



Interpretation of Geophysical Well Logging and the Relationship between the Density Log and the Calorific Value of Coal

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Abstract. Geophysical well logging is widely used in coal exploration to characterize subsurface lithology and coal seams; however, its application for rapid coal quality prediction remains limited in operational mining workflows. This study investigates the quantitative relationship between density log measurements and coal calorific value to develop a predictive approach for coal quality assessment based on geophysical logging data in the Lati and Labanan Formations within the Berau Sub Basin, which is part of the Tarakan Basin. The research uses geophysical well-logging data from 113 exploration boreholes. Bivariate geostatistical analysis and linear regression were applied to evaluate the correlation between density log values and calorific value (air-dried basis). The results show a strong positive relationship between coal density and calorific value, with coefficients of determination ranging from 0.90 to 0.98. These findings indicate that the density log measurements can serve as a reliable proxy for estimating coal energy quality. The proposed relationship model demonstrates the potential of geophysical logging data to support faster coal quality prediction. This approach contributes to the development of data-driven coal quality assessment methods that can complement laboratory testing within integrated digital mining workflows.

Keywords: Density log, calorific value, Lati Formation, Labanan Formation, linear regression, bivariate geostatistical analysis

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1. Introduction

Coal remains one of the most important energy resources for electricity generation and industrial processes in many countries [1,2]. The economic value and utilization potential of coal resources are strongly influenced by coal quality parameters, particularly the calorific value, which represents the energy content of coal and plays a critical role in mine planning, resource evaluation, and market classification [3,4]. Because coal quality can vary significantly depending on depositional environment, geological processes, and coalification conditions, accurate and efficient evaluation methods are essential for supporting mining engineering decision-making and resource management [5–7].

Conventionally, coal quality evaluation relies on laboratory testing of core samples obtained from exploration drilling [8]. Although laboratory analysis provides reliable results, this approach requires considerable time, cost, and sample preparation. In large-scale exploration and mining operations, the reliance solely on laboratory testing may limit the speed of data acquisition and reduce operational efficiency [9]. Consequently, there is increasing interest in utilizing geophysical well logging as a complementary approach for rapid subsurface characterization and coal seam evaluation [10–12]. Geophysical logging techniques, particularly density logs, provide continuous in-situ measurements that can potentially be used to estimate coal properties and support real-time geological interpretation [13].

Several previous studies have demonstrated the important role of geophysical well logging in coal exploration and characterization. Chen et al. [14] developed a geophysical logging approach to identify thin coal textures using wavelet transform and linear discriminant analysis, demonstrating that logging data can effectively distinguish coal structures. Similarly, Kang et al. [15] employed geophysical logging to characterize coal reservoirs and evaluate coal structure in Junggar Basin, while Zhang et al. [16] integrated wireline logging and core data to improve geological quality evaluation of coal-bearing formations. These studies primarily focused on lithological interpretation and reservoir characterization rather than direct prediction of coal quality.

More recent studies have expanded the application of geophysical logging toward coal quality prediction. Song et al. [3] developed predictive models using geophysical log responses to estimate coal quality parameters, whereas Kumar et al. [17] applied machine learning algorithms, including multilayer perceptron and ensemble learning, to predict proximate coal parameters and gross calorific value from geophysical logs. Likewise, Wang et al. [18] demonstrated that support vector regression can accurately estimate calorific value using coal quality indicators. These studies indicate that geophysical logging possesses considerable potential for coal quality estimation through advanced predictive techniques.

Despite these advances, previous studies have generally emphasized complex machine-learning models or integrated multi-parameter datasets that require extensive calibration and relatively large training datasets. Consequently, there remains limited evidence regarding the direct quantitative relationship between density log measurements and laboratory-derived calorific values using a practical statistical approach that can be readily implemented during routine exploration activities. This limitation is particularly relevant for mining operations where rapid preliminary coal quality assessment is required before comprehensive laboratory analyses are completed.

From an engineering perspective, developing a reliable correlation between density log measurements and calorific value could provide a faster and more cost-efficient method for coal quality estimation. Such an approach would allow mining engineers to evaluate coal resources more efficiently, reduce reliance on extensive laboratory testing, and support more responsive decision-making during exploration and production activities. Integrating logging-based coal quality prediction into digital geoscience workflows can contribute to improved operational efficiency and more sustainable resource evaluation by optimizing data utilization and reducing redundant sampling [19].

Based on the existing literature, two major research gaps can be identified. First, although numerous studies have investigated the application of geophysical logging for coal characterization, relatively few have specifically examined the direct statistical relationship between density log measurements and coal calorific value using field exploration data. Second, existing predictive studies predominantly employ sophisticated machine-learning algorithms that require large datasets and complex calibration

procedures, limiting their applicability in routine operational mining environments. Therefore, a simpler yet reliable predictive approach based on statistical correlation between density logs and calorific value remains insufficiently explored, particularly for Indonesian coal deposits represented by the Lati and Labanan Formations in the Berau Sub Basin, which is part of the Tarakan Basin.

The novelty of this study lies in the development of a practical statistical framework that directly correlates density log measurements with laboratory calorific values obtained from exploration boreholes in two different coal-bearing formations, namely the Lati and Labanan Formations. Unlike previous studies that mainly rely on machine learning or multivariate predictive models, this research employs a combination of geophysical log interpretation, bivariate geostatistical analysis, and linear regression to establish an interpretable relationship between density and calorific value. Furthermore, this study demonstrates the applicability of density logs as a rapid preliminary indicator of coal quality that can complement laboratory testing within integrated digital mining workflows.

