Research on Risk Classification and Zoning Control Strategies for Groundwater Pollution in Chemical Industrial Parks

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Abstract. This paper systematically analyzes the formation mechanism of groundwater pollution risk in chemical industrial parks and constructs a three-level risk classification index system covering pressure, state, and response dimensions, consisting of 14 core indicators. The AHP-entropy weight combination method is used to determine the indicator weights, and K-means clustering and expert judgment are combined to formulate high, medium, and low risk classification standards (high-risk area comprehensive index ≥ 0.7, medium-risk area 0.3~0.7, low-risk area ≤ 0.3). The risk assessment method is optimized by introducing the entropy weight modified analytic hierarchy process and interval number theory to improve the fuzzy comprehensive evaluation model, constructing a dynamic risk assessment model incorporating the time dimension, and proposing three original formulas to achieve spatiotemporal dynamic representation of risk. Taking a coastal chemical industrial park as an empirical study, three control zones—key, general, and potential—are divided, and differentiated control strategies are formulated, verifying the scientific validity of the system and methods. The research findings provide theoretical support and technical reference for the precise prevention and control of groundwater pollution in chemical industrial parks, contributing to the coordinated development of ecological environment and economic development.

Keywords: Chemical Industrial Park; Groundwater Pollution; Risk Classification; Zoned Management; PSR Framework; Precise Prevention and Control

1. Introduction

Chemical industrial parks, as core carriers of industrial agglomeration, play a crucial role in Chinese industrialization process. However, pollutants such as organic solvents and heavy metals generated during chemical production, storage, and transportation within these parks can easily seep into groundwater through various pathways, creating hidden pollution hazards. Groundwater, as an important source of drinking water and ecological support, is directly threatened by pollution, disrupting ecological balance and hindering sustainable economic and social development. Therefore, pollution risk management is urgently needed [1]. Traditional "one-size-fits-all" management models suffer from limitations such as low efficiency, high cost, and insufficient targeting, while graded and zoned management can optimize resource allocation and improve the precision of prevention and control [2]. The core research content of this paper is: to construct a risk classification index system for groundwater pollution in chemical industrial parks, optimize the classification evaluation method, formulate a zoned management plan, and verify and optimize it through empirical research, providing technical support for the precise prevention and control of groundwater pollution in industrial parks.

2. Formation Mechanism and Influencing Factors of Groundwater Pollution Risk in Chemical Industrial Parks

2.1 Formation Mechanism of Groundwater Pollution Risk

The release of pollutants from various sources exhibits a multi-pathway characteristic. Point sources, such as tank leaks and sewage outlets, have release rates affected by equipment aging and the level of protective measures [3]. Non-point sources diffuse through surface runoff and atmospheric deposition; the release intensity is related to precipitation intensity and pollutant accumulation. Linear sources are mainly caused by pipeline leaks; the risk is closely related to pipeline material and operating age. After entering the vadose zone, pollutants are attenuated through adsorption and degradation. Upon entering the aquifer, they diffuse through convection and dispersion, accompanied by oxidation-reduction and complexation reactions that alter their migration characteristics [4]. The

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coexistence of multiple pollution sources and pollutants easily leads to risk superposition. Under high-permeability hydrogeological conditions, the risk is amplified, while the risk decreases in thick vadose zone areas.

2.2 Identification and Classification of Risk Influencing Factors

Pressure factors focus on human activity interference, including the distribution density of high-risk enterprises, the degree of pollution source aggregation, the toxicity and persistence of pollutants, as well as production load and discharge intensity [5]. State factors focus on the natural environmental baseline, encompassing hydrogeological conditions such as aquifer lithology and permeability coefficient, geomorphological features such as topographic slope and elevation, and key parameters such as groundwater depth, vadose zone thickness, and lithology [6]. Response factors reflect prevention and control capabilities, including the construction level of facilities such as impermeable layers and monitoring wells, management effectiveness such as the completeness of management systems and the intensity of supervision, and the accessibility and maturity of remediation technologies.

3. Construction of Groundwater Pollution Risk Classification Indicator System in Chemical Industrial Parks

3.1 Principles and System Diagram for the Construction of the Classification Indicator System

The construction of the indicator system follows five principles: scientific principle, ensuring that the indicators conform to the pollution mechanism and risk formation law; targeted principle, focusing on the core pollution hazards in chemical industrial parks; systematic principle, comprehensively covering all dimensions of pressure, state, and response; operability principle, ensuring that indicator data is easily obtainable and quantifiable; and dynamic principle, adapting to the development of the park and environmental changes [7].

