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Probability mapping of petroleum occurrence with a multivariate-Bayesian approach for risk reduction in exploration, Nanpu Sag of Bohay Bay Basin, China

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Abstract

A multivariate-Bayesian approach has been applied to the Nanpu Sag of the Bohai Bay Basin, eastern China, to evaluate probability of oil occurrence. The geological data from 343 exploratory wells and seismic interpretations that were available at the end of 2004 were used for the purpose. Seventeen wells were drilled after the evaluation in 2005, sixteen of which reached their target horizon. Eight of the nine wells drilled in areas with a predicted high probability of hydrocarbon occurrence (>50%) encountered commercial oil, indeed; post-drilling analysis indicated that seven of these eight wells yielded high flow rates from thick net pay, and that one of these wells yielded a low flow rate. Seven wells were drilled in areas with a predicted relatively low probability (<50%) of oil occurrence; three of them were dry and four recovered oil with relatively low flow rates. Comparison of the post-drilling results with the pre-drilling prediction suggests that the multivariate-Bayesian approach can help visualize geological risk, thus improving exploration success by optimizing the drilling strategy.

Keywords: oil exploration, risk visualization, well planning, Nanpu Sag, probability map

Introduction

Geological-risk evaluation is one of the important components in petroleum exploration. The Nanpu Sag, with an areal extent of about 2000 km^2, is one of the many small oil-rich Tertiary depressions developed on a complex Palaeozoic-Mesozoic basement in the Bohai Bay Basin, China (Hu et al., 1998). The northern half of this sag is onshore, where active exploration and drilling have led to the discovery of four commercial oil fields and several small oil-bearing structures. The southern half extends offshore, where high exploration cost and unknown geological risk have hindered large-scale exploration. Up to 2004, only four offshore wells had been drilled, resulting in two discoveries and two dry wells. The rapid increase in demand for oil in China has sparked recent interest in the search for hydrocarbons in the offshore part, and a study aimed at regional geological-risk evaluation and resource assessment was undertaken by PetroChina in late 2004.

Risk evaluation usually starts with a play analysis, which first examines all the essential geological elements necessary for oil or gas accumulation in a region (White, 1988, 1993). Then probability values are assigned to each geological play-forming element. The probability of exploratory success is the product of the probabilities for all the geological elements for petroleum accumulation at a specific prospect (White, 1988; Otis and Schneidermann, 1997; Snow et al., 1997; Rose, 2001). There are several drawbacks to conventional geological-risk evaluation. First, substantial subjective judgments are involved in the probability assignments. In such assignments, favourability levels are judged by analogy to similar play types in other basins, and each favourable level corresponds to a range of probability values. Second, subjective judgments employed in risk evaluation may not be consistently applied, and consequently not be reproducible. For example, if independent assessments are conducted by different people, the probability values of the risk can vary significantly. A consistent and reproducible risk-evaluation result is desirable for consistent exploration decision making processes. Third, methods in published literature do not explicitly consider spatial correlations among prospects in the analysis of geological risk. Spatial correlations among prospects are desirable since petroleum occurrence at a specific prospect is not an isolated event, but rather it is a part of the result of similar geological processes within a total petroleum system of a specific play type. A better understanding of the spatial variation of the potential hydrocarbon-bearing targets, as well as of their relationship to the presence of essential geological elements, is important for geological-risk evaluation.

Evaluations of geological risk were performed in recent years by considering the spatial characteristics of exploration targets using spatial statistical tools and improved numerical manipulations of geographical information. Chen et al. (2000, 2001, 2002), Chen & Osadetz (2006a), and Rostirolla et al. (2003) have proposed several techniques for the characterization of spatial variability of geological factors and for the estimation of petroleum-accumulation probabilities at the play level. Gao et al. (2000) proposed an object-based method for estimating the probability of petroleum occurrence. Chen & Osadetz (2006b) used a geological model-based stochastic simulation for predicting the locations and potential of undiscovered petroleum resources.

The geological-risk evaluation using the multivariate-Bayesian approach proposed by Chen & Osadetz (2006a) is discussed in the following. The predicted probability map of petroleum occurrence is compared with the results of exploratory drilling, with emphasis on the oil-bearing structural play of the Oligocene Dongying Formation (Ed1 Member).

Method description

The objective of geological-risk analysis is to determine to what degree of certainty a potential drilling target is hydrocarbon-bearing (productive) or barren (non-productive), on the basis of our understanding of the basin and available data. In other words, it is aimed at finding out, prior to drilling, what is the chance of a potential prospect being a success. This problem is treated in the present study as a two-group classification with uncertainty in a multivariate space.

Suppose that the nature of an area in a petroleum play can be classified into two categories, the productive area, A, and the non-productive area, B, and that the play was penetrated by n exploratory wells that provided samples from the play. On the basis of the data from these n wells, in combination with other available geoscience information, we want to estimate the probability with which each untested location belongs to one of the two defined categories. This estimation may take the form of a conditional probability upon m geological variables. Let G(r) denote the random vector of m geological variables, containing information on the classification, and g(r) be the assumed values for a continuous variable G(r) at location r. The conditional probability that, for given observations G(r)=g(r), the area at location r belongs to A can then be written as:

$$P(A \mid g(r)) = \frac{P(A, g(r))}{P(g(r))} \tag{1}$$

where P(A, g(r)) is the joint probability of productive area, A, and observations, G(r)=g(r); and P(g(r)) is the probability of G(r)=g(r).

