Application of Geographic Information System (GIS) in Mining Exploration

A Case Study of Belvand Geotechnics.

Abel Fernando Alberto

Geotechnical Engineer

Internship Report

presented as partial requirement for obtaining a Master's Degree in Geographical Information Systems and Science

NOVA Information Management School

Instituto Superior de Estatística e Gestão de Informação

Universidade Nova de Lisboa

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by

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Geotechnical Engineer

Internship Report presented as partial requirement for obtaining the Master's degree in Geographic Information Systems, with a specialization in Geospatial Data Science

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December, 2024

STATEMENT OF INTEGRITY

I declare that the work described in this document is my own and not from someone else. All the assistance I have received from other people is duly acknowledged and all the sources (published or not published) are referenced.

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Paraphrasing or rewriting text from others/resources	X		
Coding in R, Python, etc.		✓	Chat GPT
Getting help with software	X		
Creating and editing images, maps, videos, etc.		✓	Chat GPT
Data analysis	X		
Specify below other tasks not mentioned above:	X		

DEDICATION

DURING THE MASTER'S PROGRAM, I RECEIVED TWO VALUABLE GIFTS, MY TWO CHILDREN, **ELIÉZER** AND **ÁGATA ALBERTO**, WHICH MADE IT MORE CHALLENGING TO PREPARE THIS REPORT AND FULFILL THE ROLE OF A FATHER AS WELL. I DEDICATE THIS WORK TO **THEM**, ALSO TO MY WIFE **ARMINDA ALBERTO,** TO MY PRINCESS **JAQUELINE CHICO,** MY PARENTS (**MARIA FERNANDO, EDMUNDO ALBERTO)**, AND TO MY SIBLINGS, **EMANUEL, GELSON** AND **EDNA ALBERTO**.

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Application of Geographic Information System (GIS) in Mining Exploration

A Case Study of Belvand Geotechnics

ABSTRACT

The internship report focuses on how Belvand Geotechnics used Geographic Information System (GIS) to transform its mining exploration efforts in Cuanza-Sul/Angola. GIS is acknowledged as a key player in the mining industry, enhancing decision-making, logistical planning, and operational efficiency through enhanced spatial data processing and visualization. Belvand's use of GIS demonstrates its capacity to simplify the exploration process, which includes data integration.

Furthermore, it takes a look at the benefits and outcomes of using GIS in mining exploration at Belvand. It emphasizes how GIS helps with decision-making, by combining various data sources, GIS provides a comprehensive view of geological and environmental conditions, which is critical for accurately identifying exploration locations and assessing potential environmental implications. Additionally, GIS plays an important role in engaging stakeholders by providing clear visual representations of exploration strategies, boosting transparency and collaborative efforts.

On the other hand, it addresses the obstacles and constraints encountered when using GIS in mining exploration, such as issues with data quality, integration, and the need for technical competence as well as appropriate hardware and software resources. Belvand has tackled this

challenge by creating tight data validation processes, investing in employee training, and exploring cloud-based solutions to enhance their computational capabilities.

To summarize, it underlines GIS role in modernizing mining exploration processes, as well as its support to sustainable and responsible exploration endeavours. It suggests future advancements, including predictive analytics and the incorporation of machine learning, to further maximize GIS's potential. Recommendations for Belvand involve enhancing data integration, adopting real-time monitoring, and expanding spatial analysis tools to maintain its leading position in GIS supported mining exploration. All things considered, the internship report demonstrates how GIS has revolutionized mine exploration and highlights Belvand Geotechnics' commitment to using cutting-edge technology to improve exploration outcomes.

KEYWORDS

GIS; Mining; Mineral Exploration; Satellite Images; Remote Sensing; Georeferencing; Mineral Occurrence; WGS 1984; Datum; Grid Reference; GPS; Accuracy; Precision; Uncertainty; Ordinary Kriging; Geostatistics; Copper.

RESUMO

O relatório de estágio centra-se na forma como a Belvand Geotechnics utilizou o Sistema de Informação Geográfica (SIG) para dar respostas aos seus trabalhos de exploração mineira no Cuanza-Sul/Angola. O SIG é reconhecido como uma peça importante na indústria mineira, melhorando a tomada de decisões, planeamento logístico e a eficiência operacional através de processamento e visualização de dados geoespaciais. A utilização de SIG pela Belvand demonstra a sua capacidade de simplificar processos de exploração, que inclui a integração de dados e envolvimento com as populações locais.

O relatório, analisa os benefícios e os resultados da utilização da tecnologia SIG na exploração mineira pela Belvand. Realça como o SIG ajuda na tomada de decisões. Ao combinar várias fontes de dados, o SIG fornece uma visão abrangente das condições geológicas e ambientais, o que é fundamental para identificar com precisão os locais de exploração e avaliar as potenciais implicações ambientais. Além disso, o SIG desempenha um papel importante no envolvimento das partes interessadas, fornecendo representações visuais claras das estratégias de exploração, aumentando a transparência e os esforços colaborativos.

Por outro lado, aborda os obstáculos e restrições encontrados ao utilizar o SIG na exploração mineira, tais como problemas com a qualidade dos dados, integração e a necessidade especialistas bem treinados, bem como de recursos apropriados de hardware e software. A

Belvand enfrentou este desafio criando processos rígidos de validação de dados, investindo na formação dos colaboradores e explorando soluções baseadas na cloud para melhorar as suas capacidades computacionais.

Em suma, o relatório sublinha o papel crítico do SIG na modernização dos processos de exploração mineira, bem como o seu apoio aos esforços de exploração sustentável e responsável. Sugere avanços futuros, incluindo análises preditivas e a incorporação de Machine learning, para maximizar ainda mais o potencial do SIG. As recomendações para Belvand envolvem melhorar a integração de dados, adotar a monitorização em tempo real e expandir as ferramentas de análise espacial para manter a sua posição de liderança na exploração mineira apoiada por SIG. Considerando tudo isto, o relatório de estágio demonstra como o SIG revolucionou a exploração mineira e destaca o compromisso da Belvand Geotechnics em utilizar tecnologia de ponta para melhorar os resultados da exploração.

PALAVRAS-CHAVE

SIG; Mineração; Exploração Mineral; Imagens de Satélite; Deteção Remota; Georreferenciação; Ocorrência Mineral; WGS 1984, Datum, Referência de Grelha, GPS; Exatidão; Precisão; Incerteza; Exatidão; Kriging Ordinário; Geoestatística; Cobre.

Tables of Contents

Statement of Integrity i
Dedication iii
Acknowledgements iv
Abstract v
Resumo vii
Tables of Contents ix
List of Tables xi
List of Figures xii
List of Abbreviations and Acronyms xiii
1. Introduction 1
    1.1. Objective 3
    1.2. Background 4
2. Literature Review 6
    2.1. Integration of GIS within Mining Industry 6
        2.1.1. Visualization 7
        2.1.2. Target Identification 7
        2.1.3. Geological Mapping 8
        2.1.4. Spatial Analysis and Resource Estimation Models 8
        2.1.5. Environmental Impact Assessment 9
    2.2. Case Studies and Applications 10
3. Data and Methodology 12
    3.1. Methodology 12
        3.1.1. Geological Mapping 13
        3.1.2. Geochemical Surveys 13
        3.1.3. Remote Sensing 14
        3.1.4. Geostatistics 15
    3.2. Data 17
        3.2.1. Data Collection and Preparation 18
4. Results 20
    4.1. False Colour 21
    4.2. Hydrothermal Alteration Zone 23
    4.3. Hydrothermal Alteration Zone and Alteration Minerals 25
    4.4. Field Prospecting (Field Data Collections on the Target Areas) 28
    4.5. Regional and Concession Geology 32

4.6. Geostatistics For Mineral Evaluation 33
4.6.1. Semivariogram Graph.....35
4.6.2. Cross Validation.....39
4.6.3. Ordinary Kriging.....42
4.7. Mineral Reserve Estimation 44
4.8. Uncertainty and Validation 47
5. Conclusions.....48
5.1. Challenges and Limitations.....50
5.1.1. Data Quality and Integration.....50
5.1.2. Technical Expertise.....51
5.1.3. Hardware and Software Resources.....51
5.1.4. Data Volume and Processing Speed.....52
5.1.5. Local Context and Regulatory Compliance 52
5.2. Recommendations.....53
5.3. Future Research Direction.....55
5.3.1. Real-Time Data Integration 55
5.3.2. Interdisciplinary Approaches.....55
Bibliographical References.....57
Appendix A (REMOTE SENSING).....62
Appendix B (GEOLOGICAL PROSPECTING PHOTOS).....67
Appendix C (LABORATORY RESULTS) 72

LIST OF TABLES

Table 1: Concession Boundaries coordinates (Belvand, 2022). 19
Table 2: Data quality control (ISO/TC 211). 31
Table 3: Advantages of Ordinary Kriging in Mineral Reserve (Setianto & Triandini 2013)..... 47

Table C - 1: Geochemical results with Drilling coordinates in UTM..... 72

LIST OF FIGURES

Figure 1: Methodology diagram (Generated with AI). 12
Figure 2: Site location or Concession (Belvand, 2022). 19
Figure 3: RGB Combination of the band 3/2/1 (Belvand, 2023). 22
Figure 4: Hydrothermal Alteration Zone (Belvand, 2023). 24
Figure 5: Hydrothermal Alteration Zone and Alteration Minerals (Belvand, 2023). 26
Figure 6: Map with areas prone to enhance mining (Belvand, 2023). 27
Figure 7: GPS Garmin Etrex 10. 29
Figure 8: Map of drilling and sampled areas. 30
Figure 9: Geological Map of the Concession (Belvand, 2024). 33
Figure 10: Geostatistical Wizard: step 2 of 4 – Semivariogram/Covariance modelling..... 35
Figure 11: Geostatistical Wizard: step 3 of 4 – Semivariogram/Covariance modelling..... 37
Figure 12: Geostatistical Wizard: step 4 of 4 – Semivariogram/Covariance modelling..... 39
Figure 13: Copper (Cu) Concentration on the concession. 42
Figure 14: Distribution of Cu. 44
Figure 15: Cu Concentration Patterns. 45
Figure 16: 3D model of Cu Concentration. 46

Figure A - 1: RGB Combination of the bands 9/8/7 (Belvand). 62
Figure A - 2: Colour composition for mapping ASTER bands 9, 8, and 7 (Belvand). 63
Figure A - 3: RGB Combination of the band 14/15 (Belvand). 64
Figure A - 4: RGB Combination of the bands 2/3/4 (Belvand). 65

Figure B - 1: Example of borehole excavated. 67
Figure B - 2: Granite encountered in the concession. 68
Figure B - 3: Gneiss outcrop with Granite intrusion. 69
Figure B - 4: A river passing over the Granit Outcrop 70
Figure B - 5: Sampling soil with drill fast 70
Figure B - 6: Analysis of mineralogy with hand lens. 71
Figure B - 7: Outcrop measurements. 71

Figure C - 1: Samples location coordinates (latitude, longitude and depth) 73

LIST OF ABBREVIATIONS AND ACRONYMS

3D – Three Dimensional

ASTER – Advanced Spaceborne Thermal Emission and Reflection Radiometer

AI – Artificial Intelligence

AI – Aluminium

Ag – Silver

Au – Gold

Co – Cobalt

Cu – Copper

Fe – Iron

GIS – Geographic Information Systems

IGEO – Geological Institute of Angola

OK – Ordinary Kriging

Pb – Lead

RM – Remote Sensing

RMS – Root-Mean-Square

RMS Standardized – Root Mean Square Standardized

XRF – X-ray fluorescence

QQPlot – Quantile-Quantile Plot

Zn – Zinc

1. INTRODUCTION

According to Deutsch et al. (1998), mining prospecting is a vital first step in the cycle of mineral resource development. This phase sets the stage for making informed decisions, ensuring sustainable resource extraction and economic growth. In other words, it involves the search for mineral deposits under the surface to identify feasible reserves suitable for commercial extraction. This process is inherently complex, as it encompasses various factors, such as geology, the environment, logistics, and finances.

Wafik et al. (2015) highlight the vital importance of mineral resources, from precious metals to industrial minerals, in our modern world. These resources are essential for building infrastructure, manufacturing goods, generating energy, and driving technological innovation. However, exploring these resources demands a comprehensive understanding of the Earth's underlying geology as well as the capacity to evaluate the potential value and the feasibility of extraction. In this regard, Geographic Information System (GIS) has emerged as a transformational tool, fundamentally transforming the approach to mining exploration.

Wilkinson et al, (2016) argue that GIS uses spatial data to build detailed, layered representations that enhance our understanding of geological environments. It supports the integration of various datasets, such as geological maps, satellite imagery, topographical information, geological prospecting data and so on onto a single platform. For instance, its versatile technology allows for collection, storage, and access to geographic information such

as geological mapping and georeferencing mineral occurrence (Bonham & Merriam,1994). Pereira (2019) notes that this integration allows geologists, mining engineers, and decision-makers to extract relevant insights and make educated decisions, maximize exploration efforts, and minimize costs.

Belvand Geotechnics mining exploration involves searching for mineral deposits, and GIS has greatly changed the company's approach to this process. They use GIS in conjunction with other geographic data, to offer a full knowledge of a mining project's geology, environment, and logistics. The internship will look at how Belvand has effectively used GIS for mining exploration, accuracy, and efficiency.

GIS allows Belvand to aggregate various datasets into a single platform, creating rich visualizations, by bringing together geological maps, satellite images, topographical and mining prospecting data to provide a comprehensive perspective of the study area. This integration assists in recognizing patterns and relationships that may not be obvious when examining various datasets independently. Similarly, it enables the identification of possible exploration targets. By layering geological, geochemical, and geophysical data GIS highlights regions with greater mineral potential. As a result, this technique helps to prioritize places for more extensive examination.

1.1. OBJECTIVE

This report highlights the crucial role of GIS in mining exploration, showcasing how Belvand Geotechnics effectively employs GIS to enhance mining exploration practices. It will focus on GIS's impact on data integration, visualization, illustrating its benefits through successful project in Cuanza-Sul/Angola undertaken by the company.

Furthermore, the report will delve into the advantages of GIS in mining exploration. Additionally, the obstacles and limitations faced while using GIS in this field, as well as how Belvand Geotechnics overcame or minimized these challenges, will be presented.

Finally, it will assess the future of GIS in the mining sector, exploring potential improvements, research avenues, and emerging trends that might improve exploration operations using GIS. To finish, practical insights and recommendations toward Belvand Geotechnics will be provided, focusing on strategies to enhance GIS applications, tackle challenges, and seize upcoming opportunities.

1.2. BACKGROUND

Belvand Geotechnics is a consultancy firm focused on environment and mining, based in Belas, Luanda Province, Angola. With multiple mining projects spread across the country, Belvand believes that GIS is important in mining exploration because of its capacity to:

I. **Data Integration**: GIS integrates several data sources. This comprehensive integration offers a thorough understanding of geological and environmental elements, essential for making informed decisions;

II. **Visualization:** transforming raw data into visual formats allows for complex geological and spatial information to be more accessible to clients. These visualizations help in the detection of patterns, trends, and correlations that may not be immediately apparent in raw data;

III. **Target Identification:** combine geological, geochemical, geophysical data and so on into GIS database to identify possible exploration locations that are more likely to host mineral deposits;

IV. **Environmental Impact Assessments**: by combining topographical and environmental data, these assessments can identify ecologically sensitive places and encourage environmentally friendly exploration methods. This approach encourages sustainable exploration practices, ensuring that environmental disruption is kept to a minimum.

