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ARTICLE

Lateral Dispersion Pattern of Main Indicators at the Glojeh Polymetallic Deposit, NW Iran

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ABSTRACT

The criterion-base iterative stepwise Backward Elimination (BE) method was used to predict Au according to the main variables (Ag, Cu, Pb, and Zn). The optimization process of the quadratic polynomial model are carried out on different trenches. Whereas, Pb and Zn with Ag×Zn and Pb×Zn are significant to determine the lateral dispersion of Au. It means Zn is the predominant element in near surface zone. Therefore, it point out that the polymetallic (Au-Ag-Cu-Pb-Zn) high-sulfidation hydrothermal veins may be related to a porphyry deposit at depth. Laterally, 2D surface contour maps using kriging confirms all the results of the dispersion pattern of elements at Glojeh.

1. Introduction

Different geochemical interaction processes occur between the host rock and vein in the Glojeh polymetallic deposit. By consideration of the variables interaction effects (IE) can improve the accuracy of processing or modeling [1-5]. Hence, the quadratic terms (X^2) and the first order interaction (Xi×Xj) of variables were constructed with the aim of examining the relationship between geochemical variables. Stepwise regression analysis (RA) and analysis of variance (ANOVA) can be applied to determine the interactions between elements [6, 7], the dispersion pattern and elemental associations in mineralization using some geochemical concepts. Backward Elimination (BE) is one of the Stepwise Regression methods. Stepwise regression serves to reduce the model by using the strategy to eliminate the predictors which do not contribute to model accuracy, according to reach the specific accuracy.The quadratic polynomial model (QPM) considered as a full model to elucidate the relationship between variables. BE procedure is just a one procedure within the Stepwise regression where the starting model is actually a full model (model with all possible predictors) and then algorithm sequentially removes the worst one predictor while its accuracy is improving according to one criteria. Accordingly, some criteria including different criteria (R^2, R^2 adjusted[adj.], R^2 predicted[pred.]), PRESS, and F-ratio were used more frequently [5, 8, 9]. The BE modeling applied according to p-values (or laterally t-test) and related confidence levels [10, 11]. The convergent trend of R^2, R^2(adj.), R^2(pred.) accompanied by increases

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of F-value, and decreases of PRESS (Prediction Error Sum of Squares) indicate more accurate optimization [12]. The model with the lowest PRESS may be desirable, if the prediction is the objective of using this method.All the parameter and variables contributed at the full model with the lowest significant (p-value and t-value). According step by step process of elimination of parameters the model accuracy have been optimized. Besides, the full model has the lowest criteria for prediction (R^2(pred.)) new observation. During elimination of insignificant predictors the model is optimized gradually.

In this study, the authors have tried to estimate and identify the Au dispersion by associated elements for all trench samples in veins and host rock. The research was conducted with three aims: (a) to recognize the horizontal relationship between variables, statistically and spatially (b) determine an indicator model, (c) and decrease the cost of Au analysis. The relationship between variables is conducted based on examination of drillholes and trenches to determine zonality in polymetallic veins, shear zones, and host rocks, while the results have been validated according to R^2(pred.). The approach is furnished by the BE procedure on iterative RA and ANOVA by definition of IE of elements to improve the overall performance of zonal modeling. Based on BE, gradually all the insignificant predictors were eliminated. Therefore, all the predictors with different presence (the main elements (Xi),quadratic terms (X^2), and the first order interaction (Xi×Xj)) may be related to the object element (it is Au at here). Au variation and dispersion is investigated by first and second order and interactions of other elements which are benefit to determine the elemental zoning sequence.

2. Geological Setting

The Glojeh district is located in the central part of the Tarom- Hashtjin Metallogenic Province (THMP), which is one of Iran's major metallogenic provinces. Structurally, this subduction-related continental margin arc extends from a merging between the western Alborz magmatic belt and Urmieh-Dokhtar zone [13]. The rocks along the THMP are considered equivalent to the Karaj formation. They are different from those in central Alborz in terms of the lithology and chemical composition because the lava flows do not consist only of volcani-clastic rocks along this axis, and their compositions are more basic [14, 15]. Many intrusive bodies in the area have been injected into Eocene volcani-clastic assemblages, so these bodies are post-Eocene (most likely Oligocene) in age. One characteristic of the Oligocene intrusive bodies is the creation of alteration areoles in Eocene volcani-clastics, and a lot of epithermal Au-Cu-Pb-Zn mineralization have been generally occurred due to hydrothermal reactions [14, 16]. The Glojeh district is mainly covered by rhyodacite, lithic tuff, and andesite basalts [17].

