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Development of Geostatistical Models for Assessing the Confirmability of Geomorphological Characteristics of the Geological Structures (Bashkir Svod, Perm Krai)

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Разработка геолого-статистических моделей для оценки подтверждаемости геолого-морфологических характеристик структур Башкирского свода Пермского края

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Today, despite the relatively high accuracy of preparing geological structures for deep drilling in the Perm Krai using 3D seismic, there is a discrepancy between the geological and morphological characteristics of structures before drilling and according to drilling results, which makes it necessary to develop a geological and statistical approach that makes it possible to more accurately assess the risks of non-confirmation of the geological and morphological characteristics of structures prepared for deep drilling, as well as to determine the priority of objects for further geological exploration work.
This work describes one of the options for developing a geological and statistical approach for rank differentiation of 25 structures of the II^{K} seismic reflector and 21 structures of the $II^{П}$ seismic reflector, prepared by 3D seismic exploration. These structures has been already drilled by prospecting and appraisal wells within the Bashkir arch (Perm Krai).
The initial data for the analysis were from the passport of structures prepared for deep drilling: the amplitude of the structure, the structure area according to the corresponding reflecting horizon, the ratio of the structure length to its width, the angle between the long axis of the structure and the axis of the nearest tectonic second order element, the distance from the structure to the edge of the nearest second order tectonic element and the distance from the structure to the center of the nearest second order tectonic element.
For each model, the nature and degree of influence of the studied indicators on the confirmability of the amplitude by drilling was determined and described.
The assessment of differentiation of structures by class and the accuracy of determining class boundaries were confirmed when classifying the structures of the test sample using discriminant analysis.
This geological and statistical approach can be used for a more accurate assessment of the risks associated with the problem of the unconfirmability of the geological and morphological characteristics of structures prepared for deep drilling, as well as for identifying priority objects for geological exploration work, regardless of their geographical location and belonging to tectonic elements.

Ключевые слова:
геолого-морфологические характеристики, амплитуда структуры, ранжирование структур, геолого-разведочные работы, подтверждаемость структур глубоким бурением, оценка рисков, отражающий горизонт, геолого-статистический анализ, дискриминантный анализ.

В настоящее время, несмотря на относительно высокую точность подготовки структур к глубокому бурению, в Пермском крае по данным сейсморазведочных работ 3D наблюдается несоответствие между геолого-морфологическими характеристиками структур по результатам бурения и характеристиками по данным паспорта подготовленной структуры к глубокому бурению, из-за чего возникает необходимость разработки геолого-статистического подхода, позволяющего более точно оценить риски неподтверждения геолого-морфологических характеристик подготовленных к глубокому бурению структур, а также определить первоочередность объектов для дальнейших геологоразведочных работ.
В данной работе рассматривается один из вариантов разработки геолого-статистического подхода к классовой дифференциации 25 структур отражающего горизонта $II^{К}$ и 21 структуры отражающего горизонта $II^{П}$, подготовленных сейсморазведочными работами 3D и на текущий момент уже разбуренных поисково-оценочными скважинами в пределах Башкирского свода Пермского края.
Исходными данными для анализа являлись следующие данные по паспорту подготовленных к глубокому бурению структур: амплитуда структуры, подготовленной к глубокому бурению по данным паспорта, площадь структуры по соответствующему отражающему горизонту, отношение длины структуры к её ширине, угол между длинной осью структуры и осью ближайшего тектонического элемента второго порядка, расстояние от структуры до края ближайшего тектонического элемента второго порядка и расстояние от структуры до центра ближайшего тектонического элемента второго порядка. Для каждой модели были определены и описаны характер и степень влияния изученных показателей на подтверждаемость амплитуды бурением.
Оценка дифференциации структур по классам и точность определения границ классов были подтверждены при классификации структур тестовой выборки с помощью дискриминантного анализа.
Данный геолого-статистический подход может применяться для более точной оценки рисков, связанных с проблемой неподтверждаемости геолого-морфологических характеристик подготовленных к глубокому бурению структур, а также для определения первоочередных объектов геолого-разведочных работ, независимо от их географического расположения и принадлежности тектоническим элементам.

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Introduction

At present, despite the relatively high accuracy of structure preparation for deep drilling, in Perm Krai, according to 3D seismic survey data, there is a discrepancy between the geological-morphological characteristics of structures based on drilling results and the characteristics based on the passport data of the prepared structures for deep drilling. Currently, despite the relatively high accuracy of preparing structures for deep drilling, there is a discrepancy in the Perm Krai between the geological-morphological characteristics of the structures based on drilling results and the characteristics according to the structural passport prepared for deep drilling, according to data from 3D seismic surveys. It makes necessary to develop for developing a geological-statistical approach that allows for a more accurate risk assessment of non-confirmation of geological-morphological character-ristics of structures prepared for deep drilling, as well as determining the priority of objects for further geological exploration work [1–10].

