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Article

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Abstract: The large scale and complexity of Carbon, Capture, Storage (CCS) projects necessitates time and cost saving strategies to strengthen investment and widespread deployment of this technology. Here, we successfully demonstrate a novel geologic site characterization workflow using an Artificial Neural Network (ANN) at the Southeast Regional Carbon Anthropogenic Test in Citronelle, Alabama. The Anthropogenic Test Site occurs within the Citronelle oilfield which contains hundreds of wells with electrical logs that lack critical porosity measurements. Three new test wells were drilled at the injection site and each well was paired with a nearby legacy well containing vintage electrical logs. The test wells were logged for measurements of density porosity and cored over the storage reservoir. An Artificial Neural Network was developed, trained, and validated using patterns recognized between the between vintage electrical logs and modern density porosity measurements at each well pair. The trained neural network was applied to 36 oil wells across the Citronelle Field and used to generate synthetic porosities of the storage reservoir and overlying stratigraphy. Ultimately, permeability of the storage reservoir was estimated using a combination of synthetic porosity and an empirically derived relationship between porosity and permeability determined from core.

Keywords: Carbon Capture Storage; Petrophysics; machine learning

1. Introduction

The scale and complexity of Carbon, Capture, Storage (CCS) projects demand overcoming significant cost challenges and long project lead times which delay commercial scale deployment of CCS projects worldwide. Utilizing technologies and workflows that reduce cost and accelerate storage assessments are key strategies to strengthen CCS investments [1]. Likewise, the decision to invest in a CCS project hinges on a high degree of confidence that the project site can sequester a large volume of CO_2 safely and securely. One critical yet time-consuming factor during project development occurs during the storage assessment phase where the total amount of CO_2 that may be injected into a storage formation is determined. Developing workflows that reduce the time and cost of site characterization is an important strategy that can be applied to all future CCS projects.

Time and cost saving site characterization techniques were applied at The Southeast Regional Carbon Sequestration Partnership (SECARB) Anthropogenic Test which demonstrated a fully integrated carbon capture, transportation, and storage project in the USA [2]. CO_2 was captured from Alabama Power Company's James M. Barry Generating Plant ('Plant Barry'), a coal and natural gas fired power plant, see Figure 1. The Southeast Regional Carbon Sequestration Partnership Anthropogenic Injection Test Site is situated in Citronelle, Alabama within the mature Citronelle oilfield discovered in 1955.

Oil is produced from the Lower Cretaceous Donovan sand and the field is situated on the crest of the Citronelle Dome, a large salt-cored anticline with four-way closure [3,4].

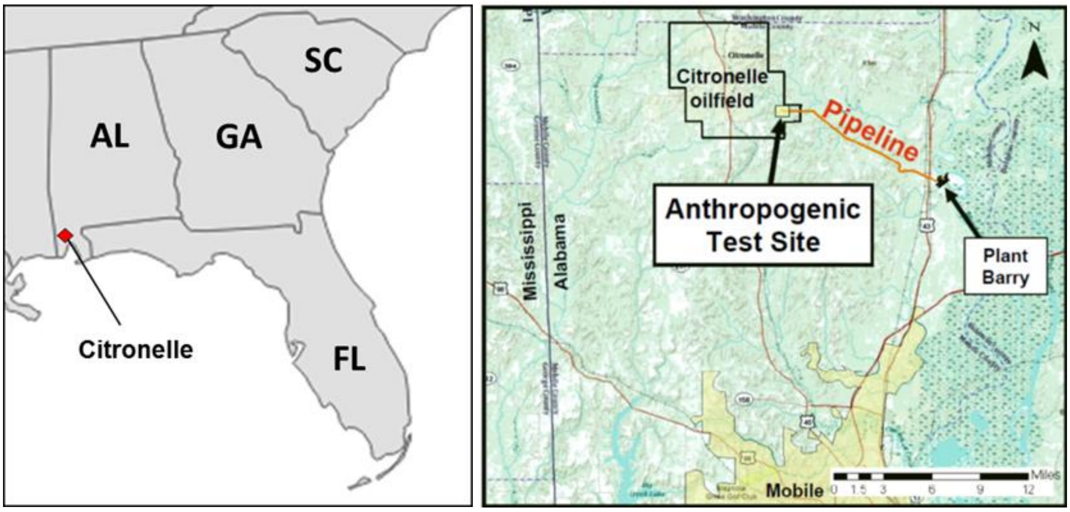

Figure 1. Location map of the Anthropogenic Test Site, the Citronelle oilfield, and Plant Berry.

The Paluxy Formation is a saline reservoir and the primary storage target that is situated approximately 1200 feet (366 m) above the Donovan sand at approximately 9400 feet (2865 m) subsea depth, Figure 2. More than 400 oil wells have been drilled in the Citronelle oilfield on 40-acre (0.16 km^2) spacing and were logged only with electrical measurement tools. Importantly, electrical logging tools do not measure porosity which is essential for storage capacity estimates and reservoir injection modeling. Typical workflows would necessitate drilling numerous wells to characterize the storage formation; however, only a limited number of stratigraphic test wells were completed within the Paluxy Formation due to project cost constraints. This project leveraged preexisting data from oil well penetrations of the storage formation to compliment three newly drilled test wells and reduce the overall time and cost of site characterization.

System	Series	Stratigraphic Unit	Major Sub Units	Potential Reservoirs and Confining Zones
Tertiary	Pliocene		Citronelle Formation	Freshwater Aquifer
	Miocene	Undifferentiated		Freshwater Aquifer
	Oligocene		Chicasawhay Fm.	Base of USDW
		Vicksburg Group	Bucatunna Clay	Local Confining Unit
	Eocene	Jackson Group		Minor Saline Reservoir
		Claiborne Group	Talahatta Fm.	Saline Reservoir
		Wilcox Group	Hatchetigbee, Bashi Marl, Salt Mountain Limestone	Saline Reservoir
	Paleocene			
		Midway Group	Porters Creek Clay	Confining Unit
Cretaceous	Upper	Selma Group		Confining Unit
		Eutaw Formation		Minor Saline Reservoir
		Tuscaloosa Group	Upper Tusc.	Minor Saline Reservoir
			Mid. Tusc. Marine Shale	Confining Unit
			Lower Tusc. Pilot Sand, Massive sand	Saline Reservoir
Cretaceous	Lower	Washita-Fredericksburg	Dantzler sand, Basal Shale	Saline Reservoir
				Primary Confining Unit
		Paluxy Formation	Upper', 'Middle', 'Lower'	CO_2 Injection
		Mooringsport Formation		Confining Unit
		Ferry Lake Anhydrite		Confining Unit
		Donovan Sand	Rodessa Fm. 'Upper', 'Middle', 'Lower'	Oil reservoir
				Minor Saline Reservoir
				Oil Reservoir

Figure 2. Stratigraphic chart of the Anthropogenic Test Site. Several major regional confining horizons, including the basal Washita Fredericksburg interval shale, the Marine Tuscaloosa shale and the Selma Group Chalk restrict vertical CO_2 migration.

