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Multi-system analysis of offshore geologic carbon storage: a review of open-source data science solutions

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Geologic carbon storage projects are maturing worldwide and the footprint of deployment in the offshore is expanding. At present, there are ten projects in operation or that have been completed, more than 50 in construction and development, and dozens of characterization studies completed or underway. Offshore geologic carbon storage offers potential benefits over onshore geologic carbon storage. These offshore projects are generally remote in location, distant from population centers, and avoid complicated pore space rights while having abundant prospective storage potential. Some offshore fields targeted for carbon storage have comparatively fewer prior borehole penetrations except for areas that have been explored for petroleum production, minimizing potential issues such as pressure interference and infrastructure impacts. Yet offshore geologic carbon storage projects face distinctive technical and economic challenges, such as seafloor geohazards (e.g., seabed instability), expensive maritime transport, and meteorological-oceanographic conditions that can damage infrastructure and impact operations. Analytical capabilities and improved computational speeds have advanced engineering, earth and energy sciences in the wake of the arrival of modern data science over the last decade. These advancements have created an opportunity for integrated, multi-systems modeling approaches utilizing artificial intelligence and machine learning that are no longer limited by computational issues. Analytical tools developed alongside this advancement in data science can be leveraged to calibrate the potential advantages and challenges of carbon storage operations in the offshore. New methods and approaches that incorporate data science to analyze multiple aspects of engineered and natural systems can provide insights that complement the characterization and onsite engineering that traditional commercial and operational software addresses. These new methods and approaches can potentially improve the outcome of energy operations and carbon storage. Providing multi-system, science-driven data analytics enhances the knowledge base that offshore developers, operators, and regulatory bodies may draw from to improve offshore site selection and operational efficiency. We provide a brief synopsis of geologic carbon storage efforts to date, an overview of the engineered and natural systems involved in offshore geologic carbon storage, and a review of publicly available, open-source, offshore and/or carbon storage related data- and science-driven tools developed by 2010 or later

that are suitable for screening and assessing regions for offshore geologic carbon storage.

KEYWORDS

AI/ML, offshore, data science, geologic carbon storage, technoeconomic, resource analysis, subsurface

1 Introduction

Carbon utilization and storage efforts are globally increasing as technologies for this sector mature. One industrial-scale approach being deployed worldwide is the permanent sequestration of carbon dioxide (CO₂) in geologic formations of offshore regions. Distinct advantages accompany offshore geologic carbon storage (GCS) in contrast to onshore GCS projects. These include simplified permitting and pore space acquisition and extensive potential GCS resource within offshore sedimentary basins and igneous deposits. However, offshore GCS projects present technical, operational and economic challenges when compared to onshore operations. For example, the feasibility of CO₂ transportation and the distance from commercial CO₂ sources where captured CO₂ is to be sequestered, cost of infrastructure installation, and variabilities in meteorological and oceanographic (metocean) and marine conditions that might impact GCS infrastructure exposed to extreme conditions or other environmental loadings (Teng et al., 2025). Additionally, regulations and operational knowledge for offshore GCS efforts are underdeveloped in many offshore exclusive economic zones and there is no international agreement on the implementation of GCS (Choisser et al., 2024). Successful deployment of offshore GCS requires a comprehensive understanding of the engineered and natural systems (ENS) involved, including analysis of the subsurface, seafloor, and metocean conditions that can impact construction and operations at wellbores, injection sites, platforms, pipelines, or other CO₂ transportation infrastructure. Coupling data science, and in particular artificial intelligence and machine learning (AI/ML), with expansive computing capabilities provides opportunities to aggregate, assimilate, analyze, and interpret available data and knowledge to improve and accelerate the characterization of engineered and natural systems and reduce uncertainty, even in relatively unexplored regions with sparse data or incomplete models (Chen et al., 2018; Yan et al., 2021; Yao et al., 2023; Rose et al., 2020). Employing data science via data-driven models and software tools to support resource and subsurface characterization, infrastructure evaluation, monitoring, cost and impact analyses and forecasts can inform commercial strategy and regulatory compliance while enabling offshore GCS implementation. These capabilities increase in importance as other offshore industries such as petroleum exploration, seabed mining, and ocean-based power generation expand and operate in the same regions as offshore GCS. Further, many models and tools applicable to offshore GCS can be applied and adapted for these other activities.

This paper provides an overview on the history and status of offshore GCS, the key ENS involved in GCS operations, and a review of open-source analysis tools that are applicable to screening and evaluating regions and sites for offshore GCS that integrate data science. The use of terms cost, risk and efficiency are generally referring to financial impacts that may be incurred because of

interactions in the ENS. The review of tools is not exhaustive through all time; it intends to reflect the evolution of scientific analytical software tools with the advent of data science, AI/ML, and increased interest in carbon storage since growth in these subjects has accelerated post-2010. The use of AI/ML in geophysical surveys, autonomous operations and robotics is not extensively included in this review, and it does not include a review of AI/ML in commercial software. Generally, commercial software is focused on field- or site-specific evaluations oriented towards engineering and development (e.g., Azizi et al., 2013). This review aims to build knowledge of multi-scale, multi-system data science tools and models that contribute novel research and development. Additionally, the review seeks to add the multi-system, ENS perspective to prospecting for operationally efficient offshore GCS sites. The review contains information and tools applicable to GCS in clastic reservoirs (i.e., saline aquifers) primarily. However, many of the tools can be utilized for depleted hydrocarbon reservoirs, carbonate reservoirs, concurrent storage and production scenarios, and igneous systems, as well as enhanced oil recovery (EOR).

2 Geologic carbon storage and data science overview

Geologic carbon storage has been under investigation since it was proposed as a geoengineering solution to emissions in the 1970s (e.g., Nordhaus, 1975; Marchetti, 1977). Early research into GCS initiated with CO₂ injection and flooding into oil-bearing reservoirs (EOR), a strategy utilized by the petroleum industry since the 1960s to sweep oil remaining in reservoirs after primary and secondary recovery (Horn and Steinberg, 1982; Ma et al., 2022). Enhanced oil recovery projects have successfully injected billions of metric tons of CO₂, in both offshore and onshore settings, providing technical insight into the conditions required for GCS operations (e.g., Sminchak et al., 2020; Hovorka et al., 2021). Deep saline formations have been utilized for GCS since 1996, when CO₂ injection began during the offshore Sleipner project in the Utsira Formation of the North Sea (Torp and Gale, 2004). More recently, leveraging CO₂ mineralization potential in basalt deposits has gained interest as demonstrated by the deployment of a sequestration plant in Iceland and several characterization studies (Goldberg et al., 2018; Fairley et al., 2013). Formation of hydrates to store CO₂ and storage within offshore salt caverns has also been explored (Lin et al., 2024). However, these technology and designs are less proven than those for deep saline aquifers (Gupte, 2024). Opportunities for storage in carbonate strata and coal seams have also been researched (e.g., Shi and Durucan, 2005; Salem and Shedid, 2013). However, depleted hydrocarbon reservoirs and saline aquifers have gained the most interest and activity for offshore

GCS deployment, due to their greater overall storage resource potential, likelihood of successful sequestration for the requisite time periods, and higher technological readiness (Callas et al., 2022; Albertz et al., 2023; Celia et al., 2015).

Offshore regions have been explored and exploited for petroleum resources for over 100 years which provide precedent for offshore GCS operations. Over the past several decades, the offshore setting has been examined for GCS potential at offshore facilities. These studies and analyses indicate the offshore as an attractive alternative to onshore GCS. For example, point sources, such as petroleum operations and industrial chemical plants, can transport CO₂ offshore to avoid conducting GCS in high-density urban areas, where the ability to install additional infrastructure may be limited (Abe et al., 2013; Global CCS Institute, 2022). Currently, dozens of offshore GCS sites have been characterized for operations, with over 30 in construction and seven in operation (Figure 1) (NETL, 2024a; Doyle et al., 2025). Technological maturity of GCS projects globally indicates offshore GCS has been successful in offshore sedimentary basins, although the cases are still few relative to subsurface operations for petroleum and onshore mining (Figure 1). Most development for offshore GCS is occurring in the North Sea region, which hosts the longest ongoing GCS injection. Significant development areas are found offshore Japan, Malaysia, Australia, and Gulf of America. The locations of characterization

studies demonstrate significant interest around offshore China, South Africa, western Europe, as well as several studies in India and other North American locations (Doyle et al., 2025). Few characterization studies have explored extreme deepwater regions, with the majority of characterization studies located in sedimentary basins nearshore that provide shorter transport routes and have existing infrastructure.

Despite the higher technological readiness for sequestration in clastic reservoirs, significant gaps in knowledge exist pertaining to the permanency of CO₂ sequestration. The success of sequestration is required for businesses to benefit from various tax credits and comply with regulations. As a result, there are a number of analysis frameworks that have been developed for potential onshore GCS projects (Blomberg et al., 2021; Dodds et al., 2011; Lackey et al., 2022; Pawar et al., 2015), and these frameworks include identifying tools and methods to be applied for analyzing different components of ENS that are found in both offshore and onshore GCS areas of interest. Analysis and assessment for these systems includes evaluating the ground surface to below the reservoir, understanding site performance (capacity, injectivity), containment, and public and market engagement (Alcalde et al., 2019; Pawar et al., 2015). Onshore and offshore GCS have potential economic benefits, including revitalization of industry and subsequent economic benefits.

