An Environmental Risk Identification Method for Polar Drilling Based on G1-Cloud Model

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ABSTRACT

The polar region possesses enormous potential for oil and gas resource development, making it a focus of worldwide attention. However, the harsh climatic and geological conditions, along with the fragile ecosystems in the Arctic, impose stringent technical requirements for oil and gas extraction. Simultaneously, drilling operations in polar regions generate substantial amounts of liquid and solid waste, which can pollute and damage the vulnerable local environment. Therefore, there is a need to establish a set of environmental risk identification techniques or risk assessment methodologies suitable for polar drilling. Current evaluation methods—including the analytic hierarchy process, Bayesian networks, neural networks, and grey correlation analysis—have limitations such as computational complexity and strong subjective influence, which may compromise the accuracy and reliability of the assessment results. Moreover, the outcomes of these evaluations heavily depend on sample sources. Given the complexity of the polar environment, data reliability and the need for rapid, efficient assessment methods are crucial. Accordingly, this paper proposes a cloud model-based environmental risk identification method for polar drilling, which enables multi-source acquisition of polar environmental data. The cloud model replaces the membership function used in conventional fuzzy evaluation methods, thereby accounting for both the fuzziness and randomness of the raw data and improving the accuracy of evaluation results. This comprehensive cloud model-based approach can reveal the randomness and fuzziness of the evaluation subject, facilitate the conversion between data and conceptual understanding, and produce evaluation results that balance subjective and objective considerations. Rooted in fuzzy mathematics and probability theory, the cloud model yields objective, reasonable, reliable, and persuasive assessment outcomes. Compared to traditional methods, the proposed approach demonstrates stronger robustness in handling uncertainty and data scarcity, offering a reliable tool for environmental risk identification and control in polar drilling.

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1 Introduction

The polar region has long attracted international attention due to its significant potential for oil and gas resources. Estimates suggest approximately 9 billion barrels of oil and 47 trillion cubic meters of natural gas remain undiscovered there [1–3]. Developing these resources holds considerable strategic importance and could substantially impact the global energy market. However, despite this vast potential, the extreme climatic conditions and fragile ecosystems of the Arctic present major challenges for extraction activities [4]. Furthermore, early-stage exploitation technologies were less mature, causing considerable environmental damage. For decades, oil and gas operations have adversely affected the polar ecological environment [5]. Therefore, conducting environmental pollution risk assessments for polar drilling is crucial.

Environmental risk assessment in polar regions is complicated by numerous factors. The cold climate and vulnerable ecosystems [6] create conditions distinct from those in temperate regions, necessitating risk assessment methods tailored specifically to the polar context.

From a methodological perspective, common environmental risk assessment techniques include the Analytic Hierarchy Process (AHP), fuzzy comprehensive evaluation, neural networks, and Bayesian networks. Among these, AHP [7] and fuzzy comprehensive methods [8] primarily offer qualitative descriptions, often lacking precise quantitative calculation. They struggle to accurately characterize the fuzziness, randomness, and other uncertainties inherent in the evaluation process. While neural network [9] and Bayesian network methods [10] support both qualitative and quantitative assessment, their performance heavily depends on data volume. The harsh polar climate makes environmental monitoring data difficult and expensive to obtain, resulting in typically small datasets that limit the applicability of these data-intensive methods.

Cloud model theory [11] offers a solution by enabling the transformation between quantitative data and qualitative concepts, while simultaneously accounting for both the fuzziness and randomness associated with polar drilling pollution risks. In this study, we employ a cloud model integrated with the G1 method (an order relation analysis method) to assess the environmental pollution risks of polar drilling. This model is specifically designed to handle the inherent fuzziness (e.g., unclear boundaries between risk levels) and randomness (e.g., the stochastic nature of pollution events) in complex systems. It integrates qualitative analysis with quantitative computation, establishing a two-way mapping that balances subjective judgment with objective data. Grounded in fuzzy mathematics and probability theory, the cloud model yields objective, reasonable, and reliable evaluation results, enhancing persuasiveness [12].

Consequently, the G1-cloud model-based method proposed here represents an effective approach for polar drilling environmental risk assessment. Unlike conventional methods, it specifically addresses the challenges of data scarcity and extreme operational conditions in polar regions. By leveraging the cloud model's capability to manage fuzziness and randomness with limited samples, and when enhanced with strategies like transfer learning and simulated data augmentation, it achieves reliable environmental risk identification under these demanding circumstances.

2 Research Purpose and Contribution

The main purpose of this paper is to solve the problem that the risk of environmental pollution is difficult to assess in the process of oil and gas exploitation in polar regions. Therefore, this paper innovatively proposes a polar drilling environmental risk assessment method based on G1-cloud model theory. The main contributions of this paper are as follows:

First of all, this is the first time that G1 method and cloud model theory are applied to polar drilling environmental risk assessment. Secondly, this paper selects the appropriate indicators and establishes a set of environmental risk factors for polar drilling. Finally, this paper constructs an environmental risk assessment system for polar drilling, and obtains the pollution risk results and comprehensive pollution risk results of each index. The proposed evaluation method realizes multi-dimensional, multi-angle, and multi-granularity assessment of the polar environment, addressing the key challenges of data scarcity and uncertainty in extreme settings. The cloud model's adaptive parameterization aligns with the dynamic adaptation paradigm seen in efficient learning systems [13,14], while its applicability in data-scarce scenarios resonates with edge-computing strategies for distributed sensing networks [15]. To the best of our knowledge, no prior study has integrated such an approach for polar drilling environmental risk assessment.

