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Study of the scale effect of filtration-capacitive properties of a complex carbonate reservoir

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Исследование масштабного эффекта фильтрационно-емкостных свойств сложнопостроенного карбонатного резервуара

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porosity, permeability, scale effect, standard core sample, full-size core sample, complex carbonate reservoir, petrotyping, machine learning, regression model.

One of the fundamental challenges in studying the properties of productive oil and gas reservoirs is the scale effect. Analysis of multi-scale research results often reveals discrepancies in data. For example, porosity and permeability properties determined from standard and full-size samples for the same depth interval can vary significantly. Similarly, these differences become even more pronounced when transitioning to the scale of the near-wellbore zone. At the same time, the type of reservoir significantly influences the scale effect. In porous reservoirs, the scale effect may not be pronounced, whereas in complex reservoirs, transitioning from one scale to another can result in properties changing by an order of magnitude. This is due to high heterogeneity caused by secondary processes such as leaching, dolomitization, and recrystallization. Neglecting the scale effect can adversely affect understanding reservoir structure.

In this study, the scale effect of properties was examined using a complex carbonate reservoir as an example. A qualitative assessment of the scale effect was performed using mathematical statistics and petrotypification methods. To quantitatively evaluate the scale effect, a multiple regression model was developed to adjust porosity values from standard core samples to full-size samples for constructing a porosity cube. Several machine learning algorithms were used to predict the permeability values of full-size samples, including gradient boosting, random forest, multilayer perceptron, and k-nearest neighbors. It was found that the random forest-based model was the most accurate. The developed models enable highly reliable predictions of porosity and permeability when transitioning between scales ($R^2 = 0.77–0.94$).

Ключевые слова:
пористость, проницаемость, масштабный эффект, стандартный образец керна, полноразмерный образец керна, сложнопостроенный карбонатный коллектор, петротипизация, машинное обучение, регрессионная модель.

Одной из фундаментальных проблем при изучении свойств продуктивных нефтегазовых резервуаров является масштабный эффект. При анализе результатов разномасштабных исследований зачастую отмечается различие данных. Например, для одного интервала глубин свойства пористости и проницаемости, определенные для стандартных и полноразмерных образцов, могут значительно различаться. Так и при переходе на масштаб околоскважинной зоны данное различие проявляется более контрастно. В то же время сильное влияние на масштабный эффект оказывает тип коллектора. Если для порового коллектора проявление масштабного эффекта свойств может быть незначительно, то в сложнопостроенных коллекторах при переходе от одного масштаба к другому свойства могут изменяться на порядок ввиду наличия высокой неоднородности, обусловленной наличием вторичных преобразований, таких как выщелачивание, доломитизация, перекристаллизация. Пренебрежение масштабным эффектом может оказать негативное влияние на понимание строение резервуара.

В рамках данного исследования проведено изучение масштабного эффекта свойств на примере сложнопостроенного карбонатного коллектора. Выполнена качественная оценка масштабного эффекта методами математической статистики и петротипизации. Для количественной оценки масштабного эффекта построена модель множественной регрессии, позволяющей скорректировать значения пористости от стандартных образцов керна к полноразмерным для построения куба пористости. Для прогноза значений проницаемости полноразмерных образцов использовалось несколько алгоритмов машинного обучения, среди которых градиентный бустинг, случайный лес, многослойный перцептрон и *k*-ближайших соседей. Установлено, что наиболее точной является модель на основе алгоритма случайного леса. Построенные модели с высокой достоверностью позволяют прогнозировать пористость и проницаемость при изменении масштаба (R^2 = 0,77–0,94).

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Introduction

The scale effect of rock properties is one of the most important factors determining the accuracy and reliability of their interpretation. In the practice of designing field development certain properties at different scales can differ significantly [1].

The phenomenon of the scale effect is determined by the change in rock properties depending on the volume of the rock. Such changes can depend on various factors, the determining one of which is geological heterogeneity [2, 3].

Along with the scale effect, there is also the concept of "upscaling". The difference between the concepts is that the scale effect is a change in rock properties with a change in the volume of the studied rock, and upscaling is the process of setting equivalent filtration-capacitive properties when moving from one scale to another, for example, from a static model grid to a dynamic model grid [4–6]. Carbonate samples are characterized by a higher scale effect step compared to terrigenous ones due to the presence of high heterogeneity caused by the presence of secondary rock transformations, such as leaching, dolomitization, recrystallization, etc. [7, 8].

Modern approaches to the design of oil and gas field development are based on the creation of geological and hydrodynamic models. One of the important components of creating geological and hydrodynamic models of oil carbonate reservoirs is the creating cubes of filtration-capacity properties – absolute permeability and porosity [9–12]. These properties directly determine the development parameters, the amount of geological and recoverable reserves.

It is generally accepted that the properties of rocks obtained in the laboratory (direct studies) are the most reliable [13]. The results of determining the properties are used at the initial stage of creating a digital geological and hydrodynamic model. However, while calculating oil reserves using the volumetric method, the coefficient of open porosity of standard-sized core samples (3×3 cm) is often used which may be unrepresentative in the case of high geological heterogeneity [14, 15]. For carbonate reservoirs, where a high degree of multi-scale heterogeneity is often observed, which is a consequence of secondary voids such as caverns and fractures, the petrophysical relationship "permeability – porosity" used as a basis for creating property cubes is most often unstable [16, 17]. Therefore, for carbonate reservoirs, the petrophysical relationship "permeability – porosity" is clarified by direct studies of the core with depth reference [18].

For carbonate reservoirs, where a high degree of multi-scale heterogeneity is often observed which is a consequence of secondary voids such as caverns and fractures, the petrophysical permeability-porosity relationship used as a basis for creating property cubes is most often unstable [16, 17]. Therefore, for carbonate reservoirs, the petrophysical permeability-porosity relationship is clarified by direct core studies with depth reference [18].

