ENERGY GeO Hackathon
Society of Petroleum Engineers

SPE International
SPE Europe Region

2023 SPE EUROPE ENERGY GEOHACKATHON

#8 Machine learning methods – 2

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19th October 2023

#DatafyingEnergy

Outline

Introduction

- Importance of Geothermal Energy
- Machine Learning's Impact
- Geophysical Solutions for Geothermal Exploration

Technologies in Geothermal Studies

- Neural Networks: Emerge & GeoAI

Case Studies

- Porosity Prediction with Emerge
- Estimating Properties with GeoAI

Python in Geothermal

- Software Integration with PowerLog, Jason, HampsonRussell
- How it works

Conclusions

Importance of Geothermal Energy

Renewable & Sustainable:

Geothermal energy is derived from the natural heat of the Earth's core. It's renewable since it taps into this vast and virtually untapped heat source which won't run out in the foreseeable human timeline.

Consistent Energy Source:

Unlike solar and wind energy which are dependent on weather conditions, geothermal energy can be harnessed consistently throughout the year, making it a reliable source of power.

Environmental Impact:

Geothermal power stations emit significantly lower amounts of greenhouse gases compared to fossil fuel power plants. Thus, they play a crucial role in mitigating the effects of climate change.

Economic Benefits:

While the initial investment for geothermal infrastructure can be high, the long-term operational costs are lower. Additionally, these projects can create local jobs and boost regional economies.

Reduction in Energy Imports:

Countries can reduce their dependency on foreign oil and natural gas by investing in local geothermal energy projects, promoting energy security.

Machine Learning's Impact

Data Analysis & Insights:

Machine learning can process vast amounts of geological and geophysical data at unprecedented speeds. This allows for the identification of patterns and relationships that might be overlooked in manual analyses, providing deeper insights into geothermal reservoirs.

Predictive Modeling:

ML algorithms can predict the most promising locations for geothermal drilling, anticipate reservoir behavior, and even project long-term energy outputs. This predictive capability reduces exploration risks and ensures better resource management.

Collaborative Decision-Making:

Combining the analytical capabilities of ML with human expertise can lead to more collaborative and informed decision-making. ML models can provide suggestions and predictions, while experts can make the final decisions, ensuring a balance between automated insights and human judgment. This collaboration can lead to more accurate and reliable outcomes in geothermal studies.

Integration with Other Technologies:

Machine learning can be seamlessly combined with other advanced tech, like IoT (Internet of Things) sensors, to monitor geothermal installations in real-time, providing instant feedback and facilitating proactive maintenance.

Geophysical Solutions for Geothermal Exploration

PowerLog: Precise Petrophysical Analysis

- Comprehensive log corrections and interpretation tools
- Advanced rock physics modeling to understand formation properties.

HampsonRussell: Advanced Reservoir Characterization and Predictions

- Efficient attribute analysis for enhanced reservoir understanding.
- Reservoir characterization and Machine learning capabilities for predictive analytics, enabling accurate reservoir forecasting.

Jason: In-depth Seismic Interpretations

- State-of-the-art inversion techniques for accurate subsurface imaging.
- Advanced tools for result interpretations, providing clearer insights into reservoir potentials.

Common feature: The Python Ecosystem – a direct link to Python open-source libraries

PowerLog

HampsonRussell

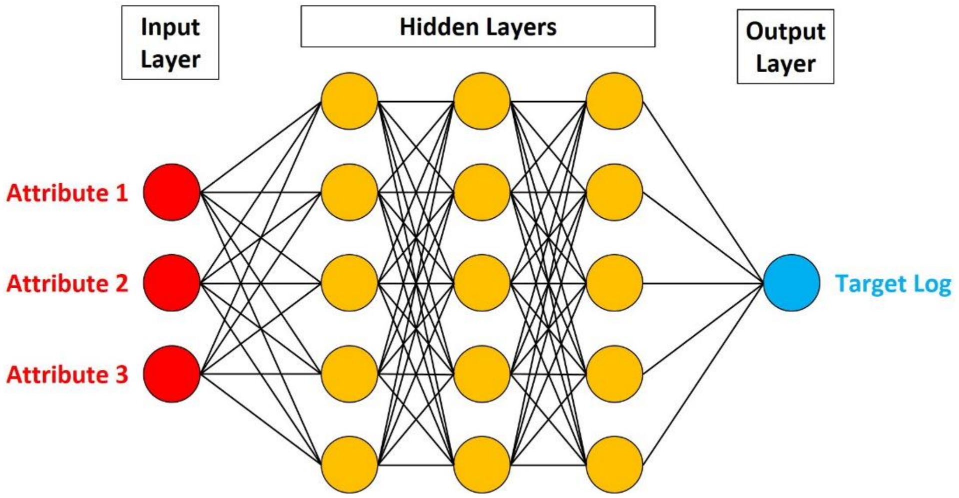
Jason

Technologies in Geothermal Studies

Deep neural networks approach

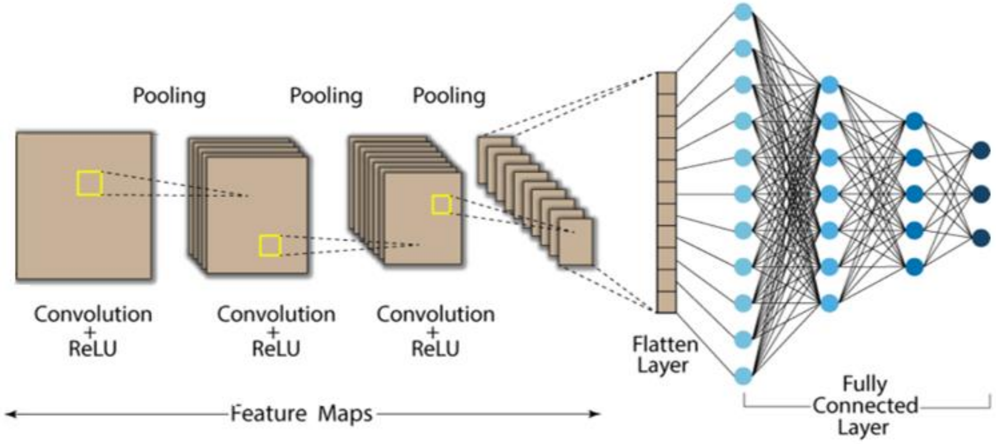
Emerge DFNN

- The input to the DFNN is post-stack seismic
- The geophysicist generates and selects a series of post-stack attributes to serve as input to the DFNN
- The DFNN can only estimate one target at a time



GeoAI CNN

- The input to the CNN are seismic gathers
- The attributes are automatically generated and selected by the CNN
- Multiple targets can be estimated simultaneously



Emerge at a Glance

Explore complex relationships between seismic, volume attributes and well curves

Requires good well control (min of 3 wells)

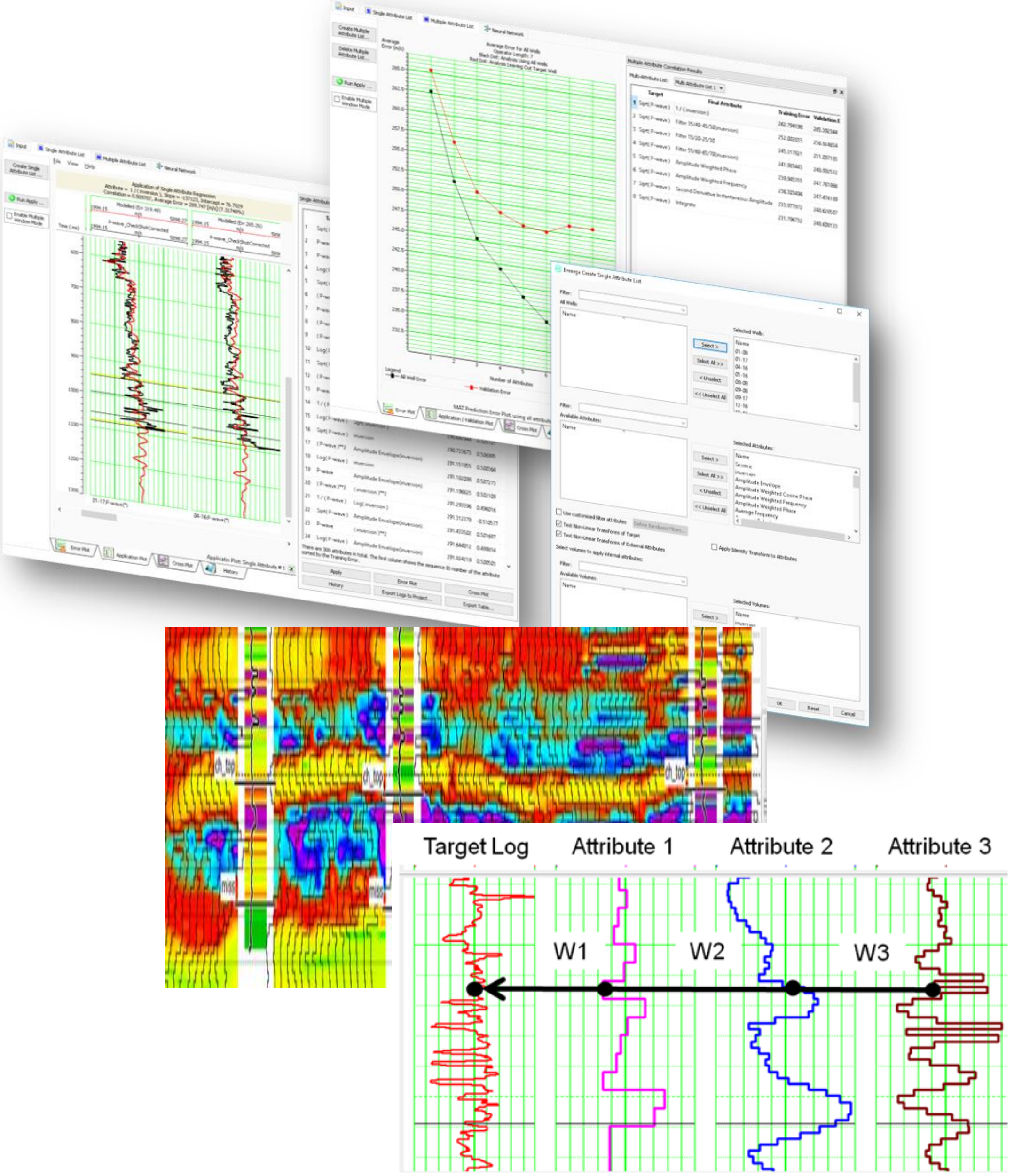
Able to predict curves at well locations from other well curves

Prediction through multiple attribute volumes

- Includes linear and non-linear transforms of input attributes into the analysis
- Clear attribute validation through blind well testing and embedded QC

Non-linear, high-resolution prediction using Neural Networks (optional)

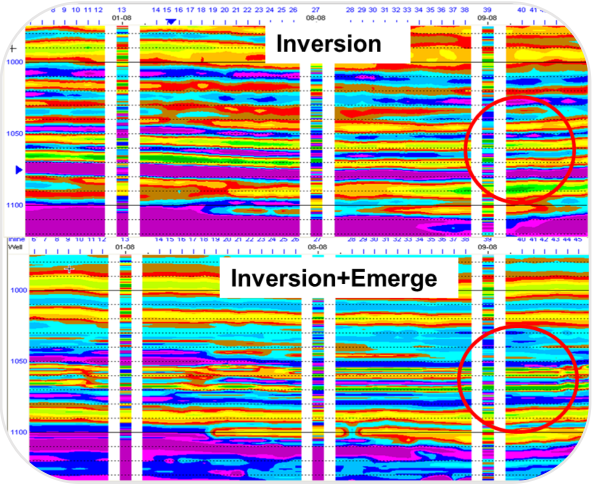
- Includes PNN, MLFN, and DFNN
- DFNN is Deep Learning algorithm.



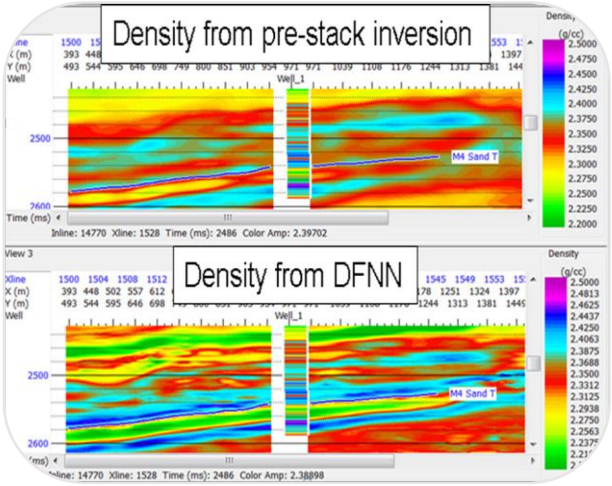
Emerge Capabilities

Performs attribute ranking	• Single attribute analysis • Multi-linear regression • Principal component analysis
Predicts of log property volumes	• Multi-linear regression • Machine learning using Neural Networks including Deep Learning
Improves resolution of inversion results	• Neural Networks • Supports time and depth domains
Can do lithology classification with probabilities	• Neural Networks in classification mode
Enhances prediction of missing log data	• Emerge Log Predict using Multi-linear regression or Neural Networks

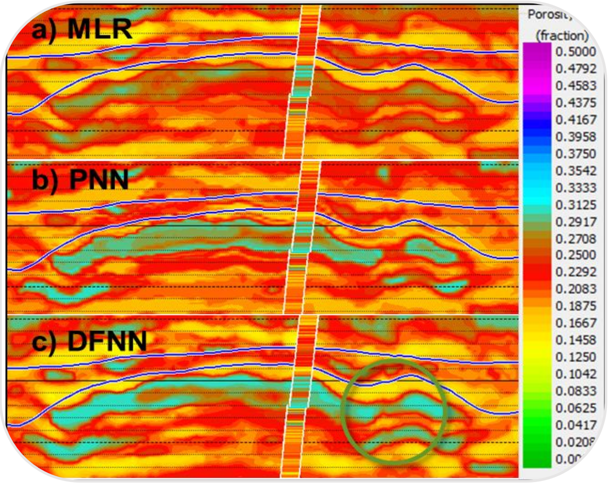
Challenges that can be resolved by Emerge



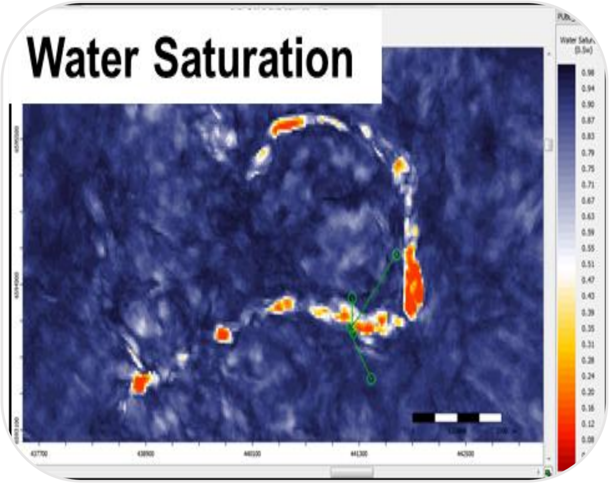
Increase the resolution of most seismic volumes



