

# **PS Identifying Flow Units of Low-permeability Sandstone Reservoirs Based on Self-organizing Map Neural Network Algorithm\***

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## **Abstract**

Daluhu Area is located in the northwestern part of Boxing Depression in Dongying Sag, Jiyang Depression, Bohai Bay Basin, China. The Middle Es<sub>3</sub> Member of the Paleogene in Daluhu area is a typical sedimentation of turbidite fans. The reservoir architecture is complex, and the sand and mud combination is diverse. At present, the study on reservoir architecture and genesis mechanism of the turbidite channel reservoir has been carried out. The research of reservoir architecture is of great significance for the study of flow unit. Therefore, the distribution of flow unit based on reservoir architecture has become the focus of current research. Based on available reservoir architecture division, this paper quantitatively evaluated the flow unit by applying the self-organizing neural network in the supervised mode. The performance of the model was tested by training samples. Finally, the distribution of flow unit was analyzed based on the study of reservoir architecture. The results are of great significance for oilfield development and residual oil prediction. The results show that: (1) According to the genetic type and sedimentary model of the turbidite channel, the reservoir in the study area can be further divided into three types of single channel. The relationship between seepage barriers and architecture surfaces was summarized from the levels of single channel, composite channel, and channel system. (2) The algorithm of self-organizing neural network can output the optimal prediction model by means of neuron competition learning and mutual supervision. The accuracy rate of the training samples reached 89.34%. The prediction results of the flow unit are basically consistent with the qualitative division results and the initial productivity characteristics of the wells. The algorithm provides a new means for the study of flow units. (3) The reservoir architecture has a great influence on the flow unit distribution. Vertically, the flow unit in different types of single channels may vary greatly, causing the difference of flow unit distribution. Laterally, influenced by the sedimentary evolution stages of channels systems, lateral division of flow unit is different. Horizontally, due to the migration and vertical accretion of the single channels, the distribution of flow unit in the composite channel is significantly different.



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## INTRODUCTION

- The Bohai Bay Basin is a major petroliferous basin located in northeast China, with an area of 200 000 km<sup>2</sup>. It is a Cenozoic rift—depression basin. The Boxing Sag is developed on the north-dip faulted block in the Dongying Depression within the Jiyang Sub-basin, Bohai Bay Basin (Fig. 1) .
- The Daluhu Oilfield is located in the northwestern part of the Boxing Sag. The average porosity and permeability of the reservoir are 15.9% and 11.6 mD, respectively (Fig. 2), a typical low-permeability reservoir.