From the point of view of describing the filtration processes occurring in the reservoir when creating a permeability cube of a geological-hydrodynamic model, full-size samples are the most representative, since they reflect the filtration of both the matrix part and the cavernous-fractured-pore part [19–21]. While standard-size samples characterize either rock properties taking into account the matrix part or the cavernous-fractured fraction of voids that predominates in a particular plug, the use of standard samples with a diameter and height of 3 cm does not correspond to the scale of the static model cell along the vertical (0.1 m); the height of the dynamic model cell is characterized by an even larger size (0.4 m) [22–24].

Many authors note the need to consider the elementary representative volume in the context of the scale effect [25–28]. Therefore this is the volume at which the fluctuation of properties is reduced to a minimum [29]. Determining this volume gives an idea of the degree of influence of the scale effect on rock properties.

The scale effect is assessed and studied using various approaches. Porosity is determined at the microlevel by studying petrographic thin sections, porosity is calculated at the mesolevel by analyzing well logging data, and porosity at the macrolevel is determined by laboratory methods. In [30], it is shown that porosity fluctuations are minimized on the macroscale. In [31], a method is proposed for studying the effect of sample scale on reservoir properties. The basis of the method is the analysis of the results of gas-volumetric studies of porosity and permeability of the same core sample with subsequent reduction of the sample size [32]. A combination of gas-volumetric studies with the results of computed tomography is used [33]. The authors of [34] proposed a method for the transition from the core scale to the scale of a 3D static model by using nuclear magnetic resonance (NMR) curves.

In the process of creating geological models and upscaling properties into a dynamic model, it is important to take into account the scale effect [35, 36]. Traditionally, upscaling the properties of a refined geological grid to a hydrodynamic one is carried out by averaging the data with arithmetic, harmonic or geometric means. A number of studies are aimed at developing upscaling methods based on hydraulic flow units [37]. In the process of upscaling, it is also important to take into account the scale effect of properties both vertically and laterally [38, 39]. The paper presents an approach for upscaling relative phase permeabilities that takes into account the scale effect for different facies zones by using digital core analysis [40]. Based on the analysis of publications, it can be noted that most of the works are aimed at a qualitative assessment of the scale effect using the results of direct studying cores of different scales. A quantitative assessment of the scale effect should also be carried out in order to clarify the initial data for creating geological and hydrodynamic models of the reservoir. Often, full-size core samples are not enough to characterize the well section; in such cases, in order to clarify the filtration properties of the reservoir, it is necessary to take into account standard-size samples. To take into account the scale effect, it is necessary to use its quantitative assessment and introduce correction factors, which is the subject of the current study. Further, the work will present a geological description of the studied object, describe materials and methods including statistical analysis and comparison of standard and full-size core samples, typification of samples by petrophysical properties, quantitative calculation of scale factors and the approach to using factors when creating models.

Geological description

The studying core samples of Yelets carbonate deposits of the Alpha field located in the Timan-Pechora oil and gas province was conducted Reef deposits of the studied fields were formed during four reef-building cycles: one Zadonsk and three Yelets (Fig. 1) with the rocks of the first cycle

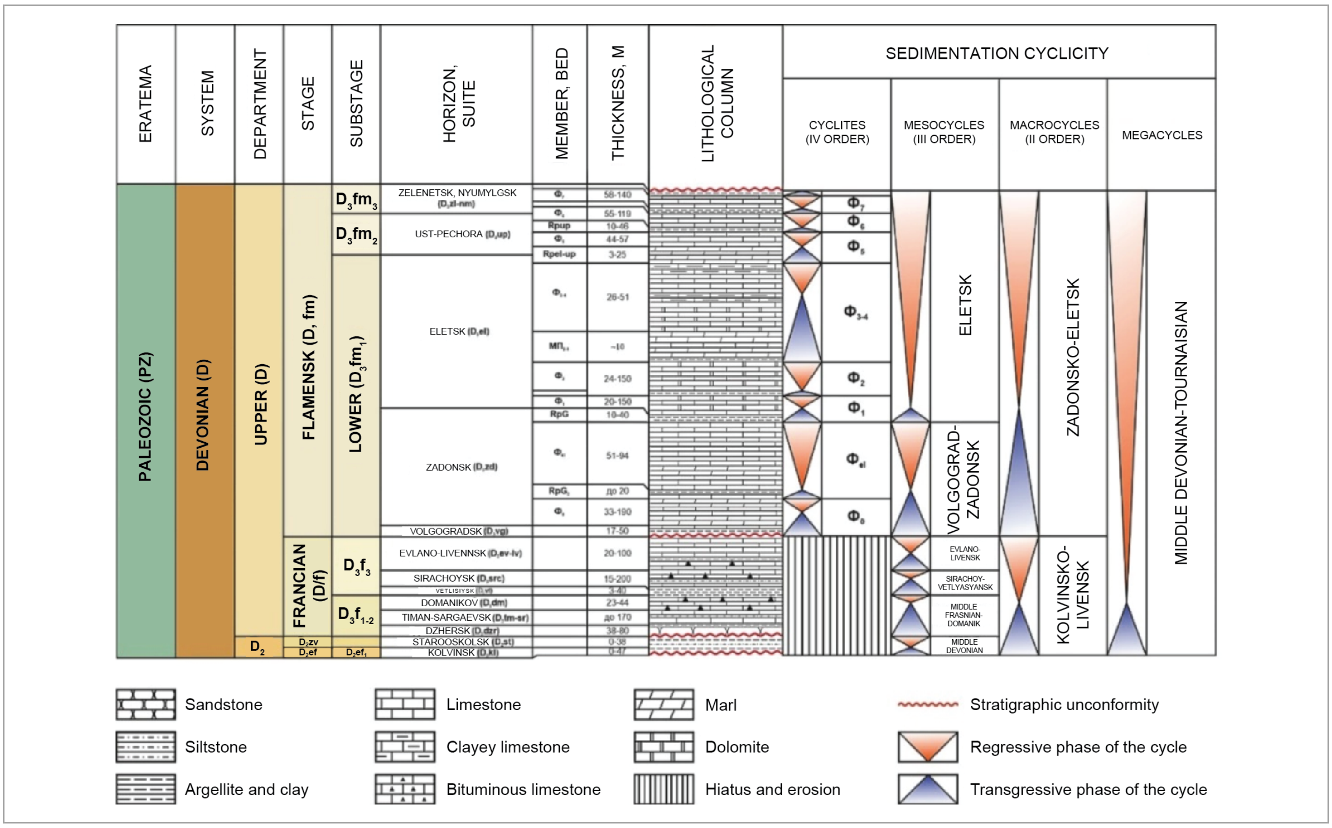
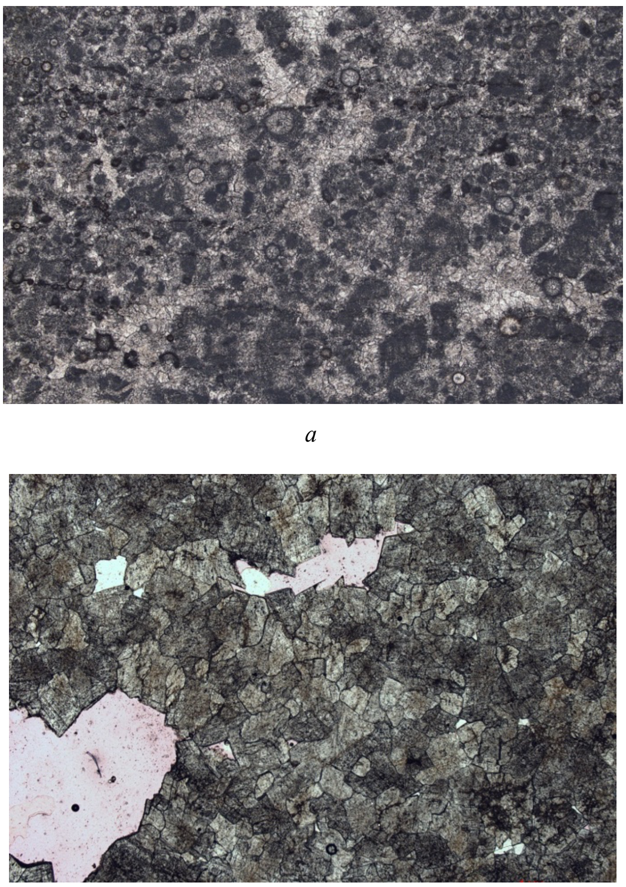


