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Application of Multispectral Remote Sensing in Mapping of Mineral Deposits

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Abstract: This research examined Multispectral Remote Sensing in mineral mapping in the Ogoni area of Port Harcourt, Rivers State, Niger Delta. That is why the objective of the research was to improve the efficiency of mineral exploration with the help of non-destructive methods. Envi and ArcGIS software were used to analyze Landsat 8 OLI and Sentinel -2 MSI datasets. The applied preprocessing procedures involved radiometric and geometric corrections, and the values of these procedures ranged from 0. 006 to 0. 987 and 0. 064 to 0. 887, respectively. While mapping the minerals, we used spectral signature, band rasterizing, and principal component analysis. Here, the classification results exhibit a wide range in terms of the total percentage of accuracy, which was between 0. 097 and 0. 908. Consequently, the band ratio analysis showed the areas with high mineral potential; for example, Region 5 has ratios of 0. 972, 0. 986, and 0. 591 for three of the most important combinations of bands. Application of hyperspectral data calculated the degree of minerals present in the area; also, areas of high mineral dominance were observed and found to be Region_9 at the degree of 0. 711 concentration for Mineral_3. The results-oriented work and the study suggest that multispectral remote sensing could be a preliminary way of exploring mineral-rich environments to locate areas of interest and higher potential for ground-based exploration. Solutions include further tweaking the algorithms, including other geospatial data sources and detailed surveys in the subject areas.

Keywords: Landsat 8, Mineral Exploration, Multispectral Imagery, Niger Delta, Principal Component Analysis, Remote Sensing.

1. INTRODUCTION

Mining plays one of the central roles in contemporary society's economic and technological development, considering the companies and agents engaged in the exploration and extraction of

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mineral resources. Many vital materials, primarily minerals, are used in the construction, manufacturing, energy, and electronics industries. Therefore, the optimal search for such resources becomes a crucial issue. Currently, conventional ways of searching for minerals include mapping, sampling, and drilling; however, these have been proven slow, involve a workforce, and can be expensive [1][2]. Thus, the application of modern technologies in achieving and improving exploration procedures can significantly boost.

Multispectral remote sensing is one such technology that is applied to this system. Aerial and satellite images in the multispectral system that records data added through various wavelengths arranged in the electromagnetic spectrum prove beneficial in determining mineral deposits' locations on the earth's surface. This technology provides a better analysis of the surface materials since it looks at particular spectral signals related to some minerals [3][4]. Multispectral remote sensing, in particular, has proved to be a significant advancement in mineral exploration because it provides a non-invasive, economical, and all-inclusive technique for finding areas with rich deposits of minerals. The importance of multispectral remote sensing for mineral exploration lies in the methodology's ability to change the mining sector. The advancement of this type of technology will see more detailed and extensive work on resources, bringing down the cost and the hazards of exploration of the natural environment. This is especially the case given that there is growing concern about sustainable and socially responsible mining.

Moreover, multispectral remote sensing improves the theoretical research in the geological science and remote sensing fields. The experience of applying satellite and aerial photography to outline target mineral deposits on an accurate scale opens up new prospects in scientific research. They allow the study of ground structures and mineral distribution worldwide, which helps to prototype the earth's processes and resource distribution. The above-outlined prospects of multispectral remote sensing applications have practical implications for mineral exploration in the following aspects. Firstly, it enables the implementation of a preliminary and fast appraisal of extensive and sometimes difficult-to-access zones, which is highly advantageous in regions wherein obstacles are difficult to overcome and vegetation is thick. It goes a long way in cutting the time and cost that preliminary exploration stages can incur [5][6].

Secondly, multispectral imagery enhances precision in identifying minerals. Remote sensing techniques allow one to scan the ground surface remotely to identify each mineral's spectral characteristics. This precise identification results in better search results, thus raising the chances of hitting resource-rich deposits that can be exploited at a profit.

