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Advanced Deep Learning Methods for CO_2 Leakage Detection and Environmental Risk Assessment

Ramandeep Singh*

Independent Researcher USA

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ABSTRACT

Carbon capture, utilization, and storage (CCUS) has emerged as a cornerstone technology in global decarbonization strategies, yet its long-term viability hinges on the ability to reliably detect CO_2 leakage and quantify associated risks across heterogeneous subsurface environments. Traditional monitoring, verification, and accounting (MVA) approaches—reliant on sparse well logs, periodic seismic surveys, and physics-based reactive transport simulations—struggle to keep pace with the spatial and temporal complexity of injected CO_2 plumes. Deep learning (DL) has recently emerged as a transformative tool capable of fusing multimodal geophysical, geomechanical, and petrophysical data streams to detect anomalies, forecast plume migration, and assess wellbore and caprock integrity in near real time. This review synthesizes recent advances in deep learning applications for CO_2 leakage detection and risk assessment, drawing on case studies from depleted gas reservoirs, geothermal analogues, and offshore geomechanical systems. It further examines cross-domain methodological parallels with large-scale predictive analytics frameworks developed for public health and healthcare economics, which offer transferable insights into national-scale risk stratification and cost-benefit modeling. The review concludes by identifying persistent challenges—data scarcity, model interpretability, and regulatory validation—and charts a research agenda for physics-informed, uncertainty-aware deep learning systems capable of supporting safe, scalable geologic carbon storage.

Introduction

The urgency of climate change mitigation has placed geologic carbon storage (GCS) at the center of national decarbonization portfolios. Depleted hydrocarbon reservoirs, saline aquifers, and geothermal-adjacent formations are increasingly being repurposed as long-term CO_2 sinks, with injection volumes projected to scale into the gigatonne range over the coming decades. However, the success of GCS as a climate mitigation strategy is contingent not merely on injection capacity, but on the assurance that stored CO_2 remains permanently and safely sequestered. Leakage pathways—whether through faults, fractures, degraded wellbore cement, or caprock heterogeneity—pose environmental, financial, and reputational risks that could undermine public trust in CCUS as a viable climate solution.

Historically, leakage detection and risk assessment have relied on deterministic and stochastic reactive transport models, time-lapse seismic monitoring, and geomechanical simulations calibrated against sparse field data. While these physics-based approaches remain foundational, they are computationally expensive, require extensive parameterization, and often struggle to generalize across the heterogeneous, multiscale nature of subsurface reservoirs. The advent of deep learning—particularly convolutional neural networks (CNNs), recurrent architectures, graph neural networks, and generative adversarial networks (GANs)—has introduced a complementary paradigm capable of

***Corresponding Author:** Ramandeep Singh

Address: Independent Researcher USA

Email ✉**:** ramandeepsinghamaze@gmail.com

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learning complex nonlinear relationships directly from geophysical, petrophysical, and geomechanical datasets, often at a fraction of the computational cost of full-physics simulation.

This review article synthesizes the current state of deep learning applications for CO_2 leakage detection and risk assessment. It draws on recent case studies spanning depleted gas reservoirs, geothermal reservoir characterization, reactive heat exchanger design, and machine-learning-enhanced geomechanical assessment, while also incorporating the foundational deep learning literature specific to CO_2 leakage detection—including seismic-based convolutional network detection (Zhou et al., 2019), pressure-based anomaly detection using convolutional LSTM architectures (Zhong et al., 2019), artificial neural network models for wellbore leakage risk (Li et al., 2018), and deep-learning surrogate models for plume migration and coupled flow-geomechanics prediction (Wen et al., 2021; Tang et al., 2022). The review further situates these developments within the broader context of AI-driven risk stratification frameworks that have matured in adjacent high-stakes domains such as public health and healthcare economics (Nguyen, 2026a, 2026b, 2026c, 2026d). The objective is to provide researchers, engineers, and policymakers with a comprehensive synthesis of methodological advances, practical applications, and outstanding challenges in this rapidly evolving field.

