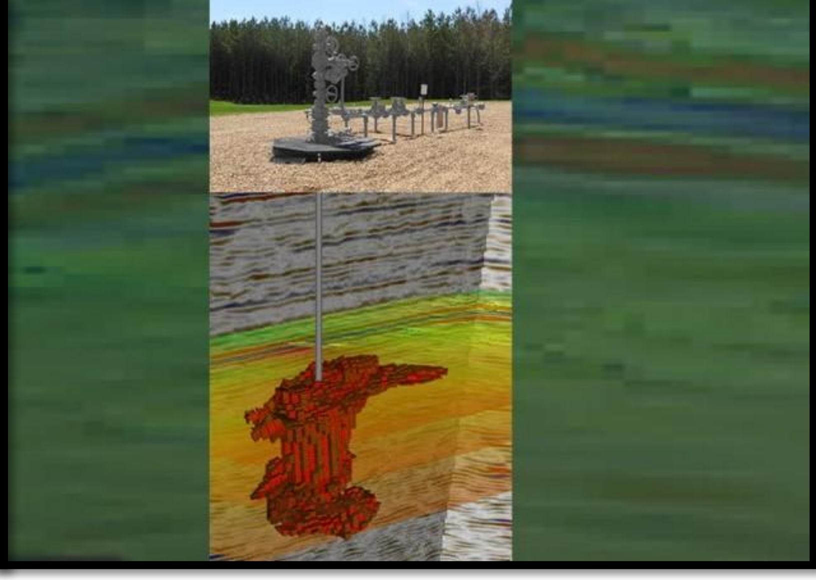
ENVITRACE - AI for Earth Sciences Workshop 2026
March 23-24, 2026 | Santa Fe Convention Center

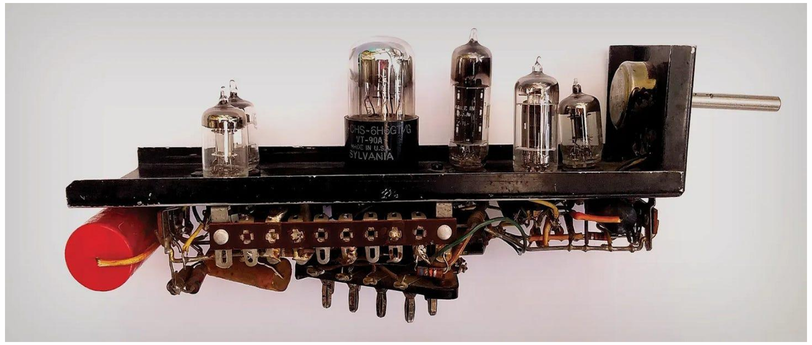


Artificial Intelligence for Geophysical Subsurface Modeling: Applications to Carbon Sequestration

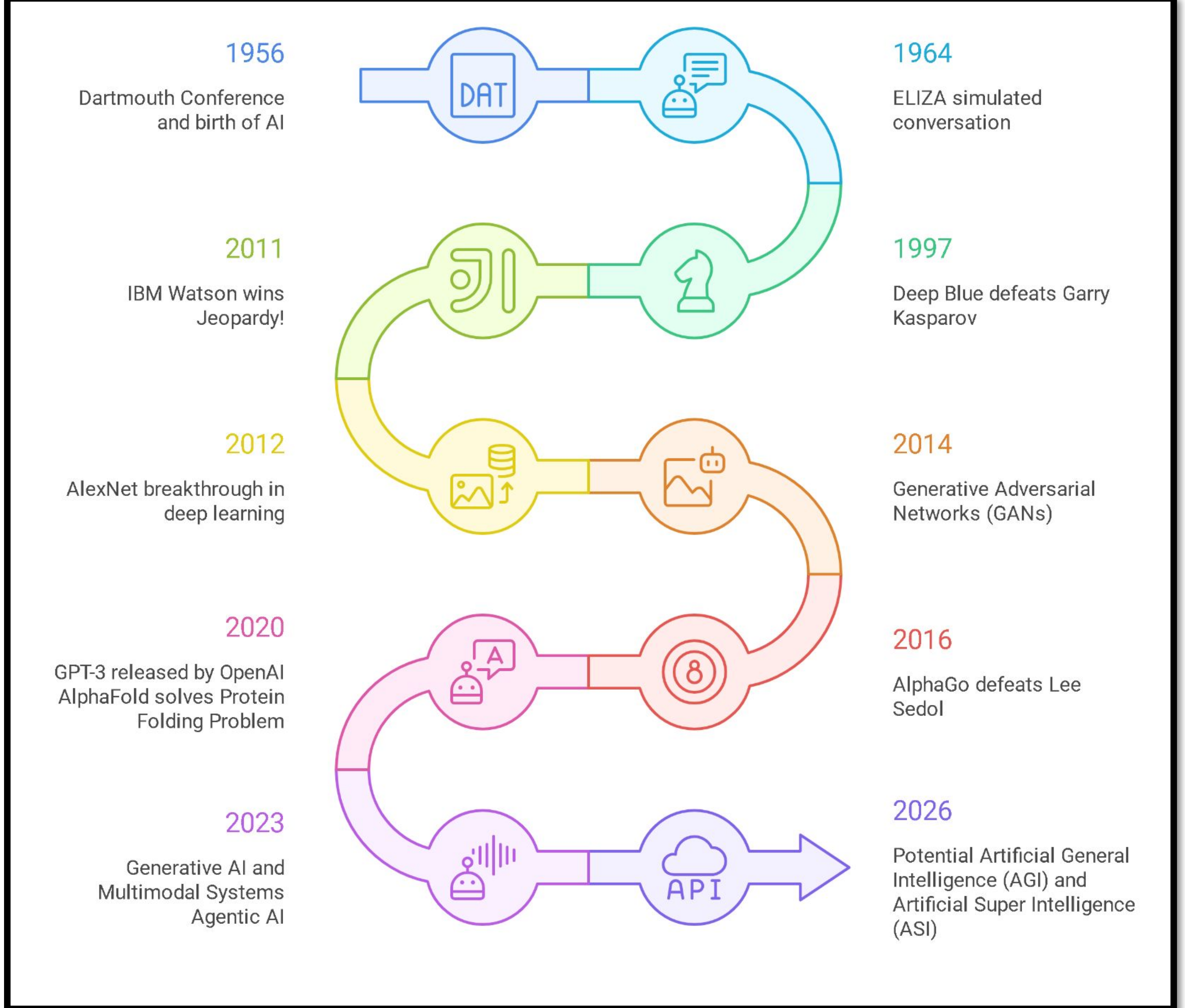
Adewale Amosu
Petroleum Recovery Research Center
New Mexico Tech
Socorro, NM

A Brief History of AI

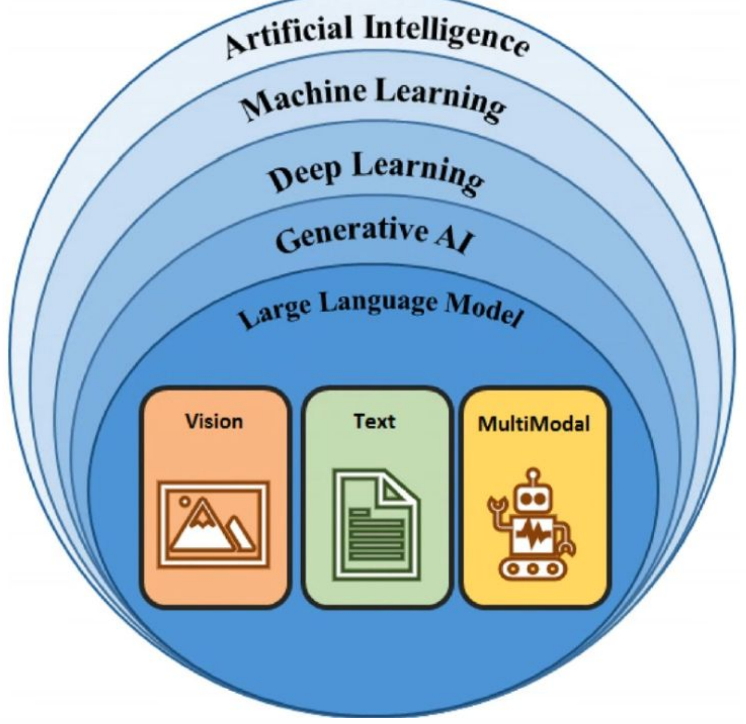
Stochastic Neural Analog Reinforcement Calculator (SNARC)

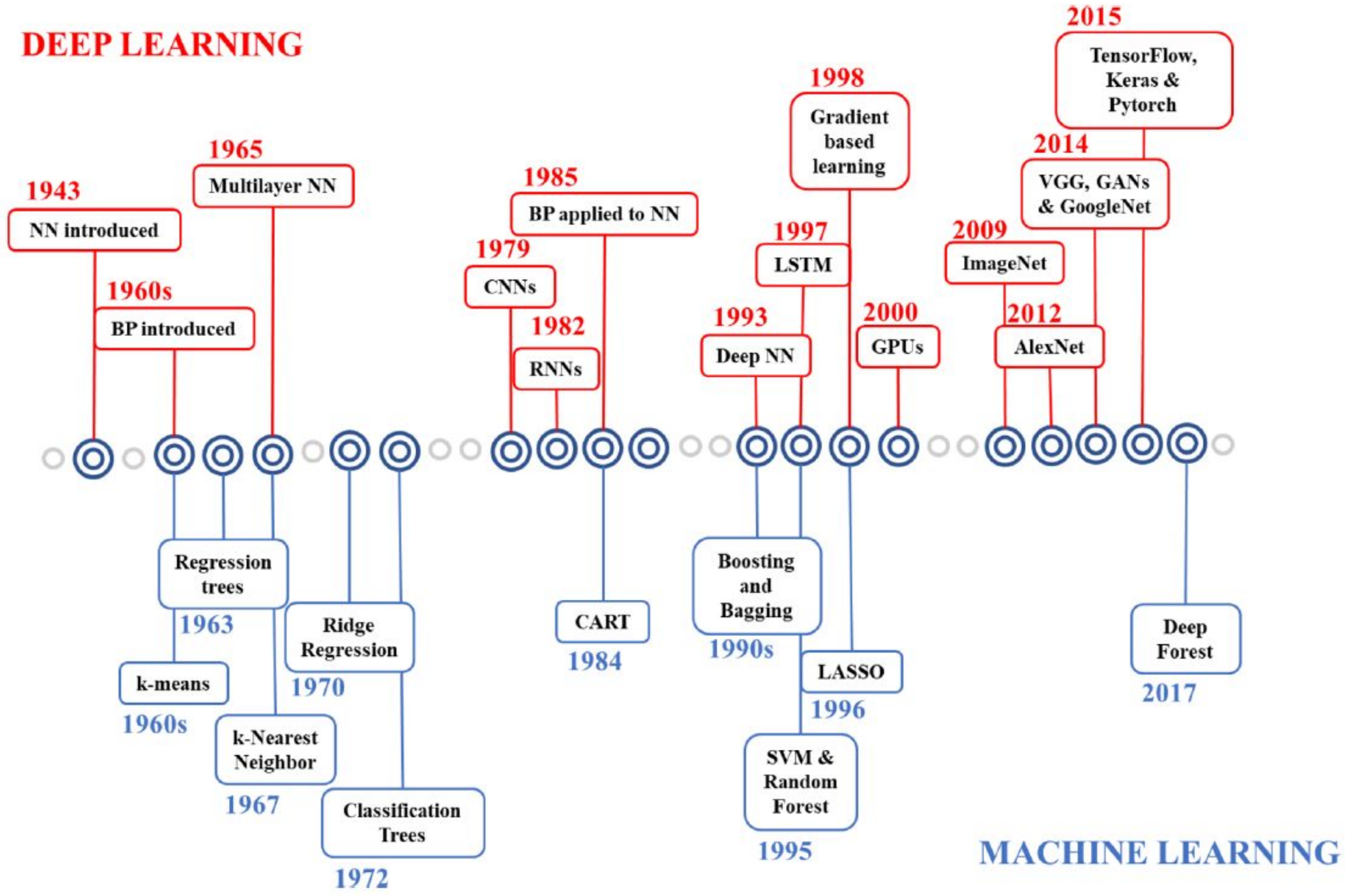


- Developed by Marvin Minsky
- The SNARC machine included 40 artificial neurons (one pictured),
- Interconnected via a plugboard and held in racks in a system about the size of a grand piano



Structure and Key Milestones

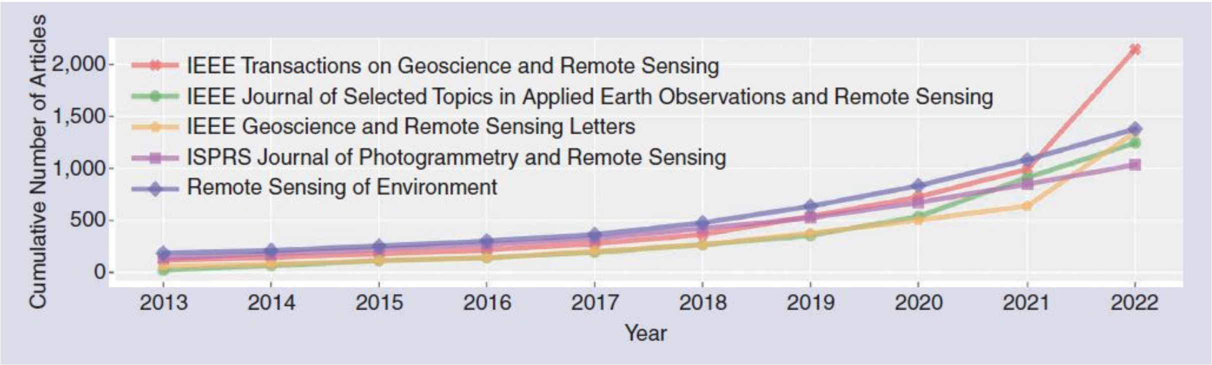


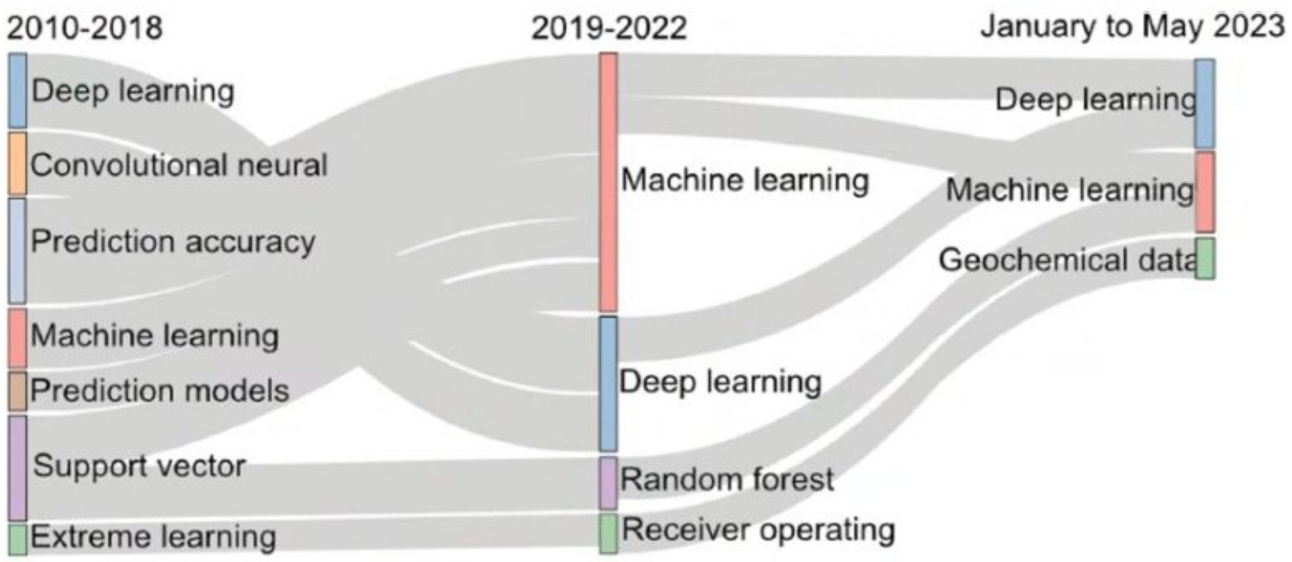


Okoroafor et al. (2022)

