

Intégration de l'expertise militaire, des systèmes d'information géographique et de l'apprentissage automatique pour le déminage post-conflit : une approche basée sur la connaissance

Adib Saliba

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Par

Adib SALIBA

Integrating Military Expertise, Geographic Information Systems and Machine Learning for Post-War Landmine Clearance: A Knowledge-Driven Approach

Thèse présentée et soutenue à l'Université Libanaise le 26 Septembre 2025

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Abstract

This thesis presents a hybrid decision-support framework that integrates Geographic Information Systems (GIS), Machine Learning (ML), and operational military expertise for the prediction, classification, and prioritization of minefields in post-conflict environments. Using Lebanon as a case study, the research tackles key challenges in humanitarian demining by combining spatial analysis with rare-event modeling techniques, expert-validated features, and risk-based zoning strategies. The framework employs high-resolution proximity layers and terrain data to train and compare several machine learning classifiers, including XGBoost, Random Forest, LightGBM, and SVM, achieving robust predictive performance across diverse geospatial contexts.

A core innovation of this work is the integration of domain-specific military knowledge into the feature engineering and model validation process. This includes data such as historical confrontation lines, tactical priority zones, and clearance difficulty thresholds. The model's outputs are operationalized through GIS-based risk maps that identify areas of high mine density, clearance complexity, and humanitarian urgency. To ensure practical relevance, the system was validated through an iterative feedback process involving over 85 experienced military officers, resulting in high alignment between predicted risk zones and expert ground-truth assessments.

In addition, the study explores the ethical and legal dimensions of AI-supported demining, advocating for a Human-In-The-Loop (HITL) approach, adversarial debiasing, and privacy-preserving learning protocols. The proposed framework demonstrates significant potential to support mine action authorities and peacekeeping missions in resource allocation, clearance prioritization, and long-term urban recovery planning.

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List of Abbreviations

UAV: Unmanned Aerial Vehicle

LiDAR: Light Detection and Ranging

AI: Artificial Intelligence

IA: Intelligence Artificielle

ML: Machine Learning

GIS: Geographic Information Systems

SIG: Systèmes d'information Géographique

GPR: Ground Penetrating Radar

EOD: Explosive Ordnance Disposal

UXO: Unexploded Ordnance

ERW: Explosives Remnant of War

UNMAS: United Nations Mine Action Service

GICHD: Geneva International Center for Humanitarian Demining

DEM: Digital Elevation Model

Biography

As a PhD candidate in Geomatics and Computer Science (Machine Learning), my professional journey has been deeply rooted in military engineering, leadership, and operational planning, with a particular focus on humanitarian demining and Explosive Ordnance Disposal (EOD), shaped by continuous collaboration with governmental and non-governmental organizations (US Central Command, UN, GICHD, MAG, Dyncorp and many others). Over two decades of service in the Lebanese Armed Forces, I have held key leadership positions, including QA and Operations officer for humanitarian demining, Head of the Geospatial Intelligence Section and Head of the Joint Operations and Intelligence Center. These roles have provided me with a comprehensive understanding of operational complexities and the critical role of geospatial intelligence in strategic decision-making.

In my capacity as Head of the Geospatial Intelligence Section, I led the development of advanced GIS frameworks and predictive models, facilitating more accurate detection of mined areas and enhancing intelligence capabilities. As Head of the Joint Operations and Intelligence Center, I spearheaded efforts to integrate GIS and ML solutions into national security strategies, streamlining resource allocation and optimizing time-critical operations. These experiences have allowed me to bridge innovative technologies with practical applications in military contexts.

This thesis reflects my commitment to leveraging my expertise in GIS, ML, and military operations to improve landmine clearance processes. It incorporates the critical validation and insights provided by military demining experts, enabling a direct comparison of traditional demining operational planning with technology-driven models in terms of time efficiency and resource allocation. By combining academic rigor with practical experience, this research aims to contribute to the development of safer and more efficient demining strategies.

Part 1

Introduction, Context and Related Work

Chapitre 1
Introduction

1.1. Déminage Humanitaire : un Défi Mondial

Le déminage humanitaire, ou dépollution des mines, est une initiative mondiale essentielle visant à atténuer les conséquences dévastatrices des mines antipersonnel qui, vestiges des conflits armés, menacent la vie des civils, freinent la croissance économique, perturbent le développement des infrastructures et entravent les efforts de reconstruction post-conflit. Malgré l'adoption de traités internationaux tels que la Convention d'Ottawa (1997) [1] et les progrès significatifs des technologies de détection et de neutralisation, le déminage demeure une opération complexe, coûteuse en ressources et dangereuse, en raison de contraintes logistiques, environnementales et géopolitiques.

Les mines terrestres ont été largement déployées depuis la Seconde Guerre mondiale, avec une utilisation massive durant la guerre froide. Bien que les initiatives internationales aient réduit leur dissémination et favorisé la coopération en matière de déminage, la situation reste critique: plus de 58 pays, dont l'Afghanistan, le Cambodge, l'Angola et la Bosnie-Herzégovine [2], sont encore lourdement contaminés. Les efforts conjoints d'organisations telles que les Nations unies (ONU), l'OTAN et de nombreuses ONG se heurtent toutefois à des contraintes financières, à des limites technologiques et à la persistance des conflits.

Les effets des mines s'étendent bien au-delà des victimes immédiates: des communautés entières sont déplacées, la productivité agricole chute drastiquement et les projets de développement sont suspendus à cause du risque permanent d'explosion. Ainsi, au Cambodge et en Angola, de vastes terres fertiles demeurent inexploitées, perpétuant la stagnation économique et l'insécurité alimentaire. À l'inverse, dans les régions assainies, la reprise économique est notable ; le Mozambique, déclaré exempt de mines en 2015 après des décennies d'efforts, illustre l'efficacité d'une intervention mondiale coordonnée. Cependant, la durée et le coût élevés de telles opérations soulignent l'urgence de solutions plus innovantes, efficaces et sûres.

Face à l'ampleur persistante de la contamination, les stratégies combinant les systèmes d'information géographique (SIG) et l'apprentissage automatique (Machine Learning, ML) répondent à la demande croissante de solutions avancées : elles améliorent la précision de détection, optimisent l'allocation des ressources et accroissent l'efficacité opérationnelle. En associant ces outils aux connaissances militaires, le déminage humanitaire peut passer d'interventions réactives à des opérations proactives et guidées par le renseignement, réduisant les risques et accélérant la progression vers un monde sans mines.

1.2. Impact Environnemental et Socio-Economique des Mines

Les mines antipersonnel génèrent des risques immédiats et de long terme pour les régions touchées. Leur présence restreint l'accès aux terres agricoles, frappant durement les économies dépendantes de l'agriculture, comme on le constate au Cambodge et en Angola. Le

développement des infrastructures est lui aussi freiné : routes, écoles et centres de santé sont retardés ou déplacés lorsque les zones sont contaminées. De plus, la pollution par les mines provoque le déplacement des populations, empêche le retour des communautés dans leurs foyers et entretient ainsi un cercle de pauvreté qui ralentit la reprise économique régionale.

Les facteurs environnementaux compliquent encore les opérations de déminage. Les mines se trouvent souvent dans des terrains inaccessibles ou dangereux, forêts denses, déserts, champs cultivés. Les variations saisonnières, telles que les inondations et l'érosion, peuvent déplacer les engins, rendant leur détection et leur neutralisation plus difficiles. Le changement climatique aggrave ces enjeux en modifiant la composition des sols, en accentuant l'érosion et en transformant les paysages d'une manière qui rend la localisation des mines encore plus imprévisible.

1.3. Contexte du Liban : Étude de Cas

Petit pays du Levant aux paysages contrastés, plaines côtières, massifs montagneux et vallées profondes, le Liban porte les stigmates de conflits prolongés qui ont laissé un vaste héritage de mines et de munitions non explosées (UXO). Cette topographie variée complique l'utilisation des terres et la construction d'infrastructures, tandis que de nombreux champs de mines sont nichés dans des zones difficiles d'accès, exigeant des techniques et des équipements de dépollution spécialisés.

La guerre civile libanaise (1975-1990), le conflit de 2006 et les affrontements frontaliers récurrents ont lourdement contaminé le territoire, constituant une menace majeure pour les civils et un frein à la reprise économique. Le Centre libanais d'action contre les mines (LMAC), en coordination avec l'UNMAS, le GICHD et plusieurs ONG, supervise les opérations de déminage ; cependant, les archives incomplètes, le relief accidenté, la végétation dense et le manque de financements ralentissent les progrès. Par comparaison avec d'autres pays fortement minés tels que l'Afghanistan ou le Cambodge, le terrain montagneux libanais impose des défis uniques qui exigent des solutions adaptées à l'altitude, aux formations rocheuses et à la densité végétale.

L'analyse des défis et des solutions libanais fournit des enseignements transférables à d'autres régions post-conflit présentant des contraintes similaires. Si chaque pays possède un contexte géographique et politique spécifique, l'intégration des SIG et du ML dans les opérations de déminage peut être reproduite moyennant quelques ajustements. La méthodologie élaborée pour le Liban, tenant compte de la complexité du terrain, du manque de données historiques fiables et de l'allocation optimale des ressources, peut éclairer les stratégies de dépollution en Bosnie-Herzégovine, en Colombie ou ailleurs. En posant les bases d'un cadre adaptable, cette recherche contribue à l'amélioration globale des opérations de déminage à travers le monde.

1.4. Efforts de Déminage Actuels et Défis

Les opérations de dépollution reposent sur un éventail de méthodes, chacune présentant des avantages et des limites spécifiques. Le déminage manuel reste la technique la plus répandue pour sa précision, mais il est lent, exige beaucoup de main-d'œuvre et génère un taux élevé de fausses alertes en raison des débris métalliques dispersés. Le déminage mécanique accélère les opérations, mais il rencontre des difficultés sur les terrains accidentés et engendre des coûts d'entretien élevés. Les chiens détecteurs de mines (MDD) se révèlent efficaces en zone ouverte,

mais leur performance dépend des conditions météorologiques et d'un entraînement et d'une prise en charge vétérinaire conséquents. Le radar à pénétration de sol (GPR) améliore la détection des mines à faible teneur métallique, mais ses performances sont limitées par la composition du sol et l'état de surface.

Au-delà de ces contraintes techniques, des limites opérationnelles persistent: archives de champs de mines inexactes, relief difficile et pénurie de personnel qualifié freinent l'efficacité globale. Par ailleurs, des conditions environnementales telles que les inondations ou l'érosion peuvent déplacer les mines, rendant leur localisation plus complexe. Ces défis cumulés soulignent la nécessité de stratégies novatrices et fondées sur les données, capables d'accroître la précision, de réduire les faux positifs et de soutenir des opérations de dépollution plus sûres et mieux ciblées.

1.5. Systèmes d'Information Géographique et Apprentissage Automatique

Les SIG ont révolutionné l'analyse des données spatiales, ouvrant la voie à une prise de décision plus sophistiquée dans de nombreux domaines, dont le déminage humanitaire [3] [4]. Ils intègrent des jeux de données variés : imagerie satellite, archives de poses de mines, informations topographiques et cartes pédologiques. Dans le déminage, les SIG servent à cartographier les zones contaminées, hiérarchiser les priorités d'intervention et faciliter la coordination entre autorités gouvernementales, forces armées et organisations humanitaires. En centralisant les informations relatives aux mines dans un format visuel et accessible, les SIG améliorent la planification stratégique et l'efficacité opérationnelle, limitent les redondances et dirigent les ressources vers les secteurs les plus critiques.

L'apprentissage automatique, sous-domaine de l'intelligence artificielle, vient compléter les SIG en automatisant la reconnaissance de motifs et la prédiction des risques dans les régions contaminées. En s'entraînant sur de vastes ensembles de données (localisations historiques de mines, chronologie des conflits, conditions environnementales), les algorithmes ML identifient avec une grande précision les zones à haut risque. Ces approches affinent en continu la classification des champs de mines, optimisent les stratégies de dépollution et réduisent l'incertitude dans la détection. De plus, le ML renforce les technologies de capteurs, radar à pénétration de sol, télédétection, en filtrant le bruit et en améliorant la détection d'anomalies, accroissant ainsi leur fiabilité sur des terrains varies [5] .

L'un des principaux atouts du ML réside dans sa capacité à traiter rapidement d'énormes volumes de données géospatiales et issues de capteurs, ce qui s'avère crucial dans des environnements où l'inspection classique est lente et sujette aux erreurs humaines. Couplé aux SIG, le ML permet des évaluations de risque adaptatives et réactives grâce à l'apprentissage continu des données de terrain et des changements environnementaux. Cette synergie améliore la prise de décision, rationalise l'allocation des ressources et accroît la précision de détection, renforçant, en définitive, l'efficacité et la sécurité des opérations de déminage [6].

1.6. Une Nouvelle Approche du Déminage

Forts d'une longue expérience des opérations de dépollution au sein de l'armée libanaise et d'une expertise approfondie en SIG et en apprentissage automatique, nous constatons que les techniques traditionnelles souffrent d'inefficiences opérationnelles, de contraintes logistiques et de risques élevés. Le déminage **manuel**, bien que méticuleux, reste lent et exigeant en main-

d'œuvre, ce qui limite le rythme d'élimination des mines dans les zones à haut risque. Les méthodes **mécaniques** offrent une plus grande rapidité, mais leur efficacité diminue face à un terrain irrégulier, à une végétation dense ou à des sols instables. De même, les **chiens détecteurs** (MDD), efficaces dans certains contextes, sont sensibles aux conditions climatiques et nécessitent un entraînement et une maintenance intensifs. Ces défis persistants soulignent la nécessité d'une approche fondée sur les données et enrichie par la technologie pour accroître la précision, l'efficacité et la sécurité des opérations.

La fusion des **SIG** et du **ML** constitue une réponse transformatrice à ces obstacles en proposant un cadre plus systématique et guidé par le renseignement [4] [3]. Les SIG offrent une plateforme solide pour collecter, stocker et visualiser des données spatiales critiques, permettant aux équipes de mener des évaluations détaillées du terrain, d'identifier les zones à haut risque et de rationaliser la planification opérationnelle. Les algorithmes de ML affinent ensuite l'évaluation des risques en détectant des corrélations spatiales complexes et des motifs invisibles à l'analyse conventionnelle. Cette approche combinée assure une allocation plus ciblée des ressources, concentrant les efforts de dépollution sur les secteurs prioritaires tout en limitant les interventions superflues. La capacité du ML à apprendre en continu à partir de nouvelles données garantit, en outre, que les stratégies demeurent adaptatives face aux conditions évolutives du terrain.

Si la littérature démontre l'intérêt de l'intégration SIG-ML dans le déminage, les modèles purement axés sur les données manquent souvent de réalisme opérationnel. Ce fossé peut être comblé en intégrant l'expertise militaire : connaissance stratégique des champs de bataille, tactiques de pose des mines et comportements adverses. Ces apports renforcent la précision contextuelle des cartes générées par l'IA et adaptent les algorithmes aux situations non conventionnelles. Ce cadre hybride améliore non seulement la prédiction et la classification, mais garantit aussi que la technologie demeure ancrée dans les réalités éprouvées du terrain, la rendant à la fois efficace et déployable.

1.7. Questions de Recherche et Cadre Proposé

Les questions de recherche qui orientent cette étude sont issues d'une évaluation critique des difficultés actuelles du déminage et des avancées technologiques en SIG et en apprentissage automatique. Une revue approfondie de la littérature et des pratiques de terrain a mis en évidence plusieurs insuffisances des méthodes traditionnelles, notamment en matière de précision de détection, d'allocation des ressources et de prise de décision opérationnelle. Bien que des travaux antérieurs aient démontré le potentiel du ML et des SIG pour améliorer les résultats du déminage, une lacune majeure a été relevée: l'absence d'intégration structurée de l'expertise militaire dans les modèles prédictifs. Cette constatation a servi de base à la définition des deux questions centrales de cette thèse.

S'appuyant sur ce constat, la thèse traite deux questions de recherche clés :

a) Comment l'intégration du ML et des SIG peut-elle améliorer la précision, l'efficacité et la prise de décision opérationnelle dans les opérations de déminage humanitaire ?
b) Quel cadre méthodologique permet d'incorporer de façon systématique l'expertise militaire aux solutions de déminage fondées sur le duo ML-SIG afin d'affiner l'évaluation des risques, l'allocation des ressources et l'efficacité opérationnelle ?

La première question découle des limites observées dans les méthodes actuelles : taux élevés de fausses alertes, adaptation limitée aux terrains complexes et difficulté à hiérarchiser efficacement les zones de dépollution. En tirant parti du ML et des SIG, il devient possible d'améliorer les capacités prédictives, d'optimiser le déploiement des ressources et d'accroître la précision de détection. Cette question vise donc à explorer comment la fusion de ces technologies peut répondre de façon systématique aux inefficacités persistantes du déminage humanitaire.

La seconde question naît de la reconnaissance du rôle essentiel, mais souvent informel, de l'expertise militaire dans le déminage. Les experts militaires disposent d'informations stratégiques sur les schémas de pose des mines, la dynamique des champs de bataille et les méthodologies d'évaluation des risques susceptibles de renforcer considérablement les modèles de dépollution. Toutefois, il n'existe pas encore de cadre structuré pour intégrer ces connaissances aux évaluations de risque pilotées par ML-SIG. Cette question cherche donc à combler cette lacune en développant une approche systématique d'intégration de l'expertise militaire, afin d'améliorer la précision de l'évaluation des risques, l'allocation des ressources et l'efficacité globale des opérations.

Pour répondre à ces questions, l'étude propose un modèle de recherche qui combine de manière systématique les technologies ML et SIG avec les connaissances opérationnelles militaires. Ce cadre vise à renforcer l'évaluation des risques en localisant plus précisément les zones à haut risque, à assurer une meilleure allocation des ressources et à réduire les dangers opérationnels. En intégrant l'expertise militaire, le modèle aligne les outils prédictifs sur la réalité dynamique des champs de bataille, accroissant ainsi leur applicabilité dans des environnements complexes.

Au-delà de l'amélioration de l'efficacité du déminage, cette approche doit faciliter la réhabilitation post-dépollution en favorisant un retour rapide à un usage civil sécurisé des terres. En définitive, cette recherche entend fournir une solution globale, fondée sur les données, qui renforce la sécurité publique, optimise les stratégies de déminage et contribue au développement durable dans les régions post-conflit comme le Liban.

Figure 1 offre une vue d'ensemble des questions de recherche et du cadre proposé: l'application conjointe des SIG et du ML, intégrée à l'expertise militaire, converge vers l'objectif ultime de restauration de la vie et de développement durable.

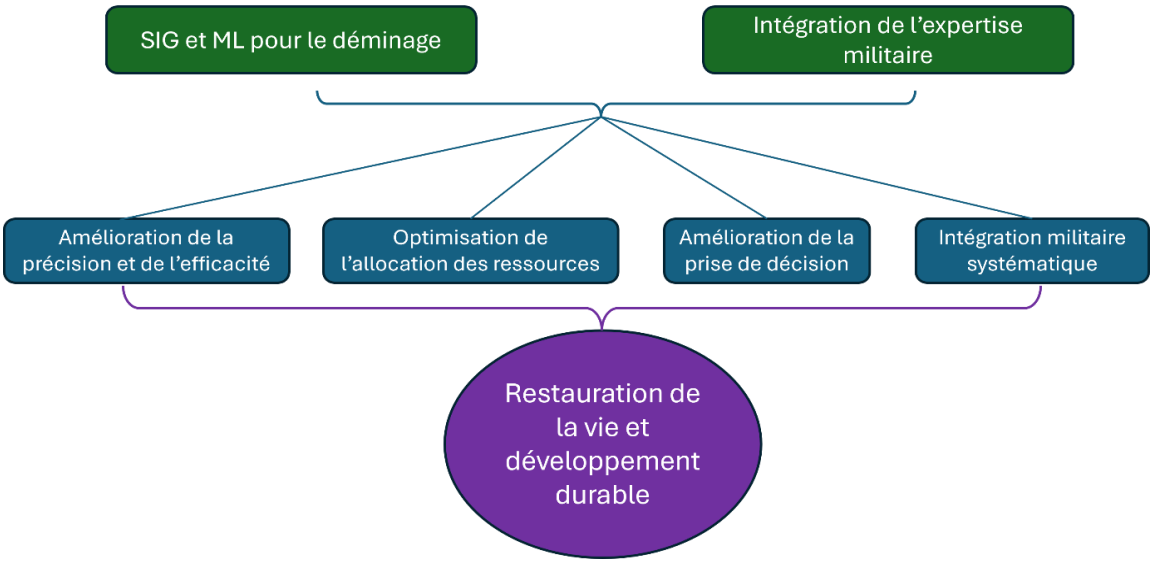


Figure 1: Questions de recherche et aperçu du cadre

1.8. Structure de la Thèse

Cette étude se penche sur les défis propres au Liban, illustrant les menaces durables que les mines font peser sur la sécurité des civils, le développement économique et la reconstruction post-conflit. Elle évalue de manière critique les méthodes de déminage traditionnelles, manuelles, mécaniques et assistées par les animaux, en soulignant leurs risques, leurs besoins en ressources et leurs limites respectives. Elle examine en outre les obstacles environnementaux, techniques, logistiques et sociopolitiques qui freinent l'efficacité des opérations, tout en explorant des pistes de solution telles que la coopération internationale, les progrès de la détection et l'engagement des communautés locales.

Les chapitres suivants s'appuient sur ces fondations:

- Chapitre 2 : présente le contexte du déminage au Liban..
- Chapitre 3 : passe en revue les recherches sur le déminage fondé sur le ML et les SIG.
- Chapitre 4 : détaille la méthodologie et le cadre expérimental.
- Chapitre 5 : expose les résultats de validation.
- Chapitre 6 : examine les considérations éthiques, juridiques et humanitaires du déminage piloté par l'IA.
- Chapitre 7 : consolide les conclusions et trace les perspectives futures, y compris les applications élargies à la réponse aux catastrophes et à la reconstruction post-conflit.

Par l'innovation technologique, l'expertise opérationnelle et la collaboration internationale, cette recherche vise à promouvoir des pratiques de déminage plus sûres, plus efficaces et fondées sur les données, contribuant ainsi à guider le Liban vers un avenir sans mines.

La Figure 2 ci-dessous illustre la structure de la thèse.



Figure 2: Structure de la Thèse

Chapter 2
Context and Motivation

2.1. Context of humanitarian demining

This section provides a comprehensive overview of the global landmine crisis, with a particular focus on Lebanon's contamination landscape, its socio-economic implications, and the pressing need for sustained and coordinated clearance efforts.

Landmines remain a global humanitarian challenge because, even after hostilities end, these non-selective weapons continue to pose a severe threat to civilian populations. In 2022 alone, there were 4,710 recorded casualties from landmines and explosive remnants of war in 51 countries, of which 1,661 were fatal [7]. Although landmines were first used extensively during World War II, their deployment became especially widespread throughout the Cold War due to their low cost and ease of distribution. As a result, entire regions in Africa, Asia, and Europe became heavily contaminated. Ironically, while deploying landmines is both inexpensive and simple, demining is extremely costly, time-consuming, and dangerous, a situation that has left vast areas around the world laden with explosive devices long after conflict periods have ended.

Over time, demining techniques have evolved from manual methods involving metal detectors and probing equipment, to the use of mechanical machinery and trained dogs, and more recently, robotics and drones [8]. International agreements, notably the Ottawa Treaty [1], have reduced landmine deployment among many nations by encouraging global cooperation and funding. Despite these efforts, large numbers of active and unmarked landmines remain, restricting the use of vital resources, jeopardizing lives, and constraining development.

Nowhere is this more evident than in Lebanon, which has experienced multiple waves of conflict. Lebanon's terrain is marked by extensive contamination from both landmines and unexploded ordnance (UXO). Recent hostilities along its southern border in 2024 have further worsened the situation. Thousands of landmines are believed to be scattered throughout Lebanon, with incomplete records on precise locations. The sheer volume of contamination, estimated at over 450,000 landmines across roughly 150 million square meters, means that comprehensive clearance will likely require decades of sustained effort and resources.

The impacts of landmines in Lebanon are profound and multifaceted. They have caused at least 2,374 casualties since 1971, including 631 fatalities [9]. Beyond the immediate human toll, landmines impede agricultural production by rendering farmland unsafe, undermining local economies in rural areas that once served as the country's agricultural backbone. They also hinder infrastructure development and delay the return of refugees and internally displaced persons to their home regions, thus perpetuating a cycle of displacement and economic stagnation. The psychological burden is equally significant, as the constant threat of injury or death instills pervasive fear and anxiety in communities, particularly among children.

In response, various international and national organizations, including United Nations affiliates and non-governmental bodies, have joined forces with the Lebanese government to remove these deadly remnants of war. The Lebanese Mine Action Center (LMAC) coordinates these efforts, although it faces challenges ranging from difficult terrain and inclement weather to an absence of accurate maps and records [9]. An estimated 24 square kilometers of contaminated territory remain in Lebanon as of 2024, with only 26 square kilometers cleared in recent years. Overcoming these obstacles requires sustained funding, enhanced technologies, and robust international support.

In summary, landmines continue to exact a grave toll on Lebanon, inhibiting progress in critical sectors like agriculture, infrastructure, and the reintegration of displaced populations. The path to a safer future lies in rigorous mine clearance operations, encompassing thorough surveys, careful clearance, and safe disposal, coupled with community education on the risks. Achieving these goals demands ongoing collaboration among national agencies, international donors, and local communities. Only through long-term commitment and well-coordinated efforts can Lebanon hope to eliminate the scourge of landmines, rebuild affected regions, and foster sustainable development.

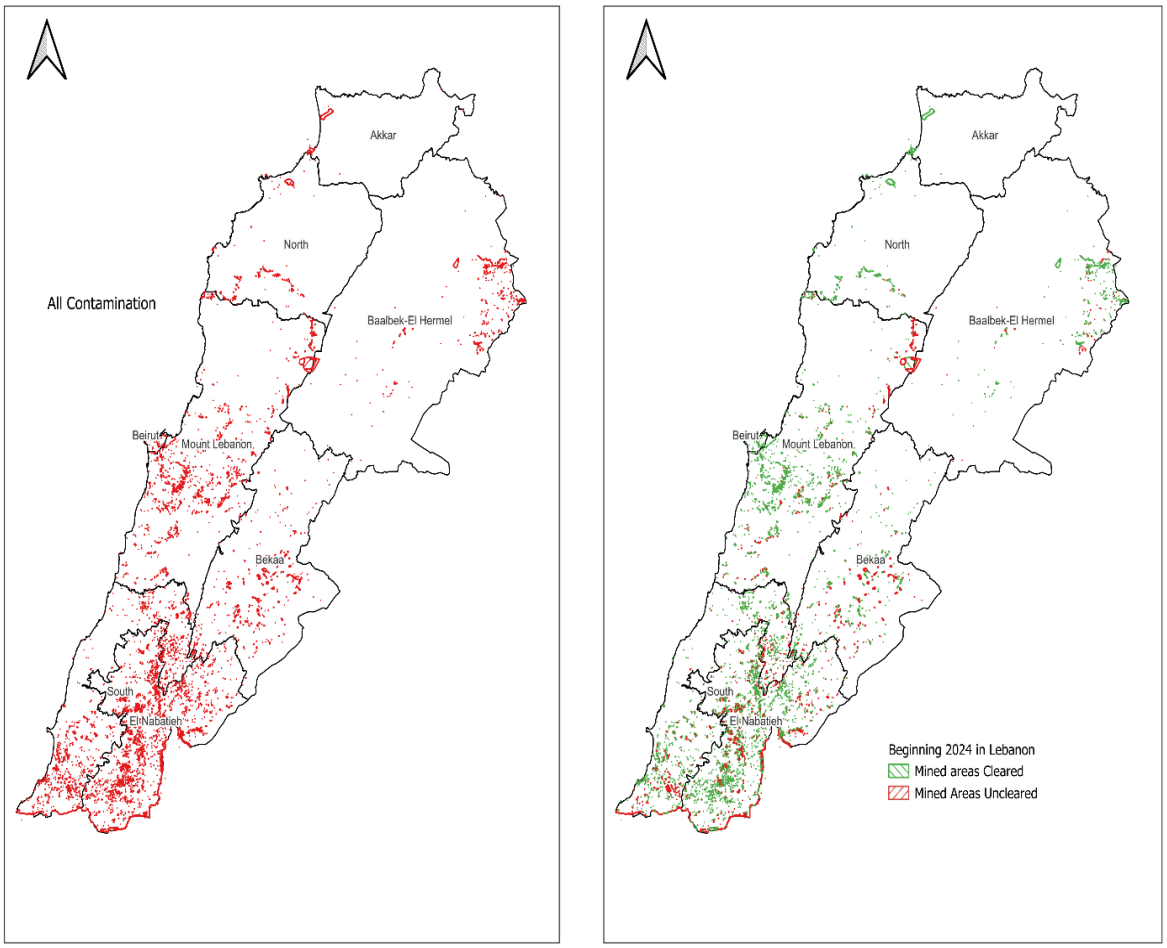


Figure 3: Progress in Mine Clearance Efforts in Lebanon: From Widespread Contamination to Significant Areas Cleared by 2024 Produced from LMAC databases

Figure 3 produced by the LMAC illustrates the mine contamination in Lebanon, where the map on the left shows in red the extent of the comtaminated areas, indicating the widespread of minefields across the country. The map on the right highlights the demining progress made

by early 2024, with green areas representing regions that have been cleared of mines, demonstrating significant advancements in demining efforts. However, substantial contamination remains, underscoring the ongoing challenge in achieving complete landmine clearance.

