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RESEARCH ARTICLE

USING GIS AS A SPATIAL SUPPORT TOOL TO DISCRIMINATE BETWEEN TRUE AND FALSE GEOCHEMICAL ANOMALIES AT THE NORTHERN MARGIN OF THE ASANKRAGWA GOLD BELT IN THE PALEOPROTEROZOIC KUMASI BASIN, GHANA

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ABSTRACT

This study uses Geographical Information Systems (GIS) as a support tool for gold exploration to distinguish between true and false soil geochemical anomalies at the northern segment of the Asankragwa gold belt in the Paleoproterozoic Kumasi Basin, Ghana. The main objective of this study is to identify potentially mineralized zones within the northern segment of the Asankragwa gold belt by integrating GIS, structural and soil geochemical datasets. To reduce the probability of delineating false anomalies as true anomalies, diverse graphical threshold determination methods, namely histogram, box plot, QQ plot, mean+2SD, Jenks Natural Break and Probability plot, as well as advanced threshold determination methods like the Mean Absolute Deviation (MAD) and double MAD were employed. The threshold values established from the graphical methods are 175 ppb, 96 ppb, 335ppb, 384 ppb and 100 ppb respectively. However, the MAD and double MAD methods produced threshold values of 74.5ppb and 130ppb respectively. Based on the high variability in the threshold values, anomalous areas were delineated using thresholds values of 100ppb and 130ppb respectively established from the Jenks Natural Break and Probability plot and double MAD method. About 40%, 35% and 20% of the selected anomalous areas are located within soils overlying volcanoclastic, clastic sedimentary and marine volcanoclastic rocks respectively. These anomalies are not lithologically controlled since they are not confined to a particular rock type. Superimposing the selected aanomalies over geological structures and Landsat imagery, 90% of the anomalies can be linked to the NE-SW geological structures. Upon integrating the anomalies with structural data and illegal mining activities and using the Booleon analysis, not all anomalies may be true anomalies. True gold anomalies within the Asankragwa gold belt are consistent with the central> northern> southern portions. Hence, the discovery of gold in the Asankragwa gold belt has been enhanced using GIS as a spatial support tool.

KEYWORDS

Geospatial, Remote sensing, GIS, Geochemical anomalies, Threshold, Asankragwa gold belt

1. INTRODUCTION

Geological data is mostly heterogeneous and does not follow a normal distribution (Carranza, 2009). Hence, it is difficult to choose a robust threshold detection method that will not be affected by complex distribution properties (Reimann et al., 2005). Geochemical exploration methods, which often extract anomalies based on classical statistical and frequency methods (such as histogram construction, Q-Q plots, probability plots, and box-plot) are commonly used for anomaly separation (Sinclair, 1974, 1991; Hoang & Nguyen, 2016; Barati et al., 2018). These methods are subjective and not very suitable for outlier detection. Hence, graphical data inspection is often recommended to determine inherent distribution for possible outlier identification and better comprehension of the geochemical data before applying any advanced statistical technique (Filzmoser, 2000). Researchers in 2005 suggested that statistical methods are more suitable for determining thresholds than frequency methods (Reimann et al., 2005).

In exploration geochemistry, values within the range mean plus or minus two standard deviation ($\mu \pm 2\sigma$) are often defined as the geochemical background, which is a range and not a single value (Reimann et al., 2005). Unfortunately, the mean plus or minus two standard deviation method (($\mu \pm 2\sigma$)) breaks down when used to analyze data that is not normally distributed. This may result in generating thresholds that yield false anomalies. Generally, it is expected that using data that is log-normalized should generate better results, however, the core of the problem is that the standard deviation is based on squared distances, so extreme points are much more influential than those close to the mean. More so, this method is very unlikely to detect outliers in small samples (Cousineau and Chartier, 2010; Reimann et al., 2005). The Median Absolute Deviation (MAD) seemed to be a better option than the $\mu \pm 2\sigma$ since it is immune to the sample size and strongly overestimates the number of outliers (Hampel, 1974; Leys et al., 2013; Reimann et al., 2005). However, the MAD breaks down when about 50% of the values are finite. Further, when the distribution is unsymmetrical, the standard deviation (σ), mean (μ) and MAD all break down since they all apply the same cut-off. Under such circumstances, the double MAD (median ± 2MAD) is the best option. The double MAD works well with different kinds of non-parametric distributions, including nonsymmetric and bimodal data sets (Rousseeuw & Croux, 1993); however, these statistical methods are somewhat

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arbitrary because they exchange the real geochemical landscape for formal statistical or mathematical models (Sinclair, 1991). Furthermore, it is a very difficult task to properly identify and establish thresholds, particularly when the study area has many factors such as soil types, geologic units, climatic zones and land use. A threshold that is too low may result in high exploration costs.

Locating the exact spatial extents of an ore body with only the traditional exploration method is sometimes difficult due to geological heterogeneity (Ombiro et al., 2021), hence, using one technique is not adequate for locating areas of probable mineralization. To reduce this uncertainty and depending on the characteristics of mineralization and host rock, it is always advisable to incorporate different methods in the determination of the anomalies to help screen off false anomalies. It is, therefore, of major essence that Geographical Information System (GIS) techniques are incorporated with statistical methods to ensure significant derivation of true anomalies. Employing spatial information for the identification of anomalies in exploration geochemistry results in a less subjective process than other traditional approaches (Cheng et al., 1996). Recent developments from remote sensing/GIS approaches have been invaluable for exploring a wide range of mineralization across numerous mineral belts around the world (Ahmadirouhani et al., 2018; Mirzababaei et al., 2016; Pour & Hashim, 2015). Remote sensing/GIS dataset remains the most suitable technique owing to its ability to map and delineate hydrothermal alterations as well as geological structures associated with gold occurrence (Adekeye et al., 2015; Garba, 1988; Oke et al., 2014; Tende et al., 2021).