This study aims to investigate the quantitative relationship between density log measurements and coal calorific value obtained from laboratory analysis using exploration borehole data from the Lati and Labanan Formations. Specifically, this research seeks to (1) interpret coal seams using geophysical density logs, (2) evaluate the statistical correlation between density log values and calorific value through bivariate geostatistical analysis and linear regression, and (3) assess the potential of density logs as a practical tool for rapid preliminary coal quality estimation to support exploration activities and mine planning.

2. Methods

2.1 Research Design

This research was conducted through several systematic stages, including literature review, data acquisition, data preprocessing, geophysical log interpretation, and statistical analysis. The workflow was designed to evaluate the quantitative relationship between density log measurements and coal calorific value using geophysical well logging data and laboratory coal quality analysis. Each stage of the research process is illustrated in the workflow diagram shown in Figure 1.

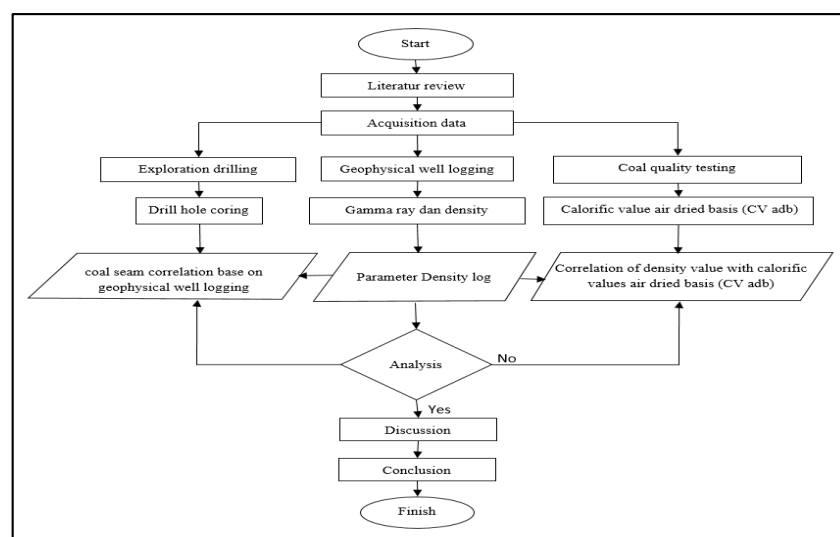


Figure 1. Research Flowchart

The analytical framework integrates geophysical interpretation and statistical modeling to assess whether density log measurements can serve as a practical indicator for coal quality estimation in mining engineering applications.

2.2 Data Acquisition

1. Exploration drilling

Exploratory drilling was carried out prior to geophysical measurements using the core drilling method with a three-layer core tube to maintain the integrity of the rock core [20]. The data produced consists of coal cores for laboratory analysis and other lithological cores. Drilling was carried out at 113 points, divided into Pit A in the Lati Formation (BOR01–BOR56) and Pit B in the Labanan Formation (BOR57–BOR113).

2. Geophysical well logging

During the geophysical well logging stage, primary data was collected from radioactive responses at 113 core drilling points in Pit A and Pit B, which represent the Lati Formation and Labanan Formation, respectively. The logging data was recorded in 1:100 scale LAS format containing depth, gamma ray, and density log information. Of the two types of density logs available, this study used the Long Spacing Density (LSD) parameter.

3. Coal quality testing

The results of the core drilling are used to collect coal samples, which are then quality tested in the laboratory. The quality analysis results used for this research are the calorific value parameter on air dried basis (CV adb) [13].

2.3 Data Preprocessing and Log Interpretation

Well logging data is recorded in LAS format as raw data before being converted into logging curves. Geophysical log interpretation is performed to determine the lithology and thickness of subsurface layers, particularly coal, based on the response of the density log curve. Coal identification is performed through analysis of density curve deflection correlated with lithological descriptions and core photo documentation, with layer boundaries determined using appropriate transition methods [14]. The limits for each log are $1/3$ the length of the line toward the low-density layer for the LSD log, whereas the SSD log used $1/2$ length of the deflection line. This can be seen in Figure 2.

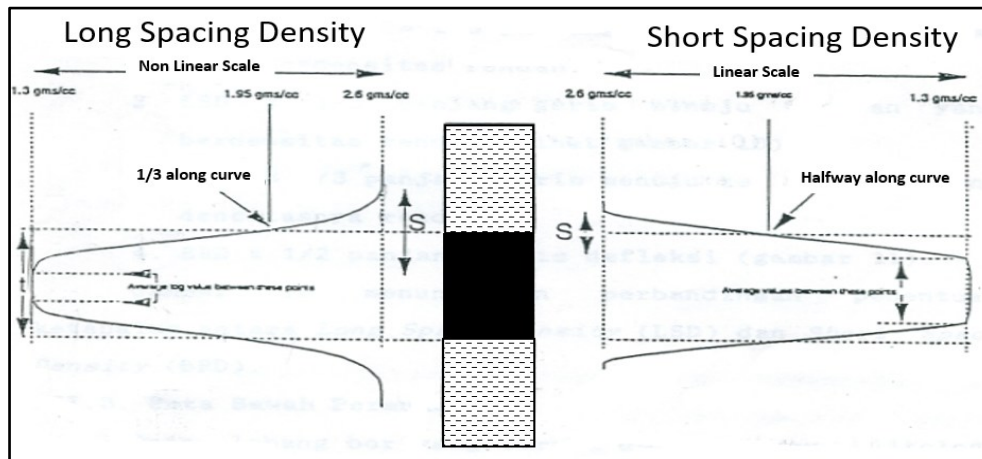


Figure 2. Determination of thickness between LSD (Long Spacing Density) and SSD (Short Spacing Density) logs.