Let P(HC|Fav) denote the conditional probability of petroleum occurrence, given a favourable geological condition and let P(Dry|Unfav) be the probability of a dry hole, given an unfavourable condition. P(HC|Fav) is a measure of exploration success, thus an indicator suggesting which prospect we should drill and which we should not; on the other hand, P(Dry|Unfav) is a measure of opportunity, thus an indicator showing which prospect should better be avoided and which should not. A balanced exploration strategy for risk reduction would be to achieve a high exploration success without compromising the loss of opportunity. The product of these two probabilities, F(Phc,Pdry) = P(HC|Fav)P(Dry|Unfav), provides a useful measure for optimizing the exploration strategy.

To avoid the complexity of a multivariate Bayesian formulation, the Mahalanobis Distance (MD) is used in the present study to integrate all available geological variables and then to calculate the probability of petroleum occurrence. MD is a distance in multivariate space, first introduced by Mahalanobis (1936). The measure is based on correlation and is scale invariant, which differs from Euclidean distance. The geological favourability of a location for petroleum accumulation is measured as the MD, which is defined as (Mardia et al., 1989):

$$MD = (X_k - X_s)^T S_s^{-1} (X_k - X_s) \quad (2)$$

where X_k is the k^{th} row vector of X (the data set consisting of p observations and m variables), or the kth observation, X_s is the mean vector of the data set X, $(\ldots)^T$ is the transposed matrix, and S_s is the covariance matrix of the data set X. Details of the Bayesian and MD approaches can be found in Chen & Osadetz (2006a) and Hu et al. (2007). Other application examples of the usage of MD in hydrocarbon exploration have been described by Harff et al. (1992) and Harbaugh et al. (1995).

Taking MD as the measure of classification, the conditional probability in Eq. (1) can be rewritten as:

$$P(A \mid D(r)) = \frac{P(A, D(r))}{P(D(r))} \quad (3)$$

where D(r) represents the MD between the geometrical center of the geological characteristics of the productive petroleum group and the geological characteristic vector at an untested location in a multivariate space.

Geological setting and data

The Nanpu Sag (Figs. 1 and 2) is a small rift sub-basin with a maximum infill thickness of 7500 m. Bounded in the north by the Yanshan Fold Belt (Fig. 1), the Nanpu Sag is situated in the northernmost part of the Bohai Bay Basin. The rifting phase started during the Eocene and a renewed faulting-related subsidence was followed in the Neogene after a major tectonic inversion. Regional structural analysis indicates that strike-slip faulting had a significant impact on the sedimentational pattern and current structural style (Dong et al., 2008). Figure 3 is a generalized stratigraphic column showing the sedimentary infill of the Nanpu Sag.

The sandstone structural play of the Oligocene Ed1 Member is a play that was established by onshore discoveries. The trap styles are predominantly fault blocks and roll-over structures. The Ed1 sandstone is predominantly composed of fluvial-fan and deltaic sediments (Fig. 4). The regional seal consists of shale-dominated intervals in the Miocene Guantao Formation. Seismic interpretations and geological analysis indicate that the Ed1 structural play extends into the offshore, and that the basic geological controls for hydrocarbon accumulation in the offshore part appear to be similar to those in the onshore area.

Organic-rich shales occur in the transgressive portion of successions, usually at or near the base of shaly members/formations. However, the abundance and areal distribution of such shales vary considerably. Organic-rich shales are the thickest and most widespread in three Palaeogene successions, the Es3 and Es1 Members of the Shahejie Formation and the Ed2 Member of the Dongying Formation in the sag. The organic geochemistry of 2321 samples from 92 exploration wells suggests that the source rocks are of lacustrine origin and that the organic matter is predominantly

