

Evaluation of radar and hyperspectral data for the identification of placers in the Rias Baixas region

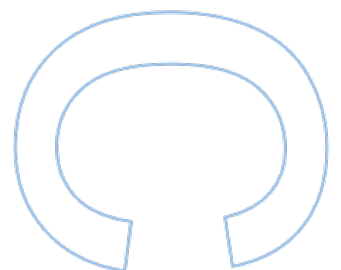
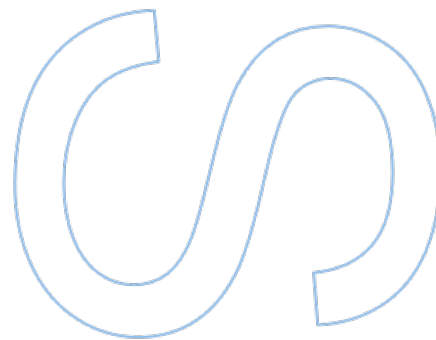
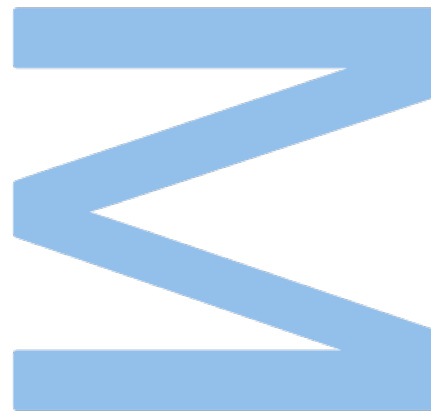
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Master in Geology

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2024



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Dissertation carried out as part of the Master in
Geology

Department of Geosciences, Environment and Spatial Planning
2024

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Agradecimentos

Primeiramente, expresso o meu agradecimento às minhas orientadoras, Doutora Joana Cardoso Fernandes e Professora Doutora Ana Cláudia Teodoro, por me terem proporcionado a oportunidade de integrar este projeto, pela orientação e ensinamentos ao longo deste percurso.

Agradeço igualmente aos meus colegas, António Azzalini e Morgana Carvalho, por toda a ajuda que tão generosamente sempre se prontificaram a me oferecer e, acima de tudo, pela partilha de momentos de boa disposição.

Agradeço também ao Douglas Santos pela assistência na análise dos dados de EnMAP e no uso do software ENVI.

O meu muito obrigada a todos os meus amigos, que sempre estiveram ao meu lado nos bons e maus momentos, e por sempre conseguirem arrancar-me gargalhadas, mesmo nos dias menos risonhos.

Aos meus irmãos e irmã, por sempre me incentivarem a encarar a vida com otimismo e por serem, para além de meus irmãos, também os meus melhores amigos. Vocês tornam os meus dias mais divertidos e sei que, mesmo com a distância, pude e posso sempre contar convosco.

Do fundo do coração, um agradecimento especial aos meus pais, por todos os sacrifícios que fizeram para investirem na minha formação académica e pessoal, e por serem verdadeiros exemplos de bondade, resiliência e força. Obrigada por me darem toda as ferramentas que preciso, por sempre terem acreditado em mim e por me acompanharem em todas as etapas, desde o 1º ano da escola primária até à conclusão do meu mestrado.

This work is supported by the EU under grant agreement no. 101091616 (<https://doi.org/10.3030/101091616>), project S34I.

Resumo

Matérias-primas Críticas (CRMs) desempenham um papel essencial em indústrias-chave, como as energias renováveis, eletrónica, defesa e exploração espacial. Estas matérias-primas são cruciais para alcançar os objetivos da União Europeia (UE) de uma economia neutra em carbono até 2050 e apoiar a transição verde e digital. Devido ao alto risco de fornecimento, a UE está a priorizar o desenvolvimento das suas próprias fontes para reduzir a dependência europeia de fontes externas, através do investimento na prospeção e na exploração mineral doméstica.

Esta dissertação aborda estas necessidades críticas, explorando técnicas de deteção remota para identificar depósitos de placers de minerais pesados (HM) na Ria de Vigo, em Espanha. Situada ao longo da costa atlântica da Galiza, na região das Rias Baixas, a Ria de Vigo alberga depósitos de placers ricos em Ti, Sn, Li, Elementos de Terras Raras, Au, Fe e Cu – classificados como CRMs.

Numa primeira abordagem, foi realizado um mapeamento estrutural usando dados de Sentinel-1 e LiDAR. A identificação de alinhamentos geológicos ajuda a localizar possíveis áreas mineralizadas e áreas com alteração hidrotermal, dado que qualquer fratura pode constituir um caminho para fluidos hidrotermais, além de fornecer informações sobre os contextos tectónicos da mineralização. Tanto extrações manuais, como automáticas, foram realizadas e comparadas, tendo sido última efetuada na plataforma Google Earth Engine (GEE).

As extrações manuais são geralmente mais demoradas e os resultados podem variar conforme o utilizador. Consequentemente, os métodos automáticos têm sido amplamente utilizados devido ao processamento mais rápido de grandes conjuntos de dados e à redução da variabilidade nos resultados. Neste trabalho, foram aplicados o Algoritmo Canny, para deteção de bordas, e a Transformada de Hough para deteção de linhas.

Foram realizadas um total de 3 extrações manuais: 2 usando dados de Sentinel-1 e 1 usando dados de LiDAR. Em contraste, foram realizadas 7 extrações automáticas: 3 usando dados do Sentinel-1 e 4 usando dados do LiDAR. Várias técnicas foram empregues para auxiliar a extração de alinhamentos, incluindo a bem estabelecida técnica consistindo em filtros direcionais, utilizando filtros Prewitt, e uma nova abordagem, utilizando a classificação não supervisionada K-Means como alternativa aos filtros Prewitt, para dados Sentinel-1. Para dados de LiDAR, foi utilizado o

hillshading nas direções N-S, E-O, S-N e O-E, para melhorar a visualização das estruturas em todas as direções.

Sentinel-1 destaca-se no mapeamento regional devido à sua ampla cobertura e disponibilidade, enquanto o LiDAR produz mapas de alinhamentos mais detalhados em escalas menores, devido à sua maior resolução espacial. A extração manual, embora precisa, constitui um processo longo e subjetivo, enquanto a extração automática foi significativamente mais rápida e identificou um maior número de alinhamentos, embora a sua eficácia dependa fortemente dos parâmetros definidos para os algoritmos.

Complementarmente, foi realizado um mapeamento mineral, utilizando dados hiperespectrais de EnMAP. Inicialmente, foi aplicada a técnica de rácio de bandas, para identificar possíveis áreas de mineralização. Uma vez que esta técnica não é direcionada para minerais específicos, foram realizadas duas classificações de Mixture Tuned Matched Filtering (MTMF), uma utilizando a biblioteca espectral USGS e a outra uma biblioteca espectral obtida para concentrados de HM. Estas classificações identificaram com sucesso a maioria dos HM conhecidos na Ria, como sillimanite, granadas, turmalina, ilmenite, rutilo e monazite.

Palavras-chave: CRMs, Minerais pesados, Placers, Deteção Remota, Sentinel-1, LiDAR, Extração automática de alinhamentos, GEE, EnMAP, Rácio de Bandas, MTMF

Abstract

Critically Raw Materials (CRMs) are vital in key industries, such as renewable energy, electronics, defence and space exploration. These materials are crucial for achieving the European Union's (EU) goals of a climate-neutral economy by 2050 and supporting the green and digital transition. Due to their high supply risk, the EU is prioritising its own sources, to reduce European dependency on external sources, by investing in domestic mineral exploration and exploitation.

This dissertation addresses these critical needs, by exploring remote sensing techniques to identify heavy-mineral (HM) beach placer deposits in the Ria de Vigo, Spain. Situated along Galicia's Atlantic coast, within the Rias Baixas region, Ria de Vigo hosts placer deposits rich in Ti, Sn, Li, Rare Earth Elements, Au, Fe, and Cu – all of which are classified as CRMs.

In a first approach, structural mapping was performed using Sentinel-1 and Light Detection and Ranging (LiDAR) data. Identifying geological lineaments aids in locating possible mineralized areas and hydrothermally altered areas, as any fracture could constitute a pathway for hydrothermal fluids, as well as provides insights into the tectonic settings of mineralization. Both manual and automatic lineament extraction were performed and compared, the latter performed in the Google Earth Engine (GEE) platform.

Manual extractions are typically more time-consuming, and results can be quite subjective, according to the user that's performing it. Consequently, automatic methods have been widely used for their faster processing of larger data and reduction of variability in the results. In this work, the Canny Algorithm, for edge detection, and the Hough Transform, for line detection, were applied.

A total of 3 manual extractions were conducted: 2 using Sentinel-1 data and 1 using LiDAR data. In contrast, 7 automatic extractions were carried out: 3 using Sentinel-1 data and 4 using LiDAR data. Various techniques were employed to assist in lineament extraction, including the well-established directional filtering, using Prewitt filters, and a new approach, using K-Means unsupervised classification, as an alternative to Prewitt filters for Sentinel-1 data. For LiDAR data, hillshading in N-S, E-W, S-N and W-E directions was employed to enhance the visualization of structures in all directions.

Sentinel-1 excels in regional mapping due to wide coverage and availability, while LiDAR produces more detailed lineament maps at smaller scales, owing to its higher spatial

resolution. Manual extraction, although accurate, was a lengthy and subjective process, whereas automatic extraction was notably faster and identified a larger number of lineaments, yet its effectiveness relies heavily on the parameters set for the algorithms

A complementary mineral mapping was performed, using hyperspectral EnMAP data. Initially, band ratios was applied to identify possible mineralization areas. Since this technique does not target specific materials, two Mixture Tuned Matched Filtering (MTMF) classifications were carried out: one utilizing the USGS spectral library, and the other employing a HM concentrate spectral library. These classifications successfully identified most HM known to occur in the Ria, such as sillimanite, garnets, tourmaline, ilmenite, rutile and monazite.

Keywords: CRMs, Heavy-mineral, Placers, Remote sensing, Sentinel-1, LiDAR, Automatic Lineament extraction, GEE, EnMAP, Band Ratios, MTMF

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List of Abbreviations

BRW	Browse
CIZ	Central Iberian Zone
CNIG	Centro Nacional de Información Geografica
CRMs	Critical Raw Materials
DEM	Digital Elevation Model
DN	Digital Number
EO	Earth Observation
EMS	Electromagnetic Spectrum
ETM	Enhanced Thematic- Mapper
EnGeoMAP	EnMAP Geological Mapper
ENVI	Environment for Visualizing Images
EnMAP	Environmental Mapping and Analysis Program
ESA	European Space Agency
EU	European Union
EW	Extra Wide-swath mode
GTMZ	Galicia-Trás os Montes Zone
GIS	Geographic Information System
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
GEE	Google Earth Engine
GLCM	Grey-Level Co-occurrence Matrix
GRD	Ground Range Multi-look Detected
HM	Heavy Mineral
HSI	Hyperspectral Imager
IF	Infrared
IW	Interferometric Wide-swath mode
LIDAR	Light Detection and Ranging
MF	Matched Filter
MTMF	Mixture Tuned Matched Filtering
MT	Mixture Tuning
NASA	National Aeronautics and Space Administration
NIR	Near-Infrared
PNOA	Plan Nacional de Ortografía Aérea
PCA	Principal Component Analysis
REE	Rare Earth Elements
SNAP	Sentinel Application Platform
SWIR	Short-wave Infrared
SRTM	Shuttle Radar Topography Mission
SLC	Slant Range Single-look Complex
SM	Strip Map mode

SAR	Synthetic aperture radar
USGS	United States Geological Survey
UAS	Unmanned aerial systems
WV	Wave mode

1. Introduction

The European Union (EU)'s growing demand for sustainable materials to achieve a climate-neutral economy by 2050, support the green and digital transition, and reduce European dependency on non-European material sources led to the formation of the Critical Raw Materials (CRMs) Act (European Commission et al., 2023). CRMs are essential for the European economy as they support a wide range of industries, such as environmental technologies, including solar panels, wind turbines, electric vehicles and energy-efficient lighting, consumer electronics, health, steel-making, defence, space exploration, aviation, among others (Hool et al., 2023). These materials are considered critical, not only due to their economic importance but also due to their supply risk, since most are imported from non-European countries, with most of them in war conflict zones.

Therefore, now more than ever, it is crucial for EU member countries to discover and develop their own sources of CRMs. This involves investment in domestic mineral exploration and exploitation, as well as encouragement of innovation in the mining cycle and further contributing to a circular economy.

This dissertation was developed under the scope of S34I – Secure and Sustainable Supply of Raw Materials for EU Industry project, funded by the European Union under grant agreement no. 101091616 (<https://doi.org/10.3030/101091616>), which fits into European needs through the development of data-driven methods to analyse Earth Observation (EO) data to support mineral exploration and monitoring of the complete mining cycle in its exploration, closure and post-closure phases. This project aims to enhance EU autonomy regarding CRMs, support the green transition, as well as address environmental challenges within the mining cycle.

To contribute to those goals, this work applied remote sensing techniques to identify Heavy Mineral (HM) beach placer deposits in the Ria de Vigo, located in the Rias Baixas region, Spain. These HM placer deposits, known to occur in this region since the 70's (IGME, 1976), are rich in Ti, Sn, Li, Rare Earth Elements (REE), Au, Fe and Cu - all of which are classified as CRMs by the European Commission.

In a first approach to identify and characterize these placers and the geological mechanisms in which they are formed, structural mapping was conducted in the Ria de Vigo region. The study of geological lineaments, which are geological features that can be identified through remote sensing, is important since it gives us key insights into the identification of zones of hydrothermal alteration and mineralization, as well as in understanding the tectonic settings in which this mineralization took place (Gabrielsen &

Olesen, 2024). Structural mapping constitutes the core of this work and was conducted using Sentinel-1 and Light Detection and Ranging (LiDAR) data. Furthermore, with a more direct approach, complementary mineral mapping was also conducted for the Vigo beaches, using hyperspectral Environmental Mapping and Analysis Program (EnMAP) data.

The present dissertation is structured into 10 chapters.

The first chapter is the “Introduction”. In the second chapter, the “State of the Art” provides a review of existing literature relevant to the topic. The third chapter, “Geographic and Geomorphological Setting”, describes the geographical location of the study area, as well as the geomorphological features of the Ria de Vigo. This is followed by an important chapter on the “Geological Setting”, encompassing both regional and local geology, where the geological background of the study region, as well as HM placer deposits, is described. The “Methodology” chapter, as the name indicates, outlines the research methods and techniques used in this study for structural and mineral mapping. The findings of this dissertation are presented in the “Results” chapter, which is divided into structural and mineral mapping. The results are followed by the “Discussion”, where all results are interpreted and correlated, considering the existing knowledge. The “Conclusions” chapter summarizes key findings, highlights their significance, addresses the challenges encountered throughout the research for this dissertation and makes recommendations for further research. Finally, the “Appendices” chapter includes conference proceedings, abstracts and posters submitted to national and international conferences, as well as complementary results, such as band ratios, that are not included in the Results chapter, but complement the main findings.

2.State of the art

Several studies concerning the identification and characterization of HM placer deposits using remote sensing have been carried out using multiple approaches. Geological structures, such as faults, can enhance sedimentation and control the distribution of HMs in coastal areas (Gosen et al., 2014; Hou et al., 2017) and, as such, this dissertation includes a review of structural mapping methodologies. Afterwards, various approaches of mineral mapping using different sensors are examined. Given the focus of this work on EnMAP hyperspectral data, this chapter further explores its application by various authors.

In the field structural mapping and lineament extraction, one of the foundational research was carried out by Canny (1986). His work takes a computational approach to edge detection, by developing a mathematical form, to simplify image analysis through the reduction of the amount of data to process while preserving key structural information in the form of edges. Forghani (2010) demonstrated that the Canny edge filter gave the best results, when compared to Sobel and Deriche filters, in semi-automatic detection and enhancement of linear features in aerial photography.

Hung et al. (2005) use ASTER and Landsat Enhanced Thematic Mapper (ETM) imagery to automatically extract lineaments and carried out a band comparison to identify the ones better for lineament extraction, concluding that the Visible and Near InfraRed band 3 of ASTER and the fused Band 4 of Landsat ETM are the best for that purpose.

Landsat images have also been widely used for automatic lineament extraction, such as in the works of Christopher et al. (2013), Hashim et al. (2013) and Ibrahim and Mutua (2014). Many studies also incorporate the use of ASTER images, such as those by Moradi et al. (2014) and Prasad et al. (2013).

Santos et al. (2023) adopted a different method using high-resolution imagery Worldview-3 and LiDAR data. The authors generated a Digital Elevation Model (DEM) using the LiDAR point cloud, from which they automatically extracted lineaments through the lineament algorithm LINE in PCI Geomatica software (version 2018).

Similar studies have been conducted using radar data. Boutirame et al. (2018) used a combined analysis of aeromagnetic and Sentinel-1 data to distinguish fracture networks. In Nguemhe Fils et al. (2018), A Sentinel-1A radar image was used to process regional-scale mapping in an area under dense vegetation. The authors used textural analysis

based on the Grey-Level Co-occurrence Matrix (GLCM) followed by Principal Component Analysis (PCA), and application of RGB colour composite to the mean, variance and homogeneity indices to highlight structures. Cardoso-Fernandes et al. (2022) evaluated Sentinel-1 and ALOS-derived shaded relief models to identify structures on a regional scale.

Adiri et al. (2017) and Javhar et al. (2019) carried out studies comparing the results of Landsat-8, ASTER, Sentinel-2 and Sentinel-1 data, and in both studies, it is concluded that Sentinel-1 images provide better results in automated lineament extraction.

For mapping of HM placers, Chandrasekar et al. (2011) used Landsat 7 Enhanced Thematic Mapper Plus data and the Environment for Visualizing Images (ENVI) software to carry out a standardized hyperspectral analysis to allow the identification and mapping of HM deposits, such as garnet, ilmenite, zircon and monazite along the South Tamil Nadu coast, in India. Gazi et al. (2019), combined field methods with remote sensing to map heavy mineral deposits on the beaches of Cox's Bazar, in Bangladesh. The authors analysed Landsat-8 OLI images using ENVI, ArcGIS and Erdas Imagine software to map heavy mineral-rich zones. Rejith et al. (2020) studied the beach sediments from the coast of Thiruvananthapuram, in India, to understand the variation of grain size using the bands of ASTER and Landsat 8, successfully achieving their mapping using the Spectral Angle Mapper classification algorithm.

With a different approach, Rejith et al. (2022) carried out a study to map and estimate beach placer minerals on the east coast of Nadu, India. The authors used EO-1 Hyperion data and applied a hyperspectral analysis such as SAM image classification to carry out sub-pixel mapping of minerals, as well as Random Forest regression to estimate the concentration of zircon, using the relationship between measured absorption parameters (from laboratory and image spectra) and known zircon concentrations.

EnMAP hyperspectral data has also been applied to geological mapping in the scope of mineral exploration. Yokoya et al. (2016) performed a fusion method using Sentinel-2 and EnMAP data, both simulated from a Hymap scene, to produce a resolution-enhanced hyperspectral image with the intention of mineral mapping in the gold mine located in Rodalquilar, in southeastern Spain.

Rogge et al. (2014) also produced EnMAP simulated data, but this time from airborne hyperspectral AISA imagery, using the EnMAP End-to-End Simulation tool, applied to the Ni-Cu- (Platinum-group Elements) deposit in Nunavik, Canada. The authors compared the ability of both AISA and EnMAP to map the distribution of geological

materials, concluding that EnMAP data, even with a lower resolution, was able to discriminate mafic and ultramafic units, providing a similar spatial distribution as the one produced from the AISA data.

With a similar approach, Neave et al. (2016) produced EnMAP simulated data from AVIRIS airborne platform with the intention of mapping and exploring strategies to efficiently exploit diagnostic features in the reflectance spectra of REE-rich materials in carbonatite-hosted REE deposits in China. Although lacking in spatial resolution compared to airborne data, the authors concluded that EnMAP data has the spectral resolution necessary to detect the narrow Nd absorption features.

Mielke et al. (2016) tested EnMAP-Box's tool, the EnMAP Geological Mapper (EnGeoMAP), comparing it to USGS Tetracorder or MICA, to map distinct mineral zonation patterns, using airborne HyMap and simulated EnMAP data, applying it to the hydrothermal gold-alunite deposit in Rodalquar, Spain, and the Haib River porphyry copper deposit in southern Namibia. The authors concluded that EnGeoMAP had the additional ability to map areas of mineral anomalies such as gossans, which is not a part of USGS Tetracorder or MICA. Likewise, EnGeoMAP has also been tested with hyper and multispectral data by Salehi et al. (2020). The authors compared EnGeoMAP and Iterative Spectral Mixture Analysis for mapping ultra-mafic rocks in areas covered by abundant lichens in the Nagssugtoqidian Orogen, in West Greenland, using HyMAP airborne hyperspectral data and Sentinel-2, ASTER and Landsat-8 OLI multispectral data.

More recently, Schodlok et al. (2022) assessed the feasibility of airborne and satellite-borne hyperspectral data to map the lithology of the lead-zinc-copper deposit in Aggeneys, in South Africa. The authors produced a detailed mineral map using the approach included in ENVI using airborne Hypex data and simulated EnMAP from the airborne hyperspectral dataset.

Besides geological mapping, EnMAP and simulated EnMAP data have had other applications. For example, it has been applied to water monitoring (Samarinas et al., 2023), soil science (Bracken et al., 2019; Castaldi et al., 2019; Chabrillat et al., 2014; Chabrillat et al., 2023), plant biology (Dotzler et al., 2015); and burnt areas mapping (Nolde et al., 2021). Additionally, Becker et al. (2018) applied simulated EnMAP data to bathymetric charting and land-use classification in the context of military naval operations.

3. Geographic and geomorphological setting

3.1. Geographic setting

The Rias Baixas region is located on the Atlantic margin of southwestern Galicia, in north-western Spain, close to the border with Portugal. (Fig. 1). It is composed of four morphologically identical estuaries, known as Rias, of which the Ria de Vigo, the target of this study, is the southernmost. The Ria de Vigo is located between 42°09' and 42°21' N, 8°36' and 8°54'W (ETRS89 UTM 29N), south of Cape Finisterre and about 30 km north of the Minho River.

With a population of about 300.000 inhabitants, Vigo's main urban area is home to a variety of economic activities, including tourism, industry, and harbour infrastructures (Méndez, 2005). Additionally, the nutrient-rich water creates the ideal conditions for mussel aquaculture farming, where many moored squared rafts float at the surface.

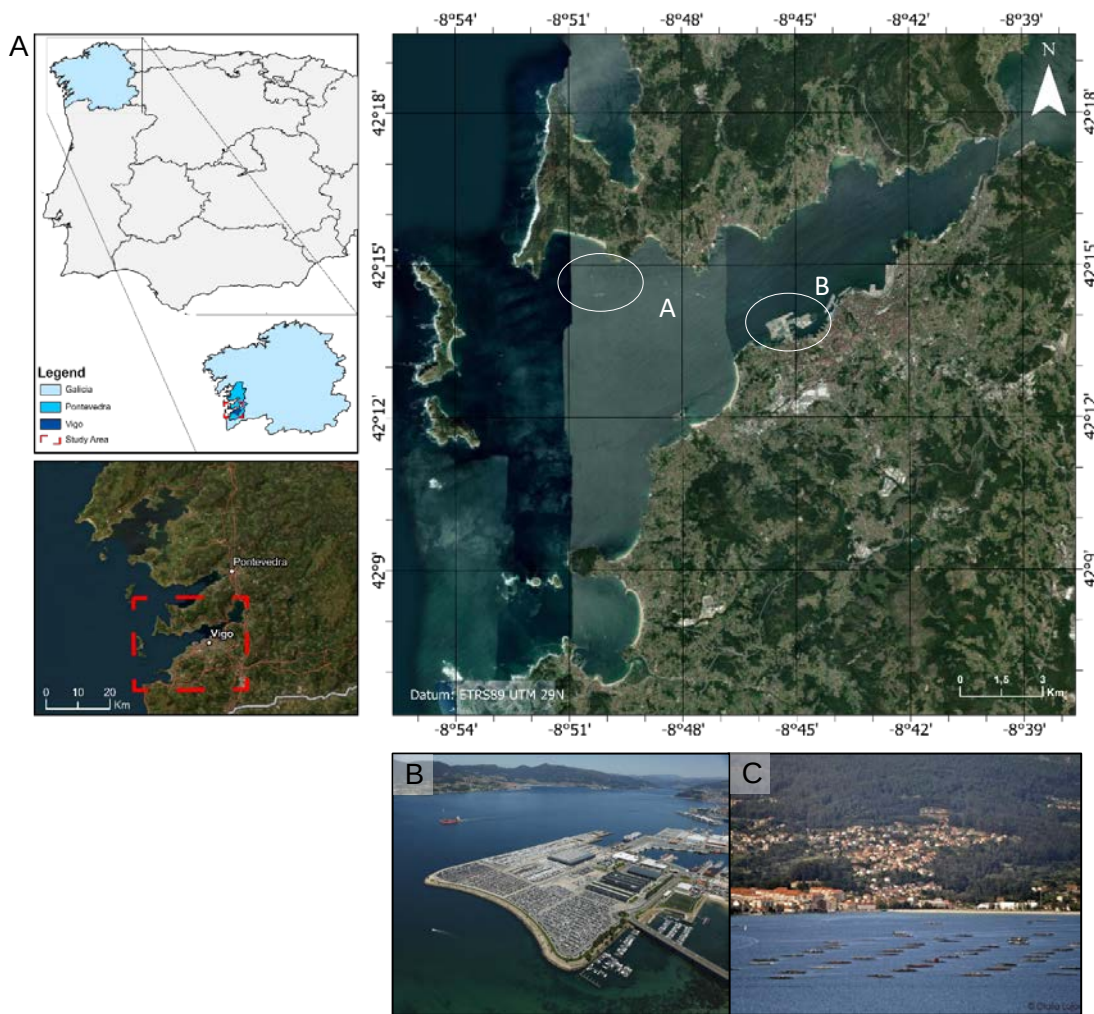


Figure 1 – A) Geographical location of the Ria de Vigo; B) Harbour infrastructures – Image credits: European Sea Ports Organisation;.C) Mussel aquaculture farming – Image credits: Turismodevigo.org

3.2. Geomorphological setting

Geomorphologically, the Rias Baixas give the coastline an irregular appearance and correspond to tectonic valleys inclined towards the sea, formed due to subsidence and uplift, caused by the fracture systems formed during the Alpine orogeny (Nonn, 1966). During the Pliocene, the blocks suffered rotation towards the west and were impacted by the Flandrian transgression in the Holocene (Chamorro et al., 2022).

With this knowledge and taking into consideration the extensive literature discussion to define the term “ria”, the Grupo de Oceanoloxía (1996) classified the Galician rias as “relatively deep sunken river valleys that dynamically behave as partially mixed positive estuaries and are influenced by the NW upwelling system of the Iberian Peninsula”.

The Ria de Vigo is 32.5 km long, measuring 1 km in width at its inner part, gradually expanding as it extends towards the mouth of the Ria, where it becomes 10 km wide, and therefore exhibiting a distinctive funnel-shaped morphology, positioned with a NE-SW direction (Méndez & Vilas, 2005).

It is constituted by two sectors: a smaller cone, which encompasses San Simón Bay and corresponds to the head of the ria, where interaction with freshwater occurs, with the Verdugo-Oitaben River as the main fluvial contributor, and a larger cone. The inner region of the larger cone functions as a mixing area of both marine and freshwater, transitioning to predominantly marine influence as it nears the open sea, connecting to it through two entrances divided by the Ciés Islands (Martín et al., 2008).

The borders of the ria are defined by a variety of erosive and accumulative coastal formations, of the Quaternary age, such as terrace sediments, bays, tidal flats, deltas, marshlands, beaches and dunes (Vilas et al., 2019). The surrounding area is characterized by mountain massifs, with elevations reaching 600 m that gradually decrease towards the sea, separated by depressions (Fig. 2). The main depression has been considered a Tertiary rift zone (Carlé, 1947) and originates in Portuguese territory, following a S-N direction, distanced approximately 20 km from the coast and subsequently intersecting the upper edges of the Ria de Vigo and Pontevedra.

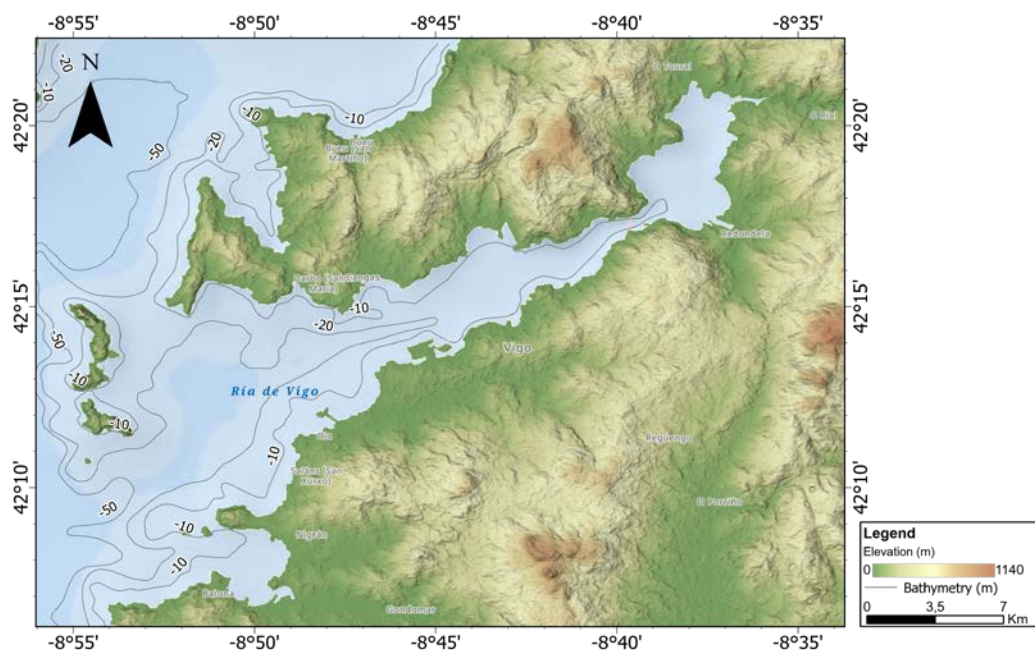


Figure 2 – Topographical map of the region of Vigo, based on DTM05 (Digital Terrain Model) of Spain.

4. Geological setting

4.1. Regional geology

4.1.1. The Iberian Massif

The Iberian Massif represents the easternmost segment of the European Variscan Belt, resulting from the collision of the continents Laurussia and Gondwana during the Devonian and Carboniferous periods (Catalán et al., 2008; Franke, 1989; Matte, 1986). It outcrops in the western part of the Iberian Peninsula and is made up of Precambrian and Palaeozoic terrains that are generally deformed and metamorphosed. The various igneous intrusions are also part of the massif (Ribeiro et al., 1990).

In fact, according to stratigraphic, tectonic, magmatic, and metamorphic criteria, the Iberian Massif has been divided into various geotectonic zones, elongated parallel to the direction of the Variscan structures. Lotze (1945) presented the first division proposal, which was later revised and redefined by Julivert et al. (1974) and Farias et al. (1987). Thus, the following zones are currently considered to be the Cantabrian Zone, Asturian-Leonese Zone, Central Iberian Zone (CIZ), Galicia-Trás os Montes Zone (GTMZ), Ossa Morena Zone and South Portuguese Zone (Fig. 3). The studied region falls within the GTMZ..

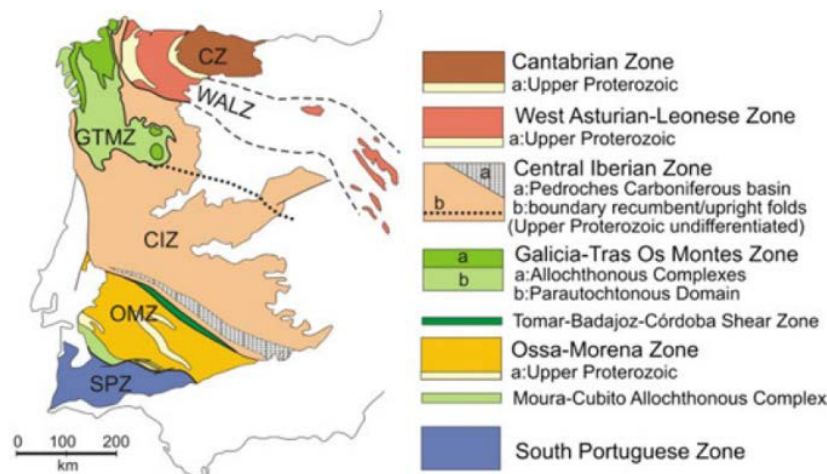


Figure 3 – Zonation of the Iberian Massif, according to the proposition by Lotze (1945), Julivert et al. (1974) and Farias et al. (1987) (Adapted from Simancas (2019)).

4.1.2. Galiza Trás-os-Montes Zone

The GTMZ is formed by the stacking of tectonostratigraphic units of parautochthonous and allochthonous nature, separated by thrust faults, and emplaced above the autochthonous terrains of the CIZ (Farias et al., 1987). These units outcrop in the north-western part of the Iberian Massif in a discontinuous 300 km long segment, and their limit with the CIZ is established by the Main Trás-os-Montes Thrust (Ribeiro et al., 1990).

Tectonostratigraphy

The parautochthonous terrain is represented by the Schistose Domain of GTMZ and structurally lies below the allochthonous terrains and above the CIZ. This domain has been interpreted as the most external part of the continental margin of the Gondwana (Fig. 4) (Martínez Catalán et al., 1997) and can be subdivided into two lithostratigraphic groups – Nogueira and Paraño (García, 1984).

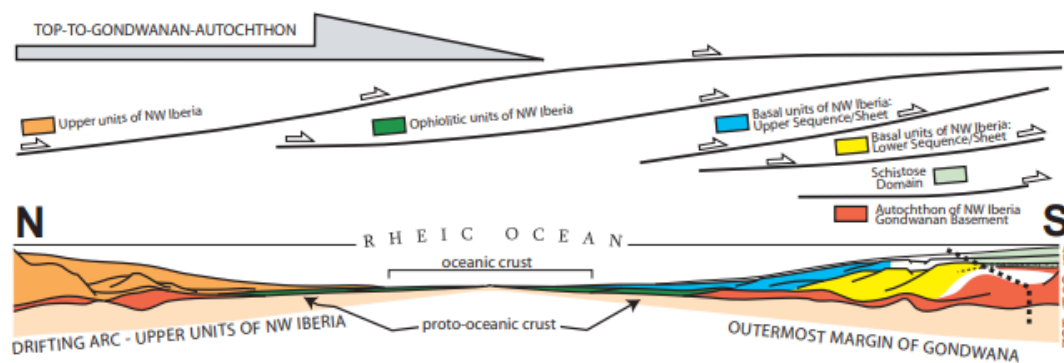


Figure 4 - Simplified model of the formation of the Rheic Ocean near the Cambrian-Ordovician boundary, illustrating the paleogeographic arrangement of terranes and sedimentary sequences involved in the Rheic suture (adapted from Fernández (2011)).

It is primarily constituted of over 3500 km thick metasedimentary and metavolcanic sequences of Silurian-Devonian age, with a supposed lithologic and paleogeographic affinity with the autochthon units of the CIZ (Farias et al., 1987). These sequences were the hosts of a significant Variscan granitic magmatism and were affected by regional green-schist facies metamorphism (Catalán et al., 2004).

The overlying Allochthonous terrain corresponds to the Domain of Allochthonous Complexes and includes a thrust stack of exotic continental terrains, high-pressure units and ophiolitic rocks (Marques, 1994; Martínez Catalán et al., 1997). These units are Cabo Ortegal, Órdenes and Malpica-Tui, in Spain, and Bragança and Morais, in Portugal.

The basal units are constituted of exhumed metasedimentary sequences alternating with orthogneisses and metabasites, affected by subduction-related high-pressure metamorphism in the blueschist facies during the Variscan orogeny (Catalán et al., 2004;

Schermerhorn & Kotsch, 1984), followed by the middle allochthon ophiolitic sequences, representing the remains of the Rheic Ocean, and finally the upper allochthon, comprising metasediments and ultrabasic rocks of impacted by high-grade metamorphism (Ribeiro et al., 1990) (Fig. 5).

The description of the lithostratigraphic groups, as well as aspects of magmatism and metamorphism, will be further explained in the next chapter, with emphasis on the region of Vigo.

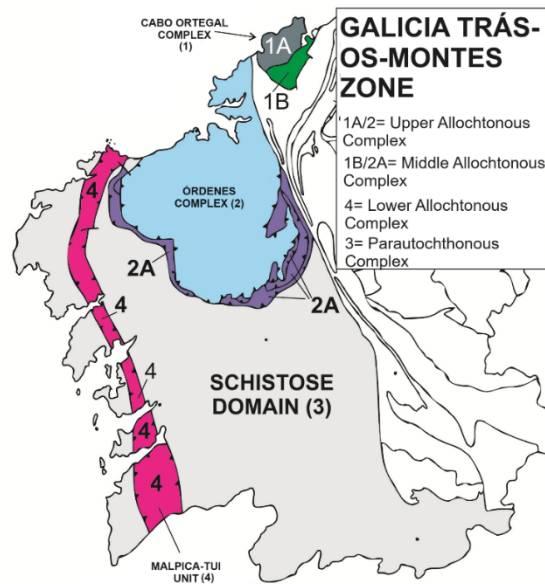


Figure 5 - Complexes forming the Galicia Trás-os-Montes zone (adapted from Pin et al. (2006)).

4.2. Local geology

The region of Vigo is represented in sheet 223 (Vigo) of the MAGNA 50 - Geological Map of Spain at a scale of 1:50 000.

For the purpose of this study, especially for structural mapping, the study area was expanded beyond central Vigo. Therefore, sheets 185 (Pontevedra), 186 (Puente Caldelas), 222 (Ciés), 224 (Punteareas), 260 (Oya) and 261 (Tuy) were also considered (Fig. 6).

From those sheets, a digitalized geological map was created in ArcGIS PRO (Fig. 7).

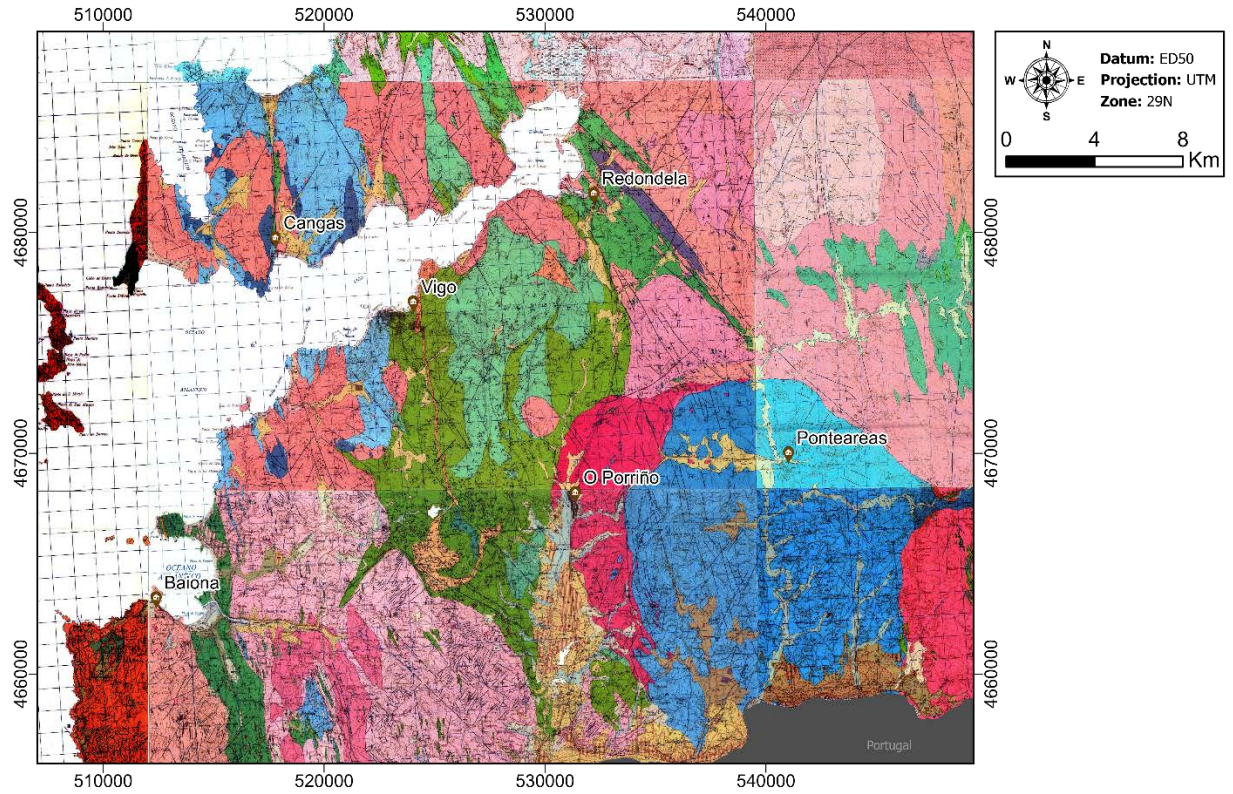


Figure 6 - Map with sheets 185, 186, 222, 223, 224, 260 and 261 of the MAGNA 50 – Geological Map of Spain, at scale 1:50 000.

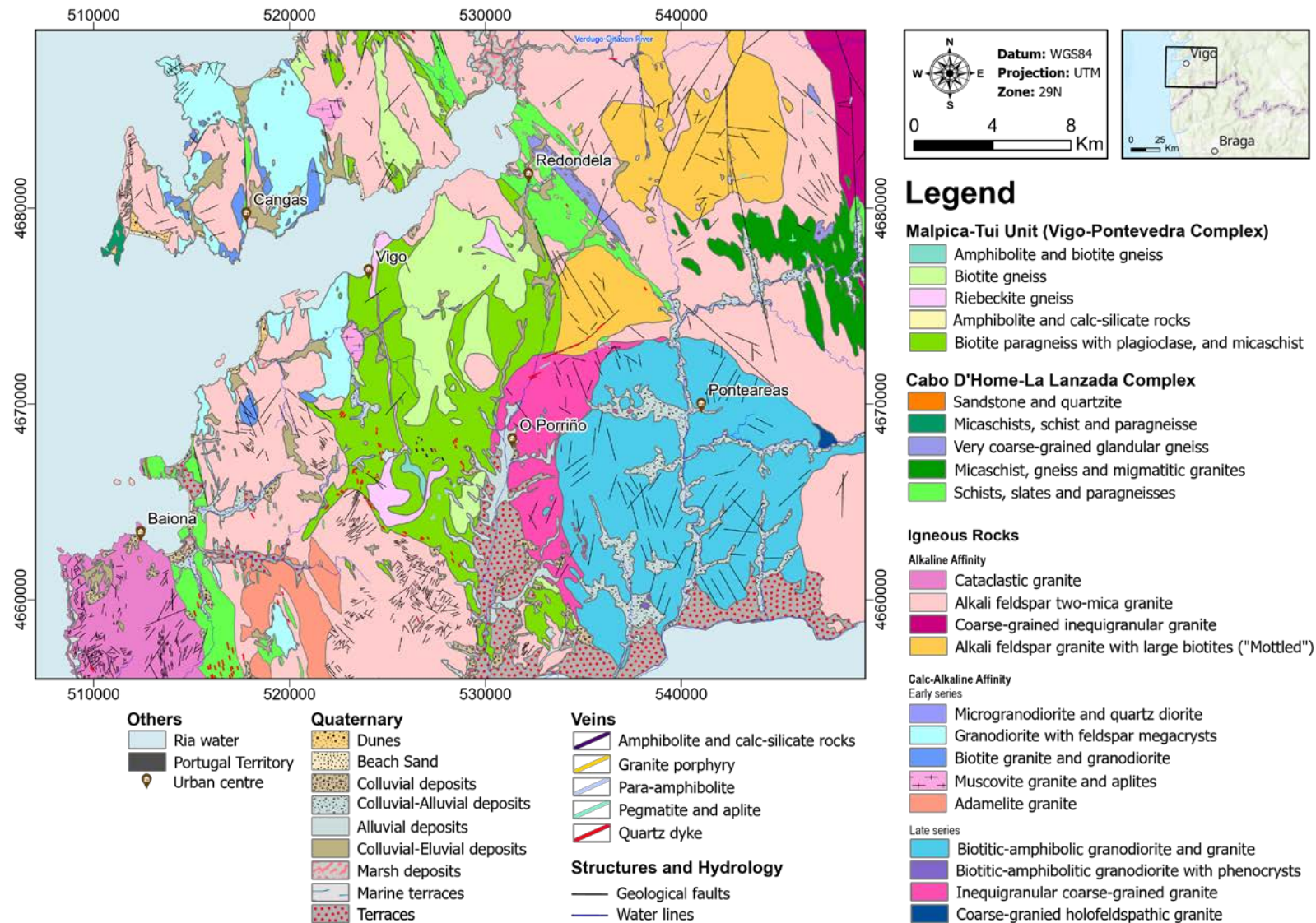


Figure 7 - Geological map of the study area, based on the geological sheets mentioned, at scale 1:50 000.

4.2.1. Metasediments

In the region comprised in the geological map (Fig. 6), outcrops belong to the Nogueira and the Paraño groups, although with little expression. They have been attributed to a Precambrian-Silurian age.

The Nogueira group is at the base of the succession and is constituted of a sequence of black and grey carbonaceous shales that give the rocks a graphitic appearance. Centimetric to metric lydite levels are frequent, with lenticular bodies extending several meters (Farias & Marcos, 2004). The maximum thickness of this sequence is about 1000 meters. The Paraño group is composed of detrital sequences of mainly green, brown, orange and ochre-coloured phyllites, quartzophyllites and greywackes, with interlayered greywacke and quartzites, as well as minor levels of felsic volcanic rocks (Farias & Marcos, 2004).

Within the Schistose Domain, the most expressive unit in the region is the Cabo D´Home-La Lanzada complex (Navas & Corretgé, 1997) (Fig. 7). The outcrops are more pronounced in the southernmost part of the region in an almost N-S direction, as opposed to fewer and less thick outcrops in the occidental part.

This complex is not very diverse, being mainly composed of two mica schists derived from pelitic sediments, interlayered with lenticular bodies of quartzite and paragneisses, that differ from the ones found in the allochthonous complex by having a greater dominance of plagioclase. Although less common, amphibolites derived from the metamorphism of volcanic levels have been found. The most frequent paragenesis in the schists are quartz, muscovite, chlorite, biotite, andalusite and garnet (Navas & Corretgé, 1997).

4.2.2. Malpica-Tui unit

The Malpica-Tui unit belongs to the Domain of Allochthonous Complexes. It is a 15 kilometres-long N-S band with a synform structure that is oriented NNW-SSE from Corunna until the Minho sector of Tui (Llana-Funez, 2001). In sheet 223 of the Geological Map of Spain at a scale of 1:50 000, this unit is also named as Vigo-Pontevedra Complex.

This unit outcrops in the central part of the study area. It is composed of plagioclase and biotite gneisses, as well as micaschists and gneisses with riebeckite. The most characteristic aspect is the presence of amphibolites, although with less expression. The micaschists are more abundant in the northern part and differ from paragneisses by the absence of plagioclase metablasts. The amphibolites are usually found interstratified in the complex or as xenoliths in the biotite orthogneisses (Navas & Corretgé, 1997).

4.2.3. Deformation Phases and Structures

4.2.3.1. Variscan orogeny

The structures of the GTMZ, affecting the Vigo region, are a result of the three phases of deformation of the Variscan orogeny: D_1 , D_2 and D_3 (Ribeiro et al., 1990). Within units in the Variscan orogenic belt, the structures are usually oriented NNW-SSE and are cut by fractures with $N45^\circ$ and $N180^\circ$ orientation.

The first phase is thought to have started around 360 million years ago (Ábalos et al., 2002). An axial-plane cleavage, S_1 , is formed with a direction between $N0-50^\circ$ in the Malpica-Tui unit and $N40-80^\circ$ in the Cabo D'Home-La Lanzada complex (Navas & Corretgé, 1997).

The second phase is related to the emplacement of the Malpica-Tui unit. The main structural effects are usually around the thrust faults. In this region, D_2 is also represented by the formation of macrostructures such as synforms and antiforms (Llana-Fúnez & Marcos, 2001). Additionally, the main cleavage, S_2 , is present in the metasediments with an axial direction of $N140^\circ$, forming a crenulation cleavage.

Between the second and the third phases, an extensional period allowed the intrusion of the Variscan granitoids (Catalán et al., 2008). After the emplacement of the allochthonous units, shear zones were formed with a N-S direction (Pamplona et al., 2015).

The D_3 phase is highly associated with the emplacement of the variscan granites. Structurally, it has a small impact on local structures.

4.2.3.2. Alpine orogeny

The alpine orogeny reactivated Variscan structures and is associated with the uplift of the Galicia Bank, located along the entire north-western margin of Galicia (Boillot et al., 1979). Additionally, it also formed folds, inverted gabrens and reverse faults utilized by many of the current rivers and in which the Paleogene-Neogene sediments deposits (Muñoz et al., 2003).

4.2.4. Granitic rocks

4.2.4.1. Variscan granites

One of the most distinguishing characteristics of both the CIZ and the GTMZ is the significant magmatism, accompanied by medium to high metamorphic grade (Martinez et al., 1988).

The granitic plutonism occurred during the D₃ phase. According to the same authors, magmatism was due to crustal thickening, resulting from the collision phase and emplacement of the allochthonous units, causing partial melting of crustal rocks, leading to the emplacement of granites (Fig. 8).

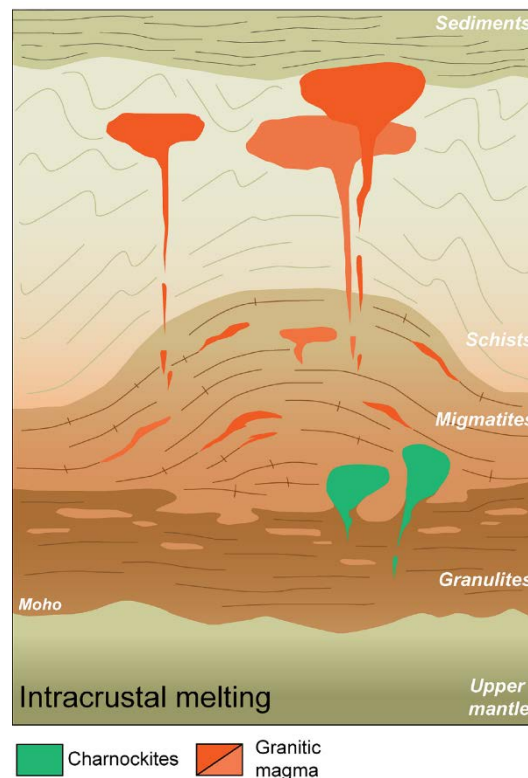


Figure 8 - Intra-crustal melting model, showing the formation of silicic magmas in middle-to-lower crustal regions and their emplacement in the middle-to-upper crust (Adapted from Pichavant et al. (2024)).

Based on geochronological, structural, petrographic, and geochemical criteria, different classifications have been proposed for the granites of the GTMZ and CIZ (Azevedo & Valle Aguado, 2006).

The most widely accepted classification for both zones is that of Ferreira et al. (1987), who classified these granites according to temporal relations with deformation, namely the D₃ phase, therefore, according to their period of installation (Fig. 9). They are subdivided into two groups:

- i) Pre-orogenic, corresponding to intrusions with ages between Upper Proterozoic and Lower Paleozoic;
- ii) Synorogenic, distinguishing between ante-D₃, syn-D₃, late-D₃ and post-D₃.

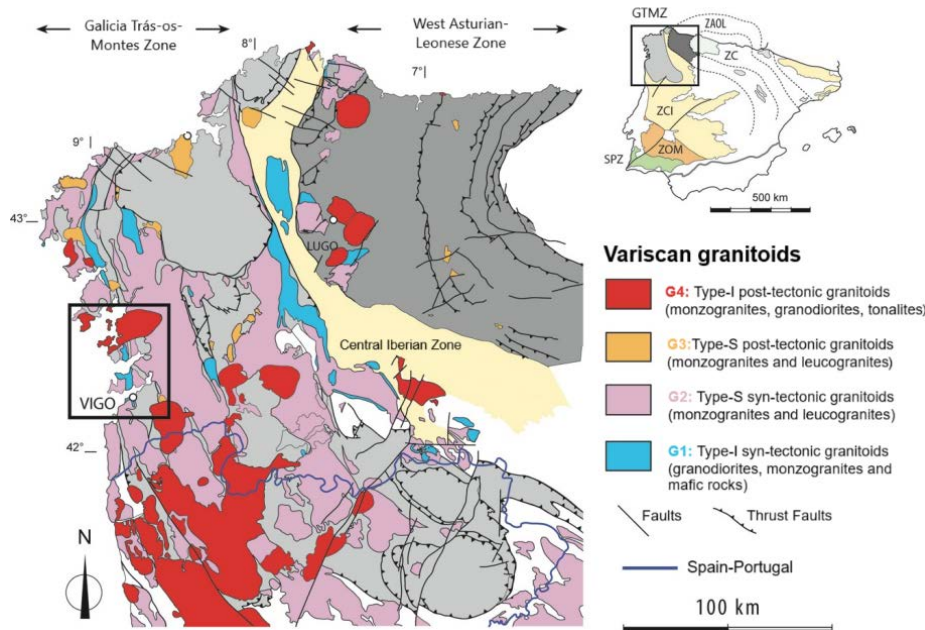


Figure 9 - Simplified geological map of the variscan granitoids in the northwest of the Iberian Massif (Adapted from Menéndez et al. (2019)).

However, for this region, the Geological Map of Spain at a scale of 1:50 000, following the works of Floor (1967), Matte (1968) and Capdevila (1969), categorizes them from a geochemical perspective, differentiating them as granites with alkaline affinity or calc-alkaline affinity.

The alkaline series are mainly leucocratic two-mica granites that never show hornblende or pyroxene but may have apatite as an accessory mineral. On the other hand, in the calc-alkaline series, the granites are predominantly biotite and oligoclase granites, and hornblende and/or pyroxene are present (Navas & Corretgé, 1997)

Au and W-Sn mineralization in the Schistose Domain often occurs in proximity to granites, suggesting their association (Gloaguen et al., 2003). These elements' primary concentration mechanism is fractional crystallization, followed by an increase in concentration due to hydrothermal processes (Almeida et al., 2002).

4.2.4.2. Post-kinematic granites

In the southeastern region of the geological map, there is a series of granites of the Late Carboniferous period, unaffected by the Variscan orogeny, indicating a post-kinematic nature. Among these granites, there are three distinguishable facies – Granodiorite and biotite-amphibole granite, coarse-grained granite and coarse-grained feldspar granite (Navas & Corretgé, 1997).