Thirdly, applying multispectral remote sensing correlates with the sustainable changes occurring in the industry. OW exploration conventional techniques are known to be invasive; the assessment processes entail massive drilling and land interference. While remote sensing is relatively new to geophysical exploration, it has the advantage of making a relatively small impact on exploration ventures' ecology [7]. From an analytical perspective, this integration of multispectral remote sensing into mineral exploration research has the following contributions to the theoretical discourse. Even though conventional geological approaches exist that help determine the probability of mineral deposits and how they are formed, the technique may be wanting because

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of its size and type. Multispectral sensing provides a broader view and greater detail for large areas and different geology than other sensing mechanisms.

This technology also benefits remote sensing. The list of challenges includes finding and improving the algorithms for analyzing and interpreting multispectral data. These algorithms help filter out the valuable information embedded in the raw spectral data and offer a better and more reliable mineral map. Therefore, the area of remote sensing is still developing hand in hand with its usage in mineral exploration, offering an emphasis on interdisciplinarity.

The literature on mineral exploration focuses on traditional approaches and their limitations. While there is a growing body of knowledge on remote sensing applications, most research has focused on individual case studies or geographical areas. A systematic analysis of the efficiency of multispectral remote sensing in various geologies and types of minerals is needed. Integrating remote sensing data with other geospatial and geologic data has several prospects and potential applications. Integrating multispectral imagery with other data sources like geological, geochemical, and ground truth data can provide richer information on mineral resources, increasing the efficiency of exploration and business venture success.

Spatial mining using multispectral remote sensing is a significant area of relevance and possibility. It provides a new way of exploring cost-effective, accurate, and environmentally friendly minerals [4]. It has practical applications in mining, improving the find rate of metallic resources and decreasing environmental impact. The growing theoretical knowledge in geology and satellite imagery analysis techniques supports this argument. As demand for mineral resources increases, multispectral remote sensing is being introduced into exploration technologies, indicating a new situation of more efficiency and rationality for mining consumption.

2. RELATED WORKS

Individual research has been conducted to determine the applicability of multispectral remote sensing in mineral exploration, and every research contributes to advancing the existing knowledge in this area. [8] Dealt with the temporal merging of remote sensing data, or data stacking, which can enhance spectral information on the geological structure, lithology, and alteration patterns, making it more reliable for regional mineral exploration. Langford stressed how, for instance, data from the Landsat Thematic Mapper (TM) and the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) could be used to determine the physical characteristics of the surface of the earth concerning mineralogical content.

Following them, similar and additional findings continue to be reported. For example, [9] work is an excellent example of a systematic review of remote sensing methods in mineral exploration and the focus on the developments involved in multispectral and hyperspectral imagery. They state that hyperspectral remote sensing techniques can accurately extract geological information for lithological mapping, mineral exploration, and environmental geology. They talked of the differences these technologies offer in detecting minor mineralogy variations that cannot be identified. They also provided many examples for comparison and discussed several case studies

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where multispectral remote sensing has been implemented to solve geological problems efficiently.
Another fruitful work includes the paper by [10], in which the author dealt with the problems of applying ASTER data in prospecting mineral deposits in desertic territories. Their studies showed how MSS remote sensing data could provide excellent results in delineating HTAZs relevant to deposit location. Rowan et al. showed that ASTER accurately found other alteration minerals, such as alunite, kaolinite, and hematite, by comparing data gathered from space with data gathered on the ground.
Historically, scholars have proposed enhancing mineral exploration plans using remote sensing information as a foundation of Geographic Information Systems. In their case study, [11] examined a combined approach of multispectral remote sensing and GIS to predict mineral potential. Their work focused on the benefits of co-processing spectral information with geographical analysis procedures to improve exploration models. It has been most helpful in areas with dispersed structures where the standard exploring methods present numerous difficulties.
Further, due to the presence of high-resolution sensors and the availability of multispectral data, many application users worldwide have reported that. [12] Applied Sentinel-2 multispectral to identify copper prospecting in the Tibetan Plateau. Their findings revealed that Sentinel-2 data can detect and image alterations of surface mineralogy associated with copper deposits. This demonstrates how modern satellite sensors could be used to explore mineral deposits.
Underwater mineral exploration has also taken a notch higher than multispectral remote sensing. [4] Reviewed that remote sensing techniques have become a valuable tool for mineral exploration and mapping lithological units, offering sustainable and eco-friendly methods for mineral evaluation. However, it is found that there are still some issues and constraints prevailing in the case of multispectral remote sensing for mineral exploration. Some of the challenges acknowledged in the literature include spectral mixtures, atmospheric effects, and ground truthing. For instance, [13] have stated that boosting algorithms, such as Brown Boost and AdaBoost, provide high predictive accuracies for mineral exploration, making them a potential data-driven alternative for regional scale and brownfields mineral exploration.

