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Game-theoretic and MILP-based resource allocation for wildfire response

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Abstract. Wildfires are increasingly severe and frequent, necessitating efficient resource allocation strategies amid potential misinformation. This study proposes a novel framework integrating Game Theory and Mixed Integer Linear Programming (MILP) to optimize wildfire response. By modeling cities as rational agents in a repeated game, the framework introduces severity-dependent penalties for dishonesty and adaptive strategies to incentivize truthful reporting. The MILP formulation maximizes system-wide utility by weighting allocations based on true fire severity, damage-cost correlations, and penalties for misreporting. Simulations involving five U.S. cities demonstrate the model's effectiveness in balancing resource distribution, penalizing exaggeration, and prioritizing high-risk areas. Results highlight the importance of honest reporting and correlation-based allocation, offering actionable insights for emergency responders.

Keywords: wildfire response, game theory, MILP optimization

1. Introduction

Wildfires are becoming increasingly severe and frequent, requiring real-time decision-making and resource coordination. In such scenarios, misinformation (intentional or strategic exaggeration) can skew perception and allocation. As of June 9, 2025, more than 1.2 million acres have burned in the U.S. this year, in 29,239 fires [1]. As of July 21, 2025, fires have also scorched 14 million acres in Canada [2], expected to persist until September across most of the country. Hot weather and strong winds have fuelled several bushfires in Western Australia [3], including one in the Wheatbelt region that has burnt about 11,000 ha. In Europe, the area burned by wildfire by July exceeded 237,000 ha [4], 119% above the 2006-2024 average for this period. Wildfire has burnt more than 629,000 ha in Zabaykalsky Krai and Buryatia by May, 2025 [5], about 97% of all active Russian wildfires, and at least RUB 459 million (~US $5.8 million) of economic lost. A study in *The Lancet* [6] estimated 1.53 million all-cause deaths annually due to air pollution from landscape fires, with a large portion attributed to respiratory and cardiovascular issues.

During major wildfires in California and Australia in recent years, rumors and false reports about fire containment, evacuation routes, and even intentionally started fires led to confusion [7]. False evacuation orders or misleading information about the containment of fires caused some people to stay in dangerous areas or delay evacuating. This often results in unnecessary deaths and increased pressure on emergency responders.

Many existing studies focus on wildfire detection and response mechanisms but largely overlook the possibility of misreporting or strategic exaggeration of disaster information by local communities. For instance, Alqahtani et al. [8] uses high-level dynamic simulation incorporating fire behavior, surveillance, communication, and mitigation strategies to show how situational awareness can enhance containment and reduce firefighter injuries. Similarly, Mohsan et al. [9] applies Artificial Intelligence, Machine Learning, and 5G technology to detect wildfires in the U.S. and relies on government databases, drones, and IoT devices to enable a safer response mechanism. Mu et al. [10] proposes mixed-integer optimization and multi-criteria goal programming for evacuation and relief resource distribution. Likewise, Vilor et al. [11] focuses on learning-based UAV swarm trajectory planning with a wireless communication architecture for dynamic wildfire tracking, maintaining connectivity and optimizing energy and coverage. In Fouda et al.'s study [12], a layered AI architecture on drones' switches adaptively between lightweight and full CNNs for early detection. John et al. [13] presents a decentralized sequential planner using a bidding mechanism and time-prioritized cost function for fast task assignment under limited resources. The resource management approach in Zhou and Erdogan's study [14] seeks to minimize property damage and evacuation numbers in high-risk areas across different wildfire spread scenarios. Collectively, these studies demonstrate strong advances in detection and response technologies but largely overlook the possibility of misreporting or strategic exaggeration of disaster information by local communities, which could significantly influence decision-making and resource allocation.

Another major limitation across much of the literature is the lack of consideration for recovery processes or post-disaster resource allocation. For example, McLennan et al. [15] introduces the concept of a "possibility space" comprising eight dimensions—problem identification, incident development, capability, collaboration, management, logistics, legal framework, and time available. The drone-based system in Khosravi et al.'s study [16] effectively combines sensing technology, navigation, and decision-making algorithms for wildfire search and detection in complex environments. Castellnou [17] proposes a long-term wildfire response strategy incorporating uncertainty, fire potential, and opportunity cost to anticipate fire behavior. Similarly, Jiang et al. [18] introduces WFNet, a hierarchical CNN to predict wildfire spread based on spatial patterns, which aids land and resource planning. Lelis et al. [19] uses drones and machine learning for wildfire risk assessment, enabling proactive mission planning. Flores et al. [20] utilizes thermal and RGB imagery with a YOLOX L model on resource-limited hardware for fast and accurate early-stage detection. While these works contribute to situational awareness and strategic deployment, they give limited attention to how post-disaster recovery is organized and how resources are allocated to affected areas, particularly in the context of diverse community needs and inter-city coordination.

The contributions of this study are summarized as follows:

Contribution 1: By framing cities as rational agents in a repeated game, the model introduces severity-dependent penalties (e.g., utility deductions for dishonesty) and adaptive strategies (e.g., switching to truth-telling once a city catches fire). This bridges the gap between behavioral decision-making and operational logistics, offering a more realistic simulation (using Game Theory) of resource competition under misinformation.

Contribution 2: This study unifies fire propagation modeling (via probabilistic graph-based spread) with optimized resource allocation (via MILP). The formulation maximizes system-wide utility by weighting allocations to cities based on (1) true/projected fire severity, (2) damage-cost correlations, and (3) penalties for misreporting. This end-to-end approach mitigates cascading impacts by proactively directing limited resources (e.g., from Kansas depot) to high-risk areas while disincentivizing exploitation by low-risk communities.

