ProSafeNet

International Journal of Disaster Risk Management • Vol. 8. No. 1 • https://doi.org/10.66050/sja2vn07

Publisher: Scientific-Professional Society for Disaster Risk Management

International Journal of Disaster Risk Management

Article

Beyond Platform Type: Effects of Vegetation Density, Sensor Modality, and Search Strategy on Aerial Search and Rescue Performance

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Received: 20 April 2026; Revised: 28 May 2026; Accepted: 8 June 2026; Published: 12 June 2026.

ABSTRACT

Timely detection of missing persons is critical for successful Search and Rescue (SAR) operations, especially under challenging environmental conditions. Modern SAR efforts utilize both manned helicopters and unmanned aerial systems (UAS), often equipped with electro-optical (EO) and infrared (IR) sensors, while helicopters may also employ visual observers. Despite their widespread use, limited empirical data exists on how these platforms, sensor types, and search techniques perform across varying terrain and vegetation densities. To our knowledge, no prior field study has jointly examined how platform type, sensor modality, search strategy, and vegetation density affect detection performance in realistic SAR conditions. This study presents results from the SAVIOUR 2024 quasi-experimental field experiment, conducted during a large-scale SAR exercise in Rogaland, Norway. Twelve professional SAR aircrews (six helicopters, six UAS teams) conducted 48 search sorties across sectors with low, medium, and high vegetation density, targeting 251 human subjects. Key metrics were Probability of Detection (POD) and Time to Detection. Both platforms achieved high detection rates (mean POD >83%), with 54% of sorties reaching 100% POD. Vegetation density was the strongest predictor of POD, with reduced performance in high-density forest (helicopters: 71.4%, UAS: 73.3%). Platform type was not a significant predictor of POD when controlling for vegetation density; in contrast, vegetation density and sensor modality seemed to have stronger effects on detection performance. Helicopters detected targets faster, likely due to initial sweep strategies. UAS teams favored systematic detailed searches, resulting in longer detection intervals. Sensor-based searches outperformed visual-only methods, though visual-only data were limited. As an operational implication, we suggest that coordinated, vertically separated operations - helicopters at high altitude and UAS at low altitude - may enhance efficiency through concurrent coverage. However, this coordination model was not directly tested as an intervention and should be validated in future studies. These findings offer guidance for integrated SAR practices and highlight future research needs, including AI-assisted detection and performance evaluation under diverse thermal and geographical conditions.

KEYWORDS

Nilsen, A. A., Størdal, T. R., Johansen, V., Ronge, J. L., & Grytting, E. (2026). Beyond Platform Type: Effects of Vegetation Density, Sensor Modality, and Search Strategy on Aerial Search and Rescue Performance. *International Journal of Disaster Risk Management*, 8(1), 511-538.

Search and Rescue (SAR); Unmanned Aerial Systems (UAS); helicopter; probability of detection (POD); comparative analysis; airspace management; synergistic aerial operations.

1. Introduction

Search and Rescue (SAR) operations for missing persons are time-critical missions in which rapid location can be crucial for survival (Goodrich et al., 2008; Xing et al., 2022). Airborne assets have long been a cornerstone of SAR, offering the ability to cover vast and often inaccessible terrains far more efficiently than ground teams (Ferrari, 2020; Kerrin, 2018; Olsen, 2016). Traditionally, this role has been fulfilled by manned aircraft, relying on visual observation by human crew members (International Civil Aviation Organization & International Maritime Organization, 2016; Frost, 1996) or by using advanced camera sensor technology (Antonsen et al., 2015). However, the technological landscape of aerial SAR is undergoing a fundamental transformation, driven both by the widespread proliferation of Unmanned Aerial Systems (UAS), commonly known as drones (Zhang & Zhu, 2023; Lyu, Zhao, Huang & Huang, 2023; Niedzielski, Jurecka, Miziński, Pawul & Motyl, 2021; Ajith & Jolly, 2021; Quero & Carranza, 2025), and potentially by the development of increasingly advanced sensor capabilities on manned aircraft.

Modern UAS are increasingly equipped with sophisticated sensor payloads, including high-resolution thermal infrared (IR) and electro-optical (EO) cameras (Nguyen, Rosser & Chahl, 2021; Silvagni, Tonoli, Zenerino & Chiaberge, 2017; Quero & Carranza, 2025). This technology offers novel capabilities for detecting human subjects, particularly in challenging conditions such as low light or through vegetation canopy (Lyu et al., 2023; Norwegian Police Unmanned Air Support Unit, 2023; Nguyen et al., 2021). The integration of UAS into SAR missions has become widespread, creating a mixed fleet of airborne assets. However, the rapid adoption of these technologies has progressed faster than the empirical research required to guide their optimal use.

While manned and unmanned platforms possess partially overlapping capabilities, such as the ability to carry advanced EO/IR sensors, they are also characterized by fundamentally different operational envelopes (National Search and Rescue Committee, 2016). These differences include flight endurance, speed, weather minima, and the regulatory frameworks that govern flight altitude (Quero & Carranza, 2025; Xing et al., 2022), where most UAS operations are limited to 120m above ground level in most national airspaces (Norwegian Ministry of Transport, 1993; Norwegian Civil Aviation Authority, 2015). Recognizing these distinctions is key to maximizing the operational benefit, where each asset is deployed to leverage its unique strengths. Yet, while the potential strengths of UAS are frequently cited, there remains a significant gap in the empirical evidence base that directly compares their performance against traditional helicopter assets under realistic field conditions (Kerrin, 2018). This knowledge is essential for moving from simple asset co-existence to truly optimized, coordinated operations.

In Norway, all SAR operations are coordinated by the Joint Rescue Coordination Centre (JRCC). National guidelines from the JRCC govern the use of multiple air assets, but their focus is primarily on airspace deconfliction to ensure flight safety through vertical, geographical, or temporal separation (Norwegian Joint Rescue Coordination Center, 2024). Critically, these guidelines stop short of providing tactical directions on how to best leverage the unique and often complementary capabilities of different platforms. Operational experience in Norwegian search and rescue suggests that this lack of evidence-based coordination protocols, coupled with uncertainty regarding drone aerial search performance, may lead to UAS being sidelined in favor of manned helicopters, thereby limiting the potential benefits of combined use.

The performance of any aerial search is governed by a complex interplay of factors. Key performance metrics, such as the Probability of Detection (POD) and the required search effort (e.g., time per unit area), are influenced not only by the choice of platform (helicopter or UAS) but also by the sensor modality (EO vs. IR vs. visual search) and the search strategy executed by the crew (Lyu et al., 2023; Silvagni et al., 2017; International Civil Aviation Organization & International Maritime Organization, 2016; Goodrich et al., 2008). Vegetation density poses a major challenge by obscuring targets and thereby affecting the efficacy of different sensors and observation angles (Zhang, Feng, Wang, Lu & Mei, 2025; Norwegian Police Unmanned Air Support Unit, 2023). Although numerous studies have investigated specific aspects of aerial SAR, such as calculating theoretical POD for UAS in open terrain or modeling visual search patterns (Bashyam & Guggenheim, 2019; Mayo, 2015), a comprehensive, multi-variable field study is lacking. We argue that there is a pressing need to generate robust, comparative data derived from trials involving experienced operational crews performing realistic tasks.

This paper addresses these knowledge gaps by presenting the findings from the SAVIOUR 2024 (Systematic Airborne Visual & Infrared Observational Unified Research) field experiment. We conducted a large-scale, quasi-experimental study involving 12 professional SAR air crews (six helicopters and six UAS teams) executing a total of 48 search sorties for 251 static human targets. The experiment was designed to systematically evaluate the performance of current aerial SAR assets and methods across different terrain types. This study addresses the following research questions:

1. How do platform type (helicopter vs. UAS), sensor modality (sensor-only, hybrid, visual-only) and vegetation density influence detection performance (POD)?
2. How do platform type, vegetation density and search strategies (initial sweep search, detailed search) influence search efficiency (time to detection) across detected targets?

By addressing these research questions, the study aims to generate operationally relevant data to guide the coordinated use of manned and unmanned aerial assets, ensuring that each platform's unique strengths are leveraged in complementary ways to maximize detection performance, and enhance the overall effectiveness and efficiency of future SAR operations.

2. Methods

This section details the study area, experimental setup, participating assets, data collection procedures, and the analytical methods used to evaluate the collected data. The study was conducted as a quasi-experimental field trial adhering to pre-defined protocols as part of the SAVIOUR project during the Rogaland Rescue 2024 exercise.

2.1. Study Area

The field experiment was conducted in Gjesdal municipality, Rogaland, Norway (approx. 58.8° N, 6.0° E), at an elevation of approximately 350 meters above sea level (illustrated in figure 1). Three distinct search areas, hereafter referred to as "sectors," were established to represent typical operational environments encountered in SAR missions in the region. The sectors were chosen to reflect different levels of vegetation density, from open terrain to dense forest.

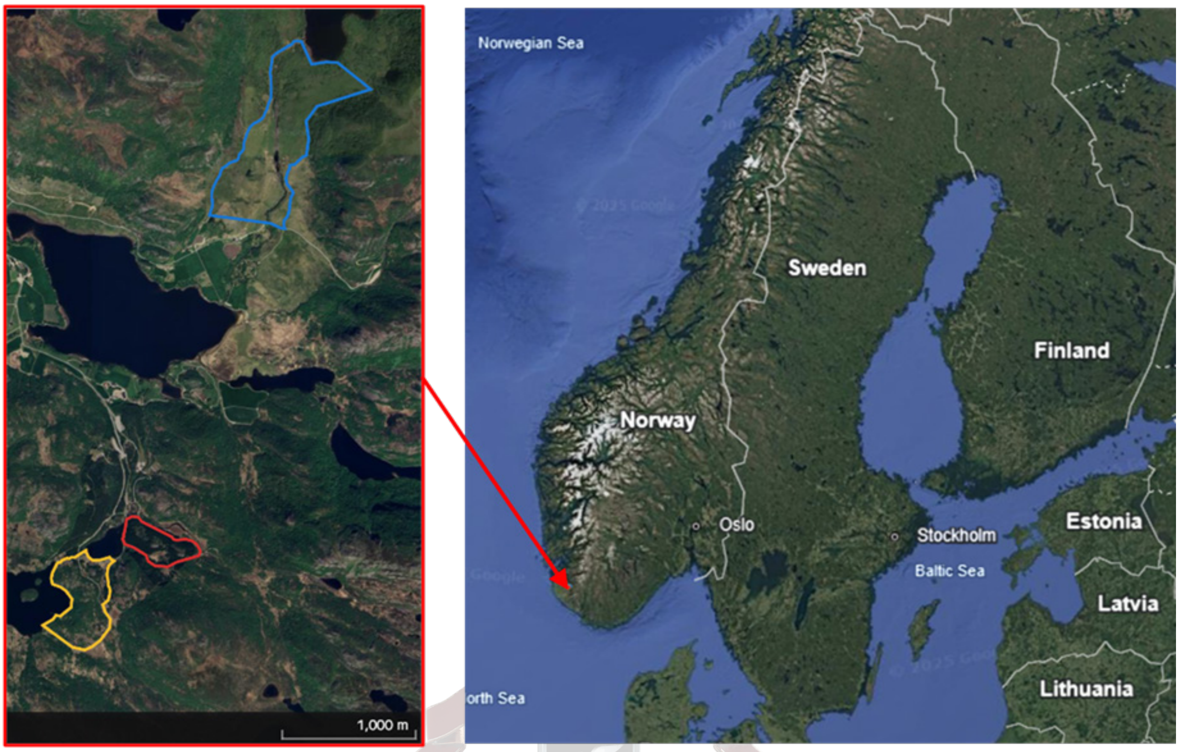

Figure 1. Study area. Gjesdal municipality in Rogaland, Norway.
Sector 1 (Blue), Sector 2 (Yellow), Sector 3 (Red). Maps retrieved from Google Earth.

