INVESTIGATING THE USE OF AGENT-BASED MODELING FOR WILDFIRE PREVENTION: A SIMULATION STUDY

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Abstract

Wildfires pose a growing threat resulting from climate change, biodiversity loss, and human activity (Jones et al., 2024). This research explores economic and sustainable firefighting approaches using autonomous drone swarms, traditional aircraft, and hybrid models. A simulation framework created in Python using the agent-based modeling library Mesa (ter Hoeven et al., 2025) simulates these methods, focusing on cost, environmental impact, and computational efficiency. Drones, planes, fires, and resource stations were modeled as agents in the environment with parameters supported by current research. Results from 1,000 steps over 1,000 simulation iterations demonstrate that drone swarms significantly and consistently outperform manned aircraft in both sustainability and cost-effectiveness. Hybrid systems offer the fastest response times but with higher emissions and operational costs. This research contributes an open-source framework for evaluating aerial firefighting strategies, designed to support evidence-based guidelines and encourage sustainable and frugal fire management practices.

1 DATA SOURCE, ETHICS, CODE, AND TECHNOLOGY (DSECT) STATEMENT

1.1 *Data Source*

This thesis does not use any datasets or human/animal data. All data used in the project is synthetically generated through simulations developed by the author. No external data owners are involved, and no consent was necessary. All data was produced locally using custom agent-based models created in Python using the mesa library. The parameters of the simulation are taken from cited research.

1.2 *Figures*

All Figures, plots, tables and visualizations included in the thesis were created by the author using the original simulation output. No external or copyrighted images were used. Visuals were generated using Python libraries such as `matplotlib` and `seaborn`. The creation of the visuals is documented and explained in the GitHub repository (Speidel, 2025)

1.3 *Code*

The simulation uses multiple open-source Python libraries such as `mesa`, `numpy`, `pandas`, their implementation is documented in the Methodology section 4 and the referenced GitHub repository.

1.4 *Technology*

The thesis was typeset using the standard LaTeX thesis template provided by the university, with additional formatting packages such as `fancyhr`, `tikz` for formatting preferences. References were managed using BibTeX and LaTeX's built-in bibliography environment. Zotero was used as a reference manager. Generative models such as GitHub's Copilot, Claude and ChatGpt were used for harsh feedback on personal created text and code. The content was not directly copied; instead used as a valuable tool to generate feedback and point out room for improvement. All conceptual, experimental, and implementation work was done by the author, with inspiration from the documentation of the mentioned libraries.

2 INTRODUCTION

Wildfires pose an escalating global threat, driven by climate change and human activity, with 96% of wildfires being human-induced (Cañizares et al., 2017). These events cause ecological, economic, and societal damage (Saffre et al., 2022), emitting over 2,000 megatons of carbon emissions globally in 2023 alone (Lelis et al., 2024). The UN Environment Program (UNEP2) forecasts a 50% increase by the end of the century in extreme wildfires if no countermeasures are taken (Sullivan et al., 2022). Escalating wildfire frequency also threatens agricultural productivity (Intergovernmental Panel on Climate Change, 2023) and poses significant health risks through smoke exposure (Finlay et al., 2012). These combined effects make wildfires one of the most urgent environmental and societal challenges today.

Wildfire research traditionally employs different methodological approaches with different advantages and limitations. Historical analysis creates the foundation of wildfire research. Researchers examine fire records, satellite imagery and climate data to identify patterns, trends and correlations between environmental factors and fire behavior (Jones et al., 2024; Intergovernmental Panel on Climate Change, 2023). These studies offer valuable insights into long-term fire cycles and climate relationship, but their retrospective nature limits their adaptability in the accelerating climate change.

Field studies including controlled burns present another critical research approach (Santoni et al., 2011). While these approaches offer scientists valuable real-world data about fire physics and suppression in a controlled environment, they are inherently limited by safety concerns, high costs and their impossibility of testing extreme scenarios or comparing multiple suppression strategies simultaneously.

Traditional aerial firefighting and data collection relies heavily on manned aircraft such as Helicopters or fixed-wing planes. For decades this has been the backbone of wildfire suppression (Janney, 2012). These aircraft deliver water or fire retardant directly to the fire zones, often in dangerous conditions such as limited visibility. Their effectiveness comes with safety constraints, high operational cost and substantial carbon emissions (Spicer et al., 2009).

Recent technological advancements have sparked growing interest in autonomous drone systems for wildfire suppression. Modern drone technology potentially offers operation in extreme conditions without risking human life while being lower in cost and emissions. Research done by Yan and Chen (2024) effectively demonstrates the possibility of using coordinated swarm behavior to detect forest fires. Current research presents promising applications such as new suppression techniques like the "fireball" by Aydin et al. (2019).

While the development is promising especially with more applied drone applications being tested, scientists have also turned to simulation studies as they provide evidence for fire spread behavior at a lower cost. One of the earliest tools in this domain was the fire area simulator FARSITE (Finney and Andrews, 1999), which established a baseline for future work. This laid the groundwork for more advanced systems, such as the model proposed by Hu and Ntaimo (2009), which integrates fire simulation with optimization-based analysis. This is where Agent-Based Modeling (ABM) plays an important role.

Based on Wilensky and Rand (2015), ABM is defined as a methodology for conducting computer-based experiments that enables the study of complex systems by simulating the actions and interactions of autonomous agents within natural, social, or engineered contexts. These dynamic interactions generate complex, system-level patterns, commonly referred to as *emergent behavior*. In wildfire research, ABM enables researchers to model fires, suppression vehicles, and environmental factors as independent agents with distinct behaviors and decision-making capabilities. This approach captures the emergent properties of complex firefighting scenarios that would be difficult or impossible to study through traditional analytical methods or real-world experiments. ABM provides evidence through the analysis of emergent behavior, which can inform real-world firefighting strategies.

ABM is particularly suited for wildfire suppression research because it allows for the modeling of dynamic, spatially distributed systems where multiple autonomous agents must coordinate to achieve common objectives. The framework enables systematic comparison of different suppression strategies under controlled conditions while varying key parameters such as swarm size, resource allocation, and path-finding algorithms.

As wildfires grow in intensity and frequency, traditional suppression methods face increasing limitations. Agent-Based Modeling (ABM) presents a powerful tool for simulating complex scenarios involving autonomous firefighting drones. However, there is limited research directly comparing different suppression strategies, such as drone swarms, hybrid systems, and traditional aircraft, within the same simulation environment.

2.1 *Research Question*

Given the critical need for sustainable wildfire suppression and potential of autonomous approaches, this research addresses the following question:

"How can agent-based modeling be used to evaluate and optimize autonomous aerial wildfire suppression strategies across drone, plane, and hybrid systems, using path-finding algorithms to assess effectiveness, efficiency, and sustainability?"

Accordingly, the following sub-questions this research:

1. "What are path-finding algorithms and how do they influence the performance autonomous drone swarms in wildfire scenarios?"

2. "How do drone swarms, hybrid systems, and planes compare in wildfire suppression?"

3. "What trade-offs emerge among suppression effectiveness, efficiency and sustainability?"

2.2 *Findings*

The strength of this thesis is that it presents a robust open-source agent-based simulation framework developed in Python using the Mesa library. Its object-oriented and well-documented architecture promotes interdisciplinary research. Presenting the possibility of an easy integration for different algorithms such as Ant Colony Optimization and Artificial Bee Colony underlines its strengths. The framework provides researchers and relevant stakeholders such as policymakers, emergency response planners, and environmental scientists, with a flexible tool to build on top of and evaluate custom aerial vehicle models and coordination strategies across a range of simulated scenarios. Its public availability offers societal benefit, especially in resource-limited regions, by enabling access to advanced simulation and planning tools.

In the scope of this research different wildfire suppression methods, namely traditional aerial firefighting, autonomous drone swarms and a hybrid system are modeled. These approaches have been simulated and compared focusing on cost, emissions, and water usage. The work combines agent-based modeling, swarm properties, and environmental sustainability. While drone technology has advanced tremendously in both hardware and software, practical evaluations in firefighting contexts remain limited, especially when compared directly. Current systems heavily depend on manned aircraft's despite the growing need for scalable, efficient, and sustainable alternatives.

3 RELATED WORK

3.1 *The Importance of preventing Wildfires*

As already mention wildfires are increasing, creating devastating destruction. Additionally, the economic damage from wildfires is immense, while the annual cost of wildfire management in the U.S. is estimated to be $7.6 billion to $62.8 billion, the economic damage is estimated between $63.5 billion to $285.0 billion (Afghah et al., 2019). This highlights the importance of this research topic and the need for practical, cost-effective and quick solutions. Aiming for a sustainable approach should be emphasized as traditional methods are costly and emit a lot of CO_2 (Saffre et al., 2022). The ecological impact especially on the agricultural sector is seen as a societal threat as several sources report (Steiner et al., 2020; Intergovernmental Panel on Climate Change, 2023).

3.2 *Traditional Methods*

(Traditional) Aerial firefighting using manned planes has been employed since the 1950s, originating from repurposed military aircraft's (Janney, 2012). Important advancements in the 1960s introduced specialized tactics and retardants, which significantly improved effectiveness (Struminska and Filippone, 2024). These methods made access to remote areas feasible and led to the development of aircraft specifically for firefighting roles (Struminska and Filippone, 2024; Corporation, 2018). Modern firefighting-fleets include a range of aerial vehicles for specific operational tasks (Aviation, 2018).

Despite their effectiveness, these methods are costly and "dangerous and risky for the crew involved" (Struminska and Filippone, 2024, p. 1896). Struminska and Filippone (2024) also pointed out that aerial firefighting is fast and capable but economically and operationally demanding. Additionally, emissions from aircraft like the C-130 Hercules are immense and difficult to quantify (aviationzone, 2022; Spicer et al., 2009), highlighting the need for lower-emission alternatives. Traditional aerial firefighting faces limitations regarding coordination and situational awareness, which motivate the development of autonomous alternatives. Current operations rely heavily on human pilots making real-time decisions in dangerous, low-visibility conditions due to smoke, wind and turbulence (Struminska and Filippone, 2024). These complex situations present challenges for human operators, which can result in suboptimal suppression strategies and safety risks. Autonomous systems offer the potential for real-time data sharing, coordinated swarm behavior and quick adaptation to changing fire conditions, forming the foundation for more effective suppression strategies. With multiple sources reporting that the frequency and intensity of wildfires are increasing (Jones et al., 2024; Intergovernmental Panel on Climate Change, 2023; Steiner et al., 2020), the development of more responsive and autonomous strategies is of high importance.

3.3 *Emergence of Drone-Based Solutions*

With advancement of global technologies in recent years, drone systems, including both hardware and software components, went through significant development in terms of functionality and operational capabilities. Unmanned Aerial Vehicles (UAV) are increasingly integrated across a range of industrial sectors, including agriculture, healthcare, logistics, and military operations (Emimi et al., 2023). Their main advantages being their adaptability, precision and cost-efficiency. However, these benefits go in line with by persistent regulatory, operational, and ethical challenges (Emimi et al., 2023). In the context of firefighting, drones are establishing themselves as promising tools, offering new approaches to increasing problems in wildfire management. Research conducted by Saffre et al. (2022) demonstrates that autonomous drone swarms are capable of effectively containing wildfire while also reducing greenhouse gas emissions compared to traditional methods (Saffre et al., 2022). In addition, drones are increasingly recognized for their energy efficiency, making them a promising solution for sustainable disaster response strategies (Stolaroff et al., 2018).

Emerging drone-specific firefighting techniques further expand the potential of UAV's in this domain. For example, the "Firefighting Ball" represents a novel condemning technology designed specifically for aerial deployment via drones (Aydin et al., 2019). Building upon this, an autonomous system that integrates the fireball concept into a coordinated drone-based suppression framework got introduced (Alkhatib et al., 2024).

The effectiveness of drone-based firefighting systems is evident, specifically in terms of cost-efficiency and their potential to reduce environmental impact through lower emissions. However, for these systems to achieve optimal performance, early wildfire detection is crucial. Fast and confident identification of fire outbreaks is one of the most critical factors in minimizing damage, especially during the initial stages of a wildfire event (Sudhakar et al., 2020). In comparison, Traditional risk assessment measures are delayed and have low confidence, especially in remote areas (Afghah et al., 2019), highlighting the potential for improvement in autonomous data collection (Lelis et al., 2024) with drones.