Differentiation of structures by prospectivity classes and justification of the boundaries of the identified classes

To analyze the amplitude dependencies of structures according to the data of prospecting and appraisal drilling (A_D) on various geological and morphological parameters, such as the amplitude of the structure prepared for deep drilling according to the passport data (A_P), the area of the structure according to the corresponding reflecting horizon (S_{RH}), the ratio of the structure's length to its width (D/S), the angle between the long axis of the structure and the axis of the nearest tectonic element of the second order (γ), the distance from the structure to the edge of the nearest tectonic element of the second order (L_E), the distance from the structure to the center of the nearest tectonic element of the second order (L_C), a stepwise multiple regression was performed in the Statistica software for groups of different numbers of structures N, drilled by prospecting and appraisal wells in the territory of the Bashkir arch of the Perm Krai [10–34].

The regression was performed for N from 3 to 18 structures including reflecting horizons (RH) II^E and II^P.

The ranking of the sample was made in increasing order of structure amplitudes confirmed by deep drilling (A_D).

Tables 1 and 2 present the results of the regression study $A_D = f(A_P, S_{RH}, D/S, \gamma, L_E, L_C)$ *for* RH II^E and II^P.

Results of the regression study for RH II^E and II^P allowed to combine the obtained geological-statistical models, similar in the nature of the influence of significant parameters. Thus, for both RH II^E and II^P, three classes of structures were identified [12–14].

The results of the regression study for RH II^E are presented in Table 1.

Class "0" RH II^E characterizes the interval N, where the formation of the first geological-statistical model is observed, caused by a gradual increase in N from 3 to 8. Stabilization of the first geological-statistical model occurs at N equal to 9. There are no statistically significant parameters in class “0”.

Class "1" RH II^E corresponds to the first stable geological-statistical model, observed at N from 9 to 12.

Statistically significant parameters that control the model in this interval are the angle between the long axis of the structure and the axis of the nearest second-order tectonic element (γ) and, fragmentarily, the amplitude of the structure prepared for deep drilling according to the passport data (A_P).

The coefficient of multiple correlation (R^2) in this interval varies from 0.629 to 0.777. The value of the p-criterion in the interval of the formed geological-statistical model varies from 0.051 to 0.002.

The reconstruction of the geological-statistical model from the first to the second occurs at N equal to 13.

Class "2" RH II^E corresponds to the second stable geological-statistical model, which can be observed at N from 13 to 18.

A statistically significant parameter in this interval is the amplitude of the structure prepared for deep drilling according to the pasport data (A_P).

The coefficient of multiple correlation (R^2) in this interval varies from 0.558 to 0.893. The value of the p-criterion in this interval of the formed geological-statistical model varies from 0.017 to 0.000.

The results of the regression study for RH II^E are presented in Table 2.

Class "0" RH II^P characterizes the interval N, where the formation of the first geological-statistical model is observed, caused by a gradual increase in N from 3 to 6. Stabilization of the first geological-statistical model occurs at N equal to 7. There are no statistically significant parameters in class “0”.

Class "1" RH II^P corresponds to the first stable geological-statistical model, observed at N from 7 to 14.

A statistically significant parameter controlling the model in this interval is the angle between the long axis of the structure and the axis of the nearest second-order tectonic element (γ).

The coefficient of multiple correlation (R^2) in this interval varies from 0.682 to 0.886. The value of the p-criterion in this interval varies from 0.000 to 0.004.

The reconstruction of the geological-statistical model from the first to the second occurs when N equals 15.

Class "2" RH II^P corresponds to the second stable geological-statistical model, which can be observed at N from 16 to 19.

Statistically significant parameters in this interval are the amplitude of the structure prepared for deep drilling according to the passport data (A_P), and, in part, the angle between the long axis of the structure and the axis of the nearest second-order tectonic element (γ).

The coefficient of multiple correlation (R^2) in this range varies from 0.847 to 0.880. The value of the p-criterion varies around 0.000.

A different dependence of A_D on the A_P, S_{RH}, D/S, γ, L_E, and L_C parameters is observed in different N intervals, which indicates the possibility of differentiating the A_D value into three ranges (classes) for each reflecting horizon.

The calculated boundary values of different A_D classes are taken as average values between the actual boundary values of the classes (Table 3) [32–38].

The dependencies of the free term (B) on the structure amplitude (A_D) for RH II^E and RH II^P are shown in Fig. 1.

