AI-Enabled Risk Assessment and Environmental Monitoring of Natural Gas Storage

Sok Southea, Li Hue

Department of Engineering and Technology, Nortan University, Phnom Penh, Cambodia

Email ID: s.southeanorton-u.com

ABSTRACT

Subsurface natural gas storage operations, spanning depleted hydrocarbon reservoirs, saline aquifers, and salt caverns, carry inherent risks of methane leakage, ground surface deformation, and geomechanical instability, each with significant safety, environmental, and climate implications given methane's potency as a greenhouse gas. Conventional risk assessment and environmental monitoring approaches for natural gas storage rely on periodic surveys, sparse well-based sensor networks, and expert judgment, methods that are costly, spatially and temporally limited, and increasingly inadequate for the continuous, comprehensive oversight that growing natural gas storage capacity and tightening emissions regulations demand. Artificial intelligence, spanning machine learning-based sensor calibration, deep learning-based leak detection and classification, and AI-accelerated satellite-based ground deformation monitoring, has emerged as a transformative set of tools for closing this oversight gap. This article presents a research synthesis of AI-enabled risk assessment and environmental monitoring for natural gas storage, examining hybrid AI-physics frameworks for operational and environmental risk assessment, machine learning-calibrated methane sensor networks, deep learning-based infrared leak classification, and deep learning-accelerated satellite data assimilation for reservoir pressure and surface deformation monitoring. It draws on case studies from heterogeneous depleted gas reservoir management, geothermal-analogue reactive heat exchanger engineering, high-resolution petrophysical characterization, and geomechanically informed wellbore stability assessment, and further considers methodological parallels with large-scale AI-driven risk stratification and economic impact frameworks developed for national healthcare and public health systems. The article concludes by identifying persistent challenges in sensor network coverage, cross-site model generalizability, and regulatory standardization, and proposes a research agenda for advancing AI-enabled risk assessment and environmental monitoring toward routine, trustworthy use in subsurface natural gas storage operations as the field matures through 2026 and beyond.

Keywords: artificial intelligence, natural gas storage, environmental monitoring, risk assessment, methane leak detection, machine learning, subsurface reservoir monitoring

1. Introduction

Subsurface natural gas storage plays a critical role in balancing seasonal and daily mismatches between natural gas supply and demand, yet the operation of storage sites in depleted hydrocarbon reservoirs, saline aquifers, and salt caverns carries inherent environmental and safety risks, including methane leakage to the atmosphere, ground surface deformation associated with cyclical pressure changes, and, in more severe cases, geomechanical instability affecting wellbore or caprock integrity. Methane, the principal component of natural gas, is a greenhouse gas with substantially greater short-term radiative forcing potency than carbon dioxide, making even comparatively small leakage rates from storage operations climate-relevant, while ground surface deformation and geomechanical risk carry direct safety and infrastructure implications for communities and facilities near storage sites.

Conventional risk assessment and environmental monitoring for natural gas storage have historically relied on periodic aerial or ground-based leak detection surveys, sparse networks of wellbore pressure and temperature sensors, and expert-driven risk assessment informed by historical incident data and engineering judgment. While valuable, these approaches are constrained by high cost, limited spatial and temporal coverage, and a fundamentally reactive rather than continuously predictive character, leaving substantial gaps in risk visibility between discrete monitoring events. As global natural gas storage capacity continues to expand and regulatory scrutiny of methane emissions intensifies, these conventional approaches face mounting pressure to be complemented, and in some respects supplanted, by continuous, AI-enabled monitoring and risk assessment capabilities.