Data from coal seams identified in the logging interpretation were then paired with corresponding laboratory calorific value data for statistical analysis. In this study, the unit for the density log is counts per second (CPS). To simplify calculations, the unit conversion from CPS to gr/cc was performed. The CPS unit value is inversely proportional to the gr/cc unit value (Figure 3). If the log deflection in CPS units shows a high value, it will indicate a low value in gr/cc units.



Figure 3. Relationship between CPS units and gr/cc

Based on Figure 3, the following equation can be obtained:

$$Y = 177598 e^{-2.4325x} \quad (1)$$

Where, Y is density value in cps units and X is density value in gr/cc units

Log density consists of 3 types: Long Spacing Density (LSD), Short Spacing Density (SSD) or Bed Resolution Density (BRD), and High Resolution Density (HRD). The BRD log is more effective for determining the density in porous zones within the borehole. The penetration depth of the Bed Resolution Density (BRD) is 14 cm, making it more sensitive to porous zones. To determine the top and bottom of the coal layers, the logs used are Long Spacing Density (LSD) and High Resolution Density (HRD). Both of these logs have a wider range of exposure, with HRD (28cm) and LSD (48 cm), allowing them to detect the top and bottom of the density.

2.4 Statistical Analysis

1. Correlation coefficient Analysis

Correlation analysis between density and calorific value was performed on the main seams J and L in Pit A (Lati Formation) and seams Z_1 and Z in Pit B (Labanan Formation) using statistical methods with interpretation based on correlation coefficients.

The strength of the relationship between these variables was quantified using the coefficient of determination (R^2). Higher R^2 values indicate stronger relationships between density and calorific value. The interpretation of correlation strength follows standard statistical guidelines where values approaching 1 indicate a very strong relationship. In general, an R^2 value between 0.00 and 0.20 indicates a very weak correlation, 0.20 to 0.40 indicates a weak correlation, 0.40 to 0.70 indicates a fairly strong correlation, 0.70 to 0.90 indicates a strong correlation, and 0.90 to 1.00 indicates a very strong correlation.

Generally, the correlation coefficient is written in the Pearson equation (R), which is equation (2) as follows:

$$R = \frac{N(\sum X_I Y_I) - (\sum X_I)(\sum Y_I)}{\sqrt{(N(\sum X_I^2) - (\sum X_I)^2) \times (N(\sum Y_I^2) - (\sum Y_I)^2)}} \quad (2)$$

In Equation (2), R denotes the Pearson correlation coefficient, N is the number of paired observations, X represents the values of the independent variable, and Y represents the values of the dependent variable included in the correlation analysis.

A correlation analysis between logarithmic density values and coal quality was conducted to determine the strength of the relationship between the two variables through the correlation coefficient (R^2). Logarithmic density values (gr/cc) were used as the independent variable (X), while the calorific value on a dry air basis (ADB) was used as the dependent variable (Y). The relationship between the two was analyzed using a comparison graph to obtain the R^2 value as an indicator of the correlation level.

2. Bivariate geostatistic

Bivariate geostatistical analysis was applied to evaluate the spatial and statistical relationship between density log measurements and calorific value obtained from laboratory testing. This method was selected because the two variables originate from the same spatial locations within the boreholes, making it suitable for analyzing paired geological and geophysical data. Compared with more complex predictive models such as machine learning algorithms, the bivariate geostatistical approach was selected due to several considerations. First, the available dataset consists of a relatively limited number of boreholes, which may reduce the reliability of complex predictive models that require larger datasets. Second, the objective of this study is to evaluate the fundamental statistical relationship between density and calorific value rather than to develop a high-complexity predictive algorithm [21]. Bivariate data are represented through scatter diagrams to display data distribution and linear regression. This method was chosen based on the primary objective of the research, which was to establish a simple, easily interpreted, and practically applicable empirical relationship between one independent variable (density log) and one dependent variable (calorific value). This approach allows for rapid estimation of coal quality based on geophysical well logging data, thus meeting the needs of coal resource exploration and evaluation (3).

$$\mu_{Y/X} = \alpha + \beta x \quad (3)$$

Regression coefficient, based on equation (4)

$$\begin{aligned} \hat{y} &= a + bx \\ a &= \bar{y} - b\bar{x} \quad b = R \frac{J_{xy}}{J_{xx}} \end{aligned} \quad (4)$$

To evaluate the predictive performance of the developed regression equations, the regression outputs were further assessed using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). These evaluation metrics quantify the deviation between predicted calorific values and laboratory measurements, thereby providing an objective assessment of model prediction accuracy.

RMSE quantifies the average magnitude of prediction errors by assigning greater weight to larger errors due to the squared residuals. Lower RMSE values indicate higher prediction accuracy.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (5)$$

where: y_i = observed calorific value, $\hat{y}_i$ = predicted calorific value, N = total number of observations.

MAE measures the average absolute difference between predicted and observed calorific values.

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i| \quad (6)$$

where: y_i = observed calorific value, $\hat{y}_i$ = predicted calorific value, N = total number of observations. Smaller MAE values indicate better predictive performance.

