Probabilistic Risk Analysis of Colorado Wildfires

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Abstract

In recent years, Colorado, among other states, has seen rapid urban expansion. Termed wildland-urban interfaces, or WUIs, these areas are particularly vulnerable to hazards such as landslides, avalanches, and wildfires. This danger has motivated new risk analysis of natural disasters and investigations into preventative measures. The work in this paper is primarily intended to be a proof of concept for combining Markov models, decision analysis, and probabilistic risk analysis to simulate wildfire propagation, assess damages, and guide policy. We present a framework for assessing the effectiveness of pre-event mitigation actions in reducing wildfire risk in the WUI. We build and test a stochastic wildfire propagation and loss model on different scenarios, where each scenario is a different type of community-wide pre-event mitigation action as specified by the International Wildland Urban Interface Codes (IWUIC). The results give the expected damages from wildfire events in each scenario. We approximate the costs associated with each scenario and use decision analysis to find the optimal implementation of the IWUIC for the community in question. In this way, we are able to assess the value of pre-event wildfire mitigation in the wildland-urban interface.

1 Introduction

As climate change increases year-round temperatures and disrupts precipitation patterns, wildfire risk has increased in many western states, including Colorado [1]. This hazard is of particular concern for communities in the wildland-urban interface (WUI), where abundant vegetation strengthens fires and makes suppressing them more difficult.

Foresters, fire scientists, and ecologists have extensively studied wildfires via geospatial data and physical fire behavior models. However, these models typically only determine the most likely path a wildfire will take. They do not account for the full range of outcomes nor the probability that each outcome will occur. These models do not calculate the damage that wildfires inflict on land, property, and people. As such, using these models to evaluate the effectiveness of pre-event mitigation strategies, firefighting techniques, and evacuation efforts has been highly speculative.

This paper uses probabilistic risk analysis to (1) model wildfire propagation, (2) quantify the expected damages from wildfires, and (3) compare wildfire prevention efforts. Our model could be applied to many types of preventive measures, including pre-event mitigation, firefighting, and evacuation protocols, but we focus on assessing the effectiveness of the International Wildland-Urban Interface Codes, or IWUIC. We model the implementation of various components of the IWUIC on a test county and compare the damage wildfires cause with or without each component. We use simulation data to determine which codes are most effective, how cost-effective each code is, and ultimately whether the IWUIC are worth implementing.

2 IWUIC Components

We distilled the IWUIC into four main components: (1) building with fire-resistant materials, (2) reducing the fuel load in residential and open space areas, (3) creating and maintaining defensible spaces around homes and buildings, and (4) constructing roads and firebreaks throughout a community. We considered six decision scenarios: implementations of each component individually, the implementation of all components together, and implementation of zero components. For each scenario, we adjusted the values of our covariates and/or the structure of the grid itself to model the IWUIC implementation under consideration. For a more detailed explanation of our covariates and grid, see Section 3: Model. For the initial covariate values, see Figure 6.

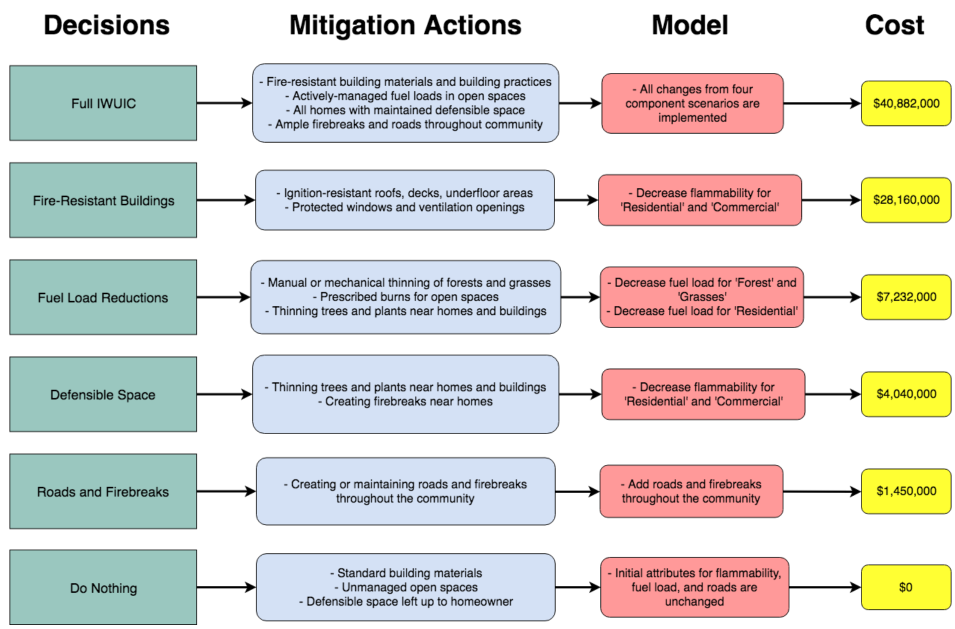


Figure 1: IWUIC Decision Scenarios

From left to right, this diagram shows our six decision scenarios, typical executions in a real community, the adjustments we made to model each decision, and approximate cost of implementing each decision for 20 years.

We simulated many wildfires under each scenario and aggregated the outputs. We compared the expected losses from wildfires to the approximate cost of each IWUIC component to determine which parts are most cost-effective.

Fire-Resistant Buildings

The "Fire-Resistant Buildings" scenario is based on requirements from Chapter 5 of the IWUIC [2]. While this chapter lists dozens of actions, we consider only three: (1) the replacement of all roofs with metal roofs, (2) the replacement of all decks with treated decks, and (3) the covering of windows, ventilation openings, and underfloor areas with mesh to prevent embers from entering the building envelope. We assume a uniform cost of $8,500 for roof replacement, $1,500 for deck replacement, and $1,000 for the protection of openings per house [7]. With our sample grid, the "Fire-Resistant Buildings" decision costs $28,160,000. We assume that these improvements last for 20 years [5]. We model this decision by decreasing the flammability values for residential and commercial cells from [0.1,0.3] and [0.05, 0.15] to [0.05,0.1] and [0.05,0.1], respectively.