Improve Inversion Results



With Deep Learning, reveal more subtle variations than previously possible



Make better drilling decision by analyzing ready-to-go property volumes

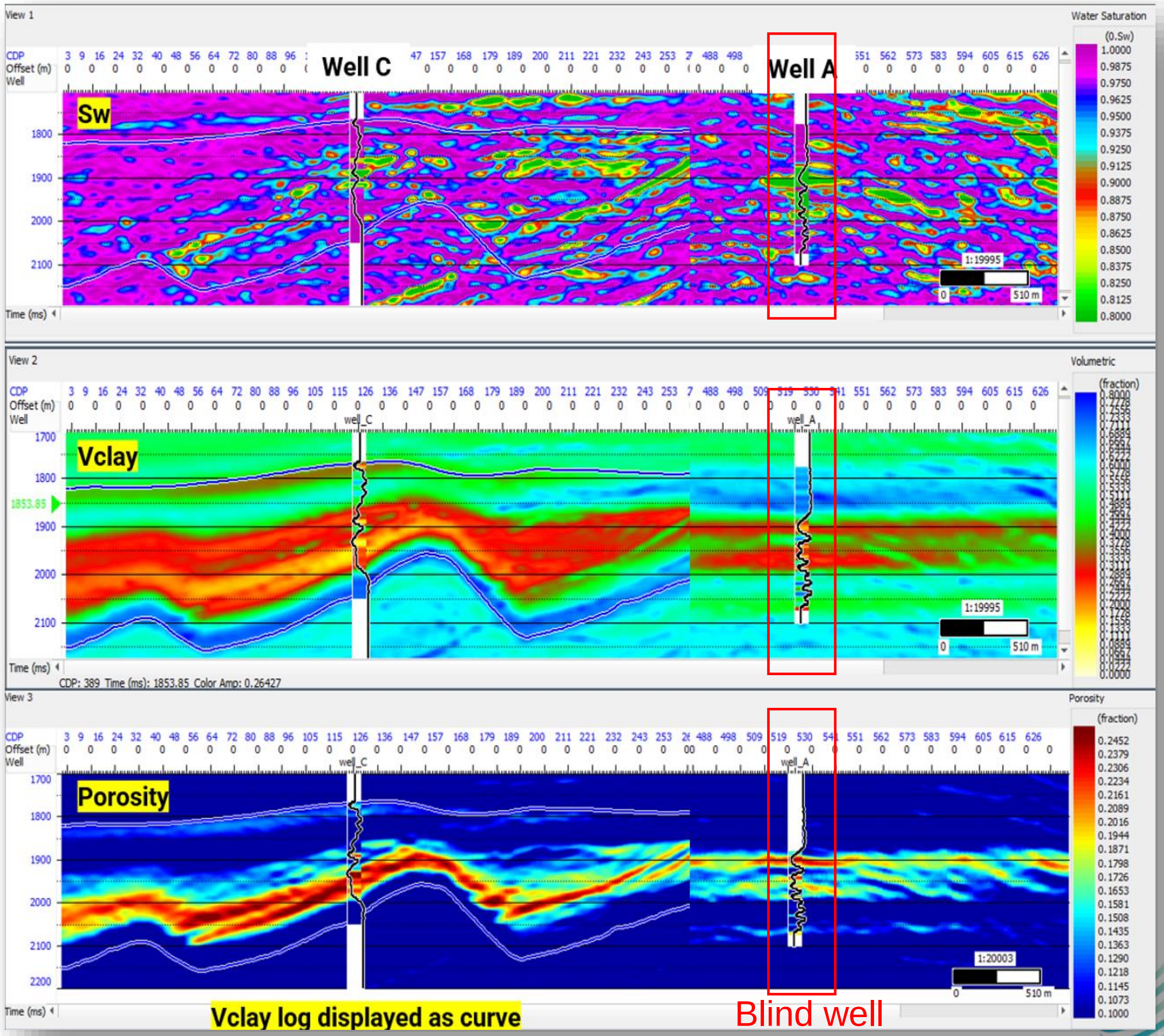
GeoAI Approach

Objective:

Predict reservoir properties

Challenges:

- Complex lithology: Lithology varies from shales, siltstones, coal beds, sandstones, sands with calcite cementation
- Limited well control (two wells)



GeoAI Solution:

Rock properties can be estimated by either:

- Theory-based approaches such as **Seismic Inversion**

- Data science-based approaches using **Neural Networks**

- Theory and Data science based approaches using **Rock Physics, Statistical analysis, AVO modeling and Neural Networks (Theory guided deep machine learning)**

Proposed Solution ➡

Benefits of Theory Guided Deep Machine Learning

(Convolutional Neural Network)

- Can Address “Not Enough Data” Problem
- Multiple predictions of rock and elastic properties simultaneously
- Ability to transfer learning

Rock Physics Driven Machine Learning

Reservoir characterization challenges

LIMITED WELL CONTROL

↓

USE PSEUDO-WELLS SIMULATED BASED ON ROCK PHYSICS

THIN BED DETECTION, COMPLEX GEOLOGY

↓

HIGH-DETAILED RESULTS, WORK WITH COMPLEX GEOLOGY FIELDS

ASSUMPTIONS ARE VIOLATED

↓

DON'T RELY ON ASSUPTIONS

TWO-STEP APPROACH FOR RESERVOIR PROPERTIES PREDICTION

↓

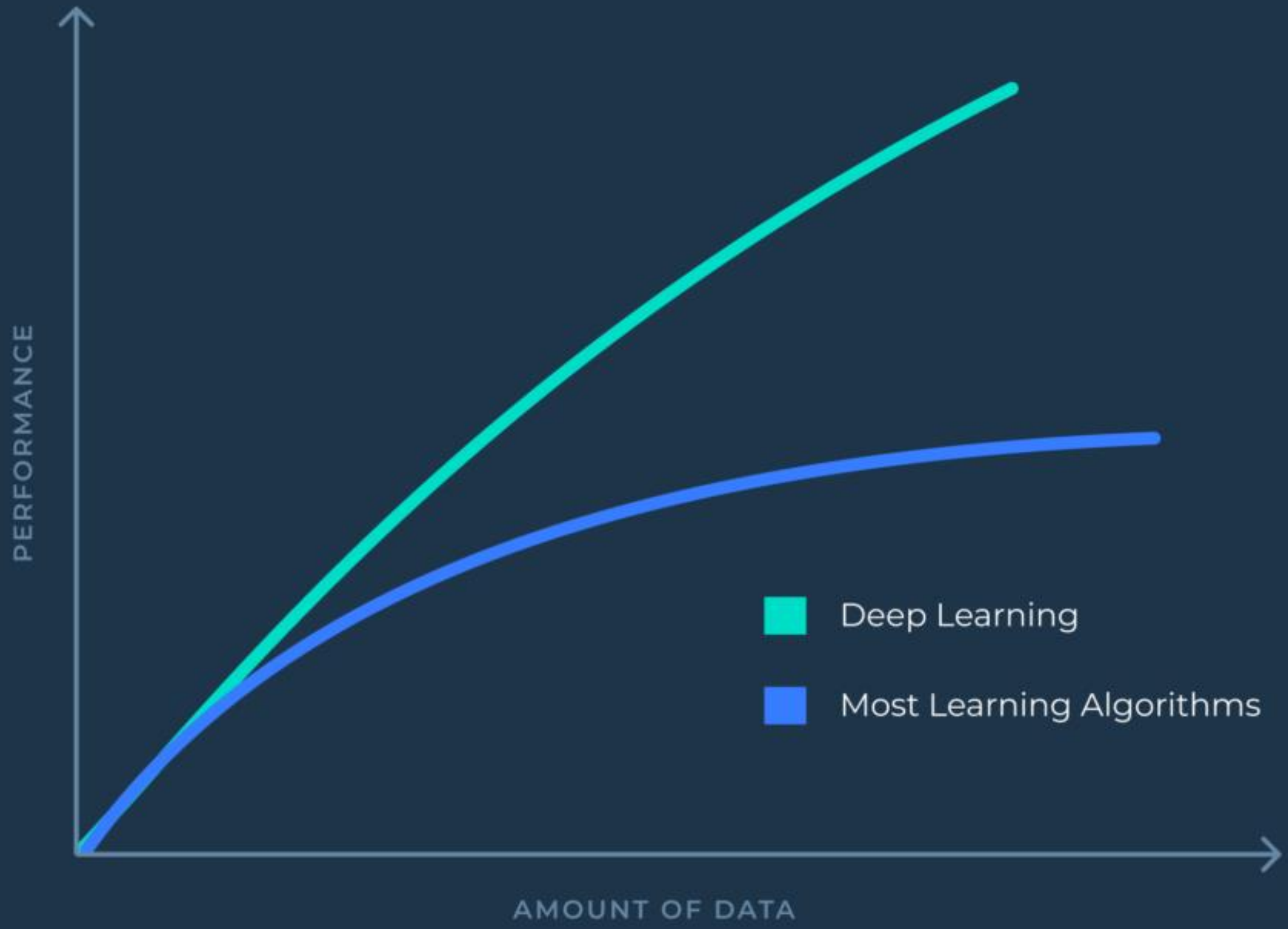
DIRECT RESERVOIR PROPERTIES PREDICTION

TIME-CONSUMING

↓

SPEED-UP RESERVOIR CHARACTERIZATION

Deep Learning benefits from extensive amounts of data



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Proposed solution

HampsonRussell

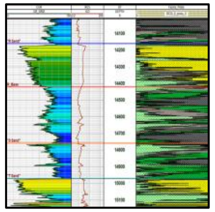
- Generate **synthetic catalog**, consisting of well log and seismic data, based on **rock physics modeling** and **statistical analysis**!

Rock physics modeling

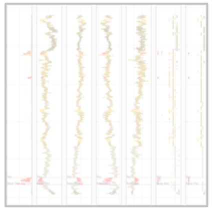
Synthetic catalog generation

Convolutional Neural Network

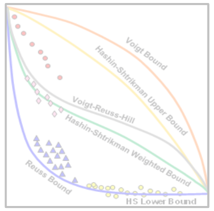
WORKFLOW



PETROPHYSICAL ANALYSIS



LITHOLAYER CLASSIFICATION



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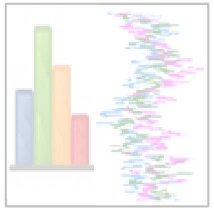
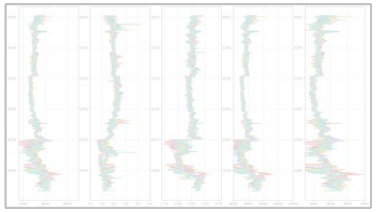
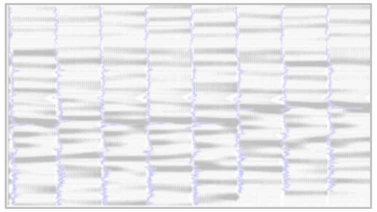


STATISTICAL ANALYSIS

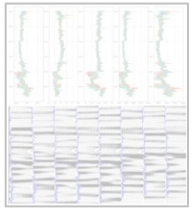
PSEUDO-WELLS SIMULATION



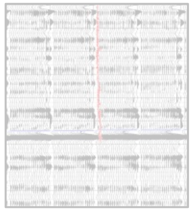
SYNTHETIC MODELING



CONVOLUTIONAL NEURAL NETWORK

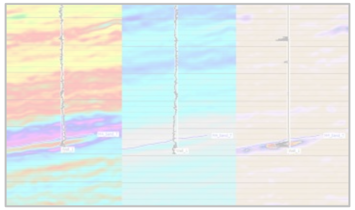


TRAINING



TRANSFER LEARNING

APPLYING

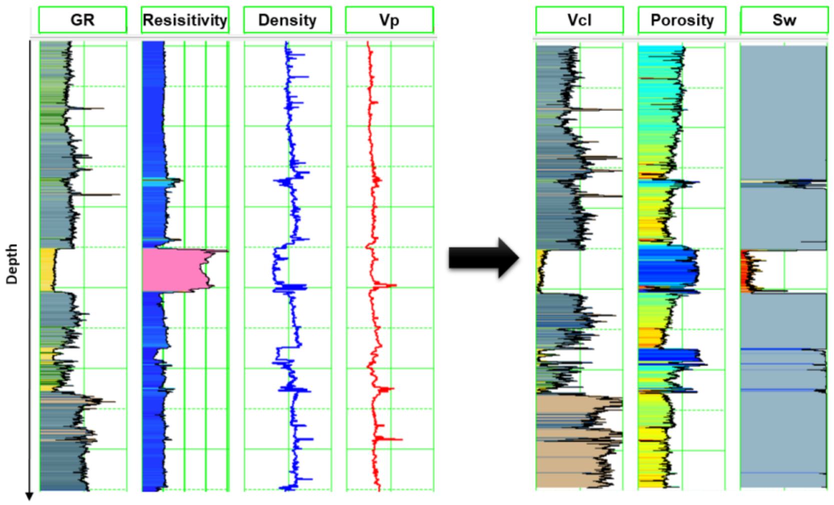


UNCERTAINTY ANALYSIS

Petrophysical analysis

- Well data QC and preparation:
  - Log data conditioning
  - Computation of petrophysical properties used in the rock physics modeling

- Required input data:
  - At least 1 well
  - Curves needed to establish RPM(s):
    - Vp
    - Density
    - Porosity
    - S_w, etc.



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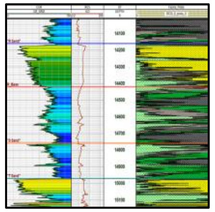
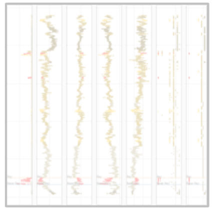


PETROPHYSICAL ANALYSIS



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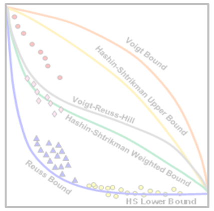

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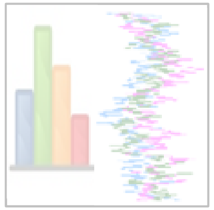
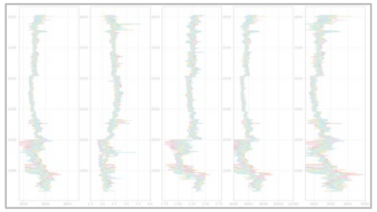
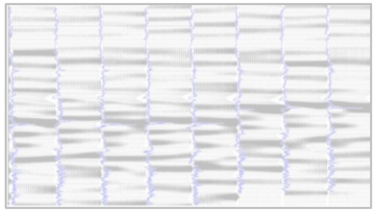


STATISTICAL ANALYSIS

PSEUDO-WELLS SIMULATION



SYNTHETIC MODELING



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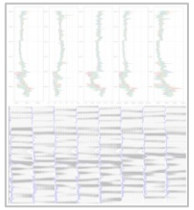

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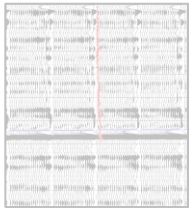

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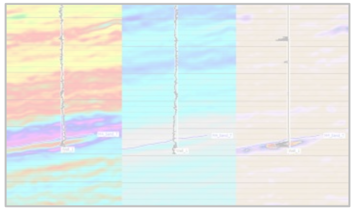
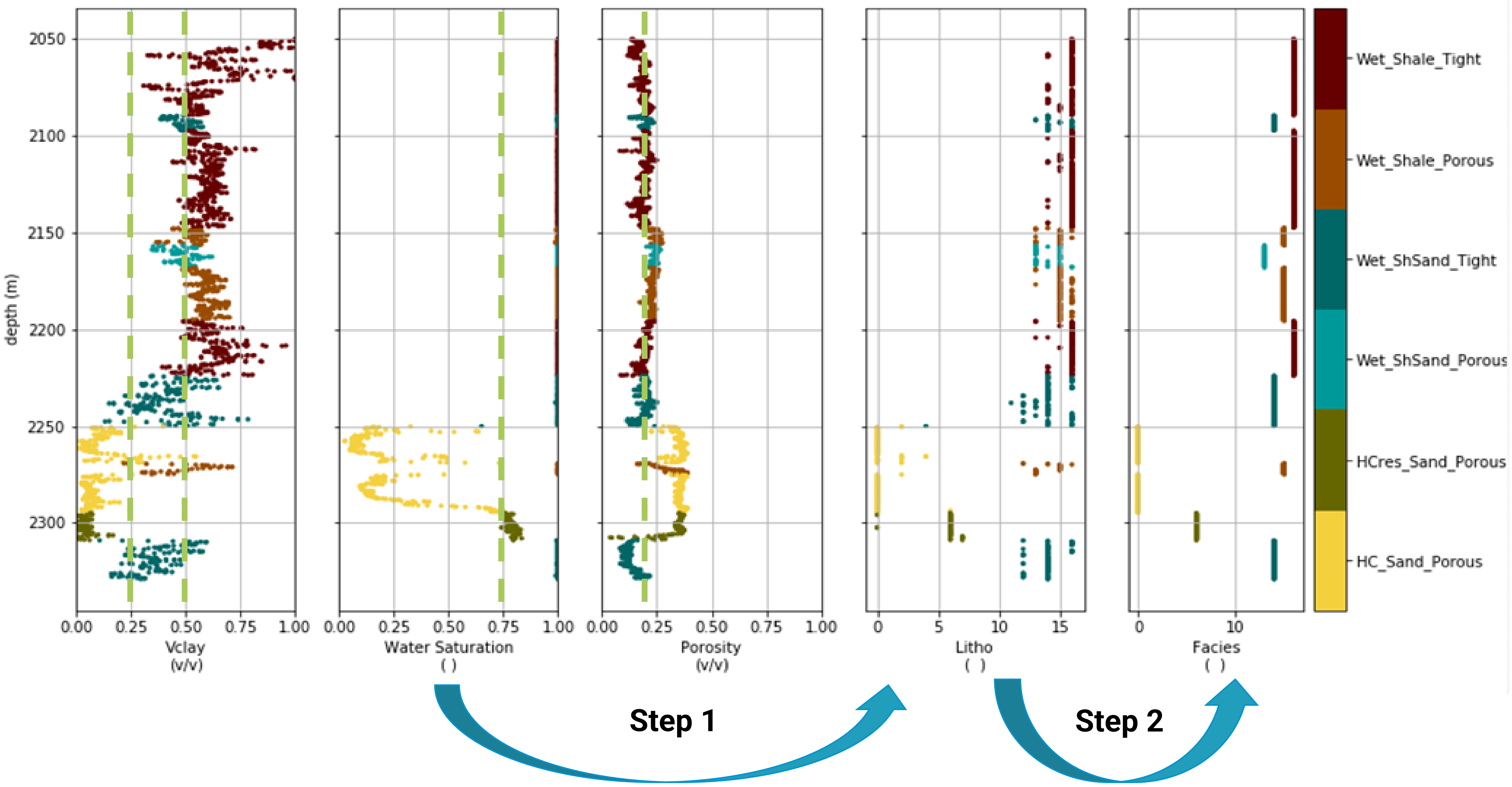


