

Data Driven Predictive Modelling of Mineral Prospectivity Using Principal Component Analysis: A Case Study of Riruwai Complex

Adeyinka Olasehinde^{1*}, and Edafetano C Ashano²

1 Department of Geology, Gombe State University, Gombe, Nigeria

2 Department of Geology, University of Jos, Jos, Nigeria

Abstract

The present work presents integrated data-driven approach using geochemistry, aeromagnetic data, airborne radiometric data and Landsat ETM Imagery in the study. The study is aimed at producing mineral potential exploration model of the study area, which would serve as a model for other Younger Granite Complexes in the Province with unknown mineralization. The various exploratory dataset involve creating spatial database of the geology, geochemical data, the aeromagnetic (total field magnetic intensity), airborne radiometric (K, Th, U count), and Remote Sensing (Landsat ETM imagery). Principal Component Analysis (PCA) of forty-two exploratory variables was employed in organizing and producing the mineral potential zones. The first three components of the Principal Component Analysis, account for over 50% of the total variability. The high, moderate to low moderate loading on the components represents background population of the study area and also reflects the combined effect of the geochemical, geophysical and the lithology, and hence mineral potential of the complex especially. The PC1 of the Riruwai data variability of 21.54% reflect alteration associated with mineralization of Sn, Zn, Nb, U, Th within the granitic rocks. The PC2 of the study area has data variability of 20.84% signifies increases in alteration within the lithology especially the biotite granites and albite arfvedsonite granite. Data variability of 10.78 is accounted by PC3 and its significance is interpreted as pyrochlore mineralization within the albite arfvedsonite granite. The study, not only predict known areas of mineral occurrence (Sn, Nb, Ta, Zn, Zr, U, Th), but also identified areas of favourable mineralization potential. This approach can thus be applied to areas with similar geological setting but unknown mineralization.

Keywords: Riruwai complex; Data-Driven, Mineral exploration; Principal Component Analysis

***Corresponding author:**

Adeyinka Olasehinde

✉ yinka516@gmail.com

Department of Geology, Gombe State University, Gombe, Nigeria.

Tel: +2348039266151

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Introduction

The application of GIS in geosciences is fast growing [1-5]. In mineral deposit exploration the diver's maps which include disparate geophysical, geological, and geochemical datasets, each having particular specifications are collected, processed and integrated (**Figure 1**). After analysing each stage, mineral potential map is produced. Mineralization recognition criteria are identified based on mineral deposit model and expert knowledge which help in data modelling, selecting features to be enhanced and extracted as evidence, and deciding how to weight the relative importance of evidence in estimating mineral potential.

In mineral exploration geologists deal with various types and sources of data to explore for new economical mineral deposits [6-8]. The data sources vary from geological maps, multispectral satellite images, and hyper-spectral airborne and geophysical images to data in many formats [9-11]. The aim of this work is to carry out an applicability of the use of integrated data in investigation of mineral potential of the Riruwai Complex. The data include geochemical data, aeromagnetic, airborne radiometric and Landsat ETM Imagery to produce mineral potential model which would serve as an exploratory model for other Younger Granite Complexes in the Province. Data from geochemistry, aeromagnetic and radiometric surveys, topographic and geologic