Fig. 1. Stratigraphic column



a

b

Fig. 2. Lithotype: *a* – microbial limestone spherical-patterned; *b* – secondary dolomite calcareous fine-medium-grained, porous

Table 1

Reservoir properties

Bed	Parameter	Average value.	Min.	Max.
D_3fm_1 (el_1)	*k*, мД	86.05	0.1	9058.2
	φ, %	7.5	0.4	21.2
D_3fm_1 (el_3)	*k*, мД	128	0.1	18143
	φ, %	6.45	0.9	29.6

separated from later formations by a layer of dense but brittle carbonate rocks of variable thickness and composition. The growth of organogenic structures in the Zadonsk-Yelets time was accompanied by repeated local breaks caused by a slowdown in the growth of organogenic structures, which was reflected in a change in the color of limestones. The samples are represented by microbial-detrital limestone (spherical-patterned) (Fig. 2, *a*) with a secondary clotted-lumpy structure, locally pigmented bituminous organic matter and secondary calcareous dolomite, fine-medium-grained, porous (Fig. 2, *b*).

The capacitive space of the studied section is determined mainly by pores and leaching caverns, dolomitization/recrystallization pores and fracturing.

The reservoir properties are presented in Table 1.

Materials and methods

The study was based on the results of standard (3499 pcs.) and full-size (678 pcs.) rock samples collected from 12 wells at the Alpha field. Based on the results of the study a consolidated database of petrophysical properties was created. Full-size and standard samples were compared at depth marks within one drilling.

The statistical indicators of the sample properties were analyzed and compared using mathematical statistics methods. The degree of scale effect was calculated as the ratio of porosity and permeability between full-size and standard samples.

The R35 parameter was calculated – the radius of pore channels corresponding to 35 % saturation of the pore volume with a non-wetting phase (mercury) (1):

$$\lg R35 = 0.732 + 0.588\lg K_{pr} - 0.864\lg K_p, \quad (1)$$

where R35 is the radius of the pore channel corresponding to 35 % saturation of the pore volume with a non-wetting phase, μm; K_{pr} is the permeability coefficient, mD; K_p is the porosity coefficient, %.

For a detailed statistical analysis of the filtration and capacity properties, petrophysical typing of core samples was carried out using the hydraulic flow units (HFU) method, since this approach is justified and used by many authors for typing carbonate reservoirs [41, 42]. The method is also largely applicable for typing rocks in geological and hydrodynamic modeling [43].

The method is based on the calculation of a complex parameter – the hydraulic flow unit indicator (Flow Zone Indicator – FZI):

$$\mathrm{FZI} = \frac{\mathrm{RQI}}{\varphi_z}, \quad (2)$$

where RQI (Reservoir Quality Index) is the reservoir quality index, μm; φ_z is the normalized porosity index, fractions of units. RQI is determined by the expression:

$$\mathrm{RQI} = 0.0314\sqrt{\frac{k}{\varphi}}, \quad (3)$$

where k is the permeability coefficient, mD; φ is the porosity coefficient, fractions of a unit. φ_z characterizes the ratio of the volume of voids to the volume of the solid phase of the rock and is determined by the expression:

$$\varphi_z = \frac{\varphi}{1-\varphi}. \quad (4)$$

Differentiation of core samples into different classes by the FZI parameter was carried out using the DRT (distribution of relaxation time) method [44]. The formula for determining the DRT class is given below:

$$\mathrm{DRT} = 2\ln(\mathrm{FZI}) + 10.6. \quad (5)$$

Multiple regression methods were used to identify the parameters that most determine the degree of scale effect. The equation for multiple linear regression is:

$$Y = \beta_0 + \beta_1 \cdot X_1 + \beta_2 \cdot X_2 + \ldots + \beta_k \cdot X_k + \varepsilon. \quad (6)$$

In this case, the variable Y depends on k explanatory variables X, i.e. regressors, ε is a random error. The model is linear with respect to the unknown parameters β. Estimates of the model parameters (β_0, β_1, β_2) are usually calculated using the ordinary least squares (OLS) method which minimizes the sum of the squares of the forecast errors. The corresponding parameter estimates will be denoted as b_0, b_1 and b_2.