3. Materials and Methods

3.1 Exploration Drilling

Tuff, rhyolite, and andesite, tuff- rhyolite and rhyodacite, tuff-rhyolite, and rhyodacite to latite are the host rocks of the TR1, TR2, and TR3, respectively, while TR4, TR5, and TR6 were excavated in rhyodacite to latite rocks. The sample numbers of trenches TR7 and TR8 are only 8 and 6 samples, respectively (Table 1). It is not enough to modeling and they were examined for 2D surface contour maps.The trenches TR4 and TR5 were excavated in rhyolite to rhyodacite with interbedded tuff and ignimbrite and have been covered by silicified alteration (Figure 1 and Table 1).

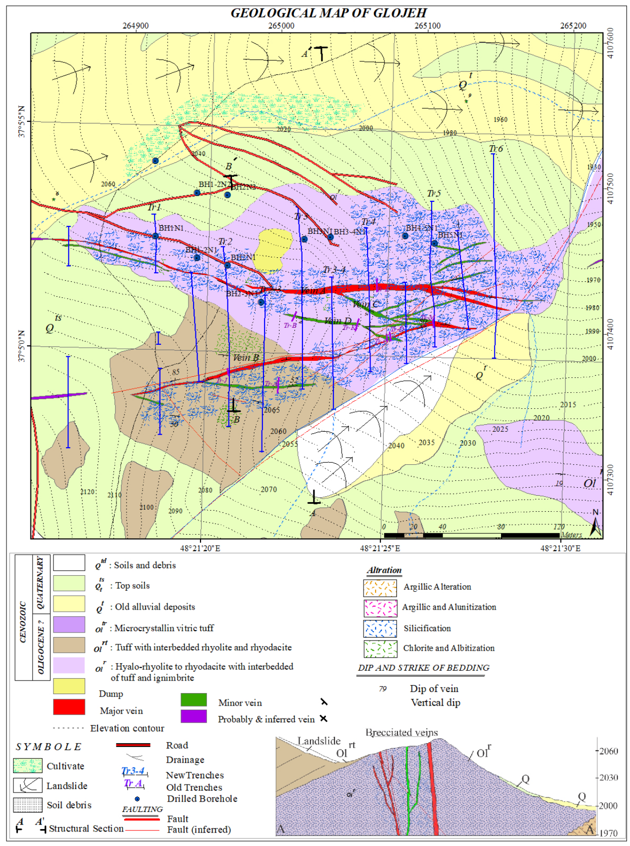

Figure 1. Location and geological map of the Glojeh deposit, including the main trenches

3.2 Backward Elimination

The interaction effect (IE; e.g. X^2 and Xi×Xj) of variables (Ag, Cu, Pb, and Zn) were defined considering different interaction processes between meteoric water and mag-

Table 1. Specifications of the trenches from TR0 to TR8 (ppb was used for all the concentration measurements)

Trench	Length	Alteration	Host rock	Samples	Vein samples	Average Au concentration	Maximum Au concentration	Minimum Au concentration
TR0	96	-	Rhyodacite to latite	43	3	103.9	2980	2.1
TR1	155	Hematite- Limonite	Tuff and Rhyodacite	39	13	1080	6760	3.2
TR2	136	Silicic, Hematite+Argillic	Tuff, Rhyolite, Rhyodacite	62	5	568	4370	4.2
TR3	130	Silicic, Hematite+Argillic	Tuff, Rhyolite, Rhyodacite to latite	60	23	1570	12900	4.9
TR4	103	Silicic, Hematite	Rhyodacite to latite	71	20	2180	21400	30
TR5	103	Silicic, Hematite+Argillic	Rhyodacite to latite	76	38	2275	19450	27
TR6	155	Silicic, Limonitic	Rhyodacite to latite	36	10	480	3540	4.5
TR7	15	Silicic	Rhyodacite	8	1	507.6	3440	34
TR8	14.5	Silicic And week Argillic	Tuff	6	1	141.7	730	8.4

matic fluids as well as host rock and vein in the polymetallic Glojeh deposit. These mathematical interaction revealed by geochemical properties of elements in different lithology and level of mineralization, considering to the level of definition of interaction effects. Therefore, IE play an important role for geochemical exploration and mineral deposition studies, especially in polymetallic hydrothermal ore deposits [18, 19]. Raudenbush and Liu [1], Diggle [2] and Leon and Heo [3] have argued for the use of main and IE of variables in their studies, which lead to improve the accuracy of processing or modeling. In this study, RA and ANOVA were done within BE process. The QPM that is constructed in the first step of BE modeling is given by:

$$Y = \alpha_1 X_1 + \ldots + \alpha_{r-1} X_{r-1} + \beta_1 X^2_1 + \ldots + \beta_{r-1} X^2_{r-1} + \chi_1 X_1 X_2 + \ldots + \chi_n X_{r-1} X_r + \varepsilon \quad (1)$$

where α, β and χ are the coefficients, and X_r is variable. The modeling is restricted to the main effects (variable X_i; Ag, Cu, Pb, and Zn), quadratic terms (covariates X_i^2; Ag^2, Cu^2, Pb^2, Zn^2), and the first order interaction (covariates $X_i \times X_j$; Ag×Cu, Ag×Pb, Ag×Zn, Cu×Pb, Cu×Zn, Pb×Zn) of variables [20]. The coefficient, standard error (SE), t-value ($\text{coeficient}/\text{SE}$), and p-value (indicate significance of all variables and covariates) associated with each predictor that contribute in the model were calculated from RA [21, 22]. Accordingly, at RA the parameter R^2 indicates how well the model fits the data and tends to increase as additional predictors added in the model. In order to overcome this effect, the parameter R^2(adj.) which could compare the two linear models with their complexity is utilized. R^2(pred.) was used with ease to compare how well the two model predicts responses for new observations that were not included in model estimation based on leave-one-out cross validation [23, 24].

The ANOVA analysis parameters are shown in Table 2. The F-ratio and R^2 can be obtained as follows (n is equal to the total number of observations in the analysis):

$$F-ratio = \frac{SSR/p}{SSE/(n-p-1)} = \frac{MSR}{MSE} \quad (2)$$

$$R^2 = \frac{SSR}{SST} \quad (3)$$

Table 2. The ANOVA analysis parameters

Source of Variation	Sum of Squares (SS)	Degrees of freedom (df)	Mean Squares (MS)	F ratio
Regression	SSR	p	MSR	MSR/MSE
Error	SSE	(n-p-1)	MSE	
Total	SST	(n-1)		

4. Results: Trenches Investigation

Overall, 401 trench samples were included in this study. They were collected from trench TR0 to TR8 where totally 907.5 meters were excavated. The BE approach has been applied on TR2 and explained in detail. At the first step, the QPM was set to be:

$$\begin{aligned} Au &= 1.13 - 0.87 Ag + 0.29 Cu - 0.38 Pb + 1.35 Zn \\ &- 0.12 Ag \times Cu + 0.44 Ag \times Pb - 0.50 Ag \times Zn + 0.47 Cu \\ &\times Pb + 0.26 Cu \times Zn - 0.289 Pb \times Zn + 0.25 Ag^2 - 0.319 Cu^2 \\ &- 0.252 Pb^2 + 0.128 Zn^2 \end{aligned} \quad (4)$$

Accordingly, all the t-test values (accompanied with p-values) of predictors (14 ones) were calculated to determine significant and insignificant predictors. The results of RA and ANOVA are summarized in the Table 3 for different steps and insignificant predictors are determined according to highest p-values. The Ag×Cu and

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Pb (p-values equal to 0.952 and 0.861, respectively) are removed at the 1st step, because the majority of prediction error that causes uncertainty in the model has been related to these predictors. The eliminating process (BE) was carried out by removing the least useful variables according to partial F ratio, R^2, R^2(adj.), and R^2(pred.) criteria. The R^2 and R^2(pred.) in this step equal 85.50 % and 15.36 %, respectively. When there is a high R^2, while the R^2(pred.) is low, it indicates that the model cannot give very good performance for predicting new observations. This implies that a lot of predictors create huge errors in modeling. Therefore, the model must be optimized by removing the special predictors that create the highest error (Ag×Cu and Pb at first step; Table 3 and Figure 2). At the second step, a new model is generated, while Ag×Cu and Pb have been deleted, and R^2(pred.) increased to 48.08% when R^2 has no significant changes (Figure 2 and Figure 3). An increase of R^2(pred.) accompanied by partial F-test value indicates improvement in the modeling [25]. Subsequently, Cu, Cu×Zn, Ag×Pb, Ag×Zn, Pb^2, Zn^2, threshold value, Cu^2, Ag, and Ag^2 were eliminated, and Reduced QPM (RQPM) was constructed with three predictors (df