Fuel Load Reductions

The "Fuel Load Reductions" scenario is based on recommendations from Appendices A and B of the IWUIC [2]. While these appendices are not part of the formal code, they offer best practices for wildfire risk mitigation. In our analysis, we consider thinning of forests, grasses, and other vegetative fuels in open spaces and near residential neighborhoods. We assume a cost of $500 per acre of grassland and $5,000 per acre of trees [3]. We assume fuel load reductions at this cost last for five years. For our grid, this decision costs $1,808,000 for five years, or $7,232,000 for 20 years. We model this decision by decreasing the fuel load values for forest, grasses, and residential cells from [0.1,0.3], [0.8,1.2], and [0.3,0.5] to [0.03,0.07], [0.5,0.6], and [0.2,0.4], respectively.

Defensible Space

The "Defensible Space" scenario is based on requirements from Chapters 4 and 6 of the IWUIC [2]. These chapters require the clearing or treating of combustible materials near the home to prevent the advance of fire, as well as the maintenance of open spaces near structures to allow for safe and effective firefighting. As our current model does not consider fire suppression, we analyze only the effect of defensible spaces on preventing the spread of wildfire. For this solution, we assume a cost of $2,750 per acre in both residential and commercial neighborhoods [3]. We assume that defensible space treatments at this cost last ten years. For our grid, this decision costs $2,020,000 for ten years, or $4,040,000 for 20 years. We model this decision by decreasing the flammability values for residential and commercial cells from [0.1,0.3] and [0.05, 0.15] to [0.1,0.2] and [0.05,0.1], respectively.

Roads and Firebreaks

The "Roads and Firebreaks" scenario is based on requirements from Chapter 4 of the IWUIC [2]. This chapter requires roads for (1) ingress for firefighters, (2) egress for evacuees, and (3) firebreaks that slow or prevent the advancement of a flame front. Our current analysis considers only the effect of roads on fire propagation, though model could be adapted to consider the first two as well in future versions. We assume a cost of $2,000,000 per mile of road added [4]. We model this decision by converting residential, commercial, or open space grid squares to road squares with an assigned flammability value of 0. Under this scenario, we converted 13 squares, which span approximately 1,170 meters. For our grid, this decision costs $1,450,000, and we assume the roads last 20 years.

Full IWUIC

The "Full IWUIC" scenario is meant to represent a full implementation of the wildland codes. To model this scenario, we combine the four component scenarios into one. We take the covariate values for flammability and fuel load to match those used in each component scenario. We assume a total cost to be $40,882,000 for twenty years, which is the sum of the costs of the four component scenarios.

Do Nothing

The "Do Nothing" scenario represents a community that has not undertaken any significant pre-event mitigation actions. The values for flammability and fuel load are unchanged from those given by the table of initial values. We assume that this solution costs $0 for any length of time.

Limitations on Assigning Cost Values

The cost of each decision may vary greatly depending on a number of factors. Among these include the exact location under consideration, the duration of time over which solutions are needed, and mechanisms like insurance and grant funding that could be used to offset costs. The cost of building with fire-resistant materials or creating defensible space depends on terrain, slope, access (roads and space for equipment), and environmental factors like snow and hail that may affect the longevity of the project. A community that has already implemented pre-event mitigation to a certain degree would likely pay less for a decision than one that has not. Costs may be better modeled as ranges, or as time-dependent functions that account for capital costs and maintenance costs separately. A more rigorous analysis would consider ancillary benefits of the decision scenarios including things like improving firefighter access, enabling evacuation, improving the health of forest and grassland ecosystems, and increasing the longevity of homes by using stronger building materials, or clearing tree branches that could fall and cause damage. Finally, further analysis might examine funding sources like insurance and federal grants to offset the cost of the decisions.

3 Model

3.1 Influence Diagram

We began by consulting with experts to create an influence diagram of the key uncertainties and parameters of our problem. These included factors contributing to wildfire risk, the physics of wildfire propagation, and the impacts of the IWUIC.

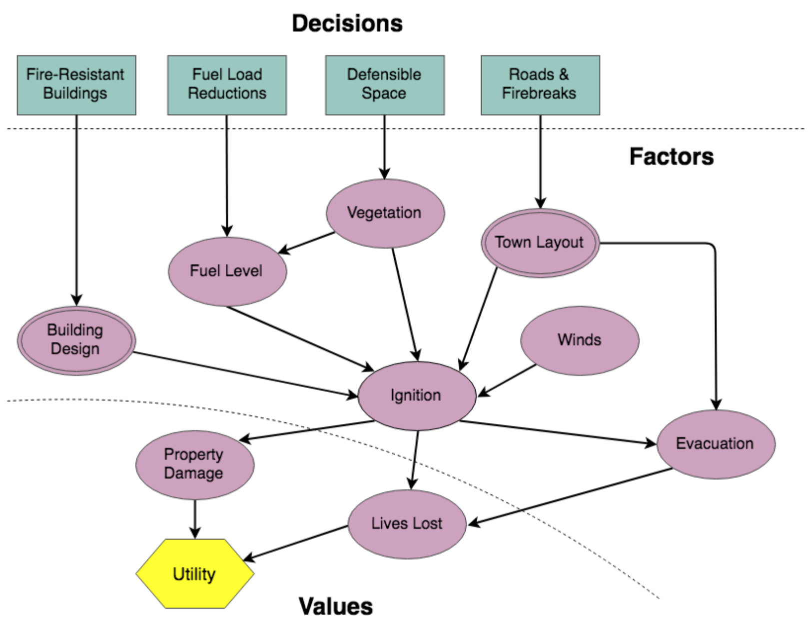


Figure 2: Wildfire Risk Influence Diagram

We identified 5 key uncertainties: the level of vegetation, the kinds of vegetation, the wind, the evacuation process, and the course of the wildfire. The layout of the county and the design of its buildings, including the materials, are important parameters. We evaluate damage severity based on property loss and number of deaths.

