

Article

Integrated Multisource Radar and Geophysical Data for Depth-Resolved Structural Analysis and Mineral Prospectivity: DEM, NISAR, BIOMASS, and Aeromagnetic Data

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Abstract

This study introduces a multisource, multiscale approach to delineate structural lineaments and assess mineralization controls in Wadi El-Markh, Central Eastern Desert, Egypt. Four datasets (ALOS PALSAR DEM, NISAR L-band SAR, BIOMASS P-band SAR, and aeromagnetic data) were processed using tailored workflows to extract lineaments at complementary depths, from the surface to deep crustal levels. The AP-DEM workflow employed multi-azimuth hill-shading and directional Prewitt filtering. NISAR data were speckle-denoised before directional filtering of the HH and HV polarizations. BIOMASS data underwent polarimetric decomposition followed by directional filtering. Aeromagnetic data were reduced to the pole, analyzed using power-spectrum for depth estimation and regional-residual separation, and then processed using a CET grid-analysis workflow for lineaments extraction and generation of a Contact Occurrence Density (COD) map. Directional analysis revealed sensor-dependent biases: NISAR HH favored an E-W trend, whereas HV yielded a more isotropic distribution; BIOMASS surface scattering highlighted E-W and N-S trends, whereas volume scattering emphasized NW-SE and NE-SW trends. Aeromagnetic data identified both shallow- and deep-seated structures, with a dominant NW-SE trend. GIS-based fuzzy overlay produced a consensus structural complexity map. Validation against 15 known mining sites showed spatial coincidence rates ranging from 60% (AP-DEM and NISAR HH) to 86.7% (BIOMASS volume scattering and fuzzy overlay) for mining sites falling within high-structural-complexity zones. The results establish a reliable framework for identifying structurally controlled mineralization targets in arid terrains.



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1. Introduction

Mineral resources constitute a strategic foundation of modern civilization, underpinning economic development, technological advancement, and the global transition to renewable energy systems [1]. Yet mineral exploration is inherently challenging, as it requires the identification of buried or obscured ore bodies across vast, often remote terrains, with escalating costs, operational risks, and environmental sensitivities further compounding the difficulty. In arid and semi-arid shield terrains, maximizing target-selection efficiency while

minimizing exploration expenditure requires robust, cost-effective tools for delineating the geological structures that control mineralization [2–4].

Structural lineaments, defined as mappable linear or curvilinear features representing faults, fractures, joints, and shear zones, are among the most critical controls on hydrothermal mineralization [5–7]. These features serve as primary conduits for mineralizing fluids, and their spatial distribution, density, and intersection patterns largely govern the emplacement of ore deposits [8–11]. Consequently, accurate three-dimensional mapping of the structural framework is essential for developing predictive exploration models and narrowing the search space for prospective mineralization targets.

Remote sensing technology has emerged as a powerful tool for regional-scale structural mapping, providing synoptic, cost-effective, and multi-source datasets capable of revealing surface and near-surface geological structures [12–15]. Multispectral optical data from sensors such as ASTER, Sentinel-2, and Landsat have been widely used for geological applications, including edge enhancement of linear features [16–18]. Digital Elevation Models (DEMs) enable terrain and geomorphological analysis through multi-azimuth hill-shading, illuminating topographic lineaments from different directions and revealing structures that might otherwise remain hidden [19–25]. Synthetic aperture radar (SAR) data, which are sensitive to surface roughness and slope, offer particular advantages in arid terrains, where sparse vegetation enhances the radar response to geological structures [26–28].

Despite these advances, significant gaps remain in our ability to resolve the full structural spectrum from the surface to depth using a single sensor or wavelength. Co-polarized SAR backscatter (HH and VV) is strongly modulated by the geometric orientation of structures relative to the radar look direction, introducing pronounced orientation biases that can suppress or entirely mask structurally important trends [29–31]. Cross-polarized data (HV and VH) mitigate this bias by capturing depolarized energy from surface roughness and volume-scattering, yet the extent of this mitigation and its implications for mineral exploration remains underexplored in arid shield terrains. Furthermore, while L-band SAR (~24 cm wavelength) penetrates only the very near surface, P-band SAR (~70 cm wavelength) offers greater penetration into the regolith and shallow subsurface, potentially revealing structural fabrics invisible at shorter wavelengths. The comparative structural information content of L-band versus P-band polarimetric SAR, has not been systematically evaluated for lineament extraction in the Arabian-Nubian Shield (ANS).

Equally important is the subsurface dimension. Remote sensing datasets (optical, DEM, and SAR) are fundamentally limited to the surface and near-surface expression of geological structures. Airborne geophysical data, particularly aeromagnetic surveys, are indispensable for probing the subsurface structural architecture at variable depths [11,32–35]. Techniques such as power-spectrum analysis, vertical derivatives, analytic signal, and contact occurrence density (COD) enable the mapping of deep-seated (regional) and shallow-seated (residual) magnetic sources, providing a depth-resolved perspective on structural controls that surface remote sensing alone cannot achieve [12,33,36].

The integration of these complementary data sources, each probing different depths, offers a pathway toward robust, consensus-based structural mapping. Multi-criteria decision analysis, weighted overlay, fuzzy logic, and related approaches have been applied to integrate remote sensing and geophysical datasets for mineral prospectivity mapping [13,15,37,38]. However, the specific combination of topographic DEM, L-band dual-polarized NISAR, P-band fully polarimetric BIOMASS, and aeromagnetic structural layers has not been systematically evaluated for arid shield terrains such as ANS. This represents an important research gap: while individual sensors and methods have been evaluated separately, their synergistic integration for depth-resolved (from the surface to deep subsurface) structural analysis and mineral targeting in arid shield terrains remains unexplored.

The Central Eastern Desert of Egypt, situated within the northern ANS, provides an ideal natural laboratory for addressing this gap. The ANS is a Neoproterozoic juvenile crustal province formed through arc accretion, continental collision, and post-orogenic extension, resulting in a complex structural architecture dominated by NW-SE Najd-related shear systems which is consistent with the Red Sea rifting trend, complementary NE-SW complementary trends, and younger E-W and N-S fracture sets [39–45]. In the Central Eastern Desert specifically, the prevailing structural trends are NW-SE and WNW-ESE [44].

This study addresses the identified research gap through a comprehensive multi-source, multi-scale methodology designed to delineate structural lineaments from the surface to deep crustal levels and evaluate their implications for mineral exploration targeting. The specific objectives are: (1) to extract surface and near-surface lineaments using multi-source satellite remote sensing data, including ALOS PALSAR DEM, NISAR L-band dual-polarized (HH/HV) SAR, and BIOMASS P-band fully polarimetric SAR; (2) to map shallow- and deep-seated subsurface structural features using aeromagnetic data; (3) to conduct quantitative structural analyses of all extracted lineament sets using orientation statistics, rose diagrams, spatial density estimation, and complexity mapping to identify predominant trends, structural domains, and high-density convergence zones; (4) to integrate all structural layers using a GIS-based fuzzy overlay model with conservative logic, producing a consensus structural complexity map that highlights zones of multi-source agreement; and (5) to validate the integrated approach against known mining localities and extensive artisanal excavation sites in the study area, thereby assessing the predictive capacity of the consensus map for identifying structurally controlled mineralization.

The principal strength of this approach lies in its multi-source, multi-wavelength, and multi-depth design. It captures structural information across complementary physical domains by combining topographic expression (DEM), electromagnetic scattering at different wavelengths and polarizations (NISAR and BIOMASS), and variations in magnetic intensities. The fuzzy overlay approach, using conservative logic, ensures that only the most structurally robust zones receive high prospectivity scores, where all or most independent datasets converge. A limitation is that this inherent conservatism may exclude mineralized zones where only a subset of sensors detects elevated structural density. Additionally, hydrothermal alteration mapping should be conducted and integrated with structural controls and field verification to delineate potential mineralization targets more precisely. Nevertheless, the methodology provides a conceptually transferable framework for mapping structural lineaments at complementary depths, which is crucial for mineral exploration in comparable arid shield terrains worldwide.

2. Study Area and Geological Setting

The Wadi El-Markh area (Figure 1a) lies within the Central Eastern Desert (CED) of Egypt, a region renowned for hosting economically significant mineralization. The study area encompasses several prominent geological landmarks, including Gabal Rie' El-Garrah, Gabal El-Gidami, and Gabal Semna. It is dissected by numerous wadis trending in multiple directions that exert strong geomorphological control on the terrain, including Wadi El-Markh, Wadi Abu Shih, and Wadi El-Bula. They are filled with Quaternary to Recent sediments, which artisanal miners occasionally exploited extensively for placer gold extraction.

Despite its geological importance, the region lacks comprehensive structural analyses. Geologically, the foundational layer is primarily composed of granitic and metavolcanic rock units (Figure 1b). The granitic rocks exhibit a wide compositional range, from older to younger granites. The older granites, consisting mainly of tonalites and granodiorites, are the most widespread and occur predominantly in the northwestern and central parts of

the study area. Younger granites, including monzogranites and alkali-feldspar granites, intrude the metavolcanic rocks with distinct contacts and occur in the southwestern part of the study area, particularly at Gabal Rie' El-Garrah and Gabal El-Giddami. Minor intrusive bodies, characterized by concentrated dike swarms, occur at Gabal Abu Qarahish and northeast of Gabal Rie' El-Garrah. The metavolcanic rocks range in composition from acidic to intermediate and basic types and are exposed mainly in the eastern part of the study area, particularly at Gabal Semna in the south-central zone, and near Gabal Rie' El-Garrah. An extensive sequence of Hammamat molasse sediments occur east of Gabal Abu Kalb. Serpentinities and associated talc-carbonate rocks occur as two minor outcrops in the central-eastern part of the study area, adjacent to the Abu Marawat gold mine [46].

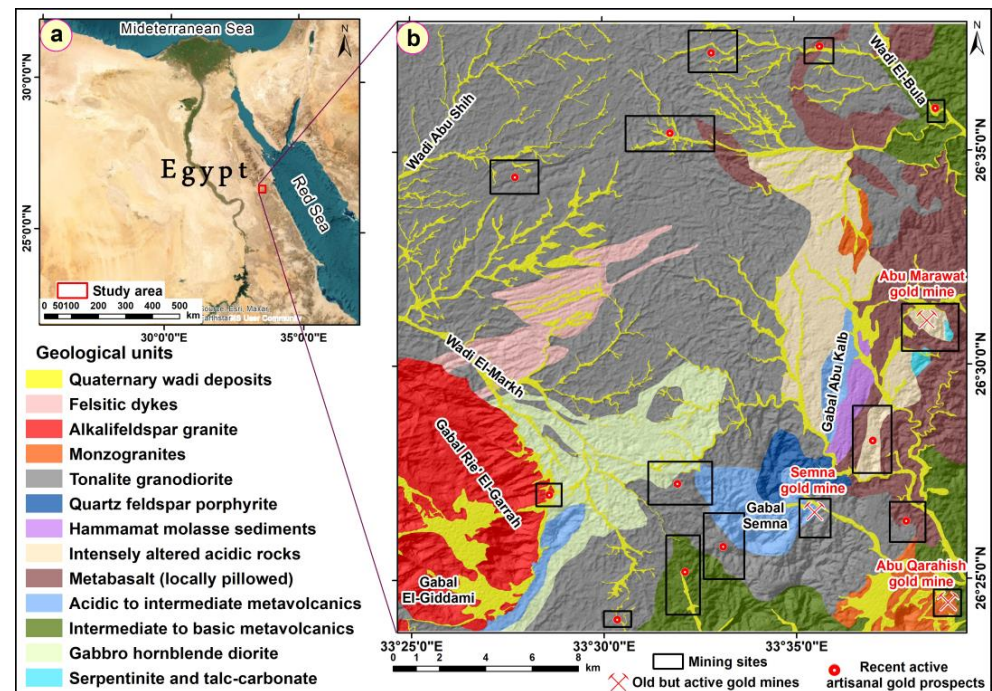


Figure 1. (a) Location map of the study area in the Central Eastern Desert of Egypt; (b) geological rock units with known mining sites indicated (modified after [9,46]). Mining sites are superimposed on the geological map; all are related to gold mining; and correspond either to historical gold mines that are still active or have been reactivated, or to extensive artisanal gold excavations developed in recent years in both bedrock-hosted quartz veins and placer sediments.

The study area hosts several significant gold mining sites and occurrences (Figure 1b), including the Semna, Abu Qarahish, and Abu Marawat mining districts. Structurally, the area lies within the broader CED tectonic framework, which has been profoundly shaped by major shear systems (e.g., the Atalla, Duwi, and Najd shear zones), that are widely recognized as first-order controls on mineralization throughout the CED [47–52]. The combination of demonstrated mineral potential, strong structural control by shear zones, and the paucity of integrated remote-sensing (particularly multi-wavelength polarimetric SAR) and geophysical investigations makes this area an ideal test site for the present study.

3. Materials

3.1. DEM Data

The Digital Elevation Model (DEM) used in this study is the ALOS Phased Array L-band Synthetic Aperture Radar (PALSAR) high-resolution terrain-corrected product, hereafter referred to as AP-DEM. It is not derived directly from the ALOS PALSAR observations; rather, it is an existing DEM that was modified and used for terrain correction

processing of the ALOS PALSAR data. According to the Alaska Satellite Facility (ASF), various DEM data sources have been used for the terrain correction, depending on their availability and spatial coverage.

The source DEM for the AP-DEM data used in this study is the Shuttle Radar Topography Mission (SRTM) DEM with a spatial resolution of 30 m. Preprocessing by ASF included geoid correction to convert orthometric heights to ellipsoidal heights for terrain correction and resampling of the pixel spacing, with the high-resolution product distributed at 12.5 m [53]. Although the resulting AP-DEM preserves the geometric relationships of ground features, geoid correction alters the elevation values; therefore, it should not be used as a substitute for a standard DEM [54]. In this study, geometric fidelity is the primary requirement because the main objective is to identify the spatial distribution of geological structures, irrespective of absolute elevation values. Two AP-DEM scenes (identifiers: ALPSRP120310510 and ALPSRP120310520), generated by ASF on 23 August 2015, were used for subsequent analyses.