Table 3. Regression analyses and ANOVA for BMA of TR2 in Glojeh deposit

step	criteria	value	Source	DF	SS	MS	F	P	Predictor	P-value
1	S	0.515	Regression	14	23.467	1.676	6.33	0.001	Ag×Cu	0.952
	R^2	85.50%	Residual Error	15	3.972	0.265			Pb	0.861
	R^2(adj.)	72.00%	Total	29	27.438					
	PRESS	23.224								
	R^2(pred.)	15.36%								
2	S	0.484	Regression	12	23.458	1.955	8.35	0	Cu	0.885
	R^2	85.50%	Residual Error	17	3.981	0.234			Cu×Zn	0.746
	R^2(adj.)	75.30%	Total	29	27.438					
	PRESS	14.246								
	R^2(pred.)	48.08%								
3	S	0.459	Regression	10	23.427	2.343	11.1	0	Ag×Pb	0.868
	R^2	85.40%	Residual Error	19	4.011	0.211			Ag×Zn	0.719
	R^2(adj.)	77.70%	Total	29	27.438					
	PRESS	11.659								
	R^2(pred.)	57.51%								
4	S	0.439	Regression	8	23.399	2.925	15.21	0	Pb^2	0.69
	R^2	85.30%	Residual Error	21	4.040	0.192			Zn^2	0.54
	R^2(adj.)	79.70%	Total	29	27.438					
	PRESS	9.035								
	R^2(pred.)	67.07%								
5	S	0.428	Regression	6	23.220	3.870	21.1	0	Constant	0.199
	R^2	84.60%	Residual Error	23	4.218	0.183			Cu^2	0.155
	R^2(adj.)	80.60%	Total	29	27.438					
	PRESS	7.933								
	R^2(pred.)	71.09%								
6	S	0.450	Regression	5	389.874	77.975	384.45	0	Ag	0.724
	PRESS	7.033	Residual Error	25	5.071	0.203			Ag^2	0.894
			Total	30	394.945					
7	S	0.435	Regression	3	389.84	129.95	687.29	0	Pb×Zn	0.001
	PRESS	6.062	Residual Error	27	5.1	0.19				
			Total	30	394.94					
8	S	0.528	Regression	2	387.13	193.56	693.13	0		
	PRESS	9.051	Residual Error	28	7.82	0.28				
			Total	30	394.94					

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equals to 3 at the 7^{th} step) for 30 samples (total df). It is noteworthy that the $R^2$is reduced a little from 85.5% at QPM to 84.6% at RQPM. It could reveal that R^2 is not an appropriate criterion to improve modeling performance, individually. In the 8th step, it is clear that if Pb×Zn is eliminated, the PRESS and S criteria increase and it is not in order to model optimization. The removal of insignificant predictors cause changes in the t-values of other predictors. Therefore, at TR2, the Zn, Cu×Pb and Pb×Zn predictors with t-values equal to 10.27, 4.53, and 3.79 are the most important predictors for Au modeling (Table 3 on 7^{th} step, Table 4). An improvement in modeling was achieved according to convergent trends through seven steps for R^2, R^2(adj.), and R^2(pred.) accompanied by increases in R^2(pred.) [26, 27]. After the 6^{th} step due to elimination of the threshold value MINITAB software unable to calculateR^2(adj.) and R^2(pred.), therefore the decrease in PRESS and increase in F value indicate the improvement in modeling (Table 4, Figure 2). Finally, through BE procedure the R^2(pred.) is increased from 15.36% in QPM to 71.09% in RQPM, which indicates the ability to predict Au for new samples. It was satisfied only by the genetic relationship between Ag, Cu, Pb, and Zn elements, since many factors are involved in mineralization. The RQPM for TR2 was introduced by the following equation:

$$Au= Zn +0.181\ Cu\times Pb - 0.183\ Pb\times Zn \quad (5)$$

According to the significant predictors that contributed in RQPM for TR1, TR2, TR3, and TR6, Pb and Zn were the main predictors, and Pb×Zn was the significant interaction for Au modeling. In these trenches, Ag and the threshold value unusually show high dependency with each other in the process of elimination (Table 4), because the threshold value at step 5 has the largest p-value equal 0.199 but when it was eliminated the p-value of Ag and Ag^2 show sudden increases.