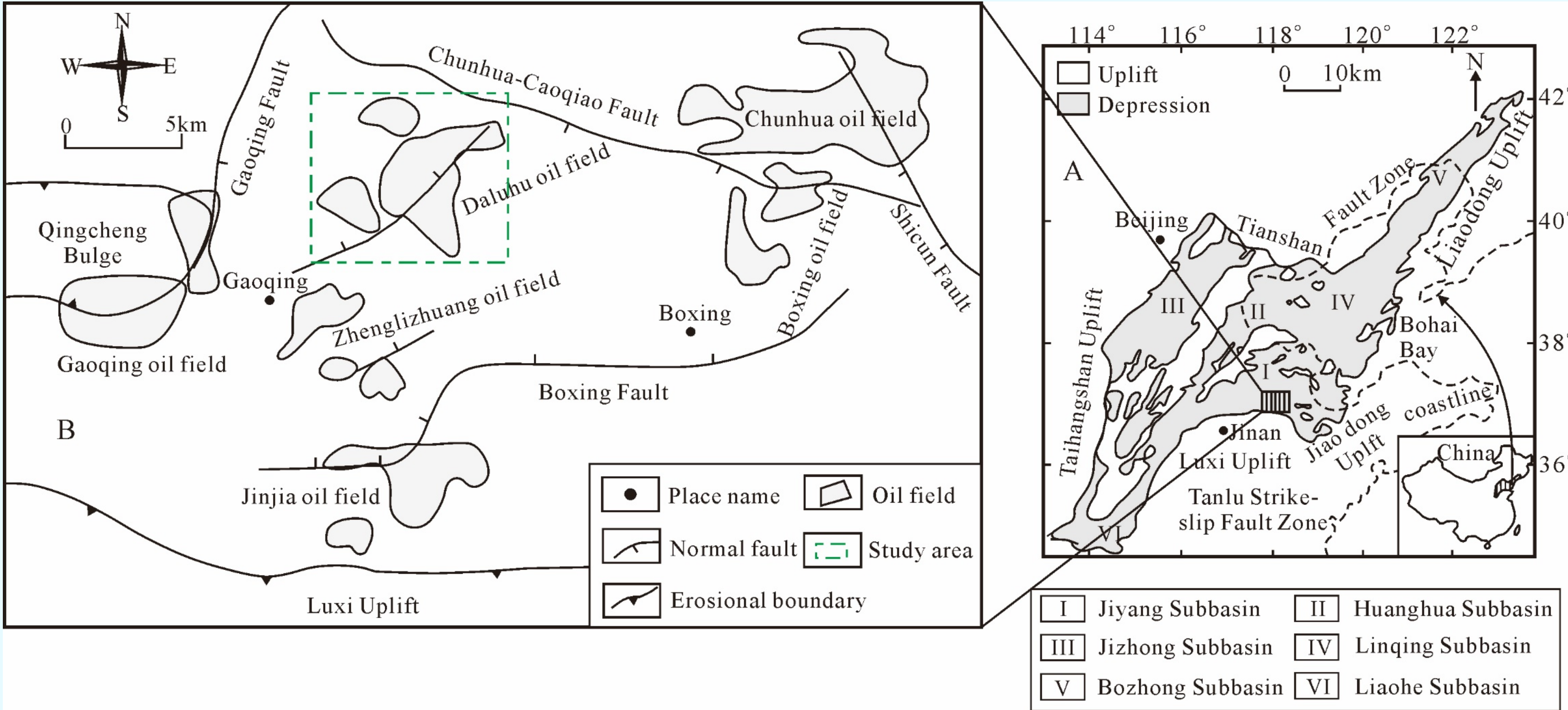


Fig. 1 Geological location of the Daluhu Oilfield in the Bohai Bay Basin

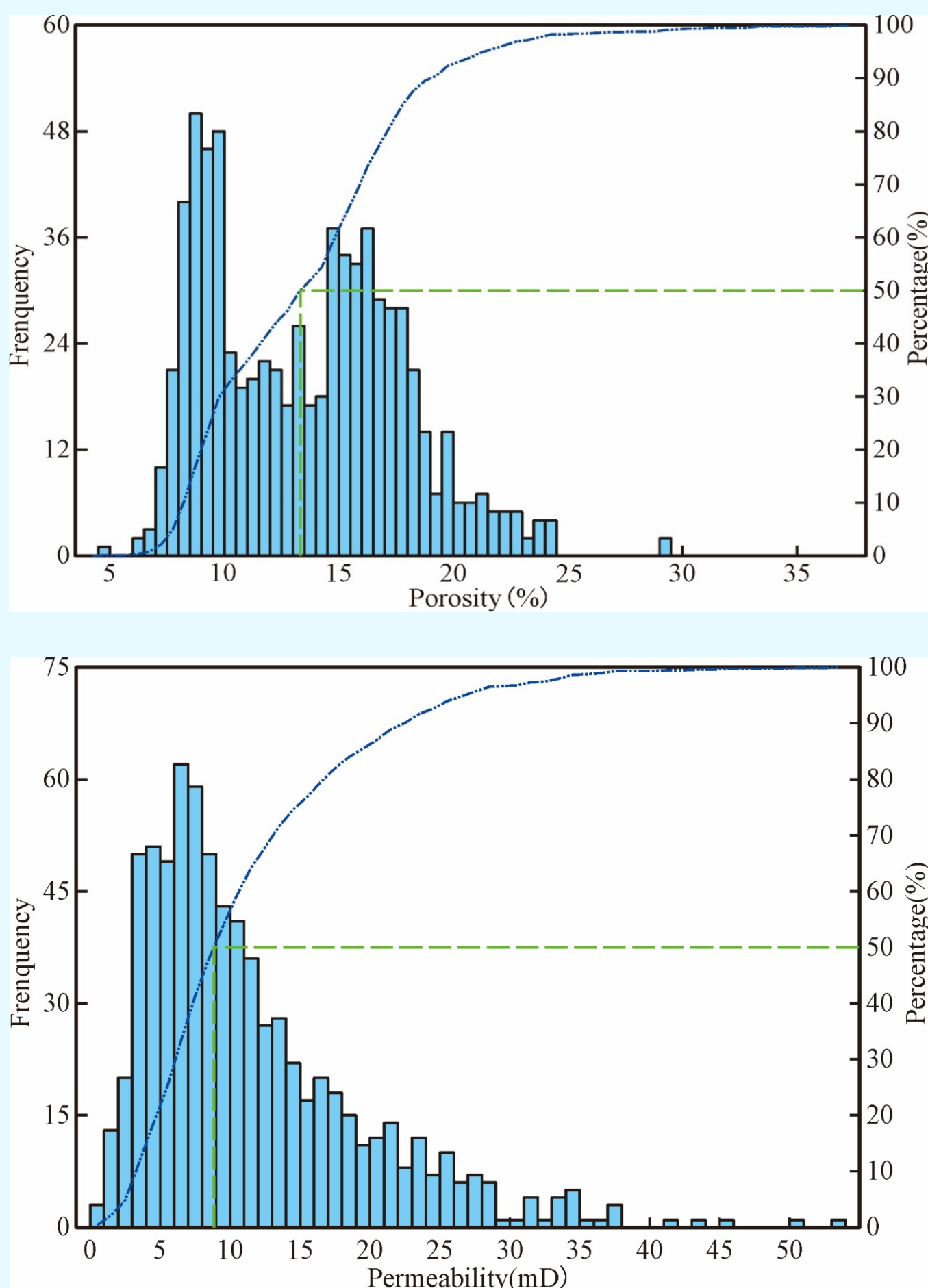


Fig. 2 Petrophysical properties of the reservoirs investigated

## THEORY AND METHOD

➤ Self-organizing map (SOM) neural network in the supervised mode (SSOM) was employed to quantitatively evaluate the flow units in the Daluhu Oilfield . SSOM is a machine learning algorithm based on SOM. The network structure consists of an input layer, a competition layer and an output layer. The essence of the algorithm is to compute the weighted correction of the competing layer neuron nodes by analyzing the matching degree between the predicted and the actual flow unit types (Fig. 3) .

