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Spatial coal seam modeling and reserve estimation using geostatistical methodologies by GIS technique in a selected coalfield in Ermenek Basin, Turkey

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Abstract
The accurate and reliable calculation of tonnage and quality of coal is vital for the success of mining projects. The Ermenek coal basin is located in the Western Taurus Mountains in the southern part of Turkey, which covers an area of approximately 620 km^2 and is a Neogene coal basin. This paper generates spatial modeling of Pamuklu-Tepebaşı coal seams in the Ermenek Basin and the prediction of coal reserve by using geostatistical methods with Ordinary Kriging (OK) based on the GIS technique. The data used in the study were obtained from 82 boreholes belonging to a private company that has actively produced coal in the Pamuklu-Tepebaşı coalfield. In this study, the OK method was applied to spatial coal seam modeling for comparison of the performance of 11 distinct models. Using the rational quadratic models better explained the spatial structure of the coal seam depth data. The nugget-sill ratio indicated high spatial dependency with 0.01 and 0.02 for coal seam upper-lower surfaces, respectively. The kriged coal depth maps for upper and lower coal seam surfaces have been created using ArcGIS 10.2 software. As a result of these analyses, it was calculated that there is a coal reserve of 3.734.017 m^3 using the determined surfaces with OK in the study area. Furthermore, developed spatial distribution maps in the study area could be helpful to plan further exploration activities.

Keywords
Geostatistics, spatial analysis, coal reserve estimation, ordinary kriging, GIS technique

Introduction

Geostatistical methodologies have been widely used in many different disciplines of engineering in recent years (Uyan & Dursun, 2021). Especially in mining, prediction of coal reserve or ore bodies, quality parameters such as grade of ore body and calorific values of coal and dimensions of coal seam and ore bodies have been determined by using geostatistical simulation methods (Heriawan & Koike 2008a, 2008b)(Li, Heap, Potter, & Daniell, 2011)(Ertunc, Tercan, Hindistan, Unver, Unal, Atalay, & Killioglu, 2013)(Olea, 2013)(Srivastava, 2013)(Tercan & Sohrabian, 2013) (Webber, Costa, & Salvadoretti, 2013)(Li & Heap, 2014)(Jeuken, Xu, & Dowd, 2020)(Maxwell, Rajabi, & Esterle, 2021a, 2021b). Spatial modeling is a regression technique that estimates properties at unknown locations based on measured values (Li & Heap, 2014). It has been stated that the Kriging method is the most accurate and successful technique in reserve estimation and other operations using geostatistical methodologies in mining (Ertunç et al., 2013)(Saikia & Sarkar, 2013)(Srivastava, 2013)(Tercan & Sohrabian, 2013)(Olea & Luppens, 2015)(Li, 2016)(Jeuken, Xu, & Dowd, 2017)(Karacan & Olea, 2018)(Hengl, Nussbaum, Wright, Heuvelink, & Gräler, 2018)(Georganos, Grippa, Niang Gadiaga, Linard, Lennert, Vanhuysse, Mboga, Wolff, & Kalogirou, 2021)(Jeuken et al., 2020)(Maxwell et al., 2021a)(Maxwell, Rajabi, & Esterle, 2022). Furthermore, the Kriging is widely used as the most and as an optimal interpolation in other engineering disciplines. A spatial analysis that is the basis of geostatistics in many engineering disciplines has been applied using the GIS technique, which provides reliable, accurate, and powerful possibilities. The biggest challenge in predicting coal reserves in mining is the spatial uncertainty of coal seams. Due to the strong mapping and visualization properties of the GIS, this technique has facilitated spatial coal seam modeling and estimation of reserves in mining. The spatial analysis, interpolation techniques, and geospatial databases in GIS are the important achievement facilities used to accomplish these uncertainties and difficulties in mining (Paraskevis, Roumpos, Stathopoulos, & Adam, 2019)(Uyan & Dursun, 2021)(Xu & Zhang, 2023).

In mining, reserve estimation is usually made by processing and interpreting borehole data. The classical geometric method was the most used method for reserve estimation in previous years. However, the classical geometric method is no longer preferred due to disadvantages such as indeterminate or high error rate, low precision of obtained data, high calculation error rate, and hard and time-consuming calculation operations. Nowadays, geostatistical methods are frequently used in mining for coal reserve estimation activities worldwide instead of classical geometric methods.

The geostatistical methods especially various Kriging techniques have been applied to different engineering disciplines by using various geostatistical modules with different software (Matheron, 1963)(Krige, 1984)(Olea, Luppens, & Tewalt, 2011)(Wang & Haung, 2012)(Daya, 2012)(Karacan, Olea, & Goodman, 2012)(Shahbeik, Afzal, Moarefvand, & Qumarsy, 2014)(Jacob, Prins, & Oelofsen, 2014)(Daya, 2015)(Daya & Bejari, 2015) (Switon, 2015)(Pavlides, Hristopulos, Roumpos, & Agioutantis, 2015)(Thakur, Samanta, & Chakravarty, 2016)(Gharechelou, Tateishi, Sharma, & Johnson, 2016)(Uyan, 2016)(Silva & Almeida, 2017)(Daya, 2019)(Adeli & Emery, 2021)(Habibirad, Roohi, Hesameddini, & Heydari, 2021). Today, the geostatistical method is frequently used especially in mining as well as other geosciences that are concerned with the spatial distribution of the regional variable. In recent studies, many researchers have preferred geostatistical methods for reserve estimation of coal or ore bodies in various mining areas.

