

Remote Sensing Prospecting Method Based on Random Forest in Eastern Botswana Mining Area

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Abstract

In this study, multi-source remote sensing data and machine learning algorithms were used to delineate the prospect area of remote sensing geological prospecting in eastern Botswana. Landsat 8 remote sensing images were used to produce iron stain and hydroxyl anomaly maps, ASTER remote sensing images were used to extract chalcopyrite mineral distribution maps, and Microsoft high-resolution remote sensing data were used to extract lithology and structure maps to comprehensively analyze regional metallogenic information. Then, the random forest, classification regression tree (CART) and gradient Lift Tree (GBT) classification algorithms were used to compare the models. The results showed that the random forest algorithm had the best performance in identifying mineralization potential areas, and its accuracy reached 0.95. Finally, the remote sensing geological prospect area of eastern Botswana was delineated based on random forest algorithm, which provided important technical support for mineral resource exploration in this area. This study shows that the combination of multi-source remote sensing data and efficient classification algorithm has great potential in geological prospecting, and provides scientific methods and technical means for the follow-up remote sensing prospecting research.

Keywords

Random Forest Model, Alteration Information, Mineral Resource Potential Assessment, Prospecting in Botswana, Remote Sensing Geology, Metallogenic Prediction

1. Introduction

The application of remote sensing technology in geological prospecting has made

remarkable progress in recent years, especially in the context of the combination of multi-source remote sensing data and machine learning algorithms, providing a more efficient and accurate means for mineral resource exploration [1]. The eastern region of Botswana is rich in important mineral resources such as copper and nickel, with complex geological structures and diverse metallogenic mechanisms [2]. These characteristics make traditional geological prospecting methods face many challenges, while remote sensing image brings a new breakthrough for prospecting in this region due to its advantages of wide coverage, low cost and rich information [3].

The mineralization in this area is closely related to basic-ultrabasic magmatic activity, submarine volcanic eruption and hydrothermal cycle [4]. Metal-rich magmatic hydrothermal deposits are often formed during these geological activities, and the potential mineralization areas can be effectively delineated by analyzing the spectral characteristics of these ore-forming related rocks and minerals [5]. In recent years, remote sensing data such as Landsat 8 and ASTER have been widely used for extraction of geological alteration anomalies and analysis of mineral distribution due to their high spectral resolution, and have become an important data source for remote sensing prospecting [6].

The effective utilization of multi-source remote sensing data requires the combination of advanced data processing and analysis methods, especially the application of machine learning algorithms in feature extraction and classification of high-dimensional data, which has greatly improved the efficiency of remote sensing prospecting [7]. The wide application of algorithms such as Random Forest, classification regression tree (CART) and gradient lifting tree (GBT) in geological data analysis provides important technical support for ore prospecting under complex geological background [8]. With its high precision and strong generalization ability, random forest algorithm performs well in the integrated analysis of multi-source data, especially in lithology identification and delineation of mineralization prospects [9].

In this study, based on Landsat 8, ASTER and Microsoft high-resolution remote sensing data set, combined with machine learning algorithms such as Random Forest, CART and GBT, the metallogenic prospect area in eastern Botswana was systematically studied. The results show that the random forest algorithm performs better than other algorithms in prospective area identification, with an accuracy of 0.95, which provides scientific basis and strong technical support for mineral resource exploration. This result validates the great potential of multi-source remote sensing data combined with efficient machine learning algorithms in complex geological environments, and provides technical reference for prospecting in Botswana and other similar regions [10].

2. Geological Background

Located in southern Africa, Botswana is a landlocked country bordered by South Africa to the south, Namibia to the west, Zimbabwe to the east and Zambia to the

north. Botswana is rich in mineral resources and is the third largest mineral resource country in Africa. The main mineral resources include copper, nickel, gold and platinum [11]. Large scale fault structures are developed in this area. The eastern part of Botswana is dominated by east-west faults, and a large number of magmatic rock bodies are exposed. The main lithologies include quartzite diorite, granite and amphibolite. The emergence of these structures and magmatic rocks provided an important geological background for mineralization. The metallogenic mechanism in eastern Botswana is complex and has experienced the influence of various geological processes such as magmatic activity, tectonic movement, sedimentation and metamorphism [12]. It is of great significance to explore the metallogenic mechanism and its ore-forming signs in this region, and the application of remote sensing technology makes it more convenient and accurate to grasp the metallogenic mechanism and signs.

