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MINERAL MINING TECHNOLOGY

Reserve Estimation in Multivariate Mineral Deposits Using Geostatistics and GIS[1]

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Abstract—In this study, drilled core values from the Magnesite Incorporated Company—its original Turkish name being Manyezit Anonim Sirketi (MAS)—Beylikova Magnesite Open-Pit Mine in Eskisehir-Turkey provided multivariate ore grade and reserve estimates that were used to integrate geostatistical estimation methods with Geographic Information Systems (GIS) technology. GIS technology is known for with its visual and spatial query capabilities in three-dimensional (3D) environments. Using the company's topographical maps, a digital terrain model of the mine area of interest was generated in a GIS environment. Bore hole locations, drilled core values and cutting depths were also input to the sophisticated spatial geodatabase. Ore impurity grade values were analyzed according to their lognormal distributions, then evaluated by applying their corresponding variogram and cross-variogram models — models used in ordinary cokriging. To estimate ore reserve and grade, ordinary cokriging techniques were used: a two-variable model with two different variable combinations and a three-variable model. Spatial queries were applied to estimation results in a 3D GIS platform in order to determine the location, shape, and quantity of the ore body. Subsequently, the Mean Standardized Square Error (MSSE) statistical procedure was applied to the estimation results to assess and compare their accuracy. Based on these assessments, it was determined that ordinary cokriging with three variables was the most appropriate and accurate approach for estimating ore grade distribution and reserve in Beylikova Open-Pit Mine.

Keywords: Geographic information systems, multivariate geostatistics, ordinary cokriging, cross-variogram, reserve estimation, 3B, magnesite.

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INTRODUCTION

In mineral deposits, ore grade dispersion has both structural and random qualities. Although mineralization can be characterized by certain rules of geology, the process has inherent irregularities that prevent its accurate predetermination [1]. Accordingly, developing scientific estimates of mineralization requires accounting for both structural and random factors of ore grade dispersion. Such estimates are possible by applying statistical concepts when examining geological structure. Merging these two disciplines, geology and statistics, creates a third one, geostatistics [2, 3]. As a branch of applied statistics, it examines the geological structure of mineral deposits in the context of spatial relationships between data samples of different quality and quantity. In other words, geostatistics is a spatial analysis method that investigates relationships between data samples by taking their locations into account [4, 5].

Spatial Analysis is a statistical method for determining the properties and the relationships of sample points, while taking into account the distance between them. The first law of geography specifically that "*everything is related to everything else, but near things are more related than distant things*" [6], emphasizes that such dependency is a key concept in the relationships of spatial phenomena.

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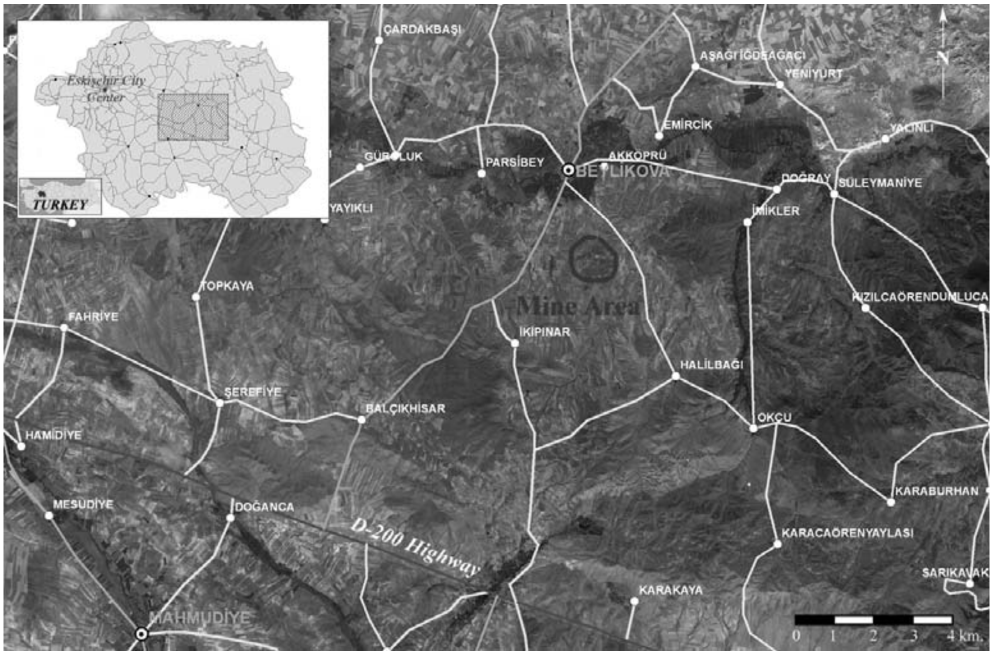

Fig. 1. Location map.