The environmental footprint of oil and gas extraction is significantly shaped by activities during drilling and well completion. These stages encompass a sequence of interventions where the release of specific waste streams can impair local ecosystems. Among the most consequential effluents are drill cuttings and spent fluids, carriers of toxic constituents like heavy metals and persistent hydrocarbons that endanger terrestrial and aquatic habitats. Simultaneously, the management of produced water—a complex brine containing dissolved salts, naturally occurring radioactive materials, and residual organics—demands rigorous treatment to prevent freshwater resource degradation. The application of hydraulic fracturing, while enhancing resource recovery, introduces the risk of injected fluids migrating into groundwater zones through potential wellbore failures. Atmospheric emissions from these operations, encompassing not only methane and volatile organics but also combustion particulates, further exacerbate environmental impacts. Compounding these issues, inadequate protocols for managing solid debris and used chemical supplies can lead to secondary contamination of soils and waterways. In aggregate, these interdependent pollution vectors threaten to destabilize ecological integrity, endanger public health in proximate areas, and incur lasting environmental liabilities.

Environmental pollution from oil and gas operations often originates during the drilling and completion phases, which comprise various stages requiring careful oversight. A primary source of risk is the release of drilling fluids and cuttings; these materials frequently contain heavy metals, hydrocarbons, and chemical additives that can adversely affect soil and aquatic environments. Produced water, typically high in salts, radionuclides, and organic pollutants, also presents serious disposal concerns, as inadequate management may lead to freshwater contamination. The practice of hydraulic fracturing, widely used in well completion, introduces high-pressure fluids into formations, creating a potential pathway for leaks into groundwater if well barriers fail. Air quality impacts further compound these risks, resulting from emissions of volatile organic compounds (VOCs), methane, and particulate matter generated by flaring, venting, and diesel equipment. Moreover, improper handling of solid waste and chemical containers during these operations increases the likelihood of soil and surface water pollution. Together, these factors can contribute to ecosystem decline, pose health risks to local populations, and result in persistent environmental harm.

3 Polar Drilling and Completion Environmental Risk Factor Set

3.1 Low Temperature Simulation

The drilling cuttings samples selected in this paper were taken from the polar oil and gas drilling site, and the samples were black-brown and relatively viscous solid-liquid two-phase mixtures at room temperature and pressure, accompanied by a pungent petroleum odor. The water content and oil content of drill cuttings can be determined by azeotropic distillation method and Soxhlet extraction-infrared oil tester, and the water content and oil content of the samples are 8.28% and 18.35%.

The drilling cuttings samples selected for this study were obtained from the oil and gas drilling site in the Arctic region of China. At ambient temperature and pressure, the samples were a black-brown and viscous mixture of solid and liquid phases, accompanied by a pungent petroleum odor. After low-temperature pyrolysis treatment, the drilling cuttings were analyzed for water content, oil content, using the co-boiling distillation method and Soxhlet extraction-infrared oil analyzer. The results showed a water content of 8.28% and an oil content of 18.35% in the samples. A comparison of the appearance of oil-containing drilling cuttings before and after low-temperature pyrolysis treatment is shown in Fig. 1. As shown in Fig. 1, there were noticeable changes in color and morphology of the polar oil-containing drilling cuttings before and after treatment: before treatment, the polar drilling waste appeared black and viscous, with solid particles agglomerating together; after treatment, the color of the oil-containing drilling cuttings became lighter compared to before treatment, and the dispersion between solid particles became more apparent.

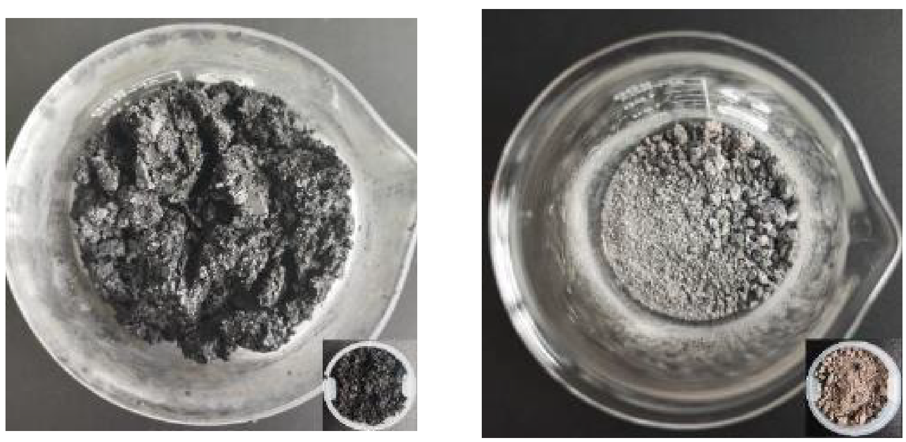

Figure 1: Comparison of polar drill cuttings samples before and after low-temperature pyrolysis

The polar oil-bearing drill cuttings samples were soaked in 2.5% glutaraldehyde solution, placed in a 4°C refrigerator to fix their structure for 4 h, and then added absolute ethanol solutions with different content gradients and dehydrated multiple times. The processed polar oil-bearing drill cuttings Dry in a freeze-drying box for 12 h, and finally observe the microstructure on a scanning electron microscope.

3.2 Pollution Partitioning Method Based on Optimized Radial Basis Network

This section outlines the methodologies used in this study, focusing on our proposed cloud model framework for uncertainty modeling and domain adaptation. A key distinction must be emphasized between the cloud model and the traditional AI models (RBF and GAN) used here for comparative benchmarking. While RBF and GAN represent established approaches for function approximation and deep learning-based adaptation, their standard architectures and training protocols are well-documented in the literature.

