AI-Enabled Monitoring, Verification, and Accounting of Stored CO_2

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Abstract

Monitoring, verification, and accounting (MVA) constitute the regulatory and operational backbone of geological CO_2 storage (GCS), providing the evidentiary basis for confirming that injected CO_2 remains safely contained, quantifying stored volumes for carbon credit accounting, and satisfying the compliance requirements of regulatory frameworks governing carbon capture, utilization, and storage (CCUS). Traditional MVA relies on a combination of geophysical surveys, downhole sensor networks, and physics-based reservoir simulation, all of which are constrained by high costs, limited monitoring frequency, and the computational burden of full-physics interpretation. Artificial intelligence (AI), spanning deep learning, reinforcement learning, and explainable machine learning, is increasingly being integrated into MVA workflows to accelerate data interpretation, enable near-real-time anomaly detection, and support adaptive monitoring network design under geologic and operational uncertainty. This review examines the state of AI-enabled MVA across the CO_2 storage lifecycle, synthesizing recent advances in machine-learning-based monitoring design, deep-learning-based seismic and pressure anomaly detection, reinforcement-learning-based reservoir management, and reactive transport and geomechanical characterization relevant to long-term storage verification. It draws on case studies from heterogeneous depleted gas reservoirs, geothermal-analogue reservoir and heat exchanger systems, and geomechanically informed reservoir characterization, and further considers methodological parallels with AI-driven monitoring, auditing, and cost-accounting frameworks developed for national-scale healthcare systems. The review concludes by identifying persistent challenges in ground-truth data scarcity, model transferability, and regulatory standardization, and proposes a research agenda for advancing AI-enabled MVA toward routine, auditable use in commercial-scale CO_2 storage projects.

Keywords: artificial intelligence, monitoring verification and accounting, geological CO_2 storage, deep learning, reinforcement learning, carbon accounting, reservoir monitoring

Introduction

Monitoring, verification, and accounting (MVA) is the set of technical and regulatory processes by which operators of geological CO_2 storage (GCS) projects demonstrate that injected CO_2 remains contained within the intended storage complex, quantify the mass of CO_2 stored for carbon credit and regulatory accounting purposes, and provide the evidentiary basis required for long-term liability transfer and public trust. As CCUS scales toward gigatonne-level annual injection volumes required to meaningfully contribute to global decarbonization, MVA workflows face mounting pressure to operate more frequently, more comprehensively, and at lower cost than the periodic, resource-intensive geophysical surveys and downhole sensor deployments that have historically defined the field.

Artificial intelligence has emerged as a central technology for meeting this challenge. Deep learning models can interpret geophysical and sensor data at a fraction of the computational cost of full-physics inversion or simulation, reinforcement learning frameworks can support adaptive, risk-informed reservoir management decisions under uncertainty, and explainable machine learning techniques can render AI-generated monitoring outputs auditable to the regulators and stakeholders who must ultimately certify a project's compliance. A recent critical review of machine learning applications across the CO_2 storage lifecycle identifies MVA as a domain where machine learning can meaningfully enhance monitoring frequency and interpretive speed, while cautioning that any such enhancement must be pursued with explicit attention to verifiability, given the regulatory stakes involved.

This review synthesizes recent advances in AI-enabled MVA, integrating insights from heterogeneous reservoir case studies (Williams et al., 2026), geothermal-analogue reservoir characterization and reactive heat exchanger engineering (Williams, 2024), and petrophysical reservoir quality evaluation relevant to monitoring network design (Yeboah et al., 2026), alongside the growing machine learning literature applied directly to CO_2 sequestration monitoring design, deep-learning-based anomaly detection, and reinforcement-learning-based reservoir management (Chen et al., 2018; Sun, 2020; Wang et al., 2026; Zhong et al., 2019; Zhou et al., 2019). It further draws methodological parallels with AI-driven auditing, cost-accounting, and population-level monitoring frameworks developed for national-scale healthcare systems (Nguyen, 2026b, 2026c, 2026d), which offer transferable lessons on deploying large-scale, verifiable AI monitoring infrastructure in regulated domains. The objective is to provide a comprehensive synthesis for researchers, operators, and regulators seeking to advance AI-enabled MVA from research demonstration toward standardized, auditable use in commercial-scale CO_2 storage projects.

