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Remote Sensing Prospecting for Guanyinshan Iron Ore in Dongchuan District, Kunming, Yunnan Province

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Abstract

This study takes Guanyinshan Iron mining area, Dongchuan District, Kunming City, Yunnan Province as the research object, and uses remote sensing technology to carry out ore prospecting. Firstly, the information of iron hydroxyl alteration was extracted by Landsat 8 remote sensing image, and the distribution characteristics of iron mineralization were analyzed. Secondly, ASTER remote sensing image was used to extract the distribution of hematite, magnetite and other minerals, and to clarify the mineral composition of iron ore in the region. On this basis, combined with multi-source data, the improved integrated learning method is used to comprehensively analyze the iron ore potential, and delineate the prospecting prospect area. The research shows that the combination of remote sensing technology and geological data can effectively assist the exploration of iron ore resources and provide a scientific basis for future mineral exploration.

Keywords

Remote Sensing Prospecting, Landsat 8, ASTER, Iron Ore

1. Introduction

With the continuous development of remote sensing technology, its application in the field of geological prospecting is increasingly extensive. In recent years, using remote sensing image to extract mineral information, geological structure characteristics and alteration information has become an important means of mineral exploration. In particular, the combined application of multi-source remote sensing data is helpful to improve the accuracy and efficiency of mineral resources exploration. Guanyinshan Iron mining area, Dongchuan District, Kunming City, Yunnan Province, as an iron mining area with great potential, has rich mineral resources, but the traditional surface exploration methods are limited by funds and time. The mineral resources exploration method based on remote sensing image has high spatial coverage and strong timeliness, which can provide an effective supplement to the traditional prospecting work [1] [2]. Based on multi-source remote sensing images and combined with improved integrated learning algorithm, this study carried out the ore prospecting research of Guanyinshan Iron ore in Dongchuan District, aiming to provide a new idea for mineral resources exploration in this area.

With the continuous progress of remote sensing technology and computer algorithm, its application in geological prospecting has gradually become the mainstream. Remote sensing image data can quickly acquire geological information in a wide range of areas, including mineral distribution, alteration characteristics and geological structure information, which has shown great potential in mineral resource exploration [3]. Traditional geological exploration methods rely on on-site sampling and ground survey. Although they have high accuracy, they are often limited by time and funds and are not suitable for rapid exploration of large-scale areas [4]. In contrast, remote sensing image technology has the advantages of wide space coverage, relatively low cost and strong real-time, which provide an efficient technical means for mineral exploration.

In recent years, the fusion application of multi-source remote sensing data has become a hot topic in mineral exploration. The extraction of alteration information by Landsat data, the acquisition of mineral distribution information by ASTER image, and the interpretation of geological structure combined with high-resolution images have been proved to be an effective method for mineral resource assessment [5] [6]. In addition, remote sensing image data can also help reveal potential mineralized anomaly areas, which provides strong support for traditional exploration work [7]. However, due to the differences in spectral resolution, spatial resolution and band selection of different remote sensing data, the analysis method of a single data source is often limited, and it is difficult to fully reveal the mineral distribution law.

In order to overcome the above problems, ensemble learning method is widely used in the comprehensive analysis of remote sensing data. Ensemble learning improves the classification performance and robustness of the model by combining the advantages of multiple base learners [8]. For example, support vector machines perform well in high-dimensional data classification, decision trees have strong interpretability, and Naive Bayes has advantages in efficient classification [9]-[11]. The integration of these algorithms can effectively make up for the shortcomings of a single model, and shows great potential in multi-feature fusion analysis of remote sensing images [12].

Guanyinshan Iron mining area in Dongchuan District of Kunming, Yunnan Province, as an area with complex geological structure and significant mineralization characteristics, provides an ideal application scenario for the combination of multi-source remote sensing data and machine learning methods. Based on Landsat 8, ASTER and Gaofen-2 remote sensing image data, combined with the improved integrated learning method, the iron ore distribution and prospecting potential in Guanyinshan Iron mine area were systematically analyzed. The research aims to provide a new technical path for the exploration of mineral resources in this area, and verify the effectiveness of the combination of remote sensing technology and machine learning.

2. Geological Overview

The research area is located in Guanyin Mountain, Dongchuan District, Kunming, Yunnan Province, which is located in the metallogenic belt of East Yunnan Province. The main geological units in this area are Mesozoic igneous rocks and metamorphic rocks. The main occurrence forms of iron ore in this area are iron stain alteration and vein type iron ore, which are often closely related to the activities of tectonic belt. The Guanyinshan Iron mining area has a complex structural background, the main fault zone strikes NW and near NW, and multiple tectonic movements provide favorable conditions for the formation of ore bodies. Iron stain alteration is common in the mine area, and the degree of iron mineralization is high. It is a typical iron ore prospecting area.