In Ghana, the Asankragwa gold belt (Figure 1a) has been a focus of gold exploration for many years. There is limited information that relates geological structures and geochemistry to GIS on this belt since most researchers (Adomako et al., 2022; Amoah et al., 2021; Tourigny et al., 2019; Amedjoe et al., 2016) centered on the gold mineralization potential over some small portions of the northern part of the belt. This research seeks to delineate gold potential zones within the Asankragwa gold belt in the Paleoproterozoic Kumasi basin of Ghana using GIS as a spatial support tool.

2. Materials and Methods

2.1 Study area

The Asankragwa gold belt has a thrusted structural contact within the Kumasi Basin which forms part of the Archean to Paleoproterozoic Man Shield mainly consisting of NE-SW trending metasedimentary and metavolcanic rocks of the Paleoproterozoic Birimian Supergroup (Lompo, 2010; Jessell et al., 2012; Brako et al., 2020). The metavolcanic units that have been intruded by belt-type granitoids are unconformably overlain by the Tarkwaian Group and represent erosion products of the Birimian Supergroup (Leube et al., 1990). The metasedimentary units are intruded by basin-type granitoids. The Birimian Supergroup in the Kumasi basin comprises metasedimentary rocks (wacke, sand- and siltstone and phyllites), fault-bound slices of metavolcanic rocks (basaltic, dacitic and rhyolitic flows and minor interbedded volcaniclastics) and granitoids of the Eburnean plutonic suite that intruded the basin sequences from ca. 2116 to 2088 Ma (Adadey et al., 2009).

Locally, the Asankragwa area (Figure. 1b) is truncated to the southwest and northern parts by large granitoid batholiths. The geology is characterized by thick sequences of metasedimentary rocks mainly greywacke, argillite and phyllite. Regional traverses and airborne geophysical data indicate the presence of extensive volcaniclastics with narrower mafic flows and mafic sills (Griffis, 1998). The dominant intrusive body is the basin-type granitoid, consisting of coarse and medium-grained adamellite and granodiorite. The principal drainages in the central Kumasi Basin are the Offin and Oda rivers. Gravels in these rivers are partially sourced from known mineralized trends in the Kumasi Basin.

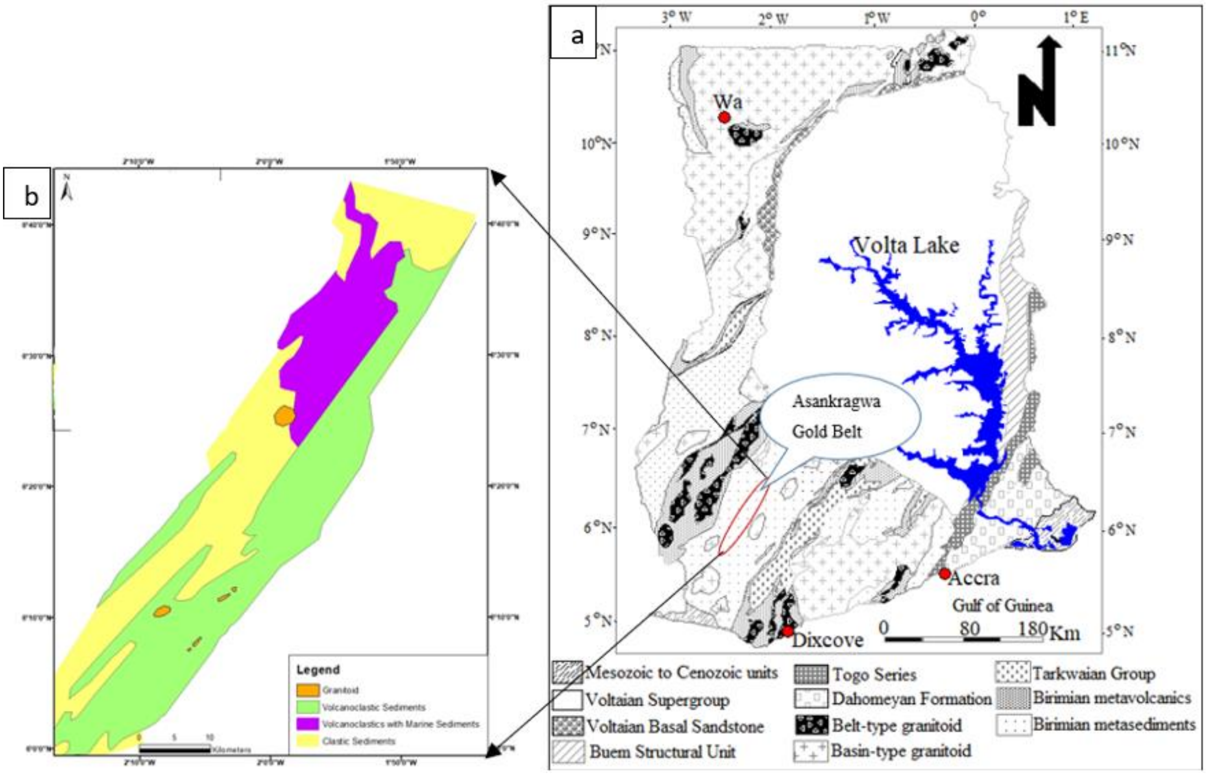

Figure 1: a) Geological map of Ghana (after Petersson et al., 2018) insert is the Asankragwa gold belt (study area) b) local geological map of the study area

2.2 Methodology

Quality control and quality assurance checks were performed to check the precision and accuracy of samples as well as contamination of samples at any stage of the process right from sampling in the field through to laboratory analysis. Confirmation of coordinates for geochemical data was done with geospatial techniques. A histogram was generated to observe how the gold was distributed within the area (Figure 2). Frequency analysis such as the histogram, box plot, QQ plot, Mean+2SD and Jenks Natural Break and probability plot was also used to determine the threshold of the geochemical data. Advanced methods of determining thresholds, such as MAD and double MAD, were also considered in the determination of the threshold for the geochemical data. The threshold obtained using the double MAD method was then used to create thematic maps to determine the anomalous areas. The geochemical anomaly obtained was then integrated with other spatial data mainly geological, Landsat and structural information after which Booleon analysis was done to aid in determining the true anomalies.