The deposit formation in eastern Botswana is closely related to submarine magmatic activity and sedimentation. The magma rises to the seabed along the weak zone of the crust and erupts, bringing out rich metallic minerals such as copper and nickel. These minerals mix with the submarine sediments and eventually form sedimentary rocks rich in metal elements, which provide the necessary material basis for mineralization [13]. In addition, the intrusion of mafic to ultrabasic magmas plays a key role in the mineralization process by providing thermal energy and mineralizing materials. During these magmatic invasions, gravitational differentiation separates copper, nickel and other metallic elements from the melt and forms ore bodies [14]. Therefore, the identification of magmatic rocks, sedimentary rocks and intrusive rocks in eastern Botswana is of great significance for understanding the local metallogenic setting, and the differences in spectral reflection and absorption characteristics among these lithologies can be effectively observed by remote sensing images. Thereby helping to understand the metallogenic mechanism and provide regional clues for prospecting [15].

Most of the deposits in eastern Botswana are magmatic hydrothermal deposits, with submarine volcanism accompanied by hydrothermal cycle processes. Hydrothermal fluids from volcanic eruptions are rich in metallic elements, which rise through cracks in the sea floor and release metallic elements when cooled to form sulfide, carbonate and other sediments, which then accumulate to form deposits [16]. The hydrothermal cycle process is closely related to the formation of ore deposits, so studying the hydrothermal cycle mechanism is of great significance for ore prospecting [17]. In the process of hydrothermal cycling, the chemical reaction between hydrothermal fluid and surrounding rock will trigger the alteration of surrounding rock and form a specific type of altered mineral association [18]. These altered minerals have unique spectral characteristics, which can be distinguished from normal rocks by remote sensing technology, providing an important basis for identifying hydrothermal deposits [19].

The formation of the deposits in eastern Botswana is also closely related to the development of rift structures. The region consists of two Quaternary rift zones

located at the intersection of multiple tectonic units, including the interaction zone between the Zimbabwe Craton, Kapuvu Craton and Congo Craton [20]. The interaction of these tectonic units provides ascending channels for magmatic hydrothermal solutions, thus facilitating the enrichment and formation of deposits [21]. The tectonic movement not only provided the physical conditions for magmatic hydrothermal, but also controlled the specific location of the deposit. Exploring the geological structural features such as faults, folds and joints formed by these tectonic movements plays an important role in determining the location of mineral deposits [22]. Remote sensing images can directly display the geological phenomena of the surface. Structural features such as fracture zones and fissures are usually presented as linear or curved geological features in remote sensing images.

The deposits in eastern Botswana were oxidized by the superbiotic environment, such as atmosphere, water and organisms after emerging from the surface, forming the oxidation zone. The color characteristics of metal minerals change significantly during the oxidation process. By analyzing the spectral reflection characteristics of these oxidation zones in remote sensing images, the mineralized regions can be effectively determined, thus providing theoretical support for ore prospecting [23].

The metallogenic mechanism and metallogenic markers provide the theoretical basis for remote sensing prospecting. As an efficient and convenient means of exploration, remote sensing plays an important role in identifying surface mineralization markers and geological structure characteristics. Through the interpretation of metallogenic markers by remote sensing technology, the spatial location of the deposit can be better determined, and it can provide clear direction for the exploration of mineral resources. The geological map of the study area is shown in **Figure 1**.

The mineralization background in the eastern region of Botswana is closely related to complex geological processes, including volcanic activity, tectonic movements, sedimentation, and metamorphism. Mineralization in this area is primarily influenced by mafic-ultramafic magmatic activity, submarine volcanic eruptions, and hydrothermal circulation. Magmatic intrusions provide heat and mineralizing substances for mineralization, forming copper, nickel, and other metal deposits. Tectonic processes, such as east-west trending fault structures, provide pathways for the ascent of magma and hydrothermal fluids, promoting the enrichment of minerals. At the same time, sedimentation provides the material basis for mineralization during the formation of submarine sedimentary rocks, especially during submarine volcanic eruptions when hydrothermal fluids accumulate large amounts of metal elements. Metamorphic processes, on the other hand, involve chemical reactions between hydrothermal fluids and surrounding rocks, leading to metamorphism and the formation of specific mineral assemblages associated with mineral deposits.