- Sector 1 (Low Vegetation Density): An area of 0.61 km² (606,000 m²) characterized by open pastureland with scattered shrubs (figure 2).

Figure 2. Aerial photo of sector 1 (Blue map marker).

- Sector 2 (Medium Vegetation Density): An area of 0.22 km² (222,000 m²) consisting of mixed deciduous forest and bushes (figure 3).

Figure 3. Aerial photo of sector 2 (Yellow map marker).

- Sector 3 (High Vegetation Density): An area of 0.11 km² (105,000 m²) defined by a tall, dense spruce forest with a closed canopy (figure 4).

Figure 4. Aerial photo of sector 3 (Red map marker).

The size of each sector was inversely scaled with vegetation density with the intent to achieve roughly equivalent search times across sectors, thereby preventing operator fatigue from becoming a confounding variable.

2.2. Experimental Design

The study employed a quasi-experimental design where participating units used their standard, self-selected search procedures to reflect real world practices. This approach allows for high ecological validity (Campbell & Stanley, 1963). The quasi-experimental design was chosen to examine how different crews and platforms operate search tasks when instructed to perform them in accordance with real-world search and rescue practices. By preserving naturalistic decision-making and procedural autonomy, the study aimed to capture how search operations are enacted in practice, thereby providing insight into emergent operational behaviors under ecologically valid conditions. In addition, due to the operational and logistical constraints inherent in search and rescue training contexts, random assignment of e.g. crews or platforms was not feasible.

By allowing participating crews to use their standard, self-selected procedures, the study maximizes ecological validity, that is, the extent to which findings reflect real-world practices and can generalize to operational settings. Variables such as search strategy, altitude, and sensor modality could in principle have been randomly assigned across crews and platform types. However, full experimental control was not feasible, as not all platforms (e.g., helicopters) had access to equivalent sensor modalities. More fundamentally, the decision to prioritize ecological validity by allowing crews to operate according to their standard procedures entails an inherent methodological tradeoff. In particular, the absence of randomization introduces important limitations for causal inference and consequently reduces the internal validity of the study (Holgado-Tello, Chacón-Moscoso, Sanduvete-Chaves & Pérez-Gil, 2016), as observed effects may be influenced by confounding factors (e.g., differences between crews, platforms, or operational preferences). Consequently, the results should be interpreted as observational associations within realistic operational contexts rather than as definitive causal effects of platform type, search strategy, or sensor modality.

Several data measures were collected during the field trial. The primary independent variables for our further analysis are: (1) Platform Type (helicopter or UAS), (2) Sensor Modality (EO/IR sensor, visual observation and hybrid search combining EO/IR sensor and visual observers), (3) Search Strategy (Pattern-based detailed search or initial sweep search), and (4) Vegetation Density (low, medium, or high).

Within the sensor modality variable, EO and IR were not separated into distinct variables, as they are integrated within a single camera module and used in a complementary and often seamless manner during operational search workflows. This precludes reliable attribution of observations to either EO or IR, and the modalities were therefore analyzed as a combined system.

The primary dependent variables are Probability of Detection (POD), calculated as the percentage of targets found, and Time to Detection, measured as the time elapsed from search start to each detection.

Each of the 12 aerial units conducted one or more search sorties in each of the three sectors, resulting in 48 completed search efforts and 251 total detection opportunities analyzed in this study. A rotation system was implemented to manage the sequence of search efforts and ensure airspace deconfliction. Table 1 presents the distribution of vegetation sectors, including the number of targets placed, the number of sorties performed, and the total detection opportunities in each sector.

Table 1. *Distribution of sectors by number of targets, sorties and total detection opportunities.*

Sector	Number of targets	Number of sorties	Total detection opportunities
1 – Low vegetation density	6	11	66
2 – Medium vegetation density	5	18	90
3 – High vegetation density	5	19	95
Total	-	48	251

2.3. Participating Platforms and Sensor Systems

A total of 12 aerial search units participated in the experiment, comprising six helicopter crews and six UAS teams from various Norwegian government and volunteer SAR organizations. The fleet represented a diverse cross-section of the platforms and sensor technologies currently deployed in Norwegian SAR operations.

All missions were carried out by trained professionals with certifications for the specific aircraft types and methods employed. All aircrew members had significant experience in aerial SAR searches and had received organization specific training in SAR methodologies.

All drone operations were conducted beyond visual line of sight (BVLOS). The participating UAS units held operator authorizations approved by the Norwegian Civil Aviation Authority, permitting BVLOS operations up to 120 m above ground level (AGL). A temporary danger area was established over the exercise area up to 760 m above mean sea level (AMSL), corresponding to approximately 520 m AGL at the exercise site, allowing UAS operations within the designated vertical airspace limits. Each unit used its standard operational procedures, resulting in three distinct search methodologies: sensor-based search only (Helicopter and UAS), visual search only (Helicopter), and a combined approach using both sensors and concurrent visual observers (Helicopter). One of the UAS teams utilized additional support from an AI operator using a standalone computer running artificial intelligence (AI) software specialized in object detection of persons in video imagery. The AI model was pre-trained on datasets reflecting relevant terrain conditions. Due to the single instance of AI-assisted search, this methodology was not included as a separate variable in the statistical analyses. However, its use highlights an important emerging technology in SAR, with the potential to drastically increase performance while decreasing the drone pilot's cognitive load (Quero & Carranza, 2025). An overview of the platforms, primary search sensors, and crew configuration is provided in Table 2.

Table 2. *Overview of participating aerial platforms, sensor systems, and crew configuration*

Platform type	Aircraft	n	Primary sensor payload	Thermal image resolution	Thermal sensor focal length (mm)[1]	Operator display screen size	Crew members	Concurrent visual observers[2]
Helicopter	AW 101	4	FLIR Star Safire 380-HDc	1280 x 720 px	25mm/500mm	17″	6	5
Helicopter	AW 169	1	L3 Harris Wescam MX-15	1280 x 1024 px	30mm/880mm	17″	3	0
Helicopter	Airbus H135	1	N/A	N/A	N/A	N/A	3	3
Quadcopter UAS	DJI Matrice 300 RTK	1	Zenmuse H20N	640 X 512 px	53mm/196mm	24″	1	0
Quadcopter UAS	DJI Matrice 300 RTK	2	Zenmuse H20N	640 X 512 px	53mm/196mm	24″	2	0
Quadcopter UAS	DJI Matrice 350 RTK	1	Zenmuse H30T	1280 x 1024 px	52mm	32″	2	0
Quadcopter UAS	DJI Matrice 30T	1	Integrated M30T Sensor	640 x 512 px	40mm	7″	2	0
Quadcopter UAS	DJI Matrice 30T	1	Integrated M30T Sensor	640 x 512 px	40mm	19″	2	0

Note.[1] Focal length for thermal sensor, indicating minimum and maximum optical zoom capabilities. Single values denote a fixed focal length.

[2] Number of crew members whose primary task was to conduct visual search out of the aircraft, in parallel with any sensor operations.

2.4. Target and Environmental Conditions

Human targets were used in all trials. Five targets were placed in each of the medium and high vegetation density sectors, while six targets were placed in the low vegetation density sector. The variation in target numbers occurred due to unforeseen withdrawal of some volunteer markers. A total of 45 volunteers served as human targets throughout the experiment, distributed across the three sectors. Participation varied between individuals, with some volunteers participating for a single day and others across multiple days. A rotation system was implemented to ensure adequate rest periods and compliance with health and safety considerations during prolonged field operations. Consequently, each sector contained either five or six active targets depending on the operational circumstances during a given sortie (as seen in table 1). To ensure realistic thermal signatures, participants wore seasonally appropriate outdoor clothing, including base layers, insulation layers, and shell garments. For unambiguous detection verification, each target wore a unique combination of a solid-colored t-shirt and hat as their outermost layer (illustrated in figure 5, 6 and 7). Targets remained stationary at pre-assigned GPS coordinates during each trial. To prevent location memorization, target positions were changed between sorties involving the same search unit. The exact number of targets was unknown to the search crews.

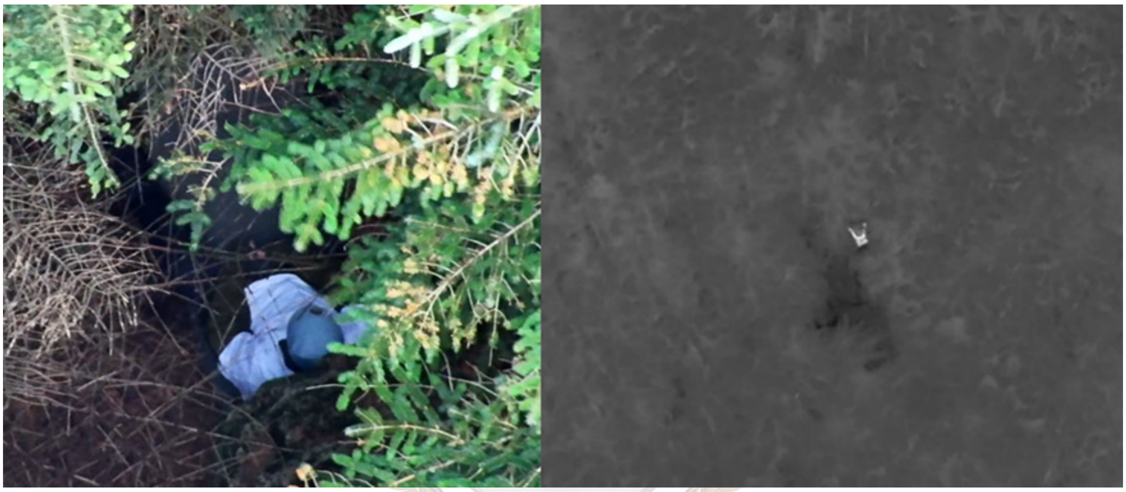

Figure 5. Example of a human target positioned in sector 3 – high density vegetation.