The relatively low cost and compact size of drones also make simultaneous deployment of multiple units possible, therefore enabling coordinated swarm behavior which is a logical progression in UAV-based wildfire management (Hocraffer and Nam, 2017). Swarm behavior supports the application of bio-inspired algorithms, such as Ant Colony Optimization (Cañizares et al., 2017) and Artificial Bee Colony algorithms (Karaboga and Basturk, 2007), which increase in effectiveness as swarm size increases. These algorithms allow drones to efficiently compute optimal paths to fire sites, managing speed and resource use. Hocraffer and Nam (2017) identified that, interest in swarm-based UAV systems is growing rapidly, and this area of research is expected to become increasingly important in addressing complex real-world challenges such as wildfire detection and suppression.

While the physical and algorithmic capabilities of drones develop rapidly, coordinating a swarm of autonomous UAVs in uncertain, large-scale environments, especially extreme ones such as wildfire zones, remains a significant challenge. These systems involve many interacting agents reacting to various parameters. This introduces a level of behavioral and environmental complexity that is difficult to model using top-down or deterministic approaches. As a result, Agent-Based Modeling (ABM) has emerged as a promising computational framework to explore and test swarm coordination strategies, especially in complex domains such as wildfire detection and suppression.

3.4 *Agent-Based Modeling*

Agent-Based Modeling (ABM) is a computational methodology used for conducting experiments that enable the study of complex systems by simulating actions and interactions of autonomous agents within different domains (Wilensky and Rand, 2015). Each Agent follows a set of simple, rule-based behaviors, and through repeated interaction with other agents and their environment "sustainable patterns can emerge in systems that are completely described by simple rules" (Macal and North, 2005, p.5). These dynamic interactions generate complex, system-level patterns, commonly referred to as emergent behavior. These emergent patterns reveal dynamics that are difficult to predict analytically, providing valuable insights for informed decision-making. ABM is grounded in the principles of complexity theory, which studies how individual agents interact within a system, leading to emergent behaviors and patterns. As Wilensky and Rand (2015) explain, complexity theory provides a framework for understanding systems in which "order emerges without central control," making is specifically relevant for wildfire management, where conditions are dynamic and decisions must be made in real time without centralized control. By modeling planes and drones as autonomous agents, ABM provides a framework where each agent is equipped with its own sensors, movement capabilities and objectives (e.g., resource management or fire suppression). The simulated environment can be defined and modeled to represent real-world elements such as terrain, vegetation and fire spread mechanics, making it a powerful tool for investigating wildfire response strategies. ABM has been widely applied in wildfire research. Early models such as the NetLogo Forest Fire simulation demonstrated how simple ignition and spread rules can mimic the dynamic growth of wildfires (Wilensky and Rand, 2015). Recent implementations of ABM for wildfire management have demonstrated the capabilities of this approach for simulation complex environments and testing different suppression strategies to understand forest fires. For instance, Moreno-Espino et al. (2025) applies ABM through the GAMA platform (Taillandier et al., 2019) to simulate wildfire propagation by modeling fire cells, vegetation, and weather as interacting agents. Their approach integrates geographic data to reflect real-world terrain, highlighting how environmental variables like wind speed and fire outbreaks influence fire spread and intensity. Similarly, Dorrer and Yarovoy (2020) presented an agent-based model which integrates a simulated environment onto actual terrain data, combining both fire agents and firefighting agents. Their model provides insights into fire control strategies by demonstrating how emergent behaviors from the agents' interaction with the spreading fire can give evidence for informed resource allocation and decision-making.

These studies demonstrate the relevance of ABM in capturing the dynamics of wildfire events. Building on this foundation, this thesis takes a comparative approach to evaluate coordination strategies in UAV-based wildfire response by contrasting autonomous drone systems with plane only and hybrid models. However, the effectiveness of autonomous drone swarms in ABM simulations for wildfire suppression depends on the path-finding algorithms which dictate the agents movement and coordination strategies.

3.5 *Nature-inspired Path-finding Algorithms*

Path-finding algorithms are computational methods designed to find efficient routes between two points in a space, often while avoiding obstacles or minimizing costs (such as time, distance or energy). These algorithms often use heuristics, which are informed problem-solving techniques to efficiently explore potential solutions in a solution space under the premise that exploring every possible solution is computationally infeasible. When the heuristic is admissible, it guarantees that the algorithm will find an optimal path (Hart et al., 1968). In the context of autonomous drone swarms for wildfire suppression, these algorithms must balance competing objectives: minimizing travel time to fire sites, avoiding collisions with other agents, optimizing resource consumption, and adapting to dynamic fire spread.

A* SEARCH The A* algorithm, introduced by Hart et al. (1968), is the foundation of modern heuristic path-finding, It calculates:

$$f(n) = g(n) + h(n) \tag{1}$$

where $g(n)$ represents the actual cost from the start node to node n, and $h(n)$ is the heuristic estimate of the cost from node n to the goal. When the heuristic $h(n)$ is admissible (never overestimates the true cost) and consistent, A* guarantees finding the shortest path while expanding fewer nodes than uninformed search methods (Hart et al., 1968). While A* performs well in known environments, it faces limitations in dynamic scenarios where conditions change rapidly and multiple agents must coordinate simultaneously. This is where nature-inspired algorithms offer an alternative. Nature-inspired path-finding algorithms draw their inspiration and theoretical concepts from biological systems that exhibit efficient collective navigation and optimization behaviors. These approaches are specifically valuable in wildfire suppression contexts because they enable decentralized decision-making, adaptive behavior, and emergent coordination, making them essential for effective swarm operations in unpredictable environments.

ANT COLONY OPTIMIZATION (ACO) mimics the foraging behavior of ant colonies, where individual ants leave pheromone trails to guide other ants towards food sources (Dorigo et al., 1996). The original ACO algorithm, developed by Dorigo et al. (1996), has since been applied across various optimization domains (Dorigo and Stützle, 2019). In drone applications, virtual pheromones can represent fire intensity levels or success suppression paths. This mechanism enables drones to converge on high-priority areas while maintaining swarm coordination. Cañizares et al. (2017) demonstrates how ACO can be applied in wildfire scenarios by developing a system that coordinates multiple agents for fire prevention and mitigation. ACOs main advantage lies in its ability to find near-optimal solutions through emergent collective intelligence without requiring centralized control, making it perfectly suitable for wildfire suppression in ABM simulations.

ARTIFICIAL BEE COLONY (ABC) is a swarm-based meta-heuristic algorithm. Inspired by the behavior of honeybee swarms, the algorithm simulates the decision-making processes of honeybee colonies during nectar foraging (Karaboga and Basturk, 2007). The algorithm divides the swarm into three types of bees: employed bees that exploit existing food sources, onlooker bees that select among these sources based on information shared by employed bees, and scout bees that search for new food sources randomly when existing ones are exhausted (Karaboga and Basturk, 2007). In wildfire suppression contexts, this translates to drones that can exploit known fire locations (employed behavior), explore new fire areas based on information from other drones (onlooker behavior), and conduct random searches when no fires are detected (scout behavior). This behavioral division enables effective load balancing between exploitation of current fire sites and exploration of potential new outbreaks. This property highlights the strength of ABC, which lies in its inherent balance of exploration and exploitation, making it particularly useful for dynamic environments where fire conditions and resource availability change rapidly.

These nature-inspired algorithms provide the needed computational foundation for autonomous coordination. However, as demonstrated in the following sections the integration of human oversight with the mentioned autonomous capabilities can further enhance system performance and adaptability.

3.6 *Human-Drone Teaming*

As the complexity of drone systems is increasing, maintaining effective coordination presents a growing trade-off between autonomy, control, and performance. Human drone teaming (HDT) offers a promising middle ground by balancing centralized oversight with distributed decision-making (Asavasirikulkij and Hanif, 2023). Integrating humans into the loop, enhances strategy flexibility while reducing cognitive load. Chen and Barnes (2014) demonstrate that system where human operators oversee multiple UAVs and intervene only when necessary, enhance both situational awareness and mission reliability. This supervised control enables operators to take strategic decisions without managing each drone independently, thus reducing cognitive load and improving the flexibility of the operation. Similarly, Lewis et al. (2012) show that human operators can effectively direct swarm behavior by influencing a subset of agents rather than all agents at once. These findings, suggest that humans are essential for providing strategic decisions and maintaining oversight, while autonomous systems such as drone manage local coordination and provide situational data. This division of tasks supports flexible and informed decision-making in a highly complex environment. In this thesis such interactions are explored in a simulated environment ABM environment, where the agents provide date about the dynamic environment and respond to the changing conditions. The emergent interactions and collected data can be used for informed decision-making by providing evidence about drone and plane behavior.

3.7 *Summary*

While ABM research is growing especially in the field of swarm behavior and novel techniques to apply UAV in extreme situations, a research gap remains in comparative simulation studies that evaluate different aerial firefighting techniques within the same framework. Current literature often focuses on individual aspects such as drone swarms, sustainability, or suppression effectiveness, without systematic comparative analysis.

Furthermore, while nature-inspired path-finding algorithms show promise for autonomous coordination, their practical application and comparative performance in wildfire suppression scenarios remain underexplored in ABM. This thesis addresses these gaps by developing a comprehensive simulation environment that enables direct comparison of autonomous drone systems, traditional aircraft, and hybrid approaches, while integrating sophisticated path-finding algorithms to evaluate their combined impact on suppression effectiveness and sustainability. In the context of this research, sustainability is evaluated by water consumption, carbon emissions (kg CO_2), and operational costs. This approach enables informed assessment of environmental and economic trade-offs across different aerial firefighting strategies.

4 METHODOLOGY

This study uses a simulation-based computational approach to evaluate different wildfire suppression strategies. At its core the methodology involves agent-based modeling, swarm path-finding algorithms, and machine learning-based post hoc analysis. The goal is to determine the operational, environmental, and economic effectiveness of drones, manned aircraft, and hybrid firefighting systems. All simulations are implemented in Python using the Mesa framework (ter Hoeven et al., 2025), as it is ideal to study complex emergent behavior. Given the complexity inherent in agent-based simulation studies, a detailed description of the initialization process and agent setup is provided to ensure clarity, reproducibility, and transparency.

4.1 *Simulation Design and Setup*

ENVIRONMENT The simulated environment consists of a 250×250 discrete grid (62,500 total cells) representing the landscape where wildfire events occur, where one cell is equivalent to 10 meters. This creates a simulation area of 2.5 km × 2.5 km (6.25 km^2), representing a realistic wildfire scenario. This grid size was selected to balance computational efficiency, while maintaining an appropriate size for meaningful agent interactions and fire dynamics. Each cell tracks state information about occupancy status, fire state and resource station allocation, it can contain agents or fire. The simulation proceeds in fixed time steps defined by the steps variable. Fires can ignite, grow in intensity, and spread to adjacent cells probabilistically. Fire suppression agents attempt to extinguish them while managing internal resource constraints. (e.g., water supply, energy).

AGENT CONFIGURATION To answer RQ2's comparative research focus, the simulation employs three different suppression approaches, while following ABM methodology introduced by Wilensky and Rand (2015).

1. **Drone-only approach**: 30 autonomous drone agents are employed. Reflecting a frequently used a swarm size in swarm optimization studies of 30 ($Z_{max} = 30$) (Kozlov et al., 2022, 2024). This size ensures meaningful coordination strategies while balancing computational efficiency. The drones are initiated with an individual water capacity of 50 L which results in a total swarm capacity of 1500 L. Research Question 2 (RQ2) is addressed by implementing, comparing different path-finding algorithms, and analyzing how their distinct behaviors influence emergent wildfire suppression outcomes.

2. **Plane-Only**: 4 firefighting aircraft are employed, reflecting a realistic firefighting fleet in extreme scenarios (Sherry and Chaudhari, 2025). Given an individual water capacity of 18 184 L per plane, the total fleet capacity is 72 736 L. Considering that firefighting planes are the most used suppression technique, this approach acts as a baseline for the comparative assessment of RQ2.