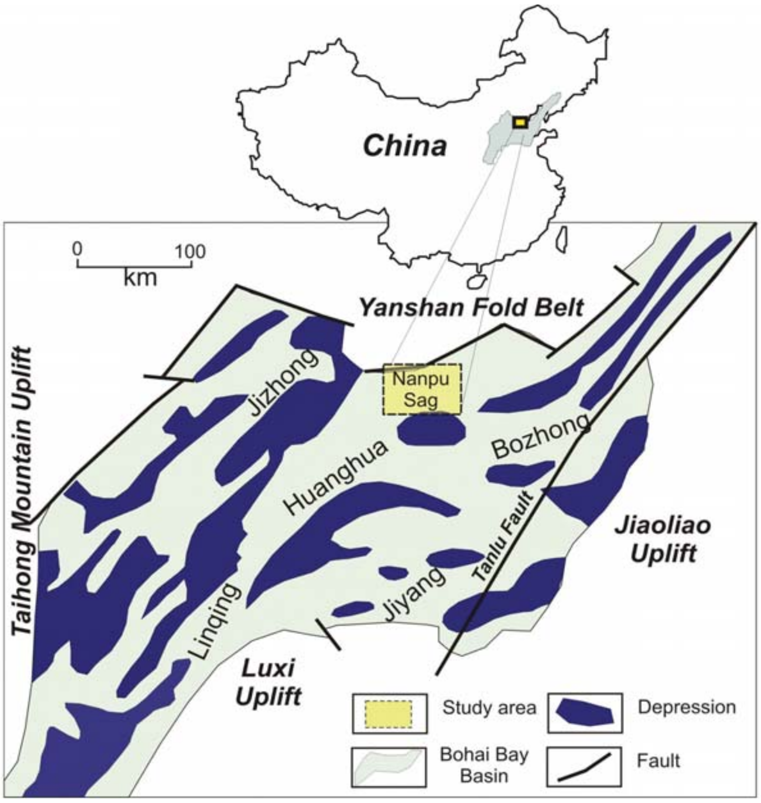


Fig. 1. Location of the Bohai Bay Basin and the study area of Nanpu Sag (Bohai Bay Basin map redrawn from Liu et al., 2007).

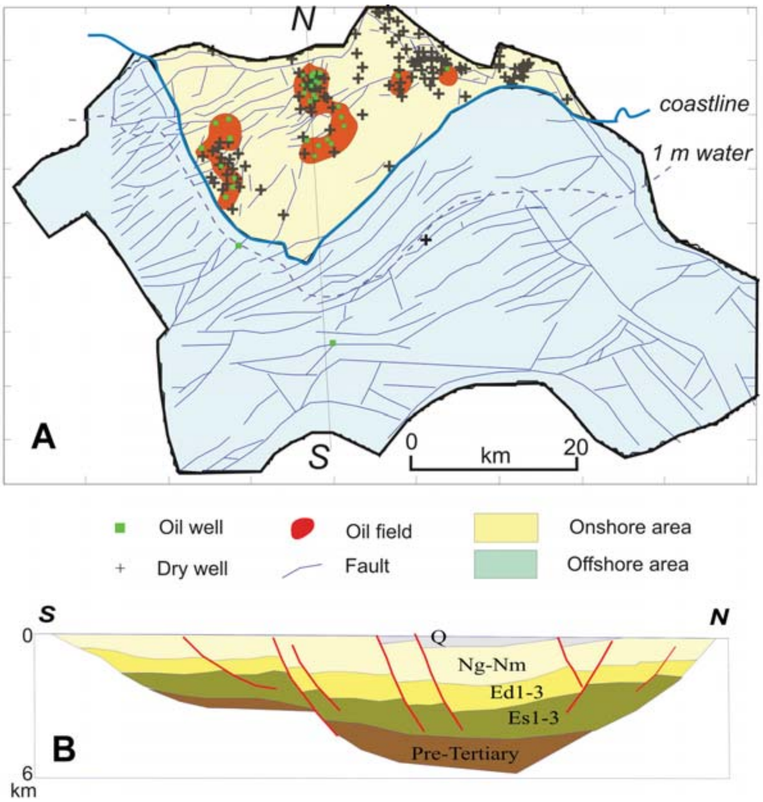


Fig. 2. General geological features of the Nanpu Sag study area, with **A:** Map with well locations from the pre–2005 data set (production wells: green squires; non-producing wells: white crosses); **B:** Cross-section (see Fig. 2A for location).

