

**РОЗДІЛ 3. БЕЗПЕКА, УПРАВЛІННЯ РИЗИКАМИ ТА РІШЕННЯ  
В НАДЗВИЧАЙНИХ СИТУАЦІЯХ**

**CHAPTER 3. SAFETY, RISK MANAGEMENT, AND  
EMERGENCY RESPONSE**

**ARTIFICIAL INTELLIGENCE SUPPORTED FIELD RECOGNITION OF  
BIOLOGICAL, CHEMICAL AND ENVIRONMENTAL THREATS IN WARTIME**

**ВИЯВЛЕННЯ БІОЛОГІЧНИХ, ХІМІЧНИХ ТА ЕКОЛОГІЧНИХ ЗАГРОЗ У  
БОЙОВИХ УМОВАХ ЗА ДОПОМОГОЮ ШТУЧНОГО ІНТЕЛЕКТУ**

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**Abstract.** Wartime biological, chemical and environmental threats increasingly arise from damaged industrial infrastructure, disrupted public-health systems, contaminated water networks, fires, hazardous transport corridors and ambiguous hostile actions. Predictive prevention is defined here as the ability to identify probable escalation pathways from incomplete and time-sensitive signals before full incident confirmation is available. This article develops an operational model for uniformed services and civil-protection actors that combines multi-source data, provenance control, anomaly detection, unmanned stand-off reconnaissance, dynamic geospatial risk mapping, artificial intelligence (AI) staff-support modules and exercise-based validation. The model does not transfer decisions to AI. It uses AI to rank information gaps, expose uncertainty, structure reports and support safer reconnaissance, while legally responsible human command remains accountable for warning, sampling, isolation, evacuation and stand-down decisions. The practical value of the framework is earlier recognition of weak signals, reduced responder exposure, better prioritization of sampling and more auditable command reasoning during wartime emergencies.

**Keywords:** wartime threat prevention, biological threats, chemical threats, environmental threats, artificial intelligence, unmanned systems, geospatial intelligence, dynamic risk mapping, chemical, biological, radiological and nuclear (CBRN) defence, command decision support.

**Анотація.** У воєнний час біологічні, хімічні та екологічні загрози дедалі частіше виникають внаслідок пошкодження промислової інфраструктури, порушення роботи систем охорони здоров'я, забруднення водопровідних мереж, пожеж, використання небезпечних транспортних коридорів та неоднозначних ворожих дій. Прогнозна профілактика визначається тут як здатність ідентифікувати ймовірні шляхи ескалації на основі неповних та термінових сигналів до того, як буде отримано повне підтвердження інциденту. У цій статті розроблено оперативну модель для служб у формі та суб'єктів цивільного захисту, яка поєднує дані з різних джерел, контроль походження, виявлення аномалій, безпілотну розвідку на відстані, динамічне геопросторове картування ризиків, модулі підтримки персоналу на основі штучного інтелекту (ШІ) та валідацію на основі навчань. Модель не передає прийняття рішень ШІ. Вона використовує ШІ для ранжування інформаційних прогалин,

виявлення невизначеності, структурування звітів та забезпечення безпечнішої розвідки, тоді як юридично відповідальне людське командування залишається відповідальним за рішення щодо попередження, відбору проб, ізоляції, евакуації та припинення дій. Практична цінність цієї структури полягає у більш ранньому розпізнаванні слабких сигналів, зменшенні ризику для реагуючих служб, кращому визначенні пріоритетів відбору проб та більш контрольованому обґрунтуванні рішень командування під час надзвичайних ситуацій у воєнний час.

Ключові слова: запобігання загрозам у воєнний час, біологічні загрози, хімічні загрози, екологічні загрози, штучний інтелект, безпілотні системи, геопросторова розвідка, динамічне картографування ризиків, хімічна, біологічна, радіологічна та ядерна (ХБРЯ) оборона, підтримка прийняття рішень командуванням.

## INTRODUCTION

Biological, chemical and environmental emergencies in wartime do not usually begin as cleanly observable events. They begin as partial, noisy and spatially dispersed signals: an odour report, a smoke column, a sudden change in water quality, a rise in non-specific symptoms, a damaged storage tank visible in imagery, a meteorological change that redirects a plume, or a cluster of contradictory field reports. Traditional chemical, biological, radiological and nuclear (CBRN) preparedness is therefore necessary but not sufficient. North Atlantic Treaty Organization (NATO) doctrine on CBRN defence<sup>1</sup> and NATO CBRN defence policy<sup>2</sup> preserve warning, reporting, protection, reconnaissance, decontamination, medical response and restoration of operational control as core functions, while World Health Organization guidance on biological and chemical weapons<sup>3</sup> frames public-health response, risk communication and medical preparedness as essential response domains. These functions must be complemented by earlier risk anticipation and information prioritization in situations where delayed recognition can increase casualties and environmental damage.

The wartime context makes this shift especially important. Industrial plants, water intakes, fuel depots, laboratories, energy infrastructure, waste-storage sites and transport routes can become secondary hazard sources when damaged by attack, sabotage, fire or infrastructure collapse. In Ukraine, peer-reviewed analysis of environmental health impacts<sup>4</sup>, the Organisation for Economic Co-operation and Development (OECD) assessment<sup>5</sup>, the Organization for Security and Co-operation in Europe (OSCE) platform report<sup>6</sup>, Rawtani et al.'s environmental-damage perspective<sup>7</sup> and the United Nations Environment Programme (UNEP) preliminary review<sup>8</sup> have documented broad environmental and public-health consequences of

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<sup>1</sup> North Atlantic Treaty Organization. (2010). ATP-3.8.1 Volume I: CBRN defence on operations. <https://nllp.jallc.nato.int/cmmt/ciedcoi/CIED%20PUBLICATIONS/STANAGs/STANAG%202521%20CBRN%20Defence%20Operations%20ATP%203.8.1%20vol.%20I.pdf>

<sup>2</sup> North Atlantic Treaty Organization. (2022). NATO's chemical, biological, radiological and nuclear defence policy. [https://www.nato.int/cps/cn/natohq/official\\_texts\\_197768.htm](https://www.nato.int/cps/cn/natohq/official_texts_197768.htm)

<sup>3</sup> World Health Organization. (2004). Public health response to biological and chemical weapons: WHO guidance. <https://www.who.int/publications-detail-redirect/public-health-response-to-biological-and-chemical-weapons-who-guidance-%282004%29>

<sup>4</sup> Hryhorczuk, D., Levy, B. S., Prodanchuk, M., Kravchuk, O., Bubalo, N., Hryhorczuk, A., & Erickson, T. B. (2024). The environmental health impacts of Russia's war on Ukraine. *Journal of Occupational Medicine and Toxicology*, 19(1), 1. <https://doi.org/10.1186/s12995-023-00398-y>

<sup>5</sup> Organisation for Economic Co-operation and Development. (2022). Environmental impacts of the war in Ukraine and prospects for a green reconstruction. OECD Publishing. <https://doi.org/10.1787/9e86d691-en>

<sup>6</sup> Organization for Security and Co-operation in Europe. (2022). OSCE-supported platform highlights environmental risks stemming from war in Ukraine. <https://www.osce.org/project-coordinator-in-ukraine-closed/520442>

<sup>7</sup> Rawtani, D., Gupta, G., Khatri, N., Rao, P. K., & Hussain, C. M. (2022). Environmental damages due to war in Ukraine: A perspective. *Science of the Total Environment*, 850, 157932. <https://doi.org/10.1016/j.scitotenv.2022.157932>

<sup>8</sup> United Nations Environment Programme. (2022). The environmental impact of the conflict in Ukraine: A preliminary review. <https://wedocs.unep.org/handle/20.500.11822/40746>

war, including risks related to industrial contamination, damaged infrastructure, water pollution, hazardous waste and long-term ecological harm. These examples demonstrate that wartime threat prevention cannot be reduced to one agency, one dataset or one sensor. It requires an interdisciplinary operating model linking emergency management, epidemiology, environmental monitoring, geospatial analysis, robotics, command procedures and legal accountability.

This article argues that predictive prevention should be treated as a command-support capability rather than as a technological slogan. Its aim is to identify probable escalation pathways before an incident becomes operationally irreversible. The proposed framework does not replace field reconnaissance, laboratory confirmation, medical judgement, public-health authority or command responsibility. Instead, it gives uniformed services and civil-protection actors a disciplined way to integrate weak signals, uncertainty and operational constraints into earlier and more auditable decisions.

