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System-Level Performance Analysis of Cooperative Multiple Unmanned Aerial Vehicles for Wildfire Surveillance Using Agent-Based Modeling

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Abstract: In this paper, we propose an agent-based approach for the evaluation of Multiple Unmanned Autonomous Vehicle (MUAV) wildfire monitoring systems for remote and hard-to-reach areas. Emerging environmental factors are causing a higher number of wildfires and keeping these fires in check is becoming a global challenge. MUAV deployment for the monitoring and surveillance of potential fires has already been established. However, most of the scholarly work is still focused on MUAV operations details. In wildfire surveillance and monitoring, evaluations of the system-level performance in terms of the analysis of the effects of individual behavior on system surveillance has yet to be established. Especially in an MUAV system, the individual and cooperative behaviors of the team affect the overall performance of the system. Such systems are dynamic and stochastic because of an ever-changing environment. Quantifying the emergent system behavior and general performance measures of such a system by analytical methods is challenging. In our work, we present an agent-based model for MUAV surveillance missions. This paper focuses on the overall system performance of cooperative UAVs performing forest fire surveillance. The principal theme is to present the effects of three behaviors on overall performance: (1) the area allocation and (2) dynamic coverage, and (3) the effects of forest density on team allocation. For area allocation, three behaviors are simulated: (1) randomized, (2) two-layer barrier sweep coverage, and (3) full sweep coverage. For dynamic coverage, the effects of communication and resource unavailability during the mission are studied by analyzing the agent's downtime spent on refueling. Last, an extensive simulation is carried out on wildfire models with varying forest density. It is found that cooperative complete sweep coverage strategies perform better than the rest and the performance of the team is greatly affected by the forest density.

Keywords: unmanned aerial vehicles; agent-based simulation and modeling; wildfire surveillance; forest fire model

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1. Introduction

In the last decade, there have been several extreme wildfire events around the world. These wildfires have caused substantial social, economic, and environmental losses. According to the World Health Organization (WHO), wildfires have affected 6.2 million people between 1998 and 2017. Also, 2400 deaths worldwide [1] are directly or indirectly caused by wildfires. The magnitude and frequency of wildfires are projected to grow in the near future because of environmental factors. There is a desire for effective monitoring and surveillance of wildfires. Wildfire surveillance is difficult and expensive for man-operated aircraft, especially when dealing with uncontrolled fires. The most common UAV-based application in the wildfire remote sensing domain is fire mapping. Projects such as FireRS [2] and COMET [3] aim to achieve autonomous wildfire detection and mapping to augment emergency response teams.

The primary aim of using multiple agents in any system is to improve overall performance. Especially in the case of wild forest fire monitoring (FFM) using MUAVs, the cost of the system is measured against the improvement of the overall system-level performance. The estimation of the quality of the surveillance and related performance measures of Unmanned Aerial Vehicles (UAVs) is a crucial yet challenging task. Modeling the inherent complexity of surveillance tasks and their stochastic environment through analytical methods is difficult. The applicable models, such as maximal coverage and queuing models, lead to NP-Hard problems without a workable solution. In this paper, we present agent-based modeling for establishing the performance of surveillance factors and the effects of UAV behavior.

The surveillance and monitoring of an area of interest is the fundamental application of UAVs [4]. Because of their low cost, small size, autonomous structure, and high mobility [5], UAVs are frequently used in intelligence, surveillance, and reconnaissance in both civil and military territory [6]. Properly equipped UAVs can provide information about the region of surveillance without jeopardizing the human pilot, which makes them highly desirable for surveillance and wild forest fire monitoring [6,7]. Cooperative MUAVs could perform wide-area surveillance. UAVs are more helpful than a human-piloted vehicle in the sense they are low cost and can fly through hazardous areas. The aim of assigning MUAVs for a particular task is to achieve a better performance than a single UAV. MUAVs are supposed to be helpful over a single UAV by increasing the performance and reliability. However, a challenge yet remains as to how to quantify the performance of the MUAV system. It is easy to compare different features of single UAVs, such as fuel consumption, flight time, broad sensors, etc.

In the MUAV system, the aggregation of individual UAV features may not provide an accurate performance estimate. With an MUAV, the manner in which unique UAV features are employed affects the entire system's performance. However, the same features that make MUAVs better candidates for the missions also make the overall performance estimation an immense challenge. Yet, it is essential to establish a system-level performance measure. Such a measure is crucial to quantify the effectiveness of the resources deployed for monitoring and to find an optimal configuration of a fixed number of resources.

Our work aims to answer two questions:

1. How can the estimation of system-level performance measures of MUAV wildfire monitoring be achieved?
2. Would such an assessment be helpful in the planning, resource allocation, and creating an optimal team formation for wildfire monitoring?

In our work, we focused on the system-level study to establish performance parameters using ABM. ABM is a method of system modeling comprising individual, cooperative agents playing specific roles according to their capabilities and behaviors. Initially, we have a given fixed number of UAVs that will operate in an environment, i.e., surveillance area. The surveillance area is to be allocated to the number of UAVs. The UAVs will observe a Fire Instance (FI) in that area; when an FI comes into the field of view of the surveillance agent, the surveillance agent reports the event as observed. Multiple parameters are assigned to each agent in each strategy, i.e., initial placement, surveillance area, sensor capability, fuel capacity, and communication constraints.

The objectives of the research are:

- To model and simulate an MUAV wildfire surveillance and monitoring system for effective resource management and planning.
- To analyze the effect of different surveillance strategies on the overall system performance.
- To estimate the impact of forest density (fire fuel) on the team size and formation of an MUAV performing fire surveillance.

The goal of this research is to evaluate the overall system performance. The system having multiple agents assigned for surveillance is simulated and analyzed. An environment for surveillance with a team of agents and dynamic FI occurrences is given. The development and simulation of these strategies are carried out in Net Logo. The important and key contributions of this research are the following:

- We have proposed simulations of different strategies, i.e., random strategy, two-layer barrier sweep coverage strategy and full sweep with local communication, and full sweep with global communication strategy. The results are evaluated by comparing each of the above strategies.
- The simulation and analyses of different strategies are presented to show each strategy's performance and resources efficiencies.
- The model is also extended to detailed forest fire monitoring by enhancing the forest fire model presented by [8] and implemented by [9]. We analyzed the effects of forest density on surveillance with four different forest density levels, i.e., 25%, 50%, 75%, and 99%.
- The analysis of the simulation is performed using statistical methods, an Analysis of Variance (ANOVA) to a confidence level of 0.01.

The rest of this paper is organized as follows: Section 2 describes the literature review. Our proposed model is described in Section 3. The designs of the experiments are presented in Section 4. The simulations of the experiments and their results are presented in Section 5. The discussion on the results is carried out in Section 6. Finally, the paper is concluded in Section 7, followed by the future work in the References Section. For ease in referencing abbreviations and the notations used in the article, their explanations are provided in Back Matter.