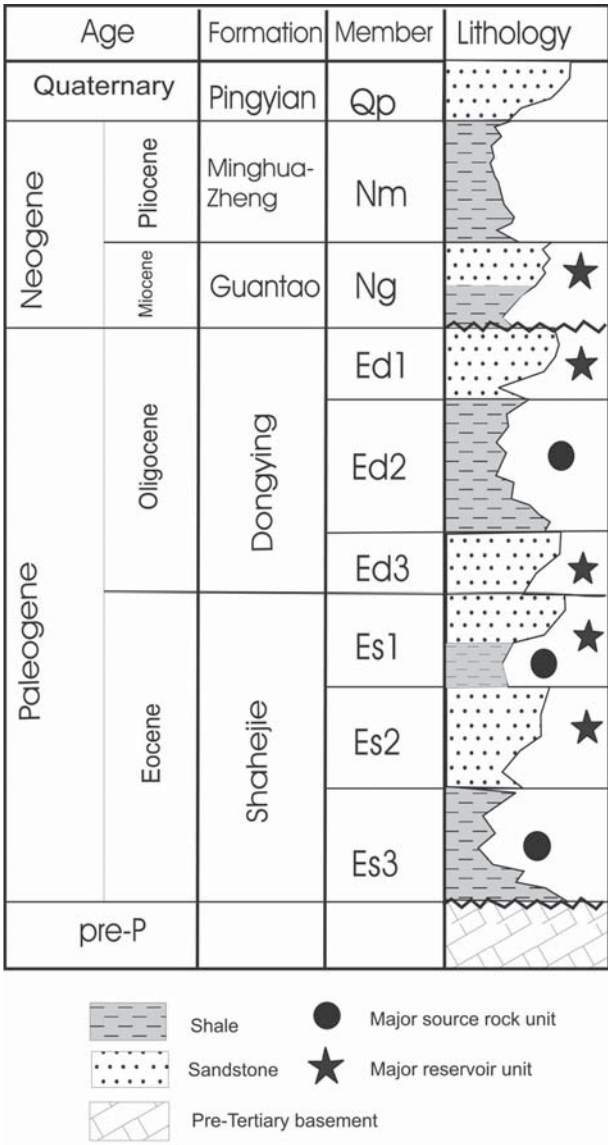
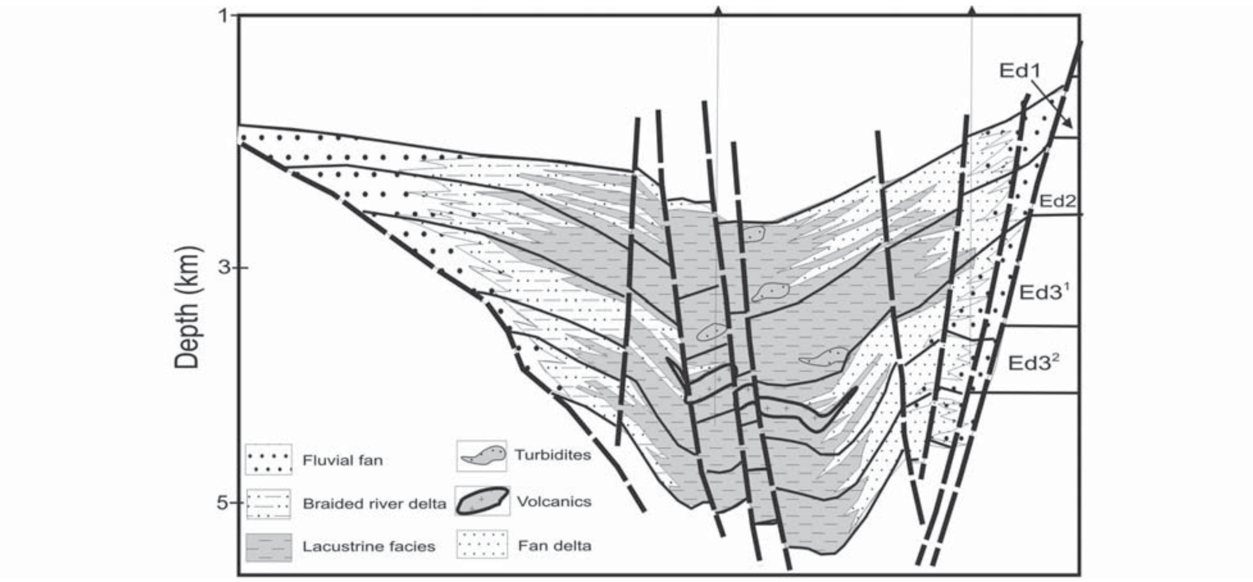


Fig. 3. Generalized stratigraphy of the Nanpu Sag, with major source rock and reservoir intervals.

type-II kerogen. One-dimension basin modeling indicates multiple oil-generation/expulsion/migration phases. The Es3 Member, the richest source-rock interval (Zheng et al., 2007), passed through its 90% oil-generation capacity at the end of the Paleogene, around 25 million years ago, and massive expulsion and oil migration from this source rock started in the early Neogene, coinciding with major tectonic reactivation in the region. The modeling suggests that the Es3 Member reached its peak oil generation about 32 million years ago, before deposition of the regional Guantao Formation cap-rock. Thus, the Es3 Member may not be the major contributor to the trapped hydrocarbons in the Dongying Formation. The other source rocks (Es1 and Ed2 Members) entered the oil-generation window in the middle Miocene, about 10 million years ago, after deposition of the Guantao Formation. Major expulsion did not start until the Pliocene, about 5 million years ago, coinciding with a second pulse of tectonic reactivation. The shale-dominated Es1 and Ed2 Members are inferred to be the most important sources for oil accumulations in the Dongying Formation and younger reservoirs, which is consistent with the results from a re-

Fig. 4. Schematic facies model for the Oligocene Dongying Formation in the Nanpu Sag (modified from Xu et al., 2006).



cent study of potential source rocks in the sag (Zheng et al., 2007).

Of the 343 wells (339 onshore and 4 offshore) drilled prior to 2005 (see Fig. 2 for the locations of the pre–2005 well locations), 224 reached the Dongying Formation onshore, and three offshore. Data available for the geological-risk evaluation included information from the 224 wells as well as seismic interpretations completed prior to November 2004. Results of geochemical analyses and basin modeling were also available for the present study. Of the 224 wells that reached the Dongying Fm., 34 are productive wells, whereas the other 190 wells are non-productive in this play. The productive and non-productive wells thus form two populations; these were used for the geological-risk evaluation. In 2005, seventeen new exploration wells were drilled in the offshore area, sixteen of which reached the Ed1 Member. The data from these wells form a validation data set for our post-drilling analysis.

Exploration-risk mapping of the play

Selection of geological variables in risk analysis

In its third national-wide petroleum-resource assessment (Zhao et al., 2008), PetroChina established an in-house look-up table of geological variables for risk evaluation (Guo et al., 2004). About one fourth of the 22 geological factors in the table were found to contain useful information for the geological-risk evaluation in the present study. We use the sandstone percentage in the Ed1 play as an example to illustrate how a geological variable is selected for the geological-risk analysis. The spatial variation of the sandstone percentage is shown in Figure 5a, and the frequency distributions of the sandstone percentage from the productive and non-productive wells are displayed in Figure 6a. The majority of the productive wells encountered the reservoir unit in

Table 1 . Geological variables for the risk evaluation and calculated conditional probability values. See text for definitions of P(HC | Fav), P(Dry | Unfav) and F(HC, Dry).

