Accelerated regional stratigraphic framework building for subsurface CO_2 storage assessment

Sougata Halder[1]*, Keyla Gonzalez[1], Alex Fick[1], Vi Ly[1], Ben Lasscock[1], Zoltan Sylvester[2] and Cameron Snow[3] present a novel workflow for developing a basin-scale stratigraphic architecture for defining the major saline reservoirs and sealing units within a basin.

Introduction

Carbon Capture and Storage (CCS) is a proven and safe technology that involves capturing (purifying) carbon dioxide (CO_2) released from point emission sources or directly removed from the atmosphere, compressing it for transportation and then injecting it into a carefully selected subsurface reservoir for permanent storage. The success of CO_2 storage relies heavily on the identification and characterisation of suitable subsurface reservoirs for secure and permanent storage. Geologic formations, whether they are depleted hydrocarbon or deep saline reservoirs, present unique challenges and opportunities for CO_2 storage. The advantages of saline reservoirs over depleted hydrocarbon reservoirs include potential access to a large volume of available pore space, and a smaller number of well penetrations, which results in reduced risks of potential leakage pathways through these wells. However, the lack of comprehensive reservoir data in saline reservoirs increases uncertainty in defining reservoir confinement, cap rock integrity, and fluid flow behaviour. Therefore, saline reservoir storage assessment requires comprehensive reservoir characterisation and modelling to be carried out before large-scale CO_2 storage planning is possible.

Some important parameters to consider for subsurface CO_2 storage are depth of injection and density of CO_2, which is dependent on subsurface temperature and pressure. The density of CO_2 increases with pressure at temperatures above critical conditions (Klins and Bardon, 1991). At about 1084 psi pressure and 88°F temperature, CO_2 reaches a supercritical state (Qi et al., 2010), after which the volume decreases dramatically with depth, along with the increase in CO_2 density. These conditions generally correspond to a depth of around 2600 to 3000 ft. In a supercritical state, CO_2 acts as a gas-like compressible fluid, resulting in complete pore volume utilisation and mobility within a reservoir (Ketzer et al., 2012), with a liquid-like density. The main advantage of storing CO_2 in a supercritical state is that the required storage volume is substantially less than what it would be at surface conditions (Donaldson, 2021).

Most of the onshore and offshore sedimentary basins in North America have sufficient data for subsurface evaluation to identify regional fairways for CO_2 storage. Integration of geological, geophysical, and petrophysical assessment from the well log data helps in evaluating deep saline reservoir zones for their storage suitability. The initial step in any subsurface assessment is to accurately map the geological units at the well level. This involves correlating these units along strike and dip-oriented sections to understand their distribution and variability across the basin. Building a basin-scale stratigraphic framework by correlating a large number of geophysical well logs is a crucial but labor-intensive process. This task is especially challenging

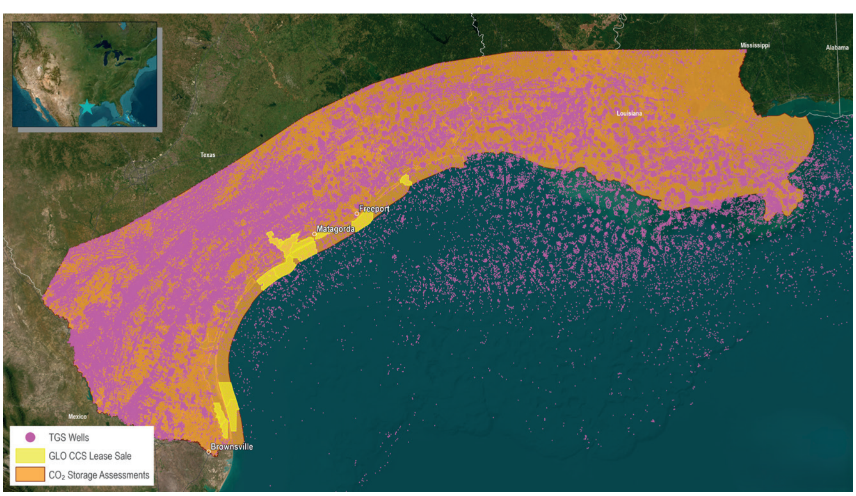

Figure 1 Study area across Texas and Louisiana Gulf Coast covering CCS lease areas.

