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THE PERFORMANCE OF ESTIMATION TECHNIQUES FOR NICKEL LATERITE RESOURCE MODELING

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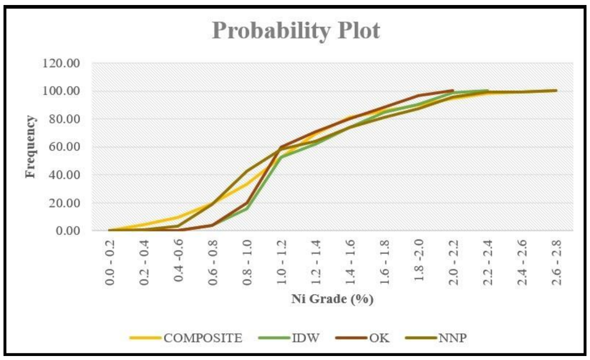
Graphical abstract



Abstract

The choice of estimation technique according to geological conditions and mineralization character is the main problem in estimating block grade of nickel laterite. CV (coefficient of variance) and variogram determine the choice of estimation technique for nickel laterite resource classification. This study aims to evaluate various techniques for estimating block grades and to select the appropriate method for the classification of nickel laterite resources. The basic statistical analysis is to find out the description of the data, while the variography is to find out the spatial correlation between the data. Nickel grade estimation results are based on Near Neighbor Polygon (NNP), Inverse Distance Weighting (IDW), and Ordinary Kriging (OK) techniques to determine the classification of nickel resources. Accuracy levels are based on cross-sectional visualization comparisons, plan views, probability plots and linear regression analysis. The OK technique were not superior in grade estimation, especially in nickel laterite deposits. The results showed that the IDW technique was suitable to be applied to the limonite zone, while the NNP technique was suitable to be applied to the saprolite zone. Based on the performance of the estimation technique, the weighted average method can be applied for the classification of inferred, indicated, and measurable resources. The grade-tonnage curve shows the nickel laterite resource potential in the study area.

Keywords: Estimation, NNP, IDW, OK, nickel laterite

1.0 INTRODUCTION

Nickel laterite is a supergene deposit that originates from weathering of serpentinized ultramafic rocks and typically accounts for about 70% of the world's land-based Nickel (Ni) resources [1]. Ni laterite is characterized by low Ni content, and zoned in limonite, saprolite and bedrock, complex mineralogy, high water content [2]. Chemical and mineralogical analysis of each drilling data needs to be done carefully due to the condition of the drill core and the heterogeneity of the sample [3]. Heterogeneity or homogeneity is a challenge in the estimation of nickel laterite grades. Modeling and estimating the spatial variability and uncertainty of mineral deposits is critical for capital investment in mining projects as well as operational issues after a mine is developed. The stationarity decision is a fundamental prerequisite for geostatistical estimation and characterization of laterite nickel resource uncertainty [4]. The limonite, saprolite, and bedrock zoning represents the population of spatial statistics relevant for modelling. Laterization is one of the geological processes for the formation of the three zones in laterite nickel ore. The genesis of mineral deposits is important for the development of geological models [5]. The rapid worldwide increase in nickel (Ni) consumption in various industries requires more precise estimation techniques of Ni grade content and identification of factors controlling grade distribution. To fulfill these requirements, this study applies geostatistical techniques for spatial modeling of Ni content in laterite Ni deposits. Estimation accuracy requires a good and informative semivariogram model. The semivariogram model is defined by a mathematical function, the parameters of which are usually estimated from experimental data [6]-[8]. The variation function is an important tool to describe the spatial correlation characteristics of regionalized variables in geostatistical methods [9]. The variogram model determines the sample search distance for estimation. Furthermore, estimation at unsampled locations uses NNP, IDW, or kriging estimation techniques. This estimation technique is very popular in the estimation of mineral resources. The two estimation techniques, NNP and IDW, depend solely on distance, while the kriging estimation technique considers the spatial correlation between data. Strict validation of the resource model was carried out to establish the quality and reliability of the estimation technique. Resource model estimates were analyzed against original borehole data, statistical analysis included linear regression, via QQ Plot comparisons, and histograms [10]-[12]. Geostatistics has been thoroughly developed and improved to address the challenges experienced in estimating geological ore bodies. Modern estimation of mineral resource grades always uses this geostatistical method. The accuracy of the estimation technique determines the classification of the nickel laterite resource.

