GEOLOGICAL CARBON STORAGE IN NIGER DELTA: A SOLUTION FOR NIGERIAN`S CARBON FOOTPRINT.

BY

SHOLA GODWIN IDOWU
ENG1905817

DEPARTMENT OF PETROLEUM ENGINEERING
FACULTY OF ENGINEERING
UNIVERSITY OF BENIN
BENIN CITY

MARCH 2025

GEOLOGICAL CARBON STORAGE IN NIGER DELTA: A SOLUTION FOR NIGERIAN`S CARBON FOOTPRINT.

BY

SHOLA GODWIN IDOWU

ENG1905817

A PROJECT SUBMITTED TO THE DEPARTMENT OF PETROLEUM ENGINEERING, FACULTY OF ENGINEERING, UNIVERSITY OF BENIN, BENIN CITY

IN PARTIAL FULFILLMENT OF THE REQUIREMENT FOR THE AWARD OF BACHELOR OF ENGINEERING

MARCH 2025.

CERTIFICATION

This is to certify that this project work was carried out by SHOLA GODWIN IDOWU (ENG1905817) of the Department of Petroleum Engineering, University of Benin.

PROF. K.O. Bello **DATE**

(PROJECT SUPERVISOR)

Dr. O, A. TAIWO **DATE**

(PROJECT CORDINATOR)

DR. OHENHEN IKPONWOSA **DATE**

(HEAD OF DEPARTMENT)

PROF. S, O. ISEHUNWA **DATE**

(EXTERNAL SUPERVISOR)

DEDICATION

This project is dedicated to God Almighty, and to my ever loving mum, Shola Joy Ilori.

ACKNOWLEDGEMENT

At the outset, I would like to express my heartfelt gratitude to God Almighty for His unwavering love and support. He is the most gracious and faithful father who has always been there for me, through thick and thin.

I would also like to express my profound gratitude to Prof. Kelani Bello, my esteemed project supervisor and Mr Ame Enosolease, my project co-supervisor, for his unwavering support and guidance. His invaluable assistance was integral to the success of this project. I would like to take this opportunity to express my gratitude to the head of the department, Dr. Ohenhen Ikponwosa, for his unwavering support and guidance throughout my academic journey.

I am also deeply grateful to my lecturers who have tirelessly impacted knowledge to me during my time here. Their passion and expertise have inspired me to pursue my academic goals with even greater determination. In particular, I would like to extend a special shoutout to the late Prof. K.I. Idigbe, who was a true inspiration to me, and to Prof Olafuyi, Prof Steve Adewole,Dr. D.O. Onaiwu, Dr. O, A. Taiwo, Dr Sunny Agbos Igbinere, amongst others, who have made a significant impact on my education.

However, my special and profound gratitude goes to my gorgeous and loving mother Shola Joy, my wonderful and amazing brother, Shola Oladapo, my mentor, Engr. Dr. Chukwu Emeke and Mrs Chioma. I am also grateful to my friends and love one, Osayi Osarumen,Nmakama Gabriel, Lawani Favour for their prayers, patience, understanding, and physical and financial support during my sojourn in Uniben, I love you all.

Table of Contents

ABSTRACT

Geological Carbon Storage (GCS) presents a promising solution to mitigate greenhouse gas emissions, especially in regions with intensive hydrocarbon activities such as the Niger Delta of Nigeria. This region, characterized by extensive oil and gas production, possesses a complex sedimentary basin structure with deep saline aquifers, depleted oil and gas reservoirs, and suitable cap rocks — all of which are essential for safe and long-term CO_2 storage.

This study explores the geological potential of the Niger Delta for carbon storage by evaluating reservoir characteristics such as porosity, permeability, depth, and cap rock integrity. Depleted hydrocarbon reservoirs in the delta, which already have well-characterized geologic and production histories, offer immediate prospects for CO_2 injABection and monitoring.

Moreover, saline aquifers within the region's deep stratigraphic sequences provide additional storage capacity, although they require more extensive characterization. Challenges such as fault reactivation, induced seismicity, and monitoring complexities in densely populated and ecologically sensitive areas are acknowledged.

The study also highlights the role of advanced tools like basin modeling, reservoir simulation, and machine learning in optimizing site selection and predicting long-term storage performance. Overall, the Niger Delta holds substantial promise for geological carbon storage as part of Nigeria's broader climate change mitigation strategy, provided that technical, environmental, and regulatory challenges are addressed through integrated research and stakeholder engagement.

CHAPTER ONE

INTRODUCTION

Geological Carbon Storage (GCS) in the Niger Delta is a promising solution to Nigeria's carbon footprint challenge, addressing the growing concerns of climate change by capturing and securely storing CO_2 emissions underground. Nigeria, being one of the largest oil and gas producers, has contributed significantly to global greenhouse gas emissions, exacerbated by widespread gas flaring and industrial activities. The Niger Delta, a region extensively explored for oil and gas, offers significant potential for geological carbon storage due to its unique geological formations, including depleted oil and gas fields and deep saline aquifers.

Geological carbon storage involves capturing CO_2 emissions from sources such as power plants, industrial facilities, and gas processing units, compressing the captured gas, transporting it via pipelines or other means, and injecting it into deep underground rock formations for permanent storage.

Once it is sequestered, the CO2 undergoes different trapping scenarios .The trapping mechanisms progressively helps in securing and converting the injected CO2 into immobile material that can remain permanently in the subsurface. So far, more than 200 million tonnes of anthropogenic CO2 have already been injected into geological formations worldwide (Bappah Adamu Umar, 2020).

The Niger Delta's depleted oil and gas fields provide an excellent opportunity for carbon storage, as these fields are already well-understood geologically and have infrastructure in place, reducing the costs and complexity associated with new projects. These depleted reservoirs, sealed by impermeable cap rocks, can securely trap injected CO_2, and the use of existing oil infrastructure further supports cost-effective implementation. Additionally, GCS in this region could facilitate Enhanced Oil Recovery (EOR), a process where CO_2 injection helps to extract additional oil from mature reservoirs, thereby offering both environmental and economic benefits.

Deep Saline aquifers, another option for CO_2 storage in the Niger Delta, are large, porous, and deep underground formations saturated with saltwater. These formations can store CO_2 at high pressures, ensuring that it remains trapped over geological timescales. With estimates suggesting that the Niger Delta's saline aquifers have vast CO_2 storage capacity, the region stands out as a strategic site for large-scale carbon sequestration efforts.

This project aims to illuminate the essential role of Carbon Capture and Storage (CCS) in reducing CO_2 emissions, focusing specifically on the environmental and global implications of CO_2 and the integrated function of CCS in the Niger Delta. It offers an in-depth analysis of geological CO_2 sequestration, showcasing multiple geological CO_2 sinks such as ocean storage, deep saline formations, depleted oil and gas reservoirs, CO_2-enhanced oil recovery (CO_2-EOR) sites, unmineable coal seams, and organic-rich shales. These formations, capable of containing hundreds of gigatons of carbon (GtC) or more, vary widely in their storage capacities and mechanisms.

The project highlights the diversity of trapping mechanisms in geological formations, including chemical, physicochemical, and physical trapping, with each approach tailored to specific types of formations. Given these differences, a matrix evaluation of CO_2-trapping processes is proposed to better understand the interactions and storage potential of these mechanisms. This evaluation is critical in developing an accurate model of CO_2 sequestration, offering a structured approach to analyze and predict the behavior of CO_2 in subsurface storage.

The study underscores the need for more precise assessments of storage capacity at global, regional, and local scales, along with an improved understanding of long-term CO_2 storage dynamics, including migration and leakage risks. To address these issues effectively, advancements in tracking, verification, and monitoring technologies are essential. Additionally, a deeper exploration of emerging CCS technologies will play a pivotal role in enhancing the security and effectiveness of CO_2 storage now and in the future.

The sudden rise in the average atmospheric concentrations of CO2 to unprecedented 403 parts per million in 2016 (Bappah Adamu) is largely attributed to the increase in burning of the fossil fuels and cement production (Bappah Adamu Umar Global CCS, 2017 and WMO, 2017).The release of greenhouse gases are generally believed to be responsible for the global warming (Bachu 2002 & Semere et al., 2014). CO2 being the most abundant of the released gases, constitute about 64% of the enhanced greenhouse effect (Bryant, 1997).

Studies have shown that the concentration of the CO2 at the atmosphere can remain for hundreds of years (IPCC, 2007). Therefore, mitigation technologies are required to reduce the amount of the CO2 by the year 2050 (IEA, 2008). Among the mitigation technologies employed in the recent time, CCS has been quite promising (IEA, 2004) and is believed to play a vital role in reducing future CO2 emissions significantly (Bachu, 2016). A large volume of potential storage, effective trapping of hydrocarbons, gainful experience with CO2 injection for enhanced oil recovery (EOR) and successful monitoring and verification in numerous injection projects builds increased confidence in storage security and safety in the subsurface formations or 46 locations (Jenkins et al., 2015).

The Niger Delta is in Nigeria's coastal plain between 3°N and 6°N and 5°E and 8°E. According to Odigwe, Efe, and Atubi (2020) and Emoyan et al. (2008), the area under consideration includes 8600 square kilometres of stagnant swamplands and 2,370 square kilometres of rivers, creeks, and estuaries. The area under study has many wetlands, including mangrove forests, swamps, coastal ridges, and woodlands (Eyinla & Ukpo, 2006). Giwa et al. (2019) reported that Nigeria's Niger Delta gas reserves cover 70,000 km2, with 20,000 km2 on land. Due to its large gas reserves, the Niger Delta has been gas flaring, which has harmed the environment (Okechukwu & Ukeje, 2016). More emissions raise ambient temperature, which should offset CO2 production and absorption.

1.1 RESEARCH BACKGROUND

The Niger Delta region, rich in oil and gas reserves, also harbors extensive sedimentary basins that are particularly favorable for geological carbon storage. The delta is primarily composed of three sedimentary formations: the Akata, Agbada, and Benin formations, with the Agbada and Benin formations being ideal candidates for CO_2 storage due to their sandstone reservoirs and structural traps. These rock formations have accumulated thick layers of sand and shale from fluvial and deltaic processes, creating porous and permeable rock suitable for CO_2 injection and long-term containment

Depleted hydrocarbon reservoirs in the Niger Delta are particularly attractive for GCS because they have demonstrated their ability to trap fluids over millions of years. Using these reservoirs for CO_2 storage not only leverages existing infrastructure, reducing overall project costs, but also provides a path for the oil and gas industry in the Niger Delta to transition toward carbon mitigation while still utilizing its operational expertise and knowledge base. Saline aquifers, which are abundant in the region, offer additional storage potential, though their suitability is generally more challenging to assess due to less historical data compared to depleted reservoirs. The containment capacity, injectivity, and cap rock integrity of these aquifers are evaluated through detailed geophysical surveys and laboratory tests.

The use of reservoir simulation software is essential in managing the complex interactions within the geological formations of the Niger Delta. Programs like CMG and Eclipse allow reservoir engineers and geoscientists to build 3D reservoir models that simulate the injection of CO_2 under different pressure and temperature conditions. These models are crucial for predicting how injected CO_2 will behave—whether it will remain stable, dissolve into formation water, or mineralize with reservoir rock over time.
Detailed deep learning also help identify safe injection rates, manage pressure buildup, and predict plume migration, thereby minimizing risks of CO_2 escape through faults or abandoned wells. Advanced monitoring systems, such as seismic surveys and electromagnetic imaging, are then integrated with these models to continuously monitor CO_2 distribution and containment over time, ensuring compliance with

environmental standards and regulatory requirements.

A key focus about this project is centered around the Niger Delta by mitigating some potential leakage through existing faults or abandoned wells, which could compromise both storage security and environmental safety. With the help of simulation software, engineers can identify optimal injection sites, model the risk of CO_2 escape, and implement monitoring strategies that use real-time data to detect and respond to irregularities. Advanced geophysical monitoring tools, including seismic and electromagnetic techniques, further support these efforts by providing ongoing surveillance of subsurface conditions post-injection.

Geological Carbon and Storage is the cornerstone of the 'Net Zero' aspiration as outlined in the Intragovernmental Panel on Climate Change (IPCC) 2022 report. While there is ongoing research on improving the efficiency of carbon capture, particularly direct air capture, and carbon utilization outside chemical Enhanced Oil Recovery (EOR) processes, carbon storage is relatively the most understood process, owing to its multiple overlaps with the traditional oil and gas industry (Fig. 1).

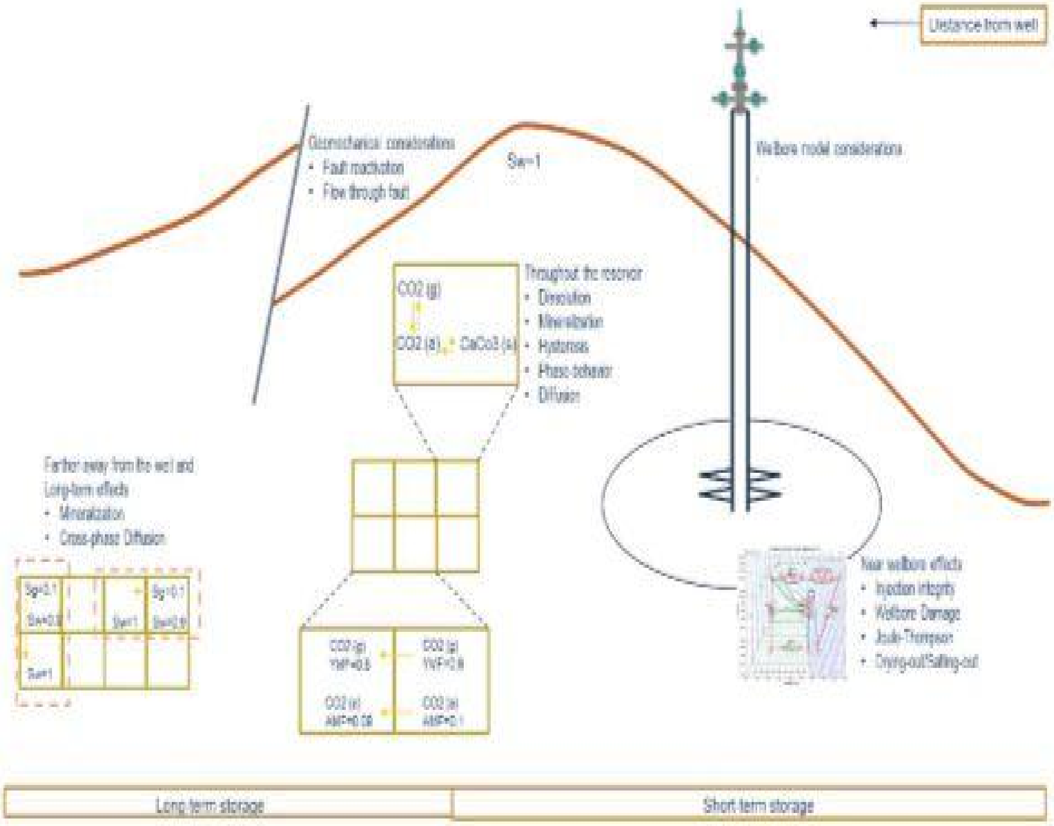


Fig: An outline of physical processes involved in CO2 storage in a subsurface aquifer, highlighting overlaps with the traditional oil and gas industry, classified in terms of distance from the well and time cycle of CO2 storage.

