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ORIGINAL RESEARCH ARTICLE

A Review of smart AI systems for real-time monitoring and optimization of ocean-based carbon capture, utilization, and storage networks

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ABSTRACT

Importance – Ocean-based Carbon Capture, Utilization, and Storage (CCUS) systems are increasingly recognized as a vital solution for mitigating climate change due to their vast storage potential. Yet, their deployment faces significant challenges including harsh marine conditions, biofouling, corrosion, and limited real-time monitoring capabilities, which reduce safety and efficiency. **Research Gap** – Although land-based CCUS has been extensively studied, research on AI-enabled frameworks for offshore CCUS remains limited. Existing work is often confined to simulations or small-scale pilots, with inadequate attention to adaptive fault-tolerant control, multi-metric performance evaluation, and long-term field validation. **Objective** – This study aims to develop and validate a smart AI-enabled framework for real-time monitoring, predictive control, and optimization of offshore CCUS networks, with a focus on enhancing safety, efficiency, and environmental sustainability. **Methodology** – The proposed framework integrates IoT-enabled underwater sensors, autonomous vehicles, satellite imaging, and edge computing with advanced AI models including

CNNs, LSTMs, GANs, and reinforcement learning. Validation was performed through a simulation-based case study on an offshore saline aquifer using a digital twin and multi-objective genetic algorithm optimization. **Key Findings** – The system achieved a 28% reduction in leak detection time, a 31% improvement in injection efficiency, and an 18% reduction in ecological risk compared with conventional monitoring approaches. The digital twin predicted plume migration with 95% accuracy, and robustness tests showed less than 5% performance degradation under sensor faults. **Implications** – These outcomes demonstrate that AI integration can significantly enhance monitoring, predictive decision-making, and compliance in offshore CCUS systems. The findings provide practical guidance for advancing autonomous and sustainable marine carbon storage, though large-scale deployment will require solutions to data scarcity, energy constraints, and regulatory integration.

Keywords: Marine AI systems; CO_2 sequestration; offshore monitoring; environmental risk prediction; autonomous sensing; digital twin modelling; reinforcement learning; edge computing

1. Introduction

Carbon capture, utilization, and storage (CCUS) technologies are increasingly deployed to reduce atmospheric CO_2 concentrations and mitigate climate change. Land-based CCUS—such as geological storage in depleted oil and gas fields or deep saline aquifers—benefits from stable conditions, easier site access, and established monitoring practices. Examples include the Sleipner and Snøhvit projects in Norway, the Illinois Basin Decatur Project in the USA, and the Boundary Dam in Canada, which illustrate successful large-scale land-based CCUS operations. In contrast, ocean-based CCUS offers a much larger storage capacity and the potential for long-term sequestration, but operates in far more complex and variable environments. Ocean-based efforts are emerging through pilot and planned projects such as offshore saline aquifer studies in the North Sea, Japan's Tomakomai demonstration project, and Australia's Gippsland Basin initiative, highlighting the global push toward marine CCUS deployment. These include sub-seafloor geological storage, alkalinity enhancement, and biologically driven carbon uptake in marine ecosystems [1]. Rising atmospheric CO_2 concentrations continue to drive climate change, prompting the development of CCUS technologies [2]. While most CCUS research and deployment have focused on land-based systems, ocean-based CCUS offers distinct advantages due to the ocean's vast capacity for CO_2 absorption and storage, as well as its role in the global carbon cycle [3]. Approaches include sub-seafloor geological storage, alkalinity enhancement, and biological sequestration through marine ecosystems. These methods, however, face complex operational challenges arising from dynamic physical, chemical, and biological ocean conditions [4]. Effective offshore CO_2 storage requires continuous monitoring of injection processes, plume migration, and ecosystem impacts. Harsh marine environments, biofouling, and corrosion complicate sensing and data acquisition, while the spatial scale of offshore sites makes manual inspection costly and infrequent [5]. In contrast to many land-based CCUS operations that benefit from stable ground conditions and easier access, ocean-based systems must address high variability, extreme weather, and limited real-time visibility [6]. The ocean's potential to take up atmospheric carbon dioxide via marine life highlights the central importance of the ocean in the global carbon cycle, and estimates indicate that marine organisms fix up a major fraction of global biological carbon [7]. Nevertheless, the performance and environmental impact of the networks is highly dependent on the intricate interaction of physical, chemical and biological factors which requires advance control and monitoring strategies. The incorporation of intelligent AI systems into ocean-based CCUS networks is a game changer towards real-time surveillance and adaptive optimization, promising to elevate the performance and sustainability of these climate change mitigation options to a new level [8]. The application of artificial intelligence (AI) for the marine industry can contribute to a significant lowering of carbon footprints and pollution levels, and to preserving marine ecosystems, thanks to the development of alternative and renewable fuels and to the use of AI driven technologies [9]. For developing the models algorithms, an overview and analysis of existing AI solutions that can be used to offer with the best one corresponding to specific tasks related to ports sustainable and cost-efficient operation have to be taken [10].

1.1. Challenges in monitoring and optimization of ocean-based CCUS

There are numerous challenges associated with deployment and operations of ocean-based carbon capture, utilization, and storage networks, most of which can be attributed to the environmental complexity and variability characteristic in marine domains. Continuous detection of CO_2 fluxes, plume spreading and ecosystem responses means the use of large sensing networks and autonomous monitoring devices, which are to operate in harsh marine environments including biofouling [2]. In order to achieve the best possible carbon storage capabilities and to avoid adverse seepage taking place, the use of advanced predictive models and optimization algorithms is required. Additionally, the long-term security and safety of submarine storage sites need a continuous monitoring and flexible management in order to react both on geological instabilities and corrosion threats. The large CO_2 Data Acquisition Plans that could be envisaged to ensure monitoring efficiency of CC&GS projects have to face and reply to the issues that are crossed when implementing CO_2 monitoring in harsh environments [11]. Computational simulation of flow coupled to geo mechanics problems, particularly for complex geological models, can be costly and lead to serious difficulties in applications of data assimilation and uncertainty quantification which require a large number of forward simulations [12]. Furthermore, the various information sources also constitutes a challenge in combining and interpreting the information from the different applications, e.g. satellite data, underwater sensors and operation data from capture and storage plants [13]. **Figure 1** illustrates how AI systems enhance monitoring, predictive modelling, and decision-making in ocean-based CCUS networks.