2. Related Work

Due to the recent abnormal increase in wildfires all over the world, it is important to predict and monitor the wildfires. There has been a significant amount of research carried out to predict the likelihood of bushfire breakout [10,11]. By analyzing the historical data of bushfires along with the weather data, the likelihood of bushfires is predicted using statistical models [12–14]. Recently, many studies focused on the application of UAVs for wildfire monitoring and surveillance [15–18]. UAVs have two main applications in forest fire monitoring. Firstly, the surveillance of large areas for potential fire breakout [19] and, secondly, in the case of wildfire monitoring of the progress and containment of a fire [20]. UAVs are also used to map large-scale fire damage [21]. As mentioned earlier, the focus of these studies is to achieve the specific behavior of a team of UAVs. The design of the specific features and operational control for UAVs is crucial for any system. Thus, most scholarly work focuses on formation control, flight controls, sensor integration, team communication, etc.

Presently, there is a research gap in the literature targeting surveillance performance, particularly the MUAV mission. On a closer look, the nearest similar research we found is related to a Multiple Wireless Sensor Network (M-WSN), specifically the sweeping coverage. It shares many similarities to the MUAV FFM mission, as sensors in an M-WSN are in constant motion, regularly visiting the points of interest. To perform task allocation in an M-WSN, [22] established the quality of the performance by measuring the interval between two consecutive instants of the visit to the same point of interest. Another performance measure is used by [23], which estimates the probability of target node coverage by measuring the overlapping of the area, radius, and angle of the fan area of randomly deployed sensor nodes. However, as these articles mostly use these measures as a supportive qualifier for acquiring the coverage arrangements/orientations, measuring cooperative performance is not addressed. Performance evaluation is a complex task as [24] establishes that min-nodes timely sweep coverage (MNTSC) is an NP-Hard problem. In [25], NASA has used Monte-Carlo sampling with modeling and a simulation-based approach for parametric analysis of conflict detection in air traffic control. This motivated our approach of employing agent-based modeling and simulation for an FFM MUAV mission [26,27]. In recent years, considerable research has been carried out, focused on achieving and improving certain UAV behavior. Mainly, surveillance area allocation and coverage are addressed by [28], in which Caillouet proposes a full-coverage algorithm for covering multiple static targets by minimizing the cost and altitude of UAVs. Garcia, in [27], introduced a behavioral model of multiple agents with different behaviors. The complete area coverage of a known area using multiple robots is proposed in [29]. In [30], Gustavo et al. propose a method for the coverage of the ground area in minimum time using MUAVs. Dimitrios et al. [31] proposed a solution for finding the best location for drones to survey static targets with minimum cost. Several surveillance behaviors are developed in recent studies. In [32], Diana et al. proposed an object-tracking algorithm from a UAV. In [33], Janaina et al. proposed an algorithm for solving task allocation problems in an MUAV. Each study contributes toward perfecting the coverage behavior; however, whether that achieved behavior affects overall performance in a desirable manner is yet to be established. Also, most of the research [6,7] is performed on the static environment, and the static targets analysis of the dynamic occurrence of an FI in the surveillance environment is yet to be performed. Target localization and acquisition behavior are addressed by [26,33–36]. The notable behavior in these articles is how MUAVs cooperatively perform surveillance in the environment. Mostly, each UAV has sensing, processing, and communication capabilities. The UAV searches for the Object of Interest (OI) and observes it. Once the OI is observed, it processes the information specified for a particular mission to achieve the desired goal. The UAV sends information of the OI to the ground station to perform actions. The UAV may track the OI until the ground station action arrives. In [5], Fu et al. propose a multi-UAV cooperative localization algorithm. UAVs search in the surveillance area and locate the OI with the help of the sensors onboard each UAV.

The FFM carried out by an MUAV also bears many similarities to the sweep coverage models of a Mobile Wireless Sensor Network (M-WSN) [37,38]. Sweep coverage with a decentralized allocation is proven to be an NP-Hard problem [39,40]. The queuing model for estimating the effects of a stochastic environment composed of randomly appearing threats monitored by the MUAVs is the M/G/K queue. M/G/k is a queuing model where arrivals are Markovian (modeled as a Poisson process), service times have a general distribution, and there are k servers in the FFM mission; UAVs can be seen as "K" servers, forest fires appear as processes with Markovian "M" arrivals, and UAV threat detection rates with the general distribution "G". These models are also proven to be hard to approximate [41].

Table 1 shows the comparison of possible performance estimation methods that can be employed to MUAV FFM missions. Four key feature estimates, i.e., area coverage, missed OI, team behavior/organization, and overall system-level performance, are considered. It can be seen that ABM is the most suitable method for system-level performance evaluation for the MUAV FFM mission. The above-stated literature survey helped us in selecting the candidate factors of surveillance. We chose coverage strategy, range of detection, communication, and downtime as key factors for our experiments.

The study can be divided into five key activities, as shown in Figure 1. Firstly, after the analysis of the system, a model of the environment is presented. The environment model specifies the forest fire behavior in a region. The rate of appearance of the FI and forest density, rate of burnout, and reduction in fire burnout rate after discovery are modeled independently of the agent's design. Secondly, the agent's behaviors are selected and designed, for instance, the area coverage strategy of the team of a UAV is selected, the speed, the range of its sensors, the communication range, fueling, static or dynamic area allocation, etc. In the third step, the design of the experiment is carried out by selecting what team sizes need to be simulated, how many simulations of each experiment are carried out, how a bigger area space is to be selected, and at what density levels the study needs to be made. After the careful design of each experiment, the simulations are performed using behavior space in Netlogo, and the data of all of the experiments are then stored in separate files for analysis. In its last step, the analysis of the data generated by simulations of an experiment are analyzed using statistical measures (mean and standard deviation) and an ANOVA. An ANOVA is employed on the results of the simulation in order to establish whether the change in behavior significantly affects the experiment results.

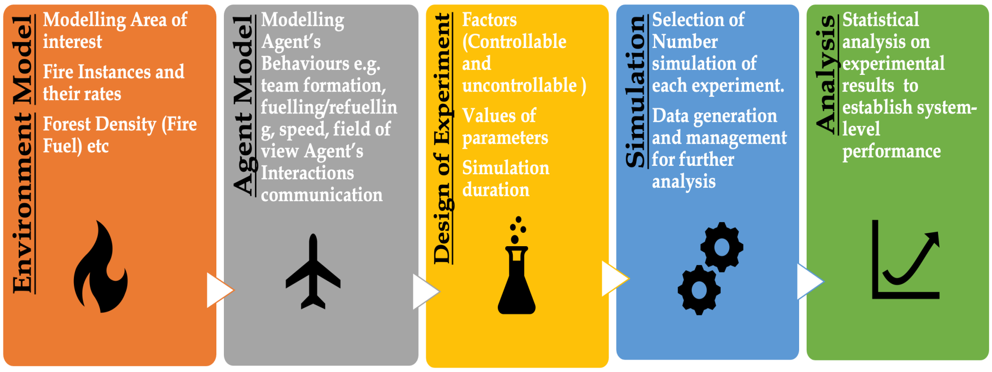


Figure 1. Key Processes.

Table 1. Comparison of Existing Methods.