MAPE expresses the prediction error as a percentage of the observed value, allowing comparison of prediction accuracy across different datasets.

$$MAPE = \frac{100}{N} \sum_{i=1}^N \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (7)$$

where: y_i = observed calorific value, $\hat{y}_i$ = predicted calorific value, N = total number of observations. Lower MAPE values indicate higher prediction accuracy.

2.5 Uncertainty and Potential Sources of Bias

This study acknowledges several sources of uncertainty and potential bias associated with the acquisition, interpretation, and analysis of geophysical well logging and laboratory data. First, the accuracy of density log measurements may be influenced by borehole conditions, including borehole enlargement, drilling fluid characteristics, and tool calibration, which can affect the recorded logging response. To minimize these effects, only density log data acquired under acceptable logging conditions and quality-controlled during data processing were included in the analysis. Second, the conversion of density log responses from counts per second (CPS) to density values (gr/cm³) introduces uncertainty because the conversion depends on instrument calibration and logging system characteristics. The same calibration procedure was consistently applied to all observations to ensure comparability among the datasets. Third, the paired dataset was established by matching density log measurements with laboratory-derived calorific values from the corresponding coal seam and depth interval. Although the matching process was carefully performed using geological interpretation and seam correlation, minor discrepancies between logging intervals and laboratory sampling intervals may still introduce measurement uncertainty. To reduce this potential bias, only paired observations with consistent seam identification and corresponding depth intervals were retained for regression analysis. Fourth, natural geological variability within each coal seam, including differences in coalification, mineral matter content, and depositional conditions, may contribute to variations in calorific value that cannot be fully explained by density log measurements alone. To minimize the influence of geological heterogeneity, separate regression models were developed for each coal seam (J, L, Z_1, and Z) rather than combining all observations into a single model. To reduce the influence of these uncertainties, this study uses only data pairs that have been verified through geological interpretation, conducts separate analyses on each seam, and evaluates model performance using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) so that the level of model accuracy can be measured quantitatively.

2.6 Methodological Limitations

This study focuses on evaluating the statistical correlation between density logs and calorific value using a relatively simple analytical approach. More advanced predictive models, such as machine learning or multivariate regression techniques, may provide higher predictive accuracy. However, such models require larger datasets and more complex calibration procedures. Therefore, this research emphasizes a practical and interpretable approach that can be readily applied within operational mining workflows. Future studies may expand the dataset and explore more advanced predictive methods to further improve coal quality prediction models.

3. Results and Discussion

3.1 Interpretation of coal seam Pit A in the Lati Formation based on geophysical well logging

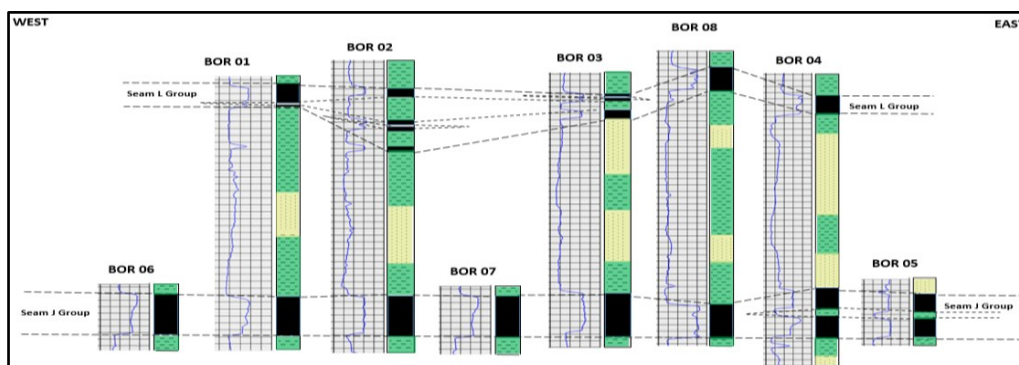


Figure 4. Generally correlation of coal seams in Pit A (J group, L group) within the Lati Formation based on geophysical well logging

Based on Figure 4, interpretation of geological and geophysical well logging data in Pit A in the Lati Formation shows that the main seam J has split to the secondary stage towards the east with clay lithology, while the main seam L has fractured to the tertiary stage towards the west with clay lithology. The average values of coal cps, coal thickness, and the results of cps conversion to gr/cc are presented in Table 1.

Table 1. Paired Density Log and Laboratory Calorific Value Data for Coal Seams in Pit A (Lati Formation)

Hole Name	Seam	Average, CPS	Conversion, Density log,	Lab, Analysis CV adb (Kcal/Kg)
			CPS to gr/cc	
BOR 01	J	7,653	1.29	5,184
BOR 02	J	7,595	1.30	5,282
BOR 03	J	8,140	1.31	5,349
BOR 04	J	7,067	1.33	5,697
BOR 05	J	6,879	1.33	5,687
BOR 06	J	6,626	1.35	5,937
BOR 07	J	6,807	1.34	5,820
BOR 08	J	6,713	1.34	5,894
BOR 09	J	6,948	1.32	5,542
BOR 10	J	6,995	1.33	5,681
BOR 11	J	7,161	1.34	5,705
BOR 12	J	8,105	1.31	5,371
BOR 13	J	7,490	1.30	5,375
BOR 14	J	7,648	1.31	5,446
BOR 15	J	7,540	1.31	5,434
BOR 16	J	7,440	1.30	5,349
BOR 17	J	7,378	1.32	5,464
BOR 18	J	7,444	1.31	5,458
BOR 19	J	7,237	1.32	5,484
BOR 20	J	7,544	1.30	5,316
BOR 21	J	6,713	1.35	5,874

