Problem Chosen	2021 MCM/ICM Summary Sheet	Team Control Number
B		2125835

0.1 Background:

The 2019-2020 season of Australian bushfires caused catastrophic damage, burning through over 18 million hectares across the nation. One of the worst hit regions was the state of Victoria, which had 150,000 square kilometers of damage in its approximately 237,000 square kilometer area. Victoria's new Country Fire Authority (CFA) hopes to utilize SSA drones equipped with thermal cameras and Radio Repeater (VHF) drones, for fire detection and management communication purposes.

Our project is a four-part mission: We aim to (1) build a model to **estimate the appropriate number of SSA drones and Radio Repeater drones necessary, balancing both safety and economics**. In addition, we (2) construct a model for **optimizing the location of our allotted Radio Repeater drones throughout the Victoria region**, as well as (3) a **simulation to measure model performance**. Finally, we (4) propose a **budget to request resources necessary for the CFA** to effectively use drone technology to prevent and fight wildfires.

0.2 Methods:

We modeled the number of pairs of SSA drones required by estimating the number of drones necessary to cover the entire Victoria region once per battery lifespan, or 2.5 hours. In addition, we modeled the number of pairs of radio repeater drones needed by modeling fire size and duration as exponential distributions and the fire frequency within an hour-long interval as a Poisson distribution. The total cost was calculated by multiplying the total number of drones by $10,000$, the price per unit. To model an optimal spatial distribution for the radio repeater drones, we took the cluster centers resulting from a K-Means clustering of a sampling of points from a probability distribution constructed from rainfall deficiency, topography, and population density. To measure performance, we built an agent-based model simulating fire events from frequency and size distribution, as well as drone assignments in response to those events.

0.3 Results:

Our Drone Inventory Model resulted in a total number of 144 SSA and 240 radio repeater drones, giving an estimated total cost of 3.84 million AUD using parameters estimated from the 2019-2010 Australian bushfire season. With these same parameters, our Radio Repeater Spatial Distribution Model reduced the average wait time for a drone request by a factor of 6.93 and performed 1.36 times better than a naive model according to our improvement factor metric. With our model, 85.6 percent of drone requests were able to be satisfied within an hour and 95 percent within one day.

0.4 Conclusion:

We propose a budget with a $4,074,000 dollar upfront cost and $1,296,640 yearly upkeep to supply resources that will help prevent and fight wildfires, as well as suggestions as to how to best utilize these resources for this purpose.

Game of Drones: Optimizing Drone Inventory and Distribution to Tackle Australian Wildfires

Contents

1 Introduction

As the fire response service responsible for a region exceptionally susceptible to bushfires, Victoria's Country Fire Authority (CFA) needs every advantage it can get to detect fires quickly and respond efficiently. The CFA maintains 1218 brigades located throughout Victoria, but despite this extensive coverage, rapid fire detection poses a significant challenge [2]. However, rapid detection is crucial to effective fire management, as the rate of spread of bushfires can easily exceed 10 km/hr, depending on environmental and meteorological factors [12]. Furthermore, even once fires have been detected, coordinating an emergency response requires reliable two-way communication between Emergency Operations Centers (EOCs) and emergency personnel on the ground.

In light of the catastrophic 2019-2020 bushfire season, which saw over 77,000 square kilometers burned in populated areas of southern Australia [9], the CFA hopes to use drones to bolster its ability to rapidly detect fires and to improve communication capabilities when responding to fires. In particular, the CFA aims to use two types of drones: Surveillance and Situational Awareness (SSA) drones, which are equipped with infrared cameras and can autonomously patrol regions for fires; and Radio-Repeater drones, which carry repeaters to extend the range of two-way radio communications between EOCs and firefighters. We seek to develop a model to determine the optimal number of SSA drones and Radio-Repeater drones, taking fire frequency and size as parameters; to predict the behavior of this model over the next decade; and to design a model to optimize the positioning of Radio-Repeater drones depending on topography and fire size.

2 Brief overview of our models

We have two primary models:

- Drone Inventory Model, which allows us to estimate the appropriate number of SSA and Radio Repeater drones to effectively combat wildfires.
- Radio Repeater Spatial Distribution Model, which optimizes the locations of radio repeater drones and manages their assignments to fire events.

In addition, both of these models are built on top of a model for fire occurrence and spread.

3 Assumptions

3.1 General drone behavior and purpose

A first goal in establishing our models was to delineate the macroscopic functionality of the drones - in particular, how they would be activated and the general behavior they would exhibit. A clear realization was that Radio-Repeater drones would only be deployed upon the discovery of a fire, but SSA drones would be deployed continuously. Additionally, each fire station would serve as a potential node in a resource allocation map, containing either no drones, or some number of Radio-Repeater and SSA drones. Stations with the same number and type of drones would then clearly have identical behavior. The schematic below, for illustrative purposes, covers the case where **a fire station harbors at least one SSA and Radio-Repeater drone, and the SSA drone sees a fire and one repeater drone**

is needed in combatting it. Given the algorithmic nature of drone behavior, the schematic naturally lends itself to a step-by-step analysis. **This schematic is further elaborated on the figure in page 5**.

Steps taken by drones:

1. The SSA drone leaves the fire station to go on its reconnaissance trek for as long as its battery life lasts. The path is programmed so that the drone returns to its fire station right as its battery is about to end. There, it is recharged and sent out again, **in a continuous reconnaissance/recharging loop**.

2. The SSA drone has a certain heat camera sight line through which it surveys the land it covers in its reconnaissance trek. In our diagram, **the sight line passes over a wildfire**.

3. The drone is operated remotely from the fire station. So, discovery of a wildfire by the drone leads to instant **discovery by fire station personnel**.

4. The **fire is too far away from the station** for the boots-on-the-ground fire combat teams to keep constant communication channels with the fire station active using only their walkie-talkies. So, **a Radio-Repeater drone is sent out to a location between the firefighting radius and the fire station**, to allow these human units to keep in touch with the fire station.

5. The communication channel established by the Radio-Repeater drone allows **firefighting units to keep their communication among each other and with the fire station always active**.