Methods	Estimations			
	Area Coverage	**Number of OI Missed**	**Team Behavior**	**System-Level Performance**
Probabilistic	Yes	No	No	Infeasible
Analytical	Infeasible	Infeasible	Infeasible	Infeasible
Agent-based modeling	Yes	Yes	Yes	Yes

3. Model Definition

In our simulation, we have simulated FFM surveillance missions [42] where a team of UAVs (watch agents) are tasked to detect and report fires erupting/spreading in the area under surveillance. Let W be the number of watch agents. Thus, $W = \{w_1, w_2, w_3, \ldots, w_k\}$, and E is the area available for surveillance. Thus, the area of surveillance is divided among the available number of agents. $E = \{e_1, e_2, \ldots, e_l\}$. Each agent is assigned its own area in which it will conduct surveillance, e_i assigned to w_j where $i = 1, 2, \ldots, l$ and $j = 1, 2, 3, \ldots, k$. The mission area is modeled as grid workspace where the coordinates are 0 to X_{max} , 0 to Y_{max}. Each agent x, and y axis coordinates are $X_{min}, X_{max}, Y_{min}, Y_{max}$. Total area given for surveillance in terms of cells is:

$$E_{total} = (X_{max} - X_{min} + 1) \times (Y_{max} - Y_{min} + 1) \tag{1}$$

Each watch agent's area of surveillance is:

$$A_s^{w_i} = \left(X_{max}^{w_i} - X_{min}^{w_i} + 1\right) \times \left(Y_{max}^{w_i} - Y_{min}^{w_i} + 1\right) \tag{2}$$

where $X_{min}^{w_i}$, $X_{max}^{w_i}$, $Y_{min}^{w_i}$, and $Y_{max}^{w_i}$ are corresponding coordinates in which the watch agent w_i will perform surveillance. The watch agent w_i will perform surveillance in the corresponding cells that lie inside its area of surveillance $A_s^{w_i}$. The watch agents observe FI in their field of view.

$$FOV_{w_i} = r\theta \tag{3}$$

where r is the radius and θ is the angle. FIs are appearing at random locations at random time intervals, so the positions of FIs $u_i = (x_{random}, y_{random})$. The FI u_i is observed by watch agent w_i when the distance d_{wu} between w_i and u_i is less than r_{w_i}.

$$d_{wu} = \sqrt{(x_w - x_u)^2 + (y_w - y_u)^2} \leq r_{w_i} \tag{4}$$

where (x_w, y_w) and (x_u, y_u) are the coordinates at which watch agent and FIs are located, respectively.

Threats are erupting in the area at random positions at a random time interval. Let $T = t_1, t_2, \ldots, t_n$ be the number of FIs occurring in the surveillance area. The specific FI t_i position is given by

$$T_n(x, y) = (X, Y) \tag{5}$$

where $X \sim U([u_{min}, u_{max}])$ and $Y \sim U([u_{min}, u_{max}])$ are random numbers between u_{min} and u_{max}. The FI t_i randomly moving in the area. Figure 2 shows details of Netlogo model for simulation of MUAV surveillance mission. The controls in the left are used to adjust factors (strategy, number of UAVs, speed of UAV; detailed list is provided in Table 1) for each experiment. The middle canvas simulates the mission and displays the movements of OI (shown as flags) and UAVs (shown as planes). The left pan displays the results of each simulation. Notations used in the model definitions are presented in Back Matter.

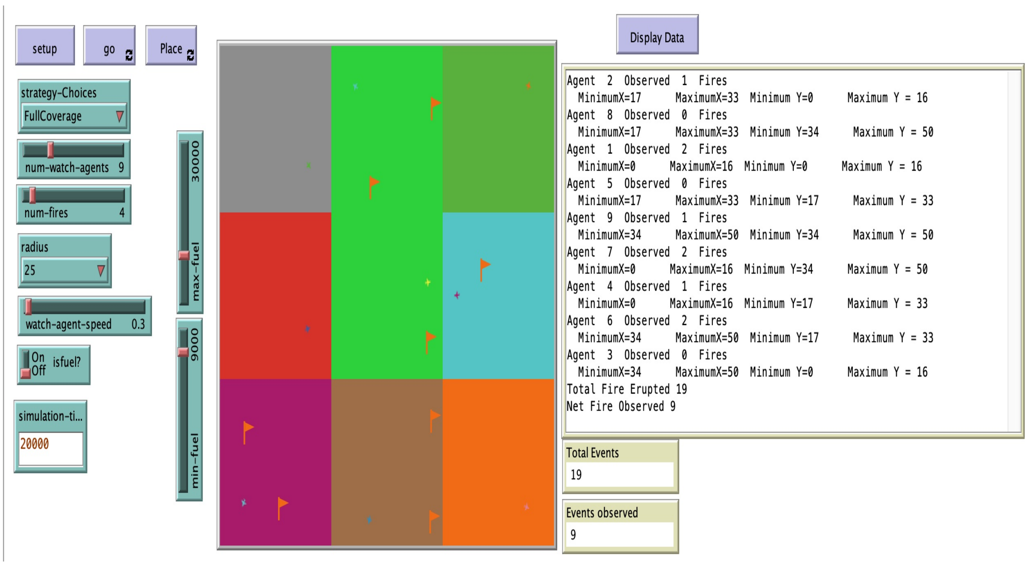


Figure 2. Mission Simulation in Net Logo.

3.1. Allocation Strategies

In our study, we have modeled three allocation strategies, random, two-layer barrier, and sweep coverage. Details of the allocation models are as follows.

3.1.1. Random Strategy

In order to establish the baseline performance, the first experiment is simulated using the random strategy. In random strategy, as the name suggests, the watch agents are placed at random x_{random}, y_{random} positions. The agents perform surveillance in the whole provided environment irrespective of their own area. FIs occur randomly at random positions. Watch agent observes and reports FI under its FOV as shown in (3) with radius r = 5 and angle $\theta = 360$. Watch agents survey the area randomly in the whole area given in Equation (1). Thus, the next x_w, y_w coordinates of the watch agent are as follows

$$x_{i+1}^{w_j} = x_i^{w_j} + \theta \tag{6}$$

$$y_{i+1}^{w_j} = y_i^{w_j} + \theta \tag{7}$$

where $\theta \sim U([-\alpha, \alpha])$ is a random angle between $-\alpha$ and α. Detailed steps of random strategy are defined in Algorithm 1.

Algorithm 1 Random Strategy

```
1: Given Area E, Watch agents W
2: Watch agents are placed at random position x_random, y_random
3: Notable Fire Related Event FI occurs at random intervals and at random positions
4: Watch agents W survey the area E
5: while Resources Available do
6:    Perform surveillance
7:    if FI Observed then
8:       Closely monitor event, till it is managed
9:    else
10:      Survey the area
11:   end if
12: end while
```

3.1.2. Two-Layer Sweep Strategy

This strategy is inspired from linearized coverage [43] where the total area of surveillance E as given in Equation (1) is divided horizontally in two sections E_1 and E_2. The watch agents W_n are divided into two groups G_1 and G_2. Agents in G_1 are placed in area E_1 and agents in G_2 are placed in area E_2. Each sectioned area is divided by the number of agents in the respective group. Thus, dividing the area horizontally, we obtain

$$E_{sub} = (X_{max} - X_{min} + 1) \times \left(\frac{Y_{max} - Y_{min} + 1}{2} \right) \tag{8}$$

Dividing watch agents in two groups

$$G_1 = round(\frac{W_n}{2}) \tag{9}$$

and

$$G_2 = W_n - G_1 \tag{10}$$

Thus, each agent obtains an area of surveillance as

$$A_{surveillance}^{w_i} = (\frac{X_{E_{sub}}}{G_j} \times Y_{E_{sub}}) \tag{11}$$

Each agent w_i will perform surveillance in its own area $A_{surveillance}^{w_i}$ and will observe FI inside its FOV as given in Equation (3). Surveillance behavior of UAV using two-layered barrier strategy is given in Algorithm 2.