4.2.4.3. Filonian rocks

All around the region, there are several quartz veins and pegmatite dykes, generally forming intertwined families of veins particularly associated with granite and granodioritic bodies. They are usually small, but in the southeastern part of the region, there is a 6 km quartz vein positioned WNW-ESE (Navas & Corretgé, 1997)

4.2.5. Metamorphism

4.2.5.1. Regional metamorphism

The regional metamorphism, previous to the Variscan orogeny, is generally considered to have been a high-pressure low/ medium temperature regional metamorphism, causing the blastesis of plagioclase and cordierite, with inclusions of garnet, mainly in the Malpica-Tui Unit (Floor, 1967).

The Variscan orogeny's induced metamorphism is well present in the region, with the distribution of metamorphic bands parallel to the Variscan structures and metamorphic facies ranging from the biotite zone to sillimanite (Martínez et al., 1990).

4.2.5.2. Contact metamorphism and metasomatism

The magmatic intrusions, associated with the emplacement of the variscan granites, caused contact metamorphism, forming muscovite lepidoblasts, occasionally containing sillimanite (Floor, 1967). The formation of hornfels is also documented in the southeastern region, although with minimal expression. Likewise, tourmaline frequently occurs in the area surrounding the plutons (Floor, 1967).

4.2.6. Quaternary formations

The Quaternary is represented in a series of sedimentary formations.

Eluvial-Alluvial deposits

They are mostly composed of siliceous gravel with some clay levels, resulting from the weathering of schists, gneisses and granites in the substrate. This type of sediments is usually located in valley areas and present-day river beds, as well as in depressions (Navas & Corretgé, 1997).

Intertidal flat deposits

They are located in the N and NE parts of the region, where the Verdugo-Oitaben River flows into the mouth of the ria. They are mainly composed of organic matter-rich silts. Two sectors can be distinguished: one under permanent tidal influence, and the other only affected during a tidal level rise (Ferrero Arias et al., 2004).

Coastal deposits

They essentially correspond to quartz and feldspar sand deposits that originated from the wave and wind action, such as beaches, dunes and cusate forelands (Navas & Corretgé, 1997).

4.2.7. Economic geology of the study area

4.2.7.1. History of exploitations

The main exploitation in the region of Galicia, and Vigo in particular, is centred around industrial minerals and rocks, highly sought after by the construction sector (Méndez et al., 2000). Rock fragments and non-metallic sedimentary deposits, such as sand and gravel, associated with the coastal and fluvial sedimentary environments, are the primary sources of aggregates. Currently, the majority of these mines and quarries are abandoned, with only a few operating outside of Vigo.

4.2.7.2. Heavy-mineral placer deposits

This work focuses on marine HM placer deposits, which are known to occur in the beach sediments of Vigo. Over the years, numerous studies have documented and characterized these deposits in the Rias Baixas region (Galván, 2002; Gent et al., 2005; Méndez et al., 2000; Pérez et al., 2008; Prego et al., 2009). HM are those that have a

density higher than $2,9 \text{ g/cm}^3$, while minerals with a density below that are considered light minerals (Gosen et al., 2014).

Placers are sedimentary clastic deposits where there is an accumulation and concentration of HM through physical and mechanical processes (Hou et al., 2017). The process starts inland, where the disaggregation and erosion of rocks generate clasts of different granulometries and shapes. HM's primary source has been identified as igneous and high-grade metamorphic rocks. These sediments are then transported to a coastal area through stream drainages and can deposit in different coastal settings, such as deltas, beach foreshore and shoreface, barrier islands, dunes, tidal lagoons, and also estuaries, which is the case of the Galician rias (Gosen et al., 2014; Martín et al., 2008).

The weathering processes are particularly significant in the formation of these placers and can be divided into four phases for most types of deposits (Gosen et al., 2014):

- 1) The weathering of the source igneous and metamorphic rocks, which leads to the destruction of less stable minerals and liberation of HM to the fluvial system;
- 2) Weathering during the fluvial transport, where HMs are subjected to mechanical forces, such as tumbling, abrasion and rounding, and less to chemical weathering due to being more chemically stable;
- 3) Within intermediate sedimentary rocks;
- 4) Processes following the deposition in the coastal environment, such as wave and tidal action, aeolian processes, sea-level changes and chemical weathering.

In the particular case of HM beach placers, the deposits typically occur at latitudes lower than 35° , are usually found in the passive margins of continents and in shallow depth or near the surface, and can contain over 2% of HM (Gosen et al., 2014; Hou et al., 2017).

In addition to the processes mentioned above, HM sands can be influenced by other processes, such as (Hou et al., 2017):

- 1) Wave and tide action, which lead to a natural sorting of mineral grains by density, segregating higher density from lower density minerals. The heaviest and finest-grained HM are the most effectively sorted. The resulting HM sands form elongated layers, which are well-sorted, medium to fine-grained and well-rounded, and are oriented parallel to the coast and paleo strand lines.
- 2) Wind also effectively sorts heavy, dense minerals from lighter grains, such as quartz. After sand accumulation, the wind can rework these sediments to form

aeolian deposits that may contain substantial concentrations of HM (Gosen et al., 2014).

- 3) The direction and strength of coastal currents, as well as the geomorphology of the coast, will influence the location of the HM placer deposits.
- 4) Sea level changes due to cyclical climatic changes may affect the preservation of HM sands. During transgressions, the sea can flood the mouth of rivers, leading to reduced sedimentation in the coastal area. On the flipside, sediments may also become buried and preserved during transgressions. When it comes to regressions, the weathering processes increase both inland and near the shore, increasing sedimentation;
- 5) Tectonic events that lead to faulting enhance sedimentation and may structurally control the distribution of HM deposition;
- 6) Post-deposition weathering is thought to cause a relative increase in the TiO_2 content of ilmenite due to iron leaching from ilmenite.

In most beach placers, ilmenite is usually the most abundant HM, followed by zircon, rutile, leucoxene (altered ilmenite), garnet, kyanite, staurolite, sillimanite, tourmaline and monazite, which all remain mainly intact. Meanwhile, biotite, feldspar, amphibole, pyroxenes, and feldspar are usually scarce or absent (Gosen et al., 2014). On the other hand, clay and iron oxides, such as hematite, are very common, the latter giving the sediments a reddish hue.

High-grade metamorphic terrains are thought to be the primary source of HM sediments, and igneous rocks are the secondary. The presence of ilmenite, garnets, staurolite, monazite, kyanite and sillimanite indicates amphibolite to granulite metamorphic facies. Meanwhile, igneous rocks can also contribute with ilmenite, as well as rutile (Hou et al., 2017). The main specificities of HM, like their density origin and other specificities are described in Table 1 (Gosen et al., 2014).

Table 1 - Description of the heavy minerals typically found in marine placer deposits, according to Gosen et al. (2014).

Heavy Minerals	Ideal composition	Specific gravity	Source rocks
Magnetite	Fe_3O_4	5.2	Igneous and metamorphic rocks, hydrothermal veins
Monazite	$(\text{Ce}, \text{La}, \text{Y}, \text{Th})\text{PO}_4$	4.9 – 5.5	Igneous and metamorphic rocks

Ilmenite	FeTiO_3	4.5 – 5	Igneous and metamorphic rocks
Zircon	$(\text{Zr,Hf,U})\text{SiO}_4$	4.2 – 4.9	Igneous and metamorphic rocks
Xenotime	YPO_4	4.4 – 5.1	Igneous and metamorphic rocks
Rutile	TiO_2	4.2 – 4.3	Igneous and metamorphic rocks
Leucoxene	FeTiO_3 to mostly TiO_2	3.5 – 4.5	Igneous and metamorphic rocks
Staurolite	$\text{Fe}_2\text{Al}_9\text{O}_6(\text{SiO}_4)_4(\text{O,OH})_2$	3.7 – 3.8	Metamorphic rocks
Garnet	$(\text{Mg,Fe,Mn,Ca})\text{Al}_2\text{Si}_3\text{O}_{12}$	3.1 – 4.3	Mostly metamorphic, but also igneous rocks
Kyanite	Al_2SiO_5	3.5 – 3.7	Metamorphic rocks
Sillimanite	Al_2SiO_5	3.2	Metamorphic rocks, sometimes igneous (granites)
Tourmaline	$(\text{Na,Ca})(\text{Li,Mg,Al})(\text{Al,Fe,Mn})_6(\text{BO}_3)_3(\text{Si}_6\text{O}_{18})(\text{OH})_4$	3.0 – 3.3	Igneous rocks (granites)
Scheelite	CaWO_4	5.9-6.1	Skarns, hydrothermal veins
Gold	Au	19.3	Hydrothermal veins
Cassiterite	SnO_2	6.8-7.1	Igneous rocks, hydrothermal veins

The beaches of the Galician rias are favourable environments for the formation of shallow marine and aeolian placer deposits due to their local geology (characterized by source rocks with a high HM content), geomorphology, coastal hydrodynamics, and especially because the area did not suffer the effects of the Last Glacial Maximum about 20,000 years ago (Gent et al., 2005; Martín et al., 2008; Pérez et al., 2008). The presence of ilmenite, garnet, zircon, cassiterite, tin, Au, spodumene, rutile and tourmaline have been known to occur since the 70's (IGME, 1976).

Additionally, the works of Pardillo and Soriano (1929), Ibarra and Gironés (1985) and more recently Prego et al. (2009) led to the identification and characterization of REE-enriched sediments occurring in the beaches of the Ria de Vigo. These are Light REEs, present in the monazite and allanite associated with riebeckite gneisses, belonging to the Malpica-Tui geological unit. Prego et al. (2019) found that La and Ce were the most abundant REE elements.

These placer deposits occur in Límens, Santa Marta, Alemáns, Canabal, Ratas, Patos and Vao beaches (Fig. 10). In late summer/early autumn, there is a slightly higher HM

accumulation on the northern margin of the ria. In contrast, in late winter/early spring, the accumulation is higher in the southern part.



Figure 10 - Location of the beaches where HM placers occur. On the bottom: appearance of the HM accumulation at a distance.

5. Remote Sensing – An Introduction

Remote sensing involves obtaining information about the Earth's surface, atmosphere, and oceans without being in direct contact (Lillesand & Kiefer, 2015). It is a valuable tool across various fields, including meteorology, oceanography, agriculture, land use mapping and monitoring, disaster management, geology and many others (Estes et al., 2001).

The basis of most data collected through remote sensing lies in interactions that occur when electromagnetic radiation hits the surface of the Earth, where it can either be reflected, transmitted into the surface or absorbed and emitted by the surface (Fig. 11).

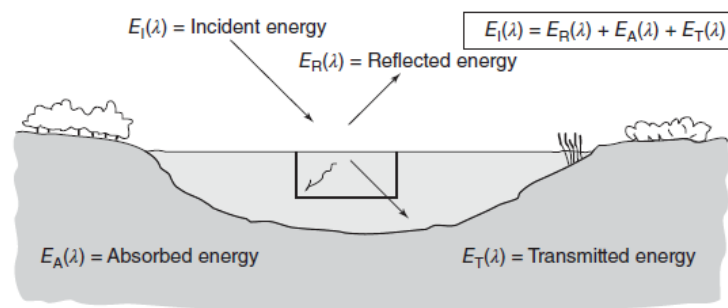


Figure 11 - Interactions between electromagnetic energy and the Earth's surface, where Incident energy (E_I) can either be reflected (E_R), absorbed by the surface (E_A) or transmitted into the surface (E_T). Therefore, $E_I = E_R + E_A + E_T$ (Adapted from Lillesand and Kiefer (2015)).

Remote sensing systems can either be active or passive. Passive sensors rely on external energy sources, such as the reflected solar radiation and thermal radiation emitted by the surface. Active sensors, on the other hand, have their own source of energy and measure the radiation that is reflected to them by emitting a signal towards the surface (Janga et al., 2023) (Fig. 12).

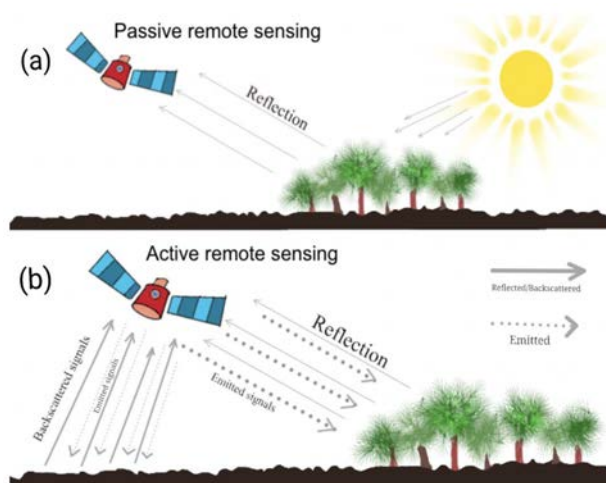


Figure 12 - Passive and active remote sensing systems (Adapted from Janga et al. (2023)).

In remote sensing, the most typical way to categorize electromagnetic waves is by their wavelength location within the electromagnetic spectrum (EMS) (Lillesand & Kiefer, 2015) (Fig. 13). The sensors will measure and record the radiation in different spectral bands, where each band represents a segment of the electromagnetic spectrum (Gupta, 2018).

Visible light is only a small portion of the EMS, from 0.4 and 0.7 μm , proceeding only ultraviolet. It ranges from violet to red: blue colours are in the range of 0.4-0.5 μm , green is 0.5-0.6 μm , and red is 0.6-0.7 μm (Prost, 2013). Beyond red is the infrared (IR) region, where there are three different types of infrared: the near-infrared (NIR) and the mid-infrared, also called short-wave infrared (SWIR), included in the reflected infrared, and the thermal infrared (Lillesand & Kiefer, 2015). The infrared and visible light regions comprise the optical range, where passive sensors operate. At the end of the EMS, which has much longer wavelengths, is the microwave region, where active radar sensors operate.

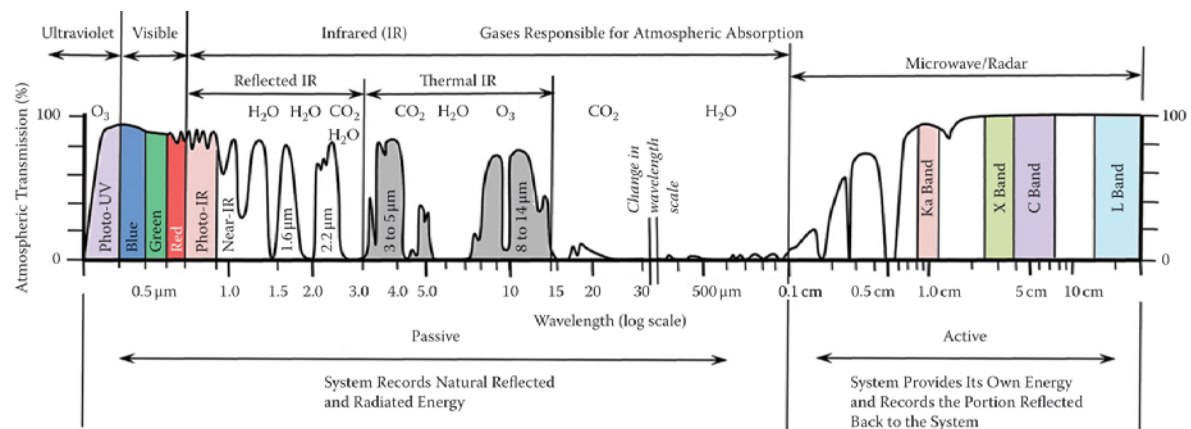


Figure 13 - The electromagnetic spectrum regions, with information about passive and active sensors (Adapted from Prost (2013)).

Different materials reflect and absorb at different wavelengths in the EMS, forming the spectral signature of the material and allowing their identification since all materials have unique spectral signatures. The spectral signature is the ratio of the reflected energy to incident energy as a function of the wavelength (Lillesand & Kiefer, 2015).

Each band collected by a remote sensing sensor is composed of pixels representing an area on the field. A radiance value is stored in each pixel, and the pixel's intensity corresponds to a discrete numerical value called a Digital Number (DN). Each image collected can, therefore, be described in terms of spatial, spectral, radiometric and temporal resolution (Sanderson, 2003) (Table 2).

Table 2 - Description of the spatial, spectral, radiometric and temporal resolution according to Sanderson (2003).

Spatial Resolution	The area of the surface contained in one pixel, and the smaller the area, the higher the spatial resolution of an image.
Spectral Resolution	Sensor's ability to measure finer wavelength intervals and, therefore, the number and width of spectral bands that it can discern. The finer the wavelength, the higher the spectral resolution.
Radiometric Resolution	Equivalent to the sensitivity of a sensor, which is its ability to measure and distinguish changes in electromagnetic energy within the same spectral band. The data is measured in bits, in which each bit is a binary value of 0 or 1. The number of brightness levels is determined by the bit depth of an image. For example, 8-bit images represent 256 brightness levels, and the higher the bit value, the greater the number of grey levels stored.
Temporal Resolution	It corresponds to the measurement of a repeat cycle or frequency with which a sensor revisits the same part of the Earth's surface.

The remote sensing data acquisition platforms can be of various types: aerial, like helicopters, aircraft and, more recently, unmanned aerial systems (UAS), space-borne, such as satellites and ground-based, such as LiDAR sensors, spectrometers and other geophysical surveys techniques (Gupta, 2018).

According to Sabins (1999), remote sensing can be applied to mineral exploration for two main purposes: (i) structural mapping to localize ore deposits and (ii) identification of hydrothermally altered rocks by analysing their spectral signatures.

For structural mapping, radar data is typically used, and in this work, Sentinel-1 and LiDAR data were utilized. Mineral mapping through spectral analysis relies on optical data, which can be either multispectral or hyperspectral, depending on the spectral resolution.

The European Space Agency (ESA) launched the Sentinel missions in the frame of the Copernicus program. These missions include Sentinel-1, Sentinel-2, Sentinel-3, Sentinel-4 and Sentinel-5. In this work, only Sentinel-1 data was used.

The Sentinel-1 mission consists of a constellation of two satellites – Sentinel 1A and Sentinel-1B. The Sentinel-1A was launched on 3 April 2014 and Sentinel-1B on 25 April 2016, although the mission for Sentinel-1B ended in 2022.

Sentinel-1A operates in a near-polar, sun-synchronous orbit at an altitude of 696 km, with a 12-day revisit cycle, obtaining a vast geographical coverage, potentially being able to cover the entire world every cycle (Torres et al., 2012). It is equipped with a CSAR active sensor, which is a synthetic aperture radar (SAR) operating in the C-band at a frequency of 5.405 GHz (Fig. 14) (Fletcher & Agency, 2012). The sensor enables image acquisition under all weather conditions, and since it is an active sensor, it does not depend on light conditions. Due to the longer wavelength of the C-Band, the ground penetration depth is optimal, and the radar waves can penetrate through vegetation foliage to some extent, as well as soil, ice and snow. Dry soil tends to be more transparent to radar waves, allowing for deeper penetration, while moist or wet soil can absorb more radar energy, leading to shallower penetration (Arii et al., 2019).

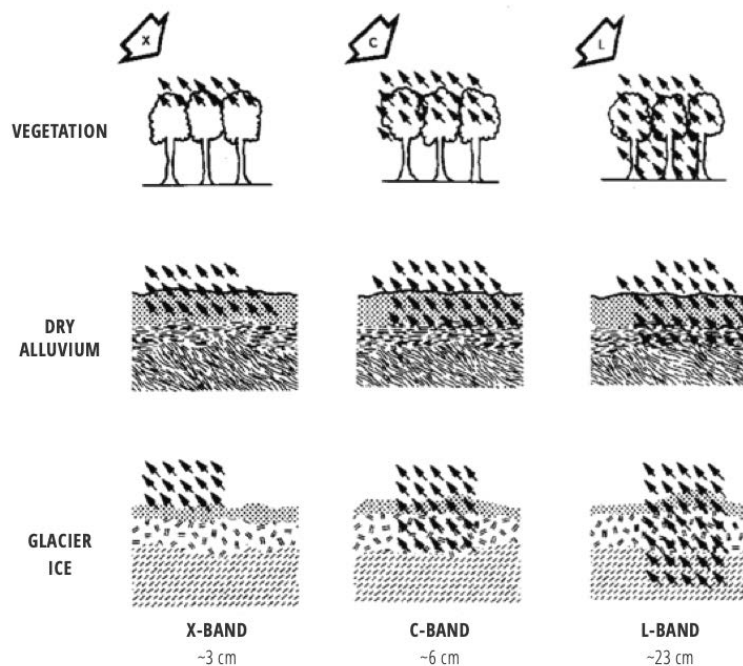


Figure 14 - Effects of X, C and L-band of SAR data on the penetration of surfaces (Adapted from Flores et al. (2019)).

The emitted waves reach the surface, and the reflected signals are called backscatter. There are different types of backscatter waves, and their strength indicates the relative roughness of the imaged surfaced (Arii et al., 2019) (Fig. 15). On one hand, rough surfaces will induce a strong return and a diffuse backscatter due to the waves going in various directions. On the other hand, smoother surfaces will produce none to little amount of signal backscatters. For human-made structures, the waves will double

bounce off the surface, causing a bright and clear backscatter (Ottinger & Kuenzer, 2020).

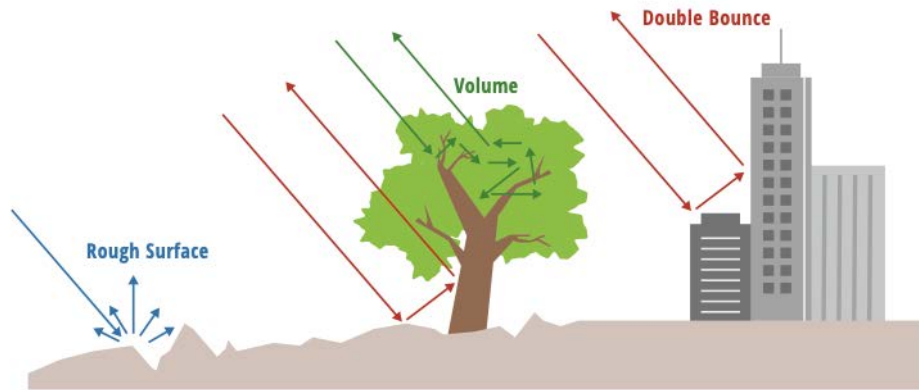


Figure 15 - Scattering mechanisms of the emitted waves of the CSAR (Adapted from Flores et al. (2019)).

Sentinel-1 captures images in different polarizations, which correspond to the waves travelling direction. It uses four different combinations, HH, VV, HV, and VH, where H stands for horizontal polarization and V corresponds to vertical polarization (Torres et al., 2012) (Fig. 16). The first letter indicates the transmitted polarization while the second letter indicates the return signal polarization.

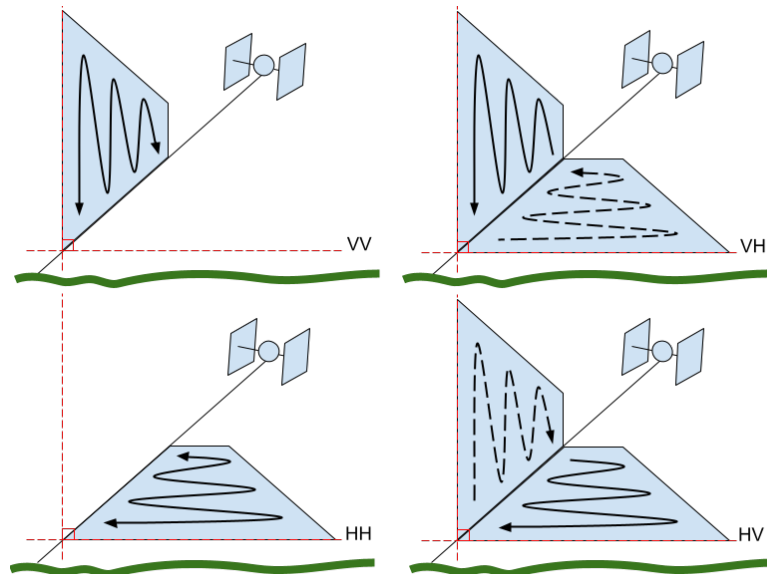


Figure 16 - Transmission of SAR waves, either vertically (V) or horizontally (H) (Credits: ASF).

This satellite generates three different types of products: Slant Range Single-look Complex (SLC), Ground Range Multi-look Detected (GRD) and Browse (BRW). Four operational modes were implemented – Interferometric Wide-swath mode (IW), Wave mode (WV), Strip Map mode (SM) and Extra Wide-swath mode (EW), with the following characteristics (Table 3) (Torres et al., 2012). The main operational mode used over land is the IW mode, with VV+VH polarization.

Table 3 - Characterization of the operational modes of Sentinel-1.

	IW	WV	SM	EW
Polarization	Dual (HH+HV, VV+VH)	Single (HH,VV)	Dual (HH+HV, VV+VH)	Dual (HH+HV, VV+VH)
Spatial resolution	5 x 20 m	5 x 5 m	5 x 5 m	20 x 40 m
Swath	250 km	Vignette 20x20 km	80 km	410 km

Over the years, Sentinel-1 has been used for a wide range of applications. For land monitoring applications, it can be used for agriculture, forestry, soil moisture monitoring and urban mapping. Its scope also extends to marine and coastal monitoring, where it is particularly valuable for oil spill detection, glaciers and coastal erosion monitoring, and ship detection, all of which contribute to marine safety (Torres et al., 2012). The satellite's all-weather imaging is especially beneficial in disaster management, providing critical data during situations with cloud cover, such as floods, wildfires and tornadoes. Additionally, it offers significant value in geological applications, including the assessment of geological hazards, like earthquakes, volcanic activity, landslides and subsidence, and it can also be particularly useful in structural mapping (Fletcher & European Space, 2012).

LiDAR is equipped with a laser, a scanner and a Global Positioning System (GPS) receiver. It is an active sensor that emits light in the form of a pulsed laser, and the reflected light returns to the sensor, where it is recorded (Dong & Chen, 2017; Hodgson & Bresnahan, 2004) (Fig. 17). The system measures the time it takes for emitted light to travel to the ground and back, called the two-way travel time, which is then used to calculate distance travelled (Prost, 2013). In the end, the distance is converted to elevation.

The sensor is usually coupled in different platforms, such as airplanes and helicopters, and there are two types of LiDAR – topographic and bathymetric. The topographic uses a NIR laser to map the land, while the bathymetric uses water-penetrating green light to measure the seafloor and riverbed (Quadros et al., 2008).

LiDAR data is available as discrete points, and a collection of them is known as LiDAR point cloud (Chen, 2007). All points have an associated X, Y location and Z values, corresponding to elevation. They also have an intensity value, representing the amount of light recorded by the sensor (Dong & Chen, 2017).

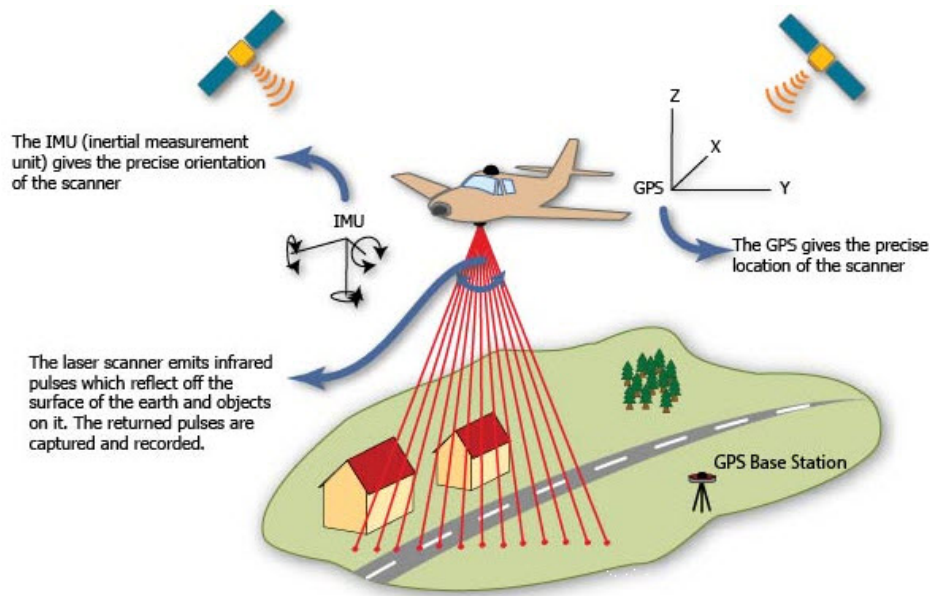


Figure 17 - Mechanisms from which LiDAR obtains elevation data (Credits: EIProCus).

The point cloud data is stored in a “.las” file format, or a “.laz”, which is a highly compressed version. Data products derived from the point cloud data are often high-resolution rasters in GeoTIFF formats.

LiDAR excels in mapping the Earth’s structure by acquiring high-resolution, three-dimensional data and, therefore, providing accurate shoreline maps or DEMs, regardless of vegetation (Dong & Chen, 2017). It excels in capturing both natural and anthropic environments with exceptional accuracy and precision.

This work employed hyperspectral data from the ENMAP mission for mineral mapping. Hyperspectral imaging is a passive remote sensing technique where simultaneous images are captured in many narrow spectral bands, as opposed to multispectral imaging, where the spectral bands are wider (Sabins, 1999).

EnMAP is a German satellite mission managed by the German Space Agency and launched on April 1st, 2022 (Storch et al., 2023). It operates on a sun-synchronous orbit at 653 km of altitude and has a revisit time of 27 days (Guanter et al., 2016).

It is equipped with a passive push-broom type hyperspectral imager (HSI) that records reflected radiation between 420 nm to 2450 nm in 246 bands, covering the VNIR and the SWIR range of the electromagnetic spectrum (Storch et al., 2023) (Fig. 18). The spectral resolution is of 6.5 nm, in the visible and NIR range, and of 10 nm in the SWIR, while the spatial resolution is 30 m, providing a swath width of 30 km (Guanter et al., 2016). The high spectral resolution is particularly valuable for mineral exploration since it is more

sensitive and can identify a wide variety of minerals based on their unique spectral signatures (Sabins, 1999).

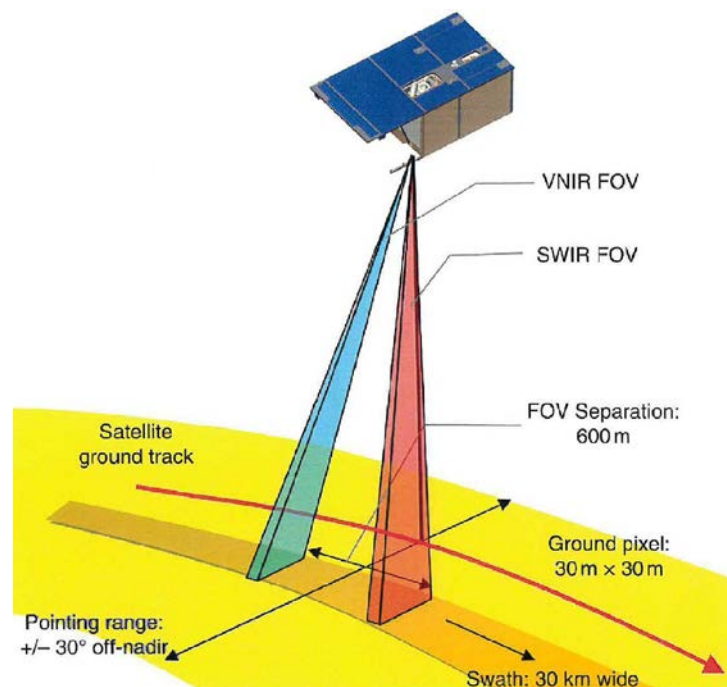


Figure 18 - Schematic view of observation technique of the HSI instrument (Credits: OHB).

The main fields of application are diverse, supporting agriculture and forestry, urban planning, and coastal and marine environment monitoring and disaster management (Guanter et al., 2016). Due to its high spectral resolution, it can be essential for geology and soil mapping. It can map many visible and NIR-SWIR active minerals on the Earth's surface, proving to be essential for mineral and resource exploration and has been applied several economic mineral systems such as porphyry copper, epithermal gold, Carlin-type gold, volcanogenic massive sulfide, iron-oxide-copper gold, skarns and polymetallic deposits, Pb-Zn mineralization, uranium mineralization, carbonatite and associated REE and niobium, kimberlites, lithium resources, iron ore deposits, bauxites, and many others (Guanter et al., 2016).

6. Methodology

6.1. Data

For structural mapping, Sentinel-1 data and LiDAR data were utilized.

A Sentinel-1 Level-1 GRD product was obtained for the Rias Baixas region. The image was acquired on 19 January 2024, in IW acquisition mode, on descending orbit, with dual polarization VV and VH.

The Sentinel-1 image was downloaded from the Copernicus Browser, an open data source of satellite images that can be accessed through "<https://browser.dataspace.copernicus.eu/>".

In addition, several LiDAR mosaics with a spatial resolution of 2 meters were downloaded from the Spanish Centro de Descargas (Download Center) of the Organismo Autónomo Centro Nacional de Información Geográfica (CNIG – Autonomous Body National Centre for Geographic Information). The LiDAR data, accessible at "<https://centrodedescargas.cnig.es/CentroDescargas/index.jsp>", was generated through interpolation from LiDAR flights under the scope of the second phase of the Plan Nacional de Ortografía Aérea (PNOA – National Aerial Orthophotography Plan), which began in 2015 and plans to provide complete coverage of the Spanish territory.

For mineral mapping, EnMAP data was employed. The EnMAP image, a Level-2A product consisting of 224 spectral bands, was acquired on 26 June 2024. EnMAP data can be accessed by submission of an acquisition request through the EnMAP Instrument Planning portal (<https://planning.enmap.org>).

6.2. Preprocessing

The main objective of preprocessing is to enhance the quality of the data by minimizing unwanted noise, correcting distortions, and enhancing key image features. Therefore, applying preprocessing steps is crucial, as it ensures that subsequent manual or automatic analysis is performed on accurate data.

For Sentinel-1 data, with the purpose of structural mapping, preprocessing was achieved using two platforms: the Sentinel Application Platform (SNAP) 10.0, for all data that was used for manual extraction, and Google Earth Engine (GEE), for all data used for automatic extraction.

For manual extraction, the Sentinel-1 pre-processed image was imported from SNAP into ESRI'S ArcGIS Pro. All the LiDAR data was also handled on ArcGIS PRO. On the other hand, the automatic extraction was achieved on GEE and the resulting lineaments were also imported into ArcGIS PRO.

SNAP and GEE are freely available and offer a significant advantage, as they eliminate the need for expensive commercial licenses, making remote sensing more accessible.

The EnMAP data was also processed using SNAP and ENVI 6.0

6.2.1. Sentinel-1

The preprocessing of the Sentinel-1 product followed similar workflows on both SNAP and GEE, with only minor variations due to platform differences. This consistency was essential to minimize potential discrepancies that could happen due to different preprocessing techniques, ensuring that the geological lineament extraction, both manual and automatic, was based on uniformly processed data.

6.2.1.1. Sentinel Application Platform

SNAP is an open-access EO software that analyses and processes satellite data, whether optical (either multi or hyperspectral) or radar. For this, the software contains all Sentinel Toolboxes (Sentinel-1, Sentinel-2 and Sentinel-3) and supports other third-party missions such as EnMAP, Landsat, PRISMA, SPOT, ALOS, among others. The interface of the software can be seen in Figure 19. The processing workflow is schematized in Figure 20.

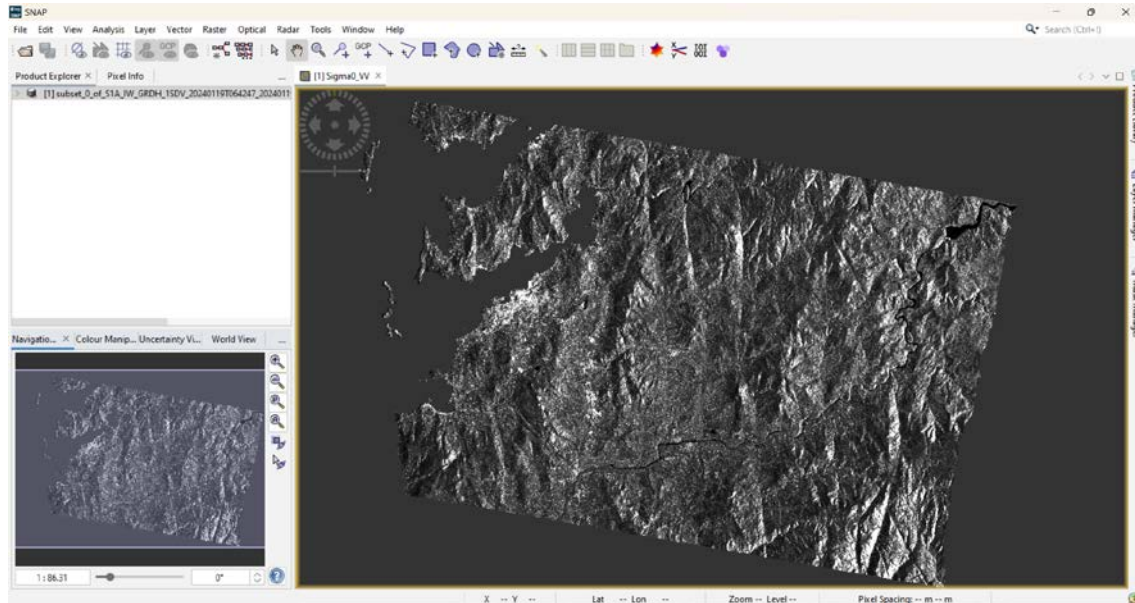


Figure 19 - Interface of SNAP. At the top, the taskbar can be found to access tools and functions. The Product Explorer window on the left offers a tree-like view of existing products. The central area is the Image View, where bands can be displayed. On the bottom left, users can find the Navigation Window, where they can move the viewport of the image window, as well as other panels such as Colour manipulation and World View. Users can access the Product Library, Layer Manager and Mask Manager on the right. The user can define which windows are displayed and their location.

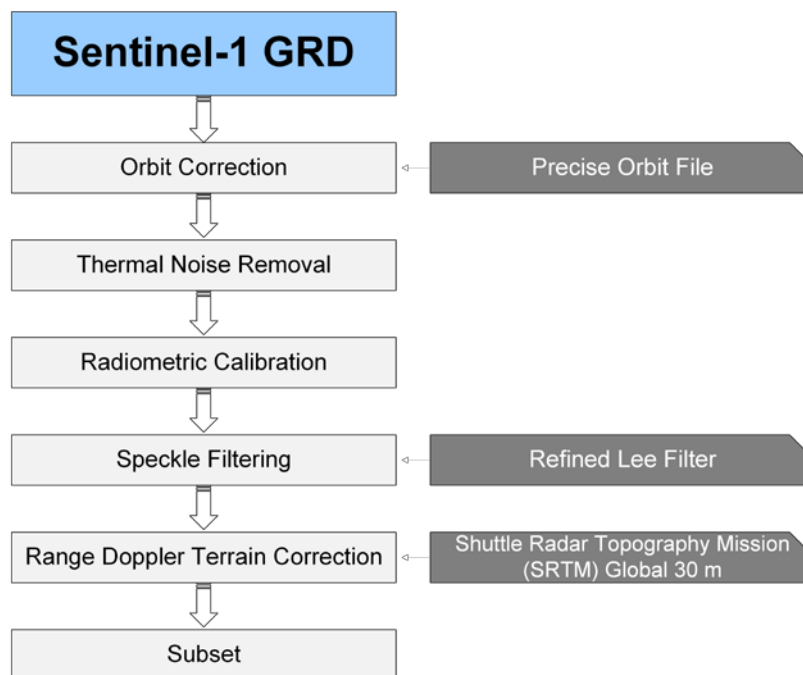


Figure 20 - Workflow employed for preprocessing Sentinel-1 data in SNAP.

Each of the preprocessing steps will be briefly described.

Orbit correction

Orbit correction is an essential first step in the preprocessing of radar data.

Over time, the precise location of the satellite may drift, so there is a need for periodic adjustments. Therefore, orbit state vectors provided in the metadata information of a Sentinel-1 product are usually not accurate (Torres et al., 2012). To correct this, the satellite position is recorded by the Global Navigation Satellite System (GNSS) during acquisition. The consequent orbit file is produced a few weeks after acquisition and can be downloaded and applied to the image.

After this step, the accuracy of the satellite's position and velocity information is ensured, which impacts the quality of the georeferencing and subsequent data (Filipponi, 2019).

Thermal Noise Removal

Thermal noise is an unwanted background signal consisting of two additive noises, one stemming from the antenna pattern and varying in range direction. The other is a scalloping noise, varying along the azimuth direction (Park et al., 2018). This noise is more evident in cross-polarization SAR images, such as VH and HV.

Due to this, thermal noise removal is performed to normalize the backscatter signal, enhancing the quality of the radar image.

Radiometric Calibration

SAR data is measured in digital pixel values, also known as DNs. Radiometric calibration aims to convert these values to radiometrically calibrated backscatter of the reflecting surface (Filipponi, 2019). Pixel values can then be converted into beta, sigma and gamma nought values. For these images, DNs were converted into sigma nought values, which represent the averaged radar cross section per unit ground area in m^2 , meaning it accounts for the terrain's effects on the backscatter signal.

In this step, Amplitude and Intensity bands, in both polarizations VV and VH, are converted into the Sigma0_VV and Sigma0_VH bands.

Speckle Filtering

Due to the homogeneity of the surface illuminated by the SAR sensor, it will then be comprised of different types of individual scatterers that may interfere with each other, creating granular noise that appears as a salt and pepper texture. Due to this, filters can be applied to reduce noise and enhance image quality. The filters available in SNAP are: Boxcar (mean), Median, Frost, Lee, Refined Lee, Gamma-MAP, Lee Sigma and Iterative Dual Adaptive Non-local.

The filter used for this image was the Refined Lee since it has been tested ((Ghosh et al., 2022; Tzong-Dar & Lee, 2007) to be more suitable for preserving edges and linear features.

Range Doppler Terrain Correction

SAR sensors measure the distance to objects, i.e. the range, and their movement, i.e. the Doppler shift. However, data collected usually has a varying viewing angle greater than 0 degrees due to topographic variations and the tilt of the satellite sensor, leading to distortions (Park et al., 2018). Therefore, terrain correction must be performed to undo these distortions and accurately represent the surface. For this, the method is applied for geocoding SAR images from single 2D raster geometry. This method uses information about the topography, usually provided by a DEM, and the orbit state vector information to attribute a precise geolocation to each pixel, obtaining the geographic coordinates for the Sentinel-1 image.

For these images, the DEM used was the National Aeronautics and Space Administration's (NASA) SRTM with a 30-meter resolution.

Since the image was obtained in descending orbit, it appears flipped vertically, which was also rectified by terrain correction.

Subset

The Sentinel-1 image has a swath width of hundreds of kilometres, incorporating areas that are not included in this study. Therefore, a subset of the study area was created.

6.2.1.2. Google Earth Engine

GEE is a cloud-based platform that allows users to visualize and analyse satellite imagery on a global scale. It offers an extensive collection of satellite images, with data spanning over 40 years. The main programming language used is JavaScript, and the platform provides the necessary tools to analyse large volumes of data (Fig. 21).

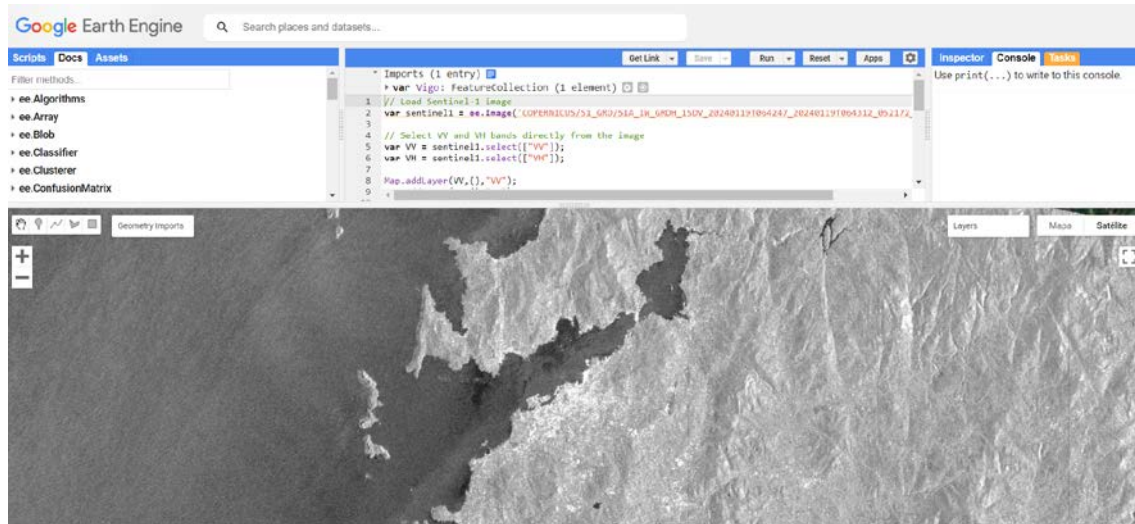


Figure 21 - Interface of GEE. On the left is the Scripts panel, where scripts are stored; the Docs panel, where information about algorithms and tools is found; and the Assets panel, where users can upload and manage geospatial datasets. The central panel is where scripts are written, usually in JavaScript. On the right, the Inspector panel allows for the examination and retrieval of data; the Console panel displays results; and finally, the Tasks panel, where it is possible to manage running tasks, such as data exports.

The same Sentinel-1 image was retrieved from GEE's Image Collection through the path "COPERNICUS/S1_GRD". When imported, this image had already been pre-processed by GEE, using Sentinel-1 Toolbox, and the steps applied were Thermal Noise removal, Radiometric Calibration and Terrain Correction using SRTM 30m. Unlike in SNAP and apart from the VV and VH bands, each scene also includes an additional "angle" band, which contains the approximate incidence angle from the ellipsoid at every point.

The Sentinel-1 bands can then be added to the map for visualization, and the visualization parameters are manually inserted, usually using the maximum and minimum values of the band. These values can be inspected by printing the image details in the console window.

6.3. Geological lineament extraction

In this subchapter, the methodology employed for lineament extraction is described for both types, manual and automatic. Manual lineament extraction consists of the direct

digitalization of structures by image interpretation. Meanwhile, in automatic extraction, structures are detected and extracted through algorithms with minimal human intervention.

Different methods were used for both types of extraction. For Sentinel-1 data, two methods were tested, while for LiDAR data, only one method was applied. The goal was to standardize the methods for both types of extraction in order to produce results that would be consistent and could be directly comparable. This way, an accurate assessment of the effectiveness of each extraction can be performed.

The overall workflow for the methods is illustrated in Figure 22. Each method will be described further in the next subchapters.

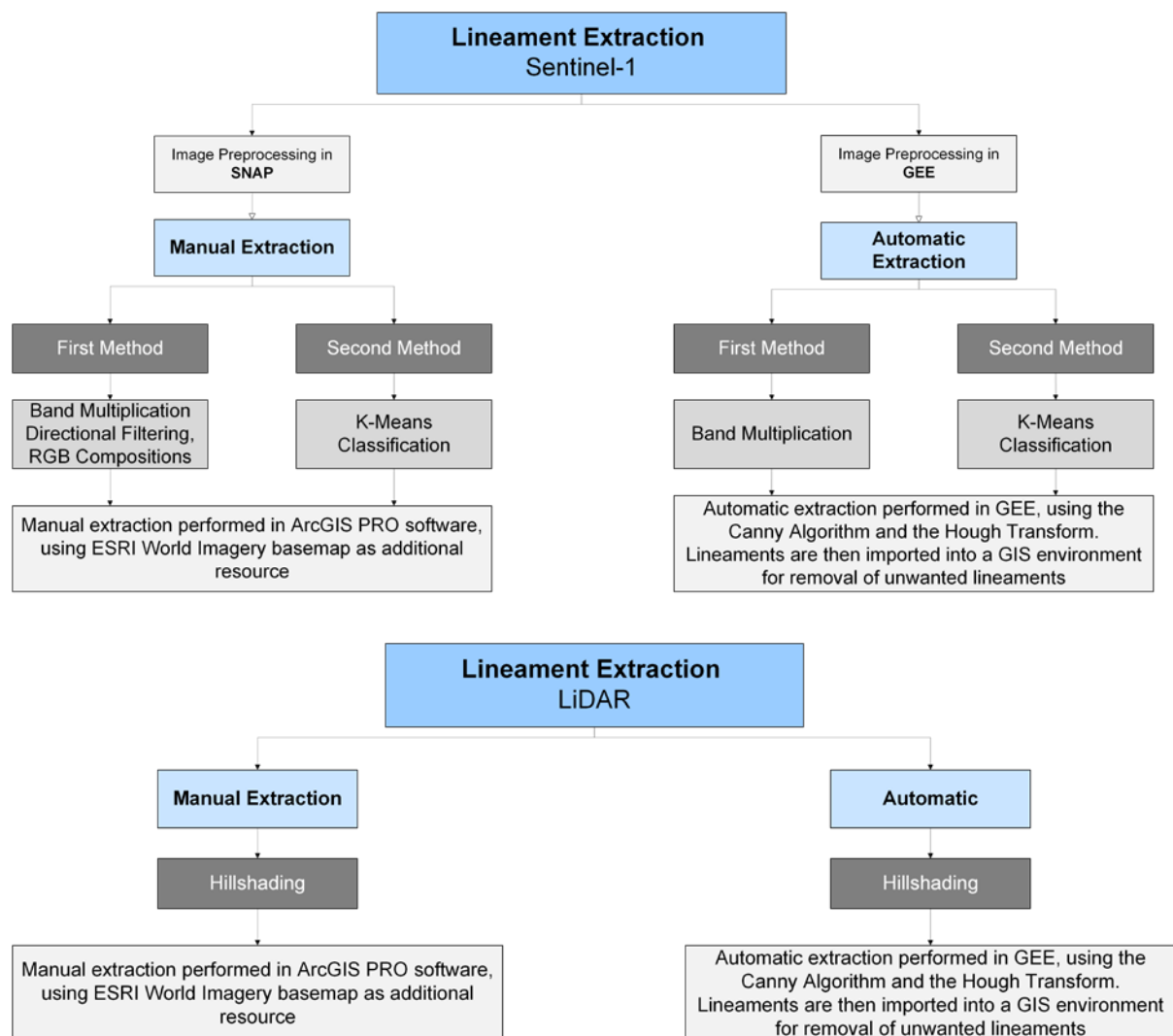


Figure 22 - Top workflow summarizing the two manual and automatic extraction methods using Sentinel-1 data. The bottom workflow summarizes the manual and automatic extraction methods using LiDAR data.

6.3.1. Manual extraction

As mentioned, for Sentinel-1 data, the first method consists of band multiplication, Prewitt filtering and RGB Compositions, while the second method consists of mainly performing K-Means Unsupervised Classification. Each method is described in detail below, as “First method” and “Second method”, respectively. For LiDAR data, only one method was employed, which consisted mainly of hillshading.

6.3.1.1. Sentinel-1

6.3.1.1.1. First method

All the steps involved in the first method are schematized in Figure 23.

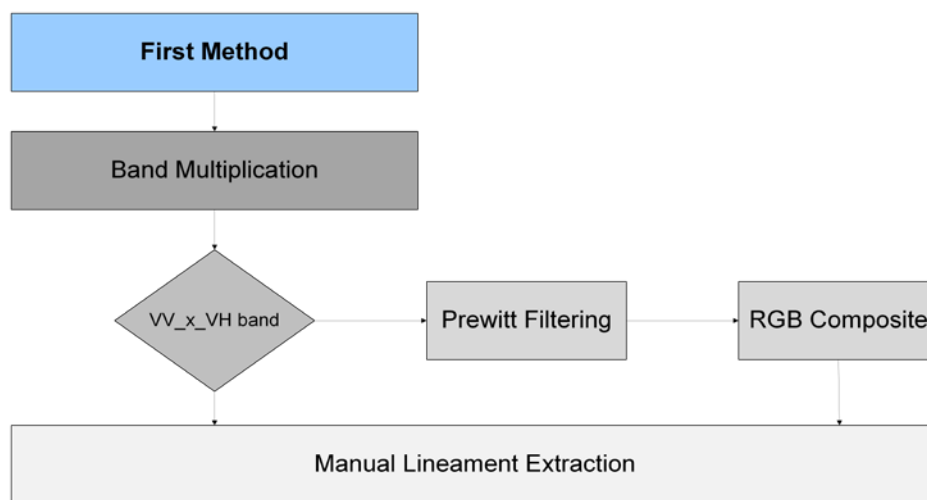


Figure 23 - Workflow for the first method of the manual extraction using Sentinel-1 data.

Band Math

Band math is a tool that creates new bands from existing bands by building expressions. Different types of operators exist, such as binary, logical, mathematical functions, mathematical constants and arithmetic operators. The last one was the one used in this work.

Two operations were tested – addition and multiplication. The addition of the VV and VH bands reflects the overall backscatter from both V and H polarization signals. However, it does not highlight the different types of scattering and, therefore, cannot distinguish different surface roughness levels. This results in a loss of detail, which is necessary to identify geological structures.

On the other hand, the multiplication of VV and VH does not reduce detail since it incorporates the different types of scattering from both polarizations. This makes it more suitable for identifying geological structures since it captures the different scattering proprieties of these structures, which are dependent on their orientation and surface roughness.

Using this tool, a band was created from the multiplication of the Sigma0_VV and Sigma0_VH bands, resulting in a new band named "VV_x_VH".

Directional Filtering

Directional filtering is a technique used for edge enhancement, highlighting image features with different directional gradients. For this, Prewitt filtering, comprising 3x3 kernels, was employed to help identify edges and features by detecting changes in image intensity. The directional filters were applied to the VV_x_VH band in four different directions: N-S, NE-SW, E-W and NW-SE (Ahmadi, Pekkan, & Seyitoglu, 2023; Cardoso-Fernandes et al., 2018) (Fig. 24).

N-S			E-W			NE-SW			NW-SE		
-1	-1	-1	-1	0	1	0	-1	-1	-1	-1	0
0	0	0	-1	0	1	1	0	-1	-1	0	1
1	1	1	-1	0	1	1	1	0	0	1	1

Figure 24 - Prewitt filters applied to the Sentinel-1 image (Adapted from).

RGB Composite

RGB (Red, Green, Blue) composite bands combine three different bands into one colour image. Following the method in Javhar et al. (2019), an RGB composite of the three directional filters was created using the following combination: NE-SW (R), E-W (G) and NW-SE (B).

This combination aids visual interpretation by leading to improved contrast on geological features and, therefore, serves as a manual lineament extraction tool.

6.3.1.1.2. Second method

The second method employed is based on K-Means Unsupervised Classification to assess its ability to delineate and classify structures as an alternative to other structural enhancement techniques, such as Prewitt filtering (Fig. 25).

The K-Means Cluster Analysis categorizes objects into different groups, known as clusters or classes, where each cluster comprises data that share a common trait.

In SNAP software, the K-Means algorithm is implemented as follows:

- i. Random selection of k pixels to define the initial cluster centers;
- ii. Assign each pixel to the nearest cluster center based on Euclidean distance;
- iii. Recalculate the cluster centers by averaging the values of all pixels assigned to each other.

