AI-Enhanced Swarm Drones: Decentralized Solutions for Sustainable Environmental Monitoring Applications

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Abstract

Swarm intelligence, a subfield of AI, offers a promising approach for enhancing environmental monitoring, which is critical for managing and preserving natural ecosystems, particularly in addressing issues like deforestation, crop health, and soil quality. Traditional centralized monitoring systems are prone to single points of failure, are less efficient, and are often ecologically disruptive. To address these challenges, we present a decentralized swarm robotic system using drones that are equipped with AI-based algorithms for efficient exploration and data integrity. We proposed and tested a hybrid exploration algorithm combining Correlated Random Walk (CRW) and Levy Flight (LF), which achieved a significantly lower mean absolute error (3.75%) compared to CRW (7.21%) and LF (11.64%) individually. Additionally, we implemented a two-factor authentication system to enhance data integrity, reducing the impact of faulty sensors in drones from a mean absolute error of 30.61% to 20.23%. Our results demonstrate that the decentralized swarm system outperforms traditional approaches, providing more accurate, efficient, and reliable environmental monitoring. This research contributes to sustainable land management practices, aligning with UN SDG 15, and showcases the potential of AI-driven swarm robotics in advancing environmental conservation efforts.

Keywords

swarm robotics, environmental sustainable monitoring, AI-driven systems

1. Introduction

Artificial intelligence (AI) encompasses a wide range of fields and areas across various domains. In this study, we explore the field of Swarm Intelligence (SI), particularly swarm robotics, which is a subdomain of AI that is focused on deploying a decentralized network of robots [1]. We contextualize the application to environmental monitoring, which is further discussed in this section.

1.1. Background of Study

Environmental monitoring and surveillance are fundamental processes for maintaining and protecting natural ecosystems and resources worldwide [2], [3]. These practices involve systematically collecting data to understand and manage the environment's health, which is crucial for sustaining biodiversity, ensuring food security, and mitigating climate change impacts. Here, environmental monitoring helps identify ecosystem changes, such as deforestation, pollution, and land degradation, enabling timely interventions to prevent further damage [4], [5] that may even apply to sustainable management of resources, such as water [6]. The importance of these activities aligns with the United Nations Sustainable Development Goal (SDG) #15, which focuses on

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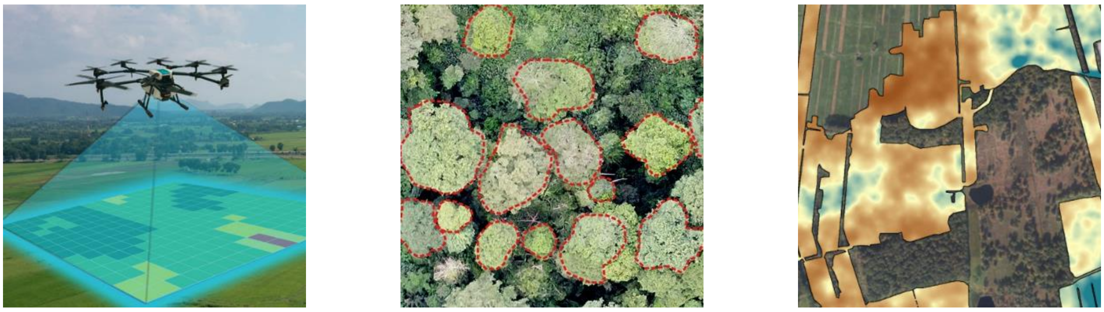
protecting, restoring, and promoting the sustainable use of terrestrial ecosystems, managing forests sustainably, combating desertification, halting and reversing land degradation, and halting biodiversity loss.

In this study, we concentrate on three specific scenarios within environmental monitoring: crop health monitoring, deforestation, and soil quality monitoring, which are shown in Figure 1. Crop health monitoring is essential for detecting diseases and pests that can devastate agriculture, affecting food production and security [7]. Deforestation monitoring is crucial for preserving forests, which are vital for carbon sequestration and biodiversity [8]. Soil quality monitoring helps maintain fertile lands necessary for agriculture and prevent land degradation [9]. While these scenarios represent the deployment end goal of our research, the current study assumes that these contexts are used as sample scenarios where more effective methodologies for environmental monitoring may be implemented.



(a) (b) (c)

Figure 1: Environmental Monitoring for (a) Crop health [10], (b) Deforestation [11], and (c) Soil Quality [12].

Classical and conventional environmental surveillance techniques involve manual data collection and remote sensing technologies. Manual methods, although accurate, are labor-intensive, time-consuming, and limited in scope. Remote sensing, including satellite imagery and aerial surveys, offers broader coverage but can be expensive, dependent on weather conditions, and lacks the necessary resolution for detailed analysis [13], [14], [15]. Additionally, centralized approaches to environmental monitoring are prone to single points of failure, are less efficient in data processing, and often disrupt ecological balance due to their intrusive methods. Data integrity is another significant issue, as centralized systems can be vulnerable to data corruption and loss. Drones, especially when deployed as a swarm, present a promising solution to these challenges. Swarm intelligence maximizes decentralized control, enhancing resilience and efficiency and minimizing ecological disruption [16], [17], [18]. Applying swarm intelligence to drones can revolutionize environmental monitoring by providing more robust, scalable, and adaptive systems.

1.2. Research Gap

Current centralized environmental monitoring techniques face significant challenges, including susceptibility to single points of failure, inefficiency, and ecological disruption. Decentralized systems offer potential benefits such as improved resilience and scalability, yet there is a lack of efficient swarm exploration algorithms that leverage AI to maximize these benefits [16], [19], [20]. Additionally, ensuring data integrity in decentralized swarm systems remains unresolved. Without robust methods to secure data, the reliability of the collected information is compromised[21].

In summary, the primary research gaps identified are the limitations of centralized environmental monitoring, the need for efficient AI-based swarm exploration algorithms, and the importance of securing data integrity in decentralized systems. Addressing these gaps is crucial for developing advanced environmental monitoring solutions that align with sustainable development goals.