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3. Results and Discussion

3.1 Statistical Analysis

Before applying map visualization and analytical procedures, geochemical data may be evaluated to characterize its statistical distributions (Howarth, 1983). Descriptive statistics including histograms and normal probability plots were done to provide insights into the statistical distribution of the geochemical data. Most of the samples understudy have gold values ranging between 0 ppb to 1000 ppb (Figure 2).

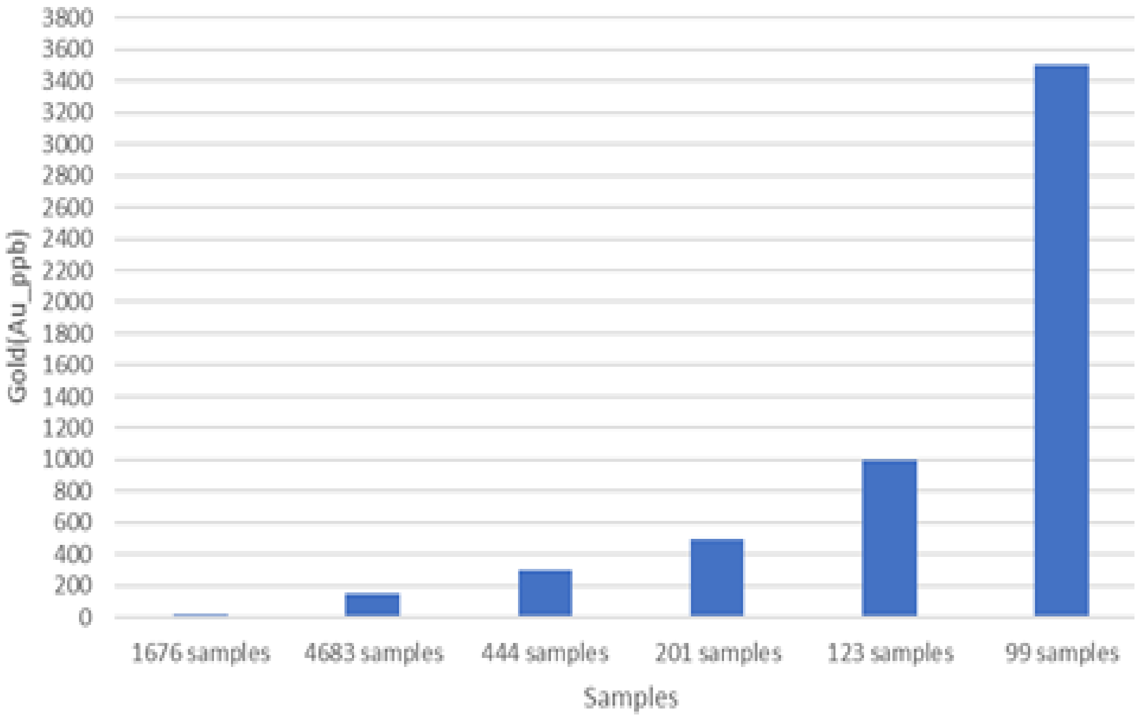

Figure 2: Distribution of Gold within the study area

After log transforming the data about seven different populations were derived from the dataset. The first break-off from the histogram chart is around 175ppb (Figure 3a). Normally when one is using the histogram to determine the threshold, the first break-off in trend is the threshold value. Therefore, the threshold value for the soil samples in the study area is 175ppb and anything between 0 to 174ppb will be considered as the background (Figure 3a). A graphical analysis of the box plot shows a threshold value of 96ppb (Figure 3b). Using just the box plot (Figure 3b), a background range of 0 to 96ppb is chosen. This approach might be cumbersome, as indicated by the significant variance in threshold between the box plot and the histogram analysis hence the need to consider an alternative method.

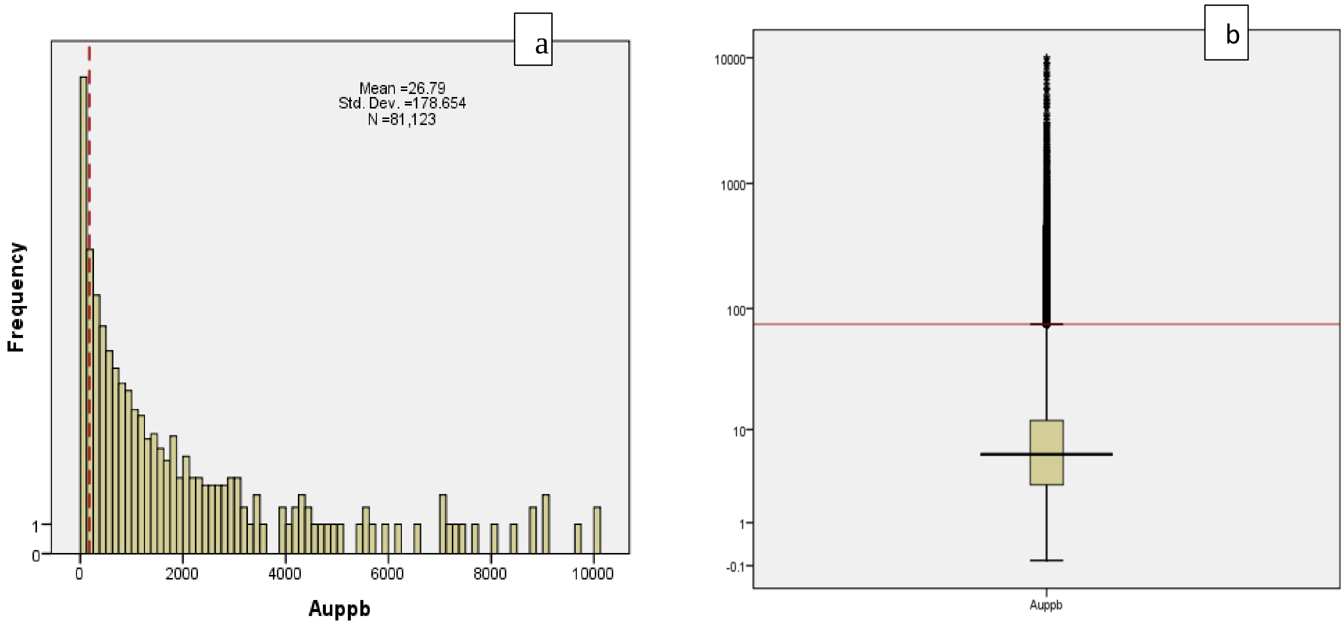

Figure 3: Threshold gold values estimation for soils in Asankragwa gold belt using a) Histogram b)Box plot

