Problem Chosen	2021 MCM/ICM Summary Sheet	Team Control Number
B		2125629

In this problem, we were asked to find the optimal mix of and positioning of Surveillance and Situational Awareness (SSA) drones and radio repeater drones to combat wildfires in Victoria state, Australia. The number of drones purchased must be subject to a budget constraint. Furthermore, our model should take Victoria's topography, and fire event size and frequency into account. This model must be adaptable to future changes in extreme fire events, and equipment costs.

We collected MODIS fire data from NASA's Fire Information for Resource Management System, and analyzed the fire hot spot data from 2000 to 2019. We then used a budgeted coverage maximization model to determine the mix of SSA and radio repeater drones that would maximize the surveillance and communications coverage of fire areas in Victoria. Since the SSA drones and the radio repeater drones have different purposes, we optimize the number of SSA drones and the number of radio repeater drones separately. Since the SSA drones are meant for surveillance and telemetry, we position the SSA drones over the fire covered regions so that they can gather data about the interior of the fires; whereas the optimal position of radio repeater drones depends on the population of ground personnel, who are primarily along the perimeter of the fire.

We assume that we have a \$1.5 million budget to work with since the Australian government dedicated \$46 million toward advanced fire management in 2020-2021. Using our model, we found that the maximum optimal number of SSA and radio repeater drones subject to a \$1.5 million budget is 26 and 40 respectively. This yields a total purchase cost of \$660,000 for this bundle of drones. However, these drones also incur a maintenance cost, yielding a total cost of \$1,224,000 per year. As the likelihood of future extreme fire events increases due to climate change effects, the number of drones and the cost will increase too.

Don't Burn, Baby Don't Burn: Optimizing the Number Of Drones To Fight Bushfires in Victoria, Australia

February 9, 2021

Contents

1 Introduction

In January 2020, wildfires ravaged the Australian landscape, wreaking havoc on wildlife, people, and homes. The possibility of such devastation in the future is only increasing with our worsening global climate. This presents an urgent need for solutions to tackle the generation, observation, and extermination of fires. A major factor of interest in solving this problem is increasing the efficiency of observation and communication methods when tracking the spread of fires so that we may reduce the time and effort required to combat them.

Firefighters use drones for surveillance and situational awareness (SSA) for high definition thermal imaging and telemetry to monitor and report data from wearable devices on front-line personnel. They also use drones carrying radio repeaters to extend the range of low power radios on the front lines. Determining an optimal mix of SSA and radio repeater drones for deployment is paramount to ensuring efficient and effective communication and data collection/transmission regarding live fires.

In this paper, we examine MODIS fire data to measure the spread and frequency of bush fires in Australia's Victoria state to model the optimal mix of surveillance and situational awareness drones (SSA drones) and radio repeater drones required to combat the fires subject to Victoria state's budget. Since we live in an ever-changing climatic landscape, we examine the predictions of our model for varying likelihoods of future extreme fire events due to a changing climate. Lastly, we model the optimal placement of radio repeater drones for fires of different sizes across the Victorian landscape.

2 Motivation

Bushfires are frequent in Victoria being exceptionally damaging during the 2019-2020 season. These so-called Black Summer fires were responsible for the destruction of almost 19 million hectares, over 3,000 houses, and the death of 33 people [2]. Data showed that they were unprecedented in terms of impact on all areas and it would take years to recover economically and ecologically.
The use of drones would not only save the number of lives of firefighters by extending the range they can fight the fire and alert others if their vitals are in danger, but also recognize these fires before they have had a chance to spread. They can operate as patrol aircraft that can operate during the night or during the direct firefighting effort.
However, these drones will only cover a certain fraction of the land and are another tool in addition to the human personnel and machinery already in place. There are already more than 500 aircraft are available for firefighting across Australia, but autonomous drones will help coordinate the firefighting effort where the only the presence of aircraft is required, not human operation.

