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A Hierarchical Evaluation Method for Dominant Flow Fields in the Ultra-High Water Cut Stage Based on Viscous Fingering Characterization

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Abstract

Aiming at the problems of well-developed dominant seepage channels, prominent viscous fingering phenomenon, complex dynamic evolution of flow fields, and difficulty in fine characterization and quantitative evaluation by conventional methods in oil reservoirs during the ultra-high water cut stage, a hierarchical evaluation method for dominant flow fields based on the dynamic characterization of viscous fingering is proposed. By conducting microscopic visualization displacement experiments with different displacement directions and fluid viscosities, the formation mechanism and influencing factors of viscous fingering are revealed. The concepts of viscous fingering number and viscous fingering growth function are put forward to realize the cross-scale characterization of the viscous fingering phenomenon and achieve fine characterization of the flow field in the ultra-high water cut stage. On this basis, combined with the AHP (Analytic Hierarchy Process) and time-varying aqueous phase displacement flux, two comprehensive flow field evaluation indicators, namely the static development index and dynamic oil-flux ratio, are established. The concept of silhouette coefficient is introduced to determine the optimal classification category for flow field grading, avoiding the influence of subjective experience on the classification category. A grading template is established, and finally a complete three-dimensional hierarchical system for dominant flow fields is formed to guide the establishment of flow field grading regulation strategies. The application example shows that compared with other methods, this flow field characterization and hierarchical evaluation method has the advantages of more detailed flow field characterization and more accurate and intuitive flow field grading results. Through this research, a technical chain of "dynamic characterization - intelligent grading - targeted regulation" is formed, which provides theoretical and technical support for flow field regulation in ultra-high water cut oilfields.

Keywords

Ultra-High Water Cut Stage, Dominant Seepage Channel, Viscous Fingering, Time-Varying Flow Field Grading, Flow Field Regulation

1. Introduction

As most of China's onshore main oilfields have generally entered the ultra-high water cut development stage (water cut ≥ 90%), the fluid flow characteristics in the reservoir have changed significantly. The traditional flow field evaluation methods based on Darcy's seepage theory and single-factor evaluation indicators are facing new technical challenges. Studies have shown that in the ultra-high water cut stage, the viscous fingering phenomenon of oil-water two-phase flow in reservoir pores has gradually become a key factor affecting the distribution of remaining oil. The dominant seepage channels formed by this phenomenon lead to the aggravation of ineffective injection-production cycles and restrict the improvement of oil recovery. Therefore, it is urgent to establish a flow field hierarchical evaluation system suitable for the ultra-high water cut stage.

In the past, scholars have carried out extensive research on reservoir flow field evaluation and grading methods, but most of them ignored the impact of the viscous fingering phenomenon on the formation process of dominant flow fields. In addition, in previous studies on reservoir flow field grading methods, most scholars [1]-[7] focused on static dominant flow field grading methods, which can be divided into two categories: empirical methods and statistical methods. Among them, the commonly used statistical methods include machine learning [1], fuzzy comprehensive evaluation [4], grey correlation analysis [8], and cluster analysis [9] [10]. Jiang Ruizhong [1] used logical analysis combined with BP neural network technology to evaluate the reservoir flow field. Yu Chenglin [11] calculated four parameters such as the well group variation coefficient and realized the quantitative identification of the development area of channeling channels by applying the comprehensive discrimination parameter method. Wang *et al.* [2] [3] directly clustered the indicators selected for grading; however, the clustering results of this method have the characteristics of multi-dimensional instability and cannot distinguish the sensitivity of different indicators to the development of dominant flow fields. Peng Shimi [12] proposed a macropore comprehensive index to describe the dominant seepage channel, using 7 parameters (including porosity and permeability) for analytic hierarchy process and fuzzy evaluation. This method ignores the actual scouring intensity of the oil reservoir and thus cannot reflect the current flow field situation. In addition, some scholars [13]-[15] have considered time-varying dominant flow field grading methods. Ma Kuiqian [16] proposed a new flow field evaluation index "oil-flux ratio" and a flow field heterogeneity evaluation index "oil-flux ratio heterogeneity coefficient" from the perspective of water displacement efficiency. Although this method considers the actual scouring intensity of the flow field, it ignores the influence of static geological factors on the formation of dominant flow fields.

