ISSN 2230-5734

JournalofSAR.com

VOLUME 9
ISSUE 1

JOURNAL of SEARCH+RESCUE

Volume 9, Issue 1, April 2026
Pages 1-95
ISSN 2230-5734
https://doi.org/10.61618/SPRV2377

The Journal of Search and Rescue (JSAR) is an open access peer-reviewed electronic journal for the collation and distribution of original scholarly material on search and rescue (SAR).

It is being supported by the in-kind work and contributions of the Editorial Board. There is still the need for a dedicated journal serving those with a direct interest in all disciplines of search and rescue including: rope rescue, water (flat, swift and marine), ice rescue, wilderness search and rescue, structural collapse rescue, trench collapse rescue, cave rescue, dive rescue, motor vehicle extrication, canine search, technical animal rescue, air rescue, search theory, search management, and mines rescue. JSAR exists to fulfil that need.

Article submissions from these and other SAR disciplines are welcome. Launching this journal on the internet offers a relatively cost-effective means of sharing this invaluable content. It affords the prompt publication of articles and the dissemination of information to those with an interest in SAR.

JSAR will provide a forum for the publication of original research, reviews and commentaries which will consolidate and expand the theoretical and professional basis of the area. The Journal is interested in theoretical, strategic, tactical, operational and technical matters.

Advertising within JSAR will be considered in the future to ensure sustainable funding is available to enhance and continue the work of the journal. The publication of an article in the Journal of Search and Rescue does not necessarily imply that JSAR or its Editorial Board accepts or endorses the views or opinions expressed in it.

Cover Image
Photographer: Peter Bailey

Volume 9, Issue 1, April 2026
Pages 1-95
ISSN 2230-5734
https://doi.org/10.61618/SPRV2377

JOURNAL of SEARCH+RESCUE

In partnership with

https://www.theicpem.org/

https://nasar.org/

www.isrid.net/

www.maritimesar.org

www.landsar.org.nz

www.rescue-institute.org

IASARC
International Association of Search and Rescue Coordinators
ADVOCATE - ADVANCE - CERTIFY

Re:Searchers

Volume 9, Issue 1, April 2026
Pages 1-95
ISSN 2230-5734
https://doi.org/10.61618/SPRV2377

JOURNAL of SEARCH+RESCUE

Page

Contents ii

Volume 9, Issue 1, April 2026
Pages 1-95
ISSN 2230-5734
https://doi.org/10.61618/SPRV2377

Editorial

https://doi.org/10.61618/JDKE7250

This issue of the Journal of Search and Rescue reflects a field increasingly concerned with the quality, transparency, and defensibility of decision-making under uncertainty. Across the contributions, a common thread emerges: search and rescue is not simply a matter of deploying effort, but of understanding where effort is most likely to matter, how confidence should be calibrated, and how operational decisions can be communicated, reviewed, and improved.

The issue brings together work on terrain-based reasoning, Bayesian search theory, probability-informed tasking, operational case analysis, professional coordination, and human-factors assurance. These contributions collectively point to a maturing SAR discipline in which search planning is becoming more explicit, evidence-informed, and auditable. Several papers address the practical use of probability concepts such as probability of area, probability of detection, probability of success, coverage, sweep width, and search effort. Importantly, they do so not as abstract mathematical constructs, but as operational tools for prioritising sectors, comparing search strategies, interpreting unsuccessful searches, and supporting decisions about re-search, resource substitution, continuation, or suspension.

A second theme is the translation of theory into practice. This issue shows that models and terminology only improve SAR outcomes when they are understood, consistently applied, and adapted to real operational conditions. Contributions from New Zealand and Mexico illustrate both the promise and the difficulty of this translation: practitioners bring substantial experience and sound operational judgement, but variations in terminology, spatial reasoning, cartographic practice, data capture, and training can constrain the effective use of search theory. These are not merely technical gaps; they are system-level issues that affect interoperability, assurance, and public confidence.

The letters to the editor extend this discussion by considering the professional and human foundations of SAR. They remind us that effective search depends not only on methods and tools, but also on coordination, competence, shared standards, cognitive resilience, and the ability to make reasoning visible during complex and time-pressured incidents. In this respect, the issue invites reflection on what the SAR community means by professionalism and assurance, and whether current systems adequately capture the judgement behind operational decisions.

Taken together, this issue offers a concise but significant contribution to the continuing development of SAR as an evidence-informed discipline. It does not suggest that probability, doctrine, or professionalisation can replace field expertise. Rather, it argues implicitly and persuasively that expertise is strengthened when supported by clear language, robust methods, calibrated uncertainty, disciplined coordination, and reflective learning. This is the continuing task for SAR research and practice alike.

A further strength of the collection is its measured pragmatism. The contributions acknowledge uncertainty, imperfect data, uneven capability, incomplete detection, and the practical constraints under which SAR teams operate. They resist the temptation to overclaim, offering instead methods, examples, concepts, and questions that can be tested, refined, and adapted. In doing

Volume 9, Issue 1, April 2026
Pages 1-95
ISSN 2230-5734
https://doi.org/10.61618/SPRV2377

so, they reinforce the role of an applied academic journal in a practice-based field: to support rigorous inquiry while remaining close enough to operational reality to be useful.

On behalf of the *Journal of Search and Rescue*, I thank the authors, reviewers, and contributors whose work has made this issue possible. Their papers and letters advance an important conversation about the continuing development of SAR as both a practical craft and an evidence-informed discipline.
Dr. Alun Newsome, Editor

Terrain, Terminology, and Insights: A Thematic Review of Conceptual and Spatial Reasoning in Land Search and Rescue New Zealand

Ed Cook, BSs; Aly Curd, MEmergMgt

Land Search and Rescue New Zealand

Email terrainbasedprobability@gmail.com

https://doi.org/10.61618/ZLHL6375

Abstract

This study presents an empirical qualitative thematic analysis of SAR practitioner responses collected during a structured workshop-based assessment at the New Zealand Land Search and Rescue Hui (Conference) in Tamaki Makaurau, Auckland. The workshop aimed at exploring Search and Rescue (SAR) personnel's understanding of key SAR planning concepts. A structured 15-minute quiz was administered to 70 participants, divided into 16 groups, to assess their knowledge of terminology and operational concepts related to search theory. The analysis revealed a general consensus on fundamental terms such as "Search," "Rescue," and "Recovery," with minor variations in the interpretation of terms like "Lost" versus "Missing" and the relationship between Initial Planning Points (IPP), Place Last Seen (PLS) and Last Known Points (LKP). Additionally, the study highlighted SAR personnel's preferences for specific search strategies and operational decision-making, such as prioritising localised search efforts over broader expansions. The findings highlight the importance of standardising terminology, improving conceptual Search Theory understanding and refining training approaches to enhance consistency and efficiency in SAR operations. Recommendations include developing a shared lexicon, scenario-based training, and ongoing stakeholder engagement to improve the application of research insights in operational settings. This analysis contributes to the refinement of SAR training and operational strategies, aiming to increase the effectiveness and adaptability of SAR teams in Aotearoa New Zealand.

KEY WORDS: *Search and Rescue, Terrain-based Probability, Human Factor, Decision-making, Thematic Analysis.*

Introduction

This paper presents a thematic analysis of responses gathered from the "Terrain-based Probability in SAR" workshop at the New Zealand Land Search and Rescue Hui (Conference) in Tamaki Makaurau, Auckland that took place on Saturday 15th March 2025 (Cook & Curd, 2025). The primary aim of this study was to examine how Search and Rescue (SAR) personnel understand and apply key concepts in Search Theory, particularly in relation to common SAR terminology and operational procedures. By analysing the recurring themes and identifying variations in understanding, the researchers aim to uncover both areas of consensus and divergence within the SAR community. These insights can guide improvements in SAR training, enhance operational consistency, and help inform future research. Furthermore, this analysis provides an opportunity to refine the communication of research findings within the SAR sector, ensuring that terminology and concepts are accessible and applicable to SAR teams at all levels. The results offer valuable perspectives on the challenges faced by SAR practitioners, emphasising the importance of clear definitions, adaptability in real-world decision-making, and ongoing refinement of SAR practices to align with evolving operational needs (Entwistle & Smith, 2010).

Method

This study utilised a structured, time-limited quiz to collect data from participants during the "Terrain-based Probability in SAR" presentation at the Land Search and Rescue Hui (Conference) in Tāmaki Makaurau Auckland that took place on Saturday 15th March 2025. The quiz, designed to assess operational understanding of key Search Theory concepts, consisted of 14 questions spanning multiple-choice, open-ended, and four map-based scenario questions.

Participant Grouping and Instructions

Seventy SAR professionals participated, divided into 16 groups. Grouping was intentional, reflecting the collaborative nature of SAR operations where decisions are rarely made in isolation (Vijayaratnam, 2012). Before commencing, participants were given minimal instructions beyond being told that the quiz was anonymous, and that no names or distinguishing features were to be recorded on the answer sheets. The instruction given was simply: "Work together to answer the following 14 rapid-fire questions". This approach aimed to minimise social desirability bias and reduce the influence of individual status within the group dynamic (Gordon, 1987).

Groups received blank sheets of paper for written answers rather than structured answer forms. This decision was grounded in cognitive research suggesting that free-form response formats reduce anchoring effects that may occur when individuals are presented with structured layouts (Jensen, Whiles, & Mirza, 2025). For the four map-based questions, separate answer sheets with maps were provided. Participants were instructed to mark or highlight directly onto these maps as part of their responses.

Each question was allocated a one-minute time limit to simulate the time-pressured conditions under which SAR personnel operate. This approach reflects real-world environments where rapid interpretation of incomplete information is required (Epstein & Katz, 1992: Fig & Recker, 2016: Goldhammer, 2015). The quiz was conducted directly following a brief presentation introducing the concept of Terrain-Based Probability (TBP) in SAR. No additional instruction or training was provided, to ensure that responses reflected participants' pre-existing knowledge, intuitive understanding, and immediate interpretation of TBP concepts as presented.

The design of the quiz was intentionally aligned with operational realities of SAR environments. The one-minute time constraint reinforced these time-pressured decision-making conditions characteristic of SAR operations. Group-based responses were selected to reflect the collaborative nature of SAR planning, where decisions are typically made within teams rather than by individuals. The use of free-form responses, rather than structured answer sheets, was intended to minimise anchoring effects and allow participants to express their conceptual understanding in their own terms. Collectively, these design choices aimed to increase ecological validity by approximating the cognitive and social conditions of real-world SAR operations.

Data Collection and Analysis

All responses were collated and entered into a spreadsheet for analysis. A qualitative thematic analysis approach was used to identify patterns in how participants understood and applied SAR concepts. Coding was conducted independently by the authors using an inductive approach, allowing themes to emerge from the data rather than being imposed from predefined categories (Delve, 2025; Perenara-Wilkinson, 2025).

Data familiarisation involved repeated reading of responses prior to coding to ensure depth of interpretation. Initial codes were generated through close reading of the responses and were iteratively refined into broader themes through comparison across participant groups. Particular attention was given to areas of consensus, variation, and ambiguity in terminology and decision-making.

To enhance analytical rigour, coding decisions were discussed and reviewed between the authors to ensure consistency in interpretation. While formal inter-rater reliability statistics were not calculated, an iterative consensus-based approach was used to strengthen the credibility of the findings.

Map-based responses were analysed separately as a distinct dataset, focusing on spatial reasoning, terrain interpretation, and the clarity of visual communication. These responses were compared against model answers to assess alignment with expected SAR planning principles.

The analysis was primarily inductive, but was informed by established SAR concepts including Lost Person Behaviour (Koester, 2008) and applied search theory frameworks. This allowed findings to be interpreted in relation to both emergent participant understanding and existing operational doctrine.

As the data were collected within a workshop setting facilitated by the authors, it is acknowledged that the context may have influenced participant responses. However, the use of anonymous, time-limited, and group-based responses was intended to minimise individual bias and better reflect operational decision-making conditions.

Results

This section presents the findings from the quiz responses, analysed through thematic analysis to identify recurring themes and insights. The responses to each question are examined to highlight common understandings and areas of divergence among SAR personnel. By interpreting these responses, we aim to uncover key patterns in how SAR Search Theory concepts are understood and applied in practice. This analysis provides a foundation for refining SAR training, improving operational consistency, and developing clearer communication within the SAR community.

Definitions of "Search," "Rescue," and "Recovery"

Participants were asked to provide their definitions of the terms “Search,” “Rescue,” and “Recovery” within the context of search and rescue operations. The aim was to capture how these core concepts are commonly understood and interpreted by practitioners in the field. The majority of responses define:

- Search as the act of locating a missing person.
- Rescue as bringing a person to safety, often requiring specialised skills and resources.
- Recovery as retrieving a deceased individual from a search area.

Some responses also emphasise the procedural aspects of search operations, highlighting that searching involves organised efforts rather than random exploration. Additionally, a few groups mention the emotional and logistical challenges associated with recovery operations, which can impact SAR personnel.

Difference Between "Lost" and "Missing"

Participants were asked to explain how they differentiate between the terms “Lost” and “Missing” in the context of search and rescue operations. This question sought to understand the operational and conceptual distinctions made by practitioners when categorising incidents or individuals. A clear distinction emerges between these terms:

- Lost is typically described as when an individual is disoriented and unable to navigate back to a known location.
- Missing refers to an individual whose whereabouts are unknown to others, even if the person themselves does not feel lost.

While most groups align on this distinction, some responses indicate that in real-world scenarios, there can be overlap, as individuals who are "missing" often also perceive themselves as "lost." This suggests a need for standardised definitions in operational guidelines (Stoffle & Stoffle, 2017).

Differentiating IPP, LKP, and PLS

Participants were asked to describe the differences between the Initial Planning Point (IPP), Last Known Point (LKP), and Point Last Seen (PLS), three critical reference locations in the planning and execution of search operations. Clarifying these distinctions is important for ensuring consistency in how search areas are defined and prioritised. Most responses define:

- IPP: The designated starting point for search operations, typically based on statistical models, last known intentions, or reported sightings.
- LKP: The last confirmed location of the missing person based on verifiable evidence, such as witness accounts or physical clues (e.g., footprints, dropped gear).
- PLS: The precise location where the subject was visually observed before disappearing.

While there is broad consensus on these terms, discrepancies exist in how groups describe the relationship between IPP and LKP. Some responses suggest that IPP is dynamic and can be adjusted as new information arises, whereas others state it is fixed. Training reinforcement could help clarify this distinction (Mansfield, Carlson, Merrifield, Rosenberg, Swanson, & Templin, 2024).

Hunter vs. Tramper

Participants were asked to explain the difference between a "hunter" and a "tramper," recognising that subject profile influences search behaviour predictions, mobility patterns, and risk assessment. Most groups classify:

- Hunters as individuals navigating terrain based on game tracking, often moving off established trails and possessing survival skills related to their activity.
- Trampers as recreational walkers who follow designated tracks and typically plan their routes in advance.

Some responses suggest that hunters are better prepared for survival situations due to their knowledge of the environment and gear (e.g., firearms, knives, and navigation tools). However, other responses indicate that preparedness levels vary widely among both hunters and trampers, with some trampers being well-equipped and experienced in navigation.

Categorisation of a "Daywalker" Carrying a Rifle

Participants were presented with a scenario in which they are responding to a callout involving a daywalker who is carrying a rifle. They were asked to determine whether this individual should be categorised as a "hunter" or a "tramper" for the purposes of search planning and subject profiling. This question aimed to explore how SAR personnel interpret hybrid or ambiguous subject behaviours, and which cues they prioritise when assigning a category. Responses to this scenario were mixed, highlighting the complexity of classification in real-world SAR operations:

- Some groups strictly categorised the individual as a hunter, given the presence of a rifle and the implication of game tracking.
- Others acknowledged that a person could be both a hunter and a tramper, depending on their intent and movement patterns.
- A few groups noted that context matters, if the individual was following a track and not actively hunting, they might fit the tramper category more closely.

These variations suggest that SAR teams must assess multiple contextual factors when identifying subjects. As such, it is recommended that SAR training include targeted refreshers and scenario-based exercises to reinforce the application of LPB principles in complex or ambiguous cases. This variability reflects a well-documented challenge in applying Lost Person Behaviour (LPB) categories in operational settings, particularly where subject intent and behaviour are ambiguous or overlapping (Koester, 2008). While LPB provides a structured framework for predicting subject movement, its application in real-world scenarios often requires interpretation under uncertainty, which can lead to inconsistencies in classification and subsequent planning decisions.

Definition of "Injured" vs "Uninjured"

Participants were asked to define what constitutes an "injured" versus an "uninjured" subject in a SAR context. This question was designed to clarify how SAR personnel interpret these classifications and how such distinctions influence the urgency, resource allocation, and tactical approach of an operation.

The definitions of injured/uninjured from participant responses reflect a clear understanding centred on physical and medical status, as well as the need for assistance. The key themes identified include:

- Physical or Medical Impairment: Injured individuals have sustained injuries or medical conditions that affect their physical or mental capacity.
- Need for Assistance: Injured subjects often require first aid, medical treatment, or help with mobility.
- Mobility: Injured persons are frequently less mobile or immobile, while uninjured individuals retain full mobility.
- Severity of Injury: Minor or trivial injuries that do not impair the subject's ability to move, make decisions, or self-evacuate, typically fall under the uninjured category.
- Operational Implications: Injured subjects usually demand urgent medical attention and prioritised resource allocation, whereas uninjured subjects are generally capable of self-rescue.

These distinctions are important for SAR operations, influencing how subjects are prioritised and the resources allocated (Stoffle & Stoffle, 2017). Overall, the injured/uninjured classification helps shape the immediate reflex response and informs search area priorities, extraction planning, and resource deployment.

Definition of the "Water Recreation" Subject Group

Participants were asked to define the “water recreation” subject group, a common classification used in SAR operations. The aim was to understand how SAR personnel interpret this category, including the types of activities, behaviours, and risks typically associated with individuals engaged in recreational use of water environments such as rivers, lakes, or coastal areas. Responses indicate that the "Water Recreation" subject group includes individuals engaging in water-based activities such as kayaking, canoeing, boating, fishing, and swimming. Key characteristics of this group include:

- Environment Exposure: These individuals are often in dynamic environments, including lakes, rivers, and coastal areas, which can lead to rapid changes in situational risk.
- Potential Hazards: Drowning, hypothermia, and getting swept away by currents are primary concerns associated with this group.
- Varying Levels of Preparedness: Some participants noted that individuals in this group range from highly experienced water users with proper safety equipment (e.g., lifejackets, radios) to casual users who may lack necessary precautions.

This classification is important for SAR teams to determine the likelihood of survival, possible drift patterns, and the urgency of response efforts in water-based searches.

Response to High-Probability Clue in the 95th Percentile

Participants were presented with a scenario where a high-probability clue was found in the 95th percentile, and it was confirmed that the IPP was not the LKP. The response distribution was as follows:

- 12 participants selected option C: Plan a tasking area around the clue (close-in search) while maintaining the current search boundary.
- 2 participants selected option B: Keep the IPP where the search initially started but redraw probability rings.
- No participants selected option A: Move the IPP to the LKP (the clue location).

The overwhelming preference for option C suggests that SAR practitioners prioritise immediate and focused tasking around high-probability clues rather than altering fundamental search parameters mid-operation. This aligns with best practices in SAR, where a critical clue in a high-probability zone warrants a concentrated search effort to maximise the likelihood of finding additional evidence or the missing person nearby.

The lack of support for option A highlights a key operational principle: while the LKP is important for refining search efforts, the IPP remains an anchor point for overall search planning. Moving the IPP entirely to the LKP might undermine prior probability calculations and disrupt broader search strategies.

The minor support for option B (redrawing probability rings but keeping the IPP static) indicates that some practitioners recognise the importance of recalibrating search parameters but may prefer a broader adjustment rather than a localised focus. However, the low number of responses selecting this option suggests that most participants prioritised immediate tactical response over strategic reconfiguration.

These results highlight a strong consensus on operational decision-making in SAR when confronted with high-probability clues. The emphasis on localised search intensification over structural realignment suggests that experienced SAR practitioners prefer to capitalise on concrete evidence before making significant modifications to the broader search plan.

Ranking of Extended Search Options

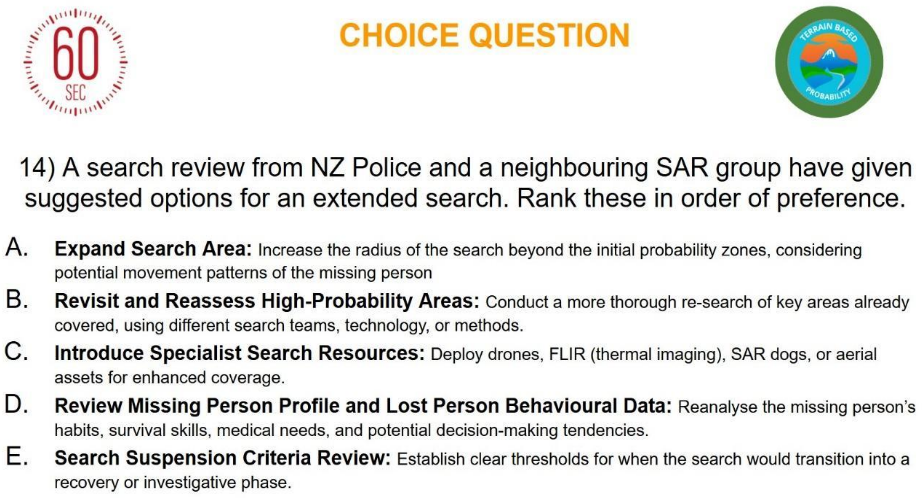


Figure 1: Quiz slide presented at the LandSAR Hui (Conference) - ranking of extended search options

Participants were asked to rank five search expansion strategies (A, B, C, D, and E) in order of preference. The most frequently occurring sequences were:

- DBCAE (6 times) and DBACE (1 time)
- CBDEA (1 time) and DBCEA (1 time)
- DCBEA (1 time) and BDCAE (2 times)
- BDACE (1 time) and BCDAE (1 time)

A strong preference emerges in favour of options D (Review Missing Person Profile and Lost Person Behavioural Data) and B (Revisit and Reassess High-Probability Areas) as primary steps before expanding search boundaries or introducing specialised resources. This prioritisation aligns with applied Search Theory frameworks that emphasise iterative refinement of POA through behavioural reassessment and re-evaluation of high-probability areas before expanding the search footprint (Mansfield et al., 2023). Rather than treating search expansion as a primary response, this approach reinforces a structured decision-making process grounded in evidence and probability management.

The dominance of option D (Review Missing Person Profile and Behavioural Data) in the rankings highlights the importance of understanding the individual's characteristics before committing additional resources. In almost all cases, this option appeared in the first or second position, reflecting the belief that profiling the missing person's likely actions and decision-making can refine search strategies more effectively than expanding search zones blindly. This aligns with contemporary SAR methodology, which emphasizes behavioural analysis as a key factor in predicting movement patterns and improving search efficiency (Koester, 2008).

A strong priority was also placed on option B (Revisiting High-Probability Areas), which consistently appeared in the top two positions. This suggests a widespread belief in the value of re-examining previously searched areas, recognising that missed clues, environmental changes, or searcher oversight can lead to important evidence being overlooked in the initial sweep. The use of different teams, technologies, or search techniques is seen as an essential step before committing to resource-intensive expansions, ensuring that high-probability zones are thoroughly covered before moving outward (Mansfield, Carlson, Merrifield, Rosenberg, Swanson, & Templin, 2024).

Option C (Specialist Search Resources), which includes deploying drones, FLIR, SAR dogs, or aerial assets, was consistently ranked as a mid-priority step. While these resources are considered valuable, the fact that they typically appeared after reviewing behavioural data and reassessing high-probability areas suggests that SAR practitioners view them as enhancements rather than primary search tools (Stoffle, 2006). This pragmatic approach ensures that fundamental search efforts are maximised before incorporating more complex and sometimes costly resources.

A lower preference for option A (Expanding the Search Area) was evident, with most rankings placing it later in the list. This suggests a reluctance to extend search boundaries without solid justification, aligning with best practices in probability-driven SAR (Stoffle, 2006). Rather than immediately broadening the search, planners prioritise refining existing search efforts to maximise efficiency within established probability zones before committing to a larger operational area. This reflects a core principle of Search Theory: that expanding search areas without sufficient evidential basis risks diluting effort and reducing overall probability of success (Mansfield et al., 2023).

Finally, option E (Search Suspension Criteria Review) was almost universally ranked last, demonstrating a strong operational mindset of perseverance. SAR teams focus on refining and improving search efforts rather than prematurely considering a transition to a recovery or investigative phase (Burgess, 2021). The placement of this option at the bottom of most rankings suggests that defining search suspension criteria is viewed as a strategic decision that should only occur once all other viable search avenues have been exhausted. This reinforces the commitment of SAR practitioners to continue search efforts for as long as operationally feasible.

These findings suggest that SAR training and operational strategies should continue to emphasise the importance of refining searches around high-probability clues rather than prematurely making large-scale changes to search parameters. By ensuring that teams prioritise immediate, evidence-based adjustments, search efficiency can be maximised while reducing unnecessary resource deployment (Jacobs, 2015).

A structured approach to extending searches should be reinforced, starting with behavioural analysis and area reassessment before committing to expanded boundaries or additional specialised resources (Koester, 2008). This systematic process ensures that SAR teams make evidence-driven decisions and allocate resources effectively, rather than relying on instinctive or reactive measures (Mansfield, Carlson, Merrifield, Rosenberg, Swanson, & Templin, 2024).

Encouraging an evidence-driven mindset remains important, as prioritising evidence review and search refinement leads to more precise operational strategies. By consistently assessing search data and integrating findings into decision-making, SAR teams can optimise their response while maintaining a high level of adaptability in dynamic environments (Koester, 2008).

Lastly, the resilience of SAR teams in prolonging search efforts is evident, with a strong preference for exhaustive exploration before considering suspension. Training programmes should reinforce the mindset of sustained search operations, ensuring that responders are equipped with the tools and strategies necessary to persist through challenging and uncertain search conditions. By aligning training and field strategies with these insights, SAR organisations can improve efficiency, maximise resource effectiveness, and enhance operational outcomes in search efforts (Hammond, 2004).

Map Questions

Four of the questions proposed were map questions. The exercise involved interpreting four different topographic map scenarios, each posing operational challenges for search planning. The aim of the analysis is to evaluate how well participants engaged with core SAR principles such as terrain interpretation, hazard identification, and planning concepts. The participants' annotated maps were analysed against exemplar answers, with the aim of evaluating their understanding of key SAR principles.

Map 1: Probability Area Based on Subject Category and Terrain Type

Question:

Ed the Tramper has gone missing and this subject is known to have a 75% likelihood of his subject category being found in native bush. The search area is 50% exotic forest and 40% native bush. Where would you draw a higher probability area?

Model Answer Summary: The highest probability zones are expected within the native bush areas due to the statistical likelihood from the subject profile (See *Figure 2: Model Answers for Map 1).* Focus should be on the 40% native bush sections, particularly those closest to access points, known routes, or logical travel corridors.

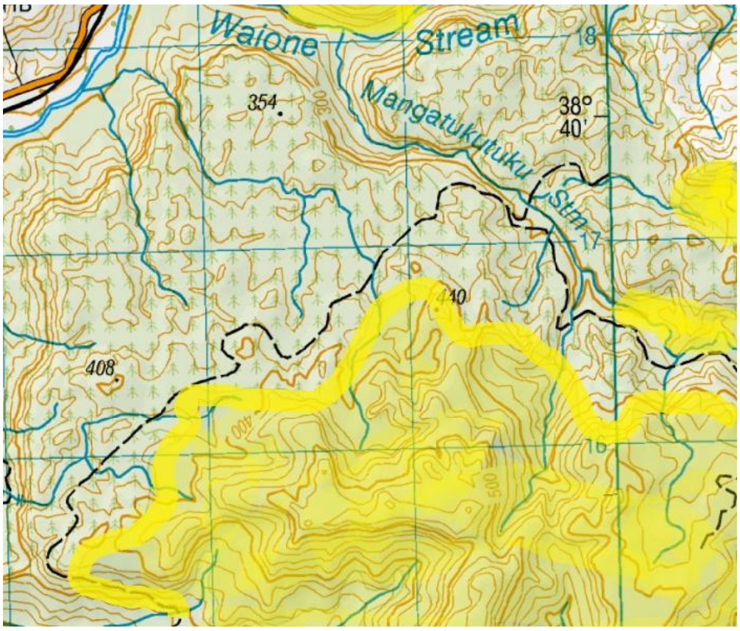


Figure 2: Model Answers for Map 1

Themes in Participants Responses:

- Correct Prioritisation of Native Bush: Most participants placed their highest probability zones within the native bush regions, correctly interpreting the statistical clue.
- Hazard and Access Considerations: Some students also factored in nearby hazards or ease of access.
- Variable Clarity: While many maps correctly prioritized the terrain type, clarity in boundaries and communication of reasoning varied.

Figure 3: Participant Response for Map 1

This map revealed solid comprehension of how subject category statistics influence area prioritisation (See *Figure 3: Participants Response for Map 1)*. Most participants accurately identified native bush as the focal point. However, some confusion between native bush and exotic forests was inconsistent, highlighting an opportunity for future training to incorporate revision of basic key/legend understanding and application.

Map 2: Adjusted Terrain Composition with Same Subject Profile

Question: *Ed the Tramper has gone missing (again) and this subject is known to have a 75% likelihood of being found in native bush. The search area is 40% tussock and 30% native bush. Where would you draw a high probability area?*

Model Answer Summary: Despite the smaller amount of native bush, it remains the most statistically significant area. The high probability zone should again be placed within the native bush sections, particularly those connected by logical movement paths or close to entry/exit points (See *Figure 4: Model Answers for Map 2)*.

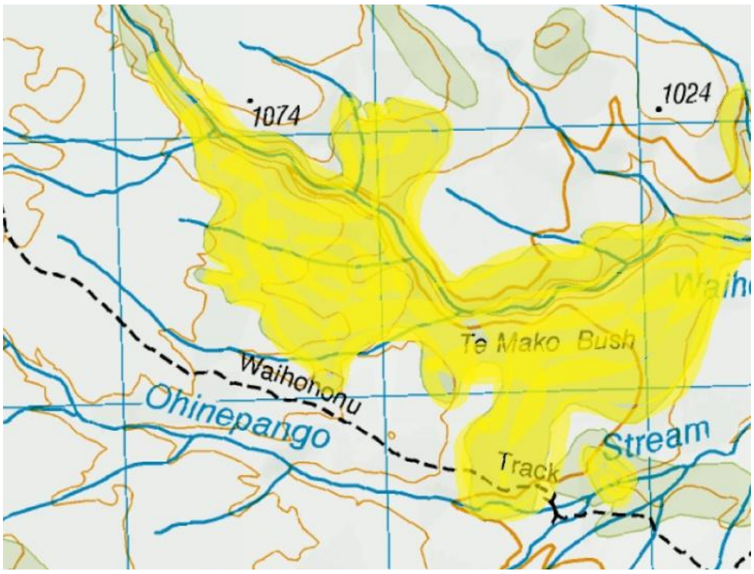


Figure 4: Model Answers for Map 2

Themes in Participants Responses:

- Prioritisation Consistent with Native Bush Preference: Like Map 1, most students correctly placed their primary search zones in the native bush (See *Figure 5: Participants Responses for Map 2*).
- More Hesitation or Fragmentation: A few responses split their focus between tussock and bush or marked wider areas, possibly due to the reduced bush percentage.
- Route-Based Reasoning: Several responses attempted to incorporate subject movement logic (e.g., proximity to tracks or spurs).