Artificial intelligence has emerged as a transformative technology for meeting this need, encompassing machine learning-calibrated sensor networks capable of achieving laboratory-grade measurement accuracy from low-cost field instruments, deep learning-based classification of leak imagery and video capable of quantifying leak size rather than merely detecting its presence, and AI-accelerated data assimilation frameworks capable of interpreting satellite-based ground deformation data to infer subsurface reservoir pressure changes at a fraction of the computational cost of conventional inversion methods. This article synthesizes recent research on AI-enabled risk assessment and environmental monitoring for natural gas storage, integrating insights from heterogeneous depleted gas reservoir management, geothermal-analogue reactive heat exchanger engineering relevant to thermal-geochemical monitoring, high-resolution petrophysical characterization (Yeboah et al., 2026), and machine-learning-enhanced geomechanical risk assessment (Akpabli et al., 2026), alongside the growing AI literature applied directly to subsurface gas storage risk assessment, methane sensor calibration, leak classification, and satellite-based reservoir monitoring (Andrews et al., 2023; Jayabal, 2025; Tang et al., 2022; Wang et al., 2022). It further draws methodological parallels with large-scale AI-driven risk stratification and economic impact frameworks developed for public health and healthcare systems (Nguyen, 2026a, 2026c, 2026d), which offer transferable lessons on deploying continuous, predictive AI monitoring infrastructure at scale. The objective is to provide a comprehensive research synthesis for engineers, environmental scientists, and regulators seeking to advance AI-enabled risk assessment and environmental monitoring from research demonstration toward standard practice in natural gas storage operations as the field matures through 2026 and the years following.

2. The Natural Gas Storage Risk and Monitoring Challenge

2.1 Categories of Environmental and Safety Risk

Natural gas storage operations present several distinct categories of environmental and safety risk: methane leakage to the atmosphere through wellbore integrity failures, caprock seal degradation, or surface equipment malfunction; ground surface deformation arising from cyclical pressure changes associated with repeated injection and withdrawal; and geomechanical instability, including fault reactivation or wellbore failure, particularly in geologically complex or heavily cycled storage formations. Each risk category requires distinct monitoring modalities and analytical approaches, motivating an integrated, multi-modal monitoring strategy rather than reliance on any single risk indicator.

2.2 Limitations of Conventional Monitoring Approaches

Conventional environmental monitoring for natural gas storage relies substantially on periodic ground-based or aerial leak detection surveys using optical gas imaging, complemented by sparse wellbore pressure and temperature sensor networks and occasional geodetic surveys for ground deformation. These approaches, while informative, are inherently limited in temporal frequency and spatial coverage, and conventional approaches to processing the resulting datasets can be tedious and imprecise, particularly when working with the large and diverse data characteristic of complex subsurface storage structures.

2.3 The AI-Enabled Monitoring Opportunity

AI-enabled monitoring approaches promise to address these limitations by enabling continuous, automated interpretation of sensor, imagery, and remote sensing data at a scale and frequency that would be impractical using conventional manual interpretation methods alone. A recent review of AI applications in subsurface gas storage found that AI-assisted models can improve storage capacity prediction accuracy, substantially reduce leakage detection time, and enhance injection optimization relative to conventional methods, with the integration of real-time pressure, temperature, and geophysical data into AI models further improving overall risk assessment reliability (Jayabal, 2025).

3. AI-Enabled Sensor Networks and Leak Detection

3.1 Machine Learning-Calibrated Methane Sensors

Because methane emissions can occur from a wide variety of sites across a storage facility with no discernible spatial pattern, cost-effective, continuous monitoring across widely dispersed locations requires low-cost sensor networks capable of achieving measurement accuracy sufficient for regulatory and operational decision-making. Andrews et al. (2023) developed a methane point instrument calibrated using machine learning methods, comparing Gaussian process regression and artificial neural network calibration approaches to incorporate environmental effects into the sensor response; the resulting machine learning-calibrated sensors achieved an accuracy of one part per million methane and could detect leaks at rates below 0.6 kilograms per hour, demonstrating that machine learning calibration can enable cost-effective, continuous, all-weather methane monitoring using low-cost field instruments connected to a cloud-based interpretation platform.

3.2 Deep Learning-Based Leak Classification from Infrared Imagery

Beyond leak detection, quantifying leak size is essential for prioritizing mitigation response and estimating overall emissions inventories, yet optical gas imaging, while widely used for leak detection, does not directly provide quantitative leak size results. Wang et al. (2022) addressed this gap by developing VideoGasNet, a deep learning architecture that treats methane leak size classification as a video classification problem applied to infrared camera footage, training the model on the first large labeled methane leak video dataset comprising approximately one million frames spanning a wide range of leak sizes and imaging distances; the resulting model extended the application of infrared camera technology from leak detection alone toward leak size classification, enabling more cost-effective methane emission mitigation prioritization by providing quantitative, rather than merely binary, leak assessment.