There are many types of research in the literature using a geostatistical method for the calculation of coal tonnage, modeling of coal seam with seam thickness, and determination of coal quality parameters such as calorific values, ash, sulfur and moisture contents (Tercan & Karayiğit, 2001)(Watson, Ruppert, Bragg, & Tewalt, 2001)(Heriawan & Koike, 2008a, 2008b)(Kapageridis & Kolovos, 2009)(Hindistan, Tercan, & Ünver, 2010)(Olea et al., 2011)(Hatton & Fardell, 2012)(Hohn & Britton, 2012)(Ertunc et al., 2013)(Pardo-Iguzquiza, Dowd, Baltuille, & Chica-Olmo, 2013)(Saikia & Sarkar, 2013)(Tercan, Ünver, Hindistan, Ertunç, Atalay, Ünal, & Kıllıoğlu, 2013)(Webber et al., 2013)(Siddiqui, Pathan, Ünver, Tercan, Hindistan, Ertunç, Atalay, Ünal, & Kıllıoğlu, 2015)(Paraskevis et al., 2019)(Uyan & Dursun, 2021).

Many researchers have applied geostatistical method for the determination of tonnage and grade of ore bodies in various mineral deposits (Asghari & Hezarkhani, 2006)(Salman, Ibrahim, Saffarini, & Al-Qinna, 2009)(Daya, 2012)(Wang & Huang, 2012)(Jalloh, Kyuro, Jalloh, & Barrie, 2016)(Chanderman, Dohm, & Minnitt, 2017)(Mery, Emery, Caceres, Ribeiro, & Cunha 2017)(Silva & Almeida, 2017)(Abdessattar, Dimitriy, & Messaoud, 2019)(Daya, 2019). Furthermore, some researchers have estimated various natural stone reserves using geostatistical methods (Onur, Konak, & Karakuo, 2008)(Yünsel, 2012)(Akeju & Afeni, 2015)(Ovinnikov, Kobzev, Pereverzeva, Berdichevskaya, & Vaskova, 2018)(Gusman, Muchtar, Syah, Akbar, & Deni, 2019)(Afeni, Akeju, & Aladejare, 2021).

The aim of this study is spatial coal seam modeling and coal reserve estimation by using a geostatistical method with the GIS technique in the Pamuklu-Tepebaşı coalfield of the Ermenek basin. An economic coal seam stretches to the different parts of the Ermenek basin. Active working coal mines gather in two different coalfields named Pamuklu-Tepebaşı and Çanakçı. At present, private companies continue to produce coal in these two coalfields. In this study, the OK method is utilized to produce a spatial map of the lignite seam potential of the

Pamuklu-Tepebaşı coalfield. To accurately determine the amount of coal reserve, spatial analysis with the OK method was applied using the input data obtained from 82 boreholes. The data used in the study were obtained from 82 boreholes belonging to a private sector that has actively produced coal in the Pamuklu-Tepebaşı coalfield of the Ermenek basin. The selected coalfield covered an area of almost 0.51 km^{2,} and lignite coal seams located at depths between 9.26 m and 126.64 m; the average seam thickness is between 0.10 m and 25.80 m.

Material and Methods

Materials

Geological setting of Ermenek coal basin

The lacustrine Ermenek basin is located in the Tauride orogenic belt of southern Anatolia of Turkey, which is a Neogene coal basin positioned on the Late Cretaceous-Late Eocene nappe system of the Taurides Mountains. Fig. 1 shows a geological map of the Ermenek basin (Demirel, 1989)(Demirel & Karayigit, 1999)(Demirel, Sarac, & Sen, 2000)(Ilgar & Nemec, 2005). The basic formation of the Ermenek Basin is the Çakozdağı Formation, consisting of Jurassic-Cretaceous aged cream-beige colored recrystallized limestones, which are basement rocks of the Basin. They lie upon the Çakozdağı formation, highly fragile and brittle green-colored Upper Cretaceous aged serpentinites (ophiolitic melange). This formation has become clay from place to place as a result of advanced surface degradation. The serpentinites were settled in this region in the form of huge blocks by tectonic contact. The Eosen Tepebaşı formation upon the serpentinites consists of nummulitic limestone with dirty cream-colored hard layered conglomerate-sandy limestone-limestone, marl alternations. The early Miocene Yenimahalle Formation, including alluvial-lacustrine sediments and the economic coal seam, rests unconformably upon the basement. The Yenimahalle Formation consists of mudstone, sandstone, and conglomerates. The Yenimahalle Formation is subdivided into two members, from upward, Özlüce and Çanakçı, and consists of a coal seam that is seen within lacustrine sediments located at the boundary between the two members which is in a range of 0.3-6.5 m in thickness (Fig. 1). The Özlüce member, with a thickness of 50-300 m, contains conglomerates in the lower part and alternations of sandstone and marl in the upper part. The Çanakçı member, 125-250 m thick, alternates fine-grained sandstone, marl, claystone, and sandy limestone. There is fossiliferous, carbonated, clayey, silty marl at the base of the coal seam. The late Burdigalian-Serravallian Mut Formation overlain the Yenimahalle formation and is generally characterized by reef limestones with marine fauna and karstic cavities. Quaternary alluvium constitutes the youngest unit in the Ermenek Basin. An economic coal seam stretches to the different parts of the Ermenek basin. Active working coal mines gather in two different coalfield areas named Pamuklu-Tepebaşı and Çanakçı. At present, private companies continue to produce coal in these two coalfield areas.