Two of the main concerns with CO_2 storage in subsurface reservoir or CO_2 sequestration, however, are the large time cycle involved in its permanent storage and the associated environmental risks. As the other CO_2 trapping mechanisms (especially solubility and residual) involve reversible mechanisms, both these concerns hinge heavily on the time required for solidification/mineralization of CO_2 into a component such as calcite ($CaCO_3$).

1.2 PROBLEM STATEMENT

The Niger Delta Formation holds significant potential for geological storage of carbon dioxide (CO_2) and other gases due to its extensive subsurface reservoirs. However, several challenges must be addressed to ensure safe and effective storage. One of the primary concerns is reservoir characterization, as the formation consists of interbedded sandstones and shales with varying permeability, which influences the injectivity, distribution, and long-term containment of injected fluids. The integrity of the sealing caprock is another critical issue, as the region is characterized by active fault systems and overpressure zones that could create leakage pathways, undermining the security of stored gases.

Additionally, the geomechanical stability of the formation must be carefully evaluated, since changes in pressure resulting from injection could alter stress conditions, potentially triggering subsurface movements or compromising caprock integrity. Another important factor to consider is the displacement of formation brines, as the migration of saline water due to injection activities could pose risks to shallow groundwater systems, leading to contamination concerns.

Furthermore, regulatory and environmental considerations present additional challenges, as Nigeria currently has limited policies governing geological storage, and public perception of CO_2 storage safety remains a concern. Addressing these complex issues requires a multidisciplinary approach, including advanced reservoir modeling, geomechanical assessments, long-term monitoring strategies, and the development of appropriate regulatory frameworks to ensure that geological storage in the Niger Delta Formation is both safe and sustainable.

The increasing need for carbon capture and storage (CCS) as a climate change mitigation strategy has highlighted the potential of the Niger Delta Formation as a suitable site for geological storage. However, the successful implementation of CO_2 and other gas storage projects in this region faces significant technical, geological, and environmental challenges. The complex lithology of the Niger Delta, characterized by interbedded sandstones and shales with varying porosity and permeability, raises concerns about storage capacity, injectivity, and long-term containment. Additionally, the presence of numerous fault systems and overpressure zones increases the risk of leakage, which could undermine the effectiveness of storage efforts and pose environmental hazards.

Furthermore, changes in subsurface pressure due to gas injection could alter stress regimes, potentially triggering fault reactivation or compromising caprock integrity, leading to unintended migration of stored fluids. The displacement of deep formation brines during injection also poses risks of contamination to shallow aquifers, which could impact local water resources. Despite the potential benefits of geological storage, there is limited regulatory oversight and public awareness in Nigeria, which raises concerns about long-term monitoring, liability, and environmental safety.

1.3 AIM AND OBJECTIVES

Aim:

The aim of this research project is to systematically apply a machine learning algorithm for a petrophysical data and well history data in a depleted reservoirs and deep saline formation.

Objectives:

1. Evaluate the suitability of reservoirs within the Niger Delta Formation for long-term geological storage of CO_2 and other gases by analyzing porosity, permeability, and overall capacity.

2. Conducting a comprehensive review to assess the optimal depleted hydrocarbon reservoir for carbon storage using a sites selection tools in a Niger Delta Formation.

3.Conducting a real time high resolution CO2 geological storage prediction using a deep learning algoritm (FNO) to predict heterogeneity and injection schemes in contexts of multiple wells.

4. Establish real-time monitoring systems for tracking the movement of injected gases, detecting leaks, and ensuring long-term storage security.

1.4 RESEARCH QUESTION

1. What are the most promising geological formations in the Niger Delta for CO2 storage based on their reservoir characteristics?

2. How can 3D seismic data be utilized to accurately map potential storage sites and identify potential geological hazards?

3. What are the optimal injection strategies to maximize CO2 storage capacity while minimizing leakage risks?

4. How can monitoring systems be implemented to ensure long-term integrity of the CO2 storage site and the socio-economic implications of implementing a CCS project in the Niger Delta region?

1.5 SCOPE OF RESEARCH

The scope of this research focuses on evaluating the feasibility, risks, and implementation strategies for geological storage of carbon dioxide (CO_2) and other gases in the Niger Delta Formation. This study will encompass geological, geophysical, geochemical, geomechanical, and environmental assessments to provide a comprehensive understanding of storage potential and associated challenges.

First, the research will involve geological and reservoir characterization, analyzing the lithology, stratigraphy, and structural framework of the formation. Reservoir properties such as porosity, permeability, and thickness will be examined to identify suitable storage sites. Additionally, seal integrity and containment analysis will be conducted to assess the effectiveness of caprock in preventing gas leakage, while evaluating the impact of fault networks and fracture systems that could compromise containment. Geochemical interactions between injected gases and reservoir rocks will also be studied to understand long-term storage behavior.

Furthermore, geomechanical and seismic risk assessments will be performed to analyze how CO_2 injection affects subsurface pressure and stress conditions, as well as the potential for fault reactivation and induced seismicity. Numerical models will be developed to predict long-term geomechanical behavior. Another critical aspect of the research is environmental and groundwater protection, where potential impacts on shallow aquifers and risks associated with brine displacement will be evaluated. Mitigation strategies will be proposed to prevent contamination and ensure environmental sustainability. To support long-term storage security, monitoring and verification strategies will be developed, incorporating real-time monitoring systems using geophysical and geochemical techniques. Leak detection methods and best practices for continuous performance assessment will also be established.

The study will also examine regulatory frameworks and policy development, analyzing existing laws governing geological storage in Nigeria, identifying gaps, and proposing policy recommendations that align with international carbon capture and storage (CCS) standards. Additionally, public awareness and stakeholder engagement will be a key component, as the research will assess public perception of geological storage, develop strategies for community engagement, and involve government agencies, industry stakeholders, and research institutions. The research will further explore optimization of injection and storage techniques, investigating efficient injection strategies, developing reservoir management plans, and using simulation tools to optimize CO_2 distribution within formations. Finally, the study will emphasize the integration of multidisciplinary approaches, utilizing geological, geophysical, and engineering expertise while incorporating data-driven techniques such as machine learning for reservoir behavior prediction. By addressing these areas, this research aims to contribute to climate change mitigation, supporting Nigeria's commitment to reducing greenhouse gas emissions and evaluating the economic feasibility of CCS deployment in the region. Ultimately, this study will provide the necessary scientific and technical foundation for safe and sustainable geological storage in the Niger Delta Formation.

1.6 JUSTIFICATION OF RESEARCH

The justification for this research is based on the need for a detailed evaluation of the Niger Delta Formation's suitability for geological storage, using petrophysical data, well history data, and black oil data. The petrophysical data provides crucial insights into the reservoir properties, including porosity, permeability, water saturation, and lithology variations, which determine the storage capacity and injectivity of the formation. By analyzing the rock and fluid properties, this study will assess how effectively CO_2 or other gases can be stored without significant leakage or migration.

Additionally, well history data from previously drilled wells in the Niger Delta will be utilized to understand past reservoir performance, pressure variations, and production history. This will help in identifying depleted reservoirs or underutilized formations that could serve as ideal storage sites, ensuring the selection of safe and viable locations for long-term storage.

Furthermore, black oil data, which includes pressure-volume-temperature (PVT) characteristics, reservoir fluid composition, and production behavior, is essential in evaluating the interaction between injected CO_2 and existing hydrocarbons or formation fluids. This data will help determine the impact of gas injection on reservoir pressure, phase behavior, and potential secondary recovery benefits, particularly in depleted oil reservoirs.

The integration of these datasets will allow for a more precise reservoir simulation and modeling approach, enabling accurate prediction of storage efficiency, fluid movement, and potential risks such as caprock failure or unintended leakage through faults. Additionally, the Niger Delta's history as a major hydrocarbon-producing region means that substantial subsurface data is already available, reducing uncertainty in site selection and enhancing the reliability of predictions regarding storage performance. By leveraging these datasets, this research will provide a scientific basis for safe and efficient geological storage, addressing key concerns such as containment integrity, reservoir stability, and environmental safety.

The findings will support Nigeria's energy transition efforts and global climate commitments by enabling a data-driven approach to carbon capture and storage (CCS). This research will also aid in developing best practices for CO_2 injection strategies, ensuring that storage sites are optimized for long-term security. Ultimately, the integration of petrophysical data, well history records, and black oil reservoir behavior will enhance the feasibility of geological storage in the Niger Delta Formation, contributing to both sustainable energy solutions and climate change mitigation.

CHAPTER TWO

LITERATURE REVIEW

Carbon dioxide (CO_2) emissions in the Niger Delta primarily stem from the combustion of fossil fuels, occurring in both large-scale facilities such as gas-fired power plants and smaller sources like automobile engines and residential or commercial generators. Additionally, CO_2 is released through industrial activities, resource extraction processes, and land-use changes, including deforestation and gas flaring, which are prevalent in the region.

Geological Carbon Capture and Storage (GCCS) presents a viable solution to mitigate these emissions by targeting large point sources, such as oil and gas processing plants and other industrial facilities. Furthermore, certain facilities could produce decarbonized fuels, such as hydrogen, to support the transportation, industrial, and building sectors, reducing emissions from more dispersed sources.

GCS operates through a multi-step process, beginning with the capture and concentration of CO_2 from industrial and energy-related sources, followed by its transportation to a suitable geological storage site. The Niger Delta's deep sedimentary formations, which have historically served as hydrocarbon reservoirs, offer significant potential for long-term CO_2 storage. By implementing GCCS, fossil fuel use in the region can continue with considerably lower greenhouse gas emissions, contributing to both environmental sustainability and climate change mitigation efforts.

The subsurface is the Earth's largest carbon reservoir, where the vast majority of the world's carbon is held in coals, oil, gas organic-rich shales and carbonate rocks. Geological storage of $CO2$ has been a natural process in the Earth's upper crust for hundreds of millions of years. Carbon dioxide derived from biological activity, igneous activity and chemical reactions between rocks and fluids accumulates in the natural subsurface environment as carbonate minerals, in solution or in a gaseous or supercritical form, either as a gas mixture or as pure $CO2$. The engineered injection of $CO2$ into subsurface geological formations was first undertaken in Texas, USA, in the early 1970s, as part of enhanced oil recovery (EOR) projects and has been ongoing there and at many other locations ever since.

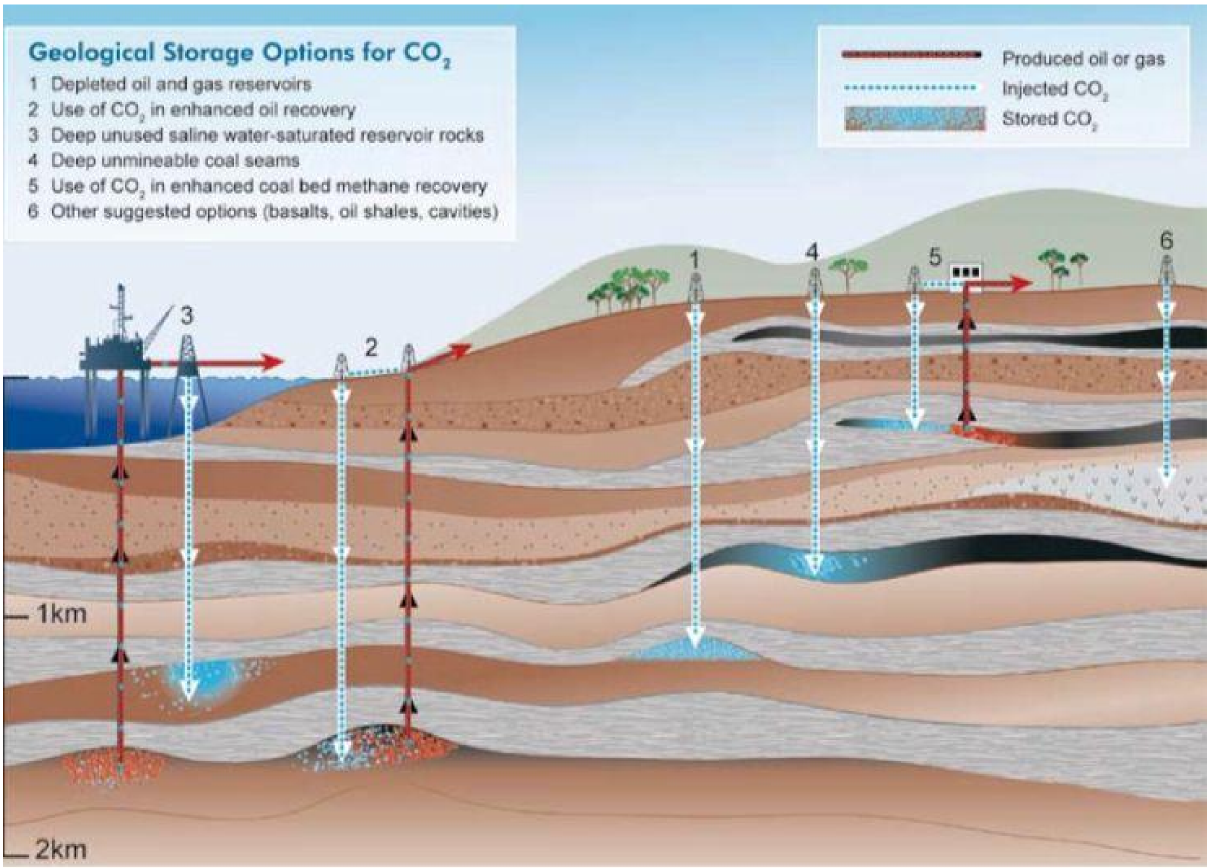


Fig: Options for storing CO_2 in deep underground geological formation IPCC (after cook, 1999)

2.1 STORAGE MECHANISM

Geological subsurface formations in the Niger Delta consist of transported and deposited rock grains, organic material, and minerals that develop over time. The pore spaces between these grains and minerals are typically filled with fluids, predominantly water, with smaller quantities of oil and natural gas.