Guanyinshan Iron deposit in Dongchuan District, Kunming City, Yunnan Province is located in the ore-forming belt of East Yunnan Province. The geological background of this area is dominated by Mesozoic igneous rocks and metamorphic rocks. The main lithology of this area includes granite, quartzite and gneiss. The iron ore in the ore area is mainly of iron stain alteration type, and the mineralization phenomenon is closely related to the regional tectonic activities. Studies have shown that the Guanyinshan Iron mining area is located on an important fault zone, the fault trend is NW and near NW, and the activities of the main fault zone provide fluid channels and mineral deposition conditions for iron mineralization [7]. The distribution of hematite and magnetite in the mining area shows a strong correlation with the tectonic lines and fault zones, especially in the intersection area of fault zones, the degree of iron mineralization is more significant [12]. The study of geological structure shows that tectonic movement not only controls the distribution of ore bodies, but also promotes the enrichment of iron ore resources, providing important clues for further exploration of mining areas [1]. The geological map of the study area is shown in **Figure 1**.

A thorough analysis of the geological background of the study area indicates that the formation of the Guanyinshan iron deposit is the result of the superposition of multiple geological processes. The Proterozoic metamorphic basement provided the initial mineral source layer for mineralization, while the Mesozoic tectono-magmatic activities activated and migrated iron through hydrothermal processes, leading to mineral enrichment in favorable structural locations. The NW-trending fault system, as an important ore-conducting structure, controlled the spatial distribution and morphological characteristics of the ore bodies through its multi-phase activities. In addition, regional metamorphism and subsequent hydrothermal overprinting further enhanced the grade of the ore, forming iron deposits with industrial value.

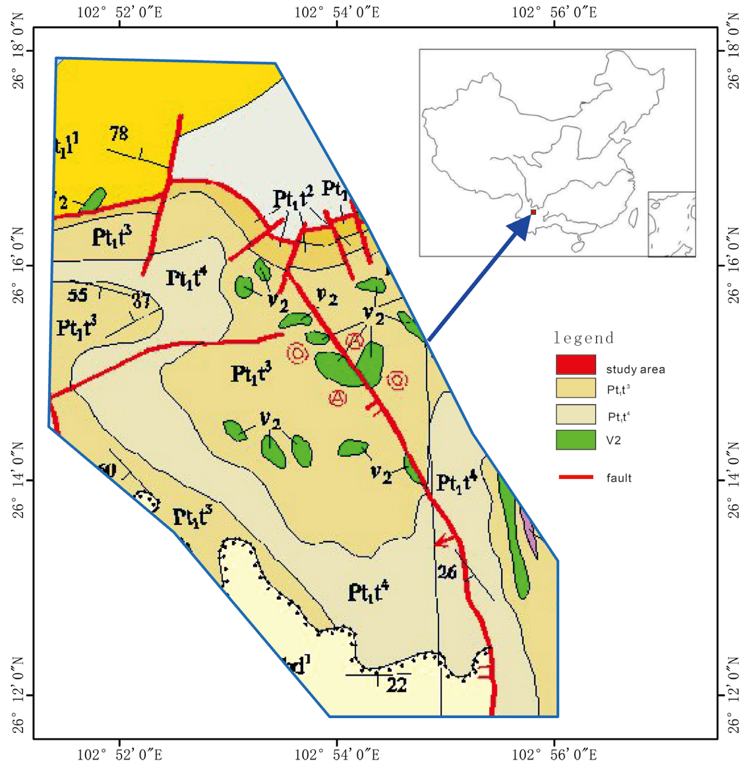

Figure 1. Geological map of the study area.

The research findings hold significant implications for future exploration and resource management. Firstly, tectonic zones, especially the intersections of fault zones, are key areas for iron mineralization enrichment, and exploration efforts should focus on these regions. Secondly, the distribution and intensity of iron staining alteration zones can serve as important indicators for mineral exploration, and combining them with geophysical exploration methods can improve exploration efficiency. In terms of resource management, a three-dimensional geological model should be established to accurately delineate the spatial distribution of ore bodies, providing a scientific basis for mine design. Moreover, differentiated mineral processing schemes should be developed based on different mineralization types and grade characteristics to enhance resource utilization. Additionally, the research findings can provide important references for studying regional mineralization patterns and guide exploration efforts for similar deposits in the eastern Yunnan region. By integrating geological, geophysical, and geochemical methods with modern information technologies, detailed exploration and intelligent management of mining resources can be achieved, promoting the sustainable development and utilization of mineral resources. The remote sensing map of the study area is shown in Figure 2.

