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2025

University of the Witwatersrand, Johannesburg

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Mongala, Neo. (2025). Towards a reformed mining cadastre in South Africa through the assessment of Artisanal and Small-Scale Mining (ASM) [Master's dissertation, University of the Witwatersrand, Johannesburg]. WIReDSpace. https://hdl.handle.net/10539/50291

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University of the Witwatersrand

Faculty of Science

School of Geography, Archaeology and Environmental Studies

Towards a reformed mining cadastre in South Africa through the assessment of Artisanal and Small-Scale Mining (ASM)

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06 – December – 2025

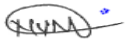
A research report submitted to the Faculty of Science, University of the Witwatersrand, Johannesburg, in partial fulfilment of the requirements for the degree of Master of Science (Geographical Information Systems and Remote Sensing) at the School of Geography, Archaeology & Environmental Studies

Declaration

I, **Neo Mongala**, hereby declare that this dissertation, titled **"Towards a Reformed Mining Cadastre in South Africa Through the Assessment of Artisanal and Small-Scale Mining (ASM),"** is my original work and has not been submitted to any other institution for the purpose of obtaining an academic qualification.

This research is the result of my independent investigation and analysis, except where otherwise acknowledged. All sources of information, including literature, datasets, and geospatial methodologies, have been properly cited in accordance with academic and ethical standards.

Furthermore, I affirm that this study adheres to ethical research principles, including transparency, integrity, and accuracy in the collection, processing, and interpretation of data. The use of **Google Earth Engine (GEE), Sentinel-2 imagery, NICFI datasets, and blockchain-based cadastral modeling** was conducted with the utmost scientific rigor and aligns with the objectives of this research.

Signature: 

Date: 06 – 12 – 2025

Abstract

This research presented an integrated remote sensing framework designed to reform South Africa's mining cadastre through the comprehensive assessment of artisanal and small-scale mining (ASM) activities. Utilising the Google Earth Engine (GEE) cloud computing platform and Geographic Object-Based Image Analysis (GEOBIA), the study mapped ASM activity within historical mine dumps in the Witwatersrand Basin, quantified their environmental impact, and assessed the feasibility of integrating ASM into a formalised, blockchain-based digital mining cadastre. The research leveraged multi-temporal Sentinel-2 and NICFI imagery processed through advanced algorithms to ensure high-quality data fusion. Spatial analysis from the study indicated that within the Ekurhuleni Municipality, the total mining cadastre area was approximately 105.80 km², with significant overlap identified in the region of interest, where registered large-scale operations coexisted with ASM activities. This underscored the need for a transparent cadastral framework to manage co-existing mining rights within the same geographic boundary. The classification process yielded perfect performance metrics (overall accuracy, precision, recall, and F1 scores of 1.00), affirming the robustness of the GEOBIA approach for identifying ASM activities. Temporal analysis revealed that ASM open-pit areas increased modestly from 0.014 km² in 2021 to 0.015 km² in 2022, followed by a decline to 0.011 km² in 2023, coinciding with intensified enforcement under Operation Vala Umgodi, and a partial rebound to 0.013 km² in 2024.

Concurrent ASM mining-induced deforestation trends demonstrated a steady rise in NDVI and EVI values until 2023, with a subsequent sharp decline in vegetation health coinciding with mining expansion in 2024, the latter being more pronounced in EVI due to its enhanced sensitivity to canopy structure. This study emphasised the superiority of EVI over NDVI for assessing mining-induced deforestation, given its sensitivity to high biomass areas and atmospheric conditions. The analysis detected ASM-induced vegetation loss from 2021 to 2024. NDVI analysis revealed a net vegetation loss of 0.013 km², while EVI detected a higher loss of 0.029 km², indicating that ASM activities had significantly altered biomass structure. Classified change maps confirmed that most stable areas coincided with detected ASM open pits. These findings underscored the necessity for a blockchain-based digital mining cadastre that leverages Unique Parcel Identifiers (UPIs) to mitigate overlapping permits, preventing illegal mining encroachment and ensure transparent mining rights management. This approach provides a scalable model for sustainable resource governance and regulatory reform in South Africa, by bridging geospatial analytics and blockchain technology. This research offers a scientific and policy framework for reforming South Africa's mining cadastre, ensuring that ASM contributes to economic development while minimising its environmental footprint. The proposed blockchain-integrated cadastral system could serve as a replicable model for resource governance in other mining economies facing similar challenges.

Keywords: ASM, Blockchain, Deforestation, GEOBIA, GEE, Mining Cadastre, Sustainable Mining

Acknowledgment

I extend my deepest gratitude to my supervisor, **Professor Paida Mhangara**, whose invaluable advice, patience, and insightful discussions have been instrumental in shaping this research. Your unwavering support, constructive feedback, and expertise in GIS and Remote Sensing have greatly enriched my academic journey. Your guidance has not only refined my research approach but has also instilled in me a deep appreciation for scientific rigor and critical thinking.

I also wish to express my sincere appreciation to **my lecturers and academic mentors** who have provided me with the foundational knowledge and technical skills necessary for this study. Your dedication to teaching and research excellence has significantly contributed to my intellectual growth and ability to conduct advanced geospatial analyses.

A special thank you goes to my **family and friends** for their unwavering encouragement, emotional support, and understanding throughout this demanding research journey. Your belief in my potential has been a source of strength, and your support has been invaluable in helping me remain focused and motivated.

I am profoundly grateful to the **Department of Agriculture, Land Reform, and Rural Development, Surveyor General's Office** for funding my studies and providing me with the opportunity to explore innovative solutions for mining cadastral management. It is my sincere hope that this research will contribute meaningfully to their ongoing efforts as cadastral data custodians in publishing a WebGIS platform that will facilitate the sharing of land cadastre data in the form of shapefiles. Such an initiative will not only enhance transparency and accessibility but will also prevent duplication of efforts and promote compliance with the Spatial Data Infrastructure (SDI) Act of 2003.

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Abbreviations and Acronyms

3D – Three-Dimensional

AI – Artificial Intelligence

AMD – Acid Mine Drainage

API – Application Programming Interface

ASM – Artisanal and Small-Scale Mining

ASL – Above Sea Level

BSI – Bare Soil Index

CIL – Carbon-in-Leach

CSI – Clay Silica Index

CSV – Comma-Separated Values

DLT – Distributed Ledger Technology

DMRE – Department of Mineral Resources and Energy

EIA – Environmental Impact Assessment

EITI – Extractive Industries Transparency Initiative

EVI – Enhanced Vegetation Index

GEE – Google Earth Engine

GEOBIA – Geographic Object-Based Image Analysis

GeoJSON – Geographic JavaScript Object Notation

GIS – Geographic Information System

GLCM – Gray-Level Co-occurrence Matrix

GNSS – Global Navigation Satellite System

HTI – Hydrothermal Index

IOI – Iron Oxide Index

IoU – Intersection over Union

ISO – International Organization for Standardization

KML – Keyhole Markup Language

LGAF – Land Governance Assessment Framework

LULC – Land Use and Land Cover

LSM – Large-Scale Mining

MDI – Mining Disturbance Index

MODIS – Moderate Resolution Imaging Spectroradiometer

MSAVI2 – Modified Soil Adjusted Vegetation Index 2

MSI – MultiSpectral Instrument

NDVI – Normalised Difference Vegetation Index

NDWI – Normalized Difference Water Index

NICFI – Norway's International Climate and Forest Initiative

NIR – Near-Infrared

NSIF – National Spatial Information Framework

OA – Overall Accuracy

OGC – Open Geospatial Consortium

PI – Parcel Identifier

QA60 – Quality Assessment 60-meter band (Sentinel-2)

QGIS – Quantum Geographic Information System

QML – Quantum Machine Learning

REEs – Rare Earth Elements

RF – Random Forest (Classifier)

ROI – Region of Interest

RS – Remote Sensing

SASDI – South African Spatial Data Infrastructure

SAMRAD – South African Mineral Resources Administration System

SAVI – Soil Adjusted Vegetation Index

SDGs – Sustainable Development Goals

SDI – Spatial Data Infrastructure

SEEDS – Superpixels Extracted via Energy-Driven Sampling

SNIC – Simple Non-Iterative Clustering

SR – Surface Reflectance

SWIR – Short-Wave Infrared

TEAL – Transaction Execution Approval Language (Algorand)

TI – Tailing Index

UPI – Unique Parcel Identifier

WebGIS – Web-Based Geographic Information System

1. INTRODUCTION

Artisanal and small-scale mining (ASM) is a critical socio-economic activity in many resource-rich countries, providing livelihoods for millions of individuals while contributing significantly to mineral production (Barenblitt et al., 2021). However, ASM also presents numerous challenges, including environmental degradation, unregulated resource extraction, and conflicts over land use (Hilson et al., 2019). In South Africa, ASM has a long history intertwined with the country's broader mining sector, which has been a cornerstone of its economy for over a century (Mhangara et al., 2020). Despite its significance, ASM activities often remain informal or illegal, exacerbating their environmental and social impacts (Konguka et al., 2022).

The Witwatersrand Basin, located in Gauteng Province, is one of the most mineral-rich regions globally and a focal point for ASM activities (Creamer, 2023; Chingwaru et al., 2023). Historical mine dumps and abandoned shafts in areas such as Ekurhuleni Municipality provide opportunities for small-scale miners to extract residual gold (Dixon et al., 2021). However, these activities have profound implications for environmental management, land use planning, and socio-economic stability (Chingwaru et al., 2024). Current governance structures, including South Africa's mining cadastre, face limitations in effectively monitoring and managing these activities, highlighting the need for reform (Tang et al., 2023).

Geospatial technologies offer powerful tools for addressing ASM challenges (Barenblitt et al., 2021). These technologies enable the detection and monitoring of mining activities, the quantification of their impacts, and the integration of spatial data into decision-making processes (Mhangara et al., 2020). For example, high-resolution satellite imagery and spectral indices such as the Normalised Difference Vegetation Index (NDVI) and the Mining Disturbance Index (MDI) are effective in identifying ASM-induced land cover changes (Maus et al., 2020). The incorporation of cloud-based platforms like GEE further enhances the scalability and efficiency of these analyses (Zhang et al., 2021).

In addition to geospatial tools, emerging technologies such as blockchain have the potential to revolutionise mining governance. Blockchain-based systems can enhance the transparency and security of mining cadastres by providing immutable records of mining rights and transactions (Gaur et al., 2023). The integration of blockchain with GIS offers a novel approach to ensuring accountability and reducing corruption in resource management (Nivas et al., 2020). In the South African context, such innovations could address longstanding issues in ASM governance, paving the way for more sustainable and equitable mining practices (Matshusa and Leonard, 2022).

This research aimed to assess ASM activities within the Witwatersrand Basin using Geographic Information Systems (GIS) and Remote Sensing (RS) tools and to explore the potential for mining

cadastre reform through the integration of advanced geospatial technologies. Specifically, the study focused on the detection of ASM activities in Ekurhuleni Municipality, quantifying their spatial footprint and environmental impacts. By combining high-resolution satellite data, spectral analysis, and machine learning classification, this research provided actionable insights to support sustainable mining governance. Furthermore, it examined how blockchain technology can be integrated into mining cadastre systems to enhance transparency, efficiency, and inclusivity. This research thus sought to bridge the gap between advanced geospatial techniques and innovative governance models, contributing to a reformed mining cadastre system that balances economic development with environmental stewardship. By adopting this integrated approach, South Africa can better harness the potential of its mining sector while ensuring sustainable use of its natural resources (Matshusa and Leonard, 2022)..

1.1 Significance of the research

The study was significant on multiple fronts, as it addressed critical gaps in South Africa's mining rights management and provided actionable insights for integrating advanced geospatial technologies to improve ASM management by leveraging state-of-the-art remote sensing and geospatial processing techniques via the GEE platform. The research contributed to both academic knowledge and practical policy reform, with implications that extend beyond the national context. The study's detection of overlapping mining activities highlighted a systemic regulatory failure that leads to the double-granting of mineral rights (Konguka et al., 2022). This overlap not only fosters corruption but also impedes effective resource management and equitable economic development (Ledwaba et al., 2020). By providing spatially explicit evidence of these overlaps, the research underscored the urgent need for digital reform. The proposed blockchain-based cadastre system, when integrated with the remote sensing framework, would create a secure audit trail, ensuring that each mining permit is uniquely identified and transparently managed (Gaur et al., 2023). This has profound implications for mitigating regulatory lapses and enhancing governance in the mining sector (Mhlongo et al., 2019).

This research equipped policymakers with empirical evidence and geospatial insights to guide reforms in the mining sector. The ability to detect and monitor ASM operations over time, as evidenced by the study's analysis of ASM expansion and contraction influenced by initiatives like *Operation Vala Umgodi* which caused spatial displacement of ASM operations, underscored the need for informed policy interventions. The integration of such data into decision-making frameworks will ensure that mining rights are allocated responsibly, and that land-use planning aligns with environmental and social priorities**.** These findings provided valuable insights into the ecological footprint of ASM and serve as a critical input for environmental remediation and sustainable land management policies (Yang et al., 2018). The ability to monitor vegetation changes in near real-time using GEE reinforced the utility of remote sensing as a decision-support tool for regulatory agencies.

Despite the growing recognition of ASM's impact on land use and ecosystems, limited research exists on leveraging advanced geospatial tools for its assessment and regulation (Gabriel et al., 2023). This study filled a critical knowledge gap by showcasing the application of GEOBIA and vegetation indices in ASM monitoring. It set a precedent for future research and provides a roadmap for incorporating geospatial intelligence into national mining cadastre systems. This research was significant for its innovative integration of advanced remote sensing algorithms, robust object detection techniques, and blockchain technology into a unified framework for a reformed mining cadastral management. By addressing critical issues of transparency, regulatory overlap, and environmental degradation, the study not only contributed to academic discourse but also provided actionable insights for policymakers, regulatory bodies, and industry stakeholders. The approach outlined herein promises to enhance sustainable resource management and equitable economic development in South Africa, while also offering a scalable model for global application.

1.2 Aim and Objectives

The primary **aim** of this research was to assess the spatial distribution, temporal dynamics, and environmental impacts of ASM activities as a foundation for reforming the national mining cadastre to promote sustainability, transparency, and regulatory compliance. The specific **research objectives** were as follows:

1. **Mining Cadastre Assessment and Spatial Analysis**: To identify the spatial distribution of mining areas and quantify their footprint within the study area, thus providing a robust basis for preventing overlapping mineral rights and promoting transparent governance in the mining sector,
2. **ASM Pit Detection and Growth Analysis:** To detect and analyse the spatial and temporal dynamics of ASM activities within the region of interest using advanced GEOBIA techniques and multi-temporal satellite imagery, to track the expansion of mining pits, assess their expansion over time, and estimate their growth trajectories. This provided critical insights into the dynamic nature of ASM and its evolving footprint in the study area.
3. **Mining-Induced Deforestation Assessment:** To analyse changes in vegetation and quantify the stability, gain, and loss of forested areas in relation to ASM activities to evaluate their environmental impact over time.

These objectives systematically addressed the research aim by combining advanced remote sensing techniques, spatial analysis, and digital transformation strategies to support the reform of South Africa's mining cadastre system. Each objective built upon the previous one, creating a comprehensive framework for understanding and managing ASM activities while promoting sustainable mining practices through improved cadastral management. This framework therefore sought to address the

challenges posed by the absence of a comprehensive mining cadastral system, quantify the spatial footprint of mining activities, and evaluate their environmental impacts, particularly deforestation (Hilson., 2020). The ultimate goal was to provide actionable insights for the establishment of a transparent, blockchain-based mining cadastral system that promotes sustainable mining practices, prevents the double-granting of mineral rights, and mitigates the socio-environmental challenges associated with ASM.

2. LITERATURE REVIEW

The literature review consolidated diverse strands of research, establishing the theoretical and practical foundations for a reformed mining cadastre system in South Africa. It highlighted the integration of advanced remote sensing techniques and blockchain technology as a promising pathway to enhance transparency, prevent overlapping mineral rights, and mitigate the environmental impacts of mining activities.

2.1 Overview of Artisanal and Small-Scale Mining (ASM)

The increasing prevalence of unlawful ASM actions has grown into a global concern and has garnered significant research attention (Nyamekye et al., 2021a). Previous studies have focused on the socio-economic and environmental impacts associated with ASM activities (Ngom et al., 2023). Although ASM has historical roots dating back to historical times, current worries revolve around issues of regulation, welfare, labour, socio-economic factors, and ecological impact (Bansah., 2023a). It is projected that at most 30 million individuals are involved in ASM internationally, particularly in ostracised communities in sub-Saharan Africa and South America (Utembe et al., 2015).

Artisanal mining is predominantly casual and unfettered in most parts of Africa, facing legal, trade, financial, and technological challenges (Gerassis et al., 2021a). While it contributes to poverty alleviation and the mainstream economy, it is also known for its harmful environmental effects compared to automated mining (Dreschler., 2001). Ecological harm caused by ASM includes deforestation, water pollution, land cover change and contamination by substances like mercury and cyanide (Xulu et al., 2021). Dust and smoke from ASM activities also contribute to air pollution, leading to health risks, such as tiger's-eye pneumoconiosis in South Africa (Mhangara et al., 2020).

ASM represents a critical livelihood strategy for millions globally, including South Africa. It contributes significantly to poverty alleviation, but its unregulated nature often results in adverse environmental and social impacts. According to Brown et al. (2022), ASM operations are generally characterised by informal practices, weak institutional oversight, and limited technological capabilities, which make their regulation challenging. In South Africa, ASM has emerged as a key issue in mining

governance due to its potential to generate income for marginalised communities but also its association with land degradation, deforestation, and resource conflicts (DeWitt et al., 2017). Addressing these challenges requires innovative monitoring and governance mechanisms that can adapt to ASM's dynamic and dispersed nature (Barenblitt et al., 2021).

In post-apartheid South Africa, ASM gained renewed attention due to its potential to support economic development in marginalised communities. The 1998 Minerals and Mining Policy recognised ASM as a sector requiring support and regulation (Ashanti., 2020.). However, implementation challenges, such as limited technical capacity and inadequate access to markets, have hindered formalisation efforts (Gallwey et al., 2020). Gauteng Province, the heart of South Africa's mining economy, is home to the Witwatersrand Basin, one of the richest gold reserves in the world. Historically, small-scale miners were integral to gold discoveries in the late 19th century, working alongside larger operations (Ledwaba, 2017). Over time, industrial mining became the predominant activity, relegating ASM to abandoned mines and marginal areas (Seccatore et al., 2014b).

Recent years have seen a resurgence of ASM in Gauteng, particularly in areas where historical mine dumps and abandoned shafts remain accessible (Konguka et al., 2022). The provincial government has initiated programs to formalise ASM operations, aiming to mitigate environmental degradation and integrate informal miners into the formal economy (Hilson., 2002a). However, illegal mining - commonly referred to as *zama-zama* activities - remains a persistent challenge. These activities are often associated with socio-economic vulnerabilities, crime, and environmental hazards, particularly in urban centers like Johannesburg (Chamber of Mines of South Africa, 2017). Ekurhuleni, part of Gauteng Province, has a long history tied to South Africa's gold mining legacy. Historically known as the East Rand, the city was a hub for industrial mining in the early 20th century (Todes et al., 2010). The municipality hosts numerous abandoned mines and tailings, making it a focal point for ASM activities (Matshusa and Leonard, 2022; Ashanti, 2020).

ASM in Ekurhuleni is predominantly informal and often illegal, driven by economic hardship and the availability of historical mining infrastructure (Chingwaru et al., 2022). The extraction of residual gold from tailings and mine dumps is the primary focus of ASM operations in the region (Ledwaba et al., 2020). However, these activities have significant environmental and social impacts, including water pollution, mercury contamination, and unsafe working conditions (Hilson., 2002b). According to Dixon et al., 2021, efforts to regulate ASM in Ekurhuleni have been met with mixed success. While initiatives like the Small-Scale Mining Support Program aim to formalise operations and improve safety standards, the lack of enforcement capacity and limited access to resources hinder progress (Gerassis et al., 2021a). Integrating GIS and remote sensing tools into local governance frameworks offers a promising approach to monitoring ASM activities and mitigating their impacts (Corbett et al., 2017).

2.2 Composition of Mine Dumps

Extensive research has explored the composition of mine dumps in the Witwatersrand Basin, revealing a complex mix of finely ground rock, residual gold, and associated minerals such as uranium and pyrite (Hilson, 2020). Historical gold extraction methods, noted for their inefficiency, left approximately 40% of the original gold content in tailings, sparking significant ASM efforts to recover these remnants (Ledwaba, 2017). Studies highlight the dual nature of these dumps as both environmental liabilities and economic resources, shaped by their mineralogical makeup (Chingwaru et al., 2023a).

Investigations into the presence of "invisible gold", ultrafine particles too small for conventional recovery, have identified three primary forms within the tailings. Submicroscopic gold is frequently embedded within sulfide minerals like pyrite and arsenopyrite, often as nanoscale inclusions or lattice-bound atoms, posing extraction challenges due to resistance to traditional cyanidation (Chingwaru et al., 2022; Ngom et al., 2022). Additionally, gold adsorbed onto mineral surfaces, particularly iron oxides and clays, are dispersed within aluminosilicate phases, further complicating liberation, necessitating advanced techniques such as roasting, ultrafine grinding, or bioleaching (Dixon et al., 2021). Chingwaru et al. (2024) estimate that these tailings retain substantial gold, underscoring their potential value.

ASM activities, driven by local miners known as zama zamas, rely on rudimentary methods like mercury amalgamation and cyanide leaching to target this residual gold, though these approaches are largely ineffective against invisible gold and contribute to environmental degradation (Volkov et al., 2017). Research indicates that prior reprocessing by large-scale mining companies has reduced recoverable gold concentrations, limiting ASM success (Shirmard et al., 2022). Environmental concerns dominate the literature, with elevated uranium levels linked to radioactive contamination and pyrite oxidation leading to acid mine drainage (AMD), affecting local water systems (Balaniuk et al., 2020). In response, scholars have explored modern reprocessing technologies, including bacterial leaching, pressure oxidation, and carbon-in-leach (CIL) methods, to enhance gold recovery sustainably (Ngom et al., 2023). Biohydrometallurgical approaches, using bacteria to break down sulfides, are gaining attention for their efficiency and reduced ecological footprint (Jones et al., 2019).

The spatially dispersed and transient nature of ASM further complicates systematic documentation and regulation (Mhangara et al., 2020). Socio-economic dimensions are also well documented (Konguka et al., 2022). Mine dumps pose risks to nearby communities through reduced property values and health hazards, yet they offer opportunities via re-mining and rehabilitation (Ashanti, 2020). Emerging cyanide free technologies and re-vegetation efforts aim to recover valuable metals while stabilising dumps and repurposing land, aligning with sustainable development goals (Volkov et al., 2017). This synthesis

underscores the need for advanced recovery methods and governance strategies to balance economic benefits with environmental stewardship in the Witwatersrand region (Dixon et al., 2021).

2.3 The Mining Cadastre System and Its Challenges in South Africa

The mining cadastre plays a central role in regulating mineral rights, recording concessions, and guiding sustainable extraction. Numerous studies and reports have highlighted systemic weaknesses within the mining cadastres that have undermined transparency, accountability, and investment confidence (Creamer, 2023; Konguka et al., 2022). Research indicates that administrative inefficiencies, such as protracted licence application processing and inconsistent record updates, have created uncertainty for both large-scale operators and ASM actors (Nyamekye et al., 2021b). These issues are compounded by technical limitations, including inadequate digital infrastructure and restricted public access, which inhibit external scrutiny and limit opportunities for stakeholders to monitor mineral rights allocations (Barenblitt et al., 2021).

