OPEN ACCESS
Journal of Multidisciplinary Applied Natural Science Vol. 5 No. 2 (2025) https://doi.org/10.47352/jmans.2774-3047.252

Check for updates

Research Article

Geostatistical Modeling using Ordinary Kriging for Estimating Nickel Resources in Sulawesi Indonesia

Irfan Marwanza*, Danu Putra, Masagus Ahmad Azizi, Wiwik Dahani, Rhazes Eesha Gumay, and Silvia Immanuela Sahetapy

Received : August 26, 2024	Revised : January 12, 2025	Accepted : January 25, 2025	Online : March 2, 2025

Abstract
Geostatistic is a statistical tool used in the mining sector to estimate and classify mining resources at a specific location. The purpose of this study was to evaluate the distribution or model of nickel resources, as well as estimate and classify nickel resources using a geostatistical approach. This study used data from exploration drilling at one of the nickel mining concessions in Sulawesi, Indonesia. The data set included 464 drill holes with an average distance of 50–100 m. The initial stage in this study was to develop a geological model, followed by descriptive statistical analysis, with the results of the variance coefficient ranging from 0.5 to 1.5 and normal distribution, indicating that the ordinary kriging method can be used and is considered adequate to produce sound and consistent findings. The values obtained from the variogram analysis on the spherical model will be used as parameters in the ordinary and efficiency kriging processes. Based on the estimation and classification of nickel resources using ordinary and efficiency kriging, the total measured, indicated, and inferred nickel resources are 39, 1.25, and 3 million tons, respectively, with an average Ni content of 1.16%.

Keywords: nickel, geostatistic, variogram, ordinary kriging, resource estimation

1. INTRODUCTION

Nickel is a mining material needed in various applications and industries, such as the batteries, electronics, textiles, and steel coating materials [1]-[3]. This causes demand to meet nickel needs to continue to increase. Therefore, to meet these needs, the nickel mining industry must continue to be carried out and developed [4]. The success and smooth operation of a mining project, including nickel mining, depends on a series of stages that need to be carried out. One of the stages in question is exploration activities [5]. Exploration is the essential stage of determining the quality and quantity of nickel deposits in the area to be mined. As a bare stage, exploration activities must obtain optimal results. Optimal results in exploration activities can be obtained through modeling stages and calculating the number of nickel resources. The modeling stages carried out will produce a resource model as an illustration of the form of nickel deposits to be used as a consideration in determining mining methods [6].

Meanwhile, the results of calculating the number of resources can be used for mining evaluation activities during the feasibility study process and the implementation of mining activities. Resource modeling and calculations can be done by applying a spatial statistical approach, namely geostatistic. Geostatistic is a spatial statistical approach used in the mineral industry to estimate the number of minerals with data containing spatial diversity on large and small scales [6][7]. Spatial interpolation is a method used to predict an unknown value based on the value obtained from an observation. Resource estimation using a geostatistical approach can be done with various work methods, including the kriging method. Kriging is a method that can be used to analyze geostatistical data to estimate the value of an unsampled point based on the sampled points around it. The kriging method has developed and is divided into several methods: simple kriging, ordinary kriging, and universal kriging. The three methods are differentiated based on what they know whether or not the average value (mean) is in the data population to be analyzed [7]. The first step in performing ordinary kriging interpolation is to form an experimental semivariogram. The experimental semivariogram is calculated from the measurement data and then plotted as a function of distance [8]. This research aims to model the 3D shape of nickel deposits and classify and estimate resources using the ordinary kriging method. The

Publisher's Note:
Pandawa Institute stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Figure 1. Map Location of Study Area at PT. X.

expected benefit of this research is that the resulting 3D nickel resource model can be used for reserve calculation.

2. MATERIALS AND METHODS

2.1. Materials

This study uses the following data: a topographic map, a mining business license boundary, geological data, exploration data (drilling and geophysical well logging), a 3D geological model (block model), and resource and reserve estimation and classification.

2.2. Methods

The study area is a nickel mining company (PT. X), located in Langgikima District, North Konawe Regency, Southeast Sulawesi Province.

This research uses statistical and geostatistical analysis tools to describe data distribution and mineralization characteristics before resource estimation. The data used in this research is secondary data related to the geological condition of laterite nickel deposits in the PT X block area Makmur Lestari Primatama (Figure 1). This data was obtained from the results of geological drilling carried out by the company's exploration team. Next, the data are processed using a geostatistical approach, in this case, the ordinary kriging method, to obtain resource classification and estimate the amount of resources contained in the block X area. Stages analysis composed of obtaining data from exploration drilling results, consisting of drill hole coordinates, data on the depth and distribution of laterite layers, and data on Ni levels and other minerals contained [9]. Geological modeling is carried out to visualize the shape of nickel deposits in the block X area. Furthermore, a model can be formed using model blocks. Modeling was carried out using Surpac 6.6.2 software. Validation of the data was done from the analysis statistics base. The semivariogram analysis was carried out to obtain values that become parameters in estimating levels and quantities of resources. The content and quantity of resources in each laterite layer were estimated based on a geological model limited by topography mining business licence boundaries. Estimation of resource levels and quantities was carried out using the Ordinary Kriging method. Estimation was carried out using Surpac 6.6.2 software with a company license. Classification of the resources was based on mark kriging efficiency, efficiency as well as count. The tonnage of each classification is based on the volume and density values for each block.

2.2.1. Statistics Univariate

Univariate statistics is a statistical analysis used to describe data in a population. It has three roles in the data analysis process, i.e., calculating measures of data centrality, calculating measures of data diversity, and visualizing data distribution [10][11].

Size spread data are the device statistics that can state how much the variation in values in a population. Data distribution size parameters include variance, standard deviation, and coefficient of variance. Visualization of distribution forms can present data in the form of curves or graphs that can describe the form of data distribution, including size slope curve (Skewness) and size tapered curve (Kurtosis).