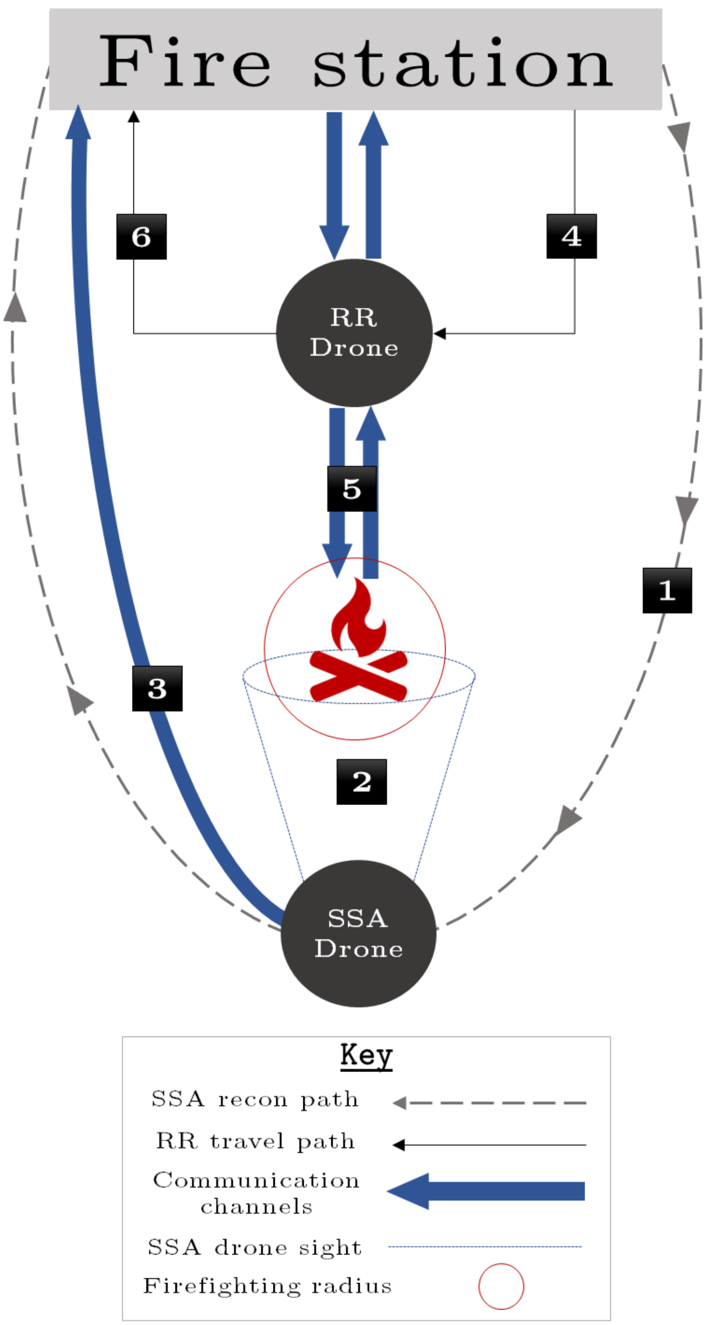
6. The **Radio-Repeater drone returns to the fire station**. This happens either because the **fire has been extinguished** and the operation is complete, **or** because the **Radio-Repeater drone will run out of battery**. If the latter is the case, it is **substituted by another Radio-Repeater drone, the closest one to the fire within the model as a whole** so communication channels remain functional throughout the firefighting mission.

Having established the general behavior we desire from our drones, and how individual nodes will behave when allocated "resources" (the drones), a few final notes are in order: (1) steps 1-3 pertain specifically to SSA drones, while steps 4-6 pertain to Radio-Repeater drones specifically; (2) the fire may be sufficiently close to the station that firefighting teams do not need Radio-Repeater drones to establish contact; (3) more than just one repeater drone may be needed if the fire is too large or too far away from the station.

3.2 Drone specifics and limitations

D-1. *Drone Specifications*: Drones (both SSA and Radio-Repeater) each cost $10,000 (AUD), have a maximum flight range (i.e. maximum distance from controller) of 30 km, maximum flight speed of 20 m/s, and a maximum flight time of 2.5 hours.

D-2. *Fire Detection Range*: SSA drones detect fires as soon as the fire is within 9,000 meters of the drone's location. This figure is a conservative estimate of infrared camera range based on a survey of current commercially available drone-mounted infrared cameras [5].



D-3. *Positioning*: Drones (either SSA or Radio-Repeater) must take off from and land at fire stations or temporary EOCs. Due to the flight range constraints given, this means that SSA drones are flight-constrained to a circle of 30 km radius around their takeoff point.

D-4. *Information Flow for SSA drones*: When an SSA drone discovers a wildfire, its home fire station immediately learns of it. This is reasonable because these drones will be operated remotely from their home stations, so if a drone heat camera sees a wildfire, so too will the drone operator.

D-5. *Path Efficiency*: SSA Drones can achieve arbitrarily close to 100% path efficiency, meaning that, in any given flight, they do not observe any point twice. Given the density of fire stations throughout Victoria (see the Fire Spread Model), this is a reasonable assumption. Additionally, within its flight radius, any number of path-covering algorithms could yield adequate surface-covering paths for drone operators to follow.

D-6. *Radio-Repeater Drone Capabilities*: Radio-Repeater drones can extend the range of any and all radios that are able to communicate with them by 20 km. Radio-Repeater drones can also operate in sequence with other Radio-Repeater drones to extend radio range by more than 20 km if needed.

D-7. *Flying over a fire:* We assume that there is no justification for drones to fly atop larger-scale fires. We define a larger-scale fire as any fire with coverage greater than 2 km^2, a number where fire flames already drastically impair visibility. SSA drone path efficiency should not be greatly affected by this constraint, but Radio-Repeater drone positioning will be. This is because the repeater drone will need to allow emergency response units to communicate around the perimeter of the fire, but will not be able to position itself atop the fire itself.

3.3 Emergency response crews

E-1. *GPS armband* Crew members always wear Personal Locator Beacons, which help them orient themselves toward the fire location and guarantees to fire stations that they are within communications range of the radio repeater drone.

E-2. *Portable radios:* These teams carry a 5-watt radio, that has a nominal range of 5 km over flat, unobstructed ground, but drops to 2 km in an urban area. Similarly, it will also drop to 2km under topographically challenging conditions, like mountainous areas.

E-3. Crew behavior We chose not to model crew behavior, assuming instead that the bottleneck to the start of fire combat was the time it took for radio repeater drones to reach the wild firesite. This was done to simplify the number of independent actors in the model, a necessary assumption (though leading to a clear decrease in accuracy) in order to increase the tractability of our calculations.

3.4 Infrastructure

I-1. *Fire Station Distribution*: Fire stations are positioned according to a probability distribution based on population density. We observed that such a distribution generates a map of fire stations that reasonably approximates the official map provided by the CFA [2].

I-2. *Station Communication*: All fire stations can communicate with one another instantaneously. This is a reasonable assumption as they all have access to electricity and thus likely also at the very least phone lines.

I-3. Fire fighting prerequisite: Fires will only start shrinking (being fought) after all necessary radio repeater drones have reached the fire location.

3.5 Fires

F-1. *Distribution*: Fires start randomly according to the probability distribution generated from the rainfall deficiency heatmap in Figure 2.

F-2. *Independence*: Fires start independently from one another, so the probability of a fire starting depends solely on the fire risk heat map from the previous assumption.

F-3. *Size and Representation*: All fires are modeled as circles that begin at their full size, and decrease at a constant rate with respect to area.

