EP-JOURNALS

JOURNAL OF NATURAL SCIENCE AND RESEARCH REVIEW

Available on: https://jnsrr.ep-journals.org/ E-ISSN: 3051-3766 P-ISSN: 3051-3758

Journal of Natural Science Research and Review

Volume: 01 Issue: 06 December-2025

Advances in Ai-Powered Analytics for Carbon Capture and Storage (CCS) in Reservoir Management

Lymmy Ogbidi
Schlumberger Oilfield UK Ltd, UK

Benneth Oteh
TotalEnergies Exploration and Production Kampala, Uganda

Published Date: December 31, 2025 **Article DOI: 10.65150/EP-jnsrr/V1E6/2025-11**

ABSTRACT: The escalating challenge of mitigating carbon emissions has positioned Carbon Capture and Storage (CCS) as a critical technology for combating climate change. This paper explores the transformative role of artificial intelligence (AI) in enhancing CCS's efficiency, safety, and scalability, focusing on reservoir management. Key advancements include the application of machine learning for precise reservoir characterization, predictive analytics for optimizing injection and storage processes, and neural networks for accurate subsurface behavior predictions. The discussion extends to data acquisition systems and advanced monitoring techniques that enable real-time tracking and improved decision-making. AI-driven risk assessment tools are also highlighted for their role in identifying and mitigating leakage and instability risks while optimizing storage site selection and operations. The paper addresses current limitations, recommends further integration of explainable AI and interdisciplinary collaboration, and identifies future research directions to ensure long-term storage security and scalability.

KEYWORDS: Carbon Capture and Storage, Artificial Intelligence, Reservoir Management, Machine Learning, Risk Assessment, Predictive Analytics

INTRODUCTION

The increasing concentration of greenhouse gases in the atmosphere, primarily carbon dioxide (CO_2), has become a pressing global challenge. The Intergovernmental Panel on Climate Change (IPCC) underscores that mitigating these emissions is critical to limiting global warming to well below 2°C above pre-industrial levels (Ritchie & Roser, 2017). Industrial processes, energy production, and transportation sectors remain significant contributors to atmospheric CO_2, necessitating innovative solutions to reduce and manage emissions effectively (Ramirez-Corredores, Goldwasser, & Falabella de Sousa Aguiar, 2023). Governments, industries, and researchers are now focusing on strategies that minimize emissions and actively remove CO_2 from the atmosphere to achieve carbon neutrality (Canadell et al., 2023).

Carbon Capture and Storage (CCS) emerges as a key technology in addressing the climate crisis. By capturing CO_2 emissions at their source—such as power plants, manufacturing facilities, or other industrial sites—CCS prevents these gases from entering the atmosphere (Esiri, Jambol, & Ozowe, 2024). Once captured, the CO_2 is transported and securely stored in geological formations, such as depleted oil fields or deep saline aquifers (Bui et al., 2018). This process significantly reduces the net emissions from sectors that are hard to decarbonize, thus complementing renewable energy adoption and energy efficiency measures. In addition, CCS enables a pathway for carbon-negative technologies when combined with bioenergy, further enhancing its role in achieving global climate goals (Ikpe, Ekanem, & Ekanem, 2024).

Artificial intelligence (AI) has emerged as a transformative force across numerous industries, and its integration into CCS represents a significant leap forward. By leveraging machine learning, advanced analytics, and predictive modeling, AI enhances CCS processes' precision, efficiency, and reliability. From optimizing site selection to real-time monitoring of CO_2 storage, AI tools enable better decision-making and risk mitigation (Sahith & Lal, 2024). These technologies also improve the interpretation of large, complex datasets generated during geological assessments, injection operations, and long-term storage monitoring. Consequently, AI reduces operational costs and strengthens the overall viability of CCS, accelerating its deployment at scale (Saxena et al., 2024).

This paper aims to explore the intersection of AI and CCS, focusing on how advanced analytics and computational techniques are revolutionizing reservoir management. The discussion will delve into key innovations, such as predictive modeling for storage optimization, data-driven monitoring systems, and AI-powered risk assessment tools. By examining these developments, the paper seeks to highlight the potential of AI to address existing challenges and unlock new opportunities in CCS. This work also outlines recommendations for future research and development, ensuring that AI continues to enhance the efficiency and scalability of CCS solutions.