Table 4. The order of elimination insignificant predictors using BE stepwise regression to create RQPM for each trenches

	TR1			TR2			TR3		
	Predictor	P-value	t-value	Predictor	P-value	t-value	Predictor	P-value	t-value
insignificant predictors that eliminated by several optimization steps	Ag	0.963		Ag×Cu	0.952		Constant	0.909	
	Pb×Zn	0.91		Pb	0.861		Ag	0.863	
	Constant	0.837		Cu	0.885		Ag×Pb	0.747	
	Cu×Zn	0.883		Cu×Zn	0.746		Cu^2	0.681	
	Cu	0.472		Ag×Pb	0.868		Cu×Pb	0.502	
	Ag^2	0.441		Ag×Zn	0.719		Zn^2	0.548	
	Ag×Cu	0.658		Pb^2	0.69		Cu	0.336	
	Ag×Pb	0.551		Zn^2	0.54		Cu×Zn	0.416	
	Pb^2	0.853		Constant	0.199		Pb^2	0	4.38
	Zn^2	0.663		Cu^2	0.155		Pb	0	4.28
	Zn	0.17		Ag	0.724		Pb×Zn	0.002	3.34
significant predictors that contributed in RQPM	Pb	0	9.39	Ag^2	0.894		Ag^2	0.005	2.9
	Ag×Zn	0.003	3.18	Zn	0	10.27	Ag×Cu	0.034	2.17
	Cu×Pb	0	4.43	Cu×Pb	0	4.53	Zn	0.052	1.99
	Cu^2	0	4.03	Pb×Zn	0.001	3.79	Ag×Zn	0.113	1.61
	TR4			TR5			TR6		
	Predictor	P-value	t-value	Predictor	P-value	t-value	Predictor	P-value	t-value
insignificant predictors that eliminated by several optimization steps	Ag^2	0.518		Ag×Pb	0.856		Zn	0.998	
	Pb^2	0.568		Ag^2	0.889		Pb^2	0.938	
	Cu	0.001	3.79	Ag	0.836		Ag×Zn	0.92	
	Pb	0.001	3.59	Pb^2	0.885		Ag×Pb	0.807	
	Ag	0.007	2.86	Ag×Cu	0.862		Ag^2	0.874	

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significant predictors that contributed in RQPM	Ag×Zn	0.009	2.79	Zn	0.49		Cu×Zn	0.824	
	Ag×Pb	0.017	2.52	Pb	0.43		Cu×Pb	0.756	
	Zn	0.014	2.6	Cu	0.28		Cu	0.608	
	Pb×Zn	0.023	2.38	Cu^2	0.395		Constant	0.336	
	Cu^2	0.036	2.18	Constant	0	14.27	Ag	0.163	
	Constant	0.099	1.7	Ag×Zn	0	6.16	Cu^2	0.321	
	Zn^2	0.105	1.66	Zn^2	0.096	1.69	Pb	0	9.11
	Cu×Pb	0.2	1.31	Cu×Pb	0.113	1.61	Pb×Zn	0	4.32
	Cu×Zn	0.236	1.21	Pb×Zn	0.14	1.49	Zn^2	0.001	3.83
	Ag×Cu	0.275	1.11	Cu×Zn	0.265	1.12	Ag×Cu	0.033	2.23

Note: The highlighted ones indicates the importance of Pb, Zn, and Pb×Zn predictors in the RQPM for all trenches after several steps of optimization. The order of elimination insignificant predictors is showed by p-values (α level), and t-values indicates the importance of the predictors in the RQPM.

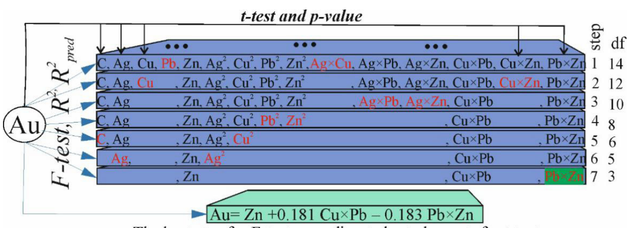

Figure 2. The differences between the t-test and F-test for optimizing model in TR2

Note: The F-test, R^2, and R^2(pred.) consider the linear relationship between Au and set of predictors which participate in modeling, while t value and p-values were calculated with the TDIST function using calculated t-values and the df for probability density function; TDIST(t, df, 2 tails)=P-value. It reveals that selecting a different predictor and model is complicated and with BE process might be facilitated by using controlling t-test and the F-tests.

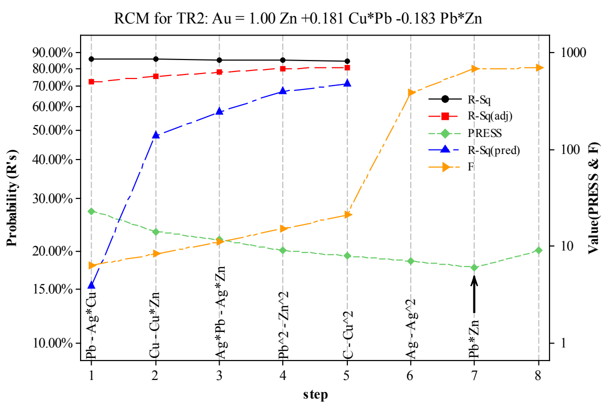

Figure 3. Optimization trend of the stepwise regression of BE using different R's (R^2, R^2[adj.], R^2[pred.]), PRESS and F-ratio criteria for TR2Discussion

