Using Optimization Modeling to Determine Locations for Aerial Firefighting Resources Based on Wildfire Risk Data

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ABSTRACT

The increase of the global mean temperature likely leads to more frequent and prolonged fire weather periods, with hot and dry conditions. This would also lead to increased frequency and magnitude of wildfires, and increased risk of spatial and temporal co-occurrence. A key to control and suppress wildfires during fire weather is a strong initial response, for which aerial firefighting resources can be used. This paper investigates the potential of optimization modeling to support pre-wildfire location planning of aerial firefighting resources, by developing a binary integer programing model and test it on Swedish case data. The model produces useful results given considerably less amount of available input data to determine the locations, compared with the manual planning. With relatively short solution times, it shows potential to support fast relocation of resources during sudden changes of circumstances, and to facilitate implementation of a standard operating procedure, with less expert knowledge dependence.

Keywords

wildfire suppression, initial attack, fire weather, preparedness, planning.

INTRODUCTION

Due to increased amounts of greenhouse gases in the atmosphere, the global mean temperature has increased, and evidence suggest that the warming trend will continue (IPCC, 2021). The mean temperature change will affect temperature extremes, which are already observed in northern Europe (IPCC, 2021), and the warming trend will lead to increased frequencies of all kinds of hot extremes (Seneviratne et al., 2021). Due to strong correlation, increased frequencies of hot extremes will likely lead to more frequent and longer periods of dry conditions or droughts (Zscheischler & Seneviratne, 2017). For the reasons above, there will be more periods with fire weather, which is related to hot and dry conditions, and driven by high temperatures, and low soil moisture and humidity (Turco et al., 2017). More and longer periods of fire weather, will likely lead to increased frequency and magnitude of wildfires (Mueller et al., 2020), with increased risk that wildfires occur spatially and temporally close to each other. This increased risk will require improved preparedness for wildfires.

A key to control and suppress wildfires during periods of fire weather is a strong initial attack (Pierce 1970, via Greulich, 2003), which can be done using aerial firefighting resources (e.g., helicopters and scooping airplanes) (Plucinski et al., 2007). The effectiveness of initial attacks using aerial firefighting resources is restricted by the response times (McCarthy, 2003), which depends on the distance between fire ignition points and the resource locations. This calls for research on pre-wildfire locations of aerial firefighting resources as an effort to improve the preparedness for future events. To date, this is a underdeveloped area of research (Belval et al., 2022).

The purpose of this paper is to investigate if optimization modelling of short-term pre-wildfire location of aerial firefighting resources can improve the preparedness for wildfires. This is done by developing an optimization model to determine where to locate the resources based on the current risk of wildfires. The results of the optimization model are then compared with a real case to determine its potential to enhance the preparedness for wildfires. The real case includes the historical locations of aerial firefighting resources in Sweden, as well as the historical incidents where the resources were used, during the high-risk wildfire season (June-August) of 2021.

Related Work

According to previous research, some factors are considered critical for the success and effectiveness of managing and suppressing wildfires. In a retrospect analysis of wildfires where aerial suppression was used, Plucinski et al. (2007) finds that the area burning on arrival, the fire danger index, the time to initial attack, and the fuel hazard score were all statistically significant factors to the success of the initial attack. In a similar analysis of aerial suppression effectiveness in Australia, McCarthy (2003) also finds the time to initial attack as a critical factor for the effectiveness, and argues that the earlier the resources can reach the fire, the more likely they will be able to contain it.

Regarding the time to initial attack, previous studies have used different quantitative methods to address it, from visualizations of retrospective analyses (Belval et al., 2022) to more advanced optimization models (Shahparvari et al., 2021). For example, Greulich (2003) developed a spread-sheet based procedure to determine locations of air bases to improve the preparedness for a given protection area. For a similar purpose, Fried et al. (2006) used stochastic simulation to, for instance, determine long-term locations for the stationing of firefighting resources. More recent studies chose to use the same method as presented in this paper, which is optimization modeling. Both Griffith et al. (2017) and Shahparvari et al. (2021) have developed models to address resource allocation to ongoing fires. The former developed a model to solve dynamic resource allocation problems to ongoing suppression efforts, based on the fire spread direction and environmental conditions (Griffith et al., 2017). The latter focused on resource coordination during suppression efforts requiring collaboration between aerial and ground firefighting resources, by optimizing the allocation of resources and the assignment of tasks required in the effort (Shahparvari et al., 2021).