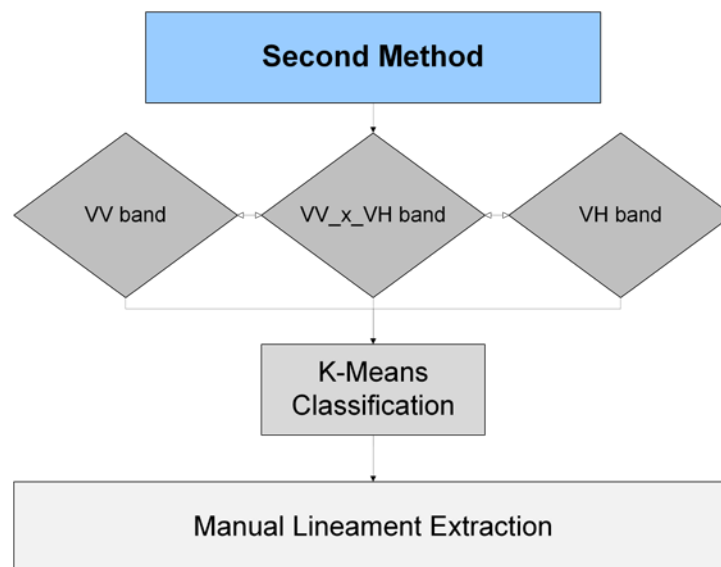


Figure 25 - Workflow for the second method of the manual extraction using Sentinel-1 data.

The number of clusters is defined as parameters, followed by the maximum number of iterations over which the cluster analysis stops. The random seeds are used to generate the initial clusters, and for this analysis, the default seed number of 31415 was used. Finally, the source bands for the analysis are selected.

Therefore, several combinations can be tested, and the following six were performed (Table 4).

Table 4 - Parameter combinations for the K-Means Classification to be used for manual extraction.

Combination	Bands	Clusters	Iterations
A	Sigma0_VV	8	15
B	Sigma0_VH	8	15
C	Sigma0_VV Sigma0_VH	8	15
D	Sigma0_VV Sigma0_VH	12	15
E	VV_x_VH	8	15
F	VV_x_VH	12	15

Six combinations were tested, but combinations A and F were selected for manual lineament extraction since they provided superior structure visibility.

6.3.1.2. LiDAR

In ArcGIS PRO software, all the LiDAR mosaics were merged into a single raster and hillshading was applied. Hillshading is a technique used for terrain visualization, which simulates the illumination of the terrain surface based on the sun’s angle and the slope of the elevation surface.

Four hillshade maps were created with azimuth directions of 0°, 90°, 180° and 270° (Fig. 26). The illumination angle was set to the default number of 45.

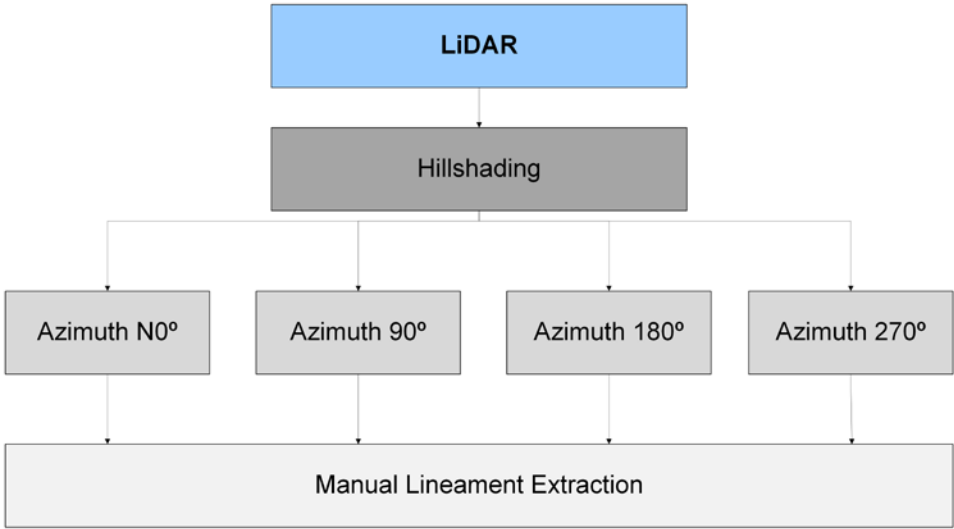


Figure 26 - Workflow of the method applied to LiDAR data..

Azimuths of 0° and 180° are expected to enhance lineaments oriented along an E-W direction, while azimuths of 90° and 270° will highlight lineaments oriented N-S. This is due to the way shadows are cast. For example, when the light comes from the north, it casts shadows to the south, emphasizing lines perpendicular to the illumination direction and, therefore, oriented E-W.

6.3.1.2.1. Lineament extraction

The manual lineament extraction was carried out in ArcGIS PRO software, with the Imagery basemap by Earthstar Geographics, to help differentiate between man-made and natural lineaments.

For Sentinel-1 data, referring to the first method, the base image utilized was the VV_x_VH band, with the RGB composite as a supplementary tool to visualize features better.

To avoid bias in the results and truly assess the abilities of these methods, the only basemap used was the one mentioned above. However, the lineaments were then compared to those mapped in the MAGNA 50 - Geological Map of Spain at a scale of 1:50 000. Furthermore, lineament length, direction, density, and intersections were analysed.

6.3.2. Automatic extraction

As seen previously in the workflow illustrated in Figure 22, for the automatic extraction, similar to the manual one, two methods were utilized for the Sentinel-1 data, which again include band math and K-Means clustering. For the LiDAR data, only hillshading was applied, just like the manual method. The automatic extraction was performed in GEE.

6.3.2.1. Sentinel-1

6.3.2.1.1. First method

Band math

The Sigma0_VV and Sigma0_VH bands were multiplied, following the manual extraction procedure, to produce a second VV_x_VH, which was given the designation VV_x_VH_GEE (Fig. 27).

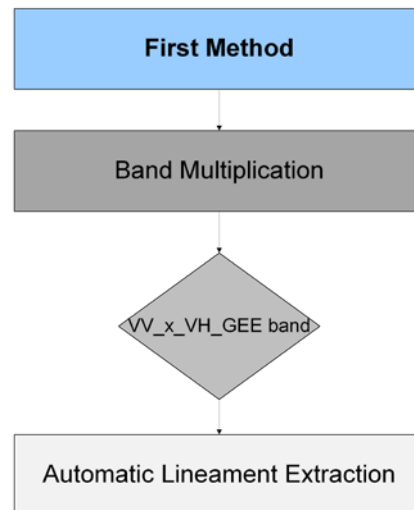


Figure 27 - Workflow for the first method of the automatic extraction using Sentinel-1 data.

6.3.2.1.2. Second method

The second method, just like the manual extraction, is based on K-Means classification (Fig. 28). In GEE, firstly, a training area needs to be specified by inserting a scale and number of pixels. Through trial and error, a scale of 10 was chosen and a number of pixels of 4000.

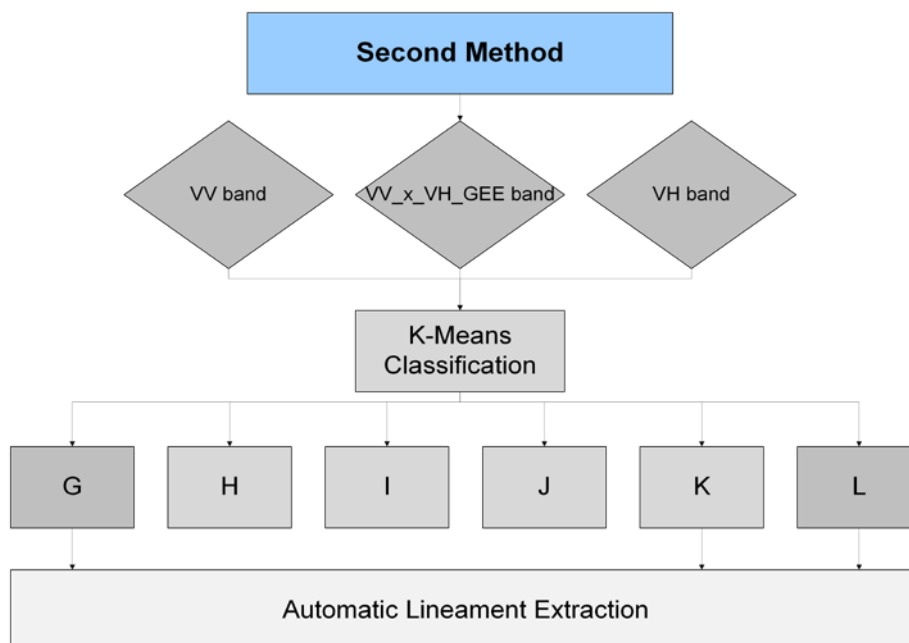


Figure 28 - Workflow for the second method of the automatic extraction using Sentinel-1 data.

In GEE, for the clustering, the VV_x_VH band and the VV and VH bands were used, but unlike in the manual method, only one band was used as input at once since GEE doesn't support the selection of multiple bands at once for the K-Means Classification, like it happens in SNAP. Therefore, the K-Means combinations in GEE were the following (Table 5):

Table 5 - Combination parameters of the K-Means Classification to be used for automatic extraction.

Combination	Bands	Clusters
G	Sigma0_VV	8
H	Sigma0_VV	12
I	Sigma0_VH	8
J	Sigma0_VH	12
K	VV_x_VH_GEE	8
L	VV_x_VH_GEE	12

Through observation, only the two best combinations were selected for the lineament extraction: combinations K and L. While combination G provided a good result, only the combinations containing the VV_x_VH_GEE band as input were considered for further analysis, as this band is the main one used for lineament extraction in this work.

6.3.3.LiDAR

Hillshading

For the LiDAR data, the same hillshading was applied, just like in the manual one. Four hillshades were created, with an azimuth of 0°, 90°, 180° and 270°, and an illumination angle of 45°.

6.3.3.1. Lineament extraction

The technique for automatic lineament extraction is somewhat more complex than manual extraction. Firstly, edge detection is required, followed by line detection from the resulting edges.

Edge detection – Canny Algorithm

Edges correspond to a region in an image with a sudden change in brightness. In image processing, edge detection is a known technique for identifying and locating boundaries in an image, detecting discontinuities, and extracting the outlines of an object present in an image (Canny, 1986).

There are several edge detection algorithms, but the one available in GEE is the Canny edge detection algorithm, developed in 1986. It is a multi-stage algorithm that includes image smoothing, gradient finding, none-maximum suppression, double thresholding, and edge tracking by hysteresis (Canny, 1986).

In GEE, the only parameters that need to be specified are the line threshold and the sigma values. The threshold will determine which pixel is considered for edge detection. In GEE, only a minimum threshold is considered instead of a double threshold. Thus, a pixel is only considered if the gradient magnitude exceeds the defined threshold. A high threshold may miss important information, while a threshold that is too low may lead to unwanted noise.

Prior to most edge detection algorithms, image smoothing is usually used. Image smoothing consists of applying a spatial filter to produce a smoother image with reduced noise and highlighting edges in the image (Rajashekar et al., 2005). This step is already incorporated in the Canny algorithm, and the user only needs to specify a value of sigma, which represents the standard deviation of a Gaussian filter. The smaller the sigma value, the narrower the filter, which is equivalent to less smoothing, preserving finer details. On the other hand, a larger sigma value will result in a wider Gaussian filter, leading to even smoother images. It was observed that Sentinel-1 data needed a narrower filter, while LiDAR data needed a wider one due to having a higher spatial resolution.

Several threshold and sigma values combinations were tested through trial and error and observation. The best combinations of parameters are those described in Table 6:

Table 6 - Parameters used for the Canny Algorithm in GEE.

Image	Threshold	Sigma
VV_x_VH_GEE	120	2
Combination G	1.5	1.5
Combination K	1	4
Combination L	1.2	4.1
LiDAR Hillshade – Azimuth 0°	30	3
LiDAR Hillshade – Azimuth 90°	30	3
LiDAR Hillshade – Azimuth 180°	30	3
LiDAR Hillshade – Azimuth 270°	30	3

Line Detection – Hough Transform

After edge detection, line detection must be performed. The technique available in GEE is the Hough Transform, developed by Paul Hough in 1962 (Duda & Hart, 1972). This transform can detect simple geometric shapes such as lines and circles. To detect features, it transforms the image space into a parameter space consisting of the X-Y coordinates and the circle's radius. The shapes will be detected through the identification of patterns (Moulin, 2005).

In GEE, the user needs to define several parameters. The first parameter is the input image, which needs to be a thresholded edge detected image. Then, the grid size over which the computation is performed needs to be specified. After, a value for the input threshold is defined, where pixels equal to or above the value are considered active, and the same input threshold as Canny was defined. Another threshold is the line one, where values equal to or above that value are considered to be detected lines. The same line threshold was applied to all images.

Table 7 - Parameters used for the Hough Transform in GEE.

Image	Grid size	Input Threshold	Line Threshold
Canny_VV_x_VH_GEE	256 (default)	120	10
Canny_Combination G	256 (default)	1.5	10
Canny_Combination K	256 (default)	1	10
Canny_Combination L	256 (default)	1.2	10
Canny_LiDAR Hillshade – Azimuth 0°	256 (default)	30	10
Canny_LiDAR Hillshade – Azimuth 90°	256 (default)	30	10
Canny_LiDAR Hillshade – Azimuth 180°	256 (default)	30	10
Canny_LiDAR Hillshade – Azimuth 270°	256 (default)	30	10

6.4. Mineral Mapping

EnMAP's L2A products are considered analysis-ready, so no further processing is needed except for spectral subsetting to remove bad quality bands, which are corrupted data layers containing no data pixels (Alicandro et al., 2022). In this case, bands number 131 (1342.82 nm), 132 (1354, 76 nm), 133 (1366,69 nm), 134 (1378, 60 nm) and 135 (1390,48 nm) were manually identified and removed. As a result, the final product consists of 219 bands out of the original 224.

For mineral mapping, band ratios were performed in a first instance to detect zones of alteration and possible mineralization. Additionally, the Mixture Tuned Matched Filtering (MTMF) approach was employed to detect specific mineral signatures within the image through a spectral unmixing approach. This method was performed in ENVI Classic 6.0 software (Fig. 29)

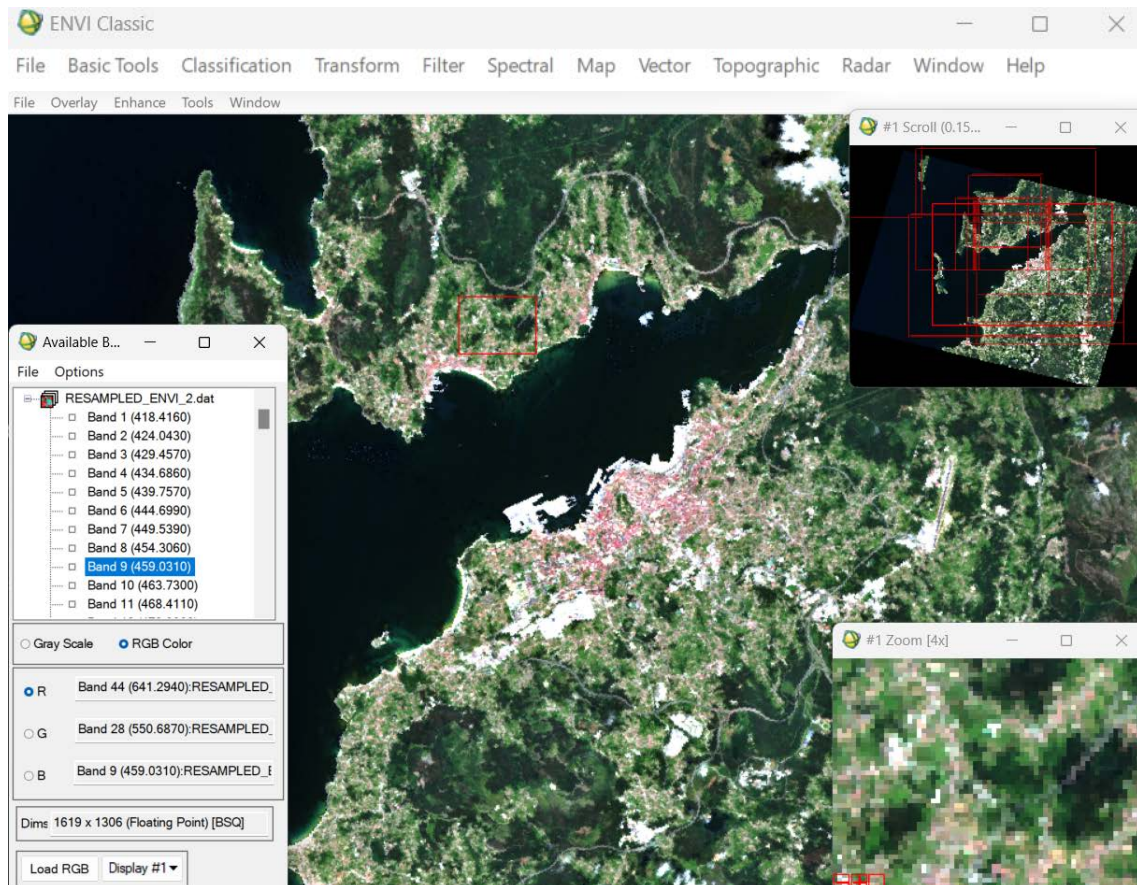


Figure 29 - Interface of the ENVI Classic 6.0 software. At the top, the taskbar provides access to all the tools needed for the image analysis. The Available Bands list is displayed in the bottom left corner, where all products are displayed. The main image view is in the centre, accompanied by two smaller windows representing the zoom and scroll functionalities.

6.4.1. Band ratios

Band ratios are one of the most common image enhancement techniques used in remote sensing image processing since it effectively displays spectral variances that become difficult to detect in a standard image while being a fairly fast technique to perform (Ghrefat, Awawdeh, Howari, et al., 2023; Sabins, 1999). This technique works through the division of DNs at peaks/maxima and troughs/minima in a reflectance curve (Prost, 2013). To perform this, typically, a band with higher reflectance is divided by a band with lower reflectance, and the final product consists of an image showing the distribution of specific minerals based on their unique reflectance highs and absorption features (Prost, 2013). This technique effectively sharpens subtle differences in the spectral reflectance characteristics of rocks and soils while suppressing other types of information, such as topographic effects (Ghrefat, Awawdeh, & Al-Rawabdeh, 2023).

Since early, band ratios have been used for mineral exploration since many minerals associated with hydrothermal alteration, such as iron oxides, clay minerals, which include illite, kaolinite and montmorillonite, and carbonates are easily detected and observed through band ratios (Abrams et al., 1977; Prost, 1980; Sabins, 1999).

Clay minerals usually have a characteristic absorption centered at 2200 nm (Prost, 2013). Iron oxides have a characteristic absorption in the ultraviolet and blue spectral regions but are strongly reflective in the red and IF regions at around 600 and 700 nm (Canton et al., 2021). Carbonates usually have strong absorption features between 2320 nm and 2510 nm in the SWIR region (Prost, 2013; Sabins, 1999).

Different band ratios were tested in this work to highlight areas of possible hydrothermal alteration, mainly several ratios for clay minerals, iron oxides and silicates, as well as carbonates. Henrich et al. (2012) previously defined these band ratios, which can be consulted at <https://www.indexdatabase.de/>. These ratios are described in Table 8.

Table 8 - Band ratios tested to identify hydrothermal alteration zones.

General Formula	Specific Formula	Type of mineral featured
$\frac{1642.1\text{ nm}}{2165.5\text{ nm}}$	$\frac{153}{189}$	Alteration
$\frac{(1642.1\text{ nm} + 2224.6\text{ nm})}{2165.5\text{ nm}}$	$\frac{(153 + 196)}{189}$	Alunite/Kaolinite/Pyrophyllite
$\frac{2165.5\text{ nm} * 2290.1\text{ nm}}{2224.6^2\text{ nm}}$	$\frac{189 * 204}{196^2}$	Clay
$\frac{2290.1\text{ nm}}{2165.5\text{ nm}}$	$\frac{204}{189}$	Kaolinite

$\frac{(2290.1 \text{ nm} + 2392.3 \text{ nm})}{2322.1 \text{ nm}}$	$\frac{(204 + 217)}{208}$	Carbonate/Chlorite/Epидote
$\frac{(2224.6 \text{ nm} + 2392.3 \text{ nm})}{(2290.1 \text{ nm} + 2322.1 \text{ nm})}$	$\frac{(196 + 217)}{(204 + 208)}$	Epидote/Chlorite/Amphibole
$\frac{660.2 \text{ nm}}{555.9 \text{ nm}}$	$\frac{46}{29}$	Ferric iron
$\frac{2165.5 \text{ nm}}{808.9 \text{ nm}} + \frac{555.9 \text{ nm}}{653.8 \text{ nm}}$	$\frac{189}{68} + \frac{29}{45}$	Ferrous Iron
$\frac{1642.1 \text{ nm}}{808.9 \text{ nm}}$	$\frac{153}{68}$	Ferric Oxides
$\frac{2165.5 \text{ nm}}{1642.1 \text{ nm}}$	$\frac{189}{153}$	Ferrous Silicates
$\frac{2143 \text{ nm} + 2229 \text{ nm}}{2206 \text{ nm}}$	$\frac{187 + 197}{194}$	Al-sheetsilicates
$\frac{2224.6 \text{ nm}}{2322.1 \text{ nm}}$	$\frac{196}{208}$	Amphibole
$\frac{2224.6 \text{ nm} + 2392.3 \text{ nm}}{2322.1 \text{ nm}}$	$\frac{196 + 217}{208}$	Amphibole/ MgOH

6.4.2. Mixture Tuned Matched Filtering

Hyperspectral images contain a combination of component materials within each pixel. Due to this, spectral unmixing techniques are usually employed to calculate the relative abundance of materials within a hyperspectral image based on a set of endmembers with unique spectral characteristics (Abay et al., 2022; Jakob et al., 2016; Kumar et al., 2022; Lorenz et al., 2016).

The MTMF supervised classification is based on partial unmixing since it can unmix an endmember from an unknown background. It uses a Matched Filter (MF) to match the known spectral signature to the image spectra, maximizing the response of the target spectra and suppressing the response of unknown elements in the image (Kumar et al., 2022). The result is a target abundance image where each pixel has an MF score. The other part of the classification consists of applying a Mixture Tuning (MT) method to reduce false positives by using a linear spectral mixing model to add an infeasibility image to the results. The results are a set of rule images that correlate to the MF and infeasibility scores, for each pixel, when compared to each endmember spectra.

In this work, two different MTMF classifications were performed. The MTMF method can be done through the Spectral Hourglass Wizard in ENVI software, and several steps are included in the workflow:

1. The input EnMAP image is selected.

2. Minimum Noise Fraction (MNF) Transform is applied to determine the dimensionality of image data. It uses two cascaded Principal Component (PC) transformations, where the resulting bands are ranked with the largest amount of variance in the first few bands and decreasing data variance with increasing band number. In this step, the number of output MNF bands is determined by visualizing the output bands and using expert knowledge to identify from which band the noise starts to increase. Based on this assessment, 30 MNF output bands were selected.
3. The Data Dimensionality is determined considering the eigenvalues and MNF images. This step includes thresholding MNF bands to separate the noise from the data. A threshold of 0.62 was chosen, equivalent to 13 output bands.
4. After, the endmembers can be derived or selected. Endmembers represent the pure spectral response of various materials (Shi & Wang, 2016). In this work, endmembers were selected from two different spectral libraries, one used for each classification attempt. The first library was derived from the USGS spectral library, (Kokaly et al., 2017), and the minerals that constitute the endmembers were selected due to their known occurrence in the Ria de Vigo. The second spectral library was built during the S34I project, under which this dissertation was carried out. To create the second spectral library, heavy-mineral concentrates of Vigo beach placer samples were collected in a laboratory, and their spectral signature was identified with an ASD FieldSpec4 spectroradiometer. While these HM concentrates are not spectrally pure, they were used as endmembers since they represent the mix of materials found in Vigo beaches. Table 9 describes the endmembers used in the classification.
5. For each classification, 20 rule images were obtained – 10 of them containing the MF scores and the other 10 containing the infeasibility scores.

Table 9 - Endmembers selected for MTMF method. The first classification was performed using endmembers chosen from the USGS spectral library. While the second classification was performed using endmembers obtained from the spectral analysis of HM concentrates from Vigo beach placer samples collected in the scope of the S34I project.

First Classification (USGS)	Second Classification (HM spectral library)	
	Endmember	Manual Interpretation
Almandine (HS114.3B)	UPO_1	Montmorillonite
Goethite (HS36.3)	UPO_2	Biotite/Phlogopite/ Montmorillonite
Grossular (HS113.3B)	UPO_3	Biotite/Phlogopite/ Montmorillonite

Ilmenite (HS231.3B)	UPO_4	Biotite/Phlogopite/ Montmorillonite
Monazite (HS255.3B)	UPO_5	Chlorite/Biotite
Rutile (HS126.3B)	UPO_6	Montmorillonite
Silimanite (HS186.3B)	UPO_7	Tourmaline/Garnet
Spessartine (HS112.3B)	UPO_8	Tourmaline/Garnet
Tourmaline (HS282.3B)	UPO_9	Tourmaline/Garnet
Zircon (WS522)	UPO_10	Tourmaline/Garnet

At the

end of the MTMF method, the rule images were classified using the Rule Classifier tool based on thresholds that can be visualized on a histogram and then defined by the user. The thresholds used for both classifications are described in Table 10. Each category, corresponding to each endmember, is assigned a different colour.

To interpret the results further, it is important to understand the relation between the MF and the infeasibility scores. A pixel with an MF score of 1 is a true match, while a pixel with a value of 0 is considered a background representation. Meanwhile, the higher the infeasibility score, the more likely the pixel is an MF false positive. Therefore, correctly mapped pixels will have an MF score above the background distribution, closer to 1, and a low infeasibility value. This relation can be visualized in a scatter plot, with the MF score on the X-axis and the infeasibility score on the Y-axis (Lorenz et al., 2016). In the scatter plot, the correctly mapped pixels will be found on the bottom-right region of the plot (Fig. 30).

The interpretation of the histograms and scatter plots for each endmember improves the general accuracy of the classification by ensuring the majority of the pixels are correctly mapped. Additionally, in a Geographic Information System (GIS) environment, the pixels assigned to urban areas were also manually removed. All these steps led to the generation of the final classification maps.

Table 10 - Threshold applied to each endmember of the spectral libraries used.

USGS endmembers	Threshold	Heavy concentration endmembers	Threshold
Almandine (HS114.3B)	0.195	UPO_1	0.602
Goethite (HS36.3)	0.796	UPO_2	0.455
Grossular (HS113.3B)	0.279	UPO_3	0.465
Ilmenite (HS231.3B)	1.429	UPO_4	0.433
Monazite (HS255.3B)	0.042	UPO_5	0.230
Rutile (HS126.3B)	0.158	UPO_6	0.310
Silimanite (HS186.3B)	0.397	UPO_7	0.135

Spessartine (HS112.3B)	0.190	UPO_8	0.100
Tourmaline (HS282.3B)	0.174	UPO_9	0.109
Zircon (WS522)	0.161	UPO_10	0.143

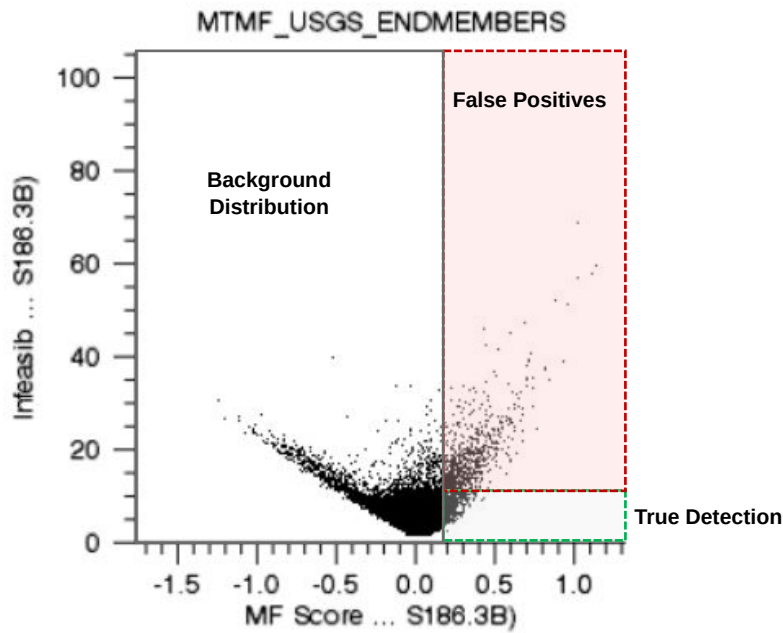


Figure 30 - Example of scatter plot between the MF and infeasibility score for the sillimanite endmember, showing the zones that relate to the background distribution, false positives and true detection.

7. Results

7.1. Structural Mapping

7.1.1. Sentinel-1 Sigma0 bands

After radiometric calibration in the preprocessing steps, the Sigma0_VV and Sigma0_VH bands were obtained, serving as the base for the subsequent band multiplication, so examining their original characteristics is important before the technique application (Fig. 31, 32).

Given that the Sentinel-1 was acquired in descending orbit, and the satellite typically operates in right-looking mode, it is expected that the Sigma0_VV band will emphasize lineaments aligned E-W, while the Sigma0_VH will highlight those aligned N-S. Although both bands share the same vertical transmitted polarization, they can distinguish similar lineaments and features in different directions. Furthermore, SAR data is highly sensitive to variations in surface roughness and textures, which is essential to identify geological lineaments since they are associated with more textured terrain around them.

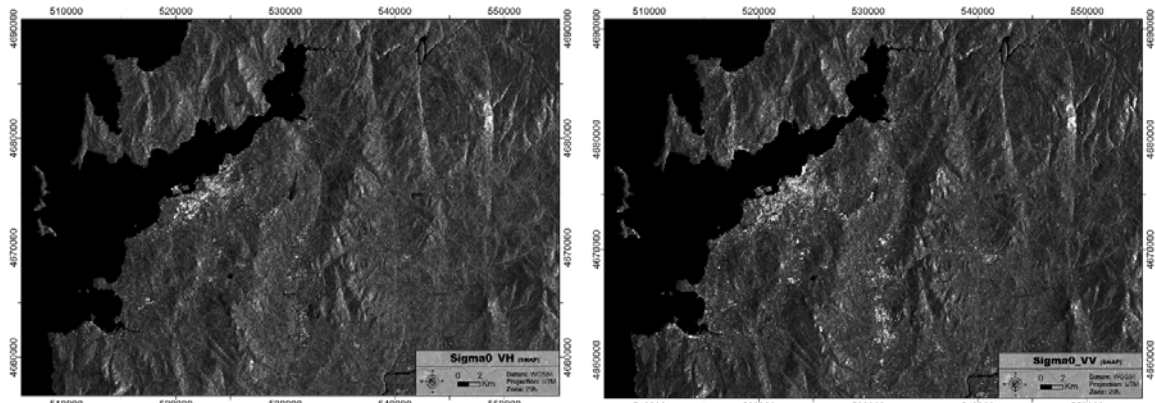


Figure 31 - Sigma0_VV and Sigma0_VH bands, obtained from Sentinel-1 data after preprocessing in SNAP.

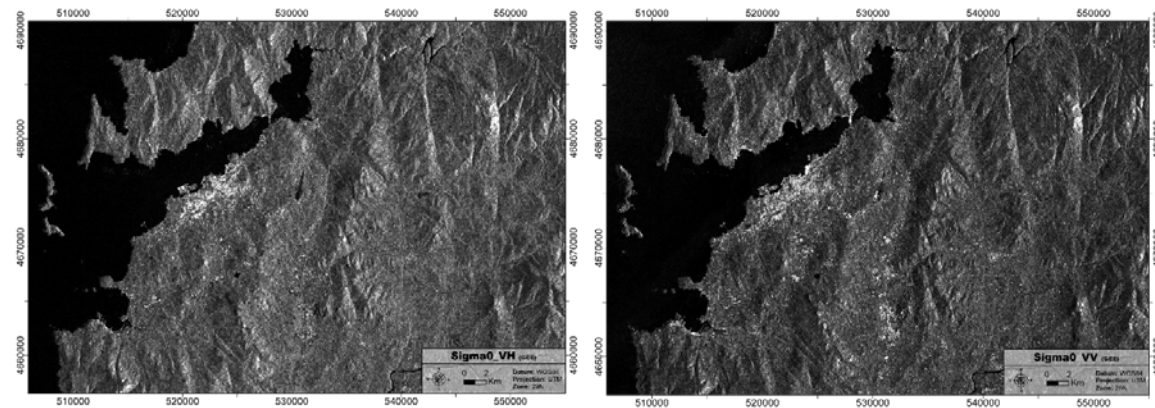


Figure 32 - Sigma0_VV and Sigma0_VH bands, obtained from Sentinel-1 data after preprocessing in GEE.

7.1.2. Band multiplication

After band multiplication, the final VV_x_VH and VV_x_VH_GEE bands were produced (Fig. 33, 34). These images effectively combined the information from both original bands, enhancing common features to both polarizations while highlighting lineaments in different orientations from both VV and VH polarizations, previously only visible in separate bands. By amplifying the signals of common lineaments, it provides an overall more accurate and balanced view of the lineament's location and directions. As a result, this band proved to be the ideal foundation for all further analysis since it offers a well-rounded and integrated representation of geological lineaments of interest.

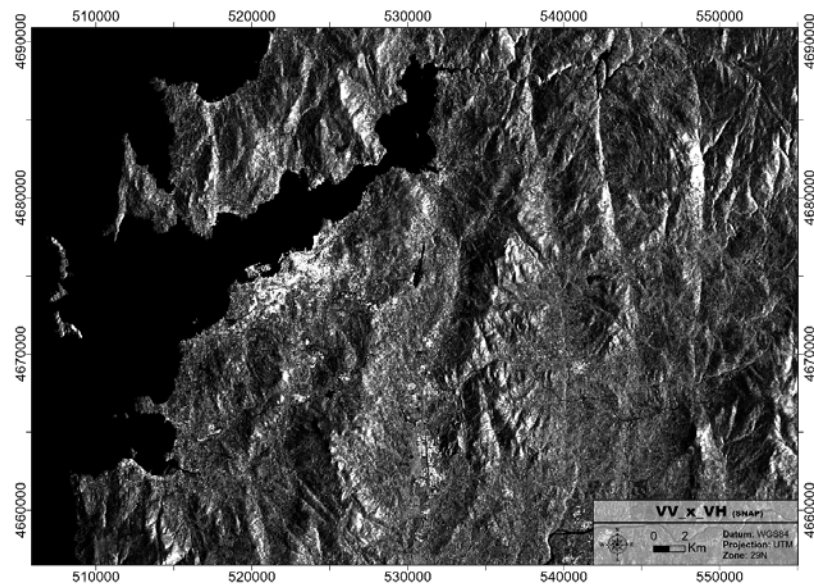


Figure 33 - VV_x_VH band, obtained in SNAP and used for manual extraction.

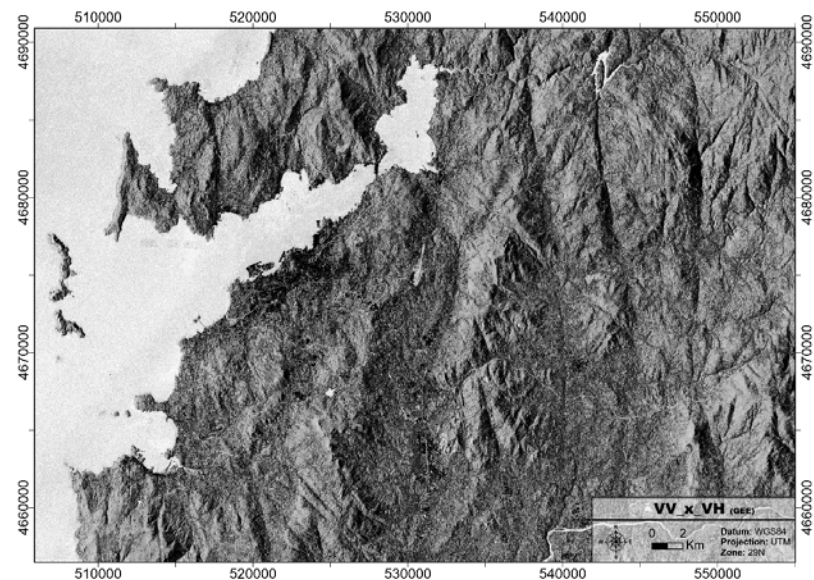


Figure 34 - VV_x_VH band, obtained in SNAP and GEE used for manual extraction.

7.1.3. Directional Filtering

After performing the Prewitt directional filtering, four grey-scale images were obtained (Fig. 35). Each filter effectively highlighted lineaments in N-S directions, including the two prominent geological faults on the eastern side of the map. While the N-S would be expected to enhance these faults better, it delivered the noisiest result among the four filters. Therefore, even though all four filters reveal the main lineaments, the best results were achieved with the NE-SW, NE-SW and E-W filters. Notably, the highlighted lineaments correspond to areas with significant altitude changes, which align with larger fault zones. However, when it becomes more challenging to detect smaller lineaments that do produce such pronounced contrasts in surface altitude and texture.

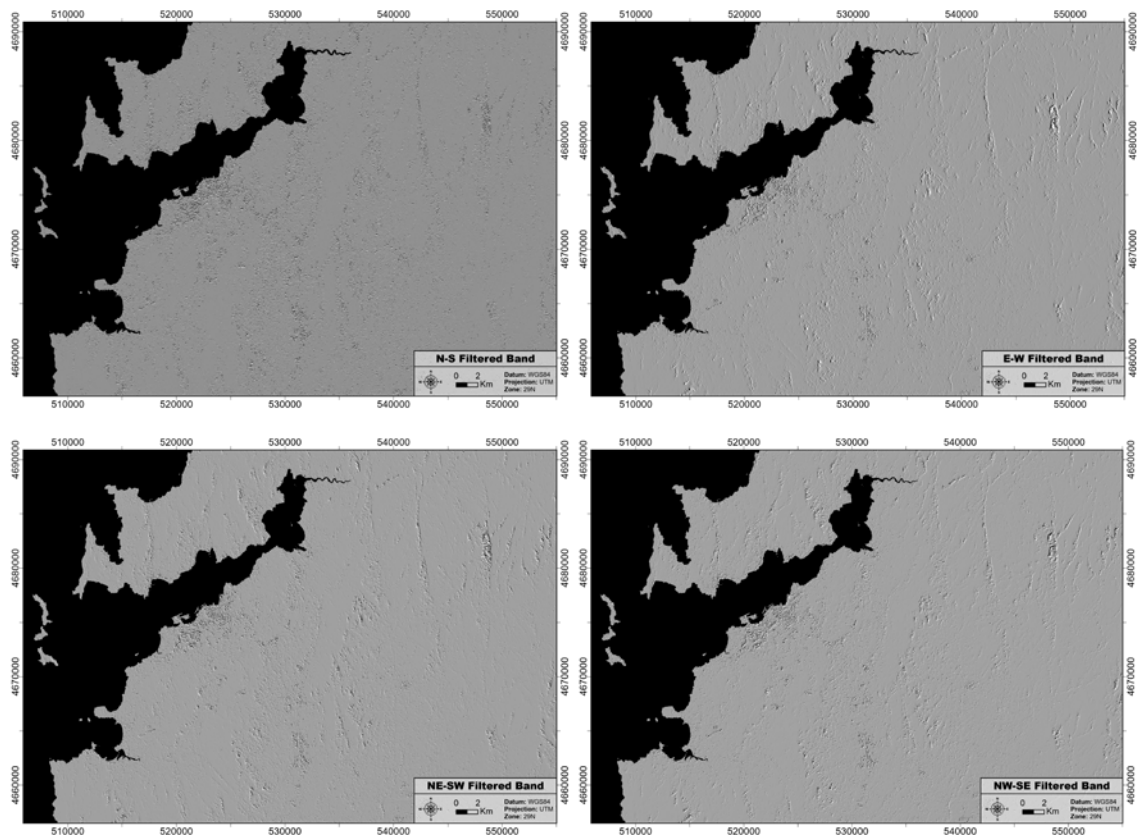


Figure 35 - Images resulting from Prewitt filtering: N-S (top left), E-W (top right), NE-SW (bottom left), and NW-SE (bottom right) filters.

The RGB combination of the best three filters is valuable because it displays the main lineaments in different hues, making them easier to manually detect (Fig. 36). When viewed in RGB, the smaller lineaments also become more visible, as it provides better visualization of surface roughness and variations throughout the entire image, rather than just around the most prominent lineaments. This approach also provided better visibility of contrast along the borders of lineaments. It can be concluded that displaying

the Prewitt filters in RGB colour space effectively aids precise extraction by providing additional visual information.

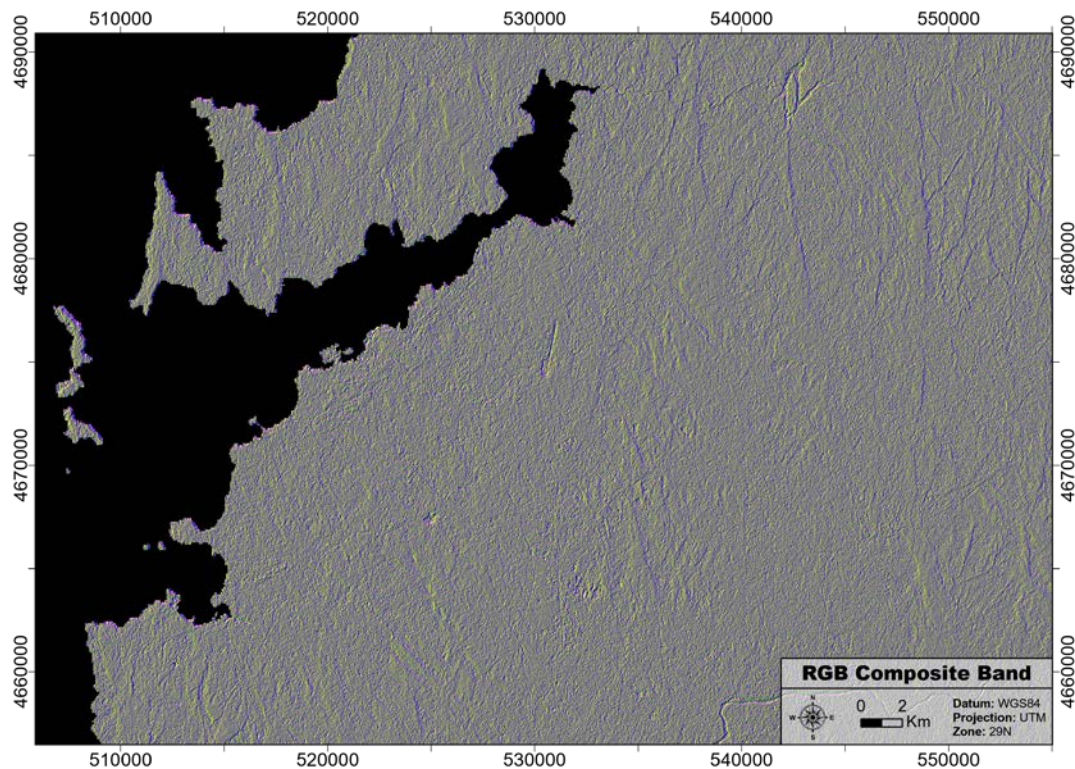


Figure 36 - RGB composite of the three best Prewitt filter bands.

7.1.4. K-Means Clustering

The K-Means combinations displayed very different results, depending on whether they were generated in SNAP software (Fig. 37) or GEE platform (Fig. 38).

For the manual results, combinations A and E showed a good ability to highlight topographical aspects. In combination A, slopes oriented to the east were classified as cyan and greenish clusters. In contrast, those oriented to the west were assigned purple clusters, making it easier to understand overall terrain conditions. Although combination E is similar to A, it did not offer such a clear visualization of structures. In both combinations, the clusters were distinctly assigned based on slope orientation, but the additional four clusters in combination E were not particularly beneficial for lineament mapping since they did not provide better visualization of the structures.

On the other hand, combinations B, C and D yielded different results than combinations A and E, with topography being less prominent. In combination B, structures are not very visible, and the clustering appears somewhat noisy. Higher altitudes were classified with a purple-blue cluster and lower altitudes with a green cluster. However, despite the

highlighted main geological lineaments, detecting finer details and smaller lineaments was not as straightforward and easy. Combination C, while similar to B, was less noisy. The worst results are observed in combination D since even longer lineaments were difficult to distinguish. This combination highlighted the main lineaments in darker green clusters, but the noise made it very challenging to visualize structures.

Combination F produced very good results, classifying longer and smaller structures in white clusters, leading to optimal visualization conditions. It also classified slopes facing W in purple clusters, giving additional insight into structural information. In this case, using 12 clusters in Combination F was more effective than the 8 clusters of Combination D, and the result was also different from Combination E, even when using the same input band.

For manual lineament extraction, combinations A and F were used for several reasons. Combination A is helpful in visualizing topographical aspects and changes in altitude, while combination F distinctly highlighted structures in white clusters, making them complementary for further analysis.

When comparing Prewitt filters to K-Means, K-Means images were easier to interpret and provided additional information, such as urban areas, which helps to create a more accurate result by excluding those regions. Additionally, K-Means made it easier to visualize structures than Prewitt filters. However, Prewitt filters can highlight specific orientations, while K-Means cannot. Nonetheless, K-Means appears to be a good method to apply for lineament extraction.

For the K-Means produced in GEE, the ones directly comparable to those generated in SNAP are combinations G, I, K and L. The K-Means classification yielded significantly different outcomes, even when using the same combination of parameters. However, a clear distinction remains between combinations that emphasize topography and those that do not, similar to SNAP results.

Overall, K-means classification in GEE produced noisier results, and the lineaments are less defined when compared to those from SNAP. Nevertheless, the most effective combinations were G, K and L, which correspond to the same parameters in SNAP as A, E and F, respectively. Once again, and just like in the SNAP results, the Combinations G and E provided valuable insights into topographical features. In contrast, Combination L enhanced the visibility of longer and shorter lineaments.

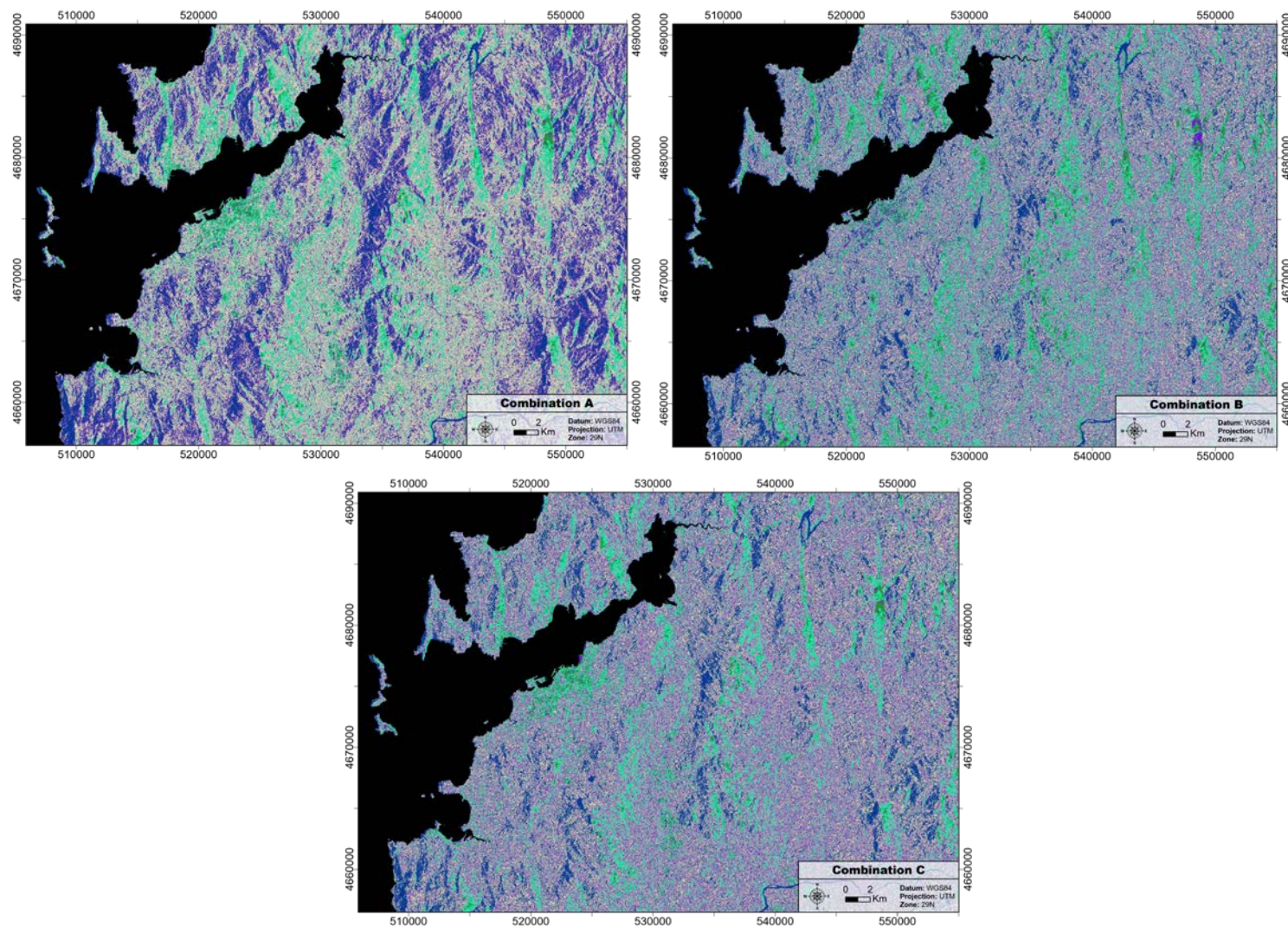


Figure 37 - Bands obtained from K-Means Combination in SNAP – Combination A to F

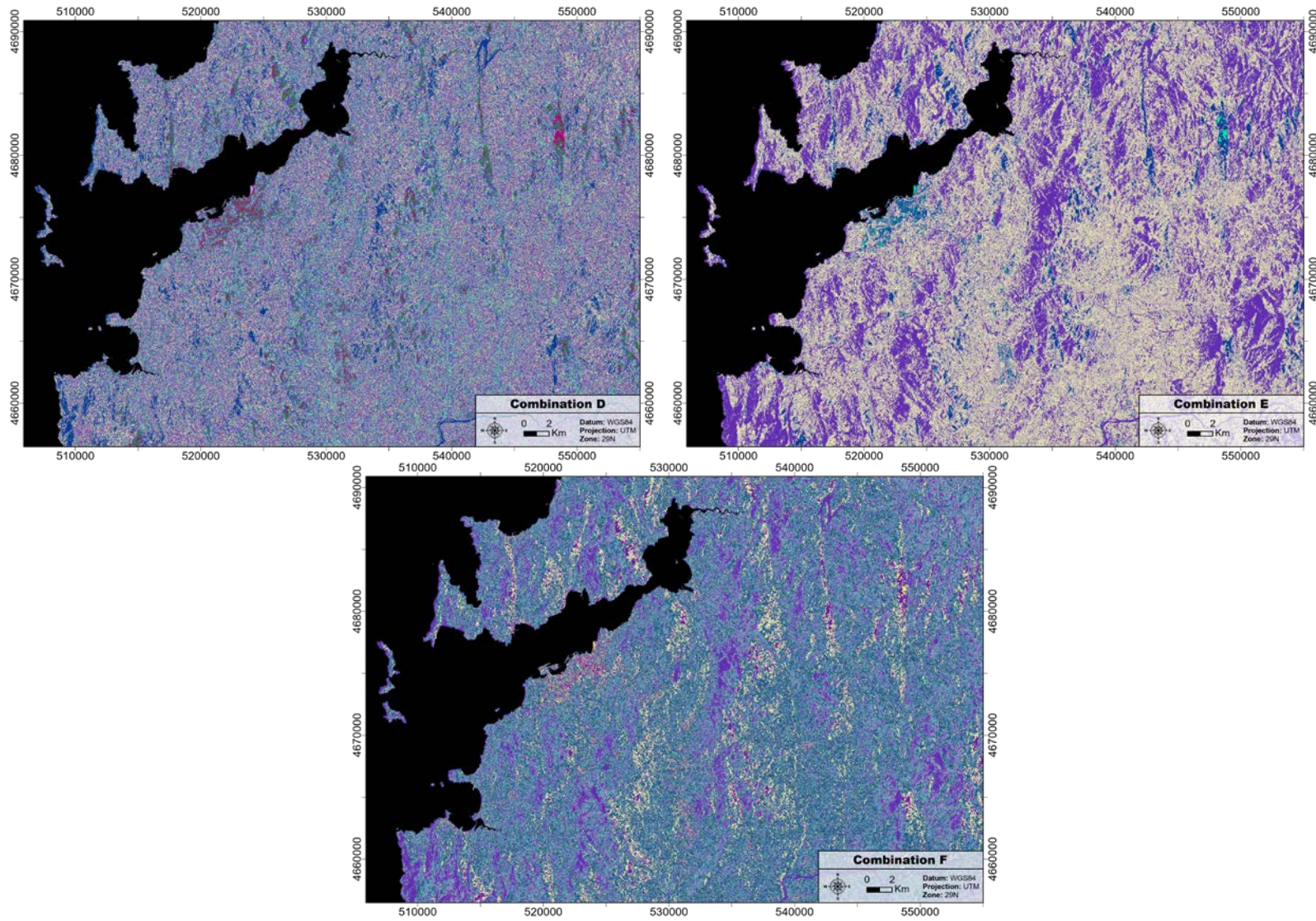


Figure 37 (cont.) – Bands obtained from K-Means Combination in SNAP – Combination A to F.