Figure 4 below, also produced from LMAC databases, represents the progress of demining in Lebanon as of early 2024, showing the clearance percentages of different contamination types. Mines have been cleared from 69.82% of affected areas, covering 16.17 km², while 91.63% of cluster-munition areas and 92.30% of dangerous areas (areas containg unexploded ordnance other than mines and cluster-munitions) have been successfully addressed, with remaining contaminated areas at 4.65 km² and 3.18 km², respectively. Despite these efforts, 24 km², or 15.95% of the total contaminated land, still requires clearance.

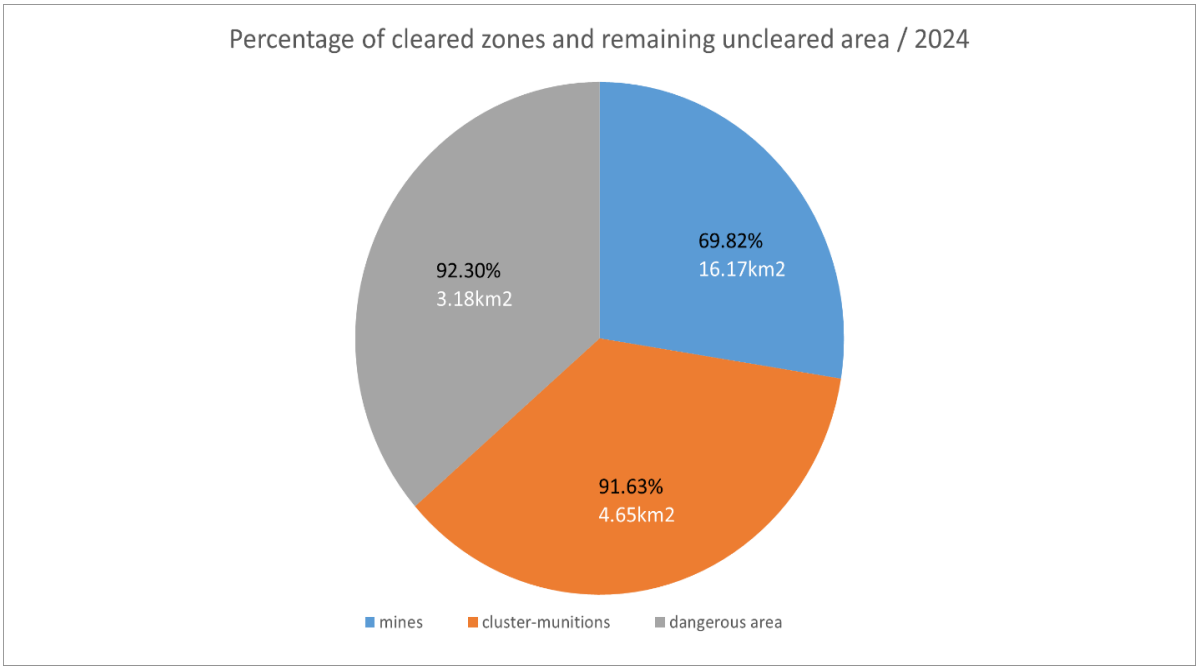


Figure 4: UXO Clearance by type and area in Lebanon by Early 2024 - Produced from LMAC databases

2.2. Demining Methods

This section outlines the primary demining methods currently in use, manual, mechanical, canine-assisted, and sensor-based, and highlights the operational challenges associated with each approach.

Humanitarian demining faces a range of obstacles, from the inherent dangers of handling explosive devices to the logistical and environmental complexities of clearance operations. This section first outlines the principal demining methods currently in use and then examines their limitations, as well as other technical, logistical, environmental, data-related, and community-based challenges. Finally, it addresses emerging technologies and strategies for mitigating these constraints.

Demining techniques include Manual, Mechanical, and Mine detection dogs (MDD) as well as the use of GPR which has recently been introduced [10].

2.2.1. Manual Demining

Manual demining involves the physical probing of the ground using tools such as metal detectors and handheld probes. Although it is the most traditional and direct approach, it is extremely slow and labor-intensive, clearing large or rugged terrains can take years, while remaining inherently dangerous, as even careful probing may detonate sensitive mines. Moreover, this method is prone to high false alarms because metal detectors pick up all metallic fragments, including harmless debris or mineral-rich soils, and are less effective for plastic or low-metal mines.

2.2.2. Mine Detection Dogs

Canines are trained to detect volatile compounds in explosives and can often scan larger areas faster than manual deminers. However, they require extensive training and care, as Mine Detection Dogs (MDDs) need significant resources and skilled handlers. Their effectiveness can also be severely impacted by extreme weather conditions, such as high heat, cold, or humidity, which can diminish a dog's olfactory abilities, particularly with low-volatile mines. Furthermore, MDDs have limited application in harsh terrains; very dense vegetation or steep, rocky areas can hinder a dog’s movement and concentration, reducing overall efficiency.

2.2.3. Mechanical Demining

This approach employs specialized machinery, such as flails and rollers, to detonate or destroy mines, enabling larger areas to be cleared more quickly and reducing some of the risks associated with manual methods [11] . Nonetheless, it faces significant terrain constraints, as heavy machinery proves less effective in steep, rocky, or densely vegetated landscapes. Additionally, maintenance and operating costs can be prohibitively high, and despite mechanization, a certain margin of uncertainty often remains in mine clearance.

2.2.4. Ground-Penetrating Radar

Ground-Penetrating Radar (GPR) transmits electromagnetic waves into the ground to detect buried objects, including low-metal mines [12] [13]. Although more advanced than traditional methods, GPR requires skilled operators because data interpretation is complex, and it is also highly sensitive to environmental factors; for example, high soil moisture and mineral content can degrade signal quality and produce false alarms. Furthermore, thick vegetation, rocky substrates, and uneven surfaces present significant terrain limitations that can reduce GPR effectiveness.

2.2.5. Quality Assurance

Regardless of the primary technique, a mandatory Quality Assurance (QA) process (re-inspection of cleared areas) ensures that the land is safe before handing it back to the owner or the community. Errors at this stage can be fatal.

Despite advances in demining methodologies, existing approaches remain hindered by efficiency constraints, terrain adaptability issues, and high operational risks. Given these persistent challenges, there is an urgent need for data-driven, predictive solutions that can optimize mine clearance operations, enhance safety, and improve decision-making. GIS and ML have emerged as promising technologies that can complement existing methods by analyzing spatial risk factors, prioritizing clearance zones, and refining mine detection accuracy. The following sections examine how these technologies can transform demining efforts, particularly in Lebanon's complex terrain.

2.3. Limitations of Demining Methods and Operations

Despite significant progress, current demining practices face a series of limitations spanning technical, logistical, environmental, data, and community-related domains, all of which impede clearance speed, safety, and sustainability.

2.3.1. Technical Limitations

Mines vary widely in their composition, some are entirely metallic, others predominantly plastic, and some combine both materials, making detection particularly difficult. For instance, plastic mines like the PMN-2 contain only 1–10% metal, rendering them harder to locate with standard metal detectors [10]. Moreover, detection equipment can lose 20–30% efficiency in environments with rocky terrain, dense vegetation, or high soil moisture and mineral content, while false alarms may increase by 25%. Compounding these technical hurdles is the unpredictable placement of some mines, which have been scattered indiscriminately, further extending clearance timelines and increasing both labor and costs.

Ground-Penetrating Radar (GPR) requires relatively open, flat ground for optimal effectiveness. Even when appropriate equipment is available, soil erosion and flooding can bury mines one to two meters underground, well beyond the reach of standard detectors. Furthermore, mechanical demining methods, though capable of covering larger areas, are hampered by difficult terrain and risk damaging the surrounding environment, underscoring the need for careful method selection and ongoing innovation [14].

2.3.2. Logistical Limitations

Clearing vast areas, such as those needed for the safe return of displaced populations, demands enormous resources and can take decades. In Lebanon, for example, about 24 skm of land remain contaminated after 23 years of demining efforts [9]. Despite technological advances, accidental explosions continue to pose severe safety concerns, with an estimated 5–10% risk of serious injury or fatality among demining personnel. Compounding these issues, high operational costs for machinery, specialized labor, and protective measures place an additional strain on demining initiatives.

2.3.3. Environmental Limitations

Heavy rain, flooding, or extreme temperatures can significantly delay demining operations and even relocate buried mines, exacerbating clearance challenges [15]. In

many regions, snow or ice seasonally blocks access routes, halting progress altogether. Furthermore, common clearance methods, such as bulldozing and controlled detonations, can harm vegetation and wildlife habitats, underlining the need for approaches that balance operational efficiency with ecological considerations [16].

2.3.4. Data Limitations

In many conflict zones, detailed records of mine placements are incomplete or entirely absent [17], complicating efforts to pinpoint hazardous areas. Ongoing surveys, such as Non-Technical Surveys in Lebanon, continually redefine contaminated perimeters, further extending already lengthy demining operations. Additionally, integrating historical data, local testimony, and terrain analyses requires meticulous planning and coordination among multiple stakeholders, emphasizing the importance of efficient data management and collaboration.

2.3.5. Community Limitations

In regions plagued by ongoing conflict or political instability, communities may be unwilling or unable to cooperate, hindering demining operations and prolonging clearance timelines. High security risks can also render entire areas inaccessible to demining teams. Yet, building trust with local populations, through consistent engagement and transparency, can expedite the process by helping to identify potential hazard zones and facilitating safer, more efficient operations.

In summary, demining operations are constrained by difficult detection conditions, resource-heavy logistics, harsh environments, fragmented data, and limited community involvement. These interrelated issues call for a multidisciplinary approach, one that combines the predictive strength of ML, the spatial context of GIS, and the operational acumen of military expertise. Table 1 illustrates how these domains intersect and where targeted innovations are most needed.

To better understand the limitations of current demining methods, Table 1 provides a cross-referenced overview correlating key domains with identified constraints:

Domain	Key Limitations
Technical	Low-metal content mines, environmental interference, high false alarm rates
Logistical	High operational costs, resource-intensive processes, slow clearance rates
Environmental	Terrain complexity, soil movement, climate-induced displacement of mines
Data	Lack of historical mine records, need for accurate spatial information
Community	Security threats, reluctance to report known mine locations

Table 1: Correlation between Deminig Domains and their Key Limitations

This table underscores these limitations, highlighting the necessity of an integrated ML-GIS approach to address them comprehensively.

2.4. Addressing Limitations through Military and GIS-ML integration

To overcome the constraints of traditional methods, this section explores how the integration of GIS, machine learning, and military expertise offers a transformative approach to mine detection and clearance optimization.

The integration of multiple sensor systems has been a key advancement in modern demining efforts, significantly improving detection rates while reducing false alarms. Combining different technologies, such as metal detectors, GPR, and chemical sensors, allows for a more robust and reliable identification of explosive devices. For example, metal detectors remain the most widely used and cost-effective solution, particularly for detecting mines with significant metallic content. However, they struggle with modern low-metal-content mines or those buried in mineral-rich soils, where signal interference is high. To overcome these limitations, GPR can be used alongside metal detectors to differentiate between metal debris and buried mines, reducing false alarms by up to 95% [18]. GPR provides subsurface imaging by emitting electromagnetic waves and detecting anomalies in soil density, making it particularly useful in detecting plastic mines. However, its performance is affected by soil composition, requiring skilled operators and advanced signal processing to interpret the data effectively.

Similarly, chemical sensors represent another promising detection method, particularly for identifying explosives that have minimal or no metallic components. These sensors detect trace amounts of explosive vapors or residues in the soil, offering an additional layer of confirmation. While highly sensitive, chemical detection is often limited by environmental conditions such as wind, temperature, and humidity, which can disperse or dilute explosive traces. Consequently, chemical sensors are most effective when used in combination with other technologies, enhancing overall detection reliability [13].

Meanwhile, robotic systems and unmanned aerial vehicles (UAVs), including drones, are revolutionizing demining operations by minimizing human exposure to hazardous areas. Drones equipped with high-resolution cameras, multispectral sensors, and Light Detection and Ranging (LiDAR) technology can survey large areas rapidly, identifying potential minefields through surface anomalies or vegetation disturbances indicative of buried explosives [19]. Their ability to provide real-time imaging and thermal detection enables teams to map hazardous zones without direct human involvement. However, their effectiveness is limited in dense forests, urban rubble, or regions with electromagnetic interference, where visibility and communication with ground operators can be disrupted. Moreover, while drones excel in data collection, they do not physically neutralize landmines, requiring follow-up operations by ground-based teams.

Robotic ground vehicles, such as remotely operated demining machines and autonomous platforms, offer a more direct solution for clearing minefields [20]. These systems can be equipped with metal detectors, GPR, or mechanical excavation tools to identify and neutralize mines while keeping operators at a safe distance. They are particularly useful in open terrains where controlled detonations or mechanical clearance can be performed efficiently. However, they struggle in rocky landscapes, marshlands, and areas with dense vegetation, where mobility and maneuverability become significant challenges. Additionally, their high operational costs and maintenance requirements necessitate careful resource allocation to ensure sustainability.

The integration of GIS and ML presents a transformative approach to overcoming key limitations in humanitarian demining. By leveraging geospatial intelligence, predictive modeling, and military expertise, this framework enhances mine detection, optimizes resource allocation, and improves operational efficiency. However, the extent to which ML-GIS can mitigate each limitation varies, requiring complementary technological and strategic solutions.

Table 2 summarizes the extent to which the proposed ML-GIS approach addresses the previously identified limitations:

Domain	**Key Limitations**	**ML-GIS Contribution**
Technical	Low-metal-content mines, environmental interference, high false alarm rates	Enhances risk mapping to guide sensor deployment, reducing false positives. Improves predictive modeling for identifying high-risk areas.
Logistical	High operational costs, resource-intensive processes, slow clearance rates	Prioritizes clearance zones, optimizing resource allocation and reducing unnecessary operations.
Environmental	Terrain complexity, soil movement, climate-induced displacement of mines	Integrates terrain data and environmental models to predict soil movement and mine migration patterns.
Data	Lack of historical mine records, need for accurate spatial information	Aggregates and analyzes multi-source geospatial data, leveraging military knowledge to refine predictions.
Community	Security threats, reluctance to report known mine locations	Engages communities through spatial risk assessments, making clearance operations more transparent and efficient.

Table 2: Addressing Limitations

2.4.1. Addressing Technical Limitations

One of the most significant challenges in demining is detecting mines with low metallic content or those buried in difficult terrain. The integration of ML with GIS enhances detection rates in several ways. First, it refines spatial risk mapping by leveraging ML models trained on geospatial data and historical conflict patterns, allowing for the inference of high-risk areas and reducing the need for exhaustive, ground-based

searches. Additionally, it improves sensor deployment by pre-identifying zones with a higher probability of contamination, enabling more effective use of multi-sensor systems such as GPR, chemical sensors, and metal detectors, ultimately reducing false alarm rates. Furthermore, ML-GIS integration enhances adaptability to terrain conditions by incorporating environmental factors like soil composition and vegetation density, which significantly influence detection accuracy.

2.4.2. Addressing Logistical Limitations

The high cost and slow pace of demining operations necessitate smarter resource allocation. GIS-ML integration optimizes clearance priorities by using predictive models to narrow down high-risk areas, allowing teams to focus efforts where mines are most likely located instead of sweeping entire regions indiscriminately. It also enhances decision-making efficiency by training ML algorithms on past demining successes to refine clearance strategies, minimizing redundancy and improving cost-effectiveness. Moreover, by utilizing UAV-based reconnaissance and remote sensing, initial surveys can be conducted without exposing personnel to unnecessary danger, thereby reducing risks to demining teams.

2.4.3. Addressing Environmental Limitations

Extreme weather conditions, soil movement, and inaccessible terrain often complicate demining efforts. ML-GIS integration mitigates these issues by predicting mine displacement through the analysis of hydrological and soil erosion patterns, which helps anticipate how rain, flooding, or snow may shift buried mines and ensures risk maps remain up to date. Additionally, UAV-based terrain modeling and remote sensing improve accessibility planning by optimizing route selection for demining teams, minimizing delays caused by environmental barriers. Another key benefit is the reduction of environmental impact, as targeted demining approaches limit the use of mechanical clearance methods to only confirmed contaminated areas, preventing unnecessary destruction of ecosystems.

2.4.4. Addressing Data Limitations

Many demining efforts are hindered by incomplete or outdated records of mine placements. ML-GIS integration helps overcome this challenge by integrating multi-source datasets, combining historical mine records, satellite imagery, local surveys, and military intelligence to create a more comprehensive picture of contamination risks. Additionally, ML algorithms continuously refine risk maps based on new field data, improving data validation and updating mechanisms to reflect evolving ground conditions. Moreover, a centralized GIS platform facilitates information sharing among demining agencies, local governments, and humanitarian organizations, ensuring more coordinated and efficient operations.

2.4.5. Addressing Community Limitations

Political instability and a lack of cooperation from local communities can slow demining efforts. While ML-GIS cannot directly resolve security threats, it plays a crucial role in fostering trust and engagement. Community-driven GIS initiatives allow locals to contribute valuable information about suspected mine locations, thereby

improving risk assessments. Furthermore, more precise minefield predictions minimize unnecessary disruptions to civilian areas, increasing community support for clearance operations. Additionally, GIS-ML integration strengthens coordination with local authorities by enabling data-driven communication with government agencies and NGOs, fostering collaboration in high-risk zones.

2.4.6. The Role of Military Expertise

Military experts play a crucial role in refining GIS-ML predictions, leveraging their knowledge of combat strategies and mine-laying patterns to enhance model accuracy. Their expertise helps identify anomalies in GIS-ML models where unconventional tactics may have been used, ensuring that predictions account for real-world complexities. Additionally, military professionals validate AI-generated risk maps, ensuring that they align with practical demining challenges and providing crucial insights to improve the effectiveness of clearance operations.

2.5. Hypothesis and Research Objectives

This section defines the core hypothesis of the study and outlines the key research objectives that guide the development of a GIS-ML-powered decision-support framework for humanitarian demining.

This study hypothesizes that GIS-ML integration, guided by military expertise, enhances landmine detection by improving predictive accuracy, optimizing clearance prioritization, and reducing false alarms. Through AI-driven spatial analytics and operational insights, this approach refines risk assessments, improves resource allocation, and increases demining efficiency and safety.

To validate this hypothesis, this study develops a GIS-ML-powered demining model integrating AI-driven risk assessments and military insights. The framework will: (1) incorporate spatial and historical data for precise risk mapping, (2) apply ML-based mine classification for better hazard differentiation, (3) embed military expertise to enhance operational relevance, and (4) optimize demining efficiency through improved resource allocation and real-world validation. The final output will be an open-source, GIS-compatible decision-support tool for humanitarian demining efforts.

This research presents to the practical domain the following benefits:

- Advancing Technology: It extends frameworks for landmine detection by integrating ML techniques and refining GIS applications in humanitarian demining.
- Fostering Collaboration: It bridges military expertise, ML, and GIS, promoting synergies between these fields.
- Improving Decision-Making: The findings assist in strategic policy-making for landmine clearance, area reconstruction, and post-conflict land-use planning.
- Influencing Global Practices: By providing robust methodologies and frameworks, the research supports international humanitarian demining and post-conflict recovery efforts.

Figure 5 summarizes the central research question: "*How can the integration of GIS and ML, framed within Military Expertise, improve the outcomes of humanitarian demining operations?"* It presents the flow from problem identification to a proposed solution, positioning the hypothesis within real-world operational and technical constraints.

The figure begins by outlining the core challenges of conventional demining:

- Detection limitations due to soil types, dense vegetation, and low-metal content mines.
- Logistical constraints, including the high cost and resource intensity of manual operations.
- Environmental barriers, such as extreme weather and rough terrain affecting clearance efforts.
- Community concerns, particularly the trust gap between operators and local populations.

To address these issues, the hypothesis proposes an integrative approach combining GIS and ML, guided by military expertise, to enhance demining in three key ways:

- Accuracy – Predicting mine presence and distribution through ML models trained on spatial and historical data.
- Safety – Mapping and classifying risk zones to enable safer planning and deployment.
- Efficiency – Prioritizing clearance zones to optimize time and resource allocation.

Figure 5 also outlines the methodological triad:

- GIS provides spatial context and environmental awareness.
- ML offers predictive analytics and pattern recognition.
- Military expertise ensures operational relevance, drawing from tactical experience and historical data.

This integration supports targeted classification of minefields by type, terrain difficulty, and urgency, with the ultimate goal of accelerating post-conflict recovery, restoring civilian mobility, and reducing casualties. The figure serves as a conceptual anchor for the thesis, offering a visual framework for subsequent chapters. It captures the interdisciplinary essence of the work, uniting technology, expert knowledge, and spatial reasoning to address a complex humanitarian challenge.

Additionally, the proposed GIS-ML-powered framework directly addresses key demining challenges by embedding AI-driven analytics within a military-informed decision-making process. It hypothesizes that such integration improves predictive accuracy, optimizes clearance prioritization, and reduces false positives, thereby increasing both efficiency and safety.

The research objectives include:

- Developing a structured approach for precise risk mapping using spatial and historical data.
- Applying ML-based classification to differentiate hazards.
- Embedding military insights to ensure field-level operational relevance.

By refining risk assessment and resource allocation, this methodology aims to deliver a GIS-compatible decision-support tool for humanitarian demining. The study contributes to the advancement of landmine detection technology, promotes interdisciplinary collaboration, and supports evidence-based policymaking for post-conflict land rehabilitation.

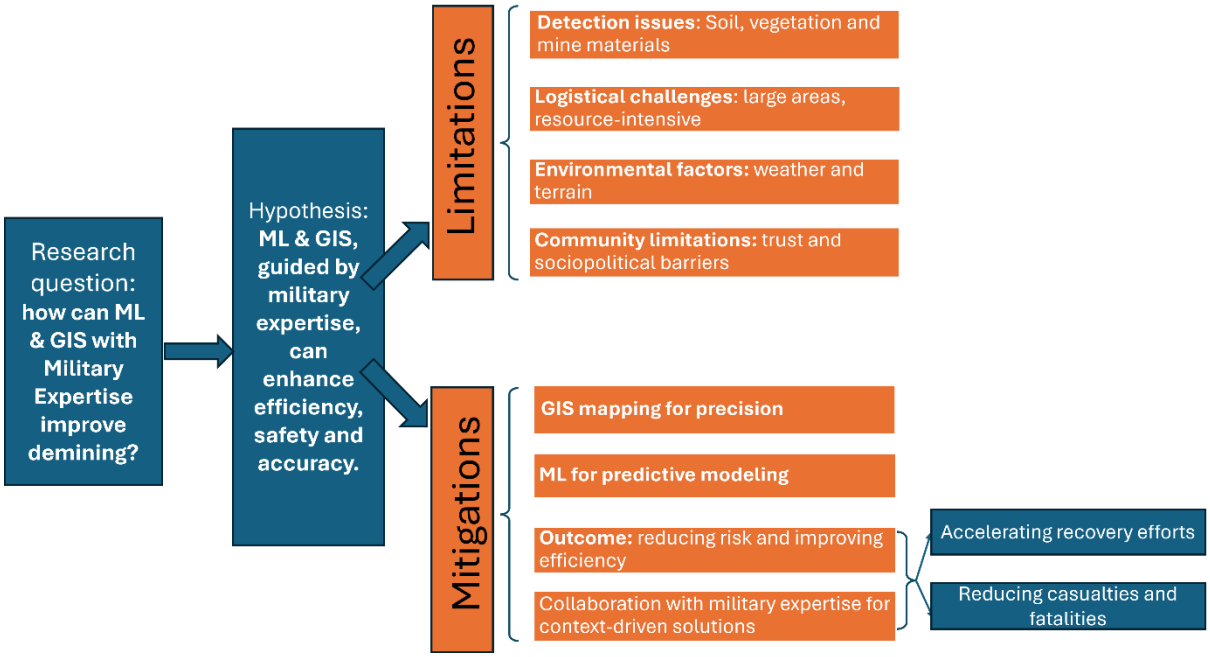


Figure 5: Hypothesis, Limitations and Mitigations

2.6. Summary and Outlook

This section consolidates the chapter's insights and sets the stage for the methodology and implementation chapters that follow, emphasizing the interdisciplinary foundation and future potential of the proposed framework.

Given the persistent risks posed by landmine contamination in Lebanon, there remains an urgent need for scalable, data-driven solutions that enhance clearance efficiency and safety. While GIS supports precise minefield mapping and ML improves detection accuracy, the integration of military expertise ensures the operational applicability of predictive models in real-world demining scenarios. This study provides a foundation for leveraging AI-driven methodologies to accelerate recovery efforts and reduce casualties in humanitarian demining missions. Looking ahead, further advancements will depend on real-time GIS integration, ML-enhanced detection algorithms, and robotics-assisted clearance. Future research should also consider the ethical and operational challenges of AI deployment in high-risk environments to ensure responsible and effective humanitarian applications. Strengthening collaboration between AI researchers, geospatial analysts, and military experts will be essential in driving innovation and achieving sustainable mine-free landscapes in Lebanon and beyond.

As demonstrated, Lebanon's landmine problem requires scalable solutions grounded in technology and field expertise. GIS enhances spatial analysis [21] [10], ML increases

predictive precision [22] [5] [23], and military knowledge ensures real-world relevance. The proposed GIS-ML framework—guided by operational insights—offers a promising path forward. Future developments should focus on real-time analytics, federated data sharing, and robotics-assisted clearance, while carefully considering the ethical implications of AI use in sensitive environments.

The following chapter reviews related research in ML-GIS-based demining, identifying where current methods fall short and how this study advances the state of the art.

Chapter 3
Related Work

3.1. Introduction

Over the last few years, the combination of GIS and ML has been viewed as an effective combination in tackling challenging spatial problems such as urban development [24], environmental assessment, and disaster management [25]. Such technologies assist scholars to work with unmanageable amounts of data and pull relevant information useful in decision making. For example, GIS and ML have been used in emergency response planning by delineating high risk zones and appropriate assistance to these areas [26]. Few studies tackled the landmine problem based on historic data due basically to data access restrictions [3]. A significant limitation of these models for post-conflict landmine removal is the lack of integration of military expertise. Military experience plays a critical role in understanding the strategic and practical factors involved in landmine placement and their associated preventive measures. Without this perspective, models often rely on overly simplistic assumptions, failing to account for the nuanced and deliberate strategies used during the placement of landmines in conflict zones.

This chapter delves into the latest advancements in GIS and ML methods applied to environment, urban [27] [28] and landmine clearance [4]. It provides a comprehensive review of these state-of-the-art approaches, evaluates their effectiveness in real-world scenarios, and identifies key gaps that remain unaddressed. A particular focus is placed on highlighting how incorporating military knowledge into GIS and ML frameworks can enhance the predictive accuracy and practical applicability of these models. This integration also lays the groundwork for responsible urban redevelopment in post-conflict zones, linking mine clearance with sustainable planning. By bridging this gap, we can move toward solutions that not only improve efficiency but also significantly enhance safety and precision in landmine clearance operations.

Through this discussion, the chapter underscores the importance of military and computing collaboration, where technological innovation is enriched by the domain expertise of military professionals, ultimately addressing the complex challenges of post-conflict recovery efforts. Thus, the chapter aims to foreground the threefold contribution of this thesis: data and algorithmic approach innovation, expert military knowledge, and urban planning potential. By emphasizing the synergies among these domains, we propose a holistic path forward for humanitarian demining.

Since landmines negatively impact the environment [29] and their challenges from an ML and data structure perspective resemble rare event occurrences like floods and earthquakes, and given the limited research on applying GIS and ML to humanitarian demining (precisely on historic demining records), I will present related work focusing on GIS and ML applications in both the environmental and urban domains, particularly in areas such as disaster management, land use planning, and risk assessment.

In the following chapter, I will review the application of GIS and ML in the environmental domain, with a particular focus on demining, alongside the regulations and standards governing demining operations [30]. This will be followed by a summary table outlining their limitations. I will then provide a critical evaluation of GIS and ML applications in demining before concluding with a discussion of the thesis contributions and a final conclusion.

Figure 6 below illustrates the structure of this chapter, starting by the application of GIS and ML in the Environmental and Urban domain: applications in landmine and rare event detection, in urbanism, and the role of human in monitoring ML approaches. Then a summary table of reviewed studies is introduced, followed by a critical evaluation regarding this application, and finally th contribution of this thesis and a conclusion.

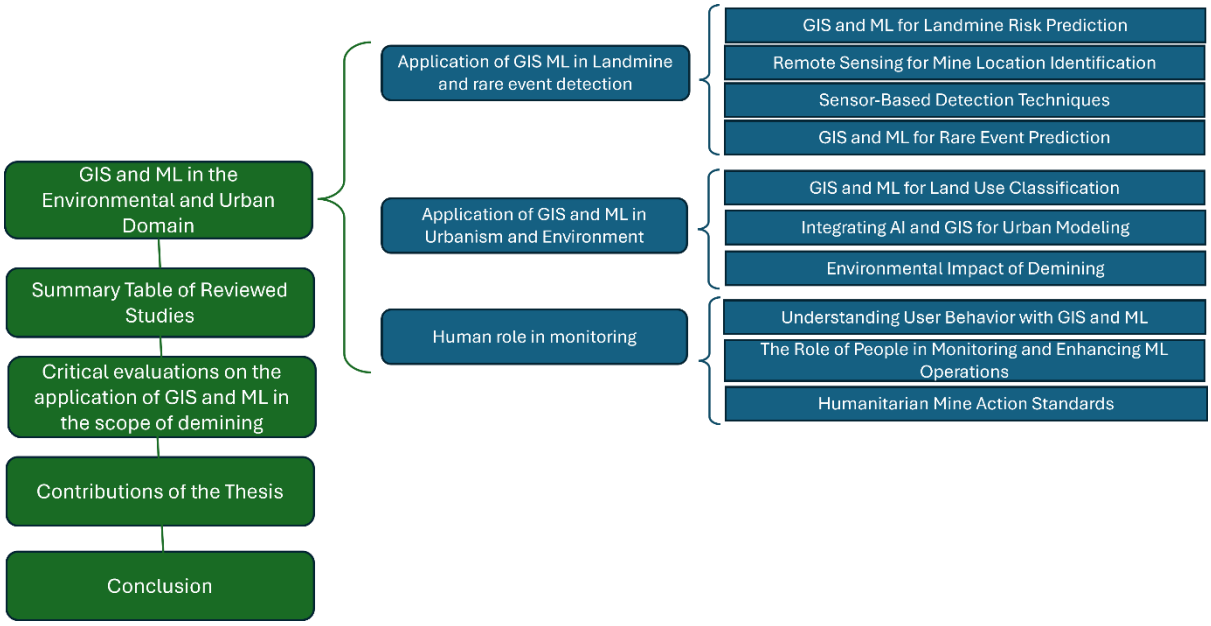


Figure 6: GIS and ML fields of application in the environmental domain

3.2. Application of GIS and ML in Environmental and Urban Domain

This section explores how GIS and machine learning have been applied across environmental and urban domains, focusing on their relevance to landmine risk prediction, rare event modeling, and spatial planning in post-conflict areas.

