GEOLOGY

https://doi.org/10.33271/nvngu/2025-2/005

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ESTIMATION OF COAL FIELD RESERVES WITH GRADING BY TECHNICAL CHARACTERISTICS OF COAL

Purpose. To improve the method of coal field reserve estimation with consideration of coal grading based on its technical characteristics.

Methodology. The study employed modern approaches, including geophysical surveys and geochemical analysis and geological disturbances. Generalized linear regression and regression analysis methods were applied to account for the spatial heterogeneity of technical coal characteristics, such as moisture content, ash content, sulfur content, volatile matter, and calorific value.

Findings. The analysis revealed significant variations in technical coal characteristics depending on seam depth. Ash content decreases with depth, while moisture content and volatile matter content exhibit substantial variability. Anomalies with elevated sulfur content were identified in deep seams, reaching maximum values at depths of 100–140 m. The application of generalized linear regression enabled high-accuracy modeling of the spatial distribution of coal technical characteristics across the field.

Originality. For the first time, a comprehensive analysis of the impact of geological disturbances on ash content, moisture content, and calorific value of coal was conducted in conditions of complex tectonic structure. An integrated approach to reserve estimation using modern statistical methods was proposed, improving the accuracy of estimates by 15 % compared to traditional methods.

Practical value. The study's results enable the optimization of coal resource forecasting processes. The proposed methods can be applied to mine planning under complex geological structure of deposits.

Keywords: *reserve estimation, coal, ash content, moisture content, volatile matter, regression analysis*

Introduction. The coal industry is the most important sector of the economy of Kyrgyzstan, providing a significant part of the country's energy needs. In Kyrgyzstan, the coal sector is also critical for rural employment and local economic development, often serving as a lifeline for remote communities. Despite its economic importance, the industry must address growing environmental concerns and adopt sustainable practices. This includes reducing greenhouse gas emissions, implementing advanced mining technologies, and rehabilitating lands disturbed by mining activities. Such measures are essential for balancing economic benefits with environmental responsibility and resource availability.

Around the world, coal is used in both thermal power and industry, contributing to infrastructure development and job creation [1]. However, mining faces a number of challenging geologic conditions such as disturbed seams, unstable rocks [2], water-cut, and the presence of tectonic faults [3]. These factors require the use of integrated resource management and production planning methods [4].

Difficult mining-geological conditions in mining practice lead to a decrease in the quality characteristics of coal, which negatively influences its efficiency and environmental performance [5, 6]. The key characteristics of coal are moisture content, ash content, chemical composition, particle size and calorific value. High moisture content reduces the calorific value of coal and increases energy consumption during its combustion, while high ash content deteriorates environmental performance, increasing the level of harmful emissions into the atmosphere. Coal moisture content is subdivided into analytical and operating moisture, while its level depends on coal grade [7]. Despite the negative impact of high moisture content on the combustion process, wetting the coal can improve its permeability to gases, which is important for efficient combustion [8].

The second important indicator of coal quality is ash content, or the content of mineral impurities. In the thermal power industry, ash content directly affects the level of environmental pollution associated with harmful emissions into the atmosphere [9]. The number of mineral impurities depends on the conditions of peat accumulation, which leads to variations in ash content of different coal grades. Ash is subdivided into external ash, containing rock interlayers, and internal ash, associated with the organic part of the coal. External ash is easily removed in all types of beneficiation processes. However, internal ash, (insignificant, not more than 10 %) is practically not removed during beneficiation. It is worth emphasizing that the ash content requirements vary considerably from one industry to another. For example, the thermal power industry uses brown coal and hard coal with higher ash content, which requires special types of combustion. But in any industry, coals are classified based on ash content, that is, the ratio of ash content (in %) to the heat of coal combustion (kcal/kg). In practice, two ash content indices are mainly used: those related to its operating state and to absolutely dry fuel.

This underscores the necessity for ongoing research and innovation aimed at developing advanced methods for quality assessment and utilization. Such efforts should focus on optimizing the combustion process, minimizing environmental impacts, and enhancing the economic efficiency of coal use across various industries, while simultaneously addressing the challenges posed by complex geological conditions and varying coal characteristics.

Literature review. Understanding the quality characteristics of coal and the complexities of coal mining becomes particularly important in light of the shortcomings of existing reserve estimation methods [10, 11]. Shortcomings in the methods used to estimate coal reserves and limitations of geological models have a significant impact on the accuracy of reserve estimates, which, in turn, may lead to errors in planning and mining of deposits.