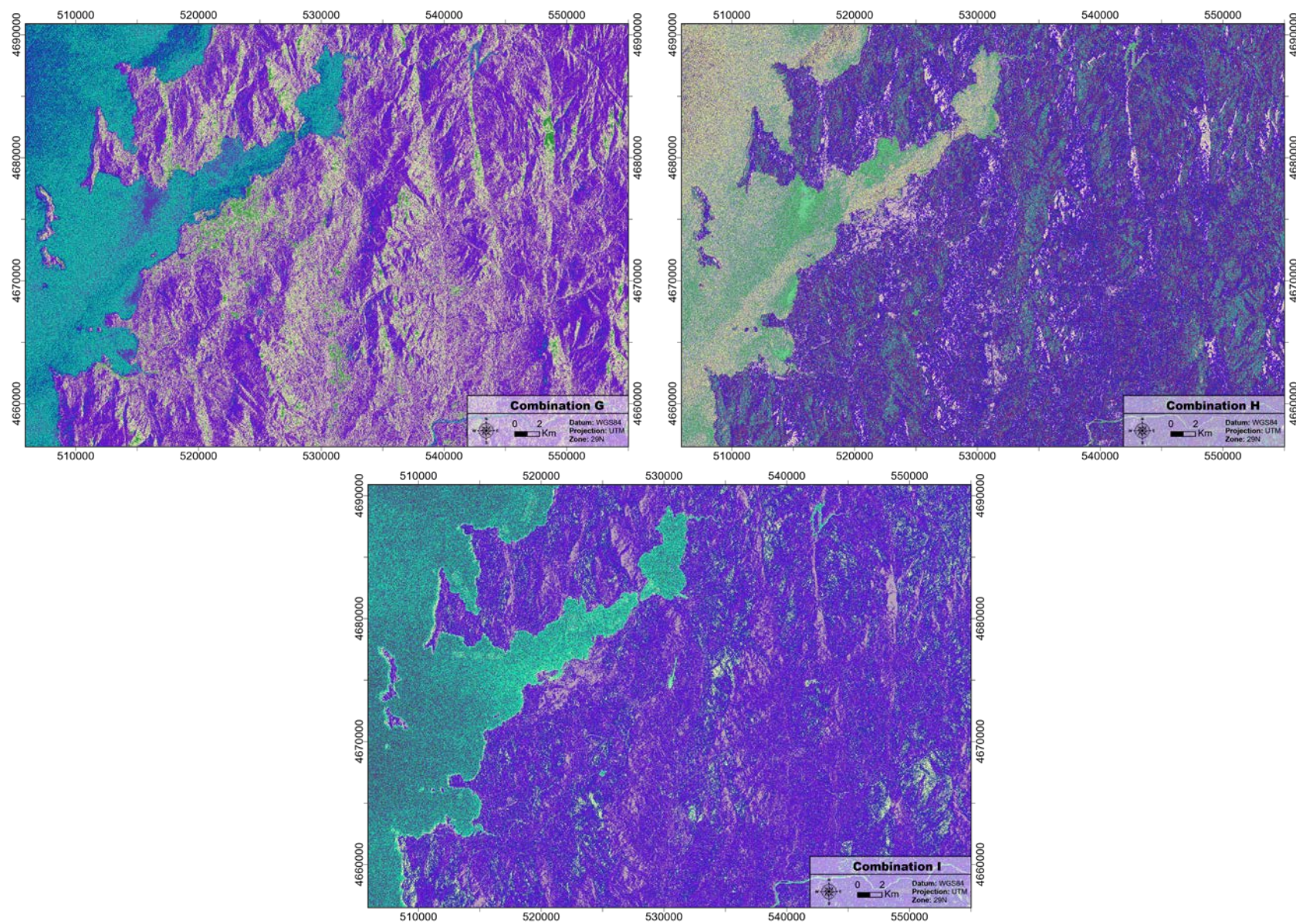


Figure 38 - Bands obtained from K-Means Combination in GEE – Combination G to L.

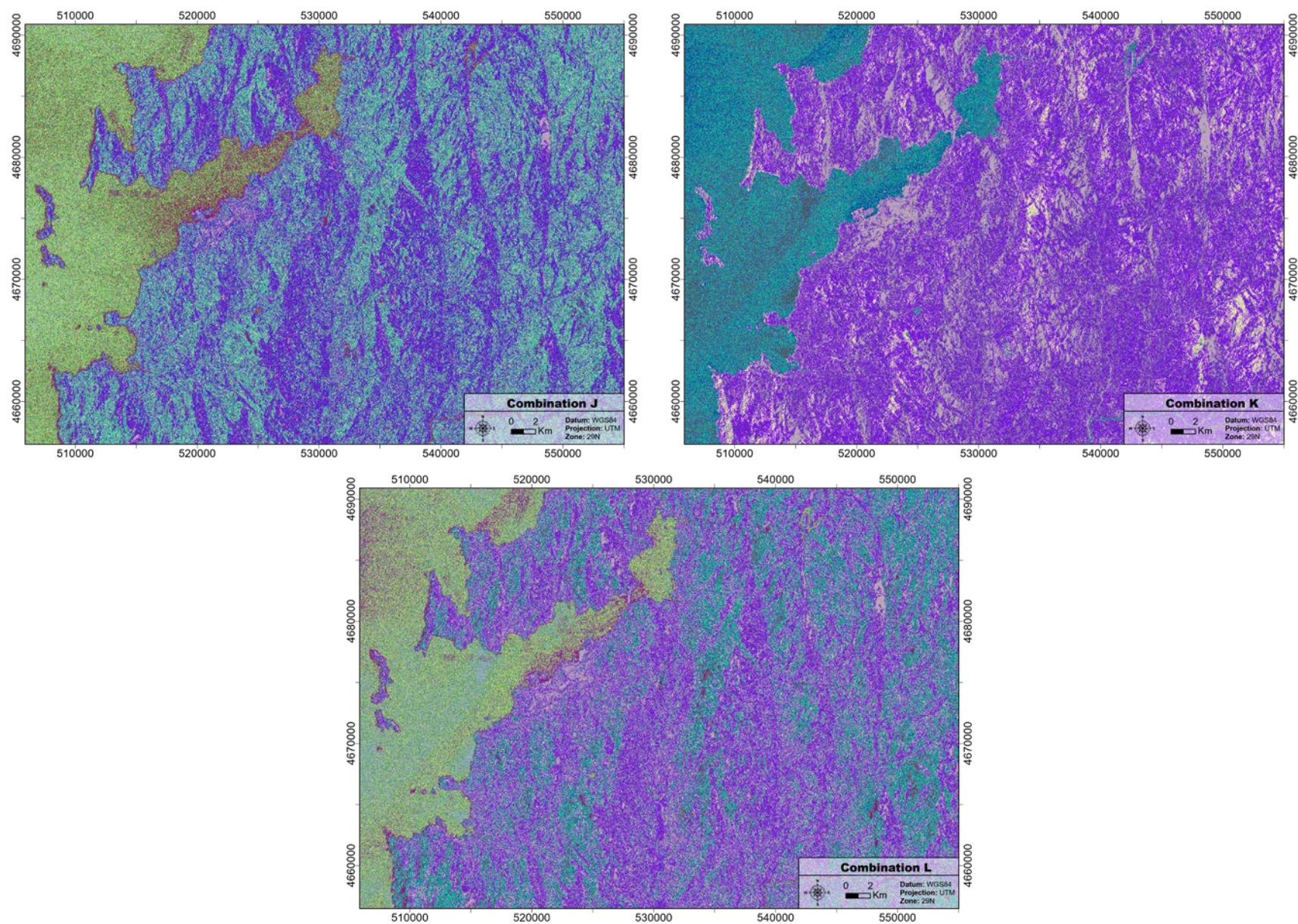


Figure 38 (cont.) – Bands obtained from K-Means Combination in GEE – Combination G to L.

In all combinations, whether produced in SNAP or GEE, the K-Means clustering method also highlighted urbanized areas and anthropic lineaments, such as the Vigo airport and roads, which can be beneficial when performing lineament extraction because it allows for quick differentiation between natural lineaments and man-made ones (Fig. 39).

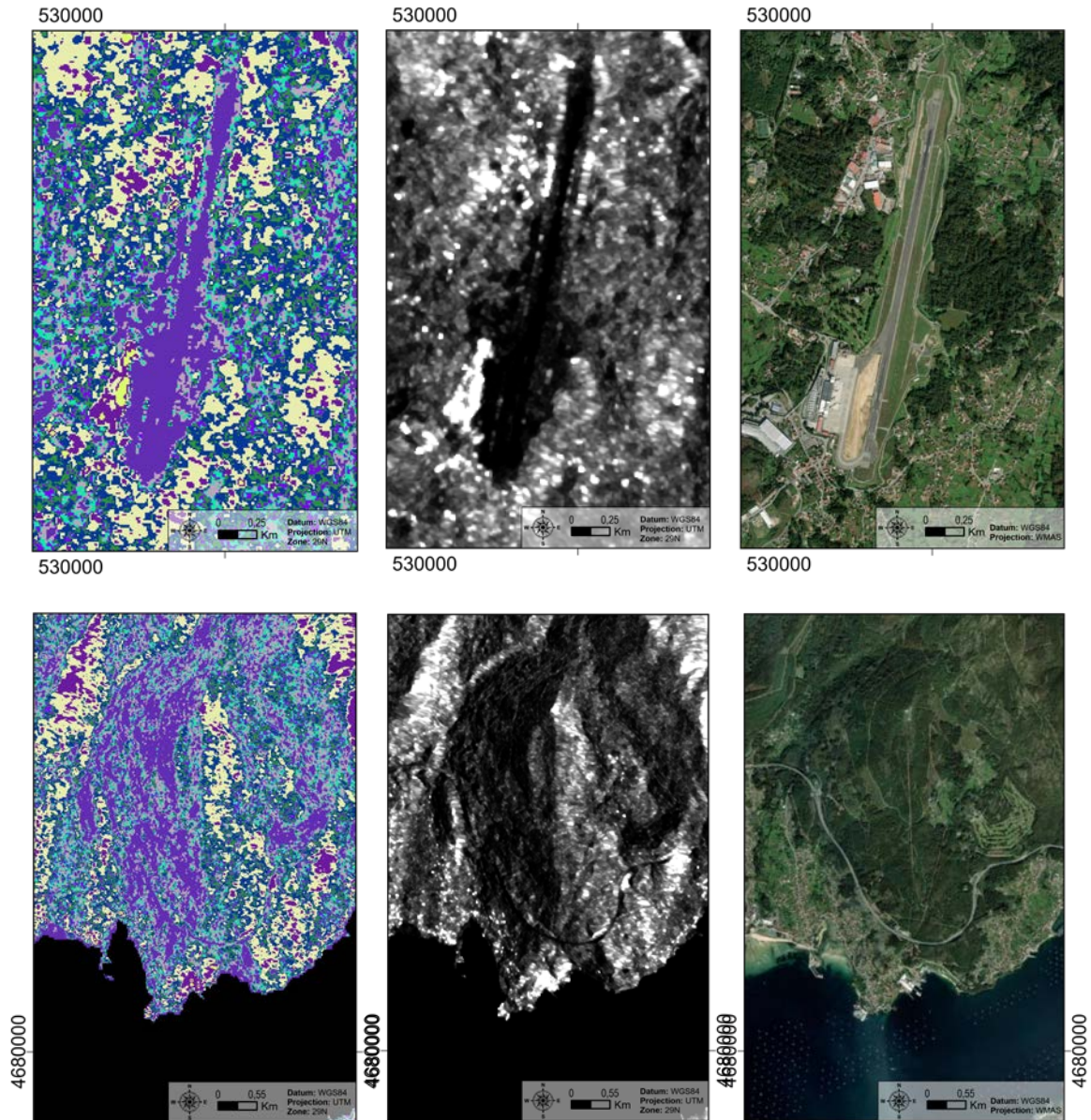
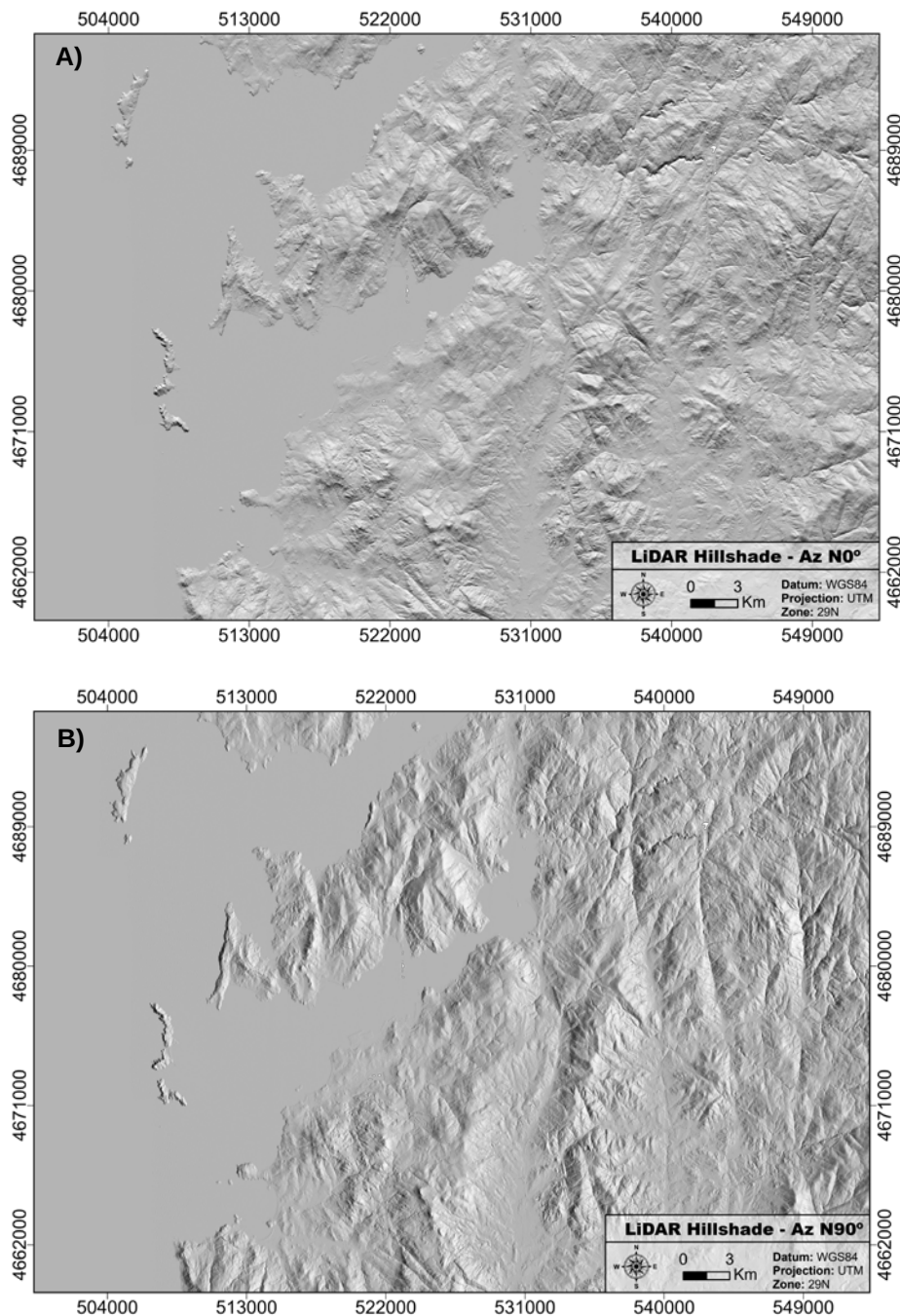


Figure 39 - Comparison of K-Means Combination F (left), with Sentinel-1 VV_x_VH band (middle) and ESRI Satellite Imagery (right), where it is possible to observe the differentiation of the Vigo airport (top) and roads (bottom) in the K-Means classification.

7.1.5. LiDAR Hillshading

The hillshading applied to the LiDAR DEM produced four distinct images emphasizing lineaments oriented in different directions. With these four images, it is possible to extract lineaments from all orientations (Fig. 40).

Comparing LiDAR and Sentinel-1 images, LiDAR provides more detail due to a higher spatial resolution. However, when displayed in a hillshade, areas of lower altitudes appear to have a smoother appearance than in Sentinel-1, making it harder to detect lineaments in those regions.



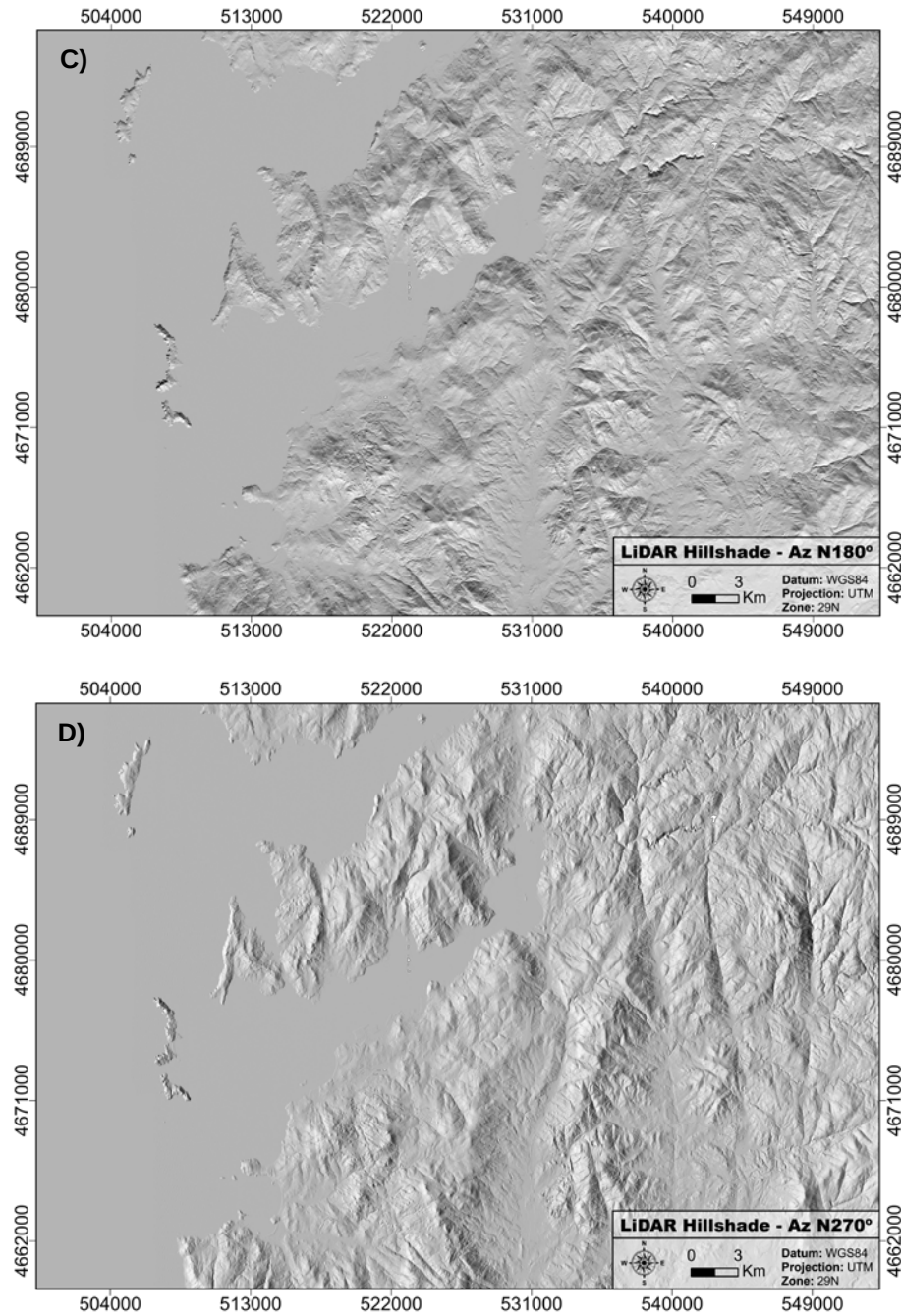


Figure 40 - Hillshades obtained from LiDAR DEM with different azimuths: A) N0°; B) N90°; C) N180°; D) N270°. Az – azimuth.

7.1.6. Lineament extraction

7.1.6.1. Lineament maps

The manual lineament extraction process produced 415 lineaments using the VV_x_VH band, 301 with the K-Means combinations (Fig. 41, A and B) and 3906 with the four LiDAR hillshades (Fig. 42).

While first observing the lineament maps, several key observations stand out. The results from the VV_x_VH and K-Means bands were relatively similar. Although the K-Means combinations produced fewer lineaments, the distribution pattern remained consistent, with the two prominent N-S geological faults being particularly evident, and a strong correlation between the other lineaments was maintained.

Compared to the lineaments extracted from the LiDAR hillshade, the LiDAR data produced a significantly more detailed result. However, there was still a noticeable correlation with the lineament's distribution pattern identified in the VV_x_VH and K-Means band.

Overall, the automatic extraction process expectedly resulted in a much higher number of lineaments than the manual methods.

Specifically, for Sentinel-1 data, 2327 lineaments were extracted from the VV_x_VH band (Fig. 43A), 1426 from the K-Means combination K (Fig. 43B) and 1065 from the K-means combination L (Fig.43C). Despite the higher lineament count, the overall distribution pattern remained consistent, even when compared to the manual extraction. However, it can be observed that the K-Means automatic extraction resulted in more curvilinear lineaments compared to those identified using the VV_x_VH band.

From the LiDAR data, the automatic extraction produced four sets of lineaments, which are different according to the azimuth of the hillshades. The hillshade with azimuth 0° produced 8407 lineaments (Fig. 41A), azimuth 90° produced 9392 lineaments (Fig. 41B), azimuth 180° led to 8419 lineaments (Fig. 41C) and azimuth 270° resulted in 9530 lineaments (Fig. 41D).

Hillshades with azimuths of 0° and 180° primarily highlighted E-W oriented lineaments, while the hillshades with azimuths of 90° and 270° led to the extraction of lineaments oriented mainly N-S. Although azimuth parts 0°-180° and 90°-270° highlighted lineaments in the same directions, there are subtle variations between them. For instance, some lineaments detected in hillshade with azimuth 180°, at the left corner of the map, are not detected in the azimuth 0°. Similarly, the 90° and 270° hillshades

showed differences, particularly in the map's lower left and right corners. These subtle variations are essential to detect lineaments.

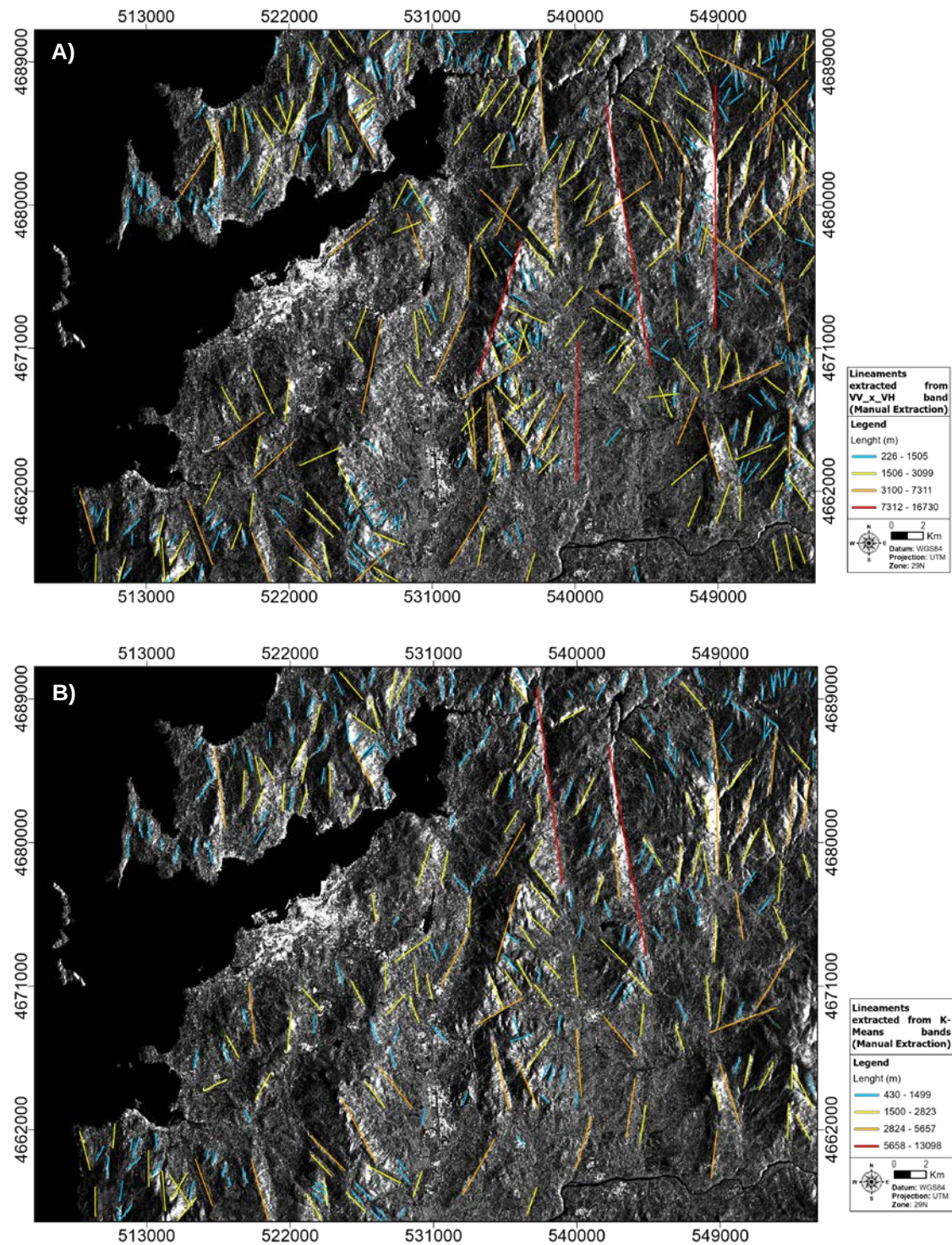


Figure 41 - Lineaments maps from manual extraction using Sentinel-1 data (colours according to the respective length). Lineaments extracted from A) the VV_x_VH band; B) from the K-Means combinations. NOTE: In the lineament maps of K-Means classification, the basemap is the VV_x_VH band, exclusively for visualization purposes.

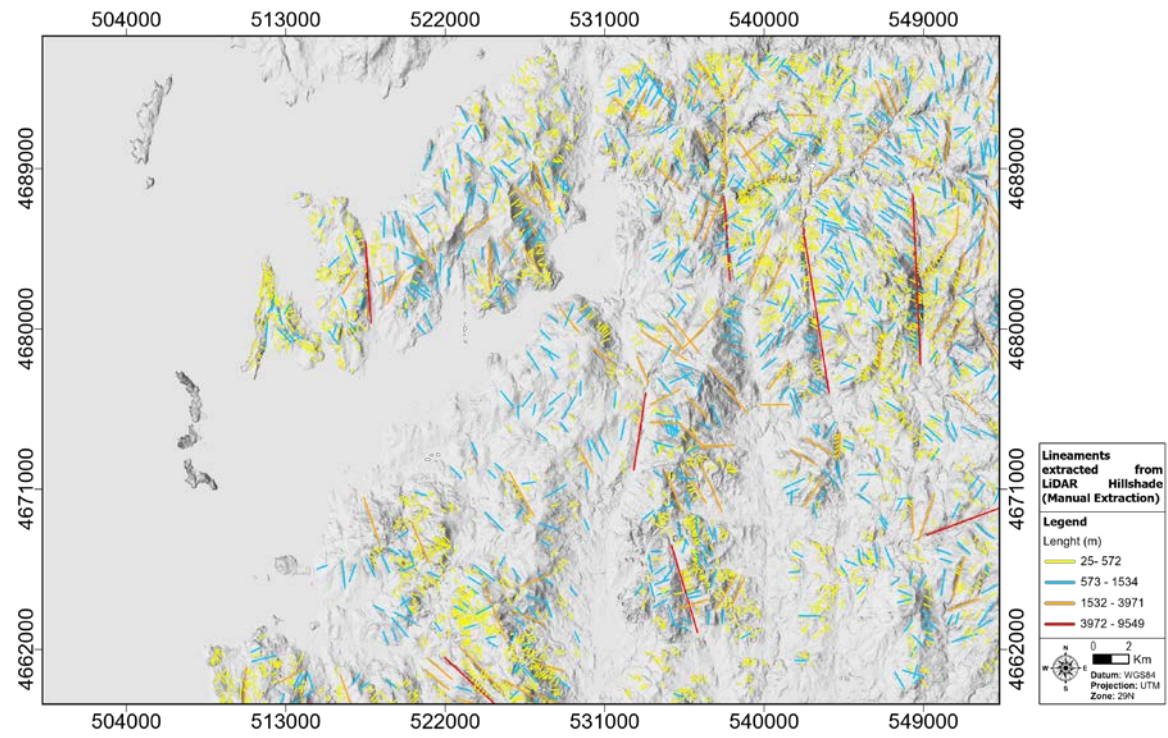
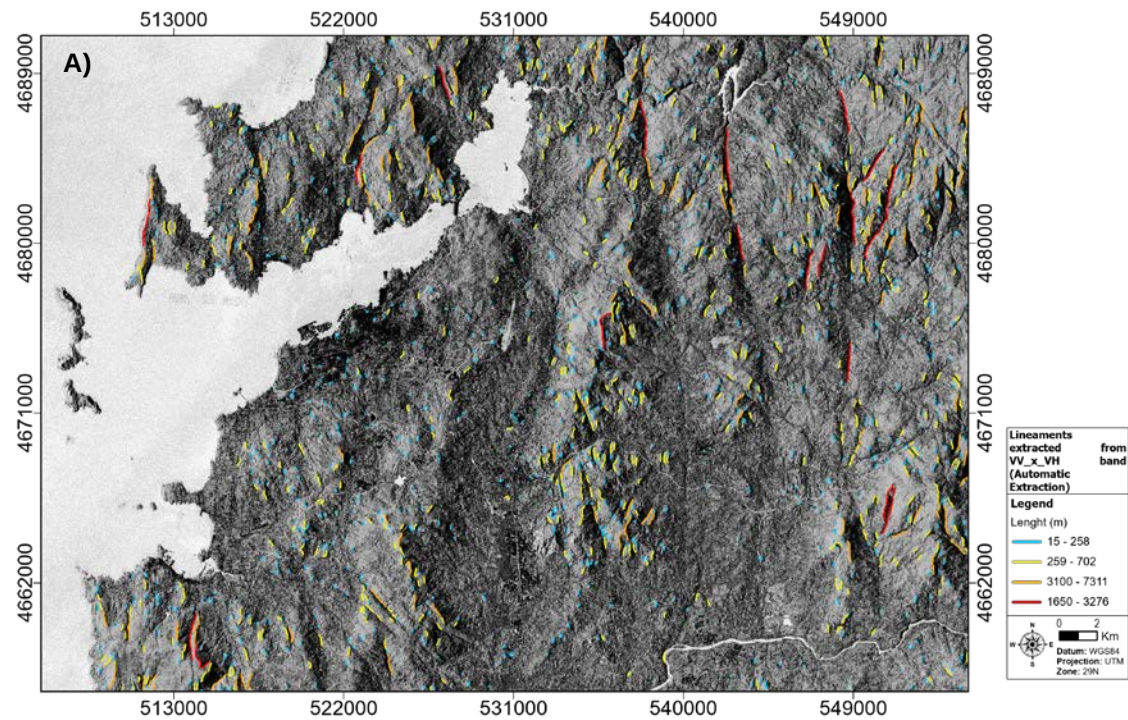


Figure 42 - Lineaments maps from manual extraction using LiDAR data (colours according to the respective length).



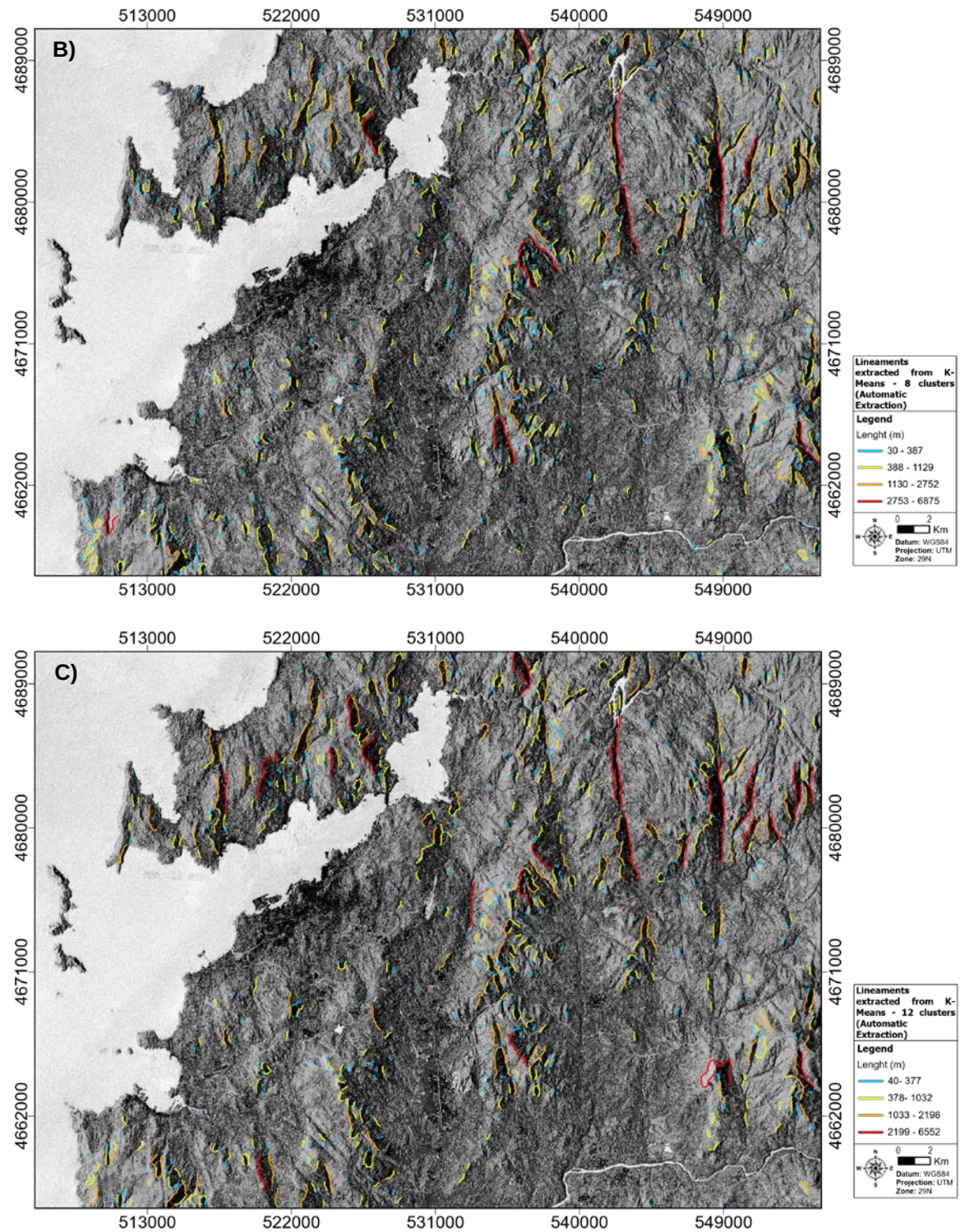
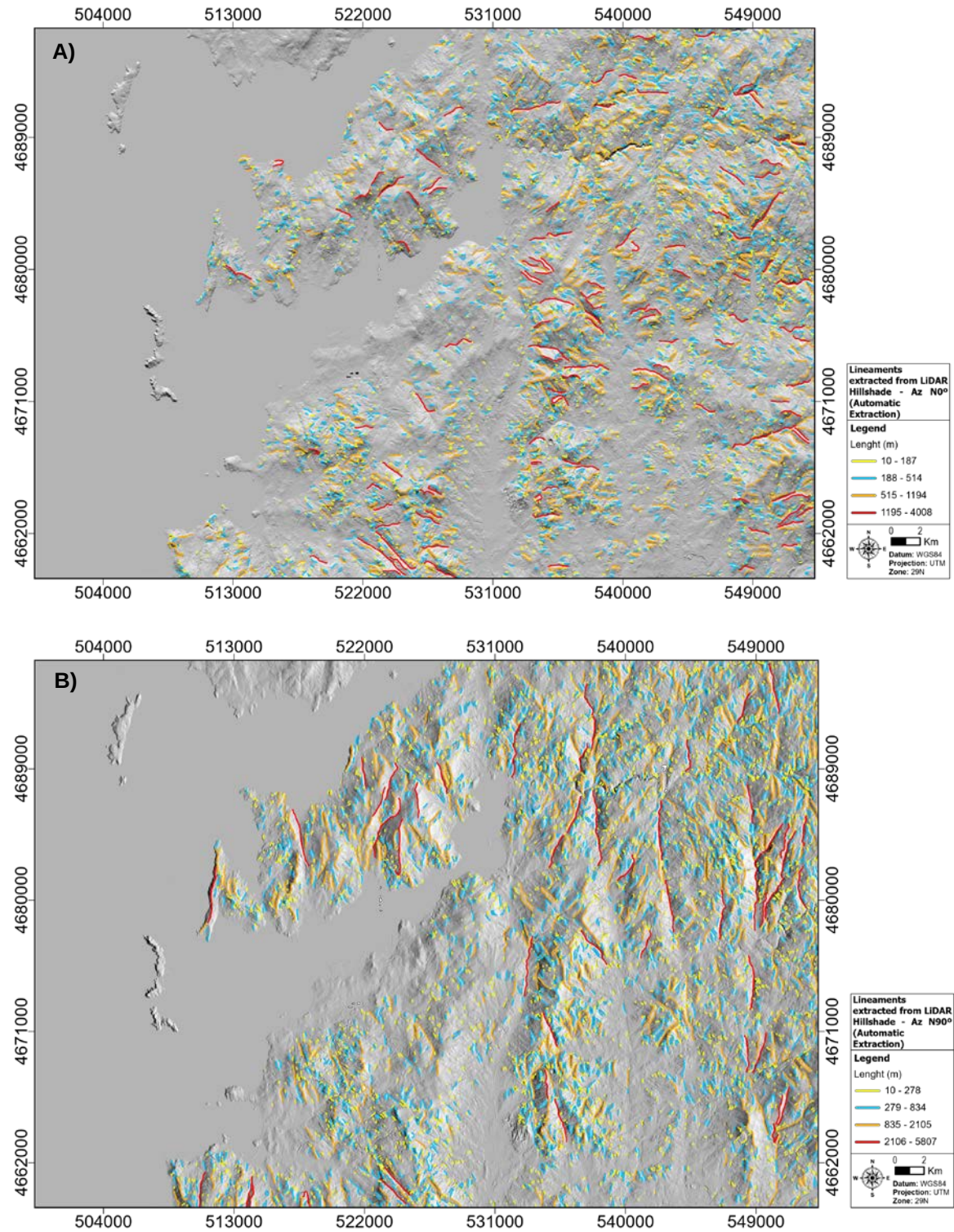


Figure 43 - Lineaments maps from automatic extraction, using Sentinel-1 data (colours according to the respective length). Lineaments extracted A) from the VV_x_VH_GEE band; B) from the K-Means Combination K; C) from the K-Means Combination L. NOTE: In the lineament maps of K-Means classification, the basemap is the VV_x_VH_GEE band, exclusively for visualization purposes.



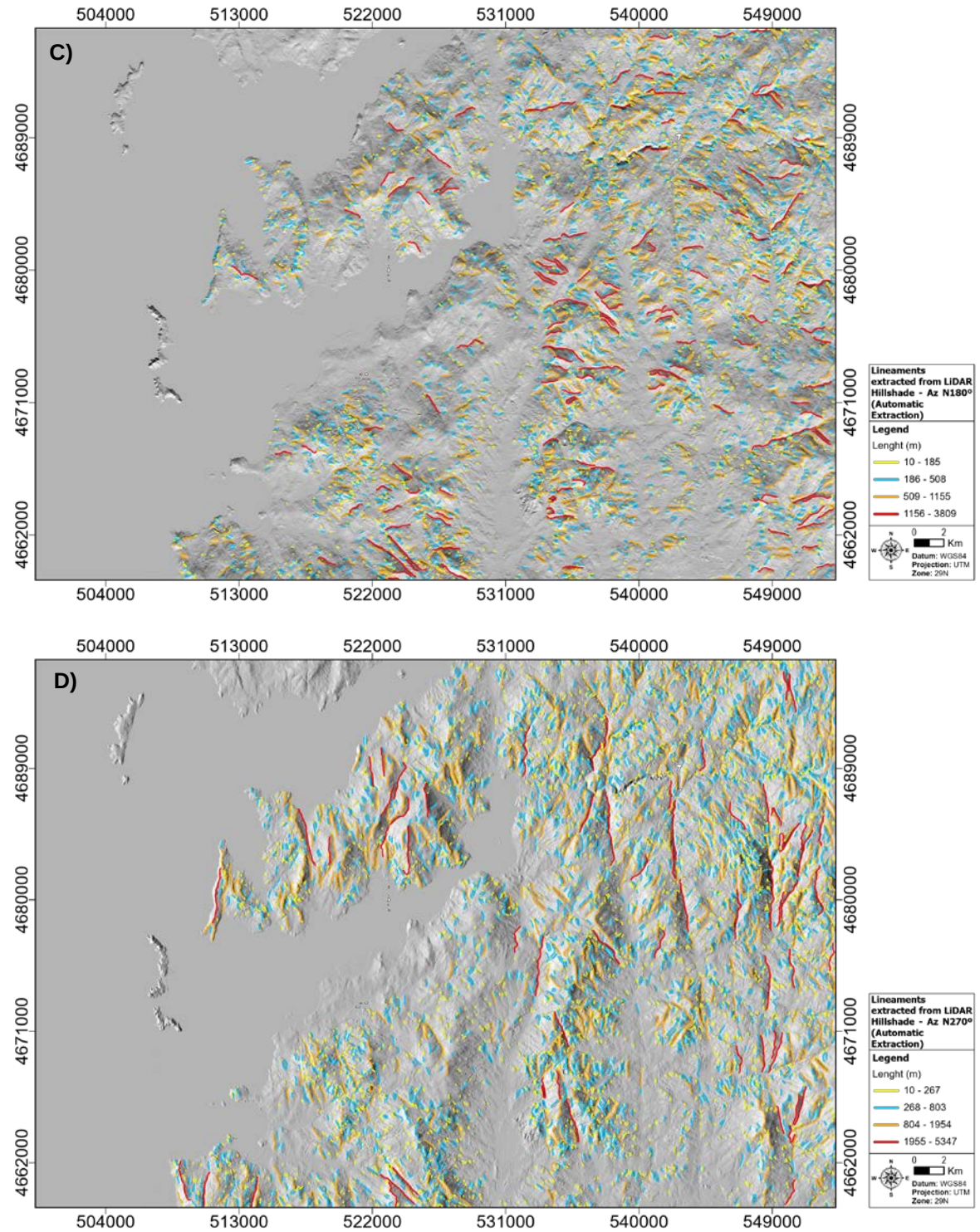


Figure 44 - Lineament maps from automatic extraction using LiDAR data (colours according to the respective length). Lineaments extracted from hillshade produced with A) azimuth N0°; B) azimuth N90°; C) azimuth N180°; D) azimuth N270°. Az – azimuth.

7.1.6.2. Rose diagrams of extracted lineaments

The orientation of the extracted lineaments was displayed in rose diagrams (Fig. 42) for all extractions and compared with the geological lineaments depicted in the Geological Map of Spain at a scale of 1:50 000.

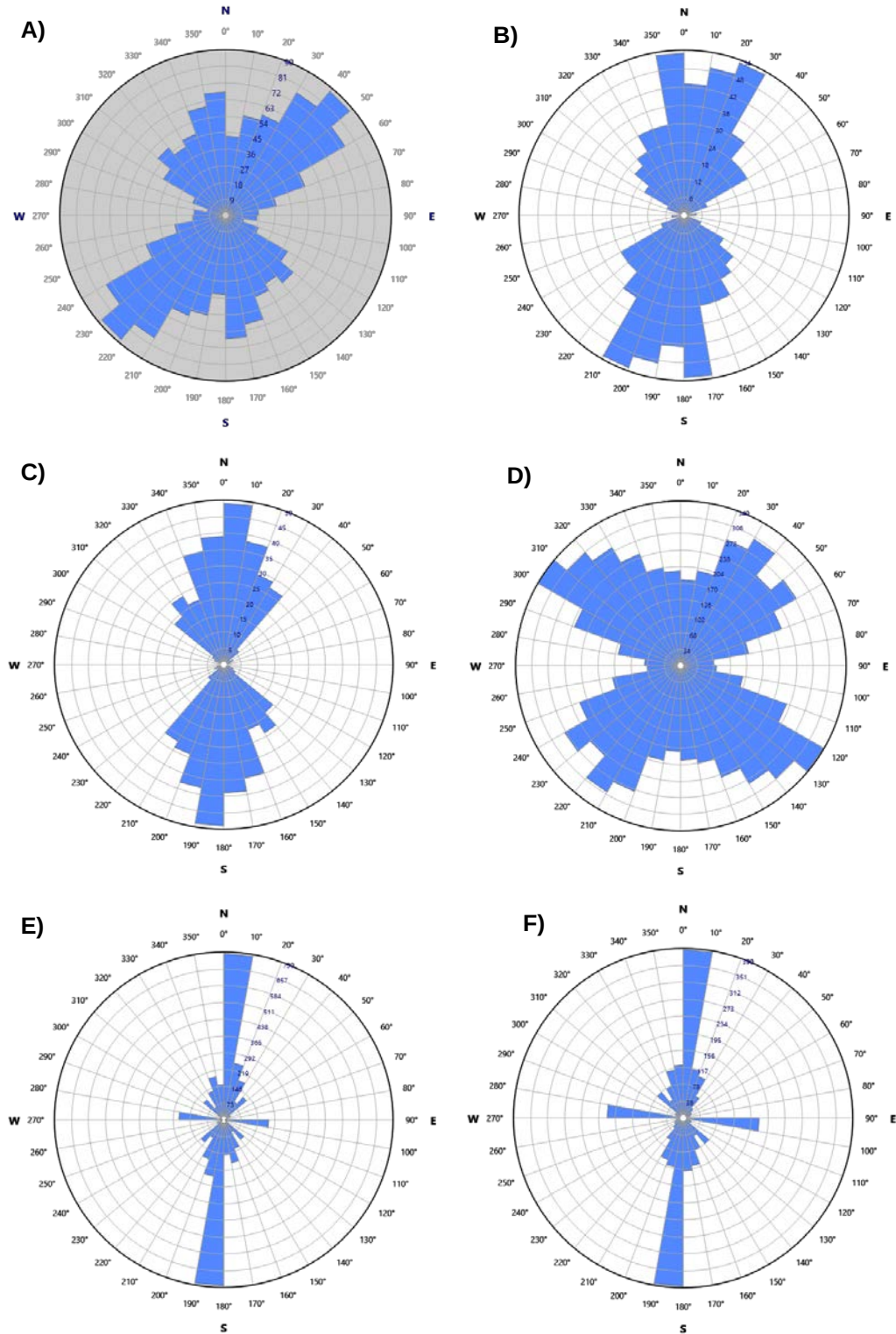


Figure 45 (cont.).

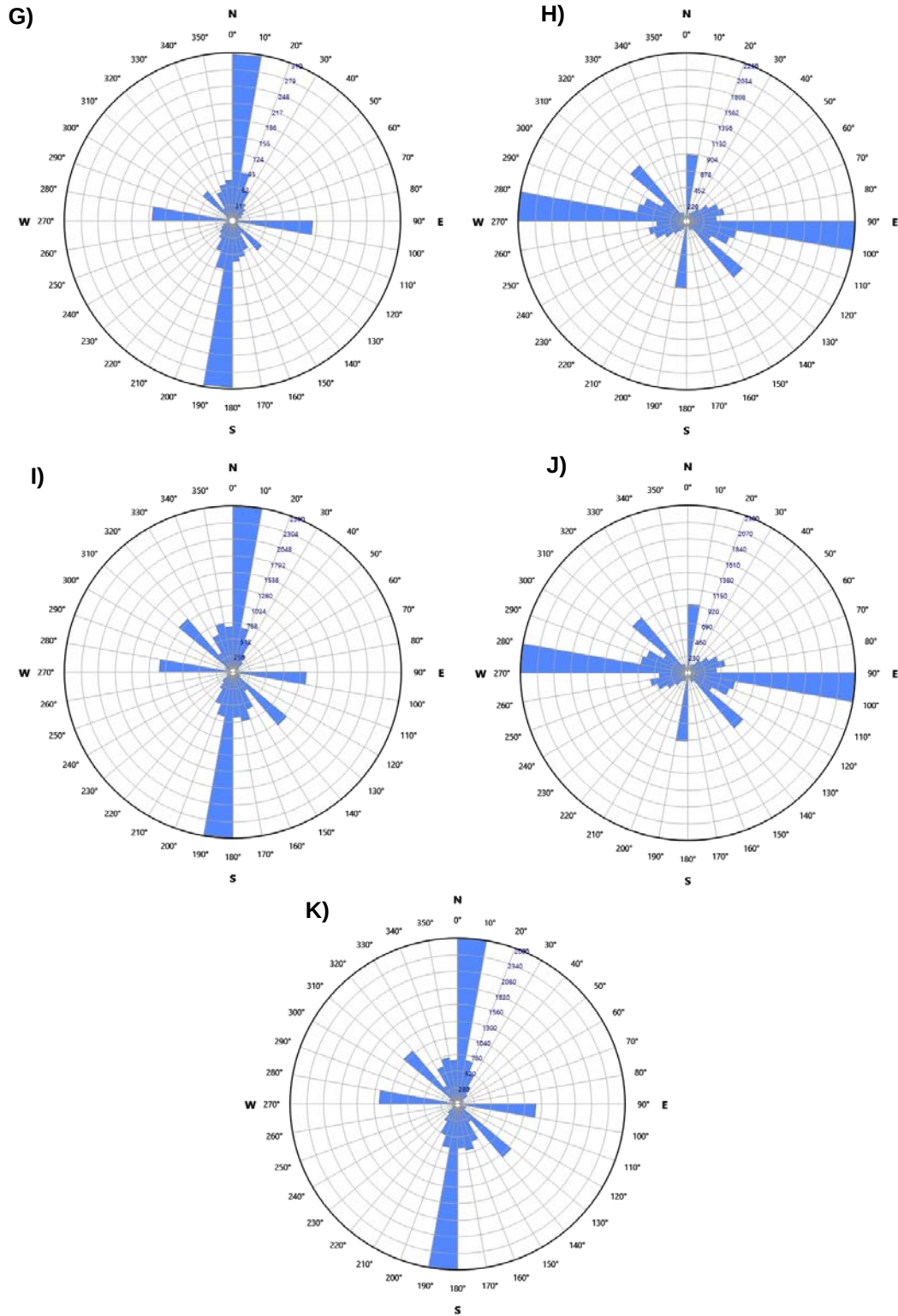


Figure 45 - Rose diagrams of the extracted lineaments. Rose diagram of the lineaments A) from the MAGNA 50 – Geological Map of Spain, at a scale of 1:50 000. B) manually extracted from the VV_x_VH band; C) manually extracted from K-Means combinations; D) manually extracted from the LiDAR-derived Hillshade; E) automatically extracted from the VV_x_VH_GEE; F) automatically extracted from the K-Means Combination K; G) automatically extracted from K-Means Combination L; H) from the LiDAR-derived hillshade produced with azimuth N0°; I) from the LiDAR-derived hillshade produced with azimuth N90°; J) from the LiDAR-derived hillshade produced with azimuth N180°; K) from the LiDAR-derived hillshade produced with azimuth N270°.

The primary trending orientations are NE-SW and N-S, with NW-SE being less prominent.

In the case of manual extraction, the VV_x_VH band yielded results similar to the K-Means extraction but showed slight differences when compared to the geological map lineaments. Specifically, the VV_x_VH band identified main orientations as nearly N-S (in the N0° to N10° range) and NE-SW, while the K-Means extraction predominantly highlighted N-S orientations. The LiDAR data also indicated NE-SW orientations and introduced the additional NW-SE orientation.

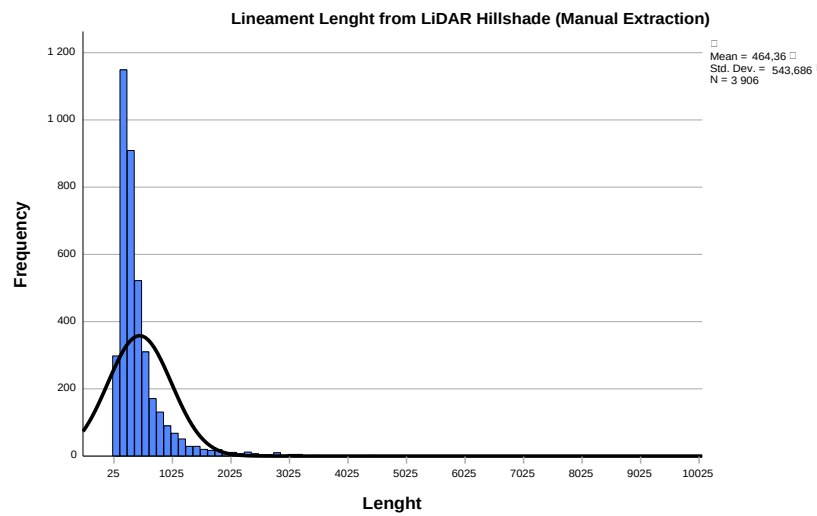
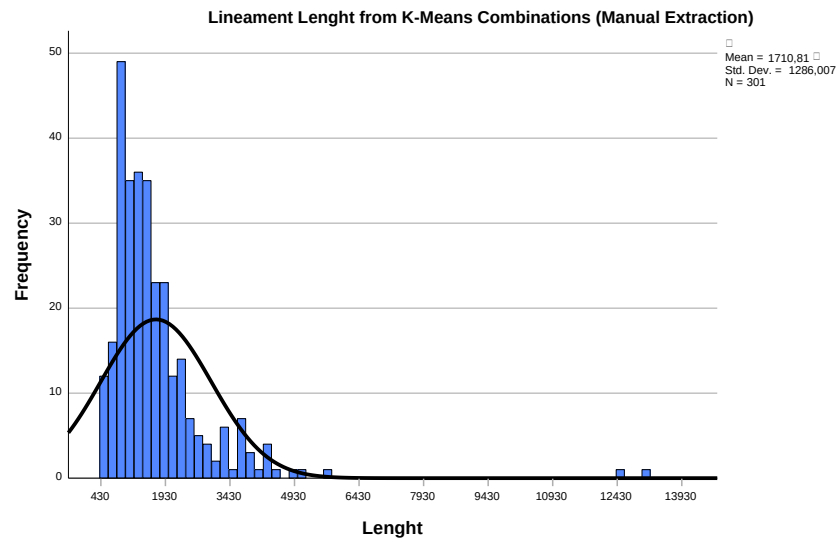
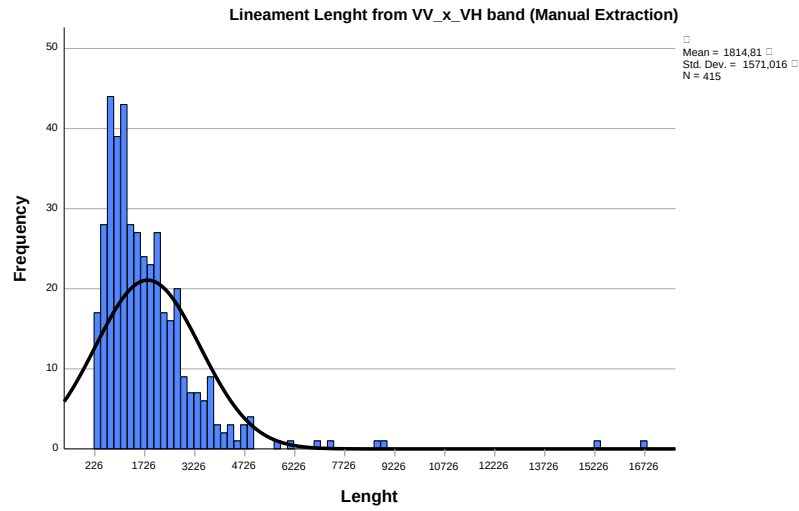
For automatic extraction, using Sentinel-1 bands, the VV_x_VH predominantly displayed a nearly N-S orientation, with a smaller E-W orientation. This pattern was also observed in the K-Means bands with 8 and 12 clusters, although the E-W orientation was more pronounced in the K-Means bands than in the VV_x_VH band. The automatic K-Means results are somewhat similar to the K-Means extraction, except that the E-W orientation was not as visible in the manual K-means extraction.