1. AI-DRIVEN INNOVATIONS IN CARBON STORAGE OPTIMIZATION

1.1 Key Advancements in Machine Learning Models for Reservoir Characterization

The accurate characterization of geological reservoirs is a fundamental aspect of successful carbon storage operations. Machine learning (ML) has revolutionized this process by providing powerful tools to analyze and interpret vast amounts of subsurface data. Traditional methods, which often rely on manual seismic, petrophysical, and geological data interpretation, are time-intensive and prone to errors. In contrast, ML algorithms can efficiently process these datasets, identifying patterns and correlations that might go unnoticed (Misra, Li, & He, 2019).

Supervised learning techniques, such as support vector machines and random forests, have been applied to classify rock types, predict porosity, and determine permeability in subsurface formations. Unsupervised methods, such as clustering, further aid in identifying distinct geological zones with similar properties (Erofeev, Orlov, Ryzhov, & Koroteev, 2019). By combining these approaches, ML enables more accurate modeling of reservoir heterogeneity, reducing uncertainties and improving the selection of suitable storage sites. This advancement enhances operational efficiency and bolsters the long-term safety and reliability of carbon storage projects (Rodriguez-Galiano, Sanchez-Castillo, Chica-Olmo, & Chica-Rivas, 2015).

1.2 Applications of Predictive Analytics for Monitoring CO_2 Injection and Storage Efficiency

The injection of carbon dioxide into geological formations requires precise monitoring to ensure that the gas is effectively stored without compromising reservoir integrity. Predictive analytics plays a crucial role in this context by forecasting CO_2 behavior based on historical and real-time data. These tools leverage advanced algorithms to simulate injection scenarios, predict plume migration, and estimate the pressure build-up within the reservoir (Ajayi, Gomes, & Bera, 2019).

For instance, regression models and time-series analysis are commonly used to predict changes in reservoir pressure, enabling operators to adjust injection rates accordingly. This helps to prevent risks such as over-pressurization, which could lead to caprock failure or leakage. Additionally, predictive analytics aids in estimating the efficiency of CO_2 trapping mechanisms, including structural, residual, and mineral trapping. By providing insights into these processes, analytics tools help operators optimize injection strategies, maximize storage capacity, and minimize environmental risks (M. D. Aminu, Nabavi, Rochelle, & Manovic, 2017).

Moreover, these techniques enhance post-injection monitoring by predicting long-term storage behavior. Such insights are vital for developing effective monitoring, verification, and reporting (MRV) protocols essential for regulatory compliance and stakeholder confidence. The integration of predictive analytics thus ensures that carbon storage operations remain both effective and accountable (Okedele, Aziza, Oduro, & Ishola, 2024a, 2024c).

1.3 Integration of Neural Networks for Subsurface Behavior Predictions

Neural networks, a subset of AI inspired by the human brain's architecture, have shown remarkable potential in predicting subsurface behavior in carbon storage projects. These networks are particularly well-suited for handling complex, nonlinear relationships within large geological datasets. For example, convolutional neural networks (CNNs) are frequently employed for analyzing seismic images, enabling the identification of subsurface features such as faults, fractures, and stratigraphic boundaries (Liu et al., 2023).

On the other hand, recurrent neural networks (RNNs) are adept at modeling temporal data, making them valuable for analyzing time-lapse changes in reservoir conditions during and after CO_2 injection. By incorporating data from multiple sources, such as well logs, pressure sensors, and geophysical surveys, these models can provide highly accurate predictions of subsurface dynamics (Asante, Ampomah, Tu, & Cather, 2024).

Another promising application lies in the use of deep reinforcement learning, where neural networks are trained to optimize injection strategies by simulating various operational scenarios. This approach allows operators to explore a wide range of possibilities and identify optimal conditions for maximizing storage efficiency while minimizing risks.