Comparative evidence from other African countries underscores the significance of an effective cadastre in improving governance outcomes (Konguka et al., 2022). For example, Ghana's transition to an online mining cadastre system enhanced transparency by allowing real-time access to license data, while Tanzania's Mining Cadastre Portal facilitated external oversight and reduced opportunities for corruption (Gaur et al., 2023). In contrast, South Africa's reliance on an outdated and partly closed system has left it vulnerable to overlapping rights allocations, conflicting claims, and disputes that erode confidence in regulatory institutions (Ledwaba et al., 2020). This lack of transparency has been cited by both scholars and industry observers as a major obstacle to addressing illegal ASM, since reliable information on rights and concessions is a prerequisite for distinguishing authorised from unauthorised operations (Mhlongo et al., 2019).

The governance implications of these cadastre weaknesses extend beyond administrative inefficiency. Scholars emphasise that opaque and inaccessible systems create fertile ground for informal mining practices to flourish (Hilson et al., 2019). Without accurate, timely, and accessible data, enforcement agencies are hampered in their efforts to detect and address illegal mining, while communities remain excluded from decision-making processes that affect local land use. The result is a cycle of weak compliance, escalating environmental impacts, and diminished public trust in the mining sector.

Emerging literature suggests that integrating digital innovations, such as blockchain, could address several of these shortcomings by providing immutable, decentralised, and transparent records of mineral rights transactions (Gaur et al., 2023; Nyamekye et al., 2021a). Such integration would not only reduce opportunities for manipulation but also create a verifiable record of ASM related activities, enabling

both regulators and the public to hold operators accountable. Synthesising these insights highlights that the challenges facing South Africa's mining cadastre are not simply bureaucratic but represent a broader governance gap that requires both institutional reform and technological innovation (Xulu et al., 2021).

2.4 The Role of GEE and Machine Learning in ASM Detection

Recent advances in remote sensing have established GEE as a transformative platform for large-scale environmental monitoring, particularly in detecting and analyzing ASM activities (Tamiminia et al., 2020; Velastegui-Montoya et al., 2023). The integration of machine learning with GEE's computational infrastructure has enabled researchers to overcome traditional limitations in processing multi-temporal, multi-sensor datasets at continental scales (Tamiminia et al., 2020; Crowley et al., 2023). The literature demonstrates that successful ASM detection relies on a multi-layered analytical approach combining data fusion, feature extraction, and advanced classification. Studies by Zhang et al. (2021) and Chen et al. (2018) have demonstrated that integrating Sentinel-2's spectral richness with higher-resolution planet scope imagery significantly enhances the detection of small-scale mining features that may be overlooked when using single data sources. This fusion approach capitalizes on the complementary strengths of different satellite systems to create composite datasets optimized for feature identification (Majji et al., 2022).

Feature extraction methodologies have evolved beyond conventional spectral indices to incorporate textural and morphological characteristics. Research by Liu et al. (2023) and Marghany (2020) demonstrates that Gray-Level Co-occurrence Matrix (GLCM) texture analysis provides crucial spatial pattern information that helps distinguish mining disturbances from natural landscapes. Concurrently, edge detection algorithms coupled with morphological operations have proven effective in refining the boundaries of mining pits and tailings, enabling precise demarcation of ASM features (Lu et al., 2024). These advanced feature extraction techniques captured both spectral and spatial patterns essential for accurate classification. Object-based image analysis (GEOBIA) has emerged as a superior alternative to pixel-based methods for ASM monitoring. The Simple Non-Iterative Clustering (SNIC) algorithm with seed points, optimized within GEE's computational environment, efficiently generates homogeneous image objects that form the basic units for classification (Tassi and Vizzari, 2020; Karakuş, 2024). This approach incorporates spatial context and reduces salt-and-pepper noise commonly associated with traditional classification techniques, as evidenced in mining detection studies across diverse geographical contexts (Van Der Werff et al., 2024; Wu et al., 2024).

Machine learning classifiers, particularly Random Forest, have demonstrated consistent efficacy in handling the high-dimensional feature spaces common in ASM detection. Studies by Magidi et al. (2021) and Gallwey et al. (2020) confirm that ensemble methods like Random Forest effectively

manage the spectral heterogeneity of mining landscapes while minimizing overfitting through built-in regularization. The algorithm's ability to process diverse inputs including spectral bands, vegetation indices, texture features, and segmentation outputs, makes it particularly suitable for the complex classification tasks inherent in ASM monitoring (Xulu et al., 2021). The integration of these methodologies within GEE's cloud-computing environment represents a significant advancement in ASM monitoring capabilities. As noted by Liang et al. (2023) and Velastegui-Montoya et al. (2023), GEE enables the processing of multi-temporal datasets at scales previously impractical with desktop systems, while maintaining computational efficiency. This technological synergy has facilitated the development of robust monitoring frameworks capable of achieving high accuracy metrics (Overall Accuracy > 0.95) in detecting ASM activities across varied landscapes (Tang et al., 2023; MacDonald et al., 2023).

Collectively, these technological advances have established a new paradigm in ASM monitoring, moving from isolated case studies to systematic, large-scale detection systems. The integration of GEE's computational power with sophisticated machine learning algorithms has created unprecedented opportunities for understanding the spatial and temporal dynamics of artisanal mining, with significant implications for environmental governance and resource management (Wu et al., 2024; Barenblitt et al., 2021). Bringing together these techniques yields powerful ASM mapping capabilities. Recent research by Tang et al. (2023) and Maus et al. (2020) has demonstrated end-to-end GEE based workflows, for example, image segmentation (via SNIC), combined with Random Forest classification and GLCM texture inputs, can precisely delineate open pits in complex environments. Indeed, by merging spectral indices, object-based segmentation, and machine learning, these advanced approaches "have the potential to significantly improve the classification accuracy and monitoring of environmental impacts associated with artisanal mining". In other words, the scholarly consensus is that GEE-enabled remote sensing, underpinned by objected based image analysis and machine learning, greatly enhances our ability to detect, quantify, and track ASM activities at scale, compared to traditional monitoring methods (Xulu et al., 2021; Cechim et al., 2023).

2.5 Environmental Impacts of ASM

The environmental impacts of ASM are profound, including deforestation, loss of biodiversity, and contamination of water resources with heavy metals such as mercury and arsenic (Chingwaru et al., 2023a). Remote sensing studies have consistently highlighted ASM-induced deforestation, with Sentinel-2 and Landsat imagery serving as key data sources for quantifying vegetation loss (Sedona et al., 2020). These satellite imagery, allows for the observation of changes in land cover and land use over time, which is essential for detecting the expansion of ASM operations and their environmental impacts (Mhangara et al., 2020). Satellite data from platforms such as Landsat, MODIS, NICFI, and

Sentinel-2 has been widely used for monitoring deforestation, soil degradation, and water pollution in mining areas (Wu et al., 2024).

Vegetation indices play a central role in detecting ASM driven environmental change (Ogunro et al., 2022). Indices such as the NDVI and EVI are widely used to quantify vegetation loss in mining areas. Studies by Osei et al. (2021) and Shirmard et al. (2022b) demonstrate how declines in NDVI/EVI reliably indicate forest disturbance from mining, making these indices sensitive proxies for ASM induced deforestation. In practice, researchers compute NDVI/EVI time-series across ASM hotspots to reveal trends in canopy health. By comparing index values before and after mining expansion, one can directly link ASM activity to vegetation decline as demonstrated by Wu et al. (2021). GEE's multi-temporal analysis tools facilitate exactly this kind of time-series monitoring: for instance, Zurqani et al. (2024) used GEE to map global forest change annually, and the same methods are now applied to ASM sites. Thus, satellite indices analysed via GEE allow for robust quantification of ASM's environmental footprint over time.

Remote sensing technologies have revolutionised environmental monitoring, providing valuable insights into land-cover changes associated with mining activities (Zhang et al., 2021). Platforms like GEE offer unparalleled capabilities for processing large volumes of satellite imagery, enabling high-resolution analysis of vegetation loss, land-use dynamics, and anthropogenic impacts. Studies by Osei et al. (2021) and Nyamekye et al. (2021a) highlight the utility of vegetation indices such as the NDVI and EVI in detecting environmental changes caused by ASM. These indices are sensitive to changes in vegetation health, making them suitable for assessing mining-induced deforestation (Karakus, 2024).

The NDVI and EVI indices are widely used in vegetation monitoring, each with unique strengths. NDVI is a robust indicator of vegetation density and health, leveraging the difference between near-infrared and red spectral bands (Chen et al., 2018). However, NDVI is prone to saturation in areas of high vegetation density and is sensitive to atmospheric effects. EVI, by contrast, incorporates an additional correction for atmospheric and soil background noise, making it more effective in areas with dense vegetation (Hilson et al., 2019). Recent research comparing these indices by Gabriel et al., (2022) suggests that EVI provides more reliable assessments of vegetation health in dynamic environments, particularly those affected by mining.

Monitoring vegetation dynamics is essential for assessing the environmental impacts of mining activities. Vegetation indices such as the NDVI and the EVI are widely used to evaluate changes in vegetation health and cover. Chen et al., 2018 and Marlecha et al., 2016 have highlighted the effectiveness of these indices in capturing subtle variations in vegetation due to land disturbances. In mining regions, declines in NDVI and EVI can serve as proxies for deforestation and ecosystem degradation (Seki et al., 2020). The present research leverages these indices to document significant

vegetation loss in areas experiencing intensified ASM activity, thereby linking mining operations directly with environmental degradation, both indices are employed to capture a comprehensive picture of ASM's environmental impacts. The observed trends in NDVI and EVI time-series data align with mining-induced deforestation, with EVI showing greater sensitivity to subtle changes in vegetation.

2.6 Blockchain-Based Mining Cadastral Systems

Blockchain technology has gained increasing attention in recent years as a tool for improving transparency, trust, and accountability in governance systems processes (Dhillon et al., 2017). At its core, blockchain provides a decentralised, immutable ledger of transactions, ensuring that records cannot be altered without consensus (Bambara and Allen, 2018). In the mining sector, scholars and practitioners have argued that blockchain-enabled cadastres can help address persistent governance challenges, including overlapping mineral rights, corruption, and limited public access to records (Nyamekye et al., 2021a). By providing secure, verifiable, and real-time updates of mineral concessions, blockchain can create an environment of trust among government agencies, industry stakeholders, and local communities (Gaur et al., 2023).

International examples illustrate the potential of blockchain integration into land and mineral rights systems. In Ghana, blockchain-based pilot projects for land registration demonstrated significant improvements in record security and accessibility (Barenblitt et al., 2021). Tanzania has explored blockchain applications to strengthen mineral rights management, providing transparent transaction histories that can be audited independently (Konguka et al., 2022). These initiatives show that blockchain can overcome limitations of conventional cadastre systems by decentralising control and enabling open verification of transactions (Bansah, 2023).

From a sustainability perspective, blockchain-enabled cadastres are particularly valuable for managing ASM (Yang et al., 2018). Research indicates that a transparent and tamper-proof record of mineral rights reduces opportunities for illegal operations by clearly delineating concession boundaries and ownership rights (Konguka et al., 2022). Furthermore, integrating spatial data into blockchain records allows remote sensing outputs, such as detected ASM sites, to be directly linked with verified cadastral information. This integration supports both enforcement and formalisation efforts by ensuring that unauthorised operations are rapidly identified and addressed (World Bank, 2019).

However, the literature also cautions that blockchain is not a stand-alone solution. Studies note that successful implementation requires supportive institutional frameworks, adequate technical infrastructure, and policies that balance openness with data protection (Nivas et al., 2020). Without these, blockchain adoption risks reinforcing existing inequalities by privileging actors with greater technological capacity. Thus, while blockchain offers strong potential for modernising mining

cadastres, it must be embedded within broader governance reforms and aligned with local realities of ASM management (Shirzad et al., 2014). Synthesising these insights, blockchain-based cadastral systems provide a conceptual pathway for addressing South Africa's cadastre challenges. By ensuring transparent, verifiable, and accessible mineral rights records, blockchain could strengthen ASM governance, reduce disputes, and promote sustainable exploitation of mineral resources (World Bank, 2019). When integrated with geospatial monitoring frameworks, blockchain technology can move the cadastre from being a static repository of rights to an active governance tool capable of supporting sustainable mining practices (Konguka et al., 2022).

2.7 Implications for Sustainable Mining Governance

Sustainable mining governance requires a multi-faceted approach that combines technological innovation with policy reform. This research demonstrates the potential of integrating remote sensing, geospatial analysis, and blockchain technology to modernise South Africa's mining cadastre system. Similar studies, such as those by Hilson et al. (2019), emphasise the importance of participatory governance and community involvement in regulating ASM. The reviewed literature highlights that effective ASM governance requires a combination of institutional reform, technological innovation, and community engagement. Remote sensing offers scalable and cost-efficient monitoring of mining-related disturbances, while machine learning and object-based approaches enhance the accuracy of ASM detection. Blockchain-enabled cadastres can provide the transparency and trust necessary to support regulatory enforcement and reduce conflicts over mineral rights. Together, these tools suggest that the integration of geospatial monitoring with secure digital governance frameworks has the potential to transform ASM management from a reactive, enforcement-driven model into a proactive system of sustainable oversight (Nyamekye et al., 2021a; Barenblitt et al., 2021).

Importantly, the literature emphasises that technological solutions alone are insufficient without supporting institutional capacity and community participation. Successful governance depends on policies that ensure equitable access to cadastral information, safeguard environmental sustainability, and recognise ASM as a legitimate livelihood activity when conducted within a regulated framework (Hilson, 2020; Mhlongo et al., 2019). By linking geospatial monitoring with transparent rights management, governments can reduce the risks of environmental degradation and conflict, while also creating pathways for ASM formalisation and sustainable economic development.

2.8 Gaps in Current Research

Although significant progress has been made in applying remote sensing and blockchain to ASM governance, several gaps remain. Firstly, most studies have focused on either detection methods or cadastral reform in isolation, with few attempts to integrate these approaches into a unified framework.

Secondly, while Random Forest and other machine learning classifiers have achieved high accuracy in experimental contexts, there is limited research on their operational deployment within resource-constrained government agencies. Thirdly, blockchain applications in mineral governance remain largely at the pilot stage, with little empirical evidence on their long-term sustainability, scalability, or socio-political impacts (Gaur et al., 2023; Shirzad et al., 2014).

A further gap concerns the contextual adaptation of these technologies to South Africa. While international studies provide valuable precedents, they do not fully account for the unique governance challenges of the South African mining sector, such as overlapping rights allocations, legacy mine dumps, and the persistence of large-scale illegal ASM networks. More research is needed to test integrated geospatial and blockchain solutions under these conditions and to evaluate their potential for strengthening transparency, compliance, and sustainability in the national mining cadastre. (Nivas et al., 2020).

3. DATA AND METHODOLOGY

The methodology for this research was structured into three interconnected phases. Each phase employed advanced GIS and RS techniques using the GEE cloud platform, supported by post-processing in QGIS and Google Earth. The methodology aimed to delineate mining cadastre areas, assess ASM activity footprints, and evaluate deforestation caused by ASM operations. The overall objective was to evaluate the geographical distribution of ASM mining activities, their spatial displacement, and their environmental impact.

3.1 Description of the study area

Ekurhuleni is situated on the highveld plateau at an altitude of approximately 1600 meters above sea level (asl) (Figure 1). The peak point in the city is Gillooly's Ridge – Bill Stewart Side – Fisher's Hill, reaching 1772 meters asl. On the other hand, the lowest point lies at 1552 meters asl. The region is characterised by an abundance of wetlands, pans, streams, and rivers. Despite being highly urbanised, the northern part of Ekurhuleni possesses fertile agricultural land with significant potential (Matshusa and Leonard, 2022).

Most of the precipitation occurs between October and March, with an average monthly precipitation of up to 148 mm. This precipitation is typically in the form of convective thundershowers. In the months of October to March, the average daily maximum temperatures hover around 27°C. Winters in Ekurhuleni are predominantly dry, with only a few cold fronts reaching the highveld from the southern Atlantic Ocean (Matshusa and Leonard, 2022). The total area of Ekurhuleni is 1,975 square kilometers

(763 square miles), and it has a population of approximately 3,178,470 people. The population density is around 1,600 individuals per square kilometer (4,200 individuals per square mile) (Todes et al., 2010)

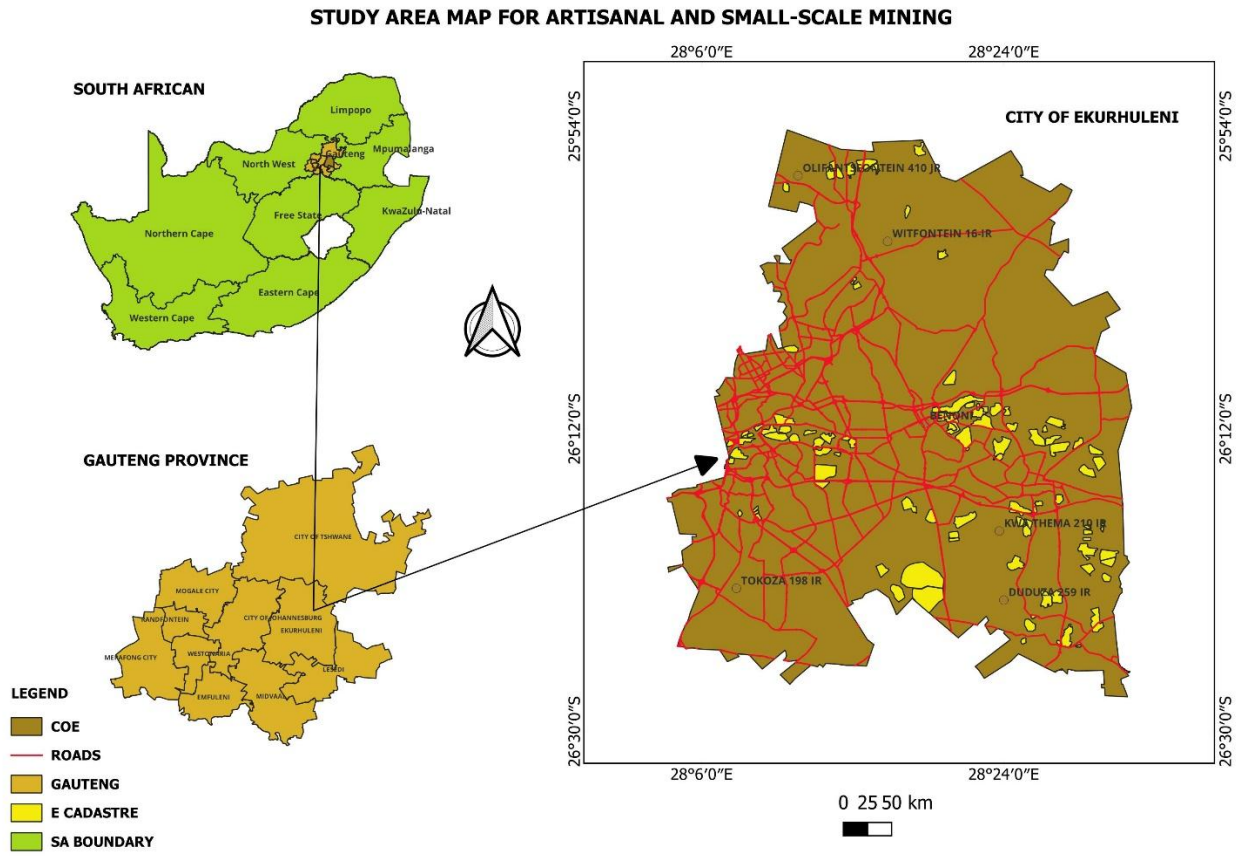


Figure 1: The City of Ekurhuleni Metropolitan Municipality Location within the Gauteng Province

3.2 Software and Data Used

Software

The analysis for this research leveraged a combination of powerful geospatial software platforms to ensure comprehensive and efficient geospatial data processing and visualisation.

1. Google Earth Engine (GEE): GEE served as the primary analytical platform for the spatial data processing. It is a cloud-based geospatial platform with advanced capabilities for handling massive datasets through its integrated Python and JavaScript API (Wu et al., 2024). GEE provided access to a wide array of publicly available geospatial datasets and offered the computational power necessary for tasks such as raster analysis, image classification, and zonal statistics. Its cloud-based nature allowed for scalable processing as seen in Figure 2, making it ideal for analysing global mining footprints (Tang et al., 2023).

2. QGIS (Quantum GIS): QGIS, an open-source desktop GIS platform, was employed for additional data visualisation and spatial data integration tasks. It facilitated post-processing of outputs derived from GEE, as well as the creation of maps and figures for presenting results. QGIS also allowed for more detailed vector-based analysis and the customisation of spatial datasets (Crowley et al., 2023).

3. Google Earth Online Platform: The Google Earth online platform was used to visually explore mining sites and validate spatial features. Its high-resolution imagery, combined with an intuitive interface, supported qualitative assessments and comparative analyses for site-specific investigations.

Data

The study utilised a variety of datasets to conduct the analysis, ensuring high accuracy and spatial detail:

1. **Global Mining Footprint Dataset:** This dataset, derived from high-resolution satellite imagery, provided a global inventory of mining activities, enabling the identification and spatial delineation of mining footprints (Tang et al., 2023). It served as the primary data source for this research.
2. **Sentinel-2 Optical Imagery:** Sentinel-2 provides multispectral optical imagery with a spatial resolution of 10–60 meters, enabling detailed analyses of land cover and vegetation indices (Kulinan et al., 2024). This imagery was used to complement mining footprint data by visualising surrounding land cover changes and to assist in the qualitative validation of ASM mining footprint.
3. **Norwegian International Climate and Forest Initiative (NICFI) Planet Imagery:** The Planet-NICFI mosaics 4.77 meters high-resolution imagery from the PlanetScope satellites, available on subscription through GEE platform, was utilised to examine mining activities and surrounding areas at a finer spatial resolution. NICFI imagery offers unprecedented access to high-quality data for monitoring environmental changes in tropical regions, making it particularly valuable for analysing ASM activities (Gašparović et al., 2018).
4. **Artisanal Mining Data:** Ground-truth data from field surveys and local sources provided direct evidence of ASM activities. These image datasets of ASM open pits were critical for validating remote sensing results and refining the analysis. The integration of ground-truth data with remote sensing data helped to more accurately map the locations and extent of ASM operations.
5. **Google Earth Imagery:** High-resolution imagery from the Google Earth platform was used to visually inspect and validate the spatial accuracy of identified mining footprints. Its time-series capabilities also allowed for comparative analyses of historical and current mining activities.

