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Evaluating the Use of a Contextual Information Extraction Technique to Identify Mineralized Zones in a Semi-Arid Environment from Aster Satellite Data

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ABSTRACT

Identification of regions of mineralization by traditional techniques where spectral information of pixel alone is applied during classification, either at pixel or sub-pixel level, is usually accompanied by some level of un-satisfaction. Impulse noises that are usually experienced in digital images from sudden sharp disturbances in the signal degrade the output. This effect often referred to as the salt and pepper noise could further cause information loss, and change the colour of an RGB image. The use of filters (median and morphological) has not totally eliminated the effects. Object-based methods came in with higher filter smoothers to make it better yet, there is potential limitation because of possible negative impact of under segmentation. The errors of under-segmentation cannot be adjusted within a unit of features, which apparently affect the potential accuracy of the entire classification. Thus, this study evaluates the contribution of the contextual information to reduce the effects of noise in the data for effective mineral identification. Rule-based technique was applied for information extraction from a threshold values derived from band ratio (BR) transformation operations on ASTER data. The result indicates clay has the highest mineral density of 47% in the study area, with silicate having the least (3%), among others. This study provides a robust test for contextual cues as anticipated to be most effective and shall contribute towards reducing environmental impacts and protecting biodiversity which is one of the major aspects of sustainable development in relation to mining and mineral processing.

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Introduction

Remote sensing satellite system and the images derived from them have been making an unprecedented contribution to geological resource mapping, which includes structural, lithological, hydrothermal alteration zones and individual mineral categories. A variety of sensor data exists which are multispectral, superspectral, and hyperspectral, and every considerable effort made with them in the research circle is to apply them for information extraction [1-7]. Formerly, photographic products were used before the satellite sensing data began to be used in research. Human photo-interpretation was the main activity in data mining from photographic products at the time, and specialised keys often referred to as interpretation keys that define features with credibility were in use. Within these elements are three that belonged to the contextual cues, which were very important for information extraction in the exploitation of photographic data. The categories of the contextual information are illustrated in Figure 1.