2.2.2. Statistics Spatial

When working with spatial data using a statistical approach, a variogram is needed to quantify the correlation between spatial data [12][13]. Two spatial data that are close together have the possibility of having relatively the same value compared to two values that are further apart. The variogram can be formulated with the Equation 1 [14]-[16].

$$\gamma(h) = \frac{1}{2}\sum_{i=1}^{n}\left[z_{(x_i)} - z_{(x_i+h)}\right]^2 \quad \textbf{(1)}$$

where $\gamma(h)$ is mark variogram with distance h, $N_{(h)}$ is Lots partner data which own distance h, $z_{(x_i)}$ is mark observation on location sample point, $z_{(x_i+h)}$ is mark observation on partner point sample which distance h and h are the distance between samples. Experimental and theoretical semivariograms have goodness-of-fit parameter values. With this fitting, the values of the fit parameters for the semivariogram can be obtained [17]. Parameter values are used as a reference in determining the model on a theoretical semivariogram and as a reference for the estimation process [16][17].

2.2.3. Ordinary Kriging Method

Kriging is a method that can estimate the number of resources using a geostatistical approach, which refers to data analysis techniques that predict unknown data values using other known values [15]-[17]. This can help estimate unknown variable values at unsampled locations with known values at nearby sampled locations [18][19]. Kriging is known by the acronym BLUE, or the best linear unbiased estimator [20]. Ordinary kriging is now a well-accepted method in mining grade control and mine reserve estimation [21]. The ordinary kriging method is a linear combination of sample variables according to the Equation 2 [22][23].

$$\hat{z}_{(s)} = \sum_{i=1}^{n} W_i \cdot z_{(s_i)} \quad \textbf{(2)}$$

where $\hat{z}$ is mark estimation on location which no sampled, w_i is weight coefficient of sampled locations with $\Sigma_{i=n}^{\prime} W_i = 1$. The $z(S_i)$ is mark on that location sampled, and n is Lots sample.

2.2.4. Mineral Resource Classification

Mineral resources are materials with economic value with a particular concentration or occurrence located below the earth's surface or above the earth's crust and have a particular form, quality, and quantity. They are assessed for prospects based on specific reasons so that they can be extracted economically [24][25]. Resources can be classified into inferred, indicated, and measured mineral resources [26][27]. The classification of resources and reserves is determined based on two criteria: confidence in geological conditions and improvement of mine feasibility [28][29]. Mineral resources with the highest level of geological confidence are measured resources. In contrast, the resource classification with the lowest level of geological confidence is inferred resources, and the indicated resource classification is considered to have sufficient confidence [30]. Classification of resources with a fair to high level of confidence can be converted into reserves. One of the kriging parameters that can be used for resource classification is Kriging efficiency (KE). KE is expressed by Kriging variance normalized by block variance in the form of a percentage; if the KE value is high it means that the kriging variance is low or vice versa. KE is used as a metric to evaluate

Table 1. Kriging Efficiency Range for Classification Resources.

Kriging efficiency (KE)	Classification Resource
KE ≥ 0.5	(*measured*)
KE < TO < 0.5	(*indicated*)
KE ≤ 0.3	(*inferred*)

Table 2. Drill hole data.

Data Type	Lots of Data	Description
Collars	464	ID Drill Hole, Coordinate, Depth, *Hole path*
Survey	464	ID Drill Hole, Depth, *Azimuth* , Dip
Geology	17.188	ID Drill Hole, From - To, Layer of geology, Layer of nickel
Samples/Assays	17.188	ID Drill Hole, From - To, type, Elevation

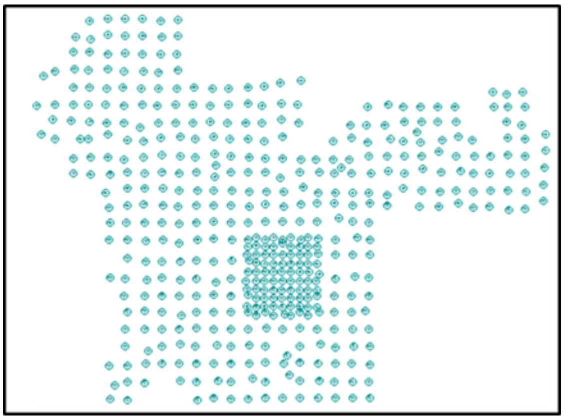

Figure 2. Drill hole distribution view.

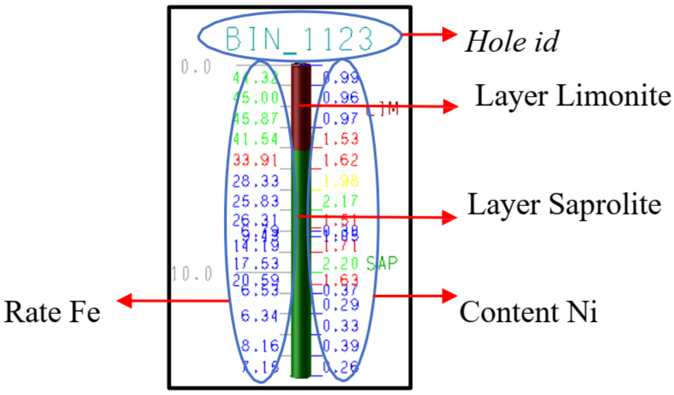

Figure 3. Details appearance of drill hole.

the efficiency of block estimation (Eq. 3) [21]. The classification of nickel resources based on Kriging Efficiency is described in Table 1.

$$KE_{(Uv)} = 1 - \frac{\sigma_K^2(Uv)}{\sigma^2 - \bar{\gamma}(v,v)} \quad \textbf{(3)}$$

where $\sigma^2_K(uV)$ is the KV, σ^2 is the variance of the data for the domain, and $\bar{\gamma}(V,V)$ is the average semivariogram within the blocks. The following are the provisions for the value of kriging efficiency in determining resource classification [30].

The explanation of the term mineral resources refers to SNI 4726 of 2019, namely, inferred mineral resources are part of resources where tonnage, grade, and mineral content can be estimated with a low level of confidence. Indicated mineral resources are part of mineral resources whereas tonnage, density, shape, physical characteristics, grade, and mineral content can be estimated with a reasonable level of confidence. The measured mineral resources are part of mineral resources where tonnage, density, shape, physical characteristics, grade, and mineral content can be estimated with a high level of confidence.