Increase Use of AI in Earth Sciences

AI-related articles





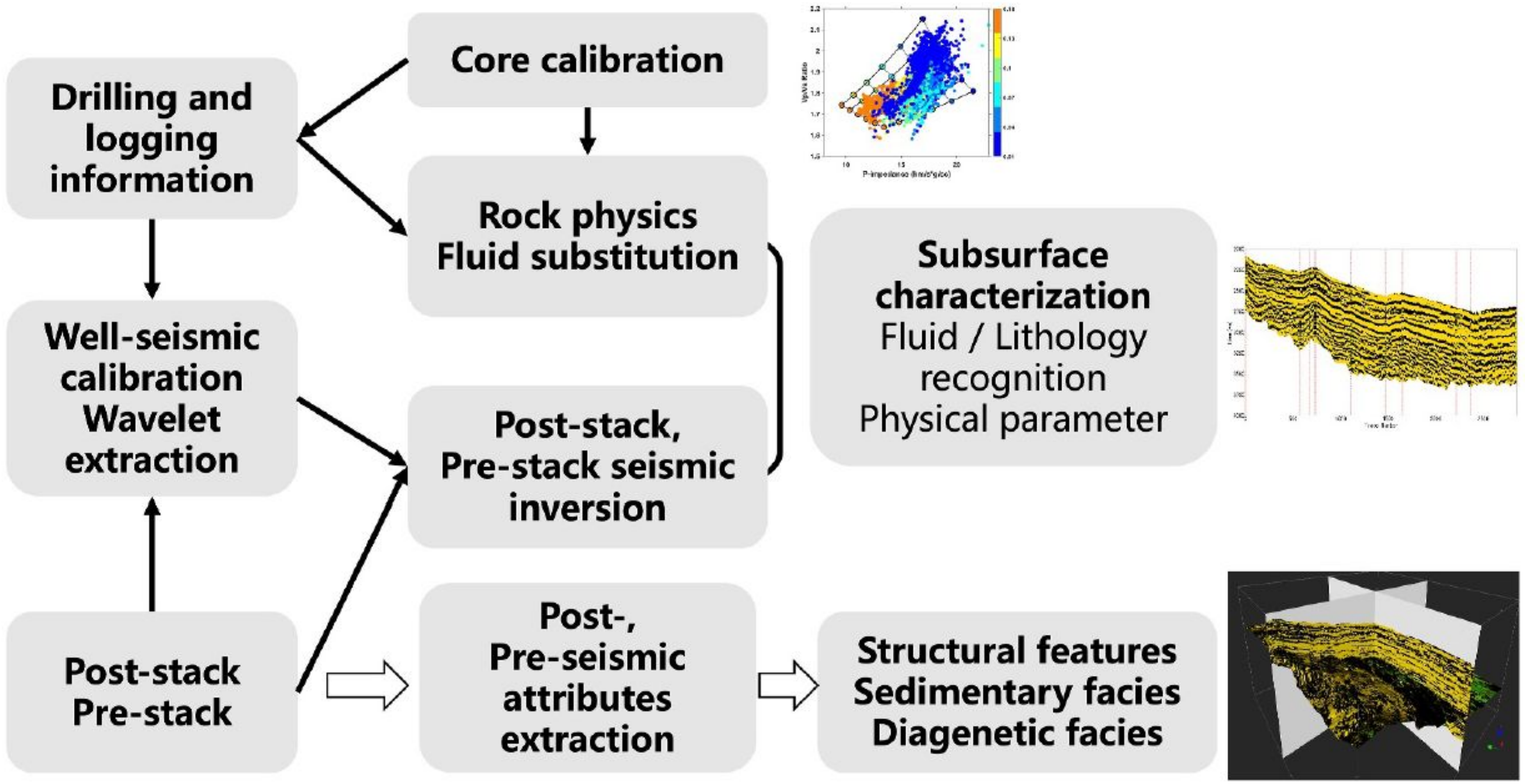
Application field	Model	Pre-trained model	Objectives
Remote sensing	CSPT[444]	ViT	improving the expressive ability of the pre-trained model
	RingMo[456]	ViT/Swin Transformer	a remote sensing foundation model with masked image modeling
	Scale-MAE[450]	Transformer	a pre-trained framework that introduces scale invariance into encoders that are used for a diverse set of downstream tasks
	SatMAE[447]	Transformer	pre-training Transformers for temporal and multi-spectral satellite imagery
	pre-trained ViT[427]	ViT	remote sensing foundation model
	GFM[454]	ViT	building geospatial foundation models via continual pre-training
	SatViT[455]	ViT	pre-training transformers for Earth observations
	Masked ViT[457]	ViT	self-supervised masked image reconstruction to advance transformer models for hyperspectral remote sensing imagery
	SpectralGPT[433]	ViT	the first customized foundation model designed explicitly for spectral remote sensing data
Weather and climate	Earthformer[458]	Transformer	a space-time Transformer for Earth system forecasting
	FourCastNet[438]	Fourier Neural Operator	provide accurate short- to medium-range global predictions
	GraphCast[157]	GNN	medium-range global weather forecasting
	NowcastNet[232]	physics-conditional generative network	a nonlinear nowcasting model for extreme precipitation
	MetNet[439]	U-Net + ViT	high-resolution predictions of several core weather variables
	Pangu-weather[187]	3D Transformer	accurate medium-range global weather forecasting
	ClimateX[428]	ViT	a foundation model for weather and climate
Others	K2[459]	Generative model (LLaMA-7B)	Earth science large language model
	DisasterResponseGPT[442]	Generative model	provide a versatile and adaptive framework for disasters
	OceanGPT[429]	Generative model	a large language model for ocean science tasks

Chen et al. (2024)
Zhao et al. (2024).

Subsurface Modeling

Subsurface Modeling

- Exploration
- Seismic Interpretation
- Seismicity
- Drilling
- Petrophysics
- Reservoir Characterization
- Reservoir Engineering
- Production/Injection Engineering

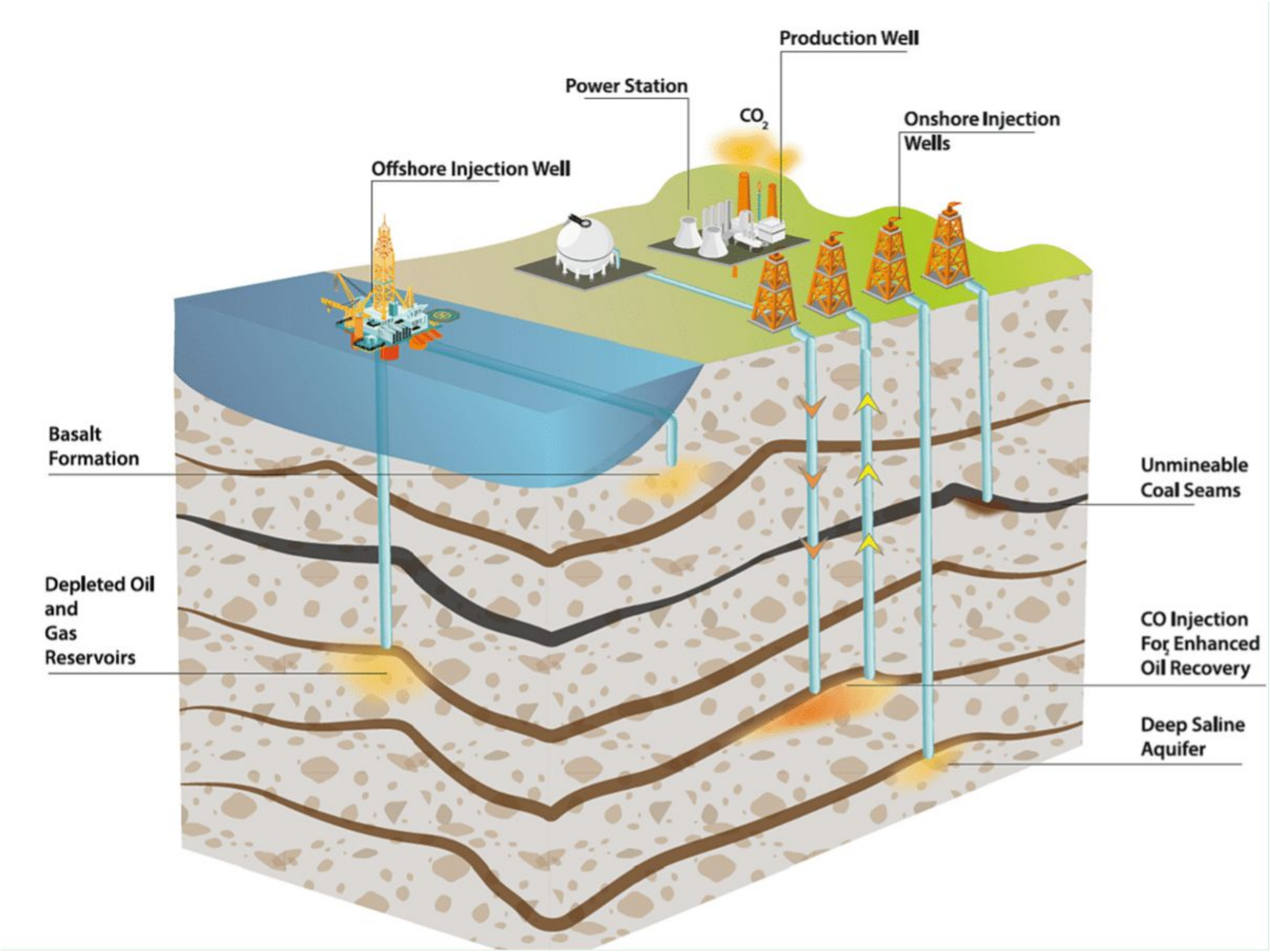


Xu et al. (2025)

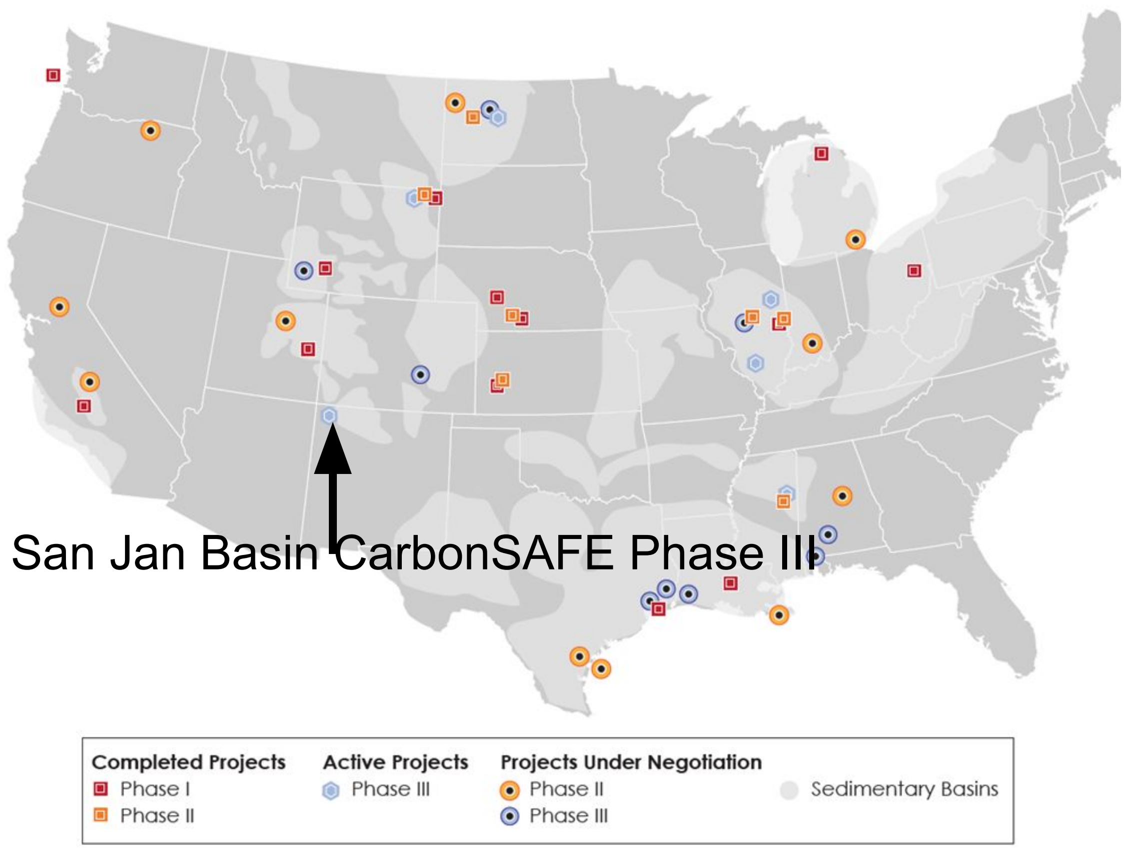
Use of ML in Subsurface Modeling

Research Area	Machine Learning Technique (s) used	Problem(s) being addressed	Refs.
Exploration	SNN, NMFk, Deep Neural Networks	Inversion of geophysical data; gravity data interpretation; Play Fairway analysis; prospectivity analysis;	Holtzman, et al. (2018), Bauer et al. (2020), Ahmmed and Vesselinov (2021), Siler et al. (2021),
Seismicity	NMFk, hidden Markov chain, K-means clustering, CNN	Earthquake detection, detection and location of microseismic events and velocity model inversion from microseismic data, exploration of changes in seismic source spectra	Holtzman et al. (2018), Shaheen et al. (2021), Tanaka et al. (2021)
Drilling	Shallow NN, Multiple Linear Regression	Predicting rate of penetration (ROP)	Diaz et al. (2018), Diaz et al. (2019), Diaz and Kim (2020)
Petrophysics	Shallow NN, kNN, decision trees, gradient boosting, random forest, GAN, deep NN	Prediction of porosity and permeability, lithological facies identification, geothermal reservoir characterization	Feng et al. (2020), Kiran and Salehi (2020), Allo et al. (2021), Elsworth and Marone (2021)
Reservoir Characterization	ACE, k-means clustering, ANN, PCA, NN, MLP, SVM, Deep learning classifier	Interwell connectivity and fracture characterization, reservoir temperature prediction from gas-phase compositions of fluids, small-scale discrete fractures characterization, reservoir temperature classification, prediction of synthetic permeability distribution, fault detection	Akin (2005), Gudmundsdottir and Horne (2018), Pérez-Zárate et al. (2019), Hawkins et al. (2020), Zheng et al. (2021), Gudmundsdottir and Horne (2021), Tut Haklidir and Haklidir (2021), Suzuki et al. (2021), Perozzi et al. (2021), Wu et al. (2021)
Reservoir Engineering	ANN, decision trees, random forest, SVM, deep NN, GMDH-ANN, MLP, LSTM, PCA	Well placement optimization, pressure and thermal drawdown estimation, temperature and pressure prediction in geothermal wells, production enthalpy prediction, predictive modeling of tracer returns, mapping of vertical permeability	Akin et al. (2010), Gudmundsdottir and Horne (2020), Pandey and Singh (2021), Beckers et al. (2021), Gudala and Govindarajan (2021), Shi et al. (2021), Ishitsuka et al. (2021), Li et al. (2017), Aydin et al. (2020)
Production and Injection Well Engineering	Shallow NN, LSTM, DNN, decision trees	Development of proxy models for production and injection quantities and decline rates, prediction of missing production data and future production flow rates, prediction of temperature profiles of geothermal wells	Shi et al. (2021), Harry et al. (2021), Aydin et al. (2020), Bassam et al. (2015), Ariturk (2018), Baser et al. (2021), Shi et al. (2020), Porkhial et al. (2015)

