SWIPACS

Smart Wildlife Integrated Prediction and Containment System

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Problem Statement

Current methods of predicting and containing wildfires are ineffective since they only take one primary variable into consideration. This limits the potential to actively detect or predict future fires. Once wildfires begin to spread, they are hard to put out and put lives and homes in danger.

The National Interagency Fire Center has documented an average of 72,000 wildfires each year since 1983, an average that is increasing every year. Furthermore, it has been estimated that the prolonged annual losses due to wildfires are approximately $63.5 billion and $285 billion. This outrageous number is in line with direct and indirect losses, including business values, potential revenue lost, property damage, and loss of resources.

Initial Solution and Background Knowledge

- Our initial solution was the installation of rod-shaped devices throughout forest areas near developed areas.
- The systems would be equipped with low-quality IR cameras that would detect small high temp areas, indicating a fire starter (cigarette butts, campfires, embers, etc.)
- The devices send data to a server, where a machine learning algorithm will process the sensor output and identify a possible wildfire. A non-toxic chemical suppressant would be sprayed on a detected threat.
- A signal would be sent that deploys a drone that investigates the area in question with HR FLIR cameras and also suppresses any remaining threats. If a fire is out of control, the drone would give an aerial perspective of the fire and track it.
- Using different data, a machine learning algorithm will predict the movement of the fire and attempt to control it by triggering certain rods to release a fire retardant to coat nearby fuel and/or release chemical suppressant to control the fire.

Hypothesis

A machine learning algorithm can use collected data to control rod-systems and drones to predict and prevent the start and spread of wildfires.

Results

We conducted a combination of experiments, research, and program testing in order to determine the feasibility of our project. We also these results to iterate and adjust our original design and determine a more effective solution. The following slides describe each aspect we tackled as well as the methodology for each.

Results: Conditions for a Wildfire

After extensive research, we have established that the following metrics may be attributed to increased wildfire potential:

- Soil moisture less than 50% moisture content)
- Temperatures above 30° Celsius
- Humidity below 30%
- Wind speed above 20 Kilometers per hour
- Vegetation:
    - Lichen create the fastest burn and conifer needles have the slowest burn (Shown in diagram)
    - Grasses, shrubs, and brush have the fastest fire spread rates

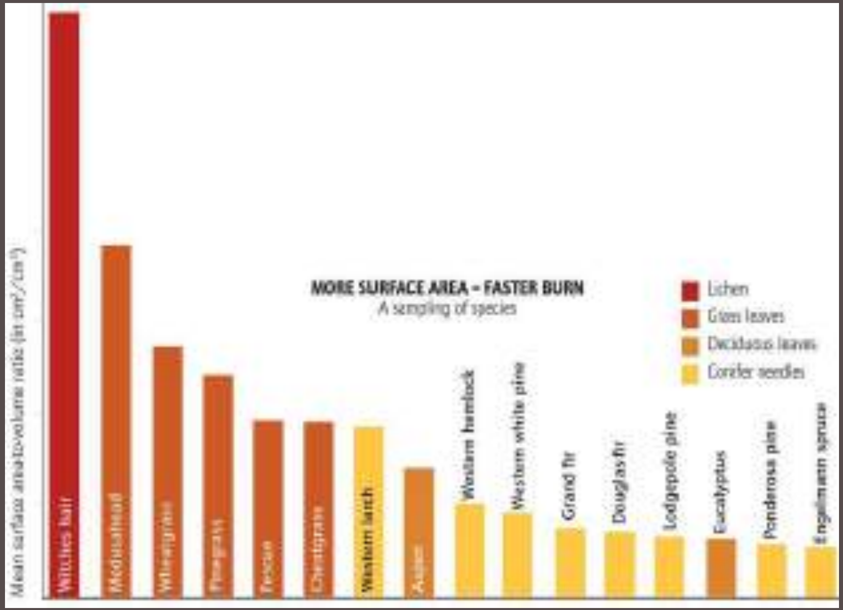

Figure 1. Mean surface area of different types of vegetation

Results: Machine Learning Algorithm (Data processing)