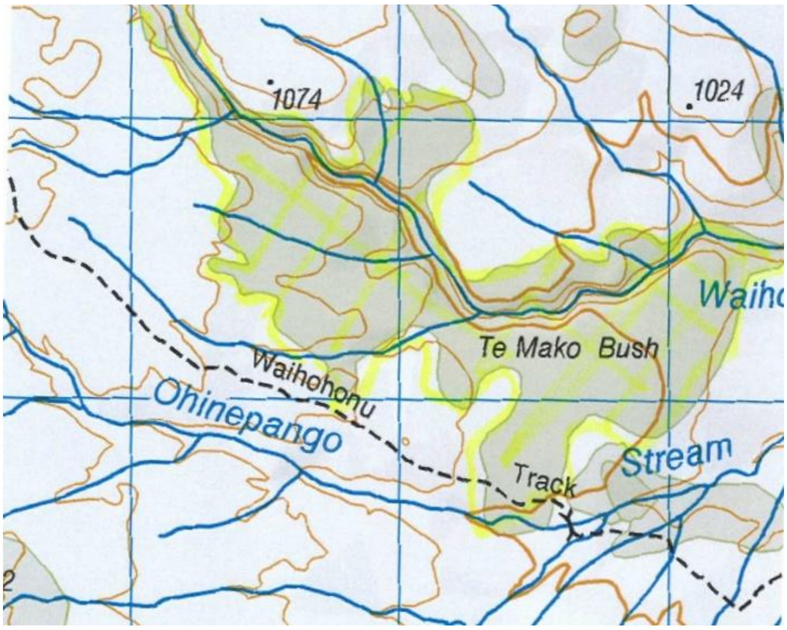


Figure 5: Participants Response for Map 2

This scenario tested whether participants could maintain statistical focus even when the preferred terrain type was less available. The slight drop in confidence and clarity (compared to Map 1) suggests that participants may benefit from exercises that explicitly train decisions under constraints or imperfect distributions. Reinforcing the concept of prioritisation over area dominance could be helpful.

Map 3: Linear Feature Identification

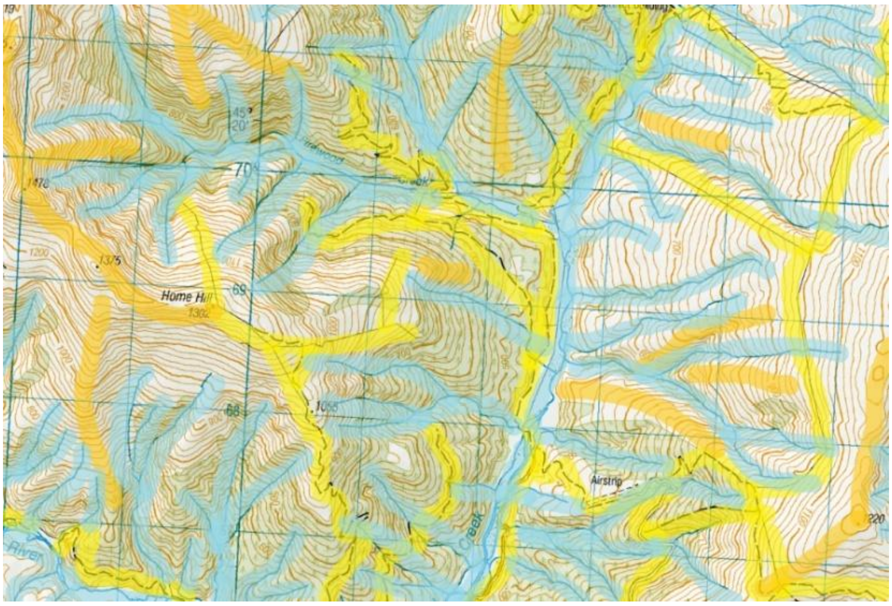


Figure 6: Model Answers for Map 3

Question: *Using the highlighters provided, highlight the linear features that are present.*

Model Answer Summary: Linear features including waterways (streams, rivers), roads, tracks and trails, powerlines and fences, as well as topographical elements like ridgelines or gullies inferred from contours (See *Figure 6: Model Answers for Map 3*).

Themes in Participants Responses:

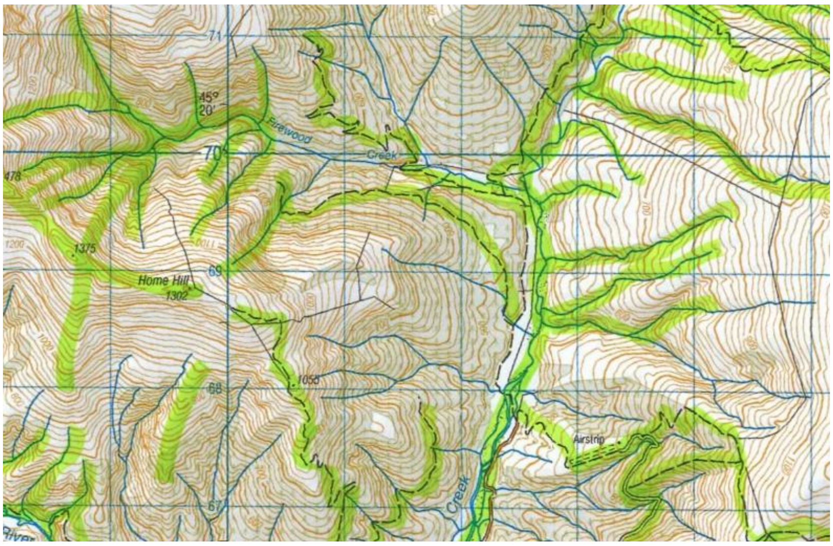


Figure 7: Participant Responses for Map 3

- Waterways and Tracks Consistently Identified: Nearly all participants highlighted visible tracks and streams, which are standard linear features in SAR navigation and search planning.
- Some Missed Subtle Features: The map omitted less obvious features such as contour-defined spurs or drainage lines.
- Cartographic Literacy Use Varied: There was inconsistency in how well participants understood the map legend to confirm features. It was assumed participants had sufficient map-reading knowledge. However, inconsistencies emerged in how less common features were interpreted, suggesting varying levels of confidence and familiarity with non-standard map elements.

This task focused on observational and cartographic literacy (See *Figure 7: Participants Responses for Map 3*). While most participants demonstrated strong basic map-reading skills, deeper attention to terrain-shaping features was sometimes lacking. Reinforcement through layered exercises, first identifying, then ranking linear features by navigational value, could improve higher-order interpretation.

Map 4: Linear Feature Identification in a Different Terrain Context

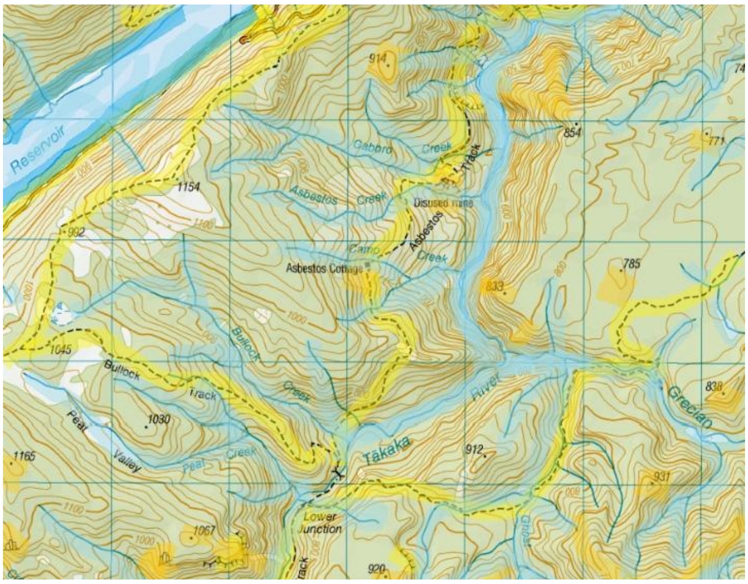


Figure 8: Model Answers for Map 4

Question: *Using the highlighters provided, highlight the linear features that are present.*

Model Answer Summary: As in Map 3, features included waterways (streams, rivers and reservoir), roads, tracks and trails, powerlines and fences, attractants, as well as topographical elements like ridgelines or gullies inferred from contours (See *Figure 8: Model Answers for Map 4*).

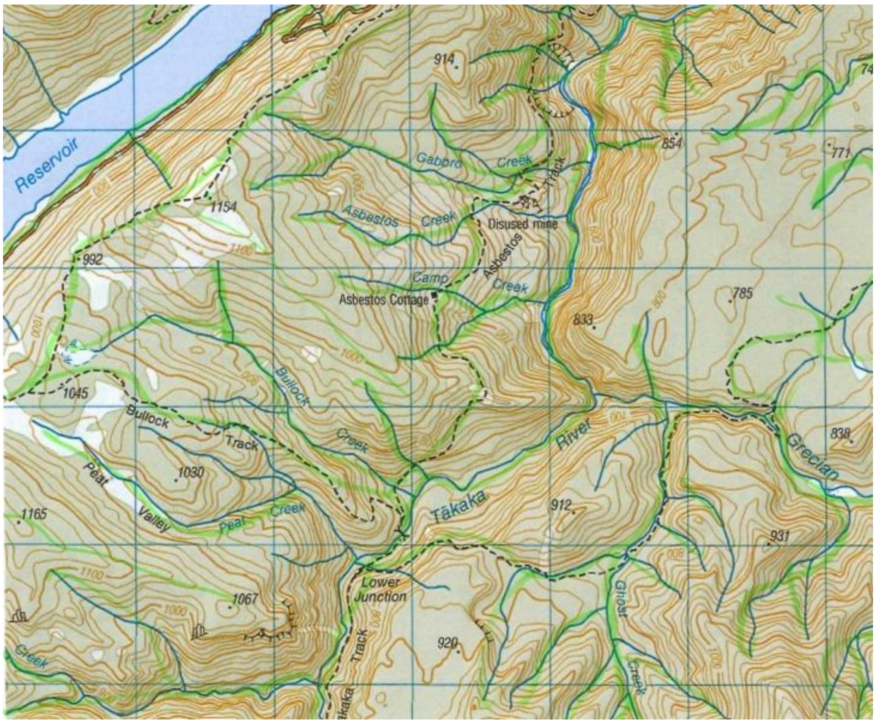


Figure 9: Participants Response for Map 4

Themes in Participant Responses:

- Increased Detail in Some Responses: Compared to Map 3, several participants included more nuanced features like fence lines or inferred terrain elements.
- Inconsistent Highlighting Techniques: Some annotations were cluttered or unclear, making it hard to assess intent.
- Improved Integration: A few responses integrated linear feature identification with planning thoughts (e.g., movement corridors).

By repeating the task in a new context, Map 4 allowed comparison of participants consistency and map adaptability (See *Figure 9: Participants Response for Map 4*). While many improved on their first attempt, annotation clarity remained a challenge. Explicit teaching on symbol standardisation and expected output format may support better communication of spatial reasoning.

Cross-Map Themes and Observations

Participants demonstrated growing comfort with applying subject profile statistics to terrain selection, particularly when the preferred terrain type was dominant in the map area. However, some confusion arose when the preferred terrain made up a minority of the available area, indicating a need for greater confidence in prioritisation logic despite uneven distributions.

In terms of linear feature literacy, most participants successfully identified basic features such as tracks and rivers, but fewer consistently recognised or highlighted more subtle topographical elements like spurs or gullies inferred from contour lines. Map annotations reflected varied levels of confidence and clarity; while many responses showed evidence of sound SAR thinking, inconsistencies in annotation style and visual communication may limit the interpretability of these maps in real-time operational contexts.

Encouragingly, several participants began to demonstrate emerging operational thinking by incorporating elements such as access routes and logical movement paths, suggesting a growing awareness of the practical application of terrain analysis in search planning.

The analysis demonstrates encouraging development in map interpretation and SAR reasoning among participants. Participants are clearly engaging with terrain and statistical data, though depth and confidence vary. Linear feature identification is strong at the basic level but could be strengthened through structured contour analysis.

Continued emphasis on scenario-based exercises and training that blends visual interpretation with operational context will further develop the competencies required in field-based search planning (Hammond, 2024).

Discussion

Beyond the core topics, the responses reveal several underlying themes that highlight opportunities for improvement in SAR operations and research communication. One key theme is variability in terminology. While most groups agree on fundamental definitions, slight differences in wording suggest the need for greater standardisation in training and learning materials.

Aligning terminology across teams and organisations will help ensure consistency in communication and reduce potential misunderstandings during search operations (New Zealand Government, 2019).

Challenges relating to terminology consistency are not unique to the New Zealand context. Internationally, multi-agency SAR and disaster response environments have similarly identified difficulties in maintaining shared operational language, particularly where terminology evolves across organisations and jurisdictions. Efforts such as lexicon standardisation projects and INSARAG-aligned guidance highlight the importance of common definitions to support interoperability and reduce miscommunication in high-tempo environments (INSARAG, 2020). The findings of this study therefore align with broader international trends, reinforcing the need for deliberate terminology harmonisation within SAR systems.

Another important theme is the real-world ambiguity that SAR personnel frequently encounter. Some scenarios do not fit neatly into predefined categories, requiring responders to exercise flexible, situation-based judgment. Training programs should emphasise critical thinking and adaptability to equip personnel with the skills needed to make sound decisions in unpredictable environments.

Finally, the operational implications of clear and consistent definitions cannot be overlooked. Standardised terminology improves communication and coordination during search operations, reducing the risk of misinterpretation in critical situations. Establishing a shared lexicon across SAR teams will enhance overall efficiency and effectiveness, ultimately improving outcomes in search and rescue missions.

Operational Implications and Recommendations

To address the variability identified in terminology, conceptual reasoning, and terrain-based decision-making, a set of practical, system-level interventions is required to strengthen consistency and operational effectiveness within SAR practice.

A nationally consistent SAR lexicon should be developed to support shared understanding across agencies and operational contexts. Variability in the interpretation of core terms such as Initial Planning Point (IPP), Last Known Point (LKP), and Point Last Seen (PLS), as well as distinctions between "Lost" and "Missing," highlights the need for standardisation to reduce ambiguity in both planning and field environments. The importance of shared terminology is well established in multi-agency and high-tempo operational settings, where inconsistent language can undermine coordination and situational awareness (Jezek, 2016; INSARAG, 2020). A national lexicon should therefore include not only standardised definitions, but also guidance on how terms are applied across planning, intelligence, and operational contexts. Integration into national training doctrine, including courses such as Manage the Initial Response (MTIR) and Extended Search Planning (ESP), would support consistent application, while ongoing governance and version control led by NZSAR would ensure the lexicon remains current and operationally relevant.

In parallel, training programmes should move beyond conceptual understanding and place greater emphasis on applied, scenario-based learning that reflects the realities of SAR decision-making (Rodriguez, 2022). The variability observed in terrain interpretation and subject classification suggests a need for training that reinforces decision-making under uncertainty. Time-constrained exercises can simulate the cognitive pressures experienced in operational environments, encouraging intuitive and experience-driven reasoning (Goldhammer, 2015). Similarly, terrain-constrained probability tasks, particularly where preferred terrain types are not dominant, can strengthen practitioners' ability to prioritise effectively under imperfect conditions. Enhanced cartographic literacy is also required, particularly in the interpretation of contour-derived features such as spurs and gullies, which are critical to terrain-based search planning (Speake & Axon, 2012). In addition, scenario-based classification exercises involving ambiguous or mixed-profile subjects can improve the application of Lost Person Behaviour (LPB) principles, particularly in situations where behavioural cues are unclear or conflicting (Koester, 2008).

The findings also highlight variability not only in terrain interpretation, but in the communication of spatial reasoning. Inconsistent map annotation reduces the clarity of operational products and may limit shared situational awareness during planning and tasking. Standardised annotation conventions, including the use of symbols, colour, and boundary definition, should therefore be incorporated into both training and operational processes such as Incident Action Plan (IAP) development. Improving the consistency and readability of map-based outputs will enhance communication across teams and support more effective coordination in dynamic environments (Schaefer et al., 2017).

Finally, the results indicate the presence of an implicit decision-making hierarchy among SAR practitioners that warrants explicit recognition within training and doctrine. Participants consistently prioritised behavioural reassessment and the refinement of high-probability areas before deploying specialist resources or expanding search boundaries. This aligns with established principles of search theory, which emphasise the iterative refinement of probability of area (POA) and the importance of evidence-based decision-making in optimising search effectiveness (Koester, 2008; Mansfield et al., 2023). Formalising this hierarchy within training frameworks would support more consistent decision-making and reduce the likelihood of premature or inefficient expansion of search efforts.

Limitations

While the findings presented in this report provide valuable insights into the thematic understanding of key SAR concepts, several limitations should be acknowledged.

One of the primary limitations of this study is the demographic composition of the participants. The individuals who took part in the LandSAR Hui (Conference), where the quiz was administered, were predominantly experienced leaders in the SAR field. With extensive expertise in SAR operations, their responses are likely shaped by advanced knowledge and practical experience. As a result, the findings may not accurately represent the perspectives of less experienced personnel or those new to SAR. This disparity in experience could lead to a more sophisticated interpretation of terminology and concepts, potentially differing from how these terms are understood by novice SAR responders in real-world situations (Randel, Pugh, & Reed, 1996).

Another key limitation relates to the context in which the quiz was conducted. The quiz was designed to assess participants' instinctive responses under time constraints, mirroring real-world SAR conditions where rapid decision-making is important. However, this format may not fully capture how individuals process and apply these concepts in a more reflective or deliberate setting (Vijayaratnam, 2012). Given more time to consider their answers, participants might provide responses that reflect deeper reasoning or more nuanced interpretations (Sherman, Harvey, Royse, Heim, Smith, Romano, King, Lyons, & Holt, 2019).

The generalisability of the findings is also limited by the specific sample of participants involved in this analysis. The quiz was administered at a national conference held in Tāmaki Makaurau Auckland, meaning the responses reflect the knowledge and experiences of SAR personnel operating within the North Island context. While these individuals are highly skilled, the findings may not be directly applicable to SAR teams in other regions or those with differing levels of experience. The unique challenges and environmental conditions of SAR operations in this region could shape the interpretation and application of key concepts in ways that differ from practices in other locations (Giles, 2008).

Additionally, variability in terminology and interpretation of SAR concepts among participants may be influenced by personal or organisational preferences rather than fundamental differences in understanding (Jezek, 2016). While these variations provide valuable insights, they do not necessarily indicate a broader inconsistency in SAR terminology across different teams. Further research involving a more diverse sample of SAR practitioners could help determine whether these variations are widespread or unique to specific groups.

Furthermore, it is important to acknowledge that some quiz questions were designed to probe respondents' implicit biases or assumptions regarding how theoretical outputs, such as TBP models, could be translated into operational tools. While this provided valuable insight into participants' real-world reasoning, it also introduced variability based on personal experience and comfort with applying academic theory in high-stakes, time-sensitive environments (Rodriguez, 2022). These questions may not have been interpreted uniformly, and responses could reflect differences in how individuals conceptualise the operational value of research outputs.

In light of these limitations, it is important to interpret the findings with caution and consider the specific context in which the study was conducted when applying the results to broader SAR training or operational improvements.

Future Research

To strengthen the effectiveness of SAR operations and align training with both theoretical insights and practical realities, several key recommendations have emerged from this analysis. First, the development and adoption of a national SAR lexicon is essential (Papier, Chalmers, Byrnes, & Goldsmith, 2004). A shared and standardised set of definitions, particularly around terms such as Initial Planning Point (IPP), Last Known Point (LKP), Point Last Seen (PLS), and the distinction between "Lost" and "Missing", will improve clarity and consistency across operational contexts, reducing the likelihood of miscommunication in time-critical scenarios.

Building on this, scenario-based training should be expanded to incorporate both conceptual and map-based exercises that mirror the complexity of real-world situations. Specifically, training should include constrained terrain scenarios, where preferred subject environments are less dominant, to build confidence in statistical prioritisation despite imperfect distributions. Enhanced cartographic literacy is also needed (Speake & Axon, 2012), with a focus on identifying and prioritising terrain features inferred from contour lines, such as spurs, gullies, and ridgelines. This should be complemented by standardised visual annotation techniques to ensure clarity and operational alignment during planning and briefings. Additionally, subject classification training should emphasise ambiguous profiles, such as mixed-activity individuals (e.g., a daywalker carrying a rifle), to reinforce flexible, evidence-based application of Lost Person Behaviour (LPB) theory (Koester, 2008). A continued emphasis on evidence-driven planning should remain central to all training frameworks, reinforcing the preference for localised tasking around high-probability clues before implementing broader search changes (Snaprud, 2022). Training modules should also encourage critical thinking and adaptability to prepare teams for uncertain and evolving conditions (Rodriguez, 2022).

Scenario-based training and field exercises are essential for developing SAR personnel's ability to navigate ambiguous situations. By incorporating real-world case studies, SAR personnel can strengthen their critical thinking skills and improve their ability to classify incidents effectively (Anderson, Pitel, Weerasinghe, & Papazoglou, 2016). Exposure to varied scenarios will reinforce decision-making frameworks, enabling teams to apply theoretical knowledge in practical contexts. Field exercises provide hands-on experience that allows SAR teams to simulate operations with diverse subject profiles, such as lost hikers, hunters, and mixed-use recreationalists. These exercises help refine decision-making processes and reinforce the application of standardised terminology in dynamic environments, preparing SAR personnel for the complexities of real-world search operations (Rodriguez, 2022).

To support the uptake of research findings, communication strategies should be tailored to account for varying levels of SAR experience (Baxter, & Braverman, 2004). Findings should be presented in accessible formats that bridge the gap between academic research and field application, improving knowledge transfer and application. Further, regular evaluation of how SAR personnel interpret and apply key concepts in operational contexts should be built into national training frameworks, creating a continuous feedback loop for learning and improvement (Hodges & Larra, 2021).

Lastly, strong stakeholder engagement is essential to aligning theoretical insights with practical realities (Goodman, & Sanders Thompson, 2017). Involving SAR practitioners in research development will enhance the relevance and applicability of findings. A collaborative research approach will ensure that academic insights contribute meaningfully to operational advancements, supporting innovation and continuous improvement in the SAR field.

Conclusion

This analysis reveals that SAR personnel demonstrate a strong foundational understanding of core concepts and a high level of operational reasoning, particularly in prioritising evidence and behavioural cues in search planning. However, variations in terminology interpretation, confidence in terrain analysis under constraints, and inconsistency in map-based visual communication highlight important areas for development. The inclusion of the map-based questions provided a critical layer of insight, revealing how theoretical knowledge is applied spatially and visually under operational conditions. While participants generally performed well when dominant terrain matched the subject profile, confidence wavered when terrain distribution was more complex. This suggests that training must move beyond ideal scenarios and into the nuanced decision-making required in the field.

Encouragingly, many participants demonstrated emerging operational thinking and a willingness to integrate subject movement logic and terrain assessment. Reinforcing these skills through immersive, scenario-driven training and clear operational language will help develop even greater consistency and agility among SAR teams.

However, the findings also highlight that research outputs, even those designed with SAR in mind, such as statistical models or theoretical frameworks, require thoughtful adaptation to be usable in the ambiguous, time-constrained contexts of field operations. To bridge this gap, it is essential that future research and training initiatives focus not only on producing data or models but also on translating these into intuitive, actionable tools for practitioners under pressure. By implementing these recommendations and improving the interface between theory and practice, SAR organisations can enhance the effectiveness, responsiveness, and clarity of their operations in Aotearoa New Zealand.

Acknowledgements

The authors would like to acknowledge the support of Land Search and Rescue New Zealand Research & Development Fund, whose contributions made this research possible. Their commitment to advancing evidence-based practice in search and rescue has provided a resource and encouragement for exploring new approaches such as terrain-based probability. The fund's support reflects a shared dedication to improving outcomes for the lost, missing and injured.

About the author

Edward Cook (BSc)

Ed is a volunteer for Land Search & Rescue Wellington, with over 8 years of operational experience in search & rescue incidents across New Zealand and internationally. Outside of Search & Rescue Ed is a GIS Account Manager, Emergency Management Lead at Eagle Technology, and a volunteer of the National Oil Spill Response Team, Maritime New Zealand. This operational role sits alongside a technical advisor role to the UNOCHA International Search & Rescue Advisory Group (INSARAG) Information Management Working Group.

Aly Curd (MEmergMgt)

Aly is a volunteer for Southland Search & Rescue with over 8 years of operational experience in search & rescue incidents across New Zealand and internationally. Outside of Search & Rescue, Aly is the Group Planning Manager for the Wellington Regional Emergency Management Office and a PhD candidate at the Joint Centre for Disaster Research, Massey University.

Abbreviations

ESP	Extended Search Planning
IPP	Initial Planning Point
INSARAG	International Search and Rescue Advisory Group
LandSAR	Land Search and Rescue

LKP	Last Known Point
MTIR	Managing the Initial Response
PLS	Place Last Seen
SAR	Search and Rescue
TBP	Terrain-based Probability

References

Adams, A. L., Schmidt, T. A., Newgard, C. D., & et al. (2007). Search is a time-critical event: When search and rescue missions may become futile. *Wilderness & Environmental Medicine, 18*(2), 95–101. https://doi.org/10.1580/06-WEME-OR-035R1.1

Andersen, J. P., Pitel, M., Weerasinghe, A., & Papazoglou, K. (2016). Highly realistic scenario-based training simulates the psychophysiology of real-world use-of-force encounters: Implications for improved police officer performance. *Journal of Law Enforcement, 5*(4).

Baxter, L. W., & Braverman, M. T. (2004). Communicating results to different audiences. In M. T. Braverman, N. A. Constantine, & J. K. Slate (Eds.), *Foundations and evaluation: Contexts and practices for effective philanthropy* (pp. 281–304). Jossey-Bass.

Burgess, M. (2021). *Category I search suspension*. New Zealand Search and Rescue.

Cook, E., & Curd, A. (2025, March 14–16). Terrain-based probability in SAR [Conference presentation]. *Land Search and Rescue Hui*, Tāmaki Makaurau Auckland, Aotearoa New Zealand.

Delve. (2025). *Delve tool*. https://app.delvetool.com/

Entwistle, N., & Smith, C. (2010). Personal understanding and target understanding: Mapping influences on the outcomes of learning. *British Journal of Educational Psychology, 72*(3), 321–342. https://doi.org/10.1348/000709902320634528

Epstein, S., & Katz, L. (1992). Coping ability, stress, productive load, and symptoms. *Journal of Personality and Social Psychology, 62*(5), 813–825.

Figl, K., & Recker, J. (2016). Exploring cognitive style and task-specific preferences for process representations. *Requirements Engineering, 21*(1), 63–85. https://doi.org/10.1007/s00766-014-0210-2

Giles, D. (2008). Local cognitive load in simultaneous interpreting and its implications for empirical research. *International Journal of Interpretation and Translation, 6*(2), 59–77. https://doi.org/10.1075/forum.6.2.04gil

Goldhammer, F. (2015). Measuring ability, speed, or both? Challenges, psychometric solutions, and what can be gained from experimental control. *Measurement: Interdisciplinary Research and Perspectives, 13*(3–4), 133–164. https://doi.org/10.1080/15366367.2015.1100020

Goodman, M. S., & Sanders Thompson, V. L. (2017). The science of stakeholder engagement in research: Classification, implementation, and evaluation. *Translational Behavioral Medicine, 7*(3), 486–491. https://doi.org/10.1007/s13142-017-0495-z

Gordon, R. A. (1987). Social desirability bias: A demonstration and technique for its reduction. *Teaching of Psychology, 14*(1), 40–42. https://doi.org/10.1207/s15328023top1401_11

Hammond, S. C. (2024). *Highly reliable teams: Nine team qualities when failure is not an option*. HPT Press.

Hodges, L. R., & Larra, M. D. (2021). Emergency management as a complex adaptive system. *Journal of Business Continuity & Emergency Planning, 14*(4), 354–368.

INSARAG. (2020) INSARAG guidelines. https://insarag.org/wp-content/uploads/2021/06/INSARAG20Guidelines20Vol20I.pdf

Jacobs, M. (2015). *Terrain-based probability in SAR*. https://mra.org/wp-content/uploads/2016/05/TerrainProbabilityModelsReport.pdf

Jensen, D., Whiles, B. B., & Mirza, M. (2025). Chapter 38: Surveys and questionnaires. In A. E. M. Eltorai, A. Arab, A. Atala, & M. M. Siddiqui (Eds.), *Handbook for designing and conducting clinical and translational research* (pp. 189–194). Academic Press.

Jezek, J. (2016). *The lexicon: An introduction*. Oxford University Press.

Koester, R. (2008). *Lost person behaviour*. DPS Productions.

Land Information New Zealand (LINZ). (2024). *NZ topo maps*. https://www.topomap.co.nz/

Mansfield, G., Carlson, J., Merrifield, D., Rosenburg, E., Swanson, E., & Templin, P. (2023). A pragmatic approach to applied search theory. *Journal of Search and Rescue*, *4*(1), 84-107

NZ Topo Map. (2025). New Zealand topo maps for android. https://www.topomap.co.nz/

Papier, A., Chalmers, R. J. G., Byrnes, J. A., & Goldsmith, L. A. (2004). Framework for improved communication: The Dermatology Lexicon Project. *Journal of the American Academy of Dermatology, 50*(4), 630–634. https://doi.org/10.1016/S0190-9622(03)01571-8

Perenara-Wilkinson, J. (2025). *Thematic analysis: An overview and guide*. https://getthematic.com/insights/thematic-analysis/

Schaefer, K. E., Straub, E. R., Chen, J. Y. C., Putney, J., & Evans, A. W. (2017). Communicating intent to develop shared situation awareness and engender trust in human-agent teams. *Cognitive Systems Research, 46*, 26–39. https://doi.org/10.1016/j.cogsys.2017.02.002

Sherman, T. J., Harvey, T. M., Royse, E. A., Heim, A. B., Smith, C. F., Romano, A. B., ... Holt, E. A. (2019). Effect of quiz format on student performance and answer-changing behaviour on formative assessments. *Journal of Biological Education, 55*(3), 306–320. https://doi.org/10.1080/00219266.2019.1687106

Snaprud, M. (2022). *Project report: Lessons learned from terminology harmonisation* [INSITU project report]. University of Agder.

Speake, J., & Axon, S. (2012). "I never use 'maps' anymore": Engaging with sat nav technologies and the implications for cartographic literacy and spatial awareness. *The Cartographic Journal, 49*(4), 326–336. https://doi.org/10.1179/1743277412Y.0000000021

Stoffle, R. (2006). *The textbook for managing land search operations*. Emergency Response International Inc.

Stoffle, R., & Stoffle, B. (2017). *Managing the inland search function*. National Association for Search and Rescue.

Randel, J. M., Pugh, H. L., & Reed, S. K. (1996). Differences in expert and novice situation awareness in naturalistic decision making. *International Journal of Human-Computer Studies, 45*(5), 579–597. https://doi.org/10.1006/ijhc.1996.0068

Rodriguez, M. (2022, October 21–23). The need for reality in training scenarios [Conference presentation]. *Rescue 22*, Reykjavik, Iceland.

