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Beyond Platform Type: How Vegetation, Sensors, and Tactics Shape Aerial Search and Rescue Outcomes

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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.This study presents results from the SAVIOUR 2024 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 did not significantly affect POD when controlling for vegetation. 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.We propose that coordinated, vertically separated operations—helicopters at high altitude and UAS at low altitude—can enhance efficiency through concurrent coverage. 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: search and rescue (SAR); unmanned aerial systems (UAS); helicopter; probability of detection (POD); comparative analysis; airspace management; synergistic aerial operations

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1. Introduction

Search and Rescue (SAR) operations for missing persons are time-critical missions in which rapid location can be crucial for survival [1,28]. 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 [17,18,21]. Traditionally, this role has been fulfilled by manned aircraft, relying on visual observation by human crew members [2,9] or by using advanced camera sensor technology [23]. 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

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[4,5,7,16,27], 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 [3,13,27]. This technology offers novel capabilities for detecting human subjects, particularly in challenging conditions such as low light or through vegetation canopy [5,6,13]. 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 [24]. These differences include flight endurance, speed, weather minima, and the regulatory frameworks that govern flight altitude [27,28], where most UAS operations are limited to 120m above ground level in most national airspaces [19,20]. 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 [21]. 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 [12]. 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 effectiveness, may lead to UAS being sidelined in favor of manned helicopters, thereby limiting the potential benefits of combined use.

The effectiveness 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 [1–3,5]. Vegetation density poses a major challenge by obscuring targets and thereby affecting the efficacy of different sensors and observation angles [6,8]. 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 [10,11], 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. The primary objectives of this study were to:

1. Quantify and compare the detection performance (POD) and search efficiency (time to detection) between helicopters and UAS.
2. Evaluate and compare POD for three sensor modalities: IR/EO, visual only, and hybrid (IR/EO plus visual), across different levels of vegetation cover.
3. Assess the effects of "initial sweep search" versus "pattern based detailed search", on search efficiency (time to detection).

By addressing these objectives, 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

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strengths are leveraged in complementary ways to maximize detection performance, and enhance the overall effectiveness of future SAR operations.