Remote sensing technology can effectively reveal the presence and types of mineral deposits by identifying iron staining and hydroxyl anomalies. Iron

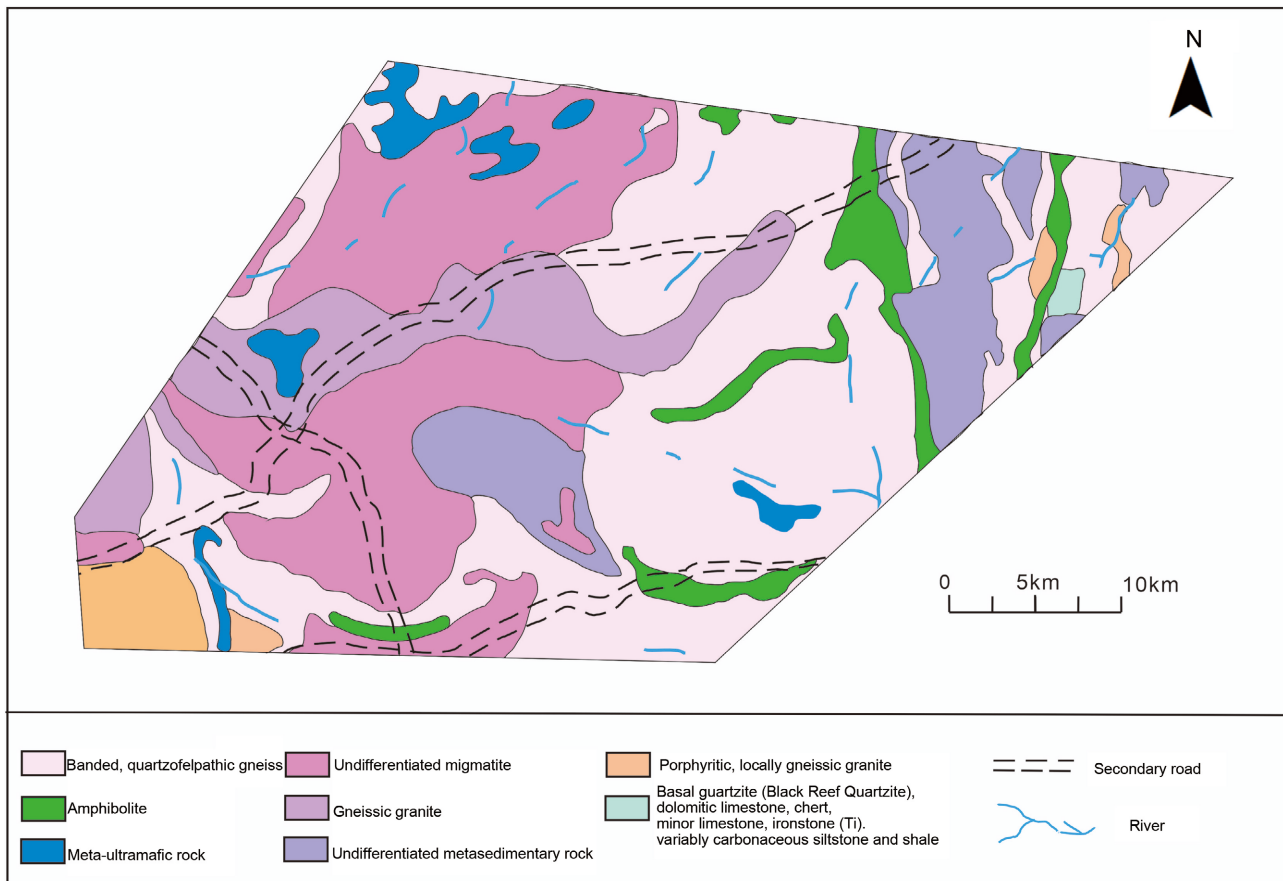


Figure 1. Geological map of the study area.

staining anomalies are closely related to iron minerals in the oxidation zone, typically appearing in the oxidation belts or secondary enrichment zones of the ore body. Remote sensing technology helps determine the location and extent of mineralized areas. Hydroxyl anomalies reflect mineral changes caused by hydrothermal or metamorphic processes, particularly the transformation of hydrous minerals, and these anomalies can be detected in the short-wave infrared (SWIR) bands of remote sensing data. They are closely associated with the distribution of hydrothermal and metamorphic deposits. Through remote sensing image analysis, the efficiency and accuracy of mineral deposit identification can be significantly improved, especially in complex geological settings, helping to reveal mineralization types and spatial distribution.

3. Research Methods

1) Collection and preprocessing of remote sensing data

Landsat 8, ASTER and Microsoft high-resolution remote sensing image data were used in this study. Landsat 8 images were used to map iron stain and hydroxyl anomalies, which are common indicators of mineralized areas [24]. ASTER images were used to extract the distribution of chalcopyrite minerals, as chalcopyrite is an indicator mineral closely associated with hydrothermal alteration and

mineralization activities [25]. In addition, Microsoft high-resolution remote sensing datasets are used to extract lithology and structural features to capture details of geological structure and thus enhance the accuracy of mineralization information [26]. Data pre-processing steps include geometric correction, atmospheric correction, and fusion of spectral data to ensure data accuracy and consistency [27].