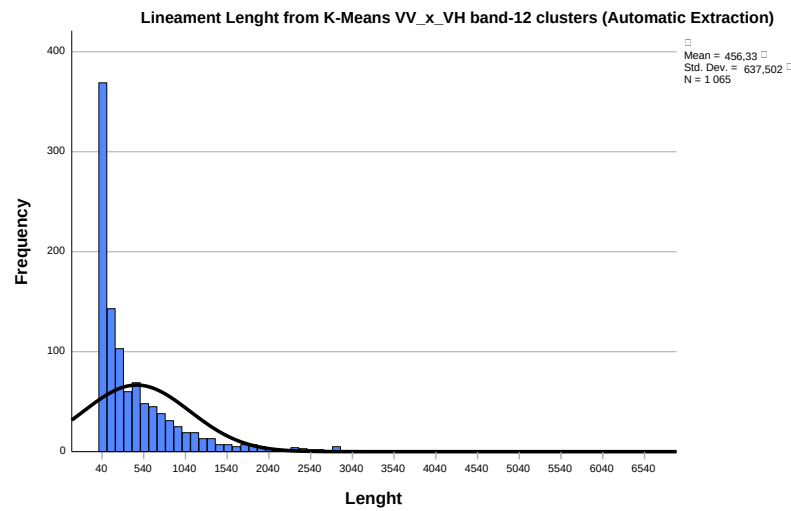
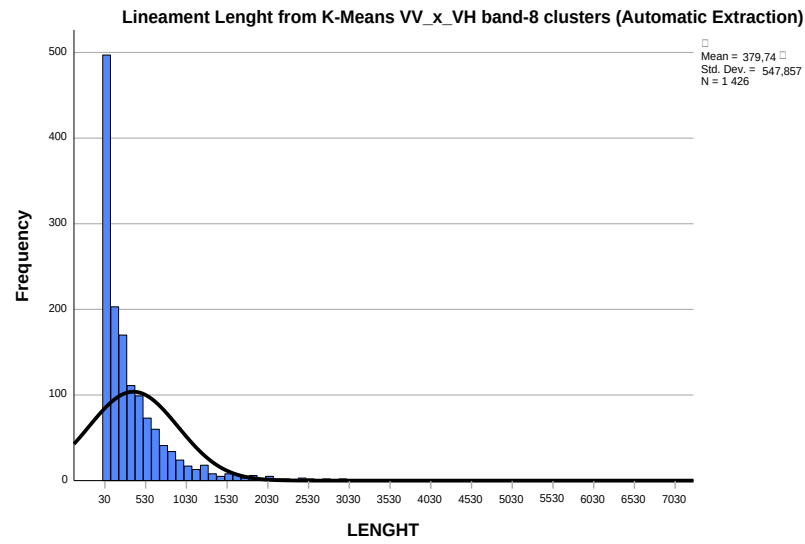
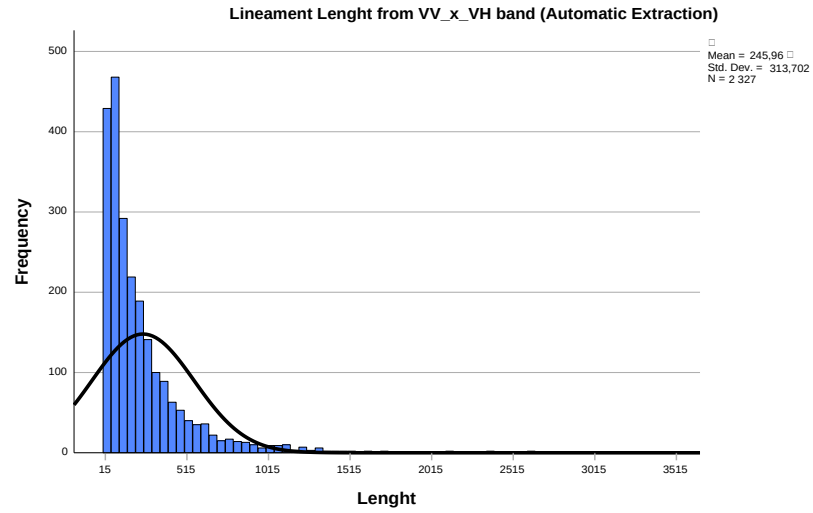
For the LiDAR data, the orientations vary according to the azimuth used on the hillshade. They were predominantly E-W for azimuths of 0° and 180° and primarily N-S for azimuths of 90° to 270°, with only a smaller number of lineaments oriented NW-SE. This is well aligned with the overall lineament distribution observed on the lineament maps.

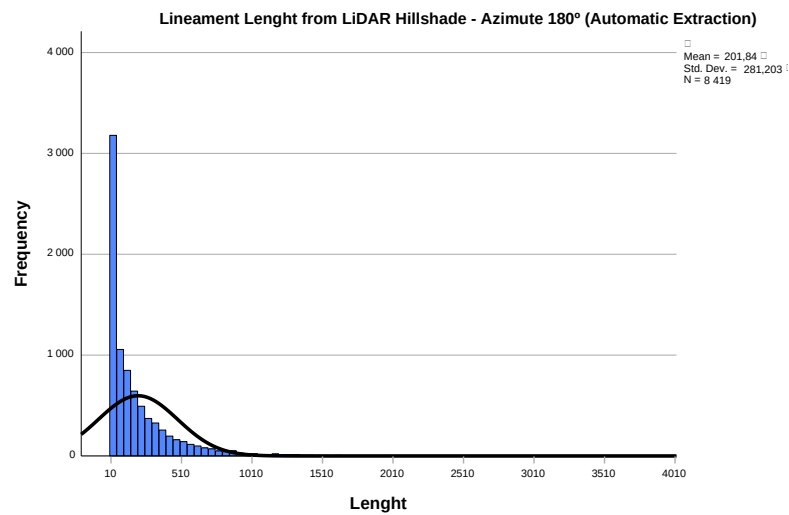
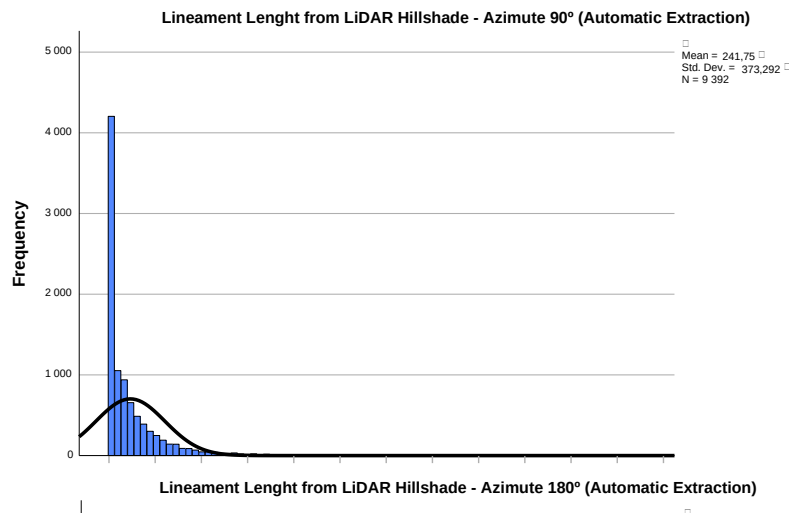
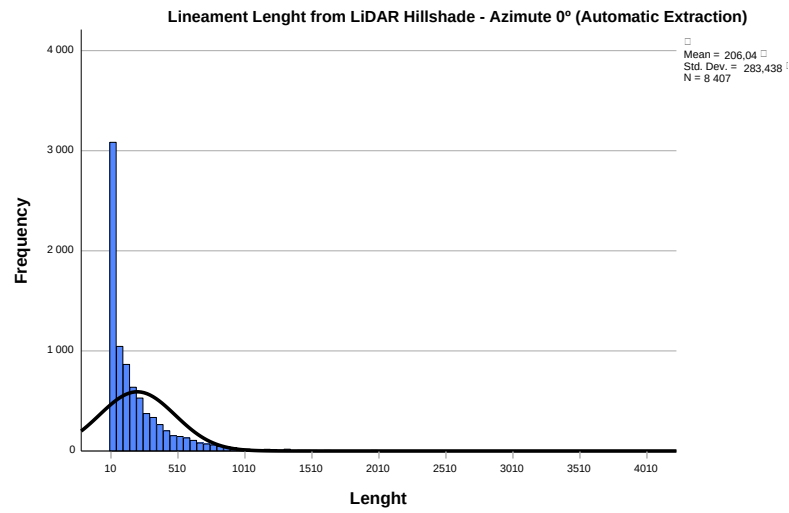
Overall, the extraction most similar to the lineaments on the geological map is the manual LiDAR extraction. However, all other extractions are closely correlated and show no significant discrepancies. The predominant orientations across all extractions are N-S (in the range of N0° to N10°) and NE-SW (from N20° to N60°), with NE-SE being present but less prominent.

7.1.6.3. Length analysis of extracted lineaments

Although the pattern of the lineaments appears to be the same, the lengths differ. The length of lineaments was analysed in histograms (Fig 46). The smallest lengths were obtained from the LiDAR data, both in manual and automatic extractions, with the automatic yielding even smaller lengths. On the other hand, the longest lineaments were observed in the manual extraction using the VV_x_VH band and the K-Means combinations. Overall, automatic extraction produced the smallest lineaments. The medium and median lengths, as well as the minimum and maximum lengths are provided in Table 11.







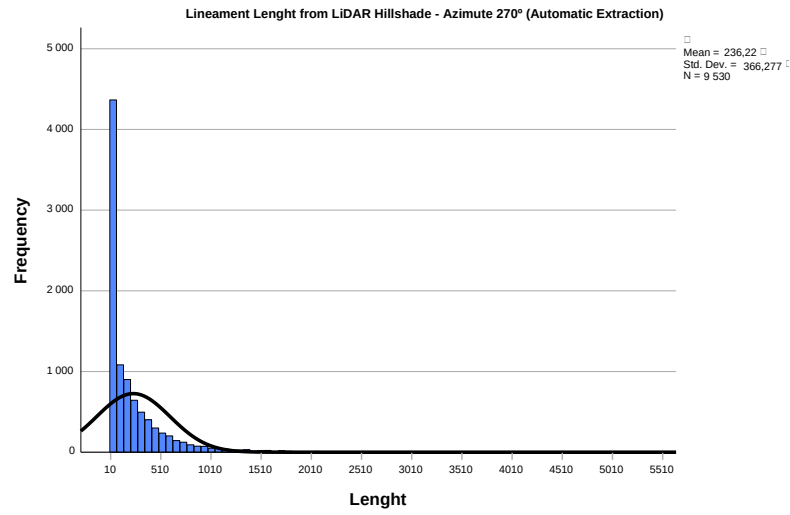


Figure 46 - Histograms of the lengths of lineaments, with standard deviation curve, as well as calculated number and mean.

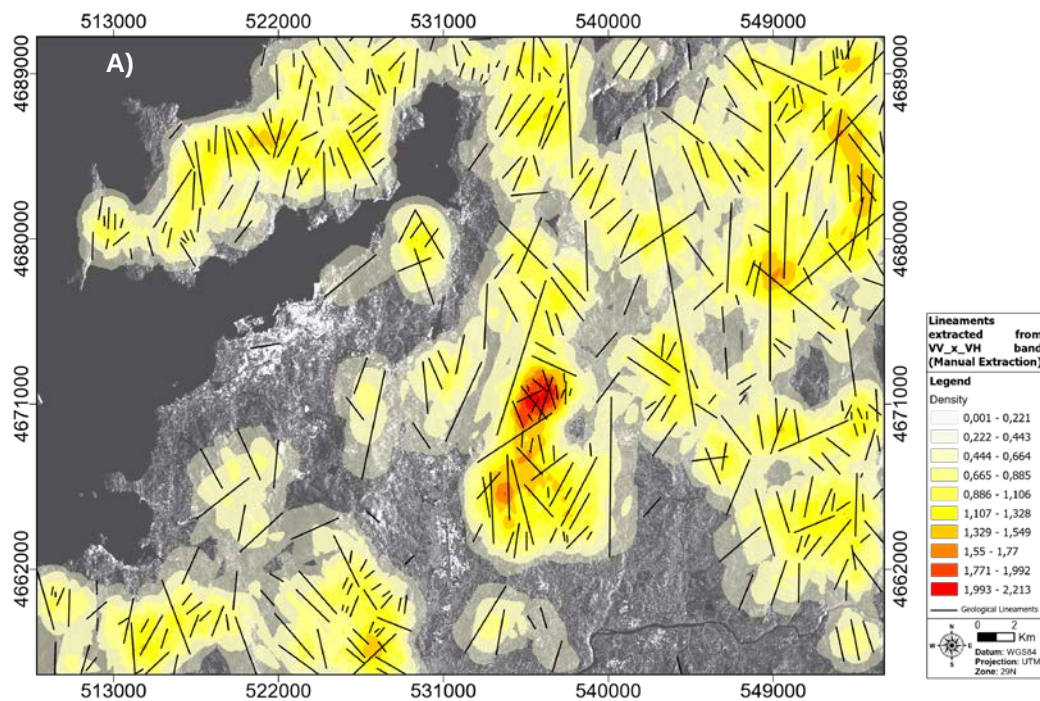
Table 11 - Table describing the type of analysis, the input data used, and comparison of the number of lineaments extracted from manual and automatic methods. Additionally, it includes a comparison of the total length of lineaments, as well as the minimum (Min), maximum (Max), mean and median values for all extractions.

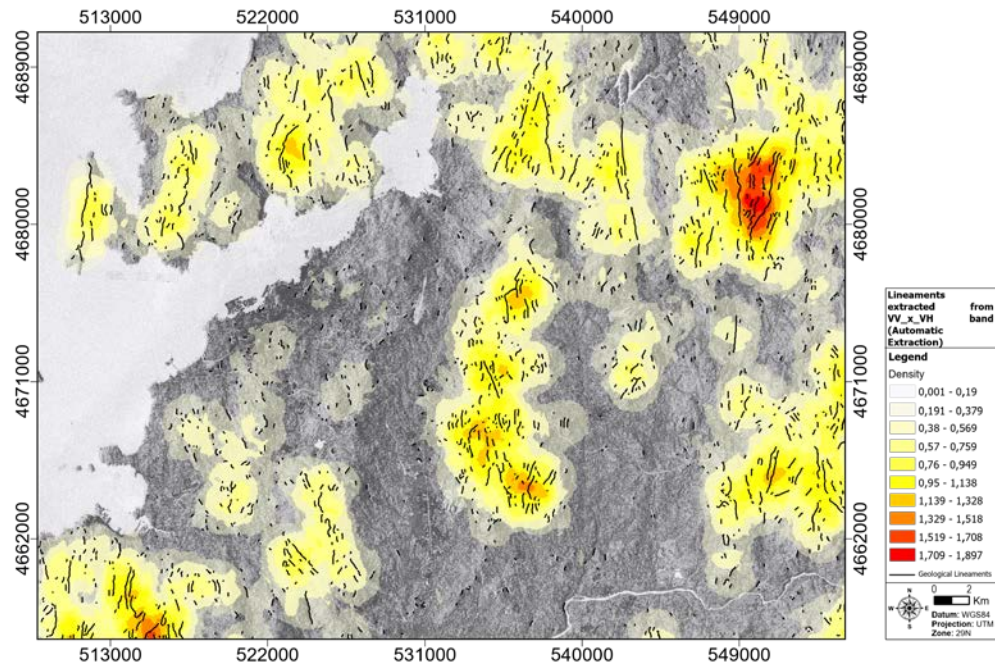
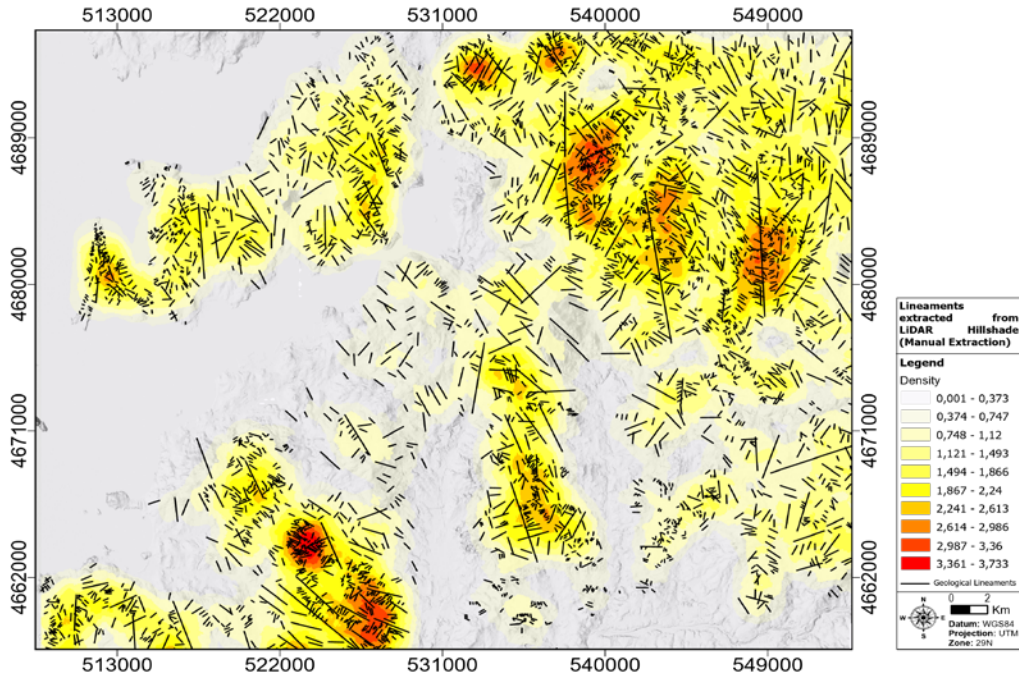
Type of Extraction	Input Data	Number of Lineaments	Length			
			Min	Max	Mean	Median
Manual	VV_x_VH band	415	226	16730	1814,812	1492
	K-Means Combinations	301	430	13098	1710,8073	1402
	LiDAR Hillshade	3906	25	9549	464,35945	313
Automatic	VV_x_VH band	2327	15	3276	245,95531	142
	K-Means VV_x_VH band (8 clusters)	1426	30	6875	379,74474	210
	K-Means VV_x_VH band (12 clusters)	1065	40	6562	456,32864	204
	LiDAR Hillshade (Azimute 0°)	8407	10	4008	206,03592	103
	LiDAR Hillshade (Azimute 90°)	9392	10	5807	241,74957	100
	LiDAR Hillshade (Azimute 180°)	8419	10	3809	201,83585	96
	LiDAR Hillshade (Azimute 270°)	9530	10	5347	236,22036	91

7.1.6.4. Density, lineament intersection and intersection density

The density and lineament intersections were analysed for only five of the ten extractions. The analysis focused on the manual VV_x_VH and LiDAR lineaments and the automatic VV_x_VH band LiDAR with hillshade azimuth of N0° and N090° (Fig. 47).

Across all density maps, a consistent pattern can be observed where the density is higher in the northeast part of the map, as well as in the centre massif and southwest region. Due to the higher number of lineaments produced in the LiDAR data, these maps show more extensive zones of increased density.





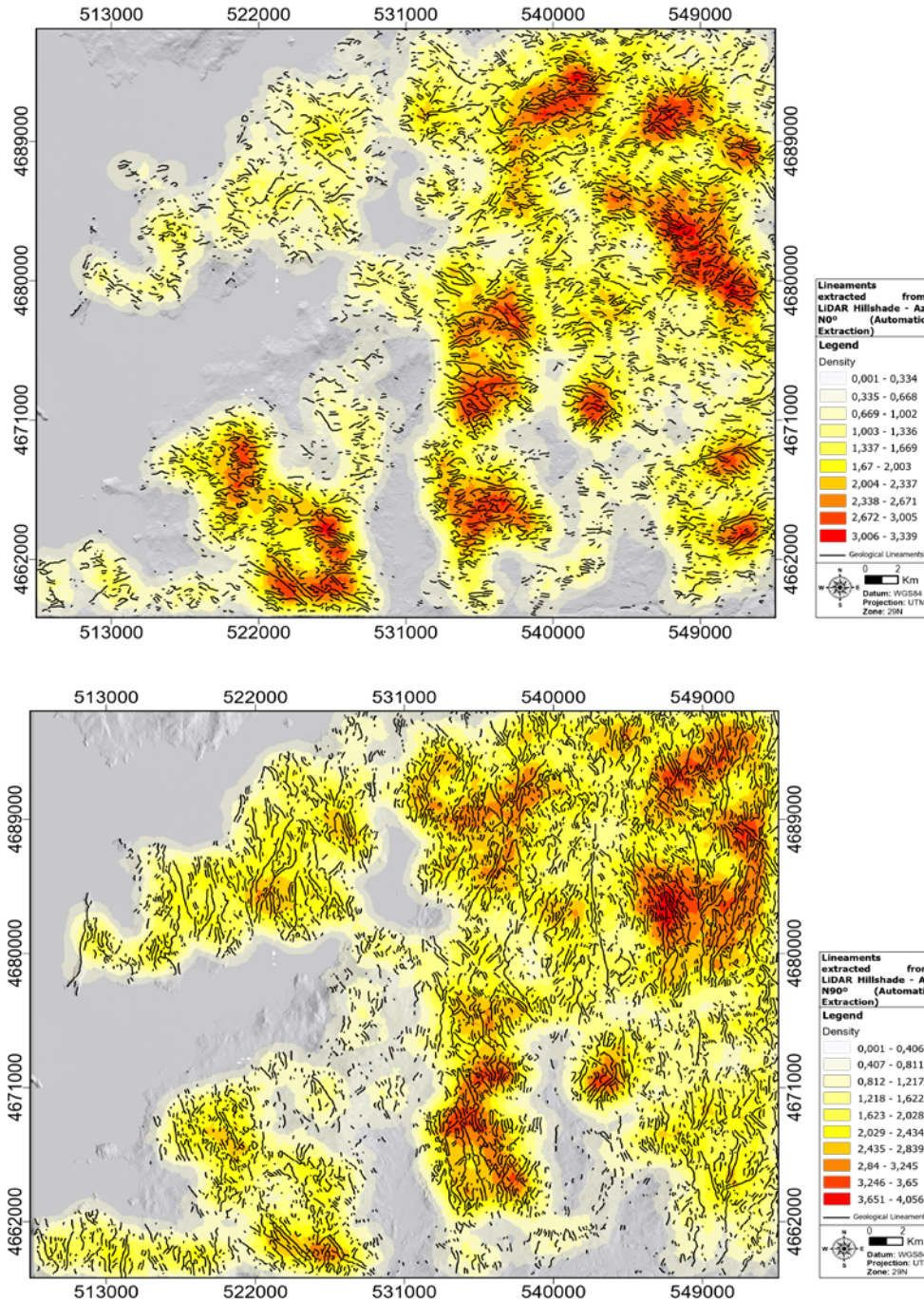
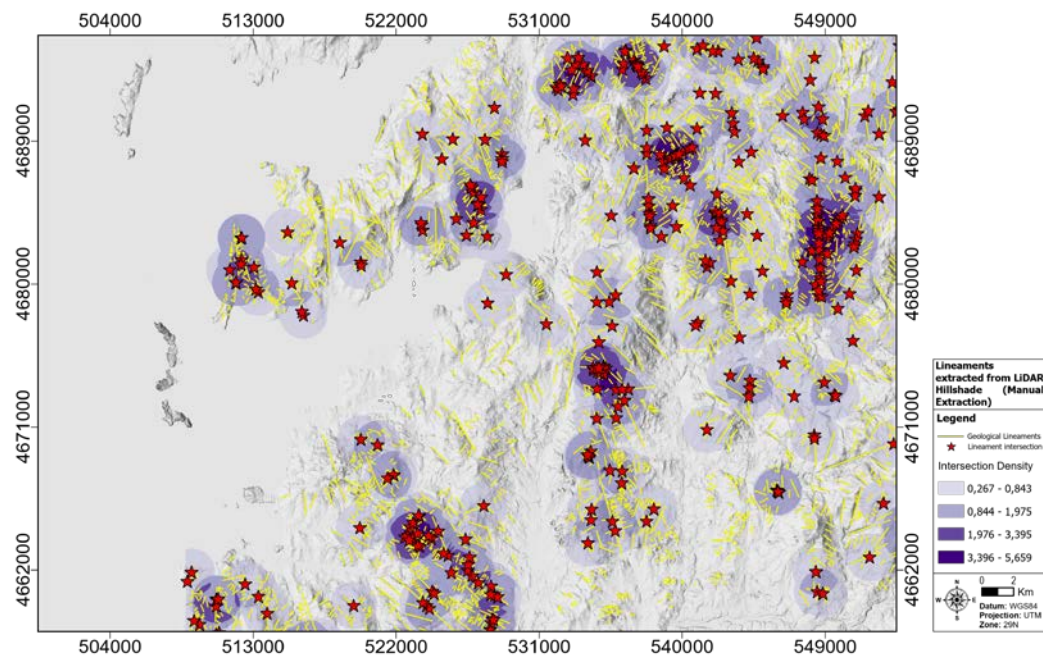
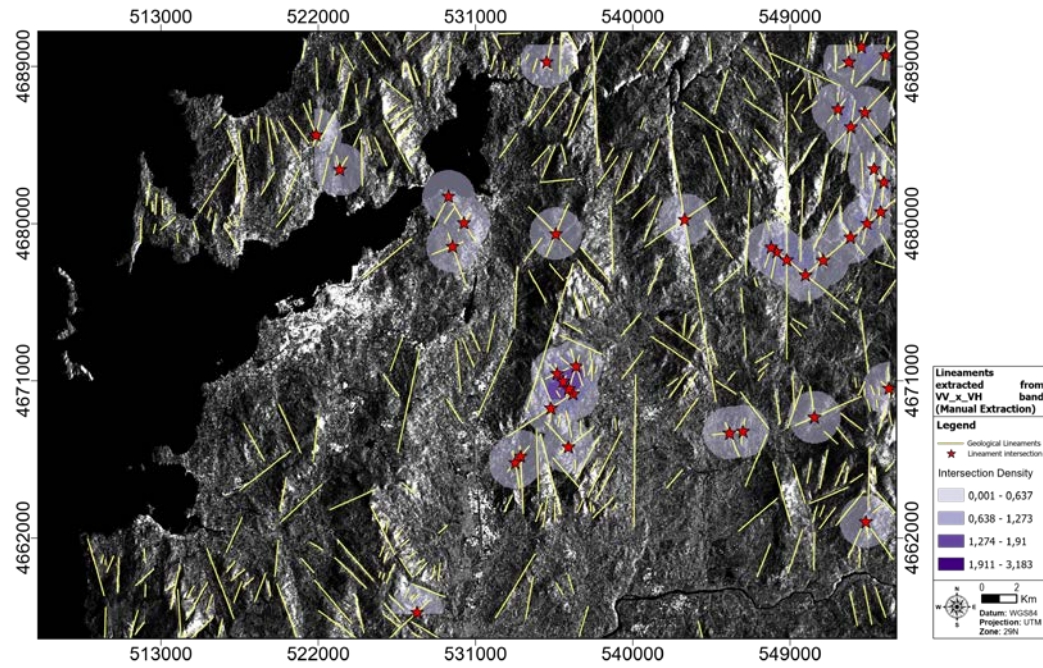
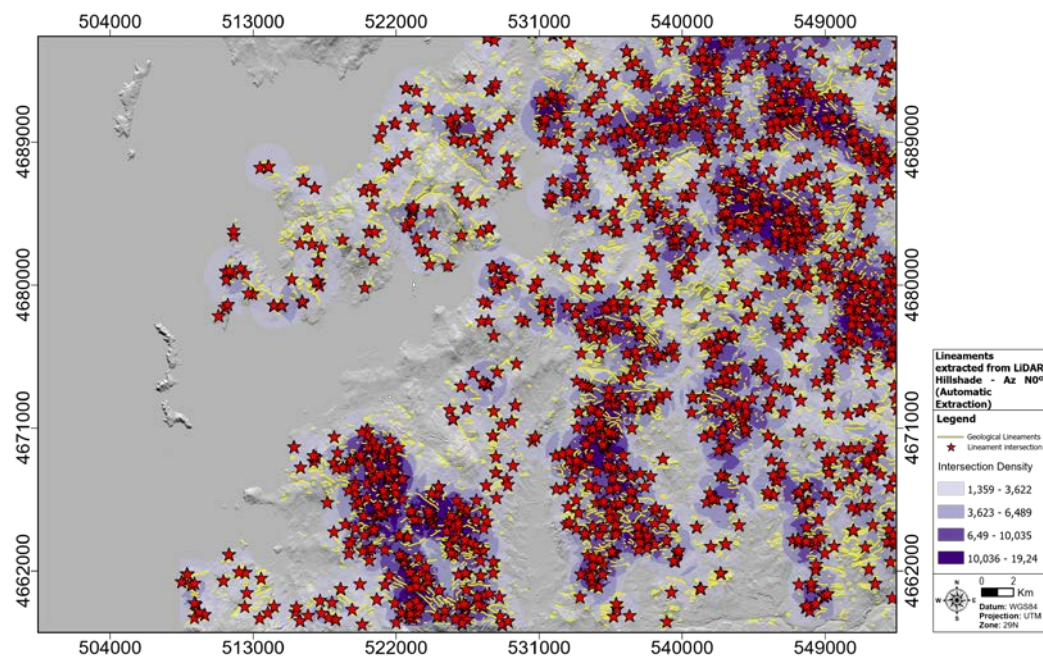
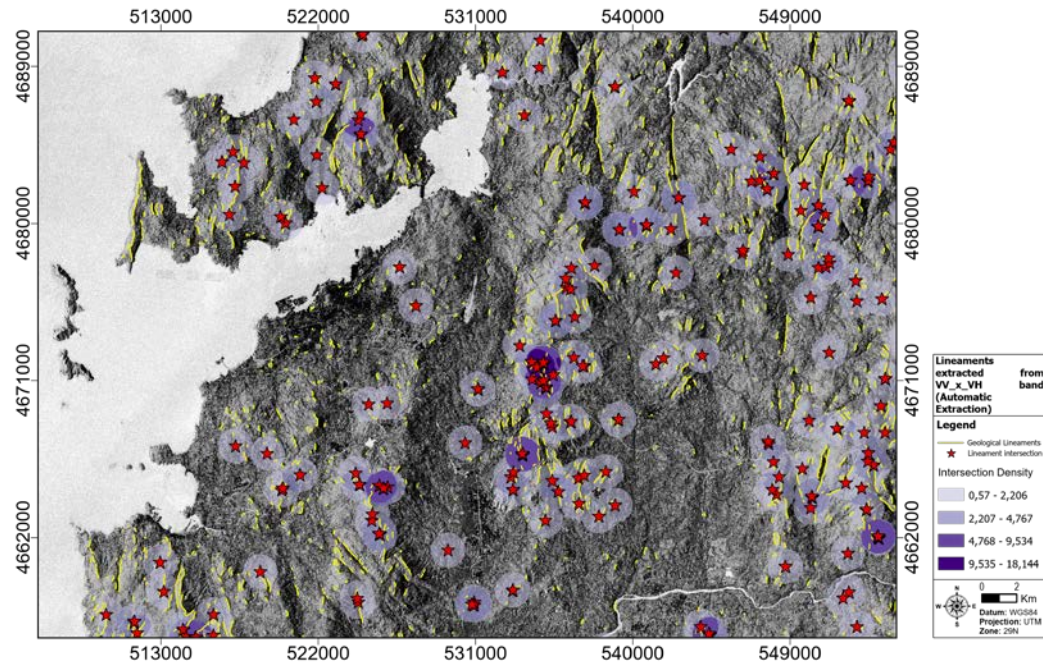


Figure 47 - Lineament density maps of five extractions; A) VV_x_VH band from manual extraction; B) LiDAR Hillshade from manual extraction; C) VV_x_VH_GEE band from automatic extraction; D) LiDAR Hillshade produced with azimuth N0° from automatic extraction; E) LiDAR Hillshade produced with azimuth 90° from automatic extraction.

The lineament intersections and intersection density naturally correlate with areas of higher lineament density, resulting in almost identical maps in terms of where the highest density can be found (Fig. 48). The zones with higher density, both in terms of lineaments and intersection density, correspond to granite massifs or areas where major faults have been identified.





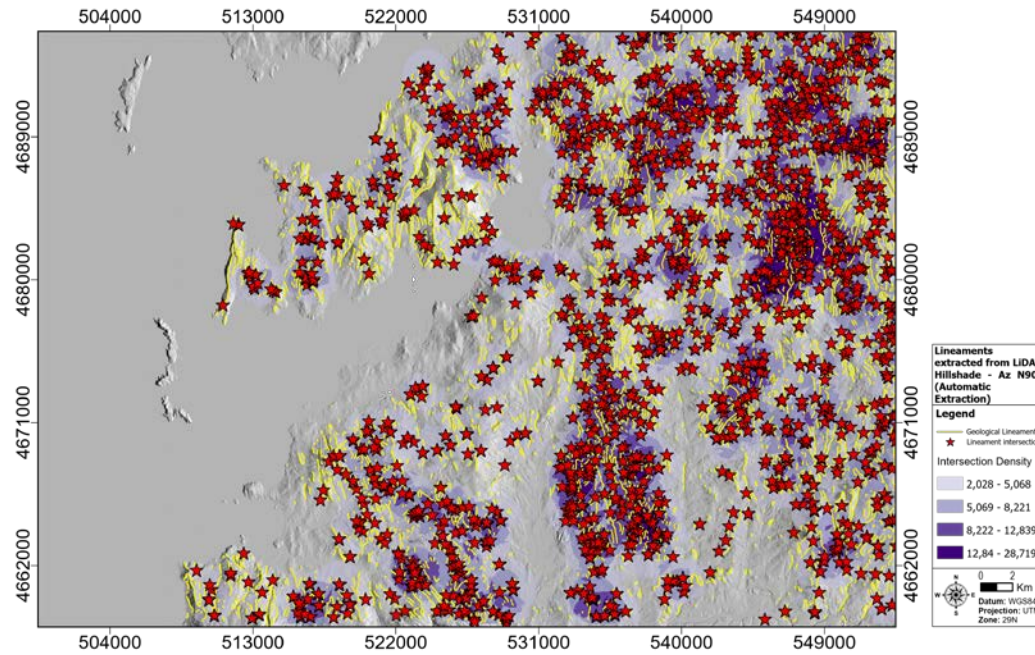


Figure 48 - Lineament intersections and lineament intersection density maps of five extractions; A) VV_x_VH band from manual extraction; B) LiDAR Hillshade from manual extraction; C) VV_x_VH_GEE band from automatic extraction; D) LiDAR Hillshade produced with azimuth N0° from automatic extraction; E) LiDAR Hillshade produced with azimuth 90° from automatic extraction.

7.2. Mineral mapping

7.2.1. Band Ratios

Only the alteration (Fig. 49), carbonate/chlorite/epidote (Fig. 50), ferric oxides (Fig. 51) and amphibolite (Fig. 52) band ratios were considered as they correspond to the best results. The other band ratios are included in Appendix II.

The band ratio that highlights alteration was able to identify areas with possible significant hydrothermal alteration. These areas closely align with regions known to be affected by metamorphism and are characterized by a higher density of lineaments.

In the case of the carbonate/chlorite/epidote band ratio, the results were less distinct and hard to interpret. A possible pattern was observed indicating a potential concentration of chlorite within biotite-rich rocks.

The ferric oxides ratio exhibits a uniform distribution across the image, with no significant localized concentrations, although there was a slight increase in ferric oxide presence within igneous rock formations.

Lastly, the amphibolite ratio displayed warmer colours in areas where amphibolitic rocks are known to outcrop.

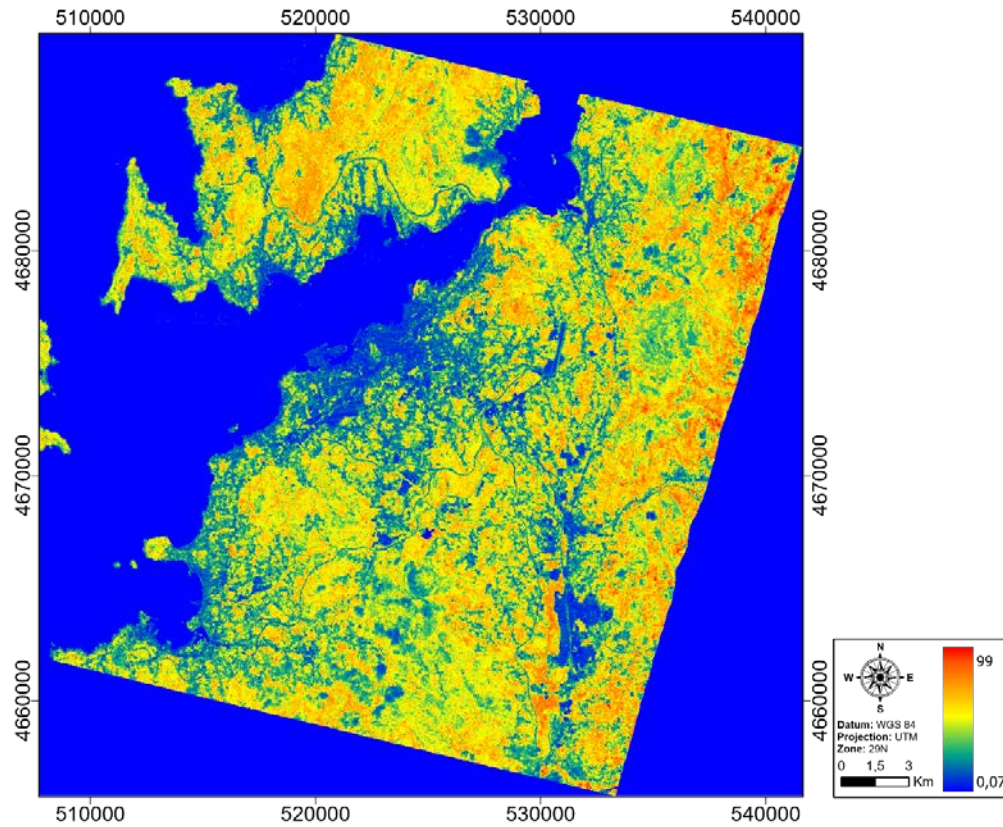


Figure 49 - Alteration band ratio, highlighting areas of highest values in red and lowest values in blue colour.

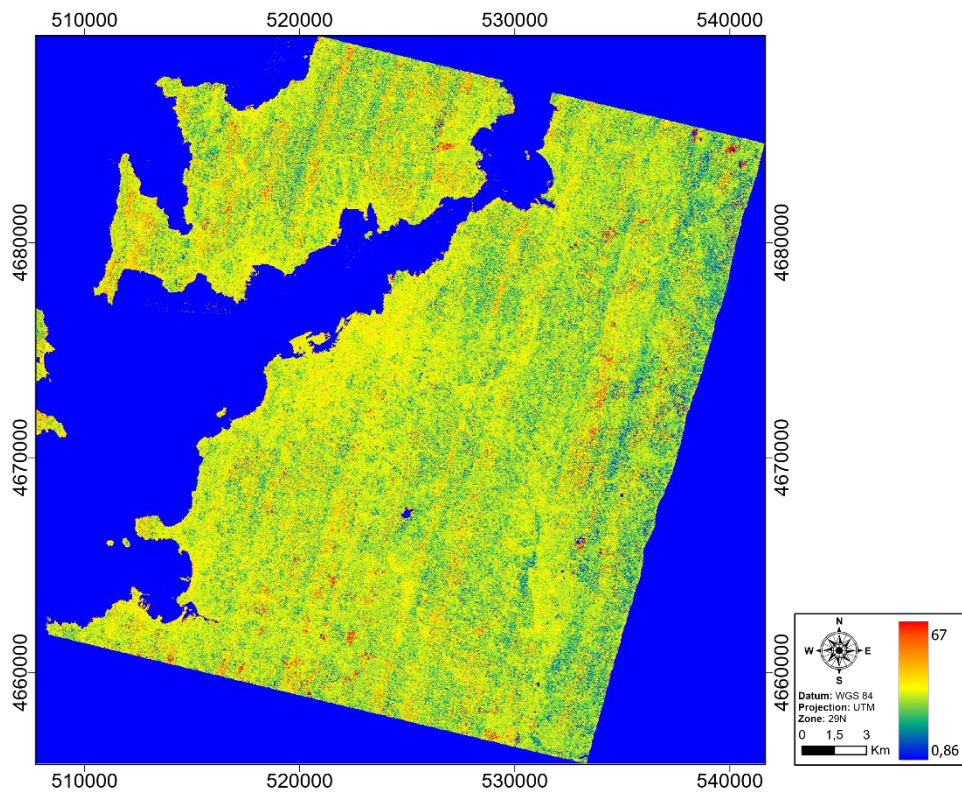


Figure 50 - Carbonate/Chlorite/Epilote band ratio, highlighting areas of highest values in red and lowest values in blue colour.

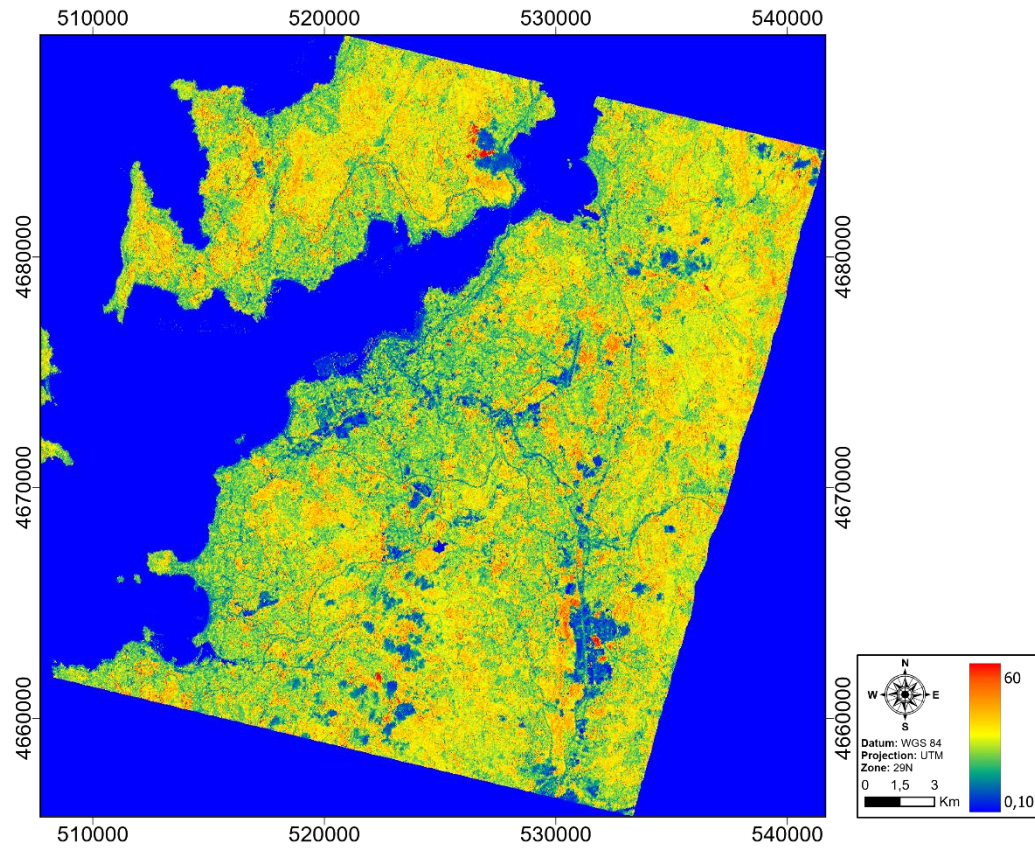


Figure 51 - Ferric oxides band ratio, highlighting areas of highest values in red and lowest values, in blue colour.

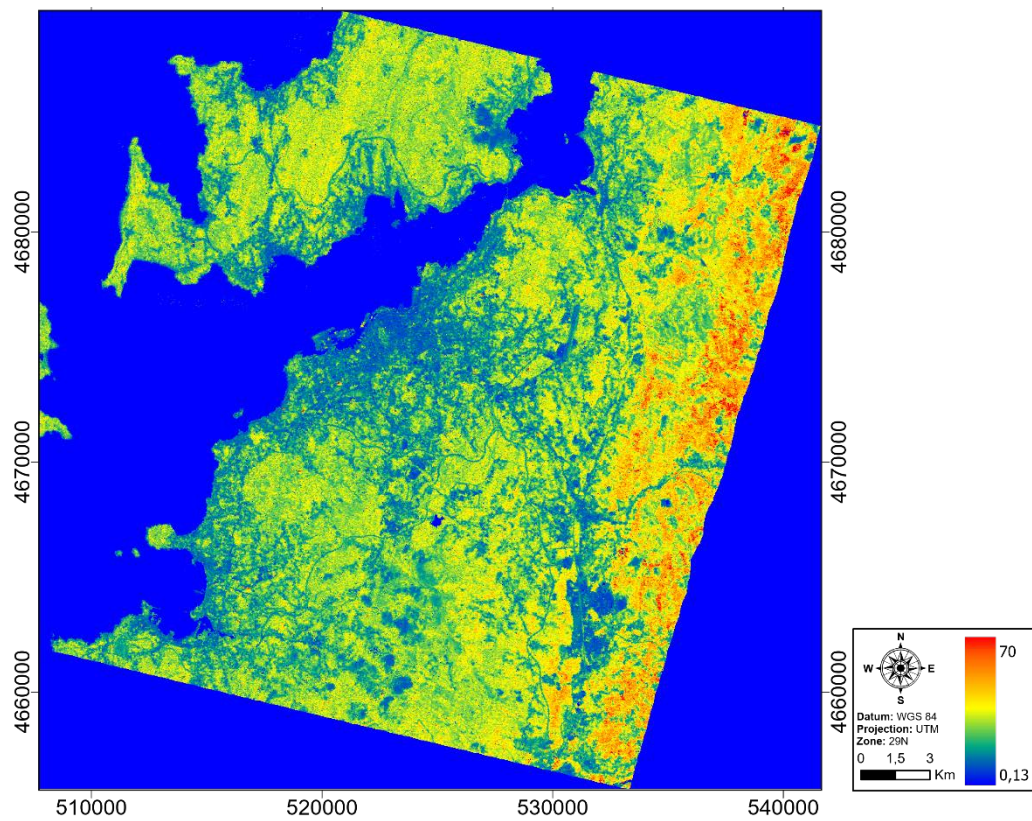


Figure 52 - Amphibole band ratio, highlighting areas of highest values in red and lowest values in blue colour.

7.2.2.MTMF classification

For both MTMF classifications, two distinct maps were produced using the Rule Classifier (Fig. 53 and 54). These maps contain all identified endmembers, with each class represented by a different colour. Most of the map area, shown in black, corresponds to unclassified regions where no specific endmember was detected. The unclassified regions might indicate background materials, noise, or areas where the classification did not detect any spectral match.

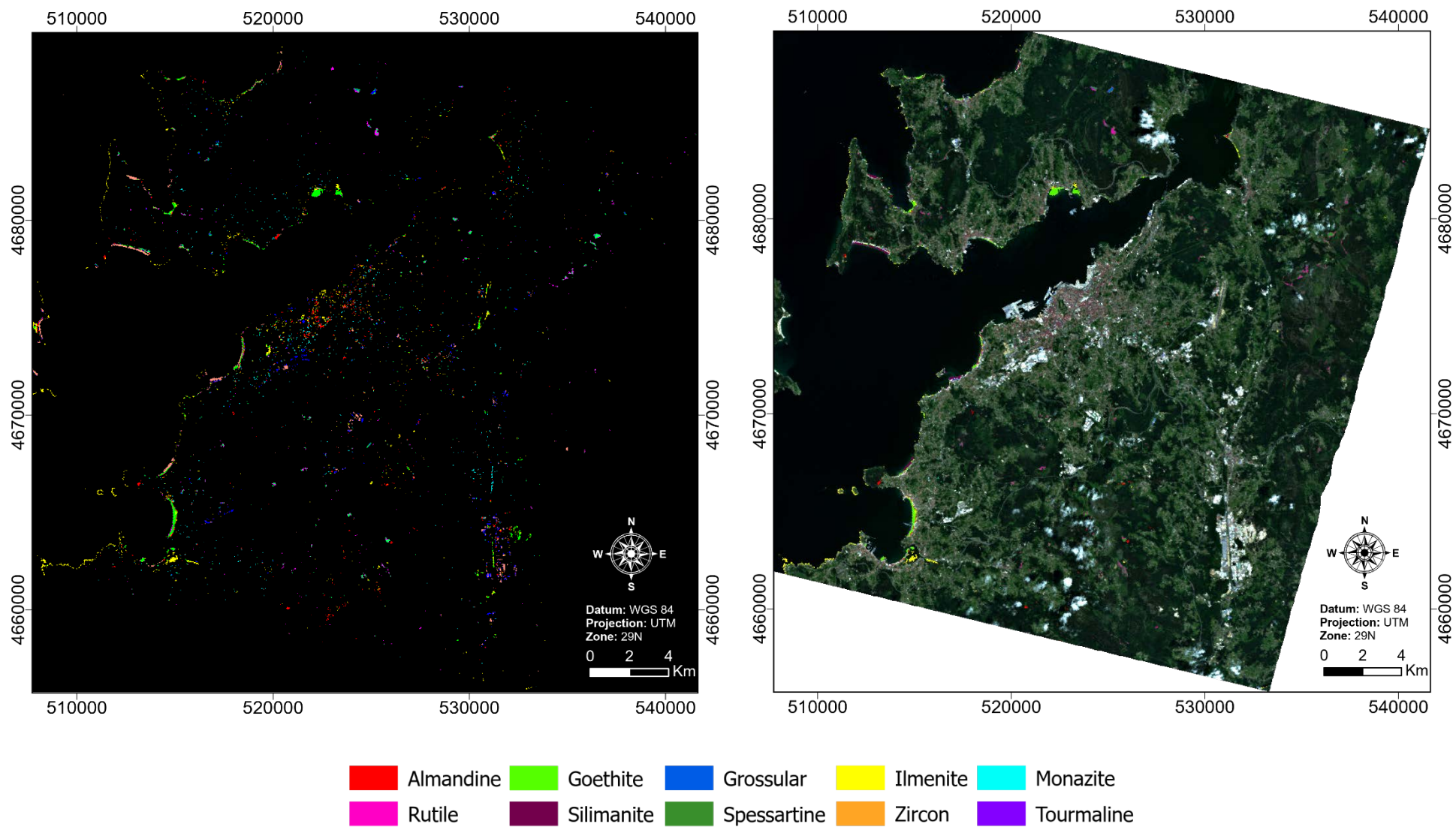


Figure 53 - Classification map, derived from MTMF, using the USGS spectral library. On the left, the classification map, with the black region referring to the unclassified pixels. On the right, the classes are overlaid on a true colour composite of the EnMAP image.

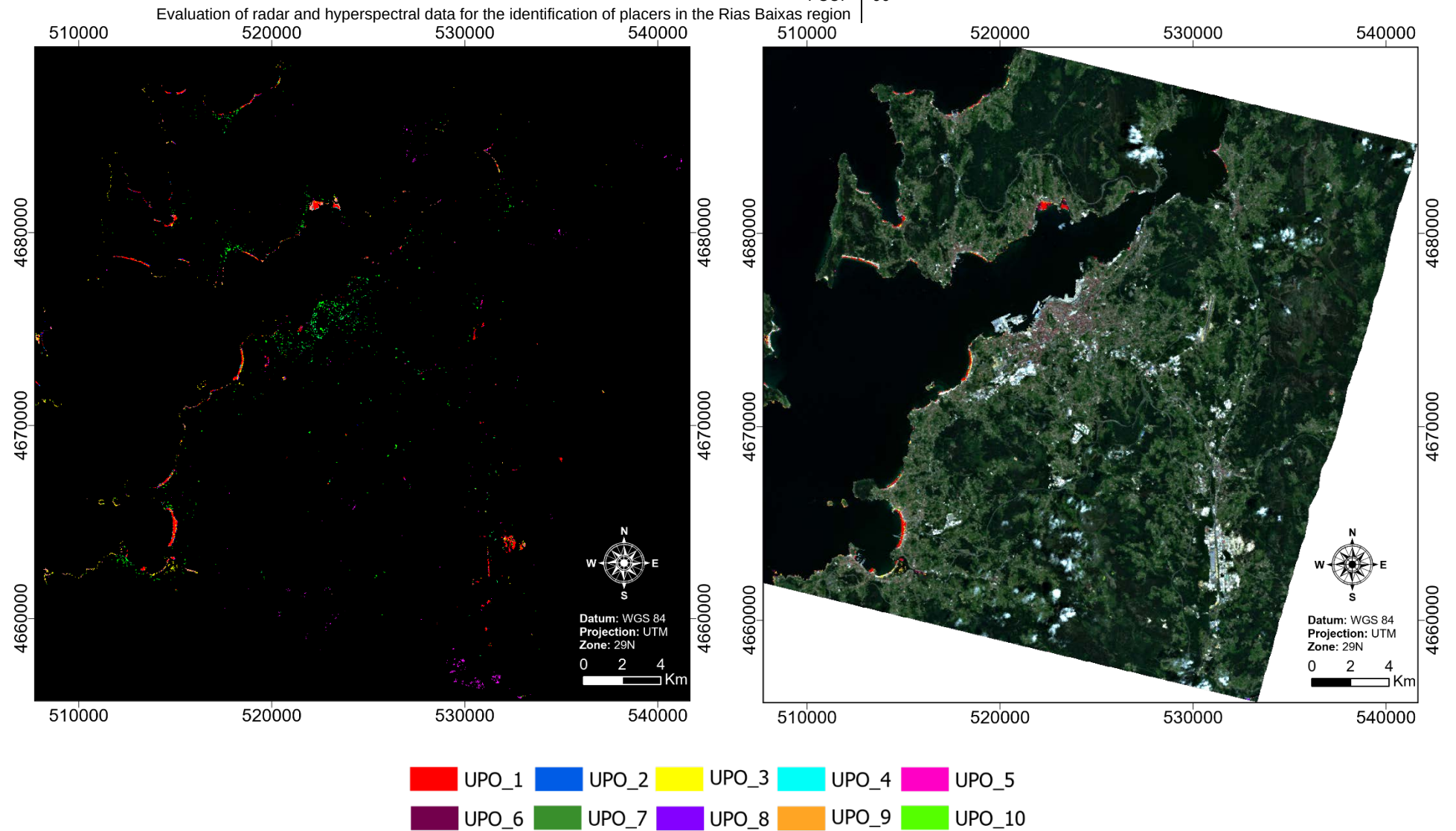


Figure 54 - Classification map, derived from MTMF, using the HM concentrates spectral library. On the left, the classification map, with the black region referring to the unclassified pixels. On the right, the classes are overlaid on a true colour composite of the EnMAP image.