In view of this, this paper deeply analyzes the viscous fingering phenomenon, innovatively integrates technical means such as AHP and dynamic oil-flux ratio, and constructs a new time-varying three-dimensional hierarchical system for dominant flow fields, which provides strong theoretical support for flow field regulation and helps to improve oilfield recovery.

2. Characterization of Viscous Fingering Mechanism

2.1. Viscous Fingering Growth Function

Under the macro-constraints of the sedimentary characteristics of Oilfield Q, a heterogeneous pore network model was generated and a microscopic visualization model was fabricated. Microscopic visualization displacement experiments with different displacement directions and fluid viscosities were conducted to reveal the formation mechanism of viscous fingering; parameters such as the number, width, and scale of viscous fingers were quantified, and the influencing factors of viscous fingering in heterogeneous reservoirs were identified. Additionally, the impact of viscous fingering channels on the classification of micro-flow fields during the ultra-high water cut stage was studied.

The fabrication of the heterogeneous pore network model follows the steps below: 1) Engrave the heterogeneous pore network diagram based on the information from casting thin sections. 2) Etch the heterogeneous pore network diagram onto a glass chip using etching technology. 3) Assemble the pore network model into a displaceable chip by bonding technology. 4) Conduct displacement experiments on the heterogeneous pore network using microfluidic technology.

The experimental parameters are as follows:

Simulated formation water: $NaHCO_3$ type with a salinity of 4505 mg/L; Simulated formation crude oil: with a viscosity range of 22 - 260 mPa·s; Displacement intensity in microfluidic experiments: controlled within the range of 0.5 - 2.0 mL/min (converted to linear velocity) based on the similarity criteria of physical simulation.

To characterize the viscous fingering phenomenon, a new viscous fingering growth model is proposed to describe the flow law of oil-water two phases. The schematic diagram of this model is shown in **Figure 1**. All finger-like flows are combined into an effective finger-like flow, which grows dynamically with water displacement.

The viscous fingering growth function is defined as the following functional equation:

$$\lambda_f = \alpha \bar{S}_w^{\beta} \tag{1}$$

In the formula, λ_f is the cross-sectional ratio of the viscous fingering development area; α reflects the size of the maximum cross-section of viscous fingering; β is the growth exponent of viscous fingering.

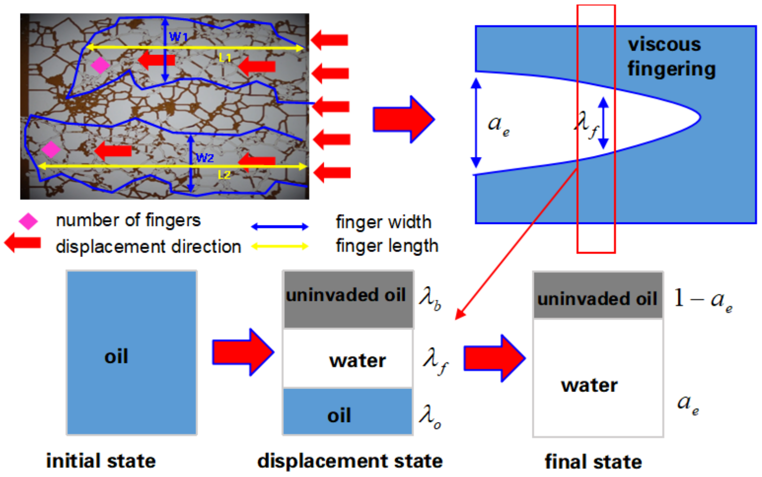

Figure 1. Mechanistic modeling of the viscous fingering model.

Based on the viscous fingering modeling, through function fitting, the fitting relationships of the viscous fingering growth function under different experimental conditions are obtained, as shown in Figure 2; the fitting coefficients are α and β.