The core of our work, however, lies in the cloud model, which operates on a fundamentally different principle. Unlike data-driven networks that learn parameters through iterative training, the cloud model is a cognitive model for uncertainty reasoning. It is constructed via a statistical transformation (the backward cloud algorithm) to obtain its digital characteristics (Ex, En, He), requiring no traditional training phase and containing no trainable parameters. Consequently, standard practices of detailing network architectures and hyperparameters are not applicable. Its validation, therefore, shifts from pure error minimization (e.g., MAE, R^2) to evaluating the reasonableness of its conceptual transitions and the physical plausibility of its inference outcomes.

The optimized radial basis function (RBF) network constructs a multi-layer nonlinear mapping structure to project pollution indicators into a high-dimensional feature space, using a Gaussian kernel to compute sample similarity and optimizing network weights via backpropagation [16–18]. Under polar low-temperature conditions, the network inputs include heavy metal concentration, BOD, pH, etc., in wastewater, and outputs pollution levels. The transfer learning method employs a deep domain adaptation (DDA) module to align features between the source domain (e.g., temperate drilling data) and the target domain (simulated polar data). A polar feature constraint module (e.g., low-temperature feature injection) is introduced, and a generative adversarial network (GAN) dynamically adjusts inter-domain differences. Finally, a domain adaptation loss function aligns the distributions, enabling reliable pollution assessment data in data-scarce polar environments. In view of waste liquid pollution and waste solid pollution, this paper obtains pollution data through low temperature simulation experiment. The waste solid samples were taken from the drilling site of the Northeast Oilfield (similar to the polar low temperature environment), and the waste liquid samples were prepared according to the drilling fluid ratio used in the polar region in the research literature, and the pollution index was determined by simulating the polar low temperature conditions. The key indicators of waste solid pollution include oil content, heavy metal content and polycyclic aromatic hydrocarbons (PAHs) characteristics; the pollution indexes of wastewater include heavy metal concentration, biological oxygen demand (BOD), pH value, salinity and suspended solids concentration. Fig. 2 presents the classification results of pollution indicators based on the optimized RBF network. Different colored regions represent different pollution levels, demonstrating the model's ability to effectively distinguish complex pollution features in polar regions. In the study of exhaust gas pollution and noise pollution, the transfer learning method of deep domain adaptation is applied. By extracting key pollution features from source domain data, and using generative adversarial network (GAN) to construct a deep learning model, a polar feature constraint module (such as low temperature feature injection) is introduced in the middle layer of the model to dynamically adjust the difference of domain features [19,20]. Finally, the domain adaptation loss function is used to align the distribution characteristics of the source domain and the target domain, and the model adaptability is optimized to accurately obtain the polar pollution data.

The applicability of the transfer learning method in the polar environment is due to its superiority in dynamically adjusting the difference of characteristics. In particular, the distribution difference between the source domain and the target domain is effectively reduced by the feature injection module. Even in the case of significant differences in environmental characteristics, this method can still ensure high prediction accuracy, thus becoming the best choice in the case of large differences in environmental characteristics between the polar region and other regions.

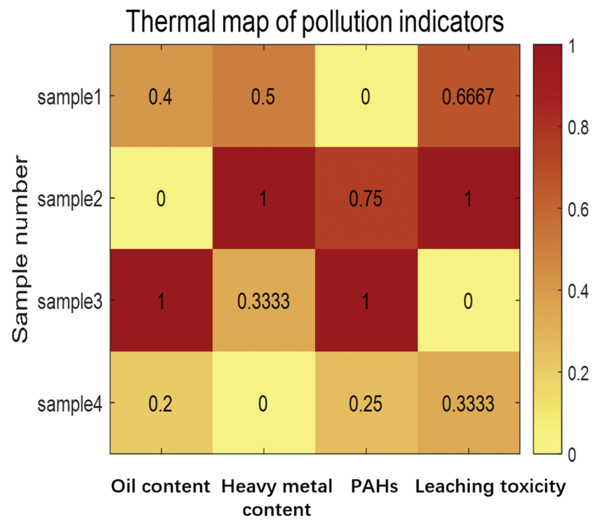

Figure 2: Classification results of pollution indicators

4 Research Methods

4.1 Polar Drilling Environmental Risk Assessment Method

4.1.1 Technical Route for Environmental Risk Assessment of Polar Drilling

The G1-cloud model evaluation framework constructed in this study is tailored to the polar environment's data scarcity and extreme climate. By integrating transfer learning and simulated data expansion, along with the cloud model's strengths in uncertainty modeling, it enables high-precision risk assessment with limited data. First, drawing on the literature on drilling-related environmental pollution, appropriate pollution indicators are selected to establish the set of risk factors for polar drilling. Second, an evaluation dataset is obtained from low-temperature simulation experiments, and the weights of the indicators are determined using the G1 method. Finally, by integrating these weights, a cloud-model of polar-drilling environmental-pollution risk is established, from which the risk associated with each indicator and the overall composite risk are computed. This procedure delivers a comprehensive assessment that integrates subjective structure (indicator selection and weighting) with objective experimental evidence.

4.1.2 Polar Drilling Environmental Risk Assessment System

Based on the reference to the relevant drilling environmental pollution [21–23], literature, this paper constructs the evaluation system of polar drilling environmental pollution, as shown in Fig. 3 The system refines the evaluation content of each index, and constructs a multi-level evaluation system of target layer, criterion layer and index layer. After referring to the relevant literature, this paper selects four indicators that may have a greater impact on the polar environment, namely: polar drilling waste liquid pollution risk [24], polar drilling waste gas pollution risk [25] polar drilling waste solid pollution risk [26], and polar drilling noise pollution risk (U_1–U_4).

