1	7521.55
Homes2	7521.05
Homes3	7522.31
Homes4	7521.38
Homes5	7521.54
Homes6	7520.34
Homes7	7520.84
Homes8	7520.7
Acres1	7521.38
*Acres2**	7524.92
*Acres3**	7524.92
*Acres4**	7524.92
*Acres5**	7524.92
*Acres6**	7524.92
*Acres7**	7524.92
Acres8	7524.71
HomesAtRisk	7521.14

* indicates that the selected model does not include the development variable.

4 Cross Validation on the Best Model

One way to assess the predictive accuracy of a model is to drop some observations from the dataset, fit the model using the remaining observations, and use the new fitted model to predict the deleted observations. This is a process known as cross validation (Stone, 1974). After computing the predicted values and prediction errors for each observation in this manner, we can compute the mean squared error in these predictions (called the mean squared error of prediction, MSEP) to obtain an estimate of the prediction error. Taking the square root of MSEP gives us an estimate of the standard deviation of the predictions from the model.

Ordinarily, researchers cross validate by dropping one observation from the dataset at a time. In our case, where we are modeling the dependence of observations as a time series within each fire, dropping one observation at a time does not preserve the same basic model structure, and therefore does not make sense. We can get around this problem by dropping all observations from a fire at the same time, fitting the model on the other 17 fires, and then computing the predicted values and prediction errors for the deleted observations in the same fire.

We applied the *leave one fire out cross validation* process described in the previous paragraph to the `Homes6` model from the previous section to obtain an estimate for the standard deviation of predictions from the model. Using this process, we estimated the standard deviation of predictions from the `Homes6` model to be $205,107.20, or a little more than half of the mean average daily cost.

The *leave one fire out cross validation* also allows us to assess how the model performed on different fires, allowing us to learn more about the scope of inference that we can draw our model. We computed three measures of prediction variability for each fire: (A) the proportion of the prediction sum of squares attributed to each fire, (B) the square root of MSEP for each fire, and (C) the square root of MSEP divided by the mean average daily cost for that particular fire (a measure similar to the coefficient of variation).

Fires that showed up as contributing a great proportion to the prediction sum of squares were typically large fires with a large mean average daily cost like Jocko Lakes or Skyland. Fires that showed up as having a large sqrt(MSEP) were typically larger fires than those that did not have a large estimate for the prediction standard deviation. Lastly, most of the fires on measure (C) had a smaller standard deviation of prediction estimate than its mean average daily cost – the sole exception being Pattengail whose standard deviation estimate was 2.68 times the mean average daily cost.

5 Introducing Weighting of the Residuals

The fact that bigger fires have bigger prediction variability suggests that weighting the residuals may improve on the final model. Table 4 presents AIC values for each of the selected models with and without weighting the residuals. For every model, weighting improves the fit. The `Acres1` model has the lowest AIC after weighting. Among the housing variables, `Homes1` has the lowest AIC when the residuals are weighted.

The fact that the `Acres1` model improves so much more dramatically than the other models under a weighted regression scheme suggests that the unweighted fit of `Acres1` model (which was the best model selected among unweighted models) may have been affected by some extreme observations. For this reason, we interpret the coefficient estimates from weighted versions of `Homes6` and `Homes1`, as well as the `Acres1` model. Looking at the interpretations on the coefficient estimates from several competing models can give us a more complete picture of the underlying process.

Table 4: AIC Values for selected models without weighting, and allowing for weights as a power of the mean.		
	AIC Without weights	*AIC With weights*
Homes1	7521.55	7510.433
Homes2	7521.05	7511.357
Homes3	7522.31	7513.334
Homes4	7521.38	7514.053
Homes5	7521.54	7514.363
Homes6	7520.34	7513.865
Homes7	7520.84	7514.505
Homes8	7520.7	7514.666
Acres1	7521.38	7490.087
Acres8	7524.71	7514.754
HomesAtRisk	7521.14	7510.09

6 Basic Interpretations of Coefficient Estimates

Table 5 presents the estimates of the effect of a standard deviation increase `Homes1`, `Homes6`, and `Acres1` in comparison to a standard deviation change in the other predictors in the model. This gives us a comparable scale on which to compare the effects of development variables to the other predictors in the model. The development variables appear to have quite large effects compared to the other variables in the model. Regardless of the model, a standard deviation increase in the amount of development is associated with at least $50,000 of additional cost per day of firefighting, compared with comparable effects ranging from $80,000 to $115,000 for the other variables.