Firstly, simplified geologic models are often used, which, while being practical, cannot always accurately reflect the complex structure of deposits [12]. Coal deposits are typically characterized by a complex geological structure, including numerous faults, lenses and non-uniform coal distribution in terms of thickness and quality of seams. Simplification of these models results in the loss of much of the geological information, which can adversely affect the reserve estimation process and lead to erroneous conclusions about the profitability of mining.

Secondly, spatial variability of coal characteristics such as ash content, moisture content, sulfur content and volatile-matter content is often insufficiently considered [13]. These parameters may vary depending on the location and depth of the coal seam occurrence, which is important for a more accurate assessment of its quality and suitability for further processing or use for energy purposes. Insufficient attention to the variability of these characteristics leads to the creation of models that do not reflect the full pattern of the field, which, in turn, complicates the reserve estimation process.

The third problem is the use of interpolation methods when constructing geologic models [14]. Although interpolation can compensate for missing data in certain areas of the field, it often causes significant errors, especially in those areas where exploration data density is insufficient [15]. This may lead to excessive increase or decrease in estimated coal reserves, creating uncertainty in calculations and increasing risks for mining companies.

Another significant problem is that existing geologic models are insufficiently detailed [16]. These models often do not provide a sufficient level of detail to estimate coal reserves in localized areas of the field, where there may be significant changes in coal characteristics and distribution. Lack of detail means that small but important details are not noticed, which can adversely affect the accuracy of reserve estimates and the development of mining strategies.

Finally, one important but often neglected aspect is the insufficient consideration of technological limitations when estimating coal reserves [17]. These limitations include physical-mechanical properties of coal, such as hardness, fracturing, and the difficulties associated with mining of coal in certain geologic conditions [18, 19]. Failure to take these factors into account could result in overestimating coal reserves, which in reality may not be available or economically feasible to mine [20].

Unsolved aspects of the problem. Despite the significant advances in coal reserves estimation techniques, there remain unresolved challenges that hinder the accuracy and reliability of these methods. One of the key issues is the insufficient consideration of the complex geological conditions in coal deposits, which often lead to oversimplified models. These models fail to adequately capture the variability of geological structures, such as faults, lenses, and uneven coal distribution, which are crucial for precise reserve estimation. The lack of accurate representation of these geological factors creates uncertainty in the estimation process and can affect subsequent mining strategies and resource management decisions.

Another critical problem is the inadequate accounting for the spatial variability of coal characteristics. While some methods attempt to consider factors such as ash content, sulfur levels, moisture content, and volatile matter, the level of detail remains insufficient. Variations in coal quality based on location, depth, and seam structure are not always captured, resulting in an incomplete assessment of coal reserves. The failure to accurately model this variability can lead to misjudgments regarding the economic viability of coal deposits and may result in inefficient mining practices.

Moreover, the widespread use of interpolation methods in geological modeling presents its own set of challenges. Although interpolation can help fill gaps in data, it often leads to significant errors, particularly in areas with sparse exploration data. This introduces a risk of either overestimating or underestimating coal reserves, leading to incorrect predictions about the amount of recoverable coal. Additionally, these methods fail to reflect the dynamic nature of coal deposits, further complicating the estimation process.

The technological limitations of mining operations are also often overlooked when estimating coal reserves. Factors such as the mechanical properties of coal, including hardness and brittleness, significantly affect the feasibility of mining in certain geological conditions [21]. Without incorporating these limitations, reserve estimations may not accurately reflect the true potential of a deposit. This oversight can result in overestimation of coal reserves that are, in practice, either difficult to mine or economically unfeasible [22].

These unresolved issues highlight the need for more comprehensive and nuanced approaches to coal reserve estimation. Without addressing these challenges, existing models will continue to fall short in providing the accuracy and reliability required for effective resource management and sustainable mining operations.

The purpose of this research is to improve the accuracy and reliability of coal reserves estimation; it is required to develop more complex and detailed geological models that take into account the variability of coal characteristics, as well as to apply more accurate interpolation methods and to take into account all possible technological limitations.

Study area. The main type of fuel for CHPPs in Bishkek is brown coal, mined by open-pit mining method at coal sections of the Kavak Coal Basin, as well as at Kara-Keche, Min-Kush and other fields, the total balance reserves of which exceed 2 billion tons. The Kavak Basin coals belong to grade B (brown) and to group 3B (third brown), with subgroup 3BF (third brown fusinite) and code number 0452005. These coals are used as an energy fuel.