BOR 22	J	7,137	1.32	5,521
BOR 23	J	6,570	1.35	5,873
BOR 24	J	7,602	1.30	5,226
BOR 25	J	6,866	1.34	5,725
BOR 26	J	7,167	1.32	5,486
BOR 27	J	7,251	1.31	5,442
BOR 28	J	6,966	1.34	5,787
BOR 29	J	7,593	1.29	5,223
BOR 30	J	6,989	1.33	5,675
BOR 31	J	6,876	1.34	5,704
BOR 32	J	7,092	1.32	5,623
BOR 33	L	7,793	1.29	5,316
BOR 34	L	7,235	1.30	5,347
BOR 35	L	7,169	1.32	5,549
BOR 36	L	6,895	1.34	5,620
BOR 37	L	6,599	1.35	5,718
BOR 38	L	6,916	1.34	5,706
BOR 39	L	6,995	1.35	5,708
BOR 40	L	7,084	1.33	5,627
BOR 41	L	7,814	1.28	5,283
BOR 42	L	7,968	1.28	5,240
BOR 43	L	7,221	1.32	5,505
BOR 44	L	7,793	1.29	5,251
BOR 45	L	7,235	1.33	5,609
BOR 46	L	7,993	1.27	5,202
BOR 47	L	6,804	1.34	5,621
BOR 48	L	7,928	1.28	5,220
BOR 49	L	7,424	1.31	5,410
BOR 50	L	7,913	1.28	5,162
BOR 51	L	7,250	1.31	5,500
BOR 52	L	6,686	1.35	5,726
BOR 53	L	7,613	1.29	5,384
BOR 54	L	8,008	1.27	5,123
BOR 55	L	6,680	1.35	5,804
BOR 56	L	8,045	1.27	5,139

Based on the Table 1, the interpreted density log values expressed in counts per second (CPS) ranged from 6,570 to 8,140 CPS for Seam J and from 6,599 to 8,045 CPS for Seam L. After conversion, the corresponding density values ranged from 1.29 to 1.35 gr/cm³ for Seam J and from 1.27 to 1.35 gr/cm³ for Seam L. Laboratory analyses indicated calorific values (CV adb) ranging from 5,184 to 5,937 kcal/kg for Seam J and from 5,123 to 5,804 kcal/kg for Seam L. The observed variations in CPS, converted density values, and calorific values reflect differences in coal characteristics among the identified seams and drilling locations within the Lati Formation.

3.2 Interpretation of coal seam Pit B in the Labanan Formation based on geophysical well logging

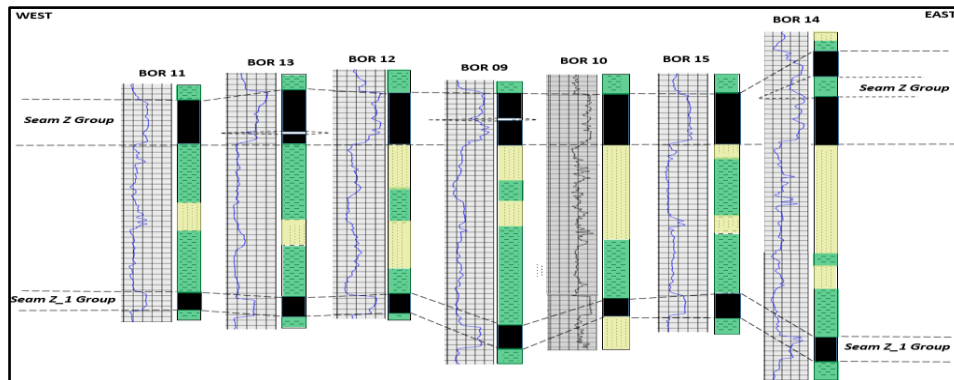


Figure 5. Generally correlation of coal seams in Pit B (Z group, Z_1 group) within the Labanan Formation based on geophysical well logging

Based on Figure 5, interpretation of geological and geophysical well logging data in Pit B of the Labanan Formation shows that the main seam Z has undergone secondary fracturing with clay lithology, while the seam Z_1 has not developed in the Pit B area. The Labanan Formation consists of sandstone with varying grain sizes up to conglomerate. The average coal cps values, coal thickness, and cps to gr/cc conversion results are presented in Table 2.

Table 2. Paired Density Log and Laboratory Calorific Value Data for Coal Seams in Pit B (Labanan Formation)

Hole Name	Seam	Average,	Conversion,	Lab, Analysis
		CPS	Density log, CPS to gr/cc	
BOR 57	Z 1	8,576	1.24	5,312
BOR 58	Z 1	8,266	1.26	5,410
BOR 59	Z 1	7,858	1.28	5,531
BOR 60	Z 1	8,638	1.24	5,252
BOR 61	Z 1	8,828	1.22	5,151
BOR 62	Z 1	7,799	1.28	5,534
BOR 63	Z 1	7,815	1.28	5,509
BOR 64	Z 1	8,600	1.24	5,270
BOR 65	Z 1	7,957	1.28	5,516
BOR 66	Z 1	8,134	1.27	5,408
BOR 67	Z 1	7,998	1.27	5,484
BOR 68	Z 1	8,638	1.24	5,256
BOR 69	Z 1	8,947	1.23	5,182
BOR 70	Z 1	8,518	1.25	5,337
BOR 71	Z 1	8,345	1.26	5,392
BOR 72	Z 1	8,555	1.25	5,318
BOR 73	Z 1	8,453	1.25	5,338
BOR 74	Z 1	8,576	1.25	5,332
BOR 75	Z 1	8,632	1.24	5,281
BOR 76	Z 1	8,040	1.27	5,482
BOR 77	Z 1	8,965	1.23	5,240
BOR 78	Z 1	8,065	1.27	5,455
BOR 79	Z 1	7,999	1.27	5,499