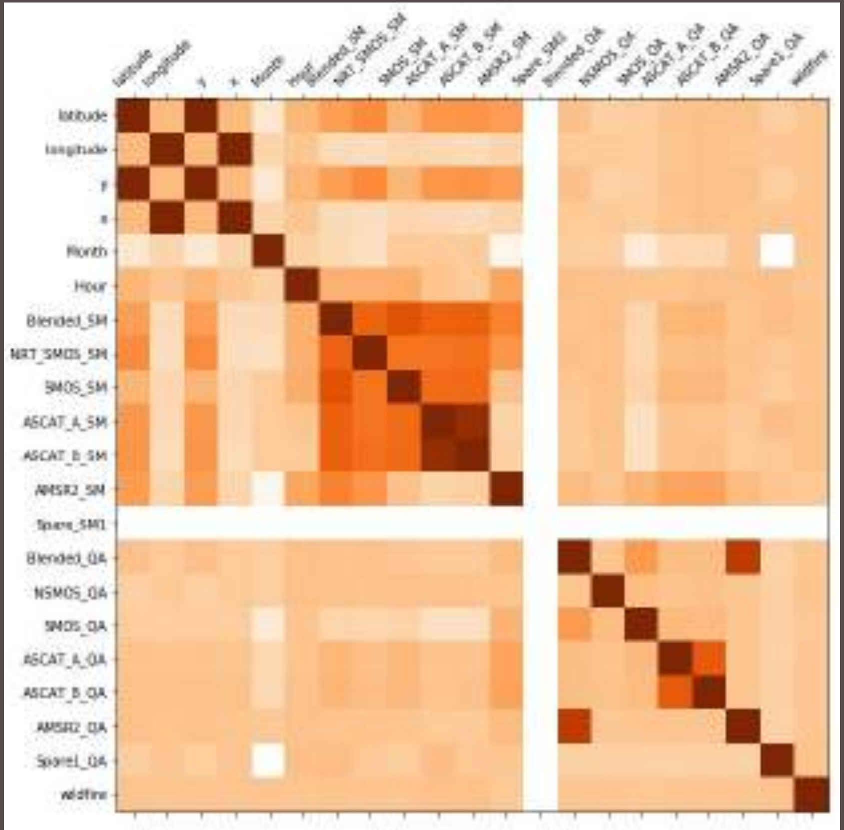

Figure 2. Correlation matrix for soil humidity data with wildfire occurrences

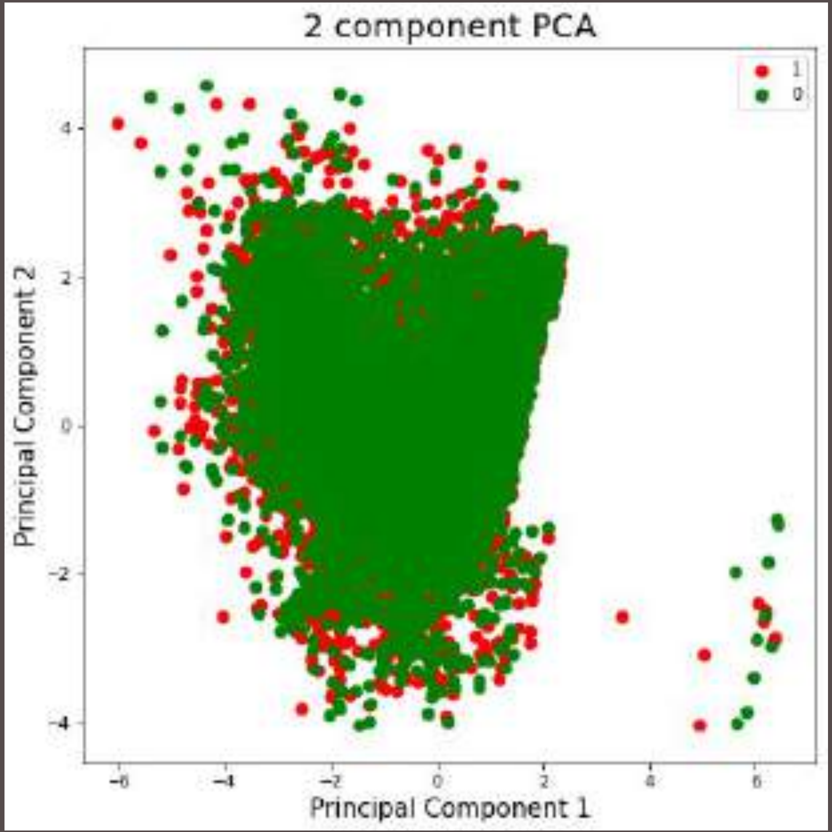

Figure 3. PCA plot to check for correlation of variables

Results: Machine Learning Algorithm (Discussion of Data)

- The decision tree model found it difficult to predict wildfires across the world and could get an accuracy of only 56%
    - Because over half of the data was missing from the soil moisture dataset
    - The NASA wildfire dataset only had data for the days that had wildfires and it was assumed that other days did not have wildfires
    - Data was taken only for 4 months due to the high volume of data
    - The hardware used was not sufficient for the amount of data that had to be processed
    - The data was limited only to satellites
    - The correlation between wildfires and the satellite data was lower than expected
- This accuracy will be increased by:
    - Using a server to train the algorithm on all the available datasets
    - Having more accurate and complete datasets
- Github link: https://github.com/hypercosmac/predicting-wildfireshttps://github.com/hypercosmac/predicting-wildfires**https://github.com/hypercosmac/predicting-wildfires**

```
In [46]: print(confusion_matrix(y_test,y_pred))
         print(classification_report(y_test,y_pred))
         print("Accuracy: ", accuracy_score(y_test, y_pred))

[[   1 2349]
 [   2 2950]]
              precision    recall  f1-score   support

           0       0.33      0.00      0.00      2350
           1       0.56      1.00      0.72      2952

   micro avg       0.56      0.56      0.56      5302
   macro avg       0.45      0.50      0.36      5302