A threshold of about 335 ppb was also established using the QQ plot (Figure 4a). Commonly, a log-normally distributed population of background samples may constitute one population while samples near the ore and affected by dispersion can be considered as a second population. However, samples related to different rock types or unusual aspects of the environment may define additional populations (Rose et al., 1979). Since it is difficult to conclude on only the graphical methods the probability plot method in conjunction with the Jenks method for threshold determination which reduces within-class variance while maximizing between-class variance was employed. A threshold of 100ppb was obtained using the Jenks Natural Break and probability plot (Figure 4b).

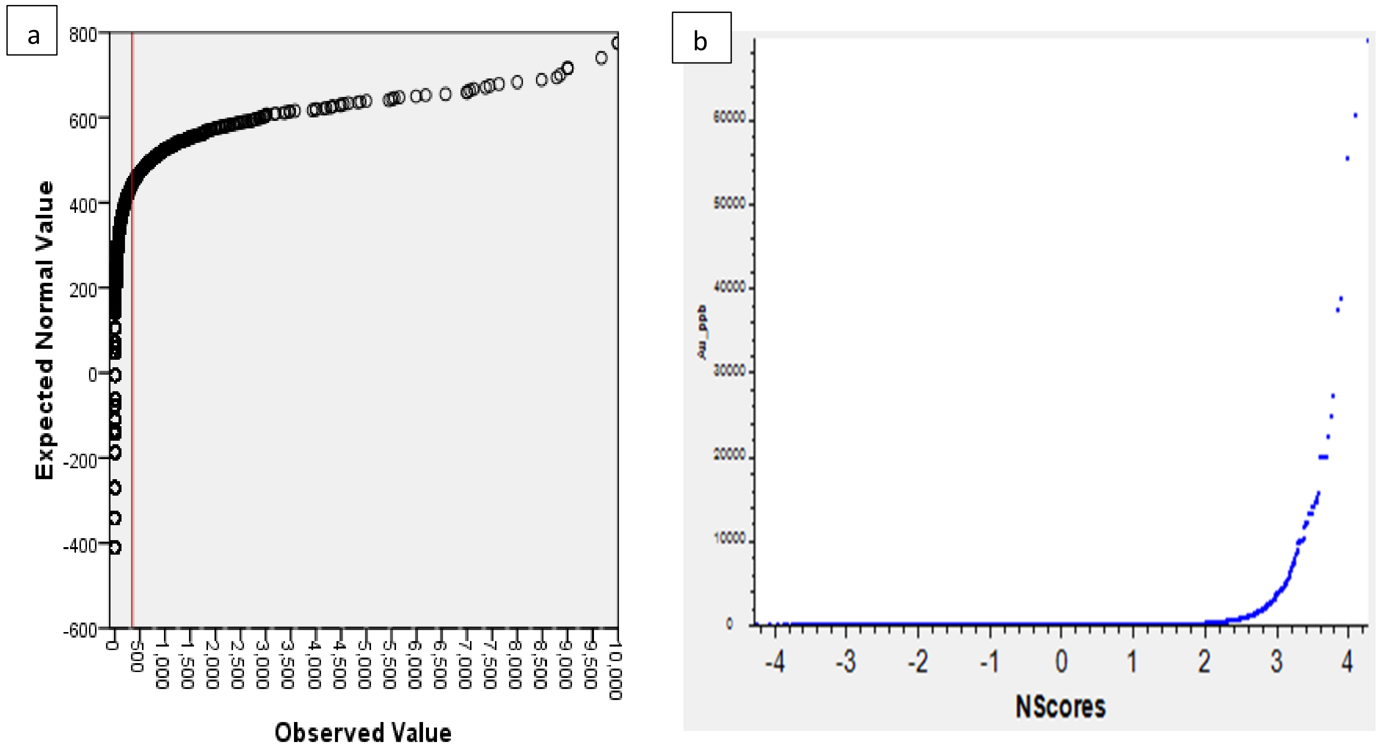

Figure 4: a) QQ plot of soil samples b) Analysis of gold distribution within soils using Jenks Natural Break and probability plot

The standard deviation method, the MAD and the double MAD methods were also considered since they offer a better threshold than the graphical methods which are subjective. It was observed that the μ ±2σ method breaks down when used to analyze data that is not normally distributed. This may result in generating thresholds that yield false anomalies. Generally, it is expected that using data that is log-normalized should produce better results, however, the core of the problem is that the standard deviation is based on squared distances, so extreme points are much more influential than those close to the mean.

The double MAD works well with different kinds of non-parametric distributions, including nonsymmetric and bimodal data sets (Rousseeuw & Croux, 1993) and hence was selected for use in the analyses. The double MAD was finally selected since it is immune to sample size and can manage non-symmetrical data than all the other methods that have been used earlier on. This gave a threshold value of 130 ppb (Table 1).

Table 1: Statistical analysis of soil geochemical data for threshold determination

Lithological type	QQ Plot	μ+2σ	Jenks Natural Break and Probability plot	MAD	Double MAD
All Soils	335	384	100	74.5	130
Clastic Sedimentary	900	357.7	170	41.9	172.3
Volcanoclastic Sedimentary	1290	376.9	130	44.14	107.3
Volcanoclastic and Marine Sediments	1350	392.56	185	54.35	197

The μ ±2σ gave a very high threshold to the effect that the mean and standard deviation that are being used to spot outliers are themselves strongly affected by the outliers. The core of the problem is that the standard deviation is based on squared distances, hence, extreme points are much more influential than those close to the mean.

