Reliable Carbon Transport and Storage:

Roles for Artificial Intelligence in Support of FECM RDD&D Priorities

U.S. DEPARTMENT OF ENERGY

Fossil Energy and Carbon Management

Artificial intelligence (AI) holds the potential to accelerate the transition to a carbon-neutral economy and help achieve the technology research, development, demonstration, and deployment (RDD&D) goals set forth by the DOE Office of Fossil Energy and Carbon Management (FECM) in its *Strategic Vision*. FECM and the National Energy Technology Laboratory (NETL) continuously expand, maintain, and curate extensive scientific data sets and AI tools essential to carbon management, and they are now standing up a robust AI Multi-Cloud Infrastructure to enable the DOE research community to share and leverage a collection of tailored resources to expedite progress toward equitable and sustainable solutions.

As one step toward prioritizing AI development activities, FECM is exploring specific roles for AI in meeting the top RDD&D needs identified in the Vision. This document summarizes a series of discussions in which a range of specialists from FECM, NETL, and the DOE Office of Science suggested potential roles for AI in **Reliable Carbon Transport and Storage**. This document should be viewed as a representative sample of the types of AI applications that may be needed; it is by no means a comprehensive list.

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AI Role in Dedicated and Reliable Carbon Transport and Storage

Achieving America's goal of a net-zero carbon economy by 2050 will require developing an expansive new carbon transport and storage industry and robust supporting infrastructure. This critical infrastructure must be able to safely transport and securely store vast quantities of carbon dioxide (CO_2) captured at point sources or directly from the air. The needed technology and infrastructure must be deployed at an unprecedented pace and scale nationally and globally. Success in this undertaking is an essential part of addressing the climate impacts that increasingly threaten the safety, health, food supply, and economic security of our nation.

Vision

Establish the foundation for a successful carbon storage and transport industry by making key investments in RD&D, large-scale transport and storage facilities, and regional hubs to support rapid deployment of carbon storage necessary to enable the decarbonization of the U.S. economy.

Strategic Vision (DOE/FECM 2022)

To meet the 2050 goal, a recent study estimates that by 2030 the U.S. infrastructure for carbon storage (both on and offshore) will need to accommodate at least 65 million tonnes of CO_2 per year—roughly the amount used by today's CO_2-enhanced oil recovery (EOR) industry, which has developed over 50 years. By 2050, the same study estimates that storage capacity will need to accommodate roughly one billion tons of CO_2 annually. Storing CO_2 at this scale is likely to require at least 1,000 capture facilities, a 21,000–25,000-km network of interstate CO_2 trunk pipelines, 85,000 km of spur pipelines to supply the trunklines, and thousands of injection wells (Larson 2020).

Developing the necessary infrastructure within the next 20 years will require maximizing and expanding existing infrastructure, developing hundreds of new facilities, and discovering innovative and efficient approaches, including novel subsurface analysis tools, transport modes, materials, equipment, and systems. Artificial intelligence (AI) and machine learning (ML) are needed both to expedite development and optimize the performance of this critical infrastructure and its components. Specifically, AI holds the potential to accelerate progress in the foundational science and understanding needed to accurately assess the capacity and long-term integrity of subsurface environments, surface and subsurface mineralization processes, and other potential carbon containment resources—*and* to enable a highly reliable transport network that efficiently connects carbon sources to sinks. As the transport and storage industry grows, AI can also potentially minimize the risks associated with early demonstration and deployment projects and reduce basin-scale impacts.

The U.S. Department of Energy's Office of Fossil Energy and Carbon Management (FECM) has amassed extensive data on carbon storage through more than two decades of research in partnership with industry, academia, the national laboratories, and other research institutions (see inset). As summarized in Figure 1 on pages 2–3 and on the following pages,

FECM Program and Other Resources

- **Carbon Storage Atlas**: Estimated national storage resources of onshore saline formations (2015)
- **Regional Carbon Sequestration Partnership (RCSP)**: Demonstrated safe CO_2 storage at seven large facilities
- **Regional Initiative**: Stakeholders in four regions help address challenges and facilitate CCUS projects
- **CarbonSAFE**: Five operating facilities help reduce technical risk and cost of commercial saline storage
- **SMART**: Science-informed ML for Accelerating Real-Time (SMART) Decisions in Subsurface Applications
- **Core R&D:** Advancing storage site characterization, monitoring, modeling, and management tools
- **EDX4CCS:** Refining, advancing, and deploying CS data-driven products to facilitate DOE/stakeholder research
- **National Risk Assessment Partnership** (NRAP): Science-based methodology to assess carbon storage risks
- **Pipelines**: The U.S. CO_2 pipeline infrastructure today consists of more than 5,000 miles in 13 states.