2) Extraction of ore-forming information

After data preprocessing, iron stain and hydroxyl anomaly information were extracted from Landsat 8 images, and spectral characteristics related to mineralization were enhanced by band ratio method [28]. The short-wave infrared (SWIR) band of ASTER data was used to extract the spectral characteristics of chalcopyrite because of its excellent performance in identifying altered minerals [29]. Microsoft high-resolution imagery is used to extract surface lithology and major structural features, such as fractures and folds, which are often associated with metallogenic processes [30].

3) Establishment of machine learning classification model

In order to effectively delineate the mineralization prospect area, three machine learning classification algorithms, Random Forest, classification regression tree (CART) and gradient lift Tree (GBT), are adopted. Random forest algorithm is a method based on ensemble learning, which can effectively deal with high-dimensional data and noise, and has high classification accuracy. CART and GBT algorithms use tree structure and gradient optimization respectively for classification [31]. In the process of model establishment, the data set is first divided into training set and test set, which are respectively used for training and verification of the model to ensure the stability and reliability of the model.

4) Model accuracy evaluation and prospect delineation

In this study, the model was evaluated by various performance indicators, including accuracy, confusion matrix, and ROC curve. The results showed that the random forest algorithm performed best in the recognition of mineralized prospect areas, with an accuracy of 0.95 [32]. Based on this algorithm, we successfully delineated mineralized prospect areas in the eastern region of Botswana. The integrated nature of random forests gives them a significant advantage in dealing with the complexity and heterogeneity of the data, thereby improving the accuracy of mineralized zone identification.

5) Verification and application of results

The delineated mineralization prospect area was compared with the existing mine data to verify the reliability of the model. The results show that the method has good feasibility and accuracy in geological prospecting, and provides effective technical support for regional mineral resources exploration. This research result shows that the combination of multi-source remote sensing data and efficient machine learning algorithm has broad application prospects in the field of geological prospecting [33].

In this study, three algorithms—Random Forest (RF), Classification and Re-

gression Trees (CART), and Gradient Boosting Trees (GBT)—were selected based on their ability to handle complex geological data. Random Forest, an ensemble learning method, is highly effective in managing high-dimensional data and noise, offering excellent classification accuracy. Its ability to integrate multiple decision trees makes it particularly well-suited for identifying mineralization potential in complex geological backgrounds, especially for integrating multi-source remote sensing data. CART, which uses a tree-based structure to classify data, is useful for revealing important patterns in non-linear relationships, even though it is sensitive to noise. It was chosen to compare its performance with other algorithms in geological data. GBT, which enhances tree models through gradient optimization, offers strong fitting capabilities and high predictive accuracy. It is effective for handling complex datasets, particularly in mineral exploration, where incremental optimization improves classification accuracy.

To enhance the performance of these algorithms, parameter optimization is essential. For Random Forest, key parameters include the number of trees (`n_estimators`), which balances model stability and computation time; the maximum number of features (`max_features`), which helps reduce overfitting; and the maximum tree depth (`max_depth`), which prevents excessive depth and overfitting. For CART, optimizing the maximum tree depth (`max_depth`), the minimum sample split (`min_samples_split`), and the minimum sample leaf (`min_samples_leaf`) helps reduce complexity and overfitting. For GBT, parameters like the learning rate (`learning_rate`), the number of trees (`n_estimators`), and the maximum depth (`max_depth`) control model complexity and accuracy. Parameter tuning through methods such as cross-validation significantly improves model precision and stability in mineralization mapping, ensuring good generalization and adaptability.

4. Results

In this study, multi-source remote sensing data and a variety of machine learning algorithms were used to conduct a comprehensive analysis and delineation of mineralization prospects in the eastern region of Botswana. The results are as follows:

1) Results of data extraction and anomaly analysis

The iron stain and hydroxyl anomaly maps produced by Landsat 8 images revealed the existence of several abnormal regions in the study area, which had obvious iron stain characteristics and might be closely related to potential mineralization. At the same time, the chalcopyrite distribution map extracted from ASTER image shows that there are significant altered mineral accumulation in certain areas of the region, which is consistent with the metallogenic alteration zone, suggesting that these areas have metallogenic potential. Microsoft high-resolution remote sensing data successfully extracted the lithology and structural information, revealing the main lithology types and fault structure characteristics, and providing the spatial information basis for further delineating the mineralization prospect area. The iron-stained alteration information is shown in **Figure 2**, and the

hydroxyl alteration information is shown in **Figure 3**.