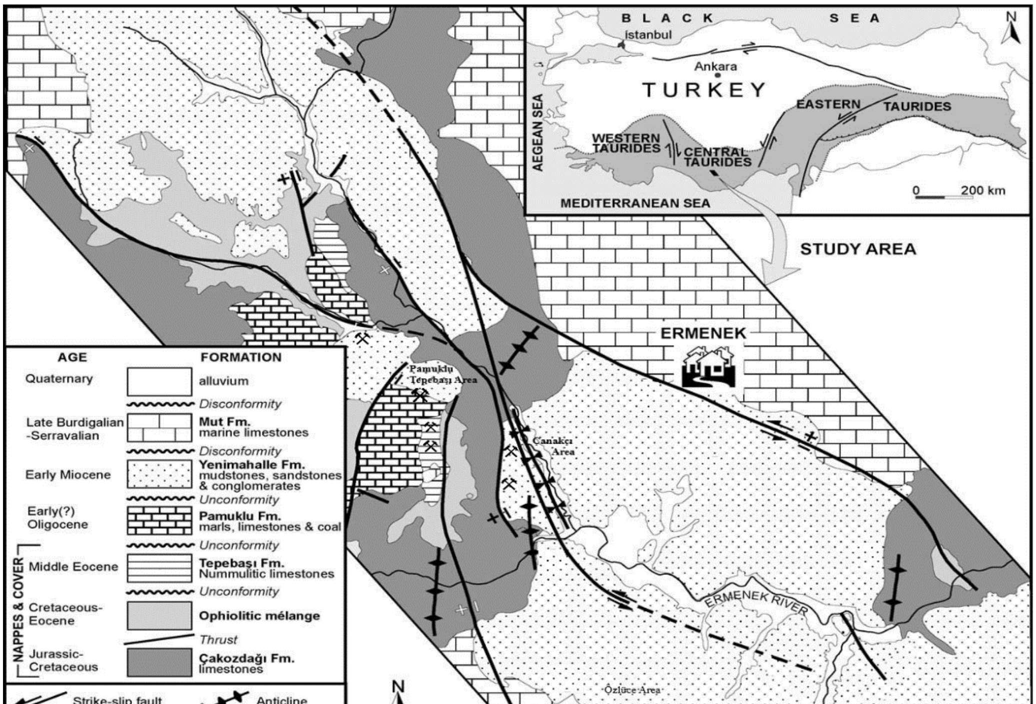

Fig. 1. Geology map of Ermenek basin and location of study area

The borehole data used in this study was obtained from 82 boreholes drilled by private companies working in a Pamuklu-Tepebaşı coalfield. Various data, such as collar coordinates, geological information, and coal quality parameters, have been obtained from these boreholes. The specialties of drilling outputs are given in Tab. 1. and the location of boreholes is illustrated in Fig. 2.

Tab. 1. Summary of drilling activities

Number of boreholes	Total drilled meters (m)	Minimum depth (m)	Maximum depth (m)	Average drill hole depth (m)
82	4478	9.26	126.64	54.61

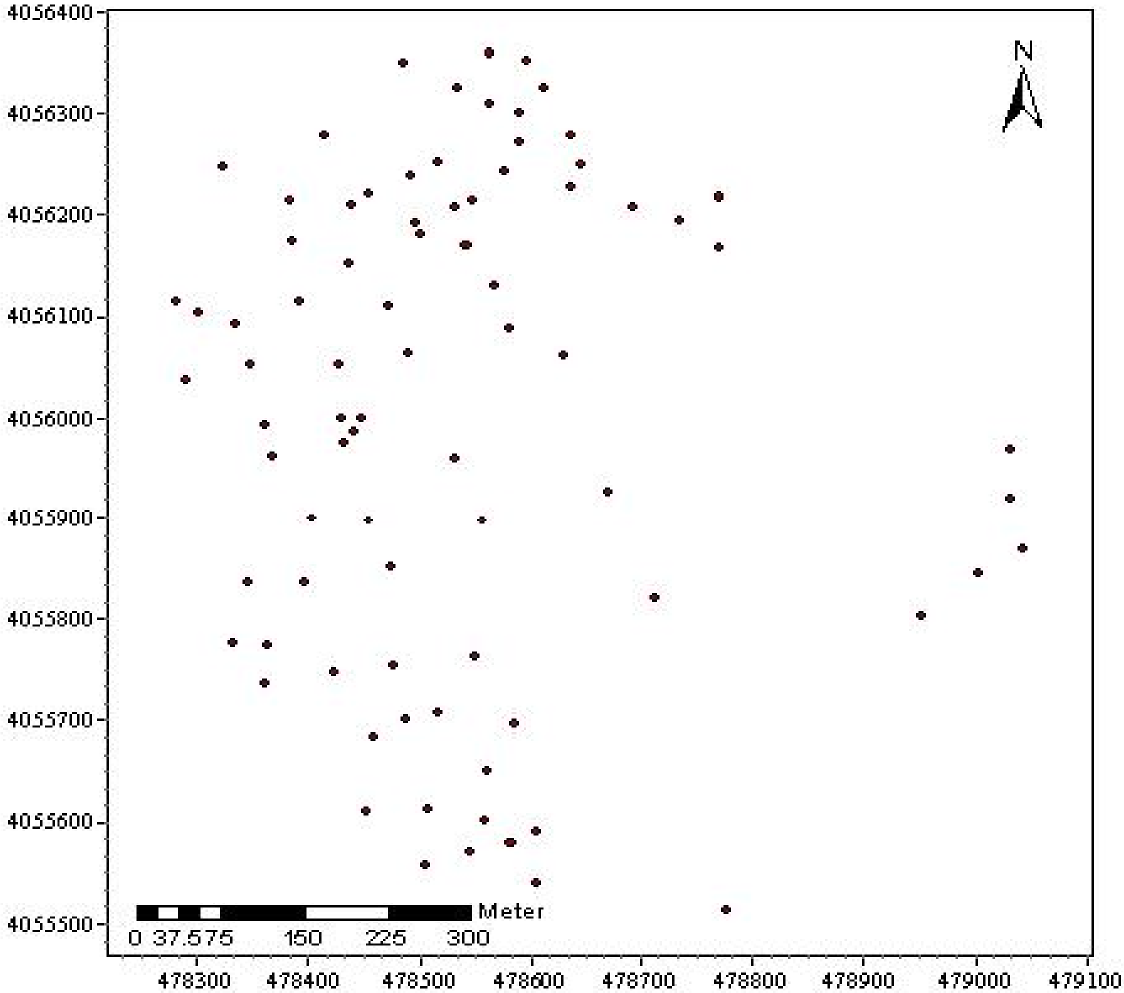

Fig. 2. Boreholes sample location map of the study area

Methods

Geostatistics, as a section of statistics used for prediction methods in many different disciplines, is interested in spatial or spatial-time-concerned analysis to supply information about solutions to uncertainty (Heriawan, Hafizsyah, Hanunah, Hede, & Malik, 2020). The geostatistical methodology is based on a stochastic model that solves the uncertainty events using optimal predictions with interpolation techniques at unknown points in a selected study area. It allows us to use spatial analysis to determine the relation between connected studies and includes different reaching lying from conditional predictor to simulation, either parametric or indicator reaching (Uyan & Cay, 2013)(Uyan, 2016).