The error ε has a random nature and its own distribution function with a mean value equal to 0 and a variance σ equal to 2. Multiple regression allows us to decompose the total influence of factors into its constituent parts, more accurately identifying the marginal contribution of each factor.

At the next stage, machine learning methods are used to create a model for predicting the scale effect, or in other words the properties of full-size samples based on standard ones.

Since the models are prepared with data with true values, this regression problem is considered as supervised learning. Therefore, the most common and well-established algorithms were used: random forest [45, 46], gradient boosting [47–49], multilayer perceptron and k-nearest neighbors.

Random forest is a machine learning method that is an ensemble of decision trees. Gradient boosting is a machine learning method based on sequential model construction. Each subsequent model tries to correct the errors of the previous one [50, 51].

Multilayer perceptron [52, 53] is a class of feedforward artificial neural networks consisting of at least three layers: input, hidden, and output.

K-nearest neighbors [54] is a metric algorithm for automatic classification of objects or regression. In the case of using the method for regression, the object is assigned the average value of the k-nearest objects to it which values are already known.

Hyperparameters were also tuned for greater accuracy. Hyperparameters are adjustable parameters of a machine learning model that cannot be learned during the training process and must be specified in advance. The hyperparameters were selected using the Grid Search method. Grid search is a method for optimizing hyperparameters of machine learning models which involves trying all possible combinations of hyperparameter values and selecting the best one.

To analyze the accuracy of the constructed models, the convergence of the predicted and actual data was assessed using a number of metrics:

– MAE (mean absolute error) – the degree of discrepancy between the actual and predicted value in absolute values;

– MAPE (mean absolute percentage error) is the degree of discrepancy between the actual and predicted value in percent;

– MSE (mean square error) is the arithmetic mean of the squares of the differences between the actual and predicted values;

– R^2 (coefficient of determination) – estimates the proportion of dispersion, which gives an idea of the degree of conformity.

Results

Statistical analysis. Qualitative assessment of the scale effect. At the first stage, the petrophysical dependence of the permeability of porosity for standard and full-size core samples was constructed (Fig. 3).

While analyzing the petrophysical dependence, it can be noted that, in general, the cloud of values for full-size

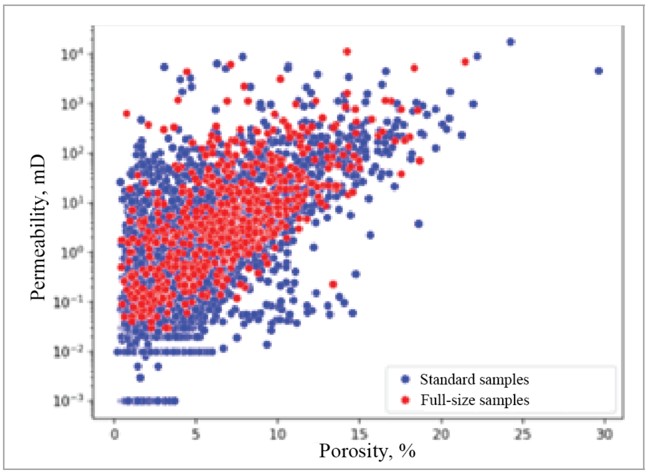


Fig. 3. Permeability-porosity relationship for standard and full-size core samples

and standard core samples overlap each other, being mainly in the same ranges. However, for standard samples a significant proportion of samples with low reservoir properties is noted, while a pair of samples are characterized by high porosity values (more than 22 %), which is not typical for the main part of the sample. Statistical indicators are presented in Table 2.

The standard deviation and dispersion of the permeability parameter for standard samples are lower than for full-size ones but if you look at the relative value of the spread relative to the average value – the variation coefficient, it is almost twice as high for standard samples. For porosity, while calculating the standard deviation and dispersion, the samples are comparable; but while relative assessing the value of the spread, it is significantly higher for standard samples (1.6 times).

Next, the histograms of the distributing properties for full-size and standard samples are constructed (Fig. 4, *a*, *b*).

Figure 4, a shows the distributing porosity for samples of different scales, it can be noted that the mode for standard samples is 2 %, for full-size samples 6 %, that is, a significant proportion of standard samples is located in the non-reservoir zone, justified from the point of view of the economic efficiency of field development (3.6 %).

Figure 4, *b* shows the distributing the logarithm of different scales samples permeability. A significant difference in the mode is noted – 3.5 (standard samples) to 1.5 for full-size samples. Also, a significant proportion of samples correspond to the non-reservoir value (less than 0.6 mD), that is, it characterizes the matrix component of the rock without taking into account the influence of caverns and microcracks.

Fig. 4, *c*, shows the histogram of the distribution of the logR35 parameter for samples of different scales. When comparing the distribution of the logR35 parameter, the presence of a scale effect for the mode shift and the influence of the scale effect are also noted.

At the next stage, petrotyping of rocks was carried out using the DRT method (Fig. 5, *a*, *b*).

Due to the significantly larger number of samples, a more uniform distribution of values by classes for standard samples is visually noted (see Fig. 5, *a*), however, while examining the distribution histogram in a relative equivalent, it is clear that both samples are characterized by similar distribution laws. However, for standard samples, a slight shift in mode towards low classes and a more uniform distribution of middle classes are noted.