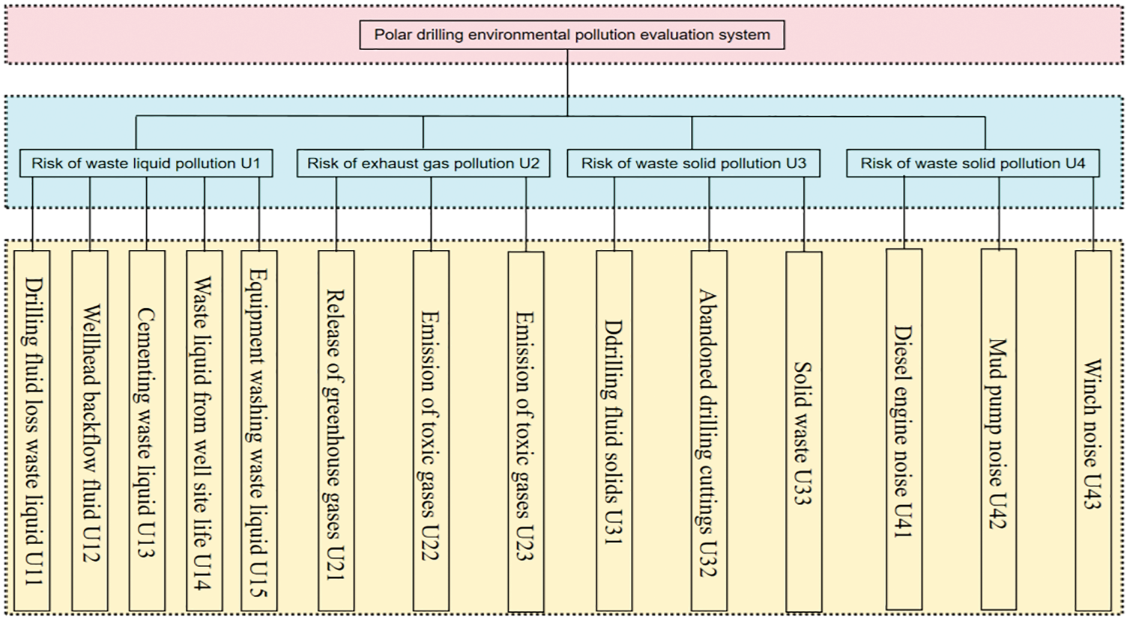

Figure 3: The set of environmental risk factors for polar drilling a completion

4.2 The Environmental Risk Assessment Model of Polar Drilling Based on G1-Cloud Model Is Established

4.2.1 Cloud Model Theory

The cloud model was first proposed by Li in 1995. He proposed the cloud model on the basis of studying fuzzy mathematics and probability theory [27–30]. The cloud model, as defined in this study, is a cognitive model capable of facilitating the bidirectional transformation between qualitative concepts and quantitative values. Its core is parameterized by three numerical characteristics: Expectation (Ex), Entropy (En), and Hyper-Entropy (He). This model differs fundamentally from other homonymous models and is uniquely suited for environmental risk assessment under uncertainty, as it simultaneously captures the vagueness of human judgment (fuzziness) and the stochasticity of measured data (randomness). The cloud model has the characteristics of randomness and fuzziness at the same time, which can realize the qualitativeization of quantitative data and the quantification of qualitative concepts, that is, the mutual transformation between quantitative and qualitative [31–33]. With the extensive research of scholars at home and abroad, cloud model is also widely used in the field of risk identification. The cloud model theory is mainly based on the characteristics of Ex, En, and He to generate cloud droplets [34–36], resulting in different cloud models [37–39]. Expectation Ex: the expectation of the distribution of cloud droplets in the domain words is the most representative point of the qualitative concept, and it is also the most typical sample of the quantification of the I have completed the confirmation.

target concept. Entropy En: The randomness and fuzziness of the evaluation object are reflected in the value of entropy. The randomness of concept quantification is reflected in the 'breadth' of entropy. The wider the range of cloud droplets is, the larger the entropy is, and the wider the cloud is. Super-entropy He: is the embodiment of the uncertainty of entropy, which represents the randomness and fuzziness of entropy. It is manifested in the 'thickness' of cloud droplets. The thicker the cloud droplets are, the greater the super-entropy is. The specific implementation process is shown in Fig. 4.

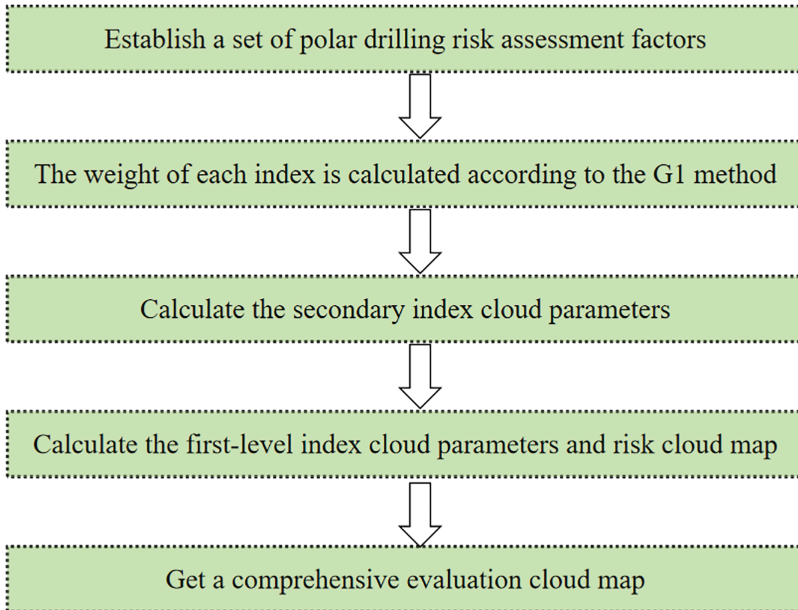

Figure 4: Risk assessment algorithm flow chart

The cloud model needs to be implemented by specific algorithms. For example, the forward cloud generator and the path cloud generator are the two algorithms of the cloud model [40–42]. As shown in Fig. 5, the former mainly realizes the quantification of qualitative concepts and can convert the numerical characteristics of the cloud into a certain number of cloud droplets [43,44]. The latter mainly realizes the qualitative analysis of quantitative data, which can convert a certain number of cloud droplets into the numerical characteristics of clouds [45,46]. In this paper, the two conversions are realized by MATLAB program. The generation of cloud droplets is the core and essence of cloud model theory.