Table 5: The effect of a standard deviation increase in each quantitative predictor			
	`Homes1` model	`Homes6` model	`Acres1` model
Homes1	$59,505	-	-
Homes6	-	$51,643	-
Acres1	-	-	$153,579
Acres	$96,925	$114,666	-
Acres Growth / Day	-$7,511	-$8,294	-$3192
# of Access Points	$88,574	$81,719	$100,414
The entries in the table are based on coefficient estimates from a weighted gls fit accounting for CAR(1) errors. The standard deviation increase is computed using the daily cost measurements.			

Table 6 presents the coefficient estimates (p-values in parentheses) for the predictors in each of the best models we selected in the previous section. Any measure of development pressure in these selected models has a positive relationship with daily wildfire firefighting cost. For example, an additional home within one mile of the fire perimeter is associated with $344.90 more in average daily wildfire fighting cost. To put this in perspective, if one house is within a mile of the fire perimeter for the entire duration of the firefighting effort (on average approximately 38 days), this would be associated with an additional $13,106 in wildfire firefighting cost. However, more commonly homes are only within a mile of the fire for a portion of the time the fire is burning. We found that, on average, when fires burn near homes, homes are within a mile of the fire perimeter for 23 days. Therefore, after accounting for differences in fire size, terrain, and road access, each additional home within one mile of a wildfire is associated with a $7,933 increase in suppression costs and each additional home within six miles of a wildfire is associated with a $1,240 increase in suppression costs (Figure 2). Put differently, 125 homes within one mile of a wildfire are associated with a $1 million increase in fire suppression costs.

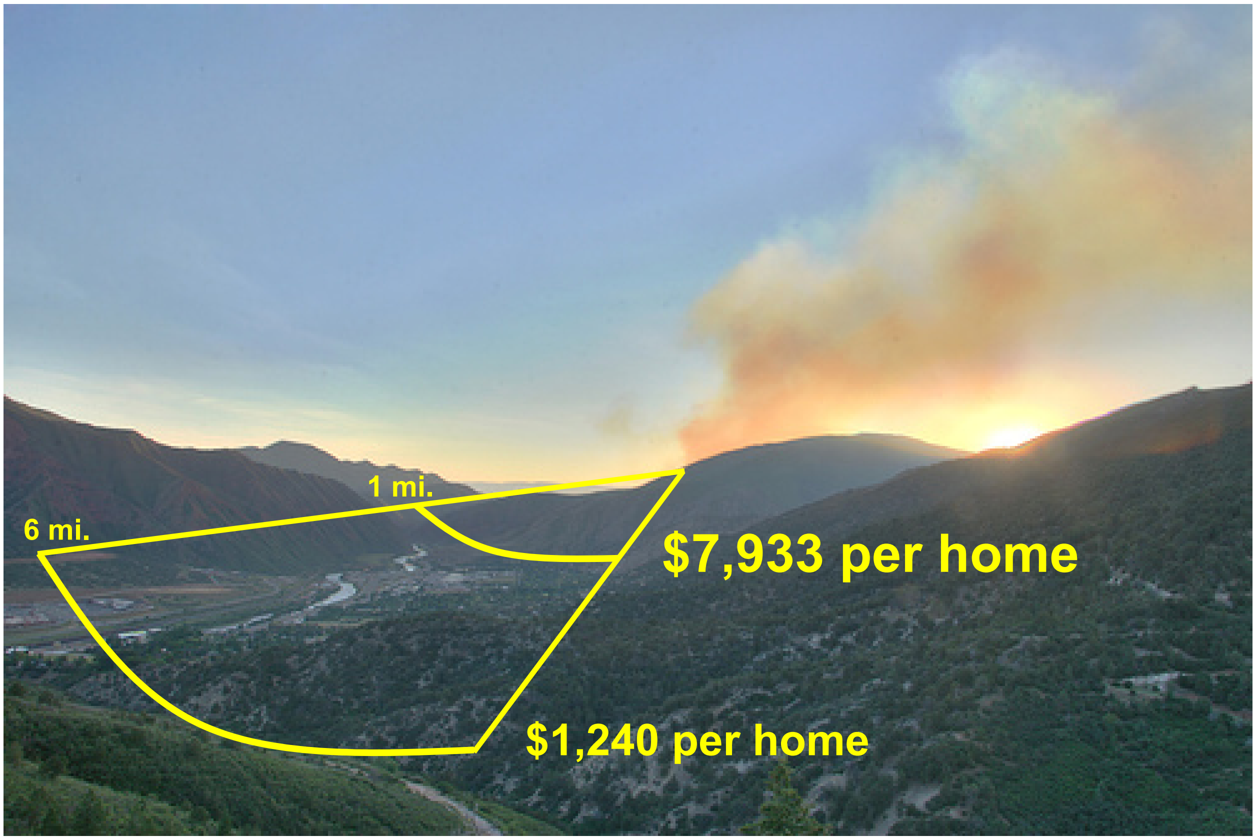


Figure 2. After accounting for differences in fire size, terrain, and road access, each additional home within one mile of a wildfire is associated with a $7,933 increase in suppression costs and each additional home within six miles is associated with a $1,240 increase.