Visually, coals from the Min-Kush deposit range from black to bright, semibright or matte. The break of coals is irregular, and in bright varieties – shell-like. Laminated coals are easily broken along the planes of bedding, and their color feature varies from dark brown to black. Macroscopically, the coals are represented by durain, duroclarain, clarain-durain, and fusoxylain types [23]. Seam 6 is dominated by duroclarain coals, while the lower seams are dominated by clarain-durain coals. Results of technical analysis of samples are presented in Table 1.

According to the results of technical analyses, in the Min-Kush deposit coals analytical moisture ranges from 2.37 to 10.55 % and averages 6.3 %. The minimum average moisture content is noted in seam 5, the maximum – in seam 7.

Ash content per dry fuel varies from 2.14 to 36.88 %, with an average content of 12.2 %. This coal ash content is calculated taking into account high-ash coal units (30–40 %), accepted for calculation of reserves, if the ash content of the seam, taking into account these units, does not exceed the standard ash content (30 %). The minimum ash content is fixed for seam 5 and maximum ash content is fixed for seam 7. The average minimum ash content is in seam 6 (9.30 %) and the average maximum ash content is in seam 7 (19.48 %).

During field exploration, the ash composition is identified as alumina-siliceous, closer to siliceous. The average silica content is 37.7 %, alumina – 20.7 %, iron oxide – 13.5 %, and calcium oxide – 11.7 %. Increased silica content is noted in the ash of seam 2 + 3, and an increased content of iron oxides (16.7 %) and calcium oxides (15.7 %) is confined to seam 6.

Total sulfur content per dry fuel ranges from 0.04 % (seam 5, 6) to 9.84 % (seam 6), while average sulfur content – 0.98 %.

The volatile yield per combustible mass ranges from 29.27 to 52.01 %, averaging 38.49 %. The lowest volatile yield is recorded for seams 5 and 6 (29.3 and 29.27 %), and the highest for seam 5 (52.01 %). In terms of volatile yield (GOST/049-70) the coals of the field are classified as B-3 (V – 28 %).

The heat of fuel combustion per combustible mass varies from 4,336 kcal (seam 7) to 6,439 kcal (seam 5) and averages 5,905 kcal. Average hydrogen content is 4.4 %, oxygen + nitrogen content is 19.5 % and carbon content is 76.2 %.

As can be seen, the wide range of variations in some of the technical sample analysis results above appears to be determined by:

- complex geological structure of the field;
- shortcomings of the existing methods for estimating coal reserves.

The geologic structure of the Min-Kush deposit (Fig. 1) involves sedimentary rocks from various geologic eras, including the Proterozoic, Paleozoic (Ordovician and Carboniferous), Mesozoic (Upper Triassic and Jurassic), and Cenozoic (Paleogene, Neogene, and Quaternary). These rocks form a complex geologic structure that reflects a long history of sedimentary formation and tectonic processes. The tectonic structure of the field is determined by its position in the Kavak graben-syncline, which on a district scale represents an alpine structure of the second order.

All major plicative and discontinuous structures were formed during Alpine tectogenesis, indicating sig-

Table 1

Main technical characteristics of coal from the analysis data of geological exploration results

Coal seam numbers	In the numerator there are variations from-to, in the denominator there is the average value (number of samples in brackets)				
	Moisture (as received), W^a, %	Ash content (dry basis), A^d, %	Total sulfur (dry basis), S_t^d, %	Volatile matter (dry ash-free basis), V^{daf}, %	Specific heat of combustion, MJ/kg
2 + 3	5.17–5.59 5.35 (5)	10.5–21.47 16.72 (5)	0.5–1.02 0.74 (5)	33.3–45.59 37.85 (5)	23.68–31.67 29.72 (5)
5	4.78–6.26 4.71 (87)	10.05–24.82 16.41 (87)	0.57–1.55 0.92 (87)	32.89–43.60 38.82 (87)	23.55–32.1 29.51 (87)
6	4.83–6.67 5.63 (104)	9.56–28.78 16.11 (104)	0.46–1.97 0.87 (104)	33.07–42.55 38.13 (104)	23.67–31.87 30.5 (104)
7	4.66–7.02 5.76 (114)	6.15–29.24 19.48 (114)	0.39–2.77 0.91 (114)	32.46–46.45 39.07 (114)	21.62–31.42 28.04 (114)