BOR 80	Z 1	7,779	1.27	5,429
BOR 81	Z 1	7,765	1.29	5,566
BOR 82	Z 1	8,026	1.27	5,488
BOR 83	Z 1	8,896	1.23	5,251
BOR 84	Z 1	7,779	1.29	5,552
BOR 85	Z 1	8,116	1.27	5,461
BOR 86	Z 1	9,124	1.22	5,142
BOR 87	Z 1	8,222	1.26	5,397
BOR 88	Z	9,046	1.22	5,037
BOR 89	Z	8,829	1.24	5,161
BOR 90	Z	8,273	1.26	5,425
BOR 91	Z	8,452	1.25	5,382
BOR 92	Z	8,315	1.25	5,381
BOR 93	Z	8,234	1.26	5,495
BOR 94	Z	8,536	1.26	5,387
BOR 95	Z	8,647	1.24	5,324
BOR 96	Z	8,768	1.24	5,173
BOR 97	Z	8,536	1.25	5,381
BOR 98	Z	8,548	1.25	5,350
BOR 99	Z	8,318	1.26	5,408
BOR 100	Z	8,829	1.23	5,160
BOR 101	Z	8,733	1.24	5,203
BOR 102	Z	8,658	1.24	5,247
BOR 103	Z	8,595	1.24	5,287
BOR 104	Z	8,433	1.25	5,398
BOR 105	Z	8,273	1.26	5,426
BOR 106	Z	8,680	1.24	5,283
BOR 107	Z	8,738	1.24	5,282
BOR 108	Z	8,928	1.23	5,152
BOR 109	Z	8,922	1.23	5,165
BOR 110	Z	8,799	1.24	5,247
BOR 111	Z	8,336	1.26	5,472
BOR 112	Z	8,926	1.23	5,231
BOR 113	Z	8,825	1.23	5,205

Based on the interpretation of geophysical well logs in Pit B of the Labanan Formation, as presented in Table 2, two major coal seams, namely Seam Z_1 and Seam Z, were successfully identified, yielding a total of 57 paired observations, comprising 31 observations from Seam Z_1 and 26 observations from Seam Z. The average density log measurements, expressed in counts per second (CPS), ranged from 7,765 to 9,124 CPS for Seam Z_1 and from 8,234 to 9,046 CPS for Seam Z. After conversion, the corresponding density values ranged from 1.22 to 1.29 g/cm³ for Seam Z_1 and from 1.22 to 1.26 gr/cm³ for Seam Z. Laboratory analyses indicated that the calorific value (CV adb) ranged from 5,142 to 5,566 kcal/kg for Seam Z_1 and from 5,037 to 5,495 kcal/kg for Seam Z. The observed variations in CPS, converted density values, and calorific values among the boreholes indicate heterogeneity in coal characteristics within the Labanan Formation, reflecting differences in local geological conditions and coal depositional processes.

3.4 Correlation of Density Log Values with Coal Quality

1. Correlation of Density Log Values with Air Dried Basis (ADB) Calorific Value in Pit A at the Lati Formation.

Based on Figure 6, the correlation between density and calorific value (CV adb) in seam J - Pit A shows a positive linear relationship with a value of 12.236, where an increase in coal density is followed by an increase in calorific value. The high correlation coefficient ($R^2 = 0.9748$) indicates a very strong positive correlation between the two variables.

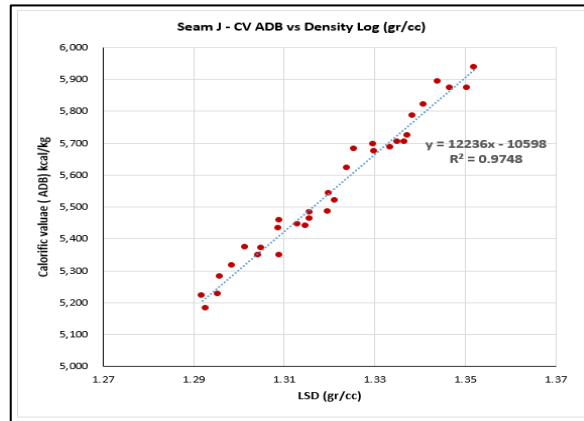


Figure 6. Graph of the relationship between calorific value (CV adb) and density (gr/cc) – seam J

The relationship between density and calorific value (CV adb) for seam L – Pit A, as seen in Figure 4, shows a positive trendline with a value of 7.531. This indicates that the higher the density of the coal in gr/cc, the higher the calorific value. Based on the correlation coefficient between the two variables, with an $R^2 = 0.9735$, indicates a very strong positive correlation with a positive trendline