When CO_2 is injected into the pore spaces and fractures of a permeable formation, several interactions can occur. The injected CO_2 may displace the in-situ fluids, dissolve into or mix with the existing fluids, or react chemically with the mineral grains within the formation. In many cases, a combination of these processes takes place, influencing the long-term storage potential of CO_2 in the Niger Delta's deep sedimentary basins. Given the region's extensive hydrocarbon reservoirs and high permeability formations, these mechanisms play a crucial role in the feasibility and effectiveness of Geological Carbon Storage (GCS) as a climate mitigation strategy.

2.2. STORAGE MECHANISMS IN GEOLOGICAL FORMATIONS.

The effectiveness of geological storages depends on the combination principles of physical and geochemical trapping mechanisms. The most effective storage sites are those where CO2 is immobile because it is trapped permanently under a thick, low-permeability seal or is converted to solid minerals or is adsorbed on the surfaces of coal micropores or through a combination of physical and chemical trapping mechanisms (IPCC).

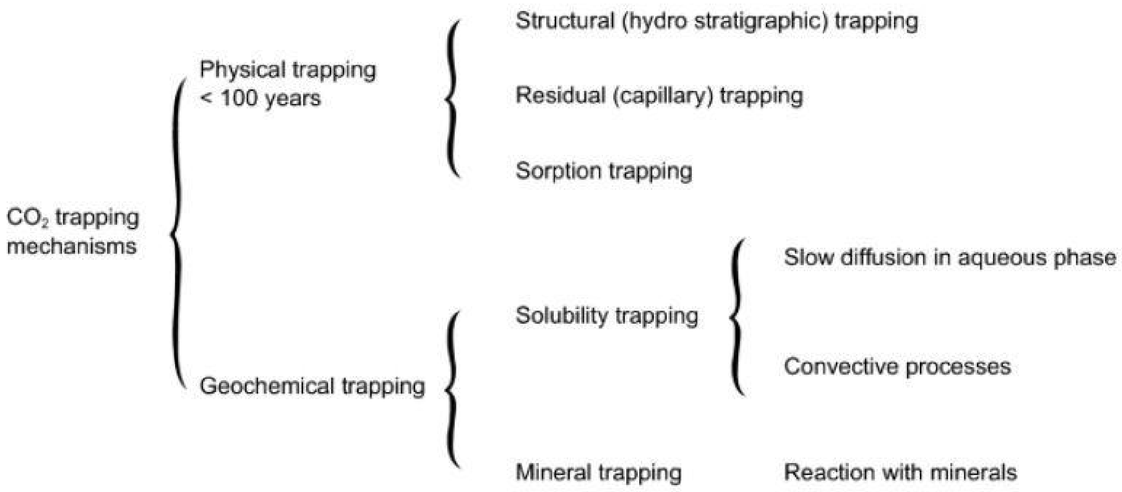


Fig: Different CO_2 trapping mechanisms during the geological storage process (coninck et al. 2005)

2.2.1 PHYSICAL TRAPPING MECHANISMS.

Physical trapping is the mechanisms where CO_2 maintains its physical nature after injection into an aquifer. It can be subdivided into structural (hydrostratigraphic) and residual (capillary) trapping. Generally, the time period for physical trapping is believed to be less than a century (Juanes et al. 2006).

2.2.1.1 STRUCTURAL TRAPPING

Structural trapping is the primary geological sequestration, and a similar mechanism has kept oil and gas securely stored underground for millennia. Geological structures such as anticlines covered with cap rocks (an ultra-low-permeability layer), stratigraphic traps with/without sealed faults are employed for the storage of CO_2 as a mobile phase or supercritical fluid. Maximization of this storage mechanism to ensure that CO_2 injected remains underground in the long term is essential. During the injection process in the targeted formation, viscous forces are the dominant forces for the migration of CO_2. CO_2 is then stored in either the supercritical or the gas phase as a function of depth at the associated pressure and temperature. rock as a result of the buoyancy effect created by its density difference compared to other reservoir fluids and laterally via preferential pathways until a cap rock, fault or other sealed discontinuity is reached (Han 2008).

In depleted oil and gas fields, the movement of the CO_2 can also be halted by abandoned wells sealed with solid cement plugs. The risk associated with such trapping is leakages behind casing or through the mentioned plugs. Thus, many studies have been conducted on the leakage of CO2 through geological structures and existing wells (Ambrose et al. 2017 and Eke et al. 2011).

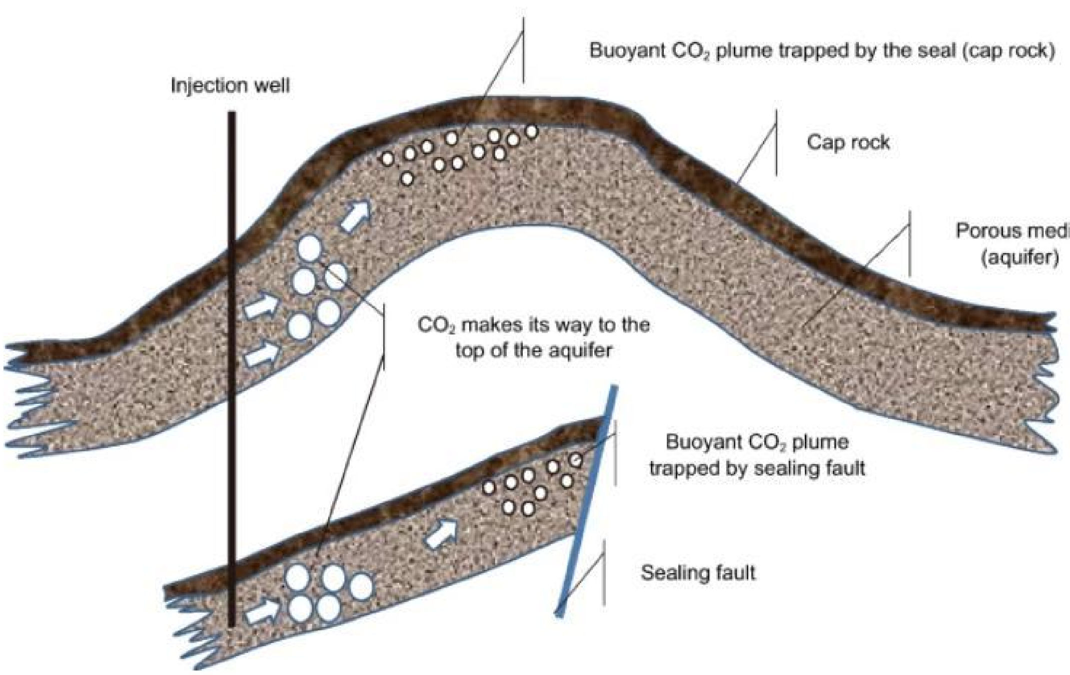


Fig: physical trapping of injected CO_2 as a result of the formation structure (.

2.2.1.2 RESIDUAL (CAPILLARY) TRAPPING

Residual trapping is a mechanism that occurs when the buoyancy of CO_2 is not sufficient to surpass the capillary entry pressure within the pore throats of the reservoir rock, preventing its entry into adjacent upper pores. This subsequently enables CO_2 storage at high saturations at locations below or outside structural and stratigraphic closures. Capillary trapping requires the fluid to be the nonwetting phase in the reservoir system (Hermanrud et al., 2009; Krevor et al., 2015). Unlike structural trapping, the effectiveness of capillary trapping does not depend on the integrity of the caprock (Saadatpoor et al., 2010).

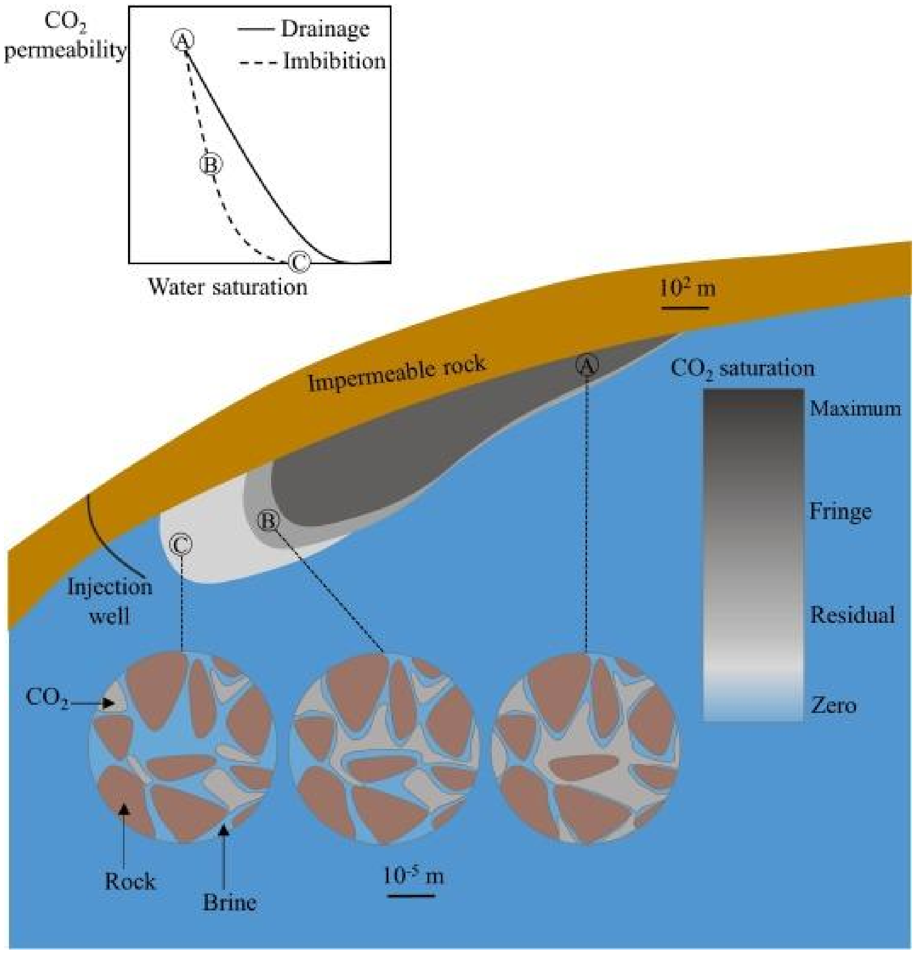


Fig: Capillary (residual) trapping of CO_2 subsurface formations. Modified from (Krevor et al., 2015).

2.2.1.3 SORPTION TRAPPING

Sorption trapping occurs when CO_2 is sorbed into an accessible pore space bulk due to a weak physical interaction. Sorption and structural entrapment are two processes that are considered complementary, despite the fact that they take place in the same pore spaces. It is important to note that a sorbed layer will cover a certain volume of the pore space depending on its physical parameters (density and volume). Because of this, the amount of pore space that is accessible to bulk CO_2 is decreased. If the sorbed phase density is greater than the bulk density, any storage capacity will benefit from this trapping process, since part of the injected CO_2 will not contribute to pressure building and will instead improve the total storage capacity, regardless of the storage capacity (Fatima Al Hameli.).

2.2.2 GEOCHEMICAL TRAPPING

This mechanisms undergoes a sequence of geochemical interactions with the rock and formation water that will further increase storage capacity and effectiveness. This trapping occurs when CO_2 changes its physical and chemical nature by undergoing series of geochemical reactions with the formation brine and the rock and ceases to remain in the mobile or immobile phase.

2.2.2.1 SOLUBILITY TRAPPING

Solubility trapping occurs as a result of the dissolution of the CO_2 in the brine, leading to dense CO_2-saturated brine. At this point, it ceases to remain a separate phase which eliminates any buoyancy effect. The dissolution of CO_2 in the aqueous phase leads to the formation of weak carbonic acid which decomposes over time into H^+ and HCO_3^- ions. It can also react with other cations in the formation brines to form insoluble ionic species as highlighted in the equation below.

$CO_2(g) + H_2O \leftrightarrow H_2CO_3 \leftrightarrow HCO_3^- + H^+ \leftrightarrow CO_3\ 2^- + 2H^+$

The CO2 solubility in formation water decreases as temperature and salinity increase. Dissolution is rapid when formation water and CO2 share the same pore space, but once the formation fluid is saturated with CO2 , the rate slows and is controlled by diffusion and convection rates.

2.2.2.2 MINERAL TRAPPING

Mineral trapping occurs as a result of the conversion of CO_2 into calcite due to reactions with solid minerals. This trapping is believed to be relatively slow since it occurs during/after solubility trapping and considered as the most permanent form of storage. CO_2 in the aqueous phase forms a weak acid which reacts with rock minerals to form bicarbonate ions with different cations depending on the mineralogy of the formation.

CO2 dissolved in water produces a weak acid, which reacts with the sodium and potassium basic silicate or calcium, magnesium and iron carbonate or silicate minerals in the reservoir or formation to form bicarbonate ions by chemical reactions approximating to:

$3\ \text{K-feldspar} + 2H_2O + 2CO_2 \leftrightarrow \text{Muscovite} + 6\ \text{Quartz} + 2K+ + 2HCO_3$

2.3 GEOLOGICAL CARBON STORAGE SITES

2.3.1 SALINE AQUIFER FORMATION

Saline aquifer formations represent the best salted sink for storage of CO_2 among all geological options due to their enormous storage capacity (Grobe et al. 2009). These formations are deep sedimentary rocks saturated with formation waters or brines containing high concentrations of dissolved salts. These formations are widespread and contain enormous quantities of water, but are unsuitable for agriculture or human consumption. Saline brines are used locally by the chemical industry and formation waters of varying salinity are used in health spas and for producing low-enthalpy geothermal energy. Because the use of geothermal energy is likely to increase, potential geothermal areas may not be suitable for CO2 storage. It has been suggested that combined geological storage and geothermal energy may be feasible, but regions with good geothermal energy potential are generally less favourable for CO2 geological storage because of the high degree of faulting and fracturing and the sharp increase of temperature with depth. In very arid regions, deep saline formations may be considered for future water desalinization.

2.3.2 DEPLETED RESERVOIRS

Depleted oil and gas reservoirs are excellent candidates for CO_2 storage due to several key factors. Firstly, the hydrocarbons that originally accumulated in structural and stratigraphic traps remained contained for millions of years, proving the reservoirs' long-term integrity and reliability. Secondly, most oil and gas fields have been extensively analyzed, with their geological structures and physical properties well-documented. Additionally, advanced computer models developed in the petroleum industry can be adapted to simulate CO_2 movement, displacement behavior, and trapping mechanisms. Lastly, existing infrastructure and wells within these reservoirs can potentially be repurposed for CO_2 storage operations, reducing the need for entirely new developments.