weighted avg       0.46      0.56      0.40      5302

Accuracy:  0.5565824217276499
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=[illegible], stratify=y, random_state =

X_train[0]

array([[illegible]])
```

Training decision tree model

```
from sklearn.tree import DecisionTreeClassifier
classifier = DecisionTreeClassifier()
classifier.fit(X_train, y_train)

DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=None,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=None,
            splitter='best')
```

Testing accuracy of decision tree model

```
y_pred = classifier.predict(X_test) #predicting results for test split
```

Figure 4. Sample program of the machine learning algorithm

Results: Machine Learning Algorithm (Prediction)

- Using the results collected from the ML, we established that with more data it is very possible to accurately predict the areas most prone to wildfires.
- We plan on using the ML to create live maps that combine the different data sets input, whether those data sets are ones collected by the rod systems, drones, or by external data sources (weather stations, satellite images, etc).
    - The maps would determine the likelihood of a fire starting in a specific area, and categorize it under: extremely likely, likely, possible, somewhat possible, very unlikely, and impossible (for water bodies).
- We expect an increase in the previously mentioned prediction accuracy with more complete datasets, as the datasets available online were mostly incomplete and vague.
    - The theoretical data to be collected should make this ML model extremely accurate at predictions, since it will be the first to combine all of the conditions and factors of a wildfire mentioned before.