Reliable Carbon Transport and Storage

Challenge — *AI Assist*

Reliable Carbon Transport and Storage

Carbon Storage in Sedimentary Formations

Improve data utilization & tools to assess subsurface

Leverage Data Resources

- Assess diverse data types to find new storage reservoirs
- Leverage data to screen for safe and economical storage
- Enable data extraction/curation from images
- Interpret field monitoring data in near-real time
  - Prioritize collection of highest-value data
  - Accelerate history matching to enhance operations
  - Enable rapid updates and visualization of subsurface
  - Inform management and risk-related decision making

Build Improved Models

- Infuse AI/ML into manual geo-science techniques
- Build more accurate stochastic geologic models
- Advance 3D subsurface prediction using STA tool
- Develop models integrating geologic context into analytics
- Combine/weight surface/subsurface factors into models

Safely Expand Capacity of Existing Sites

Safely Optimize Capacity

- Optimize CO_2 injection for specific sites in near-real time
- Rapidly assess plumes to inform site capacity and safety

Inform Site Management To Ensure Security

- Accurately estimate areal extent of seal integrity/quality
- Monitor operations in real time to assure containment
- Develop models to prioritize inspection/management

Repurpose Oilfield Infrastructure

- Forecast future CO_2 injection/storage performance
- Characterize region/basin to guide decision making
- Develop SIMPA-based model to assess field potential

Characterize Potential New Sites

Characterize Capacity and Integrity of Specific Sites

- Develop geologic models to accelerate site screening
- Rapidly, accurately predict site capacity/injectivity

Inform Decision Making and Permitting

- Expedite UIC permitting and reduce costs
- Improve communications among stakeholders

Figure 1. Summary of Potential AI Roles in Reliable Carbon Transport and Storage

Characterize at Basin or Regional Scale

- Define limits on extrapolating from data on other sites
- Rapidly forecast deployment scenarios at basin scale
- Design efficient monitoring to manage risk across basins
- Probe well integrity/stress to de-risk storage in basin

Mineralization Resources

Locate/characterize reactive materials in subsurface

- Devise AI/ML-informed geostatistical approaches
- Spatially characterize areas of high reactivity

Spatially locate and characterize critical minerals*

- Identify geochemical relationships to predict/map
- Characterize/identify mineralization pathways

Strategic Planning for Transport

Improve CO_2 transport safety and decision support

- Optimize sensor placement to find leaks fast
- Identify new signals to predict and avoid failure
- Forecast diverse threats in real time

Improve CO_2 transport performance and operations

- Find/develop new materials to improve CO_2 transport
- Assess dedicating current infrastructure to CO_2 transport
- Boost efficiency and lower cost to transport CO_2
- Forecast remaining life and risk profiles of pipelines
- Update pipeline maintenance based on range of data
- Develop geospatial layers for transport/storage models

Inform routing/demo/deployment with place data

- Perform social and environmental justice sensitivity
- Incorporate state/community views on routing
- Optimize routes integrating energy/social justice issues
- Identify routes through a fragmented cost surface
- Add physics-informed ML (PIML) to storage models
- Model climate impacts on equipment/operations
- Locate areas of high risk to offshore infrastructure (OGA)

* Critical materials discovered will be reported to the appropriate FECM program.

Figure 1. Summary of Potential AI Roles in Reliable Carbon Transport and Storage (continued)

AI/ML shows promise to leverage federal, state, local, and industry data and accelerate progress in three main areas: expanding *carbon storage* (trapping) in the subsurface; locating and assessing *mineralization resources*; and planning for safe and efficient *carbon transport* systems.

Sustained investment to advance the deployment of CO_2 sequestration in deep sedimentary reservoirs and develop CO_2 mineralization should "lead to a deeper understanding of the reservoir characteristics from the nano- to kilometer scale, some of which may include:

- Distribution of reaction products
- Reaction rate of the minerals
- Permeability evolution
- Pressure build-up in the reservoir
- Large-scale impact of chemicophysical processes leading to clogging or cracking
- Effects of potential geochemical contamination, etc."

Peter B. Kelemen et al, *Frontiers in Climate* (Kelemen 2019)

Carbon Storage in Sedimentary Formations

The most mature and cost-effective option for geologic carbon storage today involves injecting supercritical CO_2 (sCO_2) deep in the pore spaces of sedimentary rocks. The sCO_2, which acts like a gas with the density of a liquid, can be stored in deep saline formations, depleted oil and gas reservoirs, or organic shale formations.[1] Storing at a depth of a half a mile (800 meters) or greater ensures the temperature and pressure required to maintain the injected CO_2 in a dense, supercritical state.[2] Captured CO_2 can also be stored in reactive rock formations such as basalts, in which CO_2 mineralization processes are highly accelerated.