Background: CO_2 Storage and the Leakage Problem

Mechanisms of CO_2 Leakage

CO_2 injected into subsurface reservoirs can migrate through several pathways: (i) capillary and buoyancy-driven flow through unswept caprock heterogeneities, (ii) reactivation of pre-existing faults and fractures under elevated pore pressure, (iii) degradation of wellbore cement and casing, and (iv) diffusive transport through low-permeability seals over geologic timescales. Reactive transport processes—mineral dissolution, precipitation, and geochemical alteration of the rock matrix—further complicate leakage pathways by dynamically altering porosity and permeability over the injection lifecycle. These coupled hydro-thermo-mechanical-chemical (HTMC) processes make leakage prediction inherently multiscale and multiphysics in nature, motivating the search for computationally tractable surrogate models.

Heterogeneity and Site-Specific Complexity

Field-scale heterogeneity remains one of the most significant barriers to reliable leakage forecasting. The Evetts site case study in the Permian Basin illustrates how depleted gas reservoirs exhibit substantial spatial variability in porosity, permeability, and residual saturation, all of which influence CO_2 plume migration and storage efficiency. Optimizing injection strategies in such heterogeneous reservoirs requires models that can rapidly evaluate thousands of geologic realizations under uncertainty—a task for which deep learning surrogate models are particularly well suited, given their ability to approximate expensive reservoir simulations after training on representative datasets.

Analogues from Geothermal and Offshore Systems

Geothermal reservoirs provide valuable methodological analogues for CO_2 storage risk assessment, given their shared reliance on reactive transport modeling, thermal-hydraulic coupling, and long-term performance prediction. Similarly, the development of reactive heat exchangers for enhanced geothermal energy recovery demonstrates how coupled thermal and geochemical processes can be engineered and monitored at the wellbore scale—insights directly transferable to CO_2 injection well design and integrity monitoring. Petrophysical characterization efforts in geothermal reservoirs, such as the Three Forks formation in the Williston Basin, further underscore the importance of high-resolution reservoir quality evaluation for predicting fluid migration behavior, a principle equally applicable to caprock and reservoir characterization in CO_2 storage contexts. Offshore geomechanical studies, such as wellbore stability assessment in the South Tano Field, Ghana, exemplify how machine learning can be integrated with geomechanical characterization to proactively identify integrity risks before they manifest as leakage events.

Deep Learning Foundations for Subsurface Risk Detection

Convolutional Neural Networks for Spatial Pattern Recognition

CNNs have become the workhorse architecture for interpreting spatially structured geophysical data, including seismic amplitude volumes, resistivity maps, and CO_2 saturation fields derived from time-lapse monitoring. By learning hierarchical spatial features—edges, textures, and higher-order plume geometries—CNNs can automatically flag anomalous saturation patterns indicative of unexpected migration pathways, often outperforming manual interpretation in both speed and consistency. Zhou et al. (2019) demonstrated one of the earliest end-to-end data-driven leakage detection frameworks, combining one-dimensional and two-dimensional densely connected CNNs to learn a direct mapping between time-lapse seismic data and CO_2 leakage mass, achieving robust detection performance across randomized and sequential leakage test scenarios in a synthetic sandstone storage reservoir.

Recurrent and Temporal Architectures

Because leakage risk evolves over injection and postinjection timescales spanning years to decades, temporal modeling is essential. Recurrent neural networks (RNNs), long short-term memory (LSTM) networks, and temporal convolutional networks are increasingly applied to time-series data from downhole pressure gauges, distributed fiber-optic sensing, and periodic geochemical sampling to forecast plume evolution and detect early deviations from expected pressure-saturation trajectories. Zhong et al. (2019) illustrated this approach through a convolutional long short-term memory (ConvLSTM) framework that fused static reservoir properties with dynamic bottom-hole pressure measurements from the Cranfield, Mississippi enhanced-oil-recovery field, successfully detecting anomalies corresponding to controlled CO_2 release experiments and demonstrating that the inclusion of static reservoir information further improved detection robustness.

Graph Neural Networks for Fractured and Faulted Media

Fault networks and fracture systems are naturally represented as graphs, making graph neural networks (GNNs) well suited to modeling flow and reactivation risk along discrete discontinuities. GNNs can propagate information across connected fault segments, enabling more physically consistent predictions of fault reactivation risk than grid-based architectures alone.