Utilizing GIS in geological prospecting makes it easier to create precise and comprehensive geological maps, the digitization and georeferencing of field observations as well as existing paper maps. Consequently, it improves the understanding of subsurface geology, geological structures, and the relationships among various rock formations. As a result, Belvand experts have assessed possible environmental effects and offered solutions to several clients around Angola. Find ecologically vulnerable sites, water bodies, and habitats that need to be protected by superimposing environmental data over exploration plans.

The use of GIS by Belvand in mining exploration has significantly changed their approach to decision making, planning, and sustainability. By combining and analysing various geospatial data, the company improves the precision and effectiveness of exploration operations. This enables them to more readily identify potential targets, plan logistics, evaluate environmental impacts, and engage with local communities in a more meaningful way.

2. LITERATURE REVIEW

GIS is widely used in the mining sector to improve exploration operations and ensure sustainability (Knox-Robinson, & Wyborn, 1997). The combination of GIS and other geospatial technologies has transformed how geologists and mining companies perform exploratory activities, manage resources, and estimate mineral reserves. This literature review examines numerous research and uses of GIS in mining exploration.

2.1. INTEGRATION OF GIS WITHIN MINING INDUSTRY

GIS plays a crucial role in bringing together various datasets, which greatly improves the understanding of geological and environmental conditions. A study by Murgante et al. (2016) highlights how GIS combines geological, geophysical, and geochemical data to help geoscientists identify hidden relationships and patterns that could impact mineralization. Adopting this integrated approach, can minimize data fragmentation and enhance the precision of exploration target selection.

Researchers Carranza and Laborte (2016) believe that GIS allows for the merging of varied information such as geological maps, satellite imaging, geophysical surveys, and geochemical data. This integration helps to build a robust database that enhances decision-making in exploration processes.

2.1.1. Visualization

The visual aspect of GIS is essential to its success. Bonham-Carter (1994) underlined that GIS capacity to build visually comprehensible maps helps geologists communicate difficult information to those who may not have a technical background. Visualization not only facilitates the comprehension of geographical data, but it also allows decision-makers to better understand the geological context.

The visualization features of GIS make it possible the creation of comprehensive maps and 3D models. These visual tools support in understanding the geographical distribution of minerals and geological features. As noted by Bonham-Carter (1994), utilizing GIS for visualization helps to clarify complex geological data, resulting in more precise exploration results.

2.1.2. Target Identification

The use of GIS in target identification has become increasingly important. In Carranza et al.'s 2007 study, the team effectively incorporated geological, geophysical, and Remote Sensing (RM) data through GIS to find locations with greater mineral potential. This approach facilitated the creation of prospectivity maps that enhanced exploration operations, resulting in more targeted and successful drilling programs.

In a subsequent study in 2008, Carranza illustrated how GIS based predictive modelling could identify promising zones by examining the spatial correlations between known mineral

occurrences and a range of geological factors. This means that GIS is useful in finding possible exploration targets.

2.1.3. Geological Mapping

Geological mapping is an essential part of in mining exploration. Research from Harraz (2010) emphasizes how GIS tools allow the construction of precise and detailed geological maps, which are vital for understanding the distribution of mineral resources, geological structures, and lithological features. GIS's ability to overlay geological data with various other data layers improves the quality of these maps.

Furthermore, the digitization and georeferencing of field observations are required to produce accurate geological maps. Burrough and McDonnell (1998) demonstrated that GIS simplifies the transformation of traditional maps into digital formats while guaranteeing they are correctly aligned with spatial coordinates.

2.1.4. Spatial Analysis and Resource Estimation Models

Spatial analysis tools in GIS allow for the evaluation of geological characteristics and their interconnections. Malczewski (1999) highlighted the application of GIS in spatial statistics, underlining its importance in understanding the distribution patterns of mineral resources.

GIS facilitates the creation of resource estimate models by combining geographical data with statistical and geostatistical techniques. As noted by Carlson (2019), models that utilize GIS

increase the precision of mineral resource estimations through the integration of spatial variability and uncertainty.

Furthermore, Zhu et al. (2023) demonstrated the application of GIS in constructing 3D models of ore bodies, allowing accurate measurements of size and mineral concentration. Additionally, GIS helps in determining the volume and grade of mineral deposits effectively.

2.1.5. Environmental Impact Assessment

The use of GIS in environmental evaluation encourages sustainable mining operations. Mining businesses can minimize their environmental impact and comply with environmental laws by evaluating geographical data. Environmental concerns are integral to responsible mining practices. A study by Esteves and Amaral (2011) demonstrated how GIS help in environmental impact assessment by integrating spatial data on ecosystems, water bodies, and sensitive areas. This integration assists the identification of potential impacts and helps mining companies devise strategies to mitigate them.

Additionally, researchers such as Saha and Paul (2021) employed GIS to identify environmentally sensitive areas and analyse possible dangers, assisting in the creation of mitigation plans. In essence, GIS is critical in determining the environmental impacts of mining activities.

2.2. Case Studies and Applications

In their 2009 study, Peters and Partington explored the use of GIS to combine geological, geochemical, and geophysical data for Iron (Fe), Copper (Cu), and Gold (Au) exploration in Zambia and Namibia. The study showed how models based on GIS can significantly improve target identification and lower exploration costs. Similarly, Ngada (2009) and Sun et al. (2019) utilized GIS in Australian for Au prospecting, illustrating how predictive modelling techniques can effectively outline promising zones. By combining spatial with geological data, they succeeded in identifying new areas mineralized.

A study by Amoka and Jatau (2010) have effectively combined exploration data with GIS to improve the acquisition, analysis, and interpretation of complex issues, particularly data deficit. By digitizing geophysical data, including drill hole information and resistivity profiles from Ungwar-Doka and Rafin-Gabas, they were able to incorporate this data into GIS. As a result, this integration allowed the production of isopach maps, which were then used to compute mineral reserves. Therefore, the study reveals how GIS can accelerate and ensure the successful completion of mineral exploration operations.

Identically, Uygucgil and Konuk (2015) integrated various datasets, such as drilled core values, borehole locations, cutting depths, ore grades, topographic maps, and digital terrain models of the interest mining areas, into a GIS database. They employed geostatistical estimation methods, specifically Ordinary Kriging (OK), to estimate reserves. Additionally, spatial queries

were utilized to quantify the ore body and ascertain its shape and location. Similarly, Dursun (2023) effectively implemented OK, to assess coal reserves in a mining project located in southern Turkey. The integration of data from at least 82 boreholes, along with additional information through GIS, enabled the development of 11 models, including rational quadratic models. The analysis revealed an estimated coal reserve of 3,734,017 m^3.

In summary, the utilization of GIS in mining exploration has revolutionized the industry. It offers robust tools for integrating data, visualizing results, identifying targets, assessing environmental impact, and mineral estimation. The reviewed studies underscore the considerable benefits of GIS, such as enhanced decision-making capabilities, and estimation of mineral resources. As technology progresses, GIS is expected to become even more essential for promoting sustainable and efficient mining practices. By utilizing GIS, mining companies can optimize exploration processes and mitigate environmental.

3. DATA AND METHODOLOGY

The methodology employed to meet the outlined in this report consisted of systematic, multi-phase strategy that utilizes RM technology with field data collection. This approach allowed for the analysis, identification, and evaluation of areas with mineral potential (Figure 1).

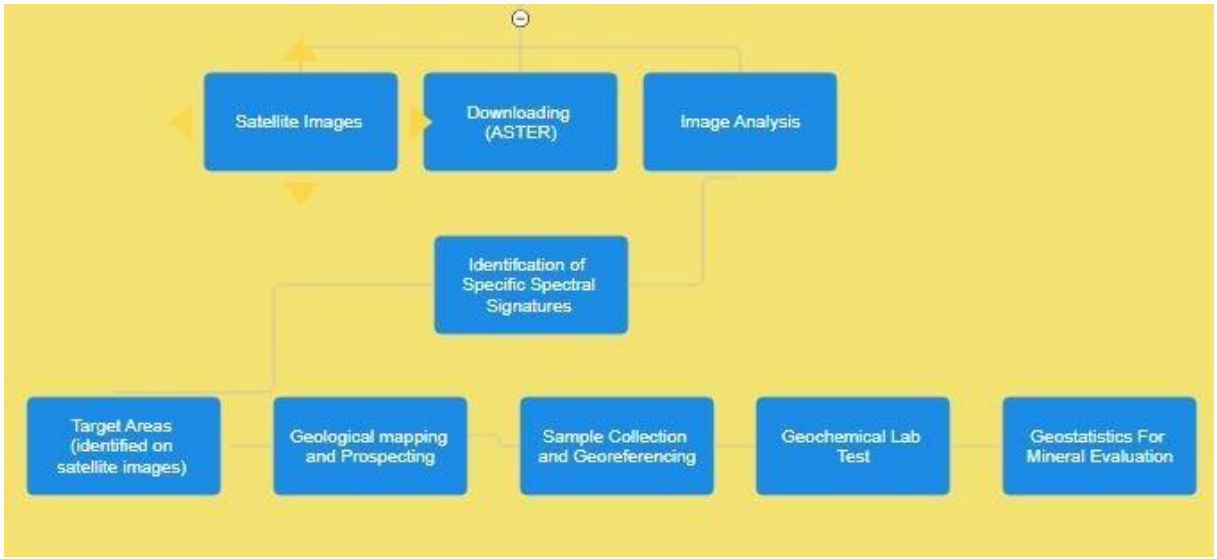

Figure 1: Methodology diagram (Generated with AI).

3.1. METHODOLOGY

Marjoribanks (2010) states that geological methods play a critical role in mineral exploration and mining by helping to identify, assess, and extract valuable mineral resources efficiently and sustainably. According to Belvand geologists these methods encompass a range of techniques that involve fieldwork, laboratory analysis, and computer modelling. The methods used in this report are presented below:

3.1.1. Geological Mapping

The objective of the geological prospecting was to document the geology of the concession, including rock types, structural features, faults, and folds, which may influence the localization and distribution of mineral deposits. This process involved mapping outcrops, collecting rock samples, and making observations regarding rock formations. The gathered data was subsequently represented on geological maps (refer to section 4.5).

As noted by Brimhall et al. (2005), geological mapping or prospecting is essential for the exploration of mineral deposits. It enables geologists to closely examine outcrops, focusing on rock types and shapes, as well as the chronological relationships among different rock units. This knowledge is instrumental in identifying ore-bearing host rocks, the orientations of veins, and post-ore faults, all of which are vital for making predictions about the underlying geology or adjacent areas obscured by post-ore rocks.

3.1.2. Geochemical Surveys

Geochemical surveys focused on identifying the chemical signatures associated with mineral deposits by collecting and analysing samples of rock, soil, and stream sediments. All samples were submitted for laboratory test, such as X-ray fluorescence (XRF), to measure Cu grade concentrations (refer to section 4.6).

Kyser et al. (2015) contend that mineral deposits represent geochemical anomalies, underscoring the importance of applied geochemistry throughout the entire mineral resource

lifecycle, from the early exploration to mine closure. That means, geochemical surveys enhance the understanding of element mobility specifically, the movement and retention of elements in the near-surface environment facilitating the identification of mineral deposits situated deep underground, mapping element distributions in proximity to these deposits, assessing the broader geochemical context, and formulating effective, environmentally sustainable extraction and waste management strategies.

Conversely, Grunsky (2010) points out that collecting and integrating geochemical data can be complex due to the diversity of media and size fractions involved. Nevertheless, the development of integrated datasets can reveal a multitude of geochemical processes associated with geological factors, weathering, and mineralization. The application of data analysis and statistical visualization techniques, in conjunction with GIS, provides a robust framework for identifying processes and discerning patterns within these comprehensive datasets.

3.1.3. Remote Sensing

RM involved the acquisition of satellite images, specifically from Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), to gather preliminary data and visuals relevant to the area. The imagery was subsequently analysed to identify spectral signatures that may signify the presence of Cu mineral, altered rocks, which could indicate possible mineral deposits.

As appointed by Dey et al. (2018), there are several techniques to visualize and analyse RM data, including **Spectral Analysis, Alteration Mapping**, **and Multispectral Image Analysis**.

According to Belvand specialists, the Spectral Analysis method is particularly effective for identifying spectral patterns in the data, facilitating the identification of mineral present in specific area. Babadi & Brown (2014) agree with this perspective, further validating the importance of Spectral Analysis in this investigation.

CRÓSTA (1996), states alteration mapping method entails the detection of changes in the spectral signatures of rocks that result from the presence of specific minerals. This approach is particularly effective for identification of areas rich in minerals. Combining with multispectral image analysis which consisted of multiple spectral bands, to distinguish diverse mineral types and geological formations (Adam et al., 2010).

Software tools like ENVI was used for the analysis of these images (refer to section 4.1 to 4.3 and Appendix A).

3.1.4. Geostatistics

Geostatistical methods were employed to predict the distribution of Cu mineral within the concession and to develop block models for estimating ore reserve. Methods such as OK, facilitated the interpolation values between sample points. Tools like ArcGIS and the Python

programming language were utilized to create 3D representation and distribution of the ore bodies.

According to Wackernagel & Wackernagel (2003), OK is a popular geostatistical method for evaluating mineral reserves and performing spatial interpolation. It allows the estimation of values at locations that have not been sampled, while considering the spatial correlation between sampled points.

Further supporting this, Lamamra et al. (2019) highlight that for each unsampled location, OK determines a set of weights for the known samples based on their spatial arrangement and the variogram model. These weights are designed to ensure that the estimates are unbiased and has minimum variance.

Exploratory data analysis was performed to understand the distribution of grade, identify outliers, and evaluate the presence of trends in the data. Additionally, the experimental variogram was also computed to measure the degree of spatial correlation between sample points as a function of the distance separating them, which was crucial for understanding the spatial variability of mineral grades.

To corroborate the data acquired from RM and to facilitate further examination, multidisciplinary team formed by geologists, GIS Specialist, mining engineer and so on conducted ground mass assessment to the designated areas identified through satellite

imagery (refer to Appendix B). During these visits, they performed geological mapping and collected samples of rock, soil, and sediment. To ensure precise geographical positioning of each sample gathered during the fieldwork, GPS coordinates were assigned to the samples, enabling accurate mapping and analysis within GIS environment.

Subsequently, to evaluate the spatial distribution of minerals within the concession area and to estimate both the quantity and quality of the mineral resources, geostatistical techniques were employed on the data obtained through laboratory test.

3.2. DATA

The information presented in this report was sourced from Belvand Geotechnics, specifically a shapefile detailing the concession boundaries (refer to Table 1 and Figure 2) in the local Datum WG84 Zone 33S.

For satellite imagery, ASTER format version 003 dated 08/12/2000 were downloaded from https://earthexplorer.usgs.gov/ (U.S.G.S., 2023) and subsequently analysed using ENVI software version 4.7. Various spatial bands, including 3/2/1, 4/6/8, 2/1 and 4:6/5:6/5:8, were processed to assess the geology within the concession area, examine vegetation patterns, and identify regions exhibiting hydrothermal alterations indications that might correlate with mineralization.