Carbon Sequestration

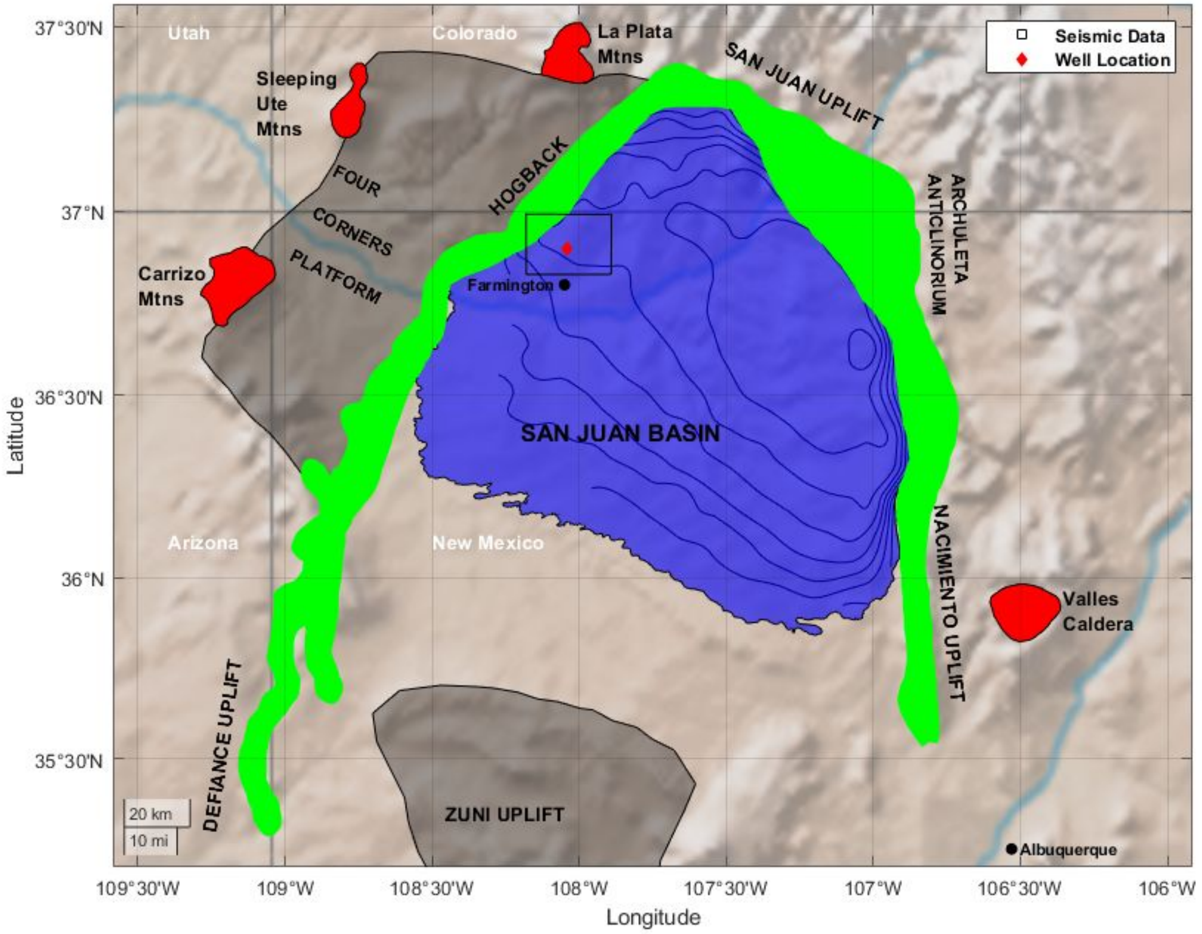


The San Juan Basin

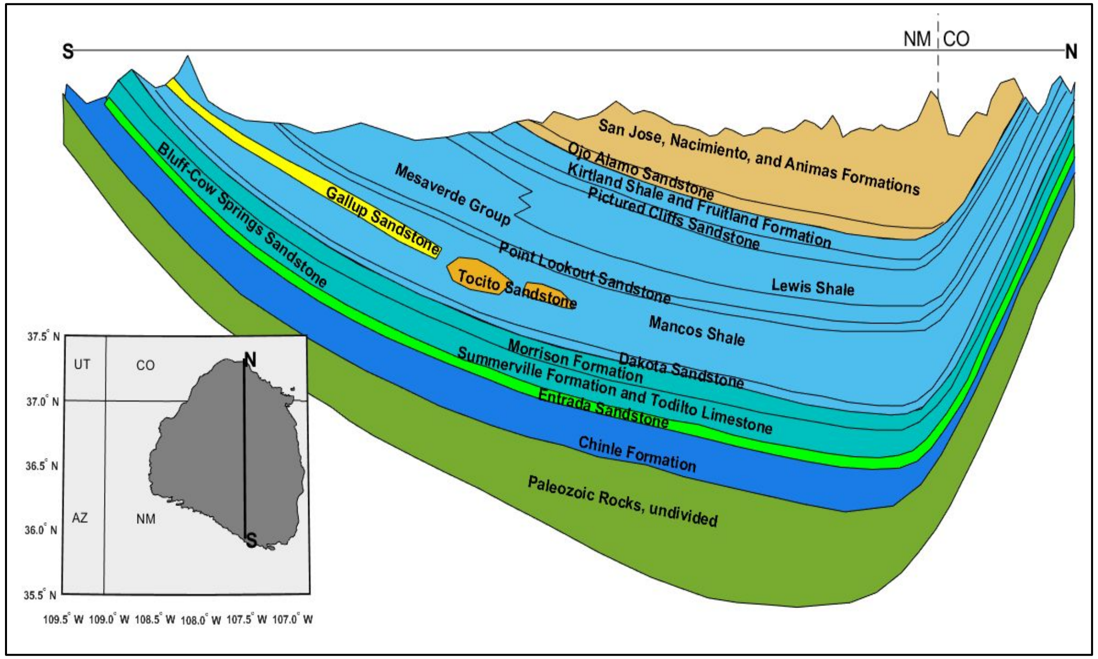


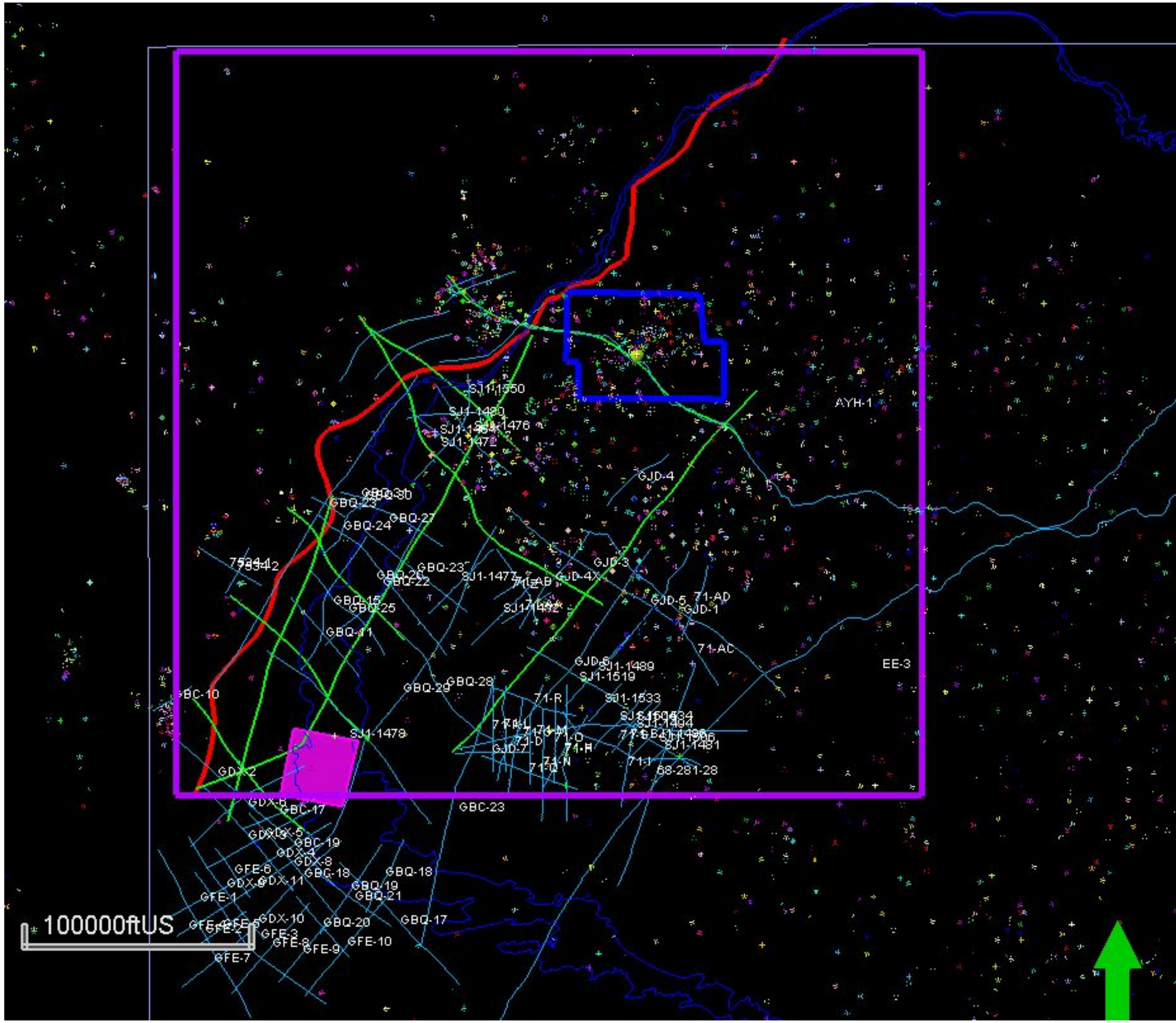
San Jan Basin CarbonSAFE Phase III

As of 2023, Source: https://netl.doe.gov/



San Juan Basin Stratigraphy and Data

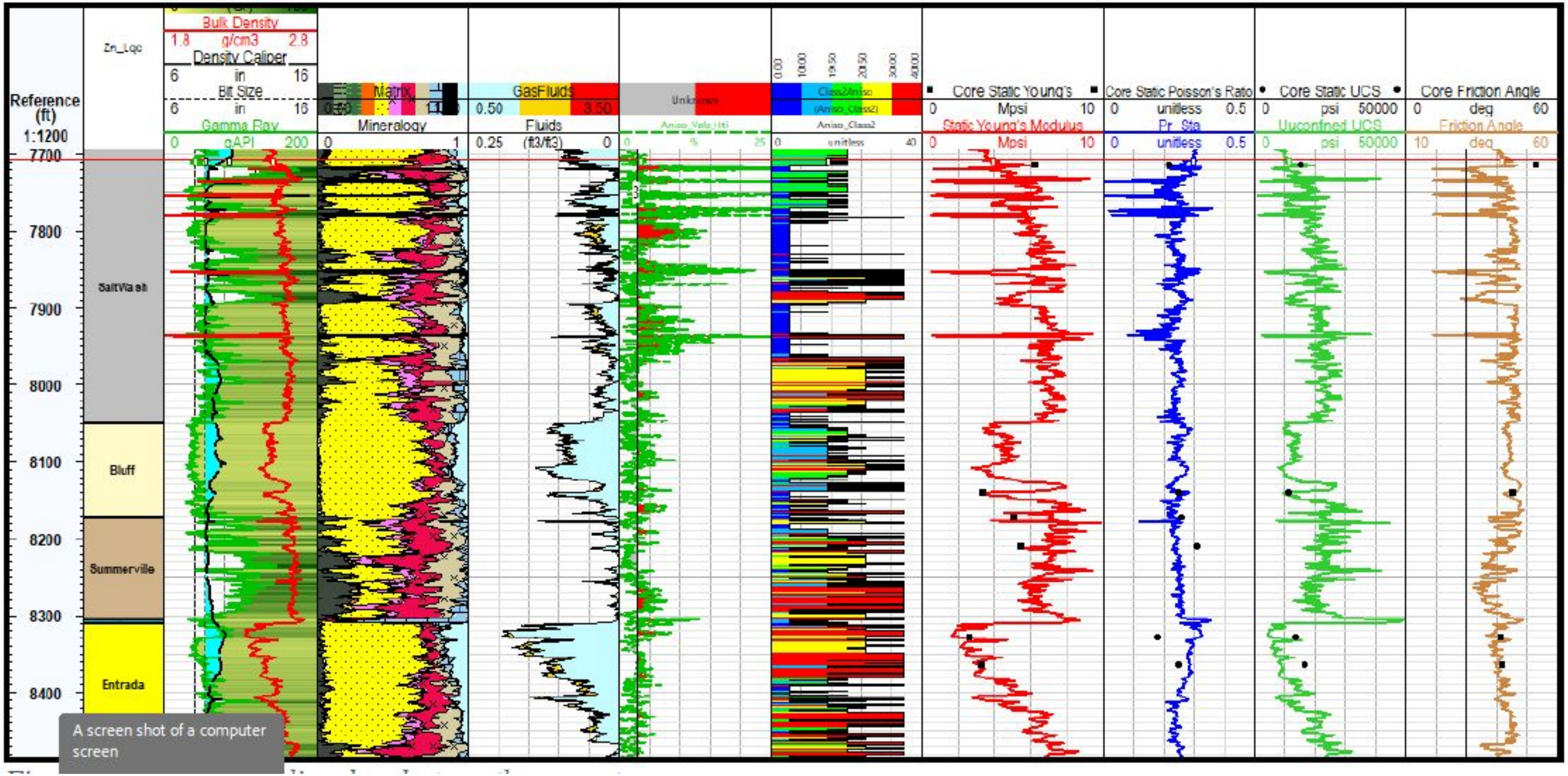




1. Basin-wide prediction of geomechanical properties from triple-combo logs

- Use density, log of resistivity, gamma ray logs and porosity as input
- Train model to predict P-velocity
- Compute S-velocity and geomechanical parameters

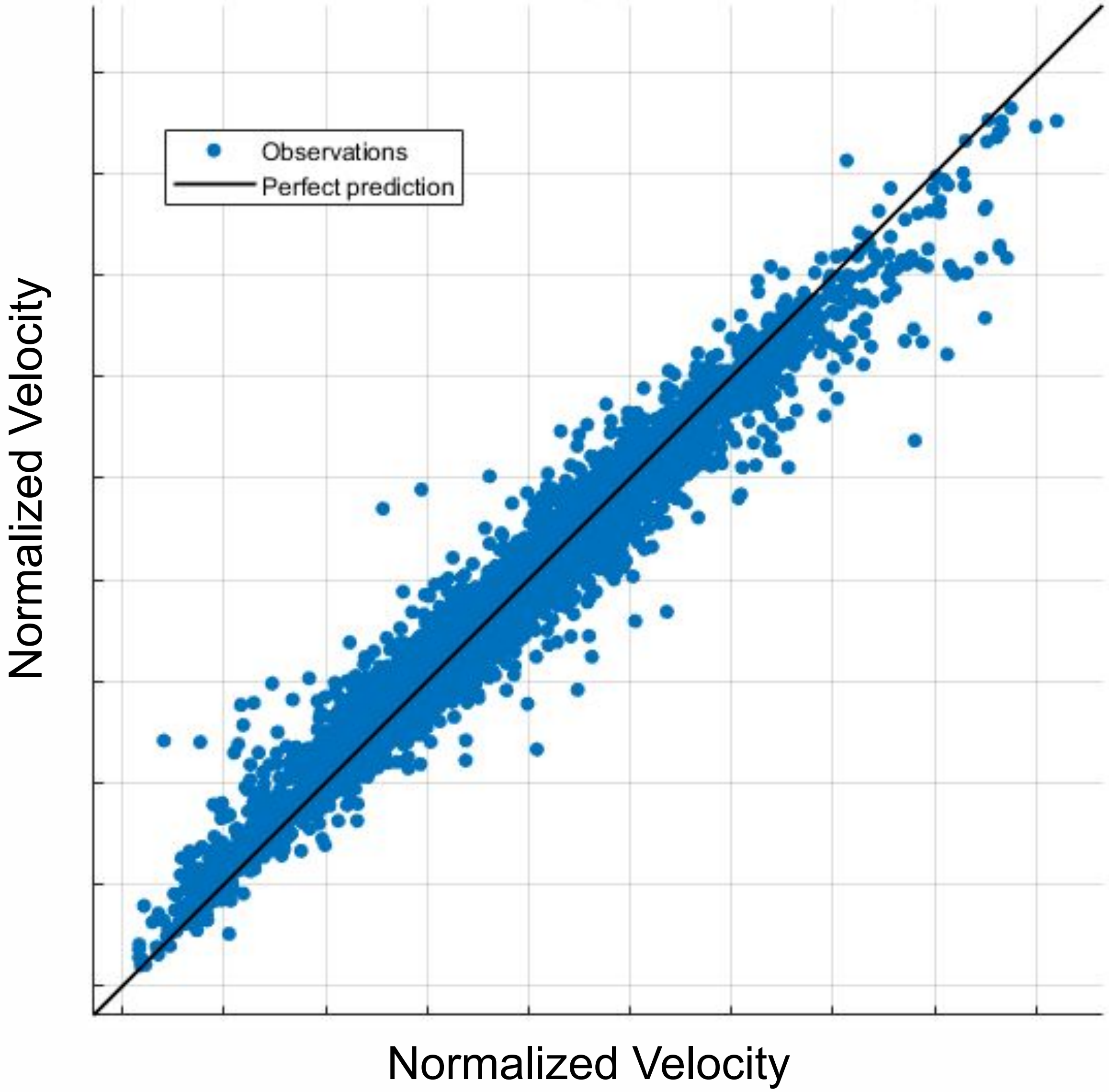
Static Moduli and Rock Strength Parameters