1.1. Geologic Background of the Paluxy Formation

The Paluxy Formation is a regionally extensive Cretaceous aged stratigraphic horizon that extends over much of the Gulf Coast. This formation is a member of the Gulf Coast Wedge comprising a group of sedimentary rocks that span the entire Southeast Regional Carbon Sequestration Partnership region with an estimated CO_2 storage capacity of 850–11,700 billion metric gigatons (Gt) [5]. The Paluxy Formation is one of the most significant CO_2 storage targets within the Gulf Coast Wedge consisting of high reservoir quality intervals of sandstone interbedded with shale, see Figure 2 [6]. Paluxy sandstones in Alabama represent a fluvial-deltaic depositional environment marked by incised channel deposits with high porosity and permeability [7]. The Paluxy Formation is immediately overlain by mudstone confining units of the Washita-Fredericksburg Group followed by the Tuscaloosa Group, Eutaw Formation, and Selma Group, see Figure 2.

Initial site characterization investigated the thickness and extent of Paluxy sands that were mapped by interpreting responses from vintage well log curves to define reservoir from non-reservoir horizons, see Figure 3. Paluxy sandstones are saturated with saline pore fluids that produce negative spontaneous potential responses and low resistivity measurements in electrical logs that delineate reservoir cutoffs. These cut-offs were used to construct cross sections that determined the continuity of sand bodies within the vicinity of the proposed injection well location (Well D-9-7 #2). Preliminary site characterization using vintage well logs suggested that the Paluxy Formation is a laterally continuous, thick, and structurally undeformed saline reservoir capped by thick sequences of mudstone.

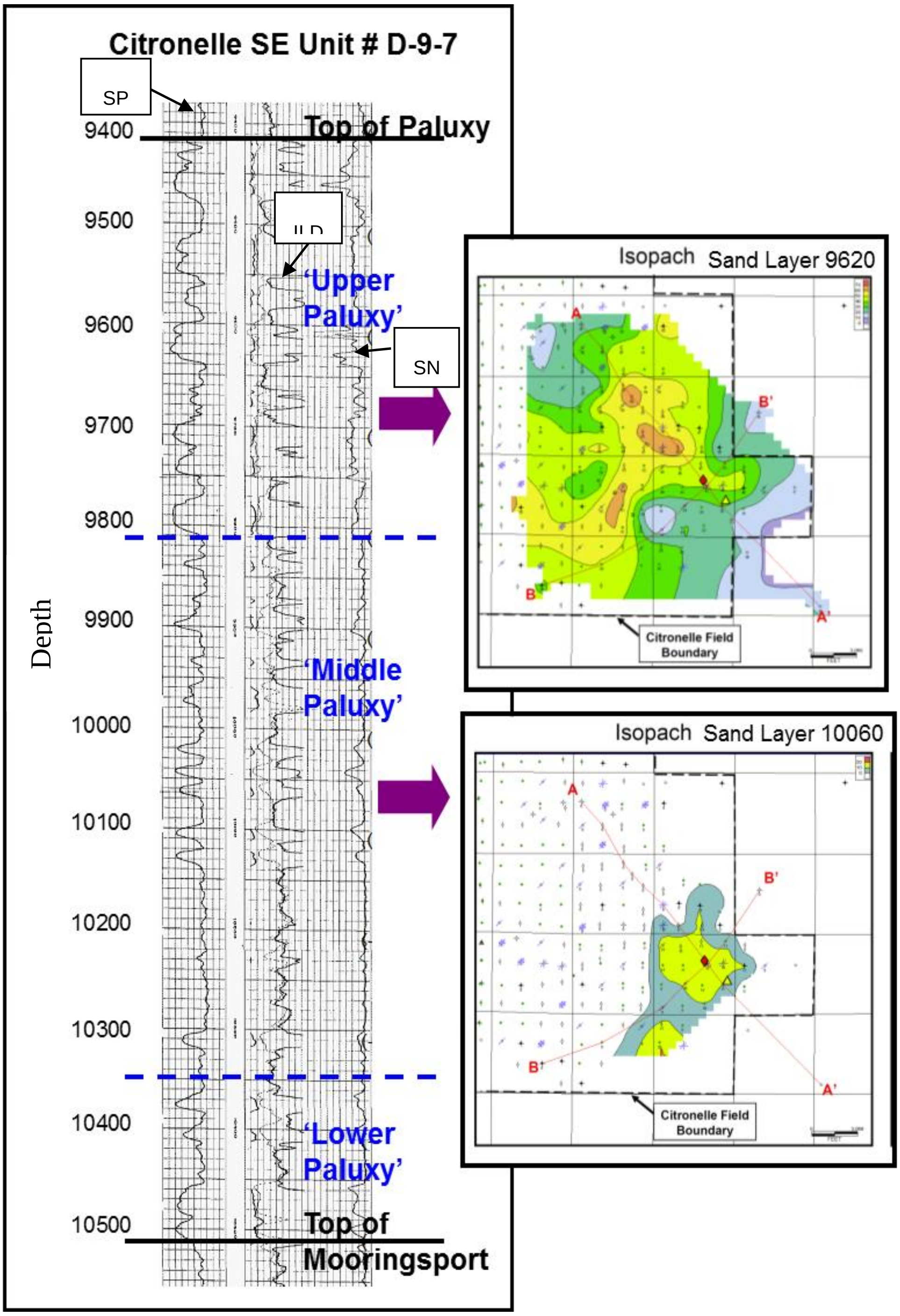

Figure 3. Vintage well log (left) showing the Paluxy Formation interval. The left track is spontaneous potential (SP) and the track to the right shows the induction (ILD) and short normal (SN) electrical logs. Paluxy sand maps (right) constructed from the vintage well logs. Source: Author Conception. (Right) Isopach map generated using Petra ®.

The Paluxy Formation and overlying stratigraphy occur above the Citronelle Dome located in southern Alabama. The Citronelle Dome is a broad and elliptical salt-cored anticline in a four-way closure configuration with limbs that dip away from the structural crest at 1–2° [3]. The Citronelle Field occurs near the crest of the Citronelle Dome, which has provided a structural trap for hydrocarbon accumulations in the Donovan sand that underlies the Paluxy Formation. Due to the cost constraints of project funding, a 2-dimensional seismic line could not be acquired across the field site. In addition, the multiple stacked sand beds of the Paluxy Formation are too thin to be captured by the resolution of a seismic image. However, the occurrence of roughly 36 well penetrations of the Paluxy Formation that contain vintage well logs provide adequate log coverage to identify the structural and lithological variation that occurs within the Paluxy Formation. Across the Citronelle Field, vintage logs indicate that the Paluxy Formation has multiple stacked sand beds with a relatively flat-lying stratigraphic geometry, see Figure 4.