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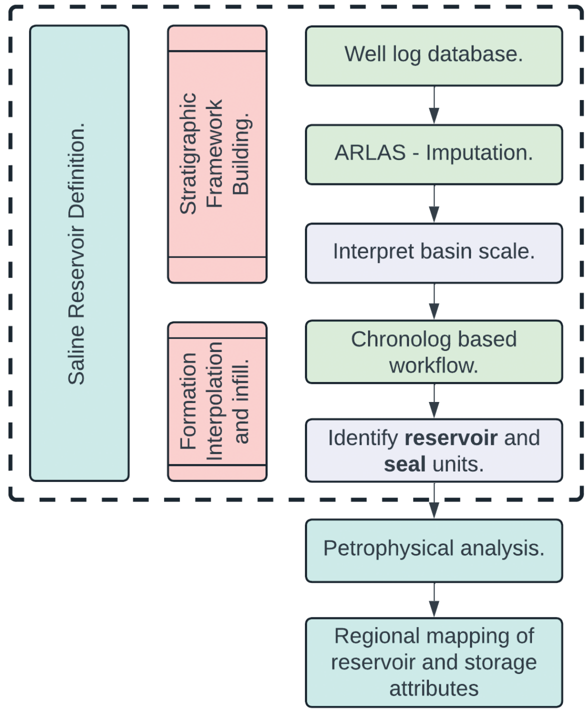

Figure 2 Storage assessment workflow with the dashed-line-box highlighting the focus of this study, the saline reservoir definition.

when dealing with dense well-log datasets, such as those found in many US onshore basins. This calls for the development of an automated approach (Shaw and Cubitt, 1979, Wu and Nyland, 1987) that is scalable and reproducible across various basins. Earlier attempts to use computers for well log cross correlation algorithms used time equivalent sample pairs (Mann & Dowell, 1978; Rudman & Lankston, 1973). Currently, the Dynamic Time Warping (DTW) algorithm is widely used for these purposes, due to its ability to better handle log variabilities (Baville et al., 2022, Grant et al., 2018, Hladil et al., 2010; Wu et al., 2018; Zoraster et al., 2004, Sylvester, 2023).

Building on these foundations, we present a novel workflow for developing a basin-scale stratigraphic architecture for defining the major saline reservoirs and sealing units within a basin. With a sample size of 155,732 subsurface logs from Gulf Coast basin, we demonstrate a comprehensive interactive workflow developed for large-scale regional stratigraphic mapping, providing a basin-wide database of well tops for the subsurface geologic units that is required for subsequent reservoir characterisation. Our semi-automated, user-guided workflow enhances the efficiency of the regional stratigraphic mapping significantly and can be scaled up to any other basin.

Study Area

The study area extends across 53 million acres of southern US Gulf Coast of Texas and Louisiana that includes onshore coastal areas and the state waters, including the recent CCS lease areas from the Texas General Land Office (GLO), (Figure 1). Presence of numerous local point emission sources of CO_2, with availability of nearby storage opportunities, and existing infrastructure makes the US Gulf Coast an attractive area for subsurface CO_2 storage. The availability of an extensive dataset of 155,732 wells in the study area allows ample opportunity for mapping and characterisation of the key geologic units for subsurface CO_2 storage.

Data and methodology

Our subsurface CO_2 storage assessment workflow begins with saline reservoir definition, which includes identification of the key saline reservoir and sealing units and map their distribution within the study area, which is the focus of this paper. This is subsequently followed by the petrophysical characterisation of these geologic units for their storage suitability assessment. Figure 2 outlines our CO_2 storage assessment workflow, with the saline reservoir definition highlighted to emphasise the focus of this study.

Regional mapping of the subsurface storage and sealing units and defining the depth, thickness of each of these units and mapping their lateral continuity, and variability along the basin is not a trivial task. Manual attempts for basin-scale well log correlation lack the vertical resolution to adequately define individual saline reservoirs and their regional and intra-formational sealing units. Furthermore, incomplete log coverage from the surface to the base of the wellbore in most well locations limits our ability to generate a comprehensive, high-resolution stratigraphic framework for a basin. Our semi-automated workflow allows efficient regional well log correlation and quality control, providing the highest stratigraphic resolution across the basin for identification and mapping of the key geologic units within a basin.