Table 1

Results of the regression study for RH II^{E}

No	A_P, m	A_D, m	*B*, fractions of units	Coefficients for parameters, fractions of units.						R^2, fractions of units	*p*-cr., fractions of units	Class
				A_P	S_{RH}	D/S	γ	L_E	L_C			
1	10	3										
2	16	8										
3	14	9	-1.837		0.005				0.000	1.000		0
4	11	10	9.797		-0.001			-0.001	0.000	1.000		0
5	13	10	**7.866**					-0.001	0.000	0.957	0.043	0
6	11	11	**7.679**					-0.001		0.323	0.240	0
7	16	12	-0.311	1.334	-0.004		-11.989			0.575	0.405	0
8	15	13	**6.023**			1.543				0.305	0.156	0
9	13	17	7.138	0.573			**-0.202**			0.629	0.051	1
10	18	18	6.822	0.606			**-0.206**			0.745	0.008	1
11	15	19	7.353	**0.618**			**-0.230**			0.776	0.003	1
12	17	19	4.809	**0.818**			**-0.224**			0.754	0.002	1
13	17	19	-5.727	**1.575**		-1.946				0.558	0.017	2
14	20	26	-6.139	**1.708**		-2.061	-4.786			0.728	0.004	2
15	27	29	-2.119	**1.380**		-1.706	-5.074			0.785	0.001	2
16	26	31	-2.345	**1.399**		-1.735	-5.017			0.841	0.000	2
17	33	35	-0.983	**1.320**		-1.754	-5.668			0.880	0.000	2
18	29	39	-1.977	**1.402**		-1.992	-4.401			0.893	0.000	2

Note: statistically significant parameters are highlighted in bold here and in table 2, for which the value is *p*-criteria, characterizing the probability of an error of the first-order, less than or equal to 0.05; *N* – ordinal number of structures; *B* – free term of the regression model.

Table 2

Results of the regression study for RH II^{P}

No	A_P, m	A_D, m	*B*, fractions of units	Coefficients for parameters, fractions of units.						R^2, fractions of units	*p*-cr., fractions of units	Class
				A_P	S_{RH}	D/S	γ	L_E	L_C			
1	9	7										
2	14	7										
3	16	11	23.000				-24.000			1.000		0
4	15	14	14.407		0.007	-1.957	-18.397			1.000		0
5	14	16	12.512			1.357	-17.644	0.000	0.000	1.000		0
6	16	16	11.609		0.001	1.022	-18.136	0.000	0.001	1.000		0
7	18	18	**19.860**				**-0.204**			0.838	0.004	1
8	20	20	**19.915**				**-0.205**			0.883	0.001	1
9	21	20	**20.442**				**-0.216**			0.886	0.000	1
10	17	24	**21.303**				**-0.235**			0.886	0.000	1
11	18	26	**22.464**				**-0.252**			0.762	0.001	1
12	24	26	**23.101**				**-0.268**			0.784	0.000	1
13	19	28	**24.043**				**-0.279**			0.701	0.000	1
14	23	28	**24.816**				**-0.293**			0.682	0.000	1
15	31	36	6.972	**1.048**		-1.931	-0.115			0.847	0.000	2
16	34	36	7.590	**1.017**		-1.920	**-0.121**			0.878	0.000	2
17	32	39	4.113	**1.165**		-1.891	-0.080			0.880	0.000	2
18	33	45	1.203	**1.276**		-2.326				0.879	0.000	2

Table 3

Actual and calculated boundaries of classes

Class	Structure type	A_D for RH II^{E}, m		A_D for RH II^{P}, m	
		actual interval	calculated interval	actual interval	calculated interval
"0"	Low-potential	< 13	< 15	< 16	< 17
"1"	Medium-potential	17 < … < 19	15 < … < 19	18 < … < 28	17 < … < 32
"2"	High-potential	19 <	19 <	36 <	32 <

Table 4

Free term dependence of the regression equations (B) on the amplitude of the structure (A_D)

Parameter	RH	Class	Dependence equation	Coef. corr. r	Nature of correlation
A_D	II^E	"0"	$2.2536 + 0.2415 \cdot A_D$	0.074	Positive weak
		"1"	$16.5285 - 0.5478 \cdot A_D$	-0.449	Negative weak
		"2"	$-10.6977 + 0.2508 \cdot A_D$	0.812	Positive high
	II^P	"0"	$46.1277 - 2.1576 \cdot A_D$	-0.978	Negative high
		"1"	$10.9544 + 0.4648 \cdot A_D$	0.957	Positive high
		"2"	$31.3071 - 0.6753 \cdot A_D$	-0.977	Negative high