F-4. *Fire Season*: The 2019-2020 bushfire season lasted for 98 days, from November 19, 2019 to February 27, 2020 [8]. We assume fire seasons last exactly this amount of time.

F-5. Firefighting: Fire fighting occurs from the perimeter of the fire always, and the perimeter decreases in size gradually.

4 Drone Inventory Model

This model determines the absolute number of SSA and Radio-Repeater drones the CFA should purchase to maximize wildfire response effectiveness. Importantly, estimations of quantity are somewhat independent of estimations of allocation (quantity is affected more by the overall behavior of a system at scale, while allocation is a constrained optimization, given quantity and the local behavior of a system at various points). Thus, we calculated this overall number first.

Also, the number of SSA drones is in general independent from the number of Radio-Repeater drones. As explained before, while functionally identical, the purpose and behavior of these drones does not overlap. We strove to maximize SSA reconnaissance coverage and Radio-Repeater timeliness to get into position, but these are constrained differently.

4.1 Modelling the number of SSA and Radio-Repeater drones needed

Number of SSA drones

Interestingly, the number of SSA drones, assuming our goal is full coverage of the Victoria region, **does not depend on anything related to fire spread**. That is, the number of drones needed to cover a certain reconnaissance area depends on the drone constraints and geographical size, and nothing more.

With that in mind, we consider the key facts at hand. The total area of the Victoria region is roughly 237,000 km^2 [3]. The Opgal thermal camera is able to achieve a 9,000 m detection range [5], and our drones are able to move at 20 m/s (72 km/h). Clearly, a straight line path of exactly 1 hour would cover a rectangle of width $9+9=18$ and length 72, leading to area coverage of $18 \times 72 = 1296$ km^2 per hour, or 3294 km^2 per battery life of 2.5 hours, assuming a 100% path. From this number, the **minimum number of SSA drones needed to cover the entire area of Victoria in one reconnaissance round is then 72**.

However, drones have a limited battery life. After those 2.5 hours, **there would be a 1.75 hour buffer before another round of reconnaissance** could even start around the region. In order to avoid any downtime, and considering that the 1.75 hour charging time is smaller than the 2.5 hour battery life, we can simply **double the number of drones to 144**, thus housing 2 instead of 1 in each node.

With this, no downtime will ever happen in the system. Overall, this means we can get **1 round of full coverage of the entire Victoria region every 2.5 hours, with no downtime, using 144 drones.**

Number of Radio-Repeater drones

Unlike SSA drones, the number of radio repeater drones will depend heavily on fire frequency and size distribution. Thus, we spend the beginning of this section setting the **system-wide behavior of our fire spread model**.

First, we can look at how many repeater drones should be necessary for a fire of area A. Note: we are modelling our fires as circles, drones cannot position themselves directly above large fires, and fire monitoring by response units occurs along the fire's perimeter exclusively. Given the radio reach of a Radio-Repeater drone, **one repeater should be enough only for a fire with radius no larger than 10 km**. This is because a repeater at the edge of the 10 km radius fire is just able to cover the entire circumference of the fire, thus successfully maintaining a communications channel between any emergency response team anywhere on the circumference.

Because fire monitoring occurs along the perimeter, we say that the number of repeaters needed should be roughly linear with respect to fire radius, as a circle's radius is linearly proportional to its circumference. As a result, we formulate **the number of repeaters necessary, R, for fire of size,** s, as follows:

$$R(s) = \lceil \frac{s}{10} \rceil$$

We also model the **distribution of fire sizes as an exponential probability distribution**, as the vast majority of fires will be on the smaller end, with few extremely large fires. For example, the ... largest fires in the 2019-2020 Australian bushfire season accounted for ...% of the damage by area [14].

It is true we could have chosen from an array of similar distributions, but the literature tends to find greater fire spread modelling accuracy with either the exponential or Pareto distributions (the latter being usually considered slightly better) [10]. That said, the exponential distribution was numerically simpler for our calculations with a near-negligible accuracy trade-off compared to the Pareto.

We give the **probability P of a fire having area A as**

$$P(A = a) = \lambda_1 e^{-\lambda_1 a}$$

Fire duration follows a similar pattern. Most fires will have a short duration, while a few may last for a very long time. For example one of the largest fires in New South Wales during the last season burnt 5000 km^2 and lasted 74 days, the majority of the season.So, **for D the fire burn duration is given by the following probability P**:

$$P(D = d) = \lambda_2 e^{-\lambda_2 d}$$

We can reasonably assume that $d \propto a$, an intuitively valid claim as it makes sense that smaller fires will tend to last less time than larger fires, and that since both fire duration and duration are modelled exponentially, then their relationship can realistically be linear.

Given an average frequency f in fires per hour, we can estimate the number of events that occur at sometime during our hour-long interval through the following relationship:

$$\sum_{d=0}^{\infty} (\lambda_2 e^{-\lambda_2 d}) f = \sum_{a=0}^{\infty} (\lambda_1 e^{-\lambda_1 k a}) f$$

for some constant k. (Note that this estimate would be more precise with smaller time interval used for frequency duration.)
From this, we want to get an estimate of repeaters that would be needed at any given time (in a worst-case scenario that all fires need repeaters). The expected value of fire size is λ_1, so the **average number of repeaters per fire should be around** $\lceil \frac{1}{10\lambda_1} \rceil$.

Thus, given fire frequency f and exponential distribution constant λ_1 for fire, we get the following distribution U of radio repeater drones needed at any time:

$$U(f, \lambda_1) = \lceil \frac{1}{10\lambda_1} \rceil \sum_{a=0}^{\infty} (\lambda_1 e^{-\lambda_1 ka}) f$$

Note that this is only an expected value, as f is an expected value of a Poisson distribution, the variance of which is the same as f itself.

Rather, we want a number that will maximize the coverage of repeater drone use. We expect the overwhelming majority of this distribution to be accounted for by events below the 3rd variance above the mean of $U(f, \lambda_1)$. So, as our conservative lower bound for the effectiveness of we will take three variances above the mean of $U(f, \lambda_1)$.

We call this new probability $V(f, \lambda_1)$, which gives us:

$$V(f, \lambda_1) = \left(3\lceil \frac{1}{10\lambda_1} \rceil \sum_{a=0}^{\infty} (\lambda_1 e^{-\lambda_1 ka})\right)^2 f + \lceil \frac{1}{10\lambda_1} \rceil \sum_{a=0}^{\infty} (\lambda_1 e^{-\lambda_1 ka}) f$$

repeater drones.

That said, similarly to the reasons why we doubled our number for the SSA drones, we'll want to double our number to account for the battery. This is particularly important for repeater drones because there should never be any downtime while fires are being explicitly monitored or extinguished.