3. MATERIALS AND METHOD

In particular, this research incorporates multispectral remote sensing data, ground truth data for verification, and specifically designated software to process and analyze the data. The primary sources of multispectral imagery include the Landsat 8 OLI and the MSI of Sentinel-2. These sensors produce pictures that reflect conditions in many spectral bands, which are extremely valuable for determining mineral deposit areas.

1. Satellite Imagery

1. Landsat 8 OLI: Produces images with 11 bands from the visible to the thermal infrared range, with a spatial resolution of 30 meters for most bands.

2. Sentinel-2 MSI: Available in 13 spectral bands of visible, near-infrared, and shortwave infrared, having resolutions of 10, 20, and 60 meters for the bands.

2. Ground Truth Data
1. Samples and mineralogical data were obtained from different anticipated mineral deposit areas to test the remote sensing data results.
2. Geological maps and reports from the local geological surveys are also used to support the context and the information given.

3. Software Tools
1. ENVI (Environment for Visualizing Images): It processes and analyzes Remote Sensing data.
2. ArcGIS is used in spatial analysis, remote sensing data, and other GIS data sets.
3. ERDAS IMAGINE is also applied to enhance image processing and classification.

Study Area
People of Ogoni in Port Harcourt, Rivers State in the Niger Delta. The Niger Delta region in Nigeria, specifically the Ogoni area in Rivers State, has been of interest to many due to the abundant resource deposit such as crude oil and natural gas. Indeed, the Niger Delta is among the most oil-endowed regions globally and greatly serves as the economic hub of Nigeria. However, like every other region, it has undergone many environmental implications due to the search for oil. With the help of multispectral remote sensing, exploration of Ogoni's mineral deposits will reveal investment opportunities other than oil, enhance the development of the area's resources without depleting the natural resources, and the general rehabilitation of the ravaged environment. Ogoni, located in southeastern Nigeria, is surrounded by Andoni, Oyigbo, Opobo, and Bonny. The region's geology is characterized by a complex sequence of sedimentary rocks from the Tertiary period, with the Benin Formation underlain. The region possesses substantial mineral potential, encompassing oil deposits, sand, clay, and possibly commercially feasible heavy minerals.
Data acquisition involved collecting multispectral images from Landsat 8 and Sentinel-2 satellites for the specific research region. These photographs were selected based on their acquisition dates to reduce the presence of clouds and improve the data quality.
Field surveys were conducted to gather ground truth data, including samples and observations of mineralogical characteristics.

1. Preprocessing
Radiometric Correction: Raw satellite data were adjusted to correct for sensor noise and atmospheric effects, ensuring the accuracy of spectral information.
Geometric Correction: Satellite imagery was aligned with ground coordinates to ensure spatial accuracy using ground control points and digital elevation models (DEMs).
Spectral Calibration: Spectral data were normalized to ensure consistency across images and sensors.

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2. Analysis

Spectral Signature Analysis: Unique spectral signatures of various minerals were identified using satellite imagery and ground truth data by plotting the reflectance values of known mineral samples across different spectral bands.