The original contribution of this article is an operational model that translates predictive prevention into a practical command-support architecture for wartime biological, chemical and environmental threat management. The model is composed of seven elements: multi-source operational data, quality and provenance control, anomaly and pattern detection, unmanned stand-off reconnaissance, dynamic geospatial risk mapping, human-in-the-loop AI staff support and exercise-based validation. The model is intended for uniformed services, civil-protection institutions, public-health authorities, environmental agencies and critical-infrastructure operators that must act before uncertainty is fully resolved.

## **REVIEW METHODOLOGY AND SOURCE SELECTION**

A structured narrative review with transparent source documentation was conducted on May, 2026. The review should not be interpreted as a systematic review or meta-analysis. It was designed as a transparent evidence-consolidation process because the evidence base includes heterogeneous doctrine, standards, official reports, environmental assessments, robotics studies, public-health surveillance studies, geospatial methods and AI governance documents. The objective was to synthesize operationally relevant evidence and convert it into a framework for wartime prevention, early warning, reconnaissance prioritization and staff decision support.

Searches covered scientific metadata sources and targeted institutional repositories. Query groups addressed CBRN defence, including systematic review evidence on chemical, biological, radiological and nuclear threat management<sup>9</sup>, biological early warning, chemical sensing, environmental monitoring, atmospheric dispersion, geospatial risk mapping, unmanned systems, data fusion, disaster-response situation awareness, public-health intelligence, artificial intelligence (AI) decision support and environmental impacts of the war in Ukraine. The governance search also included the European Union Artificial Intelligence Act (AI Act)<sup>10</sup>, the National Institute of Standards and Technology (NIST) Artificial Intelligence Risk Management Framework (AI RMF)<sup>11</sup> and NATO's revised artificial intelligence strategy<sup>12</sup>. Sources were eligible when they supported at least one of four claim categories: operational doctrine and governance, data and modelling methods, unmanned or remote reconnaissance, or implementation and validation safeguards.

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<sup>9</sup> Gawlik-Kobylńska, M. (2022). Current issues in combating chemical, biological, radiological, and nuclear threats to empower sustainability: A systematic review. *Applied Sciences*, 12(16), 8315. <https://doi.org/10.3390/app12168315>

<sup>10</sup> European Parliament and Council of the European Union. (2024). Regulation (EU) 2024/1689 laying down harmonised rules on artificial intelligence. <https://eur-lex.europa.eu/eli/reg/2024/1689/oj>

<sup>11</sup> National Institute of Standards and Technology. (2023). Artificial intelligence risk management framework (AI RMF 1.0) (NIST AI 100-1). <https://doi.org/10.6028/NIST.AI.100-1>

<sup>12</sup> North Atlantic Treaty Organization. (2024). Summary of NATO's revised artificial intelligence strategy. [https://www.nato.int/cps/en/natohq/official\\_texts\\_227237.htm](https://www.nato.int/cps/en/natohq/official_texts_227237.htm)

Sources were excluded when they were unrelated to biological, chemical or environmental threats, lacked operational relevance, contained unsupported claims, duplicated other records or could not be connected to the practical objective of predictive prevention.

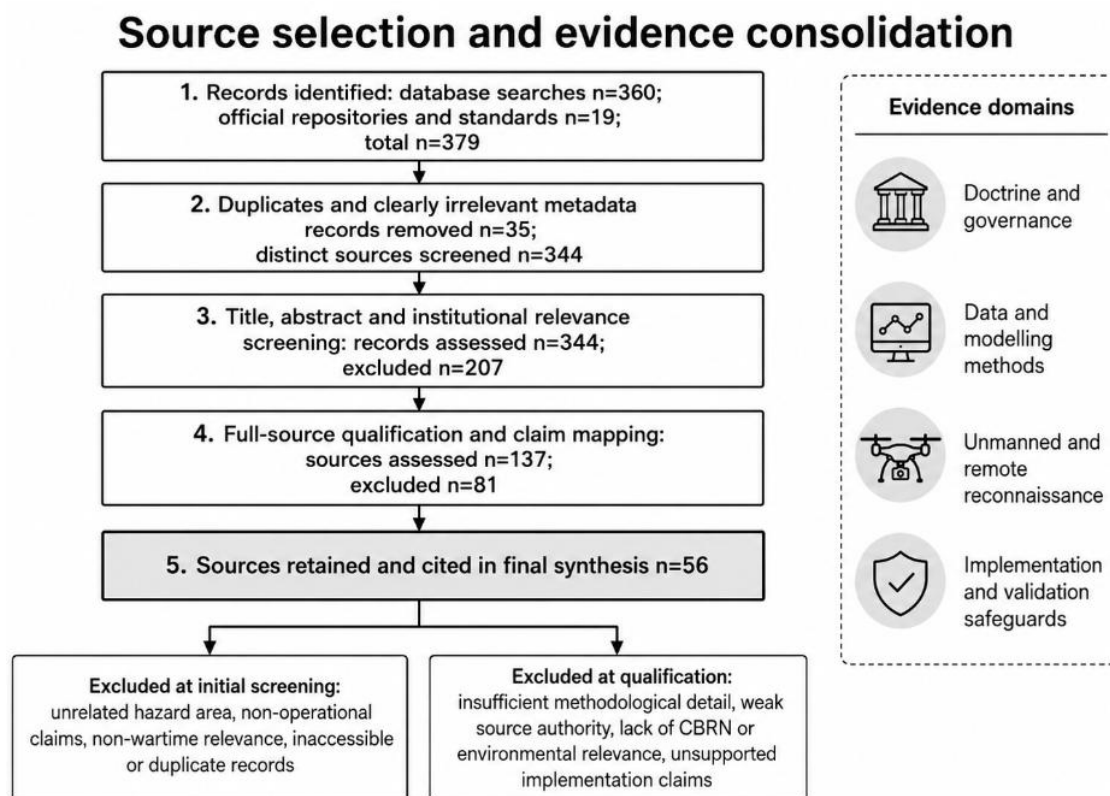
The screening process identified 379 records. After removal of 35 duplicates, 344 distinct sources were screened. 137 records underwent full-source qualification and claim mapping. 56 sources were retained and cited in the final synthesis. Source qualification was conducted as authorial expert screening based on relevance to wartime or degraded operations, methodological transparency, institutional authority, operational usefulness and direct applicability to biological, chemical, environmental, geospatial, unmanned or AI-supported prevention. No pooled effect size, formal meta-analysis or independent dual-review adjudication is claimed. The retained sources include official documents from NATO, the World Health Organization, the International Atomic Energy Agency, the International Organization for Standardization, the United Nations, the OECD, the Organisation for the Prohibition of Chemical Weapons and the European Union, systematic or scoping reviews, empirical studies on unmanned and remote sensing, and methodological papers on anomaly detection, data fusion, geospatial analysis and disaster decision support.

**Table 1**

Source inclusion and exclusion criteria used during structured source qualification.

<b>Criterion area</b>	<b>Inclusion rule</b>	<b>Exclusion rule</b>	<b>Purpose</b>
Threat relevance	Sources addressing biological, chemical, environmental or CBRN-related hazards under emergency, conflict or critical-infrastructure conditions.	Sources limited to ordinary industrial safety, generic disaster management or unrelated cyber/physical security without a threat-prevention component.	Keep the synthesis aligned with the BCET 2026 scope and wartime hazard-prevention objective.
Operational usefulness	Doctrine, standards, official reports, field-oriented studies and methods that could inform warning, reconnaissance, sampling, mapping or command support.	Purely theoretical, promotional or speculative sources without operational decision relevance.	Prioritize evidence that can be translated into procedures for uniformed services and civil protection.
Methodological transparency	Sources with identifiable methods, data sources, institutional authority or documented technical assumptions.	Sources with unsupported implementation claims, unclear provenance or unverifiable technical assertions.	Reduce the risk of adopting unvalidated AI, sensing or mapping claims.
Wartime or degraded-context relevance	Sources directly related to conflict effects, degraded infrastructure, emergency surveillance, damaged environments or stand-off reconnaissance.	Sources assuming ideal communications, complete data, stable infrastructure or routine public-health conditions only.	Ensure that the framework remains realistic under missing, delayed and misleading data.
Governance and accountability	Sources supporting human responsibility, auditability, risk management, evidence handling, chain of custody or legal constraints.	Sources implying autonomous high-consequence decision-making without verification and accountability controls.	Preserve the distinction between AI support and legally responsible command decisions.