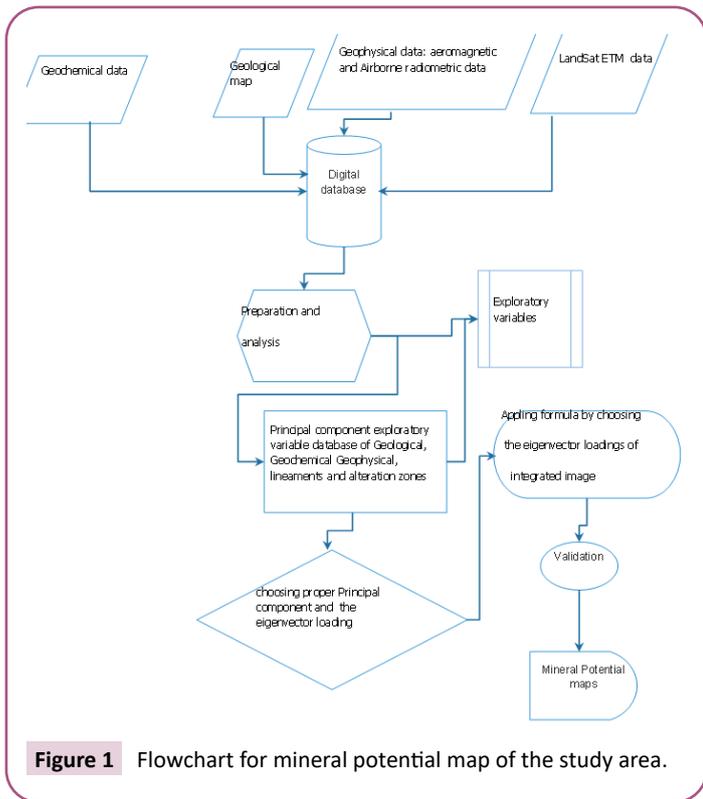


Figure 1 Flowchart for mineral potential map of the study area.

the Complex, and in the south east and extreme north-west, the underlying vent structures can be seen. Towards the end of the volcanic cycle a large plug of quartz-fayalite-porphyry was emplaced in the centre of the Dutsen Shetu vent Complex. During the plutonic cycle, the peripheral ring-dyke of the granite-porphyry, one of the major structural features of the Complex, and the central granite plutons of biotite- and arfvedsonite-granite were emplaced beneath the volcanic pile. Erosion has preceded in such a depth that all the major units of the cycles are exposed and their structural relationship clearly defined. In common with all volcanic ring complexes in the Younger Granite province the lavas are entirely confined within the peripheral ring-faults, and there is a little doubt that they owe their preservation at their present levels to down-faulting. Subsidence probably occurred during the volcanic stage and during the subsequent intrusion of the ring-dyke. It is believed that the ring-fault developed at an early stage, and that it provides a convenient channel for the upward passage of lava to a series of peripheral vents.

Detailed description of the geology of the Riruwai Complex and the cassiterite mineralized lode has been provided by Abaa, Turner, Bowden, Ogunleye, Ogunleye [12,17-19]. The Riruwai lode extends for a distance of 5 km in an east-west direction at a depth of over 400m and dips to the south at 85°. The maximum surface width of the lode system is 8 m. The extensively

maps, LandSat-ETM satellite imagery and structures were integrated in GIS environment using the Principal Component Analysis (PCA) to give insight into economic mineral potential of the study area which can serve as mineral exploration model in area of the same geology with unknown mineralization. Principal component analysis is one of the methods for spatial analysis and integrating the geological data set. This method was used to for the spatial and integration of the geological dataset.

Geological Setting and Mineralization

The Riruwai Younger Granite Complex provides one of the finest examples of the complete cycle of ring complex magmatic activities within the Younger Granite of Nigeria [12]. The Complex lies roughly between latitudes 10° 40'N to 10° 50' N and longitudes 8° 40'E to 8° 50'E located 140 km south of Kano. The distribution of the Mesozoic alkaline ring complexes, magmatic migration and the structures has been well studied by various authors Black & Liegeois, Ike, Kinnaird & Bowden, Smith & Bailey [13-16] considered Riruwai an excellent example of resurgent subvolcanic cauldron. Pre caldera ignimbritic units and minor flows are preserved in the collapsed caldera. The Riruwai Complex (Figure 2) provides a good example of complete cycle of ring complex magmatic activity in the Younger Granite of Nigeria. Jacobson and Macleod showed that during the initial volcanic stage a considerable volume of acid lavas and associated pyroclastic was erupted, and the volcanic succession includes occasional flows of basalt. Also, that the volcanism was accompanied by the formation of large surface cauldron or caldera about thirteen kilometres in diameter, in which the bulk of effusive volcanic materials accumulated. The extrusive volcanic rocks are well preserved in the north-western half of