An example of a study similar to the one presented in this paper is Maritano et al. (2016), who developed a model to determine a helipad network on Sicily, Italy. However, the network is not primarily used to increase the preparedness for wildfires, but a set of services performed by helicopter (e.g., transport, medical services, tourism services, civil protection). Also, the locations they suggest are long term implementations, and the location of helipads is not based on wildfire risk data. The only study found that is closely related to the study presented in this paper is Zeferino (2020), who developed a model to locate aerial firefighting resources in Portugal. The differences in this paper are that we consider tactical, short-term locations, that we have less resources available to locate, and that our locations are based on wildfire risk data.

One contribution of this paper is an optimization model to determine the best locations of a finite set of aerial firefighting resources, based on wildfire risk data. As far as we know, this kind of model has not been developed and validated before. Another contribution is that the model is tested and compared to the historical, manual planning, which is done by experts. The results show that the model manages to produce results that are close to what the experts achieve, by using only wildfire risk data, while the experts have access to much more information. This proves the usefulness of both the Fire Weather Index (FWI) that we use to estimate wildfire risk, and optimization modeling as a base for decision support. In wildfire suppression practices, the model could potentially be used as a support for day-to-day dynamic resource preparedness planning to increase the effectiveness of aerial firefighting resources used for initial attacks.

Method

In this paper, an operations research approach was used by applying optimization modeling to solve a set of instances to the aerial firefighting preparedness location (AFPL) problem. The input data were processed using the programming language R through the platform RStudio, while the model was formulated using the language AMPL through the platform AMPL IDE. Through AMPL IDE, the model and the specific input data for each instance of the problem were sent to the solver CPLEX. Through a case study, the results of the model were tested and compared with aerial firefighting preparedness locations from a real case.

A MODEL FOR THE AERIAL FIREFIGHTING PREPAREDNESS LOCATION PROBLEM

This section presents the problem studied and the assumptions made in our formulation. Furthermore, the mathematical formulation of the model is presented, including sets, parameters, variables, objective function, and constraints.

Problem Description and Assumptions

The problem to be solved in this paper is called the aerial firefighting preparedness location (AFPL) problem, here solved as a *p-median* problem (Daskin & Maass, 2015). The problem can be stated as

To determine a finite number of preparedness locations for aerial firefighting resources that minimizes the weighted distance between the locations and all risk points based on their wildfire risk value.

The goal is to minimize the total "risk distance", which is the sum of the products between the distance and the risk value. The following assumptions have been made:

- The risk value for each risk point is known
- There is a finite number of resource locations to be determined
- Since the resources are aerial, Euclidian distances between each pair of location and risk point can be used
- Although aerial firefighting resources might have different characteristics in reality (e.g., speed, capacity), the resources in the model all have the same characteristics

Model Formulation

The AFPL problem was formulated as a binary integer program (BIP). The notation used in the mathematical representation of the model is presented below.

Sets

$I = \{1, \ldots, n\}$, *the set over all risk forecast points*
$J = \{1, \ldots, m\}$, *the set over all possible resource location points*

Parameters

d_{ij} = *the Euclidean distance between risk point i and location point j*
h_i = *the risk value in risk forecast point i*
p = *the number of aerial resources to be located*

Variables

$$y_j = \begin{cases} 1, if\ aerial\ resources\ are\ stationed\ at\ location\ point\ j \\ 0, otherwise \end{cases}$$

$$x_{ij} = \begin{cases} 1, if\ aerial\ resources\ in\ point\ j\ respond\ to\ risk\ point\ i \\ 0, otherwise \end{cases}$$

Using the above notation, the objective function (1) and constraints (2)-(5) below were constructed.