Table 5

Dependence of A_D on different parameters

Parameter (x)	RH	Class	Equation of dependence	Coef. corr. r	Nature of correlation
A_P	II^E	"0"	$6.25 + 0.3438 \cdot A_P$	0.482	Positive weak
		"1"	$14.7797 + 0.2203 \cdot A_P$	0.510	Positive average
		"2"	$3.0385 + 1.0577 \cdot A_P$	0,890	Positive high
	II^P	"0"	$32.2727 - 1.1818 \cdot A_P$	-0.479	Negative weak
		"1"	$14.6591 + 0.4545 \cdot A_P$	0.291	Positive weak
		"2"	$19.5 + 0.6 \cdot A_P$	0.183	Positive weak
γ	II^E	"0"	$12.5476 - 0.0857 \cdot \gamma$	-0.487	Negative weak
		"1"	$18 + 0.0667 \cdot \gamma$	0.522	Positive average
		"2"	$22.8814 + 0.3144 \cdot \gamma$	0.960	Positive high
	II^P	"0"	$17.2727 - 0.1152 \cdot \gamma$	-0.700	Negative average
		"1"	$24 - 2.5714 \cdot \gamma$	-0.058	Negative weak
		"2"	$30.2169 + 0.2602 \cdot \gamma$	0.807	Positive high
D/S	II^E	"0"	$8.7102 + 0.898 \cdot D/S$	0.751	Positive high
		"1"	$19.1133 - 0.6101 \cdot D/S$	-0.282	Negative weak
		"2"	$47.0413 - 11.3281 \cdot D/S$	-0.650	Negative average
	II^P	"0"	$14.7429 - 0.1969 \cdot D/S$	-0.093	Negative weak
		"1"	$30.0038 - 3.3265 \cdot D/S$	-0.719	Negative average
		"2"	$50.58 - 7.9237 \cdot D/S$	0,420	Positive weak
S_{RH}	II^E	"0"	$10.7303 + 8.3461E\text{-}5 \cdot S_{RH}$	0.034	Positive weak
		"1"	$18.6987 - 0.0002 \cdot S_{RH}$	-0.404	Negative weak
		"2"	$25.2196 + 0.0026 \cdot S_{RH}$	0.417	Positive weak
	II^P	"0"	$16.0155 - 0.0015 \cdot S_{RH}$	-0.372	Negative weak
		"1"	$26.0356 - 0.0011 \cdot S_{RH}$	-0.343	Negative weak
		"2"	$33.9529 + 0.0028 \cdot S_{RH}$	0.602	Positive average
L_E	II^E	"0"	$10.9675 + 0.0002 \cdot L_E$	0.268	Positive weak
		"1"	$18.0263 + 8.3775E\text{-}5 \cdot L_E$	0.632	Positive average
		"2"	$29.88 + 0.0002 \cdot L_E$	0,050	Positive weak
	II^P	"0"	$14.1998 + 0.0007 \cdot L_E$	0.696	Positive average
		"1"	$23.6705 + 0.0001 \cdot L_E$	0.174	Positive weak
		"2"	$39.0214 + 0.0003 \cdot L_E$	0.121	Positive weak
L_C	II^E	"0"	$10.9056 - 1.1629E\text{-}5 \cdot L_C$	-0.045	Negative weak
		"1"	$17.5669 + 6.2671E\text{-}5 \cdot L_C$	0.540	Positive average
		"2"	$24.5051 + 0.0006 \cdot L_C$	0.355	Positive weak
	II^P	"0"	$12.2836 + 0.0002 \cdot L_C$	0.424	Positive weak
		"1"	$22.9692 + 0.0001 \cdot L_C$	0.245	Positive weak
		"2"	$26.6512 + 0.0012 \cdot L_C$	0.531	Positive average

From Fig. 1 it is evident that according to RH II^E for class "0" there is a weak positive dependence of B on the A_D parameter, for class "1" – a weak negative dependence, for class "2" – a high positive dependence; according to RH II^P for class "0" – a high negative dependence; for class "1" – a high positive dependence; for class "2" – a high negative dependence [32–37].

The analysis of free member dependence of the regression equations (B) on the amplitude of the structure (A_D) for RH II^E and RH II^P are presented in Table 4.

The analysis of free member dependence of the regression equations (B) on the amplitude of the structure (A_D) for RH II^E and RH II^P proves that the definition of the boundaries of classes "0", "1" and "2" is performed correctly.

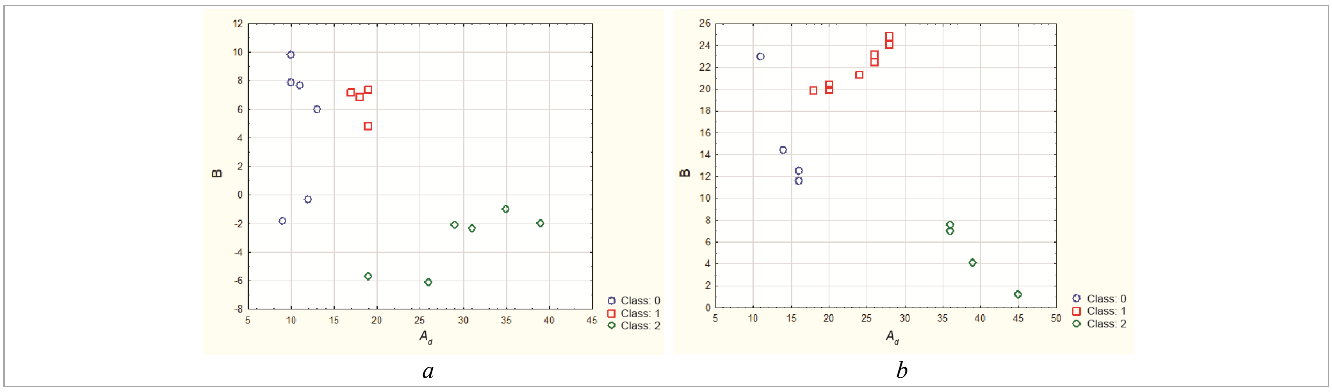

Fig. 1. Correlation fields $B = f(A_D)$ for RH II^E (*a*) and RH II^E (*b*)