2. Materials and 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.

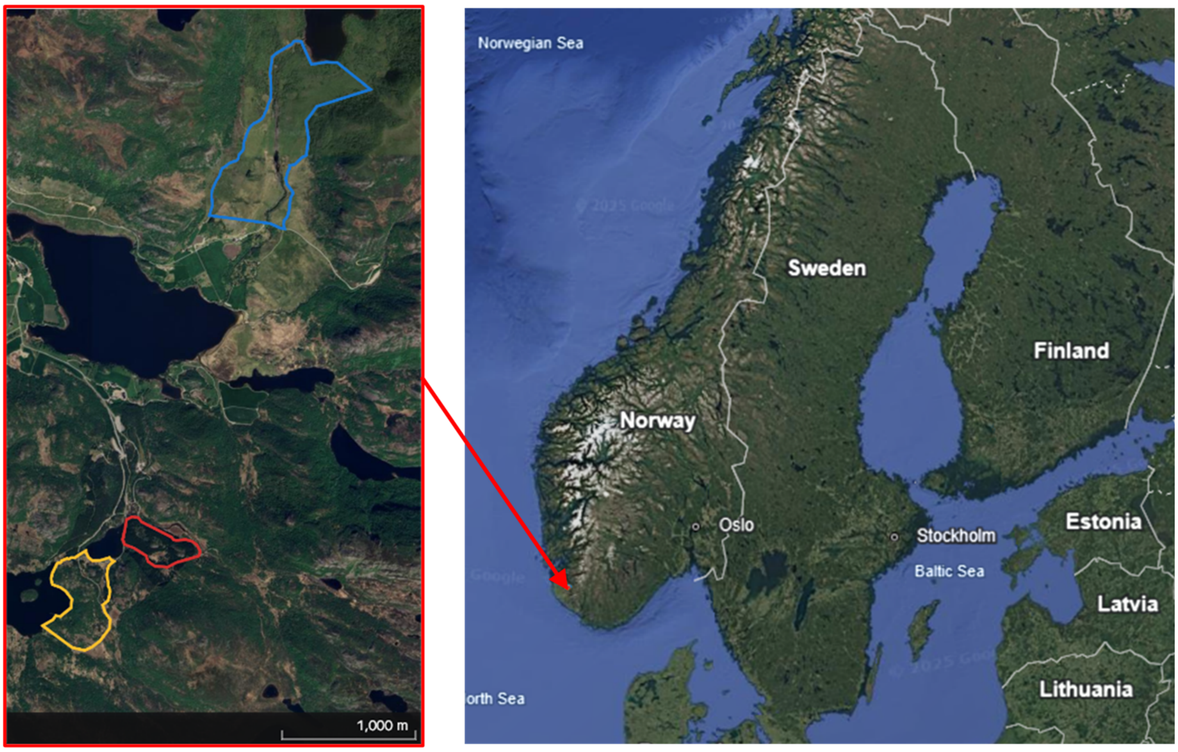

Figure 1. Study area, Gjesdal municipality in Rogaland, Norway. Sector 1 (Blue), Sector 2 (Yellow), Sector 3 (Red). Maps retrieved from Google Earth.

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

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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).

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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 [22]. 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 (thermal IR sensor, EO sensor, visual observation), (3) Search Strategy (Pattern based detailed search or initial sweep search), and (4) Vegetation Density (low, medium, or high). 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 analyzed in this study. A rotation system was implemented to manage the sequence of search efforts and ensure airspace deconfliction.

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). 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 effectiveness while decreasing the drone pilot's cognitive load [27]. An overview of the platforms, primary search sensors, and crew configuration is provided in Table 1.

Table 1. 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 MX15	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 300RTK	1	Zenmuse H20N	640 x 512 px	53mm/ 196mm	24″	1	0
Quadcopter UAS	DJI Matrice 300RTK	2	Zenmuse H20N	640 x 512 px	53mm/ 196mm	24″	2	0
Quadcopter UAS	DJI Matrice 350RTK	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

[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 (n = 45 volunteers) 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. 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 1. Human target wearing blue hat and light blue t-shirt located in sector 3 (Dense vegetation).

Figure 2. Human target wearing white hat and brown t-shirt located in sector 2 (Medium vegetation).

Figure 3. Human target wearing green hat and red t-shirt located in sector 3 (Medium dense 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 2.

Table 2. 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

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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.

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

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.

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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. Overall Performance Summary

A total of 48 search sorties were completed, generating 251 individual target detection opportunities. 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.