Algorithm 2 Two-Layer Barrier Strategy

Given Area E, Watch agents W
Area is divided into two sections horizontally $E_{subsection}$
Watch agents are divided into two groups G_1 and G_2
Each agent is assigned area linearly as given in Equation (11)
FI occurs at random intervals at random positions
Watch agents w_i survey its own area $A^{w_i}_{surveillance}$
while Resources Available **do**
  Do surveillance
  if FI Observed **then**
    Closely monitor event, till it is managed
  else
    Survey the area
  end if
end while

3.1.3. Sweep Coverage Strategy

As mentioned in Algorithm 3 in the sweep coverage strategy, the surveillance area is equally divided among the available number of watch agents. The agents perform surveillance in their area with available resources.

Algorithm 3 Sweep Coverage Strategy

Given Area E, Watch agents W
Area is divided into Rows and Columns
Watch agents are given its own area
Each agent do surveillance in the assigned area
FI happening at random intervals at random positions
Watch agents w_i survey its own area $A^{w_i}_{surveillance}$
while Resources Available **do**
  Do surveillance
  if FI found **then**
    Closely monitor event, till it is managed
  else
    Survey the area
  end if
end while

Let $W = \{w_1, w_2, \dots w_n\}$ be number of agents. $E = (X_{max} - X_{min} + 1) \times (Y_{max} - Y_{min} + 1)$ be the total area available for surveillance. Thus, the agents W are placed in C columns and R rows. Calculate columns C and rows R

$$R_{total} = round(\sqrt{W}) \tag{12}$$

Number of columns C in row R_i is

$$C_{R_i} = ceiling\left(\frac{(W - \sum_{j=1}^{i} C_{R_{j-1}})}{(R_{total-i+1})}\right) \tag{13}$$

where W is the total number of agents available for surveillance, R_{total} is the total number of rows as given Equation (12), C_{R_i} is the number of columns in row R_i. Each watch agent w_i performs surveillance in its own area given by X_{min}, X_{max}, Y_{min}, and Y_{max}. Each watch agent X_{axis} size and Y_{axis} size are given by

$$X^{w_i}_{axis} = \frac{X_{max} + 1}{C_{R_i}} \tag{14}$$

$$Y_{axis}^{w_i} = \frac{Y_{max} + 1}{R_{total}} \tag{15}$$

At each column C_i, $X_{min}^{w_i}$ and $X_{max}^{w_i}$ of every watch agent w_i in that column have same values. $Y_{min}^{w_i}$ and $Y_{max}^{w_i}$ are same for all agents across the same row R_i.

$$X_{min}^{w_i} = \left\{ \begin{array}{cc} 0, & c = 1 \\ X_{max}^{w_{i-1}} + 1, & i > 1 \end{array} \right\} \tag{16}$$

where c is column index

$$X_{max}^{w_i} = X_{min}^{w_i} + X_{axis} \tag{17}$$

$$Y_{min}^{w_i} = \left\{ \begin{array}{cc} 0, & r = 1 \\ Y_{max}^{w_{i-1}} + 1, & i > 1 \end{array} \right\} \tag{18}$$

where r is row index

$$Y_{max}^{w_i} = Y_{min}^{w_i} + Y_{axis} \tag{19}$$

Thus, each watch agent w_i is given its own area for surveillance.

$$A_s^{w_i} = \left(X_{max}^{w_i} - X_{min}^{w_i}\right) \times \left(Y_{max}^{w_i} - Y_{min}^{w_i}\right) \tag{20}$$

3.2. Cooperative Behavior: Refueling

In order to observe the effects of cooperative behavior, we have simulated refueling behavior in all three strategies. If the agent goes for refueling, it communicates with its neighbors, and the neighbors pass the message to their neighbors to cover the area of the agent that has gone for refueling. When an agent refuels, it notifies its neighbors, so it further passes the message to cover the area.

3.3. The Forest Fire Model

A forest fire model is a dynamical systems model exhibiting self-organized criticality in connection to fuel, i.e., forest density. A fuel reduction treatment assesses the effects of fire suppression on forested landscapes. It has the following features:

The model is defined on a grid with L^d cells. L is the side length of the grid and d is its dimension. A cell can be empty, occupied by a tree, or burning. As per [8], system is governed by and defined by four rules executed concurrently:

- A burnt cell turns into an empty cell that cannot ignite.
- Any tree may ignite with probability f.
- A burning tree will ignite at least one of its neighbors.
- A space fills with a tree with probability p (density).

4. Design of Experiment

Simulation of this research is carried out in Net Logo. This research is carried out to analyze the overall system performance. Low-level details, i.e., UAV movement, target localization, target tracking, etc., are not in the scope of this research.

Figure 2 shows the total area for simulation set to be 51*51 patches; each patch in this simulation is 8.12 pixels. The area starts from $X_{min} = 0$ to $X_{max} = 50$ and $Y_{min} = 0$ to $Y_{max} = 50$. The area is divided according to different strategies, i.e., in random, two-layer barrier sweep, and sweep coverage, the area is divided differently. Each watch agent is given its specific area for surveillance, and each agent surveys its area and does not enter other agent areas. The background color of each agent surveillance area is different so that it can be easily identified. Each agent has been given the capability to locate FIs in its field of view. Once the FI is in the sight of the watch agent, the FI is reported. The algorithm is flexible and can adopt any size of the environment and any number of watch agents. For example, if the area is changed to 100*100, the algorithm will adopt the changes and perform the same, i.e., divide the space among the agents. If the number of agents is changed, the algorithm will handle it. When an agent goes for refueling, the remaining agents are adjusted accordingly to cover the area. The speed and size of watch agents and FIs can be changed from the interface. The agents are assigned an initial fuel, and once that fuel is consumed, they go for refueling. Static and dynamic variables are given in Table 2. We have modeled and simulated the following five experiments:

1. To establish the working of ABM, our first experiment estimates the effects of size on overall system performance.
2. Our second experiment simulates different team organizations for area coverage to access the impact of surveillance strategy on the performance.
3. In our third experiment, we introduced UAV downtime for refueling and estimated its effects on overall performance.
4. For our fourth setup, we introduced local and global communication constraints to check if the range of communication makes any significant difference.
5. Last but not least, in our fifth experiment, we simulated MUAV fire monitoring on a different level of forest density.

Table 2. Design of Experiment.