We identified 4 primary components of the IWUIC to investigate: using fire-resistant building material, reducing vegetation levels, building in defensible spaces, and constructing roads to act as firebreaks. Using different building materials naturally influences building design, and constructing roads changes the town layout. Vegetation control and space maintenance affect vegetation levels and types.

3.2 Model Pipeline

From that, we created the following model pipeline.

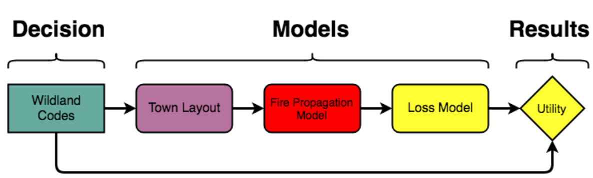


Figure 3: Model Pipeline

We began by identifying 4 components of the IWUIC to investigate. Next, we created a map of our target county, encoding the local characteristics necessary for our model. We worked out how each IWUIC component would influence our map, then fed maps representing the implementation of each component into a fire propagation simulation. From that, we assessed the expected damage a wildfire would cause in each paradigm and determined whether each IWUIC component was worth its cost.

3.3 Town Layout

3.3.1 Classification Grid

Working from an overhead photograph of Jefferson County, we classified each acre of a 2500 acre square section as either road, grasses, forest, residential, commercial, or highway. We treat each of these acres as a cell in a grid. Working with experts, we then assigned 4 characteristics to each type of grid cell: flammability, fuel load, property value, and population. We assign land cover type a range for each of these covariates, then generate a map by selecting values in each range uniformly at random. More detailed descriptions of our calculations and assumptions follow.

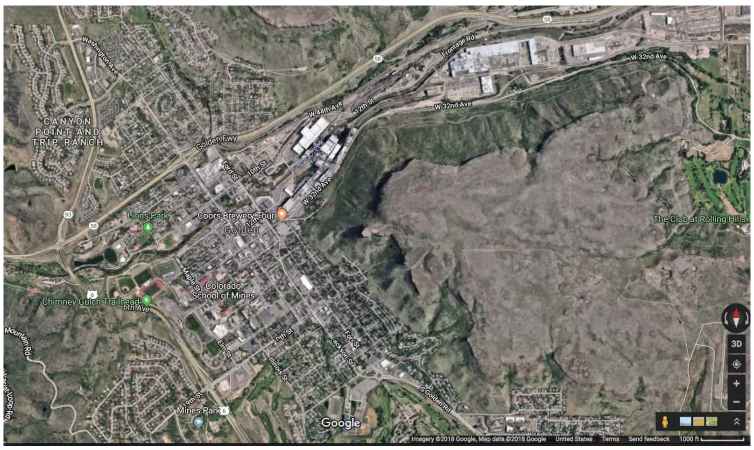


Figure 4: Overhead Photo of Jefferson County

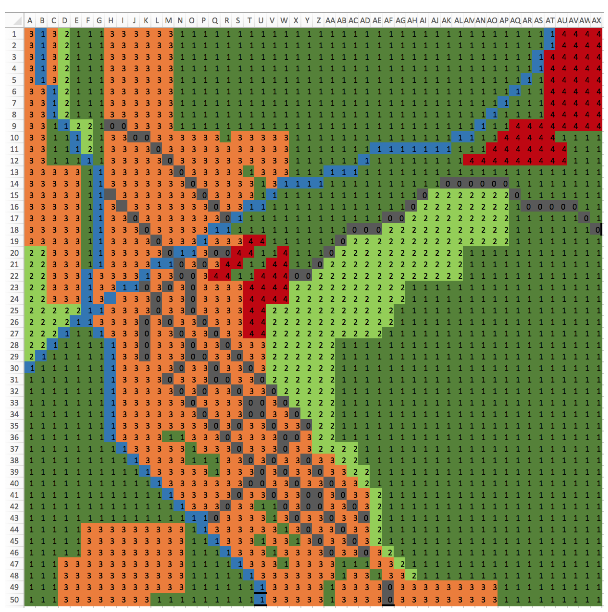


Figure 5: Model County Map

Land Cover	Flammability (Ignition probability)	Property Value (Dollars)	Lives (Based on county population density)	Fuel Load (Normalized score)
Road	0	$70,000 - $84,000	0	0
Grasses	0.75 - 0.85	$5,900 - $6,900	0	0.1 - 0.3
Forest	0.65 - 0.7	$5,900 - $6,900	0	0.8 - 1.2
Residential	0.1 - 0.3	$1,500,000 - $2,500,000	2 - 7	0.3 - 0.5
Commercial	0.05 - 0.15	$2,000,000 - $3,000,000	0	0.2 - 0.4
Highway	0	$180,000 - $220,000	0	0

Figure 6: Ranges for Cell Covariates by Land Cover Type

Firebreaks

Creating or maintaining roads and firebreaks throughout the community enables access for firefighters, egress for civilians, and slows the spread of flame front. While our current analysis considers only the effect of roads on slowing propagation, we add four roads to allow residential and commercial neighborhoods direct access to roads or highways in the event of an emergency evacuation. To model this, we converted residential, commercial, forest, and grass squares to roads in our initial grid.

3.4 Covariates

Flammability

The higher a cell's flammability, the more likely that cell is to catch fire. Currently, these values are assigned based on the relative flammabilities of the six different land cover types. For example, grasses tend to be more flammable than homes, so we assigned grasses a higher flammability value than we did for residential neighborhoods. The flammability value does not change over the course of a simulation.