The concept of spatial information and analysis is intrinsic to a widely used computer information system, Geographic Information Systems (GIS). GIS technology with spatial data processing and interpretation capabilities can be described as a visual decision support system [7, 8].

In this study GIS-based visual and interactive analyses were used to examine the relationship of study area data to the data as a whole in an integrated spatial database. This study's objective was to integrate geostatistics with GIS capabilities such as spatial analysis, exposition, 3D data visualization and processing, etc. In nearly every field, computer-generated virtual environments enhance operation and understanding. Such techniques have substantially minimized production expenses by determining required levels of investment early in the implementation stage. Mining operations are known for high production expenditures and sizeable initial investment risks. As a result, industry investments have been directed toward high-grade ore bodies close to the surface, also known as outcrops. As these resources have been depleted, geologists have used estimation methods to provide ore reserve and grade assessments. By comparison, using virtual environments to characterize spatial attributes of mineral deposits, estimate the quality and the quantity of ore bodies, and model production methods can significantly reduce mining operating expenses [9].

1. MATERIALS AND METHODS

1.1. Study Area

The Magnesite Incorporated Company (MAS) Beylikova Magnesite Open-Pit Mine in Eskişehir-Turkey was selected as the study area. In this mine exploration drillings were ongoing but production was not yet underway. Eskişehir province is located in the northwestern part of Anatolia, Turkey and is equidistant from İstanbul, the country's largest metropolitan city, and its capital, Ankara. The Beylikova mine is located in the southern Beylikova County, 17 km north of the highway connection between Eskişehir and Ankara and designated as D–200 in Fig. 1.

1.2. Data Sampling and Statistical Analyses

Geodatabase was established in a 3D GIS environment using data from MAS. First, a digital elevation model (DEM) of the mine area was generated. Thereafter, drilling locations were added including drilling depths in XYZ coordinates as line features. Impurity grade values obtained from drilling cuttings were identified as point features in 3D space. In this particular mine, drilling areas were at random locations rather than in a regular network, and drilling depths varied from hole to hole.

Normal and lognormal distributions of three impurities—calcium oxide (CaO), silicon oxide (SiO_2), and ferric oxide (Fe_2O_3)—were monitored by univariate statistical parameters (Tables 1 and 2). To determine the appropriate distributions for the variables, chi-square tests were applied to both normal and logarithmic grade values for 130 sample points obtained from drillings. The chi-square examinations demonstrated that the latter scale was more suitable in this context. Using the logarithmic grade values, geostatistical analyses were performed for all three impurities (Tables 3 and 4).

Table 1. Statistical parameters of normal values

Parameters	CaO	SiO_2	Fe_2O_3
Mean	1.5841	0.9093	0.1574
Variance	0.9434	1.2893	0.0262
Standard deviation	0.9713	1.1355	0.1619
Min	0.2300	0.0100	0.0200
Max	4.9300	5.9800	0.8200
Median	1.2834	0.4743	0.1068
Skewness	1.3799	2.2791	2.0013
Curtosis	4.6898	8.9571	7.2878
Coefficient of variation	0.6131	1.2487	1.0285
Count	130	130	130

Table 2. Statistical parameters of logarithmic values

Parameters	lnCaO	$\ln SiO_2$	$\ln Fe_2O_3$
Mean	0.2869	-0.8770	-2.3067
Variance	0.3630	1.9835	0.9644
Standard deviation	0.6025	1.4084	0.9820
Min	-1.4697	-4.6052	-3.9120
Max	1.5953	1.7884	-0.1985
Median	0.2543	-0.8345	-2.2909
Skewness	-0.2266	-0.4027	0.0409
Curtosis	3.2913	2.6072	2.2016
Coefficient of variation	2.1000	-1.6059	-0.4257
Count	130	130	130

Table 3. Chi-square test results for normal values

	95% confidence level			
	Chi-square values		Degree of freedom	Normal distribution
	Observed	Expected		
CaO	42.1767	24.9958	15	Reject
SiO_2	54.2162	24.9958	15	Reject
Fe_2O_3	56.8370	24.9958	15	Reject