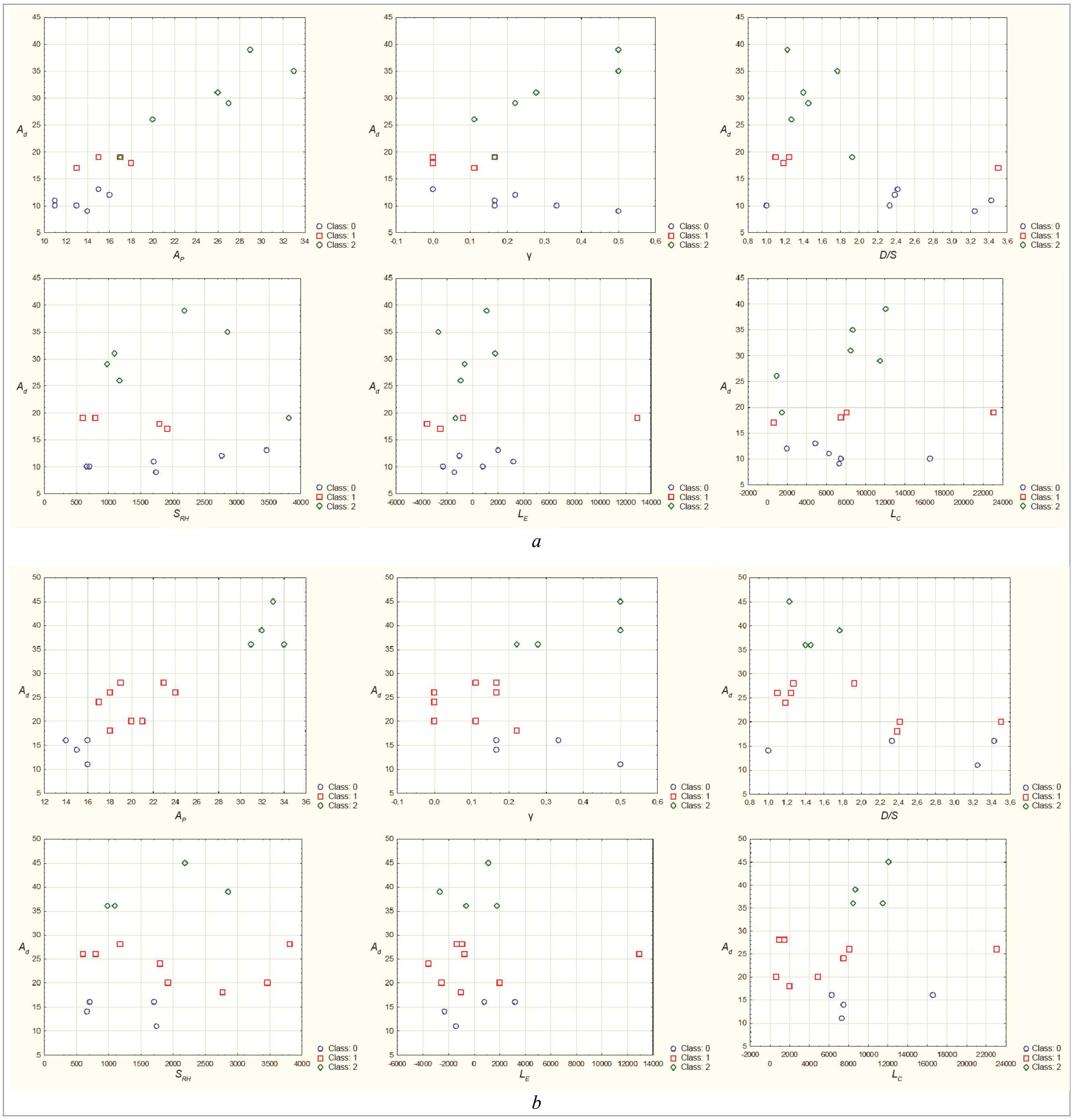

Fig. 2. Correlation fields $A_D = f(X)$: *a* – for RH II^E; *b* – for RH II^P

Table 6

Canonical discriminant functions

RH	Root	Constant	A_P	S_{RH}	D/S	γ	L_C	eigenvalue
RH II^E	Cor. 1	-3.006	0.266	0.000	-0.380	-0.808	0.000	3.036
	Cor. 2	0.782	0.020	0.000	0.116	-5.271	0.000	0.559
RH II^P	Cor. 1	-11.581	0.492	0.001	-0.402	2.178	0.000	15.748
	Cor. 2	-2.241	0.032	-0.001	0.552	6.035	0.000	1.815