Table 6: Coefficient estimates and significance levels for models predicting the average daily wildfire firefighting cost.

	`Homes1` model	`Homes6` model	`Acres1` model
Homes1	344.90 (0.0223)	-	-
Homes6	-	53.92 (0.0150)	-
Acres1	-	-	28.88 (0.0000)
Acres	2.24 (0.0012)	2.65 (0.0006)	-
Acres Growth / Day	-2.40 (0.0312)	-2.65 (0.0183)	-1.02 (0.2696)
High Terrain Difficulty	636.91 (0.9764)	2744.57 (0.9011)	-13527.90 (0.4702)
Med. Terrain Difficulty	125567.49 (0.0225)	138867.36 (0.0095)	100232.98 (0.0910)
# of Access Points	3375.97 (0.0001)	3114.71 (0.0003)	3827.26 (0.0000)

The entries in the table are coefficient estimates from a weighted gls fit accounting for CAR(1) errors. P-values in parentheses.

Interestingly, the most accurate predictions of daily suppression costs were yielded by incorporating information about the area of residential lots rather than the counts of homes within 1 mi. of wildfires. We found that after accounting for differences in terrain difficulty, fire size, and road access, each additional acre of residential property within 1 mile of a wildfire is associated with a $664 increase in wildfire costs. The average lot size of homes that were threatened by the 18 fires in our sample was 12 acres, and if you multiply the cost per acre ($664) by 12 acres, you get roughly $8000 (the cost per home). One possible reason that the Acres1 model outperformed the Homes1 model is that the Homes1 model is missing information about the spatial distribution of those homes. In other words, the pattern of development (dense vs. spread out) appears to be related to fire suppression costs.

7 Past and Future Expenditures on Home Protection

7.1 How much is protecting homes from wildfires currently costing Montana?

Within our sample of 18 fires, we found that the portion of the fire suppression costs related to housing varied from 0 to 60% depending on how much development there was around the fire. For all of large forest fires that occurred in more densely developed areas, the costs related to housing exceeded $1 million (Figure 3).