3. RESULTS AND DISCUSSIONS

3.1. Database

Exploration activities include geological mapping, drilling, and sediment content testing in the area to be mined. The exploration data are then used as a reference in geological modeling and estimating the grade and quantity of resources. This data includes the name of the drill hole (hole ID), coordinate (easting, northing, elevation), intervals depth (from-to), total depth of the drill hole (depth), slope of the drill hole, and data on Ni content and other supporting elements and minerals (Fe, Co, SiO_2, CaO, MgO). Next, the data are divided into four types: data collars, data surveys, data geology, and data samples/assays (Table 2). Data can be distributed by need processing on-device software. Furthermore, data correction was carried out to ensure the completeness of the data and that it was valid for use. The research area has 464 drilling holes with an average regional drilling distance of 100 m, a detailed drilling distance of 50 m, and varying drill hole depths. The distribution map of drill point locations and sample borehole cross-sections are shown in Figure 2. The software also corrects the four types of data during the data entry process to confirm that the data are complete and valid and can be used for the following process.

3.2. Block Model Construction

For the projectile configuration comprising a conical forebody and boattail, the effect of the boattail shape on the drag is shown in Fig. 3 as a function of Mach number. For that, the higher the angle of the boattail, the lower the drag.

3.2.1. Topographic Model

The topographic model is created based on the results of map digitization of the area to be mined. In resource estimation, topography is needed as a limit when extrapolating sediment levels in the vertical direction. A solid topographic map of the study area can be seen in Figure 4.

3.2.2. Geological Model

A geological model is needed to limit the estimation of the content and quantity of resources in the research area so that the estimation results are not extrapolated too far. This model is based on geological data relating to information about the distribution of laterite layers, as shown in Figure 5.

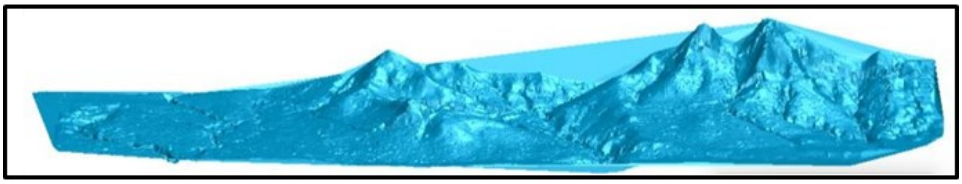

Figure 4. Topography of the research area in three dimensions.

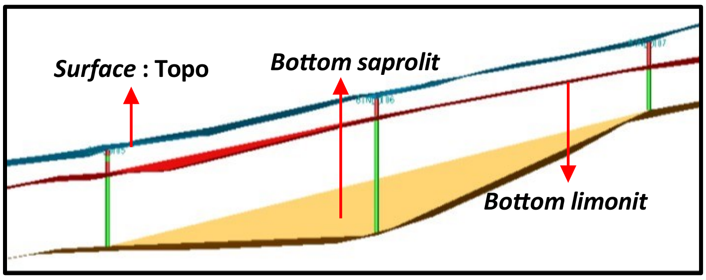

Figure 5. Geological model cross section in two dimensions.

Figure 6. Ore body domain viewed from the side view in a three-dimensional geological model.

Table 3. Parameter size and coordinate constraints for block models.

Direction	Coordinate		Block Size (m)
	Minimum	Maximum	
East	418600	420600	12.5
North	9635600	9637200	12.5
Elevation	- 100	400	1.0

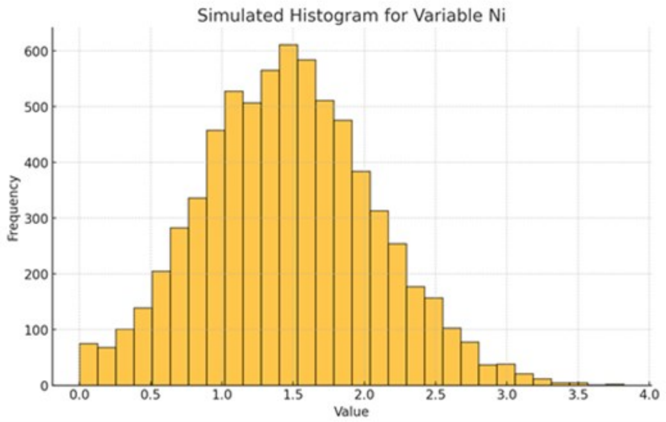

Figure 7. Nickel assay histogram.

The three-dimensional geological model of the ore body when viewed from the side view can be seen in Figure 6.

3.2.3. Nickel Modeling using the Block Model Method

The block model is a three-dimensional block composed of smaller blocks than the entire model block, which must cover the entire ore body domain. The block model was produced in research. This is arranged on 261,955 blocks. Information regarding the size skeleton block model, as well as the maximum and minimum values for east, north, and elevation coordinates (Table 3).

3.3. Statistical Analysis

Statistical analysis was carried out on each grade data to be estimated, as well as Ni grade data in the limonite and saprolite layers. Statistical analysis was carried out to validate that the data could be used for the estimation process using the ordinary kriging method [9]. The following are the results of the statistical analysis obtained. The ordinary kriging method can be applied and will produce optimal and reliable results if the data's coefficient of variance (CV) value ranges between 0.5–1.5. A CV value of less than 0.5 produces a reliable estimate, while CV results greater than 1.5 are deemed unable to give good results [29]. Based on the results of statistical analysis in Tables 3 and 4, the CV value is between 0.5 - and 1.5, so it can be used for the resource estimation process using the ordinary kriging method and is considered to provide good and reliable results [31][32]. It is also known that data tends to have a positive skewness; this shows that the median value is less than the mean. The same thing also happens to the kurtosis value, which shows a positive value in the analysis results. The histogram of statistical calculation results is needed to determine the distribution and symmetry of the data so that it can be used to interpret the character of all data in general. The histogram of nickel assay data can be seen in Figure 7.