2. Proposed system description

Additional to the number listed in the "Motivation Part", more specifically, as of July 24, 2025 the Los Angeles wildfires claimed at least 31 lives lost, fueled by dry conditions and strong winds. Destroying over 18,000 structures, these fires highlight the urgent need for wildfire rescue/response optimization. Optimized strategy is needed to support the decision makers for better resource allocation when a wildfire strikes the cities. In the first step, we gather the history wildfire dataset of the US including multiple elements like damage cost, wildfire severity, and etc. After collecting these data, the "wildfire severity" and "damage cost" in each city are selected as the most affecting dimensions in our research based on the correlation calculation. As Shown in the Figure 1, this process includes statistical methods to identify trends and relationships, providing a clearer picture of the emergency resource prioritization.

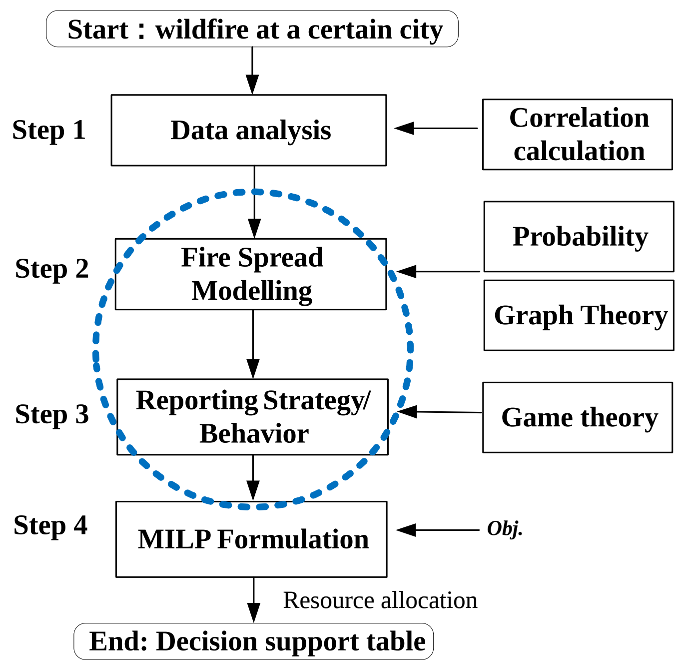

Figure 1. System flowchart of 4-step decision support optimization

Following the data analysis, wildfire spreading model is proposed using Probability Theory and Graph Theory (Step 2). This approach considers strategic interactions between affected and unaffected regions, adding a layer of tactical planning. For example, Los Angeles is suffering wildfire, and it is likely that the fire can be spread to Phoenix. This strategy considers geographical proximity, increasing the model's relevance. However, New York city is safe, since the distance between these two cities is far. The probability of the spread of wildfire is set to a certain level to approach the possibility in reality.

Significant amount of damage can be caused by wildfire; therefore, the federal government need to allocate resources efficiently in response to each cities' report to minimize the damage cost. Efficient allocation requires coordination with local authorities to prioritize high-risk areas. However, some cities with no fire tend to exaggerate and receive extra resources. This behavior can strain limited supplies, necessitating careful monitoring. Game Theory is applied to eliminate strategic misreporting, maintaining fairness in resource distribution. The two steps in the "blue" dashed circle represents the during disaster synchronized dynamic modelling.

Afterwards, we use MILP to maximize the overall utility of the cities considering the objective (utility), variables, and resources constraints. In the end, a decision support table is provided to transform the prior steps into actionable schemes. This table provides clear guidelines for emergency responders, ensuring swift and effective action during crises.

3. Mathematic modelling

3.1. Fire spread modelling

To simulate the dynamics of wildfire propagation across the main cities, we represent the geographic and infrastructural layout of cities as an undirected graph $G=(V,E)$, where: $V=v_1,v_2,\ldots,v_n$ denotes the set of n cities (nodes), $E\subseteq V\times V$ represents the set of edges modeling direct connections (e.g., highways, proximity, or communication links) between cities. Let $S_t\in\{0,1\}$ denote the fire status vector at time step t , $S_t(i)=1$ if city v_i is burning at time t, otherwise $S_t(i)=0$. We initialize the system by seeding a fire randomly in one city $v_k\in V$, such that $S_0(k)=1$ and $S_0(i)=0$ for $i\neq k$.

The fire spreads probabilistically across the network. For each edge $(v_i,v_j)\in E$, if city v_i is burning at time t , then the neighbor city v_j becomes burning at time $t+1$ with probability $p\in(0,1)$. The stochastic transition rule (based on conditional probability) is defined as:

$$P(S_{t+1}(j)=1\mid S_t(i)=1)=p,\quad \text{for all } (v_i,v_j)\in E \tag{1}$$

Assuming the fire spreads only from currently burning cities, the expected spread function over time can be simulated as:

$$S_{t+1}(j)=\begin{cases}1, & \text{if } S_t(j)=1\\ 1, & \text{with probability } p \text{ if } \exists\, i \text{ such that } (v_i,v_j)\in E \text{ and } S_t(i)=1\\ 0, & \text{otherwise}\end{cases} \tag{2}$$

To operationalize this in computer understand environment, we define N_i as the neighborhood of node i in graph G. At each time step, the simulation iterates over all currently burning nodes and updates the fire status of each unburned neighbor city $j\in N_i$ according to independent Bernoulli trials with parameter p. This probabilistic formulation captures both spatial adjacency and stochastic behavior characteristic of real wildfire spread.

This model forms the dynamic foundation upon which game-theoretic reporting behaviors and optimization-based resource allocations are later synchronized and executed in a multi-round simulation environment.