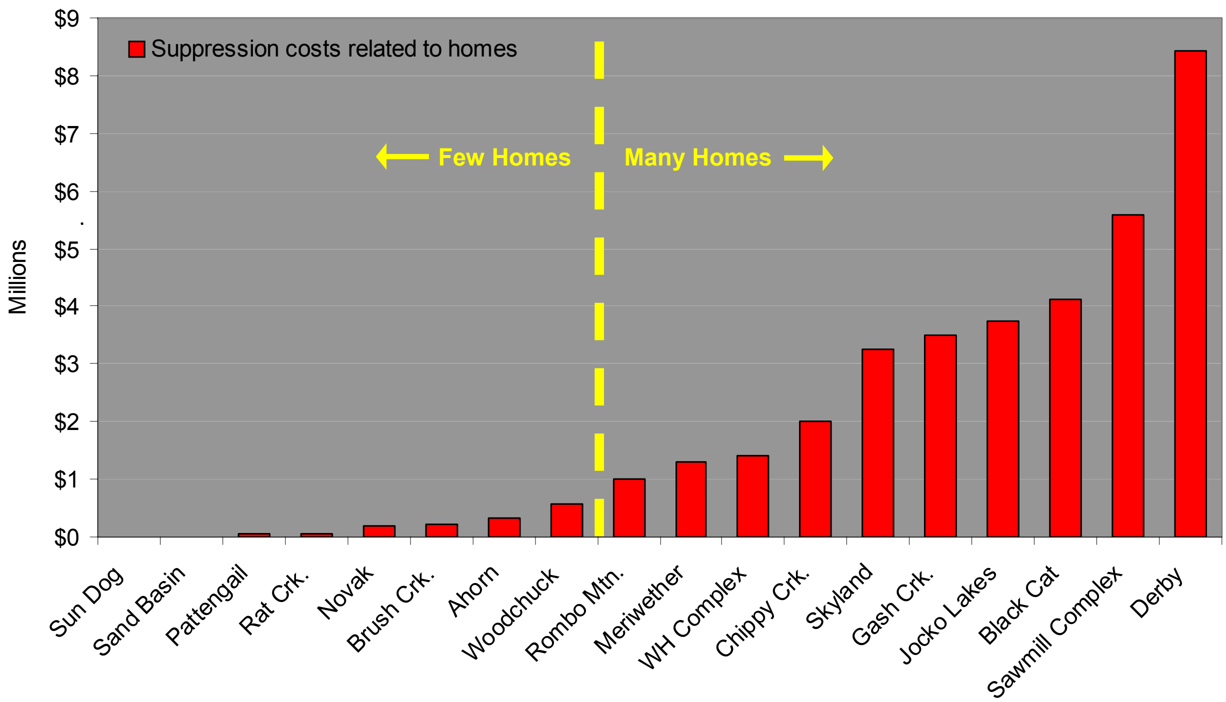
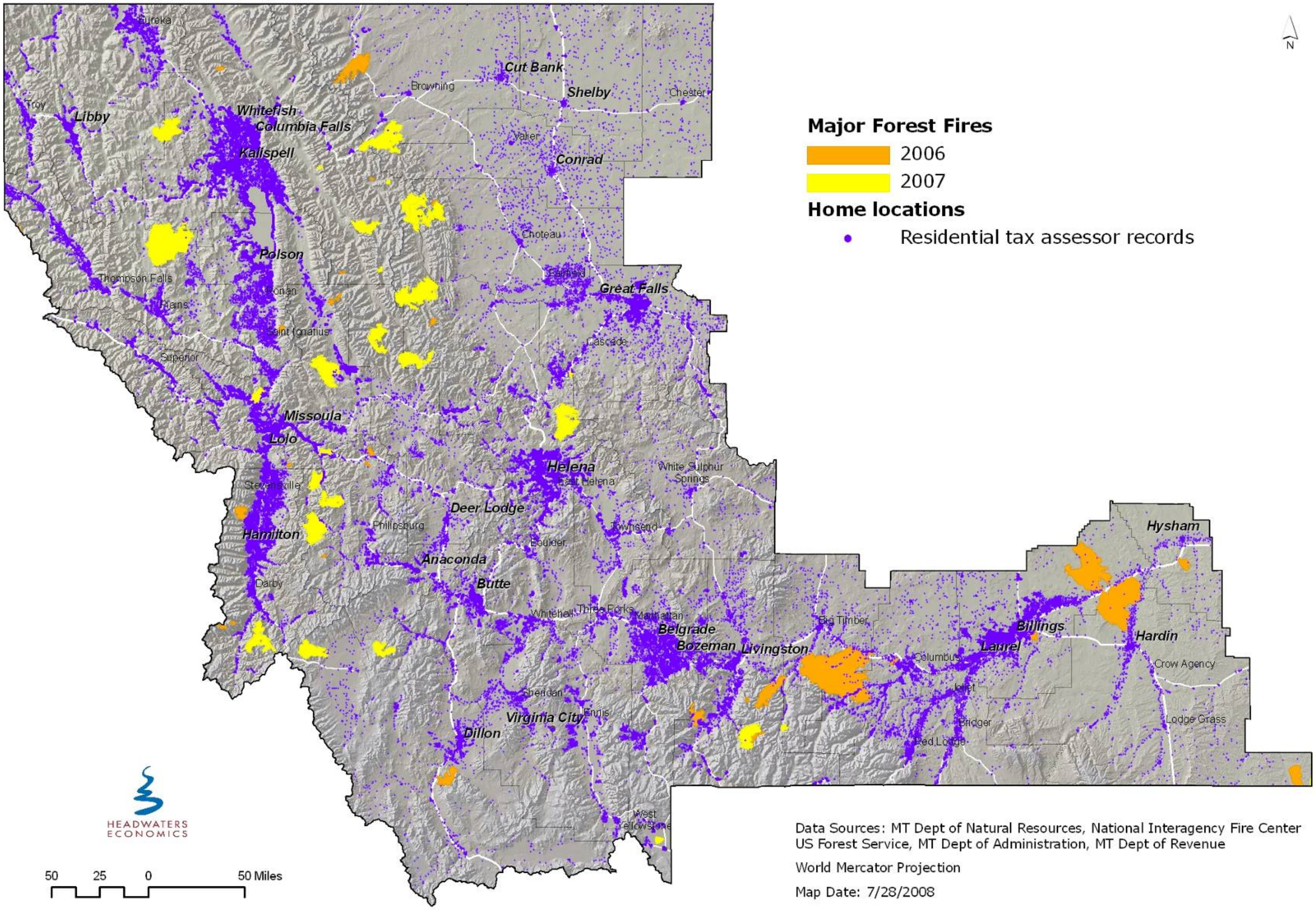


Figure 3. For the fires on the right side of this figure, suppression costs related to housing totaled $35 million (30% of the total firefighting costs). Fires on the left side were remote or small.