1.3. Objectives of the Study

The primary aim of this study is to explore and develop innovative methodologies for decentralized environmental monitoring using swarm robotics. By maximizing the capabilities of artificial intelligence and swarm intelligence, the research seeks to address the limitations of traditional environmental surveillance techniques. This study focuses on enhancing monitoring systems' efficiency, accuracy, and resilience by deploying autonomous drones in a swarm configuration. The goal is to contribute to sustainable development practices by providing advanced tools for environmental surveillance that align with the United Nations Sustainable Development Goals (UN SDGs).

The specific objectives and contributions of this study are as follows:

- Implement a decentralized environmental monitoring system utilizing a swarm of aerial drones with AI-based algorithms.
- Identify and develop efficient exploration techniques for environmental monitoring, particularly in crop health monitoring, deforestation, and soil quality assessment scenarios.
- Ensure the integrity of data collected by swarm systems through applying two-factor authentication approaches, enhancing the reliability and security of the monitoring process.
- Evaluate the performance of the proposed system in various environmental scenarios to validate its effectiveness and scalability.
- Contribute to the broader field of environmental monitoring by providing insights and methodologies that can be adapted to different ecological contexts, thereby supporting sustainable land management practices.

2. Review of Related Literature

Having established the setting and the goals of the study, this section discusses the necessary concepts and existing works relevant to the paper. Here, we break down the components of the study, identifying what has been done and what is lacking in the approaches.

2.1. Conventional Environmental Monitoring Techniques

Conventional environmental monitoring techniques primarily involve manual data collection and remote sensing technologies such as satellite imagery and aerial surveys. While manual methods provide high accuracy, they are labor-intensive, time-consuming, and limited in spatial coverage. Remote sensing, although offering broader coverage, often suffers from high costs, dependency on weather conditions, and sometimes insufficient resolution for detailed analysis [13], [14], [15]. These centralized approaches are also prone to single points of failure, making the systems vulnerable to disruptions.

Moreover, traditional methods can be ecologically disruptive, involving significant human intervention and potentially harming the ecosystems they aim to monitor. The limitations of these classical techniques highlight the need for innovative solutions that can offer decentralized, efficient, and minimally invasive monitoring, such as the deployment of drone swarms [16] equipped with advanced AI algorithms.

2.2. Random Exploration Swarm Algorithms

Random exploration algorithms are pivotal in swarm robotics because they enable autonomous robots to cover and explore large, unknown environments efficiently. These algorithms help distribute the exploration tasks among multiple drones, reducing redundancy and increasing overall coverage.

Correlated Random Walk (CRW) is an exploration strategy where each drone moves in a direction correlated with its previous movement, balancing exploration and exploitation [22]. On the other hand, Lévy Flight (LF) involves taking long, straight paths interspersed with short, random movements, which is particularly effective for searching in environments where targets are sparsely distributed [23]. Combining these strategies can use both approaches' strengths, leading to more efficient exploration and data collection in environmental monitoring scenarios [24].

2.3. Vulnerability of Swarm Robots

Swarm robotics systems, despite their robustness and adaptability, are vulnerable to the influence of malfunctioning or compromised drones, which can affect the behavior and data integrity of the entire swarm. For instance, a drone with a faulty sensor may transmit incorrect data, leading the swarm to make erroneous consensus decisions [16], [21], [25]. This scenario is critical in environmental monitoring, where accurate data collection is essential. A compromised drone might falsely report healthy conditions in a degraded area, skewing the overall assessment and hindering timely intervention. Ensuring data integrity within the swarm is thus crucial, necessitating robust mechanisms to detect and mitigate the impact of such faults, thereby maintaining the reliability of the swarm's collective decision-making process [26].

3. Proposed System and Algorithms

This paper integrates a drone swarm system with random exploration algorithms to ensure efficient and secure data collection for the environmental monitoring application. For this section, we discuss in detail how the decentralized network of drones' functions in environmental collective sensing scenarios and present the relevant algorithms employed to explore and gather data that is secured by a two-factor authentication system.

3.1. Swarm Robotics System

The proposed system operates as a distributed network of drones, where each drone acts as a node participating in the environmental monitoring application. As illustrated in Figure 2, the network of drones collaborates to cover extensive areas efficiently. Each drone in the swarm is equipped with ground sensors to detect environmental features, proximity sensors to navigate effectively, and communication modules such as range and bearing sensors to interact with other drones. These drones are tasked with reaching a consensus on the environmental state, specifically detecting the percentage of white tiles in a square grid environment, simulating various environmental features.

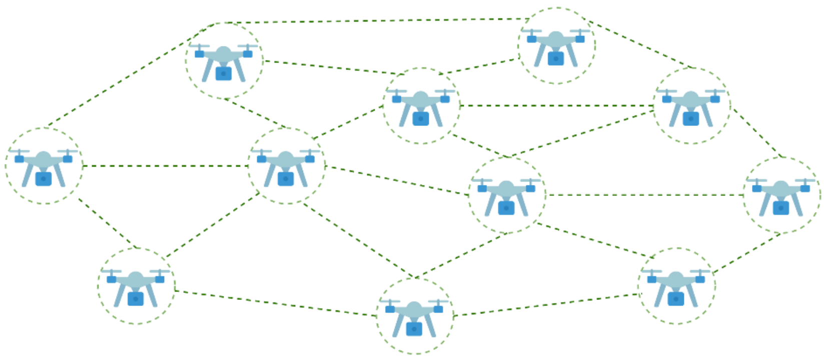


Figure 2: Swarm Drone Network

This system achieves consensus through iterative communication and data sharing among the drones. Each drone independently collects data from its assigned area and shares it with its neighbors. The drones collectively converge on a shared understanding of the environment through repeated exchanges and updates. This decentralized approach not only enhances the robustness and scalability of the system but also mitigates the risks associated with single points of failure in centralized systems. The consensus mechanism ensures that the collective decision reflects the aggregated data from all drones, improving the accuracy and reliability of environmental monitoring.

