Problem Chosen	2021 MCM/ICM Summary Sheet	Team Control Number
B		2119042

Fire Field Drones Arrangement Based On Rectangular Wildfire Field Coverage and DBSCAN

Since Australia entered the forest fire season in July 2019, forest fires have moved from the most economically developed, most densely populated, southeastern coastal areas, where NSW and Victoria are located, to Tasmania, Western Australia and the Northern Territory. Forest fires are burning in almost every state. As of July 28, 2020, bushfires in Australia may have killed 3 billion animals. The important factor to achieve effective control of forest fires is timely and comprehensive monitoring. With the development of science and technology, fire-proof drones also play a pivotal role in emergency fire monitoring in countries around the world. Therefore, the deployment of drones has become the key to the Australian government's grasp of fire information. In this modeling, we are going to provide reliable deployment for drones under the premise of ensuring economy and safety.

In practicethe shape and size of the wildfire fields are variable and not fixed. Therefore, it is difficult to analyze an irregularly shaped field. To disscuss the number of droneswe abstract the shape of the wildfire field as rectangle, and discuss that based on rectangles of different size.When discussing the number of RDs, we introduce two different drone arrangements4-neighbors and 6-neighbors. Then, we determined the different working positions based on different drone arrangements. Since the drone cannot work continuously, it needs to return to the starting point for recharging after a period of work. So we conduct an analysis on the timing of the "shift" of the drone, and calculate the number of drones needed at that position based on the distance between the starting point and the working position. Next, in order to Maximize the utilization of drones, we used a dynamic programming algorithm to calculate how to split a certain length.When optimizing the model, we proposed the concept of R_s which represents the proportion of the space and reflects the probability of "boots-on-the-ground" forward teams losing contact with the EOC, and gave the relationship between the number of drones required and the R_s.

In order to find the connection between scattered wildfire points, and cluster them into a wildfire field, we use the DBSCAN for wildfire field division and noise data processing based on the data from Australian Government Bureau of Meteorology and NASA Fire Information for Resource Management System. When we Determine a model for fires of different sizes on different terrains, we use data comes from the open-elevation API and Google Earth API. After data review, analysis and discussion, we finally decided to use latitude, longitude, altitude, frp (reflecting the degree of combustion), land type, combustion frequency, scan and track (reflecting the combustion range) as the input indicators for clustering. Then, we combined the analysis of fire field with different scales and the results of clustering to analyze the optimal numbers and mix of SSA drones and Radio Repeater drones to purchase, and predict the extreme fire conditions that may occur in Australia over the next decade.

After completing the external division and the internal modeling of the fire field, we obtain the cost reflecting economic factors and the R_s reflecting safety factors. Then, we use feature engineering and weighted processing methods to fuse them into our final comprehensive coefficients to evaluate the quality of the model.

Keywords: Wildfire; Drones; Circle coverage; Clustering; DBSCAN.

Contents

1 Introduction

1.1 Background

The 2019-2020 fire season in Australia saw devastating wildfires in every state, with the worst impact in New South Wales and eastern Victoria. In eastern and north-eastern Victoria large areas of forest burnt out of control for four weeks before the fires emerged from the forests in late December.

As of 9 March 2020, the fires burnt an estimated 18.6 million hectares, and killed at least 34 people. Nearly 80 percent of Australians were affected either directly or indirectly by the bushfires.

In order to be able to respond to the fire in a timely manner, we have provided Victorias *Country Fire Authority* (CFA) with a rapid bushfire response program, allowing us to eliminate the fire before it causes greater damage.

1.2 Restatement of the Problem

In fact, in addition to the parameters of the drone, the information given in the title is very vague. In order to clarify the situation of the problem so that we can build the model, we have made the following assumptions and regulations:

- SSA drones are used to detect and monitor the real-time status of the fire site, and transmit the data to the EOC, and then the EOC transmits the rescue instructions to the forward teams, and two-way transmission can be achieved between these two ends.
- When we put out a fire in a fire place, it is usually carried out from the outside to the inside. Therefore, SSA drones only need to cover a ring area on the outer circle of the fire.

At the same time, the problems we need to solve include:

- Established a model of Rapid Bushfire Response. While ensuring that the fire site can be fully monitored, it spends the lowest cost.
- Illustrate how your model adapts to the changing likelihood of extreme fire events over the next decade.
- Taking Eastern Victoria as an example, the optimized model can be used to deal with fires that occur on different terrains.
- Prepare a one- to two-page annotated Budget Request.

2 Discussion on the number of drones

In practice, the shape and size of the wildfire fields are variable and not fixed. It's too hard to analyze an irregularly shaped field. So in the discussion below, we abstract the shape of the wildfire field as rectangle, and assume that the entire fire field lies on the plane.

Considering the same cost of the drones equipped with either a radio repeater or video telemetry capability, the number of all drones we need measuring economic costs.

In this section, we will explore the number of drones based on rectangles of different sizes.

2.1 The number of Radio Repeater drones

"Boots-on-the-ground" forward teams use two-way radio communication to give status report to the EOC and allows the EOC to give orders directly to forward teams. Deployed personnel carry handheld two-way radios operating in the VHF/UHF bands, which means a 5-watt handheld radio has a nominal range of 5 km over flat and limited range of 2 km in an urban area. In the following, we use RD to represent drone equipped with radio repeater.

When the "boots-on-the-ground" forward teams are fighting the fire, we should try to avoid some points in the fire field with a distance greater than 5km from the nearest RD. In other words, these locations can't be contacted with EOC. Therefore, the problem we have to consider is to cover an m * n rectangle.

The model of the drone we are considering is WileE15.2X Hybrid Drone, the capabilities of the drone are listed in Table 1.