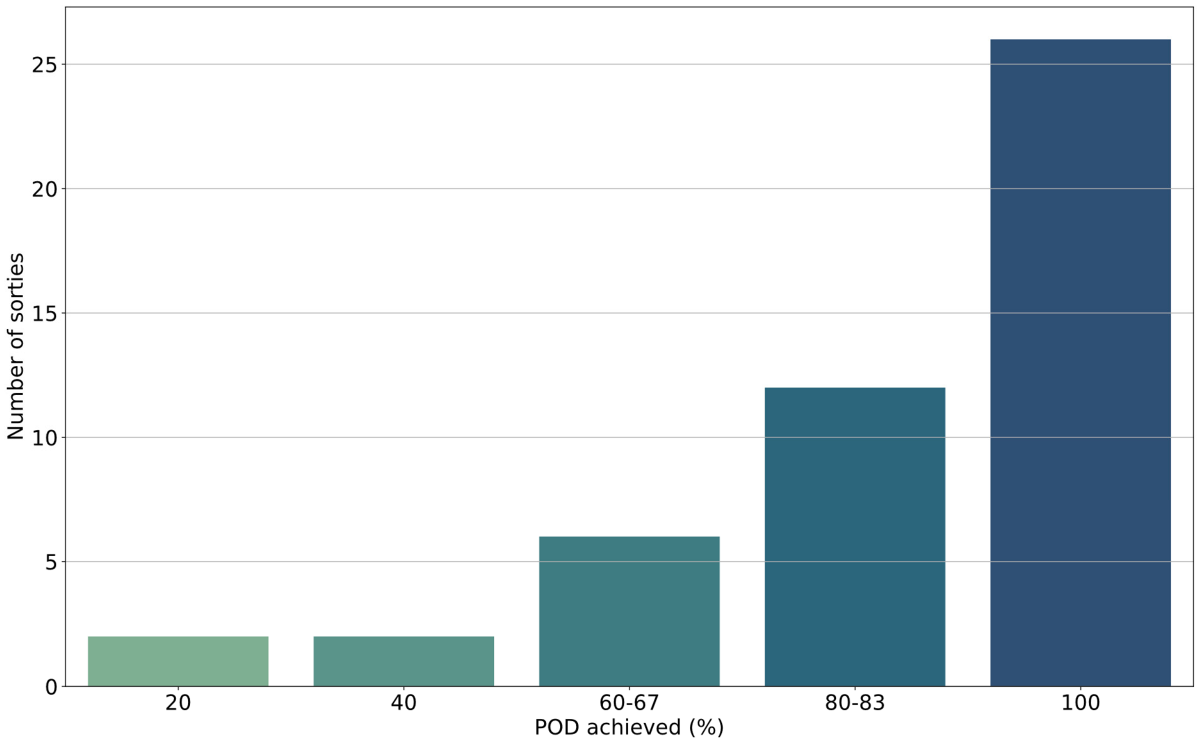

Figure 8. Frequency distribution of POD across all 48 sorties.

3.2. 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.

The primary factor differentiating platform performance was vegetation density. Table 3 presents the summary statistics for POD achieved by each platform type within each vegetation sector.

Table 3. Descriptive statistics for Probability of Detection (POD) by platform and vegetation sector.

Platform	Vegetation Sector	N	Mean POD (%)	Median POD (%)	Std. Dev. (%)
Helicopter	Low Density	6	83.33	83.33	14.76
	Medium Density	7	94.29	100.0	9.76
	High Density	7	71.43	80.0	32.37
	Total	20	83.00	91.5	22.71
UAS	Low Density	5	93.2	100.0	9.31

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	Medium Density	11	96.36	100.0	8.09
	High Density	12	73.33	80.0	25.87
	Total	28	85.95	100.0	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.

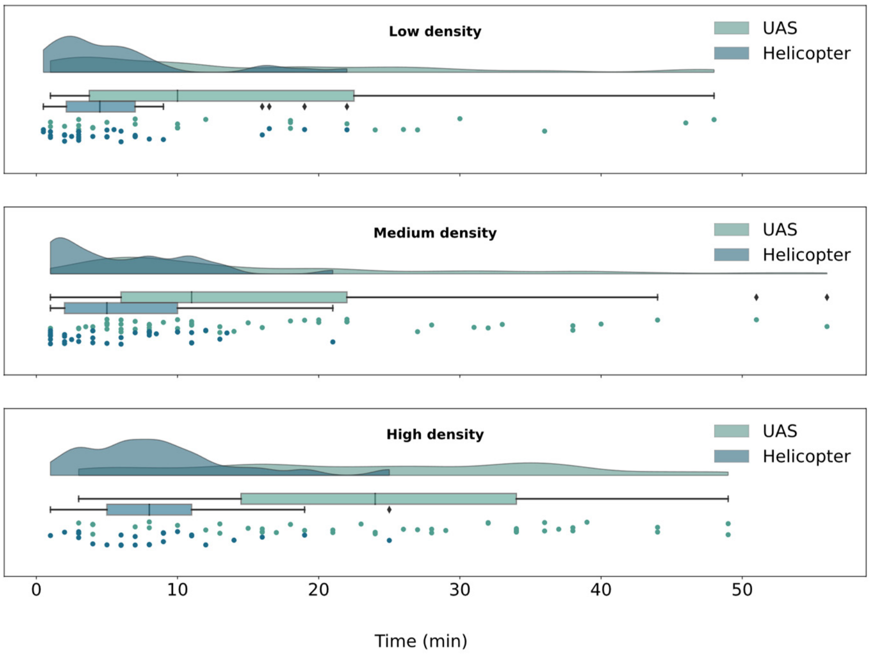

Figure 9. Time to detection by aerial resource and terrain.

