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Prediction Model and Risk Quantification of Natural Gas Peak Production in Central Sichuan Paleo-Uplift Gas Reservoirs

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Located in the Sichuan Basin of China, the central Sichuan paleo-uplift is a geological structure that spanned several areas in Sichuan province and was formed 500 million years ago. It is the bottom layer with rich conventional natural gas resources of more than 3×10^{12} m^3, and the proven reserves are about 30%, while the recovery rate is only 1.4%. In this paper, the Hubbert and Gauss models are used to study the peak production of natural gas. The Monte Carlo simulation method is used to predict the realization probability of future medium and long-term production, evaluate the risk level of natural gas production, and realize the whole process research from scale prediction to risk quantification of gas reservoirs. According to the Gauss model, under the realization probability of P50, the gas reservoir in the central Sichuan paleo-uplift can reach a peak production value of 145×10^8m^3/a, in 2040, and maintain a stable production state in 2034-2046. The risk grade evaluation matrix, through which the dispersion degree $C \in$ (5% and 10%) in the rising stage and rapid production decline stage can be obtained, and the dispersion degree $C \in$ (10% and 25%) in the stable production stage and slow production decline stage can be obtained. The dispersion degree and realization probability can be integrated to obtain the risk level at different stages.

1. Introduction

In the central Sichuan area, the surface outcrop is the Jurassic Upper Shaximiao Formation, which plunges from Huaying Mountain to the southwest. The central Sichuan paleo-uplift is a large nose-shaped uplift, which is characterized by basement uplift and overburden thinning. The research on the exploration results of oil and gas discovery and gas acquisition from several wells has confirmed that the Sinian Lower Paleozoic strata in the slope zone of the ancient uplift also have good exploration potential for multistrata. The researched area and stratigraphic structure of the central Sichuan paleo-uplift involved in this paper are shown in Figure 1. At present, nine gas reservoirs have been discovered in the central Sichuan ancient uplift, and the proven reserves are about 650 billion cubic meters. The sum of proven reserves, predicted reserves, and controlled reserves exceeds trillion cubic meters. In the calculated natural gas resources of the central Sichuan paleo-uplift, the Middle Triassic and Lower Triassic account for 1/8 of the total resources, the Permian accounts for 2/8, and the Lower Paleozoic and Sinian Dengying Formation together account for 5/8 of the total resources. The natural gas resources in the central Sichuan paleo-uplift have great development potential [1, 2].

At present, the research work on the prediction of medium-term and long-term oil and gas production changes and risk quantification has been widely carried out all over the world. Countries around the world attach great importance to the research work of oil and gas resource trend prediction and risk quantification [3]. In order to formulate the energy exploitation plan and optimize the development

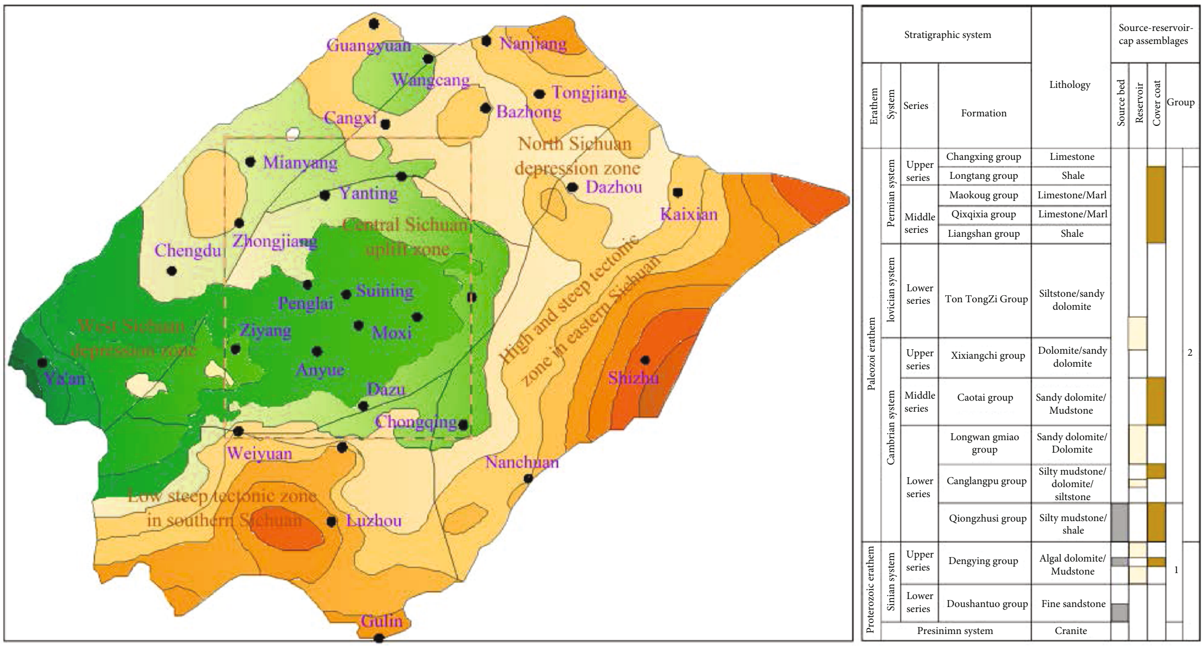


Figure 1: Predepositional form of the Permian in the Sichuan Basin.

strategy of the gas field in the central Sichuan paleo-uplift, it is necessary to carry out medium-term and long-term forecasts of its natural gas production and conduct quantitative research on development risks. The research results have important guiding significance for the next step of natural gas exploration and development.

The central Sichuan paleo-uplift is located in the central part of the Sichuan Basin, covering an area of about 7,000 square kilometers, mainly including the Gaoshiti block, the Moxi block, and the Longnvsi block. The natural gas resources in this area are more than 3×10^{12} m^3, the proven rate is about 30%, and the recovery degree of proven reserves is only 1.4%, which is in the early and middle stages of exploration [4, 5]. The gas reservoirs in the central Sichuan paleo-uplift are rich in resources and have great potential for exploration and development, which can greatly promote the increase in production and benefit of natural gas in the Sichuan Basin.

However, the gas reservoirs in the central Sichuan paleo-uplift have strong reservoir heterogeneity, complex pressure system and oil and gas migration laws, and other geological characteristics, which are not conducive to determining the production scale of the gas reservoirs in the future. Among the numerous factors that affect the natural gas production, the most important one is the permeability of the rock stratum [6–8]. Some scholars have studied this problem, established a flow model of shale gas in the fractal double porosity, and verified the experimental data. It is concluded that with the increase of the fracture porosity, the gas transport in the shale natural fracture gradually becomes more priority in the double porosity rock; some scholars used the real gas model and elastic hard ball model to study and obtained the migration rule of free gas in shale nanopores; some scholars established a gas apparent permeability model based on percolation mechanism for high-pressure tight sandstone reservoir by combining molecular dynamics, gas transport mechanism, and apparent permeability and realized the influence on gas transport permeability [9–11]. At the same time, determining the production scale through reasonable research methods is the key to the efficient development of gas reservoirs. Therefore, strengthening the research on the prediction of natural gas production growth trend and risk quantification of gas reservoirs in the central Sichuan paleo-uplift can further clarify the resource exploration and development potential of the central Sichuan paleo-uplift area and play an important guiding role in the medium and long-term scientific and rational planning of natural gas production in the Sichuan Basin [12–15].