Flight range	Maximum speed:	Maximum flight time	recharge time
30km	20m/s	2.5hr	1.75hr

Table 1: WileE15.2X Hybrid Drone Capabilities

According to the data in Table 1, we can see that the maximum flight range of the drone is 30km.When a wildfire occurs, forward teams can only extinguish fire gradually from the outside to the inside, and the corresponding drone release points and charging points should also be on the periphery. Therefore, a rectangle with both length and width less than 60km can be fully covered. We use m, n to denote their length and width of the rectangle. When m > 60km or n > 60km, we can't fully cover the full fire field because of the limits on the maximum range of drones. Accordingly, for this kind of large rectangle, The drone can fly up to 30km inward from the periphery of the rectangle. For instance, to deal with a rectangle with m = 150km, n = 100km, the drones cannot access the internal rectangular range of m1 = 90 and n1 = 40. In this case, in order to ensure the safety of forward team personnel, their area of activity should be restricted to within the large rectangle and outside the small rectangle.

After the fire outside is extinguished, the entire team and the release point and charging point of the drone will be pushed forward.

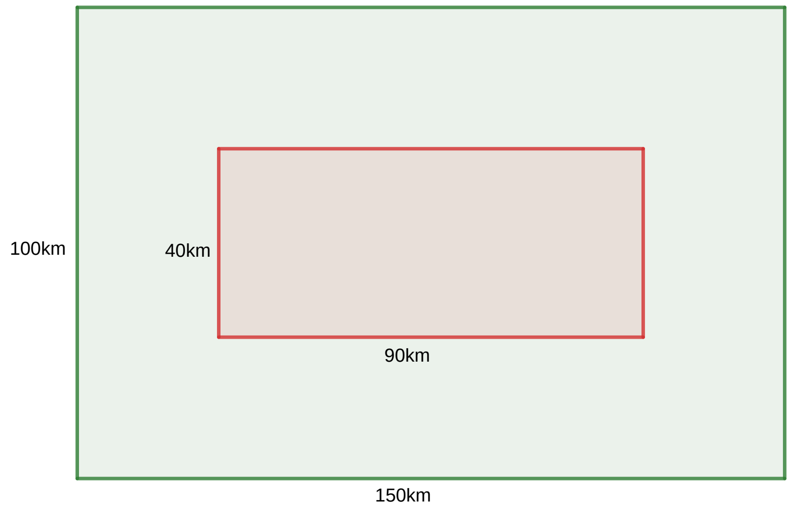

Figure 1: Rectangule with $m = 150km, n = 100km$

2.1.1 $m < 60$ *and* $n < 60$

In this case, the entire rectangular wildfire field can be fully covered, that is to say, at any position in the wildfire field, we can directly or indirectly communicate with EOC (signal propagation through RD). Please note that the current discussion is based on the entire rectangular fire field on the plain.

On the plain, the maximum range of the "boots-on-the-ground" forward team's handheld two-way radio equipment is 5km. Therefore, each RD can cover a circle with a radius of 5km around it.

Two different coverage methods are proposed in the following discussion. One is 4 neighbor, the other is 6 neighbor. 4 neighbor means that for each RD, there are 4 nearest RDs around it. And 6 neighbor means that for each RD, there are 6 nearest RDs around it.

We use r to denote the coverage radius of RD, and d to denote the distance between two adjacent RDs.

2.1.1.1 4 neighbors In order to meet the security requirements, we need to consider the distance between the two nearest RDs.

As shown in the figure below, in the rectangle, there are still some areas that do not belong to any circle. We call this "space".

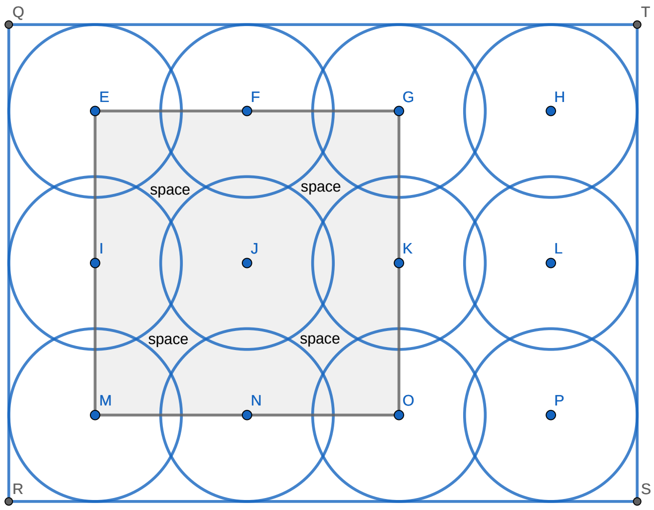

Figure 2: Schematic diagram of "space"

We use R_s to denote the space rate:

$$R_s = \frac{4S_{\text{space}}}{\text{total area of } 9RDs} \tag{1}$$

It is obvious that we can use r (coverage radius of RD) and d (distance between two nearest RDs) to denote R_s.

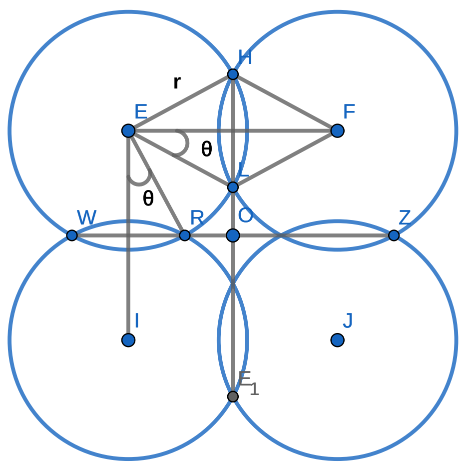

Figure 3:

$$\theta = \arccos \frac{d}{2r} \tag{2}$$

$$S_{RLO} = \left(\frac{d}{2}\right)^2 - 2 \times \frac{1}{2} \times \frac{d}{2} \times \frac{d}{2} \tan\theta - \frac{1}{2}\left(\frac{\pi}{2} - 2\theta\right) r^2 \tag{3}$$

$$S_{space} = 16\, S_{RLO} \tag{4}$$

$$S_{\text{all}} = 9\pi r^2 - 24\left(\frac{1}{2} \times 2\theta r^2 - 2 \times \frac{1}{2} \times \frac{d}{2} \times \sqrt{r^2 - \frac{d^2}{4}}\right) \tag{5}$$

$$R_{\text{s}} = \frac{S_{\text{space}}}{S_{\text{all}}} = \frac{16\left[\frac{d^2}{4}\left(1-\sqrt{\frac{4r^2}{d^2}-1}\right)-\left(\frac{\pi}{4}-\arccos\frac{d}{2r}\right)r^2\right]}{9\pi r^2-24\left(r^2\arccos\frac{d}{2r}-\frac{d}{2}\sqrt{r^2-\frac{d^2}{4}}\right)} \tag{6}$$