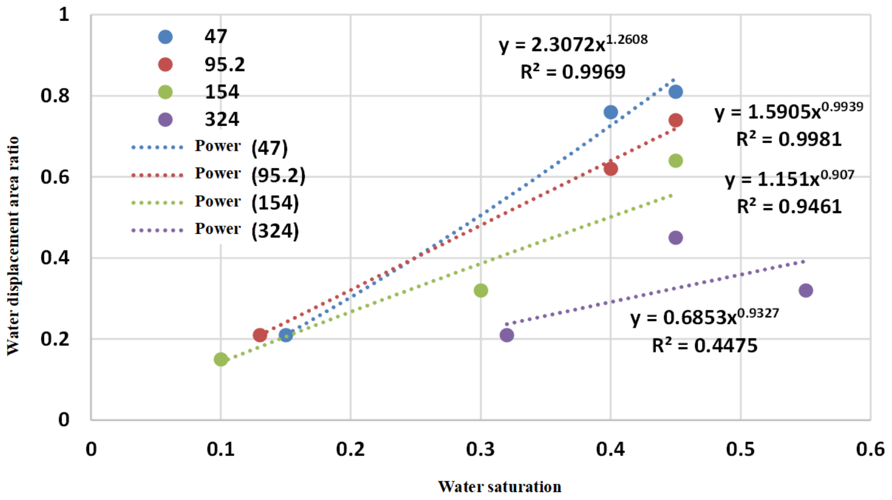

Figure 2. Fitting of viscous fingering growth function under different conditions.

To realize the macroscopic characterization of the viscous fingering law, the viscous fingering number is defined:

$$N_{vf}=\left(\frac{\mu_o}{\mu_w}\right)^2\frac{\mu_w u_l}{\sigma}A_c k^{-1} \tag{2}$$

In the formula, N_{vf} denotes the viscous fingering number, which is dimensionless with a value range of 10^9 - 10^{11}; μ_o represents the oil phase viscosity, mPa·s; μ_w stands for the water phase viscosity, mPa·s; u_l is the displacement velocity, mL/min; A_c refers to the cross-sectional area, in m^2; k denotes the permeability (permeability anisotropy not considered), mD; and σ represents the interfacial tension (reflecting the magnitude of capillary force), N/m.

Based on the displacement experiment, the relationship between the viscous fingering number and the viscous fingering growth function is established, which reveals the relationship between the development intensity of viscous fingering during the water flooding process in Q Oilfield and reservoir physical properties, fluid physical properties, displacement methods, and displacement velocity from a microscopic perspective, as shown in Figure 3. This relationship can be applied in numerical simulation to reveal the formation of dominant flow fields and the development process of ineffective circulation channels caused by the development of viscous fingering during the water flooding process.

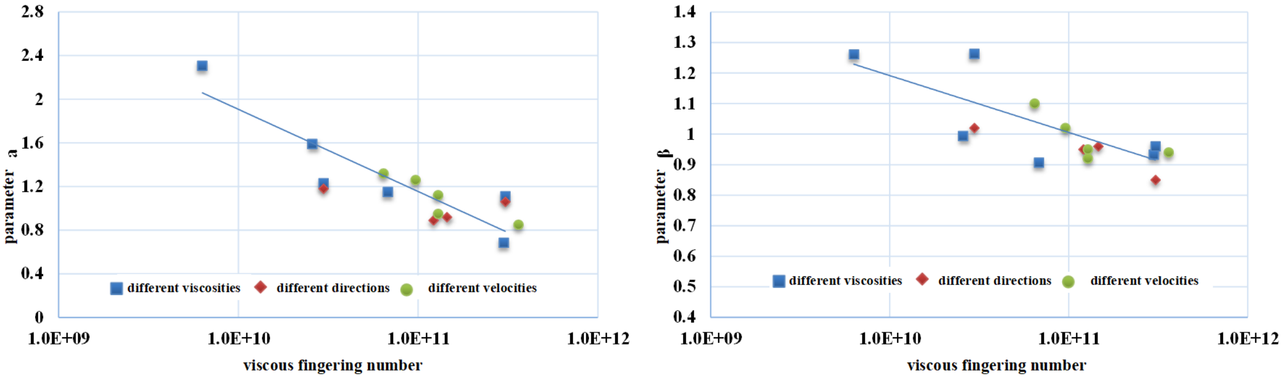

Figure 3. Relationship between viscous fingering number and parameters α and β.