Many researchers have introduced methods for classifying mineral resources [13]-[14]. Practitioners in the field need tools for fast and accurate classification of mineral resources. The introduction of the application of the kriging variance to the classification of mineral resources has raised problems for further understanding of ordinary kriging theory. However, traditional approaches to geological domain modeling and geostatistical estimation provide a smooth representation of the deposit attributes in question, ignore spatial variability and, thus, may mislead downstream decisions [15]-[16], so the NNP or IDW model is the estimation technique of choice. Classification of Mineral Resources as Measured, Indicated, or Inferred depending on the level of confidence. Nickel laterite resource geologists need precise deposit estimation techniques. This is based on various factors such as the geological or geometric model, the quality of the sampling and, from a geostatistical point of view, the distance between the boreholes. However, many of the methods or criteria used for classification are not based on actual measures of uncertainty [17]-[18]. Therefore, this study introduces the concept of classification using the average distance method. The population in the histogram shows the inferred, indicated, and measured classifications of resources.

2.0 METHODOLOGY

The valuation of a mining project depends upon the accuracy of geological block model. Sampling density, estimation method, and proper block size mainly affect the accuracy of estimated block [19]. The geological model of nickel ore, the distance between the boreholes and the geometry of the mining bench determine the block size.

The geological model is to limit the extrapolation of block grades, so that grades are not extrapolated out of the model area. The distance between drill holes is a consideration of block size in the geological model. Furthermore, each block will receive a grade estimate based on the estimation technique. Each block will receive an estimated grade and tonnage.
Determination of block size in nickel laterite grade estimation based on bench geometry and loading equipment specifications [20]-[22].

In the early stages of selecting the estimation technique based on the CV (coefficient variation). A small CV indicates flexibility in the choice of estimation technique. Ore grade estimation is one of the most key and complicated aspects in the evaluation of a mineral deposit [23]. Its complexity originates from scientific uncertainty the most popular block grade estimation methods are NNP, IDW, and OK. The three estimators have the same formula:

$$Z^* = \sum_i w_i Z_i \tag{1}$$

remarks: Z^*= estimated grade, w_i = weight , Z_i = *grade*
The largest NNP weight occurs at the closest sample distance to the estimated block. While the weight of IDW is the inverse of the distance to each known point [24]:

$$\boldsymbol{w_i} = \frac{\left(\frac{\mathbf{1}}{\boldsymbol{d_i^k}}\right)}{\Sigma \frac{\mathbf{1}}{\boldsymbol{d_i^k}}} \tag{2}$$

remarks: $\boldsymbol{d_i^k}$: distance; k : power
Ordinary kriging system solve OK weight (w_i) using the equation system as follows [25]:

$$\sum_{i=1}^{n} w_j.\sigma_{ij} - \mu = \sigma_{0i} \tag{3}$$

$$\sum_i w_i = 1 \tag{4}$$

remarks: σ_{ij} : sample and sample covariance
σ_{01} : block and sample covariance
μ : lagrange multiplier

The determination of the accuracy of the estimation technique is based on linear regression between the estimated grade and the composite grade, the comparison of the trend of the block model and grade on the drilling data, and the probability plot.

The classification of mineral resources is carried out using the best estimation technique [26]. Classification is based on a weighted average approach. The final result is a classification of inferred, indicated, and measurable resources.