Angola geology data was provided by the Geological Institute of Angola (IGEO). Additionally, during the prospecting and geological mapping phases, drilling coordinates (latitude and longitude) were obtained through a georeferencing process utilizing a Garmin Etrex 10 GPS device (refer to section 4.4 for further details).

The data employed in the OK method for estimating the mineral reserves in the study area was gathered as follows:

3.2.1. Data Collection and Preparation

During the geological prospecting process, samples from multiple drill sites, the location coordinates (latitude and longitude) and depth (z) along with relevant variables, such as borehole identifiers, volume, and mineral grade ore density, were recorded. This information was compiled into an Excel file and subsequently transferred to a GIS database (refer to Figure C-1).

It is noteworthy that Belvand executed a total of 2,364 borehole excavations, each reaching a depth of 30 meters. However, this report focuses exclusively on data derived from 30 boreholes, each with a depth of 5 meters.

The geochemical analyses were performed in Namibia by Analytical Laboratory, with the results detailed in Appendix C.

Table 1: Concession Boundaries coordinates (Belvand, 2022).

Points	LAT_S	LONG_E
A	9°50'1.208"	14°33'34.803"
B	9°50'2.201"	14°54'52.228"
C	10°12'18.922"	14°54'56.912"
D	10°12'17.89"	14°33'32.999"

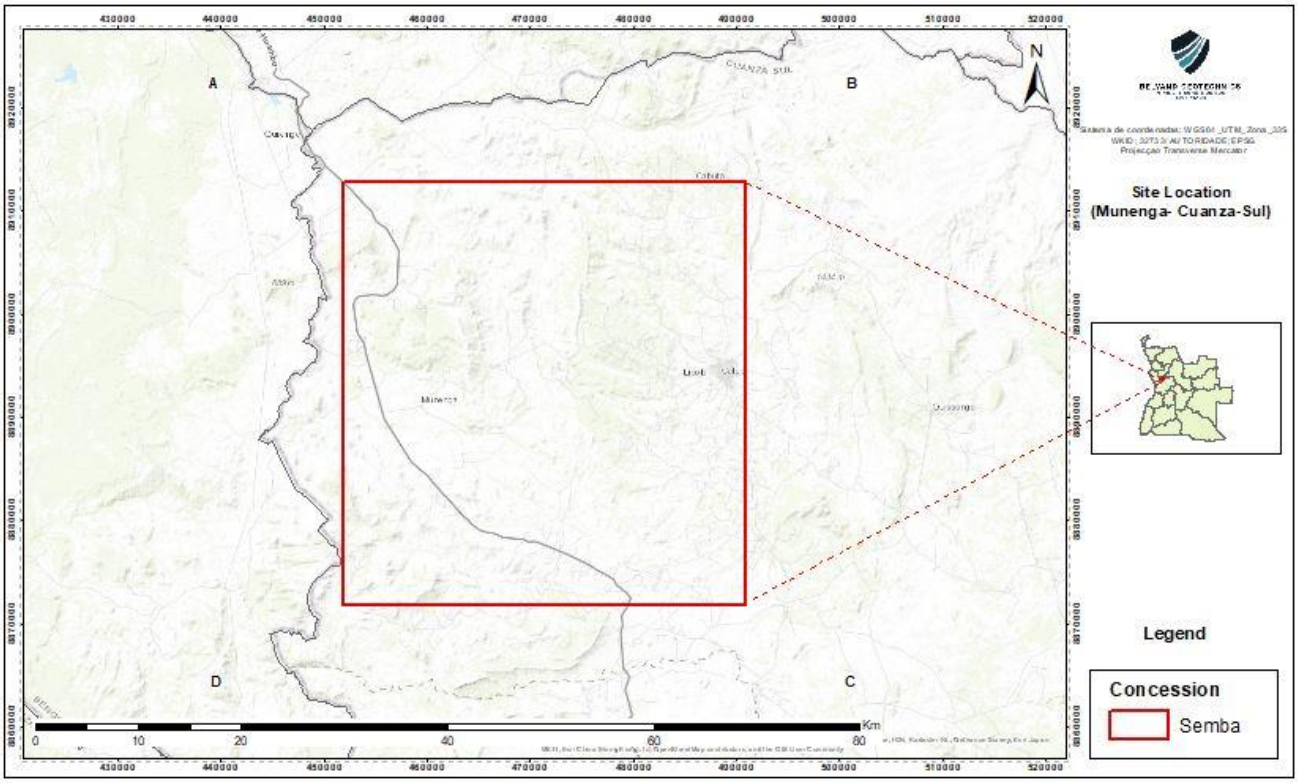

Figure 2: Site location or Concession (Belvand, 2022).

4. RESULTS

The concession is situated in the northwest region of Angola, within the Munenga Municipality in Cuanza-Sul province (see Figure 2), encompassing a total area of 1,600 km². The study area is located 66 Km from its capital, Sumbe. The access can be achieved by car or bus from the Capital city of Angola, Luanda, utilizing the EN100 road, which takes approximately 5 hours and 5 minutes covering roughly 388.8 Km and passing notable landmarks such as the National Institute of Petroleum and Binga Waterfall. Alternatively, the EN120 road takes approximately 4 hours and 11 minutes and involves about 283 km, with routes passing through Dondo and Cambambe.

A multidisciplinary team from Belvand, including geologists, GIS specialists, surveyors, mining, and geotechnical engineers, conducted geological prospecting to identify a deposit with an economically viable quantity of mineral resources. The exploration work primarily involved geological mapping through techniques such as photogeology, RM, geochemical mapping, geological and topographic surveys, sampling, and drilling (refer to Appendices A and B). These investigations provide comprehensive details regarding the project, encompassing its geographical limits, as well as the volume and grade of the reserves and mineral resources available in the concession area.

The analysis and visualization of RM data for mining purposes were crucial in identifying mineralized areas and evaluate mineral resources. A variety of methods, techniques, and tools

were employed in the analysis and visualization, such as spectral analysis, alteration mapping, multispectral image analysis (Dey et al., 2018). Satellites images was utilized to analyse mineralogy and hydrothermal alteration zones, thereby, facilitating the identification of areas likely to host Cu mineral occurrence and significant geological features.

Furthermore, examining the mineralogy of hydrothermal alteration zones, ore minerals, and the igneous rocks that host these ores along with oxidized and leached rocks typically present at the surface above sulphide-bearing ores was complemented with geochemical data (Brimhall et, al., 2005). This integrative approach enables to create zonation patterns that can accurately indicate potential ore locations. Combinations of different bands were used, and the result is presented below:

4.1. FALSE COLOUR

The false colour image, created by combining RGB bands 3, 2, and 1 (Figure 3), proved valuable in the identification of specific areas and enhanced the understanding of environmental changes, including variations in vegetation cover and instances of soil erosion (Papadaki et al., 2011).

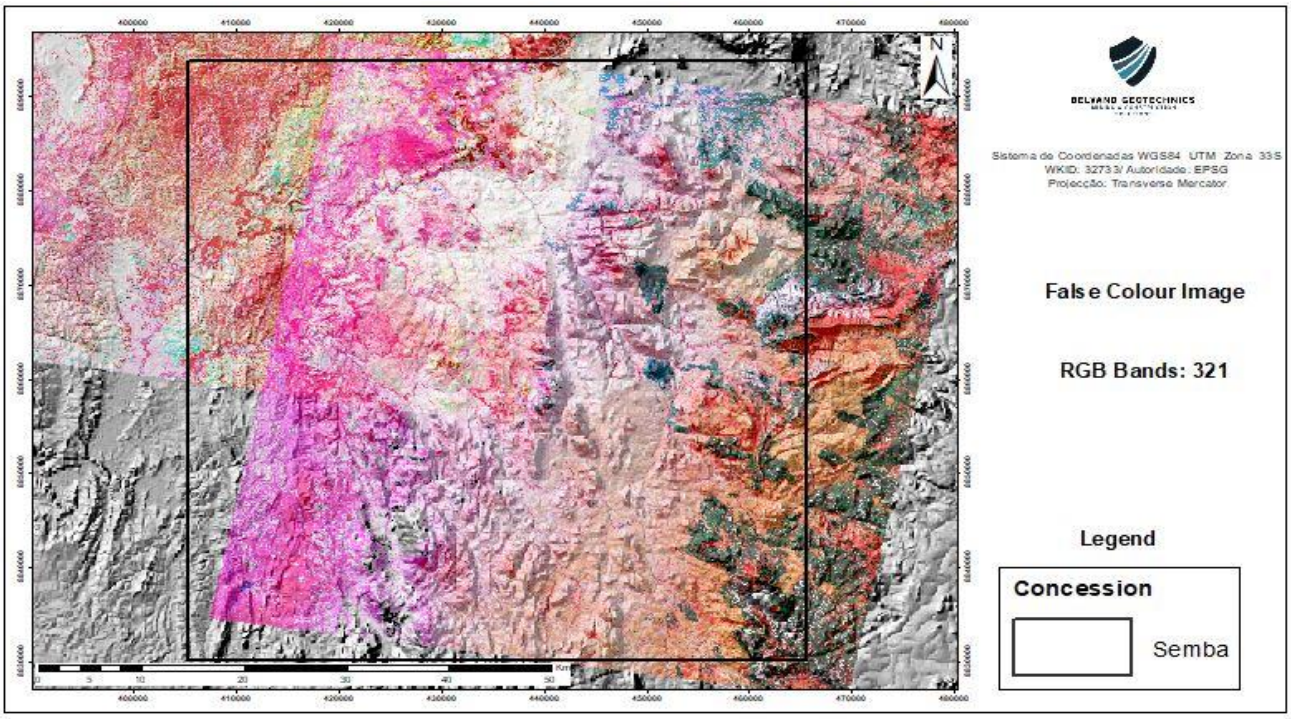

Figure 3: RGB Combination of the band 3/2/1 (Belvand, 2023).

Spectral analysis of the ASTER 3/2/1 bands was performed using ENVI image processing software to compute spectral indices such as the Fe, clay, and sulphide index, which are essential for identifying and mapping mineralized areas. As noted, Liu et al. (2014), the different colours observed in the above image correspond to different geological features, such as rock types, mineral alterations, or topography. This method assigns colours to different wavelengths of the electromagnetic spectrum and can be explained as follows:

i. Igneous rocks tend to look lighter, often ranging from grey to white, whereas sedimentary rocks typically present darker tones;

ii. Shades of red indicate the presence of Fe and manganese minerals, while blue and green are associated with Cu and Cobalt (Co) minerals;

iii. Clay minerals are usually found in lighter blue tones. It is important to emphasize that the interpretation of the ASTER 3/2/1 bands for mining purpose was supported by additional techniques such as spectral analysis, alteration mapping, and multispectral image analysis.

Corrêa et al. (2012) highlight the importance of analysing the spectral data from the ASTER 3/2/1 band by using false colour combinations. This technique aids in distinguishing areas with varying levels of reflectance across different wavelengths. Building on this approach, spectral indices were calculated pinpoint zones that exhibit potential for mineralization. Furthermore, the interpretation was corroborated on-site through geological prospecting with sampling, geochemical laboratory tests on the samples to verify the presence of target minerals, along with a review of the existing geological data in the concession (refer to Appendix B).

4.2. HYDROTHERMAL ALTERATION ZONE

Crosta et al., (1998) describe a hydrothermal alteration zone as an area in a rock where its original characteristics have been altered by the interaction of hydrothermal fluids This process can result in alterations to the rock´s texture, colour, mineralogy, as well as the formation of veins and fractures, all of which suggest hydrothermal alteration. That means, these alteration zones can serve as indicators of mineral deposits since hydrothermal fluids are often rich in valuable minerals.

For mining purposes, analysing the spectral data from ASTER bands 4, 6, and 8 (Figure 4) involves the identification and mapping spectral anomalies that may be associated with various types of mineral deposits and/or hydrothermal alteration. To enhance the accuracy of these interpretations, was integrated this spectral analysis with geological mapping, sampling, and laboratory tests to accurately delineate the geological features of the area under investigation (Crosta et al., 1998).

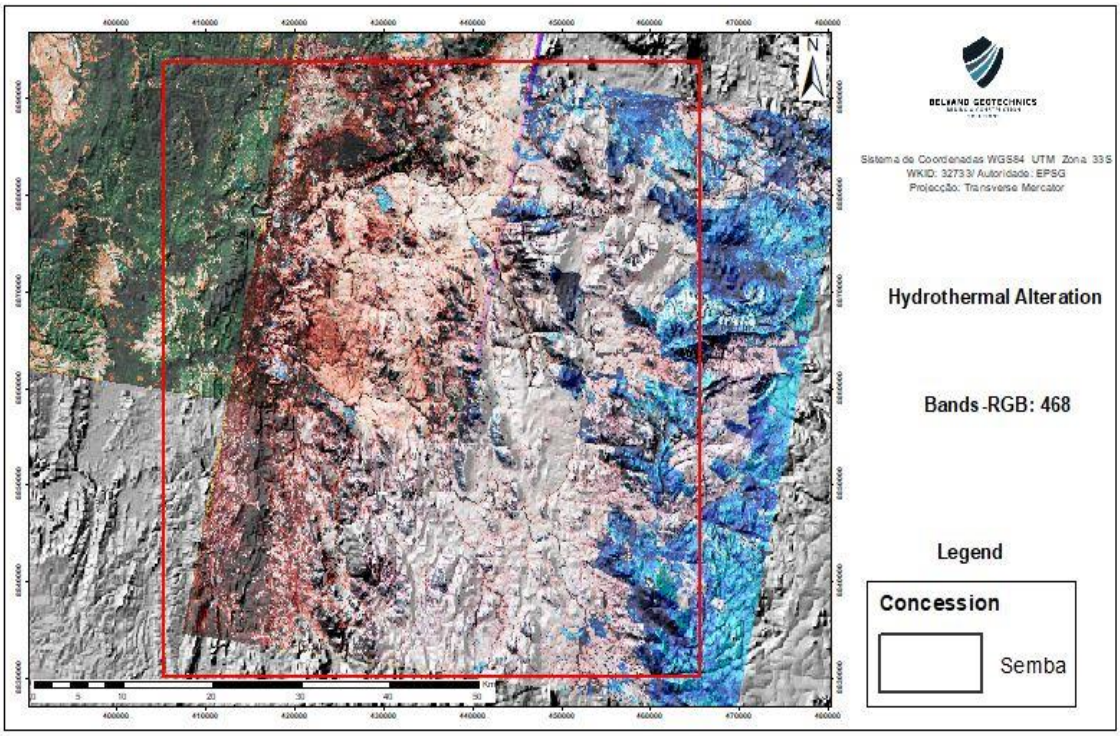

Figure 4: Hydrothermal Alteration Zone (Belvand, 2023).

Geologists at Belvand Geotechnics emphasize that to interpret the ASTER 4/6/8 bands effectively, requires supervised or unsupervised classification of the data. It is essential to conduct either supervised or unsupervised classification of the data. These spectral classes

can be assigned to different types of minerals, rocks, and/or hydrothermal alterations (Burnham, 1962).

As depicted in Figure 4, the combination of the ASTER 4/6/8 bands produces a spectrum of colours that indicate varying intensities of reflectance of the Earth surfaces across each spectral band. Experts from Belvand Geotechnics argue that band 4 displays areas of higher reflectance in red, while in band 6 highlights locations in green, and band 8 showcases higher reflectance areas in shades of blue. Hook et al., (1992) suggest that these bands are particularly responsive to specific minerals and geological alterations. Thus, precious minerals like Au, Silver (Ag), Cu, Zinc (Zn), and Lead (Pb) may be found in areas experiencing hydrothermal changes like argillization and silicification.