Variables	P(HC | Fav)	P(Dry | Unfav)	P(HC, Dry)
Net sand thickness	0.36	0.88	0.32
Formation thickness	0.41	0.81	0.33
Sandstone percentage	0.37	0.88	0.33
Generation intensity	0.35	0.87	0.31
Fault-intensity index	0.23	0.85	0.19
Structural residuals	0.34	0.84	0.29
Relative structure	0.35	0.89	0.32
Erosion	0.31	0.88	0.27
Cap-rock thickness	0.33	0.79	0.26
MD	0.50	0.90	0.45

P(HC | Fav): probability of HC given favorable condition
P(Dry | Unfav): probability of dry given unfavorable condition
F(HC, Dry): favorability defined as P(HC | Fav)×P(Dry | Unfav)

areas with an average sandstone percentage > 35%. In contrast, the non-productive holes generally are located in areas where the reservoir sandstone percentage is below 35%. We set 35% as the threshold value for distinguishing between areas with a favourable reservoir condition (>35%) and those with an unfavourable reservoir condition (≤35%) for economic petroleum accumulation. The calculated P(HC | Fav), P(Dry | Unfav) and F(Phc,Pdry) are listed in Table 1.

P(HC | Fav)=0.37 implies that, if an exploration target is situated within an area with a favourable reservoir condition, the chance of finding an economic petroleum occurrence in that target is 37%, whereas P(Dry | Unfav)=0.85 means that, if the reservoir is unfavourable, the chance of that target being non-productive is 85%. In other words, the chance of success for the latter case is only 15%. Comparison with the past average exploration success rate of 34 out of 244 wells (~ 14%) suggests that considering the reservoir condition when selecting an exploration target could improve exploration success. It thus seems that the reservoir quality