In the medium and long-term planning of oil and gas, the prediction models for natural gas reserves and production mainly include the peak prediction method, grey system method, and neural network method. At present, the peak forecasting method is a common and simple medium and long-term forecasting method. For natural gas areas that are still in the early stage of development or production stage, the use of neural network prediction models to predict natural gas reserves and production in medium and long-term forecasts has higher accuracy and more practicability [16–21]. In recent years, there have been many studies on the prediction of natural gas storage and production: firstly, according to historical data, the multicycle Hubbert model has been used to predict the medium and long-term oil production, and it is determined that the peak production will occur in 2030. Secondly, using the model correction method based on multiples and exponential correction coefficients, the optimal solution is selected to build a peak prediction model that conforms to the actual production development characteristics, so as to achieve accurate prediction of medium and long-term production in the gas region. Thirdly, a variety of prediction models such as the single-peak Weng model, the single-peak Weibull model, and the multipeak Gauss model are selected for improvement, and the full life cycle prediction is quantitatively conducted. Fourthly, since the postfracturing production prediction has an important impact on the construction optimization design and economic evaluation results, a prediction model of shale gas production in the early stage of unstable seepage is established by analyzing some factors, and the prediction results are very similar to the actual results. Fifthly, using the theory of percolation mechanics, the principle of gas reservoir engineering, and mathematical and physical methods, the pressure dynamic well test model of gas wells with three continuous media, fractures, matrix, and caverns, is established, and the analysis method of production decline of normalized pressure integral is studied, as well as the production prediction method of gas wells with fixed production pressure after fixed production, which provides convenience for the development of carbonate gas reservoirs. Sixthly, the existing single-cycle model is improved, and a multicycle prediction model is established. The results show that the multicycle prediction model is more effective and practical than the single-cycle model [22–32].

In the field of oil and gas exploration and development, the main methods for quantifying the risk of natural gas reserves and production include probabilistic methods, neural network methods, and fuzzy cluster analysis methods. Among them, the probability method has been widely used in the quantification of natural gas production risk. At present, there are some researches on the quantification of reserves risk; on the one hand, the application of risk quantification technology has been analyzed from four aspects: the basic principles of risk quantification, risk classification and reference standards, risk quantification evaluation system, and effective methods of risk quantification, which have strengthened the effect of risk quantification in drilling engineering and avoided the impact of risks on drilling engineering [33]. On the other hand, the risk of the natural gas industry chain has been simulated and evaluated, the transmission simulation model reflecting the risk transmission of the industry chain has been constructed, the risk evaluation framework of the natural gas industry chain has been proposed combining short-term and long-term risk evaluation, the short-term evaluation model has been constructed using measurement methods, and the long-term evaluation has been realized using the analytic hierarchy process. And put forward some suggestions and opinions on the prevention of risks in the natural gas industry chain and the long-term development of the industry chain [34, 35].

The innovation of this paper is to provide a more quantitative basis for guiding the exploration and development of natural gas in gas reservoirs in the central Sichuan paleo-uplift. In this paper, the peak model prediction is firstly carried out on the midterm and long-term production prediction of gas reservoirs in the central Sichuan paleo-uplift, and then the production risk quantification research is carried out according to the prediction results. The steps of the research work are shown in Figure 2. Firstly, calculate the ultimate recoverable reserves (URR) of the gas reservoirs in the central Sichuan paleo-uplift and use the Hubbert and Gauss models to obtain the growth law of natural gas production under different URR scenarios. Then, based on the Monte Carlo simulation method, the distribution probability and cumulative probability of production in each year are calculated, and the natural gas production with the highest probability of realization in different years is determined, which provides a scientific basis for the planning target of natural gas production.

2. Method

2.1. Natural Gas Production Prediction Theory

2.1.1. The Hubbert Predictive Model. In 1956, the famous petroleum geologist M. King Hubbert proposed the Hubbert production peak prediction model and accurately estimated the ultimate recoverable resources of natural gas in the United States, the production peak, and its occurrence time [36]. The Hubbert model is a commonly used life cycle model for the prediction of peak natural gas production [37, 38]. The model believes that after the oil and gas field is put into development, the output will rise with the extension of the development time from 0 and then decline with the extension of the development time after reaching the high peak. When the development time approaches infinity, the area of the production curve and time is equal to the ultimate recoverable reserves of the oil and gas field [39–42]. The Hubbert model equation is as follows:

$$Q = \frac{\mathrm{URR}}{1 + e^{-b(t-t_m)}}. \tag{1}$$

In the formula, Q is the cumulative production, and the unit is $10^8 m^3/a$; URR is the ultimate recoverable reserves, the unit is $10^8 m^3$; t is the production and mining time, the unit is year; t_m represents the peak production time, the unit is year; b is the model parameter, which can represent the slope of the peak to a certain extent.

Formula (1) takes the derivative of t to get the formula for calculating annual output.

$$P = \frac{dQ}{dt} = \frac{b \times \mathrm{URR} \times e^{-b(t-t_m)}}{\left[1 + e^{-b(t-t_m)}\right]^2}. \tag{2}$$

In the formula, P represents the annual output, the unit is $10^8 m^3/a$.

When $t = t_0$, the output growth reaches its peak; at this time, the change rate of the cumulative output Q is the largest, that is, dQ/dt is the largest.

$$P_m = b \times \mathrm{URR}/4. \tag{3}$$

In the formula, P_m is the peak annual output, the unit is $10^8 m^3/a$,

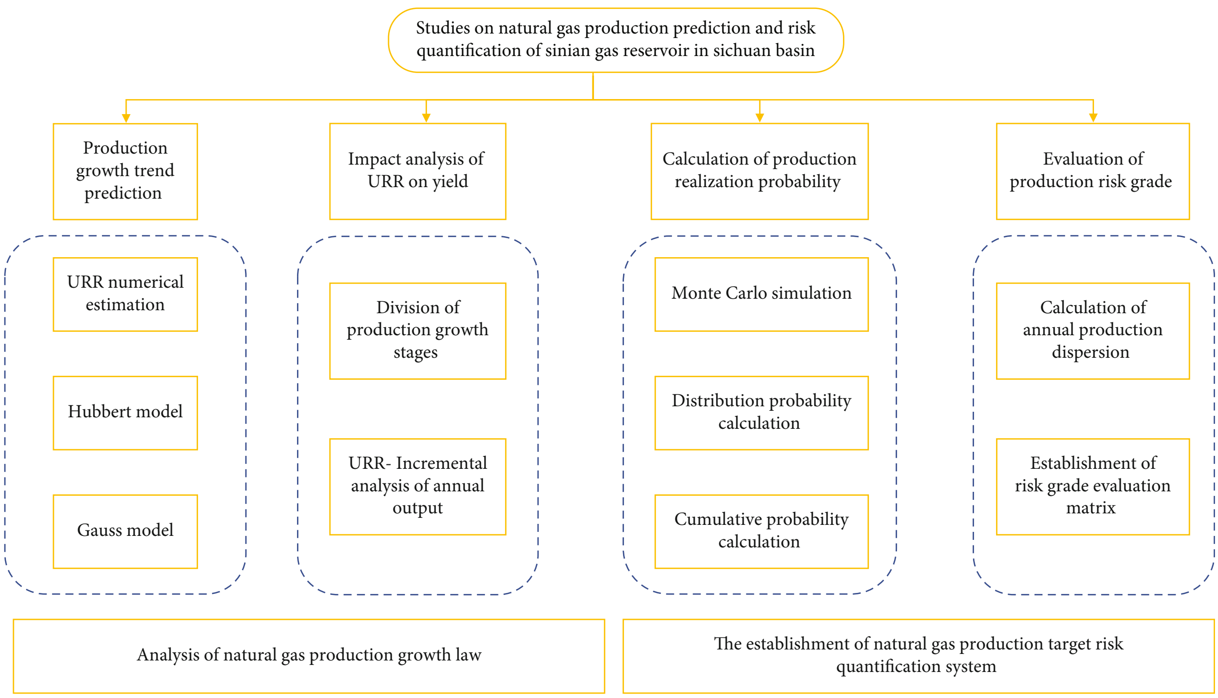


Figure 2: Flow chart of natural gas production prediction and risk quantification.