2.2. Numerical Simulation Characterization of Viscous Fingering

To characterize the viscous fingering phenomenon in the numerical model, the main steps are as follows:

1) Calculate the viscous fingering number of each grid:

$$N_{vf} = \left(\frac{\mu_o}{\mu_w}\right)^2 \frac{\mu_w u_l}{\sigma} A_c k^{-1} \tag{3}$$

2) Calculate the parameters of the viscous fingering function for each grid through interpolation:

$$\lambda_f = a\bar{S}_w^{\beta} \tag{4}$$

3) Update the relative permeability curve of each grid.

The viscous growth exponent is embedded into the oil-water relative permeability to modify the relative permeability. The mathematical model is as follows, where the water phase is:

$$k_{rw} = \lambda_f k_{rw}^0 \left(\bar{S}_w\right)^{n_w} = a k_{rw}^0 \left(\bar{S}_w\right)^{n_w+\beta} \tag{5}$$

The development characteristics of viscous fingering lead to the enhancement of connectivity between oil and water wells; the larger the viscous fingering number, the more severe the development of viscous fingering, which is reflected in the relative permeability as a significant increase in water phase permeability.

Taking the C3 well group in Oilfield Q as an example, after considering viscous fingering, the fitting error of the model for production performance is significantly reduced. The fitting error of oil production rate is decreased by 62.4%, and the fitting error of water cut is reduced by 71.2%.

3. Optimization of Hierarchical Evaluation Indicators for Dominant Flow Fields

Fundamentally, the indicators affecting the formation of dominant channels in oil reservoirs include static geological indicators and dynamic development indicators. Static indicators describe the geological basis for the formation of dominant channels, which are the inherent conditions for the formation of dominant channels and can indicate the potential for the formation of dominant channels. The direct characterization indicators of dominant channels in oil reservoirs are dynamic indicators, whose values reflect the actual scouring intensity of the oil reservoir. The overall development degree of dominant channels is determined by static and dynamic indicators.

3.1. Establishment of Static Evaluation Indicators

Static parameters can indicate the potential for the formation of dominant channels, and the heterogeneity and pore-throat radius of sandstone reservoirs are important factors for the formation of dominant seepage channels [17]. Therefore, it is scientifically based to judge the development level of dominant flow fields by combining the heterogeneity and seepage capacity of the reservoir.

In this paper, the static development index is proposed as the static evaluation indicator for flow field grading. This indicator is based on the idea of AHP (Analytic Hierarchy Process), combined with the actual oilfield production and the experience of reservoir engineers. AHP is a multi-criteria decision-making method used to help people make trade-offs and choices in complex decision-making environments [8]. The key steps are to construct a parameter judgment matrix, conduct qualitative analysis using mathematical methods, and then solve the problem based on the weights calculated for each scheme.

Based on AHP, permeability, pore-throat radius, permeability ratio, and permeability variation coefficient are selected as evaluation parameters, and pairwise comparisons of the above parameters are made. The results are shown in **Table 1**.

After the consistency test of the above matrix is passed, the arithmetic mean method, geometric mean method, and eigenvalue method are used to calculate the weights of the three methods respectively, and the static development index (S) is obtained as follows:

$$S = 0.071 * A + 0.413 * B + 0.316 * C + 0.2 * D \tag{6}$$

The selection of the four static parameters is closely aligned with the heterogeneity characteristics of the fluvial heavy oil reservoirs in Oilfield Q, enabling a comprehensive characterization of the geological basis for the development of dominant flow fields. The determination of the AHP weight matrix is centered on expert judgment, with the priority of parameter influences clarified through industry experience. Sensitivity analysis of weights verifies that this weight allocation method can accurately reflect the actual contribution of each parameter to the dominant flow field, providing reliable static indicator support for the subsequent hierarchical evaluation of flow fields.

Table 1. Results of the AHP judgment matrix.