Regional stratigraphic mapping

The first step in our storage assessment workflow is to map the regional geologic units across the study area. We employed a cloud-based web application, which provides integrated data management and facilitates easy visualisation and interactive mapping of the regional geologic units. We used an extensive well-log database, for interpretation and training a machine learning-generated model, Analytics Ready LAS (ARLAS) (Gonzalez et al., 2023), to predict missing logs and/or log intervals within the Gulf Coast area. This approach provides a comprehensive basin-scale database of quad combo log data (actual and imputed) for every well and allows geologists to interpret on any of the logs, inferred or actual. This well-log database is integrated into the cloud-based application with interactive tools for stratigraphic interpretation.

The application enables interpreters to view and interpret data from 155,732 digitised well-logs and ARLAS predictions by annotating cross-sectional views of the basin. An interpreter can visualise up to 1500 wells in a cross-section, with consistent colour-coded log signals. This facilitates identifying and mapping of the major depositional units and allows rapid interpretation of the formation tops with both depth and regional context (Figure 3). This methodology is systematically applied to create strike- and dip-oriented line of sections across the basin, which forms the basis for a basin wide stratigraphic correlation.

The application also allows quality control of the interpreted sections, through interactive selection of log curves from the line of section and manual well top adjustments for quality assurance (Figure 4). The interpreted well top picks from this regional interactive interpretation tool were then exported and incorporated into our standard interpretation software platform Kingdom

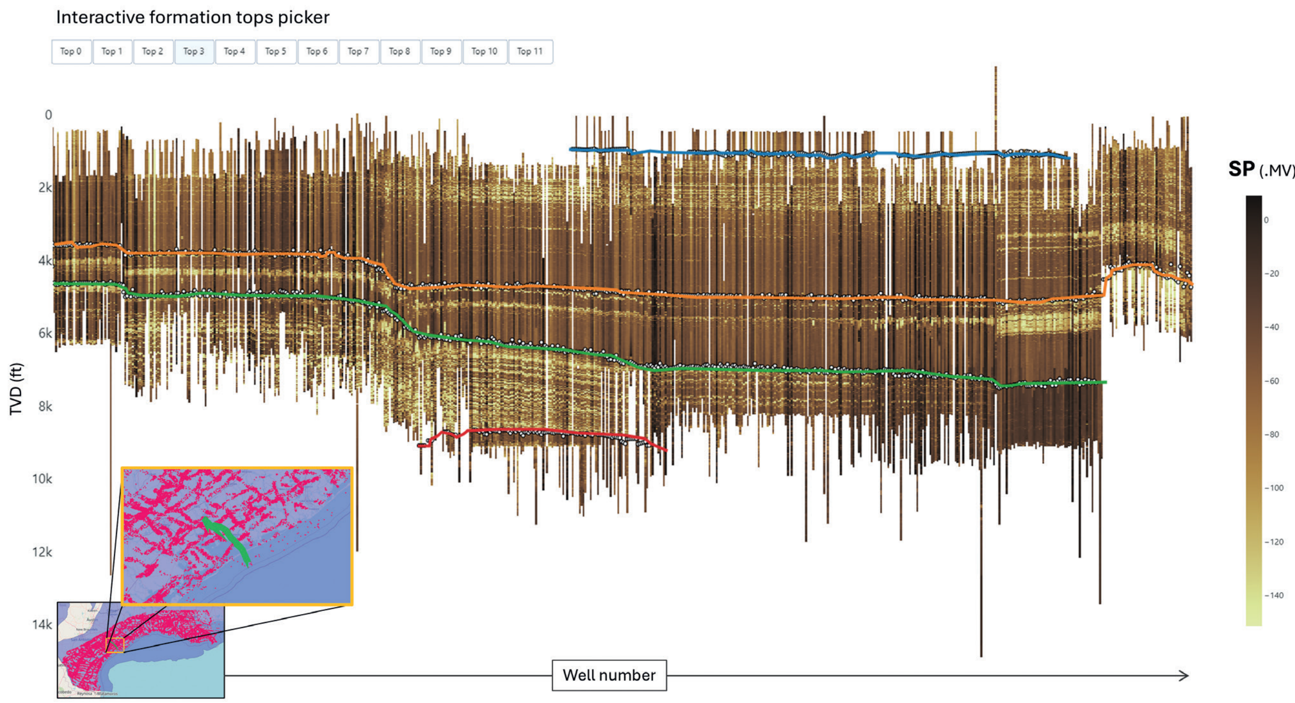

Figure 3 Regional cross-sectional view of Spontaneous Potential (SP) logs displaying depositional units for basin-scale mapping. The application enabled interactive interpretation of 12 formation tops across the study area and direct saving of standardised names and cross-section numbers to a cloud database for further quality assurance.