4.3. Hydrothermal Alteration Zone and Alteration Minerals

To identify mineral deposits, the ASTER bands 4/6, 5/6, and 5/8 (Figure 5) are frequently utilized for detection of clay and hydroxide minerals, which are useful in identifying mineral deposits.

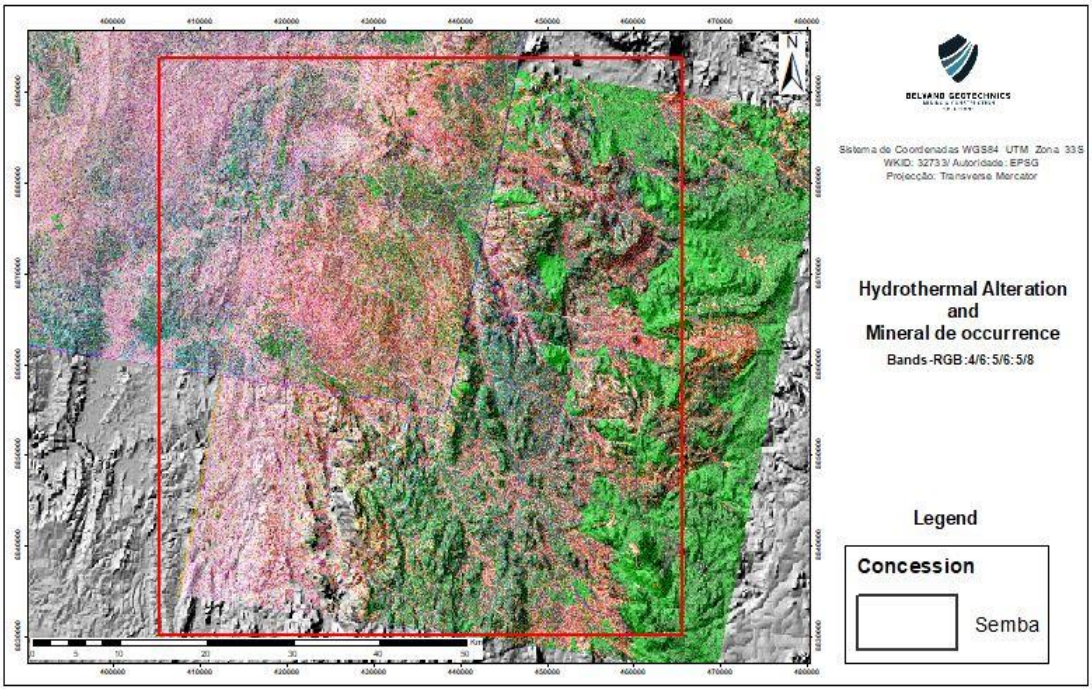

Figure 5: Hydrothermal Alteration Zone and Alteration Minerals (Belvand, 2023).

The colours produced by these bands in Figure 5 can be understood as follows, per Belvand Geotechnics geologists:

I. Green on Band 4/6 denotes hydroxide minerals, such as goethite and jarosite, which show the existence of Fe ore and sulphate deposits. Red indicates clay minerals, such as kaolinite and montmorillonite, which might indicate the existence of metal deposits including Aluminium (AI), Fe, Au, Cu and other metals;

II. Hydroxide minerals are shown in red on Band 5/6, whereas clay minerals are shown in green;

III. On Band 5/8, silicate minerals like olivine and pyroxene are presented by green, whereas hydroxide minerals are represented in red.

Carbonatic minerals, which are indicators for Cu, Zn, and Pb mineral resources, were analysed using the ASTER band 2/1(Figure 6). The following is how Belvand Geotechnics geologists interpret the colours:

I. Carbonatic minerals like calcite and dolomite, which are suggestive of deposits of Cu, Pb, and Zn sulphide minerals, are represented by green;

II. Clay minerals, such as kaolinite and montmorillonite, which are linked to Fe, Au and AI, may be represented by red;

III. Blue might stand for silicate minerals like biotite, which is a reliable indicator of the existence of Fe and precious metals.

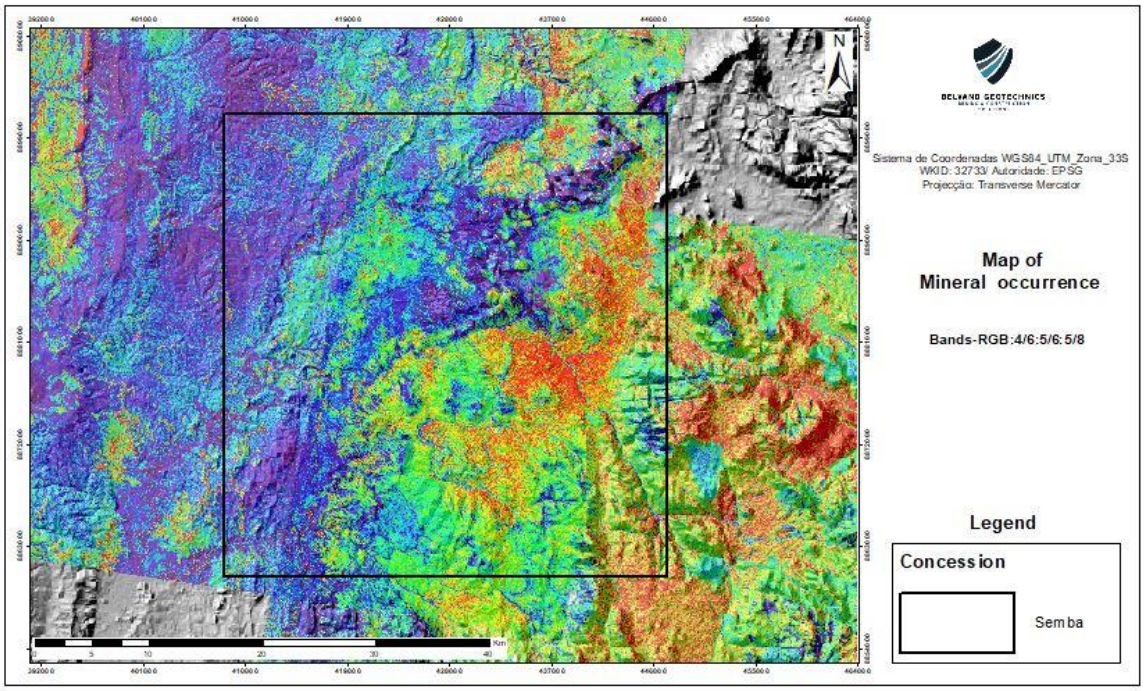

Figure 6: Map with areas prone to enhance mining (Belvand, 2023).

Figures 5 and 6 were utilized to extract geographic coordinates of the target zones and used in geological prospecting (see Figure 8).

In summary, the colours displayed in the images generated from the ASTER bands are merely visual representations of spectral data. They do not guarantee the presence of specific minerals or mineral deposits. This information provided a foundation for geological prospecting using sampling and laboratory analyses.

4.4. Field Prospecting (Field Data Collections on the Target Areas)

Marjoribanks (2010) asserts that potent method for understanding RM data is by combining with geological prospecting, making powerful approach for mapping geological features. While geological prospecting entails more direct measurements and sampling, RM offers a large scale, non-invasive way to gather data about the Earth's surface. Accordingly, the Belvand geologist combines these two methods by linking the information gathered from RM and fusing it with mapping.

To assess the degree of accuracy of the georeferencing process, the mapping activities included statistical and visual parameters, datasets from georeferenced sources, descriptive (textual) information about the mapping processes, and the discrepancy between the field coordinates and the extracted geographic coordinates in RM. The Garmin Etrex 10 GPS was used to ensure the georeferenced data was accurate (Figure 7).

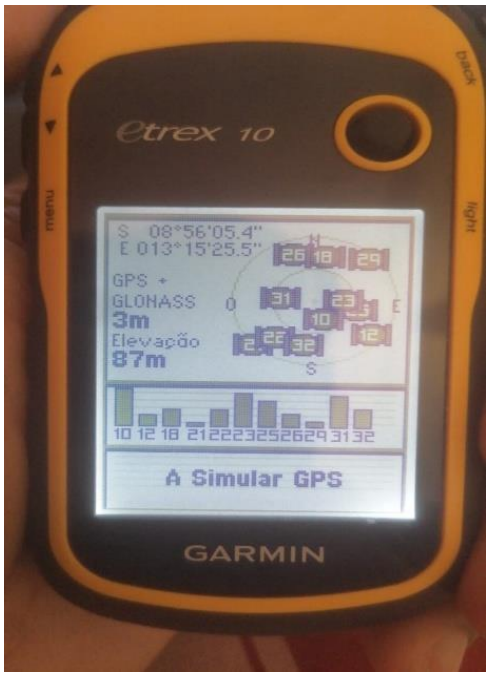

Figure 7: GPS Garmin Etrex 10.

Maintained a quality control during the prospecting and geological mapping. Geographic items, places, and their relationships were specified by Belvand's topographers and GIS experts. The WGS-84 Geodetic Reference System (WGS-84 Zone 33S), which includes a reference ellipsoid, a Geoid that specifies the nominal sea level, and a standard coordinate frame for the Earth, was used as the datum for Angola. The map drilling and sampled locations are shown in Figure 8.

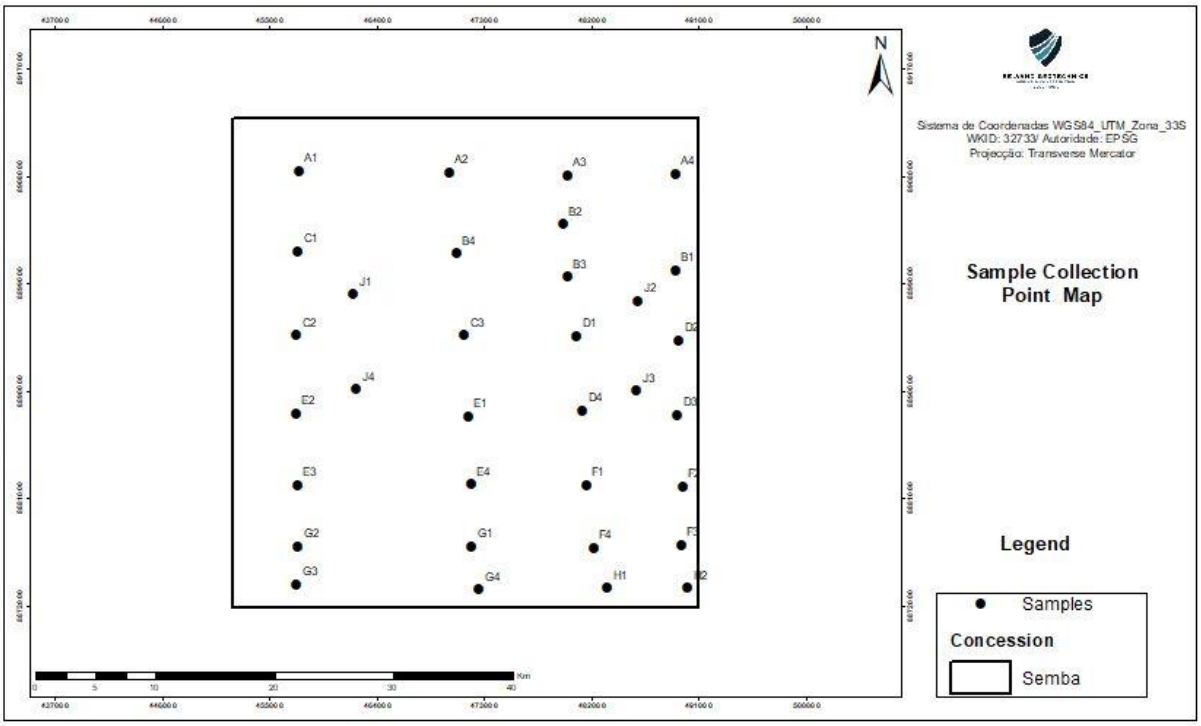

Figure 8: Map of drilling and sampled areas.

The technicians at Belvand used GPS to gather the data, and whenever feasible, they recorded the coordinates in accordance with the best procedures for georeferencing that Biedron (2016) defined. Furthermore, the adopted local coordinate system (WGS 1984 Zone 33S) was selected on the GPS. Additionally, it was guaranteed that the estimation of genuine values was closely correlated with accuracy, precision, and uncertainty.

Uncertainty was defined as the maximum distance from the coordinate center (Datum WGS-84 Zone 33S) of a georeferenced to the furthest point where the true location could be, a combination of all potential error sources given as distance, assuming that error is a measure of precision the difference between an estimated value and the true value during georeferencing (Table 2).

Table 2: Data quality control (ISO/TC 211).

Precision (Latitude/Longitude)	Description
9°S, 14°E	Relate with some space.
9°5'S, 14°3'E	Related specifically to one zone
9°50'S, 14°33'E	Related specifically to one zone and one object.
9°50'1''S, 14°33'3''E	Related specifically to one zone and one object.
9°50'1.208"S, 14°33'34.803" E	Related specifically to one zone and one object with precision.

For geographic georeferencing, three different types of information were identified and used, which are:

I. **Geometric Information (Polygon)**: describes the boundaries of the study area, as well as additional properties such as road segment´s layout and shape;

II. **Topological Information**: includes the continuous deformations of features like highways, rivers and so on;

III. **Semantic Information**: comprises information on a specific physical location, such as place´s name, route, sample and drilling.

The GPS was placed in a location free of aerial obstructions and reflective surfaces, with a good field of view for a large portion of the sky, to achieve the highest accuracy possible. This was done in consideration of Chapman's (2006) assertion that GPS is not effective in areas with dense forest cover. Signals from the GNSS satellite system's GLONASS constellation might be picked up by the GPS.

4.5. REGIONAL AND CONCESSION GEOLOGY

According to the geological map of Angola at a scale of 1:1 000 000, provided by the IGEO, the province of Cuanza-Sul comprises seven geological formations. However, data obtained during the geological mapping show the concession is made up of three groups formed by rocks from the Lower Archaic, Cretaceous, and Paleogene periods (Figures 9).

i. **Lower Archaic**: include sandstones, dolomite, conglomerates, biotite granites from the Quibala Formation;
ii. **Metamorphic rocks** in the area include gneisses, schists, amphibolite, and quartzites.
iii. **Cretaceous and Paleogene**: composed of marl (a soft rock within clay and lime) and limestones;
iv. Tonalites, plagiomigmatites, plagiogranites, enderbites, and charnockites from the **Lower Archaic** period can be found in ultrametamorphic zones.

This diverse geological composition indicates a complex geological history and varied mineral potential within the concession area.