The principal limitation of this review is that it integrates heterogeneous evidence rather than comparable experimental studies. It therefore does not claim pooled effectiveness of any AI, unmanned or geospatial method. Its purpose is to define a defensible operational architecture, identify practical validation metrics and specify safeguards that should be tested during exercises before deployment in real incidents.



**Figure 1.** Structured source selection and evidence consolidation process used for the review.

## FROM RESPONSE DOCTRINE TO PREDICTIVE PREVENTION

The shift toward predictive prevention should be understood as an extension of doctrine, not as a substitute for it. NATO CBRN doctrine and policy<sup>13,14</sup> define capabilities for detection, identification, monitoring, warning, reporting, protection, hazard management, medical countermeasures and recovery. World Health Organization (WHO) guidance on biological and chemical weapons<sup>15</sup> similarly emphasizes public-health response, risk communication, medical preparedness and coordinated management of biological and chemical events. These functions remain the backbone of crisis response. Predictive prevention adds an earlier analytical layer that asks where reconnaissance, sampling and command attention should be directed before the hazard is fully confirmed.

This temporal shift is consistent with disaster-risk reduction thinking. The Sendai Framework for Disaster Risk Reduction<sup>16</sup> emphasizes understanding risk, strengthening governance, investing in risk reduction and improving preparedness before disaster consequences accumulate. In CBRN and environmental threat contexts, the analogous task is to transform hazard registers, sensor streams, weather

<sup>13</sup> Ibid 1

<sup>14</sup> Ibid 2

<sup>15</sup> Ibid 3

<sup>16</sup> United Nations Office for Disaster Risk Reduction. (2015). Sendai Framework for Disaster Risk Reduction 2015-2030. <https://www.undrr.org/publication/sendai-framework-disaster-risk-reduction-2015-2030>

data, public-health signals, geospatial layers and field reports into anticipatory decisions. Such decisions may include dispatching unmanned aerial vehicle (UAV) reconnaissance before a team enters a site, sampling a water intake before contamination reaches a population centre, pre-positioning protective equipment, warning hospitals about possible exposure or rejecting a false alarm when evidence remains weak.

The operational logic is probabilistic. A chemical release is shaped by wind, atmospheric stability, terrain, drainage, buildings and source characteristics. A biological signal is shaped by incubation periods, population movement, disrupted healthcare access and reporting bias. Environmental degradation depends on hydrology, soil, fire, damaged treatment systems, industrial inventories and delayed measurement. In each case, the operational question is not whether AI can predict the future with certainty. The question is whether a system can reduce uncertainty early enough to improve reconnaissance tasking, responder safety and public-protection decisions.

Prediction, early warning and decision support should therefore be kept analytically distinct. Prediction estimates probable threat development under stated assumptions. Early warning detects signals that justify verification before full confirmation exists. Decision support structures evidence, uncertainty and operational options for human command. A mature predictive-prevention capability connects these three functions without presenting any of them as autonomous decision-making.

## **WARTIME THREAT ENVIRONMENT AND OPERATIONAL CONSTRAINTS**

Wartime environments differ from ordinary hazardous-materials incidents because the hazard source, the information environment and the response system may all be degraded at the same time. A damaged facility may release chemicals while local sensors are destroyed. Water contamination may spread while laboratories are overloaded or inaccessible. Epidemiological signals may be confounded by displacement, disrupted care-seeking behaviour, sheltering conditions and interruptions in vaccination, sanitation or routine surveillance. Field teams may face shelling, mines, damaged roads, contaminated debris, communications outages and electromagnetic interference.

The most consequential operational constraints are missing data, wrong data and delayed data. Sensor drift can produce false trends. Location data may be imprecise. Reports from residents may be duplicated across social channels. Adversarial actors may amplify rumours or mask real releases, which is consistent with the need for intelligent-adversary risk analysis in bioterrorism and deliberate threat management<sup>17</sup>. Global Positioning System (GPS) interference can degrade the quality of unmanned reconnaissance. Weather forecasts may be insufficient for street-level plume prediction. These constraints do not make predictive prevention impossible, but they require explicit confidence levels, provenance tracking and human verification before operational escalation.

For uniformed services, the practical implication is that a predictive system must support degraded operations rather than assume ideal data conditions. It must be able to mark uncertain coordinates, separate confirmed measurements from unverified reports, retain the history of assumptions, and show which decisions are robust to missing data. The system should also identify when the evidence is too weak for a high-consequence action and when additional reconnaissance is safer than immediate commitment of personnel.

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<sup>17</sup> Parnell, G. S., Smith, C. M., & Moxley, F. I. (2010). Intelligent adversary risk analysis: A bioterrorism risk management model. *Risk Analysis*, 30(1), 32-48. <https://doi.org/10.1111/j.1539-6924.2009.01319.x>

## **DATA SOURCES AND QUALITY CONTROLS**

Data are a source of operational advantage only when they are interpreted through their uncertainty. Reviews of disaster-response technologies show that information systems contribute most when they improve shared situational awareness and convert observations into usable decisions across agencies<sup>18</sup>. In CBRN and environmental prevention, relevant data include fixed sensors, mobile detectors, meteorology, hydrology, facility inventories, satellite and UAV imagery, public-health alerts, clinical syndromic indicators, laboratory results, field reports, crowdsourced observations and geospatial layers. Data fusion literature provides the methodological basis for integrating such streams<sup>19,20</sup>, but also shows that fusion without provenance control can amplify errors.

Environmental sensor networks, UAVs and crowdsensing can increase observation density in areas where conventional monitoring is sparse or disrupted. Reviews of wireless sensor networks, UAVs and citizen-sensing approaches show potential for air, water and environmental surveillance<sup>21, 22, 23</sup>, provided that calibration, coverage, communication quality and interpretation limits are addressed. Remote sensing can support water-quality and environmental monitoring<sup>24,25</sup>, although optical retrieval is affected by cloud cover, turbidity, atmospheric correction, spatial resolution and the need for field validation. Meteorological and precipitation products such as Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS)<sup>26</sup> can complement local observations when extreme rainfall or runoff affects contamination transport.

Public-health data must be handled with particular caution. Syndromic surveillance, event-based surveillance and epidemic intelligence can detect unusual patterns, but they do not prove intentional release or identify the agent without follow-up investigation. WHO guidance on Early Warning, Alert and Response systems<sup>27</sup> and the WHO Epidemic Intelligence from Open Sources strategy<sup>28</sup> emphasize structured alerting, verification and response coordination, not automatic attribution. The Centers for Disease Control and Prevention (CDC) BioSense Platform<sup>29</sup> illustrates the operational value of platform-based syndromic data, but such systems require context, baseline understanding and protection against overinterpretation.

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<sup>18</sup> Kedia, T., Ratcliff, J., O'Connor, M., Oluic, S. H., & Rose, M. A. (2022). Technologies enabling situational awareness during disaster response: A systematic review. *Disaster Medicine and Public Health Preparedness*, 16(1), 341-359. <https://doi.org/10.1017/dmp.2020.196>

<sup>19</sup> Castanedo, F. (2013). A review of data fusion techniques. *The Scientific World Journal*, 2013, 704504. <https://doi.org/10.1155/2013/704504>

<sup>20</sup> Hall, D., & Llinas, J. (1997). An introduction to multisensor data fusion. *Proceedings of the IEEE*, 85(1), 6-23. <https://doi.org/10.1109/5.554205>

<sup>21</sup> Fascista, A. (2022). Toward integrated large-scale environmental monitoring using WSN/UAV/crowdsensing: A review of applications, signal processing, and future perspectives. *Sensors*, 22(5), 1824. <https://doi.org/10.3390/s22051824>

<sup>22</sup> Goodchild, M. F. (2007). Citizens as sensors: The world of volunteered geography. *GeoJournal*, 69(4), 211-221. <https://doi.org/10.1007/s10708-007-9111-y>

<sup>23</sup> Kamel Boulos, M. N., Resch, B., Crowley, D. N., Breslin, J. G., Sohn, G., Burtner, R., Pike, W. A., Jezierski, E., & Chuang, K. Y. (2011). Crowdsourcing, citizen sensing and sensor web technologies for public and environmental health surveillance and crisis management: Trends, OGC standards and application examples. *International Journal of Health Geographics*, 10, 67. <https://doi.org/10.1186/1476-072X-10-67>

<sup>24</sup> Gholizadeh, M., Melesse, A., & Reddi, L. (2016). A comprehensive review on water quality parameters estimation using remote sensing techniques. *Sensors*, 16(8), 1298. <https://doi.org/10.3390/s16081298>

<sup>25</sup> Yang, H., Kong, J., Hu, H., Du, Y., Gao, M., & Chen, F. (2022). A review of remote sensing for water quality retrieval: Progress and challenges. *Remote Sensing*, 14(8), 1770. <https://doi.org/10.3390/rs14081770>

<sup>26</sup> Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., & Michaelsen, J. (2015). The climate hazards infrared precipitation with stations: A new environmental record for monitoring extremes. *Scientific Data*, 2, 150066. <https://doi.org/10.1038/sdata.2015.66>

<sup>27</sup> World Health Organization. (2022). Early warning, alert and response in emergencies: An operational guide. <https://iris.who.int/handle/10665/365730>

<sup>28</sup> World Health Organization. (2024). Epidemic intelligence from open sources strategy 2024-2026. <https://iris.who.int/handle/10665/382406>

<sup>29</sup> Centers for Disease Control and Prevention. (2026). BioSense Platform. <https://www.cdc.gov/nssp/php/about/about-nssp-and-the-biosense-platform.html>

**Table 2**

Operational data sources for predictive prevention of wartime biological, chemical and environmental threats.

