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Permeability Measurements Facilitate the Assessment of Spatial Differences in Grain Size Distributions Present in an Outcrop

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Abstract

In 1996, Koopman and van Vooren conducted a study showing that the geological composition of Brunei and adjacent Malaysia is Neogene sediments, particularly shales and sandstones. These deposits vary in thickness from a few meters to around ten kilometers and are organized into three delta complexes. Notably, these assemblages show an east-to-west decrease in the southeastern region of Asia. The primary objective of this paper is to predict spatial variation in grain-size distribution among outcrops using permeability measurements. A total of thirty-six samples were collected from the Lamunin outcrop in Brunei Darussalam to record baseline data on each sample for further analysis. Various instruments were used in the current paper, the main ones being a portable air permeameter (Tiny Perm 3) to measure the permeability of the samples and a sieve machine to determine the particle size distribution of the samples.

Keywords: *Thickness; Grain size; Permeability; Samples; Outcrop; Particle size.*

1. Introduction

The Miri in Malaysia and Seria Formations in Brunei represent the Champion Delta strata, which is renowned for its significant petroleum reserves. In contrast, the Belait formation primarily consists of sandstone but also includes interbedded shales and coals. This formation provides a comprehensive record of the depositional system of the Champion Delta in Brunei, spanning from the early to late Miocene period. In 1961, Wilford conducted a study on these deposits, with a particular focus on those located along the coast and coastal plains, which originated from various sedimentary environments, including a large delta. Additionally, van Borren observed in 1996 that the sandstones in the region are of fluvial nature. Lambiase study in 2000 revealed that a vast diversity of coastal and marine environments exists within the Belait Formation. Similarly, there is evidence to suggest that specific regions of the formation were situated in structurally controlled tidal coastal embayment and along open marine shorelines using processes other than those associated with deltas, as indicated by their facies. This implication implies that the Champion Delta falls into the category of complex depositional systems that formed in shallow marine environments. Consequently, there are minimal distinctions between it and other formations such as the Belait Formation or the Lambir, Miri, and Seria Formations [1-2]. The outcrop in Lamunin, Tutong District, depicted in Figure 1, can be identified using this knowledge. By following careful procedures at this site, it is expected that an accurate and reliable result can be achieved. There are three approaches to classify size categories, including the use of the Wentworth scale to sort particles by size or employing phi or psi unit measurements to determine their dimensions. Additionally, the Wentworth scale is used to broaden linear grain size classifications. Therefore, fluvial gravel exhibits a logarithmic distribution of grain frequency across size categories. Following the Wentworth scale, the grain size categories were adjusted to reflect a standard distribution of grain sizes. Thus, boulders, cobbles, gravel, sand, silt, and clay represent the six distinct size categories that assist in sediment classification [3-4].

Figure 1. An outcrop located in Lamunin, Tutong, Brunei.

The representation of different grain size classes often involves the use of relative frequency and cumulative distribution curves. The level of sorting in a sample can be determined by observing the shapes present on a relative frequency distribution curve. Well-sorted samples typically exhibit a small size range or a Gaussian shape curve, while poorly sorted samples show greater curve asymmetry [5], a higher modality of the sample is indicated by a single distribution with increased curve asymmetry, often leading to a higher frequency of distinct peaks in the grain size range, while grain size distribution parameters are influenced by the method of data analysis and typically require statistical evaluation, moreover, to extract oil from the reservoir, it is imperative for the petroleum reservoir fluids, which are present in the pore spaces, to move through the reservoir rock's significant porosity. When evaluating the ability of a production to gather hydrocarbons, permeability plays a crucial role and is considered one of the key factors [6]. The equipment developed by NER is used to assess the permeability of rock formations, whether they are exposed to the surface or at the core level. By employing the Tiny-Perm software on the Android device provided by NER, users can conveniently wirelessly store measurement data from the permeameter. This data can subsequently be seamlessly transferred to a desktop computer for in-depth analysis, which may include sample images, location specifics, and other relevant environmental factors. [7-8].