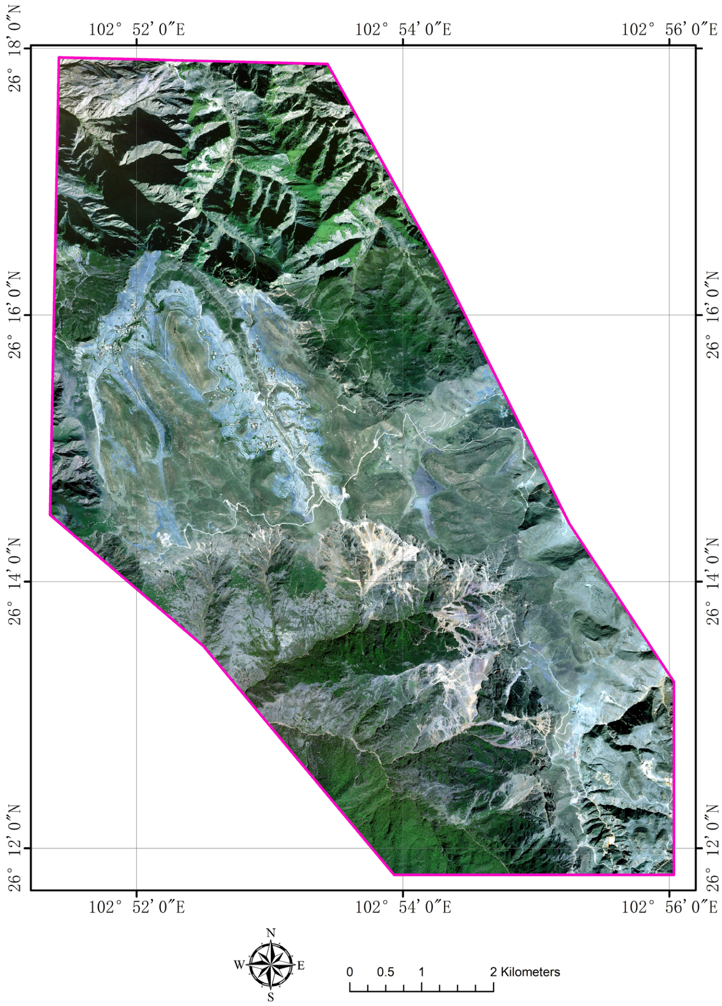

Figure 2. Remote sensing map of the study area.

3. Data Preprocessing and Research Methods

3.1. Data Preprocessing

In order to ensure the quality of input data and the stability of the model, the following preprocessing of remote sensing image data was carried out in this study:

1) Image correction: Radiometric correction, atmospheric correction and geometric correction were performed on Landsat 8, ASTER and Gaofen-2 image data to eliminate environmental interference and data noise [3].

2) Feature extraction: The ratio method was used to extract the iron stain and hydroxy-alteration characteristics from Landsat 8, the mineral distribution information of hematite and magnetite was extracted based on the specific band combination of ASTER images, and the geological structure characteristics of the study area were extracted combined with the Gaofen-2 images [4].

3) Data set construction: All extracted features were integrated into a multidimensional feature matrix, and standardized processing was carried out to eliminate dimensional differences among different data sources [5].

Gaofen-2 image with its excellent spatial resolution (0.8 m panchromatic, 3.2

m multispectral) provides important data support for the identification of regional geological structures [4]. In this study, by combining image interpretation with Digital Elevation Model (DEM), the main fault and structural features of the study area were extracted. Firstly, the Gaofen-2 image is geometrically corrected to ensure its spatial matching with the geological map. Then, linear enhancement and principal component transformation techniques were used to highlight the linear features of fault structures [5]. Geological interpretation software ArcGIS was used to label the major faults and tectonic units. This method can effectively identify the structural characteristics of the study area and provide support for further comprehensive analysis of mineralization information.

3.2. Research Methods

Landsat 8 remote sensing image is widely used in mineral resources exploration because of its wide coverage of multi-spectral data and moderate spatial resolution. In order to extract iron stain and hydroxyl alteration characteristics, bands related to iron mineralization were selected in this study, and atmospheric correction and radiometric correction were performed on Landsat 8 images to eliminate interference caused by environmental conditions [3]. Secondly, NDVI values were calculated to distinguish vegetation cover areas from possible mineralization anomaly areas, so as to reduce the interference of vegetation on mineralization information [13]. At the same time, the custom alteration index enhanced the iron staining information by band ratio method (e.g. B4/B2), which significantly improved the ability to identify iron mineralization anomalies [14]. Finally, the extracted alteration features were further dimensionally reduced by Principal Component Analysis (PCA) to retain the most representative mineralization information. The method for extracting iron staining anomalies involves selecting Landsat 8 bands 2, 4, 5, and 6, performing principal component analysis (PCA), and choosing the second principal component (PC2) as the result layer.