Objective Function and Constraints

$$Minimize \quad \sum_{i=1}^{n}\sum_{j=1}^{m}\left(h_i d_{ij} x_{ij}\right) \tag{1}$$

$$s.t. \quad y_j \geq x_{ij} \qquad \forall i \in I, j \in J \tag{2}$$

$$\sum_{j=1}^{m} x_{ij} \geq 1 \qquad \forall i \in I \tag{3}$$

$$\sum_{j=1}^{m} y_j = p \tag{4}$$

$$x_{ij},\ y_j \in \{0,1\} \quad \forall i \in I, j \in J \tag{5}$$

The model is solved for a specific day and finds operational locations for the resources to match the risk values that day. The objective (1) is to minimize the distance between resource locations and risk points, based on their risk values. Hence, the goal is to minimize the total "risk distance", which is the product between h_i and d_{ij} for all risk points i covered by the closest resource location j. This corresponds to minimizing the total time spent on travelling to incidents, given that the number of incidents in a risk point, over time, is directly proportional to the risk value. The constraints in (2) ensure that a risk point i can only be covered by a selected resource location j if there is a resource located there. The constraints in (3) ensure that all risk points i are covered by at least one resource location j. The single constraint in (4) ensures that the total number of resource locations selected must be equal to a finite number p. In this paper, the value of p is determined by the historical number of resources located during each studied date.

CASE STUDY

To test and validate the potential of the model, a case study was performed for Sweden using data from the wildfire high-risk season (June-August) of 2021. Looking at days when the aerial resources were used at a wildfire effort, a comparison was made between the locations that were suggested by the model (BIP locations) and the historical locations (Real locations) determined by experts before the effort. For each wildfire location, the distance from the closest resource was calculated and compared.

The Swedish Decision-Making Process

In Sweden, the aerial firefighting preparedness locations are decided by the Directions and Priority Function (IPF), with representatives from different departments of the Swedish Civil Contingencies Agency (MSB). The IPF holds regular meetings twice a week during the fire season, with the possibility of increased frequency during periods with multiple ongoing missions or high fire risk and uncertainty.

Before the meeting, an analysis is performed and documented based on the weather and fire risk forecasts. A fire risk forecast is available on daily level for the coming six days, and on hourly level for the coming 48 hours. Beside the forecast data, the conducted analysis is based on the forecast uncertainty and reports from external actors in the Swedish emergency response system. To complement the nationwide analysis, critical and uncertain geographical areas may be studied further, especially concerning previous weather, extreme fire behavior, and the ability to manage a potential fire in the area.

After an IPF meeting, the preparedness location proposals are put forward to the deputy decision maker of the MSB, and if approved, a formal decision is signed and documented. The decision is formulated as the number of resources (helicopters and planes, respectively) that should be prepared to respond, together with their determined locations during the specified period. The decision is then forwarded as orders to the operational unit level.

Input Data

The main set of input data used covers the utilization of aerial firefighting resources, constituting scooping airplanes and helicopters, in wildfire suppression efforts during the case period. In total, the set consists of 54 suppression efforts where aerial resources were initiated, during 34 different dates. This means that the case included 34 instances of the AFPL problem to be solved. For each date where aerial resources were used, a set of wildfire risk data was provided by the Swedish Meteorological and Hydrological Institute. Each date included a set of 62 351 points with risk values based on the Fire Weather Index (FWI). The FWI is a compiled index accounting for the effects of soil moisture and wind on the fire's behavior in terms of build-up and spread (National Wildfire Coordinating Group, 2021). However, these points were aggregated into a network of 1 335 20x20 km zones, where the FWI value of each point included in each zone were added together.

The set of possible resource locations included 286 points, representing the center coordinates of the most densely populated cities in each municipality of Sweden. The reason for using this set is that the current selection of preparedness locations in Sweden is on municipal level. The number of resource locations is finite in each instance of the problem. Thus, the finite number denoted p in the formulation was set to the real number of resource locations determined. This enables comparison between the model's solution and the locations used in the real case. In summary, each of the 34 case instances of the AFPL problem included:

- 286 possible resource locations
- 1335 risk points
- 1335 FWI values, one for each risk point
- A distance matrix with the distance between each pair of risk point and possible resource location.
- A finite number of selected resource locations (varies between 2 and 8)

COMPUTATIONAL RESULTS

Each of the 34 instances were solved to integer optimality using the solver CPLEX, with a relative MIP gap tolerance of 0.0001. The average solution time over the instances was 764 seconds, with the minimum and maximum time at 217 and 1162 seconds, respectively. The problems were solved on a PC with an Intel® Core™ i7-8565U CPU at 1.8-1.99 GHz, and with a RAM of 16 GB.