Fuel Load

The fuel load value represents the amount of combustible material in each grid cell. Currently, the value is given as a normalized score. The maximum possible fuel load is 1, and the least possible fuel load is 0. For example, forests are expected to have a larger fuel load than grasses, so forest cells begin with a higher score than do grasses cells. As a cell burns, its fuel load decreases.

Property Value

The initial property value represents the total worth of land and structures for one grid cell of each land cover type. We assumed that one acre in a typical WUI neighborhood covers four parcels. We used the median parcel value in Evergreen, CO of $500,000 [6], multiplied it by four, and used it as the mean property value for residential squares. We assumed that commercial properties were 1.25 times more valuable than residential properties, and scaled our numbers for property value accordingly. According to the American Road and Transportation Builders Association, roads cost $1,250 per meter and highways cost $3,125 per meter. Each grid cell is approximately 90 meters across diagonally, which we used as the length per grid cell when determining the property value for roads and highways. Finally, we assigned the property value for forest and grasses given an online estimate of the cost of open space land in Colorado [8].

Lives

Dividing the total population by the total area, we found that the population density of Jefferson County was approximately 1.16 people per acre. Our grid covers about 2,500 acres, meaning there should be approximately 2,900 lives accounted for in our grid. With 640 squares representing residential neighborhoods, we needed an average of roughly 4.5 lives per residential square, which we used as the mean value of lives. We assumed there were no lives to account for under other types of squares.

Limitations

The validity of the values chosen for our covariates could be improved in several ways. First, there might be ways to derive flammability and fuel load values using scientific equations, satellite imagery or geospatial land cover data, or the values used in existing fire behavior models. Once more accurate numbers are chosen, our model could be validated by comparing its outputs to historical events or to simulations carried out by existing models. Potential model improvements are explained further in the "Future Work" section of this paper.

3.5 Fire Propagation Simulation

Simulation Loop

```
Data: Grid of town layout
Result: Total building damage and casualties
Determine wind direction
Initialize fire
while fire is ongoing do
    for cell in grid do
        Calculate transition probabilities
        Determine state in next time step
        if cell is on fire then
            Calculate damages and casualties in cell
            Calculate fuel consumption
            if cell is not alerted of fire then
                Cell is alerted of fire
            end
        end
        if cell is alerted of fire then
            Calculate how many people evacuate
        else
            Check whether cell becomes alerted of fire
        end
    end
    Update grid state
end
return Total damages
```

Algorithm 1: Simulation loop

We choose the cell where a fire starts at random based on the relative probabilities of each cell, then follow the fire until it's fully extinguished. In each time step, for each cell, we perform 4 operations. First, we calculate how likely the cell is to remain safe, catch fire, keep burning, or extinguish. Then we randomly determine the cell's state in the next time step. Next, if the cell is burning, we calculate how much damage the fire inflicted. Lastly, we check whether the cell has been alerted of the fire and how many people successfully evacuate from that cell. We track how much damage the fire causes overall and return the total at the end.

Because the total fuel in the system only decreases and the fire is guaranteed to extinguish when all fuel has been consumed, the main while loop is guaranteed to terminate.

Fire Transition Probabilities

When a cell is not on fire, we calculate the probability that it catches fire using the following formula.

$$P(\text{cell } ij \text{ catches fire}) = \min(\alpha_{ij} \cdot |\{n \text{ is on fire} \mid n \in N_{ij}\}|, 1) \cdot (1 - e^{-\beta_{ij}})$$

Where α_{ij} is the flammability of the cell, N is the set of neighboring cells and β_{ij} is the fuel level. The higher a cell's flammability and fuel level, the more of its neighbors are on fire, and the higher its fuel level, the more likely it is to catch on fire. By default, N is the eight cells immediately surrounding ij. Each cell's cohort of neighbors is also affected by wind, which we'll discuss next.

If a cell is already on fire, then the probability it extinguishes is:

$$P(\text{cell } ij \text{ extinguishes}) = e^{-\beta_{ij}}$$

As a cell runs low on fuel, it's more likely to extinguish. When a cell has no fuel, it's guaranteed to extinguish. If a cell has infinite fuel, then it's guaranteed to keep burning.

3.5.1 Wind

At the beginning of each episode, we determine wind direction. We grow the set of each cell's neighbors based on how the wind is blowing. For example, if the wind is blowing east, then the cell's neighbor cohort is the 8 cells immediately surrounding it and the set of three cells to its left. This causes cells on fire to have greater influence on the cells east of them.

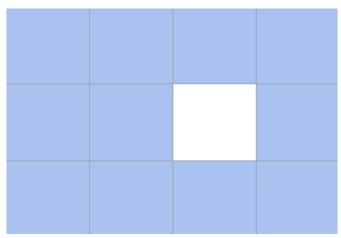


Figure 7: Neighbor Cohort for Cell ij With an East Wind

3.6 Building Damage and Casualties

If a cell is on fire at the beginning of a time step, then the fire destroys k_b% of the building value in the cell and kills k_l% of the people in it. This is a simple way to cause fires to inflict an exponentially decreasing amount of damage over time. Currently $k_b = k_l = 5$.

Fuel Consumption

Similarly, in each time step, a constant k_f percentage of fuel burns in each cell. We set $k_f = 10$.

Alert System

In each time step, if a cell has not been alerted, we calculate the probability the cell receives an alert using the following formula.

$$P(\text{alert}) = p_{\text{base}} + (1 - p_{\text{base}}) \frac{|\{n \text{ is on fire} \mid n \in N_{ij}\}|}{|N_{ij}|}$$

Each cell in the grid has a baseline probability of receiving an alert, which reflects electronic communication and public service announcements. This probability is proportionally improved based on how many of the cell's neighbors are on fire. If all of a cell's neighbors are on fire or the cell itself is on fire, then it becomes alerted with probability 1. Once a cell has been alerted, it remains alerted for the duration of the simulation. We track how long each cell has been alerted. Currently, $p_{\text{base}} = 0.05$.