Total number and cost of drones

We calculated a value of **72 pairs** of drones of the SSA variety, and developed a function to model $V(f, \lambda_1)$. We **can assume this function outputs pairs of drones, so that we work in terms of pairs**. This is a valid change-of-variable to make because in our stipulations the drones operate in pairs - when one experiences downside its twin is in operation.

For nomenclature purposes, let $S(f, \lambda_1)$ be the probability distribution for SSA drones. We know $S(f, \lambda_1) = 144$, but this nomenclature will help with abstractions later on.

Finally, given that each individual drone costs \$10,000, and considering we are calculating in terms of pairs, our total cost (in AUD) is modelled by the function $C(f, \lambda_1)$, as follows:

$$C(f, \lambda_1) = 20,000\Big(S(f, \lambda_1) + V(f, \lambda_1)\Big)$$

4.2 Parameter Estimation

We have two inputs, f and λ_1 and one parameter for our model k, which is our conversion factor between fire duration (in hours) and fire area. We can get a rough estimate for k from the aforementioned data point: the Currowan fire in New South Wales burnt around 5000 square kilometers over 74 days, giving a value $k = 0.3552$.

The relevant values for inputs f and λ_1 for the 2019-2020 season were estimated as follows. During a 98-day period of this season from November 19^{th} 2019 to February 27 2020, 3500 fires had occurred, giving an average frequency of $f = 1.488$ fires per hour [8]. In addition, 15,000 square kilometers were burned during this period, giving an average fire size of 4.285 square kilometers [8]. Since the expected value of the exponential distribution is $\frac{1}{\lambda_1}$, per properties of exponential distributions in general, this gives us $\lambda_1 = 0.233$.

We input these parameters into $V(f, \lambda_1)$, yielding the following:

$$V(1.488, 0.233) = \left(3\lceil\frac{1}{10 * 0.233}\rceil \sum_{a=0}^{\infty}(0.233 \cdot e^{-0.233 \cdot 0.3552a})\right)^2 1.488 +$$

$$+ \lceil\frac{1}{10 \cdot 0.233}\rceil \sum_{a=0}^{\infty}(0.233 \cdot e^{-0.233 \cdot 0.3552a})1.488 = 120 \text{ pairs of drones.}$$

Thus, in total, we need **72 pairs of SSA drones and 120 pairs of radio repeater drones**. Monetarily, we have $C(1.488, 0.233) = 20,000(72 + 120) = 3840000$, a total of **3.84 million AUD**.

4.3 Model Illustration and Analysis

We now analyze the parameter influences on our model. Graphs of the total cost function $C(f, \lambda_1)$ as a function of one variable in terms of f and λ_1, respectively, are included in Figure 1. As expected, given the definition of C, the graph of C for fixed λ_1 exhibits linear growth with f. In other words, the cost of the drones needed increases linearly as the expected frequency of fires increases. In contrast, the graph of C for fixed f exhibits polynomial (specifically, quartic) growth in terms of λ_1. Crucially, as λ_1 decreases (i.e. as the expected fire size $\frac{1}{\lambda_1}$ increases), the sensitivity of $C(f, \lambda_1)$ to variation of λ_1 decreases, whereas as expected fire size decreases, sensitivity of $C(f, \lambda_1)$ to variation of λ_1 increases. However, for all reasonable values of λ_1, $C(f, \lambda_1)$ is more sensitive to variation of f by a given percent (relative to its estimated value) than to variation of λ_1 by an equal percent. Specific values of $C(f, \lambda_1)$ for different values of both parameters, listed relative to the estimated values, are included in Table 1.

	$\frac{\lambda_1}{0.5}$	$\frac{\lambda_1}{0.75}$	λ_1	$\frac{\lambda_1}{1.25}$	$\frac{\lambda_1}{1.5}$
$0.5f$	2.73	2.67	2.64	2.62	2.60
$0.75f$	3.38	3.28	3.23	3.21	3.19
f	4.03	3.90	3.84	3.79	3.77
$1.25f$	4.68	4.51	4.43	4.38	4.35
$1.5f$	5.32	5.12	5.03	4.97	4.93

Table 1: Predicted cost of drones for various values of f and λ_1, relative to the estimated baseline values $f = 1.488$ and $\lambda_1 = 0.233$, in millions of AUD.