3.0 RESULTS AND DISCUSSION

3.1 Descriptive Statistics

The benefit of descriptive statistical analysis is to analyze the description of the data. Table 1 below shows the results of statistical analysis between assays and composite in the limonite and saprolite zones. The variance and standard deviation are statistical parameters for assays and composites.

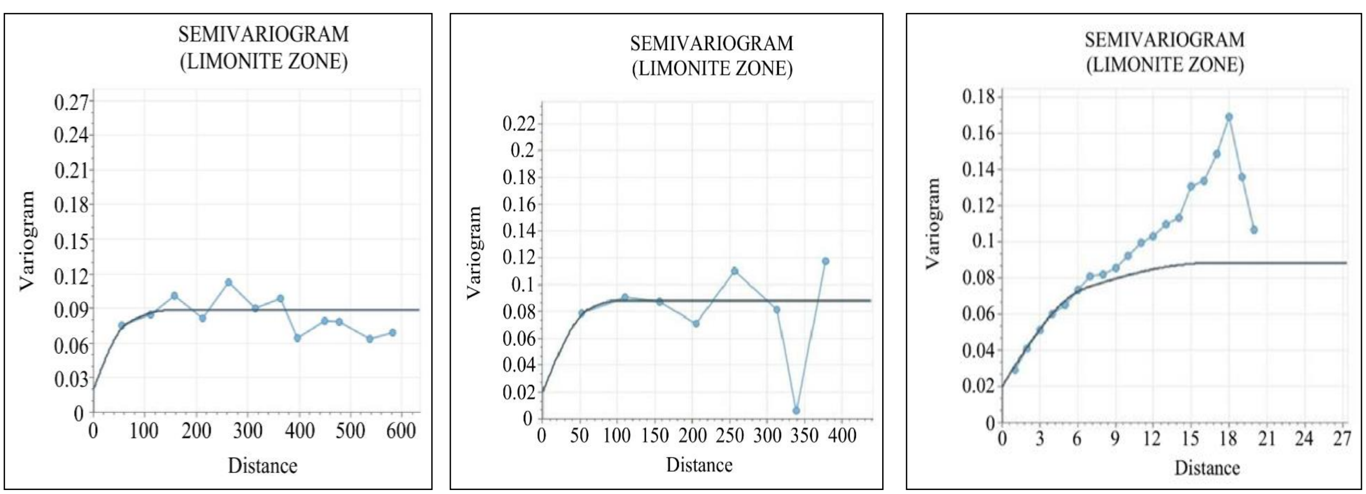
Table 1 Statistical analysis result of assay and composite in limonite and saprolite zones

Parameter	Assay		Composite	
	Limonite	Saprolite	Limonite	Saprolite
Minimum (%Ni)	0.23	0.20	0.33	0.27
Maximum (%Ni)	2.47	3.57	2.00	2.64
N	836	554	192	138
Mean (%Ni)	1.03	1.60	1.05	1.44
Variance $(\%Ni)^2$	0.09	0.43	0.07	0.40
Standard Deviation	0.30	0.66	0.26	0.63
Coeff. of Variation	0.29	0.46	0.24	0.43
Median	1.03	1.65	1.06	1.55
Skewness	0.27	-0.17	-0.04	-0.29
Kurtosis	0.32	-0.06	0.23	-0.91

Based on the Table 1 above, the value of the coefficient of variation of the data is less than 0.5. The value of the coefficient of variation affects the choice of accuracy of nickel grade estimation techniques. The next step is to create a geological model of the limonite and saprolite zones of the nickel deposit.

