

International Journal of Advanced Geosciences

Website: www.sciencepubco.com/index.php/IJAG

Research paper



A GIS-based modified frequency ratio model for gold potential mapping in Kelantan Malaysia

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Abstract

Mineral system factors control the distributions of orogenic gold deposits in our immediate geological environment. The spatial knowledge of the relationship between the mineral factors and the gold deposits are crucial to locating these deposits in the environment. However, there is a current challenge in understanding the spatial correlation between ore genesis factors and orogenic deposits. Our paper analysed the spatial relationship between ore controlling factors and orogenic gold deposits in the Gua Musang area Kelantan, Malaysia. The procedure applied a modified frequency ratio model (MFR) to generate the gold potential map of the study area. The model relied on the spatial distribution of known gold deposits to predict new ones. Eight (8) known gold deposits and five (5) selected factors were used in the analysis. These factors include NE-SW lineaments, NW-SE lineament, host rock, heat source, alteration of iron and clay. The new findings show the factor with the highest predicting rate (Lineaments NE-SW) as the major gold deposits distribution factors within the study area. The created map highlight both known and new deposit locations. The area under curved (AUC) statistical graphs were used for the accuracy test. The results show 92.50% accuracy; thus, the approach is adaptable for gold mapping in Malaysia.

Keywords: Geographic Information System; Gold Deposits; Modified Frequency Ratio Model; Mineral Potential Mapping; Kelantan; Malaysia.

1. Introduction

Mineral system factors governing the distributions of orogenic gold deposits in geological terranes. The spatial knowledge of the relationship between the mineral factors and the gold deposits remains a prerequisite to locating these deposits in the environment. However, there is a current challenge in understanding the spatial correlation between ore genesis factors and orogenic deposits. Our paper analysed the spatial relationship between ore controlling factors and orogenic gold deposits in the Gua Musang area Kelantan, Malaysia. The state of Kelantan holds more than 50% of the gold deposits found in Malaysia (Khamar Shah, 2012). Mineral system factors distribute the gold deposits all over the country. The locating and finding of the deposits are usually expensive and time-consuming (Robert et al., 2007). Fortunately, prediction maps speed up exploration time and reduce cost. Early day exploration had mapped a considerable number of deposits in the state. However, several deposits are still hidden. Due to its limitations, the early days mapping method locates only a few deposits. The conventional techniques usually integrate and interpret gold occurring factors on a light table to generate a predictive map. This old technique is complex and can take much time (Robert et al., 2007).

Recently, predictions mapping has been done using GIS technology. The GIS platform capture, store, analyse and visualise geospatial data. GIS mapping is faster and cheaper compared to the conventional mapping technique. Research had reported GIS applications in pieces of literature, including (Carranza 2017; Hoggar et al., 2016; He et al., 2010; Pablo and Palomera, 2004; Keller, 1995). Some research even reported the synthesis of mineral system processes for potential gold mapping (Carranza et al., 2015; Partington et al., 2013; Barnet and Williams, 2006). The use of mineral system factors to generate prediction maps is a new focus in Malaysia. This current study determines the accuracy of maps produced by synthesising mineral system factors. The study uses a modified frequency ratio model (MFR) to generate the potential map. The MFR is a probability-based model applied to model the spatial relationship between eight (8) known gold deposits and five (5) factors of the mineral system to generate a binary map. After which, combine the binary maps to produce a final gold potential map. The final map predicts gold deposits within the study area. The area under curved (AUC) methods determines the prediction accuracy.