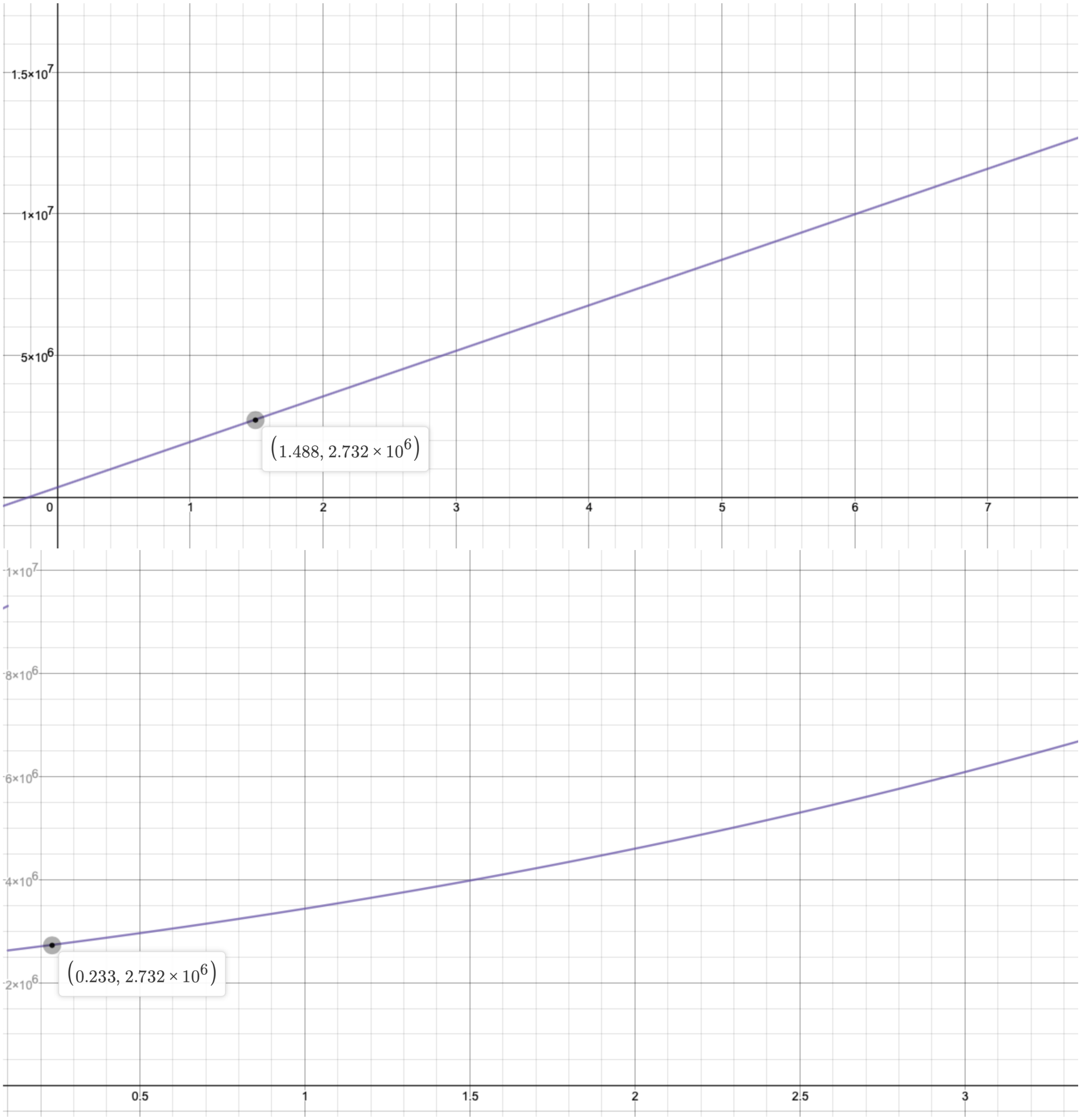


Figure 1: Graph of $y = C(f, \lambda_1 = 0.233)$ as a function of f (top) and graph of $y = C(f = 1.488, \lambda_1)$ as a function of λ_1 (bottom), showcasing the behavior of the model over reasonable domains for both parameters.

5 Radio Repeater Spatial Distribution Model

We outline an agent-based model for placing drones and simulating their performance over a 98-day period, the time assumed for a wildfire season.

5.1 Drone Placement

Given the fire frequency and size distribution, as well as our resulting number of radio repeater drones from our Drone model, we now formulate how to **best spatially distribute those drones across the Victoria region**. To do this, we first make use of three maps of Australia: a rainfall deficiency map from June 2018 to November 2019 (an 18 month range prior to the start of the season of interest), a topography map, and a population density map. All three maps were processed such that the Victoria region was isolated and extraneous markings were removed to create a heat map images for our following uses. Each map was 250 by 500 pixels, each pixel length corresponding to roughly 2 km.

We use the rainfall deficiency map [15] as a proxy for fire risk and probability distribution, as it roughly follows the distribution of the fires in the 2019-2020 season [4].

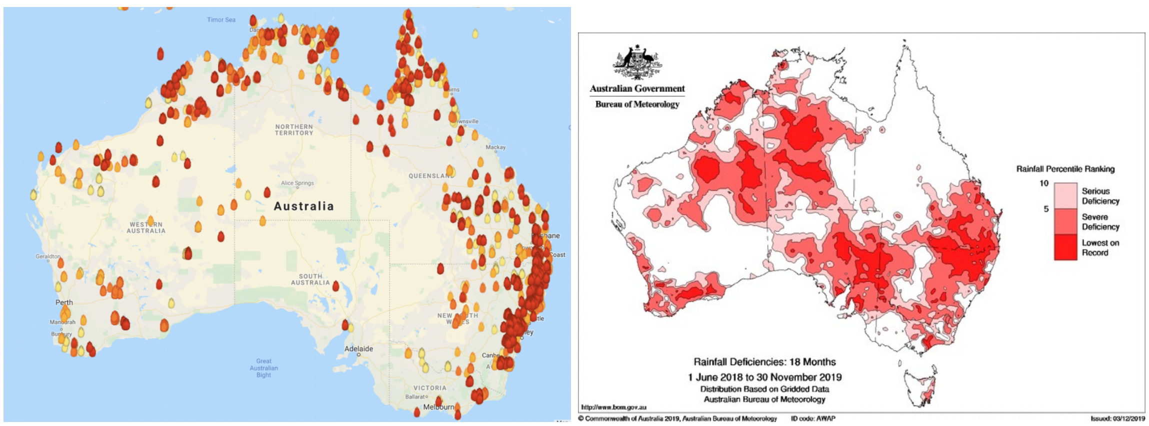


Figure 2: Actual map of bushfires in the 2019-2020 season from [4] (left) and map of rainfall deficiency from the 2018-2019 season from [15] (right), highlighting the close correlation between the two, particularly in the Victoria region. The use of the prior year's rainfall deficiency map is reasonable, given the need to predict future fire behavior from already-collected data.

Treating the map image as a matrix P, we generated the spatial probability distribution

$$N^* = f\frac{N}{\sum_{i,j} N}$$

such that the expected value of fires per hour across the entire region is f.

The topography map [1] and population density maps [13] were used for identifying regions that had limited range without the use of a repeater, that is, hilly areas and urban areas. The topography map was first transformed into a "ruggedness" map by computing the gradient of the image matrix and taking the magnitude element-wise, followed by a Gaussian blur with a 25x25 kernel. Both the ruggedness map and population density map were then thresholded to include the most rugged and dense regions. The union of these two thresholds denoted all regions where handheld radios had a range of 2km rather than 5km. We call this the *limited range* map L

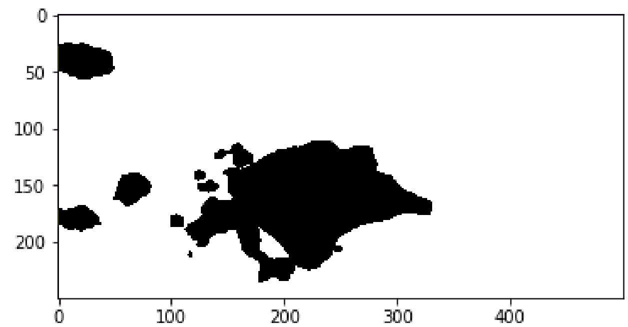


Figure 3: *Limited range* map of Victoria.

In order to identify optimal locations to place our radio repeater drones, we first note two considerations:

1. We want to minimize the distance that any point on the map (where fires are possible) is to a drone location.

2. We want more drones where they are more need, that is, where there are more fires and where there are more limitations without them.

To account for these two considerations, we take a K-Means clustering approach. We first take a weighted sum of our probability distribution (or *fire risk*) map N and our normalized *limited range* map ($L^* = L \sum_{i,j} L$). In addition we multiply this sum by one twentieth of the area of or region A_r, so we can generate one point every 20 pixels on average. This gives us a spatial distribution matrix W such that

$$W = 0.05A_r(kN^* + (1-k)L^*)$$

such that $0 << k < 1$. For our purposes, we will use $k = 0.9$. See Figure 4 for an illustration of the result.