<b>Data source</b>	<b>Operational contribution</b>	<b>Typical uncertainty</b>	<b>Preventive use</b>
Environmental sensors	Air, water, radiation or volatile organic compound measurements.	Calibration drift, weather exposure, power loss, false positives.	Trigger confirmatory sampling and define reconnaissance corridors.
Meteorology and hydrology	Wind, precipitation, temperature, atmospheric stability, drainage and flow direction.	Local variability, forecast error, missing micro-scale data.	Forecast plume movement, runoff and downstream contamination risk.
Satellite and UAV imagery	Optical, thermal and structural indicators across inaccessible or dangerous areas.	Cloud cover, revisit time, visual ambiguity, sensor limits.	Prioritize sites, identify fires, damaged containment and water-colour changes.
Health and syndromic data	Early indication of abnormal clinical patterns or exposure-related symptoms.	Reporting delay, displacement, care access changes, non-specific symptoms.	Prompt epidemiological investigation and environmental verification.
Field and civilian reports	Local observations, odours, smoke, dead animals, unusual water or access problems.	Duplication, misinformation, inaccurate geocoding, panic effects.	Support triage and identify locations for verification.
Facility and infrastructure registers	Hazard inventories, water intakes, hospitals, depots, transport routes and storage sites.	Outdated records, damaged assets, incomplete ownership data.	Estimate source terms and prioritize assets requiring protection.

## ARTIFICIAL INTELLIGENCE FUNCTIONS AND VALIDATION METRICS

Artificial intelligence (AI) should be described by function rather than by a general label. In predictive prevention, the most relevant functions are anomaly detection, classification, sensor fusion, time-series forecasting, geospatial risk ranking, natural language processing, information-gap detection and decision triage. Anomaly-detection literature provides methods for identifying deviations in multivariate streams<sup>30, 31, 32</sup>, but also shows that algorithm choice, baseline definition and local context strongly affect false alarms. Therefore, AI outputs should be used to prioritize verification, not to declare a confirmed hazardous event.

The practical output of AI in this field is rarely a single prediction. A more useful output is a ranked set of areas, hypotheses and missing information. Examples include: verify possible chlorine release near a damaged industrial zone, sample downstream water intake within two hours, check whether odour reports align with wind direction, task UAV imagery over the suspected storage area, or request medical review of an unusual cluster of respiratory symptoms. A CBRN-specific machine-learning decision-support

<sup>30</sup> Centers for Disease Control and Prevention. (2026). BioSense Platform. <https://www.cdc.gov/nssp/php/about/about-nssp-and-the-biosense-platform.html>

<sup>31</sup> Goldstein, M., & Uchida, S. (2016). A comparative evaluation of unsupervised anomaly detection algorithms for multivariate data. *PLOS ONE*, 11(4), e0152173. <https://doi.org/10.1371/journal.pone.0152173>

<sup>32</sup> Zhang, C., Song, D., Chen, Y., Feng, X., Lumezanu, C., Cheng, W., Ni, J., Zong, B., Chen, H., & Chawla, N. V. (2019). A deep neural network for unsupervised anomaly detection and diagnosis in multivariate time series data. *Proceedings of the AAAI Conference on Artificial Intelligence*, 33(1), 1409-1416. <https://doi.org/10.1609/aaai.v33i01.33011409>

framework<sup>33</sup> illustrates how protective decisions can be structured, but field deployment still depends on data quality, operational validation and human review.

Validation must be operational, not only statistical. Useful metrics include time from first signal to alert, time from alert to reconnaissance tasking, false-alarm rate, missed-event rate, spatial agreement between predicted and measured hazard zones, ranking accuracy of sampling locations, reduction in responder exposure, completeness of audit trail, robustness to missing data and operator acceptance during exercises. These measures are more relevant for uniformed services than abstract model accuracy alone because the cost of an error depends on whether people are sent into danger, warned too late or warned unnecessarily.

**Table 3**

AI functions, outputs, failure modes and validation controls.

AI function	Input examples	Operational output	Validation and control requirement
Anomaly detection	Sensor time series, emergency department (ED) syndromes, water-quality indices.	Deviation alerts and baseline breaks.	Local baselines, false-alarm review, recalibration after exercises.
Classification	Spectral imagery, sensor signatures, report text.	Probable hazard class or incident type.	Training-data documentation and expert validation.
Forecasting	Meteorology, hydrology, dispersion outputs, case reports.	Likely spread direction and time window.	Uncertainty intervals, model comparison and conservative assumptions.
Natural language processing	Field logs, social reports, open-source alerts, medical notes.	Extracted entities, locations, dates and contradictions.	Source verification, deduplication and protection against hallucinated content.
Geospatial risk ranking	Hazard, exposure, vulnerability and accessibility layers.	Prioritized reconnaissance or sampling zones.	Comparison with field results and sensitivity to missing layers.
Information-gap detection	Incomplete maps, missing source terms, sparse sensors.	Questions for staff and tasking recommendations.	Human review of necessity, feasibility and safety.

The operational consequence of model error must be assessed before deployment. A false positive can divert teams, generate unnecessary warnings and weaken trust. A false negative can delay sampling, expose responders and leave affected populations without protection. For this reason, each AI output should be paired with a failure mode, verification action and responsible human reviewer before it enters the operational briefing.

### **BIOLOGICAL EARLY WARNING UNDER CONFLICT CONDITIONS**

The biological component requires particular analytical discipline because early signals are rarely specific. Fever, diarrhoea, respiratory symptoms or unusual absenteeism can reflect natural outbreaks, displacement, poor sanitation, interrupted healthcare access, seasonal variation, psychological stress or

<sup>33</sup> Kegyes, T., Süle, Z., & Abonyi, J. (2024). Machine learning-based decision support framework for CBRN protection. *Heliyon*, 10(4), e25946. <https://doi.org/10.1016/j.heliyon.2024.e25946>

deliberate biological release. AI-based epidemic and pandemic early-warning reviews<sup>34, 35</sup> and infectious-disease natural language processing reviews<sup>36</sup> show potential for earlier recognition of abnormal patterns, but they consistently require careful validation, clinical context and response integration.

In conflict settings, biological surveillance should therefore be framed as a hypothesis-generation tool. Big-data infectious-disease surveillance<sup>37</sup>, automated hospital outbreak detection<sup>38</sup> and early-warning system evidence<sup>39</sup> indicate that abnormal patterns deserve investigation, but the operational response must still involve epidemiological assessment, laboratory confirmation when possible, environmental review and comparison with population movement and healthcare-access data. The correct decision may be to increase surveillance, sample water, inspect sanitation infrastructure, warn medical facilities or reject an alert as a data artefact.

A practical biological early-warning module should combine syndromic baselines, event-based reports, healthcare-capacity information, displacement data, weather, water-system status and local expert review. For example, a sudden increase in gastrointestinal symptoms after damage to a water-treatment facility should not be classified automatically as intentional biological activity. The system should compare the signal with water-quality anomalies, repair logs, population displacement, rainfall, damaged sewage infrastructure, downstream hydrology and laboratory sampling capacity. Only after environmental verification, epidemiological review and laboratory confirmation should the hypothesis be escalated from public-health anomaly to confirmed biological or waterborne emergency. Laboratory confirmation should be treated as the diagnostic anchor whenever it is available, while AI and syndromic surveillance should only determine where verification is most urgent. This distinction is crucial in wartime because disrupted sanitation, displacement and interrupted healthcare access can mimic deliberate or unusual biological events.