3.2. Hybrid Correlated Random Walk with Lévy Flight

Random exploration algorithms are essential for efficiently covering unknown and unexplored areas, which is fundamental in applications like environmental monitoring. Swarm robotics, in particular, benefits from these algorithms' ability to enhance robustness, scalability, and efficiency. The movement strategy of drones is crucial for effective exploration, and random movement patterns help cover larger areas, avoid obstacles, and prevent getting stuck in local minima.

The Correlated Random Walk (CRW) algorithm ensures that each drone's movement direction is correlated with its previous movement, favoring smaller turning angles. This approach leads to a tendency for the drone to continue moving in the same direction, which is modeled using a wrapped Cauchy distribution, as shown in (1). The algorithm updates the drone's position by taking steps influenced by a correlation factor and a small random deviation, resulting in a path with correlated consecutive steps, reducing the likelihood of abrupt directional changes.

$$P(\phi_{t+1}|\phi_t) = \frac{1}{2\pi} \cdot \frac{1}{1+\rho^2-2\rho\cos(\phi_{t+1}-\phi_t)}, \quad (1)$$

where ρ is the correlation coefficient and ϕ is the turning angle. Lévy Flight (LF), another random walk variation, is characterized by a power-law step-length distribution, resulting in a series of short turns followed by occasional long straight-line movements. This behavior allows drones to perform extensive explorations with periodic long jumps, enhancing coverage efficiency. The Lévy Flight algorithm updates the drone's position using the step-length distribution, as shown in (2).

$$P(\delta) \sim \delta^{-\mu}, \quad (2)$$

where δ is the step length and μ is a factor between 1 and 3. Integrating these strategies, the hybrid approach leverages the strengths of both CRW and LF, ensuring thorough coverage and efficient navigation. The combined algorithm, presented in Algorithm 1, optimizes the exploration efficiency of the robotic system by balancing local exploration and long-distance travel.

Algorithm 1

Pseudo-code Algorithm for Hybrid Correlated Random Walk and Lévy Flight
Procedure: HybridRandomWalk(N, ρ, μ)
Input: Number of steps N, Correlation factor ρ, Lévy exponent μ
Output: Position (x, y) after N steps
INITIALIZE $x \leftarrow 0, y \leftarrow 0$
FOR $i \leftarrow 1$ to N **DO**
IF $random() < 0.5$ **THEN**
Randomly choose $\delta\theta$ from normal distribution $\mathcal{N}(0, \sigma)$
Update direction $\theta \leftarrow \rho\theta + (1-\rho)\delta\theta$
ELSE
Randomly choose θ from a uniform distribution over $[0, 2\pi]$
Randomly choose L from a Lévy distribution $P(L) \propto L^{-\mu}$
END IF
Set $\Delta x \leftarrow \mathrm{L} \cdot \cos(\theta), \Delta \mathrm{y} \leftarrow \mathrm{L} \cdot \sin(\theta)$
Update $x + \Delta x,\ y + \Delta \mathrm{y}$
END FOR
RETURN (x, y)

3.3. Multi-factor Swarm Data Authentication

We implement a multi-factor data authentication approach to ensure the integrity of data collected by the swarm. The first verification level occurs within the swarm, where drones cross-verify the data collected by their peers. This internal verification helps identify and correct discrepancies early in the data collection process. The second level involves using a decentralized ledger, employing smart contracts like those used in blockchain technology, to validate the consensus reached by the swarm. This additional layer of verification ensures that the data integrity is maintained, and the information is secure from tampering or corruption.

Algorithm 2 presents the pseudocode for multi-factor swarm data authentication. The process begins with each drone validating its data with neighboring drones, followed by recording the validated data on the decentralized ledger. The smart contracts facilitate the consensus validation, ensuring that only verified data is accepted. This two-tiered approach not only secures data integrity but also enhances the reliability of the environmental monitoring system by preventing the propagation of erroneous data.

Algorithm 2

Pseudo-code Algorithm for Two-Factor Authentication
Procedure: TwoFactorAuth()
Input: Drone Data $(estimates, validation\ keys)$
Output: Authenticated Estimates, Consensus
FOR each robot i in swarm **DO**
Validate data with neighboring drones (1st Factor)
IF validation $successful$ **THEN**
Submit validated data to the decentralized ledger
Record and update consensus estimate using smart contract
END IF
END FOR

4. Methodology

This section of the paper presents the methods that are implemented to achieve the objectives of the study. These methods are implemented using different experimental setups, representing hypothetical scenarios to simulate environmental monitoring applications that include (1) crop health monitoring, (2) deforestation surveillance, and (3) soil quality monitoring. Here, we represented specific parameters and characteristics as simplistic quantities and targets, such as white tile percentages, to serve as proof of concept to test algorithms before actual deployment.

4.1. Experimental Setups

The general goal of these experiments is for the swarm to reach a consensus on the percentage of white tiles in an unexplored environment. This framework applies to all experiments, with the representation of what white tiles signify varying per experiment. The black-and-white square grid used in the experiments represents any unexplored environmental scenario, with white tiles indicating specific targets or conditions and black tiles indicating different targets or conditions. Figure 3 shows the consensus task of the swarm with the environmental setup. These experiments are done via simulation using the ARGoS software in Ubuntu.

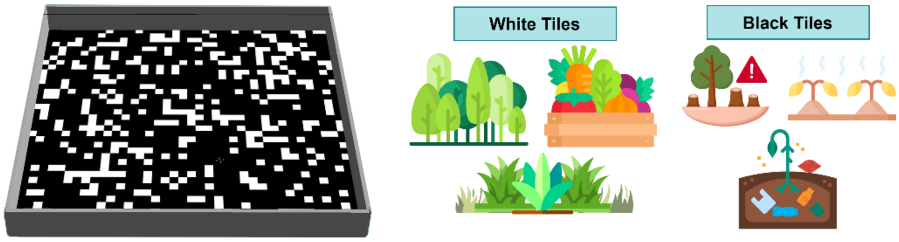


Figure 3: Environmental Setup for all the Test Consensus Scenarios with White and Black Tile Representations

As a summary, Table 1 presents all the experimental setups, together with pertinent descriptions and configurations for each.