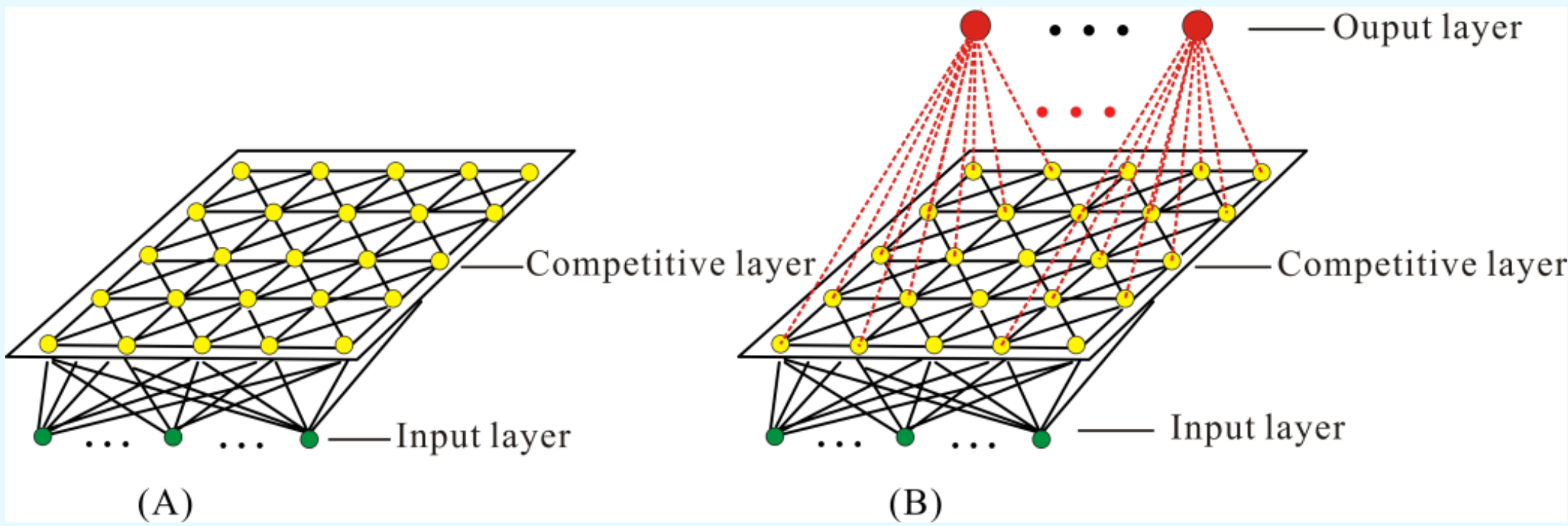


Fig. 3 Diagrams illustrating the neuron network structures of SOM (A) and SSOM (B)

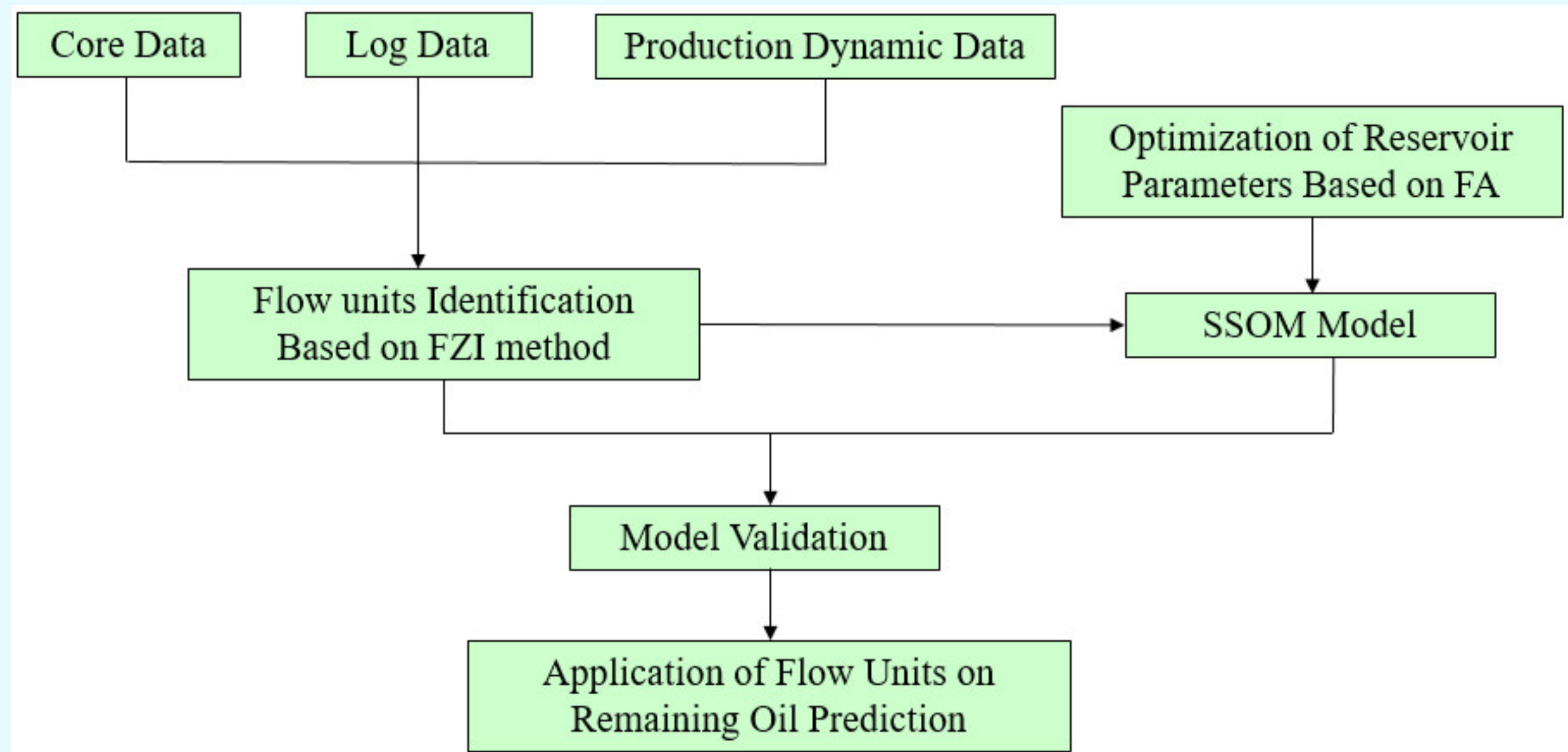


Fig. 4 Flow units identification workflow

➤ As pore structure has a great influence on the distribution of flow units in low-permeability reservoirs, this paper selected the Flow Zone Index (*FZI*) method, and combined with the petrophysical characteristics and dynamic production data to identify flow units in cored wells (Fig. 4) .