Transform Formula (3) into $\text{URR} = 4Q_m/b$, and substitute it into Formula (2).

$$P = \frac{2P_m}{1 + \left(e^{b(t-t_m)} + e^{-b(t-t_m)}/2\right)}. \tag{4}$$

Substitute the hyperbolic cosine function $\cosh(x) = e^x + e^{-x}/2$ into Formula (4) and obtain the annual output calculation formula of the Hubbert model [38] as follows:

$$P = \frac{2P_m}{1 + \cosh\left[b(t - t_m)\right]}. \tag{5}$$

The change process of the Hubbert model curve is a gradual increase from the beginning, then a stable period at the apex, and finally, a rapid decline until the resources are completely exhausted.

The Hubbert model is relatively mature in the prediction of recoverable reserves of oil and gas reservoirs, but it takes the cumulative production corresponding to the time of production approaching infinity as the ultimate recoverable reserves. In fact, the result is technology recoverable reserves, which is larger than the required ultimate recoverable reserves.

2.1.2. The Gauss Predictive Model. Both the Gauss and Hubbert models are based on growth curves obtained from life cycles, so they both present symmetrical shapes [43, 44]. The Gauss model equations are as follows:

$$f(t) = \frac{1}{s\sqrt{2\pi}} e^{-(t-\mu)^2/2s^2}. \tag{6}$$

In the formula, μ is the mean; s is the standard deviation.

In the process of natural gas exploitation, the cumulative production of the exploitation time t in the interval $(0, \infty)$ is regarded as the ultimate recoverable reserves URR. Multiplying the distribution density function $f(t)$ by the ultimate recoverable reserves URR, the formula for calculating the annual production Q can be obtained [45].

$$Q = \frac{\text{URR}}{s\sqrt{2\pi}} e^{-(t-\mu)^2/2s^2}. \tag{7}$$

Differentiating Formula (7) with respect to the mining time t,

$$\frac{dQ}{\text{dt}} = \frac{\text{URR}}{s\sqrt{2\pi}} e^{-(t-\mu)^2/2s^2} \left(-\frac{t-\mu}{s^2}\right). \tag{8}$$

When production growth reaches its peak, the annual rate of change in production is $(dQ/dt) = 0$. At this time, the peak time of annual production is as follows:

$$t_m = \mu. \tag{9}$$

Substitute $t_m = \mu$ into Formula (8) to obtain the peak annual production Q_m.

$$Q_m = \frac{\text{URR}}{s\sqrt{2\pi}}. \tag{10}$$

Substituting Formulas (9) and (10) into Formula (7), the annual production calculation formula of the Gauss model can be obtained.

$$Q = Q_m e^{-(t-t_m)^2/2s^2}. \tag{11}$$

In the formula, the model parameter s can characterize the fluctuation of the peak to a certain extent.

2.2. Production Risk Quantification Theory

2.2.1. The Monte Carlo Probability Method. The Monte Carlo method is also called the statistical simulation method and statistical test method. It is a numerical simulation method that takes probability phenomenon as the research object. It is a calculation method for estimating unknown characteristic quantities by obtaining statistical values according to the sampling survey method. The Monte Carlo probability method is based on probability theory and mathematical statistics theory. The idea of this method is to establish a calculation model of occurrence probability and then obtain the statistical characteristics of probability through a "sampling test", so as to obtain the approximate results of realization probability [46].

When the Monte Carlo probability method is used for probability calculation, the problem to be solved is first transformed into the expected value of a probability model, and then the established prediction model is randomly sampled. In the calculation process of the simulation test, enough random numbers should be drawn and the problem to be solved should be statistically analyzed; otherwise, the calculation accuracy will be affected [47, 48].

The equation for establishing the mathematical expectation and the probability distribution density function is as follows; then, the mathematical expectation of the variable $f(x)$ is

$$E = \int_{x_0}^{x_1} f(x)\psi(x)\mathrm{d}x. \tag{12}$$

$f(x)$ is a function of random variables; $\psi(x)$ is the distribution density of random variables, according to the distribution density function. $\psi(x)$ randomly select N samples x_i. The arithmetic mean value of the function value $f(x_i)$ corresponding to the sample point is taken as the integral estimation value.

$$\bar{E_N} = \frac{1}{N}\sum_{i=1}^{N} f(x_i). \tag{13}$$

According to the probability distribution density function of the variable, the value of the variable is randomly selected in sequence and after a large number of repeated independent simulations of the value of the variable. The probability density distribution of the objective function can be obtained, and the Monte Carlo simulation can realize the calculation process of a random sampling of variables [49].

The advantages of the Monte Carlo method are: (1) the error of the method is independent of the dimension of the problem; (2) it can directly solve the statistical problem; (3) it can directly deal with the continuous problem. The premise of applying the Monte Carlo simulation is to determine the mathematical model of the objective function and the probability distribution of the variables in the model. Each parameter generates a large number of random samples according to the given probability distribution and substitutes them into the model to calculate the probability density distribution curve of the objective function. The role of the Monte Carlo method in experiments is to ensure the objectivity of the experiment and avoid deviations due to subjective reasons. The specific steps are shown in Figure 3.

2.2.2. Risk Level Evaluation Matrix. When quantifying the production risk level, it is necessary to combine two indicators (realization probability P and dispersion degree C). The realization probability P of output represents the realization probability of reaching a certain output in a certain year. The dispersion degree C of the output represents the degree of difference between the output value and the rest of the output values. Therefore, the smaller the value of the dispersion degree C, the smaller the influence of the risk factors, the stronger the output stability, and the smaller the risk. The main formula applied to the degree of dispersion of yields is the coefficient of variation formula. The advantage of this formula over standard deviation for the coefficient of variation is that it does not require the mean of the reference data.

The formula for calculating the discrete degree of output is as follows:

$$C = \frac{s}{\mu}. \tag{14}$$

The meaning of the parameters in the formula is as follows: μ is the mean; s is the standard deviation.

In order to realize the evaluation of risk level, it is necessary to comprehensively realize the two evaluation indicators of probability P and degree of dispersion C and establish a risk evaluation matrix. The risk assessment matrix divides production risks into four levels (Figure 4) and quantifies risks according to the forecast results of natural gas production.

The regions of the yield risk matrix and their corresponding risk levels are shown in Table 1.