UNCERTAINTY ANALYSIS

Statistics – Litholayers identification



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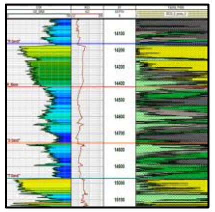

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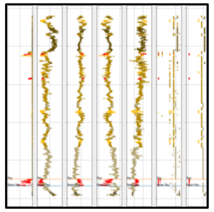

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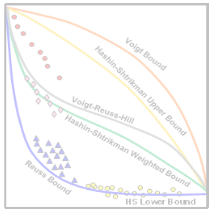

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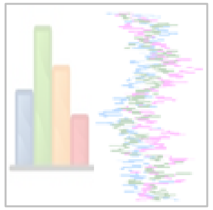

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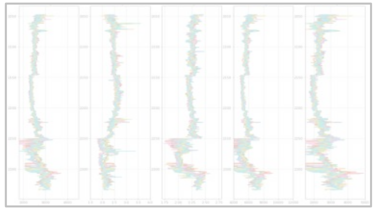

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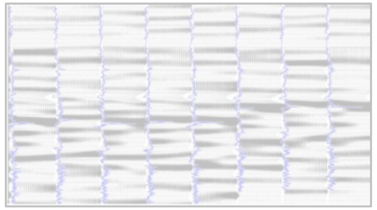

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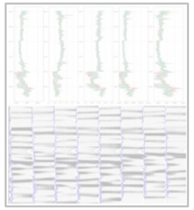

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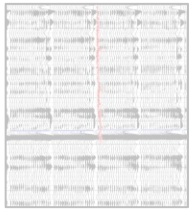

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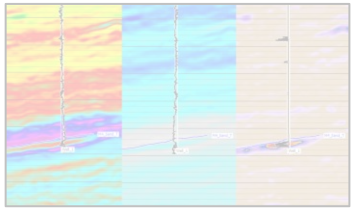
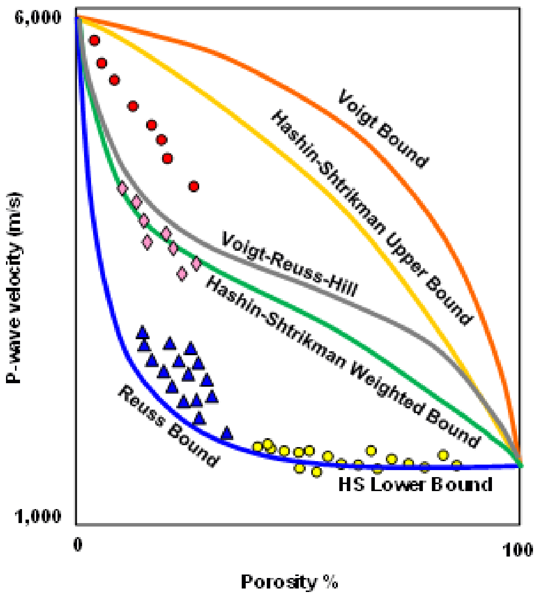


UNCERTAINTY ANALYSIS

Rock physics model creation

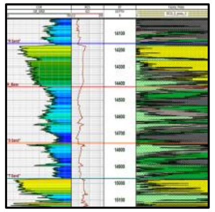
- The goal is to establish the rock physics model (RPM)

$$Vp, Vs, \rho = \mathrm{RPM}\ (\varphi, V_{cl}, S_w, \ldots)$$



- And then calibrate this model on your data

WORKFLOW



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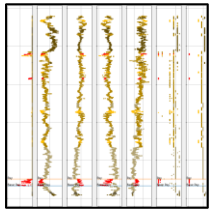

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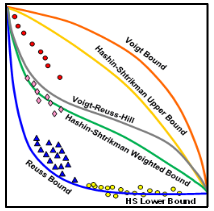

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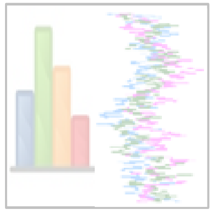
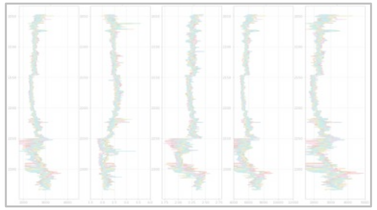
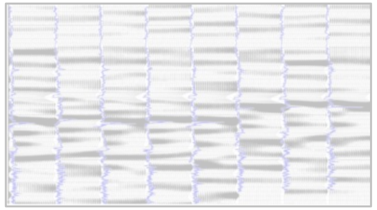


STATISTICAL ANALYSIS

PSEUDO-WELLS SIMULATION



SYNTHETIC MODELING



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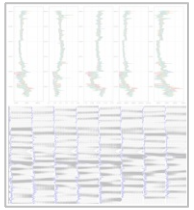
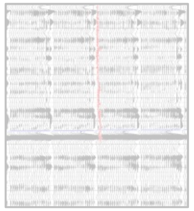


TRAINING



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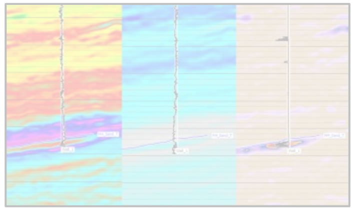
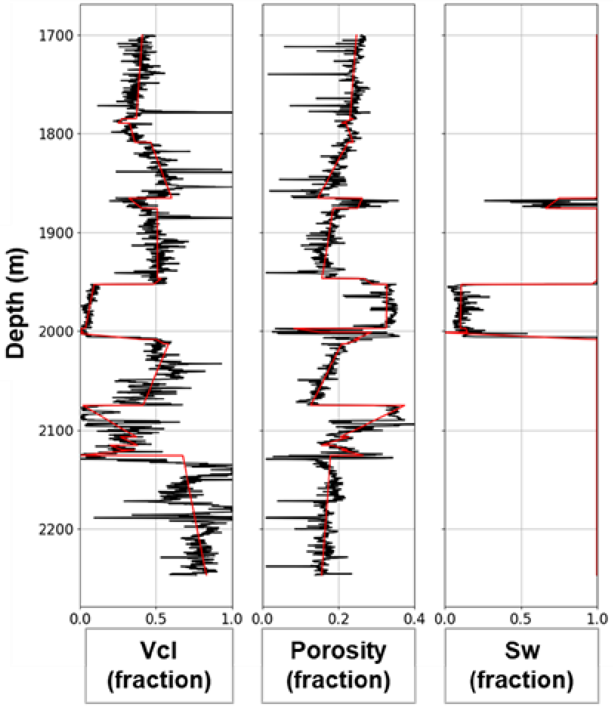


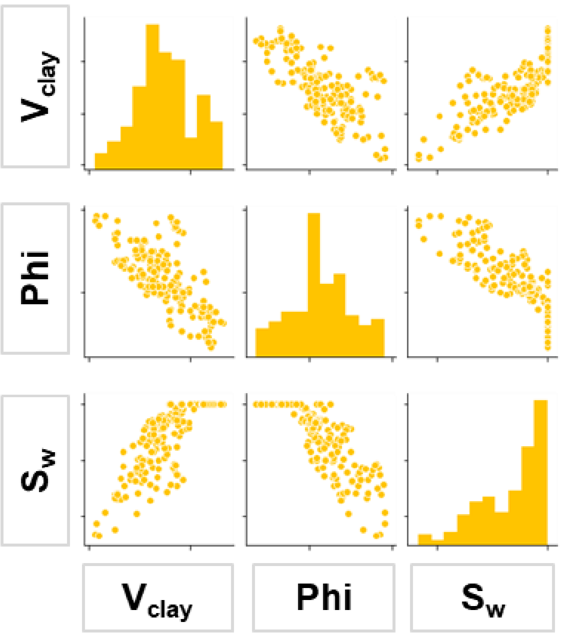
UNCERTAINTY ANALYSIS

Statistics – Background trend & covariance matrix

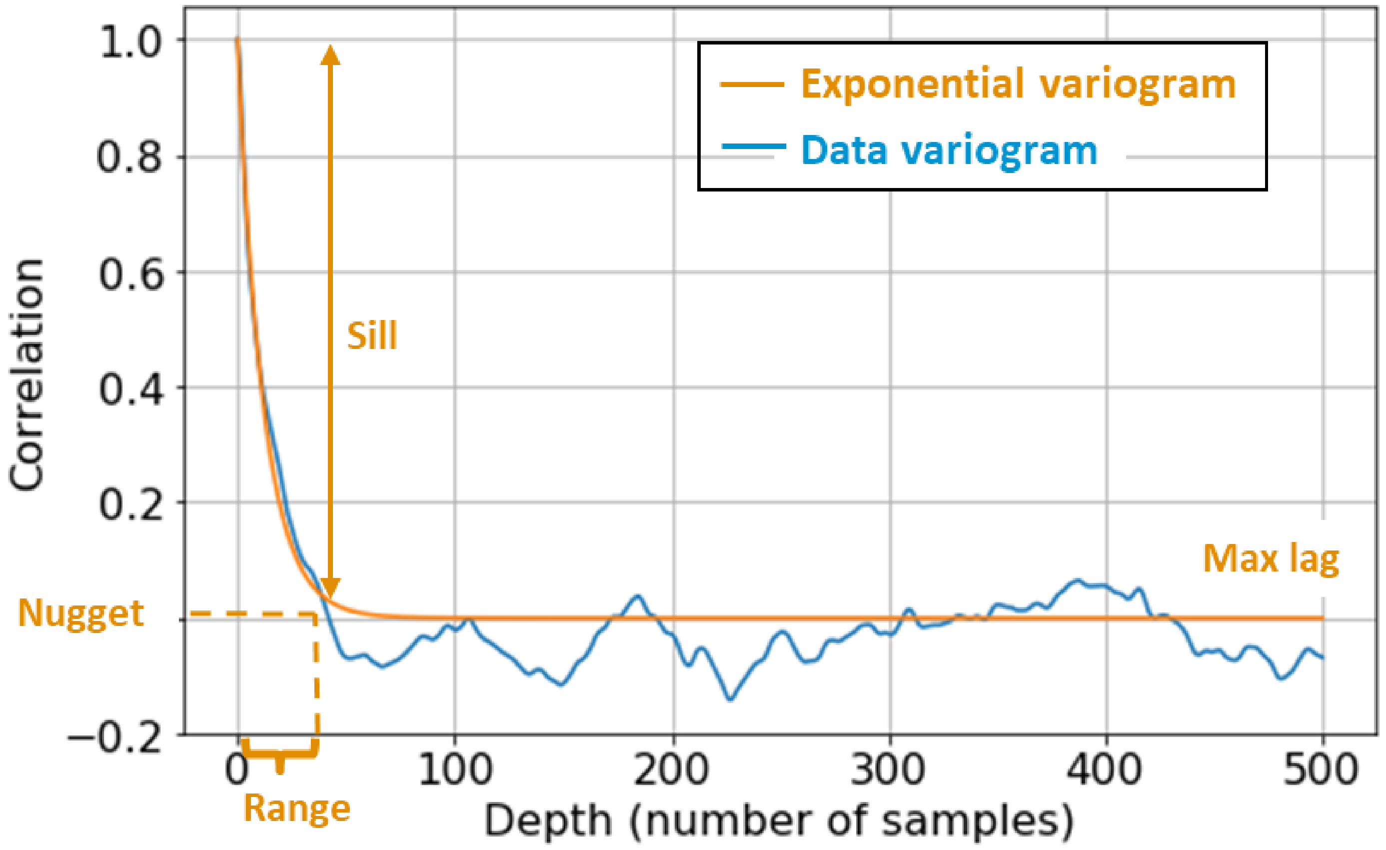
BACKGROUND TREND



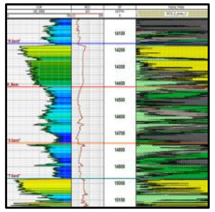
COVARIANCE MATRIX



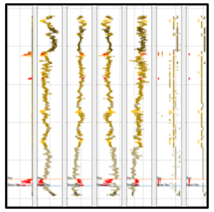
Statistics – Vertical variability (variograms)



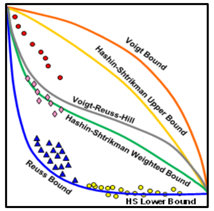
WORKFLOW



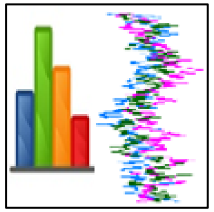
PETROPHYSICAL ANALYSIS



LITHOLAYER CLASSIFICATION



ROCK PHYSICS



STATISTICAL ANALYSIS

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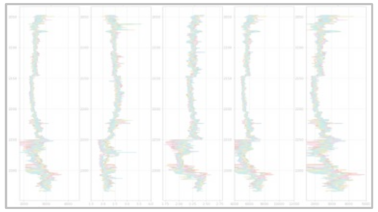
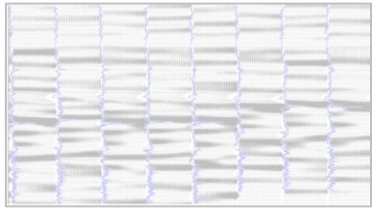
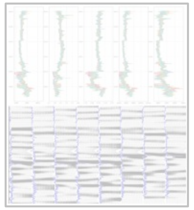