2. Geology of study area

The study area is part of the Kelantan State bounded by Latitudes $4^{\circ} 38' 20'' - 4^{\circ} 56' 40''$ N and longitudes $101^{\circ} 49' 50'' - 102^{\circ} 1' 55''$ (Figure 1). The study area occupies approximately 593km². This region was selected because a similar study (Yusoff et al., 2015) had applied

a different approach to produce a potential gold map of the area. The choice of the region allows comparison prediction accuracy between the current studies with previous research. The general geology map of the study area is shown in Figure 1. Gua Musang sedimentary Formation of Middle-Upper Triassic age is identified in the eastern region (Mohamed et al., 2016; Hutchinson, 1989). It consists mainly of argillaceous facies, mudstone and pelitic hornfels, slate and phyllite, sandstone metasandstone rocks (Mohamed et al., 2016). In the western part of the Area, Gunung Rabong sedimentary formations of Middle-Upper Triassic age rocks have been noted (Hutchinson, 1989). The Gunung Rabong comprises mainly sandstone with subordinate shale, mudstone, siltstone, conglomerate and volcanic rocks. Limestone occurring as lenses, cliff-bound ridges, and rows of isolated tower-like hills of the Triassic age occupied the southwest region (Hutchinson, 1989). Two sets of lineaments characterised the Area; N-S to NW_SW and NE-SW. The N-S to NW-NSW trending direction dominates the terrane (Khamar Shah, 2012; Heng and Singh, 1986). The structures are the aftereffect of past orogenies activities on the area's geology. Structural studies identified two sets of faults to control gold deposits occurrence. The first set NE-SW is more significant than N-S (Heng and Singh, 1986). The gold deposits within this study area are mainly contained within hydrothermal veins, including low sulphide and high sulphide quartz veins, in shared granitoid and structurally controlled quartz veins (Khamar Shah, 2012).



Fig. 1: Geological Map of the Study Area (Modified from Yusoff Et Al., 2015).

3. Spatial datasets

3.1. Mineral deposits database

The study area contains eight (8) known gold prospects (Figure 2 (f)). The mineral and Geoscience Department of Malaysia (JMG) provided the locations of gold prospects. The eight (8) known gold prospects form the basis of all the analysis involved in this research because gold is the sought mineral in this research, and thus all other factors depend on it.

3.2. Lithology

The research creates a lithological map of the study area from the geological map of Kelantan provided by JMG. All maps were processed using WGS UTM Zone 47N on a scale of 1:200,000. The created lithological maps were used to delineate the host rock and the heat source (Figure 2 (c) and (d)).

3.3. Geological structure

Landsat 8 imagery was used to delineate the lineaments (Figure 2) (a) and (b)). The Landsat 8 imagery (path 127, Row 57 acquired on 3rd July 2016) was freely downloaded from the USGS web page. Principal component analysis and band rationing were applied to the downloaded images. The resultant images, PCA 123 (RBG) and Band ratio RGB combination (6/7, 6/5 and 8/5), highlight lineaments within the study area. Gamma stretching and directional filtering were applied on the resultant images to facilitate the extraction of lineaments. The lineament extraction focused on NE-SW and NW-SE directions. The NE-SW and NW-SE are the significant control regarding the gold deposition pathway within the study area.

3.4. Hydrothermal alteration

The hydrothermal alteration of iron and clay minerals were mapped using Landsat 8 images (Figure 2 (e)). PCA and Band rationing were applied to enhance the satellite images. The improved images highlight both the iron and clay alteration zone. Alteration zones were identified based on the mineral's reflectance and absorption characteristics features. The alteration map was generated using PCA 123, band ratio 4:2 and 6:5.



Fig. 2: Lineament NE-SW, Lineament NW-SE, Host Rock, Heat Source, and Alteration of Iron and Clay and Gold Deposits.

4. Research methodology

The research first of all reviews the basic theory of the frequency-based model. The factors of gold deposits in the area were also identified. Data such as the geological maps, mineral deposits, and Landsat 8 OLI imagery were then collected. The process of generating the potential map using ArcGIS 10.3 was done following three steps (Figure 3). The first steps, i.e. research preparation stage, involve a review of the gold mineral systems of the study area identified and constrained factors controlling the deposit distribution. The factor includes; (i) NE-SW lineaments, (ii) NW-SE lineaments, (iii) host rocks, (iv) heat source and (iv) alteration zone (iron and clay). The spatial database comprising eight gold deposits and all the identified factors were compiled using GIS at this research stage. The second step, i.e. GIS Analysis: This stage analysed all the data in the database. Evidence maps for the five factors were created. The GIS overlay method was adopted to combine the gold deposits and factors. The MFR quantitatively determined the spatial relationship between factors and gold deposits. The known gold deposits were split into two groups (training and testing) for analysing and validating purposes. The third step, i.e. generation and validation, applied the MFR model to generate a predictive gold potential map. The generated map was validated using the testing datasets, and the accuracy was determined using the AUC.



