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Determining Coal Thickness Through Compositional Kriging: An Approach Based on Geostatistics

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Abstract

In the exploration and mining industry, accurately estimating the thickness of coal is crucial for resource assessment and mine planning. Traditional geostatistical methods, like ordinary kriging, have been used for this purpose. However, they often struggle to manage compositional data, where the sum of multiple components, such as coal, must remain constant. Compositional kriging offers an innovative approach to address this challenge, providing a robust framework for predicting coal thickness while considering the interdependency between components. This article presents an overview of compositional kriging, discussing its theoretical foundations and practical applications in the context of coal thickness estimation. It explains the key steps involved in the compositional kriging process, including data transformation, variogram modeling, and prediction. The article also emphasizes the importance of comparing the distribution shapes between the original data and the kriged data obtained from wireline logs in Queensland. This study demonstrates the potential of compositional kriging to improve the accuracy and reliability of coal thickness predictions in complex geological settings. As a result, compositional kriging is becoming increasingly significant as a valuable tool for geoscientists and mining professionals who require precise and geologically sound estimates of coal thickness for further informed studies.

Keywords: *Compositional kriging; Coal thickness; Thickness estimation; Geostatistical methods.*

1. Introduction

Over the past few years, the mining and geostatistical sectors have acknowledged the necessity for creative methods to address the challenges posed by compositional data in estimating coal thickness. Precisely estimating coal thickness is crucial in geological exploration and mining, playing a vital role in resource evaluation, mine planning, and various mining industry operations [1]. Traditional geostatistical techniques, like ordinary kriging, have been widely used to forecast coal thickness using sampled data points. These methods have played a crucial role in estimating coal thickness by revealing the spatial distribution of this important geological parameter. Nevertheless, they face challenges when dealing with compositional data where the total sum of components remains constant. In such cases, compositional kriging emerges as a viable solution as it considers the relationships between coal and other constituents, leading to more precise predictions of coal thickness [2]. The thickness of coal is merely a single aspect of a broader compositional entity, in which the varying proportions of these elements play a role in the complete geological makeup. Compositional kriging is introduced as an innovative remedy, broadening the geostatistical toolkit to address the intricacies of compositional information and the methodology is based on the concept that estimating coal thickness should not be done independently but rather in the context of the broader geological composition, in addition, compositional kriging uses spatial correlations within the compositional dataset to provide more precise and reliable predictions of coal thickness, while also respecting the compositional constraints that are essential to the geological reality. The field of compositional data analysis, which is still developing, has demonstrated potential in addressing these issues. By explicitly acknowledging the compositional nature of the data, it offers a strong framework for understanding how coal thickness is closely related to the presence of other geological constituents [3].

2. Methodology

2.1. Data information

Geological data on coal thickness in Queensland was acquired from the Queensland Government's data portal by the Geological Survey of Queensland (GSQ).

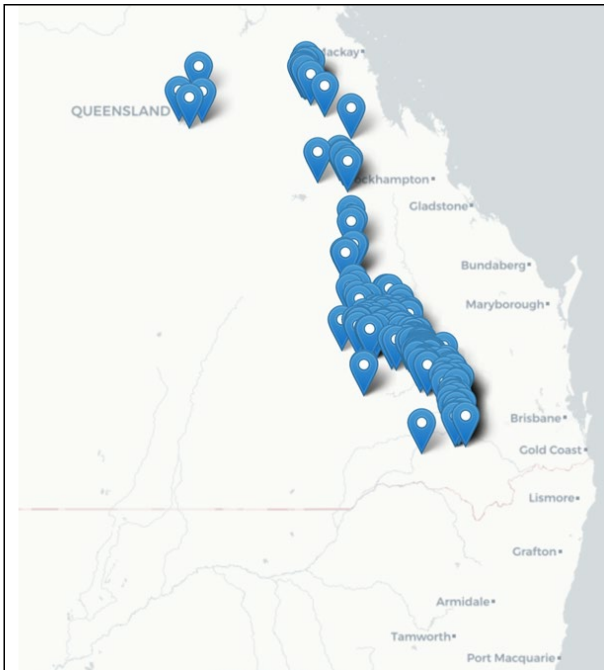

Figure 1. Generating a coal data map.