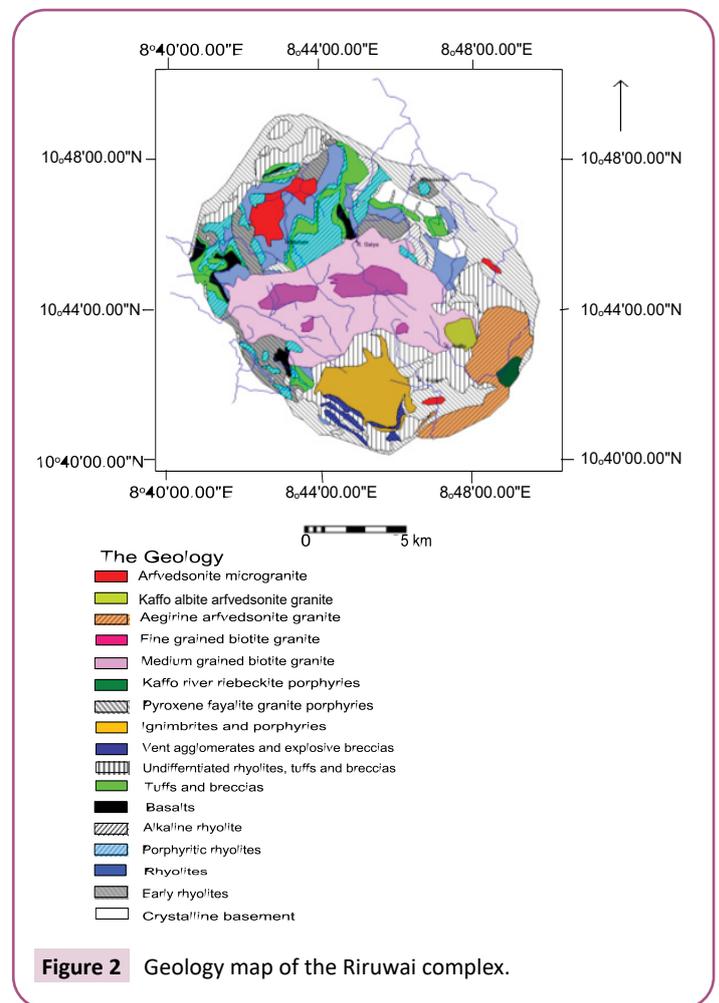


Figure 2 Geology map of the Riruwai complex.

mineralized lode which consists of series of parallel to sub parallel or braided quartz vein enclosed by zones of grey greisens grading outwards into reddened wall rock and occasionally through a narrow buff-coloured zone out into the pale pink equigranular biotite perthite granite as revealed by Turner and Bowden [18]. Aspects of the mineralogy, geochemistry and mineralization of the Riruwai Complex studied by Kinnaird [20] revealed that hydrothermal alteration of the biotite granites began with potash metasomatism and perthic feldspar adjacent to the fissure was microclinized. Early monazite, zircon and ilmenite deposition was followed by the formation of cassiterite, wolframite and rutile and finally by the intrusion of molybdenite [21]. During subsequent hydrogen ion metasomatism as studied by Kinnaird [20] the microcline was altered and the greisen formed, consisted of green coloured lithium siderophyllite or grey zinnwaldite and quartz, localized concentrations of ore associated with clusters of mica were also reported.

Methodology

Principal component analysis for mineral potential mapping

The available forty-two exploratory variables related to mineralization comprise geochemical data of SiO₂, CaO, Fe₂O₃, K₂O, Na₂O, TiO₂, P₂O₃, Al₂O₃, V, Cr, Cu, Sr, Zr, Ba, Zn, Ce, Pb, Sn, Ga, Y, Ni, Rb, Nb, La, Eu, Mo, Co, Ta, W, Hf, Pr, Lu, Gd, U, Th, and Nd; geophysical data: total magnetic, ternary radiometric, K /U ratio map, K/Th ratio, Structures, the geology, altered zones from Landsat imagery. All of these data represents factors used within spatial database with a pixel size of 100 m × 100 m. Principal component analysis is widely used for mineral exploration mapping in metallogenic provinces [22,23]. ILWIS 3.3 academic software, Oasis montaj 7.0, golden surfer 11 and ArcGIS 10.2 products were used to perform the bulk of the data pre-processing, data analysis, and modelling, visualization and product generation. This involve the processing of the satellite imagery, digitizing the maps, visualization and product generation. Exploratory variables with eigenvectors loading less than 0.3 were not considered significant component and were excluded. The exploratory variables were integrated and transformed by using the eigenvector loading of the first, second and third principal components using the following equation:

$$PC_i = a_{i1}x_1 + a_{i2}x_2 + \dots + a_{in}x_n \quad \text{..... Equation (1)}$$

Where PC is the principal component a_i (i=1,2,...n) exploratory variables and x_i (i= 1,2,...n) eigenvector loading of the Principal component. The predictive mineral potential maps of the study area were produced using equation (1) which was applied to the entire study area, and subsequently maps of these potential zones classified into favourability maps using probability index on scale of 5 (Figures 3 -5).