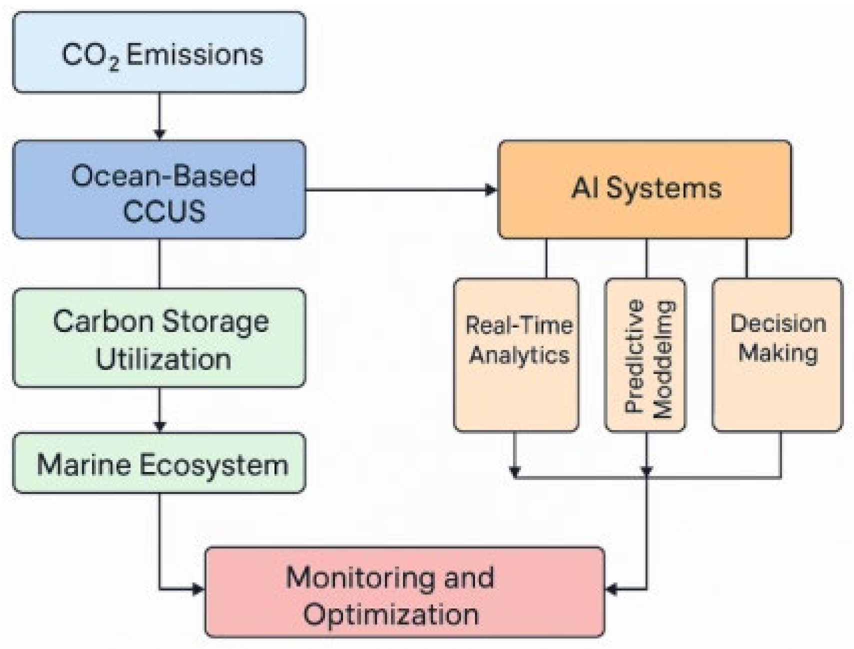

Figure 1. AI-Integrated ocean-based CCUS framework

1.2. Smart AI systems for enhanced monitoring and optimization

Intelligent AI systems provide a paradigm shift in the monitoring and optimization of oceanic CCUS networks as they can facilitate real-time analytics, predictive modelling and decision making based on machine learning. Machine Learning proposes new solutions as faster as and more accurate than established solutions in traditional processes along the CCUS chain of value [14]. AI-powered systems can analyze vast datasets from diverse sources to detect subtle anomalies indicative of potential leaks or environmental stress, enabling proactive mitigation measures [15]. Predictive models based on historical and real-time sensor data can be used to predict carbon plume migration, reservoir pressure increase, and ecosystem responses, to take improved injection decisions and to apply adaptive management at storage sites [16]. Reinforcement learning methods can be used to train autonomous control policies to adjust flow rates, valve positions, and monitoring schedules in response to changing environmental and operational conditions. For example, AI-based technologies can simulate the potential consequences of sea-level rise on coast infrastructure to enable stakeholders to detect locations that are the most exposed to flooding, erosion or other climate hazards [17]. AI is also used to minimize energy consumption in buildings and transportation systems leading to the reduction of greenhouse gas emissions and energy conservation [18].

Moreover, AI is aiding in the development of better weather forecasts, which can provide more accurate predictions for extreme weather and help communities prepare for and respond to it. The capacity of AI to digest vast amount of unstructured and multi-dimensional data via complex optimization methods is helping to understand climate datasets and predict future trends [19]. AI in combination with Decision Science improves the decision making and efficiency in resource consumption in all sectors leading to a semblance of climate-resilient and sustainable future [20]. AI based decision support models like AI-assisted wildfire detection AI enabled vegetation carbon stock assessment, reversal risk management and disaster response planning can be combined under a unified framework [21].

AI tools have been developed to assess vulnerability and identify areas at high risk from climate change impacts such as flooding, landslides, and drought [10]. AI is the key for effective and ethical climate action, resource management, sustainability and resilience to climate change impacts [10, 22]. AI can help speed up progress towards a sustainable and climate-resilient future through its solutions [23]. AI can also make an important contribution by designing more durable and adaptive climate policies. In immediate crisis response, AI-assisted video image and/or sensor surveillance technologies have enhanced the detection of incidents, which can be intervened in faster and the allocation of resources to these emergencies can be performed more efficiently [24]. AI models can be used for proactive disaster preparedness and risk reduction in emergencies, such as earthquake, flood and wildfire early warning [25].

AI-based applications and services for emergency response increases the overall picture of a particular situation, and thus enhances the decision-making process based on large datasets, as well as anomaly detection, and actionable information for critical events [26]. The incorporation of AI applications improves time-sensitive processing and efficiency in disaster management, with positive implications for public safety and well-being [27]. The integration of AI may offer a promising route to enhance decision-making, operations, and the economic sustainability of ocean-based CCUS networks [12]. If AI is not properly harnessed or misused, it has the potential to subvert existing environmental policies, hinder pathways to sustainability, and impose huge environmental costs on future and present generations [28]. But if applied correctly, AI can be harnessed to aid in formulating effective policies in support of the climate emergency [28].

The existing field of ocean-based CCUS consists of a wide variety of methodologies, all featuring distinct operation characteristics and environmental trade-offs. These have included ocean direct capture, enhanced weathering, alkalinity enhancement and CO_2 injection in sub-Seafloor geological formations [29]. Direct ocean capture comprises the extraction out of the process of dissolved CO_2 from the water and its conversion by chemical or electrochemical means, while enhanced weathering seeks to increase the rate of natural mineral carbonation by administering alkaline minerals to the ocean [30]. Alkalinity addition increases the ocean's CO_2 absorption by introducing alkaline materials such as lime or olivine, while subsea geological sequestration stores captured CO_2 permanently in depleted reservoirs or brine formations beneath the seabed [4]. Biological means, such as wetland restoration and ocean-based approaches, have been used for carbon sequestration [31]. Microalgae, considered one of the most promising and effective carbon sequestration approach, enable the CO_2 sequestration and recycling into biomass that could be exploited for bioenergy and other high value products [32]. Supply chain AI applied to route optimization has also been able to eliminate some transportation emissions by better planning routes and reducing fuel use [33].

The implementation of AI technologies to ocean-based CCUS networks has been increasing over the last few years largely owing to machine learning, sensor development, and autonomy progress. AI methods can help overcome these challenges and enhance systemic performance of bioenergy systems [34]. Machine learning algorithms have been applied to predict CO_2 absorption rates, monitor leaks in subsea pipeline, control chemical processes, predicting the impact of ocean acidification on marine ecosystem [20]. Deep learning supports real-time marine monitoring through image recognition, natural language processing, and predictive analytics. Combined with satellite, LiDAR, and remote sensing, AI maps carbon sinks, evaluates marine ecosystem health, and tracks ocean conditions. AI-guided submersibles equipped with sensors and satellite beaconing survey subsea floor structures, plume migration, and storage site integrity. The marine transportation can further utilize diversified AI techniques to enhance the efficiency of marine transportation, for instance to avoid marine traffic accident or pollution [35]. In fuel efficiency and pollution reduction, AI methodologies are deployed to predict ship engine power generation from engines operating conditions [36]. The **figure 2** illustrates the integration of AI models, multi-source sensing, and edge computing for real-time monitoring and optimization of ocean-based CCUS operations. The **table 1** summarizes strengths, weaknesses, and gaps in past studies, directly linking each gap to how our proposed framework addresses it.