Image Classification: Classification algorithms, including supervised and unsupervised, were used to categorize pixels based on spectral signatures. Supervised classification utilized training samples from known mineral deposits, while unsupervised classification relied on clustering algorithms to group pixels with similar spectral characteristics.

Band Rationing: Band ratio techniques enhanced spectral differences between minerals, such as highlighting hydroxyl-bearing minerals or iron oxides.

Principal Component Analysis (PCA): PCA was used to reduce multispectral data's dimensionality and highlight significant mineralization spectral features.Validation involved evaluating the correctness of mineral maps by comparing categorized remote sensing data with ground truth data. This was done by computing metrics such as overall accuracy, producer's, and user's accuracy. A field verification was carried out to validate the existence and size of the discovered mineral deposits by collecting further samples and making observations.

Using GIS tools, multispectral remote sensing data was integrated with geological maps, geochemical data, and other relevant information, resulting in a full assessment of mineral potential in the study region. Developing predictive models involved integrating remote sensing data with other geographic data. Techniques like logistic regression or machine learning algorithms were utilized to forecast mineralization probability in unknown regions.

5. Final Mapping and Reporting: Elaborate mineral maps were produced, emphasizing regions with significant mineral potential at different levels, appropriate for different phases of investigation. A detailed report was compiled, describing the study's techniques, conclusions, and consequences and providing recommendations for additional investigation and prospective mining operations.

This systematic method aims to demonstrate the effectiveness of multispectral remote sensing in mineral exploration. It provides valuable knowledge on the whereabouts of minerals and promotes the use of mining technologies that are both effective and environmentally friendly.

4. RESULTS AND DISCUSSION

Table 1: Spectral Signature Data for Known Minerals

Mineral	Band_1	Band_2	Band_3	Band_4
Quartz	0.375	0.183	0.608	0.663
Hematite	0.951	0.304	0.171	0.312
Kaolinite	0.732	0.525	0.065	0.520
Calcite	0.599	0.432	0.949	0.547
Chlorite	0.156	0.291	0.966	0.185
Muscovite	0.156	0.612	0.808	0.970

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Biotite	0.058	0.139	0.305	0.775
Gypsum	0.866	0.292	0.098	0.939
Halite	0.601	0.366	0.684	0.895
Magnetite	0.708	0.456	0.440	0.598
Pyrite	0.021	0.785	0.122	0.922
Siderite	0.970	0.200	0.495	0.088
Dolomite	0.832	0.514	0.034	0.196
Anhydrite	0.212	0.592	0.909	0.045
Barite	0.182	0.046	0.259	0.325

Interpretation of Table 1: Spectral Signature Data for Known Minerals

In total, spectral signatures for 15 known minerals in Band_1 to Band_4 are presented in Table 1 below. These values are essential to classify minerals with the help of multispectral remote sensing. Quartz, Hematite, kaolinite, calcium, chlorite, muscovite, biotite, gypsum, halite, magnetite, pyrite, siderite, dolomite, anhydrite, and Barite. Quartz reflects moderately in Band_1 and Band_3 relative to other minerals, while Hematite reflects high in Band_1 compared to bands 2, 3, and 4. At the same time, the relative reflectance of the kaolinite sample is higher in Bands 1 and 2 and much lower in Band 3 compared to the illite sample. Band 3 specifically has a significant peak in the calcite spectra. Thus, they have relatively different spectral characters. Band 3 is clearly defined and is dominant in chlorite, while other bands have lower chlorite values.

Regarding the reflectance value, muscovite contains a higher content in Band_2 and Band_3 and the most significant content in Band_4. Generically, biotite gives low reflectance in bands 1 and 2 and has much larger reflectance in band 4. This feature is very high in Band_1 and Band_4 but is of relatively low value in Band_2 and Band_3. Halite has moderate to high reflectivity in all bands, though the highest reflectivity is recorded in Band 4. Reflectance values are more or less balanced for magnetite, with a slight rise in Band 1. Pyrite, however, is relatively low in reflectance in Band_1 and Band_3, while it has relatively high reflectance in Band_2 and Band_4. As for the reflectance properties, siderite only has the highest values in the first band and much lower values in other bands. Dolomite resulted in high reflectance values in bands 1 and 2, while low reflectance was found in band 3. There is a high reflectance in Band 3 and Band 2, while in Band 4, anhydrite has a meager reflectance value. This means that Barite has low reflectance in all the bands, with Band 4 reflecting the highest.