Results: Machine Learning Algorithm (Detection and Prevention)

- By integrating an infrared processing program (that analyzes the shade of each pixel from an infrared camera to detect fires) into the ML algorithm, we may easily detect fires.
  - It is important to note that the IR cameras on the rods are low-quality but high-range FLIR cameras that will reduce price and cover a larger area per rod. Therefore, the program analyzes the intensity of white rather than the color in regular FLIR cameras
- Based on the position of the detected pixels, the coordinates of the fire will be translated into an XY plane, which will be used to estimate the location relatively.
- It is fairly simple for the ML to determine the secondary rod (mentioned under system design) that is closest to the fire, and control its nozzle position based on the IR position reported.
- The ML will also continue to analyze the area where a fire was detected and will order spraying the area with fire suppressant if a fire is detected once more.
- A drone will also be deployed to analyze the area with a high definition colorized IR camera and a regular camera.
  - The ML will use the drone to suppress any small embers or spark shown after initial spraying. As it is possible that these small embers are undetectable by the low resolution rod cameras.

Figure 5. (top) Black and White IR image (rod output), vs (bottom) colored IR image (drone output)

Results: Machine Learning Algorithm (Tracking and Containment)

- We added a tracking ability to ML algorithm, which utilizes the map mentioned in prediction.
- Based on wind, pressure, vegetation type, moisture, and temperature data collected from weather stations, rod systems, and existing data, the ML is able to predict the movement of a wildfire through a forest.
    - The prediction is based on wind speed, areas of differentiated pressure, moisture content, and combustion rates of different types of vegetation.
- After accurately predicting the path of the fire, the ML will trigger all rod systems in the given path to release a chemical retardants. When the fire reaches rod systems, they release the chemical suppressant to attempt to reduce the intensity of the fire.

Results: Moisture Sensor Prototype

The prototype is built with an Arduino UNO with a self made moisture sensor. The Soil Moisture Sensor uses capacitance to measure dielectric permittivity of the surrounding medium. In soil, dielectric permittivity is a function of the water content. The sensor creates a voltage proportional to the dielectric permittivity, and therefore the water content of the soil. The sensor averages the water content over the entire length of the sensor. The measured moisture content is then compared to the threshold that was found experimentally and through Big Data analysis, following that whenever the moisture content is below the specified threshold a text message is sent to the server every hour with the current moisture content in the soil.

GitHub link to the code:
https://github.com/Rishabhjava/MoistureSMS

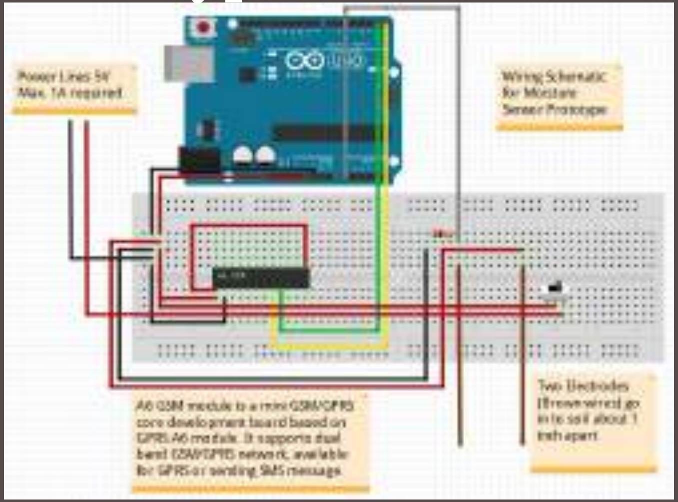

Figure 6. Overview of the circuit model used for moisture input

Figure 7. Prototype for the Moisture Sensor

Results: Chemical Assistance (Fire Retardant)

- While researching possible flame retardants, we discovered a flame retardant developed by the American Chemical Society's James Grunlan. They have developed a "cost-effective nano coating" that coats polyurethane and other sources of fuel with a thin gas-blanket that prevents oxygen from reaching the fuel.
- We plan on using a similar concept of a nanocoating that would be more viscous than the nanocoating in order to withstand the higher temperatures of wildfires for prolonged periods, whilst preventing or minimizing burning of wood and other fuels.
- It is not planned to halt the fire altogether, rather slow down its movement to perhaps give emergency services or the systems enough time to suppress and control the fire.