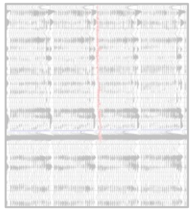
SYNTHETIC MODELING



CONVOLUTIONAL NEURAL NETWORK

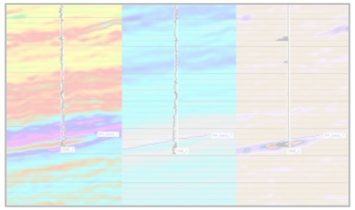


TRAINING



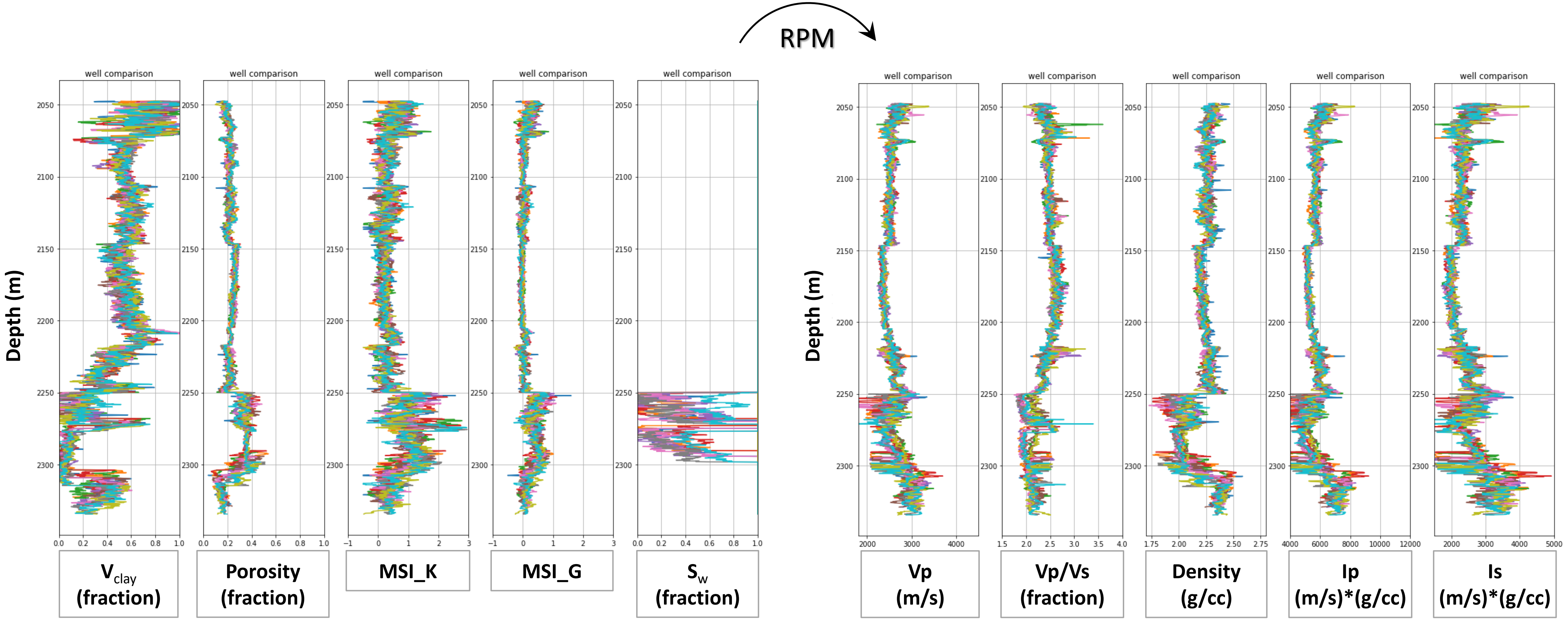
TRANSFER LEARNING

APPLYING

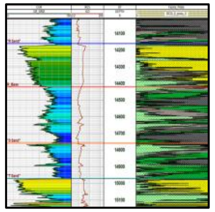


UNCERTAINTY ANALYSIS

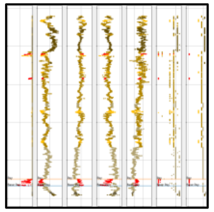
Simulations



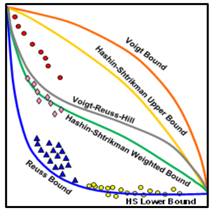
WORKFLOW



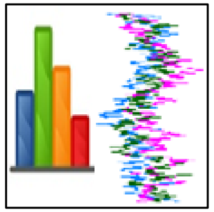
PETROPHYSICAL ANALYSIS



LITHOLAYER CLASSIFICATION

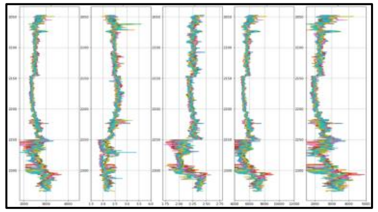


ROCK PHYSICS

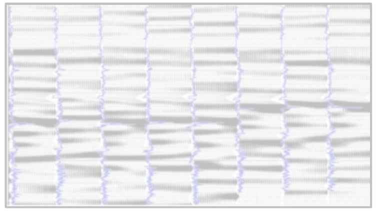


STATISTICAL ANALYSIS

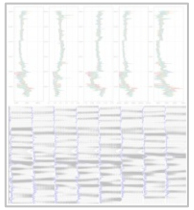
PSEUDO-WELLS SIMULATION



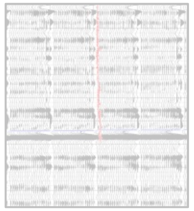
SYNTHETIC MODELING



CONVOLUTIONAL NEURAL NETWORK

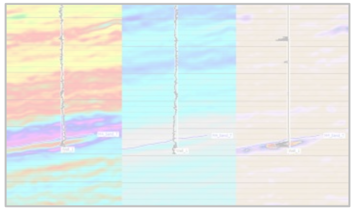


TRAINING



TRANSFER LEARNING

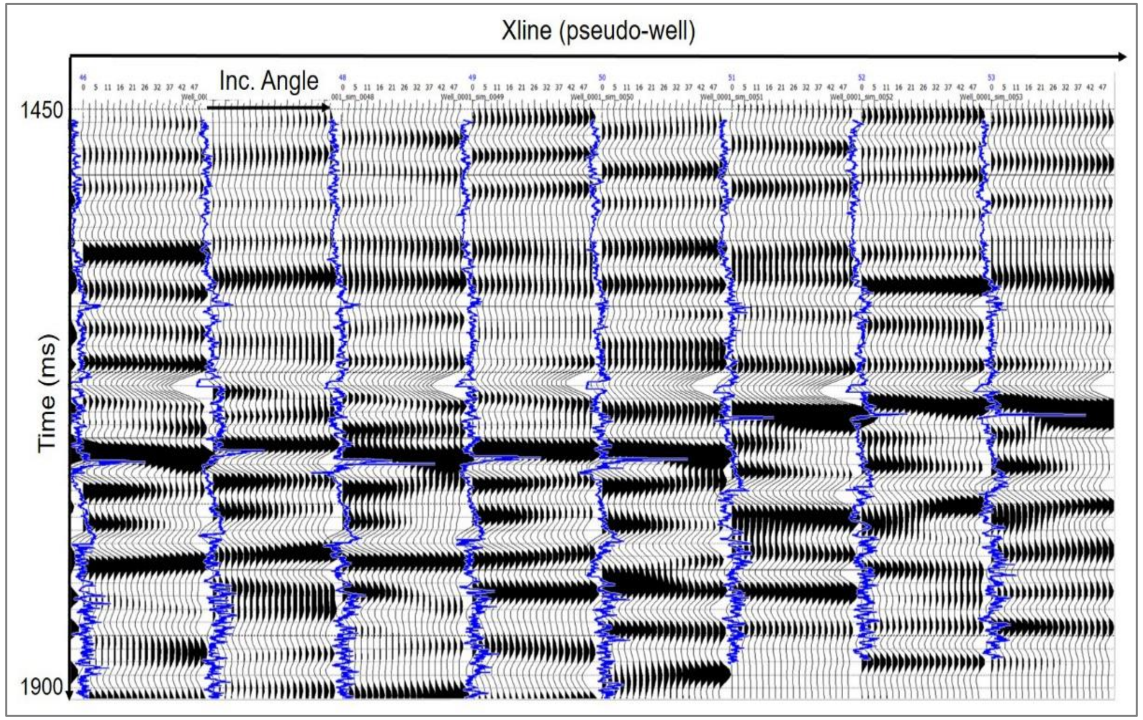
APPLYING



UNCERTAINTY ANALYSIS

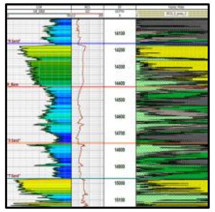
Synthetic modeling

- The synthetic gathers are generated to match the seismic gathers
- The synthetic gathers are calculated using the P-wave reflection coefficients calculated using the Zoeppritz (1919) equations and a convolutional model using a wavelet extracted from the real seismic data
- Transmission losses, converted waves, and multiples are not incorporated in this model and are assumed to be addressed through the processing

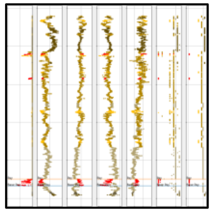


Subset of synthetic gathers generated from pseudo-wells

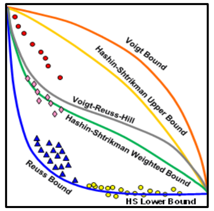
WORKFLOW



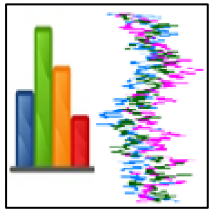
PETROPHYSICAL ANALYSIS



LITHOLAYER CLASSIFICATION



ROCK PHYSICS

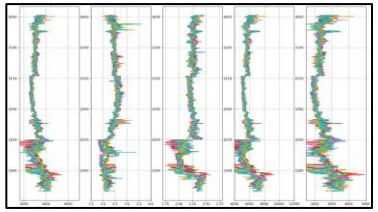


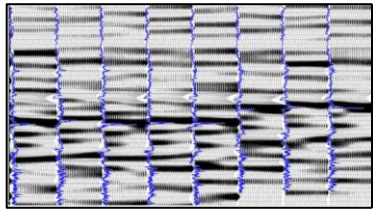
STATISTICAL ANALYSIS

PSEUDO-WELLS SIMULATION

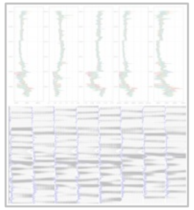
SYNTHETIC MODELING

Synthetic catalog

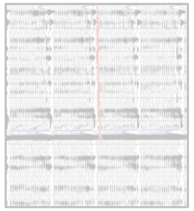




CONVOLUTIONAL NEURAL NETWORK

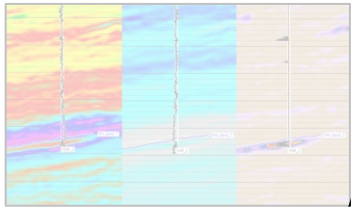


TRAINING



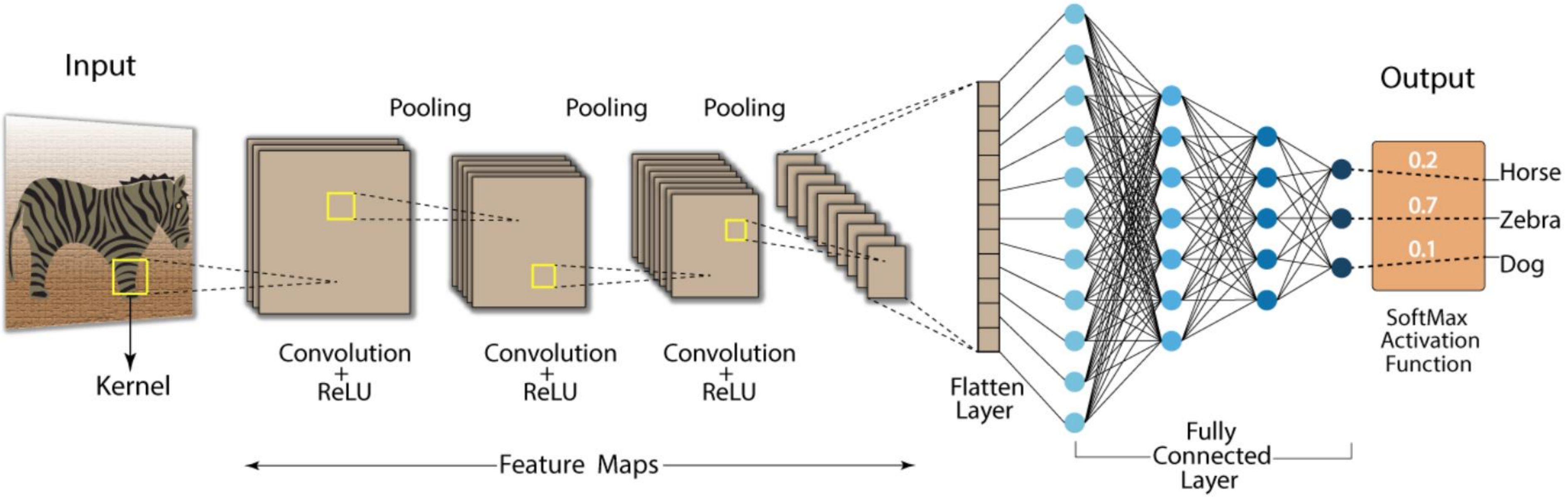
TRANSFER LEARNING

APPLYING



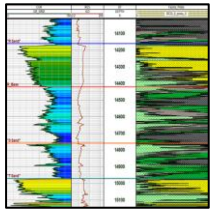
UNCERTAINTY ANALYSIS

CNN

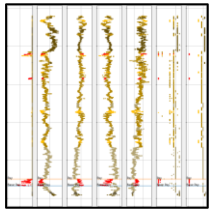


- Used in image classification
- The input consists of three sets of pixel maps (Red, Green and Blue)
- Two main steps: convolution and pooling
- The output is then flattened and input into an FC NN
- The output of the CNN can either be categories or continuous variables