The obtained statistical estimates and graphs of the distribution of properties quantitatively show the presence of a scale effect between standard and full-size properties. The scale effect affects the properties of samples, and as a consequence, the results of petrotyping of samples, which must also be taken into account when assessing the scale effect. The histogram (Fig. 6) shows that the modal value for both samples is located in the area of class 13, and the samples are generally characterized by a similar distribution, which indirectly indicates the possibility of quantitatively assessing the scale effect within each petrotype.

Identification of parameters influencing the scale effect. Development of an approach for quantitatively assessing the scale effect. At the next stage, an additional database was collected to develop an approach for quantitatively assessing the scale effect. The database compares standard and full-size core samples by sampling depths in order to analyze the scale effect of properties for identical samples and intervals. A total of 171 core samples from the common database remained after the comparison. The correlation fields of porosity (Fig. 7, *a*) and permeability (Fig. 7, *b*) between standard and full-size samples are presented below.

While analyzing the correlation fields, the presence of a scale effect is noted for both porosity and permeability for samples compared by depth and chiselling. The degree of scale effect influence on rock permeability (R^2 = 0.02) is significantly stronger than on porosity (R^2 = 0.64). This is generally explained by the large scatter and heterogeneity of the initial data for permeability.

Next, multiple regression models were built to quantify the scale effect and the degree of influencing the parameters. The target variables were the porosity of the full-size sample; the scale factor of permeability (the ratio of the permeability of the full-size sample to the standard one), since a direct prediction of the permeability value of the full-size sample did not show any results. The following parameters were considered as predictors: porosity of the standard sample, permeability of the standard

Table 2

Comparison of statistical parameters for standard and full-size core samples

Parameter	Amount	Av.value	Stand. deviation	Min.	Max.	Dispertion	Variation coef.
Permeability by standard samples, mD	3159	54.4	504.30	0.001	18143.0	254 318	927.21
Permeability by all samples, mD	657	113.7	675.27	0.03	11543.8	455 988.7	593.67
Porosity by standard samples, %	3499	4.7	3.83	0.10	29.6	14.6	81.57
Porosity by all samples, %	678	7.0	3.65	0.43	21.4	13.3	52.50

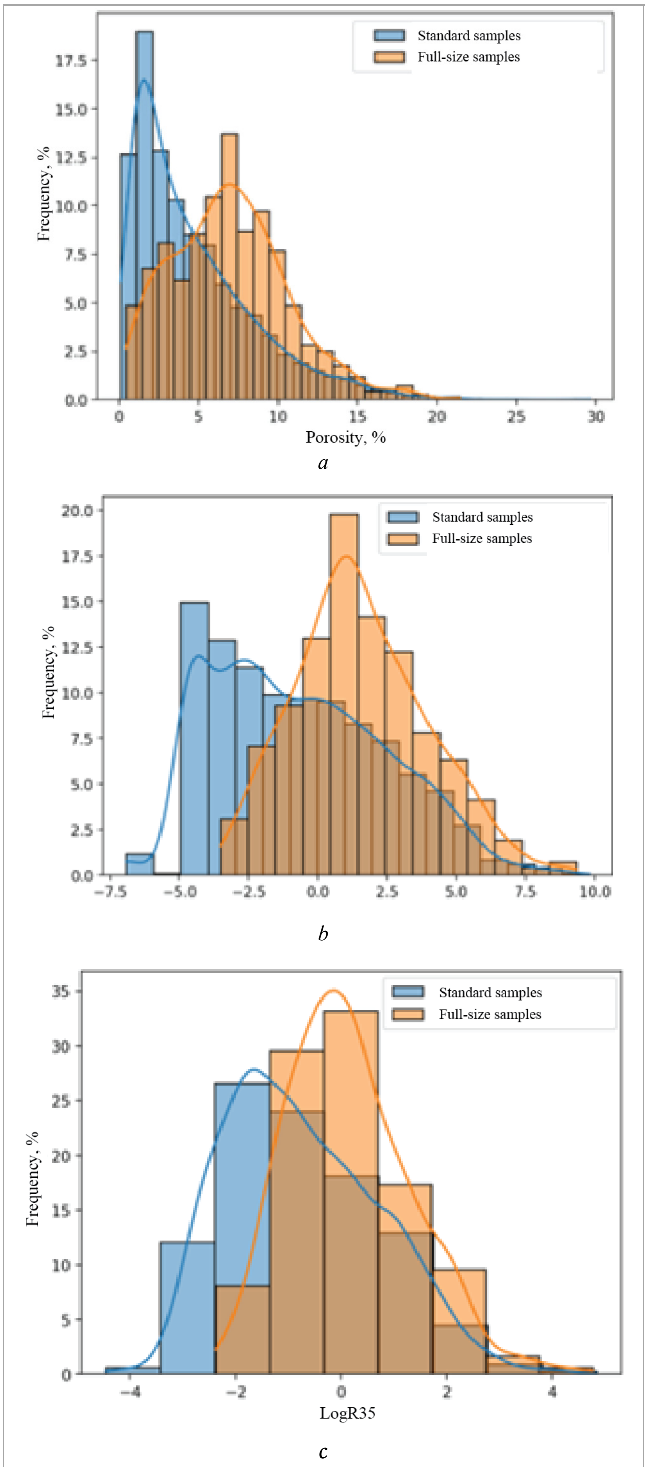


Fig. 4. Histograms: *a* – distributing porosity of different scales samples; *b* – distributing the logarithm of different scales sample permeability; *c* – distributing the logR35 parameter for samples of different scales

sample, sampling depth, FZI, R35. Based on the calculation results, the following scale effect model was obtained for porosity:

$$\varphi_{\text{wcs}} = 0.76 \cdot \varphi_{\text{plug}} - 0.99954 \cdot k_{\text{plug}} - $$
$$- 0.078 \cdot \text{FZI}_{\text{plug}} + 0{,}21 \cdot R35_{\text{plug}} + 3.034,$$
$$R^2 = 0.94, \qquad (7)$$

where φwcs is the porosity of full-size samples, %; φplug is the porosity of standard samples, %; kplug is the permeability