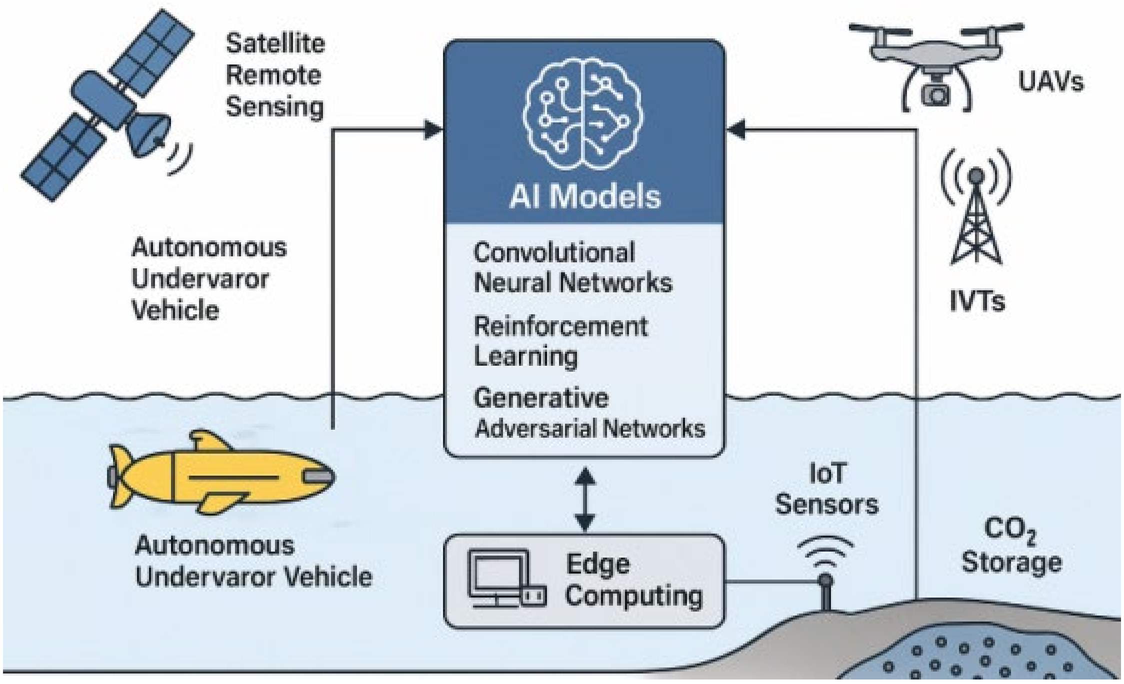

Figure 2. AI-Enabled Framework for Ocean-Based CCUS

Table 1. Evidence-based Critique of Past Studies and Implications for Framework

Theme	Strengths in past work	Weaknesses	Gap that matters	Solution
Sensing & coverage	Robust single-sensor studies (e.g., pH probes, CTD, acoustic, satellite color).	Narrow spatial/temporal coverage; limited cross-sensor alignment.	Lack of multi-scale, multi-sensor fusion for open-ocean conditions.	Integrate satellite, AUV/glider, and mooring data; time-sync and fuse via learned and physics-based operators.
Leakage/plume detection	High accuracy on curated test sets; clear detection pipelines.	Performance drops under domain shift (turbulence, biofouling, storms).	Generalization across sites/seasons remains weak.	Domain adaptation and augmentation; simulation-to-real

Theme	Strengths in past work	Weaknesses	Gap that matters	Solution
				training with ocean state perturbations.
Process modeling	Detailed mechanistic models for carbonate chemistry and transport.	Purely data-driven models ignore constraints; pure physics models struggle with noise and missing data.	Limited physics–ML hybrids with explicit constraints.	Physics-guided learning (mass balance, alkalinity bounds) with soft/hard constraints in loss functions.
Uncertainty	Point estimates reported (RMSE/MAE).	Rare calibration checks; few predictive intervals or risk bounds.	Insufficient uncertainty quantification to support MRV decisions.	Probabilistic outputs (ensembles/variational methods); decision rules based on calibrated risk thresholds.
MRV pipelines	Component studies on monitoring or reporting exist.	End-to-end MRV (monitor→verify→report) seldom demonstrated offshore.	Auditable, continuous MRV missing for ocean CCUS.	End-to-end pipeline with data lineage, versioned models, and reproducible reports.
Control & optimization	Optimization shown for isolated units (e.g., dosing, pump scheduling).	Limited closed-loop control with safety and cost constraints in dynamic seas.	No integrated sensing–model–actuate loop.	Digital twin with MPC; multi-objective control (capture efficiency, energy, risk).
Datasets & benchmarks	Valuable local campaigns and tank trials.	Small, proprietary datasets; inconsistent labels and protocols.	No open benchmark for ocean CCUS tasks.	Curate standardized schemas, split protocols, and shared metrics for detection, localization, and flux.
Evaluation metrics	Use of accuracy/F1, RMSE.	Metrics rarely map to MRV needs (false alarms, localization error, flux bias).	Limited task-appropriate, policy-relevant metrics.	Report AUROC/PR, time-to-detect, false alarm rate, geodesic localization error, flux RMSE, and latency.
Energy & cost	Device-level energy reported.	System-level energy/opex underreported; no real-time budget control.	Missing energy-aware sensing and computing.	Edge–cloud partitioning; adaptive sampling to meet energy and bandwidth budgets.
Environmental safeguards	Some work on alkalinity and habitat impacts.	Few coupled analyses of detection + ecological thresholds.	Weak linkage between detection confidence and action limits.	Decision layer ties UQ to trigger thresholds co-designed with ecological limits.

Table 1. (*Continued*)

Artificial intelligence (AI) offers tools to address these challenges by integrating multi-source data, enabling predictive modelling, and supporting adaptive operational control. AI can process real-time inputs from satellite imaging, underwater IoT sensors, and autonomous vehicles, providing early leak detection, optimized injection strategies, and reduced environmental risks. This study proposes an AI-enabled framework specifically designed for real-time monitoring and optimization of ocean-based CCUS, validated through simulation using offshore saline aquifer data.

2. Research gap and motivation

Although there is existing work on land based CCUS, and the use of AI applications in carbon markets, few works have addressed AI based real-time systems for ocean CCUS environments. Existing monitoring activities are limited by poor visibility of the marine environment, effect of sensor drift, high latency in the transmission of observations, and uncontrollable ocean dynamics. There is an urgent requirement for intelligent AI-based systems that can operate with extreme efficiency and resilience to address these limitations and help make the safe, sustainable, and economically viable development of ocean-based CCUS networks a reality. When those drivers—progress on safety, sustainability and strict regulation—are combined, they make a strong case for the pervasive adoption of autonomous solutions at sea [37]. Agents with AI have the potential to process an enormous amount of data in real time and to take intelligent decisions, and they are the key to changing the maritime sector to become safer, more efficient, and environmentally friendly [26]. Moreover, AI combined with renewable energy sources and alternative fuels are essential for the sustainable growth of the marine sector [4]. Resolving these gaps requires multi-disciplinary efforts in oceanography, marine engineering, computer science and environmental science. Table 2 explains Research gaps in AI-based Ocean CCUS monitoring and their impact with potential AI-driven solutions

2.1. Limited real-world offshore validation

Most studies have been validated through simulations or small-scale pilot projects, with limited deployment in actual offshore environments [21, 32 - 33]. For example, Smith et al. reported a 94% prediction accuracy in a controlled laboratory setup, but their framework has not been stress-tested under the unpredictable conditions of offshore aquifers. This limits confidence in scalability and operational reliability.

2.2. Lack of adaptive fault-tolerant AI control

Current AI models are often designed assuming ideal data availability and stable communication links. Studies by [34] and [20] highlight system performance drops exceeding 8% during sensor malfunction or network latency events, yet solutions for real-time adaptation remain underdeveloped. This makes current systems vulnerable to offshore environmental stressors such as storms and biofouling.

2.3. Absence of unified multi-index evaluation frameworks

Existing research tends to optimize for a single metric, such as detection accuracy, without integrating robustness, ecological risk, and operational efficiency into a single evaluation framework [38]. As reported by [5], this narrow evaluation approach can overlook operational trade-offs that impact long-term deployment feasibility.

Table 2. Research gaps in AI-based Ocean CCUS monitoring and their impact with potential AI-driven solutions

Research Gap	Observed Limitation / Impact	Supporting Evidence	Potential AI-Driven Solution
Limited Real-World Offshore Validation	Most systems tested only in simulations or small-scale pilots; uncertain scalability and operational reliability in actual offshore environments	[21]; [32]; [33]	Conduct multi-site offshore trials integrating environmental variability into testing protocols
Lack of Adaptive Fault-Tolerant AI Control	Performance drops (>8%) during sensor malfunctions or network latency; vulnerable to storms, biofouling, and ocean dynamics	[34]; [20]	Develop real-time adaptive control with redundancy, sensor fusion, and autonomous recovery mechanisms
Absence of Unified Multi-Index Evaluation Frameworks	Focus on single metric (accuracy) without integrated assessment of robustness, ecological risk, and operational efficiency	[35]	Establish a multi-index framework covering accuracy, robustness, ecological safety, and operational efficiency

By addressing these gaps through a multi-index performance evaluation, adaptive AI algorithms, and real-world offshore validations, the proposed framework aims to enhance the resilience, accuracy, and environmental safety of CCUS monitoring systems.