3.2 Variogram

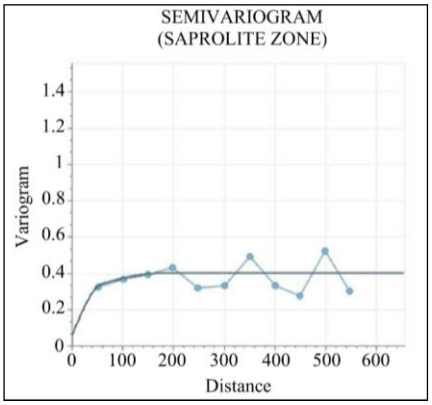
Variogram is a tool to analyze spatial correlation between data. Figure 1 and Figure 2 show the results of variographic analysis in the limonite and saprolite zones. The limonite and saprolite zones show the appearance of nugget values.



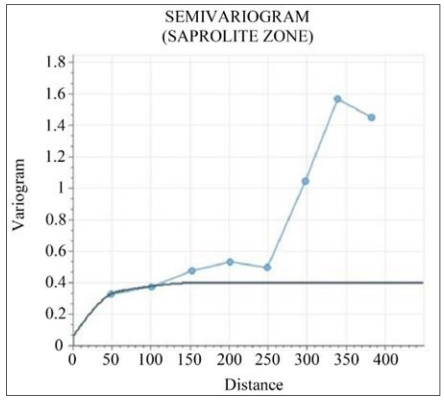
(a)Major direction (20^0) (b) Semi-major direction (110^0) (c) Minor direction

Figure 1 Variogram model in limonite zone

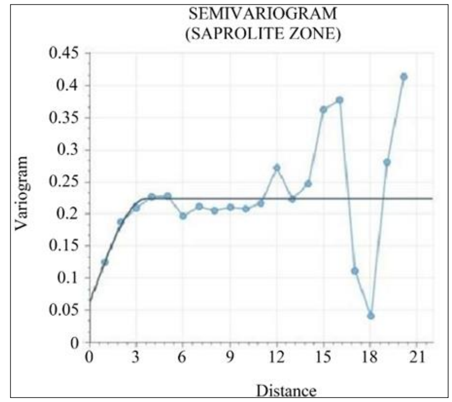
The determination of the nickel grade estimation technique in this research considers the CV value from the data and the nugget value from the variogram.



(a) Major direction (200)



(b) Semi-major direction (1100)



(c) Minor direction

Figure 2 Variogram model in saprolite zone

The NNP model extrapolates nickel grade too far compared to the IDW and OK models. The estimation of nickel grade in the limonite zone for the IDW model looks more conservative than the OK model. The IDW model indicates a more average grade estimate, while the OK model is too conservative. Based on the estimation results, the NNP model shows quite accurate in the saprolite zone.

Comparison of model and grade of nickel from drilling is a measure of estimation accuracy as well. The three estimation techniques show the same tendency, namely underestimation at low grades, and a slight tendency to overestimate at high grades. It seems that the NNP model has similarities with the composite in detailed observations on the probability curve (Figure 3).