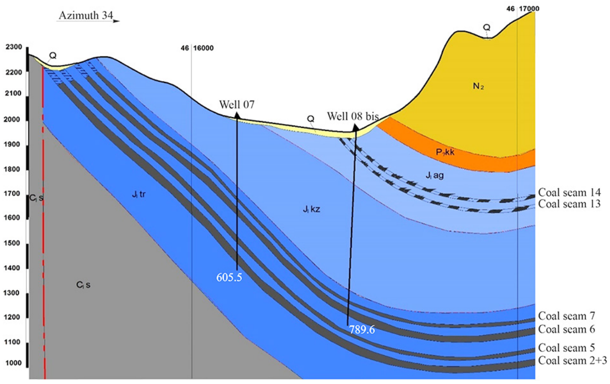

Fig. 1. Geological section of the Min-Kush deposit

nificant tectonic activity in this region. These structures tend to be complex and some of them are inherited, meaning that they may have originated from earlier geologic processes and continued to exist in an altered form. Thus, the geological structure of the Min-Kush deposit is the result of centuries-long interaction of various geological processes and plays a key role in the formation of coal reserves in the region.

As a result of tangential sub-meridian stresses, the Min-Kush synclinal structure was formed within the depression, complicated by higher-order folds and tectonic blocks (Fig. 2). The structure of the field is determined by second-order folds relative to the Min-Kush syncline. In addition to folded structures, both large and small discontinuities are developed in the field, significantly affecting ash content, moisture content and calorific value of coal.

Where tectonic disturbances have occurred, faults and folds can form that alter fluid migration pathways and potential mineral dilution. This can lead to increased ash content, especially if the coal is in contact with minerals rich in metal oxides. Tectonic processes can cause more ashy mineralized layers to be drawn into the coal seam, which also increases its ash content.

Tectonic disturbances can alter the structure of the coal-bearing rock mass, increasing porosity and permeability, which can lead to increased water inflow into coal seams [24]. If tectonic disturbances are in contact with aquifers, this can create conditions for significant water inflow, increasing the moisture content of the coal. If the tectonic disturbances lead to the contact of coal with other rocks, this can affect its chemical composition and thus its calorific value. For example, coal that has been under high pressure and temperature at great depths (for example, through folding) may have a higher calorific value. In some cases, tectonic disturbances can cause coal to degrade, reducing its calorific value. In general, the influence of tectonic disturbances on ash content, moisture content and calorific value of coal can be diverse and multifactorial. Thus, in-depth geologic study and data analysis will help to better understand exactly how tectonic factors influence the coal-rock resources in a particular location.

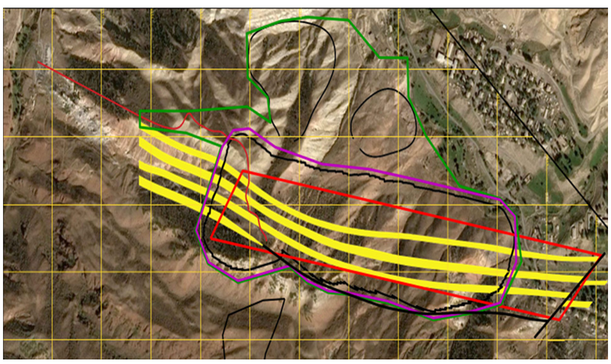

Fig. 2. Plan of coal seams of the first-stage coal section, combined with the surface topographic map

Methods. Modern methods, including geophysical surveys, geochemical analysis, computer modeling and geostatistical methods, are used to accurately and precisely estimate coal reserves with gradation by technical characteristics [25, 26]. These approaches, complemented by the use of machine learning, provide innovative solutions to optimize the coal reserve estimation process [27, 28]. The ability to analyze large datasets and identify complex relationships can significantly improve the accuracy of estimates by considering key parameters such as moisture content, calorific value and ash content.

The study involves coal quality prediction, sample selection optimization, and uncertainty assessment.

Spatial distribution modeling involves the creation of detailed maps reflecting variations in coal quality throughout the field. Regression analysis can be used to predict changes in quality, represented by the formula

$$Q = \beta_0 + \beta_1 D + \beta_1 G + \varepsilon,$$

where Q is the coal quality; D is the depth of occurrence; G is the geological conditions; β_0, β_1, β_2, are regression coefficients; ε is the prediction error.