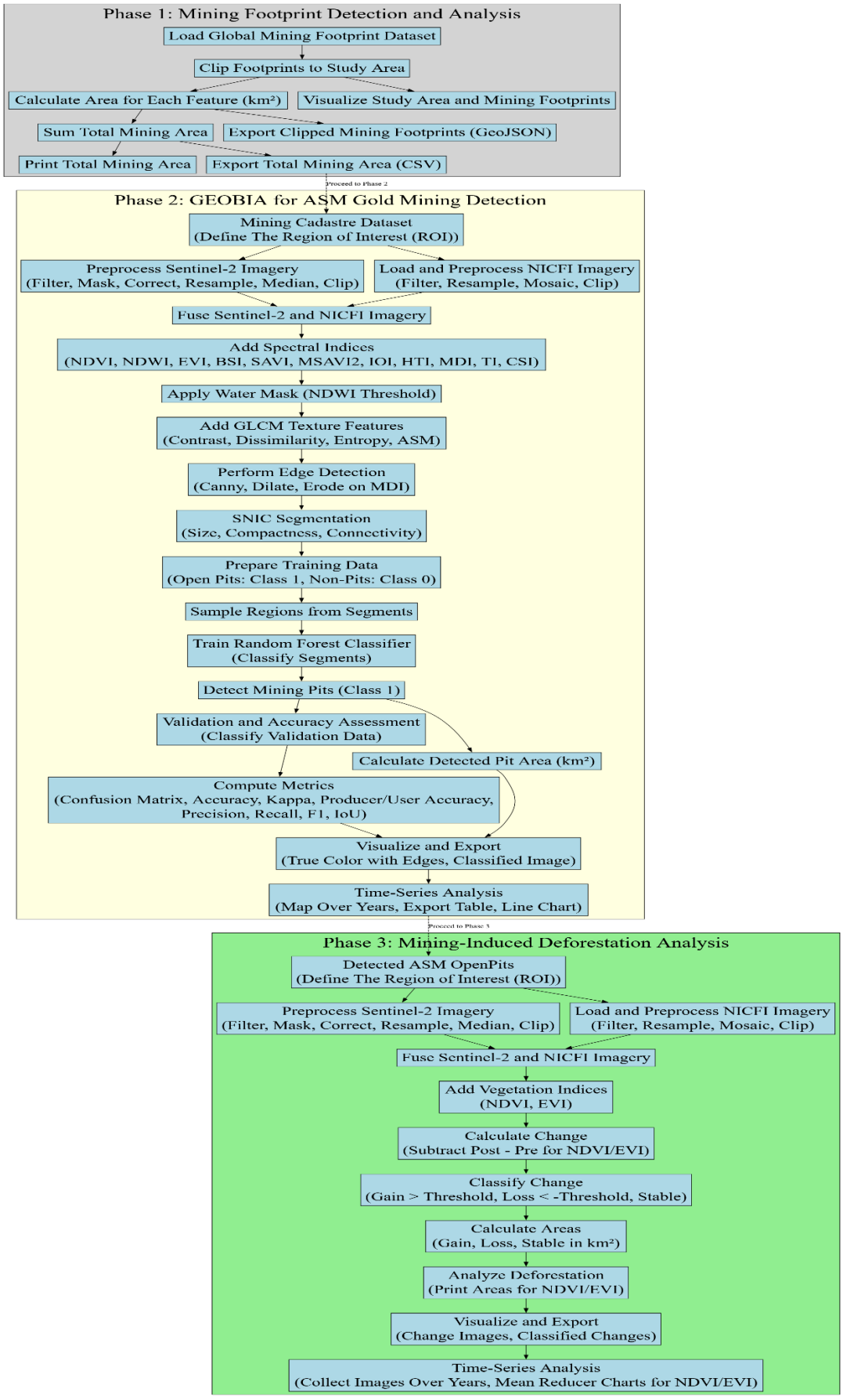


Figure 2: Research Methodological Flowchart

The combination of datasets and platforms enabled a comprehensive analysis of ASM activities, ensuring a robust spatial assessment. By integrating the high-resolution mining footprint dataset with Sentinel-2, NICFI, Google Earth imagery, ground-truth data from field surveys and local knowledge allowed for validation of remote sensing results and the calibration of detection algorithms (Gallwey et al., 2020). The research achieved a multi-scale perspective on ASM mining activities and their environmental impacts.

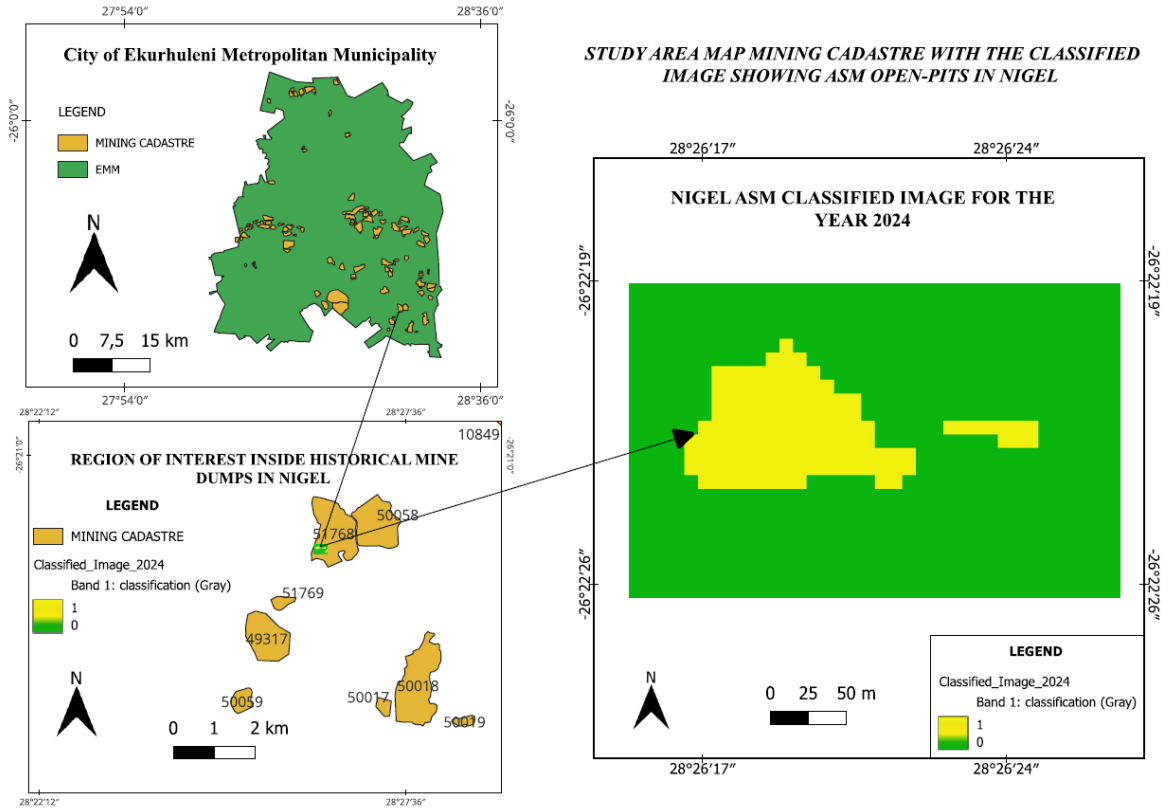


Figure 3: Location of the ROI within the Study Area

3.3 Phase 1: Mapping and Assessing the Mining Cadastre

This phase focused on identifying the spatial distribution of mining cadastre areas and quantifying their total footprint within the study area and assess the extent of ASM activities. The specific objectives included delineating the ROI as shown in figures 3 to 5, calculating the areas covered by formal mining operations, and detecting ASM activity footprints. Using GEE, the global mining footprints dataset was processed as follows:

1. **Data Preparation**: The global mining footprint dataset from GEE was used as the primary input to delineate mining activities. The dataset was acquired from the *projects/sat-io/open-datasets/global-mining/global_mining_footprints* (Tang et al., 2023) repository which was then loaded and clipped to the study area shapefile data imported into the GEE platform through the assets button

2. **Spatial Analysis**: The areas covered by mining footprints were calculated in square kilometers using GEE's geometry operations. This step quantified the extent of active mining operations as well as historical tailings dams as detailed below.

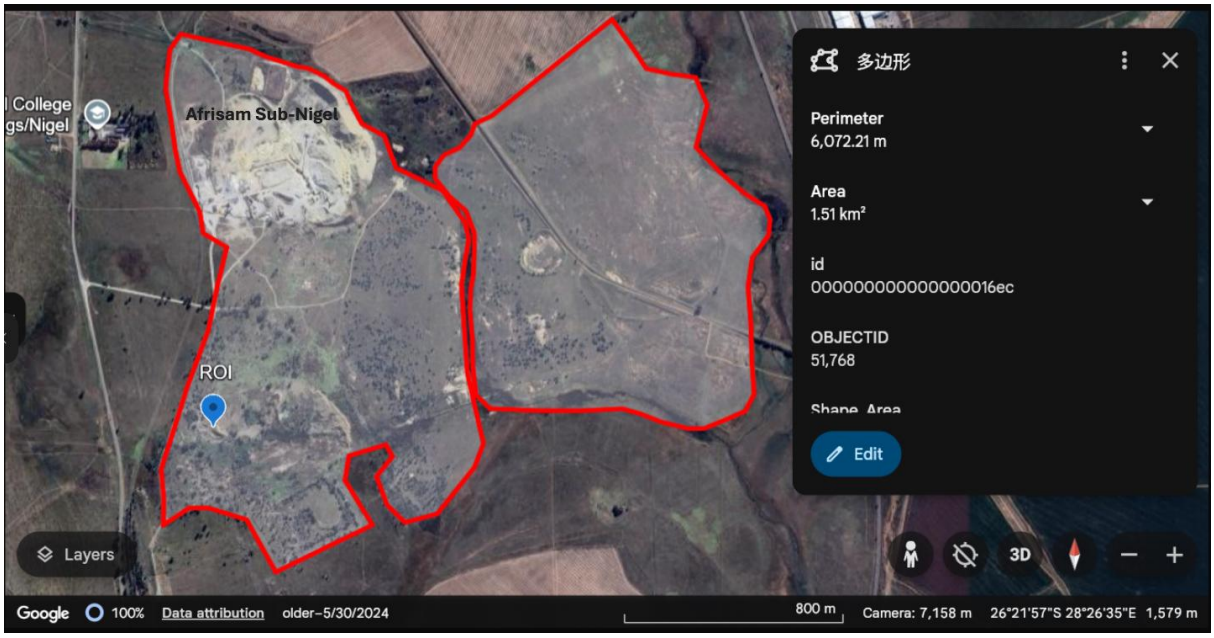


Figure 4: Google Earth online high-resolution imagery showing the ROI location within the mining cadastre with parcel ID 51768

Calculation of Mining Footprint Areas: To quantify the extent of mining activities, the area of each mining footprint within the study area was calculated. This was done using the geometry (). area () method, which computed the area in square kilometers. These area measurements were then added as a property (area_km2) to each mining footprint feature, enabling further statistical analysis of the mining footprint distribution. Additionally, the total mining area within the study area was calculated by summing the areas of individual mining footprints using the reduceColumns function. This provided a comprehensive assessment of the total extent of mining activities within the study area. Visualisation of the mining cadastre was achieved by overlaying the study area shapefile and clipped mining footprints on a base map in the GEE platform.

3. **Export and Validation**: The clipped mining footprint dataset was exported in GeoJSON format for further analysis in QGIS. The total mining area statistics were exported as a CSV file.

4. **Integration with QGIS and Google Earth**: QGIS was used to convert the GeoJSON data into KML format, which was then imported into the Google Earth online platform, this enabled the visualisation of mining cadastre areas with high resolution imagery from the platform to better view all mining activities in the municipality and within the ROI as seen in figures 4 and 5.

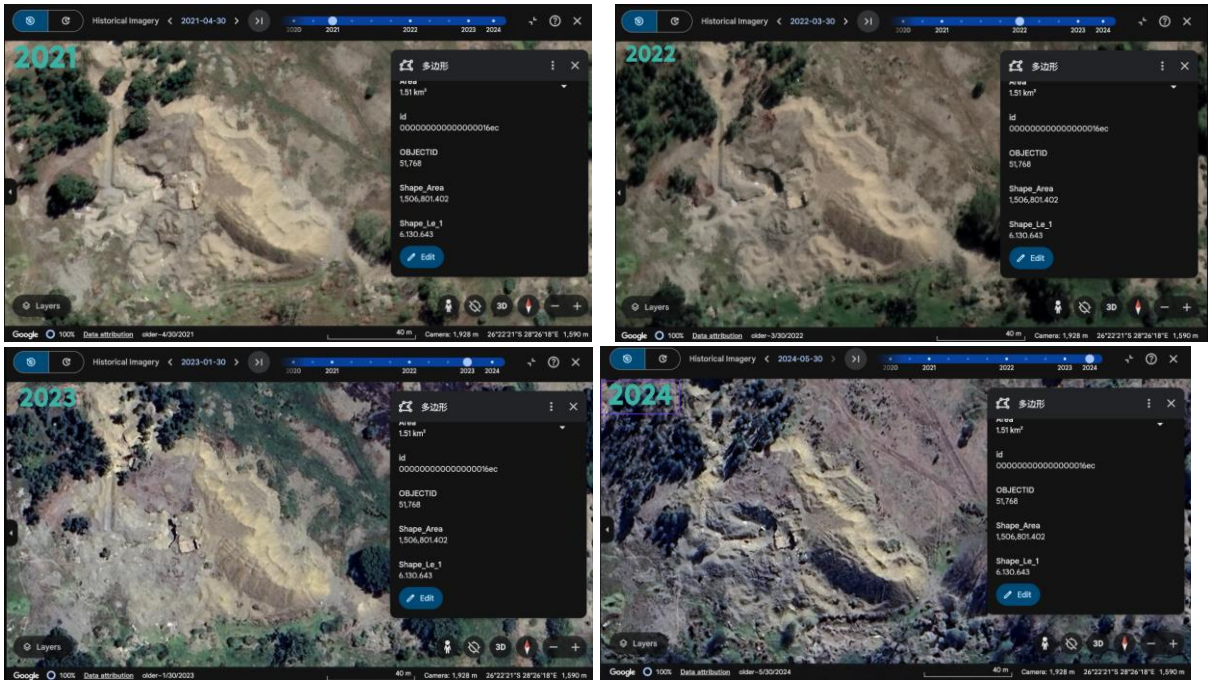


Figure 5: Google Earth online high-resolution imagery of the ASM open-pits growth pattern

5. Assessment of ASM Compatibility:

Field Validation: Ground truthing was an essential part of this methodology. Images of the mining site, labelled as Figure 6, were collected through field visits to confirm the presence of ASM operations. The field data imagery was crucial for verifying the authenticity of the detected ASM footprints and assessing their alignment with the spatial data provided by the remote sensing analysis.

Cross-Referencing with Operating Mines: The exported GeoJSON file was downloaded and further processed in QGIS for the conversion to the KML format, which is compatible with Google Earth. This KML file was then imported into Google Earth to visualise the location of the mining footprints relative to the operating mines boundaries. To validate the extent of ASM activities, the KML file was used to check whether the ROI shares a boundary with any registered active mines. Ground-truthing, supported by figures 4 to 6, confirmed the presence of ASM activities adjacent to the operational mine.

6. Selecting the Region of Interest (ROI)

The Google Earth Web's Historical Imagery tool proved to be an essential resource for this study, offering an efficient and effective way to track the temporal and spatial growth of ASM activities. Through the Google Earth Web platform, users can zoom into a specific location and select the date range of imagery they want to explore. By using the tool's timeline slider, a user can choose imagery from different years and compare the spatial features at different points in time as seen on figure 5. The ability to compare images from different time periods allowed for the identification of changes in ASM open-pits, providing valuable insights into the expansion of illegal mining in South Africa's mining

regions. The ability to visualise these changes on the platform played a pivotal role in assessing the environmental and regulatory challenges posed by ASM.

One of the primary uses of the Historical Imagery tool on the google earth online platform, in this study was to define the ROI as shown in figures 3 to 5, an area where ASM activities were suspected to occur. In this study, the ROI was identified based on initial field knowledge provided by my uncle, a former ASM worker in the area who had also advised on other ASM regions known for crimes and gangs. This local insight, combined with known mining zones, and the presence of historical mine dumps as shown on Figure 6, further informed the selection of the ROI. The imagery from several years were reviewed to observe any indications of ASM-related activities as seen from figure 5, such as open pits, mine dumps, foot paths, and informal settlements, which often accompany small-scale mining operations. This allowed for an accurate delineation of the area for further analysis, including cross-referencing with the global mining footprint dataset.

3.4 Phase 2: ASM Detection Using Advanced GEOBIA Techniques

This phase involved the detection and classification of ASM activities within the ROI using a GEOBIA framework. This phase used multi-sensor data fusion, spectral indices, and advanced classification techniques.

1. Data Preprocessing:

The preprocessing of satellite imagery was conducted within the GEE platform to ensure data quality and compatibility. For the Sentinel-2 Surface Reflectance (SR) data, the initial step involved filtering the MultiSpectral Instrument (MSI), Level-2A (SR) image collection to the ROI and the specified annual timeframe from 2021 to 2024, January to December of each year. A custom function was applied to perform cloud masking using the 'QA60' quality assessment band and shadow masking based on a reflectance threshold in the Near-Infrared (NIR) band (B8 > 0.15) (Wu et al., 2024). Atmospheric correction was inherently handled by the dataset's built-in Sen2Cor processor (Khadka et al., 2023). Subsequently, all images were resampled using a bicubic algorithm to enhance spatial consistency. The final preprocessed Sentinel-2 composite for each year was generated by calculating the median value from the cleaned collection, and retaining key spectral bands (Blue, Green, Red, NIR, SWIR1, SWIR2) (Koo et al., 2023). In parallel, NICFI PlanetScope basemaps were preprocessed by filtering the collection to the corresponding year, applying bicubic resampling to align with the Sentinel-2 data, and mosaicking the tiles into a single, high-resolution image clipped to the ROI. This standardized preprocessing of both datasets established a foundational, co-registered stack optimized for subsequent multi-sensor fusion and analysis (Jena et al., 2021).

2. Fusion of Imagery:

Sentinel-2 and NICFI imagery were merged to leverage Sentinel-2's spectral richness and NICFI's high spatial resolution, creating a comprehensive dataset for ASM analysis. The fusion of Sentinel-2 and NICFI imagery combined the strengths of both datasets, Sentinel-2's high spectral resolution (important for vegetation and mineral indices) and NICFI's high spatial resolution (useful for detailed analysis of small-scale activities). By combining data from different sources, the resulting fused image contained rich spatial and spectral information that improved the accuracy of mining feature detection (Zhang et al., 2021). This fusion was key for identifying ASM activities, which often require the analysis of both vegetation (for distinguishing disturbed vs. natural areas) and finer-scale spatial changes (for identifying physical mining pits).



Figure 6: Ground Truth Imagery of the ASM Open-Pits Workings

3. Spectral Indices and Their Relevance:

The study calculated a comprehensive set of standard spectral indices and mining-specific indices, as shown in Table 1, each serving different analytical purposes. NDVI, EVI, NDWI, BSI, SAVI, and MSAVI2. These are classical spectral indices used to monitor plant health, water stress, and vegetation cover. In the context of ASM, these indices assisted in identifying deforestation and land degradation. NDVI and EVI were particularly relevant for vegetation health and biomass, while NDWI helps identify water bodies, which was then used to mask out water bodies. Since mining activities may alter hydrological patterns, masking out water bodies ensured that open pits mining features were not misclassified as water bodies (Tassi and Vizzari, 2020).

Table 1: Computation of Spectral Indices for ASM Detection

Index Category	Index Name (Abbreviation)	Formula (as implemented in GEE)
Standard Indices	Normalised Difference Vegetation Index (NDVI)	(B8 - B4) / (B8 + B4)
	Normalised Difference Water Index (NDWI)	(B3 - B8) / (B3 + B8)
	Enhanced Vegetation Index (EVI)	2.5 * (B8 - B4) / (B8 + 6*B4 - 7.5*B2 + 1)
	Bare Soil Index (BSI)	((B11 + B4) - (B8 + B2)) / ((B11 + B4) + (B8 + B2))
	Soil-Adjusted Vegetation Index (SAVI)	(1.5 * (B8 - B4)) / (B8 + B4 + 0.5)
	Modified Soil-Adjusted Vegetation Index 2 (MSAVI2)	$(2*B8 + 1 - \sqrt{((2*B8+1)^2 - 8*(B8-B4))}) / 2$
Gold-Mining Indices	Iron Oxide Index (IOI)	(B4 / B2) * (B11 / B8)
	Hydrothermal Index (HTI)	(B12 / B8) * (B4 / B2)
	Mining Disturbance Index (MDI)	((B12 - B11)/(B12 + B11)) * ((B8 - B4)/(B8 + B4))
	Tailing Index (TI)	(B12 / B11) + (B12 / B8)
	Clay Silica Index (CSI)	$(B12^2) / (B11^2)$

Gold-Mining-Specific Indices included indices like Iron Oxide Index (IOI), Hydrothermal Index (HTI), and Mining Disturbance Index (MDI) which are designed to highlight mining disturbances (Shirmard et al., 2022). These indices were crucial for identifying gold extraction areas and mapping their spatial distribution. The Tailings Index (TI) and Clay Silica Index (CSI) assisted in detecting tailings deposits and distinguishing areas disturbed by mining processes, such as soil and mineral alterations associated with gold extraction. (Xulu et al., 2021).

4. Texture Analysis and Edge Detection:

GLCM (Gray-Level Co-occurrence Matrix): This added textural features (contrast, entropy, dissimilarity, ASM) to the spectral data. These features were particularly useful in detecting and characterising ASM pits, as they highlighted spatial patterns within the mining and surrounding environments, distinguishing between naturally occurring and mining-disturbed areas (Wu et al., 2024).

Edge Detection: The study used **Canny Edge Detection** and **Morphological Operations** (dilation and erosion) to refine the boundaries of mining pits. This step enhanced the detection of smaller-scale mining features and accurately demarcated pit edges, which was crucial for assessing the extent and growth of mining areas over time. Canny Edge Detection, this method detected edges by identifying areas where there was a sharp contrast in pixel intensity. It used two thresholds, one for edge detection (threshold = 0.6) and one for noise reduction (sigma = 1). Morphological Operations (Dilation and Erosion), these operations refined the edges by expanding and then shrinking the detected edges. Dilation emphasised the edges, while erosion removed noise or small irregularities (Koo et al., 2023).

5. Object-Based Classification:

SNIC Segmentation: The **Simple Non-Iterative Clustering (SNIC)** segmentation algorithm was applied to group pixels into homogeneous regions based on their spectral and textural properties. This step aided in creating meaningful objects for further classification, a crucial precursor to accurate object detection, especially for small or fragmented mining pits (Gxokwe et al., 2022).

SEEDS Algorithm (Superpixels Extracted via Energy-Driven Sampling): SEEDS is another algorithm for extracting superpixels, which works by first applying a grid-based initial segmentation, followed by a refinement process that merged nearby pixels with similar colour and texture. The refinement step helped to create superpixels that adhere more closely to object boundaries, thus improving the segmentation's spatial accuracy (Jena et al., 2021).

The SNIC algorithm was applied to the fused image, selecting specific bands related to spectral and texture features (e.g., NDVI, EVI, IOI, MDI, etc.). Key parameters such as compactness (3), connectivity (4), and neighbourhood size (2) control the behaviour of the segmentation, while a seed grid ensured the creation of superpixels with the specified characteristics. SNIC was ideal for generating initial, computationally efficient segments, grouping pixels based on similarity (Majji et al., 2022).

Training Data: The classification was supervised using training data derived from known open-pit mining and non-mining areas. These open-pit areas were identified using available ground truth image data (Fig. 6) and labelled as ‘1’, while non-mining areas were labelled as ‘0’ on the class property. The Random Forest machine learning classifier was employed to classify image segments based on the extracted features (e.g., texture, indices, and segmentation results). The classifier was trained using a set of labelled training data (e.g., points where the class of land cover is known). The algorithm used 369 decision trees to create a classification model. Each tree in the forest decides based on a subset of features, and the final classification was determined by a majority vote (Wu et al., 2024). This is important for accurately distinguishing between mining activities and other types of land cover in ASM regions. The classifier was trained using spectral and texture features, with an emphasis on those related to mining disturbance (IOI, HTI, MDI, CSI) (Tang et al., 2023; MacDonald et al., 2023).

6. **Validation and Metrics**:

Accuracy metrics, including the confusion matrix, overall accuracy, precision, recall, F1 score, and Intersection over Union (IoU), were computed to evaluate classification performance.

7. **Temporal and Area Analysis**:

Area Calculation: The Detected mining areas over time (2021-2024) were quantified, which was essential for understanding the extent of ASM activities. This step used pixel area multiplication and reduceRegion functions to compute the total mining area in square kilometers for each year. This quantification was vital for monitoring the expansion of mining activities over time and for assessing their environmental consequences.

Time-Series Analysis: The time-series analysis mapped the changes in the mining area over multiple years (2021-2024). This temporal dimension was critical for detecting trends, understanding seasonal variations in mining activity, and assessing how mining grows and interacts with surrounding environments. The results were visualised in a line chart that presented the total area of mining pits over the years.