3 Assumptions

i **Polygon Region of Victoria** To limit the MODIS fire data to the Victoria region, we only considered points that are within a polygon that will be later defined in the Data Collection and Interpreation section.

ii **SSA Drones is a Turboprop Aircraft** Since most commercial quad/octo-copter drones have a flight time of less than 30 minutes, it is unreasonable to assume that drone that has a flight range of 30km and a flight time of 2.5 hours will have the same form, since these drones cannot move that quickly and will be too heavy with all the batteries required for such a flight time.
We will assume that the SSA drones will be a turboprop style airplane that would need to take off from an airstrip. The wings on the aircraft will allow it to carry more weight and generate lift that will let it achieve its 30km range.
Radio repeater drones will resemble a quadcopter since they can be launched from anywhere, and only need to hover in a a relatively single spot to increase the radio signal between personnel on the ground.

iii **Concentration of Fires for SSA Drones**

polygon area, drone assumption as a plane, concentration of fires most important

4 Data Collection and Interpretation

We collect MODIS fire hot spot data from NASA's Fire Information for Resource Management System (FIRMS) [6] to examine the distribution of fire hot spots across Victoria over a period of 20 years from 2000 to 2019. The data collected includes the location (latitude and longitude) of hot spots, the confidence of hot spot detection, and the fire radiative power (FRP) of the hot spot.