Figure 6. Example of a human target positioned in sector 2 - medium density vegetation.

Figure 7. *Example of a human target positioned in sector 2 – medium density vegetation.*

Data collection occurred between 16th and 18th October 2024 during daylight hours (08:30–18:30 local time). Weather conditions were challenging, particularly on the first two days, with strong winds (gusting 15–35 m/s at 100–300 m AGL) and occasional light rain. On the third day, winds were significantly lighter (5–10 m/s). Ambient temperatures ranged from 9°C to 15°C, providing a strong thermal contrast between human targets and the background environment, which is favorable for thermal imaging. However, solar loading on the final day warmed exposed rocks, creating some thermal clutter in the low-vegetation sector. A summary of daily weather conditions and their reported operational impact is provided in table 3.

Table 3. *Overview of weather conditions and reported operational impact.*

Parameter	16th Oct. 2024	17th Oct. 2024	18th Oct. 2024
Temperature (°C)	9-11	9-11	13-15
Cloud cover	100% overcast	100% overcast	Partly cloudy
Air pressure at mean sea level	1012-1018 hPa	1006-1011 hPa	1013-1015 hPa
Precipitation	Occasional light rain	Occasional light rain	Dry
Maximum wind speed @ 100m AGL (m/s)	20-25	15-20	~5
Maximum wind speed @ 200-300m AGL (m/s)	30-35	25-30	~10
Key thermal factors	High thermal contrast	High thermal contrast	High thermal contrast, solar loading on exposed rocks created thermal clutter
Reported weather effects for manned helicopters	Helicopters conducting visual searches had to fly with the wind direction, adjust their search patterns, and reported increased time consumption.	Helicopters conducting visual searches had to fly with the wind direction, adjust their search patterns, and reported increased time consumption.	No helicopter searches were conducted.

Reported weather effects for UAS	The UASs used significantly more battery energy per flight hour (approximately halved flight time), with more frequent battery changes, resulting in increased time consumption.	The UASs used significantly more battery energy per flight hour (approximately halved flight time), with more frequent battery changes, resulting in increased time consumption.	The sun heated the rocks in open terrain, making it more difficult to detect human thermal signatures.

Note. Wind speed ranges are estimates based on operational crew reports and pilot weather assessments, as direct meteorological measurements were not available at relevant altitudes.

Weather conditions were not included as predictors in the regression models because the vast majority of sorties (n = 43/48) were conducted under broadly similar meteorological conditions during the first two days of data collection. Weather variation was limited to a small number of observations (n = 5) on the third day and was not sufficiently distributed across the full set of operational conditions to allow reliable estimation of its independent effect.

Given this data structure, weather could not be treated as an independent explanatory variable without risking unstable parameter estimates due to insufficient variation. Weather was therefore treated as a contextual operational condition and is reported descriptively in Table 3.

2.5. Data Collection Protocol

A standardized data collection protocol was followed for all sorties.

- Flight Logging: Aircraft position and altitude were continuously recorded. Manned aircraft were tracked using ADS-B receivers. Since ADS-B provides barometric altitude based on a standard atmosphere, these values were corrected using hourly local pressure readings to determine accurate altitudes above mean sea level (AMSL) and locally above ground level (AGL). UAS flights were logged using a combination of ground-based Remote ID data and exported digital flight logs from the ground control stations (DJI RC Plus), yielding detailed track logs for each sortie.
- Flight log analysis: All flight track logs were integrated into a proprietary digital 3D terrain model, along with GPS coordinates for each target. This enabled playback of the flights to evaluate flight pattern characteristics and continuous flight altitude at each successful localization.
- Detection Reporting: Search crews reported each detection in real-time via radio to a sector official. The report included the target's unique color identifier when visible. The time of each confirmed detection was logged by the official.
- Post-Sortie Debriefing: After each sortie, the crew completed a standardized form detailing the search strategies employed (e.g., "initial sweep search," "detailed search," specific flight patterns), flight parameters (altitude, speed), and sensor settings used. They also provided a subjective estimate of their own POD for the completed sector.
- Video Recording: Whenever technically feasible, video feeds from the camera sensor (both EO and IR) were recorded for post-mission verification and analysis.
- Categorization: Search patterns were categorized based on crew debriefings and flight log analysis into "Initial sweep search" (initial high-level overview, e.g., orbit or high-altitude pass) and "Detailed Search" (systematic, low-level pattern, e.g., parallel track or grid). This categorization was further validated by a manual review of recorded video footage, which also served to quality-assure the logged detection times.

2.6. Definition of variables

The collected data were compiled and synchronized into a unified database.

- POD Calculation: POD for each sortie was calculated as the number of correctly identified targets divided by the total number of active targets in the sector.
- Time to Detection: The time from the start of the search to each successful detection was calculated for each found target.

Dependent Variables: These are the primary performance metrics that were measured.

- Probability of Detection (POD): For each sortie, POD was calculated as the number of correctly identified targets divided by the total number of active targets in the assigned sector. This yields a performance score for each of the 48 sorties.
- Time to Detection: For each successfully located target, this was calculated as the time elapsed in minutes from the official start of the search until the target was reported as detected.

Independent Variables: These are the factors hypothesized to influence the dependent variables.

- Platform Type: A categorical variable with two levels: Helicopter and UAS.
- Vegetation Density: A categorical variable with three levels representing the search sectors: Low, medium, and high, as described in Section 2.1.
- Search Strategy: A categorical variable with two levels: Initial sweep search and detailed search.
- Search modality: A categorical variable with three levels based on the primary search method employed by the crew:
  - Sensor-only: Search conducted exclusively using thermal and/or EO sensors.
  - Hybrid: A combined approach using both sensors and concurrent visual observation by dedicated crew members.
  - Visual-only: Search conducted exclusively by visual observers without the aid of advanced sensors.

3. Results

This section presents the main findings from the field experiment. The results are structured to first provide an overall summary of detection performance, followed by detailed analyses comparing platform performance, the impact of search strategies on detection time, and finally, statistical modeling of the variables influencing detection success.

3.1. Distribution of sorties

A total of 48 search sorties were completed, generating 251 individual target detection opportunities. Table 4 illustrates the distribution of sorties by platform type, vegetation density and search modality.

Table 4. *Distribution of sorties by platform type, vegetation density and search modality*

Variable	Category	Number of sorties	Percent of total
Platform type	Helicopter	20	41.67
	UAS	28	58.33
Vegetation density	Low	11	22.92

	Medium	18	37.50
	High	19	39.58
Search modality	Sensor only	32	66.67
	Hybrid	12	25.00
	Visual only	4	8.33
Total number of sorties		48	100

3.2. Overall Performance Summary

Across all platforms and conditions, no sortie resulted in zero detections, indicating a baseline level of effectiveness for all participating units.

The overall Probability of Detection (POD) was high. Of the 48 total sorties, 54.17% (*n*=26) resulted in the detection of every available target (100% POD). Furthermore, 79.17% (*n*=38) of sorties achieved a POD of 80% or higher. This demonstrates that under the observed conditions, all aerial assets were highly effective at locating human targets. The distribution of POD across sorties is illustrated in figure 8.

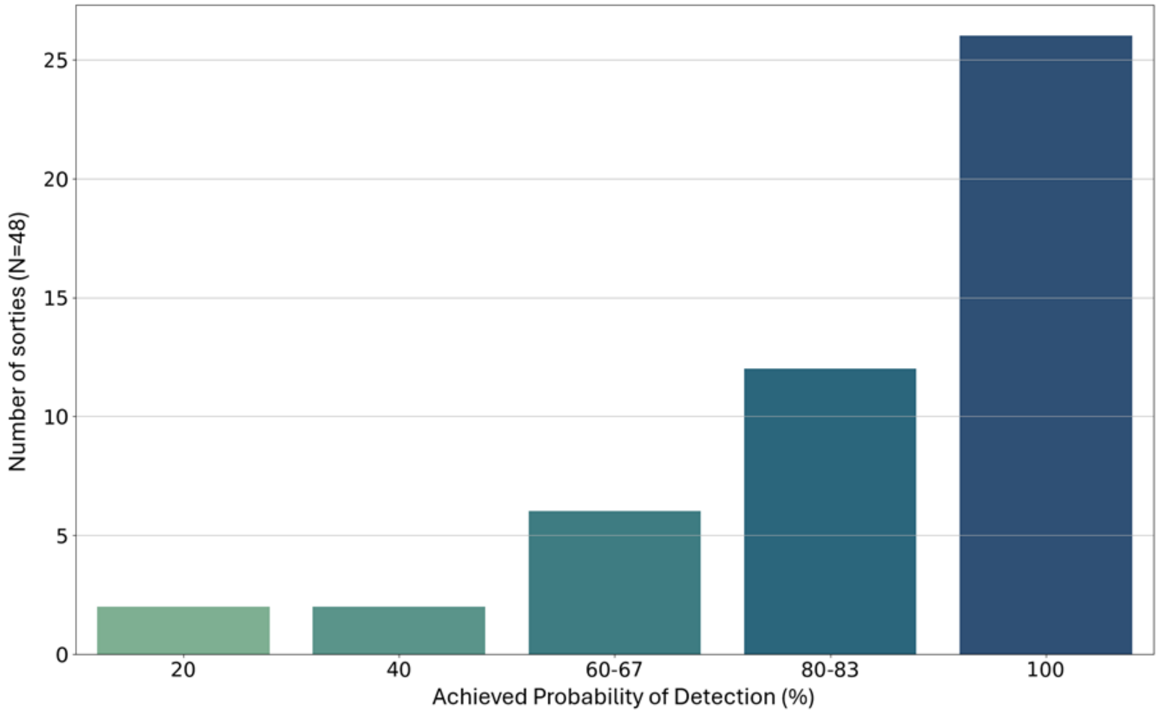

Figure 8. Frequency distribution of POD across all 48 sorties. The x-axis shows POD expressed as percentages, grouped into categories based on observed values.
The y-axis indicates the number of sorties achieving each POD level.