2.3.3 DEEP UNMINEABLE COAL BEDS

CO_2 has been utilized to enhance methane recovery from coal seams through the Enhanced Coal Bed Methane (ECBM) process (Busch and Gensterblum 2011; Mukherjee and Misra 2018; Pan et al. 2018b). The extracted methane can serve as a valuable energy resource. Coal beds contain extensive fracture networks that allow gas molecules to diffuse into the matrix, facilitating the desorption of tightly adsorbed methane. Studies have shown that CO_2 injection can increase methane recovery rates from approximately 50% to nearly 90%, significantly improving extraction efficiency compared to

conventional methods. Once methane is recovered, the injected CO_2 remains stored within the coal formations.
Unlike other geological storage options, coal beds allow CO_2 storage at relatively shallow depths, relying on adsorption onto the coal surface. However, the effectiveness of this storage method is highly dependent on coal permeability, which is influenced by depth and the associated variations in effective stress on coal fractures (Metz et al. 2005).

2.3.4 ENHANCED OIL RECOVERY

CO_2 is used for enhanced oil recovery (EOR) from mature fields. CO_2 for EOR operations has been employed in the miscible and immiscible states. When injected into oil, CO_2 has the capability to swell the oil, reduce its viscosity and reduce interfacial tension and in some cases become miscible with the oil allowing for single-phase flow. Of the two miscible states for EOR via CO_2 injection, miscibility of CO_2 in oil usually provides higher recoveries. The ability of CO_2 to become miscible in oil is determined by the minimum miscibility pressure (MMP). At and above this pressure, CO_2 is miscible in oil and below, it is immiscible. Though CO_2 injection in this process is done primarily for EOR, it comes with the added benefit of storage of CO_2 contributing to minimizing the global warming scourge.

2.4 GEOLOGICAL CARBON TRANSPORT

Geological carbon transport refers to the movement of CO_2 within underground formations, primarily in the context of carbon capture, utilization, and storage (CCUS**)**. It involves the migration, trapping, and long-term containment of CO_2 within deep geological reservoirs. This process is essential for mitigating climate change by preventing CO_2 from reaching the atmosphere.

2.4.1 PIPELINE TRANSPORT

Pipeline transport in geological formations refers to the movement of CO_2 through subsurface pipelines for injection into deep underground reservoirs, primarily for carbon capture, utilization, and storage (CCUS) and enhanced oil recovery (EOR). The process begins with CO_2 being captured from industrial sources and compressed into a supercritical state to facilitate efficient transport. Pipelines, designed to withstand high pressure and resist corrosion from CO_2 interactions with water, then deliver the gas to geological storage sites. Once at the injection site, CO_2 is pumped through wellbores into porous rock formations such as deep saline aquifers, depleted oil and gas reservoirs, or unmineable coal seams.

The efficiency of CO_2 transport in geological formations depends on maintaining controlled pressure and temperature conditions within the pipeline to prevent phase changes that could cause operational challenges.

2.4.2 SHIP TRANSPORT

CO_2 ship transport is an emerging alternative to pipeline transport, particularly for long-distance, offshore, and international carbon capture, utilization, and storage (CCUS) projects. Unlike pipelines, which require extensive infrastructure and high upfront costs, ships offer flexibility and scalability, making them suitable for projects that need to transport CO_2 across oceans or between regions where pipelines are not feasible. Typically, CO_2 is transported in a liquefied state under cryogenic conditions at temperatures between -50°C to -60°C and pressures of 6-7 bar. This ensures efficient storage and transport while minimizing the risk of phase changes that could disrupt operations.

Specialized CO_2 carriers, similar in design to LNG or LPG tankers, are equipped with insulated cryogenic tanks and pressure control systems to maintain CO_2 in its liquid phase. The transport process begins with CO_2 capture from industrial sources, followed by compression and cooling to achieve liquefaction. Once at a CO_2 export terminal, the liquefied gas is transferred into ships using insulated pipelines. During the voyage, temperature and pressure are continuously monitored to ensure safe transport. Upon arrival at the destination, CO_2 is offloaded to geological storage sites, enhanced oil recovery (EOR) fields, or industrial utilization plants. In offshore storage projects, CO_2 is often injected directly into deep saline aquifers or depleted oil and gas reservoirs, ensuring long-term containment.

Despite its advantages, CO_2 ship transport faces several challenges, including high energy demands for refrigeration, the need for specialized port infrastructure, and strict safety regulations imposed by the International Maritime Organization (IMO). Additionally, while ship transport is more flexible than pipelines, it remains costlier per ton of CO_2 for large-scale continuous transport. However, its ability to facilitate cross-border CO_2 trade makes it a critical component of international CCUS initiatives. Projects like Norway's Northern Lights have already demonstrated the feasibility of CO_2 shipping for offshore sequestration, paving the way for global deployment. Beyond CCUS, CO_2 ship transport is also being explored for applications in CO_2-plume geothermal (CPG) systems, where CO_2 is used as a working fluid for geothermal heat extraction. As carbon management strategies continue to evolve, ship-based CO_2 transport is likely to play a significant role in enabling decarbonization and large-scale CO_2 sequestration efforts worldwide.

2.5 GEOLOGICAL CARBON INJECTION MECHANISMS

Once captured, the CO_2 is compressed into a fluid almost as dense as water and pumped down through a well into a porous geological formation. The pores in underground formations are initially filled with a fluid – either oil, gas, or salty water. Whilst a majority of existing CCS facilities utilise storage associated with EOR, future deployment of CCS will increasingly require storage in deep saline aquifers, which have wider geographical distribution and larger theoretical storage resources in comparison to oil and gas reservoirs. Because injected CO_2 is slightly more buoyant than the salty water that co-exists within the storage formation, a portion of the CO_2 will migrate to the top of the formation and become structurally trapped beneath the impermeable cap rock that acts as a seal. In most natural systems, there are numerous barriers between the reservoir and the surface. Some of the trapped CO_2 will slowly start to dissolve into the saline water and become trapped indefinitely (called solution trapping); another portion may become trapped in tiny pore spaces (referred to as residual trapping). The ultimate trapping process involves dissolved CO_2 reacting with the reservoir rocks to form a new mineral. This process, called mineral trapping, may be relatively quick or very slow, but it effectively locks the CO_2 into a solid mineral permanently.

CHAPTER THREE

METHODOLOGY

3.1 Data Acquisition

Data acquisition in the Niger Delta formation for geological carbon storage (GCS) involves integrating advanced modeling techniques to enhance reservoir characterization, injection efficiency, and long-term containment assessment. A 2-D reservoir model is essential for simulating CO_2 injection dynamics at a finer scale, capturing variations in porosity, permeability, and fluid flow behavior within the reservoir. This helps in evaluating injectivity, pressure buildup, CO_2 gas saturation, reservoir pressure, mole fraction of dissolved phase, sweep efficiency and potential leakage pathways.

At a broader scale, a basin 3D model provides a comprehensive geological framework, incorporating stratigraphy, tectonic history, and hydrogeological processes to identify 3D dipped saline reservoir with multiple vertical injection wells. We used a semi-adaptive local grid refinement approach to achieve high resolution around each injection well suitable for CO_2 sequestration.

For site selection, a site selection tool utilizes multi-criteria analysis, integrating geological, geomechanical, and economic factors to prioritize locations with optimal storage potential while minimizing environmental and operational risks. Advanced machine learning techniques, such as the Nested Fourier Neural Operator (Nested FNO), further enhance the accuracy of predictive models by learning complex spatial and temporal patterns in subsurface data. By leveraging frequency-domain representations, Nested FNO improves computational efficiency in simulating CO_2 plume migration, reservoir pressure evolution, and caprock integrity over extended timescales. The combination of these data acquisition and modeling approaches ensures a robust evaluation of storage capacity, injectivity, and long-term containment security, supporting the safe and effective implementation of carbon storage projects in the Niger Delta.

3.2 Machine Learning Model Development

Machine learning is one of the fastest developing intelligent technology fields at present era which is considered as a substantial means to realize forecast demand relying on computer science and data statistics. This project work provided a comprehensive review of ML applications in CCS, based on classical ML methods and mainstream research directions in CCS.

The study shown that ML algorithms such as artificial neural network (ANN) and convolutional neural network (CNN) were widely used, mainly for predicting physical properties, evaluating mechanical stability, and monitoring CO_2 plume migration and leakage during CO_2 storage.

Support vector machine (SVM) was generally combined with other ML methods for the prediction of petrophysical properties and sensitivity analysis of influencing factors. Deep learning (DL) algorithms, represented by generative adversarial network (GAN) and long short-term memory (LSTM), had shown good results in real-time monitoring of CO_2 migration and leakage. Decision tree (DT) and random forest (RF) were mainly used to establish risk assessment and decision analysis framework, and estimate the success probability of CCS.

The diagram below shows a flowchart representing the steps utilized for the development of the machine learning models to be/used for/in this study. The data generated from the CMG software was stored in an excel workbook format. The data was then exported to a python environment (Jupyter notebook), where all data processing and machine learning operations was carried out.

The models utilized in this work were SVM, ANN,FNO, CO_2 gas saturation distribution and comparative computational efficiency, which were all implemented in the python environment (Jupyter Notebook) using different libraries and their appropriate versions. We would talk more extensively in this session when the models and have been developed and all necessary information are consequentially made available.

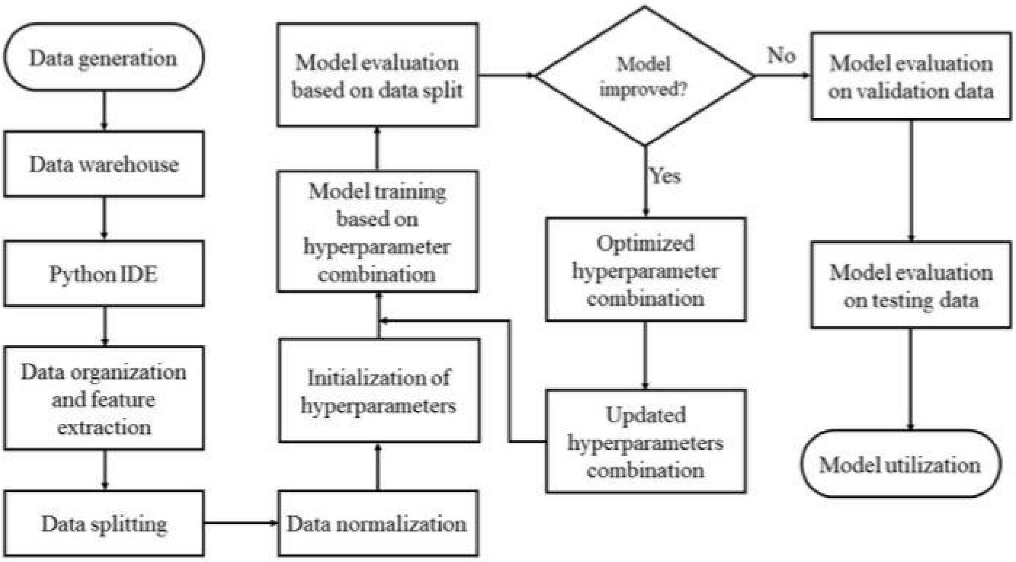


Fig: Machine Learning Workflow

3.2.1. Support Vector Machine (SVM)

SVM is a popular supervised learning algorithm that can be used for classification or regression problems. The SVM model maps the input data into a higher-dimensional space to find the best hyperplane that separates the data points into different classes. It is desirable if the hyperplane is far from the closest training data points for any class (Katongtung et al., 2022).

SVM has been generalized to be used for regression purposes and in this regard, it is termed support vector regression (SVR). For a given vector of input features (x = $xi \in \mathbb{R}$; i, …, n) and for a vector of target outputs (y = $\mathbb{R}\ n$), SVR produces a linearly correlated regression model of the form shown in Equation 1.

$$f(x) = w^{T}\phi(x)+b \quad (1)$$

where w and b are the vectors of model weight and bias determined by solving Equation 2, which involves minimizing the cost function.

$$Tw + C \sum \zeta\, i\, n\, i=1 + \zeta\, i\, * \quad (2)$$

where C and ζ are hyperparameters referring to the penalty term and error term away from the hyperplane. Prediction by the SVR model is estimated using the lagrangian dual method as shown in Equation 3.

$$f(x) = \sum (\alpha i \; n \; i{=}1 + \alpha i *) K(xi , xj) + b \qquad (3)$$

where α and K refer to the Lagrange multiplier and kernel. Various kernels that were assessed to determine the most suitable one included radial basis function (RBF), polynomial, sigmoid, and linear.

3.2.2 Artificial Neural Network

Artificial neural network (ANN) is an analogue model, that simulates the neural network system of human brain for information processing. Neuron is the basic unit of neural network, and each neuron has two ports of input and output. A large number of neurons build each other, and different networks can be formed by different connection patterns (Peiye yao .et.al).

This is also a computational model inspired by the structure and function of the biological neural networks that make up the brain. The ANN model used for this study was a feed-forward neural network consisting of n hidden layers each with a set of neurons that can estimate a given output response (y) from provided input data (x).

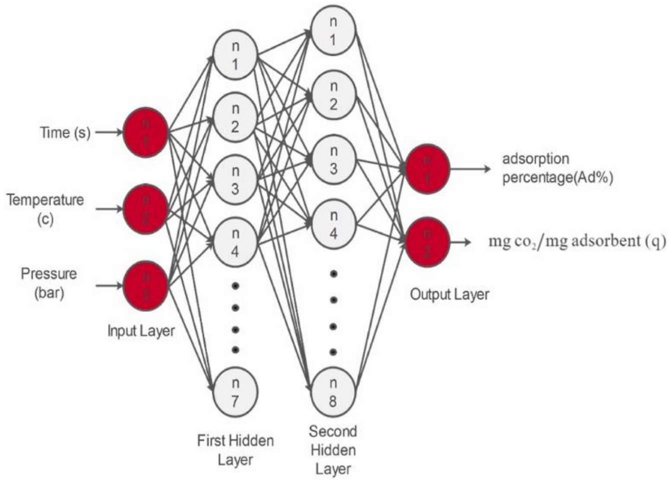


Fig: ANN Architecture for the implemented dataset (H.J. Jung, 2011)

The mathematical concept of ANN involves a set of interconnected nodes or neurons that process and transmit information. Each neuron calculates a linear combination (z) of n input features ( ) with corresponding weight (w) and bias (b) as shown in Equation 4. The weights of the connections between the neurons are adjusted during training to minimize the error between the predicted output and the true output. The selection of the right activation function is very essential in the ANN modelling process as it is chiefly responsible for the mapping of the inputs to the outputs.

$$z = \sum xiwi\ n\ i{=}1 + b \qquad (4)$$

During the ANN process, the transformed version of the output data is forwarded from one hidden layer to another. The network is trained through an updating process that tunes the model weights to minimize model loss (L) which is typically taken as the root mean square error (RMSE) as shown in Equation 5

where $\hat{y}i$ is the model prediction. The minimization is done through a gradient descent method where the weights are manipulated as a function of L and scaled using the learning rate (λ).