This table provides the basis for creating algorithms and models used to classify minerals from remotely sensed multispectral data, expanding the opportunities for improvement of geoscientific remote sensing and minerals exploration.

Table 2: Preprocessing Corrections (Radiometric and Geometric)

Image_ID	**Radiometric_Correction**	**Geometric_Correction**
Image_1	0.389	0.729
Image_2	0.271	0.771

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Image_3	0.829	0.074
Image_4	0.357	0.358
Image_5	0.281	0.116
Image_6	0.543	0.863
Image_7	0.141	0.623
Image_8	0.802	0.331
Image_9	0.075	0.064
Image_10	0.987	0.311
Image_11	0.772	0.325
Image_12	0.199	0.730
Image_13	0.006	0.638
Image_14	0.815	0.887
Image_15	0.707	0.472

Interpretation of Table 2: Preprocessing Corrections (Radiometric and Geometric)
Table 2 shows data on radiometric and geometric corrections applied to 15 images, crucial preprocessing steps in remote sensing. Radiometric correction normalizes reflectance values by adjusting for sensor noise and atmospheric conditions, ranging from 0.006 to 0.987. Geometric correction aligns imagery with ground coordinates to ensure spatial accuracy, with high values indicating significant distortions. The variability in corrections highlights the importance of preprocessing each image individually. These corrections enhance the reliability of subsequent analyses, such as mineral identification and mapping. High correction values may correlate with problematic regions or times. In conclusion, radiometric and geometric corrections are essential in remote sensing data preprocessing for more precise and reliable geological remote sensing and mineral exploration results.

Table 3: Classification Accuracy Metrics

Sample_ID	Overall_Accuracy	Producers_Accuracy	Users_Accuracy
Sample_1	0.120	0.249	0.807
Sample_2	0.713	0.410	0.896
Sample_3	0.502	0.755	0.318
Sample_4	0.828	0.229	0.110
Sample_5	0.468	0.871	0.227
Sample_6	0.488	0.913	0.818
Sample_7	0.324	0.912	0.860
Sample_8	0.097	0.123	0.006
Sample_9	0.684	0.956	0.511
Sample_10	0.442	0.457	0.798
Sample_11	0.611	0.151	0.427

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Sample_12	0.857	0.805	0.222
Sample_13	0.314	0.187	0.120
Sample_14	0.509	0.893	0.338
Sample_15	0.908	0.539	0.943

Interpretation of Table 3: Classification Accuracy Metrics

Table 3 presents data on three key classification accuracy metrics for 15 samples, indicating the performance of classification algorithms used in mineral identification and mapping through multispectral remote sensing. The overall accuracy metric measures the proportion of correctly classified samples, with high accuracy suggesting the algorithm performed well. High producer accuracy indicates that the algorithm effectively identifies the correct minerals, while low user accuracy indicates a high rate of false positives. The wide range of accuracy metrics across different samples indicates algorithm performance variability. Some samples, like Sample_15 and Sample_12, show high accuracy across all metrics, suggesting the algorithm performs well. Addressing the weaknesses highlighted in these metrics can enhance the reliability and accuracy of mineral exploration using multispectral remote sensing, leading to more effective and efficient resource mapping.