As visualized in Figure 9, both platforms performed exceptionally 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 3). Figure 10 illustrates the general distribution of POD achieved per density.

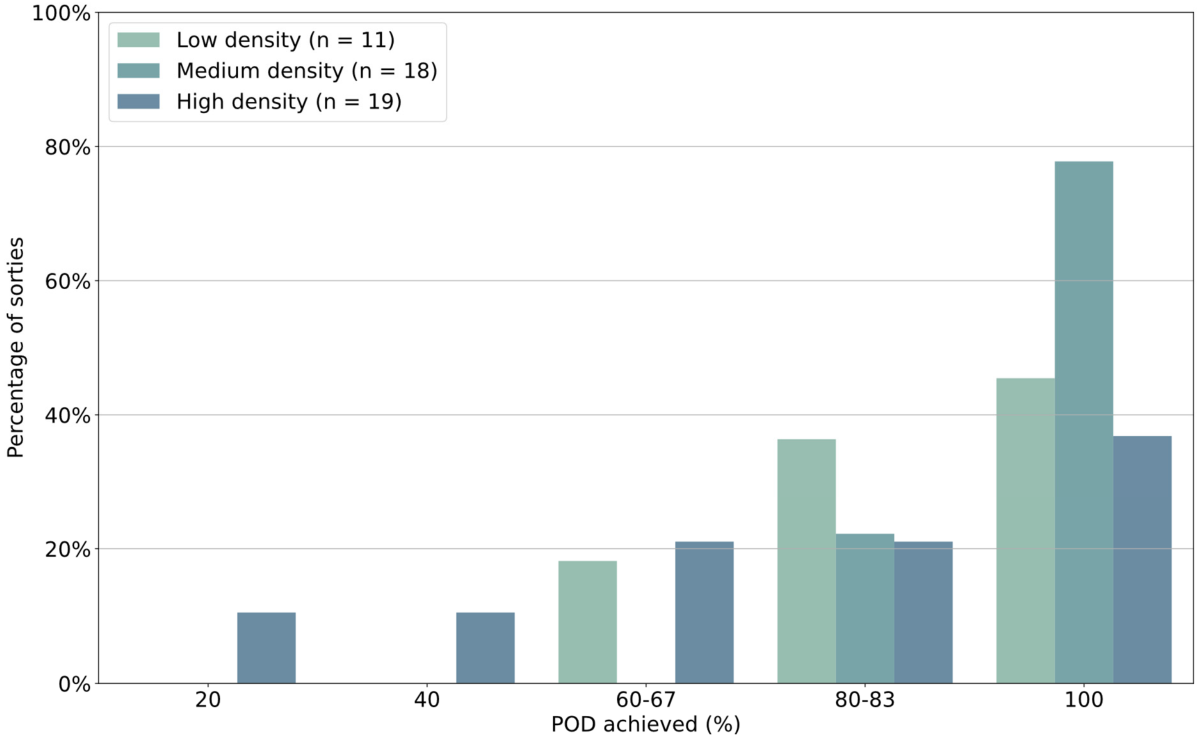

Figure 10. POD per density, normalized plot.

3.3. Search Strategy and Time-to-Detection

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 3.5), albeit at a greater time cost. This trend was less pronounced for helicopters than for UAS, as seen in figure 12.