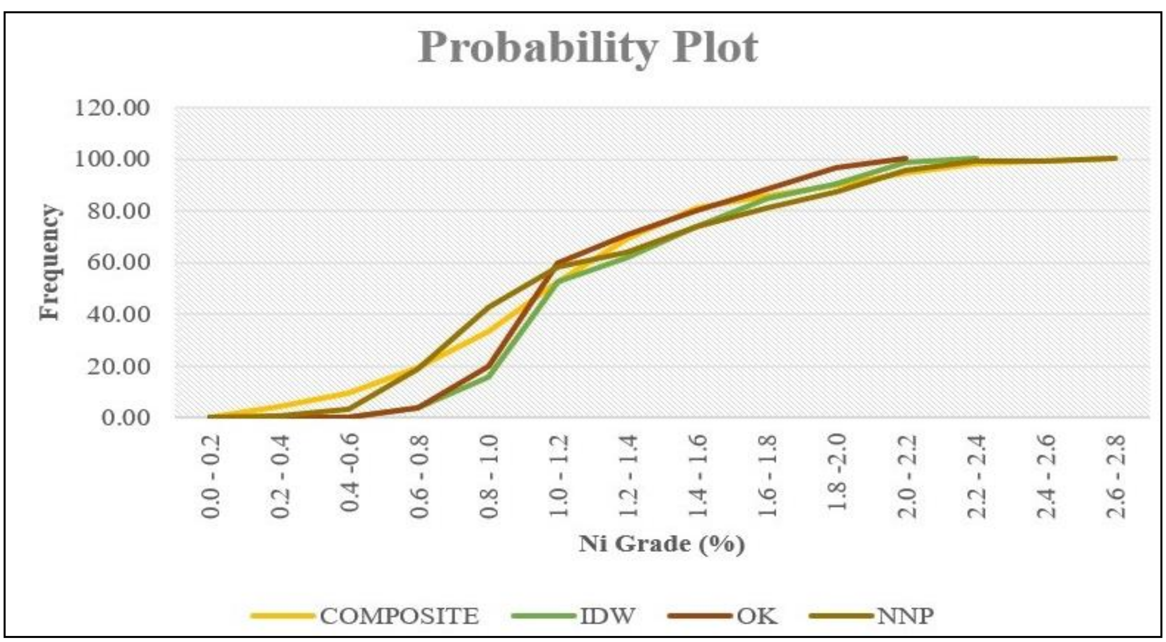


Figure 3 Probability plots of composite, NNP, IDW, and OK

Another measure of estimation accuracy is to compare the linear regression parameters. The linear regression parameter between the composite and the model determines the accuracy of the estimation technique. Table 2 shows a recapitulation of linear regression for each grade estimation technique. The linear regression parameters are correlation coefficient, Y-intercept, and slope.

Table 2 Statistical analysis of NNP, IDW, OK model

Model	Correlation coefficient	Y-intercept	Slope	RMSE
NNP limonite	0.6	0.6	0.3	0.3
NNP saprolite	0.7	1	0.5	0.7
IDW limonite	0.7	0.7	0.3	0.3
IDW saprolite	0.7	1.3	0.3	0.6
OK limonite	0.6	0.8	0.3	0.2
OK saprolite	0.6	1.1	0.3	0.7

The NNP model is quite accurate in the saprolite zone, while the IDW model is quite accurate in the limonite zone. Correlation coefficient (r) of OK model is smaller than NNP and IDW.

3.3 Resource Classification

The classification of nickel resources in this research is based on the average distance approach. The closest distance between the block and the sample provides a greater level of geological confidence than the longer distance. Figure 4 shows the average distance histogram of the IDW model in the limonite zone. Table 3 shows the model resource classification in the limonite zone, whereas Table 4 shows the NNP model resource classification in the saprolite zone.