Parameters	Pore-throat radius (A)	Permeability (B)	Permeability ratio (C)	Permeability variation coefficient (D)
Pore-throat radius (A)	1	1/6	1/4	1/3
Permeability (B)	6	1	1/2	7/4
Permeability ratio (C)	4	2	1	3/5
Permeability variation coefficient (D)	3	4/7	3/2	1

3.2. Establishment of Dynamic Evaluation Indicators

In the practical application of oilfield development, the time-varying displacement flux can only qualitatively analyze the relative distribution of reservoir scouring intensity, and cannot quantitatively divide different flow field regions, nor can it characterize the development location and degree of dominant flow fields. In addition, the time-varying displacement flux includes the combined scouring intensity of the oil phase and water phase, while the dominant channeling channels are controlled by the scouring effect of injected water. Therefore, based on the time-varying displacement flux, this paper further proposes the time-varying water phase displacement flux.

$$D_w = \frac{Q_w}{\phi A} = \sum_{i=t_1}^{t_2} \sqrt{\left(\frac{Q_{wxi}}{\phi A_x}\right)^2 + \left(\frac{Q_{wyi}}{\phi A_y}\right)^2 + \left(\frac{Q_{wzi}}{\phi A_z}\right)^2} \tag{7}$$

The time-varying water phase displacement flux characterizes the dynamic water phase scouring degree, and the change value of oil saturation characterizes the degree of oil phase displacement within a certain period of time. The two are combined into a new dominant flow field evaluation indicator—the dynamic oil-flux ratio, which refers to the change in grid oil saturation caused by the water flow over a period of time. Its expression is:

$$F = \frac{(S_{oi} - S_o)}{D_w} \tag{8}$$

where:

Q_x, Q_y, Q_z—Cumulative fluid volume in *x*, *y*, z directions, m^3;

A_x, A_y, A_z—Grid cross-sectional area in *x*, *y*, z directions, m^2;

Q_{wx}, Q_{wy}, Q_{wz}—Water volume passing through the cross-section per unit time in *x*, *y*, *z* directions, m^3/s;

S_o—Oil saturation; S_{oi}—Original oil saturation; ϕ—Porosity;

t_1—Start time; t_2—End time.

4. Evaluation Method for Time-Varying Three-Dimensional Dominant Flow Fields

To establish the flow field evaluation method, first, the indicators are screened based on logical analysis, then the static and dynamic indicators are read and calculated respectively. The normalization function is introduced for normalization to establish the dynamic and static evaluation indicators respectively. Then, fuzzy C-means clustering is used for classification, and the silhouette coefficient is used to optimize the number of classifications. Finally, the classification level and results of the dominant flow field are determined.

4.1. Normalization Processing

Since the dynamic oil-flux ratio and the static development index have different dimensions, to eliminate the influence of dimensions between them and make the model more stable and converge faster, after eliminating the extreme values in the samples that may affect the results, the membership function is selected to normalize the data. The linear normalization method is used to normalize the static development index and the dynamic oil-flux ratio respectively, mapping the data values to the range of [0, 1]. The formula is expressed as:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{9}$$

4.2. Optimization of Clustering Methods

Common classification methods include fuzzy comprehensive evaluation and cluster analysis. The fuzzy comprehensive evaluation method has heavy subjective factors in determining indicator boundaries and weights, which will affect the identification results. Cluster analysis is a commonly used data analysis method used to group samples in a dataset according to their similarity. Common clustering methods include K-means clustering, hierarchical clustering, DBSCAN clustering, etc. The K-means clustering method is sensitive to the selection of initial clustering centers, while hierarchical clustering and DBSCAN clustering are not efficient enough in processing large-scale data. Fuzzy C-means clustering analysis has higher objectivity compared with comprehensive evaluation, better robustness compared with other clustering methods, and more efficient data processing, which can greatly improve the identification accuracy. The idea of the fuzzy C-means clustering algorithm is to determine the membership matrix U and cluster centers V such that the objective function $J_m(U, V)$ is minimized. The steps of the algorithm are as follows [18]:

1) Given the sample set $X = \{x_1, x_2, \cdots, x_n\}$, determine the number of categories $C\,(2 \le C \le N)$, the fuzzy weight index m and an appropriately small iterative stop threshold ε;

2) Set the initial membership matrix $U(s)$, and set the number of iterations $s = 0$;