3.2. NISAR L-Band SAR Data

The NISAR mission, launched on 30 July 2025, is a joint Earth-observing satellite mission developed by NASA and the Indian Space Research Organization (ISRO). It operates in a sun-synchronous orbit at an altitude of approximately 747 km with a 12-day repeat cycle, providing global coverage (Table 1). The mission carries two SAR instruments operating in the L- and S-band. L-band data are distributed globally through several products at different processing levels, whereas S-band acquisitions are limited to India and selected sites in the United States.

Table 1. NISAR L2-GSLC product specifications.

Parameter	Specification
Product Level	Level-2-GSLC
Radar Band	L-band
Center Frequency	1.257 GHz ($\lambda \approx 23.8$ cm)
Polarizations	Dual-polarized (HH, HV)
Ground Resolution	5 m $\times$ 10 m (Frequency-A); 5 m $\times$ 40 m (Frequency-B)
Incidence Angle	33–47°
Orbit Altitude	~747 km
Repeat Cycle	12 days
Geometric Characteristic	Geocoded to UTM

In this study, we used the Level-2 Geocoded Single-Look Complex (GSLC) product acquired on 11 January 2026 (identifier: “NISAR_L2_PR_GSLC_010_028_A_015_2005_DHDH_A_20260111T030654_20260111T030729_X05010_N_F_J_001”) obtained from the NASA Distributed Active Archive Center (DAAC) in HDF5 format. This product contains L-band data with HH and HV polarizations, consistent with the global L-band acquisition strategy. The dataset includes two L-band frequency channels: Frequency A, with a ground resolution of approximately 5 $\times$ 10 m, and Frequency B, with a lower ground resolution at 5 $\times$ 40 m. Only Frequency A data were used in this study because their finer spatial resolution provides a more accurate representation of ground features, thereby improving the delineation of geological and geomorphological structures.

3.3. BIOMASS P-Band SAR Data

The BIOMASS data used in this study were acquired from the European Space Agency’s (ESA) mission, launched on 29 April 2025 into a sun-synchronous orbit at an altitude of about 666 km, with a repeat cycle of approximately 3 days. The mission carries a fully polarimetric P-band SAR system operating at a center frequency of 435 MHz with

a bandwidth of 6 MHz and provides global coverage. Although its primary scientific objective is to monitor and quantify global forest biomass, structure, and disturbances, BIOMASS data are also valuable for a range of other Earth-observation applications, including geological lineaments mapping, which forms the basis of the present work.

This study uses the BIOMASS Level-1a SCS (Single-Look Complex Slant-range) product (ID: BIO_S1_SCS__1S_20260512T161256_20260512T161316_T_G01_M03_C07_T025_F132_02_DRC8VN), acquired on 12 May 2026. The product contains fully polarimetric, focused complex P-band SAR data (HH, HV, VH, and VV) in slant range preserving the amplitude and phase information essential for structural interpretations. The long P-band wavelength enables greater penetration into dry near-surface materials, particularly under arid conditions, potentially enhancing the detection of geological and geomorphological structures. Detailed specifications about BIOMASS data are provided in Table 2.

Table 2. BIOMASS L1a-SCS product specifications.

Parameter	Specification
Product Level	Level-1a-SCS
Radar Band	P-band
Center Frequency	435 MHz ($\lambda \approx 69$ cm)
Polarizations	Full polarimetric: HH, HV, VH, VV
Ground Resolution	~ 46 m $\times$ 41 m.
Incidence Angle	23–35°
Orbit Altitude	~ 666 km
Repeat Cycle	~ 3 days
Geometric Characteristic	Slant-range/not geocoded

3.4. Aeromagnetic Data

The aeromagnetic data used in this study originates from an airborne magnetic survey conducted for the Egyptian government in 1984 by the Aero-Service Division of the Western Geophysical Company of America. The survey was flown using a fixed-wing aircraft equipped with high-sensitivity proton-precession magnetometers. Data were acquired along systematically spaced NE-SW flight lines 1.0 km apart, with NW-SE tie lines spaced 10 km apart. The aeromagnetic dataset was delivered to the Egyptian General Petroleum Corporation (EGPC) as contoured total magnetic intensity (TMI) maps, which were subsequently digitized for modern geophysical processing. This dataset remains one of the most widely used airborne magnetic resources for structural and mineral exploration studies in Egypt and has been used in numerous subsequent geological and geophysical investigations [37,38,55–58].

Although the data were acquired in 1984, their age does not compromise their use for structural interpretation. Aeromagnetic measurements reflect stable, long-lived magnetic properties of the crust that do not change appreciably over decades in the absence of major tectonic or magmatic events, none of which have occurred in the study area during this period. The magnetic anomalies reflect basement lithology, fault systems, and shallow- and deep-seated structural trends, all of which remain effectively unchanged over geological timescales. Therefore, despite the age of the dataset, its use for mapping structural features remains valid. The primary limitations of older aeromagnetic surveys generally relate the acquisition density and instrumentation sensitivity rather than temporal relevance. However, the Aero-Service/EGPC survey employed standard airborne magnetometers and systematic flight-line geometry, providing reliable coverage for both local and regional structural analyses. Nevertheless, the relatively coarse flight-line spacing (1 km flight lines, 10 km tie-lines) constrains the ability to resolve very fine-scale, shallow subsurface structures.

4. Methods

This study employed a multisource, multiscale approach (Figure 2) to delineate structural lineaments and assess their implications for mineralization. Four datasets with complementary penetration capabilities were analyzed in parallel. The AP-DEM was used to characterize surface structural features, providing topographic control on lineament distribution. The NISAR L-band GSLC product provides limited penetration into the very near surface, enabling the detection of scattering responses associated with near-surface structural discontinuities. The fully polarimetric BIOMASS P-band data provide greater penetration capability, allowing characterization of near-surface to very shallow subsurface structures under favorable conditions. Finally, aeromagnetic data were used to probe the subsurface structural framework at both shallow and deep levels, complementing the remote-sensing datasets with geophysical information. All datasets were processed using tailored workflows to extract lineaments, which were subsequently integrated using a GIS environment. This integration enabled the combined structural information to be evaluated in relation to known mineralization localities. The comparative analysis provided a robust framework for assessing structural controls on mineralization by identifying zones with enhanced potential for surface-to-subsurface connectivity through fault conduits. The processing procedures applied to each dataset are described below.

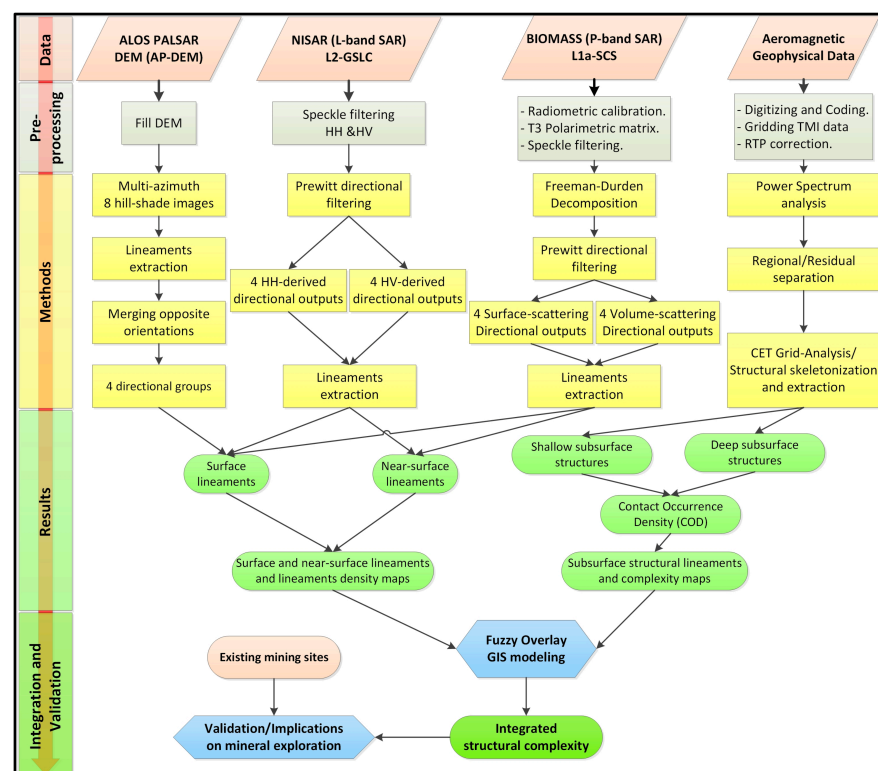


Figure 2. Flowchart of the methodology adopted in this study, organized into four parallel processing columns, each representing a distinct data source with different depth sensitivity: (1) ALOS PALSAR DEM (surface topography); (2) NISAR L-band SAR (surface and near-surface features, HH/HV polarizations); (3) BIOMASS P-band SAR (surface and shallow subsurface features, surface/volume scattering); and (4) aeromagnetic geophysical data (shallow-to-deep crustal sources). Each column progresses vertically from preprocessing through dataset-specific processing methods, to the extraction of structural layers. The resulting lineament and structural-complexity layers are integrated using a GIS-based fuzzy-overlay model that applies the conservative fuzzy “AND” operator to generate an integrated structural-complexity map. Comparison with 15 known mining sites is then used to assess the success rate of the approach in identifying structurally controlled mineralization.

4.1. DEM Data Processing

Two AP-DEM scenes with a spatial resolution of 12.5 m were processed to delineate structural lineaments in the study area. The workflow comprised preprocessing, multi-azimuth hillshading, directional filtering, automated lineament extraction, orientation analysis, and structural density interpretation. First, the two AP-DEM scenes were mosaicked together using the ENVI v. 6.2 seamless mosaicking tool, with one scene assigned as the reference for color matching and edge feathering applied. The study area was then subset from the mosaic, and the resulting DEM was corrected using the fill DEM procedure to remove spurious sinks. Next, eight hillshade images were generated at azimuths ranging from 0° to 315° at 45° intervals. Each hillshade image was then processed using the corresponding directional filter with 3×3 kernel to enhance lineaments oriented perpendicular to the illumination direction. This procedure yielded eight filtered images, each emphasizing lineaments with a specific orientation. Lineaments were subsequently extracted using the lineament extraction module in PCI Geomatica, and the outputs were saved as separate vector shapefiles. The parameters used for automatic lineaments extraction from all the adopted DEM and SAR datasets are as follows: filter radius = 10 pixels, edge-gradient threshold = 120, curve-length threshold = 30 pixels, line fitting error threshold = 3 pixels, angular-difference threshold = 30°, and linking-distance threshold = 20 pixels.

The shapefiles were imported into ArcGIS Pro v. 3.4, where the lineaments were screened to retain only those consistent with the intended orientation. Manual editing was also conducted to remove lineaments associated with non-geological features such as roads, desert tracks, gullies, and other artifacts. Opposite orientations were then merged (0° with 180°, 45° with 225°, 90° with 270°, and 135° with 315°), resulting in four directional groups: N-S, NE-SW, E-W, and NW-SE. Rose diagrams were generated for each group to illustrate the dominant directional trends. Finally, all extracted lineaments were combined into a single, accompanied by an overall rose diagram illustrating the surface structural fabric of the study area.

4.2. NISAR Data Processing

NISAR L-band Level-2 GSLC data (HH and HV polarizations) were processed to extract structural lineaments using a workflow involving speckle reduction, directional filtering, scattering-based interpretation, automated lineament extraction, and orientation and density analyses. The GSLC product was first imported into ArcGIS Pro, where the data were visualized and examined for common artifacts, such as radio-frequency interference (RFI), which can produce anomalously bright or dark patches, and antenna-pattern effects, which can generate banding in the range direction. The investigated scene was considered suitable for analysis, with no significant artifacts identified. Following this initial quality assessment, the study area was then cropped out from the image, and the dual-polarized HH and HV bands were processed using the Refined Lee filter to reduce the speckle noise while preserving linear structural contrasts relevant to lineament interpretation. The resulting speckle-filtered HH and HV backscatter images were then subjected to directional Prewitt filtering with 3×3 kernel size to enhance edge responses along preferred structural orientations. For each polarization, four directional outputs were generated corresponding to the principal structural directions (N-S, NE-SW, E-W, and NW-SE).

In this study, the filtered HH images were used as proxies for surface and double-bounce scattering responses, whereas filtered HV images were treated as proxies for cross-polarized scattering associated with more complex signal interactions, including contributions from surface roughness and structural heterogeneity that may highlight subtle linear features. Lineaments were extracted from the filtered images using PCI Geomatica, exported as shapefiles (using the same parameters detailed in Section 4.1, “DEM

Data Processing”), screened to retain only features consistent with the target orientations, and manually digitized to remove artificial artifacts. The resulting lineaments were merged to produce combined HH- and HV-derived lineament maps, and rose diagrams were generated for the eight directional datasets as well as for the combined products.

4.3. BIOMASS Data Processing

BIOMASS Level-1a SCS fully polarimetric P-band SAR data were processed to extract structural lineaments using a workflow involving calibration, polarimetric decomposition, terrain correction, directional filtering, lineament extraction, and orientation analysis. The raw BIOMASS SAR data were first radiometrically calibrated to convert digital numbers into backscatter coefficients. A coherency matrix (T3) was then generated to preserve the full polarimetric information required for scattering analysis. Freeman-Durden polarimetric decomposition [59] with window size of 5 was subsequently applied to separate the backscatter into surface-, double-bounce-, and volume-scattering components. It is important to note that the Freeman-Durden volume-scattering component represents diffuse backscatter from complex, heterogeneous media, which may include wavelength-scale surface roughness, fractured rock volumes, and multiple scattering within regolith materials, rather than uniquely representing deeper structures [59]. In the arid to hyper-arid, vegetation-free setting of the present study area, where canopy contributions are absent, we interpret the volume-scattering component as primarily reflecting structural heterogeneity and fracture complexity within the penetration depth of the P-band signal (up to a few meters in dry soils), rather than directly imaging geological structures at discrete depths. However, we acknowledge that, without ground-penetrating radar or borehole validation, the relative contributions of surface and very shallow subsurface scattering cannot be unambiguously resolved.