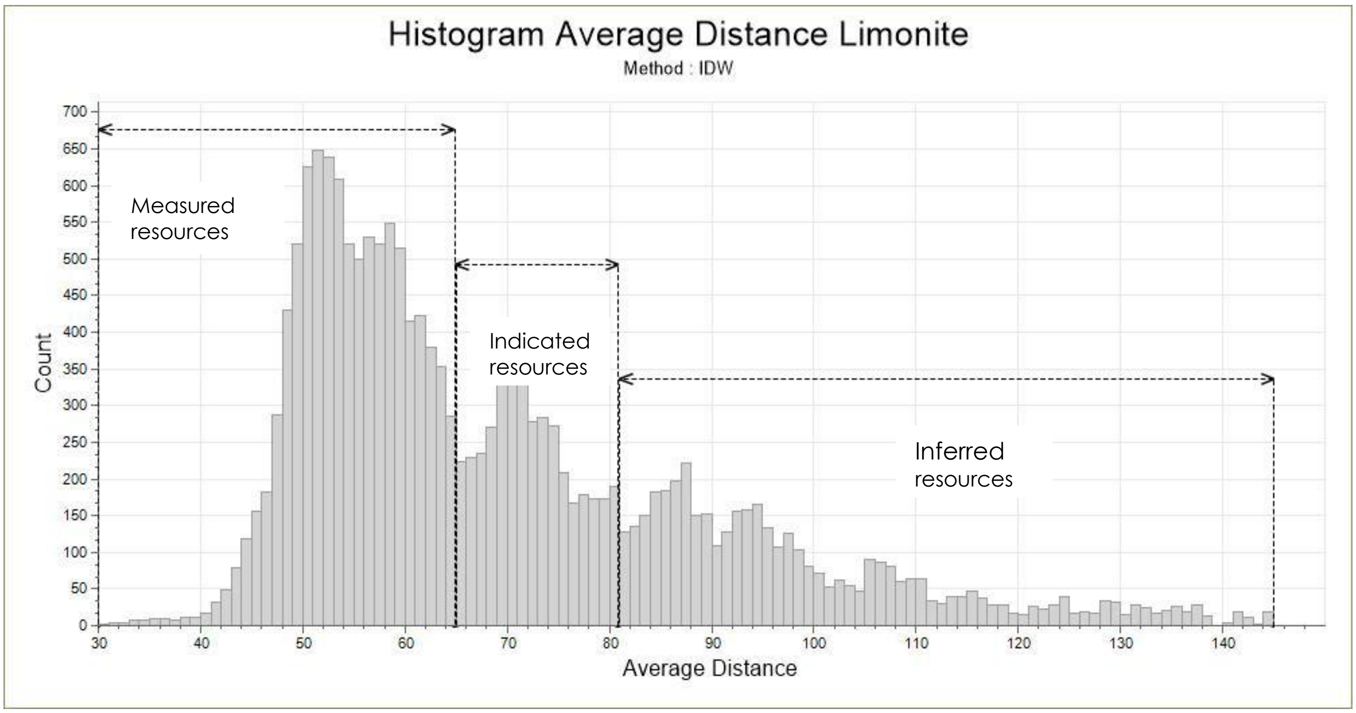


Figure 4 Histogram of average distance in the limonite zone (IDW model)

Table 3 Resources classification in limonite zone (IDW Model)

Grade Ni (%)	Resources (Ton)-IDW model Measured	Indicated	Inferred	Tonnage	Average Grade Ni (%)
0.0-0.5	0	0	0	0	0
0.5-1.0	502,031	432,578	295,586	1,230,195	0.92
1.0-1.5	2,145,664	625,625	844,648	3,615,938	1.12
1.5-2.0	0	0	0	0	0
2.0-2.5	0	0	0	0	0
Total	2,647,695	1,058,203	1,140,234	4,846,133	1.02

Figure 4 shows the classification of measured resources at a distance of 30-65 m, the classification of indicated resources at a distance of 65-81 m, the classification of inferred resources at a distance of 81-145 m. Figure 5 shows the average distance histogram of the NNP model in the saprolite zone. Classification of measured resources in the saprolite zone at a distance of 40-91 m, indicated resources at a distance of 91-112 m, and inferred resources at a distance of 112-200 m.