The histogram represents the simulated distribution of the variable Ni, based on the provided descriptive statistics. The data are generated with a slight positive skew (right skew) and a sharp peak, as indicated by the skewness and kurtosis values. The data are clipped within the range of 0.00 to 4.13, respecting the specified minimum and maximum values. The results of the statistical analysis of the data on the limonite and saprolite layers are listed in Tables 4 and 5.

3.4. Semivariogram Analysis

Based on the existing data, anisotropy analysis and determination of variogram parameters are carried out to be used in ordinary kriging estimation. This kriging method estimates the nickel content in a block with no known horizontal value. The first step in the semivariogram analysis process is determining the lag, which is the distance between data that form one or more data pairs. The lag setting applied in this research is 100 m. This lag distance is close to the sample mean distance. The work then continues with the fitting process to match the experimental semivariogram results with the theoretical semivariogram model.

Exponential, Spherical, Gaussian, and Cubic model curves are all semivariogram models used in geostatistical analysis. All these models have their own uniqueness and characteristics that can be analyzed in specific contexts. However, in the context of selecting the most suitable model for a particular geostatistical data, the best choice can be determined by comparing the model prediction error results for validation data.

Determining a variogram model involves selecting a model (e.g., spherical, exponential, Gaussian) that best fits the empirical variogram data, often using visual inspection and statistical metrics such as root mean square error (RMSE). The spherical model is commonly used in variogram modeling because it effectively represents spatial correlation in many natural phenomena, particularly in geological and environmental sciences. Variogram fittings were made with the aim of obtaining parameters for estimating Ni content to obtain range, sill and nugget effect values. The experimental variogram fitting results show that the variogram model is a spherical model. The model was chosen because it has good initial behavior and from the results of the data pattern matching analysis on the experimental variogram with the theoretical variogram model, the most suitable model is the spherical variogram

Table 4. Results of statistical analysis of data on limonite and saprolite layers.

	Variable	Ni	Fe	Co	SiO_2	CaO	MgO
Limonite Layer	***Data (n)***	8005	8005	8005	8005	8005	8005
	MinValue	0.28	35.01	0.01	6.00	0.00	0.00
	Max Value	3.08	59.48	0.79	28.71	1.06	11.74
	Mean	1,113	45,288	0.129	8,966	0.013	0.59
	Median	1.07	45.46	0.12	7.89	0.00	0.00
	Variance	0.118	19,067	0.002	7,340	0.001	0.900
	Standard Deviation	0.344	4,366	0.054	2,709	0.003	0.949
	Coeff. of Variance	0.309	0.009	0.424	0.302	1,599	1,509
	Skewness	0.683	-0.008	2,666	1,856	8,587	3,965
	Kurtosis	3,648	2,736	17,454	6,950	140,337	26,355
	Variable	**Ni**	**Fe**	**Co**	**SiO2**	**CaO**	**MgO**
Saprolite Layer	***Data (n)***	7034	7034	7034	7034	7034	7034
	Min Value	0.00	0.00	0.00	0.00	0.00	0.00
	Max Value	4.13	34.98	0.32	66.00	8,873	53.21
	Mean	1,033	14,307	0.026	34,986	0.729	22,042
	Median	0.883	11,088	0.020	35.01	0.478	23,288
	Variance	0.559	72,835	0.000	97,684	0.534	164,491
	Standard Deviation	0.748	8,534	0.021	9.88	0.731	12,825
	Coeff. of Variance	0.723	0.596	0.823	0.282	1,002	0.581
	Skewness	0.777	0.934	4,065	0.792	1.20	-0.161
	Kurtosis	2,974	2,673	29,689	5,473	5,364	1,765

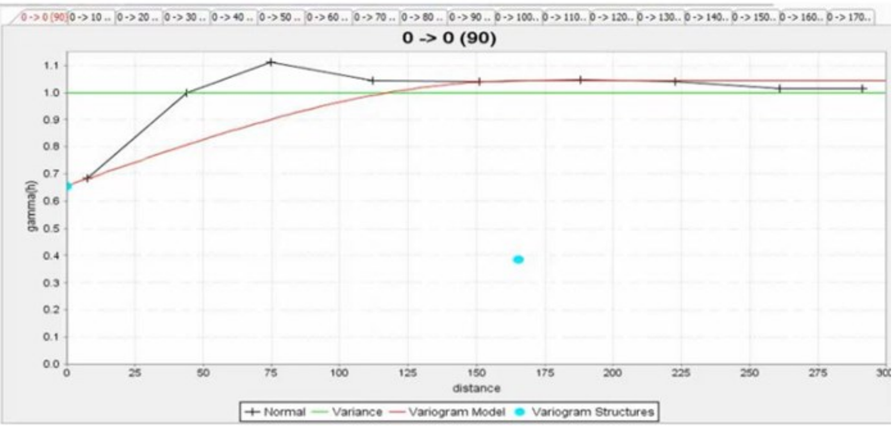

Figure 8. Ni variogram fitting results on the limonite layer.

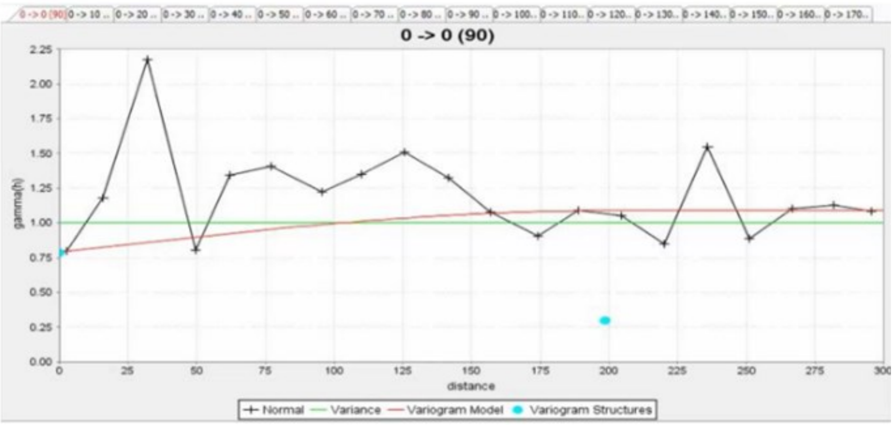

Figure 9. Ni variogram fitting results on saprolite layer.