Historical data and geostatistical methods are used to identify the most informative sampling locations. One approach is to use the kriging method, which can be presented as follows

$$Z(x_0) = \sum_{i=1}^{n} \lambda_i Z(x_1) + \mu,$$

where $Z(x_0)$ is the predicted value at a point x_0; $Z(x_i)$ are known values at points x_i; λ_i are the weights determined based on spatial correlation; μ is the average value.

This approach minimizes the number of samples and reduces exploration costs while maintaining high accuracy of estimates.

A key aspect is the error estimate quantification, which involves determining a range of possible reserve values, given the uncertainty in the input data and models. The confidence interval given by the following formula can be used to estimate uncertainty

$$CI = \bar{x} \pm Z_{a/2}\left(\frac{\sigma}{\sqrt{n}}\right), \qquad (1)$$

where CI is the confidence interval; $\bar{x}$ is the sample set mean value; $Z_{a/2}$ is the critical value of Z for a given level of significance; σ is the standard deviation for a sample set; n is the sample set size.

Another important approach to improve the accuracy of reserve estimation under uncertainty is the use of relative error (RE), which provides insight into the accuracy of the estimated mean value compared to the true value. The relative error can be calculated using the following formula

$$RE = \frac{\sigma}{\bar{x}} \cdot 100\,\%, \qquad (2)$$

where RE is the relative error, expressed as a percentage; σ is the standard deviation of the sample set; $\bar{x}$ is the sample set mean value.

Formula (2) is particularly useful for evaluating the variability in coal quality characteristics and helps determine the reliability of the reserve estimation results. By combining the confidence interval (1) and relative error (2), a comprehensive assessment of both the range and accuracy of the reserve estimates can be achieved, allowing for better decision-making in mining operations.

Risks are also considered, which allows for more informed decision-making in the field mining process.

The catalogue of drillings and mine workings additionally driven within the boundaries of influence of geological disturbances, as well as the necessary geometric, chemical and coal-technical data, presented in the map of unblocking reserves by seams, serves as initial data for reserve estimation.

The research objective is to estimate reserves using the existing plan for unblocking seam reserves. In addition to estimating rock mass and pure coal reserves by block, each block is divided into intervals every 0.5 m of coal seam thickness, considering 100 % dilution by rock interlayers. The resulting segments are classified into ash content intervals from 0 to 45 % in 5 % increments. Finally, the isohypsum map, formerly a reserve estimation block, is divided into technical grades. After performing all the procedures described above, reserves are estimated separately for each seam.

The stages of cartographic and factual material preparation for reserve estimation with gradation by technical characteristics are performed in the same sequence as for traditional reserve estimation, using ArcGIS, Leapfrog Geo, MineSight or Micromine software.

Results and discussion. The studies have provided significant data on coal quality, allowing for more accurate reserve estimates based on various technical characteristics. Table 2 contains the coal sampling results that were collected during the field survey, as well as the sample analysis. These data cover ranges of ash content, moisture content, volatile matter content and other parameters that influence the overall coal characterization.

The analysis process has revealed noticeable variations in coal quality in different intervals. For example, parameters such as ash content, moisture content, volatile matter content, etc., show significant variations depending on the depth of occurrence and geological conditions, which in turn emphasizes the importance of precise and detailed analysis, as well as optimization of sampling methods, thus reducing costs and improving the accuracy of coal reserve estimation

Comparative analysis of the obtained data with historical indicators shows that in some intervals both improvements and deterioration in coal quality are observed, which may be related to changes in geological conditions and the presence of different minerals in coal seams. Results of the analysis by grouped values are given in Figs. 3–6.

The presented graph (Fig. 3) shows the distribution of total moisture content (W^a) in coal depending on the depth of occurrence. Moisture content varies between 3.5–6.5 %, indicating non-uniform geologic conditions in different intervals. The trend line, according to the equation, shows a slight decrease in moisture content with increasing depth, which may indicate that deeper coal seams have lower moisture content compared to the upper ones. These variations can be related to differences in geologic conditions and are important for assessing coal quality, since high moisture content can reduce its calorific value and increase carbon dioxide emissions.