The MAD has the best possible breakdown point (50% twice as much as the interquartile range), and its influence function. However, if the distribution is unsymmetrical then the MAD also becomes inappropriate to use for threshold determination. In this case, the standard deviations from mean and MAD from median strategies both prove to be inappropriate for use. Unfortunately, the MAD applies the same cut-off to both tails of a sample, even if one tail is far longer than the other. In such cases, it is best to use a more sophisticated strategy for flagging outliers. The double MAD was used to see how best the drawbacks observed with the MAD could be resolved. The double MAD method worked great for the left-skewed, right-skewed, and other kinds of nonsymmetric distributions which are mostly encountered in exploration data. Therefore, the threshold of 130ppb which was obtained using the double MAD was used to determine anomalies. Based on the selected threshold value, the soil samples were grouped into five population groups. From the population groups (Table 2), the background range has about 8338 samples which constitute about 92% of the entire samples.

Table 2: Population groups of soil samples

From	To	Percentage of samples	Number of samples
0	130	92.04	8338
130	2000	7.65	693
2000	5000	0.19	17
5000	10000	0.08	4
10000	>10000	0.04	7

3.2 Spatial and thematic data analysis

The locations of residual soil samples were plotted over the geology of the area (Figure. 5a). Most of the soil samples are located within clastic and volcaniclastic sedimentary rock domains while only about 10% of the soil samples are underlain by granitic rocks. Thematic analysis is a powerful yet flexible method for analyzing qualitative data that can be used within a variety of paradigmatic or epistemological orientations (Kiger & Varpio, 2020). Five population groups were used to generate the thematic map based on the derived threshold (Figure.5b).

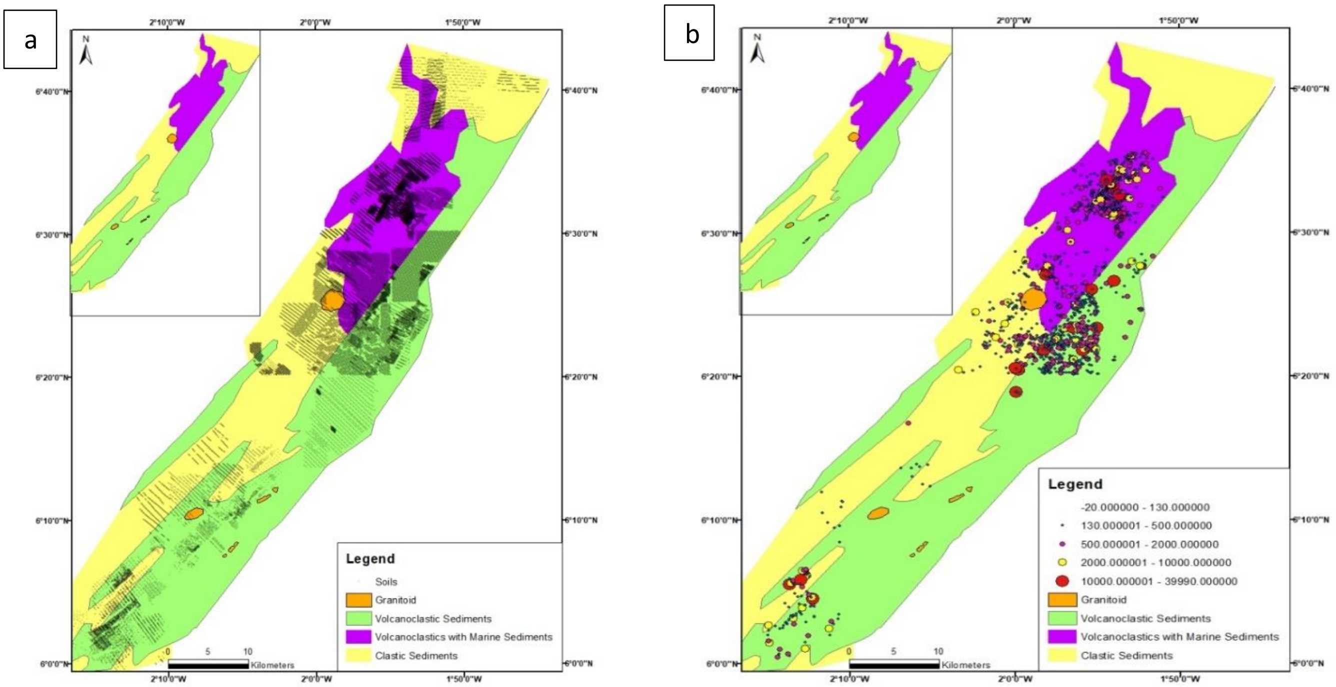

Figure. 5: a) Map showing the locations of Soil Samples b) Thematic Map of soils

This geospatial technique has been very helpful in identifying the themes and patterns in the data. A threshold of 130 ppb yields anomalies close to the northern and southern parts of the study area. Conversely, the mid-section of the area seems to have very few gold values. The thematic maps (Figures 6a and 6b) were then used to delineate anomalous areas using a threshold of 100ppb and 130ppb respectively.