The method for extracting hydroxyl anomalies involves selecting Landsat8 bands 2, 5, 6, and 7, performing principal component analysis (PCA), and choosing the third principal component (PC3) as the result layer.

ASTER remote sensing image can identify the spectral characteristics of a variety of minerals due to its coverage of near-infrared and short-wave infrared bands, which is especially suitable for the extraction of iron ore related minerals [5]. In this study, spectral band combination and ratio method were used to extract the distribution information of hematite and magnetite. Hematite and magnetite have significant spectral absorption characteristics, so bands 4, 6 and 8 were selected for feature extraction, and the ratio of bands B4/B6 and B6/B8 were calculated respectively to enhance mineral anomaly information [15]. In addition, in order to further verify the mineral distribution results, the extracted mineral information was compared with the geological map to ensure the reliability and geological significance of the data. The advantage of ASTER image is that it can refine the iron ore distribution characteristics and provide basic data for the delineation of comprehensive prospecting targets.

In order to comprehensively analyze the remote sensing image data and geological structure information, and precisely delineate the prospective iron ore prospecting area, this study proposes an integrated learning method based on Support Vector Machine (SVM), Decision Tree and Naive Bayes. By using weighted voting strategy, the classification results of these three base learners are fused to improve the classification performance of the overall model.

3.2.1. Model Structure

Support Vector Machine (SVM): Support vector machine is built on Radial Basis Function (RBF) kernel function to capture classification boundaries of nonlinear features in high-dimensional space [9].

Decision Tree: The CART algorithm is used to build a decision tree model, which takes information gain as the splitting criterion and is suitable for quickly generating interpretable classification rules [10].

Naive Bayes: Based on Bayes' theorem, it assumes that features are independent of each other and realizes classification by calculating the posterior probability of various categories, which has the advantage of high computational efficiency [11].

3.2.2. Integration Strategy

In order to improve the robustness of classification, Weighted Voting strategies are used to integrate the results of the base learner. The weights are determined based on the classification accuracy of 10-fold cross-validation, and the weight of each base learner is proportional to its classification performance [8]. The final classification result is determined by weighted average of the predictions of each base learner.

3.2.3. Model Evaluation

The classification performance of the model was evaluated by 10-fold cross-validation, and classification accuracy, recall rate, F1 score and Kappa coefficient were selected as evaluation indexes. In addition, the superiority of ensemble learning method was verified by comparing the performance of single base learner with that of ensemble model [12].

4. Results

Through comprehensive analysis and processing of remote sensing image data and application of integrated learning method, this study comprehensively analyzed the iron stain alteration characteristics, mineral distribution and geological structure information of Guanyinshan Iron mine area, and obtained the following main results.

4.1. Extraction of Iron Stain Alteration Features

Iron staining is a common secondary change phenomenon in the process of iron mineralization, which is usually related to limonite, goethite and other minerals. The alteration area of iron stain is usually closely related to the distribution of ore bodies. The high coincidence of iron stain anomaly areas with known ore spots indicates that these areas are favorable target areas for ore prospecting. The information of iron stain hydroxyl alteration extracted from Landsat 8 remote sensing image data shows that iron stain alteration is mainly distributed in the north and southeast of the study area, especially around the fault zone. The iron stain alteration area has a high consistency with the known iron body spatial distribution, showing a strong indication of mineralization. This discovery provides important guidance for further prospecting work.

4.2. Hydroxyl Feature Extraction

In the remote sensing exploration of iron ore, the extraction of hydroxyl alteration features is similar to that of iron stain alteration features. Both of them are related to secondary minerals, and the abnormal areas are often closely related to the distribution of ore bodies, showing a strong indicator of mineralization. The hydroxyl alteration information is mostly distributed in the fault zone and other specific parts, which overlaps well with the iron-stained alteration area. Its extraction is usually based on Landsat 8 images, using principal component analysis or band ratio method, and combining with iron alteration information can further improve the prospecting efficiency and provide an important basis for mineral exploration.

4.3. Analysis of Mineral Distribution Characteristics

Through the spectral analysis of ASTER image data, the main distribution range of hematite and magnetite was successfully extracted. Hematite is concentrated in the southeastern hilly area of the study area, while the distribution of magnetite is closely related to the fault structure, mainly concentrated in the central and western parts of the region. These distribution characteristics are consistent with the general trend of iron mineralization in the region, which verifies the validity and reliability of ASTER image in mineral identification and extraction.

