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Mathematical Modeling of Drone Applications in Disaster Scenarios

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Summary(Abstract) :

The growing dangers of underdeveloped disaster management technology were displayed to their fullest extent in the recent Palisades and Eaton Fires. The devastating aftermath of wildfires begs the question: Are our current methods of wildfire prevention enough? As our research question, we asked if our current drone technology could predict and prevent wildfires from becoming uncontrollable. We developed a mathematical modeling structure to optimize drone deployment for wildfire monitoring and reduction. Using Irvine's wildfire hazard maps, we divided the regions into subzones and assigned a different priority to each based on the area and risk level. Once the regions were identified, we determined a point at which drones could be deployed most efficiently. Our simulations with our chosen drone, the DJI Matrice 300 RTK, showed complete coverage of high-risk zones in Irvine within six minutes, and it was also able to withstand moderate wind conditions. The drones could extinguish fires using fire retardant or water, but they could also prevent wildfires when they are equipped with the Dragon Ball, a system that deploys small ignition-triggered spheres onto risk areas. By setting risk zones on fire beforehand, it further prevents the wildfire from growing out of control. With the rapid advancements of drone technology, we are able to better utilize it to assess and respond to potential wildfires not just within Irvine, but everywhere else around the nation.

Introduction:

40,000 acres, 18,000 structures, and 85 lives – this is what we lost in the Palisades and Eaton Fires. These are not simply numbers. They represent people, livelihoods, and entire communities that will not be the same again. In the face of such a formidable adversary, we must rise and use technology to improve reaction times and reduce further losses. Recent natural disasters, particularly wildfires, have unearthed the need for new disaster prevention technology (1) that can rapidly respond to uncontrollable and unpredictable situations like some of these wildfires. Unmanned aerial vehicles (UAVs) or drones, in particular, show promise as a means of disaster prevention due to their strengths in quick deployment and logistical support (2). This paper explores the mathematical modeling of drone applications in disaster contexts with a focus on optimizing their deployment in areas like fire detection, search and rescue, and supply delivery (3). By developing and analyzing mathematical frameworks, we aim to demonstrate how drones can be integrated into disaster response strategies to enhance efficiency, ultimately saving countless lives.

The specific area of this modeling will be in Irvine, California, as Southern California, including Orange, Los Angeles, and San Diego, is at the highest risk of Wildfires among U.S counties (Figure 4,5). This proposal aims to assess and advise on the deployment of drones as an effective solution for wildfire monitoring and response, which is made possible through the revolutionary advancement in the technical capabilities of drones in both hardware and software systems (4). Equipped with thermal cameras, GPS, and AI-fuelled image processing, drones can accurately detect hotspots, map fire perimeters, and assess damage in real time (5). With these unique advantages, drones can aid emergency personnel in fields where conventional methods of disaster prevention might fall short. The primary focus of this paper will be on discovering the Optimal placement of drone launch stations, derived using a geometric median approach and corrected for aerodynamic drag and wind effects, which will ensure full coverage of high-risk wildfire zones with response times under 6 minutes.

Results/Case study

The goal of this case study was to evaluate whether a single drone launch station, chosen by our Geocenter algorithm, could provide reliable coverage of all wildfire risk zones in Irvine under realistic wind conditions (Figure 1).

Using the weighted geometric median approach, we calculated the optimal launch point from four wildfire hazard subzones. Our code produced a single Geocenter at 33.682° N, -117.764° W, located roughly 2 km east of Mission Viejo Road. The farthest subzone centroid was 7.4 km away, confirming that a drone launched from this site could reach every high-risk area within a short flight.

We next modeled the drone's flight dynamics. Under calm conditions, the Matrice 300 RTK accelerated to its cruise velocity of 23 m/s in 11.6 s, covering 195 m during this phase before transitioning to constant-speed flight. For the 7.4 km mission, this acceleration plus-cruise-profile yielded a total one-way flight time of 334 s (5 min 34 s).