3.2.3 Carbon Capture Storage Network (CCSNet)

CCSNet is an open-source software platform developed by researchers at Stanford University for modeling CO_2 storage reservoirs using machine learning neural networks. This software is 10,000 to 100,000 times faster and more accurate compared to competitive top tier numerical simulations . CCSNet provides numerous outputs for carbon dioxide storage projects including but not limited to CO_2 gas saturation, pressure buildup, and mass balance (Gege wen, 2021).

The network is a deep learning-based framework designed for modeling CO_2 storage in geological formations. It leverages machine learning (ML) to predict CO_2 migration, assess storage capacity, and optimize injection strategies for carbon capture and storage projects. This approach is particularly useful for handling complex subsurface dynamics, where traditional numerical simulations (such as finite difference or finite element methods) can be computationally expensive and takes more time to predict Co2 sequestration.

Here we developed CCSNet, a deep-learning modeling suite that can act as an alternative to conventional numerical simulators for carbon capture and storage (CCS) problems well-represented by a 2D radial grid, for example, injection into an infinite acting saline formation with no or very small dip. CCSNet consists of a sequence of deep learning models producing all the outputs that a numerical simulator typically provides, including saturation distributions, pressure buildup, dry-out, fluid densities, mass balance, solubility trapping, and sweep efficiency. The results are 103 to 104 times faster than conventional numerical simulators.

As an application of CCSNet illustrating the value of its high computational efficiency, we developed rigorous estimation techniques for the sweep efficiency and solubility trapping.

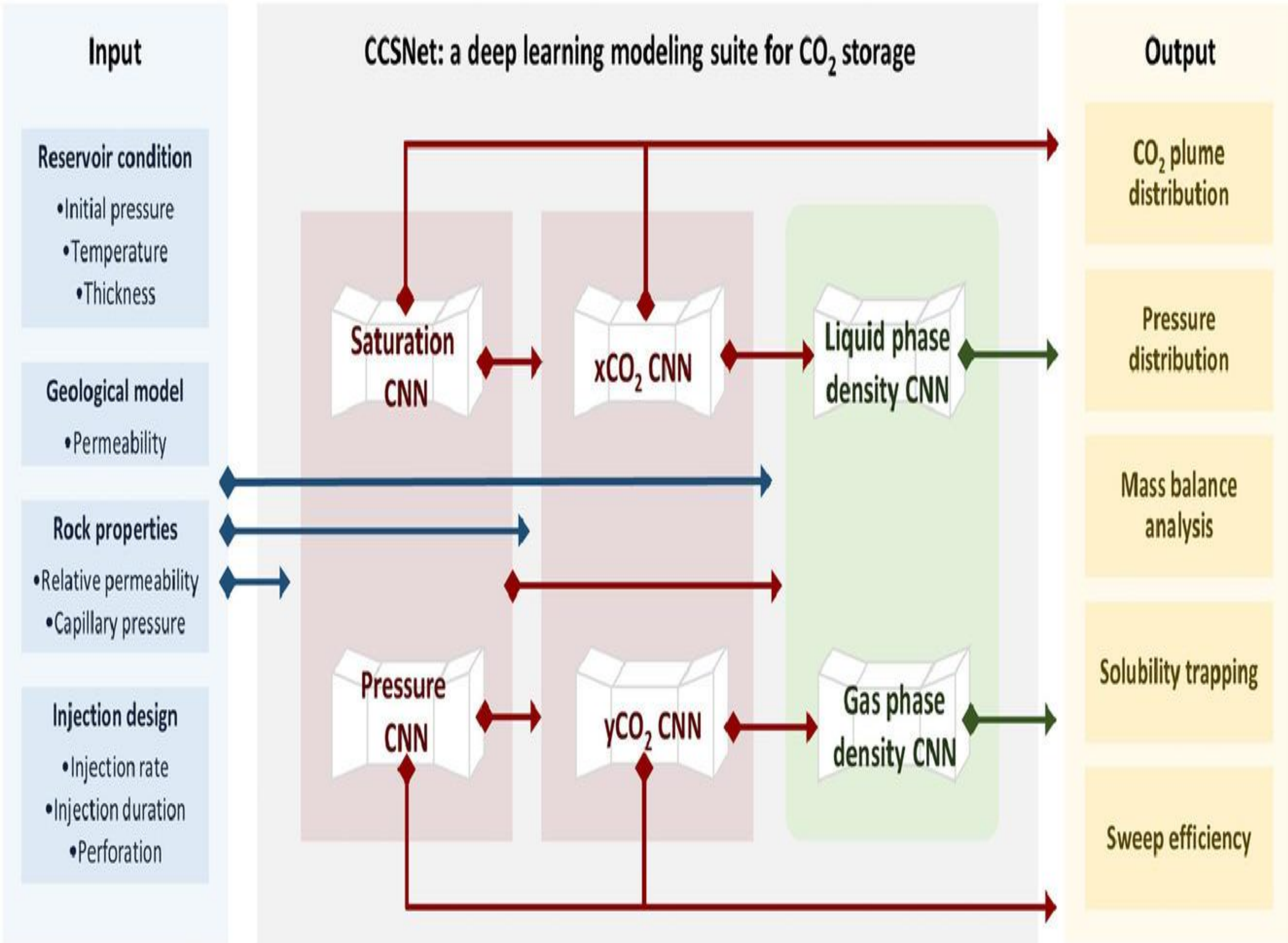


Fig: A deep learning Models for geological carbon storage (gege wen, 2021)

3.2.3.1 Convolutional Neural Network (CNN):

A Convolutional Neural Network (CNN) is a type of Deep Learning neural network architecture commonly used in Computer Vision that enables a computer to understand and interpret the image or visual data. CNN play a crucial role in geological carbon storage (GCS) by enhancing reservoir characterization, monitoring CO_2 plume migration, and assessing potential risks. In reservoir characterization, CNNs are widely used for seismic interpretation, automatically identifying faults, fractures, and stratigraphic features from seismic images, which helps in selecting optimal CO_2 injection sites.

For monitoring CO_2 migration, CNNs process time-lapse seismic data to track changes in the subsurface, allowing for the detection of unexpected plume movement or potential leakage. They also analyze satellite-based Interferometric Synthetic Aperture Radar (InSAR) data to detect surface deformation caused by CO_2 injection, providing an early warning system for potential storage integrity issues. In well logging and injection optimization, CNNs automate the interpretation of geophysical well logs, predicting rock properties and fluid saturations to optimize injection depths. They also process real-time injection data, such as pressure, temperature, and flow rate, to detect anomalies and prevent risks such as formation fracturing or wellbore failure.

Beyond monitoring, CNNs contribute to risk assessment by identifying potential leakage pathways. By analyzing seismic and geomechanical data, they predict fault reactivation risks and detect microseismic events that may indicate induced seismicity due to CO_2 injection. At the pore scale, CNNs facilitate fluid flow simulations by analyzing digital rock images, providing a faster and more cost-effective alternative to traditional numerical simulations. Overall, CNNs significantly enhance the efficiency and accuracy of geological carbon storage by automating complex image and signal analysis, ensuring safe and effective CO_2 sequestration.

In a CNN, a convolutional layer applies a filter over an input matrix to compute a feature map. Mathematically, the convolution operation between an input XXX and a filter WWW is expressed as:

$$Y(i, j) = \sum_{m-0}^{M-1} \sum_{n-0}^{N-1} W(m,n)X(i-m, i-n)$$

3.2.4 Fourier Network Operator (FNO).

Fourier neural operator (FNO) is a type of neural operator that offers especially remarkable predictability for flow-related problems. It uses the Fourier transform to learn the solution operator efficiently. A variant of FNO was recently proposed for predicting 2D CO2–water multiphase flow with great generalization and accuracy. However, despite the advances in model generalization, the development of machine learning approaches for CO2 storage is impeded by the multi-scale challenge that both high grid resolution and large spatial domain are required. Previous machine learning models are limited to either 2D problems that can only represent flat reservoirs with a single injection well,or 3D problems with very coarse resolutions that fail to capture essential physics (Gege wen, Zongyi Li, et.al, 2022).

In this project we present a machine learning framework with an unprecedented capability of high-resolution dynamic 3D modeling for basin-scale CO2 storage. We integrate the FNO machine learning architecture with a semi-adaptive LGR modeling approach for numerical simulation and present the Nested Fourier Neural Operator (Nested FNO) architecture. As shown in Fig. 1, five levels of FNOs are used to predict flow responses in five different resolutions. This approach vastly reduces the computational cost needed during data collection as well as overcomes the memory constraints in model training (Royal society of chemistry, 2023).

Using this approach, our prediction resolution exceeds many benchmark CO2 storage simulations run with existing numerical models, such as Sleipner benchmark model43 and Decatur model.Meanwhile, Nested FNO only needs less than 2500 training data at the coarsest resolution and about 6000 samples for the finer resolutions. Despite the small training size, it generalizes well to the large problem dimension with millions of cells and a diverse collection of practical input variables. In addition, Nested FNO offers real time forecasts, where the inference speed is 700 000 times faster compared to the state-of-the-art numerical solver. The fast inference enables many critical tasks for CCS decisionmaking that were prohibitively expensive. For example, we present a rigorous probabilistic assessment for maximum pressure buildup and CO2 plume footprint. Such assessment can reduce uncertainties in capacity estimation and injection designs; however, it would have taken nearly two years with numerical simulators. Using Nested FNO, this assessment took only 2.8 seconds. These high-quality real-time predictions can greatly improve our ability to develop safe and effective CCS projects (Gege wen, Zongyi Li, et.al, 2022).

.

The numerical simulation data is generated using a semiadaptive LGR approach to ensure high fidelity and computational tractability. We use global (level 0) resolution grids in the large spatial domain to mimic typical saline storage formations with infinite boundary conditions. Next, we apply four levels of local refinements (levels 1 to 4) around each well to gradually increase the grid resolutions. Going from levels 0 to 4, we reduce the cell size by 80 on the x , y dimensions and 10 on the z dimension to resolve near-well plume migration, dry-out, and pressure buildup. In addition to resolving appropriate physics, two practical constraints need to be considered when designing the LGRs: first, the refining ratio between adjacent coarser and finer-level models should be moderate in order to ensure numerical simulation stability; and second, the dimension of each refinement level is subject to the memory constraint during machine learning model training. See ESI† for full details on the LGR design, governing PDEs, and numerical simulation setups (Gege wen, Zongyi Li, et.al, 2022).

3.2.4.1 Nested FNO Architecture:

The computational domain of the Nested FNO is a 3D space with time, $D = \Omega \times T$, where T is the time interval of period of years and Ω is the reservoir domain. In this project we use a sequence of models to predict the 3D reservoir domain consisting of subdomains $\Omega_{I,j}$ at levels i around each well j (Fig. 1). At each refinement level, we extend the original FNO architecture into 4D to produce outputs for pressure buildup (P) and gas saturation (S) in the 3D space-time domain.

The input for each model includes the permeability field, initial hydro-static pressure, reservoir temperature, injection scheme, as well as spatial and temporal encoding. In CO2 storage, pressure buildup travels significantly faster than gas saturation.

3.2.4.2 CO_2 Plume Prediction

Numerical modeling of the migration of the CO2 plume prediction is a prerequisite to effective CCS projects. It is used throughout the site screening, permitting, designing, operating, monitoring and closure processes (NETL, 2017). In a geological formation, the migration of the CO2 is controlled by a complex interplay of viscous, capillary, and gravity forces. Once CO2 is injected into the formation, it migrates away from the injection well while rising upward since CO2 is lighter than the formation fluid. The injected CO2 is subject to the risk of leakage if it encounters permeable faults or leaky well bores.

Figure 1 shows a schematic of a CO2 plume in a geological formation.

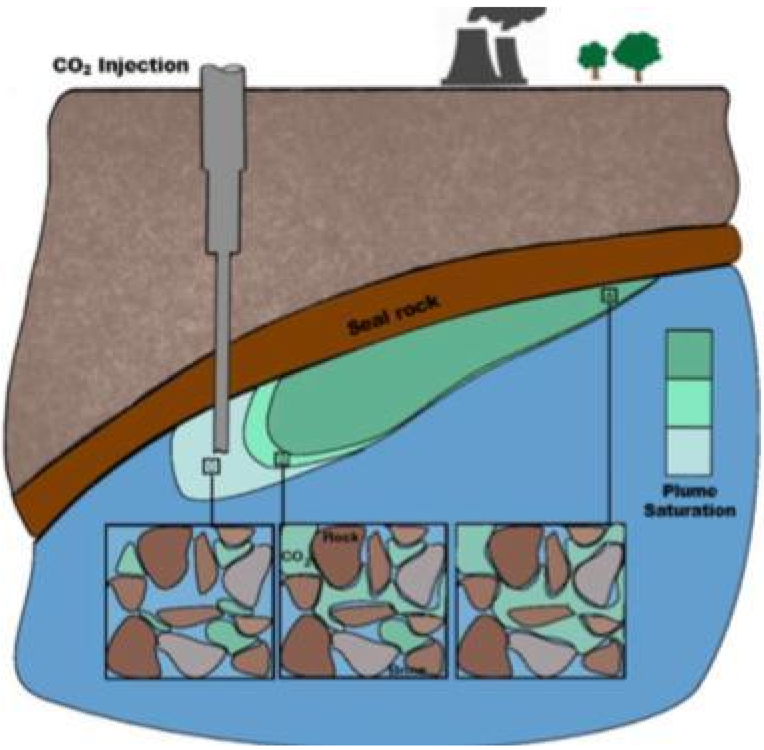


Figure: Schematic of CO2 plume in geological formation (not to scale). Figure modified from Krevor et al. (2015).

3.2.4.3 Pressure Build Up Prediction:

For basin-scale CCS projects, pressure buildups caused by different injection activities can interfere with one another. As demonstrated in Fig below, Nested FNO precisely captures the local pressure buildup responses around each well, as well as the global interaction among them. The high resolution refinements provide accurate estimates of the maximum pressure buildup, which is an essential indicator of reservoir integrity. The global level prediction provides the spatial extent of the region of pressure buildup influence, another important parameter required for regulatory purposes.49 Additionally, The figure below shows that accuracy is consistent across different resolutions and throughout the injection period. These predictions are sufficient to guide important engineering decisions, such as choosing injection rates.