4.4. Delineation of Prospecting Prospect Area

Through the combination of Landsat 8, ASTER and Gaofen-2 image data, the improved integrated learning algorithm is used to comprehensively evaluate the iron ore potential in the region. In the algorithm modeling, the characteristics of iron stain alteration, mineral distribution information and fault structure elements were considered, and a number of target areas with high prospecting potential were finally delineated. These target areas are mainly concentrated in the main fault zone and the dense secondary fault zone, especially in the southeast and north of the study area, showing significant prospecting potential. Among them, the geological background of the southeastern target area is highly consistent with the results of previous studies, which further validates the accuracy and practicability of this research method.

The hydroxyl alteration information in the study area is shown in **Figure 3**. According to **Figure 3**, the hydroxyl alteration is mainly distributed in the central part, along the northwest-southeast direction.

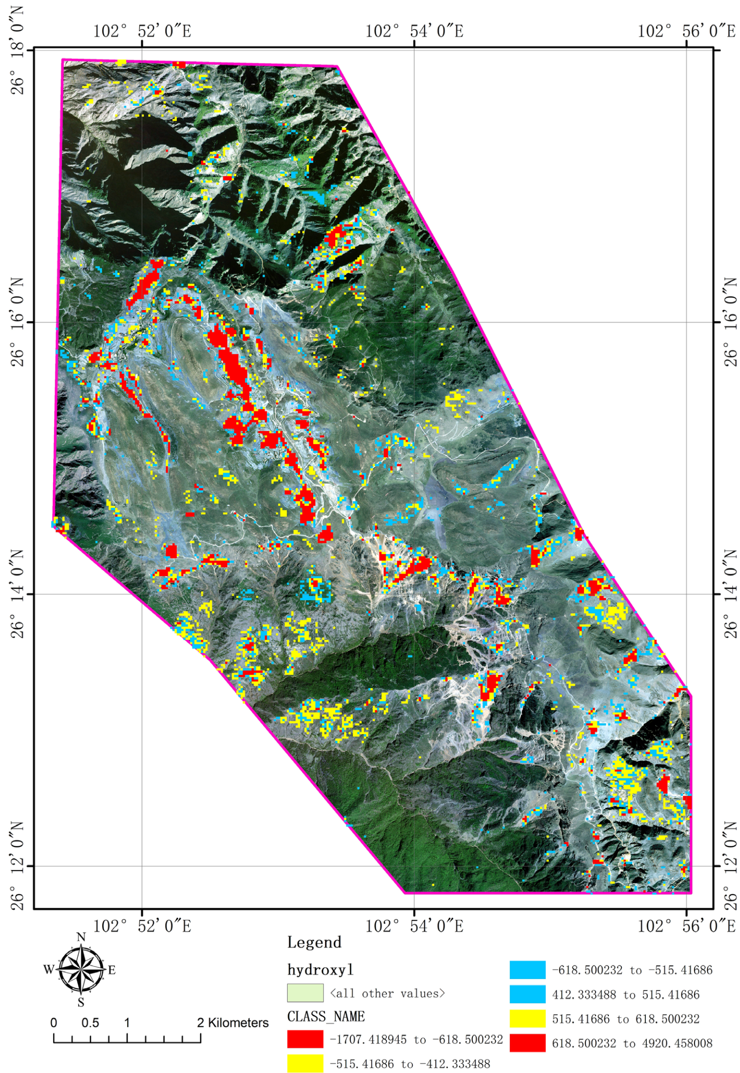

Figure 3. Information map of hydroxyl alteration.

The distribution of iron stain alteration information in the study area is shown in **Figure 4**. The iron stain alteration information is mainly distributed in the central and southeastern parts. The iron stain alteration information in the central part is distributed in the northwest-southeast direction.

The distribution of hematite in the study area is shown in **Figure 5**. Hematite is mainly distributed in the southeastern part of the study area.

The distribution of magnetite in the study area is shown in **Figure 6**. Magnetite is distributed in the northern and southeastern parts of the study area.

The prospecting perspective map of the study area is shown in **Figure 7**. The prospecting perspective areas are mainly distributed in the northwest, central-west, and southeast regions.

5. Discussion

This study shows that remote sensing technology has an important application value in the exploration of iron resources, especially in the aspects of iron staining alteration and mineral distribution characteristics extraction. Remote sensing image can better reflect the mineralization characteristics of the mine area through hyperspectral and multispectral data. Compared with the traditional surface exploration methods, it has obvious advantages in space coverage, work efficiency and cost effectiveness. In this study, Landsat 8, Sentinel-2, Aster and Gaofen-2 images were used to extract ore mineralization information comprehensively, and the applicability of remote sensing images in iron ore prospecting was verified.