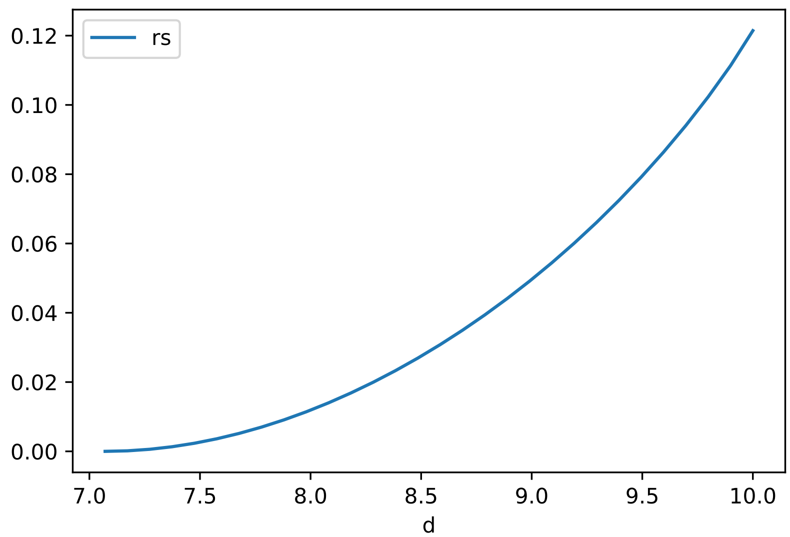

Figure 4: R_s-d Diagram

In fact, R_s represents the proportion of the space and reflects the probability of "boots-on-the-ground" forward teams losing contact with the EOC. The larger the R_s, the more likely the forward teams will lose contact with the EOC.

In this Arrangement, if we need Absolutely safety, which means R_s is 0. The relationship between d and r is:

$$d = \sqrt{2}r \tag{7}$$

Next, we will calculate the number of RDs required when $m, n < 60km$:

In order to make full use of drones, we release and recharge the drone along the direction perpendicular to the edge of the rectangle (wildfire field).

N_x denotes the number of drones in the row direction, and N_y denotes the number of drones in the column direction, then we can get the length and width of the rectangle.

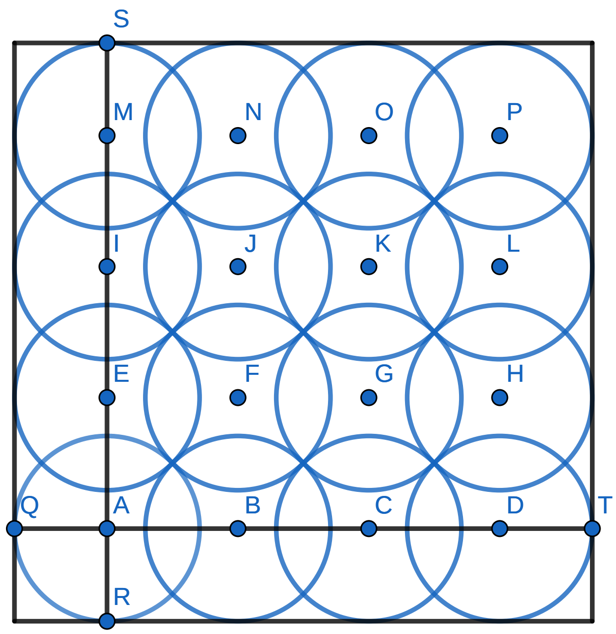

Figure 5:

$$\begin{aligned} length &= (N_x - 1)d + 2r \\ width &= (N_x - 1)d + 2r \end{aligned} \tag{8}$$

The maximum length and width are 30km:

$$(N_x - 1)d + 2r < 30 \tag{9}$$

Then we find that max value of N_x is 4 (and it is the same with N_y).

N(N_x or N_y)	Target workplace $(N-1)d + r$	Maximum coverage length $(N-1)d + 2r$	Time spend on the road
1	5.000km	10.000km	4min10s
2	12.071km	17.071km	10min4s
3	19.142km	24.142km	15min58s
4	26.213km	31.213km	21min51s

2.1.1.2 Timing Diagram So far, in this arrangement(as shown in figure 5), We have determined where the drone will work. Since the drone cannot work continuously, it needs to return to the starting point for recharging after a period of work. Therefore, it is not enough to just arrange one drone at each work position.

Here we conduct an analysis on the timing of the "shift" of the drone.

Suppose the time required for the drone to reach the work place is x min. For the existing drone A and drone B, the longest flight time of the drone is 150 minutes, and the drone charging needs 105 minutes.

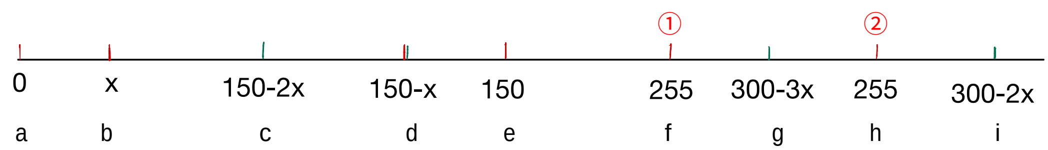

Figure 6: Timing Diagram

a: Drone A starts from the starting point

b: Drone A arrives at the destination(work position)

c: Drone B starts from the starting point

d: Drone A starts to return; Drone B arrives at the destination

e: Drone A return to starting point for recharging

g: Drone B starts to return;

i: Drone B return to starting point for recharging

Through the analysis of the working sequence of the drone, two possibilities be found:

1) $225 \leq 300 - 3x, that\ is\ x \leq 15(km)$

2) $255 \geq 300 - 3x, that\ is\ x \geq 15(km)$

From the above analysis, it can be known that when the drone's working location is less than 15km, two drone shifts are enough; when the drones working location is greater than 15km (less than 30km), three drones are required.