Table 1
Summary of Experimental Setups with Hypothetical Scenarios

Exp No.	Name/Parameter	Environmental Scenario	White Tiles Representation	Swarm Size	Exploration Algorithm
1	Decentralized Swarm Drones	Crop Health Monitoring	Healthy Crops	1, 4	Hybrid CRW-LF
2	Efficient Random Exploration Algorithms	Deforestation Monitoring	Intact Trees in Forests	4	CRW, LF, Hybrid CRW-LF
3	Data Integrity	Soil Quality Monitoring	Nutrient-rich soil with good vegetation	4	Hybrid CRW-LF

4.1.1. Experiment #1: Crop Health Monitoring via Single Robot System and Swarm of Drones

In this experiment, the environmental scenario is set in an agricultural farm where the goal is to determine the percentage of healthy crops. The white tiles represent healthy agricultural farm, while the black tiles represent those affected by disease or pests. This is a hypothetical scenario, meaning that the detailed method by which drones gather information is simplified. Figure 4 shows the setup for this experiment. We examine and compare the effectiveness of a single drone versus a swarm of drones in reaching a consensus on the crop health percentage. This experiment is relevant as it demonstrates the potential advantages of using a swarm of drones over a single drone in terms of efficiency and accuracy in environmental monitoring.

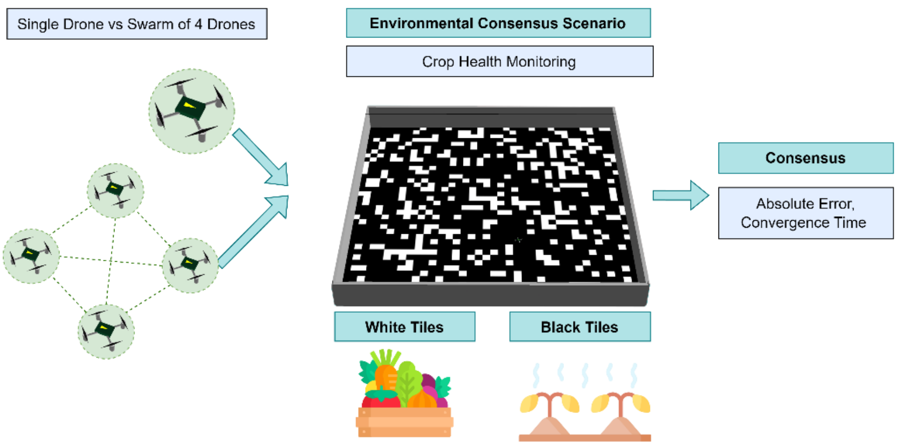


Figure 4: Experiment #1 Setup for the Single Robot System vs. Swarm of Drones

4.1.2. Experiment #2: Deforestation Monitoring Using Efficient Random Exploration Algorithms

The hypothetical scenario for this experiment involves deforestation monitoring. In this setup, the white tiles represent intact and healthy trees and forests, while the black tiles represent areas affected by illegal logging, forest fires, or other destructive activities. The goal is for the swarm to reach a consensus on the percentage of white tiles, indicating the health percentage of the forest. Figure 5 shows the setup for this experiment. Here, we test our hybrid algorithm against the correlated random walk and levy flight algorithms. This experiment is important as it evaluates the efficiency of different exploration algorithms in accurately and effectively monitoring deforestation.

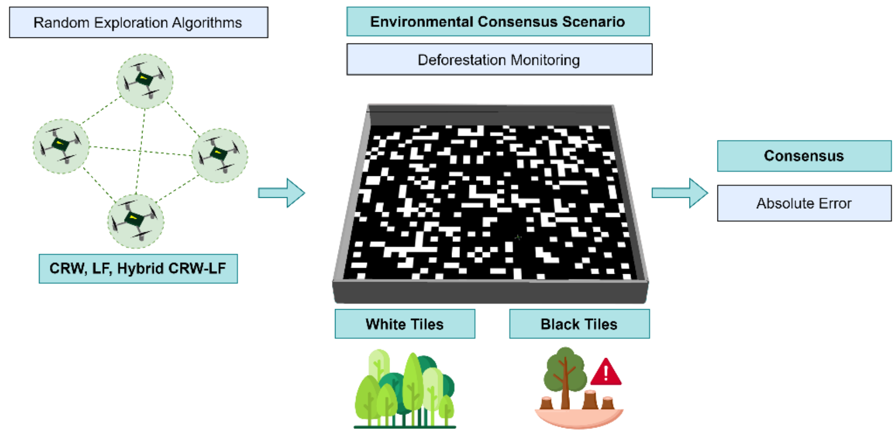


Figure 5: Experiment #2 Setup for the Efficient Random Exploration Algorithms

4.1.3. Experiment #3: Soil Quality Monitoring Ensuring Data Integrity

This experiment focuses on soil quality monitoring based on vegetation growth. The objective is to detect good soil quality based on vegetation growth, represented by white tiles, while black tiles indicate poor soil quality due to factors such as erosion, nutrient depletion, and contamination. Additionally, this experiment includes a hypothetical scenario where one drone appears to function properly but has a faulty sensor that constantly reports a 0% white tile value. Figure 6 shows the experimental setup. This experiment is crucial for assessing the impact of data integrity issues within the swarm and validating the effectiveness of our two-factor authentication approach in maintaining accurate environmental monitoring.

