

Article

High Permeability Streak Identification and Modelling Approach for Carbonate Reef Reservoir

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Abstract: Reef reservoirs are characterised by a complex structure of void space, which is a combination of intergranular porosity, fractures, and vuggy voids distributed chaotically in the carbonate body in different proportions. This causes great uncertainty in the distribution of porosity and permeability properties in the reservoir volume, making field development a complex and unpredictable process associated with many risks. High densities of carbonate secondary alterations can lead to the formation of zones with abnormally high porosity and permeability—high permeability streaks or super-reservoirs. Taking into account super-reservoirs in the bulk of the deposit is necessary in the dynamic modelling of complex-structure reservoirs because it affects the redistribution of filtration flows and is crucial for reservoir management. This paper proposes a method for identifying super-reservoirs by identifying enormously high values of porosity and permeability from different-scale study results, followed by the combination and construction of probabilistic curves of superreservoirs. Based on the obtained curves, three probabilistic models of the existence of a superreservoir were identified: P10, P50, and P90, which were further distributed in the volume of the reservoir and on the basis of which new permeability arrays were calculated. Permeability arrays were simulated in a dynamic model of the Alpha field. The P50 probabilistic model showed the best history matching after one iteration.

Keywords: porosity; permeability; reef; complex carbonate reservoir; super-reservoir; dynamic modelling



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1. Introduction

Management of carbonate reservoirs with complex structures is complicated by many reasons associated with high heterogeneity and anisotropy of properties, cyclic sedimentation, facies variability, and extensive propagation of secondary processes. These factors combine to introduce a high degree of uncertainty in the geological structure, which must be taken into account during static and dynamic reservoir model preparation [1,2]. Distinguishing zones with different secondary changes, and hence different reservoir properties, is an important task for understanding the reservoir structure. Reservoir properties can change dramatically both vertically and horizontally; therefore, the task of predicting properties in the interwell space of the reservoir has to be addressed [3].

Rational management of carbonate reservoirs requires preparation models that take into account all features of the reservoir structure. Description and modelling of carbonate reservoirs have become the focus of various studies [4–7]. There are different approaches to creating static and dynamic models of carbonate reservoirs. Rock typing and facies modelling approaches, in conjunction with seismic trends, are often used to model reservoir properties. When creating a dynamic model, studies at various scales are taken into account, such as thin sections, core, well logging, well tests, and seismic attributes, to best reflect the complex structure of the reservoir [8–12].

Reservoir permeability is the main property that determines fluid filtration in the reservoir rocks. For carbonate reservoirs, standard petrophysical dependence (permeability–porosity) often does not reflect the heterogeneity of properties [13,14]. A number of methods describe the separation of rock types in the reservoir volume and set separate dependencies for each rock type [15]. Another classical method for creating a fractured reservoir model is dual media modelling, which reflects both the matrix and the fractured components of the rock [16–18].

Modern approaches to permeability prediction in the interwell space are based on consideration of seismic trends using machine learning and statistical methods [19–22].

Approaches taking into account uncertainty and diversity are common in studying highly heterogeneous reservoirs [23,24]. Multivariate modelling allows one to go through a range of basic reservoir parameters (porosity, permeability, aquifer, etc.), perform more justified history matching, obtain several model implementations, and make optimistic, pessimistic, and realistic forecasts of technological performance. The methodology is well-proven in uncertainty assessment, but it has its own shortcomings. As a rule, the criteria of geological realism and consistency of parameters are not established, resulting in physically unfeasible model implementations [25,26].

An important factor influencing permeability heterogeneity is the presence of secondary reservoir processes. Calcitization, dolomitization, recrystallization, leaching, and fracturing are widespread in carbonate sediments of different strata [27,28].

Secondary processes can also have a major influence on changing the structure of the reservoir void space. Intervals with abnormally high permeability may form during rock leaching. Modelling of highly permeable streaks in carbonate reservoirs is an existing problem that should be taken into account when designing a reservoir management system, mostly in organising a waterflooding system, as there is a high risk of premature flooding and fingering water breakthrough [29–31].

Different conditions are associated with different genesis of highly permeable streaks in the volume of the reservoir. Some works describe the influence of karst formation processes on the occurrence of highly permeable streaks [32–35]. Other works describe the genesis of highly permeable streaks in the process of primary sedimentation caused by the peculiarities of the reef structure and the presence of spill channels [36].

The aim of this study is to develop a methodology for the identification and modelling of highly permeable streaks to create a dynamic reservoir model and optimise the history matching process. The resulting model will ensure reliable forecasting of oil production and injection control.

In the scope of this study, the Geological Settings section will describe the geological structure of the field and the main features of the area and present the concept of karst formation. The Materials and Methods section reflects the main methods for identifying highly permeable streaks along the wellbore and modelling them in the volume of the deposit, as well as the materials on the basis of which this study was conducted—the results of core studies; well logging; well testing; etc. The Results and Discussion section presents the main results of modelling highly permeable streaks in the volume of the reservoir, as well as the results of verification of the obtained models through comparison with actual field data. The Conclusion presents the main conclusions and recommendations on modelling highly permeable streaks.

2. Geological Settings

The object of this study is the Alpha field located within the Denisov depression (Figure 1). The sediments of the Alpha field are composed of reefs formed in the Early Famennian age. The process of reef structure formation in the territory under study includes four consecutive reef-building cycles: one Zadonian and three Yeletsian. The reservoir is composed of sediments from the reef itself and the backreef shelf.

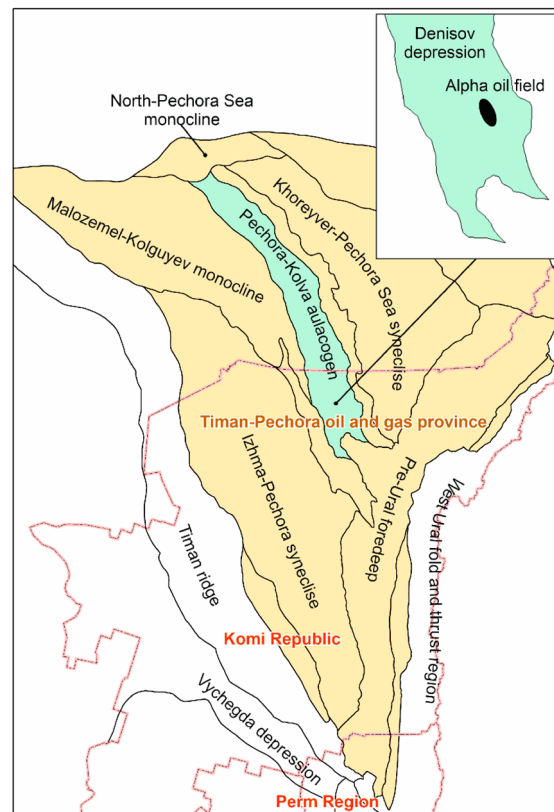


Figure 1. Extract from the tectonic map of this study area.

The lithological description of oil-saturated rocks is based on the results of core sampling taken during the drilling of nine wells. The sediments are represented by detrital-algal, spherical-patterned, organogenic-clastic, grey, grey-brown, irregularly dolomitized, and recrystallized limestones. Carbonates formed in the backreef shelf conditions are characterised by a more uniform distribution of porosity and permeability (standard deviation-349 mD), while rocks of the reef facies are characterised by a higher dispersion (standard deviation-846 mD) caused by an increased extent of secondary alterations of carbonates (Figure 2).

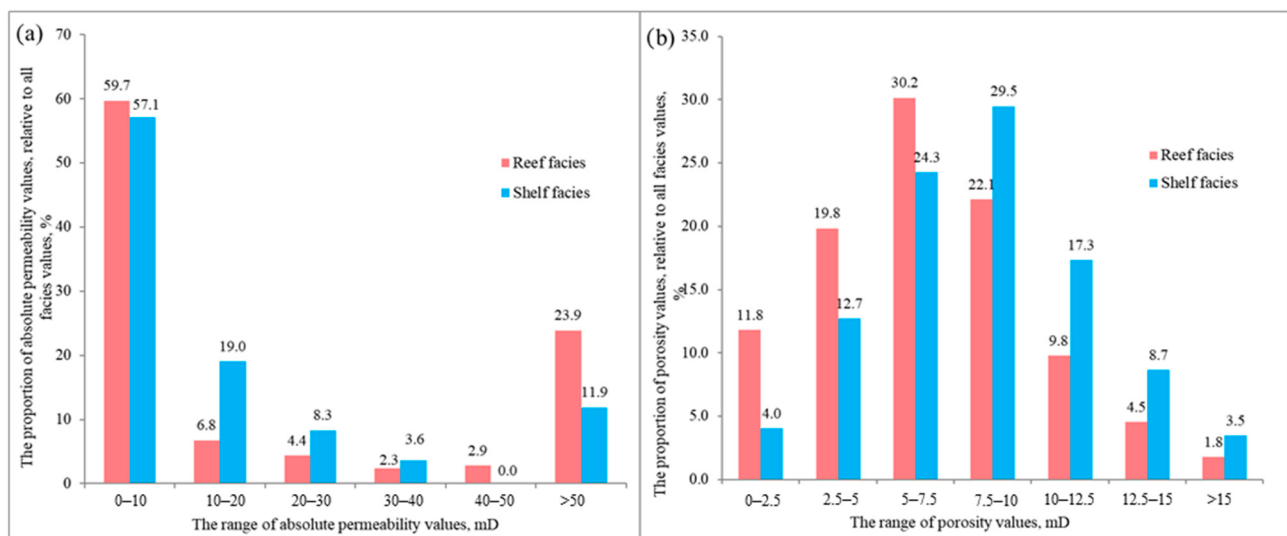


Figure 2. Histogram of the distribution of absolute permeability (a) and porosity (b) values based on core test data.