The integration of neural networks into subsurface modeling not only improves prediction accuracy but also accelerates decision-making processes. These models can rapidly analyze new data and update predictions in real-time, providing operators with actionable insights. Furthermore, the ability of neural networks to generalize across different datasets makes them a versatile tool for addressing the diverse challenges encountered in carbon storage projects (Elete, Nwulu, Omomo, & Emuobosa, 2022b; Okedele, Aziza, Oduro, & Ishola, 2024b).

2. DATA MANAGEMENT AND ENHANCED MONITORING TECHNIQUES

2.1 Data Acquisition Systems for Real-Time Reservoir Monitoring

Effective carbon storage relies on robust data acquisition systems that provide continuous, real-time insights into reservoir behavior. These systems integrate various technologies, including seismic imaging, wellbore logging, and satellite-based monitoring, to gather comprehensive data on subsurface conditions. Real-time acquisition not only enhances the understanding of injection dynamics but also facilitates immediate response to potential anomalies, such as unexpected pressure changes or indications of leakage (Digitemie & Ekemezie, 2024).

Advanced sensor networks play a pivotal role in this process. Fiber-optic sensors embedded in wellbores or placed at the reservoir surface can accurately measure temperature, pressure, and strain. These sensors provide crucial data that help operators monitor the movement of stored carbon dioxide, ensuring it remains within the designated geological boundaries. Moreover, time-lapse seismic surveys, also known as 4D seismic imaging, allow for periodic assessment of changes in the reservoir over time. These surveys are instrumental in tracking the stored gas's migration and verifying the trapping mechanisms' effectiveness (OYEDOKUN, Ewim, & Oyeyemi, 2024a; Uchendu, Omomo, & Esiri, 2024b).

The integration of automated systems further enhances the efficiency of data acquisition. Autonomous drones and remotely operated vehicles (ROVs) are increasingly used to deploy sensors and conduct surveys in challenging environments, such as offshore reservoirs. These technologies reduce human intervention, lower operational costs, and improve safety while delivering high-quality data for real-time monitoring.

2.2 Role of Advanced Analytics in Processing Large-Scale Datasets from Sensors and Simulations

Modern monitoring systems' vast amounts of data require sophisticated analytics tools to extract actionable insights. Advanced analytics, powered by algorithms capable of processing and interpreting large-scale datasets, has become indispensable in reservoir management. To create a comprehensive picture of reservoir behavior, these tools can handle data from diverse sources, such as seismic surveys, pressure sensors, and fluid composition measurements.

One significant application of advanced analytics is the development of reservoir simulation models. These models use real-world data to replicate subsurface conditions, allowing operators to predict the outcomes of various injection scenarios. For instance, data-driven simulations can estimate the impact of different injection rates on reservoir pressure and storage efficiency. These insights enable operators to optimize operational parameters and mitigate over-pressurization or caprock failure risks (M. Aminu, Akinsanya, Dako, & Oyedokun, 2024; Oyedokun, Ewim, & Oyeyemi, 2024b).

Furthermore, machine learning algorithms enhance the interpretation of sensor data by identifying patterns and anomalies that might not be apparent through traditional methods. Anomaly detection algorithms, for example, can flag unexpected changes in reservoir conditions, such as sudden pressure spikes or unanticipated plume migration. These tools improve the accuracy and reliability of monitoring efforts, ensuring that potential issues are identified and addressed promptly.

Cloud computing and distributed systems are critical in managing and processing large-scale datasets. These technologies provide the computational power necessary to handle complex models and simulations, enabling real-time analysis and decision-making. By leveraging cloud-based platforms, operators can access data and analytics tools from anywhere, fostering collaboration and improving operational efficiency (Hashem et al., 2015).

2.3 Challenges in Ensuring Data Quality and the Impact of Computational Techniques on Mitigating Uncertainties

Despite advancements in data acquisition and analytics, ensuring the quality of collected data remains a significant challenge. Factors such as sensor calibration errors, data transmission issues, and environmental noise can compromise the accuracy and reliability of monitoring systems. Poor-quality data can lead to incorrect interpretations of reservoir behavior, increasing the risk of operational failures.