Vijayaratnam, P. (2012). Developing higher-order thinking skills and team commitment via group problem solving: A bridge to the real world. *Procedia: Social and Behavioral Sciences, 69*(1), 53–63. https://doi.org/10.1016/j.sbspro.2012.11.247

Maximizing the Effectiveness of Search Effort in Land Search and Rescue: a Bayesian Priority Rating Approach

W. H. Finlay, PhD
Edmonton Regional Search and Rescue Association
Edmonton, Alberta, Canada
Email: warren.finlay@ualberta.ca

https://doi.org/10.61618/PEXK9532

Abstract

Land search and rescue (LSAR) operations often require decisions to be made between competing search strategies. Basing such decisions solely on the probability of success does not allow consideration of differences in search effort (i.e. searcher hours expended) between competing strategies. In the present work, we rely on existing optimal sequential Bayesian theory to reemphasize the utility of using a measure that considers both probability of success and effort, which we refer to as a priority rating (PR). When choosing between two competing search strategies, the more optimal strategy has a higher PR. For a search strategy employing searchers with given sweep width and travel speed in a search segment with probability density pden, PR is known to be given by PR=pden*sweep width*speed. PR values are compared for competing search strategies in a variety of scenarios, demonstrating the utility of this approach when it is used with recent developments in the literature. For example, it is found that searching by sound for a lost person in further out areas is more optimal than visual searching closer in, but this is only true out to a certain radius from the initial planning point; and dense vegetation areas have dramatically lower priority ratings, effectively concentrating search effort in them unless countermeasures are taken. The present demonstration of the use of the Bayesian priority rating approach may be helpful for search managers wanting to prioritize search efforts more effectively, including choosing the sequence to search different search segments and which search tactics are more optimal in each of these areas.

KEY WORDS: search theory, optimal, Bayesian, sequential, strategy

Introduction

Land search and rescue (LSAR) involves the use of teams of trained search and rescue (SAR) personnel, who are often volunteers, tasked either with finding a lost person, or finding evidence to support a forensic or criminal investigation on land. The large variability that is present in lost person behavior and the search environment, along with variability in the number and skills of SAR teams responding to a callout, combined with unknown values for some of the factors that determine the probability of success in a search, mean that it is not possible *a priori* to devise a single optimal strategy to conduct a given LSAR operation in the real world.

Despite this, concepts from search theory originating from operations research applied to marine searches have been adapted to develop more effective LSAR strategies (Cooper et al. 2003). Much of this work focuses on maximizing the probability of success (POS) by concentrating search efforts in areas with a higher estimated probability of containing the subject. These probabilities are typically based on statistical analyses of past searches (Koester 2008), expert judgment, or a combination of both (Stoffel 2017; Mansfield et al. 2020).

Because LSAR operations are often carried out by volunteers using personal equipment, ways to minimize labor and operating costs in LSAR are often given less importance than in marine or aerial SAR, where such expenses are considerable. This may partly explain the relatively low uptake of objective methods in LSAR for jointly maximizing POS and minimizing costs. In practice, LSAR teams that apply modern search theory tend to focus primarily on maximizing POS, without explicitly minimizing search effort in a quantitative way.

The present work highlights a simple method, based on optimal sequential Bayesian search theory, to help LSAR managers balance both objectives—maximizing POS while minimizing search effort. Here we use the term Bayesian to refer to the reliance on Bayes' theorem to derive optimal sequencing order, and to revise segmental POS values if the segment has already been searched. The essentials of this approach have long been known in the search literature (see e.g. Cooper et al. 2003), but its use is often neglected in LSAR operations. In addition, recent developments in the literature allow us here to consider its application to new comparisons, such as sound versus visual sweeps. Here, the basic search theory underpinning the approach is reiterated. We then apply it to a number of examples. that include recent developments in sound sweep methods, to choose the more optimal search strategy among competing strategies. Specific examples will be considered to illustrate how to use this approach to answer the following search strategy questions (note that the resulting recommendations in each example are not generally applicable, but are specific to the values used in each example):

- How far out from the initial planning point should sound sweeps be prioritized over visual sweeps?
- Should densely and sparsely vegetated areas be searched with equal coverage, despite the slow coverage rates in dense vegetation?
- Should off trail sound sweeps parallel to but further from trails be prioritized over visual sweeps close to trails?
- Where should drones versus visual ground search teams be sent?

Background

When conducting a land search, a number of operational search areas (called 'segments' or 'sectors' or 'regions') are usually defined. SAR personnel are then divided into strike teams, and each strike team is assigned to search a given segment. Since there are typically more segments than strike teams, a central aspect of search management involves deciding the order in which segments should be searched as time proceeds. For this purpose, the probability that the item or lost person is in a given area, commonly abbreviated as POA, is often used to assign strike teams to segments with higher POA. Values of POA are typically best defined using areas, called probability areas, that are chosen specifically for this purpose and are often different from the operational segment areas that strike teams are assigned to search (Cooper et al. 2003).

A common approach to estimating POA for an operational segment area is to multiply the segment area by the probability density, commonly abbreviated as pden, at that location. For lost persons, the value of pden can be estimated using historical data for a given subject category. For example, 25% of 568 hikers lost in temperate mountainous terrain were found within r_{25}=1100 meters of the initial planning point (IPP) (Koester 2008). Thus, an approximate estimate for pden for any operational segment area lying within a radius of r_{25} of the IPP can be estimated by dividing 25% by the area of this circle i.e.

$$pden_{25} = \frac{0.25}{\pi r_{25}^2} \quad (1)$$

Similarly, pden for the annulus lying between radii r_{25} and r_{50} where 25% and 50% of lost persons of a particular subject category have historically been found, respectively, is given by

$$pden_{25-50} = \frac{0.25}{\pi(r_{50}^2 - r_{25}^2)} \quad (2)$$

A similar approach to eqn. (2) can be used to find pden for the annulus between the 50th and 75th percentile, or the 75th and 95th percentile distances from the IPP.

As noted earlier, for an operational segment area that has area A lying entirely within one of these probability areas, the value of POA for this segment can be estimated as

$$POA = pden \times A \quad (3)$$

For operational segment areas that overlap multiple probability areas, a weighted POA can be estimated by having the portion of a segment area lying withing a given probability area inherit pden from that probability area. The reader is referred to e.g. Mansfield et al. (2020) for further explanation of estimating segmental POA values[1].

With POA values in hand for each operational segment area i, the probability of success (POS) of finding the subject in segment area i is then

$$POS_i = POA_i \times POD_i \qquad (4)$$

where POD_i is the probability of detection i.e. the probability that the strike team assigned to search operational segment i would find the subject if the subject was in that segment. POD_i is determined by the coverage c_i achieved by the assigned strike team when they search segment i of area A_i, and is given by

$$c_i = \frac{sweep\ width \times total\ track\ length}{A_i} \qquad (5)$$

In eqn. (5), sweep width is proportional to the strike team individual member's average detection range (Koester et al. 2014) and total track length is the total linear distance travelled by the strike team while actively searching that segment, obtained by adding up the distance travelled by each strike team member. For simplicity, let us assume each strike team member operates as an identical idealized definite range detector, in which case

$$POD_i = c_i \quad (6)$$

In reality, POD_i is a monotonically increasing nonlinear function of c_i (Cooper et al. 2003), but eqn. (6) suffices for our purposes here.

Using the above information, when search segments outnumber strike teams, a typical approach to assigning segments to strike teams would be to proceed in order of decreasing probability of success, POS_i. In other words, allocate strike teams first to those segments with the highest POS_i. When a strike team completes a given search segment, using Bayesian analysis arguments (Cooper et al. 2003), then POS_i should be multiplied by $(1-POD_i)$ to give a revised cumulative nonnormalized POS_i for that segment.

[1] Probability density when including two effects requires careful handling e.g. consider a wedge-shaped 25th percentile sector, labelled area 1, associated with dispersion angle, so POA_1=0.25; and the 50th – 75th percentile annulus associated with 25th – 50th percentile distance from the IPP, labeled area 2, also with POA_2=0.25; pden for the intersection of these two areas is then $\frac{POA_1 POA_2}{A_{12}}$ where A_{12} is the area of the partial annulus that is the intersection of the two areas. Thus, we see here that POA for the overlapping area is multiplicative not additive.

That strike team should then be assigned to search the segment with the highest cumulative nonnormalized POS_i.

As an aid to the reader, the table below presents a brief summary of the above notations and abbreviations as applied in the present manuscript. The reader is referred to Koester et al. (2004) for further explanation of these terms.

Symbol, abbreviation or notation	Meaning	Definition
POA	Probability of area	The probability that the lost person is within the given area
POD	Probability of detection	The probability that the lost person would be detected assuming they are in the search segment
pden	Probability density	The ratio of probability of area to its physical area
Sweep width	Effective sweep width	The width of the swath centered on the searcher's path such that the probability of failing to detect the subject within that width equals the probability of detecting the subject if it lies outside that width
c	coverage	The ratio of the area effectively swept to the area searched
i	Index whose value indicates different search segments or search strategies	i=1, 2, 3, …
j	Index whose value indicates different search segments of search strategies	j=1, 2, 3, …
PR	Priority rating	The ratio of probability of success (POS) of a given search task to the cost of that task (measured in searcher hours expended to complete the given task). Also referred to as probable success rate (PSR).

The above approach to search management is optimal in the sense that it is aimed at maximizing the overall probability of success of the search. However, it does not account for differences in search effort required to search the different search areas. For example, consider a search segment i with POA_i that has the same value of POA as segment j, but whose area A_i is twice that of segment j. Assuming searchers cover the two segments at the same rate (i.e. their search speed and sweep width is the same), it will then take a strike team twice as long to search segment i compared to segment j. Searching either segment has the same effect on the overall probability of success, so most search managers would probably intuitively assign a strike team to the smaller area first. However, more generally, it would be useful to have a quantitatively logical approach that prioritizes which segments are assigned sequentially during a search. This is the topic to which we now turn.

Prioritizing Segments

The problem of choosing the sequence in which search tasks should sequentially be assigned in order to maximize the probability of success with the least effort has been examined previously in the context of operations research (Assaf and Zamir 1985). Using a Bayesian analysis, these authors show that the optimal search strategy involves choosing tasks sequentially in order of decreasing values of $POS_i/cost_i$ where $cost_i$ is the cost of the ith task. In the context of land search and rescue, a logical measure of $cost_i$ is the number of person hours t_i required to complete that task. Although POS alone is often used in search management, the use of POS/cost (sometimes termed the probable success rate, PSR) to optimize land search has previously presented in the land search and rescue literature (Cooper et al. 2003). Let us define a priority rating PR as

$$PR_i = \frac{POS_i}{t_i} \qquad (7)$$

Here the time t_i includes transit time for searchers to deploy from a staging area to a segment, although in many cases this time is small compared to the time required to search that segment, so that we can approximate t_i simply as the number of person hours required to search that segment. In that case, t_i is related to total track length and average travel speed of the strike team by

$$t_i = \frac{total\ track\ length}{speed} \qquad (8)$$

Combining eqns. (3)-(8), it can be shown that the priority rating of the ith operational segment is given by:

$$PR_i = pden_i \times sweep\ width_i \times speed_i \qquad (9)$$

We can alternatively write eqn. (9) as

$$PR_i = pden_i \times \dot{c}_i \qquad (10)$$

where $\dot{c}$ is coverage rate, i.e. area swept per unit time. When transit time is not small compared to the time required to search a segment, we instead must use eqn. (7) directly, rather than eqn. (9) or (10). A demonstration of the inclusion of transit time is given later in the final example (see the section entitled *Where to send drones versus ground search visual teams*).

Eqn. (9), or equivalently eqn. (10), allows a priority rating PR to be calculated for each search segment, which can be used to prioritize the sequence that the segments should be searched in order to achieve the highest probability of success in the least expected amount of total active searcher time. Barring other available information, the optimal strategy to follow when sequentially choosing segments to search should therefore adhere to the following principle:

Given two search strategies with different total PR values, choose the strategy with higher PR value

(11)

Alternatively, when deciding between two search strategies it may be easier to instead examine the ratio PR_1/PR_2, in which case strategy (11) can equivalently be written

Given two search strategies with total PR values PR_1 and PR_2, choose strategy 1 if $PR_1/PR_2>1$, otherwise choose strategy 2

(12)

The value of the ratio PR_1/PR_2 tells us how many times more probable strategy 1 would be in achieving success compared to strategy 2 for a given search effort e.g. $PR_1/PR_2=5$ indicates that strategy 1 is five times more likely to find the lost person than strategy 2 if the same amount of time were to be spent searching with each strategy.

Note that when a task consists of multiple subtasks, the PR value cannot be obtained by adding up the PR values for each subtask. Instead, in such cases it is necessary to use eqn. (7) directly. Thus, for a strategy i that involves searching multiple segments j (e.g. perhaps by assigning different teams to each segment), the priority rating for the strategy is given by

$$PR_i = \frac{\sum_j POS_j}{\sum_j t_j} \qquad (13)$$

This is because unless t_j is the same for each subtask, $\sum_j \frac{POS_j}{t_j} \neq \frac{\sum_j POS_j}{\sum_j t_j}$, so that we cannot use eqn. (9) or (10) to sum up individual segment PR_j values.

Various optimal operational search strategies that follow directly by applying strategy (11), or equivalently (12), are given in the Results section.

Estimating Searcher Speed

In order to use eqn. (9) to determine a priority rating for a given search segment, it is necessary to estimate searcher speed in that segment. For this purpose, the study of Campbell et al. (2024) is useful. These authors relied on a vast database of lidar based terrain data to develop an equation for walking speed as a function of slope angle, vegetation density, and terrain roughness. They give the following equation for estimating searcher speed in meters/second that we use here for speed in eqn. (9):

$$speed = \frac{1.78251}{(1 + 15.265 \times density + 16.505 \times roughness)\left(1 + \left(\frac{slope + 2.32}{26.315}\right)^2\right)} \tag{14}$$

The variables in the denominator account for reductions in travel speed as follows:

- density captures obstruction by vegetation, with 0 meaning no vegetative obstruction; the maximum value observed in their field validation studies was 0.064
- roughness accounts for ground surface roughness , with zero being smooth ground and 0.054 being the roughest ground traversed in their field studies
- slope is the angle in degrees of the slope in the direction of travel; typical values of slope are as follows: slope=0° for flat ground, a moderately steep slope in LSAR operations would be perhaps 5°, and a slope of 15° would likely be considered quite steep terrain in LSAR operations that do not involve high angle rope teams

If traversing a side slope of angle j in degrees, based on Wood et al. (2023) we can estimate speed in a direct contouring traverse of a side slope (i.e. zero elevation change travel on a slope) by setting slope=0 in eqn. (14) and multiplying the resulting speed by $e^{-0.00731j}$.

Campbell et al. (2024) used lidar data to estimate density and roughness at 1 million random points placed within 100 random natural areas across the contiguous United States. The mode of the distribution of density values at these locations was 0.004, and the 90th percentile density value was 0.06. The mode of the distribution for the roughness values was 0.014. Finally, the approximate mode, 50th percentile and 75th percentile values of slope were 0°, 5° and 15°. We will use some of these values in the following Results section to provide estimates for searcher travel speed over a range of terrain conditions when estimating PR values from eqn. (9).

Results

Reflex tasking

A typical strategy at the start of a search is to immediately send searchers to areas with high probability density that can be searched quickly. This makes obvious use of the statement (11), since it prioritizes segments with highest PR because of high values of both $pden_i$ and coverage rate $\dot{c}_i$ in eqn. (10). Although we obtain no new understanding here, this does provide a trivial example of the use of statement (11).

Sound sweeps further out versus visual searching closer in

Consider a search for a responsive lost hiker, in a temperate mountainous ecoregion. Let us say that the inner 25th percentile circular region (Koester 2008) has been searched using the parallel sound sweep procedure given in Finlay (2024). Suppose the question now is whether to send two 2-person strike teams to search by sound within a segment in the 25th - 50th percentile annular region, or to instead combine the two teams into a single four person team that then starts visual searching in a segment within the inner 25th percentile region. We assume the two sound searchers on a single team stay together to avoid the increased risk of solo searching, since employing critical separation during sound sweeps would put separate sound sweep units beyond visual and audibility range of each other.

To answer this question in an actual situation we would need to know the ambient dB values in the field at the time the question is being asked, since sound sweep width depends on ambient dB (Finlay 2024). We would also need to know the sweep width for the proposed visual search segment. For the sake of demonstration, let us assume the detection range for the sound sweeps is the average intelligibility distance for the lodgepole pine forest measurements given in Finlay (2024) i.e. 98 m. Let us also assume the visual range of detection is the same as the value measured in the same forest for a standing human subject by Finlay (2025) i.e. 18.2 m. In addition, let us also assume that both range of detections are related to sweep width by the same multiplicative factor. Now define strategy 1 to be the case where we task the strike teams to continue sound sweeps but now in a segment in the 25th – 50th percentile zone. In strategy 2 we instead task the strike team members with parallel visual searching of a segment in the 25th percentile zone. Figure 1 depicts the two strategies schematically.

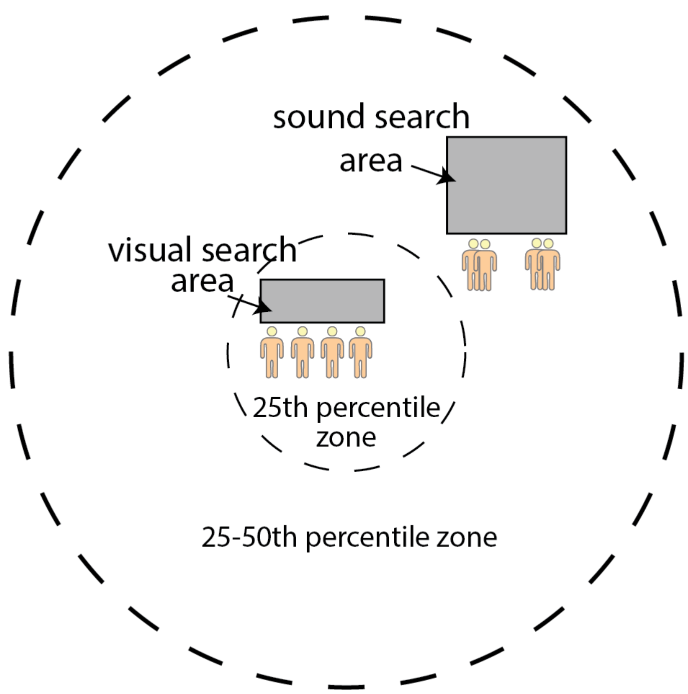


Figure 1. Schematic showing the two strategies to be chosen between. Strategy 1 involves two 2-person strike teams searching a segment by sound that lies within the 25th – 50th percentile radial zone from the IPP. Strategy 2 involves a four person strike team instead doing a visual search of a segment within the inner 25th percentile zone, where a sound search has already been done.

Finally, let us assume that the searcher travel speed would be the same in both strategies. With these assumptions, we can obtain the priority rating ratio PR_1/PR_2 as follows.

First, we find the probability density $pden_1$ for the 25th – 50th percentile zone using eqn. (2). For the present case of a lost hiker in the given ecoregion, r_{25}=1100 m and r_{50}=3100 m. Next we obtain the probability density $pden_2$ for the inner 25th percentile region using eqn. (1). But since this region has already been searched, we need to recalculate the probability density using Bayes theorem as noted earlier in the *Background* section when discussing POA, i.e. we need to multiply $pden_2$ by (1-POD) to give a revised cumulative nonnormalized probability density

$$pden_2' = (1\text{-}POD)pden_2 \qquad (15)$$

A method to determine POD from intelligibility distance is not yet available to the author's knowledge, but in the interim Finlay (2024) suggests using POD=0.8 for properly executed sound sweeps, so let us use this POD value.

With all of the above in place, we can use eqn. (9) to evaluate PR_1 and PR_2. Note that since the two people on a sound strike team walk together, their coverage rate is half that of a single person, effectively halving their coverage rate compared to the visual search team where each individual sweeps a separate path, so we divide the strategy 1 PR value by 2, and we find

$$PR_1/PR_2 = pden_1\ rd_1/(2\ pden_2'\ rd_2) \qquad (16)$$

where rd_1=98 m is the above noted sound sweep detection range and rd_2=18.2 m is the above noted visual detection range. Putting in the numbers, eqn. (16) gives PR_1/PR_2=1.94. This is larger than one, so statement (12) indicates that strategy 1 is the preferred strategy i.e. in this particular example we should send the strike teams into the 25th – 50th percentile zone to search using a parallel line sound sweep protocol, rather than having them start a parallel line visual ('grid') search inside the 25th percentile zone. Doing so would have a 1.94 times higher probability of success with strategy 1 than for strategy 2 for a given search effort. Note that this is not a general recommendation, but is specific to the values used in this example.

Note that if we had used a single four person strike team for the sound searching, all walking together as a group (instead of splitting into two pairs) during the sound searching, we would need to halve the PR for strategy 1 again, and would obtain a PR ratio of 0.97. In that case, strategy 2 is marginally preferred and we see the importance of splitting up sound searchers into teams of two to avoid reducing coverage rates.

Using the same approach, we can also consider the same question but now applied to the 50th -75th percentile zone away from the IPP i.e. if the 25th – 50th percentile zone has already been searched using sound sweeps, should we send the sound strike teams to do sound sweeps in the 50th-75th percentile zone, or should we instead have them join up to have a four person strike team start a visual search in the inner 25th percentile zone? Using the above procedure, we obtain a PR ratio of 0.7. By statement (12) then, we should have the four person strike team begin visual searching in the inner 25th percentile zone. Thus, there is a limit to how far out from the IPP that sound sweeps should be completed before visual searching begins. This distance can be extended with the use of parabolic microphones and loud signaling devices (Finlay 2025). Also note that the decision to search the inner 25th percentile zone visually, rather than re-searching it acoustically, implicitly assumes a low probability that the subject remains responsive, since otherwise the vastly larger sweep width of sound searching would give a higher PR value to re-searching this segment acoustically rather than visually.

These strategy decisions are specific to this example. In other searches, decisions may differ because PR values depend on the detection ranges for that particular search and on the radii of the 25th, 50th, 75th and 95th percentile zones (which differ with different subject categories, see Koester 2008). Thus, it is necessary to carry out the above calculations for each search in order to decide which strategy is optimal for that search.

One may also question how robust the conclusions of the above example are because of the uncertainty in values of some quantities. In particular, the factor that relates detection range to sweep width, particularly the validity of the assumption that this factor is the same for sound versus visual detection, is unknown. Also, the value of POD for sound sweeps (assumed equal to 0.8 in this example) is unknown, as noted earlier. However, the assumptions made here regarding these uncertain values were chosen conservatively i.e. favoring visual sweeps . For example, the factor that relates sweep width to detection range for sound sweeps is likely double or more the value of this same factor for visual detection, given that Finlay (2025) finds audibility detection range is typically at least double the intelligibility distance we are using here for sound detection range, whereas a value of unity has been assumed. In addition, assuming POD=0.8 for sound sweeps done with a spacing of twice the intelligibility distance is probably an underestimate, again because audibility detection range is greater the intelligibility distance. For these reasons, the ratio of PR_1/PR_2 given by eqn. (16) may be several times higher than estimated above, so that strategy 1 may be the preferable strategy for further distances than noted above.

Avoiding the trap of dense vegetation

Vegetation can impede searcher speed during off trail travel, since it can significantly obstruct a searcher's path. In addition, sweep width is typically reduced in densely vegetated areas. Thus, if pden is constant, then eqn. (9) shows that PR values in areas with heavy obstruction due to vegetation will be lower than in lightly obstructed areas. The question is, how much higher does the probability density need to be before it is cost effective to search an area of dense vegetation, as opposed to instead choosing to search an area of sparser vegetation?

To address this, we can use eqn. (14) to estimate searcher speed in areas of varying vegetation density. However, to evaluate PR values we also need to know how sweep width varies with the vegetation density variable. Unfortunately, to the author's knowledge such data does not exist. Instead, as an approximate approach we can examine the data on sweep width obtained by Koester et al. (2014) in 10 different locations in the United States, where we see sweep width varies by a factor of approximately seven from its lowest to highest measured values for a fixed type of visibility (either high or low). Presuming that this variability is due to variations in vegetation density, then assuming a simple linear relation between sweep width and density, with the lowest sweep widths associated with a 90th percentile density value of 0.06 noted earlier when presenting eqn. (14), and a density of 0 for the highest sweep widths, we find the following relation between sweep width and vegetation density:

$$\text{sweep width} = \text{unobstructed sweep width} \times (1 - 14.286 \text{ density}) \qquad (17)$$

Now consider the following two strategies: 1) search off trail in an area that is heavily obstructed by vegetation, versus 2) search off trail in an area that is lightly obstructed by vegetation.

For simplicity, let us assume also that the areas being considered are flat i.e. slope = 0°. From eqn. (14), using slope=0, density=0.004 for light obstruction, density=0.06 for heavy obstruction, and the distribution mode value of roughness=0.014 noted earlier, we find searcher speed in the lightly obstructed area is 1.66 times that in the heavily obstructed area. Using eqn. (17), we find the sweep width in the lightly obstructed area is 6.6 times that in the heavily obstructed area. Multiplying these values, we find sweep width x speed is 11 times higher in the light versus heavy obstruction areas. Based on eqn. (9) and statement (12) then, the probability density, pden, in the dense vegetation area would need to be more than 11 times higher than its value in the light vegetation area in order for searching the dense area to be as cost effective as searching the lightly obstructed area. To put this in perspective, from eqn. (1) and (2) we find the probability density for a lost hiker in temperate mountainous terrain is 6.9 times higher inside the 25th percentile zone compared to the 25th – 50th percentile zone.

If the probability density is no different between the heavy and light obstruction areas, a strike team that chooses to search a region where the vegetation heavily obstructs a searcher's path, as opposed to instead searching an area where the vegetation only lightly obstructs their path, ends up focusing many times more search effort on the heavy obstruction area without commensurately boosting POS. In the example above, giving equal coverage to densely obstructed areas is equivalent to having the team re-search a segment that was previously searched at a POD of 91%, instead of sweeping a segment that has not yet been searched. It is also an even less optimal use of search effort than having the strike team search for a lost hiker in a segment in the 50^{th} – 75^{th} percentile zone before searching the inner 25^{th} percentile zone.

Given the above perspective, search managers may wish to give instruction to strike teams regarding whether densely vegetated areas should be given the same coverage as lighter vegetation areas. In some types of searches it could be that densely obstructed areas do indeed have a considerably higher pden e.g. in a search for a deceased victim of criminal activity where the body has been intentionally placed in dense bush to reduce the likelihood of its detection. However, in searches where pden is not expected to be considerably higher in dense bush, the above example suggests that some thought should be given as to whether it is worthwhile to inadvertently misplace search effort by having teams search dense and light bush with equal coverage. To provide guidance in this regard, the ratio of priority rating normalized to PR with a vegetation density value of 0.004, with ground roughness 0.014 is shown in Figure 2. It can be seen that searching dense and light bush with equal POD, as is commonly done in SAR operations, dramatically focuses search priority on the most densely vegetated areas.

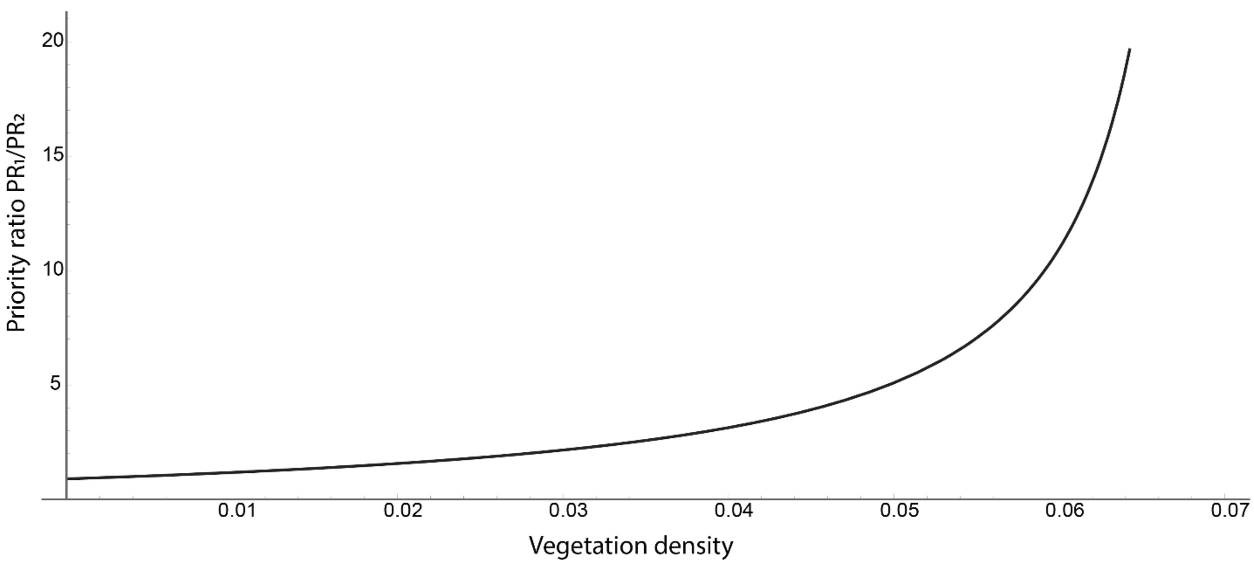


Figure 2. The priority rating ratio for searching lightly obstructed (PR_1) versus obstructed (PR_2) segments is shown as a function of vegetation obstruction density i.e. density in equation (13). Note this ratio is independent of slope angle, since slope cancels out in the priority ratio.

Given the above noted effect of heavy obstruction on PR values, three obvious approaches for searchers encountering dense vegetation are apparent, as follows:

1) reduce searcher spacing to yield the same POD that occurs in lightly obstructed regions e.g. by using the approach described in Chiacchia et al. (2025)

2) use the searcher spacing appropriate to lightly obstructed areas throughout, marking dense locations for later searching with revised (closer) spacing

3) skip the densely vegetated area, marking its location for later searching

If option 1 is chosen, densely vegetated areas will have more searcher effort allocated to them, which may not be warranted. Modern mapping and tracking tools, such as CalTopo, allow locations to be readily marked electronically and made visible to all team members at all times, improving the practicality of options 2 and 3 compared to older methods such as flagging. If option 2 or 3 is chosen, a PR value should be calculated for the marked areas so that they can put in the queue to be searched when their PR value becomes higher than other segments.

Effectiveness of sound sweeps adjacent to paths in dense forests

Costigan (2024) has already pointed out the generally higher effectiveness of sound versus visual sweeps when searching for responsive lost persons. But it is worth revisiting this in the context of the Bayesian priority rating approach presented above. In particular, consider a two person strike team that is trained on how to use the sound sweep protocol of Finlay (2024). They have measured ambient sound dB (due to wind in the forest trees) to be dB_{amb} =40 dB in a mature dense aspen forest, which is typical for this environment when treetop wind speeds are perhaps about 20 km/hr (Finlay 2024). The intelligibility distance equation from Finlay (2024), $d_i = 5619e^{-0.0978dB_{amb}}$, predicts a sound detection range of d_i=112 m for a person shouting at 88 dB at 1 m (which is a very loud shout). For lost hikers, 50% are found within a track offset of 100 m. The strike team has searched out to the 50th percentile track offset (since the intelligibility distance is > 100 m). Now define the following two strategies:

1) the strike team moves off trail and starts sound searching the 50th - 75th percentile track offset
2) The strike team instead searches visually in the 25th percentile track offset zone

For visual range of detection in a dense mature aspen forest, let us use the value measured by Finlay (2025) i.e. 8.6 m.