➤ Five principal factors (flow, sedimentary, interlayer, heterogeneity and petrophysical factors) ranked by factor analysis were taken as the input for the neural network model; while the flow unit types classified by the *FZI* method were taken as the output of the model. Finally, the prediction model with reliable accuracy and fast iteration speed is established by using the SSOM algorithm. (Fig. 4) .



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## RESULTS

➤ The reservoirs are classified into four types of flow units by using the *FZI* method and combined with petrophysical characteristics and dynamic production data (Fig. 5; Table 1) .

➤ The Type I and II flow units have the best percolation capacity and reservoir quality with the highest initial oil productivity. The Type III flow unit has a good percolation capacity and reservoir quality, whereas the Type IV flow unit has a poor percolation capacity and reservoir quality with the lowest initial oil productivity (Table 1) .

Table 1 Classification criteria for different types of flow units

Parameters	HFU1		HFU2		HFU3		HFU4	
	Range	Average	Range	Average	Range	Average	Range	Average
Porosity (%)	8.29~14.3	10.18	8.23~20.1	11.46	10.64~23.5	16.26	14.7~29.0	20.55
Permeability (mD)	12.1~53.4	22.97	5.9~33.2	12.90	3.6~28.6	11.34	3.1~16.7	8.57
R <sub>35</sub> (μm)	3.43~5.92	4.39	1.81~4.61	2.86	1.16~2.88	1.91	0.75~2.34	1.37
FZI(μm)	>0.36	0.401	0.16~0.36	0.262	0.09~0.16	0.127	<0.09	0.072
Daily oil production(t)	24.3~42.4	29.4	14.6~22.8	18.1	3.5~13.4	7.3	1.1~4.7	2.3
Daily fluid production(t)	26.4~42.9	34.2	15.9~29.1	22.1	6.7~30.2	13.7	1.7~16.7	6.8
Water content(%)	49.3~97.5	77.1	40.2~90.1	64.5	22.3~62.8	33.6	20.0~45.7	29.2
H(m)	0.7~10.6	4.17	0.7~8.8	3.77	0.6~7.6	3.35	0.5~6.4	2.55
Vsh(%)	6.75~53.55	26.65	4.34~69.19	32.71	3.29~77.35	34.15	7.58~78.05	43.69