In a geographic context, the term "spatial correlation" pertains to the statistical association between two or more variables. It quantifies the extent to which the values of these variables tend to resemble each other or exhibit proximity within a given geographical area. Spatial correlations examine the variations or similarities between nearby locations in terms of characteristics [9]. In addition, the comprehension and computation of the spatial relationships and patterns are inherent in a specific dataset or phenomenon. Through the analysis of geographical correlations, researchers can identify clusters, trends, spatial autocorrelation, or spatial heterogeneity. These attributes play a crucial role in the development of reliable assessments, predictions, and effective policies and to estimate values for sites within a geographic domain, the approach known as spatial interpolation employs the known values at sampled or observed locations as a foundation. It is a method often employed in domains like geography and other spatially related sciences to close data gaps or create continuous surfaces from discrete point data [10]. This method's objective is to forecast a target variable's values in areas that were not sampled while taking those values into account. The basis for spatial interpolation is the idea that adjacent points in space frequently have similar attribute values. To replicate the spatial correlation or relationship between the known and unknown sites, this assumption is applied [11]. The aim of this paper is to gather geological data and organize them into an Excel spreadsheet for visualization in Python. Various spatial correlations and models are utilized to support the significance of considering the spatial variability in grain size distribution when evaluating the permeability of geological formations.

2. Methodology

2.1. Permeability measurement

A total of thirty-six rock samples were chosen for permeability measurements using the TinyPerm 3, a portable handheld air permeameter. This process is conducted in a laboratory setting once the rock samples have completely dried to avoid any issues that might affect the accuracy of TinyPerm 3. Measurements are taken from both the vertical and horizontal surfaces of each rock sample to guarantee accurate results. To reduce errors, approximately three measurements are taken for each surface and then averaged to achieve the most accurate reading for each rock sample. After this, the Android device is turned on, and the TinyPerm app is launched by tapping the program icon on the device's display. Each individual sieve in the stack is weighed prior to commencing the process, subsequently, the separated sample was carefully poured onto the tightly arranged stack of sieves, which range in mesh sizes from fifty-three micrometers to six hundred micrometers, including the bottom pan. The stack of sieves was securely placed on the sieve shaker machine and firmly clamped to prevent any movement that could potentially affect the accuracy of the results obtained upon completion of the process. Once the clamp is confirmed to be fixed, the timer was set to 15 minutes before activating the sieve shaker machine. Excel was the primary software utilized for compiling data into spreadsheets, while Python was used for visualizing data correlations and interpolations. Following the permeability measurements and sieving processes, the data collected was organized in Excel spreadsheets and underwent various procedures to ensure accuracy and quality during the analysis in Python notebooks. The permeability measurements included both horizontal and vertical values in millidarcy and Darcy units. These measurements were initially stored in Excel spreadsheets along with other relevant information, then compiled into a zip file and transferred from an Android device to a desktop computer. Due to numerous permeability readings for each rock sample, only three readings from each direction were selected, averaged, and recorded in an Excel spreadsheet for all thirty-six rock samples. The collected data was utilized to generate various permeability logs, including vertical permeability against distance, horizontal permeability against distance, both permeabilities against distance, and vertical permeability against horizontal permeability. The distance data was obtained by analyzing the number of bed units and their individual thickness, which were then combined to determine the distance between each bed unit in meters. To ensure accuracy, a scale was established for this distance data. Both sets of data were compiled.

3. Results and discussions

Figure 2 illustrates the results obtained from employing Python programming to represent the relationship between horizontal and vertical permeabilities. The computed correlation coefficient is 0.71, indicating a positive correlation that suggests a linear relationship between the two variables. Additionally, the proximity of the value to 1 signifies a strong fit and high correlation. A positive correlation implies that both variables are likely to increase simultaneously. It can be concluded that the vertical and horizontal permeabilities of each rock sample exhibit close similarity in values.

Figure 3 illustrates the visualization outcome in Python. The correlation between the mean grain size and clay content. The computed correlation coefficient is -0.83, indicating a negative and linear relationship between the two variables and the proximity of the value to zero, suggesting a stronger linear relationship. However, a negative correlation implies that as one variable increases, the other variable decreases which means, as the clay content increases, the mean grain size decreases across all thirty-six rock samples [12].

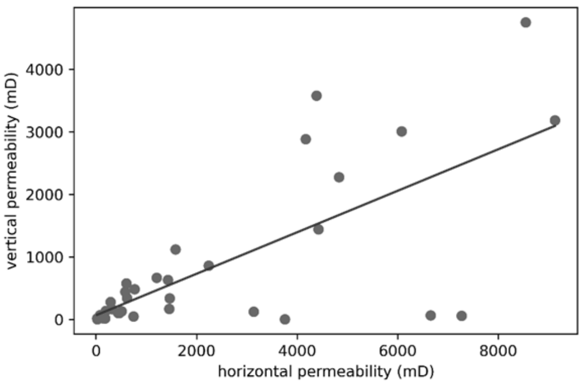


Figure 2. The correlation between horizontal and vertical permeabilities using a correction coefficient of 0.71.