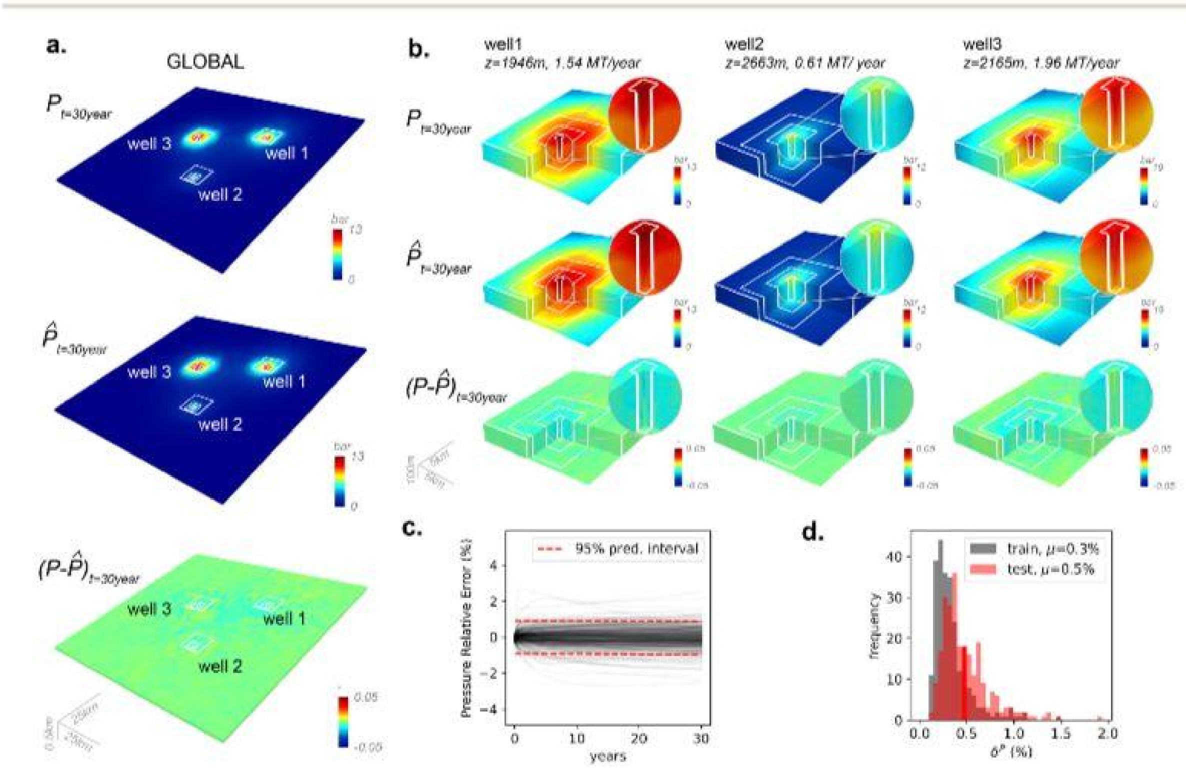


Fig: Pressure buildup prediction. (a) Global and (b) well pressure buildup predictions at 30 years. Each row shows pressure buildup ground truth, prediction, and relative error. The white lines indicate the boundary between each level. (c) Testing set pressure relative error versus time for 250 random cases. The red dotted line shows the 95% prediction bands of the error. (d) Error histograms for 250 cases in the training and test set. The solid red column indicates the error for the visualized example (Royal society of chemistry, 2023).

3.2.4.4 Computational Speed-Up

Once Nested FNO is trained, the diverse input range allows it to act as a computationally efficient alternative to simulators. Users can skip traditional simulations and directly obtain high-fidelity and high-resolution predictions by inferring the trained machine learning models. Our approach differs from the task-specific ''surrogate'' modeling approach which only considers a specific set of reservoirs for a certain use case.

We analyze the computational speedup by comparing the Nested FNO's prediction time to the numerical simulation run time of a state-of-the-art full-physics simulator ECLIPSE. Nested FNO's prediction time varies from 0.025 s to 0.085 s depending on the number of injection wells and the total number of grid cells. On average, the Nested FNO provides 400 000 (1 well case) to 700 000 (4 well case) times speedup compared to ECLIPSE. Notice that for numerical simulations, the run time can vary significantly even for cases with the same number of grid cells. Simulation time depends on the case's complexity, i.e., the number of iterations required by the linear solvers to achieve convergence. On the contrary, the prediction time of Nested FNO is irrelevant to case complexity.

3.2.4.5 Probabilistic assessment

Nested FNO's fast prediction speed enables rigorous ensemble modeling and probabilistic assessments that were previously unattainable. As an example, we conducted a probabilistic assessment for the maximum pressure buildup and CO2 plume footprint for a four-well CCS project where each well injects at a 1 MT per year rate.

To investigate the influence of permeability heterogeneity, we generate 1000 realizations using a fixed set of distribution and spatial correlations, then use Nested FNO to predict gas saturation plumes and pressure buildup for each realization. Refer to ESI,† Probabilistic assessment for detailed setups.

For CO2 storage projects in saline formations, it is common to have high uncertainties over reservoir geology due to limited well logs in the nearby region. Probabilistic assessments with a large number of permeability realizations can help project developers and regulators manage uncertainties. As shown in Fig. below, we obtained probabilistic estimates of the CO2 plume footprint and maximum pressure buildup. For example, the plume footprint helps determine the area of the land lease acquisition required;

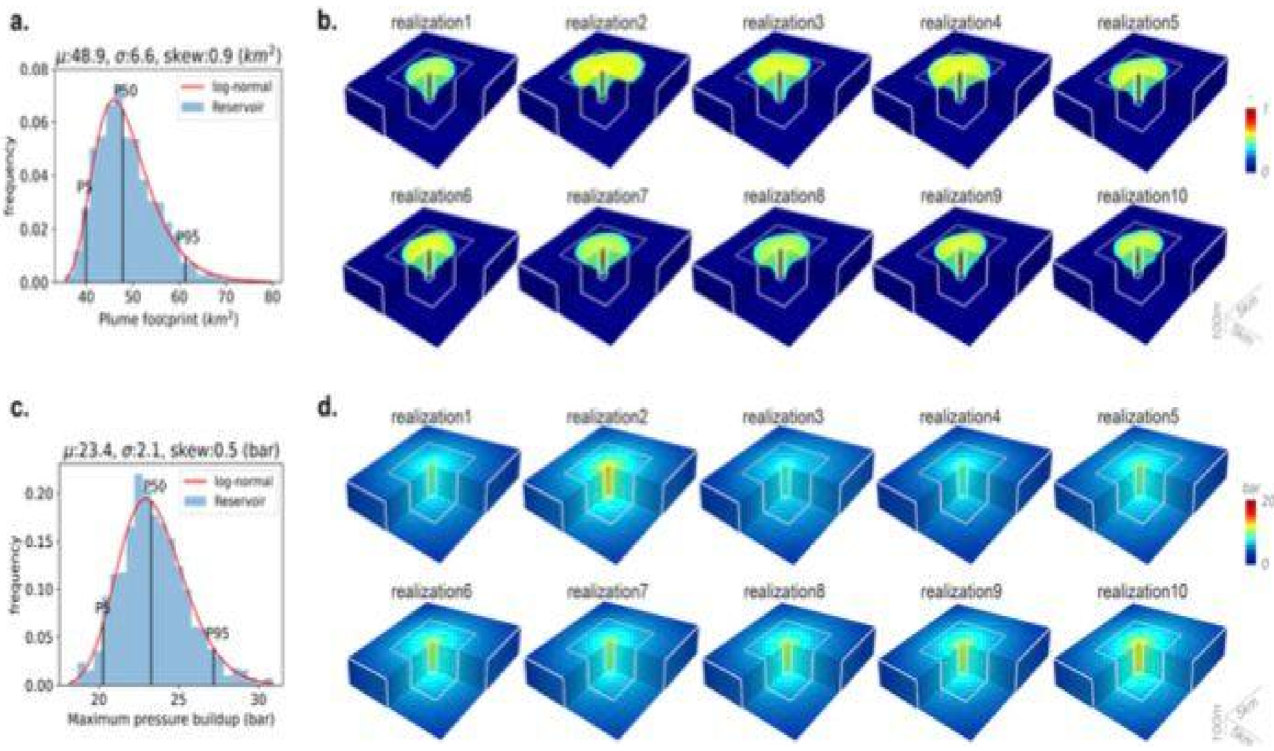


Fig: Probabilistic assessment. (a) Histogram of CO2 plume footprint predictions given 1000 permeability realizations from the same geological parameters. The result satisfies a log-normal distribution; P5, P50, and P95 are marked on the distribution. (b) Ten realizations of CO2 plume at 30 years. (c) Histogram of CO2 pressure buildup predictions given the same 1000 permeability realizations. The result satisfies a log-normal distribution; P5, P50, and P95 are marked on the distribution. (d) Ten realizations of pressure buildup at 30 years (Department of energy science, standford university).

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Data Overview

For the Modelling used,Nested Fourier Network Operator was used and the python code for the Nested FNO model architecture and data set were also used in training at the Github repository.

The Nested Fourier Neural Operator (Nested FNO) model offers a powerful solution for rapidly predicting high-resolution, time-evolving 3D fields such as gas saturation and pressure buildup in carbon capture and storage (CCS) scenarios. By dramatically accelerating the simulation process, this model enables tasks that require numerous forward runs to be performed efficiently. For instance, during the site screening phase, Nested FNO allows for fast probabilistic evaluations of key metrics like storage capacity, peak pressure, and plume extent across multiple candidate reservoirs. These rapid assessments can be integrated with ranking and decision-making workflows to improve the likelihood of selecting viable storage sites. Furthermore, the model is well-suited for optimization studies, where extensive exploration of engineering design parameters is needed to fine-tune injection strategies.

Once injection operations begin, machine learning-based approaches like Nested FNO can also be leveraged for inverse modeling tasks such as seismic data interpretation. This is particularly beneficial as traditional high-fidelity numerical simulations are computationally intensive and often impractical for repeated inversion tasks. Consequently, simpler surrogate models such as vertical equilibrium simulators have typically been used, despite their limitations. Introducing fast yet accurate surrogates like Nested FNO can lead to more robust analyses, reduced uncertainty, and faster deployment timelines for CCS technologies.

The type of data used for this field comprises of the reservoir data. The data below shows an example of data set that was used:

Table 4: Range Of Data Sets

WELL NAME	GR	RT	RHOB	NPHI	DT
Nick-005	Yes	Yes	Yes	Yes	No
Nick-019	Yes	Yes	Yes	Yes	No
Nick-023	Yes	Yes	Yes	No	No
Nick-031	Yes	Yes	Yes	Yes	No
Nick-033	Yes	Yes	Yes	Yes	No
Nick-035	Yes	Yes	Yes	Yes	No
Nick-036	Yes	Yes	Yes	Yes	No
Nick-038	Yes	Yes	Yes	Yes	No
Nick-046	Yes	Yes	Yes	Yes	Yes
Nick-056	Yes	Yes	Yes	Yes	No

The data sets that was initially provided was from offset wells in the Niger Delta Field. This data sets consists of sets of data which was completely run by simulation.

Table 4.2: Dataset of well examples

C1000

Well	NTG	Av_Shale Volume	Av_Porosity	Av_Water Saturation	Av_Permeability
NICK-019	0.684	0.177	0.356	0.756	121.482
NICK-031	0.939	0.16	0.327	0.167	98.738
NICK-033	0.871	0.112	0.346	0.485	108.917
NICK-035	0.835	0.194	0.326	0.236	58.818
NICK-036	0.975	0.158	0.299	0.664	68.302
NICK-038	0.931	0.214	0.33	0.556	60.753
NICK-056	0.972	0.06	0.318	0.994	90.257

Data Snipets Of Otumara Field

↓	Code	Field Trap Code	Sand	Sand Type	Sand Discovery Year	Water Depth	Subsea Depth	Total Net Thickness	Total Volume	Porosity	Permeability	Temperature	Pressure	Latitude	Longitude
6		Structural	Fine	B	2015	4,790	5,100	0.972	0.06	0.318	90.257	29	31	5`19"	6`28"
5		Structural	Fine	B	2015	4,690	4,990	0.931	0.214	0.33	60.753	29	31	5`19"	6`28"
4		Structural	Fine	B	2015	4,630	4,880	0.975	0.158	0.299	68.302	29	31	5`19"	6`28"
3		Structural	Fine	B	2015	4,600	4,770	0.835	0.194	0.326	58.818	29	31	5`19"	6`28"
2		Structural	Fine	B	2015	4,540	4,660	0.871	0.112	0.346	108.917	29	31	5`19"	6`28"
1		Structural	Fine	B	2015	4,480	4,550	0.939	0.16	0.337	98.738	29	31	5`19"	6`28"
0		Structural	Fine	B	2015	4,420	4,440	0.684	0.177	0.356	121.482	29	31	5`19"	6`28"

The following was done to gain the results that will be discussed below. On receiving the raw data of the different wells in the Niger Delta Field: This dataset is prepared for CO_2 sequestration site assessment and follows the required format. All data is organized in CSV format with each column representing a specific parameter and each row corresponding to a site or sample point. Units are in the metric system throughout. The following key parameters are included: depth (m), temperature (°C), pressure (MPa), porosity (fraction or %), permeability (mD), formation thickness (m), net-to-gross ratio, salinity (ppm or g/L), caprock integrity indicators, and where available, seismic or structural data. All columns are clearly labeled, and mandatory fields are complete. This format ensures that the dataset is suitable for proper evaluation of CO_2 storage potential.

4.2 RESULTS AND DISCUSSION

The results were gained and it was used to plot graphs. The graphs are shown below. In all the simulator, 70% of the data was used for training the model, 15% for validating the model performance and 15% testing the data. The figure below show the graph in the utilized data sheet.