To account for environmental effects, we introduced an 8 mph westward wind. Vector-addition analysis showed that wind increased the travel duration by 12% to 374 s (6 min 14 s) and shifted the effective launch coordinate 1.1 km east to maintain the intended ground track. The distance traveled as a function of time follows the equation:

, (Equation 1)

where d is in meters.

Finally, integrating Geocenter placement and wind-compensated travel times into our simulation code confirms that a single station at (33.682° N, -117.764° W) provides full coverage of Irvine's high-risk zones with one-way response times under 6 min, even under typical spring winds(Around 7 mph) when wildfires are most prevalent (6). For operational redundancy, we tested a two-station scheme by adding a secondary site at 33.670° N, -117.780° W, which reduced the maximum one-way distance to 4.2 km (3 min 10 s under wind), ensuring even faster access to outlying areas.

These results demonstrate that our modular framework can identify both minimal-station and multi-station deployments tailored to local hazard geometries, environmental conditions, and drone performance parameters.

Discussions:

Our model shows that drones can be a valuable tool for disaster response because they enable rapid deployment and precise coverage of high-risk zones. In our case study, a single launch station provided complete coverage of Irvine's wildfire-prone regions with one-way response times of under six minutes. In operational terms, this means that a fire perimeter could be mapped or hotspots identified before they grow out of control, giving firefighters critical minutes that can determine whether a blaze is contained or allowed to spread. The results are encouraging, emphasizing that in many emergencies, the margin between safety and tragedy is measured in minutes.

To decide where to place launch stations, we applied a weighted geometric median, giving more importance to areas that were either larger or had faced greater risk (7). This method helped target the most vulnerable regions, but it had clear limits. For example, wind was only factored in after the median had been calculated. That choice kept the model manageable yet reduced accuracy. In the real world, even a modest change in wind can alter flight times and energy use enough to make a different launch point more effective.

To keep the framework computationally feasible, several simplifications were made. Spatially, each hazard zone was represented by a centroid, and terrain/obstacles were ignored. Dynamically, a constant drag coefficient was assumed despite turbulence and payload variation. Operationally, factors such as communication latency, airspace restrictions, and no-fly zones were not modeled. While these assumptions allowed tractability, relaxing them in future versions could yield more accurate and adaptable strategies.

Building and maintaining the necessary infrastructure presents its own logistical challenges. Launch stations are costly to construct and operate. Keeping them functional during a high-stress event would require planning, consistent upkeep, and considerable investment. Without this, the most sophisticated deployment strategies cannot be implemented effectively.

Even with these limitations, the potential benefits are substantial. Faster deployment could allow responders to cover more ground and reach people sooner, reducing the overall toll of a disaster. While our focus was on wildfires, the same approach could be adapted for floods, remote search and rescue, or the delivery of critical supplies when ground access is blocked.

Looking ahead, there are several ways the model could be improved. One is to replace the point-based hazard map with a continuous risk surface, allowing for more accurate representation of long-term fire risk patterns and therefore better-informed placement of launch sites (8). Another is to approach site selection as a multi-objective problem that balances competing needs such as shorter flights, adequate battery reserves, and sufficient payload capacity, so no single factor dominates the decision.

Routing could also be expanded. Instead of planning solely for drones, future models could schedule drones and ground vehicles together, accounting for their different speeds, refueling requirements, and operating constraints. Coordination within the fleet could be improved with decentralized task allocation, enabling drones to reassign work automatically if one becomes unavailable. Predictive models trained on historical fire, weather, and vegetation patterns could identify high-risk areas in advance and position resources accordingly. These refinements could be tested in a realistic simulation before moving to field trials.

In the longer term, the system could evolve by learning from each mission. Every deployment would sharpen its predictions and strategies, leading to more efficient use of resources. Before that stage, however, the model must be tested alongside emergency teams to see how it performs under real-world conditions and where adjustments will be needed.