3.3. Platform Performance and Vegetation Impact

The experiment consisted of 20 helicopter sorties (41.7%) and 28 UAS sorties (58.3%). When comparing overall success, UAS platforms achieved 100% POD in 57.14% of their sorties, while helicopters achieved 100% POD in 50.0% of theirs.

Table 5 presents the summary statistics for POD achieved by each platform type within each vegetation sector. Across both platforms, POD decreased in high-density vegetation compared to low- and medium-density conditions. Differences between platforms were relatively small within each vegetation category, indicating that vegetation density, rather than platform type, was the primary factor influencing detection performance.

Table 5. *Descriptive statistics for Probability of Detection (POD) by platform and vegetation sector.*

Platform	Vegetation density	n	Mean POD (%)	Median POD (%)	Std. Dev. (%)
Helicopter	Low	6	83.33	83.33	14.76
	Medium	7	94.29	100.00	9.76
	High	7	71.43	80.00	32.37
	Total	20	83.00	91.50	22.71
UAS	Low	5	93.20	100.00	9.31
	Medium	11	96.36	100.00	8.09
	High	12	73.33	80.00	25.87
	Total	28	85.95	100.00	20.93

The time required to locate targets is a critical measure of search efficiency. Analysis of time to detection reveals distinct patterns associated with both platform type and search strategy. Figure 9 illustrates the distribution of detection times for all found targets, separated by platform and vegetation sector.

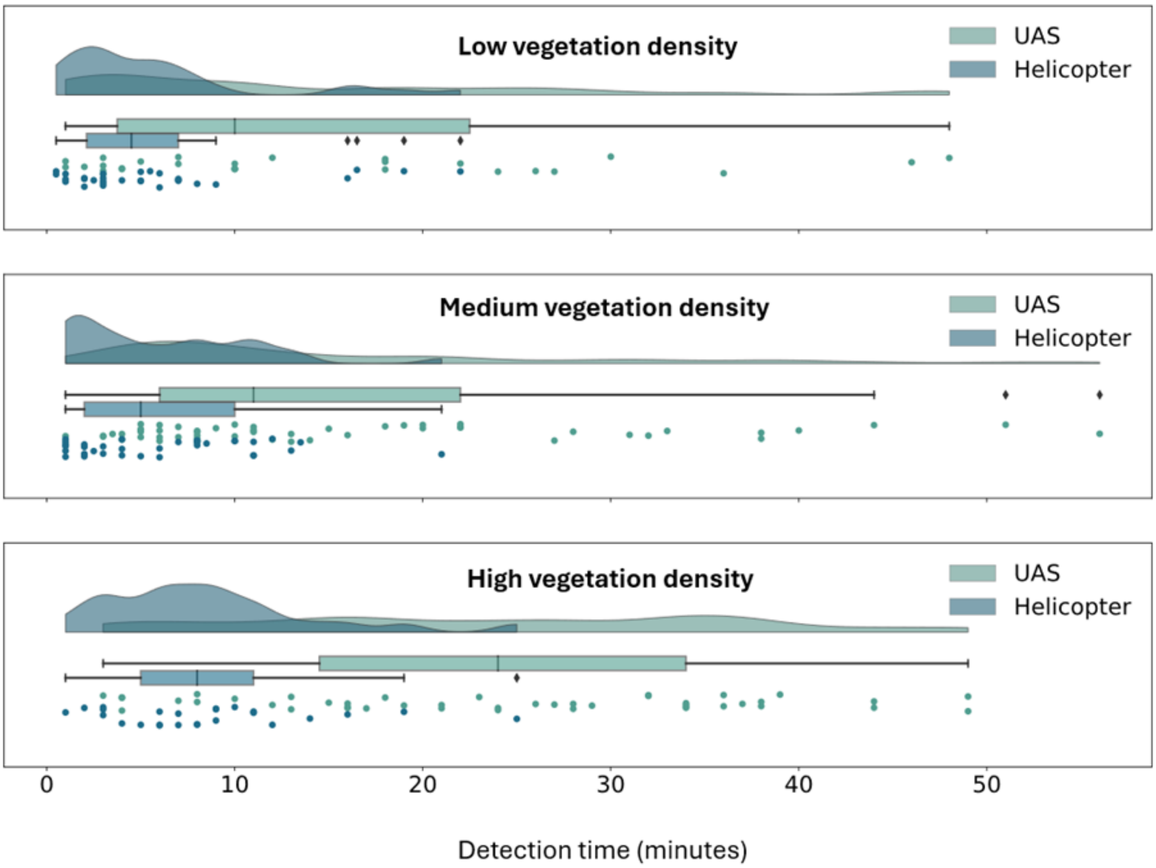

Figure 9. Time to detection by aerial resource and terrain. Points represent individual target detections, boxplots show medians and interquartile ranges, and the violin plots show the density of observations. Violin areas are normalized across groups. Time is measured in minutes from search initiation to target detection.

As visualized in figure 9, both platforms performed well in low and medium vegetation sectors. However, a significant performance divergence occurred in the high-density forest sector. POD for both helicopter and UAS platforms decreased substantially and exhibited high variability (*SD*= 32.37%, *SD*=25.87% - table 5). Figure 10 illustrates the general distribution of POD achieved per density.

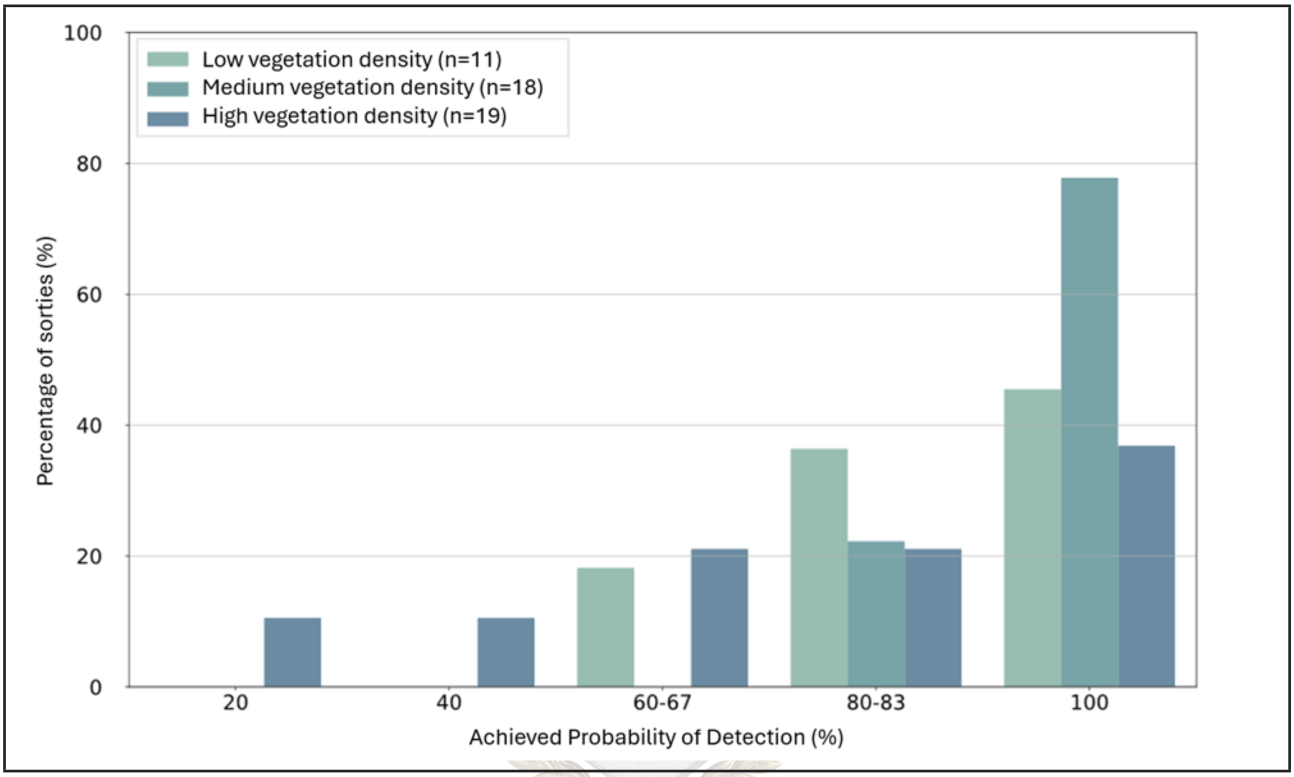

Figure 10. Distribution of achieved POD per density. The x-axis shows POD expressed as percentages, grouped into categories based on observed values. The y-axis indicates the percentage of sorties achieving each POD level within each vegetation density. Values are normalized such that percentages sum to 100% within each vegetation density group.

3.4. Search Strategy and Time to Detection

Both platform types employed initial sweep and detailed search strategies. Detections were systematically recorded according to whether they occurred during the initial sweep or detailed search phase. Table 6 presents the distribution of detections across the different search strategies, as well as the total number of targets that remained undetected.

Table 6. *Distribution of search strategy per target*

Category	Number of targets	Percent of total
Detailed search strategy	134	53.39
Initial sweep search strategy	82	32.67
Target not found	35	13.94
Total detection opportunities	251	100

Helicopters consistently achieved rapid detections, with the majority of finds occurring within the first 10 minutes of a sortie across all vegetation types. UAS detections were distributed over a longer duration, a pattern consistent with the common UAS strategy of proceeding directly to a systematic pattern-based detailed search.

When analyzing the effect of search strategy for UASs (figure 11), a clear trend emerges. Sorties employing an initial sweep search in low and medium density terrain, resulted in a higher concentration of early detections. No UAS or helicopter sorties utilized initial sweep search strategies in high density terrain. In contrast, "detailed search" strategies yielded detections more evenly throughout the search period. This suggests that an initial sweep search is highly efficient for rapidly locating targets that are conspicuous both thermally and visually, while a detailed search is necessary to achieve a higher overall POD (seen in regression analysis, chapter 3.6), albeit at a greater time cost. This trend was less pronounced for helicopters than for UAS, as seen in figure 12.