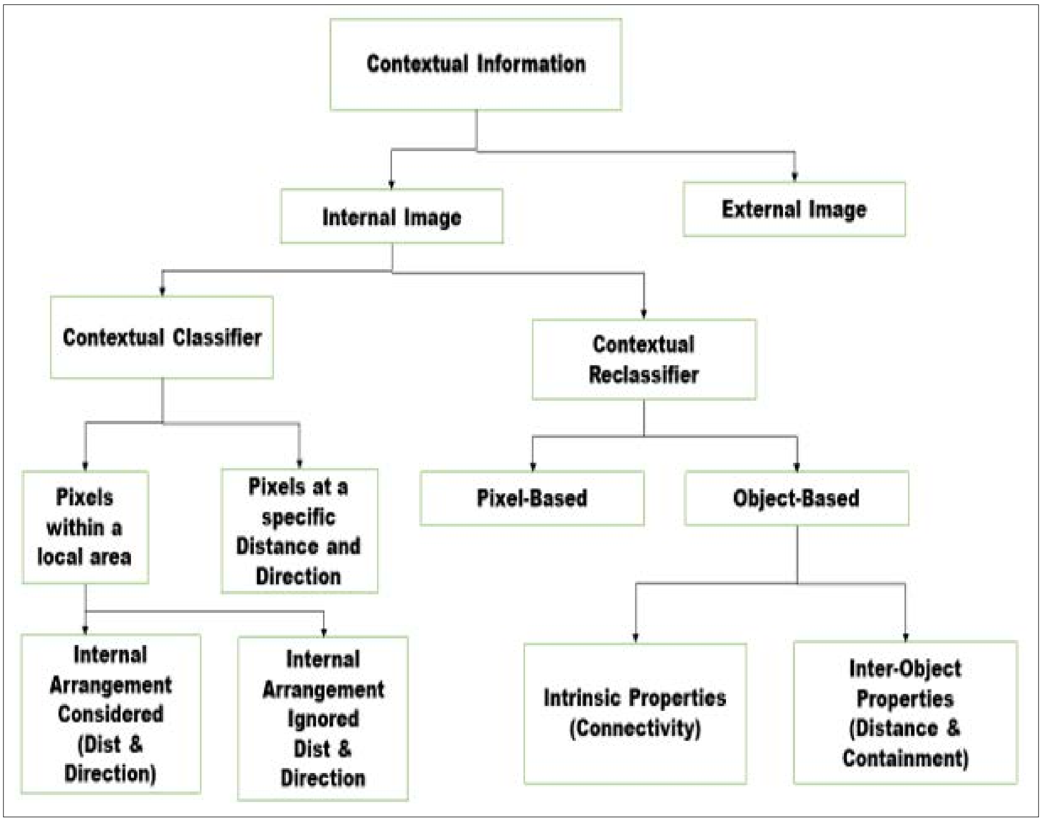

Figure 1: The typology of contextual information classification

The applications of photographic products are still active, with so much use in the MYCIN expert system, and the issues of the contextual information play an active participation [8-10]. Nevertheless, with the advent of satellite data, which comes in digital format, the methods of processing and extraction of information from them have been by the use of computers and algorithms. Every method and the algorithms applied then, have their kinds of limitation and thus, undergo constant developments and upgrade. One of such is bringing forward the contextual information into the digital image processing because of their advantages.

The use of satellite remote sensing data applies to several areas of the geoscience domain, some of which are continuous data categories [11,12] while others are not. The remote sensing processing and classification began with the spectral mapping technique, which has been very popular and vastly applied in the research world. The spectral method used to provide the means for fast and easy processing with many developed algorithms applying the principle [13]. This has found application extensively in addition to development with multi-spectral, super-spectral and hyperspectral data in many areas, including lithological and mineral mapping. A choice is always made on the algorithm type, perhaps such that accommodates training or not (i.e., supervised or unsupervised), which are further classified according to the underlying statistical assumptions regarded as parametric or non-parametric, and further by the basis of the elements called per-pixel, and sub-pixel [14]. So much literature reveals an extensive use of the spectral mapping technique for lithology and mineral exploration mapping, either at pixel or more recently at sub-pixel domain [15-19]. Problems associated with these techniques include the statistical assumption that each pixel is a representative of ground sampled area supposedly with a single feature type, whereas in reality, this is rarely the truth, such that a pixel may contain mixtures of different surface materials. These variations are called noises in classification as some are poor representative of the actual and so are related to neighbouring pixels, which of course, would result in significant intra-class spectral variations [19].

The sub-pixel approach was meant to overcome the erroneous representation and provided a degree of multiple membership to a single pixel and neighbourhood. The developed algorithms to handle the sub or mixed pixel issues are generally said to operate in spectral unmixing techniques and analysis, in which they go through and deconvolvement of the pixel spectra and quantifies the fractional abundances called end members of the relative constituents to surface materials in their variations [20,21]. But, to have a good representation of this requires prior knowledge of all features in a data, including unmixing results, which makes it difficult to achieve [22]. So many studies have been carried out using sub-pixel approach in un-mixing spectral processing in arid and semi-arid regions, characterised by largely bareness [18,23,24].

Recent advances in classification techniques have led to a paradigm shift in many fields, from the classical pixel-based approach to instead focusing on image objects [25]. The object-based image analysis (OBIA) approach, also commonly referred to as geographic object-based image analysis (GEOBIA), does not classify individual pixels of the data but rather performs segmentation of the entire image and then uses the information to classify the segments. The segmentation creates homogeneous clusters (i.e., objects) by grouping contiguous pixels that are relatively similar in terms of both their spectral and spatial characteristics [26]. Grouping pixels enables contextual (neighbourhood) information to be incorporated and thus results in the creation of image objects that represent "meaningful" entities (e.g., buildings, trees, fields, or perhaps even rock outcrops) in an image [25].

The OBIA approach creates two kinds of advantages; it makes the classification unit to become large with the movement from pixel to objects, and removing the within class variations in the spectral domain, and secondly, it has capacity to remove the impulse noises [27,28]. Image objects therefore have additional spectral (e.g., mean, median, minimum and maximum band values, band variance) and spatial attributes (e.g., shape, size, association with neighbouring objects) in comparison to individual pixels, which are limited. Consequently, OBIA has been used extensively for a variety of applications, including forestry, habitat mapping, land use/ land cover mapping, landform mapping and change detection, with numerous studies reporting that higher classification accuracies can be achieved through the OBIA approach in comparison to pixel-based approaches [29-38].