In short, this project offers a promising framework for the use of drones in disaster response. There is much still to test and refine, but the potential is clear. By improving where we launch, how we route, and how we adapt, we are not only advancing technology but safeguarding lives, livelihoods, and communities when they are most at risk.

Materials and Methods:

Framework Development

Methodology

The experiment was conducted to support disaster management in an area where frequent natural disasters occur. The specific type of natural disaster focused on in this experiment is a wildfire, considering the weather and landscape of the region. There are three major interlinked stages that were utilized for the specific methodology: Geocenter, True speed, and final integration. Each stage addresses a core aspect of drone deployment in a wildfire scenario, and the discrete frameworks reinforce the reproduction of the workflow with different drone specifications or hazard maps.

Geocenter

Our first framework identifies optimal launch sites by treating each fire-hazard subregion as a "mass point" whose weight corresponds to its area or risk level. We imported the City of Irvine's wildfire-severity shapefile into QGIS and partitioned it into four subzones, extracting centroids and computing their relative areas. These centroids and weights were passed into a Python script to converge on the weighted geometric median, which we call the "Geocenter." Dividing the map into four sections (Figure 2) and assigning individual weights ensures that high-risk areas exert greater influence on the launch-site calculation. centroids lay at (33.65° N, –117.82° W), (33.70° N, –117.75° W), (33.68° N, –117.79° W) and (33.66° N, –117.73° W), with areas of approximately 14 km^2, 18 km^2, 11 km^2 and 14 km^2 respectively. Due to its difference in types of disasters and drones with a variety of priorities, our code accepts arbitrary weight arrays and hazard-zone geometries.

We calculated the geometric median by iteration. This method is called Weiszfeld's Algorithm. Starting the guess with the mean of the coordinates of four centroids, we iterate the process of computing distances and weights, taking the better guess between each step each time. This iteration keeps on going until the difference between old and new guesses is less than the tolerance, which we kept at 10-6. By running the code, we achieved the geocenter. This geocenter ensures that the drone will travel a minimum distance.

True Speed

In fact, a drone cannot instantaneously reach its cruise velocity. It must accelerate, contend with aerodynamic drag, and account for wind drift. We therefore derived a differential equation for v(t) by fusing thrust acceleration (), with quadratic drag.

The calculation of true speed starts by first following the second-order drag force equation: (Equation 2)

where is calculated using the Drag coefficient equation with given parameters and Newton's second law (), giving us the equation:

(Equation 3)

In the case of our research:

(Equation 4)

We assumed that was derived considering the maximum speed of the drone model. Also using Newton's Second Law, we get:

(Equation 5)

Using this differential equation for Newton's second law:

(Equation 6)

(Equation 7)

Substituting the with the known equation,

= = (Equation 8)

Solving the differential equation with respect to t yields

(Equation 9)

(Equation 10)

Plugging in the initial conditions, , the time it takes to reach the final velocity of 23 m/s, is 11.5663 seconds. Integration for this:

dt (Equation 11)

, where is the distance required to reach the maximum velocity. This equation shows that in order for the drone in our research to reach its max speed, it needs to travel 195.1m. Then, we can write a final equation for the distance traveled by the drone in any given time, which is

(Equation 12)

and in our research:

, (Equation 1)

where is in meters.

Final Integration

In the concluding step, we fused the Geocenter launch sites with the True Speed and geocenter. For each candidate Geocenter, our simulation code integrates the velocity under specified wind vectors and determines whether the drone can complete a mission within its adjusted endurance. Successful launch sites are those whose coverage radii (computed from travel time and effective speed) fully encompass all hazard subregions. By iterating across multiple Geocenter weights and wind conditions, we produced a final map of viable deployment centers that maximize response speed, payload capacity, and mission reliability. This combined framework can be re-run with any new hazard map, drone parameters, or environmental inputs for temperatures, providing a turnkey solution for disaster-response planners