The decomposition components were then corrected for geometric distortions using Range-Doppler terrain correction aided by SRTM 1 Sec (30 m) DEM, to ensure accurate geolocation and alignment with study area’s topography. Directional Prewitt filtering (kernel size is 3×3) was applied separately to the surface- and volume-scattering components to enhance linear features along the four principal directions, following the same procedures used for the NISAR data. Lineaments were extracted from the filtered images using the Line extraction module in PCI Geomatica, exported as shapefiles (using the same parameters applied to AP-DEM, and NISAR directional derivatives), and subsequently checked for consistency with the intended directional classes before manual editing to remove anthropogenic artifacts. Separate lineament maps and rose diagrams were generated for each directional output. Combined surface- and volume-scattering-derived lineament maps and rose diagrams were also produced to characterize the directional patterns and overall structural fabric of the study area revealed by the BIOMASS data.

4.4. Aeromagnetic Data Processing

Aeromagnetic data were used to delineate subsurface structural features at varying depths across the study area. The data were originally provided as total magnetic intensity (TMI) contour maps, which were first digitized and assigned their corresponding TMI values. The data were then reduced to the magnetic north pole (RTP) to correct for the inclination and declination of the Earth’s magnetic field, thereby improving the spatial correspondence between magnetic anomalies and their causative sources.

4.4.1. Power-Spectrum Depth Estimation

Depths to magnetic source ensembles were estimated using the radially averaged power spectrum of the RTP grid following the method of Spector and Grant [60]. For a randomly distributed ensemble of prismatic magnetic sources, the radially averaged

power spectrum decays exponentially with wavenumber k (in cycles per unit distance) according to:

$$P(k) = A \cdot e^{-4\pi hk} \quad (1)$$

where h is the average depth to the top of the source ensemble, k is the radial wavenumber (cycles/km), and A is a constant incorporating the magnetization distribution and geomagnetic field parameters. Taking the natural logarithm yields a linear relationship:

$$\ln[P(k)] = \ln(A) - 4\pi hk \quad (2)$$

The RTP grid was transformed into the wavenumber domain using a 2-D Fast Fourier Transform (FFT). The power spectrum was then computed and radially averaged into logarithmically spaced wavenumber bins. Two distinct linear segments were identified on the $\ln[P(k)]$ versus k plot and fitted by least-squares regression to determine the slopes, intercepts, coefficients of determination (R^2), and standard errors of the slopes (σ_m). The average depth for each segment was calculated from the regression slope m as:

$$h = \frac{-m}{4\pi} \quad (3)$$

The uncertainty in the depth estimate was propagated from the standard error of the slope as:

$$\sigma_h = \frac{\sigma_m}{4\pi} \quad (4)$$

These depths represent average depths to the top of randomly distributed source ensembles rather than discrete geological boundaries. The reported statistical uncertainties reflect the precision of the regression fits, whereas the actual geological uncertainty depends on source geometry, magnetization heterogeneity, and the extent to which the source ensemble conforms to idealized random-distribution model [61].

4.4.2. Regional–Residual Separation

The slope-break point, or crossover wavenumber (k_c), between the two linear power spectrum segments was used as the cutoff frequency for Gaussian regional–residual separation. It should be noted that the depth estimates are also subject to inherent uncertainties associated with the selection of the crossover wavenumber and with survey parameters, such as flight-line spacing. The RTP grid was separated into regional (deep-source) and residual (shallow-source) components using a Gaussian frequency-domain filter implemented in Oasis Montaj v.8.4. The low-pass (regional) filter attenuates wavelengths shorter than $1/k_c$, thereby emphasizing broad anomalies associated with deeper magnetic sources, whereas the high-pass (residual) filter attenuates longer wavelengths, highlighting shallower magnetic sources.

4.4.3. Lineament Extraction and Interpretation

Lineament were extracted using the CET Grid analysis module [62–64], which applies texture analysis through standard-deviation filtering, phase-symmetry detection for lineament identification, and lineament vectorization through line thinning, skeletonization, and conversion to vectors. This workflow produced two structural maps representing shallow and deep-seated structures. Finally, a structural complexity map was generated using the COD technique [65,66] to highlight zones of elevated structural complexity. Such zones may represent potential conduits connecting deep and shallow subsurface domains, thereby identifying areas with enhanced potential for structurally controlled mineralization.

4.5. Data Integration and Validation

The outputs from the four datasets AP-DEM surface lineaments, NISAR near-surface scattering responses, BIOMASS polarimetric decomposition of shallow subsurface structures, and aeromagnetic residual and regional anomalies were integrated within a GIS-based fuzzy-overlay modeling framework. Each structural layer was first reclassified onto a common continuous fuzzy-membership 0 to 1 scale using the fuzzy linear function, where 1 represents the highest structural complexity and 0 the lowest. The full dynamic membership range of each dataset was preserved, and no subjective breakpoints or externally imposed thresholds were applied because independent criteria for defining absolute structural complexity are not available for these heterogeneous sensors.

The reclassified fuzzy-membership raster layers were then combined using the fuzzy AND operator, which assigns to each pixel the minimum membership value across all input layers, thereby emphasizing zones of structural complexity and potential connectivity between surface and subsurface fracture and fault-controlled conduits. The resulting map was subsequently compared with 15 known mining localities for validation. These sites were used solely for independent validation and were not involved in defining or tuning the fuzzy-membership functions or any other processing parameters.

The conservative fuzzy “AND” logic ensures that only locations where all input layers concurrently indicate high structural complexity receive high integrated scores, thereby suppressing spurious anomalies arising from any single dataset. However, this conservatism entails an inherent trade-off: if any single layer indicates low structural complexity at a given location, the composite score is reduced regardless of the values of the other layers. Consequently, mineralization-favorable zones detected by only a subset of the sensors may receive lower integrated scores or may be masked in the consensus map. To address this limitation and evaluate the relative performance of the consensus approach against sensor-specific detection, the integrated fuzzy-overlay results were compared with those of the individual datasets, allowing direct assessment of both the multisource consensus map and the performance of each individual dataset. This comprehensive integration provides a robust methodological framework for linking multi-sensor structural analysis with mineral exploration targeting.

5. Results

5.1. DEM-Derived Linear Structures

Lineament analysis was performed using AP-DEM-derived multi-azimuth illumination to highlight structural features across the study area in different orientations. Four separate directional maps were generated by combining opposite illumination azimuths. The E-W directional output yielded 414 extracted lineaments with a total length of 332,414 m (Figure 3a), revealing a dominant population of horizontally trending features perpendicular to the illumination directions (0° and 180°). These lineaments are concentrated mainly in the central and southern parts of the study area, with the corresponding rose diagram showing a pronounced E-W trend. The NW-SE lineaments map (Figure 3b) was generated from hill-shaded images with illumination azimuths of 45° and 225° , yielding 402 lineaments with a total length of 305,535 m. These features show moderate to high densities, particularly in the northern and central sectors of the study area, with the corresponding rose diagram confirming a dominant NW-SE trend. The N-S orientation map (Figure 3c) yielded 298 lineaments with a total length of 207,916 m, representing the lowest lineament count among the four directional datasets. These vertical to sub-vertical features are distinctly clustered in the eastern and central parts of the study area, with the corresponding rose diagram showing a strong N-S trend. The NE-SW lineaments map (Figure 3d) yielded the highest number of linear features, with 428 lineaments and a total

length of 283,607 m. These diagonally oriented features are widely distributed throughout the study area, and the corresponding rose diagrams confirms a dominant NE-SW trend.

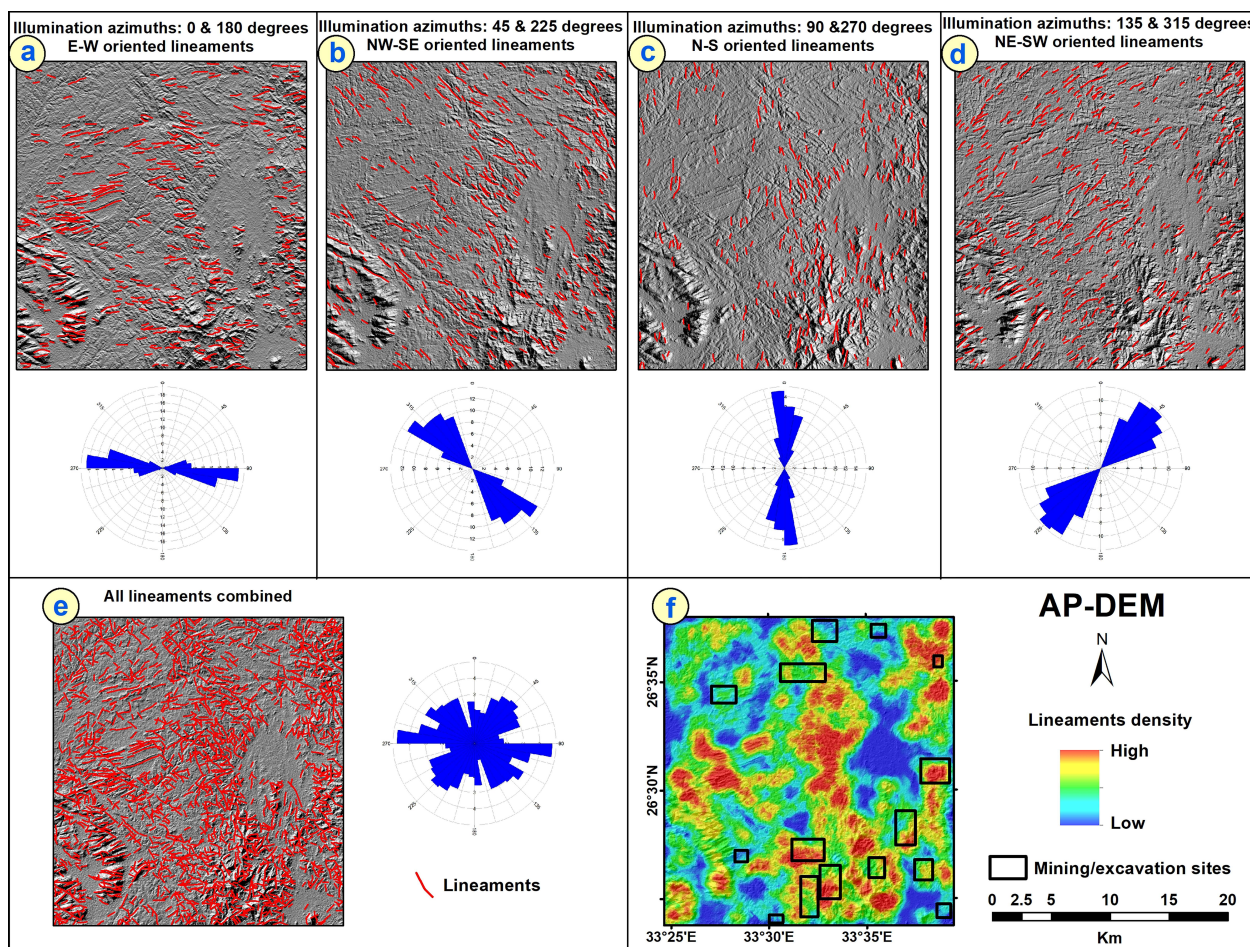


Figure 3. AP-DEM-derived lineament maps with corresponding rose diagrams; (a–d) lineament maps derived from multi-azimuth illumination; (e) combined lineament map; and (f) lineament density map. All rose diagrams depict azimuthal frequency distributions based on lineament-count statistics.

The integrated structural lineaments map (Figure 3e) combines all orientation groups into a single dense network comprising 1542 features and reveals a complex multi-directional structural fabric. The associated rose diagram exhibits a more distributed but still anisotropic pattern, with several prominent trends. The NE-SW and E-W orientations remain dominant, followed closely by the NW-SE trend, whereas the N-S trend is the least represented. This pattern is consistent with the numbers of lineaments extracted for each orientation group. The lineament density map (Figure 3f) illustrates spatial variations in structural intensity using a graded color scale ranging from blue (lowest density) through cyan, green, and yellow to red (highest density). High-density zones occur at several locations across the study area, forming belts with general NW-SE orientations. These zones are concentrated in the northeastern sector and extend toward the northeastern corner, with additional clusters in the central-eastern, south-central, and southeastern sectors, as well as isolated patches in the northwestern and western parts of the study area. Conversely, low-density zones occur in parts of the central-eastern and northwestern sectors, the southeastern corner, and along isolated narrow fringes of the eastern margin. This spatial pattern indicates strong structural control on lineaments development, with high-density corridors separated by low-density zones. Fifteen mining and extensive artisanal excavation localities, represented by black rectangular boxes, were superimposed

on the lineament density map. Visual analysis indicates that nine reference mining sites (60%) are located within or immediately adjacent to high-density yellow-to-red zones, two localities (13.3%) are associated with moderate lineament densities (green), and four localities (26.7%) occur within low-density zones (cyan and blue). This spatial association suggests that mineralization in the study area is structurally controlled, with mining and artisanal excavation activities preferentially concentrated in zones of high fracture density.