Generative Models and Uncertainty Quantification

GANs and variational autoencoders (VAEs) are increasingly used to generate ensembles of plausible geologic realizations consistent with sparse well data, enabling probabilistic risk assessment under geologic uncertainty. Coupled with Bayesian deep learning techniques, these generative approaches support the quantification of predictive uncertainty—a critical requirement for regulatory acceptance of AI-driven leakage risk assessments.

Physics-Informed and Hybrid Architectures

A growing consensus in the literature favors hybrid approaches that embed governing physical laws—mass and energy conservation, Darcy flow, geomechanical stress equilibrium—directly into neural network loss functions. Such physics-informed neural networks (PINNs) reduce data requirements, improve extrapolation beyond training domains, and enhance interpretability relative to purely data-driven models, addressing one of the central criticisms of deep learning in high-consequence subsurface applications.

Deep Learning for Seismic and Geophysical Leakage Detection

Time-lapse (4D) seismic monitoring remains the primary geophysical tool for tracking CO_2 plume migration, but manual interpretation of seismic difference volumes is labor-intensive and subject to interpreter bias. Deep learning models, particularly 3D CNNs and U-Net-style segmentation architectures, have demonstrated strong performance in automatically delineating plume boundaries, detecting amplitude anomalies consistent with unexpected vertical migration, and distinguishing genuine leakage signals from acquisition noise or repeatability artifacts.

Beyond seismic amplitude analysis, deep learning has been applied to microseismic event classification, distinguishing induced seismicity associated with fault reactivation from background tectonic noise. This capability is particularly valuable in reservoirs with pre-existing fault networks, where injection-induced pressure buildup can reactivate critically stressed faults and create new leakage pathways. Integration of microseismic classification with geomechanical stress models—an approach paralleling the machine-learning-enhanced wellbore stability workflows applied in offshore geomechanical characterization—allows for near-real-time risk flagging as injection progresses.

Electromagnetic and gravimetric monitoring datasets, while lower resolution than seismic data, offer complementary information on fluid density changes associated with CO_2 saturation. Deep learning-based data fusion frameworks are increasingly used to combine these heterogeneous geophysical modalities into unified leakage probability maps, improving detection sensitivity beyond what any single monitoring technology could achieve independently.

Complementing geophysical monitoring, deep learning has also been applied directly to wellbore-scale leakage risk. Li et al. (2018) developed an optimal artificial neural network trained on more than 500 CO_2-exposed wells across two carbon sequestration fields, producing a validated statistical tool for predicting the long-term probability of well leakage—an approach that highlights the value of deep learning not only for detecting leakage after it occurs, but for prioritizing high-risk wells for proactive intervention before failure.

Reactive Transport Modeling and Deep Learning Surrogates

Reactive transport simulation remains the gold standard for predicting long-term geochemical evolution of the CO_2-brine-rock system, capturing mineral dissolution and precipitation reactions that can either enhance or degrade caprock sealing capacity over time. However, the computational expense of coupling multiphase flow with geochemical reaction networks across field-scale grids often limits the number of scenarios that can be evaluated within practical timeframes, constraining comprehensive uncertainty quantification.

Deep learning surrogate models—trained on ensembles of full-physics reactive transport simulations—offer a computationally efficient alternative for rapid scenario screening. Once trained, such surrogates can evaluate thousands of geologic and operational realizations in seconds rather than days, enabling probabilistic risk assessment and injection strategy optimization that would otherwise be computationally intractable. This approach has direct relevance to depleted gas reservoir storage optimization, where heterogeneous reservoir properties necessitate extensive scenario evaluation to identify injection strategies that maximize storage efficiency while minimizing leakage risk.

Furthermore, insights from reactive heat exchanger development in enhanced geothermal systems illustrate how coupled thermal-chemical process models can inform the design of deep learning surrogates for CO_2 injection wells, where thermal stress cycling and geochemical alteration jointly influence near-wellbore integrity. Transferring these coupled-process surrogate modeling techniques from geothermal to CO_2 storage contexts represents a promising avenue for improving near-wellbore leakage risk prediction.