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Figures and Figure Captions

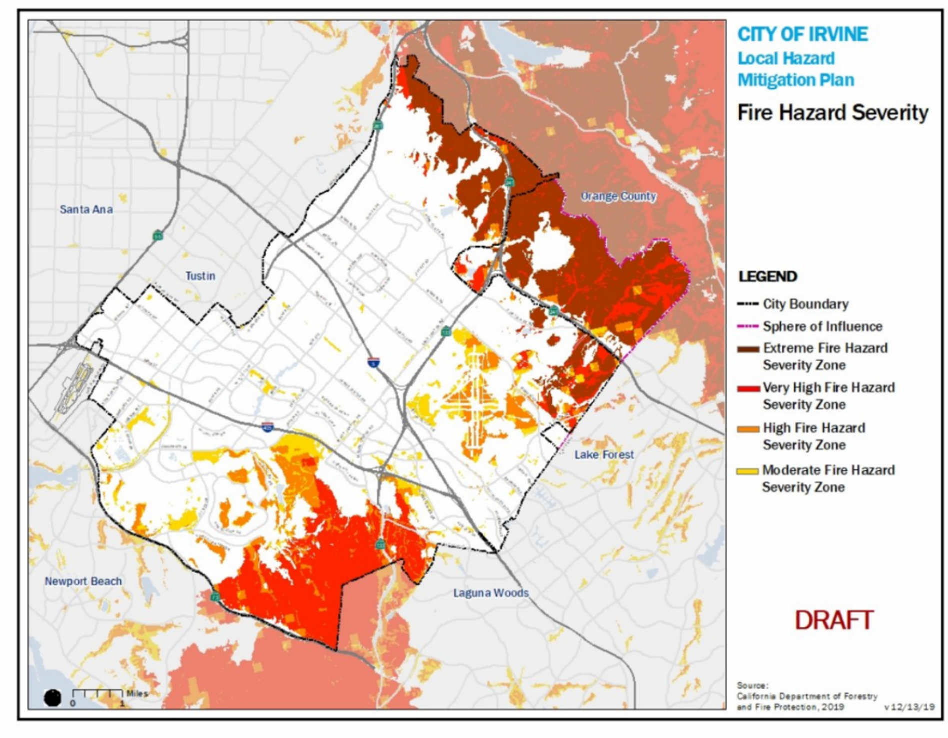

Fig. 1 **Fire Hazard Severity from City of Irvine Local Hazard Mitigation Plan**. The colored region represents an area of Irvine with fire hazard, with dark red being the highest hazard and yellow the lowest.

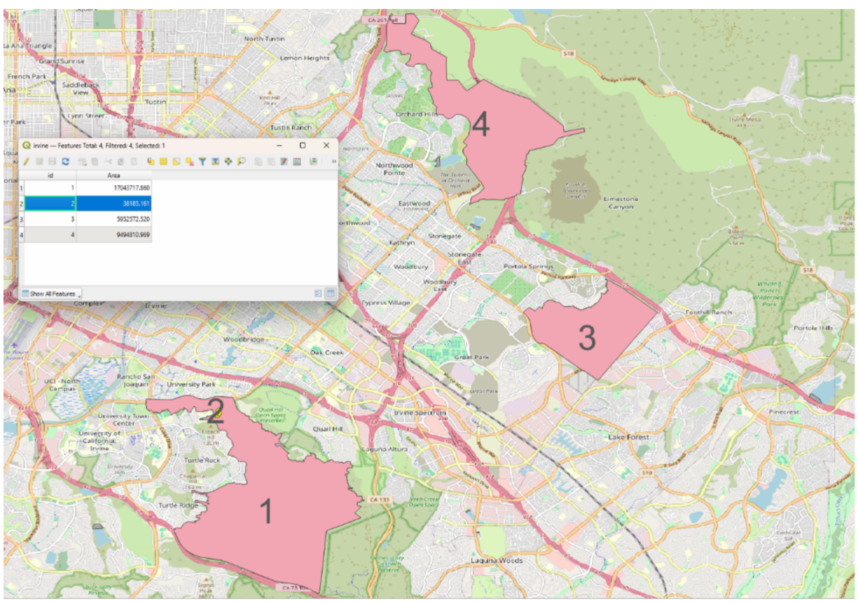

Fig.2 **Irvine Wildfire Hazard Subzones with Assigned Weights.** Four sections of the Irvine map to assign different weights, ensuring that high-risk areas lead to greater influence on the launch-site calculation.