The carbonate reservoir is characterised by a complex type of void space. It is a complex configuration consisting of fractures, vuggy pores, and intergranular porosity unevenly distributed in the rock body. Increased zonal concentration of fractures and vuggy pores leads to the formation of zones with abnormally high porosity and permeability, which, in turn, leads to the formation of super-reservoirs. Core porosity and permeability characteristics of sediments in the Alpha field are presented in Table 1.

Table 1. Porosity and permeability characterisation of the Alpha deposit.

Number of Plugs Core Samples, pcs.	Number of Full-Size Core Samples, pcs.	Porosity, Reef Facies, %		Permeability, Reef Facies, mD		Porosity, Shelf Facies, %		Permeability, Shelf Facies, mD	
		Range	Average	Range	Average	Range	Average	Range	Average
2547	300	0.1–24.2	6.77	0.001–18,143	124.29	0.1–29.6	8.43	0.001–4439	49.87

In the Famennian sediments of the field under study, there are both open and closed fractures, as well as mineralised fractures (with calcite, dolomite, and sulphate group minerals) and fractures filled with bituminous and clayey matter (Figure 3). According to the core, the fractures are scant and/or occur as series-inclined, vertical, subhorizontal, and multidirectional rectilinear, curved, and branched, with lengths ranging from a few centimetres to 1.2 m. According to the classification of fracture openness, the rocks of the Famennian age contain fractures ranging from very narrow (from a few fractions of a millimetre) to very wide (up to 7.00 mm and more) (Figure 4). The fractures cut through and go around formational elements, fenestrae, and fragments of stylolites in the rocks, often connecting fenestral cavities, etc. The fractures are especially developed in lithotypes of limestones (boundstones, rudstones, packstones, and grainstones) and are less present in secondary dolomites.

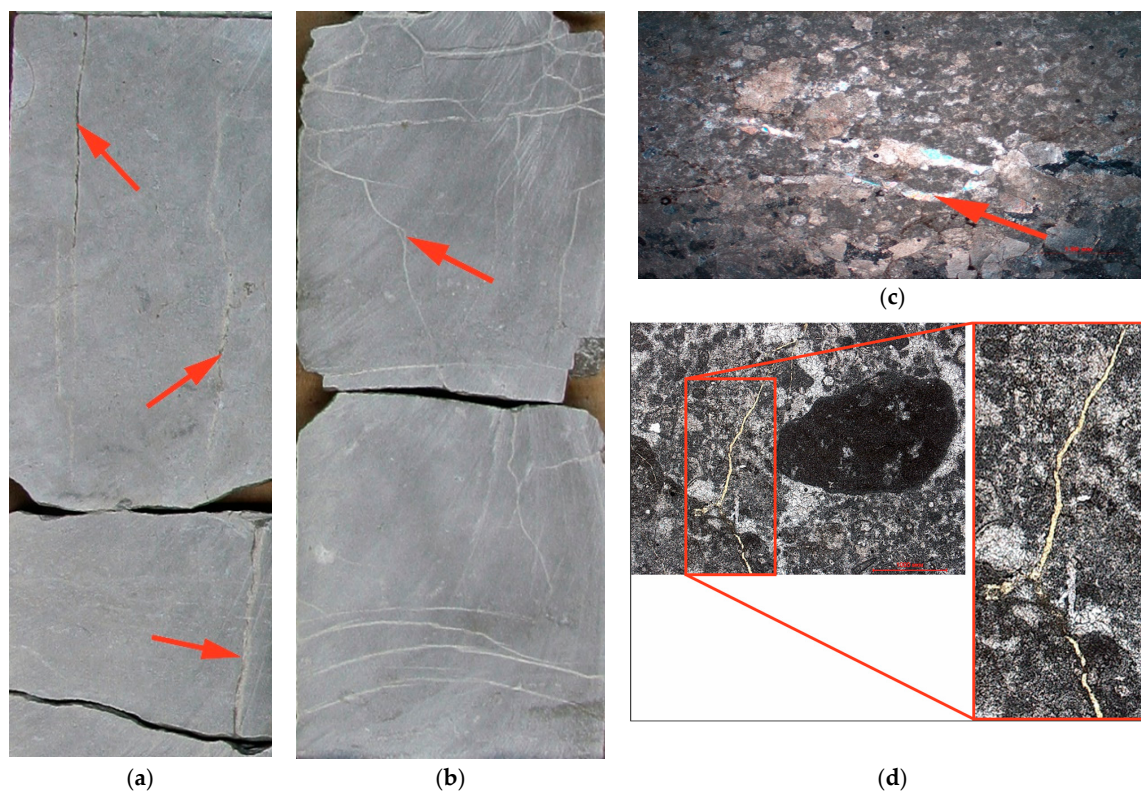


Figure 3. Fractures by openness and filling: (a)—open (core photo, arrows indicate open fractures); (b)—closed (core photo, arrow indicates closed fracture); (c)—mineralized (thin section photo, arrow indicates fracture mineralized with dolomite and sulphates); (d)—filled with bituminous and clayey matter (thin section photo, arrow indicates fracture filled with bituminous organic matter).