Fig. 3: General Methodological Workflow Chart.

5. Data analysis

The factors evidence features consist of 5 predictive maps: NE-SW lineaments, NW-SE lineaments, host rocks, heat source, clay, and iron alteration. Mineral deposits were splits randomly into two (2) subsets. The first subset of 6 (75%) of the total eight (8) known gold mineral deposits occurrence is used to generate the models (training data). The other subset of 2 (25% called testing data) of 8 known

(4)

gold mineral deposits occurrences is used to validate the probabilistic models (Testing data). A proximity distance analysis was performed for all the predicting factors (Figure 4). All binary maps were converted to a raster with Pixel size 15 X 15m. The five created rasters were then reclassified using natural breaks. The number of gold deposits in each class was determined using the training data, and their F.R. values were statistical calculated, and the prediction rate (P.R.) was determined. All the five (5) evidence maps were then reclassified based on the obtained F.R. for each factor and combined to generate a prospectivity map of the study area. The most common and reliable statistical method, "Area Under Curve." (AUC), were applied to determine and validate the prediction accuracy.



Fig. 4: Buffered Distance of Factors (A) Lineament NE-SW, (B) Lineament NW-SE, (C) Host Rock, (D) Heat Source and (E) Alteration of Iron and Clay.

6. Application of modified frequency ratio

Among the several bivariate statistical methods for potential gold mapping, the present studies adopted the modified frequency ratio model (MFR). The MFR is an understandable and straightforward probabilistic model successfully applied for potential gold mapping (Yusoff et al., 2015; Althuwaynee et al., 2014; Ford et al., 2016). The frequency ratio (F.R.) is best explained as a probability of a specific attribute such as gold deposits. The F.R. model calculates the spatial relationship between factors and gold deposits based on their spatial correlation. Implementing the MFR model for potential gold mapping requires calculating the F.R. (1). Then the F.R. was later modified to prediction rate (P.R.) (2). The pairwise values (PIR) for each prediction rate were statistically calculated to ascertain the degree of contribution level of each factor. The F.R. of each factor was multiple with P.R. of each factor and summed to calculate the mineral potential index (MPI). The mathematical equations applied in this study are expressed below (Althuwaynee et al., 2014).

$$FR = \frac{Factor class FR}{\Sigma factor classes FR}$$
(1)

$$PR = (RF_{max} - RF_{max})(RF_{max} - RF_{max})Min$$
(2)

 $MPI_{FPR} = F. R_{.1} PR_1 + F. R_{.2} PR_2 + \dots F. R_{.n} P. R_{.n} = \sum_{n} F. R_{.n} P. R_{.n}$ (3)

$$MPI_{FPIR} = FR_1PIR_1 + FR_2PIR_2 + \dots FR_nPI_n = \sum_n FR_nPIR_n$$

Where F.R., PR, PIR, MPI represent frequency ratio, prediction rate, pairwise prediction and mineral potential index, respectively.