Throughout this paper, the lateral geochemical dispersion pattern of Ag, Cu, Pb, and Zn are discussed considering their interactions at all trenches. We also propose an iterative model selection approach from QPM to RQPM, based on the main, quadratic terms and the interaction effects of elements. By applying interaction effects, different geochemical properties of elements have been considered using the BE procedure. Besides, the main elements and interactions are recognized in all trenches. After 8 steps of optimization and removing insignificant predictors at the TR2, R^2(pred.) increased from 15 % to more than 71 %. Accordingly, Zn and Pb×Zn were determined as the highest important element and interaction for Au modeling, respectively. This result is confirmed by the trends of other criteria (R^2, R^2[adj.], PRESS and F-ratio). The same process was applied for the other trenches (TR1, TR3, TR4, TR5, TR6) to interpret the lateral geochemical dispersion pattern of elements, respectively.

Based on the RQPM of trench TR2, it reveals that Zn, Cu×Pb and Pb×Zn were determined as the main predictors for Au (Table 4). Therefore, Zn and Pb are the most important predictors that show the same lateral dispersion (resulted from TR2 modeling) at the Glojeh deposit.

The results from Table 3 and Table 4 are clearly indicated in Table 5. The significant predictors contributing in RQPM for all trenches (Table 4) are depicted according to the t-values in the Figure 2.Accordingly,Pb and Zn are the main elements, and Pb×Zn is the main interaction which has the same geochemical dispersion pattern with Au within TR1, TR2, TR3, and TR6 (Table 5). Besides, the t-value from regular RQPM models for TR1, TR2, TR3 and TR6 indicates the strong effects of Pb and Zn. Whereas, TR4 and TR5 which are excavated in the high-grade zone contain mineralized quartz veins, veinlets and brecciated zones emphasizing that Cu and Pb are important elements for Au modeling.The most other important predictors is threshold value (the constant) that was derived from a lot of veinlets and brecciated zones at these trenches. All the step-by-step BE process of the trenches revealed that Pb and Zn accompanied with their interaction (Pb×Zn) have the same geochemical dispersion pattern and lateral variation with Au.

In order to identify Au, Ag, Cu, Pb, and Zn relationships with vein, veinlet, and brecciated zones and to better understand of their distribution in the region, preparation of a surface contour maps can aidin interpretation of results. The 2D contour maps were obtained based on trench data, a geological map, and scattered data from veins and veinlets using kriging technique. The parameters used to interpolate the map were the Gaussian for semivariogram model with output cell size (Lag size) equals 5 meters, search radius fixed in 10 meter distance and 3 is the minimum number of points were the kriging parameters used to create these maps. This method is the best linear unbiased estimator with the lowest estimation variance [28-30]. The possibility of occurrence of errors due to the lack of adequate information from the area is possible in this method to interpolation some cells. The highly Au concentrated samples have spread between TR2 and TR6, where the highest anomalous samples appears around TR4 and TR5 (Figure 4A). Also, ore-bearing major veins and veinlets trend are nearly east-westward (see Figure 1), while it was evident in the kriging surface variation of Au concentration (Figure 4A). The observed surface anomalies for Au show similar trend and largely overlap on Pb and Zn concentrated samples (Figure 4A, 4B, and 4C).

Table 5. The results of BE to recognize significant and insignificant predictors for trench

trench	threshold value	significant elements in RQPM	significant interactions in RQPM	insignificant predictors
TR1, Tr2, TR3 and TR6	-	Pb, Zn	Pb×Zn	Ag, C, Ag×Cu
TR4 and TR5	ok	Cu, Pb	Ag×Zn, Pb×Zn	Ag^2, Pb^2

Zn and Pb show the same variation of the concentration at deeper zones and Zn is highly enriched in superficial horizons [31]. On the other hand, these finding can be approved using BE modeling results. Mehrabi, Siani, Goldfarb, Azizi, Ganerod and Marsh [17]indicated that Au is certainly mineralized in the epithermal brecciated zones in late stages of magmatic fluids and afterward directly precipitated in associated meteoric water, whereas Cu is precipitated in early and middle stages and magmatic fluids have a greater role in mineralization. Therefore, the Glojeh deposit may be associated with a porphyry mineralization at depth.In order to the evaluation of the Au concentration by optimization process of the quadratic polynomial model, Cu, Pb and Zn are well separated laterally.