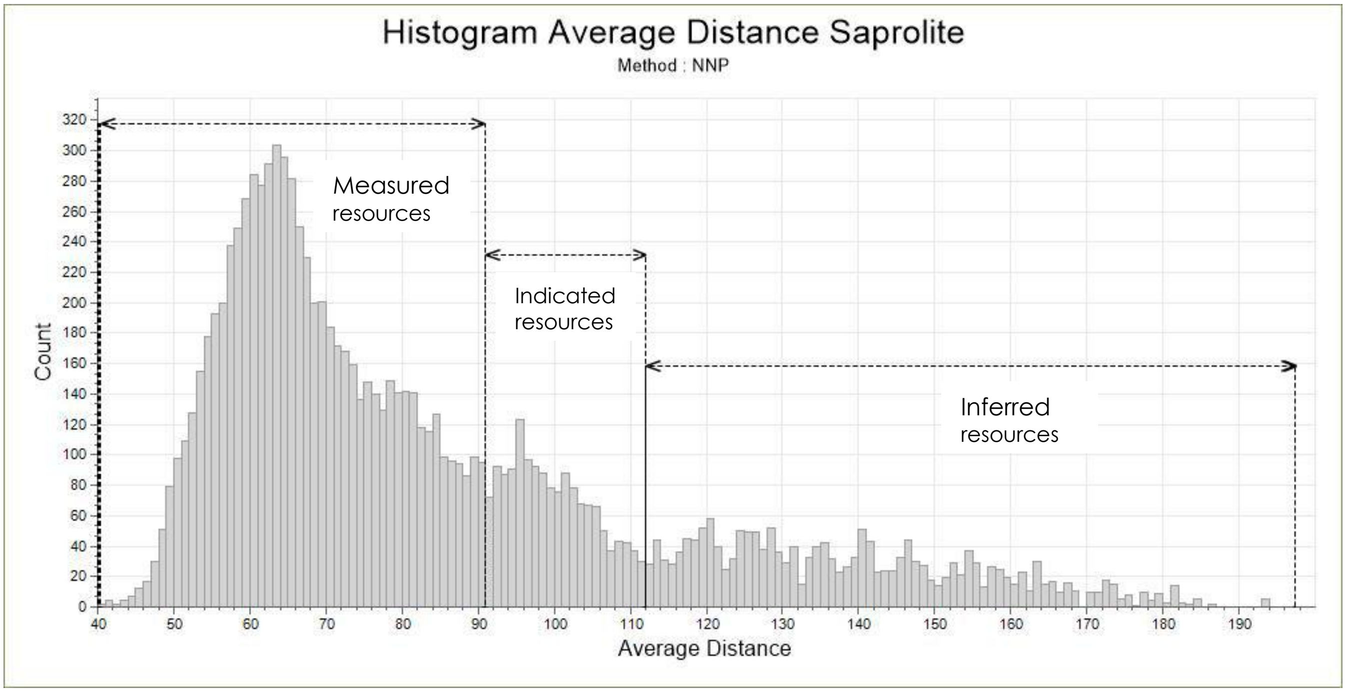


Figure 5 Histogram of average distance of the NNP model in the saprolite zone

Table 4 Resources classification in saprolite zone

Grade Ni (%)	Resources (Ton)-NNP model			Tonnage	Average Grade Ni (%)
	Measured	Indicated	Inferred		
0.0-0.5	36,914	13,945	86,406	137,266	0.40
0.5-1.0	22,148	4,648	32,266	59,063	0.70
1.0-1.5	370,234	119,219	164,883	654,336	1.34
1.5-2.0	999,414	156,953	1,252,344	1,252,344	1.75
2.0-2.5	552,891	38,008	763,984	763,984	2.15
2.5-3.0	35,547	36,367	72,461	72,461	2.64
Total	2,017,148	369,141	2,939,453	2,939,453	1.49

Base on Table 4 the most potential laterite nickel resources are in the grade of 1.0-2.0%Ni. Table 5 shows a recapitulation of tonnage and average Ni grade based on changes in cut-off grade.

Table 5 Relationship between cut-off grade tonnage and Ni grade average

Cut-off grade (%)	Avg. Ni (%)	Tonnage
0.2	1.21	7,785,586
0.4	1.22	7,699,453
0.6	1.23	7,585,430
0.8	1.35	6,152,891
1	1.55	4,308,555
1.2	1.76	2,916,211
1.4	1.85	249,938
1.6	1.98	1,836,133
1.8	2.08	1,385,234
2	2.18	879,648
2.2	2.34	353,008

Figure 6 show the relationship curve between cut-off grade, tonnage and average nickel grade based on data from Table 5, for example an average grade of 1.80% Ni with a cut-off grade of 1.3% Ni yielding 2,800,000 tons. The mine planning engineer will consider the grade-tonnage curve of the laterite nickel resource for planning the annual mining production schedule.