3. **Hybrid approach**: 20 drones + 5 planes + 3 runways. This hybrid approach employs both the firefighting aircraft and drone agents, which enables coordination testing between heterogeneous agents. Given 20 drones and 5 planes the combined capacity is 92 920 L (2000 L + 90 920 L). This approach directly addresses RQ2's systematic comparison and RQ3's optimization potential.

The significantly different water capacities of the different approaches are intentional and reflect the limitations and advantages of each agent's architecture. This strategy is chosen to reflect real-world operational constraints such as the limited carrying capacity of drones. The deployment frequency requirements, where 30 drones require coordinated refilling patterns, directly affect swarm coordination patterns relevant to RQ1's path-finding algorithm assessment. Furthermore, the different fuel and energy consumption profiles per unit of firefighting capacity provide essential data for RQ3's environmental impact evaluation. This experimental design establishes a comparative framework for evaluating wildfire suppression techniques while directly addressing RQ3's central question about trade-offs among suppression effectiveness, efficiency, and sustainability. By maintaining realistic capacity differences, the simulation enables assessment of whether nature-inspired path-finding algorithms can achieve superior cost-effectiveness and environmental performance despite significantly lower individual water capacity. This approach specifically evaluates

RQ3's sustainability trade-offs by comparing operational costs, environmental impact in kg CO_2, and resource utilization efficiency (water usage per successful suppression) across drone, plane, and hybrid approaches, potentially demonstrating the sustainable advantages of drone approaches over traditional aircraft methods.

4.2 *Agent Design and Setup*

Each approach was tested across 1000 independent simulation runs of 1000 steps each, providing statistical power for comparison. The logic of the model illustrated in the Appendix 7. For the simulation, multiple agent classes are implemented: Drone, Plane, Fires, Water Station, Recharge Station, and a Runway class. Each agent acts based on internal logic and interacts with the environment according to its proper- ties. The Agents were developed following the principles of Situation Awareness-based Agent Transparency (SAT), as shown in Figure 1 of (Chen et al., 2018) based on the original framework in Chen and Barnes (2014). The `agent_data`, which collects data at each simulation step offers insight into the agent's internal state, collecting its goals and actions (SAT Level 1), reasoning (SAT Level 2), and projections (SAT Level 3), as reflected in its chosen paths, performance history and resources.

4.2.1 *Drone Agent*

OVERVIEW AND PURPOSE The Drone Agent module simulates an autonomous firefighting drone within the agent-based model framework. Its primary function is to locate and extinguish fires efficiently while managing its own resources constraints. The agent incorporates nature-inspired path-finding algorithms, resource management systems, and decision-making mechanisms to simulate realistic drone behavior in firefighting scenarios. The parameters of the Agent are based on the " DJI AGRAS T50" —a state-of-the-art agricultural drone (DJI, 2025). The model is fully parametric, allowing for customization and implementation of other drones. To ground the findings in realistic conditions this specific drone was chosen.

The implementation draws inspiration from current state-of-the-art agricultural drones, specifically the DJI AGRAS T50 model (DJI, 2025), with modifications to adapt it for firefighting purposes. The parametric design allows for customization of drone capabilities during model initialization to facilitate sensitivity analysis and scenario testing.

DECISION-MAKING ARCHITECTURE The Drone Agent uses a state-based decision architecture that determines its behavior based on current conditions and resource levels. This approach has proven to be computationally more efficient than a rule-based approach by using a dictionary-based decision-making system that selects appropriate methods based on the drone's current mode of operation. The decision-making framework, illustrated in Figure 1, consists of three primary components:

1. State Assessment: The drone continuously monitors its current state, including position, resource levels (energy and water), and environmental conditions.

2. Mode Determination: Based on the state assessment, the drone determines its operational mode through the `determine_mode()` method, which acts as the central decision point.

3. Action Execution: Once a mode is selected, corresponding action methods are executed, such as path-finding, recharging or firefighting.

RESOURCE MANAGEMENT The Drone Agent monitors its two critical metrics constantly

- Water: Which is used for fire-fighting and released on fire site, as shown in Figure 1/: when falling bellow a certain water threshold (35% capacity) the Drones' priority becomes to refill the water and find the closest water station.

- Energy: In addition to the Water levels the Drone keeps constant track of its own energy levels and based on the same logic makes sure to not run out of energy, hence when the energy level falls below the predefined energy Threshold (40% of full capacity) it prioritizes locating and finding the closest recharge station.

PATH-FINDING Based on the defined path-finding algorithm (`self.pathfinding_method`), one of the three path-finding methods is chosen: A* search, Artificial Bee Colony, or Ant Colony Optimization. The path-finding process follows a structured protocol: The `target identification` first determines the closest target based on the drone's current needs: "fire" (suppression), "recharge", "refill" (water), or "runway" (plane specific operation). The selected target coordinates are then passed to `self.calculate_path(start, goal)` to compute the optimal route using the specified path-finding algorithm. Once a valid path is successfully calculated, it is executed through `self.move_along_path()`.

FIREFIGHTING The firefighting ability of the Drone is handled through the `apply_water()` function. Given that the Drone is at the fire location, the water gets applied respecting the water threshold and water drop rate of the drone.

Table 1: Drone Agent Model Parameters

Parameter Name	Value	Description
Basic Properties		
location	None	Current position of the drone (x,y)
goal	None	Target destination for the drone
path	[pos]	Current calculated path to destination
typ	"drone"	Type identifier for data collection
Targeting Parameters		
current_target	Fire	Current object being targeted
target_type	Fire	Type of target (fire, water, energy)
target_fire	pos[x,y]	Specific fire being targeted
Water Related Metrics		
water_capacity	50 L	Maximum water storage (DJI, 2025)
water_threshold	35%	Minimum water level before refill
water	50 L	Current water level (starts full)
water_drop_rate	3.0 L	Water used per firefighting action
water_used	0.0 L	Total water used in firefighting
Energy System		
max_energy	100	Maximum battery capacity
energy	100	Current energy level
energy_threshold	40%	Minimum energy before recharge
recharging	T/F	Boolean indicating recharge status
Firefighting Parameters		
firefighting	T/F	Boolean indicating active firefighting
time_at_fire	0	Steps spent at current fire
Weight Parameters		
weight	52 kg	Weight with battery (DJI, 2025)
payload	0 kg	Current payload weight
total_weight	52 kg	Total weight (base + payload)
Environmental Impact		
emission_rate	0.05	Base emission rate per movement

Continued on next page

Table 1 – continued from previous page

Parameter Name	Default Value	Description
total_emission	0.0	Cumulative emissions produced
Economic Metrics		
cost_per_step	0.02	Base operational cost per step
energy_cost	0.05	Cost per energy unit consumed
total_cost	0.0	Accumulated operational costs

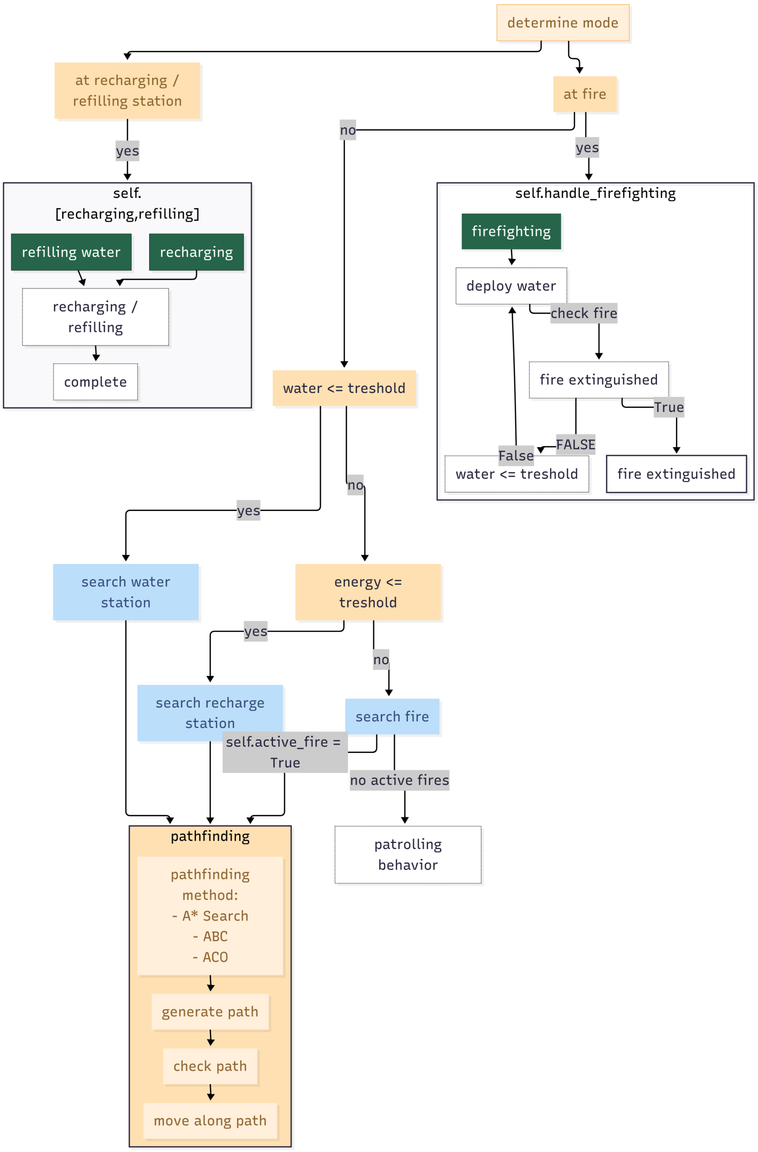

Figure 1: Drone Agent Decision-Making Logic

4.2.2 *Firefighting Plane*

The simulation framework incorporates manned aircraft as a benchmark to evaluate drone-based firefighting solutions. The Lockheed Martin C-130 Hercules was chosen as the reference platform due to its proven operational history, widespread use in aerial firefighting, and well-documented performance characteristics (aviationzone, 2022). As a repurposed military transport aircraft, the C-130 represents a conventional approach to wildfire management, providing a solid baseline for assessing the effectiveness of emerging drone-based strategies. Due to its military design heritage it offers the capability to carry heavy payloads and has proven itself in reliability. The C-130 aircraft, used as a reference for the firefighting plane, has an estimated range of 2047 M = 3791 km with max payload and 4522 M = 8375 km with an empty payload (aviationzone, 2022). Considering simplicity the simulation assumes an average range of 6000 km given the fact that the Plane is full and empty based on whether the water was dropped or is being delivered to the fire site. Considering these metrics a fuel consumption of 6 L/km is calculated.

$$\text{Fuel Consumption per km} = \frac{36000\ \text{L}}{6000\ \text{km}} = 6\ \text{L/km}$$

Given that the drone has a speed of 1 field per step which accounts for 36 km/h (DJI, 2025) (equivalent to 10 m/s). Therefore, the speed of the plane needs to be normalized. In comparison, the C-130 has a cruising speed of 600 km/h (aviationzone, 2022) (or 167 m/s), considering that the speed for firefighting is significantly lower a speed of 250 km/h ($\approx$ 69.4 m/s) is chosen resulting in a relative speed factor of:

$$\text{Speed Factor} = \frac{70\ \text{m/s}}{10\ \text{m/s}} = 7 \tag{2}$$

Therefore, the speed of the plane is defined by the value 7 (positions per step) This factor is used to scale operational parameters when comparing drone and plane behavior within the simulation. To calculate the fuel consumption with a speed of 250 km/h ($\approx$ 69.4 m/s), and simulation steps defined as 1-second intervals:

$$\text{Fuel Consumption per Step} = (6\ \text{L/km}) \times \frac{250}{3600}\ \text{km/s} = 0.417\ \text{L/step}$$

The emission rate of the firefighting plane is based on data from Spicer et al. (2009), which reports an emission of approximately 0.3073 kg CO_2

for every kilogram of fuel consumed assuming Jet-A fuel with a density of 0.8 kg/L. The emission per step is calculated as follows:

$$\text{Emission per Liter} = 0.3073\ \frac{\text{kg CO}_2}{\text{kg fuel}} \times 0.8\ \frac{\text{kg fuel}}{\text{L}} = 0.24584\ \frac{\text{kg CO}_2}{\text{L}}$$

$$\text{Emissions per Step} = 0.417\ \text{L/step} \times 0.24584\ \frac{\text{kg CO}_2}{\text{L}} = 0.1025\ \text{kg CO}_2$$

As stated by Spicer et al. (2009) is it important to point out that the emissions fluctuate significantly depending on cruising speed and weather conditions. For simplicity reasons the emissions per step are a fixed parameter calculated as mentioned.