The presented graph (Fig. 4) shows the change in ash content (A^a and A^d) depending on depth. In general, a tendency for ash content to decrease with increasing depth of occurrence can be observed, which is confirmed by trend equations: for air-dried basis ash content and dry basis ash content. Nevertheless, the data show a high degree of variability at shallow and medium depths (up to 100 m), which may be due to the heterogeneous geologic conditions or the presence of local discontinuous structures. The values above 100 m are also characterized by variations, which may indicate the influence of secondary factors such as moisture content or impurities in coal seams.

Fig. 5 shows the dependence of sulfur content for two sets of samples on depth: air-dried basis sulfur content (S^a) and dry basis sulfur content (S^d).

In the upper part of the section (up to 40 m), the sulfur content for both sets of samples is relatively stable and ranges from 0.5 to 1.5 % (Fig. 5). In the range from 40 to 100 m, there is moderate variability in sulfur content without significant peaks. However, at depths of about 100 and 140 m, strongly marked anomalies are recorded at which the sulfur content reaches maximum values, approaching 3.5 %. Linear approximations of the trends for S^a and S^d sample sets indicate a weak trend of increasing sulfur content with increasing depth for data from both sample sets.

Fig. 6 shows the dependence of volatile matter content on depth for two parameters: air-dried basis volatile matter and dry basis volatile matter.

At initial depths (up to 40 m) there is great variability in the data, especially for V^d, where the volatile matter content ranges from 30 to 40 %, while for V^a the values range between 25–35 % (Fig. 6). In the 40 to 100 m depth range, the volatile matter values for both sample sets show relatively stable trends, although V^d values remain slightly higher. At depths of about 100 and 140 m, sharp increases in volatile matter content are recorded for both sample sets, with maximum values reaching about 42 % for V^d. The linear trends for V^a and V^d indicate a weak increase in volatile matter content with increasing depth, with the trend for V^a being marked stronger.

To optimize coal reserve estimation processes, it is recommended to consider the spatial variability of coal characteristics, such as ash content, moisture content and sulfur content, by using geostatistical methods including kriging. This will allow for a more accurate assessment of the distribution of coal quality parameters and reduce errors in the estimation of reserves. It is also important to implement machine learning to analyze large geological datasets, which helps to identify complex relationships and improve coal quality prediction as other scientists suggest in their turn [29, 30]. Additionally, it is recommended to optimize the selection of samples through the use of regression analysis, which can minimize exploration costs while maintaining accuracy [31]. Classifying coal based on technical characteristics

Table 2

Test intervals and analysis result

Testing			Coal quality parameters, %						
From	To	Length, cm	Moisture (as received), W^a	Ash content (as received), A^a	Ash content (dry basis), A^d	Sulfur (as received), S^a	Sulfur (dry basis), S^d	Volatile matter (as received), V^a	Volatile matter (dry basis), V^d
11.4	12.5	110	5.35	4.37	4.62	0.67	0.71	30.72	34.03
12.5	13.5	100	6.05	5.95	7.38	0.45	0.48	28.42	32.77
13.5	14.5	100	6.25	13.8	14.72	1.05	0.12	26.01	32.54
14.5	15.5	100	6.15	10.57	11.48	0.69	0.73	28.38	34.08
15.5	16.5	100	4.3	18.73	19.57	0.84	0.88	32.71	42.5
16.5	17.5	100	4.81	17.76	18.68	0.76	0.8	30.23	39.04
17.5	18.5	100	5.27	15.55	16.42	1.02	1.08	27.6	30.86
18.5	19.5	100	4.71	29.09	25.28	0.77	0.81	25.55	35.88
15.5	20.5	100	5.21	10.24	10.8	0.59	0.62	31.66	37.45
20.5	21.5	100	5.32	5.47	16.43	0.85	0.9	28.48	35.84
21.5	22.3	80	5.17	8.72	9.2	0.32	0.34	31.85	36.99
22.3	23.1	80	5.64	3.89	4.12	0.28	0.3	30.55	33.69
23.1	23.9	80	6.18	9.56	10.19	0.55	0.59	26.59	31.56
84.5	85.5	100	6.07	9.36	9.96	0.56	0.6	27.72	32.77
85.5	86.5	100	5.36	16.88	17.84	1.45	1.53	26.31	33.83
86.5	87.5	100	5.05	29.21	30.44	0.63	0.66	24.25	36.33
87.5	88.5	100	5.25	15.76	16.65	0.72	0.76	27.78	35.3
88.5	89.5	100	6.03	15.6	16.6	0.78	0.83	26.47	33.65
89.5	90.5	100	5.93	14.91	15.52	2.06	2.14	28.76	35.43
90.5	91.5	100	5.2	9.38	9.89	0.45	0.47	30.8	36.06
91.5	92.5	100	5.59	9.91	10.5	0.47	0.5	28.14	33.3
92.5	93.5	100	5.66	17.8	18.87	0.72	0.76	28.59	37.11
93.5	94.5	100	5.23	18.31	19.32	2.62	2.76	26.49	34.64
94.5	95.5	100	6.66	22.15	23.73	0.85	0.91	23.74	33.35
95.5	96.4	90	5.01	9	9.47	0.34	0.36	28.7	33.78
96.4	97.3	90	5.06	6.28	6.61	0.43	0.45	31.51	35.54
133.2	134.0	80	4.94	4.89	5.14	0.65	0.68	32.86	36.44
134.0	135.0	100	5.95	8.87	9.43	1.29	1.37	28.48	33.44
135.0	136.0	100	5.14	7.75	8.17	1.01	1.06	29.1	33.41
136.0	137.0	100	4.9	3.7	3.89	0.3	0.31	33.88	37.07
137.0	138.0	100	4.62	6.67	6.99	0.49	0.51	33.42	37.67
138.0	139.0	100	3.56	7.67	7.95	0.66	0.68	31.25	35.2
139.0	140.0	100	5.5	16.2	17.14	3.17	3.35	29.37	30.51
140.0	141.0	100	6.5	5.06	5.41	0.28	0.3	34.2	38.67
141.0	142.0	100	5.82	6.89	7.32	0.22	0.23	35.65	40.84
142.0	143.0	100	5.77	3.18	3.37	0.36	0.38	35.84	39.37
143.0	143.7	0.7	5.71	6.63	7.02	0.76	0.81	37.15	42.37