The MVA Challenge in Geological CO_2 Storage

The Three Pillars of MVA

Monitoring refers to the collection of geophysical, geochemical, and sensor data characterizing the state of the storage reservoir and surrounding formations over time. Verification refers to the confirmation, against this monitoring data, that injected CO_2 remains within the intended storage complex and that no unacceptable leakage has occurred. Accounting refers to the quantification of stored CO_2 mass for regulatory reporting and carbon credit certification purposes. Each pillar imposes distinct technical requirements, but all three depend fundamentally on the ability to interpret complex, often sparse and noisy subsurface data in a timely and defensible manner.

Limitations of Conventional MVA Approaches

Conventional MVA relies heavily on periodic time-lapse seismic surveys, downhole pressure and temperature sensors, and physics-based reservoir simulation calibrated through history matching. These approaches, while physically rigorous, are constrained by the high cost and operational disruption associated with frequent seismic acquisition, the sparse spatial coverage of downhole sensor networks relative to the scale of the storage complex, and the substantial computational cost of full-physics simulation, which limits the frequency and resolution at which formal verification analyses can be updated (Williams et al., 2026).

The Promise and the Verifiability Requirement of AI-Enabled MVA

AI-enabled MVA promises to address these limitations by enabling faster interpretation of existing monitoring data, more efficient design of monitoring networks under uncertainty, and adaptive reservoir management informed by continuously updated risk assessments. However, because MVA outputs underpin regulatory compliance and carbon credit accounting—outcomes with direct legal and financial consequences—AI-enabled MVA systems must be held to a standard of verifiability substantially higher than that required for purely exploratory or research applications of machine learning in subsurface science. This requirement shapes much of the current research agenda in the field, motivating emphasis on physically grounded surrogate models, explainable outputs, and rigorous validation against independently obtained monitoring data.

AI for Monitoring Network Design and Data Interpretation

Machine Learning for Monitoring Network Optimization

Effective monitoring requires deciding where to place monitoring wells and which data types—pressure, temperature, saturation, geochemical composition—to prioritize collecting, given budget and access constraints. Chen et al. (2018) developed a machine learning and uncertainty quantification-based approach to geologic CO_2 sequestration monitoring design, using data-driven models to identify monitoring configurations that maximize the probability of detecting leakage or containment risk under geologic uncertainty, substantially reducing the number of expensive forward simulations required relative to conventional design-of-experiments approaches. Such monitoring design methodologies are directly applicable to heterogeneous storage sites such as the Evetts site in the depleted-gas Permian Basin, where substantial spatial variability in porosity, permeability, and residual saturation complicates the identification of optimal monitoring locations using conventional deterministic methods alone (Williams et al., 2026).

Deep Learning for Seismic Monitoring Data Interpretation

Time-lapse (4D) seismic monitoring remains a cornerstone of CO_2 plume verification, but manual interpretation of seismic difference volumes is labor- and time-intensive. Deep learning models, particularly densely connected convolutional neural network architectures, have been developed to directly map time-lapse seismic data to CO_2 leakage mass estimates, enabling near-real-time interpretation that would be impractical using conventional manual or physics-based inversion workflows alone (Zhou et al., 2019). This capability is directly relevant to the accounting pillar of MVA, where timely, quantitative estimates of stored and potentially migrated CO_2 mass are required for regulatory reporting.

Deep Learning for Pressure-Based Monitoring and Anomaly Detection

Downhole pressure monitoring offers a cost-effective, high-frequency complement to periodic seismic surveys, but extracting actionable anomaly signals from continuous pressure time series requires models capable of learning both spatial and temporal patterns in the data. Convolutional long short-term memory (ConvLSTM) architectures have been developed to fuse static reservoir property data with dynamic bottom-hole pressure measurements, enabling real-time detection of pressure anomalies consistent with controlled CO_2 release experiments and demonstrating that the inclusion of static reservoir information further improves detection robustness (Zhong et al., 2019). Petrophysical characterization workflows, such as those applied to the Three Forks geothermal reservoir in the Williston Basin, provide exactly this class of high-resolution static reservoir property information—derived from well log, core, and seismic attribute data—that can be integrated into such anomaly detection frameworks to improve their sensitivity and reduce false-positive rates (Yeboah et al., 2026).