In addition to similar parameters, the logic of the plane also works differently. A key difference is the plane specific interaction with the Runway class, simulating refueling, takeoff and landing behavior. A key difference between the Plane and Drone class is its characteristic behavior; the drone has a smaller turning radius and is able to refuel from the resource stations autonomously, whereas the plane is dependent on a runway in order to refuel water and fuel. In addition, the emissions are expected to be much higher because it runs on fossil fuels and not electricity. However, the plane moves faster and has a higher water loading capacity which enables it in theory to extinguish fires faster.

Table 2: Firefighting Plane Class Parameters

Parameter Name	**Default Value**	**Description**
Basic Parameters		
unique_id	int	Unique identifier for the plane agent
typ	"plane"	Agent type identifier
location	None	Current position of the plane
goal	None	Target destination
path	[list]	Calculated path to destination
speed	7	Movement cells per step
Resource Parameters		
water_capacity	18 184 L	= 4000 gallons C-130 (Corporation, 2018)

Continued on next page

Table 2 – continued from previous page

Parameter Name	Default Value	Description
water	2000	Current water level
water_threshold	500	Minimum water level before refill
water_used	0	Total water used during operations
water_drop_rate	8.328 L/s	= 2200 gallons/s C-130 aircraft
fuel_capacity	3600 L	= 9530 gallons (aviationzone, 2022)
fuel	1000	Current fuel level
fuel_threshold	200	Minimum fuel level before refueling
Time and State Parameters		
refill_time	10	Time steps required to refill water
refill_time_remaining	0	Countdown for current refill operation
refueling_time_remaining	0	Countdown for current refueling operation
refueling	T/F	Boolean indicating refueling state
time_at_fire	0	Time spent at current fire
max_time_at_fire	2	Maximum time to spend at a fire
Environmental Impact Parameters		
emission_rate	0.24584	Kg CO_2 / L fuel (Spicer et al., 2009)
total_emission	0.0	Cumulative emissions produced
operational_cost_per_step	0.5	Base operational cost per step
fuel_cost_per_unit	0.1	Cost per unit of fuel
total_cost	0.0	Cumulative operational cost
Target References		
current_target	None	Current target object (fire, runway, etc.)
target_fire	None	Reference to the specific fire being targeted
fires	[list]	List of all known fires
firefighting	T/F	Boolean indicating firefighting state

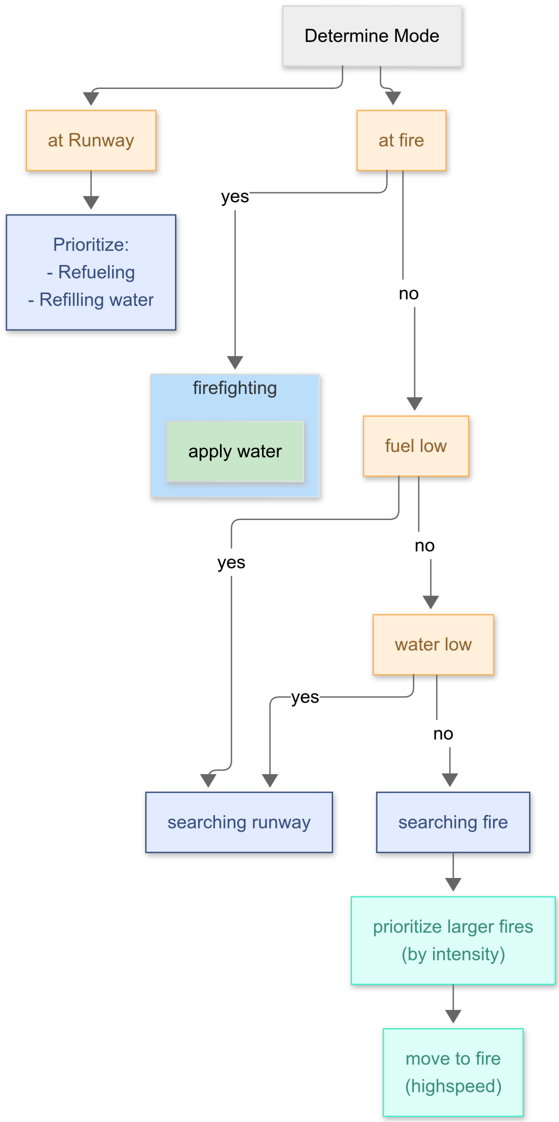

Figure 2: Plane Logic

4.2.3 *Water Station*

Water Stations are key infrastructure agents responsible for refilling the drone. Each station has a limited refill rate, introducing a time cost to each interaction. Water usage data per refill is collected for each agent, and the refill interaction contributes to total operational cost and emissions. Placement of Water Stations influences overall suppression efficiency and is therefore predefined to ensure comparability between approaches. The chosen parameters can be observed in Table 6.

4.2.4 *Recharge Station*

Environmental sustainability represents a primary design consideration for the recharge station network. Each station's operations are characterized by an emissions factor of 0.200 kg CO_2 per kWh provided, based on research conducted by Stolaroff et al. (2018), which compares energy efficiency of different drone delivery systems. It is important to highlight that emissions caused by green electricity generated through solar panels highly fluctuate and can range from "40g to 180g of CO_2 per kWh for PV" (Fthenakis and Kim, 2007), depending on various factors. For simplicity reasons the value proposed by Stolaroff et al. (2018) will be used to calculate emissions caused by the recharge station in connection with the drones. The electricity cost is based on the EU average of 2023 (eurostat, 2024), with a value of 0.2872 euro per kWh. `total_energy_provided` and `recharge_event` are metrics to calculate the usage of the recharge station and can be used for more in-depth analytics. The chosen parameters are illustrated in Table 7.

4.2.5 *Fire Agent*

As this study is in the field of multiagent systems every instance in the simulation is an agent, therefore also the fire needs to be defined as an agent. As shown in Appendix 8 the fire agent has customizable parameters which allow for complex interactions with the firefighting vehicles. To mimic the real world the fire agents spawn in the environment with different intensities and have the possibility to spread to a neighboring cell. The spread fire is its own agent with a slightly lower intensity. Through functions such as `apply_water(water_amount)` the fire agent receives water from the given firefighting agent and extinguishes. The parameters for the `FireAgent` can be observed in Appendix 8. When fire spreads to neighboring cells, new fire agents are created, meaning that a higher fire count reflects fire area growth rather than the ignition of new fires.

4.2.6 *Runway Agent*

The runway agent is created specifically for the firefighting plane. A plane needs a runway to start, takeoff and refill fuel and water, contradictory to a drone which can autonomously refill itself and charge itself through a given station. The runway is implemented to ensure a logical approach to real-world firefighting models. It is kept track of whether the runway is currently occupied to make sure multiple planes do not collide. The parameters of the runway class are explained in appendix 9

4.3 *Path-finding Algorithms*

Each drone selects paths using of one of the following algorithms:

1. A* Search: Heuristic-based algorithm with low resource usage. Efficient for small or structured environments. Implemented through the `heapq` Python library (Foundation, 2024).
2. Artificial Bee Colony (ABC): Swarm-inspired, decentralized optimization method effective in dynamic or noisy spaces (Karaboga and Basturk, 2007).
3. Ant Colony Optimization (ACO): Probabilistic method using pheromone trails to discover optimal paths over time (Dorigo et al., 1996).

The same algorithm is used for all drones within a simulation run to ensure internal consistency. All algorithms are tested across otherwise identical parameters to evaluate comparative performance. These were selected based on experimentation and prior research.

4.4 *Data-Collection*

As mentioned earlier the Simulation is created with the SAT model in mind. Therefore, a robust and extensive Data-Collector model is needed. At every step every agent's properties are stored in the `agent_data` data-frame and the models properties in the `model_data` data-frame. This data collection is enabled through the `mesa.datacollection.DataCollector` which is part of the Mesa framework. `agent_reporters` and `model_reporters` make this function possible. Extensive details can be found in the GitHub repository.

4.5 *Risk Assessment with Machine Learning*

To address the main research question of how agent-based modeling can be used to evaluate and optimize autonomous aerial wildfire suppression strategies, two unsupervised learning methods, DBSCAN and K-Means, were implemented for exploratory analysis. This analysis aims to investigate whether simulation outputs contain meaningful patterns that could support more advanced analysis and agent decision-making in future research, rather than direct comparisons between suppression approaches.

1. DBSCAN (Ester et al., 1996): A density-based clustering algorithm to identify spatial risk zone and corrdination patterns.

2. K-Means (Lloyd, 1982): A centroid-based algorithm to segment environments based on fire intensity and suppression delay.

This exploratory machine learning clustering analysis serves as a proof-of-concept, demonstrating that the ABM framework generates informative emergent patterns, which can be used for further investigation. These algorithms were applied to simulation data capturing fire intensity, suppression history, and spatial coordinates. The main algorithm used was DBSCAN, with falling back to K-Meansn if DBSCAN failed to converge. Default `scikit-learn` parameters were used (Pedregosa et al., 2011), with basic preprocessing (normalization and NaN filtering). The clustering results are presented as a foundation for future research where risk assessment is used as a tool to guide agent behavior.

4.6 *Technical Implementation and Reproducibility*

1. Language: Python 3.11 (Foundation, 2022)

2. Packages: Key packages include `mesa` (ter Hoeven et al., 2025), `numpy` (Harris et al., 2020), `pandas` (pandas development team, 2020), `matplotlib` (Hunter, 2007), `seaborn` (Waskom, 2021) , `heapq` (Foundation, 2024) `scikit-learn` (Pedregosa et al., 2011), an exhaustive list of all requirements are listed in the repository: `(see requirements.txt)`

3. Code repository: AgentBasedFirefightingModel_repository (Speidel, 2025)

The entire simulation is designed to be reproducible and configurable. All agent parameters, environment size, and algorithm settings can be controlled via parameters.

4.7 *Expected Outcomes and Performance Metrics*

Based on the research questions and experimental setup, this research evaluates the different approaches using the following metrics.

Metric	Definition
Effectiveness	Time steps required until successful fire suppression 5.2
Efficiency	Total accumulated operational cost in euros (€)
Sustainability	Resource analysis of total CO_2 emissions in (kg) and water consumption in (L)
Path-finding Performance	Comparative analysis based on effectiveness, efficiency and sustainability across A*, ACO, and ABC algorithms
Trade-off Analysis	Scenarios with higher effectiveness (faster suppression) may exhibit lower sustainability (higher emissions/costs). However, the containment of wildfires has the highest priority.

Table 3: Performance Metrics

Drone swarms are expected to demonstrate superior cost-effectiveness and lower environmental impact with higher coordination completely, in line with their individual capacity limitations. In contrast, the plane approach is likely to be the least sustainable but most capable at wildfire suppression. Hybrid systems may offer optimal trade-offs between suppression speed and sustainability. The machine learning model analysis is expected to reveal operational patterns that could inform future decision-making strategies. The performance of the path-finding algorithms is expected to reveal that the A* algorithm performs well in structured environments, while ACO and ABC excel in more dynamic environment. These hypotheses are based on the simulation architecture, agent properties, and path-finding behavior.

5 RESULTS

The following section presents the simulation outcomes in alignment with the three research sub-questions. First, the influence of different path-finding algorithms on the movement and coordination of drone agents is evaluated (RQ1). This is followed by a comparative analysis of suppression performance across drone-based, plane-only, and hybrid configurations (RQ2). Lastly, trade-offs between suppression effectiveness, operational efficiency, and sustainability—measured through CO_2 emissions, water consumption, and cost—are assessed (RQ3). These results provide a structured basis for understanding how agent-based modeling can be applied to evaluate and optimize autonomous aerial wildfire suppression strategies.