5.2. NISAR-Derived Linear Structures

Given the arid, vegetation-free nature of the study area, NISAR L-band SAR data in HH and HV polarizations were processed to extract structural lineaments that primarily correspond to surface and near-surface heterogeneities, considering the limited depth penetration of the L-band radar. The HH polarization, used as a proxy to emphasize surface and double-bounce scattering responses, yielded lineaments across multiple orientations through directional Prewitt filtering along four principal directions (E-W, NE-SW, N-S, and NW-SE) (Figure 4). The E-W orientation overwhelmingly dominated the HH-derived lineaments, with 1009 features (total length of 569,227 m), accounting for 52.5% of all the extracted lineaments. This orientation was followed by N-S, with 386 lineaments (191,345 m; 20.1%); NW-SE with 368 (192,671 m; 19.2%); and NE-SW with only 158 lineaments (75,989 m; 8.2%). The corresponding orientation maps show that the HH-derived E-W lineaments (Figure 4a) are densely distributed across the western and central parts of the study area, whereas the NW-SE (Figure 4b) lineaments and N-S (Figure 4c) lineaments are comparatively sparse and patchy, with concentrations mainly in the eastern and southern sectors. The NE-SW lineaments set (Figure 4d) is notably underrepresented in the HH data, with the fewest extracted features and a highly scattered and discontinuous distribution, mainly in the southeastern part and along the western margin of the study area. The combined HH lineaments map (Figure 4e) reveals a dense but spatially heterogeneous network strongly dominated by E-W trending features, with prominent gaps in the north-central and eastern regions. The associated rose diagram exhibits a dominant E-W peak, subordinate NW-SE and N-S trends, and only a minor NE-SW contribution. This pattern may reflect the polarization-dependent sensitivity of co-polarized backscatter to surface and near-surface structural features with specific orientations.

The HV polarization, representing cross-polarized scattering associated with surface roughness, structural heterogeneity, and volumetric contributions, produced substantially more lineaments than HH polarization (>2.3 times the HH output). In marked contrast to the HH results, the HV-derived lineaments showed a relatively balanced distribution across orientations (Figure 5a–d). The NW-SE direction (Figure 5b) yielded the highest count at 1300 lineaments (total length of 712,875 m), followed closely by NE-SW (Figure 5d) with 1170 lineaments (614,476 m); N-S (Figure 5c) with 1099 lineaments (592,031 m); and E-W (Figure 5a) with 914 lineaments (499,504 m). The HV directional maps reveal markedly denser lineament populations in all directions than the HH maps, with particularly pronounced increases in the NE-SW (7.4 times the HH count), NW-SE (3.5 times), and N-S (2.8 times) orientations. The combined HV lineaments map (Figure 5e) shows nearly continuous coverage of structural features across the entire study area, with markedly fewer gaps than in the HH product. The corresponding rose diagram reflects this more isotropic structural response, displaying pronounced peaks in all four principal directions with a relatively uniform radial distribution. This pattern indicates that the cross-polarized signal effectively captures structural complexity across a broad range of orientations.

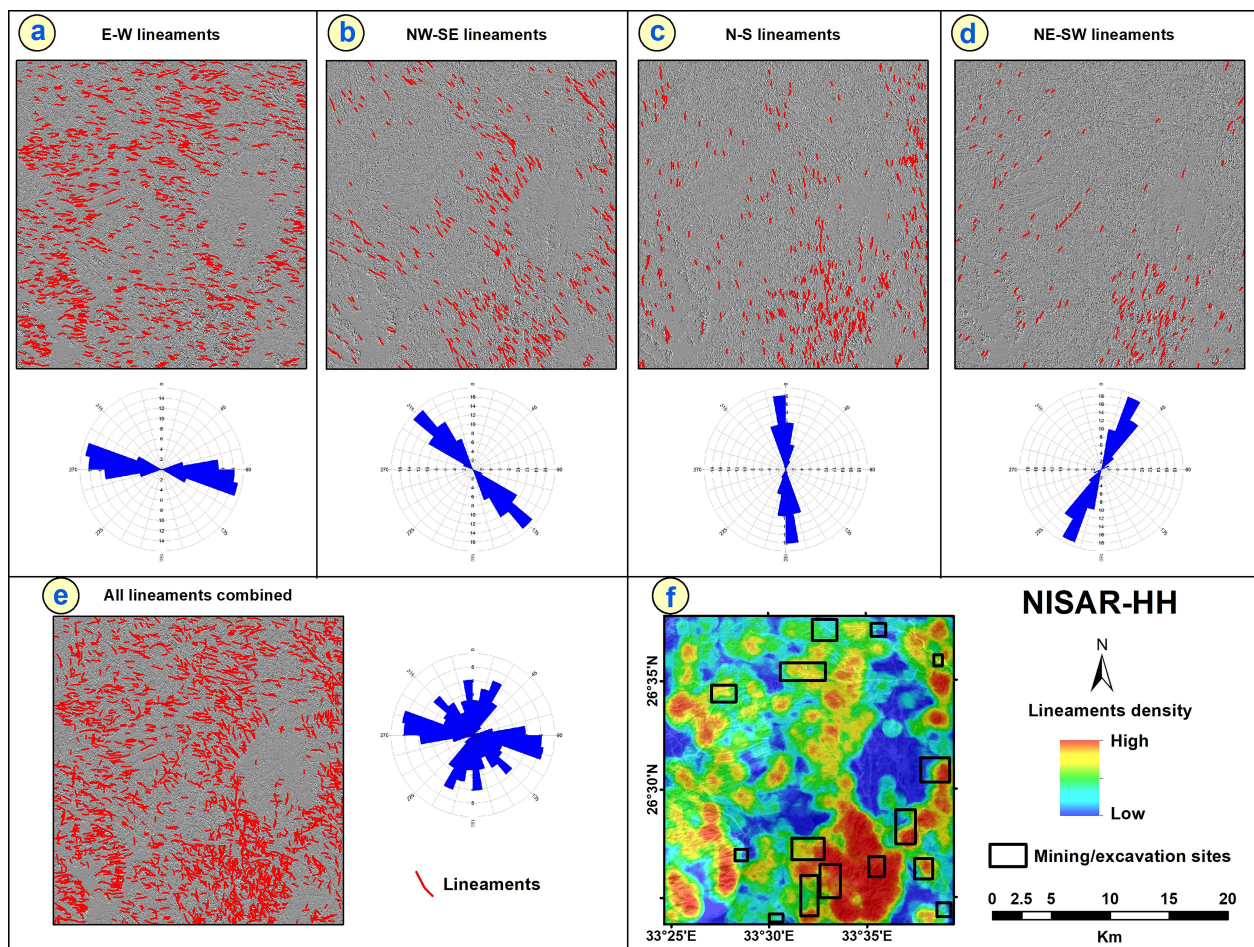


Figure 4. NISAR HH-derived lineament maps with corresponding rose diagrams: (a–d) directional lineament maps; (e) combined lineament map; and (f) lineament density map. All rose diagrams depict azimuthal frequency distributions based on lineament-count statistics.

The marked divergence between the HH and HV results underscores the polarization-dependent nature of SAR-based structural mapping in this terrain. The strong bias of HH polarization toward E-W lineaments (52.5% of the total) and the limited representation of NE-SW features (8.2%) suggest that co-polarized surface and double-bounce scattering responses are strongly influenced by the geometric orientation of structures relative to the radar look direction, favoring features that present broadside scattering surfaces. Conversely, the ability of HV polarization to resolve substantial lineament populations across all orientations, including the NE-SW set that is poorly represented in HH, suggests that cross-polarized scattering provides a more comprehensive and less orientation-dependent representation of the structural lineament network.

The lineaments density maps derived from the HH and HV data reveal distinct spatial patterns consistent with their different scattering responses. The HH density map (Figure 4f) shows the highest lineament densities (yellow and red zones) concentrated along a prominent south-central to southeastern corridor, with additional high-density patches in the western and north-central sectors. Overall, the high-density zones form connected and isolated patches with a preferential NW-SE trend. The lowest densities (cyan and blue zones) occupy broad areas of the central-eastern and northeastern sectors. In contrast, the HV density map (Figure 5f) exhibits more widespread and interconnected high-density zones, with major yellow and red corridors extending through the northeastern, central-eastern, and south-central sectors and fewer extensive low-density blue areas. The HV-

derived density pattern is more diffuse and reticulate, consistent with the sensitivity of cross-polarized signal to distributed structural heterogeneity and variations in surface roughness.

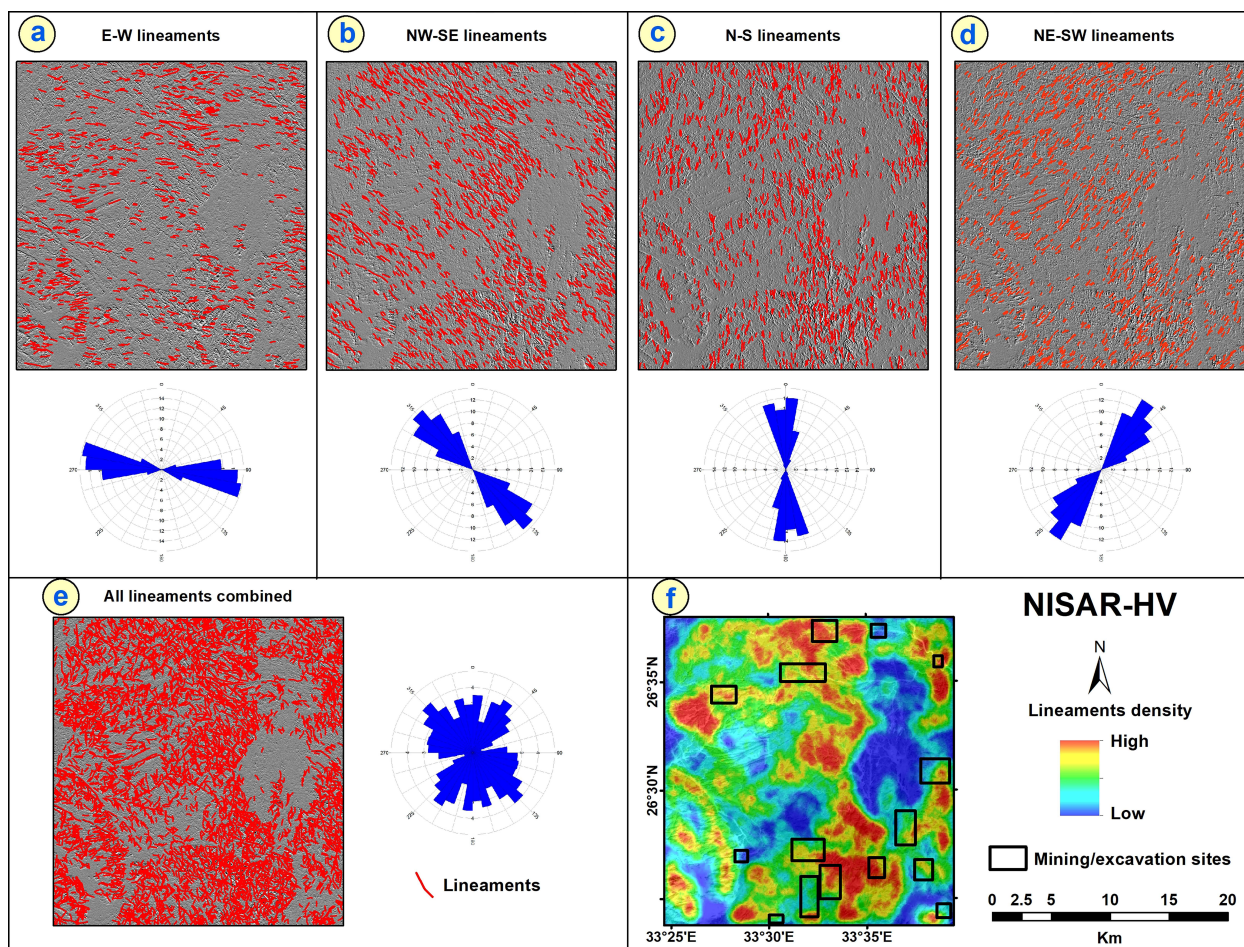


Figure 5. NISAR HV-derived lineament maps with corresponding rose diagrams: (a–d) directional lineament maps; (e) combined lineament map; and (f) lineament density map. All rose diagrams depict azimuthal frequency distributions based on lineament-count statistics.

Visual comparison with known mining sites shows that, on the HH density map (Figure 4f), the sites are predominantly clustered within or adjacent to the south-central high-density corridor. Of the 15 mining localities, 9 (60%) coincident with high-density zones (yellow and red), 4 (26.7%) with moderate-density zones (green), and 2 (13.3%) with low-density zones (cyan and blue). In contrast, on the HV density map (Figure 5f), a greater proportion of the sites—10 (66.7%)—occur within high-density zones, while 3 (20%) occur within the moderate-density zones, and 2 (13.3%) within the low-density zones. This stronger spatial association reflects the more pervasive structural expression captured by the cross-polarized HV NISAR data and its relationship with known mining sites.

5.3. BIOMASS-Derived Linear Structures

BIOMASS Level-1a SCS fully polarimetric P-band SAR data were processed using polarimetric decomposition using the Freeman-Durden algorithm that separated the backscatter into surface-, double-bounce-, and volume-scattering components. The surface- and volume-scattering components were investigated to assess how different scattering mechanisms reveal distinct aspects of linear structures.

The surface-scattering component yielded a total of 883 lineaments across the four principal orientations (Figure 6a–d). The E-W orientation produced 261 lineaments with

a total length of 126,311 m (29.6% of the surface-scattering total), closely following the N-S orientation which yielded 273 linear features (30.9%) but with higher total length of 146,725 m. The NW-SE orientation contributed 196 lineaments (108,847 m; 22.2%), whereas the NE-SW orientation contributed only 153 lineaments (71,375 m; 17.3%). The corresponding directional maps show that surface-scattering-derived E-W lineaments (Figure 6a) are moderately distributed across the western and northern sectors; NW-SE features (Figure 6b) form scattered clusters in the eastern, and southwestern areas; N-S lineaments (Figure 6c) are concentrated in the eastern and central sectors; and NE-SW lineaments (Figure 6d) are the most sparse and discontinuous throughout the southern and central-eastern parts of the study area. The combined surface-scattering lineament map (Figure 6e) reveals a patchy network with pronounced gaps in the northwestern and north-central regions. The associated rose diagram exhibits dominant E-W and N-S trends with subsidiary NW-SE and minor NE-SW directions. This indicates that the surface-scattering preferentially highlights orthogonal structural trends.