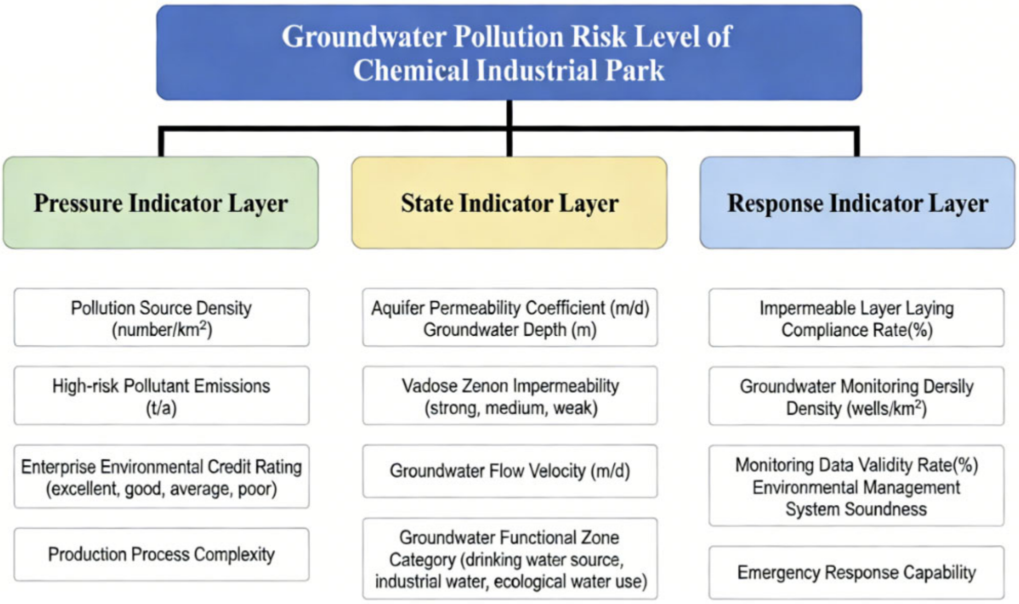

Fig 1. Indicator System Diagram

Figure 1 shows that the target layer represents the groundwater pollution risk level of the chemical industrial park; the criterion layer is divided into a pressure indicator layer, a state indicator layer, and a response indicator layer [8]. The pressure indicator layer includes four tertiary indicators, such as pollution source density and high-risk pollutant emissions; the state indicator layer includes five tertiary indicators, such as aquifer permeability coefficient and groundwater depth; and the response indicator layer includes five tertiary indicators, such as the compliance rate of anti-seepage layer laying and the density of groundwater monitoring wells, forming a three-tiered progressive system of "target layer - criterion layer - indicator layer".

3.2 Selection and Interpretation of Graded Indicators

The pressure indicator layer specifically includes: pollution source density (number/km²), characterizing the degree of pollution source aggregation per unit area; high-risk pollutant emissions (t/a), quantifying the intensity of toxic and hazardous pollutant release; enterprise environmental credit rating, quantified into four levels: excellent, good, average, and poor, based on environmental compliance; and the complexity of the production process, scored according to reaction type, operating conditions, etc. State Indicator Layer: Aquifer permeability coefficient (m/d), reflecting groundwater permeability; groundwater depth (m), affecting the length of the pollutant infiltration path; vadose zone seepage prevention performance, graded into strong, medium, and weak levels according to lithology; groundwater flow velocity (m/d), determining the pollutant diffusion rate; groundwater functional zone category, assigned values according to drinking water source, industrial water, and ecological water use [9]. Response Indicator Layer: Seepage prevention layer compliance rate (%), reflecting the level of source control; groundwater monitoring well density (wells/km²), reflecting monitoring coverage; monitoring data effectiveness rate (%), measuring monitoring data quality; environmental management system soundness, scored according to the system's coverage; emergency response capability, scored based on emergency material reserves and drill frequency.