Factors	**Random**	**Two-Layer Barrier Sweep**	**Full Sweep Coverage**
Watch agent speed	static	static	static
Number of watch agents	6, 9, 12, 16	6, 9, 12, 16	6, 9, 12, 16
Number of FIs	random with upper bound set as 10 events per 20 ticks	random with upper bound set as 10 events per 20 ticks	random with upper bound set as 10 events per 20 ticks
Watch agents placement	random	two-layer barrier sweep	sweep
FI placement	random	random	random
Watch agent surveying area	random	two-layer barrier	equally divided
Refueling	Yes/No	Yes/No	Yes/No
Simulation time	20,000 ticks	20,000 ticks	20,000 ticks
Communication	No	local/global	local/global
Detection range	5 patches	5 patches	5 patches

5. Simulations

This section describes the details of the simulation of each experiment. The results generated from each experiment are analyzed and discussed in detail.

5.1. Experiment 1

In our first experiment, in order to estimate the system-level performance, the experiment is designed with team of UAVs monitoring a specific area. As a performance measure (outcome of experiment), we counted the total number of fires a team of UAVs is able to detect out of randomly generated total number of fires. We observed the effects of team size on the number of FIs observed. However, it is intuitive that the greater the number of agents surveying the area, better the odds of identifying any FI. This experiment is designed and analyzed as the litmus test of our simulation. It is observed that in any strategy, the team size affects overall performance directly. These results also provide the baseline system behavior, which can help analyze other features such as communication and refueling.

5.1.1. UAV Team-Size Effect on the Surveillance Performance

When the UAVs team size changes, it dramatically affects the surveillance performance of the UAVs team. The data are collected for team size of 6, 9, 12, and 16 UAVs for different strategies, i.e., two-layer barrier sweep coverage, random, full sweep with local communication, and global communication coverage.

Random Strategy

In random strategy, UAVs are randomly placed in the surveillance area. UAVs perform surveillance autonomously in the whole environment. Simulation results are taken for a team of 6, 9, 12, and 16 UAVs. Results are given in figures given in Figure 3. Figure shows results in terms of total number of FIs in the region (shown in red) and number of FIs detected (shown in blue) in 20 missions each for team size. Every mission is simulated with random location of watch agents and, in each mission, the FI happening at random location with fixed arrival rate. In random strategy, watch agents are just roaming around in given region without any consideration of dividing surveillance region. Increase in team size still improves the average detection rate (shown in green); it improves from 64 in Figure 3a with team size of 6 to 80 in Figure 3d with team size of 16.

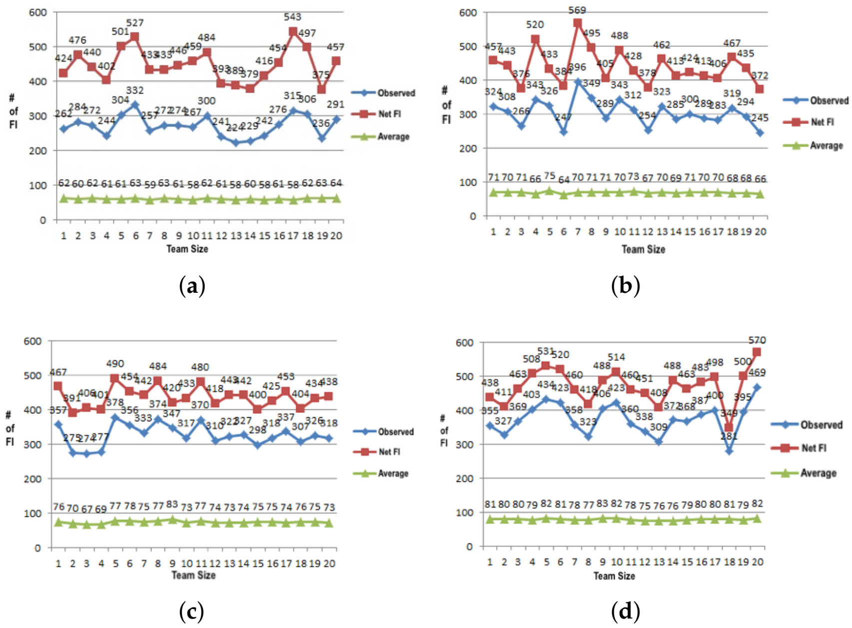


Figure 3. Random strategy results: (**a**) Team Size 6, (**b**) Team Size 9, (**c**) Team Size 12, (**d**) Team Size 16.

Two-Layer Barrier Strategy

In two-layer barrier sweep strategy, UAVs are placed linearly in two rows. Here, each UAV performs surveillance in its designated area. Linearized or layered strategy is easy to maintain and configure by a team of UAVs and is found in most research related to MUAV formation control. Simulation results of layered strategy shown in Figure 4 shows the same trend in improvement in number of average FIs observed as the team size grows. The results of 20 missions each are shown with team size 6 in Figure 4a, 9 in Figure 4b, 12 in Figure 4c, and 16 in Figure 4d.

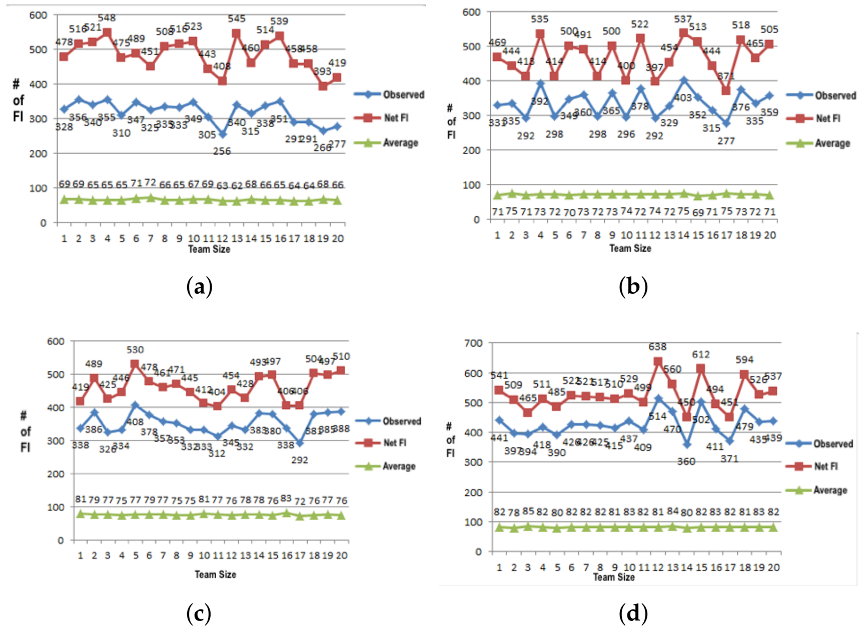


Figure 4. Two-layer barrier sweep strategy: (**a**) Team Size 6, (**b**) Team Size 9, (**c**) Team Size 12, (**d**) Team Size 16.

Full Sweep Coverage with Local Communication

In this strategy, the surveillance area is divided in $C_n \times R_n$ matrix form where C_n are columns and R_n are rows. Watch agents are placed in the center of its provided cell and perform surveillance in that cell. In this strategy, communication among the agents is local, i.e., each agent communicates with its neighbor agent to convey the message to all team members. Results are depicted in figures given in Figure 5. Here, the average number of FIs observed in twenty missions with team size 6 lies between 61 and 71 (Figure 5a), between 72 and 80 with team size 9 (Figure 5b), 78–85 for team of 12 UAVs (Figure 5c), and for team of 16, the range is 83 to 90 (Figure 5d).