Results: Chemical Assistance (Fire Suppressant)

- We developed our own environmentally friendly fire suppressant process. A reaction between a solution of 3.0 mol/L of sulphuric acid will occur with sodium carbonate, producing water, carbon dioxide, and sodium sulphate. The reaction will include 1700 mL of sulphuric acid and 560g of sodium carbonate.
- This would produce about **10.46L** of carbon dioxide at SATP.
- Sodium sulphate is also environmentally friendly as opposed to other chemical suppressants, since it partakes in the sulfur cycle. It would actually assist in the remediation of the specific burned area.
- Adding 290 mL of a surfactant would create a flame resistant foam containing the carbon dioxide and quickly extinguish the flame. The ideal surfactant would be a **non-ethoxylated polymerized sugar** that was patented in 2015 (United States Patent Application **20160053159**). This surfactant is flame resistant and is able to withhold gases effectively as mentioned in its patent report.
- We established that 15.3 seconds is a sufficient period of time in order to allow the reactants to mix and react. This time allows the majority of reactants to be consumed whilst allowing the surfactant to effectively mix with the products. The average reaction time was however 60.3 seconds. Therefore, as the reaction continues outside of the system, the foam will continue to enlarge and suppress any secondary embers.

Figure 8. The final experimental trial to produce the chemical suppressant.

Results: Chemical Assistance (Dispersal Method)

- In order to spray the chemicals, we found that using sodium azide would be the most effective approach.
- Each chemical cylinder will have a sodium azide cartridge, that would be triggered by an electric spark, resulting in an immense increase in pressure.
- This pressure will push a piston to force a chemical through a nozzle, directed at a specific location
- The use of sodium azide was determined to be able to give us a spraying range of around 25m.

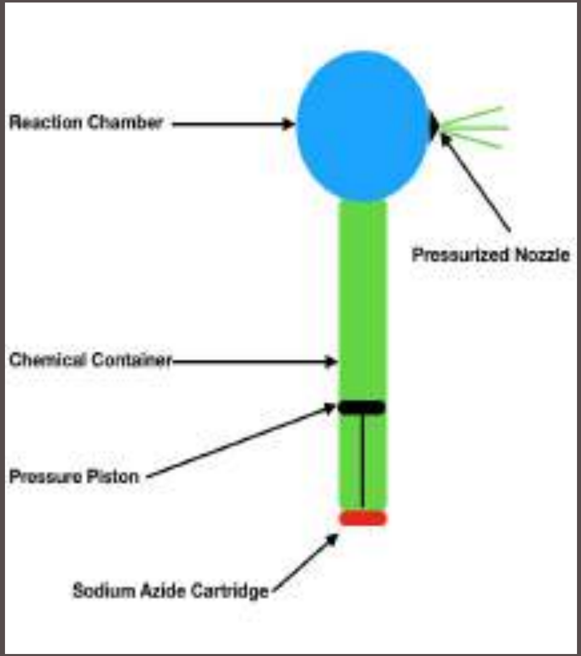

Figure 9. Model of the dispersal method

Results: System Design

We designed a 3D model of the system using a CAD program, and we were able to maximize use of space and place the different components in a relatively small size. We were also able to organize the different systems in the rod design to allow the device to conduct all the sought-after functions. The system will have a base container which will hold the system in place. The base will be an underground cylinder and have a 20cm diameter and 20 cm height. It will house a lithium-ion battery. The rod which would be above ground will be cylindrical with a diameter of 20cm and have a height of about 1.5m. Within the rod, there will be 5 of the chemical suppressant cylinders, which will have a height of 1.15m and a diameter of 5cm. There will be a central cylinder containing the chemical retardant which will have a height of 1.3m and a diameter of 6cm. Each cylinder will have a control plate separating the reactants, these plates will be removed to allow the reactants to interact. At the top of the rod, there will be a small 500ml chamber for excess CO_2 and liquid. Connected to the chamber will be a high-pressure nozzle with a motor to adjust its orientation. At the top of the rod will be an infrared camera and a small solar cell for electricity production.