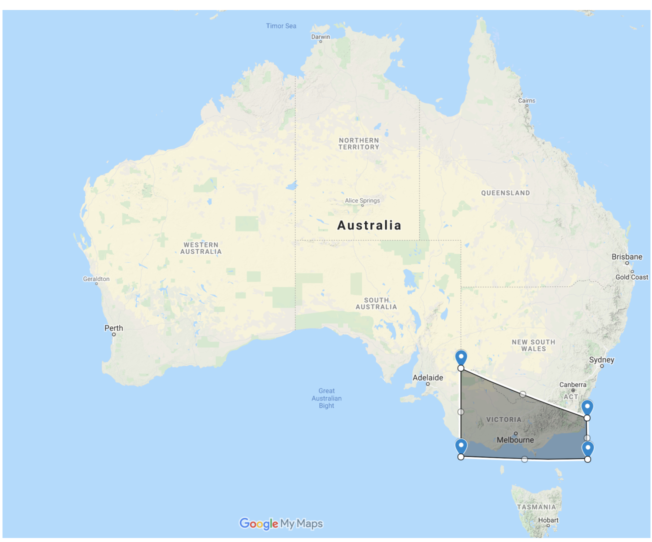


Fig. 1: The area under consideration for modeling

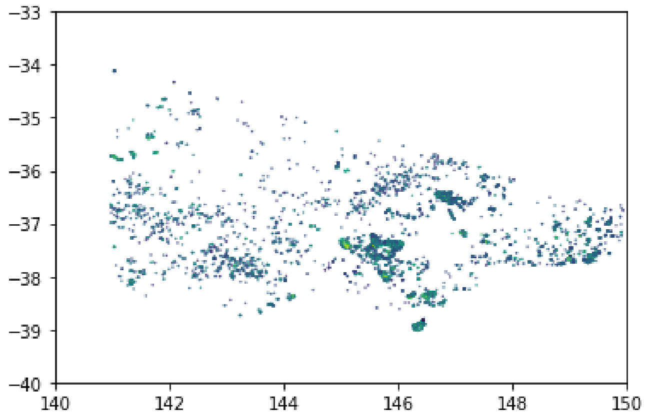


Fig. 2: Fire hot spots with confidence > 40% in Victoria state

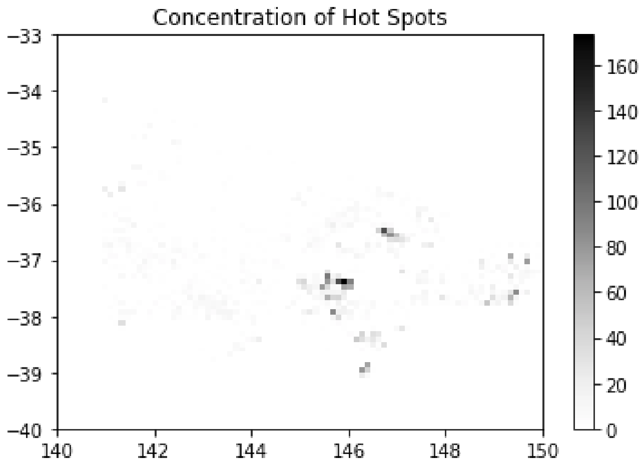


Fig. 3: 2D Histogram of the number of fire hot spots in 10km by 10km bins

The MODIS data we collected contains fire hot spot data for the entire world. To restrict the data only to Victoria, we constructed a trapezoid to estimate Victoria state (Fig. 1). The set of points (lat, lon) 140.9637 within the corners of this trapezoid are $(-39.2526, 140.9637)$, $(-39.2526, 150.1043)$, $(-33.9806, 140.9637)$, $(-36.7147, 150.1043)$. Note that this trapezoid encloses a small portion of New South Wales. However this will not matter when determining the optimal number of drones needed for combating fires because we will assume that drones can only take off from and land in Victorian airstrips.

Since the MODIS data provided us with hot spots with different confidences, we decided to discard the hot spot data with confidence < 40%. Then, we create a 2D histogram of the number of hot spots with confidence > 40% with bins of size 10km by 10km (Fig. 2 and 3). This allows us to define regions of fire measured by the number of hot spots in that bin.

5 Q1. Optimal Mix of Drones

Our objective in the first part of our analysis is to determine an optimal mix of SSA drones and radio repeater drones to survey and relay communication about fires in Victoria subject to constraints that include Victoria's budget dedicated to combating fires, and the maximum flight time and range of the drones.

In finding an optimal mix of SSA drones and radio repeater drones, we seek to maximize the surveillance coverage of the fire. Hence, we use a budgeted coverage maximization model [8] to solve this problem. Key factors in our model include the size, area, and intensity of fires over the varying topographical Victorian landscape.

5.1 The Model

We treat the problem of finding the optimal number of SSA drones and radio repeater drones separately because both drones have different purposes - SSA drones are for surveillance and telemetry, whereas radio repeater drones are for message relaying on the front lines. Thus, we want SSA drones to cover the interiors of fire regions for collecting and transmitting information about the bushfires, and we want radio repeater drones to be in optimal position with respect to the ground personnel who are near the perimeter of the fire for improved communications.

We use Gurobi's Cell Tower Coverage model [4] as a launching pad for our approach to this budgeted coverage model. Although Gurobi's model is written for maximizing signal coverage from stationary cell towers, we modified it to satisfy the dynamic conditions of this model. Using the notation from Gurobi's model [5], we may label the following:

Sets and Indices
$i \in T$: Index and set of potential launch/landing sites for a drone
$j \in R$: Index and set of bins containing hot spots.
$G(T, R, E)$: A bipartite graph defined over the set T of potential launch/landing sites, the set of bins R that we want to cover, and E is the set of edges, where we have an edge $(i, j) \in E$ if bin $j \in R$ can be covered by a a drone launching from location $i \in T$.

Parameters
$c_i \in \mathbb{R}^+$: The cost of a drone at launch/land site i.
$p_j \in \mathbb{N}$: The number of fire hot spots in bin j.

Decision Variables
$\text{covered}_j \in \{0, 1\}$: This variable is equal to 1 if bin j is covered; and 0 otherwise.
$\text{build}_i \in \{0, 1\}$: This variable is equal to 1 if drone is built/located at site i; and 0 otherwise.

Objective Function(s)
In our model, we choose to prioritize the coverage of the bins with the most number of hot spots with SSA drones since gathering information about these regions is paramount to stopping the accelerating spread of fire. Thus, we try to maximize the drone coverage over the bins most populated by hot spots.

$$\text{Max} \quad Z = \sum_{j \in R} p_j \cdot \text{covered}_j \tag{0}$$

Constraints
Coverage. For each bin $j \in R$ ensure that at least one SSA drone that covers a bin must be selected.

$$\sum_{(i,j) \in E} \text{build}_i \geq \text{covered}_j \quad \forall j \in R \tag{1}$$

Budget. We need to ensure that the total cost of purchasing drones does not exceed the allocated budget.

$$\sum_{i \in T} c_i \cdot \text{build}_i \leq \text{budget} \tag{2}$$

Since the cost of each drone is \$10,000, $c_i = 10000$. Additionally, we assume we have a budget of \$1.5 million to work with since Victoria state allocated \$46 million of their budget toward advancing bushfire management [**firemanagementbudget**].