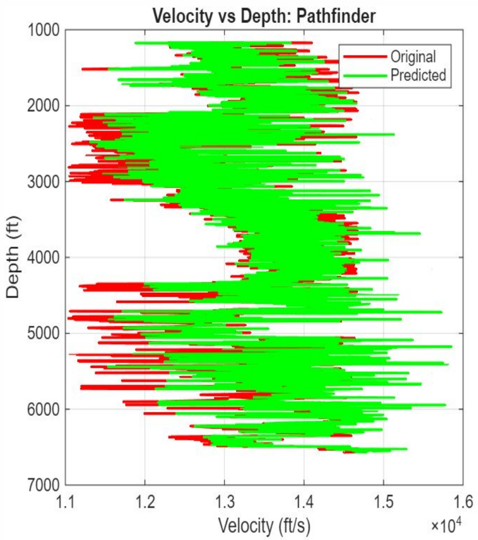


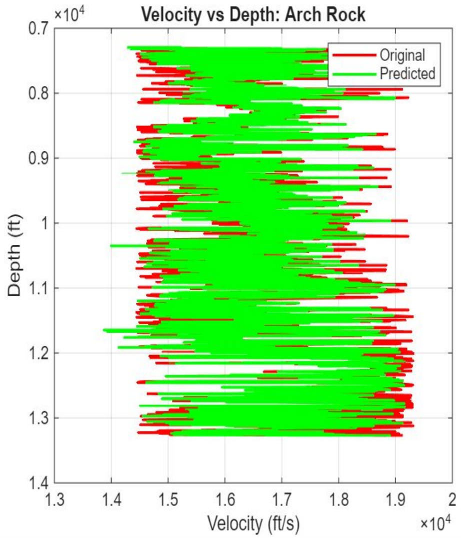
Performance Metrics

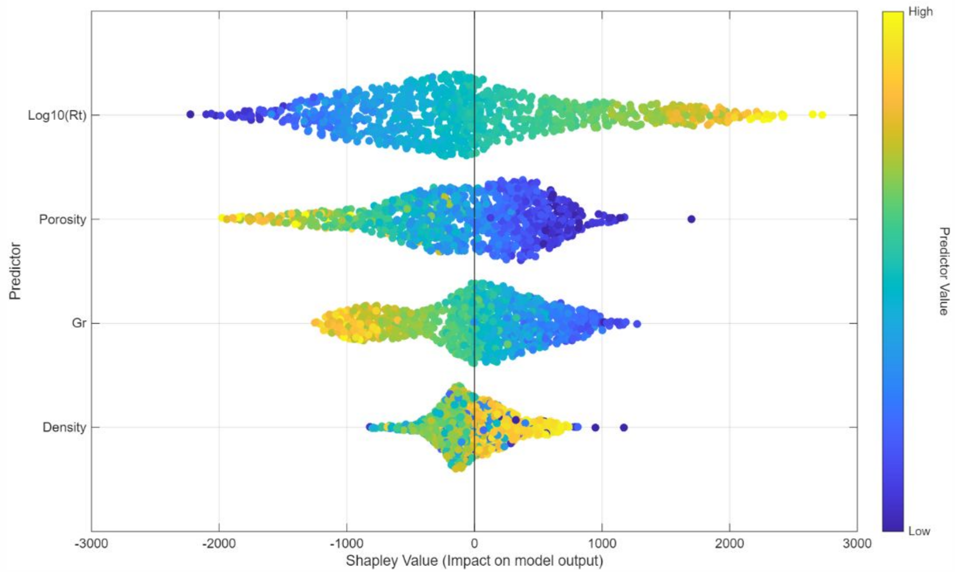
80/20	MODEL PERFORMANCE				BLIND TEST PERFORMANCE			
	Train		Test		Blind Well 1		Blind Well 2	
ML		RMSE		RMSE		RMSE		RMSE
Random Forest	0.960	385.903	0.854	528.147	0.811	310.373	0.842	439.147
ANN	0.846	750.872	0.845	758.189	0.371	565.553	0.608	692.944
SVR	0.833	785.423	0.831	781.912	0.238	622.321	0.601	698.659
Decision Tree	0.921	539.928	0.796	858.584	0.686	399.586	0.707	599.297
Boosted Trees	0.878	671.392	0.810	829.190	0.529	489.628	0.641	663.155
Linear	0.747	964.839	0.749	953.919	0.225	627.740	0.563	731.360

Velocity Prediction and Shapley Parameter



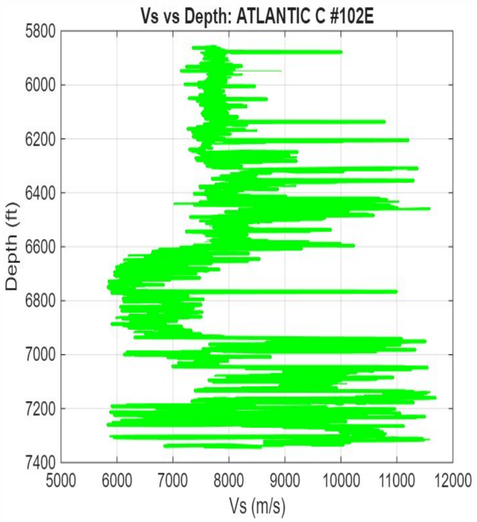


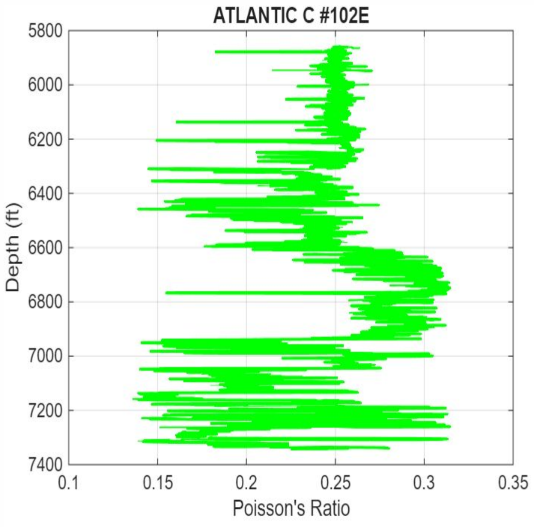


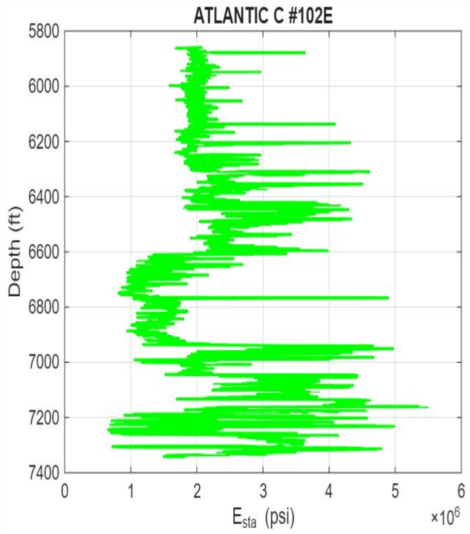


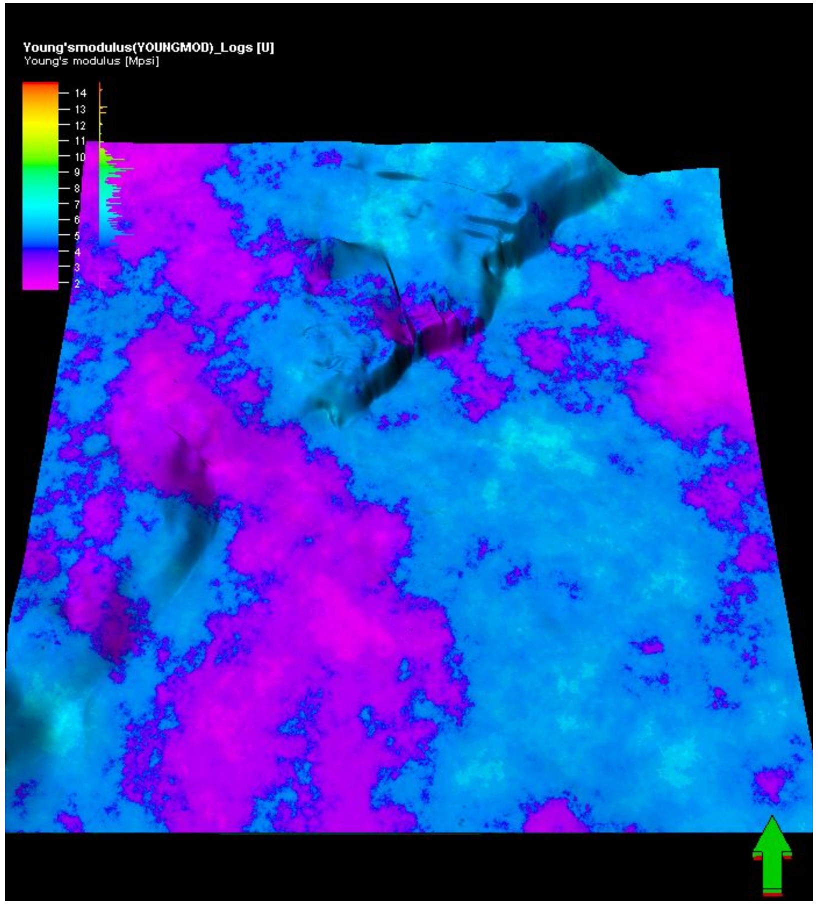
Vs, Young's Modulus, Poisson's Ratio, UCS

- S-velocity was computed using the Greenberg-Castagna empirical relationship
- Poisson's ratio was calculated from the predicted compressional velocity and the derived S-velocity
- Young's modulus (E) was computed using the Modified Morales correlation
- Uniaxial Compressive Strength (UCS) was estimated using the Coates-Denoo empirical correlation





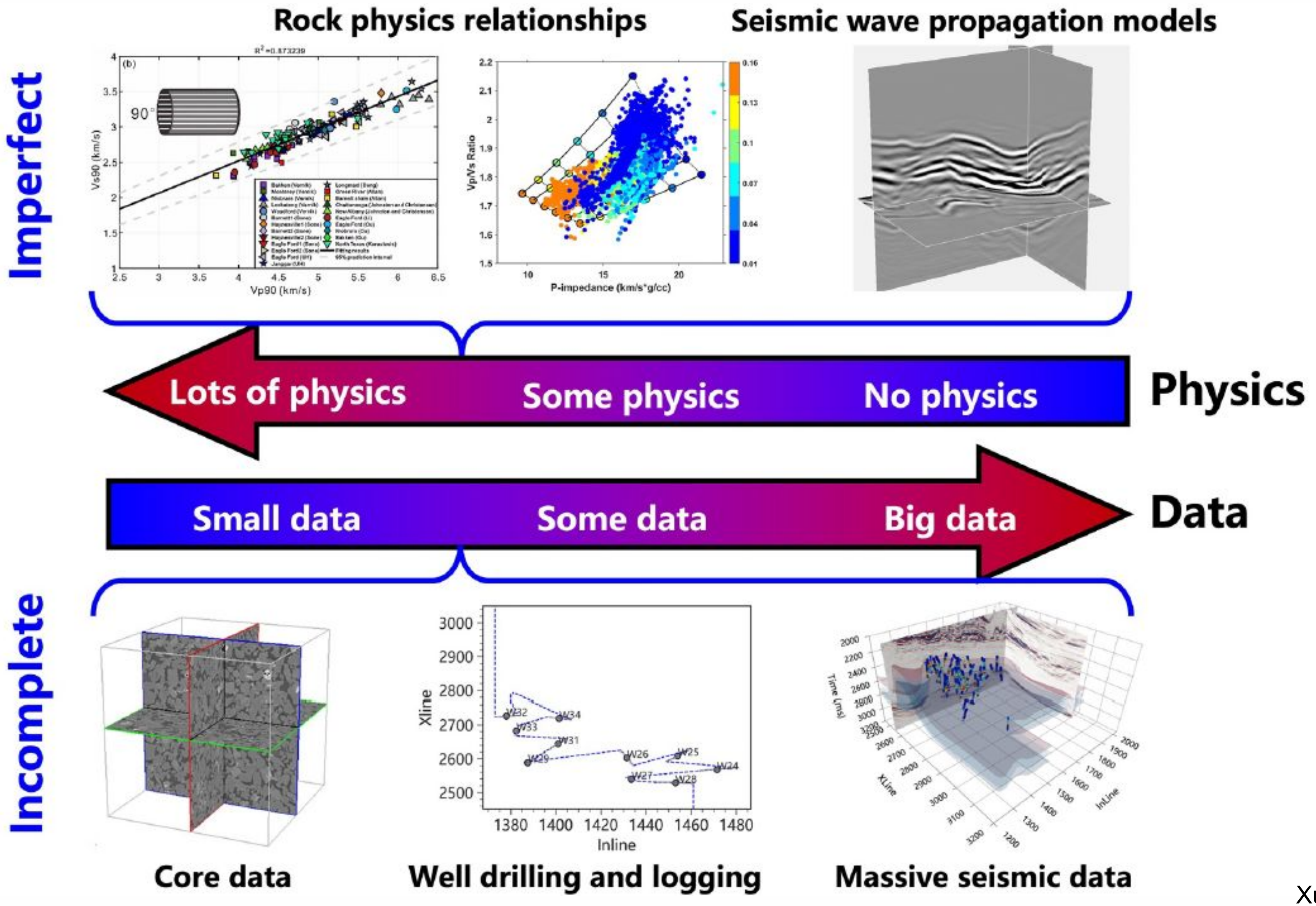




Young's Modulus

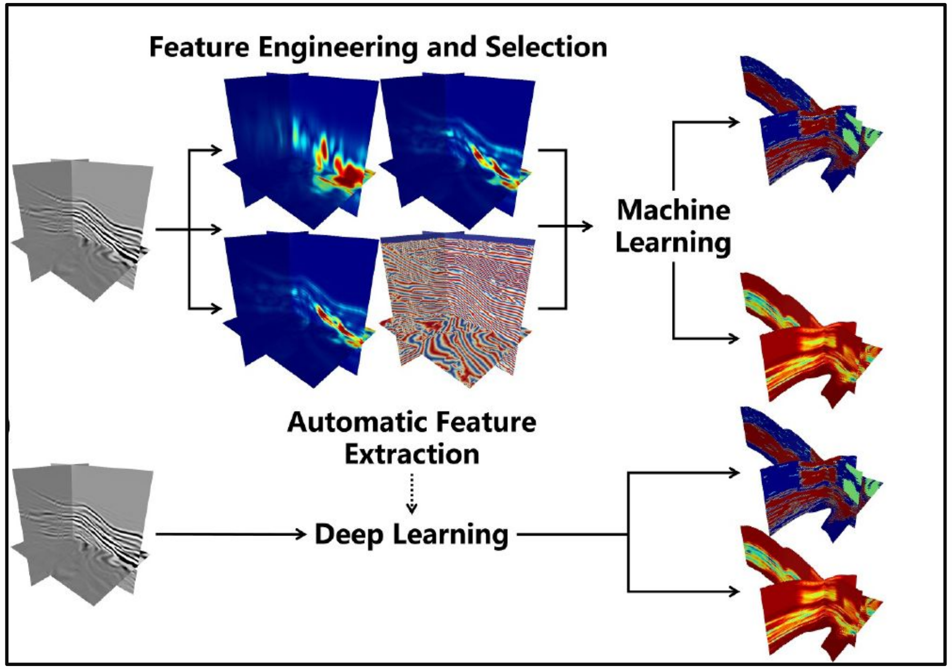
Integration of Well Log and Seismic Data