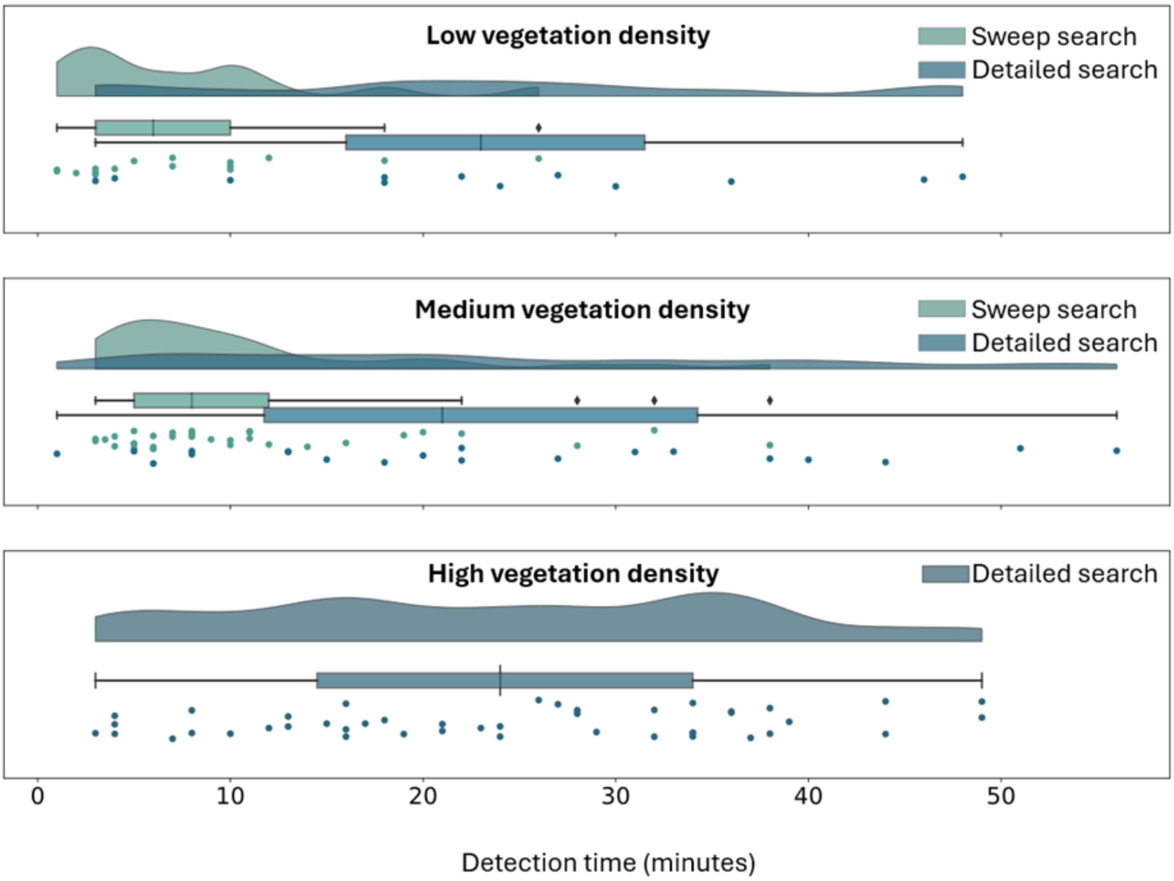

Figure 11. Time to detection by search strategy for UAS. Points represent individual target detections, boxplots show medians and interquartile ranges, and the violin plots show the density of observations. Violin areas are normalized across groups. Time is measured in minutes from search initiation to target detection.

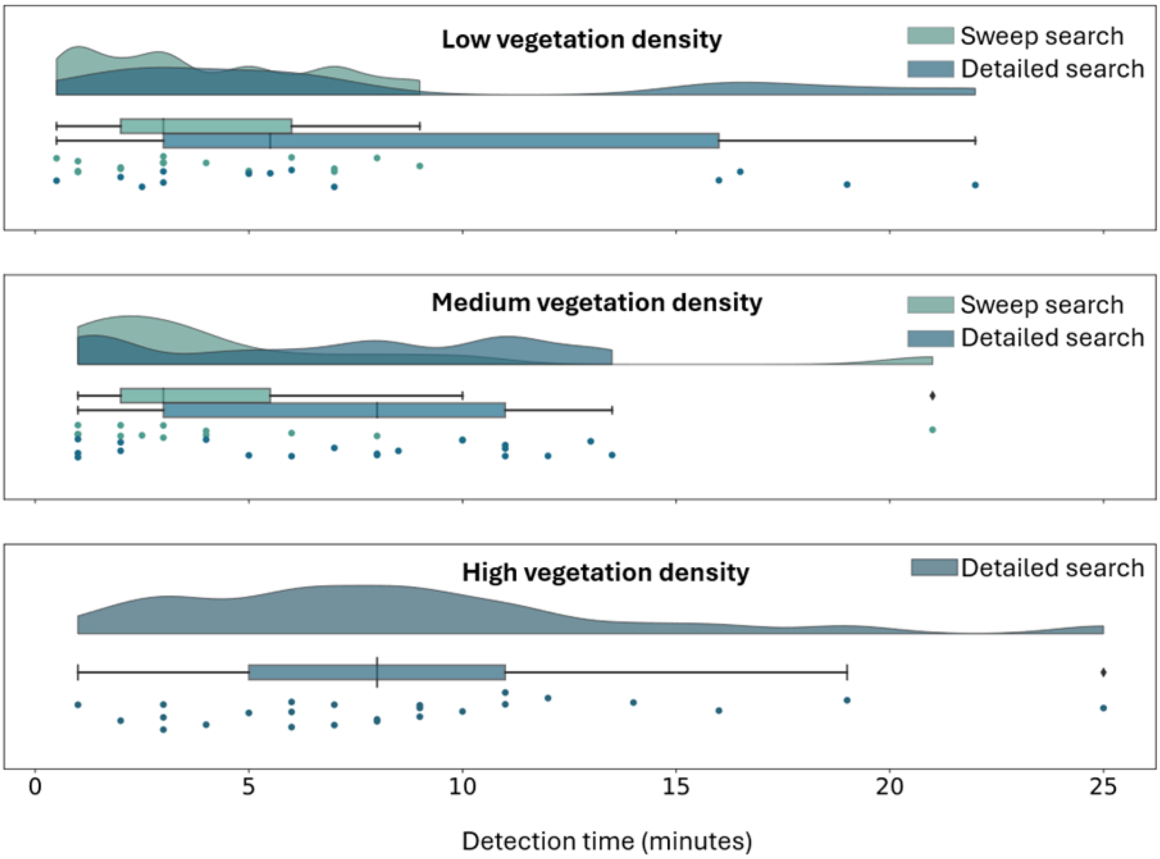

Figure 12. Time to detection by search strategy for helicopters. Points represent individual target detections, boxplots show medians and interquartile ranges, and the violin plots show the density of observations. Violin areas are normalized across groups. Time is measured in minutes from search initiation to target detection.

3.5. Flight altitude by sensor modality

Figure 13 illustrates the detection altitudes for the aerial resources for each find conducted in the sorties. As seen in the figure, detection altitude varied by sensor modality. Here, the "sensor-only" category is split into helicopter and UAS subgroups due to major differences in operational envelopes, driven by both technological capabilities and regulatory limits. Median and mean altitudes ± standard deviations were: sensor-only (helicopter) 366, 365.63 ± 73.14 m AGL, hybrid (helicopter) 160, 175.65 ± 76.17 m AGL, sensor-only (UAS) 99, 114.69 ± 52.52 m AGL, and visual-only (helicopter) 56, 59.07 ± 19.56 m AGL

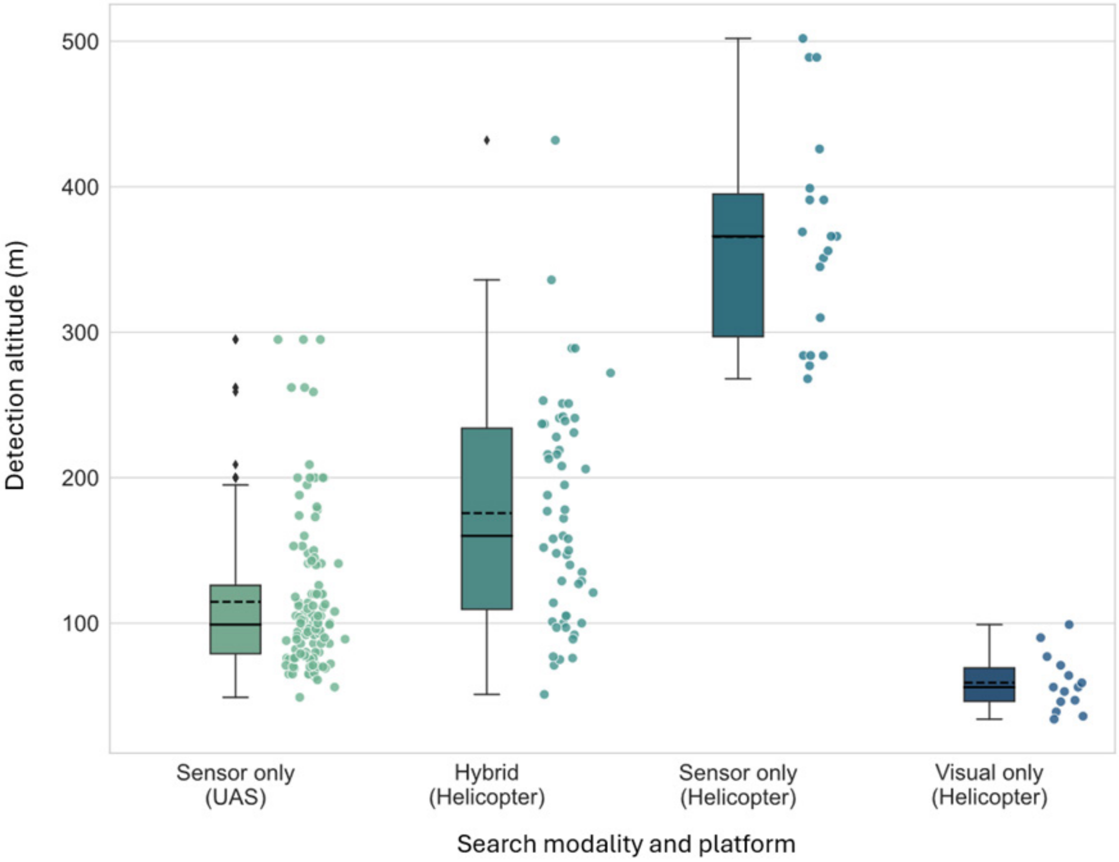

Figure 13. Detection altitude in meters AGL, separated by aerial resource and search modality. The x-axis shows search modality and platform (Helicopter or UAS), and the y-axis indicate detection altitude in meters AGL. Boxplots indicate medians and interquartile ranges, with individual points representing each observation of altitude per detected target. “Sensor only” refers to detections made using onboard sensors, “visual only” refers to detections made by human observers, and “hybrid” refers to combined sensor and visual detection.

