Short Thesis for the Degree of Doctor of Philosophy (PhD)

Advancing Lithological, Hydrothermal Alteration, and Artisanal Mining Mapping Using Multi-Sensor Remote Sensing and Machine Learning in the Red Sea Hills, Northeast Sudan

By

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1. Introduction

Mining continues to be important for societal growth of because it provides the raw materials necessary for the development of infrastructure, transformation of the economy, and advances in technology (Frolova et al., 2020). The extracting minerals has facilitated the development of civilization from earlier metallurgical discoveries to the technological revolution and the present digital businesses (Parra and Weldegiorgis, 2015). As a source of crucial materials, including lithium, cobalt, copper, and rare earth elements, which are required for electronic devices, clean energy, and industrial facilities (Ali et al., 2017). In numerous regions, notably rural and largely undeveloped ones, mining revenue supports growth and development, healthcare, and education (Hilson and McQuilken, 2014; World Bank, 2024).

Despite its importance, the mining industry, particularly, informal mining such as Artisanal and Small-Scale Mining (ASM), presents serious socio-environmental and environmental problems (Asner et al., 2013; UNEP, 2012). ASM tends to operate informally, causing unsafe working conditions, habitat destruction, water contamination, forest loss, greenhouse gases emissions, and hazardous working conditions. These effects are more pro in regions with less regulatory controls, where vulnerable populations are affected financially and medically (Chen and Evers, 2023). Therefore, the major challenge is how to balance the economic necessity of mining with the values of social justice and environmental sustainability.

Lithological mapping is a fundamental step in most geological investigations, including mineral exploration, groundwater assessment, petroleum studies, natural resource evaluation, and environmental management (Abrams and Yamaguchi, 2019; Amusuk et al., 2016). Consequently, obtaining an accurate lithological map is crucial for mineral exploration and mining. Traditionally, lithological mapping is executed mainly through interpretation of aerial photographs, followed by extensive field-based investigations (Szaniawska, 2018). However, this traditional mapping approach can be challenging because it requires skilled field geologists, is time-consuming, and requires a suitable budget to cover costs, especially in harsh environments and inaccessible or isolated places. These difficulties have recently decreased through the integration of cutting-edge technologies, such as remote sensing and machine learning, in the lithological mapping process (Abdelkareem et al., 2021; Bachri et al., 2019; Shirmard et al., 2022a).

In modern mineral exploration, advanced technologies including high-resolution remote sensing, hyperspectral and multispectral imagery, machine learning algorithms (MLAs), and geospatial analytics, have been used increasingly (Shirmard *et al.*, 2022). These tools are crucial for mapping complex lithologies, identifying hydrothermal alteration zones, and tracking ASM activities. Their use is more relevant in remote areas where the geology is cropped out, underexplored and complex, such as the Red Sea Hills (RSH). ML provides an important methods to generate geological information through processing remote sensing data, though its validity is relieses heavly on quantity and quality of reference data (Foody, 2009; Maxwell et al., 2018). Hydrothermal alteration zones are essential markers of mineralization processes, particularly when it comes to gold mineralization and base metals such as VMS deposits. These zones are developed when hydrothermal fluids change the mineralogy and chemistry of host rocks, forming unique mineral assemblages such as iron oxides, clays, and carbonates that are detectable using remote sensing since they have distinctive absorption characteristics in the VNIR and SWIR spectral regions (Rajan Girija and Mayappan, 2019; Sabins, 1999).

Considering the above context, the objectives of this dissertation are: (1) assess the efficiency of integrating machine learning (ML) and remote sensing might in lithological mapping compared to more conventional techniques. (2) Advancing the mapping of hydrothermal alteration zones linked to gold mineralization through machine learning and advanced image processing techniques. (3) Identify and track the growth and environmental impacts of ASM in the RSH. (4) Evaluate ASM impact on geological integrity and environment in the RSH. (5) The consequences of using training data collected through different approaches were tested, and a simple method for extending the available input training data by applying region-growing segmentation to augment the inputs was introduced. (6) Evaluate the effects of training data sizes on classification performance. (7) Assess the potential of remote sensing data for ASM-related hydrothermal alteration and gossan mapping. (8) Evaluate the efficiency of a developed seeded region-growing algorithm, and determine area-based accuracy and compare it with the traditional point-based technique.