In the first classification, using the USGS spectral library, several minerals were identified in the Límens-Santa Marta beaches (Fig. 55), such as rutile, 0, sillimanite, tourmaline, as well as all three varieties of garnet: almandine, grossular and spessartine. Spessartine and rutile are most present in the dune area.

At the Vao beach (Fig. 56) sillimanite was the most represented mineral, followed by grossular, with only two pixels corresponding to almandine and one to monazite. Near the boundary between Vao and Samil beaches, ilmenite and tourmaline were additionally classified on rocky terrain. In contrast to Límens-Santa Marta, rutile was not detected at Vao and iron oxides (goethite) were found to be more abundant at Límens-Santa Marta.

In comparison to Vao, at Patos beach (Fig. 57), goethite appears in higher abundance, although sillimanite remains dominant. Ilmenite, tourmaline and almandine were also classified, in smaller quantities.

Along the stretch that includes Alemáns-Ratas-Canabal beaches (Fig. 58), sillimanite continued to be the most abundant mineral, with only one pixel each of goethite and tourmaline.

Zircon was not identified on any of the beaches studied. After zircon, monazite was the least classified mineral. Sillimanite and goethite form bands parallel to the coast, with sillimanite always appearing on the backshore and goethite on the foreshore whenever they are found together. Ilmenite usually appears along the coast.

In relation to the geological map and the regional context around the Vigo beaches, it can be observed that rutile is more abundant in areas with outcrops of biotite-rich rocks, such as biotite gneiss and granites with a mottled texture due to the presence of large biotite crystals. Similarly, garnets are present in metamorphic rocks such as glandular gneisses, paragneisses, and mica schists, as well as at the geological contacts between these lithologies and granites.

In the second classification, using the spectra from HM concentrates, the most abundant endmember identified in the Límens-Santa Marta beaches is UPO_1, which corresponds to montmorillonite. Other significant endmembers include UPO_2, UPO_3 and UPO_4, which are interpreted to be biotite/phlogopite (with the differential identification of montmorillonite), as well as UPO_5, likely corresponding to chlorite/biotite. A smaller abundance of UPO_6, also linked to montmorillonite, was also identified.

At the Vao beach, the endmember UPO_1 is also present but in much lower abundance. However, its abundance increases along the transition northward to the Samil beach.

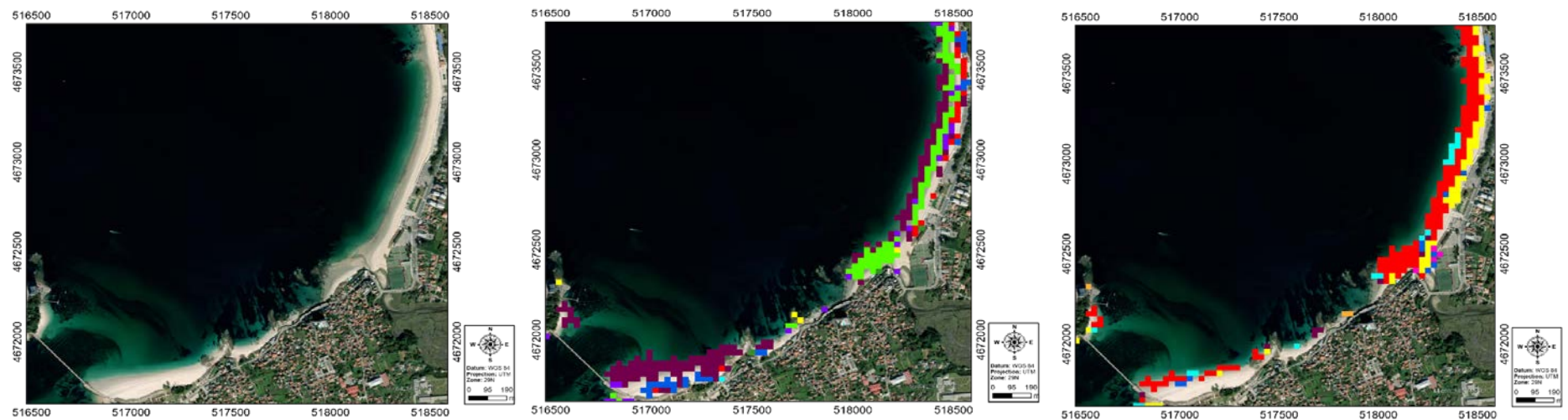
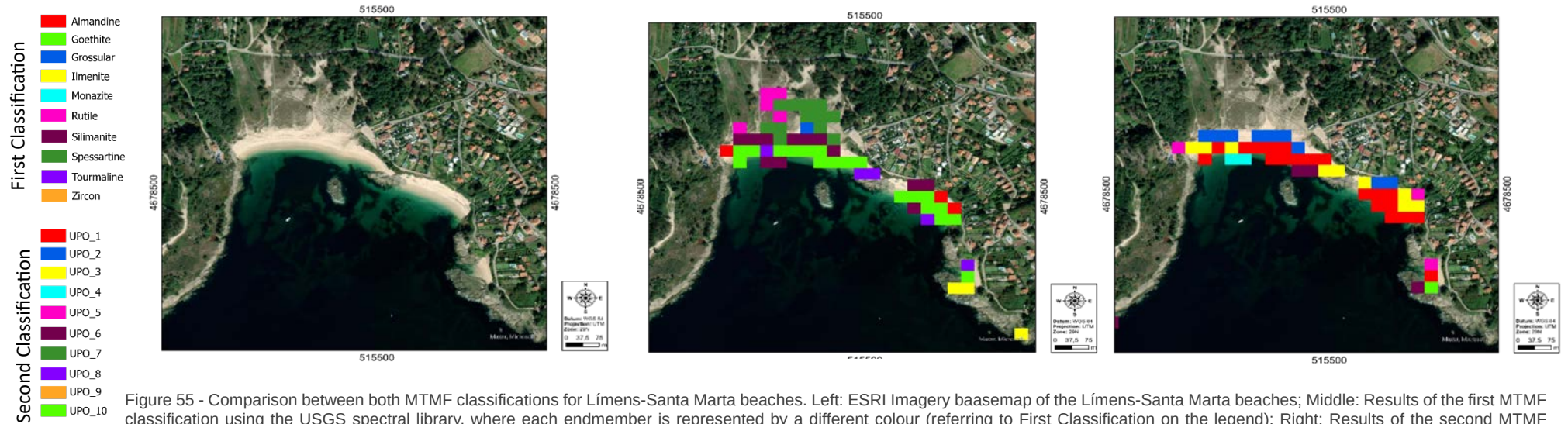
Similar to the Límens-Santa Marta beach, endmembers UPO_2 to UPO_3 are also present. At the boundary between these two beaches, in rock outcrops, the occurrence of UPO_9, corresponding to tourmaline/garnet, can be observed.

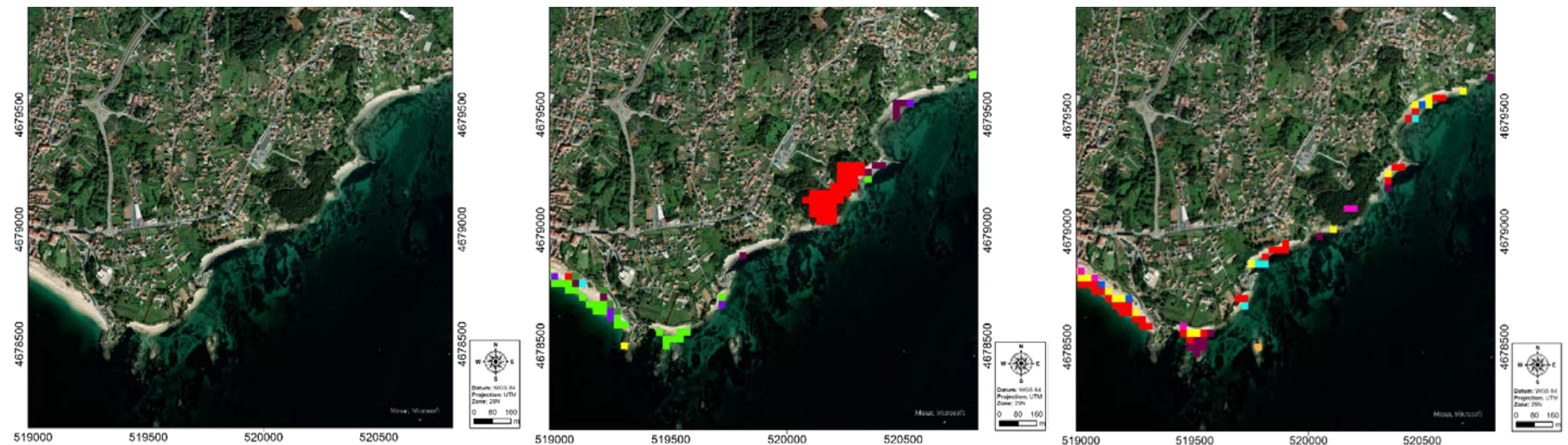
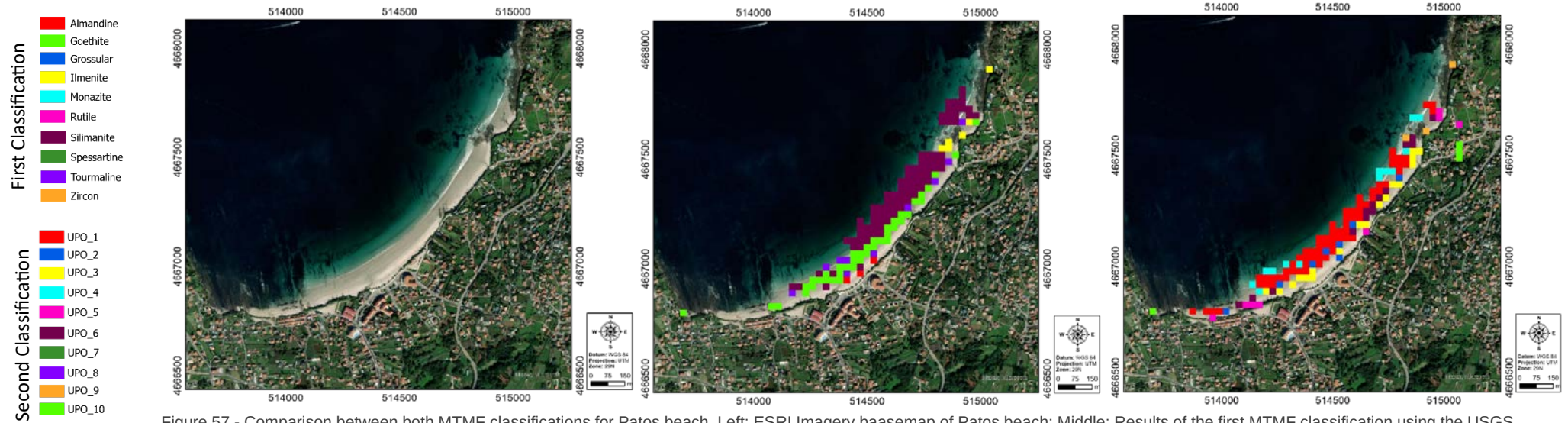
Similarly to the other beaches, the Patos beach also exhibits a high abundance of UPO_1 and smaller abundances of all the other endmembers that are also present in Vao beach, including UPO_9.

In Alemáns-Ratas-Canabal beaches, the same trend continues, with UPO_1 to UPO_4 being the most abundant endmembers.

UPO_7, 8 and 10, identified as tourmaline/garnet, were not classified on any of the beaches. However, in the regional context, UPO_10 is present, though with only a very small abundance, in alkaline granites, in both northern and southern outcrops. UPO_7 occurs, with a small abundance, on the strips of riebeckite gneisses, while UPO_8 is found in granodiorite and biotite-amphibolitic granite, maintaining a similar low abundance. The remaining endmembers are primarily observed in coastal areas.

Evaluation of radar and hyperspectral data for the identification of placers in the Rias Baixas region





8. Discussion

In the manual lineament extraction process, the lineaments extracted from the Sentinel-1 VV_x_VH band and the K-Means combination bands consistently highlighted the two most prominent N-S geological faults as well as the other repeating faults, demonstrating a strong correlation between the identified lineaments, as well as the main orientations. This suggests that despite the lower number of identified lineaments with the K-Means combinations, the main geological structures were identified, indicating that the K-Means combination is a reliable lineament enhancement technique, even compared to Prewitt filtering. However, it does not mean that one is better than the other since they both have their strong points. Prewitt filtering is a well-established image directional enhancement technique, with most Prewitt filter kernels already predefined in literature. It offers directional accuracy, faster application and simpler interpretation. Meanwhile, K-Means classification relies heavily on trial and error to find the best combinations that enhance particular features, making it more time-consuming and requiring a bigger effort to find combinations, and a deep analysis of the assigned clusters is always necessary. On the flipside, K-Means provides a more distinct visualization due to the different colours assigned to clusters and quick differentiation of anthropic lineaments, aiding lineament extraction.

Due to its higher spatial resolution, LiDAR data can depict lineaments in greater detail. As previously mentioned, the elevation data is collected through laser pulses, which may have downsides in areas with lower altitudes. Since there is no significant change in elevation in those areas, there is less visual contrast; thus, the hillshade image will appear smoother. Due to this, it can be more challenging to extract lineaments in those areas simply because they are harder to spot. On the other hand, Sentinel-1 gathers elevation data by measuring the backscatter, which means that even in lower altitude areas, the terrain will appear more textured than in LiDAR hillshades, making it easier to detect lineaments that are likely to be present in those areas, since they are generally fault zones.

In terms of lineament orientations, since four LiDAR hillshades were used, it was possible to detect lineaments in all orientations with almost the same frequency while still being able to detect main orientations.

In the automatic extraction, the number of lineaments was significantly higher when compared to manual methods, which was anticipated (Ahmadi, Pekkan, & Seyitoğlu, 2023; El-Sawyp et al., 2016; Villalta Echeverria et al., 2022). Even if it extracts different

lineaments than the manual extraction, the main reason for the discrepancy in number is that the edge and line detection algorithm leads to line segmentation. For instance, a single long geological fault can be identified with one or two lineaments at most in a manual extraction. In contrast, in automatic extraction, it is segmented into several individual lineaments. Due to its higher spatial resolution, LiDAR also detects a higher number of lineaments than Sentinel-1. This also results in smaller lineaments in automatic extraction, even when using Sentinel-1 data. However, the even smaller length of lineaments extracted from LiDAR data is exclusively due to the higher spatial resolution, which could be possibly resolved by adjusting the parameters used in the automatic extraction. When it comes to the orientation of lineaments, the difference between manual and automatic could also be due to the parameters used for the Canny algorithm and the Hough transform, or just how GEE performs these techniques.

Automatic and manual lineament extractions each come with advantages and drawbacks. For instance, manual extraction is based on direct visualization and interpretation of lineaments, allowing the user to accurately discern geological lineaments. However, this leads to a subjective interpretation, introducing variability in the results, and it is generally time-consuming. On the other hand, automatic lineament extraction allows for quicker processing of larger data and identifying a higher number of lineaments. However, this comes with a trade-off which relies on the fact that its accuracy is highly based on the selected parameters and may require prior testing to optimize the method. Consequently, there is a higher potential for errors due to unfit parameters, and careful calibration is needed.

When it comes to sensors, there is no single answer as to which is superior for lineament extraction, since it is highly dependent on the specific application and desired outcomes. For regional mapping, at a larger scale, Sentinel-1 is particularly useful since it offers a wider area coverage and is more accessible. However, if the goal is to produce a very detailed lineament extraction, then LiDAR data is more suitable due to its higher spatial resolution, which makes it able to detect lineaments on a smaller metric scale.

In this work, while LiDAR provides the most detailed and extensive representation, the VV_x_VH and K-Means bands also produce reliable results. This can be seen in how these align closely with known geological features, and a consistent lineament orientation and lineament distribution pattern can be observed. Besides, there is a higher density of lineaments in granite massifs and near fault zones, reinforcing how the extract lineaments correspond with the underlying geology.

Band ratios can be valuable tools for mineral mapping since they provide insights into potential areas of mineralization, but they cannot precisely identify specific materials. Considering this, the band ratios analysed in this study were useful for identifying broad areas of interest and to better understand the local mineralization context.

The alteration ratio provided the most conclusive insights, which could be likely due to the vast presence of granitoids in the region, which, through hydrothermal alteration and chemical weathering, lead to the formation of clay minerals (Tardy et al., 1973) and are tightly related to fault systems (Nishimoto & Yoshida, 2010).

The other band ratios, carbonate/chlorite/epidote, ferric oxides and amphibole, yielded less relevant results. The information is inconclusive.

Band ratios provided limited observations, largely due to the significant vegetation cover across the entire EnMAP image area, a challenge which could be addressed using a vegetation mask.

In this area, where dense vegetation is present in almost its entirety, the effectiveness of band ratio analysis is significantly reduced, as the vegetation difficulties the gathering of spectral information from the underlying mineralogical and lithological features. Only in patches of more spaced and sparse vegetation could some band ratio results be observed. Due to these conditions, all results must be interpreted carefully, and only limited information can be obtained.

The MTMF bypasses this limitation since it focuses on coastal and beach areas with little to no vegetation cover. When it comes to mineral mapping, the MTMF classification was able to detect most HM known to occur in the Ria de Vigo.

For the MTMF based on the USGS spectral library, it can be observed that Límens-Santa Marta and Vao beaches have the highest abundance of HM, with Límens-Santa Marta having the most abundance of goethite, as opposed to Vao beach. This happens due to seasonal variations in the accumulation of HM due to the hydrodynamics of the Ria, as mentioned before. Since the EnMAP image was acquired in June 2024 therefore, in the summer month, there is a higher HM accumulation in the northern part of the Ria, in Límens-Santa-Marta, as opposed to in the southern part of the Ria, where Vao beach is located.

After goethite, sillimanite was by far one of the most abundant minerals, which can be explained by looking at the MTMF classification based on the HM concentrates. Based on the report by the USGS describing the sample of the sillimanite sample spectra used

for the first classification, it was detailed that the sample had a slight alteration to montmorillonite. In the second classification, the most abundant mineral is montmorillonite. Therefore, sillimanite's high abundance appears to be overrepresented due to its slight alteration to montmorillonite, which is the most abundant mineral in the second classification.

Besides the two minerals, the MTMF classifications identified most commonly garnets (almandine, grossular and spessartine), followed by tourmaline, ilmenite, rutile and monazite. Zircon was not identified, likely due to its very low concentration on the beaches.

The relation between the abundance of HM and the regional lithological context can give valuable insights into where the mineralization can occur in the host rocks. For the first classification, it was observed that rutile was usually present in biotite-rich igneous and metamorphic rocks. This association may possibly result from the hydrothermal alteration of biotite and phlogopite into rutile (Schirra & Laurent, 2021; Schwartz, 1958; Shau et al., 1991), which is the end member of the biotite solid series and has a higher Ti content, although this hypothesis has not been validated yet. These conditions have been achieved in this region due to the metamorphic processes caused by the Variscan orogeny and the emplacement of igneous rocks. This supports the relation between rutile abundance and faults in the region. Likewise, garnets in the region are mostly found on metamorphic rocks since garnet is commonly known to occur in medium-to-high temperature metamorphic rocks (Müller & Schneider, 1971; Xia & Zhou, 2017).

For the second classification, as mentioned, the most commonly classified mineral was montmorillonite, an alteration product formed due to the alteration of silicate minerals in alkaline conditions (Hawkins & Roy, 1963). Since it is a clay mineral, it can be more easily washed away from rock outcrops and be transported and deposited in coastal areas, hence its high abundance in the Vigo beaches.

Despite these results, mineral mapping faced a few limitations, such as EnMAP's low spatial resolution, at 30 m, and the dense vegetation cover in the area, making it more difficult to identify the same HM on the different lithologies present in the region.

The results obtained align closely with established bibliography. For structural mapping, the effectiveness of Sentinel-1 and LiDAR, done both manually and automatically, as highlighted by Adiri et al. (2017) and Cardoso-Fernandes et al. (2022), is shown. Similarly, the efficiency of EnMAP for mineral mapping is consistent with the findings in Yokoya et al. (2016) and Mielke et al. (2016), who demonstrated its ability, despite the

low spatial resolution. The use of MTMF classification for mineral mapping, as well as its reliability, corroborates the results described in Chandrasekar et al. (2011) and Gazi et al. (2019). The results obtained align closely with established bibliography.

9. Conclusions

Sentinel-1 and LiDAR sensors excel in structural mapping. Sentinel-1 is more advantageous for regional mapping, especially due to its wider coverage, while LiDAR is better suited for producing detailed lineament maps at smaller scales. Additionally, Sentinel-1 data is generally more readily available for any location due to its open access and global coverage, unlike LiDAR, which often has limited availability.

For Sentinel-1, both Prewitt filtering and K-Means classification aided lineament extraction. Prewitt filtering offers directional accuracy and faster application, while K-Means provides distinct visualization but requires more attempts to find the proper combinations.

Manual extraction allows accurate interpretation but is time-consuming and subjective, whereas automatic extraction depends on parameter selection, but allows for quick processing of larger datasets and identification of a higher number of lineaments. GEE has demonstrated to be a reliable platform to conduct automatic lineament extraction and a viable alternative to commercial software.

Concerning mineral mapping, EnMAP data was essential to distinguish several HM in Vigo beaches due to its high spectral resolution. While band ratios detect potential alteration and mineralization, they are ineffective for detailed mapping. Dense vegetation reduces the technique's effectiveness. MTMF focused mainly on coastal and beach areas. This classification identified most HM known to be present in the Vigo beaches. Límens-Santa Marta and Vao beaches have the highest abundance of HM. The most identified HM were sillimanite (although likely to be overrepresented), garnets (almandine, grossular and spessartine), tourmaline, ilmenite, goethite and, with less abundance, rutile and monazite. Zircon wasn't identified.

In future works, new approaches for further development of these methods possibly include further testing of GEE parameters for geological lineament extraction, and a direct comparison with commercial software, like PCI Geomatica. For mineral mapping, fusing EnMAP and Sentinel-2 data may be value to enhance EnMAP's spatial resolution. Additionally, to accurately determine whether MTMF correctly classified and identified HM, ground truth data must be collected and compared to the classification results.

10. References

- Ábalos, B., Carreras, J., Druguet, Escuder-Viruete, J., Gómez-Pugnaire, M. T., Albarez, L., S.Quesada, Rodríguez-Fernández, L., & Ibarguchi, J. (2002). The Geology of Spain. Variscan and Pre-Variscan Tectonics. In (pp. 155-183).
- Abay, H., Legesse Belachew, D., Suryabagavan, K., & Atnafu, B. (2022). Mapping of ferric (Fe³⁺) and ferrous (Fe²⁺) iron oxides distribution using ASTER and Landsat 8 OLI data, in Negash Lateritic iron deposit, Northern Ethiopia. *Geology Ecology and Landscapes*. <https://doi.org/10.1080/24749508.2022.2130556>
- Abrams, M. J., Ashley, R. P., Rowan, L. C., Goetz, A. F. H., & Kahle, A. B. (1977). *Use of imaging in the 0.46-2.36 [micrometers] spectral region for alteration mapping in the Cuprite mining district, Nevada* [Report](77-585). (Open-File Report, Issue. U. S. G. Survey. <https://pubs.usgs.gov/publication/ofr77585>
- Adiri, Z., El Harti, A., Jellouli, A., Lhissou, R., Maacha, L., Azmi, M., Zouhair, M., & Bachaoui, E. M. (2017). Comparison of Landsat-8, ASTER and Sentinel 1 satellite remote sensing data in automatic lineaments extraction: A case study of Sidi Flah-Bouskour inlier, Moroccan Anti Atlas. *Advances in Space Research*, 60(11), 2355-2367. <https://doi.org/https://doi.org/10.1016/j.asr.2017.09.006>
- Ahmadi, H., Pekkan, E., & Seyitoglu, G. (2023). Automatic lineaments detection using radar and optical data with an emphasis on geologic and tectonic implications: a case study of Kabul Block, eastern Afghanistan. *Geocarto International*, 38. <https://doi.org/10.1080/10106049.2023.2231400>
- Ahmadi, H., Pekkan, E., & Seyitoğlu, G. (2023). Automatic lineaments detection using radar and optical data with an emphasis on geologic and tectonic implications: a case study of Kabul Block, eastern Afghanistan. *Geocarto International*, 38.
- Alicandro, M., Candigliota, E., Dominici, D., Immordino, F., Masin, F., Pascucci, N., Quaresima, R., & Zollini, S. (2022). Hyperspectral PRISMA and Sentinel-2 Preliminary Assessment Comparison in Alba Fucens and Sinuessa Archaeological Sites (Italy). *Land*, 11, 2070. <https://doi.org/10.3390/land11112070>
- Almeida, A., Martins, H. C., & Noronha, F. (2002). Hercynian Acid Magmatism and Related Mineralizations in Northern Portugal. *Gondwana Research*, 5(2), 423-434. [https://doi.org/https://doi.org/10.1016/S1342-937X\(05\)70733-4](https://doi.org/https://doi.org/10.1016/S1342-937X(05)70733-4)
- Arii, M., Yamada, H., Kojima, S., & Ohki, M. (2019). Review of the Comprehensive SAR Approach to Identify Scattering Mechanisms of Radar Backscatter from Vegetated Terrain. *Electronics*, 8(10), 1098. <https://www.mdpi.com/2079-9292/8/10/1098>
- Azevedo, M., & Valle Aguado, B. (2006). Origem e instalação de granitóides variscos na Zona Centro-Ibérica. *Geologia de Portugal no contexto da Ibéria*, 107-121.
- Becker, M., Schreiner, S., Auer, S., Cerra, D., Gege, P., Bachmann, M., Roitzsch, A., Mitschke, U., & Middelman, W. (2018). *Reconnaissance of coastal areas using simulated EnMAP data in an ERDAS IMAGINE environment* (Vol. 10790). SPIE. <https://doi.org/10.1117/12.2325402>
- Boillot, G., Auxietre, J.-L., Dunand, J.-P., Dupeuble, P.-A., & Mauffret, A. (1979). The Northwestern Iberian Margin: A Cretaceous Passive Margin Deformed During Eocene. In *Deep Drilling Results in the Atlantic Ocean: Continental Margins and Paleoenvironment* (pp. 138-153). <https://doi.org/https://doi.org/10.1029/ME003p0138>
- Boutirame, I., Boukdir, A., Akhsas, A., & Manar, A. (2018). Geological structures mapping using aeromagnetic prospecting and remote sensing data in the karstic massif of Beni Mellal Atlas, Morocco. *Bulletin Of The Mineral Research and Exploration*, 160, 1-10. <https://doi.org/10.19111/bulletinofmre.502094>

- Bracken, A., Coburn, C., Staenz, K., Rochdi, N., Segl, K., Chabrillat, S., & Schmid, T. (2019). Detecting soil erosion in semi-arid Mediterranean environments using simulated EnMAP data. *Geoderma*, 340, 164-174. <https://doi.org/https://doi.org/10.1016/j.geoderma.2019.01.026>
- Canny, J. (1986). A Computational Approach to Edge Detection. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, PAMI-8(6), 679-698. <https://doi.org/10.1109/TPAMI.1986.4767851>
- Canton, L. C., Souza Júnior, I. G. d., Silva, L. S., Marques Júnior, J., & Costa, A. C. S. d. (2021). Identification and quantification of iron oxides by diffuse reflectance spectroscopy with Praying Mantis accessory and integration sphere. *CATENA*, 196, 104899. <https://doi.org/https://doi.org/10.1016/j.catena.2020.104899>
- Capdevila, R. (1969). *Le métamorphisme régional progressif et les granites dans le segment hercynien de Galice Nord Orientale (NW de l'Espagne)* [PhD, Université de Montpellier].
- Cardoso-Fernandes, J., Lima, A., & Teodoro, A. (2018). *Sentinel-2 data as a tool for structural mapping* VIII Congresso Jovens Investigadores em Geociências, LEG 2018.
- Cardoso-Fernandes, J., Teodoro, A., Lima, A., Menuge, J., Brönnner, M., & Steiner, R. (2022). *Sentinel-1 and ALOS data for lineament extraction: a comparative study*. <https://doi.org/10.1117/12.2636117>
- Carlé, W. (1947). *Die westgalischen Meeresbuchten* (Vol. 77). Natur und Volk.
- Castaldi, F., Chabrillat, S., & Wesemael, B. (2019). Sampling Strategies for Soil Property Mapping Using Multispectral Sentinel-2 and Hyperspectral EnMAP Satellite Data. *Remote Sensing*, 11. <https://doi.org/10.3390/rs11030309>
- Catalán, J. R., Aller, J., Alonso, J. L., & Bastida, F. (2008). The Iberian Variscan orogen. In (pp. 13-30).
- Catalán, J. R., Fernández-Suárez, J., Jenner, G., Belousova, E., & Díez-Montes, A. (2004). Provenance constraints from detrital zircon U-Pb ages in the NW Iberian Massif: Implications for Palaeozoic plate configuration and Variscan evolution. *Journal of the Geological Society*, 161, 463-476. <https://doi.org/10.1144/0016-764903-054>
- Chabrillat, S., Foerster, S., Steinberg, A., & Segl, K. (2014, 13-18 July 2014). Prediction of common surface soil properties using airborne and simulated EnMAP hyperspectral images: Impact of soil algorithm and sensor characteristic. 2014 IEEE Geoscience and Remote Sensing Symposium,
- Chabrillat, S., Milewski, R., Ward, K., Foerster, S., Guillaso, S., Loy, C., Ben-Dor, E., Tziolas, N., Schmid, T., Wesemael, B. v., & Demattê, J. A. M. (2023, 16-21 July 2023). Monitoring Soil Properties Using EnMAP Spaceborne Imaging Spectroscopy Mission. IGARSS 2023 - 2023 IEEE International Geoscience and Remote Sensing Symposium,
- Chamorro, C., Vidal-Romani, J. R., & Sanjurjo, J. (2022). New Model of Coastal Evolution in the Ria de Vigo (NW Spain) from MIS2 to Present Day Based on the Aeolian Sedimentary Record. *Journal of Marine Science and Engineering*, 10, 159-186. <https://doi.org/10.3390/jmse10101350>
- Chandrasekar, N., Mujabar, P. S., & Rajamanickam, G. V. (2011). Investigation of heavy-mineral deposits using multispectral satellite data. *International Journal of Remote Sensing*, 32(23), 8641-8655. <https://doi.org/10.1080/01431161.2010.545448>
- Chen, Q. (2007). Airborne LIDAR data processing and information extraction. *Photogrammetric Engineering and Remote Sensing*, 73, 109-112.
- Christopher, O., Taofeek, A., & B, P. (2013). Geological Lineament Extraction Using Landsat 8 (OLI) in Parts of Osun State, Southwestern Nigeria. 2319-7064. <https://doi.org/10.21275/ART2016414>
- Dong, P., & Chen, Q. (2017). LiDAR Remote Sensing and Applications.

- Dotzler, S., Hill, J., Buddenbaum, H., & Stoffels, J. (2015). The Potential of EnMAP and Sentinel-2 Data for Detecting Drought Stress Phenomena in Deciduous Forest Communities. *Remote Sensing*, 7, 14227-14258. <https://doi.org/10.3390/rs71014227>
- Duda, R. O., & Hart, P. E. (1972). Use of the Hough transformation to detect lines and curves in pictures. *Commun. ACM*, 15, 11-15.
- El-Sawyp, E.-S., Atef, P., Saoud, W., & el bastawesy, M. (2016). Automated, manual lineaments extraction and geospatial analysis for Cairo-Suez district (Northeastern Cairo-Egypt), using remote sensing and GIS. *International Journal of Current Research in Science Engineering & Technology*, 3, 491-500.
- Estes, J., Kline, K., & Collins, E. (2001). Remote Sensing. In N. J. Smelser & P. B. Baltes (Eds.), *International Encyclopedia of the Social & Behavioral Sciences* (pp. 13144-13150). Pergamon. <https://doi.org/https://doi.org/10.1016/B0-08-043076-7/02526-2>
- European Commission, Directorate-General for Internal Market, I., Entrepreneurship, SMEs, Grohol, M., & Veeh, C. (2023). *Study on the critical raw materials for the EU 2023 – Final report*. Publications Office of the European Union. <https://doi.org/doi/10.2873/725585>
- Farias, P., Gallastegui, G., Francisco, G., Marquínez, J., Martín-Parra, L., Catalán, J. R., Maciá, J. G., & Rodríguez-Fernández, L. (1987). Aportaciones al conocimiento de la litoestratigrafía y estructura de Galicia Central. In (Vol. 1, pp. 411-431).
- Farias, P., & Marcos, A. (2004). Dominio Esquistoso de Galicia-Tras-os-Montes. In (pp. 135-138).
- Fernández, R. (2011). Evolución estructural y cinemática De una corteza continental subducida: la unidad de Malpica-Tui (no del Macizo Ibérico).
- Ferreira, N., Iglesias, M., Noronha, F., Pereira, E., Ribeiro, A., & Ribeiro, M. (1987). Granitóides da Zona Centro Ibérica e seu enquadramento geodinâmico. *Geología de los granitoides y rocas asociadas del Macizo Hespérico Libro Homenaje a LC García de Figuerola*,
- Ferrero Arias, A., Baltuille Martin, J. M., Perez Cerdan, F., & Rubio Navas, J. (2004). *Mapa de rocas y minerales industriales de Galicia: Pontevedra-A Guarda (16-26) : situación de la hoja no. 16-26 Pontevedra-A Guarda del mapa de rocas y minerales a E. 1:200.000*. Instituto Geológico y Minero de España. <https://books.google.pt/books?id=nPg9QwAACAAJ>
- Filipponi, F. (2019). *Sentinel-1 GRD Preprocessing Workflow* (Vol. 18). <https://doi.org/10.3390/ECRS-3-06201>
- Fletcher, K., & Agency, E. S. (2012). *Sentinel-1: ESA's Radar Observatory Mission for GMES Operational Services*. ESA Communications.
- Fletcher, K., & European Space, A. (2012). *Sentinel-1 : ESA's radar observatory mission for GMES operational services*. ESA Communications.
- Floor, P. (1967). Los metasedimentos y gneises graníticos ante-hercinianos. *Leidse Geologische Mededelingen*, 36(1), 223-234.
- Flores, A., Herndon, K., Thapa, R., & Cherrington, E. (2019). *The SAR Handbook: Comprehensive Methodologies for Forest Monitoring and Biomass Estimation*. <https://doi.org/10.25966/nr2c-s697>
- Forghani, A. (2010). Semi-automatic detection and enhancement of linear features to update GIS files.
- Franke, W. (1989). Variscan plate tectonics in Central Europe—current ideas and open questions. *Tectonophysics*, 169(4), 221-228. [https://doi.org/https://doi.org/10.1016/0040-1951\(89\)90088-7](https://doi.org/https://doi.org/10.1016/0040-1951(89)90088-7)
- Gabrielsen, R. H., & Olesen, O. (2024). The Concept of Lineaments in Geological Structural Analysis; Principles and Methods: A Review Based on Examples from Norway. *Geomatics*, 4(2), 189-212. <https://www.mdpi.com/2673-7418/4/2/11>
- Galván, F. M. (2002). Exploración de placeres costeros de minerales pesados y su génesis en la costa de galicia.
- García, J. L. M. (1984). *La geología del area esquistosa de Galicia Central (Cordillera Herciniana, NW de España)*. Servicio de Publicaciones, Ministerio de Industria y Energía.

- Gazi, M., Tafhim, K., Ahmed, M. K., & Islam, M. A. (2019). Investigation of heavy-mineral deposits using multispectral satellite imagery in the eastern coastal margin of Bangladesh. *Earth Science Malaysia*, 3, 16-22. <https://doi.org/10.26480/esmy.02.2019.16.22>
- Gent, M., Alvarez, M., García Iglesias, J., & Álvarez, J. (2005). Offshore Occurrences of Heavy-Mineral Placers, Northwest Galicia, Spain. *Marine Georesources & Geotechnology - MAR GEORESOUR GEOTECHNOL*, 23, 39-59. <https://doi.org/10.1080/10641190590959939>
- Ghosh, T., Hazra, S., & Kumar Das, A. (2022). Potential of ALOS-2 PALSAR-2 StripMap data for lithofacies identification and geological lineament mapping in vegetated fold-thrust belt of Nagaland, India. *Advances in Space Research*, 69(4), 1840-1862. <https://doi.org/https://doi.org/10.1016/j.asr.2021.09.007>
- Ghrefat, H., Awawdeh, M., & Al-Rawabdeh, A. (2023). Mineral exploration using multispectral and hyperspectral remote sensing data. *International Journal of Geoinformatics*.
- Ghrefat, H., Awawdeh, M., Howari, F., & Al-Rawabdeh, A. (2023). Chapter 12 - Mineral exploration using multispectral and hyperspectral remote sensing data. In N. Stathopoulos, A. Tsatsaris, & K. Kalogeropoulos (Eds.), *Geoinformatics for Geosciences* (pp. 197-222). Elsevier. <https://doi.org/https://doi.org/10.1016/B978-0-323-98983-1.00013-2>
- Gloaguen, E., Chauvet, A., Branquet, Y., Gerbeaud, O., Ramboz, C., Bouchot, V., Catherine, L., Monié, P., Cathelineau, M., Boiron, M.-C., Marignac, C., & Pourraz, N. (2003). Relations between Au / Sn-W mineralizations and late hercynian granite: Preliminary results from the Schistose Domain of Galicia Trás-os-Montes Zone, Spain.
- Gosen, B. S. V., Fey, D. L., Shah, A. K., Verplanck, P. L., & Hoefen, T. M. (2014). Deposit model for heavy-mineral sands in coastal environments. *Scientific Investigations Report*.
- Guanter, L., Kaufmann, H., Förster, S., Brosinsky, A., Wulf, H., Bochow, M., Boesche, N. K., Brell, M., Buddenbaum, H., Chabrilat, S., Hank, T. B., Heiden, U., Hill, J., Heim, B., Heldens, W., Hollstein, A., Hostert, P., Krasemann, H., Leitão, P. J., . . . Oppelt, N. (2016). EnMAP Science Plan.
- Gupta, R. P. (2018). Physical Principles. In R. P. Gupta (Ed.), *Remote Sensing Geology* (pp. 13-22). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-662-55876-8_2
- Hashim, M., Ahmad, S., Johari, M. A. M., & Pour, A. B. (2013). Automatic lineament extraction in a heavily vegetated region using Landsat Enhanced Thematic Mapper (ETM+) imagery. *Advances in Space Research*, 51(5), 874-890. <https://doi.org/https://doi.org/10.1016/j.asr.2012.10.004>
- Hawkins, D. B., & Roy, R. (1963). Experimental hydrothermal studies on rock alteration and clay mineral formation. *Geochimica et Cosmochimica Acta*, 27(10), 1047-1054. [https://doi.org/https://doi.org/10.1016/0016-7037\(63\)90065-6](https://doi.org/https://doi.org/10.1016/0016-7037(63)90065-6)
- Hodgson, M., & Bresnahan, P. (2004). Accuracy of Airborne LIDAR-Derived Elevation: Empirical Assessment and Error Budget. *Photogrammetric Engineering & Remote Sensing*, 70, 331-339. <https://doi.org/10.14358/PERS.70.3.331>
- Hool, A., Helbig, C., & Wierink, G. (2023). Challenges and opportunities of the European Critical Raw Materials Act. *Mineral Economics*.
- Hou, B., Keeling, J., & Van Gosen, B. S. (2017). Geological and Exploration Models of Beach Placer Deposits, Integrated from Case-Studies of Southern Australia. *Ore Geology Reviews*, 80, 437-459. <https://doi.org/https://doi.org/10.1016/j.oregeorev.2016.07.016>
- Hung, L., Batelaan, O., & De Smedt, F. (2005). *Lineament extraction and analysis, comparison of LANDSAT ETM and ASTER imagery. Case study: Suoimuoi tropical karst catchment, Vietnam* (Vol. 5983). SPIE. <https://doi.org/10.1117/12.627699>
- Ibarguchi, J. I. G., & Gironés, E. O. (1985). Petrology, structure and geotectonic implications of glaucophane-bearing eclogites and related rocks from the Malpica—Tuy (MT) Unit, Galicia, northwest Spain. *Chemical Geology*, 50(1), 145-162. [https://doi.org/https://doi.org/10.1016/0009-2541\(85\)90117-2](https://doi.org/https://doi.org/10.1016/0009-2541(85)90117-2)

- Ibrahim, U., & Mutua, F. (2014). Lineament extraction using landsat 8 (OLI) in Gedo, Somalia. *Internat. Jour. Sci. Res*, 3(9), 291-296.
- IGME. (1976). Investigación minera preliminar de la plataforma continental submarina de la costa gallega. In *Programa sectorial de Estudio de Fondos Marinos (FOMAR)*. Ministerio de Industria.
- Jakob, S., Gloaguen, R., & Laukamp, C. (2016). Remote Sensing-Based Exploration of Structurally-Related Mineralizations around Mount Isa, Queensland, Australia. *Remote Sensing*, 8(5), 358. <https://www.mdpi.com/2072-4292/8/5/358>
- Janga, B., Asamani, G. P., Sun, Z., & Cristea, N. (2023). A Review of Practical AI for Remote Sensing in Earth Sciences. *Remote Sensing*, 15(16), 4112. <https://www.mdpi.com/2072-4292/15/16/4112>
- Javhar, A., Chen, X., Bao, A., Jamshed, A., Yunus, M., Jovid, A., & Latipa, T. (2019). Comparison of Multi-Resolution Optical Landsat-8, Sentinel-2 and Radar Sentinel-1 Data for Automatic Lineament Extraction: A Case Study of Alichur Area, SE Pamir. *Remote Sensing*, 11(7), 778. <https://www.mdpi.com/2072-4292/11/7/778>
- Julivert, M., Fontboté, J. M., Conde, L., Aldaya, F., Capdevila, R., Delgado Quesada, M., Marcos, A., Rosell, J., Soler, M., Den Tex, E., Tamain, G., Mointinho de Almeida, F., Zbyszewski, G., Manupella, G., & Carvalhosa, A. (1974). *Mapa tectónico de la península Ibérica y Baleares a escala 1:1.000.000 y memoria explicativa*. Instituto Geológico y Mineiro de España.
- Kokaly, R. F., Clark, R. N., Swayze, G. A., Livo, K. E., Hoefen, T. M., Pearson, N. C., Wise, R. A., Benz, W. M., Lowers, H. A., Driscoll, R. L., & Klein, A. J. (2017). USGS Spectral Library Version 7.
- Kumar, V., Pandey, K., Panda, C., Tiwari, V., & Agarwal, S. (2022). Assessment of Different Spectral Unmixing Techniques on Space Borne Hyperspectral Imagery. *Remote Sensing in Earth Systems Sciences*, 5. <https://doi.org/10.1007/s41976-022-00071-8>
- Lillesand, T. M., & Kiefer, R. W. (2015). *Remote sensing and image interpretation* (7th Edition ed.).
- Llana-Funez, S. (2001). *La Estructura de la Unidad de Malpica-Tui (Cordillera Varisca en Iberia)*.
- Llana-Fúnez, S., & Marcos, A. (2001). The Malpica–Lamego Line: a major crustal-scale shear zone in the Variscan belt of Iberia. *Journal of Structural Geology*, 23(6), 1015-1030. [https://doi.org/10.1016/S0191-8141\(00\)00173-5](https://doi.org/10.1016/S0191-8141(00)00173-5)
- Lorenz, S., Gloaguen, R., & Laukamp, C. (2016). Remote Sensing-Based Exploration of Structurally-Related Mineralizations around Mount Isa, Queensland, Australia. *Remote Sensing*, 8, 358. <https://doi.org/10.3390/rs8050358>
- Lotze, F. (1945). *Zur Gliederung der Varisziden der Iberischen Meseta*. Verlag nicht ermittelbar.
- Marques, F. O. (1994). *Estudo tectónico das rochas infracrustais do manto de soco do SW do Maciço de Bragança (Trás-os-Montes)* [PhD, Universidade de Lisboa]. Lisboa.
- Martín, F., Rey, D., Rubio, B., Bernabeu, A., Martínez, G., Durán, R., & Mohamed, K. (2008). Los fondos de la Ría de Vigo. In (pp. 17-50).
- Martínez Catalán, J. R., Arenas, R., Díaz García, F., & Abati, J. (1997). Variscan accretionary complex of northwest Iberia: Terrane correlation and succession of tectonothermal events. *Geology*, 25(12), 1103-1106. [https://doi.org/10.1130/0091-7613\(1997\)025<1103:Vaconi>2.3.Co;2](https://doi.org/10.1130/0091-7613(1997)025<1103:Vaconi>2.3.Co;2)
- Martinez, F., Julivert, Schaffert, S., Arboleya, M., & Ibarguchi, J. (1988). Structural and thermal evolution of high-grade areas in the Northwestern parts of the Iberian Massif. *American Journal of Science*, 288, 969-996. <https://doi.org/10.2475/ajs.288.10.969>
- Matte, P. (1968). *La structure de la virgation hercynienne de Galice (Espagne)*. Thèse. Grenoble, impr. Allier.
- Matte, P. (1986). La chaîne varisque parmi les chaînes paléozoïques péri-atlantiques, modèle d'évolution et position des grands blocs continentaux au Permio-Carbonifère. *Bulletin de la Société géologique de France*, II(1), 9-24. <https://doi.org/10.2113/gssgfbull.II.1.9>

- Méndez, G., Rey García, D., Bernabeu Tello, A. M., Manso Galván, F., & Vilas Martín, F. (2000). Recursos minerales marinos en las rías gallegas y en la plataforma continental adyacente. *Journal of Iberian geology: an international publication of earth sciences*, 26, 67-98. <https://portalcientifico.uvigo.gal/documentos/5f92241529995257a670d7a0>
- Méndez, G., & Vilas, F. (2005). Geological antecedents of the Rias Baixas (Galicia, northwest Iberian Peninsula). *Journal of Marine Systems*, 54(1), 195-207. <https://doi.org/https://doi.org/10.1016/j.imarsys.2004.07.012>
- Menéndez, L. G., Gallastegui, G., Cuesta, A., Cuadra, P. G., & Rubio-Ordóñez, Á. (2019). Granitos y rocas metamórficas del Oeste de Galicia. 6a Reunión del Grupo Ibérico de Petrología, Geoquímica y Geocronología,
- Mielke, C., Rogaß, C., Boesche, N., Segl, K., & Altenberger, U. (2016). EnGeoMAP 2.0—Automated Hyperspectral Mineral Identification for the German EnMAP Space Mission. *Remote Sensing*, 8, 127. <https://doi.org/10.3390/rs8020127>
- Moradi, M., Basiri, S., Kananian, A., & Kabiri, K. (2014). Fuzzy logic modeling for hydrothermal gold mineralization mapping using geochemical, geological, ASTER imageries and other geo-data, a case study in Central Alborz, Iran. *Earth Science Informatics*, 8. <https://doi.org/10.1007/s12145-014-0151-9>
- Moulin, P. (2005). 4.2 - Multiscale Image Decompositions and Wavelets. In A. L. Bovik (Ed.), *Handbook of Image and Video Processing (Second Edition)* (pp. 347-359). Academic Press. <https://doi.org/https://doi.org/10.1016/B978-012119792-6/50084-X>
- Müller, G., & Schneider, A. (1971). Chemistry and genesis of garnets in metamorphic rocks. *Contributions to Mineralogy and Petrology*, 31(3), 178-200. <https://doi.org/10.1007/BF00399650>
- Muñoz, A., Acosta, J., & Uchupi, E. (2003). Cenozoic tectonics on the Galicia margin, northwest Spain. *Geo-Marine Letters*, 23(1), 72-80. <https://doi.org/10.1007/s00367-003-0126-1>
- Navas, J. R., & Corretgé, L. (1997). *Hoja 223 (Vigo) - Mapa Geológico de España, Escala 1:50.000*. Madrid, Instituto Geológico y Minero de España.
- Neave, D. A., Black, M., Riley, T. R., Gibson, S. A., Ferrier, G., Wall, F., & Broom-Fendley, S. (2016). On the Feasibility of Imaging Carbonatite-Hosted Rare Earth Element Deposits Using Remote Sensing*. *Economic Geology*, 111(3), 641-665. <https://doi.org/10.2113/econgeo.111.3.641>
- Nguemhe Fils, S. C., Bekele Mongo, C. H., Nkouathio, D. G., Mimba, M. E., Etouna, J., Njandjock Nouck, P., & Nyeck, B. (2018). Radarsat-1 image processing for regional-scale geological mapping with mining vocation under dense vegetation and equatorial climate environment, Southwestern Cameroon. *The Egyptian Journal of Remote Sensing and Space Science*, 21, S43-S54. <https://doi.org/https://doi.org/10.1016/j.ejrs.2018.05.005>
- Nishimoto, S., & Yoshida, H. (2010). Hydrothermal alteration of deep fractured granite: Effects of dissolution and precipitation. *Lithos*, 115(1), 153-162. <https://doi.org/https://doi.org/10.1016/j.lithos.2009.11.015>
- Nolde, M., Plank, S., & Riedlinger, T. (2021). Utilization of Hyperspectral Remote Sensing Imagery for Improving Burnt Area Mapping Accuracy. *Remote Sensing*, 13(24), 5029. <https://www.mdpi.com/2072-4292/13/24/5029>
- Nonn, H. (1966). *Les régions cotières de la Galice (Espagne): étude géomorphologique* (Vol. 1). Les Belles lettres.
- Oceanoloxía, G. d. (1996). 9 años de muestreo hidrográfico en la Ría de Vigo (enero 87 - enero 96). In: Consejo Superior de Investigaciones Científicas (España)
- Fundación ProVigo.
- Ottinger, M., & Kuenzer, C. (2020). Spaceborne L-Band Synthetic Aperture Radar Data for Geoscientific Analyses in Coastal Land Applications: A Review. *Remote Sensing*, 12, 2228. <https://doi.org/10.3390/rs12142228>

- Pamplona, J., Rodrigues, B. C., Llana-Fúnez, S., Simões, P. P., Ferreira, N., Coke, C., Pereira, E., Castro, P., & Rodrigues, J. (2015). Structure and Variscan evolution of Malpica-Lamego ductile shear zone (NW of Iberian Peninsula). In *Ductile Shear Zones: From Micro- to Macro-scales* (pp. 206-223). Wiley. <https://doi.org/10.1002/9781118844953.CH13>
- Pardillo, F., & Soriano, V. (1929). Hallazgo de la monacita en las arenas de la ria de Vigo. Duodécimo Congreso de la Asociación Española para el Progreso de las Ciencias,
- Park, J. W., Korosov, A. A., Babiker, M., Sandven, S., & Won, J. S. (2018). Efficient Thermal Noise Removal for Sentinel-1 TOPSAR Cross-Polarization Channel. *IEEE Transactions on Geoscience and Remote Sensing*, 56(3), 1555-1565. <https://doi.org/10.1109/TGRS.2017.2765248>
- Pérez, I. P., Bernabéu, A. M. G., Rey, D., & Vilas, F. (2008). Formación del placer de la playa de Montalvo (Pontevedra).
- Pichavant, M., Villaros, A., Michaud, J. A. S., & Scaillet, B. (2024). Granite magmatism and mantle filiation. *Eur. J. Mineral.*, 36(1), 225-246. <https://doi.org/10.5194/ejm-36-225-2024>
- Pin, C., Paquette, J., Ábalos, B., Santos, F., & Ibarguchi, J. (2006). Composite origin of an early Variscan transported suture: Ophiolitic units of the Morais Nappe Complex (north Portugal). *Tectonics*, 25. <https://doi.org/10.1029/2006TC001971>
- Prasad, D. A. D., Jain, K., & Gairola, A. (2013). Mapping of Lineaments and Knowledge Base Preparation using Geomatics Techniques for part of the Godavari and Tapi Basins, India: A Case Study. *International Journal of Computer Applications*, 70, 39. <https://doi.org/10.5120/11994-7875>
- Prego, R., Brito, P., Álvarez Vázquez, M. Á., & Caetano, M. (2019). Lanthanides and yttrium in the sediments of the lower Minho River (NW Iberian Peninsula): imprint of tributaries. *Journal of Soils and Sediments*, 19. <https://doi.org/10.1007/s11368-019-02271-0>
- Prego, R., Caetano, M., Vale, C., & Marmolejo-Rodríguez, J. (2009). Rare earth elements in sediments of the Vigo Ria, NW Iberian Peninsula. *Continental Shelf Research*, 29, 896-902. <https://doi.org/10.1016/j.csr.2009.01.009>
- Prost, G. (1980). Alteration mapping with airborne multispectral scanners. *Economic Geology*, 75(6), 894-906. <https://doi.org/10.2113/gsecongeo.75.6.894>
- Prost, G. L. (2013). Remote sensing for geoscientists : image analysis and integration.
- Quadros, N., Collier, P., & Fraser, C. (2008). Integration of Bathymetric and Topographic LIDAR: A Preliminary Investigation. *Remote Sensing and Spatial Information Sciences*, 37.
- Rajashekar, U., Bovik, A. C., Sage, D., Unser, M., Karam, L. J., & Lagendijk, R. L. (2005). 2.4 - Image Processing Education. In A. L. Bovik (Ed.), *Handbook of Image and Video Processing (Second Edition)* (pp. 73-95). Academic Press. <https://doi.org/https://doi.org/10.1016/B978-012119792-6/50069-3>
- Rejith, R. G., Sundararajan, M., Lakshmanan, G., & Loveson, V. (2020). Satellite-based spectral mapping (ASTER and landsat data) of mineralogical signatures of beach sediments: a precursor insight. *Geocarto International*, 37, 1-24. <https://doi.org/10.1080/10106049.2020.1750061>
- Rejith, R. G., Sundararajan, M., Lakshmanan, G., Seenipandian, & Chandrasekar, N. (2022). Exploring beach placer minerals in the east coast of Tamil Nadu, India, using EO-1 Hyperion data. *Journal of Applied Remote Sensing*, 16. <https://doi.org/10.1117/1.JRS.16.012017>
- Ribeiro, A., Pereira, E., Dias, R., Gil Ibarguchi, J. I., & Arenas, R. (1990). Allochthonous Sequences. In R. D. Dallmeyer & E. M. Garcia (Eds.), *Pre-Mesozoic Geology of Iberia* (pp. 220-246). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-83980-1_15
- Rogge, D., Rivard, B., Laakso, K., & Segel, K. (2014). Mapping Ni-Cu (PGE) bearing ultramafic rocks and associated gossans with airborne and simulated EnMAP satellite hyperspectral imagery, Nunavik, CANADA. <https://doi.org/10.1109/IGARSS.2014.6946411>

- Sabins, F. F. (1999). Remote sensing for mineral exploration. *Ore Geology Reviews*, 14(3), 157-183. [https://doi.org/https://doi.org/10.1016/S0169-1368\(99\)00007-4](https://doi.org/https://doi.org/10.1016/S0169-1368(99)00007-4)
- Salehi, S., Mielke, C., & Rogass, C. (2020). Mapping ultramafic complexes using airborne imaging spectroscopy and spaceborne data in Arctic regions with abundant lichen cover, a case study from the Niaqornarsuit complex in South West Greenland. *European Journal of Remote Sensing*, 53(1), 156-175. <https://doi.org/10.1080/22797254.2020.1760733>
- Samarinas, N., Spiliotopoulos, M., Tziolas, N., & Loukas, A. (2023). Synergistic Use of Earth Observation Driven Techniques to Support the Implementation of Water Framework Directive in Europe: A Review. *Remote Sensing*, 15(8), 1983. <https://www.mdpi.com/2072-4292/15/8/1983>
- Sanderson, R. (2003). Introduction to Remote Sensing. *Photogrammetric Record*, 18, 259-259.
- Santos, D., Mendes, A., Azzalini, A., Cardoso-Fernandes, J., Lima, A., & Teodoro, A. (2023). Automated lineament extraction applied to high-resolution imagery Worldview-3 and LiDAR data for pegmatite mineral exploration. <https://doi.org/10.1117/12.2679367>
- Schermerhorn, L. J. G., & Kotsch, S. (1984). First Occurrence of Lawsonite in Portugal and Tectonic Implications. In *Comunicações Geológicas* (Vol. 70, pp. 23-29). Instituto Geológico e Mineiro.
- Schirra, M., & Laurent, O. (2021). Petrochronology of hydrothermal rutile in mineralized porphyry Cu systems. *Chemical Geology*, 581, 120407. <https://doi.org/https://doi.org/10.1016/j.chemgeo.2021.120407>
- Schodlok, M., Frei, M., & Segl, K. (2022). Implications of new hyperspectral satellites for raw materials exploration. *Mineral Economics*, 35. <https://doi.org/10.1007/s13563-022-00327-1>
- Schwartz, G. M. (1958). Alteration of biotite under mesothermal conditions. *Economic Geology*, 53(2), 164-177. <https://doi.org/10.2113/gsecongeo.53.2.164>
- Shau, Y.-H., Yang, H.-Y., & Peacor, D. R. (1991). On oriented titanite and rutile inclusions in sagenitic biotite. *American Mineralogist*, 76(7-8), 1205-1217.
- Shi, C., & Wang, L. (2016). Linear Spatial Spectral Mixture Model. *IEEE Transactions on Geoscience and Remote Sensing*, 54, 1-14. <https://doi.org/10.1109/TGRS.2016.2520399>
- Simancas, J. F. (2019). Variscan Cycle. In C. Quesada & J. T. Oliveira (Eds.), *The Geology of Iberia: A Geodynamic Approach: Volume 2: The Variscan Cycle* (pp. 1-25). Springer International Publishing. https://doi.org/10.1007/978-3-030-10519-8_1
- Storch, T., Honold, H.-P., Chabrilat, S., Habermeyer, M., Tucker, P., Brell, M., Ohndorf, A., Wirth, K., Betz, M., Kuchler, M., Mühle, H., Carmona, E., Baur, S., Mücke, M., Löw, S., Schulze, D., Zimmermann, S., Lenzen, C., Wiesner, S., . . . Fischer, S. (2023). The EnMAP imaging spectroscopy mission towards operations. *Remote Sensing of Environment*, 294, 113632. <https://doi.org/https://doi.org/10.1016/j.rse.2023.113632>
- Tardy, Y., Bocquier, G., Paquet, H., & Millot, G. (1973). Formation of clay from granite and its distribution in relation to climate and topography. *Geoderma*, 10(4), 271-284. [https://doi.org/https://doi.org/10.1016/0016-7061\(73\)90002-5](https://doi.org/https://doi.org/10.1016/0016-7061(73)90002-5)
- Torres, R., Snoeij, P., Geudtner, D., Bibby, D., Davidson, M., Attema, E., Potin, P., Rommen, B., Floury, N., Brown, M., Traver, I. N., Deghay, P., Duesmann, B., Rosich, B., Miranda, N., Bruno, C., L'Abbate, M., Croci, R., Pietropaolo, A., . . . Rostan, F. (2012). GMES Sentinel-1 mission. *Remote Sensing of Environment*, 120, 9-24. <https://doi.org/https://doi.org/10.1016/j.rse.2011.05.028>
- Tzong-Dar, W., & Lee, M. T. (2007, 23-28 July 2007). Geological lineament and shoreline detection in SAR images. 2007 IEEE International Geoscience and Remote Sensing Symposium,
- Vilas, F., Bernabéu, A., Rubio, B., & Rey, D. (2019). The Galician Rías. NW Coast of Spain. In J. A. Morales (Ed.), *The Spanish Coastal Systems: Dynamic Processes, Sediments and Management* (pp. 387-414). Springer International Publishing. https://doi.org/10.1007/978-3-319-93169-2_17

- Villalta Echeverria, M. D. P., Viña Ortega, A. G., Larreta, E., Romero Crespo, P., & Mulas, M. (2022). Lineament Extraction from Digital Terrain Derivate Model: A Case Study in the Girón–Santa Isabel Basin, South Ecuador. *Remote Sensing*, 14(21), 5400. <https://www.mdpi.com/2072-4292/14/21/5400>
- Xia, Q.-X., & Zhou, L.-G. (2017). Different origins of garnet in high pressure to ultrahigh pressure metamorphic rocks. *Journal of Asian Earth Sciences*, 145, 130-148. <https://doi.org/https://doi.org/10.1016/j.jseaes.2017.03.037>
- Yokoya, N., Chan, J. C.-W., & Segl, K. (2016). Potential of Resolution-Enhanced Hyperspectral Data for Mineral Mapping Using Simulated EnMAP and Sentinel-2 Images. *Remote Sensing*, 8(3), 172. <https://www.mdpi.com/2072-4292/8/3/172>

Appendices

I. Published Materials

I.1 Peer-reviewed conference proceedings

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UNSUPERVISED LEARNING APPLIED TO SENTINEL-1 FOR SHALLOW WATERS EXPLORATION IN GALICIA (SPAIN)

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ABSTRACT

The Horizon Europe S34I project aims to enhance exploration methods to secure critical raw materials (CRM) and location management through innovative methods to process Earth Observation data. Placer detection using Copernicus optical data was recently assessed on the Iberian Peninsula Atlantic coast, but radar data potential is still unknown. This search evaluates the contributions from Sentinel-1 data for placer exploration through textural analysis and unsupervised learning with K-means. Different numbers of clusters and iterations were tested, and different attempts were created using several input features for unsupervised classification. RGB compositions were tested to further explore the contribution of the textural indices. The results show the potential of Sentinel-1 data and unsupervised learning in identifying distinct classes in the foreshore and intertidal zones. The Homogeneity textural index allowed for the discrimination of different classes within the Spanish rias while onshore it highlighted geological contacts and fault zones. This study showcases radar data's potential for placer exploration, paving the path for new future applications.