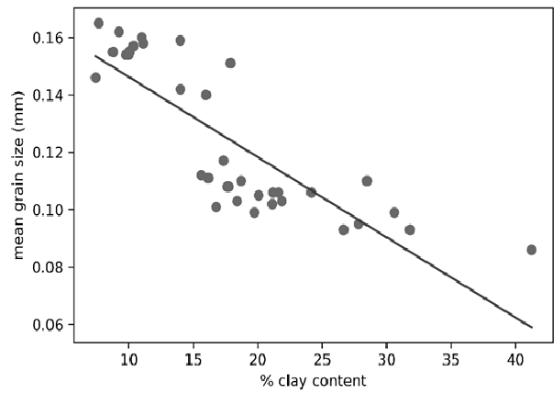


Figure 3. A strong negative correlation of -0.83 between the mean grain size and clay content.

Figure 4 depicts the visualization result obtained from Python, illustrating the correlation between mean grain size and horizontal permeability. The correlation coefficient is calculated to be 0.59, indicating a positive relationship between the two variables. This suggests that as the mean grain size increases, horizontal permeability also increases in a similar fashion. Moreover, the proximity of the correlation coefficient to zero implies a weaker linear relationship. Conversely, a positive correlation signifies that both variables rise proportionally. Additionally, the data suggests that an increase in mean grain size corresponds to a corresponding increase in horizontal permeability. The subsequent correlation is examined by the relationship between the average grain size and vertical permeability.

Figure 5 presents the correlation coefficient computed to be 0.54, indicating a positive value that suggests a positive and linear association between the two variables. Specifically, a value closer to zero signifies a weaker linear relationship. Consequently, this positive correlation confirms that both variables rise simultaneously, thus as the mean grain size of each rock sample increases, the vertical permeability also increases.

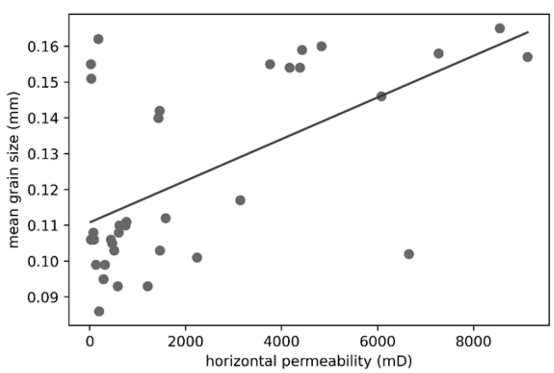


Figure 4. The correlation coefficient between the mean grain size and horizontal permeability is 0.59.

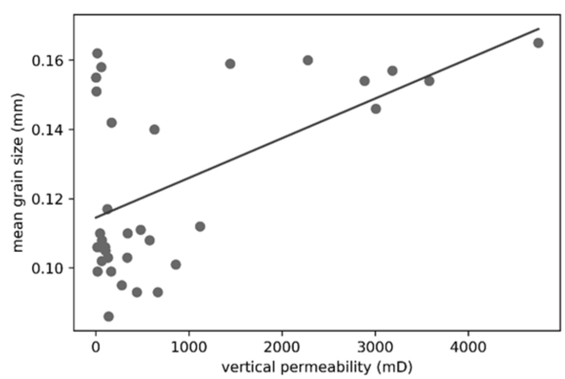


Figure 5. A correlation of 0.54 between the mean grain size and vertical permeability.

Figure 6 illustrates the correlation between horizontal permeability and clay content, as observed through Python visualization. The correlation coefficient is determined to be -0.55, indicating a negative relationship between the two variables. This negative value suggests a linear relationship, although a weaker one due to its proximity to zero. Moreover, a negative correlation implies that as one variable increases, the other variable decreases significantly and the clay content increases as the horizontal permeability value decreases across all thirty-six rock samples.

Figure 7 presents a correlation between vertical permeability and clay content, as observed in Python. This correlation exhibits a similar outcome to the previous correlation. The estimated correlation coefficient is -0.51, indicating a negative linear relationship between the two variables. In simpler terms, this suggests that the closer the value is to zero, the weaker the linear relationship compared to the previous correlation. Additionally, a negative correlation implies that as one variable increases, the other variable decreases, as the vertical permeability value decreases, the clay content tends to increase.