Computational techniques have been developed to address these challenges, enhancing data quality and reducing uncertainties. Data preprocessing methods, such as filtering and noise reduction algorithms, are applied to raw data to remove errors and improve signal clarity. Additionally, data fusion techniques combine information from multiple sensors to represent reservoir conditions accurately. Integrating diverse datasets helps mitigate the limitations of individual monitoring tools and improve overall system reliability (Zhang, 2021).

Uncertainty quantification is another critical area where computational methods play a role. Bayesian inference and Monte Carlo simulations are commonly used to assess the uncertainty associated with reservoir models and predictions. These techniques provide probabilistic estimates of key parameters, such as storage capacity and plume migration paths, allowing operators to make more informed decisions. Moreover, the adoption of blockchain technology has been explored as a means to ensure data integrity and traceability. Blockchain can create secure, tamper-proof monitoring data records, enhancing transparency and accountability in reservoir management. This innovation is particularly valuable for regulatory compliance and stakeholder communication, as it verifies storage performance and safety measures (Elete, Nwulu, Omomo, & Emuobosa, 2023; Nwulu, Elete, Aderamo, Esiri, & Erhueh, 2023; Nwulu et al.).

3. RISK ASSESSMENT AND DECISION SUPPORT SYSTEMS

3.1 Application of AI in Assessing Risks Such as Leakage or Reservoir Instability

The integrity of carbon storage projects hinges on the ability to identify, assess, and mitigate risks effectively. One of the most critical risks is the potential for leakage of stored carbon dioxide from the reservoir, which could undermine climate goals and pose environmental or health hazards. Another significant concern is reservoir instability, resulting from improper injection practices or geological factors. Artificial intelligence has emerged as a transformative tool in addressing these challenges by enabling precise risk assessment and proactive mitigation.

AI-driven models analyze large and diverse datasets to identify potential vulnerabilities in storage systems. For instance, machine learning algorithms are adept at detecting subtle patterns in seismic, pressure, and fluid composition data that may indicate early signs of leakage or instability. These predictive capabilities allow operators to address issues before they escalate, ensuring storage operations' continued safety and efficiency.

Moreover, AI tools facilitate the integration of historical data, such as records from past injection projects, to refine risk assessments. By leveraging this knowledge, operators can better understand the conditions that lead to risks and implement measures to avoid them. Advanced AI systems also incorporate geological uncertainty into their analyses, providing probabilistic risk estimates that guide decision-making and improve the resilience of storage operations(M. AMINU, AKINSANYA, OYEDOKUN, & TOSIN, 2024; Uchendu, Omomo, & Esiri).

3.2 Implementation of Decision-Making Tools

The selection of a suitable storage site is a critical decision that requires balancing multiple factors, including geological characteristics, proximity to emission sources, and regulatory requirements. Decision-making tools powered by AI streamline this process by evaluating potential sites against a wide range of criteria and recommending the most optimal locations.

These tools use multi-criteria decision analysis (MCDA) frameworks, which consider factors such as reservoir capacity, permeability, and sealing efficiency alongside economic and logistical considerations. By combining these inputs, AI-based decision-making systems comprehensively evaluate potential sites, enabling stakeholders to make informed choices that maximize storage efficiency and minimize risks (Nwaiwu, Leach, & Liu, 2023).

In operational contexts, decision-making tools assist in real-time management of injection activities. For instance, adaptive control systems use AI to monitor reservoir conditions continuously and adjust injection parameters dynamically. This capability ensures that injection rates and pressures remain within safe limits, preventing over-pressurization and maintaining caprock integrity. Additionally, AI-powered tools help allocate resources effectively, such as determining the optimal placement of monitoring equipment to achieve maximum coverage with minimal cost (Elete, Nwulu, Omomo, & Emuobosa, 2022a; Nwulu, Elete, Omomo, & Emuobosa, 2023).