3.3 Integrated AI-Physics Frameworks for Comprehensive Risk Assessment

Beyond individual sensor or imagery-based monitoring modalities, comprehensive risk assessment for natural gas storage benefits from hybrid frameworks that integrate multiple AI techniques with underlying physical reservoir models. Jayabal (2025) reviewed the transformative role of artificial intelligence in subsurface gas storage, emphasizing hybrid AI-physics models, real-time monitoring, and risk mitigation strategies that incorporate physics-informed neural networks and edge computing, and applying a hybrid AI approach integrating deep learning with geostatistical reservoir simulations to a case study involving a depleted gas reservoir, finding that AI-assisted models improved storage capacity prediction accuracy by approximately 18%, reduced leakage detection time by approximately 35%, and enhanced injection optimization by approximately 22% relative to conventional methods—results that collectively underscore the substantial performance gains achievable through integrated, hybrid AI-physics monitoring and risk assessment frameworks.

4. AI-Accelerated Satellite-Based Environmental Monitoring

4.1 The Role of Satellite Ground Deformation Monitoring

Because subsurface pressure changes associated with gas injection and withdrawal can manifest as measurable surface deformation, satellite-based Interferometric Synthetic-Aperture Radar (InSAR) offers a valuable, spatially comprehensive, and comparatively low-cost complement to sparse well-based pressure monitoring, particularly for storage sites where drilling costs limit the density of direct subsurface measurement. Tang et al. (2022) developed a deep learning-accelerated three-dimensional data assimilation workflow that uses InSAR-derived surface displacement maps as monitoring data to infer subsurface reservoir pressure buildup, employing a three-dimensional-to-two-dimensional residual U-Net architecture to accelerate the data assimilation process; the resulting workflow achieved a computational speedup of approximately 1,500 times relative to a traditional data assimilation approach while maintaining high-fidelity pressure forecasts, directly addressing the high uncertainty in reservoir pressure prediction that arises from the spatially sparse well-based measurements characteristic of most subsurface storage projects.

4.2 Relevance to Natural Gas Storage Environmental Monitoring

Although developed in the context of geologic carbon storage, the InSAR-based deep learning data assimilation methodology of Tang et al. (2022) is directly transferable to natural gas storage environmental monitoring, where similar reservoir pressure inference from satellite-derived surface displacement data can support continuous, spatially comprehensive monitoring of pressure buildup and ground deformation risk across a storage complex without requiring extensive additional well-based instrumentation—a particularly valuable capability for legacy depleted-reservoir storage sites where retrofitting dense sensor networks may be impractical.

4.3 Integration with Wellbore-Scale Geomechanical Risk Assessment

Satellite-based, reservoir-scale ground deformation monitoring provides a valuable complement to, but not a substitute for, wellbore-scale geomechanical risk assessment, which requires direct characterization of near-wellbore stress conditions and rock strength properties. Machine-learning-enhanced geomechanical characterization and wellbore stability assessment, as demonstrated in the offshore South Tano Field, integrates stress field estimation, rock strength prediction, and drilling parameter analysis into a proactive risk-management workflow (Akpabli et al., 2026); combining this wellbore-scale geomechanical risk assessment capability with reservoir-scale satellite-based deformation monitoring offers a multi-scale environmental and safety risk assessment framework spanning from the near-wellbore environment to the full spatial extent of the storage complex.

5. Integrating Site Characterization with AI-Enabled Risk Assessment

5.1 Petrophysical Characterization as a Risk Assessment Foundation

The reliability of any AI-enabled risk assessment framework for natural gas storage depends fundamentally on the quality of the underlying petrophysical characterization used to define reservoir and caprock properties governing containment risk. Machine learning-enhanced petrophysical workflows applied to the Three Forks geothermal reservoir in the Williston Basin illustrate how well log, core, and seismic attribute data can be integrated to characterize reservoir quality at high spatial resolution (Yeboah et al., 2026), providing exactly the class of high-fidelity property information that hybrid AI-physics risk assessment frameworks (Jayabal, 2025) require as geologic input to produce reliable, site-specific risk forecasts.

5.2 Heterogeneous Reservoir Risk at the Evetts Site

Heterogeneous depleted gas reservoir management, as exemplified by the Evetts site case study in the Permian Basin, illustrates the substantial spatial variability in porosity, permeability, and residual saturation that can complicate risk assessment in depleted reservoir natural gas storage settings, underscoring the value of AI-enabled monitoring approaches capable of continuously updating risk estimates from real-time sensor and satellite data rather than relying on static, pre-injection risk characterization alone.