Kriging is the best-known and most commonly used technique in geostatistics. It is used for spatial modeling to estimate an unknown value from a known value most accurately and reliably. In the geostatistical methodology, the data's spatial dispersion function is presented using variogram analysis. The basic structure of the variogram analysis is a method to find the similarity of two data by revealing their differences. The variogram is one of the basic geostatistics tools used for spatial modeling and measuring spatial autocorrelation. Kriging is a multi-stage method that includes a variogram analysis and statistical analysis of data for the advisor of uncertainty events, and it is created to a surface for replying to the analyses. There are 4 types of techniques used in the Kriging method:

ordinary, universal, indicator, and simple (Kisi, Mohsenzadeh Karimi, Shiri, & Keshavarzi, 2019). The OK technique estimates an unknown value from a known value, and one of the kriging methods was used for spatial coal seam modeling by using borehole data in this study. The equation of semi-variance, one of the Kriging functions, is used to determine the weight of the ordinary Kriging technique. An empiric semi-variance equation can be used to predict the nugget impact and the parameters of the semi-variance equation. This equation is considered a semi-variogram (Kisi et al., 2019). A semi-variogram is a fundamental operation in geostatistics adopted to discover the substantial spatial relationship within a certain sample group. It is an equation that defines the rating of spatial dependence within the data and is described as the anticipated squared increase of saved values between two locations (Karami, Fallah, Shataei, & Latifi, 2018). Semi-variogram is calculated by using Eq. 1. (Uyan, 2016):

$$\gamma(h) = \frac{1}{2(N-h)} \sum_{i=1}^{N-h} [Y(t_{i+h}) - Y(t_i))^2] \tag{1}$$

where h is the lag distance, $Y(t_i)$ is the value of the transformed data at time t_i, and $(N-h)$ is the number of pairs with lag distance h. A maximum lag distance over which to calculate the semi-variogram was defined to enable the clustering to capture differences in the temporal dependence structure.

The general equation of the kriging method is as follows Eq. 2. (Uyan, 2016):

$$Z^*(x_p) = \sum_{i=1}^{n} \lambda_i Z(x_i) \tag{2}$$

To attain just predictions in OK, the following set of Eq. 3 and 4 should be solved at the same time:

$$\sum_{i=1}^{n} \lambda_i \gamma(x_i, x_j) - \mu = \gamma(x_i, x_j) \tag{3}$$

$$\sum_{i=1}^{n} \lambda_i = 1 \tag{4}$$

Here, $Z^*(x_p)$ is the kriged value at location x_p, $Z(x_i)$ is the known value at location x_i, λ_i is the weight associated with the data, μ is the Lagrange multiplier, and $\gamma(x_i, x_j)$ is the value of variogram corresponding to a vector with origin in x_i and extremity in x_j.

Results

The achievement of a mining project depends on the prediction of reserve or calculation studies that are a basis operation that can be influential in many processes such as mine planning and decision of mining methods. Reserve estimation in mining is the most important parameter to decide whether the ore to be produced is economical and is the essential stage to start producing coal or another valuable ore. For this reason, it is essential to use fast and reliable methods that will minimize economic losses for reserve estimation in mining, and consequently, geostatistical methodologies are inevitable. The study applied spatial analysis with the OK method to estimate coal reserves and model coal seams based on borehole data. This spatial coal seam modeling was made separately for the upper and lower surfaces of the coal seams (Fig. 3). In this application, the OK method emerges as the most effective technique preferred for estimating unmeasured values from measured values. The OK is a spatial interpolation predictor applied to discover the best linear impartial prediction of a second-order stationary random field with an unknown constant means (Khakestar, Madani, Hassani, & Moarefvand, 2013). The statistical parameters were calculated to identify the variable distribution in the study area. The results of the upper/lower surfaces of the coal seam are shown in Table 2. These statistics give the important distribution features and define its center, spread, and shape. Preliminary investigation analyses were performed to evaluate correlations between data. Histogram graphics of the data were designed and illustrated in Fig. 4.

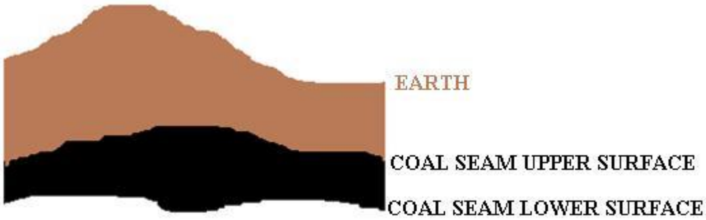

Fig. 3. Illustration of a coal seam

Tab. 2. Basic statistics of the upper/lower surfaces of coal seam

Statistics	**Upper Surface**	**Lower Surface**
Count	82	82
Minimum	814.9	813.5
Maximum	1032.5	1030.5
Mean	956.38	950.91
Std. Dev.	42.64	43.50
Skewness	-1.14	-1.13
Kurtosis	4.74	4.71
1st Quartile	941.7	933.5
Median	960.43	955.82
3rd Quartile	986.15	978.12