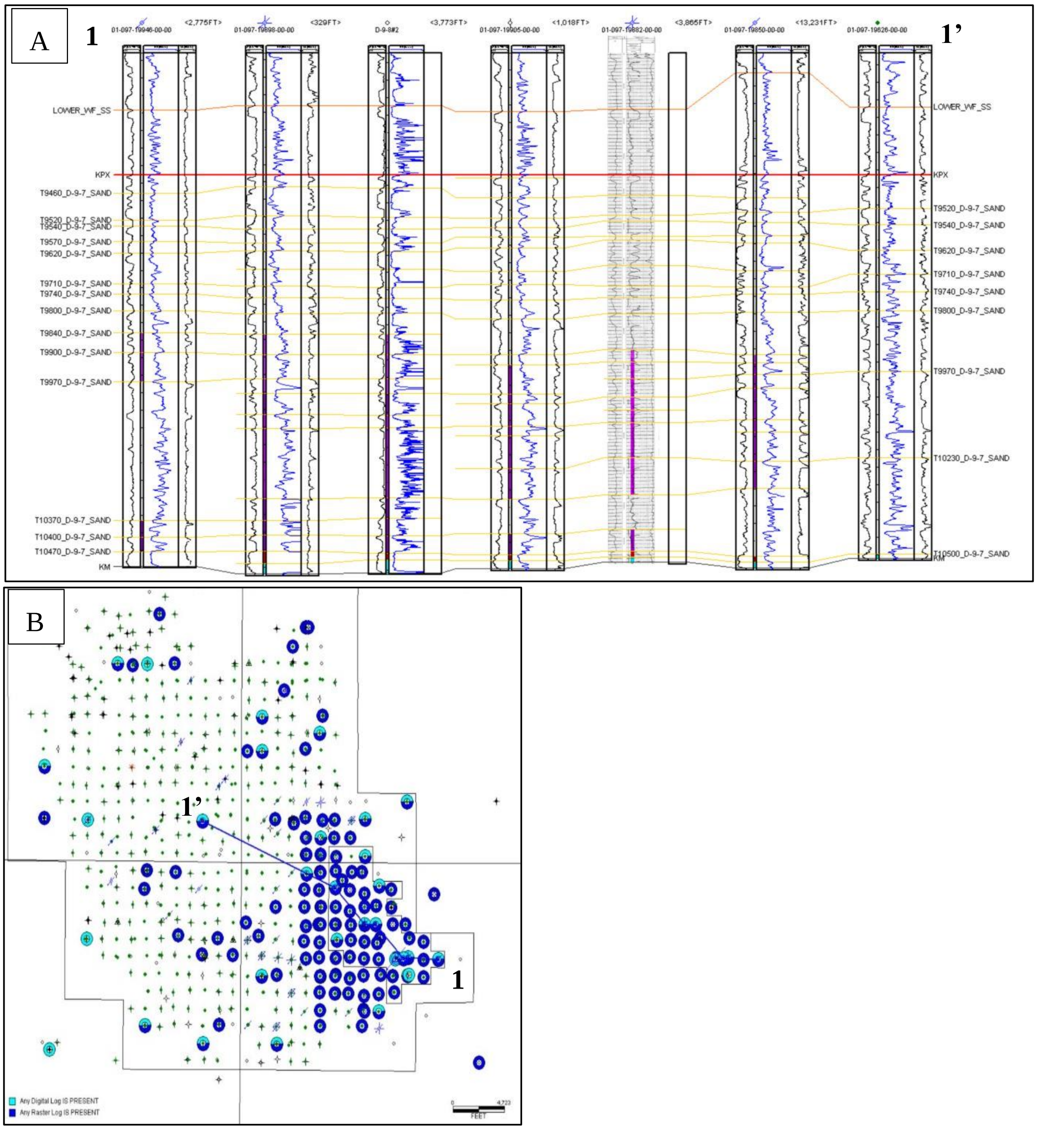

Figure 4. (A) Geological cross section through the Citronelle Field area showing the top of the Paluxy Formation (KPX) and the individual sand intervals of the Paluxy (T9460 through T10470) interpreted within the formation from vintage well logs. The log tracks from left to right are spontaneous potential (SP), induction (ILD), and short normal (SN). The cross section has been flattened to the top of the Paluxy Formation. (B) Map of the Citronelle Field area and the corresponding cross section line. Source: Author Conception. Cross section and map created in Petra ®.

1.2. Site Characterization

One of the primary objectives of the Southeast Regional Carbon Sequestration Partnership Anthropogenic Test is to constrain the storage capacity available in the Paluxy Formation. The initial storage capacity was assessed using the volumetric approach for saline reservoirs developed by the United States Department of Energy [8]:

$$G_{CO_2} = A_t h_g \phi_{tot} \rho E_{saline} \quad (1)$$

where the total mass of stored CO_2 (G_{CO_2}) expressed in mega tons (Mt) is the product of the total reservoir area (A_t), gross formation thickness (h_g), total porosity (ϕ_{tot}), CO_2 density at reservoir pressure and temperature conditions (ρ), and the saline reservoir efficiency factor (E_{saline}). To complete this, determining the porosity of the storage formation was essential to calculating the total pore volume of the Paluxy sand reservoirs which is a major component of the volumetric equation (1).

Geologic characterization was conducted at the site by combining data generated from new wells with preexisting data of the Paluxy Formation from legacy oil wells at the Citronelle field. Three new test wells were drilled in association with the project beginning in December of 2011, and modern well logs were gathered, including density porosity logs. In addition, more than 210 feet (64 m) of whole core and 70 sidewall core plugs were obtained from the new wells. The wells were drilled on existing well pads where vintage well logs were available from plugged and abandoned wells drilled in the 1950s.

Legacy oil wells within the Anthropogenic Test Site lack measurements of porosity due to the age of the formation evaluation tools available at the time of initial field development. The vintage well logs comprise only electric log data limited to spontaneous potential (SP), induction (ILD), and short normal (SN) measurements. These logging tools assess gross lithology in addition to the presence and type of fluids that saturate the pore space of the storage target [9]. However, without measurements of porosity, the storage potential of the Paluxy Formation cannot be determined. The proximity of the three new wells to the preexisting legacy wells containing vintage logs presents an opportunity to utilize machine learning in the form of an Artificial Neural Network (ANN) to determine the field-wide porosity of the Paluxy Formation. Using an Artificial Neural Network can generate estimates of porosity which would otherwise not be possible.

