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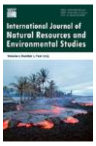

Study on Risk Assessment Methods for Geological Storage of Carbon Dioxide

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ABSTRACT

Carbon dioxide capture and storage (CCS) represents an effective approach for mitigating CO_2 emissions. However, the potential leakage of stored CO_2 poses significant risks to both the surrounding environment and human health, necessitating comprehensive risk assessment and management of CCS systems. This paper reviews the fundamental principles and applications of commonly employed methods for the risk assessment of CO_2 geological storage and provides insights into future development trends.

KEYWORDS

Carbon dioxide; Geological sequestration; Risk assessment.

1. INTRODUCTION

The continuous growth of the global economy and society has driven the extensive development and utilization of fossil fuels, resulting in substantial carbon dioxide (CO_2) emissions. The greenhouse effect caused by CO_2 has contributed to a range of global environmental challenges, making CO_2 emission reduction a critical focus of international attention[1]. Carbon capture and storage (CCS) is widely recognized as one of the most effective strategies for mitigating carbon emissions and addressing climate change[2]. This approach involves capturing and separating CO_2 from emission sources, transporting it to designated sites, and storing it in deep geological formations or marine environments to prevent or significantly reduce its release into the atmosphere. Among various storage selections, geological storage is considered the most suitable due to its high capacity and efficient volumetric storage properties[3]. Common geological storage sites include depleted oil and gas reservoirs, unmineable coal seams, and deep saline aquifers.

The primary risk associated with geological CO_2 storage is potential leakage. The most common concern involves the migration of CO_2 into groundwater recharge zones, where even minor leakage can substantially degrade groundwater quality for drinking[4]. If CO_2 breaches hydraulic seals, it can migrate upward into shallow soils, altering their physical and chemical properties, impacting soil-dwelling organisms, and eventually entering unsaturated zones and the atmosphere, leading to cascading effects on ecosystems and public health[5].

Numerous methods have been developed and applied to assess the risks of CO_2 geological storage. This paper aims to review the key risk assessment methods discussed in the literature and provide illustrative examples of their practical application.

2. RISK SOURCE IDENTIFICATION

Risk assessment involves the random selection of input parameters, the analysis of resulting outputs, and the assignment of corresponding risk values, followed by the aggregation of statistical data to develop a comprehensive risk profile. A critical component of risk assessment and management in CCS systems is the evaluation of potential hazards and their associated adverse effects. This process begins with the identification of primary hazard sources and the characterization of spill scenarios, followed by the determination of associated risks to enable a thorough risk evaluation of the CCS system.

Potential risk scenarios for geological CO_2 sequestration include[5]:

(1)CO_2 escape through injection or abandoned wells;

(2)Leakage through cracks or faults;

(3)Leakage through low-permeability caprock;

(4)Lateral migration along non-integrated surfaces;

(5)Slow leakage from geological storage reservoirs;

(6)Rapid leakage from geological storage reservoirs.

3. RISK ASSESSMENT METHODOLOGY

3.1. Hierarchical analysis

The Analytic Hierarchy Process (AHP) is a hierarchy-based, multi-criteria decision-making method used to perform trade-offs among multiple objectives within a structured hierarchy. It is regarded as a measurement theory based on pairwise comparison matrices. The calculation process involves the following steps[6-7]:

Step 1: Define the hierarchical structure of study objectives, criteria, and sub-criteria. The relative importance of each element is determined, and a comparative judgment matrix is constructed using a scale from 1 to 9, with expert scoring.

Step 2: Normalize the comparison matrix to ensure that the sum of the elements in each column equals one.

$$a_{ij}^{*} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \ . \tag{1}$$

Step 3: Compute the judgment matrix. According to positive matrix theory, the judgment matrix possesses a unique maximum eigenvalue (λmax). The maximum eigenvalue and corresponding eigenvector are determined, and the eigenvector is normalized to obtain the weight vector.

$$w_i = \frac{\sum_{j=1}^{n} a_{ij}^{*}}{n} \ . \tag{2}$$

Step 4: Evaluate consistency by comparing the consistency index (CI) of the judgment matrix with the CI of a random matrix, using the consistency ratio (CR) to ensure reliability.

$$CR = \frac{CI}{RI} \; . \tag{3}$$

where CI is calculated as shown in equation (4).