We can now use statement (12) to make a decision as to which is the more optimal strategy. Since that statement relies only on the ratio of priority ratings, we only need to know the ratio $pden_1/pden_2$, rather than absolute values of these. Here $pden_1$ is the probability density in the 50th – 75th percentile track offset zone i.e. in the region between distances o_{75} and o_{50} off path, where o_{50} and o_{75} are the track offset to the edge of the zones where 50% and 75% of hikers are found off path. Similarly, o_{25} is the track offset for the inner 25th percentile track offset zone. Koester (2008) gives o_{25}=50 m, o_{50}=100 m, o_{75}=238 m and o_{95}=424 m for a lost hiker. From equation (3), and realizing we need to use eqn. (15) (where we assume POD=0.8 for the sound sweep as before) to account for the fact that we have already searched the 25th percentile track offset (by sound), we find (using ’ to indicate the use of eqn. 15)

$$pden_1/pden'_2=0.25\, o_{25}/(0.25^* (1-0.8)^* (o_{75} - o_{50})) \qquad (18)$$

which has the value 1.8 in the present case. The ratio of coverage rates for strategy 1 versus strategy 2 can be approximately estimated as the ratio of detection ranges for the two strategies i.e. ½ (112 m/ 8.6 m) = 6.5 where the factor of ½ accounts for the fact that the two people on the sound team travel the same path when searching by sound, but not when searching visually, as noted earlier. As before, we assume the same conversion factor from detection range to sweep width for both strategies. The speed of travel is approximately the same for both strategies, since in either strategy the strike team will be moving off trail through dense bush. Now, using eqn. (10) we have

$$\frac{PR_1}{PR_2} = \frac{pden_1}{pden'_2}\frac{\dot{c}_1}{\dot{c}_2} \qquad (19)$$

and we find PR_1/PR_2 = 1.8*6.5= 11.7. This is > 1, so we find strategy 1 is the more optimal strategy i.e. the strike team should search by sound in the track offset zone 238-424 m off trail. Note that this is not a general recommendation, but is specific to the values used in this example.

Where to send drones versus ground search visual teams

As noted earlier, in cases where the strategies being compared involve multiple subtasks, we must work directly with eqn. (13) when comparing PR values. For example, consider two teams awaiting assignment during a search for a lost person. Let us assume the lost person is no longer thought to be responsive, so sound sweeps are not being considered. Of the two teams available, one team operates a drone and consists of a pilot and a spotter. The other is a four person visual search ground team. Two segments are to be searched, which have equal area but one lies in the inner 25th percentile zone from the IPP, and the other lies in the 50th-75th percentile zone. The inner area is dense bush with expected PODs of POD_{v1}=60% for the visual team, and POD_{d1} =15% expected by the drone team. The outer area is open i.e. sparse vegetation obstruction, with POD expected to be 80% for both drone and visual searches. The ground team estimates it would take 2.5 hours to search the inner area, but only 45 minutes to search the outer area, plus an hour to walk out to the outer area. The drone team estimates 30 minutes to complete a search of either area. Strategy 1 sends the ground team to the inner area and the drone team to the outer area. Strategy 2 is the opposite i.e. the visual team searches the outer area, while the drone searches the inner area. Which is the more optimal strategy?

To make this decision, we use eqn. (13) along with eqn. (3) and eqn. (4). Denoting t_{v1} as the person hours to visually search the inner area, and t_{d1} as the person hours for the drone team to search the outer area, with the above information we have t_{v1}=4*2.5=10 hours and t_{d1}=2*0.5=1 hour. Similarly, for strategy 2 we have t_{v2}=4*0.75 + 1 = 4 hours, and t_{d2}=1 hour. Adding POS values to obtain a total POS for each strategy, and similarly adding up the total person hours for each strategy, then the priority ratios are obtained using eqn. (13) and the priority rating ratio is given by

$$\frac{PR_1}{PR_2} = \frac{\frac{pden_{25}\,POD_{v1} + pden_{50-75}\,POD_{d1}}{t_{v1} + t_{d1}}}{\frac{pden_{50-75}\,POD_{v2} + pden_{25}\,POD_{d2}}{t_{v2} + t_{d2}}} \qquad (20)$$

Note the area A has canceled out since it is the same for the two segments. Using eqns. (1) and (2) to calculate probability densities, and putting in the numbers, we find a priority ratio of 1.5. This is greater than 1, so by statement (12) strategy 1 is the more optimal one. Note that this is not a general recommendation, but is specific to the values used in this example.

Discussion

The above examples highlight the ability of the Bayesian priority rating (PR) embodied by eqn. (9), or equivalently eqn. (10), to inform search management when a choice needs to be made between different search strategies.

For responsive lost persons, the increased sweep width when searching by sound (Finlay 2024) gives higher PR values than visual searching in the same segment, supporting Costigan's (2024) analysis that when searching for responsive lost persons, segments should be swept using sound before switching to visual detection. However, the rapid decrease of probability density with distance from the IPP means there is a limit to how far out sound sweeps should be completed before visual searching is begun closer in to the IPP. This distance will depend on the ratio of sound versus visual sweep width, as well as the subject category (since the rate of decrease of pden with distance from the IPP is subject category dependent), and speed of travel if it is different in the different segments under consideration. Redoing our earlier example but now using Koester's (2008) data on two different subject categories (lost hikers and lost hunters) in both temperate and dry ecological regions, as well as flat and mountainous terrain, we find that using two person sound strike teams to do sound searching in the inner 25th – 50th percentile zone (after already searching the inner 25th percentile by sound) always has a higher priority rating than visually searching the inner 25th percentile zone under the assumed conditions. For the case of a lost hiker or hunter in dry mountainous domains or a lost hunter in a dry flat domain, higher priority rating also occurs for two person strike teams sound searching the 50th -75th percentile versus visual searching of the inner 25th percentile zone. On the other hand, if sound sweep width is less than twice the visual search sweep width, as may occur on a windy day with considerable ambient environmental noise, doing two person sound sweeps (where two searchers travel the same path together) has a lower priority rating than visual searching with team members spaced at or beyond critical separation. Thus, while in many cases the optimal strategy would be to prioritize sound sweeps in the inner 50th percentile zone followed by visually sweeping the inner 25th percentile zone, this conclusion is not universal, so that PR values should be calculated during each search.

When assigning segments to strike teams, search managers may not know how fast the team will be able to travel in the assigned segment. For example, they may not know to what extent vegetation will obstruct the searchers' paths. Searcher speeds could be estimated with the use of lidar data to discern vegetation density (see Campbell et al. 2024), but many locations do not have publicly available lidar datasets for this purpose. In the author's experience, when vegetation density varies rapidly along the searcher's path, search volunteers naturally tend to cover dense and lightly obstructed regions with nearly equal searcher spacing, since it adds complexity for a team of searchers walking abreast to adapt to varying searcher spacing. However, this effectively prioritizes search effort in heavily obstructed vegetated areas versus lightly obstructed areas. If this is not desirable, e.g. if probability density is not expected to be significantly higher in densely vegetated areas, search managers may wish to advise strike teams to skip areas where vegetation cover dramatically obstructs their path, marking these areas and calculating a revised PR for such areas, queuing them for later searching once other areas with higher PR have already been searched.

One advantage of using PR values is the elimination of the need to consider segment areas explicitly. However, it does require knowing pden, which requires calculating areas of simple geometric figures (e.g. rings, circles, wedges, rectangles and their overlaps) if one starts with probabilities from the lost person behavior zones of Koester (2008). Including multiple effects, such as both track offset and radial distance from the IPP, requires multiplying probabilities and calculating overlapping areas, as illustrated earlier in footnote 1. Including non-searching person hours e.g. transit times between segments, also adds complexity to the analysis. As a result, a priority rating analysis can become somewhat tedious and prone to error if done by hand. Development of software that incorporates the present Bayesian priority rating approach while also calculating pden using intersecting zone probabilities from historical lost person behavior databases would be a powerful tool to aid land search and rescue management.

Limitations of this study

The priority rating given by eqn. (9) relies on an assumption that POD varies linearly with coverage, as given by eqn. (6). If one instead assumes an exponential 'random search' dependence (Cooper et al. 2003) where POD=$1-e^{-c}$, PR values obtained with an assumption of linear dependence on c would overestimate PR at most by a factor in the range 1.28-1.59 for c varying from 1 to 0.5, which would affect decisions only when PR ratios are not much different from 1 i.e. the two competing strategies being chosen are nearly equally optimal anyway. Our use of eqn. (6) to derive eqn. (9) simplifies the calculation of PR values, and in the author's view is worth any error introduced by the linear dependence assumption embodied by eqn. (6), particularly given that such errors are likely smaller than uncertainty in pden values in actual searches anyway. Finally, this error is only present when the two strategies being compared have different values of coverage c, since if c is the same then both PR values must be corrected by the same factor, which then cancels out in the PR ratio. In this author's experience, most strike teams aim for similar coverage values in different segments, negating concerns about linear versus exponential dependence on c.

Data that relates sound intelligibility distance to sound sweep width has not yet been obtained, to the author's knowledge. For this reason, in the above examples we have assumed the conversion factor between detection range and sweep width is the same for sound searching as it is for visual searching. This introduces an error whose extent is unknown. The conversion factor from detection range to sweep width varies from 1.1 – 1.8 for low to high visibility objects (Koester et al. 2014) for visual searching, whereas it is probably in the range of 2-5 for sound sweeps when using intelligibility distance for detection range (Finlay 2024). Thus, in the cases here where sound versus visual searching was considered, removing this error would increase the PR ratio for sound versus visual searching by a factor of perhaps 5/1.1 – 2/1.8 i.e. by a factor of 1.1-4.5. This correction would prioritize sound sweeps over visual sweeps somewhat more.

Conclusions

It has long been known that incorporating optimal sequential Bayesian decision-making into search theory makes it possible to determine the more optimal search strategy among competing strategies, accounting for both probability of success and search effort (measured as search-person hours). Here we apply this approach to various examples of search decision scenarios that include recent developments in the search literature, reemphasizing the utility of this approach, including what sequence to task search segments, which search tactics to use in different segments (e.g. remotely piloted aircraft versus visual searching versus sound sweeps), and quantifying the effect of densely obstructing vegetation on search cost effectiveness. The present restatement of the priority rating approach may be useful for searchers and search management interested in achieving more optimally effective searches.

About the Author

Warren Finlay is a Search Manager with Edmonton Regional Search and Rescue Association. He holds a PhD in Mechanical Engineering, and has published more than two hundred refereed archival journal papers in aerosol mechanics and fluid dynamics during his tenure as a Professor at the University of Alberta. He is a Fellow of the Royal Society of Canada, the Engineering Institute of Canada and the American Association for Aerosol Research.

References

Assaf, D. and Zamir, S. (1985) “Optimal Sequential Search: A Bayesian Approach”, Ann. Stat. 13(3):1213-1221.

Campbell, M. J., Cutler, S. L. and Dennison, P. E. (2024) “A singular, broadly-applicable model for estimating on- and off-path walking travel rates using airborne lidar data”, Scientific Reports 14:21838.

Chiacchia, K.B. , Billings, H. J., and Houlahan, H. E. (2025) “Head, Belt, Boots: Obtaining Consistent Probability of Detection in Human Visual Search”, J. Search and Rescue 8(1):1-27.

Costigan, R. (2024) “The Value of Searching by Voice in LandSAR”, J. Search and Rescue 7(1):1-29.

Cooper, D. C., Frost, J. R. and Robe, Q. R. “Compatibility of Land SAR Procedures with Search Theory”, Alexandria VA: Potomac Management Group, 2003.

Finlay, W. H. “Voice Calling Detection Range in Land Search and Rescue”, J. Search and Rescue 7(2):124-140, 2024.

Finlay, W. H. “Voice Calling Detection Distance with a Parabolic Microphone in Land Search and Rescue”, Wilderness and Environmental Medicine, accepted and in press, 2025.

Koester, R. J., Cooper, D. C., Frost, J. R., Robe, R. Q. “Sweep Width Estimation for Ground Search and Rescue”, Alexandria VA: Potomac Management Group, 2004.

Koester, R. J. (2008) Lost Person Behavior, dbS Productions LLC, Charlottesville, Virginia.

Koester, R. J., Chiacchia, K. B., Twardy, C. R., Cooper, D. C., Frost, J. R., Robe, R. Q. (2014) “Use of Visual Range of Detection to Estimate Effective Sweep Width for Land Search and Rescue Based on 10 Detection Experiments in North America”, Wild. Env. Med. 25:132-142.

Stoffel, B. C. (2017) Managing the Inland Search Function, National Association for Search and Rescue Centreville, Virginia.

Mansfield, G., Carlson, J., Merrifield, D., Rosenberg, E., Swanson, E., Templin, P. (2020) “A Pragmatic Approach to Applied Search Theory”, J. Search and Rescue 4(1):84-107.

First Approach to Implementing Search Theory in Mexico: Lessons Learned, Future Perspectives, and Public Policy Implications

Rafael López-Martínez[1,2,3], Jorge Belmont[4], Luis Gómez Negrete[5], Rosalba Vences Peña[5] Juan Alfonso Nicolás Martínez[6], Elsa Flores Alarcón[7]

1 Institute of Geology. National Autonomous University of Mexico. Mexico. CP: 04510

2 Rescate al Día. SAR Training Center. Insurgentes Sur 3493, Mexico City. CP:14020

3 Brigada de Rescate del Socorro Alpino de México A.C. Mexico City, Mexico

4 Collége Technique de Sauvetage en Montagne Mexico. Cuemanco 207, Mexico City, Mexico. CP:16034

5 National Commission of Search. República de Cuba 43, Piso 3 Colonia Centro (Área 1), Alcaldía Cuauhtémoc. Mexico City, Mexico. CP: 06000,

6 Medical Emergencies and Rescue Squad (ERUM). Chimalpopoca 137, Colonia Obrera, Mexico City, Mexico

7 Mexican Red Cross. Delegation Mexico City. Av. Ejército Nacional Mexicano 1032, Polanco, Polanco I Secc, Miguel Hidalgo, Mexico City, Mexico. CP:11510

Email ralopezm@geologia.unam.mx

https://doi.org/10.61618/CBVQ9155

Abstract

For the first time in Mexico, a large-scale search for a missing person was conducted using a Search Theory–based methodology. A strong Incident Command structure and effective inter-agency coordination allowed for detailed coverage of the search area. This framework enabled the calculation of key parameters—search effort, coverage, and probability of detection (POD)—which in turn provided the first quantitative assessment of search effectiveness in the country. These data supported authorities' decision-making on whether to continue or suspend the search. After three weeks, operations on the mountain concluded, and the case transitioned into a police investigation. The experience also revealed significant deficiencies in the current search and rescue system, highlighting the urgent need to improve training and methodologies to strengthen national search capabilities.

KEY WORDS: *Search Theory, Search and Rescue (SAR), Probability of Detection (POD), Incident Command System, Ajusco, Mexico*

Introduction

Search has been a fundamental challenge since the earliest stages of humankind, from locating animals for hunting to searching for missing people and objects. The formal mathematics of search theory, however, was only developed during World War II to support the search for enemy submarines. The pioneering works of Koopman (1946, 1980) laid the theoretical foundations of the field. These concepts were rapidly adopted and incorporated into search and rescue (SAR) manuals, such as the *International*

Aeronautical and Maritime Search and Rescue Manual (IAMSAR, 1999) and continue to inform contemporary SAR practices.

Despite this, Cooper et al. (2003) reported that ground SAR groups have sometimes struggled to apply search theory effectively in real-world operations. Complementing the mathematical approach, Koester (2008) introduced a behavioral perspective, offering insights into how individuals typically react and make decisions when lost. This line of research opened new possibilities for ground SAR, enabling more detailed operational planning and a deeper understanding of human behavior in survival situations.

While many countries have incorporated search theory into standard SAR training, Mexico still faces delays in both formal instruction for SAR teams and in implementing search theory. In México, there is no formal program to train SAR groups. In fact, SAR operations primarily focus on Urban Search and Rescue and involve groups from the Navy, Army, and Police, as well as volunteer organizations such as the Red Cross. In the backcountry, Search and Rescue is more informal, with each group determining what training its members need. The absence of a national doctrine of SAR makes it highly heterogeneous in terms of knowledge and capability, and sometimes difficult to manage during incidents involving multiple groups. In that sense, Search Theory is one of the forgotten subjects of SAR teams in México. It is worth noting that few individuals are knowledgeable about Search Theory because they have sought training abroad, but implementation has so far been a long way off.

In México, SAR operations in the backcountry are led by two volunteer associations, Socorro Alpino and the Red Cross, as well as several other groups (mainly volunteers) that conduct mountain rescue and, in some places, are supported by mountain police (responsible for mountain safety against criminal acts). Despite the extensive experience of mountain rescue teams in Mexico, the implementation of clear incident command systems remains incomplete, while formal search theory and search cartography are absent. Groups usually use experience-based search methods, which solve most cases with relatively low complexity.

Ajusco volcano is one of the favorite places to hike in Mexico City, with high weekend attendance and incident rates. Most incidents can be classified as delayed people who underestimate the difficulty of the routes. Usually, searches in the Ajusco area do not pose a challenge for planning because routes are relatively clear and people are found within a few hours on or near alternative trails.

A milestone occurred on July 12, when AAMG, a 19-year-old student, was reported missing at the Ajusco volcano in Mexico City. This incident marked a turning point in searches in Mexico, resulting in the largest search in the country and the first to be based on search theory.

This was possible because of the adoption of the Conjunct Incident Command, along with the requisite knowledge and willingness to conduct research based on this methodology. In this sense, also for the first time, government authorities were able to use reliable statistical data for decision-making, highlighting the usefulness of search theory and the need for its routine implementation.

The main objective of this paper is to present a case study of the pioneering application of Search Theory during the largest search operation conducted in Mexico and to assess how this experience influenced authorities' recognition of the need to implement search theory in SAR operations, as well as its potential implications for public policy and for search and rescue planning, training, and governance in the country.

Method

The search for AAMG involved an extraordinary deployment of resources, with more than 2,500 personnel participating over a three-week period. The present study is a quantitative case analysis based on operational search-and-rescue (SAR) data collected and processed daily to support planning for subsequent search operations. This data was compiled and analyzed throughout the three-week operational period. The dataset includes GPS tracks, search-area assignments, and deployment records compiled by the Conjunct Incident Command.

For the initial search phase, we interviewed the missing person's parents and obtained the last known location of the subject's cellphone. Based on this information, we classified the case using Koester's (2008) general statistics and behavioral categories with the *Lost Person Behavior* application.
For cartographic analysis, we employed CalTopo in SAR mode. Several teams also used mobile applications such as Avenza, Wikiloc, and Strava for tracking purposes. Their data was exported in KML format and subsequently imported into CalTopo for integrated analysis.

The rapid initial search focused on the main hiking routes of the Ajusco area. Teams of six searchers were deployed to cover these trails as well as areas with a documented history of accidents and locations commonly associated with lost hikers.

Assumptions of the Detection Model

Several assumptions were made for the detection model. First, we assumed that the subject remained within the containment boundary defined by the Circuito Ajusco Road during the search period. This assumption was considered reasonable because the area is bordered by a heavily trafficked road, and it is likely that a missing person who reaches the road would be quickly detected.

Second, the model assumes independence of detection events across repeated passes. In this case, the probability of detection for one search party is treated as independent from that of another, since the teams consisted of different groups with varying levels of training and operational conditions.
Finally, sweep width was treated as constant across the search area.

In the initial modelling stage, criminal activity was excluded as a causal factor because information obtained from interviews and authorities did not suggest such a scenario.

Selection of Sweep Width

A constant spacing of 5 m between searchers was selected based on studies by Mansfield et al. (2020), previous operational experience in the area, and the clothing worn by the missing person. The planning team agreed to maintain the same spacing across different terrains because it was easier for searchers without SAR training to maintain consistent spacing and for team leaders to supervise alignment.

We also decided not to modify the spacing in terrain without vegetation. Although alpine grasslands and rocky summit areas appear visually open, they contain terrain features such as cracks and gaps between rocks that create blind spots and may reduce detection probability.

Search teams were organized into groups of seven people. Six members performed the line search at 5 m spacing, while the team leader supervised the process and ensured proper spacing and parallelism. Under these conditions, the statistical sweep width used in the model was 30 m.

Probability of Containment (POC) Assignment Process

The Probability of Containment (POC) assignment was based on the consensus of four search experts familiar with the area. These experts included experienced mountain guides and members of mountain rescue organizations who have participated in numerous SAR operations in the region. Two of them regularly guide mountaineering groups in the area, typically leading one or two excursions per week.

For the analysis, the experts used historical data, terrain analysis, and were briefly trained in the use of the *Lost Person Behavior* framework and the LPB application.

During a group meeting, the search area was divided into five smaller zones based on terrain characteristics and common patterns of recreational use. Each expert independently assigned a probability to each zone. The values were then averaged, followed by a group discussion to review the results and reach a final consensus.

Coverage (C) and Probability of Detection (POD) Calculations

Coverage (C) is defined as the ratio of search effort to search area and is dimensionless. For communication with authorities, coverage was presented as a percentage because it was easier to interpret during operational briefings. However, when calculating POD using the exponential search model, coverage was expressed as a proportion, consistent with standard search theory.

Because many tracks overlapped, we limited the count to a maximum of three overlapping tracks in the coverage calculation. This approach allows cumulative POD estimation while avoiding the overestimation of search effort due to excessive track overlap.

Given the relatively small size of the search area (11.62 km²) and the fact that tracks often covered different selected areas, we calculated the total effective coverage for the operation.

To estimate POD, we applied the exponential model (Koopman, 1946):

$$POD = 1 - e^{-C}$$

where C represents the coverage.

For comparison purposes, we also retrospectively applied the Cubic model, calculating the cumulative POD for three repeated searches:

$$POD_{cum} = 1 - (1 - POD_1)(1 - POD_2)(1 - POD_3)$$

Rest of the World (ROW)

The Rest of the World (ROW) was intentionally excluded from the initial modelling because the area is bounded by a heavily trafficked road (Circuito Ajusco), which serves as a containment boundary. Additionally, the case received significant attention on social media, making it unlikely that the subject could reach the road and remain undetected.

Data Limitations

Some data limitations resulted in conservative estimates of coverage and POD. The primary limitation was the lack of cartographic training among some participating search groups, which prevented the consistent recording of GPS tracks. To avoid calculation errors, we excluded all data with inaccurate or incomplete coordinate information. This decision resulted in the removal of approximately two-thirds of all recorded search tracks.

Similarly, drone and K9 searches were excluded from the quantitative analysis because reliable spatial records of their search paths were not available. Consequently, the calculated coverage and POD values likely underestimate the actual search effort.

General description of the area

The Ajusco is the highest mountain in Mexico City, reaching an elevation of 3,930 meters above sea level (masl) at 19.21235°N, -99.25743°W (Fig. 1). Two main hiking destinations dominate the area: *Cruz de Marquez* (3,923 masl) and *Pico del Águila* (3,839 masl). Hikers often traverse a connecting route between these two peaks. Access is possible from three primary points—*El Abrevadero, Albergue Alpino*, and *La Cantimplora*—with secondary trails linking these entry routes (Figure 1).

The Ajusco features a temperate climate, with mean annual temperatures ranging from 5°C to 12°C, and minimum down to -3°C. Precipitation varies between 200 mm and 1,800 mm, peaking in July (Arriaga et al., 2000). Vegetation follows an altitudinal gradient: dense forest at the base, transitioning to alpine grasslands, and ultimately giving way to sparsely vegetated zones near the summits.

Results

SAR teams were activated after receiving a report that a young woman had begun descending from *Pico del Águila* toward *Albergue Alpino* during the night. At some point, her light was reported to have disappeared. This information could not be confirmed through a direct interview, as the individual who informed *Albergue Alpino* provided no personal details and could not be located. This represented the first difficulty in compiling reliable information.

The case quickly gained wide visibility on social media, where multiple and sometimes contradictory versions obscured the facts. Narratives ranged from her being alone on the mountain to joining a hiking group to waiting for a friend at the summit until 20:00 hours before starting her descent, after someone allegedly advised her that it was too late and too dark.

The only verifiable information came from the last position of her phone, retrieved by her brother at *Pico del Águila.* This point was established as both the Last Known Point (LKP) and the Initial Planning Point (IPP) for the search. The suspected ascent route was *La Cantimplora – Cruz de Marquez – Pico del Águila* (Figure 1)

For the initial operational phase, the Search Area was delimited by the Ajusco circuit road, which borders the volcano and served as a containment zone. The planning assumption was that the missing person's disappearance was not related to criminal activity.

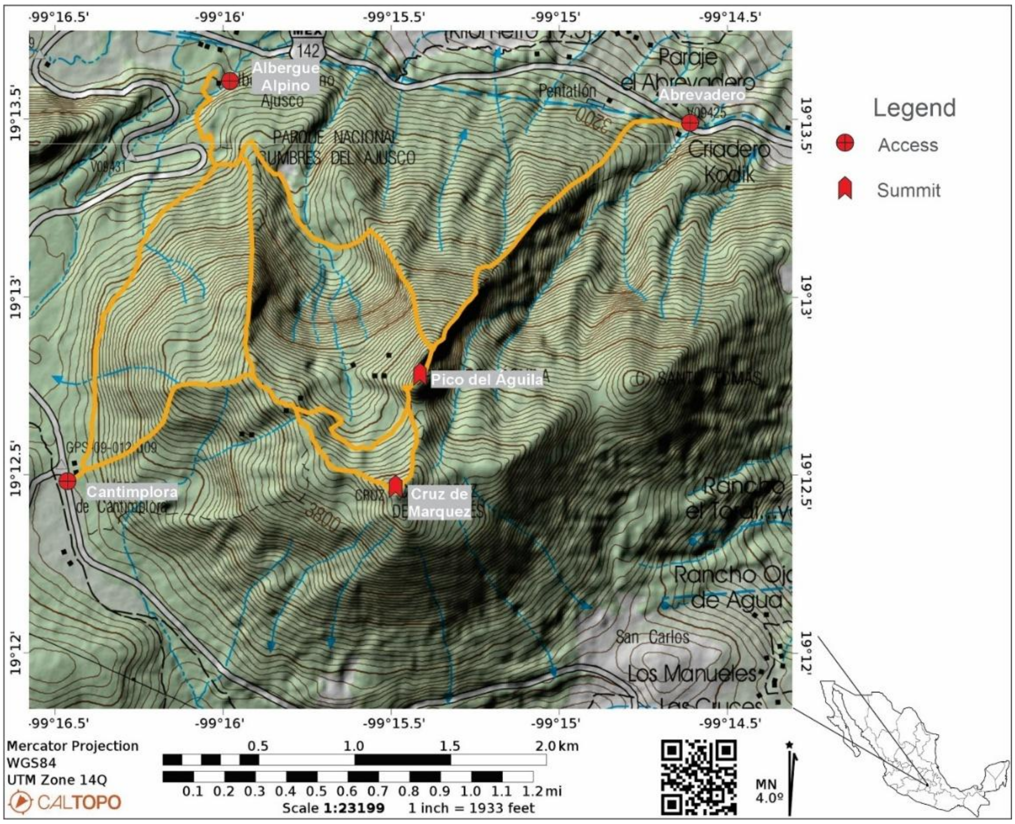


Figure 1: Location of the Ajusco Volcano in Mexico City. Three main access points are commonly used for hiking: Abrevadero, Albergue Alpino, and La Cantimplora. The volcano features two principal summits—Cruz de Márquez and Pico del Águila—each served by distinct trails.

Interviews with AAMG parents revealed that she had only recently begun participating in hiking activities and had limited experience in the Ajusco area. However, she had visited the mountain at least twice before. According to Koester's (2008) classification, she falls into the "Hiker" category. This group is characterized by a tendency to make errors at decision points, representing 56% of recorded cases. Based on this classification, we considered three initial scenarios:

1. Descent with navigation errors. AAMG may have begun her descent and become lost at one or more decision points. Within this scenario, two possibilities were identified: (a) taking the route toward *Abrevadero*, or (b) heading toward *Albergue Alpino*. Both alternatives involve multiple decision points but a general downward path.
2. Disorientation and re-ascending. AAMG may have become disoriented and attempted either to relocate the main trail or to regain cell phone coverage by ascending to higher ground. This scenario would involve retracing portions of the ascent route and encountering several decision points along the way.
3. Accidental fall. AAMG may have fallen into a ravine adjacent to the trail.

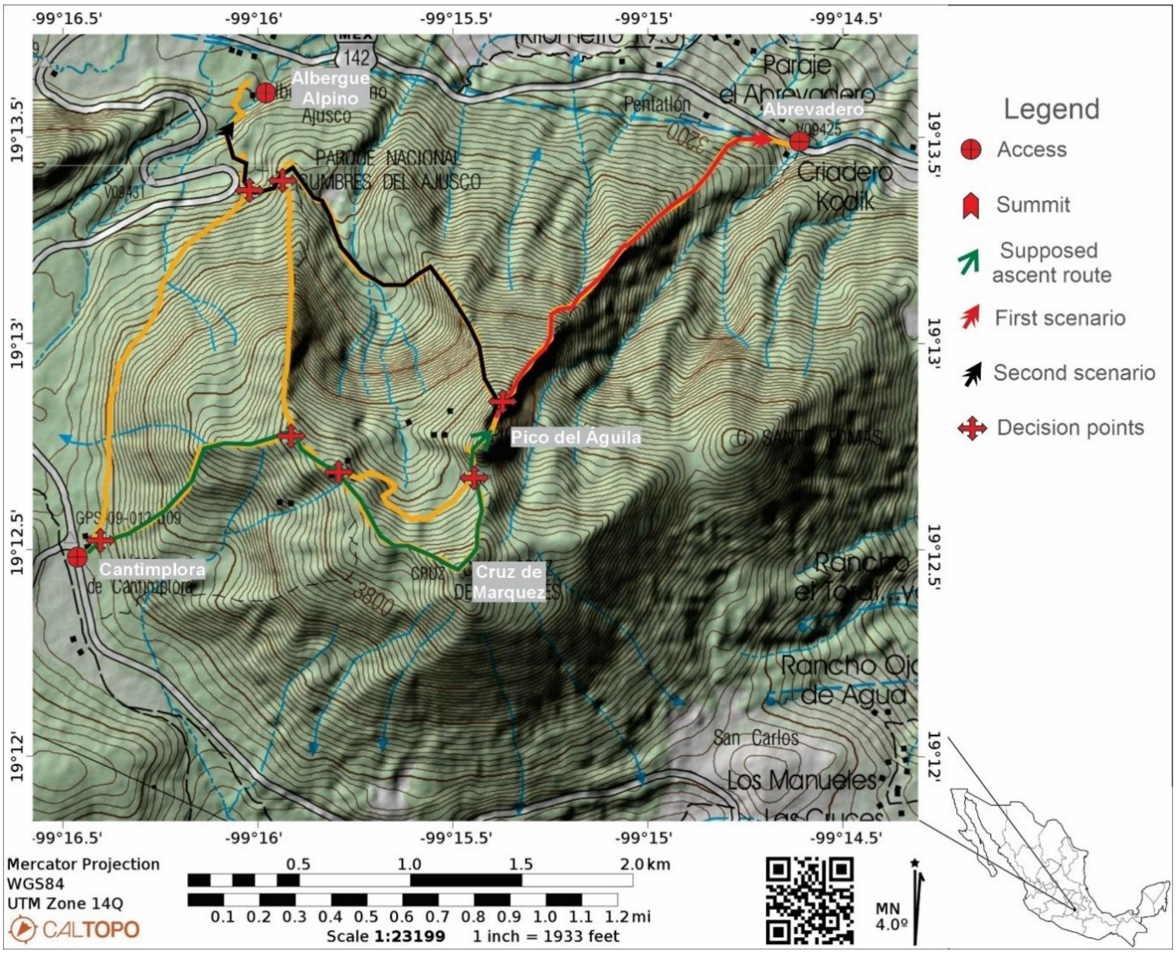


Figure 2: Analysis of routes and decision points. The presumed ascent route from La Cantimplora to Pico del Águila, including the Last Known Position (LKP), is shown in green. The path toward Abrevadero is shown in red, and the route to Albergue Alpino in black. Blue arrows indicate the location of ravines and watercourses.