N(N_x or N_y)	Target workplace (N - 1)d + r	Maximum coverage length (N - 1)d + 2r	Time spend on the road	Number of drones required
1	5.000km	10.000km	4min10s	2
2	12.071km	17.071km	10min4s	2
3	19.142km	24.142km	15min58s	3
4	26.213km	31.213km	21min51s	3

Use the table to analyze the number of drones required in a given direction:

In one direction, two drone charging points can be established on both sides of the rectangle.

For example, for a length of 20km, we only need to build one drone recharging point, so that we need 3 drones in that direction. If we split 20km into 10km + 10km, we need 2 + 2 = 4 drones.

For another example, for 48km, we can split it into 24km + 24km or 17km + 31km. If we split it into 24 + 24, then we need 6 drones; but if we split it into 17 + 31, we only need 5 drones.

Algorithm 1 DYNAMIC-DIVIDE(L, N, length)

Input: $L = l_1, l_2, \cdots, l_n$
$N = n_1, n_2, \cdots, n_n$
Initialization: $A[length] \leftarrow \infty$
Output: $arrayA$
for $x \leftarrow 0$ **to** $len(A)$ **do:**
  for $i \leftarrow 0$ **to** $len(L)$ **do:**
    for j **in** L:
      if $x < L[i] + L[j]$ **: then**
        $a[x] \leftarrow min(a[x], N[i] + N[j])$
      end if
    end for
  end for
end for
Return array A

The following tables show the dynamic programming process:

	0	10km	17km	24km	31km
0	0	10	17	24	31
10km	10	20	27	34	41
17km	17	27	34	41	48
24km	24	34	41	48	55
31km	31	41	48	55	62

Length x	Optimal split selection	One side / two sides	Number of drones
0<x <= 10	0 + 10	One side	2
10 <x <= 17	0 + 17	One side	2
17 <x <= 20	0 + 24	One side	3
20 <x <=24	0 + 24	One side	3
24 <x <=27	0 + 31	One side	3
27 <x <=31	0 + 31	One side	3

Length x	Optimal split selection	One side / two sides	Number of drones
31 <x <=34	10 + 24	two sides	5
34 <x <=41	17+24	two sides	5
41 <x <=48	17+31	two sides	5
48 <x <=55	24+31	two sides	6
55 <x <=62	31+31	two sides	6

The results are shown below:

Length x	Number of drones
X <= 17	2
17 <x <= 31	3
31 <x <=48	5
48 <x <=62	6

2.1.1.3 6 neighbors In the four-neighbor model, the repetition ratio of each RD coverage is 18.15%. And for the six-neighbor model, the repetition ratio of each RD coverage is 5.77%.

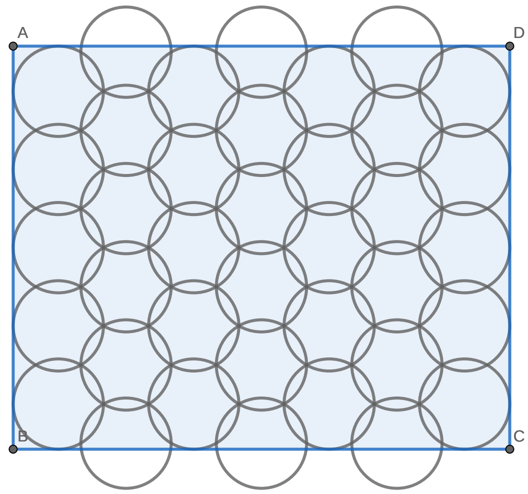

Figure 7: 6 Neighbors

We use N_x to denotes the number of drones in the row direction, and N_y denotes the number of drones in the column direction, then we can get the length and width of the rectangle.

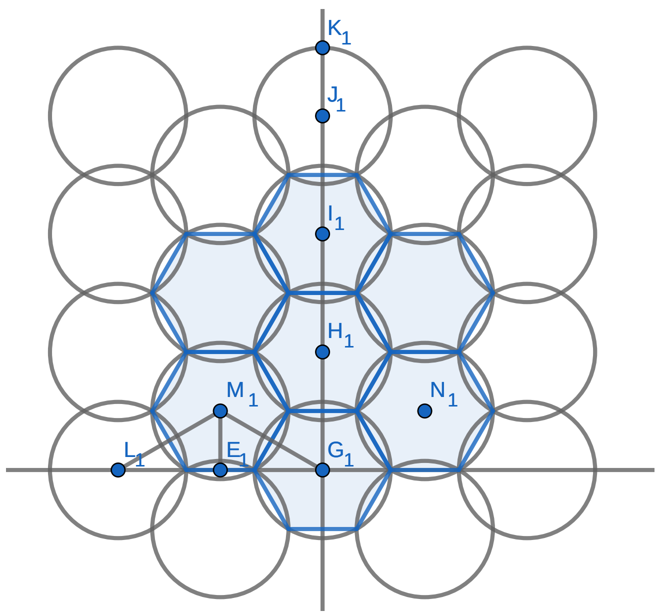

Figure 8:

$$L_{\mathrm{x}} = (N_x - 1)\,\frac{\sqrt{3}d}{2} + 2r \tag{10}$$

$$L_{\mathrm{y}} = \left(N_y - 1\right) d + 2r \tag{11}$$

$$L_{\mathrm{x}} = \frac{\mathrm{r}}{2}\,(3N_{\mathrm{x}} + 1) \tag{12}$$

$$L_{\mathrm{y}} = \mathrm{r}\left(2 + \sqrt{3}\,\left(N_y - 1\right)\right) \tag{13}$$

N_x	Target workplace (N - 1)d + r	Maximum coverage length (N - 1)d + 2r	Time spend on the road	Number of drones
1	5.000km	10.000km	4min10s	2
2	12.500km	17.500km	10min25s	2
3	20.000km	25.000km	16min40s	3
4	30.500km	35.500km	22min55s	3

N_y	Target workplace (N - 1)d + r	Maximum coverage length (N - 1)d + 2r	Time spend on the road	Number of drones
1	5.000km	10.000km	4min10s	2
2	13.660km	18.660km	11min23s	2
3	22.320km	27.320km	18min36s	3
4	30.000km	35.000km	25min49s	3

The coverage area of each drone in the X direction is smaller than that of the corresponding drone in the y direction. In order to make full use of drones, for an m * n rectangle (suppose m <n), the x direction is used to cover the sides of the rectangle with length m, and the y direction is used to cover the sides of the rectangle with length n.