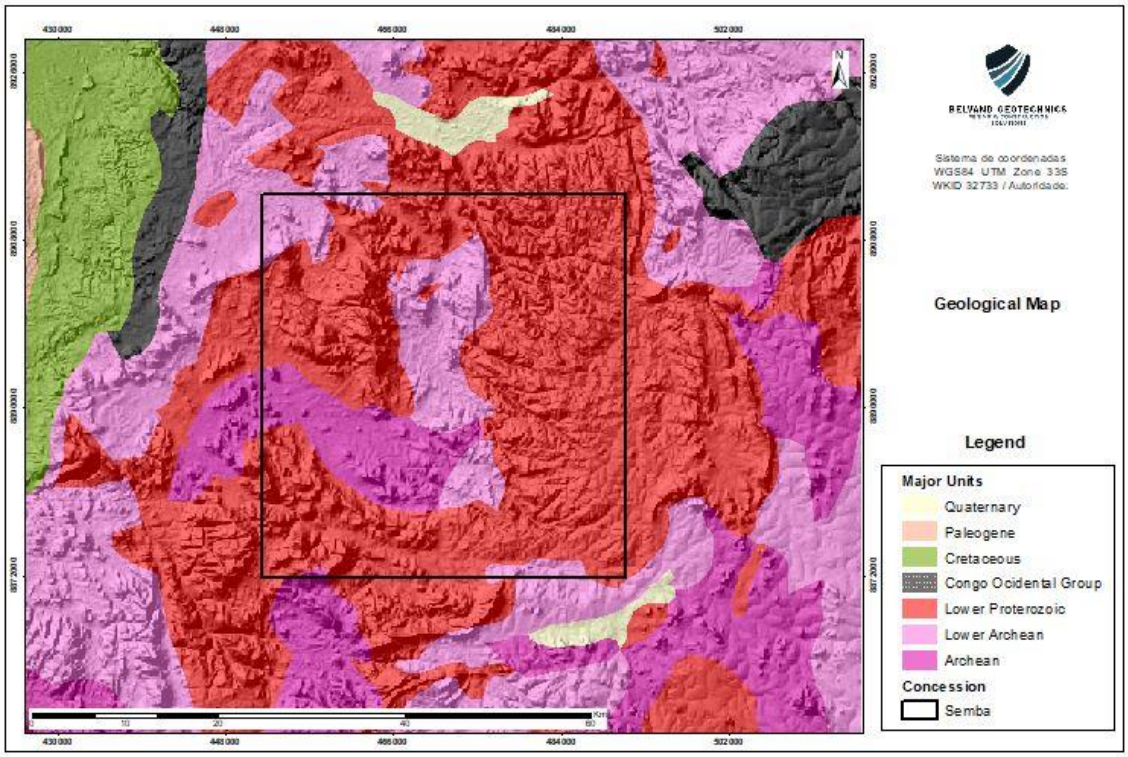

Figure 9: Geological Map of the Concession (Belvand, 2024).

4.6. GEOSTATISTICS FOR MINERAL EVALUATION

Mineral resources can be defined as a formal quantification of geological materials occurring in a specific region, determined by a set of empirical and theoretical procedures that allow inferring the quantity, quality, and spatial distribution of a given element with potential economic value (Ammerman, 1995). It is often estimated using a three-dimensional array of samples and applied to mineralization volumes that are many orders of magnitude higher than those represented by the samples.

Belvand specialists used a variety of approaches, including geostatistical methods OK, to better estimate mineral resource calculations.

According to David (2012), the OK estimators are based on the hypothesis that the attribute to be estimated is a regionalized variable, which means that samples near together have more comparable attributes than samples further apart. The process is typically divided into two phases: variographic study and variography, in which the spatial correlation between samples is quantified to define a mathematical function that represents this correlation while also allowing for the assignment of an error to each estimation and thus assessing its quality.

The experimental variogram was evaluated to determine the degree of spatial correlation between sample points as a function of the distance apart. The Gaussian fit model gave weights for the Kriging process and was critical to understanding how mineral grades vary over time. The results are shown in Figures 10 to 12.

4.6.1. Semivariogram Graph

Figure 10 shows a variogram model setup within the Geostatistical Wizard in ArcGIS with the main components:

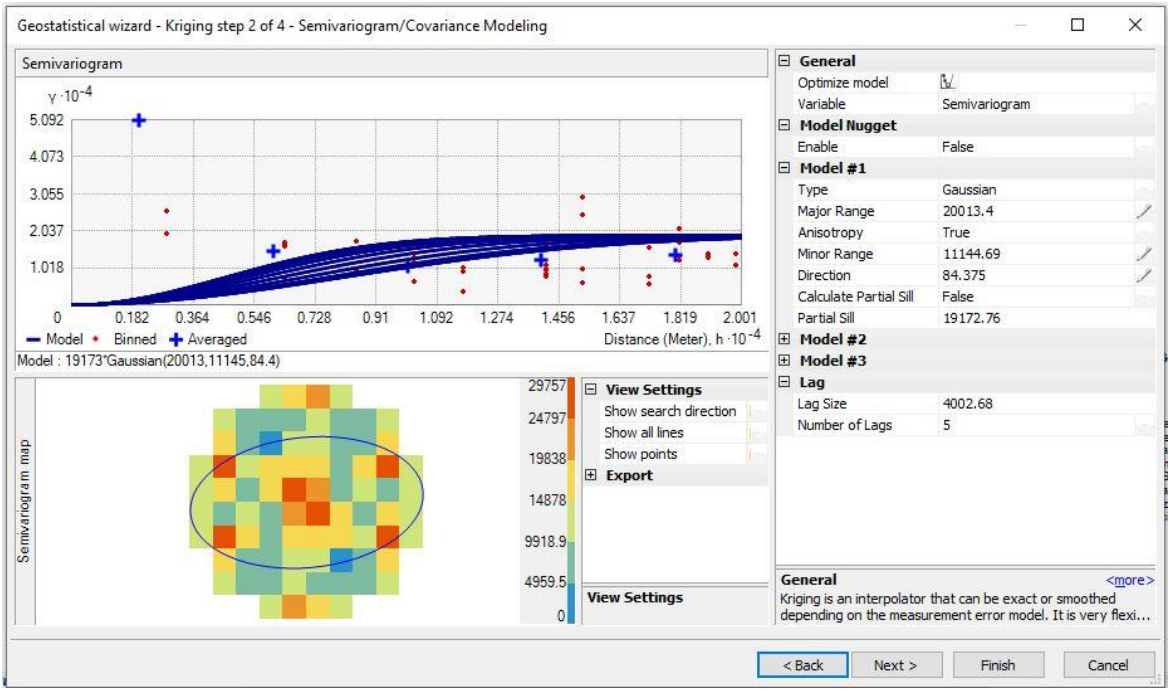

Figure 10: Geostatistical Wizard: step 2 of 4 – Semivariogram/Covariance modelling.

1. **Variogram Model Parameters (TOP)**

The semivariance, a measure of how spatially similar or dissimilar points are as a function of distance, is represented by the **Y-axis ($\gamma \times 10^{-4}$).**

The X-axis (Distance, Meter) shows the lag, or separation distance, between two points.

Model Line: the selected variogram model, in this case a Gaussian model, is shown by the blue line. To capture spatial correlation in the data, the model is fitted to the points.

Averaging semivariance values within predetermined lag distance intervals yields the **red dots**, which are binned semivariance values.

Averaged **Blue Crosses** shows the average semivariance for every lag that the model tries to fit.

2. **Variogram Model Parameters (Right Panel)**

I. **Gaussian** variogram model is used;

II. **Major Range: 20013.4** - this is the range along the principal direction of spatial continuity. Beyond this distance, the association between locations becomes weaker;

III. **Minor Range: 11144.69** - the range in the perpendicular (secondary) direction represents anisotropy in spatial continuity;

IV. **Anisotropy**: True - indicates that spatial variance varies with direction, having separate major and minor ranges;

V. **Partial Sill: 19172.76** - this is the semivariance value at which the model levels off, showing that extending distance does not significantly increase dissimilarity;

VI. **Lag Size**: 4002.68 - determines the distance between each lag in the model

VII. **Lags: 5** - the number of lags used to compute and show semivariance values.

3. **Semivariogram Map (Bottom Left)**

This map depicts the geographical connection in various orientations. The elliptical form implies anisotropy, which means that spatial continuity changes with direction. The longer axis represents the direction with greater spatial continuity (major range).

According to Cressie (1985), this arrangement defines the Gaussian variogram model parameters, which capture the spatial structure of the data by fitting the model to distance and direction-based semivariance values. This is necessary for OK interpolation because it helps in predicting values in unsampled areas by recognizing spatial correlations in the data.

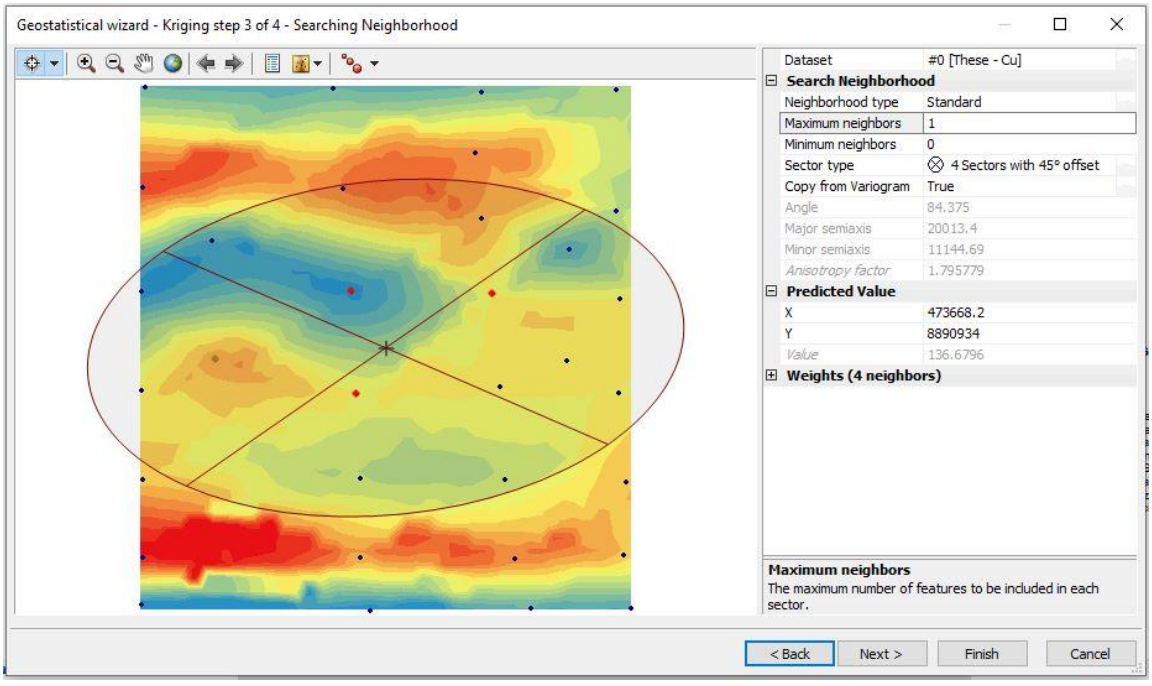

Figure 11: Geostatistical Wizard: step 3 of 4 – Semivariogram/Covariance modelling.

Figure 11 depicts Wizard step 3 defining the local search neighbourhood for OK, which allows to choose how many adjacent points to consider in each direction. This arrangement was necessary to increase the interpolation's accuracy, particularly when the data had directional

spatial continuity. In other words, show how nearby data points are chosen to estimate values at unsampled locations, with an emphasis on local neighbourhood for kriging interpolation. The big elliptical shape on the map denotes the search neighbourhood, which is the area where data points will be evaluated for kriging interpolation.

Pardo and Atkinson (2007) feel that dividing the ellipse into four sectors with a 45° offset, as given in the parameters, helps to guarantee that points are uniformly dispersed from various directions around the estimation point, hence enhancing estimate stability. Noted by Belvand Specialist, the blue dots indicate sampling locations from the dataset, and their values were utilized to estimate the unknown value at the center of the ellipse. Similarly, the cross in the center of the circle indicates the place being approximated. To achieve interpolation, the kriging algorithm searched for close points within the ellipse.

Neighbourhood Type (Standard) represents the standard search neighbourhood, which is generally elliptical in form to reflect data anisotropy (Christianson et al, 2023). Maximum neighbours 1 denotes the highest number of points to be utilized for interpolation inside each sector. In this configuration, just one neighbour per sector was utilized, yielding up to four neighbours. Similarly, minimal neighbours 0 permits the estimate to continue even when there are no neighbours in a sector (Murthy, 1989). Finally, Belvand specialists argue that setting up the Sector Type with four sectors and a 45° offset enables a fair sample of points from all directions.

4.6.2. Cross Validation

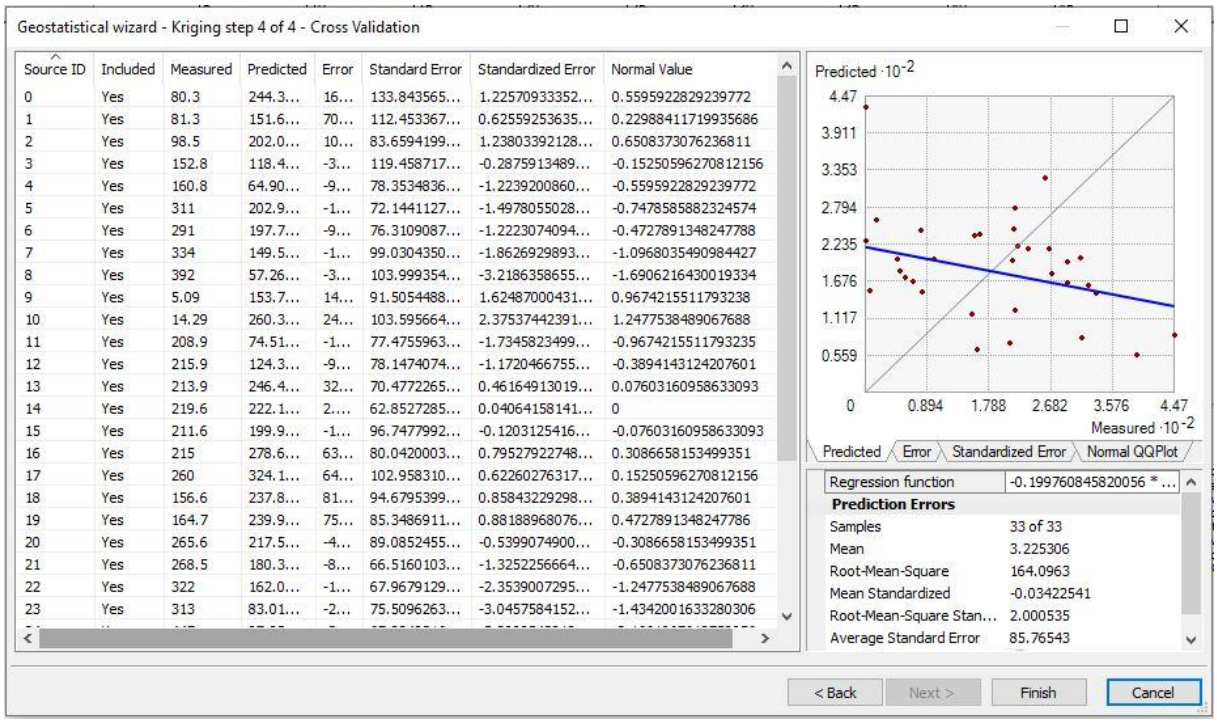

Figure 12: Geostatistical Wizard: step 4 of 4 – Semivariogram/Covariance modelling.