2. Material and Methods

2.1 The study area

Three study sites within the RSH were chosen for this study. Each assesses methodological robustness in actual mineral exploration environments through combined remote sensing datasets, field surveys, petrographic analyses, and ML. The RSH, part of the Arabian-Nubian Shield (ANS). The area has a long history of mining, both formal and informal in the past and present, and is rich in gold, base metals, critical minerals, and other minerals (Abu-Fatima et al., 2021). ASM expansion has been expedited, especially in relatively stable states such as the Nile River and Red Sea regions, with the increase in world gold prices, the secession of South Sudan in 2011 (which reduced Sudan’s oil revenues), and ongoing political instability.

2.2 Dataset

We used a variety of geospatial datasets to accomplish the aims of this study. These datasets include geological maps (Abdelrahman et al., 2024; Abdelsalam and Stern, 1993; Kenea, 1997), remote sensing, field data and petrographic analysis. Their combination and integration renders for a more thorough and precise examination of lithological features, mineral alteration zones, and ASM operations. These encompass optical and hyperspectral source data. The optical datasets include multispectral images Landsat-7 Enhanced Thematic Mapper Plus (ETM+), Landsat-8 and Landsat-9 Operational Land Imager (OLI/OLI-2), and Sentinel-2. We also employed PlanetScope imagery, which provides very high spatial resolution, as one of the first applications of such non-commercial data for ASM mapping and monitoring. This study also represents the first time that PRISMA hyperspectral data have been used to identify mineral alteration related to ASM practices and VMS-lined gossan. In addition to field and petrographic studies data.

2.3 Applied Methods

2.3.1 Image Processing Techniques

Image processing is enhancement techniques that offer powerful means for visual examination and analysis of multispectral or hyperspectral images utilising individual bands or BR (Mwaniki et al., 2015). Therefore, image processing techniques are increasingly used in geological studies in order to differentiate lithological features and mineral alteration from satellite imagery (Gupta, 2025). Tj *et al.* (2022) also emphasised the key role of image processing in the extraction of geological features, mainly when it comes to geological mapping using satellite imagery. They essentially focus on information extraction of geological features using computer-aided techniques to manipulate or modify imagery and came to the conclusion that image processing aids in the collection of clearer and more helpful observations for mapping purposes. These methods includes: Colour Composite (CC) Band Ratio (BR), Density slicing, Principal Component Analysis (PCA), Directed Principal Component Analysis (DPCA)

2.3.2 Machine learning

ML is a crucial part of the artificial intelligence field and statistical models, which allow machines (computers) to learn from data and get better over time without the need for explicit written code, and are inherently include in number fields of research (Ramos et al., 2023). It involves training a model on labelled data, where the input-output pair is known (Venkata Mahesh Babu Batta, 2024). Based on Rao *et al.* (2017), MLAs have invented a number of algorithms that are frequently used for interpreting text, identifying patterns, and other applications in business.

2.3.2. 1 Naive Bayes Algorithm (NB)

The Naive Bayes (NB) model is a probabilistic supervised ML classifier based on Bayes' theorem, and it assumes conditional independence across the predictor variables, considering the class label (Maron, 1961). NB determines the subsequent chances for every class using Gaussian distributions for continuous variables or frequency counts for discrete features by multiplying prior probabilities by likelihoods obtained from training data (Ananthkumar, 2023).

2.3.2.2 Multiple Adaptive Regression Splines (MARS)

Friedman and Steppel (1974) discovered Multiple Adaptive Regression Splines (MARS). It is an effective classifier that handles high-dimension regression problems and resolves the issue of dimensionality through focusing on lower-order relationships (Kooperberg, 2012). The algorithm uses flexibly defined spline functions, and due to its flexibility, MARS is usually able to model functions that show high variation in one part of the predictor space and are smoother in other parts (Friedman, 1991). According to our research, MARS can be a very useful tool for improving geospatial mineral exploration procedures, particularly in settings with complex structures and scarce data.

2.3.2.3 Support Vector Machine (SVM)

Vapnik (1979) and Vladimir Vapnik (1995) developed the SVM as a supervised ML algorithm for classification and regression problems based on statistical learning theory. It was primarily designed to handle binary objects; however, it extended to multiclass tasks (Melgani and Bruzzone, 2004). The SVM classifier identifies the most suitable hyperplane for splitting data into classes with the bigger variance (Vapnik, 2013).