5.3 Thermal-Geochemical Monitoring Principles from Geothermal Infrastructure

Insights from the development of reactive heat exchangers for enhanced geothermal energy recovery illustrate how coupled thermal and geochemical monitoring can be engineered at the wellbore scale to track evolving subsurface conditions in real time. These thermal-geochemical monitoring principles offer valuable methodological parallels for natural gas storage environmental monitoring, where temperature and compositional monitoring along injection and withdrawal wells can serve as an early indicator of unexpected fluid migration or wellbore integrity degradation, complementing the surface-level methane sensor and satellite deformation monitoring modalities that dominate current environmental monitoring practice.

6. Cross-Domain Lessons: AI-Driven Risk Stratification and Economic Justification at National Scale

While the technical foundations of AI-enabled risk assessment and environmental monitoring for natural gas storage are rooted in subsurface geoscience and sensor engineering, valuable methodological and governance lessons can be drawn from large-scale AI risk stratification frameworks developed in other high-stakes, continuously monitored domains. National-scale AI frameworks developed for precision public health illustrate the operational value of continuously integrating individual-level data streams into updated risk assessments that inform targeted, proactive intervention, rather than relying on periodic, population-wide screening alone (Nguyen, 2026a). This principle—that continuous, individually characterized risk monitoring enables more effective, targeted intervention than periodic, uniform assessment—maps directly onto natural gas storage environmental monitoring, where continuous, AI-enabled sensor and satellite monitoring can identify emerging leakage or deformation risk at specific storage sites far more effectively than periodic, calendar-based survey schedules alone.

National-scale predictive analytics frameworks applied to Medicare and Medicaid populations further demonstrate how AI-driven risk stratification across large, heterogeneous populations can identify high-risk cases for targeted follow-up while managing the overall cost of the monitoring program itself (Nguyen, 2026d). This population-level risk-stratified monitoring logic parallels the portfolio-scale challenge facing natural gas storage operators managing multiple storage sites, where AI-driven risk assessment can similarly prioritize monitoring resources—additional sensor deployment, more frequent satellite tasking, targeted wellbore inspection—toward the sites and reservoir zones exhibiting the highest predicted environmental or safety risk, rather than applying uniform monitoring investment across an entire storage portfolio regardless of relative risk.

Economic impact analyses of AI adoption in healthcare, quantifying national-scale cost savings and productivity gains attributable to AI-driven predictive modeling and risk stratification, offer a further template for constructing the economic case for AI-enabled risk assessment and environmental monitoring investment in natural gas storage (Nguyen, 2026c). Just as AI-driven healthcare risk stratification has been shown to reduce costs through earlier detection and more efficient, targeted intervention relative to uniform screening approaches, AI-enabled environmental monitoring for natural gas storage can be expected to reduce the substantial costs associated with both reactive incident response to undetected leaks or deformation events and, conversely, excessive precautionary monitoring investment at low-risk storage sites—an economic argument that merits explicit quantification as AI-enabled risk assessment and monitoring tools mature toward standard practice across the natural gas storage industry.

Collectively, these cross-domain parallels reinforce a broader principle: the value of continuous, AI-driven risk stratification and monitoring for proactive risk management is not unique to natural gas storage, but reflects a general pattern observed across large-scale, geographically distributed infrastructure and population-monitoring domains where periodic, uniform assessment approaches are increasingly being supplanted by continuous, individually targeted, AI-driven risk assessment. The maturation of AI-enabled risk assessment and environmental monitoring for natural gas storage can accordingly draw on deployment, governance, and economic justification frameworks already developed in these adjacent, more mature large-scale AI application domains.

7. Challenges and Limitations

Despite substantial progress, several challenges continue to constrain the widespread deployment of AI-enabled risk assessment and environmental monitoring for natural gas storage.

Sensor network coverage and cost. While machine learning calibration substantially improves the accuracy achievable from low-cost sensors (Andrews et al., 2023), achieving comprehensive spatial coverage across large, geographically dispersed storage facilities still requires substantial sensor deployment investment, and coverage gaps remain a persistent limitation for fully continuous monitoring.