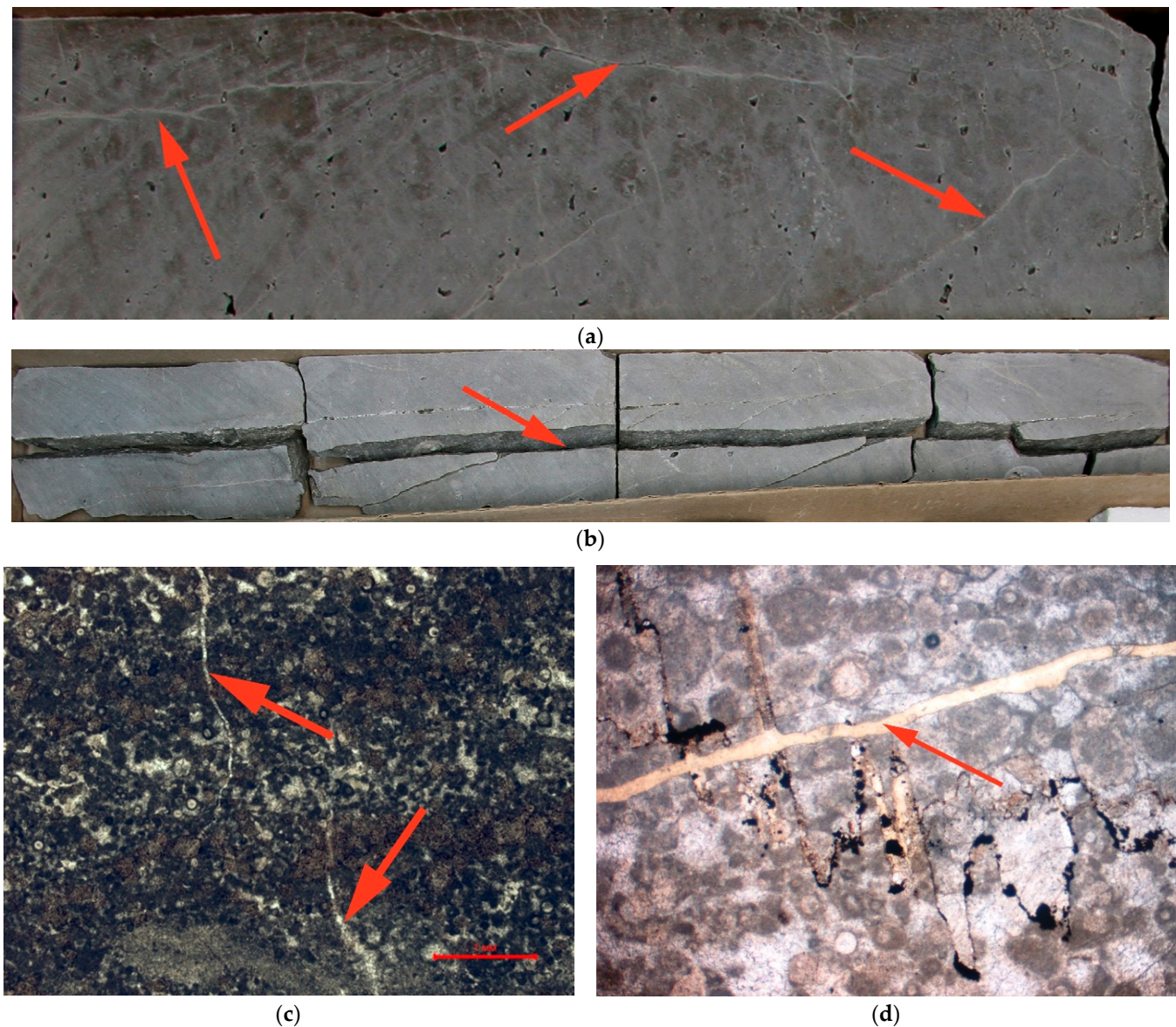


Figure 4. Fractures by size: (a)—short (core photo, arrows indicate fractures up to 10 cm long); (b)—long (core photo, arrow indicates fracture over 70 cm long); (c)—very small (thin section photo, arrows indicate fractures 0.02 mm wide); (d)—macro-fracture (thin section photo, arrow indicates fracture 2 mm wide).

Based on the geological peculiarities of the structure and formation conditions of the Timan-Pechora region, there can be two hypotheses of karst formation in the reef sediments of the Famennian age of the Denisov trough. The first mechanism of karst formation in the sediments is related to sea level fluctuations. During the periods of regressive phases of sedimentation, the reefs rose above sea level and were thus exposed to karst formation under the influence of the sun, wind, and fresh water (Figure 5a). The second concept of karst formation in reefs is related to the active tectonic regime of the basin, where younger rocks undergo erosion under the influence of inversion movements. Together, active tectonics and erosion events bring older rocks to the earth's surface, where they are exposed to atmogenic waters, causing karst formation (Figure 5b).

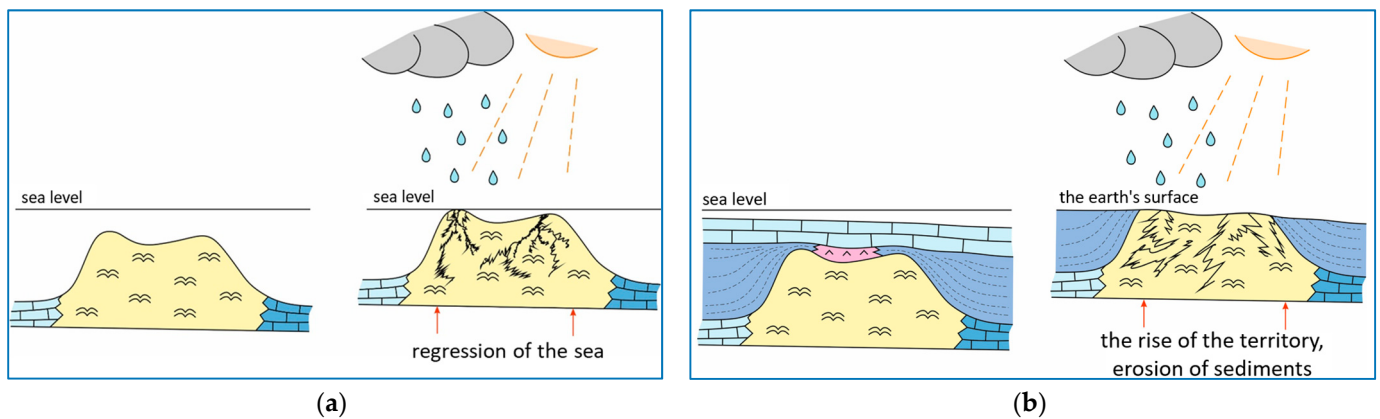


Figure 5. Mechanisms of karst formation in reef sediments: (a)—first stage, regression of the sea; (b)—second stage, erosion of sediments on the earth's surface.

The study of the core material revealed that reef rocks of the Zadonian-Yeletsian age have a complex structure of void space in both lateral and vertical directions. The complexity is caused by a significant propagation of vuggy pores (Figure 6) and karst fractures (Figure 7) in the rocks. In general, the core contains either a small or a large number of isometric or elongated vuggy pores, isolated or communicating, in sizes ranging from very small to very large (up to 80 mm).



Figure 6. Vuggy pores in Famennian reef reservoirs: (a)—small vuggy pores; (b)—medium-sized vuggy pores; (c)—large vuggy pores.

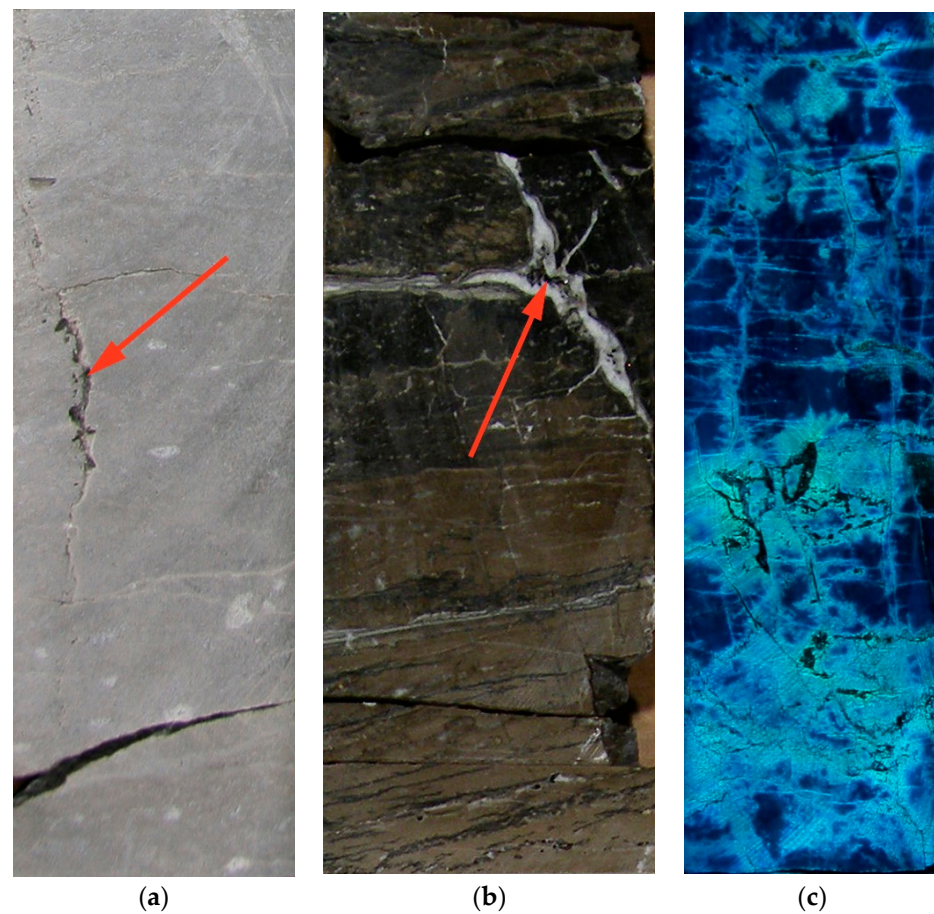


Figure 7. Karst fractures in Famennian reef reservoirs: (a)—karst fracture; (b)—karst fracture healed by calcite; (c)—karst fracture system.

3. Materials and Methods

In this work, the identification of highly permeable streaks along the wellbore is achieved through probabilistic methods using a combination of 10 different studies that characterise the porosity and permeability of the reservoir. The essence of the method is to identify intervals with abnormally high porosity and permeability for each of the studies; hence, the more anomalies of different geological and geophysical properties are observed in one interval, the higher the probability of the presence of a super-reservoir.

The first and foremost property that can be used to identify a super-reservoir is the absolute permeability value determined on 2547 plug core samples. Absolute permeability directly characterises the filtration capacity of the rock, so zones with abnormally high permeability can, with a high degree of certainty, indicate the presence of a super-reservoir in this interval. The approach of analysing the accumulated correlation between permeability and porosity values was used to assess the degree of their relationship and to identify anomalies [37,38].

Further, the values of filtration flow unit—FZI (1), which were first described by Amaefule et al. in 1993 [39] and are based on the Kozeny–Carman equation, were used to identify the super-reservoir.

$$FZI = \frac{RQI}{\varphi_z} \quad (1)$$

where “RQI” is the reservoir quality index, mD;

“ φ_z ” is the indicator of normalised porosity, unit fractions.