## **CHEMICAL AND ENVIRONMENTAL THREAT DETECTION**

Chemical and environmental threats are often more spatially immediate than biological threats, but they are not necessarily easier to interpret. Gas plumes are turbulent and intermittent. Water contamination can be delayed by hydrological transport. Fires can change source terms and produce secondary toxic releases. Damaged containment systems can release mixtures rather than single agents. Chemical-detection research using mobile platforms and AI-based data processing<sup>40</sup> shows increasing potential, but it also emphasizes sensor specificity, calibration, plume structure and the difficulty of reliable source localization.

Atmospheric dispersion models remain central to chemical and radiological risk anticipation. The Weather Research and Forecasting model coupled with Chemistry (WRF-Chem)<sup>41</sup>, fast urban dispersion

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<sup>34</sup> El Morr, C., Ozdemir, D., Asdaah, Y., Saab, A., El-Lahib, Y., & Sokhn, E. S. (2024). AI-based epidemic and pandemic early warning systems: A systematic scoping review. *Health Informatics Journal*, 30(3), 14604582241275844. <https://doi.org/10.1177/14604582241275844>

<sup>35</sup> MacIntyre, C. R., Chen, X., Kunasekaran, M., Quigley, A., Lim, S., Stone, H., Paik, H. Y., Yao, L., Heslop, D., Wei, W., Sarmiento, I., & Gurdasani, D. (2023). Artificial intelligence in public health: The potential of epidemic early warning systems. *Journal of International Medical Research*, 51(3), 03000605231159335. <https://doi.org/10.1177/03000605231159335>

<sup>36</sup> Omar, M., Brin, D., Glicksberg, B., & Klang, E. (2024). Utilizing natural language processing and large language models in the diagnosis and prediction of infectious diseases: A systematic review. *American Journal of Infection Control*, 52(9), 992-1001. <https://doi.org/10.1016/j.ajic.2024.03.016>

<sup>37</sup> Hay, S. I., George, D. B., Moyes, C. L., & Brownstein, J. S. (2013). Big data opportunities for global infectious disease surveillance. *PLoS Medicine*, 10(4), e1001413. <https://doi.org/10.1371/journal.pmed.1001413>

<sup>38</sup> Leclère, B., Buckeridge, D. L., Boëlle, P. Y., Astagneau, P., & Lepelletier, D. (2017). Automated detection of hospital outbreaks: A systematic review of methods. *PLOS ONE*, 12(4), e0176438. <https://doi.org/10.1371/journal.pone.0176438>

<sup>39</sup> Meckawy, R., Stuckler, D., Mehta, A., Al-Ahdal, T. M., & Doebbeling, B. N. (2022). Effectiveness of early warning systems in the detection of infectious diseases outbreaks: A systematic review. *BMC Public Health*, 22, 2216. <https://doi.org/10.1186/s12889-022-14625-4>

<sup>40</sup> Noh, D., & Oh, E. (2025). Chemical detection using mobile platforms and AI-based data processing technologies. *Journal of Sensor and Actuator Networks*, 14(1), 6. <https://doi.org/10.3390/jsan14010006>

<sup>41</sup> Grell, G. A., Peckham, S. E., Schmitz, R., McKeen, S. A., Frost, G., Skamarock, W. C., & Eder, B. (2005). Fully coupled online chemistry within the WRF model. *Atmospheric Environment*, 39(37), 6957-6975. <https://doi.org/10.1016/j.atmosenv.2005.04.027>

model evaluation<sup>42</sup>, general atmospheric dispersion modelling reviews<sup>43</sup>, the Flexible Particle (FLEXPART) Lagrangian particle dispersion model<sup>44</sup> and the Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) system<sup>45</sup> demonstrate different trade-offs among data requirements, computational cost, spatial detail and operational speed. In wartime, the strongest use of such models is not precise prediction of a plume edge. It is conservative prioritization of corridors where reconnaissance, warning and protective action should be considered first.

Environmental degradation must be incorporated into the same prevention logic. Contamination of water, soil and air can result from destroyed industrial facilities, fires, wastewater-system failure, fuel spills, damaged waste sites and disrupted environmental governance. The OECD assessment<sup>46</sup>, Rawtani et al.'s environmental-damage perspective<sup>47</sup> and the UNEP preliminary review<sup>48</sup> show that environmental damage during the war in Ukraine can be distributed across industrial, agricultural, hydrological and urban systems rather than confined to a single incident site. These effects may persist after visible hostilities or fires have ended, producing delayed exposure through drinking water, contaminated sediment, agricultural soil, dust resuspension and food-chain pathways. A prevention model must therefore treat environmental consequences as both immediate operational hazards and long-term public-health risks requiring repeated monitoring. Post-incident monitoring plans should define sampling intervals, responsible laboratories, reporting channels and criteria for terminating surveillance.

Operational escalation should be defined before the incident occurs. These thresholds should be written into standard operating procedures before an incident, because improvised thresholds during a crisis increase the risk of both responder exposure and unnecessary public disruption. A weak or unverified signal should trigger observation and data-quality checks. A signal consistent with facility inventories, weather or hydrological pathways should trigger an alert and conservative modelling. A signal supported by imagery, sensor readings or repeated independent reports should trigger stand-off reconnaissance and targeted sampling. A signal confirmed by field measurements, laboratory evidence or clinically consistent exposure reports should trigger public warning, zone isolation, specialist entry protocols and formal command decisions. A signal contradicted by verified measurements should trigger stand-down, but the audit trail should remain available for after-action review. This threshold sequence helps services avoid both premature exposure of response teams and delayed protection of the public.

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<sup>42</sup> Hertwig, D., Soulhac, L., Fuka, V., Auerswald, T., Carpentieri, M., Hayden, P., Robins, A., Xie, Z. T., & Coceal, O. (2018). Evaluation of fast atmospheric dispersion models in a regular street network. *Environmental Fluid Mechanics*, 18(4), 1007-1044. <https://doi.org/10.1007/s10652-018-9587-7>

<sup>43</sup> Leelőssy, A., Molnár, F., Izsák, F., Havasi, Á., Lagzi, I., & Mészáros, R. (2014). Dispersion modeling of air pollutants in the atmosphere: A review. *Open Geosciences*, 6(3). <https://doi.org/10.2478/s13533-012-0188-6>

<sup>44</sup> Pisso, I., Sollum, E., Grythe, H., Kristiansen, N. I., Cassiani, M., Eckhardt, S., Arnold, D., Morton, D., Thompson, R. L., Groot Zwaaftink, C. D., Evangeliou, N., Sodemann, H., Haimberger, L., Henne, S., Brunner, D., Burkhardt, J. F., Fouilloux, A., Brioude, J., Philipp, A., ... Stöhl, A. (2019). The Lagrangian particle dispersion model FLEXPART version 10.4. *Geoscientific Model Development*, 12(12), 4955-4997. <https://doi.org/10.5194/gmd-12-4955-2019>

<sup>45</sup> Stein, A. F., Draxler, R. R., Rolph, G. D., Stunder, B. J. B., Cohen, M. D., & Ngan, F. (2015). NOAA's HYSPLIT atmospheric transport and dispersion modeling system. *Bulletin of the American Meteorological Society*, 96(12), 2059-2077. <https://doi.org/10.1175/BAMS-D-14-00110.1>

<sup>46</sup> Ibid 5

<sup>47</sup> Ibid 7

<sup>48</sup> Ibid 8

## UNMANNED SYSTEMS AND STAND-OFF RECONNAISSANCE

Unmanned systems are operationally important because they can collect evidence in hazardous or uncertain areas while limiting responder exposure. Radiation and radiological mapping studies<sup>49, 50</sup> show that UAVs can support aerial monitoring, dose-rate mapping and reconnaissance when flight altitude, detector sensitivity, shielding and background correction are properly considered. International Atomic Energy Agency (IAEA) technical outputs on uncrewed aerial systems and radioactive-material detection<sup>51, 52</sup> provide complementary institutional guidance for radiation detection and surveillance. Radiological drone scouting and inspection research<sup>53</sup> further demonstrates the role of aerial platforms in hazardous-site reconnaissance. Broader ionizing-radiation monitoring technologies<sup>54</sup> also demonstrate the relevance of networked sensing, although field reliability remains a central concern.