Similarly, using Algorithm 1 can get the number of drones required for different length ranges.

Length x	Number of drones
X <17	2
17 <x <35	3
35 <x <52	5
52 <x <70	6

Length y	Number of drones
y <18	2
18 <y <35	3
35 <y <53	5
53 <y <70	6

2.1.2 $m \geq 60$ *or* $n \leq 60$

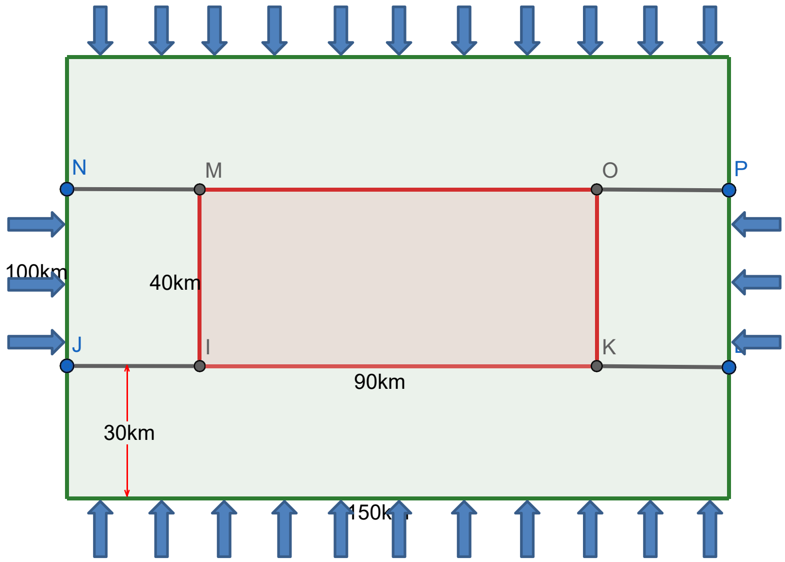

Figure 9:

When m or n is greater than 60, the drones cannot go deep into the wildfire field and can only fly over the outer ring.In this case, the outer ring can be divided into 4 rectangles: 2 m * 30 rectangles and 2 (n-60) * 30 rectangles.

In the direction perpendicular to the boundary, the length is 30km. 3 drones are required in this direction(both 4-neighbor and 6-neighbor). Suppose it requires x charging points in the direction along the boundary. Then there is:

$$(x-1)d + 2r \geq m \tag{14}$$

$$(x-2)d + 2r \leq m \tag{15}$$

$$\tag{16}$$

From the formula above, we get:

$$\frac{m-2r}{d} + 1 \leq x \leq \frac{m-2r}{d} + 2 \tag{17}$$

So m*n rectangular fire field requires

$$3\left(\lceil \frac{\mathrm{m}-2\mathrm{r}}{d} + 1\rceil + \lceil \frac{n-60-2r}{d} + 1\rceil\right) \tag{18}$$

To summarize the discussion above, the number of radio repeater drones for different size of rectangle(wildfire field) is as follows:

If m, n < 70km, the number of drones required are given in the table below:

	0<m <18 (2)	18 <m <35 (3)	35 <m <53 (5)	53 <m <70 (6)
0<n <17 (2)	4	6	10	12
17 <n <35 (3)	6	9	15	18
35 <n <52 (5)	10	15	25	30
52 <n <70 (6)	12	18	30	36

If $m \geq 70$ or $n \geq 70$, the number of drones required are given by the following formula:

$$Number\ of\ RDs = 3\left(\lceil\frac{\mathrm{m}-2\mathrm{r}}{d}+1\rceil+\lceil\frac{n-60-2r}{d}+1\rceil\right) \tag{19}$$

On plain, $r = 5, d = \sqrt{3}r = 5\sqrt{3}$

2.2 The number of Radio Repeater drones with different R_s

In the above discussion, we have given the definition of R_s

$$R_s = \frac{4S_{\text{space}}}{\text{total area of } 9RDs} \tag{20}$$

With the increase of R_s, the possibility of forward teams losing contact with EOC increases, and the number of drones required decreases.

Here are several different thresholds of R_s: 0.00, 0.02, 0.04, 0.06, 0.08, 0.10, 0.12:

R_s	d	$\sigma = \frac{d}{r}$
0.00	7.07	1.414
0.02	8.28	1.656
0.04	8.79	1.758
0.06	9.19	1.838
0.08	9.50	1.900
0.10	9.80	1.960
0.12	10.00	2.000

We can modify the model based as follows:

when m > 70km or n > 70km,

$$Number\ of\ RDs = 3\left(\lceil\frac{m-2r}{5\sigma}+1\rceil + \lceil\frac{n-60-2r}{5\sigma}+1\rceil\right) \tag{21}$$

$$\sigma = \frac{d}{r} \tag{22}$$

2.3 The number of SSA drones

The role of SSA is mainly to complete observation tasks. SSA drones can find the surrounding environment with a radius of 5km during cruising, so its route can be abstracted to a rectangle of 10km * 30km.