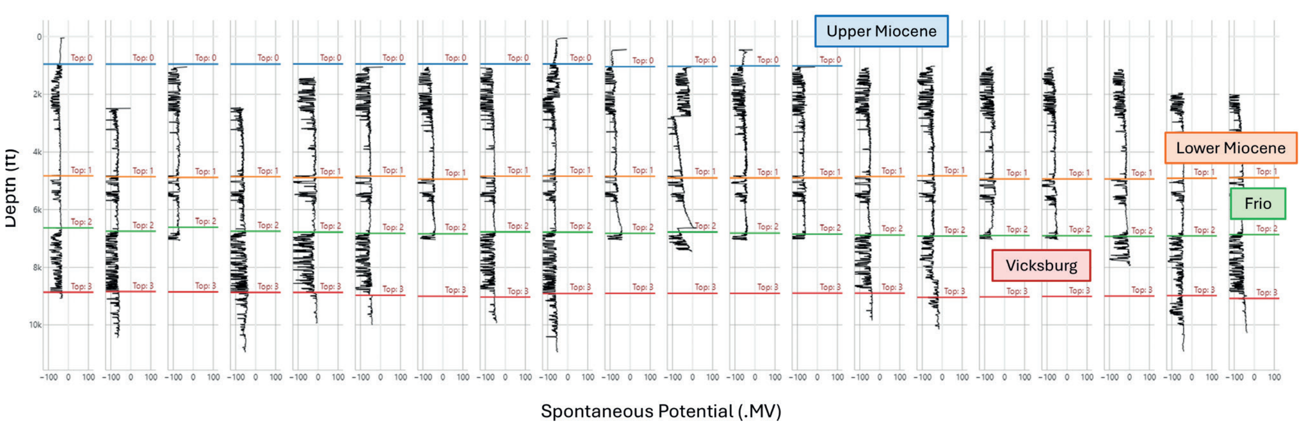

Figure 4 Interactive well log curve visualisation for quality assurance of picked tops, allowing users to adjust interpreted tops from the regional section to align with well log resolution.

suite, for further quality control through generating structural and isopach maps and iteratively updating the interpreted well tops.

Automated enhancement of stratigraphic picks

The Chronolog python module (Sylvester, 2023) provides automated tools for constructing a high-resolution stratigraphic model from an initial input set of interpreted formation tops that constrains the well-log correlation and extends geological interpretations in between the input set of formations. Chronolog workflow was extended to handle the high volume of well-log and interpreted formation top data (Gonzalez et.al., 2024). To prevent oversampling in regions with adequate data coverage and existing interpretations, we implemented a decimation process. This process allowed the selection of wells from each cross-section, based on a specified distance criterion. We have selected a decimated well set of 43,380 vertical wells from the original database as input to our Chronolog process. Table 1 shows our study focuses on 155,732 wells in the Gulf Coast area. From there, 102,513 wells have formation tops interpreted from our interactive interpretation platform, and a set of 43,380 wells, selected through a decimation process, had Chronolog tops that were used in our analysis.

We used spontaneous potential (SP) logs in the Chronolog workflow to define unsupervised tops, derived from the stratigraphic framework obtained using the cloud-based application.

Description	Number of Wells
Total wells in Gulf Coast	155,732
Wells in Gulf Coast study area with formation tops	102,513
Wells with Chronolog tops (selected through decimation process)	43,380

Table 1 Well sample size.

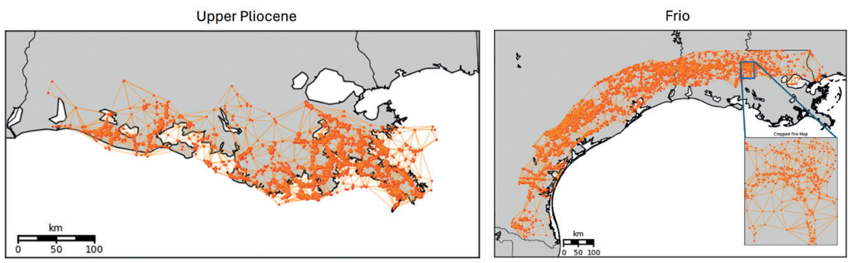

Figure 5 a) Sparse distribution of wells in the Upper Pliocene Formation. b) Extensive well distribution within the Frio Formation, and a zoomed-in view of an area with dense well distribution.