3.6. Statistical Modeling of Detection Performance

Each crew conducting searches performed at least three sorties. This implies that the identity of the crew may directly influence the performance of the platform type. To account for potential correlations arising from crews conducting multiple searches, intra-class correlation (ICC) analysis was conducted. ICC values close to 0 indicate that clustering of observations is negligible (Gelman & Hill, 2007).

The ICC analysis assessing the clustering effect of crews on the probability of detection (POD) indicated that clustering was negligible, with an ICC < .001. This result was supported by a likelihood ratio test (LR test = .00, p = 1.00). Consequently, predictions of POD were conducted without accounting for clustering effects.

For the regression analyses of time to detection, the first, third, and fourth detected targets were selected for further analysis. The second, fifth, and sixth detected targets were excluded because they largely overlapped with other variables and therefore did not provide additional independent information across analyses. Specifically, the second detected target showed very strong overlap with both the first (r = .86, n = 46) and third detected targets (r = .95, n = 44). Similarly, the fifth detected target was highly correlated with the fourth detected target (r = .87, n = 30), while the third and fourth detected targets were also strongly related (r = .95, n = 40). The sixth detected target was further excluded due to both its perfect correlation with the fifth detected target ($r = 1.00$, $n = 5$) and the very limited number of observations.

Although these variables were not included simultaneously within the same regression models, the high degree of overlap indicates that they capture closely related aspects of detection performance. To reduce redundancy and ensure a parsimonious analytical approach, only three variables were retained for further analysis. An ICC analysis of the three included dependent variables—First, third and fourth detected target—revealed a moderate clustering effect for the first detected target (ICC = .114). However, the likelihood ratio test did not indicate that a model with random intercepts would significantly improve model estimation (LR = .71, $p = .199$). In contrast, substantial clustering effects were observed for time to detection of the third target (ICC = .365; LR = 5.41, $p = .01$) and fourth target (ICC = .401; LR = 5.52, $p < .01$). Therefore, clustering by crew was accounted for in the regression analyses of time to detection for the first, third and fourth detected target.

Due to the limited number of clusters (12), 95% confidence intervals, t-tests, and p-values were estimated using wild cluster bootstrap methods (Cameron, Gelbach & Miller, 2008). This method results in more conservative estimations of significance levels.

To investigate the statistical significance of our descriptive observations, we performed a series of multiple linear regression analyses.

First, we developed an OLS regression model to predict the overall Probability of Detection (POD) per sortie, using platform type (UAS vs. helicopter), vegetation density, and search modality as predictor variables. The search modality was categorized into three distinct methods observed in the trials: sensor-only search (all UAS and the Police Helicopter), hybrid search (Rescue Helicopters), and visual-only search (Air Ambulance Helicopter). Due to high multicollinearity between platform type and search modality, they were entered into separate regression models to avoid distortion of coefficient estimates (table 7, and table 8).

Table 7 shows that vegetation density, rather than platform type, was the main statistically significant predictor of POD. While no significant differences were found across platform types, POD was significantly lower in high-density environments compared to both low- and medium-density conditions. This indicates that detection performance was primarily constrained by vegetation density, with reduced effectiveness in dense environments regardless of platform type.

Table 7. *Multiple regression analysis of POD (N=48)*

Variable	**b**	**β**	**SE**	**t**	**p**	**95%CI**
Helicopter vs. UAS	-3.90	-.09	5.74	-0.68	.50	[-15.46, 7.66]
Low density vs. high density	15.93	.31	7.42	2.15	.04*	[.98, 30.89]
Medium density vs. high density	23.00	.52	6.38	3.60	<.001***	[10.14, 35.86]
Low density vs. medium density	-7.07	-.14	7.48	-0.94	.35	[-22.14, 8.00]

Note. b = unstandardized regression coefficient; β = standardized regression coefficient; SE = standard error; t = t statistic; p = p value; 95% CI = 95% confidence interval. $^*p<.05$, $^{**}p<.01$, $^{***}p<.001$; $F(3,44)= 4.58$, $p<.01$. $AdjR^2=.19$; F = F statistic; $AdjR^2$ = adjusted coefficient of determination.

Table 8 suggests a possible lower POD for visual-only search compared to both sensor-based and hybrid search methods, controlled for vegetation density. However, this finding should be interpreted with considerable caution, as visual-only search was based on only four sorties. Further, table 8 illustrates, as in table 7, that POD was significantly lower in high-density environments compared to both low- and medium-density conditions, controlled for sensor modality.

Table 8. *Multiple regression analysis of POD (N=48)*

Variable	b	β	SE	t	p	95%CI
Sensor-only vs. hybrid	1.73	.04	6.34	0.27	.77	[-11.05, 14.50]
Visual-only vs. hybrid	-22.13	-.29	10.72	-2.06	.05*	[-43.76, -.51]
Visual-only vs. sensor-only	-23.86	-.31	9.87	-2.42	.02*	[-43.76, -3.96]
Low density vs. high density	16.43	.32	7.10	2.31	.03*	[2.12, 30.73]
Medium density vs. high density	24.34	.55	6.34	3.98	<.001***	[12.01, 36.67]
Low density vs. medium density	-7.91	-.16	7.14	-1.11	.27	[-22.30, 6.48]

Note. b = unstandardized regression coefficient; β = standardized regression coefficient; SE = standard error; t = t statistic; *p* = p value; 95% CI = 95% confidence interval. **p*<.05, ***p*<.01, *** *p*<.001; *F*(4,43)= 5.12, *p*<.001. $AdjR^2$=.26; *F* = F statistic; $AdjR^2$ = adjusted coefficient of determination.

A second set of models analyzed the time to detection for the first, third and fourth detected target. Because ICC-analyses revealed crew as a potential clustering effect, table 9, 10 and 11 reports cluster controlled standard errors, and 95% confidence intervals, t- and *p*-values based on wild cluster bootstrap t-tests (Cameron et al., 2008). The variable search modality is omitted from these regression analyses due to only one crew performing visual-only searches. When clustered, standard errors, confidence intervals, t- and *p*-values become flawed. The analyses of time to detection, reported in table 9, 10 and 11, consist of predictors: platform type, vegetation density and initial sweep search- vs. detailed search per detection.

All three regression analyses revealed the difference between helicopters and UAS as significant in time to detection, where helicopters found the targets faster compared to UAS, controlled for vegetation density and search technique. In these models (table 9-11), negative coefficients indicate shorter detection times relative to the reference category. Thus, the negative coefficient for "Helicopter vs. UAS" reflects faster detection times for helicopters compared to UAS. Table 9 illustrates that time to detection is shorter for both low density and medium density vegetation sectors, compared to high density sectors, while controlled for platform type and search technique. The analysis revealed no statistically significant difference in time to detection for the first target between the two search techniques initial sweep search vs. detailed search. It is important to note that the regression model reported in table 9 is not statistically significant at a *p*-value of < .05. This might be due to the sample size and the limited number of clusters (e.g. Cameron et al., 2008).

Table 9. *Time to detection – first target (N=48)*

Variable	b	β	SE	t	p	95%CI
Helicopter vs. UAS	-3.99	-.30	1.69	-2.37	.05*	[-8.17,-.12]
Low density vs. high density	-6.25	-.41	2.20	-2.84	.01**	[-11.31,-1.27]
Medium density vs. high density	-5.35	-.40	2.32	-2.31	.02*	[-11.50,-.79]
Low density vs. medium density	-.91	-.06	.70	-1.29	.22	[-2.39, .69]
Initial sweep search vs. detailed search	-1.19	-.09	.62	-1.91	.07	[-2.34, .08]

Note. b = unstandardized regression coefficient; β = standardized regression coefficient; SE = standard error; t = t statistic; *p* = p value; 95% CI = 95% confidence interval. **p*<.05, ***p*<.01, *** *p*<.001; *F*(4,11) = 4.09, *p* = .10, R^2=.35; *F* = F statistic; R^2 = coefficient of determination; Controlled for cluster effect of crew, wild cluster bootstrap 1000.

Table 10 and 11 reveal that vegetation density no longer posits a statistically significant prediction of time to detection for the third and fourth target, controlled for platform type and search technique. These analyses, however, reveal that search technique is a significant predictor of time to detection. The negative coefficients for initial sweep search indicate faster detection compared to detailed search. On average, the use of an initial sweep search is associated with 9.73 minutes faster detection of the third target (table 10) and 13.10 minutes faster detection of the fourth target (table 11), controlled for platform type and vegetation density.

Table 10. *Time to detection – third target (N=44)*

Variable	b	β	SE	t	p	95%CI
Helicopter vs. UAS	-13.00	-.59	2.24	-5.49	<.001***	[-18.02, -8.26]
Low density vs. high density	-3.87	-.15	3.26	-1.57	.14	[-9.12, 1.36]
Medium density vs. high density	-2.39	-.11	2.92	-.77	.46	[-8.64, 4.81]
Low density vs. medium density	-1.48	-.06	2.43	-.61	.57	[-6.67, 3.50]
Initial sweep search vs. detailed search	-9.73	-.43	2.69	-2.69	.01*	[-18.97, -1.81]

Note. b = unstandardized regression coefficient; β = standardized regression coefficient; SE = standard error; t = t statistic; p = p value; 95% CI = 95% confidence interval. *$p<0.05$, **$p<0.01$, *** $p<0.001$; $F(4,11) = 20.43$, $p = 0.994$, $R^2=0.61$; F = F statistic; R^2 = coefficient of determination; Controlled for cluster effect of crew, wild cluster bootstrap 1000.

Table 11. *Time to detection – fourth target (N=40).*

Variable	b	β	SE	t	p	95%CI
Helicopter vs. UAS	-16.79	-0.63	2.86	-5.88	<0.001***	[-23.81, -10.51]
Low density vs. high density	-1.74	-0.06	3.34	-0.52	0.58	[-9.21, 5.60]
Medium density vs. high density	-3.21	-0.12	2.69	-1.20	0.28	[-9.44, 2.94]
Low density vs. medium density	1.47	0.05	3.11	0.47	0.65	[-4.67, 8.02]
Initial sweep search vs. detailed search	-13.10	-0.49	4.07	-3.22	<0.001***	[-21.73, -2.85]

Note. b = unstandardized regression coefficient; β = standardized regression coefficient; SE = standard error; t = t statistic; p = p value; 95% CI = 95% confidence interval. *$p<0.05$, **$p<0.01$, *** $p<0.001$; $F(4,11) = 26.97$, $p = 0.002$, $R^2=.67$; F = F statistic; R^2 = coefficient of determination; Controlled for cluster effect of crew, wild cluster bootstrap 1000.