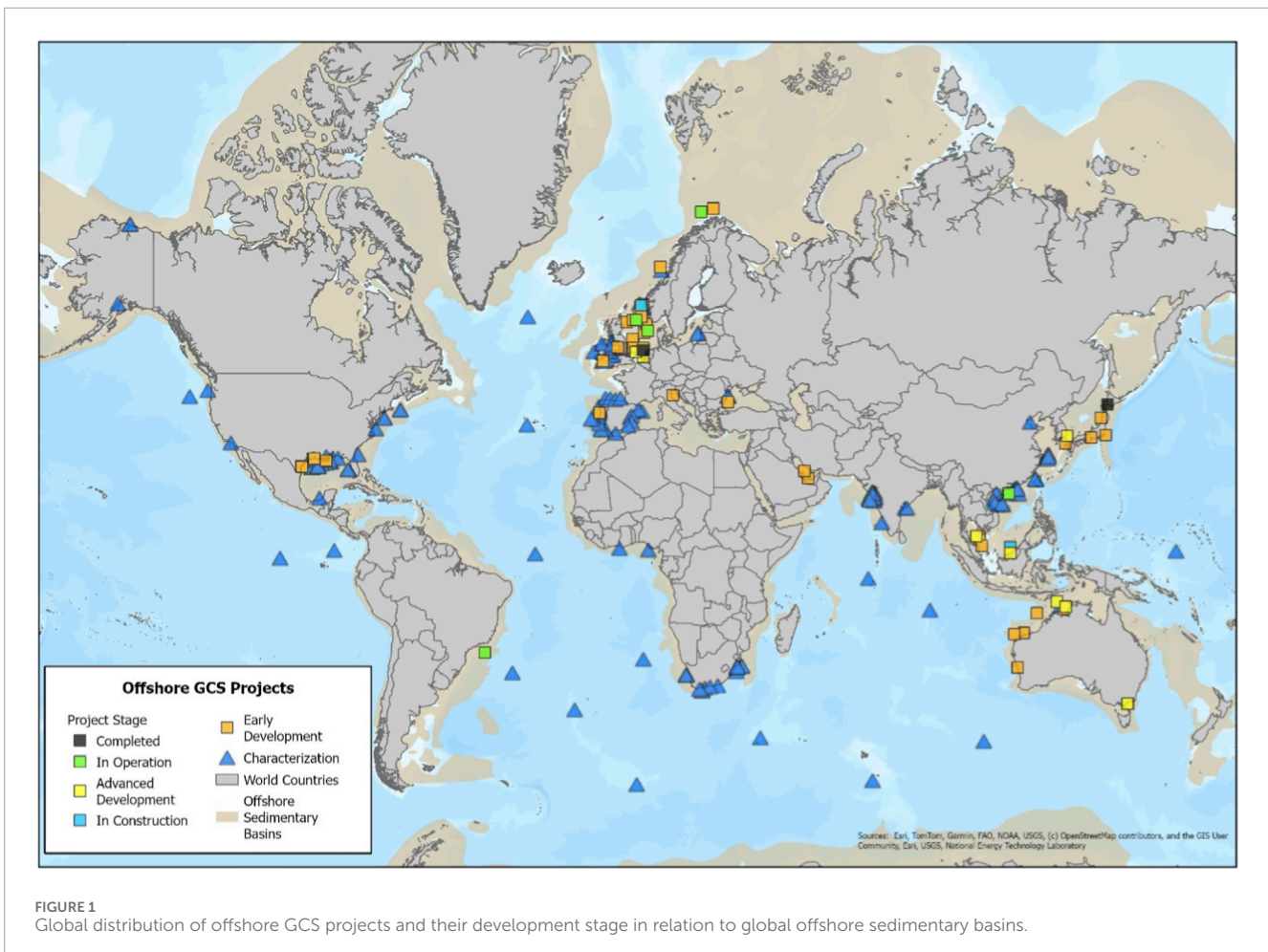


FIGURE 1 Global distribution of offshore GCS projects and their development stage in relation to global offshore sedimentary basins.

Offshore GCS contrasts from onshore GCS in key aspects, such as the simplified pore space acquisition process, greater distance from population centers, reduced impact of induced seismicity, availability of existing infrastructure, and the leakage buffer provided by the overlying water column and offshore subsurface conditions (Lin et al., 2024; Rose et al., 2024). Offshore-specific considerations for analysis frameworks should also include the difference in CO₂ density in response to pressure from the overlying water column and the sediment-water interface in offshore formations. The overlying ocean and water column also affects CO₂ transportation and operational transit and introduces complex metocean conditions that can affect infrastructure. Additionally, developing or repurposing infrastructure suitable for maritime CO₂ transport differs from these processes onshore (Ghanbari et al., 2016; Cameron et al., 2018; Romeo et al., 2022). Potential deleterious events attendant to offshore GCS include extreme metocean conditions and particle distribution (e.g., hurricanes, chemical spills) (Duran et al., 2018), and specific economic impacts (e.g., fisheries) (e.g., Flohr et al., 2021). Potential impacts between onshore and offshore GCS differ due to the location of operations: onshore, it is more likely that leakage or seismicity could impact operational efficiency and increase costs, whereas in the offshore, the direct impacts may be minimized due to the presence of the overlying water column. However, offshore GCS project impacts could affect other industries, such as petroleum production, fisheries and recreation. These potential differences in impact between the onshore and offshore demonstrate the necessity of specifically evaluating the ENS of the offshore, including modeling approaches and natural systems trends that the marine setting introduces.

3 Data science of offshore geologic carbon storage engineered and natural systems

Extensive energy exploration to date has produced a wealth of knowledge and data from both onshore and offshore operations that can be leveraged towards offshore GCS, such as subsurface geophysical data (e.g., active seismic), *in situ* geologic data via wellbores, and infrastructure data (e.g., materials integrity, incident details) (Rose, 2016). Interest in understanding metocean dynamics has resulted in complex computer models such as General Circulation Models (GCM) that have generated massive studies to collect observational data and develop theories. Models such as these have been the standard for decades until recent inquiries into the potential for AI/ML to replace them because of the opportunity for AI/ML to reduce computational burden and provide more accurate models (Weart, 2010; Balaji et al., 2022). Attendant to exploration for oil and gas are massive repositories of data for ENS, with greater data density, detail and granularity at sites and depths that have been previously explored for petroleum production. Many of these data are publicly available, and even greater amounts are retained privately (Mulhern et al., 2024). While these huge amounts of data and significant models exist, they are not always targeted to the system of interest (e.g., deep saline aquifers) or integrated to better inform site assessments. Additionally, many areas in the deepwater and ultra-deepwater, as well as extensive subsurface depths have fewer data available thereby increasing the uncertainty

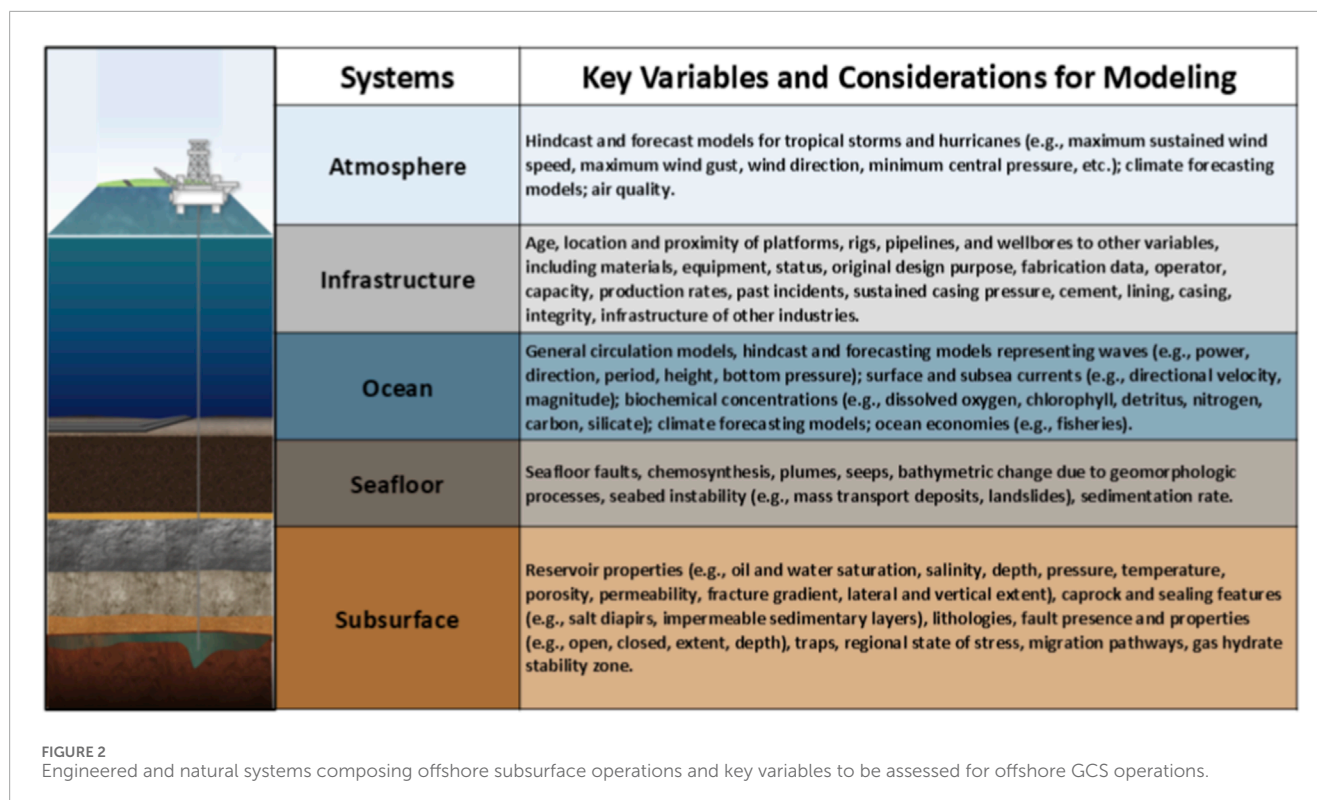
associated with potential operations in these areas (although this decreases the potential of interaction with existing wells). Thus, there is a need to better characterize the gaps in knowledge and data for offshore ENS, which have begun to be addressed using data science.

Data- and science-driven tools and methods assess ENS of the offshore by leveraging knowledge and data resources, such as those gained from characterization, modeling, and measurement, monitoring, and verification activities, in combination with models to analyze each component (Figure 2) (e.g., Chadwick, 2010; Dean et al., 2020). The usefulness of AI/ML for energy systems has been demonstrated, from data mining to data interpretation and analyses (Kuang et al., 2021). The results of analyses can be used alone or contrasted with other results to understand agreements across these analyses and assess differences in the results between each model and tool used. Further, many such tools have interoperable components that can assist in building results for entire offshore GCS ENS [e.g., the Offshore Risk Modeling Suite (NETL, 2020)]. The components of ENS can be multi-scale. Many of the tools discussed have been applied to clastic sedimentary systems but can be adapted for carbonate or igneous GCS screening and assessment analytics as well. In some cases, these tools can provide insight into previously unaccounted for aspects of the ENS. However, there remains many unexplored applications of AI/ML to offshore ENS, and there is a lack of integration across the many algorithms, models, tools, and data available to assess aspects of these systems. We discuss a cross-section of open-source tools and resources that are available for offshore GCS ENS screening and assessment analysis. Many commercial software tools exist that can address challenges of ENS, including with the use of AI/ML, however, these software tools may not provide insight for screening and assessment where data are sparse and additional disciplines (e.g., ocean hydrodynamics) may provide information indicating the potential for success of an offshore GCS project.

All ENS of the offshore can be evaluated to enable the success of GCS. These systems are outlined in Figure 2, from the atmosphere to the reservoir, including infrastructure, as well as variables needed to support strategic GCS planning, operation and completion. Each system has data and modeling strategies that can be integrated with other systems, and some systems are better understood than others. Assessing and predicting aspects of ENS rely heavily on the availability of data and/or accuracy of the models attempting to describe them. The following sections are divided by engineered or natural system. Each section discusses some of the data science-driven models and tools developed to predict consequential components.

3.1 Metocean

Atmospheric factors are interconnected with metocean factors, such as wind, wave and current patterns, and thus are a critical system to evaluate for offshore operations. Extreme weather events driven by atmospheric factors such as hurricanes have impacted energy infrastructure resulting in operational incidents, evacuations, damages, and the destruction of infrastructure (Kaiser, 2008). For oil and gas, these impacts have catalyzed offshore infrastructure design standard changes (Mourão et al., 2020; ISO, 2020; Nelson J. R. et al., 2021).