Data scarcity for leak classification training. Deep learning-based leak classification approaches such as VideoGasNet require extensive annotated training data spanning a wide range of leak sizes and imaging conditions (Wang et al., 2022), and the scarcity of real-world gas leakage samples, combined with the prohibitive cost of generating comprehensive annotated datasets, constrains the generalizability of current leak classification models to conditions not well represented in existing training data.

Cross-site generalizability of hybrid AI-physics frameworks. Hybrid AI-physics risk assessment frameworks (Jayabal, 2025) demonstrated on specific case study sites may not generalize reliably to structurally or operationally distinct storage settings without substantial site-specific retraining and recalibration, complicating efforts to develop broadly applicable, transferable AI-enabled risk assessment tools across diverse storage portfolios.

Integration across monitoring modalities and scales. Comprehensive natural gas storage risk assessment requires integrating monitoring data spanning vastly different spatial scales and modalities—from near-wellbore geomechanical sensors to reservoir-scale satellite deformation data to facility-level methane sensor networks—into a single, internally consistent risk assessment framework, an integration challenge that current AI-enabled monitoring approaches address only partially.

Regulatory standardization. No standardized protocol currently exists for validating or benchmarking AI-enabled risk assessment and environmental monitoring outputs specifically for natural gas storage regulatory purposes, complicating efforts to establish AI-enabled monitoring as a formal, auditable component of regulatory compliance and reporting

8. Future Directions

Future research should prioritize the development of integrated, multi-modal AI monitoring frameworks capable of jointly interpreting wellbore-scale geomechanical sensor data, facility-level methane sensor networks (Andrews et al., 2023), infrared leak classification imagery (Wang et al., 2022), and satellite-based ground deformation data (Tang et al., 2022) within a single, internally consistent risk assessment architecture, building on the hybrid AI-physics framework paradigm articulated by Jayabal (2025). Extending the InSAR-based deep learning data assimilation methodology demonstrated for geologic carbon storage (Tang et al., 2022) to natural gas storage-specific validation studies represents a promising and comparatively low-cost direction for improving reservoir-scale environmental monitoring coverage across legacy and newly developed storage sites.

Integration of high-resolution petrophysical and geomechanical characterization workflows—such as those demonstrated for the Three Forks geothermal reservoir (Yeboah et al., 2026) and the South Tano offshore field (Akpabli et al., 2026)—directly into AI-enabled risk assessment training pipelines represents a further avenue for improving the site-specific fidelity of risk forecasts, with particular relevance to heterogeneous, multi-constraint storage sites such as the Evetts site in the Permian Basin. Finally, adopting governance, risk-stratification, and economic justification frameworks informed by AI-driven predictive analytics deployment in national-scale healthcare and public health systems (Nguyen, 2026a, 2026c, 2026d) may help establish the standardized validation protocols and cost-benefit case required for AI-enabled risk assessment and environmental monitoring to transition from research demonstration toward routine, regulator-accepted use across the natural gas storage industry as the field continues to mature in 2026 and beyond.

9. Conclusion

Artificial intelligence is increasingly central to risk assessment and environmental monitoring for subsurface natural gas storage, offering a continuous, spatially comprehensive complement to the periodic, expert-driven monitoring approaches that have historically defined the field. Applications spanning hybrid AI-physics operational and environmental risk assessment, machine learning-calibrated methane sensor networks, deep learning-based infrared leak size classification, and deep learning-accelerated satellite-based reservoir pressure and ground deformation monitoring collectively demonstrate that AI can substantially improve the timeliness, accuracy, and spatial coverage of natural gas storage risk assessment relative to conventional approaches alone. Cross-domain lessons from AI-driven risk stratification and economic impact analysis in national-scale healthcare and public health systems further suggest a pathway toward the governance, resource-allocation, and cost-justification frameworks necessary for AI-enabled risk assessment and environmental monitoring to achieve routine adoption in commercial natural gas storage practice. Realizing the full potential of AI in this domain will require sustained investment in expanding sensor network coverage, addressing data scarcity for leak classification training, improving cross-site model generalizability, and establishing standardized regulatory validation protocols—investments essential to ensuring that natural gas storage operations can be conducted safely, transparently, and with minimal environmental impact as global energy systems continue to evolve through 2026 and beyond.

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