Reactive Heat Exchanger and Thermal Monitoring Analogues

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 (Williams, 2024). These thermal-geochemical monitoring principles are directly transferable to CO_2 injection well instrumentation, where temperature profiles along the injection wellbore can serve as an early indicator of unexpected fluid migration or geochemical alteration, complementing pressure- and seismic-based monitoring within a comprehensive AI-enabled MVA framework.

AI for Adaptive Reservoir Management and Verification Decision-Making

Reinforcement Learning for Sequential Monitoring and Management Decisions

Because MVA is inherently a sequential decision-making problem—monitoring data collected at one point in time informs management decisions that affect the reservoir state observed at subsequent monitoring intervals—reinforcement learning offers a natural framework for optimizing MVA strategy over the full project lifecycle. Sun (2020) developed a deep reinforcement learning framework, employing a deep Q-learning network agent, to identify optimal multiperiod CO_2 storage reservoir management policies under monitoring-only and active brine-extraction risk-mitigation strategies, demonstrating that the trained agent could learn policies that maximized long-term reward subject to risk and cost constraints, with learned policies substantially retaining their effectiveness when transferred to related but distinct reservoir environments. This transferability is particularly relevant to multi-site CCUS portfolios, where operators must make consistent, defensible management decisions across geologically heterogeneous storage complexes such as those characterized in the Evetts site case study (Williams et al., 2026).

Machine Learning Across the Full MVA Lifecycle

A recent comprehensive review of machine learning applications across the geological CO_2 storage lifecycle explicitly organizes the literature around four stages—site screening, injection design, operational monitoring, and monitoring, reporting, and verification accounting—identifying three recurring workflow families: surrogate-enabled scenario evaluation, assimilation-oriented hybrid state updating, and integrated monitoring-reporting-verification workflows (Wang et al., 2026). This lifecycle framing underscores that AI-enabled MVA cannot be treated as an isolated monitoring add-on but must be integrated with the broader machine learning workflows used for site characterization and injection design, including the petrophysical and geomechanical characterization approaches applied at analogous geothermal and heterogeneous reservoir sites (Yeboah et al., 2026; Williams et al., 2026).

Data Assimilation and Hybrid State Updating

Beyond static monitoring interpretation, AI-enabled data assimilation techniques—combining machine learning surrogate models with sequential Bayesian updating—allow reservoir state estimates to be continuously refined as new monitoring data arrives, providing a dynamically updated, uncertainty-quantified basis for verification decisions rather than a static, periodically recomputed assessment. This assimilation-oriented approach represents one of the workflow families identified as central to trustworthy AI-enabled MVA deployment (Wang et al., 2026), and is particularly valuable for reconciling sparse, heterogeneous monitoring data streams—seismic, pressure, geochemical—into a single, internally consistent verification narrative.

AI for CO_2 Accounting and Carbon Credit Verification

Quantitative Mass Balance Estimation

Accurate accounting of stored CO_2 mass requires reconciling injection volumes with reservoir simulation or surrogate model predictions of plume distribution and any potential leakage, a task well suited to the same deep-learning-based seismic-to-mass mapping approaches developed for leakage detection (Zhou et al., 2019). Extending these mass-quantification capabilities to routine, auditable accounting workflows—rather than research-stage leakage detection alone—represents an important direction for AI-enabled MVA, particularly given the direct financial stakes associated with carbon credit issuance under emerging regulatory frameworks.

Auditability and Regulatory Trust in AI-Generated Accounting

Because CO_2 accounting outputs directly determine carbon credit issuance and regulatory compliance status, AI-generated accounting estimates must be accompanied by a defensible, auditable basis for their derivation—an area where the interpretability and uncertainty quantification capabilities emphasized throughout the recent MVA-focused machine learning literature become directly consequential rather than merely academically desirable (Wang et al., 2026). Reinforcement-learning-based management frameworks that explicitly track risk and cost constraints over the project lifecycle (Sun, 2020) provide one avenue for generating this auditable basis, since the sequential decision trail underlying a reinforcement learning agent's actions can in principle be traced and reviewed alongside the resulting accounting outputs.

Cross-Domain Lessons: AI-Enabled Monitoring and Accounting at National Scale

While the technical foundations of AI-enabled MVA are rooted in subsurface geoscience and reservoir engineering, valuable operational lessons can be drawn from large-scale AI monitoring and accounting frameworks developed in other regulated, high-stakes domains. Frameworks for transforming prior authorization through artificial intelligence illustrate how AI systems can be designed to generate auditable, policy-consistent decisions at national scale while reducing administrative burden—an operational analogue to the verification and reporting functions required of AI-enabled CO_2 accounting systems, where automated outputs must similarly be traceable to specific, defensible justifications to satisfy regulatory review (Nguyen, 2026b).