3.6.1 Evacuation

We calculate the proportion of people who evacuate each time step using a modified sigmoid function.

$$p_{\text{evacuation}} = \frac{2}{1 + e(-t_{ij}) - 1}$$

Here, t_{ij} is how long the cell has been alerted of the wildfire. And when $t_{ij} = 0$, then $p_{\text{evacuation}} = 0$. When $t_{ij} = \infty$, then $p_{\text{evacuation}} = 1$. Our function is also concave down, so that the proportion of evacuees increases at a decreasing rate.

4 Results

Example Simulation

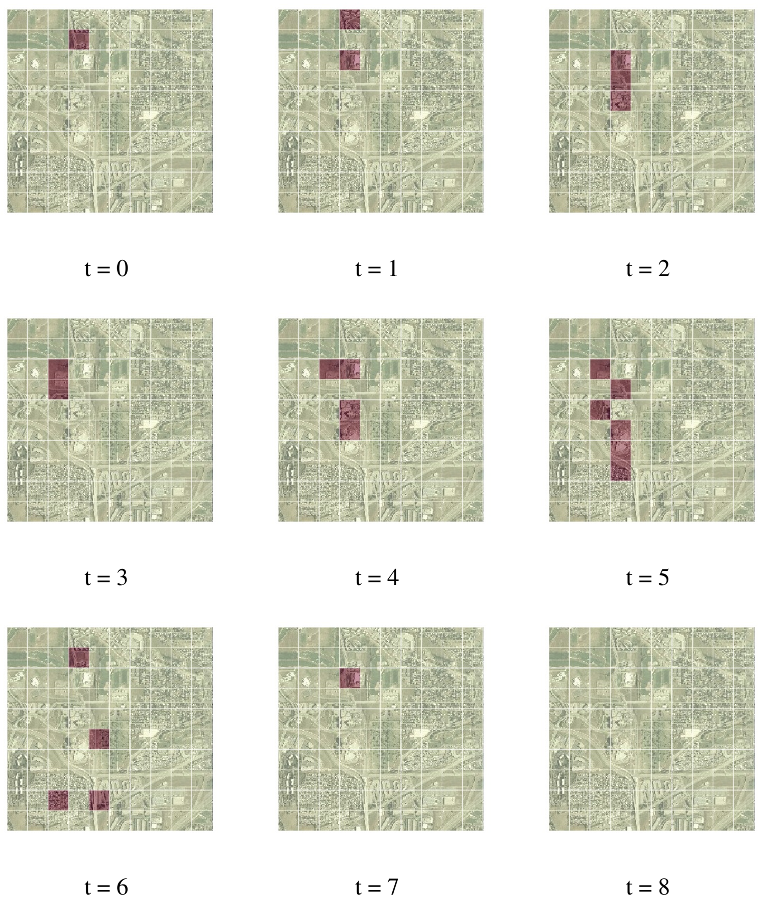


Figure 8: Example Simulation

For illustration, this is an abbreviated representation of one episode of our propagation model. In this episode, the wind is blowing east. The fire starts in the top-left corner of the map, burns there for a while, then quickly spreads south. The fire grows for a handful of time steps, then burns out.

While crude, the behavior of this wildfire reflects how we expect fires to behave. It was largely contained to one section of vegetation, burned in that area for a while, then quickly spreads out before extinguishing. Given how simple our transition functions and how broad our assumptions are, this illustration is highly encouraging.

Damages

After running our propagation model on full grids for 500 episodes, we get these damage and fire length histograms.