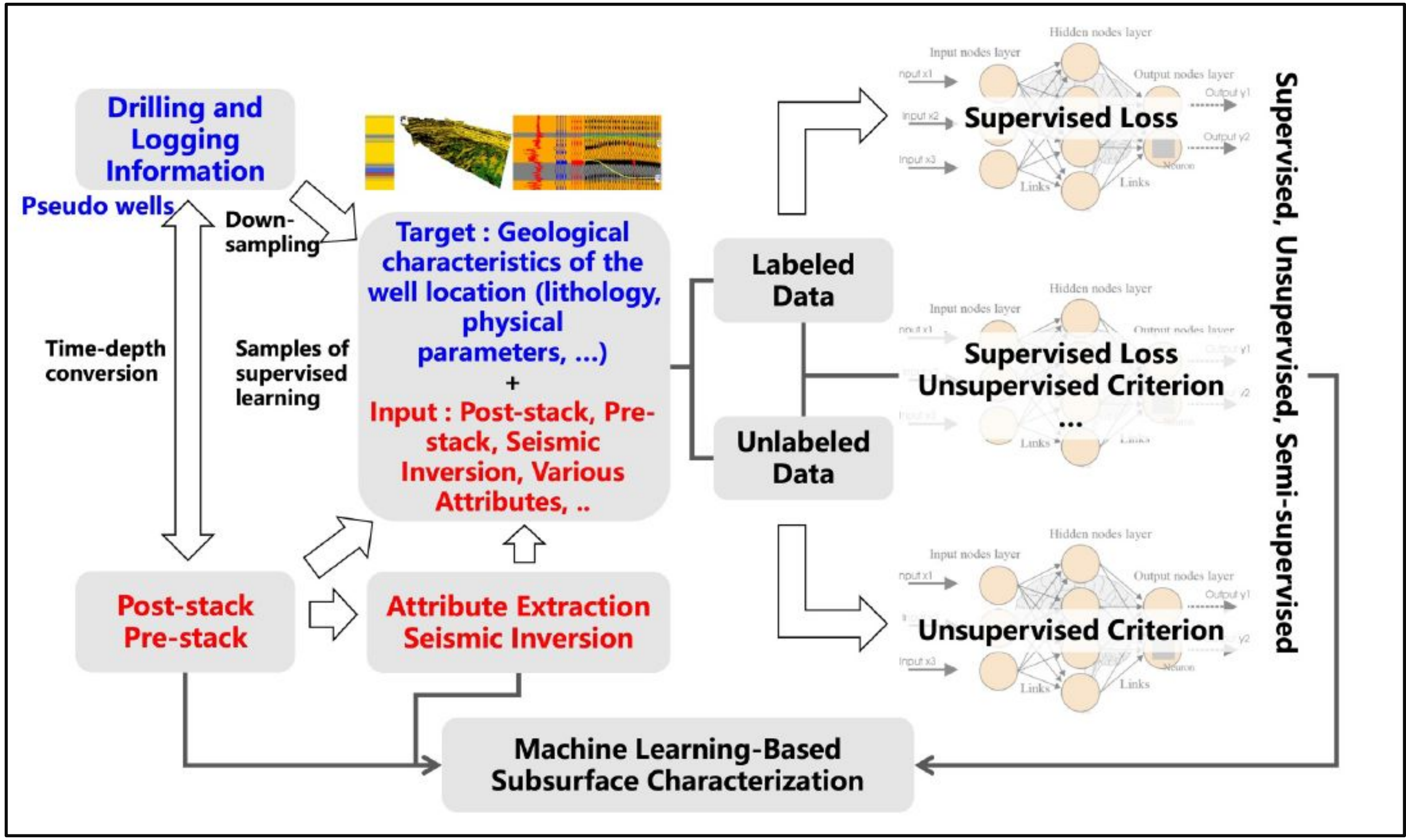
Problems of Scale and Incomplete Data



Xu et al. (2025)

Feature Extraction and ML Methodology



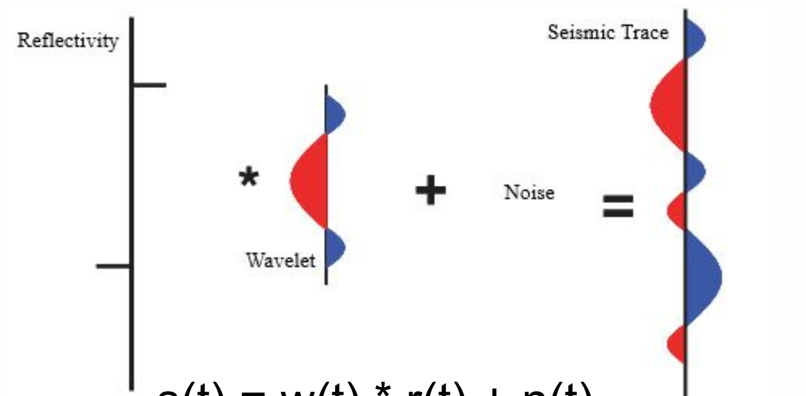


Xu et al. (2025)

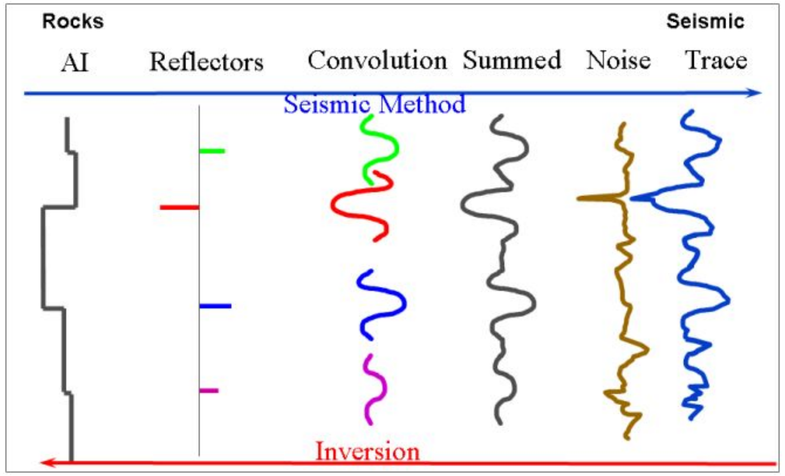
2. Prediction of petrophysical and geomechanical properties from 3D seismic volume

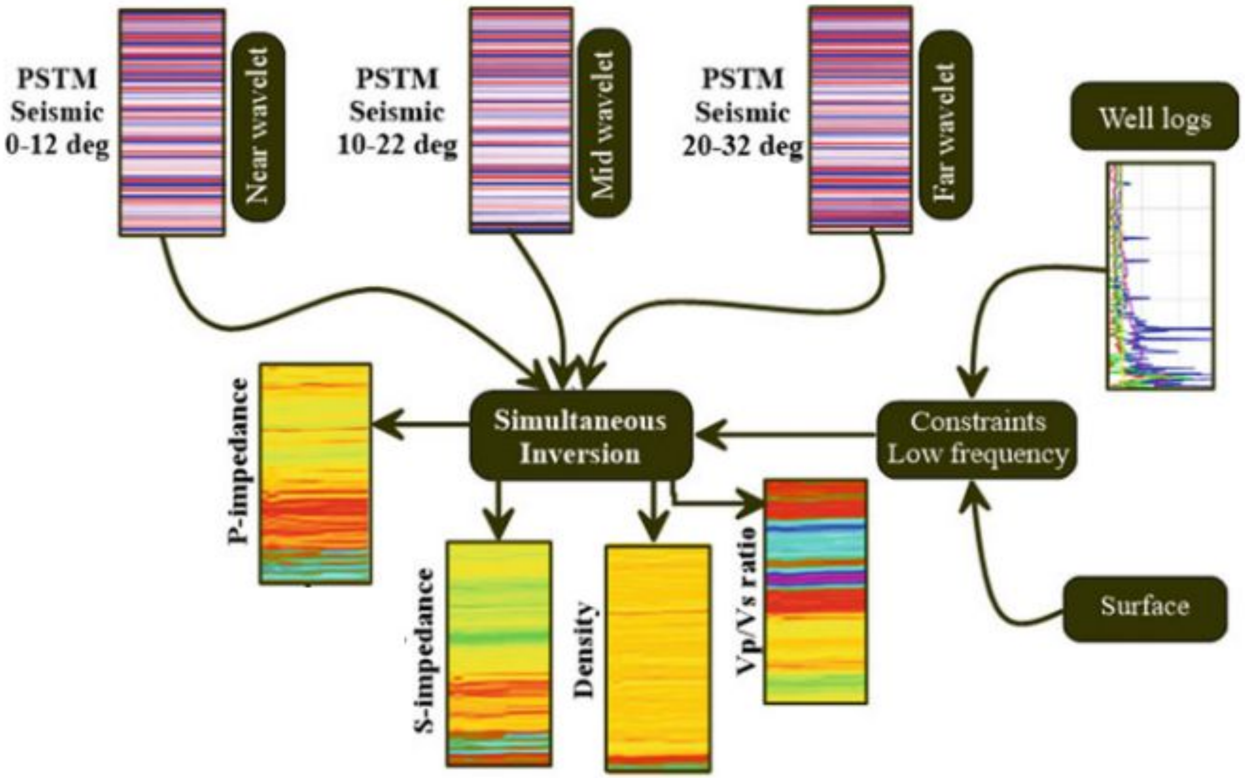
- Compute acoustic impedance, Vp/Vs, and density from seismic inversion
- Train model to predict petrophysical and geomechanical properties
- Predict properties from 3D seismic volume