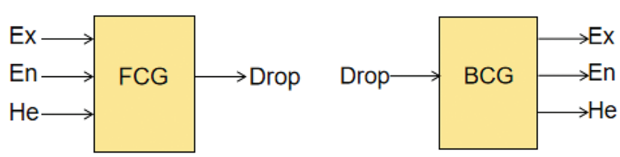

Figure 5: Forward cloud generator and back cloud generator

4.2.2 Digital Characteristics of Cloud Model for Environmental Risk Assessment of Polar Drilling

In the environmental risk assessment of polar drilling, how to determine the digital characteristic value of the cloud model evaluation system is the key to the evaluation. The environmental risk assessment set of polar drilling is used to calculate the size of the three numerical eigenvalues in the cloud model, which can be calculated by the following Formula (1), and the $x^k_{\min}$ and $x^k_{\max}$ represent the maximum and minimum values in the evaluation set. According to the ambiguity degree of the comment itself and the previous literature, the value of k is 0.1.

$$Ex_i = \frac{(x^i_{\min} + x^i_{\max})}{2}$$

$$En_i = \frac{\left(x^i_{\max} - x^i_{\min}\right)}{2\sqrt{2\ln 2}} \qquad (1)$$
$$\mathrm{He_i} = k$$

5 Evaluation and Calculation of Polar Drilling Environmental Risk G1-Cloud Model

5.1 Establish Evaluation Index Set

This paper refers to the relevant literature [47–51], and divides five risk assessment levels, namely, low risk V1, medium low high risk V2, medium risk V3, medium high risk V4, and high risk V5. The 100-point system is used to judge, and the degree of risk is increasing in turn. The evaluation results are at low risk and medium-low risk, indicating that the environmental pollution risk of polar drilling is acceptable and environmental protection measures can be temporarily not taken. The medium risk means that the environmental pollution risk of polar drilling is not obvious, and general environmental protection measures can be taken. The medium-high risk indicates that the environmental pollution risk of polar drilling is obvious, and appropriate measures must be taken to reduce the risk [52,53]. The high risk indicates that the environmental pollution risk of polar drilling is more obvious [54,55], and the consequences of the risk are more serious, which must be reduced to the allowable reasonable range. Table 1 is the risk level of polar drilling. Fig. 6 shows the standard cloud map for polar drilling risk levels, clearly illustrating the cloud droplet distributions corresponding to five risk levels, serving as a benchmark for subsequent risk visualization.

Table 1: Polar drilling risk level

Level	Remark	Comment interval	Score vector value
Level 1	Low risk V1	(0, 20]	10
Level 2	Medium-low risk V4	(20, 40]	30
Level 3	Medium risk V3	(40, 60]	50
Level 4	Medium-high risk V4	(60, 80]	70
Level 5	High risk V5	(80, 100]	90

5.2 G1 Method to Determine the Weight Index

Determine the order relationship: if the evaluation index U_i is not less important than a certain evaluation criterion U_j (target), it is recorded as. For the evaluation index set $U = \{U_1, U_2, \ldots, U_n\}$.

Determination of relative importance: Once the order relation is established, the pairwise relative importance of the evaluation indices is assessed in a consistent and rational manner. Between the evaluation index U_{k-1} and U_k, $s_k = w_{k-1}/w_k$, $k = n, n-1, n-2, \ldots, 3, 2$. Among them: the weight of the k-th evaluation index; the value of s_k is shown in Table 1. When n is large, $s_n = 1.0$.

Determine the weight coefficient: the calculation formula U_n of the weight of the evaluation index w_n is $w_n = \left(1 + \sum_{k=2}^{n} \prod_{i=k}^{n} s_i\right)^{-1}$

For each index,grading is performed with reference to the evaluation set, and the number N_{ijt} of indexes V_t belonging to the evaluation grade U_{ij} is counted. The calculation formula of the membership U_{ij} degree of the index V_t is $r_{ijt} = N_{ijt}/N$.

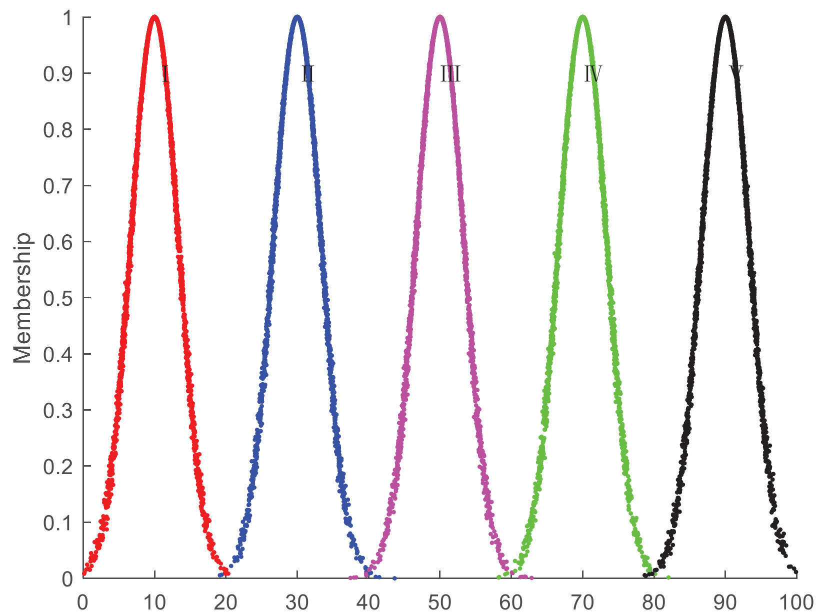

Figure 6: Risk level standard cloud

After determining the membership degree, the fuzzy evaluation matrix is obtained.