RQI is calculated according to Formula (2):

$$RQI = 0.0314 \sqrt{\frac{k}{\varphi}} \quad (2)$$

where “k” is the permeability coefficient, mD;

“ φ ” is the porosity coefficient, unit fractions.

“ φ_z ” characterises the void ratio—the ratio of pore volume to grain volume ratio—and is determined according to Formula (3):

$$\varphi_z = \frac{\varphi}{1 - \varphi} \quad (3)$$

Thus, the calculation of the FZI coefficient is reduced to Formula (4):

$$FZI = \frac{0.0314 \sqrt{\frac{k}{\varphi}}}{\frac{\varphi}{1 - \varphi}} \quad (4)$$

Hence, as the FZI value increases, the permeability will increase and the porosity will decrease as well, and it is thus possible to identify samples exposed to secondary changes that are typical of a super-reservoir.

Differentiation of core samples into different classes according to the FZI parameter was carried out using the DRT technique [40]. The formula for determining the DRT class is given below (5):

$$DRT = 2\ln(FZI) + 10.6 \quad (5)$$

At the next stage, a number of well-logging curves that characterise the reservoir properties of the rock were used to identify zones with abnormally high porosity and permeability, which may indicate the presence of a super-reservoir. A correlation matrix was built to evaluate the relationship between well logging curves and porosity and permeability based on the results of core studies. Well, logging curves that best characterise reservoir properties were selected. These curves were:

1. Porosity coefficient curves determined by acoustic (KPA), density (KPD), and neutron (KPN) methods, and the effective porosity coefficient determined by nuclear magnetic logging (CMFF);
2. Permeability coefficient curves that are determined by nuclear magnetic logging using the SDR (KSDR) model and the permeability coefficient calculated using the Timur-Coates (KTIM) model;
3. Fraction of oil in total void volume (FOIL) curve.

The presence of super-reservoir zones can be indicated by increased fracture density in a particular wellbore interval, indicating the high activity of secondary rock transformations. Formation Micro-Imager Logs (FMI) are used to identify these fractures, and, accordingly, abnormally high fracture densities derived from FMI can indicate the presence of a super-reservoir in a particular wellbore interval.

4. Results

The first criterion for high-permeable streak identification was the absolute value of permeability determined on 2547 plug core samples. Relationships between cumulative values of effective porosity and absolute permeability for the core samples were used to estimate the reservoir property relationships. Porosity and permeability data were sorted from minimum to maximum permeability values, and correlation coefficients were calculated for cumulative plugs $n = 3, 4, \dots, 2547$. These correlations enabled us to estimate the relationship of parameters over the whole range of porosity values, which made it possible to identify ranges of different types of porous space (Figure 8).

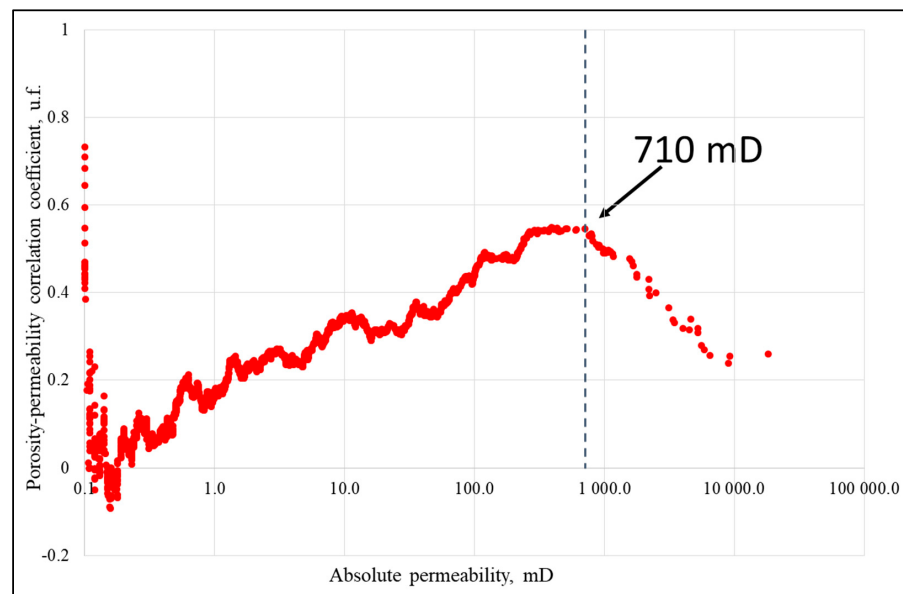


Figure 8. The dependence of the cumulative correlation coefficient between porosity and permeability on permeability values.

Figure 8 shows how the correlation coefficient between porosity and permeability gradually increases once a sufficient value is reached; that is, when permeability values increase, the relationship between porosity and permeability also becomes stronger. In other words, the increase in rock permeability is due to the increase in effective void space.

At the level of 710 mD, an inflection point is observed, after which the curve goes sharply down. This means that these core samples with abnormally high permeability are outliers relative to the total sample, and the high permeability values are not due to high values of classical intergranular porosity but to other factors, which, first of all, are fractures and communicating vuggy pores. Consequently, the value at the inflection point, equal to 710 mD, can be chosen as a boundary value to identify a super-reservoir.

The boundary value for the super-reservoir equal to 710 mD can also be seen in the absolute permeability distribution plot (Figure 9).

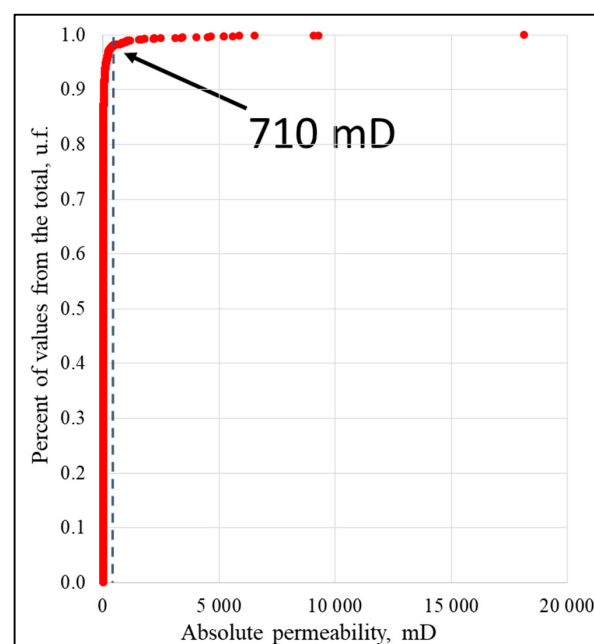


Figure 9. Absolute permeability distribution plot.

Figure 9 shows that most of the samples have relatively low permeability, forming a subvertical curve. Further, there is a sharp bend, and the curve goes to the subhorizontal position. This part of the sample characterises abnormally high values of permeability, which is not typical for the total number. Thus, 1.6% of samples are attributed to a super-reservoir by the absolute permeability value.

The next method to identify the super-reservoir was the hydraulic flow unit (FZI) calculation technique. The FZI value was calculated for each of the core samples. Further, the FZI distribution was plotted (Figure 10), and the point of inflection and exit of the distribution curve to a subhorizontal position was determined, reflecting abnormally high values that are not typical for the total sample.

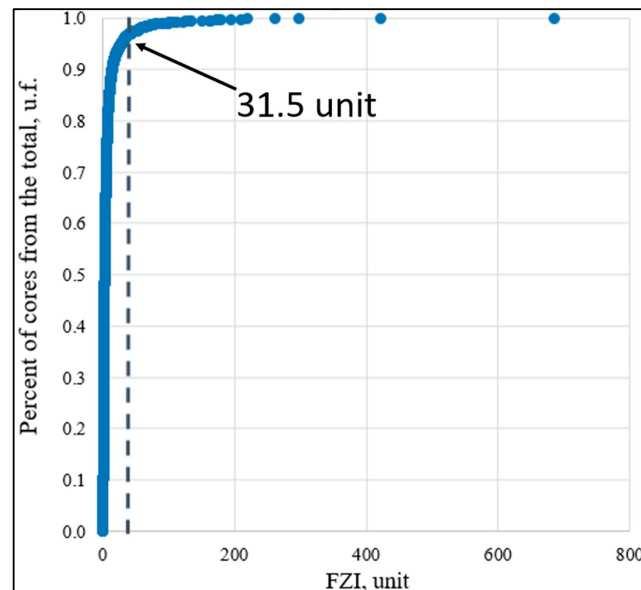


Figure 10. FZI distribution plot.

The FZI value at the inflection point is 31.5 units, which corresponds to class 18 according to the DRT classification (Figure 11).