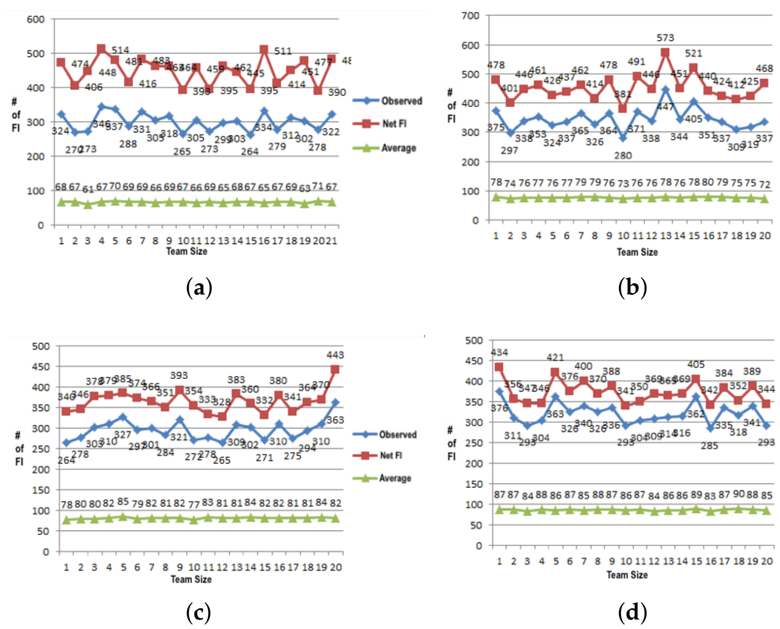
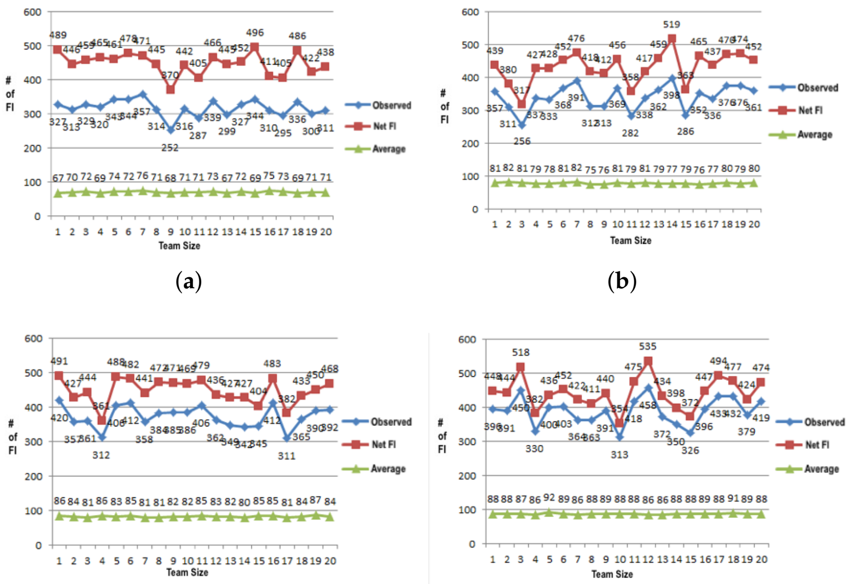


Figure 5. Full sweep with local communication: (**a**) Team Size 6, (**b**) Team Size 9, (**c**) Team Size 12, (**d**) Team Size 16.

Full Sweep Strategy with Global Communication

In this strategy, each agent is allocated area for surveillance after negotiations with rest of team as in local coverage strategy. However, these negotiations are performed with entire team instead of just with neighboring agents. Here, each agent communicates directly with all team members. Results of full sweep coverage with global communication are shown in Figure 6. The average FIs caught are around 71 for team size 6, 81 for team size 9, 84 for team size 12, and 89 for team size 16, depicted in Figure 6a, respectively. The results are consistent in each configuration that depicts increase in team size improves FI detection rates.



(**a**) (**b**) (**c**) (**d**)

Figure 6. Full sweep coverage with global communication: (**a**) Team Size 6, (**b**) Team Size 9, (**c**) Team Size 12, (**d**) Team Size 16.

Analysis of Data

Table 3 provides the summary of all of the mission results with respect to team sizes. It is evident that an increase in the number of the team size increases the performance of the system. The first column in the table shows the team size. For team size 6, the mean observed FIs is 66.5 with a standard deviation of 4.47, similarly for the team size 9, with a mean observed FIs of 74.6 with a standard deviation of 4.47. We can see a similar increase in FI observation from 78.7 for team size 12 and 83.2 for team size 16. The *F* value and Pr value with respect to team size are given in Table 4. The probability value (Pr) of the team size is less than the *F* value, which shows that the simulation results are significantly different, and the effects of the team size on the surveillance performance is considerable.

Table 3. Experiment 1: Mean number FIs observed.

Factors		Missions	Mean Number of FIs Observed	Standard Deviation
Team Size	6	120	66.5	4.47
	9	120	74.6	4.29
	12	120	78.7	4.45
	16	120	83.2	4.04

Table 4. Experiment 1: *F* value.

Factors	Df	Sum sq	Mean sq	*F* Value	Pr(>*F*)
Team Size	3	18,156	6052	325	$<2 \times 10^{-16}$

For our first experiments, we provided the graphs and the associated ANOVA results to establish and elaborate on the relation between simulation data and the results of the analysis. For our experiments 2–4, we are presenting only the statistical results of the ANOVA.

5.2. Experiment 2

After establishing the effects of team size, we analyzed the effects of team organization on system performance. The results of the barrier Algorithm 2, random Algorithm 1, and full-coverage-strategies Algorithm 3 are compared. The results show a significant effect on surveillance by different strategies. The full-coverage results are better as compared to random and layered strategies. The results from experiment 2 are significant as in most studies, the MUAV coverage is predetermined as either linear or stacked. Full coverage with constant re-organization may require sophisticated solutions for real-time dynamic team organization. Still, it improves the overall performance of the team with a similar size following any other strategies.

Different Strategy-Effect Surveillance Performance

The results are analyzed for different strategies with the same mission factors. It was found that the initial placement and coverage area of the UAVs greatly impacts the UAV teams' surveillance performance. Table 5 depicts the results of 160 simulations of each strategy, and it is evident that the performance of the full coverage is clearly better than the layered and random-allocation strategies. Table 5 shows that, irrespective of team size, the mean FIs reported by the random strategy are 71.4 and 75.4 for the two-layer barrier. The full-coverage strategy scored 80.4 as compared to other strategies. The *F* value and Pr value with respect to strategies are given in Table 6. It can be seen that the Pr is less than the *F* value, thus showing that simulated results are significant and strategy effects the surveillance performance significantly. These results are significant as the research in the field of forest fire monitoring is predominately focused on linear or elliptical formations [4,44,45]. Though the fault tolerant control of a UAV is better achieved by elliptical and linear trajectories, our results encourage the further exploration of sweep coverage as a better surveillance strategy. This can be achieved as in the work of Maqbool et al. [46]. In their work, the planning of the sweep coverage is performed at a higher level of abstraction, and the maneuverability and roaming of each UAV is achieved by elliptical trajectories.