Information on past, present, and future atmospheric systems can be obtained from global, regional, and local hindcast models, real-time data points, and forecast models. Key variables in relation to wind might include directional (i.e., horizontal or vertical) velocity and magnitude. Tropical storm and hurricane variables include maximum sustained wind speed, sea height, maximum wind gust, and minimum central pressure. These variables, in conjunction with proximity to and duration interacting with energy infrastructure, can provide additional insights to support GCS development. Atmospheric data and models can inform offshore GCS planning, utilizing lessons learned from the impact of structural stress on energy infrastructure networks (i.e., oil and gas) from long-term winds or extreme weather events. Modeling these data can inform material, design and fabrication engineering for transport and injection of CO₂ in marine environments (Table 1).

There are many oceanic systems and features for consideration when planning offshore GCS. Oceanic systems including waves and currents impact offshore energy operations and infrastructure (Dhanak and Xiros, 2016; Nelson J. R. et al., 2021). Oceanic and atmospheric systems mutually influence each other, meaning that variables in these systems can compound to control weather and initiate extreme events. The impacts might be instantaneous, such as extreme wave events, or occur over time through natural corrosion (Moan, 2018). Wave variables include power, direction, period, height, and bottom pressure. Variables relating to surface and seafloor currents, including turbidity currents, include directional velocity and magnitude. Much like atmospheric systems, information on oceanic systems including hindcasts and forecasts can be obtained from models and real-time data points from ocean-based sensors. In addition to the natural loadings that affect

infrastructure and operations, potential operational interactions may also be accounted for and assessed (e.g., hazardous material spill). Other maritime operations with economic implications include shipping, recreation, and commercial fishing. For example, dynamic ship track data can be incorporated to avoid high traffic areas.

Modeling ocean circulation and hydrodynamics using AI/ML has gained significant traction in the last decade. Metocean forecasting is computationally impacted by massive volumes of data that require processing, a problem which AI/ML is suitable to solve. However, AI/ML requires data inputs to learn, thus becoming challenging to integrate with advanced numerical models; the use of physics-informed AI/ML can overcome these issues partially (Dong et al., 2022). As a specific example, Support Vector Machine Learning has been applied to marine hydrodynamics to improve solving potential and viscous flow (Sclavounos and Ma, 2018). In any hydrodynamic modeling, it is important to consider scale, season, and spatial variation in order to properly train models and understand the limitations of their predictions (Dean et al., 2020; Dong et al., 2022). The mathematical dynamical systems theories used in metocean prediction have integrated models such as the Lagrangian coherent structures of the Climatological Instantaneous Isolation and Attraction Model (CIAM) with the unsupervised machine learning approach, self-organizing maps, to predict seasonal attracting or repulsing pathways for ocean particles (e.g., hazardous waste) (Duran et al., 2018; Allende-Arandía et al., 2023).

The fate and transport of any operationally released particulates may have significant impact on projects and operators in terms of cost. Additionally, ensuring credit for storage is predicated on successful retention of CO₂ within a reservoir. The Blowout

TABLE 1 Table summarizing models, tools, and approaches discussed in Section 3.1.

Method or tool	AI/ML, approach, model, tool	Sources
CIAM	Model	Duran et al. (2018)
SOMs	ML	Allende-Arandía et al. (2023)
Support vector for marine hydrodynamics	ML	Sclavounos and Ma (2018)
BLOSOM	Model	Sim et al. (2017)
Smart proxy	Model	Mohaghegh (2018)

Spill Occurrence Model (BLOSOM) is a more recently released model that predicts the fate and transport of particles from the seafloor, through the water column, and across the sea surface. This model contains dynamic gas and hydrate components that may be useful in analyzing potential CO₂ movement ([Sim et al., 2017](#)). Studies on the dispersion of CO₂ in the water column following release could be leveraged to adapt these models for offshore GCS (e.g., [Kano et al., 2010](#); [Chen et al., 2005](#)). The computational requirements of models solving particle trajectories in the metocean tend to be consequential; thus, there is a major opportunity to accelerate these models via integration of AI/ML. An example of AI/ML integrated ocean particulate modeling is Smart Proxy, which allows the user to conduct fate and transport studies on a regular personal computer as opposed to requiring High Performance Computational (HPC) facilities ([Mohaghegh, 2018](#)). Accessing HPC facilities is a significant barrier due to cost and availability, however in this case, this barrier is removed through the incorporation of AI/ML.

3.2 Infrastructure

Offshore regions with subsurface energy resources, such as the Gulf of America and the North Sea, have complex infrastructure networks that include platforms, rigs, pipelines, and wells in addition to non-energy infrastructure such as submarine cables. Identifying the locations and characteristics of these structures is critical for planning and permitting offshore GCS projects, informing both mitigation strategies and potential reuse opportunities. Repurposing of existing energy infrastructure offers potential cost savings and can help reduce the overall footprint of offshore infrastructure, yet many variables are needed to accurately assess these opportunities ([Cauchois et al., 2021](#); [Lackey et al., 2024](#)).

Information needed to properly assess the reusability of infrastructure can vary by structure and location. For example, operating pressure is of utmost importance for pipelines transporting CO₂ to maintain CO₂ in a supercritical or liquid state ([Wang et al., 2016](#); [Sachde et al., 2022](#)). Other variables needed for pipelines include size (e.g., length, diameter, thickness) and capacity ([NETL, 2017b](#)). For wellbores, variables to consider when repurposing from an oil or gas well to a CO₂ injection well include sustained casing pressure, materials integrity and compatibility with CO₂, lining, tubing, casing, and packer suitable for injection ([Pawar et al., 2021](#); [Enriquez et al., 2024](#)). Variables for platforms and rigs include subsurface storage resources collocated

with the infrastructure and available compression and CO₂ handling equipment. Several variables concerning infrastructure that should be considered for both repurposing and planning new infrastructure include status, age, original design purpose, materials used in fabrication, past incidents, production rates, distance to coast or port, and environmental loadings. These variables can be applied to structural integrity and leakage models, which can provide additional insights to inform reusability and planning ([Dyer et al., 2022](#)).

Infrastructure serves as the moderator between engineered and natural systems. It must be capable of withstanding both extreme events and persistent deteriorating conditions ([Figure 2](#)). Thus, models examining aspects of infrastructure often integrate across disciplines ([Table 2](#)). Models such as REX-CO₂ provide screening for the re-use of existing wellbores using decision trees and user inputs ([Pawar et al., 2021](#)). The decision tree is informed by previous research into material compatibility, structural integrity, and cement integrity, the latter including a reduced order model for geomechanical simulations. This screening tool is an example of integrating multiple disciplines to inform decision-making, which will be discussed further in [Section 4](#). A similar integrated approach was used to develop an infrastructure integrity model that leverages AI/ML to improve on integrity analysis. Multiple AI/ML models including gradient-boosted decision trees and artificial neural network algorithms, along with spatio-temporal data spanning the offshore ENS, are utilized by Advanced Infrastructure Integrity Model (AIIM) to characterize offshore infrastructure integrity. This method applies data representing key aspects of the offshore system to assess regional trends and ultimately inform local predictions of integrity and the remaining lifespan of semi-permanent and permanent energy infrastructure (e.g., pipelines, platforms). This approach offers insights into potential failure, infrastructure necessitating remediation, and opportunities for infrastructure repurposing to facilitate offshore CO₂ transport and storage ([Dyer et al., 2022](#); [Nelson J. R. et al., 2021](#); [Nelson J. et al., 2021](#)). REX-CO₂ and AIIM are both multi-disciplinary approaches, however the tool and model approach the issue from separate perspectives. REX-CO₂ utilizes predictive modeling to inform potential incidents, while AIIM ingests information on actual incidents and other offshore variables and utilizes AI/ML to indicate trends. Each approach is proven, however, integrating predictive modeling with incident modeling and AI/ML can encounter issues such as bias or model drift. Monitoring strategies onsite might include sensor data and modeled or real-time reservoir and infrastructure pressure

TABLE 2 Table summarizing models, tools, and approaches discussed in Section 3.2.

Method or tool	Application in offshore systems	AI/ML, approach, model, tool	Sources
AIIM	Onshore/offshore	AI/ML, approach	Dyer et al. (2022)
REX- CO ₂	Onshore/offshore	Tool	Pawar et al. (2014)
Internet of things, GenAI	Offshore	AI/ML	Alanazi et al. (2025)
Computer vision	Offshore	AI/ML	Ninan et al. (2025)

fluctuations (Oldenburg et al., 2003; Harbert et al., 2016). Offshore petroleum operations are now increasingly including AI/ML in active rig monitoring (e.g., Ninan et al., 2025; Alanazi et al., 2025).

3.3 Seafloor

As the interface between the ocean and subsurface, the seafloor has significant implications on the success of infrastructure in offshore applications. Seafloor features and stability are critical for offshore GCS, with potential implications for infrastructure placement, longevity, and project success. Geohazards such as submarine landslides, sediment flows, variable sedimentation rates, and subsidence can damage and destroy *in situ* or temporarily anchored infrastructure (e.g., Kaiser et al., 2009). Impacts from these hazards may result in CO₂ leaks and economic loss. Moreover, anomalies along the seafloor, such as plumes, seeps, and chemosynthetic species, might represent endpoints of subsurface migration pathways indicating the potential for poor retention of CO₂ (Noble et al., 2011; Sassen et al., 1993).

Variables of interest along the seafloor include presence of known or potential geohazards, such as where landslides have occurred before or models indicating areas of greater landslide likelihood (Figure 2) (Dyer et al., 2024). Bathymetric data and changes in bathymetry over time, where available, can also help indicate past geohazards and events (Obelcz et al., 2020). Variables nearshore are influenced by dynamic sediment deposition and transport, with less frequent instability seaward. Atmospheric events such as hurricanes can intensify wind, wave, and current speeds, which can trigger seafloor instability and result in mass transport deposits (i.e., submarine landslides). In addition, past incident reports for other energy systems (i.e., oil and gas) provide insights as to where seafloor hazards have or are likely to occur in the future. Seafloor anomaly data, including location and date identified, also help identify areas that may not be suitable or require a setback for GCS. Predicting submarine landslides and seafloor instability is challenging due to the dynamic nature of these processes and their triggers and often requires tremendous data resources for analysis. Data science, and AI/ML in particular, can assist in solving two major issues in modeling the seafloor (1) accelerating processing for big data sets (e.g., high-resolution bathymetry) and (2) improving predictions in regions with sparse or no seafloor data (Table 3) (Obelcz et al., 2020).

An ML-informed model known as the Global Predictive Seabed Model (GPSM) from the U.S. Naval Research Laboratory uses a data-driven geospatial approach that integrates a *k*-nearest

neighbor algorithm to ingest data observations and predict a given spatial variable, with success in predicting seafloor depth (Obelcz et al., 2020). The Ocean and Geohazard Analysis (OGA) toolbox contains multiple seafloor and metocean analytics that utilize probabilistic analyses and AI/ML to provide predictions of hazardous conditions (Wingo et al., 2023; Mark-Moser et al., 2024). Submarine landslide susceptibility mapping is included in this toolbox and requires the analysis and relating of multiple attributes, with a significant amount of data representing these attributes. Gradient-boosted decision trees are used to analyze these attributes and produce a machine learning-informed submarine landslide susceptibility map (Dyer et al., 2024). An additional application of AI is the identification of submarine landslides that have previously occurred via convolutional neural network analysis of bathymetry (Wingo et al., 2023). Potential triggers for seabed instability (i.e., wind, wave, current events) are analyzed using probabilistic analyses.