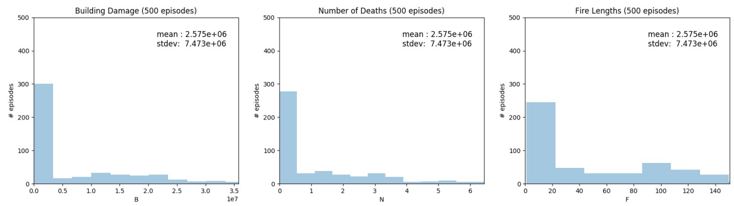


Figure 9: Baseline

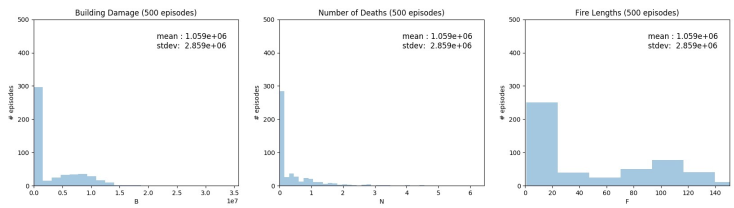


Figure 10: Building Materials

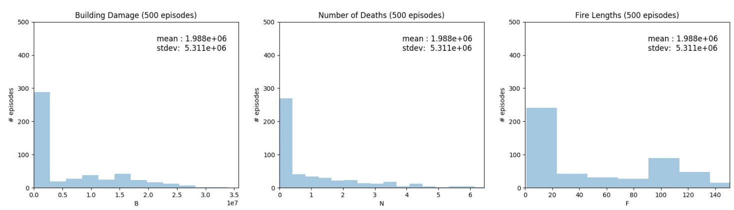


Figure 11: Defensible Spaces

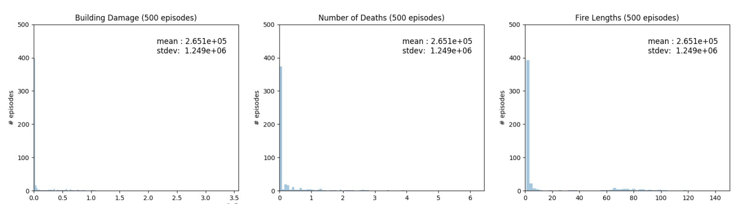


Figure 12: Vegetation Control

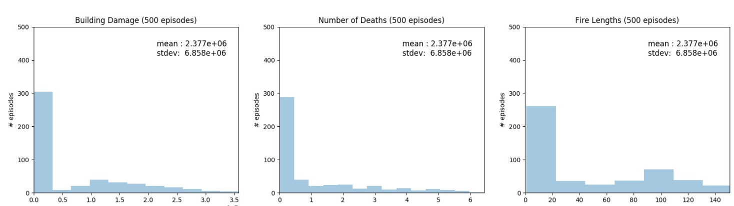


Figure 13: Firebreaks

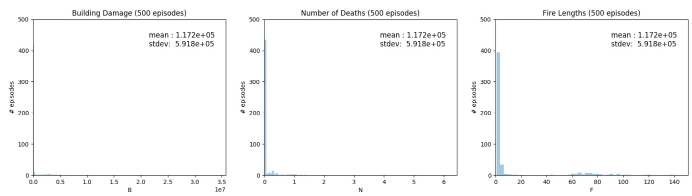


Figure 14: Full IWUIC

Further, we get the following table of expected outcomes.

Scenario	Building damage	Deaths	Length (time steps)
Baseline	7723519.094	1.370	47.288
Building Materials	3176925.809	0.425	48.41
Defensible Spaces	5963088.981	1.043	49.676
Vegetation Control	795156.155	0.232	12.244
Firebreaks	7131103.885	1.206	45.804
Full IWUIC	351620.375	0.061	11.142

Figure 15: Expected Damages Across Decision Scenarios

Visually, we can see that as we've parameterized our model, vegetation control is by far the most effective individual preventative measure. And as we'd expect, the full IWUIC is the most effective scenario.

4.1 Baseline Comparisons

Following that, we get the following bar charts of how much damage and how many casualties each IWUIC component prevents over the baseline.

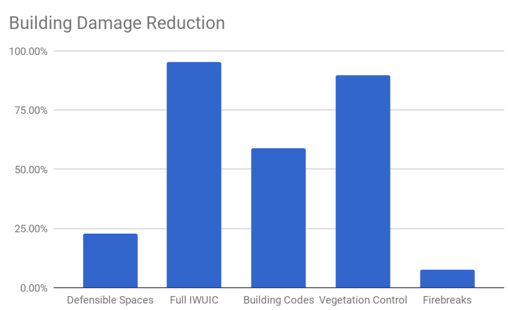


Figure 16: Building Damage Improvement Over Baseline

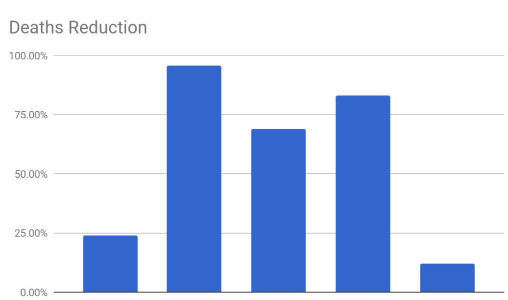


Figure 17: Casualties Improvement Over Baseline

We can see more clearly that vegetation control is by far the most effective individual component, but the full IWUIC performs best.

5 Probabilistic Risk Analysis

5.1 Decision Analysis

Decision analysis compares the expected outcomes of different decision scenarios to find the optimal choice. Here, we approximate the cost per event of each decision by multiplying its annual cost by the mean fire return interval. The mean fire return interval (MFRI) is the length of time in which one large wildfire event is expected to occur for a given land area. In the table shown below, we set the MFRI to 15 years. Our model results give us the average damage and deaths per event for each decision. Valuing each life at $100,000, we calculate a net loss per event by summing the cost, damages, and value of lives lost per event for each decision. Dividing this number by the MFRI gives the expected annual net loss under each scenario.

Solution	Cost per event	Damage per event	Deaths per event	Net utility per event	Net utility per year
Buildings	$21,120,000	$3,176,926	0.4250	$24,339,426	$1,622,628
Fuel load	$5,424,000	$795,156	0.2320	$6,242,356	$416,157
Defensible Space	$3,030,000	$5,963,089	1.0430	$9,097,389	$606,493
Roads	$1,087,500	$7,131,104	1.2060	$8,339,204	$555,947
IWUIC	$30,661,500	$351,620	0.0609	$31,019,210	$2,067,947
Nothing	$0	$7,723,519	1.3700	$7,860,519	$524,035

Figure 18: Net loss per event using MFRI = 15 years and a value of life of $100,000.

5.2 Sensitivity Analysis

The results change depending on the values chosen for the MFRI and for the value of life (VOL). As the MFRI increases above 20 years, according to our analysis, fuel load reductions become less cost-effective than doing nothing.