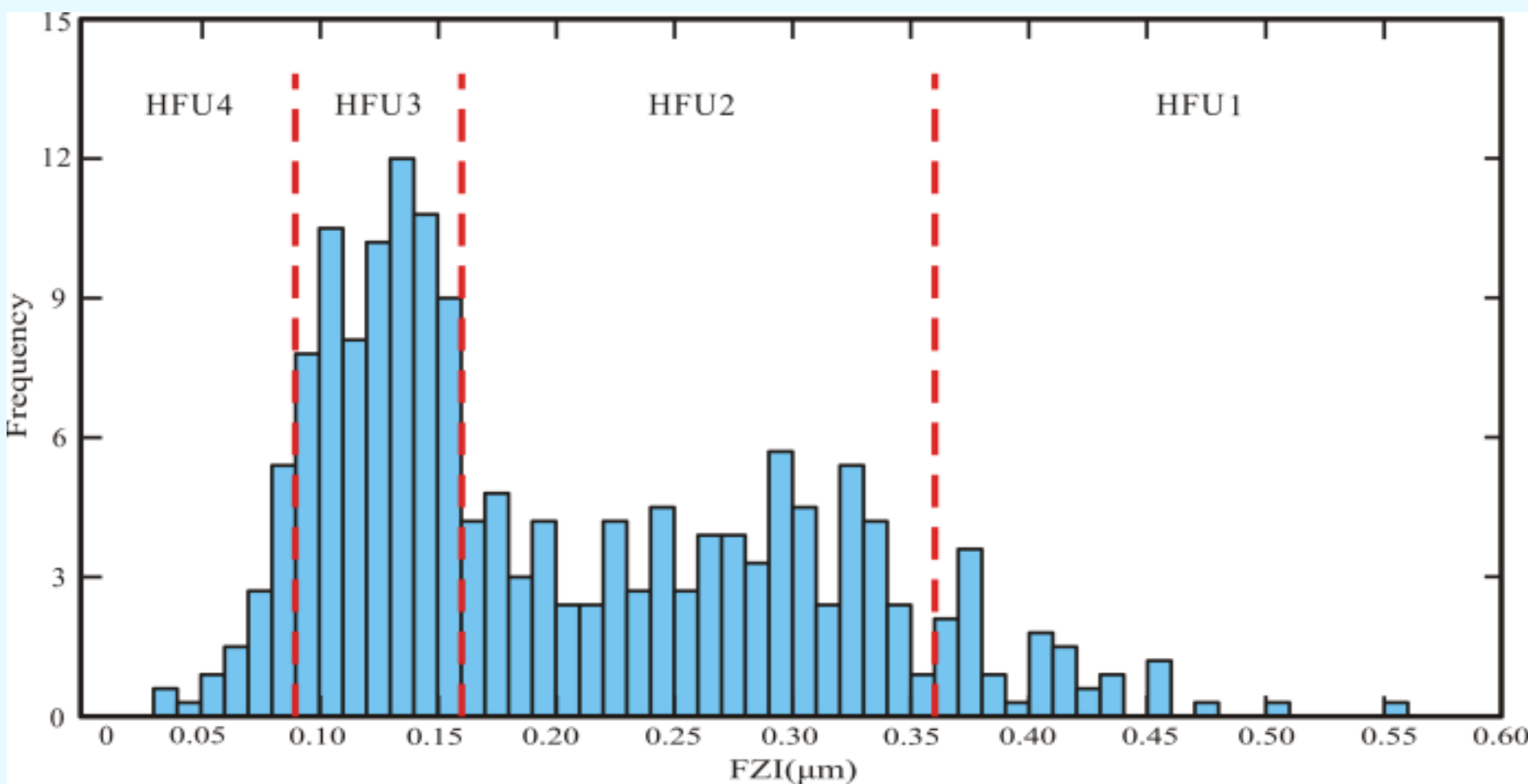


Fig. 5 Histogram and cumulative probability of *FZI*

➤ Forty-four out of 256 groups of samples were misjudged with an accuracy rate of 82.81%. Therefore the SSOM prediction model is an effective method for identifying flow units (Fig. 6; Fig. 7; Table 2) .

## DISCUSSION

➤ There is a good correlation between the flow unit types and the initial oil productivity (Fig. 8). The remaining geological reserve and recovery factor in different types of flow units are different (Fig. 9). The remaining oil is mainly stored in Type II and Type III units, where the remaining geological reserves are high (Fig. 8). They are the target units for future remaining oil development (Table 3) .

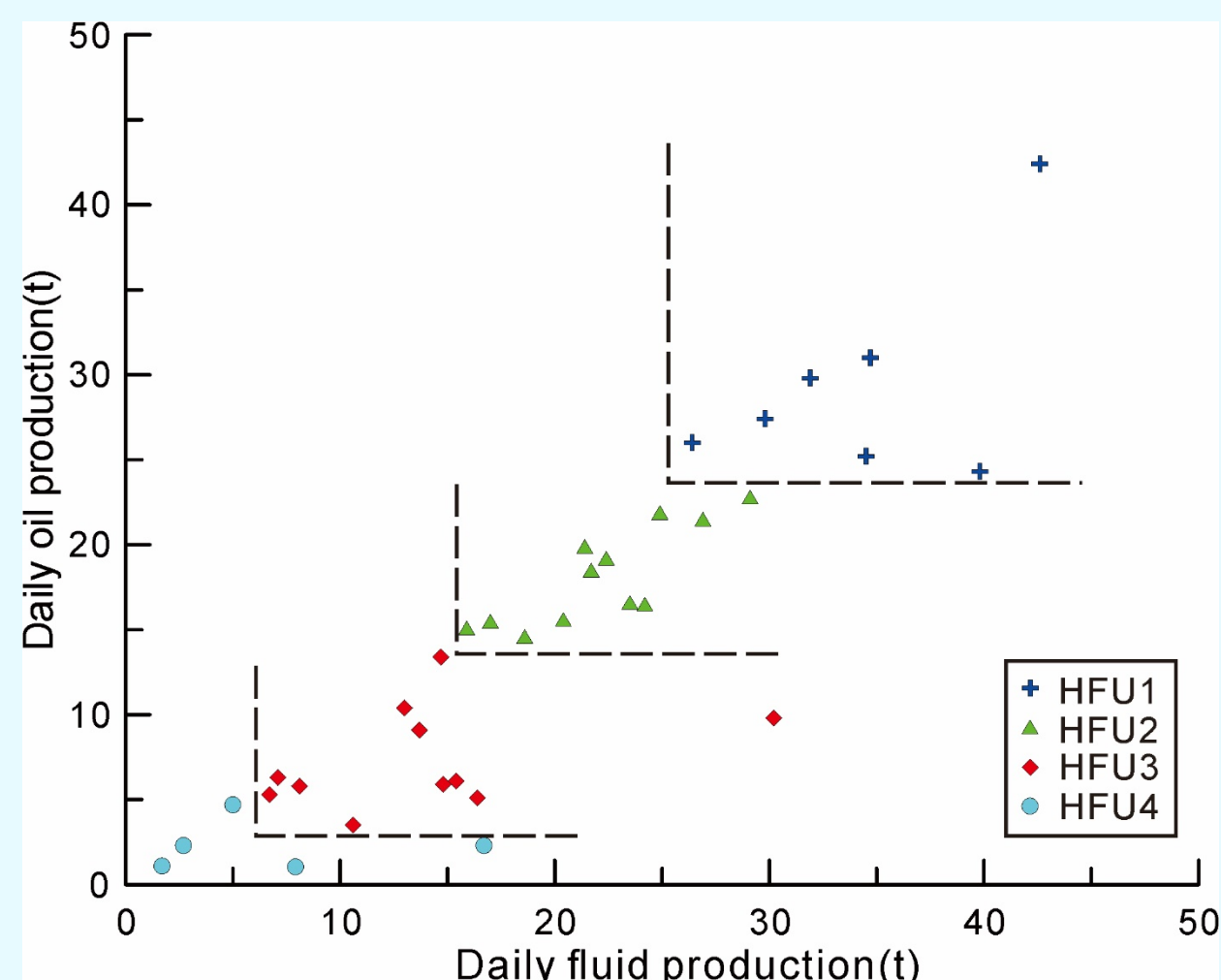


Fig. 8 Characteristics of initial oil productivity and water content of flow units