3.5 Phase 3: Mining-Induced Environmental Assessment

The final phase quantified vegetation loss attributable to ASM activities. This phase investigated the environmental impacts of ASM, particularly mining-induced deforestation within the ROI. Multi-sensor data fusion and time-series analysis were utilised to detect ecological trends, enabling an analysis of vegetation dynamics pre- and post-mining.

1. **Multi-Sensor Fusion**:

Sentinel-2 and NICFI datasets were fused to enhance spatial and spectral analysis capabilities. Pre-processing steps similar to Phase 2 were applied to generate high-quality input imagery.

2. **Deforestation Detection**:

Forested areas were delineated using NDVI and EVI thresholds. Changes in vegetation cover were quantified over time using a pixel-based change detection approach. Pre-mining (2021) and post-mining (2024) imagery were compared to identify changes in vegetation indices (NDVI, EVI) due to ASM. ASM activity areas were overlaid on deforestation maps to identify direct and indirect impacts of mining on vegetation loss.

3. **Classification of Changes**:

A threshold-based classification identified areas of vegetation gain, loss, and stability.

4. **Quantification of Changes:**

Spatial extents of vegetation gain, loss, and stable areas were calculated in square kilometers. Vegetation indices such as NDVI and EVI were analysed to detect vegetation loss over time. Changes in forest cover were linked to ASM activities through spatial correlation.

5. **Temporal Analysis:**

A time-series analysis of NDVI and EVI over the years (2021–2024) was used to visualise the progression of deforestation linked to ASM.

6. **Validation:**

Results were exported as GeoTIFF files for further visualisation in QGIS and Google Earth, supplemented by ground-truth data.

Post-Processing and Reporting: Key outputs, including classified ASM areas, vegetation loss maps, and time series graphs, were visualised in the GEE's interface.

This methodology showcased the integration of advanced remote sensing techniques and cloud-based GIS for comprehensive ASM monitoring. The multi-phase methodology employed in this study is evidenced by the GEE scripts below, which were used to perform the analysis, ensuring that this method is repeatable. Thus, providing a robust framework for assessing the spatial and environmental dimensions of ASM activities within the city of Ekurhuleni metropolitan municipality.

3.6. The Google Earth Engine Scripts used to perform the analysis:

Phase 1: Mining Cadastre Spatial Analysis & Boundary Compliance Assessment

https://code.earthengine.google.com/5d597a4a3f7dac6059ef4ba2237e491c

Phase 2: ASM Detection Using GEOBIA & Multi-Temporal Fusion (2021–2024)

https://code.earthengine.google.com/3a1be330eeee53a1b19c92dba1075efd

Phase 3: Mining-Induced Deforestation Analysis (NDVI/EVI Trends, 2021–2024)

https://code.earthengine.google.com/18edcf4b9cc8b7d0188a52e93da602e1

4. RESULTS

This study identified critical discrepancies in the spatial distribution and land utilisation of ASM activities within the municipality. A key observation was the identification of overlapping mineral rights and unauthorised operations, which underscored the necessity for a reformed, transparent, and accessible mining cadastre to support sustainable mining and policy compliance in South Africa.

4.1 Spatial Analysis of the Mining Cadastre and Assessment of ASM Footprints

The spatial assessment revealed systemic inefficiencies within the mining cadastre, directly linking them to regulatory failures. Evidence of overlapping mining rights was identified, a condition that fostered corruption and illegal mining activities. The multi-temporal analysis of historical imagery from Google Earth confirmed progressive expansion of ASM mining pits and their feasibility to coexist on shared boundaries with large-scale mining operations, highlighting a critical governance gap.

4.1.1 Unique Parcel Identification and Spatial Conflicts

The total area of the mining cadastre within the Ekurhuleni Municipality, Gauteng, was calculated to be 105.803 km². When compared to the total municipal land area of 1,924.34 km², mining activities accounted for approximately 5.5% of the land use land cover (LULC). However, despite this relatively small spatial footprint, the mining sector had outsized environmental, economic, and governance implications due to conflicting land-use claims, lack of regulatory oversight, and illegal mining expansion. A key finding of this study, upon zooming into the mining cadastre, was the identification of the ROI with Object ID 51768, covering 1.51 km², within which both ASM and a large-scale mining (LSM) company (AfriSam) operated on the same cadastral parcel as seen from the Google Earth high-resolution imagery:

1. ASM miners were engaged in informal gold extraction, primarily targeting historical mine dumps containing residual gold deposits (Chingwaru et al., 2023a).

2. AfriSam, a registered cement company, operated legally within the same parcel, extracting limestone for cement production. This information was corroborated using the list of operating mines published on the Department of Minerals and Energy website. Demonstrating the utility of integrating geospatial analysis with cadastral datasets.

The coexistence of ASM and LSM on a single cadastral parcel raised critical concerns about mining rights administration and land-use governance. This scenario underscored the need for a blockchain-based mining cadastre system with Unique Parcel Identifiers (UPIs), to prevent overlapping mineral rights allocations for the same commodity to avoid conflicts (Creamer, 2023).

4.1.2 Double Granting of Mineral Rights and the Need for a Digital Cadastre

The boundary sharing observed in this study, which is a common occurrence in other mining areas, necessitated stringent monitoring mechanisms to prevent ASM operators from exceeding their permitted area and or encroaching into adjacent cadastre parcels (Ledwaba et al., 2020). These findings showed the importance of integrating geospatial monitoring to ensure compliance with ASM regulations. Without a comprehensive and transparent digital cadastral system, it is difficult to effectively manage mining rights, detect illegal mining, or ensure policy compliance, as the lack of a transparent digital cadastre has resulted in duplicate mining permits issued for the same geographic area, leading to legal disputes and operational disruptions, as well as the opacity in permit allocation, where mining rights applications are processed manually, requiring paper-based submissions before viewing the mining cadastre and seeing the vacant lands for new mineral exploration, and the delayed permit issuance and regulatory inefficiencies which exacerbated illegal mining activities and undermined sustainable resource management (Konguka et al., 2022).

4.2. Detection and Analysis of ASM Activities Using GEOBIA

The GEOBIA process integrated object-based segmentation, spectral indices, and machine learning classifiers to extract ASM-related features with high accuracy. The Random Forest classifier was trained on the segmented image to distinguish between open pits and non-open pits areas, as seen in Figures 7 and 9. The classification results were validated using confusion matrices, with accuracy metrics such as Overall Accuracy and Kappa Coefficient computed to assess the quality of the model and visualized on the GEE interface as part of the findings (Table. 2).

Table 2: The Six Performance Indices resulted from the Advanced GEOBIA Technique for each year

Metric	***2021***	***2022***	***2023***	***2024***
Overall Accuracy	1.0	1.0	1.0	1.0
Kappa Coefficient	1.0	1.0	1.0	1.0
Precision	1.0	1.0	1.0	1.0
Recall	1.0	1.0	1.0	1.0
F1 Score	1.0	1.0	1.0	1.0
IoU (Open-pit)	0.82	1.0	1.0	1.0

4.2.1 Quantitative Accuracy Assessment

The detection process yielded exceptional classification performance for each year (2021–2024), as summarised in the accuracy metrics (Table 2) and interpreted as follows:

- **Confusion Matrix:** Across all years, the model exhibited perfect classification performance with no misclassifications in both ASM and non-ASM categories (e.g., [[63, 0], [0, 66]] in 2021).

- **Overall Accuracy (OA):** Maintained at 1.0 (100%) throughout the study period, indicating the model's ability to perfectly classify mining features and therefor distinguish ASM pits from other land cover types.

- **Kappa Coefficient:** A value of 1.0 indicated complete agreement between the classification results and ground-truth data.

- **Precision, Recall, and F1 Score:** All metrics remained at their maximum value of 1.0, signifying both high reliability in true positive predictions and complete retrieval of relevant features, reflecting the classifier's ability to accurately detect ASM pits without false positives or false negatives.

- **Intersection Over Union (IoU) for Open-pit Class:** IoU was initially 0.8157 in 2021 but achieved 1.0 in subsequent years, reflecting improved segmentation and classification precision for ASM mining features.

These metrics validated the integration of GEOBIA techniques with the fusion of high-resolution imagery and machine learning classifiers in delineating ASM features, as summarised in Table 2. The confusion matrices for all years indicated a perfect classification, with Producer's and User's accuracies for both the open-pit and background classes were similarly perfect at 1.0, confirming that no misclassification occurred during this period.

These results from Table 2 show the reliability of GEOBIA combined with GEE for operationalising mining cadastre reform. The perfect metrics for 2022–2024 indicated the absence of false positives or false negatives in the classification process. This validated the suitability of GEOBIA as a scalable approach for mining cadastre systems, enabling accurate spatial delineation of ASM activities critical for legal enforcement and policy implementation.

4.2.2 Temporal Dynamics of ASM Open-Pit Areas

The time series graph as shown in Figure 8, for ASM mining areas reveals an oscillating pattern in detected open-pit coverage. This temporal trend was indicative of several interacting factors:

- **2021–2022:** A gradual increase in ASM area from 0.014 km² to 0.015 km² is observed, indicative of expanding mining operations and minimal regulatory intervention.

- **2023:** A sudden decrease in ASM area to approximately 0.011 km² suggested a temporary cessation or reduction of mining activities, potentially linked to enforcement actions or economic factors, coinciding with the implementation of Operation Vala Umgodi, which involved sealing illegal mining pits and enforcing stricter regulations. This decline showed the immediate effectiveness of targeted enforcement operations in reducing illegal mining activities.

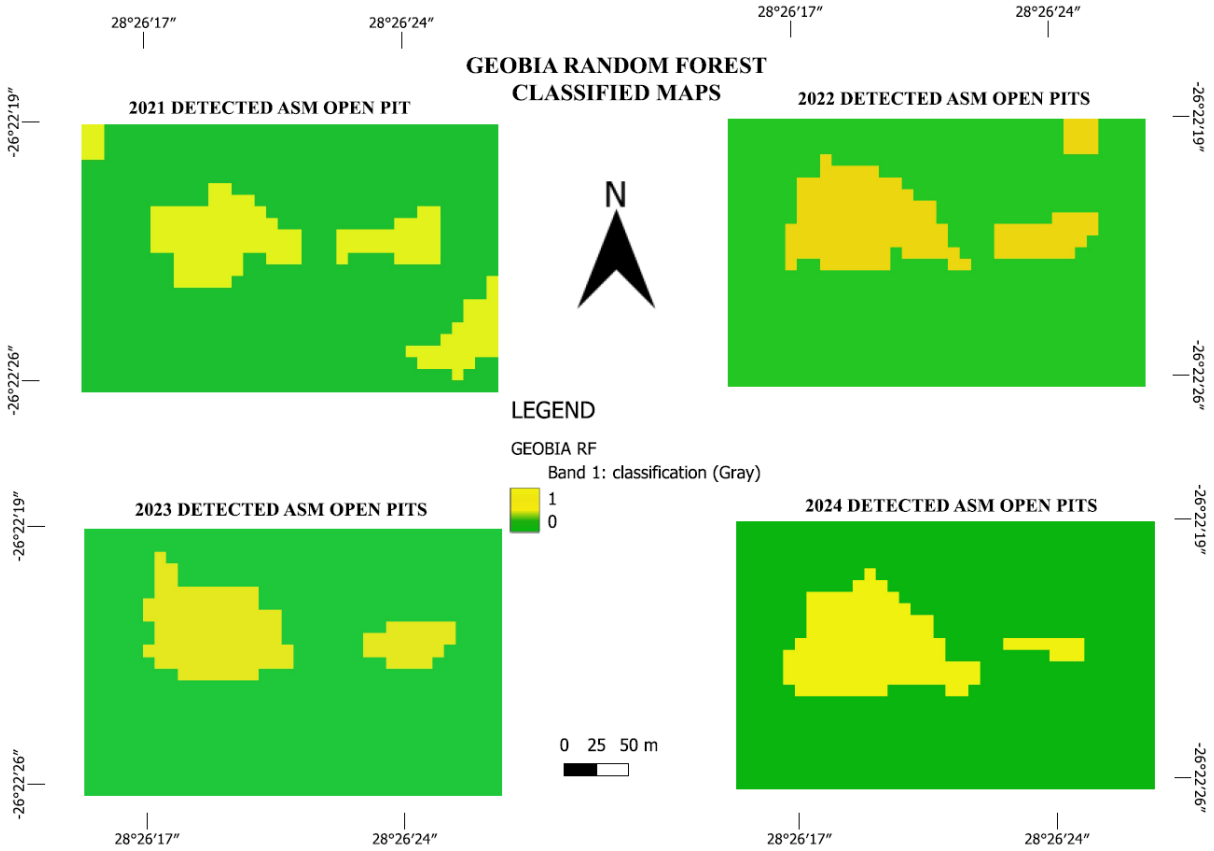


Figure 7: GEOBIA Random Forest Classified Maps

- **2024:** A marked resurgence in ASM area to 0.013 km², almost reaching 2021 levels, emphasised the transient nature of interventions and the ongoing pressure from ASM activities. This resurgence likely reflects the spatial displacement of ASM operations, as enforcement activities under Operation Vala Umgodi shifted focus to other municipalities. This phenomenon underscores the limitations of localised enforcement and the need for a more comprehensive, systemic approach to regulating ASM activities.

These findings showed the need for continuous monitoring to understand the drivers behind ASM expansion or contraction as seen in figures 7 and 9, as well as the need for formalising ASM operations, ensuring designated mining zones, environmental compliance, and regulated land rehabilitation (Mhlongo et al., 2019; Ntsaluba et al., 2018).

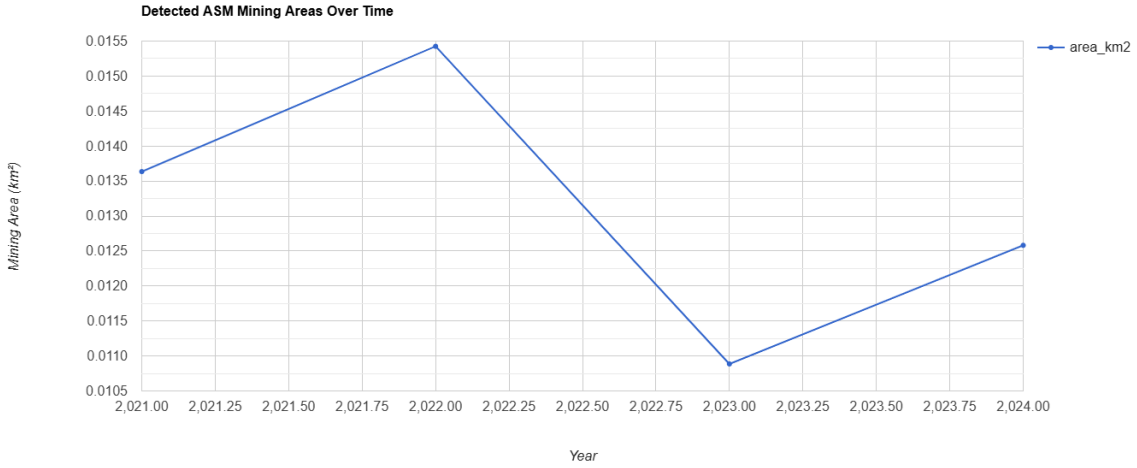


Figure 8: The detected ASM Mining Area Time Series Graph

4.2.3. Overall Impact on Model Robustness

The combination of advanced algorithms created a robust and reliable framework for mapping ASM activities. By leveraging GLCM texture features, edge detection with morphological refinement, multi-sensor data fusion, SNIC segmentation, and random forest classification, the model effectively captured both spectral and spatial patterns while minimising noise and random variations (Chen et al., 2018). This comprehensive approach reduces the risk of overfitting as seen from Table 2, ensuring that the model maintains high accuracy and generalises well to new datasets (Tassi and Vizzari, 2020). Consequently, the proposed framework is well-suited for informing a reformed mining cadastre system that utilises real-time remote sensing data for transparent and efficient management of mining rights.

4.2.4. Google Earth Engine Capabilities and Methodological Strengths

The high classification accuracy (Table 2) and temporal insights (Figure 8) achieved in this study shows the suitability of GEE as a platform for large-scale, cloud-based ASM monitoring. Key capabilities include Scalable and Distributed Analysis, meaning the GEE's ability to handle vast geospatial datasets that facilitated the seamless processing of high-resolution imagery and complex classification algorithms over multiple years. Integration of Multi-Temporal Data, this being the ability to incorporate historical imagery which enabled a robust time-series analysis of ASM activities (Figure 8), and Automated Feature Extraction which refers to the GEOBIA's object-based segmentation which allowed for the precise identification of small-scale mining features (Figures 7 and 9), outperforming traditional pixel-based methods (Hilson et al., 2019).

These advancements demonstrated the value of leveraging cloud-based geospatial platforms for reforming and managing mining cadastral systems. The observed temporal variations in ASM areas, as shown in Figure 8, underscored the need for continuous monitoring to track compliance, adapt policies,

and address socioeconomic factors influencing ASM activities. The integration of advanced GEOBIA techniques and GEE provided accurate, reliable, and policy-relevant data for detecting and assessing ASM activities (Figures 7 and 9). These results offer a strong foundation for implementing a modern, transparent, and effective mining cadastre system in South Africa, promoting sustainable mining and equitable resource allocation. Continuous technological advancements and multi-stakeholder collaboration will be critical in leveraging these tools to achieve the long-term goals of mining sector reform.

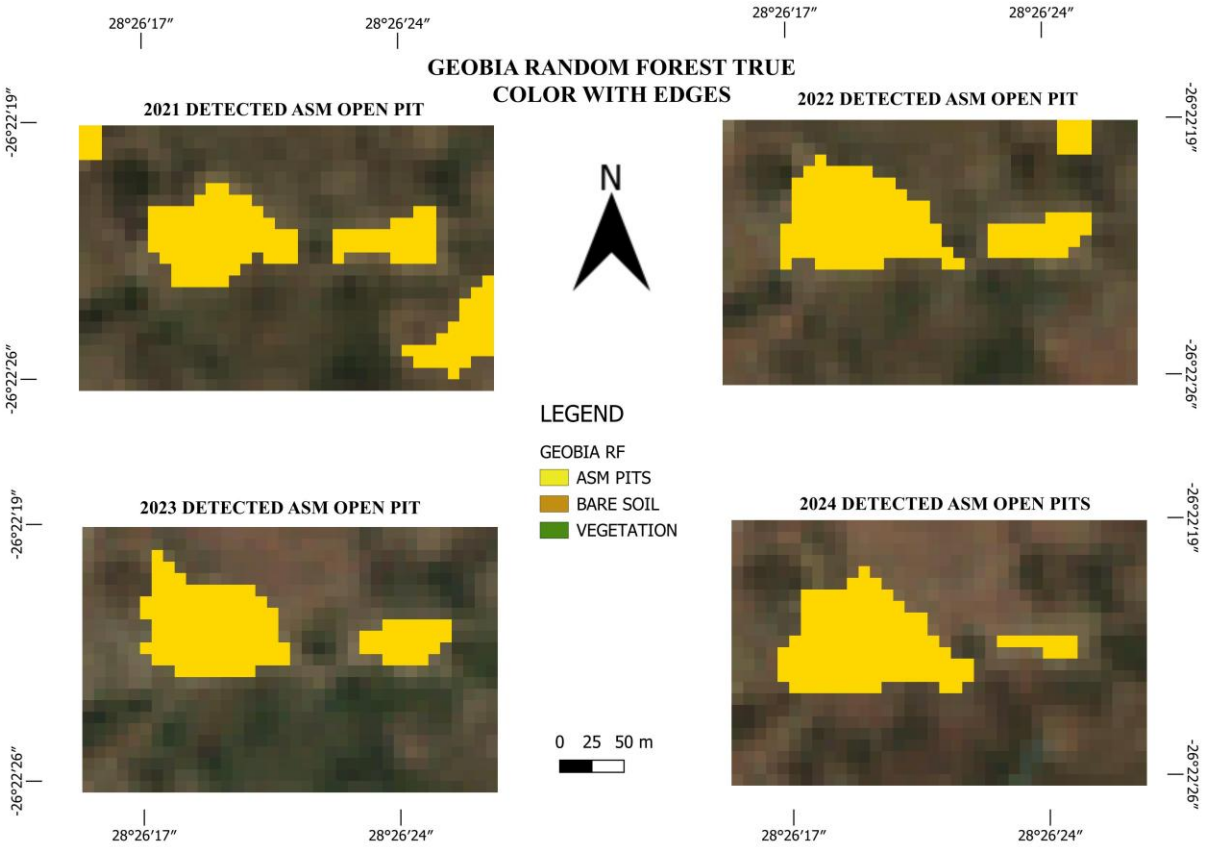


Figure 9: GEOBIA Random Forest True Color with Edges

4.3 Mining-Induced Deforestation Analysis

Mining-induced deforestation was assessed using temporal changes in NDVI and EVI, extracted using high-resolution satellite data within GEE. The results demonstrated the spatial and temporal effects of ASM activities on vegetation health and cover, providing key insights into environmental degradation patterns in the ROI between 2021 and 2024, with both indices exhibited fluctuations, correlating to mining activities and subsequent stricter enforcement efforts.

4.3.1 Vegetation Dynamics Based on NDVI and EVI Analysis

a) NDVI Time Series Analysis

The NDVI time series revealed vegetation health trends over the four-year period, showing that between 2021–2023; NDVI values exhibited a steady increase, peaking in 2023 (mean: ~0.41). This increase may have reflected periods of seasonal vegetation recovery or external reforestation efforts. Between the years 2023–2024, a sharp decline in NDVI was observed, indicating significant vegetation loss coinciding with expanded ASM activities in 2024, as supported by the detected ASM area data.

b) EVI Time Series Analysis

The EVI trends, aligned with the NDVI analysis, but provided higher sensitivity to changes in vegetation structure. This showed that between the years 2021–2023; EVI increased from ~0.8 to a peak of ~1.15 in 2023, suggesting dense vegetation cover in earlier years. Between the years 2023–2024; a steep reduction to ~0.75 occurred, corroborating widespread vegetation degradation. Both indices confirmed a significant loss in vegetation, particularly during 2024, attributed to intensified ASM operations.

4.3.2 NDVI and EVI-Based Area Change Analysis

A quantitative assessment of vegetation dynamics from 2021 to 2024 was conducted by classifying changes into areas of gain, loss, and stability. The analysis revealed distinct metrics for each index. Based on NDVI, the study area experienced a vegetation gain of 0.011 km², a loss of 0.013 km², and a stable area covering 0.044 km². In contrast, the EVI-based analysis detected a greater magnitude of change, with a gain of 0.019 km², a significantly higher loss of 0.029 km², and a substantially smaller stable area covering 0.020 km². The higher magnitude of loss and the reduced stable area captured by EVI shows its enhanced capability to detect vegetation degradation and structural biomass changes associated with mining activities (Knutton et al., 2023).

The higher magnitude of loss compared to gain in both NDVI and EVI underscores the dominance of mining-related deforestation. EVI, being more sensitive to canopy structure and biomass, indicated a greater loss (0.029 km²) compared to NDVI (0.013 km²). This divergence, as shown in Figure 9, demonstrated the utility of EVI in detecting vegetation degradation associated with open-pit mining and ground disturbance (Karan et al., 2023).

4.3.3 Insights on Environmental Impacts of ASM

It was found that the significant role of ASM in vegetation degradation and habitat disruption, with regards to Spatial Trends, the stable vegetation area was limited (NDVI: 0.044 km²; EVI: 0.020 km²), suggesting intense environmental pressures in localised ASM hotspots as seen in figure 10. And when

looking into Temporal Trends, vegetation degradation aligned closely with the detected expansion of ASM areas in 2024, reinforcing the link between increased ASM activity and deforestation. The trends from both indices aligned with the observed ASM activities, suggesting a clear association between mining operations and vegetation dynamics. Mining-induced deforestation is evident from the net losses in vegetation cover over the analysed period. The observed changes call for urgent rehabilitation measures and land management policies to mitigate the long-term environmental impacts of ASM (Mhlongo et al., 2019).