3. Results

3.1. Estimation of URR and Peak Production. By mapping the relevant data of natural gas exploration and development of gas reservoirs in the central Sichuan paleo-uplift (Figure 5), the purpose of clearly showing the growth trend of production is achieved from the map. It can be seen from the figure that the natural gas production currently maintains a rapid growth trend, which is consistent with the trend of the Hubbert and Gauss forecasting model (Formulas (5) and (11)) in the early stage of the curve growth. Therefore, these two prediction models can be used to achieve the

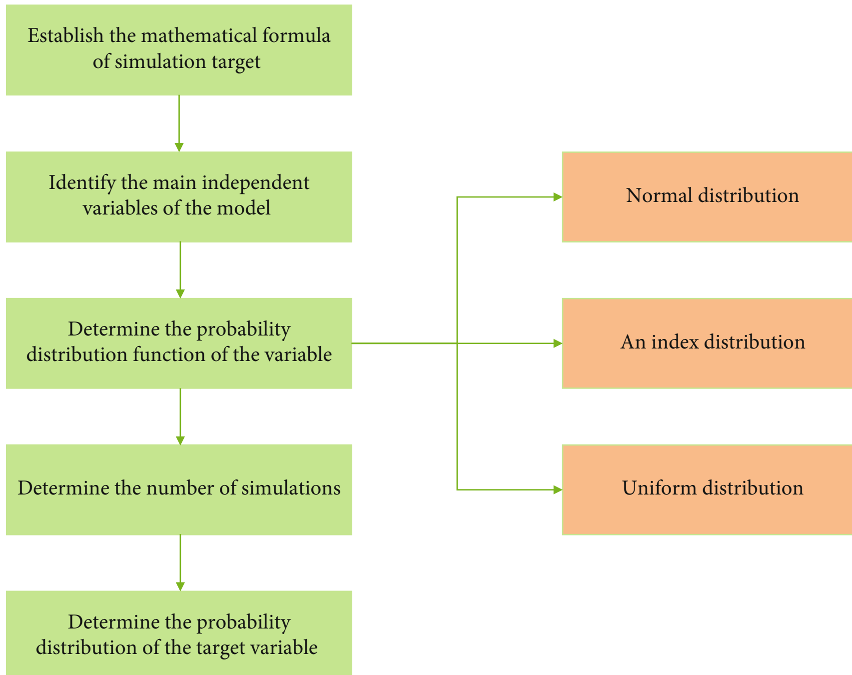


FIGURE 3: Specific steps of the Monte Carlo simulation method.

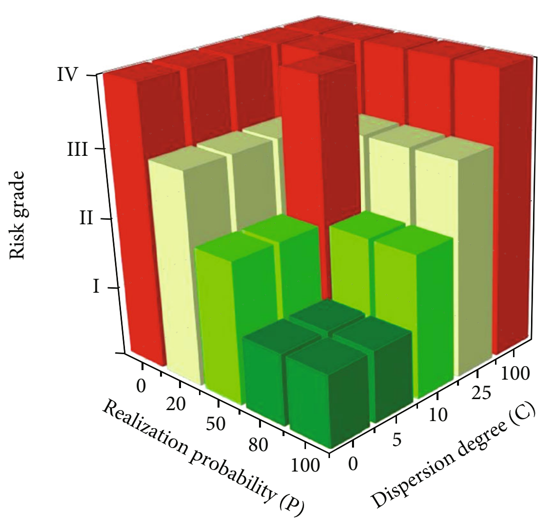


FIGURE 4: Quantization matrix of the production risk level.

purpose of predicting the natural gas production of gas reservoirs in the eastern Sichuan paleo-uplift.

In order to achieve the final purpose (natural gas production forecast), some relevant data need to be preliminarily sorted out. The first is to make a reasonable estimate of a rough range of the ultimate recoverable reserves URR (hereinafter referred to as URR), so as to determine the rough range and determine the basis for subsequent research. However, because the exploration and development of natural gas in the central Sichuan paleo-uplift gas reservoir are in the early stage, the understanding of the gas reservoir is not high, and it is impossible to master a reasonable URR estimation method. Therefore, the method adopted in this study for the approximate estimation of URR is a numerical calculation method.

In order to achieve a rough estimate of URR, it is necessary to confirm some data related to URR. First, through the geological exploration of the gas reservoir in the central Sichuan paleo-uplift, it was found that the natural gas resource of this gas reservoir is roughly $3 \times 10^{12}\,\mathrm{m}^3$. Then, according to the data of many gas reservoirs in the Sichuan Basin, the development law of gas reservoirs is found, and the approximate range of natural gas proven rate and recovery rate can be determined. According to the analysis of the current laws of natural gas exploration and development in the Sichuan Basin, it is found that the proven rate of gas reserves is roughly in the range of 40%-70%, and the recovery of the gas reservoir is in the range of 30%-70%. A rough range of recoverable reserves of natural gas can be found from the above data as $(3600 - 14700) \times 108\,\mathrm{m}^3$. In addition, due to some limitations, the mined reserves cannot be completely converted into the ultimate mined reserves URR, and the conversion rate is 55%-65%. The estimated range of URR is $(1980 - 9555) \times 108\,\mathrm{m}^3$, this method is only a simple numerical calculation method. The approximate distribution of URR is shown in Figure 6. With the deepening of the understanding of gas reservoirs, the calculation method also needs to be constantly updated.

3.2. Natural Gas Production Growth Trend Forecast. In order to better predict the peak gas production of gas reservoirs in the central Sichuan paleo-uplift, it is necessary to select a prediction model suitable for the gas reservoir. The method is to use the Hubbert and Gauss peak prediction models to predict the growth trend and peak production of natural

Table 1: Production risk grade judgment criteria.

Risk level	Describe	Judgment criteria
Risk level I (the dark green area in Figure 4)	Yield targets are very easy to achieve	$P > 80\%$, $C \leq 5\%$
Risk level II (the light green area in Figure 4)	Yield targets are easy to achieve	(1) $50\% \leq P \leq 80\%$, $C \leq 10\%$ (2) $P > 80\%$, $5\% < C \leq 10\%$
Risk level III (the light yellow area in Figure 4)	Yield targets are easier to achieve	(1) $20\% \leq P < 50\%$, $C \leq 10\%$ (2) $P > 50\%$, $10\% < C \leq 25\%$
Risk level IV (the red area in Figure 4)	Yield targets are not easy to achieve	(1) $P < 20\%$ (2) $20\% \leq P < 50\%$, $C > 10\%$ (3) $C > 25\%$

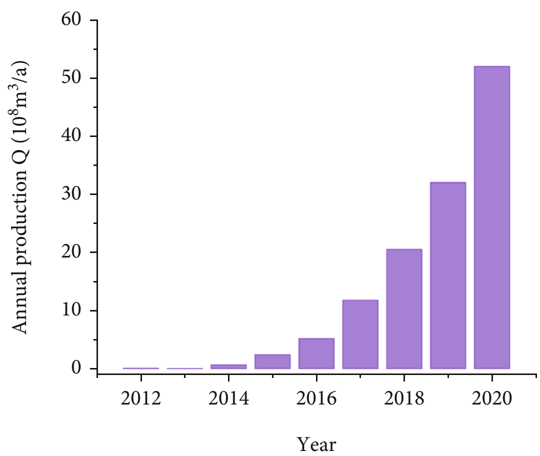


Figure 5: Growth trend of annual natural gas production of gas reservoirs in central Sichuan paleo-uplift.

gas production in the central Sichuan paleo-uplift gas reservoir. The models used in the article are mainly divided into three parts: the area enclosed by the curve (URR), the peak time of the curve (t_m), and the width coefficient of the curve (b or s). The main principle of the models is to use the historical data of natural gas production, according to the prediction curve obtained by the models; the least square method is used to achieve the fitting with the historical data, to find the best prediction value. Except for URR, other influencing factors do not need to be added for calculation, because these influencing factors have been included in the trend of historical data; when the historical data fits the curve, these factors have already played a role, so it is unnecessary to analyze these factors. The method is to bring different URR values into Formulas (5) and (11) to obtain the corresponding curves. And in order to get a more in-depth understanding of the growth law of natural gas production with URR, 100 different values are selected within the estimated range of URR, and these values are put into the above two formulas together to obtain different production forecast results. The curves are combined to obtain Figures 7(a) and 8(a), and the corresponding model parameter values are extracted in Figures 7(b) and 8(b), so as to obtain the changing relationship between URR, peak value, and parameter.