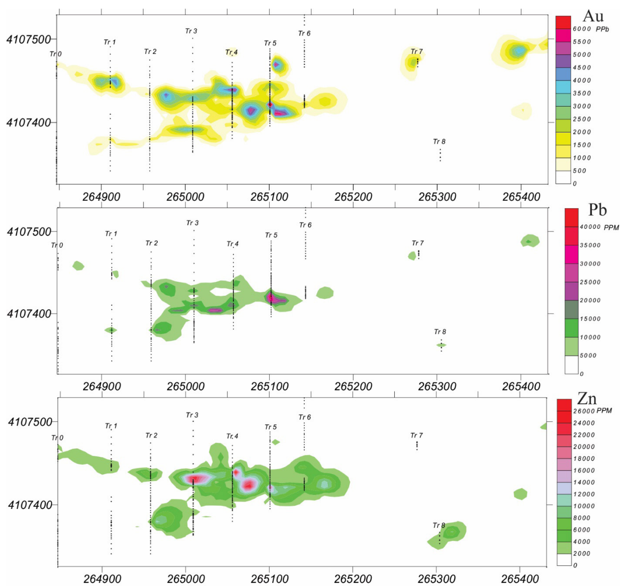

Figure 4. The 2D Glojeh surface contour map of Au (A); Pb (B); and Zn (C)

5. Conclusion

By constructing interaction effects of elements the relationship between variables could be distinguished, too much better. Where in environmental and mining science (certainly in mineralization) all the elements acts related and they must considered simultaneously, hence application of elemental interactions could ease to accurate modeling. Accordingly, model reduction process is handled until the main predictors recognized. This method could applied in different multivariable studies. In the presented study it was conducted to recognize the horizontal relationship (lateral dispersion or elemental zoning) between variables, statistically and spatially, determine an indicator model and decrease the cost of Au analysis. Iterative BE based on RA and ANOVA for 6 trenches (782 meter) indicates that optimized model consisting of interaction effects can reveal the lateral dispersion pattern of predictors. All the RQPMs were confirmed by the trends of R^2, R^2(-adj.), R^2(pred.) and F-ratio criteria. By investigating and modeling trenches, it was found that Pb and Zn are the main elements and Pb×Zn is an interacted predictor to determine linear productivity or lateral dispersion of Au. But in TR4 and TR5 trenches which located on veins/veinlets, brecciated zones, and silicic alteration, the threshold is significant parameter.

The present study indicates that by incorporation of interaction effects and application of regression analysis and the BE procedure method could easily explain the dispersion and variation of Au and associated elements. Some of the results from the BE based on iterative stepwise re-

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gression revealed that lateral dispersion of elements were overlapped and confirmed with 2D surface contour maps using a kriging technique. A distinct vertical zonation which appeared by a transition zone in depth may indicate a porphyry deposits at the depth. In addition, lateral geochemical dispersion pattern for Au determined using Zn>Cu×Pb>Pb×Zn predictors.

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References

[1] Raudenbush, S.W. and Liu, X.-F.. "Effects of study duration, frequency of observation, and sample size on power in studies of group differences in polynomial change". Psychological methods 2001, 6, 387.

[2] Diggle, P.. "Analysis of Longitudinal Data, Edited by Diggle PJ, Heagerty P, Liang KY, Zeger SL". Oxford, Oxford University Press, 2002.

[3] Leon, A.C. and Heo, M.."Sample sizes required to detect interactions between two binary fixed-effects in a mixed-effects linear regression model". Computational statistics & data analysis, 2009, 53: 603-608.

[4] Graham, M.W. and Miller, D.J.. "Unsupervised learning of parsimonious mixtures on large spaces with integrated feature and component selection". IEEE Transactions on Signal Processing, 2006, 54: 1289-1303.

[5] Samal, A.R., et al.."Backward elimination procedure for a predictive model of gold concentration". Journal of Geochemical Exploration, 2008, 97: 69-82.

[6] Garson, G.. "Multiple regression (statistical associates blue book series)". Asheboro, NC: Statistical Associates Publishers, 2012.

[7] Mohammadi, R., et al.. "Extraction optimization of pepsin-soluble collagen from eggshell membrane by response surface methodology (RSM)". Food chemistry, 2016, 190: 186-193.

[8] Yadav, V., et al.. "A backward elimination discrete optimization algorithm for model selection in spatio-temporal regression models". Environmental modelling & software, 2013, 42: 88-98.

[9] Singh, J., et al.. "Study of sruface roughness for discontinuous ultrasonic vibration assisted electric discharge machining using RSM". International Journal of Research in Engineering and Technology, 2013, 2: 727-737.