The integration of GIS and ML has significantly advanced applications in the environmental and urban domain, offering innovative solutions to complex challenges (references listed in the different sub-sections below). These scientific approaches are widely applied in areas such as rare event prediction, landmine risk modeling, land use classification, remote sensing, urban modeling, and environmental impact assessments. For instance, GIS-enabled spatial analysis combined with ML algorithms enhances precision in detecting patterns, predicting events, and evaluating ecological impacts. The synergy between GIS and ML provides powerful tools for addressing environmental challenges globally and contributes to sustainable development efforts.

The following sections delve into the research conducted in various applications of GIS and ML. Each subsection examines specific cases, identifies limitations, and explains how this

work seeks to address most of those challenges. The literature reviewed spans diverse applications, including landmine risk prediction, remote sensing, land use classification, rare event prediction, sensor-based detection, environmental impact assessment, and urban modeling.

Building on this foundation, subsequent sections explore complementary methodologies and applications. Remote sensing integrates advanced imaging techniques to enhance landmine detection and area assessments. Land use classification demonstrates broader GIS and ML applications for environmental and socio-economic monitoring in post-conflict zones. Rare event prediction parallels landmine risk modeling, as both require innovative strategies to address sparse, complex datasets. Sensor-based detection validates predictive models with high-resolution data, while environmental impact assessments ensure technical approaches align with sustainable practices. Urban modeling integrates AI and GIS to support safe and informed land redevelopment. Finally, the discussion highlights the critical human role in ML tasks and examines ML algorithms and humanitarian guidelines, framing the research within a practical and ethical context. Together, these elements lay the groundwork for advanced, human-centric solutions in environmental and mine action applications.

ML models such as Random Forest, Support Vector Machines (SVM), and XGBoost are commonly employed for pattern recognition and prediction. These models enhance accuracy in sparse or high-dimensional datasets, critical for demining where data is limited.

Yet, many reviewed works lack operational military context. For instance, risk mapping often omits tactical factors like proximity to military targets or observation lines. Such omissions reduce the models' real-world applicability.

GIS-ML outputs like land use classifications and urban growth projections have direct implications for repurposing cleared land. Models that predict future land cover changes support sustainable infrastructure development.

The following Table 3 includes descriptions and specific contributions for each GIS and ML domain, illustrating their overlap and contributions toward safer, data-informed landmine clearance and subsequent urban redevelopment.

Domain	Description	Contribution	Ref.
Landmine Risk Prediction	Uses GIS and ML to predict areas of high landmine risk based on spatial patterns and historical data.	Improves prioritization of demining efforts and resource allocation.	[3]
Remote Sensing	Applies advanced imaging techniques to identify landmine locations and assess terrain conditions.	Bridges strategic and tactical assessments with geospatial imaging.	[31]
Land Use Classification	Categorizes land use to understand socio-environmental impacts and plan safe landmine clearance.	Enhances environmental and social decision-making in mined areas.	[32]
Rare Event Prediction	Focuses on analyzing sparse datasets to predict rare occurrences like landmine placements.	Develops ML techniques for handling sparse and complex datasets.	[33]
Sensor-Based Detection	Utilizes sensor data for precise detection of landmines, complementing predictive models.	Increases accuracy and reliability of landmine detection.	[18]
Environmental Impact Assessment	Evaluates the ecological effects of demining activities to ensure sustainable practices.	Integrates environmental sustainability into demining operations.	[29]
Urban Modeling	Supports redevelopment by modeling urban dynamics and post-clearance land use scenarios.	Facilitates safe and informed redevelopment of cleared land.	[27]

Table 3: GIS and ML contributions

The data presented aligns closely with the hypothesis defined in the previous chapter by highlighting how GIS and ML can collaboratively address the challenges of landmine clearance in Lebanon. Each domain explored, such as landmine risk prediction, remote sensing, and rare event prediction, directly supports the development of a predictive model for landmine locations. For instance, landmine risk prediction leverages spatial and historical data, precisely matching the research's goal to optimize resource allocation. Remote sensing and land use classification provide vital inputs for assessing terrain and environmental variables that influence clearance difficulty and prioritization. Sensor-based detection and environmental impact assessment align with reducing operational risks and ensuring sustainable demining practices. Furthermore, rare event prediction techniques offer robust strategies for handling sparse datasets, such as demining reports. By integrating these domains and applying expert-driven interpretations, the model can classify clearance difficulty, prioritize areas for demining, and even differentiate by mine types. The use of advanced ML algorithms like Random Forest, XGBoost, and LightGBM ensures that the approach remains tailored to rare-event modeling, while the GIS-compatible outputs promise practical utility for national demining strategies. Ultimately, this approach has the potential to refine predictions, enhance operational safety, and accelerate land recovery, validating the hypothesis.

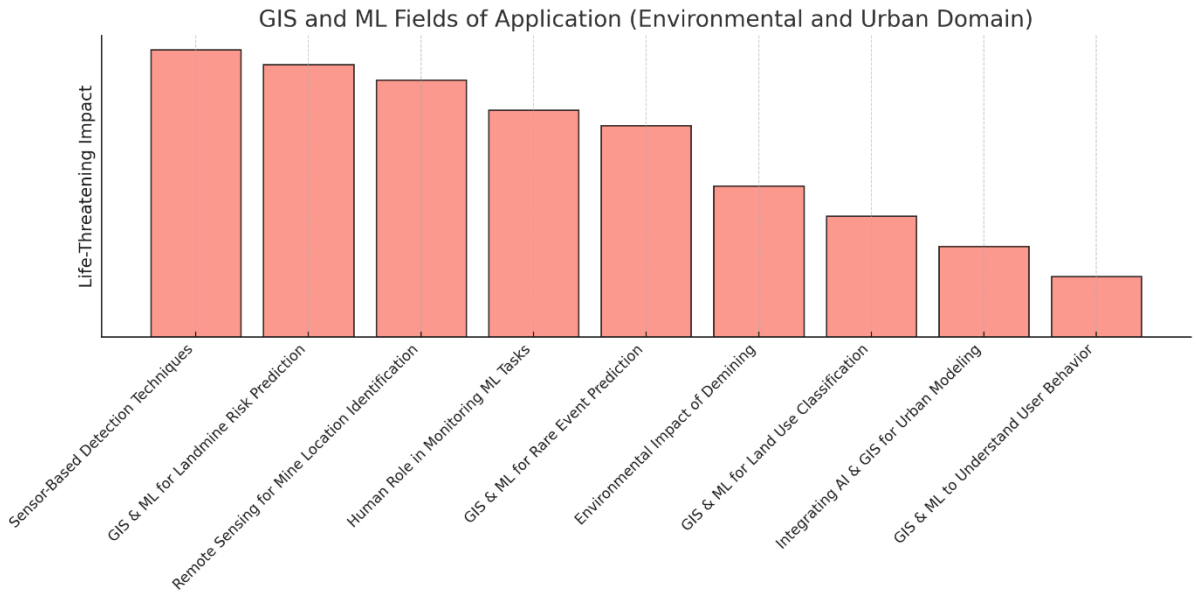


Figure 7: Life-Threatening Impact of different fields

Figure 7 illustrates the various GIS and ML application areas within the Environmental and Urban domain, ranked by their life-threatening impact levels, deduced from demining expertise and verified by demining military experts in the Lebanese Army based on a site study. The fields are sorted in descending order, with "Sensor-Based Detection Techniques" and "GIS & ML for Landmine Risk Prediction" showing the highest impact, reflecting their critical role in addressing life-threatening challenges like detecting and mitigating landmines. Lower-impact fields, such as "GIS & ML to Understand User Behavior," are included for broader context, showcasing their relatively indirect influence in this domain. The visualization highlights the prioritization of resources and efforts based on the severity of threats addressed by each field.

3.2.1. Application of GIS and ML in Urbanism and Environment

This subsection details the role of GIS and ML in land use classification, urban reconstruction, and evaluating the environmental impacts of demining, setting the foundation for their integration into sustainable post-conflict recovery.

a) GIS and ML for Land Use Classification

The classification of land use and land cover (LULC) has seen the steady evolution of ML techniques over the years. Thanks to ML, there exists the possibility to investigate and observe the different kinds of land such as urban, agricultural, and forested zones. In “Land Use Land Cover Classification of Remote Sensing Images Based on Deep Learning Approaches” [34], some weaknesses and strengths are examined where among the former SVM’s classification capability for LULC is praised with different Kappa coefficients.

GIS have made it easier to easily observe LULC trends, and these GIS approaches get even more powerful when paired with ML. For example, Islam Atef et Al's El-Fayoum case study [35] employed Landsat data and employed supervised classification methods to tracking urban growth and agricultural development. Similarly, the study "Using GIS, Remote Sensing, and Machine Learning to Highlight the Correlation between the Land-Use/Land-Cover Changes and Flash-Flood Potential" in Romania [36] demonstrated GIS's potential for environmental risk assessment by correlating LULC changes with increased flood potential. Both studies underscore the necessity of accurate classification data for planning and risk management.

Furthermore, the study "Modelling of Land Use/Cover and LST Variations" in Pakistan [37] demonstrates the transformative impact of GIS and ML in predicting future LULC changes and their implications on local climates. The methodology, combining regression analysis and Cellular Automata-Artificial Neural Network (CA-ANN) modeling, projects urban and bare soil expansion at the expense of vegetation. This study uses 30-year projections to show how ML can anticipate land use trends for long-term environmental management.

Lastly, Choi's survey paper, "GeoAI: Integration of Artificial Intelligence, Machine Learning, and Deep Learning with GIS," [38] underlines the potential of AI, ML, and deep learning in handling complex spatial datasets and offers insights into innovative methods for interpreting spatial data in various fields, from urban planning to agriculture.

GIS and ML for land use classification efficiently categorize areas into distinct classes such as urban and agricultural using spatial and spectral data. However, they often overlook mined areas as a distinct category, limiting their applicability in post-war environments. Additionally, dimensionality reduction techniques, while useful for handling high-dimensional data, may discard critical information relevant to mine detection and classification..

b) Integrating AI and GIS for Urban Modeling

The urban reconstruction and modeling strategy integrates Artificial Intelligence (AI) and GIS: AI and GIS have shown transformational impact on urban core in, explaining cities improvement, infrastructure development and resource use. While the urban modelling process and the process of mine detection is different in terms of focus, AI-GIS spatial techniques could strengthen urban spatial planning in the post-demining period by allowing optimal land development in places under clearance. In "Accelerating Uban Modelling Algorithms with Artificial Intelligence" [27], Milton and Roumpani look at integration of AI tools in particular Google TensorFlow in making the urban modelling frameworks more useful and interactive. The research demonstrates how the power of GIS within interpretation's models of spatial interaction that is controlled by Artificial Intelligence created instant rendering for web-based applications that are likely to be employed by urban planners when modelling outputs are required quickly. According to the papers of Peng et al. [39], the AI has the opportunity to participate dramatically for a changing model while multi-stage in the form of 'AI-assisted', 'AI-controlled' as well as ' AI embedded AI planning'. This research aims at building a case for how urban planners could become more effective

and proactive in meeting the demands of providing housing and environmental issues with timely response through AI dataset, scenario development for plan formulation.

Casali, Aydin, and Comes, in "Machine Learning for Spatial Analyses in Urban Areas: a Scoping Review," [24] outline the ways in which ML approaches are used in a variety of fields, such as land use, urban form, and socioeconomics, to tackle important urban issues like economic development and environmental preservation. They draw attention to the need for more standardized procedures and interdisciplinary studies in resilience and sustainable urban development.

Mortaheb and Jankowski highlight the convergence of Big Data, GIScience, and Data Science in urban planning in "Smart City Re-imagined: City Planning and GeoAI in the Age of Big Data," [28] pushing for GeoAI as a tool to promote public involvement and collaborative governance in city planning. They put out a human-centered framework in which GeoAI technologies support informed decision-making, equitable access, and urban resilience.

Finally, in "Comparison of Twelve Machine Learning Regression Methods for Spatial Decomposition of Demographic Data Using Multisource Geospatial Data: An Experiment in Guangzhou City, China," [40] Zhao et al. highlight the advantages of merging various geospatial datasets for better land-use and demographic analysis. Through the evaluation of multiple machine learning regression methods, this work demonstrates how non-linear models—like Random Forest and K-Nearest Neighbors—are able to handle complicated urban data and provide high-resolution population maps that promote sustainable urban planning.

Integrating AI and GIS for urban modeling enhances urban planning by enabling growth and infrastructure prediction. However, it requires significant computational resources and is rarely applied to post-conflict, cleared areas. Additionally, it may overlook community-driven, sustainable approaches, limiting its effectiveness in adaptive urban recovery

c) Environmental Impact of Demining

The environmental consequences of demining activities are of the utmost importance owing to the use of heavy equipment that tends to disturb the ecosystems and also causes soil erosion. Some scholarship demonstrates that while demining is important in the post conflict reconstruction effort, it has to be carried out in a way that minimizes the ecological impacts. In the article titled “Land Cover Changes: A Case Study from Halgurd-Sakran National Park in the Kurdistan Region of Iraq” [29], the authors studied the effect of landmines and their elimination on land cover changes using Landsat images for time series spanning from 1998 to 2015. It was found in the analysis that there was a general decrease in the net area cover of forest and farm lands as the area under pastures increased, categorically as it has been affected by demining operations that enhance landscape fragmentation also changes patch size and patch density. These changes are detrimental to the ecosystems and the diversity of the species, hence the need to avoid unnecessary demining activities so that ecological damage is minimized.

Ursign Hofmann and Pascal Rapillard emphasize the degradation of the quaint environment through micronization in their article “Do No Harm in Mine Action: Why

the Environment Matters" [41]. They bring up such issues as soil erosion and vegetation loss caused by the utilization of bulldozers and other heavy machines. Mechanical minesweeping disrupts soil structure, reducing fertility and natural vegetation cover. Diehl and Rapillard draw attention to the need to observe the practices of environmental consideration including the International Mine Action Standards that advocate for doing environmental impact assessment and using nondestructive measures. Furthermore, GIS and remote sensing techniques can be used for post project environmental assessment and management of the negative impacts.

The application of equipment and technologies in the process of, as well as the expenses caused by IEDs usage which Lodhammar, Pehr and Wilkinson, Mark termed 'mechanical experience in the IEDs clearance: analysis and best practices' [42] also discloses the environmental impacts of these activities. The UN remained on the focal point in the works and reiterated that despite the potential benefits of using machines from armored loaders or excavators it rather create environmental problems. UNMAS further reoriented its plans effective and safe management of the operations with little or no environmental degradation.

The environmental impact of demining is assessed by evaluating effects such as soil compaction and vegetation loss. However, the use of heavy machinery can disrupt ecosystems and compromise soil integrity, while a lack of precision in mine prediction may lead to unnecessary environmental disturbances, further exacerbating ecological damage.

3.2.2. Application of GIS and ML in Landmine and rare event detection

The focus here shifts to domain-specific applications in landmine detection and rare event prediction, highlighting how geospatial data, remote sensing, and ML models converge to support precision and risk forecasting in hazardous environments.

a) GIS and ML for Landmine Risk Prediction

The landmines prediction and detection that incorporates GIS and ML has relied on historical data as well as environmental data. Such methods include mining records, topographical data and data of areas around conflict zones. Earlier studies had clearly indicated the feasibility of employing both GIS and ML in landmines detection, however military perspective had been lacking as one of the major weaknesses. As an example, Rafique et al. (2019) [3] created a predictive model in order to optimize landmine clearance incorporating the Logistic Regression and Support Vector Machine models. They relied on the historical data of areas that were mined and later cleared to predict the possible dangers in the future. They achieved an accuracy of 89.24% with the SVM algorithm.

Similarly, Shultz et al. (2023) [5] tried to map landmine hazard in Colombia and Bosnia and Herzegovina using aspatial and spatial logistic regression models. The study found that spatial logistic regression using Geographically Weighted Regression (GWR) produced more accurate, finer-grained risk maps by accounting for regional variations in explanatory variables, such as distances from cultivated land, built-up regions, and water courses. Cirillo et al. (2023) [4] developed a system called Desk-AId that employed geospatial AI to predict landmine regions by using historical conflict data

and multi-domain amenities like buildings, highways, and health locations. The model's adoption of a hard-negative data sampling technique significantly improved risk assessment accuracy, highlighting the potential of geospatial data in demining operations.

GIS and ML for landmine risk prediction leverage historical data and environmental factors to estimate mine locations. However, they often lack integration of military expertise, relying primarily on environmental data without strategic insight. Additionally, the risk mapping may lack fine granularity, limiting its precision for targeted demining efforts.

b) Remote Sensing for Mine Location Identification

Many studies use Remote Sensing (RS) techniques, primarily based on aerial data, to identify potential mine locations. High-resolution satellite or aerial images are analyzed using remote sensing techniques to identify anomalies that may indicate the presence of mines. In recent years, there has been substantial progress in combining remote sensing data with machine learning approaches for humanitarian demining. Baur et al. [31] show the great potential of drone-based images combined with convolutional neural networks (CNN) for surface mine identification in "How to Implement Drones and Machine Learning for Landmine Detection," especially with the PFM-1 "butterfly mine." Their approach, which examines drone photos, has a 91.8% detection accuracy, demonstrating that, with the right training, CNN models can identify surface mines. Nevertheless, the approach has drawbacks in practical use, such as the incapacity to identify partially buried or vegetation-covered mines.

The TIRAMISU project [43] offers another perspective on incorporating remote sensing for demining through the development of an advanced decision support system. As highlighted in the paper "Development of the TIRAMISU Advanced Intelligence Decision Support System," this project merges air-based imagery with expert-driven geospatial analysis to prioritize high-risk areas for demining. The system applies methodologies like fuzzy logic and multicriteria decision-making to develop mine danger maps, which facilitate better resource allocation.

An investigation on the landmine detection using deep learning with the combination of maps with high resolution images includes the following study, “How Well Do Deep Learning-Based Methods for Land Cover Classification and Object Detection Perform on High-Resolution Remote Sensing Imagery?” [44] Also, a case comprises the study of the authors’ transition through CSUD and PSPNet which broadened deep learning models where spatial and spectral details are included in the process making it more efficient in areas of land cover detecting and deep learning-based classifications.

Finally, a joint fusion and detection through deep learning is proposed in “UAV-borne multispectral sensing of scatterable landmines” [23] to show the potential of UAV-mounted solutions for detecting scatterable landmine on complex terrains. The authors improve mine detection recall rates at 91.67 % by merging multispectral images to capture diversified terrain and vegetation states using a deep-learning-driven fusion framework based on the YOLOv5 model, especially in occluded scenarios. The incorporation of UAV and multispectral data fusion in mine detection, signifies that the

integration of corresponding capabilities on a single platform can highly contribute to improving performance with machine-learning approaches.

Remote sensing for mine location identification utilizes aerial and satellite imagery to detect surface mines and potential hazardous areas. However, it has limited capability in identifying buried or obscured mines and heavily relies on visual anomalies without military context. Additionally, improving accuracy with CNNs requires more diverse datasets to enhance model robustness and reliability.

c) Sensor-Based Detection Techniques

Recent sensor-based detection techniques which include the use of LIDAR, magnetometers and ground penetrating radar (GPR) have shown great success in the detection of land mines by locating certain physical heretics beneath the surface of the earth. There has been also some use of recent technology where sensors mounted on drones are now being used in demining operations making it safer and much more efficient since data collection can be done in areas that would prove to be hazardous. All these techniques however have some drawbacks when it comes to the environment in which they are utilized, they can be affected by humidity and soil type which in most cases diminishes the accuracy of data especially in GPR and magnetometers.

In the study titled “Combining Deep Learning and Location-Based Ranking for Large-Scale Archaeological Prospection of LiDAR Data from The Netherlands” [45] showcased a model from Verschoof-van der Vaart et al that allows the integration of LIDAR data with deep learning for detecting archeological objects in a way that is useful in improving the detection of landmines as well. WODAN2.0 workflow on the other hand improves accuracy of detections by making use of a Faster R-CNN model with location-based ranking that uses knowledge of the specific landscape where the operation is being carried out.

A Magnetometer Drone Detects Landmines [46], presents the status of their work on a concept that would allow the use of drones with magnetometers that can detect metallic anomalies caused by landmines. This method is much safer compared to manual methods and also helps in saving significant time as vast regions can be covered. Nonetheless, environmental magnetic noise remains a weakness and poses a myriad of problems including false alarms and challenges in identifying small/deep miner units.

GPR is addressed more fully in "An Integrated Landmine Detection Aerial System: SDR-Based GPR located on an Autonomous Drone" [47], where GPR on autonomous drones seems to exhibit a superior capability to detect buried landmines. The system claims a considerable accuracy rate of 85.7% although it appears a bit less effective in detecting non-metal dominated landmines.

Bistatic Landmine and IED Detection Using Vehicle and Drone Mounted GPR Sensors [48] presents a contemporary application of GPR in a bistatic configuration, where a vehicle-mounted transmitter and a drone-mounted receiver enhance the detection by cutting down on surface clutter. This multi-platform approach improves effective target resolution so that non-metal mines are more likely to be successful.

More work is also noticed in “A Deep Learning Approach for Landmines Detection Based on Airborne Magnetometry Imaging and Edge Computing,” [5] which describes the MAGnetometry Imaging based Classification System (MAGICS) that is introduced. UAV-based magnetometry, along with deep learning models such as YOLOv5 and EfficientDet, is employed in this system to detect and categorize the magnetic anomalies related to landmines. With edge computing, MAGICS makes possible rapid response through real-time data processing in demining operations.

Finally, “Combining Electromagnetic Spectroscopy and Ground-Penetrating Radar for the Detection of Anti-Personnel Landmines” [13] shows such approach`s advantages for detecting anti-personnel landmines in dual-modality metal spectroscopy together with GPR. The main advantages of such integrated sensor system are decreasing false alarms while increasing the thoroughness of detecting even non-metallic mines which is one of the biggest drawbacks in most conventional metal detectors.

Sensor-based detection techniques use LIDAR, magnetometers, and GPR, often mounted on drones, for direct mine detection. However, environmental conditions such as soil moisture can disrupt sensor accuracy, leading to false positives due to environmental noise. Additionally, these methods come with high operational costs, limiting their scalability in large-scale demining efforts.

d) GIS and ML for Rare Event Prediction

While predicting events that are anticipated at a low regularity like wild fires, earthquakes, floods and landslides, GIS and ML develop into key areas of interest. These events are difficult to model because they are not only rare in occurrence but also have sparse datasets, which calls for enhanced ML strategies to be able to predict correctly. The authors point out in "Flood Prediction Using Machine Learning Models: Literature Review" [33] how ML models have been able to model flood predictions better than the traditional techniques due to their ability to model nonlinear processes. Some of these models on the other hand make use of elevation, slope and historical data of floods in such a way as to integrate previous information without the need to know the flood processes in detail. However, data quality, model configuration and “the generalization problem” remain challenges that ML models are faced with where the accuracy of a ML model remains high for trained data while the accuracy of unseen data is usually often on the low spectrum.

The research “Evaluation of the Application of K-means Clustering in Earthquake Vulnerability Mapping of Istanbul, Turkey” [49] proposes a new method for earthquake vulnerability mapping based on the use of k-means clustering combined with other models like DT’s and SVM’s. This approach demonstrates that combining clustering with diverse models provides a multi-dimensional view of vulnerability, which could be adapted in mined area prediction to account for the socio-economic and geographic variability in conflict zones.

In "Comparisons of Diverse Machine Learning Approaches for Wildfire Susceptibility Mapping," [50] researchers applied various ML models, including Random Forest (RF), decision trees, and SVM, to map wildfire risk in Amol County, Iran. RF achieved the highest AUC score (88%) and proved robust in handling complex spatial data, underscoring the need for high-quality, context-specific data in rare event predictions.

The study "Automated Landslide-Risk Prediction Using Web GIS and Machine Learning Models" [51] developed a web-based GIS application integrating ML models like Bi-LSTM and RF to predict landslide risk. By combining factors such as land cover, soil properties, slope, and precipitation, the study improves prediction accuracy through real-time updates and visualization on a web platform. This approach highlights how dynamic GIS platforms combined with machine learning could be beneficial for mined area detection.

Lastly, the paper "Weighting Methods for Rare Event Identification From Imbalanced Datasets" [52] by Jia He and Maggie X. Cheng addresses the common issue of class imbalance, which leads to poor detection of rare events. The authors propose adaptive weighting methods, such as Differentiated Boosting and Adaptive Class Weights, to improve rare event prediction by focusing on minority class accuracy without compromising the majority class.

GIS and ML for rare event prediction are effective in forecasting events like floods and earthquakes by analyzing spatial and historical data. However, they are constrained by imbalanced datasets that favor the majority class, leading to generalization challenges on new data. Additionally, these models often lack socio-political context, which is crucial for understanding risk dynamics in affected regions.

3.2.3. Human role in monitoring

Recognizing that ML models cannot operate in isolation, this section emphasizes the vital role of human oversight, from understanding user behavior to ensuring ethical monitoring and iterative model improvement.

a) Understanding User Behavior with GIS and ML

Recent developments have demonstrated the potential of GIS and ML to provide real-time insights into user preferences and behaviors in addition to physical location-based analysis [53] [54]. GIS and ML can enable tailored experiences by combining spatial data with user-specific online activities, providing a fresh viewpoint on how users interact with their surroundings. Although this method is different from mine detection, the idea of integrating GIS and ML for behavioral insights may someday be used in post-demining environments to help manage community resources or predict land use requirements based on trends in local behavior.

In order to improve retail experiences, Shahriari-Mehr et al. provide a novel model in "A Store Location-Based Recommender System Using User's Position and Web Searches," [53] which combines users' real locations with their internet search data. The system makes recommendations based on both user-specific interests gleaned from internet search habits and store proximity utilizing the k-nearest algorithm and spatial analysis, particularly Voronoi diagrams. This method, which is used in District 6 in Tehran, lowers search expenses while simultaneously enhancing decision-making by offering location-sensitive recommendations. Despite being retail-focused, this research highlights the potential of GIS-ML fusion for tailored, real-time suggestions and suggests ways to forecast community preferences or behaviors in demined areas.

Another relevant study, "Predicting Online User Behaviour Using Deep Learning Algorithms" [54] by Vieira, explores advanced deep learning models for predicting user purchasing behavior on e-commerce platforms. Deep Belief Networks (DBN) and Stacked Denoising Autoencoders (SdA) outperform traditional ML models like logistic regression and random forest, especially in handling high-dimensional, sparse data and class-imbalanced datasets, which is often the case in e-commerce analytics. While this application is online-centric, its principles apply to spatial behavior analysis, where high-dimensional data and user-specific patterns must be analyzed for accurate predictions. In post-demining scenarios, such deep learning models could be applied to complex spatial datasets—capturing diverse patterns of movement, land use, and resource needs in communities, enabling a data-driven approach to post-clearance land use planning.

These studies highlight how behavioral insights may be obtained using GIS-ML integration, showing a foundation that might be modified to foresee and meet the particular requirements of populations in demined areas. Our research might include predicted insights for effective land use by utilizing location-based behavior modeling. This would ensure that post-clearance development promotes local objectives and safety while also harmonizing with community requirements.

b) The Role of People in Monitoring and Enhancing ML Operations

Human supervision, guidance, and interpretation are essential in ML processes because they improve model accuracy and reliability. By ensuring that machine learning models are modified and enhanced based on contextual insights that algorithms alone might miss, this human-in-the-loop approach enhances overall performance in complex or dynamic environments. While ML models in our research aim to predict mined areas based on GIS data, human involvement is essential in validating results, refining predictions, and ensuring ethical, context-aware application of these scientific approaches.

According to Patrizia Ribino's article "The Role of Politeness in Human-Machine Interactions: A Systematic Literature Review and Future Perspectives," [55] including social standards like politeness might enhance user experience and confidence in these interactions. This realization highlights how ML models gain from human-like interaction patterns, which encourage user acceptance and confidence. In situations like ours, where confidence in the forecast accuracy of mined area identification might impact safety, Ribino's work highlights the significance of taking social dynamics into account in machine learning applications. It also suggests that user interaction and transparency are essential. In order to maximize predictions and guarantee that stakeholders have faith in the results for practical applications, our machine learning models will be dependent on transparent communication and user input.The concept of hybrid intelligence explored in "Hybrid Intelligence: Human-AI Collaboration in Marketing Analytics" by Maria Petrescu and Anjala S. Krishen [56] illustrates the benefits of combining human creativity and judgment with AI’s data-processing capabilities. By blending these strengths, hybrid intelligence improves decision-making, personalization, and ethical compliance. In our work, human oversight can complement ML’s ability to handle large geospatial datasets, ensuring that ethical considerations, contextual accuracy, and environmental impacts are carefully managed. Although our focus is on mine detection rather than marketing, this research suggests

that ML results can be enhanced by human expertise, particularly in high-stakes applications like demining, where accuracy is paramount for safety and environmental preservation.