$$\mathbf{R}_i = \begin{bmatrix} r_{i11} & r_{i12} & \cdots & r_{i15} \\ r_{i21} & r_{i22} & \cdots & r_{i25} \\ \vdots & \vdots & & \vdots \\ r_{in1} & r_{in2} & \cdots & r_{in5} \end{bmatrix}$$

First-level evaluation: The first-level evaluation is performed by the weight vector and the fuzzy evaluation matrix, which is expressed as:

$$B_i = w_i \circ R_i$$

Thus, the comprehensive evaluation matrix is:

$$B = \left[B_1, B_2, B_3, B_4, B_5\right]^T$$

Through the G1 method, the weight results of each pollution risk index are shown in Table 2 below.

Table 2: The weight value of each risk index

First grade indexes	Weight value	Second index	Weight value
Waste liquor	0.3820	Drilling fluid loss waste liquid	0.3335
		Wellhead backflow fluid	0.2002
		Cementing waste liquid	0.2037
		Waste liquid from well site life	0.1482

(Continued)

Table 2 (continued)

First grade indexes	Weight value	Second index	Weight value
		Equipment washing waste liquid	0.1142
Exhaust gas	0.2472	Greenhouse gas	0.3939
		Toxic and harmful gas	0.2777
		Discharge of waste gas	0.3267
Waste solid	0.2017	Solid phase of waste drilling fluid	0.4183
		Drill cuttings	0.3092
		Solid waste	0.2716
Noise	0.1891	Diesel engine noise	0.4561
		Mud pump noise	0.2773
		Winch noise	0.2654

To minimize subjectivity, we constructed an experimental dataset for polar-drilling environmental-pollution risk on the basis of the preceding low-temperature simulation experiments. Four categories comprising 14 secondary indicators were considered—liquid waste, solid waste, exhaust gas, and noise—namely: drilling-fluid-loss waste liquid, wellhead backflow fluid, cementing waste liquid, well-site domestic wastewater, equipment-washing waste liquid, greenhouse gases, toxic and harmful gases, exhaust-gas discharge, solid phase of waste drilling fluid, drill cuttings, general solid waste, diesel-engine noise, mud-pump noise, and winch noise. Under simulated polar operating conditions with equipment running at nominal settings, sampling and measurements were performed to record major pollutant concentrations, emission levels, and equivalent continuous sound levels (Leq), yielding a representative raw dataset. Following the risk-grading scheme, all measurements were min–max normalized to the range [0,100], producing eight independent experimental/operational samples (N1–N8); the resulting indicator score matrix is reported in Table 3. The inverse cloud generator was then applied to obtain the expectation (Ex), entropy (En), and hyper-entropy (He) of each secondary indicator, and data-driven contributions were used to determine the ranking and weights via the G1 method [56].

Table 3: Evaluation data set

Second index	N1	N2	N3	N4	N5	N6	N7	N8
Drilling fluid loss waste liquid	75	74	84	72	76	71	82	69
Wellhead backflow fluid	52	54	47	61	53	62	57	47
Cementing waste liquid	85	92	90	83	87	89	82	91
Waste liquid from well site life	37	36	41	35	43	34	38	35
Equipment washing waste liquid	82	75	68	80	74	77	73	68
Greenhouse gas	87	92	85	84	93	91	95	91
Toxic and harmful gas	75	69	72	78	67	70	72	68
Discharge of waste gas	84	77	83	71	76	80	75	81

(Continued)

Table 3 (continued)

Second index	N1	N2	N3	N4	N5	N6	N7	N8
Solid phase of waste drilling fluid	54	61	57	63	58	61	64	52
Drill cuttings	35	27	31	37	31	33	35	29
Solid waste	68	65	71	67	73	75	77	69
Diesel engine noise	95	91	87	89	96	92	93	90
Mud pump noise	85	81	76	86	79	78	80	77
Winch noise	93	89	91	94	92	84	87	88

To obtain sufficient and reliable evaluation samples without relying on subjective scoring, the base dataset was derived from low-temperature simulation experiments. To expand the sample size while preserving the distributional properties of the measurements, Monte Carlo resampling was applied to each indicator's empirical distributio. Specifically, measurements of 14 risk factors across eight experimental scenarios (N1–N8) were arranged as an 8×14 matrix. For each indicator, the empirical cumulative distribution function (ECDF) was estimated, pseudo-random variates U (0, 1) were drawn, and inverse-transform sampling was used to synthesize 200 realizations. All samples were subsequently normalized to [0,100] according to the grading rules in Table 1, and the cloud-model parameters (Ex, En, He) were computed. Consistency checks showed that the single-factor expectations of the expanded set closely match those of the original experiments, indicating that the augmented dataset is representative and reliable.