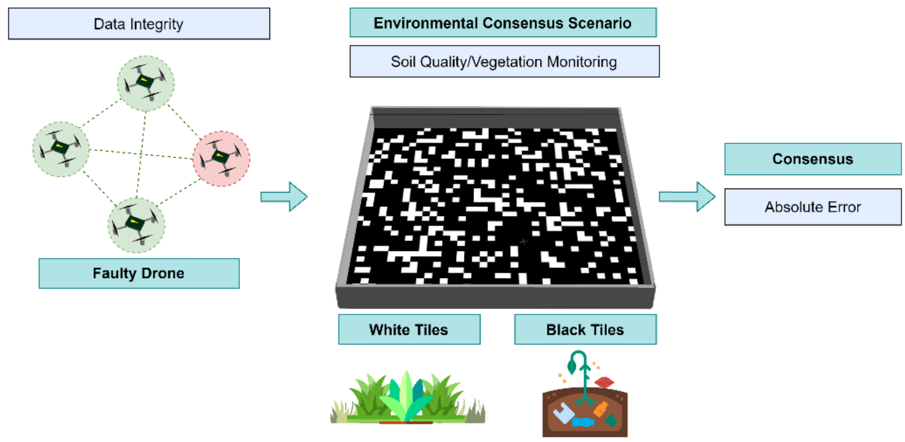


Figure 6: Experiment #3 Setup for the Data Integrity Test

4.2. Performance Metric Evaluations

This section discusses the performance metrics measured across all three experiments. The primary metrics evaluated are the absolute error percentage and the convergence time. The absolute error (AE) percentage measures the difference between the actual and estimated values of the white tile percentage, calculated using (3).

$$AE = \frac{|\rho_{actual} - \hat{\rho}_{estimate}|}{\rho_{actual}} \times 100, \tag{3}$$

This metric provides insight into the accuracy of the consensus reached by the swarm. Additionally, the convergence time, represented in seconds, is measured in some of the experiments to determine the time taken for the swarm to reach a consensus. These metrics help evaluate the effectiveness and efficiency of the proposed algorithms and systems in environmental monitoring applications.

4.3. Statistical Tests and Treatment

We employ a series of statistical tests to ensure the validity and reliability of the conclusions drawn from the experiments. Initially, the Shapiro-Wilk Test is used to assess the normality of the data distribution. This test helps determine whether the data follows a normal distribution, which is a prerequisite for certain parametric tests. Following this, Levene's Test is applied to evaluate the homogeneity of variances across different groups. This test checks if the variances are equal, which is crucial for accurate analysis in subsequent steps.

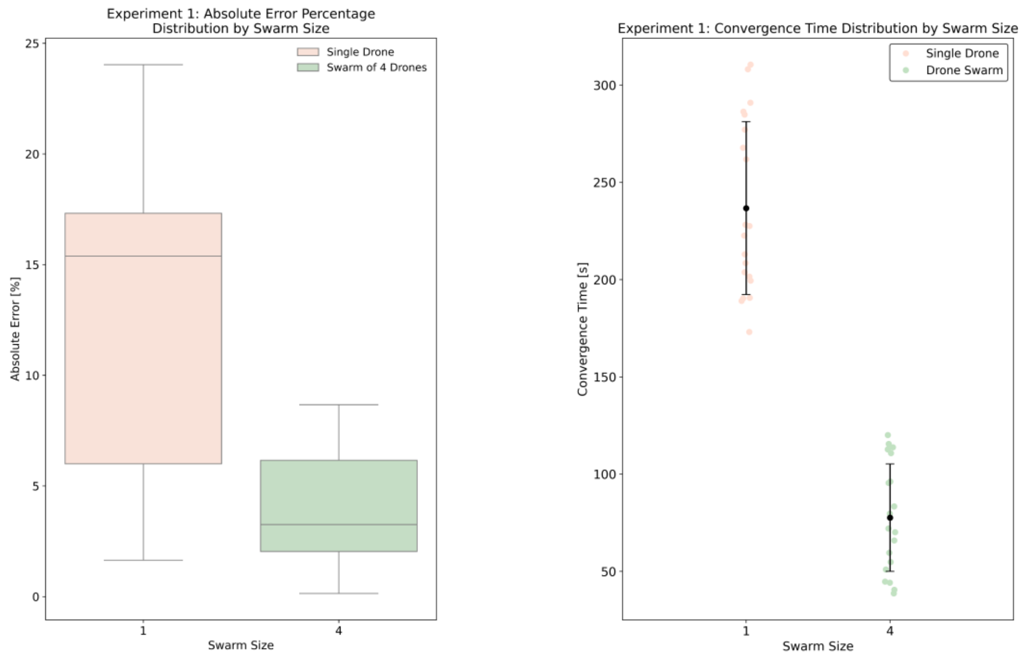
Based on the results of the normality and homogeneity tests, we proceed with either One-way ANOVA or Welch's ANOVA. One-way ANOVA is used when the data meets the assumptions of normality and homogeneity of variances, allowing us to compare the means of multiple groups to see if they differ significantly. If the assumptions are violated, Welch's ANOVA is employed as it is more robust to unequal variances. These statistical tests provide a rigorous framework for analyzing the experimental results, ensuring that the findings are statistically significant and reliable.

5. Results and Discussion

In this section, the results obtained from the experiments are presented and discussed. Pertinent analyses that are related to the objectives of the study are also presented in this section to ensure that the target contributions are met.

5.1. Implementation of a Drone Swarm Systems

In the first experiment comparing the performance of a single drone versus a swarm of four drones, the results demonstrate a significant difference in absolute error percentages. As shown in Figure 7a, the single drone system exhibited a mean absolute error of 12.95%, with a standard deviation of 7.20%. This error indicates considerable variability and a higher tendency to deviate from the true percentage of white tiles in the environment. In contrast, the swarm of four drones achieved a much lower mean absolute error of 3.75% with a standard deviation of 2.42%. This reduction in error highlights the effectiveness of utilizing multiple drones for consensus tasks, as the swarm is better equipped to accurately estimate the environmental state by aggregating data from multiple sources. Additionally, when examining the convergence time, as depicted in Figure 7b, the single drone system required an average of 236.76 seconds to reach a consensus, whereas the swarm system required significantly less time, with an average of 77.64 seconds. Based on 20 repetitions, these findings highlight the advantages of employing a swarm of drones for faster and more accurate environmental monitoring.



(a) (b)

Figure 7: Experiment 1 Results on (a) Absolute Error Percentage and (b) Convergence Time Distributions by Swarm Size

Statistical analysis further supports the observed differences between the single drone and swarm systems. The Shapiro-Wilk test results indicate that the data for both the single drone ($p = 0.147$) and the swarm of drones ($p = 0.377$) follow a normal distribution, allowing for further parametric testing. However, Levene's test for homogeneity of variances reveals a significant difference in variance between the two groups ($p = 0.000545$), suggesting that the variability in error is not consistent across swarm sizes. Given this, Welch's ANOVA was performed to compare the means of the two systems, yielding a significant F-statistic of 27.89 with a p-value of 5.50E-06. These results confirm that the swarm of drones outperforms the single drone system in terms of both accuracy and efficiency, with statistically significant differences in performance metrics.