5.2 Model Implementation - SSA Drones

For our optimization model, we need the set of regions and the number of fires within those regions, the locations of the airstrips and their bordering regions, as well as the drone cost and the budget. Each region was specified by a bin number which was indexed by 0 at $(-40, 140)°$ and enumerated horizontally until $(-33, 150)°$, always left to right. Given a coordinate pair, **getBin**(section) will return the correct bin identifying number. The shading at that bin is indicative of the number of fires within that region.
Furthermore, **getCoverage**(Appendix A) will return an array of regions indicated by their bin identifying number that the drone's range can cover. Since the drone cost is constant at $10,000$, the cost of constructing a drone anywhere remains that price.
This prioritizes the placement of drones to maximize the area of fires covered. Looking at the places that are prone to fires much more likely than other regions from historical data is helpful to predict optimal the optimal number of drones and their distribution.

5.3 Model Implementation - Radio Repeater Drones

For this model, we identify the regions as all the bins in the hist2D plot. The population of each bin was calculated using the following algorithm:

```
IF BIN NOT ALONG BORDER:
    IF FIRE INTENSITY<10000 and FIRE INTENSITY IN A ADJACENT BIN>0:
        FIX POPULATION IN BIN TO 100
    ELSE:
        FIX POPULATION IN BIN TO 0
ELSE:
    FIX POPULATION IN BIN TO 0
```

Since the radio repeaters just need to ensure communication amongst fire fighting personnel, we mainly need to focus on firefighter population distribution. Now, we have considered most of the firefighter population to be located in the periphery of the fires, or in the low-intensity fire zones (upto FRP = 10,000 MW [7]). It is assumed that entering high-intensity fire zones is extremely dangerous.

We have considered the radio drones to have a small functional travel distance (a few times the nominal range), and the bin size is greater than or equal to fit the nominal range of the VHF/UHF 5-watt radios, 5 km. Furthermore, we assume that the radio drones are located at every bin in the plot. While this does not get the Gurobi minimization algorithm working, we constrain the available budget. So, we optimize drone locations in order to get the best setup within budget.

For the topography part, we plan to find the difference between the max and min elevation in all the populated bins and reduce the number of personnel in bins (to 20% of current bin population) with a large difference.

5.4 Results

By iterating over each day of each year of the 19 dataframes, we obtain the optimal SSA and radio repeater drone distribution. After running our optimization model for every day of each year from 2000 to 2019, we plot the maximum optimal yearly number of SSA and radio repeater drones necessary for combating that year's bushfires (Fig. 4,5).