The dataset contained measurements of coal thickness along with their corresponding spatial coordinates. Prior to any analysis, the raw data was preprocessed to transform them into log-transformed data, ensuring consistency in data format and quality. Spatial interpolation techniques were employed to fill in any missing values and create a continuous representation of coal thickness across Queensland. This study encompassed a total of 317 wells, grouped into sixteen categories as shown in Table 1 based on well depth. This study encompassed a total of 317 wells as shown in Figure1. The research focused on utilizing Julia-based compositional kriging to forecast coal thickness in Queensland, emphasizing the significance of data preprocessing, algorithm implementation, and validation procedures by comparing distributions between the original and kriged data.

Table 1. Data pertaining to the group number and thickness (m).

Group number	Thickness (m)	Group number	Thickness (m)
1	0.00-0.20	9	1.75-2.00
2	0.20-0.40	10	2.00-3.00
3	0.40-0.60	11	3.00-4.00
4	0.60-0.80	12	4.00-5.00
5	0.80-1.00	13	5.00-6.00
6	1.00-1.25	14	6.00-8.00
7	1.25-1.50	15	8.00-10.00
8	1.50-1.75	16	10.00-100.00

2.2. Analysis tools

Compositional kriging, a geostatistical method for estimating the compositional Julia programming language was utilized to analyze data at unsampled locations [4]. That programming language provides a range of robust libraries and tools for spatial data analysis, including Gestalts' which is specifically designed for geostatistical modeling and interpolation. In this study, the compositional kriging technique was adapted to suit the unique characteristics of coal thickness data, such as its compositional nature and spatial autocorrelation. The approach involved modeling the spatial variability of coal thickness using a variogram model and employing a compositional kriging model to interpolate values. The Compositional kriging method was validated by comparing the distribution of the original data with the compositional kriging values [5-6]. Julia's exceptional computing capabilities facilitated rapid processing of extensive datasets and efficient model convergence. The accuracy and dependability of the compositional kriging estimates were evaluated through cross-validation and uncertainty analysis [7-8]. A portion of the data was reserved for validation purposes, and the kriging model's performance was assessed by comparing predicted values against observed measurements. Furthermore, uncertainty evaluations, such as prediction intervals or variance maps, were produced to quantify the uncertainty linked with the interpolated coal thickness values. Sensitivity analyses were conducted to explore the influence of variogram parameters and model assumptions on the reliability of the kriging forecasts. The validation outcomes and uncertainty evaluations offered valuable insights into the dependability of the compositional kriging technique for estimating coal thickness in Queensland for resource exploration and mining operations [9].

Gamma ray logging is a geophysical well logging technique used in the oil and gas industry to detect natural gamma radiation released by rocks around a borehole. Gamma rays are high-energy electromagnetic radiation released by the atomic nuclei of certain elements, such as uranium, thorium, and potassium, which are abundant in sedimentary rocks. Geologists can use transmitting an electric current through the surrounding rock. The resistance encountered by the current reveal information on the formation's conductivity, which varies based on fluid saturation, rock type, and porosity. Resistivity logs are essential for detecting hydrocarbon-bearing formations, assessing reservoir quality, and defining fluid type. The last part is density logging which measures the bulk density of subterranean formations [10]. It uses a gamma ray generator and detector to measure the attenuation of gamma radiation as it travels through the formation. The degree of attenuation is directly proportional to the material's density, allowing bulk density to be calculated. Density logs give useful information regarding lithology, porosity, and fluid content, which can help with reservoir characterization, fluid identification, and wellbore stability assessment. Gamma ray intensity to determine lithology changes, pinpoint hydrocarbon zones, and evaluate the formation features [9]. The gamma ray, resistivity, and neutron density logs were used to characterize the coal-bearing strata in the well [10-11], in addition, gamma ray log revealed low natural radiation levels typical with coal, which aided in the identification and linkage of coal seams inside the reservoir. Simultaneously, resistivity records revealed the electrical characteristics of the formations. Variations in resistivity values helped distinguish coal beds from surrounding lithologies, allowing for more precise mapping of coal reservoir boundaries. Additionally, the neutron-density logs have provided crucial information regarding the bulk density and hydrogen content, both of which play a vital role in determining porosity and fluid saturation levels within coal formations. By combining these logging techniques, a thorough understanding of the composition and structural characteristics of the coal-bearing reservoir has been achieved, leading to improved estimations of hydrocarbon concentration. The process involves the insertion of electrodes into the borehole, with gamma rays showing lower levels on the left side due to reduced radioactivity from uranium (U), thorium (Th), and potassium (K) [12-13]. Furthermore, Density-Neutron measurements reveal higher porosity in the reservoir, while non-conductive hydrocarbons result in increased resistivity on the right side, indicating the presence of coal in that specific location.