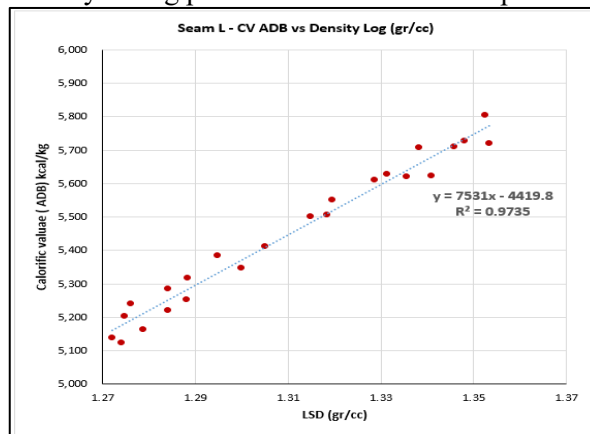


Figure 7. Graph of the relationship between calorific value (CV adb) and density (gr/cc) – seam L

3.5 Correlation of Density Log Values with Air Dried Basis (ADB) Calorific Value in Pit B of the Labanan Formation

Correlation of density to calorific value (CV adb) for seam Z_1 - Pit B, as seen in Figure 5, shows a positive trendline with a value of 6.090,6. This means that the higher the coal density in gr/cc, the higher the calorific value. The relationship between density and calorific value (CV adb) based on the correlation coefficient between the two variables, with an $R^2 = 0.9738$, indicates a very strong positive correlation with a positive trendline.

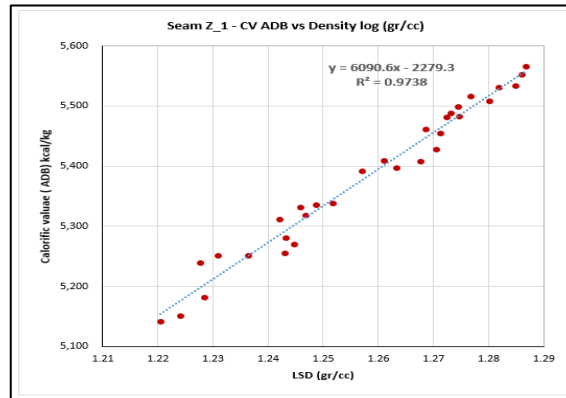


Figure 8. Graph of the relationship between calorific value (CV adb) and density (gr/cc) – seam Z₁

The relationship between density and calorific value (CV adb) of seam Z – Pit B, as shown in Figure 6, is positive with a trendline value of 10.019. This indicates that the higher the density of coal in gr/cc, the higher the calorific value. The relationship between density and calorific value (CV adb) based on the correlation coefficient between the two variables, with an $R^2 = 0.9226$, indicates a very strong positive correlation with a positive trendline.

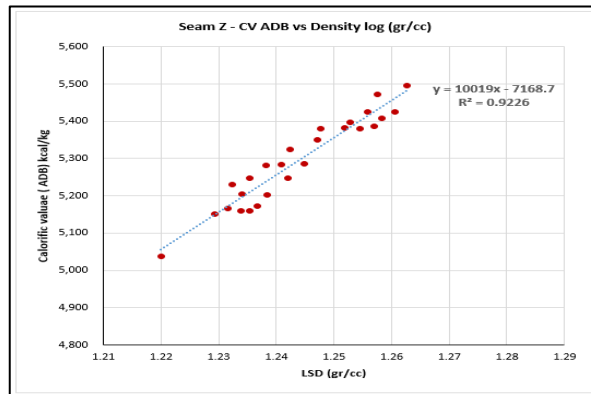


Figure 9. Graph of the relationship between calorific value (CV adb) and density (gr/cc) – seam Z

3.6 Model Performance Evaluation

Table 3. Model Performance Evaluation

Seam	N	RMSE (kcal/kg)	MAE (kcal/kg)	MAPE (%)
J	32	49.76	41.56	0.748
L	24	40.57	35.74	0.657
Z ₁	31	21.75	17.15	0.319
Z	26	42.62	35.05	0.663

Based on the Table 3, the regression models demonstrated good predictive accuracy across all investigated coal seams. The RMSE values ranged from 21.75 to 49.76 kcal/kg, while the MAE values varied between 17.15 and 41.56 kcal/kg. Among the four models, Seam Z₁ achieved the best predictive performance, with the lowest RMSE (21.75 kcal/kg), MAE (17.15 kcal/kg), and MAPE (0.319%), indicating the smallest prediction error relative to the laboratory-derived calorific values. In contrast, Seam J produced the highest RMSE (49.76 kcal/kg) and MAE (41.56 kcal/kg), suggesting relatively larger prediction errors, although the MAPE remained below 1%. Similarly, the models for Seam L and Seam Z exhibited low prediction errors, with RMSE values of 40.57 kcal/kg and 42.62 kcal/kg,

respectively. The MAPE values for all seams ranged from 0.319% to 0.748%, indicating that the average prediction error was less than 1% of the observed calorific values.

3.7 Discussion

The relationship identified between density log measurements and coal calorific value indicates that geophysical logging data can provide meaningful information about coal energy characteristics. Rather than merely reflecting numerical correlations, this relationship can be interpreted through the physical properties of coal and the geological processes that influence its formation. Coal density is closely related to the internal structure of coal, including porosity, mineral content, and the degree of coalification. As burial pressure and temperature increase during the coalification process, porosity tends to decrease and carbon concentration increases, which generally leads to higher density and greater energy content. Consequently, density log measurements may indirectly reflect variations in coal composition that influence calorific value. This finding aligns with recent studies showing that density logs can effectively predict coal quality using statistical and machine learning approaches [3,17], and that coal physical-chemical parameters strongly correlate with calorific value [18]. Density logs thus have potential to be developed into predictive models to support coal mining planning and operational decision-making [22].