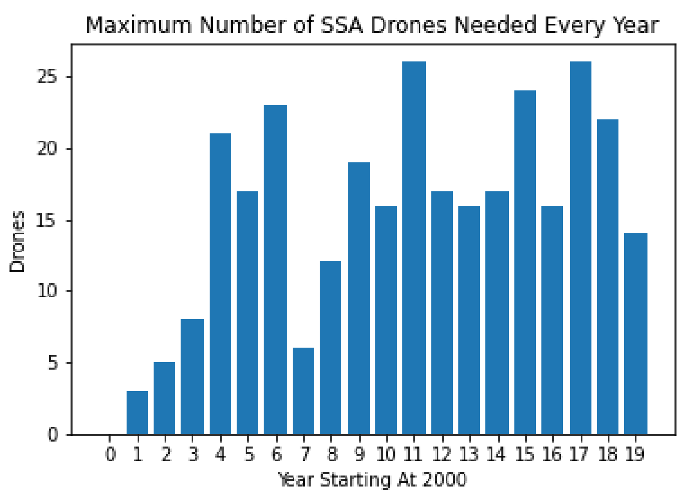


Fig. 4: Optimal SSA drone numbers

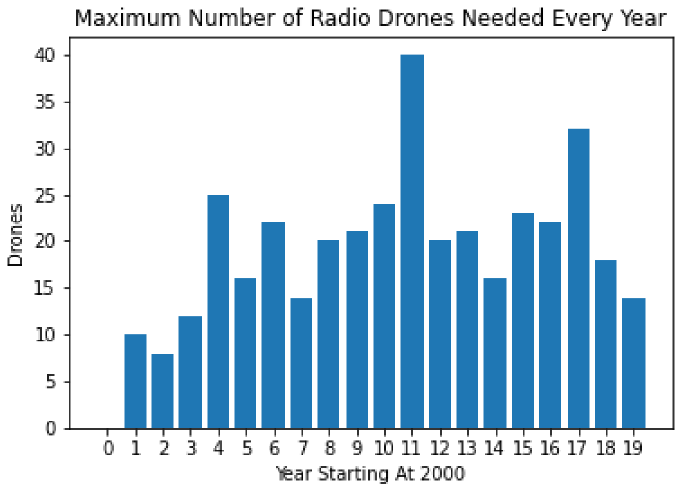


Fig. 5: Optimal RR drone numbers

From this, we advise a total optimal number of 26 SSA drones and 40 radio repeater drones since these are the overall maximum number of drones needed iterated over days and years from 2000 to 2009. Based on the cost of the drone ($10,000) and the maintenance costs as mentioned in Section 6.2, the total purchase cost of this bundle of drones is (for a given year) 66*$18,543 ≈$1,224,000 per year.

6 Q2. Our Model and Bushfires in the Future

6.1 Adaptation of Model to Future Extreme Fire Events

Initially, we obtain the number of reported hotspots each year, and plot this value in a histogram. Then we use linear regression to evaluate the overall trend, in order to understand the progression of number of bushfire hotspots with time. A 2020 study on the effect of anthropogenic climate change on Australian bushfires [**climateresearch**] finds a significant increase (of the order of 30%) in the risk of fire weather.

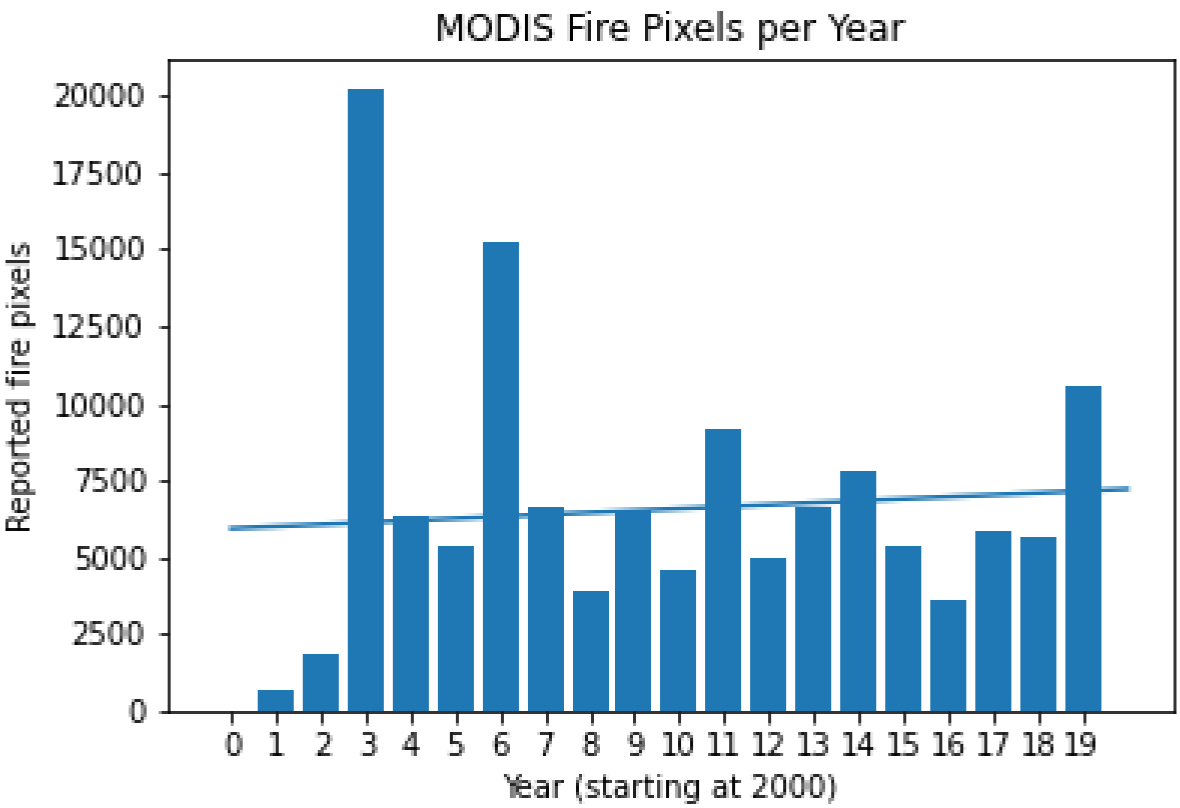
To account for this increase, we scale the coefficient of the linear regression (and values in the FRP matrix) by 30%, and estimate a ballpark value of the number of hotspots in the next 10 years.