Monitoring for successful offshore GCS utilizes instruments to detect anomalous signals that may indicate a CO₂ release. While downhole instrumentation may be used to detect these releases, most monitoring systems recommended focus on evaluation of the seafloor/seabed and water column. One tool developed for designing GCS leakage monitoring is Designs for Risk Evaluation and Management (DREAM), which utilizes full-physics simulations of CO₂ leakage at onshore GCS sites (Yonkofski et al., 2016). The DREAM tool relies heavily on optimization algorithms that, while not inherently categorized as AI/ML, are foundational to many ML methods and could be adapted for offshore scenarios. Analytical frameworks have been developed to systematically address these systems and monitoring techniques such as STEMM-CCS. The data produced by seabed monitoring systems is voluminous, so AI/ML target recognition algorithms were integrated into processing to reduce the cost of data transmission (Dean et al., 2020).

3.4 Subsurface

As a result of prospecting and energy development, tremendous subsurface data and models exist, however few are targeted to the deep saline aquifers of interest for GCS, necessitating innovative approaches to predict reservoir and subsurface conditions. Further, subsurface data and models integrate multiple scales of information and resolution. This requires sufficient data and integration of models for different process scales to avoid the risk of oversimplification in modeling

TABLE 3 Table summarizing models, tools, and approaches discussed in Section 3.3.

Method or tool	Application in offshore systems	AI/ML, approach, model, tool	Sources
GPSM	Offshore only	Model, AI, ML	Obelcz et al. (2020)
OGA	Offshore only	Tool, AI, ML	Wingo et al. (2023)
ML-LSM	Onshore/offshore	AI, ML	Dyer et al. (2024)

TABLE 4 Table summarizing models, tools, and approaches discussed in Section 3.4.

Method or tool	Application in offshore systems	AI/ML, approach, model, tool	Sources
DREAM	Onshore/adapt for offshore	Tool	Yonkofski et al. (2016)
Geomechanical screening tools to identify risk	Onshore/adapt for offshore	Tool	Wheeler et al. (2017)
CO ₂ -PENS	Onshore/adapt for offshore	Tool	Ziemkiewicz et al. (2016)
ORION	Onshore/adapt for offshore	Tool	Kroll and Sherman (2023)
OCSSC	Offshore only	Tool	Romeo et al. (2022)
SIMPA	Onshore/adapt for offshore	Tool, AI, ML	Wingo et al. (2019)
SOSAT	Onshore/adapt for offshore	Tool	Burghardt (2019)
PIDAS	Onshore/adapt for offshore	Tool	Sun (2018)
STA	Onshore/offshore	Tool, AI, ML	Rose et al. (2020)
t-SNE, k-means, DBSCAN	Onshore/offshore	AI, ML	Mark-Moser et al. (2022)
GANs	Onshore/offshore	AI, ML	Fan et al. (2025)
EASiTool	Onshore/adapt for offshore	Tool	Ganjdanesh and Hosseini (2017)
PSMT	Onshore/adapt for offshore	Tool	Chen and Huang (2019)
FracML	Onshore/adapt for offshore	Tool, ML	Kumar et al. (2025)

(Middleton et al., 2012; Lin et al., 2024). Exploration of AI/ML for subsurface characterization is extensive, spanning many disciplines, thus this section focuses on recent efforts that integrate AI/ML into models and tools for GCS in either onshore or offshore settings, noting where adjustments for offshore GCS may be required. The subsurface is evaluated from a multi-scale perspective for offshore GCS siting, from regional to *in situ* rock properties. Geologic mapping and designation of paleo-depositional settings and structural provinces provide regional insight to subsurface conditions. This enables identification of areas for higher resolution characterization via targeted geophysical surveys and commercial subsurface modeling software, while also providing contextual information on other systems interfacing with engineered systems. Geophysical techniques such as active seismic can be used to identify areas of interest for GCS from the field-to reservoir-scale, while *in situ* measurements from well logs and core interpretation lend insight into the targeted reservoirs at injection locations. Each of these techniques can incur a massive amount of data that requires

processing and modeling, tasks which AI/ML are increasingly deployed to address (Table 4).

At the site-scale, reservoir properties that are assessed for GCS include depth, thickness, lateral extent, porosity, permeability, temperature and pressure; all factors that determine the suitability of the formation for injection and can be used in fluid flow modeling for porous media (Rodosta et al., 2011; Bandilla and Celia, 2019). These determine the extent of the plume of injected CO₂ and potential for pressure interference between various subsurface energy projects (Bump and Hovorka, 2023). Depth determines the state of the CO₂ once injected, which must be kept in a liquid or supercritical state to contain the CO₂ within the formation long-term and prevent upward migration; in the offshore, the overlying water column increases the density of CO₂ at equivalent depths (from land surface or sea surface) onshore (Celia et al., 2015; Romeo et al., 2022). In addition to reservoir properties of the target prospective storage resource, containment factors such as the chemical trapping, caprock/sealing feature, faults, state of stress, and wellbore integrity and presence must be considered to ensure

containment throughout the whole subsurface system (Bachu, 2000; Alcalde et al., 2018). Sealing features or caprock unit presence is important for modeling containment of the CO₂ within the reservoir unit, as it typically serves as the main containment mechanism for CO₂ storage in GCS. Lateral extent, thickness, horizontal and vertical permeability, and variability in thickness and depth are all considered in the modeling of the caprock unit or sealing features (Shukla et al., 2010; Armitage et al., 2016).

Artificial intelligence and machine learning have been used to benefit petroleum exploration (e.g., Kuang et al., 2021; Rahmanifard and Plaksina, 2019), with a long history of integration with commercial software. These commercial software often focus on evaluating reservoir dynamics and site-specific aspects after geophysical surveys have been conducted. At a screening level, there are several open-source approaches to characterizing at the basin, regional and field scales that can be useful in down selecting for specific offshore GCS sites, potentially allowing operators to avoid costly geophysical surveys. Leveraging science-based, qualitative geologic information constrains and informs basin-wide subsurface analyses with regional heterogeneity. The Subsurface Trend Analysis (STA) tool is a spatio-temporal data science approach that integrates geologic knowledge with subsurface data to produce interpolations of subsurface property values that may inform areas with sparse data (Rose et al., 2020). The statistical component of the method allows for various analytics which were captured in an AI/ML-informed smart tool containing t-distributed Stochastic Neighbor Embedding (t-SNE), *k*-means, and density-based clustering non-parametric algorithm (DBSCAN) clustering techniques to provide greater insight into subsurface property analysis (Mark-Moser et al., 2022). For estimation of storage resource for site screening, the Offshore CO₂ Saline Storage Calculator (OCSSC) is a carbon storage resource potential estimation tool for saline sedimentary system that incorporates components of the CO₂-SCREEN tool with adaptations for the offshore (Romeo et al., 2022; Goodman et al., 2016). Increasing storage to maximize investment can be achieved through extracting formation water to improve active reservoir management, which is addressed through probabilistic system analysis by the software CO₂-PENS (Ziemkiewicz et al., 2016). To further define potential areas of interest, site selection frameworks and correlation can be employed (e.g., Wendt et al., 2022). A recent evaluation of AI/ML techniques to support site screening of the subsurface includes Extreme Gradient Boosting, Random Forest, Multilayer Extreme Learning Machine, and Deep Neural Network to evaluate offshore GCS site scores, indicating that the Deep Neural Network model provides the best accuracy in forecasting favorable sites (Nassabeh et al., 2024).

Identifying structural complexity, seismicity, and potential migration pathways is a key concern in any GCS effort, including the offshore. Structural complexity may indicate the availability of structural traps for GCS; however, it may also indicate regions with a higher likelihood for CO₂ migration from a reservoir with compromised integrity (i.e., faulted seal that is not a trap). It has become increasingly more popular to utilize AI to rapidly process and interpret seismic volumes, which present a two-fold problem of massive amounts of data with a need for feature identification of complex structural geology. Deep learning and machine learning have been successfully utilized to accelerate and

provide insights for seismic interpretation (Fernandes et al., 2025; Doyoro et al., 2025). A fuzzy logic tool known as Spatially Integrated Multivariate Probabilistic Assessment (SIMPA) utilizes existing subsurface data and subsurface knowledge-based inferential rules to predict potential fluid migration pathways (Wingo et al., 2019; Justman et al., 2020). At the reservoir scale, FracML is one of several models in the Science-informed Machine Learning for Accelerating Real-Time Decisions in Subsurface Applications (SMART) initiative platform, which aims to improve subsurface characterization that has traditionally been completed in detailed computational and mechanistic models (Bromhal et al., 2022).

Advances in computing resources allows for rapid calculation by analytical models. For reservoir-scale estimation of storage resource, tools such as the Enhanced Analytical Simulation Tool (EASiTool) can be deployed (Ganjandesh and Hosseini, 2017). Inputs to the EASiTool include pressure, temperature, thickness, salinity, porosity, permeability, rock compressibility, reservoir and basin areas, and the boundary condition, all of which can be estimated using methods written in the previous section. The EASiTool may require some adjustment for offshore reservoirs based on variation in CO₂ density (Romeo et al., 2022). Similarly, computational and data science advances can support modeling of the subsurface, such as for geomechanical and CO₂ flow solvers (e.g., Wheeler et al., 2017). Advanced AI/ML techniques such as deep learning for multiphysics networks have shown promise in monitoring CO₂ saturation, optimizing the intersection of seismic, gravity, and electromagnetic techniques, all of which require significant data and computational resources (Um et al., 2022). An example of in-reservoir CO₂ saturation monitoring using AI/ML is the utilization of a U-Net architecture and neural network approach trained on synthetic seismic datasets to interpret for subsurface properties in real-time (Um et al., 2023). Similarly, AI/ML in the form of a deep learning neural network, Generative Adversarial Networks (GANs), has been used to integrate monitoring data to predict reservoir pressure and CO₂ plume distribution over time (Fan et al., 2025). More recently, tools such as FracML, a tool which deploys unsupervised machine learning to detect clusters of microseismic events, have proven results in mapping and quantification of in-reservoir fracture quantification in onshore saline aquifers (Kumar et al., 2025). Due to the many facets of subsurface analysis and modeling, AI/ML application is still often exploratory for this system.

4 Integration of models, tools, and data science for offshore GCS

Aspects of ENS in the offshore have been the focus of decades of study. There is no shortage of models and approaches to assess these aspects in the offshore individually, which expands even further to include models that were built for onshore ENS that can be applied or modified for offshore ENS. However, approaches that integrate these aspects to produce more comprehensive, interdisciplinary, multi-systems insights as to the potential successes and issues operations may encounter are less common, as are authoritative models.