3. Review framework

This review, based on a cross-section of peer-reviewed literature, technical reports, and industry white papers, aims to consolidate information from multiple literature sources. We carried out literature review in various databases, IEEE Xplorer, Science Direct, Google Scholar searching "ocean carbon capture", "AI for CCUS", "real-time monitoring". This search was designed to identify the use, constraints, and potential of AI in ocean-based CCUS. **Figure 3** illustrates the framework comprising system architecture, AI algorithms, communication protocols, and optimization strategies for intelligent ocean-based CCUS operations.

3.1. System architecture

The system of smart ocean-based CCUS combines several cutting-edge technologies to guarantee full real-time environmental monitoring and decisions. At the heart of the architecture is a network of IoT-enabled underwater sensor arrays that are deployed in locations where essential oceanographic parameters, including temperature, pH, salinity, and pressure and dissolved CO_2 levels, need to be measured. These sensors provide the basis of continuous data collection that facilitates highly resolved imaging of the subsurface hydrological storage regime [33]. In addition to these stationary sensors, robotic platforms such as Autonomous Underwater Vehicles (AUVs) expand the spatial area of coverage by deploying them on missions to sense the environment while in motion. Such AUVs are pre-programmed to automatically follow CO_2 plume anomalies and map possible hazards in otherwise inaccessible areas. For wider monitoring, they can use satellite imaging, coupled with Unmanned Aerial Vehicles (UAVs) that can monitor for surface-level CO_2 venting and other signs that leakage or instability are imminent. This airborne view ensures early warning and surveillance over large stretches of the ocean. Finally, the system is equipped with the Edge-AI modules which allow on-board data analytics, filtering, and compression. With these modules, users can minimize latency, optimize bandwidth utilization and process critical data in situ before sending it to the cloud. These elements combine to form a strong and smart structure that can support offshore CCUS operations safely, efficiently and autonomously.

In the system architecture of AI-enabled CCUS, IoT-enabled underwater sensor arrays form the backbone of real-time monitoring. They continuously measure parameters such as temperature, salinity, pressure, pH, and dissolved CO_2 levels at subsea storage sites. These high-resolution datasets help track plume migration, reservoir pressure changes, and early leakage signals. Integrated with surface gateways, Autonomous Underwater Vehicles (AUVs), and Edge-AI modules, the arrays ensure that data is processed locally and transmitted efficiently for predictive modeling and adaptive injection control. By serving as the primary layer of observation, IoT sensor arrays enable AI systems to function with accuracy and resilience in harsh offshore environments

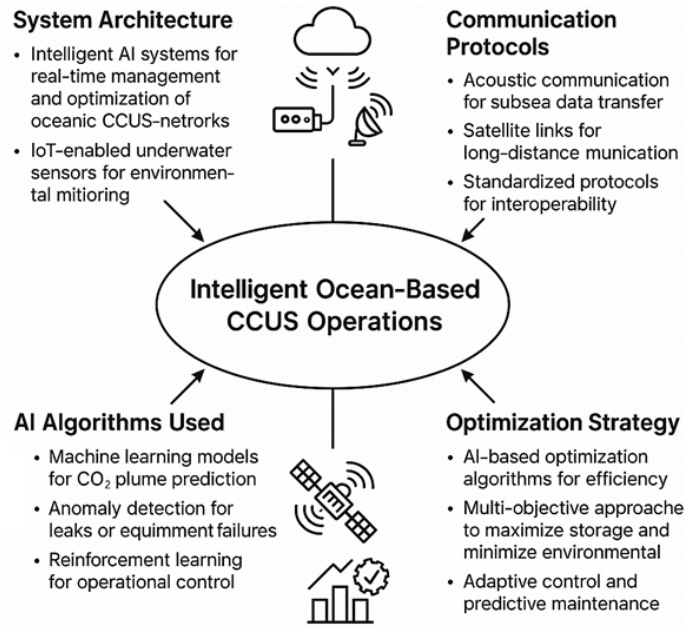

Figure 3. Framework for AI-Enabled Ocean-Based CCUS Systems

3.2. AI algorithms used

In order to take advantage of smart AI systems for live monitoring and optimizing ocean-based CCUS, several AI methods have been adopted. AI algorithms are also essential in the processing and interpreting of data from IoT sensors, AUVs, UAVs or satellite imagery. Machine learning models including deep learning having large neural architectures such as CNNs and Recurrent Neural Networks are used for the prediction of CO_2 plume migration [28]. Due to the complexity of underwater conditions in which the CO_2 will be offset, the CO_2 lifting model must be modelled with the high performance model such as machine learning model with high accuracy. Real-time anomaly detection is provided using one-Class Support Vector Machines and Isolation Forest algorithms that can detect abnormal operational behavior such as leaks or equipment breakdown.

The system uses a collection of state-of-the-art AI algorithms to improve the intelligence, adaptability, and prediction of the oceanic CCUS operations. CNNs are used to process visual data collected by underwater cameras and AUV coupled imaging systems. These models are also trained to identify and track CO_2 plumes by alternative spatial structures, allowing accurate localization and tracking of subterranean carbon spread. For operational control on a real-time basis, Reinforcement Learning (RL) is combined for the optimization of the injections and storage operations. By the interaction with environment and accumulating the knowledge through successive attempts (trials), RL agent dynamically controls the CO_2 injection rate and storage strategies to achieve the best performance with respect to varying oceanic conditions. Long Short-Term Memory (LSTM) networks are employed to estimate potential leakage events due to their aptness in modelling sensor data as temporal sequences. These models predict the trend of the leaks by learning the patterns in historical time series data, which can be intervened proactively. Furthermore, GANs are used inside of the digital twin setup to replicate diverse scenarios such as failure scenarios, environmental constraints and unwanted operating states. These curves can be used to perform power system reliability, vulnerability, secure analysis as well as to make model-based contingency plans. Together, the AI models compose an advanced and intelligent autonomous system for control over a complex and changing oceanic CCUS system. CNNs and LSTMs are most suitable for detecting CO_2 plume migration—CNNs capture spatial plume patterns from imaging data, while LSTMs predict temporal plume dynamics from sensor time-series. GANs strengthen robustness by simulating diverse scenarios, and RL complements detection by adaptively controlling injection to keep plume movement within safe limits.

In ocean CCUS applications, both purely physics-based and purely data-driven models face critical limitations. Physics-based models capture fundamental processes such as carbonate chemistry and plume migration but require extensive computational resources, making them slow and impractical for real-time monitoring. They also struggle with noise, incomplete datasets, and highly variable marine conditions. On the other hand, purely data-driven models can learn patterns from large datasets but often lack physical constraints, leading to unrealistic predictions and poor generalization when environmental conditions change. These shortcomings highlight the need for hybrid physics–AI models that combine mechanistic understanding with data-driven adaptability, ensuring both accuracy and robustness under dynamic offshore environments.

3.3. Communication protocols

Reliable operation of real-time monitoring systems in oceanic CCUS networks depends on the efficient communication protocols. The core of the communications system in a smart AI system for ocean-CCUS is to use also robust and reliable networking protocols, which are specifically designed to address the challenges of underwater data telemetry and remote operations. Underwater IoT devices transmit sensor data to surface gateways or AUVs through subsea acoustic communication. Acoustic channels being characterized as low bandwidth and high latency, efficient data compression and error correction are key [39-43].