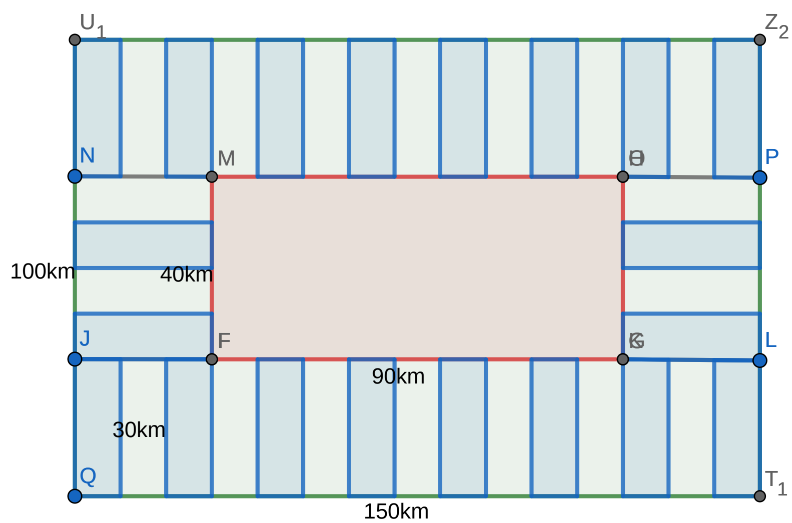

Figure 10:

If $m, n > 60km$, The number of SSA drones is

$$\frac{\mathrm{m}}{10} \times 2 \times 2 + \frac{n-60}{10} \times 2 \times 2 = \frac{2}{5}(m+n-60) \tag{23}$$

The following table shows the number of SSA drones required at rectangles with different size.

m, n (m $\geq n$)	Number of SSA drones
$m < 30$	$2\lceil\frac{n}{10}\rceil$
$30 < m < 60$	$4\lceil\frac{n}{10}\rceil$
$m > 60, n > 60$	$\frac{2}{5}(m+n-60)$

3 Clustering

3.1 DBSCAN

The analysis of the economics and safety of the model is based on the fire site, and the fire field mentioned here is composed of a fire source with similar characteristics. Based on this feature, we choose to use clustering Method to get the divided fire field.

We chose the DBSCAN (Density-Based Spatial Clustering of Applications with Noise) clustering method. We tried to use hierarchical clustering method (such as agglomerative hierarchical clustering), but its computational complexity is too high, and the result is likely to cluster into chain clusters. Then we tried distance-based clustering algorithms (such as K-means), but this method is more suitable for spherical or spheroidal clusters, and the noise processing effect in this model is not satisfactory. Finally, we observe that the principle of DBSCAN is to search for high-density areas separated by low-density areas in the data set. The search process is actually very similar to the principle of the spread of forest fires, and can find any shape Therefore, it is very reliable to choose DBSCAN as the clustering method of this model.

In view of the fact that the Australian forest fire officially believed that it started in July 2019, and in mid-January 2020, rain, low temperature, no strong wind and other favorable weather occurred in the wildfire zone, the fire was effectively controlled, so we learned from the official website of the Australian Meteorological Agency The fire data from July 1, 2019 to 2020, 31 are obtained as follows.

latitude	longitude	scan	track	acq_date	acq_time	satellite
-11.807	142.0583	1	1	2019/8/1	56	Terra
-11.7924	142.085	1	1	2019/8/1	56	Terra
-12.8398	132.8744	3.1	1.7	2019/8/1	57	Terra
-14.4306	143.3035	1.1	1.1	2019/8/1	57	Terra
-12.4953	131.4897	4	1.9	2019/8/1	57	Terra
...	...	...	...	...	...	...

satellite	instrument	confidence	version	bright_t31	frp	daynight	type
Terra	MODIS	48	6.3	297.3	6.6	D	0
Terra	MODIS	71	6.3	297.3	11.3	D	0
Terra	MODIS	42	6.3	298.7	23.1	D	0
Terra	MODIS	33	6.3	296.1	6.5	D	0
Terra	MODIS	36	6.3	298.8	27.6	D	0
...	...	...	...	...	...	...	...

Table 2: DATA Source: Australian Government Bureau of Meteorology, NASA Fire Information for Resource Management System

We choose latitude, longitude, brightness, scan and frp as input feature, because scan and track reflect actual pixel size and frp(Fire Radiative Power) can be treated as an indicator of the degree of combustion. As the subject requires consideration of two factors, terrain and combustion frequency, we got the elevation and terrain data of each row through Google Earth API and open-elevation API and specified a special rule for the simplified calculation of the combustion frequency. Simply put, the combustion frequency of all combustion sources (that is, each row of data) is initialized to 0. If it is found after the time node t1 of the combustion source A, such as t2 (for example, t2 is 2019/07/01, t1 is 2019/01/ 02) If a large fire occurs again at combustion point B within 10km from combustion source A, then we add 1 to the frequency of the data line corresponding to combustion source A. After our data is supplemented, the data composition you will see is roughly as follows.

latitude	longitude	brightness	scan	track	frp	elevation	terrain	frequency
-11.81	142.06	313	1	1	6.6	224.56	forest	89
-11.79	142.09	319.3	1	1	11.3	221.09	river	14
-12.84	132.87	311.6	3.1	1.7	23.1	402.34	forest	206
-14.43	143.3	310.1	1.1	1.1	6.5	200.98	forest	107
-12.5	131.49	310.3	4	1.9	27.6	189.76	plain	65

The current data needs to be further processed. We need to convert the latitude and longitude data unit into km according to the formula, and perform one-hot operation for the terrain column data. Finally, all data is standardized, and then the next step of clustering can be started.

$$longtitude = longtitude \times 111 \times \cos(latitude) \tag{24}$$
$$latitude = latitude \times 111 \tag{25}$$

The parameters that need to be adjusted for the DBSCAN method are only eps and min_samples, and the DBSCAN algorithm is deterministic. When the same data is given in the same order, the same cluster is always formed, that is, the fire field is stable every time. For eps, we select the value in the order of 0.5, 0.2, 0.1, 0.05, 0.08, 0.09, 0.07. For min_sample, we select the value in the order of 5, 6, 7, 2, 3, 4. Finally, we found that the clustering effect is best when eps=0.08 and min_sample=3. Mainly reflected in: First, the loss function calculated according to this value is the smallest. Second, after analyzing the data of all the fire scenes we have divided, we found that the distribution of the length, width and area of the fire scenes at this time is basically consistent with the actual experience.