Then, we can project the hotspot growth and increase in FRP for the next few years. This enables us to have a rough understanding of the propensity for extreme fire events in the future. We note that the following illustrate our model's readiness to be employed for identifying the optimal drone configuration:

1. Our model for SSA drone deployment now considers the fire population density in a given bin as the primary factor. When extreme fire events become more likely, we can start giving weightage to the FRP (that is, a measure of intensity) in each bin. This will enable a focus on the analysis of both the most intense and most populous hotspots simultaneously

2. As more extreme fire events become unchartered territory, the mixed focus on FRP and fire population density will improve understanding of the safety of venturing into terrains that have been traversed before (due to more intense fires), and thus will inform the radio repeater drone model because now, all of a sudden, these drones are not of use in certain bins due to newly inaccessible terrains

3. Our model for the radio repeater drone deployment can easily be extended to involve an increased population in the periphery of the fire. We cannot, on the other hand, continue assuming that a population of firefighters exists inside bins with low intensity fires as more extreme fire events implies quicker spread of fires and a reduction in safety with increased proximity to fires



6.2 Projected Equipment Cost Increases

Since the drones use electric motors but have the frame of a bush plane for flight range, we can use existing maintenance costs for a industrial quadcopter from the leading brand DJI and the typical maintenance costs for a bush plane.
The main consumable items were the batteries which last for only one year until they begin to lose their charge and need to be replaced. Since each DJI battery has a flight time of 22 minutes, we would need 7 of them to achieve a flight time of 2.5 hours. The inflation rate of Australia is 1.5% so we factor that too.

The following parameters are necessary for the model:

Variable	Parameter	Value	Units
α	Battery Replacement Costs [3]	2,172	AUD/Year
β	Hangar Cost [1]	4,000	AUD/Year
γ	Inspection and Safety Fees [1]	1,170	AUD/Year
δ	Insurance [1]	1,300	AUD/Year

These can be used to model the expected drone costs for d drones over y years by the given equation.

$$C(y,d) = (\alpha + \beta + \gamma + \delta) \cdot (1.015)^y \cdot y \cdot d$$

7 Q3. Placement of Radio Repeater Drones

Using our budgeted maximum coverage model, and assuming we need radio repeater drones near ground personnel on the front lines, we are able to predict that the optimal placement of radio repeater drones is along the perimeter of the fire so that fire fighters have access to communication at all times. As an example, please see Fig.7 and Fig.8 for the most optimal radio repeater distribution in Victoria on Black Saturday, Feb 7 2009 (given the following hot spot distribution):