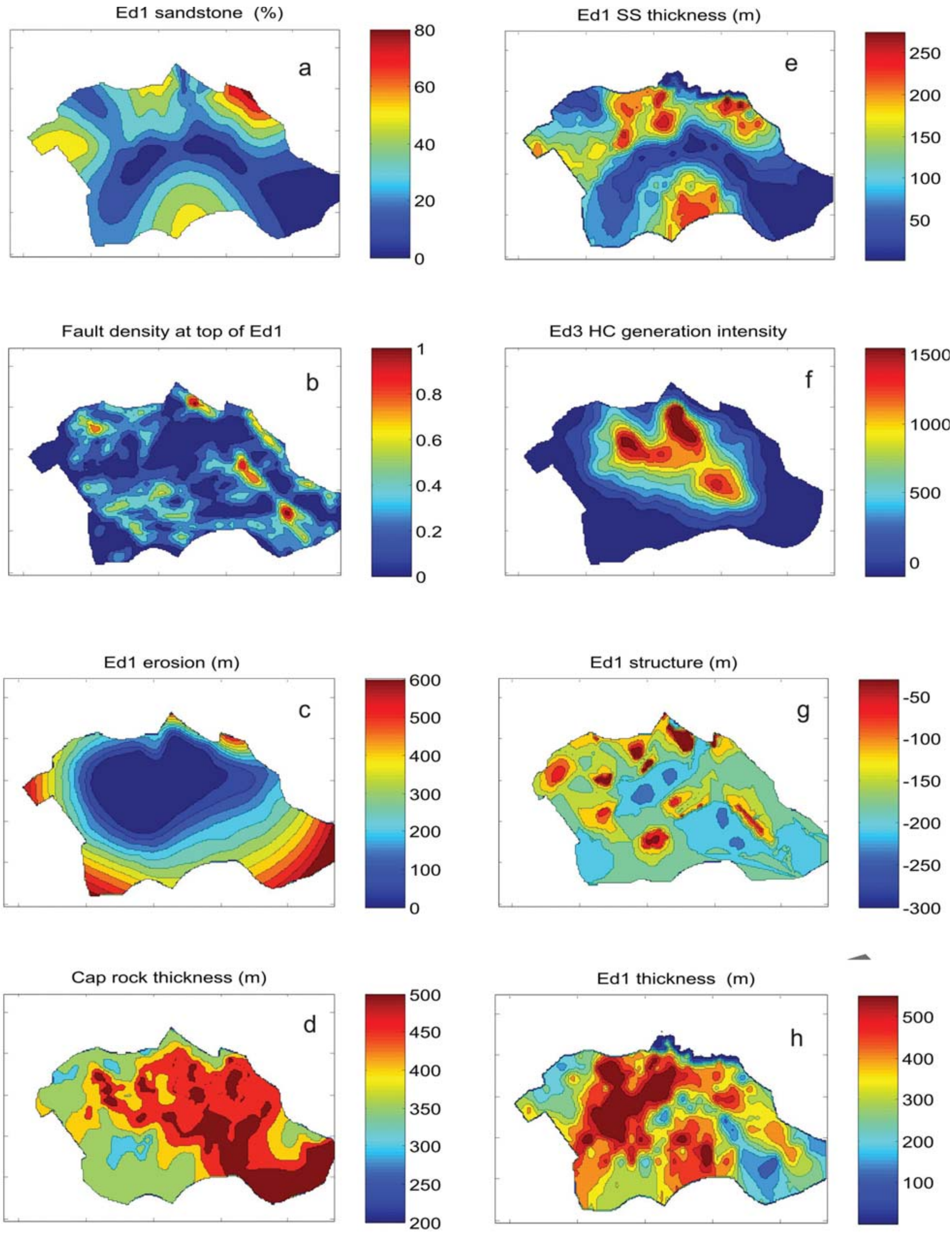


Fig. 5. Spatial variation of eight geological variables in the structure play of the Ed1 Member of the Dongying Fm. in the Nanpu Sag (from the pre–2005 data set). All the available geological variables were examined for this study using the Bayesian method to determine whether this approach would yield sufficient information for discriminating between productive and non-productive wells.

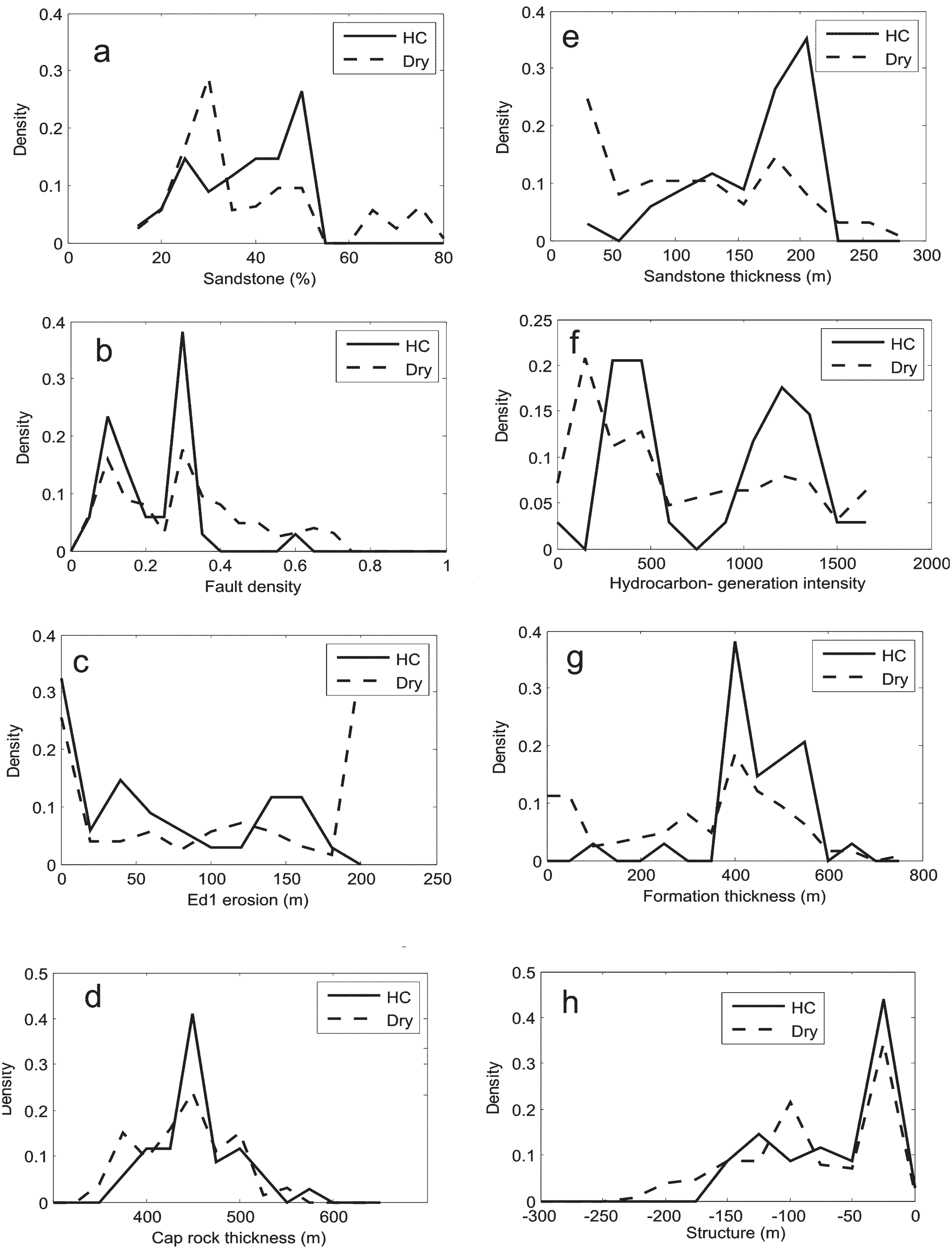


Fig. 6. Empirical probability density curves of geological variables in the Bayesian analysis for classification of the productive and non-productive groups. HC = hydrocarbons bearing (= productive); dry = non-productive.

contains useful information for discriminating between productive accumulations and non-productive prospects in this play.