Results and Discussion

The Principal component analysis operation is mathematical method to uncover relationships among many variables and to reduce the amount of data needed to define the relationships to a manageable level. With Principal component analysis,

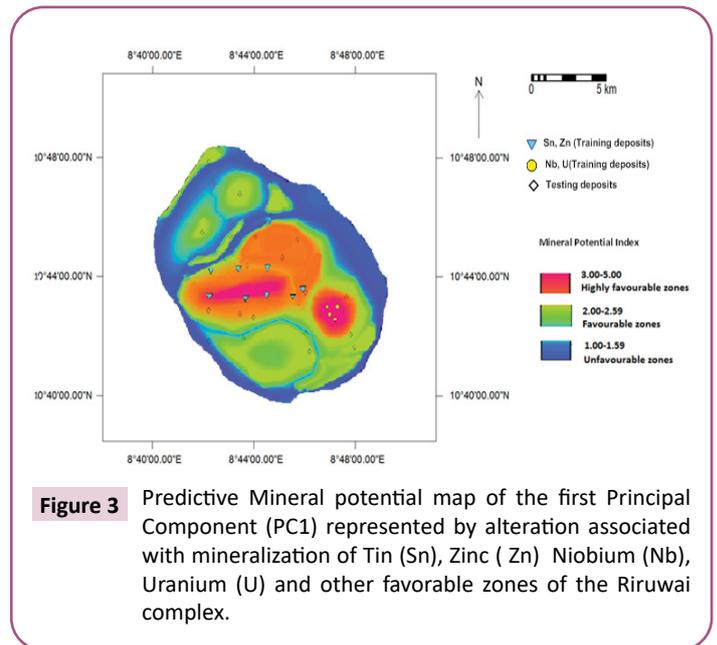


Figure 3 Predictive Mineral potential map of the first Principal Component (PC1) represented by alteration associated with mineralization of Tin (Sn), Zinc (Zn) Niobium (Nb), Uranium (U) and other favorable zones of the Riruwai complex.

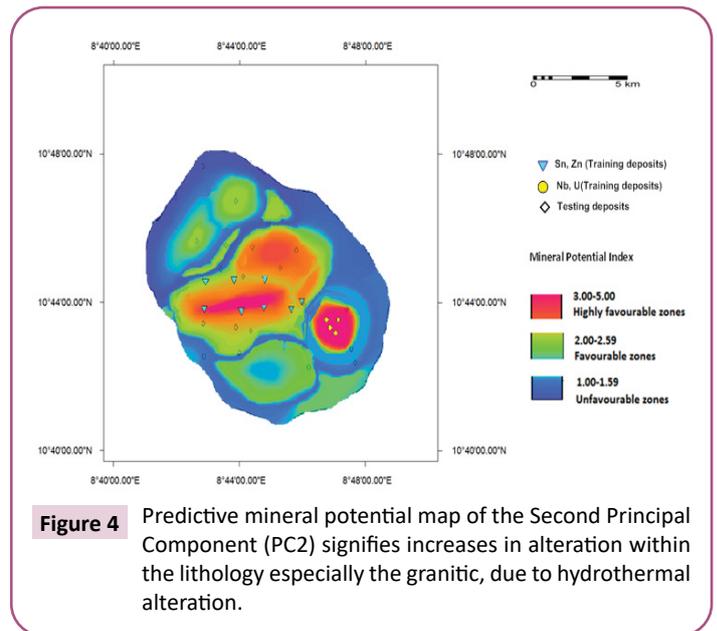


Figure 4 Predictive mineral potential map of the Second Principal Component (PC2) signifies increases in alteration within the lithology especially the granitic, due to hydrothermal alteration.

each variable is transformed into a linear combination of orthogonal common component with decreasing variation. The linear transformation assumes the component will explain all of the variance in each variable [24,25], have noted that an advantage of using PCs over a prior or user-defined group of elements as variables for investigation is that they represent linear combinations of elements that are likely controlled by mineral stoichiometry. Such linear relationships may provide a more realistic representation of geological variability and mineralization (Table 1).