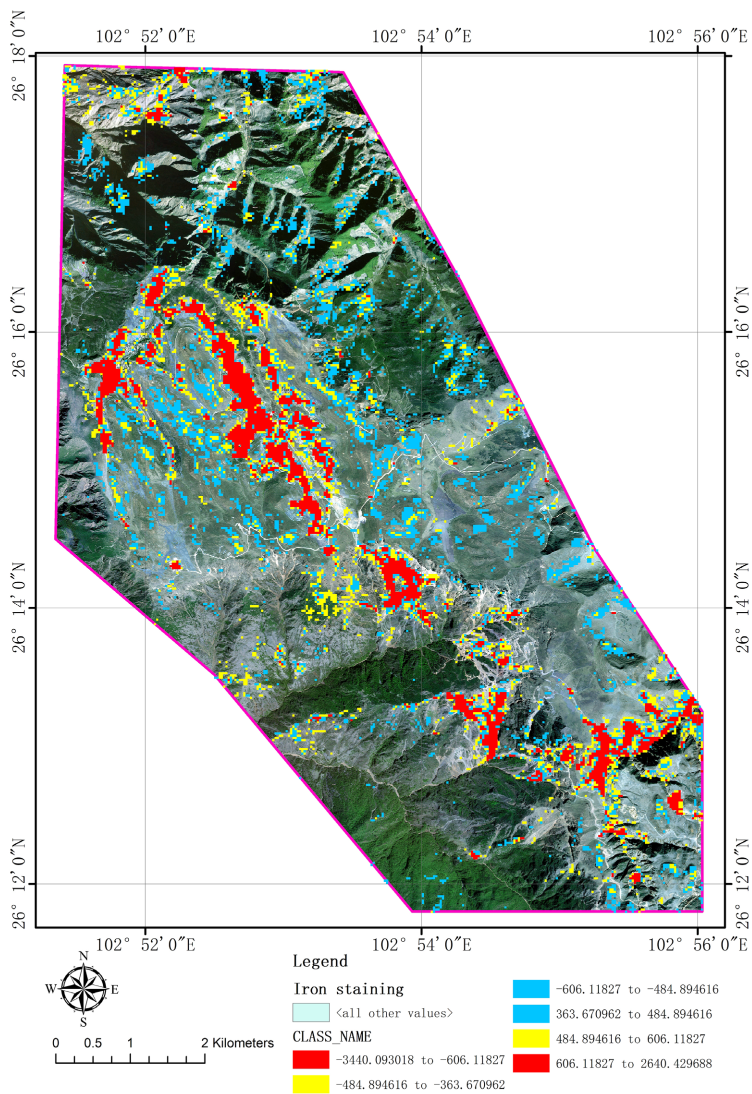

Figure 4. Information map of iron stain alteration.

Through the comprehensive analysis of multi-source remote sensing data, the accuracy and reliability of ore prospecting results were improved. Landsat 8 image shows a good ability in extracting iron hydroxyl alteration, ASTER image has an advantage in identifying mineral distribution, and Gaofen-2 image provides clear geological structure information. The combination of these data gives full play to their respective strengths, and lays a solid foundation for multi-scale and multi-dimensional prospecting research. This method of multi-source data fusion is not only suitable for iron ore exploration, but also can be extended to other mineral resources investigation.