First, we constructed well-distance graphs (Figure 5) for each formation to connect proximal wells, facilitating well-to-well correlations. These correlations are conducted using Dynamic Time Warping (DTW) and relative geological time, enabling us to define formation tops at various scales. Understanding the distribution of wells allows us to select suitable distance parameters for representative correlation. Different well networks have been created, based on the spatial distribution of the geologic units within the study area. For instance, Figure 5a (Upper Pliocene Formation) shows that the well network is located only within specific areas of the basin. In contrast, Figure 5b (Frio Formation) reveals dense well coverage across the study area, where a highly connected set of wells is used for the well-to-well correlation.

By integrating DTW with relative geological time, we achieve more accurate well-pair relationships and clearer visualisations of the correlations. Figure 6a showcases these DTW correlations across different formations within the study area, highlighting the distinct SP signal responses. Figure 6b shows a regional cross-section view of the SP logs from the cloud-based interpretation platform, displaying the final set of formation tops, including the unsupervised tops defined between the major hand-picked tops.

To ensure consistency of formation tops across all wells, we employed an iterative method to interpolate any missing tops. This process consists of two main steps: (1) creating an isopach grid between the identified tops and bases, and (2) applying thickness mapping to estimate the missing formation tops (Gonzalez et.al., 2024). In cases where a well log signal is absent, interpreted tops from the interpretation platform are used as control points to guide the interpolator in regions with

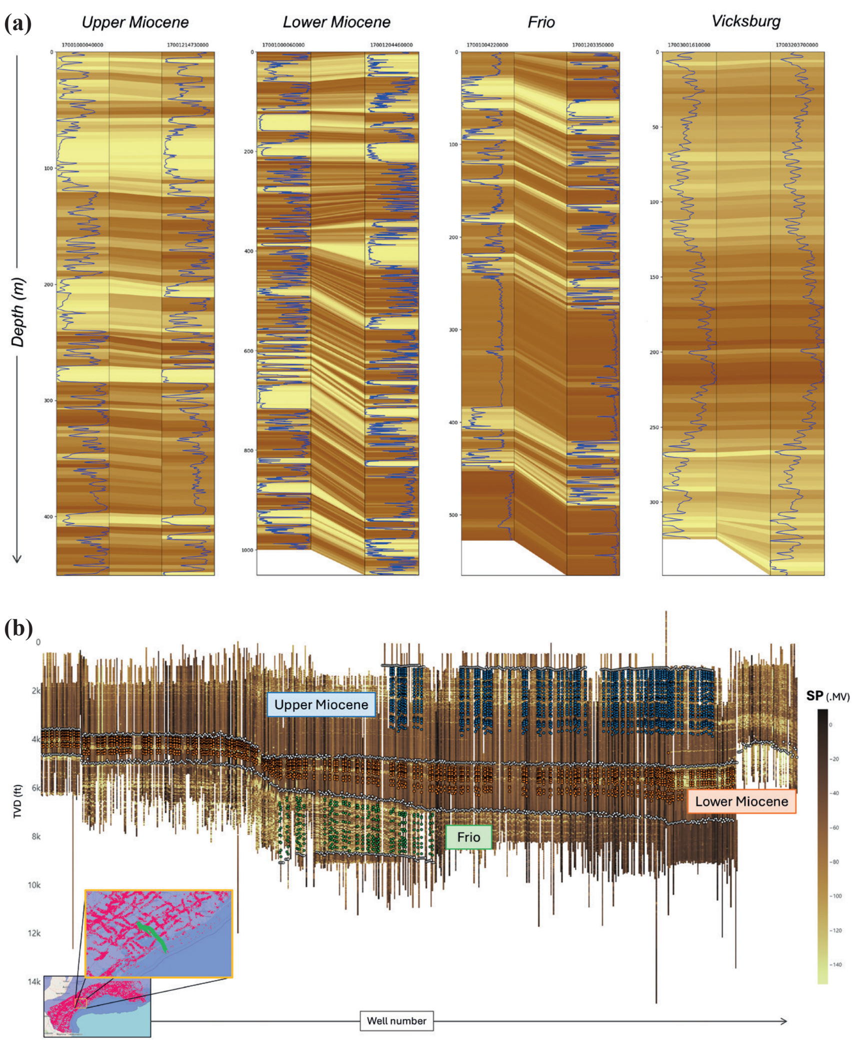

Figure 6 (a) Pairwise Dynamic Time Warping (DTW) correlations, illustrating the alignment and comparison of normalised SP log data across various geological formations. (b) Visualisation of the final set of Chronolog tops in the regional cross-section view, along with the major hand-picked tops.