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad . \tag{4}$$

Wang et al.[8] evaluated the suitability of CO_2 geological storage in a basin using hierarchical analysis and fuzzy comprehensive evaluation. Their findings indicate that areas characterized by appropriate burial depth, favorable reservoir conditions, proximity to CO_2 collection facilities, and a high degree of exploration are more suitable for CO_2 geological storage. Gao et al.[9] developed a CO_2 leakage risk evaluation index system for wellbores based on hierarchical analysis and topology theory. This framework incorporates factors such as the tubing string, cement sheath, and micro-annular air interface to comprehensively assess the leakage risk associated with CO_2 sequestration wells.

3.2. Cloud Models

The implementation of the cloud model requires two algorithms: the forward cloud generator and the reverse cloud generator[10]. Expectation (Ex), entropy (En), and hyper-entropy (He) are the numerical characteristics of the cloud model, integrating ambiguity and randomness to establish a mapping relationship between qualitative and quantitative concepts[11]. Expectation (Ex) represents the expected value of the cloud droplet distribution within the domain space, reflecting the qualitative concept. Entropy (En) characterizes the correlation between the accuracy of qualitative concepts and randomness, linking correctness to probability. Hyper-entropy (He) measures the uncertainty of entropy, indicating the degree of cohesion of uncertainty in the domain space representing all points.

In evaluating the geological storage potential of CO_2, the cloud model addresses ambiguity and uncertainty among various evaluation indicators, such as reservoir conditions, geological formations, environmental impacts, CO_2 leakage diffusion paths, and the extent of impacts. Zou[11] integrated the cloud model with the entropy weight method to develop a comprehensive evaluation framework for assessing the risk of CCS projects.

3.3. NRAP- IAM-CS

The National Risk Assessment Partnership (NRAP) of the U.S. Department of Energy has developed the NRAP Integrated Assessment Model for Carbon Storage (NRAP-IAM-CS), a predictive tool for risk assessment in carbon storage systems. This model provides four primary functions[12]: (1) Data integration, enabling users to configure parameters and combine relevant geological and injection scenario data for a given site; (2) Characterization, facilitating the description of key site features and events; (3) Model coupling, allowing fast predictive models from various components of the engineering-geological system to be integrated; and (4) Model evaluation, conducting stochastic and dynamic simulations of the entire geological carbon storage (GCS) system.

Lackey et al.[13] applied NRAP-Open-IAM to simulate CO_2 leakage risk and associated uncertainties for a hypothetical GCS site. Their study examined the influence of variations in well leakage behavior, reservoir performance, and the duration of post-injection site care (PISC) on the effectiveness of risk management strategies.

3.4. Machine Learning Algorithms

In recent years, machine learning algorithms have been extensively applied in CO_2 geological storage research. Evaluations conducted for modeling in various engineering disciplines demonstrate that machine learning offers more accessible, cost-effective, reliable, and faster solutions for addressing a wide range of complex problems. The typical process for implementing machine learning involves several key steps:

Data preparation: The dataset used for training is collected, followed by necessary pre-processing, including normalization and data cleaning.

Model selection: An appropriate machine learning model is chosen based on the type of data and the specific problem requirements.

Algorithm training: The selected model is trained using the training dataset, enabling it to learn patterns and relationships within the data.

Model evaluation: The model's performance is assessed using a validation dataset, and parameters are adjusted to enhance predictive accuracy.

Predictive application: The trained model is applied to new data for prediction or classification tasks.

Wang et al.[14] integrated machine learning algorithms with surface seismic monitoring, downhole pressure measurements, and total dissolved solids (TDS) data to detect potential leakage from wells at various depths and infer the saturation levels of supercritical and gaseous CO_2. Harati et al.[15] employed regression algorithms, including Support Vector Regression (SVR), Random Forest Regression (RFR), and Decision Tree Regression (DTR), to develop a data-driven model for predicting leakage risks in active CO_2 injection wells.

4. CONCLUDING

This paper reviews various risk assessment methods for CO_2 geological storage, emphasizing both their underlying principles and practical applications. Numerous studies have employed quantitative and semi-quantitative approaches for evaluating CO_2 storage risks; however, these methods are often influenced by subjective factors. Future advancements should focus on integrating simulation techniques with machine learning algorithms to effectively minimize uncertainties in the risk assessment process, enhancing both predictive accuracy and practical applicability.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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