Five search areas were identified, and for each, we calculated the Probability of Containment (POC) and Probability Density (Pden). The total search area covered 11.63 km². (Figure 3)

Area 1 (2.37 km²; POC = 60%; Pden = 25.3): The most popular hiking zone in Ajusco, with numerous small trails leading to both *Abrevadero* and *Albergue Alpino*. Historically, most incidents of lost hikers have occurred here, often when individuals follow side paths descending into deep ravines. This area also corresponds to witness testimony suggesting that AAMG was descending toward *Albergue Alpino* before disappearing.

Area 2 (1.0 km²; POC = 15%; Pden = 15): This scenario assumes AAMG attempted to reorient herself or find cell phone coverage by ascending. The parents reported that her last message originated from *Pico del Águila*. However, given the demanding ascent, this area was considered less probable than Area 1.

Area 3 (1.46 km²; POC = 10%; Pden = 6.8): Characterized by multiple firebreak gaps that can cause navigational errors if hikers attempt to return via the ascent route toward *Cruz de Marquez*. Accessing this area requires a strenuous climb from *Pico del Águila* to *Cruz de Marquez*, with a positive elevation gain of more than 166 m and slopes ranging from 30° to 60°.

Area 4 (4.67 km²; POC = 10%; Pden = 2.14): This zone offers direct visibility of populated areas and roads. It begins with an alpine grassland and includes trails and firebreaks that could be used for descent.

Area 5 (2.13 km²; POC = 5%; Pden = 2.34): A difficult-to-access area with steep terrain and deep ravines. No established trails or historical SAR incidents exist in this zone, though an unintended descent is possible.

At this stage, the “Rest of the World” (ROW) category was not included in planning, as the search area was bounded by a road encircling the volcano. In any direction, a descent would eventually intersect this road, where detection would be highly likely. This assumption excluded criminal activity. As the search evolved, however, the ROW concept gained greater importance.

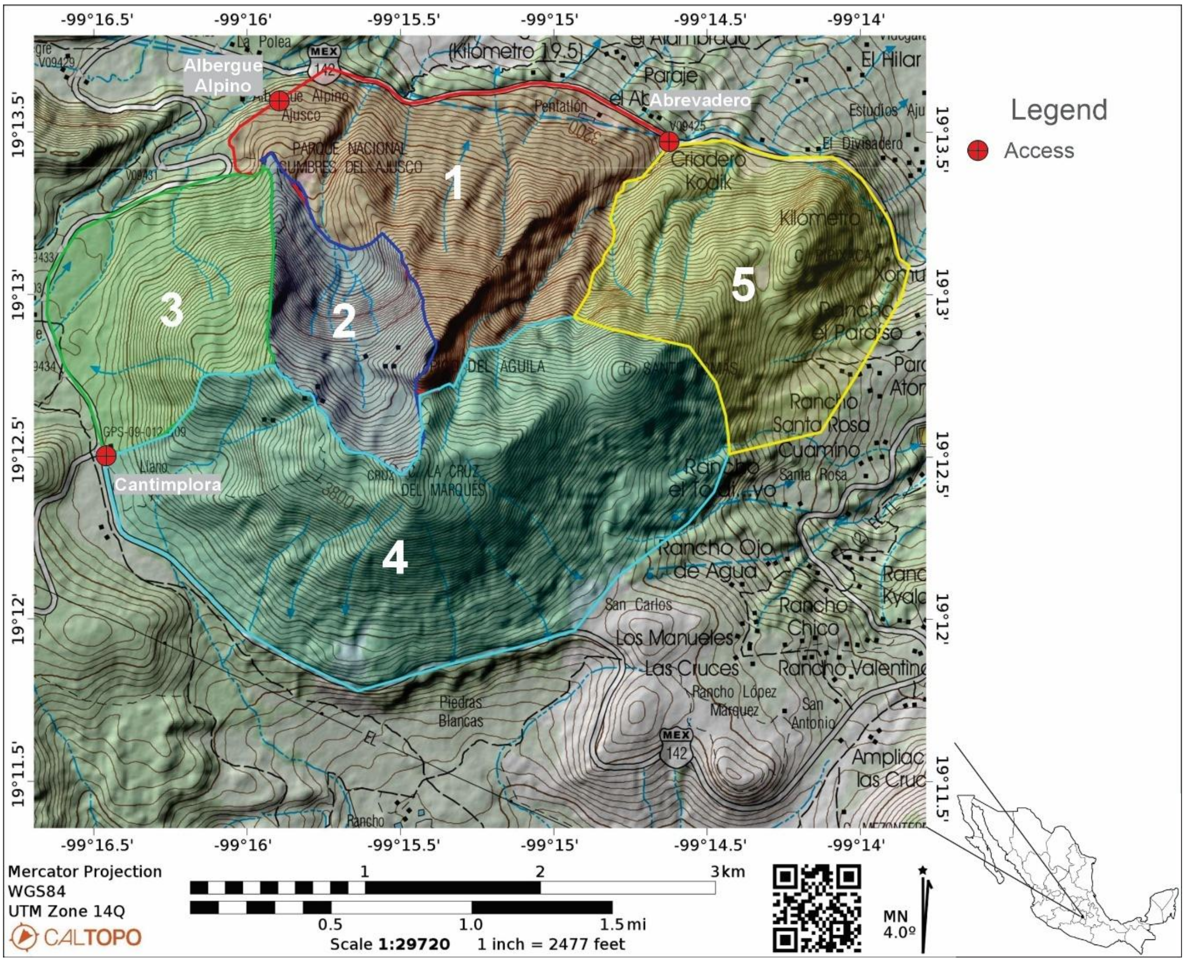


Figure 3: Delimitation of the five search areas. Areas are labelled 1 through 5 according to descending

Probability of Containment (POC)

On the second day, all possible trails had been searched at least twice, prompting a shift to a more detailed strategy with larger groups. The operation extended over three weeks and involved more than 2,500 people, three K9 teams, multiple drones, and helicopter coverage. Despite these efforts, no positive results or clues were obtained.

Subsequent statistical analysis provided insights into the quality and effectiveness of the search. This information served as a critical decision point for determining whether to continue with additional resources and strategies or to suspend operations.

Statistics of the Search

As Frost (1997) states: “The goal of search planning is to maximize the probability of success.” Following this principle, we analyzed the Probability of Success (POS) in relation to two key variables and a measurement that not only estimates the likelihood of success but also reflects the effectiveness of the search. This last element became especially relevant in the final stages of the mission.

$POS = POD \times POC$

Where:

POS: Probability of Success

POD: Probability of Detection

POC: Probability of Containment

Figure 4: Details of the search in the Ajusco. (A) Three levels of vegetation cover. The upper zone is almost barren, exposing bare rock. The middle zone features alpine grass interspersed with trees. The lower zone consists of dense forest. (B) Systematic search formation with a 5 m separation between searchers.

POD depends on multiple factors, including sweep width, search effort, and environmental conditions. For this search, we selected a sweep width (W) of 5 meters, following the studies of Mansfield et al. (2020), our previous operational experience in the area, and the high-visibility clothing worn by the missing person (as confirmed by the last available photograph at *Cruz de Márquez*, shared on Facebook by other hikers).

The vegetation gradient in Ajusco complicated this estimation: dense forest at the base, alpine grasslands above the tree line, and bare rock near the summit. In our mapping, each track corresponds to a 30 m sweep width (a team of six searchers spaced 5 m apart) (Figure 4). As previously noted, the Ajusco is encircled by a road (*Circuito Ajusco),* which served as the containment boundary.

The total search area (A) was 11.63 km², and the cumulative search distance (L), based on recorded tracks, was 370.23 km. Since the area is relatively small, several tracks crossed more than one designated search zone. (Figure 5)

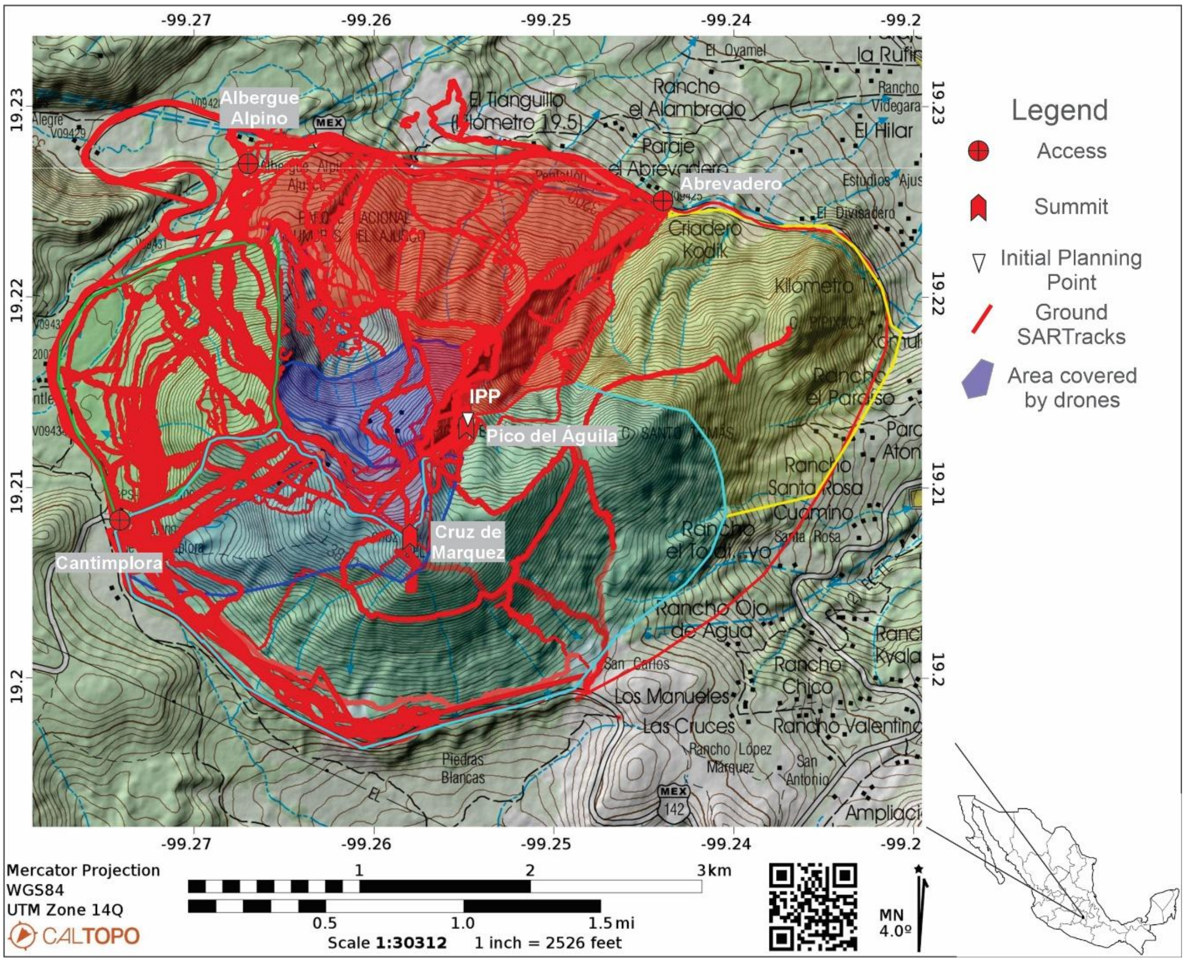


Figure 5. The cartographic base of the AAMG search shows plotted tracks of the main SAR groups and drone coverage. Approximately two-thirds of the tracks are missing from the map, as several groups were unable to record their routes.

Search effort (Z) was calculated as (Cooper, 2003):

Z= W*L

W= 0.03 km

L= 370.23 km

Thus Z=11.1069 km^2

Coverage (C) was estimated as:

C= (L(m)*W(m))/A*100

C: Coverage

L: Search distance

W: Sweep width

A: Search area

Resulting in a coverage of 94.6%

According to Frost (1999), the POD is defined as “the conditional probability of detecting the search object if it is in the area (segment) searched at the time of the search.” POD was therefore calculated using the equation:

$POD=1-e^{-C}$

Yielding a POD of 61.18%.

Discussion

The search for AAMG lasted three weeks, mobilized approximately 2,500 people, and became the most extensive search ever conducted in Mexico City—and, to our knowledge, in the country. Following a detailed analysis, the case was transferred to a police investigation. Nonetheless, the joint efforts of multiple entities operating under a strong Incident Command structure, together with the first application of search theory in Mexico, provided valuable insights for strengthening the national search and rescue system and informing the development of more effective public policies.

The application of search theory provided, for the first time, reliable data on coverage and probability of detection (POD) for decision-making authorities. This allowed authorities to determine whether to continue the search within the defined area or to expand the scope to include the "rest of the world," focusing on the possibility of criminal involvement.

It should be noted, however, that the calculated POD values are likely underestimated. Only one-third of the search tracks are represented on the final map, excluding several K9 searches, specialized drone missions, and aerial operations. These teams provided only approximate search areas, which prevented their inclusion in the calculations despite the substantial effort involved. Similarly, although Areas 4 and 5 were intensively searched, the absence of recorded tracks required us to estimate POD values by consensus, as recommended by Frost (2000) and Mansfield et al. (2020).

While POD was calculated using the classical exponential model during the operation, recent studies (Koester, 2020) suggest that the inverse-cube model provides greater accuracy for daytime ground searches. Using this approach, the estimated POD increases from 61% to 74%. Moreover, cumulative POD was calculated only for the hasty searches conducted on main trails, which were independently searched at least three times in accordance with Koester (2008).

Similarly, variations in sweep width may affect coverage and POD results; for example, a −20% variation yields a POD of 53.4%, while a +20% variation yields a POD of 68.2%.

It is also important to note that, in the exponential model used in the present study, if coverage (C) equals 1 (100%), the POD is approximately 63.2%. This reflects the fact that the model accounts for imperfections in real-world detection.

Beyond the quantitative results, the operation revealed critical weaknesses in the Mexican search system. Most groups lack formal training in SAR, including search theory, not only in planning but also in executing systematic search patterns, navigation, and basic cartography. This deficiency often resulted in inaccurate or misplaced area assignments. Furthermore, the lack of proper training prevented several groups from accurately recording search tracks or plotting them on the operational map. As a consequence, approximately two-thirds of the search paths could not be used in the modeling process or in the calculation of search quality.

In addition, several groups lack basic training in the Incident Command System (ICS), which resulted in confusion and operational difficulties during the incident.

Perhaps the most serious obstacle was related to group dynamics. Some teams distrusted the work of others, insisted on re-searching areas that had already been covered multiple times, and followed personal intuitions about the possible location of the missing person. For example, the route from Pico del Águila to El Abrevadero was searched by eleven different groups—always along the same trail—resulting in an oversaturation of effort without generating new operational information.

The search for AAMG represents an unprecedented attempt in Mexico to combine all available resources with a scientific search methodology. At the same time, it revealed significant weaknesses within existing SAR groups. Based on the data obtained during the operation, we initiated discussions with national authorities to promote the implementation of several public policy measures. Perhaps the most important of these is the urgent need to establish a National SAR System capable of coordinating efforts across institutions and volunteer groups. Another key issue currently under discussion is the need for formal training programs and for the development of a ground SAR manual in Spanish that would allow rescue groups to apply the basic principles of search theory and operational coordination.

Finally, as a direct outcome of the search and the detailed cartographic work conducted during the operation, authorities have begun developing a management plan for the Ajusco area. This initiative seeks to improve safety conditions by enhancing trail signage, strengthening cell phone and radio communication coverage for hikers, and improving operational capabilities for future rescue missions.

Limitations

The present study has several limitations. Only about one-third of the participating groups were able to record their routes. Thus, only this portion was available for analysis, excluding important contributions from drone operations, K9 teams, and aerial searches, resulting in underestimates of coverage and POD. Additionally, the lack of formal training in Search and Rescue groups diminished the accuracy of the assigned segments and areas.

Future Research

We are developing a formal training program for Search and Rescue groups in Mexico, and we expect that improved training will facilitate the application of search theory in future operations.

Conclusion

The search for AAMG marked the first large-scale application of Search Theory in Mexico. The implementation of a strong Incident Command structure, collaboration among multiple agencies, and full access to government resources enabled the most extensive search ever conducted in the country and expanded collective knowledge of SAR practices. For the first time, it was possible to calculate search parameters, such as search effort, coverage, and probability of detection (POD) and to use them in assessing both search areas and overall effectiveness. These parameters provided decision-making authorities with reliable data to determine whether to continue or suspend the operation.

High levels of coverage, search effort, and POD were decisive in shifting the operation beyond the Ajusco and into a police-led investigation. Although the calculated POD values were underestimated due to incomplete track recording, the operation still yielded valuable insights.

The aforementioned results demonstrate to the authorities the potential of the Search Theory to improve SAR effectiveness and its usefulness as a powerful tool in the decision-making process and in communicating with interagency and to the public.

After the operation, several meetings were held with the National Commission of Search and political authorities to conduct a detailed review of the results and deficiencies and to improve future operations.

Some of the opportunity areas were the need for a National SAR system to coordinate all efforts during an action. Also, the need for formal training of the groups in incident command, search theory, basic cartography, and land navigation. Another important conclusion derived from that is the need for a ground SAR manual in Spanish for national training.

While these aspects are being implemented, the authorities have begun a management plan for the Ajusco area that includes increased security, the implementation of rescue management plans, signage for routes to facilitate tourist navigation, and work to improve future telephone and radio signals.

The search for AAMG represents a turning point for ground SAR in Mexico. Beyond the unprecedented scale of the operation, it marked the first implementation of a scientific search methodology based on search theory and highlighted the importance of incorporating such approaches into the future development of a national SAR system.

Acknowledgements

We would like to thank all the agencies, search-and-rescue teams, and individuals who participated in this operation. We also thank the anonymous reviewers for their time and valuable comments, which significantly improved the quality of this manuscript. Finally, we thank the editorial team of the Journal of Search and Rescue (JSAR) for their assistance and dedication in the processing of this manuscript.

About the author

Rafael Lopez Martinez is a full-time researcher at the Institute of Geology, UNAM, and a Search and Rescue (SAR) operator with more than 20 years of experience in search and technical rescue. He is the founder of Rescate al Día, SAR Training Center, a school dedicated to training in rope rescue, public safety diving, wilderness aid, and related fields. He also collaborates with several government agencies in rescue operations and in the evaluation and management of geological risks. Rafael has published several scientific papers and is a coauthor of the Underwater Caving Rescue Manual of the Mexican Federation of Underwater Activities (FMAS).

References

Arriaga, L., J.M. Espinoza, C. Aguilar, E. Martínez, L. Gómez y E. Loa (coordinadores). 2000. Regiones terrestres prioritarias de México. Comisión Nacional para el Conocimiento y Uso de la Biodiversidad, México.

Cooper DC, Frost JR and Robe RQ (2003) Compatibility of land SAR procedures with search theory. Technical Report DTCG32-02-F-000032. Department of Homeland Security, U.S. Coast Guard Operations, Washington, DC, 183 pp

Frost J.R. Principles of search theory, parts I and II: detection, effort, coverage, and POD. Response 1999; 17, 1–15.

Frost, J. R. (1997). The theory of search: a simplified explanation. Soza Limited.

Frost, J.R. (2000) Principles of Search Theory – Part I: Detection. Response, 17(2) 1-7.

International Maritime Organization and International Civil Aviation Organization (IMO/ICAO).(1999a). International Aeronautical and Maritime Search and Rescue Manual: Vol. I. Organization and Management. London/Montreal: the International Maritime Organization (IMO) and the International Civil Aviation Organization (ICAO).

Koester, R. J. (2008). Lost person behavior: A search and rescue. dbs Productions LLC.

Koester, R. J. (2020). Land Search and Rescue Probability of Detection: New sweep widths values, correction factors, models, and detection model validation. Journal of Search & Rescue Volume, 4(1).

Koopman, B. O. (1946). Search and Screening (OEG Report No. 56, The Summary Reports Group of the Columbia University Division of War Research). Alexandria, VA: Center for Naval Analyses.

Koopman, B.O. (1980). Search and screening: general principles with historical applications. Revised. New York, NY: Pergamon Press.

Mansfield, G., Carlson, J., Merrifield, D., Rosenberg, E., Swanson, E., & Templin, P. (2020). A Pragmatic Approach to Applied Search Theory. Journal of Search & Rescue, 4(1).

Sherlock Bayes: The Curious Case of the Vanishing Posterior

Surajit Dutta

Email ralopezm@geologia.unam.mx

https://doi.org/10.61618/LLSH2304

Abstract

Search and rescue (SAR) planning repeatedly confronts the same operational challenge: how to allocate limited search effort across sectors when information is incomplete and detection is imperfect. This paper presents a Bayesian decision-support framework for SAR tasking that maintains a spatial belief map over a discretized search region (interpretable as Probability of Area, POA) and updates it after each unsuccessful search using Bayes' theorem, explicitly accounting for Probability of Detection (POD) that may vary by terrain, access, and sensing modality. At each step, the framework prioritizes the sector maximizing POA × POD, i.e., the sector with the highest immediate Probability of Success (POS). The title's "vanishing posterior" refers to a key operational insight: when POD < 1, a negative result does not drive a sector's POA to zero, formalizing why re-search decisions remain rational in low-detectability terrain. The paper further outlines practical extensions relevant to SAR: (i) terrain-aware POD models, (ii) informed priors derived from geospatial or historical cues, (iii) belief propagation for moving subjects, and (iv) a POMDP framing for longer-horizon planning under explicit costs. Proof-of-concept simulations illustrate how POA concentrates over time and how imperfect detection slows clearance of difficult terrain. Limitations of grid-based simulations are acknowledged, and a worked hypothetical SAR example demonstrates how the framework can support sector prioritization and allocation of effort in planning practice.

KEY WORDS: *Bayes' theorem; Search and rescue (SAR); Probability of Area (POA); Probability of Detection (POD); Probability of Success (POS); Imperfect detection; Terrain-aware search; Belief updating; Dynamic subject modelling*

---

1. Introduction

1.1. Why this problem matters in SAR tasking

SAR operations must make sequential tasking decisions under uncertainty: where to assign a team next, whether to re-search a sector, and how to distribute effort across terrain when subject location is unknown and detection is imperfect. In the field, a negative result rarely "clears" an area absolutely; instead, it provides evidence whose strength depends on how thoroughly the area was searched and how detectable the subject would have been under the conditions. This motivates a decision-support approach that (i) represents uncertainty explicitly, (ii) updates beliefs as evidence accumulates, and (iii) links those beliefs to a transparent tasking rule.

This manuscript develops such a framework by maintaining a probability distribution over sectors and updating it after each negative result using Bayes' theorem—capturing the operational reality that not found is informative but not definitive when POD is less than 1. The aim is not to replace SAR expertise, but to provide a principled and auditable way to aggregate evidence and justify prioritization as a mission evolves.

1.2. A SAR-native glossary: POA, POD, POS

To keep the analysis aligned with SAR planning language, we use the following mapping throughout:

• Sector / grid cell: a taskable search segment (the unit of assignment).

• POA (Probability of Area): the probability the subject is in sector i, written $b_t(i)$ at time t (1).

• POD (Probability of Detection): the probability of detecting the subject if the subject is in sector i and the sector is searched with a specified resource/technique, written p_i (1).

• POS (Probability of Success): the probability a search of sector i succeeds immediately: $POS_t(i) = b_t(i)\, p_i$. This is the immediate expected detection probability and a natural basis for prioritization (1).

This POA–POD–POS mapping allows the Bayesian belief map to be read directly as an operational prioritization surface and makes the method interpretable to a mixed practitioner–academic readership.

1.3. What is the "vanishing posterior," and why it matters operationally

A common misconception in practice is that an unsuccessful search implies a sector is "empty." Under imperfect detection, Bayesian updating formalizes the opposite: after searching sector j and not finding the subject, the posterior POA of j decreases, but does not vanish unless POD is perfect ($p_j = 1$). This provides a quantitative rationale for re-searching difficult sectors (dense forest, poor visibility, inaccessible terrain) where POD is low and a negative result should be weighted cautiously.

1.4. Paper objective and scope

Objective. The primary objective is to present a mathematically correct, SAR-interpretable Bayesian framework for sequential search tasking that updates POA using negative search outcomes and prioritizes future tasking using POS.

Scope. We demonstrate proof-of-concept behaviour using grid-based simulations and then discuss how the same framework can be strengthened for real-world deployment via terrain-aware POD calibration, informed priors from SAR intelligence inputs, moving-subject models, and longer-horizon planning formulations.

1.5. Contributions

This paper contributes:

Methodological contributions

1. A clear Bayesian belief-update rule for negative search outcomes under imperfect detection, with explicit assumptions and normalization.

2. A POS-based sector selection rule (maximize POA × POD) that is transparent and directly interpretable for tasking decisions.

SAR-facing contributions

3. An operational interpretation of belief updating—how POD and terrain influence sector prioritization, re-search decisions, and allocation of effort.

4. A worked hypothetical SAR example showing how the framework might be applied in practice.

5. A limitations and deployment pathway section specifying what additional data, calibration, and validation are required before operational use.

How this article differs from SAROPS / existing planning: (i) closed-form sector update, (ii) explicit re-search logic under POD<1, (iii) field-deployable spreadsheet/briefing workflow, (iv) minimal assumptions stated as a ‘model contract’.

1.6. Roadmap

Section 2 positions the work within SAR-oriented Bayesian and operational search-planning literature. Section 3 formalizes the problem using POA/POD language. Section 4 derives the Bayesian update and the POS tasking rule. Section 5 presents the algorithm and flow logic. Sections 6–9 introduce terrain-aware POD, informed priors, moving-subject extensions, and a POMDP framing for longer-horizon planning. Section 10 provides proof-of-concept simulation results and visualization. Section 11 presents a worked hypothetical SAR example. Sections 12–13 discuss operational implications and limitations, respectively, before concluding.

2. Related Work (Operational / Practitioner-Focused)

Search planning in search and rescue (SAR) is built around a small set of operational probability concepts—where the subject is likely to be, how detectable they are under current conditions, and how to allocate scarce effort to maximize the chance of finding them quickly. U.S. Coast Guard guidance summarizes the scientific basis behind these ideas and emphasizes that improved planning methods primarily refine how uncertainty, detectability, and prior searches are integrated into decisions. This section synthesizes (i) the operational POA/POD/POS framework used by SAR planners, (ii) Bayesian updating as implemented in real decision-support tools (notably SAROPS), and (iii) land/WiSAR developments that highlight terrain-driven variability in detectability and the role of GIS-based priors (5,6).

2.1 Operational SAR search theory: POA/POC, POD, POS, and the meaning of a “negative result”

A core operational principle is that SAR success depends on searching areas that actually contain the subject and using search methods that can detect the subject given local conditions. The U.S. Coast Guard’s Theory of Search formalizes this using probability maps and detection models, centering on (i) Probability of Area/Containment (POA/POC), (ii) Probability of Detection (POD), and (iii) Probability of Success (POS) as a practical measure of search effectiveness (1).

Foundational context. The general probabilistic foundations of search theory (including detection functions and the logic of allocating effort under uncertainty) originate in Koopman’s classic synthesis, and have been further developed in standard treatments such as Stone’s and Washburn’s texts. (2–4)

Crucially, operational doctrine treats “not found” as evidence, not proof of absence: the impact of a negative result depends on detectability and coverage. Coast Guard guidance develops detection models (including sweep width and related constructs) to quantify how much confidence should be gained—or not gained—after an unsuccessful search, motivating why rigorous planning can improve allocation and sequencing (8,9).

2.2 Decision-support in practice: CASP → SAROPS and Bayesian incorporation of unsuccessful searches

Operational SAR planning has a strong tradition of computerized decision-support, especially in maritime contexts. The Search and Rescue Optimal Planning System (SAROPS) is the U.S. Coast Guard’s operational tool for maritime search planning and is described as the successor to earlier Bayesian planning systems (CASP). SAROPS uses Monte Carlo/particle-based simulation to produce probability distributions (maps) of object location and incorporates unsuccessful searches in a Bayesian fashion to form posterior distributions that drive subsequent planning cycles (5,6).

A practitioner-relevant aspect of SAROPS is that detectability is not a single constant: SAROPS models probability of detection using sensor/platform-specific functions (e.g., lateral range curves), and it updates particle weights based on the probability that a Search and Rescue Unit would have failed to detect an object under environmental conditions. Coast Guard descriptions frame SAROPS as maximizing probability of success while accounting for drift, environment, and effects of previous searches (5,6).

The present manuscript can be seen as a deliberately simplified, transparent analogue of these operational cycles: maintain a POA-like belief surface, model POD per sector/terrain, update POA after unsuccessful search, and prioritize tasking using an immediate POS criterion.

2.3 Land SAR and WiSAR: calibrating POD in the field and avoiding "one-size-fits-all detectability"
In land and wilderness SAR (WiSAR), detectability varies dramatically with terrain, vegetation density, lighting, clue visibility, and searcher capability. Empirical work in the Journal of Search and Rescue demonstrates this explicitly: Koester reports sweep-width and detectability changes between daytime and night searching and shows how coverage–POD relationships can be validated against field experiments, underscoring that POD is strongly context-dependent and must be treated as a modeled quantity rather than assumed uniform (8,9).

Operational reviews sponsored by U.S. Coast Guard / DHS have also noted that land SAR procedures have not always incorporated formal search theory consistently and argue for standardized methodologies that connect probability maps, POD estimation, and effort allocation to operational decision-making (7).

2.4 Bayesian GIS and evidence fusion for SAR planning (worked-case orientation) (11)
A recurring practical problem is that initial probability maps often combine multiple weak or heterogeneous sources: last known position (LKP), witness reports, cellphone pings, trail networks, prior search tracks, terrain barriers, and subject-profile expectations. Practitioner-oriented case work in JSAR shows how heterogeneous evidence can be integrated into a probability search map using Bayes' theorem, directly supporting resource prioritization under uncertainty.

This is especially relevant for the present paper's emphasis on informed priors: operationally, priors are rarely uniform, and the quality of early tasking depends on how effectively planners encode and update these priors as new information arrives. SAROPS documentation similarly stresses scenario-based construction of priors and Bayesian updating after unsuccessful searches (5,6).

2.5 Decision-support systems and the practitioner–research interface (why clarity matters)
A systematic review of decision-support in SAR notes that SAR is a multi-actor, multi-agency process where GIS and analytics are frequently used (particularly in land rescue), and that decision-support tools aim to improve timeliness and quality of decisions under complexity. This reinforces a key requirement for JSAR readership: methods must remain interpretable and operationally grounded so probability outputs can be used in briefings, tasking meetings, and documentation of rationale (12).

2.6 Positioning of the present work
Unlike SAROPS' Monte Carlo/particle re-weighting, this sector-level belief map deliberately trades fidelity for transparency and auditability—POS = POA×POD can be read and briefed directly, and each update can be justified in tasking meetings and after-action reviews without a black-box step.

Relative to the practitioner-facing literature above, this paper positions its contribution as:

1. SAR-native belief updating under imperfect detection: a clear Bayesian update for negative search outcomes that matches POA/POD interpretation and explains why POA does not vanish when POD < 1.

2. Terrain-aware POD as an explicit planning lever: a sector-dependent detectability layer motivated by land SAR evidence enabling realistic interpretations of clearance and re-search decisions.

3. Informed priors and evidence fusion consistent with practice: a workflow that accommodates GIS-based cues and heterogeneous evidence, consistent with practitioner case studies and scenario-based maritime planning approaches.

4. A transparent tasking heuristic aligned with POS thinking: a prioritization rule based on immediate POS (POA×POD) with a clear path to richer optimization later.

SAROPS is a high-fidelity particle system; this paper provides a closed-form sector-level update + spreadsheet-ready workflow + explicit re-search logic under POD<1.

3. Problem Formulation (SAR tasking under imperfect detection)

This section formalizes the SAR planning cycle as a sector-tasking problem under uncertainty, using the operational concepts POA/POC, POD, and POS that underpin modern SAR search planning and decision support (1).