Chemical sensing by small UAVs is more difficult than visual reconnaissance because gas plumes are unstable and concentration fields are sparse. Experimental work on nano aerial vehicles<sup>55</sup> and volatile organic compound (VOC) detection<sup>56</sup> demonstrates feasibility for selected scenarios, but sensor response, payload, battery endurance and contamination control limit generalization. Unmanned ground vehicles (UGVs) complement UAVs when airspace is unsafe, indoor reconnaissance is needed, weather limits flight or heavier payloads are required. Reviews of gas source localization and mapping with mobile robots<sup>57</sup> show progress, but also confirm that chemical search remains sensitive to airflow, source intermittency and platform constraints.

The core preventive value of unmanned reconnaissance is not simply collecting more data. It is collecting the next most informative data point at lower risk. A predictive system should therefore task UAVs and UGVs according to the uncertainty map: verify a suspected source, cross a predicted plume corridor, inspect a water body, observe fire spread, check access routes or confirm that a suspected hazard zone is actually negative. This tasking logic is more valuable than random surveying because it links platform deployment to decision needs.

**Table 4**

Operational roles of unmanned systems in predictive prevention.

Role	Platform	Main value	Operational limitation
Stand-off visual reconnaissance	UAV	Rapid overview of damaged facilities, fires, access routes and water bodies.	Weather, airspace control, battery endurance and visual ambiguity.

<sup>49</sup> Chierici, A., Malizia, A., Di Giovanni, D., Ciolini, R., & d'Errico, F. (2022). A high-performance gamma spectrometer for unmanned systems based on off-the-shelf components. *Sensors*, 22(3), 1078. <https://doi.org/10.3390/s22031078>

<sup>50</sup> Connor, D., Martin, P. G., & Scott, T. B. (2016). Airborne radiation mapping: Overview and application of current and future aerial systems. *International Journal of Remote Sensing*, 37(24), 5953-5987. <https://doi.org/10.1080/01431161.2016.1252474>

<sup>51</sup> International Atomic Energy Agency. (2022). Use of uncrewed aerial systems for radiation detection and surveillance: Technical output from the technical meeting. [https://nucleus.iaea.org/sites/nuclear-instrumentation/Documents/TC\\_UAS\\_Rad\\_Surv\\_final.pdf](https://nucleus.iaea.org/sites/nuclear-instrumentation/Documents/TC_UAS_Rad_Surv_final.pdf)

<sup>52</sup> International Atomic Energy Agency. (2024). Detection in a State's interior of nuclear and other radioactive material out of regulatory control. <https://www.iaea.org/publications/15582/detection-in-a-states-interior-of-nuclear-and-other-radioactive-material-out-of-regulatory-control>

<sup>53</sup> Pinto, L. R., Vale, A., Brouwer, Y., Borbinha, J., Corisco, J., Ventura, R., Ferreira da Silva, M., Mourato, A., Marques, G., & Romanets, Y. (2021). Radiological scouting, monitoring and inspection using drones. *Sensors*, 21(9), 3143. <https://doi.org/10.3390/s21093143>

<sup>54</sup> Ahmad, M. I., Ab. Rahim, M. H., Nordin, R., Mohamed, F., Abu-Samah, A., & Abdullah, N. F. (2021). Ionizing radiation monitoring technology at the verge of Internet of Things. *Sensors*, 21(22), 7629. <https://doi.org/10.3390/s21227629>

<sup>55</sup> Burgués, J., Hernández, V., Lilienthal, A., & Marco, S. (2019). Smelling nano aerial vehicle for gas source localization and mapping. *Sensors*, 19(3), 478. <https://doi.org/10.3390/s19030478>

<sup>56</sup> Oliveira, A. M., Morais, A. S., Lima, G. V., Souza, R. M. J. A., & Oliveira-Lopes, L. C. (2023). Detection of volatile organic compounds in indoor environments using nano quadcopter. *Drones*, 7(11), 660. <https://doi.org/10.3390/drones7110660>

<sup>57</sup> Francis, A., Li, S., Griffiths, C., & Sienz, J. (2022). Gas source localization and mapping with mobile robots: A review. *Journal of Field Robotics*, 39(8), 1341-1373. <https://doi.org/10.1002/rob.22109>

**Continued from Table 4**

<b>Role</b>	<b>Platform</b>	<b>Main value</b>	<b>Operational limitation</b>
Radiation survey	UAV or UGV	Reduced exposure and spatial dose-rate mapping.	Detector sensitivity, altitude, shielding and background correction.
Chemical screening	UAV or UGV	Point measurements and plume-edge exploration.	Sensor specificity, turbulence, contamination and calibration.
Water and environmental inspection	UAV, unmanned surface vehicle (USV) or field robot	Observation of colour changes, spills, runoff, access and infrastructure damage.	Indirect evidence, need for physical sampling and laboratory confirmation.
Access-route verification	UAV or UGV	Safer planning for teams, vehicles and evacuation routes.	Obstacles, mines, hostile activity and degraded communications.
Communication relay or situational overwatch	UAV	Maintains observation and limited connectivity in degraded areas.	Electronic warfare, endurance, platform loss and operational security.

### **DYNAMIC RISK MAPPING AND GEOSPATIAL COMMAND SUPPORT**

Predictive prevention requires dynamic maps rather than static hazard inventories. Static maps show where hazardous facilities, hospitals, transport nodes, water intakes and vulnerable populations exist. Dynamic maps update risk as meteorology, hydrology, reports, sensor values, imagery, unit availability and population movement change. Geovisual analytics research<sup>58</sup> and geographic information system (GIS) integration research<sup>59</sup> show that spatial decision support is strongest when it enables analysts to combine model outputs, uncertainty and operational context rather than merely display layers.

A dynamic wartime risk map should integrate at least four analytical layers: hazard likelihood, exposure, vulnerability and operational feasibility. Hazard likelihood reflects source terms, plume or runoff modelling, sensor anomalies, images and threat intelligence. Exposure includes responders, civilians, hospitals, schools, water intakes, shelters and transport routes. Vulnerability reflects protective equipment, medical capacity, shelter options, evacuation constraints and social factors. Operational feasibility includes access, safety, communications, platform availability, legal authority and the probability that reconnaissance will produce useful evidence.

The map should also show confidence. A zone predicted only from unverified reports should not be visually equivalent to a zone supported by calibrated measurements and field confirmation. Confidence layers help commanders avoid both underreaction and overreaction. They also support after-action review because every change in the map can be traced to data, assumptions, model versions and operator approval.

**Table 5**

Minimum layers of a dynamic wartime risk map

<b>Layer</b>	<b>Variables</b>	<b>Update frequency</b>	<b>Decision supported</b>
Hazard likelihood	Sensor anomalies, source term, plume or runoff model, imagery indicators.	Minutes to hours.	Where to sample, where to fly, where to isolate.

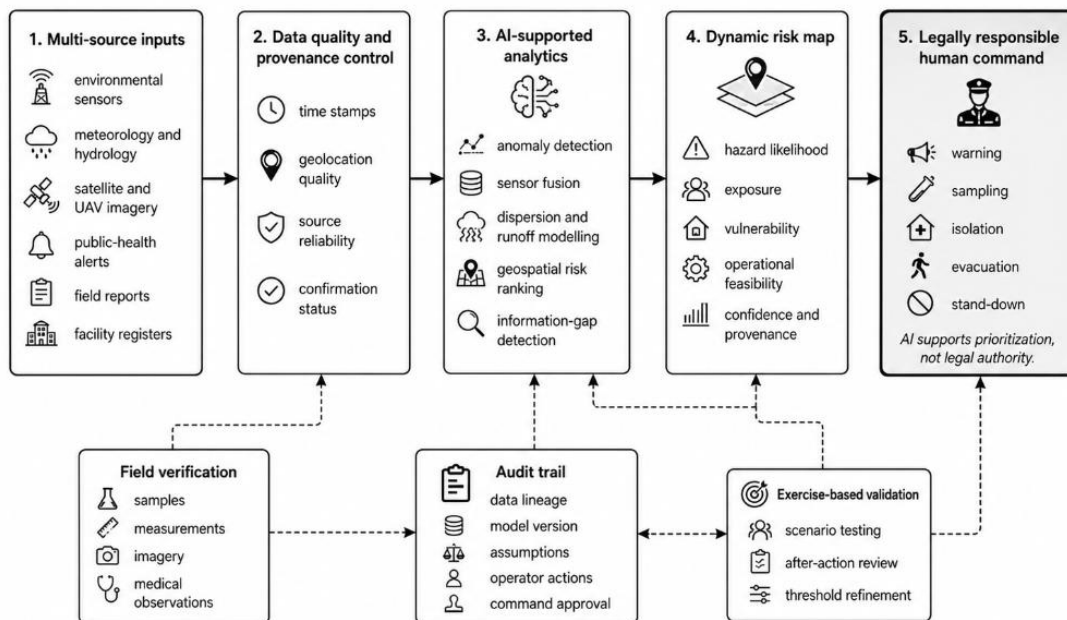
<sup>58</sup> Andrienko, G., Andrienko, N., Jankowski, P., Keim, D., Kraak, M., MacEachren, A., & Wrobel, S. (2007). Geovisual analytics for spatial decision support: Setting the research agenda. *International Journal of Geographical Information Science*, 21(8), 839-857. <https://doi.org/10.1080/13658810701349011>