Based on the statistical findings, we extrapolated beyond our sample of 18 fires to estimate the costs associated with homes for 2006 and 2007. Because our sample of 18 fires did not include grassland fires or fires smaller than 360 acres, we estimated costs only for large fires that burned predominantly in forest and shrubland. As a result, our estimates are conservative.

For 2006 and 2007, we summed the acres of residential lots within one mile of large forest fires that occurred in each year. In 2006, 83,727 acres of residential land were within one mile of large forest fires (Map 2). Since each additional acre of residential land is associated with a $664 increase in fire suppression costs, the portion of the firefighting costs related to protecting homes in 2006 was estimated to be $55.6 million. In 2007, 54,632 acres of residential land were within a mile of large forest fires. Therefore, we estimate that last year approximately $36.6 million firefighting dollars were related to home protection.



Map 2. Locations of all large forest fires that occurred in 2006 and 2007 are shown relative to housing in western Montana.

The years 2006 and 2007 are very interesting to compare since, in total, more acres burned in Montana in 2007, yet the cost related to protecting homes near the 2007 fires was less (Table 7). The reason for this has to do with the development pattern in the areas surrounding the fires. In 2006, forest fires burned in areas with more housing. In 2007, although there were more forest fires, many of those fires burned in remote areas. Since the locations of wildfires and the conditions that influence how easily they can be put out are largely outside of the state's control, the suppression costs associated with home protection will vary from year to year. For example, although years with many large fires tend to result in high costs related to home protection, the highest expenditures on home protection in the past decade occurred in 2000. This was the year in which the most residential land was threatened, but not the biggest fire year in terms of total acres burned (Figure 4).