From a geophysical perspective, density logs measure the bulk density of subsurface materials, which is influenced by both the organic matter content and the presence of mineral impurities [23]. Coal with higher organic carbon content and lower moisture or ash content tends to exhibit density responses that correspond to higher energy potential [24]. Conversely, coal seams containing higher mineral matter or moisture may display lower calorific value even when density variations appear subtle. This relationship explains why density measurements can serve as an indirect indicator of coal quality, particularly when supported by lithological interpretation from drilling cores.

The strong relationship observed between density logs and calorific value should also be interpreted with careful consideration of geological variability. Coal seams often develop under different depositional environments and diagenetic conditions, which may influence both physical and chemical properties of the coal. Factors such as sedimentary facies, compaction history, and mineral composition can affect density responses and calorific value simultaneously. As a result, the relationship identified in this study may partly reflect geological conditions that are specific to the analyzed coal-bearing formations.

In addition, the statistical strength of the relationship may also be influenced by the scale and characteristics of the dataset. When datasets are relatively limited or derived from similar geological settings, regression relationships may appear stronger than they would in more heterogeneous conditions. Therefore, although the observed correlation provides useful insight into the relationship between density and calorific value, it should not be interpreted as a universal predictive model without further validation in other geological contexts.

When viewed within a broader engineering context, the findings of this study highlight the potential role of geophysical logging in improving the efficiency of coal resource evaluation. In conventional exploration workflows, coal quality determination often relies heavily on laboratory testing of core samples, which requires time, cost, and logistical effort. The integration of geophysical logging data as a preliminary indicator of coal quality may help reduce dependence on extensive laboratory analysis and accelerate decision-making processes during exploration and mine planning.

However, the practical application of density-based coal quality estimation should be approached cautiously. The reliability of such an approach depends on the consistency of

geological conditions and the availability of calibration data from laboratory analysis. In many mining operations, geophysical logs are used primarily for lithological interpretation and seam correlation, while laboratory analysis remains the primary method for determining coal quality parameters. Therefore, density-based prediction methods are more appropriately viewed as complementary tools that support preliminary resource evaluation rather than replacements for laboratory testing.

From a technological perspective, the integration of logging-based coal quality estimation into digital mining workflows represents an important opportunity for improving data utilization. Modern mining operations increasingly rely on integrated geoscience databases and digital interpretation systems to manage exploration and production data [22]. Within such systems, geophysical logging data can provide continuous subsurface information that supports rapid geological interpretation and resource modeling. The ability to derive additional insights about coal quality from these datasets can enhance operational efficiency and contribute to more data-driven mining practices [25].

Despite these advantages, the transferability of density–calorific relationships to other coal basins remains uncertain. Coal deposits in different regions may exhibit variations in coal rank, mineral composition, and depositional history that influence the relationship between density and energy content. Consequently, correlation models developed in one geological setting may require recalibration before they can be applied reliably in other mining areas. Future research involving larger datasets and multiple coal basins would help clarify whether the observed relationship represents a broader geological pattern or primarily reflects local geological conditions.

Overall, the findings of this study demonstrate that density log measurements contain valuable information for interpreting coal energy characteristics and may serve as a practical indicator for preliminary coal quality assessment. While the relationship identified in this study cannot fully replace laboratory-based coal analysis, it provides an important step toward integrating geophysical logging data into more efficient and technologically advanced coal resource evaluation frameworks.

4. Conclusion

This study demonstrates that geophysical density log measurements contain valuable information related to coal energy characteristics and can be used to estimate coal calorific value through statistical correlation analysis. The results indicate that density logs can provide a useful preliminary indicator of coal quality, particularly for supporting rapid subsurface interpretation and resource evaluation during exploration and mine planning stages.

From a mining engineering perspective, the relationship between density log responses and coal calorific value highlights the potential role of geophysical logging data in improving the efficiency of coal resource assessment. By providing continuous subsurface measurements, density logs can complement laboratory-based coal analysis and assist in identifying variations in coal quality within boreholes. However, the findings of this study should be interpreted as an estimation approach rather than a validated replacement for laboratory testing. Laboratory analysis remains essential for confirming coal quality parameters and ensuring reliable resource evaluation. The applicability of the density–calorific relationship identified in this research may also depend on geological conditions and coal characteristics specific to the studied formations. Therefore, calibration using local geological and laboratory data is recommended before applying similar approaches in other mining areas.

Future research should focus on expanding the dataset by incorporating additional boreholes and geological settings to improve the robustness of the correlation model. Further studies could also explore multivariate or machine-learning approaches that integrate additional coal quality parameters, such as

ash content, moisture content, and volatile matter, to enhance the accuracy of coal quality prediction models. This research contributes to the development of geophysical logging applications for coal resource evaluation and highlights the potential of density log data as a practical tool for preliminary coal quality estimation within integrated mining engineering workflows.

Declaration of AI and AI assisted technologies in the writing process

During the preparation of this manuscript, the author(s) used Claude and DeepL as supporting tools for language editing, improving sentence clarity, refining academic expression, and enhancing overall readability. The author(s) independently reviewed and revised all suggested changes to ensure that the scientific content, interpretation, and meaning of the manuscript remained accurate and unchanged. Full responsibility for the final version of the manuscript rests with the author(s).

Declaration of Competing Interest

The authors declare that there are no financial, professional, institutional, or personal interests that could have influenced the conduct of the research, interpretation of the results, or preparation of this manuscript.

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