Table 5. Results of fitting variogram parameters with a spherical model in the limonite and saprolite layer.

Layer	Data	Nuggets	Sill	Range
Limonite	Ni	0.656	0.386	165,612
	Fe	0.606	0.332	237,333
	Co	0.749	0.210	206,458
	SiO_2	0.519	0.472	285,897
	CaO	0.539	0.201	209,352
	MgO	0.685	0.248	158,215
Saprolite	Ni	0.788	0.299	199,812
	Fe	0.154	0.910	221,574
	Co	0.212	0.723	267,887
	SiO_2	0.061	0.709	285,044
	CaO	0.058	0.755	207,793
	MgO	0.499	0.598	236,368

model.

In this study, model selection is more visual because it meets the following requirements are data shows a gradual increase in variability with distance and then levels off, a finite range of spatial correlation is observed, and the variogram flattens near the sill. The fitting process will produce parameters in the form of a nugget effect, which shows the variation over a short distance, sill, the average variance of the sample in general, and range, which is the distance between related data. The best-fitted variogram model was considered for ordinary kriging estimation [31]. These parameters will then become a reference in estimating the level and number of resources. Semivariogram analysis was carried out based on composite data of limonite and saprolite layers in string format and all existing grade data in the research area. The model fitting results of Ni variogram in limonite and saprolite layers can be seen in Figure 8 and Figure 9.

The parameters of the variogram fitting results can be seen in Tables 6 and 7. In semivariogram analysis, values related to the anisotropy parameter can also be obtained to be used as parameters in the search for estimates. Anisotropy is a condition where the semivariogram depends on distance (h)

Table 6. Nickel (limonite layer) variogram results.

Direction	$N0^0E$	$N45^0E$	$N90^0E$	$N135^0E$
Nugget ($\%^2$ Ni)	0.656	0.656	0.656	0.656
Sill ($\%^2$ Ni)	0.386	0.386	0.386	0.386
Range (m)	165.610	146.070	150.780	199.670

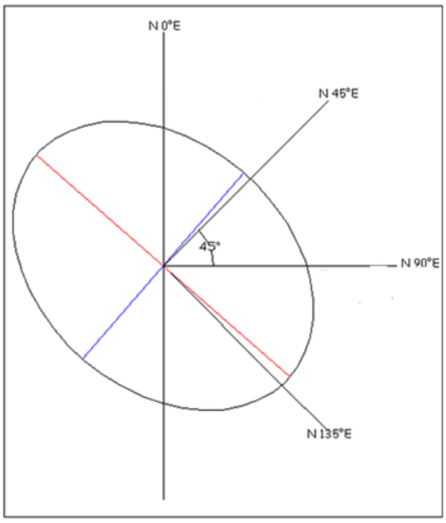

Figure 10. Nickel content anisotropy model.

Table 7. Results of anisotropy parameters in limonite and saprolite layers.

Layer	Data rate	*Ellipsoid orientation*			*Anisotropy ratio*	
		Plunge	*Bearings*	*Dip*	*Semi-major*	*Minor*
Limonite	Ni	0.000	0.000	89.627	1.000	1.127
	Fe	0.000	179.387	89.956	1.000	1.000
	Co	0.000	179.981	89.955	1.000	1.000
	SiO_2	0.000	0.000	89.793	1.015	1.000
	CaO	0.000	179.373	89.336	1.629	2.405
	MgO	0.000	179.998	89.497	1.000	1.000
Saprolite	Ni	0.000	179.993	89.403	1.390	1.033
	Fe	0.000	179.955	89.741	1.069	1.000
	Co	0.000	179.992	89.967	1.000	1.000
	SiO2	0.000	0.116	89.901	1.281	1.000
	CaO	0.000	179.980	89.253	1.283	1.301
	MgO	0.000	179.981	89.954	1.000	1.000

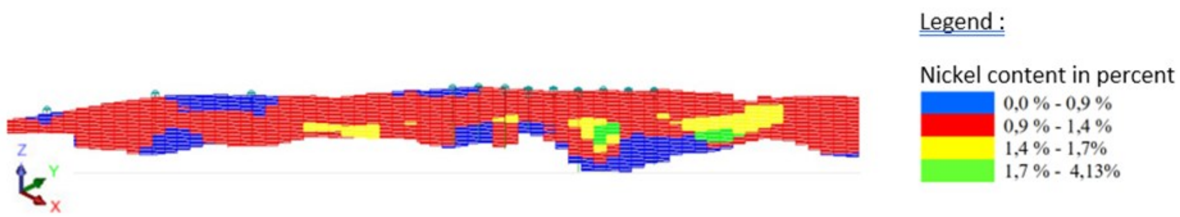

Figure 11. Cross-sectional estimation results of the block model in two dimensions.

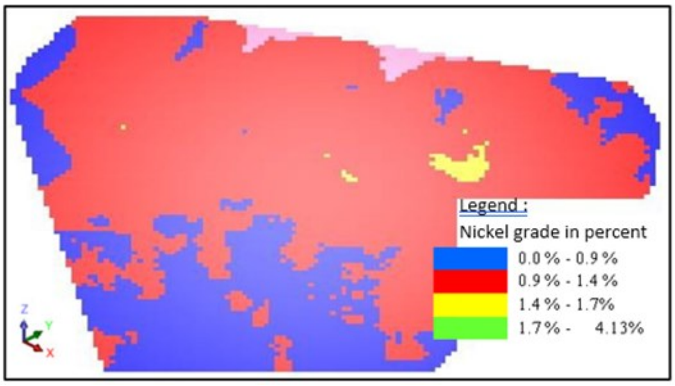

Figure 12. Block model in two-dimensional appearance (plan view).

and direction, so different values for several parameters can be obtained. The results of the variogram anisotropy calculations are shown in Table 8.