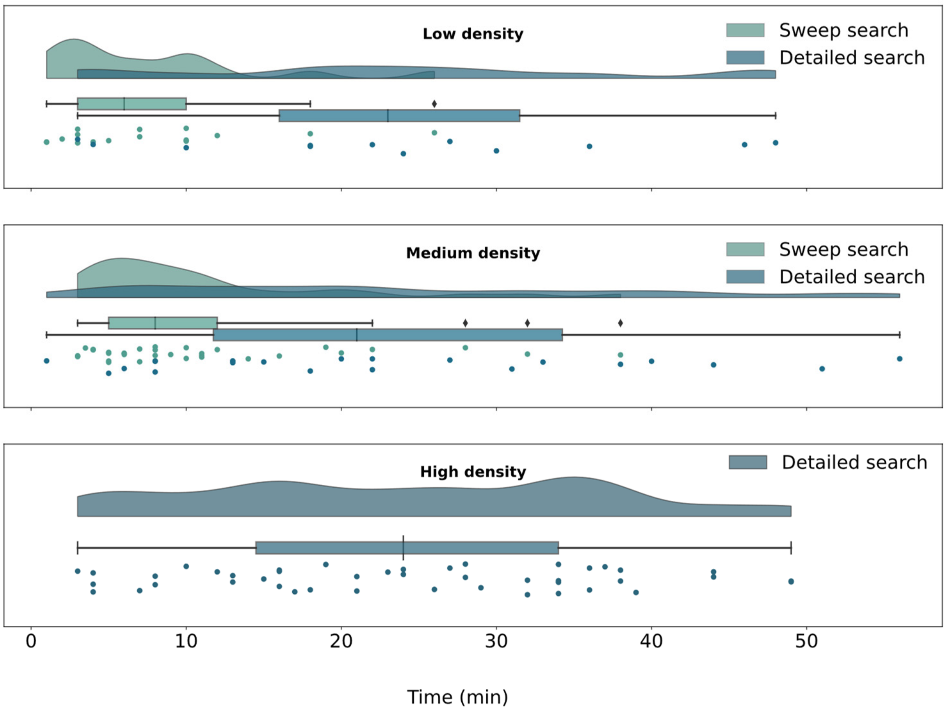

Figure 11. Time to detection by search strategy for UAS.

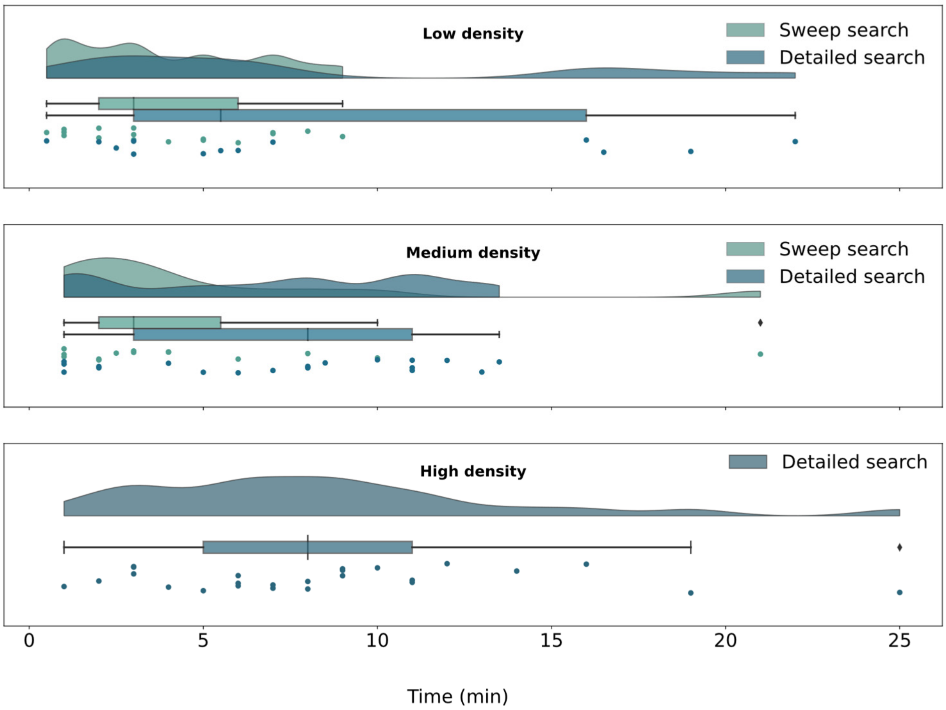

Figure 12. Time to detection by search strategy for helicopters.

3.4. 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.