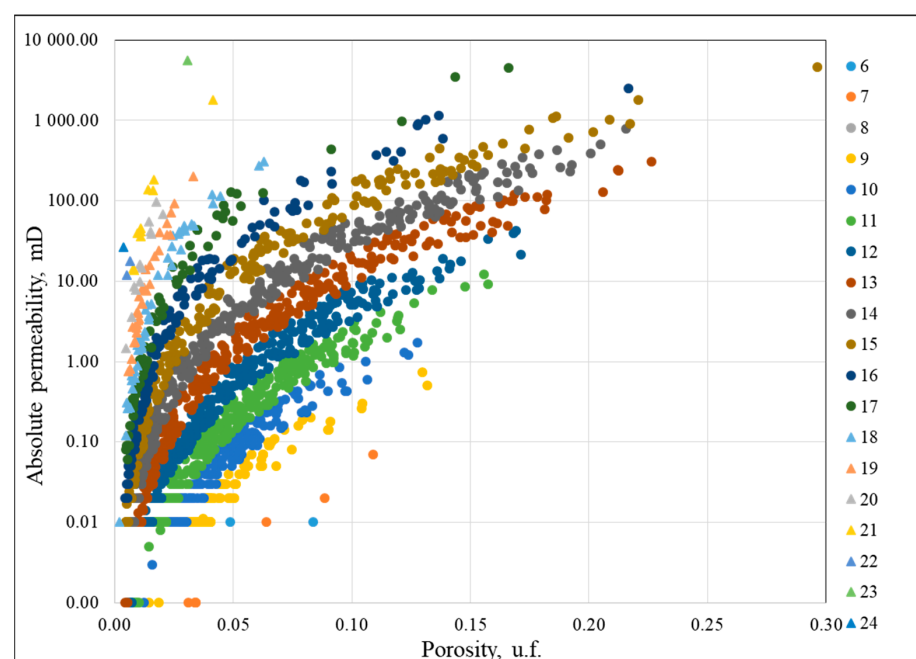


Figure 11. Classification of DRT core samples.

Core samples with abnormally high FZI values (>31.5), falling into DRT classes 18–24, are characterized by filtration typical of samples with an increased degree of secondary alterations (vuggy pores, fractures), which suggests the presence of a super-reservoir in this part of the section. Thus, only 4.5% of samples are attributed to a super-reservoir.

Next, a database of 40 well logging curves was compiled and correlated with the porosity and permeability determined in the core studies. The correlation matrix is presented in Table 2.

Table 2. Results of the correlation between core sampling and well-logging data.

	Depth	AF90	AF30	AF60	AF20	AF10	AMF	BIT	CFTC	CNTC
Permeability	0.007	0.019	0.021	0.031	0.037	−0.013	0.046 ¹	−0.036	−0.122	−0.091
Porosity	0.080	0.041	0.142	0.181	0.052	0.068	0.237	−0.109	−0.487	−0.317
	GR	HCAL	HDRA	HMIN	HMNO	HTEM	PEFZ	RHOZ	RLA1	RLA2
Permeability	−0.056	−0.070	−0.039	−0.038	−0.038	−0.052	−0.024	−0.005	−0.021	−0.028
Porosity	−0.219	−0.328	−0.194	−0.153	−0.152	−0.088	−0.189	−0.067	−0.140	−0.173
	RLA3	RLA4	RLA5	RT_HRLT	RXOZ	SP	KPA	DOLM	Kpob	KPD
Permeability	−0.024	−0.022	−0.014	−0.018	−0.045	−0.003	0.211 ²	0.019	0.161	0.188
Porosity	0.159	0.156	−0.093	0.121	−0.137	−0.162	0.670	0.007	0.343	0.622
	KPkv	KPN	KSDR	KTIM	LIME	FOIL	PORW	SHALE	TCMR	CMFF
Permeability	0.089	0.176	0.371	0.194	−0.035	0.199	−0.029	−0.015	0.042	0.254
Porosity	0.128	0.695	0.302	0.363	−0.102	0.474	0.021	0.104	0.000	0.705

¹ Statistically significant correlations are highlighted in red (p -value < 0.05 u.f.). ² Methods selected for further research are highlighted in bold font.

Out of 40 well logging curves, seven (KPA, KPD, KPN, CMFF, KSDR, KTIM, and FOIL) were selected for further work, which inherently reflect reservoir quality and show the highest correlation with core permeability.

To identify abnormally high values that may indicate the presence of a super-reservoir, distribution plots were built for each of the well logging methods (Figure 12). The super-reservoir boundary values are identified at the point of inflection and the changing direction of the distribution curve to the sub-horizontal position that characterises the abnormal properties.

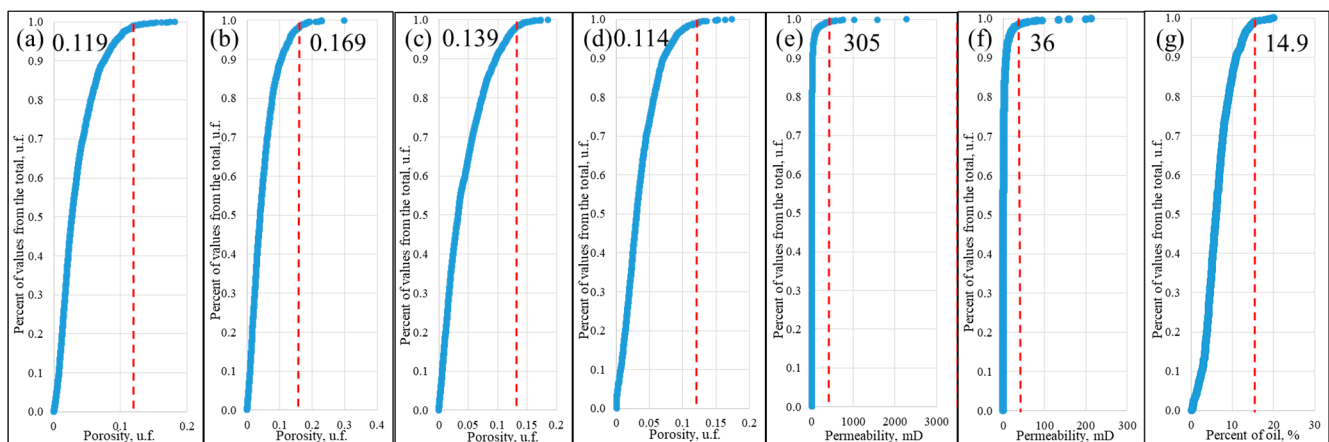


Figure 12. Distribution plots of well logging curves: (a) KPA, (b) KPD, (c) KPN, (d) CMFF, (e) KSDR, (f) KTIM, and (g) FOIL.

As a result, only 2–2.5% of the values in each of the well logging curves are attributed to the super-reservoir.

The next criterion for super-reservoir identification was FMI results. Using a moving average along the wellbore, synthetic fracture density curves according to FMI were built (Figure 13), and intervals with fracture densities above 1 fracture per metre were identified as probable high permeable streaks.

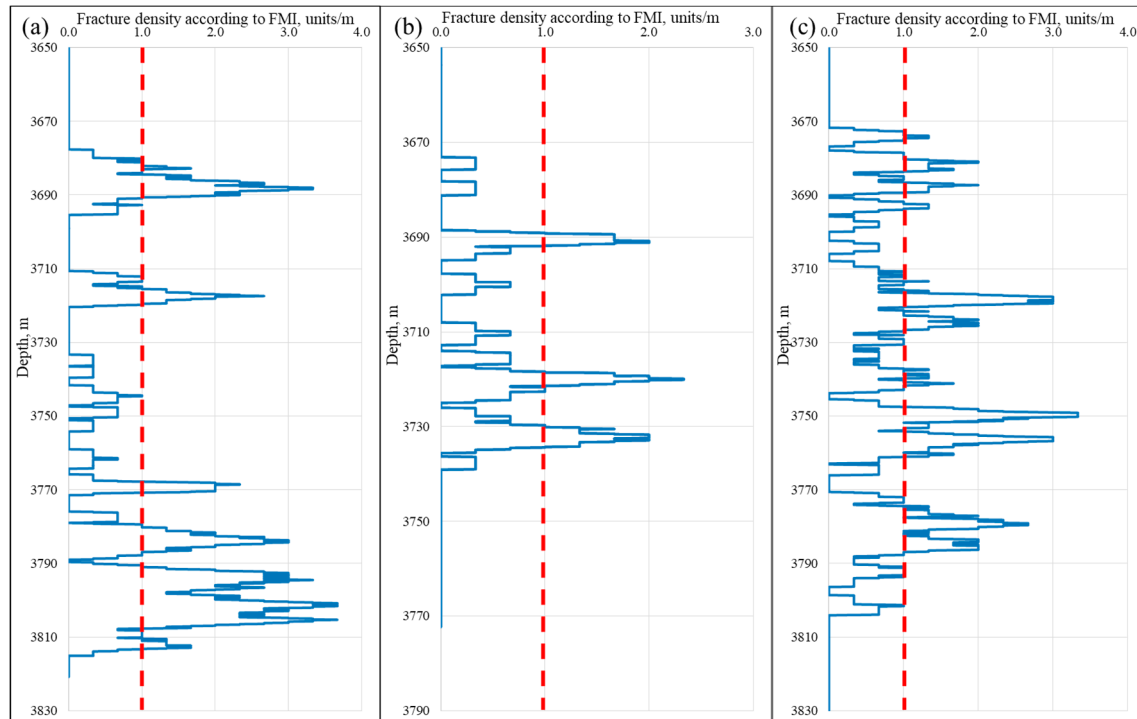


Figure 13. Synthetic fracture density curves identified by FMI: (a) well No. 1; (b) well No. 2; (c) well No. 3.