Despite seemingly having the potential to eradicate the issues associated with pixel-based approaches, the application of OBIA to mineral mapping has received minimal attention. Preliminary studies have been carried out by and were able to distinguish between lithological units respectively, through segmentation of spectral satellite imagery. More recently, OBIA has been employed to map volcanic units and landforms on active volcanoes in Indonesia, and same approach was made to delineate a region of geology that is controlled by vegetation of various kinds in the South-African Kruger National Park [39-43]. However, the potential benefit of employing OBIA over pixel-based classification approaches for mineral mapping is yet to be realised. This study therefore aims at making a contribution through the use of the contextual information in the data to address the missing link by evaluating the capability of a contextual element approach for producing detailed mineral mapping with accurately defined contacts for the Jos Plateau area of Nigeria. Accordingly, this study provides a robust test for contextual cues as anticipated to be most effective and shall contribute towards reducing environmental impacts and protecting biodiversity, which is one of the major aspects of sustainable development in relation to mining and mineral processing identified by the International Council on Mining & Metals (ICMM), the World Economic Forum (WEF), and the World Coal Association (WCA) as needing focus for sustainability of the mining industry since this approach will narrow search activities to only the most probable regions of minerals deposits [44].

Material and Method

Study area

Plateau state lies between 10^0 30’ and 09^0 00’ N to 09^0 30’ and 08^0 30’ E, and approximately covers 6700 km^2 in the north central part of Nigeria as depicted in Figure 2 [45]. The geologic setting potentially reveals the area as an environment with vast deposits of tin mineralization because of ancient schists as well as gneiss granite rocks, which later were invaded by a newer category called younger granites. These new rocks came with rich tin and fluorine. There have also been signs of volcanic deposits which have preserved the older sedimentation and made alluvial beds to keep forming by the actions of river flows and erosion activities. The region is thus a potential rich area for a variety of mineral resource types that are associated with the rock types. Figure 3 presents the geologic map of the area.

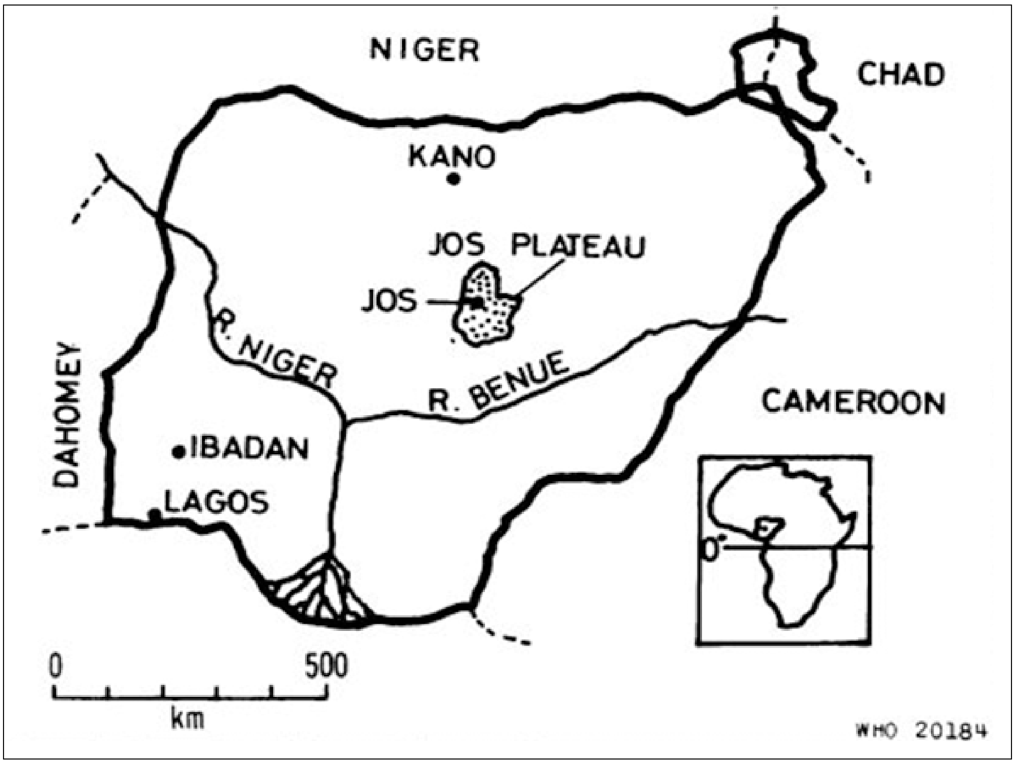

Figure 2: The map of Plateau state in Nigeria from Lee, 1972

Remote Sensing Data

The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) multi- spectral remote sensing data was the main data