The MENTOR framework, described in "MENTOR: Guiding Hierarchical Reinforcement Learning with Human Feedback and Dynamic Distance Constraint," [57] demonstrates how human feedback can guide reinforcement learning (RL) models toward achieving complex sub-goals more efficiently. MENTOR leverages human expertise to select effective sub-goals, which stabilizes training and optimizes performance in tasks with sparse rewards. This method is applicable to mined area detection, where human feedback could direct ML models to focus on high-risk zones based on historical conflict data, adjusting model priorities to reflect real-world demining knowledge. While MENTOR's RL-focused structure may differ from our ML setup, it underscores the value of human input in refining model objectives for specialized tasks.

In "Architectural Framework for Exploring Adaptive Human-Machine Teaming Options in Simulated Dynamic Environments," [58] Madni and Madni provide an adaptive framework that keeps track of human conditions and modifies task distributions in real time to maximize human-machine teamwork. In mine detection scenarios, where human input on local conditions, soil variability, or potential impediments could dynamically modify ML-based predictions, such adaptive frameworks could be essential. Despite its complexity, this framework for human-machine teaming could guide our strategy by guaranteeing that machine learning models adjust in response to real-time environmental inputs, improving mine detection operations' flexibility and safety.

Lastly, "Visual Analytics for Collaborative Human-Machine Confidence in Human-Centric Active Learning Tasks," [59] introduces ActiVAte, a visual analytics tool that incorporates human confidence levels into active learning tasks. ActiVAte allows users to interactively label data, adding confidence scores that the ML model can factor into its training process. This collaborative approach ensures that ML models incorporate human insights and confidence levels, which could reduce misclassifications in mine prediction models by allowing field experts to validate and contribute to model training. ActiVAte's collaborative framework demonstrates how confidence-based human feedback can enhance ML accuracy and reduce the need for corrections, reinforcing the value of human oversight in high-stakes applications like mine detection.

In conclusion, human intervention in machine learning activities is essential for tracking, directing, and interpreting outcomes, especially in intricate domains like mine detection where precision and safety are crucial. Our goal is to guarantee that model predictions are precise, dependable, and in line with actual demining situations by including human oversight and input into our machine learning architecture. This method produces a more efficient and responsible mine detection solution by ensuring ethical and context-sensitive deployment in addition to improving the technical robustness of our models.

While GIS and ML have demonstrated significant potential in improving landmine detection and risk prediction, their effectiveness remains constrained by technical, environmental, and operational limitations. These constraints underscore the

importance of standardized humanitarian mine action frameworks, which ensure that demining efforts align with safety protocols, legal obligations, and sustainable land management strategies. The following section examines international mine action standards and their role in shaping GIS-ML applications for humanitarian demining.

3.3. Humanitarian Mine Action Standards

This section provides an overview of relevant principles and standards for humanitarian mine action, addressing global standards, the current strategy in Lebanon specifically, and the UN landmine ban convention. Building on global frameworks like the Ottawa Treaty, and relying on technical expertise and research provided in Geneva International Center for Humanitarian Demining (GICHD), regional strategies such as Lebanon's Mine Action strategy align international principles with localized solutions to address specific socio-economic and humanitarian challenges.

First opened for signature on September 18, 1997 — the "Convention on the Prohibition of the Use, Stockpiling, Production and Transfer of Anti-Personnel Mines and their Destruction", often called the Ottawa Treaty [1]. The treaty is designed to ban the production, use, stockpiling, and transfer of anti-personnel mines worldwide because they have immense humanitarian consequences: loss of life, economic burdens, and displacement where return is made difficult. Under the Convention, State Parties are prohibited from using, producing or stockpiling anti-personnel mines and must destroy their stockpile within four years and clear areas filled with these explosives within ten years. It also promotes mine clearance, rehabilitation of victims and awareness programs on humanitarian ground by various international cooperation. The treaty aims to have all parties participate, with the purpose of eliminating anti-personnel mines from around the globe through transparency measures, compliance checks and regular review meetings.

GICHD, 2014.The "Guide to Mine Action 2014" [10] replaces the Integrated Approach to Mine Action (published in 2003) and provides a holistic overview of mine action. It explores the history of mine action programs, the regulatory instruments that structure them and main themes including land release, risk education, assistance to victims and the destruction of stockpiled mines and ammunition. Also highlighted is a focus on linking mine action to mainstream humanitarian themes including gender and diversity, the environmental implications of landmines, as well as linkages between mine action efforts with respect to security and development.

The first half is dedicated to the history, extent of contamination, and legal framework for mine action, while the second half concentrates on mine action programming. The package covers strategy, quality and information management as well as operational tasks such as land release and risk education. The guide highlights the do no harm principle to increase safety and decrease violence in mine-affected areas, acting as an essential guidance document for practitioners, policymakers and other field stakeholders.

The "Lebanon Mine Action Strategy 2011-2020" [9] outlines Lebanon's approach to addressing landmine and cluster munition contamination, developed by the LMAC. This strategy aligns with the Convention on Cluster Munitions (CCM) and the Convention on the Rights of People with Disabilities, addressing land release, victim assistance, risk education, and advocacy for treaty compliance. It emphasizes collaboration among stakeholders, community involvement, and sustainable national capacity for managing residual risks. The

strategy details Lebanon's socio-economic and humanitarian challenges from mine contamination and describes how resources will be mobilized for monitoring and evaluating progress toward a mine-free Lebanon.

These guidelines and conventions form a foundational framework for mine action, setting standards that enhance the effectiveness, safety, and sustainability of demining efforts globally and in affected regions like Lebanon.

3.4. Summary Table of Reviewed Studies and Limitations

To consolidate the literature review, this section presents a comparative summary of related studies, mapping key limitations across various GIS-ML applications and laying the groundwork for critical evaluation.

Section	Application Area	Key Limitations	References Supporting Limitations
GIS and ML for Landmine Risk Prediction	Utilizing GIS and ML to predict mine locations based on historical data and environmental factors.	Limited integration of military expertise, focusing primarily on environmental data without strategic insight. Lacks fine granularity in risk mapping.	[3] [60]
Remote Sensing for Mine Location Identification	Uses aerial and satellite imagery for detecting surface mines and potential mine locations.	Limited ability to detect buried or obscured mines, high reliance on visual anomalies without military context, requires more diverse datasets for CNNs to improve accuracy.	[31] [4]
GIS and ML for Land Use Classification	Classifies land into categories (urban, agricultural, etc.), but rarely includes mined areas as a distinct category.	Overlooks mined areas as a specialized land use category. Dimensionality reduction techniques can cause loss of crucial features.	[35] [38]
GIS and ML for Rare Event Prediction	Applies to predicting rare events like floods and earthquakes using GIS and ML techniques.	Limited by imbalanced datasets that favor the majority class, leading to generalization challenges on new data. Lacks socio-political context, making risk assessments less effective in conflict zones.	[52] [39]
Sensor-Based Detection Techniques	Direct detection of mines using LIDAR, magnetometers, and ground-penetrating radar (GPR), often drone-mounted.	Environmental conditions (e.g., soil moisture) can disrupt sensor accuracy, leading to high false positive rates. High operational costs limit scalability.	[45] [47]
Environmental Impact of Demining	Evaluates environmental effects of demining, including soil compaction and vegetation loss.	Heavy machinery disrupts ecosystems and soil integrity. Lack of precision in mine prediction increases unnecessary environmental impact.	[41] [61]
Integrating AI and GIS for Urban Modeling	Enhances urban planning using AI and GIS, often applied in growth and infrastructure prediction.	Requires significant computational resources, lacks application to post-conflict, cleared areas, may not consider community-driven, sustainable approaches.	[27] [24]
Utilizing GIS and ML to Understand User Behavior	Uses GIS and ML to assess and predict user behaviors based on location and online actions.	Limited application beyond commercial contexts, potentially lacks flexibility for diverse real-world uses. Requires high-quality, location-based data.	[53] [54]
Human Role in Monitoring and Enhancing ML Tasks	Highlights the critical role of human oversight in guiding and refining ML tasks.	High reliance on algorithmic output without contextual understanding, limited human intervention for bias correction, requires interpretability and ethical transparency.	[56] [58]

Table 4: Current Studies

Table 4 summarizes the current state of research in GIS and ML for mine detection and similar fields, identifying major key limitations.

As outlined in Table 4, existing GIS-ML approaches for landmine detection face three primary challenges: (1) lack of military expertise integration, (2) sensor and environmental constraints, and (3) insufficient interdisciplinary integration. Each of these challenges directly impacts the reliability, accuracy, and scalability of predictive models used in demining efforts. The next section critically evaluates these challenges and explores how they affect the practical implementation of GIS-ML technologies in post-conflict zones.

The limitations and gaps identified in the existing literature underscore critical challenges in the application of GIS and machine learning for humanitarian demining:

a) **Lack of Military Expertise**: Many existing models fail to incorporate military constraints, tactical insights, and expert knowledge. This oversight limits the ability of these models to account for the strategic placement of mines based on historical patterns and military tactics. Consequently, predictive models often lack the situational accuracy needed for real-world demining operations, reducing their effectiveness in identifying high-risk areas and prioritizing demining efforts.
b) **Sensor and Environmental Limitations**: Sensor-based detection methods, while valuable, are heavily influenced by environmental factors such as soil composition, terrain variability, and weather conditions. These variables can significantly affect the performance of technologies like GPR, magnetometers, and LIDAR, leading to false positives and inconsistencies in detection. Additionally, the operational use of heavy machinery during demining often results in soil compaction and ecosystem disruption, exacerbating the environmental impact. The lack of precision in current models not only increases the ecological footprint but also risks overlooking buried mines, compromising the safety and efficiency of demining activities.
c) **Insufficient Integration of Multidisciplinary Approaches**: Many existing frameworks are siloed, focusing narrowly on either environmental data, remote sensing, or machine learning techniques, without fully integrating these with socio-political, military, and community-based knowledge. This fragmented approach reduces the ability to develop holistic solutions that address the complexity of demining challenges, particularly in post-conflict regions.

To address these limitations, future approaches must emphasize a multidisciplinary integration of military, environmental, and technical expertise. Incorporating domain-specific knowledge, such as military operational insights, into GIS and machine learning models can enhance their ability to predict mine locations with greater accuracy. Furthermore, advancements in sensor technology, combined with adaptive machine learning algorithms, can mitigate environmental and technological constraints. These solutions must also prioritize sustainability, reducing the ecological impact of demining operations through more precise risk mapping and environmentally friendly methodologies. By leveraging robust, context-aware approaches and fostering collaboration across disciplines, it is possible to significantly improve the precision, reliability, and sustainability of humanitarian demining efforts.

3.5. Critical evaluations on the application of GIS and ML in the scope of demining

Drawing from the reviewed literature, this section critically examines the limitations of current GIS and ML models in demining, and identifies areas where military integration and interdisciplinary frameworks can bridge existing gaps.

Despite the advancements in GIS and ML for landmine detection, several technical, environmental, and operational challenges persist. One of the most pressing issues is the lack of integration of military expertise in existing models [3] [60]. While current ML-based risk assessments leverage spatial and historical data, they fail to incorporate strategic and tactical insights from past conflicts, leading to limited predictive accuracy in real-world demining scenarios. Additionally, sensor-based detection techniques such as GPR and magnetometers, though effective in controlled environments, suffer from false positives due to soil conditions and environmental noise [45]. Lastly, the fragmented nature of interdisciplinary approaches prevents holistic solutions, as most models focus narrowly on either environmental data or machine learning techniques, without integrating socio-political and operational constraints [39].

Despite these advancements, there still some challenges such as limited access to reliable and high-quality data, ethical concerns about data sharing, environmental diversity which hardened the generalization of models across different regions. Promising directions for future research include the integration of expert knowledge with GIS and ML techniques to handle data scarcity, leverage imaging techniques and improve predictions. Development of secure data sharing platforms could also enhance operational integration. Together, these efforts could make demining more effective and safer.

Several challenges face the implementation of ML-GIS systems, such as data availability and accessibility, computational resources and costs, and finally the need of specialized training. Data accessibility is limited by the availability of detailed, huge and reliable datasets, particularly in post-war affected areas where accurate ground truth is scarce. Processing those large datasets and training related ML models often require significant resources and high-level computational costs. Furthermore, urban planners and demining professionals need good training to effectively use these tools, this involves both ML and GIS techniques. Furthermore, the integration of user behavior data over the internet with GIS and ML aids in the understanding of human trends and behavior, but it is not without limitations. Internet-based user data is subjected to ethical concerns related to privacy, manipulation and may contain noise. Besides that, it may exclude populations with limited online access.

To overcome most of those challenges, including human expertise can enhance the reliability and effectiveness of ML-GIS systems. Human experts can validate and interpret data outputs to ensure that critical insights are always present. By serving as an "envelope" around ML models, expert input can guide decision-making, improve model robustness, and ensure that automated processes align with real-world complexities and ethical standards. It plays also a leading role in balancing huge data with computational resources and training in the integration of ML-GIS systems for urban modeling or humanitarian demining.

Challenge	Addressed in This Study	Description	Proposed Solutions / Future Directions
Lack of Military Expertise Integration	Yes Ref [32] [62]	ML models lack strategic and tactical insights from military experts, limiting predictive accuracy.	Embed operational knowledge into GIS-ML models to enhance prediction and relevance.
Fragmented Interdisciplinary Approaches	Yes Ref [32] [62]	Most models ignore socio-political and operational constraints, focusing only on narrow data domains.	Develop unified frameworks combining ML, GIS, and military inputs for holistic solutions.
Environmental Diversity	Yes Ref [32] [62]	Environmental variation reduces generalizability of models across regions.	Apply adaptive learning and region-specific calibration for better generalization.
Sensor Limitations	No	GPR and magnetometers generate false positives in complex soil and noisy environments.	Investigate sensor fusion and calibrate models for field deployment.
Data Access and Quality	No	Scarcity of large, reliable datasets in post-conflict areas reduces model effectiveness.	Establish shared datasets via partnerships and crowdsourcing.
Ethical and Privacy Concerns	Yes	Concerns over data privacy, ethical use, and secure sharing platforms hinder adoption.	Create ethical frameworks for secure data sharing and use.
High Computational Costs	No	Large data processing and ML training require significant resources and cost.	Adopt efficient models and scalable, cloud-based solutions.
Need for Specialized Training	No	Professionals require training in both ML and GIS to use tools effectively.	Develop practical training programs and user-friendly platforms.
Internet-Based Data Limitations	No	Online behavior data may be biased, noisy, or exclude non-digital populations.	Supplement online data with validated field data and ensure inclusivity.

Table 5: Operational and Modeling Challenges

While this study addresses specific operational and modeling challenges, particularly the integration of military expertise, GIS, and ML, other critical issues such as data accessibility, sensor variability, and ethical concerns present valuable opportunities for future interdisciplinary research and development, as shown in table 5.

3.6. Contributions of This Thesis

In response to the identified gaps, this section outlines the core contributions of this thesis, particularly the novel integration of military expertise, rare-event ML frameworks, and sustainable urban planning in GIS-based demining models.

To address the limitations of current studies, we provide here an example of explicit integration of military constraints and military expertise into the modeling phase that lies at the basis of existing mine detection methods, where such limitations have not been addressed. Adding military-founded variables, specifically based on confrontation lines, observation post visibility and tactical proximity achieve a higher prediction power by ensuring that model parameters help to reproduce features of realistic conflict dynamics. We refine from 4500m resolution to 10m and can then use advanced ML algorithms -- Support Vector Machine (SVM), Random Forest, XGboost and LightGBM -- for a better robustness of the models.

Although GIS-based remote sensing approaches for mine detection have advanced the state of the art, these remain limited in their effectiveness for detecting buried targets and often breaking down in more complex environments. The use of rare event prediction frameworks and its adaptation to historical military data improves prediction accuracy and suitability by overcoming challenges posed by sparse/imbalanced datasets. Such predictiveness, besides being operationally efficient and delivering high accuracy, help in reducing needless sensor deployment requiring focused demining.

Unlike conventional land-use classification (LULC) models that commonly classify LULC at a pixel scale with limited or no military or geographic impact inputs, we treat mined areas as individual LULC types to help translate research products directly into post-conflict land management and recovery. The reduction of potential exposure to hotspots through this tailored methodology allows for a safer classification framework that favors sustainable land restocking.

As part of this multi-layered validation phase, confirmation that model predictions are detectable with sensor-based methods (ground-penetrating radar (GPR), magnetometry) is made before any exploratory excavation proceeds. Novelly, this multistep approach ensures minimal use of resources by employing more costly and environmentally invasive methods only in areas posing the highest risk.

To reduce environmental foot print, we aim to minimize heavy machinery where it harms soil quality and biodiversity therefore relevant for both primary and secondary post-conflict landscapes. We enable land recovery sustainably and foster ecological resilience by accurate predictive modelling. This strategy enables landefication to continuously progress towards safe, usable spaces that can eventually foster urban growth and community sustainability.

Finally, our phased strategy, from safe mine identification to post-clearance land use planning, opens the way for the use of AI-enhanced GIS analysis to optimize urban infrastructure and resource allocation in previously mined areas. By combining safe demining with sustainable urban planning, our research will assist fostering community safety and long-term sustainability in post-conflict environments.

This thesis presents a novel approach to predicting and classifying landmines in post-war regions by combining GIS and ML under the guidance of military experts. The contributions include:

a) **Integration of Military Expertise in Mine Prediction:** Unlike prior studies, this research incorporates tactical knowledge, including confrontation lines, observation post visibility, and proximity to historical conflict sites, ensuring the model reflects realistic conflict dynamics. This integration improves prediction accuracy and

operational relevance by aligning detection methodologies with actual battlefield conditions..

b) **High-Resolution GIS-ML Fusion for Enhanced Detection**: We refine spatial resolution from 4500m to 10m, significantly improving the granularity of mine risk mapping. This finer-scale data enhances the performance of advanced ML models, Support Vector Machines (SVM), Random Forest, XGBoost, and LightGBM, which collectively improve the robustness and generalizability of demining predictions.
c) **Rare Event Prediction for Sparse and Imbalanced Data**: Traditional GIS-ML frameworks struggle with class imbalance issues. This thesis adapts rare event prediction methodologies to military-relevant datasets, increasing detection accuracy for high-risk zones.
d) **Landmine Classification as a Land Use and Land Cover (LULC) Type:** Current land-use classification approaches do not treat mined areas separately. By defining "mined land" as a unique classification, this research enhances post-conflict land management.
e) **Sustainable Demining and Environmental Protection:** Our methodology prioritizes environmentally conscious demining by reducing the use of heavy machinery where it may degrade soil quality and biodiversity, and ensuring better resource allocation from a socio-economic perspective. By improving the accuracy of predictive modeling, we contribute to sustainable land recovery, ecological resilience, and the safe repurposing of post-conflict landscapes.
f) **From Demining to Post-Clearance Urban and Infrastructure Planning:** This research extends beyond safe mine detection to post-clearance land use planning. It facilitates urban redevelopment, infrastructure optimization, and resource allocation in previously mined regions. This holistic approach ensures that mine-free areas are not only safe but also contribute to long-term community resilience and sustainable urban growth.

3.7. Conclusion

This chapter has provided a comprehensive review of GIS and ML applications in landmine detection, emphasizing their strengths, limitations, and areas for improvement. While existing studies have demonstrated promising results, they remain constrained by limited military expertise integration, environmental detection challenges, and lack of interdisciplinary frameworks. By addressing these gaps, this thesis aims to refine predictive accuracy, operational efficiency, and environmental sustainability in demining applications. By elevating the role of military insight and aligning with urban planning goals, this thesis transcends traditional GIS-ML models. Our work enables safer, smarter, and more sustainable demining, a necessary step toward post-conflict resilience and urban renewal.

The next chapter will detail the methodological framework, outlining the data collection process, feature engineering techniques, model selection, and evaluation criteria. Through this approach, we aim to demonstrate how integrating military constraints, GIS-ML enhancements, and environmental sustainability measures leads to more effective and practical mine risk prediction models.

Part 2

Contribution

Chapter 4

A Hybrid GIS-ML with Military Expertise Framework for Minefield Prediction, Classification, and Prioritization in Post-Conflict Zones

4.1. Introduction to the Integrated Methodological Approach

This section outlines the conceptual underpinnings of the methodology, highlighting how GIS, machine learning, and military expertise are integrated to address the challenges of predicting mine presence, type classification, and clearance prioritization.

The process of humanitarian demining is a multidimensional challenge, blending technological intricacies with life-critical decision-making. This research introduces a novel methodology that integrates military expertise with cutting-edge ML algorithms and GIS. The primary goal is to enhance the accuracy of minefield prediction, mine type classification, and the prioritization of clearance efforts. By harmonizing human knowledge and modern predictive technologies, this approach ensures safer, data-driven operational strategies in mine clearance.

This chapter, illustrated in two published papers [32] [62], delves into the foundational processes that underpin the methodology, encompassing data collection, cleaning, and transformation tailored to minefield prediction tasks. It further addresses the optimization of ML algorithms through feature selection, hyperparameter tuning, and robust validation. Together, these components form a comprehensive framework that bridges domain expertise and advanced technology, driving innovation in humanitarian demining operations..

4.2. Objective and Rationale

This section introduces the goals driving the proposed approach, emphasizing how it aims to optimize demining efforts through predictive analytics, domain knowledge, and operational adaptability.

The overarching aim of this methodology is to empower humanitarian demining efforts by integrating predictive models that facilitate resource allocation and risk mitigation. By systematically combining GIS data, ML tools, and military insights, the proposed approach offers an adaptive framework capable of meeting the dynamic challenges of demining. Through expert feedback loops, the system ensures responsiveness to real-world complexities, paving the way for more efficient and safe demining operations.

4.2.1. Scope and Integration of GIS, ML, and Military Expertise

Here, we define the distinct yet complementary roles of GIS, ML, and military insight in enhancing demining precision, and explain why each task, prediction, classification, and prioritization, is treated independently.

This research unifies three interconnected tasks, creating a holistic methodology designed to optimize the safety, efficiency, and resource allocation in mine clearance:

a) **Mined Area Prediction**: This task focuses on estimating where mines are most likely located, leveraging spatial models informed by GIS and ML. Accurate prediction of mined areas is vital because it reduces the risk of harm to both deminers and civilians while streamlining clearance operations. The predictive model is designed to incorporate a wide range of geospatial and environmental features, selected based on military expert input and statistical significance, such as historical conflict data extracted in our case from Lebanese Army databases where different military posts and confrontation lines are geographically defined, proximity to military installations in matter of Euclidean distance (stored as real numbers) and line of sight correlated directly to weapons ranges protecting the installations and delineating visible and invisivle parts (presented as binary variables for seen or unseen parts), and physical terrain characteristics, where the moset relevant are slope (as percentage, extracted from digital elevation models) and land cover (deduced by applying Remote Sensing techniques on high resolution imagery). By systematically analyzing these variables, the model aims to provide actionable insights that can direct demining efforts to areas with the highest probability of contamination.
b) **Mine Type Classification**: Landmines, diverse in design and intent, pose varying degrees of threat. For example, anti-personnel mines are small, numerous, and designed to incapacitate, while anti-vehicle mines are larger and capable of disrupting infrastructure and mobility. Data of minefields with anti-vehicle mines is extracted from the clearance demining reports filled by demining experts within the LMAC database and given as input feature to the model to be trained on. Accurate classification of mine types is critical for demining teams, as it informs risk assessment and dictates the tools and strategies required for clearance. This aspect of the methodology employs advanced ML models to differentiate between mine types, ensuring that demining operations are not only effective but also strategically aligned with safety and resource considerations.
c) **Clearance Prioritization and Difficulty Assessment**: Demining is as much a socio-economic endeavor as it is a technical one. Areas of high societal value, such as farmland, transportation routes, and schoolyards, often require immediate attention, distance to those features and frequency of human access is directly proportional to a high clearance priority level. Meanwhile, the difficulty of clearing an area is influenced by factors like terrain ruggedness, vegetation density, and weather conditions, as long as these factors are recurrent, the difficulty of clearance is high. This component of the methodology requires expertise, balances urgency with feasibility, ranking mined areas based on their importance to the community and the complexity of the task. By focusing efforts on zones that are both critical

and manageable, the approach maximizes the impact of demining activities while accelerating the recovery process.

Military experts, particularly Lebanese demining officers, play a pivotal role in this framework by contributing field-tested insights. These include variables such as visibility, proximity to observation posts, and terrain elevation, which are encoded as features within the predictive models. This fusion of technical sophistication and operational expertise creates a robust system for addressing the multifaceted challenges of mine clearance.

Why the Tasks Are Separated: The three tasks in this framework, mine location prediction, difficulty classification, and clearance priority ranking, are separated because they each rely on different types of information. Prediction mainly uses historical conflict reports and distances from observation posts or military bases. In contrast, difficulty is influenced more by physical terrain features like slope and vegetation, which affect how hard it is to clear an area. Meanwhile, priority depends on how often an area is accessed by civilians, with population density and proximity to infrastructure playing key roles.

Keeping these tasks separate helps the models stay focused and accurate. For example, the features that help predict mine presence may not be helpful when assessing clearance difficulty. It also makes expert feedback more useful, since military officers can give specific input for each task. At the end, the results are combined into GIS maps that give a complete picture: where the mines likely are, how hard they'll be to remove, and which areas should be cleared first.

4.2.2. Methodological Outline and Expected Contributions

This section presents a step-by-step breakdown of the methodology, from data engineering to operational mapping, and explains how each stage contributes to more effective, data-driven demining outcomes.

The methodology unfolds through three sequential stages, integrating advanced technologies with practical demining expertise:

a) **Data Preparation and Feature Engineering**: Data serves as the foundation for this methodology. GIS tools are employed to divide landscapes into detailed 10x10-meter grids, capturing terrain features, proximity to conflict zones, and environmental factors. This process creates a high-resolution dataset that mirrors real-world demining conditions, ensuring the predictive system reflects the nuanced complexities of the field.
b) **Model Training and Validation**: ML algorithms, including Support Vector Machines (SVM), Random Forests (RF), XGBoost, and LightGBM, are employed to analyze the data. These models undergo rigorous training and validation using cross-validation techniques to ensure robust and reliable predictions. Performance metrics such as accuracy, precision, recall, and the area under the curve (AUC) are used to fine-tune the models, prioritizing both effectiveness and safety by minimizing false negatives.

c) **Operational Mapping and Expert Validation**: The final stage involves translating predictive outputs into GIS-based maps that detail mined areas by type, priority, and difficulty. These maps are reviewed by experienced demining officers, ensuring their accuracy, practicality, and alignment with field requirements. This iterative feedback loop bridges the gap between technological outputs and operational usability, creating tools that are both intuitive and actionable for demining teams.

Together, these stages form a cohesive methodology that goes far beyond technical execution. It is a thoughtful, integrated approach that combines precision, efficiency, and human-centered design to make mine clearance not just effective, but truly transformative.

Figure 8 illustrates our methodology, starting, and always under military guidance, by the data preparation and feature extraction, followed by the model training, tuning and validating, and ending by experts validation and data delivery.

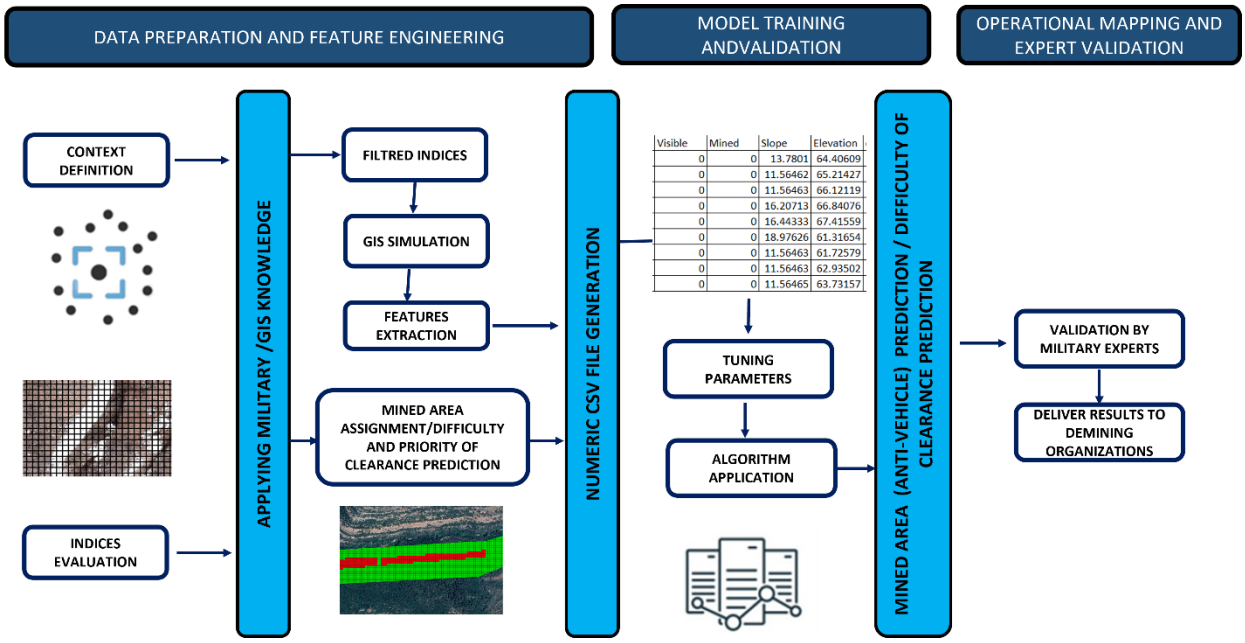


Figure 8: Methodology Principles

4.2.3. Expected Outcomes and Operational Impact

This methodology is not merely a technical framework, it is a tool for real-world change. Its potential outcomes include:

a) **Enhancing Prediction Accuracy**: With a target accuracy of 97%, the methodology provides a groundbreaking improvement in risk assessment, enabling teams to focus on high-risk zones while minimizing exposure to danger.
b) **Reducing Clearance Costs and Time**: By prioritizing socio-economically significant and logistically feasible areas, this approach is projected to reduce clearance time and costs by approximately 30%, accelerating post-conflict recovery. This estimate resulted from military demining experts testing and comparing traditional demining planning with our proposed framework.

c) **Strengthening Decision Support for Demining Experts**: The methodology presents insights through user-friendly formats such as vector and raster maps, empowering demining teams to make informed, field-relevant decisions.