<sup>59</sup> Liu, X., Wang, X., Wright, G., Cheng, J., Li, X., & Liu, R. (2017). A state-of-the-art review on the integration of building information modeling and geographic information system. *ISPRS International Journal of Geo-Information*, 6(2), 53. <https://doi.org/10.3390/ijgi6020053>

**Continued from Table 5**

Layer	Variables	Update frequency	Decision supported
Exposure	Population, responders, hospitals, schools, water intakes and transport flows.	Hours.	Who is at risk and which warnings are necessary.
Vulnerability	Shelter, protective equipment, medical capacity and social vulnerability.	Hours to days.	Which areas need priority support.
Operational feasibility	Access routes, team availability, platform readiness, communications and security.	Minutes to hours.	Which intervention is realistic and safe.
Confidence and provenance	Source reliability, model uncertainty, confirmation status and data age.	Every update.	Whether to escalate, verify or reject an alert.

**Predictive prevention architecture**



**Figure 2.** Predictive prevention architecture linking heterogeneous data, quality control, AI analytics, dynamic risk maps and human command decisions.

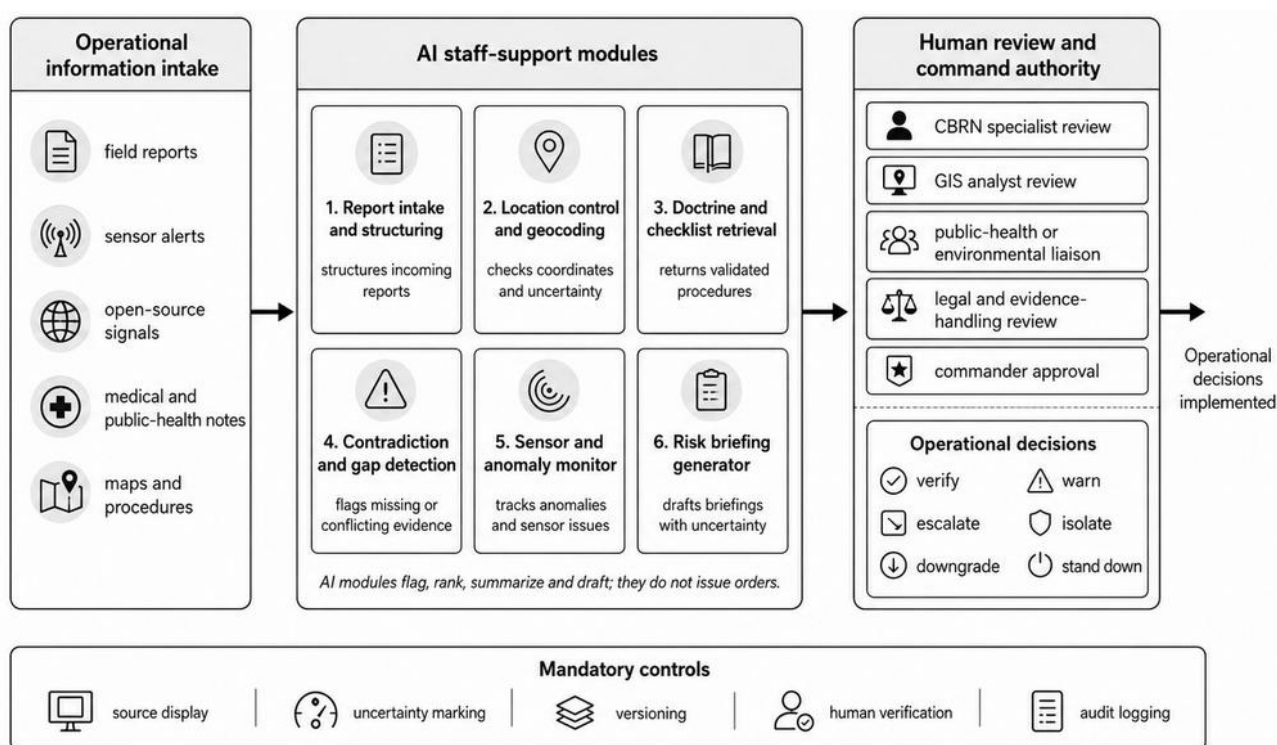
**AI STAFF-SUPPORT MODULES UNDER HUMAN COMMAND**

AI staff-support modules should not be framed as autonomous decision makers. Their realistic value in CBRN and environmental operations lies in information work: structuring incoming reports, detecting contradictions, retrieving relevant procedures, ranking missing information, summarizing evidence and preparing draft briefings for human review. This vocabulary is important for uniformed and administrative audiences because the term autonomous agent can suggest uncontrolled delegation of authority. In the model proposed here, every module remains subordinate to documented procedures and command approval.

Generative systems create a specific risk because fluent text can conceal uncertainty. A staff-support system may be useful for drafting a situation summary, but it must expose sources, distinguish facts from

assumptions and show confidence levels. An interdisciplinary review of large language model applications in disaster management<sup>60</sup> supports this cautious framing because usefulness depends on verified data, operational integration and human oversight. Wartime operation increases this risk because the underlying data may be missing, manipulated, delayed, geographically imprecise or unrepresentative of current conditions. A briefing that says probable chlorine release with high confidence is dangerous unless the system also shows the sensor source, plume assumption, field verification status and reason for confidence. Every AI-generated recommendation should therefore be treated as a hypothesis requiring human verification, not as an operational order.

A practical architecture should separate functions rather than rely on one opaque assistant. An intake module structures reports. A geocoding module normalizes locations. A doctrine retrieval module returns validated checklists. A sensor-monitoring module flags anomalies. A risk-briefing module summarizes options. An audit module records data lineage, assumptions, model version, operator actions and command approval. This separation supports accountability and makes it easier to disable or correct a faulty module without losing the entire decision-support capability.



**Figure 3.** Human-in-the-loop AI staff-support modules for CBRN and environmental threat-prevention work.

### **PRACTICAL SCENARIO: WARTIME INDUSTRIAL DAMAGE**

Consider a wartime incident in which an industrial facility storing hazardous chemicals is damaged during hostilities. Initial reports are ambiguous. Residents report odour. A patrol observes smoke. A water utility notes abnormal turbidity downstream. Weather data indicate a wind shift toward a residential district. A satellite image from the previous day shows visible structural damage, but current imagery is unavailable because of cloud cover. A direct ground inspection would expose responders to uncertain chemical and physical hazards.

<sup>60</sup> Xu, F., Ma, J., Li, N., & Cheng, J. C. (2025). Large language model applications in disaster management: An interdisciplinary review. *International Journal of Disaster Risk Reduction*, 127, 105642. <https://doi.org/10.1016/j.ijdr.2025.105642>

In a purely reactive model, services may wait for direct confirmation or send a team into a poorly characterized area. Both choices can be costly. Premature entry can expose responders to an avoidable plume, runoff or secondary explosion. Delayed warning can leave civilians, hospitals, water intakes and transport routes unprotected. Unnecessary evacuation after a false alarm can consume scarce vehicles, shelter capacity and public trust. In a predictive-prevention model, the staff first creates competing hypotheses: airborne chemical release, fire-related smoke, water contamination from runoff, false or duplicated civilian reports, and combined chemical-environmental degradation. The system then recommends the safest next evidence step rather than the most dramatic response.

AI does not decide evacuation, quarantine, road closure or entry into the hazard zone. It supports staff work by ranking reconnaissance zones, generating a short uncertainty statement, identifying missing evidence and updating the dynamic map as measurements arrive. If UAV imagery shows an intact storage tank, water sampling is normal and odour reports are geocoded upwind, the alert may be downgraded. If new data show a damaged tank, plume-compatible wind and downstream chemical abnormalities, the same system provides a transparent basis for escalation. The value is not certainty. The value is faster, safer and more auditable convergence on the next operational action.