5.1 *Path-Finding*

To address the main research question and RQ2, it is necessary to first present the results addressing RQ1, which investigates the performance of different path-finding algorithms. The simulation provides clear visual evidence that each algorithm employs a distinct movement strategy. In the visualizations, each drone's path is depicted as a blue line, recharge stations are shown as yellow circles, and water stations as blue circles. Separate figures are dedicated to A* 3, Ant Colony Optimization (ACO) 4 and Artificial Bee Colony (ABC) 5, each illustrating the algorithm's trajectory under identical initial fire conditions (`fires_n = 50`), respecting model complexity considerations **??**. Each plot is generated after 1000 simulation steps. It is important to note that results can vary between simulation runs, thus the figures presented here serve as representative examples. Accordingly, it is possible that some fires are still not contained, those are marked as red circles, with the size reflecting its intensity. The same logic applies for extinguished fires, marked as green circles. The "active" label in the plot describes ongoing fires, while the "total fires" metric represents the cumulative number of ignited fires throughout the simulation, highlighting that the fire spread mechanic is working properly.

Figure 3 demonstrates the operational success of the drone-based approach using the A* algorithm, achieving 100% fire suppression (81 out of 81 ignites fires extinguished). Its trajectory can be described as direct and efficient while maintaining coordinated suppression behavior and resource management. In contrast, the ACO algorithm exhibits emergent swarm intelligence through its distinct path trajectories, showing adaptive route optimization. Figure 4 demonstrates a simulation that does not converge, the drones do not manage to contain all fires in the given simulation steps (46.4% extinguished). In order to differentiate between extinguished and active fires, this example was intentionally selected. Accordingly, this visualization provides evidence into the drone's trajectory which can inform resource allocation decisions. For example, in this simulation, fires in three areas grew larger than others, suggesting that resource station placement in these regions should be adjusted for more effective suppression or more drones should be allocated in this area.

The trajectory of the ABC algorithm, exhibit a similar organic behavior, characterized by an initial phase of broad exploration, followed by a progressive concentration on the most promising areas. Figure 5 shows that this approach yields promising results with 98.5% effectiveness. Ad-

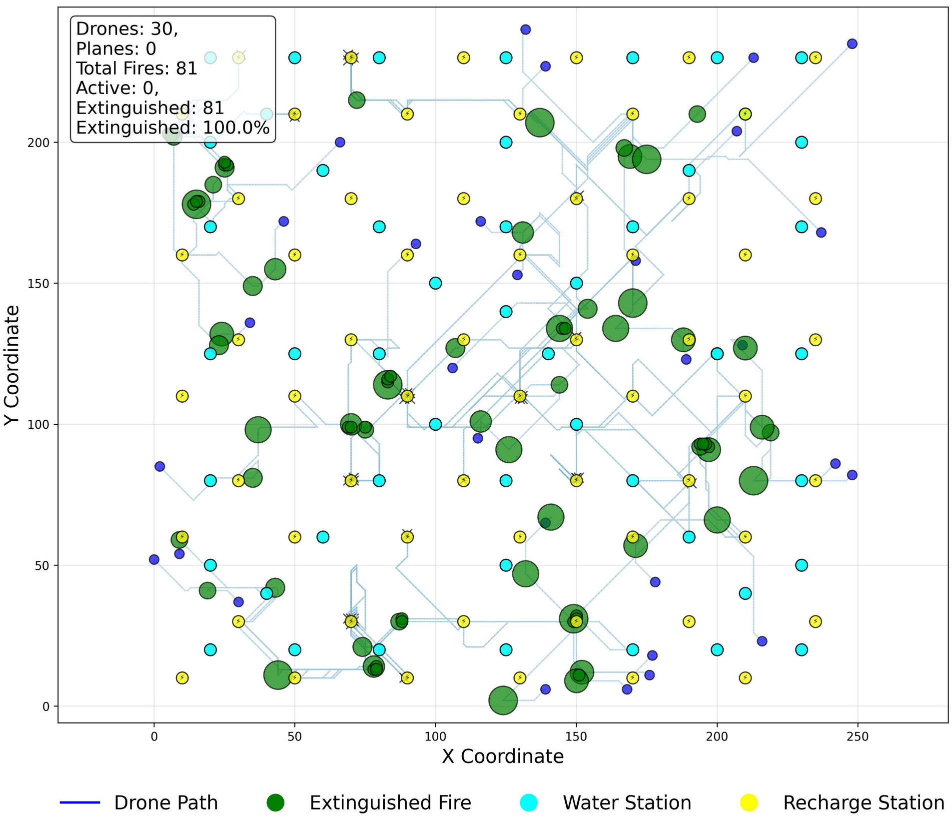

Figure 3: Path trajectories of drone agents using A*

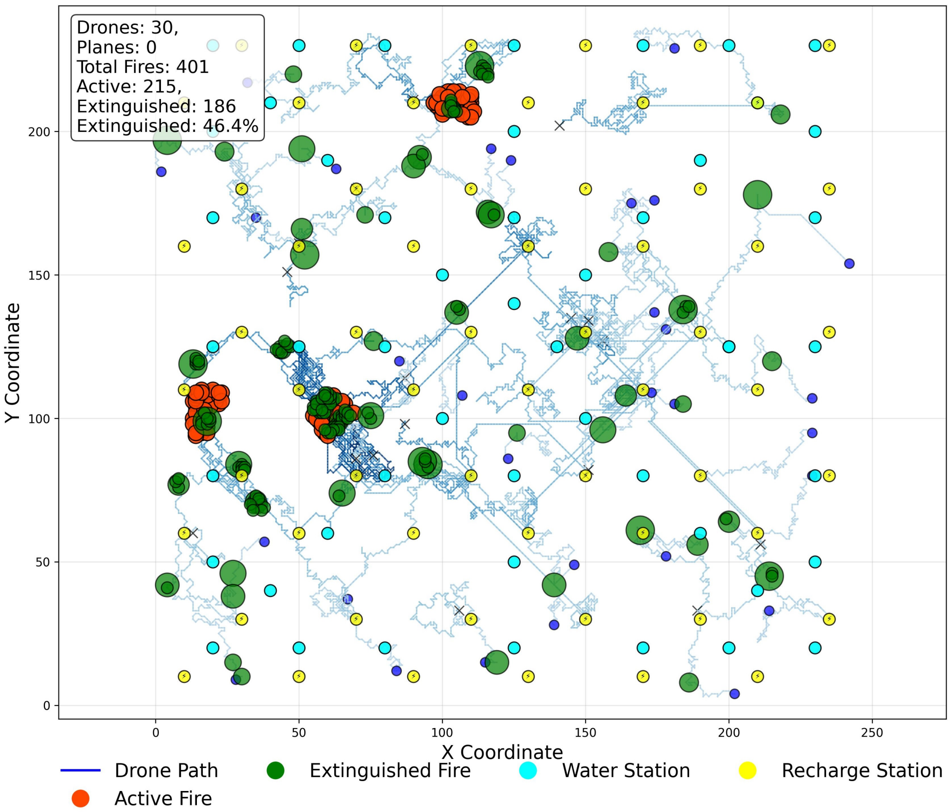

Figure 4: Path trajectories of drone agents using Ant Colony Optimization

ditionally, an interesting behavior can be observed, the paths appear less coordinated compared to the A* and ACO approaches. This phenomenon is likely attributable ABC's initial broad exploration behavior, which uses significant resources, resulting in frequent visits to resource stations, as evidenced by the denser clustering of paths around resource stations. While this intensive exploration strategy may compromise immediate efficiency, it potentially enhances long-term coverage optimization through comprehensive environmental exploration.

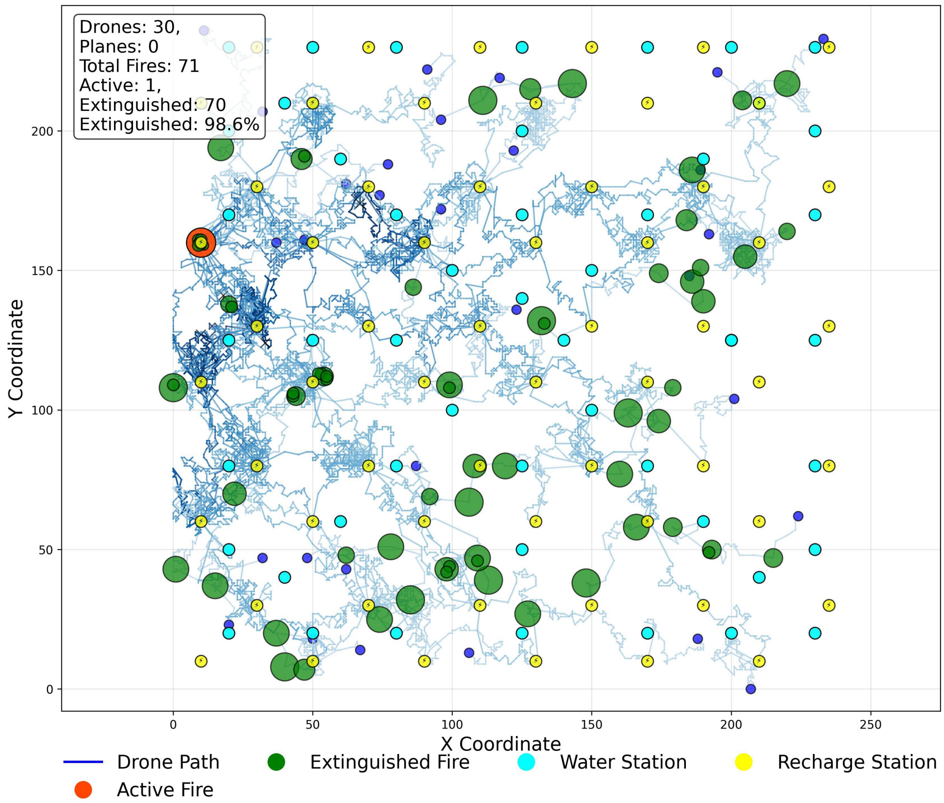

Figure 5: Path trajectories of drone agents using Artificial Bee Colony

Drones demonstrate efficient resource management by clustering around resource while maintaining distributed fire suppression coverage across the 250×250 coordinate space. The high effectiveness in fire suppression with minimal path redundancy supports the sustainability hypothesis, as efficient routing reduces energy consumption and operational costs, directly addressing RQ3. The successful coordination of 30 autonomous agents validates the scalability potential for larger environmental applications. Additional figures are provided for the plane's approach 6 and the hybrid approach **??**, each revealing unique response patterns. In contrast to the drone approaches these approaches include a runway class (purple cross).

From the figures it is evident that the behavior of the aircraft is different from the drones, this can be observed in the higher turning radius and runway dependency.