Suitable geologic storage formations must be sufficiently porous and permeable to ensure adequate capacity and injectivity and must provide at least one overlying impermeable caprock layer that serves as a seal to prevent unwanted vertical migration of the injected sCO_2, which is less dense than other fluids in the rock pores (Kelemen 2019). Caprock layers are necessary to ensure that the injected CO_2 is permanently trapped in the target storage reservoir. Since it is possible for the CO_2 to seep through a leaky wellbore or an undetected permeable fault or fracture in the caprock (NAS 2019), candidate sites must meet rigorous federal (and state) regulations and be closely monitored before, during, and after CO_2 injection to assess their capacity, injectivity, and integrity.

Currently, the process to assess and develop a storage site can require three to ten years, depending on the amount and quality of relevant geological information available. In addition to meeting applicable regulations, assessments should follow a consistent framework, such as the Storage Resource Management System (SRMS), which was adapted from the industry-accepted Petroleum Resource Management System (PRMS) (IEA 2022). A further imperative is to proactively engage local communities in decision and planning processes to ensure social equity and responsible environmental stewardship.

AI holds the potential to significantly accelerate the characterization, assessment, permitting, development, and operation of carbon storage sites that are safer and more efficient. For example, AI-enhanced understanding of subsurface structures, flows, and interactions at key interfaces will help to develop, verify, and validate tools and plans to expand operations at existing storage reservoirs, repurpose oil fields (both on and offshore), discover and analyze new storage resources, and scale information and transfer learning from specific sites to larger complexes, basins, and regions.

As described below, AI and ML can help to develop the needed carbon storage capacity by improving data utilization and tools to assess the subsurface, provide reliable guidance on how to safely expand the capacity of existing sites, and accurately characterize potential new sites.

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[1] Organic shale formations may store sCO_2 as a free gas within pores and fractures or as an adsorbed component on clay or organic matter. The latter option will require more comprehensive geologic/petrophysical data on unconventional shale reservoirs.

[2] NETL, Carbon Storage FAQs. www.netl.doe.gov/carbon-management/carbon-storage/faqs/carbon-storage-faqs

Improve Data Utilization and Tools to Assess the Subsurface

> "The R&D investments in new tools and technology to monitor underground activity near CO_2 storage sites will help us minimize risk from natural events like earthquakes, safeguard the environment and water supply, and get us that much closer to our clean energy goals."
>
> Secretary of Energy Jennifer M. Granholm (DOE 2021)

AI and ML can help make sense of massive amounts of data (micro to regional scale) and provide a better understanding of subsurface environments, flows, chemistries, seals, hazards, and other critical factors affecting the security, economics, and environmental impacts of geologic carbon storage. In some cases, researchers may face challenges in gaining access to data held by private or local entities, handling diverse data formats and storage (legacy) media, or adjusting for a broad range of measurement units, methods (e.g., sensor type and placement), intervals, and accuracy levels. Where data is plentiful, AI may help identify which data types are most valuable for specific applications (e.g., visualizing rock layer formations, predicting sCO_2 flows, managing reservoir pressure levels/avoiding seismic events, ensuring wellbore integrity, confirming permanent storage suitability, or quantifying risks and uncertainties). Where data is sparse, AI and ML can help researchers use the available data to best advantage, fill in the gaps with high-fidelity digital twins or synthetic data, apply transfer learning, identify the limits of extrapolation for different subsurface environments, and help select new data types to improve assessment accuracy. In all cases, sufficient data must be reserved to help validate the accuracy of new algorithms/models (in addition to review by scientific subject matter experts).

Leverage Data Resources: ML-developed algorithms and models often provide improved predictions when informed by larger volumes of relevant data and **diverse data types and sources**, including data that covers a wider range of relevant scenarios (spatial and temporal). AI/ML can bring together geologic data from a variety of sources (maps, reports, or logs from state, industry, or regulatory groups) and of various types (permeability, temperature, porosity, rock properties, pressure, etc.). Establishing the essential geological/geophysical context (volume, injectivity, seismic activity, seal security and/or recommended seal redundancy) can help identify potential new storage sites.

To accelerate data collection, curation, and categorization, ML can effectively **leverage sparse data** as well as **extract data from images** using natural language processing (NLP) and computer vision. For example, the National Energy Technology Laboratory (NETL) has a subsurface trend analysis (**STA**) tool with an image-embedding algorithm. Using NLP to communicate with such algorithms would expand this type of multi-modal data integration and strengthen predictive tools for the subsurface.

ML can apply pattern recognition to massive datasets, potentially leading to **near-real-time interpretation of field monitoring data**. Models can rank the contributions of certain data types to reduce uncertainty and potentially avoid the misapplication of AI/ML techniques that were developed for specific physical conditions. Assessing the value of different data types could also improve site management by better informing critical performance- and risk-related decisions. Other ML models might monitor data to help match the geologic histories (spatial and temporal) of known sites to enable extrapolation to potential new sites, improving new site evaluations and operations. AI/ML models are similarly needed to rapidly extract subsurface physical properties from raw geophysical data to inform leak detection and/or plume conformance. Models could also enable near-real-time visualization (see Figure 2, SMART Initiative) of infrastructure performance (physical and decision space) to guide operations or detect potential failure before or in the early stages of a negative event (e.g., seismicity, caprock or well leakage].