3.2. Interaction behavior modelling using game theory

In this wildfire resource allocation model, each city operates as a rational agent seeking to maximize its share of limited federal resources. The interaction among cities is modeled as a repeated strategic game with incomplete information, where each city chooses between truthful reporting and exaggeration based on its fire status and proximity to burning areas. The outcome of these decisions influences both immediate utility and long-term credibility in the system.

Rule 1: Burning cities always report truthfully

For any city i , if it is actively burning at time t (denoted $f_i^t=1$), its true severity is: $s_i^t=3$. In this state, truthful reporting is the optimal strategy ($\sigma_i^t=Truth$), as it guarantees maximum credibility and attracts the highest utility-weighted resource allocation in the MILP. This reflects a dominant strategy in game-theoretic terms that there is no benefit to misreporting when the threat is real and verifiable.

Rule 2: Severity Classifications and Strategic Exaggeration

Each city's true severity is categorized as: (i) $s_i^t = 1$: Safe: no neighbors burning; (ii) $s_i^t = 2$: At risk: one or more neighbors burning; (iii) $s_i^t = 3$: Burning: the city itself is on fire. Reported severity $\hat{s}_i^t$ depends on the chosen strategy, and drives the MILP's resource allocation decisions.

If city i is not burning ($f_i^t = 0$) but has one or more burning neighbors ($\exists j \in N(i), f_j^t = 1$), it faces a higher probability of catching fire. In this situation, the city chooses to exaggerate its severity by reporting:

$$\hat{s}_i^t = min(s_i^t + 2, 5) \tag{3}$$

This represents a preemptive strategy that the city inflates its signal to attract resources for prevention. It mimics behavior in signaling games, where less affected players seek to appear more urgent in order to influence the central decision-maker.

Rule 3: Once a city is Burning, its Report Switches to Truth

A neighboring city that was previously exaggerating will switch to truthful reporting immediately after it becomes burning. That is, if $f_i^{t-1} = 0$ and $f_i^t = 1$, then: $\sigma_i^t := Truth$. This models adaptive strategy updating, similar to best-response dynamics in repeated games. As the city's state changes, so does its optimal strategy.

Rule 4: Reporting Strategies and Penalty for ExaggerationLet the reporting strategy be denoted $\sigma_i^t \in \{\text{Truth}, \text{Exaggerate}\}$, and define the penalty function:

$$p_i^t = \begin{cases} P, & \text{if } \sigma_i^t = \text{Exaggerate} \\ 0, & \text{if } \sigma_i^t = \text{Truth} \end{cases} \tag{4}$$

where $P < 0$ is a fixed negative utility (e.g., $P = -10$). This penalty is applied during MILP optimization to discourage dishonest reporting. It introduces strategic trade-offs: exaggeration may increase short-term gains (via higher reported severity), but also lowers overall utility due to penalties.

3.3. MILP formulation

Mixed Integer Linear Programming (MILP) works by optimizing a linear objective function under a set of linear constraints, with some decision variables limited to integers. In this research, MILP is used to figure out how to efficiently allocate limited emergency resources among different cities. It takes into account the actual utility of the cities as well as their reporting behaviors. The model boosts resource allocation efficiency by prioritizing cities that are more sensitive to wildfires while penalizing cities that tend to exaggerate their reporting behavior. In this way, resources are distributed fairly and strategically, maximizing overall utility.

Formally, for each city i:

$$Utility_i = x_i(c_i) + penalty_i \tag{5}$$

where x_i is the number of emergency resources allocated to $city_i$; c_i represents the city-specific correlation coefficient between wildfire severity and damage sensitivity; $penalty_i$ applies if city i is found to be exaggerating the damage severity (e.g., due to proximity to the fire but not directly impacted).

The overall objective becomes:

$$max \sum_i utility \tag{6}$$

Which translates to:

Obj.

$$max \sum_i x_i(c_i)^T + penalty_i \tag{7}$$

This objective reflects the efficiency of allocating more resources to cities more sensitive to wildfire severity, and the strategic disincentive imposed on exaggerating cities via penalties. However, since intlinprog in MATLAB solves minimization problems, we apply the transformation:

$$min - (\sum_i utility_i) \tag{8}$$

This is equivalent to minimizing the negative utility, which yields the same optimal allocation solution.

The involved variables are listed in Table 1:

Table 1. Definition of variables

Variables (Symbols)	Descriptions
x_i	Allocated resources to city i, this is what the MILP solves for.
c_i	Sensitivity score of city i to wildfire severity.
p_i	Penalty value applied if city i is exaggerating (e.g. -10).
$S_i^{St.}$	True wildfire severity of city i; $St.$ is the severity reporting strategy for each city, and it can be either "Truth" or "Exaggerate", determines if penalty applies.
lb_i	Lower bound for city i's resource allocation. = 10 if severity > 1, else 0.
ub_i	Upper bound for city i's resource allocation (typically 50).
u_i	Final utility: $u_i = x_i \cdot c_i + p_i$

The involved constraints are listed below. For example, the involved variables are listed below, for example, the total resource capacity:

$$\sum_i x_i = X_{total} \tag{9}$$

The total resources, X_{total}, being allocated need to be restrained (e.g., x_i =100), and

$$\begin{cases} x_i \geq 10, & \text{if } S_i^{\text{Truth}} > 1 \\ x_i = 0, & \text{otherwise} \end{cases} \tag{10}$$

where S_i^{Truth} represents if the reported severity is true. The lower bound (the minimum resources being allocated to a city) is set based on two situations: if $S_i^{\text{Truth}} > 1$ the minimum value is set to 10, which means the city is currently burning; otherwise, there is no resource (the minimum value is set to 0) being distributed, representing a safe situation.

Upper bound and lower bound are:

$$lb_i \leq x_i \leq ub_i \tag{11}$$

The value of upper bound is limited to, for example, 50, indicating a maximum of 50 resources can be sent to a city. Meanwhile, integer decisions should meet:

$$x_i \in \mathrm{Z} \tag{12}$$

These constraints are all under a condition that x_i is an integer.