1.3. Artificial Neural Networks

The Artificial Neural Network (ANN) is a nonlinear mathematical model based on the structure of a biological neuron that uses machine learning to recognize patterns in numerical data [10]. Artificial Neural Networks consist of an input layer, a hidden layer containing nodes, and an output layer. To recognize patterns within data, neural networks must first be trained using a representative set of paired inputs and outputs. Input data are fed through nodes linked by connections that are adjusted during network training based on their performance. After the training process, the neural network is validated and then applied to unpaired input data for interpretation.

To train an Artificial Neural Network, a set of paired inputs and outputs are fed into the network that establish the interconnected weighting factors, or nodes, which recognize patterns between the paired dataset. Large differences between the neural network result and the predetermined output prompts the network to run additional iterations, or backpropagations, by adjusting connection weights to calculate new output values [11]. This process of backpropagation is repeated until the neural network results fall below a minimum difference threshold relative to the desired output.

Once training is complete, the Artificial Neural Network must be validated to ensure the quality of synthetic results before being applied to new data. Validation requires testing the network's ability to replicate a set of user defined input and output pairs. If validation results are not accurate, the neural network undergoes continued training. When good validation results are achieved, the network can be applied to an unpaired input dataset. The trained network will then create synthetic numerical values for unpaired input data based on the patterns learned during training. Importantly, the advantage of utilizing an Artificial Neural Network is that synthetic results can be generated with speed and high accuracy for large data sets that would otherwise be interpreted by hand.

1.4. Related Work and Literature Review: Neural Networks Applied to Well Logging and Reservoir Characterization

Artificial Neural Networks are an established tool in hydrocarbon exploration that reduce the time, cost, and repetitive nature of field-scale well log analyses [11–16]. In addition, neural networks have been used to generate porosity curves for wells lacking a complete suite of traditional logging measurements. For example, Mohaghegh et al. (1999) [15] demonstrated using a neural network to determine field-wide reservoir quality with a limited number of wells. In some cases, well logs were incomplete, and the Artificial Neural Network generated synthetic porosity data to fill gaps in log coverage throughout the field. The neural network was trained, validated, and then applied field-wide, which provided accurate reservoir characteristics such as porosity and saturation values. This work provides an example of a cost and time reduction workflow for subsurface characterization.

Helle et al. (2001) [11] used a neural network to derive porosity using a three-layer network comprising sonic, density, and resistivity values. A separate neural network was also developed to model permeability from four input layers: density, gamma ray, neutron porosity, and sonic wireline measurements. The results of this work produced accurate porosity and permeability estimates and demonstrated no prior knowledge of grain material or pore fluid resistivity was needed to derive porosity.

While the application of neural networks to well logs and field-scale porosity analyses are established, utilizing this tool for geological characterization of a Carbon, Capture, Storage project has not been attempted before. Here, an Artificial Neural Network was used to generate synthetically derived porosity curves resulting from neural network training and validation on new and vintage well logs that were collected from the same well pad location. This methodology provides an example of a technique that could be applied to all Carbon, Capture, Storage site characterization projects.

2. Methods

2.1. Methodology Overview

Three new wells were drilled near three abandoned wells that penetrate the storage formation geology at the Citronelle Field. Modern logs were collected from the new wells and paired with vintage logs from the abandoned wells. The well logs that were utilized for this study include modern porosity logs and vintage spontaneous potential (SP), induction (ILD), and short normal (SN) logs. An Artificial Neural Network was trained based on the well log relationships between the electrical logs and the porosity logs from the newly drilled wells. The Artificial Neural Network was then validated to ensure that synthetic porosity provided realistic estimates. Last, the trained and validated Artificial Neural Network was then applied field-wide to estimate porosity for zones of the storage formation geology.

2.2. Input Data

This study utilized well logs from three pairs of new and abandoned wells at the Citronelle Southeast Unit, Figure 5. The wells pairs include (1) D-9-7 #1 and D-9-7 #2 (158 feet/48 m apart), (2) D-9-8 #1 and D-9-8 #2 (318 feet/97 m apart), and (3) D-9-9 #1 and D-9-9 #2 (105 feet/32 m apart). Abandoned wells are denoted with a #1 suffix and new wells with #2. Spontaneous potential (SP), induction (ILD), and short normal (SN) vintage logs from the abandoned wells were compiled, digitized, and paired with the density porosity logs of the test wells. The digitized electrical logs and modern density porosity log pairs were corrected for logging datum depth changes to ensure that the depth scales matched. Off-scale data points, absent values, and digitization errors were either corrected or removed.

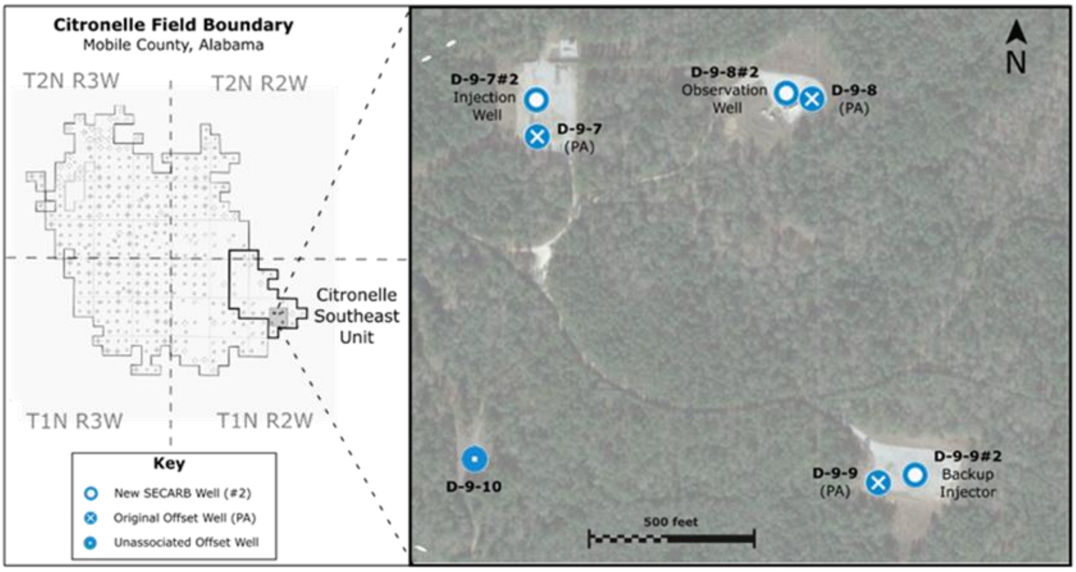

Figure 5. Map showing the location of both preexisting and newly drilled characterization wells at the Southeast Regional Carbon Sequestration Partnership Anthropogenic Test Site. #2 indicates the name of a new well drilled in 2011. PA indicates a plugged and abandoned well.