Prestack Seismic Inversion



$$s(t) = w(t) * r(t) + n(t)$$

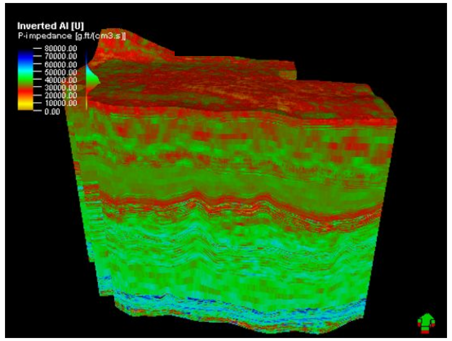




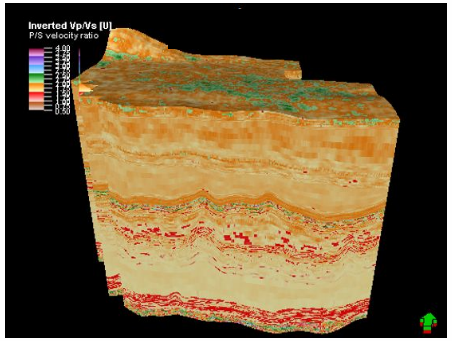
Typical workflow for seismic inversion

Neural Network Prediction: Porosity and Permeability

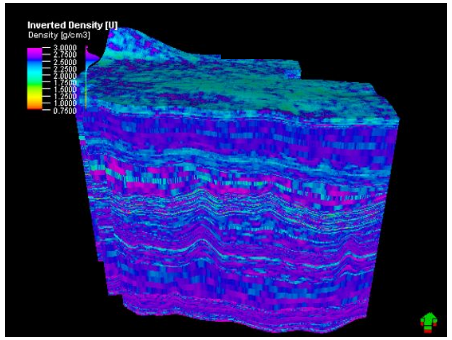
Acoustic Impedance

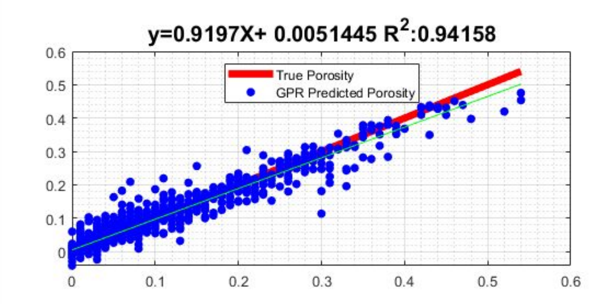


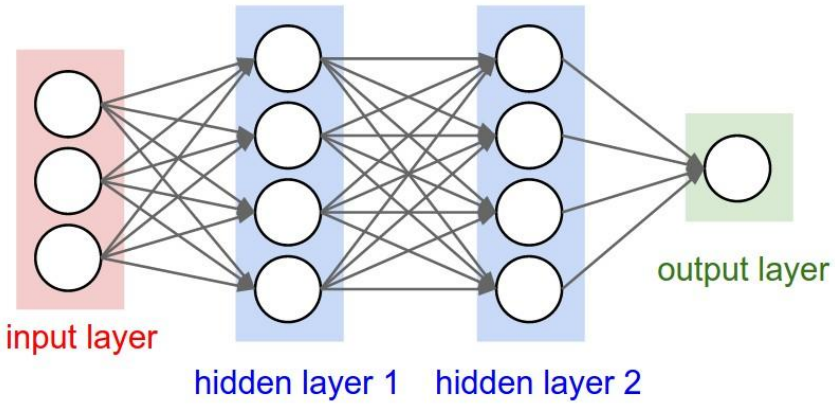
Vp/vs

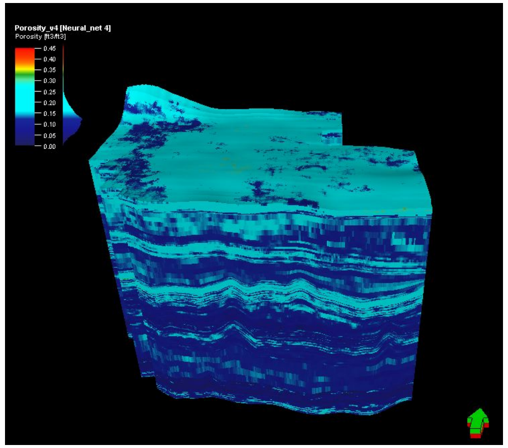


Density

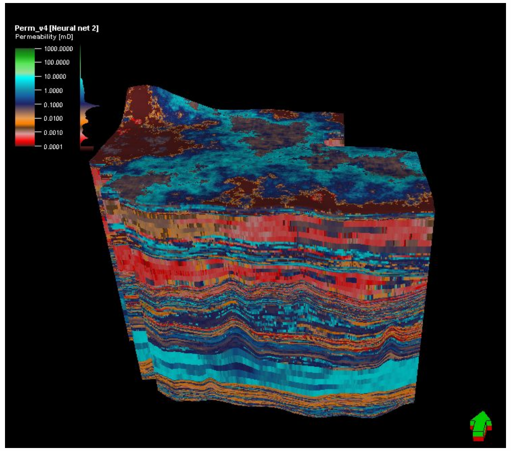






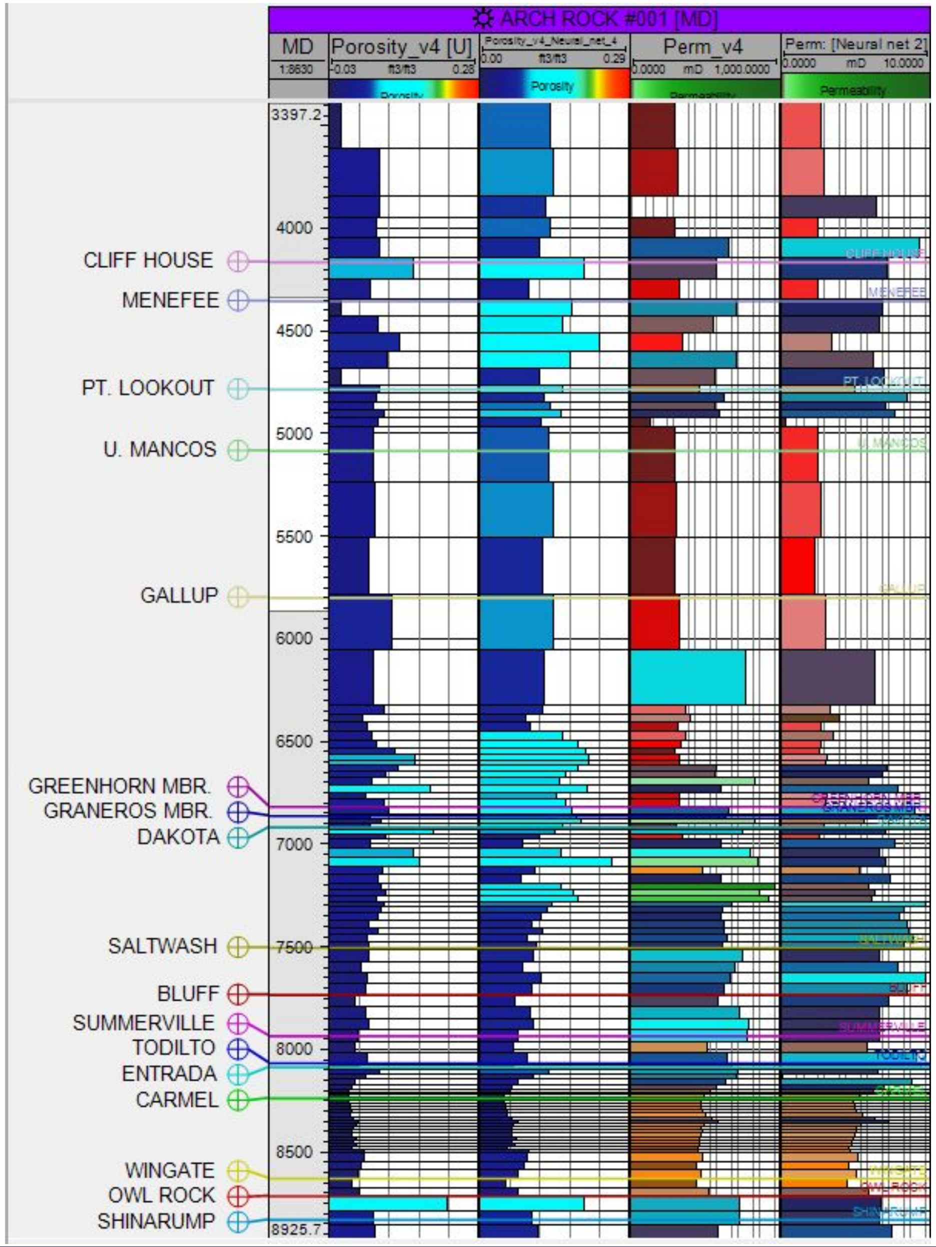


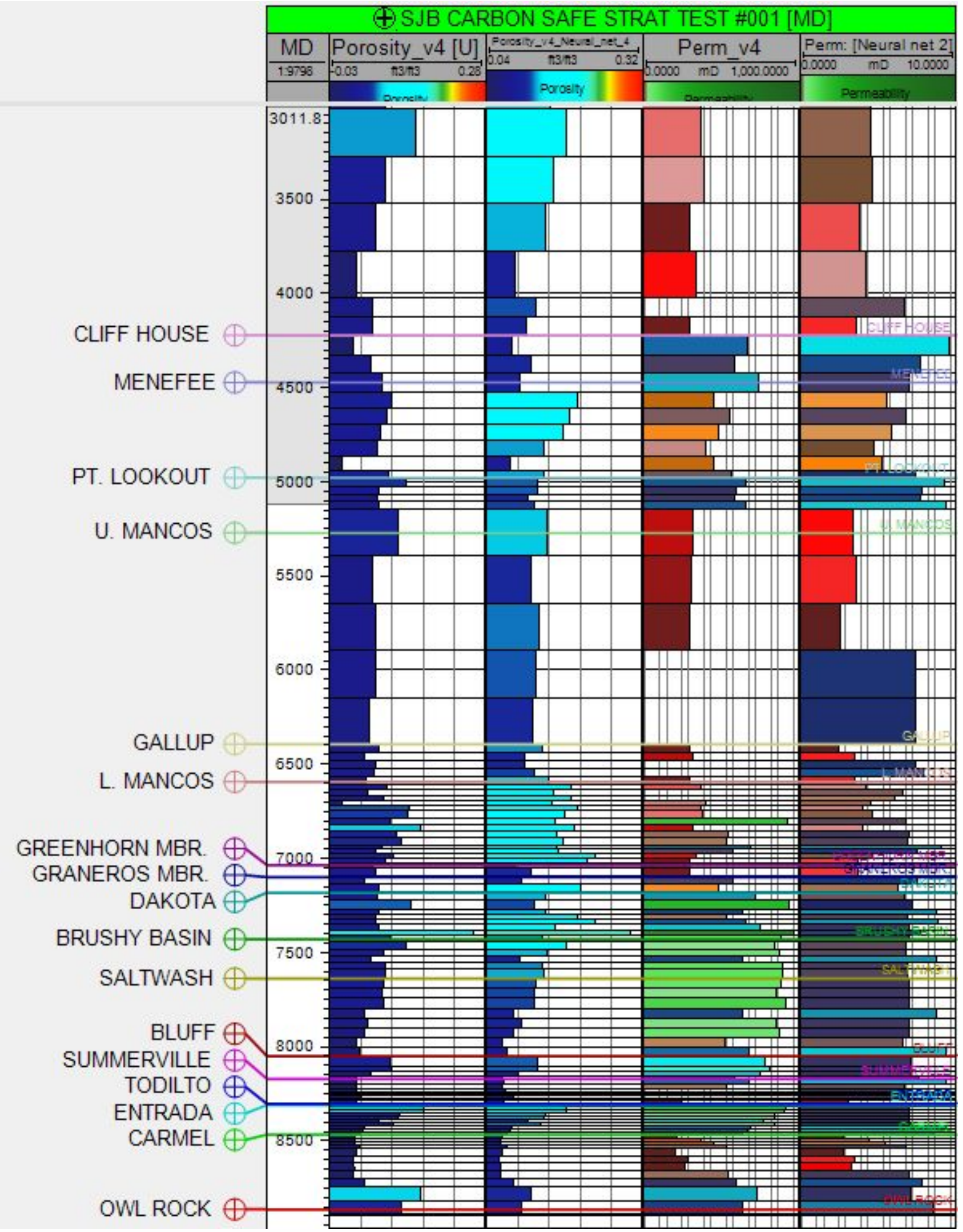
Porosity



Permeability

Porosity and Permeability at Well

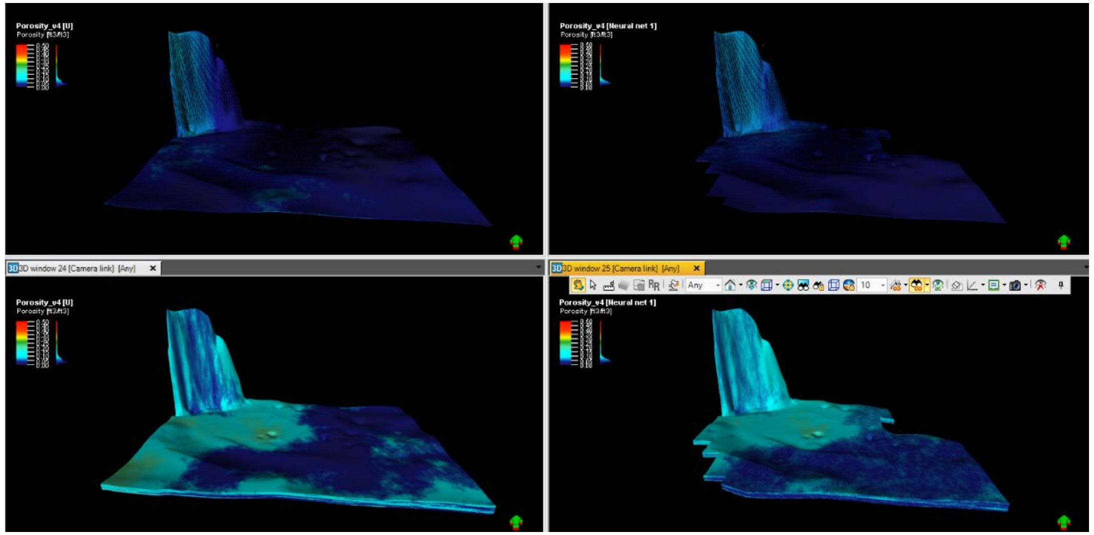


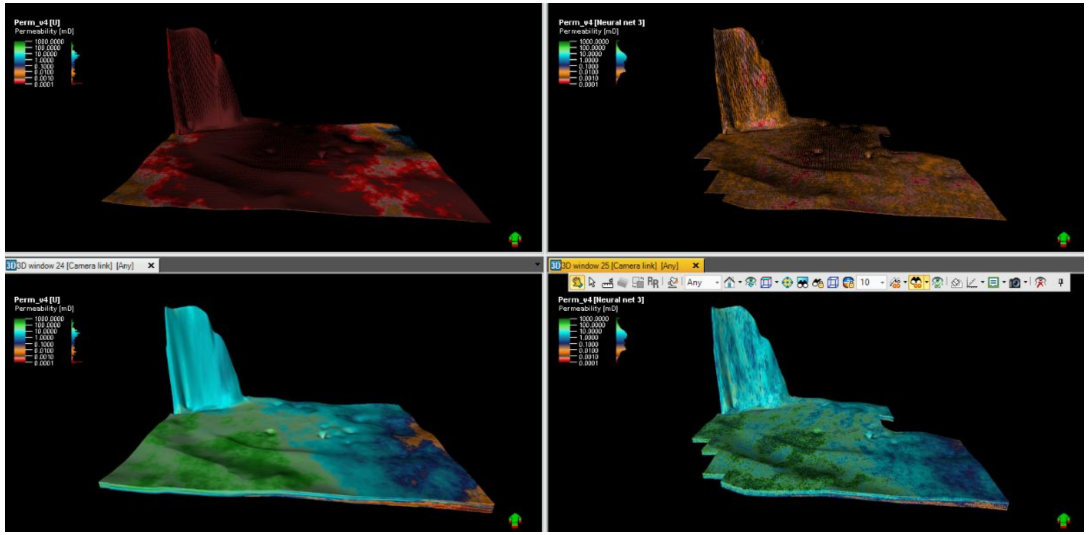


Porosity and Permeability for Formations

Porosity

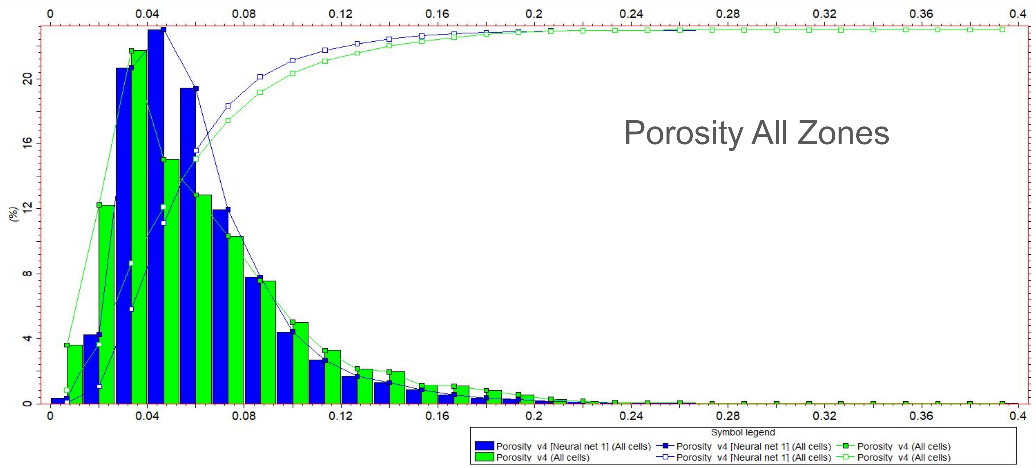
Permeability

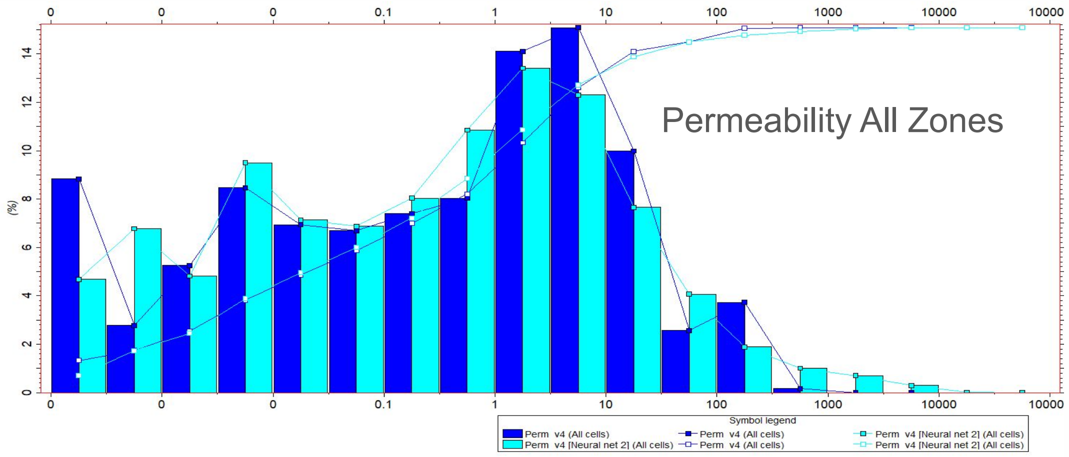




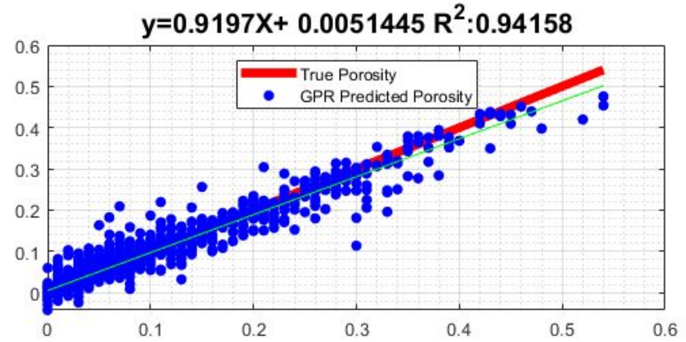
Todilto

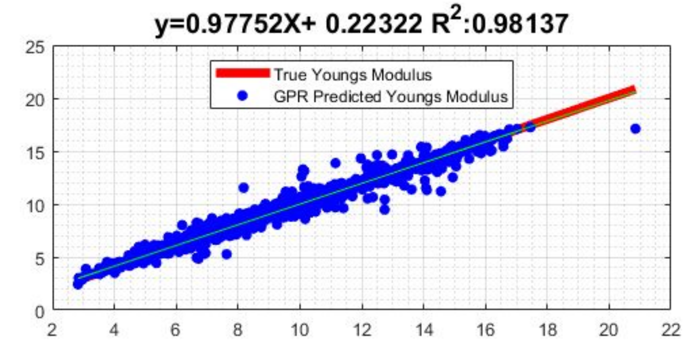
Entrada

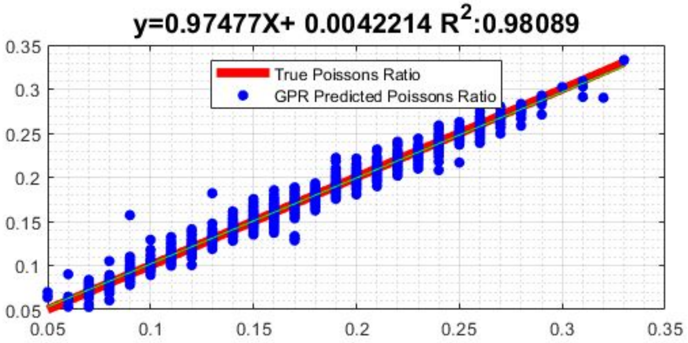


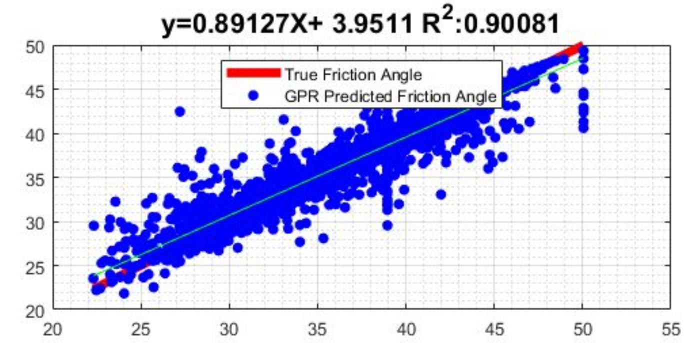


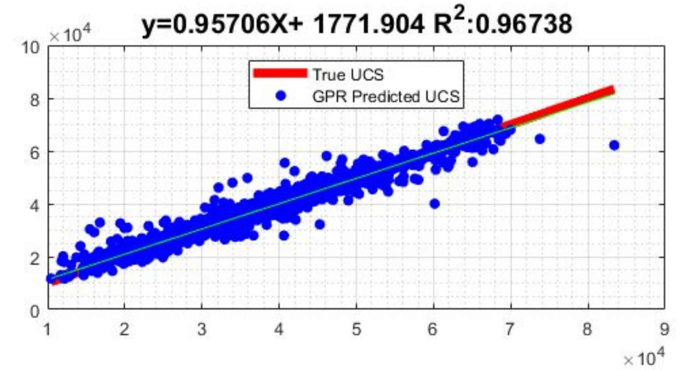
Geomechanical Model Prediction Results