It can be seen in Figures 7(a) and 8(a) and that the prediction results of the two models of Hubbert and Gauss are highly similar, and the prediction results of the two types of production can be analyzed simultaneously. To find out the variation trend of peak yield with URR, that is, peak yield and *URR* show a positive correlation; it can also be found from the figure that the peak yield is also constantly changing with the year, showing a trend of first increasing and then decreasing, and its peak time is in 2040. In the time period from 2023 to 2057, the output growth curve exhibits axisymmetric about $t = 2040$.

It can be seen in Figures 7(b) and 8(b) that in the Hubbert model, with the continuous increase of URR, its peak output Q_m and parameter b show a step-by-step growth trend. When the URR increases to a certain value, the parameter will increase from a rapid increase to a more gradual increase. In the Gauss model, with the increase of URR, the peak output Q_m increases linearly, and the parameters show a relatively smooth downward trend, and the decreasing rate gradually becomes smaller and, finally, tends to be flat. The change of the parametric model can reflect the change of output. Therefore, when the growth rate of *URR* is the same, the output prediction result of the Gauss model has a more stable growth trend than that of the Hubbert model.

According to the changing speed of output growth, the process of output growth is divided into 4 periods, that is, the period of rising production is 2023-2033, the period of stable production is 2034-2046, the period of rapid production decline is 2047-2057, and the period of slow production decline is 2057-2070. The production first increased with the growth of the years until 2040, reached the peak in 2040, and then began to decline with the growth of the years, and finally, gradually, approached 0.

In order to compare the accuracy of the results predicted by the two forecasting models, the process of correlation analysis was introduced. The advantage of correlation analysis is to better determine the accuracy of the prediction curve by fitting the historical data and the forecast curve, so as to select the curve that is suitable for the actual situation through a comparison that is carried out between the five kinds of production forecast data of the two models and the historical data distribution (Table 2). From the results of the correlation analysis, it can be seen that the correlation coefficients of the yield prediction results of the two models

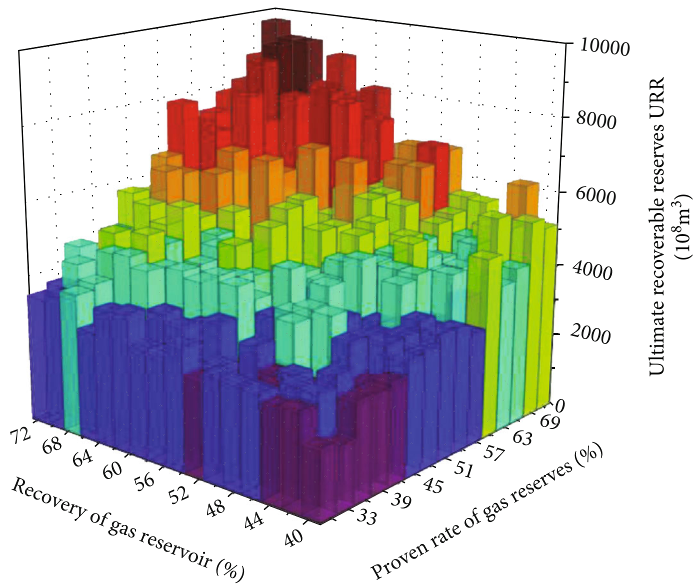


Figure 6: Ultimate recoverable reserves URR distribution map.

are both high. The average correlation coefficient of the former is about 0.98, and the average correlation coefficient of the latter is about 0.99. It can be seen that the prediction results of the Gauss model are more accurate. Therefore, the prediction method of the Gauss model is selected as the main method for the prediction of natural gas in the Sichuan-Chongqing uplift gas reservoir.

4. Discussions

4.1. Probability Calculation of Production Realization Based on the Monte Carlo Method. It is known from the foregoing that the future production growth process is divided into 4 stages, namely, the production increase stage, the production stable stage, the rapid production decline stage, and the slow production decline stage. In order to achieve the ultimate goal of peak production forecast, it is necessary to predict the realization probability of different production growth stages.

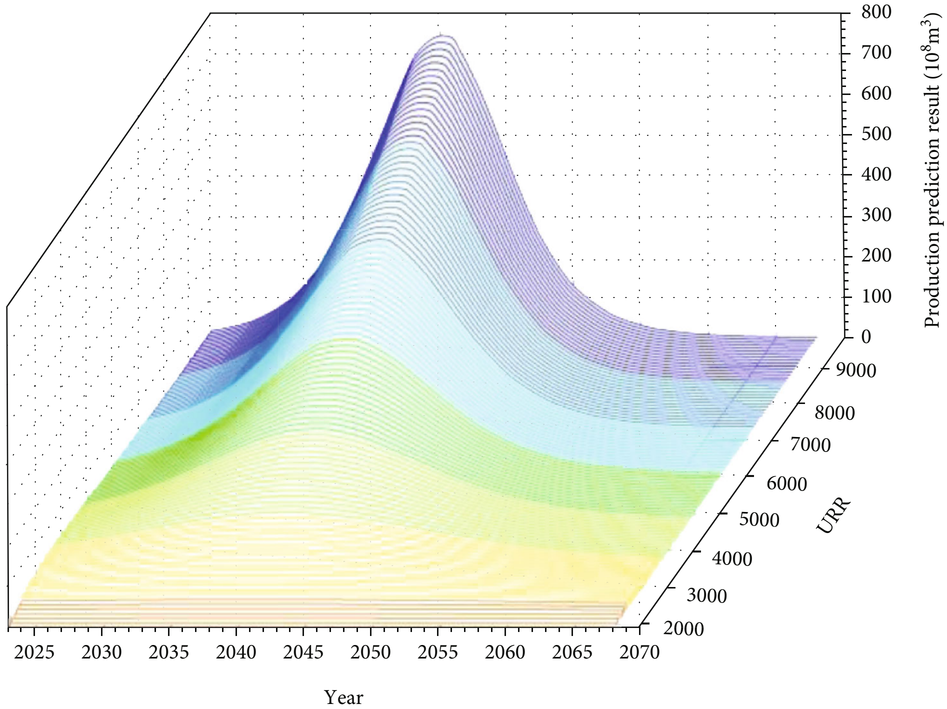
In order to find out more clearly the effect of URR on yield prediction results, the relationship between URR and annual yield in different stages was drawn graphically, and finally, the URR-yield prediction results of different years in each stage were obtained (Figure 9). The purpose is to see the relationship between URR and annual output more intuitively. From Figure 9, we can see that in the stage of yield stabilization, the change of yield with URR is most obvious, the change is gentle during the slow decline of production, and the change is symmetrical in the stage of yield rise and the stage of rapid decline of production.

Briefly explain some of the meanings in Figure 9, taking the URR-yield prediction result graph of the production rising stage in Figure 9(a) as an example. The abscissa represents different URR, the ordinate represents the annual output Q, and the lines of different colors represent the URR in different years and the corresponding annual output. What can also be clearly shown in the figure is the difference in annual production between different years at the same URR.