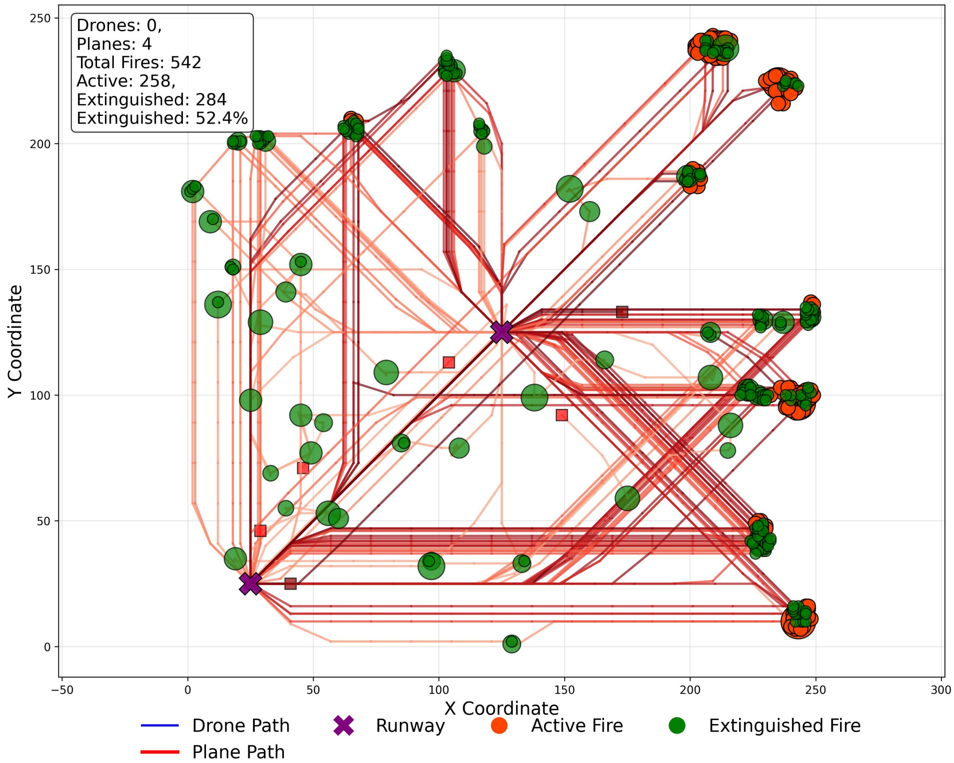

Figure 6: Path trajectories of aircraft agents

Figure 6 reveals the unique operational characteristics of the aircraft-based approach. The trajectories exhibit mainly linear patterns, constrained by mandatory runway interactions for takeoff, landing, and refueling operations. This infrastructure dependency significantly limits operational flexibility, particularly impacting the suppression of fires located at greater distances from the runway, thus achieving only 52.4% suppression effectiveness with 258 active fires remaining. The resulting coverage pattern demonstrates clear spatial differences, with reduced effectiveness in peripheral areas of the simulation environment. This emergent behavior clearly demonstrates the trade-off between aircraft capacity and operational flexibility. In contrast, the hybrid approach exhibits observable patterns suggesting intelligent resource allocation between aircraft and drone technologies. Figure 7 provides evidence of planes handling most suppression tasks, while drones appear to provide supplementary coverage for distant or smaller fires. These behavioral characteristics suggest the potential of collaborative systems, with additional evidence presented in Section **??**.

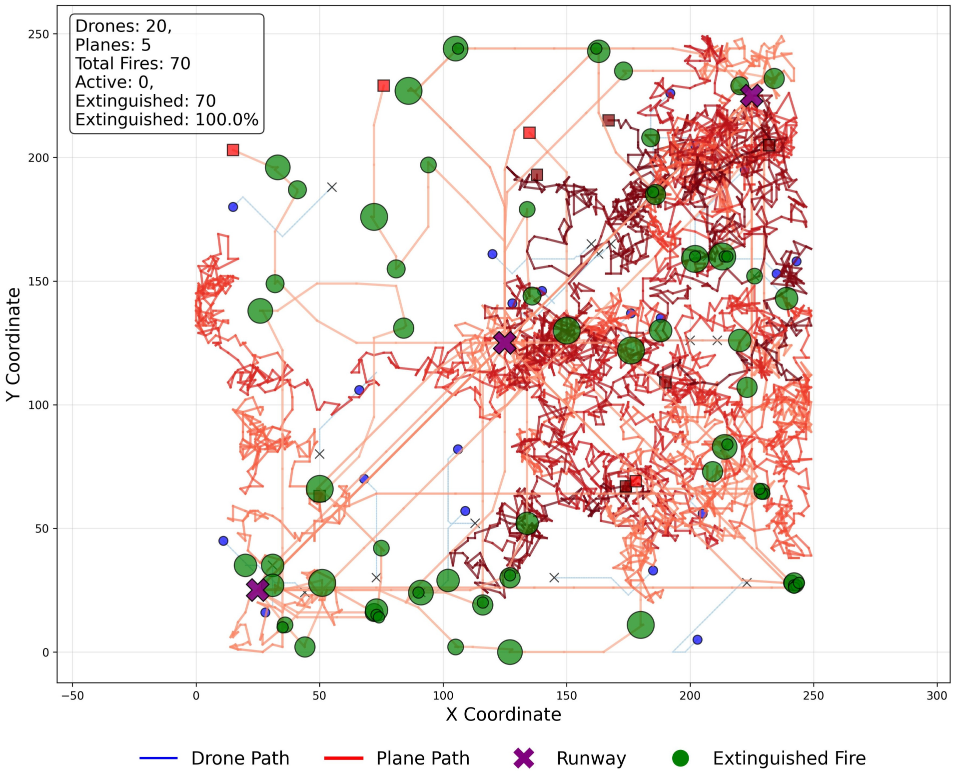

Figure 7: Path trajectories of drone agents and aircraft

Collectively, these individual plots address RQ1 and validate the correct integration of all algorithms into the simulation, showcasing how different navigation strategies and swarm behaviors emerge in the defined environment.

5.2 *Suppression Analysis*

Research Question 1 addresses the comparative effectiveness of drone swarms, hybrid systems, and planes in wildfire suppression. To evaluate this, the mean number of active fires at each time step was calculated across 1000 independent simulation runs. Figure 8 presents these results, with 95% confidence intervals (CIs) depicted as shaded regions around each suppression line. Wider confidence intervals indicate greater variability and thus lower consistency in suppression performance. The results show that drone-based approaches (using ABC, A*, and ACO algorithms) and the hybrid approach maintain consistent suppression performance, as indicated by thinner confidence intervals. In contrast, the plane-only approach displays the widest confidence intervals and the greatest variability in the number of active fires throughout the simulations. This indicates that the plane approach is less consistent in its suppression effectiveness. Overall, these findings suggest that drone-based and hybrid approaches not only achieve similar levels of effectiveness but also provide more consistent results than the plane-only approach. The results also imply that incorporating drones into traditional plane-based suppression strategies could improve consistency and reliability in wildfire management within the context of this simulation study.

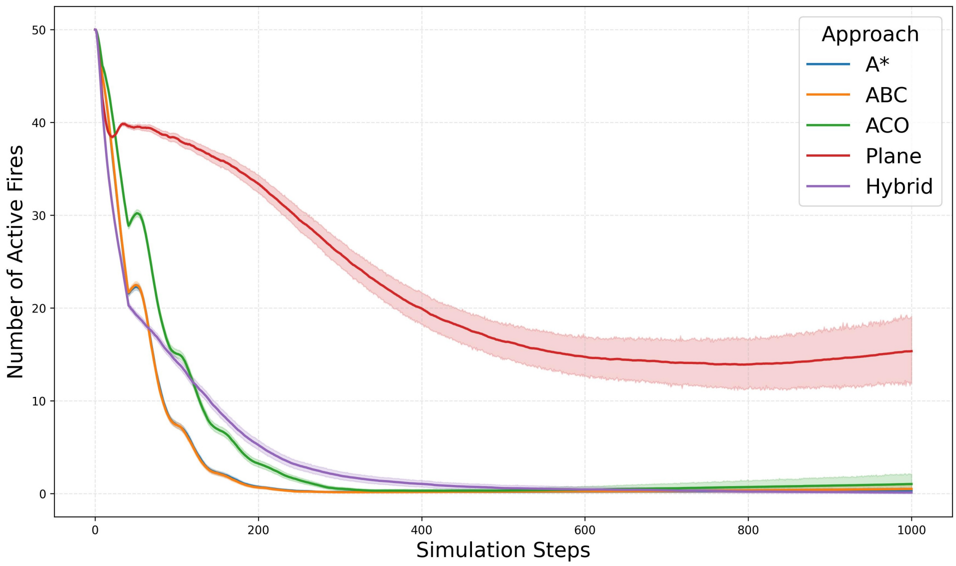

Figure 8: Fire Progression Analysis: Active Fires Across 1000 Simulations with 95% Confidence Intervals

Effectiveness was further assessed by analyzing the number of simulation steps required to achieve complete fire suppression for each approach. Figure 9 displays the mean suppression times and associated variability (as standard deviation) for each configuration, with error bars representing a 95% confidence interval. The drone-only approaches: ABC (229.3 ± 15.9 steps), A* (237.9 ± 16.2 steps), and ACO (291.6 ± 16.5 steps); consistently outperformed the aircraft-only approach (505.1 ± 14.6 steps), which also regularly failed to converge within the defined runtime. The hybrid approach (drones + aircraft) demonstrated the fastest average suppression time (223.3 ± 7.0 steps) and the lowest variability, indicating both efficiency and reliability.

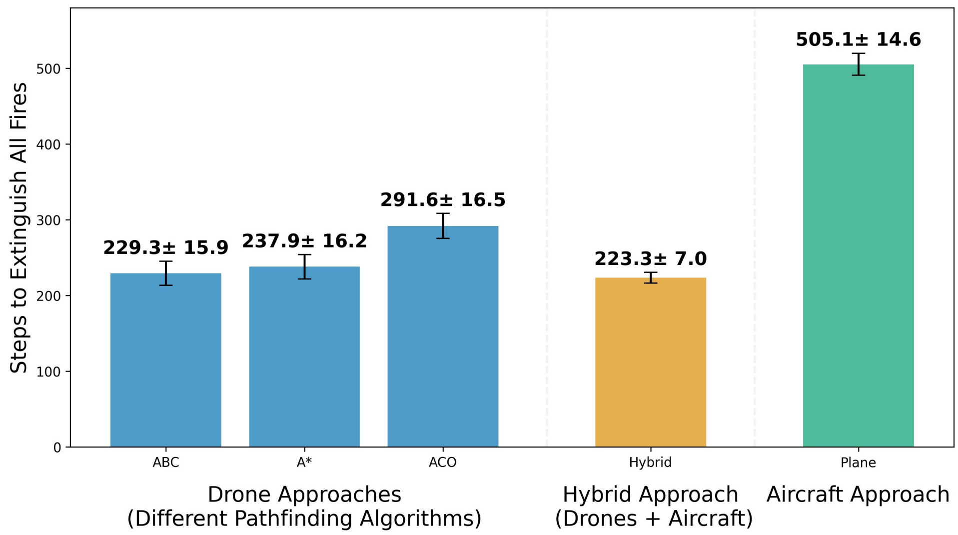

Figure 9: Mean Fire Extinction Time with 95% Confidence Intervals

5.3 *Resource Analysis*

Figure 10 reports average water use, energy/fuel consumption, and emissions per simulation with a 95% confidence interval and error bars. It is evident that the Plane approach is by far the most expensive and pollutant approach in terms of water usage and emitted CO_2 emissions. Given the significantly different resource usages the values are displayed in log scale to make them more comparable Additionally, the cost factor is significantly higher than the compared approaches. The values for the Plane approach go in line with the finding that the plane did not manage to condemn the fire in the given 1000 step time-frame. Figure 8 demonstrated the downward trend of the slope, indicated that the plane manages to condemn the fire eventually and therefore making the simulation converge. However, although possibly being able to condemn the fire, the plane approach is inferior to the drone's resource management abilities. Drones generated the lowest emissions and resource usage, supporting their role in sustainable firefighting. Accordingly, the hybrid system, despite higher emissions, achieved the fastest containment and speed-sustainability trade-off (see Figure: 11). When analyzing cost and water parameters, the same logic applies: drone approaches outperform their competitors, but the hybrid approach still significantly outperforms the plane approach. Table 4 summarizes these findings for improved readability.