Table 4. Chi-square test results for logarithmic values

	95% confidence level			
	Chi-square values		Degree of freedom	Normal distribution
	Observed	Expected		
lnCaO	12.4571	24.9958	15	Accept
$\ln SiO_2$	8.9496	24.9958	15	Accept
$\ln Fe_2O_3$	15.5828	24.9958	15	Accept

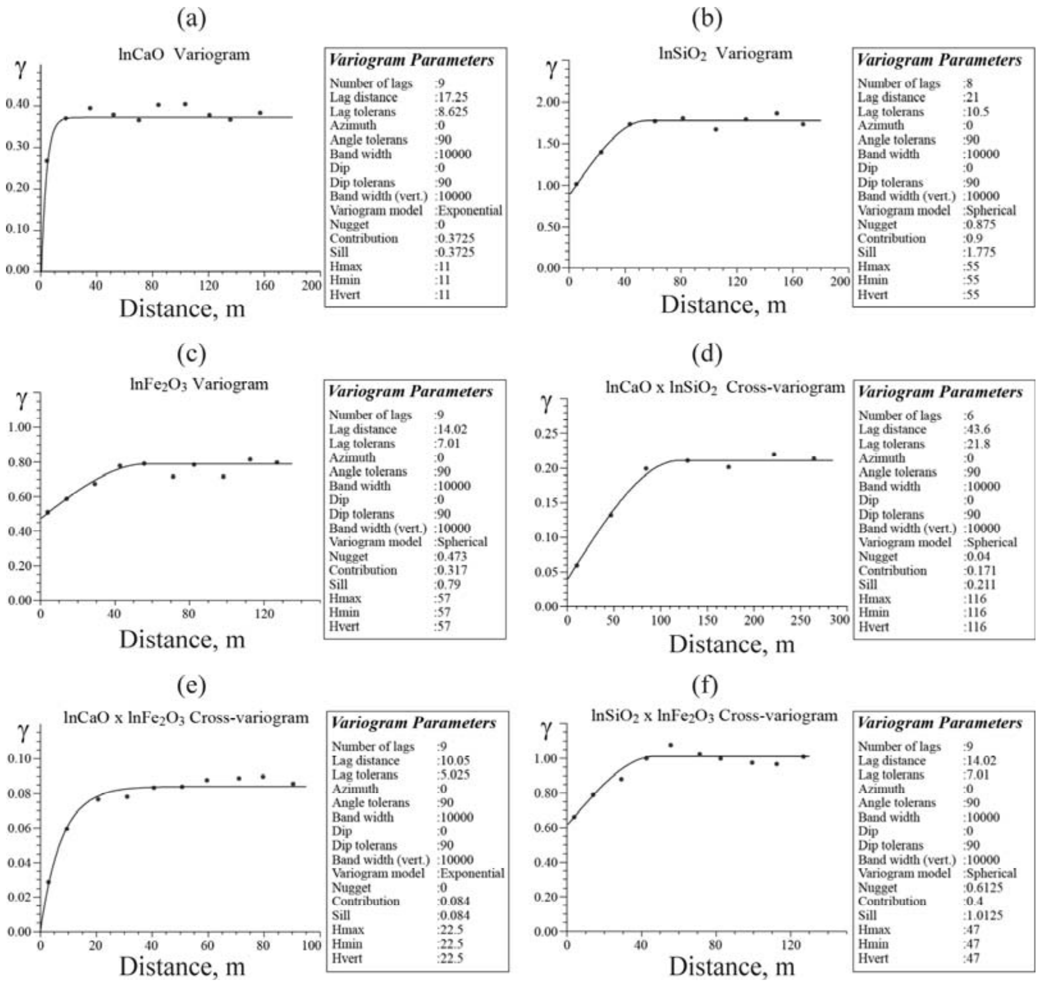

Fig. 2. Variogram and cross-variogram models and parameters.

1.2.1. Variogram and cross-variogram models

For each of the three impurities, the study investigated whether the mineralization had occurred in a certain directions by examining different axes for anisotropy. Because the geostatistical analyses were studied in 3D computer-generated platforms, anisotropy was investigated in both the vertical and horizontal resultants. In both of these axes, the azimuth and dip angle, both in 45^{o} incremental steps, were used as the components of the respective resultants. Anisotropy was investigated in 16 resultant directions for different lag distances. In some of the directions, the number of sample pairs was insufficient for anisotropic evaluation, but in those with sufficient paired data for analysis, anisotropy was not observed either in the variograms or the cross-variograms. Consequently, omnidirectional variograms and cross-variograms of all possible sample pairs were used to define the spatial auto-correlation. The details of the variogram models and their parameters are given in Fig. 2.