These results have important implications for environmental monitoring applications. In the context of crop health monitoring, where the white tiles represent healthy crops and vegetables, the lower absolute error and faster convergence time of the swarm system suggest that using multiple drones can provide more reliable and timely data. This is crucial for early detection of crop health degradation, allowing for prompt intervention and better agricultural management. The findings also emphasize the scalability and robustness of swarm systems, making them more suitable for large-scale environmental monitoring tasks. Overall, implementing a drone swarm system enhances the accuracy and efficiency of environmental surveillance, contributing to more sustainable and effective management of natural resources.

5.2. Efficient Environmental Exploration Algorithms

The results of the experiment comparing different exploration algorithms—Correlated Random Walk (CRW), Lévy Flight (LF), and the Hybrid CRW-LF—are shown in Figure 8, which presents the absolute error percentage distribution. The goal is to minimize the absolute error, with smaller values indicating more accurate exploration. The descriptive statistics reveal that the Hybrid CRW-LF algorithm achieved the lowest mean absolute error of 3.75%, with a standard deviation of 2.42%, outperforming CRW and LF individually. The CRW algorithm had a mean absolute error of 7.21%

with a standard deviation of 4.34%, while the LF algorithm exhibited the highest mean absolute error of 11.64% with a standard deviation of 4.46%. The results clearly indicate that the Hybrid CRW-LF algorithm is more effective in reducing error and achieving more accurate consensus in the environmental monitoring tasks.

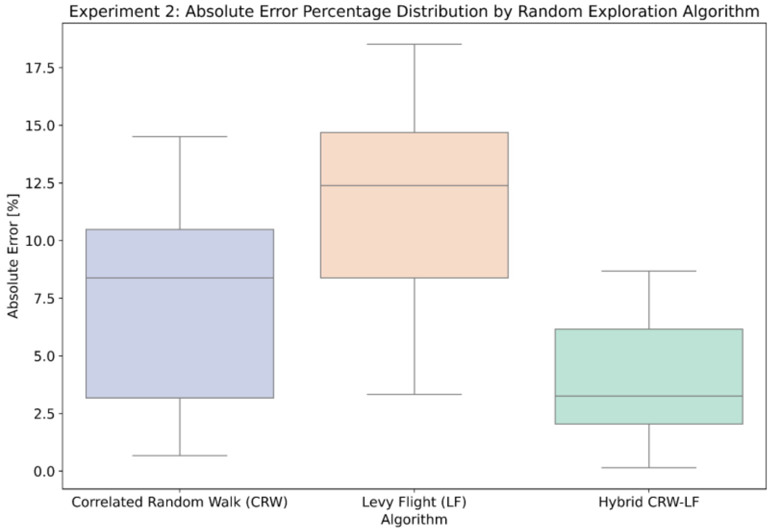


Figure 8: Experiment 2 Results on Absolute Error Percentage Distribution by Random Exploration Algorithm

The statistical tests further confirm the superiority of the Hybrid CRW-LF algorithm. The Shapiro-Wilk test results suggest that the data for all three algorithms follow a normal distribution, with p-values of 0.124 for CRW, 0.369 for LF, and 0.377 for the Hybrid CRW-LF, allowing for parametric analysis. Levene's test, however, indicates a significant difference in the variances between the algorithms ($p = 0.029$), which justifies the use of Welch's ANOVA for comparing means. Welch's ANOVA results yield an F-statistic of 24.07 with a highly significant p-value of 2.65E-08, confirming that the differences in absolute error among the algorithms are statistically significant. These findings validate the effectiveness of the Hybrid CRW-LF algorithm in providing more reliable exploration outcomes in swarm robotics.

In the context of deforestation monitoring, the white tiles represent areas of intact and healthy trees and forests. In contrast, the black tiles indicate regions affected by illegal logging, forest fires, or other destructive activities. The lower absolute error achieved by the Hybrid CRW-LF algorithm suggests that this method is more effective in accurately mapping and identifying areas of deforestation. This is critical for timely interventions and the effective management of forest resources. By employing an exploration algorithm with reduced error rates, the monitoring system can better ensure that areas requiring urgent attention are correctly identified. This contributes significantly to the broader goal of sustainable environmental management, particularly in preserving forest ecosystems, which are vital for maintaining biodiversity and combating climate change. The accuracy and efficiency of this method align with the conference's objectives of using AI-driven solutions to support sustainable development and environmental conservation.

5.3. Ensuring Data Integrity with Secured Swarm Two-factor Authentication

In the final experiment, the impact of a faulty drone on the swarm's data integrity was assessed by comparing the absolute error percentages across different configurations, as shown in Figure 9. When no faulty drones were present, the baseline configuration (without two-factor security) had a mean absolute error of 5.97% with a standard deviation of 5.64%. The two-factor security configuration slightly improved accuracy, reducing the mean absolute error to 5.76% with a standard deviation of 4.22%. However, when introducing a faulty drone—where the drone's sensor consistently reported 0% white tile estimates regardless of actual conditions—the baseline configuration's mean absolute error dramatically increased to 30.61%, with a standard deviation of 5.62%. In contrast, the two-factor security configuration managed to limit the impact of the faulty drone, reducing the mean absolute error to 20.23%, with a standard deviation of 8.73%. These results emphasize the effectiveness of the two-factor security system in mitigating the adverse effects of faulty sensors on the swarm's overall data accuracy.