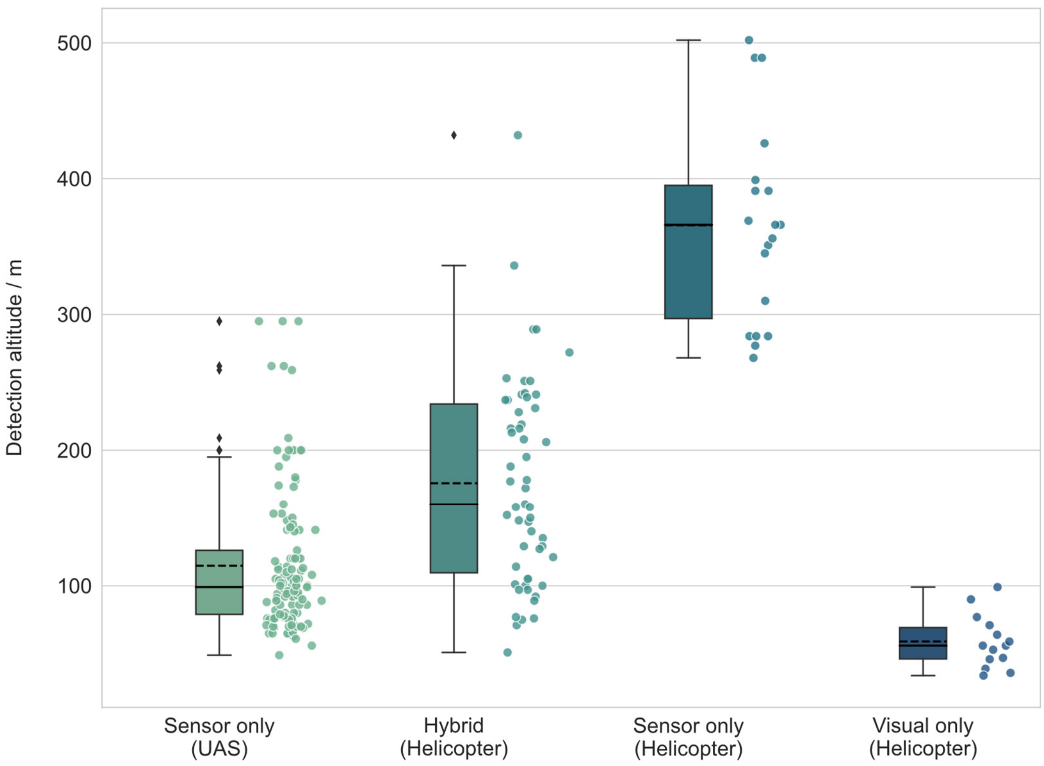

Figure 13. Detection altitude in meters AGL, separated by aerial resource and search modality.

3.5. 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 [14].

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, used to assess effectiveness, findings 1, 3, and 4 were selected for further analysis. This selection was based on intercorrelations among findings: Finding 2 was highly correlated with Finding 1 (r = .86, n = 46) and Finding 3 (r = .95, n = 44); Finding 4 was highly correlated with both Finding 3 (r = .95, n = 40) and Finding 5 (r = .87, n = 30). Finding 6 was excluded due to a limited number of observations (n = 5) and a perfect correlation with Finding 5 (r = 1.00, n = 5).

An ICC analysis of the three included dependent variables—Findings 1, 3, and 4—revealed a moderate clustering effect for Finding 1 (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 Finding 3 (ICC = .365; LR = 5.41, p = .01) and Finding 4 (ICC = .401; LR = 5.52, p < .01). Therefore, clustering by crew was accounted for in the regression analyses of time to detection for Findings 1, 3, and 4.

Due to the limited number of clusters (12), 95% confidence intervals, t-tests, and p-values were estimated using wild cluster bootstrap methods [15]. This method results in more conservative estimations of significance levels.

All regression models fulfilled assumptions of independence (due to clustering in table 6, 7 and 8) and multicollinearity, with mean variance inflation factor ranging from 1.16-1.57. Analyses reported in table 4 and 5 also fulfilled the assumption of homoscedasticity.

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 4, and table 5).

Table 4 revealed no significant differences in POD performance across platform types, controlled for vegetation density. However, the regression analysis indicated significant differences in POD performance between density conditions: specifically, POD was significantly lower in high-density environments compared to both low- and medium-density conditions, controlled for platform type.

Table 4. Multiple regression analysis of POD (*N*=48).