National-scale predictive analytics frameworks applied to Medicare and Medicaid populations demonstrate how AI-driven monitoring of large, heterogeneous populations can be used to 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 resource allocation challenge central to CO_2 storage MVA, where monitoring intensity must similarly be allocated—guided by AI-driven risk assessment—toward the wells, fault segments, or reservoir zones exhibiting the highest predicted containment risk, rather than applied uniformly and expensively across an entire storage complex.

Economic impact analyses of AI adoption in healthcare, quantifying national-scale cost savings and productivity gains attributable to AI-driven monitoring and administrative automation, offer a further template for building the economic case for AI-enabled MVA infrastructure investment in CCUS (Nguyen, 2026c). Just as AI-driven healthcare monitoring systems have demonstrated measurable cost reductions through earlier detection and more efficient resource allocation, AI-enabled MVA systems can be expected to reduce the substantial recurring costs associated with conventional seismic survey campaigns and manual data interpretation, while simultaneously improving the frequency and reliability of containment verification—an economic argument that merits explicit quantification as AI-enabled MVA systems mature toward standard industry practice.

Collectively, these cross-domain parallels reinforce a broader principle: the challenge of deploying trustworthy, auditable AI monitoring and accounting systems at national or industry scale is not unique to subsurface CO_2 storage, but reflects a general requirement shared across regulated domains where automated outputs carry direct financial and compliance consequences. The maturation of AI-enabled MVA for GCS can accordingly draw on governance, validation, and cost-justification frameworks already developed in these adjacent, more mature large-scale AI application domains.

Challenges and Limitations

Despite substantial progress, several challenges continue to constrain the operational deployment of AI-enabled MVA for GCS.

Ground-truth data scarcity. Genuine CO_2 leakage events are, fortunately, rare, and real-world data from confirmed leaking wells or plumes is exceptionally difficult to obtain, forcing most AI-enabled MVA models to be trained on synthetic leakage scenarios. This creates a persistent “sim-to-real” gap, in which a model that performs well on synthetic leakage data may generate unacceptably high false-positive or false-negative rates when confronted with the complex, ambiguous signals characteristic of real storage sites.

Model transferability across geologic settings. MVA models trained on one geologic setting—such as a depleted gas reservoir or a specific geothermal-analogue formation—may not transfer reliably to structurally or mineralogically distinct settings without substantial retraining, complicating efforts to develop standardized, broadly applicable AI-enabled MVA tools across diverse storage portfolios.

Interpretability and regulatory standardization. Regulatory frameworks such as the U.S. EPA’s Underground Injection Control Class VI permitting process and emerging international standards require demonstrable, auditable evidence of containment and accounting accuracy; the “black-box” nature of many high-performing deep learning models remains a barrier to satisfying these requirements, and no standardized protocol yet exists for validating

AI-enabled MVA outputs specifically for regulatory purposes.

Integration across heterogeneous data streams and timescales. MVA must reconcile data streams operating at vastly different spatial resolutions and temporal frequencies—from continuous downhole pressure sensing to periodic seismic surveys spanning years—into a single, internally consistent risk and accounting narrative, a data fusion challenge that current AI-enabled MVA workflows address only partially.

Real-time deployment infrastructure. Translating research-grade AI-enabled MVA models into continuously operating, real-time monitoring systems requires substantial investment in sensor networks, data infrastructure, and computational deployment capacity, investments that remain uneven across the global CCUS project portfolio and that constrain the practical realization of the near-real-time monitoring capabilities demonstrated in the research literature.

Future Directions

Future research should prioritize the development of standardized validation protocols for AI-enabled MVA systems, explicitly addressing the sim-to-real gap that currently limits confidence in models trained predominantly on synthetic leakage data (Zhou et al., 2019; Zhong et al., 2019). Closer integration of monitoring network design methodologies (Chen et al., 2018) with reinforcement-learning-based adaptive management frameworks (Sun, 2020) represents a promising direction for developing MVA systems capable of continuously optimizing both what data is collected and how that data informs verification and management decisions over the full project lifecycle, building on the lifecycle-integrated perspective articulated in recent comprehensive reviews of the field (Wang et al., 2026).