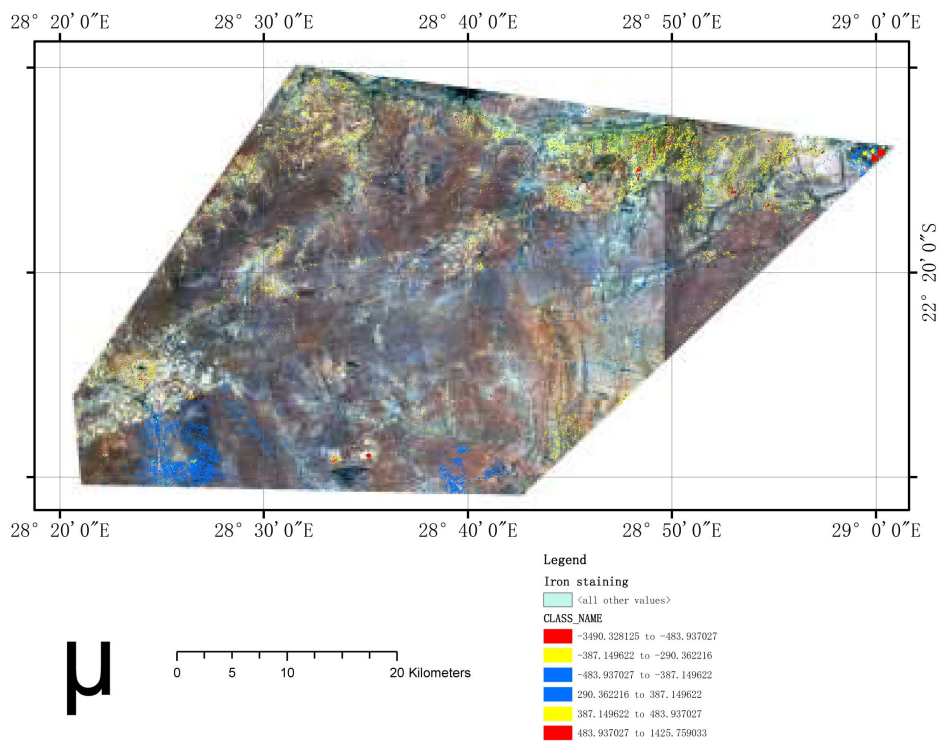


Figure 2. Iron-stained alteration information.

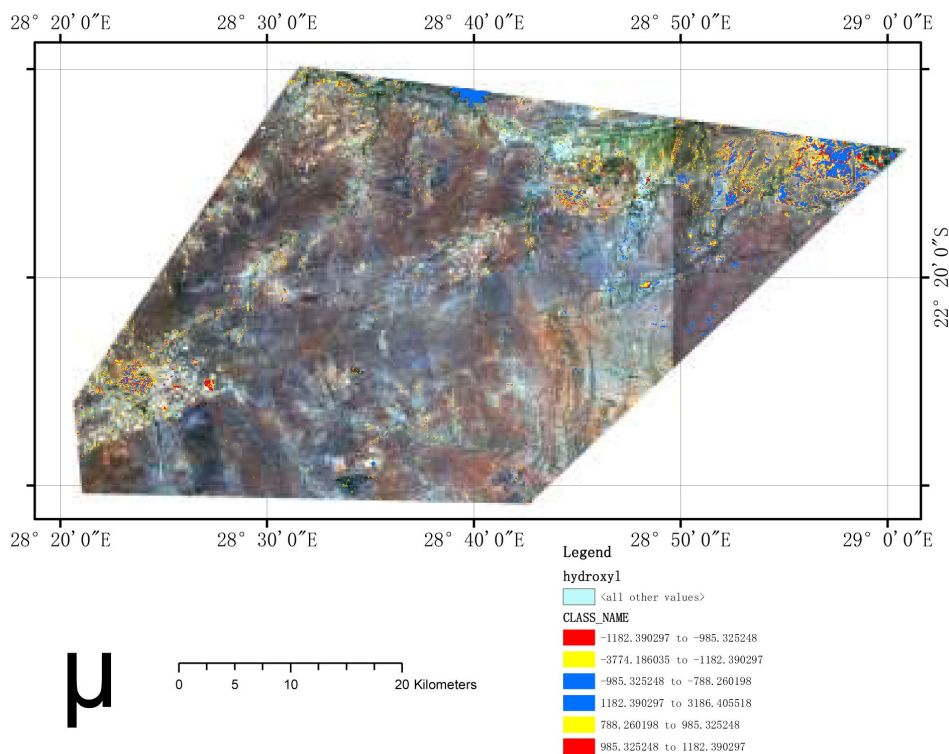


Figure 3. Hydroxyl alteration information.