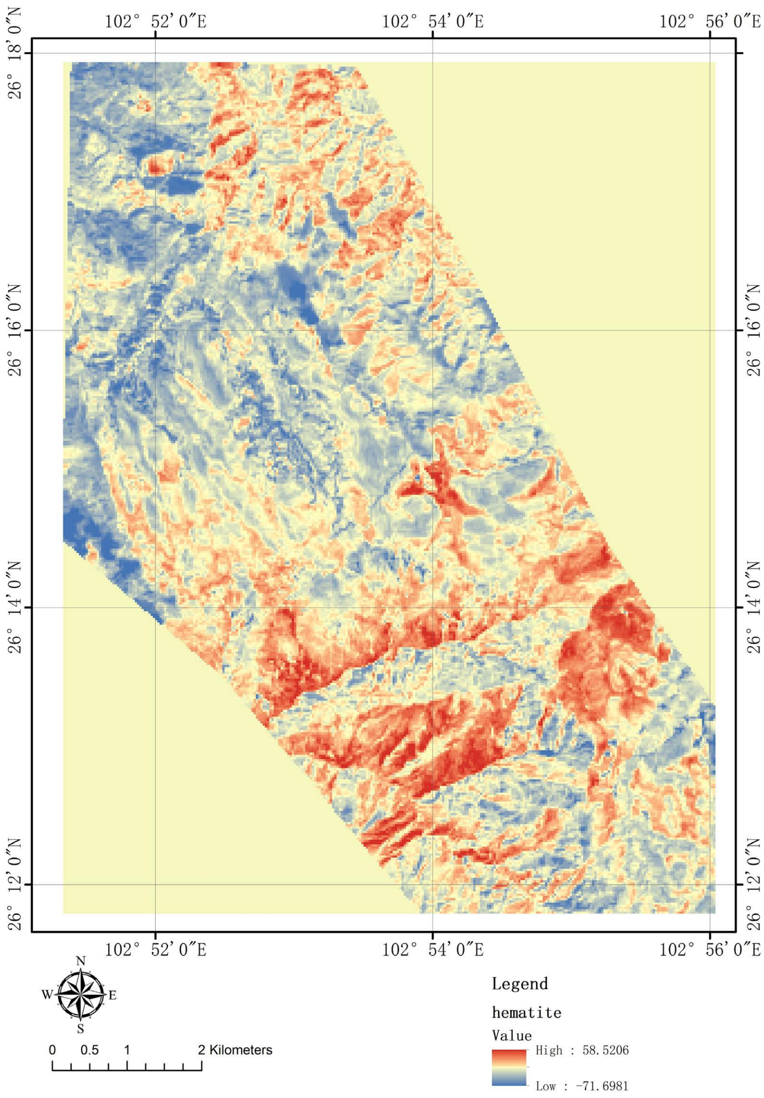

Figure 5. Distribution map of hematite.

The prospecting method of multi-source remote sensing data combined with integrated learning algorithm proposed in this study has delineated the prospecting prospect area in the study area, and has shown good practical application value. The fusion of multi-source data also puts forward higher requirements for the selection of algorithms and the construction of analysis models. The application of integrated learning algorithm in this study fully demonstrates its ability to process complex data. However, the method still has room for improvement. For example, the dependence on prior knowledge during model training may affect the generalization ability of prospect region prediction.

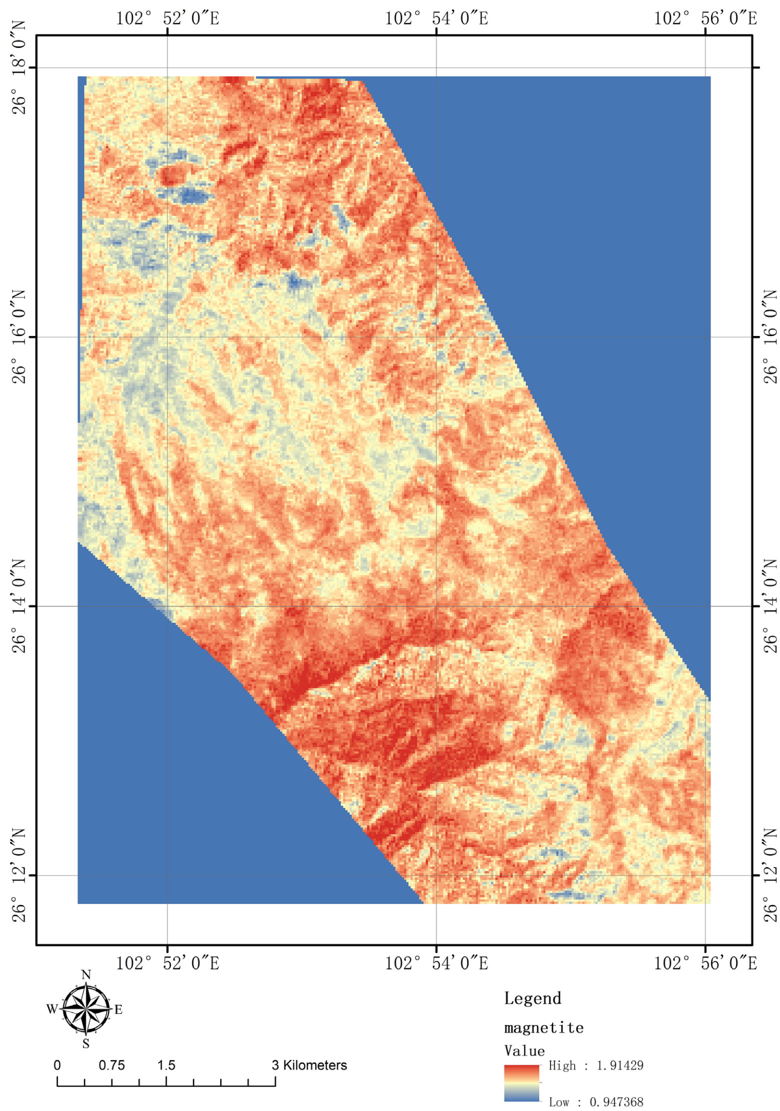

Figure 6. Distribution map of magnetite.

In conclusion, the results of this study further validate the effectiveness and reliability of the combination of remote sensing technology and data mining algorithm in mineral exploration, and provide scientific basis and technical support for future iron ore prospecting. This multi-dimensional research method has good extensibility and can be widely used in the exploration of other minerals, providing an important reference for the development and management of mineral resources.