Many of the models and techniques in this review could be or are analytically integrated, in other words, the outputs from one model may be an input for another, or the results can be overlain and/or compared to produce results reflecting multiple aspects of the offshore ENS. The NRAP effort that has produced a suite of tools (NRAP-Open-IAM) constructed to evaluate multiple aspects of the subsurface, including faults, fractures and wells (i.e., leakage pathways) (NETL, 2024b; Dilmore et al., 2022; Vasylykivska et al., 2021; Kroll and Sherman, 2023; Bacon et al., 2019; Burghardt, 2018; Chen and Huang, 2019; Juanes, 2016; Pawar et al., 2014). A tool known as the Storage Security Calculator integrates modeling for leakage and immobilization (multiple types of trapping) (Alcalde et al., 2018). These tools indicate the modeling complexity of just one aspect of the subsurface system, containment. Tools and datasets hosted by the Discover platform resulting from the EDX4CCS project (NETL, 2024c) address multiple ENS, including those that are offshore specific. Though not directly linked into an IAM, the Discover platform is supported by the increasing practice of using web service interfaces and Representational State Transfer Application Programming Interfaces (REST API) (Neumann et al., 2008). Many models and tools can be adapted to integrate with these web interfaces and/or online platforms, increasing the capability of the models and tools to be applied for immediate analysis while also increasing accessibility for users. An example of an integrated multi-systems approach specifically designed for offshore GCS is MiReCOL, which includes remediation and corrective action information for CO₂ storage sites (Brunner and Neele, 2017). Like European value chain for CO₂ (ECCO) tool and STEMM-CCS tool, these are online tools to support decision-making (Løvseth and Wahl, 2012). However, they do not yet directly leverage data science nor provide analytical capabilities for ENS as they operate similarly to decision trees, meaning that they are backed by significant analyses that are not conducted in real time.

Interoperability of data science-driven tools and AI/ML is found in the integration of geologic domain designations into the OCSSC's estimation of reservoir properties, which produces potential distributions of offshore GCS storage efficiency and resource potential (Romeo et al., 2022). Another application, the OGA toolkit, was constructed to integrate multiple AI/ML-informed offshore ENS models within a single software (Wingo et al., 2023). A case study demonstrating this integration utilized the toolkit to integrate AI/ML submarine landslide susceptibility mapping results with the pipeline integrity results of AIIM and the seasonal metocean pathway variations calculated by CIAM, showing where pipelines may be vulnerable to catastrophic submarine landslides (Mark-Moser et al., 2024). The AIIM modeling has a different approach to multidisciplinary integration; multiple AI models utilized within the approach are trained to determine the remaining lifespan of infrastructure based on variables beyond those that are infrastructure-specific, such as potential for geohazards and metocean dynamics. This demonstrates multiple approaches to data science integration: (1) integrating outputs from one AI/ML method to inform another, (2) overlay and comparison of results from separate AI/ML methods, and (3) integrated AI/ML models leveraging multiple data types and models to produce results.

In addition to understanding the ENS of a given area for offshore GCS, regulators often require an understanding of the economic

potential of the resource to delineate leasing boundaries and mitigate the interactions of other industrial installations (e.g., oil and gas). As a result of thorough accounting required for technoeconomic analysis, cost models also impart a comprehensive outline of the engineering components of the system they evaluate. These models represent multidisciplinary integration and stand to benefit from data science and computational advances. Several models have been developed in the last decade to provide screening-level cost information for onshore GCS projects, including the Carbon Capture, Allocation, Transportation, and Sequestration module of the National Energy Modeling System (EIA, 2025), CO₂_S_COM_Offshore (NETL, 2025), an offshore saline geologic carbon storage and transport cost model; CO₂_T_COM, an onshore CO₂ pipeline transportation model (NETL, 2017b); SimCCS, an integrated carbon capture and storage infrastructure design software (LANL, 2024; Middleton et al., 2020) and the ECCO tool for CO₂ source, transport, and storage options, including enhanced oil recovery, with a macro-economic model (Løvseth and Wahl, 2012). Cost modeling is inherently integrative as the models reference cost, engineering, and storage resource data to complete calculations (e.g., Ogland-Hand et al., 2022). Though there are few examples in offshore GCS of AI/ML-integrated TEA models, other energy sectors have integrated AI/ML into their technoeconomic analysis to accelerate towards insights and avoid expensive computational processes. Technoeconomic analysis often includes modeling of some component of the system, and in the case of natural processes such as fluid flow in a reservoir, requires a reduced order model to avoid computational expense. In a potentially analogous application, a regression-supervised model was used to simulate and predict bio-oil yield in solid waste in the software Aspen Plus (Omidkar et al., 2024). Other models and AI/ML that have been referenced in this review have the potential for integration into technoeconomic analysis to improve accuracy and computational speed.

Applying and adapting existing science- and data-driven models and tools can aggregate, organize, and analyze offshore GCS data according to stakeholder needs. Several open source spatial-analytical data-driven models that can be applied to offshore GCS to evaluate data availability and support geospatial analytics include Cumulative Spatial Impact Layers (CSIL), and Variable Grid Method (VGM) (Romeo et al., 2019; Wanaju et al., 2019; Bauer and Rose, 2015). These tools support spatial data analytics for a variety of purposes, such as ascertaining data availability, analytical uncertainty, and summarizing and comparing offshore GCS activities.

Tools initially designed to address the offshore petroleum system have significant potential applicability to offshore GCS. Integrating tools to analyze the full ENS can be configured for offshore GCS evaluation. Consolidation of these analyses using AI/ML or packaging within software makes them available to stakeholders without requiring the user to operate and execute complicated code scripts underlying these analyses. Tools mentioned here can be integrated into a framework or workflow suitable to the needs of the stakeholders, with the potential of hosting both data resources and tool interfaces via web services and platforms. Advances in data science and tools for the ENS offer key insights to help operators, regulators, and other stakeholders strategize the safe and efficient use, reuse, or alternative use and identify

potential operational risks. However, there are potential issues regarding the use of packaged tools where stakeholders do not have expertise. A regularly cited issue in AI/ML is the need for a human-in-the-loop approach to ground algorithms with domain-specific expertise, especially in unsupervised AI/ML (Mosqueira-Rey et al., 2023). This can avoid some of the issues AI/ML produces associated with bias and poor interpretability. Similarly, tools and models developed for stakeholder use that communicate discipline-specific context can avoid misleading or misinterpreted results.

5 Conclusion

The vast resources developed over decades of offshore petroleum exploration and metocean modeling can be leveraged to better understand the interaction of ENS of offshore GCS operations, potentially leading to improved operational efficiency. With this exploration, tremendous data resources have been accumulated, but these data are often massive in size, specific to site location, and disparate. Subsurface energy industries have produced numerous tools, such as dynamic reservoir modeling and three-dimensional static geomodels that inform and predict fluid behavior in subsurface energy operations. However, these methods can sometimes lack contextual information of the surrounding offshore natural systems that can impact infrastructure and operations, such as ocean hydrodynamics. We have reviewed a selection of primarily open-source models and tools for improving predictions about these systems. These models and tools leverage data and knowledge resources to inform decisions at all stages of operations, especially when screening for potential operational risks and optimizing down-selection of sites. Standard workflows could integrate additional contextual data science and AI/ML tools to generate insights into offshore ENS and accelerate site selection. As previously noted, it should be emphasized that the ENS of offshore GCS, and the data, methods, models and tools associated with evaluating these ENS, have broad applicability to other sectors such as enhanced oil recovery and ocean-based energy sectors as well as the infrastructure of other sectors (e.g., submarine cables).

Most available AI/ML models and tools do not address all systems involved in an offshore subsurface operation. As a result, numerous data science tools have been developed to address these gaps, with no authoritative model declared as the standard for each ENS component. This review indicates that data science for offshore GCS and subsurface energy efforts in general continue to be exploratory, addressing aspects of the ENS that were previously poorly understood. In some cases, such as revisiting general circulation models, AI/ML is considered as an option to replace and revolutionize metocean modeling. This review also indicates that integrating multi-systems and multi-algorithm models within a single platform or toolset for offshore regions is thus far not a common practice, probably due to a lack of authoritative models for ENS modeling and the challenge of bias when selecting specific models, which could omit the insights of other models that could be potentially integrated. Interrelating and integrating the data science of offshore ENS to draw from multiple models could improve efforts to screen sites, add precision to techno-economic analysis, and accelerate offshore GCS implementation.

Author contributions

MM-M: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Project administration, Resources, Supervision, Visualization, Writing – original draft, Writing – review and editing. JB: Conceptualization, Data curation, Formal Analysis, Investigation, Resources, Validation, Writing – original draft, Writing – review and editing. AM: Data curation, Formal Analysis, Investigation, Resources, Validation, Visualization, Writing – original draft, Writing – review and editing. PM: Data curation, Formal Analysis, Investigation, Resources, Validation, Visualization, Writing – original draft, Writing – review and editing. LR: Data curation, Formal Analysis, Investigation, Resources, Validation, Visualization, Writing – original draft, Writing – review and editing. KR: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Project administration, Resources, Supervision, Validation, Writing – original draft, Writing – review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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References