2.3.2.4 Random Forest (RF)

Random forest (RF) is an ensemble supervised ML method known for its robustness owing to its ability to minimize overfitting by averaging the different trees results allow it to handle large data problems (Kulkarni and Sinha, 2014; Zhao et al., 2024). RF functions by building several decision trees bootstrap replicates of training data and aggregating their outputs in order to increase classification accuracy and mitigate predictive modelling (Rose and Hassen, 2019; Schonlau and Zou, 2020). In my thesis, I evaluated the RF classification for lithological and ASM mapping.

2.3.2. 5 XGBoost (eXtreme Gradient Boosting)

XGBoost (XGB) is a ML algorithm that is effectively used in different fields due to its accuracy, rapid computation ability, and sequential learning (Yin et al., 2023). It represents an ensemble algorithm constructed to upgrade model performance, especially on multiclass imbalanced datasets using boosting techniques, which allows its applicability in several majors, for example, finance, healthcare, and image recognition (Pristyanto et al., 2023). Arif Ali *et al.* (2023) described XGB as a recently released ML algorithm that indicates exceptional capacity for modelling complex systems and superior prediction accuracy, interpretability, and classification versatility.

2.3.3 Pseudo labeling and statistical evaluation

We selected 1000 spatially random data points from the assigned area as PL-data (abbreviated as PL1000), involved in the new training phase merged with the original training data; possible duplicates were eliminated. Next, the classification step was repeated with an accuracy assessment.

2.3.4 Accuracy assessment

The process of testing the Model is an improtant step in all predictions processes (Bui and Mucsi, 2022). We uitilized previously developed module, programmed for an automated accuracy assessment, the Alassification Assessment Tool (Szabó et al., 2024), which calculates accuracies using advanced solutions by taking random subsamples from the entire testing dataset based on a predefined ratio obtained from the testing data [0-1] and the number of repetitions of random sampling. We applied 0.7 for the fraction (70% of data were used at a time with stratified random sampling), and 10 for repetitions. Boxplot diagrams were used to visualize the differences among the classes. The following class-level metrics were calculated: Precision (or User’s Accuracy, UA), Sensitivity (Producer's Accuracy, PA) (Barsi et al., 2018; Congalton, 1991), Specificity (True Negative Rate), F1-scores (or Dice Similarity Coefficient), Jaccard Index (or Intersection over Union, IOU) (Willem, 2017; Grandini et al., 2020), and Matthews correlation coefficient (MCC) (Cao et al., 2020; Chicco and Jurman, 2020).

3. Results

3.1 Lithological mapping

Thesis 1: Employing adaptive data augmentation strategies, as opposed to static ones, will enhance model accuracy and spatial coherence by simulating a wider and more geologically realistic spectrum of feature variations.

I discovered that, incorporating an adaptive data augmentation strategy improved both models' performance, particularly in complex zones, by enhancing the spatial coherence and reducing pixel-level noise. My result indicated that MARS and RF algorithms produced similar lithological maps, but with notable differences in accuracy and spatial reliability. MARS tended to overestimate WDi and produced overconfident probability values, while RF yielded more consistent and geologically realistic results than MARS. Hence, employing adaptive rather than static data augmentation strategies can significantly improve model accuracy and spatial coherence by capturing a broader range of geologically realistic variations.

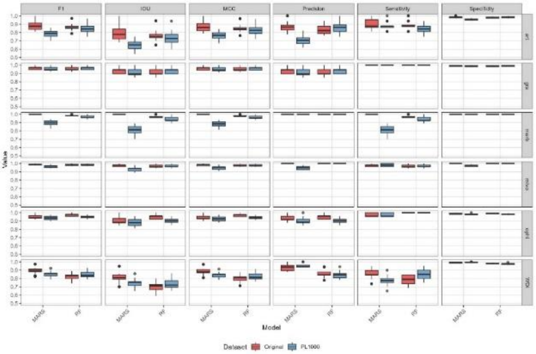

Figure 1. Accuracy metrics of RF and Multiple Adaptive Regression Spline (MARS) classifications (Original: models trained with the original training dataset, PL1000: models trained with an additional 1000 pseudo-labelled data sampled from 95% probability pixels; art: artisanal, gra: granite, marb: marble, mtvo: metavolcanic, ophi: ophiolite, WDi: wadi deposits; IOU: Intersection over Union, MCC: Matthews correlation coefficient).