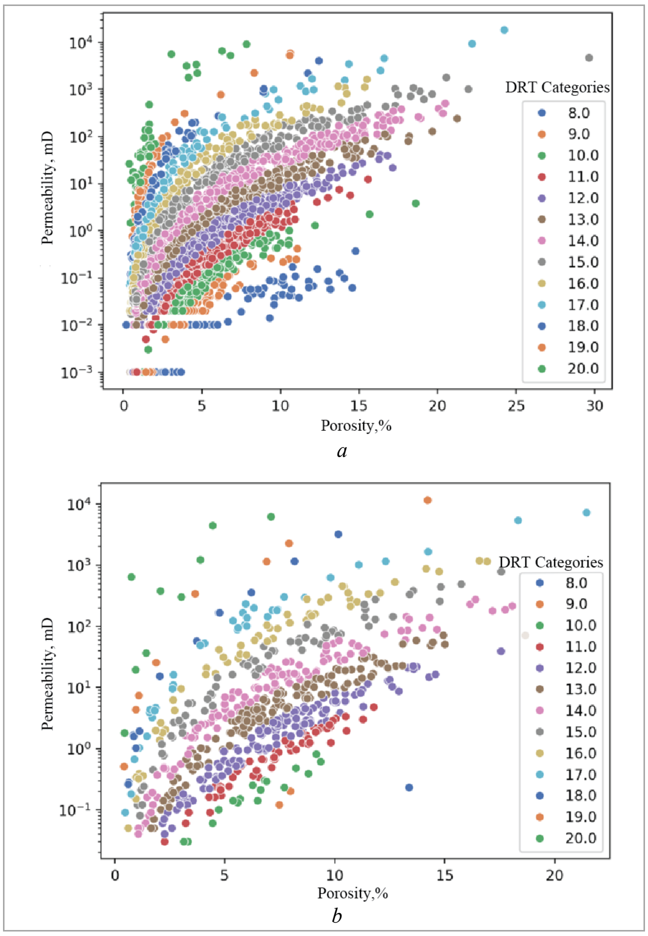


Fig. 5. Graphs of the "permeability – porosity" dependence: *a* – for standard core samples; *b* – for full-size core samples

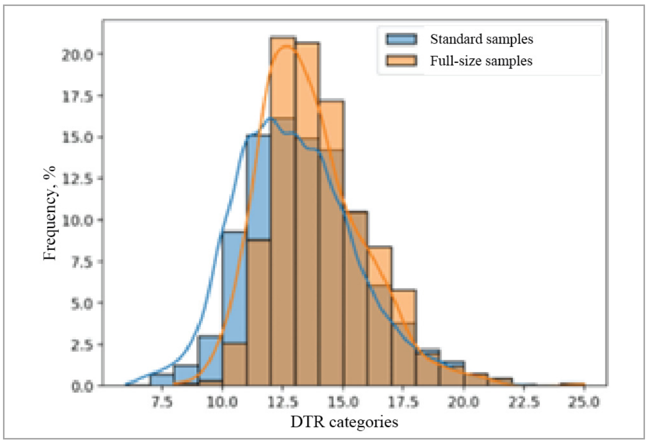


Fig. 6. Histogram of the distributing DRT categories of samples from different scales

of standard samples, mD; FZIplug is the indicator of the hydraulic unit of flow of standard samples; R35plug is the radius of the pore throats corresponding to 35 % saturation of the pore volume with the non-wetting phase.

According to the results of constructing the multiple regression model, the following parameters had a statistically significant effect (in order of influence): porosity of standard samples (p-value = 0), permeability of standard samples (p-value = 0.014), FZI (p-value = 0.028) and R35 (p-value = 0.05) of standard samples. That is, based on these parameters of standard samples, when using the obtained model, the values of standard samples are adjusted to the scale of full-size samples. Figure 8 shows the

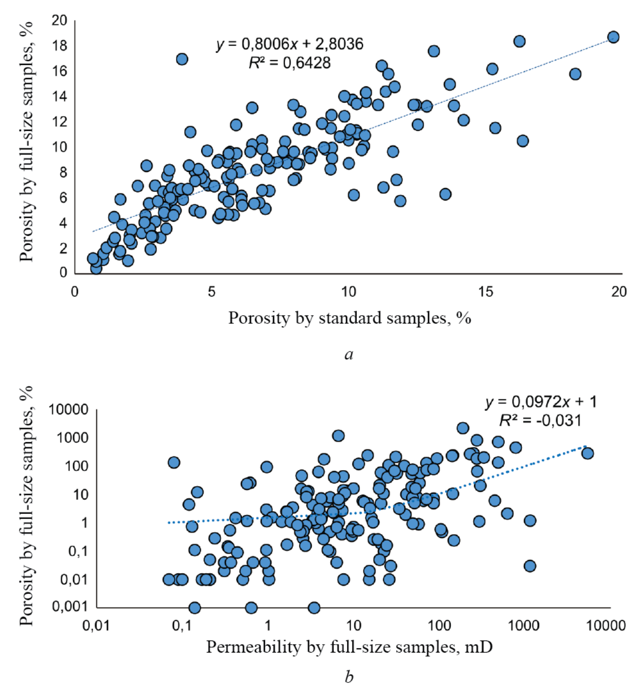


Fig. 7. Correlation fields of full-size and standard samples: *a* – porosity; *b* – permeability