Table 5. Combinations used for ordinary cokriging estimations

	Estimated value	Primary variable	Second variable	Third variable
OCK1	$\ln CaO$	$\ln CaO$	$\ln SiO_2$	-
	$\ln SiO_2$	$\ln SiO_2$	$\ln CaO$	-
	$\ln Fe_2O_3$	$\ln Fe_2O_3$	$\ln CaO$	-
OCK2	$\ln CaO$	$\ln CaO$	$\ln Fe_2O_3$	-
	$\ln SiO_2$	$\ln SiO_2$	$\ln Fe_2O_3$	-
	$\ln Fe_2O_3$	$\ln Fe_2O_3$	$\ln SiO_2$	-
OCK3	$\ln CaO$	$\ln CaO$	$\ln SiO_2$	$\ln Fe_2O_3$
	$\ln SiO_2$	$\ln SiO_2$	$\ln Fe_2O_3$	$\ln CaO$
	$\ln Fe_2O_3$	$\ln Fe_2O_3$	$\ln SiO_2$	$\ln CaO$

Table 6. Ore classes with impurity grade ranges by MAŞ

Ore classes	CaO (%)	SiO_2 (%)	Fe_2O_3 (%)
Class 1	max 1.25	0.00–0.60	max 0.20
Class 2	max 1.00	1.40–1.85	max 0.35
Class 3	max 1.30	0.61–1.00	max 0.40

1.2.2. Estimations and associated variances

Lognormal kriging is an estimation technique that was devised for handling highly skewed data distributions [10].Using the logarithmic grade values of impurities ($\ln CaO$, $\ln SiO_2$ and $\ln Fe_2O_3$), ordinary cokriging estimations were developed from three different sets of variable combinations. Two of these sets used estimates derived from the three possible combinations of two impurity variables; a third set presents estimates obtained from combining three impurity variables, the details of which are given in Table 5. Estimation and kriging variance values, calculated from log-transformed data, were back-transformed.

A 3D GIS environment was spatially defined within the mine's boundaries with georeferencing provided by real-world coordinates (in meters): X (west to east), Y (south to north), and Z (depth to elevation). The georeferenced 3D space was divided into voxels with the unit dimensions $5\times5\times5$ m—each voxel assigned a back-transformed estimate. In this GIS environment with its three-dimensional capability, voxel configurations representing different ore grade dispersion, interactive query results, and spatial analyses permit unlimited examination.

Magnesite Incorporated Company has an ore enrichment plant that produces sintered magnesite from crude ore, enriching magnesite from their own mine as well as that excavated elsewhere in Eskişehir Province. The latter was also categorized based on grade ranges of the same impurities (CaO, SiO_2 and Fe_2O_3). According to this classification scheme, MAS produces three types of crude magnesite (Table 6). All of the ore grade and reserve data were input to yield OCK1, OCK2 and OCK3 reserve and grade estimates that were spatially analyzed on the basis of these three impurities.

According to Table 6, impurity grades ranged between 0.00 and 1.30% for CaO; 0.00–1.85% for SiO_2, and 0.20–0.40% for Fe_2O_3.. For purposes of GIS imaging, these impurity estimates were assigned one of two possible values: voxels with values that were within the designated range were coded as one (1), and the remaining valued-voxels—impurity values that fell outside of the limits—were recorded as zero (0). When ore from one location contained impurities within all three specified ranges, this approach permitted determination of the shape and the spatial location of that ore-body. In other words, the GIS-generated shape and location of an ore-body in 3D space emerged from the intersecting locations of each three-impurity-derived ore-body voxel. Using the algebraic zero property of multiplication (any value multiplied by zero equals zero), recorded voxels as zero (0) and one (1) were spatially multiplied. These processes can be visualized in Fig. 3.

For each estimate (OCK1, OCK2, and OCK3), the shapes and the locations of the subsurface ore-bodies were modeled. Each of these models, coded as either one (1) or zero (0), was subsequently multiplied by its respective value (OCK1, OCK2, or OCK3). In this way, reserve estimations of the crude ore classes defined by the company, as well as their ore grade distributions, were determined (Fig. 4).