At the next stage, the super-reservoir intervals identified in the set of studies of various scales were summarised along the wellbore of each well, and synthetic curves of probability of super-reservoir presence were obtained (Figure 14).

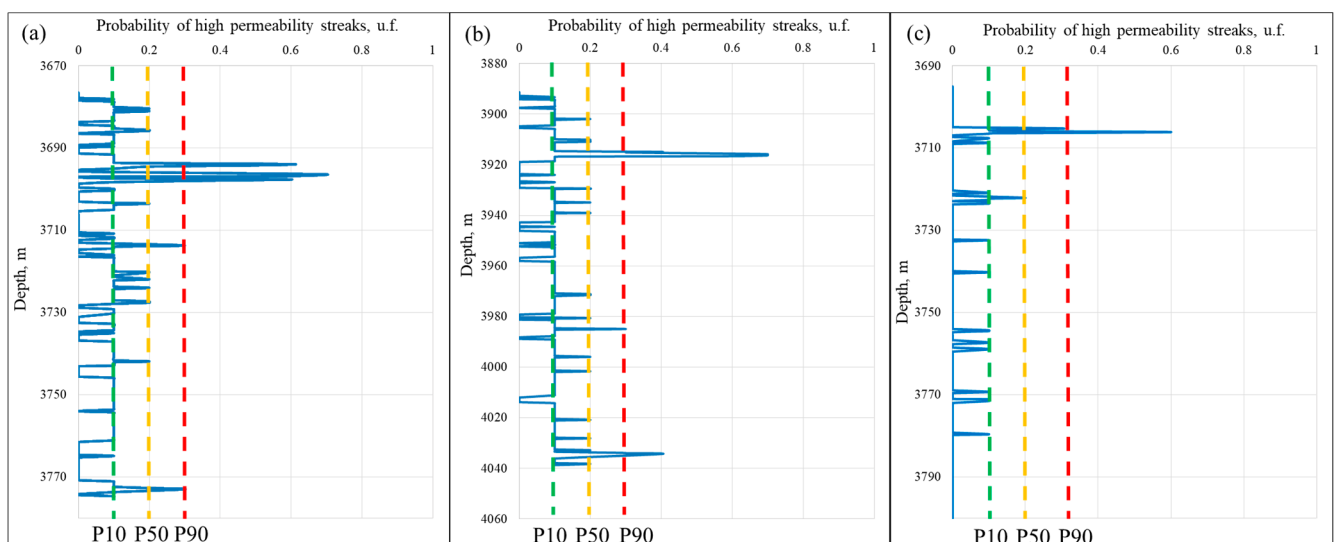


Figure 14. Synthetic curves of probability of super-reservoir presence: (a) well No. 1; (b) well No. 2; (c) well No. 3.

At the next stage, the supercollector intervals for each study are given the same weighting coefficient, which equals 0.1 units. Afterwards, all weighting coefficients were summed up for each wellbore study. Consequently, the more studies that reveal enormous reservoir properties intersect in one interval, the higher the probability of the presence of a superreservoir in this interval is expected. In this way, sums of weighting coefficients for intervals were obtained, and, as a result, synthetic curves of the probability of the presence of a superreservoir were generated (Figure 14).

As described earlier, each of the criteria has extremely strict requirements for super-reservoir identification (only 1–4% of maximum values), so the coincidence of at least two various scale studies of different natures in one scale interval of a plug core sample indicates the presence of a super-reservoir with a high degree of certainty.

To account for the uncertainties associated with the distribution of highly permeable streaks, the obtained synthetic curves were assigned criteria with different significance levels (P10, P50, and P90). Identification conditions at the P10 level reflect the maximum possible number of highly permeable streaks; in this case, all intervals where at least one of the studies indicates the presence of a highly productive interval fit the criteria for super-reservoir identification. The P50 level reflects an intermediate distribution of highly permeable reservoirs; only those intervals where two or more studies indicate the presence of a super-reservoir are eligible for super-reservoir identification, which significantly reduces the total thickness of highly productive intervals. The third level of super-reservoir identification, P90, shows the most conservative result of all. In this case, only those intervals where the presence of a super-reservoir is confirmed by three or more studies are identified as a super-reservoir.

At the next stage, LAS-files were generated for the wells and loaded into the project of the existing geological model, where the values 0 and 1 alternate along the wellbore opposite to the depth marker, 0—absence of a super-reservoir, 1—presence of a super-reservoir.

The basic parameters of the geologic model are described below:

Number of cells—45,638,389; grid type—corner points; average layer size by thickness—0.38 m, cell size— 50×50 m; number of layers—1743; formations—D_{3el3}, D_{3el2}, D_{3el1}, D_{3el_trans}, D_{3zd}.

Then, using stochastic indicator modelling, the super-reservoir was distributed in the model volume (Figure 15).

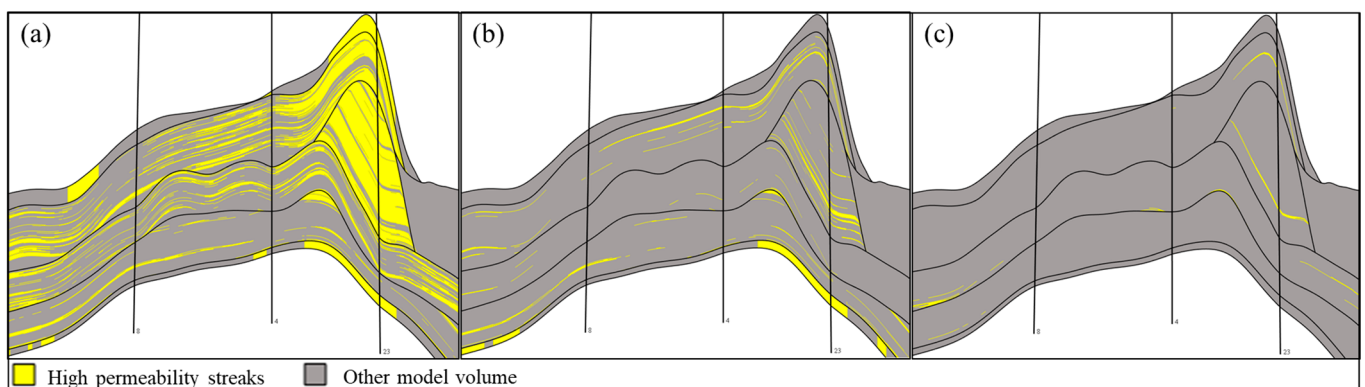


Figure 15. Distribution of the super-reservoir in the model volume: (a) P10; (b) P50; (c) P90.

Permeability arrays were built based on the distribution of highly permeable intervals. The permeability array calculated by standard petrophysical dependence is taken as a basis (Figures 16 and 17); further, for the intervals attributed to the super-reservoir with probability P10, P50, and P90, the permeability is calculated on the basis of petrophysical dependence obtained for core samples, which according to FZI are attributed to the super-reservoir (Figures 11, 16 and 17).

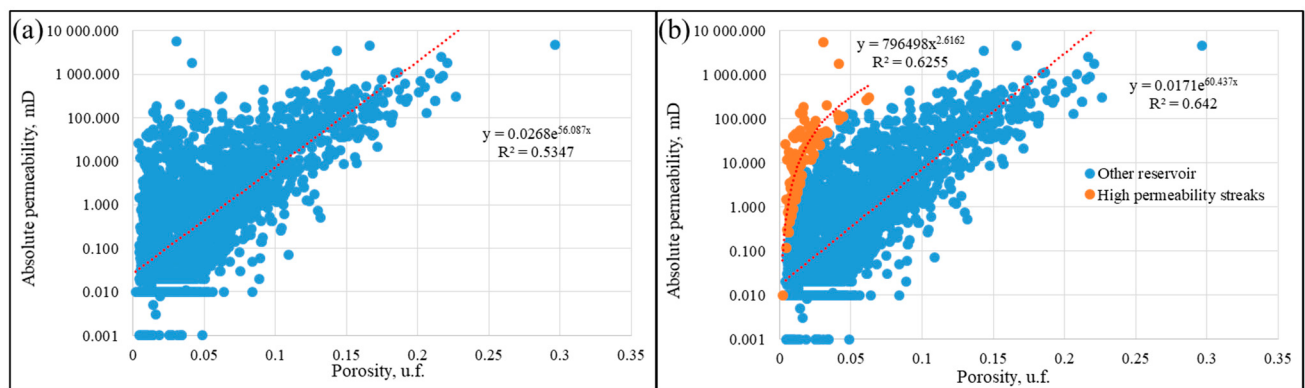


Figure 16. Permeability-porosity dependence plot: (a) standard petrophysical dependence; (b) petrophysical dependence for a super-reservoir.