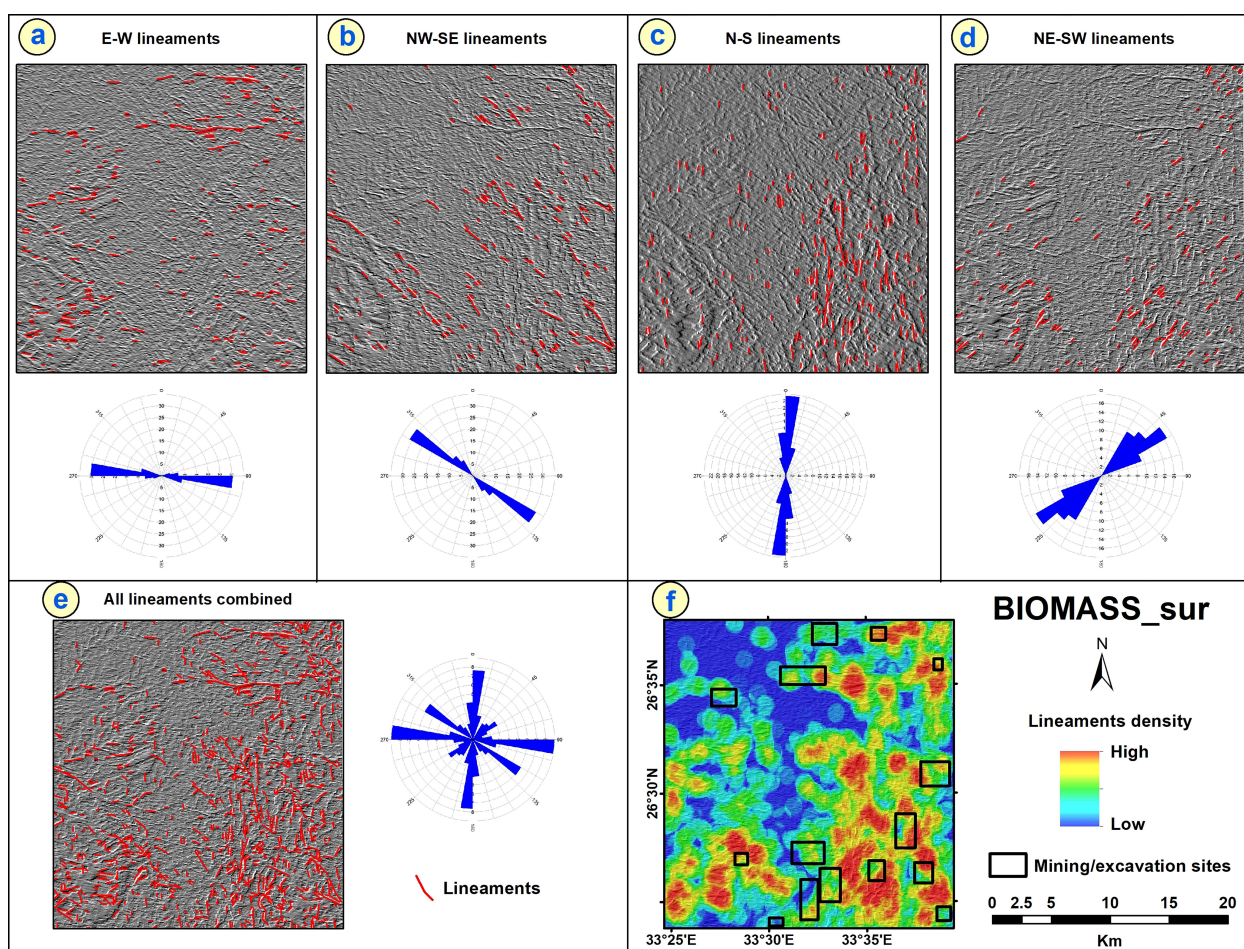


Figure 6. BIOMASS surface-scattering-derived lineament maps with corresponding rose diagrams: (a–d) directional lineament maps; (e) combined lineament map; and (f) lineament density map. All rose diagrams depict azimuthal frequency distributions based on lineament-count statistics.

The volume-scattering component yielded 1109 lineaments, modestly exceeding the surface-scattering yield. The orientation distribution in the volume-scattering dataset (Figure 7a–d) differed markedly from the surface-scattering results, with NW-SE dominant at 344 lineaments (31% of the volume-scattering total) with a total length of 172,064 m, followed by NE-SW at 300 lineaments (27%; 143,453 m length), N-S orientation yielded 255 lineaments (23%; 125,346 m total length), and E-W orientation yielded only 210 lineaments (19%; 108,847 m total length).

ments (19%; 99,365 m). Notably, the volume-scattering component exhibits a pronounced shift toward diagonal orientations, with NW-SE and NE-SW combined accounting for approximately 58% of all volume-scattering lineaments, compared to only 39.5% in the surface-scattering yield. The volume-scattering directional maps reveal denser lineament populations in the diagonal directions yielding $\sim 1.8\times$ and $2\times$ in the NW-SE and NE-SW directional outputs, while the N-S and E-W features outputs showed slight decrease. The combined volume-scattering lineaments map (Figure 7e) presents a denser, more continuous network with fewer and narrower gaps than that in the surface-scattering map. The associated rose diagram shows a strongly dominant NW-SE and E-W trends, followed by NE-SW trend and lastly the N-S trend. This reflects the volume-scattering signal sensitivity to oblique structural features that are subdued in the surface-scattering response. The contrast between surface- and volume-scattering decomposition results underscores the mechanism-specific nature of P-band SAR structural mapping. The preference of surface-scattering component for E-W and N-S trends (60.5% combined) suggests that flat-lying or gently dipping surfaces with orthogonal orientations relative to the radar geometry produce strong specular returns. Conversely, the pronounced shift in volume-scattering component toward diagonal dominance (58.1% combined for NE-SW and NW-SE) indicates that volumetrically complex structures expose a fundamentally different structural fabric dominated by oblique fracture sets.

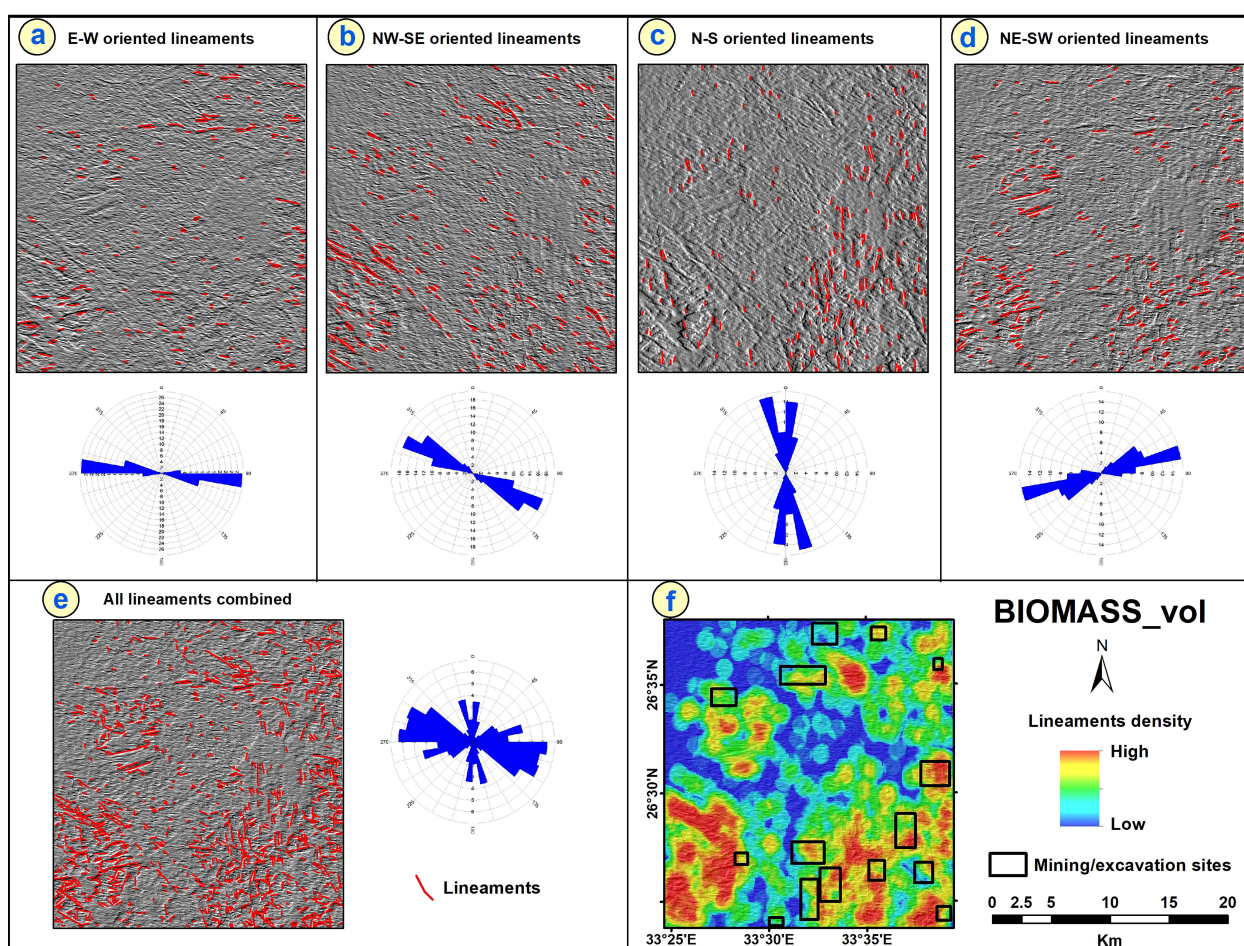


Figure 7. BIOMASS volume-scattering-derived lineament maps with corresponding rose diagrams: (a–d) directional lineament maps; (e) combined lineament map; and (f) lineament density map. All rose diagrams depict azimuthal frequency distributions based on lineament-count statistics.

The Lineament density maps derived from surface- and volume-scattering components (Figures 6f and 7f) reveal complementary spatial patterns. The surface-scattering density map (Figure 6f) shows the highest densities (yellow and red zones) concentrated in prominent southeastern and southwestern corridors, with secondary high-density patches in the northeastern and central-western sectors. The lowest densities (cyan and blue zones) occupy broad northwestern and north-central areas. In contrast, the volume-scattering density map (Figure 7f) exhibits more widespread and intense high-density zones with major red corridors extending through the eastern, south-central, and southwestern sectors, and other sporadic yellow-to-red zones of lower density occur in the northeastern and central-western parts of the study area.

In the surface-scattering density map (Figure 6f), 11 mining sites (73.3%) coincide with high-density zones (yellow and red); 3 (20%) fall within moderate-density zone (green); and only 1 (6.7%) occurs in low-density zones (cyan and blue). In the volume-scattering map (Figure 7f), 13 mining sites (86.7%) fall within high-density zones; only 1 site (6.65%) occurs in the moderate green zone; and 1 site (6.65%) is coincident with low-density cyan and blue zones. This suggests that volume-scattering-derived lineaments provide a more comprehensive spatial correlation with known mineralized zones, likely because the volume-scattering component, sensitive to structural heterogeneity and fracture complexity within the P-band penetration depth, reveals linear fabrics that are subdued or absent in the surface-scattering response. While this does not constitute direct imaging of deeper structures, the convergence of volume-scattering lineaments with known mineralized zones suggests that this component captures fracture-network characteristics relevant to hydrothermal fluid pathways.

5.4. Aeromagnetic Data Results

5.4.1. TMI and RTP

The total magnetic intensity (TMI) data for the study area (Figure 8) were reduced to the magnetic pole (Figure 9) using the reduction-to-the-pole (RTP) filter based on a Fast Fourier Transform (FFT), as expressed by the following equation:

$$F_r(U, V) = \frac{F_v(U, V)}{\left(\sin I + i \cos I \cos(D - \arctan \left[\frac{U}{V} \right]) \right)^2} \quad (5)$$

where $F_r(U, V)$ is the transformed output of the magnetic data from TMI to RTP; $F_v(U, V)$ is the transformed vertical magnetic field; (U, V) represents the wave number of (x, y) directions, respectively; and I and D represent the inclination and declination of the magnetic field, respectively. The I and D values obtained from the survey report and used for the RTP processing were 32° N and 1.9° E, respectively. These parameters are essential for correcting the spatial displacement of magnetic anomalies caused by the inclination and declination of the Earth's magnetic field.

The Reduced-to-Pole (RTP) map (Figure 9) shows that the magnetic intensity values range from 42,102.1 to 42,806.4 nT. Three distinct magnetic anomaly zones can be identified: low, intermediate, and high. Low magnetic anomalies, represented by blue to cyan colors, dominate the central and southern parts of the study area and range from approximately 42,102 to 42,260 nT. Intermediate anomalies, represented by green to yellow colors, are distributed throughout the study area and range from >42,260 to 42,334 nT. High magnetic anomalies, represented by red to pink colors, range from > 42,334 to 42,806 nT.