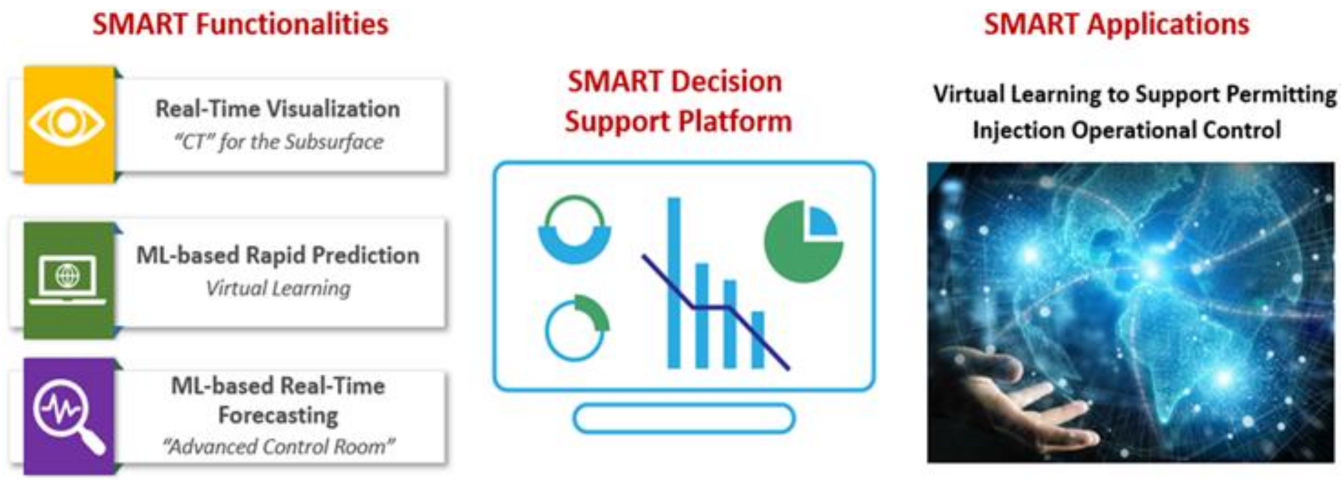

Figure 2. SMART Initiative: Visualization and Decision Support Platform (Science-informed Machine Learning for Accelerating Real-Time Decisions in Subsurface Applications). Image: NETL

Build Improved Models: AI can greatly enhance scientific understanding of the subsurface and significantly improve the efficiency and effectiveness of field-scale carbon storage. As a first step, **infusing AI/ML capabilities into traditional geoscience-based methods** can yield better and faster results. Integrating multiple data types to build **more accurate stochastic geologic models** can reduce uncertainty and risk. This opportunity is continually expanding as AI models add a temporal component to recognize the dynamic aspects of subsurface conditions (analogous to weather forecasts). ML can help interpolate data over space and time to **advance 3D subsurface prediction** and variogram calculations. That effort would significantly enhance the STA tool, as would the addition of **hybrid models that integrate geologic context into analytics** (categorical and hybrid numerical-categorical models of spatial and non-spatial phenomena).

The high complexity of site assessments for carbon storage and the uncertainties in available (non-binary) data suggest a role for fuzzy logic to deliver valuable insights on key trends and patterns or fill knowledge gaps in how fluid and/or gas migrates in the subsurface. **Fuzzy logic modeling could help combine and weight (surface and subsurface) factors** associated with storage sites (leveraging NETL's Spatially Integrated Multivariate Probabilistic Assessment (SIMPA) model).

Safely Expand the Capacity of Existing Storage Sites

AI could expedite the development of models and tools to reliably guide the expansion of existing underground carbon storage facilities while minimizing the risks of seismic hazards, CO_2 leakage to the atmosphere, or contamination of groundwater. Key challenges are to successfully integrate different data types (point source, 3D, analog) to assess properties over an extensive area and identify the most effective additional data needed to produce actionable characterizations and projections.

Safely Optimize Capacity: Near-real time tools are required to help ***optimize*** **the amount of CO_2 injected** and stored at each unique site. Improved tools might effectively measure and monitor the seal integrity of caprocks, adjust operational parameters to increase effective storage volumes, and assess the potential hazard of leakage. As the supercritical CO_2 is injected, ML tools might **use changes in CO_2 plume conformance to calculate fluid pressures and rock stresses** in near-real time to guide the process.