After correcting the digitized electrical logs and pairing them with the modern density porosity logs, wells D-9-7 #1, D-9-7 #2, D-9-8 #1, and D-9-8 #2 were used to train the Artificial Neural Network. Spontaneous potential (SP), induction (ILD), and short normal (SN) values from wells D-9-7 #1 and D-9-8 #1 were input into the neural network and the accompanying density porosity logs were assigned to the Artificial Neural Network output layer. For example, the D-9-7 well pair applied the vintage D-9-7 #1 electrical logs into the neural network input layer, while the D-9-7 #2 density porosity log was applied to the output layer. After loading the respective logs into the input and output layers, the network underwent subsequent training iterations. Wells D-9-9 #1 and D-9-9 #2 were omitted from the training process and instead utilized to validate the neural network that was trained on well pairs D-9-7 and D-9-8.

2.3. *Artificial Neural Network Training*

The MathWork's Deep Learning Toolbox, formerly the Neural Network Toolbox, was used on the MATLAB software platform to develop and run the Artificial Neural Network. The Deep Learning Toolbox uses the Levenberg–Marquardt algorithm, which is optimized for training small to moderate sized networks up to several hundred weights and commonly used to derive reservoir properties from well logs [17]. The algorithm combines an error backpropagation approach, or steepest descent method, with the Gauss–Newton algorithm to train multiple input variables to target a known output over a series of iterations [18,19]. The mean squared error is calculated for each training run and used to assess iteration performance.

The neural network in this study contained three inputs in the input layer for each electrical logging instrument, four nodes within the hidden layer, and a single synthetic porosity output, see Figure 6. During the training stage, the network converges toward the output target by adjusting the network connection weights between nodes within the hidden layer. In this network, 70% of the input data is randomly included in the training process, while the remaining 30% is incorporated for the validation phase. The network continually adjusts connection weights between nodes until the mean squared error between the desired output and Artificial Neural Network output falls below the minimum difference threshold.

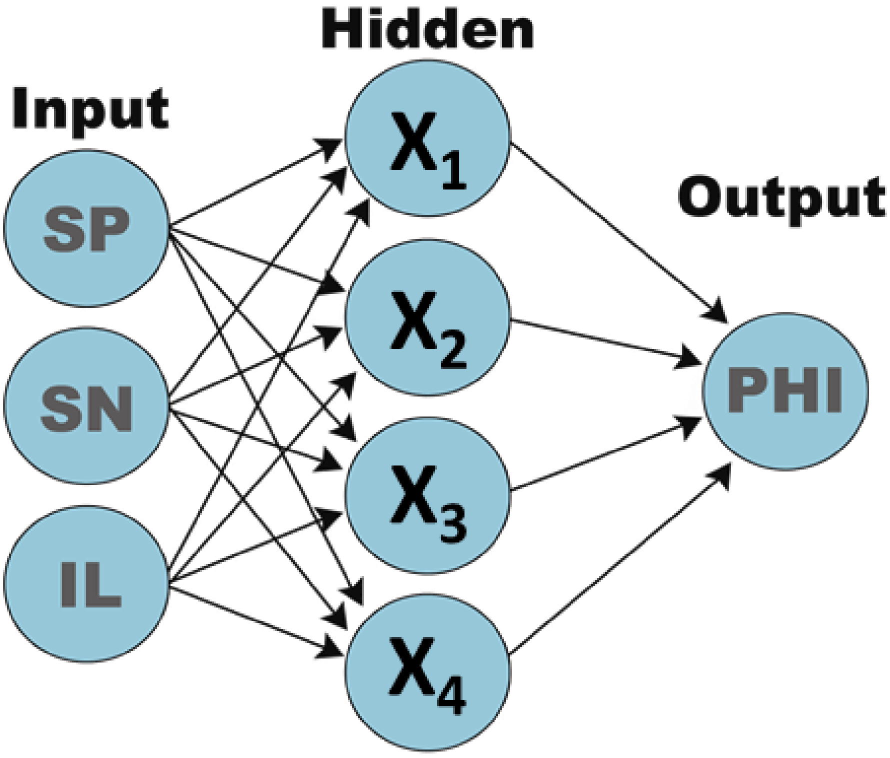

Figure 6. Structure of the Artificial Neural Network with a single input layer containing digitized SP, ILD, and SN values. The inputs are passed into the hidden layer containing four nodes which produce a synthetic porosity (PHI) output.

2.4. Validation

The Artificial Neural Network was also validated to quality control the training process before the neural network is applied to an unpaired well log dataset. Validation was conducted in two stages: where stage one occurred synchronous with training, while stage two validation occurred after training. The benefit of two validation stages, both synchronous- and post-training, enables the neural network to efficiently optimize its connection weights which reduces the time required for post training validation.

2.5. Syn-Training Validation

During stage one, a 30% subset of the training data is randomly selected in the software and divided in half. The first half of the randomly selected population is used to assess the accuracy of the training process and direct the network to continue backpropagating or complete the training. The second half of the randomly selected data are measured for accuracy and used to assess the Artificial Neural Network's ability to replicate the output data set. During the stage one validation process, the neural network achieved a coefficient of determination (R^2) of 0.704.

2.6. Post-Training Validation

The stage two component of the validation process is to test the Artificial Neural Network's ability to reasonably replicate density porosity measurements after training. The D-9-9 #1 and #2 wells were chosen for this task. Spontaneous potential (SP), induction (ILD), and short normal (SN) curves from well D-9-9 #1 were input into the trained neural network and a synthetic porosity curve was generated. This curve was loaded into geologic modeling software and analyzed alongside the modern density porosity curve from the D-9-9 #2 well to qualitatively compare the density and synthetic porosity curves, see Figure 7. At the depth of the Paluxy Formation, synthetic porosity values range from 20.3%

to 17.5%, while the actual porosity values derived from density porosity logs range from 20.0 to 16.1%. Neural network synthetic porosities generally match the actual density porosities, but in most cases slightly overestimate porosity on average by approximately 0.79% for this validation run.