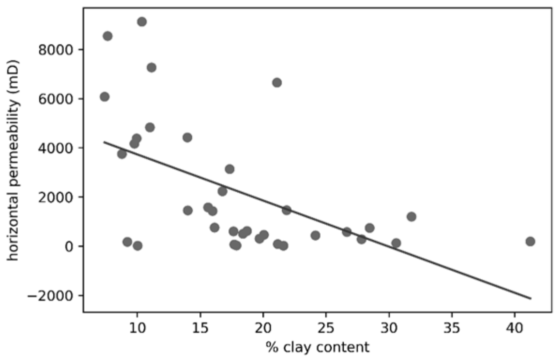


Figure 6. The correlation between horizontal permeability and clay content is represented by a coefficient of -0.55.

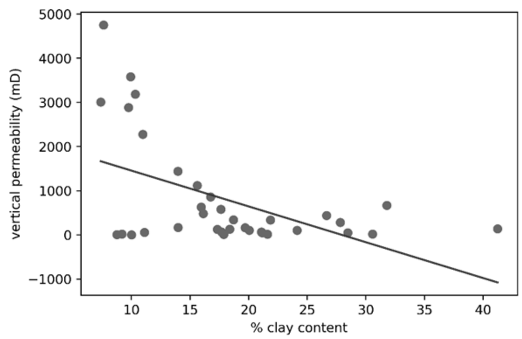
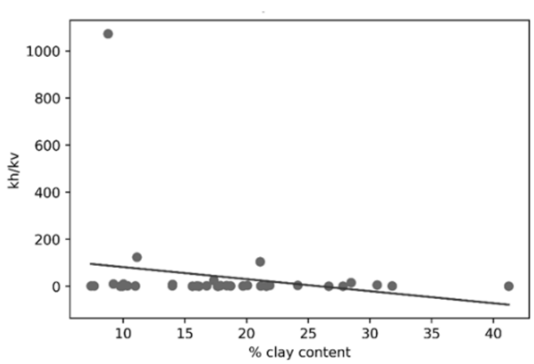


Figure 7. The correlation between the vertical permeability and clay content is at a coefficient of -0.51.

Figure 8 illustrates the correlation between permeability ratio and clay content in Python. The correlation coefficient is calculated to be -0.22, indicating a negative linear relationship between the two variables. The proximity of this value to zero suggests a weaker linear relationship. A negative correlation implies that as one variable increases, the other decreases, and vice versa, as the permeability ratio rises in rock samples, the clay content decreases.

Figure 9 displays the results obtained from interpolating vertical permeability values using both linear and cubic methods in Python. Upon examining the graphs corresponding to each method, an elusive distinction in the vertical permeability axis is evident. In the linear method, the range spans from 0 to 3200 millidarcy, whereas in the cubic method, it extends from -600 to 4800 millidarcy. The analysis reveals that, in the linear method, vertical permeability values fall between 0 and 400 millidarcy, with no negative values present as seen in the cubic method. Additionally, it is apparent from the cubic method that the vertical permeability values of all thirty-six rock samples do not exceed 3600 millidarcy and both interpolation methods offer unique advantages and disadvantages in accurately interpreting vertical permeability values.



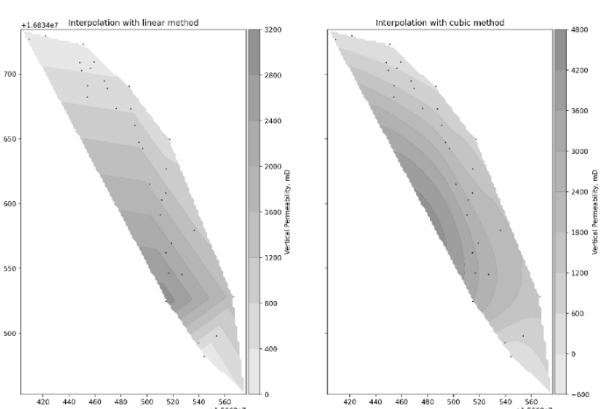


Figure 8. The correlation coefficient between the permeability ratio and clay content at -0.22.

Figure 9. Utilizing linear and cubic techniques for vertical permeability interpolation.

Figure 10 displays three distinct representations of vertical permeability in the experimental scatter plot: black dots, spherical mode variogram represented by a black line, and histogram represented by black boxes. The histogram clearly indicates that the number of available pairs fluctuates less significantly as the lag distance increases. Conversely, the semi-variance increases from below zero to two Mathesons as the distance progresses from the spherical semi-variogram. In the experimental scatter plot, it is evident that the semi-variance of vertical permeability values surpasses four Mathesons as the lag values increase. These visualizations lead to the conclusion that there is minimal correlation between the vertical permeability of the sample points.