Table 1:	Frequency	Ratio	values	for	Related	Factors
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Factor	Factor Class (m)	No. of Point	% of Points	Class area (m)	% of Class area	R (+)	RF
	0 - 100	0.00	0.00	146341	5.59	0.00	0.00
	100 -1500	6.00	100.00	1841131	70.32	1.42	1.00
Lineaments NE-SW	1500-3000	0.00	0.00	426283	16.28	0.00	0.00
	3000-4500	0.00	0.00	194435	7.43	0.00	0.00
	4500-6000	0.00	0.00	10012	0.38	0.00	0.00
	0 - 100	0.00	0.00	98948	3.78	0.00	0.00
	100 -1500	3.00	50.00	1599950	61.11	0.82	0.31
Lineaments NW-SE	1500-3000	3.00	50.00	708608	27.06	1.85	0.69
	3000-4500	0.00	0.00	191295	7.31	0.00	0.00
	4500-6000	0.00	0.00	19406	0.74	0.00	0.00
	0-100	5.00	83.33	2077228	79.34	1.05	0.53
U aat na alt	100-1500	1.00	16.67	460157	17.58	0.95	0.47
HOST TOCK	1500-3000	0.00	0.00	80444	3.07	0.00	0.00
	3000-4500	0.00	0.00	378	0.01	0.00	0.00
Heat source	0-100	2.00	33.33	568422	21.71	1.54	0.44

	100-1500	3.00	50.00	1076064	41.10	1.22	0.35	
	3000-6000	1.00	16.67	576776	22.03	0.76	0.22	
	6000-7500	0.00	0.00	384188	14.67	0.00	0.00	
	7500-8500	0.00	0.00	12794	0.49	0.00	0.00	
	0-100	2.00	33.33	642296	24.53	1.36	0.43	
	100-1500	4.00	66.67	961353	36.72	1.82	0.57	
Alteration (Iron mineral)	1500-3000	0.00	0.00	837302	31.98	0.00	0.00	
	3000-6000	0.00	0.00	174181	6.65	0.00	0.00	
	6000-7500	0.00	0.00	3072	0.12	0.00	0.00	
	Table 2:	Frequency Ratio I	Prediction Rate and	Pairwise Prediction I	Rate			
Factors	Fi	requency Ratio Pr	ediction Rate		Pairwise Prediction	Rate		
Alteration (iron minerals)	42	2.8039			32.26322			
Heat source	102.2369			77.06054				
Host rock	122.7767			92.54231				
Lineament NW-SE	161.9133			122.0413				
Lineament NE-SW	233.6236			176.0926				

7. Result and discussion

Remote sensing, GIS, and MFR models were applied to compile, analyse, and spatially integrate the deposits occurring in the Kelantan area for gold predictive mapping. The procedure modelled five (5) gold occurring factors and eight (8) known gold deposits (both training and testing data). Based on the spatial correlation, MFR was applied to determine the spatial relationship between the factors and the gold deposits. The method calculates the F.R. for each factor used in the analysis (Table 1). Statistical methods were applied to modify the F.R. to P.R. for each factor (Table 2). The prediction rate reflects the degree of control of factors regarding gold deposition within the study area. The PR values of lineaments are high, while alteration zones show the lowest P.R. The statistical approach also calculates the PIR values for each factor. Pairwise analysis was used to check the statistical relationship between all the P.R. values.



Fig. 5: Gold Potential Map Highlighting the Area of Mineralisation; (A) Based on P.R. and (B) Based on Pairwise Prediction.

A potential map of the study area was generated based on P.R. values and the PIR values using the MFR model on the training dataset (Figure 5). The potential gold maps created by the model was validated using the testing data sets and the success-rate methods to provide a better interpretation. The correlation of the potential gold maps built using the training dataset with the training data itself was used to determine the success rate. The success-rate analysis revealed how the results of the current methodology fit the training dataset. The success-rate approach divides the area of the potential map into 100 classes based on gold potential index values (highest-lowest) (Althuwaynee et al., 2014). The amount of gold deposit grid cells was determined in each class, and a cumulative success-rate curve was plotted (Figure 6). The prediction accuracy of the generated maps was determined using the area under curves (AUC). Perfect prediction accuracy is revealed by an AUC equal to 1. Based on the training, the P.R. model shows an area ratio of 0.9158 with an accuracy rate of 91.58%, while the pairwise model shows a ratio area of 0.9208%, having an accuracy rate of 92.08%. Based on the testing data, the P.R. model shows an area ratio of 0.8950, having an accuracy of the 98.50%. There is no significant difference between the prediction accuracy of the P.R. and PIR model, thus suggesting that the applied method is statistically 'fit' for predictive mapping of gold within the study area. A previous gold exploration within the study region had generated a potential gold map integrating mainly geochemical data (Yusoff et al., 2015). The prediction results of the previous work show a lower prediction accuracy (74%) compared to the prediction accuracy of this current work. Consequently, the current results encourage integrating the selected factors for potential gold mapping within Kelantan State.