In sum, this integrated framework represents a significant advancement in humanitarian demining. By uniting data-driven precision with operational practicality, it offers a comprehensive solution to the challenges of mine clearance, contributing to the global mission of restoring safety and stability in post-conflict regions.

The following Figure 9 illustrates the humanitarian demining process and the enhancements provided with our model in the matter of minimizing threats to lives and reducing planning time.

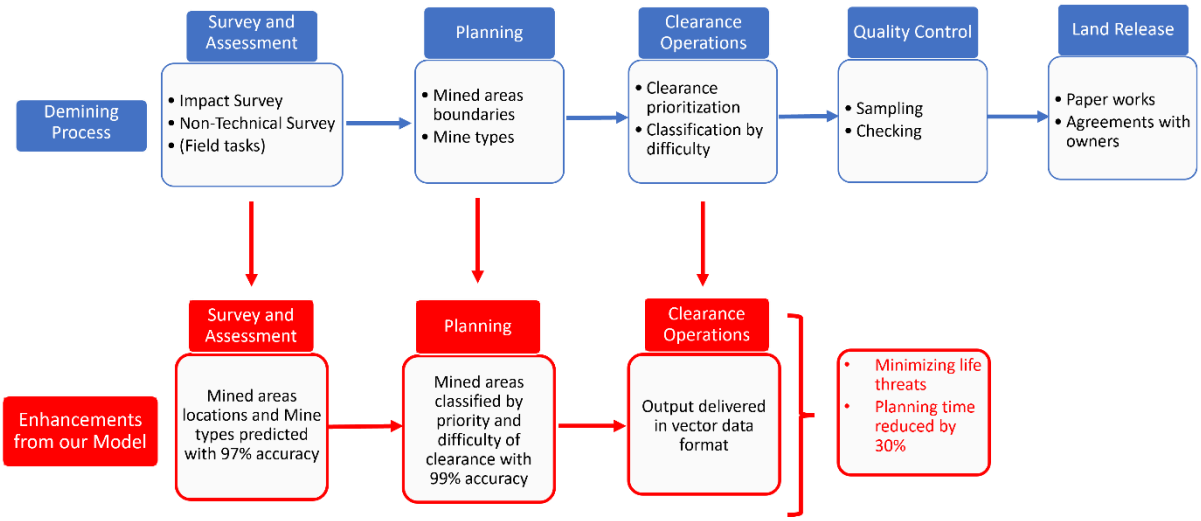


Figure 9: Demining Process and Enhancements

4.3. Data Preparation

This section details the processes involved in preparing a geospatially rich and operationally relevant dataset, including site selection, grid structuring, and the incorporation of both geographic and tactical features.

Effective data preparation is the cornerstone of constructing a predictive model capable of identifying and classifying mine locations in high-stakes applications such as demining. This phase involves carefully defining the study area based on military doctrine and historical landmine deployment patterns, integrating spatial and military-specific data, engineering meaningful features, and addressing inherent challenges like class imbalance. By combining GIS data with expert military insights, the methodology ensures the resulting dataset is robust,

high-resolution, and ready for ML applications. This structured approach not only enhances the technical accuracy of predictions but also provides actionable insights for real-world humanitarian efforts.

4.3.1. Study Area Selection and Grid Structuring

The selection of an appropriate study area is pivotal to ensuring the relevance and accuracy of the predictive model. Guided by military expertise, the methodology identifies regions near historical confrontation lines, observation posts, and critical infrastructure. These areas are carefully delineated within a 500 meters buffer from confrontation lines to focus on high-probability zones, minimizing noise from less relevant regions and ensuring the dataset reflects real-world operational contexts.

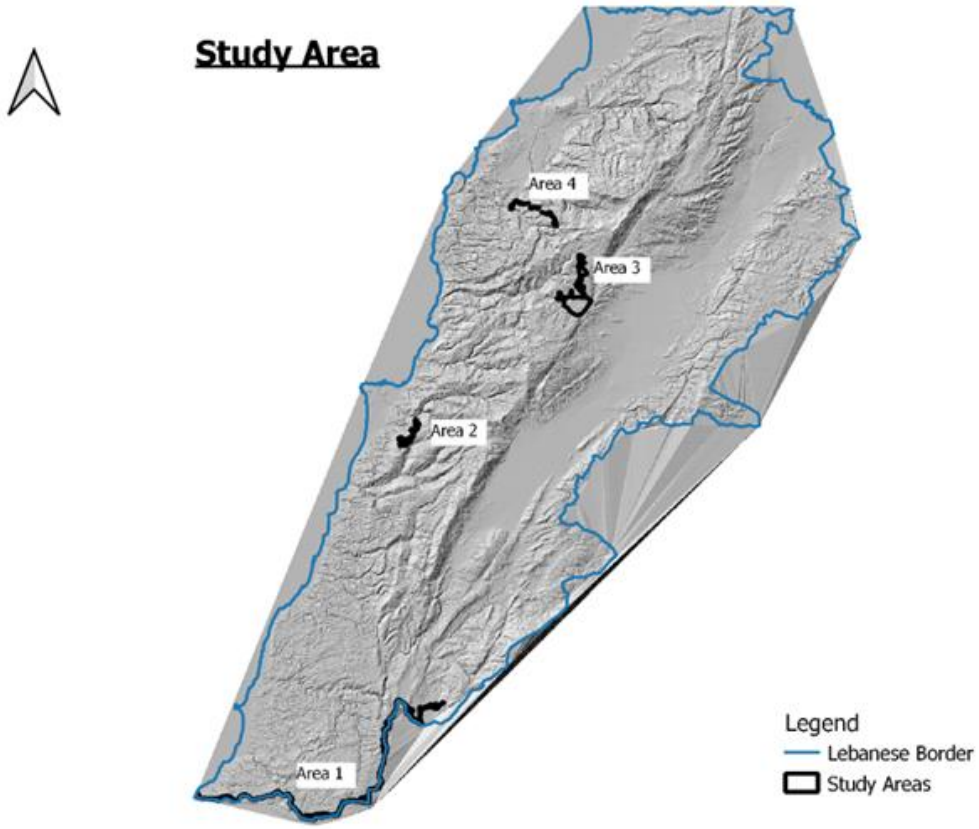


Figure 10: Study Area

Figure 10 shows the study area which consists of four parts covering the country from South to North.

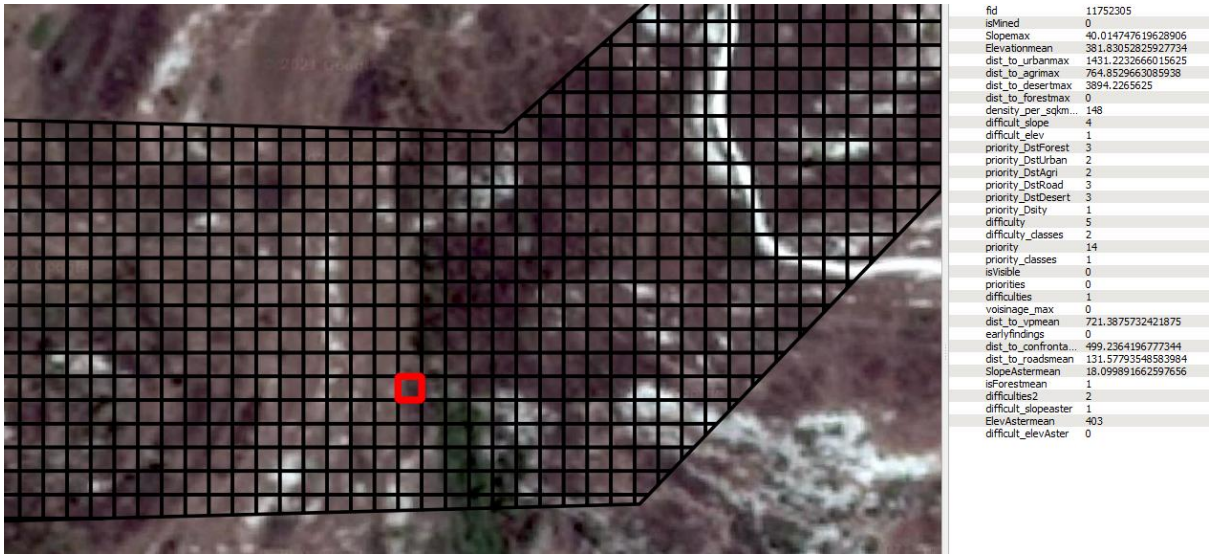


*Figure 11: Study Area samples (grid 10*10)*

Once the study area is defined, it is divided into 10x10-meter grid cells. This granular resolution is determined empirically through expert recommendation where lowering this resolution will cause extra computational cost for not much relevant output and encreasing it will widen the areas and may lead to extra allocation of resources. It allows the model to capture micro-level variations in terrain and spatial features, which are critical for distinguishing between mined and unmined zones. The grid structure also ensures consistency in data collection and analysis, supporting precise feature extraction and predictive accuracy. This method reflects the intricacies of mine-laying strategies while aligning with the operational needs of demining teams.

Figure 11 shows the 10*10 samples or the grid of 10 meters and the features assigned to each grid.

4.3.2. Feature Extraction and Engineering: Geographic and Military-Specific Features

Feature extraction transforms raw data into meaningful inputs for the predictive model, capturing both environmental and tactical dimensions of mine placement. By combining geographic and military-specific features, the methodology provides a comprehensive view of the terrain and its operational significance.

Technically speaking, each feature is transformed from vector data to raster data (using bilinear interpolation) with cell size as much as close to the study area grid of 10*10 (giving a value of 1 to where the data is), and then zonal statistics algorithm is applied to extract the values. Binary values such as mined or not mined, visible or not visible, anti-vehicle mine or not (1 or 0) are given to the cells containing those features, whereas the continuous data related to distances are obtained by applying proximity algorithm to the raster data first (where the target pixels are those containing data) and then applying zonal statistics to record the correct real numbers (distances). Any missing data encountered (with a very small ratio of this case), is manually inspected and filled.

The study established distance and population thresholds of between 500 and 2500 meters and 200 and 800 persons per square kilometer, respectively. These thresholds

were used to define priority classes. Also, for difficulty classes, mean sea elevation thresholds were set at 500 and 1000, while slope thresholds were defined as 15% and 30%. For instance, an elevation less than 500 m and a slope less than 15% received a value of 0 (easy to clean). An elevation between 500 and 1000 m and a slope between 15% and 30% received a value of 1. An elevation greater than 1000 m and a slope greater than 30% received a value of 2 (difficult to clean).

a) **Geographic Features**
   - Slope and Elevation: Mines are often laid in challenging terrains to hinder clearance efforts. Slope and elevation data, derived from Digital Elevation Models (DEM), are critical for assessing the difficulty of demining operations and for identifying areas likely to contain mines. These features enable the model to categorize zones based on terrain complexity, directly influencing clearance strategies.
   - Vegetation Density: Dense vegetation complicates mine detection and clearance by limiting visibility and access. Using remote sensing and satellite imagery, vegetation density is classified into binary or categorical indicators (e.g., "High" or "Low"). This distinction helps prioritize accessible zones while flagging areas that may require specialized equipment or approaches.
   - Land Use and Infrastructure Proximity: The proximity of mined areas to roads, urban zones, or agricultural land directly impacts socio-economic priorities. GIS tools calculate distances to critical infrastructure, encoding these as features that guide prioritization. For example, mines near roads or populated areas pose a higher risk and demand immediate attention.

b) **Military-Specific Features**
   - Visibility from Observation Posts: Mines are strategically placed in areas with reduced visibility from observation posts to avoid detection. GIS-based visibility analysis identifies these hidden zones, enhancing the model's ability to predict mine locations.
   - Proximity to Confrontation Lines: Historical confrontation lines often serve as proxies for high-risk areas. Distance from these lines is calculated for each grid cell, reflecting patterns of conflict and aiding in risk assessment.
   - Distance from Observation Posts: Mines are less likely to be placed near observation posts due to their heightened visibility. This feature helps the model contextualize spatial patterns, improving its predictive reliability.

Figure 12 gives an example of confrontation lines and observation points, and Figure 13 shows the visible areas from an observation post presented in green, which have a trivial role in area selection by converging to the areas with high priority of mining as are not visible from observation posts. Figure 14 displays a sample of mined areas containing anti-vehicle mines, drawn in yellow, along the southern border of Lebanon. The resulted maps (i.e., Figures 10, 11, 12, 13 and 14) are produced using the open-source GIS application for mapping and analysis, Quantum GIS (QGIS).

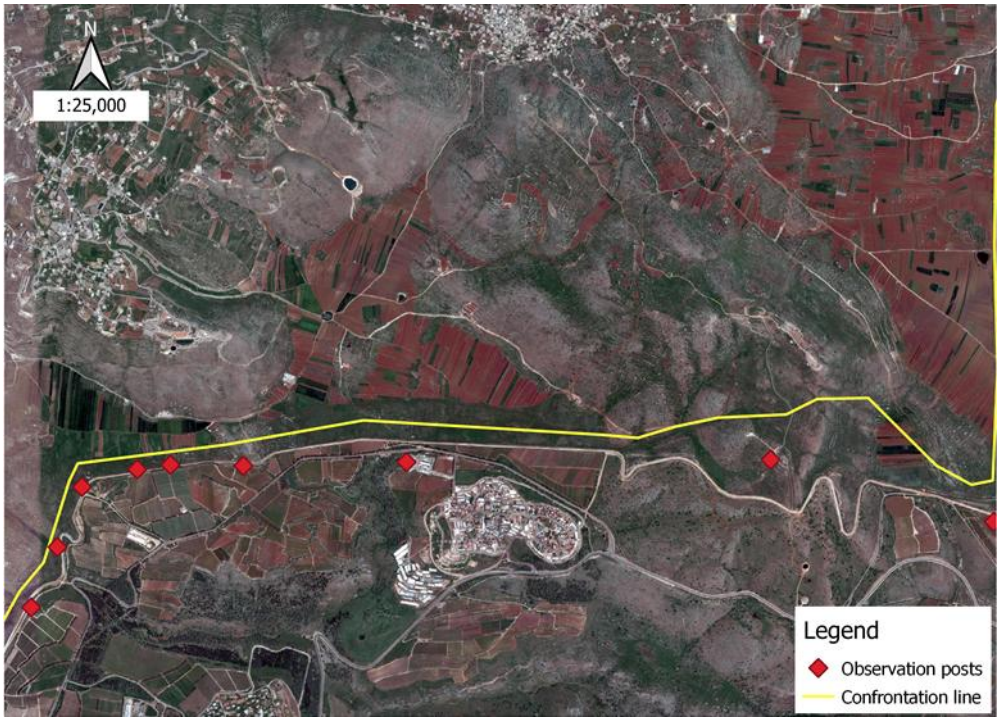


Figure 12: Observation posts and Confrontation line

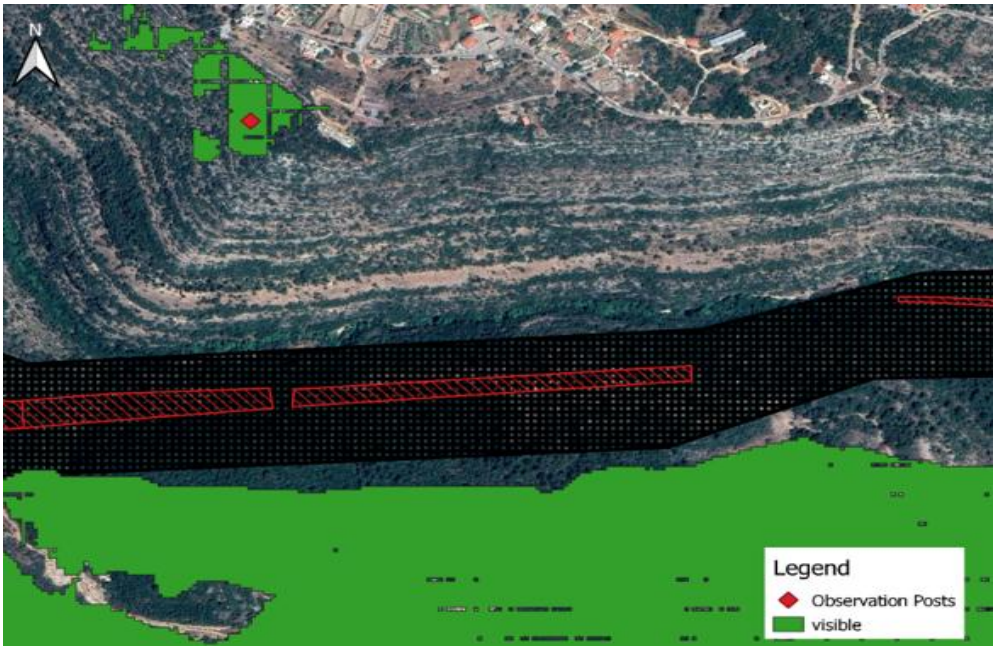


Figure 13: Visibility from an Observation Post

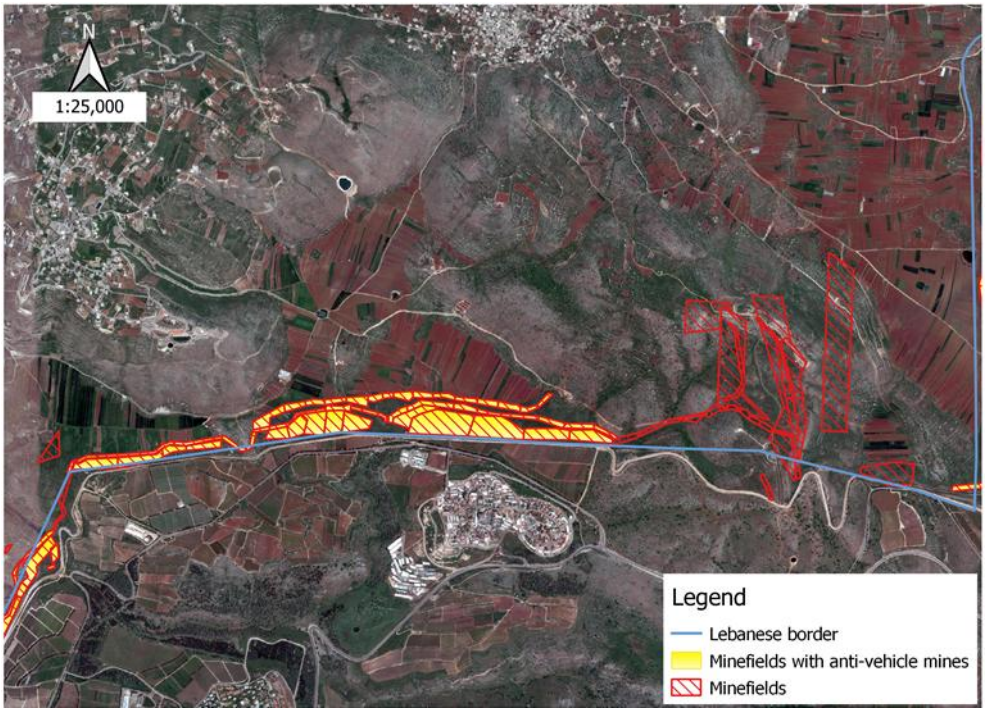


Figure 14: Anti-vehicle mines along the Southern Border

Feature engineering plays a pivotal role in transforming raw geospatial and contextual inputs into structured, model-ready features that improve the interpretability and predictive accuracy of minefield classification models. This step ensures that the data not only meets technical requirements but also aligns closely with operational and humanitarian demining objectives.

A central component of this process involved the creation of proximity layers and the application of distance normalization techniques using GIS. Proximity layers were developed for strategic features such as confrontation lines, roads, and urban centers. These layers quantify the distance from each grid cell to the nearest feature, capturing spatial relationships essential to modeling efforts. The distances were then normalized to standardize their scale, preventing any single feature from disproportionately influencing the model and ensuring that each contributes meaningfully to prediction outcomes.

Additionally, clearance zones were categorized according to both priority and difficulty, reflecting socio-economic relevance and terrain-based challenges. Priority levels were determined based on proximity to critical infrastructures such as urban centers, schools, or transport routes, with areas closer to these elements labeled as “High Priority.” On the other hand, difficulty levels were defined using topographic and environmental variables such as slope gradient and vegetation density. These were classified into discrete categories, Low, Medium, and High Difficulty, based on military expertise and operational experience. For instance, slopes exceeding 15% or 30% were flagged as increasingly difficult, as confirmed through field validation and feedback from experienced demining personnel. Trials with alternative thresholds showed that more extreme values either introduced noise or negatively impacted model accuracy, reinforcing the selected cutoffs.

Population density and accessibility metrics further contributed to the priority classification scheme. Areas with frequent human activity, such as those within 500 to 2,500 meters of roads or populated at densities between 200 to 800 persons per square kilometer, were deemed more urgent for clearance. These thresholds were fine-tuned through iterative testing to achieve a balance between model generalization and contextual precision.

The overall feature selection and engineering process was grounded in both domain knowledge and empirical analysis. Inputs were chosen not only for their availability in GIS data but also for their relevance as confirmed by military subject matter experts. The goal was to capture factors that directly influence mine presence, clearance difficulty, and the urgency of intervention, while avoiding feature redundancy or unnecessary complexity that could compromise model performance.

4.3.3. Quality Control, Dataset Structure and Exportation

An essential step in data preparation involves verifying data quality and consistency. This includes checking for missing values, ensuring feature integrity, and confirming that data transformations accurately represent field realities. Military experts reviewed the data during this stage to ensure alignment with operational knowledge, helping reinforce model reliability in real-world demining operations. The full validation process, including iterative field-based feedback, is detailed in Section 5.1.6.

Once data preparation and feature engineering are complete, the dataset is exported in a format compatible with machine learning libraries. Each grid cell is represented as a row, with columns corresponding to engineered features, including spatial, military, and socio-economic indicators. This structured format allows seamless integration with ML algorithms, facilitating model training and testing.

To optimize performance, the data is split into training, validation, and test sets, typically in a 70/15/15 ratio. This division ensures that the model's performance can be accurately evaluated on unseen data, while cross-validation techniques, such as Stratified Cross-Validation, further improve generalizability by iteratively training and testing the model on different data subsets.

In addition to the tests explained above, validation has been done on a new unseen dataset, prepared inside the country in Mount-Lebanon governorate where internal conflict took place. The dataset is filled in obeisance to the same military constraints: confrontation line and observation posts were carefully defined, and relevant data was extracted from local databases to fill the features or independent variables. Our model has achieved an accuracy of around 93%, with very low False Negative (FN) and False Positive (FP) values.

4.3.4. Summary and Significance

The data preparation process, characterized by meticulous feature extraction, transformation, and balancing techniques, establishes a solid foundation for predictive

modeling. By embedding military insights into the spatial dataset, the methodology transcends traditional predictive approaches, offering a comprehensive framework that is uniquely suited to the challenges of post-war landmine clearance.

One of the major strengths of this process is its ability to integrate domain-specific knowledge, ensuring that the model captures contextual factors beyond standard machine learning inputs. This incorporation of expert-driven features enhances model interpretability, allowing for more reliable and transparent decision-making in high-risk environments. Additionally, the careful balancing of class distributions mitigates bias, ensuring that predictions remain robust across different geographical and environmental conditions.

However, this approach is not without its challenges. The reliance on expert knowledge, while invaluable, introduces a degree of subjectivity that may affect the reproducibility of the dataset in different conflict zones, but this should be neglected with military personnel. Furthermore, the transformation and balancing techniques, while improving model performance, may also lead to the loss of certain data nuances that could have been informative in specific scenarios. There is also an inherent trade-off between the complexity of feature engineering and the scalability of the approach, as manually integrating military expertise into GIS-based models requires significant time and specialized knowledge.

Despite these limitations, the resulting model-ready dataset remains a powerful tool for improving demining effectiveness. It not only enhances the prioritization of high-impact zones but also fosters a data-driven approach to humanitarian demining efforts. By bridging the gap between machine learning capabilities and real-world operational needs, this data preparation methodology significantly contributes to safer and more efficient post-war landmine clearance operations. Table 6 illustrates the data sample values, where Fid represents the unique cell ID.

fid	Visible	Mined	Slope	Elevation	dist to urban	dist to agriculture	dist to desert	dist to forest	dist to roads	dist to confrontation	population density	difficulty classes	priority classes
12815	0	0	13.7801	64.40609	2745.778564	3599.125	60	0	20.61552811	90	148	1	2
12816	0	0	11.56462	65.21427	2745.778564	3599.125	60	0	25	78	148	1	2
12817	0	0	11.56463	66.12119	2745.778564	3641.387207	67.08203888	0	29.15475845	72	148	1	2
12818	0	0	16.20713	66.84076	2770.73999	3641.387207	67.08203888	0	26.92582321	63	148	1	2
12819	0	0	16.44333	67.41559	2770.73999	3641.387207	67.08203888	0	26.92582321	51	148	1	2
26121	0	0	18.97626	61.31654	2696.164063	3579.944336	67.08203888	0	15.81138802	129	148	1	2
26122	0	0	11.56463	61.72579	2720.918945	3579.944336	67.08203888	0	20	123	148	1	2
26123	0	0	11.56463	62.93502	2720.918945	3579.944336	67.08203888	0	22.36067963	111	148	1	2
26124	0	0	11.56465	63.73157	2720.918945	3599.125	90	0	26.92582321	102	148	1	2

Table 6: Data Sample Structure

With a clean and structured dataset now in place, rich in terrain, military, and socio-economic features, we proceed to the selection of appropriate machine learning algorithms. This next phase determines how effectively the data can be transformed into operational insights for minefield detection, classification, and prioritization.

4.4. Machine Learning Model Selection and Tuning

In this section, we evaluate a range of ML classifiers to determine their suitability for landmine detection tasks, balancing accuracy, interpretability, and computational efficiency.

The selection and tuning of ML models in the context of humanitarian demining is both a technical and operational challenge. Reliable predictions, computational efficiency, and

interpretability must be balanced to address the complexities of mine detection and classification. Given the life-critical stakes, the methodology aims to identify models that not only excel in predictive performance but also align with real-world demining requirements. This section outlines a comprehensive framework for selecting, evaluating, and optimizing ML models for mine prediction tasks, emphasizing practical applicability and technical rigor.

4.4.1. Criteria for Model Selection

Choosing the right ML model involves aligning algorithmic capabilities with the demands of demining operations. Several criteria guide this process:

a) **Accuracy, Precision and Confusion Matrix**: Accurate predictions are paramount, with a strong emphasis on minimizing false negatives (missed mines), as these can lead to life-threatening consequences. Excessive false positives must also be controlled to prevent the misallocation of limited resources. The confusion matrix provides a breakdown of errors, helping refine the model's performance on both classes.
b) **Handling Imbalanced Data**: Mined areas constitute a minority class, leading to class imbalance issues that can bias model performance. Techniques such as Synthetic Minority Oversampling Technique (SMOTE), balanced random forest, and scale_pos_weight are employed to ensure balanced learning.
c) **Interpretability**: Clear and explainable predictions are essential in high-stakes scenarios. Models that support feature importance analysis allow experts to understand and trust the factors influencing predictions, enabling operational adjustments.
d) **Computational Efficiency**: Given the scale of spatial datasets (often exceeding millions of records with geospatial attributes), models must support efficient training and inference. Gradient-based optimization techniques, feature selection, and parallel computing frameworks (e.g., GPU-accelerated training in XGBoost and LightGBM) are leveraged for faster execution.
e) **Compatibility with Cross-Validation Techniques**: Ensuring model robustness across different regions is critical. Stratified k-fold cross-validation preserves the mined/unmined ratio across training splits, reducing bias and improving generalizability.
f) **Speed of execution**: Fast inference speeds enable real-time decision support in demining operations. LightGBM and XGBoost leverage parallelism and histogram-based splitting to enhance performance, making them viable for on-field implementation.

Based on these criteria, four models were shortlisted for evaluation: Support Vector Machine (SVM), Random Forest (RF), Extreme Gradient Boosting (XGBoost), and LightGBM. Each of these models offers unique strengths suited to the challenges of mine detection.

4.4.2. Model Selection

Our study employs a diverse set of machine learning algorithms, selected for their strengths in processing GIS-based data for humanitarian demining. These models are tailored to handle spatial analysis, predictive modeling, and pattern recognition while remaining adaptable across different domains. The following section examine their

applications, strengths, and limitations in demining, emphasizing areas for further refinement.