The constraints shown above each represents a specific scenario. For the total resource cap, the aggregate resource that can be allocated to cities is set to 100. The upper bound means the maximum resources that can be sent to a city, which is set to 50 in this research.

4. Testing, simulation, analysis and discussion

4.1. Simulation setup

The simulation was conducted with five cities: New York, Los Angeles, Chicago, Houston, and Phoenix, representing varying wildfire risks, with a central depot located in Kansas for resource distribution. The simulation ran for 10 rounds, with a fire spread probability of 0.4. Cities reported their severity based on the fire's status, with a penalty of -10 utility for exaggeration, designed to discourage dishonesty. The simulation was implemented using MATLAB and run on a laptop with an Intel i7-8700 processor and 16GB of RAM. The setup aims to model fire spread dynamics and resource allocation using Mixed Integer Linear Programming (MILP) to assess the strategic interactions and effectiveness of resource distribution.

4.2. Data correlation analysis

We access the dataset from the official website of U.S. Fire Administration [21]. The variable correlation heatmap is presented in Figure 2 to find out the most affecting element idisaster resource allocation.

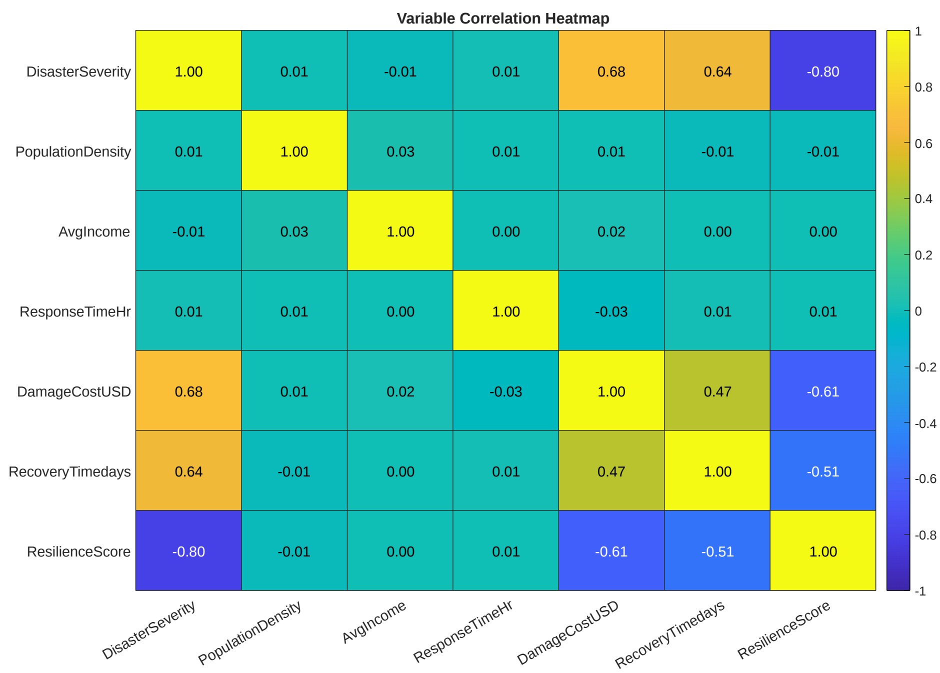

Figure 2. Results of correlation analysis for affecting element selection

Pearson's correlation coefficient, denoted as r, is used in this paper to measure the strength and direction of a linear relationship between two continuous variables. "Disaster Severity" and "Damage Cost" have a strong positive correlation (0.68), which indicates that higher disaster severity leads to higher damage costs. Damage Cost and Recovery Time are moderately correlated (0.47), suggesting that areas with higher damage costs tend to have longer recovery times. The Resilience Score has a strong negative correlation with Disaster Severity (-0.80), implying that regions with more severe disasters have lower resilience and slower recovery.

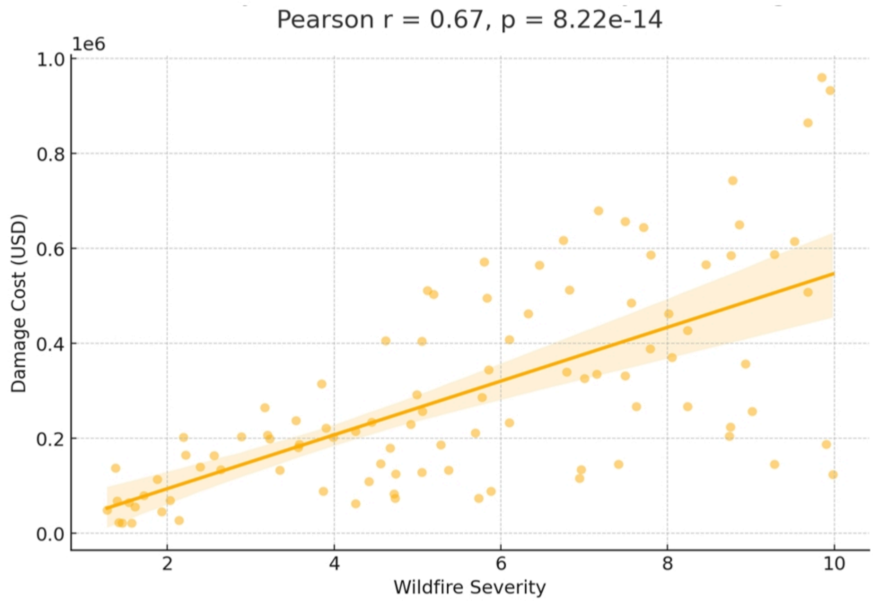

Figure 3. Correlation between "Severity" and "Damage Cost"

Figure 3 shows the correlation between "Damage Cost" and "Wildfire Severity". The "yellow" scattered points in the graph represent the history data for individual wildfire events in a city. The straight (fitting) line shown in the graph is derived from the data, indicating the general trend of how damage costs tend to change with increasing wildfire severity. Figure 3 helps to visualize the underlying linear relationship. The closeness of the scattered points to the fitting line reflects the strength of this correlation. If the Pearson correlation coefficient is 0.67 (p value is 8.22e-14), it indicates a positive linear relationship between the studied two dimensions. The data points lie closer to the line, and the tighter wildfire severity is associated with damage costs.