	Width	Heigh	Area
mean	34.10	17.92	1131.68
std	32.21	19.63	2588.67
min	0.93	0.04	0.12
0.25	9.61	3.93	39.39
0.50	27.35	11.10	306.48
0.75	48.19	25.60	1157.13
max	268.77	245.10	61167.53

At the same time, we found that the fire distribution map we obtained based on clustering is basically consistent with the fire distribution map given in Australia on October 1.

After the clustering is completed, we will get many clusters in units of days, and one cluster corresponds to a fire field. The length and width of the fire field is the length and width corresponding to the rectangle that can exactly cover all the fire sources in the cluster. The covered rectangle requires that the length and width be parallel to the latitude and longitude lines in the plane projection.

3.2 Loss Function

Taking into account the requirements of the topic to balance economy and safety, our loss function, the evaluation function, mixes the total cost(economy) and the R_s(safety). Since the two parameters of total cost and void ratio are of different magnitudes, data processing is required. Considering that the void ratio ranges from 0 to 1, we normalize the total cost and make it range from 0 to 1. Then we use the void ratio plus the scaled economic factor to get the final The smaller the comprehensive coefficient, the better the fit of our model.

$$loss = RDs + spend \tag{26}$$

Considering that the price of a single drone is 10,000$, and the cost of space movement of the drone is low and the deployment efficiency is high, we divide the fire field on a day-to-day basis and start the drone dispatch at 12 o'clock every night. We go to the day that spends the most as our final expense, which not only ensures safety, but also greatly reduces the purchase cost of drones.

Finally, according to the existence of a sigma coefficient in the rectangular fire field that we need to adjust, we selected 1.414, 1.656, 1.758, 1.838, 1.900, 1.960, and 2.000 as the typical parameters we need to consider, and plotted different sigma changes with the date. Corresponding comprehensive coefficient line chart.

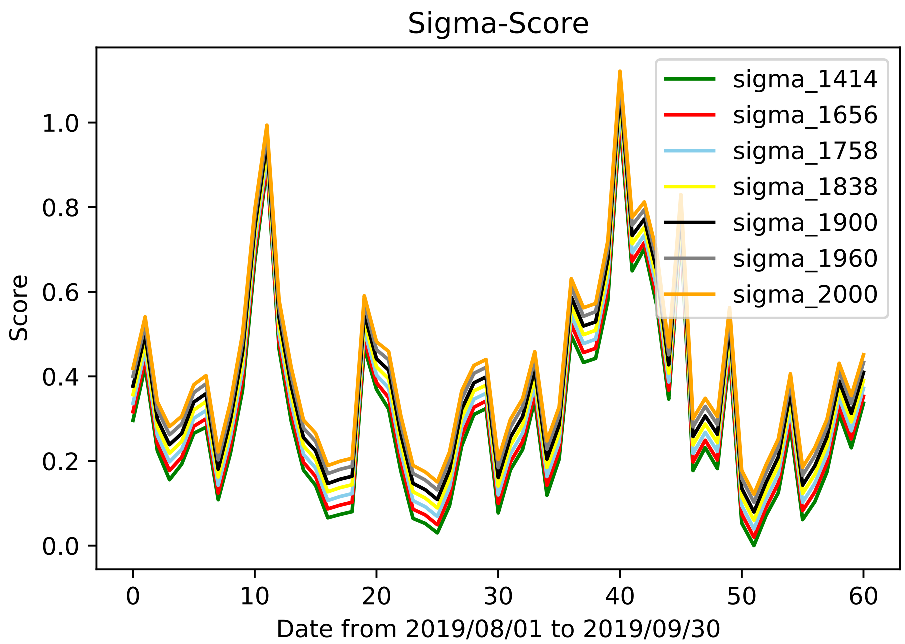

Figure 11: σ_{score}

4 Estimating the Number of the Drones

Now, we can use the results of clustering to analyze the optimal numbers and mix of SSA drones and Radio Repeater drones to purchase, and predict the extreme fire conditions that may occur in Australia over the next decade.

Drones Number	Frequency	Frequency Rates%	Cumulative Frequency%
(5, 309]	204	55.89%	55.89%
(309, 610]	115	31.51%	87.40%
(610, 912]	33	9.04%	96.44%
(912,1214]	8	2.19%	98.63%
(1214, 1516]	5	1.37%	100.00%

Table 3: Frequency distribution table for RD

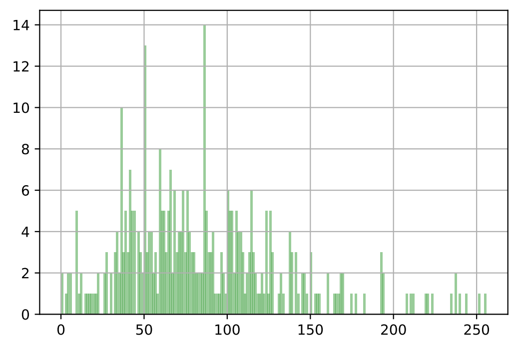

Figure 12: Required Quantity and Frequency Distribution of RD

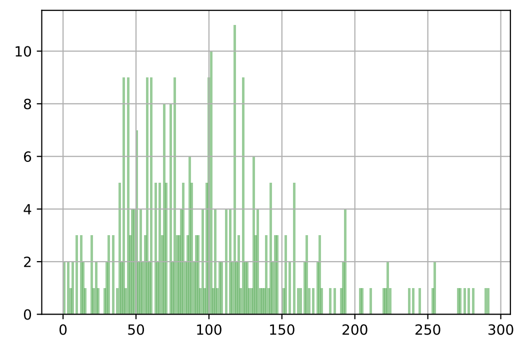

Figure 13: Required Quantity and Frequency Distribution of SSA drones

Drones Number	Frequency	Frequency Rates%	Cumulative Frequency%
(3, 312]	225	61.64%	61.64%
(312, 620]	103	28.22%	89.86%
(620, 929]	27	7.40%	97.26%
(929,1238]	6	1.64%	98.90%
(1238, 1548]	4	1.10%	100.00%

Table 4: Frequency distribution table for SSA

By analyzing the data in the above table, we recommend buying **912** drones equipped with radio repeater (meet 98.63% needs) and **1238** drones equipped with video telemetry capability (meet 98.90% needs).