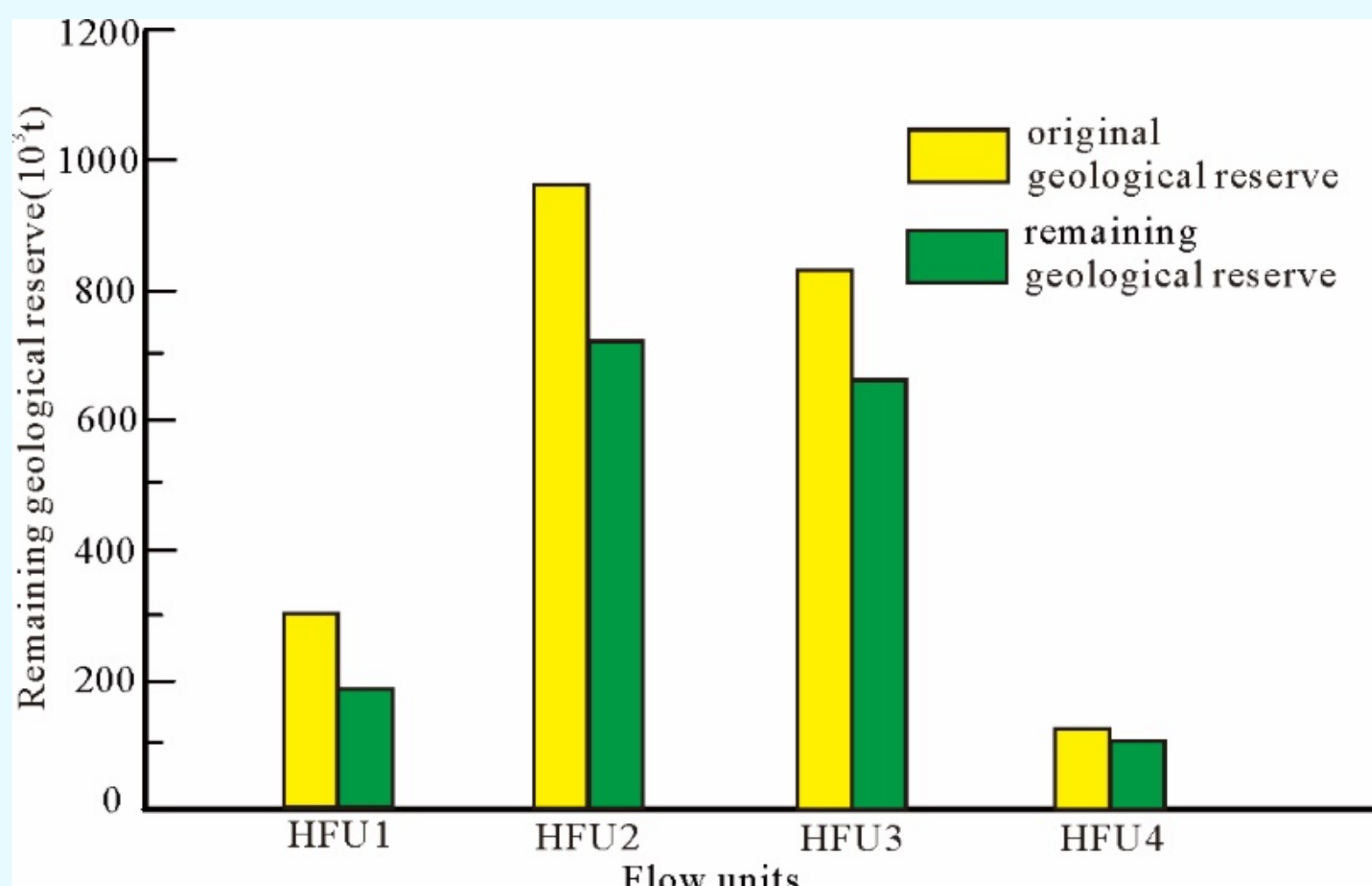


Fig. 9 Distribution (histogram) of geological reserve in different types of flow units

Table 3 Statistics of geological reserve, recovery factor and remaining oil saturation in different types of flow units

Flow unit type	Ratio of original geological reserve to total (%)	Recovery factor (%)	Ratio of remaining geological reserve to total (%)	Remaining oil saturation (%)	Cumulative production (10 <sup>3</sup> t)
HFU1	13.35	36.98	11.13	30.85	109.7
HFU2	43.42	25.11	43.07	35.53	242.3
HFU3	37.49	20.66	39.40	32.77	172.1
HFU4	5.74	15.76	6.40	24.59	20.1

➤ Model validation has been performed on the F8-22 well. The prediction results of SSOM are basically consistent with the results of core analysis and well testing, i.e. the predicted flow units are Type II and I units at depths 2823 m and 2828 m, respectively, and well testing shows a high initial productivity (Fig. 10).