3. Results and discussion

Figure 2 displays gamma rays, resistivity, and neutron-density logs illustrating the significance of well logging technologies in characterizing coal deposits within boreholes. This meticulous approach involves the careful insertion of electrodes into the borehole to obtain crucial geological data. In the realm of coal exploration, gamma ray logs exhibit noticeably lower readings on the left side of the borehole, which can be attributed to the reduced radioactivity caused by uranium (U), thorium (Th), and potassium (K) elements present in coal deposits. Density-Neutron measurements indicate increased porosity throughout the reservoir, suggesting the presence of coal seams. Conversely, the presence of non-conductive hydrocarbons leads to higher resistivity values on the right side of the borehole. These factual observations collectively support the presumed existence of coal reserves at the specified location. By integrating information derived from various logging techniques, a comprehensive understanding of coal reservoir characteristics is achieved, enabling more informed decisions regarding resource assessment and development.

Figure 2. Gamma ray, resistivity and, density-neutron.

Figure 3 displays a scatter plot that displays the connection between two coal thickness categories: 0.40-0.60 m and 0.20-0.40 m thickness. Each data point represents the 0.40-0.60 m on the x-axis and the corresponding 0.20-0.4 m on the y-axis. The scatter plot indicates a negative correlation, suggesting that areas with a higher coal proportion in the 0.40-0.60 m range tend to have a lower coal proportion in the 0.20-0.40 m range. As a result, there is a spatial relationship between them, allowing us to proceed to the next step, which is examining the variogram.

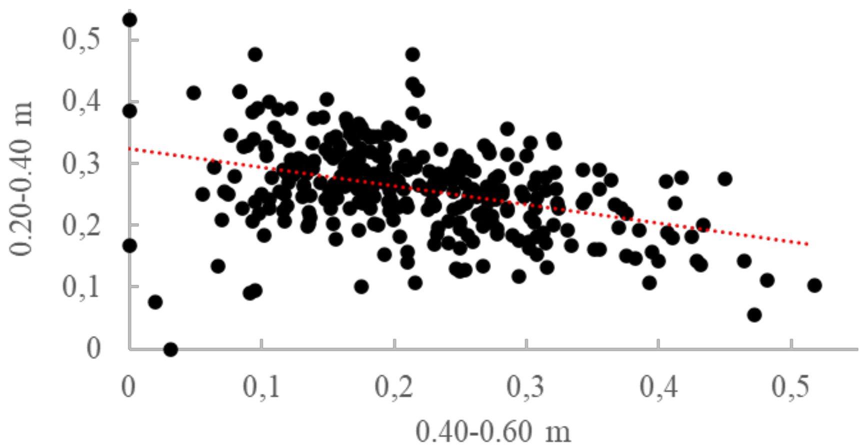

Figure 3. The scatter plot depicting the relationship between two categories of coal thickness.

The spatial variability and dependence of a specific attribute, such as the 0.20-0.40 m group, are illustrated in the variogram plot shown in Figure 4. The blue points represent the study data, while the green line depicts the fitted variogram model. On the x-axis, the lag distance between pairs of sample points is shown, and the y-axis displays the corresponding semi variance of attribute values at those distances. The variogram typically exhibits three key characteristics. Firstly, the nugget signifies the variability at short distances due to measurement error or microscale variability. The range indicates the distance at which spatial correlation peaks and then decreases. Lastly, the sill represents the overall variability of the attribute across long distances where spatial autocorrelation is minimal. For example, in the variogram for coal thickness, the line starts at 0 (nugget), the semi-variance stops increasing at 0.006 (sill), and the range is five thousand meters. This implies that within 300000m, there is spatial correlation, allowing for predictions using kriging methods.