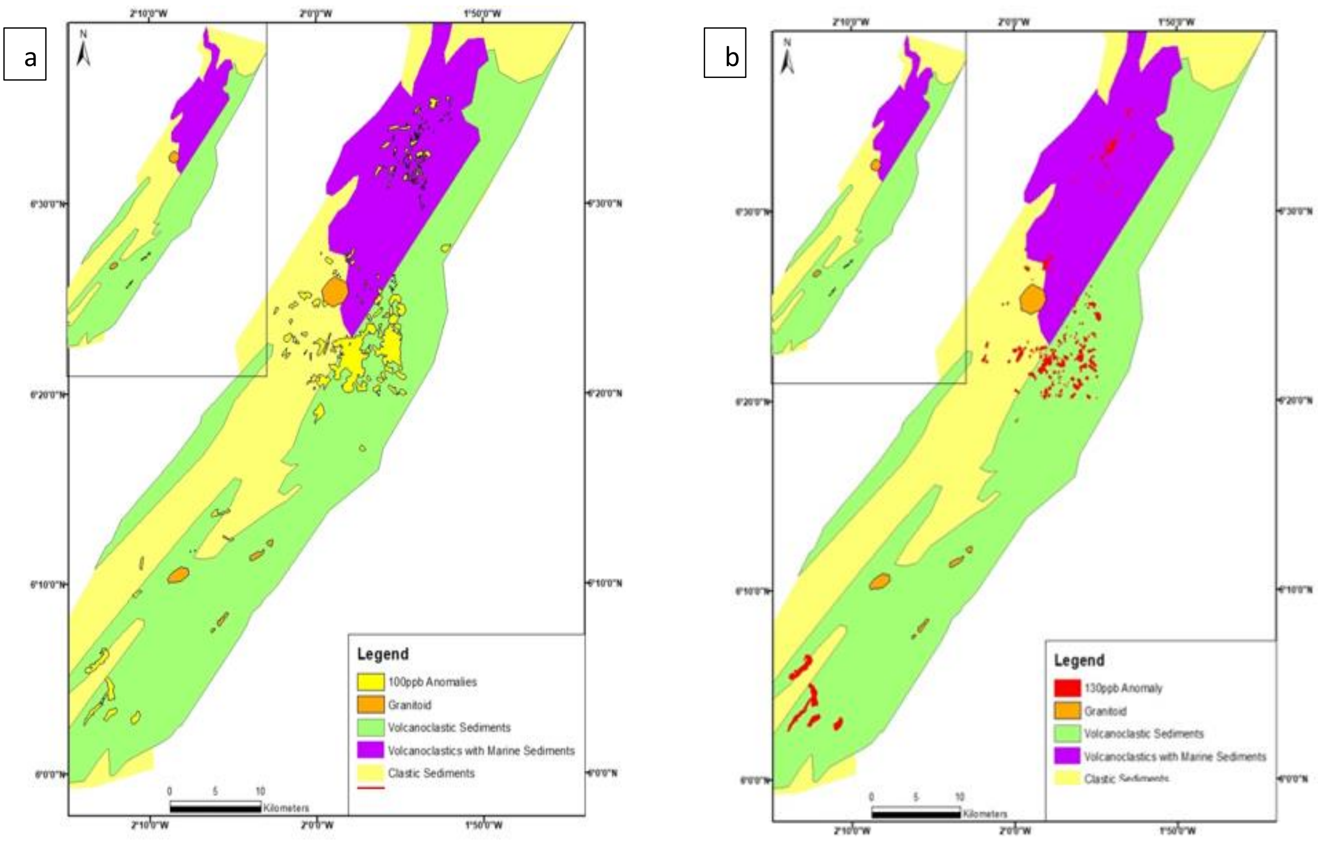

Figure 6: a) Anomalies generated from soils at 100ppb Threshold b) Anomalies generated from soils at 130ppb Threshold

3.3 Integrating statistical analysis with geographical information techniques.

The main purpose of anomaly assessment is to select areas that can be prospected effectively. Even though anomalies have been outlined, there is a need to determine whether the anomalies are significant or not. Anomalies generated using the threshold of 130ppb were overlaid on the already existing 100ppb anomaly (Figure. 7) and most of them have reduced in size as compared to the 100ppb anomaly. About 40% of the anomalies are located within the volcanoclastic sediments while about 35% are within the clastic sedimentary rocks. The marine volcanoclastic rocks seem to host about 20% of the gold anomalies in the area. This suggests that the anomaly is not lithologically controlled since it is not confined to a particular rock type.

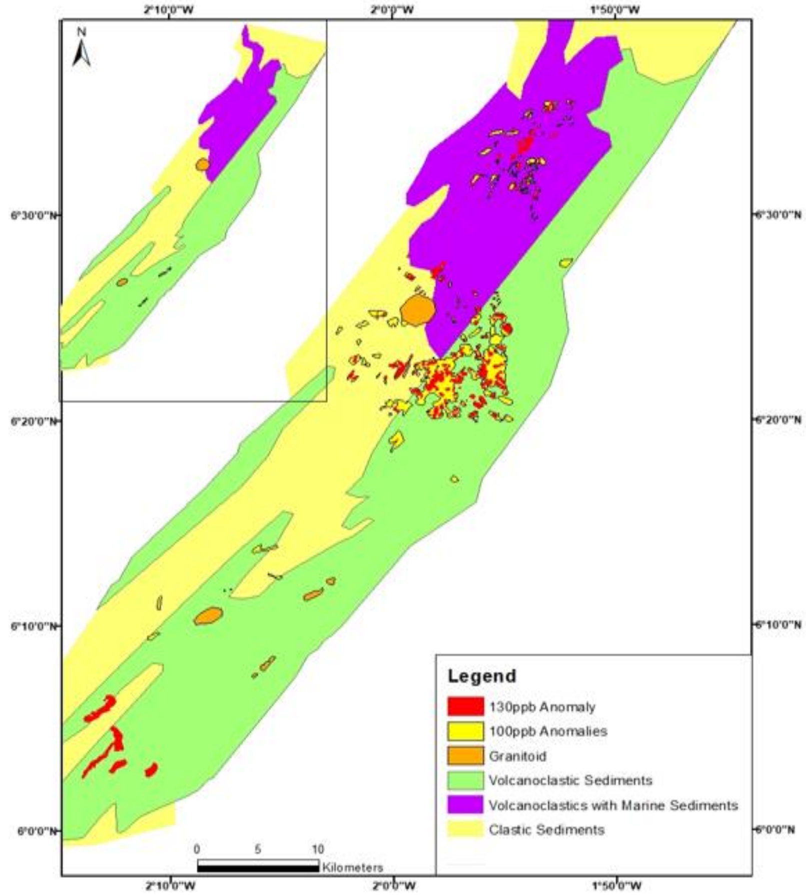

Figure 7: Comparison of anomalies generated from 130ppb threshold to 100ppb threshold

Separating geochemical data into background and anomalous populations is mainly a statistical process that does not necessarily account for spatial variations due to geological, chemical and physical factors that may also affect the anomalies. Therefore, it is very necessary to screen the anomalies for other effects that are not related to alteration or mineralization. Some of the anomalies may only be due to slope variation, analytical variation, different sampling media as well as sample spacing variability or may be related to alteration/mineralization. From Figure 8, it is observed that most of the anomalies are consistent with the major NE-SW structures on the Asankragwa gold belt. However, about 10% of the anomalies have no link with any structure.