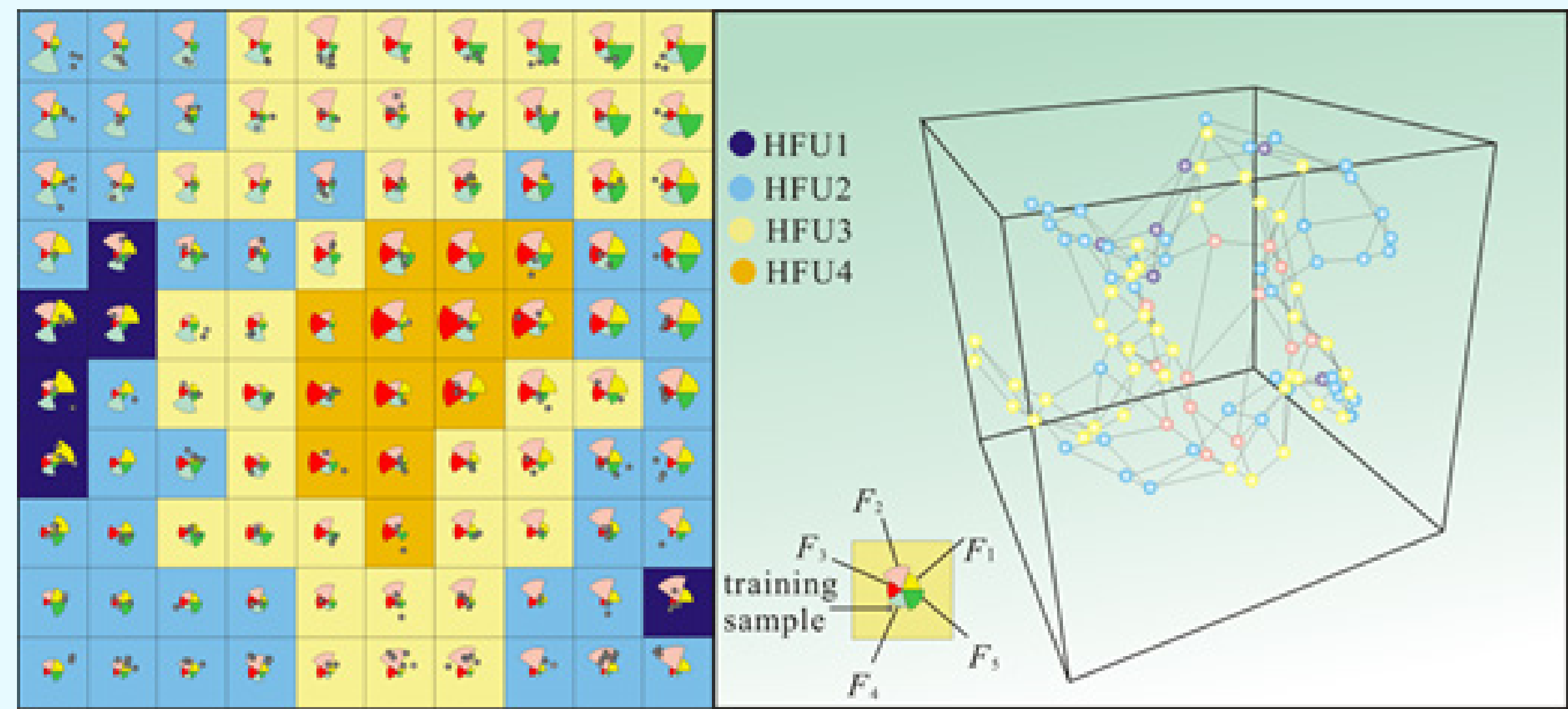


Fig. 6 Self-organizing map topology and 3D Sammon mapping projection of the competing neuron nodes