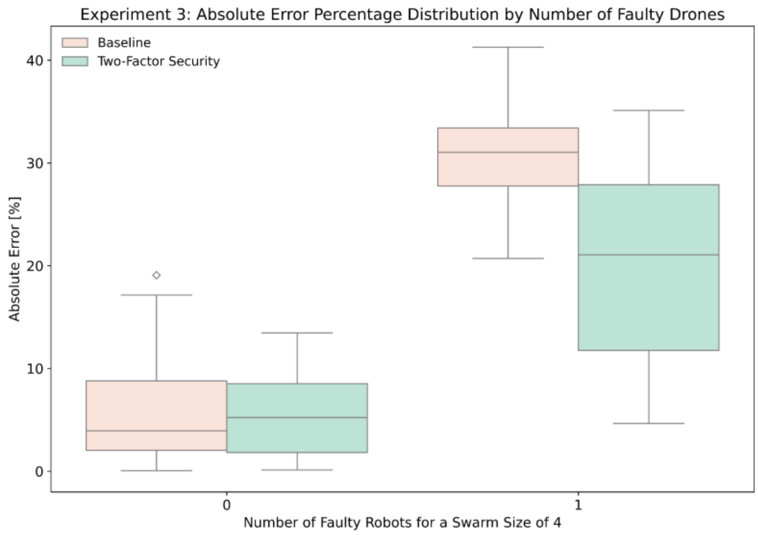


Figure 9: Experiment 3 Results on Absolute Error Percentage Distribution by Number of Faulty Drones

The statistical tests further validated these observations. The Shapiro-Wilk test results indicated that the data was normally distributed for both configurations, with p-values exceeding 0.05 in most cases, except for the baseline with no faulty drones, with a p-value of 0.0078. Levene's test revealed that variances between the groups were not significantly different when there were no faulty drones ($p = 0.571$) but became significant when a faulty drone was introduced ($p = 0.014$). This justified the use of Welch's ANOVA for the faulty drone scenario, which resulted in a highly significant F-statistic of 18.99 and a p-value of 9.61E-05. These findings confirm that a faulty drone introduces considerable variability in data accuracy, and the two-factor security system significantly reduces this variability, ensuring more reliable data collection.

These findings have important implications in soil quality monitoring through vegetation surveillance, where white tiles represent healthy vegetation, and black tiles represent poor soil conditions. Introducing a faulty sensor is a realistic scenario in field operations, where drones may experience sensor malfunctions due to harsh environmental conditions or wear and tear. The significant increase in absolute error under the baseline configuration demonstrates the potential risk of relying on a system without robust data integrity checks. By employing a two-factor authentication system, we can better safeguard against the propagation of erroneous data, ensuring that decisions based on drone-collected data are accurate and reflect actual environmental conditions. This, in turn, supports more effective and sustainable land management practices, contributing to the overarching goal of environmental sustainability through reliable AI-driven monitoring systems.

6. Conclusion and Future Work

In this study, we successfully implemented and evaluated a decentralized drone swarm system for environmental monitoring, focusing on three key scenarios: forest health monitoring, deforestation surveillance, and soil quality assessment. We developed and tested a hybrid exploration algorithm combining CRW and LF, demonstrating superior accuracy and efficiency in environmental exploration compared to individual algorithms. Additionally, we implemented a two-factor authentication system to ensure data integrity within the swarm, significantly reducing the impact of faulty drones on overall data accuracy. The findings from these experiments confirm the effectiveness of using a swarm of drones for more reliable and timely environmental monitoring, contributing to better decision-making in resource management.

There are several avenues for improving this work in the future. One potential improvement is to expand the testing to more complex and diverse environmental scenarios, further validating the proposed system's robustness and scalability. Here, practical deployment is also a possible point of expansion. Integrating more advanced AI techniques, such as machine learning for anomaly detection, could enhance the system's ability to identify and adapt to unforeseen challenges in real-time. Further development of the two-factor authentication system could also involve exploring more sophisticated consensus algorithms or blockchain-based solutions for even greater security. The use of swarm robotics in this research aligns well with the objectives of UN SDG 15, which focuses on the sustainable management of land resources. The promising results indicate that AI-driven swarm robotics can significantly achieve these goals, offering a scalable, efficient, and reliable approach to environmental monitoring.

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References

[1] P. G. Faria Dias, M. C. Silva, G. P. Rocha Filho, P. A. Vargas, L. P. Cota, and G. Pessin, "Swarm Robotics: A Perspective on the Latest Reviewed Concepts and Applications," *Sensors (Basel)*, vol. 21, no. 6, pp. 1–30, Mar. 2021, doi: 10.3390/S21062062.

[2] G. M. Lovett *et al.*, "Who needs environmental monitoring?," *Front Ecol Environ*, vol. 5, no. 5, pp. 253–260, 2007.

[3] G. Likens and D. Lindenmayer, *Effective ecological monitoring*. CSIRO publishing, 2018.

[4] F. Taffetani, M. Rismondo, A. Lancioni, and others, "Environmental evaluation and monitoring of agro-ecosystems biodiversity," *Ecosystems Biodiversity*, pp. 333–370, 2011.

[5] S. Manfreda *et al.*, "On the Use of Unmanned Aerial Systems for Environmental Monitoring," *Remote Sensing 2018, Vol. 10, Page 641*, vol. 10, no. 4, p. 641, Apr. 2018, doi: 10.3390/RS10040641.

[6] M. Talha, N. Nagpal, and M. Srivastava, "Applying Machine Learning for Ensuring Sustainable Management of Water (SDG6)," in *Proceedings of the First International Workshop on Artificial Intelligence: Empowering Sustainable Development (AISD 2023)*, N. Nagpal, M. Srivastava, S. Tiwari, and F. Ortiz-Rodriguez, Eds., Pune, India: CEUR Workshop Proceedings, Jan. 2024. Accessed: Aug. 09, 2024. [Online]. Available: https://ceur-ws.org/Vol-3619/AISD_Paper_5.pdf

[7] A. Abbas *et al.*, "Drones in Plant Disease Assessment, Efficient Monitoring, and Detection: A Way Forward to Smart Agriculture," *Agronomy 2023, Vol. 13, Page 1524*, vol. 13, no. 6, p. 1524, May 2023, doi: 10.3390/AGRONOMY13061524.