3.2 Artisanal and small-scale mining

Thesis 2: Artisanal and small-scale mining (ASM) activities are increasing continuously in the RSH and can be detected and monitored over time using satellite data and ML classifiers.

I proved that ASM activities in the RSH continuously increased over the study period. Using multi-sensor satellite data (Landsat, Sentinel-2, and PlanetScope) and machine learning classifiers (RF and XGB), ASM expansion was effectively detected and monitored across different years. The binary classification achieved higher accuracy (OA up to 0.91) compared to the multiclass approach did. Both methods consistently revealed progressive ASM spread from northern and central-eastern zones to southern and western sectors. My findings confirm that remote sensing combined with ML provides a robust and cost-effective framework for long-term ASM monitoring in complex geological terrains.

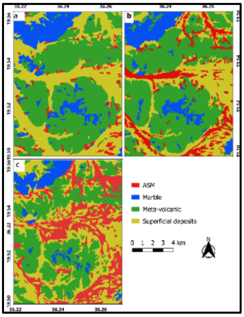

Figure 2. Distribution of ASM according to multiclass RF classification (a: 2003, b: 2013, c: 2023).

Thesis 3: Evaluating the effects of training sample collection strategies particularly the contrast between point-based and spatially explicit sampling will improve the reliability and spatial generalization of machine learning models for mapping ASM.

My study showed that extending the training dataset with well-selected additional samples improved classification accuracy, whereas adding ambiguous data degraded performance of the model. Data augmentation through region-growing segmentation enhanced model reliability, particularly for the RF classifier. Moreover, point-based accuracy metrics tended to overestimate performance compared to spatially explicit (area-based) assessments.

Overall, integrating spatially representative sampling and area-based validation enhances the generalization and robustness of ASM-detection models.

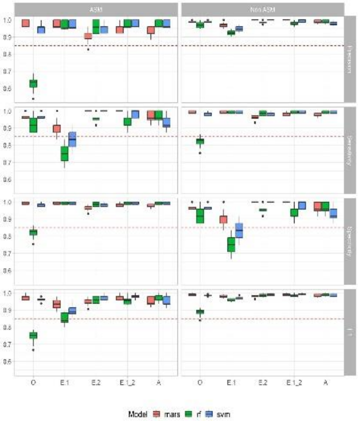

Figure 3. Accuracy metrics of the maps of Landsat image (ASM: ASMareas; rf: random forest, svm: support vector machine, mars: multiple adaptive regression splines; O: original training dataset with the least data, E.1: extended data, E.2: extended data, E.1_2: merge of E.1 and E.2, A: augmented data with the region growing algorithm; red dashed line: 85% accuracy benchmark)

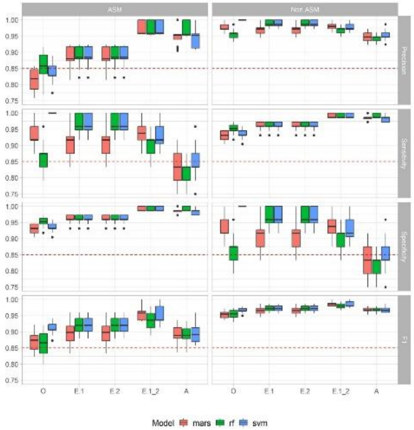

Figure 4. Accuracy metrics of the maps of PRISMA image (ASM: ASM areas; rf: random forest, svm: support vector machine, mars: multiple adaptive regression splines; O: original training dataset with the least data, E.1: extended data, E.2: extended data, E.1_2: merge of E.1 and E.2, A: augmented data with the region growing algorithm; red dashed line: 85% accuracy benchmark)

3.3 Hydrothermal alteration mapping

Thesis 4: Spatial patterns of ASM activity show a statistically significant correlation with the locations of known subsurface mineralizations, and can therefore be used as a cost-effective surface guide to delineate high-potential zones for undiscovered ore deposits.

My research revealed that ASM activity patterns exhibit a notable co-existance with known subsurface mineralization zones, particularly in meta-volcanic terrains. The progressive expansion of ASM has unintentionally exposed concealed hydrothermal alteration zones, aligning with established gold-bearing shear systems in the region. This correlation demonstrates that ASM footprints can act as reliable surface indicators of subsurface mineralization. Consequently, mapping ASM distributions through remote sensing and ML provides a cost-effective exploration tool for identifying high-potential zones of undiscovered ore deposits.