6. Conclusions

By integrating multi-source remote sensing image data and improved integrated learning algorithm, this study successfully carried out prospecting research in Guanyinshan Iron mining area, Dongchuan District, Kunming, Yunnan Province, and the main conclusions are as follows:

A) The application value of remote sensing technology in mineral exploration

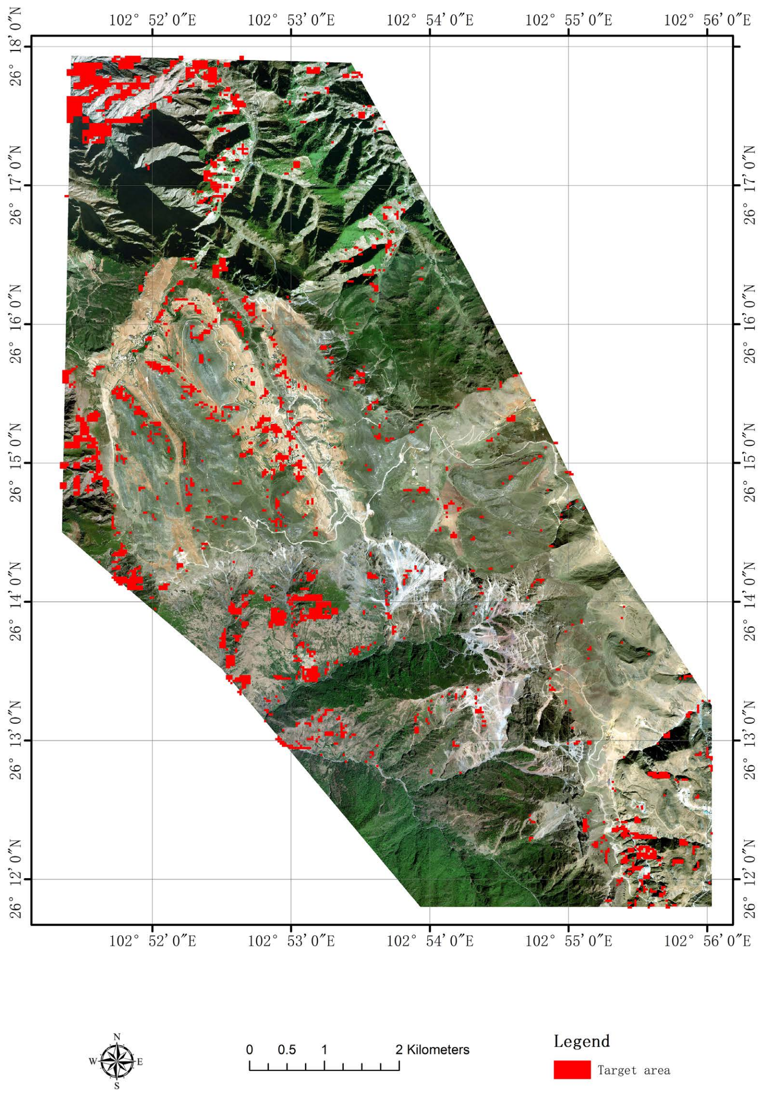

Figure 7. Map of prospecting potential area.

This study shows that the iron alteration characteristics, mineral distribution information and geological structure characteristics can be effectively extracted by using Landsat 8, ASTER and Gaofen-2 remote sensing image data. This comprehensive analysis method based on multi-source data can make up for the deficiency of a single data source and realize the comprehensive analysis of the mineralization characteristics of iron mining areas. The research results prove that remote sensing technology, as an efficient and economical exploration tool, provides a reliable basis for regional prospecting.

B) The combination advantage of multi-source data and integrated learning algorithm

By introducing an improved ensemble learning algorithm, this research successfully realizes the fusion and comprehensive analysis of multi-source remote sensing data. The algorithm fully considers the multi-dimensional characteristics of iron staining alteration, mineral distribution and geological structure, and effectively improves the accuracy and reliability of prospecting target prediction. The final delineated prospecting potential areas are highly consistent with known iron mineralization zones, which validates the feasibility and practicability of the research method.

C) Enlightenment and contribution to future mineral exploration

This study provides an efficient methodological framework for mineral resource exploration, that is, through the combination of multi-source remote sensing data and machine learning technology, quickly identify a large range of prospecting potential areas. This method is not only applicable to the exploration of iron ore, but also has good extensibility. It can be applied to the exploration and evaluation of other mineral resources. In addition, this study also provides a scientific basis for the characteristics of iron mineralization and the regularity of mineralization in the study area, and lays a foundation for the follow-up geological investigation and mineral exploitation.

Conflicts of Interest

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

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