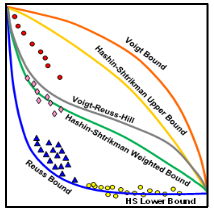
WORKFLOW



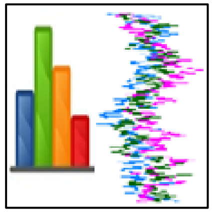
PETROPHYSICAL ANALYSIS



LITHOLAYER CLASSIFICATION



ROCK PHYSICS

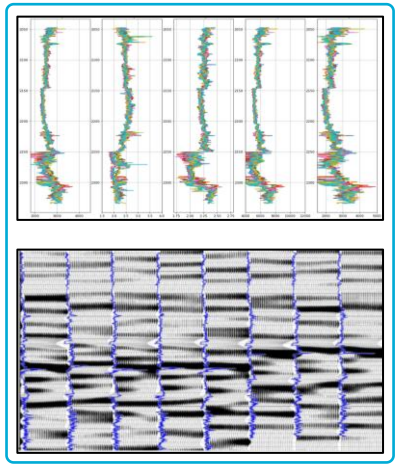


STATISTICAL ANALYSIS

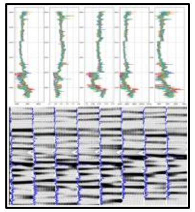
PSEUDO-WELLS SIMULATION

SYNTHETIC MODELING

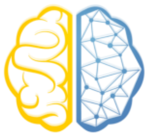
Synthetic catalog

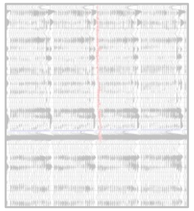


CONVOLUTIONAL NEURAL NETWORK



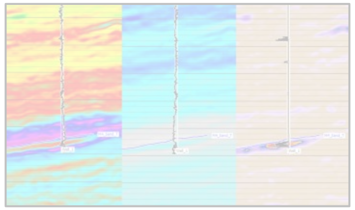
TRAINING





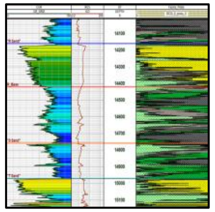
TRANSFER LEARNING

APPLYING

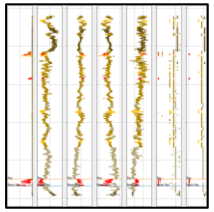


UNCERTAINTY ANALYSIS

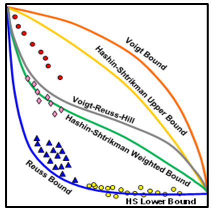
WORKFLOW



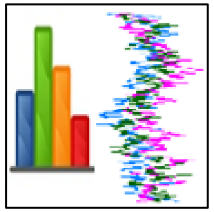
PETROPHYSICAL ANALYSIS



LITHOLAYER CLASSIFICATION



ROCK PHYSICS

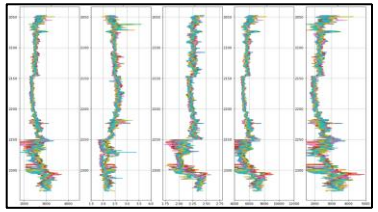


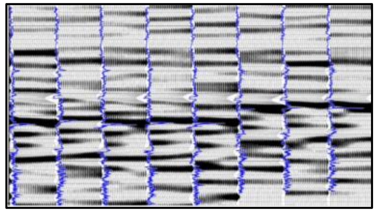
STATISTICAL ANALYSIS

PSEUDO-WELLS SIMULATION

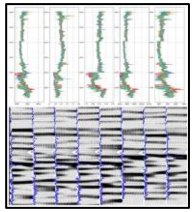
SYNTHETIC MODELING

Synthetic catalog

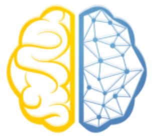


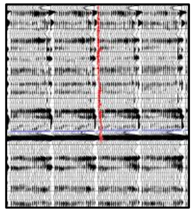


CONVOLUTIONAL NEURAL NETWORK



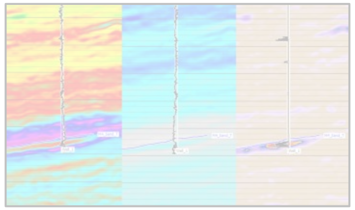
TRAINING





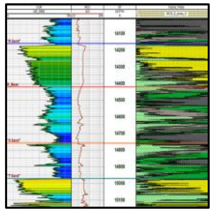
TRANSFER LEARNING

APPLYING

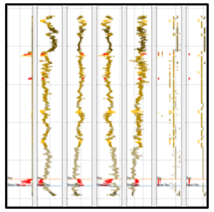


UNCERTAINTY ANALYSIS

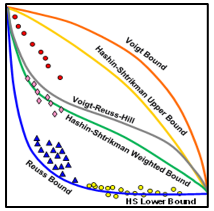
WORKFLOW



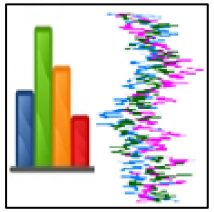
PETROPHYSICAL ANALYSIS



LITHOLAYER CLASSIFICATION



ROCK PHYSICS

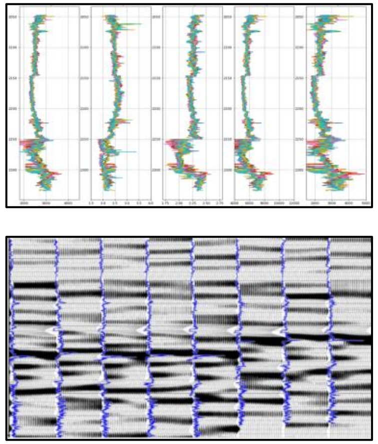


STATISTICAL ANALYSIS

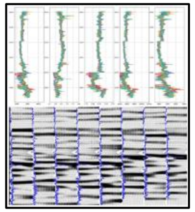
PSEUDO-WELLS SIMULATION

SYNTHETIC MODELING

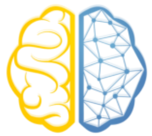
Synthetic catalog

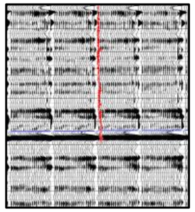


CONVOLUTIONAL NEURAL NETWORK



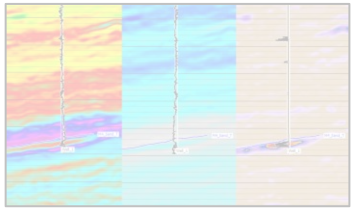
TRAINING





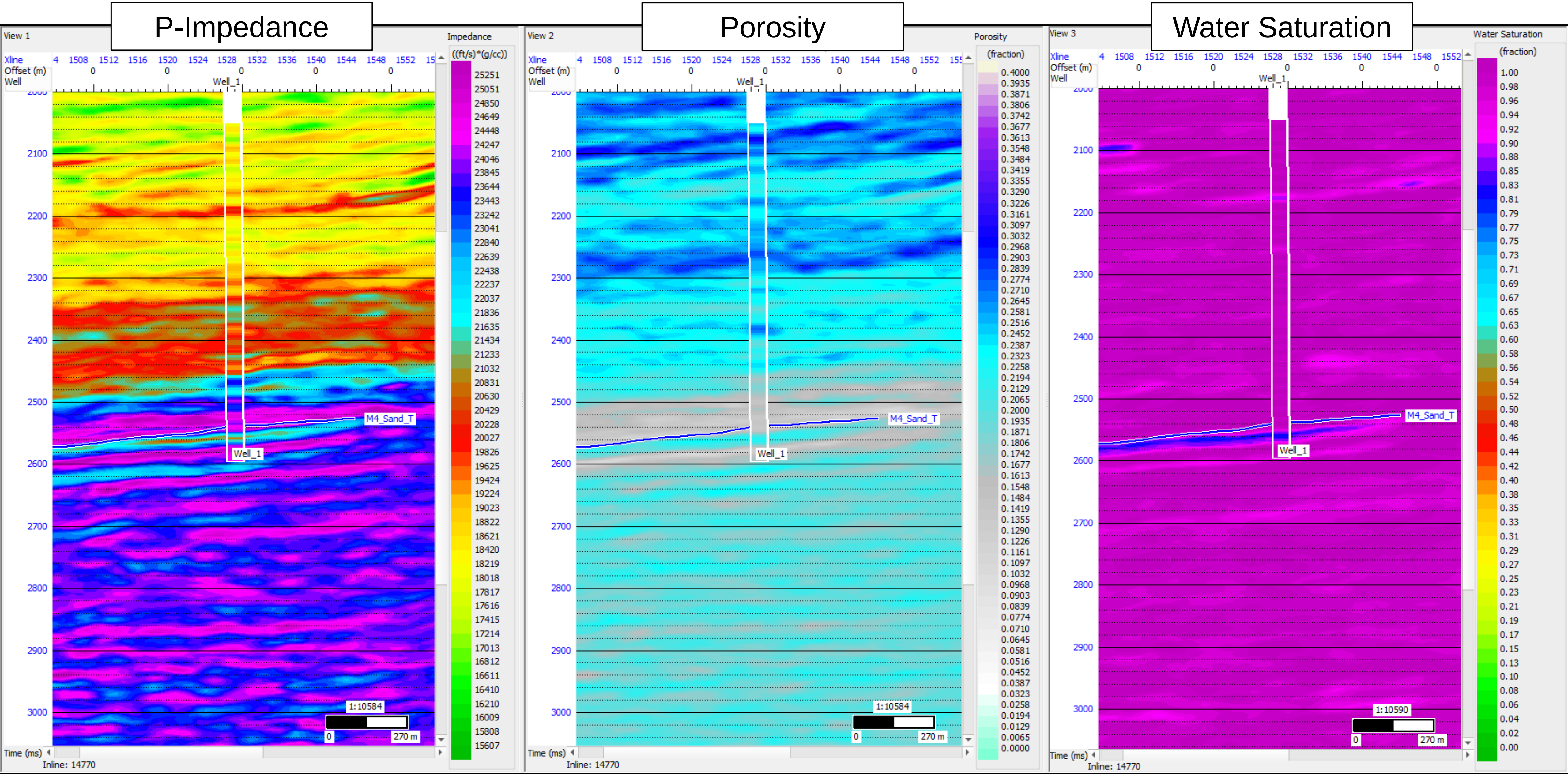
TRANSFER LEARNING

APPLYING

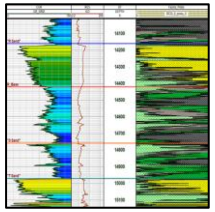


UNCERTAINTY ANALYSIS

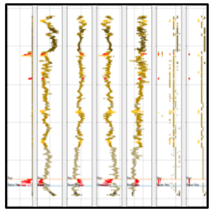
CNN PREDICTION RESULTS



WORKFLOW



PETROPHYSICAL ANALYSIS



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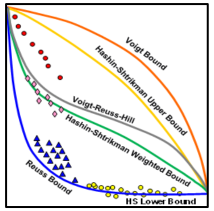
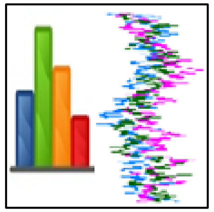


ROCK PHYSICS



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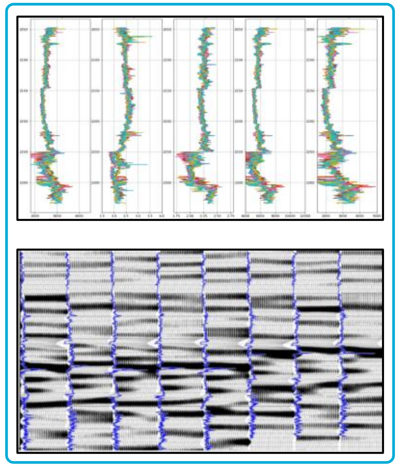

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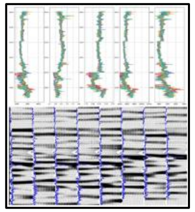
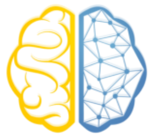
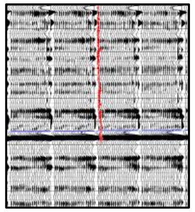


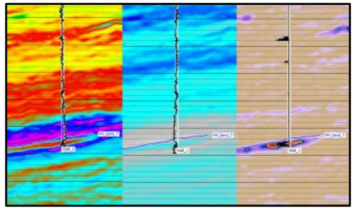
TRAINING





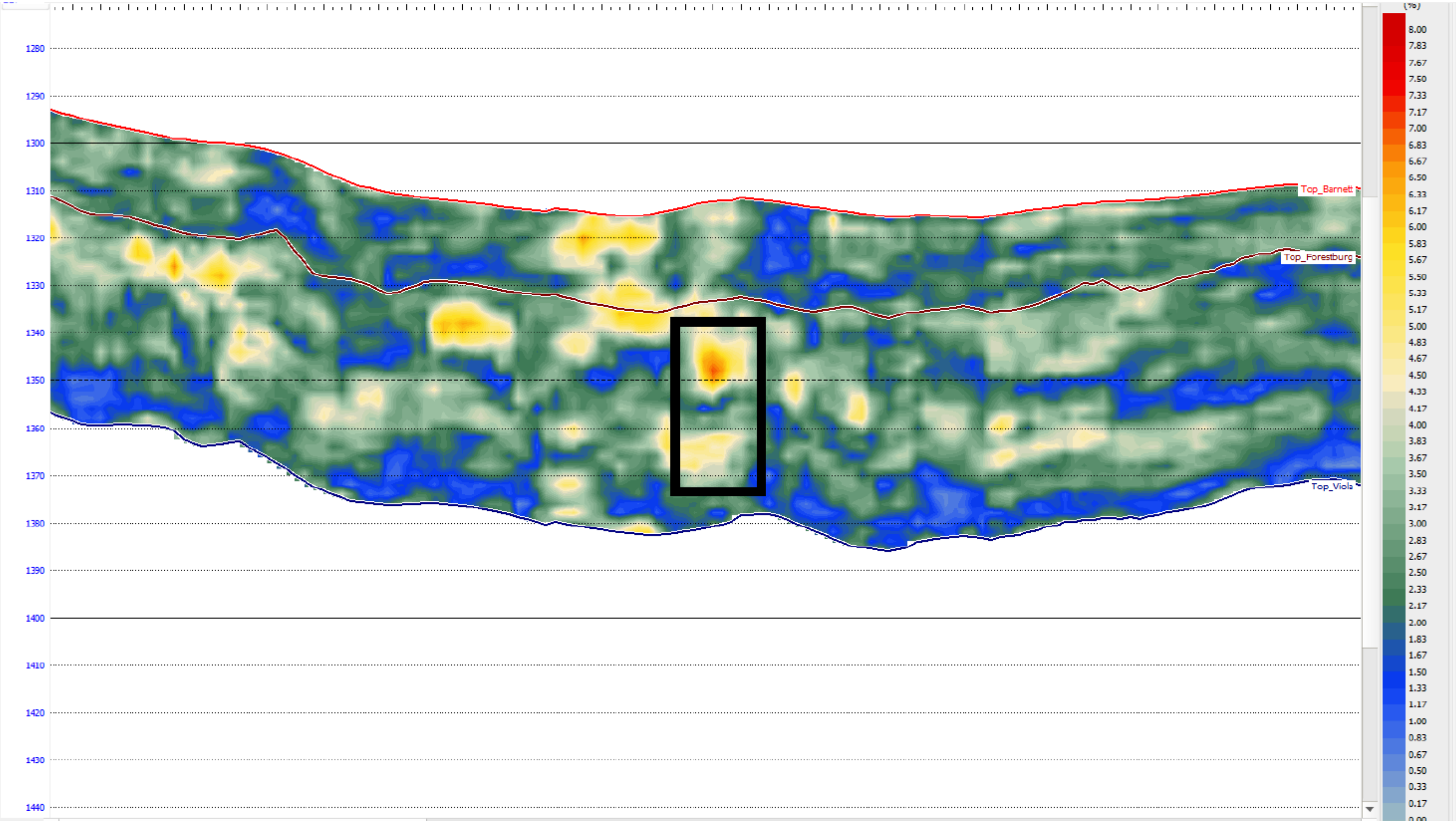
TRANSFER LEARNING

APPLYING



UNCERTAINTY ANALYSIS

Standard Deviation



Case Study #1:

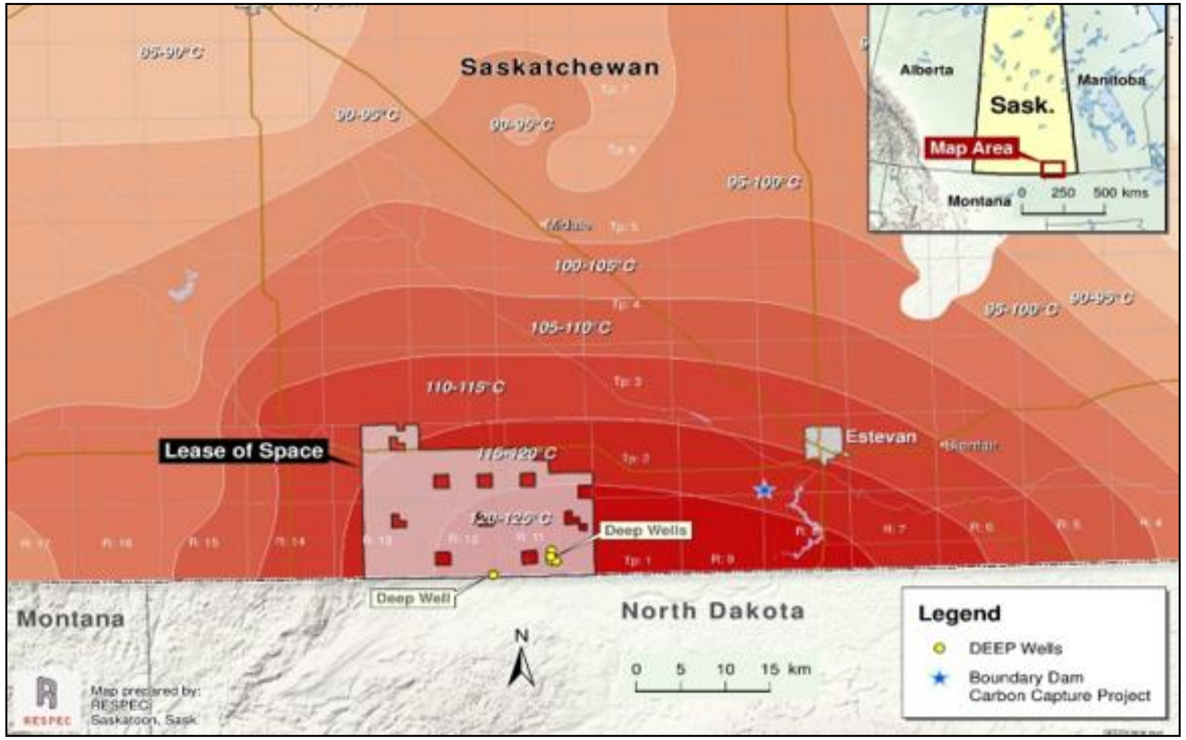
The Cambrian Deadwood sandstone reservoir, Canada

Geothermal project location

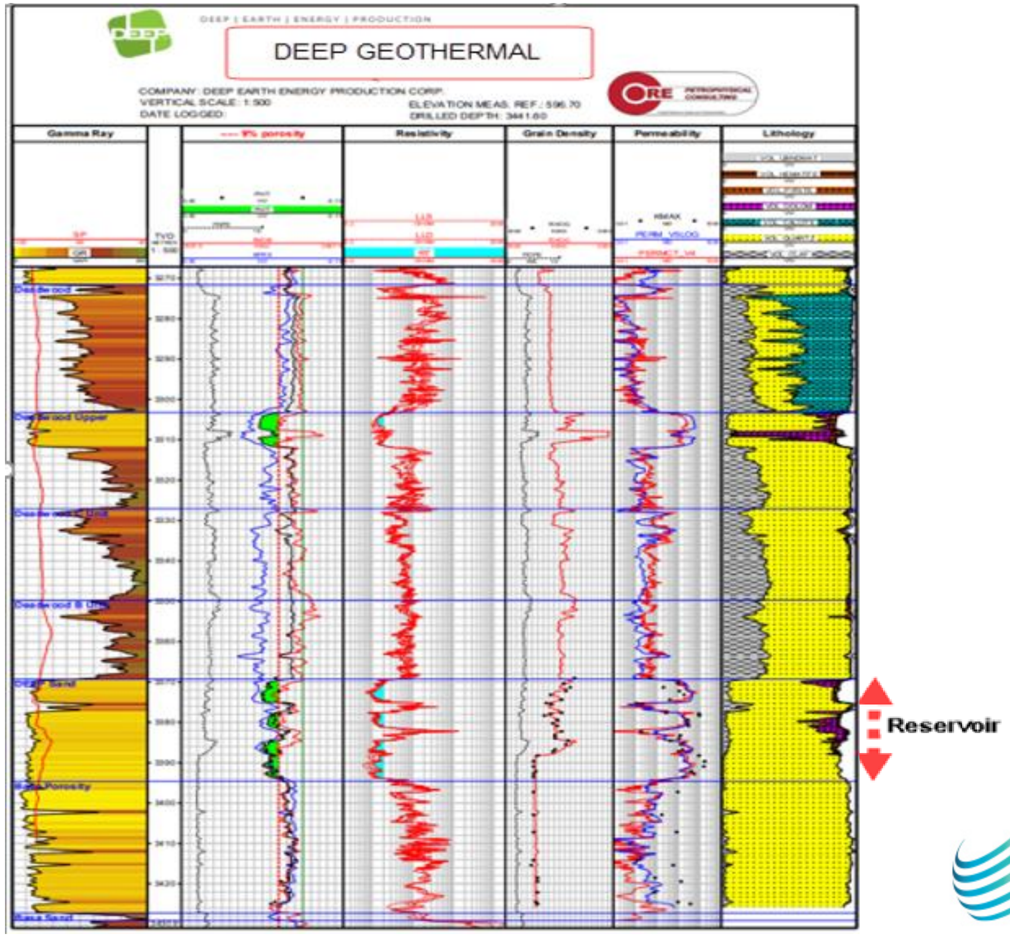
- DEEP (Deep Earth Energy Production) has targeted the Basal Sandstones of the Williston basin for geothermal production.
- The project is west of the town of Estevan, Saskatchewan, just north of the border with North Dakota.
- The Cambrian Deadwood Sandstone reservoir will be exploited by an array of horizontal producer and injector wells.
- **Seismic inversion** and **machine learning** will be used to analyze the Deadwood sand reservoir over a ~231 km^2 3D data volume.