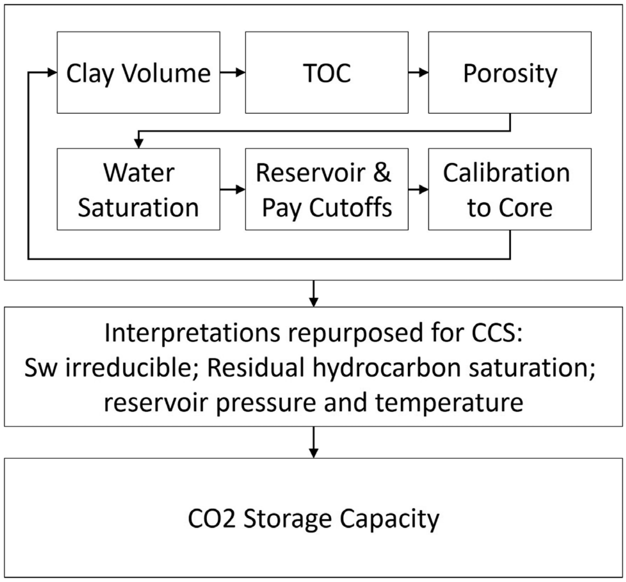

Figure 7 Diagram illustrating the petrophysical calculation workflow for CO_2 storage capacity calculation.

poor coverage. This method ensures that geological features are accurately depicted, avoiding any overlaps and ensuring stratigraphic model continuity.

Petrophysical analysis

The regional mapping of the saline reservoir units is followed by the petrophysical assessment and storage capacity estimation at the well level, currently in progress within the study area. In an assessment of CO_2 storage capacity, we need to evaluate the reservoir in much the same manner as with standard oil and gas. However, it does require additional factors such as the irreducible water saturation, residual hydrocarbon saturation, and the reservoir temperature and pressure for evaluating CO_2 density. Figure 7 shows an illustration of the updated petrophysical workflow used for our CO_2 storage calculation.

Although the calculations are identical to various interpretations for oil and gas purposes, our usage of them is focused on quantifying the CO_2 storage, as shown in Equation 1, modified from Goodman et. al., 2011.

$$CO2_{sc} = A * H * Ø * (1 - Sw_{irr} - Shc_{res}) * \rho_{CO2} * E,$$

where, $CO2_{sc}$= CO_2 storage capacity, A= Area, H= Net thickness, φ= Effective Porosity, Sw_{irr}= Irreducible water saturation, Shc_{res}= Residual hydrocarbon saturation, ρ_{CO2}= CO_2 density, E=Efficiency.

Results

The study demonstrates our ability to effectively correlate an expansive, basin-scale well database to define the stratigraphic architecture and delineate the distribution of key geologic units within the basin. We have generated 307,900 formation tops for 102,513 wells within the study area over a three-month timeframe. This was made possible by the combination of the ARLAS, and Chronolog tools, providing a complete and continuous dataset integrated into the interactive interpretation platform for analysis. The dense well distribution enabled precise mapping of structural features within the basin, enhancing our understanding of subsurface geology (Figure 8). We have generated a comprehensive set of interpolated tops, through an iterative process, using thickness/isopach maps, that help to maintain the integrity of the geological model and prevent formation grids from intersecting across unsupervised and interpreted tops. This process ensures that our geological model reflects an accurate and continuous representation of subsurface formations across the basin, providing valuable insights for further analysis and decision-making for subsurface CO_2 storage.