Index Terms— K-means, GLCM, RGB combinations, mineral placer, SAR

1. INTRODUCTION

Sentinel-1 products can provide valuable insights for several applications related to environmental monitoring and coastal management of shorelines [1]. Different backscattering properties can be useful to assess the pollution and different properties at the surface, as it can differentiate different land cover types [2], water [3, 4], and coastlines [5, 6]. The study area is located in the Galicia zone, in the north of Spain (Figure 1) where several metallic placer occurrences were recognized in the Iberian Peninsula Atlantic coast. Such metallic placers are enriched in critical metals such as titanium (Ti), tin (Sn), lithium (Li), rare earth elements (REEs) and gold (Au). Apart from Sn and Au, the previously mentioned metals are included in the critical raw materials

(CRM) list for the European Union (EU) in 2023, as they are essential to the EU's economy (namely for the energy transition) and/or present a high supply risk [7, 8]. Thus, the EU needs to secure CRM availability while guaranteeing accurate and efficient exploration of European deposits.



Figure 1: Location of the study area.

The ongoing S34I Project (<https://s34i.eu/>) aims to address the EU's needs by developing innovative data-driven methods to analyze Earth Observation (EO) data to support systematic mineral exploration both on land and shallow waters. Preliminary results of the S34I Project using Copernicus optical data (Sentinel-2) demonstrated the potential for detecting placer minerals using EO data with a self-proposed band ratio to identify garnets, a common mineral in the placers of the region [9]. The authors also highlighted the results of Sentinel-2 unsupervised classification which discriminated three distinct classes with the water. However, the potential of radar data, especially Synthetic Aperture Radar (SAR) for identifying beach placers still needs to be assessed. Thus, this research analyses how Sentinel-1 SAR data can contribute to placer exploration through textural analysis and unsupervised learning.

2. METHODOLOGY

2.1. Image acquisition and preprocessing

A Sentinel-1 image encompassing the Rias Baixas region (S1A_IW_GRDH_1SDV_20231108T064250_20231108T064315_051122_062A58_9A64), was obtained, considering the low tide period best aligned with the moment of acquisition of the image. The preprocessing was done using the European Space Agency (ESA)'s Sentinel Application Platform (SNAP; <https://step.esa.int/main/>). A pipeline of preprocessing algorithms was enforced (adapted from [10]). First, an orbit file was applied, to correct orbital errors, providing more accurate satellite positioning and velocity information. Next, the thermal noise was removed. Radiometric calibration converted digital pixel numbers into calibrated radar backscatter values. The Grey Level Co-occurrence Matrix (GLCM) method was applied to extract textural information and Speckle filtering, using the Lee Sigma filter, to reduce speckle noise, creating a higher quality image. A geographic subset of the image was created.

2.2. Image processing

2.2.1. Unsupervised learning with K-means

K-means is an unsupervised clustering algorithm that classifies the pixels depending on the characteristics in the data, i.e., it learns the clusters' centers from the data and analyses the similarity of the instances [11]. In this work, K-means was applied to different features of the preprocessed Sentinel-1 image of the Rias Baixas. Different numbers of clusters and iterations were tested, and the resulting images were analyzed generally. After analysing the K-means clustering using several input features, the Homogeneity, Dissimilarity, Angular Second Moment (ASM), Variance, and GLCM Mean were selected for an individual analysis to obtain insights into which is the specific contribution of each band. For this purpose, among the known placer occurrences in the study area, Barra Beach was designated as the main target for comparing the results since it has a broader foreshore relative to the other occurrences in the vicinities (Figure 2). For the individual analysis, both the VV and VH polarizations were used for the K-means.



Figure 2: Location of the Barra Beach.

2.2.2. RGB compositions for textural analysis

RGB compositions with Sentinel-1 products can improve the interpretability of the physical data provided [12]. For

textural analysis, different false color RGB compositions were tested to explore the backscatter coefficients VV and VH polarizations:

- 1) R=VV, G= VH, B= VH/VV
- 2) R=VV/VV, G= VV, B= VH
- 3) R=VH/VV, G= VV/VH, B= VV

Combinations no. 1 [13], 2 and 3 were tested for the amplitude and intensity bands as well as for the features derived from the GLCM, namely the Homogeneity, Dissimilarity and Contrast co-occurrence indices.

3. RESULTS AND DISCUSSION

The K-means unsupervised learning approach helped to evaluate the difference between classes in the foreshore and intertidal zones. Figure 3 shows the results of K-means where there are different classes in the foreshore, suggesting that the K-means algorithm can differentiate textural variances in the beach zone that result in different cluster assignments.

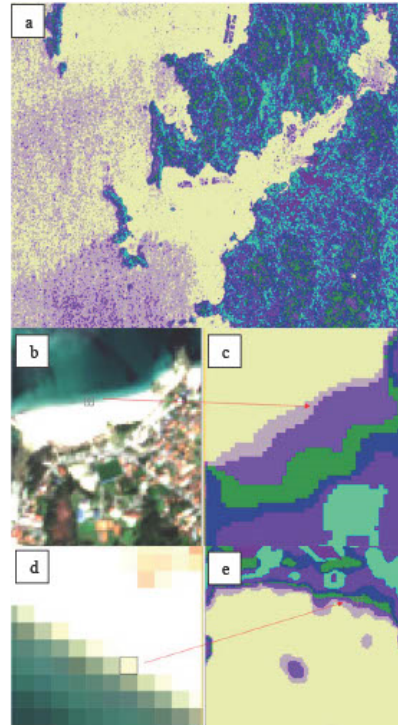


Figure 3: (a) K-means result using the features: Sigma0_VH_Contrast, Sigma0_VH_ASM,

Sigma0_VH_GLCMMean, Sigma0_VH_GLCMVariance, Sigma0_VH_GLCMCorrelation, Sigma0_VV_Contrast, Sigma0_VV_ASM, (8 cluster and 15 iterations). (b-c) close-up views of the Vao Beach where (b) is the true-color RGB composite for the corresponding Sentinel-2 image and (c) is the K-means result. (d-e) close-up views of the Barra Beach.

Comparing the specific contribution of each feature derived from the GLCM as inputs for the K-means classification (Figure 4), either the Homogeneity, Contrast and Variance indices identify distinct classes within Barra Beach, although the shape of the clusters varies according to the input used (Figure 4-b, -d, -f). Regarding the water classification, all attempts discriminate the water column under Atlantic influence from the Ria's water column (Figure 4-a, -c, -e). Within the Ria, Contrast and Variance inputs show smoother classification outputs while Homogeneity identifies several subclasses (Figure 4-b). It is also noteworthy that Figure 4-e, concerning the GLCM Variance, highlights in light blue colour structural lineaments that correspond either to lithological contacts or fault zones, demonstrating the potential for geological mapping. However, the urban agglomerate of the Vigo city is also included in the same cluster, showing the need to mask out urban areas.

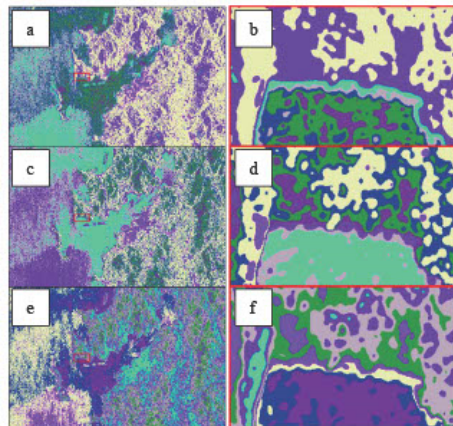


Figure 4- K means results for the homogeneity (a, b), contrast (c, d) and variance (e, f) using 8 clusters and 10 iterations.

Lastly, the RGB combinations using the GLCM Amplitude and Homogeneity indices were compared (Figure 5). Morphological elements, roads, and mussel farms are better visualised in the compositions using the Amplitude, while in the compositions using the Homogeneity the urban zones are more evident together with structural lineaments (contacts, faults, etc.) similar to what was observed in Figure 4-e. In all RGB combinations, there is a distinction between the water columns under the Ria's or Atlantic influence.

Sentinel-1 is known for its ability to distinguish between different types of land cover and identify geological and geomorphological structures like local and regional lineaments [9, 10, 12]. This is corroborated by the results of this study with clear geological contacts and fault zones identified both through RGB combinations and K-means unsupervised learning. However, its potential to differentiate mineral properties in beach zones has not been fully explored yet. This research presents the first approach in this regard.

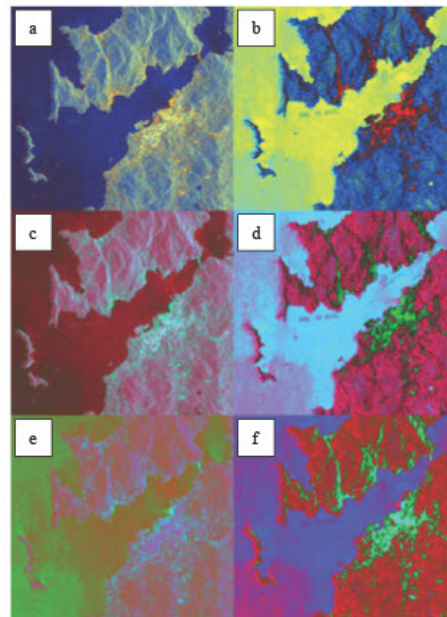


Figure 5: RGB combinations no. 1 (a, b), 2 (c, d) and 3 (e, f) using the Amplitude and Homogeneity indices, respectively.

K-means unsupervised learning algorithm was capable of discriminating different clusters within beaches where metallic placers are known. This shows an improvement regarding the K-means classification based on optical Sentinel-2 data where three different spectral clusters were identified within the water instead of the beaches. Sentinel-1 data also allowed the definition of distinct clusters within the water but there is no apparent correlation with the clusters defined for Sentinel-2. Sentinel 1 seems to be capable of detecting variations in beach zones that are related to textural aspects and were not detected as different clusters in the analysis using Sentinel-2. More in-depth studies in parallel with field surveys are needed to understand the distinct clusters identified either onshore or offshore. Nonetheless,

there is potential to use EO data for placer exploration despite its contributions only now being assessed.

4. CONCLUSIONS

This study successfully employed K-means unsupervised learning to differentiate classes in coastal zones like the foreshore and intertidal areas. Textural indices like Homogeneity, Contrast, and Variance effectively distinguished classes within beaches where metallic placers are known. Water classification accurately separated Atlantic-influenced and the Ria water columns.

In the Ria, Contrast and Variance textural inputs provided smoother classification outputs, while Homogeneity identified multiple subclasses. GLCM Variance highlighted geological features, demonstrating potential for geological mapping but false positives in urban areas suggest such areas should be masked out. The textural indices' contributions were confirmed through false color RGB combinations.

Sentinel-1 data detected unique textural variations in beach zones not found in previous Sentinel-2 classifications. Geological contacts and fault zones were identified by RGB combinations and K-means unsupervised learning. The Sentinel-1 results are a significant improvement compared to the classification derived from optical Sentinel-2 data.

However, the research in this field is still in an early exploratory phase and further studies and field surveys are necessary to comprehensively understand the identified clusters. The results indicate EO data's potential for placer exploration, though its full contribution is still being assessed. Further studies will include very high spatial resolution data such as Worldview-3 and integration with geological field data for validation.

5. ACKNOWLEDGMENTS

This study is funded by the European Union under grant agreement no. 101091616, project S34I – SECURE AND SUSTAINABLE SUPPLY OF RAW MATERIALS FOR EU INDUSTRY, coordinated by Ana C. Teodoro (<https://doi.org/10.3030/101091616>). The authors also acknowledge the support provided by Portuguese National Funds through the FCT– Fundação para a Ciência e a Tecnologia, I.P. (Portugal) projects UIDB/04683/2020 and UIDP/04683/2020 (Institute of Earth Sciences).

6. REFERENCES

[1] R. Torres *et al.*, "GMES Sentinel-1 mission," *Remote Sensing of Environment*, vol. 120, pp. 9-24, 2012/05/15/ 2012. <https://doi.org/10.1016/j.rse.2011.05.028>

[2] D. Amitrano, R. Guida, and G. Ruello, "Multitemporal SAR RGB Processing for Sentinel-1 GRD Products: Methodology and Applications," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 12, no. 5, pp. 1497-1507, 2019.10.1109/JSTARS.2019.2904035

[3] S. G. Dellepiane and E. Angiati, "A New Method for Cross-Normalization and Multitemporal Visualization of SAR Images for the Detection of Flooded Areas," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 50, no. 7, pp. 2765-2779, 2012.10.1109/TGRS.2011.2174999

[4] Z. Chen and S. Zhao, "Automatic monitoring of surface water dynamics using Sentinel-1 and Sentinel-2 data with Google Earth Engine," *International Journal of Applied Earth Observation and Geoinformation*, vol. 113, p. 103010, 2022/09/01/ 2022. <https://doi.org/10.1016/j.jag.2022.103010>

[5] W. Yang *et al.*, "Monitoring tidal flats boundaries through combining Sentinel-1 and Sentinel-2 imagery," *Environmental Technology & Innovation*, vol. 22, p. 101401, 2021/05/01/ 2021. <https://doi.org/10.1016/j.eti.2021.101401>

[6] R. Pelich, M. Chini, R. Hostache, P. Matgen, and C. López-Martínez, "Coastline Detection Based on Sentinel-1 Time Series for Ship- and Flood-Monitoring Applications," *IEEE Geoscience and Remote Sensing Letters*, vol. 18, no. 10, pp. 1771-1775, 2021.10.1109/LGRS.2020.3008011

[7] European Commission, *Proposal for a REGULATION OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL establishing a framework for ensuring a secure and sustainable supply of critical raw materials and amending Regulations (EU) 168/2013, (EU) 2018/858, 2018/1724 and (EU) 2019/1020*. COM/2023/160 final, 2023, p. 94.

[8] European Commission, Directorate-General for Internal Market Industry Entrepreneurship and SMES, M. Grohol, and C. Veeh, *Study on the critical raw materials for the EU 2023 – Final report*. Publications Office of the European Union, 2023. <https://data.europa.eu/doi/10.2873/725585>.

[9] J. Cardoso-Fernandes *et al.*, "Sentinel data for critical raw materials (CRM) exploration: first results of the S34I project," in *Proc. SPIE 12734, Earth Resources and Environmental Remote Sensing/GIS Applications XIV, 127340W*, Amsterdam, Netherlands, 2023, vol. 12734: SPIE. <https://doi.org/10.1117/12.2679373>.

[10] J. Cardoso-Fernandes, A. C. Teodoro, A. Lima, J. Memuge, M. Brönnner, and R. Steiner, "Sentinel-1 and ALOS data for lineament extraction: a comparative study," in *SPIE Remote Sensing, Earth Resources and Environmental Remote Sensing/GIS Applications XIII*, Berlin, Germany, 2022, vol. 12268: SPIE. <https://doi.org/10.1117/12.2636117>.

[11] A. Géron, *Hands-On Machine Learning with Scikit-Learn and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems*. Sebastopol, CA, USA: O'Reilly Media, Inc., 2017, p. 568.

[12] D. Amitrano, F. Cecinati, G. Di Martino, A. Iodice, D. Riccio, and G. Ruello, "Sentinel-1 multitemporal SAR products," in *2015 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*, 2015, pp. 3973-3976. 10.1109/IGARSS.2015.7326695.

[13] Digital Earth Africa. (2023, 20 December 2023). *Welcome to Digital Earth Africa (DE Africa)*. Available: <https://www.digitalearthafrika.org>

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Automatic Lineament Extraction, using Sentinel-1 data, in the Ria de Vigo, Spain

Beatriz L. Araújo^a, Joana Cardoso-Fernandes^{*a,b}, António Azzalini^a, Morgana Carvalho^{a,b}, Alexandre Lima^{a,b}, Francisco J. González^c, Ana Lobato^c, Wai L. Ng-Cutipa^c, Ana Cláudia Teodoro^{a,b}

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ABSTRACT

The Rias Baixas region in southwestern Galicia, Spain, is geologically significant for its heavy-mineral placer deposits, which include critical raw materials such as Ti, Sn, Li, Rare Earth Element (REE), Au, Nb, and Ta. These materials are strategically important to the European Union. Geologically, the region is part of the Galicia Trás-os-Montes Zone, characterised by a complex fracture system. Structural mapping of the Ria de Vigo was conducted using Sentinel-1 Synthetic Aperture Radar (SAR) data, processed on the cloud-based Google Earth Engine (GEE) and the European Space Agency (ESA)'s Sentinel Application Platform (SNAP). The Sentinel-1 data underwent preprocessing, followed by the application of the Grey Level Co-Occurrence Matrix (GLCM) on both SNAP and GEE. The computed co-occurrence indices were Contrast, Angular Second Moment (ASM), and Correlation (CORR). The GEE indices were compared with those generated in SNAP. The Contrast index yielded the best results, while ASM and CORR images were noisy and obscured geological lineaments, particularly compared to the SNAP-generated indices. Automatic lineament extraction was performed using the VV band and both Contrast bands, with the SNAP-derived Contrast band imported into GEE. The Canny Algorithm and Hough Transform were employed for automatic extraction in GEE. Finally, the length and direction of the extracted lineaments were analysed. Results showed significant differences: lineaments from the VV band and SNAP-generated Contrast band closely matched known literature, while those from the GEE-generated Contrast band were unsatisfactory, exhibiting curvilinear lineaments. This disparity is likely due to the way GLCM was employed in GEE, indicating the need for it to be explored further in future studies.

Keywords: Google Earth Engine, SAR, Sentinel-1, Lineaments, Placers, Structural mapping, Vigo, Spain

1. INTRODUCTION

This study was conducted under the scope of the S34I – SECURE AND SUSTAINABLE SUPPLY OF RAW MATERIALS FOR EU INDUSTRY project (<https://s34i.eu/>). This project focuses on researching and developing data-driven Earth Observation (EO) methods, exploiting Copernicus and other satellite sensors (optical and radar), airborne data, low-altitude platforms, ground-based, fieldwork, and others. These methods are applied to different phases of the mining cycle, such as mineral exploration, environmental monitoring, mine monitoring, and mine closure, and incorporate the entire mining cycle.

The study area of the Ria de Vigo falls within the mineral exploration phase, meeting the European Union (EU)'s growing demand for mineral exploration of Critical Raw Materials (CRMs), which are essential to Europe's growing economy and the transition to green energy [1].

The identification of geological lineaments is essential in mineral exploration for several reasons. It contributes to more detailed geological mapping and interpretation, allowing for the identification and understanding of structurally controlled areas of mineralisation and hydrothermal fluid pathways, strengthening the known correlation between mineral deposits and major lineaments [2-6].

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Usually, automatic lineament extraction is conducted using commercial software, such as PCI Geomatica [7-11]. GEE has the advantage of allowing the application of the algorithms needed for automatic lineament extraction in a free-to-use platform and, therefore, being an alternative to paid software. Recent works employed GEE to search and preprocess radar data but conducted textural analysis and/or automated lineament extraction in other third-party software, not performing the entire workflow on the GEE platform [4, 12]. This preliminary study explored different methods for the identification of geological lineaments in the Ria de Vigo using radar Sentinel-1 data. Specifically, it accessed the potential of GEE for textural analysis and automated lineament extraction for structural mapping purposes.

2. GEOGRAPHIC AND GEOLOGICAL SETTING

Located along the Atlantic coast of Galicia, northwestern Spain, the Ria de Vigo is one of four funnel-shaped estuaries that compose the Rias Baixas region (Fig. 1). Extending 32.5 km in an NE-SW direction, the ria is influenced by both freshwater and marine environments.

Geologically, this region is part of the Galicia Trás-os-Montes zone within the Iberian Massif (Variscan orogen) [13]. Two main complexes are distinguished: the Cabo D'Home-La Lanzada complex, which consists mainly of two-mica schists, quartzites, paragneisses, and amphibolites, and the Vigo-Pontevedra complex, comprising plagioclase and biotite gneisses, mica schists, and gneisses with riebeckite [14, 15]. The Variscan magmatism led to the emplacement of leucocratic two-mica and calc-alkaline granites [16].

Structurally, this region is marked by the main deformation phases of the Variscan orogeny, which led to the formation of the N-S oriented Malpica-Lamego shear zone, as well as the Vigo anticline and a fracture system oriented NE-SW and NW-SE [17]. Additionally, several Quaternary-age sedimentary formations are present, including beaches, dunes, cusate forelands, intertidal flat deposits, and marshes.

In Galicia, heavy-mineral placer deposits have been documented [18-21]. These are sedimentary clastic deposits where economically significant heavy minerals accumulate. The beaches of the Galician rias provide ideal conditions for the formation of these marine placer deposits due to their hydrodynamics and local geology. Mineralisation in the region is closely associated with the emplacement of granitic complexes, which are conducive to forming Li, Sn, and W deposits, while mafic rocks favour the formation of Fe-Cu sulfide deposits [22].

Several studies have identified marine placers in the Ria de Vigo containing magnetite, ilmenite, garnet, zircon, cassiterite, monazite, and spodumene. These deposits are rich in Ti, Sn, Li, Rare Earth Elements (REE), and Au, all classified as CRMs by the EU [23].



Figure 1. Geographic location of the Ria de Vigo.

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3. DATA

Sentinel-1 is a mission within the Copernicus program launched by ESA. Sentinel 1A, the first satellite of the Sentinel-1 series, was launched on 3 April 2014 and operates in a near-polar, sun-synchronous orbit at an altitude of 696 km, with a 12-day revisit cycle.

Sentinel-1 is equipped with a synthetic aperture radar (SAR) sensor operating in the C-band. It collects data in four acquisition modes – Interferometric Wide-swath mode (IW), Wave mode (WV), Strip Map mode (SM), and Extra Wide-swath mode. The IW is the primary and most used mode, which acquires data with a 250 km swath at a 5x20 m spatial resolution.

A significant advantage of Sentinel-1 is its ability to capture images regardless of weather conditions, such as cloud coverage and illumination, ensuring continuous and reliable data acquisition.

For this study, we utilised a single level-1 Sentinel-1 Ground Range Detected (GRD) image, obtained on 19 January 2024, using the IW mode, on descending orbit, with Vertical-Vertical (VV) and (Vertical-Horizontal) (VH) polarisation.

The image was retrieved from GEE's Sentinel-1 Image Collection. In order to process it in SNAP, the image was also downloaded from Copernicus open-source database (<https://browser.dataspace.copernicus.eu/>).

4. METHODOLOGY

The image preprocessing was primarily conducted using GEE and ESA's SNAP software. The automatic lineament extraction, however, was performed exclusively on GEE, a cloud-based platform that provides free access to a vast repository of satellite data and image processing tools, facilitating the visualisation and analysis of extensive datasets on a global scale.

ESA's SNAP is an open-access software that enables the processing and analysis of satellite data from the Sentinel missions and other missions such as Landsat, ALOS, Worldview, and SPOT.

4.1. Preprocessing

4.1.1. Google Earth Engine (GEE)

Firstly, the Sentinel-1 image was retrieved from GEE's image collection. The image had already undergone several preprocessing steps by GEE using the Sentinel-1 toolbox such as Orbit Correction (Fig. 2). The initial step was Thermal Noise Removal, which eliminated unwanted noise and normalised the backscatter signal. Next, Radiometric Calibration was performed to adjust the data and ensure it accurately represented the radar backscatter. Afterwards, Terrain Correction was applied using the National Aeronautics and Space Administration (NASA)'s Shuttle Radio Topography Mission (SRTM) at 30 m of spatial resolution. The final terrain-corrected values were also converted to decibels via log scaling ($10 \cdot \log_{10}(x)$). A subset of the image was created to fit the study area.

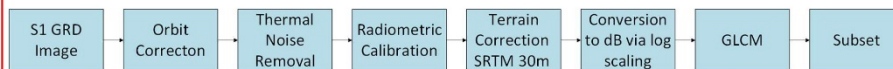


Figure 2. Workflow applied to the Sentinel-1 image by GEE using Sentinel-1 Toolbox.

4.1.2. SNAP

The same image was imported to ESA's SNAP software, where a standard preprocessing workflow was applied (Fig. 3). First, orbit correction was performed to improve geolocation accuracy, followed by Thermal Noise Removal and radiometric calibration. GLCM textural analysis was then carried out to extract the textural features from the image. Afterwards, Speckle filtering, using the Refined Lee filter, was applied to reduce speckle noise. Finally, Terrain Correction was performed using data from NASA's SRTM at 30 m resolution and a subset of the study area was created.

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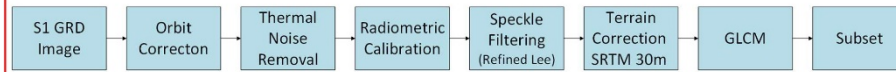


Figure 3. Workflow applied to the Sentinel-1 image in SNAP.

4.2. Grey-level co-occurrence matrix (GLCM) textural analysis

The GLCM is a statistical method used in image processing to analyse the texture of an image. GLCM evaluates the relation between pairs of pixels by considering the frequency of various combinations of pixel intensity values (grey levels) and their spatial relation to each other [24].

On SNAP, the textural analysis extracts several co-occurrence indices for both polarisations VV and VH. The same features can be extracted on GEE, but the method also generates additional co-occurrence indices (Table 1).

Table 1. Description of the GLCM indices.

Group	Co-occurrence index	Description
Contrast	Contrast	Measures the variation in intensity levels between neighbouring pixels
	Dissimilarity	Measures the difference in intensity levels between neighbouring pixels
	Homogeneity	Measures the similarity in intensity levels between neighbouring levels
	Correlation	Measures the linear dependency of grey levels on those neighbouring pixels
Orderliness	Angular Second Moment (also known as Energy)	Measures the homogeneity of an image
	Entropy or Energy	Measures the randomness or complexity of the image texture
	Maximum Probability	Identifies the most common intensity pair
Statistics	GLCM Mean	Provides the average grey level value
	GLCM Correlation	Measures the linear relationship between grey-level values of neighbouring pixels
	GLCM Variance	Measures the spread or dispersion of grey levels
GEE's additional textural features	Inverse Difference Moment	Measures the local homogeneity
	Sum Average	Measures the average of the sum of the intensity values of pixel pairs
	Sum Variance	Measures the variance of the sum of the intensity values of pixel pairs
	Sum Entropy	Measures the entropy of the sum of the intensity values of pixel pairs

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	Difference Variance	Measures the variance of the difference in the intensity of pixel pairs
	Difference Entropy	Measures the entropy of the difference of the intensity values of pixel pairs
	Max Correlation Coefficient	The highest possible value of the correlation feature calculated from the GLCM
	Inertia	Measures local variations, indicating the amount of local intensity variation
	Cluster shade	Measures the asymmetry of the distribution of elements around the mean value
	Cluster prominence	Captures the fourth moment of the distribution of elements in the GLCM around the mean value

4.2.1. GLCM parameters

Before GLCM, it was observed that the VV polarisation was better suited to the identification of structures. Due to this, the GLCM was only performed on the VV band.

To perform textural analysis using the GLCM method on GEE with Sentinel-1 imagery, first, the image pixels must be converted from decibels to integers. This conversion can be done to 8-bit, 16-bit, or 32-bit integers, each requiring a specific scale factor. Given that GEE's GLCM textural analysis supports only up to 32-bit integer images, the images were converted from float to 16-bit and 32-bit integers. The GLCM parameterisation in GEE is simpler than in SNAP since the user can only choose i) the size of the neighbourhood, also called window size (in this case, we chose 1), and ii) the kernel (which was defined as 3x3 and 9x9 kernels). After, a convolution was performed.

Due to a loss of detail after converting to an integer and unsatisfactory results, the GLCM method was also performed on the same Sentinel-1 image on SNAP, using the following parameters (Table 2). From GLCM's textural features, only Contrast, ASM and CORR were computed.

Table 2. Description of the parameters used for the GLCM textural analysis in SNAP.

Source Bands	Sigma0_VV
Window Size	9x9
Angle	ALL (0°, 45°, 90°, 135°)
Quantitizer	Probabilistic Quantitizer
Quantisation Levels	32
Displacement	4

4.3. Automatic lineament extraction

Automatic lineament extraction involved the Canny edge detection algorithm, followed by a Hough transform. This process was executed using solely GEE.

The Canny algorithm is a highly effective edge detection technique used in image processing to identify boundaries, or edges, within images [25]. Meanwhile, the Hough transform is a feature extraction technique to identify and isolate geometric shapes, such as lines, within the detected edges [26].

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Three automatic extractions were conducted on the VV band image and the two GLCM-derived Contrast images, one generated in SNAP and the other in GEE. The SNAP-derived Contrast image was imported into GEE to serve as a reference. The parameters used are described in Tables 3 and 4. These parameters were obtained through trial and error, and several were tested until the most suitable combination of values was found.

Table 3. Description of the parameters used for the Canny algorithm.

Image	Line Threshold	Sigma
VV band	15	1
VV_Contrast (imported from SNAP)	150	3
VV_Contrast (16-bit)	1600	8

Table 4. Description of the parameters used for the Hough transform.

Image	Grid Size	Input Threshold	Line Threshold
VV band	256 (default)	15	10
VV_Contrast (imported from SNAP)	256 (default)	150	10
VV_Contrast (16-bit)	256 (default)	100	40

5. RESULTS AND DISCUSSION

5.1. Comparison of GLCM indices

After performing the GLCM method, the 16-bit and 32-bit images generated were compared to the textural features obtained using SNAP, which served as the reference standard. The GLCM analysis was conducted exclusively on the VV polarisation band, as it provided superior structural visualisation compared to the VH band. The textural features assessed included Contrast, ASM and CORR for both 16-bit and 32-bit images (Fig. 4). It was observed that a 3x3 kernel size yielded the best results on GEE. In the 16-bit images, the Contrast, ASM, and CORR metrics were notably distinct. The best results were achieved with the VV_Contrast band, which demonstrated a better definition of both smaller structures (approximately 1 km in length) and larger ones (over 6 km). This band effectively differentiated urban areas, such as Vigo City, Vigo's airport, and streets, as these appeared uniform, indicating lower contrast and fewer textural differences, which was expected. However, the definition was significantly lower at a pixel level, and the noise was higher than images obtained using SNAP. The ASM and CORR images yielded poorer results. The ASM image was highly pixelated and lacked detail, only distinguishing between inland areas and water bodies, such as the Ria and the Verdugo River. The CORR image provided slightly more information, with some geological structures being defined, but it was still very noisy compared to the images from ESA's SNAP.

When comparing the 16-bit images with the 32-bit images, the results were fairly similar, though the detail appeared to decrease slightly after conversion to 32-bit, which is expected since Sentinel-1 GRD images are generated in 16-bit unsigned integer format. The Contrast images were nearly identical, with the 32-bit images exhibiting marginally more noise. The ASM and CORR results did not differ significantly from the 16-bit images. The ASM band remained barely perceptible, capable of distinguishing between water and land but lacking structural detail, except for the coastline. The CORR image also remained indistinct, with some geological lineaments visible, but the overall image was still very blurry.

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Overall, there was a noticeable disparity between the images generated by SNAP and those from GEE. This could be attributed to the method and parameters used when performing GLCM in GEE. The SNAP images, used as a reference, had good resolution and appeared standard. ESA's SNAP did not seem to reduce the quality and detail of images as observed in GEE, even when using a 9x9 kernel size, which logically should be less detailed compared to the 3x3 kernel size used in GEE's GLCM analysis.

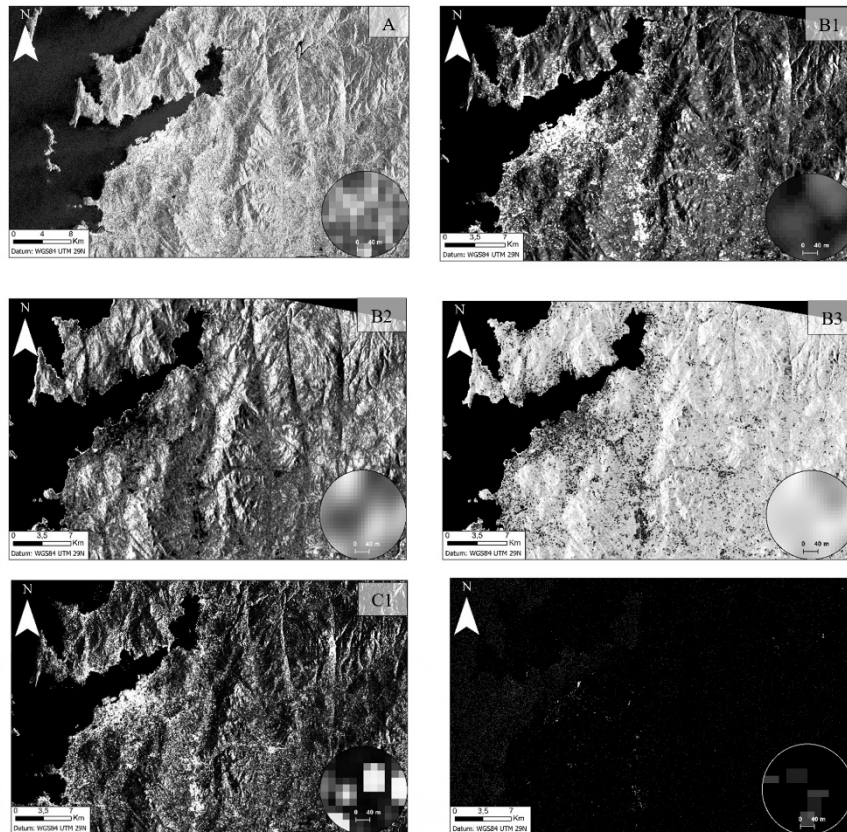


Figure 4. Images resulting from the GLCM method performed on the VV band, both in SNAP and GEE, using the original VV band, and 16-bit and 32-bit VV band. A) Original VV band. B) GLCM images generated in SNAP – B1 is Contrast, B2 is ASM, and B3 is CORR. C) GLCM images generated in GEE after conversion to 16-bit – C1 is Contrast, C2 is ASM, and C3 is CORR; D) GLCM images generated in GEE after conversion to 32-bit – D1 is Contrast, D2 is ASM, and D3 is CORR.

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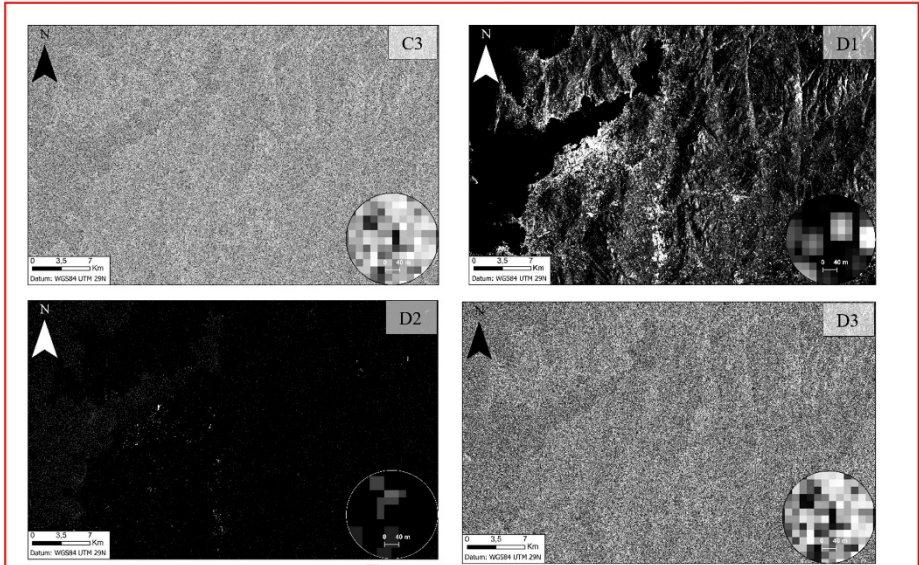


Figure 4. (cont.)

5.2. Geological lineaments

Geological lineaments were extracted from the VV band and VV_Contrast images, generated both in SNAP and GEE.

The lineaments on the VV band were the most satisfactory (Fig. 5). Notably, the delineation of the coastline and river margins stood out. Anthropogenic lineaments, such as those in urbanised areas and at the Vigo airport, appeared less defined, noisier, and more curvilinear. In contrast, natural lineaments were significantly more rectilinear, with lengths ranging from a small metric scale to about 3-4 km, with a median length of 150 m. Although longer lineaments were segmented in GEE's automatic lineament extraction, their location and direction were well-aligned with descriptions in the literature.

The results from the VV_Contrast from SNAP were not significantly different from the VV band results, except for a few differences (Fig. 6). The lineaments extracted from the VV_Contrast image from SNAP appeared noisier than those extracted from the VV band, likely due to a loss in detail after the GLCM process. It delineated the coastline and river margins and extracted curvilinear lineaments from urbanised areas. However, natural geological lineaments appeared more segmented, smaller, and dispersed than those from the VV band, with a median length of around 123 m. Nevertheless, overall, the results are comparable and fairly similar.

On the other hand, results from the VV_Contrast generated in GEE were very distinct from the results of the other two bands (Fig. 7). Geological lineaments were not discernible due to the high noise level in the image. Most lineaments, whether anthropogenic or natural, appeared curvilinear. It can also be observed that this extraction does not include the coastline like the previous ones did. The cause for this needs to be explored further since it appears to stem from the GLCM method, possibly in the kernel and convolution.

Rose diagrams for lineaments were plotted, except for the last extraction, since the lineaments' curvilinear shape prevented azimuth calculation. The density of lineaments and lineament distance were also calculated for all extractions. The areas of higher density in all extractions correspond mainly to regions of higher altitudes. The intersection of lineaments was

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also obtained. Areas of intersection of lineaments could indicate empty spaces, which could serve as pathways for hydrothermal fluids, leading to possible increased mineralisation potential.

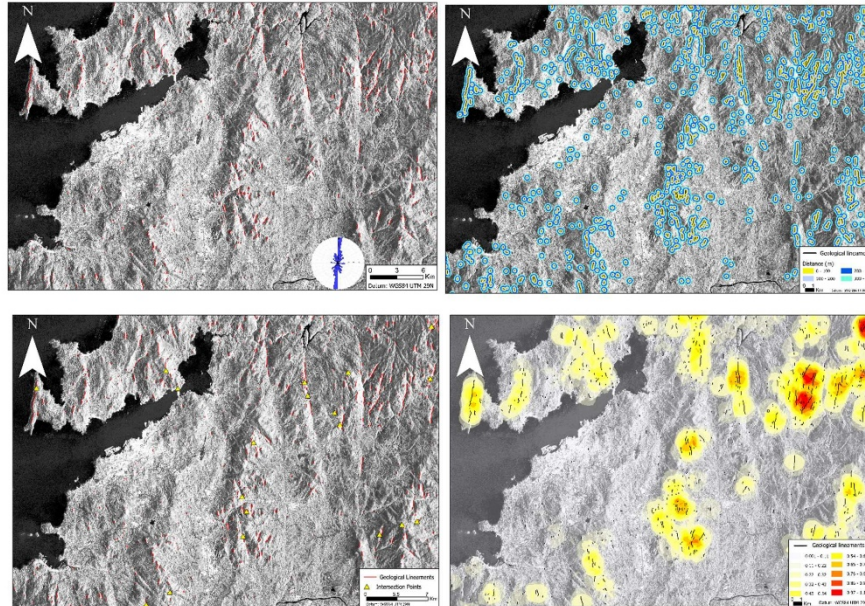


Figure 5. Top left – Lineaments extracted from the VV band with the respective rose diagram; Top right – Distance to lineament map; Bottom left – Lineament intersection map; Bottom right – Lineament density map.

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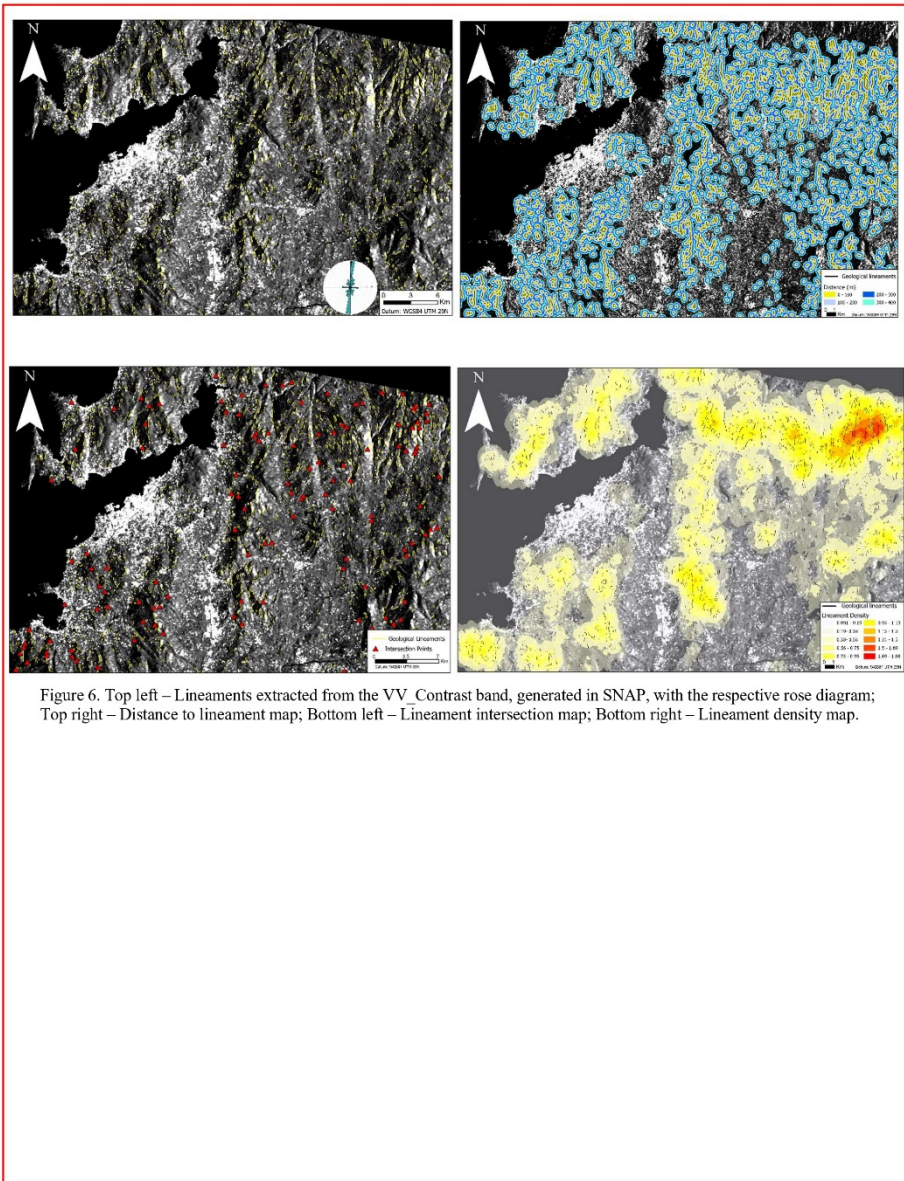


Figure 6. Top left – Lineaments extracted from the VV Contrast band, generated in SNAP, with the respective rose diagram; Top right – Distance to lineament map; Bottom left – Lineament intersection map; Bottom right – Lineament density map.

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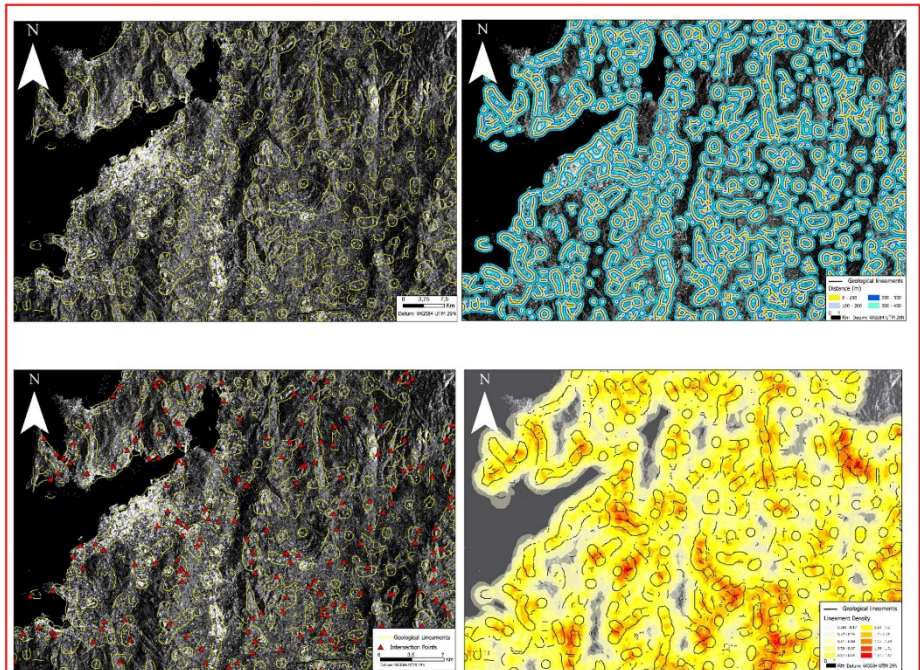


Figure 7. Top left – Lineaments extracted from the VV_Contrast band, generated in GEE; Top right – Distance to lineament map; Bottom left – Lineament intersection map; Bottom right – Lineament density map.

6. CONCLUSIONS

The automatic extraction of geological lineaments using the VV band from a Sentinel-1 image and the VV_Contrast images, generated both in SNAP and GEE, revealed significant differences in quality and clarity of results.

Firstly, the VV band provided the most satisfactory lineament extraction, with natural lineaments being rectilinear and well-aligned with the location and orientation of known lineaments. After the VV band, the most accurate extraction was done using the VV_Contrast image, generated in SNAP and imported into the GEE environment, although the extraction already showed signs of more distortion and noise. The least accurate results were achieved with the other VV_Contrast band, generated in GEE, since it exhibited high noise levels, obscuring geological lineaments and resulting in curvilinear lineaments.

It can be concluded that the automatic lineament extraction using the Canny algorithm and the Hough transform is effective in GEE, although it is highly dependent on the quality of the image used, as well as the prior processing and method used. Therefore, since the VV_Contrast band, generated in SNAP, produced satisfactory results, further investigation is needed on the implementation of textural analysis on GEE, specifically on the GLCM parameters and method code, primarily since SNAP's GLCM provided higher definition and less noisy images, even when using a 9x9 kernel size.

This discrepancy highlights the importance of user expertise and method optimisation in GEE to achieve optimal results. Despite these challenges, GEE offers substantial benefits, primarily its ability to process and analyse vast amounts of data

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on a single platform without requiring multiple software programs. This integrated approach facilitates data handling and processing, making it a valuable resource for applications in remote sensing. Moreover, when it comes to lineament extraction, it serves as a free-to-use alternative to commercial software.

ACKNOWLEDGEMENTS

This study is funded by the European Union under grant agreement no. 101091616 (<https://doi.org/10.3030/101091616>), project S34I – SECURE AND SUSTAINABLE SUPPLY OF RAW MATERIALS FOR EU INDUSTRY, coordinated by Ana C. Teodoro. Portuguese National Funds also support this work through the FCT – Fundação para a Ciência e a Tecnologia, IP (Portugal), projects UIDB/04683/2020 (<https://doi.org/10.54499/UIDB/04683/2020>) and UIDP/04683/2020 (<https://doi.org/10.54499/UIDP/04683/2020>).