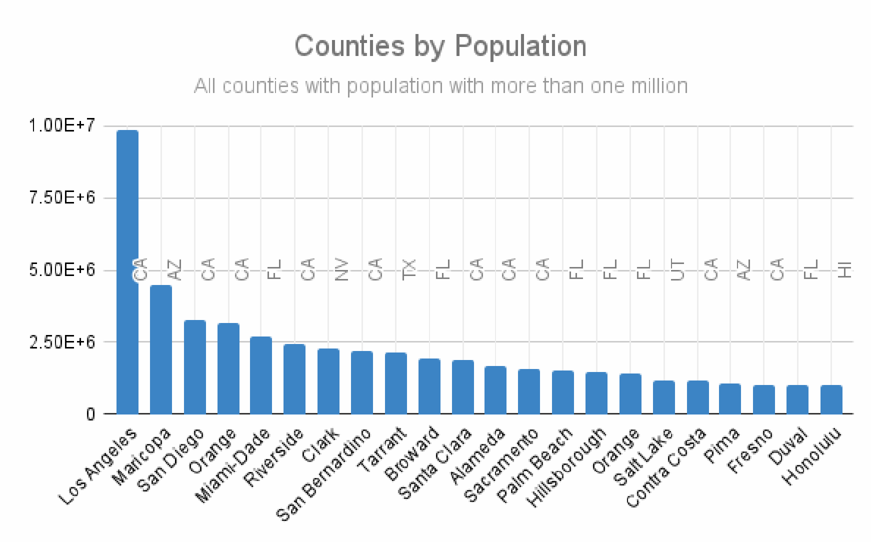

Fig 3.**Counties by Population.** This graph illustrates 22 U.S. counties with a population of more than one million. 10 out of 22 counties are located in California, the state with the highest fire risk. Los Angeles county, population of 9.8 million, has more than double the population as Maricopa county, 4.4 million. The data is from *Wildlife Risk to Communities.*

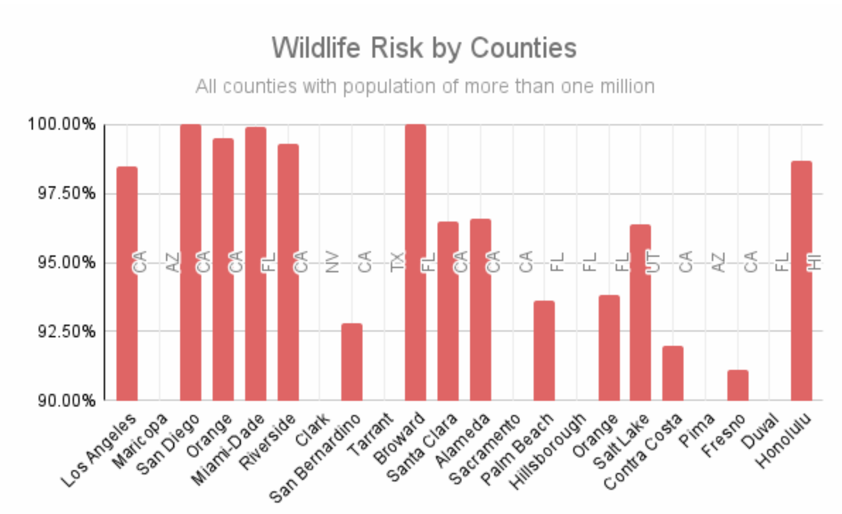

Fig 4. **Wildlife Risk by Counties.** This graph illustrates wildfire risk of all counties with the population of more than one million in a decreasing order. All California counties, except Sacramento county, have a relative wildfire risk of over 90%. San Diego and Broward counties have the highest wildfire risk of 100%. The data is from *Wildlife Risk to Communities.*