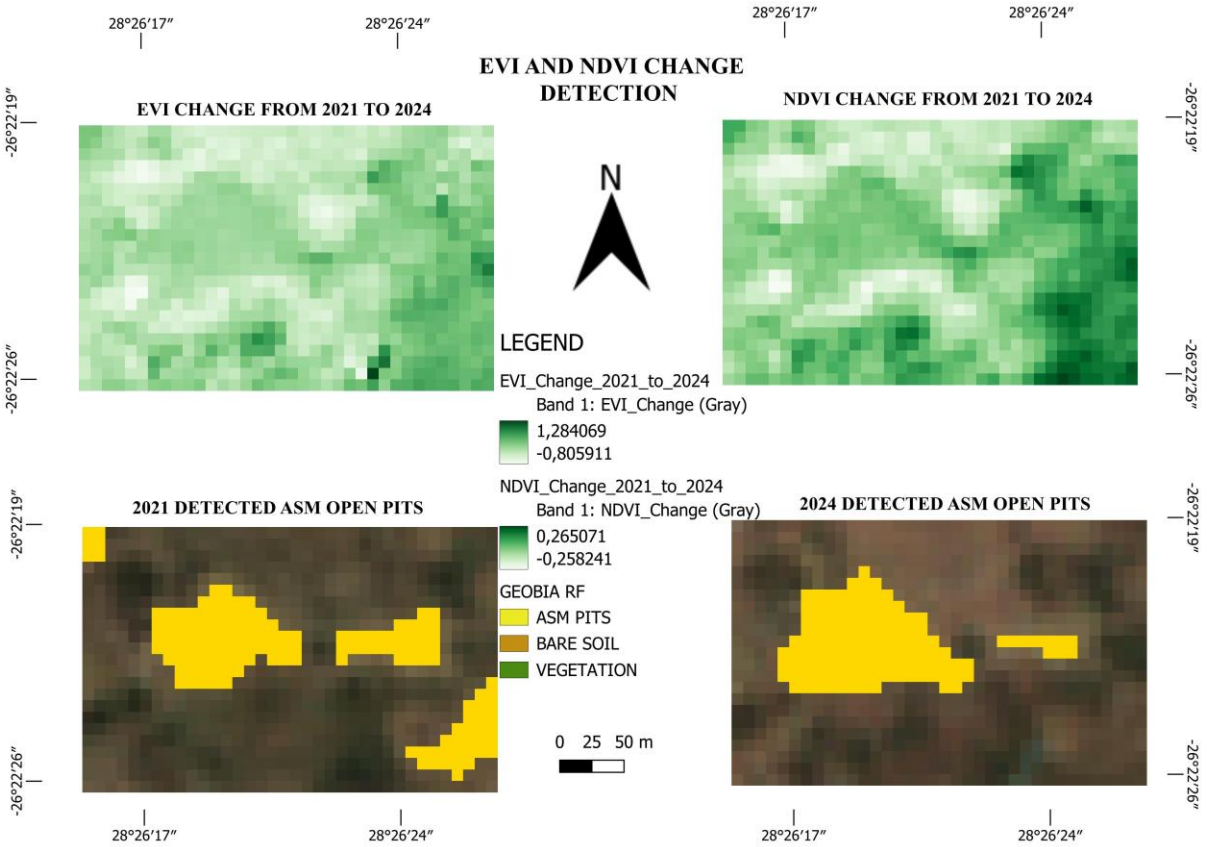


Figure 10: EVI and NDVI Change Detection Maps

4.3.4 Relationship between ASM Open-Pits and Classified Change Maps

Some of the stable vegetation cover areas corresponded to ASM open-pits, as shown in Figure 11, confirming prolonged excavation without rehabilitation. High vegetation loss zones were concentrated around newly established ASM sites, confirming continued ASM expansion. This confirmed that ASM operations lead to progressive land degradation, necessitating mandatory post-mining land rehabilitation programs and remote sensing-based environmental compliance monitoring for ASM permits.

The Utility of Google Earth Engine for Vegetation Monitoring

The GEE platform provided seamless processing and analysis of vegetation indices across time, demonstrating its effectiveness for Change Detection, where automated NDVI and EVI processing enabled consistent monitoring of vegetation health and loss (Fig. 11). And the integration with ASM Mapping, where the spatial correspondence between ASM activities and vegetation dynamics strengthens the case for using satellite-based vegetation indices in mining impact assessments (Figures 10 and 11).

Change Detection: The difference between the post-mining and pre-mining vegetation indices is calculated to identify areas affected by ASM activities. This difference showed regions where vegetation health has declined or improved, as seen on the maps with light green to dark green colours, shown in Figure 10. This change detection is crucial for identifying the impact of ASM activities on vegetation. It assisted in pinpointing areas that have experienced significant changes, enabling targeted interventions.

4.4 Synthesis of Findings and Implications for Cadastral Reform

The comparison of mining cadastre areas within the municipality showed a critical gap in spatial governance. Despite the legal cap on ASM operations (restricted to 5 hectares or 0.05 km²), the detected ASM areas remained significantly below this threshold. This indicated that formalising ASM through a robust cadastre system is feasible and would enable better regulation, monitoring, and enforcement (World Bank, 2019). The findings show the necessity for an integrated, transparent, and dynamic mining cadastre system. As such, a system could support, policy enforcement, with regular monitoring using remote sensing to assess compliance with ASM boundaries and minimise encroachment. This further showed a need for rehabilitation planning by utilising geo-spatial analysis of vegetation indices to prioritise degraded areas for restoration, and land use decision-making to supporting local authorities in balancing ASM activities with sustainable land management goals (Ledwaba et al., 2020).

The NDVI and EVI analyses (Figures 10 and 11) reveal that ASM activities have had a profound and measurable impact on vegetation cover between 2021 and 2024. Vegetation degradation intensified in 2024, corresponding to an expansion of ASM areas. These findings demonstrates the need for sustainable mining practices and immediate action on land restoration. The use of GEE and vegetation indices offers a replicable and scalable approach for monitoring environmental impacts in mining regions. These results collectively highlighted the need for an innovative and GIS-based mining cadastre system, coupled with regular remote sensing assessments, to enhance ASM regulation and promote sustainable mining practices.

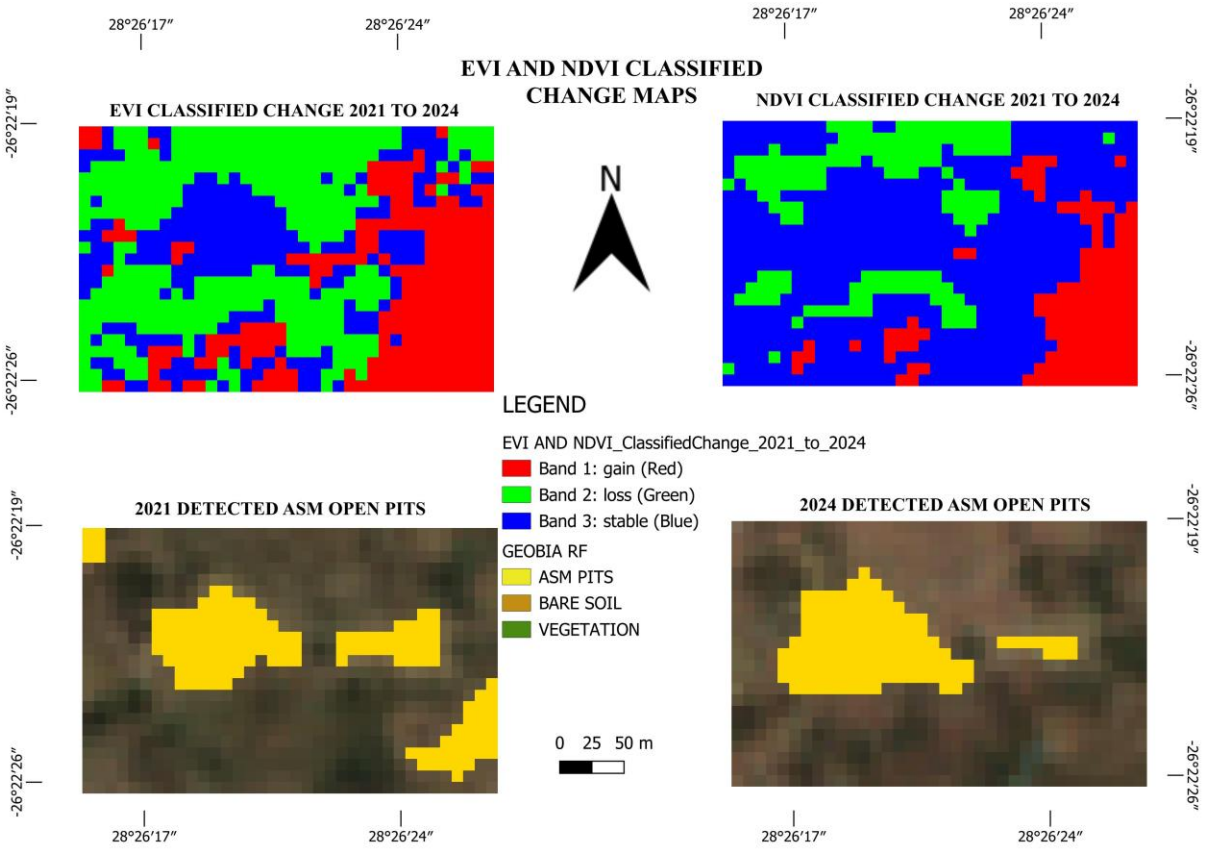


Figure 11: EVI And NDVI Classified Change Maps

The results showed the potential of integrating GEE-based methodologies into a reformed mining cadastre for South Africa to achieve, Improved Compliance Monitoring, this being the ability to detect ASM areas with high accuracy (refer to Table 2), which will enable authorities to enforce the 5-hectare restriction outlined in the 2021 Draft ASM Policy. Support for Cadastral Reform, where detailed mapping of mining areas can enhance the allocation of mining rights, reduce disputes, and improve transparency in the mining sector. As well as for Sustainability and Rehabilitation Planning, where time-series analysis (refer to Figure 8) can guide decisions on land rehabilitation and sustainable land use post-mining.

5. DISCUSSION

This discussion evaluates the findings from the operational dynamics of ASM mining footprint, explores the role of GEOBIA for ASM operations, examines the use of vegetation indices in monitoring mining-induced environmental changes, and assesses the transformative potential of a blockchain-based digital mining cadastre system for improving artisanal and large-scale mining governance. The results, combined with recent developments in mining technology and policy, underscore the urgent need for innovative approaches to address both environmental and regulatory challenges in the mining sector.

5.1. Mining Cadastre and Spatial Discrepancies

As established in previous sections, an overlap was identified. The spatial analysis revealed that mining rights overlaps are not unusual in the South African cadastral system. A case study within the ROI revealed that an artisanal mining (ASM) operation and a large-scale mining (LSM) company (AfriSam) operate on the same cadastral parcel. While these operations extracted different minerals (gold and limestone, respectively), which is permissible as opposed to the latter, where they extract the same mineral, which is not permitted according to the Minerals Act (Todes et al., 2010). The lack of a modern mining cadastre makes it difficult to prevent mineral rights conflicts, regulate operations, and ensure compliance with legal frameworks (Nivas et al., 2020). Without a centralised, digital mining cadastre, it is challenging to prevent the double-granting of mineral rights for the same land and mineral, ensure compliance with land-use planning and environmental regulations, detect and mitigate illegal ASM activities encroaching on legal mining concessions, and enhance transparency in mining rights allocation to reduce corruption and inefficiencies (Ntsaluba et al., 2018).

5.1.1 Case Study: ASM and LSM Sharing a Cadastral Parcel

This study highlighted a case where ASM and LSM operations exist within the same cadastral boundary, with no clear regulatory mechanism in place to define spatial constraints and operational oversight. Implementing UPIs within a blockchain-integrated cadastre would ensure that ASM activities remain within the legally designated 5-hectare ASM boundary, as per the ASM Draft Policy (2021), prevent unauthorised expansion into LSM operations, reducing potential legal conflicts, and enable automated monitoring using GEE to detect encroachment or boundary violations.

The comparative assessment of ASM boundaries versus industrial operations highlighted discrepancies in spatial utilisation. ASM operations, restricted to 0.05 km² (5 hectares) as per the Artisanal and Small-Scale Mining Draft Policy 2021, can feasibly share boundaries with larger mining operations due to their minimal spatial requirements. However, the analysis underscores the critical need for accurate and up-to-date cadastral records to prevent unauthorised expansion and encroachment. The identification of overlapping mining rights reinforced the systemic challenges facing South Africa's cadastral framework.

5.1.2 Challenges in South Africa's Mining Cadastre

The South African Mineral Resources Administration System (Samrad), as mentioned in previous chapters, is burdened by inefficiencies, such as overlapping permits, corruption, delayed processing, and limited public access to mining footprints (Konguka et al., 2022). These issues disproportionately affect ASM operations, which are often marginalised or operate informally due to the complexity of the permitting process (Dixon et al., 2021). The findings reinforced the systemic inefficiencies in South

Africa's mining cadastre system, which included mining overlaps. This refers to the boundary sharing and or overlapping prospecting and mining rights within the municipality and possibly other parts of the country, revealing that the absence of a systematic and functional mining cadastre contributed to inefficiencies, corruption, and illegal activities. This reflects challenges of governance and compliance monitoring within the mining sector. ASM operators require formalisation to support compliance with legal frameworks while ensuring sustainable practices, with cadastral records indicating minimal spatial demands, ASM could be effectively integrated into land management policies, reducing conflict with large-scale operations (Nyamekye et al., 2021b).

The spatial analysis in the first phase demonstrated the feasibility of granting ASM permits in proximity to industrial operations, provided that regular monitoring is conducted. Integration of remote sensing with a centralised, transparent cadastral system can improve policy implementation and ensure adherence to spatial restrictions, as well as address the regulatory inefficiencies as the current system rely heavily on centralised databases that are vulnerable to data manipulation, loss, or unauthorised changes (Creamer, 2023). This undermines the fairness of permit allocation and hampers compliance tracking. Limited accessibility to mining data prevented communities, environmental organisations, and other stakeholders from monitoring the impacts of ASM and LSM operations. This weak governance has allowed for unauthorised mining activities, leading to deforestation, water contamination, and land degradation (Yang et al., 2018). The absence of a real-time monitoring system exacerbates these challenges, leaving regulators ill-equipped to respond promptly (Ledwaba et al., 2020).

This further demonstrated that the absence of an accurate and centralised mining cadastre exposes ASM operators to the risks of encroachment and disputes over land use. The temporal spatial displacement of ASM activities observed in 2024 underscored the need for spatially consistent enforcement measures. Remote sensing, combined with GEOBIA classification, can enable continuous monitoring of ASM activities, providing data-driven insights to guide enforcement strategies and mitigate, the spatial displacement effect, reinforcing the need for a nationwide, systemic solution like the proposed cadastre as expanded upon below.

5.1.3 Addressing Double Granting of Mineral Rights Through Unique Parcel Identifiers (UPIs)

The double-granting of mining rights is one of the most pressing governance failures in South Africa's mining sector. This occurs when multiple permits are issued for the same mineral extraction on the same cadastral parcel, leading to legal disputes, operational conflicts, and inefficient resource utilisation (Yomralioglu and Mclaughlin, 2017). A key recommendation from this research is the adoption of Unique Parcel Identifiers (UPIs) as part of a blockchain-based digital mining cadastre system. UPIs function as permanent, tamper-proof identifiers that uniquely define each mining title, its geographic boundaries, assigned mineral rights, and legal status (Nivas et al., 2020). The integration of UPIs into a blockchain-based cadastral registry would ensure that each mining parcel is uniquely identified,

preventing duplicate permit issuance. All transactions related to mining rights are permanently recorded on a secure blockchain ledger where government agencies, mining companies, and the public can access real-time mining rights data, reducing bureaucratic inefficiencies (Mhilson, 2020).

The transformation of South Africa's mining cadastre system through blockchain technology offers a groundbreaking opportunity to address long-standing challenges in regulating both artisanal and large-scale mining. A blockchain-based system would introduce transparency, security, and efficiency into the permitting process, fostering an equitable balance between economic development and environmental stewardship. This phase explored the significance of blockchain in mining governance, focusing on its application to permit issuance and compliance monitoring for ASM and LSM.

Blockchain technology directly addresses these challenges by introducing a decentralised, immutable, and transparent system for managing mining cadastre data. Blockchain technology has been widely recognised as a transformational tool for land and resource governance, offering decentralisation, transparency, security, and efficiency (Kouhizadeh et al., 2021). Many mining economies, including Canada, Australia, and Botswana, have integrated digital cadastral platforms to manage mining rights efficiently and reduce corruption (World Bank, 2019). This is particularly significant for ASM operators, who often face bureaucratic hurdles when seeking formalization (Ledwaba et al., 2020). The proposed system will eliminate overlapping claims by providing a clear, time-stamped record of all mining rights, reducing disputes between ASM and LSM operators and, therefore, enabling the formalisation of ASM operations by reducing administrative bottlenecks, ensuring that artisanal miners can secure permits without undue delays (Gaur et al., 2020).

5.1.4 Compliance Monitoring and Policy Implications

The study emphasises the role of geospatial technologies, particularly remote sensing, in modernising South Africa's mining cadastre system. Key contributions will include, Policy Compliance Monitoring, where remote sensing will enable real-time assessment of ASM boundaries, ensuring adherence to the 0.05 km² policy restriction. Allow for Encroachment Detection, as high-resolution imagery can be used to detect unauthorised mining activities or boundary violations, protecting neighbouring parcels from encroachment, as well as for Environmental Impact Assessment, as geo-spatial analysis can facilitate monitoring of land-cover changes, allowing for targeted rehabilitation efforts in degraded mining areas.

By integrating remote sensing data into an online mining cadastre, decision-makers can implement an adaptive monitoring system that improves compliance, accountability, and transparency. The findings revealed that ASM formalisation requires more than legislative reform; it necessitates the integration of robust geospatial tools to monitor compliance and ensure sustainable practices (Ngom et al., 2023). A reformed mining cadastre, supported by platforms like Google Earth and GEE, can provide, transparent and equitable allocation of mining rights**.** Improved monitoring of ASM boundaries to ensure

compliance with the 2021 policy's spatial restrictions. And support for rehabilitation and land-use planning through reliable data on mining footprints and environmental changes (Mhlongo et al., 2019).

This study supports the argument that modern geospatial tools can address the challenges of governance, sustainability, and equitable resource management in South Africa's mining sector. The findings of this research emphasise the urgent need to modernise South Africa's mining cadastre system. By adopting a blockchain-based cadastral framework with Unique Parcel Identifiers (UPIs) and integrating remote sensing for environmental compliance. The integration of GEE into a cadastral management system offers a pathway toward transparent, sustainable, and equitable mining governance in South Africa. By addressing the systemic inefficiencies in mining rights allocation and monitoring, this approach can support the formalisation of ASM, reduce illegal mining activities, and promote environmental stewardship. These findings reinforced the critical role of reliable geospatial data in fostering a reformed and effective mining cadastre system. The adoption of blockchain technology for mining governance, coupled with remote sensing-powered compliance monitoring, would position South Africa as a global leader in sustainable and transparent mining administration. This technology-driven approach would ensure that ASM contributed positively to economic development while minimising conflicts with LSM and environmental degradation (Sebastianelli et al., 2022).

5.2. ASM Pit Detection and Growth Analysis

The results in the second phase of the study demonstrated the robustness of integrating remote sensing and GEOBIA for detecting and assessing ASM activities. The cloud-computing power of GEE facilitated the processing of high-resolution satellite imagery across temporal scale, enabling the detection of subtle but significant changes in ASM footprints over time. The exceptional accuracy metrics (Overall Accuracy, Kappa Coefficient, and IoU reaching 1.0) affirmed the precision of the GEOBIA framework in delineating ASM-related open pits, even in dynamic, heterogeneous environments. The detected ASM mining area displayed notable temporal dynamics, as illustrated in the "Detected ASM Mining Areas Over Time" graph. Between 2021 and 2022, ASM activities expanded steadily, reaching their peak of approximately 0.015 km². However, a marked decline in ASM area occurred in 2023, reducing to its lowest point (~0.011 km²). This decline coincided with the launch of Operation Vala Umgodi, a national initiative aimed at clamping down on illegal mining activities. The operation, spearheaded by law enforcement and mining authorities, focused on sealing illegal open pits, preventing further mining, and mitigating associated environmental degradation.

These discoveries confirmed the robustness of this methodology in generating reliable, repeatable, and scientifically validated datasets for mining cadastre reform. The fusion of Sentinel-2 and NICFI data leveraged both the high spatial resolution (from NICFI) and the rich spectral information (from Sentinel-2) to create a more detailed image for segmentation and analysis. The integration of these

datasets provided a more comprehensive view of the landscape, improving the detection of ASM-related features that might be overlooked in a single-source dataset. The SNIC and SEEDS algorithms, when applied to this fused image, benefited from the enhanced spatial and spectral detail, making it easier to identify ASM pits (Chabalala et al., 2022). The fusion of Sentinel-2 and NICFI imagery represented a significant advancement in the detection and analysis of ASM activities. By combining the spectral richness of Sentinel-2 with the spatial detail of NICFI, the fused dataset enabled precise object-based analysis critical for understanding and managing ASM impacts (Matarira et al., 2023). The classification results revealed significant ASM activity on the ROI historical mine dumps. High temporal variability in ASM areas was observed, with detected footprints expanding over time due to increased artisanal mining activity.

This approach was particularly relevant for South Africa's mining cadastre, where detailed and accurate spatial information is essential for reforming governance and ensuring sustainable resource management. SNIC ensured that open pits and tailings, which often form irregular shapes, were segmented into coherent clusters (Lobo et al., 2018). This clustering reduced within-object variability, improving the accuracy of subsequent classification steps (Ngom et al., 2022). SEEDS enhanced the delineation of mining features by leveraging energy-based refinement, ensuring that small or irregularly shaped features were not merged into larger, unrelated clusters. It was particularly effective in preserving edge detail, ensuring accurate boundaries for open pits (Gallwey et al., 2020; Maus et al., 2020). The results derived from the integration of GEE and advanced GEOBIA techniques provided critical insights into the environmental and land-use impacts of ASM. This section further delves into the implications of the confusion matrix results for open-pit detection, evaluates the temporal trends in ASM area and vegetation indices (NDVI and EVI), and assess the suitability of NDVI and EVI as indicators for vegetation health. Thus, the synergistic use of multi-sensor data, GEOBIA, and tailored spectral indices provided a comprehensive and effective approach to fulfilling the research objectives, delivering actionable insights for a reformed mining cadastre classification (Ntsaluba et al., 2018).

5.2.1 GEOBIA Confusion Matrix Analysis: Openpit vs. Non-Openpit

The confusion matrices derived from the GEOBIA classification confirmed an exceptionally high detection performance for Openpit vs. Non-Openpit mining classes from 2021 to 2024. Below is the synthesised Table 3 of the key metrics for all four years.

Table 3: GEOBIA Confusion Matrix for OpenPits vs Non-OpenPits

Year	Overall Accuracy	Kappa Coefficient	IoU (Openpit)	Producer's Accuracy	User's Accuracy
2021	1.00	1.00	0.815	1.00	1.00
2022	1.00	1.00	1.00	1.00	1.00
2023	1.00	1.00	1.00	1.00	1.00
2024	1.00	1.00	1.00	1.00	1.00

Discussion of Results:

1. The Overall Accuracy (1.00) and Kappa Coefficient (1.00) reflected perfect agreement between classified and reference data across all years, which is uncommon in typical remote sensing workflows. This underscores the robustness of the GEOBIA-based approach in segmenting mining pits from surrounding landscapes.