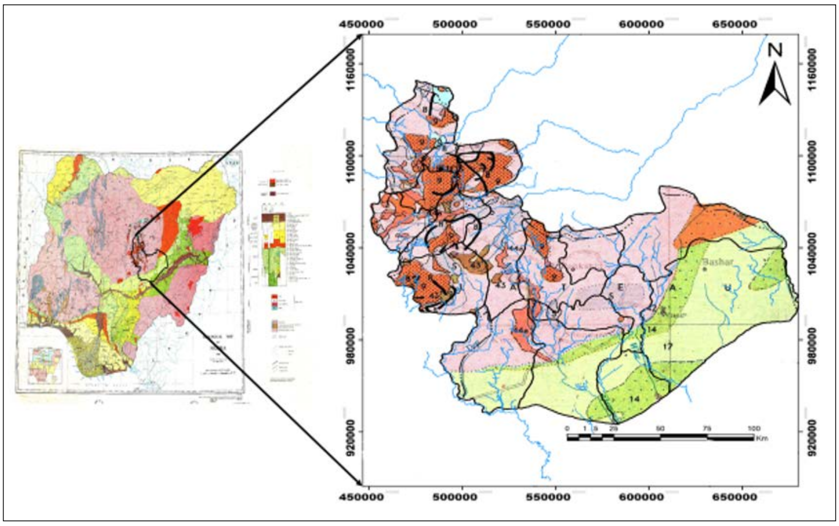

Figure 3: Geologic map of Plateau state

Utilised for the prospecting of mineral resources in the Jos Plateau, north central Nigeria. ASTER has 14 bands with unique features that are capable of recording and monitoring the earth's surface features and producing stereo imagery that could be used in the creation of digital terrain models. It has three components form: the visible near infrared (VNIR), shortwave infrared (SWIR), and the thermal infrared (TIR) (Figure 4). All these sub-systems work together to help in the success of the products that the sensor produces, as shown in Table 1, which summarises the technical details of its performance and the attributes that were used to discriminate the regions of alteration zones for regional mapping of the area of study.

Table 1: Summary of ASTER technical detail and attributes

Subsystem	Band No.	Spectral Range (um)	Spatial Resolution (m)	Quantization levels
VNIR	1	0.52-0.60	15	8 bits
	2	0.63-0.69	15	8 bits
	3N	0.78-0.86	15	8 bits
	3B	0.78-0.86	15	8 bits
SWIR	4	1.60-1.70	30	8 bits
	5	2.145-2.185	30	8 bits
	6	2.185-2.225	30	8 bits
	7	2.235-2.285	30	8 bits
	8	2.295-2.365	30	8 bits
	9	2.360-2.430	30	8 bits
TIR	10	8.125-8.475	90	12 bits
	11	8.475-8.825	90	12 bits
	12	8.925-9.275	90	12 bits
	13	10.25-10.95	90	12 bits
	14	10.95-11.65	90	12 bits

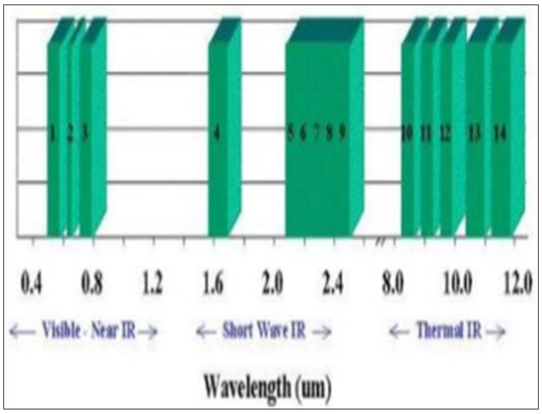

Figure 4: Operational wavelengths of ASTER multispectral sensor

Method

The Image Processing of the ASTER Data

The processing of ASTER data involves atmospheric, crosstalk, radiometric and enhancement. These were performed to provide room for feature extraction.

Band Ratioing Technique

The use of band ratios enhances the differences that exist between the individual bands as well as reduces the effects of topographic elevation and shadow cast. The basic process is the division of one band over another to produce a fresh image that reveals the relative intensity of the bands involved. Each mineral type has specific bands that are effective for identifying them as depicted in Table 2.