Basal Cambrian temperature and reservoirs

- The Temperature of the Deadwood reservoir is greater than 120º C on DEEP's Geothermal concession:

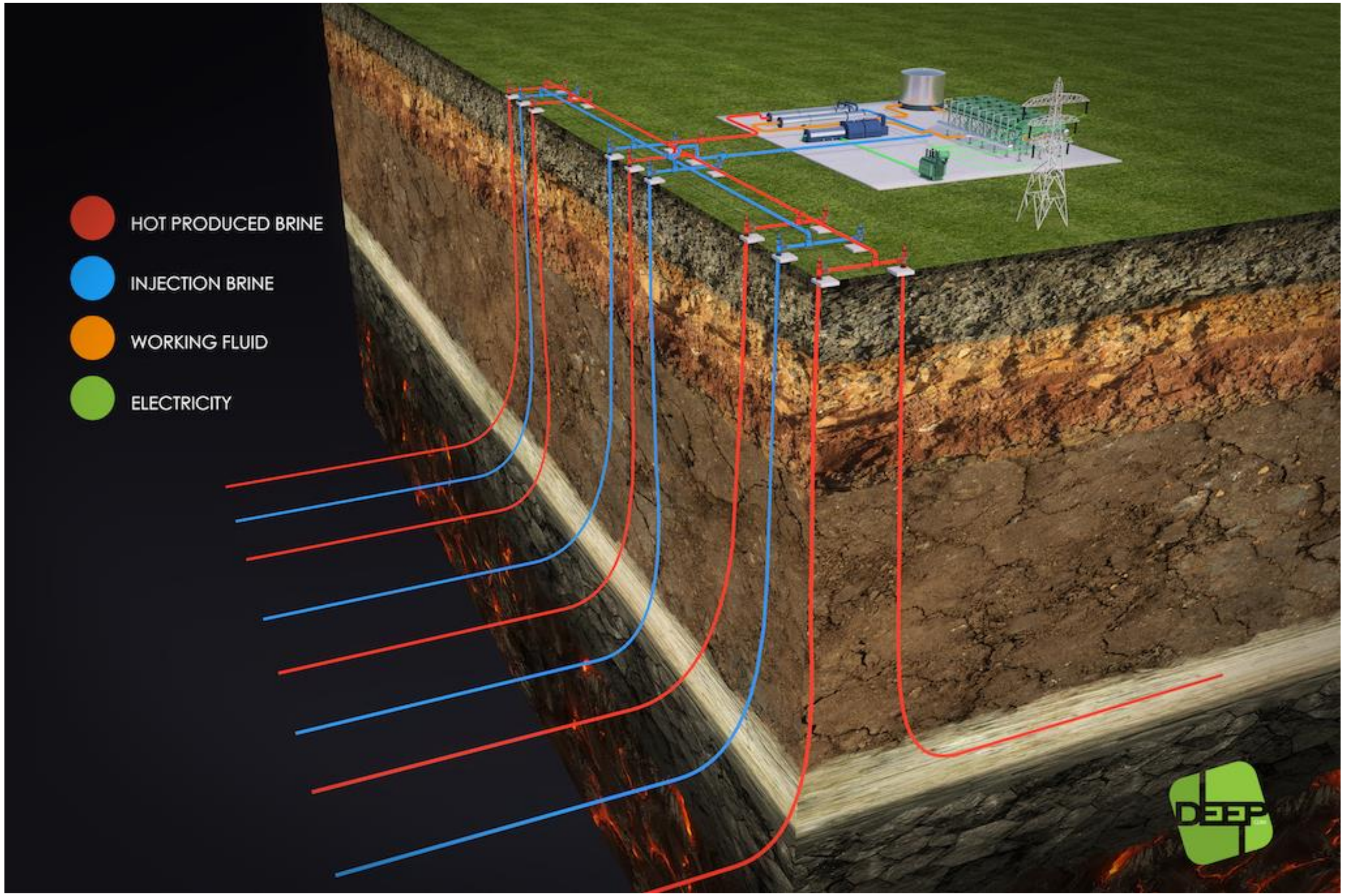


- The Deadwood reservoir target sandstone is 20-25 meters thick.



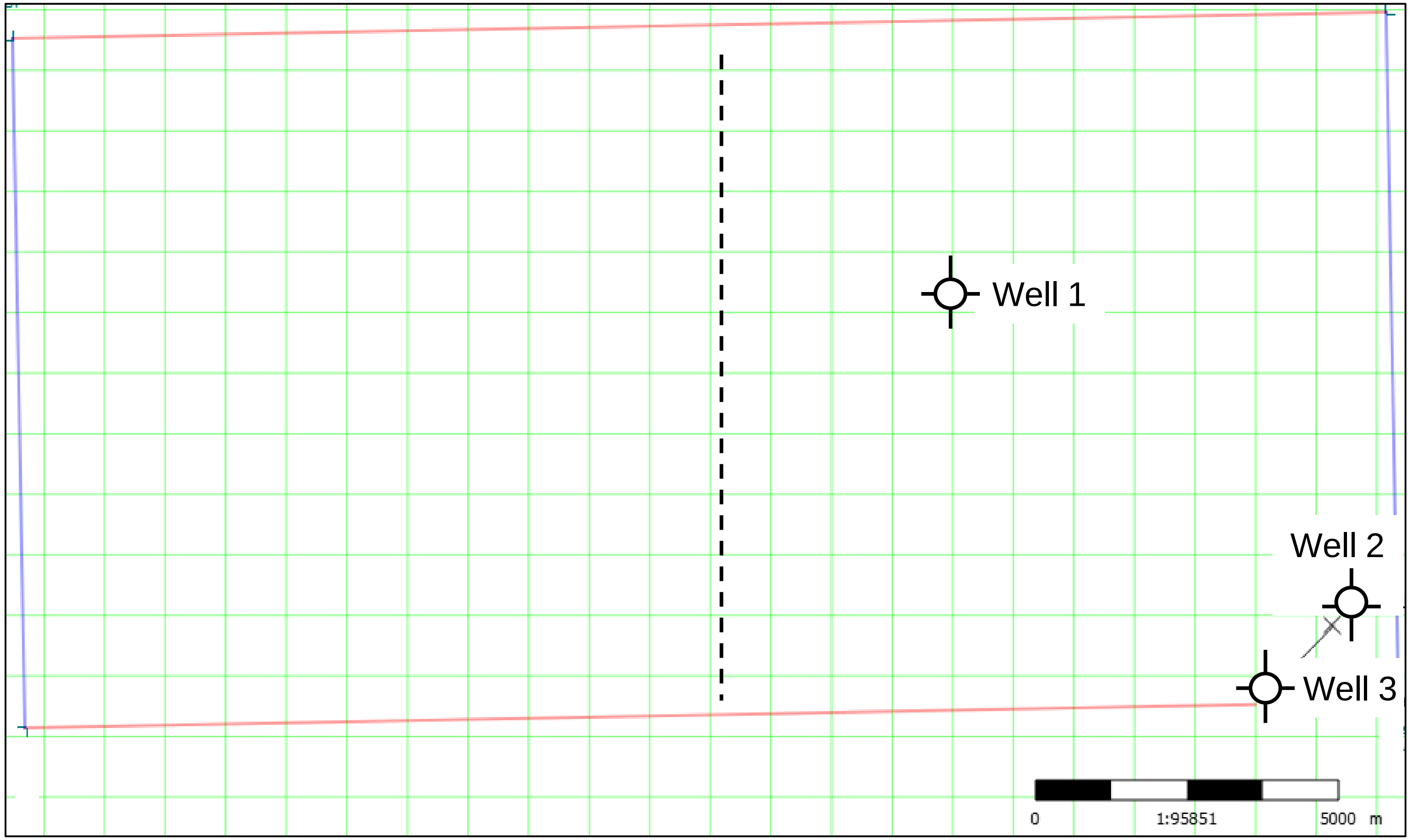
DEEP proposed well array layout

- A schematic of the DEEP production well array utilizing horizontal producing and injecting wells.
- Our objective is to map the porosity and permeability in the target zone using pre-stack inversion and machine learning.

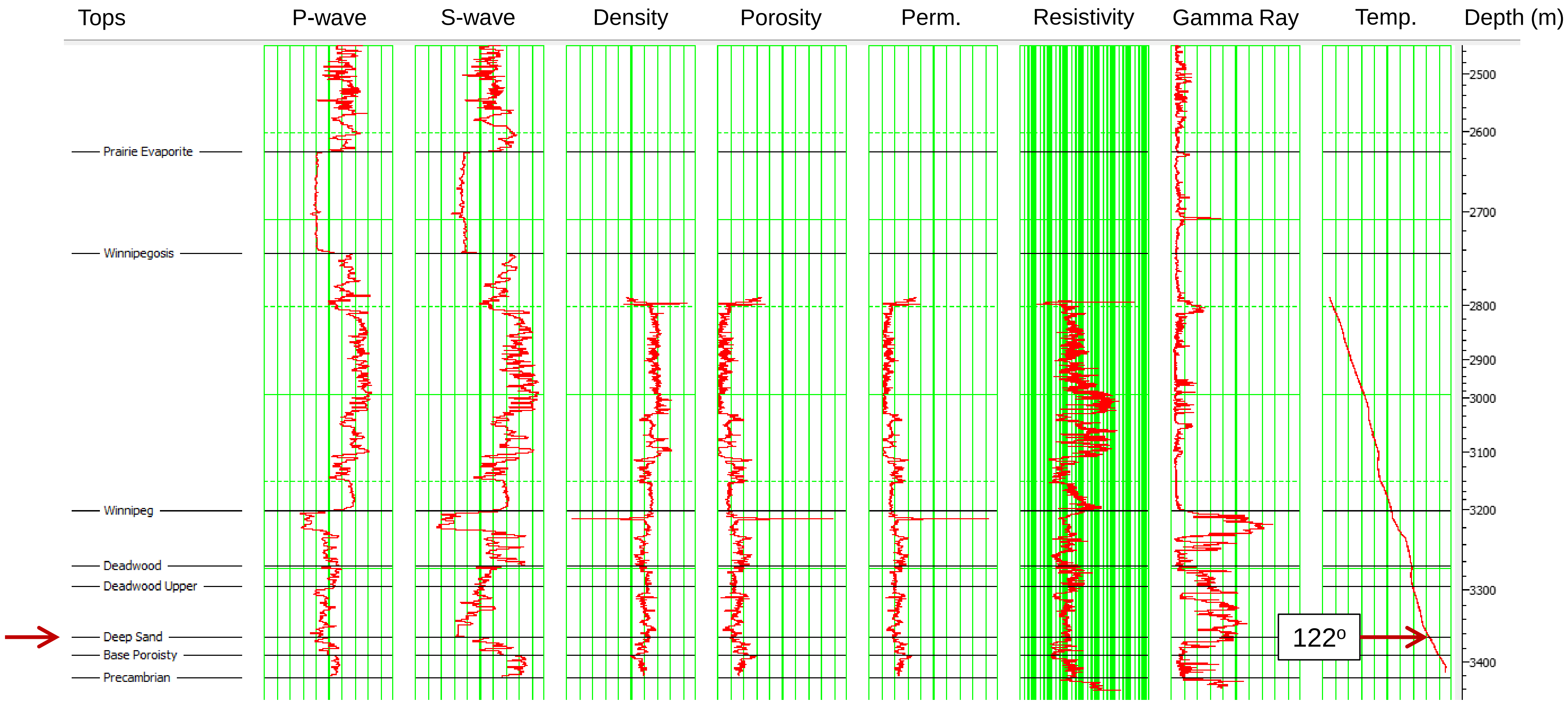


Seismic coverage

- The 3D seismic map and the three wells used.
- Wells 1 and 2 were vertical and well 3 was deviated.
- All positional information has been removed for confidentiality.
- Since there are no wells in the west, I will only show data east of the dashed line.



Well log curves for Well 1

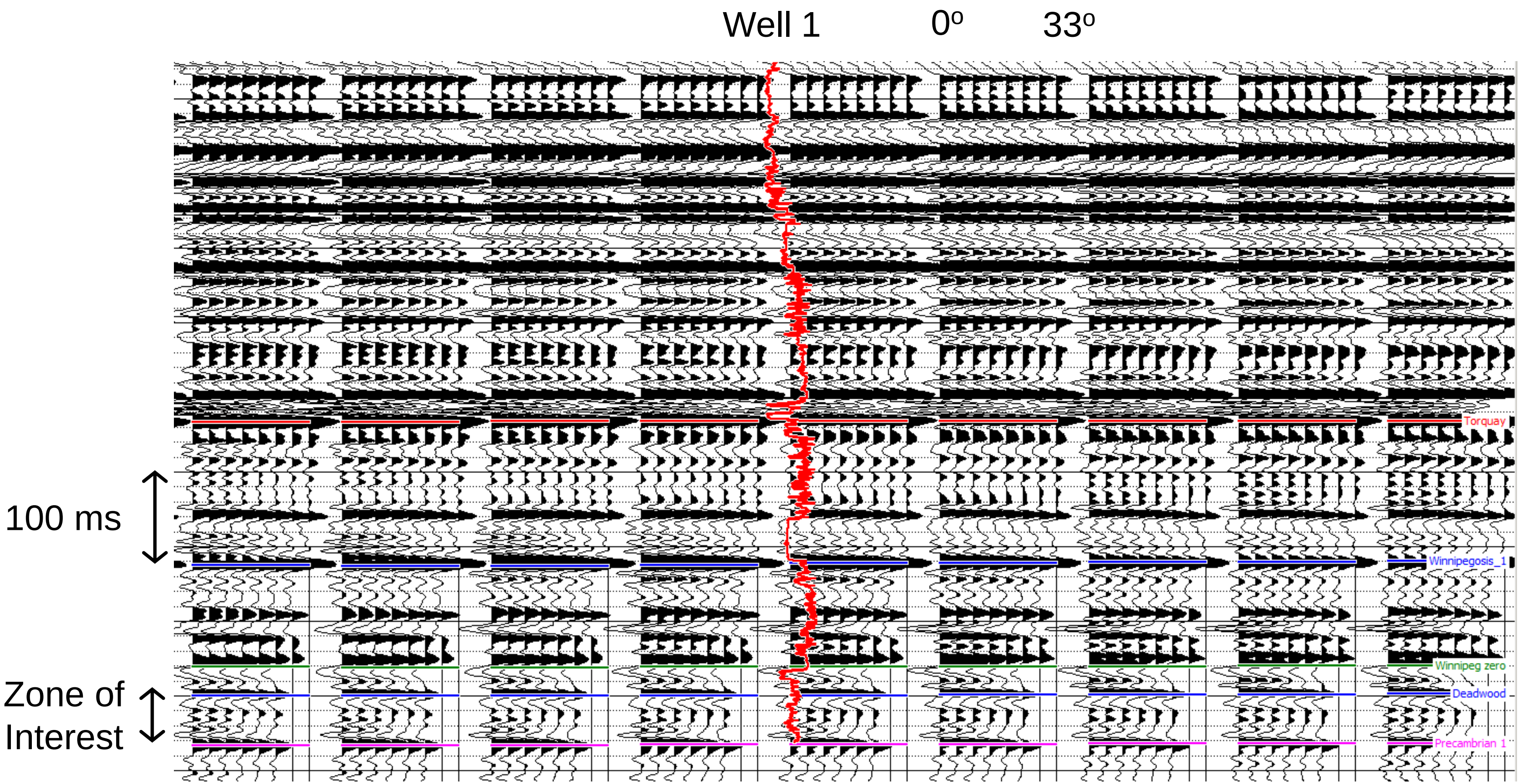


- This figure shows the well log curves from Well 1 over the geothermal target.
- The reservoir zone is the Deep Sand below the Deadwood formation, at 3380 m.