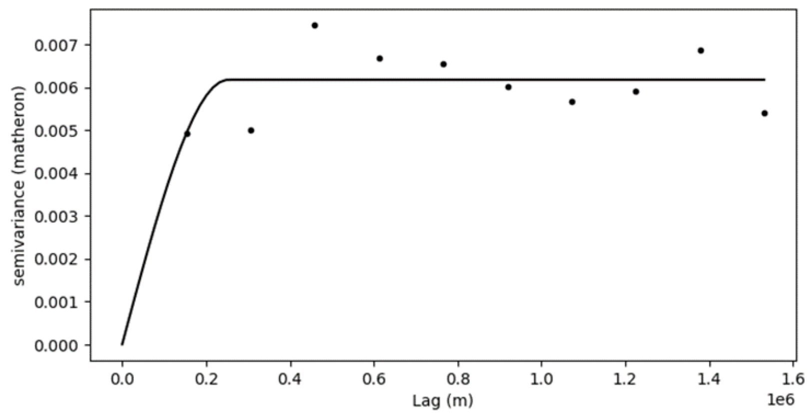

Figure 4. The variogram of the coal thickness data. (0.20-0.40m).

The histogram provided in Figure 5 illustrates the distribution of proportions for two sets of data: the original data and the compositional kriging data. It is shown in Figure 5 two diverse types as unimodal and bimodal appeared. Since it is an amount of coal thickness, and they are near to each other then it makes mostly the amount of coal has in similar groups which are group 1,2 and 3 for different location. Furthermore, when comparing the distributions of the bars between the original data and the compositional kriging data, it can be observed that the shape of the distributions is alike. The diagonal line bar represents the original coal thickness data, while the dot pattern bar symbolizes the compositional kriging data. The x-axis represents the diverse groups, ranging from group 1 to group 16, while the y-axis shows the proportions within each group. The height of each bar indicates the proportion of data within its respective coal amount.

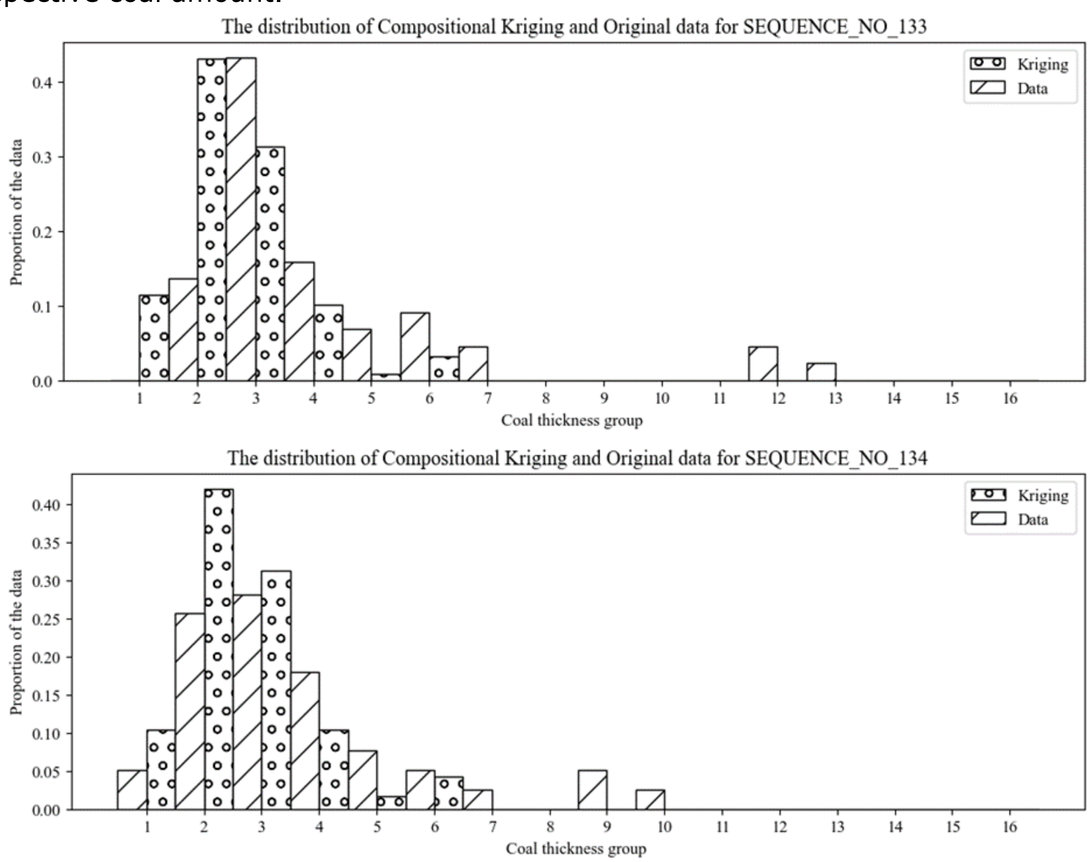

Figure 5. The histogram displays a unimodal distribution across two distinct locations.