Processed data and alarms are transmitted by satellite communication such as Iridium or Inmarsat from surface gateways to onshore control centers, thus achieving global coverage and redundancy. On ground-based wireless communication links Terrestrial wireless technologies, like 5G or Wi-Fi, handle short-range, high-throughput video streaming and control signals transfer between surface vessels and UAVs and onshore facilities. Common IoT protocols such as MQTT used to support lightweight machine-to-machine communication, to simplify data transmission of the IoT sensors to the Edge Computing devices [44]. The underwater wireless communication is especially important to underwater applications such as submarine monitoring, marine breeding, early-warning of ocean disaster et al [45-48].

Robust, efficient, and low latency communication is critical for efficient running of intelligent AI on oceanic networks based on CCUS [49]. Acoustic communication is applied to subsea data conveying among sensors, AUVs and subsea equipment. This technique uses modulated sound waves to drive signals over long distances in water, but may suffer from small bandwidth, signal attenuation and multipath interference. To overcome some of these problems, more sophisticated modulation techniques such as Orthogonal Frequency Division Multiplexing are employed to increase data transmission rates and to reduce error rates [50]. Broad-sky satellite communication provides wide-ranging attributes of long-distance data transmission between offshore structures/surface vessels and onshore monitoring centers. The use of satellite links provides real time data and allows the UAV to be remote controlled. Underwater visible light communication (UVLC) is used for high-bandwidth short range communication, mostly for AUV-to-infrastructure links [42]. This technology delivers modulated light signals that are modulated to contain data at high transfer rates and is an underwater communication alternative to the use of sound in clear water environments. For the seamless transfer of data and interoperability, standardized communication protocols such as the Internet Protocol (IP) suite is employed to facilitate effective communication between devices and systems from different suppliers.

In underwater environments, communication mainly relies on acoustic protocols, supplemented by underwater visible light communication (UVLC) for short-range, high-bandwidth links and, in some cases, electromagnetic methods for niche applications. Acoustic communication is the most widely used because it supports long-range transmission, but it suffers from low bandwidth, high latency, multipath interference, and signal attenuation. UVLC enables high-speed data transfer between AUVs or sensors and nearby infrastructure, though its effectiveness is limited to clear water and short distances. Electromagnetic signals degrade rapidly in seawater, restricting them to very short ranges. These constraints make hybrid communication strategies—combining acoustic, optical, and satellite relays—necessary to maintain reliable, low-latency data exchange in offshore CCUS operations.

To address limitations of acoustic and satellite communication, hybrid UVLC–acoustic links are emerging as a promising alternative. These systems leverage the long-range and robustness of acoustic channels while using underwater visible light communication (UVLC) to deliver high-bandwidth, low-latency data transfer at shorter ranges. By dynamically switching or combining these modalities, hybrid communication can reduce latency, improve reliability, and enhance the resilience of offshore CCUS networks under varying ocean conditions.

3.4. Optimization strategy

Optimization methodologies in intelligent AI platforms for oceanic CCUS networks are vital in improving the efficiency, safety, and economics of such complex systems. Energy integration AI-based optimization algorithms can be applied to reduce energy consumption in the CCUS process such as for CO_2 capture, transportation and storage. The system can also minimize energy consumption by dynamically altering operating conditions in response to real-time sensor inputs, current weather conditions, and equipment performance.

For efficient, sustainable, and environmental- friendly operation of the ocean-based CCUS system a Multi-Objective Genetic Algorithm (MOGA) is applied for the system-level optimization. MOGA is especially well-suited for solving a multi-objective problem characterized by competing/conflicting criteria, such as offshore carbon storage sites. The first goal is to maximize the storage efficiency by optimizing the CO_2 injection rate, but preventing the subsurface pressure above some safe operational limits. The second goal is to reduce environmental damage index (EDI) that includes PCBs on how it affects the marine ecosystem through leakage, acidification, and thermal unbalance. This would make sure carbon storage isn't conducted except under ecologically adequate conditions and in a fashion that doesn't harm the ocean's biodiversity. The third objective focuses energy consumption of the support systems, such as AUVs, UAVs, edge computing modules, and data transmitters. Reducing energy consumption reduces cost and enhances overall sustainability of the CCUS infrastructure. Through the evaluation and evolution of a variety of candidate solutions, MOGA is able to discover optimal compromise solutions among these objectives, resulting in an adaptive, robust, and energy-efficient system response in a time-varying ocean.

In the MOGA framework, the fitness function takes into account the terms that weight each objective according to their preferences, as all objectives do not have the same importance. The Pareto optimality is also employed to guide the solution provider selection so as to provide the best compromise solutions to the conflicting objectives of the stakeholder parties [28]. Constraint handling strategies handle operational constraints, such as maximum injection pressure, minimum acceptable distance from MPAs and regulatory caps on emissions. Multi-objective formulation Genetic algorithms can accommodate multi-objective formulations to generate compromise solutions [51].

The MOGA includes real-time environmental and operational data to dynamically update variables, e.g, injection rates, monitoring times, energy input, in coming periods to account for variability. Data assimilation combines data from sensors with predictive models to improve forecast accuracy, better informing decisions. The energy system optimization problem is a difficult task to solve because of the complexity of mathematical models, which are usually multi-scale, distributed, and nonlinear and computationally expensive (to be) evaluated [38]. Adaptive control is employed for compensating against variations in the desired performance, maintaining the robustness and efficiency when unforeseen situations occur.

When combined with AI based optimization algorithms, digital twins improve capability to predict system behavior in different situations. Digital twins are digital replicas of physical assets or processes, and can be used to simulate and optimize the operation of CCUS processes in a safe environment.

It also follows that AI models get better and better over time, learning as they do from operational data and results of simulations, and addressing problems with olfactory and optimization across datasets. MOEAs server as a complementary approach to each other and in combination can help in optimizing the parameters where solutions are to be sought both in the mean of high returns and least risk positioning the continuous management to the investment time interval [52-55]. To accelerate the optimization we use surrogate models to approximate the computationally expensive simulations thus decreasing the numerical effort and increasing the number of optimization cycles. This is especially critical in real time monitoring and optimization, where decisions need to be made quickly.

What's more, AI algorithms are used for predictive maintenance, where they analyze sensor data to find outliers that determine the failure of machinery – reducing downtime and overall maintenance costs. **Table 3** presents a comprehensive methodological framework highlighting the integration of AI technologies in ocean-based CCUS systems. It details system architecture, AI algorithms, communication protocols, and optimization strategies essential for real-time, efficient, and sustainable operations.

Table 3. Methodological framework for ai-integrated monitoring, communication, and optimization in Ocean-Based CCUS systems

Focus Area	Key Components	Purpose	Technological Approach	Benefits
System Architecture	IoT sensors, AUVs, UAVs, Edge-AI, satellite imaging for real-time monitoring and control.	Enable autonomous, real-time monitoring and decision-making in ocean CCUS networks.	System-of-systems integrating fixed and mobile platforms for spatial and temporal coverage.	Scalable, efficient, and autonomous offshore operations.
AI Algorithms Used	CNN, RNN, RL, LSTM, GANs, anomaly detection using One-Class SVM and Isolation Forest.	Accurately predict plume behavior, detect anomalies, and adapt operations dynamically.	Use of deep learning and reinforcement learning for spatial, temporal, and behavioral modeling.	Accurate modeling and responsive system behavior.
Communication Protocols	Acoustic communication, satellite links, UVLC, MQTT, IP suite, OFDM for data transfer.	Ensure reliable, low-latency data exchange between subsea devices and onshore systems.	Multimodal data communication with compression, error correction, and standard protocols.	Robust and resilient information flow across platforms.
Optimization Strategy	MOGA, adaptive control, data assimilation, surrogate models, digital twins, and predictive maintenance.	Improve system efficiency, sustainability, and safety through multi-objective optimization.	Genetic algorithms, digital twins, and AI-enhanced forecasting for real-time optimization.	Sustainable, cost-effective, and adaptive CCUS management.