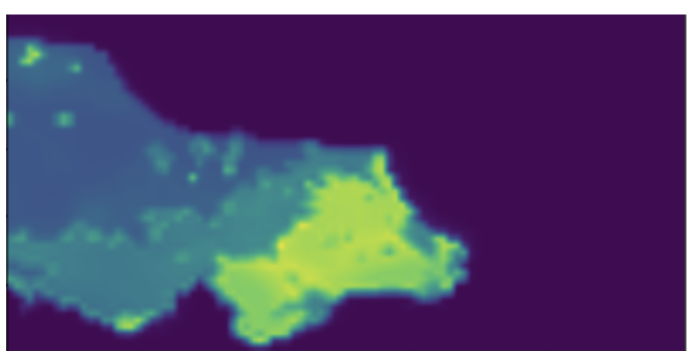


Figure 4: Repeater need map W.

We then generate points by taking a random sampling of matrix elements weighted by this distribution. For each matrix element, i.e. for each pixel, we draw a random number between 0 and 1, and if this number is less than the corresponding probability, we assign a point there. We then perform a K-Means clustering of these points where K is the number of pairs of radio repeaters necessary, as outputted by our Drone Inventory Model. According to the values we estimated for the 2019-2020 season, this was 120 drones. We then use the cluster centers as our default or *home* placements for our drones; given that fire stations are reasonably evenly distributed throughout the state according to the map provided by the CFA [2], we assume that it is possible to math these home placements with existing fire stations without significantly degrading the performance of the model. By the K-Means objective function, these cluster centers minimize the sum of the squared distances from each fire to its closest EOC or drone home. With n points partitioned into k clusters, such that each cluster center c_j has associated points $x_i^{(j)}$, we want to find the assignments of

$$\arg\min \sum_{j=1}^{k} \sum_{i=1}^{n} ||x_i^{(j)} - c_j||^2$$

With 120 drones, this gives us a distribution like the following:

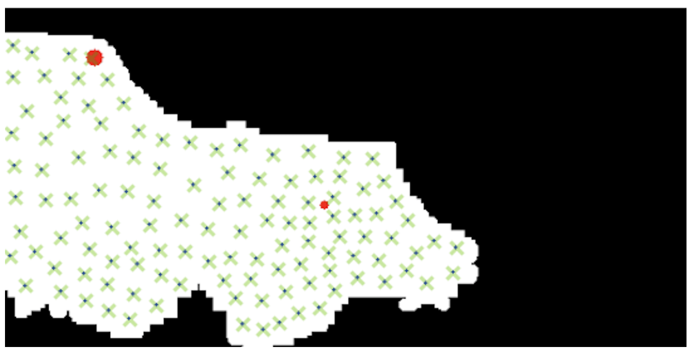


Figure 5: Default drone placement throughout Victoria with 120 drones (green exes).

5.2 Fire Dynamics

We model fire occurrences following frequency, size distribution, and our generated spatial probability map. Supposing our fires are circles, we denote each one a location and radius. At each hour timestamp, we iterate through every pixel in our region, and roll a random value from 0 to 1 and compare it to the probability at that pixel. If the rolled value is lower, we say that a fire initiates at that pixel at full size s. The fire maintains its size until all its drone needs are satisfied, that is, until it is assigned $\lceil \frac{s}{10} \rceil$ drones. Once all requests are satisfied, its area shrinks by 1 km^2 per hour.

5.3 Drone Requests

A fire may receive a drone as long as it is within range. We say a drone at location $\mathbf{d}$ is within range of a fire centered at location $\mathbf{f}$ of radius r_f of as long as

$$||\mathbf{f} - \mathbf{d}||_2 < 40 + r_f$$

Fires "request" drones on a first-come-first-serve basis. Whenever a fire is initiated, if a drone is deemed necessary, it is placed on a priority queue sorted by time of initiation. At the start of each hour, we iterate down the queue in order and see if each drone's requests may be fulfilled. Drones temporarily move toward the fire they are assigned to until the fire has been extinguished, at which point they return back to their home position.

5.4 Metrics

We want our spatial model to minimize the delay between when a drone is requested and when a drone request is satisfied with the given resources. As a result, we record this delay, rounded up in hours, for each drone request during the simulation. Because drone requests are at the start of the our, each delay is rounded up to at least 1 hour. Drone requests that are not satisfied by the end of the simulation are treated as if they are satisfied at the last time point. We look at the average delay, but as this may be skewed by some very large values, we also look at the proportion of requests that are satisfied within 1, 6, 12, or 24 hours. (In cases, where the delay is exceedingly large, we would recommend available drones to be shipped in to borrow on on a case by case basis.) We compare each of these metrics to a naive model that places drones independently of fire probability spatial distribution, topography, or population density; that is, it follows Consideration 1 but not Consideration 2. We can construct an *efficiency score* that is that is the average of the proportions of requests satisfied within 1, 6, 12, and 24 hours by our model.We also construct a summary *improvement factor* metric that is the average of the ratios of requests satisfied within 1, 6, 12, and 24 ours between our model and the naive one.

6 Solution and results

Using our baseline parameters sourced from the 2019-2020 Australian bushfire season in Victoria, our model achieved an average wait time of 5.18 hours for a drone request to be satisfied. 85.6 percent of requests were satisfied within 1 hour, with 89.7 percent in 6 hours, 92.3 percent in 12 hours, and 95 percent in 24 hours. Comparatively, the naive model achieved an average wait time of 35.89 hours for a drone request to be satisfied. 61.1 percent of requests were satisfied within 1 hour, with 65.2 percent in 6 hours, 67.5 percent in 12 hours, and 72.5 percent in 24 hours. In terms of average wait time, our model allocated drones in 14.4% of the time that it took the naive model (6.93 times faster). It also allocated drones within 1 hour 1.4 times more often, in 6 hours 1.38 times more often, in 12 hours 1.37 times more often, and in 24 hours 1.31 times more often. Overall this gives us an *efficiency score* of 90.65 percent and an *improvement factor* of 1.36.

6.1 Sensitivity analysis

We run our model with different values of fire frequency f and size distribution constant λ and adjust our number of repeater drones accordingly. Specifically, we test what happens when fires are 25% more or less frequent, and when the average size of a fire becomes 25% larger or smaller. Our *improvement factor* metric most directly allows us to evaluate our spatial distribution model's sensitivity, while our *efficiency score* also factors in the radio repeater component of our drone inventory model's sensitivity.

For all frequency and size distribution parameters tested, our model was able to achieve an *improvement factor* at least 1.06 (See Table 2). This was most sensitive to changes in λ_1 when fires were smaller, but this is likely because performance improved for both our model and the naive model. It may be that for smaller fires, spatial distribution of drones is less important.

	$\frac{\lambda_1}{0.75}$	λ_1	$\frac{\lambda_1}{1.25}$
$0.75f$		1.19	
f	2.39	1.36	1.06
$1.25f$		1.27	

Table 2: *Improvement factor* for our model for various factors of fire frequency and size distribution, compared to a naive model.

	$\frac{\lambda_1}{0.75}$	λ_1	$\frac{\lambda_1}{1.25}$
$0.75f$		84.25	
f	66.02	90.65	92.32
$1.25f$		91.4	

Table 3: *Efficiency score* (percent) for our model for various factors of fire frequency and size distribution.