5.3 Cloud Model Evaluation Results Calculation

Using the collected experimental evaluation data, the cloud parameters of the secondary indicators were computed via the inverse cloud generator. The expected calculation formula of the reverse cloud generator is as follows Formula (2), $Ex = \overline{X}$, and the calculation results are shown in Table 4.

$$En = \sqrt{\frac{\pi}{2}} \times \frac{1}{n}\sum_{i=1}^{n} |x_i - Ex|$$

$$He = \sqrt{S^2 - En^2} \tag{2}$$

$\overline{X}$ is the sample mean of the data, S^2 is the sample variance of the data.

Table 4: Secondary index cloud parameter values

Second index	Weight value	Ex	En	He
Drilling fluid loss waste liquid	0.3335	75.375	4.971	1.634
Wellhead backflow fluid	0.2002	54.125	5.522	1.276
Cementing waste liquid	0.2037	87.375	3.916	1.165
Waste liquid from well site life	0.1482	37.375	3.094	0.639
Equipment washing waste liquid	0.1142	74.625	4.857	1.453
Greenhouse gas	0.3939	89.75	4.152	1.262

(Continued)

Table 4 (continued)

Second index	Weight value	Ex	En	He
Toxic and harmful gas	0.2777	71.375	3.603	0.844
Discharge of waste gas	0.3267	78.375	4.543	1.093
Solid phase of waste drilling fluid	0.4183	58.75	4.387	1.014
Drill cuttings	0.3092	32.25	3.447	0.723
Solid waste	0.2716	70.625	4.23	0.876
Diesel engine noise	0.4561	91.625	2.977	0.515
Mud pump noise	0.2773	80.25	3.525	0.804
Winch noise	0.2654	89.75	3.447	0.723

After obtaining the cloud parameters of the secondary indicators. Using the formula of Formula (3), (λ_n representing the weight of the nth first-level index), the cloud parameters of the first-level index can be obtained, as shown in Table 5.

$$Ex = Ex_1\lambda_1 + Ex_2\lambda_2 + \ldots\ldots + Ex_n\lambda_n$$
$$En = \frac{\lambda_1^2}{\lambda_1^2 + \lambda_2^2 + \ldots\ldots + \lambda_n^2}En_1 + \frac{\lambda_2^2}{\lambda_1^2 + \lambda_2^2 + \ldots\ldots + \lambda_n^2}En_2 + \ldots\ldots + \frac{\lambda_n^2}{\lambda_1^2 + \lambda_2^2 + \ldots\ldots + \lambda_n^2}En_n,$$
$$He = \frac{\lambda_1^2}{\lambda_1^2 + \lambda_2^2 + \ldots\ldots + \lambda_n^2}He_1 + \frac{\lambda_2^2}{\lambda_1^2 + \lambda_2^2 + \ldots\ldots + \lambda_n^2}He_2 + \ldots\ldots + \frac{\lambda_n^2}{\lambda_1^2 + \lambda_2^2 + \ldots\ldots + \lambda_n^2}He_n \quad (3)$$

Table 5: The first-level index cloud parameter values

First grade indexes	Weight value	Ex	En	He
Waste liquor	0.382	67.8328	4.6883	1.3793
Exhaust gas	0.2474	80.7785	4.1502	1.1137
Waste solid	0.2017	53.7286	4.0924	0.9036
Noise	0.1891	87.2083	3.1887	0.6188

After obtaining the size of the cloud parameter values of the indicators at all levels, the MATLAB software is used to obtain the risk cloud diagram of the first-level indicators using the forward cloud generator, as shown in Fig. 7, it displays the risk cloud maps for first-level indicators, intuitively reflecting the magnitude and uncertainty of each pollution risk. Similarly, the comprehensive risk cloud map is obtained by using the forward cloud generator, as shown in Fig. 8, it shows the comprehensive risk cloud map, indicating that the overall risk of polar drilling is close to medium-high, suggesting the need for risk control measures. The risk level of each first-level index of polar drilling is above the medium risk, and the risk of the first-level index is from high to low in order: waste liquid pollution risk, waste gas pollution risk, noise pollution risk, waste solid pollution risk. And the final comprehensive risk assessment results are also close to the high risk. Therefore, the risk of environmental pollution caused by polar drilling is relatively large, and subsequent measures must be taken to control the risk.