3) Calculate the clustering center $v_i^{(s)}$ at time $U(s)$:

$$v_i^{(s)} = \frac{\sum_{j=1}^{N} \mu_{ij}^m x_j}{\sum_{j=1}^{N} \mu_{ij}^m}, \quad i = 1, 2, \cdots, C \tag{10}$$

4) Modify the membership matrix $U(s)$, and calculate the objective function J_m^s:

$$\mu_{ij}^{(s)} = \frac{1}{\sum_{k=1}^{C} \left(\frac{d_{ij}}{d_{kj}} \right)^{\frac{2}{m-1}}} \tag{11}$$

$$J_m^s \left(U^{(s)}, V^{(s)} \right) = \sum_{j=1}^{N} \sum_{i=1}^{C} u_{ij}^m d_{ij}^2 \tag{12}$$

5) For a given threshold $U > 0$, if the objective function $\left\| J_m^s - J_m^{s-1} \right\| \le \varepsilon$, the algorithm terminates; otherwise, go to step (3).

4.3. Determination of Grading Standards

The silhouette coefficient is an evaluation indicator of the density and dispersion of clusters. It is an evaluation method to reflect the quality of clustering results. The closer the silhouette coefficient is to 1, the better the clustering effect; if the silhouette coefficient is close to −1, it indicates that the clustering is unreasonable. The silhouette coefficient of a dataset for a certain clustering can be derived from the silhouette coefficient of individual samples:

$$s_k = \frac{1}{n} \sum_{i=1}^{n} \frac{b_i - a_i}{\max\left(a_i, b_i\right)} \tag{13}$$

Where, a_i is the average distance between the sample and other samples in the same cluster; b_i is the minimum value of the average distance between the sample and all samples in other clusters; n is the number of samples in the dataset; S_k is the number of clusters for the silhouette coefficient.

5. Case Application

Q Oilfield is a large-scale complex fluvial heavy oilfield with a large-scale low-amplitude anticlinal structure. The average porosity is 32%, the average permeability is 2300 mD, and the underground crude oil viscosity is 22 - 260 mPa·s. At present, the oilfield has entered the development stage of high recovery degree and ultra-high water cut. After long-term water injection development, the intra-layer and plane contradictions have become increasingly acute, the high water consumption zones are well-developed, and the problem of ineffective water circulation is prominent, resulting in high water cut and low recovery degree. To facilitate the subsequent targeted implementation of ineffective circulation channel treatment strategies, it is necessary to divide the development degree of the dominant flow field.

Since the dynamic oil-flux ratio and static development index of the model calculated by the above method have different scales, it is necessary to normalize the parameters used according to the linear normalization method, and the processed results are used for the next calculation.

For the late development stage of the reservoir dominant flow field, based on the dynamic oil-flux ratio and static development index, fuzzy C-means cluster analysis is used, and the grading categories are set to 3 - 7 respectively. The silhouette coefficients under different grading numbers are calculated. Through calculation, the grading number corresponding to the maximum silhouette coefficient that is closest to 1 is 4, so 4 is the optimal grading number. Taking 4 as the grading number, the flow field grading of Q Oilfield is carried out. Since FCM clustering is sensitive to the initial clustering center, different initial clustering centers will lead to different clustering results. If the dimension used for classification is high, the clustering results will be different each time. In this paper, the method of reducing the dimension of the target parameters is adopted, and the classification results obtained through multiple experiments are more stable.

The final clustering results are shown in **Figure 4** and **Table 2**. Among them, the injected water scouring is severe in the strong dominant flow field, and the oil displacement rate is low, followed by the weak dominant flow field; the potentially developing flow field has strong dynamic heterogeneity in this area, but the water injection has not been scoured or the scouring degree is not high. This area has the potential to develop into a dominant channel, but it has not yet developed.

Table 2. Results of flow field development levels.