Inform Site Management: Safe and economical site management will require improved tools to better understand site-specific geophysical reservoir features, measure reservoir volume, and closely monitor conditions to inform decision making. Multiple data types (e.g., core samples, well logs, pressure measurements, analog data) will be needed to accurately **estimate the spatial extent of seal integrity/quality** and storage capacity. AI should help select and interpret sensor data to **monitor reservoir performance in near-real time**, suggest operational parameters/adjustments, and assess impacts. These near-real-time performance evaluations could enable early detection and avoidance of potential storage system failures. Similarly, novel data-driven methods could be used to **prioritize wells for inspection, remediation, or plugging** and to set clear parameters for safe and economical operations.

"CO_2 transport and storage infrastructure is the critical enabler of CO_2 capture deployment."

International Energy Agency, *CO_2 Transport and Storage, Tracking Report* (IEA 2022)

Repurpose Oilfield Infrastructure: New tools to assess the suitability of existing oil fields for permanently storing captured CO_2 can potentially draw on 150 or more years of experience and data.[3] Some of the data may be in private hands, but even the readily available data will span a wide range of temporal and geographic differences in construction design, standards and regulations (municipal, state, tribal, federal), data collection methods, and data formats—as well as record-keeping protocols (e.g., recording reentries by updating old records versus starting new ones). These old records may be critical to success, and AI tools could help to identify the most valuable types of data to collect and use in evaluating future scenarios [identifying the physical conditions under which certain types of data would *not apply* is equally valuable].

ML models could be trained on historical oil field performance data (e.g., primary, secondary, and tertiary injection/production and bottom-hole pressures) to help **forecast future CO_2 injection and storage performance** at those sites. With no models of this type yet available, unsupervised learning might be used to rapidly parse available data types and test them in algorithms to identify the types of data most valuable for predicting successful transition scenarios (O&G production to CO_2 storage). Future models should also help inform the new management protocols required to reduce any risks associated with the repurposing and to optimize performance as conditions evolve in the future. Novel data-driven methods might also **use regional- or basin-scale well characterization capabilities** to guide decision making on repurposing and to prioritize needed site preparations (well inspection, remediation, plugging, etc.). Basin- or regional-scale datasets (e.g., Class II well construction data, Class II injection/production data, geologic setting information, well logs, inspections, and monitoring data) have the potential to yield new insights and inform site management. For a selected oil field, a **SIMPA-based model could be developed to assess the potential for repurposing the field** and infrastructure.

Characterize Potential New Sites

Achieving national carbon goals is estimated to require thousands of new injection wells (Larson 2020). To support this massive undertaking, AI/ML models and tools could expedite assessments of potential new storage sites across the country to make sure the injected carbon is securely sequestered for the long term.

Characterize Capacity and Integrity of Specific Sites*:* Drawing upon extensive geologic data records, AI could help **generate geologic models** to accelerate screening of new sites to determine their suitability for secure carbon storage, expediting the decision process and lowering costs. A site's storage capacity is a key factor in the screening process, and AI/ML might enable rapid reservoir modeling that incorporates multiple geologic models to **rapidly produce accurate estimates of site-specific storage capacity** and injectivity. As part of evaluating new resource storage capacity, AI/ML could be trained on existing resources to help stakeholders understand what might be expected from a new resource (e.g., strengths, weaknesses, management protocols). This capability will require best practices for the application of transfer learning from one location/reservoir to another.

Inform Decision Making and Permitting: In the interest of protecting underground sources of drinking water, the Environmental Protection Agency (EPA) carefully regulates geologic CO_2 sequestration in (Class VI) wells. The regulations address the unique nature of CO_2 injected deep in the subsurface, including its relative buoyancy

[3] Processes for injecting CO_2 into partially depleted oil fields to enhance oil recovery (EOR) do not ensure permanent carbon storage.

and mobility, corrosivity in the presence of water, and anticipated high volumes. Requirements for the necessary Underground Injection Control (UIC) permits include siting, construction, operation, testing, monitoring, and closure (EPA 2023). In this context, the National Risk Assessment Partnership (NRAP) is developing quantitative, science-based tools and methods for estimating the long-term environmental risks of geologic carbon storage (induced seismicity, leaks) to help inform long-term monitoring costs and liability. Incorporating AI/ML tools into these risk assessment workflows can expedite permitting and lower costs.

AI might significantly **accelerate the currently lengthy permitting process**. ML and virtual learning (VL) tools can expedite processes for evaluating operational scenarios, defining the Area of Review, developing an efficient and effective monitoring design, and identifying post-injection site care requirements. AI might also deliver better tools for visualizing the storage system behavior and decision space to **improve communications among stakeholders** on site performance and risk. The EPA is actively working with states to engage communities and ensure environmental justice through the permitting process.

Characterize at Basin or Regional Scale: To develop the nation's required carbon storage resources within the target time frame, developers will need to shift their focus from characterizing specific sites to examining prospects at the basin or regional scale. This broader perspective could greatly accelerate progress but will require powerful and appropriately scaled new assessment tools. AI/ML tools to handle this scale may leverage data from regulatory compliance inspections, acoustic measurements, and other sources, but uniform data sets for these much larger areas may be difficult to find.