Figure 12 shows the Cross Validation result, method for determining the accuracy of the OK by comparing measured to projected values at each sample location. Understanding the Belvand, the key elements in the Figure are:

1. **Cross-Validation Table (Left Panel)**

I. **Source ID**: is a unique identifier for each sample point in the dataset;

II. **Included**: shows whether a sample point was included in the cross-validation process;

III. **Measured**: observed values at each sample site;

IV. **Predicted**: the kriging model's projected value for each sample location after eliminating that point;

V. **Error**: is the discrepancy between measured and anticipated values (Error = Measured - Predicted);

VI. **Standard Error**: indicates the model's uncertainty at each point;

VII. **Standardized Error**: divide the error by the standard error to obtain a standardized measure that should be close to zero for a well-fitting model;

VIII. **Normal Value**: indicates the standardized error's position on a normal distribution. Values close to 0 suggest that the model is not overestimating or underestimating.

2. **Graph (Right Panel)**

I. **Scatter Plot**: this Figure contrasts the measured (x-axis) and expected values (y-axis). Every red dot denotes a sampling site;

II. **Regression Line (Blue Line)**: the blue line represents the trend in the residuals (the disparities between observed and anticipated values). Ideally, this line should be close to the 1:1 line (diagonal), indicating that the anticipated and observed values are almost identical;

III. **Normal QQPlot Tab**: this tab displays a Q-Q (Quantile-Quantile) plot, which may be used to determine if errors are normally distributed. This is important for determining whether the kriging model assumptions hold.

3. **Prediction Errors (Bottom Right Panel)**

I. **Samples**: the number of points utilized for cross-validation;

II. **Mean**: is the average of forecast errors. A mean close to zero suggests that the model has minimal systematic bias;

III. **Root-Mean-Square (RMS)**: is a measure of average error size. Lower RMS values imply higher model accuracy;

IV. **Mean Standardized**: the average of standardized errors. This number should be close to zero in a well-calibrated model;

V. **Root-Mean-Square Standardized (RMS Standardized)**: measures how accurately the model's predictions fit the variability of the actual data. Ideally, this number should be near to one;

VI. **Average Standard Error**: measures the model's uncertainty by averaging the standard errors across all locations.

The intended results were a mean error close to zero, a regression line near the 1:1 diagonal, an RMS standardized close to one, and normally distributed errors.

4.6.3. Ordinary Kriging

The OK estimator assured that the total of the weights was equal to one, indicating that the estimate was unbiased. Similarly, it computed values at unsampled locations by using weights established from known sample values to estimate the grade at the unsampled place. Basic statistical analysis was conducted to better understand the distribution of Cu grades, identify outliers, and assess the presence of patterns in the data. The OK map is shown in Figure 13.

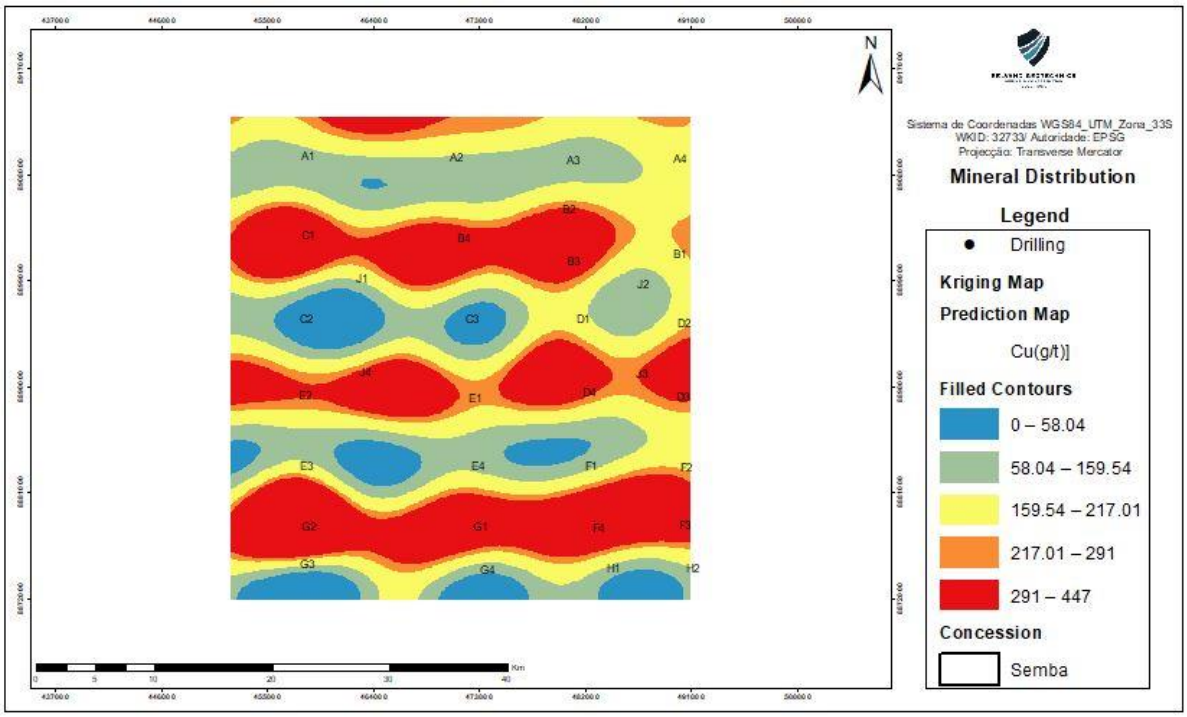

Figure 13: Copper (Cu) Concentration on the concession.

According to Figure 13, the OK map representing the spatial distribution of Cu concentration in the concession area, exhibits an anisotropic pattern due to:

1. **Directional Patterns** reflects variations that are directionally dependent. The map shows extended zones with high (red) and low (blue) Cu concentrations, indicating that the spatial correlation varies with direction. These zones are aligned northwest-

southeast, implying that the continuity or correlation of mineral concentration is higher in this direction than in others;

2. **Elongated Contours**: the filled contours representing different Cu concentration ranges (0 - 447 g/t) are not circular or uniformly distributed. Instead, they produce extended bands, which are characteristic of anisotropy, in which the range of correlation varies in various directions;
3. **Geological Structures**: the concession's geological formations, including sedimentation, faulting, and folding, result in anisotropic mineralization.

According to Belvand's mining engineers, the colors depicted in Figure 13 correspond to varying levels of priority for mining exploration and can be interpreted as follows:

1. **Red (291–447 g/t)**: indicates the highest concentration of copper, making it the **highest priority** for mining exploration;
2. **Orange (217.01–291 g/t)**: represents high copper concentrations, also of significant priority but slightly lower than red zones;
3. **Yellow (159.54–217.01 g/t)**: moderate copper concentrations, medium priority for exploration;
4. **Green (58.04–159.54 g/t)**: relatively low copper concentrations, low priority for exploration;
5. **Blue (0–58.04 g/t)**: the lowest copper concentrations, least favourable for exploration.

To conclude, focus mining efforts on **red and orange zones** to maximize resource extraction efficiency. Subsequent exploration may target yellow areas if needed.

4.7. Mineral Reserve Estimation

After estimating the grade for the entire concession, these values were combined with volumetric data, such as block models to estimate the total mineral reserves. Emery (2006), believe If working with a block model, OK may be used to estimate the average grade inside each block. Figure 14-16 shows the outcome.

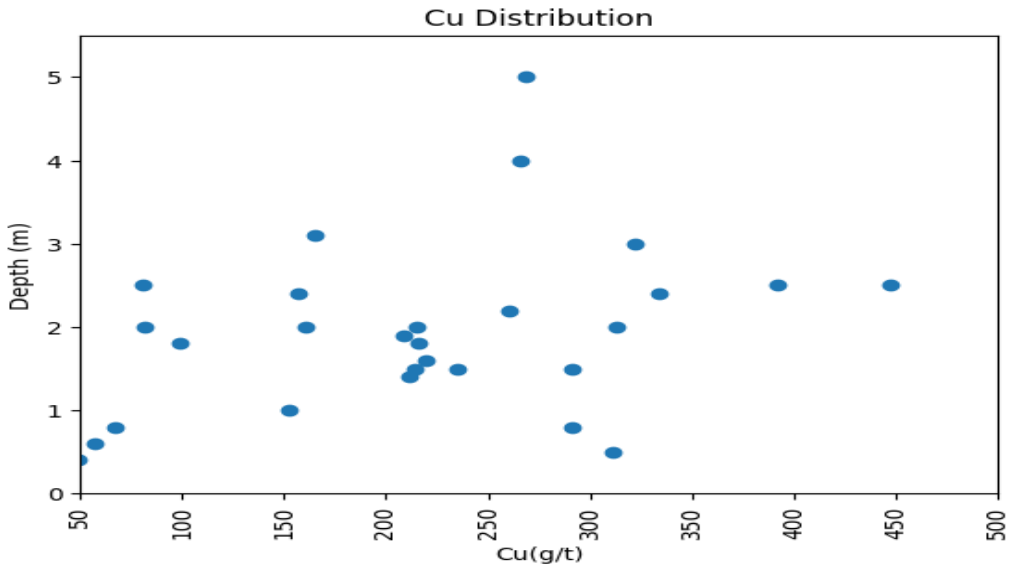

Figure 14: Distribution of Cu.

Figure 14 shows the distribution of Cu concentrations (in grams per tonne, g/t) at various depths (in meters) throughout the concession. In geology and mining engineering, evaluating the distribution Cu at different depths is critical to understanding the deposit is spatial distribution and potential value. Belvand emphasized the following Key Points on the Figure:

1. **Depth vs. Cu Concentration**: each point on the Figure represents a sample at a certain depth and Cu concentration;
2. **Variability in Cu Concentration**: the Cu concentration varies significantly across depths, with values ranging from approximately 50 g/t to over 450 g/t. In other words, it indicates different mineralization zones or geological structures influencing concentration;
3. **Potential Mineralized Zones**: clusters of points with higher copper concentrations specific depths suggest high grade zones.

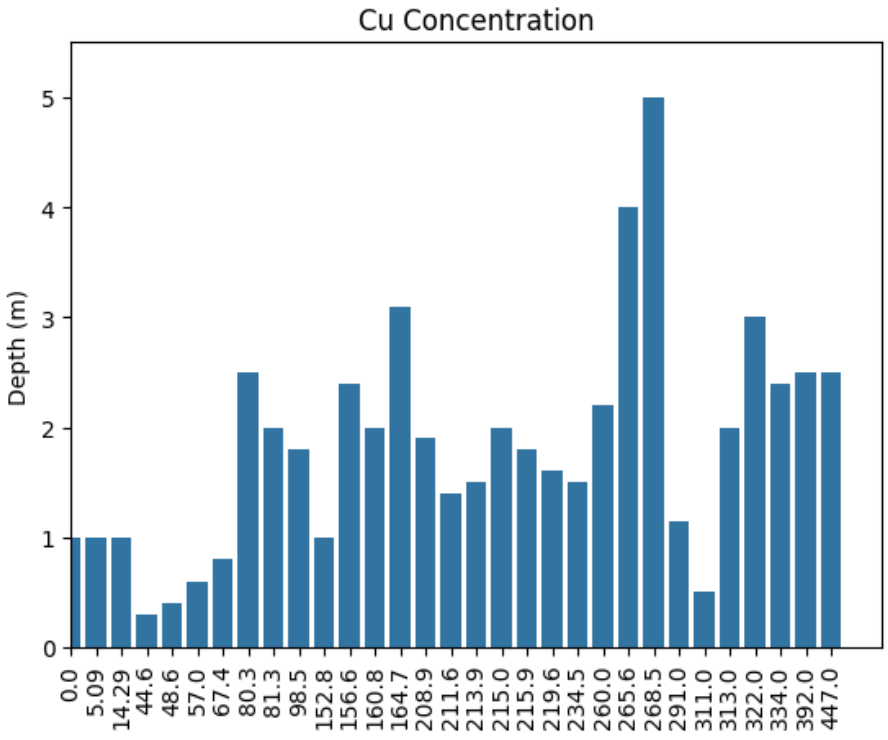

Figure 15: Cu Concentration Patterns.

Figure 15 shows Cu concentration Patterns that change significantly with depth, indicating a non-uniform distribution as depths vary. For instance, concentrations are substantially greater between 2.5 and 4.5 meters, indicating discrete zones of copper enrichment. Lower concentrations, on the other hand, are found closer to the surface and at varying depths, indicating places with less mineralization or that have been heavily weathered.

Belvand mining engineering believes that the patterns seen in Figure 15 have direct consequences for exploration, and economic feasibility assessments. For instance, the graphic indicates that Cu is higher concentrated at particular depths, which might direct extraction plans to specific zones. In contrast, depths with continuously low concentrations may be less economically viable, whereas the peaks signal potentially richer zones.

A 3D model of the copper distribution was created using Python Language based on the data above to better illustrate how Cu fluctuate geographically and inform resource extraction decisions (Figure 16).

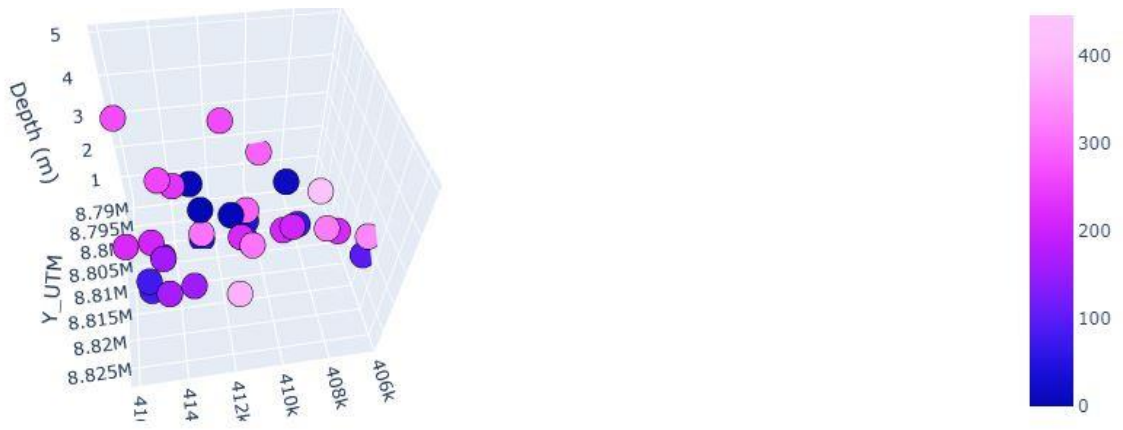

Figure 16: 3D model of Cu Concentration.

This model generates a 3D visual of Cu concentration, which is valuable for estimating mineral resources and guiding future exploration. This model assisted in the development of effective mining and resource allocation methods by recognizing depth and spatial concentration patterns.

4.8. UNCERTAINTY AND VALIDATION

OK estimated and measured the uncertainty (Kriging variance) at each position. This helps to determine the level of confidence in the predicted mineral reserves. Validate the model by comparing Kriging estimates to real sample values, and frequently use cross-validation procedures to ensure predictions are accurate. Table 3 outlines the advantages and limitations of OK found during mineral reserve estimation, according to Setianto and Triandini (2013).

Table 3: Advantages of Ordinary Kriging in Mineral Reserve (Setianto & Triandini 2013).