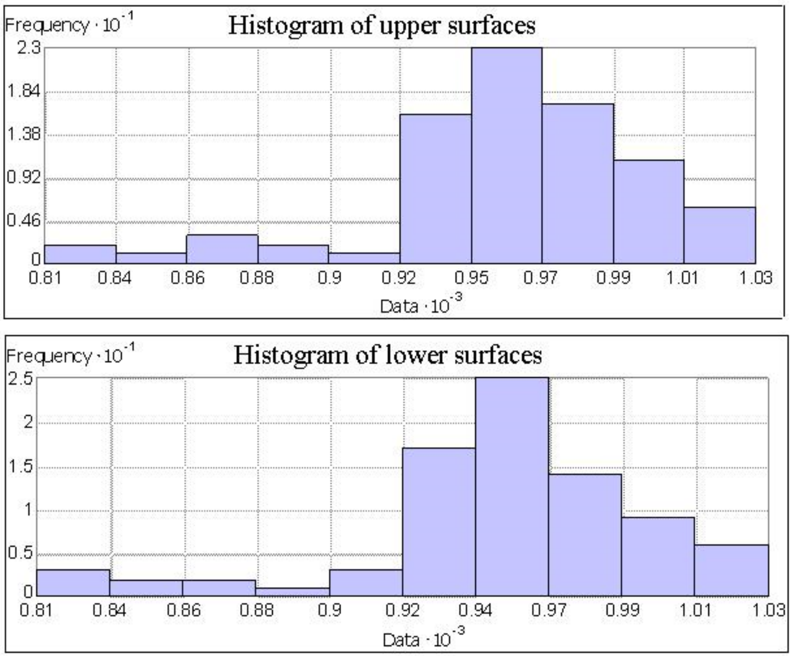

Fig. 4. Histograms of the upper/lower surfaces of coal seam

For the data to show a normal distribution, it is desired that the data are close to the mean and the median. Looking at the statistics, mean and median values are 956.38 m and 960.43 m, respectively, on the upper surface. The data here are far from each other; therefore, it is thought that the data do not show a normal distribution. The mean and median values for the lower surfaces are 950.91 m and 955.82 m, respectively. According to these values, lower surface data is thought that the data do not show normal distribution. Since the skewness values are -1.14 (Upper Surface) and -1.13 (Lower Surface), it can be said that the data distribution is skewed. Since the kurtosis should be 3 for an ordinarily dispersed data set, it is realized that the data are not ordinarily dispersed in the study for the values of 4.74 and 4.71. The obtained data can be used directly for analysis, or prediction can be made with data approaching normal dispersion by log conversion. Summary statistics and histograms obtained from logarithmically converted data are given in Table 3 and illustrated in Fig 5. The distribution of data of the coal surface is out of normal. Taking logarithms removes the disruptions (Tab. 3.), but it gives a much flatter distribution than usual. It can only transform the general shape of the distribution, not the detail (Gaus, Kinniburgh, Talbot, & Webster, 2003). Geostatistics supplies descriptive tools such as semi-variograms to qualify the spatial model of uninterrupted and categorical characteristics. Varied interpolation techniques benefit from the spatial correlation between observations to predict feature values at unsampled locations using data regarding one or several features (Panagopoulos, Jesus, Antunes, & Beltrao, 2006)(Cichon, 2016).

Tab. 3. *Basic statistics of the log-upper/lower surfaces of coal seam*

Statistics	Upper Surface	Lower Surface
Count	82	82
Minimum	6.70	6.70
Maximum	6.94	6.94
Mean	6.86	6.86
Std. Dev.	0.05	0.05
Skewness	-1.31	-1.31
Kurtosis	5.18	5.10
1st Quartile	6.85	6.84
Median	6.87	6.86
3rd Quartile	6.89	6.89

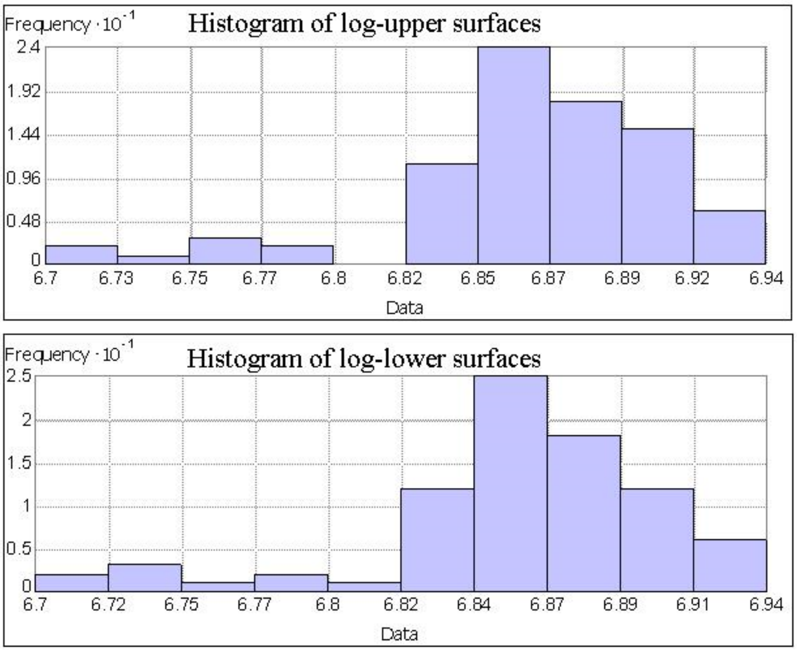

Fig. 5. Histograms of the log-upper/lower surfaces of coal seam

This study specified the empirical semi-variogram for the upper and lower surfaces of coal seams by ArcGIS 10.2 software. Spatial variation was considered isotropic in this study. Whether there is a trend in the data was analyzed by ArcGIS 10.2 software. A dataset of coal characteristics was composed of their georeferenced position obtained from boreholes in the selected coalfield. The data dispersions were examined before producing surface diagrams to understand trends and directional effects better. Fig. 6 illustrates the results of trend analysis before utilizing the Kriging method. A trend for the analysis parameters was determined, pointing out that trend-taking away was essential to produce more precise prediction maps. Trend remoting stage assisted in normalizing data dispersion. OK was performed after the trend was removed from the data. The performance of eleven models (Circular, Spherical, Tetraspherical, Pentaspherical, Exponential, Gaussian, Rational Quadratic, Hole effect, K-Bessel, J-Bessel, and Stable) were compared for OK. For these reasons, each model was assessed with raw data and log data, and the most suitable results were procured (Tab. 4.).