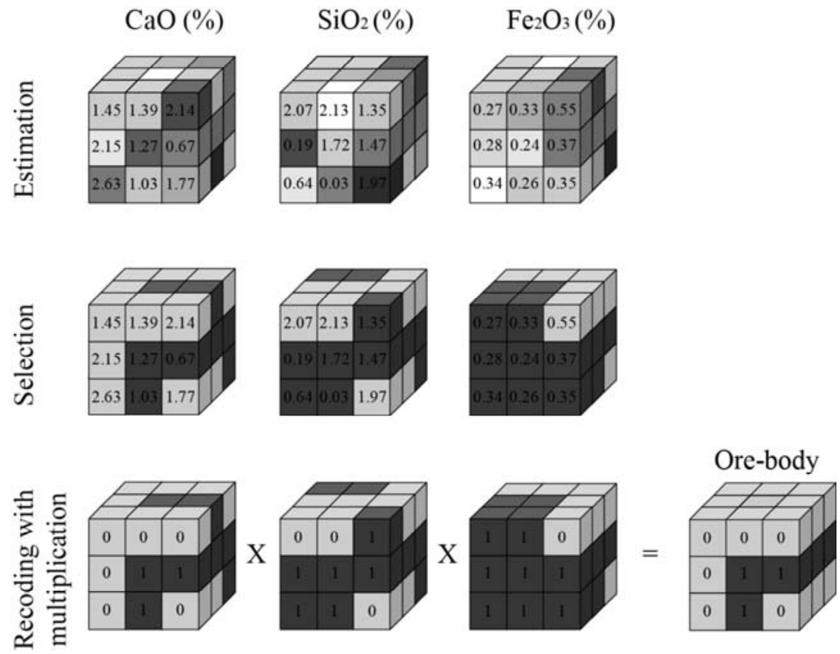

Fig. 3. Visual explanation of the three processes: estimation, selection, and recoding with multiplication.

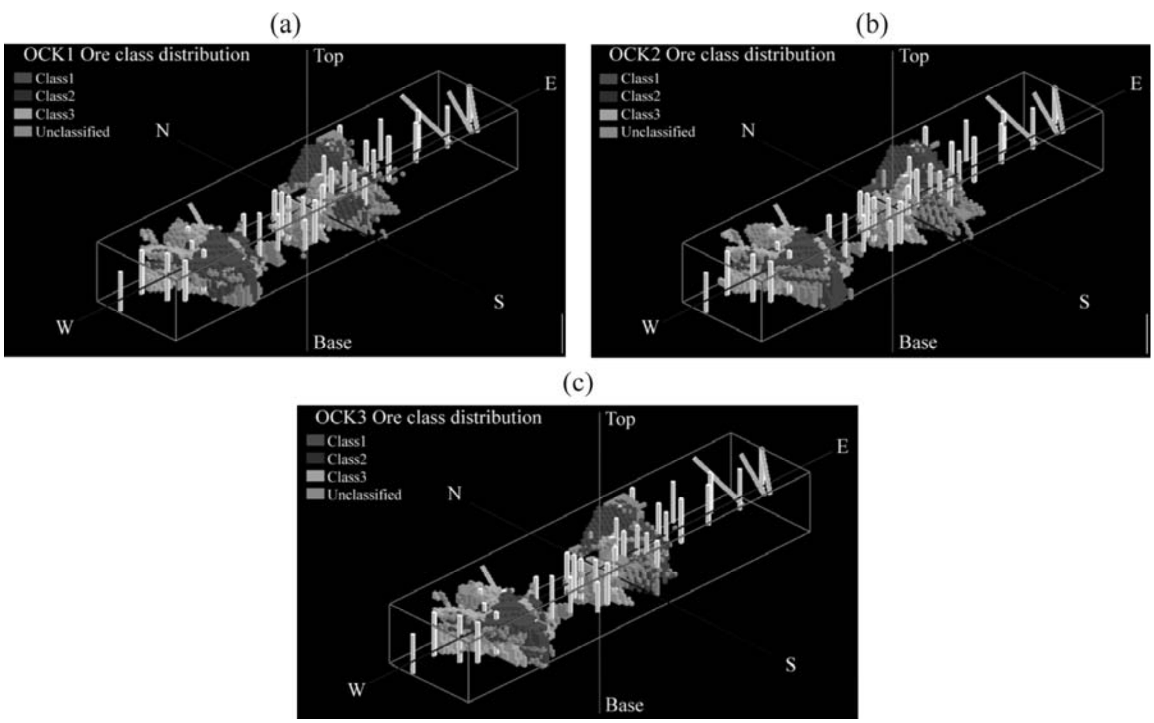

Fig. 4. Ore class distributions of estimation results.