Four models are selected:

a) **Support Vector Machine (SVM)**: SVM is well-suited for binary classification tasks, making it effective for distinguishing between mined and unmined zones. By applying kernel functions such as the radial basis function (RBF), SVM transforms non-linear data into a higher-dimensional space, enabling precise class separation. However, SVM's computational intensity and sensitivity to parameter tuning make it less efficient for large datasets.
b) **Random Forest (RF)**: As an ensemble learning method, RF constructs multiple decision trees, aggregating their outputs for robust predictions. It handles class imbalance effectively through balanced random forests, which resample the minority class during tree generation. RF's feature importance metrics provide valuable insights, highlighting the most influential variables in predicting mine presence.
c) **Extreme Gradient Boosting (XGBoost)**: XGBoost builds sequential decision trees, correcting errors iteratively for improved accuracy. Its regularization parameters (alpha and lambda) reduce overfitting, while feature importance metrics enhance interpretability. XGBoost's efficiency and high performance make it a preferred choice for handling large, imbalanced datasets in demining applications.
d) **LightGBM**: LightGBM is optimized for memory and computational efficiency. Its leaf-wise growth strategy captures complex interactions in high-dimensional data while maintaining rapid prediction speeds. This adaptability makes LightGBM particularly suitable for real-time demining operations where swift, reliable outputs are crucial.

A key challenge in mine detection is imbalanced datasets, where mined areas are significantly underrepresented as they are far less prevalent than unmined zones. Techniques like SVM-SMOTE generate synthetic samples near decision boundaries [63], while EasyEnsemble balances datasets through undersampling and ensemble learning. Zhang et al. propose SEB-XGB, which combines SVM-SMOTE and EasyEnsemble with XGBoost, fine-tuned via Bayesian optimization, to improve classification on imbalanced data [63].

Balanced Random Forest technique adjusts class weights during training, emphasizing mined zones while maintaining dataset integrity.The scale_pos_weight parameter in XGBoost calibrates the ratio of positive to negative instances, this parameter enhances model performance on imbalanced datasets. Moreover, the strategic selection of the study area, guided by military insights, mitigates imbalance by focusing the dataset on regions with higher contamination likelihood, further refining the model's predictive capacity.

High-performance models like XGBoost excel in classification due to parallelization, cache-aware split discovery, and tree pruning, making them ideal for precision-critical applications such as mine detection [64]. Random Forest (RF) is widely used in high-dimensional classification tasks, including land cover mapping, due to its robustness against overfitting [65]. Support Vector Machines (SVMs) are particularly useful for high-dimensional datasets and have extensions for multi-class classification and outlier

detection [66]. LightGBM, designed for large datasets, employs gradient-based one-side sampling and exclusive feature bundling, optimizing training times for geographic data analysis [67].

Studies comparing RF and XGBoost in remote sensing highlight XGBoost's superior accuracy in complex classifications [68]. A broader comparison of ensemble methods, including Adaptive Boosting, XGBoost, and LightGBM, underscores RF's reliability on large datasets but shows boosting methods outperform RF in imbalanced two-class problems, like mine detection [69].

Feature selection is another critical aspect. Fryer et al. critique Shapley values for misrepresenting feature significance in interrelated datasets, suggesting alternative selection approaches for high-dimensional GIS applications [70].

Each ML model offers advantages: XGBoost's efficiency, RF's robustness, SVM's adaptability, and LightGBM's scalability, making them well-suited for mine detection. However, challenges such as computational demands, hyperparameter sensitivity, and adaptability to correlated variables highlight the need for careful optimization. By fine-tuning these models, our study enhances predictive accuracy while ensuring practical deployment in real-world demining operations.

The different results are presented in the next chapter, but to list here as for speed of execution and less resources usage, LightGBM and then XGBoost were dominant, whereas for accuracy, RF and XGBoost gave the best scores. Final thing to mention is that the tuning and training were executed benefiting from GPU acceleration, except for SVM which was conducted using parallelization techniques.

The four selected models, SVM, Random Forest, XGBoost, and LightGBM, were chosen because they are reliable for classification tasks, especially with spatial and imbalanced data like in our case. Each model has its strengths. Random Forest and XGBoost gave the highest accuracy scores, especially in detecting mined areas. LightGBM was the fastest during testing, which makes it useful for large-scale or real-time use.

However, we found that SVM, while accurate on small samples, was slower and harder to tune with bigger datasets. Random Forest was easy to understand and explain to field experts, but it needed more time to process data. XGBoost offered a good balance between speed and precision, especially after tuning. LightGBM worked best when speed was critical, though it was slightly less transparent. Choosing the best model depended on what mattered most, accuracy, speed, or explainability, and that choice can be adjusted depending on the field needs.

4.4.3. Evaluation Metrics, Model Comparison and Hypertuning

Model performance is evaluated using the following metrics:

a) **Accuracy**: Represents the ratio of correctly classified samples to the total samples. While it provides a basic indicator of performance, it is less informative in imbalanced datasets.

b) **Precision**: Measures the ratio of true positives (correctly predicted mined areas) to all predicted positives, focusing on the model's ability to avoid false positives.
c) **Recall**: Represents the ratio of true positives to the sum of true positives and false negatives, emphasizing the model's capacity to detect all relevant instances of mined areas.
d) **Area Under the Curve (AUC)**: AUC provides a view of the model's ability to distinguish between classes, focusing on the trade-off between true and false positive rates.
e) **Confusion Matrix**: This breakdown of true and false predictions for mined and unmined areas is essential for understanding classification tendencies and identifying potential areas of improvement.

These metrics provide a comprehensive understanding of each model's strengths and limitations, guiding final selection based on operational relevance and predictive performance.

To maximize performance, each model undergoes hyperparameter tuning using techniques such as grid search and Optuna (an automated optimization library). This iterative process refines configurations for optimal accuracy and efficiency. For example, regarding XGBoost, the tuning values ranged from 96% to 97.5% with Optuna.

The most relevant hyperparameters include:

a) **SVM Tuning**:
    - Kernel: Determines the data transformation applied; the RBF kernel is typically selected for non-linear data.
    - C (Regularization Parameter): Balances margin maximization with classification error minimization. A higher C values allow fewer misclassifications but can lead to overfitting.
    - Gamma: Controls the impact radius of each data point; a larger gamma localizes impact, while a smaller gamma generalizes influence.
b) **Random Forest Tuning**:
    - Number of Trees (n_estimators): The number of trees impacts accuracy but also computational cost. An optimal balance is identified through grid search or Bayesian optimization.
    - Maximum Depth (max_depth): Controls tree depth, balancing between underfitting and overfitting.
    - Max Features: Specifies the subset of features considered at each split, balancing between model interpretability and accuracy.
c) **XGBoost Tuning**:
    - Learning Rate: Lower rates generally improve stability, though they require more trees.
    - Max Depth: Limits tree complexity, managing overfitting risks.
    - Gamma: Minimizes partitioning of nodes, improving interpretability and managing computational load.
    - Scale_Pos_Weight: Addresses class imbalance by increasing the weight of mined areas.

d) **LightGBM Tuning**:
   - Max Depth and Num Leaves: Control tree structure, balancing complexity with predictive power.
   - Learning Rate: Similar to XGBoost, a lower rate improves performance.
   - Min Data in Leaf: Defines the minimum sample size for leaves, reducing overfitting.
   - Feature Fraction: Controls the percentage of features selected for each tree, promoting tree diversity and reducing overfitting.

4.4.4. Cross-Validation, Performance Assessment and Feature Importance

Stratified cross-validation ensures model robustness by dividing data into balanced subsets, preserving the ratio of mined to unmined zones. Key metrics (accuracy, precision, recall, AUC) are averaged across folds to evaluate generalizability and consistency.

Interpretability is essential for operational deployment. As explained in detail in Section 4.3.2, feature importance analysis revealed that spatial features like distance to confrontation lines, roads, and observation posts consistently had the highest influence on model predictions. These align closely with expert military knowledge, which reinforces trust in the model's decision logic.

Tools such as SHAP (SHapley Additive exPlanations) values were used to quantify individual feature contributions, helping field teams understand not only what the model predicts, but also why. This transparency fosters greater confidence in using predictive outputs for mission planning and enables targeted improvements to the model based on field feedback.

4.4.5. Summary for Model Deployment and Final Selection

The final model selection was guided by a balance between predictive performance, interpretability, and operational feasibility. Among the evaluated algorithms, Random Forest and XGBoost consistently demonstrated superior classification accuracy, especially in detecting mined zones. These models were particularly effective due to their capacity to handle imbalanced datasets and their support for feature importance analysis, which enhanced trust and transparency in decision-making. LightGBM, while slightly less interpretable, stood out for its execution speed and computational efficiency, making it well-suited for large-scale analysis and real-time deployment in resource-constrained environments.

Support Vector Machine (SVM), though capable of achieving high accuracy on smaller subsets, proved less scalable. Its longer training times and sensitivity to hyperparameter tuning posed challenges when applied to the full dataset. In contrast, XGBoost offered an optimal compromise between speed and accuracy, especially when fine-tuned with GPU acceleration and cross-validation techniques. Random Forest was favored for its simplicity and ease of explanation to field experts, although it required more processing time. Ultimately, the choice of model depended on the specific context, whether rapid inference, maximum accuracy, or explainability was the highest operational priority.

Once selected, the models were integrated into a GIS-based operational platform, with outputs visualized through both raster and vector maps. These included layers indicating mine type, clearance difficulty, and prioritization level, thereby enhancing situational awareness and supporting mission-critical decisions in the field. The flexibility of the framework allows it to be adapted dynamically based on new data inputs and shifting field conditions, ensuring that it remains a responsive and practical tool for humanitarian demining.

With the final models selected and validated for both accuracy and operational efficiency, it is critical to reflect on the broader implications of this hybrid GIS-ML framework. The following section provides a comprehensive evaluation of its strengths and limitations, offering insight into how this approach transforms traditional demining practices through data-driven decision support and dynamic prioritization.

4.5. Critical Analysis of the Hybrid GIS-ML Approach: Strengths and Limitations

This section critically evaluates the performance and limitations of the proposed methodology, reflecting on its technical strengths, deployment constraints, and areas for further improvement. The integration of GIS and ML in minefield prediction, classification, and prioritization represents a paradigm shift in humanitarian demining. This hybrid approach offers enhanced precision, systematic risk assessment, and optimized resource allocation. However, despite its strengths, it is not without limitations. This section presents a comprehensive evaluation of the approach by examining both its advantages and constraints.

4.5.1. Strengths of the Approach

Our framework presents the following strengths:

a) Enhanced Predictive Capabilities with Multi-Source Data Integration

One of the key advantages of this methodology is its ability to fuse geospatial, environmental, and military intelligence data to improve minefield detection accuracy. Unlike traditional approaches that rely primarily on field reports or manual surveying, this system leverages historical conflict records, terrain properties, proximity to military installations, and GIS-driven spatial relationships to generate highly reliable risk maps. The ML algorithms used, including XGBoost, Random Forest, and SVM, optimize feature selection and classification, reducing false negatives (missed minefields), a critical factor in ensuring deminer safety. With proper hyperparameter tuning and stratified cross-validation, the methodology consistently achieves prediction accuracies exceeding 97%, significantly improving over conventional heuristic-based mapping.

b) Operational Efficiency through Prioritization Models

The framework does not merely detect minefields; it prioritizes them based on risk and clearance feasibility. By classifying areas into high, medium, and low-priority zones, it enables decision-makers to allocate resources efficiently. This is achieved using:

- Weighted Multi-Criteria Decision Analysis (MCDA), which assigns importance scores to proximity to civilian zones, past mine incidents, and infrastructure density.
- Terrain difficulty analysis leverages slope gradients, elevation models (DEM), and vegetation indices (NDVI) to evaluate operational complexity. These parameters, discussed in Section 4.3.2, form the basis for categorizing areas into clearance feasibility classes, ensuring efficient planning aligned with demining realities.

By integrating ML-based mine prediction with GIS-driven prioritization, this system minimizes resource wastage, focusing efforts on areas where mine removal has the greatest humanitarian and economic impact.

c) Dynamic and Scalable Adaptation to New Data

Unlike static risk maps, which become outdated as conditions change, this ML-GIS hybrid approach continuously adapts. As new data, such as updated military intelligence, satellite imagery, or post-clearance validation reports, becomes available, the models can retrain iteratively, refining predictions with each cycle.
This makes the framework highly adaptable across different geographic regions, provided there is sufficient training data. The methodology is transferable beyond Lebanon, allowing potential deployment in regions where demining operations share similar environmental and military contexts.

The hybrid GIS-ML approach showed strong results, especially in combining expert military knowledge with advanced prediction tools. It helped identify likely mine locations more accurately, and the prioritization models made clearance planning faster and more targeted. However, some challenges must be also highlighted. Overall, the system worked well, but making it more flexible and easier to deploy will be key in future versions.

4.5.2. Limitations and Challenges

For instance, if data was missing or outdated, especially in case of older military records, the model's reliability will drop. This shows how important high-quality and updated inputs are. Another challenge was model explainability. While tools like Feature importance helped, some team members in the field still preferred simpler logic that matched their experience. In some cases, we combined rule-based filters with model results to make the outputs easier to trust. In addition, running the models on large areas needed powerful hardware, which could be a problem in remote locations. To deal with this, we tested lighter models and simpler map layers when computing resources were limited.

The limitations and challenges facing our study could be resumed in:

a) Dependence on High-Quality and Up-to-Date Data

Despite its strengths, this approach heavily depends on the quality and completeness of input data. Key limitations include:

- Incomplete military records: Not all mine placements are well-documented, particularly those from non-state actors or improvised explosive devices (IEDs).

- Spatial inconsistencies: Satellite imagery and DEMs may not always reflect current terrain conditions, particularly in dynamic environments subject to erosion, urbanization, or vegetation growth.
- Class imbalance in training data: Minefields are a rare event in large datasets, often leading to biased model performance if not handled with appropriate oversampling techniques (SMOTE) or balanced class weighting strategies.

Mitigation strategies include data fusion with remote sensing techniques (LiDAR, hyperspectral imaging), incorporation of crowdsourced intelligence, and continuous ground-truth validation.

b) Interpretability and Decision Trust Issues

ML, particularly ensemble models and deep learning, operates as a "black box," producing results that may lack direct interpretability. While SHAP values (SHapley Additive exPlanations) and Local Interpretable Model-Agnostic Explanations (LIME) provide some degree of feature attribution, demining professionals may still require transparent decision logic.

A hybrid approach combining rule-based GIS heuristics with ML-predicted probabilities might enhance user trust, providing a balance between data-driven decision-making and expert validation.

c) Computational and Field Deployment Constraints

ML algorithms, particularly those that process high-resolution spatial data (10x10m grid cells), are computationally intensive. Challenges include:

- Training time constraints: Some models, such as SVM and XGBoost, require significant computational power, making real-time on-site processing impractical.
- Limited field accessibility: Many demining teams operate in environments with restricted internet and computing resources, limiting model deployment.

Possible solutions include:

- Edge computing and model compression for on-site processing.
- Lightweight alternatives such as decision trees or rule-based GIS filters for quick inference where computational resources are scarce.

The hybrid GIS-ML approach to demining presents a technologically advanced, scalable, and operationally efficient methodology. By leveraging multi-source data fusion, predictive modeling, and dynamic prioritization, it enhances safety, accelerates clearance efforts, and reduces costs. However, addressing data availability, interpretability, and computational efficiency is essential to maximize its effectiveness in real-world applications.

Chapter 5

Experimental Results

Building upon the methodology established in Chapter 4, this chapter presents the experimental validation and operational integration of the proposed GIS-ML framework for minefield prediction, type classification, and clearance prioritization, as published in [32] [62]. Through a combination of model evaluation, field validation with military experts, and GIS-based deployment strategies, the results demonstrate both the technical performance and practical applicability of the system. Emphasis is placed on minimizing false negatives, enhancing operational usability, and ensuring continuous alignment with real-world demining needs.

5.1. Mine Prediction, Type Classification, and Prioritization

This section presents the experimental evaluation of the GIS-ML framework. The focus here is on model performance, operational deployment, and validation outcomes. Unless otherwise specified, key spatial predictors, such as proximity to confrontation lines, observation posts, and infrastructure, consistently underpin model accuracy across all tasks.

The experimental evaluation follows the three main objectives outlined in **Section 4.2**:

- Predicting mined areas using geospatial and military-based features.
- Classifying mine types into anti-personnel and anti-vehicle categories.
- Prioritizing mine clearance based on socio-economic impact and clearance difficulty.

5.1.1. Predicting Mined Areas

Mine prediction was performed using Random Forest (RF), XGBoost, LightGBM, and Support Vector Machines (SVM). Core features, including proximity to confrontation lines, visibility from observation posts, and distance to infrastructure, enabled the models to identify high-risk zones. Minimizing false negatives, missed mined areas, was a critical priority due to its direct impact on operational safety. The best-performing models reduced the false negative rate to approximately 1.4%, with an accuracy of 97%, achieving high reliability across varied terrain conditions. Detailed performance metrics are provided in Section 5.1.4.

5.1.2. Mine Type Classification

Mine type classification distinguished between anti-personnel and anti-vehicle mines based on spatial patterns. Key predictors included proximity to confrontation lines, observation posts, and land-use characteristics. Anti-vehicle mines predominantly aligned with roadways and open terrain, while anti-personnel mines correlated with foot-traffic zones and dense vegetation. The classification models achieved an accuracy of 99%, creating a structured and interpretable dataset that supports field operations.

5.1.3. Clearance Priority and Difficulty Classification

Clearance zones were categorized across two axes: priority (High, Medium, Low) and difficulty (Easy, Moderate, Hard). Priority levels reflected socio-economic significance, proximity to sensitive infrastructure, and potential civilian impact. Difficulty ratings were derived from terrain ruggedness, vegetation density, and ground cover type. Figures 19 and 20 illustrate the predicted priority and difficulty maps. The dual classification system achieved an overall accuracy of 99%, facilitating optimized clearance planning.

5.1.4. Machine Learning Models for Mined Area and Mine Type Classification

This section summarizes the comparative performance of multiple ML models across prediction and classification tasks, supported by detailed evaluation metrics and confusion matrices. The methodology leverages advanced ML algorithms to classify both mined areas and mine types:

a) **Classifying Mined Areas**: RF and XGBoost deliver high accuracy and resilience against noise through ensemble and gradient-boosting techniques. Cross-validation and evaluation metrics, including accuracy, precision, recall (emphasized due to its critical role in minimizing life-threatening missed detections), and Area Under Curve (AUC), confirm the models' reliability, with validation datasets consistently achieving over 97% accuracy.

	Accuracy	Precision	Recall	AUC	Execution time(s)
SVM	0.955	0.978	0.93	0.955	14350
RF	0.975	0.962	0.976	0.975	7207
XGBoost	0.975	0.953	0.946	0.964	60
LightGBM	0.949	0.918	0.886	0.927	10

Table 7: Results for mined areas prediction

[[40846 772] [810 16265]]	[[40818 800] [767 16308]]	[[40917 700] [805 16271]]	[[40904 713] [843 16232]]	[[40895 722] [772 16303]]
Fold 1	Fold 2	Fold 3	Fold 4	Fold 5

Table 8: Confusion Matrices for 5 Folds (cross-validation)

Dataset	Accuracy %
Test	97.12
Validation	97.20

Table 9: Accuracy of Test and Validation Datasets

As explained earlier, the data is split into three parts for testing and validation: 70% for training, 15% for testing, and 15% for validation.

Tables 7 and 8 summarise each algorithm's cross-validated performance, listing the full metric suite, five-fold confusion matrices, and execution times. RF and XGBoost achieved the highest mean accuracies, while LightGBM and XGBoost completed training in the least time. Hold-out results in Table 9 corroborate these findings: both the validation and test sets report accuracies above 97 %, with virtually identical figures, indicating strong generalisation and minimal risk of over-fitting.

b) **Mine Type Classification**: XGBoost and LightGBM excel in handling complex, non-linear relationships. After identifying mined areas, these models, fine-tuned using the Optuna optimization library, achieve optimal accuracy for minority classes, such as anti-vehicle mines. Post-training analysis highlights critical predictors, including proximity to observation posts and terrain features, providing actionable insights for demining experts.

Hyperparameter optimization was performed using the Optuna framework, which applies a Bayesian optimization strategy to explore parameter combinations that maximize model performance. For XGBoost, optimal parameters included a deep tree structure (max_depth = 33) and a finely tuned learning rate (~0.029), enabling the model to capture complex spatial patterns while minimizing overfitting. The use of early_stopping_rounds = 8 allowed the model to halt training once improvements plateaued, preserving generalizability. For LightGBM, hyperparameters such as num_leaves = 195 and min_data_in_leaf = 211 helped maintain balance between granularity and overfitting, while a higher learning rate (~0.17) accelerated convergence without sacrificing accuracy.

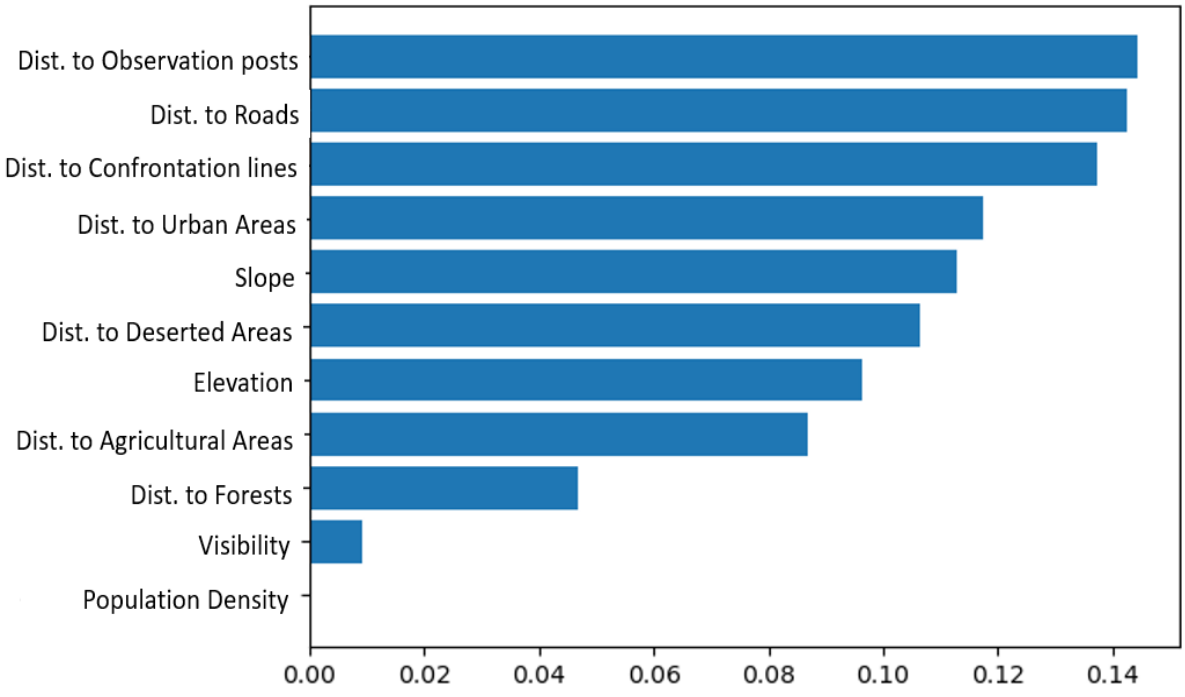


Figure 15: Feature Importance

These configurations were selected based on five-fold cross-validation performance, ensuring robustness against unseen data and improving detection rates for minority classes, such as anti-vehicle mines.

Post-training analysis confirmed that the most influential predictors for mined area and mine type classification were consistent with operational expectations. As previously detailed in Section 4.3.2, features such as proximity to confrontation lines, observation posts, and roads dominated model importance rankings. This alignment with expert knowledge enhanced model credibility and ensured practical relevance for field application. These findings are visualized in Figure 15, which displays the ranked feature importance contributing to model predictions.

In addition to the tests explained above, validation has been done on a new unseen dataset, prepared inside the country in Mount-Lebanon governorate where internal conflict took place. The dataset is filled in obeisance to the same military constraints: confrontation line and observation posts were carefully defined, and relevant data was extracted from local databases to fill the features or independent variables, giving a resulting dataset containing 44617 samples of 10*10 m.

Our model has achieved an accuracy of around 93%, with low FN and FP values. Upon examining the FN values, we discovered that they relate to samples located along the edge of the minefield, which will be accounted for by including a safety distance around the danger area when defining the minefield's perimeters before the clearance operations. For the false positive samples, they will cause no threat to the lives of the deminers, their clearance effect is a waste of resources on an empty land, but as their number is small (1.1%), their effect is reduced.

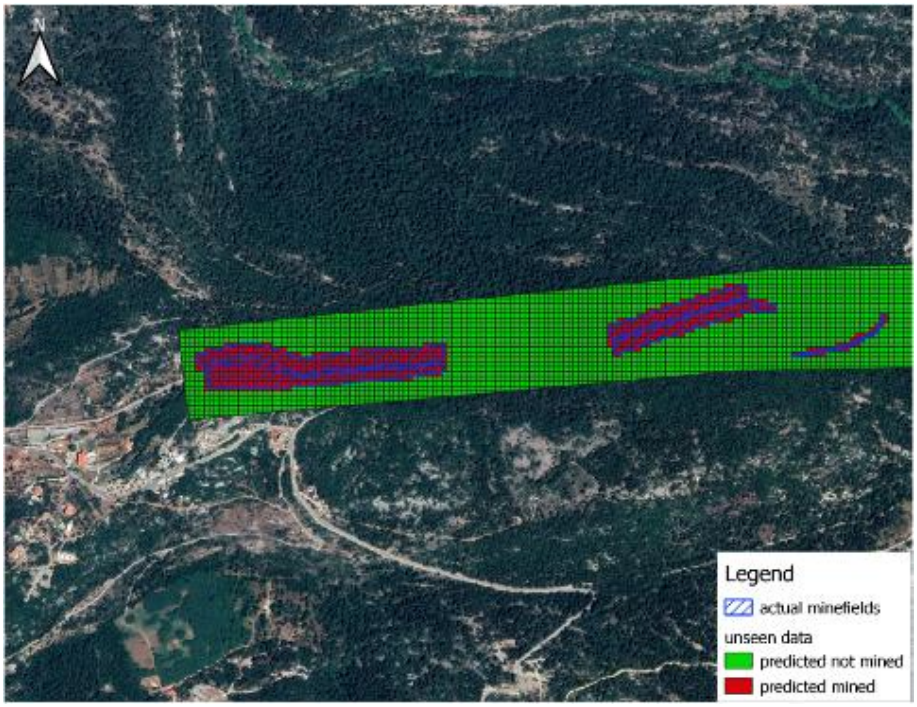


Figure 16: Predictions on unseen data

Figure 16 displays the prediction results on new data, demonstrating the alignment between actual minefields presented in blue hatched polygon and predicted mine-fields, with predicted mined in red and not mined in green.

5.1.5. Model Implementation and Operational Workflow

Machine learning outputs, predicted mine presence, mine type classification, and clearance priority/difficulty, were integrated into a GIS environment using QGIS and GDAL libraries. Predictions were exported as CSV files and spatially joined to a 10×10-meter grid shapefile via a shared Feature ID (FID). The resulting enriched dataset included spatial geometries annotated with classification scores.

These outputs were organized into interactive thematic layers (e.g., 'Mine Presence,' 'Difficulty,' 'Priority') to support mission planning and real-time field navigation on GPS-enabled devices. The GIS setup enabled map-based querying, situation awareness, and customizable operational views tailored to field clearance objectives.

Figure 16: Predictions on unseen data

5.1.6. Validation and Feedback from Military Experts

Model validation was conducted in collaboration with 85 military demining officers from the Lebanese Army. Experts evaluated prediction accuracy, assessed GIS usability, and provided operational feedback under field-like conditions.

Key refinements guided by expert feedback included adjusting proximity thresholds, enhancing symbol visibility, optimizing map layering, and ensuring responsiveness across varying zoom levels. Usability testing on GPS-enabled devices confirmed the system’s adaptability to real-world demining operations.

Scenario-based simulations across urban and remote terrains further validated the model’s robustness. Officers emphasized the critical importance of minimizing false negatives and endorsed the dual classification system (priority and difficulty) for operational planning.

Detailed insights and structured feedback outcomes are further elaborated in Section 5.3.6.

5.2. Operational Workflow and GIS Integration

To operationalize the GIS-ML framework for field deployment, this section consolidates the workflow stages validated experimentally in Section 5.1. The operational workflow mirrors real-world demining procedures, integrating spatial data collection, machine learning prediction, GIS integration, and expert-driven feedback.

The four sequential stages are summarized below:

5.2.1. Overview of the Operational Workflow

The workflow follows these major steps:

a) **Data Collection and Preparation**: Gathering high-resolution spatial data on terrain, infrastructure, confrontation lines, observation posts, and socio-economic variables. Data is standardized and structured into a 10×10-meter grid format to support spatial analysis.
b) **Model Training and Prediction**: Training machine learning models to predict mined areas, classify mine types, and assess clearance priority and difficulty. Cross-validation ensures statistical robustness, while expert input ensures operational relevance.
c) **GIS Integration and Visualization**: As detailed in Section 5.1.5, machine learning outputs are spatially integrated into GIS platforms, producing interactive thematic layers for mission planning and real-time navigation.
d) **Deployment and Expert Feedback**: GIS-based maps are deployed to demining teams using GPS-enabled field devices. Expert feedback guides iterative refinements, ensuring continuous system improvement and operational adaptability.

5.2.2. Data Collection and Preparation

Spatial data was sourced from terrain analysis, population density studies, infrastructure mapping, and military inputs. Features such as proximity to confrontation lines, observation posts, and urban areas were embedded into the dataset, maintaining operational granularity. Standardization into a 10×10-meter grid structure enabled seamless integration with GIS and ML workflows.