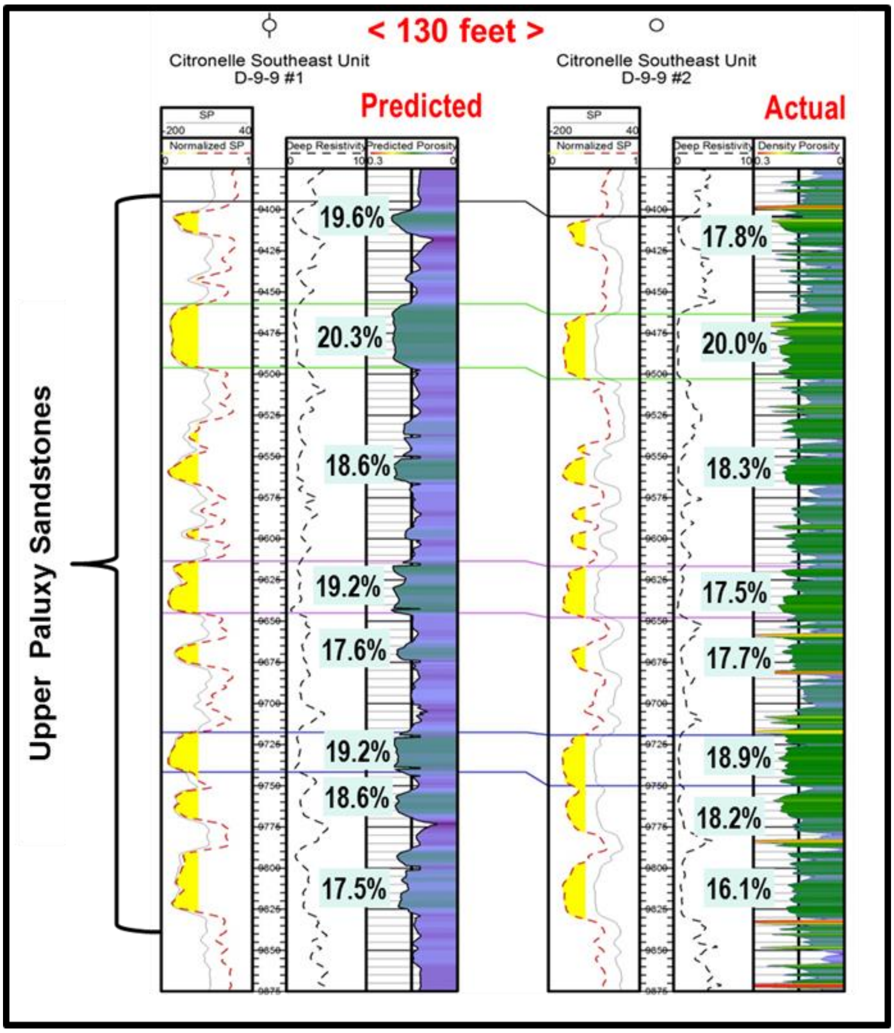

Figure 7. (Left) Predicted neural network porosity curves compared with actual density porosity logging measurements (Right) at the D-9-9 #1 and #2 well pair. Paluxy sand reservoirs are highlighted in yellow on the SP log. The wells are spaced 130 feet/40 m apart. The predicted Artificial Neural Network curve was generated from MatLab®. The actual porosity curves shown use Petra®.

Directly comparing the synthetic porosity to the density porosity measurements indicates an R^2 value of 0.54 which suggests a poor correlation. However, the small average difference between the synthetic porosity and density porosity of less than 1% suggests that the neural network is effective at closely estimating porosity reasonably well. It is interpreted that the difference between synthetic and measured porosities results from the high resolution of modern density logging tools that capture very small interbeds of low porosity lithologies. Small interbedded low porosity intervals produce more variability in the density porosity curve. The neural network derived porosity curve produces a smooth line that cannot replicate the exact resolution of the density porosity log. In addition, poor image raster quality of the electric logs could also contribute to the low correlation between the synthetic and density porosity curves.

Comparisons of synthetic porosity and actual density porosity were also evaluated in geologic formations situated at more shallow depths above the Paluxy Formation to ensure reasonable porosity estimates. Actual porosities of the Lower Tuscaloosa Group, Upper Washita-Fredericksburg Group, and

Upper Paluxy Formation were acquired from publicly available petrophysical data from the Alabama Geologic Survey. Synthetic porosity curves of the formations that overlie the Paluxy Formation compare well with porosity derived from core data acquired from the Alabama Geological Survey.

3. Results

Field-Wide Application of the Neural Network

After training and validation, the Artificial Neural Network was used to generate synthetic porosity curves for 36 wells in the vicinity of the Anthropogenic Test Site within the Citronelle Oilfield, see Figure 8. These wells were selected based on the availability and quality of the electrical logs. In addition, well locations were selected to provide adequate coverage of the Paluxy Formation throughout the Citronelle oilfield. Well coverage does not extend to the east or south of the immediate storage site because this lies outside of the Citronelle oilfield boundaries.