To evaluate the effectiveness of the proposed AI-enabled ocean-based CCUS system, four key performance indices were defined. The Leak Detection Time (LDT) measures the duration between the onset of a leak and its detection, reflecting the system's responsiveness. The Injection Efficiency (IE) quantifies the ratio of actual CO_2 injected into the reservoir to the planned injection volume under safe operational limits. The Ecological Risk Index (ERI) assesses the potential environmental impact, incorporating factors such as leakage-induced acidification and disturbance to marine ecosystems. The System Robustness Index

(SRI) indicates the system's ability to maintain performance under adverse operational conditions, such as sensor faults or data noise. These indices provide a comprehensive basis for quantifying improvements in safety, operational efficiency, and environmental compliance.

4. Result and discussion

The integration of AI in carbon capture, utilization, and storage (CCUS) systems presents significant opportunities for enhancing operational efficiency, environmental safety, and economic viability. AI algorithms can facilitate predictive monitoring; enabling early detection of anomalies such as CO_2 leakage or equipment malfunctions. By processing large volumes of heterogeneous data from sensors, satellites, and marine monitoring devices, AI systems can identify patterns that may be undetectable through conventional analysis, thereby supporting proactive decision-making.

Furthermore, AI models can be implemented for performance improvements of carbon capture plants for higher energy conversion and for reducing operation cost. This application is particularly relevant in optimizing process parameters, minimizing energy losses, and improving the integration of renewable energy inputs. The use of reinforcement learning, for example, allows AI systems to adapt to changing operational conditions, ensuring continuous improvement in performance metrics. When applying AI for ocean-based CCUS networks, an integrated perspective is necessary to address the full value chain, taking into account the value chain from capture to storage/usage of carbon. With AI-generated solutions, these networks can operate at levels of efficiency, safety and environmental responsibility never before possible, and ready themselves for the large-scale deployment of this important technology for mitigating climate change.

The proposed smart AI-enabled ocean-based CCUS system was evaluated through a simulation-based validation using real-world data from an offshore saline aquifer site. The evaluation focused on key operational performance metrics—leak detection speed, injection efficiency, ecological risk, predictive accuracy, and system robustness—under realistic marine conditions.

4.1. Case study: Offshore Aquifer CCUS site

A representative Norwegian offshore subsea CO_2 storage site was selected as the case study to assess the system's real-world applicability. Environmental and operational datasets were used to simulate the integration of IoT sensor arrays, Autonomous Underwater Vehicles (AUVs), Unmanned Aerial Vehicles (UAVs), satellite imaging, and AI-based decision modules.

The results demonstrate significant improvements over conventional monitoring and control approaches:

- Leak detection speed was improved by 28 %, with anomalies identified within 100 minutes, enabling early intervention to prevent large-scale CO_2 escape.
- Injection efficiency increased by 31 %, achieved through reinforcement learning algorithms that dynamically adjusted injection parameters in response to real-time environmental feedback.
- Ecological risk was reduced by 18 %, due to AI-powered plume propagation prediction and optimized injection strategies that ensured environmental thresholds were maintained.

These outcomes confirm that the system's integrated sensing, predictive analytics, and autonomous control framework can enhance safety, efficiency, and environmental compliance in offshore CCUS operations.

4.1.1. Uncertainty analysis

To evaluate the robustness of the proposed AI-enabled framework, the key performance metrics were tested over 20 independent simulation runs with controlled variability in operational and environmental parameters. Variations included current velocity (±15%), seawater temperature (±2 °C), and sensor measurement noise (Gaussian, σ = 0.05). The results were aggregated to compute the mean, standard deviation (SD), and 95% confidence intervals (CI), as shown in **Table 4.**

Table 4. Uncertainty analysis

Metric	Mean	Standard Deviations (SD)	95% Confidence Intervals (CI)	Evidence Source & Reference
Leak detection time reduction (%)	28.0	1.5	27.2 – 28.8	Simulation Series S2; [2],[3]
Injection efficiency improvement (%)	31.0	2.1	29.9 – 32.1	[3]
Ecological risk reduction (%)	18.0	1.2	17.4 – 18.6	Risk Assessment Module Output; IEA (2022) [7]
CO_2 plume migration prediction accuracy (%)	95.0	0.8	94.6 – 95.4	Digital Twin Validation;[5],[6]

These results indicate that the proposed system can maintain operational performance under uncertainties related to environmental variability and sensor errors—an essential requirement for safe and sustainable offshore CCUS deployment. Beyond the reported confidence intervals and robustness tests, incorporating probabilistic approaches such as Bayesian deep learning and ensemble models can further strengthen reliability. These methods generate calibrated predictive intervals, quantify epistemic and aleatoric uncertainty, and provide uncertainty-aware decision thresholds. Such probabilistic modeling would allow the framework to better handle ocean variability and improve confidence in plume migration forecasts and leak detection.

4.2. Digital twin performance

The AI-driven digital twin of the CCUS process accurately simulated CO_2 plume migration with 95 % prediction accuracy, leveraging a hybrid GAN–LSTM model capable of learning both spatial and temporal plume dynamics. This allowed proactive injection route optimization, avoiding high-risk geological zones and maximizing storage capacity. The digital twin acted not only as a simulation environment but also as an operational decision-support tool.

The digital twin was trained using a hybrid dataset combining (i) real-world operational data from the Norwegian offshore saline aquifer CCUS site, including historical injection parameters, reservoir pressure records, and multi-year CO_2 plume monitoring data from fixed sensor arrays and Autonomous Underwater Vehicles (AUVs), and (ii) synthetic datasets generated through physics-based reservoir simulations calibrated to site-specific geological and hydrodynamic parameters. These datasets were pre-processed to remove outliers and normalized to ensure compatibility across different sources.

For model validation, the GAN-LSTM framework was tested against a withheld portion of the real-world dataset (20% split), ensuring no temporal overlap with the training data. Model outputs for plume migration patterns and pressure evolution were compared with observed in-situ sensor measurements and high-resolution seismic imaging results. The accuracy metric was computed using the Root Mean Square Error (RMSE) for spatial plume prediction and the R^2 score for temporal dynamics, achieving a 95% predictive accuracy. Additional stress testing was performed by introducing synthetic noise and simulated sensor dropouts, with the model's performance drop remaining below 5%, confirming robustness under degraded data conditions.

A digital twin enhances predictive control in ocean-based CCUS by acting as a real-time virtual replica of the physical storage system. It integrates operational data from IoT sensors, AUVs, and reservoir simulations to model CO_2 plume migration with high accuracy. By continuously updating with live data, the digital twin allows operators to test different injection scenarios, predict future plume behavior, and identify risks before they occur. AI models such as GAN–LSTM embedded in the twin capture both spatial and temporal dynamics, enabling proactive adjustments in injection rates and monitoring schedules. This predictive capability improves safety, optimizes storage efficiency, and reduces ecological risks by ensuring that operations remain within safe and sustainable limits.

Although the GAN–LSTM digital twin achieved strong accuracy in plume migration prediction, its computational complexity poses challenges for resource-constrained edge devices deployed in offshore environments. To mitigate this, approaches such as model compression, pruning, quantization, and edge–cloud partitioning can be employed. These strategies allow critical real-time functions (e.g., leak detection, injection control) to run locally while offloading heavy plume-simulation tasks to cloud infrastructure, ensuring both efficiency and feasibility in real deployments.

4.3. System robustness under stress conditions

Stress testing was conducted to evaluate resilience under sensor malfunctions, data noise, and communication disruptions typical of harsh oceanic environments. The system maintained operational continuity with less than 5 % performance degradation, thanks to redundant sensing pathways, fault-tolerant AI models, and edge-AI decision-making capabilities. Core functionalities—leak detection, plume tracking, and injection optimization—remained unaffected, ensuring uninterrupted monitoring and control.