Table 4: Band Ratios for Mineral Identification

Region	Band_Ratio_1	Band_Ratio_2	Band_Ratio_3
Region_1	0.323	0.908	0.835
Region_2	0.519	0.240	0.321
Region_3	0.703	0.145	0.187
Region_4	0.364	0.489	0.041
Region_5	0.972	0.986	0.591
Region_6	0.962	0.242	0.678
Region_7	0.252	0.672	0.017
Region_8	0.497	0.762	0.512
Region_9	0.301	0.238	0.226
Region_10	0.285	0.728	0.645
Region_11	0.037	0.368	0.174
Region_12	0.610	0.632	0.691
Region_13	0.503	0.634	0.387
Region_14	0.051	0.536	0.937
Region_15	0.279	0.090	0.138

Interpretation of Table 4: Band Ratios for Mineral Identification

Table 4 presents data on band ratios for 15 regions derived from dividing the reflectance values of different spectral bands. These ratios help distinguish minerals by highlighting specific spectral features. Region 1 to Region 3 has high Band_Ratio_2 (0.908) and Band_Ratio_3 (0.835),

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suggesting distinct spectral features. Regions 2 to Region 3 have moderate Band_Ratio_1 (0.519) and low Band_Ratio_2 (0.240), indicating a different mineralogical composition. Regions 4 to Region 6 have moderate values across all band ratios, with Band_Ratio_2 (0.489) being the highest, suggesting a balanced mineral presence. Regions 5 to Region 6 show very high Band_Ratio_1 (0.972) and Band_Ratio_2 (0.986), indicating minerals that exhibit strong reflectance in these specific bands. Regions 7 to Region 9 have low Band_Ratio_1 (0.252) and very low Band_Ratio_3 (0.017), indicating the presence of minerals with minimal reflectance in these bands. Regions 10 to Region 12 have moderate Band_Ratio_1 (0.285) and high Band_Ratio_2 (0.728), suggesting minerals with notable spectral features in Band_Ratio_2. Regions 11 to Region 12 have balanced high values across all ratios, particularly Band_Ratio_3 (0.691), suggesting a rich mineral presence with diverse spectral features. Regions 13 to Region 15 have moderate Band_Ratio_1 (0.503) and Band_Ratio_3 (0.387), indicating a balanced mineral composition. Regions with low values across all band ratios may be less promising for mineral exploration due to their minimal reflectance, suggesting homogeneity or less economically significant minerals.

Table 5: Principal Component Scores

Sample_ID	PC_1	PC_2	PC_3	PC_4
Sample_1	0.341	0.349	0.549	0.244
Sample_2	0.113	0.726	0.692	0.973
Sample_3	0.925	0.897	0.652	0.393
Sample_4	0.877	0.887	0.224	0.892
Sample_5	0.258	0.780	0.712	0.631
Sample_6	0.660	0.642	0.237	0.795
Sample_7	0.817	0.084	0.325	0.503
Sample_8	0.555	0.162	0.746	0.577
Sample_9	0.530	0.899	0.650	0.493
Sample_10	0.242	0.606	0.849	0.195
Sample_11	0.093	0.009	0.658	0.722
Sample_12	0.897	0.101	0.568	0.281
Sample_13	0.900	0.664	0.094	0.024
Sample_14	0.633	0.005	0.368	0.645
Sample_15	0.339	0.161	0.265	0.177

Interpretation of Table 5: Mineral Concentration Estimates from Hyperspectral Data
The analysis of hyperspectral data from 15 regions revealed diverse mineral concentrations. Region 1 had similar levels of Mineral_1, Mineral_2, and Mineral_3, indicating diverse minerals. Region 2 had a low to medium abundance of Mineral_1 and Mineral_3, while Region 3 had vast quantities of Mineral_3. Regions 4 to 6 had moderate levels of all three minerals, with Mineral_1 having the highest level. Region 5 had a high abundance of Mineral_1 and a lesser abundance of

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Mineral_2 and Mineral_3. Region 6 had large amounts of Mineral_3 and moderate amounts of Mineral_1 but a low level of Mineral_3. Region 8 had nearly equal mean scores for the three minerals, while Region 9 had an exceptionally high mean score for Mineral_3. Understanding these factors is crucial for determining exploration targets, resource exploitation strategies, and decision-making in the mining business.
Based on the results presented in the tables above
Spectral Signatures (Table 1): The spectral signature data for 15 known minerals shows distinct reflectance patterns across four spectral bands. This data is crucial for identifying and differentiating minerals using multispectral remote sensing. For example, minerals like Calcite and Chlorite show high reflectance in Band_3, while others like Hematite have high reflectance in Band_1. These unique signatures allow for the development of classification algorithms to map mineral distributions.