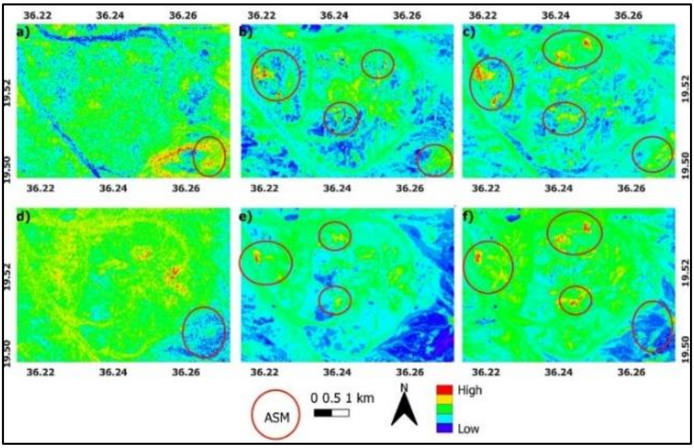

Figure 5. DPCA result a), b) and c) PC3 of Landsat7, 8 and 9 respectively for iron oxides. d) PC3, e) PC3 and f) PC4 of Landsat7, 8 and 9 respectively for hydroxyl bearing minerals.

Thesis 5: Enhancing spectral features derived from remote sensing imagery using advanced image enhancement tools and ML can effectively detect hydrothermal alteration and gossan.

I demonstrated that enhancing spectral features from hyperspectral imagery using advanced image processing and ML significantly improved the detection of hydrothermal alteration and gossan zones. PRISMA-derived spectral indices, density slicing, and RF classification effectively identified gossan anomalies with an overall accuracy of 81%, confirming the presence of jarosite-rich zones. Integration of RF results with BR and spectral analysis revealed new gossan localities in the eastern and northern sectors of the area. These findings highlight the potential of PRISMA data and RF models for automated, cost-effective mineral exploration in arid, complex geological terrains.

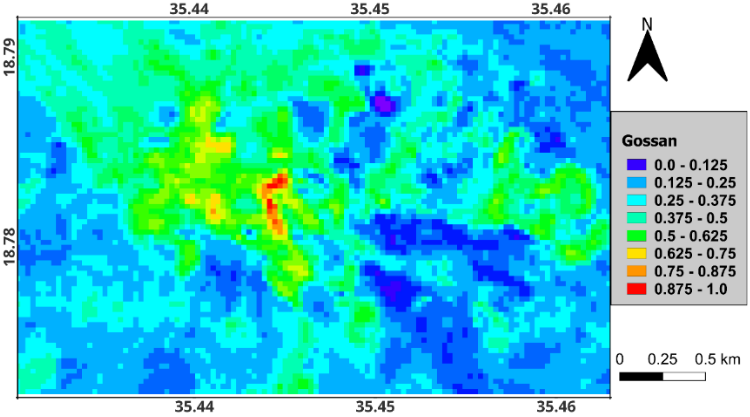

Figure 6. Final gossan map generated through the intersection of BR, density slicing, classification results, showing excellent agreement with field-observed gossan occurrences.