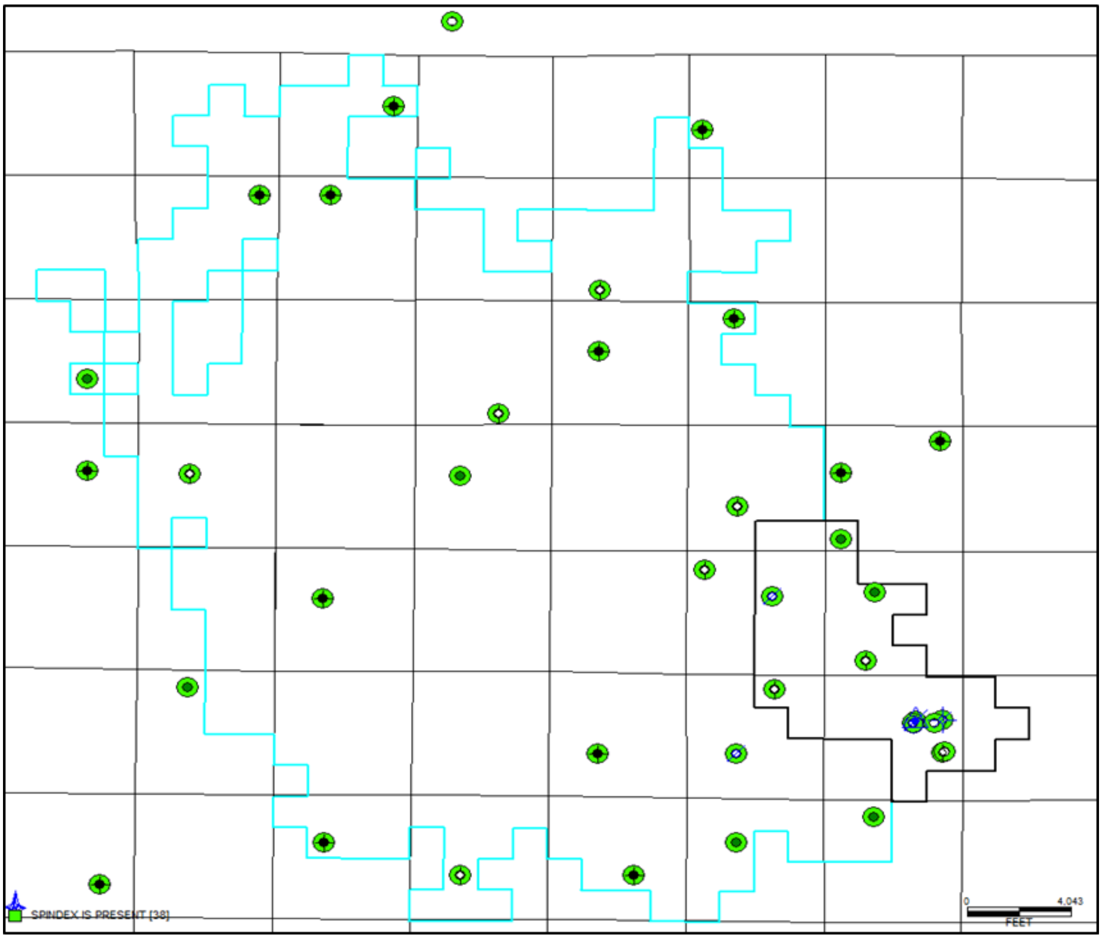

Figure 8. Locations of legacy oil wells within the Citronelle Oilfield used to generate synthetic porosity curves with the Artificial Neural Network. Green points indicate the location of each oil well used in this study. Map generated using Petra®.

An example of the synthetic porosity curve of well A-34-6 #1 is shown in Figure 9. This well is located approximately 5.5 m (8.9 km) west of the D-9-9 #1 well used to validate the neural network. A mean porosity of ~20.4% was predicted for this well within the upper Paluxy Formation. The neural network also determined multiple high porosity zones within the overlying sand reservoirs of the Washita-Fredericksburg Group and Lower Tuscaloosa Group. Together, these high porosity zones are separated by low porosity intervals interpreted as mudstones.

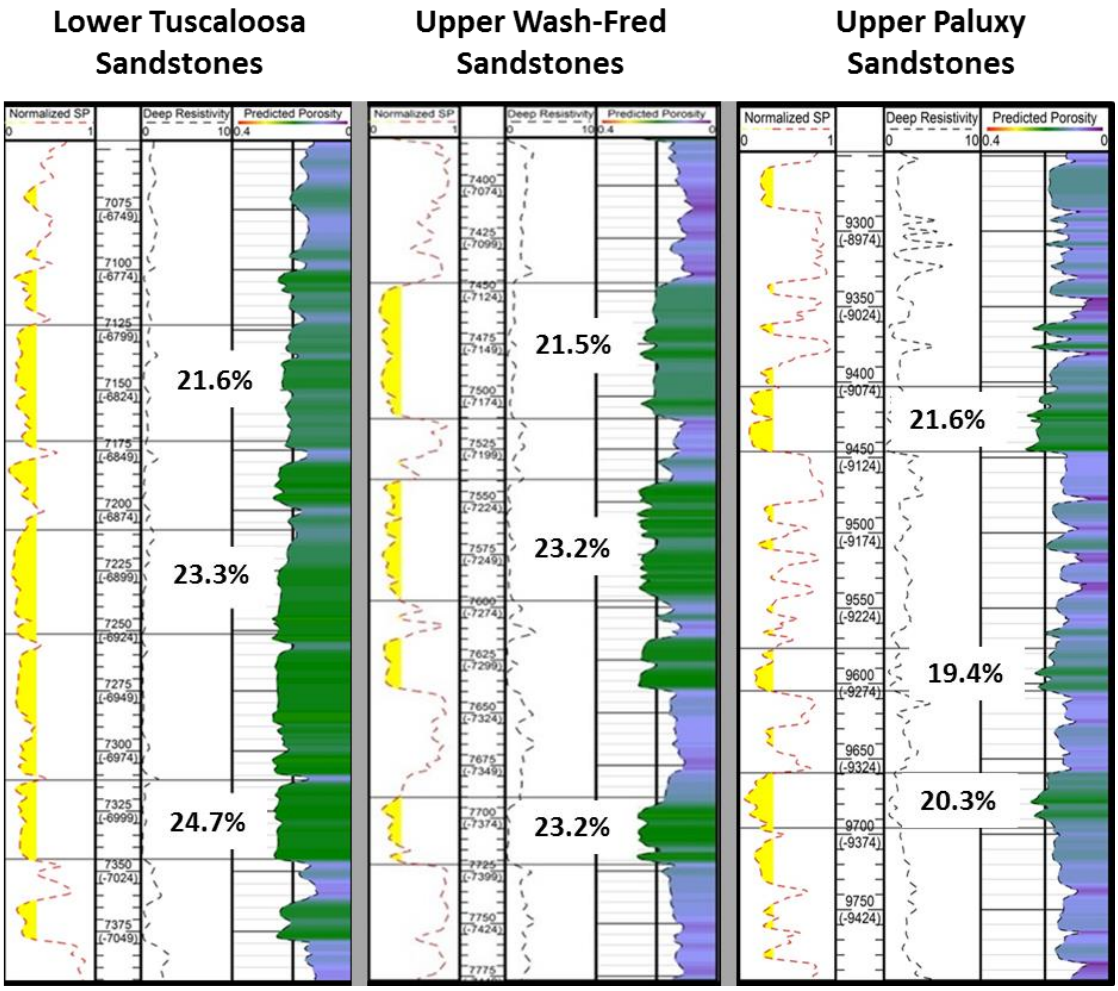

Figure 9. An example of synthetic porosity curves from well A-34-6 #1 located several miles west of the three well pairs that were used to train and validate the neural network. Source: Author Conception. Synthetic porosity curves generated in MatLab® and displayed using Petra®.

The synthetic porosity values were also used to determine permeability for the legacy wells throughout the Citronelle oilfield. Measurements of permeability in addition to porosity are critical for reservoir simulations that model injectivity and sandstone reservoir flow properties. Routine core analyses were used to determine porosity and permeability for all upper Paluxy cores that were recovered from the three stratigraphic test wells. Core derived measurements of porosity and permeability for each of the stratigraphic test wells were determined using cross-plot techniques that provide an empirical relationship between porosity and permeability for the Paluxy sands in this area, see Figure 10. Using this empirical relationship, a corresponding permeability was determined for each synthetic porosity value predicted by the neural network. Thus, utilizing an Artificial Neural Network trained on three test wells generated reservoir quality data that included porosity and permeability of the storage formation across the entire Citronelle oilfield.