Table 2. City-wise correlation with wildfire severity

City	Correlation	p_value	Count
Denver	0.950565	0.000291	8
Houston	0.879047	0.009147	7
Chicago	0.832711	0.002785	10
Los Angeles	0.824059	0.011882	8
Miami	0.728386	0.007221	12
Seattle	0.673615	0.032724	10
Phoenix	0.636177	0.06549	9
Boston	0.516277	0.190238	8
San Francisco	0.496163	0.100873	12
New York	0.366942	0.21746	13

Table 2 shows city-wise correlation between wildfire severity and damage cost. Cities at the top exhibit the strongest positive correlation, meaning they are more sensitive to wildfire intensity in terms of economic damage. These insights can inform priority in resource allocation. A p value is the probability of obtaining test results at least as extreme as the result actually observed, assuming the null hypothesis is true. If p value is less than 0.05, there is no convincing statistical evidence to show the null hypothesis, which is that there is no relationship between wildfire severity and damage cost, is wrong, representing a lower correlation. However, when the value is higher than 0.05, the null hypothesis can be proved that there is no statistical significance to show it is correct, meaning a stronger relationship between wildfire severity and damage cost. Count in the table means the number of wildfire events in a city for which data has been collected. The statistic is limited because the fact that some cities have limited statistical support (data sets). One possible solution to this is to find more data from government reports, satellites, insurance records or data augmentation (Data augmentation is the method of artificially generating new data from existing data, increasing data size and diversity. It can be used in generating additional wildfire statistic). Random cities in the table can be selected to build the disaster rescue model and make sure they are geographically and statistically (in terms of correlation distribution) diverse.

4.3. Utility outcomes using game theory

Since the utility equals to allocated resources ± penalty, when a community exaggerates, its utility should be less. Logically, exaggeration should lead to lower utility due to the penalty, which is meant to deter dishonest behaviors. However, accordingly to the results that illustrated in Figure 4 (C2, C3, C3 representing three random cities), communities that exaggerate receive a higher utility compared to the ones telling the truth (Scenario 2, "True-True- Exaggerate") because the value of penalty is set to -10. As more communities exaggerate, the utility for each of them begins to decrease. This appears to be a contradiction, as the utility function in the simulation accounts for a penalty applied to those who exaggerate. This demonstrates the importance of penalty value setting.

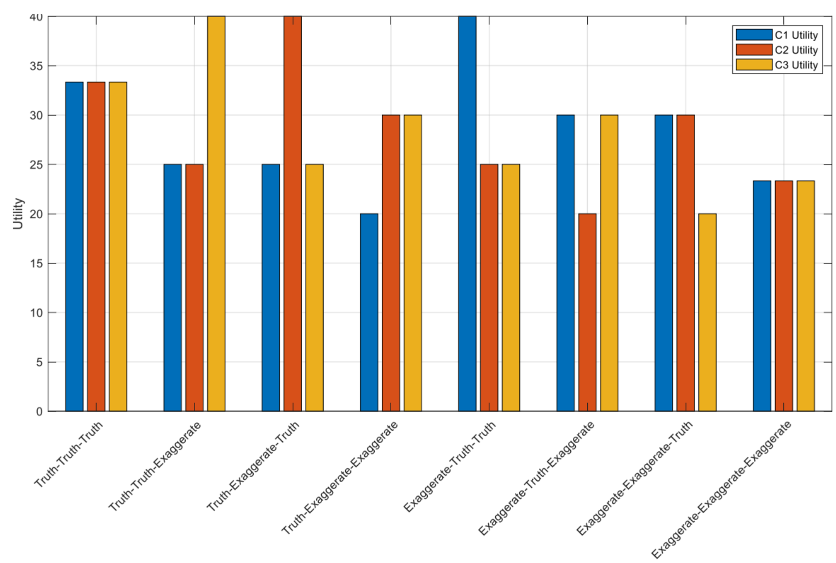

Figure 4. Utilities of communities under different wildfire reporting strategies (the value of penalty is set to -10)

In Figure 5 (C2, C3, C3 representing three random cities), we increase the value of penalty to -30 to see the impact of Game Theory in social utility changes. The 8 scenarios correctly show the relationship. When all of the 3 communities tell the truth, the utility for each community is higher than other scenarios where there are 2 or 1 community tells the truth. This aligns with the reality that when all of the communities tell the truth, the social collective benefit/social welfare is maximized/the highest. For the other scenarios, the more community exaggerates, the less utility the community telling the truth shows. The social collective benefit/social welfare is minimized/the lowest when they all lie. Overall, the second graph provides a more appropriate representation of real-world behavior. It emphasizes the importance of honest reporting and illustrates how collective integrity/penalty coefficient setting leads to better outcomes for all participants/our experiments.