5 Conclusion

5.1 Advantages

We adopted 4-neighbour and 6-neighbour methods to analyze the rectangle that can be fully covered. In 6-neighbour arrangement, the public area ratio is 5.77%, which is small enough to maximize the use of drones. We defined Rs to represent the uncovered area ratio and used it to explore the relationship between the distance of the nearest drones and the drones coverage radius.

Our model fully consider the important factors that affect the spread of fire, such as terrain, burning degree, burning frequency, altitude, burning range, etc., and integrates the evaluation index of safety and economic factors, namely the comprehensive coefficient. Due to the massive amount of data, we can get almost all fire fields with different terrain characteristics and different combustion levels during traversal, and we have achieved good fitting results, which shows that the model can adapt to different terrains and fire sizes. The clustering characteristics of the DBSCAN method used are very similar to the characteristics of fire spreading. It can well fit the fire field that meets the distribution characteristics of Australian wildfires. The clustering speed is fast and it can effectively deal with noise points(Parameters for filtering noise can be entered when needed), and the shape of the clusters is not biased.

5.2 Deficiencies and Prospects

A larger memory is required to support I/O consumption; it may be better to select the remaining polygons when building the fire field; the mixed method used for the comprehensive coefficient can try

$$\frac{2x_1x_2}{x_1+x_2} \tag{27}$$

$$\frac{e^{x_2}+e^{x_2}}{e^{-x_1}e^{-x_2}} \tag{28}$$

$$\ldots$$

6 Budget Request

According to the chart, the average number of RD and SSA required in recent years are 343 and 319. In order to balance capability and safety with economics, we recommend purchasing drones with 1.5 times the average number of RD and SSA, namely 515 and 479. To meet safety requirements, we expect to get a lower R_s parameter, but at the same time it will increase the cost of drones purchase. The table below is the reference value of R_s that we can provide.

σ	R_s
1.4140	0.0000
1.6560	0.0198
1.7580	0.0395
1.8380	0.0600
1.9000	0.0795
1.9600	0.1025
2.0000	0.1214

The model we provide takes latitude and longitude, altitude, terrain, burning degree, burning range, burning frequency and other indicators that can fully reflect the burning situation of the fire source as the model input, and has been proved to have a good fit under the training of massive data and cross detection effect. At the same time, DBSCAN is used for clustering to achieve fire division. The outward search process of DBSCAN clustering is basically consistent with the characteristics of fire spread. The use of DBSCAN division has laid a solid foundation for the analysis of SSA and RD in the fire scene. Finally, we designated the comprehensive coefficient as the evaluation index, which fully reflects the consideration of maintaining a balance between safety and economy.

Regarding macro deployment, we selected the fire source data clustering from 2019/10/01 to 2020/01/11 to draw a scatter plot here. It is obvious that the fire source is mainly concentrated in the central ring-shaped area of the Australian wildfire area (horizontal and vertical scale zoom The coefficients are basically the same). Therefore, the government should focus its resources on the surrounding area when deploying drones.

	Scale_factor
latitude	907.124117
longitude	1082.433957

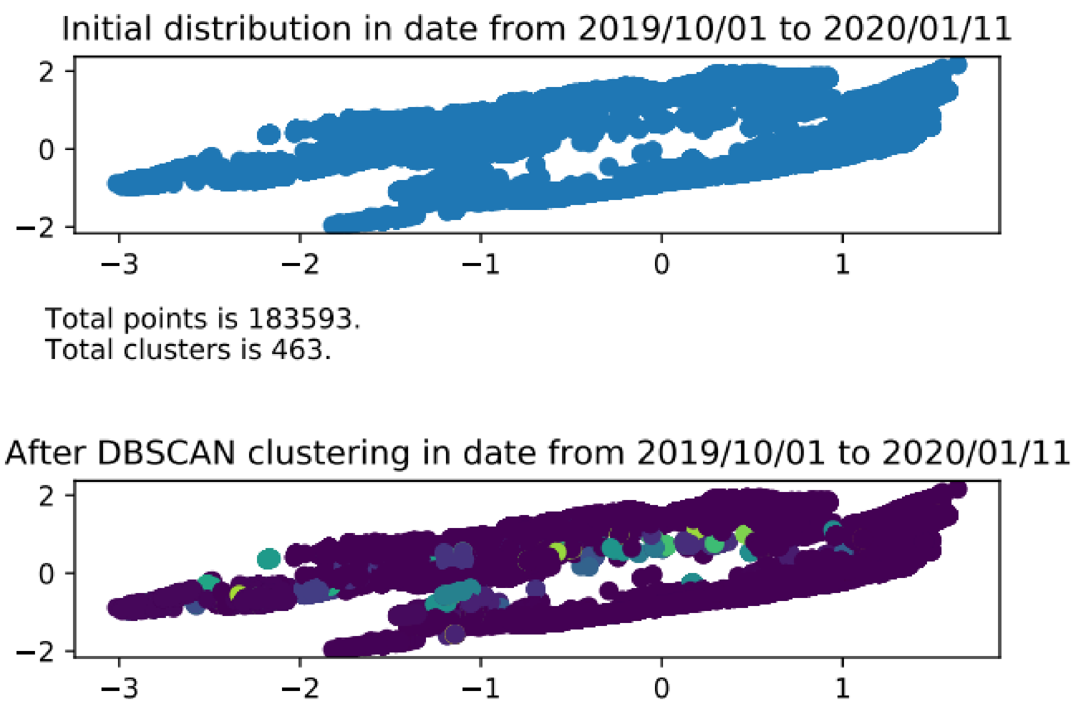

Figure 14:

In practice, we need to deal with the actual situation based on the model we provide and the real geographic factors. For example, we tend to deploy more drones in fire-prone areas; in rivers and plains we tend to deploy drones with a relatively small average number; while in forests, villages and towns, we need to deploy drones with a relatively large average number.

Yours sinserely,

Team 2119042

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