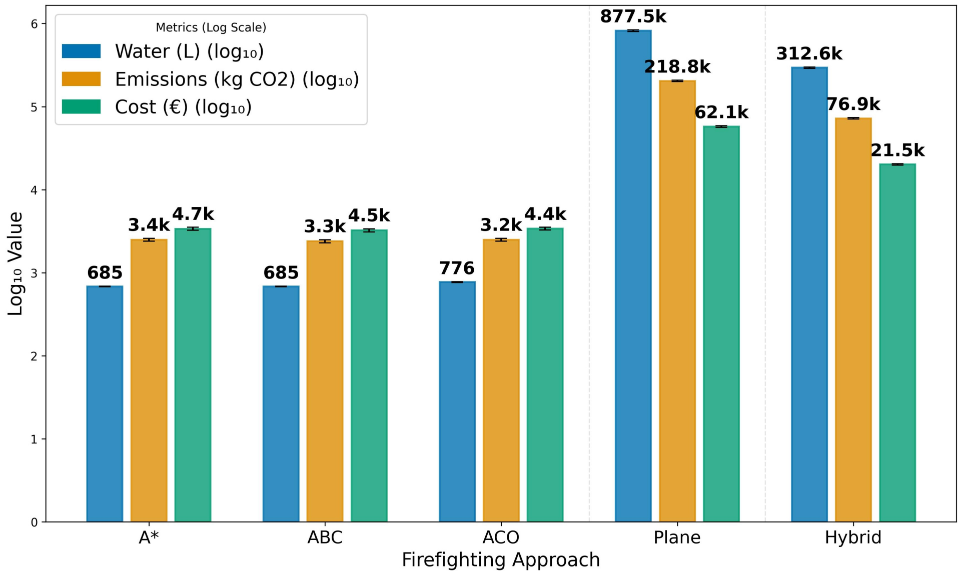

Figure 10: Comparative Analysis of Resource Usage and Environmental Impact by Approach (Log Scale)

Table 4: Resource Usage and Environmental Impact by Approach

Approach	**Water (L)**	**Emissions (kg CO_2)**	**Cost (€)**
Drone Approaches			
A*	685	3400	4700
ABC	685	3300	4500
ACO	776	3200	4400
Plane	877 500	218 800	62 100
Hybrid	312 600	76 900	21 500

5.4 *Computational Complexity*

Figure 11 presents the average simulation time required by each path-finding algorithm (1000 simulation steps). Computational efficiency is a key factor when deploying such systems; while some algorithms may find the fastest route, their high computational cost can be a significant trade-off. The results indicate that all tested path-finding methods achieved comparable performance levels, with average runtimes ranging from 0.48 seconds (Hybrid) and 1.71 seconds (A*), based on 1000 simulation iterations.

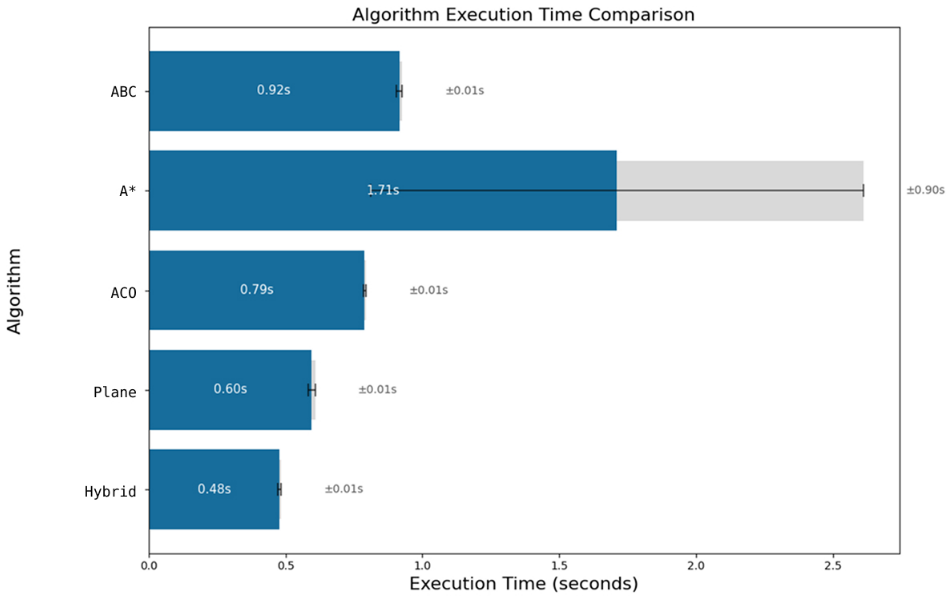

Figure 11: Computational Complexity Comparison

5.5 *Fire Risk Clustering and Analysis*

Figure 12 presents a fire risk analysis based on post-simulation data, where DBSCAN was primarily used to detect high-risk zones—areas where fires repeatedly re-ignited or were slow to extinguish. K-Means was applied only when DBSCAN failed to form meaningful clusters. The highlighted scenario shows a plane-approach that did not converge within the 1000-step limit, emphasizing the need for adaptive fire response tactics. Figure 12 illustrates a clear correlation between fire density and assigned risk levels. Areas with a higher concentration of uncontained fires are classified with higher risk scores (86.6 and 61), compared to largely contained regions (38.7, 51.2, and 56.6). These results provide evidence that the risk assessment methodology effectively distinguishes between high-risk and low-risk areas, validating its potential for data-driven risk analysis and targeted intervention strategies. Ultimately, this supports the development of more complex and adaptive suppression behaviors.

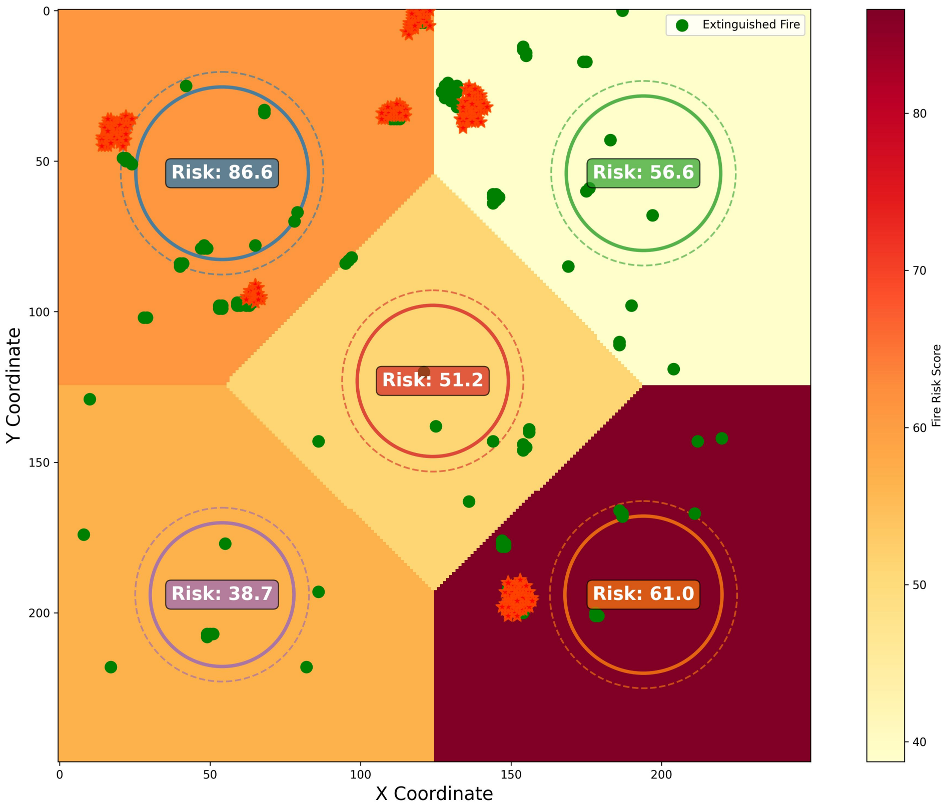

Figure 12: Risk assessment with DBSCAN on the `Plane_agent_data`

5.6 *Summary of the Results*

To address RQ3, the findings presented in Figure 9 and Table 4 suggest that the hybrid approach may demonstrate an optimal trade-off between sustainability and effectiveness. Particularly in extreme wildfire scenarios, even marginal improvements in suppression speed can have a significant impact. This conclusion is further supported by Figure 11, which illustrates that the hybrid approach exhibits the fastest computational performance.

The results hold under the assumption of initiating the simulation with 50 fires as the start, this value resulted in the best trade-off in simulation runtime and emergent patterns, as illustrated in Table 5. The analysis over 10 independent simulations demonstrates that 50 fires provides sufficient complexity to observe meaningful fire dynamics and containment behaviors (99.0% containment rate) while maintaining computational efficiency

(0.71 seconds runtime). This configuration proves to be a representative value that captures emergent fire spread patterns without overwhelming the suppression system, while also being small enough to enable running the simulation 1000 times for robust statistical analysis, unlike higher fire counts (500-1000) which result in bad performing scenarios and significantly longer runtimes (20-65 seconds).

Table 5: Fire Count Analysis Results (average results based on 10 independent simulations)

Initial Fires	Runtime (s)	Fires After 1000 Steps	Containment (%)
10	0.56	0.0	100.0
50	0.71	0.5	99.0
100	1.02	0.2	99.8
500	20.96	14 380.4	−2776.1
1000	65.08	30 877.1	−2987.7

Concluding, these results address the main research question through providing evidence on how agent-modeling can be used to evaluate and optimize aerial wildfire suppression strategies. This research establishes a simulation model that can be customized to fit the needed parameters and therefore being a valid tool to evaluate suppression strategies, the exploratory machine learning approach provides further evaluation possibilities. The simulation results on suppression effectiveness and pathfinding behavior localize areas of resource constraints, which can be used to adapt and optimize suppression strategies accordingly. While ABM can not provide proof, they provide evidence on emergent behavior, the established model can be used to optimize autonomous systems through informed decision-making. The sub-questions reinforce the high-level research question by dividing the results into: (1) the effectiveness of different pathfinding algorithms (addressing RQ1) and their comparative performance for drone-based approaches, (2) comparing different suppression approaches and demonstrating that drone strategies perform best (addressing RQ2), and (3) showing that hybrid approaches offer the best trade-off between performance metrics (addressing RQ3). The simulation under the defined parameters reveals that drones provide the most cost-effective and sustainable option, while hybrid configurations excel in speed. The modular design incorporating agent-based properties and different search algorithms demonstrates flexibility and robustness. This integrated framework not only models complex wildfire scenarios but establishes the foundation for transparent, data-driven, and adaptable fire suppression strategies applicable to real-world scenarios.

6 DISCUSSION

The main goal of this thesis was to evaluate the effectiveness of autonomous drone swarms in wildfire prevention, comparing them to traditional manned aircraft and hybrid approaches. The study aimed to assess these strategies based on suppression efficiency, emissions, operational cost, and water usage using a custom agent-based simulation framework. The project also pursued to explore the use of nature-inspired path-finding algorithms and unsupervised learning for enhancing decision-making in complex, dynamic fire environments.

6.1 *Interpretation of Key Findings*

6.2 *Interpretation of Key Findings*

The simulation results demonstrate that the choice of aerial vehicle approach significantly impacts wildfire containment success. The quantitative analysis revealed that a drone-only approach contained fires on averages under 300 steps, compared to the plane approach not converging on average. With the fastest and most consistent convergence having the hybrid approach. Regarding the cost and environmental parameters the hybrid approach had higher values, but significantly lower than those of the plane approach. However, it is to be investigated if the great performance of the drone approach holds under harsher weather conditions and fires with increased intensity, spread and volume. Considering this fact the hybrid approach might be the most interesting solution to look into considering real world applications. The nature-inspired algorithms all performed comparably well with acceptable computational complexity and successful fire contentment. The robustness of the model is important and the fact that it can easily be equipped with different path-finding algorithms is a great insight. These findings reinforce prior work by underlining the environmental advantage of electrified, decentralized suppression systems (Saffre et al., 2022; Stolaroff et al., 2018). The cost analysis showed drone-only systems to be the most cost-efficient due to lower maintenance, fuel, and infrastructure requirements. Hybrid configurations, while fastest, still produced due to the need for runways and refuel stations, high costs. These findings align with previous research employing new ways to fight wildfires and showing their potential (Aydin et al., 2019) but go further by simulating these metrics in a direct comparison. Path-finding visualization results displayed that the algorithms were functionally integrated and generated realistic emergent behavior, validating their inclusion in the simulation. This highlights the value of swarm intelligence in dynamically evolving environments and supports further integration of nature-inspired decision systems.

6.3 *Limitations*

While the simulation produced clear trends, it operates under several assumptions and simplifications. The Simulation introduces several limitations regarding the limited scope for this research, therefore it is important to acknowledge these and point out room for future improvement.

PARAMETER CONSTRAINTS The two-dimensional environment introduces dimensional constraints which lack realistic properties. Especially for aerial vehicles, a three-dimensional environment is preferable, enabling the capture of altitude-dependent factors such as visibility, wind effects, and water/retardant dispersal patterns. Additionally, incorporating realistic obstacles, dynamic weather patterns, and potentially external data sources like satellite imagery would improve the model's accuracy and complexity. The absence of seasonality is another limitation worth addressing in future developments, as the true nature of wildfires is inherently seasonal. Similarly, both the parameters for the drone and the plane agent were initialized as fixed values, whereas in reality these values are much more dynamic, with flight speed changing based on environmental factors and operational focus. Logically, the speed for firefighting should be different from approaching the fire site. For the scope and analysis of this research fixed values are acceptable; however for a deeper analysis, more complex and dynamic values are preferable. The model uses fixed cost and emission parameters, whereas in reality these values fluctuate and depend on factors such as time of day and location. This model, with location-specific parameters would yield drastically different results. For instance, electricity prices and emissions vary significantly across countries; Germany has noticeably higher electricity prices than Hungary (see Figure 1 (eurostat, 2024)). While average values serve as a reasonable indicator for the scope of this research, incorporating more realistic and adaptive parameters is valuable for future development.