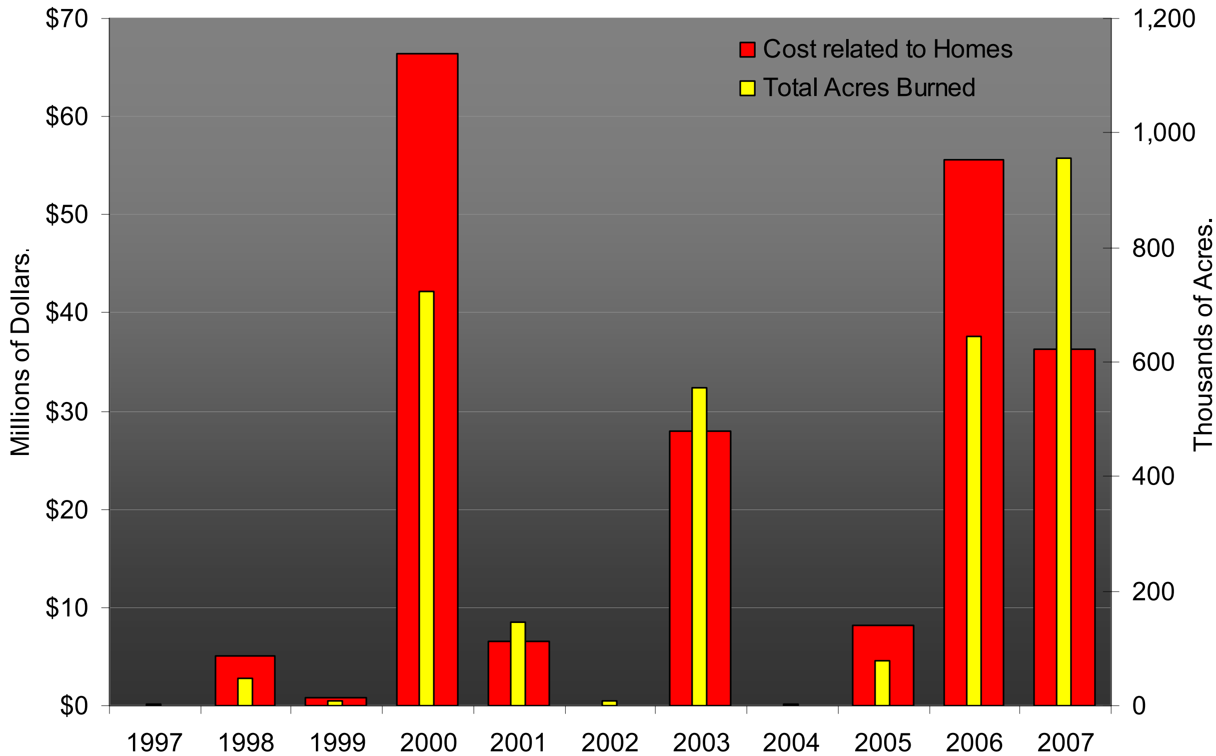


Figure 4. Four of the past ten years (2000, 2003, 2006 and 2007) stand out as having exceptionally high costs related to home protection.

The estimated $92.2 million spent on fire suppression costs related to housing in the past two years were not borne entirely by the state of Montana. Although we do not have sufficient data to estimate the portion paid by Montana, we do know that in our sample of 18 fires that involved the Montana Department of Natural Resources, the state of Montana paid approximately 20 percent of the total fire suppression costs (personal communication, Matt Hedrick, MT DNRC, July 31, 2008). Most of the remainder was paid by federal agencies and FEMA. However, when substantial numbers of homes are at risk, we found that Montana pays a higher percent of the total firefighting costs. In the twelve fires within our sample where more than 1,000 acres of residential land were within one mile of the fire, the state of Montana paid approximately 25 percent of total fire suppression costs. Therefore, we can estimate that Montana paid $13.9 million in 2006 and $9.1 million in 2007 on home protection. However, this is likely a conservative estimate because most homes in the interface occur where DNRC and local governments are responsible for providing wildfire protection. Montana may pay 25% of the total firefighting costs, but a larger share of the cost related to home protection. What's more, as the development in fire prone areas continues, it's likely that state and local will pay an increasing share of the costs related to home protection (personal communication, Bob Harrington, MT DNRC, August 6, 2008).

7.2 How will future home construction impact fire suppression costs?

Next, we asked "What if a similar fire season to 2006 or 2007 occurred in the future when more homes are present?" To answer this question, we overlaid maps of all the large (greater than 360 acres) forest fires that occurred in 2006 and 2007 on top of Headwaters Economics' 2025 development forecast, which is based on a continuation of recent growth rates and trends observed in western Montana (Gude et al. 2007) (Map 3).