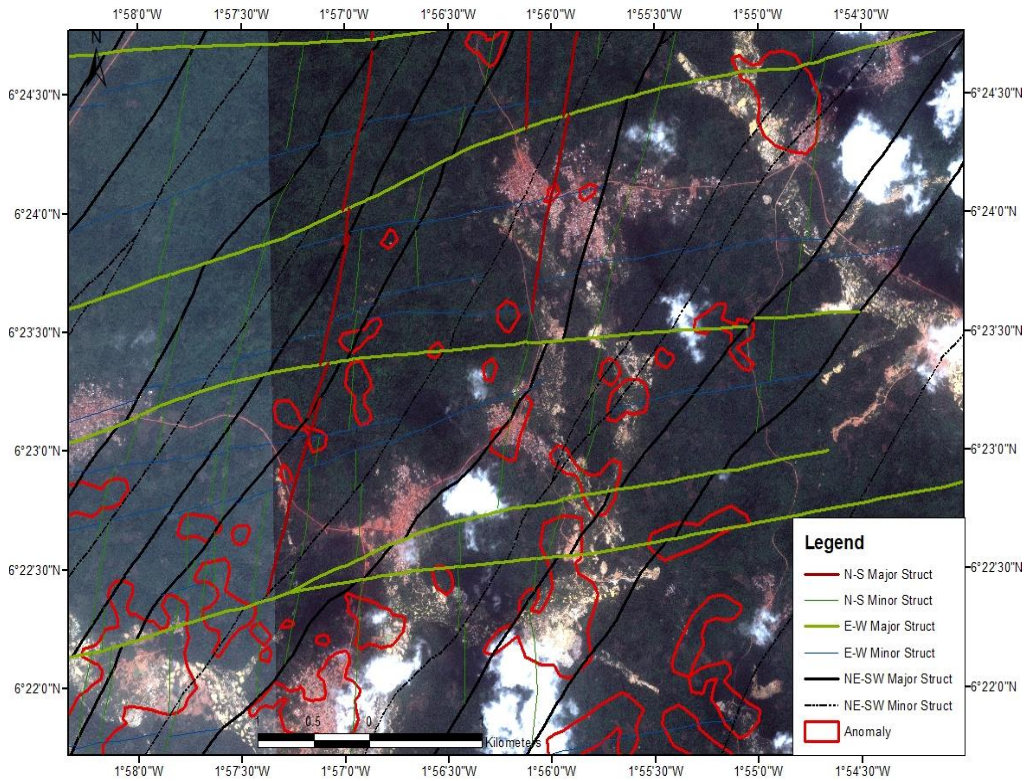

Figure 8: Anomalies over geological structures and Landsat imagery

Application of methods for geochemical anomaly recognition can be misguided and possibly result in specious anomalies therefore, it is often advisable to confirm the existence of anomalies delineated. The use of traditional methods applied in mineral exploration is very efficient. However, their effectiveness in the identification of mineralized zones is often improved by integrating other mineral exploration techniques through GIS. When the different predictor patterns are superimposed on a map, using GIS to generate a mineral potential map makes it possible to easily give high priority to areas where the different layers are anomalous. Also, analyzing the superimposed datasets helps to easily draw concrete evidence about the existence of mineralization and also enhances the interpretation and understanding of the mineralization. In a structurally controlled deposit, anomalies that are related to structures have a high potential of being mineralized. Based on this, the relation between anomalies and structures was established using the Booleon analysis (Table 3).

Table 3: Booleon analysis of soil anomaly

Anomaly Code	E-W Major	E-W Minor	NE-SW Major	NE-SW Minor	N-S Major	N-S Minor	Galamesy Activities	AU	Rank	False Anomaly
21	Y	N	Y	N	N	Y	Y	Y	5	N
22	N	N	N	Y	N	N	Y	Y	3	N
23	N	N	N	N	N	N	N	Y	1	Y
24	N	N	N	N	N	N	Y	Y	2	N
25	N	N	N	N	N	N	N	Y	1	Y
26	N	N	N	N	N	N	N	Y	1	Y
27	N	N	Y	N	N	N	N	Y	2	N
28	N	N	Y	N	N	N	N	Y	2	N
29	N	N	Y	N	N	N	N	Y	2	N
30	N	N	Y	N	N	Y	N	Y	3	N
31	N	N	N	Y	N	Y	N	Y	3	N
32	N	N	N	N	Y	N	N	Y	2	N
33	N	N	N	N	N	N	N	Y	1	Y
34	N	N	N	N	Y	N	Y	Y	3	N
35	N	N	N	N	Y	N	Y	Y	3	N
36	Y	N	N	N	N	N	Y	Y	3	N
37	N	N	N	N	N	N	Y	Y	2	N
38	N	N	N	N	N	N	N	Y	1	Y
39	N	N	N	N	N	N	N	Y	1	Y
40	N	N	N	N	N	N	N	Y	1	Y
41	N	N	Y	N	Y	N	N	Y	3	N
42	N	N	N	N	Y	N	N	Y	2	N
43	Y	N	N	N	Y	N	N	Y	3	N
44	Y	N	N	N	N	N	N	Y	2	N
45	N	N	N	N	N	N	N	Y	1	Y
46	N	Y	N	N	N	N	N	Y	2	N
47	N	Y	N	N	N	N	N	Y	2	N
48	N	N	Y	Y	N	N	N	Y	3	N
49	N	N	Y	N	N	N	N	Y	2	N
51	N	N	N	Y	N	N	N	Y	2	N
52	Y	N	N	N	Y	N	N	Y	2	N
69	N	N	N	N	N	N	N	Y	1	Y
70	N	N	Y	N	N	N	N	Y	2	N
72	Y	N	N	Y	N	N	N	Y	3	N
73	N	N	Y	N	Y	N	Y	Y	4	N
74	Y	N	Y	Y	N	Y	Y	Y	6	N
75	N	Y	Y	N	N	N	Y	Y	4	N
76	N	N	Y	N	N	Y	Y	Y	4	N
77	N	N	N	N	N	N	N	Y	1	Y
78	N	Y	Y	N	N	N	N	Y	3	N
79	N	N	Y	N	N	Y	N	Y	3	N
80	N	N	N	N	N	N	N	Y	1	Y
81	N	Y	N	N	N	N	N	Y	2	N