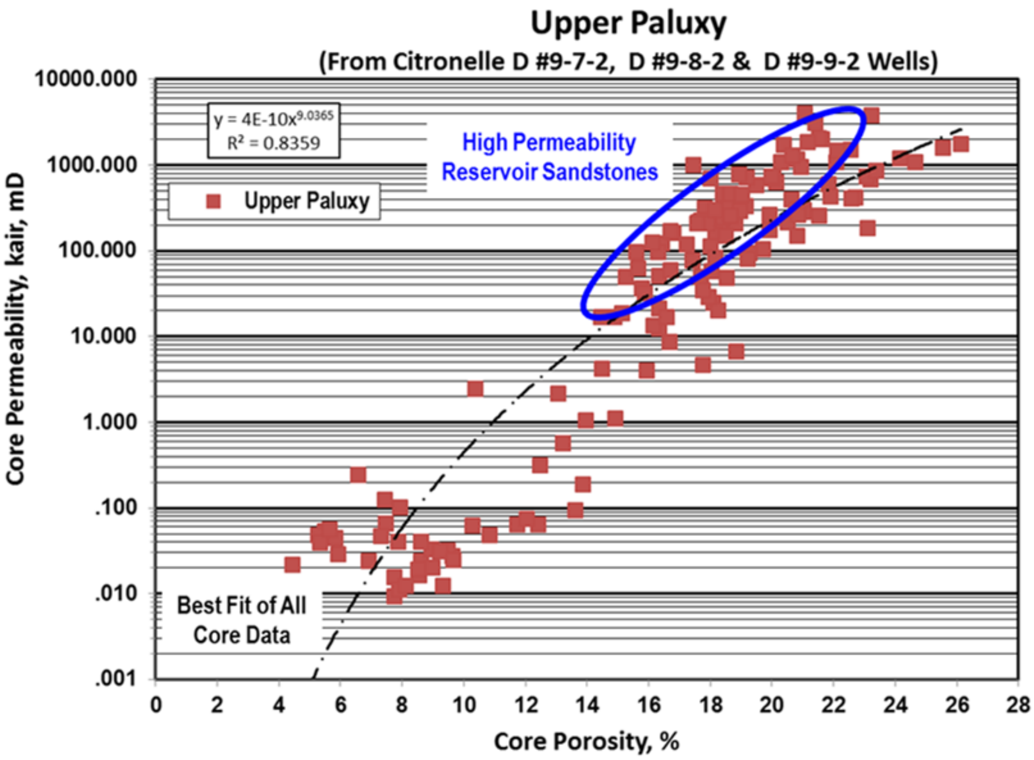

Figure 10. Cross-plot of core derived porosity and permeability for the upper Paluxy Formation from each stratigraphic test well. Source: Author conception.

Synthetic porosity and estimated permeability values for the Paluxy Formation were fed into the Test Site geologic model and used to map areas of high reservoir quality. These data revealed 260 vertical feet (79 m) of net porous upper Paluxy sandstone. In addition, the porosity of the Paluxy Formation was determined to range from 13 to 24%, averaging 19%, with a mean permeability of 300 mD.

4. Discussion

Overall, the results of the Artificial Neural Network-derived synthetic porosities were used in the final storage capacity estimates and injection simulations that occurred before and during CO_2 injection at the Anthropogenic Test Site. Predicted porosity and permeability data for each selected well was used to interpolate reservoir quality between well locations to generate total pore volume maps of the upper Paluxy Formation. Critically, the reservoir quality data of the Paluxy Formation was fed into numerical simulations that were able to model the extent and geometry of the subsurface CO_2 plume prior to and during injection operations at the Anthropogenic Test Site [20,21].

Utilizing a neural network within the site characterization workflow at the Anthropogenic Carbon, Capture, Storage Project enabled us to shorten the time and cost of evaluating the reservoir quality of the storage formation across the Citronelle oilfield. The accuracy of the neural network derived synthetic porosities suggests that this method could also be deployed to determine permeability in a similar fashion. Core-derived permeability measurements from a limited number of test wells could be loaded into the output layer of a neural network and paired with pre-existing well logs that lack permeability data. The network could be trained and validated following our methodology and synthetic permeability measurements across the field could be predicted if existing vintage well logs exist within the vicinity of a potential CO_2 injection site.

One of the major limitations of this methodology is that numerous legacy wells in addition to a few modern wells are required to estimate synthetic porosity across the entire field. Legacy wells containing logs need to have close spacing for the area under consideration so that synthetic porosity values are not extrapolated over long distances which would increase the potential for lithological variations between wells and result in potential variations in reservoir quality. For this work, legacy wells occurred on 40 acre (0.16 km^2) spacing which provided an adequate well density to suggest that major lithological variations did not occur between wells.

For future work, this site characterization methodology utilizing a neural network could also be applied to refine regional estimates of CO_2 capacity across the Gulf Coast in the United States. Leveraging existing wells and subsurface data from numerous oilfields across the southeastern United States has the potential to more accurately estimate the pore volume of multiple saline storage targets within the Gulf Coast stratigraphy. A neural network approach could generate synthetic porosities for thousands of wells along multiple horizons providing a high-density data set to calculate regional CO_2 storage capacity.

5. Conclusions

The complexity of Carbon, Capture, Storage projects necessitates developing technologies and workflows that reduce the high cost and long lead times typical of Carbon, Capture, Storage projects that hinder widespread deployment of this technology. The site characterization phase during Carbon, Capture, Storage project development is an expensive and lengthy process that can benefit from incorporating a modern workflow utilizing machine learning. Thus, a cost saving strategy using an Artificial Neural Network was successfully developed and implemented during geological characterization of the storage reservoir at the Southeast Regional Carbon Sequestration Partnership Anthropogenic Test in Citronelle, Alabama.

This workflow leveraged preexisting subsurface data from legacy oil wells combined with limited modern porosity logs to train and validate a neural network. The results of training and validation demonstrate that the Artificial Neural Network can generate accurate synthetic porosities for pairs of new and old wells. Chiefly, deployment of the neural network at 36 legacy oil wells across the Citronelle field near the Anthropogenic Test Site quickly produced reliable synthetic porosity estimates that were accurate enough to incorporate in CO_2 reservoir injection simulations.

After generating synthetic porosities across the field, core-derived porosity and permeability was determined at each of the newly drilled test wells. An empirical relationship between core-derived porosity and permeability was calculated and used to determine the permeability of the Paluxy Formation using synthetic porosity for each of the 36 legacy well locations.

This work demonstrates the beneficial use of incorporating neural networks into the site characterization workflow where field wide porosity and permeability measurements of the storage formation were determined by drilling only three new wells. Future work could expand this workflow to directly generating synthetic permeability in addition to synthetic porosity if cores are recovered from test well penetrations of the storage reservoir. Specifically, this Artificial Neural Network approach could then be applied to estimating CO_2 storage capacity in other oil fields that have numerous vintage well logs from legacy oil and gas wells. Potential CO_2 storage formations could be more quickly characterized using this methodology if they occur in oil and gas fields with numerous well penetrations of the prospective storage target. Last, utilizing neural networks to determine reservoir quality at the regional scale could further refine regional CO_2 storage capacity estimates across the entire Gulf Coast of the United States.

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