Corresponding Author: Lymmy Ogbidi

3.3 Use of Reinforcement Learning and Optimization Algorithms to Refine Strategies

Long-term storage security is a cornerstone of successful carbon storage projects, requiring strategies that ensure the stability and containment of injected carbon dioxide for decades or even centuries. Reinforcement learning (RL), a branch of AI that focuses on learning optimal actions through trial and error, has proven invaluable in this area.

RL algorithms simulate various operational scenarios to identify strategies that maximize storage security while minimizing risks and costs. For example, these algorithms can optimize injection strategies by balancing factors such as injection rate, well placement, and pressure distribution. Over time, the system learns to make decisions that enhance reservoir stability and trapping efficiency (Uchendu, Omomo, & Esiri).

Optimization algorithms also play a critical role in addressing uncertainties associated with long-term storage. By analyzing probabilistic models of reservoir behavior, these algorithms identify robust strategies that account for potential variations in geological conditions or operational parameters. This approach reduces the likelihood of unexpected events like caprock failure or unanticipated plume migration.

In addition to operational benefits, RL and optimization techniques support regulatory compliance by providing detailed storage performance and risks analyses. These insights are crucial for demonstrating the safety and effectiveness of storage projects to regulators and stakeholders. Furthermore, they enable the development of contingency plans for potential scenarios, ensuring that operators are prepared to address unforeseen challenges (Elete et al., 2022a; Uchendu, Omomo, & Esiri, 2024a).

4. CONCLUSION AND RECOMMENDATIONS

4.1 Conclusion

Integrating artificial intelligence into the carbon storage field has brought about transformative changes, addressing some of the most critical challenges in this domain. Advances in machine learning have improved the precision of reservoir characterization, while predictive analytics has enhanced the monitoring of injection operations and the efficiency of storage mechanisms. Neural networks have been particularly impactful in predicting subsurface behavior, ensuring the safe containment of injected carbon dioxide. Additionally, data management and monitoring systems, powered by real-time acquisition and advanced analytics, have enabled more effective tracking of reservoir dynamics and mitigation of uncertainties. Furthermore, the application of AI in risk assessment and decision support has significantly improved the safety, efficiency, and scalability of storage projects, cementing its role as an essential technology in climate mitigation strategies.

Despite these advancements, several challenges remain that require attention to fully unlock the potential of AI in carbon storage. First, improving data quality and availability is critical. High-quality, diverse datasets are essential for training accurate and reliable AI models. To address this need, investments in advanced sensor technologies and robust data management infrastructures should be prioritized.

Second, the development of explainable AI systems is vital for fostering trust among stakeholders. Many AI models operate as "black boxes," making their decision-making processes difficult to understand. By focusing on transparency and interpretability, researchers can ensure that AI tools are more accessible and reliable for operators, regulators, and policymakers. Finally, fostering collaboration between AI developers and domain experts in geology and engineering can enhance AI solutions' contextual relevance and applicability. Such interdisciplinary efforts will help bridge knowledge gaps and ensure that AI tools address the unique challenges of carbon storage.

Future research should focus on refining AI algorithms to account for subsurface environments' complex and dynamic nature. Incorporating physics-informed models into AI systems can improve their ability to predict reservoir behavior under various conditions. Moreover, exploring hybrid approaches that combine traditional numerical simulations with AI methods can yield more robust and reliable results.

Interdisciplinary collaboration will be essential for advancing AI applications in carbon storage. Partnerships between geoscientists, engineers, data scientists, and policymakers can drive innovation and accelerate the deployment of AI-enabled solutions. Such collaborations can also help develop standardized frameworks for monitoring, verification, and reporting, ensuring the integrity and accountability of storage projects.