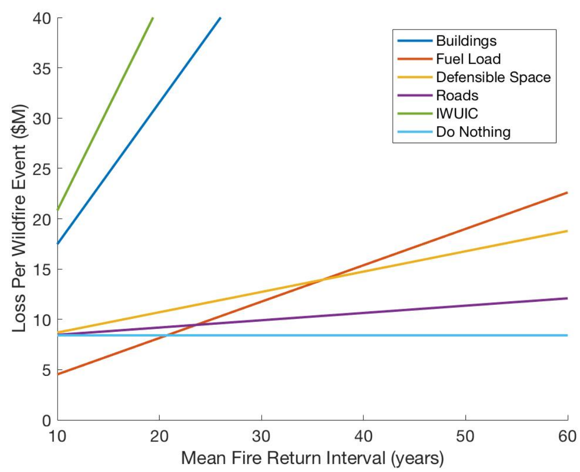
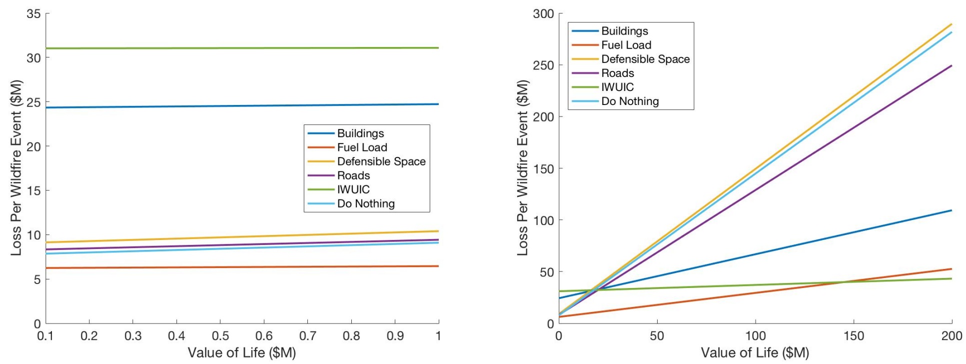


Figure 19: Expected net loss of each decision given a range of values for MFRI with VOL = $100,000.

As the value of life increases, the solutions with the smallest values for expected deaths become more cost effective. Over a range of reasonable values the optimal decision remains unchanged from fuel load reductions. As the value of life increases above $150,000,000, the optimal decision changes to the full implementation of IWUIC. We include this result as an example of a decision threshold.



(a) For Typical VOL Values

(b) For VOL Above $150,000,000

Figure 20: Value of Life Sensitivity Analysis

6 Future Work

The primary strength of our model is its modularity. Our general framework naturally extends to account for any number of phenomena, and the components we used can easily be refined. Because of time and resource constraints, we made relatively broad assumptions in our mapping, probability functions, and cost assessments. The work in this paper is primarily intended to be a proof of concept for combining Markov models, decision analysis, and probabilistic risk analysis to simulate wildfire propagation, assess damages, and guide policy. In this section, we suggest a number of ways that our model could be improved for practical use. Individual components could be improved, or the model pipeline could be extended.

6.1 Map Improvements

In this analysis, we focused primarily on the fire propagation model as that was the most complex and involved component and because we expected that organizations who might apply this model in practice would have access to much more sophisticated data than we did. As such, we considered a relatively limited number of covariates over a coarse grid. Our map could be improved in a number of ways.

Automatic Map Generation

In an ideal setting, this model would be able to pull data from a regularly maintained geospatial database and generate the relevant covariates. We included some basic support for this in our map generation script, but currently that only looks at our hand-coded feature map and our land cover type lookup tables.

Higher Grid Resolution

Failing that, a higher resolution hand-coded map would also allow for more accurate results. Our model can accommodate arbitrarily large maps, though at some point space and run-time become real constraints.

Higher Fidelity Classification

We could have also included a larger variety of cell types in our classification to account for different types of forest and vegetation, more and less densely populated neighborhoods, different kinds of road, and commercial districts.

Map Cache

We already include extensive support for generating a large cache of maps and pulling a random map from that cache for each episode, rather than using the same map across simulations. This takes greater advantage of our stochastic map generation and would lead to more accurate averages, but this benefit would primarily be realized with greater computational power than we had and over a greater number of simulations than we were able to run.

Additional Covariates

We could have also included additional covariates in each grid cell. Alongside improved resolution, additional covariates such as height could facilitate, for example, physical transition models. In practice, fires are unlikely to spread downhill, and land formations can block or enhance wind. With some refinement, our model could also account for these factors.

6.2 Model Improvements

The general framework of our model, where we model our target location as grid and treat that grid as a Markov state, is our primary contribution. The main areas where our framework could be improved are the addition of more states for each cell, refined transition functions, and more detailed simulation tracking and analysis.

Additional States

Currently, cells in our grid are either on fire or aren't. We could also include levels of fire severity, consider whether cells have previously on fire, or try to track where wildfires might be burning underground (or "hot spots"). By introducing more levels, we can account for a greater number of factors.

Improved Transition Functions

We used a heuristic set of transition functions that we believed would give the model reasonable behavior. We didn't invest many resources into improving these functions because our overall framework suggests their refinement and large number of approaches are available. For example, we could use physical propagation models to inform state transitions, fit regression models to historical data, or use something like a neural network as a subcomponent. We could also use a more refined evacuation function that accounts for the positions of roads and critical structures like fire departments. Our model could accommodate an ensemble of these approaches as well.

Additional Simulation Analysis

We could also track additional data across simulations, such as determining how much damage fires cause based on where they start. This could potentially show us areas where preventative measures are particularly critical.

6.3 Additional Considerations

Outside the framework of our model, there are a number of other considerations we could try to account for.

Projecting Future Risk

The climate and degree of human settlement in Colorado are rapidly changing over time. These factors could greatly influence wildfires. A more refined model could perhaps project future risk stemming from these factors.

Firefighting

We could also account for active fire prevention. A fun way to do this would be to introduce a firefighter agent in our model who travels around roads and puts out fires, or at least makes fires near her more likely to go out. We could also simply make fires near roads more likely to extinguish, based on the logic that firefighters are more likely to get to those cells. Alternatively, we could factor global road density into our state transition function.

Model Validation

Most ambitiously, we could attempt to use our model to predict the outcomes of real wildfires and backpropagate, validating our model. More realistically, we could bring the predictions of our model in line with tested wildfire propagation models such as Farsite and WiFire. Alternatively, we could validate our model with historical data.