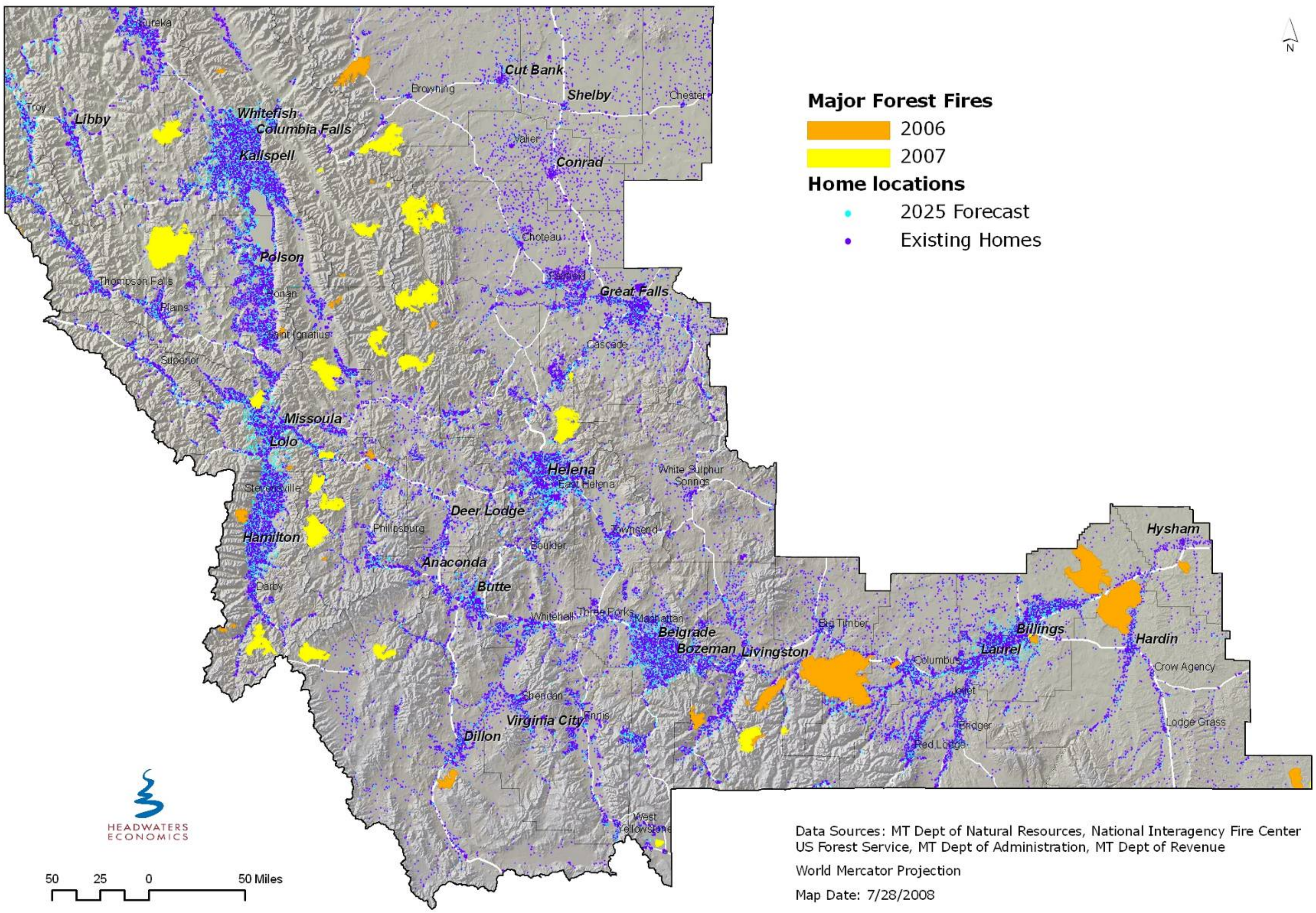
We found that the 2025 development forecast results in an additional 35 thousand acres of residential land occurring within one mile of the 2006 fires. Had these additional homes been present in 2006, firefighting costs related to home protection would have been roughly $23 million higher, totaling $78.9 million (Table 7). In 2025 dollars, this figure adjusted for inflation using the Congressional Budget Office's inflation projections is $124.0 million. We also found that the 2025 development forecast results in an additional 22 thousand acres of residential land occurring within one mile of the 2007 fires. Had the forecasted homes been present in 2007, firefighting costs related to home protection would have been roughly $14 million higher, totaling nearly $51 million (Table 7), which is $80.2 million after adjusting for inflation.

Table 7. Estimates of fire suppression costs related to housing are compared between historical fire seasons and those fire seasons overlayed with a development forecast for 2025.