Table 7

Qualitative characteristics of discriminant analysis

N	Wilks' lambda, fractions of a unit.	Partial lambda, fractions of a unit.	F-criterion – (3.18)	p- criterion, fraction of units.	Nonresponsiveness	R^2
			For RH II^E			
A_P	**0.417**	**0.381**	**8.937**	**0.005**	**0.763**	**0.237**
S_{RH}	0.164	0.971	0.167	0.849	0.655	0.345
D/S	0.166	0.955	0.257	0.778	0.687	0.313
γ	0.231	0.689	2.478	0.129	0.756	0.244
L_C	0.186	0.854	0.941	0.420	0.570	0.431
			For RH II^P			
A_P	**0.258**	**0.082**	**61.353**	**0.000**	**0.726**	**0.274**
S_{HR}	0.032	0.667	2.750	0.108	0.541	0.459
D/S	0.025	0.851	0.964	0.412	0.691	0.310
γ	**0.049**	**0.430**	**7.282**	**0.010**	**0.801**	**0.199**
L_C	0.024	0.903	0.589	0.572	0.650	0.350

The correlation fields for RH II^E and RH II^P between A_D and different parameters are shown in Fig. 2.

The analysis of correlation fields are presented in Table 5.

The assessment of dependencies was based on the values of the correlation coefficient (r).

According to the analysis of correlation fields the following conclusions can be drawn [39–43]:

1. Class "0". For low-potential structures up to 15 meters along the RH II^E a high positive dependence of A_D on the D/S parameter is observed; a weak positive dependence on A_P, L_E and S_{RH}; a weak negative dependence on γ and L_C. For low-potential structures up to 17 m along the RH II^P an average positive dependence of A_D on the L_E parameter is observed; an average negative dependence on γ; a weak positive dependence on L_C; a weak negative dependence on A_P, S_{RH} and D/S.

2. Class "1". For medium-potential structures from 15 to 19 m according to RH II^E there is an average positive dependence of A_D on the A_P, γ, L_{E}. L_C parameters; a weak negative dependence on D/S and S_{RH}. For medium-potential structures from 17 to 32 meters according to RH II^P there is an average negative dependence of A_D on the D/S parameter; a weak positive dependence on A_D, L_C and L_E; a weak negative dependence on S_{RH} and γ.

3. Class "2". For high-potential structures from 19 meters along the RH II^E a high positive dependence of A_D on the γ and A_P parameters is observed; an average negative dependence on D/S; a weak positive dependence on S_{RH}, L_C and L_E. For high-potential structures from 32 meters along the RH II^P a high positive dependence of A_D on the γ parameter is observed; average positive – on S_{RH} and L_C; weak positive – on D/S, A_P and L_C.

Assessment of the practical application of the constructed models

To assess the practical use of the developed structural differentiation model, discriminant analysis was conducted [18–20, 43–48].

Canonical discriminant functions that define the classification process follow the laws specified in Table 6.

The root eigenvalues of the function Cor. 1 and Cor. 2. which characterize the quality of differentiation are 3.036 and 0.559 for RH II^E and 15.748 and 1.815 for RH II^P, respectively. This means that in this case the most effective method will be to separate the classes based on Cor. 1 of the discriminant function as the higher eigenvalue indicates a more effective separation [43–45].

Qualitative characteristics of discriminant analysis for RH II^E and RH II^P, are presented in Table 7.

The Wilks' lambda, which characterizes the ratio of intra-group variability to total variability and determines the quality of the grouping, in this case fluctuates between 0.164–0.417 for RH II^E and from 0.024 to 0.258 for RH II^P, which means that for RH II^P, the groups are more homogeneous within themselves and practically do not overlap with each other, compared to RH II^E.

The partial lambda determines the value of a particular classification feature, i.e. it determines the degree of variability of Wilks' lambda after adding a variable. The smaller its value, the more valuable the