Figure 11 displays the ordinary kriging estimation and the kriging error estimation. In the ordinary kriging estimation, the vertical permeability values range between 0 and 2000 millidarcy. Notably, there are more values falling within the 250 to 500 millidarcy range, with only one value in the 750 to 1000 millidarcy range. Conversely, the estimated kriging error for vertical permeability ranges from 0.90 to 2.25, with the majority falling between 0.90 and 1.20, while the estimated kriging error may seem small, it can still have a significant impact on the kriging values of vertical permeability.

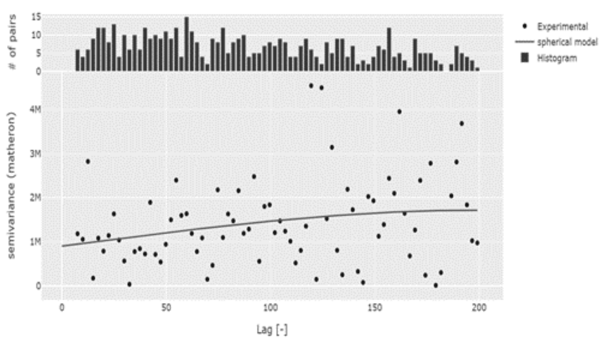


Figure 10. Various representations of vertical permeability.

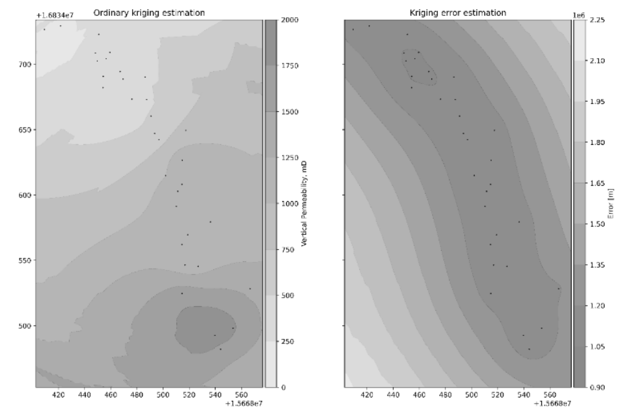


Figure 11. Conventional kriging and estimation of kriging errors for vertical permeability.

The comparison of horizontal permeability values interpolation using linear and cubic methods is illustrated in Figure 12. Analysis of the graphs for each method reveals a slight variation in the horizontal permeability axis, ranging from 0 to 7000 millidarcy in the linear method and up to 8000 millidarcy in the cubic method. The position of black points, it is evident that both methods exhibit horizontal permeability values between 0 and 1000 millidarcy. Furthermore, the cubic method indicates that none of the thirty-six rock samples have horizontal permeability values exceeding 7000 millidarcy. In addition, the cubic method proves to be more precise in determining the horizontal permeability values of all rock samples compared to the linear method.

The three distinct representations of horizontal permeability in the experimental scatter plot are as follows: black dots, black line in spherical mode variogram, and black boxes in the histogram, as displayed in Figure 13. The histogram reveals that the number of pairs available fluctuates less significantly as the lag value increases to 200. On the other hand, the semi-variance ranges from zero to ten matherons as the distance increases in the spherical semi-variogram. Furthermore, it is evident that the semi-variance of horizontal permeability values increases beyond twenty matherons as the lag values increase in the experimental scatter plot. Therefore, there is a weaker correlation between sample points in horizontal permeability values compared to vertical permeability, as fewer points are separated by greater distances.

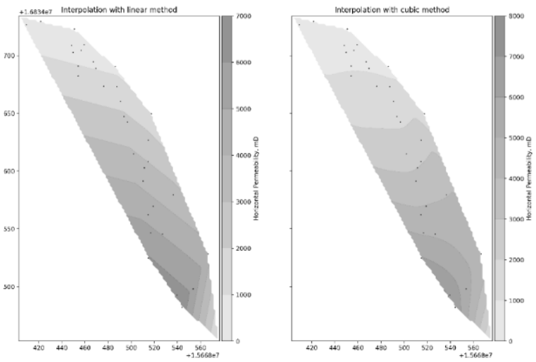


Figure 12. Utilizing linear and cubic techniques for Horizontal permeability interpolation.