In terms of *efficiency scores*, our model actually performed better when fires became smaller and more frequent (See Table 3). However, our model performed slightly worse with less frequency and a lot worse with larger average fires. The former, as handling few fires should be easier, is likely due to some weaknesses in our Drone Inventory model, where we may be underestimating the number of repeater drones needed when the frequency is lower. This is probably because our estimate for repeater drones needed does not take into account the size of the region we are aiming to cover. To remedy this, we would likely need to set some lower bound for repeaters needed, regardless of fire frequency or size distribution. The drop in *efficiency score* when fires become bigger may be because these fires in the higher extremities are much more difficult to manage. Note that since our improvement factor for this scenario is actually our best, so the weakness here most likely lies with the number of repeater drones allocated. This may indicate that our drone inventory model, specifically for repeater drones, underestimates the effect of fire size . This is also evident when looking at the percent drone usage across each simulation. In the simulations with larger fire sizes, drone usage was near capacity while only at around half capacity in the baseline.

6.2 Strengths and weaknesses

Strengths:

1. Following best practices of algorithmic interpretability, we strove to **minimize minute parameters**, thus creating a strong correlation between the parameters we did use and our simulation results. Due to this, it is quite evident what effect variables like rainfall, topography, fire spread, and others, have on our ultimate results. This will increase the replicability, generalizability, and versatility of our model in the future.

2. Our Drone Spatial Distribution Model takes advantage of a well-established technique **K-Means Clustering**. It is designed to optimize for and balance the two most relevant factors: (1) allowing drones to accomplish as much spatial coverage as possible and (2) equipping regions with higher fire risk and greater need for repeater drones with more drones. Additionally, K-means clustering works best when we expect our clusters to be bulgy and circular, which is precisely what we expected our clusters to be like.

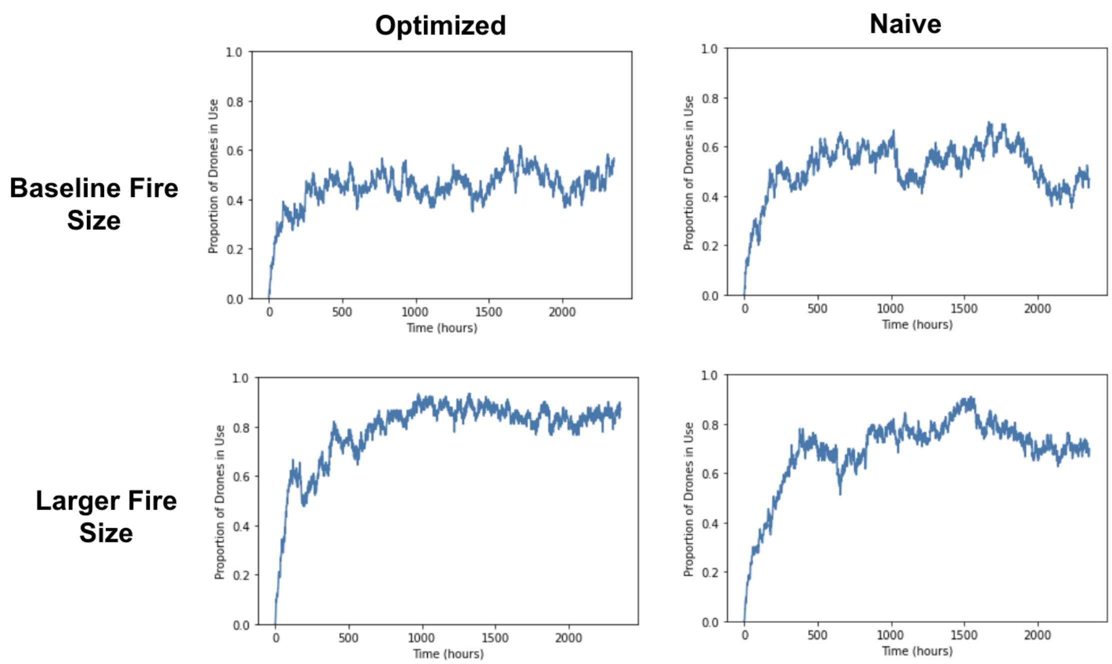


Figure 6: Drone Usage over Time for Different Fire Sizes and Distribution Models.

3. Our **use of agent-based models** allows for even easier interpretability, such as through visualization of simulations, and much flexibility for further improvements. Because we are working with a relatively small number of objects (i.e. drones and fires) of which we aim to model their behavior and interactions, a discrete model, and especially an agent-based model, is suitable for this task.

Weaknesses:

1. As a model simplification we chose to **consider each wildfire entirely independently from one another**. This is both patently untrue in real-life, as fires meet and merge to become larger flames, as well as detrimental to the quality of our model, as bigger flames become more common under a simulation that includes some level of dependence between different wildfires. Ultimately, this may have led to decreased skewness toward large flames in our model. Notoriously, 4 fires accounted for just over 87% of all 15,000 square kilometers burned in the 2019-2020 wildfire season in Victoria [11], a very low spread.

2. As another model simplification, we **modelled the fire growth for each wildfire as a circle**. This made computations easier but is also clearly not true of real life, where terrain and fuel drastically influence fire geometry (in fact, many fires look like long burn lines). However, most problematically, a circle is the 2-dimensional shape that minimizes the ratio between perimeter and area, meaning it leads to minimized radio repeater drone usage. That is, we used the opposite of a conservative model in this regard, rather ending up with the best-case scenario simulation.

3. We **never modelled the emergency response boots-on-the-ground units**, instead considering only radio-repeater drones and their time to reach a fire. However, the biggest bottlenecks for

the time taken to combat a fire would certainly come from these units, whose mobility is far lower than the 20 m/s of a drone, and affected by topography too. We assumed a fire would start decreasing in size the moment a radio repeater drone got into range, but this is, for the reasons above, clearly not true. Rather, we would have needed to model the location of these human units, and traced a topographical trek to the fire location, perhaps using the Tobler hiking function (the most commonly used estimator on GIS technology for hiking time estimation) on some cost surface, and used the maximum of that amount of time and the time for radio repeater drones to reach the same place as the time taken for a fire to start becoming smaller.

4. Our fires also did not grow naturally. That is, they were generated at their maximum size, and **did not have any sort of growth behavior built in**. As a result, then, fires could only ever shrink, but never "fight back" and grow in other directions even as they were being fought. As a result, fire detection became simplified (it is quicker to detect larger fires) and fire fighting simpler (it becomes a linear task, where recon units put the fire out at, a worst case, in a baseline rate always). This may mask the need for more equipment in firefighting.