7 Conclusion

In this report we have presented a framework for assessing the value of pre-event wildfire mitigation. We selected a WUI community in Colorado and modeled wildfire propagation and losses given scenarios of different implementations of the IWUIC. We considered the costs of each scenario to determine the optimal policy for a community to minimize its expected losses to wildfires.

Although our methodology and assumptions were crude in many places due to time and resource constraints, our results are nonetheless promising. Our propagation model produced wildfire simulations that reflect how we intuitively expect wildfires to behave in nature. Our subsequent damage distributions were relatively in line with historical data, and more radical preventative measures resulted in less damage on average.

Our overall model framework is natural, powerful, and flexible, and it produces clear results to guide decision-making. We've identified a number of approaches to improve our model so that it might one day have significant practical value.

We hope that this paper will guide stakeholders looking to determine the risks of wildfires, the value of pre-event mitigation, and better understand how to face uncertainty.

8 Related Work

8.1 Weinstein and Woodbury, 2010 [9]

According to Weinstein and Woodbury's Review of Methods for Developing Probabilistic Risk Assessments, current fire models can be grouped into one of three categories: biophysical models, statistical models, and fire behavior models.

Biophysical models, such as LANDFIRE, analyze fire risk given inputs like vegetation type, fuel load, and climate. They are predictive models that give an relative measure of fire risk for a land area. While effective in assessing relative risk, biophysical models tend to be static, meaning they are unable to model the spread of fire in a wildfire event.

Statistical models use regression to describe elements of risk, though the use of these models is incumbent on the availability of large and robust datasets. As data collection becomes more widespread, statistical fire models will likely become more popular in the future.

Fire behavior models, also known as fire propagation models, model wildfire spread and severity given inputs similar to those used by biophysical models. An example is FARSITE. These models are dynamic, meaning they are time-dependent. Fire behavior models allow one to consider a variety of factors related to wildfire propagation like fire occurrence, fire pathways, and fuel consumption. Fire behavior models can also be used to assess effects on human systems like loss of property and mortality.

When assessing risk, it is useful to distinguish between three types: fire, ecosystem, and human. Fire risk refers to the risk of ignition, spread, and intensity of fire during a wildfire event. Ecosystem risk refers to the chance of damage incurred by natural systems during and after a wildfire event. Human risk, unnamed by the paper, refers to the risk fire poses to property and material assets, human lives, and human systems.

Weinstein and Woodbury define four levels of fire modeling: (1) initial ignition, (2) the probability of fire occurring, (3) the spread of fire, and (4) the effects of fire. The realizations of these four levels depend on uncertainties including ignition source, fuel load, vegetation type, climate, topography, and suppression.

The model we built considers the uncertainties for ignition source, fuel load, wind, vegetation type, and variable controlling the fire spread like firebreaks and spotting. The model we built does not consider recent climate history, moisture content, vegetation stage, topography, or fire suppression. Most notably, our model does consider the effects of fire in the form of property damages and human lives lost. We use these results to assess policy decisions for pre-event risk reduction activities.

8.2 Scott, Thompson, and Calkin, 2013 [10]

The report Wildfire Risk Assessment Framework for Land and Resource Management describes a framework for wildfire risk assessment. Given a landscape, they use existing modeling tools like LANDFIRE and FlamMap to produce conditional burn probabilities for each grid cell by running Monte Carlo simulations and integrating the results. Their end product is a raster map of relative burn probability, which is taken as a proxy for risk.

The approach outlined by Scott, Thompson, and Calkin is powerful because it can (1) input accurate and detailed geospatial data, (2) employ tried-and-tested wildfire propagation functions from industry-standard models like FlamMap, (3) employ Bayesian updating by incorporating new data and expert feedback, and (4) convey "degree of belief" by presenting results in terms of probability.

Our model currently allows for (3) and (4), and the framework we present allows for the implementation of (1) and (2) in future versions. Furthermore, we expand on the work of Scott, Thompson, and Calkin by incorporating the consequences of policy decisions related to wildfire prevention into the propagation model. Finally, while Scott, Thompson, and Calkin consider the effects of wildfire on ecosystems, we model the effects of wildfire on structures, property, and human lives.

8.3 Haas, Calkin, and Thompson, 2013 [11]

The paper talks about a national approach for integrating wildfire simulation modeling into Wildland Urban Interface risk assessments within the United States. A variety of fire modeling systems exist that can provide spatially resolved estimates of wildfire likelihood,which when coupled with maps of values-at-risk enable probabilistic exposure analysis. This paper indicates the variety of fire modeling systems existence that can provide spatially resolved estimates of wildfire likelihood, that can integrate with maps of value-at-risk. It doesn't focus on models but more into research analysis about employing wildfire risk assessment models that can help in managing decision making, and can facilitate prioritization of investments in mitigating losses and restoring landscapes. A major contention of this paper is that next-generation WUI maps incorporating spatial, probabilistic information on the exposure of high values to wildfire are more informative than simpler analyses identifying geographic areas where populated places may or may not interact with wildfire.

8.4 The International Wildland-Urban Interface Codes (IWUIC) [2]

The International Wildland Urban Intferface Codes (IWUIC) are a set of building, planning, and open space codes designed to help communities in the wildland-urban interface reduce the risk of wildfire. The codes call for different pre-event mitigation activities. The IWUIC is produced by the International Code Council, and can be found on the ICC's website. Communities seeking to implement the IWUIC may adopt parts of the code, or the code in its entirety.

Chapter 4 of the IWUIC describes defensible space, access, and planning requirements for communities. Chapter 5 describes regulations for the design, construction, and location of buildings. Chapter 6 describes fire protection requirements to mitigate the spread of wildfire through a community, such as vegetation and open space management. The appendix sections of the IWUIC–though not technically part of the code–contain advice for best practices related to open space management.

9 Code

The code for this project can be found in the following GitHub repository: `https://github.com/nalkpas/MSE250B-2018-Project`.

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