Advantages	**Limitations**
It minimized estimation error while producing unbiased predictions.	The success of Kriging was strongly reliant on the accuracy of the variogram model.
Incorporated spatial relationships between data points, resulting in more trustworthy estimations than basic interpolation approaches such as inverse distance weighting (IDW).	Solving Kriging equations proved time-consuming for big datasets, particularly in 3D applications.
Can be utilized for a variety of geographical data and tailored to different geological situations.	OK assumed that the mean of the variable was constant over the region of interest, which was not the case with the deposits.

5. CONCLUSIONS

The internship report emphasizes the use of GIS in mining exploration techniques in Angola. It underscores how RM was integrated into GIS and improved geological prospecting. Belvand Geotechnics effective use of GIS demonstrate its dedication to innovative and prudent exploration tactics.

Key Insights:

1. **Remote Sensing:** Belvand Geotechnics employed RM techniques integrated with a GIS framework to support geological prospecting by accurately identifying surface features and mineral indicators. This approach enabled the efficient delineation of high-priority exploration zones, optimized resource allocation, and reduced environmental impact by minimizing unnecessary field activities.
2. **Geological Mapping:** GIS digitizes and georeferenced field observations, allowing for precise and thorough geological mapping. This exact information helps with exploration planning and resource allocation.
3. **Mineral Estimation:** Belvand used kriging techniques inside a GIS framework to estimate mineral distribution, which allowed identifying high-priority exploration zones. This method facilitated cost-effective resource allocation and lowered the environmental impact by minimizing superfluous exploratory actions.

4. **GIS for Informed Decision-Making:** by integrating varied datasets, GIS helps identify mineral targets. This resulted in more informed methods that increased exploration success.

5. **The Future of GIS in Mining:**

a) **Predictive Analytics:** GIS can assist mining company estimating mineralization zones and exploration success rates using historical and current data.

b) **Real-Time Data Integration:** advancements in sensor technology and connection enable GIS to incorporate real-time data from exploration locations, will allow the dynamic alterations in plans depending on changing conditions.

c) **Digital Twinning:** GIS can promote digital twinning by generating virtual reproductions of exploration locations for remote monitoring, risk assessment, and scenario modelling.

d) **Holistic Sustainability Analysis:** GIS can provide holistic sustainability assessments that consider economic, social, and environmental variables to make better informed decisions.

In conclusion, the internship report emphasizes GIS revolutionary influence on mining exploration. Belvand Geotechnics' effective integration of GIS indicates the company's dedication to safe, efficient, and exploration procedures. The future potential of GIS in the

mining industry includes exciting developments that might further optimize exploration efforts, enhance decision-making, and contribute to the sector's long-term prosperity.

5.1. Challenges and Limitations

While GIS has significant benefits in mining exploration, Belvand Geotechnics encountered certain obstacles and constraints throughout its implementation. The company took aggressive steps to overcome or reduce these issues, resulting in the successful incorporation of GIS into their exploration programs.

5.1.1. Data Quality and Integration

Challenge: ensuring the quality, accuracy, and compatibility of diverse datasets from several sources can be difficult. Inaccurate or inadequate data might result erroneous assessments and decision-making (John, 1993).

Mitigation: Belvand Geotechnics implemented stringent data validation and quality control procedures. They developed standardized protocols for data gathering, storage, and sharing, reducing discrepancies. They also invested in data cleansing and transformation solutions to maintain data consistency.

5.1.2. Technical Expertise

Challenge: e effective GIS use necessitates technical proficiency in both GIS software and geographic analysis. Limited skilled specialists might impede the effective use of GIS systems.

Mitigation: the company invested in GIS training for their employees, ensuring that the exploration team had a solid grasp of GIS tools and methodologies. They also worked with external GIS specialists as needed to address too complicated problems and assure accurate implementation.

5.1.3. Hardware and Software Resources

Challenge: GIS applications might require significant computing resources, including hardware and software licenses. Lavendel (2002) states that insufficient resources can cause delayed processing and poor analysis.

Mitigation: Belvand Geotechnics invested on reliable hardware infrastructure and maintained up-to-date GIS software licenses. Cloud-based solutions were also considered to increase computing capacity during peak demand periods.

5.1.4. Data Volume and Processing Speed

Challenge: large amounts of data, particularly in 3D modelling, might result in slower processing times and decreased responsiveness (Nguyen et al., 2015).

Mitigation: the company use data optimization strategies such as Python Language for 3D visualisation, data simplification and aggregation, to minimize data volume while maintaining accuracy. This contributed to the efficiency of GIS operations even, with large datasets.

5.1.5. Local Context and Regulatory Compliance

Challenge: local regulations, cultural sensitivities, and specific environmental conditions can all complicate the application of GIS, particularly when planned exploration in rural locations.

Mitigation: Belvand Geotechnics prioritized developing local relationships and engaging with local community early in the project. They customized GIS analyses to the local environment and followed legal requirements, ensuring that GIS solutions matched local sensitivities.

Belvand Geotechnics demonstrated a proactive and adaptive approach strategy to overcoming the constraints and limits of using GIS in mining exploration. By investing in data quality control, technical training, resilient infrastructure, data optimization, local participation, and effective communication tactics, guaranteed that GIS contributed to their exploration success in Cuanza-Sul while limiting possible failures.

5.2. RECOMMENDATIONS

Recommendations to improve GIS in Mining Exploration at Belvand Geotechnics:

I. **Remote Sensing**: continue leveraging RM techniques combined with GIS frameworks to enhance geological prospecting efforts. Future applications should focus on integrating advanced RM technologies, such as hyperspectral imaging or LiDAR, to further improve the accuracy of mineral detection and mapping. Additionally, incorporating multi-temporal analysis could enhance the understanding of geological changes over time, enabling more sustainable and efficient exploration strategies;

II. **Advanced Data Integration:** exploring sophisticated data integration strategies will help to speed the integration of varied information. Investigate the usage of data warehouses or central repositories to assure data accuracy, consistency, and usability;

III. **Real-Time Monitoring**: consider integrating real-time data streams from exploration sites with GIS. This might provide up-to-date information on drilling progress, environmental conditions, and equipment status, allowing for faster decision-making;

IV. **Interactive Stakeholder Engagement:** create GIS tools that enable concession owners to engage with exploration plans and scenarios. This may encourage more involvement, collaborative input, and a sense of ownership in decision-making;

V. **Spatial Analysis:** by researching and incorporating advanced technologies into GIS. Spatial Interpolation Approaches, Geostatistics, and Spatial modelling might all be used to improve geological feature prediction accuracy;

VI. **Geostatistics:** expand the use of kriging techniques integrated with GIS frameworks to other mineral-rich regions to enhance exploration accuracy and efficiency. Additionally, incorporating advanced geostatistical models and refining the input data quality, such as incorporating 3D geological modeling, can further improve the precision of mineral distribution estimates. Continuous training for personnel on kriging methods and GIS applications is also advised to maintain high standards of resource optimization and environmental stewardship.

Belvand Geotechnics can maintain its leadership position in GIS-enabled mining exploration by following these recommendations and pursuing new research avenues. These improvements would not only increase exploration efficiency but would also add to the company's sustainability and responsible mining practices.

5.3. FUTURE RESEARCH DIRECTION

Future research should focus on incorporating advanced analytics, Python language for data Analyse and machine learning algorithms with GIS to increase predictive modelling capabilities. Hewson and Cudahy (2011) discovered that combining GIS and machine learning may improve the accuracy of mineral exploration and estimation.

5.3.1. Real-Time Data Integration

Incorporating real-time data from RM and IoT devices into GIS can offer current information on exploratory operations. This integration will allow for more dynamic and responsive decision-making processes.

5.3.2. Interdisciplinary Approaches

Adopting multidisciplinary techniques that combine GIS with other scientific fields such as environmental science, economics, and social studies can lead to a more comprehensive knowledge of mining consequences and better resource management. Further study should focus on:

I. **Environmental Footprint Analysis:** evaluate the environmental implications of exploratory operations inside and outside the mining;

II. **Multidisciplinary Integration:** explore how GIS may be integrated with other technologies including RM, Drones, and IoT devices. This might give a more

comprehensive perspective of exploration locations, increase data collecting, and boost risk assessment;

III. **Predictive Analytics Development:** develop predictive analytics models using GIS, by using previous exploration data to forecast mineralization trends and inform future exploration tactics;

IV. **Social Impact Assessment:** expand GIS capabilities to include social effect assessments. Consider how exploration operations may affect local communities, livelihoods, and cultural heritage;

V. **Artificial Intelligence (AI):** explore AI-powered GIS applications. This might include AI-powered anomaly detection in geographical data, automated feature identification, and scenario modelling;

VI. **Climate Change Resilience:** investigate the integration of climate change data with GIS. This might be useful in determining the long-term robustness of exploration programs to changing environmental circumstances.

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APPENDIX A (REMOTE SENSING)

Belvand provided satellite images in ASTER format with the designation AST_L1T_00308122000092701_20150410235902_68295, which were processed to identify regions likely to have mineral occurrences and geological characteristics. Combinations of several bands were used, and the results are shown below:

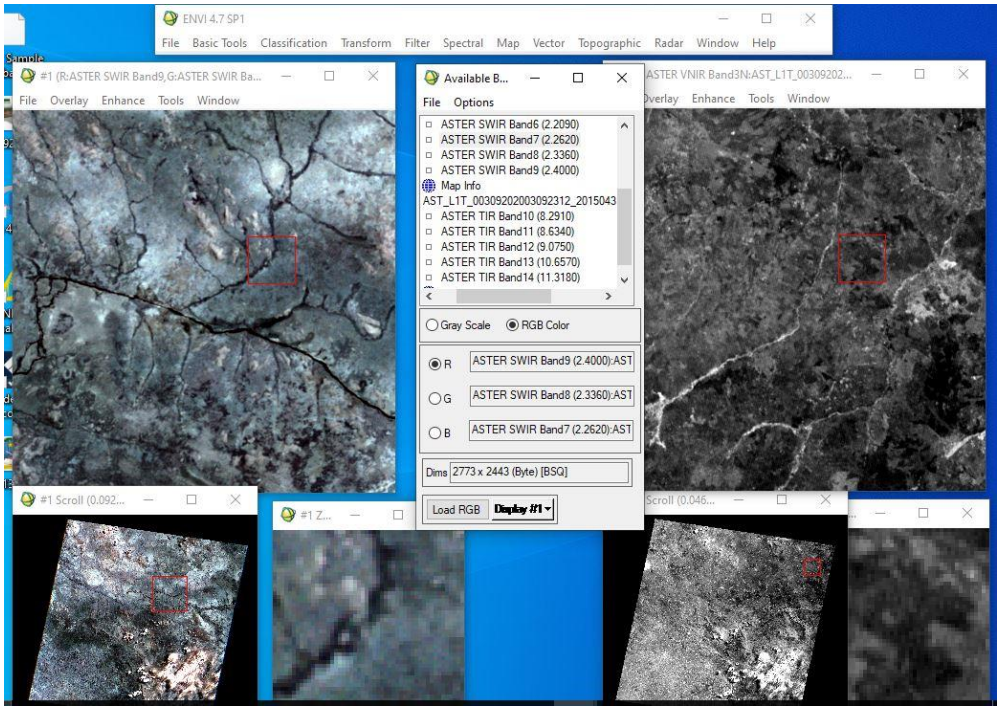

Figure A - 1: RGB Combination of the bands 9/8/7 (Belvand).

Figure A-1 shows the combination of shortwave infrared (SWIR) bands ASTER bands 9, 8, and 7 to create colour composites for mapping minerals associated with hydrothermal alteration to identify mineral deposits associated with Au, Cu, Ag, Zn, and Pb. Furthermore, the colour composite of ASTER bands 9/8/7 can be read as the following:

i. **Band 9 (2.180 - 2.300 µm)** sensitive to minerals with hydroxyl (-OH) groups, including clays and alteration mineral;

ii. **Band 8 (2.145 - 2.185 µm)** sensitive to Fe can detect iron associated minerals;

iii. **Band 7 (2.080 - 2.105 µm)** is sensitive to carbonate minerals and can identify certain mineralization types.

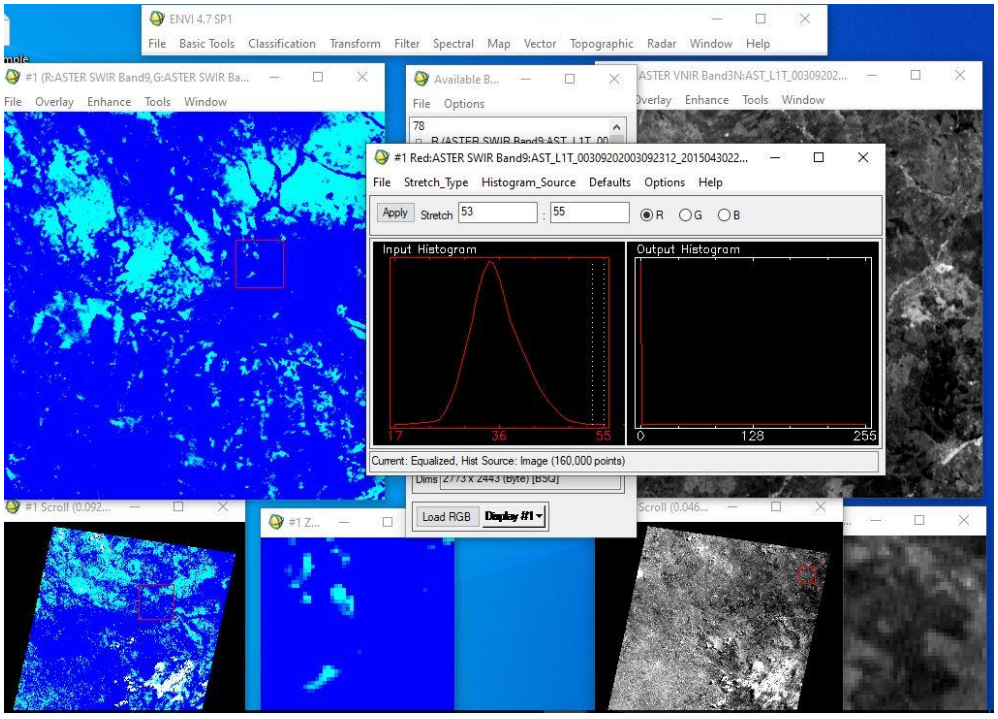

Figure A - 2: Colour composition for mapping ASTER bands 9, 8, and 7 (Belvand).

The colours seen in colour composition for bands 9, 8, and 7 in Figure A-2 indicate various mineral signatures. This composite has hydroxyl-rich regions (which may look red or pink), Fe associated mineral areas (which may appear green), and carbonate-rich areas (which may appear blue).

The combination of these bands and colours made it easier to identify and map alteration zones. However, the findings revealed a complex interpretation. As a result, new bands (Figure A-3) were interpreted and integrated with geological prospecting.