Table 5. Experiment 2: Mean number FIs observed.

Factors		Missions	Mean Value	Standard Deviation
Strategy	Full coverage	160	80.4	6.64
	Two-layer barrier sweep coverage	160	75.4	5.89
	Random	160	71.4	7.04

Table 6. Experiment 2: *F* Values.

Factors	Df	Sum sq	Mean sq	*F* Value	Pr(>*F*)
Coverage	2	6627	3314	77.51	$<2 \times 10^{-16}$

5.3. Experiment 3

The assumption of each UAV being active for an entire mission is not realistic. In order to analyze the effects of changes in the team size, refueling behavior is also analyzed. For each strategy and team size, a comparison is made between the number of FIs observed when the agent remains active for the entire mission against the case when an agent leaves its surveillance area to go to its origin and spends some time on refueling.

It is found that the effect of refueling on/off is not significant, as shown in Table 7, because if an agent goes for refueling, its area is covered by the available neighboring agents. Thus, the efficiency is maintained. The *F* value and *Pr* value with respect to the two-way ANOVA test is given in Table 8. Table 8 shows two factors: (1) the effect of refueling on all missions and (2) the effects of coverage strategies with refueling. Row two shows that even with the refueling downtime, the surveillance is affected by the coverage algorithm; however, row one of Table 8 shows that there is no significant difference between the performance of teams even with an agent leaving temporarily for refueling.

Table 7. Experiment 3: Mean Values.

Factors		Missions	Mean Value	Standard Deviation
Refueling	On	240	75.9	7.44
	Off	240	75.6	7.59

Table 8. Experiment 3: *F* Values.

Factors	Df	Sum sq	Mean sq	*F* Value	Pr(>*F*)
Refueling	1	8	8.27	0.146	0.702
Coverage	2	6627	3314	77.51	$<2 \times 10^{-16}$

The full-coverage strategy adopted by a team of UAVs is less affected by the refueling downtime of some of its agents. As per the experiment, the area vacated by an agent leaving for refueling is jointly covered by its neighboring agents. Now, as the fire monitoring environment and our simulation both are stochastic in nature, the FI occurs at random and random agents leave for refueling. The results of experiment 3 show that as long as a significant number of agents are available for surveillance, the net performance of systems is less affected by agents refueling. The effect of the random downtime of a team member does not significantly deteriorate the overall surveillance quality. Refueling/recharging are considered as a bottle neck in the performance of the UAVs. A considerable amount of research is dedicated to the optimal refueling of UAVs [47–49]. Our results are significant as they provide an alternate view of the system. The results of experiment 3 are unique as they include the stochastic environment model and an analysis of the effects on team-level performance instead of individual UAV performance. As the technology is advancing, low-cost, mid- to low-range UAVs are being deployed for FFM, and the assessment of the cost and benefits of adopting expensive refueling strategies can be considered only after assessing the overall improvement of surveillance.

5.4. Experiment 4

In experiment 4, the results data of the two-layer and full sweep coverage strategy with cooperation are analyzed. Cooperation means that the agents cooperate with the rest of the team. For instance, in the case where an agent has to temporarily leave its allocated surveillance, the neighboring agents cooperate and willingly take care of the responsibilities of the neighboring agent. With the cooperation off, the agents do not communicate with each other. If an agent goes for refueling, its area is not covered by other agents. The cooperation effects on performance are found to be dependent upon team size. As the team size increases, the effect of cooperation decreases gradually. The mean value of cooperation on and off is given in Table 9. The value of Pr for cooperation on and off is 0.0302 and $F = 4.742$.

Table 9. Experiment 4: Mean values.

Cooperation	Missions	Mean Value	Standard Deviation
On	160	77.8	6.67
Off	160	76.2	6.88

Experiment 4 is an exploration of the results of experiment 3. The statement that refueling has less impact on surveillance needed further study. In experiment 4, we establish that provided the team of agents cooperate and share the responsibility of the absent agent, the performance is not affected. However, if the agents do not share the responsibilities of the absent team members, the performance deteriorates within the team size as compared to larger team sizes.

5.5. Experiment 5

The studies performed in the previous experiments implemented a dynamical system of the forest fire model expressed in Section 3.3. The density of the vegetation matters in actual fire surveillance. In a forest with less density, the fire dies out itself, whereas in a forest with a higher density, any breakout fire may get out of control quickly.

In our extended model, we have used the forest fire model developed by [9]. The model was originally only created to simulate the spread of the fire. It does not include any external influence on the burnout rate. In the original model, the surrounding trees of a randomly lit fire burn out with a probability rate of 0.6. The burned-out trees do not burn again, and the simulation stops when 99% of the forest is burned.

The less-dense forest has fewer trees surrounding a burning tree; thus, the fires in a less-dense forest burn themselves out without causing immense harm. With low density, multiple fire breakouts are needed to destroy the entire vegetation. The forest with a higher density burns out quickly. In a higher-density forest, even a single event can cause total damage. To measure the performance of the team size and allocation style regarding the forest density, we have enhanced the model by introducing the following key features:

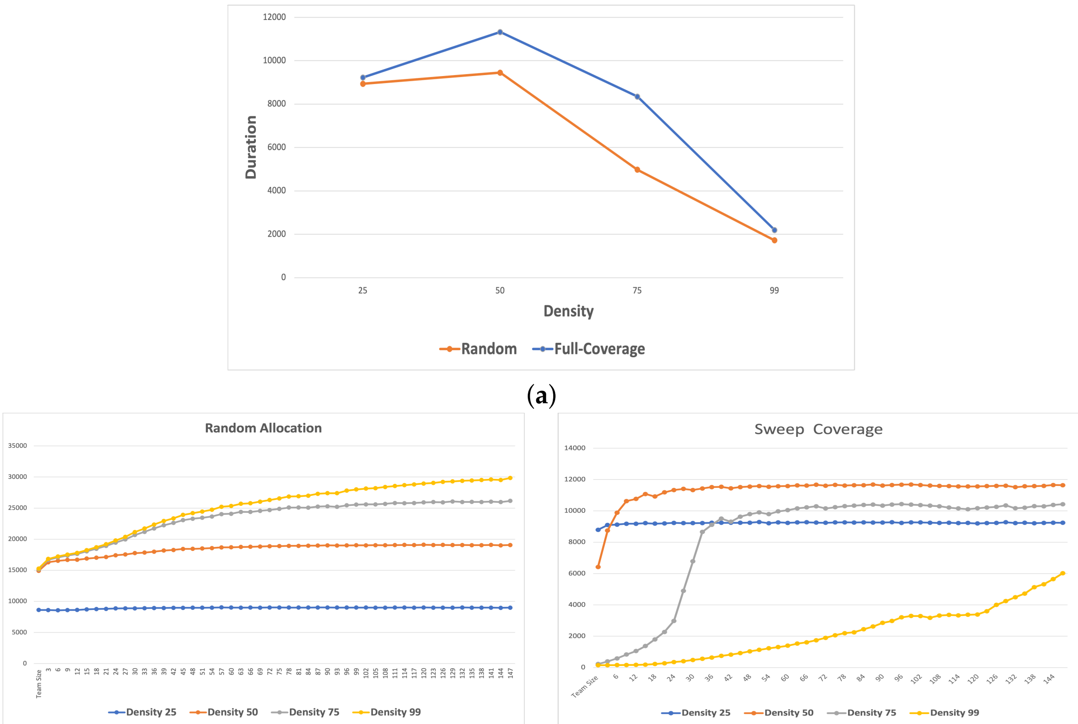
1. The workspace size is increased from (50×50) to (250×250).
2. A team of MUAVs performs surveillance of the forest.
3. The surveillance is performed either in a random or full-coverage arrangement.
4. When a UAV approaches near a burning tree, it reduces the burnout rate of the surrounding trees from 0.6 to 0.4.
5. The UAV looks for any breakout in its vicinity to reduce the burnout rate of any burning trees in a range.
6. Each experiment is repeated 20 times.