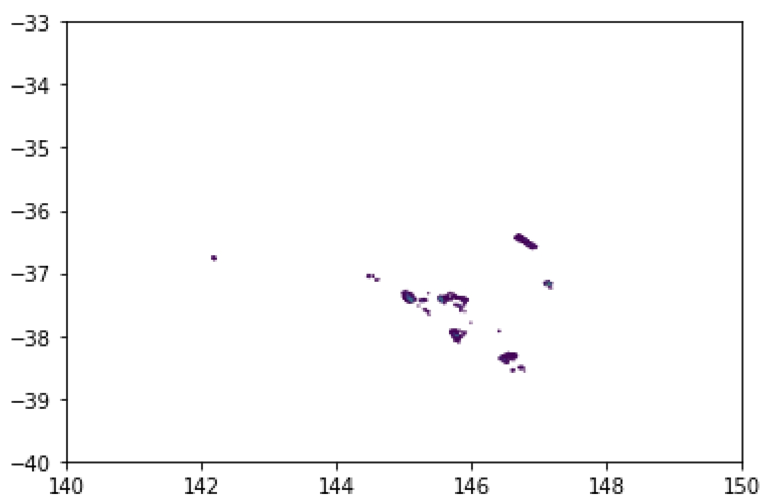


Fig. 6: Non-binned hot spots

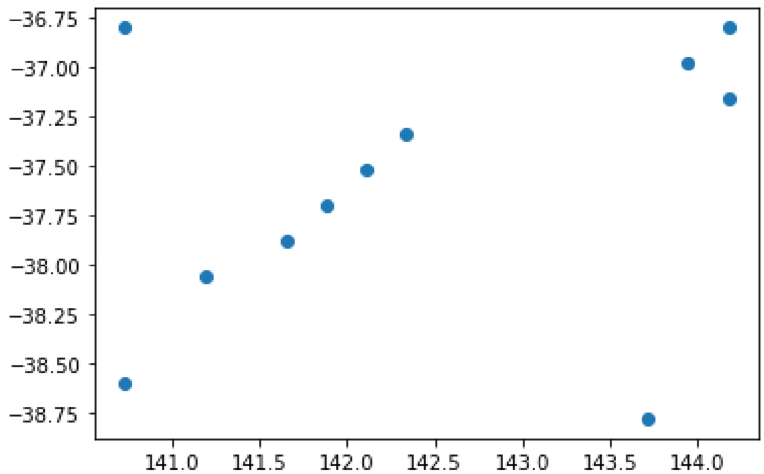


Fig. 7: Optimal radio repeater drone locations

With respect to the topography of Victoria, we plan to find the difference between the max and min elevation in all the populated bins and reduce the number of people in bins (to 50% of current bin population) with a large difference. To incorporate the fire intensity into the model, we notice that we can increase the number of personnel in the periphery of more intense fires - the nature of our code enables a simple addition of a polynomial relationship between the number of personnel and intensity of neighbouring fires.

8 Limitations

As with all models, ours has its limitations:

1. Our model relies on the confidence of MODIS data, and our confidence lower bound of 40% may exclude valid hot spot data or include invalid hot spot data. Changing this lower bound on the confidence with a more systematic and measure approach would benefit this model.

2. Since we use a wraparound of bins in our analysis, the airstrips located close to the edge of some bins may shift the coverage of each drone at that airport by one bin to the side closest to the edge of the airstrip bin. Hence, the true possible fire coverage may be slightly different.

3. In our budgeted maximization model, we used the area of bins to measure the coverage of the fire by our drones. However, this area is not the same as the area covered by the actual fires. Using smaller bin sizes will make our results for fire area covered more accurate.

9 Annotated Budget Request

Respected Budget Officer of Victoria, Australia,

Greetings!

As we are sure you are familiar with, Victoria (and often, Australia as a whole) has often been the brunt of bushfires throughout the winter-spring season. Over the past few years, as our analysis has indicated, there as been an increasing trend, attributed to anthropogenic climate change. Keeping in mind that more extreme fire events are predicted in the future, we write this letter.

Firstly, we would like to appreciate Victoria's focus on the bushfire crisis, through its allotment of $46 million in the 2020-21 fiscal year. Secondly, we would like to bring to your notice the necessity for improved drone technology, and the role that drone technology plays in mitigating the bushfire crisis. The severity of the bushfire crisis necessitates the deployment of two types of drones - radio repeater drones, to enable communication between more extensive networks of fire-mitigating personnel on the frontlines, and SSA drones, to survey and analyze the intensity and geo-spatial complexity of the fires as well as to measure health essentials of frontline personnel.