2. The Intersection-over-Union (IoU) for the Openpit class improved over time from 0.815 in 2021, peaking at 1.00 from 2022 onwards. This indicated that the model effectively captured subtle distinctions in open-pit geometries, likely attributable to improvements in training datasets and or more distinct spectral signatures of mining activities.

3. Producer's Accuracy and User's Accuracy of 1.00 further confirm that no errors of commission or omission occurred, making this approach reliable for ASM monitoring.

These results in Table 3 indicated that the segmentation, feature extraction (including spectral indices and GLCM texture features), and subsequent classification processes were executed with remarkable precision. The slight deviation in the IoU for 2021 suggested minor segmentation challenges during the initial phase of the analysis, likely due to early-stage parameter calibration, that were resolved in subsequent years (Karakus, 2024). Although perfect accuracy matrices are rare in remote sensing applications and could sometimes hint at overfitting, the comprehensive sampling and cross-validation procedures with ground truth imagery lended credence to the robustness of the advanced GEOBIA approach in this context (Xulu et al., 2021; Majji et al., 2022). These findings are in line with previous studies that have demonstrated the effectiveness of object-based image analysis for detailed land-use classification (Chen et al., 2018).

5.2.2 Temporal Changes in Detected ASM Areas

The temporal trend of detected ASM areas as seen in detected ASM pits time series graph highlighted fluctuations in ASM mining activities between 2021 and 2024. The area detected as ASM initially increased from 0.0135 km² in 2021 to 0.015 km² in 2022 before declining to 0.010 km² in 2023. A recovery was observed in 2024, with ASM areas expanding to 0.0125 km². This trend likely reflected socio-political or economic dynamics impacting ASM activities, such as, the 2021 Draft Policy for ASM may have influenced ASM operations, to increase their work probably to raise money and register their operations for compliance purposes in 2022 due to policy interventions. The sharp decline in 2023 may have correspond to stricter enforcement that coincided with the launch of Operation Vala Umgodi, a national initiative aimed at clamping down on illegal mining activities.

The operation, spearheaded by law enforcement and mining authorities, focused on sealing illegal open pits, preventing further mining, and mitigating associated environmental degradation. The rebound in 2024 suggested either a relaxation of restrictions or adaptive practices by ASM operators. This was likely due to Operation Vala Umgodi shifting its focus to other municipalities, leaving gaps in enforcement in the region of interest, suggesting that while such operations are effective in the short term, their transient nature highlighted the need for more sustainable regulatory mechanisms, such as a mining cadastre, to ensure continuous monitoring and regulation of ASM activities. These temporal patterns provided compelling evidence of the role of remote sensing in tracking the spatial and temporal evolution of ASM activities, offering invaluable data for policymakers and enforcement agencies. This trend illustrated the necessity of integrating robust temporal monitoring tools into South Africa's mining cadastre to sustain effective oversight.

5.2.3 Impacts of Operation Vala Umgodi

The study's temporal analysis of ASM activities revealed critical insights into the effects of Operation Vala Umgodi, which rendered some ASM workers unemployed with others who understood the composite of the mine dumps better continuing their work. The operation, which started in 2023, resulted in a sharp decline in ASM-related open-pit areas, demonstrating its effectiveness in curbing illegal mining activities through sealing pits and enforcing compliance. However, the resurgence of ASM activity in 2024 indicated the operation's limited temporal and spatial scope, as enforcement shifted focus to other municipalities. This spatial redistribution of ASM activities underscored the phenomenon of regulatory displacement, where enforcement in one area unintentionally stimulated illegal operations in others due to weak systemic coverage (Matshusa and Leonard, 2022).

The findings also suggested that while short-term enforcement strategies like Operation Vala Umgodi are essential, they are insufficient for sustained management. Without a permanent framework for regulating ASM, such interventions risk becoming cyclical, with illegal operations re-emerging when enforcement wanes. These results emphasised the urgent need for systemic reforms to address ASM holistically and sustainably. The detected ASM open pits over time, represented in the time series graph, revealed significant shifts in mining activities affected by Enforcement Dynamics and Regulatory Displacement as interpreted upon below:

2023: Decline in ASM Open-Pits - The consistent decline during this period is attributable to Operation Vala Umgodi, a government-led intervention aimed at clamping down on illegal mining. The operation involved closing illegal open pits and implementing stringent enforcement measures. The environmental and socio-economic impacts of this decline were notable, including reduced deforestation and potential ecosystem recovery.

2024: Sudden Resurgence of ASM Open-Pits - The sharp increase in detected open pits in 2024 suggested a spatial redistribution of ASM activities to municipalities not yet targeted by enforcement measures. This reinforced the unintended consequence of localised enforcement strategies, displacing, rather than eradicating, illegal mining operations, a phenomenon consistent with regulatory displacement (Nyamekye et al., 2021a).

Operational and Seasonal Variability: The cyclical pattern in open-pit areas also reflected underlying operational dynamics of ASM, such as fluctuating resource availability and seasonal work patterns, which are critical for understanding the resilience and adaptability of ASM operations under varying regulatory regimes. These findings further emphasised the need for a more holistic regulatory approach, incorporating continuous spatial monitoring utilising GIS and remote sensing technologies for equitable enforcement across regions to prevent the spatial displacement effect (Tran et al., 2023).

The geospatial analysis further demonstrated the critical role of remote sensing in monitoring compliance with ASM regulations. The ability to detect land-use changes, encroachments, and unauthorised activities is essential for enforcing the 2021 draft policy on ASM and ensuring sustainable coexistence between ASM and large-scale mining. Key findings included boundary management, where monitoring shared boundaries can mitigate potential conflicts and ensure adherence to ASM spatial restrictions. Rehabilitation and planning needs, where data on cadastral boundaries can inform rehabilitation efforts, particularly for areas overlapping with ecologically sensitive regions. And the issuance of ASM permits, by utilising geo-spatial analysis that can provide the evidence base for identifying suitable areas for ASM permits without encroaching on larger mining operations or protected habitats (Ngom et al., 2022).

5.3 Environmental Implications of ASM Operations

The results derived from the GEE analysis offer a detailed examination of the environmental changes caused by ASM activities within the ROI from 2021 to 2024. This discussion expands on the findings related to mining-induced deforestation, as assessed through NDVI and EVI analyses, and evaluates the spatial correlation between detected ASM open pits and classified land cover changes. Additionally, visual interpretations of pie charts and classified change maps provided further insights into the nature and extent of vegetation disturbance in ASM zones (Vasuki et al., 2019).

The correlation between ASM activities and vegetation indices revealed the environmental costs of unregulated mining. The deforestation and land degradation observed during periods of active mining posed significant threats to biodiversity, ecosystem services, and local livelihoods. Conversely, the partial recovery of vegetation during enforcement phases highlighted the potential for environmental

restoration when mining activities were curtailed. These findings reinforced the need for sustainable mining practices and post-mining land rehabilitation as integral components of a reformed mining cadastre (Ogunro et al., 2022).

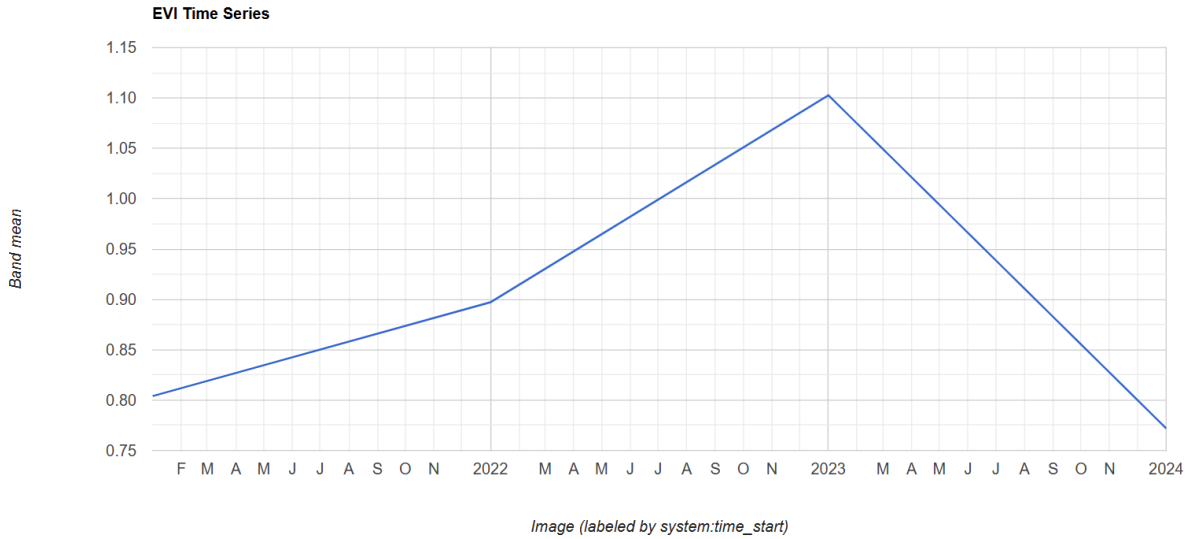


Figure 12: EVI Time Series Graph

The NDVI and EVI trends (Figures 12 and 13) revealed a strong association between ASM operations, vegetation dynamics, and enforcement phases. Both indices demonstrated vegetation recovery during the period of enforcement (2021–2023), likely due to the sealing of open pits and the cessation of active mining in the affected areas. However, the sharp decline in NDVI and EVI in 2024 signaled renewed deforestation and land degradation caused by the resurgence of ASM operations.

The vegetation loss and degradation linked to ASM activities are significant not only for biodiversity but also for local ecosystems that depend on stable land cover. This finding reinforced the dual necessity of curbing unregulated ASM operations and promoting environmental rehabilitation efforts. A mining cadastre integrated with vegetation indices, as illustrated by this research, would allow authorities to prioritise deforested areas for reclamation and restoration, thus ensuring a balance between mining development and environmental sustainability (Wu et al., 2024).

5.3.1 NDVI and EVI-Based Deforestation Analysis

Vegetation indices, particularly the NDVI and EVI, have long been utilised for detecting land cover changes associated with human activities (Hilson et al., 2019). In this study, both indices were applied to monitor the impact of ASM activities on vegetation health and quantified changes over time as follows:

NDVI-Based Vegetation Change: The NDVI results indicated a net vegetation loss of 0.013 km² and a gain of 0.011 km² between 2021 and 2024, with 0.0445 km² classified as stable. These findings suggested that ASM activities have led to a slight net decline in vegetation cover, although some areas have experienced regrowth. The stability of 44.5% of the total assessed area implied that vegetation disturbances are spatially concentrated rather than widespread, aligning with the localised nature of ASM operations (Nietupski et al., 2021). However, the overall net vegetation loss indicated that mining activities are not sufficiently offset by natural recovery processes (Ngom et al., 2023).

EVI-Based Vegetation Change: EVI results provided a more detailed assessment of biomass changes, showing a higher vegetation loss of 0.0293 km² and a gain of 0.0194 km², with 0.0199 km² classified as stable. The larger loss detected by EVI compared to NDVI suggested that ASM activities may have caused significant changes in vegetation structure and biomass rather than merely altering surface reflectance (Seki et al., 2020). The smaller stable area (19.9%) compared to NDVI further supports this observation, indicating that EVI is more sensitive to vegetation degradation in ASM zones.

5.3.2 NDVI and EVI Time Series Analysis: Assessing Vegetation Dynamics

The time series analysis (Figures 12 and 13) of NDVI and EVI provided critical insights into the environmental impacts of ASM activities:

NDVI Trends: NDVI (Figure 13) exhibited a consistent decline in vegetation health during periods of active ASM operations in the year 2022, with a partial recovery during enforcement phase of the 2023 Operation Vala Umgodi, peaking at approximately 0.41 before declining sharply in 2024. NDVI, being sensitive to chlorophyll content, likely captured the transient recovery of vegetation during mining downtimes. The 2024 decline aligned with ASM resurgence, reflecting vegetation degradation caused by surface disturbance and soil exposure (Tran et al., 2023).

EVI Trends: EVI (Figure 12) trends demonstrated a similar pattern but with higher variability, increasing from 0.8 to 1.15 (2021–2023) and dropping to 0.75 in 2024. EVI's sensitivity to canopy structure and biomass allowed it to highlight changes in denser vegetation types. The pronounced decline in 2024 reflected not only vegetation loss but also potential biomass removal caused by intensified ASM operations. The trends in both NDVI and EVI confirmed a strong association between ASM operations, enforcement activities, and vegetation dynamics. Mining-induced deforestation during periods of increased ASM activity is evident, underscoring the environmental impact of unregulated mining.

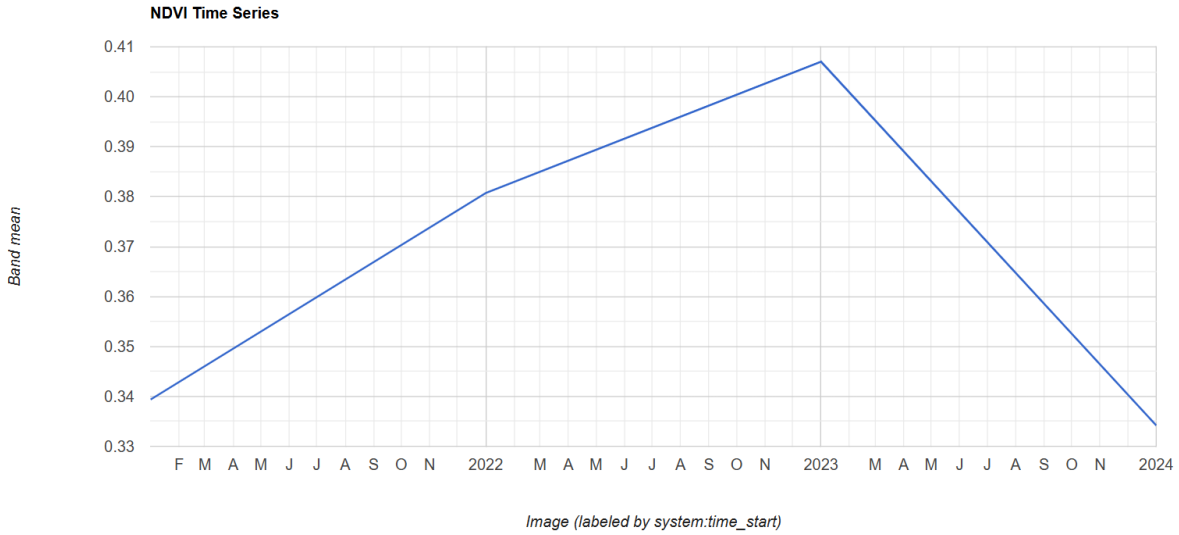


Figure 13: NDVI Time Series Graph

5.3.3 Comparative Analysis of NDVI and EVI:

Temporal trends derived from satellite indices (NDVI and EVI) revealed the environmental implications of ASM activities, particularly deforestation and vegetation recovery during enforcement phases. These results reinforced the transformative potential of integrating remote sensing with digital cadastral approaches to provide real-time, scalable, and objective assessments of ASM dynamics, with the NDVI Strengths, being that it is simpler to compute and widely validated, making it effective for broad-scale vegetation assessments. However, its susceptibility to saturation in dense vegetation limits its ability to capture variations in areas with high canopy cover (Karan et al., 2016). And the EVI Strengths, being its enhanced sensitivity to canopy structure and reduced sensitivity to atmospheric effects provide greater reliability in complex or biomass-rich environments (Ang et al., 2021). The steep declines in EVI during 2024 underscored its utility for pinpointing areas undergoing severe degradation.

While both indices provide valuable insights, EVI emerged as the more appropriate indicator for ASM-related vegetation assessments due to its robustness in detecting subtle changes in canopy structure and its reduced susceptibility to saturation effects. Its enhanced sensitivity to degraded vegetation and reduced susceptibility to noise aligns well with the objectives of assessing ASM-induced deforestation and land degradation (Bansah et al., 2023). The larger magnitude of vegetation loss and gain detected by EVI also suggests that it provides a more nuanced representation of ASM's environmental footprint, essential for crafting targeted rehabilitation strategies (Adiri et al., 2020).

The discrepancy between NDVI and EVI results reinforces the argument that EVI is a more appropriate index for detecting mining-induced deforestation. While NDVI is effective for general vegetation monitoring, it is prone to saturation in high biomass areas and is more influenced by atmospheric conditions. EVI, on the other hand, incorporates corrections for atmospheric effects and soil background

reflectance, making it more reliable in disturbed landscapes such as ASM mining areas (Acharki et al., 2024). The greater vegetation loss detected by EVI suggests that ASM activities have had a more severe impact on biomass than initially inferred from NDVI alone. This methodology aligns with the goals of modern mining cadastre systems, which aim to incorporate continuous monitoring and sustainability-focused management (Buuveibaatar et al., 2022).

5.3.4 Visualising Vegetation Change: Pie Chart Analysis

The vegetation change dynamics were further examined using two pie charts (Figures 14 and 15), which visualise the proportional distribution of vegetation gain, loss, and stability for both NDVI and EVI. These visual summaries offer a clear interpretation of dominant landscape transformation patterns associated with ASM activities. The NDVI-derived pie chart in Figure 14 revealed that stable areas account for the largest share of the landscape (65%), indicating that most of the vegetation remained unchanged during the assessment period. Vegetation loss accounts for 19% of the area and corresponds to zones where ASM-related disturbances have resulted in the removal or degradation of vegetation cover. Conversely, vegetation gain comprises 16%, reflecting pockets of natural regeneration or possible revegetation in previously disturbed or seasonally influenced areas (Jena et al., 2021).

In contrast, the EVI-based pie chart Figure 15 displays a markedly different pattern, stable areas constitute only 29%, highlighting EVI's greater sensitivity to structural vegetation changes. Vegetation loss dominates the EVI output at 43%, reinforcing evidence of substantial degradation attributable to ASM excavation and land clearing. Vegetation gain accounts for 28%, suggesting some regrowth, though occurring at a slower rate compared to vegetation decline, an indication of the challenges in ecosystem recovery within mining-impacted regions. The pronounced differences between NDVI and EVI stability proportions underscore the importance of multi-index approaches in environmental monitoring, as relying on a single vegetation index may obscure critical ecological signals (Seki et al., 2020).

5.3.5 Classified Change Maps and Open-Pit Detection

The classified change maps generated from NDVI and EVI change detection were analysed side by side with the detected ASM open pits. A key observation is that most stable areas aligned with the classified ASM open-pit locations. This finding suggested that once an area has been transformed into an open-pit mining site, it remained largely unchanged over time, indicating persistent land-use conversion. The following is the interpretation of the classified change maps:

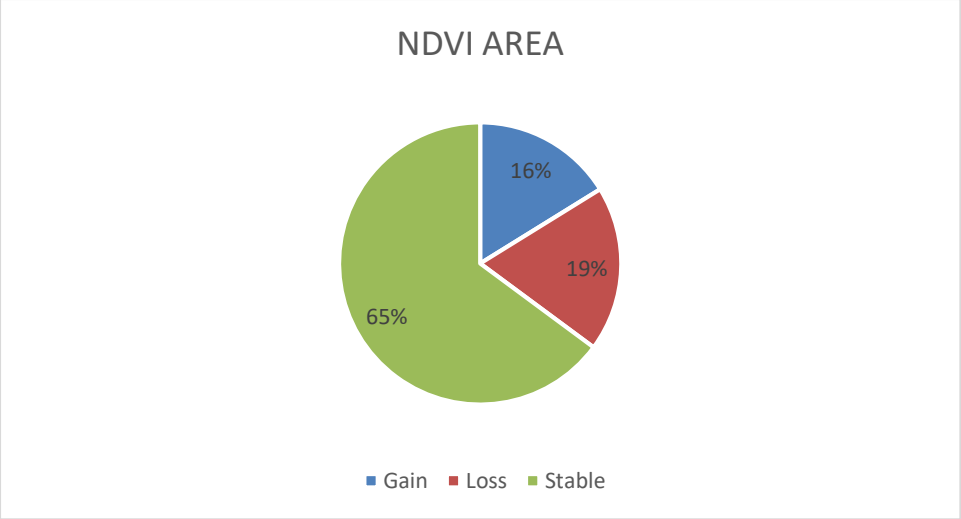


Figure 14: NDVI Pie Chart

Stable Areas Representing Open Pits: The stability in these regions implied that ASM sites experience prolonged excavation activity, preventing vegetation regrowth. These findings are consistent with previous studies indicating that ASM pits remain active for extended periods, often without rehabilitation efforts (Mhilson, 2020).

Vegetation Loss Occurring Around ASM Sites: Loss areas were predominantly found at the peripheries of active mining pits, suggesting continuous expansion of ASM activities. This pattern aligned with field studies showing that ASM operations tend to spread over time, encroaching into adjacent vegetated lands (Werner et al., 2019).

Vegetation Gain in Abandoned Areas: Some areas highlighted vegetation recovery, likely representing abandoned pits undergoing natural regeneration (Ciotola et al., 2021). However, the slow pace of regrowth indicated the need for active rehabilitation programs to restore ecological functions. The classified change maps provided a crucial insight into how ASM activities impacted the lulc stability, reinforcing the importance of continuous monitoring and policy interventions.

5.3.6 Environmental Implications and Policy Recommendations

The observed trends underscored the severe environmental toll of ASM on vegetation, wherein the vegetation Loss observed during the 2024 decline in NDVI and EVI, coupled with expanding ASM areas, demonstrated ongoing deforestation and land degradation, requiring rehabilitation needs, in that the vegetation gain metrics for both indices (NDVI: 0.011 km²; EVI: 0.019 km²) indicated only limited natural recovery as shown in Figures 12 and 13. This necessitated targeted reforestation and soil restoration programs in affected regions.

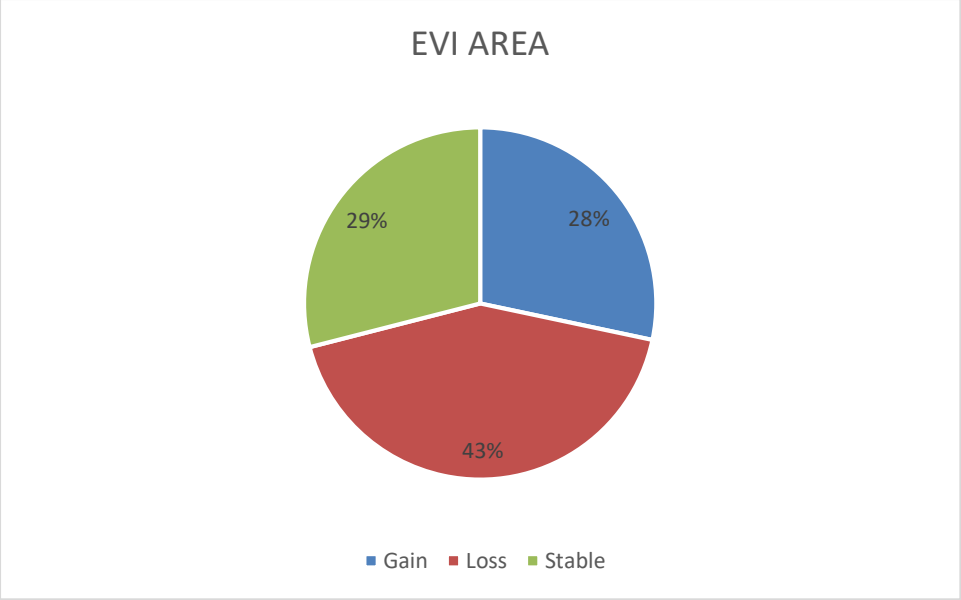


Figure 15: EVI Pie Chart

To address these issues, a reformed mining cadastre should incorporate continuous monitoring, with the integration of GEE workflows for real-time tracking of ASM impacts. Starting with index-based alerts, by utilising EVI thresholds to trigger alerts for regulatory intervention in areas experiencing vegetation degradation, as well as stakeholder collaboration**,** by engaging local communities in restoration efforts, and promoting sustainable ASM practices to mitigate long-term environmental impacts. This study demonstrated the transformative potential of GEOBIA and GEE for monitoring ASM activities and their environmental impacts. The integration of vegetation indices, particularly EVI, enhanced the ability to track and mitigate mining-induced deforestation, offering a scalable model for sustainable mining cadastre reform in South Africa.