To investigate the potential of the developed model, a comparison was made with the real resource locations during the 34 days. The analysis compared the resource locations of the model and the real case over the distance to the 54 efforts where aerial firefighting resources were used. Aggregated results are presented in Table 1.

Table 1. Aggregated results for the BIP model and the real case locations, respectively, over 54 efforts during the high-risk wildfire season of 2021

	BIP Model	Real case
Average distance to effort	96 757 m	91 046 m
Minimum distance to effort	10 206 m	8 631 m
Maximum distance to effort	205 922 m	302 548 m
Occurrences, distance > 200 000 m	1	4
Number of times closest	18	32
Average difference when closest	66 025 m	46 776 m

As can be seen in Table 1, the experts on average manage to locate the resources closer to the efforts. However, looking at efforts where the closest resources are far away (more than 200 km), the model seems to be doing a better job of ensuring that all efforts can be reached within a reasonable time. The experts consider a risk point to be reached within an hour of travelling time if it is within 200 km from an aerial resource, which is why it was used in the comparison.

For the results in Table 1, it is assumed that the resource located closest to each effort point were used. Thus, we assume that if there are two or more efforts during the same date, the location point closest to the efforts will have enough resources to initiate an attack, even if the effort points share the same closest resource location. Since this is not always realistic, further comparative analyses were done for a set of cases with several efforts during the same date. One interesting date is the 7th of August 2021, during which 5 efforts with aerial firefighting resources were initiated. The FWI values, the resource locations, and the effort points for the model and the real case scenario are presented in the two plots in Figure 1.

The assumption that all effort points will use resources from the closest resource location point means that the real historical locations have a better preparedness for the scenario in Figure 1. However, if it instead is assumed that all resource points can only initiate an attack to one effort point, the situation is the opposite. An overview of the results with the respective assumption, using a greedy approach for the model and the real case, for all days with more than one effort initialized, is presented in Table 2. Here, greedy means that for all efforts, the one with the closest available resource gets a resource allocated to it. Then, the effort with the closest available resource, not counting the ones that have already been allocated, gets a resource, and so on.

The change in results when applying the two assumptions (Table 2), comes from the changes of maximal distances for the model and the real case. This change is more tangible for the real case, which means that the suggestion of locations by the model seems more stable during days with several efforts. Only looking at the current fire risk, the model performs better in terms of being closest to the areas with high wildfire risk. However, the overall results suggest that the current preparedness planning performs better than the model in terms of the distance to efforts where aerial resources were initialized. In the following section, a discussion about possible causes for this will be made.