Variabel	**b**	**β**	**SE**	**t**	***p***	**95%CI**
Helicopter vs. UAS	-3.90	-.09	5.74	-0.68	0.50	[-15.46, 7.66]
Low density vs. High density	15.93	.31	7.42	2.15	0.04*	[.98, 30.89]
Medium density vs. high density	23.00	.52	6.38	3.60	0.001***	[10.14, 35.86]
Low density vs. medium density	-7.07	-.14	7.48	-0.94	0.35	[-22.14, 8.00]

*p<.05, **p<.01, *** p<.001; $F(3,44)$= 4.58, p<.01. $AdjR^2$=.19.

Table 5 revealed that visual-only search resulted in significantly lower POD compared to both sensor-based and hybrid search methods, controlled for vegetation density. It is important to note

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that visual-only search consisted of only 4 sorties. Therefore, the result being statistically significant should be interpreted with caution. Further, table 5 illustrates, as in table 4, that POD was significantly lower in high-density environments compared to both low- and medium-density conditions, controlled for sensor modality.

Table 5. Multiple regression analysis of POD (*N*=48).

Variabel	**b**	**β**	**SE**	**t**	***p***	**95%CI**
Sensor-only vs. hybrid	1.73	.04	6.34	0.27	0.77	[-11.05, 14.50]
Visual-only vs. hybrid	-22.13	-.29	10.72	-2.06	0.05*	[-43.76, -.51]
Visual-only vs. sensor-only	-23.86	-.31	9.87	-2.42	0.02*	[-43.76, -3.96]
Low density vs. high density	16.43	.32	7.10	2.31	0.03*	[2.12, 30.73]
Medium density vs. high density	24.34	.55	6.34	3.98	0.000***	[12.01, 36.67]
Low density vs. medium density	-7.91	-.16	7.14	-1.11	0.27	[-22.30, 6.48]

*p<.05, **p<.01, *** p<.001; $F(4,43)$=5.12, p<.001, $AdjR^2$= .26.

A second set of models analyzed the time-to-detection for the first, third and fourth found target. Because ICC-analyses revealed crew as a potential clustering effect, table 6, 7 and 8 reports cluster controlled standard errors, and 95% confidence intervals, t- and *p*-values based on wild cluster bootstrap t-tests [15]. 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 6, 7 and 8, consists of predictors: platform type, vegetation density and initial sweep search- vs. detailed search per finding.

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. Table 6 illustrates that time-to-detection is shorter for both low density and medium density sectors, compared to high density sectors, while controlled for platform type and search technique. It is important to note that the regression model reported in table 6 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. 15].

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Table 6. Time-to-detection – Finding 1 (*N*=48).

Variabel	**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]

p*<.05, ***p*<.01, * *p*<.001; $F(4,11) = 4.09$, p = .10, R^2=.35; Controlled for cluster effect of crew, wild cluster bootstrap 1000

Table 7 and 8 reveal that vegetation density no longer posits a statistically significant prediction of time to detection for findings 3 and 4, controlled for platform type and search technique. These analyses, however, reveal that search technique is a significant predictor of time to detection. The results indicate that use of initial sweep search results, on average, in 9.73 (Table 7) and 13.10 (Table 8) minutes faster detection of targets than detailed search, controlled for platform type and vegetation density.

Table 7. Time-to-detection – Finding 3 (*N*=44).

Variabel	**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]

*p<.05, **p<.01, *** p<.001; $F(4,11)=20.43$, $p=.004$, $R^2=.61$; Controlled for cluster effect of crew, wild cluster bootstrap 1000.

Table 8. Time-to-detection – Finding 4 (N=40).

Variabel	**b**	**β**	**SE**	**t**	***p***	**95%CI**
Helicopter vs. UAS	-16.79	-.63	2.86	-5.88	.000***	[-23.81, -10.51]
Low density vs. High density	-1.74	-.06	3.34	-.52	.58	[-9.21, 5.60]
Medium density vs. high density	-3.21	-.12	2.69	-1.20	.28	[-9.44, 2.94]
Low density vs. medium density	1.47	.05	3.11	.47	.65	[-4.67, 8.02]
Initial sweep search vs. detailedsearch	-13.10	-.49	4.07	-3.22	.000***	[-21.73, -2.85]

*p<.05, **p<.01, *** p<.001; $F(4,11)=26.97$, $p=.002$, $R^2=.67$; Controlled for cluster effect of crew, wild cluster bootstrap 1000.