All regression models fulfilled assumptions of independence (due to clustering in table 9, 10 and 11) and multicollinearity, with mean variance inflation factors ranging from 1.16-1.57. Analyses reported in table 7 and 8 also fulfilled the assumption of homoscedasticity.

4. Discussion

4.1. Principal findings and interpretation

Our primary finding is that while both platforms demonstrate a high probability of detection, the key performance drivers are not necessarily the platforms themselves, but rather the sensor modality employed and the search strategy executed. Across various vegetation densities, we found no operationally relevant difference in the Probability of Detection (POD) between helicopters and UAS when both were equipped with thermal sensors. The more critical operational question is how to best utilize the specific capabilities of different sensors and search methods, regardless of the aerial platform carrying them.

Both helicopter and UAS platforms perform effectively in open to moderately dense vegetation (table 5) with an average POD between 83.33-96.36% in total. POD decreased for both UAS and helicopters in high density vegetation, with an average POD between 73.33% and 71.43% respectively. Still, these numbers indicate that both platform types perform well in all three included vegetation densities. Our regression analysis of POD (table 7) is consistent with the descriptive findings suggesting no big difference in POD performance between the two platform types, when controlled for vegetation density. However, table 8 illustrates that sensor modality might be of significance in predicting POD performance, where visual-only search resulted in lower POD compared to hybrid and sensor-only searches, controlled for vegetation density. This may indicate that the observed lower performance in some helicopter sorties is statistically attributable to the search method (i.e., the absence of a thermal sensor) rather than the helicopter platform itself. As noted, visual-only searches consisted of only 4 sorties – the values of this predictor should be interpreted with caution. We argue however, that the difference between the search modalities is important to note, as it may display evidence that not only platform type should be considered when choosing who should conduct a search in SAR operations, but also search modality.

It is crucial, however, to contextualize our findings within the environmental conditions of the study. The ambient temperatures (9–15°C), combined with predominantly overcast conditions during the first two days, produced a strong thermal separation between human targets and the surrounding environment while limiting solar heating of terrain features. This likely reduced background thermal clutter and contributed to particularly favorable conditions for infrared-based detection.

In this context, the high performance of sensor-led searches should be interpreted as partly environment-dependent. In warmer climates, during summer operations, or under conditions with greater solar loading, reduced target-to-background thermal contrast and increased environmental heating may diminish the relative advantage of IR-based detection. Accordingly, the results should not be interpreted as universally transferable across all climatic conditions, but rather as reflecting performance under high-contrast thermal conditions.

While our statistical analysis did not find a significant performance difference between hybrid and sensor-only search modalities, we hypothesize that the practical application of a hybrid strategy introduces distinct operational trade-offs. A key technological advantage of modern helicopter-mounted sensors is their powerful optical and thermal zoom, which allows operators to maintain high altitudes for enhanced flight safety and wider area coverage while still achieving the necessary ground resolution for target identification (L3 Harris Technologies, 2020; FLIR Systems, n.d.). We hypothesize that this 'scan-wide, identify-narrow' approach, executed from high altitude, may offer operational advantages both for coverage and vegetation penetration. A higher altitude may provide a steeper, more nadir-oriented viewing angle, which may be advantageous for seeing through gaps in a forest canopy (Norwegian Police Unmanned Air Support Unit, 2023). A more oblique, horizontal angle, which is more common at lower altitudes, could force the sensor to look through multiple layers of foliage, significantly increasing obstruction.

However, based on operational observations during our trials, integrating unaided visual observers into a hybrid strategy often requires flying at a lower altitude to accommodate the limits of human visual acuity as seen in figure 13. This may create an operational compromise with two potential negative consequences for sensor performance. To maintain a steep viewing angle from a lower altitude, the area that can be effectively scanned becomes substantially smaller (Norwegian Police Unmanned Air Support Unit, 2023), potentially forcing the sensor to make more passes and thus increasing search time. Alternatively, to maintain area coverage rate, the sensor must cover more oblique viewing angles, which leads to greater vegetation obstruction and potentially a lower POD.

This raises a critical question: does the potential increase in POD from adding visual observers at low altitude outweigh the potential decrease in sensor effectiveness caused by a suboptimal altitude and viewing angle? Our study cannot definitively answer this, but it highlights a possible tension between optimizing for sensor performance versus human visual search that warrants further investigation. However, the present study was not specifically designed to isolate the independent effects of altitude, viewing geometry, or scan strategy, and these interpretations should therefore be regarded as exploratory.

The POD analysis revealed differences between sensor modalities, controlling for vegetation density. Sensor-only helicopter searches were conducted at the highest median altitudes (≈370 m AGL), followed by hybrid helicopter searches (≈160 m AGL), UAS sensor-only searches (≈100 m AGL), and visual-only helicopter searches (≈60 m AGL). These differences reflect the distinct operational envelopes of each modality, shaped by both technological capabilities and regulatory constraints. From an operational perspective, these altitude profiles provide a potential framework for vertical separation in coordinated multi-platform SAR operations. High-altitude sensor-only helicopter searches can cover large areas quickly with a favorable viewing angle through vegetation, while UAS can operate in lower altitude blocks to perform detailed inspections. We hypothesize that this separation could enable simultaneous operations while reducing the risk of airspace conflicts and ensuring that each asset operates within its optimal performance band.

A second key finding relates to time to detection and strategy. Helicopters generally achieved faster initial detections; a result strongly correlated with the use of an “initial sweep search” strategy upon entering a sector, a trend illustrated in figure 12. This tactic prioritizes rapid, high-altitude scanning for easily detectable targets. Our models confirmed that this strategy significantly shortens the time from the first to the fourth detection of targets. Most UAS teams, conversely, initiated a systematic “detailed search” from the outset, which distributes detections more evenly over a longer duration (As illustrated in figure 11). However, our data also suggests that UAS crews who did employ an initial sweep search phase reaped similar benefits as helicopters in early-detection efficiency. This indicates that the value of an initial, rapid assessment is a platform-agnostic principle, costing little in time but offering a high potential reward. The difference between the two search techniques ought to be further investigated.

4.2. Operational Implications for Coordinated Airspace Management

The following section discusses operational implications derived from the empirical findings. These implications should be interpreted as proposed operational concepts and hypotheses for further evaluation, rather than as coordination models directly tested in the present study. Current national guidelines in Norway for multi-asset aerial SAR operations prioritize airspace deconfliction to ensure flight safety, typically through spatial or temporal separation (Norwegian Joint Rescue Coordination Center, 2024). This approach often prevents simultaneous use in the same sector, potentially reducing operational efficiency. We propose evolving these protocols from simple spatial or temporal separation towards more use of vertical separation, which leverages the distinct strengths of each platform identified in our results.

Our results show that, under the thermal and environmental conditions of this study, helicopter-mounted EO/IR sensors achieved effective detections at relatively high altitudes (e.g., 300 - 500m AGL). This observation supports the use of high-altitude sensor-led helicopter searches as part of a vertically separated coordination model. This approach is enabled by the powerful optical zoom capabilities of their optical and thermal sensor systems, a feature that resolves the fundamental trade-off between area coverage and target detail (L3 Harris Technologies, 2020). We suggest a “scan-wide, identify narrow” approach. This technique can be performed from a high altitude, where the operator can utilize a wide field of view (FOV) to efficiently scan a large area for thermal anomalies. Upon detecting a point of interest, instead of descending, the operator can zoom in optically, thus improving Ground Sample Distance (GSD) to allow for positive identification of the target. This workflow allows the platform to remain at a consistent and safe altitude while performing both wide-area surveillance and detailed investigation, enhancing the efficiency of an initial sweep search. Simultaneously, our data supports that the UAS can effectively perform search tasks (table 5) at a much lower altitude (figure 13), focusing on detailed inspection and canopy penetration.

To further enhance this vertical separation model, we suggest the separation should be sufficient to also accommodate an initial sweep search phase for the UAS, as shown effective in this study. A UAS might conduct its initial scan at a medium altitude (e.g., 120-200m AGL) before descending for its detailed search. Therefore, a coordinated doctrine could allocate a high-altitude block to helicopters and a low-to-medium altitude block to UAS. We hypothesize that this layered approach permits concurrent operations, with each asset performing the task for which it is better suited: the helicopter providing rapid, wide-area coverage and effective verification using zoom capabilities, while the UAS delivers systematic, detailed search. This might transform the assets from being potentially redundant to being complementary, potentially increasing the overall speed and thoroughness of the aerial SAR operation. This model should be regarded as an operational hypothesis generated by the present findings, requiring validation in trials where helicopter and UAS assets operate concurrently under predefined vertical separation procedures.

4.3. Limitations of the Study

While this study provides valuable field data, its limitations must be acknowledged to ensure a balanced interpretation of the results.

Firstly, the quasi-experimental design, while maximizing ecological validity by allowing crews to use their own procedures, introduces confounding variables. For instance, platform type and preferred search strategy were highly correlated, as helicopter crews more frequently employed an initial sweep search than UAS crews. This makes it challenging to definitively isolate the independent effects of platform versus strategy on detection times.

Secondly, the statistical power of our analyses, particularly the regression models, is affected by the limited and decreasing sample size. With a limited number of observations, the robustness of these models is flawed. Therefore, while trends can be identified, caution is warranted in drawing firm conclusions from these specific sub-analyses.

Thirdly, the findings are specific to the environmental conditions under which the experiment was conducted. The high thermal contrast present during the trials was highly advantageous for thermal sensors. The performance dynamics between IR and EO/visual modalities might shift considerably in conditions of low thermal contrast, such as during warm summer days or in different climatic zones. The generalizability of our findings must therefore be considered in this context.

Fourthly, the use of static human targets does not fully replicate the challenge of searching for a missing person, who may be mobile, hide, become hypothermic, or actively seeking shelter. Dynamic targets may be more readily detected by visual observers or electro-optical (EO) sensors due to motion cues, while individuals hiding or seeking shelter may exhibit reduced thermal contrast, potentially affecting IR sensor effectiveness. Hypothermic individuals may further exhibit reduced thermal signatures, reducing detectability in IR-based searches.

Fifthly, all air crews were instructed to follow standard operational procedures and not treat the exercise as a competition. However, we must acknowledge the possibility of a performance bias. The natural desire of participants to demonstrate their capabilities may have led them to invest more time and effort than they would in a routine mission. As a result, this increased diligence could have inflated the Probability of Detection (POD) values recorded in this study, making them higher than what might be expected in a typical operational setting.

Sixthly, challenging wind conditions were reported to prolong search times for both helicopter and UAS platforms. The effect, however, is likely to have been more pronounced for UAS, given their inherent limitations in maximum air speed. On several occasions, wind gusts approached or exceeded the top speed of the UAS, which not only increased power consumption but also significantly reduced ground speed. As a result, UAS time to detection data may have been disproportionately affected compared to helicopter platforms.