Table 7. Estimation results in tons

	Ore classes	$MgCO_3$, m^3	$MgCO_3$, t	MgO, t
OCK1	Class 1	522 000	1 566 000	720 360
	Class 2	750	2 250	1 035
	Class 3	156 125	468 375	215 453
	Unclassified	297 125	891 375	410 033
	Total reserve	976 000	2 928 000	1 346 880
OCK2	Class 1	508 625	1 525 875	701 903
	Class 2	625	1 875	863
	Class 3	172 000	516 000	237 360
	Unclassified	257 250	771 750	355 005
	Total reserve	938 500	2 815 500	1 295 130
OCK3	Class 1	455 375	1 366 125	628 418
	Class 2	1 250	3 750	1 725
	Class 3	173 750	521 250	239 775
	Unclassified	283 750	851 250	391 575
	Total reserve	914 125	2 742 375	1 261 493

Table 8. MSSE values for CaO estimations

For CaO	OCK1	OCK2	OCK3
MSSE	0.7949	0.8053	**1.0826**

The company's GIS-generated reserve estimates are presented as volume measurements. To convert these values to weight in tons, the volume estimates were first multiplied by magnesite's ($MgCO_3$) approximate density (3 g/cm^3) and then by the relative magnesia (MgO) content of magnesite, assumed to be 46 per cent. The results, calculated in tons, are presented in Table 7.

1.3. Accuracy Assessment and Comparison

The study's final step involved assessing the accuracy of each of the three kriging estimates to determine which was the most precise. The statistical technique, the Mean Standardized Square Error (MSSE), was used for this purpose. In this study, MSSE values were only obtained for the CaO findings; as the major impurity at the MAS mining facility, it plays an important role in determining the shape and the location of the magnesite ore-body. Basically, MSSE compares the squared differences with the kriging variances, yielding a value that should be close to one [4]:

$$MSSE = \frac{1}{n}\sum_{i=1}^{n}\frac{(Z_i - Z_i^*)^2}{\sigma_i^2},$$

where Z_i—the sample value that spatially falls inside the voxel at position i; Z_i^*—the estimated value of the voxel at position i; σ_i^2—kriging variance value of the voxel at position i; n—number of samples.

As proposed by Chiles and Delfiner [11], the MSSE with a tolerance of $\pm 2(2/n)^{0.5}$ is calculated at the 95 per cent confidence level. Data from 130 samples at the MAS Company yielded a MSSE tolerance of $\pm 2(2/130)^{0.5} = \pm 0.2480$ and a 95% confidence range of 0.7520 to 1.2480. The MSSE values for all three study estimates of CaO fell within the 95% confidence range of accuracy—the best estimation being that closest to 1.0. In other words, OCK1, OCK2, and OCK3 estimations were all considered accurate at a 95% confidence level. Table 8 shows that, of the three values for CaO, the OCK3 estimate was the most accurate as its MSSE of 1.0826 is the closest to 1.0.

2. RESULTS

To determine the shape, spatial location, qualitative, and quantitative features of the magnesite ore-body in the Beylikova Open-Pit Mine, impurity grade ranges and crude ore classifications provided by the company were used in this study. According to these grade ranges, CaO was observed to be the key restrictive impurity, establishing the shape, location and dimensions of the magnesite ore-body.

Averaging the results (OCK1, OCK2 and OCK3), the Beylikova mine had virtually no Class 2 reserve. Fifty percent of the mine was classified as Class 1; another twenty per cent as Class 3. The remaining thirty per cent of the reserve was determined to be unclassified ore. According to the OCK3, the most accurate estimate as determined by MSSE evaluation, this unclassified ore reserve is approximately 850,000 tons of $MgCO_3$. Geostatistical analyses coupled with 3D GIS technology suggest that the company should consider this reserve as having economic value.

3. DISCUSSION

Integrating geostatistical applications with the 3D spatial visualization and query capabilities of GIS technology offers substantially enhanced information compared to that obtained from the individual techniques. GIS provides visual displays, executes spatial queries and integrates different types of data such as surface topography with ordinary cokriging estimations.

Ordinary cokriging is a method of unbiased estimation that minimizes estimation error variance by exploiting the spatial cross-correlation between the variable of interest and auxiliary variables [12]. Study findings revealed that the OCK3 estimate with three variables was more accurate than those calculated from two-variable models (OCK1, OCK2). This shows that the extra information obtained from additional auxiliary variables improves the accuracy of the estimates derived from the mining data.

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