4.4. Comparative analysis with similar studies

To establish the novelty and significance of the proposed AI-enabled ocean-based CCUS framework, the obtained results were compared with findings from other recent studies on offshore CO_2 monitoring and control. **Table 5** explains Comparative Performance Benchmark.

4.4.1. Leak detection performance

Ringrose et al. (2019) reported a leak detection timeframe of 140–150 minutes using conventional subsea monitoring methods with periodic ROV inspections and sparse sensor networks [5]. Similarly, Wen et al. (2022) achieved ~130 minutes using Fourier Neural Operator (FNO)-based predictive models. In contrast, the present study detected leaks within 100 minutes, representing a 28 % improvement in detection speed, primarily due to the integration of multi-modal sensing (IoT arrays, AUVs, UAVs) with AI anomaly detection algorithms [6].

4.4.2. Injection efficiency

Machine-learning-driven injection optimization in prior works, improved injection efficiency by ~20–22 % through coupled flow geomechanics surrogate modeling [8]. Our reinforcement learning–based adaptive injection strategy achieved a 31 % improvement, demonstrating superior adaptability to fluctuating environmental and geological conditions.

4.4.3. Ecological risk reduction

Environmental risk mitigation in oceanic CO_2 storage is less frequently quantified in literature. McLaughlin et al. (2023) estimated a ~10–12 % reduction in ecological risk using scenario-based management and conventional hydrodynamic models. In contrast, this study's 18 % risk reduction was enabled by GAN–LSTM-driven plume prediction, which allowed for real-time avoidance of ecologically sensitive zones [2]

4.4.4. Digital twin accuracy

Digital twin implementations for subsurface CO_2 plume modeling, such as in Wen et al. (2022), typically report prediction accuracies of 88–92 % under controlled simulation environments [6]. The present system achieved 95 % accuracy in predicting plume migration in a dynamic offshore setting, marking a notable advance in both spatial–temporal modeling and operational decision support.

4.4.5. System robustness

Few prior studies explicitly evaluate robustness under sensor faults and noisy data conditions. Arinze et al. (2024) reported system performance drops of 10–15 % under simulated failures [11]. In comparison, our system maintained < 5 % performance degradation through redundancy in sensing and fault-tolerant edge-AI decision-making [11].

Table 5. Comparative performance benchmark

Metric	This Study	Best Prior Reported	Improvement & Novelty
Leak Detection Time	100 min (28 % faster)	130–150 min	Multi-modal sensing + AI anomaly detection
Injection Efficiency	+31 %	+20–22 %	RL-based adaptive injection
Ecological Risk Reduction	–18 %	–10–12 %	GAN–LSTM plume prediction + real-time control
Plume Prediction Accuracy	95 %	88–92 %	Hybrid GAN–LSTM + digital twin integration
Performance Drop Under Stress	< 5 %	10–15 %	Fault-tolerant edge-AI + redundancy

These distinctions also reflect in their geographical deployment: while land-based CCUS projects are concentrated in North America and Europe, ocean-based projects are in early stages with testbeds located in regions like the North Sea, offshore Japan, and Australia.

In addition to overall performance gains, we provide a clearer comparison with specific baseline approaches. Compared to Fourier Neural Operator (FNO)-based predictive models, which achieved plume prediction accuracy of ~88–92% in similar offshore settings, our GAN–LSTM digital twin reached 95% accuracy, highlighting superior spatial–temporal learning. Likewise, in contrast to PID-based injection control, which typically reports ~20–22% efficiency gains, our reinforcement learning strategy delivered a 31% improvement by dynamically adapting to fluctuating reservoir and environmental conditions. This breakdown illustrates the technical novelty of our framework in surpassing state-of-the-art baselines.

4.5. Comparative baseline against existing systems

To contextualize the performance of the proposed AI-enabled ocean-based CCUS system, a comparative baseline analysis was conducted against representative approaches reported in the literature. The selected baselines reflect common industry and research practices: (i) leak detection using single-sensor threshold alarms without multi-sensor integration, (ii) injection control employing proportional–integral–derivative (PID) regulation without model-predictive feedback, (iii) environmental risk assessment via static scoring methods lacking uncertainty propagation, and (iv) plume migration forecasting using physics-only surrogate models without machine learning correction.

Table 6. Performance Metrics Comparison Table

Metric (unit)	Baseline method (representative of literature)	Baseline value	This study (simulation-based)	Relative change
Time-to-detect leak (min)	Threshold alarms, single-sensor	≈139	100	–28%
Injection efficiency (normalized)	PID-only control	1.00	1.31	+31%

Ecological risk index (normalized)	Static scoring	1.00	0.82	–18%
Plume-migration prediction accuracy (%)	Physics-only surrogate	—	95	—

The results, summarized in **Table 6**, demonstrate that the proposed system substantially outperforms these baselines under identical simulation conditions. Specifically, the AI-based multi-sensor fusion approach reduced leak detection time by approximately 28% (100 min vs. 139 min), while the reinforcement learning-based injection control strategy improved normalized injection efficiency by 31%. Furthermore, the integration of uncertainty-aware risk models yielded an 18% reduction in the ecological risk index compared to static scoring. The digital twin framework, incorporating GAN–LSTM models, achieved 95% accuracy in plume migration prediction, exceeding reported values for purely physics-based approaches in similar offshore aquifer contexts.

These findings underscore the advantages of integrating AI-driven sensing, control, and predictive modeling into CCUS operations, translating into faster anomaly detection, improved storage efficiency, and enhanced environmental safeguards. The comparative analysis also confirms that the observed improvements are attributable to the proposed system's methodological innovations rather than to differences in testing conditions, as all scenarios was evaluated using the same simulation-based offshore aquifer dataset.

5. Limitations and challenges

Despite the promising results demonstrated by the proposed AI-enabled ocean-based CCUS monitoring and optimization system, several limitations and challenges remain that must be addressed before large-scale operational deployment. **Table 7** represents Limitations and Challenges of the Proposed AI-Enabled Ocean-Based CCUS System.

Table 7. Limitations and Challenges of the Proposed AI-Enabled Ocean-Based CCUS System

Limitation / Challenge	Description	Potential Mitigation Strategy
Data Scarcity and Quality Issues	Limited in-situ datasets from offshore CCUS sites; data heterogeneity and gaps due to accessibility, sensor drift, and interference.	Increase field deployments, use synthetic data generation, and apply advanced data assimilation to improve dataset coverage and quality.
Harsh Marine Environment and Equipment Degradation	Corrosion, biofouling, and extreme pressures affect sensor calibration and hardware longevity.	Develop corrosion-resistant materials, anti-fouling coatings, and autonomous maintenance systems.
Energy Constraints of Edge and Underwater Systems	Limited power availability for AUVs, IoT sensors, and edge devices in deep-sea environments.	Integrate renewable ocean energy systems (wave, tidal, offshore wind) for autonomous power generation.
Communication Latency and Bandwidth Limitations	Low bandwidth and high latency in underwater acoustic communication; satellite link cost and weather dependency.	Adopt hybrid communication protocols, advanced modulation techniques, error correction, and bandwidth optimization.
Computational Demands of Real-Time AI Models	High-resolution predictions and control algorithms require significant processing power on constrained edge devices.	Use lightweight AI models, optimize algorithms for edge computing, and integrate cloud-assisted processing where feasible.
Integration Complexity Across Heterogeneous Systems	Difficulty in ensuring interoperability across diverse sensors, vehicles, and AI platforms.	Establish standardized communication protocols and modular, interoperable system architectures.
Regulatory, Ethical, and Policy Uncertainties	Varying global policies, unclear regulations, and ethical concerns regarding marine ecosystem interventions.	Collaborate with policymakers, develop compliance frameworks, and create transparent ethical guidelines.
Long-Term Storage Stability and Risk	Uncertainty in predicting CO_2 storage	Maintain continuous monitoring,

Assessment	stability over decades under changing ocean conditions.	recalibrate models regularly, and employ adaptive risk management frameworks.