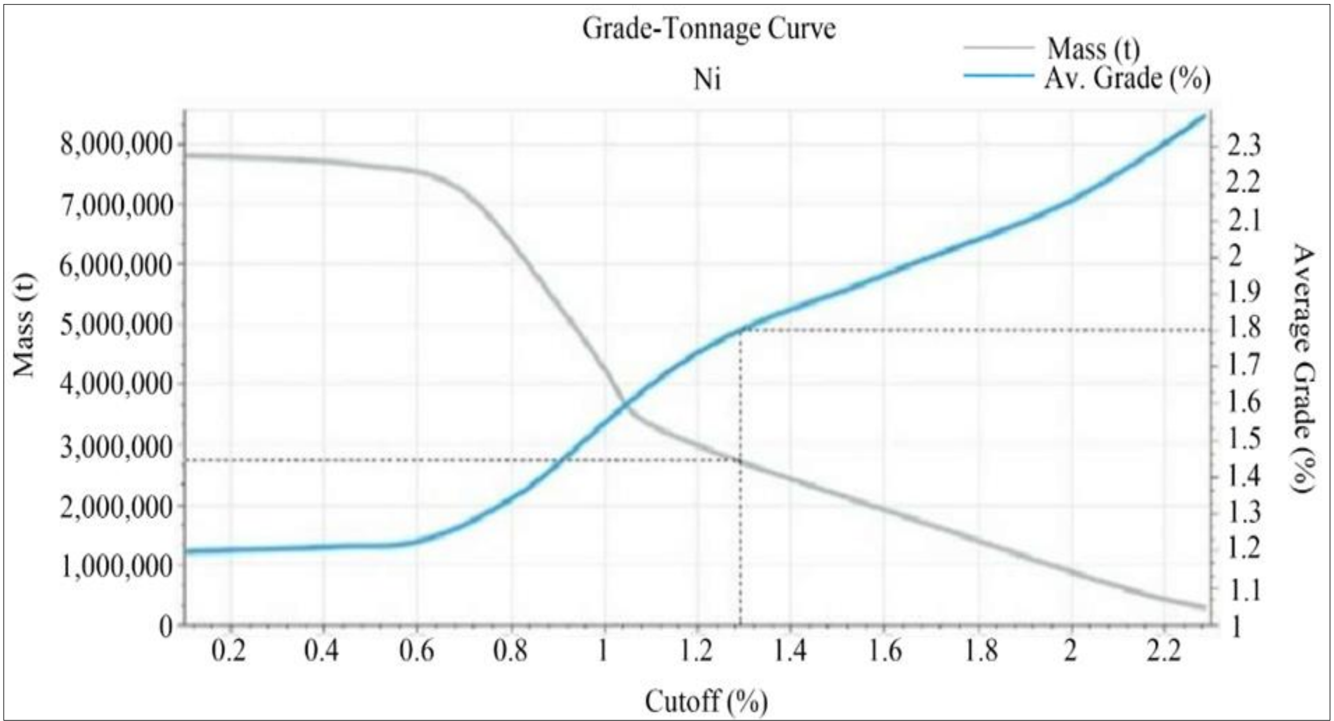


Figure 6 Grade-tonnage curve of nickel laterite resources

4.0 CONCLUSION

In this study, the ordinary kriging model did not provide an optimal estimate compared to NNP and IDW. OK is not superior in grade estimation, especially on the character and geological conditions of nickel laterite ore in this research area. The classification of nickel laterite resources introduces the weighted average method and uses the NNP and IDW models for the classification of measured, indicated, and inferred resources. The grade-tonnage curve provides the decision to determine the cut-off grade for nickel laterite mining activities in the study area.

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