3.1 Search region, sectors, and state of the subject

We represent the search region as a set of taskable sectors (segments) indexed by $I = \{1,2,\ldots,C\}$, which may be a rectangular grid, an irregular tessellation, or operationally defined polygons used in mission planning. Probability maps over such segments are standard in search planning.

Hidden state (subject location). Let the (unknown) location of the subject at time t be a random variable $X_t \in I$. In the static subject case, $X_t = X_0$ for all t. In the moving subject case, X_t evolves according to a motion/transition model (Section 8).

3.2 Operational probabilities: POA (belief), POD (detectability), POS (tasking success)

1) POA / belief. At decision step t, the planning team maintains a belief distribution (probability map) $b_t(i)=P(X_t=i)$, with $\Sigma_i b_t(i)=1$.

2) POD. If sector i is searched using a specified resource/technique under stated conditions, the probability of detecting the subject conditional on the subject being in i is $p_i \in [0,1]$.

3) POS for a single tasking. If we task a search in sector i at time t, the probability of immediate success is $POS_t(i)=b_t(i)p_i$.

3.3 Actions (tasking decisions) and observations (found / not found)

At each decision step t, the search planner chooses an action $a_t \in I$, meaning “task a search in sector a_t.” After executing the search, the team observes $O_t \in$ {Found, NotFound}. Because detection is imperfect, NotFound is not conclusive evidence of absence.

3.4 Observation model (imperfect detection made explicit)

3.4.1 Model contract (assumptions for the Bayes update)

To keep the belief update transparent and audit-friendly for SAR tasking, we adopt the following base observation model (extensions are noted in Appendix B8 and Section 13).

Sector-local information: a search tasking provides information only about the searched sector; other sectors change only through renormalization of POA.

Imperfect detection: if the subject is in the searched sector j, the search detects them with probability p(j) for that specific tasking (resource × time × conditions).

No false positives (base model): Found is not generated when the subject is not in the searched sector; ambiguous/partial observations are treated as an extension.

Operational note: many real searches can have cross-sector visibility or uncertain/partial clues. The base model is used here because it yields a simple, explainable Bayes update; richer observation models can be substituted without changing the overall POA/POD/POS workflow.

When a tasking provides information beyond the searched sector (e.g., line-of-sight from a ridgeline, clue drift, or sensor spillover), replace the sector-local likelihood with a non-local detection function $Z_j(i) = P(\text{Found} \mid X = i, a = j)$; the corresponding Bayesian update after Not-Found is given in **Proposition 3** (Appendix B8.1).

We adopt the standard imperfect-detection model:

• $P(O_t=\text{Found} \mid X_t=a_t, a_t)=p_{a_t}$.

• $P(O_t=\text{Found} \mid X_t\neq a_t, a_t)=0$.

Equivalently: $P(O_t=\text{NotFound} \mid X_t=a_t, a_t)=1-p_{a_t}$, and $P(O_t=\text{NotFound} \mid X_t\neq a_t, a_t)=1$.

Remark. When $p_{a_t}<1$, a negative result does not drive the posterior probability of that sector to zero; it reduces it—formalizing why re-search can be rational in low-detectability conditions.

3.5 Terrain and resource effects (where p_i comes from)

In practice, POD is not constant: it varies by terrain, weather, visibility, and resource type. We allow p_i to be sector-specific so terrain-aware and resource-aware detectability can be expressed directly and later modeled explicitly (Section 6).

3.6 Objective: what "optimal" means for SAR tasking

SAR planning goals are often described in two related ways:

1) Maximize probability of success within limited effort/time budget B.

2) Minimize expected time to detection E[T], where T is the first step at which Found occurs.

4. Bayesian Belief Updating and POS-Based Tasking

This section derives the Bayesian update after an unsuccessful search under imperfect detection and connects it to a transparent SAR tasking heuristic based on POS = POA × POD.

4.1 Bayes update after an unsuccessful search (Not-Found)

Notation for time indexing. Let $b_t(i)$ denote the planner's POA belief before tasking at decision step t, i.e., $b_t(i)=P(X_t=i \mid \text{history up to step } t)$. After executing the tasking at step t and observing the outcome, we write the posterior as $b_t^+(i)$. For static subjects ($X_{t+1}=X_t$), we carry $b_{t+1}(i)=b_t^+(i)$ into the next step.

Let the current belief be $b_t(i)=P(X_t=i)$. Suppose we search sector j (i.e., $a_t=j$) and observe Not-Found. Under the observation model: $P(\text{Not-Found} \mid X_t=j, a_t=j)=1-p_j$, and $P(\text{Not-Found} \mid X_t=i, a_t=j)=1$ for $i\neq j$.

Bayes' theorem gives the posterior after this observation:

$b_t^+(i)=P(X_t=i \mid \text{Not-Found in } j)= P(\text{Not-Found} \mid X_t=i, a_t=j)\, b_t(i) / P(\text{Not-Found in } j)$.

The normalizing denominator is:

$P(\text{Not-Found in } j)= (1-p_j)\, b_t(j) + \Sigma_{k\neq j}\, b_t(k) = 1 - p_j\, b_t(j)$.

Thus the posterior update is:

$b_t^+(j) = ((1-p_j)\, b_t(j)) / (1 - p_j\, b_t(j))$.

$b_t^+(i) = b_t(i) / (1 - p_j\, b_t(j))$ for $i \neq j$.

Static-subject carry-forward. When the subject is static, set $b_{t+1}(i) := b_t^+(i)$ and proceed to the next tasking decision. When the subject may move, Section 8 uses a predict–update cycle: propagate b_t^+ through a transition model to obtain the next prior, then apply the same Bayes update after each new search outcome.

4.1.1 Repeated unsuccessful searches of the same sector: closed form, clearance bounds, monotonicity, and sensitivity

Operational takeaway (re-search and clearance). In SAR tasking, repeated searches of the same sector are common—especially in low-detectability terrain. Under the imperfect-detection model, each additional Not-Found reduces (but does not eliminate) the sector's POA unless POD is perfect. What matters operationally is the rate of reduction: high-POD searches 'clear' a sector quickly, while low-POD searches only slowly reduce belief, making re-search and method substitution rational.

A planner-friendly way to see this is through odds. Let odds mean 'probability the subject is in the sector' divided by 'probability the subject is elsewhere.' Each Not-Found multiplies these odds by the miss probability $(1-p)$ for that tasking. This gives an intuitive clearance narrative suitable for briefings and re-tasking meetings; the exact closed form and clearance bounds are provided in Appendix D (Propositions 4–6).

Sensitivity to POD miscalibration. If POD estimates are off, the posterior can be too aggressive (overconfident clearance) or too conservative (unnecessary re-search). Sensitivity is often strongest early in the search and in low-POD terrain; hence POD calibration and documenting the basis of POD assumptions are operationally important. The derivative expression supporting this statement is given in Appendix D (Proposition 7; see the sensitivity derivation).

Planning note. If you need a concrete 'how many passes?' estimate for a clearance target, you can use the clearance-bound expression in Appendix D (Proposition 5) to translate a desired POA threshold into an approximate required number of re-searches at a given POD. This provides a principled way to justify continued searching (or a change of method) when terrain or conditions keep POD low.

Operational briefing phrasing. 'We searched this sector with POD p; a negative result reduces—but does not eliminate—the chance the subject is here. Because p is low/high, the reduction is modest/strong, so we should consider re-searching with a higher-POD resource or shifting effort according to updated POS.' This keeps the update interpretable while remaining faithful to Bayes' rule.

4.2 Operational interpretation: "clearance" depends on POD

Two consequences follow:

1) A negative result never clears an area completely unless POD is perfect. If $p_j<1$ and $b_t(j)>0$, then $b_{t+1}(j)>0$.

2) Higher POD produces stronger clearance for the same prior POA: as p_j increases, $b_{t+1}(j)$ decreases more sharply.

4.3 The POS tasking rule: maximize immediate probability of detection

The immediate probability of finding the subject by searching sector i at time t is $POS_t(i)=b_t(i)\, p_i$. Therefore, the simplest transparent tasking decision is: $a_t \in \arg\max_i (b_t(i)\, p_i)$.

4.4 Why the POS rule is a "myopic optimum" (and when it is enough)

Intuition on optimality. The POS-maximizing choice is exactly optimal in settings where (i) travel and switching costs are negligible or equal across sectors, (ii) each tasking consumes the same effort budget, and (iii) the only objective is immediate detection rather than information gathering for later. When these conditions do not hold (common in field SAR), POS remains a useful, auditable baseline, and the POMDP framing in Section 9 shows how to incorporate costs and lookahead without changing the belief-update logic.

The POS rule maximizes one-step success probability but does not explicitly plan multiple steps ahead (travel costs, future information gain, multi-asset scheduling). It remains valuable as an auditable, operationally interpretable baseline tightly coupled to Bayesian updates after unsuccessful searches.

4.4.1 A minimal optimality statement for POS

The POS tasking rule is often described as a myopic policy because it maximizes immediate probability of success rather than explicitly optimizing multi-step objectives. Under the base model, however, the rule is exactly optimal for the one-step objective of maximizing the probability of detection on the next tasking.

Proposition 1 (One-step optimality of POS). At decision step t with belief $b_t(i)=P(X_t=i)$ and sector-specific POD p_i for the chosen resource/technique, the action a_t that maximizes the probability of detecting the subject on the next tasking satisfies

$a_t \in \text{argmax}_i\, b_t(i)\, p_i$.

Equivalently, maximizing immediate detection probability is the same as maximizing $POS_t(i)=POA_t(i)\times POD(i)$. Detail proof is given in Appendix D(Proposition 1).

4.5 The complete SAR planning loop (task → update → re-task)

1) Start with a prior POA map $b_0(i)$.

2) At decision step t, compute $POS_t(i)=b_t(i)\, p_i$ for each sector i.

3) Task $a_t \in \text{argmax}_i\, POS_t(i)$.

4) If Found, terminate and report the location.

5) If NotFound, update to the posterior b_t^+ using Section 4.1 and renormalize.

6) Carry forward to the next step: for a static subject set $b_{t+1} := b_t^+$. For a moving subject, first predict the next prior using a motion model (Section 8), then continue.

4.5.1 Posterior after Found (Lemma 1)

Lemma 1. If a search of sector j returns Found, then $b^+(j)=1$ and $b^+(i)=0$ for all $i\neq j$.

Proof. Assuming the observation has nonzero model probability (e.g., $p_j>0$), Found can only be observed when X=j and the search is in j, hence the posterior mass collapses to j.

5. Algorithm and Implementation Details

This section presents an implementable SAR planning loop and explicitly corrects the flow logic: Found terminates and returns the location; Not-Found triggers a Bayesian update.

5.1 Overview: what the algorithm does in SAR terms

The algorithm maintains POA over sectors and uses POD to compute POS. After each tasking, it incorporates the outcome via Bayes' theorem and recomputes priorities for the next step.

5.2 Flowchart logic

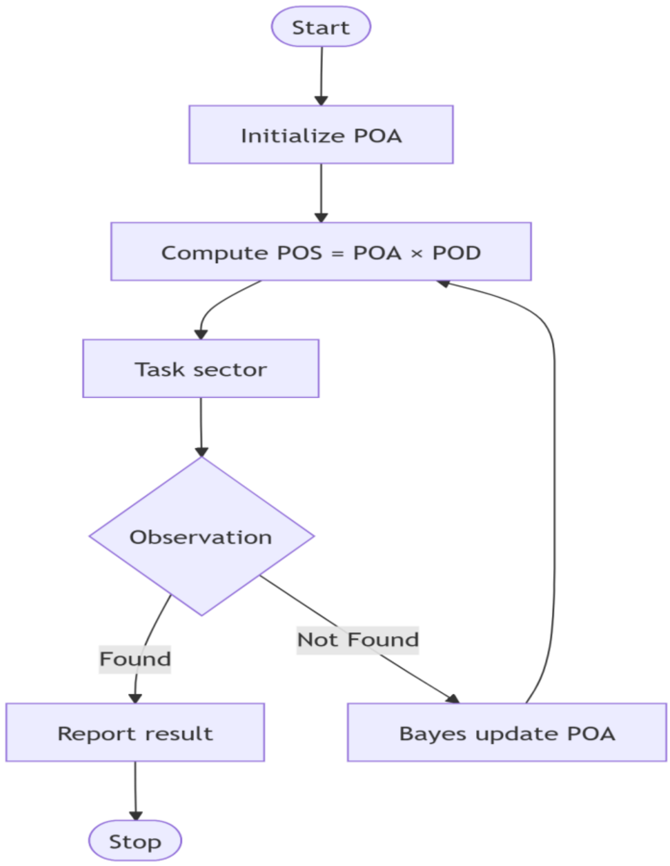


Figure 1. Bayesian SAR Tasking Loop.

5.3 Pseudocode (single-resource, sector-based tasking)

Inputs:

Sectors i = 1..C

Prior POA b0(i), sum_i b0(i) = 1

POD model p(i) in [0,1] for the chosen resource/technique

(Interpretation: p(i) is the Probability of Detection for that specific tasking—resource × time × conditions—not a permanent clearance value.) (1)

Termination condition: Found

Initialize:

b ← b0 // current prior POA map

Repeat for t = 0,1,2,... until Found:

1) For each sector i: POS(i) ← b(i) * p(i)

2) Choose sector j maximizing POS(i): j ← argmax_i POS(i) (apply operational tie-breakers if needed)

3) Execute search tasking in sector j and observe outcome O ∈ {Found, Not-Found}

4) If O == Found: return j // stop: subject located

5) If O == NotFound:

denom ← 1 - p(j)*b(j)

b_plus(j) ← (1 - p(j)) * b(j) / denom

For each i ≠ j: b_plus(i) ← b(i) / denom

b ← b_plus // carry posterior forward as next prior (static case)

continue

5.4 Implementation notes

Data structures: store POA vector b(i), POD layer(s) p(i) (possibly per resource), and sector metadata plus an evidence log.

Numerical stability and edge cases: if p(j)=0, Not-Found provides essentially no clearance; if p(j)=1, Not-Found clears the sector (b_{t+1}(j)=0). Clamp denominators against floating error.

Feasibility guard: Apply the Bayesian update only for observations with non-zero model probability. If 1 - p(j)b(j) = 0, then the event Not-Found in j has zero probability under the model; treat this as an assertion/logging condition and respecify p(j) (or review the observation) before updating.

Tie-breaking: document operational tiebreakers (travel time, safety/access, daylight, communications, etc.).

5.5 Multi-resource extension (practical SAR: POD depends on the asset)

Let resources r∈R and POD be p_r(i). Immediate POS becomes POS_t(i,r)=b_t(i)p_r(i). Choose (i*,r*) ∈ argmax_{i,r} POS_t(i,r). Bayesian updates use the POD of the resource that actually executed the search.

5.5.1 Sequential multi-asset searches of the same sector: effective POD
When multiple assets search the same sector, the Bayes update can be applied sequentially using the POD of each executed search. Under an independence assumption (conditional on the subject being present), this sequential updating is equivalent to a single update with an effective combined POD.

Proposition 2 (Effective POD for independent assets; sequential-update equivalence). Suppose sector j is searched by two assets (or two sequential taskings) with conditional detection probabilities p_1 and p_2, and suppose the detection events are independent given that the subject is in j. Then the conditional probability of failing to detect the subject after both searches is $(1-p_1)(1-p_2)$, so the effective combined POD is

$$p_{eff} = 1 - (1-p_1)(1-p_2).$$

Moreover, if both searches yield NotFound, applying the Bayes NotFound update sequentially (first with p_1, then with p_2) yields the same posterior as applying a single NotFound update with p_{eff}.

Detail proof of the above statement is provided in Appendix D(Proposition 2).

5.6 Logging and audit trail
Log per tasking: time/date, sector ID, resource/technique, assumed POD and basis, outcome Found/NotFound, and POA before/after update. This supports briefing, continuity, and after-action review.

5.7 Complexity
Per iteration: compute POS over all sectors O(C); update beliefs O(C); store belief map O(C).

6. Terrain-Aware POD (Probability of Detection) for SAR Tasking
A central message in operational search theory is that a negative search result is only as informative as the search's detectability: NotFound provides strong evidence only when POD is high. In practice POD varies with terrain, visibility, weather, access constraints, target type, and the search resource/technique. This section defines a terrain-aware POD layer that is interpretable, integrates with the Bayes update, and supports decisions about prioritization and resource selection.

6.1 Why terrain-aware POD matters
Terrain degrades detection through occlusion, line-of-sight limitations, and access constraints. Two sectors with similar POA can have different POS = POA×POD; a Not-Found in a low-POD sector should reduce POA far less than a Not-Found in a high-POD sector.

6.2 POD in SAR practice: from detection models to usable sector-level values
Operational search theory models POD via detection models tied to coverage, sweep width, and sensor performance. SAROPS uses sensor/platform functions (e.g., lateral range curves) and updates distributions after unsuccessful searches using Bayesian reasoning informed by detectability models. Land SAR field experiments also motivate condition-adjusted POD (5,6).

6.3 A simple, interpretable terrain-aware POD model (sector-level)
Let $p_r(i)$ be the POD for resource r in sector i. Model it as:

$$p_r(i) = \mathrm{clip}(p_{base\_r} \cdot \tau(i) \cdot \kappa(i) \cdot \omega(t), 0, 1).$$

Here p_{base_r} is a baseline POD for resource r; $\tau(i)$ is a terrain/cover factor; $\kappa(i)$ is an access/coverage factor; $\omega(t)$ is a time/condition factor (day/night, weather).

6.4 Terrain classes and example factors

Example terrain factors (illustrative only): open $\tau=1.0$; light forest $\tau=0.7$; dense forest $\tau=0.4$; steep/rocky $\tau=0.5$ with $\kappa<1$ due to reduced coverage; impassable/water $\kappa=0 \rightarrow p\_r(i)=0$ for ground resources.

6.5 How terrain-aware POD changes decisions

Tasking uses POS ranking: choose $(i^*,r^*) \in \mathrm{argmax}\_\{i,r\}\ b\_t(i)p\_r(i)$. Belief updating uses the executed POD: high-POD searches produce stronger clearance, low-POD searches weaker clearance.

6.6 Resource-aware POD

Maintain multiple POD layers for different assets (ground, canine, UAV, helicopter). A dense sector can have high POA but low ground POD; assigning a different asset may increase POS and yield stronger evidence after Not-Found.

6.7 Practical estimation of terrain factors

Populate τ and κ from GIS land-cover, slope/access constraints, visibility/illumination, weather, and team expertise/debrief. Treat them as planning inputs and document their basis.

Section 10 and 11 give a Proof-of-concept and a worked example.

6.8 Limitations

Sector-level POD is simplified; operational deployment requires calibration and richer detection modeling (coverage/sweep width/sensor curves) (8,9).

7. Informed Priors (POA Initialization) from SAR Intelligence Inputs

Operational SAR planning rarely starts from a uniform prior. Planners synthesize investigative information into an initial probability map (prior POA/POC) guiding early tasking. SAR doctrine emphasizes vigorous investigation and probability maps; SAROPS formalizes priors via weighted scenarios. This section describes informed priors that are mathematically consistent, auditable, and compatible with Bayesian updating (1).

7.1 What is the “prior” in SAR terms?

The prior POA is $b\_0(i)=P(X\_0=i)$ with $\Sigma\_i\ b\_0(i)=1$.

7.2 Why informed priors matter

Early tasking is leverage under time pressure and spreading uncertainty. Bayesian posteriors depend on the prior; weak priors can misdirect early effort even with correct updates.

7.3 Sources of prior information

Datums (LKP/TLK), scenario-based priors (consistent stories), GIS/terrain features, evidence fusion (tracks/pings/sightings), and standardized methodology considerations.

7.4 Three practical ways to construct informed priors

Method A (weighted layers): $\tilde{b}\_0(i)=\Sigma\_k\ w\_k\ L\_k(i)$, then normalize $b\_0(i)=\tilde{b}\_0(i)/\Sigma\_j\ \tilde{b}\_0(j)$.

Method B (likelihood multiplication): $\tilde{b}\_0(i)=b\_base(i)\ \Pi\_k\ P(E\_k \mid X\_0=i)$, then normalize.

Method C (scenario mixture): $b\_0(i)=\Sigma\_s\ \alpha\_s\ b\_0\text{^}\{(s)\}(i)$ with $\Sigma\_s\ \alpha\_s=1$.

7.5 Linking priors to tasking

First tasking uses $POS\_0(i)=b\_0(i)p(i)$. High POA but low POD may be de-prioritized or resourced differently; moderate POA but high POD may be prioritized.

7.6 A short hypothetical worked prior
With LKP proximity layer L1 and trail proximity layer L2, choose weights w1>w2: $\tilde{b}_0(i)=w1\ L1(i)+w2\ L2(i)$, then normalize.

7.7 Documentation and audit trail
Record which layers/scenarios were used, rationale for weights, and prior map version. This supports transparency and after-action review.

7.8 Limitations
Informed priors can encode bias; scenario mixtures and evidence tracking help. Bayes updates correct priors only if POD estimates are meaningful and outcomes are logged consistently.

8. Dynamic Subject Modelling (Moving Target / Drift) and Belief Propagation
Many SAR incidents involve moving subjects or drifting objects. Motion modeling is central to forming and updating probability maps; SAROPS treats object motion as a core component. We extend POA/POD to dynamic belief modeling: propagate POA forward using a motion model, then apply Bayes update after each search outcome (5,6).

8.1 Why dynamic modelling matters
Time affects both survivability and uncertainty; negative results age if the subject could move; planning should target where the subject is likely to be now.

8.2 Motion model as a transition matrix
Model movement with $T_{ij} = P(X_{t+1}=j \mid X_t=i)$, with $\Sigma_j T_{ij}=1$. Use identity for static, neighbor random walk for wandering, biased transitions for corridors/barriers, or drift-derived transitions for maritime contexts.

In WiSAR contexts, terrain-informed lost-person behavior models can help parameterize or validate these transition probabilities (e.g., terrain-feature-driven Bayesian/Markov models). (10)

8.3 Predict–update cycle
We use a predict–update cycle aligned with operational replanning epochs.

Prediction (propagate the posterior from the previous epoch): starting from $b_t^+(i)$, compute the next-epoch prior

$\hat{b}_{t+1}(j) = \Sigma_i\ b_t^+(i)\ T_{ij}$.

Tasking at epoch t+1: compute $POS_{t+1}(j)=\hat{b}_{t+1}(j)\ p(j)$ and choose the max-POS sector (or sector–resource pair).

Update after observing Not-Found in searched sector k at epoch t+1:

$denom = 1 - p_k\ \hat{b}_{t+1}(k)$.

$b_{t+1}^+(k) = ((1-p_k)\ \hat{b}_{t+1}(k))\ /\ denom$;

and for $j\neq k$, $b_{t+1}^+(j) = \hat{b}_{t+1}(j)\ /\ denom$.

Carry forward: set $b_{t+1} := b_{t+1}^+$ for the next prediction step.

8.4 Choosing the planning time step (Δt)
Choose Δt to match operational re-planning cadence (sorties, operational periods, major intel updates). Ensure transition probabilities reflect plausible movement within Δt.

8.5 How dynamic modelling changes decisions
Dynamic models support corridor/intercept searching, reinterpretation of "cleared" sectors as POA can return, and increased value of early high-POS tasking under spreading uncertainty.

8.6 Particles vs transitions
SAROPS uses particle simulation and Bayesian reweighting; the transition-matrix model is the sector-level analogue emphasizing transparency and lightweight computation (5,6).

8.7 Limitations and documentation
Transition models are uncertain and context-dependent; document assumptions, align time steps with operational cycles, and maintain auditability.

9. POMDP Framing for SAR Tasking
A Partially Observable Markov Decision Process (POMDP) provides a standard language for sequential decision-making under uncertainty and imperfect detection. This section anchors the POA/POD workflow in a POMDP and clarifies how richer planning objectives (travel cost, risk, multi-step lookahead, multi-asset assignment) can be incorporated without changing the core belief-update logic.

9.1 POMDP definition
A POMDP is specified by $\langle S, A, T, R, O, Z, \gamma \rangle$ with hidden states, actions, transitions, rewards/costs, observations, observation probabilities, and discount factor (13).

9.2 Instantiating the POMDP for sector-based SAR planning
State S: minimal state is subject sector $i \in \{1,\ldots,C\}$; optional extended state includes asset location for travel costs.

Actions A: search a sector j, or choose (j,r) for sector–resource assignments.

Transition T: identity for static; Markov transitions for moving subjects (Section 8).

Observations O: Found / Not-Found.

Observation model Z: $P(\text{Found} \mid s=i,a=j)=1[i=j]\, p_j$; $P(\text{NotFound} \mid s=i,a=j)=1-1[i=j]\, p_j$.

Reward/cost R: $+R_{find}$ on detection; otherwise negative search and travel costs.

9.3 Belief state b: POA as the sufficient statistic
Notation note: in this POMDP view, b_t is the belief (POA map) before action a_t, and b_t^+ is the updated belief after observing o_t; for static targets, $b_{t+1}=b_t^+$.

Belief update after action a and observation o: $b_{t+1}(i)=\eta\, Z(o \mid s=i,a)\, \Sigma_k\, T_{k i}\, b_t(k)$, with normalization η.

9.4 POS rule as a myopic policy
The POS tasking rule $a_t \in \text{argmax}_j\, b_t(j)\, p_j$ is a myopic policy that maximizes immediate detection probability, while POMDP framing clarifies how to add lookahead and costs if needed.

9.5 Why not solve the full POMDP here?

Exact POMDP solutions are computationally intensive for large state/action spaces. In practice, SAR applications use approximations and transparent decision rules when interpretability and auditability are key.

9.6 Operational takeaway

POA maps are belief states; POD defines the observation model; Bayesian updating after Not-Found is the correct belief update; POS-based tasking is a transparent one-step policy; POMDP is the formal home for travel/risk/multi-step planning extensions.

Related applications. POMDP-style formulations similar to Section 9 have been used to support UAV search planning and victim-finding in disaster or humanitarian settings (14–16).

10. Simulation Study (Proof-of-Concept Demonstration)

This section provides a proof-of-concept simulation to illustrate core SAR planning behaviours: maintaining POA, selecting by POS, and updating POA after unsuccessful searches with a POD-dependent Bayes update. The simulation is illustrative, not operationally validated; limitations are stated and expanded in Section 13.

10.1 Purpose and scope

Purpose: demonstrate POS prioritization, POD-dependent clearance via Bayes updates, and terrain-aware POD effects. Not a deployment claim: operational performance requires calibrated POD models and workflow integration.

10.2 Environment and experimental setup

Use a discretized region of $C=M\times N$ sectors (e.g., 5×5 for visualization clarity). The framework is independent of grid size or geometry; operational sectors can be polygons.

10.2.1 Prior POA

Use either uniform prior $b_0(i)=1/C$ or an informed prior from Section 7.

10.2.2 Detection model (imperfect detection)

Each sector i has POD $p(i)\in[0,1]$. If the subject is in searched sector i, Found occurs with probability $p(i)$; otherwise Not-Found. If the subject is elsewhere, the outcome is Not-Found.

10.2.3 Terrain-aware POD scenarios

Compare uniform POD $p(i)=p_0$ with terrain-aware POD $p(i)=p_0\times\tau(i)\times\omega(t)$ as in Section 6.

10.3 Policies compared

Baseline clarification (imperfect detection). “Without replacement” refers only to the selection rule (do not choose the same sector twice) and should not be interpreted as a claim that a sector becomes fully cleared after one negative result when POD<1. This baseline is included only as a naive comparator to highlight the value of Bayesian belief updating under imperfect detection.

1) Random with replacement.

2) Random without replacement.

3) POA-only policy.

4) POS-myopic without posterior update (static plan).

5) Bayesian POS policy (this paper): choose argmax $b_t(i)p(i)$ and update via Bayes after Not-Found.

10.4 Evaluation metrics (SAR-relevant)
Report steps-to-detection T (mean/median/std), tail risk (90th/95th percentiles), probability of success within budget B: P(T≤B), re-search frequency, and belief evolution visuals.

10.5 Experimental procedure (reproducible protocol)
Each trial: initialize b_0; sample X_0; repeat selection, simulate observation using imperfect detection with POD, update b via Bayes after Not-Found (if policy updates), stop on Found. Repeat for N trials and report metrics with uncertainty.

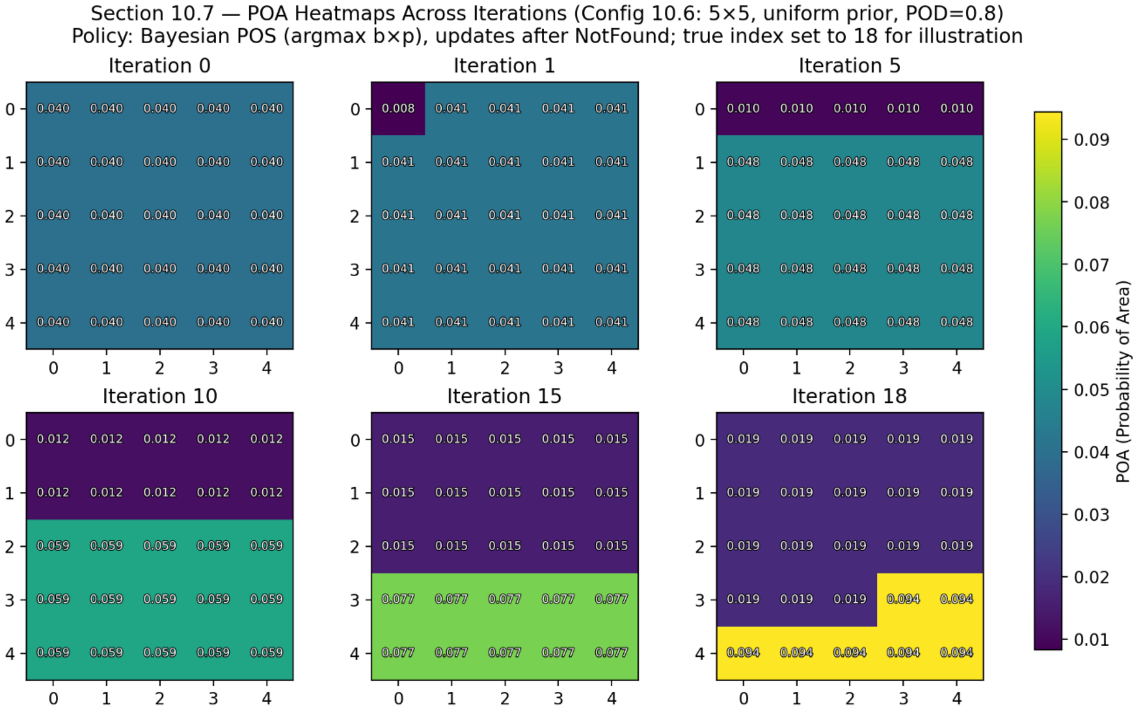
Implementation note: Found must be simulated as a Bernoulli event with probability p(a_t) even when the searched sector equals the true sector; otherwise the simulation assumes perfect detection and contradicts the model.