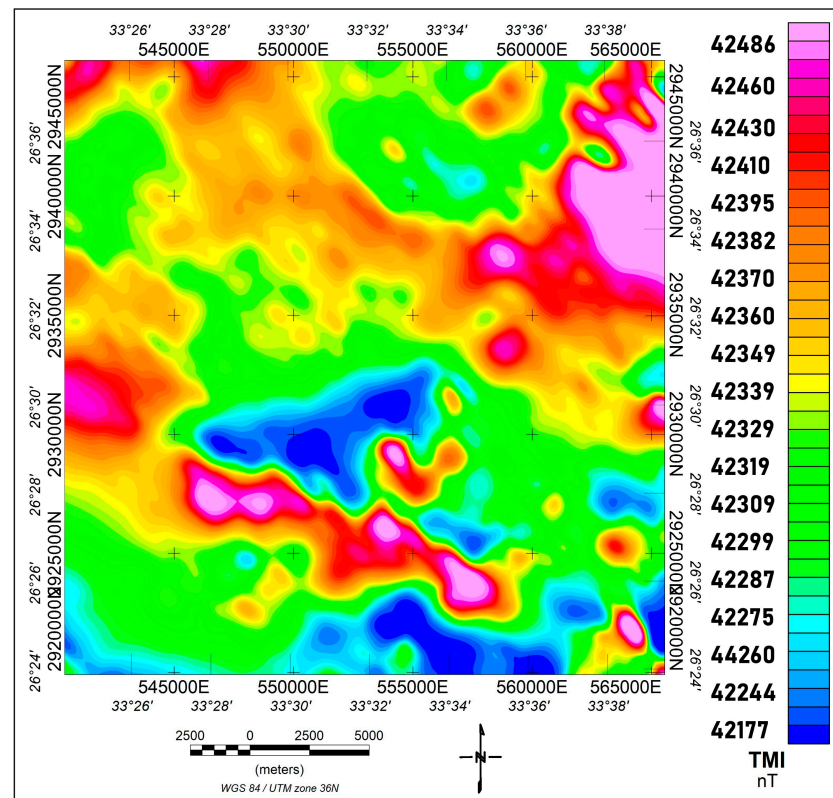


Figure 8. The total magnetic intensity (TMI) map of the Wadi El-Markh area, CED, Egypt.

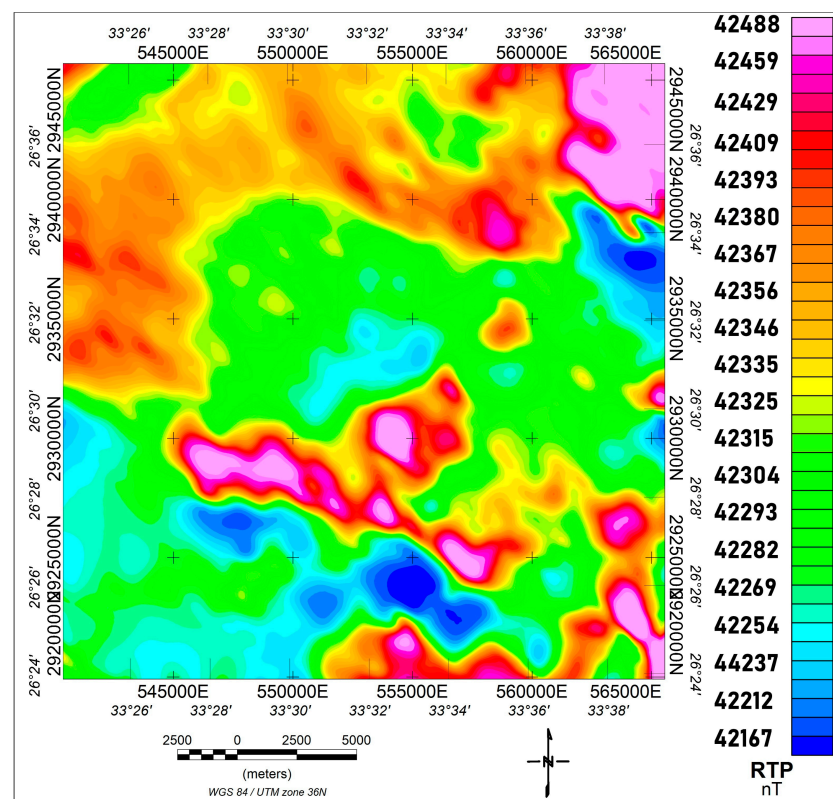


Figure 9. Reduction-to-the-pole (RTP) magnetic map of the Wadi El-Markh area, CED, Egypt.

5.4.2. Power Spectrum Analysis and Regional–Residual Sources Separation

The power spectrum plot of the study area (Figure 10) shows two distinct in the log-linear domain. The split point is determined at a wavenumber of 0.388 (cycles/km); this was

used to separate the regional and residual magnetic sources of the study area. Least-squares regression of the two power spectrum segments yielded the following fitted equations:

- Deep-source segment (low wavenumbers, $k < 0.388$ cycles/km):

$$\ln[P(k)] = -15.683 k + 9.5746 \quad (R^2 = 0.9786; \text{slope standard error} = 0.6702) \quad (6)$$

- Shallow-source segment (high wavenumbers, $k > 0.388$ cycles/km):

$$\ln[P(k)] = -7.2223 k + 6.2609 \quad (R^2 = 0.9943; \text{slope standard error} = 0.0782) \quad (7)$$

The high coefficients of determination confirm the validity of the two-segment model. The average source depths and their associated uncertainties were calculated from the regression slopes and their standard errors, respectively, using the values provided in Equations (6) and (7) and applying Equations (3) and (4).

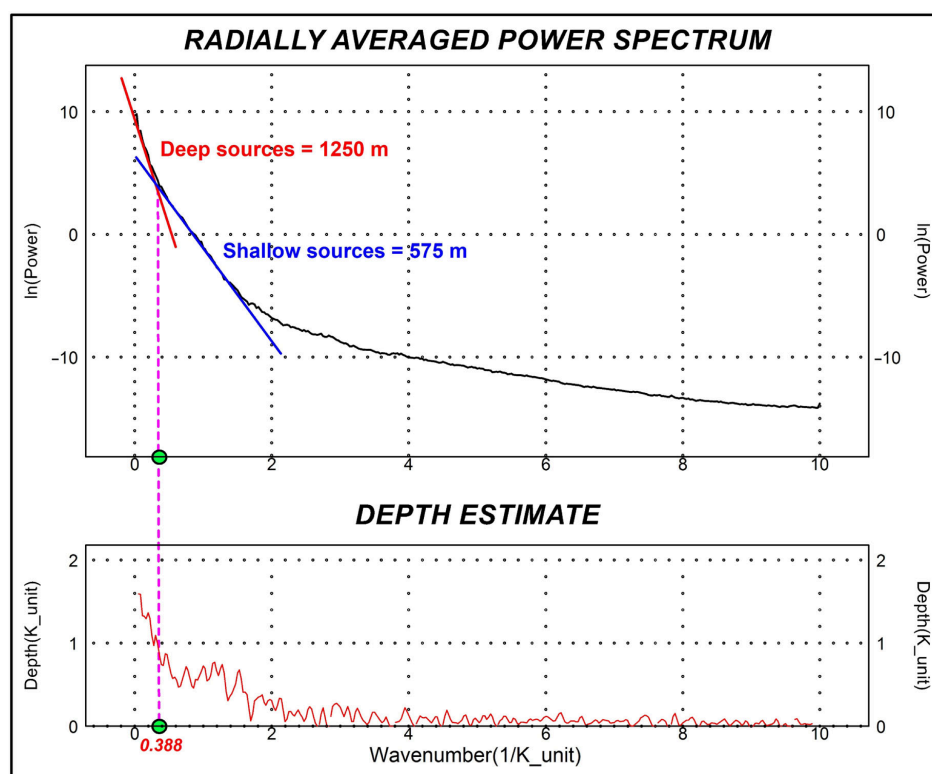


Figure 10. Power spectrum plot and depth estimation derived from the RTP data of the study area.

It is found that the average depth of the deep-source components which are mostly associated with regional anomalies is estimated at approximately 1250 m, while the shallow-sources (residual anomalies) average depth is estimated at approximately 575 m, with statistical uncertainties of 53 and 6 m, respectively. These reported depth values represent average spectral depths, and the associated uncertainties reflect only the statistical precision of the regression fits. Additional uncertainties arise from the subjective identification of the wavenumber break point (0.388 cycles/km) as small variations in this cutoff can affect the estimated depths.

The regional (low-pass) magnetic map (Figure 11a) displays large-scale magnetic anomalies, predominantly trending NW-SE and E-W, with magnetic intensities ranging from 42,165 to 42,650 nT and an average of approximately 42,330 nT. High regional magnetic anomalies occur mainly in the northeastern part of the study area and along a NW-SE-trending corridor. Intermediate and low regional magnetic anomalies are concentrated

mainly in the central and southwestern parts of the study area, respectively. The strong correspondence between the RTP and regional anomaly maps indicates that many of the magnetic sources responsible for these broad anomalies are located at considerable depths.

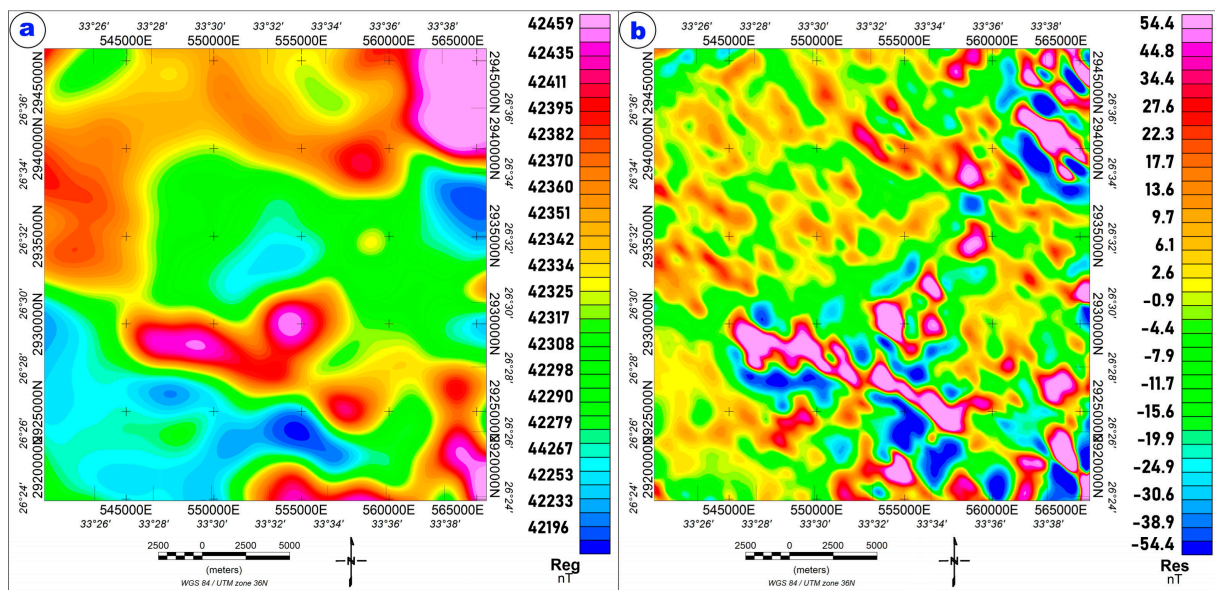


Figure 11. Magnetic anomaly maps of the study area: (a) regional and (b) residual anomalies.

In contrast, the residual (high-pass) magnetic map (Figure 11b) displays magnetic anomalies of varying sizes that are generally smaller than the regional anomalies. The residual anomalies predominantly trend NW-SE and range from -130 to 240 nT. High residual magnetic anomalies, represented by red to pink colors, are distributed throughout the study area, whereas intermediate anomalies are represented by green to yellow colors and low anomalies by blue to cyan colors. The spatial coincidence of high-amplitude residual anomalies with corresponding features on the RTP map confirms their contribution to the observed magnetic signatures and supports the interpretation of magnetic sources occurring at multiple depths within the study area.

5.4.3. Center for Exploration Target (CET) and Extraction of Structural Features

The Center for Exploration Target (CET) grid analysis workflow was used to enhance and identify linear structures from the magnetic data of the study area. This technique enabled the extraction of the deep- and shallow-seated structural features from the regional and residual magnetic anomaly maps, respectively. The maps were first statistically processed using the standard deviation of the data to enhance anomaly edges, followed by phase-symmetry analysis to detect linear discontinuities. The resulting features were then skeletonized and subjected to a thinning threshold to retain only linear features of significant length and continuity while eliminating those that did not satisfy the threshold criteria. Finally, the thinned linear features were vectorized to represent the structural framework of the study area. Deep-seated structural features (Figure 12) were extracted from the low-pass regional magnetic anomaly map, which emphasizes the long-wavelength sources, whereas shallow-seated lineaments (Figure 13) were extracted from the high-pass residual anomaly map. The deep-seated structural fabric is dominated by a NW-SE trend, with a secondary NE-SW component of slightly lower prevalence. In contrast, the shallow-seated structural fabric is almost exclusively dominated by the NW-SE orientation.

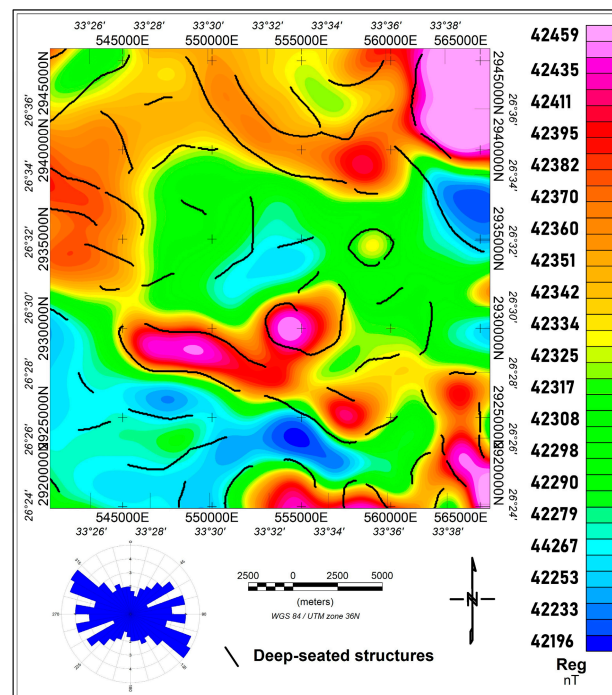


Figure 12. LPF regional magnetic anomaly map of the study area with superimposed deep-seated structures and the corresponding rose diagram depicts azimuthal frequency distributions based on lineament-count statistics.