Cross-validation was used to predict which semi-variogram models would yield the most accurate estimates of unknown values in the study area. A summary of the indicators that assist in selecting the most appropriate semi-variogram model for generating the forecast maps is given in Tab. 4. The mean error (ME) gives a deflection of predicted value, the average standard error (ASE) and root-mean-square error (RMSE) give the accuracy between the predicted and measured values, and the mean standardized error (MSE) and root-mean-square standardized error (RMSSE) give the accuracy of the standard error (Qin et al., 2020).

The estimations for a good-fitting semi-variogram are ME near 0, RMSSE near 1, and ASE-RMSE near each other (Uyan, 2016). The eleven models given in Table 4 were applied again for every parameter working following the rules referred to above, and it was selected a semi-variogram model for each one to indicate how the samples were related to each other.

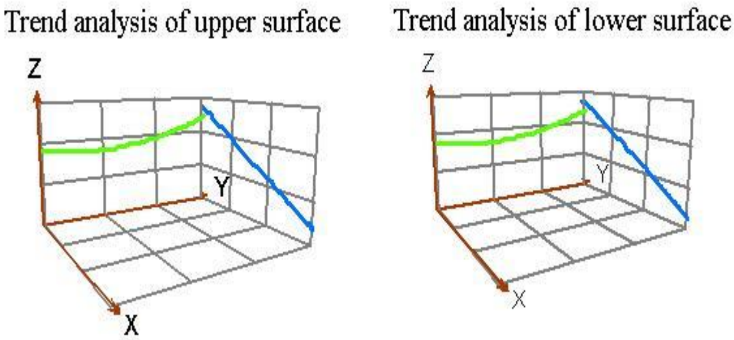

Fig. 6. Trend analysis demonstrating a North to South and an East to West trend for the upper-lower surface of coal seam

The final semi-variogram model selected for the prediction map of each parameter analyzed is given in Tab. 5. According to the results derived from cross-validation, the most fitting model for the experiential variogram is "Rational Quadratic".

The ratio of nugget to sill is used to determine the spatial dependency of variables. The spatial dependency is high if the ratio is lower than 25%. The spatial dependency is moderate if the ratio is between 25 and 75 %. The spatial dependency is low if the ratio is more than 75 % (Ramirez-Davila, Porcayo-Camargo, Sanchez-Pale, & Vázquez-García, 2012). The ratio showed a high dependency with 0.01 (1%) and 0.02 (2%) for upper and lower coal seam surfaces, respectively, for the study area.

In geostatistics, the slope of the regression line, taking into account the true value and the predicted value, is often used as a diagnosis for predictive accuracy. Ideally, the slope of this line should be equal to 1. This value cannot be reached due to estimation errors. The slope value is always less than 1. The regression line is an approximate value that will generally not equal the 1:1 line. Proximity to this value is an indication of sensitivity. Fig. 7 shows the regression lines for predicted values according to the 1:1 line. Regression lines for the upper and lower coal seam surfaces were determined as y = 0.95x + 46.40 and y = 0.95x + 44.46, respectively. These values are very reliable, with a deviation of 5%. The kriged coal depth maps for the upper and lower surface are shown in Fig. 8 using ArcGIS 10.2, GIS software. As a result of these analyses, it was calculated that there is a coal reserve of 3.734.017 m^3 using the determined surfaces with *OK* in the study area.

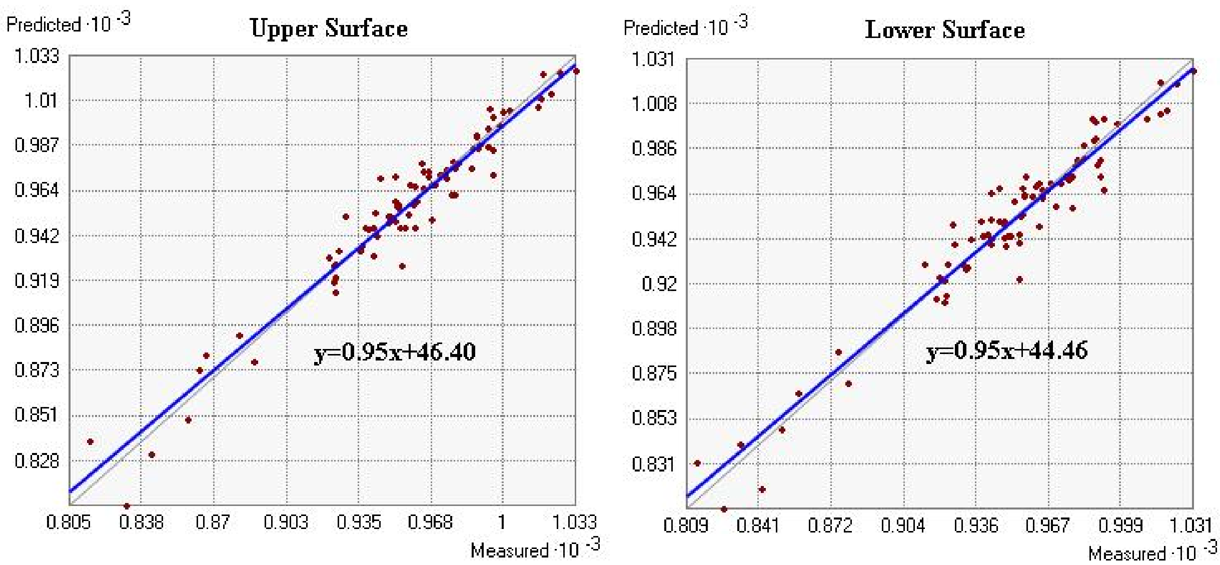

Fig. 7. Least-squares regression line and the 1:1 line between the measured and the predicted coal depth values