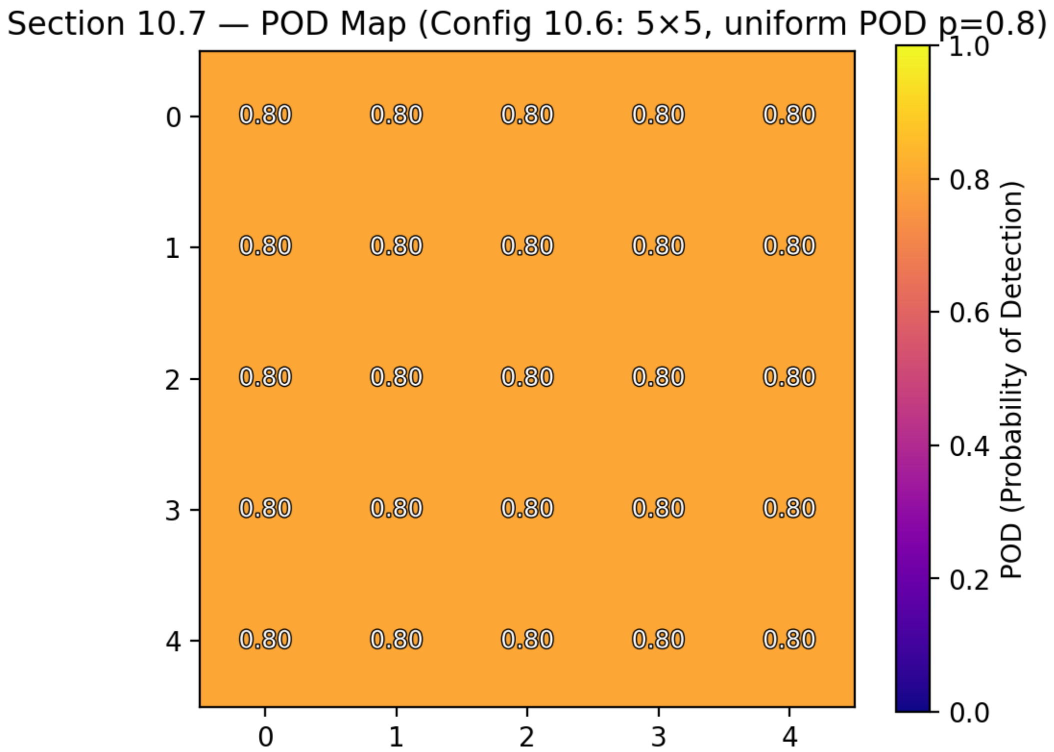
10.6 Results presentation
Configuration. 5×5 grid (C=25), **static** target, **uniform prior**, **uniform POD p=0.8**, **imperfect detection**, **N=5,000** trials per policy. Metrics: steps-to-detection mean/std, quantiles (T50, T90, T95), and budget success for . Policies: (P0) Random w/ replacement, (P1) Random w/o replacement, (P2) POA-only (with Bayes updates), (P3) POS-myopic static plan (no updates), (P4) Bayesian POS (with Bayes updates).

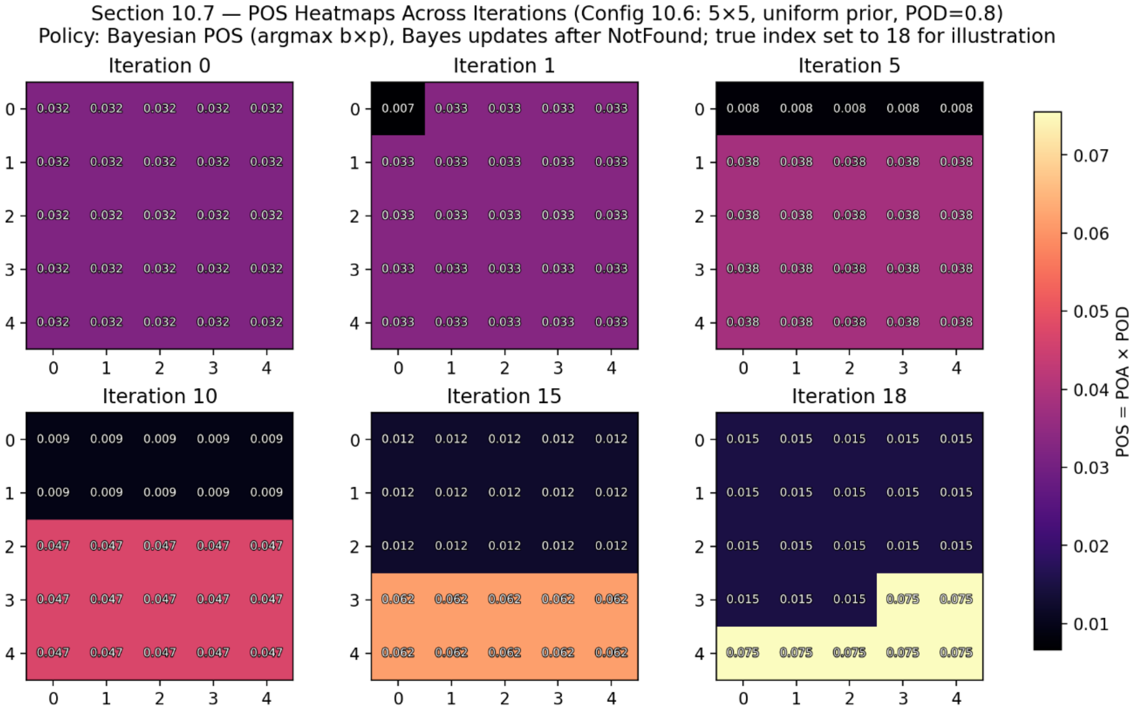
Policy	Description	N	Mean_T	Std_T	T50	T90	T95	P(T≤5)	P(T≤10)
P0	Random with replacement	5000	31.14	30.74	22.0	72.0	92.0	0.149	0.277
P1	Random without replacement	5000	19.39	15.36	16.0	41.0	49.0	0.147	0.308
P2	POA-only policy (with Bayes updates)	5000	19.53	16.14	16.0	42.0	50.0	0.158	0.316
P3	POS-myopic without posterior update (static plan)	5000	19.45	16.10	16.0	42.0	50.0	0.161	0.319
P4	Bayesian POS policy (with Bayes updates)	5000	19.17	15.63	16.0	41.0	49.0	0.171	0.321

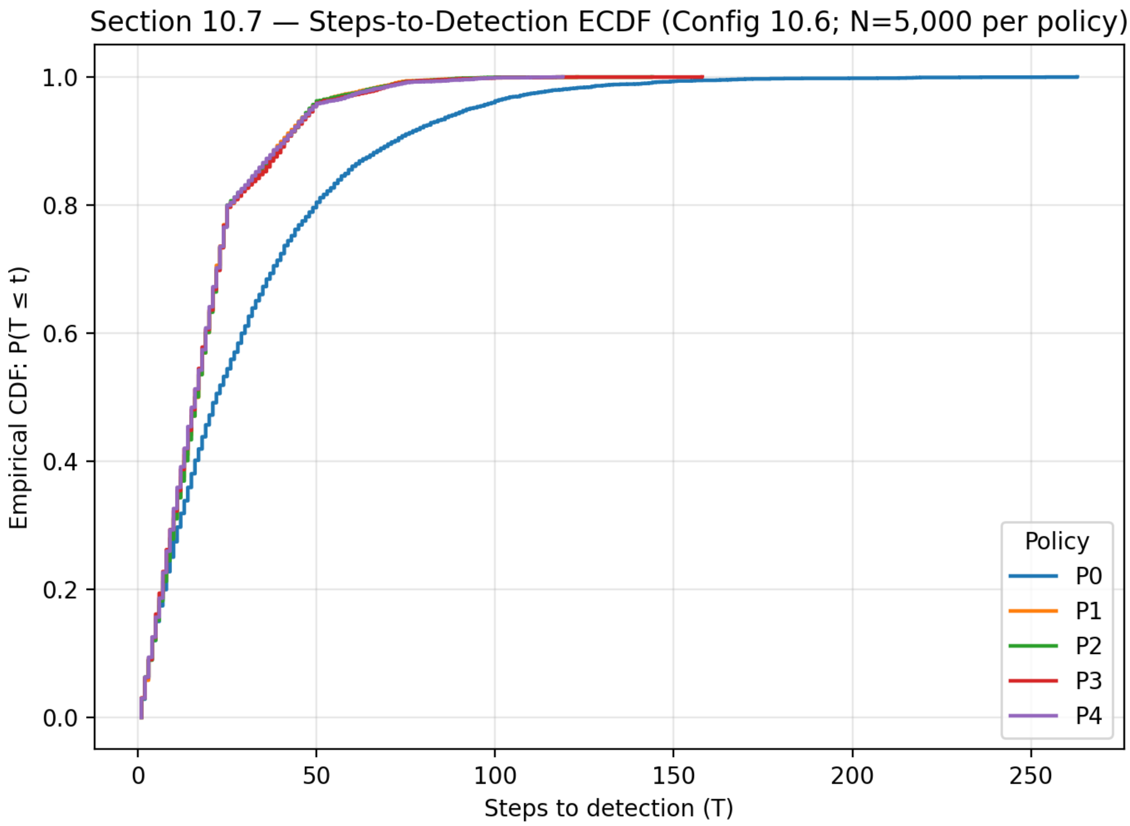
Qualitative belief concentration dynamics and quantitative metrics. [Numerical summary table after final aligned simulation runs, Python Pseudo code is given in Appendix C8]

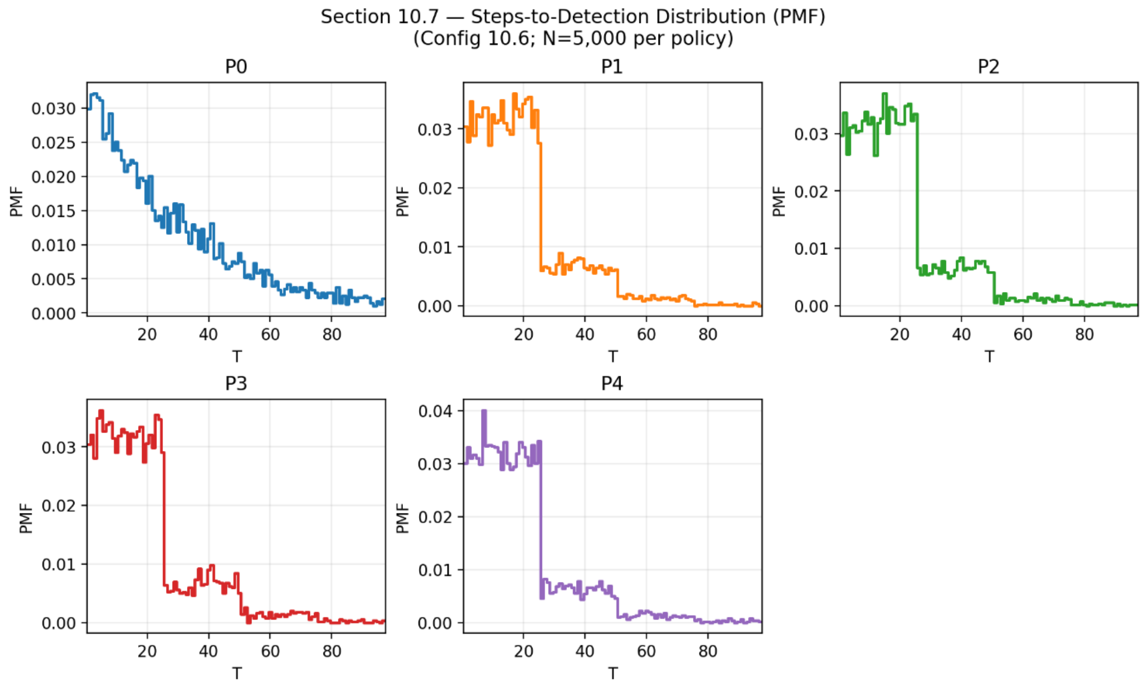
10.7 Figures: POA heatmaps across iterations, POD and POS maps, and steps-to-detection distribution plots.






Section 10.7 — POS Heatmaps Across Iterations (Config 10.6: 5×5, uniform prior, POD=0.8)
Policy: Bayesian POS (argmax b×p), Bayes updates after NotFound; true index set to 18 for illustration
Iteration 0
Iteration 1
Iteration 5
Iteration 10
Iteration 15
Iteration 18
POS = POA × POD


Section 10.7 — Steps-to-Detection ECDF (Config 10.6; N=5,000 per policy)
Empirical CDF: P(T ≤ t)
Steps to detection (T)
Policy
P0
P1
P2
P3
P4



10.8 Simulation limitations

Grid abstraction, simplified POD, single-asset simplification, and lack of mission-data validation limit operational inference; expanded in Section 13.

11. Worked Hypothetical SAR Example (How POA/POD/POS Drives Real Tasking)

This section provides a short worked example showing how POA/POD/POS tasking and Bayes updates would be used in practice. The scenario is hypothetical but mirrors SAR planning workflows.

11.1 Scenario description

A hiker is overdue in a mixed-terrain park. LKP is a trail junction. Terrain varies across sectors; resources include one ground team initially. Goal: prioritize the next two taskings and show how Not-Found updates POA and changes priorities.

11.2 Sectorization (simple 3×3 for clarity)

A	B	C
D	E	F
G	H	I

Sector E contains the LKP trail junction. A,B are more open; C,F,I are dense forest; G,H include steep or harder-access terrain.

11.3 Step 0: Build an informed prior POA

Illustrative prior: b_0(E)=0.20; b_0(B)=b_0(D)=b_0(F)=b_0(H)=0.10 each; corners A=0.05, C=0.02, G=0.02, I=0.01. Sum is 1.00.

11.4 Assign terrain-aware POD for a ground team

Assume daylight: open (A,B) p=0.70; mixed/trail (D,E,H) p=0.55; dense forest (C,F,I) p=0.30; steep/harder-access (G) p=0.35. Values are illustrative.

11.5 Compute POS and choose the first tasking

Compute POS_0(i)=b_0(i)p(i). Top candidates: E=0.110; B=0.070; D=0.055; H=0.055; A=0.035; F=0.030. Tasking 1: Search sector E.

11.6 Outcome: Not-Found in E → Bayesian update

With p_E=0.55 and b_0(E)=0.20, denom = 1 - 0.55×0.20 = 0.89. Updated b_1(E)=(0.45×0.20)/0.89 ≈ 0.1011. Other sectors scale by 1/0.89. POA in E does not go to zero because POD<1.

11.7 Recompute POS and choose the second tasking

Recompute POS_1(i)=b_1(i)p(i). Key values: B POS≈0.07865; E POS≈0.0556; D and H POS≈0.0618. Tasking 2: Search sector B (highest POS after update).

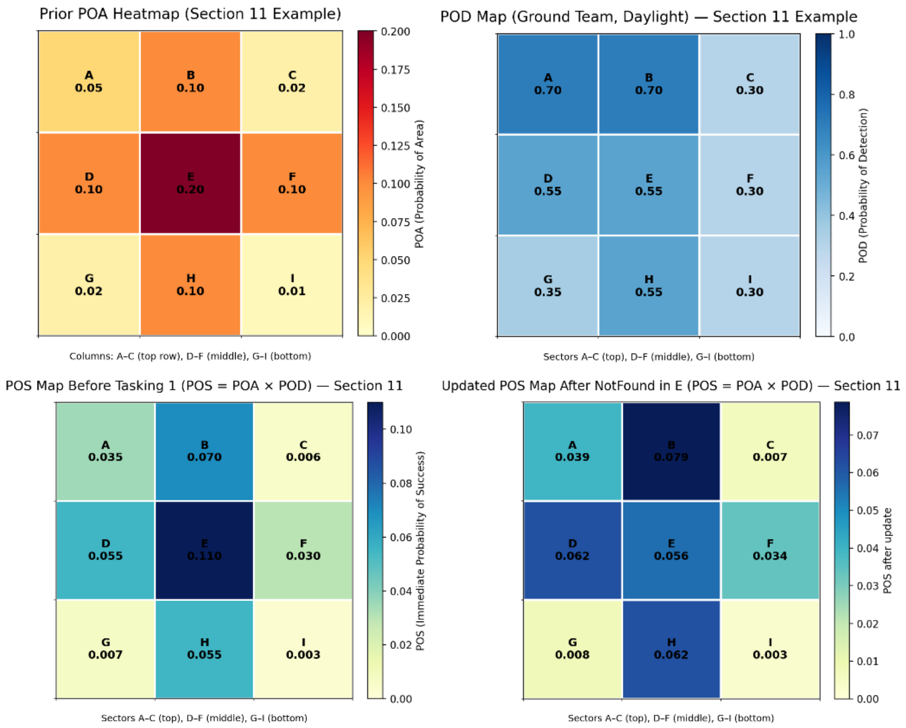
11.8 Why terrain-aware POD matters: a re-search insight

Dense forest sectors may retain nontrivial POA but have low ground POD, keeping POS modest and making negative results weak evidence. Operationally, consider resource substitution (canine/UAV/thermal) or planned re-search.

11.9 Briefing-friendly summary

Initial POA centered on LKP sector E; POD varies by terrain; task E first; NotFound partially clears E (POA decreases but does not vanish); recompute POS and task B next. Low-POD negatives should be interpreted cautiously.

11.10 Figure-ready artifacts : Prior POA heatmap, POD map, POS map before Tasking 1 and after Not-Found update.



12. Operational Implications for SAR Planning and Decision-Making

This section translates the framework into practitioner-facing implications: sector prioritization, allocation of effort, resource selection, re-search, evidence integration, and coordination.

12.1 Sector prioritization: turning POA and POD into an auditable tasking order

Rank sectors by POS = POA×POD and task the maximum-POS sector (or best sector–resource pair). This is explainable and aligns with operational search planning logic.

12.2 How belief updating changes the meaning of "Not Found"

Not-Found reduces POA in proportion to POD; sectors are not fully cleared unless POD=1. High-POD searches yield stronger clearance; low-POD searches yield weaker clearance and can justify re-search or resource substitution.

12.3 Allocation of effort across sectors

Use rolling-horizon planning: select a near-term set of high-POS sectors; update POA after each report; recompute priorities for responsive re-tasking.

12.4 Resource selection: matching assets to terrain to increase POD

Maintain $p_r(i)$ per resource. Assign assets to sectors where they maximize POS and produce meaningful evidence. This avoids false clearance under low POD and supports targeted deployment of specialized resources.

12.5 Re-search decisions

Re-search is rational when POA remains high after low-POD searches; less justified after repeated high-POD negatives. Prefer re-search with a better method that increases POD and information gain.

12.6 Integrating heterogeneous evidence into POA

Incorporate new clues mid-mission as POA updates (likelihood layers) or scenario reweighting; continue POS prioritization. This supports continuity and reduces planning churn.

12.7 Communication and coordination

POA/POD/POS provides a common language for briefings and handoffs, improving explainability, auditability, and after-action review.

12.8 Operational trade-offs made explicit

The framework makes explicit: thoroughness vs coverage, speed vs certainty, and access/safety constraints via POD layers and POS prioritization.

12.9 Deployment view

Success in deployment is a decision-support companion: updated POA map, explicit POD layer, and POS-ranked next-tasking list—integrated into planning cycles.

13. Limitations and Requirements for Operational Deployment

This paper's simulations and examples are proof-of-concept demonstrations. Operational deployment requires data, calibration, modelling refinements, and validation. This section states limitations and outlines what is needed for operationalization.

13.1 Limitations of sector/grid abstractions

Grid cells are pedagogical; real sectors are irregular. Discretization and resolution trade-offs can hide corridors/barriers and within-sector heterogeneity.

13.2 Simplified detection models vs real POD estimation

POD is not a single constant; it depends on coverage, sweep width, visibility, target type, searcher skill, fatigue, navigation accuracy, and environment. The binary Found/Not-Found observation model assumes no false positives and sector-local information; richer observation models may be required (8,9).

13.3 Motion model limitations

Transition models are uncertain and profile/terrain/weather-dependent; time-step mismatch with operational cycles can distort propagation; scenario-based modelling is recommended.

13.4 Single-agent / simplified resource constraints

Real SAR is multi-resource and multi-agency; operationalization requires coordination, scheduling, and constraint handling (safety, communications, availability).

13.5 Limits of proof-of-concept simulations

Small synthetic simulations do not support direct operational conclusions; they illustrate dynamics. Operational claims require validated models and real data.

13.6 Requirements for operational deployment (data, modeling, validation)

13.6.1 Data requirements

• GIS-ready sectorization aligned to incident management.

• POD calibration sources (field experiments, sensor models, environmental inputs).

• Evidence inputs for informed priors (LKP/TLK uncertainty, tracks, pings, sightings, scenario weights).

• Motion model inputs (terrain-based behavior data or maritime drift models) if dynamic.

13.6.2 Modeling requirements

• Resource- and condition-specific POD models tied to coverage/sweep width or sensor curves (8,9).

• Richer observation models when ambiguous observations occur (false positives, partial clues).

• Time alignment with operational cycles and reporting cadence.

• Cost/constraint integration (travel, risk, safety) if needed, potentially via POMDP framing.

13.6.3 Validation requirements

• Retrospective case validation using archived missions and comparing prioritization.

• Prospective pilots in exercises with logging and evaluation.

• Sensitivity analyses for POD and prior uncertainty to build trust.

• Human factors/usability testing for planner adoption.

13.7 Summary

Provided here: a mathematically correct, operationally interpretable POA/POD/POS Bayesian workflow with terrain-aware POD, informed priors, and optional dynamics/POMDP framing. Needed for deployment: calibration, GIS integration, multi-asset coordination, and validation.

14. Conclusion

SAR search planning is fundamentally a problem of allocating limited effort under uncertainty: deciding where to task next, interpreting negative results under imperfect detection, and accounting for terrain and conditions that influence detectability and clearance. Operational search theory formalizes these ideas through POA/POC, POD, and POS (1).

This paper presented a SAR-native Bayesian decision-support workflow. We derived a Bayes update for unsuccessful searches under imperfect detection and a transparent POS-based prioritization rule (POA×POD) for tasking. The "vanishing posterior" insight—that POA does not collapse to zero when POD<1—provides a rigorous explanation for why re-search and resource substitution can be rational in low-detectability conditions.

We also outlined operationally relevant extensions: terrain- and resource-aware POD layers, informed priors from intelligence inputs and scenario thinking, motion models for moving subjects/drift, and a POMDP framing for longer-horizon planning with explicit costs and constraints. Proof-of-concept simulations and a worked example illustrate the update dynamics and planning interpretation. We explicitly acknowledged limitations and outlined requirements for operational deployment: calibrated POD models, GIS integration, scenario/evidence handling, multi-asset coordination, and validation against mission data or training exercises.

14.1 Future work (deployment-oriented)

Future work should prioritize: POD calibration for land SAR under varied conditions; GIS-integrated priors and scenario workflows; multi-asset coordination; and retrospective/prospective validation with human factors evaluation.

References

1. Frost JR. The Theory of Search: A Simplified Explanation. Soza & Company, Ltd. and Office of Search and Rescue, U.S. Coast Guard; October 1996. Available: https://navcen.uscg.gov/sites/default/files/pdf/Theory_of_Search.pdf

2. Koopman BO. Search and Screening (OEG Report No. 56). Operations Evaluation Group, Office of the Chief of Naval Operations, U.S. Navy Department; 1946. Available: https://www.informs.org/Explore/History-of-O.R.-Excellence/Documents/Bernard-O.-Koopman-Search-and-Screening-1946

3. Stone LD. Theory of Optimal Search. New York: Academic Press; 1975. (Mathematics in Science and Engineering, Vol. 118). ISBN: 978-0126724509.

4. Washburn AR. Search and Detection. Topics in Operations Research Series. 4th ed. Linthicum, MD: INFORMS; 2002. ISBN: 978-1877640179.

5. Kratzke TM, Stone LD, Frost JR. Search and Rescue Optimal Planning System (SAROPS). Metron, Inc. / U.S. Coast Guard Office of Search and Rescue; report date 2010-06-01 (DTIC ADA564779). Available: https://apps.dtic.mil/sti/citations/ADA564779 and https://www.metsci.com/wp-content/uploads/2019/08/Search-and-Rescue-Optimal-Planning-System.pdf

6. U.S. Coast Guard. Search and Rescue Optimal Planning System (SAROPS) Information Sheet. U.S. Coast Guard; PDF. Available: https://www.dco.uscg.mil/Portals/9/CG-5R/SARfactsInfo/SAROPSInforSheet.pdf

7. Cooper DC, Frost JR, Robe RQ. Compatibility of Land SAR Procedures with Search Theory. Prepared for U.S. Department of Homeland Security / U.S. Coast Guard Operations (G-OPR). Potomac Management Group, Inc.; 30 Dec 2003. Available: https://www.dco.uscg.mil/Portals/9/CG-5R/nsarc/LandSearchMethodsReview.pdf

8. Koester RJ. Land Search and Rescue Probability of Detection: New sweep widths values, correction factors, models, and detection model validation. Journal of Search and Rescue; 2020. Available: https://journalofsar.com/wp-content/uploads/2020/04/v4-7-Koester-POD-Syrotuck.pdf.pdf

9. Koester RJ, Chiacchia KB, Twardy CR, Cooper DC, Frost JR, Robe RQ. Use of the Visual Range of Detection to Estimate Effective Sweep Width for Land Search and Rescue Based on 10 Detection Experiments in North America. Wilderness & Environmental Medicine. 2014;25(2):132–142. doi:10.1016/j.wem.2013.09.016.

10. Lin L, Goodrich MA. A Bayesian approach to modeling lost person behaviors based on terrain features in Wilderness Search and Rescue. Computational and Mathematical Organization Theory. 2010;16:300–323. doi:10.1007/s10588-010-9066-2.

11. Rossmo DK, Velarde L, Mahood T. Optimizing Wilderness Search and Rescue: A Bayesian GIS Analysis. Journal of Search and Rescue; 2023. doi:10.61618/HWOQ8554. Available: https://journalofsar.com/optimizing-wilderness-search-and-rescue-a-bayesian-gis-analysis/

12. Nasar W, Da Silva Torres R, Gundersen OE, Karlsen AT. The Use of Decision Support in Search and Rescue: A Systematic Literature Review. ISPRS International Journal of Geo-Information. 2023;12(5):182. doi:10.3390/ijgi12050182.

13. Kaelbling LP, Littman ML, Cassandra AR. Planning and acting in partially observable stochastic domains. Artificial Intelligence. 1998;101(1–2):99–134. doi:10.1016/S0004-3702(98)00023-X. Available: https://people.csail.mit.edu/lpk/papers/aij98-pomdp.pdf

14. Bravo RZB, Leiras A, Cyrino Oliveira FL. The Use of UAVs in Humanitarian Relief: An Application of POMDP-Based Methodology for Finding Victims. Production and Operations Management. 2019;28(2):421–440. doi:10.1111/poms.12930. (Bibliographic record: https://econpapers.repec.org/RePEc:bla:popmgt:v:28:y:2019:i:2:p:421-440)

15. Villani PG, Cugnasca PS. A POMDP Approach to Map Victims in Disaster Scenarios. Logistics. 2024;8(4):113. doi:10.3390/logistics8040113. Available: https://www.mdpi.com/2305-6290/8/4/113

16. Zhang Y, Luo B, Mukhopadhyay A, et al. Shrinking POMCP: A Framework for Real-Time UAV Search and Rescue. arXiv:2411.12967 (cs.RO). 2024. doi:10.48550/arXiv.2411.12967. Available: https://arxiv.org/abs/2411.12967

17. International Maritime Organization (IMO). IAMSAR Manual (International Aeronautical and Maritime Search and Rescue Manual) overview page (joint IMO/ICAO publication). Available: https://www.imo.org/en/ourwork/safety/pages/iamsarmanual.aspx. See also: IAMSAR Manual Volume II (Mission Coordination), 2019 edition (ISBN 978-92-9258-806-9) sample

Appendix A. Practitioner Implementation Checklist (POA/POD/POS Bayesian Tasking)

This appendix is a field-usable checklist to implement the workflow in an operationally interpretable, auditable manner consistent with POA/POD/POS search planning logic.

A1. One-page concept map (what the tool does)

Inputs → Models → Outputs → Iteration

1) Inputs: sector map + initial POA + POD estimates + completed-search reports.

2) Models: POS ranking + Bayes update after Not-Found + optional motion propagation.

3) Outputs: updated POA map + POS-ranked tasking list + re-search/resource flags.

4) Iteration: re-run after each sortie/tasking debrief (plan → search → update → re-plan).

A2. Minimum viable implementation (MVI) checklist

A2.1 Sectorization

• Define taskable sectors (grid or polygons); assign IDs; record metadata (terrain class, access notes, hazards, size).

A2.2 Prior POA

• Choose $b_0(i)$ (sums to 1). If informed, document sources. If scenarios, record weights and rationale.

A2.3 POD per sector and resource

• For each resource r, assign $p_r(i) \in [0,1]$. Apply condition modifiers (day/night, weather). Label whether estimated/doctrine/calibrated.

A2.4 Tasking rule

• Compute $POS(i,r)=b(i)p_r(i)$. Task the (sector, resource) with highest POS (with tie-breakers).

A2.5 After-task update

• Record outcome Found/Not Found. Found → stop/report. Not Found → Bayes update using executed POD.

A3. Operational inputs (what planners typically already have)

Priors: LKP/TLK, tracks, pings, sightings, terrain corridors/barriers. Detectability: resource type/technique, day/night, visibility/weather, terrain/cover class.

A4. Outputs (what the tool should produce)

Core outputs: updated POA map, POD layer used, POS-ranked tasking list. Enhancements: re-search flags, evidence-strength note, probability-of-success within budget view.

A5. Audit trail (non-negotiable)

Log priors (layers/scenarios), each tasking's POD and outcome, POA snapshots before/after updates, and any mid-mission evidence injections and their effects.

A6. Quality control (QC) checklist

Check normalization $\Sigma_i\, b(i)=1$ after every update; bounds $b(i),p(i) \in [0,1]$; flow logic Found→stop, NotFound→update; clearance intuition (low POD → mild POA reduction).

A7. Optional modules

Dynamic subject module (belief propagation), scenario mixtures, and cost-aware planning via POMDP framing.

A8. Field card summary

Update POA with new intel → choose POD layer → compute POS → task highest POS → Found stop; NotFound update POA → repeat.

Appendix B. Notation and Assumptions (Compact Glossary + Model Contract)

This appendix collects notation and makes explicit the assumptions under which the Bayesian update and POS tasking are valid.

B1. Operational terminology mapping (SAR ↔ model)

Sector/segment: taskable unit. POA/POC: probability subject is in a segment. POD: detectability conditional on presence and search method/conditions. POS=POA×POD (1).

B2. Core symbols

C: number of sectors. $I=\{1,\dots,C\}$. X_t: hidden location at step t. $b_t(i)=P(X_t=i)$. a_t: tasked sector. r: resource (optional). $p(i)$ or $p_r(i)$: POD. $O_t \in \{Found, NotFound\}$. $POS_t(i)=b_t(i)p(i)$. T: detection time.

B3. Observation model (imperfect detection contract)

If searching sector j and $X_t=j$, Found occurs with probability $p(j)$ and NotFound with $1-p(j)$. If $X_t \neq j$, Found has probability 0 and NotFound probability 1. (No false positives in base model.)

B4. Bayesian update after NotFound

Denom$=1-p(j)b_t(j)$. Update: $b_{t+1}(j)=((1-p(j))b_t(j))/denom$ and $b_{t+1}(i)=b_t(i)/denom$ for $i \neq j$.

B5. Policy definition

POS-based tasking: $a_t \in \mathrm{argmax}_i\, b_t(i)p(i)$. Resource-aware: $(i^*,r^*) \in \mathrm{argmax}_{\{i,r\}}\, b_t(i)p_r(i)$.

B6. Dynamic target notation

Transition matrix $T_{ij}=P(X_{t+1}=j \mid X_t=i)$. Prediction: $\hat{b}_{t+1}(j)=\Sigma_i\, b_t(i)T_{ij}$. Then apply Bayes update after Not-Found.

B7. Assumptions (model contract)

1) Single subject. 2) Subject in exactly one sector at a time. 3) Sectorization adequate for tasking/reporting. 4) Binary observations. 5) No false positives. 6) Known POD for that tasking. 7) Not-Found is sector-local information (others change by normalization). 8) Independent detection opportunities across time. 9) Task executed as assumed (POD reflects reality). 10) One sector search per update step (parallel searches require extension).