Given the multifunctional nature of drone deployment and the relative inexpensiveness of the same, we would like to propose to you an optimal drone budget framework, based on our research. We believe that we can deploy sufficient SSA drones for a years' worth of fire crisis management with $742,000 and VHF/UHF radio repeater drones with $482,000, for a total of $1,224,000 of the allocated $1.5 million budget.

We kindly request your consideration.
Thank you so much!
Sincerely,
Team 2125629

References

[1] *Economics of Owning a Small Plane*. URL: https://www.investopedia.com/articles/wealth-management/121415/economics-owning-small-plane.asp.

[2] Alexander I. Filkov et al. "Impact of Australia's catastrophic 2019/20 bushfire season on communities and environment. Retrospective analysis and current trends". In: *Journal of Safety Science and Resilience* 1.1 (2020), pp. 44–56. ISSN: 2666-4496. DOI: https://doi.org/10.1016/j.jnlssr.2020.06.009. URL: https://www.sciencedirect.com/science/article/pii/S2666449620300098.

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[8] Wikipedia. *Maximum Coverage Problem*. URL: https://en.wikipedia.org/wiki/Maximum_coverage_problem#Budgeted_maximum_coverage. (accessed: 02.05.2021).

Appendix: Python Code

A getBin

```
# returns the bin number that contains a given point
def getBin(lat, lon, histplot):
    xTick = 0
    yTick = 0

    # get leftmost lon tick
    for x in range(len(histplot[1])-1): # iterate over left values locations
        if histplot[1][x] <= lon and histplot[1][x+1] > lon:
            xTick = x
            break
    # get rightmost lat tick
    for y in range(len(histplot[2])-1):
        if histplot[2][y] <= lat and histplot[2][y+1] > lat:
            yTick = y
            break

    binNum = (y*(len(histplot[1])-1)) + x + 1
    return binNum
```

B getCoverage

```
# returns an array with the bin numbers that are covered by a drone
def getCoverage(bin, binRadius, histplot):
    bins_covered = []

    xbins = len(histplot[1])-1
    ybins = len(histplot[2])-1

    # draw a box around the airport bin
    num = binRadius
    for j in range(num):
        for k in range(num):
            next_bin = bin - int(num/2) + j + xbins*(k-int(num/2))
            if next_bin >=0:
                bins_covered.append(next_bin)

    return bins_covered
```

C Data Filtering

```
victoriaBoundary = {'minlat': -39.2526, 'maxlatslope':-0.2991,
    'maxlat':-33.9806, 'minlon':140.9637, 'maxlon': 150.1043}
fireType = 0
minConfidence = 40
for yearIndex in range(len(year_df)):
    #restrict to boundary
    year_df[yearIndex] = year_df[yearIndex][(year_df[yearIndex].latitude
        >victoriaBoundary['minlat']) &
    (year_df[yearIndex].longitude>victoriaBoundary['minlon']) &
    (year_df[yearIndex].longitude<victoriaBoundary['maxlon']) &
    (year_df[yearIndex].latitude<
        (victoriaBoundary['maxlatslope']*
            (year_df[yearIndex].longitude-victoriaBoundary['minlon'])
                +victoriaBoundary['maxlat']))]

    #restrict to type 0 fires
    year_df[yearIndex] = year_df[yearIndex][year_df[yearIndex]['type'] == fireType]

    #confidence
    year_df[yearIndex] =
        year_df[yearIndex][year_df[yearIndex].confidence >= minConfidence]

    #reorganize index
    year_df[yearIndex].reset_index(drop=True, inplace=True)
```

D Gurobi Optimization

```
# MIP  model formulation
m = gp.Model("drone coverage")

# number of vars added as the number of sites there are. Is each one built or not? (ty
build = m.addVars(len(sites), vtype=GRB.BINARY, name="Build")

# number of covered vars added as the number of regions. Is each one covered or not? (
is_covered = m.addVars(len(regions), vtype=GRB.BINARY, name="Is_covered")

m.addConstrs((gp.quicksum(build[t] for t in sites if r in coverage[t]) >= is_covered[r
                        for r in regions), name="Build2cover")
m.addConstr(build.prod(cost) <= budget, name="budget")

m.setObjective(is_covered.prod(population), GRB.MAXIMIZE)
```

```
m.optimize()
```