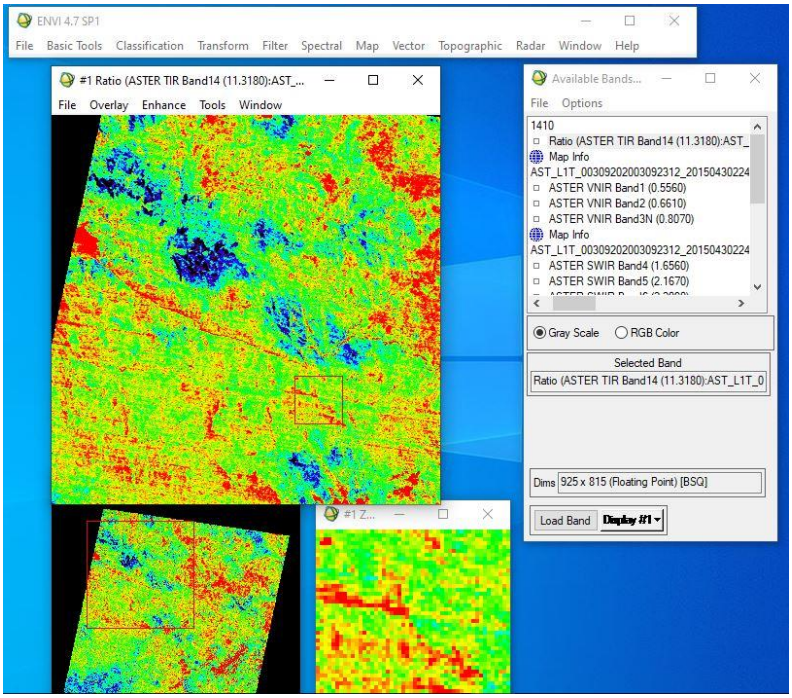

Figure A - 3: RGB Combination of the band 14/15 (Belvand).

Figure A-3 is interpreted by examining temperature changes. **Band 14 (TIR 1, 10.4-11.3 µm) and Band 15 (TIR 2, 11.5-12.5 µm)** can detect temperature changes due to geothermal activity or surface material changes. Band 14 depicts warmer temperatures, which are often brighter, whereas places with greater temperatures are depicted as brighter red. Furthermore, in Band 15, lower temperatures show as darker tones. As a result, it appears that to target the desired minerals such as Au, Cu, Ag, Zn, and Pb, the focus should be on bands in the visible, near infrared (Figure A-4), or shortwave infrared regions, as these are more sensitive to the specific mineralogical properties of these minerals.

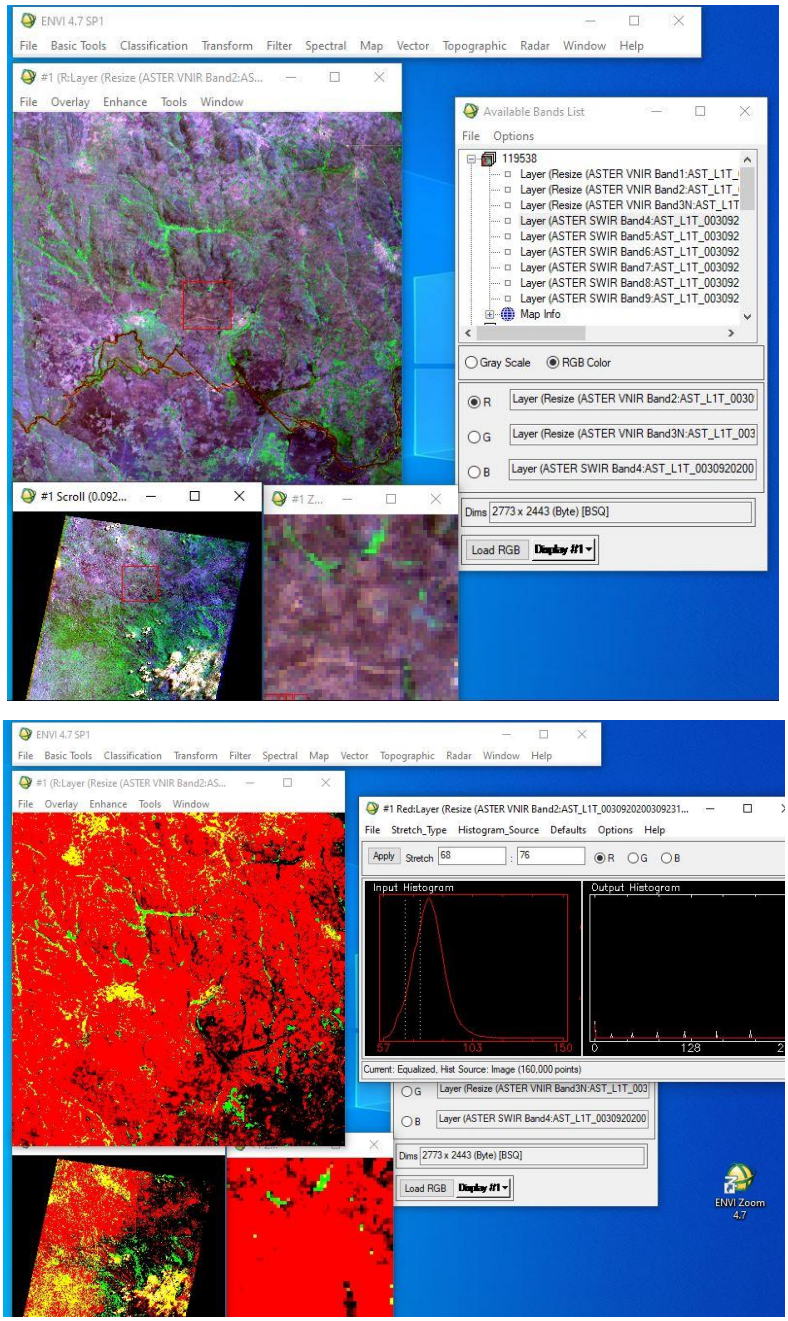

Figure A - 4: RGB Combination of the bands 2/3/4 (Belvand).

Figure A-4 shows how the combination of ASTER bands 2, 3, and 4 provides information on the Earth's surface reflectance qualities, which is useful for mapping minerals linked with Au, Cu, Ag, Zn, and Pb. Thus, the colour composite can be understood as follows:

i. **Band 2 (Visible Green, 0.52 - 0.60 μm)** detects and distinguishes healthy vegetation based on reflectance. As a result, it can emphasize differences in flora and soil/rock features and is represented by the colour red.

ii. **Band 3 (Visible Red, 0.63 - 0.69 μm)** measures plant reflectance and offers soil and rock properties. Green is the colour represented. It can improve the visibility of flora and some changes in surface materials.

iii. **Band 4 (Visible Near-Infrared, 0.76 - 0.86 μm)** measures plant health and identifies soil and rock kinds. Healthy vegetation usually seems brilliant green.

The spectral analysis performed by the GIS Specialist form Belvand leads to the conclusion that various minerals reflect and absorb light in different ways, resulting in diverse spectral signatures. Similarly, hydrothermal alterations can modify the mineral composition around ore deposits, leaving distinct fingerprints. As a result, the colour variation in figure 05-4 show changes in Soil/Rock specific minerals associated with Cu deposits, while detecting anomalies may relate to underlying mineral resources.

The data gathered by RM assisted the geologists in conducting geological structure analysis to identify structural characteristics such as faults and fractures that are strongly suggestive of aggregating mineralization, changes in land cover or surface characteristics that may also reflect geological processes.

APPENDIX B (GEOLOGICAL PROSPECTING PHOTOS)

Geological prospecting began in 2022 with the goal of verifying concession boundaries and mapping outcrops. Most of the borehole drilling was done manually at 1 to 2m depth with a hoe, pickaxe, shovel, and other tools (Figure B-1). The second phase was completed in 2023 with a drill with a depth of 30 m, followed by laboratory testing in February 2024.

Figure B - 1: Example of borehole excavated.

Geological Description

The concession is made up of outcrops of granitic rock (biotite granite) and gneiss with medium to coarse granulation and granular texture, as well as scarce concentrations of white feldspar (2-4 mm in length) that are visible to the naked eye. Mafic minerals, including biotite and mica, typically have grain sizes of ≤1 mm and are commonly accompanied by minute grains of an opaque accessory mineral, most likely magnetite.

Figure B-2 display granite composed mainly of minerals such as quartz, feldspar, and mica. It exhibits massive, foliated structures, with fine to coarse texture, and mineralization zones are associated with veins, fractures, or specific alterations in the rock. In term of mineralization, plagioclase is predominant over feldspar, and the rock is designated as monzogranite.

Figure B - 2: Granite encountered in the concession.

Geotechnical Properties

Rock mass assessment was conducted, to define rock hardness as this significantly influences the feasibility of mineral extraction and processing. The rock's strength is crucial in determining the ease of excavation and crushing. The volume of void spaces in the rock was measured to calculate porosity and permeability, leading to the conclusion that during rainy seasons, the rock's capacity to allow fluid circulation will affect the leaching of minerals during processing.

The observed Gneiss (Figure B-3) displaying alternating bands of light and dark minerals. The predominant minerals include quartz, feldspar, mica (biotite or muscovite), and amphibole minerals with Granite intrusions that appear as veins.

Figure B - 3: Gneiss outcrop with Granite intrusion.

Geotechnical Properties

The gneiss exhibits good mechanical strength, while the strength of granite may vary. The presence of granite intrusions can affect strength. Porosity and permeability depend on the characteristics of the gneiss and granite, with gneiss tending to be less porous than granite.

The foliated structure of gneiss results in anisotropy in mechanical properties. Granite exhibits anisotropy depending on the orientation of minerals. The interaction between metamorphism and igneous intrusion can create fracturing zones. The presence of minerals like mica in gneiss can influence the orientation of fractures.

An outcrop of granitic rock was observed along the river and along the road (Figure B-4), with an area of 101.27 m^2. The outcrop, with a dip of 30^0 exhibits banding of mafic minerals (dark

colour) and felsic minerals (light colour), as well as folded quartz intrusions, indicating that the rock underwent a regional metamorphism process where it was subjected to high pressure and temperatures. The alternation between mafic minerals (biotite and amphibole) and felsic minerals (quartz and feldspar) suggests that it is an outcrop of metamorphic rock gneiss. Sampling of active stream sediments was collected.

Figure B - 4: A river passing over the Granit Outcrop

Other photos from the concession are presented below:

Figure B - 5: Sampling soil with drill fast

Figure B - 6: Analysis of mineralogy with hand lens.

Figure B - 7: Outcrop measurements.

APPENDIX C (LABORATORY RESULTS)

The following independent laboratory tests were used in the preparation and sample analysis: Determination of Rare Earth Elements in Soil/Ore by ICP-MS (4Acid Digestion) and Base Metal Ores and Concentrates by XRF Identification file: UIS 58205_Report.

Sample ID	X_UTM	Y_UTM	Cu (g/t)	Weight (kg)	Densidade (W/V)	Depth (m)	Volume (m3)
A1	457491.8	8908458	80.3	1.2	68	2.5	6
A2	470114.2	8908335	81.3	1.2		2	6
A3	480040.6	8908090	98.5	1.5		1.8	6
A4	489109.2	8908212	152.8	1.1		1	6
B1	489109.2	8900124	160.8	1.6		2	6
B2	479673	8904046	311	1.1		0.5	3
B3	480040.6	8899634	291	1.6		0.8	3
B4	470727	8901595	334	1.2		2.4	8
C1	457369.3	8901717	392	1.6		2.5	8
C2	457246.7	8894732	5.09	1.2		1	2
C3	471339.7	8894732	14.29	1.6		1	2
D1	480775.9	8894610	208.9	1		1.9	8
D2	489354.3	8894242	215.9	1		1.8	8
D3	489231.7	8887992	213.9	1.7		1.5	8
D4	481266.1	8888360	219.6	1.2		1.6	8
E1	471707.4	8887870	211.6	1.7		1.4	8
E2	457246.7	8888115	215	1.2		2	8
E3	457369.3	8882110	260	1.5		2.2	6
E4	471952.5	8882232	156.6	1.2		2.4	6
F1	481633.8	8882110	164.7	1.6		3.1	6
F2	489721.9	8881987	265.6	1.1		4	8
F3	489599.4	8877085	268.5	1.7		5	8
F4	482246.5	8876840	322	1.2		3	6
G1	471952.5	8876963	313	1.2		2	6
G2	457369.3	8876963	447	1.7		2.5	6
G3	457246.7	8873776	0	1.2		1	4
G4	472565.2	8873409	0	1.6		1	4
H1	483349.4	8873531	67.4	1.2		0.8	1
H2	490089.6	8873531	57	1.7		0.6	1
J1	462026.1	8898164	44.6	1.1		0.3	1
J2	485922.9	8897551	48.6	1.7		0.4	1
J3	485800.4	8890075	234.5	1.2		1.5	1
J4	462271.2	8890198	291	1.7		1.5	1

Table C - 1: Geochemical results with Drilling coordinates in UTM.

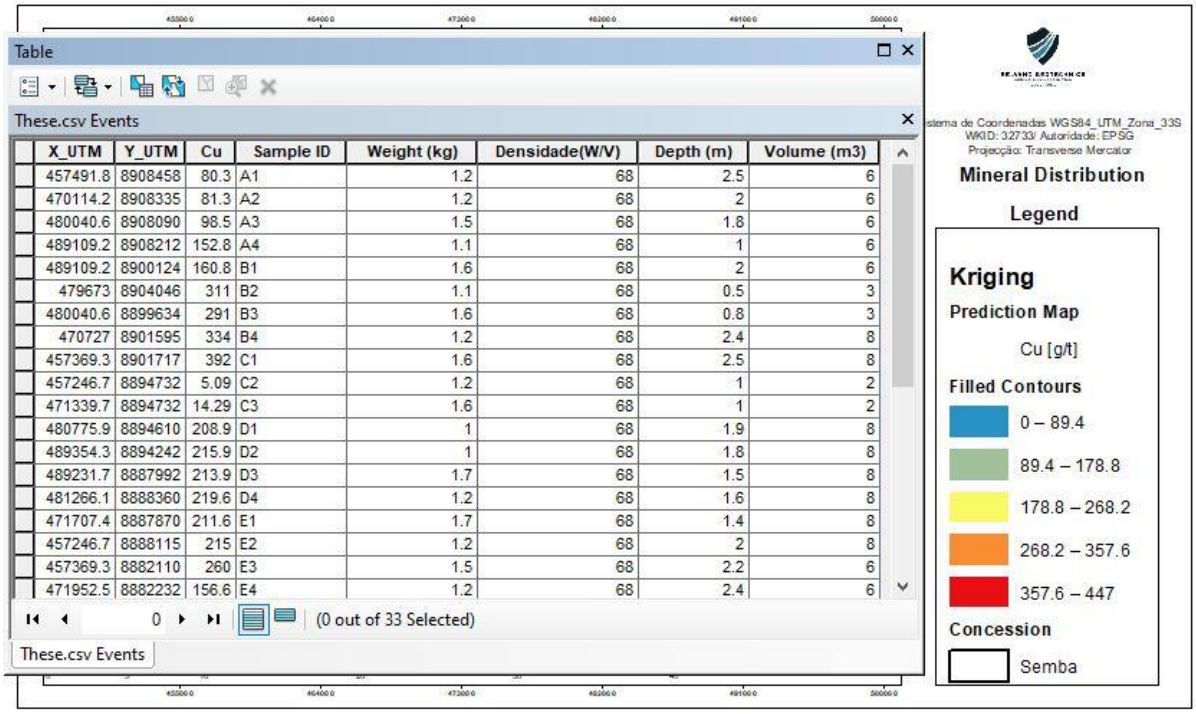

Figure C - 1: Samples location coordinates (latitude, longitude and depth)

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