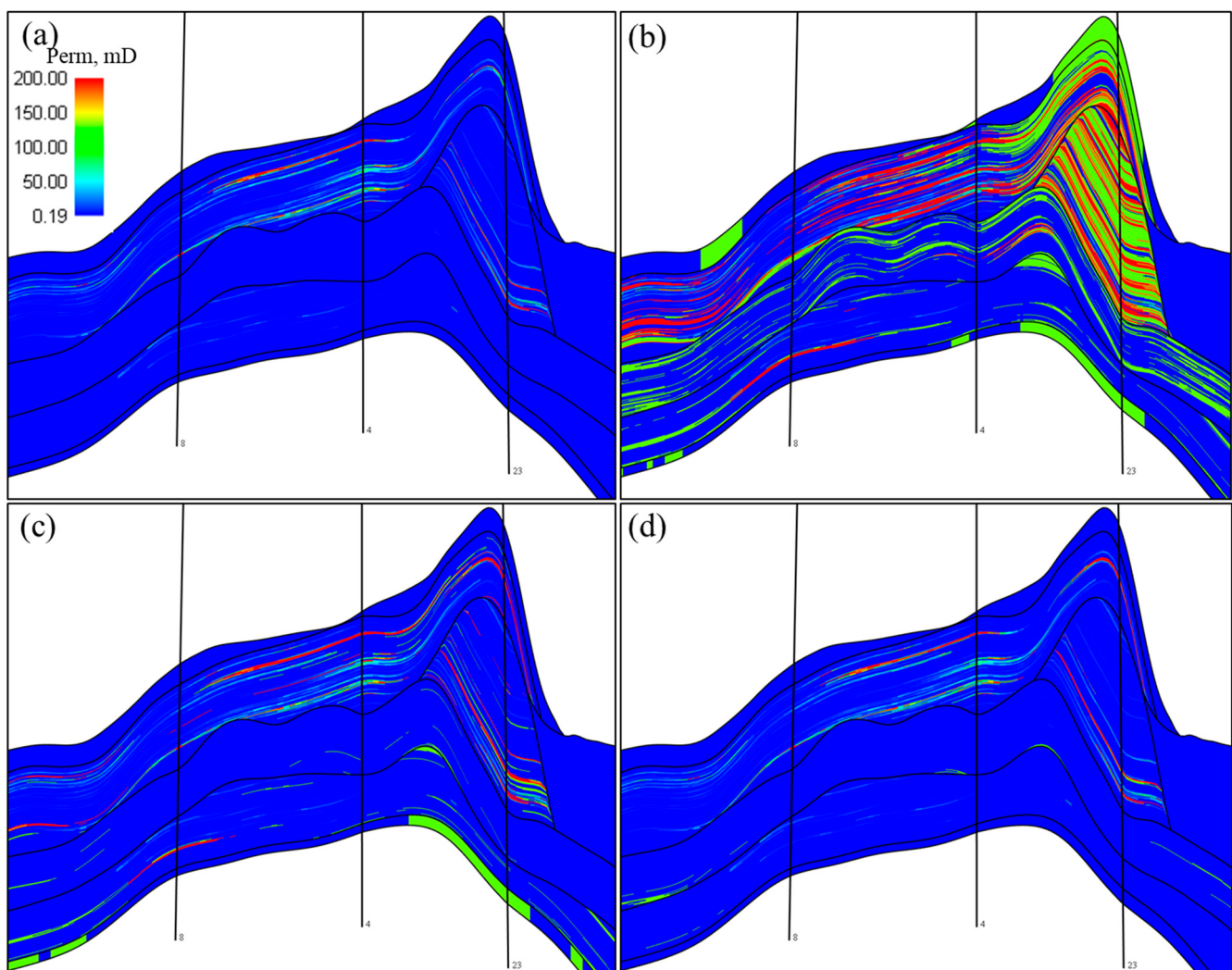


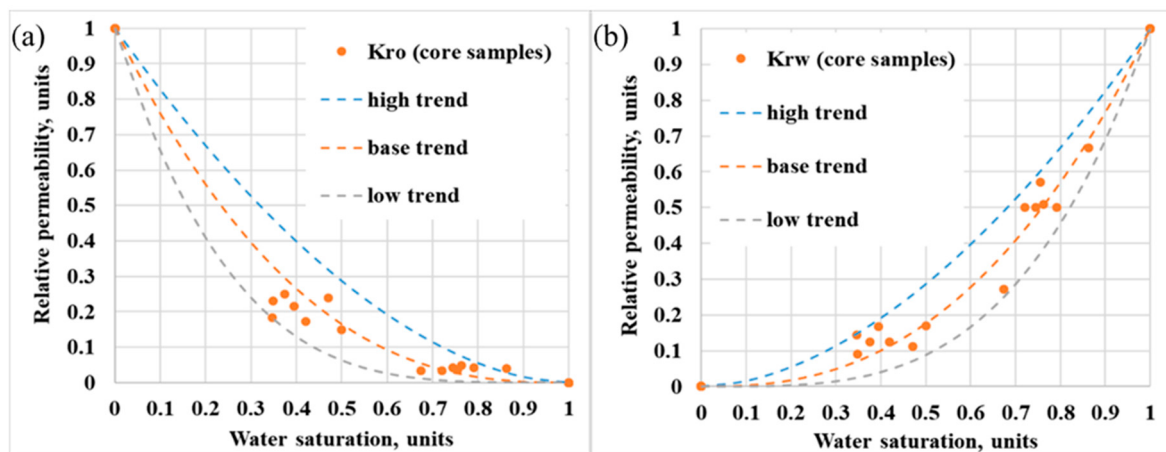
Figure 17. Comparison of obtained permeability arrays: (a) standard petrophysical dependence; (b) P10; (c) P50; (d) P90.

Comparisons of average permeability for each permeability array are shown in Table 3.

Table 3. Comparison of average permeability for the obtained permeability arrays.

	Standard Petrophysical Dependence	P10	P50	P90	Well Flow Test	Core
Average permeability, mD	28.5	523.9	53.6	49.8	93.5	24.5

After that, the obtained permeability arrays were loaded into the existing dynamic model. In the dynamic model, a PVT model was implemented with black oil and relative curves according to core studies (Figure 18). A high trend is used for supercollectors; a base trend is used for D_{3el3}, D_{3el2}, D_{3el1}, and D_{3zd}; a low trend is used for D_{3el_trans} and D_{3el2}.

**Figure 18.** Relative permeability: (a)—for oil, (b)—for water.

The history of oilfield development is 10 years: total wells-58, producers-43, injectors-15. Four wells have a horizontal ending. The main completion intervals are D_{3el3}, D_{3el1}, and D_{3zd}. Fractures and karst zones were included in the modelling of superreservoir distributions.

Further history-matching results were compared on all 4 permeability arrays by reproducing the development history with control by actual bottom hole pressure, without liquid flow rate limitations. To assess the history matching quality comparison of bottom hole pressure dynamics, it is shown in Figure 19.