Solutions may involve extrapolating from sparse data, but this will require defining the limits to which dense data for one location can be reliably leveraged to assess a much wider area. AI/ML may assist in **exploring extrapolation limits;** new methods for transfer learning may also be useful. With scientific validation, AI tools hold the potential to **rapidly forecast storage deployment scenarios**, **design efficient monitoring to effectively manage risk**, and **characterize well integrity and stress** to de-risk storage—all at the basin scale.

Carbon Mineralization Resources

In subsurface carbon mineralization, the injected sCO_2 reacts with minerals in the surrounding igneous or metamorphic rock to form a solid mineral, such as a carbonate. This happens naturally, but the process can be sped up artificially. The advantage of carbon mineralization over storage in sedimentary basins is that the carbon cannot later escape to the atmosphere. This process can also occur at the surface by exposing CO_2 to broken pieces of rock, such as mine tailings (USGS 2019).[4]

"CO_2 mineralization, where CO_2 is injected into basalts or peridotites, is becoming increasingly developed. These rocks contain a higher fraction of CO_2-reactive minerals, which can accelerate the precipitation of carbonate minerals compared to conventional storage."

CO_2 Transport and Storage, IEA (IEA 2022)

Igneous or metamorphic rocks with the best potential for mineralization through injection are basalt and ultramafic rocks (a broad category of rock with high levels of magnesium and iron). Lab studies show that ultramafic rocks have the fastest reaction times, and pilot studies indicate that CO_2 injection in basalt can lead to mineralization in less than two years. As shown in Figure 3, the potential for carbon storage through mineralization is spread widely across the United States (USGS 2019). The main risks associated with injecting carbon into the subsurface for mineralization are large water demands, land use impacts, and the potential to trigger earthquakes if pressures are not adequately managed (USGS 2018).

The full potential of reactive materials for carbon storage or conversion to durable products is constrained by a lack of knowledge of the processes that drive carbon mineralization. AI/ML approaches may be limited until we

[4] Surface mineralization is the purview of the Carbon Dioxide Reduction Program.