Finally, there is a risk of attribution errors, particularly in sorties involving multiple visual observers. In some cases, a reported detection may have referred to a target already observed by an-other crew member, or by the same observer from a different angle, without recognizing it as the same target. To mitigate this, each target wore a uniquely coloured t-shirt and hat. However, due to vegetation cover and limited visibility, these markers were not always visible in flight. All detections were reviewed post-trial using video recordings and cross-referenced with known GPS positions and target description. While this process improved data quality, a residual risk remains that some detections may reflect duplicate sightings.

4.4. Future Work

The results and limitations of this study highlight several avenues for future research, moving from the current quasi-experimental observations towards more controlled experimentation to isolate key performance variables.

1. Isolating the effects of search modality: A recommended next step is to conduct controlled experiments to decouple the interconnected variables of altitude, sensor use, and search method.
    - For helicopters, a study could be designed to directly compare the POD and efficiency of: (a) low-altitude hybrid search (visual + sensor), (b) low-altitude sensor-only search, (c) low altitude visual search only, and (d) high-altitude sensor-only search. This would provide more data on whether prioritizing high-altitude sensor operations over low altitude combined search yields superior results.
    - For UAS, a similar experiment should systematically compare the outcomes of: (a) initial sweep search only, (b) detailed search only, and (c) a combined initial sweep-then-detailed search strategy. This would rigorously quantify the trade-offs between rapid detection and overall search thoroughness.
2. Isolating the effects of flight altitude: We propose that the optimal search altitude for a camera sensor is not a fixed value, but rather a function of its field of view (FOV), ground sampling distance (GSD) and its capability for rapid zoom magnification to classify potential targets. Our study observed that manned helicopters operate effectively across a wide altitude spectrum (160-370 meters), while UAS operate consistently at lower altitudes, primarily restricted by regulatory constraints. A dedicated investigation into the optimal operational altitudes for both helicopters and UAS is therefore crucial. Such research would not only enhance mission effectiveness but also refine vertically separated airspace models and provide an empirical foundation for revising aviation regulations.
3. Validation of the vertically separated airspace model: Based on the insights from more controlled studies (as described above), a large-scale field trial should be conducted to formally test the proposed doctrine of vertically separated, concurrent helicopter and UAS operations. This would aim to quantify the real-world gains in Time to Detection.
4. Systematic evaluation of AI-assisted detection: A controlled study is needed to compare AI-assisted search directly against manual sensor operation, focusing on metrics such as POD, false alarm rates, and operator cognitive load under various conditions.
5. Performance in varied thermal conditions: To broaden the applicability of these findings, the experiments should be replicated in environments with lower or higher thermal contrast (e.g., during summer and winter) as well as different daylight conditions. This would provide valuable data on the relative efficacy of IR versus high-resolution EO sensors under different conditions when the thermal advantage is neutralized or augmented.
6. Performance in other biomes: Our findings are currently applicable to the temperate–boreal uplands of Rogaland, Norway. Norwegian boreal pine forests are relatively transparent in the thermal infrared and typically have a short lateral crown spread, enabling sensors to penetrate foliage or observe beneath branch overhangs. Biomes with different canopy architectures (e.g., leaf type, crown depth, overhang extent) may yield different outcomes; we therefore encourage replication in other biome settings to assess the broader generalizability of our findings.

5. Conclusions

This field study provides empirical evidence suggesting that both manned helicopters and unmanned aerial systems (UAS) equipped with modern EO/IR sensors can be highly capable search platforms in SAR operations. Controlled for varied vegetation densities, platform type alone was not a significant predictor of Probability of Detection (POD). Instead, vegetation density, sensor modality, and search strategy emerged as the primary drivers of detection performance, though there are some limitations to the analysis.

Helicopters tended to achieve faster initial detections, often through initial sweep search strategies, while UAS tended to apply systematic detailed searches that ensured thorough coverage with detections distributed over longer time intervals. These differences suggest that operational outcomes may be shaped by crew tactics and sensor use, in addition to the aircraft platform itself.

One potential operational implication is that EO/IR searches from helicopters could, under favorable thermal conditions, be performed effectively from high altitudes without necessarily compromising detection performance. This introduces a possible alternative to the current practice of flying at medium to low altitudes (60–250 m AGL) to accommodate both EO/IR sensors and multiple visual observers. For helicopter types with the flexibility to choose between sensor-only, hybrid, and visual search modes, opting for high-altitude sensor-only searches could potentially free lower airspace for UAS operations, enabling safe, simultaneous missions and improving overall efficiency. However, further validation would be required to confirm the viability of this approach.

The results suggest a potential opportunity to improve SAR effectiveness and efficiency through integrated, complementary use of multiple aerial assets. A vertically separated operational model where helicopters provide rapid, high-altitude scanning and verification, and UAS conduct detailed, low-altitude inspections, could enable concurrent operations that leverage each platform's strengths. However, this proposed model would require further validation through future operational trials under a wider range of conditions.

By providing quantitative, operationally relevant data, this study offers a foundation for evidence-based planning, training, and coordination protocols in aerial SAR. Future research should validate the proposed integration model under a wider range of environmental conditions, explore the role of AI-assisted detection, and further isolate the effects of altitude, sensor type, and search strategy on performance.

Abbreviations: The following abbreviations are used in this manuscript:

ADS-B	Automatic Dependent Surveillance–Broadcast
AGL	Above Ground Level
AI	Artificial Intelligence
BVLOS	Beyond Visual Line of Sight
EO	Electro-Optical
FOV	Field of View
GPS	Global Positioning System
GSD	Ground Sample Distance
ICC	Intra-class Correlation
IR	Infrared
JRCC	Joint Rescue Coordination Centre
POD	Probability of Detection
SAR	Search and Rescue
SAVIOUR	Systematic Airborne Visual and Infrared Observational Unified Research
UAS	Unmanned Aerial System

Ethics approval and consent to participate: The study was conducted in full accordance with the ethical principles of the Declaration of Helsinki. All procedures involving the collection of data from human participants were reviewed and approved as part of the project's data management plan by Sikt – the Norwegian Agency for Shared Services in Education and Research (Ref. 501152), ensuring compliance with the General Data Protection Regulation (GDPR).

Written informed consent was obtained from all volunteers acting as human targets or ground support personnel who might be recorded or observed during the experiment. The consent form provided a detailed description of the study, including its dual purpose: (1) to scientifically evaluate SAR methods for the improvement of rescue services and (2) to collect data for training machine learning detection models. These participants were fully informed about the types of data being collected (including GPS positioning, video, and thermal imagery), the voluntary nature of their participation, and their explicit right to withdraw consent at any time without prejudice.

The professional SAR aircrews participated as part of a large-scale training exercise, and their involvement in the study was covered by their respective employers' institutional frameworks for such activities. All performance data related to the aircrews has been fully anonymized in this manuscript to protect individual and team confidentiality.

Availability of data and materials: The data presented in this study is available on request from the corresponding author due to considerations related to anonymity and data protection.

Competing interests: The authors declare no financial conflicts of interest. The following potential non-financial interests are declared: The authors Nilsen, A.A., Ronge, J.L.H. & Grytting, E. hold professional roles as lead for National Police Unmanned Air Support unit (NPUAS). Johansen, V. is a certified sensor operator and instructor for the Norwegian Air Support Unit (Police helicopter). The authors affirm that their professional roles and affiliations have not biased the interpretation or presentation of the results.

Funding: This research received no external funding from any funding agency in the public, commercial, or not-for-profit sectors. The costs associated with the participation of professional entities were covered by their respective institutional budgets for research, training and exercises. All other contributions were provided on a voluntary basis.

Author Contributions: Conceptualization, Nilsen, A.A., Ronge, J.L.H. & Johansen, V.; methodology, Nilsen, A.A. & Størdal, T.R.; software, Johansen, V., Størdal, T.R. & Ronge, J.L.H.; validation, Nilsen, A.A., Størdal, T.R. & Johansen, V; formal analysis, Størdal, T.R.; investigation, Nilsen, A.A., Størdal, T.R., Ronge, J.L.H, Grytting, E. & Johansen, V.; resources, Nilsen, A.A., Størdal, T.R., Ronge, J.L.H, Grytting, E. & Johansen, V.; data curation, Nilsen, A.A., Størdal, T.R. & Johansen, V ; writing—original draft preparation, Nilsen, A.A. & Størdal, T.R.; writing—review and editing, Nilsen, A.A., Størdal, T.R., Ronge, J.L.H, Grytting, E. & Johansen, V.; visualization, Størdal, T.R. & Nilsen, A.A.; supervision, Nilsen, A.A. & Størdal, T.R.; project administration, Nilsen, A.A. & Størdal, T.R.; funding acquisition, Nilsen, A.A. All authors have read and agreed to the published version of the manuscript.

Acknowledgments: The authors wish to express their sincere gratitude to all the organizations, teams, and individuals who made the SAVIOUR 2024 field experiment possible. We extend our deep appreciation to the professional services and personnel who participated using their own resources, including the Norwegian Police National Emergency Response Centre (PNB) — with contributions from the Norwegian Police Air Support Unit with special thanks to Police Superintendent Lars Aakre, the Norwegian Police University College with special thanks to Police Superintendent Steinar Rostad, the Sør-Øst Police District and the Sør-Vest Police District. We also thank the Joint Rescue Coordination Centre of Norway (Hovedredningssentralen), the 330 Squadron - Royal Norwegian Air Force – Norwegian Search and Rescue Helicopter Service, the Norwegian Air Ambulance and the Royal Norwegian Navy Recruit School - KNM Harald Hårfagre. This study would have been impossible without the invaluable and dedicated efforts of the many volunteer organizations and their members, including the Norwegian People's Aid, Red Cross, the Norwegian Women's Public Health Association, the Scouts' Emergency Response Group, the Norwegian Rescue Dogs and the Norwegian Radio Relay League. Finally, we thank the numerous individual volunteers who acted as human targets and the landowners in the Gjesdal municipality for generously providing access to their properties for the duration of the experiment.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process: During the preparation of this manuscript, the authors utilized AI language models (Google's Gemini, Microsoft Copilot and OpenAI ChatGPT) for the purposes of language enhancement, such as improving grammar, clarity, and readability. Additionally, AI was used as an assistive tool for generating code snippets in Python for data visualization. It is important to state that AI tools had no role in the conceptualization of the study, the formal data analysis, the interpretation of the results, or the formulation of the core scientific conclusions. The authors have reviewed and edited all AI-generated text and take full responsibility for the final content of this publication.

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