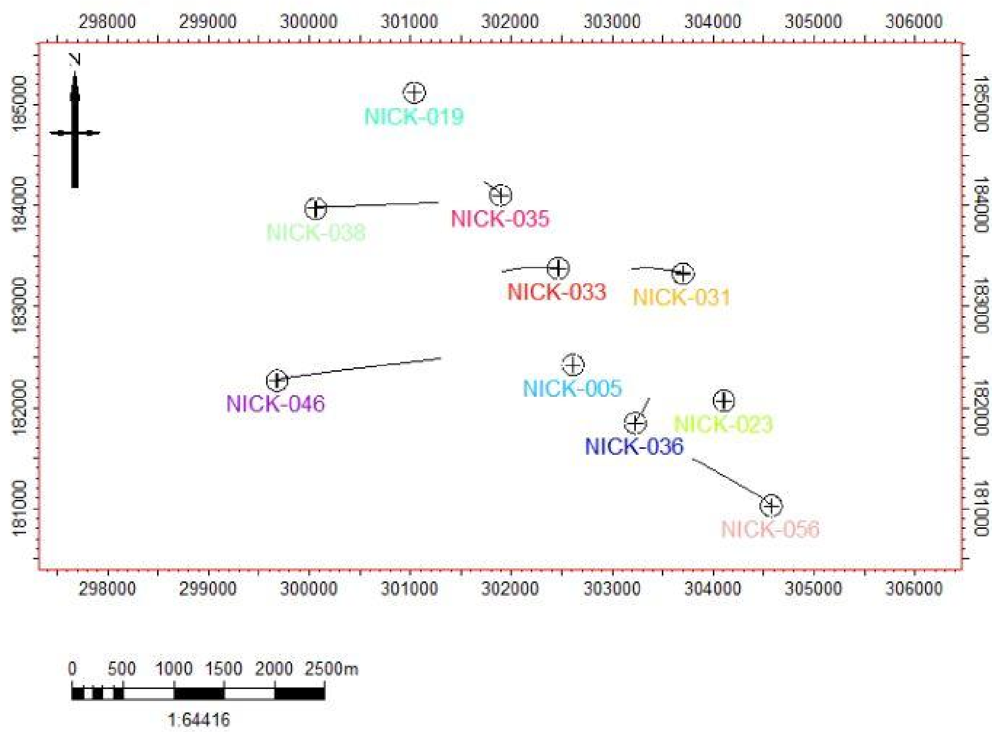


Fig: Correlations between different wells in Otumara Field in the Niger Delta Region.

Training procedure:

The Nested FNO architecture consists of models ξ_0^P...4 for pressure buildup and ξ_1^S...4 for gas saturation. To train these models, we first prepare the input–output pairs for each subdomain and train each of the nine models independently. For each model, we use the ground truth numerical simulation pressure buildup and gas saturation on the coarse-level training domain to construct the input. This approach is time efficient because it allows us to train all models concurrently instead of sequentially going from coarser-level to finer-level models.

Refer to ESI,† Training procedure for full detail:

Inference Procedure:

Algorithm 1

Predict gas saturation and pressure buildup in a reservoir with n injection wells. ξ denotes the a model, P denotes pressure buildup, S denotes gas situation, and (a) denotes input

Use ξ_0^p to predict P^0 given a_0
For each well j = 1,...,n do
Construct input (a1,j, P^0|j)
Use $\xi_0^p and$d above input to predict $P\hat{}_{ij}$
Use ξ_1^s and above input to predict $S\hat{}_{I,j}$
for each level i = 2,...,4 do
Construct input (a_{ij}, $S\hat{}_{I,j}$)
Use $\xi_i^S$and above input to predict $S\hat{}_{ij}$
Construct input (ai,j, P^i1,j)
Use ξ_i^P and above input to predict $P\hat{}_{ij}$

end for.

Once we train the nine models in the Nested FNO, we can predict the gas saturation and pressure buildup according to Algorithm 1.

The inference input can be constructed given any random combination of reservoir condition (depth, temperature, and dip angle), injection scheme (number of wells, rate, location, perforation interval), and permeability field characteristics (mean, standard deviation, correlation lengths on x, y, and z directions), as long as the variables are within the training data sampling ranges.

Notice that the number of subdomains in Ω depends on the number of injection wells. For example, a reservoir with three injection wells has 13 subdomains Ω = {Ω0, $\Omega_{\text{level1...4,well1}}$, $\Omega_{\text{level1...4,well2}}$, $\Omega_{\text{level1...4,well3}}$}. We repeat the inference procedure for each injection well.

Separate vs. sequential prediction.

As described in Algorithm 1, during inference, the input for each model in levels 1 to 4 consists of Sˆ or Pˆ predicted by their corresponding coarser-level model. However, during training, the inputs are constructed by ground truth numerical simulation data. The discrepancy in training and inference leads to error accumulation, especially for the models that appear later in the prediction sequence. Also, due to this effect, a deeper Nested FNO with more refinement levels will be more susceptible to error accumulation compared to a shallower Nested FNO.

To investigate this effect, we introduce two ways to evaluate each model: (1) separate prediction using the ground truth input taken from the numerical simulation (as in training), and (2) sequential prediction using predicted values from the coarser level as input (as in inference).

Fig. 5a shows that all models have low errors and negligible overfitting when using separate predictions. However, with sequential prediction, quickly accumulates, going from coarser to finer-level models. The validation error of level 4 using sequential prediction increased by 13 times compared to separate predictions.

Fig. 5d compares dS Oi using separate verses sequential prediction. We observed less error accumulation for gas saturation than pressure buildup, which indicates that the prediction of gas saturation does not rely as heavily on coarser-level models.

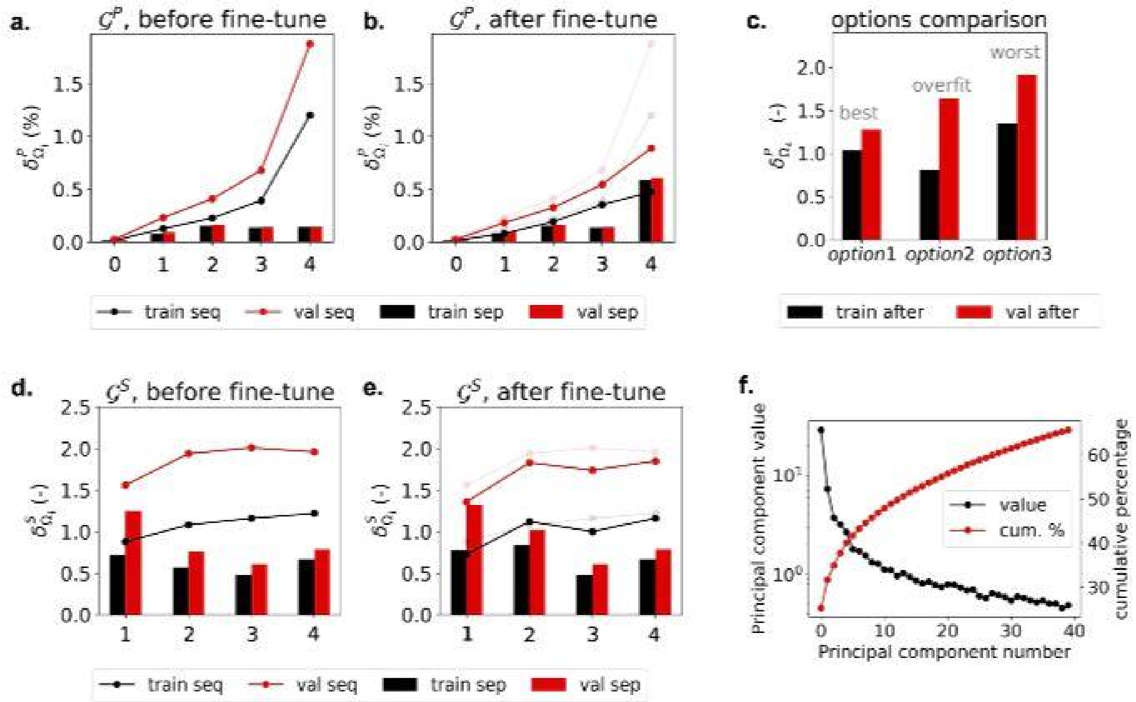
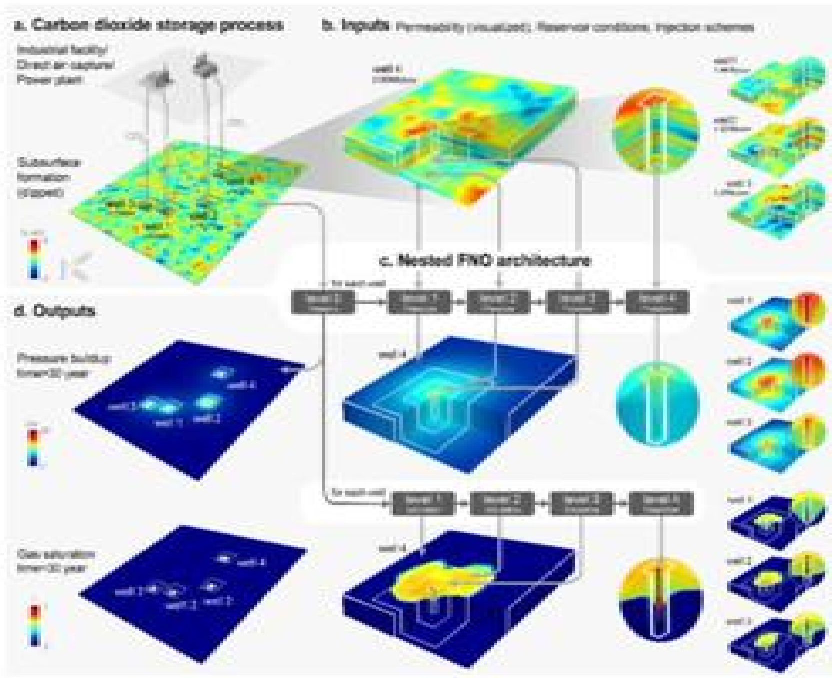


Fig. 5 Fine-tuning. Each model's separate and sequential error for (a). Pressure buildup before fine-tuning, (b). Pressure buildup after fine-tuning, (d). Gas saturation before fine-tuning, and (e) Gas saturation after fine-tuning. On the legend, 'seq' denotes sequential prediction, 'sep' denotes separate prediction. The transparent lines indicate the before fine-tune error. (e) Training and validation set δ_4^P of fine-tuning using Option 1 to 3. (f) Principle component number and cumulative percentage of the 40 strongest rank for $\xi_3^{P`}$ error.

RESULTS



Introduction to Nested FNO in a Multiple vertical wells using 3-D Model.

The Graphs/Plots below show the actual vs predicted values of the conducted CNN Models utilized in the study.

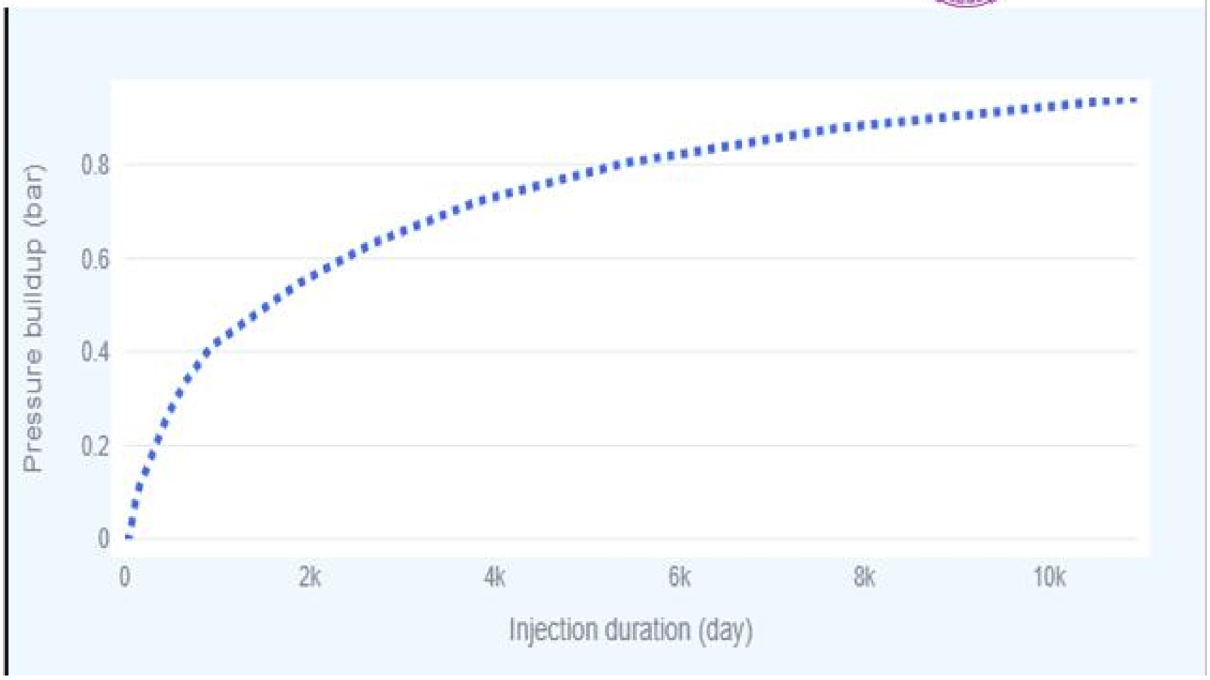
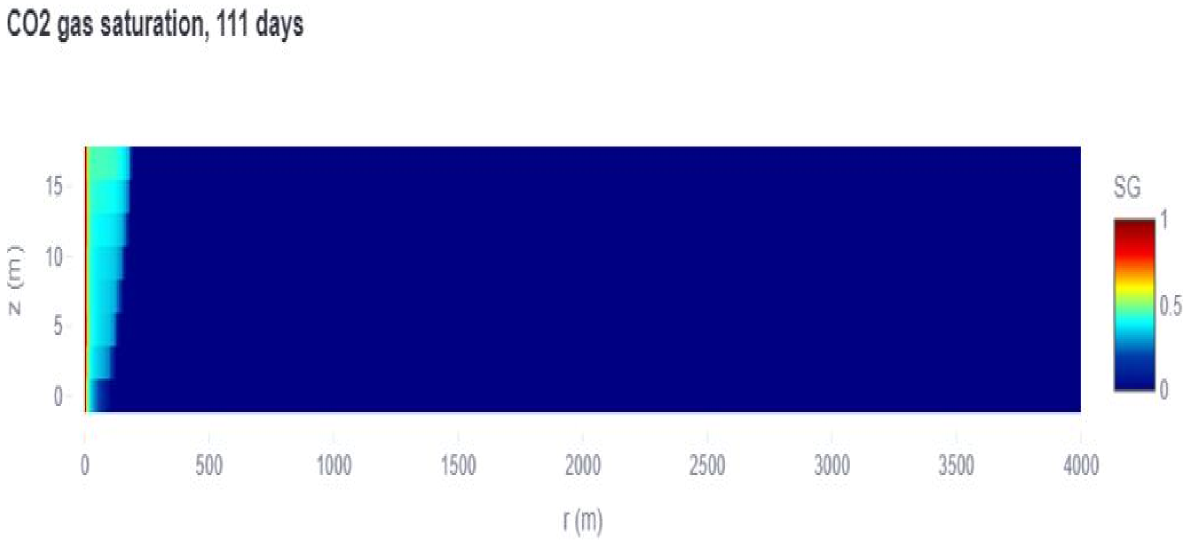


Fig: Conducting an CCNS deep learning model to predict a high sweep efficiency for a Niger delta formation.