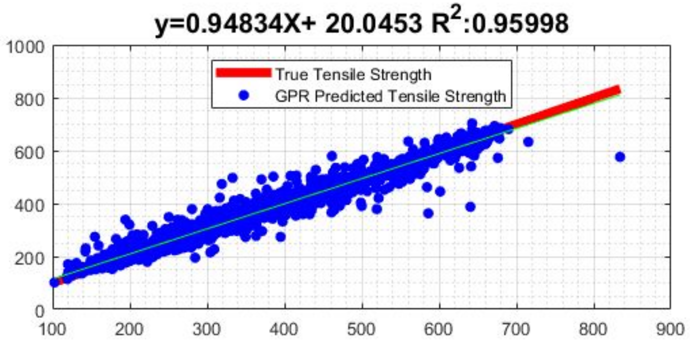


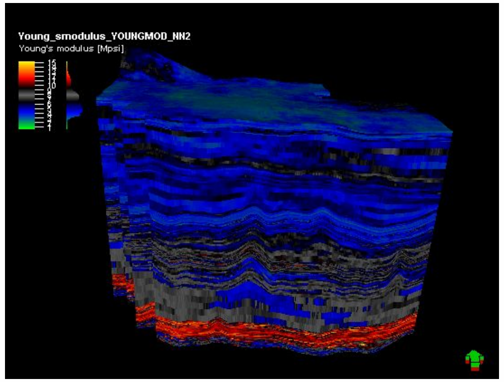




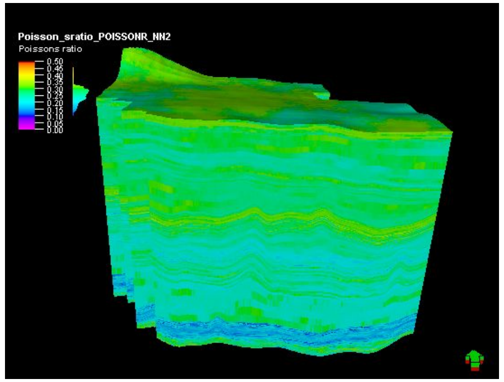




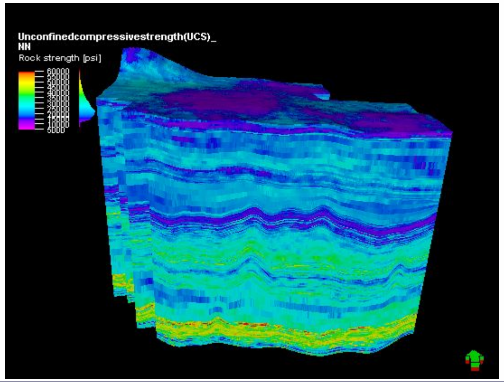




Young’s Modulus

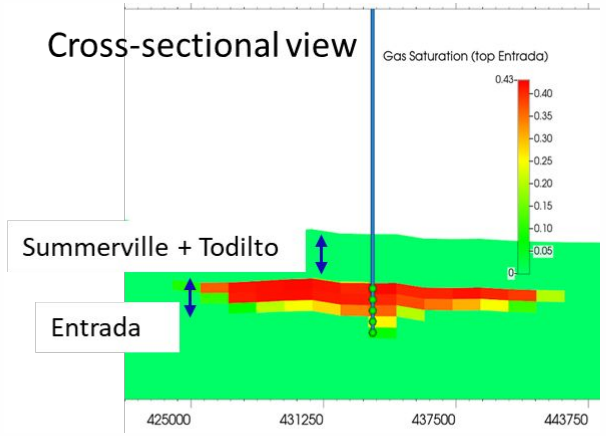


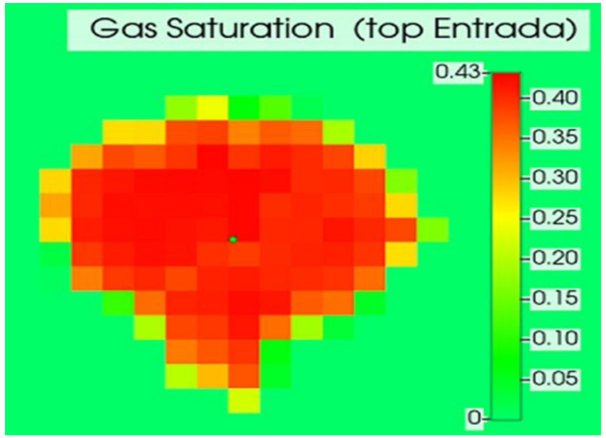
Poisson’s Ratio

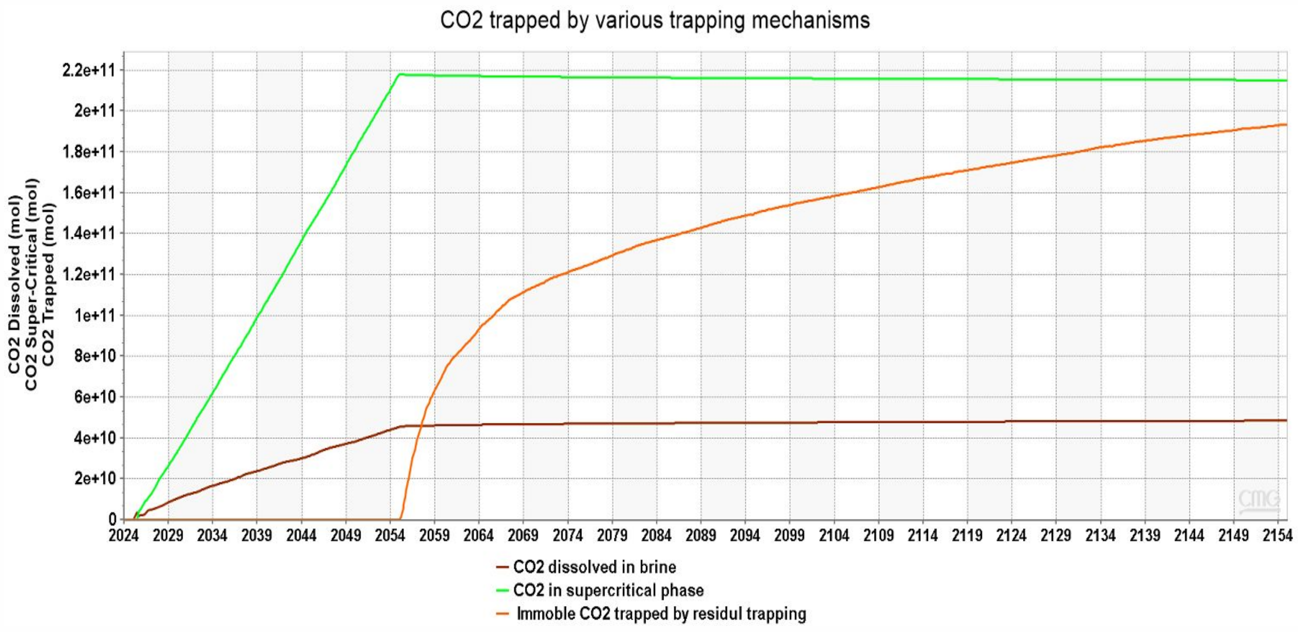


UCS

Carbon Sequestration Simulation





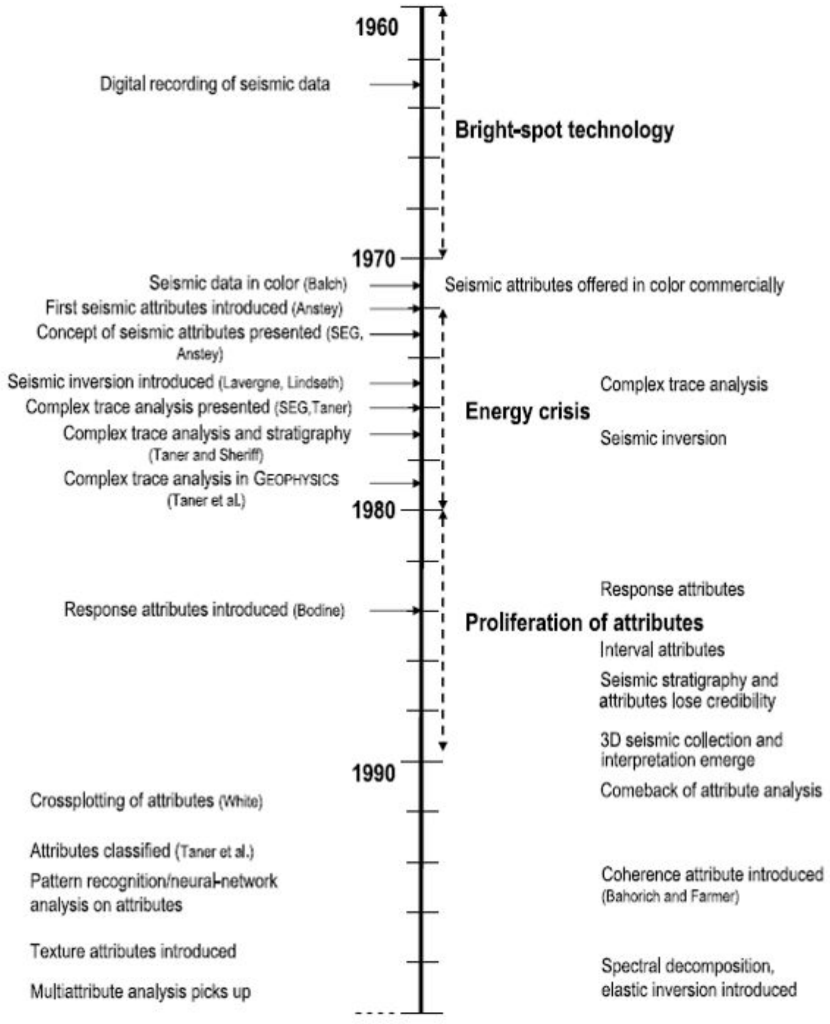


3. Prediction of lithological properties from 2D seismic data

- Compute seismic attributes along 2D lines
- Extract seismic attributes at well locations as input
- Train Model to predict Vshale
- Predict Vshale for 2D seismic lines

Seismic Attributes

- A seismic attribute is any measure of seismic data that helps us visually enhance or quantify features of interpretation interest.
- In the most general sense, seismic attributes encompass all quantities derived from seismic data.
- Any quantity derived from seismic data to enhance information that might be hidden in a traditional seismic image, leading to a better interpretation of the data.



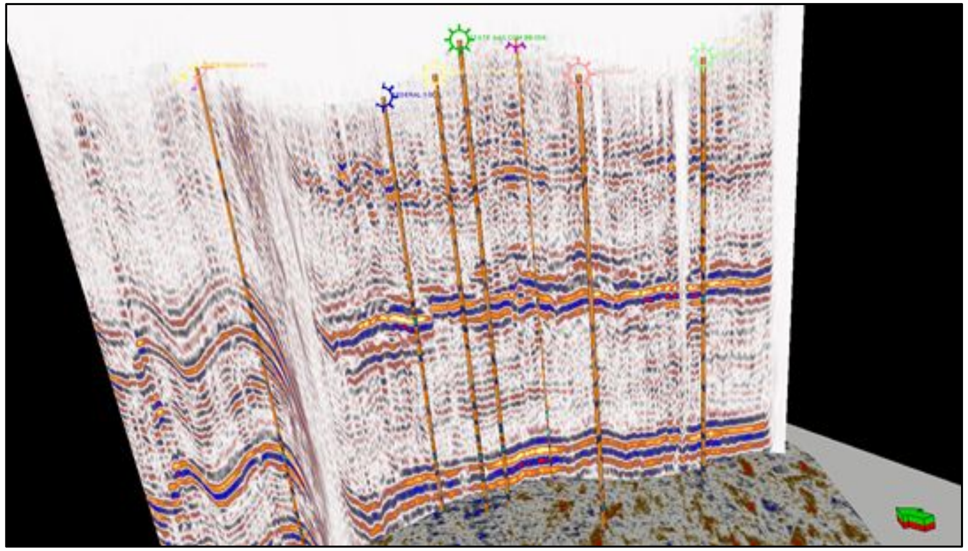
Chopra and Marfurt (2007)