Tab. 4. Valuation results for different formations of data

	Model	Data	Nugget	Sill	Range	ME	RMSE	MSE	RMSSE	ASE	R^2
UPPER SURFACE	**Circular**	**Raw**	0	4185.39	1138.15	-0.13	10.24	-0.05	0.79	15.21	0.93
		Log	0	0	1138.15	-0.09	10.24	-0.02	0.78	15.37	0.93
	Spherical	**Raw**	0	3651.13	1138.15	-0.13	10.24	-0.06	0.78	15.43	0.93
		Log	0	0.004	1138.15	-0.10	10.24	-0.01	0.76	15.60	0.93
	Tetraspherical	**Raw**	0	3313.66	1138.15	-0.14	10.24	-0.06	0.77	15.65	0.93
		Log	0	0.004	1138.15	-0.10	10.24	-0.002	0.75	15.82	0.93
	Pentaspherical	**Raw**	0	3079.63	1138.15	-0.14	10.24	-0.06	0.76	15.86	0.93
		Log	0	0.004	1138.15	-0.10	10.24	-0.002	0.74	16.04	0.93
	Exponential	**Raw**	0	2837.71	1138.15	-0.12	10.52	-0.07	0.64	18.98	0.91
		Log	0	0.003	1138.15	-0.05	10.52	0	0.62	19.27	0.91
	Gaussian	**Raw**	170.64	5131.50	1043.59	0.89	10.24	0.07	0.71	14.43	0.88
		Log	0	0.006	1061.851	0.90	10.02	0.08	0.77	13.18	0.94
	Rational quadr.	**Raw**	42.39	2866.37	1138.15	-0.84	9.98	-0.06	1.12	10.11	0.95
		Log	0	0.003	1138.15	-0.93	10.24	-0.07	1.28	9.24	0.93
	Hole effect	**Raw**	121.12	3184.57	1138.15	0.97	9.87	0.10	0.81	12.36	0.92
		Log	0	0.004	1138.15	0.96	9.81	0.10	0.84	12.02	0.93
	K-Bessel	**Raw**	122.06	4359.39	1138.15	0.28	9.56	0.04	0.76	12.98	0.90
		Log	0	0.006	1138.15	0.65	9.73	0.07	0.79	12.62	0.95
	J-Bessel	**Raw**	116.62	3631.59	1138.15	0.81	9.76	0.08	0.81	12.28	0.92
		Log	0	0.004	1138.15	0.92	9.77	0.09	0.83	12.01	0.92
	Stable	**Raw**	115.68	4833.77	1138.15	0.13	9.56	0.02	0.73	13.49	0.95
		Log	0	0.006	1138.15	0.14	9.49	0.03	0.78	12.65	0.95

	Model	Data	Nugget	Sill	Range	ME	RMSE	MSE	RMSSE	ASE	R^2
LOWER SURFACE	**Circular**	**Raw**	0	4312.17	1138.15	-0.11	11.27	-0.004	0.84	15.44	0.89
		Log	0	0	1138.15	-0.09	11.26	0	0.83	15.60	0.90
	Spherical	**Raw**	0	3763.34	1138.15	-0.12	11.27	-0.004	0.83	15.66	0.89
		Log	0	0	1138.15	-0.09	11.26	0	0.82	15.83	0.90
	Tetraspherical	**Raw**	0	3416.96	1138.15	-0.13	11.27	-0.004	0.82	15.88	0.89
		Log	0	0	1138.15	-0.09	11.27	0	0.80	16.06	0.90
	Pentaspherical	**Raw**	0	3176.95	1138.15	-0.13	11.27	-0.005	0.81	16.10	0.89
		Log	0	0	1138.15	-0.10	11.27	0	0.79	16.29	0.90
	Exponential	**Raw**	0	2935.25	1138.15	-0.11	11.53	-0.005	0.68	19.30	0.88
		Log	0	0	1138.15	-0.03	11.53	0	0.66	19.60	0.89
	Gaussian	**Raw**	157.16	5536.58	1061.85	0.98	10.70	0.08	0.77	13.89	0.90
		Log	0	0.01	1138.15	1.01	10.61	0.09	0.81	13.19	0.91
	Rational quadr.	**Raw**	46.76	2949.35	1138.15	-1.04	10.75	-0.06	1.17	10.48	0.95
		Log	0	0	1138.15	-1.16	10.99	-0.08	1.33	9.54	0.93
	Hole effect	**Raw**	125.31	3248.45	1138.15	1.01	10.48	0.10	0.84	12.56	0.91
		Log	0	0	1138.15	0.99	10.40	0.01	0.87	12.17	0.92
	K-Bessel	**Raw**	126.42	4809.37	1138.15	0.48	10.27	0.05	0.81	12.97	0.93
		Log	0	0.01	1138.15	0.89	10.46	0.09	0.83	12.83	0.91
	J-Bessel	**Raw**	124.07	3707.74	1138.15	0.93	10.44	0.09	0.84	12.56	0.91
		Log	0	0	1138.15	0.97	10.39	0..01	0.87	12.18	0.92
	Stable	**Raw**	114.88	5133.34	1138.15	0.17	10.32	0.03	0.79	13.31	0.92
		Log	0	0.01	1138.15	0.39	10.28	0.05	0.82	12.87	0.93

From the cross-validation of the models were used the mean error (ME), root-mean-square error (RMSE), mean standardized error (MSE), root-mean-square standardized error (RMSSE), average standard error (ASE) and regression coefficient (R^2)

Tab. 5. Results of the semi-variogram selected to produce the prediction maps

	Model	Data	Nugget	Sill	Range	ME	RMSE	MSE	RMSSE	ASE	R^2	Nugget/Sill
Upper surface	Rational quadr.	Raw	42.39	2866.37	1138.15	-0.84	9.98	-0.06	1.12	10.11	0.95	0.01
Lower surface	Rational quadr.	Raw	46.76	2949.35	1138.15	-1.04	10.75	-0.06	1.17	10.48	0.95	0.02