MACHINE LEARNING INTEGRATION While the model heads in the right direction by being built in Python to allow for meaningful AI implementation in the future, the agents are still lacking intelligent behavior. The path-finding algorithms could be seen as intelligent behavior since they use swarm properties to make decisions which appear smart. However, no autonomous decision-making framework is integrated. The risk assessment explored this direction: being a model-wide analyzer, which makes the drones all-knowing instead of enabling individual intelligent decision-making limits its potential benefits. More intelligent behavior could also result in too high computation time. Therefore, a trade-off between these two opposites has to be established to find an optimal solution.

6.4 *Contributions*

This thesis contributes an open-source, modular simulation environment that unifies drone and plane behavior, nature-inspired algorithms, emissions and cost modeling, and ML-based risk mapping. While prior work has focused either on UAV coordination (Afghah et al., 2019) or novel suppression techniques (Aydin et al., 2019), this project integrates these dimensions to allow direct comparison and scenario testing. It works as a baseline to build upon making the integration of potentially sustainable planes or other UAV's possible. It also demonstrates that performance trade-offs are essential when evaluating different approaches. Entailing that: certain infrastructure limitations might be advantages making certain strategies more favorable based on other parameters. This research synthesizes research from different disciplines, highlighting the potential of interdisciplinary research in the area of sustainable wildfire monitoring. From a practical perspective the findings of this thesis challenge the binary thinking often applied to wildfire management solutions. Rather than treating drones and traditional aircraft as competing technologies, dynamic and collaborative approaches between a range of technologies should be considered. The simulation framework provides a foundation for developing decision support tools.

6.5 *Future Research*

Given the strong foundation of this model several directions can be taken into consideration. The goal of this research would be a tool in which input a real world environment data works as input and then simulation runs given the specified environment taking into account seasonality, weather and other unforeseen changes in the environment. After simulating, the output would be an estimate of the cost and emissions which would be needed to effectively monitor the given environment. The tool can aid in deciding which firefighting approach to choose, based on differences in environments and local phenomena the result are different and provide valuable insight. This research was aimed to give a step in the right direction motivating cheaper and more sustainable wildfire prevention techniques. To name a few directions of development the following ideas could be pursued:

1. The integration of realistic terrain, weather and wind models.
2. Connection to live data sources such as satellite data and weather API's.
3. Applying more complex AI-driven decision-making such as deep-reinforcement learning to enable unsupervised swarm behavior.
4. Human-swarm interaction drawing inspiration form current research ensuring ethical implications and interactive planning (Lewis et al., 2012).
5. More realistic parameters such as adaptive cost, emission and speed.

Logically, there are seemingly endless possibilities in different directions. While it is beneficial to simulate the environment in greater complexity, there is a trade-off between over complicating the model by representing everything as realistically as possible and producing a fast, usable simulation. This fact must be carefully considered.

7 CONCLUSION

This thesis presents an integrated simulation framework for evaluating autonomous wildfire suppression strategies, combining agent-based modeling, nature-inspired path-finding, operational cost modeling, and machine learning-based risk analysis. By implementing drones, planes, and hybrid strategies all into a single simulation environment, the work enables a transparent comparison grounded in performance, sustainability, and cost-efficiency.

The main research question is comprehensively addressed through the ABM framework's ability to capture emergent behaviors, enable systematic comparison of heterogeneous suppression approaches, and quantify multidimensional trade-offs. The simulation validates ABM's utility for optimizing real-world wildfire suppression strategies by revealing critical performance patterns and resource allocation insights.

Addressing the research sub-questions, this work establishes that path-finding algorithm choice significantly impacts drone coordination and resource management, with A* providing optimal structured performance while nature-inspired algorithms excel in adaptive scenarios. The systematic comparison confirms drone approaches' superior performance over traditional aircraft in both speed and consistency, while hybrid configurations achieve optimal speed-sustainability trade-offs. The resource analysis quantifies the fundamental trade-off between suppression speed and environmental impact, demonstrating drone systems' substantial sustainability advantages.

These findings challenge conventional binary thinking in wildfire management by demonstrating that collaborative approaches between autonomous and traditional technologies offer superior performance characteristics. The modular simulation framework establishes a foundation for evidence-based decision-making in wildfire suppression strategy selection.

Scientifically, this work contributes a modular and extensible tool for wildfire research. It challenges the domain by linking efficiency, and technological advancement without dismissing sustainability, all within a transparent and reproducible open-source framework. Societal, it encourages a shift toward scalable, lower-emission fire response systems that reduce dependency on costly solutions through aiding in taking informed decisions.

As wildfires continue to grow in frequency and intensity, there is an urgent need for adaptable, sustainable, and fast deployable solutions. The work presented here offers a foundation for future research and policymaking.

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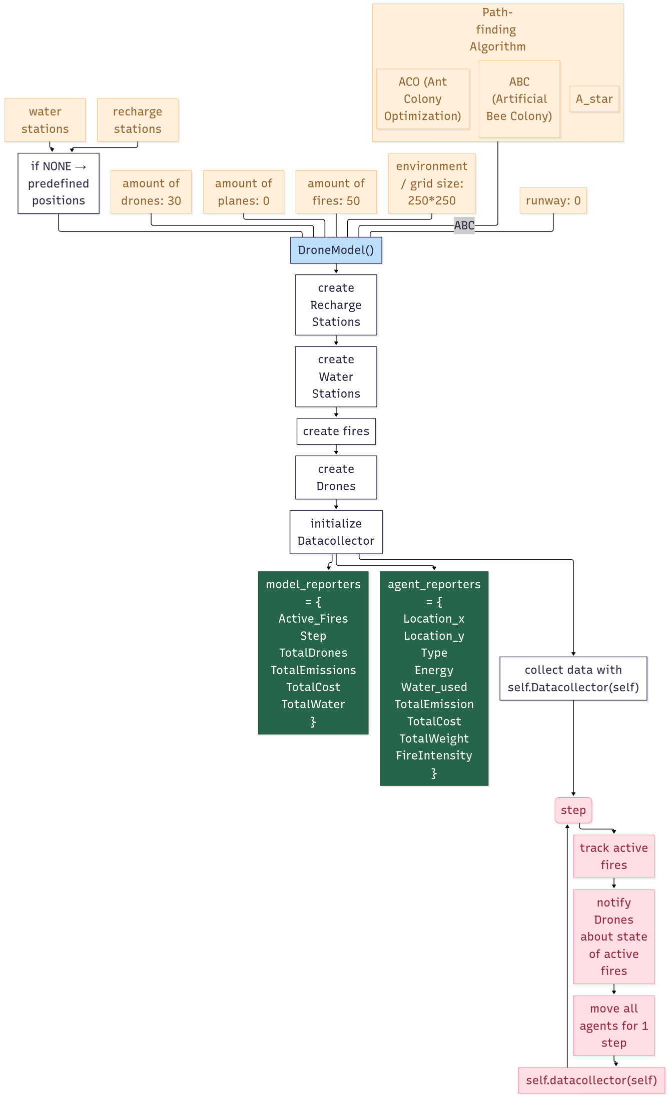

Figure 13: Complete Model Architecture and Agent Interaction Logic

Table 6: Water Station Agent Parameters

Parameter Name	Default Value	Description
Initialization Parameters		
location	[x,y]	Position of the water station
capacity	1000 L	Maximum water capacity in liters
unique_id	int	Unique identifier for the agent
typ	“water_station”	

Continued on next page

Table 6 – continued from previous page

Parameter Name	**Default Value**	**Description**
active	T/F	Boolean indicating operational status
Operational Parameters		
refill_rate	20 L	Water refilled automatically per step
multicolumn3l**Environmental Impact**		
emissions_factor	0.20	Emissions in kg of CO_2 per liter dispensed
total_emissions	0.0	Total emissions accumulated
Cost Metrics		
water_cost	€0.00061	Cost per liter of water: Given €0.6 per m^3 equals to 0.00061€ per liter (Giannakis et al., 2016)
maintenance_cost	€0.03	Fixed operating cost per step
total_cost	€0.0	Cumulative cost of operations
Usage Metrics		
total_water_provided	0 L	Total liters of water provided
refill_events	0	Accumulated number of refill events

Table 7: Recharge Station Agent Parameters

Parameter Name	**Default Value**	**Description**
Initialization Parameters		
location	[x,y]	Position of the recharge station
unique_id	int	Unique identifier for the agent
typ	"recharge_station"	
active	T/F	Boolean indicating active status
Operational Parameters		
charge_rate	100	Energy units provided per recharge step

Continued on next page

Table 7 – continued from previous page

Parameter Name	Default Value	Description
Environmental Impact		
emissions_factor	0.200	Emissions in kg of CO_2 per kWh provided. The energy emission varies based on a various factors. The given value is based on a research done by Stolaroff et al. (2018) which shows energy emission efficiency in drones.
total_emissions	0.0	Total emissions accumulated
Cost Metrics		
electricity_cost	€0.2872	Electricity cost per kWh taken from the EU average in 2023 (eurostat, 2024).
maintenance_cost	€0.05	Fixed operational cost per step
total_cost	€0.0	Total operational cost accumulated
Usage Metrics		
total_energy_provided	0.0	Total kWh of energy provided
recharge_events	0	Accumulated number of recharge events

Table 8: Fire Agent Parameters

Parameter Name	Default Value	Description
Initialization Parameters		
location	[x,y]	Coordinates of the fire area
intensity	5	Fire intensity on a scale from 1 to 10
size	1	Size of the fire (radius)
unique_id	int	Unique identifier for the agent
typ	"fire"	Type identifier for the agent
active	T/F	Boolean indicating whether the fire is currently burning
age	0	Age of the fire in simulation steps

Continued on next page

Table 8 – continued from previous page

Parameter Name	Default Value	Description
water_applied	0	Total water applied to this fire
Spreading Behavior		
spread_probability	0.05	Base chance of spreading per step
last_spread_attempt	0	Step count of last spread attempt
spread_cooldown	10	Minimum steps between spread attempts
Methods and Behaviors		
apply_water(water_amount)	—	Reduces intensity, extinguishes fire if intensity ≤ 0.5
step()	—	Ages fire, increases intensity slightly, attempts spread
attempt_spread()	—	Checks for nearby cells and spreads if possible
extinguish()	—	Manually sets fire as extinguished

Table 9: Runway Agent Parameters

Parameter Name	Default Value	Description
Initialization Parameters		
location	[x,y]	Grid location of the runway
typ	"runway"	Type identifier for the agent
is_occupied	T/F	Boolean indicating occupancy status
occupying_plane	None	Reference to the plane currently on the runway
Resource Capacities		
fuel_capacity	10 000 L	Maximum amount of fuel the runway can store
fuel_level	10 000 L	Current fuel level in the runway
water_capacity	20 000 L	Maximum amount of water the runway can store
water_level	20 000 L	Current water level in the runway

Refill Rates (Per Step)		
fuel_refill_rate	200 L	Fuel replenished per simulation step
water_refill_rate	500 L	Water replenished per simulation step
Environmental Impact Parameters		
fuel_emissions_factor	0.2 kg	CO_2 emissions per unit of fuel provided
water_emissions_factor	0.1 kg	CO_2 emissions per unit of water provided
total_emissions	0.0 kg	Cumulative emissions generated
Cost Parameters		
fuel_cost	€0.3	Cost per unit of fuel provided
water_cost	€0.05	Cost per unit of water provided
maintenance_cost	€0.5	Operational maintenance cost per step
total_cost	€0.0	Accumulated operational costs
Usage Statistics		
planes_serviced	0	Total number of planes serviced
fuel_provided	0.0	Total fuel supplied to planes
water_provided	0.0	Total water supplied to planes