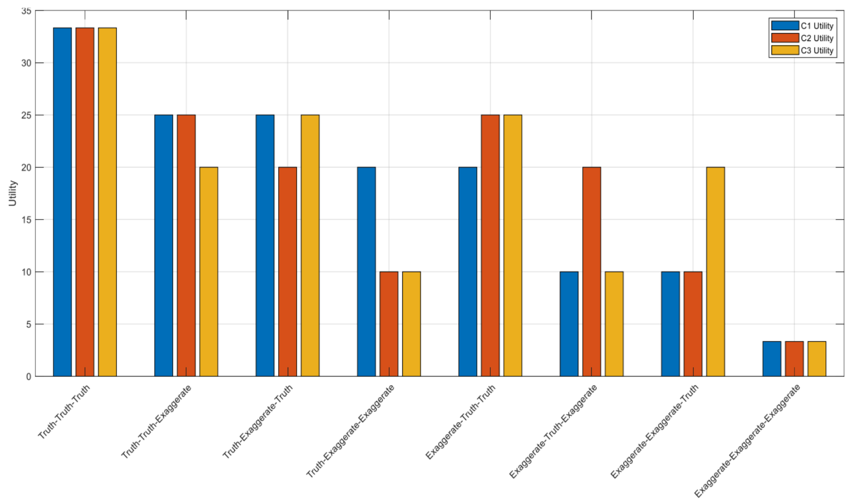

Figure 5. Utilities of communities under different wildfire reporting strategies (the value of penalty is set to -30)

4.4. Simulation of fire spread dynamics

The propagation of the wildfire in the graph follows the proposed spreading rules. Specifically, in our experiment, there are 5 connections between different cities, which represent the ways of spread. This corresponds to the real-world situation where fire spreads from the most adjacent area. The fire starts at a random city and with a spread probability of 0.4 in each of the 10 rounds. Once a city starts burning, it stays burning (mathematically, the status of this city changes from "0" to "1" it stays at "1"), and the spreading is in single direction (only from a burning city to its safe neighborhoods) in the current model. This model simulates uncertainty and risk propagation in real-world disaster scenarios.

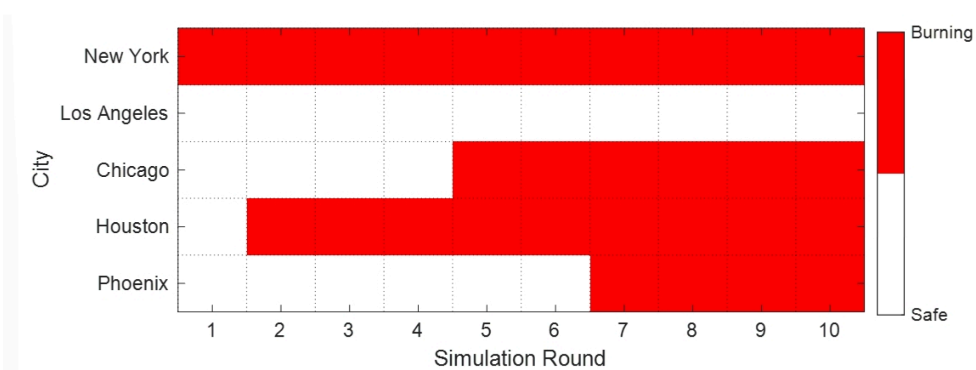

Figure 6. Time-series fire activation chart (spreading probability 40%)

The graph represents the simulation of the spread of the wildfire in each selected city in terms of rounds. The probability of the spreading is set to 40%, indicating the likelihood of a wildfire that occurs in the neighboring cities. In the first round (Figure 6), New York is burning, and the fire is spreading to Houston in the next round (being marked in "red"). In the fifth round, Chicago starts to burn and it quickly spreads to Phoenix in the seventh round. Los Angeles is fire-free over the ten rounds.

4.5. Resource allocation for decision making

The Table 3 presents the geographic coordinates and great-circle distances (the shortest distance between two points on the surface of the earth) of five major U.S. cities relative to Kansas City, which served as the central resource depot in the simulation. New York and Los Angeles are the farthest from Kansas City at approximately 1,760 km and 2,180 km respectively, while Chicago is the closest at about 664 km. Houston and Phoenix fall at intermediate distances of roughly 1,041 km and 1,686 km. These distances influence the MILP allocation model by contributing to transportation cost, response time, and resource deployment feasibility, with closer cities generally incurring lower logistical overhead and potentially receiving resources more quickly. The latitude and longitude values provide the basis for calculating these distances and for mapping the spatial network used in the wildfire spread and resource allocation simulations.

Table 3. City locations and distances from Kansas City

City	Latitude	Longitude	Distance to Kansas City (km)
New York	40.7128	-74.006	1759.861
Los Angeles	34.0522	-118.244	2179.519
Chicago	41.8781	-87.6298	663.607
Houston	29.7604	-95.3698	1041.001
Phoenix	33.4484	-112.074	1686.04

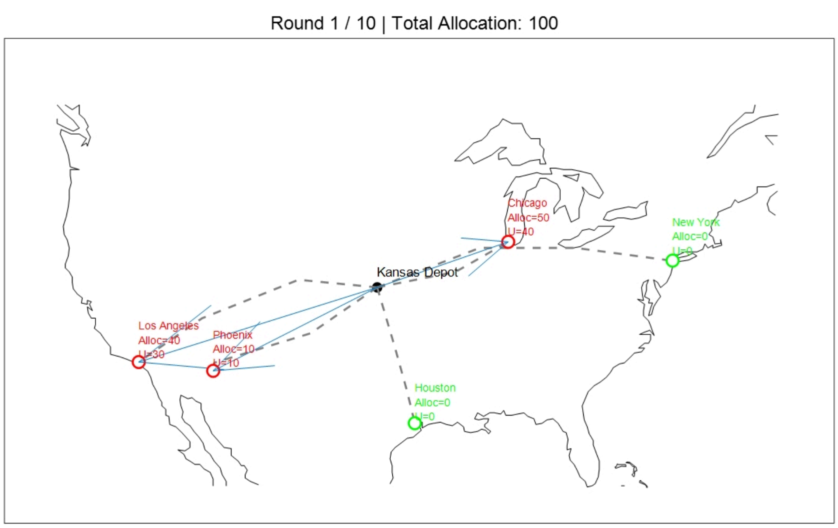

Figure 7. Geographical demonstration of Round 1

Figure 7 shows a visualization of resource allocation map. Kansas is assumed to be the center of the distribution of allocation to the other 5 cities. The arrows, representing the direction of resource distribution to each city, are only shown when city receives units that are greater than zero. No resource is distributed to the city where there is no fire occurs. The fire state of each city is depicted on different colours: "red" represents burning; "green" means safe. Further detailed simulation (for example, the time delay of transportation, etc.) can be done in future work.