We also built a prototype to test out the durability and sturdiness of the model. Using PVC piping, we were able to design a system that was sturdy, heat resistant, and could house all the proposed mechanisms.

Figure 10. Prototype of the Primary Rod

Results: System Design (Secondary Rod)

After consideration, we established that we should have a primary system that controls a series of secondary systems. The secondary rods will lack a camera, solar cell, processors, and large battery. The rods would also have chemical cylinders at a height of 1.40m instead, as there is more room for chemicals. The cylinder containing the chemical retardant would also extend into a 5L tank to increase the amount of chemicals. The secondary rods gain power through a small microbial fuel cell, and store energy in a smaller battery.

In order to connect the central rods to the secondary rods, we plan to use a wireless ad-hoc network (WANET). WANET is a decentralized wireless network, which means that we can determine which node would send out information to other nodes on the basis of the routing algorithm. We propose an approach in which a routing algorithm would be developed and consequently employed to enable the central rod to send out signals or information to secondary rods.

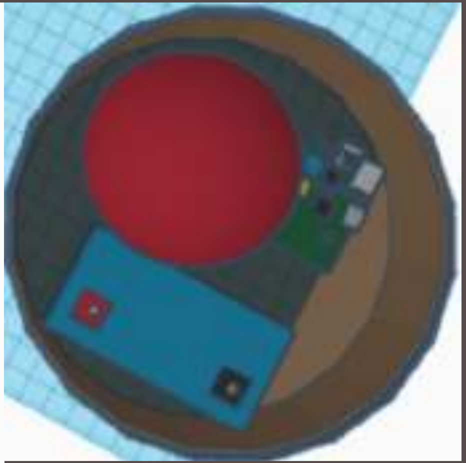

Figure 11. The 3D model of the secondary rod (left), and the internal components of the base (right).

Results: Rod Placement

- As previously mentioned, the primary rod has a camera range of 60m, and the spray nozzles have a range of 25m.
- Given this information we decided on the placement shown (right). Where the blue color represents the camera range, and the red represented the spray range.
- The reason we sought after a dense overlapping approach was that this would result in a more effective use and distribution of the chemical retardant.
  - That is because a more dispersed placement would result in more gaps between the range of the rods. These gaps would be easily overtaken by the fire and would allow to continue past the rods.
- This would also mean that each primary rod would be accompanied by 6 secondary rods, that would cover the area effectively.

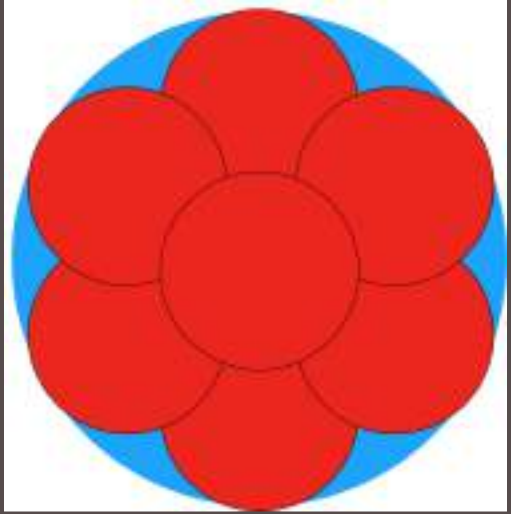

Figure 12. The placement of the primary and secondary rods. Where blue represents the range of the infrared camera, and red the range of the spray nozzles.