Table 8

Posterior probabilities for RH II^E

N	Sample	Class	Posterior probabilities		
			Class "0" (p = 0.444)	Class "1" (p = 0.222)	Class "2" (p = 0.333)
1	learning	"0"	0.999	0.001	0.000
2	**validation**	**"0"**	**0.984**	**0.016**	**0.000**
3	**validation**	**"0"**	**0.978**	**0.022**	**0.000**
4	learning	"0"	0.984	0.011	0.005
5	**validation**	**"0"**	**0.999**	**0.001**	**0.000**
6	**validation**	**"0"**	**0.950**	**0.050**	**0.000**
7	**validation**	**"0"**	**0.999**	**0.001**	**0.000**
8	learning	"0"	0.985	0.015	0.000
9	learning	"0"	0.662	0.337	0.002
10	learning	"0"	0.820	0.180	0.000
11	**validation**	**"0"**	**0.973**	**0.027**	**0.000**
12	learning	"0"	0.863	0.137	0.000
13	learning	"0"	0.782	0.147	0.071
14	learning	"0"	0.514	0.471	0.015
15	**validation**	**"1"**	**0.016**	**0.983**	**0.001**
16*	learning	"0"	0.758	0.239	0.003
17	learning	"1"	0.079	0.742	0.178
18	learning	"1"	0.230	0.769	0.000
19	learning	"1"	0.057	0.888	0.055
20*	learning	"0"	0.591	0.136	0.273
21	learning	"2"	0.013	0.080	0.907
22	learning	"2"	0.001	0.019	0.981
23	learning	"2"	0.001	0.009	0.990
24	learning	"2"	0.000	0.000	1.000
25	learning	"2"	0.000	0.001	0.999

Note: Incorrect classifications of the learning sample are marked (*) and are caused by the fact that the A_D value belongs to the boundary value of the classes.

Table 9

Posterior probabilities for RH II^P

N	Sample	Class	Posterior probabilities		
			Class "0" (p = 0.333)	Class "1" (p = 0.444)	Class "2" (p = 0.222)
1	**validation**	**"0"**	**0.929**	**0.071**	**0.000**
2	learning	"0"	1.000	0.000	0.000
3	learning	"0"	1.000	0.000	0.000
4	**validation**	**"0"**	**1.000**	**0.000**	**0.000**
5	learning	"0"	0.998	0.003	0.000
6	learning	"0"	0.871	0.129	0.000
7	learning	"0"	0.999	0.001	0.000
8	learning	"0"	0.965	0.035	0.000
9	learning	"1"	0.011	0.989	0.000
10	learning	"1"	0.000	1.000	0.000
11	learning	"1"	0.034	0.966	0.000
12	learning	"1"	0.003	0.997	0.000
13	learning	"1"	0.014	0.986	0.000
14	learning	"1"	0.000	1.000	0.000
15	learning	"1"	0.000	1.000	0.000
16	learning	"1"	0.000	1.000	0.000
17	**validation**	**"1"**	**0.000**	**1.000**	**0.000**
18	learning	"2"	0.000	0.000	1.000
19	learning	"2"	0.000	0.000	1.000
20	learning	"2"	0.000	0.000	1.000
21	learning	"2"	0.000	0.000	1.000

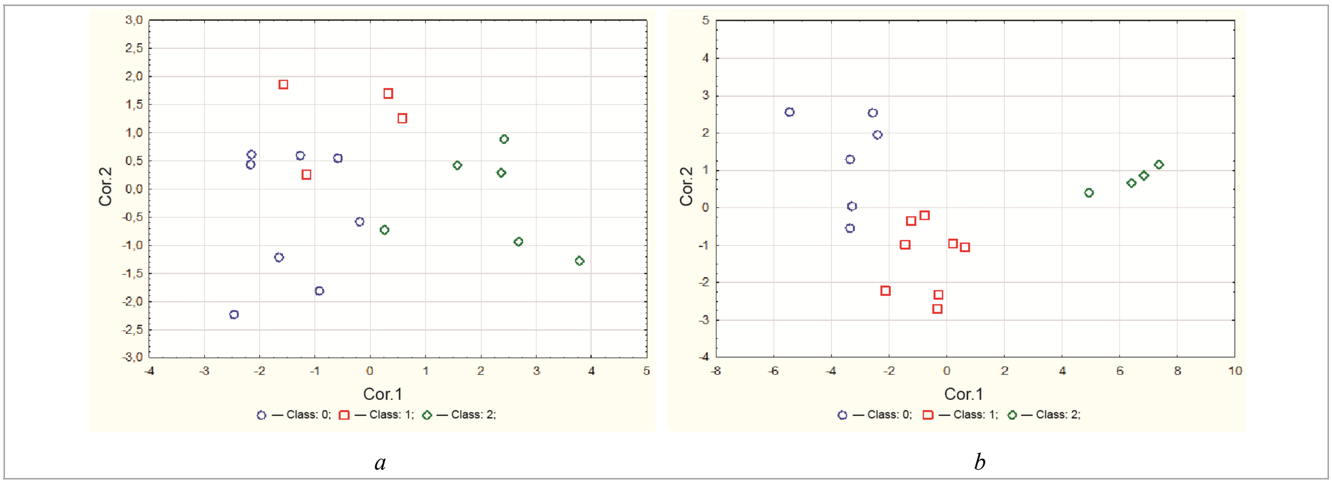

Fig. 3. Graph of the roots of discriminant functions Cor. 1 and Cor. 2 for RH II^E(*a*) and RH II^P (*b*)