Table 2: Band ratios for mineral exploration

Objects	Landsat 8	ASTER L1T	Sentinel-2A
Ferric Iron Fe^{3+}	4/3	2/1	4/3
Ferrous Iron $Fe2^{+}$	7/5 +3/4	5/3 + $^{1}/_{2}$	12/8+3/4
Ferric oxides	-	4/3	11/8
Gossan	6/4	4/2	11/4
All iron oxides	4/2	2/1	4/2
Laterite	-	4/5	11/12A
Carbonate/ chlorite/	-	7+9/8	-
Epidote/ chlorite/ Amphibole	-	(6+9)/(7+8)	-
Dolomite	-	6+8/7	-
Silicates-sericites/ Muscovites/ illite	-	5+7/6	-
Kaolinite/ Alunite	-	4+6/5	
Muscovites	-	7/6	-
Clay	-	5x7/6x6	
Alterations	6/7	4/5	11/12A
Host rock	-	5/6	-
NDV1	5-4/5+4	3-2/3+2	8-4/8+4

The processing methodology of the multispectral images in this study is summarized in Figure 5. After pre-processing, the mapping of the individual mineral types was carried out using the band ratio transformation technique. The values for each combination were computed, and applied in the development of rules that were fired in the algorithm as depicted in Figure 5.

Segmentation

This is the step that is very critical for the feature extraction where the objects are clustered in their homogeneous nature into groups. These clusters have contiguous pixels and are regarded to contain similar characteristics. The procedure undertook multi-scaled process which is embedded in the ENVI 5.3 software. The workflow begins with the threshold values for individual rule and goes through sequential clustering of the spectral values throughout the data. This scales up the spatial variability that determines the scale of each cluster. Figure 6 presents the results of the segmentation.

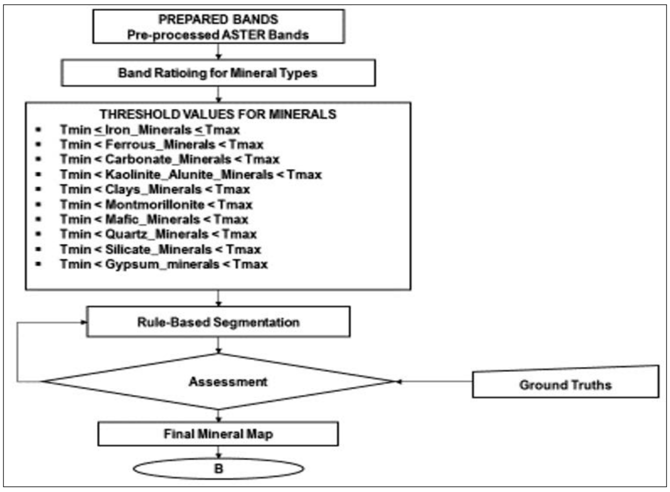

Figure 5: the rule-based creation fired for mineral extraction

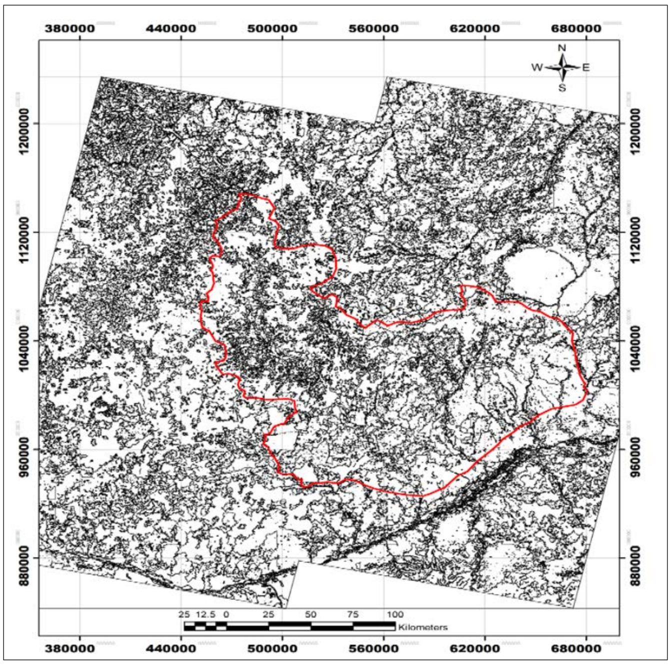

Figure 6: Result of segmentation process

Classification

Following the segmentation, the results are saved in a shapefile and an automatically developed attribute table was saved in excel format. These attributes built contain all the information about the spectral, spatial, and contextual information for all the mineral features in the image. These were accessed in ArcGIS and applied for the thematic mapping of the individual mineralization as presented in Figure 7.

Figure 8 depict the percentage quantity of each mineral density. Clay has the largest mineral density of 47%, whereas silicate has the least (3%). Carbonate and quartz have 4% each, montmorillonite and Alunite with 5% each, Kaolinite 6%, granite 7%, iron oxide 9% and mafic 10%. Figure 9 presents the spatial distribution of all the minerals.