Geometric anisotropy or ellipsoid is a popular method in geostatistical analysis for producing variograms with varying ranges in different directions (azimuth) and roughly identical sill variance. Ellipsoid anisotropy is critical in mining when a resource geologist wants to understand the spatial continuity of variables associated with geological controls on mineralization. Generally, variogram modeling is conducted in a three-dimensional (3D) dataset across a minimum of four horizontal orientations (namely, north-south (N–S), northeast-southwest (NE–SW), east-west (E–W), and southeast-northwest (SE–NW)), along with one vertical orientation or downhole direction. In order to fit the 3D ellipsoid anisotropy model, we set the statistical variance equal to the sum of the nugget and sill variances of all variograms. The Nickel Content Anisotropy Model can be seen in Figure 10. Variogram analysis of composite Ni content data was carried out in various directions by adjusting the azimuth and dip parameters to determine the continuity of the data in 3D so that representative estimation parameters were obtained in the estimation. Tables 7 and 8 are the results of anisotropy calculations from creating variograms in several different directions.

3.5. Nickel Resource Estimation and Classification

Nickel resource estimation was carried out using the ordinary kriging method. Resource estimation is carried out at grade points based on the size of the empty model block. There are several references for determining block size, one of which is often used is that the smallest size of a block should not be less than 0.25 of the average borehole interval [33]-[35]. The dimensions of blocks are chosen significantly smaller than the half spacing of the drilling grid, acceptable results are usually not obtained unless the grade has much continuity; it means that the value of the nugget effect is very low and range of variogram is very high [21][36]. The dimensions of estimation blocks should be chosen by considering the interspacing of boreholes and other engineering considerations. In this study, a block size of 12.5 m was used. This is based on a 50 to 100 m grid drilling spacing. The block elevation is adjusted to the level that will be used in mining [34][37]. Then, the estimation results for each level in each block will be obtained. Estimates are based on the parameter values resulting from semivariogram fitting analysis and anisotropy parameters. Next, each block is given a color indicator, arranged

Table 8. Nickel resources estimation and classification report.

Resources Classification	Layer	Tonnage (WMT)	Ni (%)	Fe (%)	Co (%)	SiO_2 (%)	CaO (%)	MgO (%)
Measure	Iron cap	19,188,192	1.02	44.66	0.12	9.24	0.01	0.58
	Limonite	9,703,131	1.34	45.67	0.14	9.27	0.02	0.60
	Saprolite	10,184,248	1.29	15.53	0.03	34.51	0.63	20.02
Total Measure Resources		39,075,571	1.17	37.32	0.10	15.83	0.17	5.65
Indicated	Iron cap	755,008	1.02	44.41	0.13	9.43	0.01	0.65
	Limonite	410,452	1.31	46.42	0.16	9.82	0.02	0.64
	Saprolite	93,902	1.22	15.55	0.04	35.01	0.74	20.13
Total Indicated Resources		1,259,362	1.13	42.91	0.13	11.46	0.07	2.10
Inferred	Iron cap	1,916,837	1.07	46.16	0.16	9.21	0.05	0.93
	Limonite	983,688	1.25	46.79	0.16	9.70	0.04	0.98
	Saprolite	107,243	1.12	14.84	0.03	34.56	0.93	21.02
Total Inferred Resources		3,007,768	1.13	45.25	0.16	10.27	0.08	1.66
Total Mineral Resource		43,342,701	1.16	38.03	0.11	15.32	0.16	5.27

based on the quantity of Ni content in each block. The color indicator shows the results of the Ni content estimation. The blue, red, yellow, and green color show that the block has a Ni content of 0.0%–0.9%, 0.9%–1.4%, 1.4%–1.7%, and 1.7%–4.13%, respectively. The cross-sectional estimation results of the block model in two dimensions and the block model in two-dimensional view (plan view) can be seen in Figures 11 and 12.

The estimation results are not only in the form of grade data, but the estimation results are also in the form of values related to geostatistical parameters that can be used for the resource classification process. One of the geostatistical parameter values in question is KE. The following parameters for resource and reserve classification based on the kriging efficiency ratio [38]. The calculation of KE aims to obtain the results of the resulting resource classification because the determination of resource classification for minerals is seen from the variation in the distribution of mineral content. KE is expressed by Kriging variance normalized by block variance in the form of a percentage. If the KE value is high; the kriging variance is low or vice versa. The classification of resources based on KE is as follows: (1) Inferred blocks with a KE value < 0.3; (2) Indicated blocks having a value of 0.3 < KE < 0.5; and (3) Measured blocks having a KE value > 0.5. Next, constraints are created to display blocks or areas for each resource classification in the iron cap, limonite, and saprolite layers. These constraints are also used as a reference for the process of reporting resource estimates.

The next resource estimation stage is a feasibility study and reserve calculation; the final stage is mining operation and processing. Coal mining is a long-term activity involving high technology and capital intensive. In addition, the fundamental characteristic of the coal mining industry is to clear land and change the landscape so that it has the potential to cause environmental, social, and economic impacts on the community. Environmentally, coal mining impacts landscape change, decreased soil fertility, threats to biodiversity, decreased water quality, decreased air quality, and cause environmental pollution. To avoid these negative impacts, mining must follow the concept of good mining practice, namely mining that follows good and correct mining rules, starting from exploitation and resource estimation.

4. CONCLUSIONS

According to the research objectives, the data are completed based on the available data, and the stages of descriptive statistical and variographic analysis have been carried out. Ordinary kriging and KE methods were used to estimate nickel resources. The descriptive statistical analysis results obtained a data pattern with a normal distribution, with a CV value of 0.5 to 1.5. Histogram analysis shows a slight positive skewness and a sharp peak. From the variographic analysis, the appropriate variogram model is the spherical model; there is also an anisotropy structure, which shows different variations in specific directions. The model block used has dimensions of 12.5 m, which is based on the drilling grid spacing. Nickel resource estimation uses the KE method, which is a proven method. The results are the number of measured, indicated, and inferred nickel resources of 39,075,571; 1,259,362; and 3,007,768 tons, respectively, with an overall average Ni content of 1.16%.