5.3.7 Implications for Mining Cadastre and Sustainable Governance

The findings from this study have significant implications for mining governance and policy formulation, particularly in promoting a modernised and transparent mining cadastre system that integrates real-time geospatial monitoring with blockchain technology. The observed correlation between stable areas and ASM pits underscored the urgent need for regulatory agencies to adopt continuous land-use monitoring through GEE-based analysis. Such integration would enhance oversight and enable early detection of unauthorised mining activities. Furthermore, linking permit issuance to real-time vegetation monitoring within a blockchain-based cadastral framework could effectively prevent unauthorised mining expansion, spatial displacement, and non-compliance with environmental regulations (Kouhizadeh et al., 2021). The study also revealed an imbalance between vegetation loss (43%) and gain (28%) as indicated by EVI analysis, suggesting that current rehabilitation efforts remain inadequate. To address this gap, policies should enforce stricter

reforestation and land restoration programs as prerequisites for ASM permit approval, thereby strengthening sustainable land management and responsible resource governance.

The results of this study provided a comprehensive, high-resolution assessment of ASM's environmental impact using multi-temporal satellite imagery and object-based classification. The comparative analysis of NDVI and EVI highlighted the superior sensitivity of EVI for monitoring mining-induced deforestation, while classified change maps revealed the long-term stability of ASM open pits. The integration of real-time remote sensing data with blockchain-based governance frameworks represented a viable solution for improving South Africa's mining cadastre system. By ensuring transparent, accountable, and science-driven decision-making, such innovations can help balance economic development and environmental sustainability in the ASM sector.

5.3.8 Significance of Vegetation Indices in ASM Impact Assessment

The NDVI and EVI time series trends highlighted the profound environmental effects of ASM, particularly regarding vegetation degradation and recovery, with NDVI and EVI trends, both indices showing a notable increase in vegetation health from 2021 to 2023, followed by a steep decline in 2024, correlating with expanded ASM activities and reduced regulatory oversight. The sharper decline in EVI compared to NDVI in 2024 indicated its greater sensitivity to canopy structure and biomass loss, a critical factor in mining-impacted areas. The relevance of EVI, with its reduced susceptibility to atmospheric distortions and improved sensitivity in high-biomass regions, emerged as a more reliable indicator for assessing the environmental impacts of ASM activities (Gabriel et al., 2022). This supported its application in tracking large-scale desertification and soil exposure caused by mining activities. However, NDVI remained valuable for broader, less intensive vegetation health assessments due to its computational simplicity. These findings reinforced the necessity for integrating continuous monitoring of vegetation indices within South Africa's mining cadastre system. Vegetation health metrics, particularly EVI thresholds, could serve as early-warning indicators for unauthorised or environmentally damaging ASM activities, enabling timely regulatory responses (Werner et al., 2020).

5.3.9 Environmental and Socioeconomic Implications

The GEE analysis revealed a stark dichotomy between environmental degradation caused by ASM and the potential for natural vegetation recovery. However, the limited areas of gain in both NDVI and EVI (e.g., 0.011 km² and 0.019 km², respectively) suggested that natural rehabilitation alone is insufficient to restore degraded landscapes. Environmental Costs, which entailed that ASM activities contributed to deforestation, soil erosion, and loss of biodiversity, as evidenced by the 2024 decline in vegetation indices. This underscored the need for proactive restoration initiatives, including reforestation and soil stabilisation programs. Socioeconomic Considerations, this includes ASM playing a critical role in rural livelihoods and providing income for marginalised communities. The integration of blockchain

technology and GEE-based monitoring tools into mining governance systems should prioritise social inclusivity, ensuring that ASM miners are not disproportionately penalised but are instead incentivised to adopt sustainable mining practices (Gaur et al., 2023).

5.4 The Role of Google Earth Engine in Reforming the Mining Cadastre

The research reinforced the unparalleled advantages of GEE as a distributed GIS platform for cadastral management in South Africa. GEE's multi-temporal analysis, historical imagery storage, and collaborative sharing capabilities have proven essential for this study, enabling seamless integration of diverse geospatial datasets. The following contributions were identified:

Dynamic Monitoring: GEE provided access to high-resolution, near-real-time satellite imagery (e.g., Sentinel-2 and NICFI datasets) to monitor ASM activities and their compliance with spatial restrictions. Historical datasets aided in identifying land-use changes caused by mining.

Data Integration and Automation: The platform supported the integration of mining cadastre shapefiles, vegetation indices (e.g., NDVI and EVI), and advanced object detection and classification methods (e.g., SNIC and Random Forest). Automation of geospatial analyses on a large scale is key for timely decision-making.

Stakeholder Accessibility: By utilising the GEE platform, government agencies, policymakers, and stakeholders can collaborate effectively. The ability to share geospatial results through GEE's cloud infrastructure will enhance transparency and fosters informed decision-making.

Accuracy and Scalability: The study benefited from GEE's ability to process massive datasets rapidly and accurately, making it an indispensable tool for both national-scale mapping and local-scale compliance monitoring.

5.5. The Role of a Blockchain-Based Digital Mining Cadastre

The results from the research analysis highlighted inconsistencies in the management of ASM and large-scale mining operations, particularly concerning permit issuance and environmental compliance. A blockchain-based digital mining cadastre system offers a revolutionary solution to these challenges by ensuring transparency, accountability, and efficiency. Key Features and Benefits of Blockchain-Based Mining Cadastres include:

Immutable Recordkeeping: Blockchain technology will enable the creation of a tamper-proof, time-stamped ledger for mining permits. This will ensure that records of ASM and large-scale mining activities remain transparent and verifiable, reducing corruption and inefficiencies in the permitting process.

Real-Time Monitoring and Compliance: Integrating GEE workflows with blockchain-based systems could allow for real-time updates on mining activities and compliance with environmental regulations. For instance, vegetation degradation metrics derived from NDVI and EVI can be linked to specific permits, triggering alerts if environmental thresholds are breached.

Decentralisation and Stakeholder Engagement: Blockchain technology will foster decentralisation, enabling local communities, environmental organisations, and government agencies to access and verify data on mining activities. This transparency can mitigate disputes over land use, ensure equitable resource distribution, and promote sustainable mining practices.

Enhanced Regulatory Oversight: By automating the issuance and tracking of mining permits, a blockchain-based cadastre can reduce the risk of overlapping claims, unauthorised operations, and delays in enforcement. Moreover, it streamlines the administrative burden associated with managing ASM permits, which often constitute a significant proportion of regulatory workloads.

5.6. Towards a Reformed Mining Cadastre

The research underscores the critical role a reformed mining cadastre can play in addressing the challenges of ASM regulation in South Africa. A modern mining cadastre, integrated with remote sensing technologies like those deployed in this study, would provide several key benefits to address the dual challenges of environmental degradation and governance inefficiencies, the following strategies are proposed:

Formalisation and Legitimisation of ASM: A mining cadastre can facilitate the formal registration of ASM operators, granting them legal recognition and access to resources while curbing illegal mining. This would help reduce conflicts, enhance safety, and improve accountability.

Dynamic Permitting System: By formally registering ASM operators and delineating their areas of operation, a mining cadastre can promote legal compliance and reduce the prevalence of illegal mining. A blockchain-based cadastre can link permit issuance to environmental metrics (e.g., EVI thresholds), ensuring that mining activities are contingent upon compliance with environmental standards.

Continuous Monitoring with GIS and Remote Sensing: By leveraging satellite data processed in platforms like GEE, a mining cadastre can enable continuous monitoring of ASM activities. Near-real-time data on open pits and vegetation loss would empower authorities to detect illegal operations and respond swiftly to any spatial displacement of ASM operations.

Data-Driven Decision-Making: The integration of NDVI and EVI analyses into the cadastral system would allow authorities to assess environmental impacts and prioritise areas for rehabilitation. This

aligns with broader sustainability goals, ensuring that mining activities do not irreversibly damage ecosystems.

Enhance Policy Enforcement: A centralised, dynamic database of ASM activities would allow for more effective regulation and enforcement, ensuring that small-scale miners remain within their designated 5-hectare boundaries, as per the Artisanal and Small-Scale Mining Draft Policy (2021) and interventions like Operation Vala Umgodi yield long-term benefits.

Promotion of Transparency and Accountability: A publicly accessible mining cadastre supported by blockchain's transparent tracking of compliance would enhance non-overlapping rights dispute and reduce corruption in the allocation and management of mining rights. It would also allow stakeholders, including local communities, to participate in monitoring and decision-making processes.

The findings of this research collectively highlighted the urgent need for a reformed mining cadastre system to formalise and regulate ASM activities effectively. The integration of GIS and RS technologies within the cadastre framework will not only enhance monitoring but also enable data-driven policy decisions, ensuring sustainable ASM practices while mitigating environmental impacts. The combined application of GEE and blockchain technologies offered a robust framework for reforming South Africa's mining cadastre system. By leveraging real-time vegetation monitoring and transparent permitting processes, this approach can balance the competing demands of economic development and environmental sustainability. A blockchain-based cadastre, integrated with remote sensing tools, represented a pivotal step towards equitable, transparent, and sustainable mining governance.

6. CONCLUSION

This research investigated the role of remote sensing, GEOBIA, and blockchain technology in reforming South Africa's mining cadastre system through the assessment of ASM. The study utilised GEE, Sentinel-2, and NICFI imagery to detect and quantify ASM activities within historical mine dumps in the Witwatersrand Basin, assess ASM-induced land degradation, and proposed a blockchain-based cadastral framework to improve mining governance. The research demonstrated the transformative potential of integrating advanced geospatial technologies and blockchain systems into mining governance. By leveraging the capabilities of the GEE platform, this study conducted a comprehensive assessment of ASM activities and their environmental impacts within the Ekurhuleni Municipality from 2021 to 2024. The findings highlighted critical challenges and opportunities for reforming South Africa's mining cadastre system to promote sustainability, transparency, and inclusivity.

The application of GEOBIA within GEE yielded exceptionally high classification accuracy for distinguishing ASM open-pit mining areas, validating the robustness of combining machine learning

with fused satellite imagery for detecting and quantifying ASM activities. This study demonstrated that ASM activities can be effectively detected, monitored, and analysed over time. The research revealed significant vegetation loss associated with ASM activities, as evidenced by the NDVI and EVI analyses. Time-series trends demonstrated declining vegetation health in areas affected by artisanal mining, with EVI proving to be more sensitive to subtle changes in canopy structure and a better indicator of mining-induced deforestation and biomass alteration than NDVI due to its superior performance in complex landscapes (Ashanti, 2020). These results emphasised the environmental costs of unregulated mining and the urgent need for effective monitoring and rehabilitation programs (Wu et al., 2024).

A central finding of this study was the identification of systemic inefficiencies that undermined South Africa's ability to regulate ASM and LSM boundary-sharing operations effectively, exemplified by overlapping mining rights and the coexistence of ASM and large-scale mining on a single cadastral parcel. This showed how the absence of a reliable and accessible mining cadastre system has enabled overlapping permits, spatial displacements, unauthorised operations, and environmental degradation to persist. The findings reinforced the urgent need for a digital cadastre with UPIs, ensuring that mining rights are uniquely assigned, permanently recorded, and accessible in real time. This underscored the potential of Earth Observation technologies in enforcing sustainable mining policies and strengthening environmental compliance frameworks. A blockchain-based digital mining cadastre offered a revolutionary approach to mineral rights management by preventing the double-granting of mineral rights through decentralised, immutable records, enhancing transparency in mining permits allocation, reducing corruption and inefficiencies, as well as enabling automated compliance tracking through smart contracts, ensuring ASM operators adhere to environmental and land-use regulations.

The immutability and traceability of blockchain records will significantly reduce the risk of overlapping mineral rights. When multiple mining operations, such as ASM and LSM operate on the same parcel for the same or different minerals, the unique parcel identifier and transaction history on the blockchain will ensure that no duplicate or conflicting permits are issued. By automating permit issuance and updates through smart contracts, the digital cadastre can reduce bureaucratic delays and administrative overhead. This streamlining is essential for attracting investment and ensuring that mining activities comply with both national and environmental regulations. Transparent and secure records build trust among stakeholders, including regulatory authorities, mining companies, and local communities. The public accessibility of blockchain records, while maintaining data privacy through permissioned channels, ensures accountability and promotes equitable resource management (Nivas et al., 2020).

The findings suggested that combining blockchain technology with remote sensing-based compliance monitoring would enhance mining governance, improve investor confidence, and support sustainable land-use planning. The findings further emphasised the need for a multifaceted approach to reform South Africa's mining governance. By integrating geospatial analysis with blockchain-based systems,

policymakers can enable real-time monitoring of environmental compliance, ensure equitable access to mining permits for ASM operators, and promote transparency and reduce corruption in the permit issuance process (Bambara and Allen, 2018). This approach aligned with the principles of sustainable development, addressing environmental, economic, and social dimensions simultaneously. The integration of advanced technologies also provided a scalable model for other countries facing similar ASM-related challenges. The adoption of a blockchain-based digital mining cadastre has broader implications for improving governance and regulatory oversight in the mining sector.

This research contributed to the global discourse on sustainable mining governance by providing a replicable model for mining jurisdictions facing similar challenges of ASM expansion, land-use conflicts, and cadastral inefficiencies. A reformed mining cadastre system in South Africa can ensure that ASM contributes to economic development without compromising environmental sustainability. By adopting innovative governance solutions, South Africa can set a precedent for responsible resource management in mining-dependent economies. This study provided a scientific, policy-driven, and technology-enabled framework for improving mining cadastre governance in South Africa. By integrating remote sensing, GIS, and blockchain technology, a sustainable, transparent, and efficient mining rights management system can be developed. The successful implementation of a blockchain-based cadastral system would not only regulate ASM activities but also promote economic inclusivity, environmental sustainability, and responsible resource management (World Bank, 2019).

7. RECOMMENDATIONS

Based on the comprehensive analysis conducted in this study, several recommendations are proposed to address the systemic issues in South Africa's mining cadastre and to mitigate the environmental and administrative challenges posed by ASM. These recommendations are grounded in the integration of advanced geospatial technologies and blockchain systems to modernise the mining cadastre and promote sustainable resource management, with the main recommendation being the establishment of a blockchain-based digital mining cadastre using Hyperledger Fabric, ensuring that all mining transactions, mineral rights allocations, and environmental compliance records are permanently recorded and securely managed (Gaur et al., 2023).

By leveraging Distributed Ledger Technology (DLT's) decentralised nature, smart contracts, and cryptographic security, the proposed system would revolutionise mining governance, improve permit allocation efficiency, and foster sustainable resource management. The mining cadastre manages mining rights and licenses, requiring secure, private, and efficient transactions. Hyperledger Fabric is a permissioned blockchain, meaning only authorised parties can access it, making it ideal for protecting sensitive information like financial details or proprietary data. It offers high performance and can be

customised for enterprise needs, ensuring scalability and efficiency for large transaction volumes (Bambara and Allen, 2018).

7.1. Implementation of a Blockchain-Based Digital Mining Cadastre

7.1.1. Unique Parcel Identifiers (UPIs) for Secure Mining Rights Allocation

One of the key findings of this study was the spatial displacement and instances of overlapping mining explorations, who's opacity has not only facilitated illegal mining activities but has prospects of allowing for the double granting of mineral rights over the same land parcel and mineral resource, highlighting the administrative inefficiencies in South Africa's mining cadastre system (Girones et al., 2009a). To address these issues, the government should implement a blockchain-based digital mining cadastre with Unique Parcel Identifiers (UPIs) to prevent overlapping mining claims by ensuring that each mining permit is uniquely recorded and tamper-proof, enhance transparency in the permitting process, reducing the risk of corruption and illegal land allocations, and streamline access to mining data, allowing investors, regulators, and communities to verify mining rights in real time (Pathak, N., Bhandari, A., 2018).

7.1.2. Towards a Sustainable and Transparent Mining Sector

The research findings reinforced the urgent need to modernise South Africa's mining cadastre using blockchain technology, remote sensing, and digital permit systems. By implementing the recommendations outlined in this study, South Africa can, improve mining governance through blockchain-based transparency, enhance environmental compliance using remote sensing tools like NDVI and EVI, strengthen the formalisation of ASM, ensuring economic inclusivity while preventing land-use conflicts, and develop a mining cadastral system that aligns with international best practices, promoting sustainable resource management (Girones et al., 2009a).

The integration of GIS, remote sensing, and blockchain into mining governance offers a scalable, technology-driven solution to enhance transparency, reduce illegal mining, and support sustainable land-use planning. Implementing these recommendations would ensure that ASM and LSM operations coexist under a regulated, environmentally responsible framework that benefits the economy, environment, and local communities. The adoption of DLT, specifically Hyperledger Fabric, provides an innovative solution to these challenges by creating a tamper-proof, decentralised, and highly secure mining cadastre system (Gaur et al., 2023).

7.2. Why Hyperledger Fabric for a Blockchain-Based Mining Cadastre?

7.2.1 Permissioned Blockchain for Secure Transactions

Hyperledger Fabric is a permissioned blockchain platform, meaning that only authorised entities (government agencies, mining companies, environmental regulators, geologist and financial

institutions) can participate in mining cadastre transactions (Nivas et al., 2020). Unlike public blockchains (e.g., Bitcoin, Ethereum), which are fully decentralised and open to anyone, Hyperledger Fabric ensures that only verified stakeholders can access and modify mining records. This permissioned structure is critical for mining governance as it prevents unauthorised tampering with cadastral records, ensures regulatory oversight by government agencies, allows mining companies and ASM operators to securely access their permit information, and restricts access to sensitive mining rights data, reducing the risk of fraud (Fenton Villar, 2021).

Based on the analysis of Table 4, Hyperledger Fabric is the best choice for employing DLT in a mining cadastre, offering privacy, performance, and customisability. Ethereum, while advanced, is less suitable due to its public nature and scalability issues. Advanced options like Corda and Quorum are viable but less general-purpose. For a secure, efficient, and scalable mining cadastre, Hyperledger Fabric is recommended, with implementation focusing on smart contracts for transaction automation and integration with governmental systems (Dhillon et al., 2017).

Table 4: The Types of Blockchain Framework Comparison

Feature	**Hyperledger Fabric**	**Ethereum**	**Corda**	**Algorand**
Consensus	Byzantine Fault-Tolerant	Proof-of-Stake	Consensus-algorithm	Pure Proof-of-Stake
Privacy	High (private channels)	Low (public)	High (bilateral only)	Medium (encrypted)
Transactions Per Second	3,000+	15 (base) / 7,000 (Layer-2)	1,500	6,000
Smart Contracts	Chaincode (Java)	Solidity	Kotlin/Java	TEAL (Python-like)
Regulatory Compliance	Excellent	Moderate	Excellent	High

7.2.2 Smart Contracts for Automated and Transparent Permit Issuance

Hyperledger Fabric enables smart contract execution through Chaincode, which automates transactions based on predefined rules (Bambara and Allen, 2018). This is essential for mining governance, as smart contracts can be used to enforce compliance, track permit renewals, and ensure that all mining rights are allocated according to legal frameworks. For instance, smart contracts in a Hyperledger Fabric-based mining cadastre can, automatically reject permit applications for land parcels already allocated to another miner, eliminating double-granting of mineral rights. Ensure ASM miners remain within their designated 5-hectare boundary limits, preventing encroachment on large-scale mining concessions. Enforce compliance with environmental regulations, requiring miners to submit periodic

environmental impact reports before their permits are renewed, and facilitate secure transactions for mining rights transfers, reducing corruption and ensuring transparency. By implementing smart contract-based automation, the mining cadastre system would eliminate manual processing inefficiencies, reduce corruption, and enhance transparency in mining rights administration.

7.2.3 Decentralised and Immutable Mining Records

One of the primary challenges in the current mining cadastre system is record manipulation and fraudulent modifications of mining permits. Hyperledger Fabric's distributed ledger structure ensures that all mining transactions are immutable, meaning that once a mining permit or compliance record is recorded, it cannot be altered or deleted since, every transaction (e.g., permit issuance, renewal, revocation) is recorded on the blockchain and validated by all nodes in the network, further more immutable records prevent disputes over ownership and eliminate unauthorised permit alterations, and the distributed nature of Hyperledger Fabric ensures that cadastral data is not stored on a single vulnerable server but replicated across multiple nodes, reducing the risk of system failures or cyberattacks (Fenton Villar, 2021). This immutable, decentralised structure provides a trustworthy, verifiable, and tamper-proof mining cadastre, ensuring long-term stability and regulatory compliance.

7.2.4 Proposed Implementation Framework for a Blockchain-Based Mining Cadastre

The Implementation Strategy would involve the South African Department of Mineral Resources and Energy (DMRE), which should transition to a decentralised blockchain mining cadastre, integrating GIS-based parcel tracking to ensure real-time updates, stakeholders, including mining companies, artisanal miners, and local communities, who should have digital access to mining rights records to promote public accountability and compliance monitoring, as well as collaboration with blockchain technology experts and GIS specialists to create a secure, scalable, and efficient mining cadastral system. For implementation, Hyperledger Fabric can record mining rights on the blockchain and use smart contracts to automate transfers or changes, ensuring tamper-proof records. As it integrates well with other systems, which is crucial for governmental operations (Jalloh et al., 2016).

Mining Cadastre Network Participants

A Hyperledger Fabric-based mining cadastre would consist of the following authorised participants, starting with the DMRE, this being the regulatory authority responsible for issuing and monitoring mining permits. Mining Companies (LSM and ASM Operators), this refers to any entities applying for mining permits and required to comply with environmental regulations. Environmental Agencies, these being registered organisations monitoring environmental impact and ensuring compliance with rehabilitation policies. Financial Institutions which can be local and international banks and investors verifying mining rights before funding projects, as well as the Local Government and Communities,

which can be municipalities and affected communities providing input on mining activities in their jurisdiction (Yomralioglu and Mclaughlin, 2017).

The WebGIS architecture flowchart (Figure 16) illustrates the multi-tiered system architecture and smart contract workflow for the proposed blockchain-based mining cadastre using Hyperledger Fabric as the core infrastructure. Beginning with either a large-scale mining company or ASM operator submitting an online permit application via a frontend interface, selecting a geospatially defined cadastral parcel; the smart contract then automatically verifies parcel availability in the Hyperledger Fabric, proceeding to DMRE approval if unallocated or rejecting the application to prevent double-granting if already assigned. Upon approval, the permit is recorded on the blockchain with details such as Unique Parcel Identifier (UPI), permit holder information, mineral type, validity period, and compliance requirements, while satellite-derived environmental impact assessments (e.g., NDVI, EVI, MDI, HTI, etc.) are linked for ongoing tracking via the GEE platform, triggering automatic warnings for non-compliance like illegal expansions or deforestation.

The last step would involve miners submitting periodic compliance reports, where smart contracts verify status using remote sensing data to determine if the permit remains valid, requires environmental remediation, or faces revocation, flagging violations for regulatory intervention. Overall, this workflow ensures transparent, secure, and efficient mining rights management, integrating real-time geospatial monitoring to promote sustainable governance and prevent overlaps. Beyond the mining sector, the architecture demonstrates how blockchain and geospatial technologies can be integrated to bridge the geospatial digital divide in South Africa. The system can be adapted to other sectors, such as agriculture, urban planning, and environmental conservation, thereby broadening equitable access to spatial information and strengthening evidence-based decision-making across the country (Sequeira et al., 2016; Phillips and Whiting, 2016).