and consideration of geologic disturbances affecting coal quality will help improve resource management. These measures will ensure more efficient planning of mining and minimization of environmental risks.

Conclusions. The research conducted has shown that the use of modern methods, such as geostatistical models and machine learning, significantly improves the accuracy of coal reserve estimation. These tools allow for more efficient analysis of spatial variability in key coal characteristics, including ash content, moisture content and sulfur content. Prediction based on such methods helps to reduce errors in reserve estimation and to per-

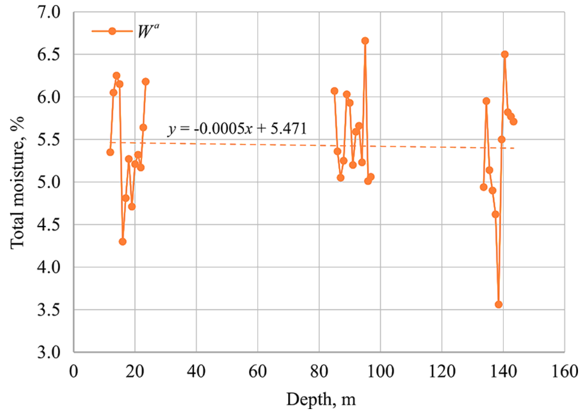

Fig. 3. Dependence of total moisture change on depth

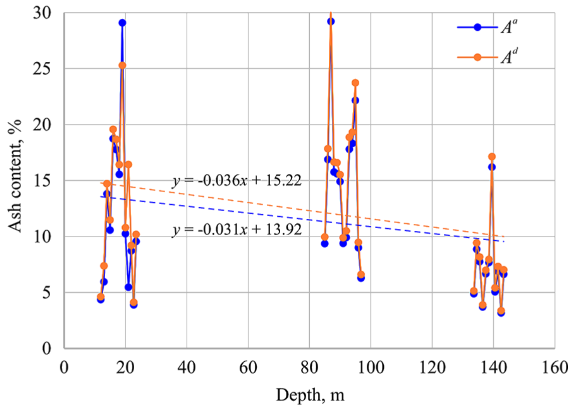

Fig. 4. Dependence of ash content change on depth

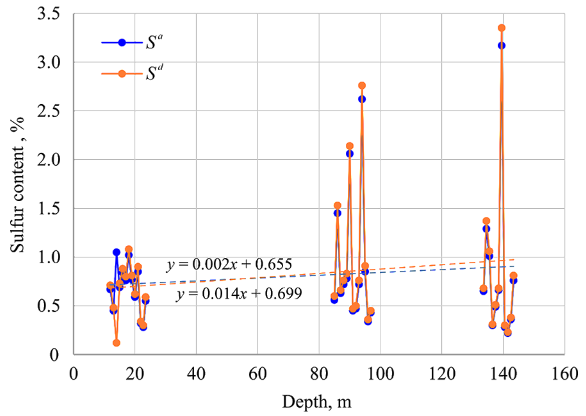

Fig. 5. Dependence of sulfur content change on depth

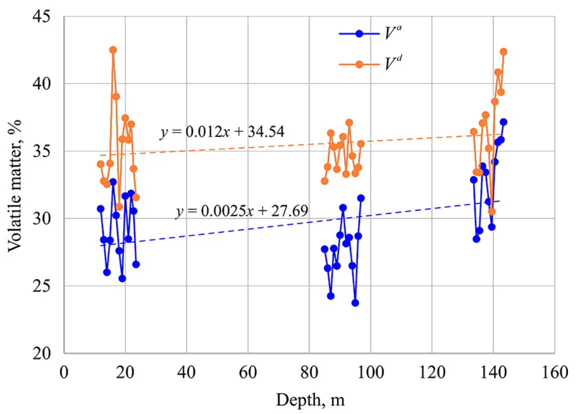

Fig. 6. Dependence of sulfur content change on depth

form more accurate planning of mining operations.

Optimization of selecting samples and classification of coal by its technical characteristics, such as ash content and volatile matter content, provides more efficient use of coal resources depending on their purpose. This approach helps to increase the economic efficiency of coal mining, as well as improve environmental performance by taking more accurate account of coal quality parameters. The study also highlights the importance of accounting for depth-dependent variations in coal characteristics. It was found that deeper coal seams generally exhibit lower moisture content (average 4.3 %) and ash content (average 9.3 %), making them more suitable for energy production, whereas shallower seams show higher variability in these parameters.

Accounting for geologic disturbances such as faults and folds is a key factor in the accurate reserve estimation. Tectonic structures can have a significant influence on the moisture content and ash content of coal, requiring detailed analysis to prevent errors in resource estimation. Thus, an integrated approach, including analysis of geological peculiarities and application of advanced modeling methods, provides sustainable and effective management of coal fields.