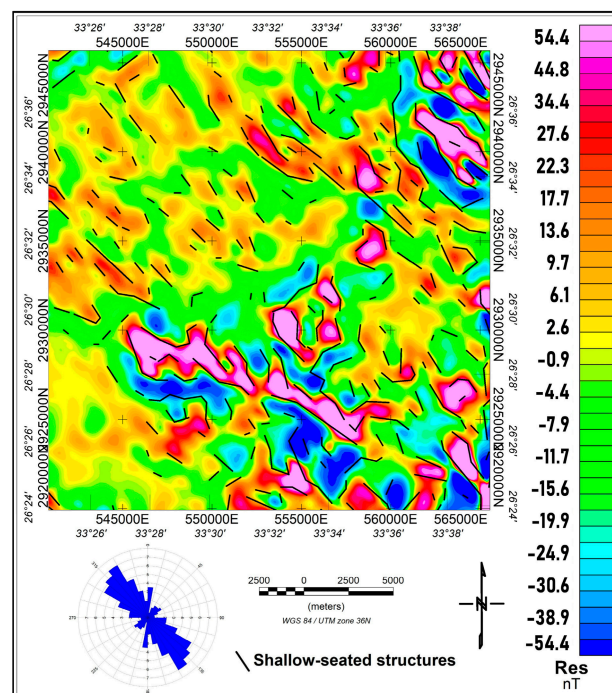


Figure 13. HPF residual magnetic anomaly map of the study area with superimposed shallow-seated structures and the corresponding rose diagram depicts azimuthal frequency distributions based on lineament-count statistics.

5.4.4. Contact Occurrence Density

The COD technique was used to highlight structural complexity by delineating the density of structural features across the study area. Visual comparison of the structures extracted from the LPF and HPF maps (deep- and shallow-seated structures, respectively) with the corresponding structural complexity zones on the COD heat map (Figure 14) shows

strong spatial coincidence between low- and high-complexity zones. This consistency supports the reliability of the resulting COD map.

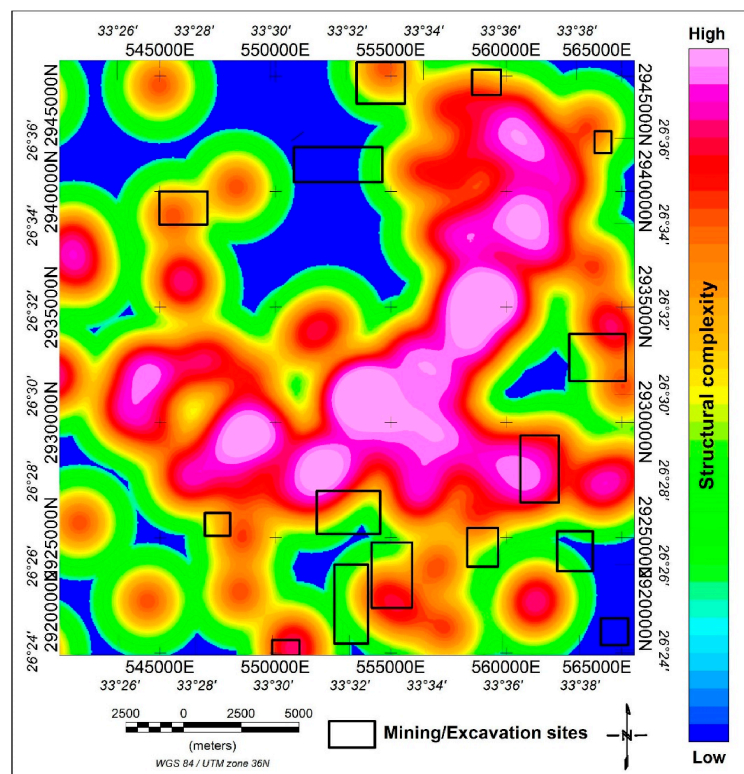


Figure 14. COD map showing integrated structural complexity of deep- and shallow-seated structures.

Overlying the known mining localities shows that 12 (80%) of the 15 sites coincide with high structural-complexity zones (red to pink), 1 site (6.7%) occurs within the moderate-complexity zones (green), and 2 sites (13.3%) occur within low-complexity zones (cyan and blue). The strong spatial association between known mining and active excavation sites and zones of high structural complexity identified by the COD map suggests that mineralization in the study area is strongly structurally controlled.

5.5. Data Integration Through Fuzzy Overlay Modeling

To synthesize structural information across multiple sensors and wavelengths, six lineament-density maps derived from four independent data sources (AP-DEM, NISAR, BIOMASS, and aeromagnetic data) were integrated using a fuzzy-overlay approach. The input layers comprised the AP-DEM hillshade-derived lineament-density map; NISAR L-band HH- and HV-derived lineament density maps; BIOMASS P-band surface- and volume-scattering-derived lineament density maps; and the aeromagnetic COD map integrating deep- and shallow-seated structural features. Each layer was first reclassified into fuzzy membership grades on a continuous scale from 0 to 1 using the “Fuzzy Membership” tool, where 1 represents the highest structural complexity and 0 the lowest. The six fuzzy membership raster layers were then combined using fuzzy “AND operator”, which assigns each pixel the minimum membership value among all input layers. Consequently, high integrated scores occur only where all six datasets concurrently indicate high structural complexity. This conservative integration approach suppresses anomalies identified by only a single dataset while emphasizing structurally robust zones supported by independent data sources.

The resulting integrated structural-complexity map (Figure 15) ranges from 0.17 (low) to 1 (high) and reveals a highly heterogeneous spatial distribution. The highest-complexity zones (red, approaching 1) form sparse, locally interconnected patches, with a prominent corridor extending through the south-central to southeastern sector, approximately between $33^{\circ} 31' \text{ E}$ and $33^{\circ} 36' \text{ E}$ and south of $26^{\circ} 30' \text{ N}$, where all six datasets indicate intense structural development. Additional high-complexity zones occur in the central-eastern, north-eastern, southwestern, central-western, and northwestern sectors. The western anomalies are particularly noteworthy because they emerge from the integrated analysis despite being less pronounced in several individual datasets, indicating that the multi-source integration can identify structurally significant features that may be overlooked in individual datasets.

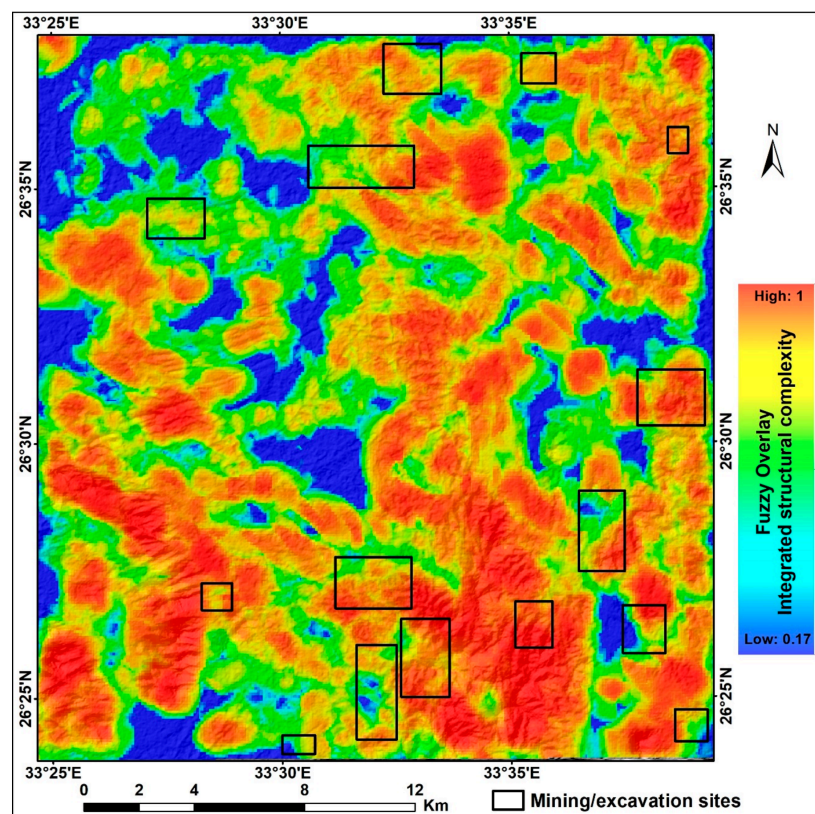


Figure 15. Fuzzy-overlay structural-complexity map; high values (yellow to red) indicate strong multisource agreement.

Conversely, the lowest-complexity zones (blue, approaching 0.17) are concentrated along the western margin, in the central-western and central-eastern sectors, and in scattered patches within areas of moderate complexity. Their fragmented distribution reflects the stringent fuzzy “AND” logic, whereby a low membership value in any single dataset reduces the integrated score. This produces a mosaic of structurally contrasting zones that may not be evident from individual datasets alone.

The 15 mining sites used for validation (black boxes) were superimposed on the integrated structural-complexity map (Figure 15) to assess the spatial relationship between known mineralization and multisource structural complexity. Of these sites, 13 (86.7%) occur within very high-complexity zones (orange to red), while 2 (13.3%) occur within moderate- to high-complexity zones (yellow to orange); none coincide with low-complexity blue zones. This strong spatial association indicates that known mineralized localities are preferentially associated with structurally complex zones consistently identified by AP-DEM, L-band SAR, P-band SAR, and aeromagnetic data. The results demonstrate that the fuzzy “AND” approach effectively identifies structurally favorable areas supported

by multiple independent datasets, providing a robust framework for targeting additional mineral exploration zones.

6. Discussion

6.1. Multi-Sensor Structural Expression

The integration of six independent structural datasets spanning DEM-derived topography, L-band SAR (NISAR HH/HV), P-band SAR (BIOMASS surface/volume scattering), and aeromagnetic derivatives provides a unique opportunity to assess how sensor wavelength, polarization, and scattering mechanisms govern the detectability and orientation bias of geological lineament networks in arid terrains. The total number of extracted lineaments (Table 3) varies markedly among datasets (Figure 16), from 883 for BIOMASS surface scattering to 4483 for NISAR HV, reflecting fundamental differences in how each sensor interacts with surface, near-surface, and subsurface structures.

Table 3. Summary of lineament yields by dataset and orientation.

Dataset/Orientation	E-W	NW-SE	N-S	NE-SW	Total
AP-DEM	414	402	298	428	1542
NISAR HH	1009	368	386	158	1921
NISAR HV	914	1300	1099	1170	4483
BIOMASS_sur	261	196	273	153	883
BIOMASS_vol	210	344	255	300	1109

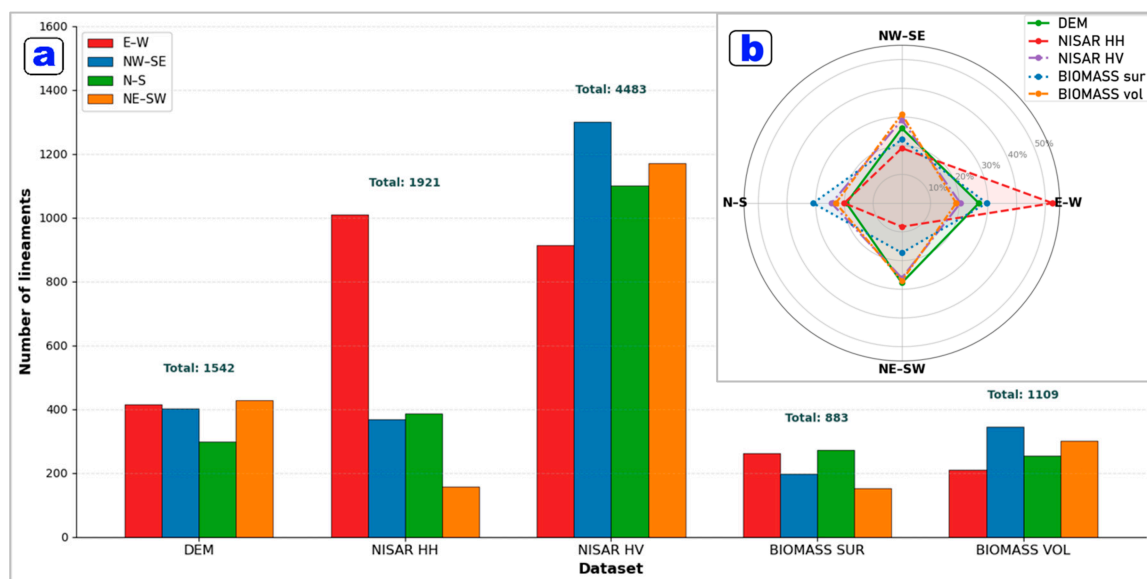


Figure 16. (a) Lineament counts by orientations across all the remote-sensing datasets. (b) Radar chart shows the normalized orientation distributions for the different datasets; orientation percentages were normalized relative to the total lineament count within each respective dataset.

The most striking divergence occurs between the NISAR polarizations. The HH polarization, which is sensitive to surface and double-bounce scattering, yields only 1921 lineaments and exhibits a strong orientation bias towards E-W structures (52.55%), whereas the NE-SW set accounts for only 8.2%. This pattern reflects the geometric dependence of co-polarized backscatter on the radar look direction, whereby structures oriented favorably relative to the radar geometry produce stronger returns, whereas other orientations may produce weaker responses because of shadowing, foreshortening, and layover effects inherent to the side-looking SAR geometry [30,31]. In contrast, HV polarization, which

captures cross-polarized energy associated with surface roughness, structural heterogeneity, and volumetric depolarization, yields 2.3 times more lineaments (4483) and a markedly more balanced distribution across the four principal orientations. The NE-SW set, poorly represented in HH (158 lineaments), becomes the second most prominent orientation in HV (1170 lineaments). This increase demonstrates the ability of cross-polarized scattering to reveal structural information that may be masked by polarization-dependent geometric effects [29,67,68]. This observation is consistent with recent comparative analyses showing that cross-polarized data can outperform co-polarized backscatter for automated lineament mapping [29].