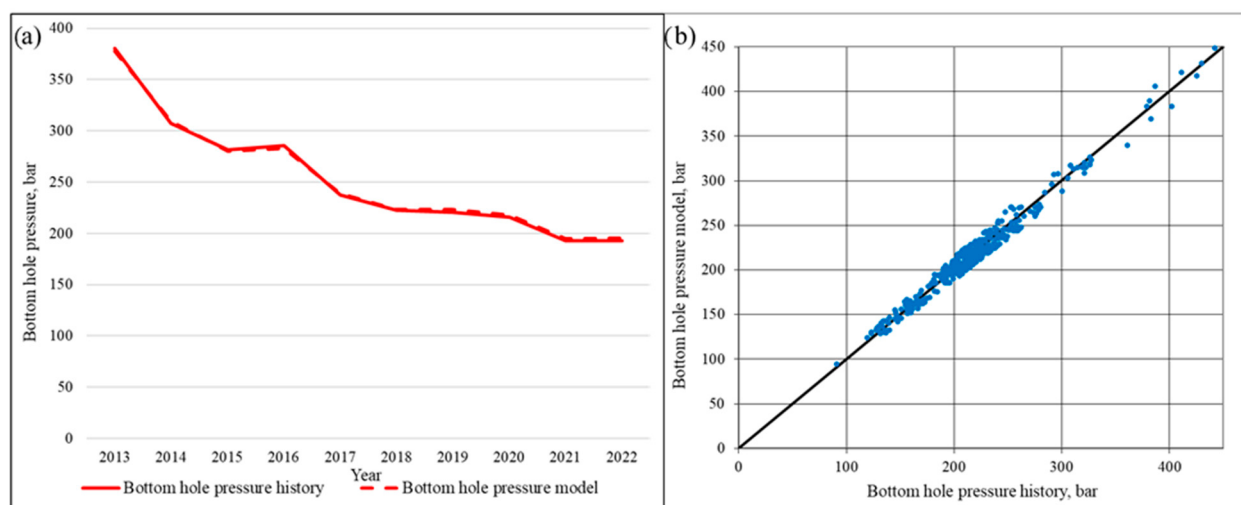
**Figure 19.** Comparison of simulated and historical bottomhole pressures: (a) comparison of the bottomhole pressure dynamics; (b) cross-plot between simulated and historical data.

Figure 19 shows a high convergence of calculated and historical bottomhole pressures, which allows us to assert that the initial conditions for carrying out calculations with bottomhole pressure control are correct.

The comparison was carried out in equal conditions after the first iteration of history matching.

When high permeability streaks were factored into the model, in just one iteration, it was possible to achieve better convergence with historical oil and liquid production than when using the permeability array derived from standard petrophysical dependence (Figure 20, Table 4).

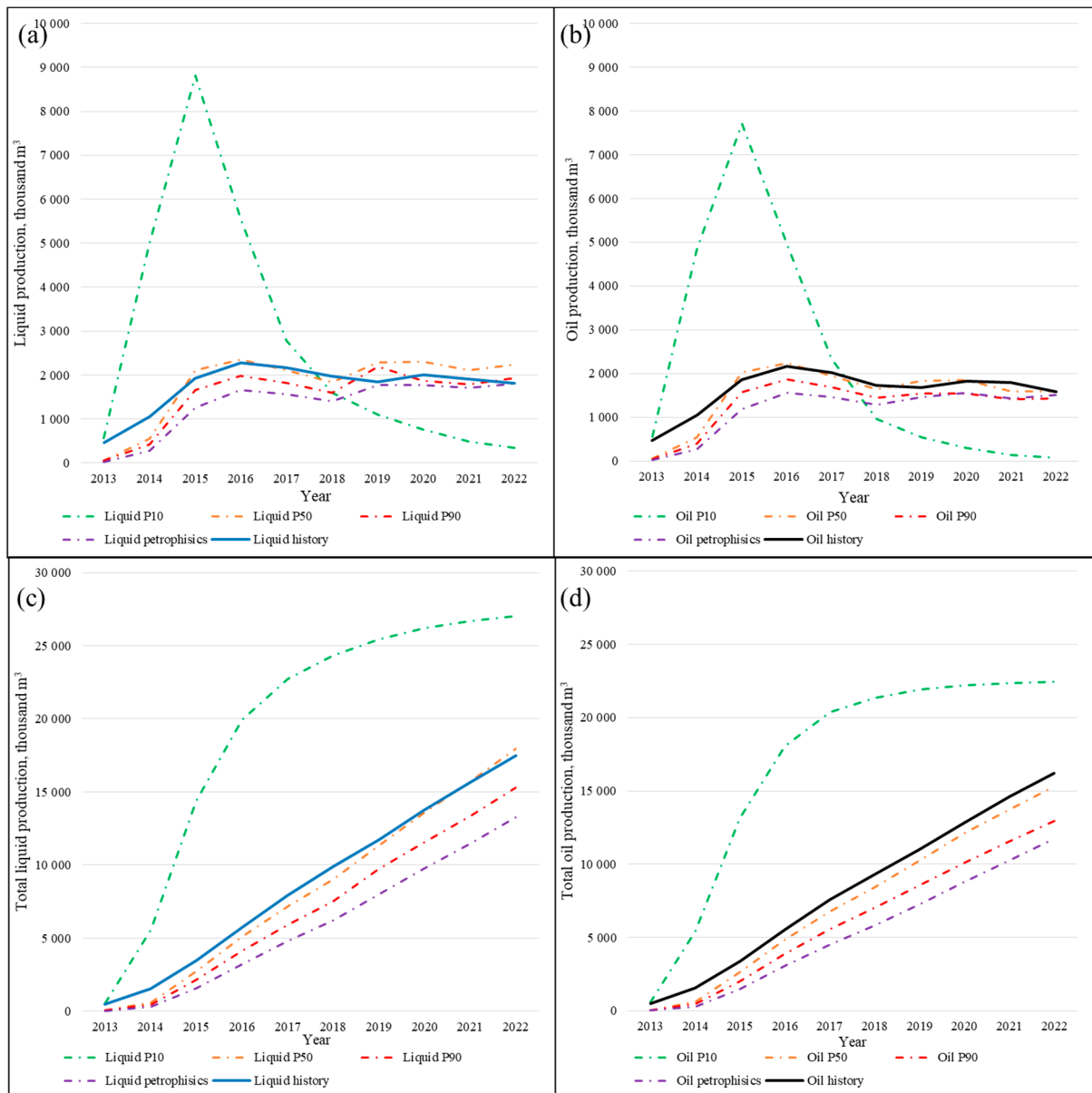


Figure 20. Comparison of actual and model oil and liquid production using all permeability arrays: (a) comparison of annual liquid production; (b) comparison of annual oil production; (c) comparison of cumulative liquid production; (d) comparison of cumulative oil production.

Table 4. Comparison of historical and model-calculated cumulative oil and liquid production for each permeability array.

	History	Petrophysics	P10	P50	P90
Total liquid production, thousand m ³	17,478	13,266	27,037	17,969	15,303
Total oil production, thousand m ³	16,191	11,760	22,428	15,304	12,972
Deviation of the liquid from history, %		24.1	−54.7	−2.8	12.4
Deviation of oil from history, %		27.4	−38.5	5.5	19.9

The best convergence with historical oil and liquid production was achieved using a permeability array with a super-reservoir distributed according to the P50 probability (deviation in cumulative liquid production—−2.8%, deviation in cumulative oil production—5.5%).

Figure 20 and Table 4 show that variants with permeability calculation according to standard petrophysical dependence and super-reservoir distribution with probability P90 underestimate formation potential; wells produce less liquid than according to history; hence, the productivity of wells with this permeability array is lower than real. The opposite is the situation with the distribution of super-reservoir with probability P10: this permeability array significantly overestimates the formation potential and well productivity at the peak production moment, thereby depleting the energy of the deposit. As a consequence, there are sharp rates of liquid and oil production decline, as well as faster water breakthroughs. The most favourable results are obtained in reservoir distribution with a probability of P50. Using this version of the permeability array, it was possible to reproduce the reservoir potential and, as a consequence, productivity in the most accurate way.

5. Conclusions

This study gives a detailed description of the geological structure of the Alpha field, which has a carbonate reef reservoir with a complex void structure. The core was analysed, and a detailed description was given to the nature of fractures and vuggy pores whose high density leads to the formation of super-reservoirs.

Super-reservoirs have a huge impact on reservoir management. They both ensure high well productivity and impose the risk of premature water breakthroughs. In order to reduce uncertainty in the distribution of highly productive intervals in the model volume, a methodology for probabilistic identification of super-reservoirs was proposed.

The methodology includes consideration of 10 studies of various scales. At the initial stage, possible super-reservoirs are identified for each study separately, after which the super-reservoirs are summed to form a general probability curve of super-reservoir distribution. The probability curve is then used to identify super-reservoir intervals with different degrees of uncertainty: P10, P50, and P90.

In the next step, all three cases of super-reservoir identification are distributed in the model volume, and permeability arrays are calculated for each variant; besides, a permeability array is calculated through a standard petrophysical dependence for comparison.

Then, the obtained arrays were loaded into the existing dynamic model, and the convergence of calculated and actual indicators of the Alpha field development after the first iteration of history matching was compared. Calculations with each permeability array were carried out in equal conditions, with control by drawdown pressure and without control by liquid rates. The best convergence with actual oil and liquid production was shown by the calculation using permeability array P50; deviations on accumulated liquid and oil were only −2.8% and 5%, respectively, which indicates the most accurate and correct distribution of permeability in the model volume.

Thus, the application of this technique reduces the uncertainty of the distribution of highly productive intervals in the volume of the reservoir, which makes it possible to take into account the risks of premature watering of wells as well as to predict the rate of oil

production. Using this technique, it was possible to recreate reservoir potential and adjust well productivity with high accuracy in the model, which increased the overall adaptability of the model.

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