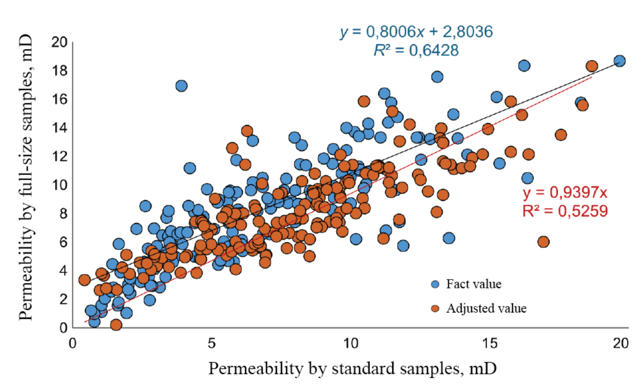


Fig. 8. Cross-plot of porosity between full-size and standard samples

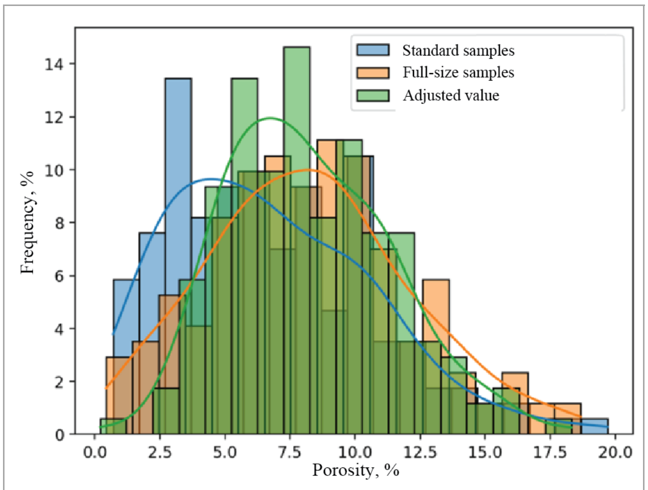


Fig. 9. Histogram of the porosity distribution of standard samples, full-size samples and values corrected by the obtained model

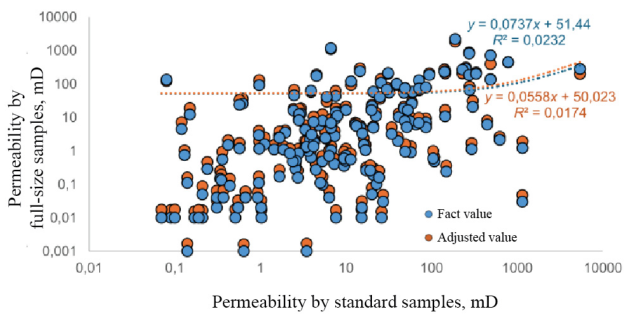


Fig. 10. Correlation field of permeability of full-size and standard samples

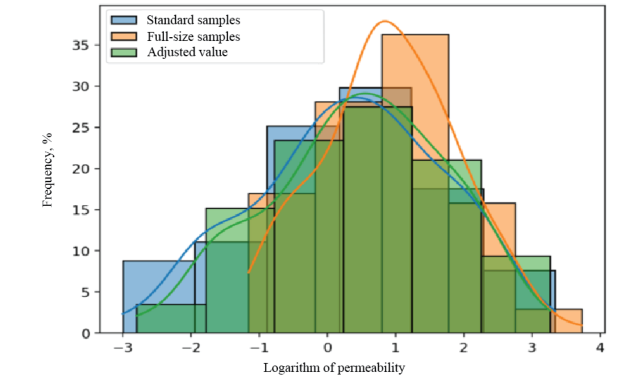


Fig. 11. Histogram of permeability distribution for standard, full-size and corrected values of standard samples

cross-plot of porosity between full-size and standard samples. Figure 9 shows a histogram of the porosity distributing standard samples, full-size samples and adjusted values according to the obtained model.

The obtained model allows reliable predicting the porosity values of a full-size core based on the parameters of a standard core (see Fig. 7, *a*).

Based on the calculation results, the following model of the scale effect coefficient for permeability was obtained:

$$K = 0.00023 \cdot D_{\text{epth}} - 0.68 \cdot \varphi_{\text{plug}} - \\ - 0.000027 \cdot k_{\text{plug}} - 0.00487 \cdot \text{FZI}_{\text{plug}}, \\ R^2 = 0.017, \qquad (8)$$

where K is the scale effect coefficient for permeability; Depth is the core sampling depth, m; φplug is the porosity of standard samples, %; kplug is the permeability of standard samples, mD; FZIplug is the indicator of the hydraulic unit of standard samples flow.

Based on the results of constructing the multiple regression model, it was revealed that the following parameters had a statistically significant effect (in order of influence): core sampling depth, porosity of standard samples, permeability of standard samples, FZI. That is, based on these parameters of standard samples, while using the obtained model, the scale factor is predicted, and then with its help the values of standard samples are adjusted to the scale of full-size samples.

However, the coefficient of determing the model does not allow it to be used for a reliable forecast (Fig. 10, 11).

Therefore, another approach is proposed for a quantitative assessment of the scale effect of permeability, b which consists of building machine learning models.

Table 3

Comparison of the effectiveness of machine learning algorithms

Algorithm	R^2, training sample	R^2, test sample	MAE, training sample	MAE, , test sample	RMSE, training sample	RMSE, , test sample
Gradient Boosting	0.56	0.13	0.54	0.89	0.67	0.89
Multilayer perceptron	0.43	0.17	0.6	0.69	0.77	0.88
Random forest	0.91	0.61	0.25	0.5	0.31	0.44
K-nearest neighbors	0.37	0.17	0.63	0.67	0.8	0.87