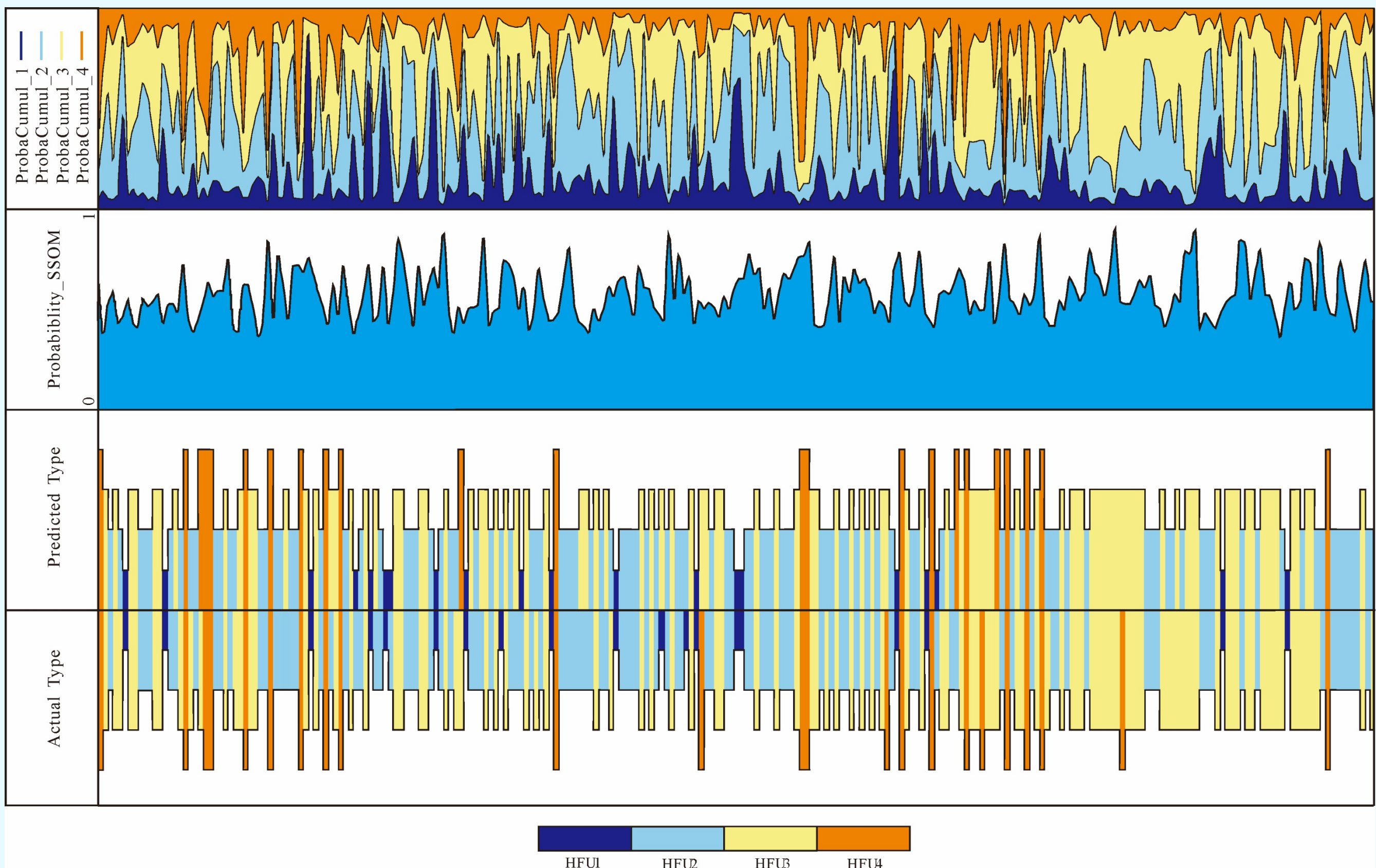


Fig. 7 Classification results of flow units using SSOM

Table 2 Prediction accuracy of flow units based on SSOM

Flow unit type	HFU1	HFU2	HFU3	HFU4	Total
Number of training samples	19	106	108	23	256
Number of predicting samples	16	90	87	19	212
Prediction accuracy	84.21%	84.91%	80.56%	82.61%	82.81%

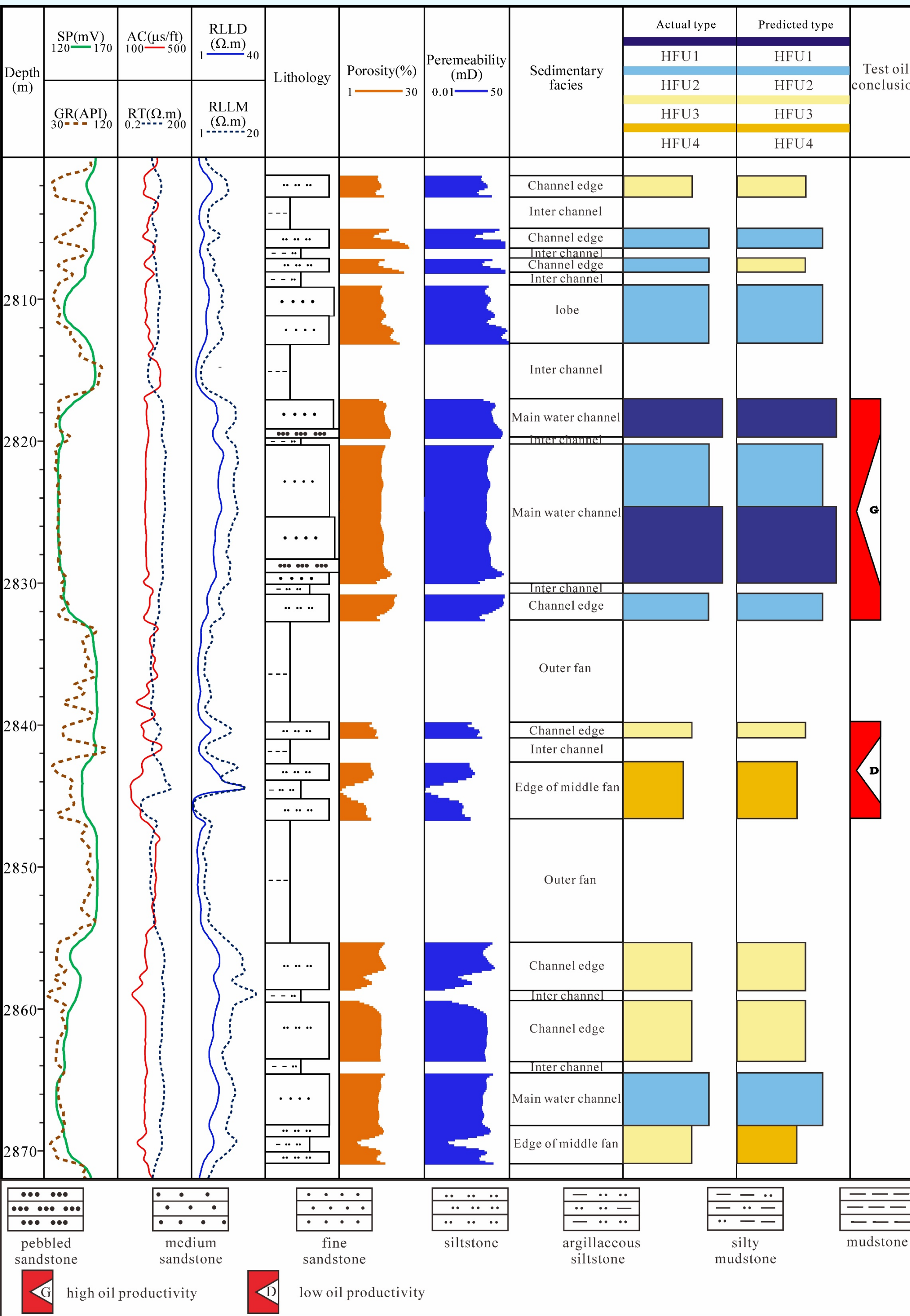


Fig. 10 Flow unit type prediction for Well F8-22