All available geological variables that represent the essential geological elements necessary for petroleum accumulation were examined in the same way, using the Bayesian statistical measures discussed above (Fig. 5). The analysis indicates that the relative structural amplitude at the top of the Ed1 play, the sandstone percentage and sandstone thickness of the Ed1 Member, the thickness of the cap rock in the Guantao Formation, and the generation intensity of the source rock are good indicators for separating productive and non-productive prospects (Fig. 6 and Table 1). In order to calculate the Bayesian statistics, variable threshold values for the individual geological variables are determined based on the frequency-distribution characteristics, so that the likelihood of classification errors is minimized.

Table 1 lists all geological variables and associated Bayesian conditional probabilities and F(Phc,Pdry) values. We set the F(Phc,Pdry) value of 0.3 as a cut-off, and took all the geological variables with F(Phc,Pdry) > 0.3 into consideration in the geological-risk mapping. All selected geological variables were then integrated using the MD to produce a comprehensive classification criterion for the calculation of the conditional probability. The estimated probability densities for each of the groups show a large separation with an overlap between 1 and 4 of the MD (Fig. 7). The overlap implies uncertainty in the classification. The calculated probabilities and F(Phc,Pdry) from MD (in Table 1) are the highest compared to the values derived from a single geological variable. The F(Phc,Pdry) value from MD is about 27% higher than the highest F(Phc,Pdry) value from a single geological variable, suggesting that, by combining several geological variables, MD contains more information for classifying the productive and non-productive targets.

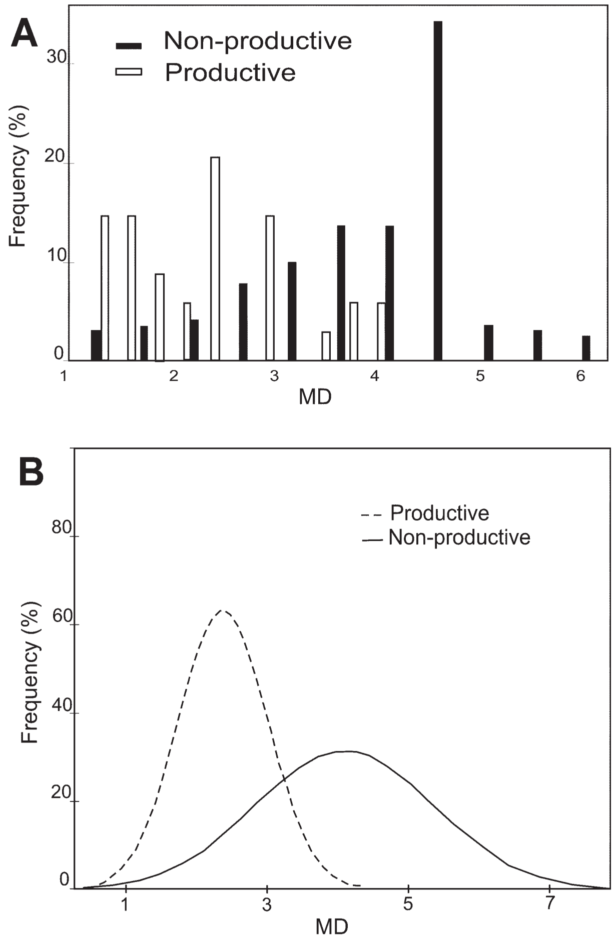


Fig. 7. Classification of productive and non-productive wells using the MD criterion derived from the selected geological variables in the pre–2005 data set. **A:** histograms (empirical probability densities) of calculated MD of the productive and dry well groups. **B:** fitted probability density models for the two groups.

Probability mapping

Only three wells penetrated the Ed1 Member in the offshore area; the rest of the wells are clustered around four major structures onshore. This uneven distribution of previous exploration wells in the study area provides little information about the petroleum potential in the offshore area. However, geological synthesis from seismic interpretation and regional geological study suggests that the geological factors controlling petroleum accumulations in both onshore and offshore are similar. To evaluate the geological risk in the offshore area, an MD map was generated using geological maps of the five selected geological variables and wells in the pre–2005 dataset. By fitting the empirical distributions of MD for the productive and non-productive wells (Fig. 7A), respectively, two probability density models (Fig. 7B) were prepared. These were used to calculate