[8] M. B. Nuwantha, C. N. Jayalath, M. P. Rathnayaka, D. C. Fernando, L. Rupasinghe, and M. Chethana, "A Drone-Based Approach for Deforestation Monitoring," *2022 13th International Conference on Computing Communication and Networking Technologies, ICCCNT 2022*, 2022, doi: 10.1109/ICCCNT54827.2022.9984404.

[9] W. Xiao, H. Ren, T. Sui, H. Zhang, Y. Zhao, and Z. Hu, "A drone-and field-based investigation of the land degradation and soil erosion at an opencast coal mine dump after 5 years' evolution of natural processes," *Int J Coal Sci Technol*, vol. 9, no. 1, p. 42, 2022.

[10] J. Sharma, "Role & Benefits of Crop Health Monitoring | agriKnow | agribazaar," agribazaar. Accessed: Aug. 09, 2024. [Online]. Available: https://blog.agribazaar.com/role-benefits-of-crop-health-monitoring/

[11] T. A. Ouattara, V. C. J. Sokeng, I. C. Zo-Bi, K. F. Kouamé, C. Grinand, and R. Vaudry, "Detection of Forest Tree Losses in Côte d'Ivoire Using Drone Aerial Images," *Drones 2022, Vol. 6, Page 83*, vol. 6, no. 4, p. 83, Mar. 2022, doi: 10.3390/DRONES6040083.

[12] R. Koomans, H. Limburg, and S. van der Veeke, "Soil mapping with drones | GIM International," GIM International. Accessed: Aug. 09, 2024. [Online]. Available: https://www.gim-international.com/content/article/soil-mapping-with-drones

[13] A. Bender, F. G. A. Francisco, and J. Sundberg, "A Review of Methods and Models for Environmental Monitoring of Marine Renewable Energy," in *Proceedings of the 12th European Wave and Tidal Energy Conference :* , EWTEC, 2017.

[14] G. Katarki, H. Ranmale, I. Bidari, and S. Chickerur, "Estimating Change Detection of Forest Area using Satellite Imagery," in *2019 International Conference on Data Science and Communication (IconDSC)*, IEEE, Mar. 2019, pp. 1–8. doi: 10.1109/IconDSC.2019.8816956.

[15] N. Joshi *et al.*, "A Review of the Application of Optical and Radar Remote Sensing Data Fusion to Land Use Mapping and Monitoring," *Remote Sens (Basel)*, vol. 8, no. 1, p. 70, Jan. 2016, doi: 10.3390/rs8010070.

[16] M. Dorigo, G. Theraulaz, and V. Trianni, "Swarm Robotics: Past, Present, and Future [Point of View] Swarm robotics: past, present and future," *Institute of Electrical and Electronics Engineers*, vol. 109, no. 7, 2021, doi: 10.1109/JPROC.2021.3072740ï.

[17] A. A. Bandala, E. P. Dadios, R. R. P. Vicerra, and L. A. Gan Lim, "Swarming Algorithm for Unmanned Aerial Vehicle (UAV) Quadrotors – Swarm Behavior for Aggregation, Foraging, Formation, and Tracking –," *Journal of Advanced Computational Intelligence and Intelligent Informatics*, vol. 18, no. 5, pp. 745–751, Sep. 2014, doi: 10.20965/JACIII.2014.P0745.

[18] M. Bakhshipour, M. Jabbari Ghadi, and F. Namdari, "Swarm robotics search & rescue: A novel artificial intelligence-inspired optimization approach," *Appl Soft Comput*, vol. 57, pp. 708–726, Aug. 2017, doi: 10.1016/J.ASOC.2017.02.028.

[19] A. R. Cheraghi, S. Shahzad, and K. Graffi, "Past, Present, and Future of Swarm Robotics," *Lecture Notes in Networks and Systems*, vol. 296, pp. 190–233, 2022, doi: 10.1007/978-3-030-82199-9_13.

[20] M. Schranz, M. Umlauft, M. Sende, and W. Elmenreich, “Swarm Robotic Behaviors and Current Applications,” *Front Robot AI*, vol. 7, p. 512421, Apr. 2020, doi: 10.3389/FROBT.2020.00036/BIBTEX.

[21] V. Strobel, A. Pacheco, and M. Dorigo, “Robot swarms neutralize harmful Byzantine robots using a blockchain-based token economy,” *Sci Robot*, vol. 8, no. 79, Jun. 2023, doi: 10.1126/SCIROBOTICS.ABM4636/SUPPL_FILE/SCIROBOTICS.ABM4636_SM.PDF.

[22] Y. Zhang, D. Boley, J. Harwell, and M. Gini, “A Correlated Random Walk Model to Rapidly Approximate Hitting Time Distributions in Multi-robot Systems,” *Lecture Notes in Networks and Systems*, vol. 577 LNNS, pp. 724–736, 2023, doi: 10.1007/978-3-031-22216-0_48.

[23] D. K. Sutantyo, S. Kernbach, P. Levi, and V. A. Nepomnyashchikh, “Multi-robot searching algorithm using Lévy flight and artificial potential field,” *8th IEEE International Workshop on Safety, Security, and Rescue Robotics, SSRR-2010*, 2010, doi: 10.1109/SSRR.2010.5981560.

[24] L. Van Calck, A. Pacheco, V. Strobel, M. Dorigo, and A. Reina, “A blockchain-based information market to incentivise cooperation in swarms of self-interested robots,” *Scientific Reports 2023 13:1*, vol. 13, no. 1, pp. 1–18, Nov. 2023, doi: 10.1038/s41598-023-46238-1.

[25] A. Pacheco, V. Strobel, and M. Dorigo, “A Blockchain-Controlled Physical Robot Swarm Communicating via an Ad-Hoc Network,” *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 12421 LNCS, pp. 3–15, 2020, doi: 10.1007/978-3-030-60376-2_1.

[26] V. Strobel, E. C. Ferrer, and M. Dorigo, “Managing Byzantine Robots via Blockchain Technology in a Swarm Robotics Collective Decision Making Scenario,” *IFAAMAS*, vol. 9, May 2018, Accessed: Jul. 20, 2024. [Online]. Available: https://dspace.mit.edu/handle/1721.1/115883