Seismic processing

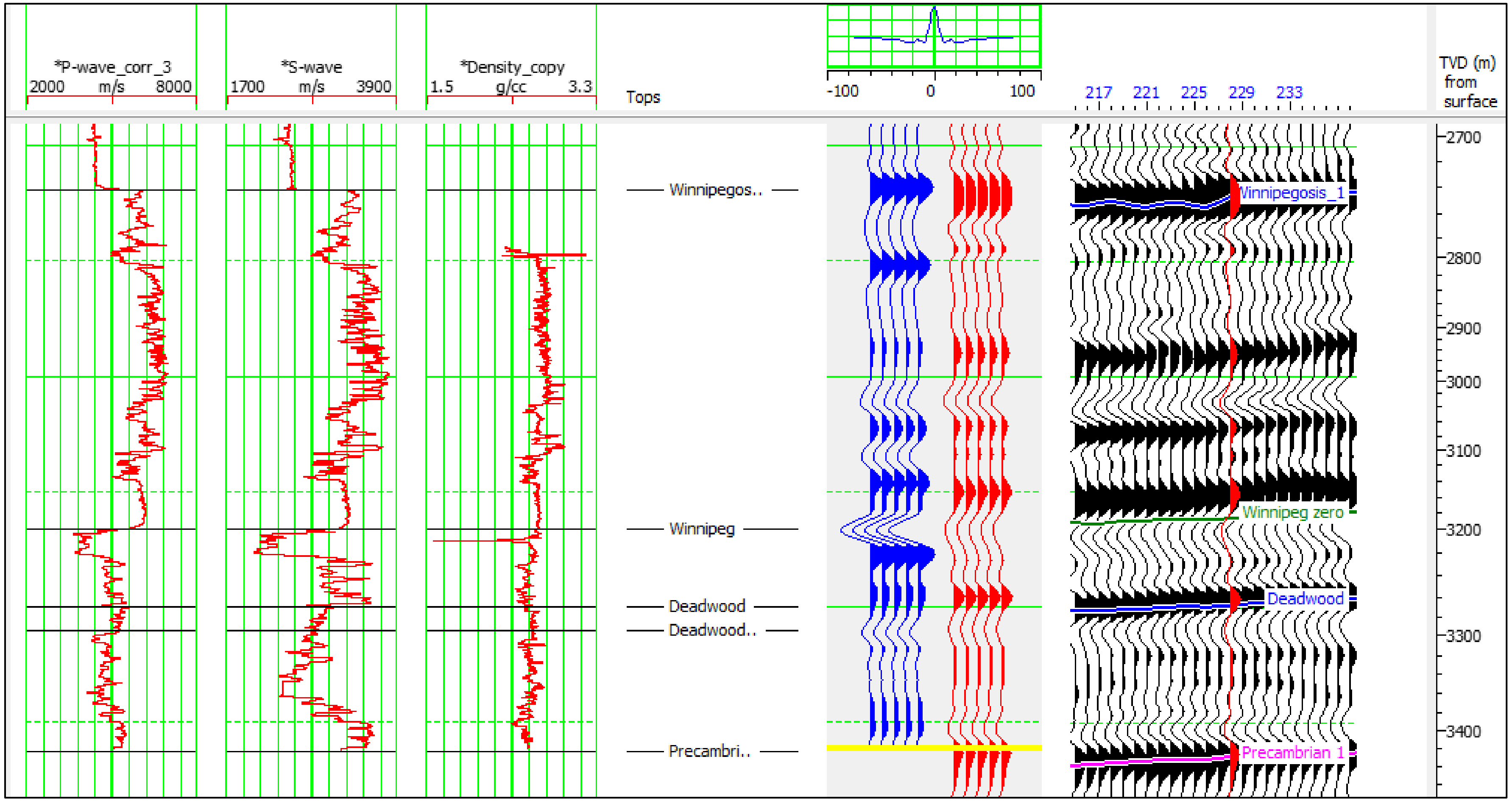
- The input seismic data was a set of 3D post-stack time migrated gathers, which had been stacked and then picked and interpreted by the client.
- Since the gathers were not AVO and pre-stack inversion compliant the following processing flow was applied in HampsonRussell:
    - Trim statics were applied on a 1300 ms window centered on the Winnipegosis pick.
    - A parabolic Radon transform was applied to remove both multiples and random noise.
    - A super-gather was created using a 3x3 rolling window, 12 offset bins and a far offset cutoff of 2500 m.
    - An angle stack was created with a far angle of 30o at the zone of interest.

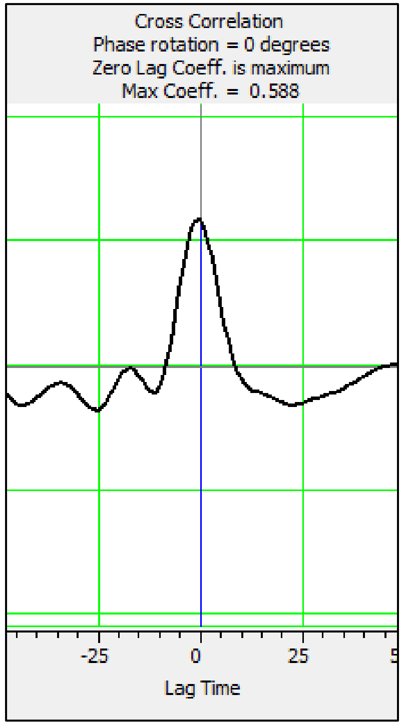
Angle gathers near Well 1



- Angle gathers over the geothermal target, with the correlated Well 1 sonic log inserted.

Well to seismic correlation – Well 1



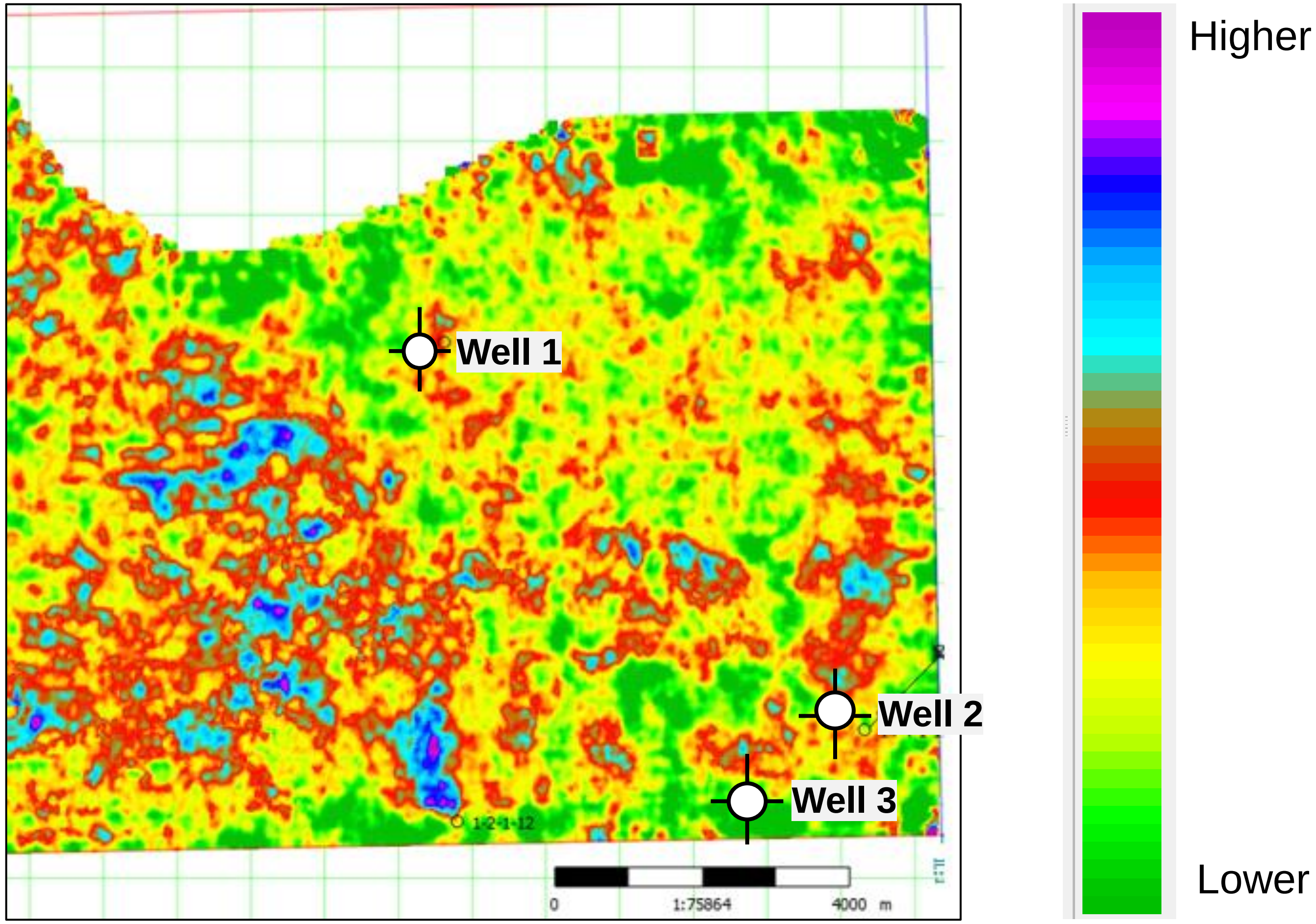


- The well to seismic correlation for Well 1, with the zero-phase wavelet at top.
- The cross-correlation is shown on the right.

P-impedance map slice

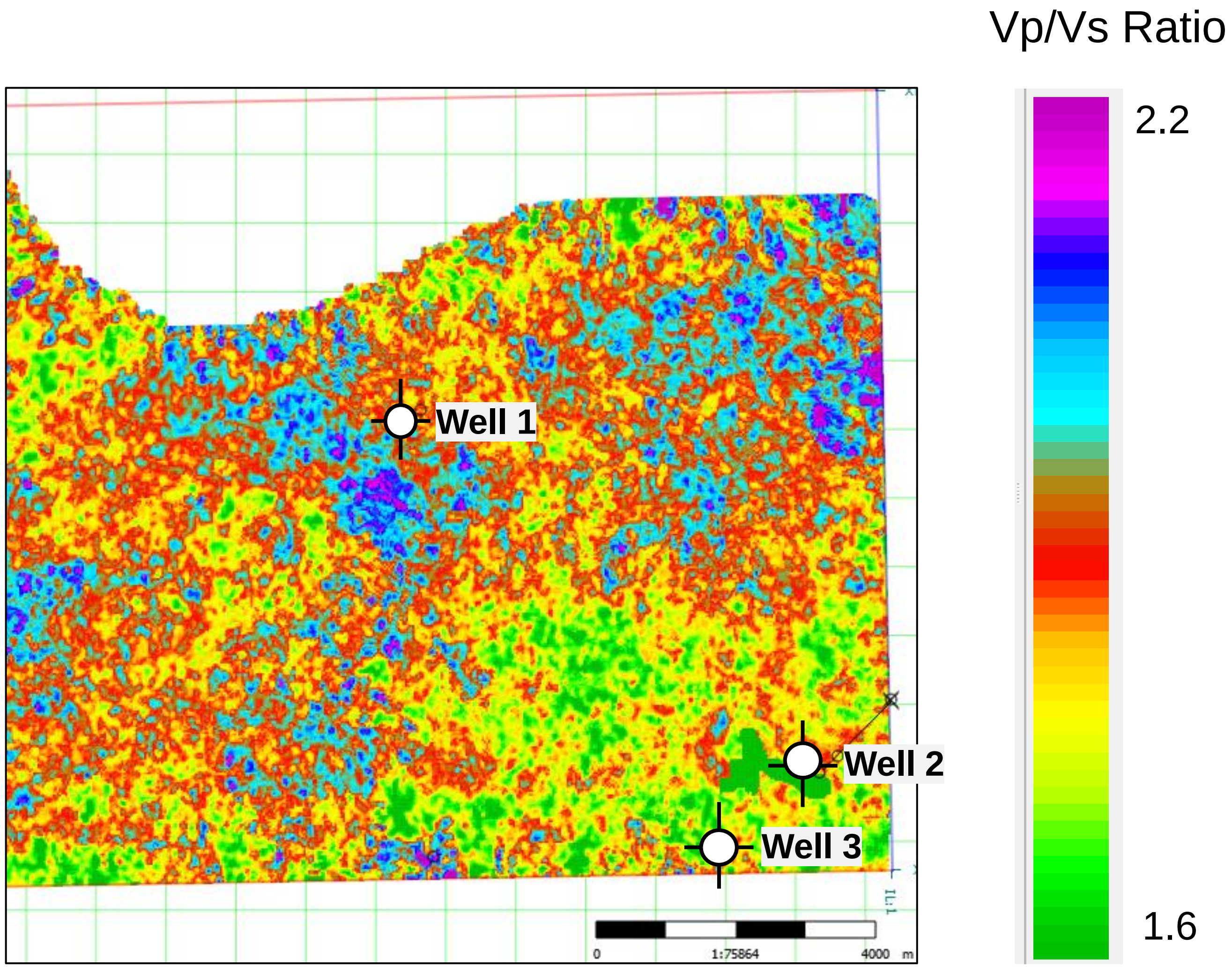
- A map slice of inverted P-impedance over the geothermal target, with the wells shown.
- Low impedance values in a sandstone zone are usually indicative of good porosity.
- But this can be confused with other lithologies like shales.
- Therefore, an independent estimate of Vp/Vs ratio is important.

Relative P-Impedance



Vp/Vs ratio map slice

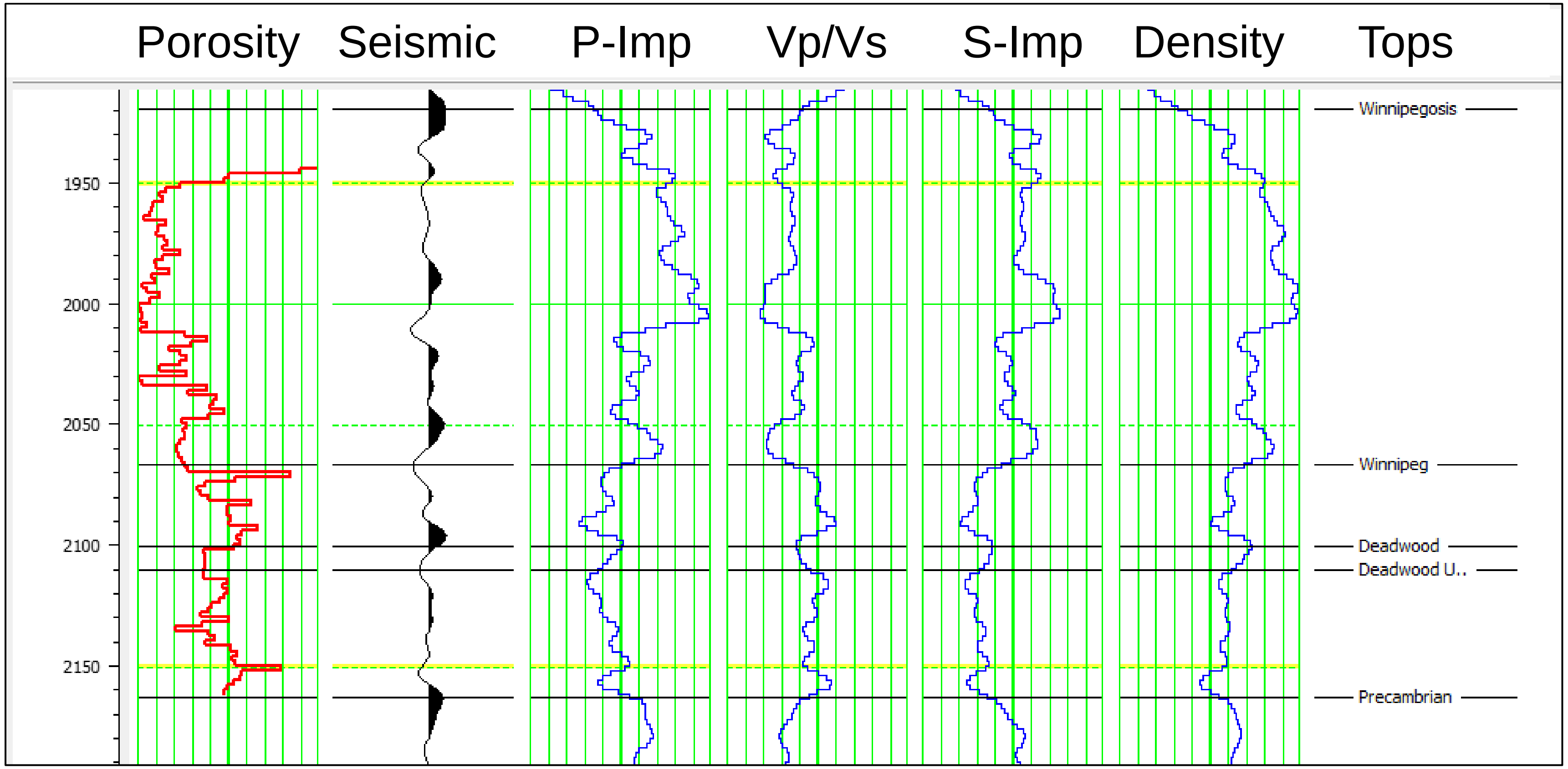
- A map slice of inverted Vp/Vs ratio over the geothermal target.
- Note that the lowest Vp/Vs ratios are found in the lower part of the survey, near wells 2 and 3.
- We will now use ML to transform these results into porosity and permeability.