2) Comparative analysis of algorithm models

On the basis of remote sensing data, three classification algorithms, random forest, classification regression tree (CART) and gradient lift Tree (GBT), were used to delineate the mineralized prospect area in eastern Botswana. Through model training and test set verification, the random forest algorithm has the best performance, and its classification accuracy reaches 0.95. Compared with CART and GBT, it has higher accuracy and generalization ability. Confusion matrix shows that random forest has high stability in correctly identifying both mineralized and non-mineralized regions, and low misjudgment rate, which proves its effectiveness in processing multi-source data in complex geological background.

3) Delineation of mineralized potential areas

Based on the random forest algorithm, the final delineation of the mineralized prospect area of the region was carried out. The delineation results indicate that there are multiple mineralization prospects in eastern Botswana, which are mainly concentrated in the vicinity of identified iron staining and hydroxyl anomalies and chalcopyrite mineral accumulation areas. The positions of these prospects are consistent with known metallogenic belts and tectonic lines, indicating a high degree of consistency between the geological setting of mineralization and the data analysis. Remote sensing data combined with the application of machine learning algorithm have effectively identified potential mineralization zones, providing important directions for further geological exploration. The distribution information of chalcopyrite is shown in **Figure 4**.

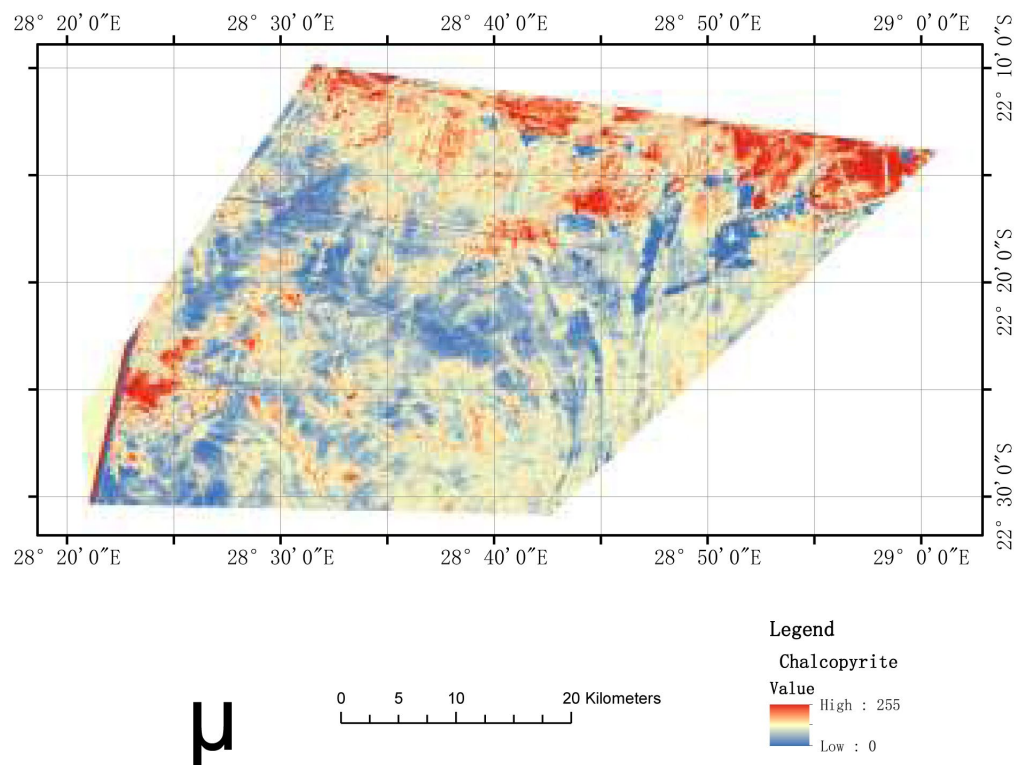


Figure 4. Distribution information of chalcopyrite.

4) Model evaluation and validation

In order to verify the effectiveness of the random forest algorithm, this study compares the delineated prospect area with the existing mine sites. The results show that more than 95% of the known mineral sites are covered by the delineated prospect area, which indicates that the delineation results of the random forest model have high reliability. In addition, the ROC curve analysis results show that the AUC value of the random forest model is close to 1, which further proves the superior performance of the model in identifying mineralized areas.

5) The spatial characteristics of the mineralization prospect

Remote sensing images and machine learning results reveal that the spatial characteristics of the mineralized prospect area in eastern Botswana are mainly concentrated in the areas with dense faulted structures and alteration anomalies. Most of these areas are the confluence of lithologic and tectonic boundaries and have strong metallogenic conditions. Combined with spatial coverage of remote sensing data and high-precision algorithm classification, this study provides a scientific basis for ore-forming potential assessment in the eastern region of Botswana. The ore prospecting target area in the study area is shown in **Figure 5**.