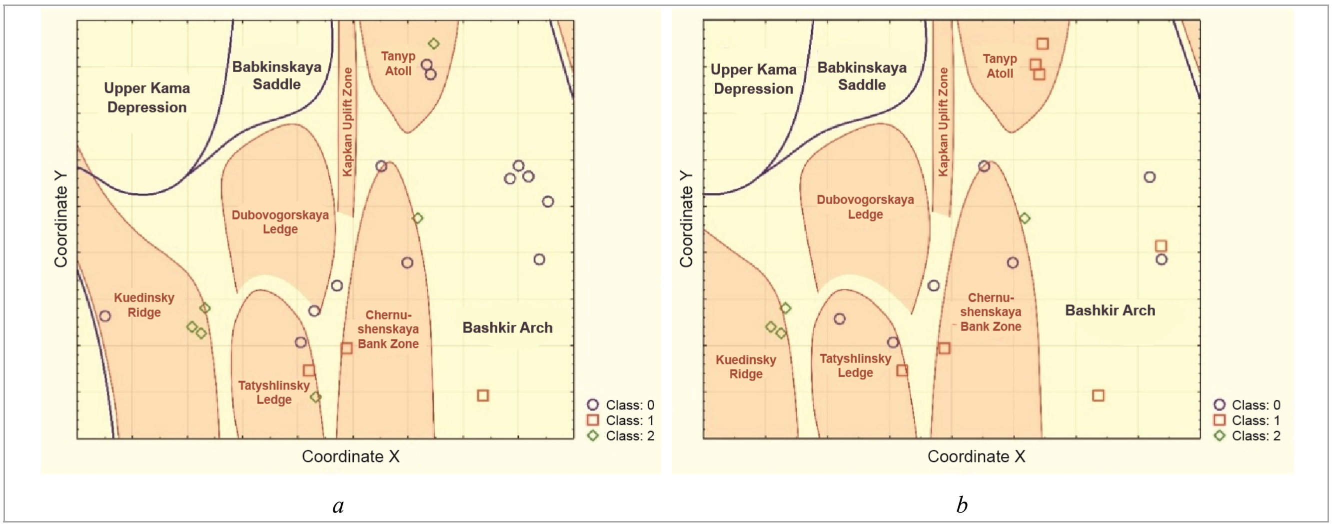

Fig. 4. Distribution diagram of different structure classes based on the results of the posterior probability analysis for RH II^E (*a*) and RH II^P (*b*); the boundaries of the first-order tectonic elements are highlighted in blue, the second-order – in red

feature is. In this case, the most valuable variable for RH II^E is A_D, while for RH II^P, it is both A_D and γ.

The root graphs of discriminant functions Cor. 1 and Cor. 2 for RH II^E and RH II^P are presented in Fig. 3.

According to RH II^E class "0" is located only in negative values of Cor. 1 and in both negative and positive values of Cor. 2; class "1" is located in both negative and positive values of Cor. 1 and only in positive values of Cor. 2; class "2" is located only in positive values of Cor. 1 and in both negative and positive values of Cor. 2.

According to RH II^P class "0" is located only in negative values Cor. 1 and as in both negative and positive values of Cor. 2; class "1" is located both in negative and positive values of Cor. 1 and only in negative values of Cor. 2; class "2" is located only in positive values of Cor. 1 and only in positive values of Cor. 2.

The posterior probabilities obtained from the discriminant analysis, which characterize the probability of the structure belonging to a specific class, are presented in Tables 8 and 9 for for RH II^E and RH II^P, respectively [38, 41–42].

The diagram of the joint distribution of different structure classes based on the analysis of a posterior probabilities obtained using discriminant analysis is presented in Fig. 4.

From the figure, it can be concluded that this approach to ranking can be applied to various structures, despite their geographical location and belonging to tectonic elements, since structures of all classes are distributed universally.

Conclusion

As a result of analyzing the dependencies of structure amplitudes based on exploration and appraisal drilling data on various geologic-morphological parameters such as amplitude of the structure prepared for deep drilling according to the passport, area of the structure on the corresponding reflecting horizon, ratio of the structure length to its width, angle between the long axis of the structure and the axis of the nearest second-order tectonic element, distance from the structure to the edge of the nearest second-order tectonic element, and distance from the structure to the center of the nearest second-order tectonic element, geological-statistical structure models of three classes with different prospects were developed. For each model, the character and degree of influence of the studied parameter on the confirmation of drilling amplitudes were determined and described.

The differentiation of structures by classes and the accuracy of determining the boundaries of classes were confirmed when classifying the test sample structures using discriminant analysis.

This geological-statistical approach can be used for a more accurate risk assessment of geologic-morphological characteristics of structures prepared for deep drilling, as well as for determining priority geologic exploration targets, despite their geographical location and belonging to tectonic elements.

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