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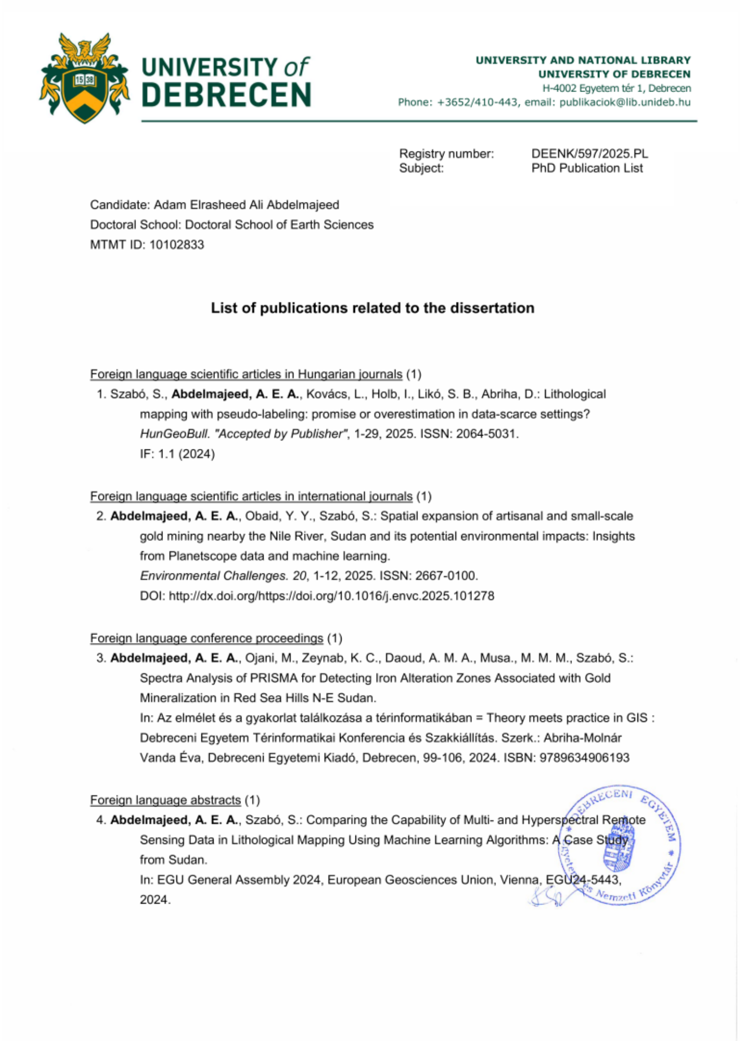

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Registry number: DEENK/597/2025.PL
Subject: PhD Publication List

Candidate: Adam Elrasheed Ali Abdelmajeed
Doctoral School: Doctoral School of Earth Sciences
MTMT ID: 10102833

List of publications related to the dissertation

Foreign language scientific articles in Hungarian journals (1)

1. Szabó, S., **Abdelmajeed, A. E. A.**, Kovács, L., Holb, I., Likó, S. B., Abriha, D.: Lithological mapping with pseudo-labeling: promise or overestimation in data-scarce settings? *HunGeoBull. "Accepted by Publisher"*, 1-29, 2025. ISSN: 2064-5031. IF: 1.1 (2024)

Foreign language scientific articles in international journals (1)

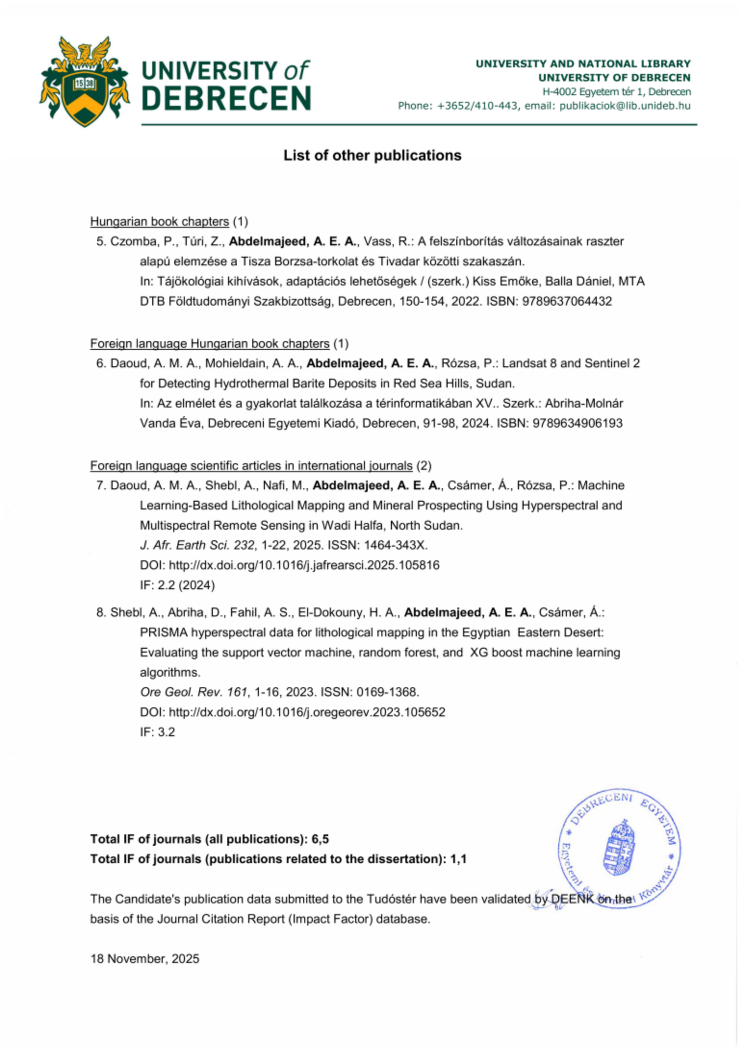
2. **Abdelmajeed, A. E. A.**, Obaid, Y. Y., Szabó, S.: Spatial expansion of artisanal and small-scale gold mining nearby the Nile River, Sudan and its potential environmental impacts: Insights from Planetscope data and machine learning. *Environmental Challenges. 20*, 1-12, 2025. ISSN: 2667-0100. DOI: http://dx.doi.org/https://doi.org/10.1016/j.envc.2025.101278