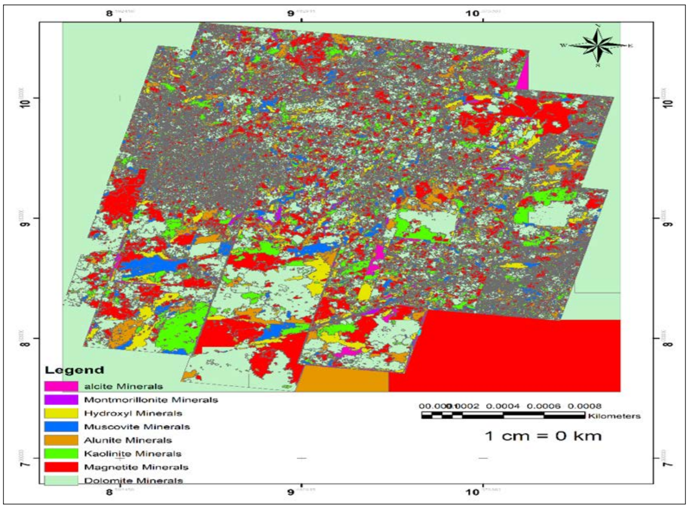

Figure 7: The thematic mapping of the individual mineral distribution throughout the study

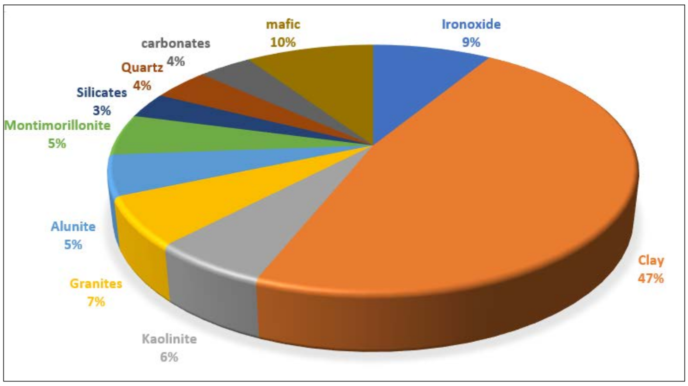

Figure 8: Quantitative representation of the individual mineral density

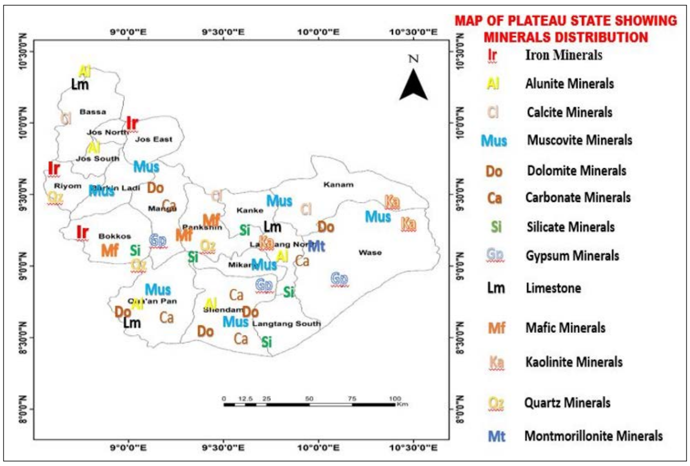

Figure 9: Individual mineral distribution in a GIS environment

Conclusion

Comprehensive mineral prospecting over the entire study area is for the first time achieved with the help of this approach. The use of band ratio transformation for mineralogy is not new, but in this case was to create a threshold for individual mineral types which were fed into the workflow for segmentation and classification. This operation is the state-of-the-art in data mining in recent times, as suggested by many researchers that exploitation of contextual information in addition to other methods could enhance the output of classification. The algorithm performs segmentation first and then builds an attribute table that consists of the spectral, spatial, and contextual information for thematic display. The classification is then undertaken and saved in vector format as a shape file so that further operations like symbolization can be added to the thematic information. This approach can be applied universally to any kind of feature that need to be extracted. Nevertheless, this will depend on the rules built, the scale selected for the spatial content and the edge detection classifier. Despite that this study was carried out at greenfield state, with ASTER data, any sensor data could be applied to brownfield surveys provided the rule-based system is maintained. Nonetheless, by producing detailed greenfield maps with accuracy, this will serve as reference material for small scale and district-scaled mapping.

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