- Abe, M., Saito, S., Tanase, D., Sawada, Y., Hiram, Y., and Motoyama, Y. (2013). CCS large-scale demonstration in Japan. *Energy Procedia* 37, 6326–6334.
- Alanazi, A. M., Altuwaijri, I. A., Bagabas, A. M., Khan, F., and Otaibi, B. (2025). Generative edge artificial intelligence at oil rigs. *Pap. Presented at SPE/IADC Middle East Drill. Technol. Conf. Exhib.* D021S007R002, doi:10.2118/225701-MS
- Albertz, M., Stewart, S. A., and Goteti, R. (2023). Perspectives on geologic carbon storage. *Front. En. Res. 10* 10, 1071735. doi:10.3389/feeng.2022.1071735
- Alcalde, J., Flude, S., Wilkinson, M., Johnson, G., Edlmann, K., Bond, C. E., et al. (2018). Estimating geological CO₂ storage security to deliver on climate mitigation. *Nat. Commun.* 9, 2201. doi:10.1038/s41467-018-04423-1
- Alcalde, J., Heinemann, N., Mabon, L., Worden, R. H., de Coninck, H., Robertson, H., et al. (2019). Acorn: developing full-chain industrial carbon capture and storage in a resource- and infrastructure-rich hydrocarbon province. *Of Clean. Prod.* 233, 963–971. doi:10.1016/j.jclepro.2019.06.087
- Allende-Arandía, M. E., Duran, R., Sanvicente-Añorve, L., and Appendini, C. M. (2023). Lagrangian characterization of surface transport from the equatorial Atlantic to the Caribbean Sea using climatological Lagrangian coherent structures and self-organizing maps. *J. Geophys. Res. Oceans* 128, e2023JC019894. doi:10.1029/2023JC019894
- Armitage, P. J., Worden, R. H., Faulkner, D. R., Butcher, A. R., and Espie, A. A. (2016). Permeability of the mercia mudstone: suitability as caprock to carbon capture and storage sites. *Geofluids* 16, 26–42. doi:10.1111/gfl.12134
- Azizi, E., Cinar, Y., Allinson, G., and Karsten, M. (2013). A new tool to predict injection well number for a total injection rate and given formation properties. *Energy Procedia* 37, 3259–3266. doi:10.1016/j.egypro.2013.06.213
- Bachu, S. (2000). Sequestration of CO₂ in geological media: criteria and approach for site selection in response to climate change. *Energy Conv. and Man.* 4, 953–970. doi:10.1016/s0196-8904(99)00149-1
- Bacon, D. H., Yonkofski, C. M., Brown, C. F., Demirkanli, D. I., and Whiting, J. M. (2019). Risk-based post injection site care and monitoring for commercial-scale carbon storage: Reevaluation of the FutureGen 2.0 site using NRAP-Open-IAM and DREAM. *Intl. J. Greenh. Gas. Control* 90, 102784. doi:10.1016/j.jggc.2019.102784
- Balaji, V., Couvreur, F., Deshayes, J., Gautrais, J., Hourdin, F., and Rio, C. (2022). Are general circulation models obsolete? *Proc. Natl. Acad. Sci.* 119 (47), e2202075119. doi:10.1073/pnas.2202075119
- Bandilla, K., and Celia, M. (2019). Chapter 8 – numerical modeling of fluid flow during geologic carbon storage. *Science of carbon storage in deep saline formations.* 181–208. doi:10.1016/B978-0-12-812752-0.00008-3
- Bauer, J. R., and Rose, K. (2015). Variable grid method: an intuitive approach for simultaneously quantifying and visualizing spatial data and uncertainty. *Trans. GIS* 19 (3), 377–397. doi:10.1111/tgis.12158
- Blomberg, A. E. A., Waarum, I.-K., Totland, C., and Eek, E. (2021). Marine monitoring for offshore geological carbon storage—A review of strategies, technologies and trends. *Geosciences* 11 (9), 383. doi:10.3390/geosciences11090383
- Bromhal, G., Mishra, S., George, G., Alumbaugh, D., Crandall, D., White, J. A., et al. (2022). “The SMART initiative: applying machine learning to enable efficient and effective real-time decisions for geological carbon storage operations (December 7, 2022),” in 16th International Conference on Greenhouse Gas Control Technologies GHGT-16, Lyon, France, October 23–27th, 2022.
- Brunner, L., and Neele, F. (2017). MiReCOL—A handbook and web tool of remediation and corrective actions for CO₂ storage sites. *Energy Procedia* 114, 4203–4213. doi:10.1016/j.egypro.2017.03.1561
- Bump, A. P., and Hovorka, S. D. (2023). Minimizing exposure to legacy wells and avoiding conflict between storage projects: exploring area of review as a screening tool. *Int. Jour. Of Greenh. Gas Control.* 129, 103967. doi:10.1016/j.jggc.2023.103967
- Burghardt, J. (2018). Geomechanical risk assessment for subsurface fluid disposal operations. *Rock Mech. Rock Eng.* 51 (7), 2265–2288. doi:10.1007/s00603-018-1409-1
- Callas, C., Saltzer, S. D., Davis, J. S., Hashemi, S. S., Kovscek, A. R., Okoroafor, E. R., et al. (2022). Criteria and workflow for selecting depleted hydrocarbon reservoirs for carbon storage. *App. Energy* 324, 119668. doi:10.1016/j.apenergy.2022.119668
- Cameron, E., Thomas, R., Bauer, J., Bean, A., DiGiulio, J., Disenhof, C., et al. (2018). *Estimating carbon storage resources in offshore geologic environments.* Albany, OR: National Energy Technology Laboratory Technical Report Series 32. doi:10.18141/1464460
- Cauchois, G., Simon, M., Dale, D., Guo, Y., Nermoen, A., Merat, C., et al. (2021). Potential for re-use of oil and gas infrastructure on the Norwegian Continental shelf. *Proc. 15th Greenh. Gas Control Tech. Conf.*, 15–18. doi:10.2139/ssrn.3820790
- Celia, M. A., Bachu, S., Nordbotten, J. M., and Bandilla, K. W. (2015). Status of CO₂ storage in deep saline aquifers with emphasis on modeling approaches with practical simulations. *Water Res. Res.* 51 (9), 6846–6892. doi:10.1002/2015WR017609
- Chadwick, R. A. (2010). Measurement and monitoring technologies for verification of carbon dioxide (CO₂) storage in underground reservoirs. *CO₂ Capture Storage Tech.* 2, 203–239. doi:10.1533/9781845699581.2.203
- Chen, T., and Huang, L. (2019). Optimal design of microseismic monitoring network: synthetic study for the kimberlina CO₂ storage demonstration site. *Int. Jour. Greenh. Gas Control.* 95102981 95, 102981. doi:10.1016/j.jggc.2020.102981
- Chen, B., Song, Y., Nishio, M., Someya, S., and Akai, M. (2005). Modeling near-field dispersion from direction injection of carbon dioxide into the ocean. *Jour. Of Geophys. Res. Oceans.* 110, C9. doi:10.1029/2004JC002567
- Chen, B., Harp, D. R., Lin, Y., Keating, E. H., and Pawar, R. J. (2018). Geologic CO₂ sequestration monitoring design: a machine learning and uncertainty quantification based approach. *App. Energy* 225, 332–345. doi:10.1016/j.apenergy.2018.05.044
- Choisser, A. C., Mark-Moser, M., Mulhern, J., and Rose, K. (2024). Scoping review of global offshore geologic carbon storage activities. *Natl. Energy Technol. Tech. Rep. Ser. DOE/NETL-2024/4798.* doi:10.2172/2299542
- Dean, M., Blackford, J., Connelly, D., and Hines, R. (2020). Insights and guidance for offshore CO₂ storage monitoring based on the QICS, ETI, MMV, and STEMM-CCS projects. *Int. Jour. Of Greenh. Gas Control.* 100, 103120. doi:10.1016/j.jggc.2020.103120
- Dhanak, M. R., and Xiros, N. I. (2016). *Springer handbook of ocean engineering* (Springer).
- Dilmore, R., Appriou, D., Bacon, D. H., Brown, C., Cihan, A., Gasperikova, E., et al. (2022). Computational tools and workflows for quantitative risk assessment and decision support for geologic carbon storage sites: progress and insights from the U.S. DOE’s national risk assessment partnership. *Proc. Of 16th Greenh. Gas Control Tech. Conf.* doi:10.2139/ssrn.4298480