These models confirm that vegetation density and search strategy are key determinants of search efficiency.

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 statistically significant 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

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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 3) 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 71.43% and 73.33% respectively. Still, these numbers indicate that both platform types perform well in all three included vegetation densities. Our regression analysis of POD (Table 4) 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 5 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) created a strong thermal contrast, making human targets highly conspicuous to thermal sensors. The superior performance of sensor-led platforms in this study is therefore contingent on this thermal advantage; the performance dynamics could shift significantly in conditions with low thermal contrast (e.g., hot weather).

While our statistical analysis did not find a significant performance difference between hybrid and sensor-only search modalities, 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 [25,26]. We hypothesize that this 'scan-wide, identify-narrow' approach, executed from high altitude, is highly efficient not only for coverage but also for vegetation penetration. A higher altitude provides a steeper, more nadir-oriented viewing angle, which is advantageous for seeing through gaps in a forest canopy [6]. A more oblique, horizontal angle, which is more common at lower altitudes, forces 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 creates an operational compromise with two potential negative consequences for sensor effectiveness. To maintain a steep viewing angle from a lower altitude, the area that can be effectively scanned becomes substantially smaller [6], potentially forcing the sensor to make more passes and thus increasing search time. Alternatively, to maintain area coverage rate, the sensor operator must accept a more oblique viewing angle, 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 an inherent tension between optimizing for sensor performance versus human visual search that warrants further investigation.

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

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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 and with a favorable viewing angle through vegetation, while UAS can operate in lower altitude blocks to perform detailed inspections. 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. Implications for Coordinated Airspace Management

Current national guidelines in Norway for multi-asset aerial SAR operations prioritize airspace deconfliction to ensure flight safety, typically through spatial or temporal separation [12]. 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 demonstrate that a helicopter equipped with a high-performance camera sensor, can operate effectively at a considerable altitude (e.g., 300 - 500m AGL) in advantageous thermal conditions as seen in figure 13. 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 [25]. 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 increasing 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, maximizing the efficiency of an initial sweep search. Simultaneously, our data supports that the UAS can effectively perform search tasks (Table 3) 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. 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 transforms the assets from being potentially redundant to being complementary, potentially increasing the overall speed and thoroughness of the aerial SAR operation.

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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 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 seeking shelter may exhibit reduced thermal contrast, potentially affecting the relative effectiveness of different sensor modalities.

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 another 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 colored 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 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 that both manned helicopters and unmanned aerial systems (UAS) equipped with modern EO/IR sensors are 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 achieved 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 as much by crew tactics and sensor use, as by the aircraft platform itself.

A key operational implication is that EO/IR searches from helicopters can, under favorable thermal conditions, be performed effectively from high altitudes without loss of detection performance. This introduces an alternative to 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

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high-altitude sensor-only searches could free lower airspace for UAS operations, enabling safe, simultaneous missions and improving overall efficiency.

The results highlight an opportunity to improve SAR 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 maximize each platform's strengths.

By filling a key knowledge gap with 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.

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.bThe 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.

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Abbreviations

The following abbreviations are used in this manuscript:

ADS-B	Automatic Dependent Surveillance–Broadcast
AGL	Above Ground Level
AI	Artificial Intelligence
APC	Article Processing Charge
BVLOS	Beyond Visual Line of Sight
CI	Confidence Interval
EO	Electro-Optical
FOV	Field of View
GDPR	General Data Protection Regulation
GPS	Global Positioning System
GSD	Ground Sample Distance
ICC	Intra-cluster Correlation
ICAO	International Civil Aviation Organization
IR	Infrared
JRCC	Joint Rescue Coordination Centre
NPUAS	Norwegian Police Unmanned Air Support Unit
OLS	Ordinary Least Squares
POD	Probability of Detection
SAR	Search and Rescue
SAVIOUR	Systematic Airborne Visual and Infrared Observational Unified Research
SE	Standard Error
UAS	Unmanned Aerial System

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