The details of the design of experiment 5 are given in Table 10.

In our model, in order to simulate the countermeasures taken by fire-fighting agencies after the discovery of FIs, we have introduced the reduction in the burnout of the surrounding trees by a random factor of 0.5. The mission is simulated until the full forest is burned out. The measure of performance is the duration taken by the forest to reach maximum burnout. A better allocation and team size will slow down the burnout rate, thus increasing the duration of the simulation.

There is a clear impact of the sweep coverage on the mission performance with respect to the forest density, though the improvement in permanence is not significant with extreme values of forest density, i.e., 25 and 99. However, in mean values, the sweep coverage performs much better, as shown in Figure 7a. The figure shows the duration/iteration of the mission until there is complete burnout against four levels of forest density. The blue line shows the time taken by a team of UAVs allocated using sweep coverage, and the orange line shows random coverage. The average duration of a sweep coverage mission for 20 repetitions of 150 experiments at each density level is better than its random counterpart.

Figure 7a shows an overall performance of two allocation strategies; however, on closer observation, a clear distinction appears in the team behavior. With the random strategy, the effect of the team size on the overall performance is less significant. Figure 7b shows a steady performance of all of the team sizes ranging from 3 to 150. However, Figure 7c shows a notable transition in performance with a varying team size, particularly in the case of a forest density of 50 or 75. Once an appropriate team size is reached, the performance of the sweep coverage becomes steady. For instance, in Figure 7c, the gray line shows the team permanence against a forest density of 50; here, the duration of the mission increases until the team size approaches 42. After that, the effect of the team size on the overall performance diminishes. Thus, the second finding of the experiment is that the forest density effects the team size, and once an optimum team size is achieved, increasing the number of UAVs does not affect the performance.



(**b**) (**c**)

Figure 7. Effects of Allocation with respect to Forest Density. (**a**) Average Mission duration of Random and Full Converge till total burnout at different forest density; (**b**) Performance of Random allocation at different forest density and team sizes; (**c**) Performance of Full-Coverage at different forest density and team sizes.

Table 10. Design Parameters of Experiment 5.

Factors	Values
Team Size	3–150 (with step size 3)
Forest Density F_d	25, 50, 75, 99
Neighborhood Burnout Probability NB_p without discovery	0.6
Neighborhood Burnout Probability NB_p with discovery	0.4
Experiment Replication	20 times
X_{max}	25
Y_{max}	25

6. Results and Discussion

Referring back to our objectives, we have presented ABM for the estimation of the system-level performance. Our work presents in-depth details of the model and design of the experiment and then simulation results for an effective system-level performance estimation. We have also been able to address the second objective of establishing the effect of individual behavior on overall performance. We have presented a direct relationship between team size and performance, regardless of team organization. Secondly, the organization of the team is analyzed, and full coverage is performed better than the rest. Even though, due to low-level constraints, most of the scholarly work focused on linear trajectories, we have established that a sweep coverage provides better monitoring. We also evaluated the effects of the temporary downtime of a few team members for refueling on overall performance. It is found that downtime affects smaller teams more. Thus, in the case of frequent downtime, an increased team size can maintain the quality of surveillance. Furthermore, we tried to establish the effect of the range of communication on the overall performance. It is found that no significant impact on the overall performance is made if agents can only communicate to their neighbors compared to the entire team.

We extended our model by implementing the sweep coverage and random allocation of a forest fire model with density levels ranging from 25 to 99. Our experiment made two significant findings on team performance in relation to forest density. First, our extended model verified our previous results that sweep coverage gives a better performance. Secondly, the impact of team size is significant in sweep coverage as compared to random allocation. However, once a team size reaches its optimum level, the additional UAV(s) make less to no effect on team performance in a specific forest density.

The lack of low-level control details is the main limitation of our model. At present, we have not considered individual UAV dynamics, sensor capacity, and other detailed features. In our model, we have presented a homogeneous UAV as a simple abstract agent.

7. Conclusions

In this study, we attempted to ascertain how different design factors affect the overall surveillance quality of forest fire monitoring by a team of MUAV(s). A fair amount of research is dedicated to achieving behaviors such as arrangements, cooperation, and communication. Each behavior comes with a cost, but evaluating how much each behavior improves overall performance has not been studied. We have found that analytical methods employed chiefly fall in the category of being NP-Hard. Thus, we proposed agent-based modeling and simulation using Netlogo to analyze the overall performance. To verify our model, we have performed the analysis of team size and found out that team sizes affect performance. A bigger team size performs better until a team approaches the optimal size with respect to the area of surveillance and the forest density. We have also established that organized area allocation, i.e., sweep coverage, significantly outperforms any other investigated allocation strategy.

For future work, we aim for a two-fold expansion of our current model. First is the analysis of system performance effects by incorporating mid- and low-level controls, obstacle avoidance, etc. Second, the model will be extended to include the likelihood of bushfires [13] for better resource allocation. Also, we would formulate the mechanism to ascertain the optimum team size depending on the forest density and the likelihood of a bushfire.

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Abbreviations

The following abbreviations are used in this manuscript:

ABM	Agent-Based Modeling
ANOVA	Analysis of Variance
FFM	Forest Fire Monitoring
FI	Fire Instance
MNTSC	Min-Nodes Timely Sweep Coverage
M-UAV	Multiple Unmanned Autonomous Vehicles
M-WSN	Multiple Wireless Sensor Network
NP-Hard	Non Polynomial
OI	object of interest
UAV	Unmanned Autonomous Vehicles

Notations used in UAV Model

$A_s^{w_i}$	Area under surveillance by watch agent *i*
d_{wu}	Distance between FI and watch agent
E	Net area of surveillance *i*
e_i	*i*th section of *E*
FOV_{wi}	Field of view of watch agent *i*
r	Radius of watch agent's sensors range
T	All FIs
θ	Watch agent heading *i*
u_i	*i*th FI *i*
y_w	Watch agent's location on y axis
y_u	FI location on y axis
W	Set of watch agents
w_i	Watch agent *i*
X_{max}	Maximum value of x coordinate of *E*

X_{min}	Minimum value of x coordinate of E
x_u	FI location on x axis
x_w	Watch agent's location on x axis
Y_{max}	Maximum value y coordinate of E
Y_{min}	Minimum value of y coordinate of E
F_d	Forest density
NB_p	Neighborhood Burnout Probability

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