Results: Drone Testing

- We are using a drone to help live track, spray foam and contain fires on a grassroot level.
- We built a model of this drone as shown in Figure 14.
- The drone will have a live video-feed relaying back to the ground station that will be controlled mechanically.
- The drone will have a proprietary algorithm that will help detect fires by comparing the chrominance and luminance values of the frame within the video feed to the chrominance and luminance values of actual fire.
- If this comparison matches, the drone will follow the fire and spray the foam.
- This drone was built solely for the purpose of relaying the fire and helping track it while other measures are being employed to stop it from spreading.
- When the drones are not in use, they are left idle in fire stations, awaiting to be triggered by a system.
- GitHub Code: (https://github.com/arunimasen/Predicting-Wildfires)

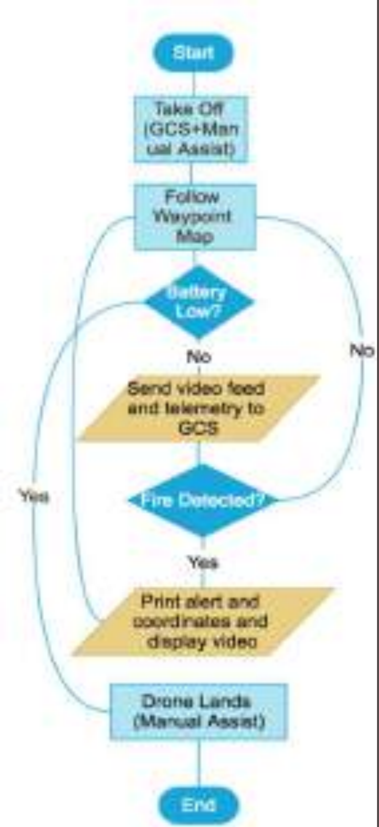

Figure 13. The flowchart for the drone movement, detection and suppression

Figure 14. Prototype of the drone model (with camera and suppressant tank)

Results: Financial Viability

Based on the aforementioned placement of the rod systems, each central rod will be accompanied by six secondary rods. Given the 60m range of the infrared cameras, each 11300 sqm area will cost 187.75 USD. Therefore, covering a square kilometer would require around 88 systems and cost approximately 16522 USD.Also, it is important to consider the aspect of the losses of wildfires. Most articles display the immediate direct costs. However, Headwater Economics' study took analysis of indirect costs, potential revenue losses, socioeconomic effects, as well as post-fire losses over-time (such as rehabilitation costs). They estimated annual US losses due to wildfires to be between $63.5 billion and $285 billion. Given this fact, spending a little over $7 billion to cover the entire state of California is not an impossible proposal. However, the ML algorithm will map out the areas most prone to wildfires, maximizing efficiency of placement. Moreover, given that 84% of wildfires are human-caused, it would make most sense to place the systems in popular camping sites, as well as the borders of those areas.

Primary Rod		**Secondary Rod**	
Item	**Price in USD**	**Item**	**Price in USD**
PVC	$5.00	PVC	$5.00
Infrared Camera	$42.00	Base Container	$3.00
Solar Cell	$7	Fire-Retardant Paint	$2.00
Base Container	$3.00	Battery Pack	$2.00
Fire-Retardant Paint	$2.00	Motor	$2.50
Battery Pack	$10.00	AT Tiny	1.75$
Motor	$2.50	Microbial Fuel Cell	1.25
AT Tiny	1.75$		
A6 GSM	6$		
Other Components	2$		
Total	**$81.25**	**Total**	**$17.75**

Final Solution

Stage 1: Pre-Fire

The first stage of our solution occurs before a fire begins. The ML model uses moisture, temperature, and vegetation data to predict areas most prone to wildfires. The ML model then creates a map displaying the different areas and their vulnerability to wildfires (as shown on the right). The ML model also suggests areas of implementing the system in order to prevent a fire. Based on vulnerability, the model will also suggest areas where fire permits should be strictly enforced, and where fire permits should be revoked. If an individual requests a fire permit, they must inform authorities of the location where they plan on starting the fire, in order to temporarily shut down systems in that area for the period of the permit. Civilians will be able to monitor the area most prone to wildfires, areas where fire permits are required and areas where fires are strictly prohibited through a mobile app.