Foreign language conference proceedings (1)

3. **Abdelmajeed, A. E. A.**, Ojani, M., Zeynab, K. C., Daoud, A. M. A., Musa., M. M. M., Szabó, S.: Spectra Analysis of PRISMA for Detecting Iron Alteration Zones Associated with Gold Mineralization in Red Sea Hills N-E Sudan. In: Az elmélet és a gyakorlat találkozása a térinformatikában = Theory meets practice in GIS : Debreceni Egyetem Térinformatikai Konferencia és Szakkiállítás. Szerk.: Abriha-Molnár Vanda Éva, Debreceni Egyetemi Kiadó, Debrecen, 99-106, 2024. ISBN: 9789634906193

Foreign language abstracts (1)

4. **Abdelmajeed, A. E. A.**, Szabó, S.: Comparing the Capability of Multi- and Hyperspectral Remote Sensing Data in Lithological Mapping Using Machine Learning Algorithms: A Case Study from Sudan. In: EGU General Assembly 2024, European Geosciences Union, Vienna, EGU24-5443, 2024.



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List of other publications

Hungarian book chapters (1)

5. Czomba, P., Túri, Z., **Abdelmajeed, A. E. A.**, Vass, R.: A felszínborítás változásainak raszter alapú elemzése a Tisza Borzsa-torkolat és Tivadar közötti szakaszán.
In: Tájökológiai kihívások, adaptációs lehetőségek / (szerk.) Kiss Emőke, Balla Dániel, MTA DTB Földtudományi Szakbizottság, Debrecen, 150-154, 2022. ISBN: 9789637064432

Foreign language Hungarian book chapters (1)

6. Daoud, A. M. A., Mohieldain, A. A., **Abdelmajeed, A. E. A.**, Rózsa, P.: Landsat 8 and Sentinel 2 for Detecting Hydrothermal Barite Deposits in Red Sea Hills, Sudan.
In: Az elmélet és a gyakorlat találkozása a térinformatikában XV.. Szerk.: Abriha-Molnár Vanda Éva, Debreceni Egyetemi Kiadó, Debrecen, 91-98, 2024. ISBN: 9789634906193

Foreign language scientific articles in international journals (2)

7. Daoud, A. M. A., Shebl, A., Nafi, M., **Abdelmajeed, A. E. A.**, Csámer, Á., Rózsa, P.: Machine Learning-Based Lithological Mapping and Mineral Prospecting Using Hyperspectral and Multispectral Remote Sensing in Wadi Halfa, North Sudan.
J. Afr. Earth Sci. 232, 1-22, 2025. ISSN: 1464-343X.
DOI: http://dx.doi.org/10.1016/j.jafrearsci.2025.105816
IF: 2.2 (2024)

8. Shebl, A., Abriha, D., Fahil, A. S., El-Dokouny, H. A., **Abdelmajeed, A. E. A.**, Csámer, Á.: PRISMA hyperspectral data for lithological mapping in the Egyptian Eastern Desert: Evaluating the support vector machine, random forest, and XG boost machine learning algorithms.
Ore Geol. Rev. 161, 1-16, 2023. ISSN: 0169-1368.
DOI: http://dx.doi.org/10.1016/j.oregeorev.2023.105652
IF: 3.2

Total IF of journals (all publications): 6,5
Total IF of journals (publications related to the dissertation): 1,1

The Candidate's publication data submitted to the Tudóstér have been validated by DEENK on the basis of the Journal Citation Report (Impact Factor) database.

18 November, 2025