3.3 Indicator Weight Determination Method

The AHP-entropy weight combination method is used to determine the indicator weights. First, through subjective weighting using AHP, experts in hydrogeology, environmental engineering, and other fields are invited to conduct pairwise comparisons of the relative importance of each indicator to construct a judgment matrix, calculate the subjective weights, and pass the consistency test ($CR<0.1$). Then, objective weighting is applied using the entropy weighting method. Objective weights are calculated based on the information entropy of the measured indicator data to reflect the dispersion of the data itself. The final comprehensive weight = α × subjective weight + (1-α) × objective weight (α is set to 0.5 to balance subjective experience and objective data). Sensitivity analysis is used to verify the stability of the weights, ensuring that the weight allocation is scientific and reasonable.

3.4 Risk Classification Standard Formulation

K-means clustering is used to initially classify risk levels based on the comprehensive risk index. Combined with expert judgment and correction, high, medium, and low risk zones are finally determined. The classification thresholds refer to the Class III water limit in the "Groundwater Quality Standard" (GB/T 14848-2017) and the relevant requirements of the "Guidelines for Groundwater Pollution Prevention and Control in Chemical Industrial Parks." Combined with data from three typical chemical industrial park pollution cases, the thresholds are determined through iterative verification: the comprehensive index for high-risk areas is ≥0.7, for medium-risk areas it is 0.3~0.7, and for low-risk areas it is ≤0.3, ensuring that the classification standard is both scientific and practical.

4. Optimization of Groundwater Pollution Risk Classification Assessment Method in Chemical Industrial Parks

4.1 Improvement of Adaptability of Traditional Assessment Methods

Traditional analytic hierarchy process (AHP) suffers from significant subjective bias, and fuzzy comprehensive evaluation method is insufficient in handling boundary ambiguity, making it difficult to adapt to the complex pollution scenarios in chemical industrial parks. An entropy-weighted modified AHP is introduced, adjusting subjective weights through entropy weight coefficients to reduce human bias. The fuzzy comprehensive evaluation model is optimized using interval number theory, expressing both index values and weights as interval numbers, improving adaptability to uncertainties [10]. The improved model can accurately quantify multi-source and multi-path pollution risks, solving the problem of insufficient accuracy of traditional methods in complex scenarios and improving the reliability of assessment results.

4.2 Construction of Dynamic Risk Assessment Model

Combining the industrial upgrading of the park, changes in pollution sources, and dynamic hydrogeological characteristics, a dynamic risk assessment model is constructed. A time-dimensional variable is introduced to represent the risk evolution law. The formula for the dynamic risk comprehensive index is shown below:

$$R(t) = \sum_{i=1}^{n} W_i \cdot I_i(t) \cdot \beta(t) \cdot \gamma(h(t)) \qquad (1)$$

In the formula: $R(t)$ is the comprehensive risk index of the evaluation unit at time t; W_i is the comprehensive weight of the i indicator; $I_i(t)$ is the standardized value of the i indicator at time t, which is dynamically updated with pollution source emissions and facility operation status; $\beta(t)$ is the time decay coefficient, which characterizes the natural decay effect of pollutants, $\beta(t) = e^{kt}$ (k is the decay coefficient, t is time); $\gamma(h(t))$ is the dynamic correction coefficient of groundwater level, $h(t)$ is the groundwater depth at time t, the greater the depth, the smaller the correction coefficient, which characterizes the increased difficulty of infiltration; n is the total number of indicators. The formula for the dynamic release intensity of pollution sources is as follows:

$$Q(t) = Q_0 \cdot (1+\delta)^t \cdot \eta(s(t)) \qquad (2)$$

In the formula: $Q(t)$ is the pollution source release intensity at time t; Q_0 is the initial release intensity; δ is the industry growth coefficient, reflecting changes in production load; $s(t)$ is the integrity rate of protective facilities at time t; $\eta(s(t))$ is the protective effectiveness coefficient, which increases linearly with the improvement of the integrity rate. The dynamic prediction formula for pollutant migration distance is as follows:

$$L(t) = \int_0^t v(\tau) \cdot \mu(\tau) d\tau \qquad (3)$$

In the formula: $L(t)$ is the pollutant migration distance at time t; $v(\tau)$ is the groundwater flow velocity at time τ, which varies with the flow rate; $\mu(\tau)$ is the pollutant migration efficiency coefficient at time τ, which is related to the aquifer lithology.

The model achieves dynamic risk characterization by updating index data in real time. Kriging interpolation is used to spatially interpolate the risk index of the evaluation unit, and GIS technology is combined to generate a risk spatial distribution map, clearly presenting the spatiotemporal evolution characteristics of risk and providing dynamic support for precise control.