REFERENCES

- [1] E. Commission, I. Directorate-General for Internal Market, Entrepreneurship, SMEs, M. Grohol, and C. Veeh, "Study on the critical raw materials for the EU 2023 – Final report", Publications Office of the European Union, (2023).
- [2] J. Cardoso-Fernandes, A. C. Teodoro, A. Lima, J. Menuge, M. Brönnner, and R. Steiner, "Sentinel-1 and ALOS data for lineament extraction: a comparative study." 12268, <https://doi.org/10.1117/12.2636117>
- [3] R. Hariharan, "Application of remote sensing and GIS in mineral: Resource mapping - An overview," Journal of Mineralogical and Petrological Sciences, 99(26), 67-97 (2004).10.2465/jmps.99.83
- [4] H. Ahmadi, and E. Pekkan, "Fault-Based Geological Lineaments Extraction Using Remote Sensing and GIS—A Review," Geosciences, 11(5), 183 (2021)
- [5] J. D. Takodjou Wambo, A. B. Pour, S. Ganno, P. D. Asimow, B. Zoheir, R. d. R. Salles, J. P. Nzenti, B. Pradhan, and A. M. Muslim, "Identifying high potential zones of gold mineralization in a sub-tropical region using Landsat-8 and ASTER remote sensing data: A case study of the Ngoura-Colomines goldfield, eastern Cameroon," Ore Geology Reviews, 122, 103530 (2020).<https://doi.org/10.1016/j.oregeorev.2020.103530>
- [6] D. A. D. Prasad, K. Jain, and A. Gairola, "Mapping of Lineaments and Knowledge Base Preparation using Geomatics Techniques for part of the Godavari and Tapi Basins, India: A Case Study," International Journal of Computer Applications, 70, 39 (2013).10.5120/11994-7875
- [7] L. Hung, and O. Batelaan, "Lineament extraction and analysis, comparison of LANDSAT ETM and ASTER imagery. Case study: Suoimuoi tropical karst catchment, Vietnam," Proc SPIE, 5983, (2005).10.1117/12.627699
- [8] D. Santos, A. Mendes, A. Azzalini, J. Cardoso-Fernandes, A. Lima, and A. Teodoro, [Automated lineament extraction applied to high-resolution imagery Worldview-3 and LiDAR data for pegmatite mineral exploration], (2023).
- [9] Z. Adiri, A. El Harti, A. Jellouli, R. Lhissou, L. Maacha, M. Azmi, M. Zouhair, and E. M. Bachaoui, "Comparison of Landsat-8, ASTER and Sentinel 1 satellite remote sensing data in automatic lineaments extraction: A case study of Sidi Flah-Bouskour inlier, Moroccan Anti Atlas," Advances in Space Research, 60(11), 2355-2367 (2017).<https://doi.org/10.1016/j.asr.2017.09.006>
- [10] A. Javhar, X. Chen, A. Bao, A. Jamshed, M. Yunus, A. Jovid, and T. Latipa, "Comparison of Multi-Resolution Optical Landsat-8, Sentinel-2 and Radar Sentinel-1 Data for Automatic Lineament Extraction: A Case Study of Alichur Area, SE Pamir," Remote Sensing, 11(7), 778 (2019).10.3390/rs11070778
- [11] M. Z. Khedr, S. Kamh, A. A. Al Desouky, E. Takazawa, C. Hauzenberger, S. A. Whattam, and A. El-Awady, "Remote sensing and geochemical investigations of sulfide-bearing metavolcanic and gabbroic rocks (Egypt): Constraints on host-rock petrogenesis and sulfide genesis," Gondwana Research, 119, 282-312 (2023).<https://doi.org/10.1016/j.gr.2023.03.021>
- [12] G. R. Caballero, G. Platzeck, A. Pezzola, A. Casella, C. Winschel, S. S. Silva, E. Ludueña, N. Pasqualotto, and J. Delegido, "Assessment of Multi-Date Sentinel-1 Polarizations and GLCM Texture Features Capacity for Onion and Sunflower Classification in an Irrigated Valley: An Object Level Approach," Agronomy, 10(6), 845 (2020)

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- [13] M. Julivert, J. M. J.M Fontboté, A Ribeiro, and L Conde, [Mapa tectónico de la península Ibérica y Balcares a escala 1:1.000.000 y memoria explicativa] Instituto Geológico y Mineiro de España, (1974).
- [14] J. Rubio Navas, and L. G. Corretgé, [Mapa y Memoria explicativa. Hoja 223 (Vigo) - Mapa Geológico de España, Escala 1:50.000] Instituto Geológico y Minero de España, Madrid(1997).
- [15] S. Llana-Funez, [La Estructura de la Unidad de Malpica-Tui (Cordillera Varisca en Iberia)], (2001).
- [16] R. Capdevila, [Le métamorphisme régional progressif et les granites dans le segment hercynien de Galice Nord Orientale (NW de l'Espagne)] Université de Montpellier, (1969).
- [17] S. Garcia-Gil, A. García-García, and F. Vilas, "Identificación sísmico-acústica de las diferentes formas de gas en la Ría de Vigo (NO España)," *Rev Soc Geol España*, 12, 301-307 (1999)
- [18] F. M. Galván, [Exploración de placeres costeros de minerales pesados y su génesis en la costa de Galicia] Univ. de Vigo, (2001).
- [19] M. Gent, M. Alvarez, J. García Iglesias, and J. Álvarez, "Offshore Occurrences of Heavy-Mineral Placers, Northwest Galicia, Spain," *Marine Georesources & Geotechnology - MAR GEORESOUR GEOTECHNOL*, 23, 39-59 (2005).10.1080/10641190590959939
- [20] R. Prego, M. Caetano, C. Vale, and J. Marmolejo-Rodríguez, "Rare earth elements in sediments of the Vigo Ria, NW Iberian Peninsula," *Continental Shelf Research*, 29(7), 896-902 (2009).<https://doi.org/10.1016/j.csr.2009.01.009>
- [21] I. P. Ramos, A. M. G. Bernabéu, D. Rey, and F. Vilas, "Formación del placer de la playa de Montalvo (Pontevedra)."
- [22] E. Gloaguen, A. Chauvet, Y. Branquet, O. Gerbeaud, C. Ramboz, V. Bouchot, L. Catherine, P. Monié, M. Cathelineau, M.-C. Boiron, C. Marignac, and N. Pourraz, "Relations between Au / Sn-W mineralizations and late hercynian granite: Preliminary results from the Schistose Domain of Galicia Trás-os-Montes Zone, Spain." (2003)
- [23] A. Bernabeu, F. Manso, G. Martínez, D. Rey, and F. Vilas, "Recursos minerales marinos en las rías gallegas y en la plataforma continental adyacente," *Journal of Iberian Geology*, 2000.10.5209/JIGE.34011
- [24] R. Haralick, K. Shanmugam, and I. Dinstein, "Textural Features for Image Classification," *IEEE Trans Syst Man Cybern*, SMC-3, 610-621 (1973)
- [25] J. Canny, "A Computational Approach to Edge Detection," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, PAMI-8(6), 679-698 (1986).10.1109/TPAMI.1986.4767851
- [26] R. O. Duda, and P. E. Hart, "Use of the Hough transformation to detect lines and curves in pictures," *Commun. ACM*, 15, 11-15 (1972).10.1145/361237.361242

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Building a Ground-Based Spectral Library for Remote Sensing image processing of Heavy Mineral Placers in Rias Baixas, Spain

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Abstract. Critical raw materials (CRM) are currently considered essential for the European Union (EU) energy transition. In the scope of the Horizon Europe S34I (SECURE AND SUSTAINABLE SUPPLY OF RAW MATERIALS FOR EU INDUSTRY; <https://doi.org/10.3030/101091616>) project, new remote sensing methods to support the exploration and ensure the EU autonomy in CRM are being explored. The region of Rias Baixas, in Galicia, Spain, contains marine placer deposits of several CRMs, including rare earth elements (REEs), and it is suitable to demonstrate the effectiveness of Earth Observation (EO) methods applied to the identification of these deposits. Building a spectral library for the target mineralogy is one important step in many studies that approach remote sensing data when applied to mineral deposits. In this work, we describe the process of creating the spectral library for Rias Baixas and identifying targets for beach placer minerals such as garnet and tourmaline.

Keywords: Critical raw materials, marine placers, Earth Observation, Reflectance spectroscopy, Coastal areas.

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1 Introduction

Marine placer deposits comprise heavy minerals, heavy metallic minerals, and gemstones eroded from various, but usually igneous, rocks on land [1]. Fluvial systems transport these materials to the sea. These minerals have characteristic densities that do not favour their deposition in fluvial systems. Instead, they are deposited in sandy beach systems by waves, tides, and currents. Important marine placer minerals include rutile, ilmenite, cassiterite, garnet, magnetite, and monazite [2, 3]. Marine placers are referred to by the European Commission [4] as an important source of Critical Raw Materials (CRM) essential for the production of a broad range of goods and services, as well as for the development of new technologies for the Green Transition, playing a significant role in the global economy.

The region of Ria de Vigo (Figure 1) includes placer deposits of zircon, garnets, monazites, tourmaline, pyroxene, ilmenite, pyrite, magnetite, hematite, goethite, and lithium minerals like spodumene associated with pegmatites [5].

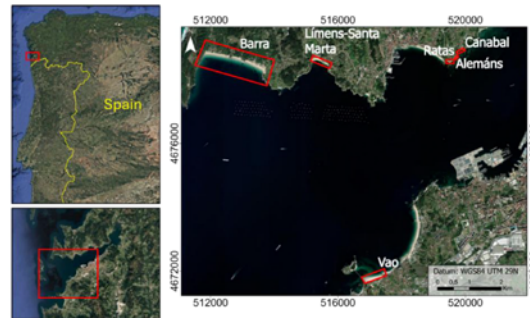


Fig.1. Geographic setting of the Ria de Vigo study area. Location of beaches where samples were collected.

These are controlled by river discharges, wind regimes over the continental shelf, and the semidiurnal mesotidal regimen on the Atlantic coast [6, 7]. Initial research on the Vigo placers is currently ongoing in the scope of the S34I (Secure Sustainable Supply of Raw Materials for EU Industry) project, which aims to develop Earth Observation (EO) methods that are effective in detecting beach placer deposits. Building a spectral library for the target mineralogy is a critical step in many studies that approach remote sensing data when applied to mineral deposits and improves the qualitative and quantitative analysis of spectral signatures [8].

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match the USGS spectral library using the Python library `spectres` and later compared with the USGS using the SAM algorithm. The result is given according to the similarity of the measured spectra, i.e., to the reference spectra with the smallest angle compared with the one measured in the laboratory.

Secondly, the spectra were manually interpreted based on known literature [16-19] by observing the location, depth, asymmetry and other characteristics of absorption features. Manual interpretation allows the identification of the main spectrally active minerals that could contribute to the mineral mixture.

3 Results

When using SAM to compare spectra from Santa Marta (Fig.3a), spessartite was identified. However, manual interpretation shows clear diagnostic features indicative of tourmaline in the SWIR range: two sharp and narrow absorptions at 2207 nm and 2247 nm coupled with a distinctive absorption at 2362 nm attributed to stretching vibrations (B–OH, Al–OH, Mg–OH, Mn–OH) [16, 19, 20]. Nonetheless, the absorption peak at ~900 nm followed a broad Fe-related absorption around 1344 nm, together with several absorptions in the VNIR at 412 nm and 503 nm are compatible with garnet spectra [17, 18]. For Vao Beach (Fig.3b), after comparison with the USGS spectral library, the garnet with the best match is almandine. Similarly, besides the tourmaline features in the SWIR, garnet is manually identified through VNIR features. For both concentrates from the two beaches, the second and third matches with USGS also correspond to almandine.

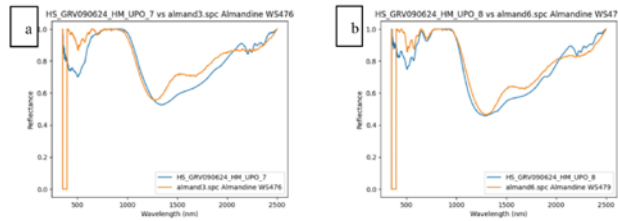


Fig.3. Best matches with the USGS spectral library for the spectra from Santa Marta (a) and Vao (b) beaches.

4 Conclusions

Some target minerals, such as garnet and tourmaline, can be interpreted even without their pure spectral signature, i.e., in mixed spectra. However, some spectral signatures can interfere with other minerals, as is the case for the garnet

2 Methodology

2.1 Field sampling

The samples were collected in two field campaigns in March of 2023 and September of 2023. The field sampling campaign included collecting sands of placers on the beaches of Barra, Límens, Santa Marta, Vao, Canabal, Alemans and Canabal (Figure 1). The collected samples were restricted to the superior layer of sand on the beach, and plastic bags were used for storage (Figure 2a). After sampling, the heavy minerals were separated from the original sample for IGME (Geological Survey of Spain).

2.2 Laboratory Spectral Collection

Only the heavy mineral (Figure 2c) portion was used for the spectral library. The spectra were collected in the laboratory using the spectroradiometer Field-Spec 4 standard resolution (ASD Inc., Boulder, CO, USA) in the 400 to 2500 nm interval, with additional characteristics described in [9, 10].

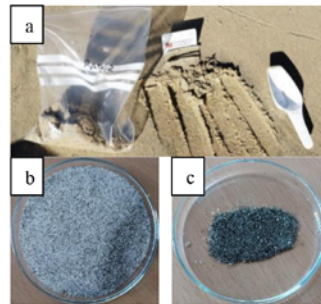


Fig.2. a) Sample collected on the field; b) whole sample; c) heavy mineral fraction.

2.2 Spectral Interpretation

Two approaches were evaluated for interpreting the spectral data after continuum removal by applying the hull quotient technique using a Python routine [9]. First, we applied the Spectral Angler Mapper (SAM) algorithm in Python to compare and match the collected spectral data with the USGS Spectral Library. SAM is a widely applied technique used to compare spectra [11, 12], where the spectral similarity between two spectra is calculated by computing the angle between them in a multidimensional space [13, 14]. The USGS spectral library [15] was loaded using spectral.io.envi module from the Spectral Python library. The spectral data collected in the laboratory was resampled to

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and tourmaline, and the context of the area is important in interpreting the results. Manual/expert interpretation showed higher capabilities in this regard, considering mixed spectra, as spectral matching with SAM could not identify tourmaline. The process of spectral matching is useful for mineral identification, as well as for broader applications and local references. The ground-based spectral library can be integrated with EO data and has great value applied to the validation and uncertainty assessment of remote sensing studies that involve the identification of the placers. The results also increase the knowledge about the local variations and patterns of the minerals in Vigo.

5 Acknowledgements

This work is supported by national funding awarded by FCT - Foundation for Science and Technology, I.P., projects UIDB/04683/2020 (<https://doi.org/10.54499/UIDB/04683/2020>) and UIDP/04683/2020 (<https://doi.org/10.54499/UIDP/04683/2020>); and by the EU under grant agreement no. 101091616 (<https://doi.org/10.3030/101091616>), project S34L.

References

1. Hou, B.; Keeling, J.; Van Gosen, B. S. Geological and Exploration Models of Beach Placer Deposits, Integrated from Case-Studies of Southern Australia. *Ore Geology Reviews* **2017**, *80*, 437-459. DOI: <https://doi.org/10.1016/j.oregeorev.2016.07.016>.
2. Cronan, D. S. *Handbook of Marine Mineral Deposits*; CRC Press, 2000.
3. Alcom, T.; Monteys, X.; Blasco, I.; Lobato, A.; González, J. Are the pan-European seas a promising source for critical metals supply? GeoERA-MINDeSEA Marine Data and Information Management Best Practices. *Bollettino di Geofisica Teorica ed Applicata* **2021**, *62*.
4. Vallius, H. T. V.; Kotilainen, A. T.; Asch, K. C.; Fiorentino, A.; Judge, M.; Stewart, H. A.; Pjetursson, B. Discovering Europe's seabed geology: the EMODnet concept of uniform collection and harmonization of marine data. In *From Continental Shelf to Slope: Mapping the Oceanic Realm*, Asch, K., Kitazato, H., Vallius, H. Eds.; Geological Society of London, 2022.
5. Vilas, F.; Bernabeu, A.; Méndez, G. Sediment distribution pattern in the Rias Baixas (NW Spain): main facies and hydrodynamic dependence. *Journal of Marine Systems* **2005**, *54* (1-4), 261-276.
6. Alvarez, I.; Decastro, M.; Gomez-Gesteira, M.; Prego, R. Inter-and intra-annual analysis of the salinity and temperature evolution in the Galician Rias Baixas-ocean boundary (northwest Spain). *Journal of Geophysical Research: Oceans* **2005**, *110* (C4).
7. Bernabeu, A. M.; Lersundi-Kanpistegi, A. V.; Vilas, F. Gradation from oceanic to estuarine beaches in a ria environment: A case study in the Ría de Vigo. *Estuarine, Coastal and Shelf Science* **2012**, *102-103*, 60-69. DOI: <https://doi.org/10.1016/j.ecss.2012.03.001>.

8. Manzo, C.; Valentini, E.; Taramelli, A.; Filipponi, F.; Disperati, L. Spectral characterization of coastal sediments using Field Spectral Libraries, Airborne Hyperspectral Images and Topographic LiDAR Data (FHyL). *International Journal of Applied Earth Observation and Geoinformation* **2015**, *36*, 54-68. DOI: <https://doi.org/10.1016/j.jag.2014.11.003>.
9. Cardoso-Fernandes, J.; Silva, J.; Dias, F.; Lima, A.; Teodoro, A. C.; Barrès, O.; Cauzid, J.; Perrotta, M.; Roda-Robles, E.; Ribeiro, M. A. Tools for Remote Exploration: A Lithium (Li) Dedicated Spectral Library of the Fregeneda-Almendra Aplite-Pegmatite Field. *Data* **2021**, *6* (3), 33. DOI: [doi:10.3390/data6030033](https://doi.org/10.3390/data6030033).
10. Carvalho, M.; Cardoso-Fernandes, J.; Lima, A.; Teodoro, A. C. Convolutional Neural Networks Applied to Antimony Quantification via Soil Laboratory Reflectance Spectroscopy in Northern Portugal: Opportunities and Challenges. *Remote Sensing* **2024**, *16* (11), 1964.
11. Kruse, F. A.; Boardman, J.; Huntington, J. Comparison between AVIRIS and hyperion for hyperspectral mineral mapping. *IEEE Trans Geosci Remote Sens* **2003**, *41*, 1388-1400.
12. van der Meer, F. The effectiveness of spectral similarity measures for the analysis of hyperspectral imagery. *International Journal of Applied Earth Observation and Geoinformation* **2006**, *8* (1), 3-17. DOI: <https://doi.org/10.1016/j.jag.2005.06.001>.
13. Yuhas, R. H.; Goetz, A. F.; Boardman, J. W. Discrimination among semi-arid landscape endmembers using the spectral angle mapper (SAM) algorithm. In *JPL, Summaries of the Third Annual JPL Airborne Geoscience Workshop. Volume 1: AVIRIS Workshop*, 1992.
14. Kruse, F. A.; Lefkoff, A.; Boardman, J.; Heidebrecht, K.; Shapiro, A.; Barloon, P.; Goetz, A. The spectral image processing system (SIPS)—interactive visualization and analysis of imaging spectrometer data. *Remote sensing of environment* **1993**, *44* (2-3), 145-163.
15. Kokaly, R. F.; Clark, R. N.; Swayze, G. A.; Livo, K. E.; Hoefen, T. M.; Pearson, N. C.; Wise, R. A.; Benz, W.; Lowers, H. A.; Driscoll, R. L. *USGS spectral library version 7*; US Geological Survey, 2017.
16. Pontual, S.; Merry, N.; Gamson, P. Spectral Interpretation Field Manual: GMEX Spectral Analysis Guides for Mineral Exploration. *Victoria, AusSpec International Pty* **2008**.
17. Hunt, G. R. Spectral signatures of particulate minerals in the visible and near infrared. *Geophysics* **1977**, *42* (3), 501-513.
18. Clark, R. N.; Swayze, G. A.; Gallagher, A. J.; King, T. V. V.; Calvin, W. M. *The U. S. Geological Survey, Digital Spectral Library: Version 1 (0.2 to 3.0um)*; 1993. <https://pubs.usgs.gov/publication/ofr93592> DOI: 10.3133/ofr93592.
19. Bierwirth, P. LABORATORY AND IMAGING SPECTROSCOPY OF TOURMALINE – A TOOL FOR MINERAL EXPLORATION. 2008.

I.2. Conference abstracts



¿1899 | Evaluating K-Means Classification for Manual Lineament Extraction: A Comparative Study with Band Ratio from Sentinel-1 imagery, in the Ria de Vigo, Spain

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Background & Aim: The Rias Baixas region, located on the Atlantic margin of southwestern Galicia, is composed of four funnel-shaped estuaries, of which the Ria de Vigo is the southernmost. The Galician Rias lie within the Galiza Trás-os-Montes Zone. The local geology is dominated by Variscan granites hosted in Palaeozoic metasediments, overlain by Quaternary-age sediments. The fracture system is NE-SW and NW-SE oriented [1]. This region is of special interest due to the occurrence of heavy-mineral placer deposits of Ti, Sn, Li, REEs, Au, Fe and Cu, classified as Critical Raw Materials by the European Union [2]. This work assesses K-Means Classification's feasibility to differentiate structural features, comparing it with a manually extracted lineament map to evaluate the results. **Methods:** A Sentinel-1 image was acquired. To pre-process, first an orbit file was applied, followed by Speckle Filtering and lastly Terrain Correction was conducted [3,4]. The K-Means image, using VH_Amplitude, VH_Intensity, VV_Amplitude and VV_Intensity bands (8 clusters, 15 iterations) was selected for lineament extraction. The VH and VV bands were obtained by a band ratio of VH_Amplitude/VH_Intensity and VV_Amplitude/VV_Intensity [3,4]. The band VH was chosen for manual lineament mapping, to serve as a comparison. Four Prewitt directional filters were applied to highlight lineaments in N-S, E-W, NE-SW and NW-SE directions [5]. An RGB composite of the three best directional filters was created. **Results:** For the VH band, 372 lineaments were extracted, compared to 172 for the K-Means image. Out of the 172 lineaments, only 24 don't align with the ones extracted from the VH band. This is mainly due to textural alterations. However, the medium orientation lineaments from both extractions are well aligned, being 139° N and 143° for the VH band and K-Means image, respectively. **Conclusion:** K-Means efficiently classified the most prominent lineaments with good accuracy, although in less detail and number when compared to the VH band.

Keywords: SAR, Sentinel-1, K-Means, Lineaments, Placers.

Acknowledgements

This study is funded by the European Union under grant agreement no. 101091616, project S34I – SECURE AND SUSTAINABLE SUPPLY OF RAW MATERIALS FOR EU INDUSTRY, coordinated by Ana C. Teodoro. This work is also supported by Portuguese National Funds through the FCT – Fundação para a Ciência e a Tecnologia, I.P. (Portugal), projects UIDB/04683/2020 (<https://doi.org/10.54499/UIDB/04683/2020>) and UIDP/04683/2020 (<https://doi.org/10.54499/UIDP/04683/2020>).

References:

- [1] Ribeiro, A., Pereira, E. & Dias, R. (1990). Structure of the Northwest of the Iberian Peninsula. In: Pre-Mesozoic Geology of Iberia (eds. Dallmeyer, D. & Martinez Garcia, E.). Springer, 220-236.
- [2] Méndez, G.L., Rey, D., Bernabéu, A.M., Manso, F., & Vilas, F. (2000). Recursos minerales marinos en las rías gallegas y en la plataforma continental adyacente. *Journal of Iberian Geology*, 26.
- [3] Javhar, A., Chen, X., Bao, A., Jamshed, A., Yunus, M., Jovid, A., & Latipa, T. (2019). Comparison of Multi-Resolution Optical Landsat-8, Sentinel-2 and Radar Sentinel-1 Data for Automatic Lineament Extraction: A Case Study of Alichur Area, SE Pamir. *Remote. Sens.*, 11, 778.
- [4] Heine, I., Jagdhuber, T., & Itzerott, S. (2016). Classification and Monitoring of Reed Belts Using Dual-Polarimetric TerraSAR-X Time Series. *Remote. Sens.*, 8, 552.
- [5] Cardoso-Fernandes, J., Lima, A., Teodoro, A. (2018). Sentinel-2 data as a tool for structural mapping. VIII Congresso Jovens Investigadores em Geociências, LEG. Estremoz.

S34I – Visão global de dados de observação da Terra em várias fases do ciclo mineiro

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O projeto S34I (<https://doi.org/10.3030/101091616>) financiado por fundos europeus está a explorar e desenvolver protótipos de novos métodos de análise de dados de Observação da Terra (OT), demonstrando o seu valor para a indústria, comunidades locais e legisladores no que respeita à transformação digital da indústria mineira. O consórcio de projeto reúne 19 parceiros de 12 países da Europa. Combinando conhecimentos de diversas áreas e juntando a academia, indústria, organizações estatais, fundações e centros de investigação, o projeto S34I contribui para a sustentabilidade, segurança e soberania das matérias-primas da União Europeia (EU), apoiando a prospeção mineral e a monitorização contínua das atividades mineiras, quer sejam elas de extração, encerramento e pós-encerramento.

Como tal, o S34I utiliza a OT não só para a gestão de questões técnicas e ambientais para uma transição verde, mas também apoia a sensibilização do público, a aceitação social da mineração e contribui para uma melhor legislação. Sendo assim, o projeto adquiriu dados de OT em diversas escalas e tipos de plataformas, nomeadamente satélites, aviões, veículos aéreos não tripulados (VANTs), robots subaquáticos e equipamentos portáteis para levantamentos terrestres. Os dados óticos utilizados são multiespectrais (Sentinel-2, Landsat-8/-9, Worldview-2, Worldview-3, Pleiades-NEO) e hiperespectrais (EnMap, PRISMA). Já os dados radar por satélite incluem dados de média resolução espacial (Sentinel-1) e alta resolução espacial (ALOS PALSAR-2, COSMO-SkyMED). Duas campanhas de avião permitiram recolher dois tipos de dados: LiDAR e dados óticos hiperespectrais (AISA Fenix). Os VANTs, por sua vez, permitiram adquirir imagens multiespectrais de elevada resolução espacial. Uma inovação do projeto é a aplicação de sensores hiperespectrais em robots subaquáticos, bem como câmaras multiespectrais em VANTs subaquáticos para adquirir dados do fundo do mar (em águas pouco profundas). Dados de campo foram ainda adquiridos para calibração e validação dos dados de OT, nomeadamente através de espectrorradiómetros portáteis e de recetores GNSS in-situ.

Para cobrir o ciclo mineiro completo, diferentes tipos de caso de estudo foram selecionados:

- (i) prospeção em terra (mina de Áramo, Espanha);
- (ii) prospeção na transição costeira-marinha (Ria de Vigo, Espanha);
- (iii) mina ativa a céu aberto (mina de Gummern, Áustria);
- (iv) mina encerrada com problemas de drenagem ácida de mina – DAM (Lausitz na Alemanha e Outokumpu na Finlândia); e
- (v) mina encerrada com problemas de subsidência (mina de Aijala, Finlândia).

Com base nos resultados obtidos, o projeto S34I está a desenvolver três categorias de serviços para as diferentes fases do ciclo mineiro com base em dados de OT: (i)

mapeamento de matérias primas críticas para prospeção mais eficiente, (ii) sistema de alerta precoce de riscos de operação em minas a laborar, e (iii) monitorização ambiental de minas encerradas com ênfase na DAM.



*IX International Symposium on Marine Sciences
Valencia (Spain), 10-12th July 2024*

EARTH OBSERVATION APPROACH TO UNDERSTAND COASTAL MORPHOLOGY, SHORELINE DYNAMICS, AND THEIR RELATIONSHIP WITH MINERAL PLACER DEPOSITS: THE CASE OF SANTA MARTA BEACH (RÍA DE VIGO, NW SPAIN)

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Abstract: Santa Marta Beach is situated in the N part of the Ría de Vigo, an estuary system in NW Spain. It is approximately 155 m long and is separated from Limens Beach by an igneous rocky outcrop in the middle part. Both beaches are enclosed and sheltered by rocky outcrops, and are sandy beaches. This study analyses the dynamics of the coastline in different seasons and spatial resolutions using PNOA (National Aerial Orthophotography Plan), Google Earth and unmanned aerial vehicle (UAV) images of Santa Marta beach, collected between 2001 and 2024, as well as field data from marine placer occurrences acquired in 2023 and 2024. Two profiles across the beach, with available PNOA LIDAR information from 2020, were studied to better understand the morphology, and to know where the heavy mineral placer deposits occur.

Image analysis shows that the coastline is generally stable (non-erosive and non-accreting), however a large variability in the shoreline is observed, caused by low and high tides, depending on the season. During storm events in Google Earth images, waves reach the backshore zone, covering almost the entire beach. Two types of dense mineral accumulations forming placer deposits were distinguished during the field trips in 2023 and 2024: surface occurrences, deposited by the current swell, and deeper ones up to about 80 cm depth, found in the sediment-test excavations, that formed during the last decades. The heavy mineral source, is a stream at the East of the beach with dynamic behaviour during the last two years of observation. It shows an initial period of heavy mineral input (without erosion of the beach, as in the field trip in March 2023), an advanced period of heavy mineral input (with transverse erosion of the beach and formation of a stream that reaches the sea,

I.3 Posters

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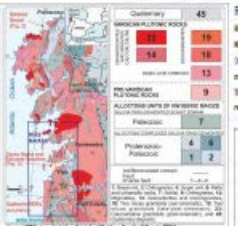
S34

SECURE AND SUSTAINABLE SUPPLY OF RAW MATERIALS FOR EU INDUSTRY

Where beach and sea meet: New tools applied to CRMs exploration in Ría de Vigo (NW Spain)

RÍAS BAIXAS: A PROMISING EXPLORATION AREA

Rías Baixas, a funnel-shaped estuarine inflow system in the coastal drainage area located in NW Spain, is mainly surrounded by Tertiary metamorphic and intrusive coastal outcrops (Fig. 1). Heavy mineral placers occur in the Rías Baixas (Fig. 2), mainly in the Ría de Vigo, where they were exploited in the 19th century (Fig. 3). They were explored in the 20th century (Fig. 4) and more recently by the S34 project (Fig. 5).



FROM TRADITIONAL TO THE MOST MODERN EARTH OBSERVATION TECHNIQUES EXPLORING MINERALS IN THE SHORELINE

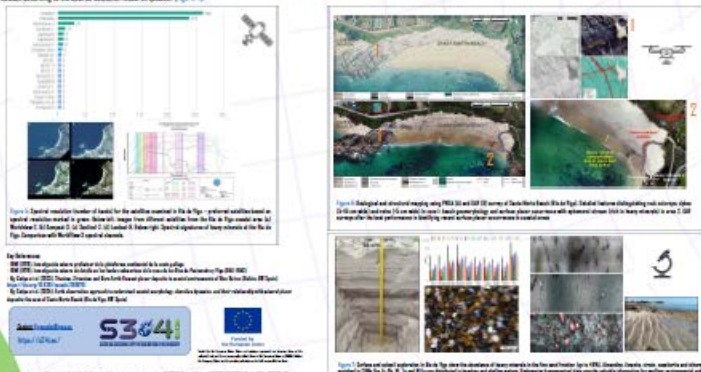
Critical Raw Materials (CRM) mineralizations, including U, Th, Pa, U, K, and Au, are being investigated. S34 project results improve mineral mapping using novel Earth Observation (EO)-based methods supporting traditional geological mapping and on-land studies to explore the connection between onshore and coastal areas (Fig. 6).





MAPPING MINERALS AND IMPROVING KNOWLEDGE IN COASTAL AREAS

Ría de Vigo is a CRM prospect area where modern high-resolution technologies have been applied to the exploration and management of CRMs in a sustainable, economic and non-invasive way. This study is providing solutions (data and new methods) by selecting the most adequate EO dataset according to the desired outcome/research question (Fig. 5-7).



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Funded by the European Union

Projeto S34I – Contribuição de novos métodos de detecção remota na prospeção e exploração mineral

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INTRODUÇÃO

O Projeto S34I - Secure and Sustainable Supply of Raw Materials for EU Industry, financiado pela União Europeia, através do programa Horizon Europe, conta com um consórcio constituído por 19 parceiros provenientes de 12 países europeus, juntando a academia, indústria, organizações estatais, fundações e centros de investigação.



Fig. 1 – Consórcio do projeto constituído por 19 parceiros de 12 países europeus.

OBJETIVOS

O principal objetivo deste trabalho é o desenvolvimento de métodos inovadores de detecção remota, usando dados de observação da Terra (OT) aplicando-os à prospeção de matérias-primas consideradas críticas pela União Europeia, além da contínua monitorização de atividades mineiras, nas suas fases de extração, encerramento e pós-encerramento, englobando todo o ciclo mineiro. Efetivamente, este projeto contribui para uma Europa mais segura, sustentável e autossuficiente em matérias-primas, essenciais para a economia e para a transição energética.

DADOS

Satélite (Copernicus e missões contributivas)

Óticos Multiespectrais
Sentinel-2, Landsat-8/9, Worldview-2, Worldview-3, Pleiades-NEO

Óticos hiperespectrais
EnMAP, PRISMA

Radar de média resolução espacial
Sentinel-1

Radar de alta resolução espacial
ALOS, PALSAR-2, COSMO-SkyMed

Campanhas de avião

Sensor activo
LIDAR

Ótico hiperespectral
AISA Fenix

ROVs

Ótico hiperespectral
Sensores hiperespectrais em Remotely Operated Vehicles (ROVs) subaquáticos

VANTs

Ótico multiespectral
Sensores multiespectrais em Veículos Aéreos Não Tripulados (VANTs)

Trabalho de campo

Espectrorradiômetros portáteis e receptores GNSS in-situ

Áreas Piloto

Prospeção

Em Terra

Mina de Aramo, Espanha
Localizada nas Astúrias, esta mina explora um depósito epitermal de Cu-Co-Ni. O estudo centra-se na identificação de alterações hidrotermais nas áreas circundantes à mina e de novas áreas com potencial de mineralização, visando uma possível expansão das zonas de prospeção.

Zona costeira

Ria de Vigo, Espanha
A Ria de Vigo pertence a um conjunto de estuários, denominados de Rias Baixas, localizadas na Galiza. São reconhecidas ocorrências de placers marinhos de Ti, Sn, Li, Terras Raras (REE) e Au, pelo que o estudo desta área passa pela identificação e pesquisa destas mineralizações, passando por um mapeamento mineral dos fundos marinhos, explorando a transição marinho-continental.

Extração

Mina activa a céu aberto

Gumern, Áustria
Produzindo cerca de 1 milhão de toneladas de mármore de alta qualidade, esta mina enfrenta desafios técnicos que passam pelo controlo adequado da qualidade, bem como a estabilização contínua de taludes e escombrelas.

Mina encerrada com problemas de subsidência

Aijala, Finlândia

Localizada no sudoeste da Finlândia, esta mina subterrânea de Au, Ag, Cu, Pb e Zn, encontra-se inundada, desde o seu fecho em 1961. Atualmente, a mina é um alvo de estudo, devido aos seus problemas de estabilidade, que se tornaram evidentes desde o colapso de um túnel em 2017.

Mina encerrada com problemas de drenagem ácida

Lausitz, Alemanha | Outokumpu, Finlândia

As três minas antigas de Outokumpu, e de Lausitz enfrentam um problema comum – a drenagem ácida mineira. Na área de Outokumpu, o estudo foca-se na lagoa Outokumpu, atualmente não monitorizada e com pH inferior a 2, e no lago Sysmäjärvi, parte da Rede Natura 2000, afetado pelas atividades mineiras. Em Lausitz, um grande número de poços, lagos e canais, previamente usados para bombear água para a superfície, apresentam padrões significativos de drenagem ácida.



Fig. 2 – Fotografias e imagens de satélite das áreas de estudo.

RESULTADOS FINAIS



Este estudo é financiado pela União Europeia ao abrigo do acordo de subvenção nº 101091616, projeto S34I, coordenado por Ana C. Teodoro. Este trabalho é também apoiado por Fundos Nacionais Portugueses através da FCT – Fundação para a Ciência e a Tecnologia, I.P. (Portugal), projetos UIDB/04683/2020 (https://doi.org/10.54499/UIB/04683/2020) e UIDP/04683/2020 (https://doi.org/10.54499/UIP/04683/2020).



II. EnMAP band ratios

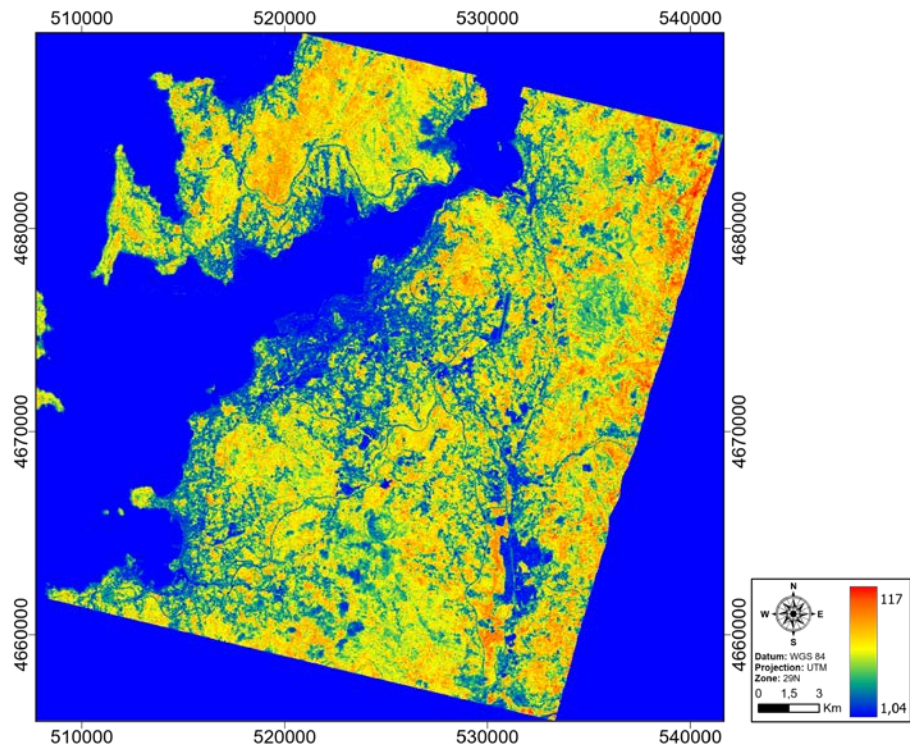


Figure 59 - Alunite/Kaolinite/Pyrophyllite band ratio

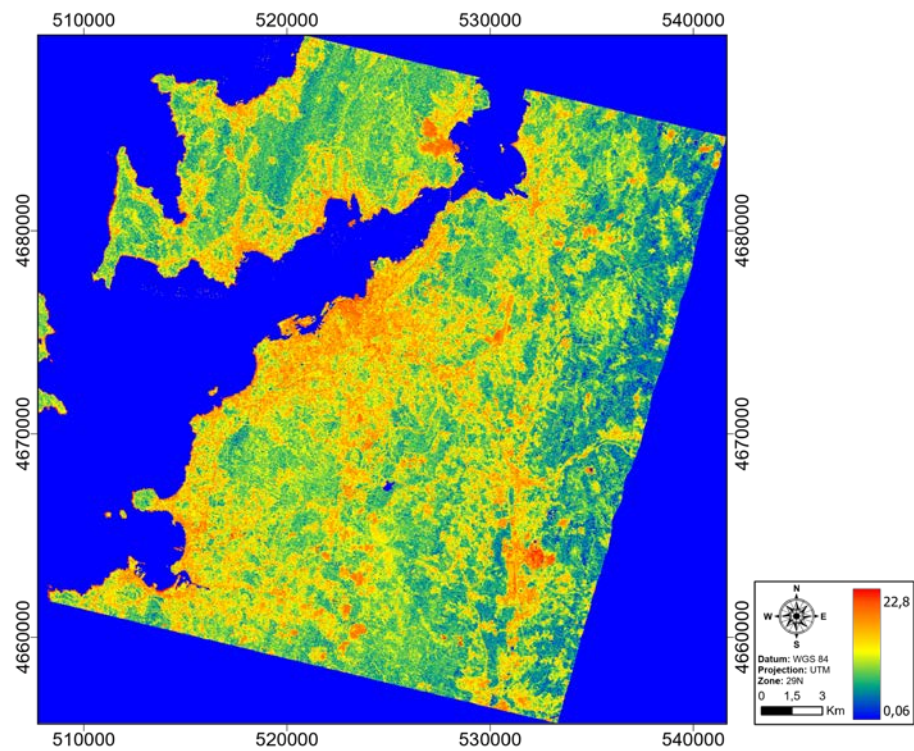


Figure 60 – Clay band ratio.

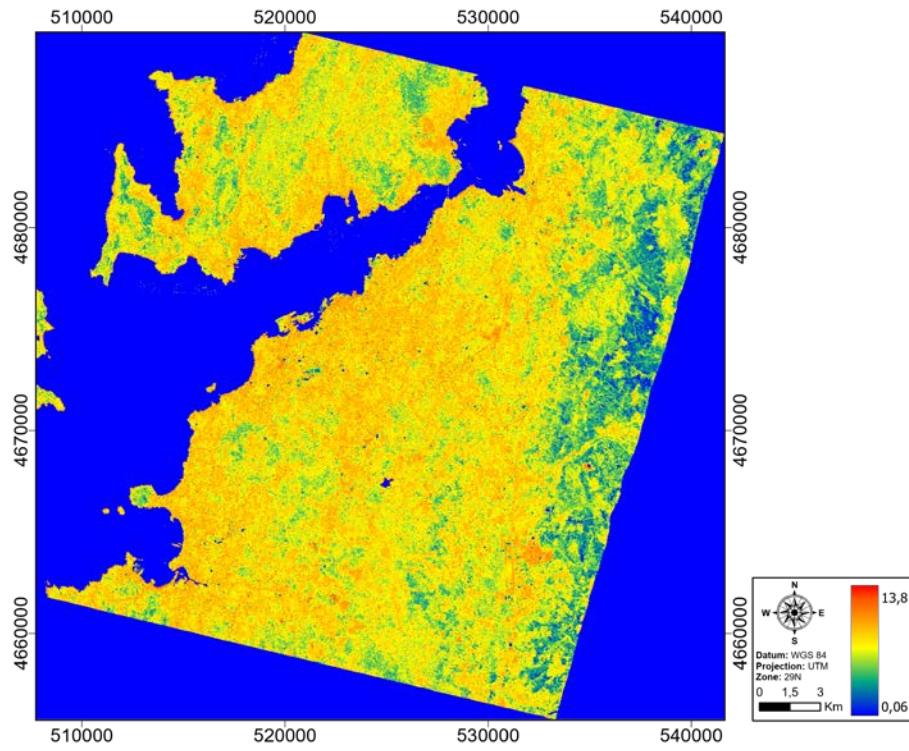


Figure 61 – Kaolinite band ratio.

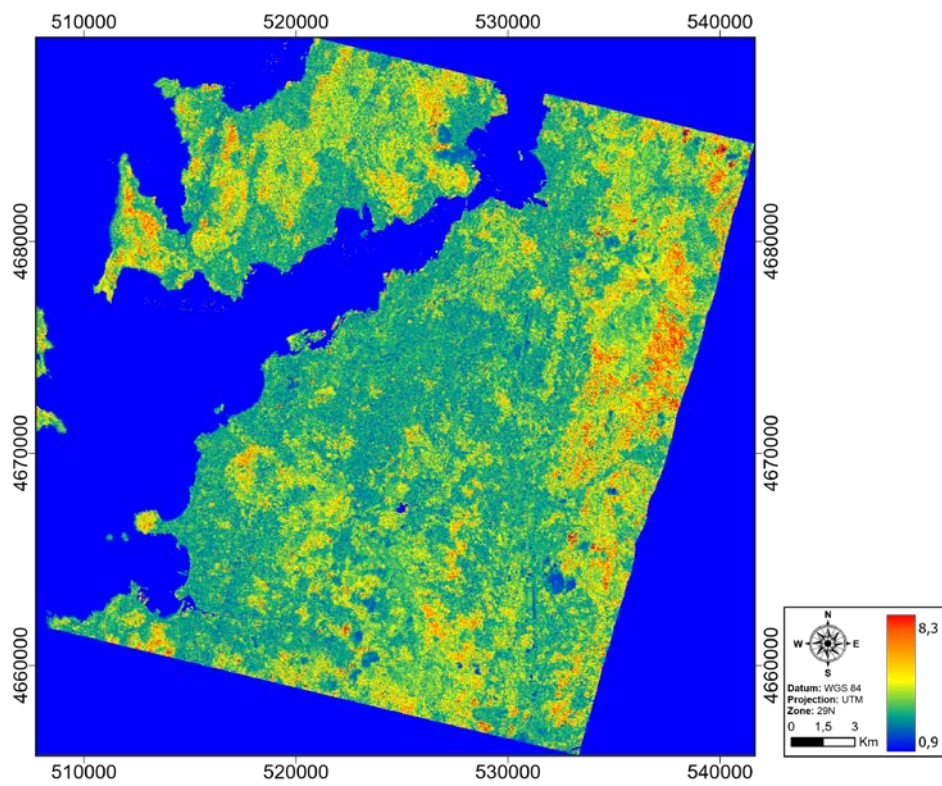


Figure 62 – Epidote/Chlorite/Amphibole band ratio.

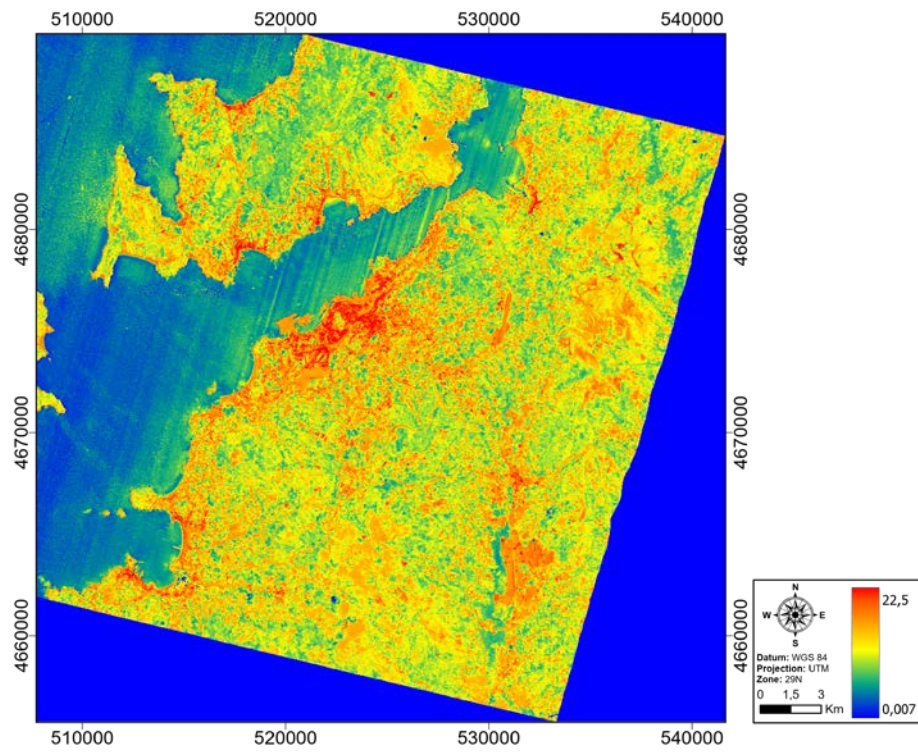


Figure 63 – Ferric iron band ratio

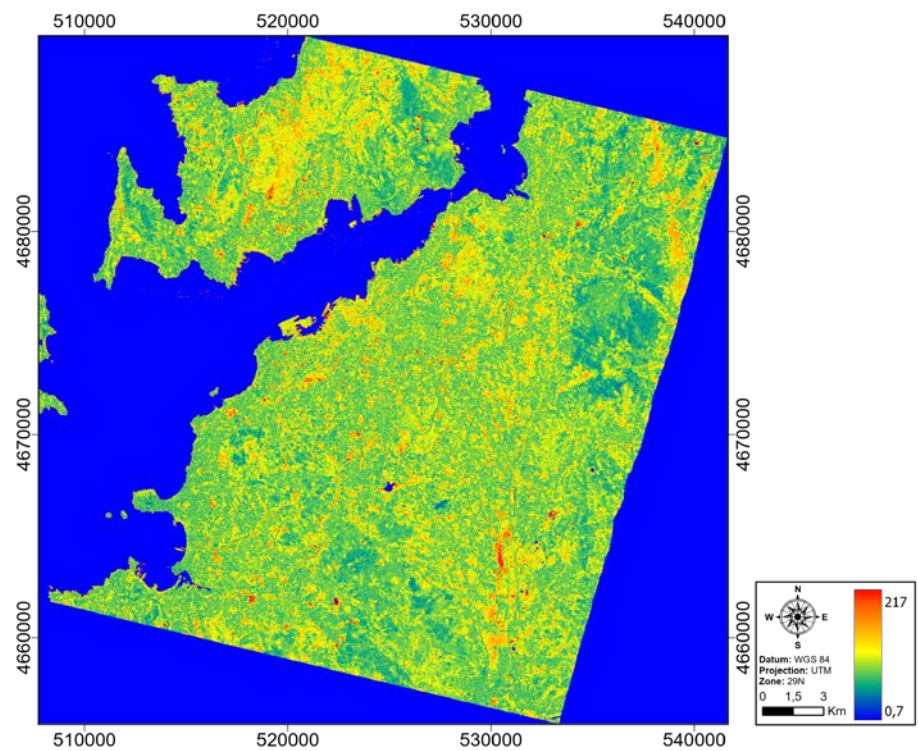


Figure 64 – Ferrous iron band ratio.

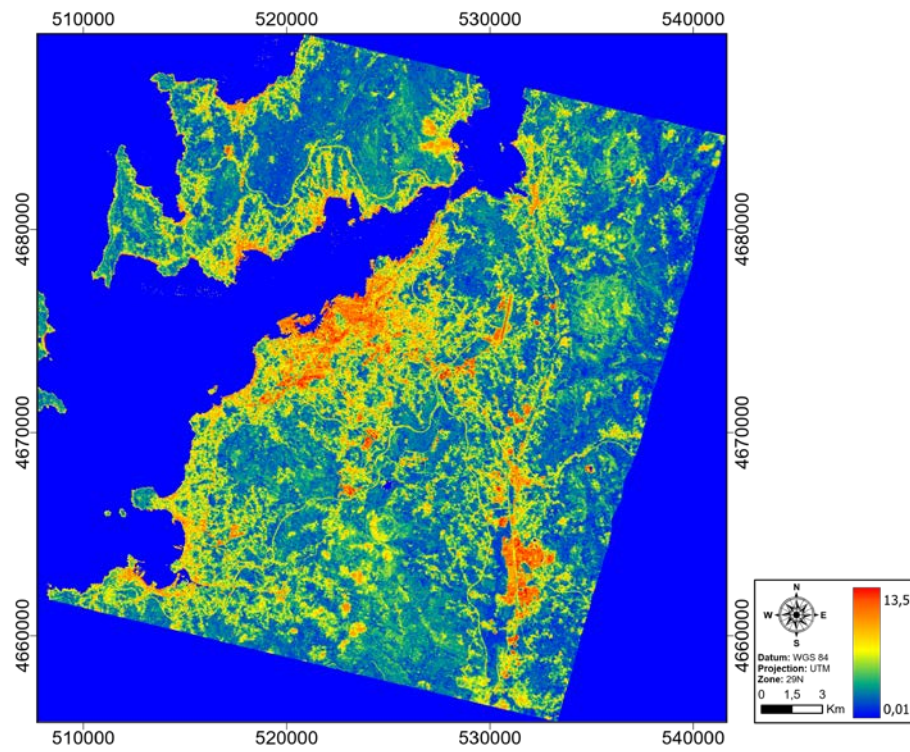


Figure 65 – Ferrous silicates band ratio.

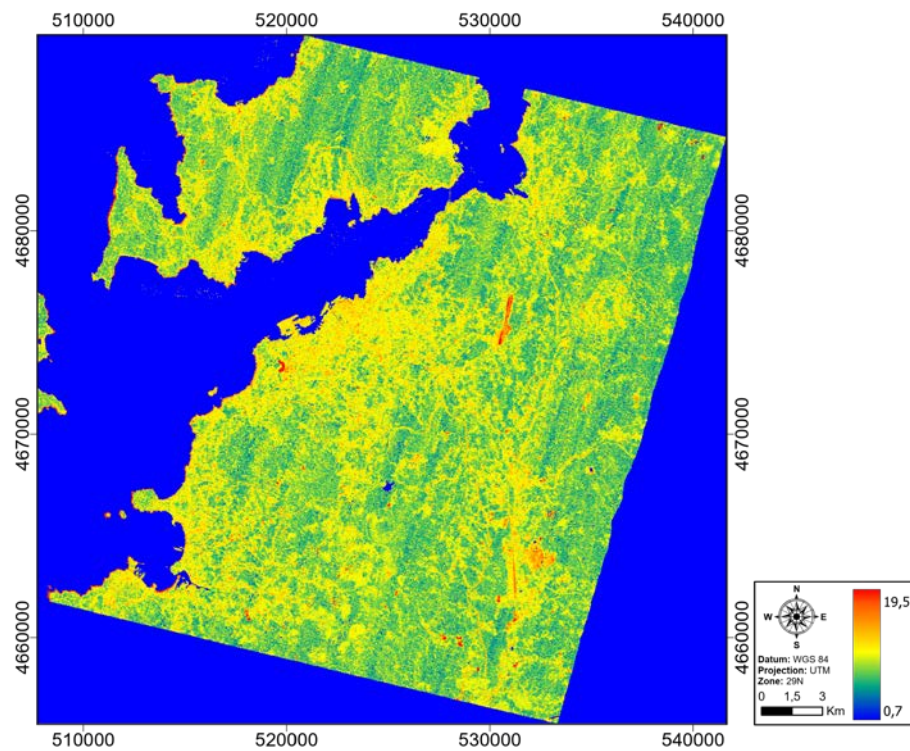


Figure 66 – Al-sheetsilicates band ratio.

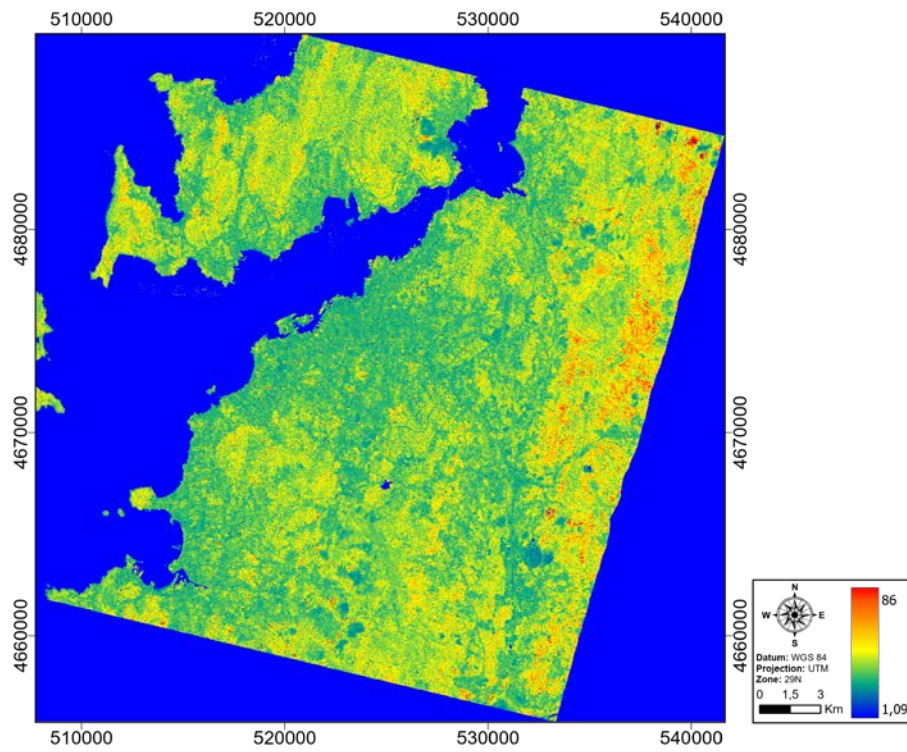


Figure 67 – Amphibole/MgOH band ratio.