Extending high-resolution petrophysical and thermal-geochemical characterization capabilities—such as those demonstrated for the Three Forks geothermal reservoir (Yeboah et al., 2026) and reactive heat exchanger systems in enhanced geothermal energy recovery (Williams, 2024)—directly into AI-enabled monitoring network design represents a further avenue for improving the sensitivity and specificity of anomaly detection at heterogeneous CO_2 storage sites such as the Evetts site (Williams et al., 2026). Finally, adopting governance, auditability, and cost-justification frameworks informed by AI-driven monitoring and accounting deployment in national-scale healthcare systems (Nguyen, 2026b, 2026c, 2026d) may help establish the standardized validation protocols required for AI-enabled MVA systems to transition from research demonstration to routine, regulator-accepted use in commercial-scale CO_2 storage operations.

Conclusion

Artificial intelligence is increasingly central to the monitoring, verification, and accounting functions that underpin the regulatory and financial legitimacy of geological CO_2 storage. Applications spanning machine learning-based monitoring network design, deep-learning-based seismic and pressure anomaly detection, reinforcement-learning-based adaptive reservoir management, and lifecycle-integrated monitoring-reporting-verification workflows collectively demonstrate that AI can substantially accelerate and enhance the interpretive and decision-making processes at the heart of MVA, provided that verifiability and auditability are treated as first-order design requirements rather than afterthoughts. Cross-domain lessons from AI-driven monitoring and accounting deployment in national-scale healthcare systems further suggest a pathway toward the governance and cost-justification frameworks necessary for AI-enabled MVA to achieve regulatory trust and routine operational adoption. Realizing the full potential of AI-enabled MVA will require sustained investment in closing the sim-to-real gap, improving cross-site model transferability, and establishing standardized validation protocols—investments essential to ensuring that geological CO_2 storage can be monitored, verified, and accounted for safely, transparently, and at the scale required to meet global climate objectives.

References

1. Chen, B., Harp, D. R., Lin, Y., Keating, E. H., & Pawar, R. J. (2018). Geologic CO2 sequestration monitoring design: A machine learning and

uncertainty quantification based approach. *Applied Energy, 225*, 332–345. https://doi.org/10.1016/j.apenergy.2018.05.041

2. Nguyen, T. T. (2026b). Transforming prior authorization through artificial intelligence: A national framework for reducing administrative burden and improving patient access. *International Journal of AI, BigData, Computational and Management Studies, 7*(3), 17–27.
3. Nguyen, T. T. (2026c). The economic impact of AI adoption in healthcare: Estimating national cost savings, productivity gains, and long-term health outcomes. *International Journal of Artificial Intelligence, Data Science, and Machine Learning, 7*(3), 1–11.
4. Nguyen, T. T. (2026d). National-scale predictive analytics for Medicare and Medicaid: An AI-driven approach to identifying high-risk populations and reducing healthcare costs. *Journal of Advanced Scientific Research, 17*(6), 1–10.
5. Sun, A. Y. (2020). Optimal carbon storage reservoir management through deep reinforcement learning. *Applied Energy, 278*, 115660. https://doi.org/10.1016/j.apenergy.2020.115660
6. Wang, C., Zhao, Y., Xu, H., Liu, Q., Diwu, P., Tiong, M., Xian, C., Ye, H., Wu, S., Zhang, S., & Liu, H. (2026). Machine learning across the lifecycle of geological CO2 storage: Applications, workflows and requirements for trustworthy deployment. *Clean Energy*, zkag027. https://doi.org/10.1093/ce/zkag027
7. Zhong, Z., Sun, A. Y., Yang, Q., & Ouyang, Q. (2019). A deep learning approach to anomaly detection in geological carbon sequestration sites using pressure measurements. *Journal of Hydrology, 573*, 885–894. https://doi.org/10.1016/j.jhydrol.2019.04.015
8. Zhou, Z., Lin, Y., Zhang, Z., Wu, Y., Wang, Z., Dilmore, R., & Guthrie, G. (2019). A data-driven CO2 leakage detection using seismic data and spatial–temporal densely connected convolutional neural networks. *International Journal of Greenhouse Gas Control, 90*, 102790. https://doi.org/10.1016/j.ijggc.2019.102790