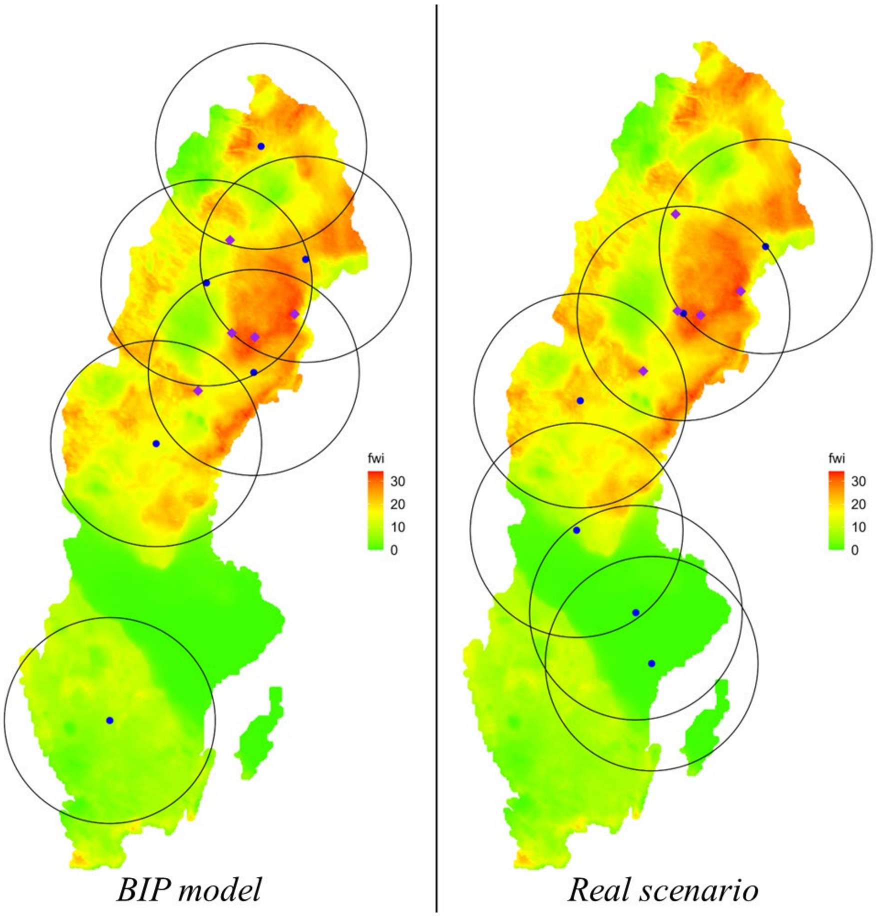

Figure 1. The FWI risk values (green-red), resource location points (blue points), and initiated effort points (purple diamonds) during the 7th of August 2021. The black circles represent the reach (200 km) within one hour from takeoff

Table 2. Aggregated results over the 11 days with more than one effort initialized, with a total of 31 efforts, for the BIP model and the real case scenario, respectively, while influenced by two different assumptions

	Closest resource location		**Closest available resource location**	
	BIP	**Real case**	**BIP**	**Real case**
Average effort distance	90 952 m	83 466 m	122 237 m	128 632 m
Minimal effort distance	10 206 m	8 631 m	10 206 m	8 631 m
Maximal effort distance	193 334 m	257 119 m	481 692 m	747 161 m
Distance > 200 000 m	0	1	4	5
Number of times closest	8	21	9	20

DISCUSSION

The first things to discuss are the situations where the real case locations are close to effort points with low or moderate fire risk. Such cases are extremely difficult, if not impossible, to include in a preparedness planning using optimization modeling, at least without including more aspects than the fire risk in the objective function. Now this is the sole factor determining the resource locations in our model. Figure 2 presents the locations and efforts from the 1st of June 2021, which is such a case.

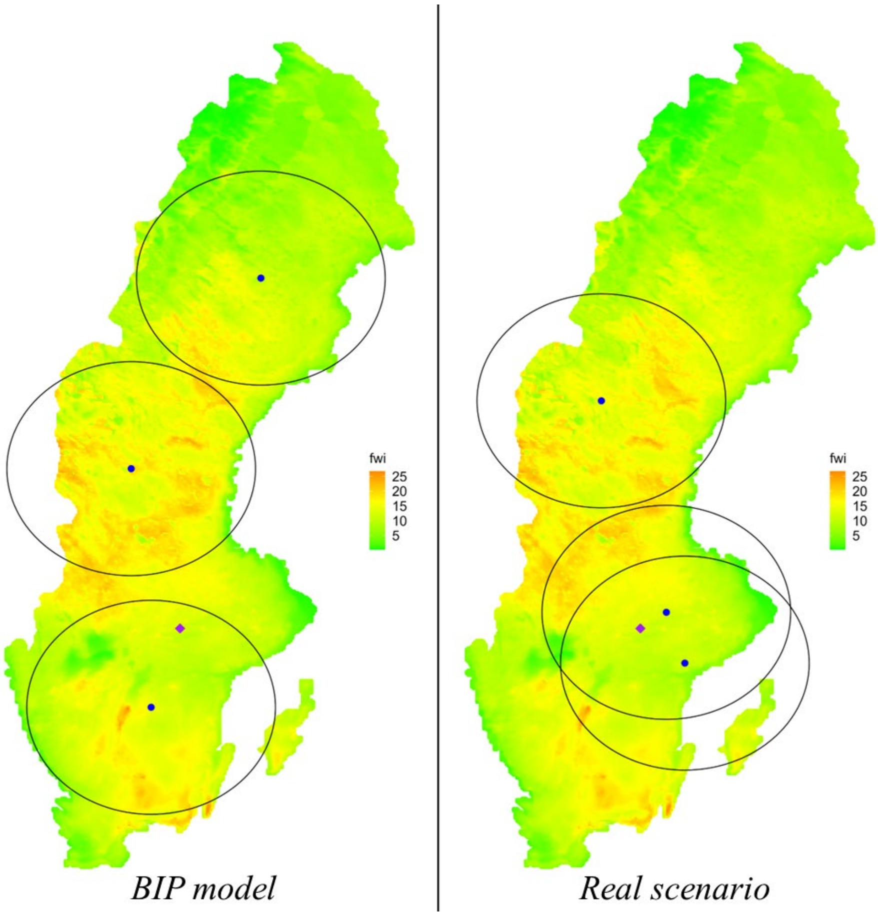

Figure 2. The FWI risk values (green-red), resource location points (blue points), and initiated effort points (purple diamonds) during the 1st of June 2021. The black circles represent the reach (200 km) within one hour from takeoff