The BIOMASS P-band results provide a wavelength-dependent perspective. Although BIOMASS penetrates deeper than NISAR into the regolith and weathering profile, its total lineament yields are lower. This apparent paradox can be exploited by the decomposition approach. The Freeman-Durden algorithm partitions the backscatter into distinct physical scattering mechanisms [59]. The surface-scattering component produces the lowest lineament yield among all datasets (883). The volume-scattering component, representing volumetrically complex and potentially subsurface structures, yields slightly more lineaments (1109) but still considerably fewer than NISAR HV. These lower absolute yields likely reflect the coarser spatial resolution of BIOMASS. NISAR GSLC Frequency-A data achieves a ground resolution of approximately 5×10 m, whereas BIOMASS Level-1A SCS data have a pixel size of approximately 46×41 m. Thus, a single BIOMASS pixel integrates structural information that is resolved across multiple NISAR pixels. Consequently, NISAR can detect short discontinuities and subtle roughness features that may not be resolved by BIOMASS because of its coarser spatial resolution. Therefore, higher lineament counts do not necessarily imply greater geological significance; rather, they partly reflect the sensor's ability to resolve fine-scale surface textures and the lower selectivity of single-channel backscatter compared with physically constrained polarimetric decomposition products.

Importantly, BIOMASS surface scattering favors the orthogonal E-W and N-S trends (60.5% combined), whereas volume scattering shifts markedly toward the diagonal NW-SE and NE-SW trends (58.1% combined). This mechanism-dependent orientation partitioning suggests that relatively smooth or gently dipping surfaces may produce strong specular returns in the surface-scattering component, whereas oblique, steeply dipping, or volumetrically complex structures, as well as rough weathered surfaces, may be preferentially expressed in the volume-scattering component.

The DEM-derived lineaments, representing the topographic expression of structures at the surface, show the most balanced orientation distribution among all datasets. This near-isotropic pattern likely reflects the cumulative surface expression of multiple deformation events, where differential weathering and drainage incision have exposed structures of various orientations without the polarization- or wavelength-dependent biases inherent to SAR [68]. The aeromagnetic COD map, integrating deep- and shallow-seated structures derived from magnetic analysis, provides a complementary subsurface perspective, characterized by a NW-SE-dominated deep-seated structural fabric and a predominantly NW-SE shallow-seated structural pattern (Figures 12 and 13). Overall, these results demonstrate that no single dataset captures the complete structural fabric, and that sensor characteristics strongly influence the observed orientation distribution. This highlights the importance of multisensory, multicriteria analysis and its direct implications for mineral exploration.

6.2. Deep- and Shallow-Seated Structural Controls

The NW-SE structural trend emerges as the most persistent and pervasive orientation throughout the crustal column within the investigated depth domains. In the aeromagnetic analysis, the deep-seated structural fabric, extracted from low-pass filtered regional anoma-

lies representing sources at an average depth of $\sim 1250 \pm 53$ m, is dominated by NW-SE trends, with a secondary NE-SW component of slightly lower prevalence. In contrast, the shallow-seated structures, derived from high-pass filtered anomalies at an average depth of $\sim 575 \pm 6$ m, are almost exclusively dominated by the NW-SE orientation. This contrast suggests that the tectonic event responsible for the NW-SE fabric may have been more intense and/or prolonged than that associated with the NE-SW set. Its stronger expression potentially may have enabled the NW-SE fabric to develop across a broader depth range, whereas the NE-SW structures can be comparatively interpreted as weaker and shorter lived, leaving a detectable signature only at depth and less prominently expressed in the shallowed structural record [41,42]. It must be emphasized, however, that this interpretation is based on the tectonic history of the study area and that orientation distributions and depth persistence alone cannot unequivocally establish the relative intensity, duration, or age of tectonic events without supporting kinematic evidence, cross-cutting relationships, or absolute geochronological constraints.

The SAR datasets support this depth-dependent interpretation. NISAR HV, with its sensitivity to distributed structural heterogeneity and cross-polarized-scattering, records the highest NW-SE count among the SAR products (1300 lineaments; 29.0% of the total), suggesting that this orientation is expressed not only as discrete surface fractures but also as a pervasive structural fabric within the regolith and near-surface domain. BIOMASS volume-scattering, sampling structural heterogeneity within a greater penetration depth than NISAR, yields a high proportion of NW-SE lineaments (344 lineaments; 31% of the total). The convergence of aeromagnetic, BIOMASS volume-scattering, and NISAR HV results toward NW-SE dominance supports a model in which this trend represents the principal regional structural control, likely related to the Najd transpressional tectonic regime that affected the Central Eastern Desert during the Neoproterozoic [39–41].

In contrast, the NE-SW trend exhibits a more restricted depth expression. It is prominent in the deep-seated aeromagnetic fabric but weakly represented in the shallow structures, sparse in BIOMASS surface-scattering data (17.3%), and nearly absent in NISAR HH data (8.2%). Conversely, the E-W and N-S trends are most strongly expressed in surface-sensitive datasets (NISAR HH, BIOMASS surface scattering, and DEM), suggesting that they may represent younger and shallower fracture sets superimposed on the deeper NW-SE structural fabric, possibly related to post-orogenic extension, Red Sea rifting, or local stress reorientation [40,69]. This interpretation is necessarily speculative because orientation distributions alone cannot establish the relative ages of structural events; additional chronological investigations, or absolute dating of fault movements would be required for confirmation.

6.3. Multi-Source Consensus Mapping and Fuzzy Overlay Approach

The fuzzy-overlay integration using the “AND” operator produces a conservative structural-complexity map in which a pixel receives a high score only when all six input layers concurrently indicate high structural density. The stringency of the “AND” operator is both a strength and a limitation; it suppresses false positives arising from noisy or biased individual layers but may underestimate structurally significant zones where only a subset of sensors indicates high structural complexity.

The selection of the fuzzy “AND” operator over alternative integration rules was deliberate and physically motivated. In structurally controlled hydrothermal mineralization systems, ore emplacement requires structural connectivity across different depth domains. The fuzzy “AND” operator enforces this requirement by demanding multisource agreement: a prospective pixel must exhibit elevated lineament density or structural complexity in all the input layers, representing different depth domains from the surface to

the deeper subsurface. Alternative operators were rejected for specific reasons. The fuzzy “OR” (maximum) operator would assign high scores wherever any single layer indicates high structural complexity, potentially generating excessive false positives and thereby undermining the objective of multisource validation. A weighted linear combination would require weighting coefficients for which no independent empirical basis exists in this study. Assigning equal weights would also be arbitrary, whereas deriving weights from the known mining sites could bias the model toward these validation sites. Consequently, the fuzzy “AND” operator was selected as the most conservative, physically consistent, and reproducible approach for identifying zones where independent structural measurements from complementary sensors, wavelengths, and depth sensitivities converge.

The resulting integrated structural-complexity map ranges from 0.17 to 1.0, with the highest values (red zones) forming sparse but strategically distributed patches concentrated along the south-central to southeastern corridor, in the central-eastern sector, and as discrete anomalies in the northeastern and southwestern sectors. The fragmented blue inclusions—low-complexity zones embedded within areas of moderate to high complexity—represent zones of structural discordance where one or more sensors indicate relatively low fracture intensity. The validation results (Table 4) demonstrate the effectiveness of the multisource approach. The fuzzy-overlay model places 13 of the 15 known mining sites (86.7%) within high complexity orange-to-red zones, with the remaining two sites (13.3%) occur within moderate-to-high-complexity yellow-orange zones; none occur within low-complexity blue zones. This represents an improvement over individual datasets: AP-DEM and NISAR HH each place only 60% of the sites within high-density zones, whereas the best performing individual dataset, BIOMASS volume scattering, achieves the same proportion (86.7%) as the fuzzy-overlay model. The aeromagnetic COD map also performs strongly (80%), reflecting its integration of deep- and shallow-seated structures. Overall, the fuzzy-overlay approach provides a more consistent multisensory representation by ensuring that the identified high-complexity zones are supported by all six structural datasets.

Table 4. Correlation of mining sites with structural-density and structural-complexity classes across all datasets (n = 15 sites).

Dataset	High (% Sites)	Moderate (% Sites)	Low (% Sites)	Success Rate (%)
DEM	9 (60%)	2 (13.3%)	4 (26.7%)	60%
NISAR HH	9 (60%)	4 (26.7%)	2 (13.3%)	60%
NISAR HV	10 (66.7%)	3 (20%)	2 (13.3%)	66.7%
BIOMASS_sur	11 (73.3%)	3 (20%)	1 (6.7%)	73.3%
BIOMASS_vol	13 (86.7%)	1 (6.7%)	1 (6.7%)	86.7%
Aeromagnetic COD	12 (80%)	1 (6.7%)	2 (13.3%)	80%
Fuzzy Overlay	13 (86.7%)	2 (13.3%)	0 (0.0%)	86.7%

6.4. Structural Complexity as a Mineralization Proxy: Validation and Exploration

The progressive improvement in validation success rates across the dataset hierarchy establishes a clear relationship between the detection of structural complexity and mineralization potential. The performance of BIOMASS volume-scattering component is particularly noteworthy, with 86.7% of the known mining sites occurring within high-density zones, matching the performance of the multisource fuzzy-overlay model despite being based on a single dataset. This suggests that P-band volumetric scattering may effectively capture structural connectivity, including the surface expression of structural complexity and fracture-network characteristics that play an important role in controlling hydrothermal fluid flow and ore deposition within the Neoproterozoic basement of the Central Eastern Desert [39,41]. The contrast between the DEM and the integrated fuzzy-

overlay approaches in terms of the proportion of mineralization sites identified within high-complexity zones (60% vs. 86.7%) and low-complexity zones (26.7% vs. 0%) underscores an important advantage of multisource integration. Topography-based DEM lineament mapping alone may be less effective where weathering, alluvial cover, or subdued relief obscure structural expression of the structure, whereas SAR and aeromagnetic data provide complementary information on near-surface and sub-surface structures. Similarly, the lower mining sites detection success rates of the NISAR HH than in HV data highlights the limitations of relying solely on co-polarized SAR in terrains where polarization-dependent geometric effects may suppress structurally important orientations [29,30].

For exploration targeting, the fuzzy-overlay map provides a reproducible framework for prioritizing ground investigations. The red high-complexity zones, where all data converge on intense fracturing, represent the most robust targets. The orange-to-yellow moderate- to high-complexity zones, where structural evidence is less consistently expressed across the datasets, represent secondary targets that may warrant further investigation, particularly where they coincide with favorable lithologies or geochemical anomalies. Conversely, the blue low-complexity zones are generally lower-priority targets for initial exploration; however, they are not interpreted as entirely barren of mineralization. This distinction allows resources to be focused on structurally more prospective areas.

The proposed methodology is potentially transferable to other arid shield terrains worldwide. Future studies should integrate alteration mapping, geochemical data, radiometric signatures, and gravimetry surveys to further refine the exploration targeting framework. Nevertheless, the multisensor structural framework established here provides a robust and physically grounded basis for identifying areas favorable for structurally controlled mineralization.

7. Conclusions

This study demonstrates that structural lineament analysis integrating multisource remote-sensing and geophysical data provides a robust and potentially reproducible framework for mineral exploration targeting in arid shield terrains, where structurally controlled hydrothermal mineralization represents a major ore-forming process. The key findings and conclusions are summarized as follows:

1. Sensor-dependent orientation biases are pronounced and physically explicable. NISAR HH co-polarized backscatter is strongly influenced by structural orientation relative to the radar look direction, producing a marked E-W dominance and limited representation of NE-SW features. In contrast, NISAR HV cross-polarized scattering yields a much larger and more balanced structural inventory, demonstrating the importance of cross-polarized data for reducing orientation bias in SAR-based fracture-network mapping.
2. P-band volumetric scattering effectively captures structural connectivity. It resolves diagonal structural fabrics that are less prominently expressed in surface-sensitive datasets. Its high validation success rate matches that of multi-source fuzzy-overlay model. This result highlights the strong discriminatory potential of P-band polarimetric decomposition for structural mineral exploration.
3. Aeromagnetic analysis reveals a persistent NW-SE structural control. The NW-SE trend dominates both deep- and shallow-seated magnetic structures, whereas the NE-SW trend is more prominently expressed at deeper levels. This distribution suggests that the tectonic event responsible for the NW-SE fabric may have been more intense and/or prolonged, producing a structural imprint over broader depth range than the NE-SW event. Nevertheless, we acknowledge that orientation distributions and

depth persistence alone cannot demonstrate relative event timing or intensity without independent kinematic or geochronological constraints.

4. Multisource consensus mapping using fuzzy “AND” overlay provides the most robust structural targeting framework, outperforming individual datasets. The conservative fuzzy “AND” operator suppresses anomalies supported by only individual sensors while emphasizing zones where topographic, SAR, and aeromagnetic structural indicators converge. This multisensor consensus therefore provides a robust basis for prioritizing field investigations and optimizing exploration resources.
5. The methodology is potentially transferable to comparable arid shield terrains worldwide, noting the limitation of lacking adequate independent validation datasets. Future studies should integrate alteration mapping, geochemical data, detailed geophysical investigations, geomechanical analysis, and fieldwork with the structural framework developed here to further refine predictive exploration models. Overall, this study demonstrates that multisensor structural consensus mapping based on the convergence of independent physical measurements, can provide greater confidence in identifying structurally favorable mineral exploration targets than reliance on any single dataset alone.

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