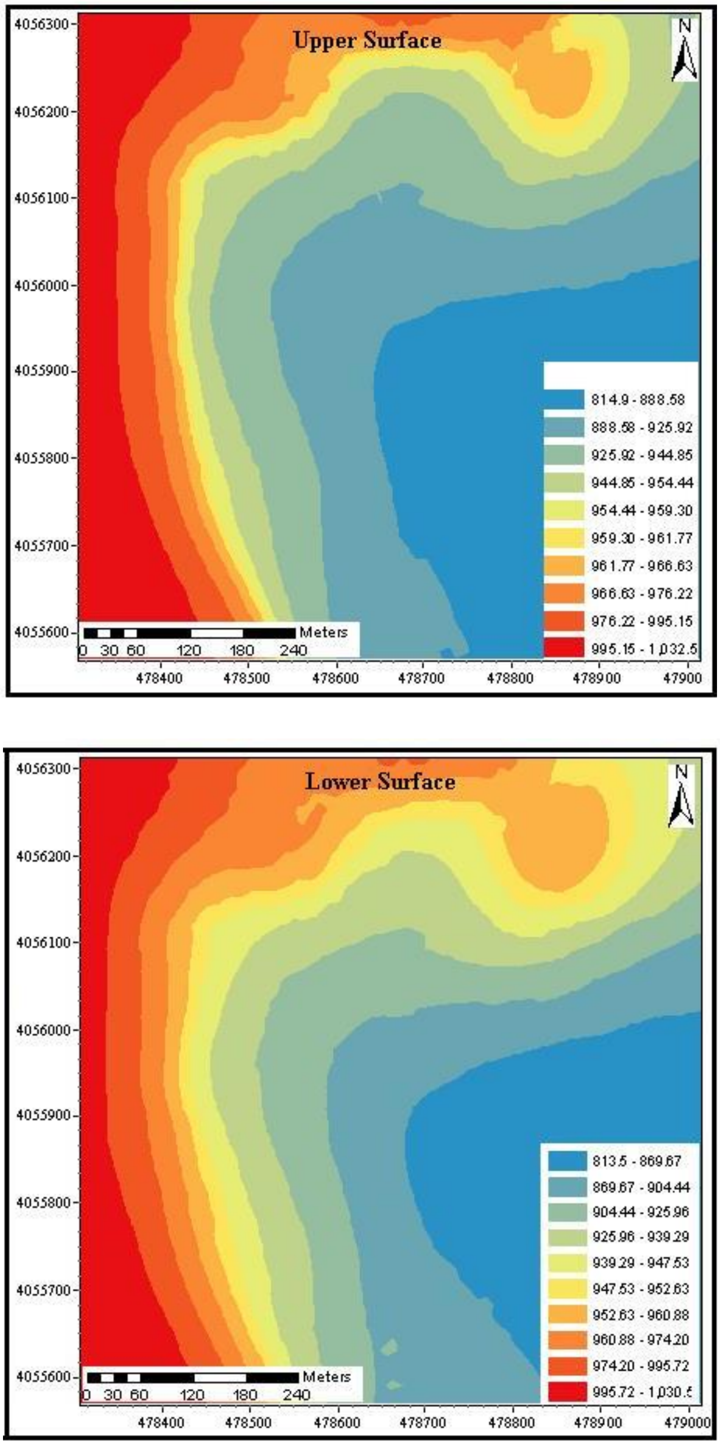

Fig. 8. Coal deposit map obtained by ordinary kriging estimation for upper and lower surfaces of coal seam

Conclusions

Energy is an important factor for sustainable development and poverty eradication. Depending on the need for increased production, as Turkey's population grows and technological advances, energy demands are increasing daily. Countries competing in the global economic structure aim to meet their energy needs most efficiently and at the lowest cost. For this reason, the resource's cost must be considered when determining the preferred energy source. The electricity generation of coal-based thermal power plants is 20.4% of Turkey's total installed electricity generation capacity. The first two national energy resources in Turkey are hydraulic energy and natural gas. However, it imports all of the natural gas, which second ranks in electricity generation in Turkey, from other countries and spends serious money. Turkey has high coal reserves where coal must be used for electricity generation. For this reason, this study aims to attract attention to the use of geostatistical methods that are faster and the most reliable method frequently used in recent years, which is to determine the important coal reserves of Turkey.

Today, reserve estimation in mining projects is usually determined by processing and interpreting drilling data. Reserve estimation is extremely important in the success of mining projects. Reserve estimation that is far from precision can lead to bad consequences for the business. Therefore, reliable and important resource estimates from all over the world are attached. In mining studies, the Kriging method is one of the frequently used models to estimate the reserve most accurately. In this study, the *OK* method is utilized to produce a predictive map of the lignite potential of the Pamuklu-Tepebaşı coalfield. To accurately determine the amount of coal reserve, spatial analysis with the *OK* method was applied using the input data obtained from 82 boreholes. Cross-validation was used to predict which semi-variogram models could accurately estimate the unknown values. Cross-validation showed that the most suitable model for the experimental variogram is circular. The ratio of nugget to sill is used to determine the spatial dependency of variables. The spatial dependency is strong if the ratio is less than 25%. The ratio showed a high dependency with 0.01 and 0.02 for upper-lower surfaces, respectively, for this study. The kriged coal depth maps for upper and lower coal seam surfaces have been created using ArcGIS 10.2 software. As a result of spatial analysis, it was calculated that there is a coal reserve of 3.734.017 m^3 using the determined surfaces with the *OK* in the study area.

In Ermenek coalfields, the Kriging methods have not yet been applied to coal reserve estimation and spatial coal seams modeling. Instead of the Kriging method, the classical geometric method was applied to calculate coal reserves. However, the dimensions of coal seams, amount of coal, and other parameters have not been determined. For this reason, this study has emphasized taking into account the spatial analysis of coal reserve estimation in the Ermenek Basin. Thus, by preventing the wrong reserve calculation and the production of coal seams without knowing the size and depth, both economic losses will be prevented, and producers will be helped to make their future plans accurately and reliably. This study is aimed to be a guide for other areas related to geosciences in Turkey for modeling coal seam or ore bodies using one of the geostatistical methods, ordinary kriging with GIS technology.

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