Classification level	Dynamic oil-flux ratio	Static development index	Development type
Level I	0.02	0.215	Strongly developed area
Level II	0.41	0.249	Weakly developed area
Level III	0.97	0.395	Potentially developed area
Level IV	0.99	0.188	Undeveloped area

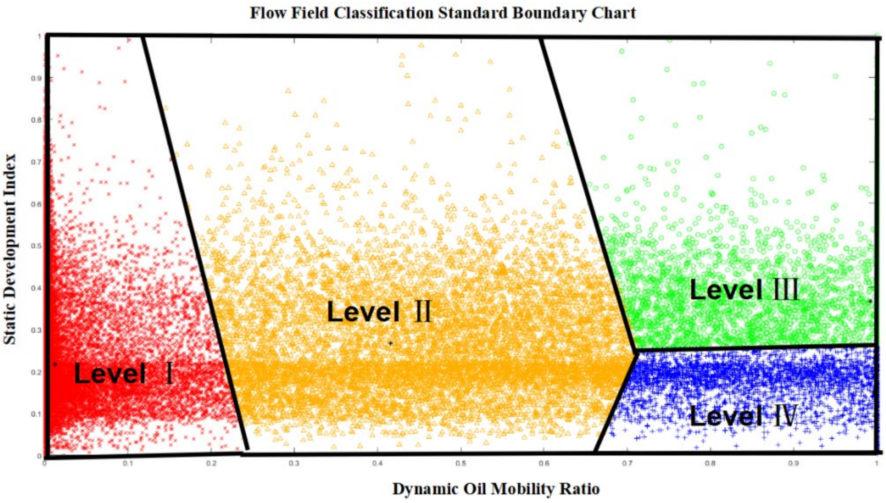

Figure 4. Distribution map of clustering results.

During the production and development process of the oilfield, different periods have different degrees of water phase scouring and oil phase displacement, thus resulting in different dynamic oil-flux ratios. Based on the dynamic oil-flux ratio and static development index in different periods, the dominant flow field is classified, and the time-varying classification results of the dominant flow field are formed as shown in **Figure 5**.