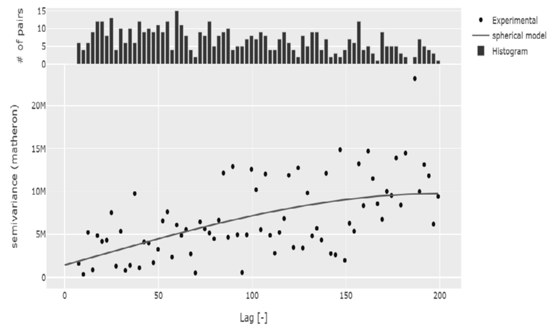


Figure 13. Various representations of Horizontal permeability.

4. Conclusion

The objective of predicting the spatial variability in grain size distribution of an outcrop based on permeability measurements has been successfully accomplished through a comprehensive analysis of the results obtained. It is evident that there is a significant spatial variability in both distribution and permeability across all thirty-six rock samples. This was achieved by implementing the procedures, including collecting samples from the outcrop, conducting permeability measurements, and performing sieve processes using a sieve shaker machine. It can be inferred that the semi-variance experiences a substantial increase in horizontal permeability as the distance between sample points increases. Conversely, there is only a slight increase in vertical permeability, and it means grain size sample points with increasing distance. To clarify further, there is a stronger correlation observed between the mean grain size of sample points and vertical permeability compared to horizontal permeability. In conclusion, these findings demonstrate that there are only two distinct types of grain size distributions present in the rock samples: very coarse sand and coarse sand. These distributions do not differ significantly from each other.

Conflict of interest*: The authors assert that there are no conflicts of interest.*

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References

[1] Curiale J, Morelos J, Lambiase J, and Mueller W. Brunei Darussalam: Characteristics of selected petroleum and source rocks. Organic Geochemistry, 2000; 31(12): 1475–1493. https://doi.org/10.1016/S0146-6380(00)00084-X.
[2] Johari AK, Busahmin B, Tyson S. Prediction of Spatial Variability in Grain Size Distribution on Outcrop from Gamma Ray Measurement. Petroleum and Coal, 2024, 66(3), pp. 914–922.
[3] Bunte K. Sampling Surface and Subsurface Particle-size Distributions in Wadable Gravel- and Cobble-bed Streams for Analyses in Sediment Transport, Hydraulics, and Streambed Monitoring. Rocky Mountain Research Station, 2001. https://doi.org/10.2737/RMRS-GTR-74.
[4] Bakar AA, Tyson S, Busahmin B. Determination of Clay Minerals In Brunei's Outcrop and Spatial Variability of the Radioisotopes. ARPN Journal of Engineering and Applied Sciences, 2024. 19(10): 604–611.
[5] Carter MR, and Gregorich EG. Soil sampling and methods of analysis. Earth Sciences, Environment & Agriculture, Physical Sciences Boca Raton, 2007; 2nd Edition eBook ISBN 9780429126222: 1264. https://doi.org/10.1201/9781420005271
[6] Dandekar AY. Petroleum reservoir rock and fluid properties. Earth Sciences, Boca Raton, 2013; 2nd Edition eBook ISBN 9780429109362: 544. https://doi.org/10.1201/b15255
[7] Kim A, Busahmin B, Tyson S. Compositional Kriging Analysis: A spatial Interpolation method for Distribution. ARPN Journal of Engineering and Applied Sciences, 2024; 19(1): 9–15.
[8] Kim A, Busahmin B, Tyson S. Determining Coal Thickness Through Compositional Kriging: An Approach Based on Geostatistics.. Petroleum and Coal, 2024; 66(3): 1124–1130.

[9] Haining RP. Spatial Data Analysis: Theory and Practice. Springer Nature, 2023. Communications in Computer and Information Science Creativity in Intelligent Technologies and Data Science, p. 568-578, https://doi.org/10.1007/978-3-031-44615-3_40

[10] Fotheringham AS, Brunsdon C, and Charlton M. Spatial Variations in Geographical and Environmental Modelling, 5(1):43-66, 2001, https://doi.org/10.1080/13615930120032617

[11] Burrough PA, McDonnell RA, and Lloyd CD. Principles of Geographical Information Systems. OUP Oxford, 2015; Third Edition eBook ISBN 9780198742845: 544.

[12] Kim A, Busahmin B, Tyson S. Prediction of Grian Size Distribution Using Ordinary Kriging and Compositional Kriging Methods. ARPN Journal of Engineering and Applied Sciences, 2024; 19(9): 556–562.

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