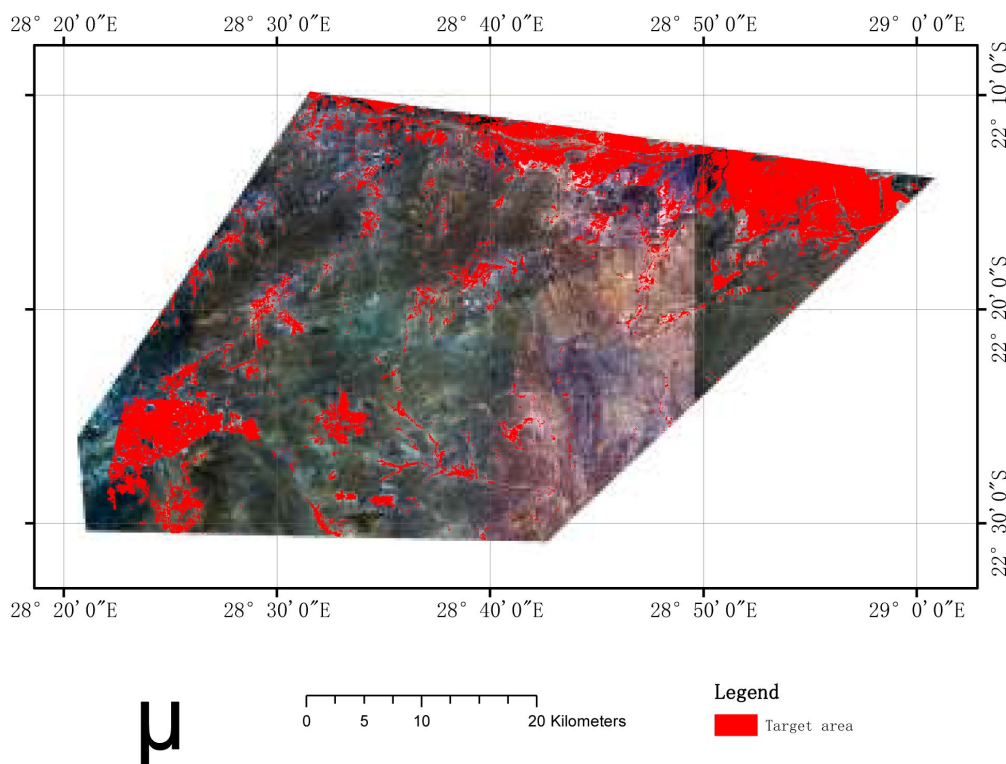


Figure 5. Target area.

Through the comprehensive utilization of multi-source remote sensing data and the combination of efficient machine learning algorithms, this study realized the accurate delineation of mineralization potential in eastern Botswana. The random forest algorithm has the best performance, and the precision of the prospect

area is 0.95, which shows the superiority of the algorithm in processing multi-source remote sensing data in complex geological environment. This study provides important technical support for the subsequent geological prospecting work, and proves the great potential of multi-source remote sensing data combined with machine learning algorithm in geological prospecting.

5. Discussion

Combining multi-source remote sensing data with a variety of machine learning algorithms, this study successfully delineated the mineralization prospect area in the eastern region of Botswana, demonstrating the great potential of remote sensing technology and machine learning in geological prospecting. The discussion will focus on the validity of the results of this study, the applicability of the method, and the direction of future improvement.

1) The validity of multi-source remote sensing data

Through comprehensive use of Landsat 8, ASTER and Microsoft Gaofens remote sensing data, this study successfully extracted a variety of geological information closely related to mineralization, such as iron stain anomaly, hydroxyl anomaly, chalcopyrite mineral distribution, lithology and structural characteristics. The combination of these multi-source data enhances the identification accuracy of regional geological characteristics, and provides an important basis for delineating prospective mineralization areas. Iron staining and hydroxyl anomalies reflect the location of oxidation and alteration zones, while chalcopyrite, as a hydrothermal alteration mineral, is a strong indicator of mineralization. Therefore, the comprehensive use of these multi-source remote sensing data complements each other in spatial resolution and spectral resolution, providing strong support for the efficient delineation of metallogenic potential areas.