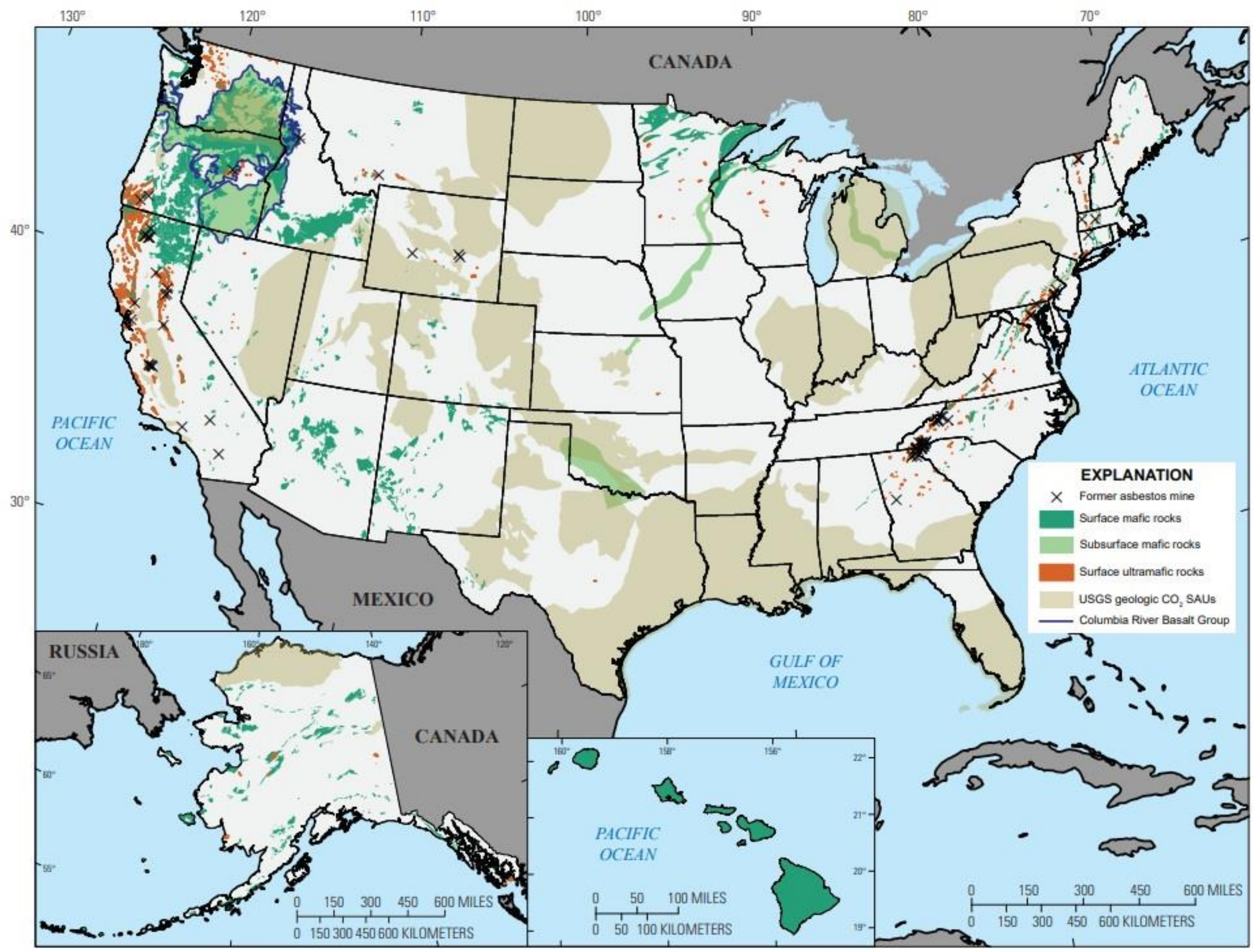

Figure 3. Potential sites for geologic carbon storage via mineralization Public domain (USGS 2018)

gain a comprehensive understanding of the key interactions and multi-scale processes necessary to achieve successful carbonation operations for permanent storage or conversion to durable products.

Locate and characterize reactive materials in the subsurface for permanent CO_2 storage

AI/ML-informed geostatistical approaches may be devised to assist in identifying prime areas for carbon mineralization, (e.g., variograms calculated using neural networks in the STA Tool). Alternatively, AI/ML could help mine and place geochemical data in a flexible data format (e.g., DAT file, CSV), enabling **neural or artificial neural networks to spatially characterize areas of high reactivity**.

Spatially locate and characterize critical minerals

AI/ML could leverage knowledge and data (possibly using SIMPA, STA, and supervised/unsupervised neural networks) to **identify geochemical relationships and map locations with mineralization potential**. More fundamentally, AI can also help **clarify mineralization pathways**, potentially building upon the structural complexity approach used in SIMPA. Detailed characterizations of the subsurface may identify locations likely to contain relatively high concentrations of various critical minerals. Any analyses or explorations that uncover critical minerals, rare earth elements, or low-temperature geothermal resources are to be automatically reported to the appropriate FECM programs.

Strategic Planning for Carbon Transport

Captured CO_2 can be transported by pipeline, rail, truck, ship, and barge. Pipelines and ships are currently the most scalable and lowest-cost options, but novel approaches, including multi-modal transport systems, may emerge. Initial build out of the needed carbon storage and transport network must be accomplished in close coordination with (and a bit ahead of) other components to appropriately accommodate/direct the volume captured and ensure its safe, efficient, and economical handling. Carbon transport planning is complicated by the evolving policy framework as well as uncertainties associated with the siting of future facilities, storage basin capacities, regulatory bodies, and locations of specific injection sites (Net Zero America 2021).

Improve CO_2 transport safety and decision support

Safety is particularly imperative at this early stage of infrastructure development as any failures could significantly impede progress. AI can play a vital role in detecting, predicting, and avoiding leaks. One challenge in developing the AI is to select the most useful data out of the massive data sets collected for decades across thousands of miles of O&G pipelines and, more recently, mixed fluid and dedicated CO_2 pipelines. The wide range of sensor types, deployment strategies, time frames, and environments may introduce considerable noise in the data. In addition, the available data for developing decision support tools is tied to current technologies and best practices, potentially constraining innovation.

AI/ML can rapidly parse data collections and recorded events and swiftly evaluate various scenarios to help select the most valuable types of data for leak detection. AI-empowered edge computing might then extract the high-value data near the point of collection to share it with the network (or initiate direct remedial action). Streamlining the amount of data communicated and stored will increase efficiency and reduce costs. Based on the selected data types (potentially including types not previously considered), AI could help **optimize sensor placement to minimize time to leak detection**. In addition, AI might generate models to **identify new signals to predict and avoid failure** based on (or further informed by) data collected prior to and during failures recorded during the transport of other commodities. AI analysis of sensor data should help **forecast threats in near-real time** (leaks, quakes, material failures, and equipment issues, etc.), enabling preventive action. As cybersecurity threats to infrastructure continue to grow, AI may help identify the vulnerabilities of carbon transport networks, anticipate attacks, and prepare protective actions or ensure resiliency.[5]

Improve CO_2 transport performance and operations

At this early stage of planning, optimization of CO_2 transport performance and operations may include leveraging existing infrastructure; developing novel materials and transport media; building sophisticated routing algorithms; and advancing decision support[6] to maximize capacity and lower costs. AI can assist in making regional CO_2 transport networks agile and resilient by integrating and accurately interpreting data from connected technologies across all scales.