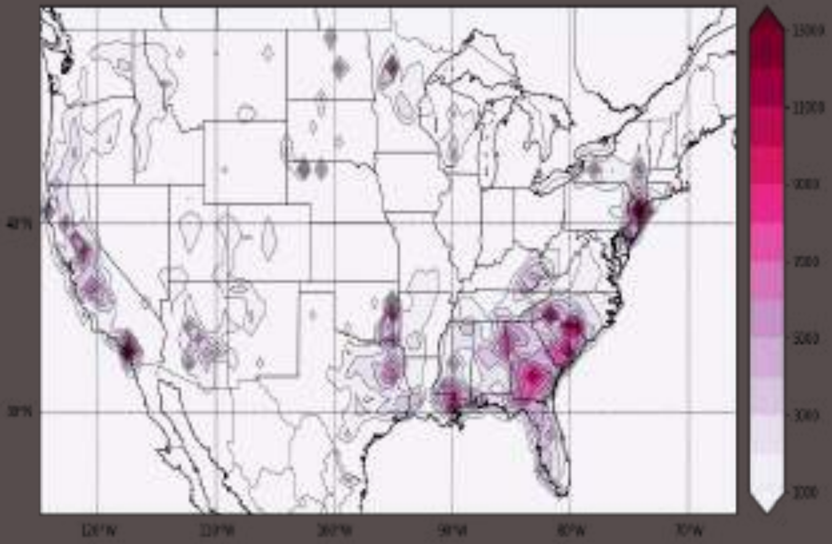

Figure 15. Concept Map to show how prone areas are to wildfires

Stage 2: Fire Starter

In case of a fire, the central rods detect it using IR cameras. The data from the IR cameras is processed by a server at headquarters. Two images are sent every minute for a 360° perspective. If a fire is detected, in the form of an ember or small fire starter, the position is estimand and communicated with their counterpart secondary rods through WANET to release chemical suppressants in that specific area. During that time, the primary rod also communicates with headquarters the detected fire, and provides live images of the area every 10 seconds. Consequently, a drone is employed in the affected area, which is determined by the predetermined GPRS ID. The drone arrives and using the aforementioned code, scans the area and puts out any remaining fire whilst sending back live high definition images headquarters.

Stage 3: Spreading

In the case where the drone detects that a fire has spread beyond control, it will first alert headquarters of the situation so that emergency services may be deployed. The rods in the area are then ordered to spray the chemical retardants in order to coat nearby fuel sources and prevent combustion. The rods then begin to release all of their chemical suppressants in an attempt to prevent the spread of the fire and to suppress it. The drone gives a live update of the situation to headquarters. Using data input, the ML model will begin to track the spread of the fire and predict its path using moisture data collected from different rods, vegetation type data, temperature, wind movement, and differential pressure areas. The predicted path of the fire is used for emergency services to start a more effective plan of action. Moreover, rod systems in the predicted path of the fire begin to release chemical retardants in order to slow down the movement of the fire near it. Once the fire reaches the rods, they release the aforementioned chemical suppressants to slow the movement of the fire.

Conclusion

Based on the results gathered and the final solution, it is safe to accept the initial hypothesis, as the system is feasible and effective.

The proposed solution is feasible since:

- The system is financially viable
- The machine learning algorithm can accurately predict the start and spread of fires. The ML also gives accurate predictions on the vulnerability of areas to wildfires, therefore reducing the likelihood of wildfires starting as authorities will be me more alert in those areas.
- It is the first system to completely integrate types of vegetation for more accurate predictions
- The overall system resulted in effective communication between the primary and secondary rods, as well as the drone systems. This is an immediate result of similar coding functions.

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