The PC1, PC2 and PC3 accounted for over 50% of the total variability in the original data. The first principal component (PC1) has the highest percentage variance of 21.54%. The second potential (PC2) with 20.84% and third principal (PC 3) with 10.78% highlight the mineral potential zones.

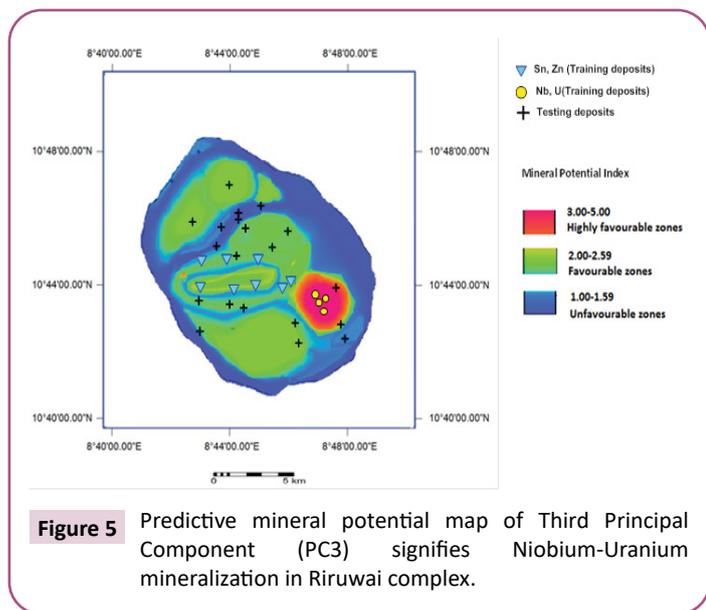


Figure 5 Predictive mineral potential map of Third Principal Component (PC3) signifies Niobium-Uranium mineralization in Riruwai complex.

Table 1 Principal components of exploratory variables of the rocks of Riruwai complex.

Exploratory Variables	Principal Components				
	1	2	3	4	5
SiO ₂	0.47	-0.35	-0.4	-	-
Fe ₂ O ₃	-	-0.42	-	-	-
CaO	0.54	-0.45	-	-	-
Na ₂ O	-0.42	-	-0.55	-	-
K ₂ O	0.44	0.35	-	-	-
TiO	-	-0.33	-	-	-
Al ₂ O ₃	-	-0.45	-	-	-
V	-	-	-	0.53	-
Cr	-	-	0.4	0.54	-
Cu	-	-	0.41	-	-
Sr	-	-	-	-	0.32
Zr	-	-0.38	0.32	-0.4	0.31
Ba	-	0.6	-	-0.3	-
Zn	0.74	-	-0.56	-	-
Ce	0.77	-	-	-0.3	-
Pb	0.69	-	-	0.31	-0.4
Sn	0.87	0.39	-	-	-
Ga	0.86	-	-	-	-
Y	0.94	-	-	-	-
Ni	0.33	-0.44	-	0.45	-
Rb	0.78	0.44	-	-	-
Nb	0.92	-	-0.62	-	-
La	-	-0.36	-	-	-
Eu	0.52	-0.43	-	-0.3	0.34
Mo	0.3	-	-	-0.4	-
Co	-	-	0.47	-	-0.5
Ta	-	-	0.42	-	-
W	-	0.44	-	-	-0.5
Hf	0.92	-	-	-	-
Pr	0.78	-0.4	-	-	-
Lu	0.87	-	-	-	-
Gd	0.74	-0.41	-	-	-

Exploratory Variables	Principal Components				
	1	2	3	4	5
U	0.94	-	0.41	-	-
Th	0.94	-	-	-	-
Nd	-	-0.5	-	0.36	-
Magnetic Anomaly	-	0.49	-0.44	0.46	0.33
Ternary Radiometric	0.7	0.35	-	-	0.4
K/U	0.46	-	-0.77	-	-0.4
K/Th	0.68	0.79	-0.65	-	-0.4
Structures	0.57	0.54	-0.45	-	0.31
Geology	0.57	0.64	0.44	-	-
Altered zones	0.62	0.63	-	-	-
Standard deviation	0.38	0.37	0.27	0.25	0.24
% of variance	21.5	20.8	10.8	9.31	8.76