* ***Yes=Y and No = N***

Areas where illegal mining (galamsey) has taken place, are places where there is high certainty that anomalies exist upon critical examination of remote sensing images and field observations. In view of this, illegal mining (galamsey) areas and structures were used to help in screening the anomalies obtained from geochemistry (Figure. 9). This will help distinguish true and false anomalies. Upon integrating the anomaly with structural data and illegal mining (galamsey) activities and using the Booleon analysis, it was observed that not all anomalies may be true anomalies. From the Booleon analysis, seven of the anomalies are unrelated to any geological structure or galamsey activities within the area (Figure 9) which may imply false anomalies. On many occasions, time and resources have been wasted in the drilling of false anomalies.

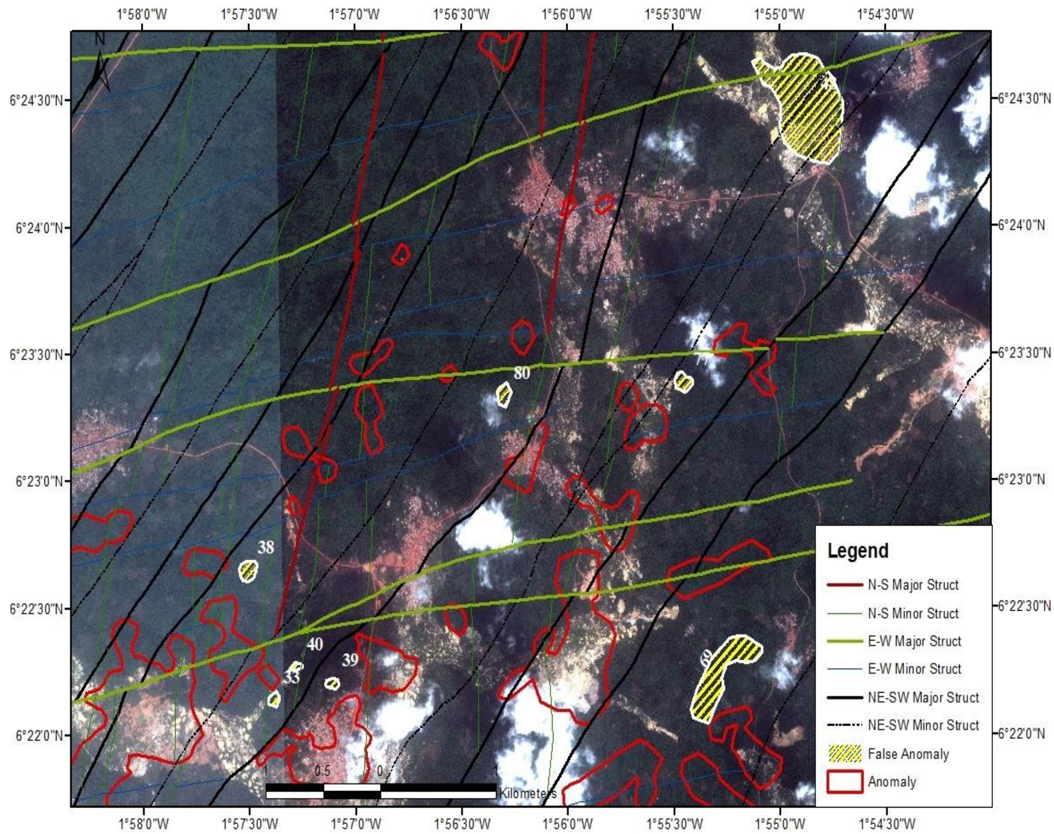

Figure 9: Screened anomalies over Landsat imagery

4. Conclusions

The northern segment of the Asankragwa belt is underlain predominantly by clastic and volcaniclastic sedimentary rocks and few granitic rocks. Most of the soil samples analyzed had gold values ranging between 0 ppb to 1000 ppb. Variable threshold values were established for gold in the study area using different methods. According to the histogram method, the threshold value for gold in the study area is 175ppb, and anything between 0 to 175ppb will be considered as the background. Meanwhile, the box plot shows a threshold value of 96ppb. Conversely, the threshold of about 335 ppb was also established using the QQ plot. 100ppb was obtained as the threshold using the Jenks and the probability plot. The double MAD method also produced a threshold of 130ppb, which was considered suitable for this study. Anomalous areas were delineated using thresholds of 100ppb and 130ppb respectively. About 40% of the anomalies are located within the volcanoclastic sediments while about 35% are within the clastic sedimentary rocks. The marine volcanoclastic rocks seem to host about 20% of the gold anomalies in the area. The anomalies are not lithologically controlled since it is not confined to a particular rock type, even though about 90% can be linked to the NE-SW geological structures. The integration of the obtained anomalies and the other datasets using GIS methods established that seven of the anomalies are unrelated to any geological structure and galamsey activities, which is indicative of false anomalies. True gold anomalies within the Asankragwa gold belt are consistent with the central> northern> southern portions. In this study, statistical analysis used in conjunction with geospatial techniques has proved very helpful in the screening of geochemical anomalies obtained from soil samples, however, further investigations (trenching or drilling) should be carried out over the selected anomalous areas for confirmation.

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