**Table 6**

Operational workflow in a wartime industrial-damage scenario

Stage	Evidence used	Decision supported	Safeguard
1. Initial signal triage	Odour reports, smoke observation, water anomaly and facility register.	Decide whether the signal requires structured verification.	Mark all reports as unconfirmed and deduplicate sources.
2. Hypothesis generation	Hazard inventory, weather, hydrology and damage indicators.	Separate airborne, waterborne, fire-related and false-alarm pathways.	Require human review of generated hypotheses.
3. Conservative modelling	Wind, terrain, source assumptions and downstream flow.	Identify initial corridors for sampling and reconnaissance.	Show uncertainty interval and model assumptions.
4. Unmanned reconnaissance	UAV imagery, UGV access assessment and platform telemetry.	Verify source area and access without unnecessary exposure.	Respect airspace, electronic warfare and contamination limits.
5. Field and laboratory verification	Water, air or surface samples and medical observations.	Confirm, downgrade or escalate the incident.	Separate screening results from confirmatory evidence.
6. Command briefing and update	Dynamic risk map, confidence layer and audit trail.	Support warning, isolation, medical alerting or stand-down.	Final decision remains with legally responsible authorities.

The workflow in Tab. 6 should be read as a decision discipline rather than as a software sequence. Its purpose is to prevent the staff from jumping directly from ambiguous signals to irreversible action. Each stage converts uncertainty into a safer reconnaissance or verification task, while preserving the evidence trail needed for later accountability.

### **IMPLEMENTATION FRAMEWORK FOR UNIFORMED SERVICES**

Implementation should begin with a minimal viable predictive-prevention cell rather than with procurement of a monolithic AI platform. The first practical step is to identify existing data owners, sensors, GIS layers, meteorological sources, health-alert channels, facility registers, UAV assets, laboratory contacts and reporting procedures. The second step is to standardize time, location, metadata, access rules and update

frequency. Only after these foundations exist should services introduce anomaly detection, risk scoring, language processing or automated briefing functions.

The minimal team should include a CBRN or hazardous-materials specialist, a GIS analyst, a UAV or robotic-platform operator, an environmental or public-health liaison, a data analyst responsible for model outputs, a legal or evidence-handling officer and a command representative authorized to approve operational actions. In smaller organizations, one person may cover more than one function, but the functions themselves should remain explicit because they determine who validates data, who interprets uncertainty, who controls field assets and who accepts legal responsibility.

At levels 1 and 2 of maturity, a small coordination cell may be sufficient if it can catalogue data owners, harmonize coordinates and maintain a verified contact structure. At levels 4 to 6, the capability requires full cooperation among CBRN specialists, GIS analysts, UAV or UGV operators, public-health and environmental liaisons, laboratories, legal officers and command staff because the system begins to influence reconnaissance tasking and public-protection decisions.

Uniformed services should also conduct exercises in which the system is deliberately exposed to missing, delayed and wrong data. A realistic exercise should include contradictory reports, sensor failure, an outdated facility inventory, degraded communications, a false social-media claim and a weather shift. The purpose is to test whether the system identifies uncertainty and information gaps, not whether it creates a visually attractive map. International Organization for Standardization (ISO) 22320<sup>61</sup> supports this emphasis on incident-management coordination, information management and shared situational awareness.

Interdisciplinary cooperation is essential. Chemical specialists, epidemiologists, environmental inspectors, GIS analysts, UAV operators, medical coordinators, legal officers and command staff must agree on alert thresholds, terminology, escalation criteria and documentation. The same agreement should specify who can downgrade an alert, who can request laboratory confirmation and who has authority to approve a public warning. Organisation for the Prohibition of Chemical Weapons (OPCW) verification principles and the Chemical Weapons Convention<sup>62</sup>, together with IAEA guidance on detection of nuclear and other radioactive material out of regulatory control<sup>63</sup>, illustrate why evidence, chain of custody and responsible authority remain critical in chemical and radiological contexts.

Five operational implications follow for uniformed services. First, the first purchase should not be an AI platform, but a verified inventory of data, sensors, maps, procedures and responsible owners. Second, every alert should display uncertainty, source age and verification status. Third, unmanned reconnaissance should be tasked to answer the most safety-critical information gap, not to collect visually attractive imagery. Fourth, exercises should deliberately include false, delayed and contradictory inputs. Fifth, commanders should treat AI outputs as structured staff work requiring approval, not as decisions delegated to software.

**Table 7**

Maturity levels for implementing predictive prevention in uniformed services

Level	Capability	Main deliverable	Readiness criterion
1	Data inventory.	Catalogue of sensors, maps, reports, health feeds and hazard registers.	Data owners and update frequencies are identified.

<sup>61</sup> International Organization for Standardization. (2018). ISO 22320:2018 Security and resilience: Emergency management: Guidelines for incident management. <https://www.iso.org/standard/67851.html>

<sup>62</sup> Organisation for the Prohibition of Chemical Weapons. (1997). Chemical Weapons Convention. <https://www.opcw.org/chemical-weapons-convention/>

<sup>63</sup> Ibid 52

**Continued from Table 7**

<b>Level</b>	<b>Capability</b>	<b>Main deliverable</b>	<b>Readiness criterion</b>
2	Interoperability.	Common geocoding, timestamps, metadata and access rules.	Operational data can be fused without manual re-entry.
3	Analytics.	Anomaly detection, dispersion models and risk scoring.	Outputs include uncertainty and data provenance.
4	Unmanned verification.	Tasking logic for UAV, UGV or other stand-off reconnaissance.	Platforms verify the highest-value information gaps.
5	Staff-support AI.	Auditable briefing, contradiction detection and doctrine retrieval.	Human approval and audit trail are mandatory.
6	Exercise-based validation.	Scenario tests with degraded and misleading data.	Metrics show faster, safer and more reliable decisions.

## **LIMITATIONS AND GOVERNANCE**

The proposed framework has several limitations. First, prediction in wartime is inherently uncertain. The system may reduce uncertainty but cannot remove it. Second, AI methods depend on baselines that may be disrupted by conflict, displacement or infrastructure damage. Third, unmanned systems can fail, be lost, be jammed or introduce contamination-control problems. Fourth, geospatial outputs can create false confidence if confidence layers and source provenance are hidden. Fifth, staff-support language models can hallucinate, omit caveats or summarize contradictory evidence too aggressively.

Governance should therefore be built into the system design. Every operational output should show source data, data age, model assumptions, confidence level, responsible operator and verification status. Every alert should also create an audit log containing the input dataset identifiers, model or rule version, timestamp, operator identity, confidence score, uncertainty statement, verification action, command decision and later after-action assessment. High-consequence actions such as evacuation, isolation, quarantine, closure of water intakes, entry into a contaminated zone or public warning must remain human decisions. AI may prepare options and identify missing information, but it must not be the authority that determines legal or operational action.

Ethically, predictive prevention must avoid two opposite failures. Underreaction exposes people to preventable harm. Overreaction can produce unnecessary panic, resource diversion and loss of trust. Transparent uncertainty, documented verification and after-action learning are the main mechanisms for balancing these risks. The strongest near-term value of AI is therefore not the replacement of expertise, but the disciplined acceleration of expert work under pressure.

## **CONCLUSIONS**

Wartime biological, chemical and environmental threats require a prevention model that operates before full confirmation is available. The central operational need is not autonomous AI decision-making, but earlier detection of weak signals, safer prioritization of reconnaissance, explicit management of uncertainty and faster preparation of command-relevant information. A predictive-prevention capability can support these needs when it integrates environmental sensors, public-health alerts, geospatial layers, unmanned reconnaissance, dispersion modelling, dynamic risk maps and auditable staff-support AI modules.

For uniformed services, the practical lesson is clear. Implementation should start with data quality, common geocoding, hazard inventories, exercise scenarios and human accountability. AI should then be introduced as a modular support layer that structures reports, detects anomalies, identifies information gaps and helps maintain a transparent audit trail. The result is not a system that decides instead of commanders,

epidemiologists or environmental experts. The result is a system that helps them ask the right questions earlier, send people into danger less often and justify decisions more transparently in conditions of uncertainty.

The most defensible path forward is incremental: build a minimal predictive-prevention cell, test it against realistic wartime scenarios, measure time-to-detection and false-alarm behaviour, validate maps against field observations, and refine thresholds after exercises. The decisive innovation is not automated decision-making. It is the ability to combine incomplete data into auditable, command-relevant reasoning quickly enough to move from weak signal to safe reconnaissance before preventable harm occurs. In this form, artificial intelligence, unmanned systems and geospatial analysis become credible components of interdisciplinary threat prevention because they are governed, auditable and subordinate to responsible human command.

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