5. We did not model the fact that, as the fire decreases in size, **less radio repeater drones will be needed to maintain communication channels between firefighting teams on the ground**. That is, these drones could be reallocated elsewhere. So, we may have been excessively conservative in our decision to not implement this functionality in this case.

Overview: Generally, it seems that to the extent that our models used the correct framing structures (such as k-means, for example, being an ideal candidate for our purposes), we had to make some generalizations and assumptions in order to guarantee the tractability of our calculations, which ultimately may have contributed to a less conservative baseline than we would have preferred. The fact is dynamic systems have an inherent sense of chaos associated with them, and modelling that chaos procedurally is a challenging goal due to the need to experimentally set parameters. It remains an important next step in terms of our model' accuracy, however, and while the generalizations we assumed allowed us a sufficiently robust starting point, the next step is working off these more asymmetric variations on our model.

7 Conclusion

Our drone inventory model predicts that a total of 384 drones will be needed if fire size and frequency match the estimated parameters based on the 2019-2020 fire season, while also providing safe estimates for the number of drones needed should current trends continue, with fires becoming more common and larger. Meanwhile, our spatial distribution model for Radio-Repeater drones provides an efficient distribution and behavioral algorithm for Radio-Repeater drones to minimize the response time in as many cases as possible; with current parameters, this algorithm satisfies nearly 86 percent of requests within an hour. Like the inventory model, this spatial distribution model can be updated as needed using the outputs of modified versions of the drone inventory model, allowing it to adapt to future trends. Equipped with these models, we anticipate that the CFA will be able to optimize its use of drones in detecting and responding to bushfires to significantly bolster its current firefighting capabilities.

8 Budget Request for the CFA Rapid Bushfire Response Unit

Purpose: The purpose of the Country Fire Authority's proposed Rapid Bushfire Response (RBR) unit is to use drone technology to quickly detect bushfires and to facilitate rapid, coordinated responses to detected bushfires. The devastating bushfires of the 2019-2020 season, which burned over 1.2 million hectares in Victoria and cost the state hundreds of millions of dollars [6], justify a significant investment in the proposed RBR unit, whose activities will help minimize the costs of future bushfire events.

8.1 Drones

SSA Drones: $1,440,000 AUD for 144 Surveillance and Situational Awareness (SSA) drones at $10,000 each. Each drone is equipped with an infrared camera (included in cost). These WileE–15.2X Hybrid Drones have a maximum operating range of 30km, a maximum flight speed of 20 m/s, and a maximum flight time of 2.5 hours. With 144 such drones distributed appropriately among fire brigade stations, it will be possible to survey nearly the entire state once every 2.5 hours, which will enable much more rapid detection of bushfires.
Radio-Repeater Drones: $2,400,000 AUD for 240 Radio-Repeater drones at $10,000 each. Each drone is equipped with a VHF radio repeater that will extend the maximum range of two-way radio communications between Emergency Operations Centers (EOCs) and actively responding emergency personnel by 20km each, thus allowing for more efficient, more coordinated, and safer response to fires. These WileE–15.2X Hybrid Drones have identical flight specifications to the SSA drones and are simply equipped with a VHF radio in place of the infrared camera of the SSA drones.
Drone total: $3,840,000 AUD for 384 drones.

8.2 Personnel

Drone Operators: $234,000 AUD for drone training and Remote Operator Certificates (ReOCs) for 120 drone operators, at $1950 per person, via AviAssist. SSA drones are autonomous, as they fly predetermined paths, so operators are only needed for Radio-Repeater drones. These drones are distributed in pairs, with only one operator is needed per pair; furthermore, we assume that current volunteers or employees may be trained in place of hiring new employees specifically to operate drones.
Personnel total: $234,000 AUD for 120 ReOC training courses.

8.3 Repair and Upkeep

Battery Replacement: $138,240 AUD *per year* for 768 replacement batteries (2 for each drone) at $180 per battery. We anticipate replacing each drone's battery twice a year. WileE (the drone manufacturer) does not publish replacement battery costs, so an optimistic estimate based on twice the normal cost of consumer drone batteries was used [7].
Damaged Drone Replacement: $390,000 AUD *per year* for 39 replacement drones at $10,000 per drone. This adopts the pessimistic assumption that 10% of drones are destroyed or need replacement for some other reason per year.
Regular Drone Replacement: $3,840,000 AUD *per 5 years* for 384 replacement drones at $10,000 each. Distributed evenly over 5 years, this is equivalent to $768,000 *per year*. This is based on the (again, highly pessimistic) assumption that all drones have a maximum shelf life of 5 years, after which

they must be replaced. In reality, we anticipate fewer drones needing regular replacement, particularly if 10% of drones undergo unplanned replacement per year.
Repair and Upkeep total: $1,296,640 AUD *per year* for drone maintenance and replacement.

$\boxed{\textbf{GRAND TOTAL: \$4,074,000 AUD upfront plus \$1,296,640 AUD } \textbf{\textit{per year}} \textbf{ upkeep.}}$

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9 Appendix

9.1 Additional Figures

Sample run of our agent-based model: gif
Topography Map of Australia

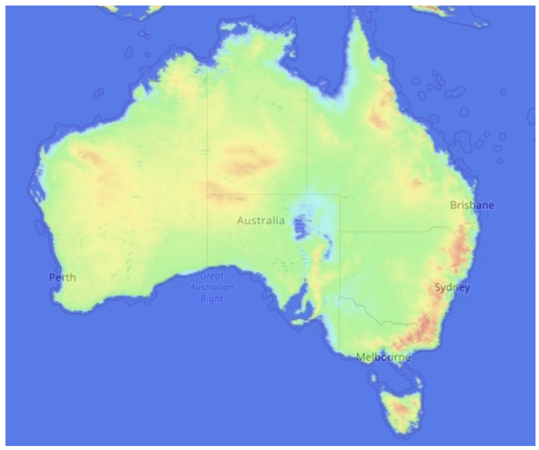

Figure 7: Source

Population Density Map of Australia

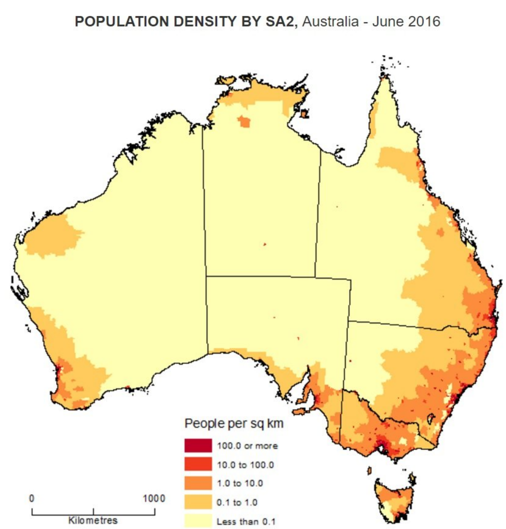

Figure 8: Source

9.2 Code

Code is viewable here.