2) The performance and applicability of machine learning models

In this study, machine learning models such as random forest, classification regression tree (CART) and gradient lift Tree (GBT) were used to classify remote sensing data and delineate mineralization prospects. The results show that the accuracy of random forest algorithm is the highest, reaching 0.95. This result is in line with expectations. By integrating multiple decision trees, random forest can effectively reduce overfitting phenomenon and improve the ability to capture complex nonlinear relationships. Under the background of complex geological environment and multiple mineralization information crossing, the integrated learning characteristic of random forest is particularly applicable. In contrast, CART and GBT performed slightly less well in this study, which may be mainly due to their high sensitivity to data noise and the complex and diverse geological features in the study area. It can be seen that random forest has significant advantages in processing multi-source and complex remote sensing data.

Although the Random Forest algorithm shows high accuracy (0.95) in identifying mineralization potential areas in eastern Botswana, it faces limitations such as overfitting, sensitivity to noise, and difficulties with abnormal data. Its lack of

interpretability hinders understanding of the decision-making process, which is crucial in fields like geological exploration, and its high computational cost limits practical use with large datasets or real-time processing. Furthermore, while Random Forest automatically selects important features, it may struggle with high data redundancy or poor preprocessing, affecting performance and efficiency.

3) The reliability of delineation of mineralization prospects

In this study, based on the randomized forest algorithm, the mineralized prospect area is delineated, and the comparison results with known mineral sites show that the model has a high recognition accuracy, especially the coverage rate of the mineralized area reaches more than 95%. This result validates the reliability and validity of the method used. The delineated mineralized prospect area is highly consistent with the main fault structure and lithologic boundary in the region, indicating the key role of tectonic activity and alteration in mineralization. This further proves the feasibility and advantage of using multi-source remote sensing data combined with machine learning algorithm to delineate prospective areas in complex geological environment.

4) Implications for future remote sensing prospecting

This study shows that multi-source remote sensing data combined with efficient machine learning algorithms can play an important role in the delineation of mineralization prospects. This method is especially suitable for areas with complex geological structures and high human exploration costs. The application in the eastern region of Botswana also provides a useful reference for other mineral exploration with similar geological background. In the future prospecting work, integration methods of different data sources and more adaptive algorithms can be further explored to promote the wider application of remote sensing technology in geological prospecting. By delineating mineralization prospects in eastern Botswana, this study validates the feasibility and effectiveness of combining multi-source remote sensing data with machine learning algorithms. Random forest algorithm shows excellent classification ability in processing complex geological data, and provides technical support for accurate identification of mineralized areas. Future research should further explore the expansion of data sources and optimization of algorithms to improve the overall effect of remote sensing prospecting and provide a more scientific and efficient solution for global geological prospecting.

6. Conclusions

By using multi-source remote sensing data and a variety of machine learning algorithms, this study has carried out systematic delineation of mineralized potential areas in eastern Botswana, and achieved remarkable results. The specific conclusions are as follows:

- 1) Effective integration of multi-source remote sensing data: This study successfully integrated Landsat 8, ASTER and Microsoft Gaofen remote sensing data, which were used to extract iron stain, hydroxyl anomaly, chalcopyrite mineral

distribution, lithology and structural characteristics, respectively. This combination of multi-source data significantly enhanced the ability to identify regional geological characteristics, and provided a solid foundation for the accurate delineation of mineralized potential areas.

2) Application of machine learning algorithm in remote sensing prospecting: Compared with random forest, classification regression tree (CART), gradient Lift Tree (GBT) and other machine learning algorithms, the results show that random forest has the best performance in the recognition of mineralized prospect areas, and its classification accuracy reaches 0.95. This algorithm shows strong adaptability and robustness in processing complex geological data and multi-source data, which verifies its application potential in remote sensing prospecting.

3) Successful delineation of mineralized prospects: Based on the random forest model, several mineralized prospects in eastern Botswana were successfully delineated. The delineated areas are highly consistent with known mineral sites with a coverage rate of more than 95%, which proves the reliability and practicability of this research method and provides a clear direction for subsequent mineral resource exploration.

4) Technical support and future prospects: This study shows that the combination of multi-source remote sensing data and efficient machine learning algorithms has important application prospects in geological prospecting. This method is especially suitable for areas with complex geological structures and difficult traditional prospecting, and provides a valuable technical reference for resource exploration of similar mining areas around the world. In future studies, more advanced deep learning models can be further combined with geophysical and geochemical data to improve the accuracy and efficiency of mineralized area identification.

To sum up, this study demonstrates the great potential of multi-source remote sensing data and machine learning algorithms in geological prospecting, providing scientific basis and technical support for mineral exploration in eastern Botswana. The methods and results of this study not only have practical significance for regional mineral resource development, but also provide an important reference for remote sensing geological prospecting in other areas.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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