AUTHOR INFORMATION

Corresponding Author

Irfan Marwanza — Department of Mining, University of Trisakti, Jakarta-11450 (Indonesia);
orcid.org/0000-0003-3544-4886
Email: irfanm@trisakti.ac.id

Authors

Danu Putra — Department of Mining, University of Trisakti, Jakarta-11450 (Indonesia);
orcid.org/0000-0002-7950-2593
Masagus Ahmad Azizi — Department of Mining, University of Trisakti, Jakarta-11450 (Indonesia);
orcid.org/0000-0003-2965-8124
Wiwik Dahani — Department of Mining, University of Trisakti, Jakarta-11450 (Indonesia);
orcid.org/0000-0002-6791-3117
Rhazes Eesha Gumay — Business Analytics, University of Western Australia, Crawley WA-

6009 (Australia);
orcid.org/0009-0005-0271-4845
Silvia Immanuela Sahetapy — Department of Mining, University of Trisakti, Jakarta-11450 (Indonesia);
orcid.org/0009-0003-8808-8288

Author Contributions

The authors contributed equally to this work.

Conflicts of Interest

The authors declare no conflict of interest.

ACKNOWLEDGEMENT

All of us as authors–would like to thank PT Prosperous Lestari Primatama (MLP) which has gave permission to use company data in this research and has helped throughout the author did research at the PT MLP Molore Site. The author also would like to thank the Mining Engineering Study Program at Trisakti University for their support.

REFERENCES

[1] A. van der Ent, A. J. M. Baker, M. M. J. van Balgooy, and A. Tjoa. (2013). "Ultramafic nickel laterites in Indonesia (Sulawesi, Halmahera): Mining, nickel hyperaccumulators and opportunities for phytomining". *Journal of Geochemical Exploration.* **128** : 72-79. 10.1016/j.gexplo.2013.01.009.

[2] L. Lu, Y. Lei, Y. Yang, H. Zheng, W. Wang, Y. Meng, C. Meng, and L. Zha. (2023). "Assessing nickel sector index volatility based on quantile regression for Garch and Egarch models: Evidence from the Chinese stock market 2018–2022". *Resources Policy.* **82**. 10.1016/j.resourpol.2023.103563.

[3] S. A. Al-Khirbash. (2020). "Mineralogical characterization of low-grade nickel laterites from the North Oman Mountains: Using mineral liberation analyses – scanning electron microscopy-based automated quantitative mineralogy". *Ore Geology Reviews.* **120**. 10.1016/j.oregeorev.2020.103429.

[4] F. Usman, G. M. Tinungki, and E. T. Herdiani. (2021). "Efficiency of Ni Content in Laterite Nickel Deposits through The Least Square Method Approach on Semivariogram". *Journal of Physics: Conference Series.* **2123** (1). 10.1088/1742-6596/2123/1/012015.

[5] X. Yan, T. Yang, Y. Xu, L. Tosi, E. Stouthamer, H. Andreas, J. Lin, and X. Huang. (2019). "Impact, Mechanism, Monitoring of Land Subsidence in Coastal Cities (Annual Work of IGCP 663)". *Acta Geologica Sinica - English Edition.* **93** (S3): 158-159. 10.1111/1755-6724.14276.

[6] S. S. P, Y. Sibaroni, and M. Nur Heriawan. (2016). "Spatial Analysis 3d Geology Nickel Using Ordinary Kriging Method". *Jurnal Teknologi.* **78** (5). 10.11113/jt.v78.8340.

[7] M. Mälicke, A. Guadagnini, and E. Zehe. (2023). "SciKit-GStat Uncertainty: A software extension to cope with uncertain geostatistical estimates". *Spatial Statistics.* **54**. 10.1016/j.spasta.2023.100737.

[8] M. N. Heriawan and K. Koike. (2008). "Identifying spatial heterogeneity of coal resource quality in a multilayer coal deposit by multivariate geostatistics". *International Journal of Coal Geology.* **73** (3-4): 307-330. 10.1016/j.coal.2007.07.005.

[9] W. S. Bargawa. (2022). "The Performance of Estimation Techniques for Nickel Laterite Resource Modeling". *Jurnal Teknologi.* **84** (4): 1-8. 10.11113/jurnalteknologi.v84.17560.

[10] T. Wendler and S. Gröttrup. (2021). In: "Data Mining with SPSS Modeler, ch. Chapter 3". 191-305. 10.1007/978-3-030-54338-9_3.

[11] R. G. Arancibia, P. Llop, and M. Lovatto. (2023). "Nonparametric prediction for univariate spatial data: Methods and applications". *Papers in Regional Science.* **102** (3): 635-673. 10.1111/pirs.12735.

[12] P. Kumar, B. Rao, A. Burman, S. Kumar, and P. Samui. (2023). "Spatial variation of permeability and consolidation behaviors of soil using ordinary kriging method". *Groundwater for Sustainable Development.* **20**. 10.1016/j.gsd.2022.100856.

[13] C. Y. S. Ip, H. Rahardjo, and A. Satyanaga. (2019). "Spatial variations of air-entry value for residual soils in Singapore". *Catena.* **174** : 259-268. 10.1016/j.catena.2018.11.012.

[14] N. A. Amri, W. S. Bargawa, and T. A. Cahyadi. (2021). "Multi Criterion Priority On Kriging Of Gold Resources Prediction". *Journal Techno.* **7** (2).

[15] R. Faidatulaila, I. Marwanza, and T. T. Purwiyono. (2023). "Variography analysis on the assessment of coal deposit quality using the ordinary kriging method". *AIP Conference Proceedings.* 10.1063/5.0126896.

[16] B. Anggara, I. Marwanza, M. Ahmad Azizi, W. Dahani, and Subandrio. (2021). "Fitting the variogram model of nickel laterite using root means square error in Morowali, Central Sulawesi". *IOP Conference Series: Earth and Environmental Science.* **882** (1). 10.1088/1755-1315/882/1/012042.

[17] M. Abzalov. (2016). In: "Applied Mining Geology, (Modern Approaches in Solid Earth Sciences, ch. Chapter 17". 233-237. 10.1007/978-3-319-39264-6_17.