In this case, the effort is a wildfire in Arboga, not far from Västerås, which is one of the fixed locations for firefighting helicopters currently used in Sweden. As can be seen in Figure 2, the resource locations are much closer to the initiated effort point in the real case scenario compared to the BIP model. Since the wildfire risk in the effort point is small compared to other areas in Sweden during this time, the BIP model would never suggest locating resources any closer to that point. However, it might be argued that the BIP model determines a more equal resource location regarding the actual fire risk, which is one of the critical factors for initial response success (Plucinski et al., 2007).

Although the comparative results show that the current resource preparedness locations are better on average, we argue that the BIP model shows potential for several reasons. Firstly, it determines the resource locations with considerably less amounts of information compared to the real case. Despite this, the difference in average distance to the effort points is only about 7 km. With information available in the real case, e.g., status of ongoing wildfire efforts, resource availability, and the ability to reach the effort point with ground resources, the BIP model might give even better results. The second reason is the solution time. For the instances of the AFPL problem tested, the solution time for the BIP model was on average 13 minutes (with minimum 4 and maximum 19 minutes). With the intended use as input and decision support during pre-planned IPF meetings, these solution times can be considered adequate. It may also enable optimized relocation of resources if the circumstances suddenly change, which is considerably more difficult, complex, and time-consuming without the model. However, of course there still exist improvement opportunities regarding the solution time. Thirdly, the BIP model enables the implementation of a standard operating procedure in the location planning of aerial firefighting resources. Due to the complexity of the current planning procedure, it is dependent on the knowledge of a small group of experts. With a support tool including the BIP model, the planning procedure can become more standardized, hence, less dependent on individual knowledge and skill. Lastly, the model shows potential in minimizing the maximal distances to efforts during instances of the AFPL with several simultaneous effort initializations. This can be seen in Table 2, where the BIP model does have longer minimum distances, but considerably shorter maximum distances.

However, to fully investigate the potential of the BIP model as a support tool for resource location planning, more data is needed on the utilization of aerial firefighting resources during wildfire suppression efforts. Although the dataset used includes all aerial fire suppression efforts in the selected period, they count to 54 separate efforts on 34 different dates, which is too few to be certain about the model's potential. Also, to enable a fair and thorough comparison between the model and the real case scenario, their locations need to be based on the same risk data, which currently is not the case. Here, the real case locations are based on forecast data, while the model's locations are based on analyzed risk data. Therefore, this paper should be considered a first step to investigate the potential of optimization modeling for resource preparedness planning, which is identified as a research area with high potential (Belval et al., 2022).

CONCLUSIONS

With increased recognition of the interactions between climate change and the frequency and magnitude of wildfires, more attention is needed on how to improve the preparedness for wildfires in emergency response systems. In a first step to address this, we have investigated the potential of optimization modeling to support pre-wildfire location planning of aerial firefighting resources, utilizing available wildfire risk data based on the Fire Weather Index. This, by developing a BIP model for resource location planning and test it on a case which included 54 separate efforts utilizing aerial fire suppression on 34 different dates during the high-risk fire season 2021 in Sweden. The model's results were then compared with the real resource location planning during this period. Although the model did not outperform the real resource location planning in all cases, it showed potential concerning solution time and the implementation of a standard operating procedure. Additionally, given the considerably less amount of information the model results are based on, the overall results can be argued to be satisfying.

To fully investigate the potential of optimization modelling to support pre-wildfire resource location planning, more research is needed. The future research plan includes incorporating extended wildfire risk data which provides risk forecasts not only for the current day, but a few consecutive days. The plan also includes extensions in terms of other types of data besides the wildfire risk to include in the model, for example resource availability, wildfire reachability, population density, vulnerability, and critical infrastructure.

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