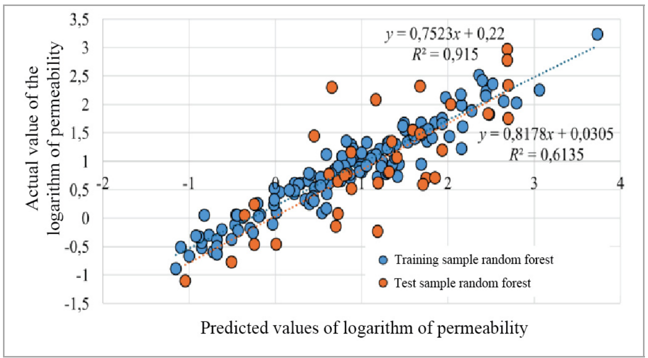


Fig. 12. Graph of the ratio of actual and predicted permeability

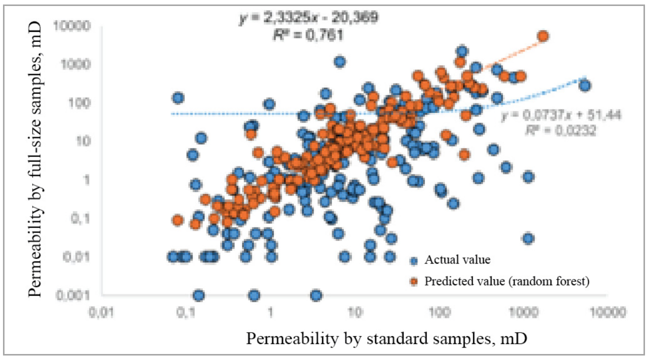


Fig. 14. Comparison of forecast and initial data

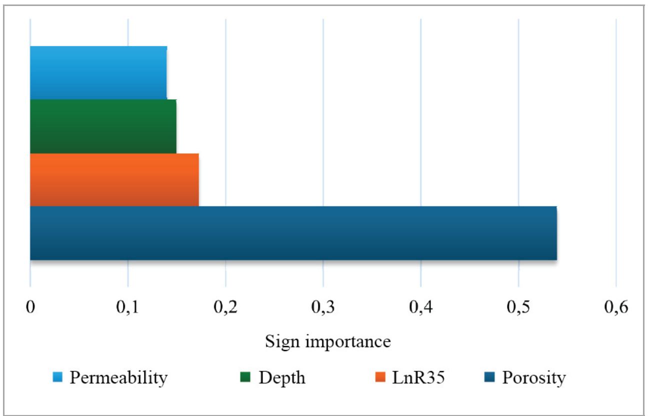


Fig. 13. Importance of features
(parameters of standard samples)

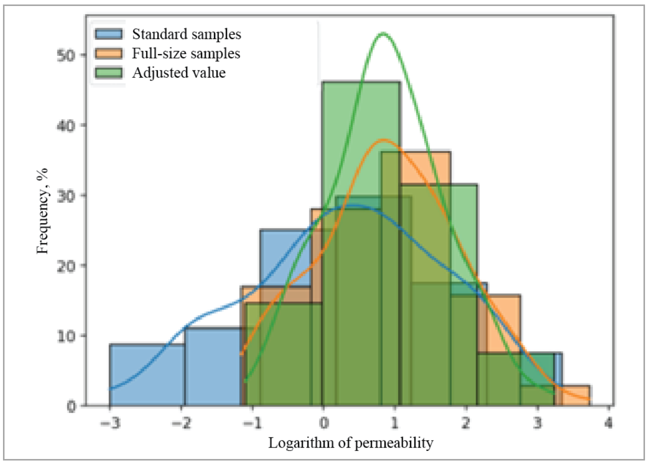


Fig. 15. Histogram of permeability distribution for standard, full-size and corrected standard samples

Machine learning methods for predicting the permeability scale effect. While compiling a model for predicting the permeability of full-size samples (permeability logarithm), the main influence was exerted by the parameters of standard sample porosity, standard sample permeability, sampling depth and LnR35 for standard samples. All algorithms were trained on these parameters.

The comparing the efficiency of algorithms for predicting the porosity of full-size samples based on the parameters of standard samples is presented in Table 3.

From Table 3 it is clear that only the random forest algorithm is applicable for this problem, where the determination coefficients were 0.91/0.61 for the training and test samples, respectively.

Below there is the correlation field between the actual and predicted values (Fig. 12). According to Fig. 12, a high correlation is noted between the actual and predicted values.

Next, the degree of importance of the features is calculated (Fig. 13).

Figure 13 shows that the most significant parameter is the porosity of standard samples (0.54), followed by logR35 (0.172), sampling depth (0.15) and permeability (0.14). That is, the greatest influence on the scale effect is exerted by the capacity and filtration properties, their interrelation and vertical zoning. Below is a comparison of the predicted values with the initial values of standard and full-size samples (Fig. 14, 15).

The model obtained based on the random forest algorithm allows to significantly reduce the degree of influencing the scale effect on the permeability of samples (from $R^2 = 0.023$ to $R^2 = 0.761$).

Conclusion

Based on the results of the statistical analysis, the presence of a scale effect for porosity and permeability with a change in the size of samples of the carbonate reservoir of the Alpha field was established at a qualitative level. Multiple regression models were built to quantitatively assess the scale effect. It was found that the magnitude of the porosity scale effect is most influenced by the porosity and permeability of standard samples, the indicator of the hydraulic unit of flow of standard samples, and the radius of the pore channels. The magnitude of the permeability scale effect is influenced by the core sampling depth, porosity and permeability of standard samples, and the indicator of the hydraulic unit of flow of standard samples. The resulting model of the scale effect for porosity also allows reliably reducing the values of standard samples to the scale of full-size ones – the determination coefficient was 0.94. For the permeability scale effect model, the determination coefficient was 0.017 which allows using the model only to estimate the parameters affecting the magnitude of the scale effect. For a quantitative assessment, an approach based on the use of machine learning algorithms is proposed. For the purposes of forecasting the scale effect of permeability (permeability of full-size samples), the most reliable evaluation metrics were demonstrated by the random forest algorithm, the determination coefficients were 0.91/0.61/0.761 for training, testing and on average for the studied sample. While analyzing the parameters of predictors, the most significant is the porosity of standard samples (0.54), followed by logR35 (0.172), sampling depth (0.15) and permeability (0.14).

The resulting approach allows using standard samples reduced to the scale of full-size ones in order to refine geological and hydrodynamic models. The authors will present the testing of the method on the Alpha field model in future works.

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