[18] C. Zhou, L. Wang, and Y. Chen. (2023). "Active learning-based structural reliability evaluation Kriging model and sequential importance sampling". *Structures.* **56**. 10.1016/j.istruc.2023.104956.

[19] Y. Pang, Y. Wang, X. Lai, S. Zhang, P. Liang, and X. Song. (2023). "Enhanced Kriging leave-one-out cross-validation in improving model estimation and optimization". *Computer Methods in Applied Mechanics and Engineering.* **414**. 10.1016/j.cma.2023.116194.

[20] D. Ali Akbar. (2012). "Reserve estimation of central part of Choghart north anomaly iron ore deposit through ordinary kriging method". *International Journal of Mining Science and Technology.* **22** (4): 573-577. 10.1016/j.ijmst.2012.01.022.

[21] D. G. Krige. (1997). In: "Geostatistics Wollongong' 96, (Quantitative Geology and Geostatistics, ch. Chapter 14". 799-810. 10.1007/978-94-011-5726-1_14.

[22] C. Munyati and N. I. Sinthumule. (2021). "Comparative suitability of ordinary kriging and Inverse Distance Weighted interpolation for indicating intactness gradients on threatened savannah woodland and forest stands". *Environmental and Sustainability Indicators.* **12**. 10.1016/j.indic.2021.100151.

[23] W. A. K. Conoras and A. A. Lamburu. (2020). "Modeling and Resource Classification Lateritic Nickel Deposits on a Heterogeneous Block in The Haul-Sagu Area using Estimation and Simulation Geostatistical Method". *Journal of Physics: Conference Series.* **1569** (4). 10.1088/1742-6596/1569/4/042079.

[24] S. Al-Ali and S. Al-Khafaji. (2023). "Spatial distribution and reserve estimation of sand and gravel deposits using geostatistical methods in west Basrah, southern Iraq". *Kuwait Journal of Science.* **50** (2): 127-137. 10.1016/j.kjs.2023.02.017.

[25] M. L. C. M. Henckens, F. H. B. Biermann, and P. P. J. Driessen. (2019). "Mineral resources governance: A call for the establishment of an International Competence Center on Mineral Resources Management". *Resources, Conservation and Recycling.* **141** : 255-263. 10.1016/j.resconrec.2018.10.033.

[26] C. Tang, M. Irfan, A. Razzaq, and V. Dagar. (2022). "Natural resources and financial development: Role of business regulations in testing the resource-curse hypothesis in ASEAN countries". *Resources Policy.* **76**. 10.1016/j.resourpol.2022.102612.

[27] F. Isatelle and J. Rivoirard. (2019). "Mineral Resources classification of a nickel laterite deposit: Comparison between conditional simulations and specific areas". *Journal of the Southern African Institute of Mining and Metallurgy.* **119** (10). 10.17159/2411-9717/660/2019.

[28] P. C. F. Crowson. (2011). "Mineral reserves and future minerals availability". *Mineral Economics.* **24** (1): 1-6. 10.1007/s13563-011-0002-9.

[29] O. Zerzour, L. Gadri, R. Hadji, F. Mebrouk, and Y. Hamed. (2021). "Geostatistics-Based Method for Irregular Mineral Resource Estimation, in Ouenza Iron Mine, Northeastern Algeria". *Geotechnical and*

Geological Engineering. **39** (5): 3337-3346. 10.1007/s10706-021-01695-1.

[30] S. M. Jowitt and B. A. McNulty. (2021). "Geology and Mining: Mineral Resources and Reserves: Their Estimation, Use, and Abuse". *SEG Discovery*. **125** : 27-36. 10.5382/Geo-and-Mining-11.

[31] M. M. Zaki, S. Chen, J. Zhang, F. Feng, A. A. Khoreshok, M. A. Mahdy, and K. M. Salim. (2022). "A Novel Approach for Resource Estimation of Highly Skewed Gold Using Machine Learning Algorithms". *Minerals*. **12** (7). 10.3390/min12070900.

[32] M. Uyan and A. E. Dursun. (2021). "Determination and modeling of lignite reserve using geostatistical analysis and GIS". *Arabian Journal of Geosciences*. **14** (4). 10.1007/s12517-021-06633-2.

[33] A. A. Daya and H. Bejari. (2014). "A comparative study between simple kriging and ordinary kriging for estimating and modeling the Cu concentration in Chehlkureh deposit, SE Iran". *Arabian Journal of Geosciences*. **8** (8): 6003-6020. 10.1007/s12517-014-1618-1.

[34] M. J. Mihalasky. (2016). "Mineral Resource Estimation (M.E. Rossi and C.V. Deutsch)". *Economic Geology*. **111** (1): 272-274. 10.2113/econgeo.111.1.272.

[35] A. Daya. (2015). "Ordinary kriging for the estimation of vein type copper deposit: A case study of the Chelkureh, Iran". *Journal of Mining and Metallurgy A: Mining*. **51** (1): 1-14. 10.5937/jmma1501001d.

[36] T. B. Afeni, V. O. Akeju, and A. E. Aladejare. (2021). "A comparative study of geometric and geostatistical methods for qualitative reserve estimation of limestone deposit". *Geoscience Frontiers*. **12** (1): 243-253. 10.1016/j.gsf.2020.02.019.

[37] Y. Sun, J. Zuo, M. Karakus, L. Liu, H. Zhou, and M. Yu. (2021). "A New Theoretical Method to Predict Strata Movement and Surface Subsidence due to Inclined Coal Seam Mining". *Rock Mechanics and Rock Engineering*. **54** (6): 2723-2740. 10.1007/s00603-021-02424-z.

[38] M. Taghvaeenezhad, M. Shayestehfar, P. Moarefvand, and A. Rezaei. (2020). "Quantifying the criteria for classification of mineral resources and reserves through the estimation of block model uncertainty using geostatistical methods: a case study of Khoshoumi Uranium deposit in Yazd, Iran". *Geosystem Engineering*. **23** (4): 216-225. 10.1080/12269328.2020.1748524.