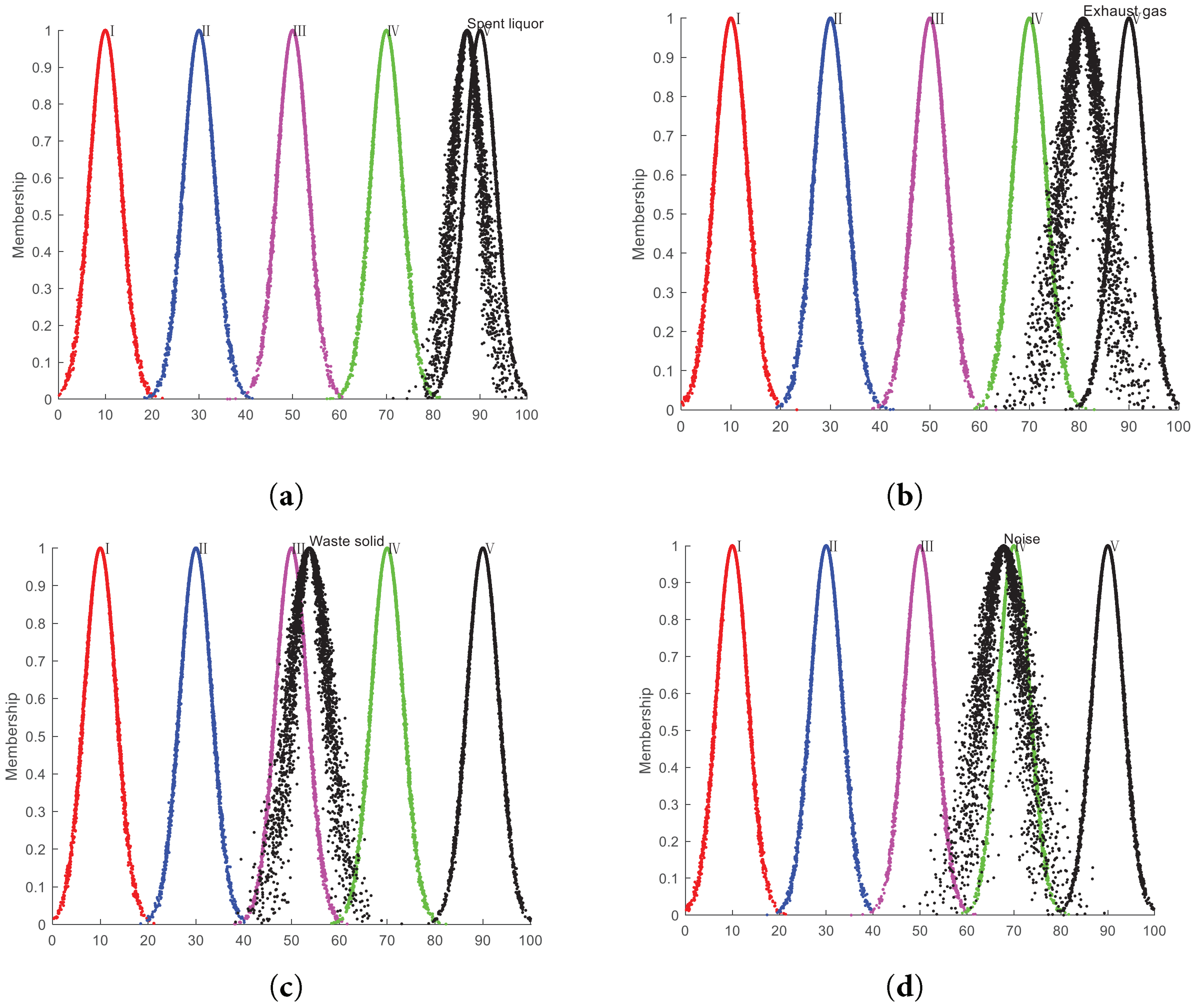

Figure 7: Risk cloud diagram of first-level indicators Risk cloud diagrams for the first-level indicators of polar drilling environmental pollution: (**a**) waste liquid pollution, high risk with concentrated droplets; (**b**) waste gas pollution, relatively high risk with uncertainty; (**c**) waste solid pollution, moderate risk with concentrated droplets; (**d**) noise pollution, comparatively high risk

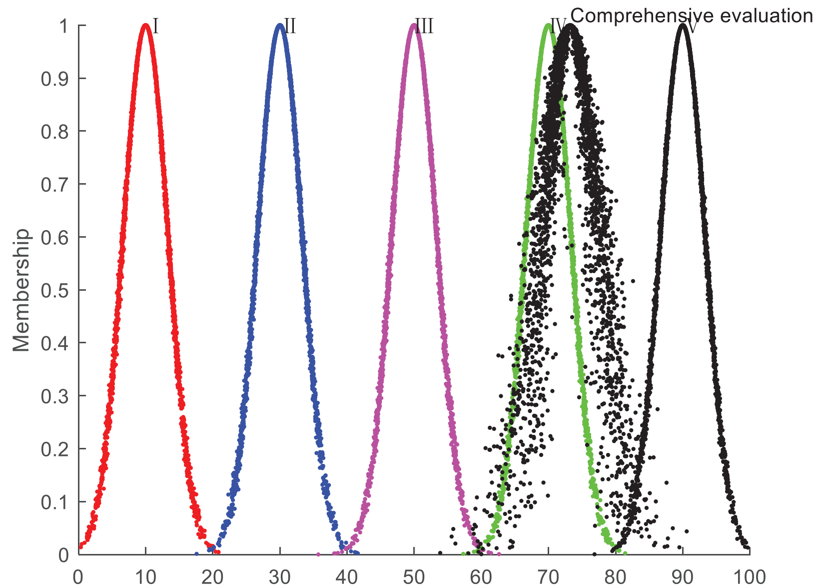

Figure 8: Comprehensive risk cloud map

6 Conclusions

Environmental risk assessment for polar drilling constitutes a multi-index and multi-level comprehensive evaluation system. Given the fragile ecosystem and limited monitoring data in polar regions, traditional risk assessment methods may not be fully applicable, and their results can be biased due to subjective factors or overreliance on data volume.

In this study, an uncertainty cloud model is introduced for the first time into the comprehensive environmental risk assessment of polar drilling. By accounting for both fuzziness and randomness in the process of environmental pollution risk in polar areas, and balancing subjectivity with objectivity, the evaluation results are more scientific and objective. A risk cloud map is generated, which visually presents risk levels in the form of cloud droplets. The assessment indicates that the environmental risk of polar drilling is medium to high, warranting serious attention. Future efforts should focus on identifying relevant measures to mitigate these risks. Furthermore, among the first-level indicators evaluated, waste liquid pollution risk and waste gas pollution risk rank the highest, and thus should be prioritized in subsequent pollution control measures.

This paper offers a new approach for research on polar oil and gas exploitation and polar environmental protection, providing a risk assessment method that combines quantitative calculation with qualitative analysis. However, it should be noted that there remains a lack of relevant data to validate the environmental risk assessment of polar drilling, which is necessary to further examine the reliability of the model and refine it. Future work could involve experiments under simulated polar conditions to enhance the preliminary evaluation results.

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