7.3. Transforming Mining Governance with Blockchain-Based Cadastre

The adoption of Hyperledger Fabric for a blockchain-based mining cadastre presented an innovative and transformative solution for securing mining rights, preventing fraud, and improving environmental compliance in South Africa's mining sector (Table 5). By leveraging DLT's transparency, automation, and immutability, this system will, prevent double granting of mineral rights, ensuring that every cadastral parcel has a unique and verifiable permit holder, enhance compliance monitoring, integrating satellite-based environmental assessments with blockchain records would streamline mining permit allocation, reducing bureaucratic inefficiencies and improving investor confidence, and protect ASM operations from encroachment, ensuring that artisanal miners operate within legally designated areas by assigning designated ASM mining zones within the digital cadastre, ensuring that ASM operators are allocated legal mining areas with clear boundaries and fencing (Konguka et al., 2022).

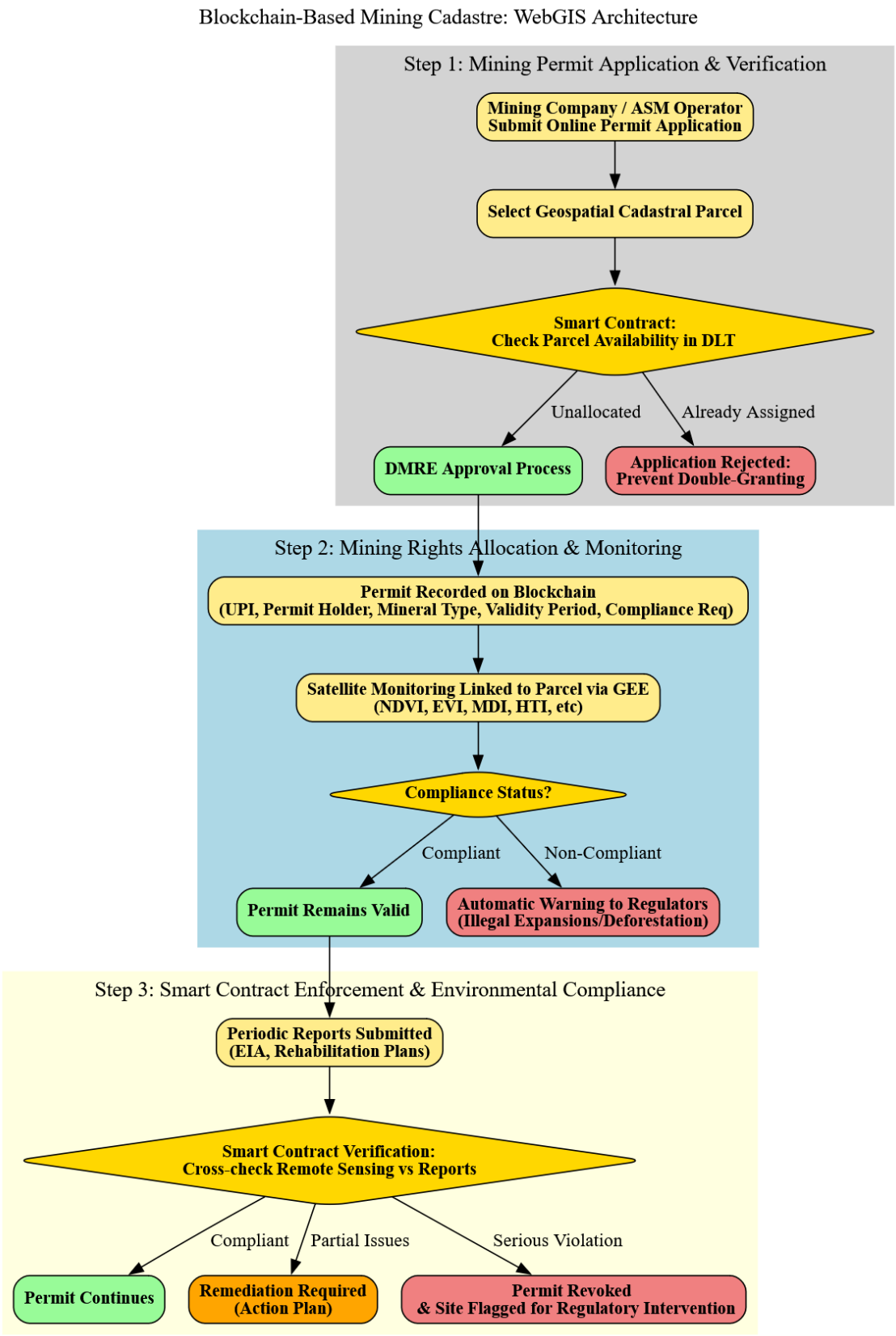


Figure 16: System Architecture and Smart Contract Workflow

Table 5: The Benefits of Hyperledger Fabric for Mining Cadastre Management

Feature	Impact on Mining Governance
Decentralisation	Eliminates reliance on a single authority, reducing corruption and improving transparency.
Immutability	Ensures mining permits cannot be fraudulently altered or deleted.
Smart Contracts	Automates compliance monitoring, preventing permit fraud and unauthorised land use.
Enhanced Security	Private channels for sensitive mining data. Uses cryptographic encryption to protect mining data from cyber threats.
Real-Time Access	Enables instant verification of mining rights, reducing delays in permit processing.

The results of this research highlighted the critical role of spatial analysis and geospatial technologies in reforming South Africa's mining cadastre system. The findings demonstrated that ASM operations can coexist with large-scale mining activities under a transparent and well-regulated cadastral framework (Nielsen et al., 2019). However, the absence of a comprehensive mining cadastre perpetuates inefficiencies, illegal activities, and environmental degradation. By integrating remote sensing and real-time spatial data into a centralised mining cadastre system, South Africa can enhance its mining governance, promote sustainable practices, and support biodiversity conservation.

These insights provide a foundation for addressing systemic challenges in the mining sector, aligning ASM practices with national policies, and fostering a sustainable and equitable approach to resource management. To achieve this, government agencies, mining companies, and technology developers must collaborate to implement a fully functional Hyperledger Fabric mining cadastre, ensuring a secure, efficient, and sustainable mining rights management system (Nivas et al., 2020). This integration of blockchain and remote sensing represented the future of mining governance, aligning South Africa with global best practices in digital cadastral systems. Pilot studies should be conducted in ASM-dominated regions to assess the feasibility and scalability of such systems, with a focus on interoperability with existing geospatial data platforms like GEE (Pathak, N., Bhandari, A., 2018).

7.3.1. The Role of a Digital Mining Cadastre in Spatial Data Infrastructure and Global Mining Governance

The establishment of a blockchain-based digital mining cadastre using Hyperledger Fabric is a transformative step toward enhancing mining governance, spatial data management, and sustainable resource allocation in South Africa. This initiative aligns with the South African Spatial Data Infrastructure (SASDI) framework by improving spatial data accessibility, interoperability, and transparency in land administration. Additionally, the adoption of DLT for mining cadastre

management supports the World Bank's Extractive Industries Transparency Initiative (EITI) and global best practices in mineral rights administration (Gaur et al., 2023).

7.3.2. Strengthening Spatial Data Interoperability and Mining Land Governance

SASDI is designed to ensure standardised spatial data sharing across government entities, private stakeholders, and the public (Siebritz et al., 2022). A blockchain-based mining cadastre aligns with SASDI's objectives by creating a decentralised, verifiable, and transparent record of mining rights and land use, ensuring interoperability between mining cadastre records and other spatial datasets (e.g., environmental impact assessments, land tenure records, infrastructure development plans), and reducing administrative fragmentation by centralising mining rights data into a nationwide, real-time, and publicly accessible registry (Bambara and Allen, 2018). Therefore, by integrating Hyperledger Fabric with SASDI, the DMRE, Department of Environmental Affairs, and municipal governments can access real-time mining permit information, enhancing policy coordination, enforcement, and compliance monitoring (Nivas et al., 2020).

7.3.3. Enhancing Transparency and Accessibility of Mining Spatial Data

One of the primary challenges in South Africa's mining sector is the lack of public access to mining rights information. Unlike other competitive mining jurisdictions where digital mining cadastres are publicly accessible, South Africa's current system is opaque, requiring manual applications and payment of fees to access cadastral data (Dhillon et al., 2017). Therefore, a Hyperledger Fabric mining cadastre would**, i**mprove public access to spatial mining data, aligning with SASDI's goal of open and standardised spatial information dissemination, enable mining companies, investors, and communities to verify mining rights in real time, reducing disputes over land allocations, and provide an immutable record of mining permits and compliance reports, fostering accountability and reducing fraudulent land transactions (Siebritz et al., 2022). The standardisation and data quality control would entail adopting common standards and protocols defined within SASDI, the blockchain-based cadastre will benefit from consistent data quality and interoperability. The use of unique parcel identifiers (UPIs) within the digital cadastre will ensure that each mining claim is uniquely traceable and verifiable, reducing conflicts and preventing the double granting of mineral rights. This standardisation is critical for maintaining high data integrity and supporting evidence-based decision-making in the mining sector (Pathak, N., Bhandari, A., 2018).

7.3.4. Advancing Digital Transformation in South African Land Administration

The National Spatial Information Framework (NSIF) under SASDI has advocated for the adoption of modern geospatial technologies to improve land administration. Blockchain integration into SASDI's mining cadastre would, ensure digital verification of mining rights, eliminating inefficiencies associated

with paper-based cadastral records, enable real-time tracking of land-use changes in mining areas, integrating satellite imagery from GEE, Sentinel-2, and NICFI with blockchain smart contracts, and streamline decision-making processes for land-use planning, rehabilitation programs, and environmental impact assessments (EIAs). Therefore, by leveraging blockchain and remote sensing technologies, South Africa can modernise its mining governance and spatial data infrastructure, ensuring efficient resource management and improved investor confidence. The enhanced data accessibility will allow for real-time environmental assessments and facilitate timely interventions in cases of illegal or environmentally harmful mining practices. Such capabilities are essential for protecting sensitive ecosystems and ensuring sustainable resource management (Konguka et al., 2022).

7.4. Alignment with the World Bank's Mining Governance and Spatial Data Initiatives

7.4.1. Supporting the Extractive Industries Transparency Initiative (EITI)

The World Bank's EITI framework promotes good governance, transparency, and accountability in extractive industries. The lack of transparency in South Africa's mining cadastre has led to, Illicit mining activities due to unregulated land allocations, corruption in the granting of mineral rights, undermining economic development, as well as disputes over mining permits, causing legal conflicts and delays in project implementation (Fenton Villar, 2021). Therefore, a blockchain-based cadastre would directly support the EITI framework by, providing an immutable, verifiable record of all mining rights transactions, ensuring transparency in permit issuance, automating permit renewals and compliance tracking, reducing human intervention and opportunities for corruption, and ensuring that mineral rights are allocated fairly and equitably, preventing double-granting of mining licenses. Therefore, by adopting Hyperledger Fabric, South Africa can align its mining governance with EITI standards, improving its global mining investment attractiveness and compliance with international transparency requirements (Chu, 2018; Yomralioglu and Mclaughlin, 2017).

7.4.2. Enabling Sustainable Mining through the World Bank's Land Governance Framework

The World Bank's Land Governance Assessment Framework (LGAF) emphasises the importance of secure, accessible, and well-managed land records. The current inefficiencies in South Africa's mining cadastre contradict these principles, leading to unclear land tenure rights for ASM operators, limiting formalisation efforts, unregulated expansion of illegal mining, contributing to environmental degradation, and difficulty in enforcing land-use regulations and ensuring responsible resource management (Dhillon et al., 2017). Therefore, a Hyperledger Fabric-based mining cadastre would enhance land governance in the mining sector by providing legally verifiable cadastral records, ensuring mining rights security, enhancing environmental monitoring by integrating satellite-based change

detection methods (NDVI, EVI, and GEE analytics), and strengthening land-use planning by ensuring that ASM operations are formalised and operate within designated areas (Nivas et al., 2020).

7.4.3. Blockchain for Land Tenure Security and Investment Confidence

The World Bank has identified blockchain technology as a key tool for improving land administration in developing economies (Chu, 2018). A secure, transparent mining cadastre would increase investor confidence in South Africa's mining sector, ensuring that mining licenses are allocated legally and fairly, improve access to financial services for ASM operators, as secure land tenure enhances their ability to seek investment and financing, and facilitate responsible mining by ensuring that environmental and social obligations are embedded in blockchain-based mining permits (Fenton Villar, 2021). Therefore, engagement with the World Bank can facilitate capacity building within South African governmental agencies. Training programs and knowledge exchange initiatives focused on blockchain technology, remote sensing, and spatial data infrastructure management will be critical to the system's success (World Bank, 2019). These efforts will help build institutional resilience and ensure that the digital cadastre is sustainably managed over the long term (Konguka et al., 2022).

7.5 The Future of Mining Cadastre Management in South Africa

The integration of Hyperledger Fabric into the South African mining cadastre would fundamentally transform mining governance by ensuring transparency, efficiency, and sustainability (Nivas et al., 2020). By aligning with SASDI's spatial data management principles and the World Bank's mining governance frameworks, this system would, eliminate double granting of mining rights by assigning UPIs to cadastral parcels, ensuring every mining transaction is verifiable and secure (Todes et al., 2010). Enhance interoperability between the mining cadastre and other land administration systems, improving decision-making and spatial planning. Improve environmental compliance monitoring, integrating remote sensing and blockchain smart contracts to enforce rehabilitation obligations. Increase transparency in the extractives sector to reduce corruption and foster responsible resource management, thereby enhancing South Africa's compliance with global mining governance standards and strengthening its position as a responsible mining jurisdiction (Sequeira et al., 2016).

Hitherto, by anchoring South Africa's mining cadastre to SASDI and World Bank frameworks, this initiative transcends national borders, offering a replicable model for ethical mineral governance (Siebritz et al., 2022). The fusion of blockchain's security, SASDI's interoperability, and the World Bank's sustainability mandates positions South Africa as a global leader in spatial data innovation. Success hinges on legislative agility, stakeholder inclusivity, and relentless adherence to the Open Geospatial Consortium / International Organization for Standardization (OGC/ISO) standards, a blueprint for turning resource wealth into equitable development (Dhillon et al., 2017). The adoption of

DLT in mining cadastral systems is no longer optional but a necessity for ensuring equitable resource allocation, sustainable land use, and long-term economic growth. South Africa must take decisive action to modernise its mining governance infrastructure, ensuring that its cadastre system meets the demands of the 21st-century digital economy (Gaur et al., 2023).

7.5.1. Significance for ASM and LSM Permit Issuance

Artisanal and small-scale mining (ASM) plays a vital role in South Africa's economy by contributing to local livelihoods, job creation, and poverty reduction. However, the informal and often unregulated nature of ASM operations frequently excludes these miners from essential regulatory protections, financial support, and development opportunities. The study found that many ASM operators function outside formal frameworks due to the absence of an accessible and efficient permitting system. To enhance formalisation and integration into the formal economy, several strategic measures are proposed. The decentralised nature of DLT should be prioritised to streamline ASM permit issuance, reducing administrative bottlenecks and ensuring transparency in allocation (Chu, 2018). Through a blockchain-based online cadastre system, artisanal miners can obtain permits without undue delays, while regulatory authorities can ensure spatial compliance and prevent overlapping claims. Such formalisation not only legitimises ASM activities but also expands miners' access to financial resources, training initiatives, and environmental rehabilitation programs, thereby promoting responsible mining (World Bank, 2019). Concurrently, technical support is essential to build capacity among ASM operators. Government agencies and stakeholders should provide training programs focusing on sustainable mining practices, environmental management, and digital literacy. These initiatives will facilitate a smoother transition from informal to formal operations while improving safety and sustainability (Sequeira et al., 2016; Phillips and Whiting, 2016).

Furthermore, enhanced environmental accountability can be achieved by linking ASM permits to real-time environmental monitoring through blockchain. Smart contracts can automate sustainability enforcement by tracking compliance indicators and incentivising responsible behaviour, such as offering rewards or reduced fees for adherence to environmental standards. Monitoring of shared boundaries between ASM sites and large-scale mining companies, such as Afrisam, is also critical to prevent encroachment and policy violations. High-resolution satellite imagery, coupled with periodic field inspections, can provide accurate oversight of boundary integrity. Finally, conflict resolution mechanisms must be strengthened through the development of a centralised and transparent cadastral system that integrates real-time spatial data. Such a system will reduce overlapping claims, enhance accountability, and provide time-stamped records of mining rights, thereby minimising disputes between boundary sharing mining operators. Together, these measures ensure that ASM and LSM activities coexist within a sustainable, transparent, and technologically advanced mining governance framework (Chu, 2018; Yomralioglu and Mclaughlin, 2017).

7.5.2. Integrate Real-Time Geospatial Monitoring

To address the environmental impacts of ASM, it is critical to implement real-time geospatial monitoring systems. The research demonstrated that ASM operations are expanding within historical mine dumps, leading to gradual environmental degradation over time. Automated alerts should be generated whenever ASM operations expand beyond designated boundaries, allowing for immediate enforcement action. This necessitates the institutionalisation of the advanced GEOBIA technique applied in this study for precise mining footprint delineation within government monitoring frameworks to regularly update and validate the mining cadastre (Shirzad et al., 2014).

The use of vegetation indices, specifically NDVI and EVI, as demonstrated in this research, is crucial for tracking vegetation loss and recovery in mining-affected areas. EVI should be prioritised for its sensitivity to canopy structure and atmospheric corrections, making it particularly recommended as an indicator of mining-induced deforestation (Sikakwe et al., 2023). The integration of geospatial monitoring with automated alerts for detecting non-compliance with environmental regulations is proposed. Such alerts could be triggered when vegetation indices fall below predefined thresholds, enabling proactive intervention. This monitoring would inform ecological impact assessments and support timely remedial actions in areas experiencing degradation. These measures will help regulators in identifying and addressing mining-induced environmental and land degradation. Formalisation not only benefits ASM miners but also facilitates better data collection and compliance monitoring by regulatory agencies (Okada et al., 2020).

7.5.3 Strengthening ASM Environmental Compliance Monitoring

ASM activities have been linked to deforestation, land degradation, and uncontrolled expansion, as demonstrated by the NDVI and EVI-based land change analysis in this research. To enforce sustainable mining practices and ensure that ASM permits are linked to compliance monitoring tools, using remote sensing data to track mining activities in real time. The DMRE should mandate ASM miners to submit environmental management and rehabilitation plans as a condition for permit issuance. Remote sensing (NDVI and EVI monitoring) should be integrated into the permit renewal process, ensuring that ASM miners comply with environmental regulations. Local authorities should implement ASM capacity-building programs to educate miners on environmentally responsible mining practices and land rehabilitation strategies (Pathak, N., Bhandari, A., 2018).

The integration of blockchain and GEE workflows provides a comprehensive framework for addressing the environmental and social impacts of mining. Rehabilitation efforts should be monitored using geospatial technologies to ensure long-term sustainability. The study analysis demonstrated significant vegetation loss in ASM-impacted areas, as indicated by declining NDVI and EVI values in 2024. Blockchain can enable regulators to link vegetation degradation directly to specific mining permits,

holding operators accountable for restoration efforts. Transparent access to mining data allows local communities to monitor environmental impacts and advocate for their rights. Blockchain can also ensure that communities receive their fair share of royalties and benefits from mining activities (Nivas et al., 2020).

7.5.4. Alignment with International Best Practices and the Sustainable Development Goals (SDGs)

South Africa should align its mining governance with global best practices by adopting lessons from countries that have successfully implemented digital mining cadastral systems, such as, Botswana that uses a transparent, publicly accessible mining cadastre to manage mineral rights efficiently, Peru which implemented blockchain-based land registries to ensure secure and verifiable property ownership, and Australia who are already using remote sensing for mining compliance enforcement, ensuring that environmental regulations are upheld (Bambara and Allen, 2018).

The proposed reforms should align with the United Nations Sustainable Development Goals, particularly, SDG 15 (Life on Land) by reducing deforestation and promoting land rehabilitation, SDG 13 (Climate Action) by mitigating the environmental impacts of mining, SDG 16 (Peace, Justice, and Strong Institutions) by fostering transparent and accountable mining governance, and SDG 9 (Industry, Innovation, Infrastructure) by positioning the mining cadastre as critical infrastructure under the World Bank's Digital Economy for Africa Initiative (Pathak, N., Bhandari, A., 2018).

Integrating Hyperledger Fabric into the digital mining cadastre represented a transformative approach to mining rights management in South Africa. The distributed ledger technology's inherent features, such as immutability, transparency, and secure access, coupled with the real-time remote sensing capabilities of GEE, provide a robust solution to prevent overlapping permits and mitigate regulatory lapses. This integrated framework not only enhances the efficiency and transparency of the mining cadastre but also sets a precedent for sustainable and equitable governance in the mining sector (Chu, 2018).

7.6. Limitations and Future Directions

While blockchain offers transformative potential, its implementation in South Africa's mining cadastre faces several challenges, such as infrastructure and capacity as the adoption of blockchain technology requires significant investment in digital infrastructure and training, particularly in rural areas where ASM operations are concentrated, interoperability as integrating blockchain with existing systems, such as GEE-based monitoring tools, requires careful planning to ensure seamless data exchange, scalability as the system must be designed to handle the large volume of ASM and LSM permits in South Africa, ensuring scalability and reliability. Investigation of cloud-computing optimisations for national-scale

implementation is required, and a blockchain implementation for cadastral management is required, meaning a pilot study should be conducted to test the feasibility of blockchain technology in South Africa's mining governance, as well as the utilisation of GEE and WebGIS platforms to demonstrate the feasibility and benefits of the proposed solutions (Shirzad et al., 2014).

Future research should focus on building a centralised, publicly accessible 3D mining cadastre system incorporating real-time updates from remote sensing platforms (Whittal et al., 2017). The use of artificial intelligence (AI) for automated detection of mining activities and encroachments, combined with participatory mapping initiatives, can further support sustainable mining practices in South Africa. Future studies should therefore explore additional vegetation indices and quantum-enhanced geospatial algorithms for ASM feature extraction, improving the accuracy of GEOBIA-based classification and change detection techniques to capture ASM activities with higher precision (Adegun, et al., 2023). Traditional remote sensing methods for ASM detection face challenges in highly dynamic, small-scale, and cluttered mining environments. Quantum-enhanced algorithms offer a paradigm shift in object recognition, classification, and pattern analysis by leveraging the power of quantum computing (Baek et al., 2023). Advantages of Quantum-Enhanced Object Detection include higher computational efficiency where quantum algorithms process massive datasets exponentially faster than classical algorithms, significantly reducing the time required for ASM mapping, and superior image classification accuracy as quantum machine learning (QML) can improve the precision of mine pit identification, tailings volume estimation, and environmental degradation assessments (Liu et al., 2023; Konar et al., 2021).

Beyond the mining sector, the proposed WebGIS workflow will contribute significantly to bridging the geospatial digital divide in South Africa by embedding transparent, spatially enabled governance into national decision-making systems. By coupling blockchain with geospatial analytics, the framework enhances equitable access to cadastral and environmental data, enabling communities, regulators, and industries to interact with spatial information in real time. This represents not only a reform of mining governance but also a forward leap for sectors such as agriculture, forestry, and urban planning, where similar systems can be deployed. Furthermore, the integration of such digital infrastructures positions South Africa to better manage and capitalise on its rare earth elements (REEs), ensuring their sustainable extraction under transparent governance structures (Bambara and Allen, 2018).

The recommendations outlined above provide a roadmap for modernising South Africa's mining cadastre system and addressing the challenges posed by ASM. By integrating advanced geospatial tools and blockchain technology, these reforms can promote transparency, environmental sustainability, and socioeconomic equity. Such innovations are not only critical for South Africa but also serve as a replicable model for other resource-dependent economies. A blockchain-based digital mining cadastre represented a paradigm shift in mining governance, offering an innovative solution to South Africa's

regulatory challenges. By integrating real-time monitoring tools and ensuring transparent permit management, blockchain can enhance the sustainability, equity, and efficiency of mining operations. For South Africa, this technology holds the potential to not only transform its mining cadastre system but also serve as a global model for responsible and inclusive resource management (World Bank, 2019).

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