Structural distribution and thickness variability of the reservoir units mapped across the study area include Upper and Lower Pliocene, Upper, Middle, and Lower Miocene, Frio, Vicksburg, Upper and Lower Claiborne, Upper, middle and Lower Wilcox,

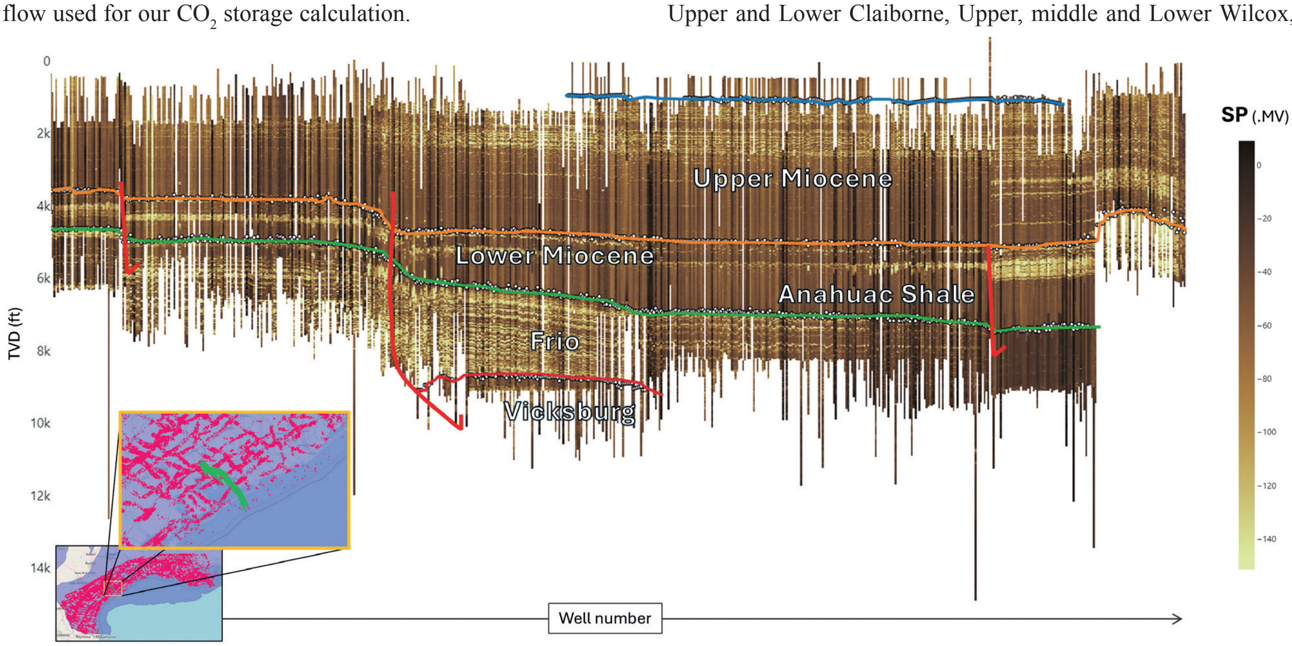

Figure 8 Regional dip-oriented section from the Texas Gulf Coast, displaying compressed SP log responses and the picks for key formation tops. The inset map shows the location of the cross-section within the Texas Gulf Coast, where 1091 cross-sections were created to define the stratigraphic framework.