Deep learning surrogates have also matured to capture flow-geomechanics coupling directly relevant to leakage risk. Wen et al. (2021) trained deep neural networks to predict CO_2 plume migration across heterogeneous reservoir realizations with substantially reduced computational cost relative to full-physics reservoir simulation, while Tang et al. (2022) extended this line of work with a deep-learning-based coupled flow-geomechanics surrogate model capable of jointly predicting pressure buildup, saturation evolution, and geomechanical deformation during CO_2 sequestration—capturing the stress-dependent permeability changes that govern fault reactivation and caprock integrity risk.

Geomechanical and Petrophysical Characterization via Machine Learning

Petrophysical Reservoir Quality Evaluation

Accurate characterization of reservoir and caprock properties is foundational to leakage risk assessment. Machine learning-enhanced petrophysical workflows, such as those applied to the Three Forks geothermal reservoir in the Williston Basin, integrate well log, core, and seismic attribute data to predict porosity, permeability, and mineralogical composition at higher spatial resolution than conventional deterministic methods. These techniques are directly transferable to CO_2 storage site characterization, where accurate delineation of caprock heterogeneity is essential for predicting containment integrity.

Wellbore Stability and Geomechanical Risk

Wellbore integrity failure is among the most common leakage pathways in engineered CO_2 storage systems. Machine learning-enhanced geomechanical characterization workflows, as demonstrated in offshore wellbore stability assessments, integrate stress field estimation, rock strength prediction, and drilling parameter analysis to proactively identify wells at elevated risk of failure. Applying similar workflows to CO_2 injection and monitoring wells enables operators to prioritize integrity interventions—such as cement remediation or casing inspection—before leakage events occur, shifting risk management from reactive to predictive.

Integration Across Scales

A recurring theme across these case studies is the value of integrating deep learning across spatial and temporal scales: from near-wellbore geomechanical stability, through reservoir-scale reactive transport, to basin-scale fault and fracture risk. Multiscale deep learning frameworks—often implemented as hierarchical or multi-fidelity architectures—are increasingly being explored to unify these disparate scales into coherent, site-wide leakage risk assessments.

Risk Assessment Frameworks: Cross-Domain Lessons from AI-Driven Predictive Analytics

While the subsurface engineering literature provides the technical foundation for deep learning-based leakage detection, valuable methodological lessons can also be drawn from AI-driven risk stratification frameworks developed in other high-stakes, data-intensive domains. In public health, national-scale AI frameworks have been developed to target chronic disease prevention and early intervention by identifying high-risk populations from heterogeneous administrative and clinical datasets (Nguyen, 2026a). The underlying principle—using predictive analytics to prioritize limited monitoring and intervention resources toward the highest-risk subpopulations—maps directly onto CO_2 storage contexts, where monitoring budgets must similarly be allocated toward wells, fault segments, or reservoir zones exhibiting the highest predicted leakage probability.

Similarly, national-scale predictive analytics frameworks applied to Medicare and Medicaid populations have demonstrated how AI can identify high-risk cohorts and reduce systemic costs through early, targeted intervention (Nguyen, 2026d). This risk-stratification logic parallels emerging CCUS regulatory frameworks, which increasingly require operators to demonstrate risk-based monitoring plans rather than uniform, resource-intensive monitoring across entire storage complexes. Deep learning-based leakage risk models, by analogy, can support similarly targeted, cost-effective monitoring network design.

Economic impact modeling of AI adoption in healthcare—estimating national cost savings, productivity gains, and long-term outcome improvements (Nguyen, 2026c)—also offers a template for quantifying the economic value proposition of deep learning-enhanced CO_2 monitoring. Just as AI-driven healthcare interventions have been shown to reduce long-term costs by enabling earlier detection and intervention, deep learning-based leakage detection systems may substantially reduce the financial liabilities associated with late-detected leakage events, remediation costs, and regulatory penalties, strengthening the economic case for investment in AI-enhanced monitoring infrastructure across CCUS projects.

Finally, frameworks for reducing administrative burden through AI-driven prior authorization transformation (Nguyen, 2026b) illustrate how AI can streamline complex, multi-stakeholder regulatory and verification processes. CCUS projects similarly involve extensive monitoring, verification, and accounting (MVA) reporting requirements; deep learning systems capable of automating anomaly detection and generating standardized, auditable risk reports could substantially reduce the administrative burden associated with regulatory compliance, mirroring efficiency gains observed in AI-driven healthcare administration.