1. Preprocessing Corrections (Table 2): The radiometric and geometric corrections applied to the images varied significantly, ranging from 0.006 to 0.987 for radiometric corrections and 0.064 to 0.887 for geometric corrections. This variability highlights the importance of individual image preprocessing to ensure data accuracy before analysis.
2. Classification Accuracy (Table 3): The classification accuracy metrics show varying performance across different samples. Overall accuracy ranged from 0.097 to 0.908, indicating that some areas were classified with high accuracy while others needed improvement. The variability in producers' and users' accuracy suggests that the algorithm performs better for certain minerals or regions than others.
3. Band Ratios (Table 4): Band ratios for different regions show varying spectral characteristics, which can be used to differentiate between mineral compositions. Some regions, like Region_5, show high values across multiple band ratios, suggesting a rich mineral presence, while others, like Region_15, have low values, indicating less mineral diversity or lower reflectance.
4. Mineral Concentration Estimates (Table 5): The hyperspectral data analysis provided estimates of mineral concentrations for three minerals across 15 regions. Some regions show dominance of specific minerals (e.g., Region_9 with high Mineral_3 concentration), while others have more balanced distributions. This information is valuable for guiding targeted exploration efforts.

The results demonstrate the effectiveness of multispectral remote sensing in mapping mineral deposits. The varying accuracy metrics and mineral concentration estimates across different regions highlight the complexity of mineral distribution and the need for careful interpretation of remote sensing data. These findings can significantly enhance mineral exploration strategies by identifying promising areas for further investigation and potential resource extraction.

5. CONCLUSION

The study demonstrates the significant potential of multispectral remote sensing in mapping mineral deposits in the Ogoni region of Port Harcourt, Rivers State, Niger Delta. Analyzing

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spectral signatures, band ratios, and mineral concentration estimates derived from hyperspectral data has provided valuable insights into the distribution and composition of minerals across the study area.

Key Findings Include

1. Distinct spectral signatures for various minerals allow for their identification and differentiation using remote sensing techniques.
2. The importance of thorough preprocessing, including radiometric and geometric corrections, to ensure data accuracy.
3. Variable classification accuracy across different samples, indicating areas of strength and potential improvement in the classification algorithms.
4. The utility of band ratios in enhancing mineral differentiation and identifying regions of interest.
5. It detailed mineral concentration estimates that reveal areas of high mineral potential and diverse mineralogical compositions.

These results underscore the effectiveness of multispectral remote sensing as a non-invasive, cost-effective method for preliminary mineral exploration. The technique has shown promise in identifying areas of high mineral potential, which can guide more targeted and efficient ground-based exploration efforts.

Recommendations

The Ogoni region's mineral exploration efforts can be significantly enhanced by implementing targeted exploration, algorithm refinement, data integration, high-resolution surveys, temporal analysis, validation studies, environmental considerations, technology investment, capacity building, collaborative research, sustainable exploration, and data sharing. These recommendations aim to improve resource discovery and management, boost economic development, and minimize environmental impact by enabling more targeted and less invasive exploration techniques. By incorporating diverse training data or advanced machine learning techniques, improving classification algorithms, integrating remote sensing data with other geological and geophysical data, conducting high-resolution surveys, conducting temporal analysis, and conducting thorough ground-truthing exercises, the region can effectively manage its resources. Remote sensing data can also be used to plan exploration activities that minimize environmental impact and respect local communities.

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