Validation of mineral potential maps

The mineral potential maps were validated by comparison with known mineral deposit locations and for this, the success rate curves were calculated for quantitative prediction and area of under the curves was calculated. The rate shows how well the integrated approach and factors predict the mineral deposit occurrence. Thus, the area beneath the curve qualitatively assesses the prediction accuracy. The calculated index values of all the pixels in the study area were ordered in descending order to obtain relative ranking for prediction pattern. The ordered pixel values were then divided into 100 classes with accumulated 1% intervals. The validation rate appears as a graph. The validation rate appears as a graph (Figure 6). For 75-100% class (25%) in which the mineral potential index had a high rank could explain over 80% of all the mineral deposit occurrences. Ground truthing indicates that the potential zones of the mineral deposit occurrences are accurately delineated. The results are satisfactory and useful as model for further exploration of undiscovered mineral potential zones of the same geological setting and or other settings where similar evidences may occur.

Implication for mineralization and predictive mineral potential zones

The PC1, PC2 and PC3 accounted for over 50% of the total variability in the original data. The PC1 of the Riruwai data variability reflects 21.54% which represent background population of the study area and also reflects the combined effect of the lithology, geophysical and geochemical controls. The high loading and moderately positive loading on the components explain background geology of the Riruwai Complex represented by alteration associated with mineralization of Tin (Sn), Zinc(Zn), Niobium (Nb), Uranium (U),Thorium (Th).

The PC1 which also has high loading (0.92) Niobium (Nb) reflects its presence in pyroclore in the Kaffo albite arfvedsonite granite. Mineralization of the granite according to Ogunleye et al. [12], is a product of both the development of an alkali volatile-rich phase during the magmatic stage and auto-metasomatic process of albitization close to the period of consolidation of granite. The positive loading (0.57) on structures in PC1 suggest significant role structure played in mineralization in the Riruwai Complex

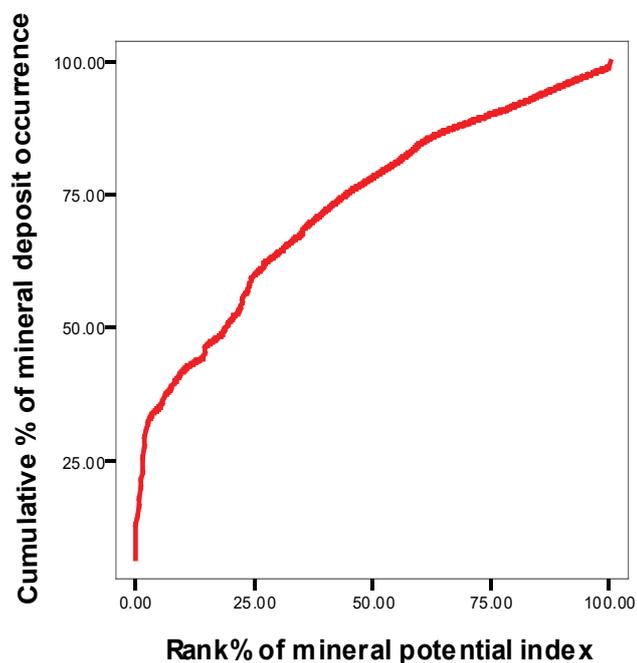


Figure 6 Cumulative frequency diagram showing rank (%) of mineral potential index (x-axis) occurring in cumulative percent of mineral deposit occurrence (y-axis).

providing the pathway for mineralizing fluid. The Riruwai lode which is extensively mineralized is most significant and consists of series of parallel to sub parallel or braided quartz vein enclosed by zones of grey greisens grading outwards into reddened wall rock and occasionally through a narrow buff-coloured zone out into the pale pink equigranular biotite perthite granite it contain disseminated columbite and also host Zinc (Zn), Tin (Sn) mineralization.

The PC2 of the study area has data variability of 20.84% represented by Y, La, Sn, Zr, Zn, Ni, Ta, U and K count all of them with negative weights, i.e., this component is more important where these elements don't present high values. Thorium (Th) count with positive loading on the lithology and altered zones signifies increases in alteration within the lithology especially the granitic rocks. It played major role in the oxide deposition and this could possibly explain hydrothermal alteration which began with potash metasomatism and perthic feldspar. They enhance mineralization associated with potash metasomatism which includes disseminated oxide assemblage dominated by cassiterite and wolframite with tabular crystals of monazite, zircon and columbite crystals. Data variability of 10.78 is accounted for by PC3.