[10] Vaske, J.J.. "Communicating judgments about practical significance: Effect size, confidence intervals and odds ratios". Human Dimensions of Wildlife, 2002, 7: 287-300.

[11] Eggenhuisen, J.T., et al.. "Small-scale spatial variability in turbidity-current flow controlled by roughness resulting from substrate erosion: field evidence for a feedback mechanism". Journal of Sedimentary Research, 2010, 80: 129-136.

[12] Mousavi, J. and Parvini, M.. "A sensitivity analysis of parameters affecting the hydrogen release and dispersion using ANOVA method". International Journal of Hydrogen Energy, 2016, 41: 5188-5201.

[13] Mehrabi, B., et al.. "The genesis of the epithermal gold mineralization at North Glojeh veins, NW Iran". IJSAR , 2014, 15: 479-497.

[14] Ghorbani, M.. The economic geology of Iran: mineral deposits and natural resources. Springer Science & Business Media, 2013.

[15] Alavi, M.. "Tectonostratigraphic synthesis and structural style of the Alborz mountain system in northern Iran". Journal of Geodynamics, 1996, 21: 1-33.

[16] Bahajroy, M. and Taki, S.. "Study of the mineralization potential of the intrusives around Valis (Tarom-Iran)". Earth Sciences Research Journal, 2014, 18: 123-129.

[17] Mehrabi, B., et al.. "Mineral assemblages, fluid evolution, and genesis of polymetallic epithermal veins, Glojeh district, NW Iran". Ore Geology Reviews, 2016, 78: 41-57.

[18] Barnes, H.L.. Geochemistry of hydrothermal ore deposits. John Wiley & Sons, 1997.

[19] Cheng, Q.. "Mapping singularities with stream sediment geochemical data for prediction of undiscovered mineral deposits in Gejiu, Yunnan Province, China". Ore Geology Reviews, 2007, 32: 314-324.

[20] Braams, B.R., et al.. "Longitudinal changes in adolescent risk-taking: a comprehensive study of neural responses to rewards, pubertal development, and risk-taking behavior". The Journal of Neuroscience, 2015, 35: 7226-7238.

[21] Darabi-Golestan, F. and Hezarkhani, A.. "Quadratic investigation of geochemical distribution by backward elimination approach at Glojeh epithermal Au (Ag)-polymetallic mineralization, NW Iran". Journal of Central South University, 2018, 25: 342-356.

[22] Preacher, K.J., et al.. "Computational tools for probing interactions in multiple linear regression, multilevel modeling, and latent curve analysis". Journal of educational and behavioral statistics, 2006, 31: 437-448.

[23] Ali, K., et al.. "Application of empirical and semi-analytical algorithms to MERIS data for estimating chlorophyll a in Case 2 waters of Lake Erie". Environmental Earth Sciences, 2014, 71: 4209-4220.

[24] Coruh, S. and Elevli, S.. "Optimization of malachite green dye removal by sepiolite clay using a central composite design". Global NEST Journal, 2014, 16: 339-347.

[25] Nelson, J.B.. "A Robust Function to Return the Cumulative Density of Non-Central F Distributions in Microsoft Office Excel". Psicologica: International Journal of Methodology and Experimental Psychology, 2016, 37: 61-83.

[26] Darabi-Golestan, F. and Hezarkhani, A.. "Applied statistical functions and multivariate analysis of geochemical compositional data to evaluate mineralization in Glojeh polymetallic deposit, NW Iran". Frontiers of Earth Science, 2019, 13: 229-246.

[27] Darabi-Golestan, F. and Hezarkhani, A.. "Discrimination geochemical interaction effects on mineralization at the polymetallic Glojeh deposit, NW Iran by interative backward quadratic modeling". Acta Geochimica, 2019.

[28] Wackernagel, H.. " Kriging Weights". In Multivariate Geostatistics, 2003: 89-95, Springer.

[29] Samal, A.R., et al.. "Modelling spatial anisotropy of gold concentration data using GIS-based interpolated maps and variogram analysis: Implications for structural control of mineralization". Journal of earth system science, 2011, 120: 583-593.

[30] Asghari, O., et al.. "The comparison between sequential gaussian simulation (SGS) of Choghart ore deposit and geostatistical estimation through ordinary kriging". Australian Journal of Basic and Applied Sciences, 2009, 3: 330-341.

[31] Darabi-Golestan, F. and Hezarkhani, A.. "Evaluation of elemental mineralization rank using fractal and multivariate techniques and improving the performance by log-ratio transformation". Journal of Geochemical Exploration, 2018, 189: 11-24.

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