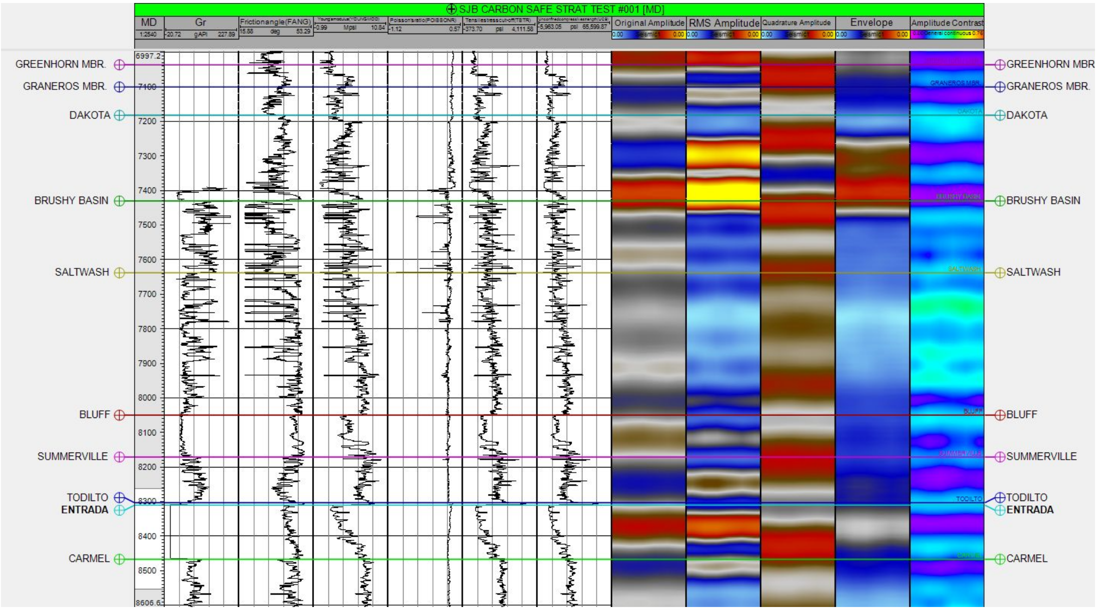
Categories of Seismic Attributes

Seismic Attribute Type	Uses	Examples
Amplitude Attributes	Lithology, Porosity, Fluid content, DHIs, Bedding Continuity	Original Amplitude, RMS Amplitude, Quadrature Amplitude, Amplitude Contrast, Envelope,
Geometric Attributes	Continuity/Discontinuity, Faults, Fractures, Folds, Anisotropy, Regional Stress Fields	Dip and Azimuth, Coherence, Curvature.Semblance
Frequency Attributes	Layer Thickness, Tuning Effects	Instantaneous Frequency, Dominant frequency, Bandwidth, Spectral decomposition
Texture Attributes	Lithology Changes, Seismic Facies, Stratigraphic Boundaries, Reservoir Properties	Entropy, Energy, Homogeneity, Contrast, Correlation

Attributes At Well Locations Along 2D Line

- Resample seismic and well log to same resolution
- Train machine learning model to predict Vshale
- Predict Vshale for each seismic trace





$y^{(1)}$
$y^{(2)}$
$y^{(3)}$
.
.
.
$y^{(n)}$

$X_1^{(1)}$	$X_2^{(1)}$	…	$X_n^{(1)}$
$X_1^{(2)}$	$X_2^{(2)}$	…	$X_n^{(2)}$
$X_1^{(3)}$	$X_2^{(3)}$	…	$X_n^{(3)}$
.	.	…	.
.	.	…	.
.	.	…	.
$X_1^{(n)}$	$X_2^{(n)}$	…	$X_n^{(n)}$

Methodology: Handling Uncertainty

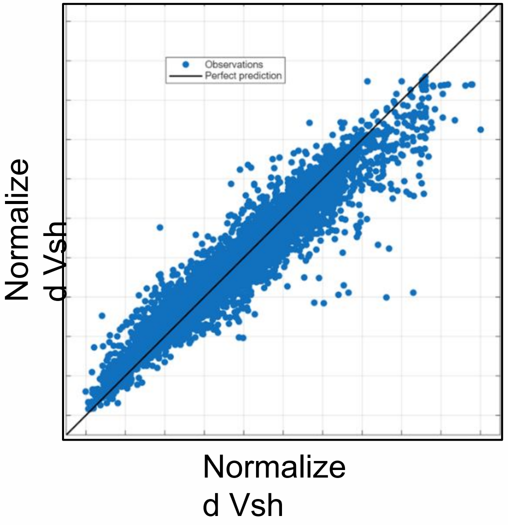
$y^{(1)}$
$y^{(2)}$
$y^{(3)}$
.
.
.
$y^{(n)}$

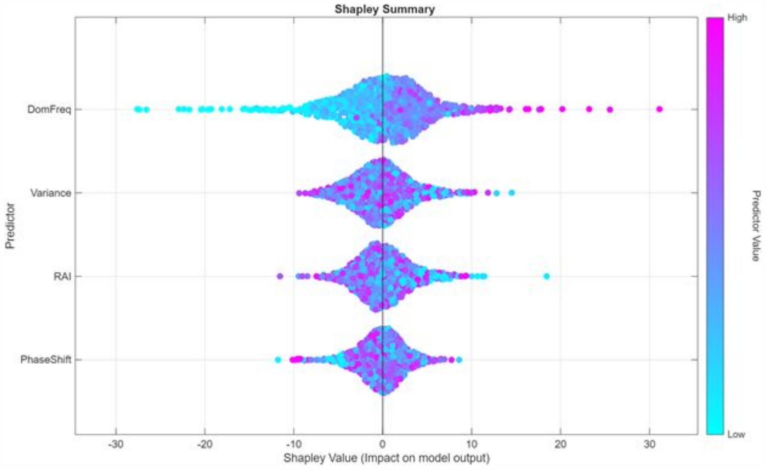
$X_1^{(1-m)} \ldots X_1^{(1+m)}$	$X_2^{(1-m)} \ldots X_2^{(1+m)}$	…	$X_n^{(1-m)} \ldots X_n^{(1+m)}$
$X_1^{(2-m)} \ldots X_1^{(2+m)}$	$X_2^{(2-m)} \ldots X_2^{(2+m)}$	…	$X_n^{(2-m)} \ldots X_n^{(2+m)}$
$X_1^{(3-m)} \ldots X_1^{(3+m)}$	$X_2^{(3-m)} \ldots X_2^{(3+m)}$	…	$X_n^{(3-m)} \ldots X_n^{(3+m)}$
.	.	…	.
.	.	…	.
.	.	…	.
$X_1^{(n-m)} \ldots X_1^{(n+m)}$	$X_2^{(n-m)} \ldots X_2^{(n+m)}$	…	$X_n^{(n-m)} \ldots X_n^{(n+m)}$

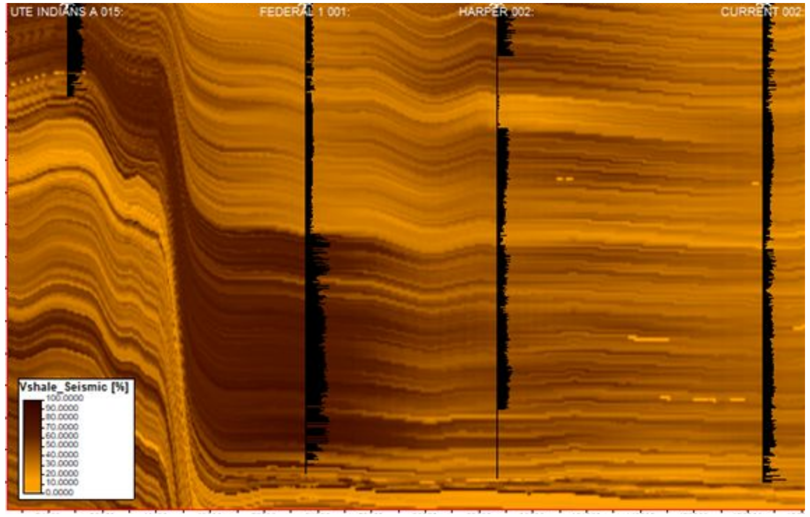
Seismic Attributes Computed

Attribute	Category	Description	Primary Use
Original Amplitude	Amplitude-based	Raw seismic reflection amplitude representing reflection strength at interfaces.	Identifies reflection strength related to lithology, porosity, or fluid changes.
Relative Acoustic Impedance (RAI)	Amplitude-derived	Approximate measure of acoustic impedance contrast derived from amplitudes.	Highlights lithologic variations, depositional boundaries, and stratigraphic layering.
Phase Shift (Instantaneous Phase)	Phase-based	Measures phase angle changes of the seismic signal.	Identifies reflector continuity, subtle structure, and stratigraphic pinch-outs.
Variance	Geometric	Quantifies local trace-to-trace dissimilarity; measures reflector coherence.	Detects faults, fractures, channels, and discontinuities.
Second Derivative (of Amplitude)	Amplitude	Measures curvature or rapid changes in amplitude with time/depth.	Highlights thin beds, small-scale stratigraphic or tuning features.
Chaos	Texture-based	Measures randomness or incoherency of local reflection patterns.	Maps structurally disturbed or faulted zones, collapse features.
Dominant Frequency	Spectral	Frequency with highest spectral energy or instantaneous frequency content.	Indicates attenuation, lithology changes, and fluid effects.

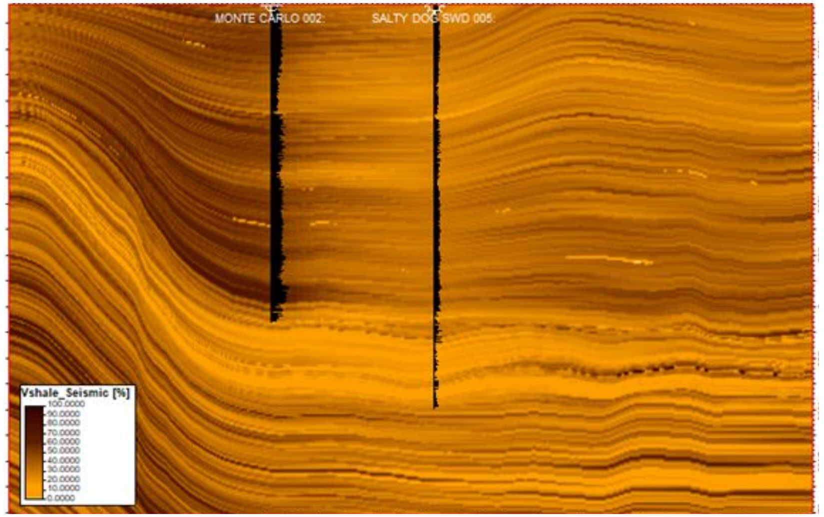
Vshale Prediction Results



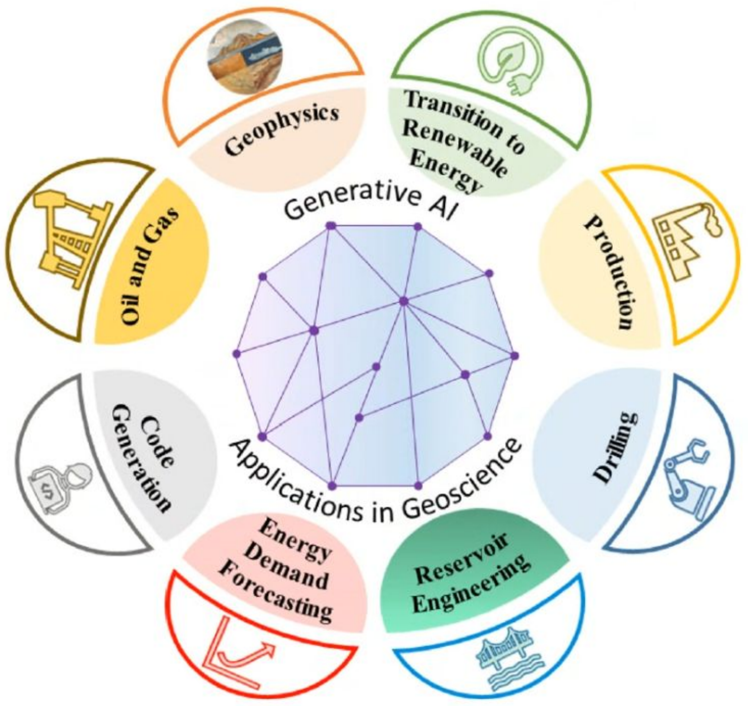


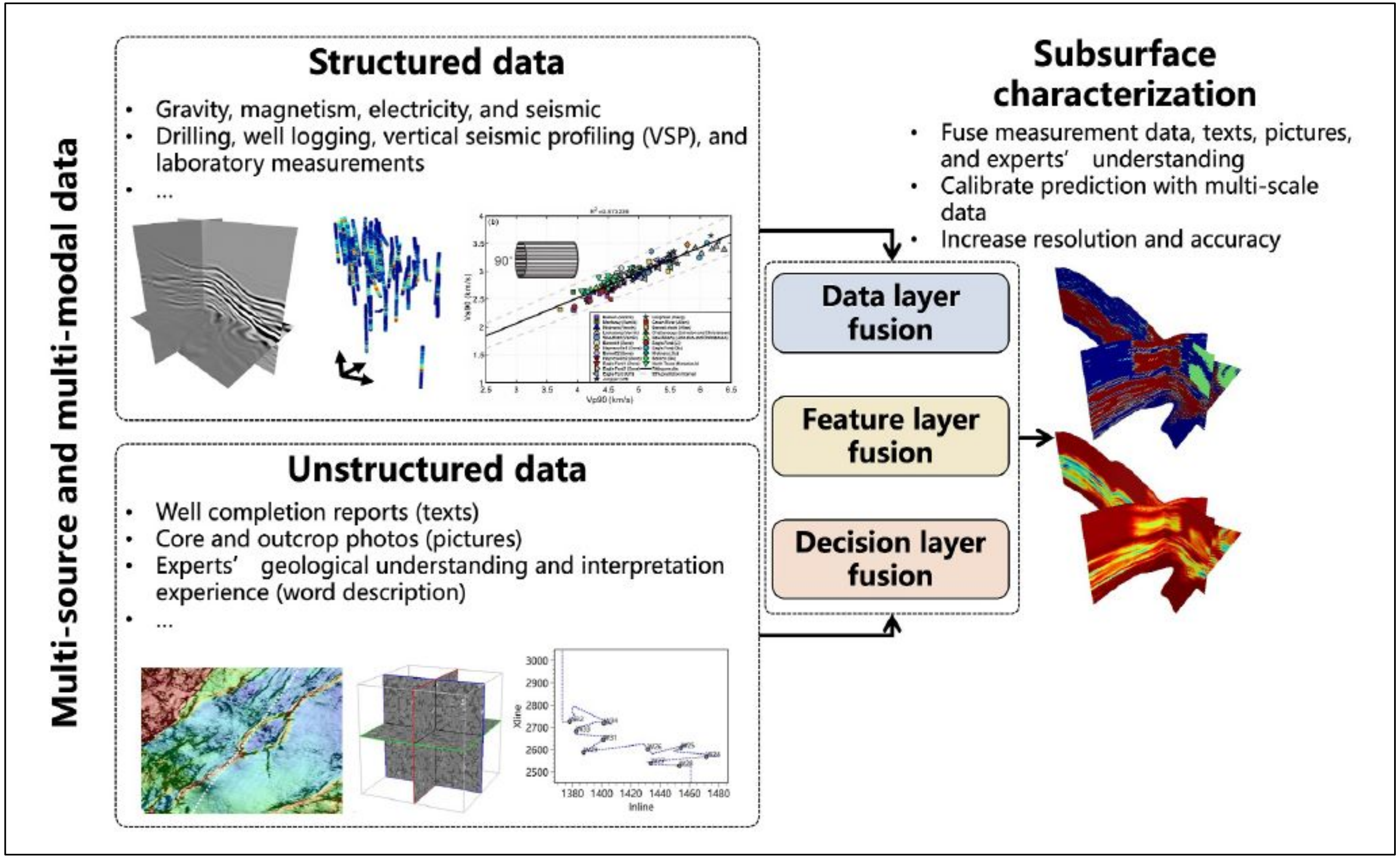


Model Type	MAE	MSE	RMSE	RSquared
Bagged Tree Ensemble	2.36211416	13.42703936	3.664292478	0.923622314
Fine Tree	2.406468527	17.42772986	4.174653262	0.90086499
Fine Gaussian SVM	3.4806032	31.67859722	5.628374296	0.819801083
Wide Neural Network	6.528822848	75.68600644	8.699770482	0.569471582



Generative AI in Geoscience





Xu et al. (2025)

Hadid et al. (2025)

Darthmouth Conference Proposal

"We propose that a 2-month, 10-man study of artificial intelligence be carried out during the summer of 1956 at Dartmouth College in Hanover, New Hampshire. The study is to proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it. An attempt will be made to find how to make machines use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and **improve themselves**. We think that a significant advance can be made in one or more of these problems if a carefully selected group of scientists work on it together for a summer."

Courtesy of the Minsky Family

Conclusion

- We have demonstrated how AI can be used for subsurface property modeling
- AI facilitates integration of multiple datasets for improved interpretation
- Generative AI will play a vital role in the future of Earth Sciences

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Thank You
Questions?

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