B8. Common extensions

B8.1 Non-local observations (cross-sector visibility / clue drift)

The base model assumes a search tasking provides information only about the searched sector (Section 3.4.1). In practice, some taskings provide partial information about neighboring sectors (e.g., line-of-sight from ridgelines, clue drift, or sensor spillover). This can be modeled by allowing the probability of observing Found to depend on the true sector i as well as the searched sector j.

Proposition 3 (Generalized Not-Found update for non-local observation models). Let $Z_j(i)$ denote the probability of observing Found when the true sector is i and the searched sector is j, i.e., $Z_j(i)=P(Found \mid X=i, a=j)$, with $0 \leq Z_j(i) \leq 1$. After searching sector j and observing NotFound, the posterior is

$b^+(i) = ((1 - Z_j(i))\, b(i)) / (\Sigma_k (1 - Z_j(k))\, b(k))$.

In the sector-local base model, $Z_j(i)=1[i=j]\, p_j$, and this reduces to the update in Section 4.1.

Proof is given in Appendix D3.

B9. Sanity checks

Normalization; clearance intuition; flow logic Found→stop, NotFound→update.

Appendix C. Reproducible Simulation Protocol (Baselines, Metrics, and Reporting Template)

This appendix specifies a reproducible simulation protocol ensuring consistency with imperfect detection, fair baselines, and SAR-relevant reporting.

C1. Goal and scope

Demonstrate POS-based tasking, Bayesian updating after Not-Found, and terrain-aware POD effects under controlled conditions. Not an operational calibration claim.

C2. Experiment design: factors, conditions, and seeds

Vary map size, prior type, POD type, and target dynamics. Record master seed and deterministic per-trial seeds. Recommend N≥1000 trials per condition for stable estimates; N=100 is acceptable for illustrative figures with clear labeling.

C3. Policies (baselines) — explicit definitions

P0: Random with replacement. P1: Random without replacement. P2: POA-only (with or without update, specified). P3: Static POS plan (no posterior update). P4: Bayesian POS (this paper) with Bayes updates.

C4. The imperfect detection simulation step (non-negotiable)

When searching the true sector, Found must occur with probability p(j) (Bernoulli). If the subject is elsewhere, the observation is Not-Found. Then apply Bayes update if the policy updates.

C5. Metrics (include academic and operationally interpretable ones)

Primary: steps to detection T. Tail: T50, T90, T95. Budget: P(T≤B). Diagnostics: re-search count, average POD used, optional POA entropy.

C6. Reporting standards

For each condition × policy: N, mean T, std, quantiles, P(T≤B) for two budgets, SE and optional 95% CI. State baseline fairness: same priors, POD maps, target sampling, and termination rule.

C7. Figure templates

Belief evolution heatmaps; POD layer maps; steps-to-detection distributions (CDF/boxplots). Captions must state relevance to sector prioritization, clearance strength, and tail risk.

C8. Configuration "contract" and Pseudocode

```
# Config
seed = 123456
rows, cols = 5, 5
C = rows * cols
N = 5000
b0 = [1/C] * C                # uniform prior (POA)
p  = [0.8] * C                # uniform POD
# Bayes update after NotFound in sector j
def bayes_update_notfound(b, j, p_j):
    denom = 1 - p_j * b[j]           # total prob of NotFound
    b_plus = b.copy()
    b_plus[j] = (1 - p_j) * b[j] / denom
    for i != j: b_plus[i] = b[i] / denom
    return b_plus
# Policy selectors
# P0: random w/ replacement              P1: random w/o replacement (per-cycle)
# P2: POA-only (argmax b), with updates     P3: POS static plan (no updates)
# P4: Bayesian POS (argmax b*p), with updates
def select(policy, b, p, state, rng):
```

```
    if policy == 'P0': return rng.randint(C), state
    if policy == 'P1':                  # walk a random permutation cyclically
        order, k = state or (rng.permutation(C), 0)
        j = order[k]; k = (k + 1) % C
        if k == 0: order = rng.permutation(C)
        return j, (order, k)
    if policy == 'P2': return argmax(b), state
    if policy == 'P3':
        order, k = state or (range(C), 0)     # fixed 0..C-1 cycling
        j = order[k]; k = (k + 1) % C
        return j, (order, k)
    if policy == 'P4': return argmax(b * p), state
# One trial
def run_trial(policy, rng):
    X = sample_state(b0, rng)  # true location
    b = b0.copy()
    state = None
    t = 0
    while True:
        j, state = select(policy, b, p, state, rng)
        t += 1
        if j == X and rng.bernoulli(p[j]) == 1:
            return t                # Found
        else:
            if policy in ['P2', 'P4']:     # Bayesian update only for these
                b = bayes_update_notfound(b, j, p[j])
# Monte Carlo loop: run N trials for each policy, collect steps-to-detection T
# Then compute: mean/std, quantiles (T50/T90/T95), and budget success P(T≤5), P(T≤10).
```
``

C9. Reproducibility checklist

Confirm: imperfect detection is simulated correctly; baselines are explicit and fair; metrics include tail and budget success; code/config/seed are documented; figures are clean and captions SAR-relevant.

Appendix D. Detailed Proofs of Propositions 1–7

This appendix provides complete, step-by-step derivations for Propositions 1–7 stated in the manuscript. The proofs use only Bayes' theorem, algebra, and (where convenient) odds transformations; they are included for completeness and to support auditability.

D.1 Proof of Proposition 1 (One-step optimality of POS)

Proof. If sector i is tasked next, then under the observation model the probability of Found on that tasking equals $P(X_t=i)\cdot P(\text{Found} \mid X_t=i,a_t=i)=b_t(i)\, p_i$. Therefore, choosing i that maximizes $b_t(i)\, p_i$ maximizes the one-step detection probability. This one-step optimality does not imply global optimality for multi-step objectives when travel costs, risk, time-varying POD, or information-gathering value are significant; the POMDP framing in Section 9 provides the formal setting for such longer-horizon trade-offs.

D.2 Proof of Proposition 2 (Effective POD and equivalence)

Proposition 2 restated. Two independent searches of the same sector j with PODs p_1 and p_2 have effective POD $p_{eff} = 1 - (1-p_1)(1-p_2)$, and two sequential NotFound Bayes updates are equivalent to one NotFound update with p_{eff}.

Proof. (a) Effective POD: conditional on the subject being in j, each search fails with probabilities $(1-p_1)$ and $(1-p_2)$. Independence implies joint failure probability $(1-p_1)(1-p_2)$. Thus detection probability over the two searches is $p_{eff} = 1 - (1-p_1)(1-p_2)$.

(b) Equivalence: let $r=b/(1-b)$ be odds for sector j. A NotFound update with POD p multiplies odds by $(1-p)$ (see Proposition 4 below). Two NotFound updates multiply by $(1-p_1)(1-p_2)$. A single NotFound update with p_{eff} multiplies odds by $1-p_{eff}=(1-p_1)(1-p_2)$. Hence posteriors coincide.

D.3 Proof of Proposition 3 (Generalized Not-Found update for non-local observation models)

Proof. Fix a searched sector j and let $Z_j(i)=P(\text{Found} \mid X=i, a=j)$ denote the probability of observing Found when the true sector is i and the action searches j. Under this observation model, the likelihood of NotFound is
$P(\text{NotFound} \mid X=i, a=j) = 1 - Z_j(i)$.

Let $b(i)=P(X=i)$ be the prior belief before searching j. By Bayes' theorem, after observing NotFound we have
$b^+(i)=P(X=i \mid \text{NotFound}, a=j) = [P(\text{NotFound} \mid X=i, a=j) * b(i)] / [\sum_k P(\text{NotFound} \mid X=k, a=j) * b(k)]$.

Substituting $P(\text{NotFound} \mid X=i, a=j)=1-Z_j(i)$ gives
$b^+(i) = [(1-Z_j(i)) * b(i)] / [\sum_k (1-Z_j(k)) * b(k)]$,
which is the claimed update. In the sector-local base model, $Z_j(i)=1[i=j]\, p_j$, so the expression reduces to the update derived in Section 4.1.

D.4 Proof of Proposition 4 (Repeated NotFound; closed form)

Proposition 4. Fix a sector j with constant tasking-specific POD $p_j = p \in [0,1]$. Suppose sector j is searched k times and the outcome is NotFound each time. Then: (a) $b_k(j) = b_0(j) (1-p)^k / ((1-b_0(j)) + b_0(j) (1-p)^k)$; (b) for $i \neq j$, $b_k(i) = b_0(i) / ((1-b_0(j)) + b_0(j) (1-p)^k)$.

Proof. Let b(j) denote the POA of sector j before a search of j, and let $q = 1-p$. Under the base observation model, when j is searched and NotFound is observed, Bayes' theorem gives the one-step update (Section 4.1):

$b^+(j) = (q\, b(j)) / (1 - p\, b(j)) = (q\, b(j)) / ((1-b(j)) + q\, b(j))$.

Define the odds of sector j as $r = b(j) / (1 - b(j))$. We compute how r transforms under the update:

$r^+ = b^+(j) / (1 - b^+(j))$.

Substitute $b^+(j) = (q\, b)/((1-b) + q\, b)$:

$1 - b^+(j) = 1 - (q\, b)/((1-b) + q\, b) = ((1-b) + q\, b - q\, b)/((1-b) + q\, b) = (1-b)/((1-b) + q\, b)$.

Therefore

$r^+ = [(q\, b)/((1-b) + q\, b)] / [(1-b)/((1-b) + q\, b)] = q\, b/(1-b) = q\, r$.

So each NotFound update in sector j multiplies the odds by q. After k consecutive NotFound outcomes,

$r_k = q^k r_0 = (1-p)^k \cdot [b_0(j)/(1-b_0(j))]$.

Convert odds back to probability using $b_k(j) = r_k/(1+r_k)$:

$b_k(j) = [q^k b_0(j)/(1-b_0(j))] / [1 + q^k b_0(j)/(1-b_0(j))]$

$= [b_0(j) q^k] / [(1-b_0(j)) + b_0(j) q^k]$

$= b_0(j) (1-p)^k / ((1-b_0(j)) + b_0(j) (1-p)^k)$, proving (a).

For $i \neq j$, the base model implies $P(\text{NotFound} \mid X=i, a=j)=1$, so Bayes' rule gives $b^+(i)=b(i)/\text{denom}$ where $\text{denom} = 1 - p\, b(j)$. Under repeated NotFound searches of j with constant p, the same normalization factor after k steps is $((1-b_0(j)) + b_0(j) (1-p)^k)$. Because all $i \neq j$ scale by the same factor and the distribution renormalizes,

$b_k(i) = b_0(i) / ((1-b_0(j)) + b_0(j) (1-p)^k)$, proving (b).

D.5 Proof of Proposition 5 (Clearance bound)

Proposition 5. Assume $0 < p < 1$ and $0 < \varepsilon < b_0(j)$. Let $b_k(j)$ be as in Proposition 4. Then the smallest integer k such that $b_k(j) \leq \varepsilon$ satisfies $k \geq \log(\varepsilon (1-b_0(j)) / (b_0(j) (1-\varepsilon))) / \log(1-p)$.

Proof. Start from the closed form in Proposition 4 with $q=1-p$:

$b_k(j) = b_0(j) q^k / ((1-b_0(j)) + b_0(j) q^k)$.

Solve $b_k(j) \leq \varepsilon$. Multiply both sides by the positive denominator:

$b_0(j) q^k \leq \varepsilon[(1-b_0(j)) + b_0(j) q^k] = \varepsilon(1-b_0(j)) + \varepsilon\, b_0(j) q^k$.

Bring q^k terms to the left and factor:

$b_0(j)(1-\varepsilon) q^k \leq \varepsilon(1-b_0(j))$.

Divide by the positive quantity $b_0(j)(1-\varepsilon)$:

$q^k \leq \varepsilon(1-b_0(j)) / (b_0(j)(1-\varepsilon))$.

Since $0<q<1$, $\log(q)=\log(1-p)<0$. Taking logs and dividing by $\log(q)$ reverses the inequality direction, yielding the stated lower bound on k.

D.6 Proof of Proposition 6 (Monotonicity)

Proposition 6. Fix $b_0(j) \in (0,1)$. For any $k \geq 1$: (i) $b_k(j)$ is strictly decreasing in p on (0,1); (ii) for fixed $p \in (0,1)$, $b_k(j)$ is strictly decreasing in k; (iii) if $p<1$ then $b_k(j)>0$ for finite k, while if $p=1$ then $b_1(j)=0$.

Proof. Let $q=1-p$ and write $b_k(j)=f(q^k)$ with $f(x)=b_0(j)x/((1-b_0(j))+b_0(j)x)$. Differentiate:

$f'(x)= b_0(j)(1-b_0(j)) / ((1-b_0(j)) + b_0(j)x)^2 > 0$ for $x>0$, so f is strictly increasing.

For fixed $k\geq 1$, q^k strictly decreases in p on (0,1), hence $b_k(j)=f(q^k)$ strictly decreases in p. For fixed $p\in(0,1)$, $q\in(0,1)$ so q^k strictly decreases in k, hence $b_k(j)$ strictly decreases in k.

If $p<1$ then $q>0$ so $q^k>0$ for finite k and thus $b_k(j)>0$. If $p=1$ then $q=0$ so for $k\geq 1$, $b_k(j)=f(0)=0$; in particular $b_1(j)=0$.

D.7 Proof of Proposition 7 (Sensitivity to POD miscalibration)

Proposition 7. Under Proposition 4 with $0<p<1$,

$\partial b_k(j)/\partial p = - k\cdot b_0(j)\cdot(1-b_0(j))\cdot(1-p)^{k-1} / (((1-b_0(j)) + b_0(j) (1-p)^k)^2) < 0$,

and therefore

$|\partial b_k(j)/\partial p| = k\cdot b_0(j)\cdot(1-b_0(j))\cdot(1-p)^{k-1} / (((1-b_0(j)) + b_0(j) (1-p)^k)^2)$.

Proof. Let $b0=b_0(j)$, $q=1-p$, and $D(q)=(1-b0)+b0\, q^k$. Then $b_k(j)=b0\, q^k / D(q)$. Differentiate with respect to q:

$d/dq\, [b0\, q^k / D] = (b0\, k\, q^{k-1}\cdot D - b0\, q^k\cdot D')/D^2$.

Compute $D'(q)=b0\, k\, q^{k-1}$. Substitute and simplify:

$d\, b_k/dq = b0\, k\, q^{k-1}(D - b0\, q^k)/D^2 = b0\, k\, q^{k-1}(1-b0)/D^2$.

Since $q=1-p$, $dq/dp=-1$, so $\partial b_k/\partial p = -(d\, b_k/dq)$. Taking absolute values and substituting $q=1-p$ yields the stated expression.

Letter to the Editor

Search and Rescue Coordination: An Emerging Profession

Matthew J. Mitchell
Founder and CEO, IASARC, www.iasarc.org
Email info@iasarc.org
https://doi.org/10.61618/PAID3355

If you were to assign a letter grade to humanity for its efforts in aiding people in distress, what would it be? Few would dispute that all people and nations have a fundamental moral obligation to assist those in need. Additionally, countries have an internationally recognized duty to provide search and rescue (SAR) services and to ensure coordinated planning for those services. Unfortunately, according to the International Civil Aviation Organization (ICAO), SAR "continues to represent the major challenge for States when performing their safety oversight function. The overall EI [Effective Implementation] … is below 50 percent" [1] (emphasis added). From a global standpoint, we are failing.

Furthermore, the ICAO data reveal significant deficiencies: 54% of nations lack regular training for their SAR coordinators, 61% operate rescue coordination centers that are inadequately staffed, and 67% fail to coordinate SAR efforts with neighboring countries. Consequently, even in the world's most advanced nations, 81%[2] of "person in water" incidents fail to result in a life saved. This alarming statistic suggests that an individual who goes overboard and requires SAR intervention faces a mere 19% probability of survival.

The core challenge is that the most vital component of global SAR programs—coordination—remains critically underdeveloped and underresourced. SAR coordination is the essential, frequently overlooked function responsible for receiving distress alerts, analyzing complex information, conducting investigations, formulating detailed search plans, and orchestrating disparate resources that often possess widely varying capabilities and are subject to distinct jurisdictional controls. Despite its role as a single point of failure for the world's life-saving enterprise, it has lagged behind analogous public safety sectors, such as fire and law enforcement.

While SAR coordination has progressed, it largely remains unprofessionalized. Professionalization can be defined as an evolutionary process by which self-directed work gradually transitions into work that supports larger organizations and serves the public interest. Fields that successfully navigate this evolution are typically characterized by: universal duty of care, specialized knowledge and skills, protracted, standardized training based on accepted criteria, and a robust, unique body of knowledge derived from theoretical and empirical research. To be clear, professionalization has nothing to do with an individual's dedication or even their status as a paid employee or volunteer, but the maturity of the field writ large.

[1] ICAO Univeral Safety Oversight Programme, Triennial Report 2022-2024, page , page 36. https://www.icao.int/usoap
[2] Derived from US Coast Guard data spanning 2013-2023, released via FOIA in 2023.

Although standards exist for individuals and organizations involved in SAR coordination, such as those detailed in the IAMSAR Manuals, their implementation varies across organizations and national authorities. Unlike other public safety professions, such as emergency management and law enforcement, SAR coordination has lacked an independent certifying body or association to uphold accepted standards, advocate for the profession as a whole, and advance its collective body of knowledge. This deficit in professionalization directly compromises SAR effectiveness globally.

The watershed moment in a field's evolution is the establishment of a qualifying association—a body comprising the field's leading experts, unified to increase professional conformity, enhance the status of its members, and engage in research to advance the profession. The emergence of such an association is both necessary and inevitable. Presently, no recognized profession operates without the support of at least one such association.

The primary function of these associations is to provide a mechanism for validating that an individual practitioner has achieved a particular level of knowledge and skill in the field, a process generally known as certification. This process constitutes a formal attestation by an independent body that a practitioner has attained a level of competence that satisfies the underlying standards.

The International Association of Search and Rescue Coordinators (IASARC) was founded to promote the sustained professionalization of search and rescue coordination globally. This international professional association is composed of leading subject-matter experts from SAR organizations and the scientific community, united by the shared mission to fully professionalize SAR coordination through challenging professional certifications, advocacy for improved legal, regulatory, and policy frameworks, and scientific and technological advancement.

IASARC is spearheading a landmark global initiative to establish the world's inaugural ISO-compliant certification for SAR coordinators. By convening multinational committees of preeminent SAR experts, IASARC is developing a rigorous, competency-based program that will standardize training, assessment, and professionalism across international borders and in all domains: land, maritime, and aeronautical. This endeavor will strengthen global interoperability, enhance decision-making in high-risk operations, and elevate the profession through transparent governance, impartial evaluation, and robust quality assurance.

Call to Action

SAR coordination achieves its maximum efficacy when all participating organizations, responders, and partners adhere to uniform standards, share a common objective, and commit to cooperation. We are currently presented with a pivotal opportunity—and a corresponding professional obligation—to elevate the standards of professionalism within our domain.

We must forge a cohesive unity across agencies, international boundaries, diverse disciplines, and distinct cultures to establish a common bedrock of training, accreditation, and exemplary operational procedures. By harmonizing our collective capabilities and raising our benchmarks, we are able to ensure more rapid deployment, safer operational environments, and superior outcomes for those relying on us during their gravest emergencies.

The present moment necessitates a concerted effort to convene, collaborate, and formalize the professionalization of SAR coordination to ensure that every mission is executed with paramount excellence, thereby maximizing the probability of survival for every life in jeopardy.

SAR coordination stands at a critical juncture. The path forward requires a decision: to persist within an inconsistent, underrecognized framework, or to elevate SAR coordination into a fully professionalized, scientifically advanced discipline. The imperative for change is unequivocal - join the IASARC mission.

The IASARC Vision

A vision drives the International Association for Search and Rescue Coordinators (IASARC): to ensure that every life in distress that can be saved is saved. This moral imperative to save lives transcends all national, political, governmental, and industrial boundaries. Achieving this requires incident response coordination by exceptionally skilled professionals who utilize the most advanced technological capabilities.

The endeavor of saving lives cannot be finitely quantified; life is of infinite value. Therefore, the commitment to this mission must advance and improve without limit. We must act decisively now. Regardless of how excellent a nation’s current Search and Rescue (SAR) system may be, the continuous ability to render aid in all environments demands that SAR professionals remain ever vigilant and the organizations supporting them constantly enhance their systems. Our guiding principle is "Amplio Infinite - Improve Infinitely."

Letter to the Editor

Search assurance and human decision-making in SAR: Do current frameworks measure the right thing?

Mags Kelly MInSTR
RES-Q360™
Email mags@res-q360.com, www.res-q360.com
https://doi.org/10.61618/XUOM7451

Search & Rescue (SAR) has evolved through advances in technology, coordination and doctrine, alongside more formal approaches to search planning and assurance. Within that progress, an ongoing discussion is how assurance practice should balance evidence of process completion and analytic outputs with the quality of the human judgements that generate, interpret and adapt them. This letter therefore invites sector-wide reflection on a question: to what extent do search assurance frameworks account for human decision-making under uncertainty, particularly cognitive load, bias and the maintenance of shared situational awareness across distributed teams?

One way to advance this discussion is to outline an author-proposed assurance concept that foregrounds human factors; for convenience it is labelled here human factor search assurance. It is offered as a discussion aid rather than as a definitive standard, a proprietary method, or a replacement for established doctrine. In brief, the concept treats the reasoning that links information to decisions (e.g., assumptions, uncertainties, confidence judgements, and thresholds for adaptation) as assurance-relevant artefacts alongside traditional measures of planning and execution, with particular attention to cognitive workload, bias and the development of shared situational awareness.

Over recent decades, search assurance in SAR has developed alongside planning doctrine and analytic methods, including more explicit documentation of intent, the use of coverage and probability-of-detection concepts, and structured debriefing to support learning and accountability. These developments have improved transparency in what was planned and what was done; a continuing question is how well assurance practices also represent the human judgements that connect evolving information to operational choices during time pressured incidents.

Cognitive vulnerability in SAR decision making

Here, “cognitive vulnerability” refers to predictable vulnerabilities in human performance under uncertainty, time pressure and high cognitive load, rather than individual negligence or lack of commitment. Operational learning literature, including reporting associated with the International Search and Rescue Incident Database (ISRID), indicates that while formal training is essential, cognitive factors can remain a challenge in improving non-find cases, i.e., cases where organised search activity does not locate the subject. Published case analyses and research have highlighted situations in which cognitive factors contributed to missed opportunities. These accounts help illustrate why a human-factors lens may be relevant to assurance, alongside planning and coverage analytics.

Such examples are not confined to high-profile cases. Operational accounts also describe occasions where searches have focused on the wrong area, teams have been in the right place but searched ineffectively, or plans have been executed without access to basic information. These outcomes are not necessarily attributable to poor intent or lack of effort, but may reflect predictable cognitive challenges inherent in complex, time-pressured environments. The central premise is therefore straightforward but intentionally challenging: if assurance is intended to increase confidence in search decisions, it may need to make decision quality more visible, not just task completion.

SAR practice has benefited substantially from improving tools and processes, including more developed approaches to planning, resource deployment and coverage modelling. However, the field is arguably less consistent in making the quality of the judgements that underpin these activities explicit. In particular, this includes how information is interpreted, how uncertainty is handled, and how decisions are adapted as conditions change. This is not a critique of intent or professionalism, but an observation that decision quality is often assumed, rather than deliberately supported and assessed, within search assurance practice. Concepts such as situational awareness (Endsley, 1995), recognition-primed decision-making (Klein, 1993) and cognitive load are well established across aviation, healthcare, and military domains.

Similarly, research into high-reliability organisations highlights the importance of collective mindfulness, sensitivity to operations and disciplined reflection in maintaining performance under uncertainty (Weick and Sutcliffe, 2007). SAR shares many of these same characteristics, including dynamic conditions, incomplete information, distributed teams and high-consequence outcomes; however, the explicit integration of these principles into everyday search practice varies across organisations and contexts. This raises a key question: to what extent is search assurance currently a measure of process compliance rather than a reflection of decision quality? A recurring limitation in assurance practice is that what can be easily counted or audited (e.g., task completion, documented plans, coverage summaries, or adherence to agreed processes) is not always a reliable proxy for decision quality. In complex incidents, the most consequential cognitive demands often concentrate at specific SAR decision points.

These decision points include framing the initial working hypothesis and search objectives; delineating and prioritising search areas and segments; allocating resources and selecting tactics under time and capability constraints; evaluating ambiguous clues and deciding whether to widen, narrow, or re-orient the search; managing re-tasking and mid-mission plan changes as new information arrives; deciding on suspension, continuation, or escalation; and executing handovers between shifts or agencies without loss of context. At each of these points, cognitive workload, judgement bias and breakdowns in shared situational awareness can shape what is searched, how well it is searched and how quickly the plan adapts. The practical challenge, therefore, is not simply to “do the plan well”, but to ensure assurance frameworks can also make the reasoning behind these decisions—and the conditions under which they should change—visible and reviewable, including attention to established judgement biases (Tversky and Kahneman, 1974) and team-level shared mental models (Mathieu et al., 2000). Against this background, the next section briefly sketches one illustrative example of how a human-factors-oriented assurance approach might be expressed in practice, without implying that any single framework is sufficient or universally applicable.

An example of a human-factors-oriented assurance approach

One response to these issues is to treat certain elements of team cognition as assurance relevant artefacts, such as explicit assumptions, uncertainty statements, confidence judgements, alternative hypotheses, and agreed triggers for adaptation, captured in a way that is feasible during live incidents. In practice, these may be recorded briefly in existing briefing notes, decision logs, map annotations, or debrief prompts, so they can be reviewed alongside coverage and execution data. The framework referenced here is offered as one example of human-factors-oriented assurance for discussion; at a high level, it combines (i) brief training and shared language for common cognitive risks, (ii) structured prompts at key decision points, and (iii) mechanisms to record decision rationale.

To link prompts and documentation to operational rhythm, it may be useful to organise assurance supports around the search mission lifecycle: pre-search alignment (shared intent and thresholds), in-search cognition (maintaining situational awareness and adaptive replanning under load), and post-search assurance (review of decision rationale and learning). This framing provides a natural bridge from established assurance practices to a discussion of how human judgement might be represented within them.

Discussion: potential contribution and implications

The potential contribution of an approach of this kind can be considered in three areas. First, it may support calibrated confidence by encouraging transparent articulation of assumptions, uncertainty and decision thresholds, rather than relying on implicit judgement. In principle, making reasoning explicit can help teams coordinate under uncertainty and identify where additional information or challenge is needed.

Second, it provides one possible way to broaden what is meant by search assurance. If assurance is intended to be more than procedural verification, it may need to include at least some account of the reasoning that informed key operational choices, particularly when plans are adapted in response to new information. A process-compliant search can still be undermined by unexamined assumptions or cognitive bias; documenting decision rationale and uncertainty may therefore help make assurance claims more interpretable and support post-incident review.

Third, this approach could be put into practice with little extra effort if it is incorporated into current briefings, decision reviews, information displays, and debriefings, instead of relying on new technology or significant resources. Whether this can be achieved without adding undue burden is an empirical question, but it is a relevant design requirement in resource-constrained SAR environments. The next section notes preliminary observations from an exercise context and highlights what would be needed to evaluate such supports more rigorously.

Preliminary observations from an exercise

A preliminary trial of elements associated with the illustrative concept described above was undertaken during a Search & Rescue exercise in May 2025, following familiarisation and iterative refinement with experienced search management practitioners. Feedback gathered during and after the exercise suggested that structured prompts may help some teams externalise assumptions, articulate uncertainties and reduce perceived cognitive pressure at key decision points. Participants also noted that prompts supported more consistent capture of decision rationale for subsequent review. These observations are indicative only and should not be interpreted as evidence of effectiveness beyond the trial context. Over the subsequent year, elements similar to those described above were reportedly used within one team's routine practice. Systematic evaluation (e.g., defined measures, comparison conditions, and multi-team replication) would be required to establish reliability, transferability and any effect on operational outcomes. A next step would be independent assessment of whether human-factors-oriented assurance prompts produce measurable differences in decision quality, shared situational awareness and the interpretability and defensibility of assurance claims under realistic operational constraints.

Acknowledging concerns

Formalising aspects of cognition may raise concerns that such frameworks could constrain professional judgement or introduce unnecessary structure. However, human factors research indicates that, when appropriately designed and used, structured supports can complement expertise by reducing unhelpful variability and improving shared understanding, while still allowing professional judgement to be exercised where it matters. The intention of the example described above is not to prescribe how individuals should think, but to illustrate how teams might make critical assumptions and decision rationale more explicit. SAR effectiveness is rarely the product of isolated expertise; it emerges from coordinated sense-making, shared awareness, and collective decision-making under pressure. Structured prompts, where appropriate, may support that coordination by encouraging constructive challenge and clearer articulation of uncertainty. The example outlined here is intended to support discussion about how human-factors concepts might be represented within search assurance and how such approaches could be evaluated under operational constraints. Further work could examine what information about decision rationale is feasible to capture during live incidents, how it can support shared situational awareness across distributed teams and what forms of review meaningfully improve learning without imposing undue burden. In that context, a constructive question for the sector is whether current search assurance frameworks sufficiently capture the human aspects of search management: how uncertainty is handled, how cognitive load and bias are managed, and how shared situational awareness is maintained and repaired as information changes. If gaps exist, what minimum set of practical decision-quality indicators would be useful, auditable, and acceptable across diverse

SAR contexts? Clarifying these indicators could support more consistent learning, review, and evaluation across organisations.

References

Endsley, M.R. (1995) 'Toward a theory of situation awareness in dynamic systems', Human Factors, 37(1), pp. 32–64. doi:10.1518/001872095779049543

Klein, G.A. (1993) 'A recognition-primed decision (RPD) model of rapid decision making', in Klein, G.A., Orasanu, J., Calderwood, R. and Zsambok, C.E. (eds.) Decision Making in Action: Models and Methods. Norwood, NJ: Ablex, pp. 138–147.

Tversky, A. and Kahneman, D. (1974) 'Judgment under uncertainty: heuristics and biases', Science, 185(4157), pp. 1124–1131. doi:10.1126/science.185.4157.1124

Reason, J. (2000) 'Human error: models and management', BMJ, 320(7237), pp. 768–770. doi:10.1136/bmj.320.7237.768

Weick, K.E. and Sutcliffe, K.M. (2007) Managing the Unexpected: Resilient Performance in an Age of Uncertainty. 2nd edn. San Francisco: Jossey-Bass.

Flin, R., O'Connor, P. and Crichton, M. (2008) Safety at the Sharp End: A Guide to Non-Technical Skills. Aldershot: Ashgate.

Mathieu, J.E., Heffner, T.S., Goodwin, G.F., Salas, E. and Cannon-Bowers, J.A. (2000) 'The influence of shared mental models on team process and performance', Journal of Applied Psychology, 85(2), pp. 273–283. doi:10.1037/0021-9010.85.2.273

Hashimoto, A., Heintzman, L., Koester, R. and Abaid, N. (2022) 'An agent-based model reveals lost person behavior based on data from wilderness search and rescue', Scientific Reports, 12, Article 5873. doi:10.1038/s41598-022-09502-4

Koester, R.J. (2016) Lost Person Behavior: A Search and Rescue Guide on Where to Look—For Land, Air and Water. 2nd edn. Charlottesville, VA: dbS Productions.

Neubauer, N.A., Miguel-Cruz, A. and Liu, L. (2021) 'Strategies to locate lost persons with dementia: a case study of Ontario first responders', Journal of Aging Research, 2021, Article ID 5572764. doi:10.1155/2021/5572764