Figure 5 displays the unimodal distribution shape commonly performed from the study data. This distribution has a single peak in the data. For example, sequence_no_133 and 134, since they are located near to each other, and their distribution are similar. The former point is located at longitude 150.2939556° E and at latitude 26.67716667° S (150.2959694, -26.69720833) and the later point is situated at longitude 150.2959694° E and at latitude 26.69720833° S (150.3092583 , -26.69053333). both exhibit the same unimodal distribution; it shows a similarity in their characters estimated. The unimodal distribution found in both datasets indicates the presence of a single dominating mode. This is indicated by the presence of a significant peak in the frequency distribution of each dataset, around which the data cluster. Unimodality suggests a homogenous distribution of values, with most observations sharing similar traits across both datasets such as a location. This implies that most coal seams in both areas have a thickness like this amount, which represents the central tendency of the distribution in each dataset. Likewise, the distribution of commotional kriging data follows original data even though there are group 12 and 13 are shown.

The other distribution type obtained from the coal thickness data is bimodal. The bimodal distribution of the data shows that there are two separate modes. Figure 6 which is Sequence_no_235, the analysis of coal thickness data collected from a mining site revealed a bimodal distribution, with peak thicknesses observed at group 1 which is 0.20m-0.40m and 3 which is 0.60m-0.80m, respectively. This data is in COXON_CREEK_10 at longitude 149.0963389 ° E and at latitude 26.36855833° S (149.0963389, -26.36855833). Remarkably, the compositional kriging and original data display identical bimodal patterns since it was chosen to calculate the compositional kriging as a sample. The alignment of the original and kriging data's bimodal distributions demonstrates the kriging method's ability to capture the geographic heterogeneity contained in the original dataset.

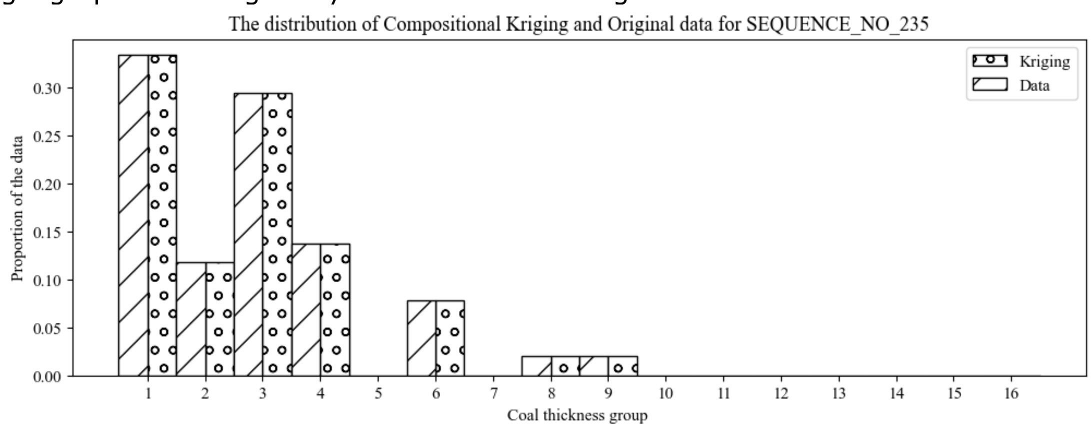

Figure 6. The histogram bimodal distribution of the well COXON_CREEK_10.

4. Conclusion

When comparing the coal thickness distribution between the original dataset and the kriging data, strong parallels appear, indicating adaptability in the compositional kriging method's ability to approximate the genuine underlying distribution. Both datasets have similar frequency distributions over different coal thickness intervals, demonstrating that the kriging interpolation efficiently reflects the spatial variability in the original dataset. This consistency demonstrates the validity of kriging as a spatial interpolation approach for determining coal thickness across the research region. As a result, our findings support the use of kriging as a beneficial tool in geological research, allowing for confident estimates of resource distribution and improving in the petroleum field.

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