Collectively, these cross-domain parallels suggest that the maturation of deep learning-based risk assessment in CO_2 storage need not proceed in isolation. Methodological and policy lessons from AI adoption in public health and healthcare economics—particularly regarding risk-based resource allocation, economic justification, and regulatory streamlining—offer a valuable blueprint for accelerating the responsible deployment of deep learning in the CCUS sector.

Challenges and Limitations

Despite substantial progress, several challenges constrain the widespread deployment of deep learning for CO_2 leakage detection and risk assessment.

Data scarcity and class imbalance. Genuine leakage events are, fortunately, rare, resulting in severely imbalanced training datasets that bias models toward predicting the majority "no-leakage" class. Synthetic data generation via reactive transport simulation and generative models offers a partial solution, but the fidelity of synthetic training data to real-world conditions remains an open question.

Interpretability and regulatory acceptance. Regulatory bodies overseeing CCUS projects require transparent, auditable justification for risk assessments. The "black-box" nature of many deep learning architectures poses a barrier to regulatory acceptance, motivating continued investment in explainable AI (XAI) techniques and physics-informed architectures that preserve interpretability.

Transferability across sites. Models trained on one geologic setting—such as a depleted gas reservoir in the Permian Basin—may not generalize well to structurally or mineralogically distinct settings, such as saline aquifers or geothermal-adjacent formations. Transfer learning and domain adaptation techniques are active areas of research aimed at addressing this limitation.

Integration of multiphysics and multiscale processes. True leakage risk emerges from the coupled interaction of flow, geomechanics, and geochemistry across scales ranging from pore-scale mineral reactions to basin-scale fault networks. Fully integrated multiscale deep learning frameworks remain an aspirational rather than fully realized capability.

Real-time deployment infrastructure. Translating research-grade deep learning models into operationally deployed, real-time monitoring systems requires substantial investment in sensor networks, data infrastructure, and edge-computing capabilities—investments that remain uneven across the global CCUS project portfolio.

Future Directions

Future research should prioritize the development of physics-informed, uncertainty-quantified deep learning architectures capable of operating reliably under the sparse-data conditions characteristic of real-world CO_2 storage sites. Multiscale, multiphysics integration—linking near-wellbore geomechanical models, reservoir-scale reactive transport surrogates, and basin-scale fault reactivation models—represents a particularly promising direction, building on the site-specific characterization advances demonstrated across depleted gas reservoirs, geothermal analogues, and offshore geomechanical systems reviewed here (Williams, 2023, 2024; Williams et al., 2026; Yeboah et al., 2026; Akpabli et al., 2026).

Cross-sector collaboration with AI practitioners in domains such as public health and healthcare economics, where risk-stratified, economically justified AI deployment frameworks have already achieved national-scale implementation (Nguyen, 2026a, 2026b, 2026c, 2026d), could accelerate the translation of deep learning research into operationally deployed CCUS risk assessment systems. Finally, continued development of explainable AI techniques tailored to subsurface applications will be essential to building the regulatory and public trust required for deep learning to play a central role in ensuring the safety and permanence of geologic carbon storage at the scale required for meaningful climate mitigation.

Conclusion

Deep learning is rapidly transforming the technical foundations of CO_2 leakage detection and risk assessment, offering computationally efficient, data-fusing alternatives and complements to traditional physics-based reactive transport and geomechanical modeling. Case studies spanning depleted gas reservoirs, geothermal analogues, and offshore geomechanical systems demonstrate the breadth of applicability of these methods across the full lifecycle of CO_2 storage—from site characterization and injection optimization to wellbore integrity monitoring and long-term containment verification. At the same time, methodological and policy lessons from AI-driven risk stratification frameworks in public health and healthcare economics offer valuable, transferable insights for designing economically justified, regulatorily acceptable deep learning systems for CCUS. Realizing the full potential of deep learning in this domain will require sustained investment in physics-informed architectures, explainable AI, multiscale integration, and real-time monitoring infrastructure—investments that are essential to ensuring that geologic carbon storage can be deployed safely and at the scale required to meet global climate objectives.

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