Fig. 6: AUC for Validating of the Potential Map (A) Using Training Data for Both the Frequency (91.58%) and Pairwise (92.08) Prediction Rate (B) Using the Testing Data for Both the Frequency (90.50) and Pairwise (89.50%) Prediction Rate.

In this study, the generated potential gold map predicts the known gold deposits and reveals new potential mineralisation locations. Different areas of high gold potential are identified within the study areas. Some areas with high potential mineralisation coincide with known deposits. The newly discovered area of mineralisation are sites for future exploration. The MFR was a suitable method for combining gold ore genesis factors for potential gold mapping in this study.

The prediction accuracy is dependent on how well the known gold deposits model fit the analysed factors. The prediction rate values of all analysed factors show each factor's contribution level in predicting the gold deposits. Lineaments trending NE-SW are major gold deposits distribution factors within the study area. Alteration zones within the study may not always indicate gold deposits; it had the lowest predicting rate than host rock, heat source and lineaments. The prediction accuracy of 92.80 and 91.20 demonstrate that the applied methodology is helpful for gold exploration in Malaysia. Also, the research demonstrates the usefulness of Landsat 8 imagery for potential gold mapping. However, the study focused only on locating the gold deposits without considering the economic value of deposits (grade). The methodology will be more beneficial for Greenfield exploration.

8. Conclusion

Despite the application of GIS modelling in Malaysia, this study is considered the first to identify and constrain gold occurring factors using the ore genesis approach. Thus this study provides a new research phase regarding potential mapping in Malaysia. GIS (ARCGIS) and Excel provide a unique environment to analyse and visualise geospatial data for predictive mapping purposes. The MFR model adopted for this study effectively combines integrated factors to generate a potential gold map. The generate potential maps highlight known deposits and locate the new area of mineralisation. The prediction rate of each factor reflects their importance during deposits formation processes. The factor with the highest predicting rate (Lineaments NE-SW) is the major gold deposits distribution factor within the study area. The Prediction accuracy shows P.R. model and pairwise model performed at 91.58 and 92.08 accuracies, respectively. The results show that all factors were successfully used in predicting known areas of gold deposits and the unknown areas where no deposits occur. The generated potential map can be used to aid exploration in the search for undiscovered gold deposits in Malaysia

References

- Althuwaynee, O.F., Pradhan, B., Park, H.J., Lee, J.H., 2014. A novel ensemble bivariate statistical evidential belief function with knowledge-based analytical hierarchy process and multivariate statistical logistic regression for landslide susceptibility mapping. Catena 114, 21–36. <u>https://doi.org/10.1016/j.catena.2013.10.011</u>.
- Barnet, C.T., Williams, P.M., 2006. Mineral Exploration Using Modern Data Mining Techniques. Wealth Creat. Miner. Ind. Integer. Sci. Business, Educ. 295–310. <u>https://doi.org/10.3997/1365-2397.24.1097.27027</u>.
- [3] Carranza, E.J.M., 2017. Natural Resources Research Publications on Geochemical Anomaly and Mineral Potential Mapping, and Introduction to the Special Issue of Papers in These Fields. Nat. Resour. Res. 26, 379–410. <u>https://doi.org/10.1007/s11053-017-9348-1</u>.
- [4] Carranza, E.J.M., Sadeghi, M., Billay, A., 2015. Predictive mapping of prospectivity for orogenic gold, Giyani greenstone belt (South Africa). Ore Geol. Rev. 71, 703–718. <u>https://doi.org/10.1016/j.oregeorev.2014.10.030</u>.
- [5] Ford, A., Miller, J.M., Mol, A.G., 2016. A Comparative Analysis of Weights of Evidence, Evidential Belief Functions, and Fuzzy Logic for Mineral Potential Mapping Using Incomplete Data at the Scale of Investigation. Nat. Resour. Res. 25, 19–33. <u>https://doi.org/10.1007/s11053-015-9263-2</u>.
- [6] He, B., Chen, C., Liu, Y., 2010. Gold resources potential assessment in eastern Kunlun Mountains of China combining weights-of-evidence model with GIS spatial analysis technique. Chinese Geogr. Sci. 20, 461–470. <u>https://doi.org/10.1007/s11769-010-0420-6</u>.