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- Dodds, K., Waston, M., and Wright, I. (2011). Evaluation of risk assessment methodologies using the In Salah CO₂ storage project as a case history. *En. Proc.* 4, 4162–4169. doi:10.1016/j.egypro.2011.02.361
- Dong, C., Xu, G., Han, G., Bethel, B. J., Xie, W., and Zhou, S. (2022). Recent developments in artificial intelligence in oceanography. *Ocean-Land-Atmosphere Res.* 2022. doi:10.34133/2022/9870950
- Doyle, J., Mulhern, J., Mark-Moser, M., and Morkner, P. (2025). Offshore geologic carbon storage inventory dashboard. doi:10.18141/2507445
- Doyoro, Y. G., Gelena, S. K., and Lin, C. P. (2025). Improving subsurface structural interpretation in complex geological settings through geophysical imaging and machine learning. *Eng. Geol.* 344, 107839. doi:10.1016/j.enggeo.2024.107839
- Duran, R., Beron-Vera, F. J., and Olascoaga, M. J. (2018). Extracting quasi-steady Lagrangian transport patterns from the ocean circulation: an application to the Gulf of Mexico. *Sci. Rep.* 8 (1), 5218. doi:10.1038/s41598-018-23121-y
- Dyer, A. S., Zaengle, D., Nelson, J. R., Duran, R., Wenzlick, M., Wingo, P. C., et al. (2022). Applied machine learning model comparison: predicting offshore platform integrity with gradient boosting algorithms and neural networks. *Mar. Struct.* 83, 103152. doi:10.1016/j.marstruc.2021.103152
- Dyer, A. S., Mark-Moser, M., Duran, R., and Bauer, J. R. (2024). Offshore application of landslide susceptibility mapping using gradient-boosted decision trees: a Gulf of Mexico case study. *Nat. Hazards* 120, 1–22. doi:10.1007/s11069-024-06492-6
- Energy Information Administration (EIA) (2025). *Carbon capture, allocation, transportation, and sequestration (CCATS) module of the national energy modeling system: model documentation 2025*. Washington, DC: U.S. Department of Energy. Available online at: <https://www.eia.gov/analysis/pdfs/ccats.php> (Accessed July, 2025).
- Enriquez, H. C., Davis, M., Cavaliere, C., and Salter, R. (2024). “Repurposing existing Wells for CO₂ storage: drivers, challenges, and solutions,” Fifth EAGE Global Energy Transition Conference & Rotterdam, The Netherlands, 2024, 1–5. doi:10.3997/2214-4609.202421147
- Fairley, J., McLing, T., and Podgorney, R. (2013). Sub-seafloor Carbon Dioxide Storage Potential on the Juan de Fuca Plate, Western North America. *Energy Procedia* 37, 5248–5257. doi:10.1016/j.egypro.2013.06.441
- Fan, M., Liu, Y., Lu, D., Wang, H., and Zhang, G. (2025). A novel conditional generative model for efficient ensemble forecasts of state variables in large-scale geological carbon storage. *Jour. Of Hyd.* 648, 132323. doi:10.1016/j.jhydrol.2024.132323
- Fernandes, G. L., Figueiredo, F., Hatushika, R. S., Leão, M. L., Mariano, B. A., Monteiro, B. A. A., et al. (2025). A systematic review of deep learning for structural geological interpretation. *Data Min. Knowl. Disc.* 39, 3. doi:10.1007/s10618-024-01079-y
- Flohr, A., Schaap, A., Achterberg, E. P., Alendal, G., Arundell, M., Berndt, C., et al. (2021). Towards improved monitoring of offshore carbon storage: a real-world field experiment detecting a controlled sub-seafloor CO₂ release. *Int. Jour. Of Greenh. Gas Control.* 106, 103237. doi:10.1016/j.jggc.2020.103237
- Ganjdanesh, R., and Hosseini, S. A. (2017). Geologic carbon storage capacity estimation using enhanced analytical simulation tool (EASiTool). *Energy Procedia* 114, 4690–4696. doi:10.1016/j.egypro.2017.03.1601
- Ghanbari, S., Mackay, E. J., and Pickup, G. E. (2016). Comparison of CO₂-EOR performance between offshore and onshore environments. *Off. Tech. Conf. Asia Proc.*, D011S002R002. doi:10.4043/26590-MS
- Global CCS Institute (2022). CCUS projects in Europe. Available online at: <https://iogpeurope.org/wp-content/uploads/2022/10/Map-of-EU-CCS-Projects-draft-221024.pdf> (Accessed January 31, 2023).
- Goldberg, D., Aston, L., Bonneville, A., Demirkanli, I., Evans, C., Fisher, A., et al. (2018). Geological storage of CO₂ in sub-seafloor basalt: the CarbonSAFE feasibility study offshore Washington state and British Columbia. *Energy Procedia* 146, 158–165. doi:10.1016/j.egypro.2018.07.020
- Goodman, A., Sanguinito, S., and Levine, J. S. (2016). Prospective CO₂ saline resource estimation methodology: refinement of existing US-DOE-NETL methods based on data availability. *Int. Jour. Greenh. Gas. Control.* 54 (1), 242–249. doi:10.1016/j.jggc.2016.09.009
- Gupte, E. (2024). World's largest direct air capture plant enters operation in Iceland. Available online at: <https://www.spglobal.com/commodityinsights/en/market-insights/latest-news/energy-transition/050824-worlds-largest-direct-air-capture-plant-enters-operation-in-iceland> (Accessed June 28, 2024).
- Harbert, W., Daley, T. M., Bromhal, G., Sullivan, C., and Huang, L. (2016). Progress in monitoring strategies for risk reduction in geologic CO₂ storage. *Int. Jour. Greenhous Gas. Control.* 51, 260–275. doi:10.1016/j.jggc.2016.05.007
- Horn, F., and Steinberg, M. (1982). Control of carbon dioxide emissions from a power plant (and use in enhanced oil recovery). *Fuel* 61 (5), 415–422. doi:10.1016/0016-2361(82)90064-3
- Hovorka, S. D., Smyth, R. C., Romanak, K. D., Yang, C., Nicot, J. P., and Hardage, B. (2021). SACROC research project. *Bur. Econ. Geol.* Available online at: <https://www.beg.utexas.edu/gccc/research/sacroc>.
- International Standards Organization (ISO) (2020). ISO petroleum and natural gas industries—fixed steel offshore structures. *Internat. Stand. Organ. ISO 19902:2020 622*. Available online at: <https://www.iso.org/standard/65688.html> (Accessed June 28, 2024).
- Juanes, R. (2016). Enhanced simulation tools to improve predictions and performance of geologic storage: coupled modeling of fault poromechanics, and high-resolution simulation of CO₂ migration and trapping. doi:10.2172/1345666
- Justman, D., Creason, C. G., Rose, K., and Bauer, J. (2020). A knowledge-data framework and geospatial fuzzy logic-based approach to model and predict structural complexity. *J. Struct. Geol.* 141, 104153. doi:10.1016/j.jsg.2020.104153
- Kaiser, M. J. (2008). The impact of extreme weather on offshore production in the Gulf of Mexico. *App. Math. Mod.* 32 (10), 1996–2018. doi:10.1016/j.apm.2007.06.031
- Kaiser, M. J., Yu, Y., and Jablonowski, C. J. (2009). Modeling lost production from destroyed platforms in the 2004–2005 Gulf of Mexico hurricane seasons. *Energy* 34 (9), 1156–1171. doi:10.1016/j.energy.2009.04.032
- Kano, Y., Sato, T., Kita, J., Hirabayashi, S., and Tabet, S. (2010). Multi-scale modeling of CO₂ dispersion leaked from seafloor off the Japanese Coast. *Mar. Poll. Bull.* 60 (2), 215–224. doi:10.1016/j.marpolbul.2009.09.024
- Kroll, K., and Sherman, C. (2023). ORION: operational FoRecasting of Induced seismicity. doi:10.18141/1958726
- Kuang, L., Liu, H., Ren, Y., Luo, K., Shi, M., Su, J., et al. (2021). Application and development trend of artificial intelligence in petroleum exploration and development. *Pet. Exp. And Dev.* 48 (1), 1–14. doi:10.1016/S1876-3804(21)60001-0
- Kumar, A., Harbert, W., Myshakin, E., Liu, G., and Siriwardane, H. (2025). *FracML: a machine learning based tool to quantify reservoir scale fracture network for CO₂ storage*. Pittsburgh, PA: National Energy Technology Laboratory NETL. Morgantown, WV, and Albany, OR (United States).
- Lackey, G., Mitchell, N., Schwartz, B., Liu, G., Vasyukivskaya, V., Strazisar, B., et al. (2022). A quantitative comparison of risk-based leak mitigation strategies at a geologic carbon storage site. *Proc. 16th Greenh. Gas Control Tech. Conf. (GHGT-16)*. doi:10.2139/ssrn.4271578
- Lackey, G., Pantaleone, S., Montgomery, J. K., Busse, K., Aylor, A. W., and Moffett, T. J. (2024). Evaluating offshore legacy wells for geologic carbon storage: a case study from the galveston and brazos areas in the Gulf of Mexico. *Int. J. Greenh. Gas Control* 139, 104276. doi:10.1016/j.jggc.2024.104276
- Lin, Z., Kuang, Y., Li, W., and Zheng, Y. (2024). Research status and prospects of CO₂ geological sequestration technology from onshore to offshore: a review. *Earth-Science Rev.* 258, 104928. doi:10.1016/j.earscirev.2024.104928
- Los Alamos National Laboratory (LANL) (2024). SimCCS: CO₂ capture, transport, and storage infrastructure decision support. *Model*.
- Løvseth, S. W., and Wahl, P. E. (2012). ECCO tool: analysis of CCS value chains. *Energy Procedia* 23, 323–332. doi:10.1016/j.egypro.2012.06.069
- Ma, J., Li, L., Wang, H., Du, Y., Ma, J., Zhang, X., et al. (2022). Carbon capture and storage: history and the road ahead. *Eng* 14, 33–43. doi:10.1016/j.eng.2021.11.024
- Marchetti, C. (1977). On geoengineering and the CO₂ problem. *Clim. Change* 1 (1), 59–68. doi:10.1007/bf00162777
- Mark-Moser, M., Wingo, P., Zaengle, D., Pantaleone, S., Okoli, C., Shay, J., et al. (2022). Subsurface trend analysis 2D tool. Available online at: <https://edx.netl.doe.gov/dataset/subsurface-trend-analysis-2d-tool>.
- Mark-Moser, M., Romeo, L., Rodrigo, D., Bauer, J., and Rose, K. (2024). Advanced offshore hazard forecasting to enable resilient offshore operations. *Proc. Offshore Tech. Conf.*, 2024. doi:10.4043/35221-MS
- Middleton, R. S., Keating, G. N., Stauffer, P. H., Jordan, A. B., Viswanathan, H. S., Kang, Q. J., et al. (2012). The cross-scale science of CO₂ capture and storage: from pore scale to regional scale. *Energy and Environ. Sci.* 6. doi:10.1039/C2EE03227A
- Middleton, R. S., Yaw, S. P., Hoover, B. A., and Ellett, K. M. (2020). SimCCS: an open-source tool for optimizing CO₂ capture, transport, and storage infrastructure. *Env. Mod. and Softw.* 124, 104560. doi:10.1016/j.envsoft.2019.104560
- Moan, T. (2018). Life cycle structural integrity management of offshore structures. *Struct. Infrastruct. Eng.* 14, 911–927. doi:10.1080/15732479.2018.1438478
- Mohaghegh, S. D. (2018). “Contribution of artificial intelligence and machine learning in US DOE’s efforts during the aftermath of deepwater horizon,” in *SPE annual technical conference and exhibition* (Dallas, TX: SPE), D021S011R004.
- Mosqueira-Rey, E., Hernández-Pereira, E., Alonso-Ríos, D., Bobes-Bascarán, J., and Fernández-Leal, Á. (2023). Human-in-the-loop machine learning: a state of the art. *Artif. Intell. Rev.* 56, 3005–3054. doi:10.1007/s10462-022-10246-w
- Mourão, A., Correia, J. A. F. O., Ávila, B. V., de Oliveira, C. C., Ferradas, T., Carvalho, H., et al. (2020). A fatigue damage evaluation using local damage parameters for an offshore structure. *Proc. Inst. Civ. Eng. Marit. Eng.* 173, 43–57. doi:10.1680/jmaen.2019.24
- Mulhern, J., Mark-Moser, M., and Rose, K. (2024). *Offshore geologic carbon storage data collection and data gaps analysis*. Albany, OR: National Energy Technology Laboratory Technical Report Series.