5. Empirical Study – A Case Study of a Coastal Chemical Industrial Park

5.1 Overview of the Study Area

A coastal chemical industrial park, located on the eastern coastal plain, has a planned area of 25 km². Its leading industries are petrochemicals and fine chemicals, housing 42 enterprises, 15 of which are high-risk. Hydrogeological conditions: The regional groundwater type is loose rock pore water, with the main aquifer thickness of 15-20 m, a permeability coefficient of 8-12 m/d, and a groundwater flow velocity of 0.05-0.1 m/d, flowing from northwest to southeast. The groundwater depth is 2-5 m, and the vadose zone lithology is mainly silt and silty clay, with a thickness of 2-4 m. Current groundwater pollution status: Monitoring data shows that benzene, toluene, and other organic compounds were detected in some areas of the park, with concentrations of 0.05-0.3 mg/L. The areas exceeding the standards are mainly concentrated in the northern tank area. Heavy metal detection values were within acceptable limits. A total of 12 potential pollution points were identified, mainly due to damaged tank linings and leaking sewage outlets.

5.2 Risk Classification and Assessment Practice

Data Collection and Processing: Pollution source data from 42 enterprises, 10 sets of hydrogeological measurement data, and park environmental management data were collected. Extreme value standardization was used to normalize the indicator data and eliminate the influence of dimensions.

Weight Calculation and Risk Index Calculation: Weights were calculated using the AHP-entropy weight combination method, with higher weights for high-risk pollutant emissions and aquifer permeability coefficients (0.18 and 0.15 respectively). An optimized dynamic evaluation model was used to calculate the risk index for 200 evaluation units.

Risk Level Classification and Spatial Distribution: Combining K-means clustering and expert assessment, a high-risk area of 3.2 km² (northern tank area, surrounding sewage ditch), a medium-risk area of 8.5 km² (central production area), and a low-risk area of 13.3 km² (southern living area, marginal ecological area) were defined. The spatial distribution map clearly shows the high-risk clustering characteristics in the north.

5.3 Zoning and Strategy Formulation for Control Areas

Using GIS spatial overlay analysis technology, risk level maps, industrial layout maps, and hydrogeological maps were overlaid to divide the area into key control areas (corresponding to high-risk areas), general control areas (corresponding to medium-risk areas), and potential control areas (corresponding to low-risk areas). Key control areas implemented strict source control and real-time monitoring, including replacing damaged anti-seepage layers, increasing the density of monitoring wells to 3 per km², and establishing a real-time early warning system. General control areas strengthened routine monitoring, conducting two anti-seepage tests annually, and setting up monitoring wells at 1 per km². Potential control areas were subject to strict planning and control, prohibiting the addition of new high-risk projects and protecting the southern groundwater recharge area.

5.4 Result Verification and Optimization Recommendations

Table 1. Comparison of Risk Assessment Results and Measured Data

evaluation Unit	Risk level	Evaluation Index	Measured pollutant concentration (mg/L)	Exceeding the standard	Verification results
North A1	High	0.82	Benzene 0.30, Toluene 0.25	Exceeding the standard	Consistent
North A2	High	0.78	Benzene 0.28, Toluene 0.22	Exceeding the standard	Consistent
Central B1	Medium	0.52	Benzene 0.08, Toluene 0.06	Not exceeding the standard	Consistent
Central B2	Medium	0.48	Benzene 0.06, Toluene 0.05	Not exceeding the standard	Consistent
South C1	Low	0.25	Not detected	Not exceeding the standard	Consistent
South C2	Low	0.22	Not detected	Not exceeding the standard	Consistent

Table 1 shows that the risk assessment results are completely consistent with the measured pollution situation, verifying the scientific validity of the classification system and evaluation method. Figure 2 shows the simulation curve of the risk index of the park over time (horizontal axis is time, ranging from 0 to 10 years; vertical axis is the risk index), indicating that after the implementation of control measures in the key control area, the risk index decreased from 0.82 to 0.45, verifying the effectiveness of the control strategy. Figure 3 shows the simulation curve of pollutant migration distance (horizontal axis is distance, ranging from 0 to 500 m; vertical axis is pollutant concentration), clearly presenting the attenuation law of pollutants in different hydrogeological sections, providing a basis for optimizing the layout of monitoring points.