REFERENCES

1) Ajayi, T., Gomes, J. S., & Bera, A. (2019). A review of CO 2 storage in geological formations emphasizing modeling, monitoring and capacity estimation approaches. *Petroleum Science, 16*, 1028-1063.
2) Aminu, M., Akinsanya, A., Dako, D. A., & Oyedokun, O. (2024). Enhancing cyber threat detection through real-time threat intelligence and adaptive defense mechanisms. *International Journal of Computer Applications Technology and Research, 13*(8), 11-27.
3) AMINU, M., AKINSANYA, A., OYEDOKUN, O., & TOSIN, O. (2024). A Review of Advanced Cyber Threat Detection Techniques in Critical Infrastructure: Evolution, Current State, and Future Directions.
4) Aminu, M. D., Nabavi, S. A., Rochelle, C. A., & Manovic, V. (2017). A review of developments in carbon dioxide storage. *Applied Energy, 208*, 1389-1419.
5) Asante, J., Ampomah, W., Tu, J., & Cather, M. (2024). Data-driven modeling for forecasting oil recovery: A timeseries neural network approach for tertiary CO2 WAG EOR. *Geoenergy Science and Engineering, 233*, 212555.
6) Bui, M., Adjiman, C. S., Bardow, A., Anthony, E. J., Boston, A., Brown, S., . . . Hackett, L. A. (2018). Carbon capture and storage (CCS): the way forward. *Energy & Environmental Science, 11*(5), 1062-1176.
7) Canadell, J. G., Monteiro, P. M., Costa, M. H., Cotrim da Cunha, L., Cox, P. M., Eliseev, A. V., . . . Koven, C. (2023). Intergovernmental Panel on Climate Change (IPCC). Global carbon and other biogeochemical cycles and feedbacks. In *Climate change 2021: The physical science basis. Contribution of working group I to the sixth assessment report of the intergovernmental panel on climate change* (pp. 673-816): Cambridge University Press.
8) Digitemie, W. N., & Ekemezie, I. O. (2024). Enhancing carbon capture and storage efficiency in the oil and gas sector: an integrated data science and geological approach. *Engineering Science & Technology Journal, 5*(3), 924-934.