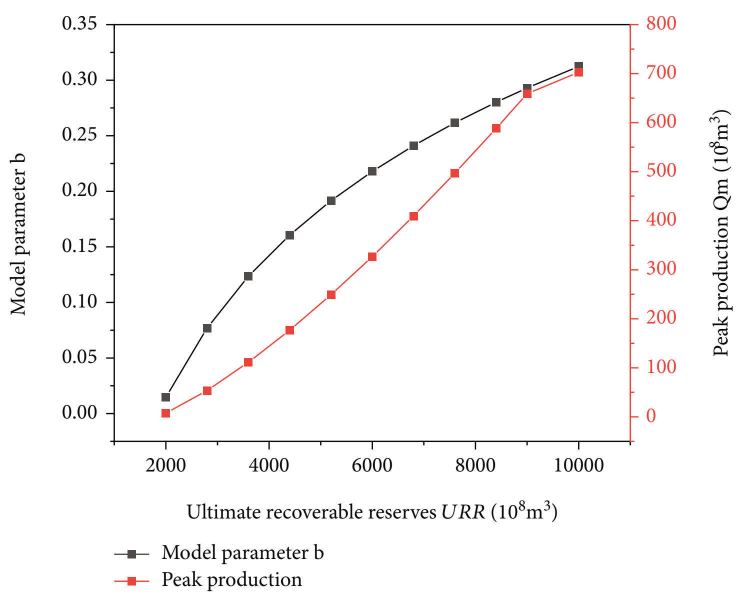
In order to calculate different production realization probabilities in different production growth stages and years, the Monte Carlo method introduced in Section 2.2.1 above is applied. Now, 2040 is taken as an example to introduce the calculation process of realization probability. The Gauss yield calculation equation of Formula (11) is used as the mathematical model for probability simulation, URR is the main factor affecting yield, and the value of URR is obtained by uniform extraction. The method is mainly to divide the URR into 300 parts evenly in the estimation interval of $\mathrm{URR}(1980-9555)\times 108\,\mathrm{m}^3$, conduct random sampling for many times at the same time, and set the number of times of sampling of URR to 1,000,000 times. Each time a URR value is extracted, the corresponding values of Q_m and t_m are found from the Figure 8(b), and $t=2040$ is substituted into Formula (11) at the same time to obtain the output Q in 2040. According to the above description, the cumulative probability corresponding to the annual output reaching Q (URR = 1980) and above is 100%, and the cumulative probability corresponding to the annual output reaching Q (URR = 9555) is 1%.

After the Monte Carlo simulation, the distribution probability of the annual output Q is calculated, and the corresponding cumulative probability is obtained by one accumulation. The obtained cumulative probability is the realization probability of the output. The cumulative probability of the statistics is shown in the following figure.

In Figure 10, you can clearly see the probability that a certain production is likely to be achieved each year, and it can also be seen that in 2040, the slope is the gentlest compared to other curves, and it is gradually steeper on both sides with 2040 as the center. Calculate the yield realization probability results of typical years in the realization probability map and make a statistical table (Table 3). In the table,



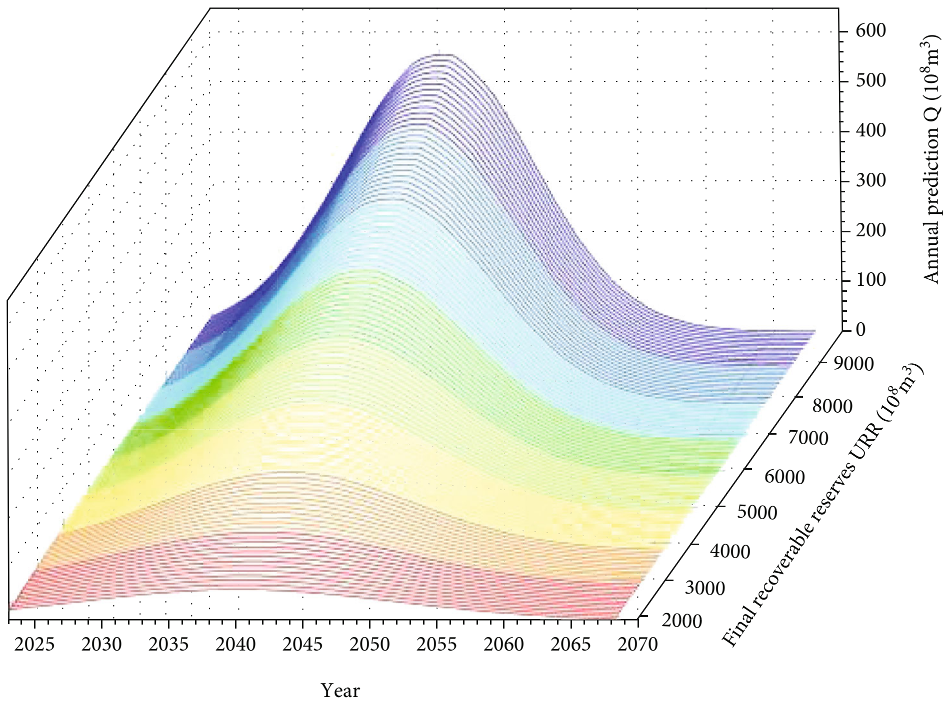
(a) Yield forecast results



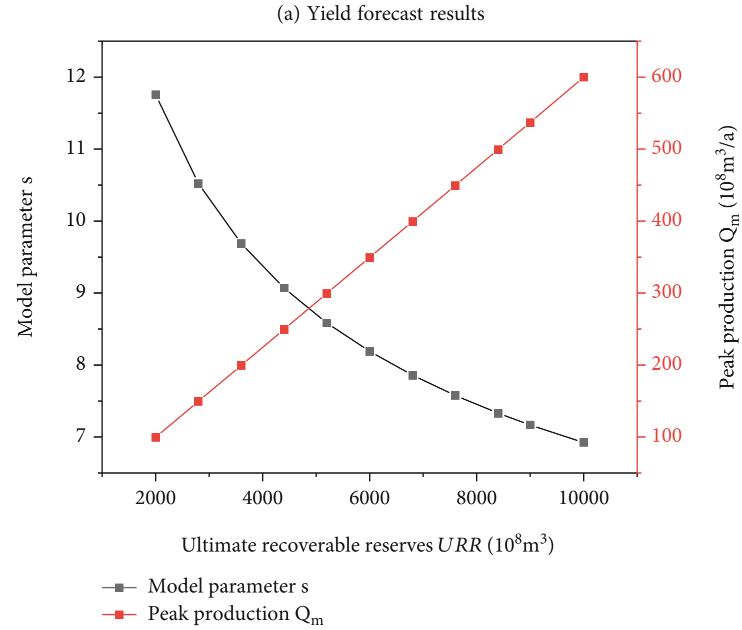
(b) Model parameter prediction results

Figure 7: Prediction results of natural gas production by the Hubbert model.

the output corresponding to P80 is the guaranteed output, the output corresponding to P50 is the average output, and the output corresponding to P20 is the ideal output. Through the horizontal comparison of the statistical table (Table 3), it can be seen that the probability of yield realization decreases with the increase of yield. It can be seen from the longitudinal comparison of the statistical table that under the same probability of realization, the average annual output Q shows a trend of first increasing and then decreasing with the years. Taking the realization probability of average production as an example, the realization lower limit of Q in 2040 is $245.74 \times 108\,m^3$, the realization lower limit of Q in 2030 is $159.28 \times 108\,m^3$, and the realization lower limit of Q in 2051 is $145.22 \times 108\,m^3$, indicating that the average annual production peaks in 2040. In this paper, natural gas production is calculated in the probability interval of 0%-100%, and the risk of production in different probability intervals is also quantified. The results of production simulation can obtain the realization probability of different natural gas development goals. It has an important reference and