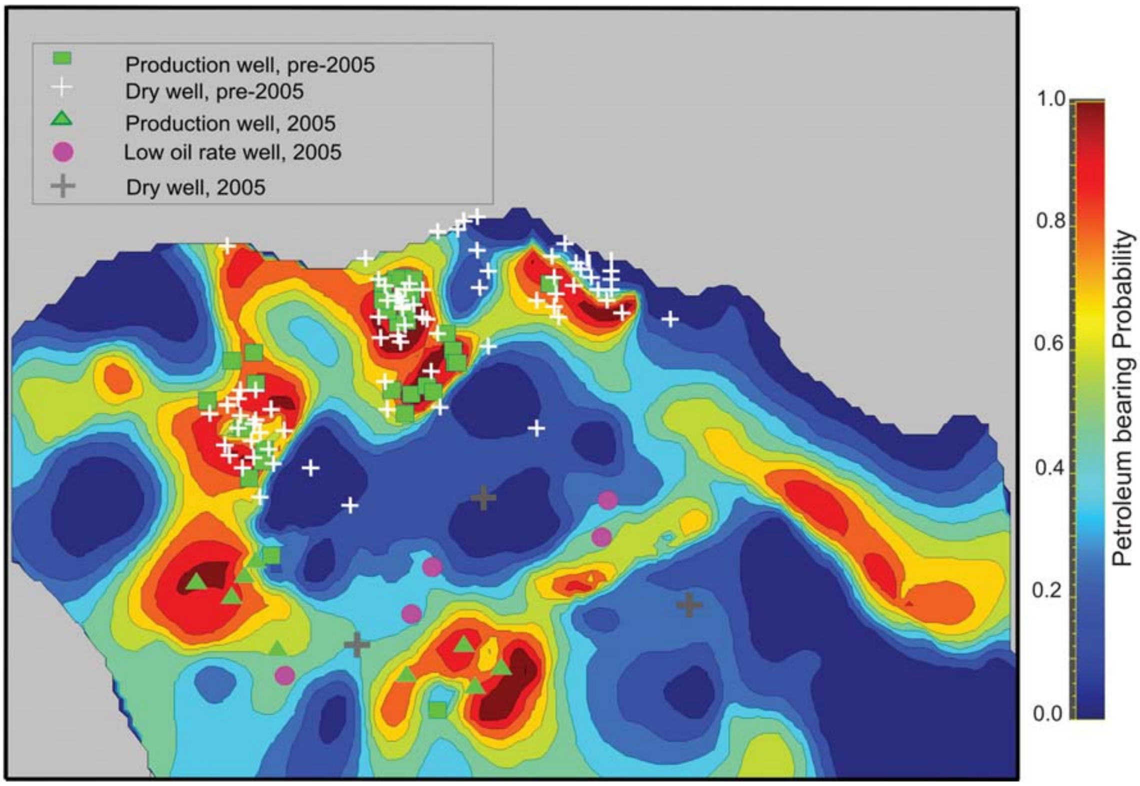


Fig. 8. Probability map of petroleum occurrence in the Ed1 play, produced from the multivariate-Bayesian approach using the pre–2005 data set. Red and yellow colors indicate a high probability of oil occurrence. All wells that showed a high oil-flow rate are located in the red-coloured areas.

the conditional probability of petroleum occurrence. Figure 8 is the Bayesian probability map of petroleum occurrence, which represents the spatial variation of the geological risk in the play.

Discussion

The geological-risk mapping using the multivariate-Bayesian approach resulted in a probability map of petroleum occurrence, outlining the play risk geographically for the Ed1 play (Fig. 8). On this map, all productive wells drilled prior to 2005 (green squares) are clustered onshore in areas with a high conditional probability value of petroleum occurrence. Most of the "dry" wells are situated in the areas with low probabilities. All 17 new wells drilled in 2005 are offshore. Of these 17 wells, 16 penetrated the Ed1 play and were tested for oil and gas rates. Nine wells were drilled in areas with a predicted probability of petroleum occurrence >50%; eight of them, tested high oil-flow rates from thick pay zones, one of which with a commercial oil-flow rate. The other seven wells are located in areas with a predicted probability <50%. Four encountered oil with low flow rates, and the other three are dry. The study thus shows that higher predicted probabilities not only correlate with a higher success rate, but also with relatively high flow rates.

In general, wells drilled in areas with predicted probability values >40% had a success rate of >80%. The average probability value of the eight wells with p(hc | MD)>50% was 70%. The actual success rate of commercial oil flow is 100% and the success rate for encountering a high oil flow is 86%. Apparently, the predicted absolute probability is slightly below the average success rate. It is expected, however, that – with increasing exploration and evaluation drilling – the drilling success rate will slightly decrease as some wells could miss production zones or be out of the accumulation boundaries. On the other hand, some of the "dry" wells in the pre–2005 data set are perhaps not really dry, but the Ed1 reservoir was not tested. This may dilute the success rate in the data set and be extrapolated into the prediction. Therefore, in some cases, the predicted probability is of more relative significance.

Conclusions

The application of geological-risk mapping to the Ed1 structural play of the Nanpu Sag depression has resulted in a probability map of petroleum occurrence that depicts the spatial variation of regional geological conditions that are favourable for petroleum accumulation, thus providing a systematic and consistent basis for risk evaluation and prospect ranking (cf. Chen & Osadetz, 2006a). The probability map and estimated resource of potential targets can be used to highlight areas with a high resource potential and a high probability of petroleum occurrence.

Post-drilling results show that wells drilled in low-risk areas are mostly productive with high oil-flow rates. In contrast, the wells drilled in areas of predicted low probability of petroleum occurrence have a much lower success rate. It therefore turns out that the multivariate-Bayesian method effectively integrates available geological and exploration information to visualize geological risk, thus reducing the geological risk through optimizing the exploration strategy by avoiding the drilling of high-risk and low-resource potential targets.

The application of the multivariate Bayesian approach to the Nanpu Sag demonstrates two major advantages: (1) the geological risk for all prospects can be evaluated consistently and simultaneously, using the same method, criteria and data, resulting in reproducible and easily updateable results that clearly reflect relative prospectivity; (2) the use of established, mathematically valid classification methods produces an objective result not affected by a possible bias of the assessor.

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