Table 4. Decision support table of resource allocation for wildfire response

Round	City	Is Burning	Strategy	True Severity	Reported Severity	Allocated Resources	Utility
1	New York	0	Truth	1	1	0	0
1	Los Angeles	0	Exaggerate	2	4	40	30
1	Chicago	0	Exaggerate	2	4	50	40
1	Houston	0	Truth	1	1	0	0
1	Phoenix	1	Truth	3	3	10	10
2	New York	0	Exaggerate	2	4	10	0
2	Los Angeles	0	Exaggerate	2	4	10	0
2	Chicago	1	Truth	3	3	20	20
2	Houston	0	Exaggerate	2	4	50	40
2	Phoenix	1	Truth	3	3	10	10
3	New York	0	Exaggerate	2	4	10	0
3	Los Angeles	1	Truth	3	3	10	10
3	Chicago	1	Truth	3	3	20	20
3	Houston	0	Exaggerate	2	4	50	40
3	Phoenix	1	Truth	3	3	10	10
4	New York	1	Truth	3	3	10	10
4	Los Angeles	1	Truth	3	3	10	10
4	Chicago	1	Truth	3	3	20	20
4	Houston	0	Exaggerate	3	5	50	40
4	Phoenix	1	Truth	3	3	10	10
5	New York	1	Truth	3	3	10	10
5	Los Angeles	1	Truth	3	3	10	10
5	Chicago	1	Truth	3	3	20	20
5	Houston	0	Exaggerate	3	5	50	40
5	Phoenix	1	Truth	3	3	10	10
6	New York	1	Truth	3	3	10	10
6	Los Angeles	1	Truth	3	3	10	10
6	Chicago	1	Truth	3	3	20	20
6	Houston	1	Truth	3	3	50	50
6	Phoenix	1	Truth	3	3	10	10
7	New York	1	Truth	3	3	10	10
7	Los Angeles	1	Truth	3	3	10	10
7	Chicago	1	Truth	3	3	20	20
7	Houston	1	Truth	3	3	50	50
7	Phoenix	1	Truth	3	3	10	10
8	New York	1	Truth	3	3	10	10
8	Los Angeles	1	Truth	3	3	10	10

Table 4. Continued

8	Chicago	1	Truth	3	3	20	20
8	Houston	1	Truth	3	3	50	50
8	Phoenix	1	Truth	3	3	10	10
9	New York	1	Truth	3	3	10	10
9	Los Angeles	1	Truth	3	3	10	10
9	Chicago	1	Truth	3	3	20	20
9	Houston	1	Truth	3	3	50	50
9	Phoenix	1	Truth	3	3	10	10
10	New York	1	Truth	3	3	10	10
10	Los Angeles	1	Truth	3	3	10	10
10	Chicago	1	Truth	3	3	20	20
10	Houston	1	Truth	3	3	50	50
10	Phoenix	1	Truth	3	3	10	10

Table 4 shows the simulation results of the resource allocation in the spread of wildfire of the five selected cities in ten rounds. In the first round, Los Angeles is safe, but it exaggerates the severity and receive the allocation (10 units), but since this is not the truth, utility of New York is subtracted by 10 as a penalty. This situation is the same as that in New York and Chigago. For Houston, it is not burning and telling the truth, getting no resources and utility. The situation in Pheonix is reversed, it admits the burn and receives 10 units of resources, resulting in a utility of 10.

From a game-theoretic perspective, strategic exaggeration can yield short-term utility gains for individual cities, whereas truthful reporting supports the maximization of collective utility across all participants. The correlation analysis in Section V-B helps explain why cities such as Los Angeles and Chicago received greater resource allocations (for example, in Round 1, they received 40 and 50 unit of resources in Table 3) when multiple cities reported active fires. The historically higher correlation between wildfire severity and damage costs leads the MILP optimization model to assign them higher priority, reflecting the model's sensitivity to potential economic losses.

The wildfire spread dynamics were governed by the predefined adjacency matrix and a spread probability of 0.4, meaning fire transmission occurred only between directly connected cities. For instance, in Round 2, Phoenix transmitted fire to Chicago but not to other cities, in accordance with both probability constraints and network connectivity. The behavioral interaction model further indicates that once a city's "Is Burning" status transitioned from 0 to 1, it remained in the burning state for the remainder of the simulation, and its reporting strategy shifted from exaggeration to truthful reporting in subsequent rounds (for example, from Round 5 onwards, all the cities tell the truth). By comparing the column of "True Severity" and "Reported Severity", we can see the reported severity values are increased by two units to simulate inflated urgency, which in turn directly influenced the allocation outcomes. Meanwhile, the imposed both lower and upper bounds on allocations are also validated in the table.

The decision support table underscores the value of incorporating correlation-based weighting into the allocation framework, ensuring that scarce resources are directed toward locations with the greatest potential impact. The resulting allocation pattern demonstrates the MILP model's effectiveness in integrating sensitivity measures into decision-making.