(a) Yield forecast results



(b) Model parameter prediction results

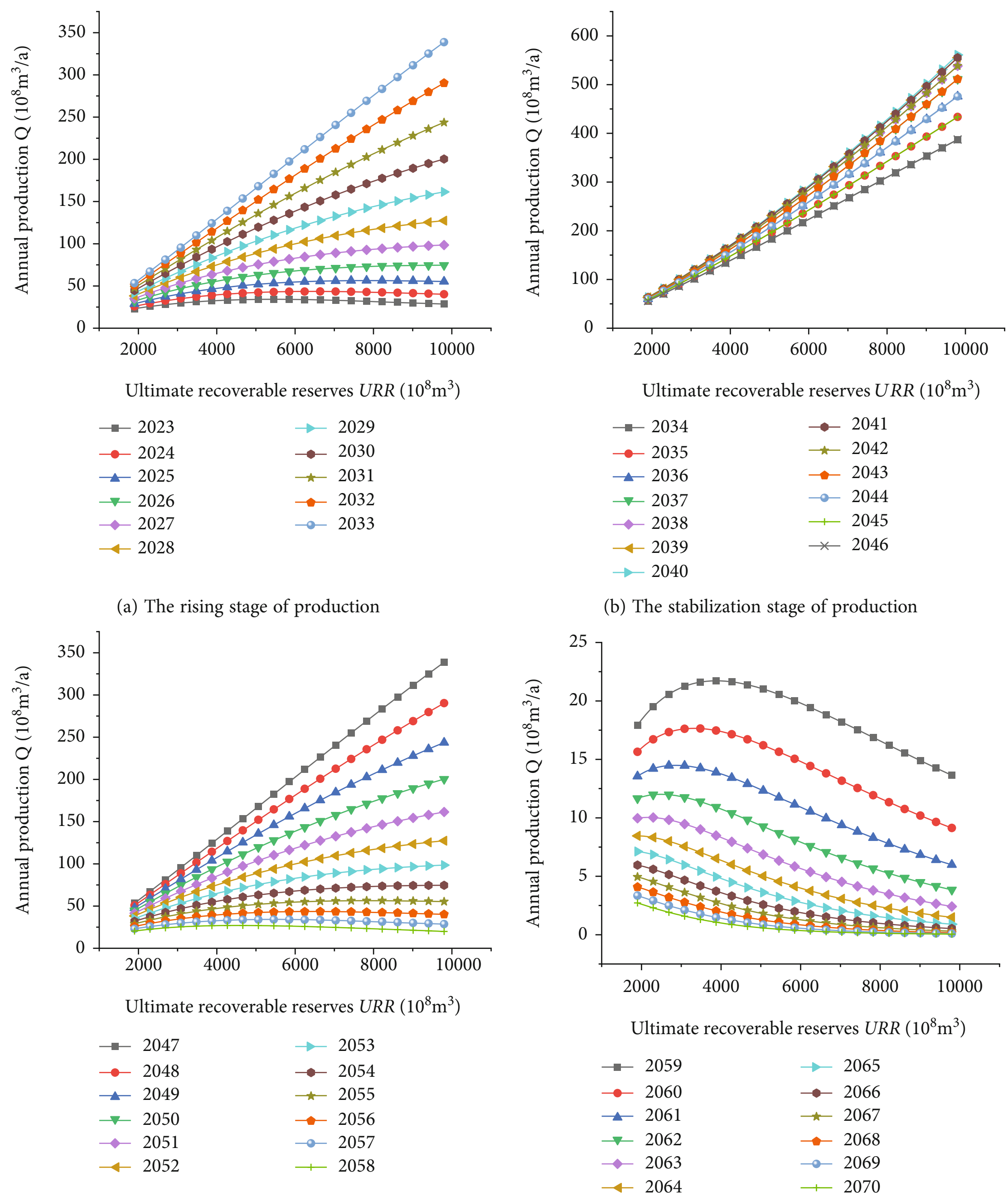
Figure 8: Prediction results of natural gas production by the Gauss model.

Table 2: Correlation analysis of yield prediction results.

URR$(10^8 m^3)$		2000	3875	5750	7625	9555
Correlation coefficient	Hubbert model	0.9891	0.9793	0.9815	0.9813	0.9848
	Gauss model	0.9894	0.9875	0.9952	0.9871	0.9913

guiding role for the formulation and implementation of natural gas exploration and development plans for gas reservoirs in the central Sichuan paleo-uplift.

4.2. Production Risk Level Evaluation Based on Matrix Analysis. In order to realize the purpose of risk quantification of natural gas production of gas reservoirs in the eastern



(a) The rising stage of production

(b) The stabilization stage of production

(c) The rapid decline stage of production

(d) Slow decline stage of production

Figure 9: Prediction results of annual yield under different URR conditions.

Sichuan paleo-uplift, it is necessary to introduce the risk matrix in Section 2.2.2 to evaluate the production risk level. It is necessary to obtain the realization probability curve of the output of each year according to the calculation method of the relevant probability in Section 2.2. At the same time, the mean μ and standard deviation s of the annual output are also required, and the dispersion degree C of the annual output is calculated according to Formula (14). Finally, combine the two to finally realize the evaluation of the production risk level.

According to the value ranges of the four different stages of production growth, the realization probability curves of the four stages are superimposed with the different regions of the risk matrix to obtain the target risk levels of yield in different stages and years. The degree of dispersion $C \in$ (5% and 10%) in the rising stage and the stage of rapid decline in production, the degree of dispersion $C \in$ (10% and 25%) in the stage of stable production and the stage of a slow decline in production. The degree of dispersion and the probability of realization are integrated to obtain the risk

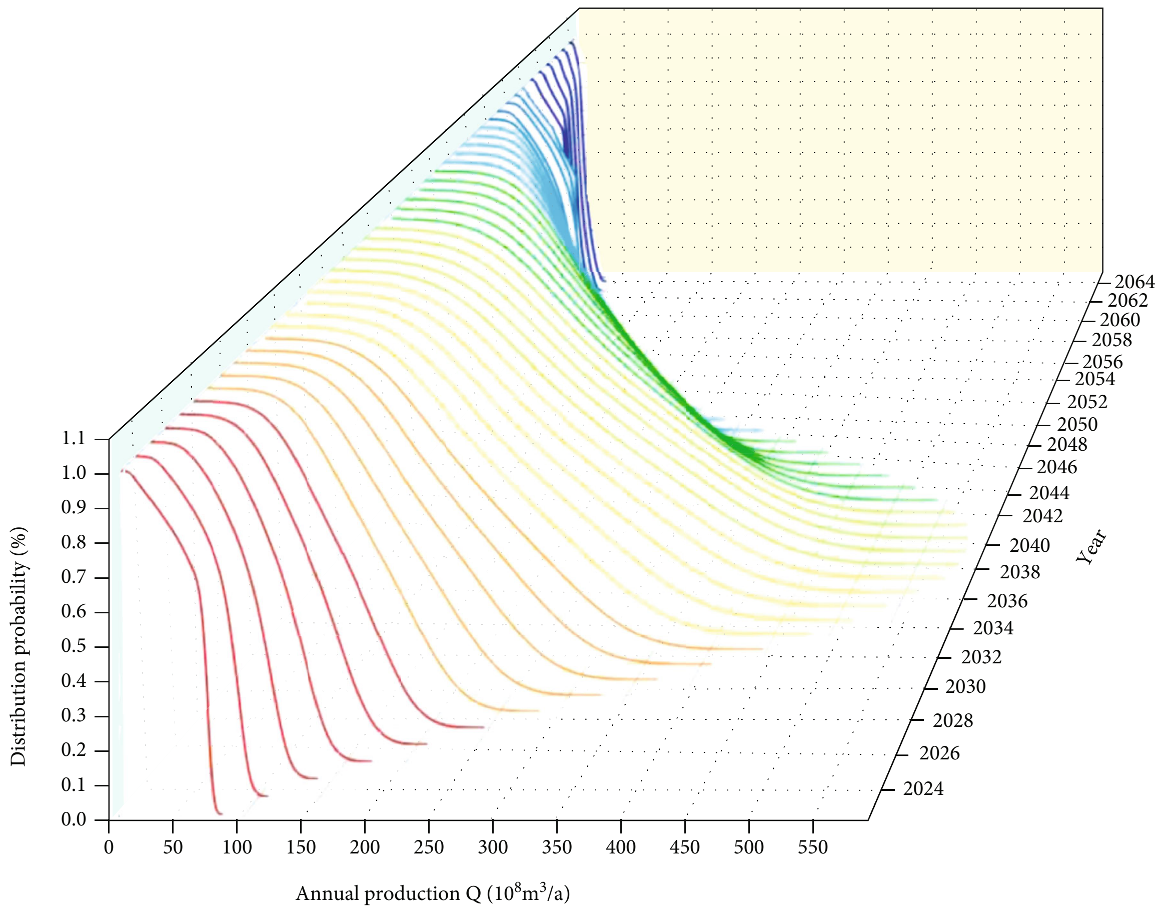


Figure 10: Yield realization probability calculation in different years.