5.2.3. Model Training and Prediction

Machine learning models predicted mined zones based on spatial indicators, including proximity to infrastructure, visibility from observation posts, and terrain characteristics. Post-prediction, the models classified mine types and ranked zones by clearance priority and difficulty. Validation combined statistical methods (cross-validation) with field-based expert reviews to align outputs with operational realities, as elaborated in Sections 5.1.4 and 5.1.6.

5.2.4. GIS Integration and Visualization

The detailed GIS integration methodology, including CSV export, spatial joins, and thematic layer generation, is fully described in Section 5.1.5. Predicted mine presence,

mine types, clearance priorities, and difficulty levels were visualized through layered outputs, designed for deployment on GPS-enabled devices supporting real-time field operations.

5.2.5. Deployment and Expert Feedback

Deployed GIS maps enabled real-time navigation and situational awareness for demining teams. Both vector (shapefiles) and raster formats were used to optimize field usability. Expert feedback, collected through field tests and structured questionnaires, informed iterative refinements, including threshold adjustments, label visibility improvements, and model retraining where necessary. This dynamic feedback loop ensured that system outputs remained adaptable to evolving field conditions.

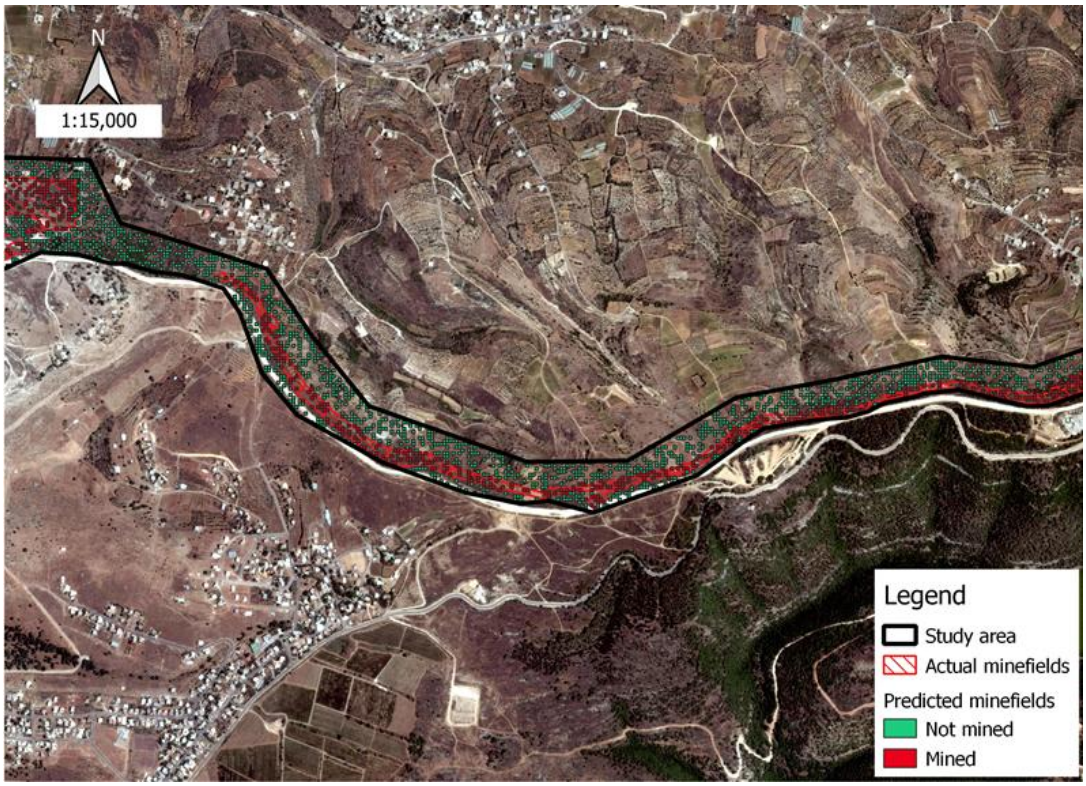


Figure 17: Predictions for mined areas along the southern border

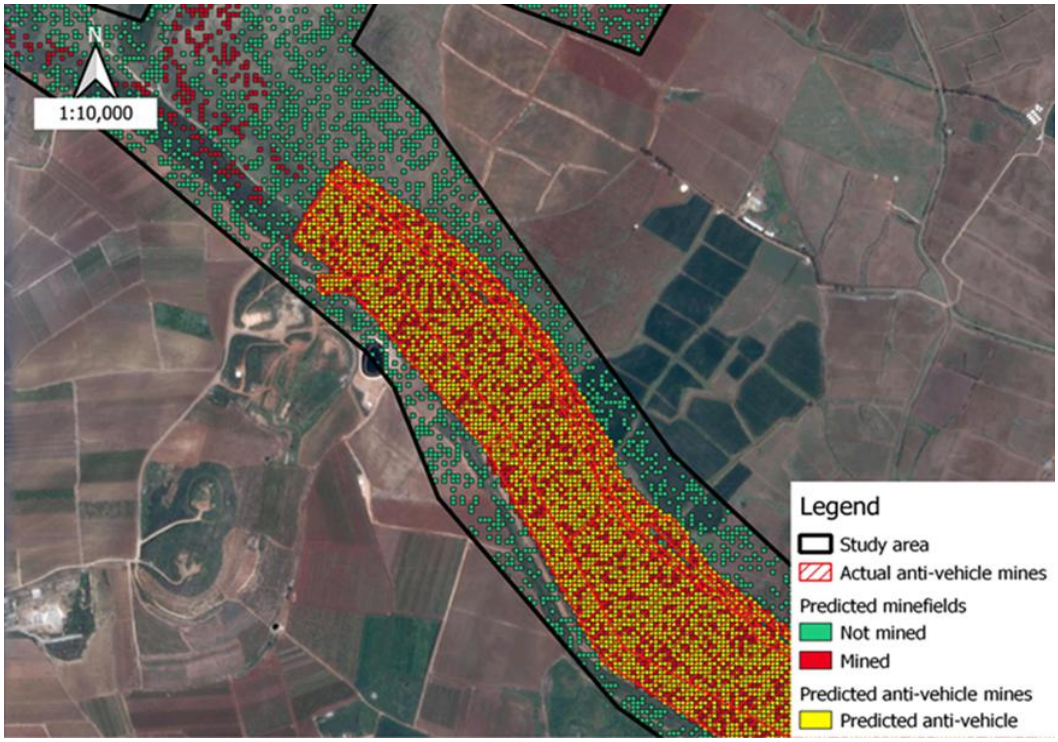


Figure 18: Predictions for anti-vehicle mined areas

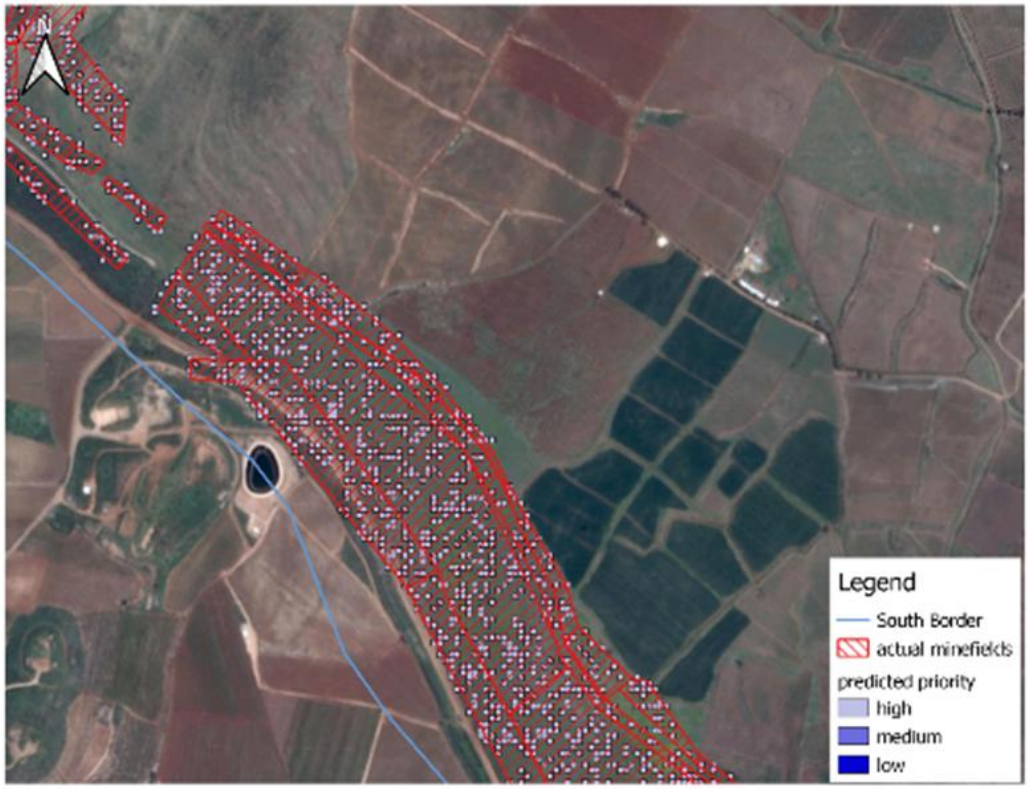


Figure 19: High-priority prediction in agricultural areas

Figure 17, along with subsequent figures created using QGIS, displays the prediction outcomes for the selected testing splits (10x10 m). These results are part of a 70/30 split where 30% of the samples were used for testing and 70% for training.

Figure 17 displays the mined areas predictions, where the study area is presented in black, the actual minefields in hashed red, while the predictions are in red squares for the mined areas and green squares for the not mined areas.

Figure 18 shows the prediction results obtained for mined areas containing anti-vehicle mines presented in yellow, and as shown, the results were quite accurate with the actual anti-vehicle minefields presented in hashed red, and converged well towards an excellent prediction.

In an agricultural area, the predictions for priority are shown in Figure 19, and graduated from light blue representing the highest priority to dark blue for the lowest priority. The results indicate that high priority is given, as expected.

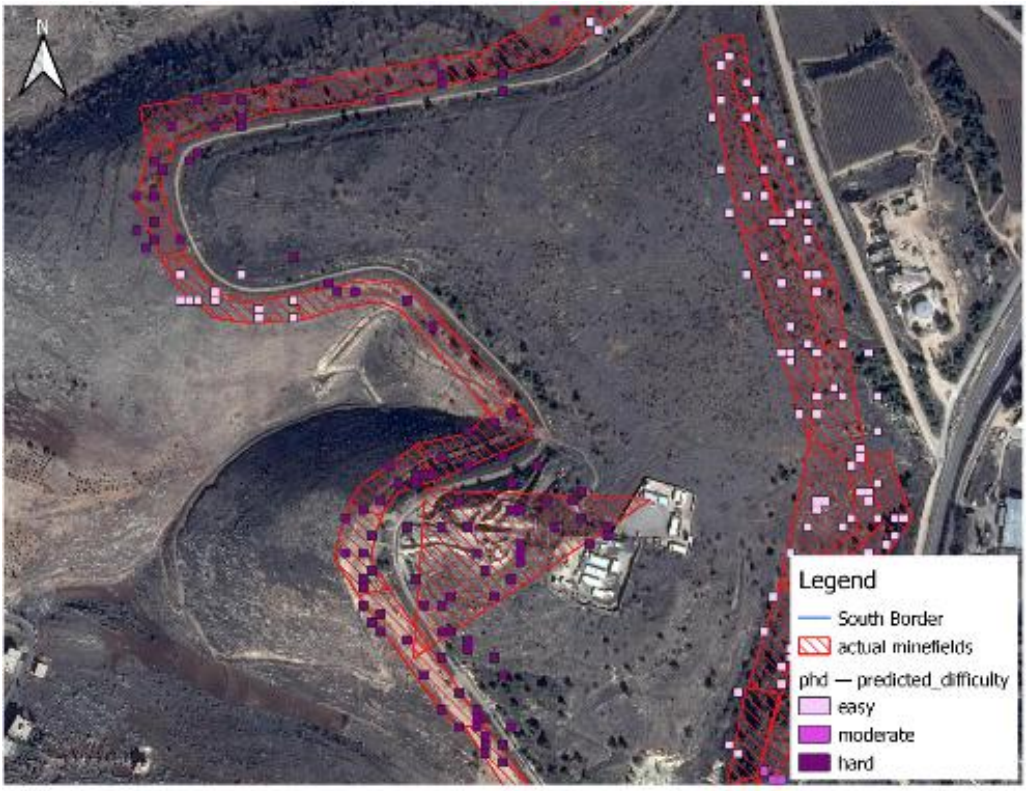


Figure 20: Difficulty prediction

Meanwhile, Figure 20 shows the difficulty predictions and their relative homogeneity, graduated from light pink for an easy clearance prediction, to dark pink for a hard clearance operations predictions.

GIS maps, exported in both vector and raster formats, were uploaded to GPS-enabled field devices, providing real-time operational guidance. Continuous updates and expert feedback loops ensured that predictions remained aligned with field observations and operational needs.

5.3. Concluding Integrated Methodology Schema

This section consolidates the GIS-ML framework into a structured, end-to-end methodology that supports humanitarian demining operations. The integrated schema connects data preparation, machine learning prediction, GIS visualization, and expert-driven refinement into a unified operational workflow.

The core components of the methodology are summarized as follows:

5.3.1. Objectives of the Integrated Schema

This schema is designed to achieve four main goals:

a) **Improve Prediction Accuracy**: By leveraging high-resolution spatial data and advanced machine learning models (Random Forest and XGBoost).
b) **Optimize Clearance Priority**: Focusing resources on zones with the highest humanitarian and economic impact.
c) **Incorporate Expert Feedback**: Iteratively refining model outputs based on operational field insights.
d) **Support Scalable Field Use**: Through GIS-based visualization and adaptability to diverse terrain and conflict settings.

5.3.2. Data Preparation and Feature Engineering

The process begins with detailed data preparation, using a 10×10-meter spatial grid to break down the study area into manageable analysis units. Each grid cell includes a consistent set of features grouped into three categories:

a) **Geographic features**: terrain slope, elevation, and vegetation density.
b) **Military-relevant features**: distance to observation posts and confrontation lines.
c) **Socio-economic indicators**: proximity to urban centers and infrastructure.

All features are normalized and standardized to ensure consistency across the dataset. This structured preparation improves the quality of predictions and ensures that the model captures both physical terrain conditions and tactical deployment patterns.

5.3.3. Machine Learning Model Selection and Optimization

Model selection focuses on choosing algorithms that balance high predictive accuracy with interpretability and robustness. Random Forest and XGBoost were selected due to their strong performance in handling imbalanced data and their ability to explain predictions through feature importance analysis.

To ensure the models perform well across different regions and terrain types, stratified cross-validation is used. This keeps class proportions consistent and helps prevent overfitting.

Finally, model parameters are fine-tuned using the Optuna optimization library, which automates the search for the best combination of settings to maximize metrics like recall and precision, critical for safely detecting mined areas.

5.3.4. Mine Type Classification and Prioritization

After identifying mined areas, the model classifies them as follows:

a) **Mine Type Classification**: Distinguishes anti-personnel vs. anti-vehicle mines based on spatial patterns**.**
b) **Priority Ranking**: (High, Medium, Low) based on socio-economic significance**.**
c) **Difficulty Assessment**: (Easy, Moderate, Hard) based on terrain ruggedness and vegetation density.

This system helps teams plan operations more effectively by matching clearance urgency with zone accessibility.

5.3.5. GIS Integration for Data Visualization and Accessibility

A key component of the operational workflow is the integration of machine learning outputs into GIS platforms to support field deployment. Using QGIS and GDAL libraries, model predictions, including mine presence, mine type, clearance priority, and difficulty levels, are transformed into spatially-referenced thematic layers.

These outputs are exported in both vector formats (e.g., shapefiles) and raster formats, offering flexibility for different operational needs. Vector layers enable in-field querying and editing, while raster layers provide fast rendering on GPS-enabled field devices.

The resulting maps are designed to maximize usability, featuring scalable symbols, readable labels, and toggleable classification layers tailored to demining mission planning and execution. As field conditions evolve, the system supports continuous updates, ensuring that predictions remain aligned with real-world developments.

5.3.6. Validation with Military Experts and Iterative Refinement

Validation played a critical role in refining the system's operational relevance and technical robustness. The model was assessed in close collaboration with 85 military demining officers from the Lebanese Army, through both structured validation questionnaires and field-based simulations.

Experts reviewed multiple aspects of system performance, including:

a) **Prediction accuracy,** with particular focus on minimizing false negatives.
b) **GIS map readability,** zoom functionality, label clarity, and symbol scaling.

c) **Classification thresholds** for priority and difficulty levels based on operational experience.

Iterative feedback cycles led to the recalibration of spatial thresholds, retraining of machine learning models where necessary, and enhancements to GIS visualization outputs. This validation approach ensured that the system evolved in parallel with practical field requirements, maintaining high levels of accuracy, usability, and trust among operational teams.

5.3.7. Integrated Workflow for Field Operations

The final integrated workflow reflects the logical sequence of real-world demining operations, seamlessly linking data collection, machine learning prediction, GIS visualization, and expert-driven validation. The process unfolds as follows:

a) **Data Collection & Preparation**: Spatial and military-relevant data are gathered, standardized, and structured into a 10×10-meter grid to ensure analytical consistency.
b) **Model Training & Prediction**: Machine learning algorithms identify mined zones, classify mine types, and rank zones based on priority and difficulty assessments.
c) **GIS Integration & Visualization**: Predictions are converted into operational map layers, facilitating mission planning and real-time field navigation.
d) **Field Deployment & Expert Feedback**: GIS maps are deployed to demining teams equipped with GPS-enabled devices. Continuous expert feedback informs ongoing refinements, ensuring the system adapts dynamically to operational realities.

This workflow supports scalable field operations across various terrains, enhancing clearance efficiency and ensuring the highest levels of safety and resource optimization.

5.3.8. Expected Outcomes and Operational Impact

The integrated GIS-ML methodology delivers significant improvements in minefield detection, classification, and prioritization, offering a data-driven decision-support system tailored for humanitarian demining missions. Key outcomes include:

a) **High Prediction Accuracy**: Accuracy rates exceeding 97% across mined area predictions, minimizing dangerous false negatives and operational risks.
b) **Efficient Resource Allocation**: Clearance time and operational costs are reduced by up to 30% through targeted prioritization of high-impact zones.
c) **Improved Field Safety**: Difficulty classification and mine type mapping allow teams to prepare context-appropriate clearance strategies, reducing personnel risks.
d) **System Scalability and Flexibility**: Difficulty classification and mine type mapping allow teams to prepare context-appropriate clearance strategies, reducing personnel risks.

Future enhancements may focus on extending model generalizability to other countries and conflict settings, incorporating seasonal satellite data to account for environmental changes, integrating real-time UAV imagery, and introducing uncertainty quantification measures to enhance transparency and decision confidence in high-stakes operations.

Overall, the proposed system offers a scalable, adaptable, and operationally validated framework that strengthens the safety, efficiency, and effectiveness of humanitarian demining efforts in post-conflict environments.

Part 3

Ethical Considerations and Future Work

Chapter 6

Ethical, Legal, and Humanitarian Considerations in AI-Driven Demining

6.1. Introduction

The integration of AI and GIS into humanitarian demining represents a transformative leap in modern clearance operations. These technologies promise increased efficiency, enhanced predictive capabilities, and smarter resource allocation. Yet, their deployment raises critical ethical, legal, and humanitarian questions. Concerns about algorithmic transparency, data bias, human accountability, and the unintended consequences of automation must be addressed to ensure that technological advancement does not compromise human dignity, safety, or rights. This chapter explores these challenges, proposing a framework for ethical governance and responsible deployment of AI-assisted demining systems in alignment with international humanitarian standards and community-centered approaches.

6.2. Ethical Considerations

This section explores the ethical dimensions of integrating AI in mine action, focusing on transparency, fairness, and the indispensable role of human oversight in safeguarding against algorithmic risks.

6.2.1. AI Transparency and Explainability

AI-driven demining systems typically rely on advanced machine learning models, such as ensemble classifiers or deep neural networks, to predict mine presence and classify risk levels. However, these models often act as “black boxes,” producing outputs that are difficult to interpret by non-technical stakeholders. This opacity undermines trust, particularly in life-critical scenarios like demining.

Explainability is therefore essential, not only for technical validation but also for operational accountability. Techniques like SHapley Additive exPlanations (SHAP) or Local Interpretable Model-Agnostic Explanations (LIME) allow experts to visualize the rationale behind each prediction, providing interpretable insights for field personnel. For example, a SHAP analysis may reveal that soil conductivity and proximity to historical conflict zones were dominant factors influencing a high-risk prediction.

Bias in landmine prediction models often originates from skewed historical datasets, such as intelligence reports collected predominantly from specific terrains or conflict-prioritized areas. This can result in models that perform disproportionately well in familiar zones (e.g., military-occupied regions) while generalizing poorly to less-documented, rural, or politically marginalized areas. To mitigate such risks,

algorithmic-level interventions are necessary. Two prominent techniques, adversarial debiasing and fairness-aware learning, can be employed to enhance model robustness and equity.

Adversarial debiasing introduces a dual-model structure wherein the main predictor is trained to forecast the target variable (e.g., landmine presence), while an adversarial network simultaneously attempts to predict a protected or potentially biased attribute (e.g., data source, terrain type, or region class). The learning objective penalizes the predictor whenever the adversary succeeds, thereby encouraging the model to learn representations that are less dependent on the biased attribute. In the context of humanitarian demining, this ensures that predictions are not unduly influenced by region-specific data imbalances, leading to more generalized detection capabilities.

Fairness-aware learning, on the other hand, integrates fairness constraints directly into the training process. These constraints aim to equalize performance metrics, such as true positive rate, false negative rate, or risk classification distribution, across diverse subgroups or geographic areas. This can be achieved at various stages: through preprocessing (balancing datasets), in-processing (modifying the learning algorithm), or post-processing (adjusting outputs). For demining models, this means ensuring that mine risk assessments are not systematically biased toward or against any particular region due to historical data limitations.

Together, these methods contribute to the development of models that are not only technically accurate but also ethically sound and operationally inclusive, especially critical in post-conflict settings where underrepresentation can lead to life-threatening oversights.

Aspect	Adversarial Debiasing	Fairness-Aware Learning
Core Idea	Uses an adversary model to detect and suppress bias in the predictor	Adds fairness objectives or constraints during training
Mechanism	Penalizes predictor when bias signals are detectable by the adversary	Optimizes both accuracy and fairness across defined groups or regions
Target Bias Source	Implicit patterns related to terrain, source type, or demographic data	Disparate outcomes across geographic or population subgroups
Application Phase	In-processing (during training)	Pre-processing, in-processing, or post-processing
Use Case in Demining	Reduces over-reliance on intelligence from well-documented military areas	Ensures balanced performance across both military and civilian or remote regions
Output Benefit	More generalized predictions, less region-specific overfitting	Equitable model behavior, aligned with humanitarian and ethical principles

Table 10: Adversarial Debiasing and Fairness-Aware Learning

Table 10 is a comparison table of Adversarial Debiasing and Fairness-Aware Learning in the context of landmine risk modeling.

6.2.2. Human-In-The-Loop Decision Making

Even with the integration of advanced machine learning and geospatial analytics, artificial intelligence systems remain inherently limited in understanding the full complexity of real-world, high-stakes environments such as landmine clearance. Human-In-The-Loop (HITL) is a critical framework that addresses these limitations by embedding expert decision-makers, such as military Explosive Ordnance Disposal (EOD) teams, humanitarian engineers, or local field specialists, directly into the AI-assisted decision-making pipeline.

In the HITL framework, AI systems are responsible for automated data analysis, such as generating risk heatmaps, flagging suspicious areas based on terrain and historical data, or classifying zones by clearance difficulty or priority. However, these outputs do not translate directly into autonomous action. Instead, they are presented through intuitive, user-facing tools such as interactive dashboards, geospatial overlays, and risk scores, allowing human operators to interpret, validate, or override AI-generated recommendations.

This approach offers several critical advantages:

- Reduction of Critical Errors:
    - False positives (clearing safe zones unnecessarily) waste time, resources, and increase operational costs.
    - False negatives (missing actual minefields) can lead to fatalities or injury.

    By retaining final control, human experts mitigate these risks, drawing on contextual knowledge that AI may not possess.

- Operational Trust and Accountability:

HITL fosters a collaborative model in which AI supports rather than replaces human judgment. This maintains ethical oversight and provides a clear line of accountability, particularly important in humanitarian contexts where lives are at stake.

- Contextual Awareness:

Local conditions, such as recent weather changes, population movements, or political tensions, may affect operational decisions in ways that are not reflected in training data. Human operators can adapt and respond with flexibility.

- User-Centered Design: HITL systems require intuitive interfaces, e.g., heatmaps indicating high-risk zones, filters for terrain type or data source, and annotated confidence scores, so that decision-makers can easily understand and act on AI outputs.

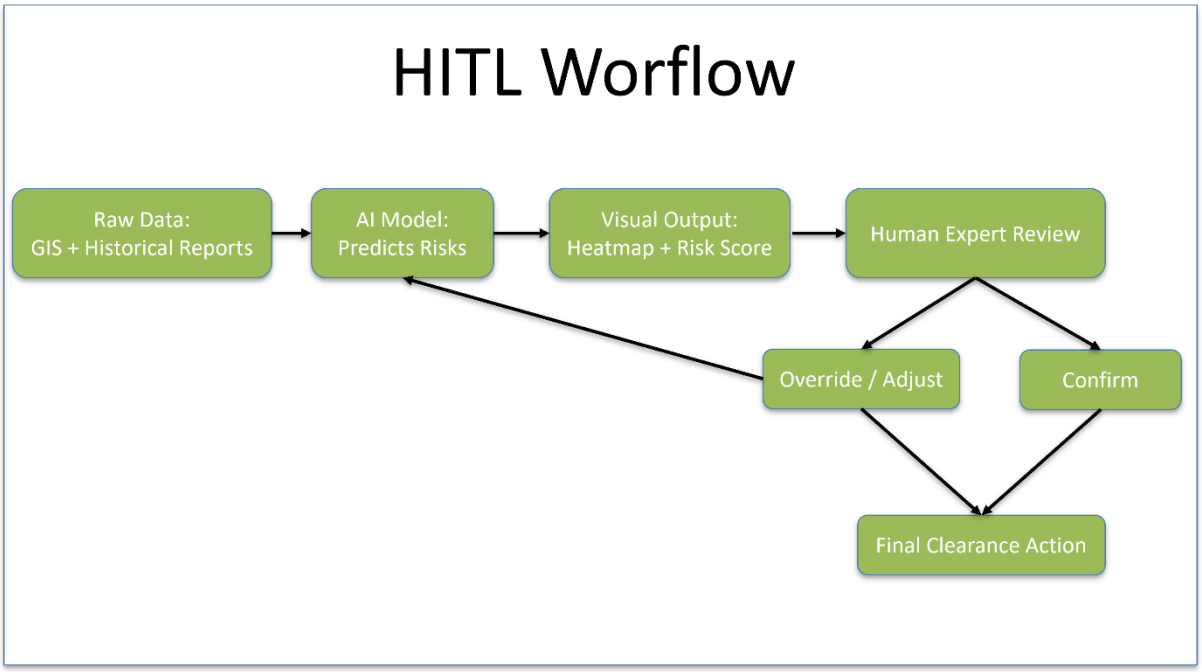


Figure 21: HITL Worflow

Figure 21 illustrates the Human In The Loop workflow for landmine clearance using AI and GIS. It illustrates how AI predictions are integrated with expert human review before final operational actions are taken.

6.3.Legal Frameworks and Compliance

As AI becomes increasingly embedded in mine action strategies, legal and regulatory compliance must evolve to ensure data protection, operational accountability, and adherence to international humanitarian law.

The use of AI in demining must adhere to both international humanitarian law and national security regulations. The Ottawa Treaty (1997) prohibits the use and stockpiling of anti-personnel mines while promoting their removal, this underpins the ethical and legal legitimacy of demining operations. AI-enhanced tools must comply with these principles, particularly when handling sensitive spatial and military data.

Compliance with United Nations Mine Action Service (UNMAS) standards further ensures that AI applications align with accepted operational and safety protocols. These standards mandate transparency in data processing, accountability in reporting, and risk mitigation during clearance activities.

A key legal and operational concern in the integration of GIS and ML in humanitarian demining is data privacy and security. The datasets used, such as military records, high-resolution terrain models, and location-specific intelligence, often include classified or sensitive information that, if exposed, could pose risks to national security, operational confidentiality, or civilian safety. These concerns are particularly acute in post-conflict settings, where even metadata (e.g., coordinates of cleared zones, troop movement logs, or sensor placements) can be exploited if not properly protected.

To address this, robust data governance frameworks are essential. These frameworks must go beyond traditional access controls and employ advanced techniques to ensure both data utility and privacy. For instance:

- Encryption protocols safeguard data at rest and in transit, ensuring that unauthorized access to datasets does not result in readable or usable information.
- Secure multi-party computation (SMPC) allows multiple parties (e.g., military units, demining NGOs, or international agencies) to collaboratively analyze data and train models without revealing their individual datasets to one another. Computations are distributed and results are aggregated without exposing the raw data inputs.
- Federated learning takes this concept further by enabling model training to occur locally at each data-holding node (e.g., a military branch or regional command post), while only sharing model updates (gradients or weights) with a central aggregator. This approach preserves data sovereignty and drastically reduces the risk of data leakage.

For example, in a federated learning setup applied to minefield risk prediction, each participating entity, such as a humanitarian organization, a UN observer mission, and the national armed forces, can train on their own secure datasets, while contributing to a global model without exchanging raw location or threat data. This not only respects operational secrecy but also aligns with international data protection regulations (e.g., GDPR) and military protocols for information classification.