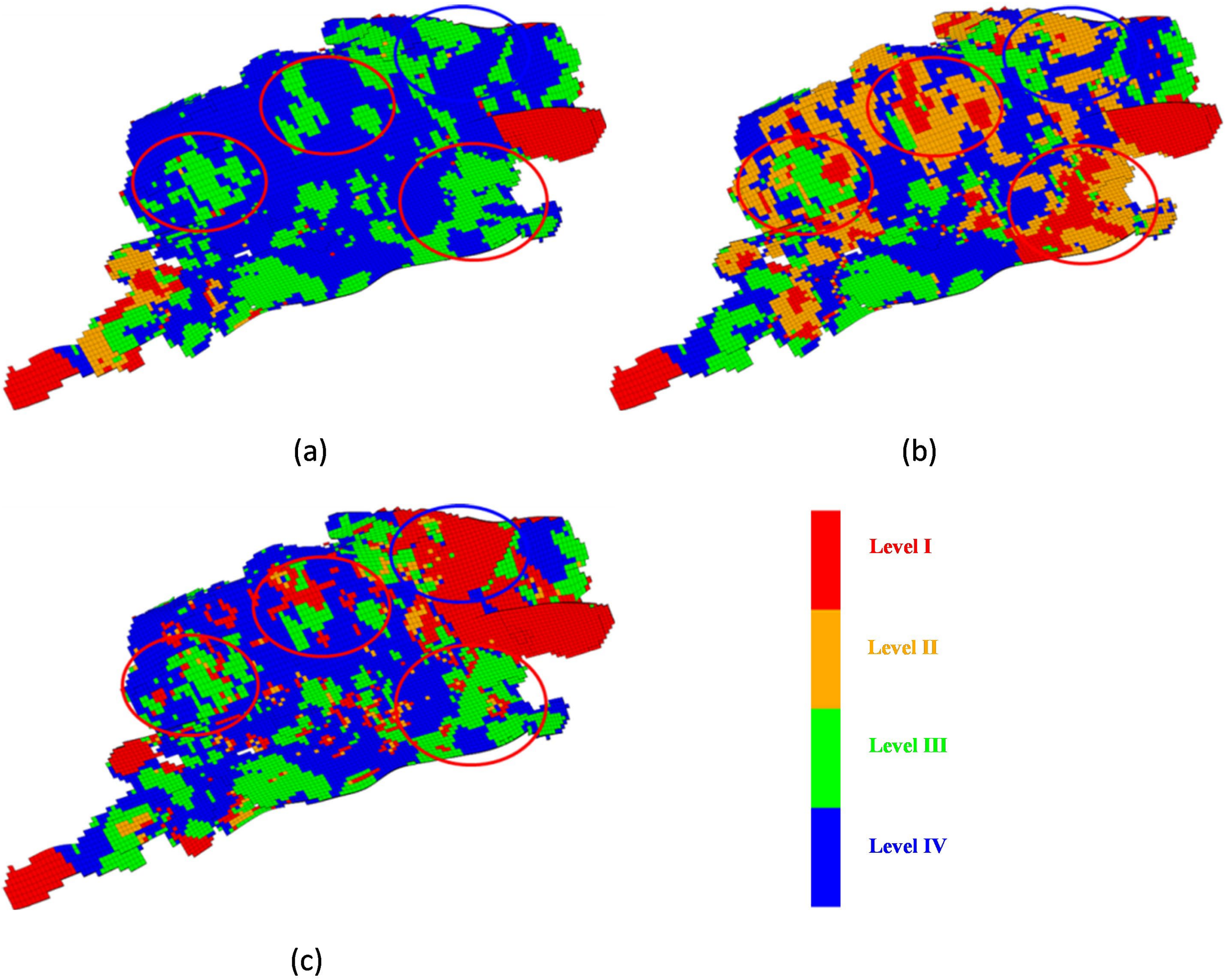

Figure 5. Classification results of dominant flow fields in different periods of area S, Q oilfield. (a) Undeveloped Stage; (b) Early Development Stage; (c) Late Development Stage.

Before the development of the dominant flow field, there were no obvious channeling areas except for the serious water flooding in the southwest and east edge water areas. In the early development stage of the dominant flow field, the dominant channeling channels began to develop, and most of the flow field development areas were the potentially developed areas identified in the undeveloped flow field, indicating that this method has a certain predictive significance. In the early stage of dominant flow field development, the dominant channeling channels were not fully developed, and the dominant flow fields were not concentrated. In the late development stage of the dominant flow field, the dominant channeling channels were maturely developed, the dominant flow fields began to develop concentratedly, and most of the development levels were Level I.

To further verify the effectiveness of the hierarchical evaluation method for dominant flow fields in the ultra-high water cut stage based on viscous fingering characterization proposed in this paper, a typical technology applied in reservoir flow field evaluation in recent years—namely the "flow field hierarchical method based on unsupervised machine learning (FCM + silhouette coefficient)" proposed by Yin Yanjun [19]—was selected for quantitative comparison. The results show that in terms of flow field classification accuracy, when the method in this paper is applied to Oilfield Q, the accuracy reaches 92.5%, which is 4.2 percentage points higher than the 88.3% accuracy of the unsupervised machine learning method applied to Oilfield D. Moreover, the recognition deviation for "potentially developing flow fields" is controlled within 4.2%, which is significantly better than the 5% - 7% deviation range of the latter method. In terms of computational efficiency, the method in this paper simplifies the analysis through AHP dimension reduction, with the evaluation time per well group being 5.2 hours—23.5% shorter than the 6.8 hours required by the unsupervised machine learning method. While ensuring evaluation accuracy, it also takes computational efficiency into account, making it more suitable for the flow field evaluation needs of complex reservoirs in the ultra-high water cut stage.

6. Conclusions

1) Based on experimental analysis, this paper proposes the viscous fingering growth function and viscous fingering number to describe the microscopic viscous fingering phenomenon and realize the numerical simulation characterization of viscous fingering.

2) The numerical simulation correction method embedded with viscous fingering parameters proposed in this paper can accurately locate ineffective circulation channels, and the supporting flow field classification template can quickly determine the priority of regulation. It can support the planning of development stages and the optimization of resource allocation, providing reliable technical support for extending the economic development life of ultra-high water cut oilfields (especially fluvial heavy oil reservoirs).

3) This method has significant scale dependence. The grid size directly changes the distribution of the viscous fingering number and the flow field classification results by affecting the characterization accuracy of seepage parameters. Without recalibration, when migrating to a more refined model, some core functions can be retained, but the accuracy will be limited by parameter adaptability; when migrating to a coarser model, the error is significant, making it difficult to ensure the reliability of evaluation.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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