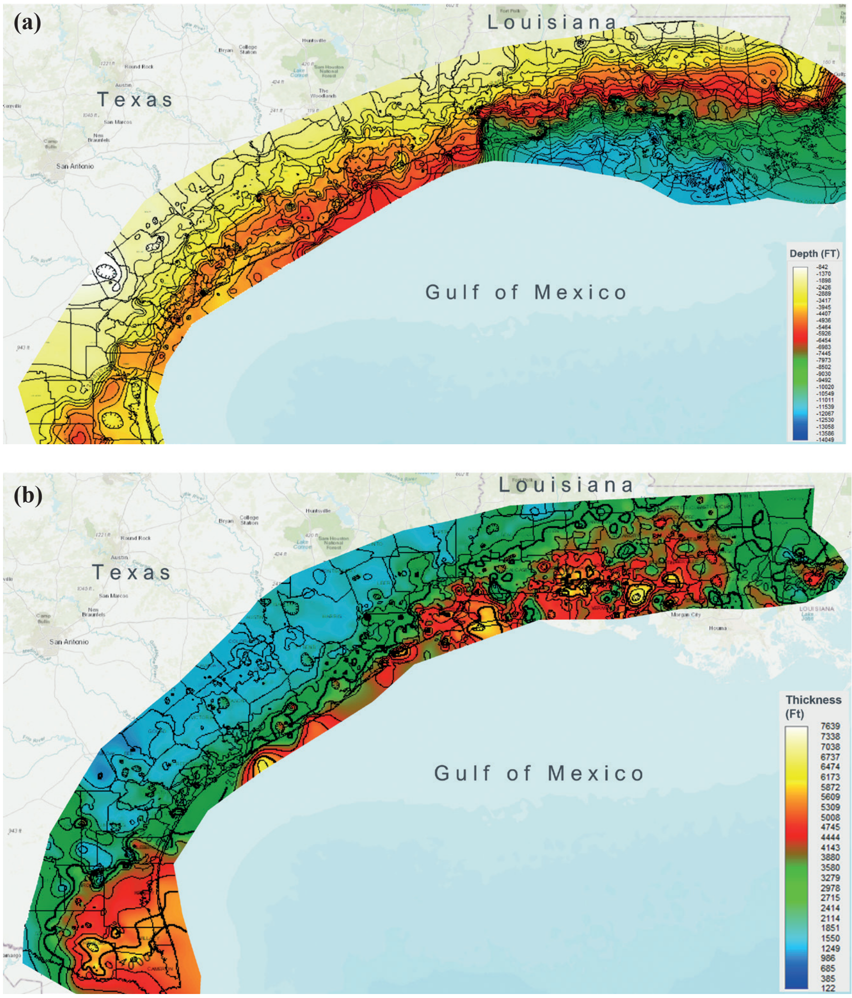

Figure 9 (a)Structure and (b) isopach maps of the Lower Miocene saline reservoir units from the study area.

and Cretaceous. Regional and intra-formational seal units, such as Amph-B shale, Anahuac Shale, and Midway, are also mapped for the purpose of storage integrity assessment. We demonstrate that the prospectivity of the Tertiary section varies significantly across the basin. Regional structure and depositional slopes can be characterised and through extensive mapping, penetrations for stratigraphic surfaces are recognised, allowing for the intelligent subdivision of the basin for petrophysical interpretations. The availability of the expansive well log data, including ARLAS logs and other standardised, pre-processed well data, ensures that our interpretations are based on robust and reliable information, thereby increasing the accuracy and confidence in our saline reservoir definition. These saline reservoir zones are then evaluated for their storage suitability assessment and capacity estimation by generating a basin-wide petrophysical model for the study area.

Figure 9 presents the structure (a) and isopach (b) maps of the Lower Miocene reservoir units, highlighting the variability of reservoir depth and thickness along the basin resulting from the basin architecture. Structural changes impose geologic constraints on the reservoir suitability assessment, highlighting areas with pressure and temperature conditions suitable for CO_2 injection. Through extensive mapping, we can characterise the variability of regional structure and depositional slopes. These varying conditions will guide the petrophysical model building for each of the distinct structural settings.

Conclusions

Identifying and mapping CO_2 injection units and their regional barriers presents a major challenge in scaling up CO_2 storage assessments. Over half of the geoscience effort is dedicated to stratigraphic interpretation when evaluating new basins for saline reservoir suitability. This is largely due to the time- and labour-intensive manual processes involved in well-log correlation and top identification.

Therefore, we introduce an accelerated workflow for basin-scale stratigraphic modelling in the US Gulf Coast, leveraging extensive subsurface data, an interactive interpretation workflow, and automation through the ARLAS and Chronolog tools. Our study showcases the effectiveness of interactive visualisation and quality control of the high-frequency Chronolog tops in defining reservoir units and mapping seals across the basin. This methodology condenses up to 1500 well log data into a single section, enabling intuitive interpretation of stratigraphic surfaces. This is crucial for complex basins like the Gulf Coast, where facies variability occurs along both depositional strike and dip direction.

By analysing 43,380 well log data, core data, and expert geological and petrophysical interpretations, we have developed a comprehensive regional stratigraphic architecture. This architecture identifies key saline reservoir units, such as the Upper and Lower Pliocene, Miocene, and Frio, and highlights important seals like the Amph-B Shale and Anahuac Shale. This detailed mapping is vital for assessing storage integrity and supporting successful CO_2 storage projects. This integrated approach not only streamlines the stratigraphic interpretation process but also improves the accuracy and efficiency of identifying potential CO_2 storage sites.

Our continued work involves a petrophysical assessment at the well level, followed by the regional mapping of the key reservoir attributes and estimated storage, which is currently in progress within the study area. Building on the success of our current study, we plan to replicate this workflow across other basins to further validate and refine our methodology. By applying our semi-automated, user-guided process to different geological settings, we aim to assess the adaptability and robustness of our approach in a variety of environments.

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