Ultimately, embedding privacy-preserving mechanisms into the ML pipeline ensures that the ethical and legal boundaries of data use are respected, while still enabling collaborative intelligence to support safe and efficient demining operations. This is especially critical when the decision-making process depends on sensitive sources whose exposure could compromise both mission integrity and civilian trust.

Accountability is another legal grey area. If an AI system misclassifies an area as mine-free and casualties ensue, responsibility must be clearly assigned. Legal frameworks should establish liability protocols, outlining the roles of software developers, data curators, field operators, and oversight bodies. Drawing from global examples like the EU's AI Act, future policies should adopt tiered responsibility structures and mandate auditability for all high-risk AI systems.

6.4. Humanitarian and Socioeconomic Impacts

Beyond technical deployment, AI-driven demining carries significant humanitarian and socioeconomic consequences, affecting community safety, land use, and long-term recovery in post-conflict zones.

6.4.1. Balancing Efficiency and Human Safety

Speeding up mine clearance through AI must not come at the expense of safety. Algorithms must be validated in multiple field conditions, across varying terrain types, vegetation densities, and climate zones, before being deployed. Field trials must incorporate redundancy checks, including manual validation, drone-assisted verification, and proximity-based geofencing for alerts.

Community involvement is critical. In many post-conflict regions, local populations possess unique historical knowledge of mine presence and land use changes. Incorporating this insight through participatory mapping or community-led surveys enhances model accuracy and fosters mutual trust. Education campaigns should also demystify AI tools, explaining their benefits and limitations to affected communities. This transparency strengthens collaboration and minimizes fear or misinformation.

6.4.2. Long-Term Socioeconomic Effects

AI-assisted demining not only removes physical threats but also catalyzes economic recovery. Cleared land can be repurposed for agriculture, infrastructure, or resettlement, accelerating post-conflict rehabilitation. However, sustainability must be considered. Mechanized clearance, if unsupervised, may damage soil fertility or disrupt ecosystems.

AI systems should be designed to align with ecological rehabilitation strategies. GIS models can incorporate environmental indices (NDVI, soil quality) to recommend phased clearance that prioritizes both safety and ecological resilience. For instance, integrating clearance outputs with local zoning plans could optimize land restoration without compromising biodiversity or agricultural potential.

6.5. Future Outlook and Recommendations

As AI systems continue to evolve and integrate into high-stakes humanitarian operations, their governance must be designed to uphold ethical integrity, operational transparency, and human safety. In the context of mine action, this calls for a robust, forward-looking framework that ensures AI technologies support, rather than replace, the expertise and judgment of field personnel. Looking ahead, the responsible deployment of AI in demining will require more than technical excellence; it will demand structured collaboration, clear accountability, and adherence to humanitarian values.

One of the most pressing needs is the development of ethical AI governance protocols tailored specifically to humanitarian contexts. Global demining organizations should establish standardized guidelines that address transparency, fairness, and bias mitigation throughout the AI lifecycle. These policies should mandate third-party audits, performance evaluations, and mechanisms for redress when systems fail. Investing in explainable AI (XAI) tools is equally critical, interpretable models foster trust among field operators and ensure that algorithmic decisions remain understandable and challengeable in the field.

Cross-sector collaboration will be essential to sustaining innovation and accountability. Partnerships among governments, military experts, humanitarian agencies, and AI researchers can enable both the validation and contextual refinement of demining tools. These partnerships should prioritize knowledge exchange, shared operational standards, and joint evaluation platforms.

Equally important is the need for secure and transparent data-sharing protocols. Because demining datasets often include sensitive military or geospatial information, frameworks must balance operational utility with privacy and security. Technologies such as federated learning, secure multiparty computation, and encryption-at-rest can help maintain data sovereignty while still enabling collective model training and improvement.

In sum, the future of AI-driven demining depends not only on better models, but on the responsible ecosystems built around them. Governance, trust, and cooperation will be as vital as algorithmic performance in ensuring that technological advancements translate into safe, ethical, and effective field outcomes.

6.6. Conclusion

The integration of AI and GIS in humanitarian demining presents a promising yet complex landscape. While these technologies offer unparalleled advancements in efficiency and accuracy, they also introduce ethical, legal, and humanitarian challenges that must be carefully managed. Ensuring AI transparency, maintaining human oversight, and adhering to legal frameworks are crucial for responsible implementation. By incorporating military expertise, ethical AI governance, and community engagement, AI-driven demining can maximize its life-saving potential while upholding humanitarian principles. This chapter underscores the necessity of a multidisciplinary approach that combines technological innovation with ethical responsibility, ultimately contributing to safer and more sustainable post-conflict recovery efforts.

Chapter 7

Conclusion et Perspectives Futures

7.1. Évaluation de l'Hypothèse et des Résultats de Recherche

Cette thèse a avancé l'hypothèse qu'une intégration de l'apprentissage automatique, de l'analyse géospatiale et de l'expertise militaire pouvait accroître de manière significative l'efficacité, la précision et la sécurité des opérations de déminage humanitaire. Plus précisément, elle postulait que les connaissances militaires propres au domaine pouvaient orienter les algorithmes d'apprentissage automatique pour générer des prédictions de champs de mines exploitables et sensibles aux risques.

Les travaux de recherche ont confirmé cette hypothèse grâce à un développement itératif des modèles et à une validation par des experts. Le cadre SIG-ML intégré a démontré une amélioration de la précision de détection, produisant des cartes de chaleur de contamination et des schémas de classification surpassant les méthodes traditionnelles. Surtout, le modèle ne se limitait pas à la détection de la présence de mines : il intégrait également la difficulté du terrain, l'urgence du déminage et la différenciation des types de mines, permettant ainsi une prise de décision tactique conforme aux réalités du terrain.

Au-delà de ces avancées techniques, le cadre a offert une valeur opérationnelle tangible. La planification sur le terrain a été améliorée par des outils visuels et une stratification des risques, tandis que des garde-fous de type « human-in-the-loop » (HITL) garantissaient que les recommandations de l'IA demeurent toujours soumises à l'examen d'experts. Cet équilibre entre automatisation et supervision a permis au système de fonctionner de manière fiable dans des environnements complexes.

En définitive, les résultats étayent un changement de paradigme : passer d'un déminage réactif à des stratégies proactives guidées par le renseignement. L'association des capacités de l'IA, de la logique militaire et du contexte géospatial constitue une solution validée et prête à être déployée sur le terrain, avec le potentiel de réduire considérablement les délais de dépollution, d'optimiser l'allocation des ressources et de sauver des vies dans les zones post-conflictuelles.

7.2. Réponse aux Questions de Recherche

Cette thèse a traité deux questions de recherche centrales:

- Comment l'intégration du ML et des SIG peut-elle améliorer la précision, l'efficacité et la prise de décision opérationnelle dans les opérations de déminage humanitaire ?
- Quel cadre méthodologique permet d'incorporer de façon systématique l'expertise militaire aux solutions de déminage fondées sur le duo ML-SIG afin d'affiner l'évaluation des risques, l'allocation des ressources et l'efficacité opérationnelle?

7.2.1. Intégration SIG-ML pour la Précision et l'Efficacité

La première question a trouvé réponse en montrant que l'analyse spatiale renforcée par l'IA pouvait remplacer les relevés manuels, exigeants en main-d'œuvre, par un zonage des risques automatisé. En exploitant les données historiques des conflits, les variables topographiques et les rapports post-dépollution, les modèles d'apprentissage automatique ont généré des cartes de chaleur indiquant les zones de contamination probable, facilitant ainsi l'évaluation rapide de vastes territoires.

Le SIG, jouant le rôle d'interface spatiale pour ces prédictions, a permis de produire des cartes de priorisation du déminage. Ces cartes ont aidé les planificateurs opérationnels à visualiser les régions nécessitant une attention immédiate en raison de la proximité des populations ou de l'intensité des combats passés. De plus, la scalabilité du cadre SIG-ML garantit son adaptation à divers terrains et historiques de conflit, que ce soit dans le Sud-Liban ou dans de futures zones post-conflit.

Si l'intégration du ML et du SIG a constitué la base d'évaluations des risques automatisées et extensibles, la vision stratégique des experts militaires est restée indispensable pour ancrer ces prédictions dans une logique opérationnelle. En fusionnant les résultats algorithmiques avec la logique militaire propre au domaine, le cadre a offert à la fois une précision prédictive et une validité tactique sur le terrain.

7.2.2. L'Expertise Militaire comme Ancrage Stratégique

La deuxième question de recherche portait sur la manière d'intégrer systématiquement l'expertise militaire aux solutions IA-SIG afin d'améliorer l'évaluation des risques et la priorisation des opérations de dépollution. Cette thèse a montré que l'apport militaire n'est pas seulement bénéfique : il est indispensable pour contextualiser les prédictions algorithmiques dans une logique opérationnelle concrète.

L'expertise militaire a été intégrée à plusieurs étapes du flux de travail:

- **Orientation Stratégique du Modèle**: des officiers de terrain ont fourni des connaissances sur les tactiques historiques de pose de mines, les positions défensives et les stratégies d'utilisation du terrain, éclairant ainsi les hypothèses du modèle et la sélection des variables d'entrée.
- **Annotation et Validation**: du personnel militaire a participé à l'annotation d'images satellites, à la vérification des archives historiques et à l'interprétation des sorties de risque, ce qui a amélioré la qualité des données et la fidélité de la validation.
- **Classification Opérationnelle**: leur expertise a guidé l'étiquetage de la difficulté de dépollution en fonction des caractéristiques du terrain (densité rocheuse, couverture végétale, altitude, etc.) et la logique de priorisation selon la proximité des centres de population, des infrastructures clés ou des zones d'affrontements connues.

Cette collaboration, structurée autour d'entretiens d'experts, de sessions de retour d'expérience et de simulations sur le terrain, a permis au système de tenir compte de la guerre asymétrique, des distributions irrégulières de mines et des anomalies tactiques

non documentées, des schémas qu'un modèle purement axé sur les données manque souvent de détecter. En fusionnant l'analytique prédictive et le jugement humain, la méthodologie a renforcé le réalisme, la pertinence et la fiabilité du cadre de déminage obtenu.

7.3. Synthèse des Contributions et Implications

Cette thèse a présenté un nouveau système d'aide à la décision qui combine analyse spatiale, intelligence artificielle et expertise sectorielle pour accélérer et améliorer le déminage humanitaire. Les principales réalisations sont les suivantes:

- Prédiction des champs de mines avec une précision de 97 % : le modèle a appris les signatures spatiales de risque, réduisant l'incertitude et augmentant la puissance prédictive par rapport aux approches traditionnelles.
- Classification opérationnelle avec une précision de 99 % : les types de mines, les niveaux de difficulté et les priorités de dépollution ont été classés afin d'associer les moyens de déminage (manuel, mécanique ou cynophile) aux conditions du site en tenant compte des contraintes socio-économiques.
- Intégration Human-in-the-Loop (HITL) : l'IA a opéré dans un cadre contrôlé où ses prédictions étaient validées et ajustées par des opérateurs humains, garantissant ainsi sécurité et responsabilité.
- Scalabilité méthodologique : l'approche peut être transférée à d'autres régions post-conflit, pourvu que des jeux de données pertinents et une collaboration militaire soient disponibles.
- Soutien à la planification stratégique : les résultats du modèle peuvent éclairer non seulement les opérations de dépollution, mais aussi la réhabilitation foncière et la planification de la reconstruction après dépollution.

Ensemble, ces contributions illustrent la force d'une approche triangulée : capacité algorithmique, jugement humain et intelligence spatiale agissant de concert pour sauver des vies et restaurer les terres.

7.4. Orientations Futures de la Recherche

Les résultats obtenus dans cette thèse ouvrent plusieurs pistes importantes pour de futurs travaux, portant à la fois sur les perfectionnements techniques et sur les cadres de gouvernance nécessaires pour déployer le déminage assisté par l'IA de manière responsable dans divers contextes de conflit.

7.4.1. Boucles de rétroaction en temps réel et IA adaptative

Les travaux futurs devraient se concentrer sur le développement de systèmes d'IA capables d'intégrer des rétroactions en temps réel. Ces systèmes ajusteraient dynamiquement leurs prédictions en fonction des résultats validés sur le terrain et des mises à jour des capteurs durant les opérations en cours. De tels systèmes en boucle fermée pourraient accroître la précision dans des conditions volatiles ou évolutives, telles qu'un terrain se modifiant rapidement ou de nouveaux rapports de contamination.

7.4.2. Cartographie micro-précise des champs de mines

Plutôt que de produire de vastes cartes de chaleur de contamination, les modèles futurs devraient viser à localiser individuellement chaque mine au sein des zones à haut risque. Cela exige l'intégration de données issues de capteurs haute resolution, imagerie par drone, géoradar (GPR) et imagerie multispectrale, dans des chaînes de fusion multi-capteurs. Une résolution spatiale accrue permettrait de réduire significativement les faux positifs et d'optimiser le déploiement des moyens de dépollution.

7.4.3. Systèmes de recommandation des moyens de dépollution

Une autre piste prometteuse consiste à développer des systèmes intelligents capables d'associer les moyens de déminage aux conditions du terrain et aux types de contamination. Par exemple, les zones accidentées et boisées peuvent être mieux abordées avec des chiens détecteurs de mines (MDD), tandis que les terrains plats riches en débris métalliques conviennent davantage aux fléaux mécaniques ou aux équipes EOD manuelles. Des systèmes d'IA pourraient apprendre ces correspondances à partir des données opérationnelles afin d'optimiser la logistique et la planification.

7.4.4. IA pour le renseignement stratégique post-conflit

En s'appuyant sur la doctrine militaire et les schémas historiques de pose de mines, l'IA pourrait servir à inférer la présence probable d'anciens postes de combat, de caches dissimulées ou de périmètres défensifs. Une telle capacité contribuerait à stabiliser les zones libérées, à soutenir les recherches médico-légales militaires et à aider les urbanistes à hiérarchiser la reconstruction en toute sécurité.

7.4.5. Apprentissage fédéré et gouvernance éthique de l'IA

En s'appuyant sur le chapitre 6, les recherches futures devraient étudier le déploiement de cadres d'IA fédérée, permettant à plusieurs organisations d'entraîner collaborativement des modèles sans échanger de données sensibles. Cette approche est cruciale dans des contextes multi-acteurs associant forces armées, ONG et observateurs internationaux. Parallèlement, il convient de développer des dispositifs de gouvernance assurant l'équité, la transparence et l'auditabilité des systèmes décisionnels fondés sur l'IA, en particulier pour les applications humanitaires à haut risque**.**

7.4.6. Évaluations des impacts à long terme

Enfin, les travaux futurs devraient analyser les impacts économiques et environnementaux à long terme du déminage piloté par l'IA. Le déminage n'est pas seulement une activité technique, mais aussi un pilier essentiel de la reconstruction post-conflit. La recherche devra évaluer comment les outils d'IA influencent la restauration des terres, la réinstallation des populations, l'agriculture et les écosystèmes locaux, afin de s'assurer que les solutions technologiques favorisent à la fois la sécurité et la durabilité.

7.5. Remarques Finales

Alors que cette recherche touche à sa fin, il est essentiel de réfléchir de manière critique à ses points forts, ses limites, ainsi qu'à sa portée plus large dans le contexte du déminage humanitaire.

7.5.1. Évaluation critique

Cette thèse propose un cadre novateur et opérationnellement solide qui intègre les SIG, l'apprentissage automatique et l'expertise militaire pour relever les défis complexes du déminage humanitaire. Elle démontre avec succès comment l'analyse spatiale et la classification basée sur l'IA peuvent améliorer la prédiction de la contamination, la difficulté de dépollution et la hiérarchisation des priorités.
Les principales contributions comprennent :

- Des cartes de risques (heatmaps) à haute précision ;
- Des modèles de classification sensibles aux caractéristiques du terrain.
- L'intégration de mécanismes human-in-the-loop (HITL) assurant une supervision éthique.
- La prise en compte des enjeux éthiques et juridiques majeurs, avec des propositions de cadres de gouvernance pour une utilisation responsable de l'IA en zones de conflit.

Cependant, plusieurs aspects restent en dehors du périmètre de cette étude :

- La localisation individuelle des mines.
- L'adaptation du modèle en temps réel.
- Le déploiement des moyens de dépollution piloté par l'IA.

7.5.2. Conclusion

Malgré ces contraintes, cette thèse établit une base solide pour l'avenir du déminage intelligent. En combinant modélisation géospatiale, inférence algorithmique et expertise militaire, le système proposé fait passer les opérations d'un déminage manuel réactif à une prise de décision prédictive et fondée sur les données. Il améliore non seulement la détection et la hiérarchisation des risques, mais il soutient également la réhabilitation des terres et la planification de la reconstruction post-conflit.
Grâce à sa conception modulaire et évolutive, l'approche est transférable à d'autres zones de conflit, pourvu que des données adéquates et une collaboration appropriée soient disponibles. Les travaux futurs devraient se tourner vers :

- Des systèmes d'IA capables de rétroaction en temps reel.
- Une cartographie micro-précise utilisant des capteurs avancés.
- Des infrastructures d'apprentissage fédéré qui respectent la souveraineté des données tout en favorisant un partage d'intelligence.

La gouvernance éthique doit évoluer en parallèle, afin de garantir la transparence, l'équité et la responsabilité dans les applications d'IA à haut risque. En définitive, cette recherche offre un modèle reproductible et tourné vers l'avenir pour renforcer la

sécurité, l'efficacité et l'intégrité éthique des opérations de déminage à l'échelle mondiale.

Le tableau 11 résume les contributions de ma thèse selon les trois dimensions clés : SIG, apprentissage automatique et expertise militaire. Chaque ligne met en évidence un domaine d'impact majeur et montre comment notre travail intègre ces trois composantes pour y répondre.

Domaine de contribution	Rôle des SIG	Rôle de l'AA (apprentissage automatique)	Rôle de l'expertise militaire
Prédiction des champs de mines	Cartographie spatiale des zones à haut risque à l'aide de couches environnementales et de données topographiques	Modélisation prédictive avec 97 % de précision sur la présence de mines	Entraînement des modèles à partir d'annotations issues du renseignement de combat
Classification du déminage	Classification géospatiale de la priorité et de la difficulté de dépollution	Classification automatisée des types de mines et du risque opérationnel	Étiquetage du terrain et de la difficulté basé sur le risque et l'expérience
Boucle humaine (HITL)	Cartographie des points de validation HITL et des décisions sur le terrain	Boucles de rétroaction pour mettre à jour les prédictions après revue d'experts	Validation finale des prédictions et supervision critique des missions
Scalabilité opérationnelle	Transfert régional du modèle grâce à la généralisation spatiale	Réentraînement flexible pour différentes régions aux caractéristiques similaires	Fourniture d'un contexte stratégique pour l'adaptation spécifique à la région
Intégration communautaire	Soutien à la cartographie participative et aux connaissances foncières locales	Apprentissage à partir de données locales annotées et adaptation des sorties	Engagement et partage de connaissances avec les parties prenantes locales
Reconstruction post-conflit	Zonage pour l'agriculture, la réinstallation et la planification des infrastructures	Priorisation des zones de reprise basée sur les données après dépollution	Contribution à la priorisation des zones au bénéfice des communautés
Intégration de la doctrine militaire	Visualisation de l'intensité du conflit et des zones de champs de bataille historiques	Reconnaissance de motifs pour déduire les positions de postes ou d'armes	Perspectives historiques sur la doctrine et les tactiques de pose de mines
Cadre de gouvernance éthique	Garantir la confidentialité liée à la localisation et des protocoles de gouvernance des données	Atténuation des biais et explicabilité grâce à l'audit des modèles	Rôle consultatif dans l'élaboration de politiques d'utilisation responsable de l'IA

Tableau 11: Contributions de la Thèse

À l’avenir, ce cadre pourra être adapté à d’autres environnements post-conflit tels que la Bosnie, la Colombie ou l’Ukraine. Pour soutenir ces applications transrégionales, les travaux futurs devront intégrer des jeux de données de conflit localisés, ajuster les variables propres au terrain et collaborer avec les autorités régionales de déminage. L’établissement de partenariats avec des organismes internationaux d’action contre les mines, tels que le GICHD, facilitera en outre la validation et l’adaptation du modèle à des contextes géopolitiques et environnementaux variés. Cette feuille de route inclura également le développement d’interfaces SIG multilingues ainsi que de métriques de risque sensibles aux spécificités régionales, garantissant la scalabilité et la pertinence de la solution dans les zones minées du monde entier.

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Annex 1
Questionnaire

Validation Questionnaire

To assess the effectiveness and usability of the GIS-ML framework in demining operations, a structured questionnaire was conducted among demining officers with varying levels of experience and operational roles. The survey aimed to evaluate the system's ability to enhance mine prediction, classification, and clearance prioritization while improving decision-making and reducing risks to personnel. Sixteen targeted questions covered key aspects, including the importance of predictive modeling, the role of classification by priority and difficulty, officers' familiarity with GIS tools, preferred data formats (vector vs. raster), and challenges in interpreting GIS outputs. The responses provided valuable insights into field-specific requirements, with strong support for integrating military-relevant spatial features such as confrontation lines and observation posts, refining GIS-based visualizations, and ensuring multi-scale map adaptability for both strategic planning and on-site clearance. This feedback was instrumental in optimizing the system's accuracy, usability, and operational relevance, ensuring its alignment with real-world demining challenges.

The questions are as follows:

1. How many years of experience do you have in demining?

a. Less than 10 years

b. More than 10 years

Justification:

Experience is a crucial factor in shaping the perspective of demining officers. Respondents with less than 10 years of experience may have more familiarity with modern technologies like GIS and ML, while those with more than 10 years bring deep operational expertise and knowledge of historical demining trends. This distinction helps analyze how experience level influences attitudes toward predictive modeling in demining..

2. What is your level of involvement in demining operations?

a. On-site

b. Supervision

c. Other (please specify)

Justification:

Different roles in demining require different kinds of decision-making and technological support. On-site personnel benefit from real-time predictions for operational safety, whereas supervisors require high-level analytics for strategic planning. This question helps assess how GIS and ML can be tailored to different demining responsibilities..

3. Is the idea of predicting mined areas helpful for your work?

a. Helpful

b. Not needed

c. Other (please specify)

Justification:

The core objective of GIS and ML integration in demining is to enhance predictive capability. This question seeks to validate whether demining officers see practical benefits in predictive mapping. If negative responses are high, it may indicate a gap in understanding or trust in AI-driven predictions.

4. How extensively are you familiar with reading GIS graphs and interpreting spatial data in demining operations?

a. Good knowledge of GIS

b. Not familiar with GIS

c. Other (please specify)

Justification:

GIS literacy is key to effective decision-making. Officers who struggle with GIS may need additional training, while those well-versed in GIS can offer insights on improving usability. Understanding these competency levels ensures the final system is accessible to all users.

5. In your demining experience, have you encountered challenges related to the interpretation of GIS graphs? If yes, what was the reason?

a. Error in coordinates

b. Resolution not enough

c. Old imagery

d. Other (please specify)

Justification:

By identifying common GIS-related challenges, this question helps refine data accuracy, enhance resolution, and ensure updated imagery is used in mine prediction models.

6. How do you evaluate the adequacy of resolution in demining maps, and what criteria do you consider for determining a resolution as "good" in this context?

a. Terrain details clear (access routes, landmarks)

b. Minefield limits well defined

c. Both of the above

d. Other (please specify)

Justification:

The resolution of spatial data impacts decision-making speed and accuracy. If maps lack clarity in terrain details or minefield boundaries, they may compromise safety and require improvements in spatial resolution..

7. In the division of an area of study for demining, what, in your experience, is the optimal size of a sample square (e.g., 10x10m, 20x20m)? Is it related to the type of mine or the specifications of the post-war zone?

a. 10×10m

b. 20×20m

c. 50×50m

d. Other (please specify)

Justification:

Determining the ideal spatial sampling unit ensures that mine predictions are granular enough for field application, yet computationally efficient. Larger sample sizes may miss minefield variations, while smaller ones may increase processing costs.

8. What role does the differentiation between anti-personnel and anti-tank mines play in the planning and effectiveness of demining strategies?

a. Allow the right allocation of resources

b. Add safety measures to deminers

c. Both of the above

d. Other (please specify)

Justification:

Different mine types require distinct clearance strategies. This question validates whether GIS and ML models should explicitly classify mine types to optimize resource allocation and safety measures..

9. Is the classification of mined areas by priority of clearance good for demining operations?

a. Very good from a socioeconomic perspective

b. Not relevant

c. Other (please specify)

Justification:

Prioritization helps efficiently allocate limited demining resources to areas of highest risk. If responses indicate low relevance, the classification model may need adjustments to reflect operational realities..

10. Is the classification of mined areas by difficulty of clearance good for demining operations?

a. Very good from a socioeconomic perspective

b. Not relevant

c. Other (please specify)

Justification:

This question validates whether ML models should incorporate clearance difficulty into predictions, ensuring realistic deployment of demining units.

11. Are the maps' resolutions in the previous figures enough, or a higher resolution is needed?

a. Yes, the resolution is enough

b. No, more details are needed

c. Other (please specify)

Justification:

Assessing the sufficiency of resolution ensures GIS outputs meet operational needs without unnecessary computational overhead.

12. Are the maps’ scales convenient, or multiple scales would be better?

a. A general map scale covering the entire area is enough

b. Just the scale that covers the correspondent minefield is enough

c. The output in multiple scales is better

d. Other (please specify)

Justification:

Understanding scale preferences improves data usability and ensures GIS outputs match field needs.

13. Do you prefer to deliver the output as vector data so you will be able to generate your own maps?

a. Yes, vector data (e.g., shapefile)

b. Raster data (maps)

c. Both formats together

Justification:

Different formats serve different needs: vector data allows further analysis, while raster data provides quick reference. This question ensures data is provided in the most useful format.

14. What factors, based on your experience, do you consider crucial in predicting potential mined zones?

a. Confrontation lines and military posts

b. Military terrain aspects

c. Land-use aspects

d. All of the above

e. Other (please specify)

Justification:

Ensuring that ML models account for real-world mine placement patterns improves predictive accuracy.

15. Do you believe there is a certain pattern in post-war zones where mines are typically located?

a. Near confrontation lines

b. Around hidden military posts

c. Along access routes

d. Other (please specify)

Justification:

Identifying patterns in mine placement helps refine predictive models for better risk assessment.

16. To what extent does the demining process involve human expertise in decision-making?

a. Demining experts must lead

b. Expertise is not key

c. Other (please specify)

Justification:

This question assesses the role of human intuition and experience in complementing ML-based mine prediction

COLLEGE SCIENCES
DOCTORAL DE LA MER
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Université de Bretagne Occidentale

Titre : Intégration de l'Expertise Militaire, des Systèmes d'Information Géographique et de l'Apprentissage Automatique pour le Déminage Post-Conflit : Une Approche Basée sur la Connaissance

Mots clés : Déminage Huamitaire, SIG, AA, Expertise Militaire

Résumé : Le déminage des mines terrestres et des munitions non explosées (UXO) dans les environnements post-conflit demeure un défi humanitaire et sécuritaire majeur. Les méthodes traditionnelles de déminage reposent largement sur des relevés manuels coûteux en ressources et des technologies de détection, mais elles souffrent souvent d'inefficacités dues à un manque d'intelligence spatiale complète et à la complexité des environnements. Cette recherche intègre les Systèmes d'Information Géographique (SIG) et l'Apprentissage Automatique (AA) afin d'améliorer la priorisation et la précision des opérations de déminage. Une approche novatrice est proposée, incorporant les connaissances d'experts militaires dans des modèles d'évaluation des risques basés sur l'AA, permettant ainsi une prise de décision plus éclairée et adaptative. En exploitant des données spatiales, des archives de contamination historique, des analyses topographiques et des images satellitaires, le système développé optimise la prédiction des zones à risque, réduisant ainsi l'incertitude liée à l'identification des zones potentiellement minées. La méthodologie est validée à travers des études de cas réelles issues de régions post-conflit, démontrant son efficacité dans l'amélioration de la sécurité et de l'efficacité opérationnelle. Les résultats indiquent que l'intégration de l'expertise du domaine avec l'intelligence basée sur les données améliore la performance prédictive, offrant ainsi un cadre évolutif et adaptable pour les futurs efforts de déminage. Cette recherche contribue au développement des opérations humanitaires assistées par l'IA et constitue une base solide pour des stratégies de mitigation des mines terrestres plus efficaces.

Title : Integrating Military Expertise, Geographic Information Systems and Machine Learning for Post-War Landmine Clearance: A Knowledge-Driven Approach

Keywords : Humanitarian Demining, GIS, ML, Military Expertise

Abstract : The clearance of landmines and unexploded ordnance (UXO) in post-war environments remains a critical humanitarian and security challenge. Traditional demining efforts rely heavily on resource-intensive manual surveys and technological detection methods, yet they often suffer from inefficiencies due to incomplete spatial intelligence and environmental complexities. This research integrates Geographic Information Systems (GIS) and Machine Learning (ML) to enhance the prioritization and accuracy of landmine clearance operations. A novel approach is proposed that incorporates military expert knowledge into ML-driven risk assessment models, enabling more informed and adaptive decision-making. By leveraging spatial data, historical contamination records, terrain analysis, and remotely sensed imagery, the developed system optimizes hazardous area prediction, reducing uncertainty in the identification of mine-contaminated zones. The methodology is validated using real-world case studies from post-conflict regions, demonstrating its effectiveness in improving operational efficiency and safety. The results indicate that integrating domain expertise with data-driven intelligence enhances predictive performance, offering a scalable and adaptable framework for future demining efforts. This work contributes to the growing field of AI-assisted humanitarian operations, providing a robust foundation for more effective post-war landmine mitigation strategies.