The carbon transport chain is as strong as its weakest link, so every weld, section of pipe, and pump can make a difference. AI can help develop **new and novel materials to improve CO_2 transport safety and integrity**, rapidly assessing and down-selecting from hundreds of new candidate steels, alloys, polymers, coatings, or non-metallic materials that offer superior durability (e.g., against the corrosive properties of sCO_2). AI can similarly help to **assess the feasibility of converting existing infrastructure to dedicated CO_2 transport**. For example, AI/ML models might assess existing components of the onshore and offshore transport infrastructure to determine

[5] CESER provides cybersecurity for existing critical infrastructures and interfaces.

[6] The AI-Informed Infrastructure Integrity Model (AIIM) within NETL's Science-based AI/ML Institute (SAMI) generates maintenance regimes for offshore pipelines based on environment loading and incident histories, anticipated life spans, historical storms, etc.

their suitability for conversion to CO_2 use (including consideration of impurities in CO_2 from anthropogenic sources). AI could also efficiently **explore more efficient and cost-effective ways to transport CO_2**. This effort might include improving existing transport modes (e.g., better containers, railcars with reduced leakage due to periodic pressure bleed off) or developing entirely new ones (e.g., transport as carbon black or in other CO_2-dense phases that remain secure under a wide range of pressures and temperatures). In addition, AI can help **forecast the remaining useful life and risk profiles of pipelines** (potentially by applying multiple ML models, including gradient-boosted regression trees and artificial neural networks).

On a larger scale, AI might help **develop and regularly update pipeline maintenance strategies**. As part of this effort, AI/ML would find and update data on pipeline materials/structures and past incidents and continuously assess sensor data to devise preventive maintenance strategies. To optimize transport performance on a regional scale, AI could **develop geospatial layers for incorporation into broader routing, cost modeling, and analytic tools**, ultimately improving the certainty and security of permanent CO_2 storage. NETL's Advanced infrastructure Integrity Modeling (AIIM) for pipelines may provide a useful foundation for this work.

Inform routing, demonstration, and deployment using place-based inputs

The design and development of a robust carbon transport network that meets all regional and national goals must carefully consider the unique characteristics of the various places it serves, goes through or under, or bypasses. The network can impact local populations, environments, and economies, and the local environments can affect the network. As a first step, AI might **analyze social and environmental justice sensitivity** to the transport network. This effort might apply ML techniques to analyze aggregated location-specific health indices, income levels, employment data, property values, or some appropriate mix of data to help focus local engagement activities within a region. ML and NLP applied to digital news sources could potentially **acquire current data on state- and community-level views on pipeline infrastructure** within defined boundaries.

To **optimize pipeline routing**, AI can help generate models that integrate a range of social equity, logistic, and energy issues, including local initiatives, routing regulations, and geospatial analytics (to lower risk). These models may *adapt* and apply ML models previously developed for the natural gas infrastructure. AI can also **identify potential pipeline routes through a fragmented cost surface** (areas with abruptly or widely varying land uses and values) to support the evaluation of potential corridors for installation. To improve property predictions and reduce uncertainty in pipeline routing, **physics-informed ML (PIML) approaches might be integrated with qualitative/ categorical AI/ML** models. Reducing these uncertainties can potentially expedite the necessary demonstration and deployment efforts (see inset on Hubs).

Regional Hubs for Geologic Storage & Carbon Management

FECM currently supports four projects that provide region-specific technical assistance on secure geologic carbon storage across the country. Upcoming awards (Sept. 2023) will augment and extend those efforts to include regional stakeholder engagement. This work lays the groundwork for deploying large-scale, regional geologic storage facilities or carbon management hubs capable of storing hundreds of millions of metric tons of CO_2 at an injection rate of more than 5 million metric tons per year.

FECM Funding Notice (DOE/FECM 2023)

Strategic carbon transport planning must also consider that all critical infrastructures are vulnerable to climate change impacts such as hurricanes, ground subsidence, wildfires, sea-level rise, heat waves, and drought. **Multivariate modeling to project the impacts of climatological events** on equipment and operations can deliver valuable new design parameters. This effort could use up-to-date or real-time data and advanced climatological models to improve forecasting of onshore hazards. For off-shore transport, this effort may leverage existing Ocean and Geohazard Analysis (**OGA**) work and improve the forecasting of near-subsea currents (affecting offshore pipelines and ship transport) with data from NOAA monitoring buoys. An **AI/ML model to suggest areas of greatest risk to offshore infrastructure** could combine existing models for submarine landslides, extreme wind/wave/current events, etc. (see OGA above). Improved characterization of seabed-related hazards in the offshore environment would help manage and minimize or avoid costs, risks, and catastrophic incidents.

Challenges in developing AI tools for transport planning include the large amount of disparate data from multiple sources that must inform any predictions or decision making, especially when drawing from data systems that don't typically interact with each other (e.g., maritime versus land topography data systems). In addition, AI model developers must take steps to avoid model bias toward areas or regions in which infrastructure already exists or communities already burdened by developed infrastructure.

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