Acknowledgements. *The authors of the paper express their gratitude to the Kyrgyz State Technical University for providing a software package for processing field materials, as well as to the Ministry of Education and Science of the Kyrgyz Republic for financial assistance in carrying out the research work.*

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Оцінка запасів вугільних родовищ з урахуванням класифікації вугілля за технічними характеристиками

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Мета. Удосконалення методу оцінки запасів вугільних родовищ з урахуванням класифікації вугілля за його технічними характеристиками.

Методика. У роботі використовувалися сучасні підходи, включаючи геофізичні дослідження та геохімічний аналіз. Застосовані методи узагальненої лінійної регресії та регресійного аналізу, що дозволяють ураховувати просторову неоднорідність технічних характеристик вугілля, таких як вологість, зольність, вміст сірки, летких речовин і теплота згоряння.

Результати. Аналіз показав суттєві варіації в технічних характеристиках вугілля залежно від глибини залягання й геологічних порушень. Зольність вугілля зменшується із глибиною, тоді як вологість і вміст летких речовин демонструють значну варіабельність. У пластах глибокого залягання виявлені аномалії з підвищеним вмістом сірки, що досягають максимумів на глибині 100–140 м. Застосування узагальненої лінійної регресії дозволило з високою точністю моделювати розподіл технічних характеристик вугілля по родовищу.

Наукова новизна. Уперше проведено комплексний аналіз впливу геологічних порушень на зольність, вологість і теплоту згоряння вугілля в умовах складної тектонічної будови. Запропоновано інтегрований підхід до оцінки запасів із використанням сучасних статистичних методів, що забезпечує підвищення точності оцінок на 15 % у порівнянні із традиційними підходами.

Практична значимість. Результати дослідження дозволяють оптимізувати процеси прогнозування вугільних ресурсів. Запропоновані методи можуть бути використані для планування видобутку в умовах складної геологічної будови родовищ.

Ключові слова: *оцінка запасів, вугілля, зольність, вологість, леткі речовини, регресійний аналіз*

The manuscript was submitted 30.08.24.