The Test were run using a CO2 gas saturation and the results were attained to achieve a real time prediction For 111 Days.



fF

Fig: Simultaneously Running The ML more than 100 times in a period of 111 Days for predicting the pressure build up for a saturated C02 gas pressure.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

The study has investigated the application of deep learning techniques for a geological carbon storage in the Niger delta formation. A comprehensive Literature review highlighted the importance of storage mechanisms in the formation. The reviews also tells us about the potential sites for storing the carbon dioxide emissions into either the depleted reservoir or deep saline aquifers.

Through the methodology employed in this study, including data acquisition, machine learning models, convolutional neural network, nested FNO were applied to predict real time pressure build for gas saturations. However, it became evident that the available data were insufficient to fully capture the complexity of geological formations. Futhermore, the absence of a nested CCS deep learning tools posed a significant challenge in the training, inference and fine-tuning procedures models effectively.

Despite these limitations, the results obtained from the study shed light on the potential of nested fourier neural networks and deep learning to capture pressure in C02 gas saturations for days.

5.2 Recommendations

Based on the findings and limitations of this study, the following recommendations are proposed for future research.

1. Characterization Of Deep Saline Aquifers And Depleted Reservoir:

Future research should focus on mapping and evaluating deep saline formations and depleted hydrocarbon reservoirs across the Niger Delta. Emphasis should be placed on reservoir depth, porosity, permeability, salinity, and caprock integrity to identify viable CO_2 storage sites.

However, many of these formations remain poorly characterized at the resolution required for storage planning. Future research should aim to generate high-resolution geological maps and 3D reservoir models that detail critical properties such as porosity, permeability, temperature, pressure, and brine salinity.

Additionally, hydrocarbon-depleted reservoirs offer a unique advantage due to their known history, existing infrastructure, and proven sealing capacity. Studying these sites can reduce the uncertainty and cost of implementation. Core sampling, well logging, and basin-scale modeling should be employed to systematically identify and rank storage candidates.

2. CO2 Injection And Plume Migration Simulation:

Efforts are made to understand how the injected CO_2 behaves over time is essential for designing safe and efficient injection strategies. Future studies should involve dynamic reservoir simulation using tools such as TOUGH2, CMG-GEM, or Schlumberger's Eclipse, supported by geological models specific to the Niger Delta. These simulations help predict the spatial and temporal evolution of the CO_2 plume, the pressure front, and the interaction between CO_2, formation water, and reservoir rock. Such models can be used to evaluate different injection rates, well configurations, and the impact of heterogeneities like channel sands or shale streaks. Advanced techniques like Nested Fourier Neural Operators (FNO) can further enhance prediction accuracy by integrating large datasets and reducing computational cost.

3. Integration Of Machine Learning And Data-Driven Approach:

The complexity and data volume associated with GCS can be efficiently handled using artificial intelligence and machine learning. Future research should explore the application of data-driven models to enhance predictions of storage capacity, injectivity, leakage probability, and plume dynamics.

Machine learning algorithms, trained on historical well data, production records, and geological surveys, can identify hidden patterns and generate probabilistic forecasts. These tools can also be used for real-time decision support during injection operations. Techniques like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and physics-informed neural networks can be adapted for use in the Niger Delta context.

4. Practical Implementation:

Future studies should focus on practical implementation of machine learning-driven decision support systems for plume migration in real-world carbon storage. Considerations such as model interpretability, computational efficiency, and scalability should be addressed to facilitate adoption by industry practitioners.

5. Collaborative Research:

Collaboration between academia and industry stakeholders is essential to address the challenges and complexities associated with geological carbon storage. Joint efforts in data sharing, research funding, and knowledge exchange can accelerate progress and drive innovation in this field.

APPENDIX

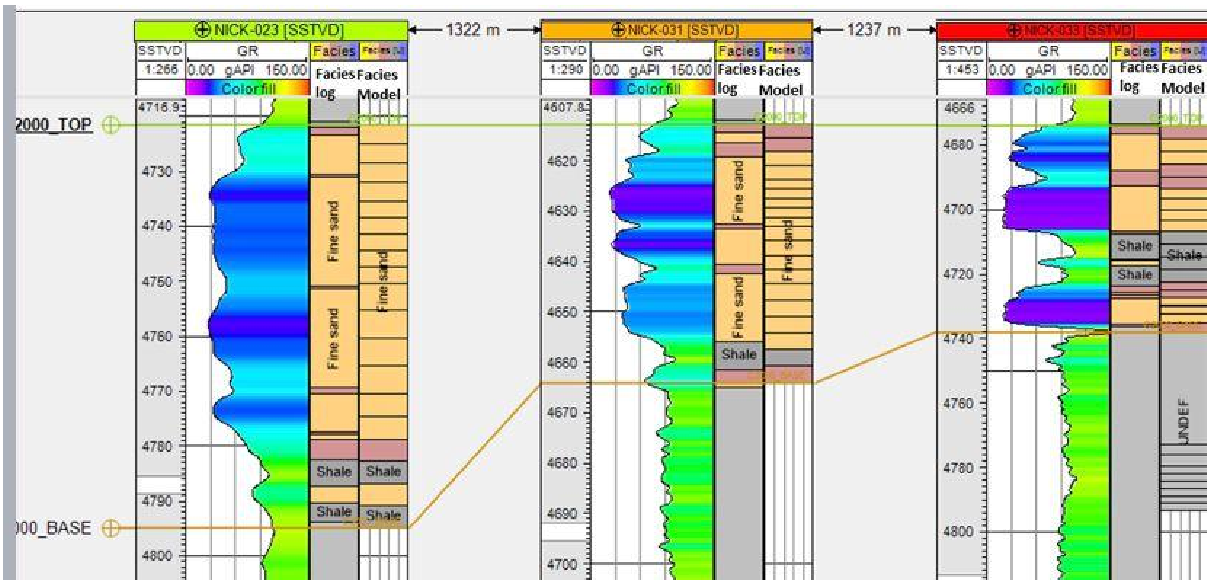
```
File "/usr/local/lib/python3.8/site-packages/streamlit/runtime/scriptrunner/script_runner.py", li
    exec(code, module.__dict__)
File "/app/ccs-net/pages/4-Site-selection-tool.py", line 612, in <module>
    df["CO2 Storage Capacity (tonne)"] = df.apply(calculate_co2_storage, axis=1)
File "/usr/local/lib/python3.8/site-packages/pandas/core/frame.py", line 8740, in apply
    return op.apply()
File "/usr/local/lib/python3.8/site-packages/pandas/core/apply.py", line 688, in apply
    return self.apply_standard()
File "/usr/local/lib/python3.8/site-packages/pandas/core/apply.py", line 812, in apply_standard
    results, res_index = self.apply_series_generator()
File "/usr/local/lib/python3.8/site-packages/pandas/core/apply.py", line 828, in apply_series_gen
    results[i] = self.f(v)
File "/app/ccs-net/pages/4-Site-selection-tool.py", line 312, in calculate_co2_storage
    rcf = row["GRF"]
File "/usr/local/lib/python3.8/site-packages/pandas/core/series.py", line 942, in __getitem__
    return self._get_value(key)
File "/usr/local/lib/python3.8/site-packages/pandas/core/series.py", line 1051, in _get_value
    loc = self.index.get_loc(label)
```

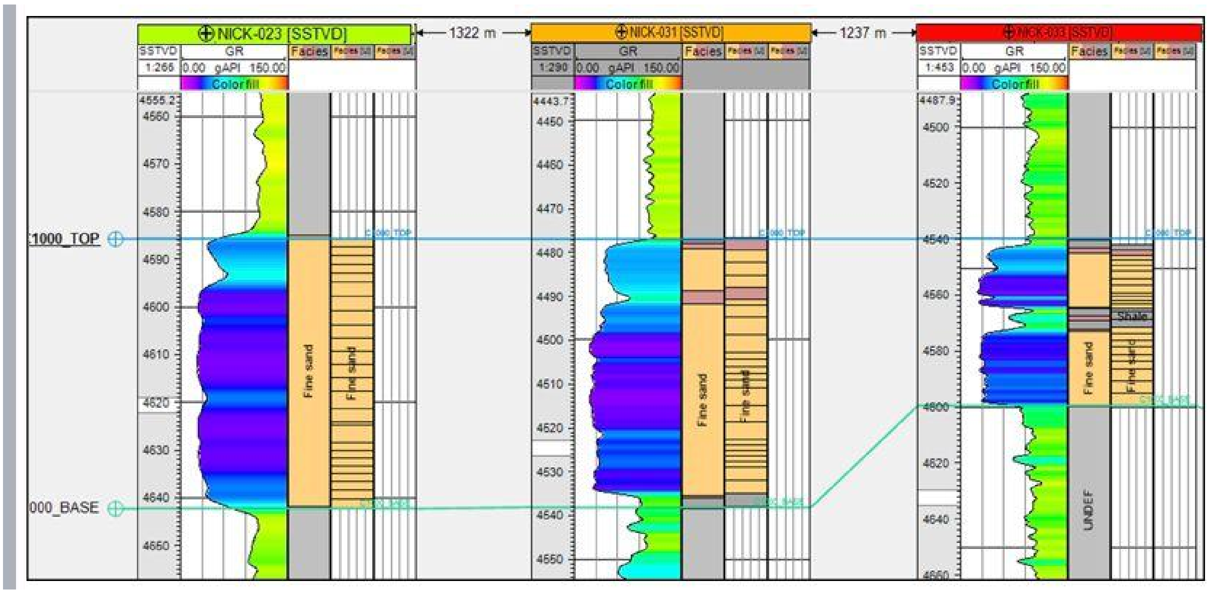
C100
0

Capillary pressure model built by Techlog (unit system: SW [v/v], HAFWL [ft], PERM [mD], POR [v/v])	
Python	min(1, max(0, (-0.369712 + 3.13961 * POR) * ((3.141534 * sqrt(PERM / POR) * (HAFWL * 0.3048 * (RHO_WATER - RHO_GAS/OIL) * 0.0980665 * (1.0 / (IFT_RES * cosTHETA_RES)))) ** (-0.441045 + 1.28043 * POR)) + (0.262387 - 0.00683815 * PERM))
Excel	MIN(1, MAX(0, (-0.369712 + 3.13961 * POR) * ((3.141534 * sqrt(PERM / POR) * (HAFWL * 0.3048 * (RHO_WATER - RHO_GAS/OIL) * 0.0980665 * (1.0 / (IFT_RES * cosTHETA_RES)))) ^ (-0.441045 + 1.28043 * POR)) + (0.262387 - 0.00683815 * PERM))
Petrel	Min(1, Max(0, (-0.369712 + 3.13961 * POR) * Pow((3.141534 * sqrt(PERM / POR) * (HAFWL * 0.3048 * (RHO_WATER - RHO_GAS/OIL) * 0.0980665 * (1.0 / (IFT_RES * cosTHETA_RES)))), (-0.441045 + 1.28043 * POR)) + (0.262387 - 0.00683815 * PERM)))

C200
0

Capillary pressure model built by Techlog (unit system: SW [v/v], HAFWL [ft], PERM [mD], POR [v/v])	
Python	min(1, max(0, (0.322605 + 5.14554 * POR) * ((3.141534 * sqrt(PERM / POR) * (HAFWL * (RHO_WATER - RHO_GAS/OIL) * 0.0980665 * (1.0 / (IFT_RES * cosTHETA_RES)))) ** (0.129467 - 0.00193117 * PERM)) + (0.292333 - 1.14386 * log10(PERM))))
Excel	MIN(1, MAX(0, (0.322605 + 5.14554 * POR) * ((3.141534 * sqrt(PERM / POR) * (HAFWL * (RHO_WATER - RHO_GAS/OIL) * 0.0980665 * (1.0 / (IFT_RES * cosTHETA_RES)))) ^ (0.129467 - 0.00193117 * PERM)) + (0.292333 - 1.14386 * LOG10(PERM))))
Petrel	Min(1, Max(0, (0.322605 + 5.14554 * POR) * Pow((3.141534 * sqrt(PERM / POR) * (HAFWL * (RHO_WATER - RHO_GAS/OIL) * 0.0980665 * (1.0 / (IFT_RES * cosTHETA_RES)))), (0.129467 - 0.00193117 * PERM)) + (0.292333 - 1.14386 * Log(PERM))))





NICK-023 [SSTVD]
1322 m
NICK-031 [SSTVD]
1237 m
NICK-033 [SSTVD]
SSTVD
GR
Facies
1:265
0.00 gAPI 150.00
1:290
1:453
Color fill
C1000_TOP
C1000_BASE
Fine sand
Shale
UNDEF

REFERENCES

EA, Exploring Clean Energy Pathways: The Role of CO2 Storage, IEA technical report, 2019.

G. Luderer, Z. Vrontisi, C. Bertram, O. Y. Edelenbosch, R. C. Pietzcker, J. Rogelj, H. S. De Boer, L. Drouet, J. Emmerling and O. Fricko, et al., Nat. Clim. Change, 2018, 8, 626–633.

S. Fankhauser, S. M. Smith, M. Allen, K. Axelsson, T. Hale, C. Hepburn, J. M. Kendall, R. Khosla, J. Lezaun and E. Mitchell-Larson, et al., Nat. Clim. Change, 2022, 12, 15–21.

K. Riahi, D. P. Van Vuuren, E. Kriegler, J. Edmonds, B. C. O'neill, S. Fujimori, N. Bauer, K. Calvin, R. Dellink and O. Fricko, et al., Global environmental change, 2017, 42, 153–168.

L. Cozzi, T. Gould, S. Bouckart, D. Crow, T. Kim, C. Mcglade, P. Olejarnik, B. Wanner and D. Wetzel, World Energy Outlook 2020, IEA technical report, 2020.

J. Lane, C. Greig and A. Garnett, Nat. Clim. Change, 2021, 11, 925–936.

NAS, Negative Emissions Technologies and Reliable Sequestration, National Academies Press, 2018.

K. Pruess, C. M. Oldenburg and G. Moridis, TOUGH2 user's guide version 2, Lawrence berkeley national lab technical report, 1999.

M. J. Blunt, Multiphase flow in permeable media: A pore-scale perspective, Cambridge University Press, 2017.

K. Pruess and J. Garcia, Environ. Geol., 2002, 42, 282–295.

C. Doughty, Transp. Porous Media, 2010, 82, 49–76.

G. Wen and S. M. Benson, Int. J. Greenhouse Gas Control, 2019, 87, 66–79.

K. Pruess and N. Mu¨ller, Water Resour. Res., 2009, 45, 0043–1397.

L. Andre´, Y. Peysson and M. Azaroual, Int. Greenhouse Gas Control, 2014, 22, 301–312. 16 R. Chadwick, P. Zweigel, U. Gregersen, G. Kirby, S. Holloway and P. Johannessen, Energy Procedia, 2004, 29, 1371–1381.