5. Conclusion

This study presents an integrated decision-support framework that combines game-theoretic modeling of city-level reporting behavior with MILP-based optimization for wildfire resource allocation. By incorporating severity-dependent penalties, correlation-weighted prioritization, and probabilistic fire spread modeling, the proposed approach addresses two critical gaps in existing literature: the neglect of misinformation dynamics and the limited consideration of post-disaster allocation strategies.

Simulation results using five representative U.S. cities demonstrate that the framework effectively deters strategic exaggeration, improves fairness in allocation, and prioritizes high-risk locations based on their sensitivity to wildfire severity and economic loss correlations. The findings highlight that collective utility is maximized when truthful reporting dominates, and that correlation-informed allocation enhances the resilience of the overall system. The probabilistic spread model and network-based connectivity further validate the operational realism of the simulation, showing alignment between spatial adjacency, spread likelihood, and resource deployment outcomes.

Overall, the proposed system offers a scalable and adaptable solution for emergency managers. Beyond wildfires, the methodology can be extended to other disaster contexts where limited resources, strategic reporting, and spatial dynamics intersect, providing a robust foundation for policy-making and operational planning in high-stakes, time-critical environments.

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This research was carried out as part of my independent study project under the guidance of my instructors, Mr. Yang Xiaoan and Mr. Sun Haijun, IT teacher at the Affiliated High School of South China Normal University (SCNU). I wish to first express my deep gratitude to them for their patient mentorship, insightful suggestions, and consistent encouragement throughout the course of the work. Their role was that of an academic mentor, helping me to refine my ideas, structure the research plan, and remain aligned with scientific rigor. Importantly, their guidance was provided entirely on a voluntary, in the spirit of nurturing independent research ability. The entire process of data acquisition, model building, coding, simulation, and manuscript writing was completed independently by myself as the student researcher.

From my early years in junior high school, I developed a profound passion for mathematics and computer science. I started with self-taught Python programming through online resources like tutorial videos and programming books, which sparked my interest in data analysis and developed my logical thinking skills. This foundational curiosity motivated me to dive deeper into using my programming knowledge to solve real-life issues. I independently searched for and learnt various methods to solve challenges in statistical analysis including how to include correlation into the final formula to align with the reality, which helped me bridge my knowledge gaps from basic concepts to more advanced techniques. However, I could not have progressed the use of methods in this research from novice to proficient without the invaluable support from my teacher Mr. Yang Xiaoan, who patiently introduced Matlab as a visualization tool to my simulation of resource allocation and explained complex algorithms under its built-in functions.

The research topic arose from my personal interest in the growing challenge of resource distribution during natural disasters, with a particular focus on wildfires. In recent years, wildfires have increasingly exposed the limitations of current emergency resource allocation systems, where incomplete or exaggerated information may lead to inefficient or unfair distribution of critical supplies. Motivated by this, I set out to develop a computational and game-theoretic simulation framework to model fire spread, strategic behavior of affected

cities, and optimal allocation of limited federal resources. The choice of topic was encouraged and validated by my instructor, who provided feedback on its academic value and feasibility.

The research process can be divided into several stages, each requiring distinct efforts:

1. At the initial stage, I reviewed prior work on wildfire modeling, graph-theoretic approaches, and applications of game theory in disaster management. My instructor recommended relevant references and guided me to refine the scope so that the problem was both academically rigorous and feasible within the competition timeline.

2. I independently searched for open-access datasets on climate resilience and natural disasters. After acquiring the "Climate Resilience Simulation Dataset", I applied filtering techniques to extract wildfire-related entries and conducted preprocessing to ensure data usability. This included handling missing values, normalizing severity indicators, and constructing correlation metrics between cities and wildfire damage.

3. The modeling process consisted of three interlinked parts:

A fire spread model, where cities were represented as nodes in a graph with probabilistic spread dynamics.

A strategy behavior model, inspired by game theory, where cities could either report truthfully or exaggerate their severity depending on fire proximity.

A resource allocation model, formulated as a Mixed Integer Linear Programming (MILP) problem, to optimize distribution of limited resources while incorporating penalties for exaggeration.The coding and simulation were carried out in MATLAB, where I developed the entire pipeline and conducted multiple iterations to ensure correctness.

4. To illustrate the dynamics clearly, I implemented animated maps of the United States, showing fire spread across connected cities and the evolution of reporting strategies. The MILP-based optimization was integrated into the simulation, allowing allocation outcomes to adapt across multiple rounds. This stage required substantial debugging and algorithm refinement, especially when constraints initially led to infeasible solutions.

5. I wrote the research report independently, structuring it in the standard scientific format: introduction, methodology, results, and discussion. My instructor reviewed drafts and suggested improvements in academic expression and logical flow but left the analysis and writing work entirely to me.

Throughout the process, I encountered several difficulties. One major challenge was ensuring that the MILP optimization converged properly given the complexity of constraints. After multiple failed attempts, I redefined the problem with simplified constraints and gradually introduced complexity, which successfully yielded feasible solutions. Another difficulty was integrating the dataset into the fire spread model, since the data covered multiple disaster types. I solved this by filtering wildfire-related entries and recalculating city-level correlations, which ultimately enhanced the accuracy of the model.

This project has sharpened my skills in data analysis, optimization, and computational modeling, while also improving my ability to think critically about real-world applications. It was both challenging and rewarding to carry out every stage independently—from idea conception, coding, and simulation to the preparation of the final manuscript.

Finally, I would like to thank the Affiliated High School of SCNU for providing an environment that strongly encourages independent research and innovation. This platform has enabled me to engage deeply with real-world problems, to practice applying mathematical and computational reasoning to societal challenges, and to develop as an independent thinker and problem solver.

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