- Nassabeh, M., You, Z., Keshavarz, A., and Iglauer, S. (2024). Sub-surface geospatial intelligence in carbon capture, utilization and storage: a machine learning approach for offshore storage site selection. *Energy* 305, 132086. doi:10.1016/j.energy.2024.132086
- National Energy Technology Laboratory (NETL). (2017b). FECM/NETL CO₂ transport cost model (CO2_T_COM).
- National Energy Technology Laboratory (NETL) (2020). Advanced risk and impact models for offshore systems fact sheet. Available online at: https://www.netl.doe.gov/sites/default/files/rdfactsheet/R-D208_6.pdf (Accessed June 29, 2024).
- National Energy Technology Laboratory (NETL) (2024a). Offshore geologic carbon storage inventory. doi:10.18141/1963815
- National Energy Technology Laboratory (NETL) (2024b). National risk assessment partnership. Available online at: <https://edx.netl.doe.gov/sites/nrap/> (Accessed June 28, 2024).
- National Energy Technology Laboratory (NETL) (2024c). Discover. Available online at: <https://edx.netl.doe.gov/sites/discover/> (Accessed June 28, 2024).
- National Energy Technology Laboratory (NETL). (2025). FECM/NETL CO₂ offshore saline storage cost model (CO2_S_COM_Offshore).
- Nelson, J. R., Romeo, L., and Duran, R. (2021a). Exploring the spatial variations of stressors impacting platform removal in the Northern Gulf of Mexico. *J. Mar. Sci. Eng.* 9 (11), 1223. doi:10.3390/jmse9111223
- Nelson, J., Dyer, A., Romeo, L., Wenzlick, M., Zaengle, D., Duran, R., et al. (2021b). *Evaluating offshore infrastructure integrity: DOE/NETL-2021/2643; NETL technical report series*, OR. Albany: U.S. Department of Energy, National Energy Technology Laboratory, 70. doi:10.2172/1780656
- Neumann, A., Laranjeiro, N., and Bernardino, J. (2008). An analysis of public REST web service APIs. *Int. Elec. Electron. Eng.* 14 (4), 957–970. doi:10.1109/TSC.2018.2847344
- Ninan, A., Le Gouhinec, N., Scott, J. J., Salameh, F. Y. M., Elouri, M. N., and Alqahani, H. M. H. (2025). AI/ML-Based safety monitoring system for offshore drilling rigs: enhancing safety, compliance and operational efficiency. *SPE/IADC Middle East drilling technology conference and exhibition*. doi:10.2118/225680-MS
- Noble, R., Orange, D., Decker, J., Teas, P., and Baillie, P. (2011). Oil and gas seeps in deep marine sea floor cores as indicators of active petroleum systems in Indonesia. *Indonesian pet. Ass. Proc. 3rd Ann. Conv.* doi:10.29118/IPA.219.09.G.044
- Nordhaus, W. D. (1975). Can we control carbon dioxide? *Int. Inst. App. Sys. An.*, 2015–2035. doi:10.1257/aer.109.6.2015
- Obelcz, J., Wood, W. T., Phrampus, B. J., and Lee, T. R. (2020). Machine learning augmented time-lapse bathymetric surveys: a case study from the mississippi river Delta front. *Geophys. Res. Lett.* 47, 10. doi:10.1029/2020GL087857
- Ogland-Hand, J., Cohen, S. M., Kammer, R. M., Ellett, K. M., Saar, M. O., Bennett, J. A., et al. (2022). The importance of modeling carbon dioxide transportation and geologic storage in energy system planning tools. *Front. Energy Res.* 10, 855105. doi:10.3389/feeng.2022.855105
- Oldenburg, C. M., Lewicki, J. L., and Hepple, R. P. (2003). "Near-surface monitoring strategies for geologic carbon dioxide storage verification," in *Technical report*. Berkeley, CA: Lawrence Berkeley National Laboratory.
- Omidkar, A., Alagumalai, A., Li, Z., and Song, H. (2024). Machine learning assisted techno-economic and life cycle assessment of organic solid waste upgrading under natural gas. *Appl. Energy* 355, 122321. doi:10.1016/j.apenergy.2023.122321
- Pawar, R., Bromhal, G., Carroll, S., Chu, S., Dilmore, R., Gastelum, J., et al. (2014). Quantification of key long-term risks at CO₂ sequestration sites: latest results from US DOE's national risk assessment partnership (NRAP) project. *Energy Procedia* 63, 4816–4823. doi:10.1016/j.egypro.2014.11.512
- Pawar, R. J., Bromhal, G. S., Carey, J. W., Foxall, W., Korre, A., Ringrose, P. S., et al. (2015). Recent advances in risk assessment and risk management of geologic CO₂ storage. *Int. Jour. Greenh. Gas Control* 40, 292–311. doi:10.1016/j.ijggc.2015.06.014
- Pawar, R. J., Brunner, L., van der Valk, K., van Bijsterveldt, L., Harp, D. R., Chen, B., et al. (2021). A screening tool for assessing feasibility of re-using existing oil and gas wells for CCUS operations. *Proc. 15th Int. Conf. Greenh. Gas Control Tech.* doi:10.2139/ssrn.3819822
- Rahmanifard, H., and Plaksina, T. (2019). Application of artificial intelligence techniques in the petroleum industry: a review. *Art. Int. Rev.* 52, 2295–2318. doi:10.1007/s10462-018-9612-8
- Rodosta, T. D., Litynski, J. T., Plasyński, S. I., Hickman, S., Frailey, S., and Myer, L. (2011). US department of Energy's site screening, site selection, and initial characterization for storage of CO₂ in deep geological formations. *Energy Procedia* 4, 4664–4671. doi:10.1016/j.egypro.2011.02.427
- Romeo, L., Nelson, J., Wingo, P., Bauer, J., Justman, D., and Rose, K. (2019). Cumulative spatial impact layers: a novel multivariate spatio-temporal analytical summarization tool. *Trans. GIS* 00, 1–29. doi:10.1111/tgis.12558
- Romeo, L., Thomas, R., Mark-Moser, M., Bean, A., Bauer, J., and Rose, K. (2022). Data-driven offshore CO₂ saline storage assessment methodology. *Int. Jour. Greenh. Gas Control* 119, 103736. doi:10.1016/j.ijggc.2022.103736
- Rose, K. (2016). Signatures in the subsurface – Big and small data approaches for the spatio-temporal analysis of geologic properties and uncertainty reduction. Available online at: <http://hdl.handle.net/1957/59459>.
- Rose, K., Bauer, J. R., and Mark-Moser, M. (2020). A systematic, science-driven approach for predicting subsurface properties. *AAPG Int.* 8 (1), T167–T181. doi:10.1190/int-2019-0019.1
- Rose, K., Creason, C., Mark-Moser, M., Mulhern, J., Pantaleone, S., Tetteh, D., et al. (2024). The Co-Saline storage method: advanced modeling to accelerate offshore CCS. *Proc. Offshore Tech. Conf.*, 2024. doi:10.4043/35052-MS
- Sachde, D., Dombrowski, K., Davis, D., McKaskle, R., and Lundeen, J. (2022). Offshore oil and gas infrastructure reuse for CCS: opportunities and challenges in the US Gulf of Mexico. *Proc. 16th Greenhous Gas Control Tech. Conf. GHGT-16*. doi:10.2139/ssrn.4285894
- Salem, A. M., and Shedid, S. A. (2013). Variation of petrophysical properties due to carbon dioxide (CO₂) storage in carbonate reservoirs. *Journ. Of Pet. Gas Eng.* 4 (4), 91–102. doi:10.5897/JPE2013.0152
- Sassen, R., Brooks, J. M., MacDonald, I. R., Kennicutt II, M. C., Guinasso, Jr., N. L., and Requejo, A. G. (1993). Association of oil seeps and chemosynthetic communities with oil discoveries, upper Continental slope, Gulf of Mexico. *Gulf Coast Ass. Of Geol. Soc. Trans.* 43, 349–355.
- Sclavounos, P. D., and Ma, Y. (2018). Artificial intelligence machine learning in marine hydrodynamics. *Proc. Int. Conf. Offshore Mech. And Arct. Eng.*, V009T13A028. doi:10.1115/omae2018-77599
- Shi, J. Q., and Durucan, S. (2005). CO₂ storage in deep unminable coal seams. *Oil and Gas Sci. Tech. – Rev. IFP.* 60 (3), 547–558. doi:10.2516/ogst:2005037
- Shukla, R., Ranjith, P., Haque, A., and Choi, X. (2010). A review of studies on CO₂ sequestration and caprock integrity. *Fuel* 89, 2651–2664. doi:10.1016/j.fuel.2010.05.012
- Sim, L., Vielma, J., Duran, R., Romeo, L., Wingo, P., and Rose, K. (2017). *BLOSOM—Release, 2017-09-26. Energy data eXchange*. Albany, OR: U.S. Department of National Energy Technology Laboratory.
- Sminchak, J. R., Mawalkar, S., and Gupta, N. (2020). Large CO₂ storage volumes result in net negative emissions for greenhouse gas life cycle analysis based on records from 22 years of CO₂-Enhanced oil recovery operations. *Energy and Fuels* 34 (3), 3566–3577. doi:10.1021/acs.energyfuels.9b04540
- Sun, A. (2018). *Pressure-based inversion and data assimilation system (PIDAS) for CO₂ leakage detection (final report)*. United States. doi:10.2172/1494374
- Teng, Y., Chen, Y., Wang, P., An, S., Li, C., Zhu, J., et al. (2025). An overview of the full-chain key technical features in offshore geological carbon sequestration. *Energy Rev.* 4 (2), 100140. doi:10.1016/j.enrev.2025.100140
- Torp, A., and Gale, J. (2004). Demonstrating storage of CO₂ in geological reservoirs: the sleipner and SACS projects. *Energy* 29 (9-10), 1361–1369. doi:10.1016/j.energy.2004.03.104
- Um, E. S., Alumbaugh, D., Commer, M., Feng, S., Gasperikova, E., Li, Y., et al. (2022). Deep learning multiphysics network for imaging CO₂ saturation and estimating uncertainty in geological carbon storage. *Geophys. Prospect.* 72. doi:10.1111/1365-2478.13257
- Um, E. S., Alumbaugh, D., Lin, Y., and Feng, S. (2023). Real-time deep-learning inversion of seismic full waveform data for CO₂ saturation and uncertainty in geological carbon storage monitoring. *Geophys. Prospect.* 72, 199–212. doi:10.1111/1365-2478.13197
- Vasylykivska, V., Dilmore, R., Lackey, G., Zhang, Y., King, S., Bacon, D., et al. (2021). NRAP-open-IAM: a flexible open-source integrated-assessment-model for geologic carbon storage risk assessment and management. *Env. Mod. and Softw.* 143, 105114. doi:10.1016/j.envsoft.2021.105114
- Wanaju, P., Bloomfield, R., Bauer, J., and Rose, K. (2019). "Bringing uncertainty to the forefront of informed decision making in oil and gas exploration and development," in *SPE annual technical conference and exhibition* (Calgary, AB: Society of Petroleum Engineers). doi:10.2118/196094-MS
- Wang, Z., Weihs, G. F., Neal, P. R., and Wiley, D. E. (2016). Effects of pipeline distance, injectivity and capacity on CO₂ pipeline and storage site selection. *Int. J. Greenh. Gas Control* 51, 95–105. doi:10.1016/j.ijggc.2016.05.006
- Weart, S. (2010). The development of general circulation models of climate. *Stud. Hist. Philosophy Sci. Part B Stud. Hist. Philosophy Mod. Phys.* 41 (3), 208–217. doi:10.1016/j.shpsb.2010.06.002
- Wendt, A., Sheriff, A., Shih, C. Y., Vikara, D., and Grant, T. (2022). A multi-criteria CCUS screening evaluation of the Gulf of Mexico, USA. *Int. J. Greenh. Gas Control.* 118, 103688.
- Wheeler, M., Srinivasan, S., and Espinoza, D. (2017). *Development of geomechanical screening tools to identify risk: an experimental and modeling approach for secure CO₂ storage final technical report*. United States. doi:10.2172/1418156
- Wingo, P., Justman, D., Creason, G., Jones, K., Bauer, J., and Rose, K. (2019). SIMPA, 2019-03-29. doi:10.18141/1503876

- Wingo, P., Zaengle, D., Duran, R., Mark-Moser, M., Bauer, J., Harris, J., et al. (2023). Ocean and geohazard analysis tool. doi:10.18141/1963841
- Yan, Y., Borhani, T. N., Subraveti, S. G., Pai, K. N., Prasad, V., Rajendran, A., et al. (2021). Harnessing the power of machine learning for carbon capture, utilisation, and storage (CCUS) – a state-of-the-art review. *Energy and Env. Sci.* 14, 6122–6157. doi:10.1039/d1ee02395k
- Yao, P., Yu, Z., Zhang, Y., and Xu, T. (2023). Application of machine learning in carbon capture and storage: an in-depth insight from the perspective of geoscience. *Fuel* 333 (1), 126296. doi:10.1016/j.fuel.2022.126296
- Yonkofski, C. M., Gastelum, J. A., Porter, E. A., Rodriguez, L. R., Bacon, D. H., and Brown, C. F. (2016). An optimization approach to design monitoring schemes for CO₂ leakage detection. *Int. J. Greenh. Gas Control* 47, 233–239. doi:10.1016/j.ijggc.2016.01.040
- Ziemkiewicz, P., Stauffer, P., Sullivan-Graham, J., Chu, S. P., Bourcier, W. L., Buscheck, T. A., et al. (2016). Opportunities for increasing CO₂ storage in deep, saline formations by active reservoir management and treatment of extracted formation water: case study at the GreenGen IGCC facility, tianjin, PR China. *Int. Jour. Green. Gas. Cont.* 54 (2), 538–556. doi:10.1016/j.ijggc.2016.07.039