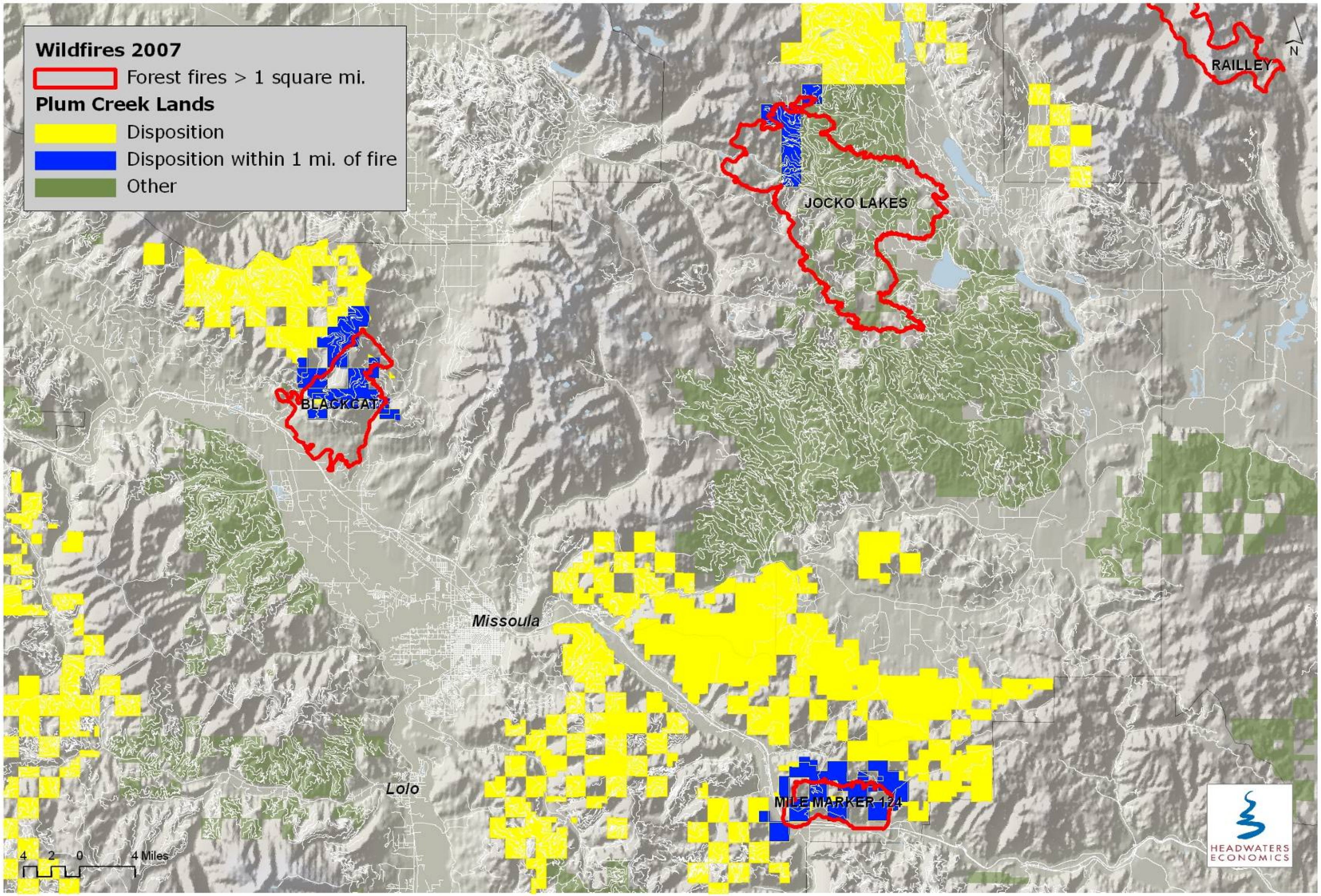
	2006	2006 Fire Season with 2025 Homes	2007	2007 Fire Season with 2025 Homes
Total Size of Fires (acres)	645,640	645,640	956,151	956,151
Development within 1 mile (acres)	~~83,727~~	118,734	~~54,632~~	76,847
Homes within 1 mile	~~5,148 (16 ac lots)~~	6,056 (20 ac lots)	~~3,536 (15 ac lots)~~	4,137(19 ac lots)
Costs related to Homes	~~$55.6 million~~	$78.9 million	~~$36.6 million~~	$51.0 million

7.3 How will the Montana Legacy Project impact fire suppression costs?

Due to the potential for the proposed Montana Legacy Project to significantly alter future development in Western Montana, we investigated the project's potential to impact fire suppression costs. Following a similar method to the one described above, we overlaid maps of all the large forest fires that occurred in 2006 and 2007 on top of the Plum Creek land proposed for purchase. In 2007, 20.5 thousand acres of these lands were within 1 mile of three large forest fires that occurred in 2007 (Jocko Lakes, Black Cat, and Mile Marker 124) (Map 4). Given the proximity of these Plum Creek parcels to Missoula, the high level of road access, and the ability of Plum Creek to opt out of zoning, it seems reasonable that these lands could be subdivided and developed if the Montana Legacy Project fails. Had these parcels been subdivided into 160 acre lots, as few as 150 homes distributed across these lands could have added $13 million in costs to 2007's fire suppression bill.



Map 3. Locations of all large forest fires that occurred in 2006 and 2007 are shown relative to existing and forecasted housing in western Montana.



Map 4. The large forest fires that burned in 2007 around Missoula are shown in relation to Plum Creek lands.

Summary

- Firefighting costs are highly correlated with the number of homes threatened by a fire.
- The pattern of development (dense vs. spread out) is an important contributing factor.
- When large forest fires burn near homes, costs related to housing usually exceed $1 million per fire.
- As few as 150 additional homes threatened by fire can result in a $13 million increase in suppression costs in a single year.
- For all agencies involved in fire suppression in Montana, the estimated annual costs related to home protection for 2006 and 2007 were approximately $55 million and $36 million, respectively.
- If current development trends continue, fires seasons similar to 2006 and 2007 could cost $15 to $23 million more by 2025, bringing total fire suppression costs associated with homes to between $51 and $79 million dollars. Adjusted for inflation, future costs could be as high as $124 million in 2025.
- A conservative estimate is that 25% of all costs of protecting homes from wildfires within Montana are paid for by the state. Therefore, Montana's costs for home protection in 2006 and 2007 are estimated to have been $13.9 million and $9.2 million, respectively. By 2025, Montana's future costs, adjusted for inflation, could be as high as $31 million.

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