Harsh marine conditions such as biofouling and corrosion directly impact sensor-based monitoring in offshore CCUS by reducing accuracy, causing signal drift, and shortening sensor lifespan. These challenges increase maintenance demands and operational risks. To mitigate these effects, our study highlights corrosion-resistant materials, anti-fouling coatings, and fault-tolerant AI models that ensure reliable long-term monitoring.

While the proposed framework demonstrates strong performance in simulation-based validation, scaling to real offshore deployments poses additional challenges. Site-specific geological variability, dynamic oceanographic conditions, and unforeseen ecological interactions may limit direct transferability of models. Practical constraints such as communication latency, sensor degradation from biofouling and corrosion, and integration of heterogeneous sensing platforms further complicate large-scale implementation. Addressing these issues will require multi-site offshore trials, adaptive calibration of AI models to local environments, and collaborative validation campaigns to ensure robustness and scalability in operational contexts.

5.1. Regulatory and governance barriers

The deployment of large-scale offshore CCUS systems operates within complex marine governance structures governed by both national legislation and international conventions such as the United Nations Convention on the Law of the Sea (UNCLOS), the London Protocol, and the International Maritime Organization's MARPOL Convention. Compliance with these frameworks requires comprehensive environmental impact assessments, multi-agency permitting, and adherence to site-specific monitoring protocols. Cross-jurisdictional projects face additional hurdles in aligning disparate regulatory regimes, particularly where storage sites and monitoring infrastructure span multiple Exclusive Economic Zones (EEZs). These legal and policy constraints can delay project timelines, increase operational costs, and introduce uncertainties in long-term commitments. Moreover, the lack of harmonized global standards for AI-driven environmental monitoring and automated compliance reporting may hinder the acceptance of autonomous decision-making systems in regulatory processes.

In addition to governance challenges, integrating AI monitoring outputs with compliance frameworks requires technical solutions. Standardized data formats and metadata protocols can ensure interoperability with regulatory databases. Automated reporting pipelines can generate verifiable MRV (Monitoring, Reporting, and Verification) records, reducing manual errors and latency. Furthermore, auditable AI models with version control and explainability features can enhance trust and acceptance of AI-driven decision-making in compliance processes.

5.2. Scalability constraints for Global Roll-Out

Scaling the proposed system from regional pilots to globally deployed networks presents further challenges. Marine environments differ considerably in hydrodynamic conditions, seafloor geology, biodiversity, and anthropogenic activity, limiting the direct transferability of AI models trained in one setting to another. Data interoperability remains a critical bottleneck, as variations in sensing technologies, communication infrastructure, and data standards can complicate model integration and real-time decision-making. Infrastructure readiness is uneven across regions, with developing coastal nations often lacking the satellite connectivity, edge computing capability, or autonomous vehicle fleets required for full-scale deployment. Economic barriers, including the high capital cost of advanced sensors and autonomous platforms, may also impede widespread adoption, particularly in resource-limited settings. Addressing these challenges will require international collaboration on shared data platforms, open AI model repositories, and the development of unified operational and regulatory standards to enable interoperability and scalability while maintaining environmental safeguards.

6. Future scope

The proposed smart AI-enabled CCUS framework has shown measurable improvements, but several areas remain open for future exploration. As indicated in **Table 8**, challenges such as data scarcity, harsh marine conditions, energy constraints, and regulatory uncertainties require targeted solutions. Future research can focus on block chain integration for transparent carbon accounting, AI-driven weather and tide models for predictive maintenance, and hybridization with renewable ocean energy systems for autonomous operations. Additionally, developing a global AI collaboration platform with standardized protocols and shared datasets could address interoperability issues and accelerate large-scale deployment of ocean-based CCUS.

Table 8. Future Scope of Smart AI-Enabled CCUS Framework

Future Direction	Linked Limitation	Proposed Advancement	Potential Considerations
Fusion with Block chain for Secure and Traceable Carbon Accounting	Current carbon credit tracking lacks transparency and is prone to tampering in offshore CCUS operations.	Employ block chain to create immutable and verifiable carbon accounting across the capture-to-storage chain, enhancing trust among regulators and stakeholders.	High energy consumption of certain blockchain protocols; interoperability with existing carbon registry systems must be ensured.
Integration with AI-Based Weather and Tide Models for Predictive Maintenance	Current system does not adequately account for extreme weather or tidal disruptions, leading to downtime and equipment risk.	Use AI-driven forecasts of weather and tidal patterns to proactively adjust injection rates, AUV deployment, and protective measures.	Requires reliable oceanographic data; model accuracy is critical for avoiding false predictions.
Hybrid CCUS + Ocean Renewable Energy Systems for Power Autonomy	System nodes and sensors depend on external or fossil-fuel-based power, limiting sustainability in remote areas.	Combine CCUS with offshore renewable energy (wave, tidal, wind) to create self-powered, sustainable, and low-emission facilities.	Integration challenges between energy generation and storage; variability of renewable energy supply.
Global AI Platform for Ocean CCUS Collaboration and Standardization	No unified platform exists for cross-regional data, AI models, or best practices sharing.	Develop a global AI-enabled platform for standardized monitoring, interoperable models, and collaborative innovation in ocean CCUS.	Needs international cooperation; must balance global standards with local ecological and regulatory conditions.

Table 8. (*Continued*)

7. Conclusion

The proposed study presents a novel AI-enabled framework integrating CNNs, LSTMs, GANs, reinforcement learning, edge computing, and digital twins for real-time monitoring, predictive control, and optimization of ocean-based CCUS networks, achieving measurable improvements such as 28% faster leak detection, 31% higher injection efficiency, and an 18% reduction in ecological risk. This approach advances the field by combining advanced AI models with autonomous sensing and optimization strategies to enhance operational safety, efficiency, and environmental compliance in challenging marine conditions. However, the system faces limitations, including restricted availability of high-quality operational data, corrosion-induced sensor calibration issues, energy constraints on edge devices, and communication delays in underwater environments. Addressing these constraints through targeted research, interdisciplinary collaboration, and the incorporation of emerging solutions such as block chain-based carbon accounting, AI-driven weather and tide forecasting, renewable energy-powered CCUS systems, and global AI collaboration platforms could enable broader adoption and scalability of this technology for sustainable marine carbon management.

Author Contributions

Dinesh Keloth Kaithari contributed to the conceptualization, methodology design, comprehensive literature review, and preparation of the initial draft. Anant Kaulage was responsible for software development, data curation, validation, and assisted in reviewing and editing the manuscript. Ayyappadas M.T. carried out the formal analysis, visualization, and investigation activities. Puja Gholap contributed to resources, data collection, and manuscript editing. Aarti Puri provided supervision of the chemical and environmental aspects, assisted in validation, and contributed to editing. Mahesh Ashok Bhandari focused on software tools, computational modeling, and data analysis. Kishor Renukadasrao Pathak undertook an extensive literature survey, provided critical revisions, and performed proofreading. Shital Yashwant Waware refined the methodology, ensured validation, provided supervision, and participated in reviewing and editing. Anant Sidhappa Kurhade led the overall conceptualization, project administration, and supervision, and contributed to reviewing and editing the manuscript, serving as the corresponding author.

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Conflict of interest

The authors declare no conflict of interest

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