9) Elete, T. Y., Nwulu, E. O., Omomo, K. O., & Emuobosa, A. (2022a). Data analytics as a catalyst for operational optimization: A comprehensive review of techniques in the oil and gas sector.
10) Elete, T. Y., Nwulu, E. O., Omomo, K. O., & Emuobosa, A. (2022b). A generic framework for ensuring safety and efficiency in international engineering projects: Key concepts and strategic approaches.
11) Elete, T. Y., Nwulu, E. O., Omomo, K. O., & Emuobosa, A. (2023). Alarm rationalization in engineering projects: analyzing cost-saving measures and efficiency gains.
12) Erofeev, A., Orlov, D., Ryzhov, A., & Koroteev, D. (2019). Prediction of porosity and permeability alteration based on machine learning algorithms. *Transport in Porous Media, 128*, 677-700.
13) Esiri, A. E., Jambol, D. D., & Ozowe, C. (2024). Best practices and innovations in carbon capture and storage (CCS) for effective CO2 storage. *International Journal of Applied Research in Social Sciences, 6*(6), 1227-1243.
14) Hashem, I. A. T., Yaqoob, I., Anuar, N. B., Mokhtar, S., Gani, A., & Khan, S. U. (2015). The rise of "big data" on cloud computing: Review and open research issues. *Information systems, 47*, 98-115.
15) Ikpe, A. E., Ekanem, I., & Ekanem, K. R. (2024). Conventional trends on carbon capture and storage in the 21st century: a framework for environmental sustainability. *Journal of environmental engineering and energy, 1*(1), 1-15.
16) Liu, B., Yasin, Q., Sohail, G. M., Chen, G., Ismail, A., Ma, Y., & Fu, X. (2023). Seismic characterization of fault and fractures in deep buried carbonate reservoirs using CNN-LSTM based deep neural networks. *Geoenergy Science and Engineering, 229*, 212126.
17) Misra, S., Li, H., & He, J. (2019). *Machine learning for subsurface characterization*: Gulf Professional Publishing.
18) Nwaiwu, U., Leach, M., & Liu, L. (2023). Development of an Improved Decision Support Tool for Geothermal Site Selection in Nigeria Based on Comprehensive Criteria. *Energies, 16*(22), 7602.
19) Nwulu, E. O., Elete, T. Y., Aderamo, A. T., Esiri, A. E., & Erhueh, O. V. (2023). Promoting plant reliability and safety through effective process automation and control engineering practices.
20) Nwulu, E. O., Elete, T. Y., Aderamo, A. T., Esiri, A. E., Omomo, K. O., & Nigeria, L. Optimizing shutdown and startup procedures in oil facilities: A strategic review of industry best practices.
21) Nwulu, E. O., Elete, T. Y., Omomo, K. O., & Emuobosa, A. (2023). Revolutionizing turnaround management with innovative strategies: Reducing ramp-up durations post-maintenance.
22) Okedele, P. O., Aziza, O. R., Oduro, P., & Ishola, A. O. (2024a). Assessing the impact of international environmental agreements on national policies: A comparative analysis across regions.
23) Okedele, P. O., Aziza, O. R., Oduro, P., & Ishola, A. O. (2024b). Carbon pricing mechanisms and their global efficacy in reducing emissions: Lessons from leading economies.
24) Okedele, P. O., Aziza, O. R., Oduro, P., & Ishola, A. O. (2024c). Climate change litigation as a tool for global environmental policy reform: A comparative study of international case law.
25) OYEDOKUN, O., Ewim, S. E., & Oyeyemi, O. P. (2024a). A Comprehensive Review of Machine Learning Applications in AML Transaction Monitoring. Retrieved from https://www.ijerd.com/paper/vol20-issue11/2011730743.pdf
26) Oyedokun, O., Ewim, S. E., & Oyeyemi, O. P. (2024b). Leveraging advanced financial analytics for predictive risk management and strategic decision-making in global markets. *Global Journal of Research in Multidisciplinary Studies, 2*(02), 016-026.
27) Ramirez-Corredores, M. M., Goldwasser, M. R., & Falabella de Sousa Aguiar, E. (2023). Carbon dioxide and climate change. In *Decarbonization as a Route Towards Sustainable Circularity* (pp. 1-14): Springer.
28) Ritchie, H., & Roser, M. (2017). CO_2 and other greenhouse gas emissions. *Our world in data*.
29) Rodriguez-Galiano, V., Sanchez-Castillo, M., Chica-Olmo, M., & Chica-Rivas, M. (2015). Machine learning predictive models for mineral prospectivity: An evaluation of neural networks, random forest, regression trees and support vector machines. *Ore Geology Reviews, 71*, 804-818.
30) Sahith, J. K., & Lal, B. (2024). Artificial Intelligence for Enhanced Carbon Capture and Storage (CCS). *Gas Hydrate in Carbon Capture, Transportation and Storage: Technological, Economic, and Environmental Aspects, 159*.
31) Saxena, A., Prakash Gupta, J., Tiwary, J. K., Kumar, A., Sharma, S., Pandey, G., . . . Raghav Chaturvedi, K. (2024). Innovative Pathways in Carbon Capture: Advancements and Strategic Approaches for Effective Carbon Capture, Utilization, and Storage. *Sustainability, 16*(22), 10132.
32) Uchendu, O., Omomo, K. O., & Esiri, A. E. The concept of big data and predictive analytics in reservoir engineering: The future of dynamic reservoir models.
33) Uchendu, O., Omomo, K. O., & Esiri, A. E. Conceptual advances in petrophysical inversion techniques: The synergy of machine learning and traditional inversion models. *Engineering Science & Technology Journal, 5*(11).
34) Uchendu, O., Omomo, K. O., & Esiri, A. E. (2024a). Conceptual Framework for Data-driven Reservoir Characterization: Integrating Machine Learning in Petrophysical Analysis. *Comprehensive Research and Reviews in Multidisciplinary Studies, 2*(4), 001–013. doi:DOI:10.57219/crmms.2024.2.2.0041
35) Uchendu, O., Omomo, K. O., & Esiri, A. E. (2024b). Theoritical Insights into Uncertainty Quantification in Reservoir Models: A Bayesian and Stochastic Approach. *International Journal of Engineering Research and Development, 20*(11), 987–997.
36) Zhang, J. (2021). Modern Monte Carlo methods for efficient uncertainty quantification and propagation: A survey. *Wiley Interdisciplinary Reviews: Computational Statistics, 13*(5), e1539.