- Heng, C.L., Singh, D.S., 1986. The nature and potential of gold mineralisation in Kelantan, peninsular Malaysia. GEOSEA V Proceedings, Vol. I. Publ. Bull. Geol. Soc. Malaysia 19, 431–440. <u>https://doi.org/10.7186/bgsm19198632</u>.
- [8] Hoggar, C., Zeghouane, H., Allek, K., Kesraoui, M., 2016. GIS-based weights of evidence modeling applied to mineral prospectivity mapping of Sn-W and rare metals in Laouni area, Arab. J. Geosci. <u>https://doi.org/10.1007/s12517-015-2188-6</u>.
- [9] Hutchinson, C.S., 1989. Geological Evolution of South-East Asia.
- [10] Keller, C.P., 1995. Geographic information systems for geoscientists: Modelling with GIS. Comput. Geosci. 21, 1110–1112. https://doi.org/10.1016/0098-3004(95)90019-5.
- [11] Khamar Shah, a., 2012. Mesothermal lode gold deposit Central Belt Peninsular Malaysia. Imran Ahmad, D. (Ed.). Earth Sci. 314–342. <u>https://doi.org/10.5772/26179</u>.
- [12] Mathew, T.G., Ariffin, K.S., 2018. Remote Sensing Technique for Lineament Extraction in Association with Mineralisation Pattern in Central Belt Peninsular Malaysia. J. Phys. Conf. Ser. 1082. <u>https://doi.org/10.1088/1742-6596/1082/1/012092</u>.
- [13] Mohamed, K.R., Joeharry, N.A.M., Leman, M.S., Ali, C.A., 2016. The gua musang group: A newly proposed stratigraphic unit for the permotriassic sequence of northern central belt, peninsular Malaysia. Bull. Geol. Soc. Malaysia 62, 131–142. <u>https://doi.org/10.7186/bgsm62201614</u>.
- [14] Pablo, R., Palomera, A. De, 2004. Application of Remote Sensing and Geographic Information Systems for Mineral Predictive Mapping, Deseado Massif, Southern Argentina by.
- [15] Partington, G.A., Peters, K.J., Puccioni, E., 2013. Exploration Targeting from Prospectivity Modelling of Multiple Deposit Types in the Lachlan Fold Belt, 1–11.
- [16] Robert, F., Brommecker, R., Bourne, B., Dobak, P., McEwan, C., Rowe, R., Zhou, X., 2007. Models and Exploration Methods for Major Gold Deposit Types. Proc. Explor. 07 Fifth Decenn. Int. Conf. Miner. Explor. 48, 691–711.
- [17] Tagwai, M.G., Jimoh, O.A., Ariffin, K.S., Abdul Razak, M.F., 2019. Investigation based on quantified spatial relationships between gold deposits and ore genesis factors in northeast Malaysia. J. Spat. Sci. 00, 1–24.
- [18] Yusoff, S., Pradhan, B., Manap, M.A., Shafri, H.Z.M., 2015. Regional gold potential mapping in Kelantan (Malaysia) using probabilistic based models and GIS. Open Geosci. 7, 149–161. <u>https://doi.org/10.1515/geo-2015-0012</u>.