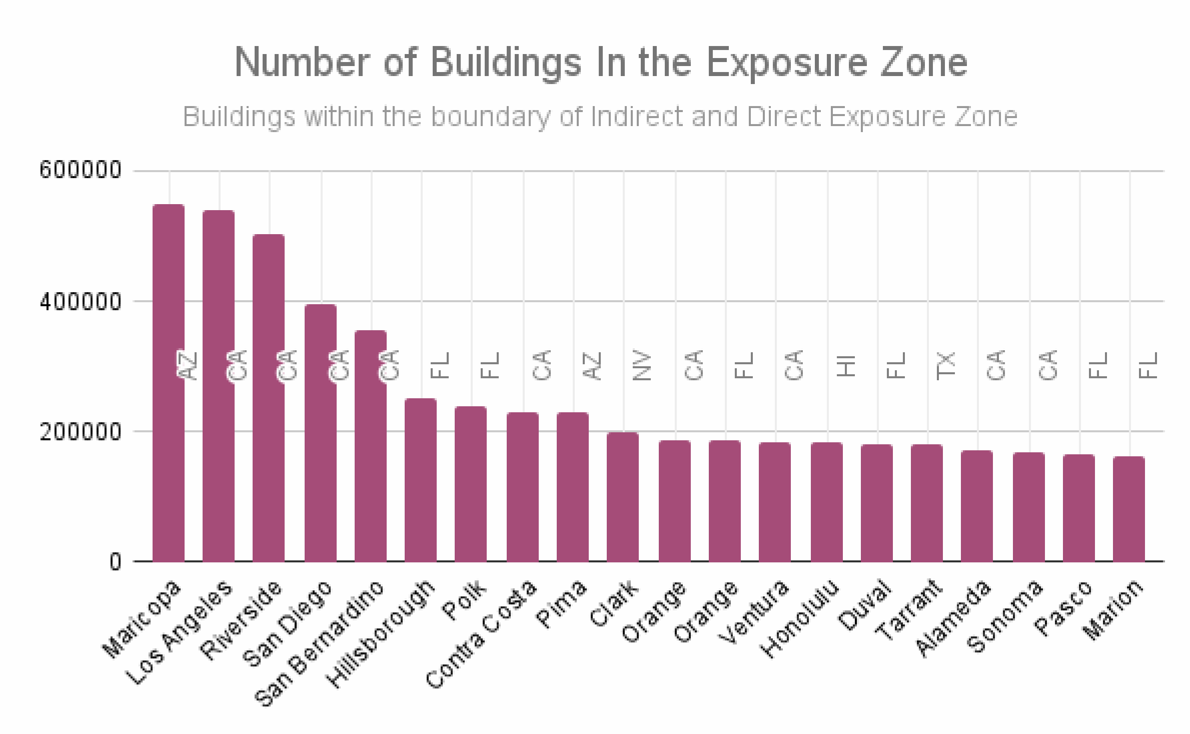

Fig 5. **Number of Buildings In the Exposure Zone.** This graph illustrates the number of buildings within the boundary of the Indirect and Direct Exposure Zone. Multiplied the total number of buildings in the county by the sum of percentages of buildings in the Indirect Exposure zone and Direct Exposure zone. The data is from *Wildlife Risk to Communities.*

Table and Table Captions

Zone	Latitude	Longitude	Area (m²)
1	33.62057	–117.79181	1.704×10^7
2	33.6541	–117.80730	3.819×10^4
3	33.67728	–117.69881	5.953×10^6
4	33.72948	–117.79181	9.498×10^6

Table 1. **Values of location for the four sub-zones of Irvine.** This table shows the zone number, the area, and the latitude & longitude of the centroid of each zone. All Latitudes and longitudes are in decimal degrees.