Table 3: Calculation results of yield realization probability in different years.

Average annual production $Q(10^8m^3/a)$	P90	P80	P70	P60	P50	P40	P30	P20	P10
2030	89.60	109.51	126.10	142.69	159.28	179.19	195.78	212.38	235.60
2040	119.87	155.84	185.81	209.78	245.74	281.70	317.67	359.63	491.48
2049	81.20	98.60	116.11	130.50	145.22	159.50	174.22	191.19	208.79
2060	11.03	13.68	11.45	16.77	18.54	20.30	22.95	26.04	30.45

levels of different stages, and finally, the output target risk levels of different stages are integrated to form a comprehensive output risk level.

As can be seen in Figure 11, with the continuous increase of the output, the corresponding realization probability is also constantly decreasing, resulting in a gradual increase in the risk of output realization. According to the yield quantification results at different stages, the realization probability and risk level of different yields in each year can be directly obtained. The production risk level indicates how easy it is to achieve the production target. Therefore, the research on production risk quantification has an important guiding role in the exploration and development of natural gas and the decision-making and deployment. At the same time, it also provides a theoretical basis for the feasibility of natural gas production targets at different time nodes.

5. Conclusion

(1) The main research purpose of this paper is to form a prediction model for peak gas production of gas reservoirs in the central Sichuan paleo-uplift. Firstly, the resources in this area are used to estimate a rough range of the ultimate recoverable reserves, and the URR is used as the boundary condition in the Hubbert and Gauss model to predict the production. Combined with the Monte Carlo method to quantify the risk of yield, the probability of yield realization in different years is calculated

(2) Bring the URR into the Hubbert and Gauss model to predict the general trend of natural gas production in Sinian gas reservoirs, use correlation analysis to compare

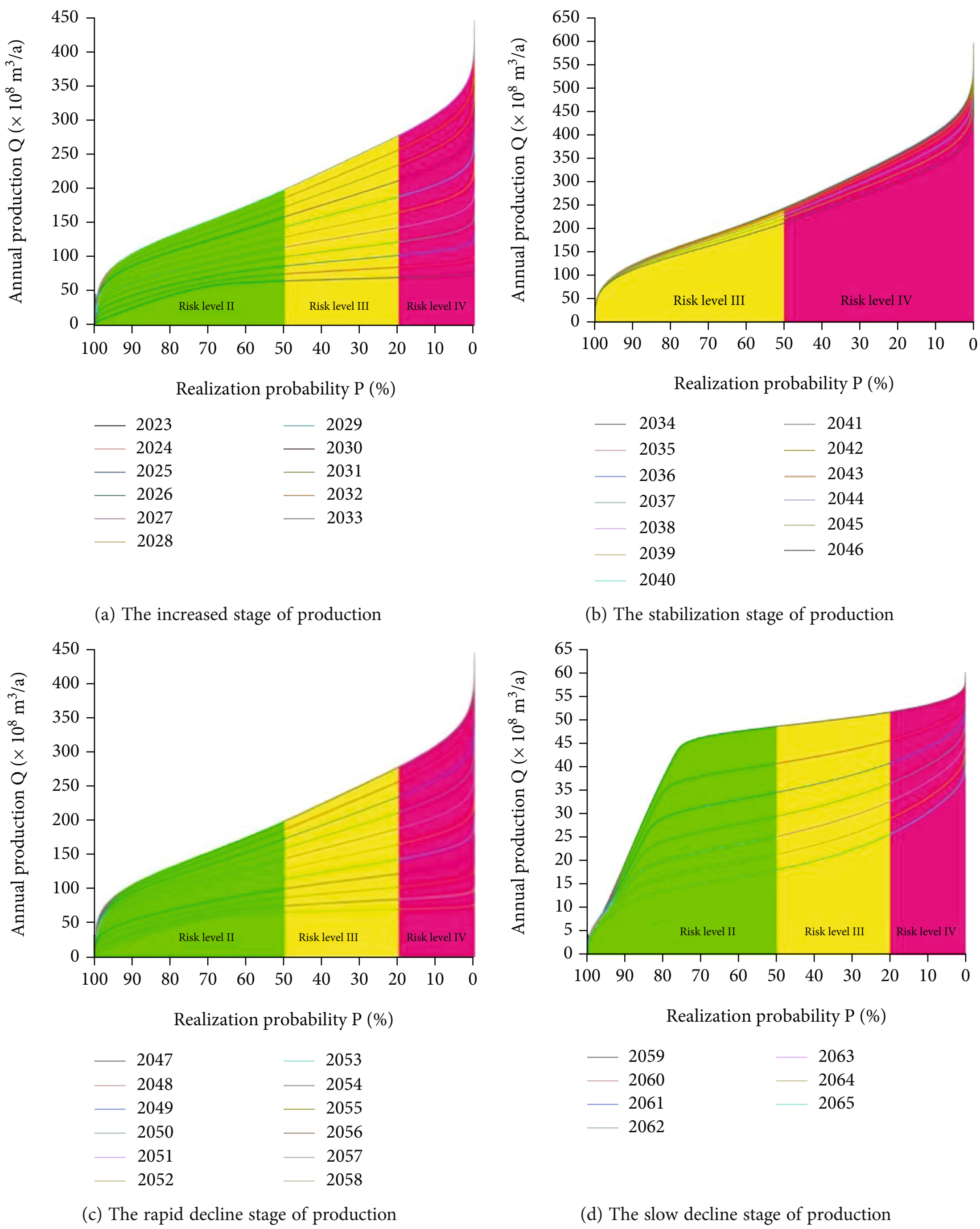


Figure 11: Production risk rating assessment.

the accuracy of the Gauss model and Hubbert model, and select a more suitable prediction model (Gauss model). The production forecast results show that the gas reservoir in the central Sichuan paleo-uplift will reach its peak value $(73 - 561) \times 10^8 \mathrm{m}^3/\mathrm{a}$ in 2040, and maintain a stable output from 2034 to 2046

(3) To realize the research of risk quantification, firstly, the URR is used as the independent variable to carry out the Monte Carlo simulation of the yield growth curve. Thus, the realization probability P of yield in each year with URR as the influencing factor is obtained, and then the dispersion degree C of yield is obtained. Combining the probability of output realization and the degree of dispersion, a risk level evaluation matrix is established, and finally, quantitative research on output risk is carried out. Promoted the establishment of a quantitative analysis system for natural gas production in the central Sichuan paleo-uplift gas reservoir

Data Availability

The experimental data supporting the conclusions are available from the corresponding author on request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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