The high positive loading with respect to U count, Ta, Cr, U, and Zr with negative loading with respect to Nb, K/Th, K/U, total magnetic count and Zn can be interpreted as indicating pyrochlore mineralization. The low score on the total magnetic intensity and ternary radiometric count show correlation of mineralization of economic importance which is confirmed by the high loading on the Uranium. The data variability of 9.51% is given by PC4 with positive loading (0.31) Lead (Pb) probably indicating Pb anomaly represented by PbS (galena) mineralization. High

loading (0.40) radiometric count of PC5 signifies mineralization due to alteration which reflects the potassium enrichment associated with the mineralization within the lithology.

The principal component analysis has been used to study and identify the alteration zones and mineralization characteristics of intrusion in the Xiemisitai area, west Junggar, Xinjiang China by Liu et al. [26], the alteration mineral were mapped using Crosta technique, a principal component analysis based method using the association band 1, 3, 4 and 7 for extracting hydroxyl-bearing and carbonate minerals and that of band 1, 3, 4 and 5 for iron oxides and in targeting new mineralization. The geological map was overlapped by the remote sensing data.

The incorporation of other geological dataset which strengthen the prediction of mineralization with more certainty. In gold mineralization and lithostratigraphy study of the Agnew Gold Mine, Western Australia by Fisher, et al. [27], made use of only chemical elements, comprises a series of discrete lodes located along a sheared mine corridor. To differentiate between lithological variations and hydrothermal alteration in the geochemical data, a robust PCA was carried out to limit the impact of outlying data points. The eigenvectors for K and Ba show an antipathetic relationship to the Ca-As-Au trend, suggesting that although these elements are not controlled by lithology they are not part of the alteration assemblage associated with mineralization either, and that the mineral phases that host K and Ba may be replaced during alteration associated with mineralization. The PCA explore elements associated with Au mineralization. This association also played a major in this present work which has more geological variables and reflects the combined effect of the lithology, geophysical and geochemical controls in the Riruwai complex, thus enhancing more areas of mineralization.

Looking at the Lanping basin area of China with copper, lead and zinc mineralization [5]; Abra area of Philippines with porphyry copper potential [28]; Sanjiang region Southwestern China mineral-resource prediction and evaluation [29]; Central Lapland Greenstone Belt of Finland gold occurrences and deposits [30,31] and epithermal –gold deposits in Great Basin of western United State where weight of evidence (WofE) has been engaged to delineate zones with potential for mineralization which has positive spatial association between prospects and spatial evidence, proportion of number of prospects in zones where spatial evidence is presence and the geological interpretation of positive spatial association between prospects and spatial evidence. The PC1, PC2 and PC3 of the Riruwai Complex highlight the areas with mineral potentials: Sn, Nb, Ta, Zn, Zr, U, Th. This technique is also found useful and appropriate for delineating of mineral potential zones which in turn provides information about mineralization type. The integrated approach not only predict known areas of mineral occurrence (Sn, Nb, Ta, Zn, Zr, U, Th), but also identify areas of favourable mineralization potential. Robust correlations between different rock units and identification of alteration or mineralogical associations that are not evident in two dimensional plots are often readily identified through principal component multivariate approaches.

Conclusion

The integrated study of the Riruwai Complex involves analysis dataset of whole rock geochemical data, airborne magnetic, airborne radiometric and Landsat ETM+ data in a GIS system. The Principal component analysis (PCA) is particularly helpful in anomaly detection since it can reduce the data dimensionality into a smaller set of independent variables. The technique is found useful in delineating mineral potential zones by providing some information about the mineralization type which includes Sn, Nb, Ta, Zn, Zr, U and Th. Data driven approach were used

to study the spatial association between known mineral deposits and the geological features. Among the lithologic units, the medium grained biotite granite, Kaffo albite arfvedsonite granite and aegirine arfvedsonite granite were found to be important host for Tin – Niobium (Sn-Nb) mineralization in the Riruwai Complex. Validation conducted on the mineral potential map by ground truthing indicates that the potential zones are accurately delineated. The results are satisfactory and useful as model for further exploration of undiscovered mineral potential zones of the same geological setting and or other settings where similar evidences may occur.

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