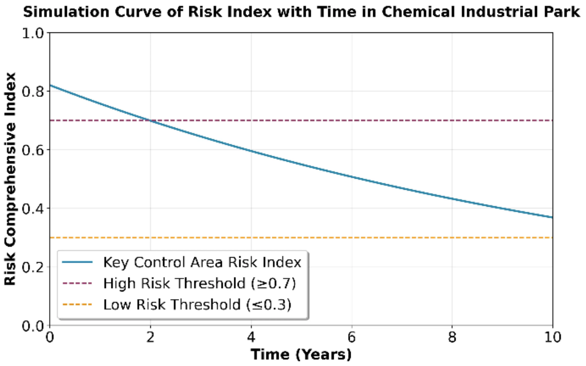

Fig 2. Simulation curve of park risk index changing over time

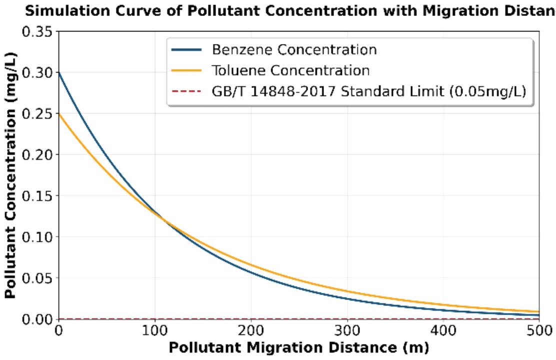

Fig 3. Simulation Curve of Pollutant Migration Distance

Firstly, addressing the issues of delayed acquisition and fragmented information regarding environmental credit rating data for some enterprises, there is an urgent need to construct an integrated environmental data sharing platform for enterprises within industrial parks. By integrating regulatory data from ecological and environmental departments, self-reported data from enterprises, and third-party testing data, real-time updates and interconnectivity of key information such as enterprise environmental credit ratings, pollution intensity, and the operational status of environmental protection facilities can be achieved. This will provide data support for the dynamic correction of risk classification indicators and address the pain point of insufficient timeliness of indicator data. Secondly, the adaptability of existing dynamic risk assessment models to seasonal changes in hydrogeology needs improvement, requiring the supplementation of long-term continuous hydrogeological monitoring data. Emphasis should be placed on strengthening the seasonal monitoring of key parameters such as groundwater depth, flow velocity, and permeability coefficient, establishing a dynamic database of hydrogeological parameters, optimizing the calculation methods for the dynamic correction coefficient of groundwater level and the pollutant migration efficiency coefficient in the model, and improving the model's accuracy in representing the evolution of pollution risk in different seasons. Thirdly, considering the significant differences in pollution characteristics among different types of chemical industrial parks, future research should focus on fine chemical industrial parks. In response to the characteristics of fine chemical products—diverse types, highly toxic pollutants, and complex production processes—this paper refines the risk grading index system, supplements relevant indicators for characteristic pollutants, and improves the weight allocation scheme. This makes the risk grading and control strategies more aligned with the actual needs of fine chemical industrial parks, further expanding the applicability of the research findings.

6. Conclusion

This paper constructs a three-tiered risk grading index system for groundwater pollution in chemical industrial parks, covering 14 core indicators across three dimensions: pressure, state, and response, based on the PSR framework. It combines the AHP-entropy weighted combination method with K-means clustering to achieve accurate risk quantification. By optimizing traditional evaluation methods, a dynamic risk assessment model incorporating the time dimension and three original formulas are constructed to achieve dynamic spatiotemporal representation of risk. A differentiated zoning control strategy integrating "risk level - spatial characteristics - functional requirements" is proposed. Empirical verification in a coastal chemical industrial park shows that the risk assessment results are completely consistent with the measured pollution situation. The control strategy can reduce the risk index of key control areas from 0.82 to 0.45, demonstrating good scientific validity and practicality. This paper innovatively constructs a dynamic grading-control integrated system adapted to the characteristics of chemical industrial parks. The study has limitations, including difficulties in obtaining data for some indicators and the need for further verification of the model's long-term applicability. Future research should focus on strengthening the integration and application of multi-source data, deepening the study of the cumulative effects of multiple pollutants, and promoting the deep integration of this system with smart park construction to further improve the intelligence and precision of groundwater pollution control.

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