Emerge Training Data for Well 1

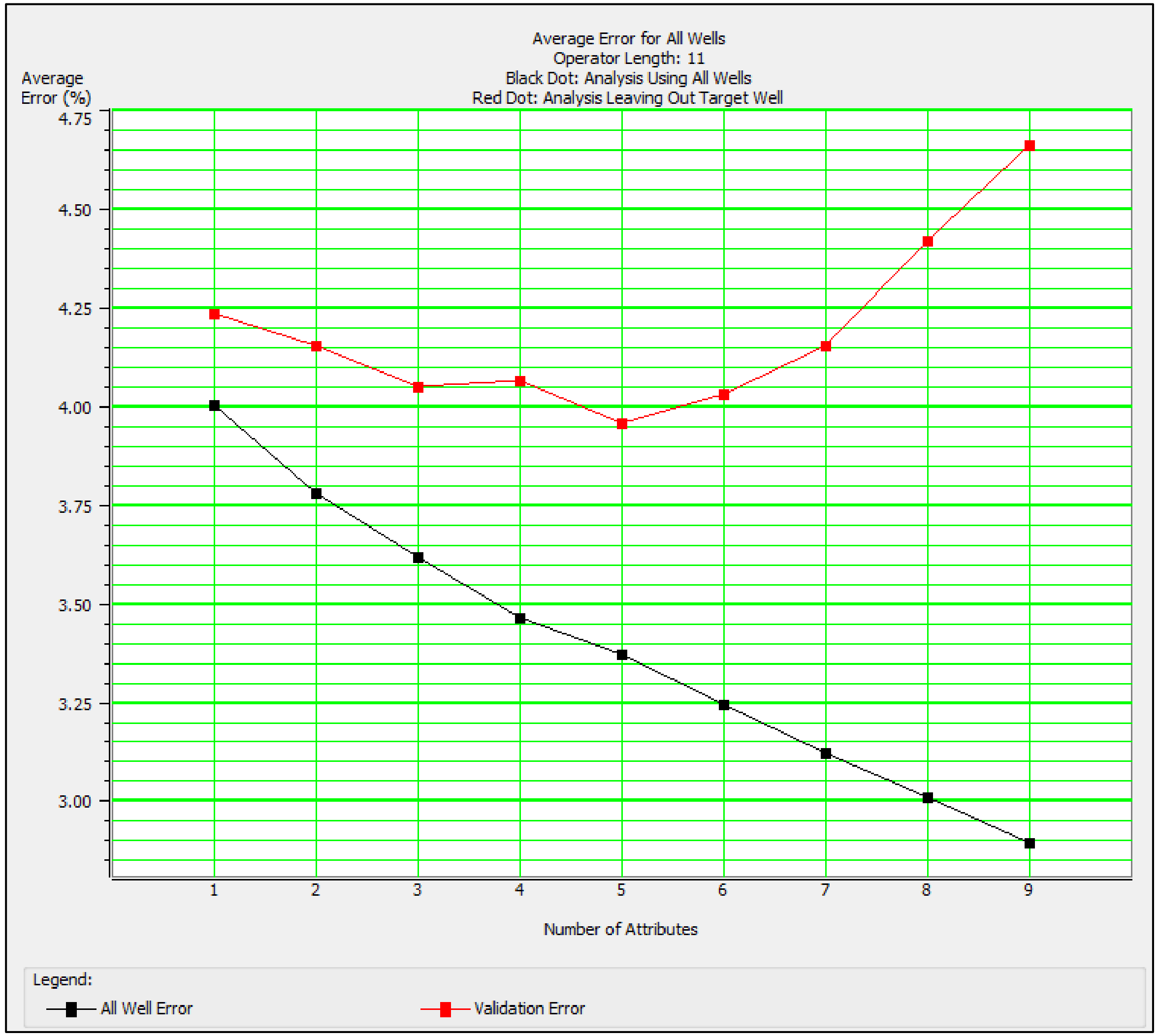
- This figure shows the training data extracted around Well 1, where the porosity log is shown on the left.
- These attributes are used in the training using three different methods: MLR, DFNN and PNN.

Emerge training data – Well 1



Training versus cross-validation error

- This figure shows both the training error (which uses all the wells) in black, and the cross-validation error (which leaves wells out and predicts them from the others) in red.
- Note that the training error will always decrease, but the cross-validation error shows a minimum, after which the attributes over-predict the target log.
- As seen, only 5 attributes should be used in the training.

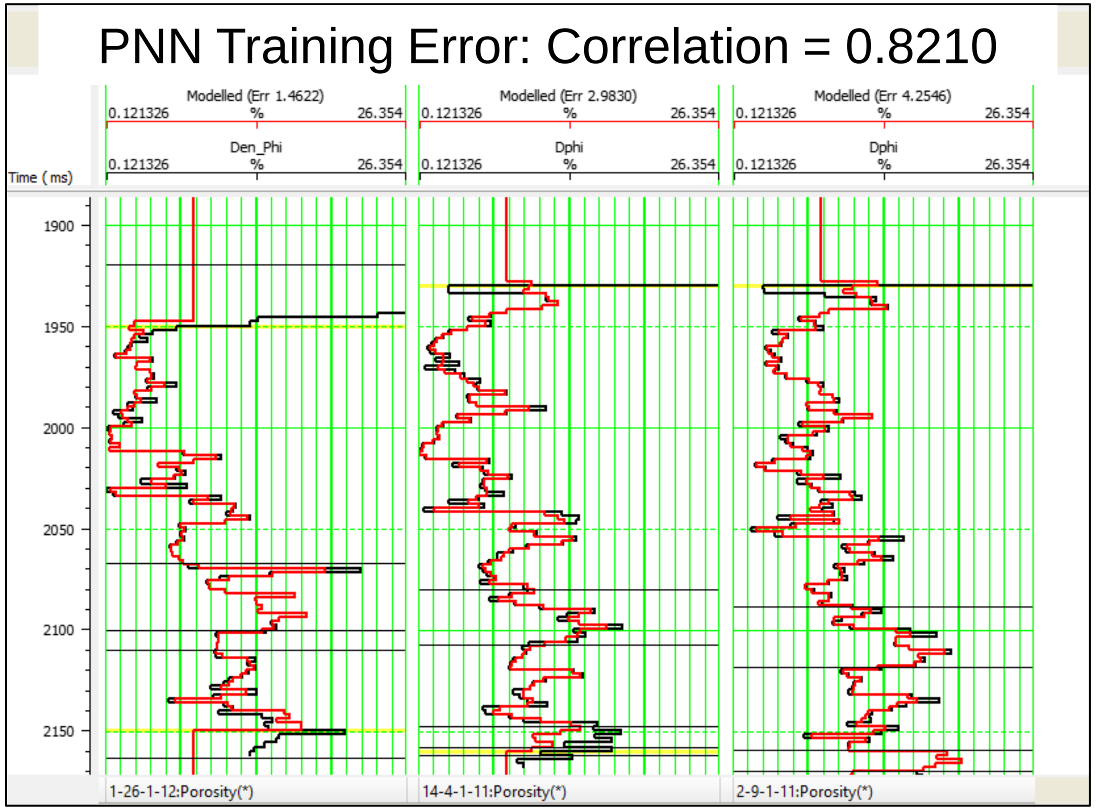


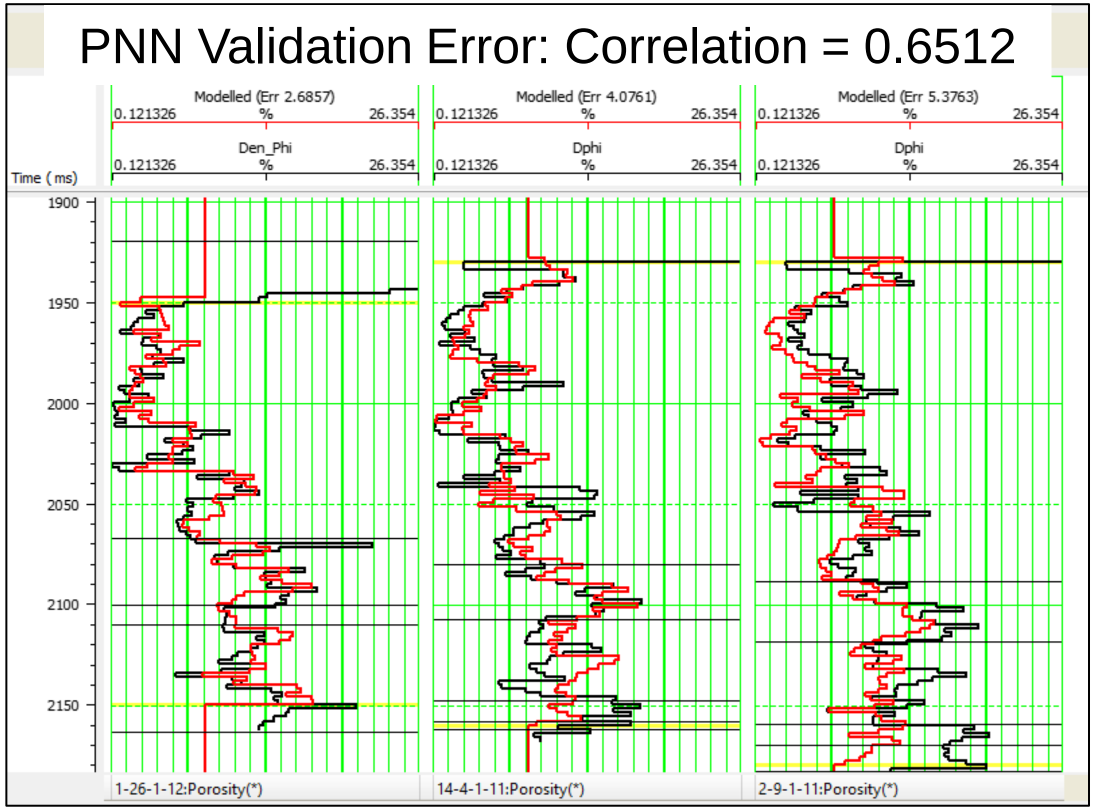
Emerge Training Attributes

- Here is a list of the final attributes, with the numerical values of the error shown.
- The red box shows the attributes with decreasing cross-validation error.
- We have also used non-linear transforms of the input attributes.
- Because DFFN needs many training wells, and we are restricted to only three wells, we decided to use PNN as our neural network.

	Target	Final Attribute	Training Error	Validation Error
1	Sqrt(Porosity)	1/(Prestack_Inversion__2_Zs)	4.006055	4.237843
2	Sqrt(Porosity)	Filter 15/20-25/30	3.785451	4.159208
3	Sqrt(Porosity)	(Prestack_Inversion__2_Dn)**2	3.622563	4.054750
4	Sqrt(Porosity)	Apparent Polarity	3.469089	4.070477
5	Sqrt(Porosity)	Instantaneous Phase	3.374360	3.961873
6	Sqrt(Porosity)	Filter 5/10-15/20	3.250150	4.034163
7	Sqrt(Porosity)	Instantaneous Frequency	3.125676	4.157635
8	Sqrt(Porosity)	1/(Prestack_Inversion_Zp)	3.013130	4.424116
9	Sqrt(Porosity)	Second Derivative	2.897348	4.666686

PNN Error

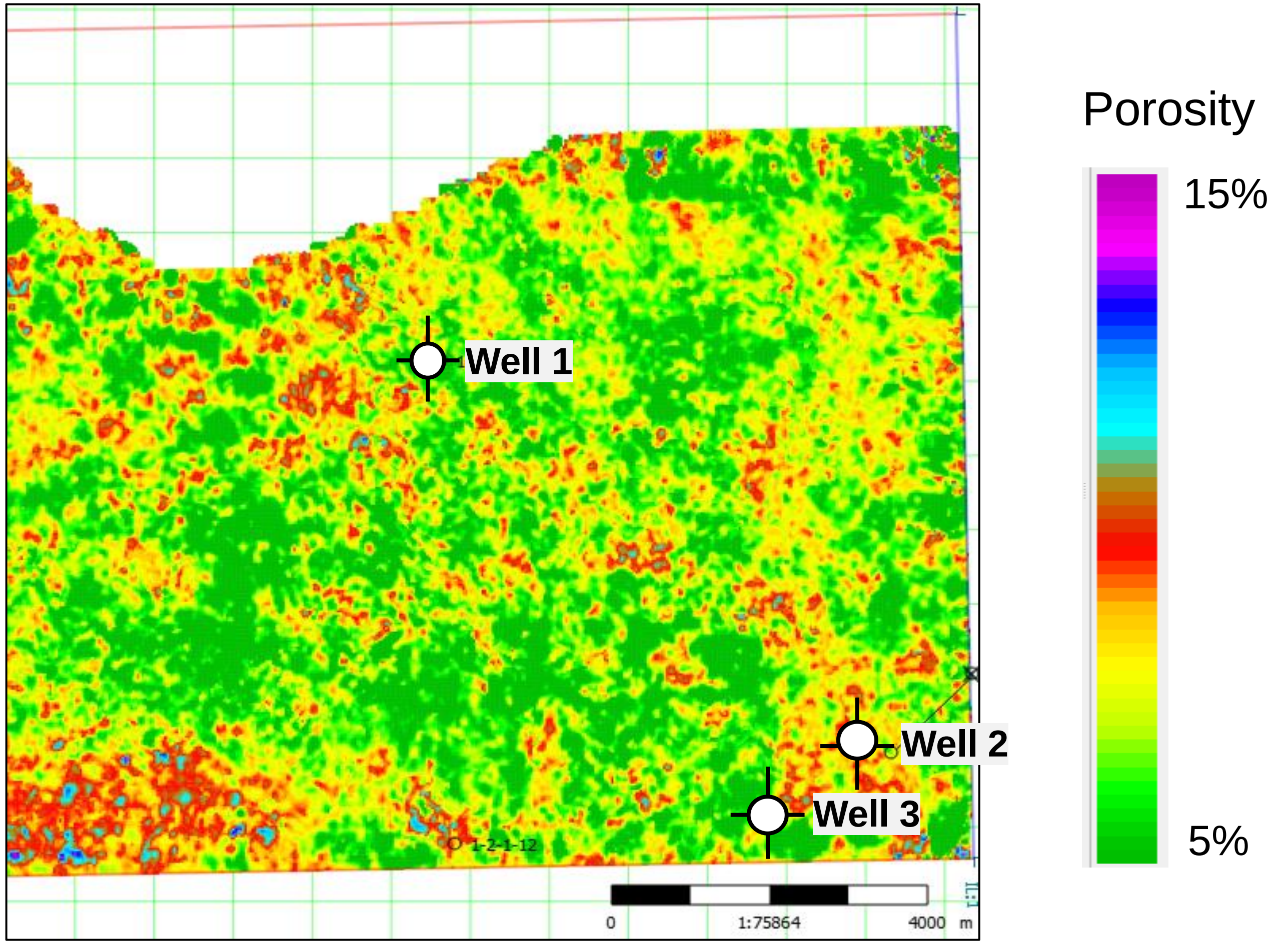




- Training error (left) and Validation Error (right) for predicted porosity using PNN, black line = original log, and red line = prediction.
- The Validation error is a more realistic way to judge the accuracy of the method than the Training error.

Porosity map slice with PNN

- The predicted porosity map using Emerge PNN.
- The map is averaged over a 10 ms window picked 42 ms below the Deadwood.
- The key thing to note is that the porosity range is quite small and that we see consistently high porosity throughout the zone of interest.

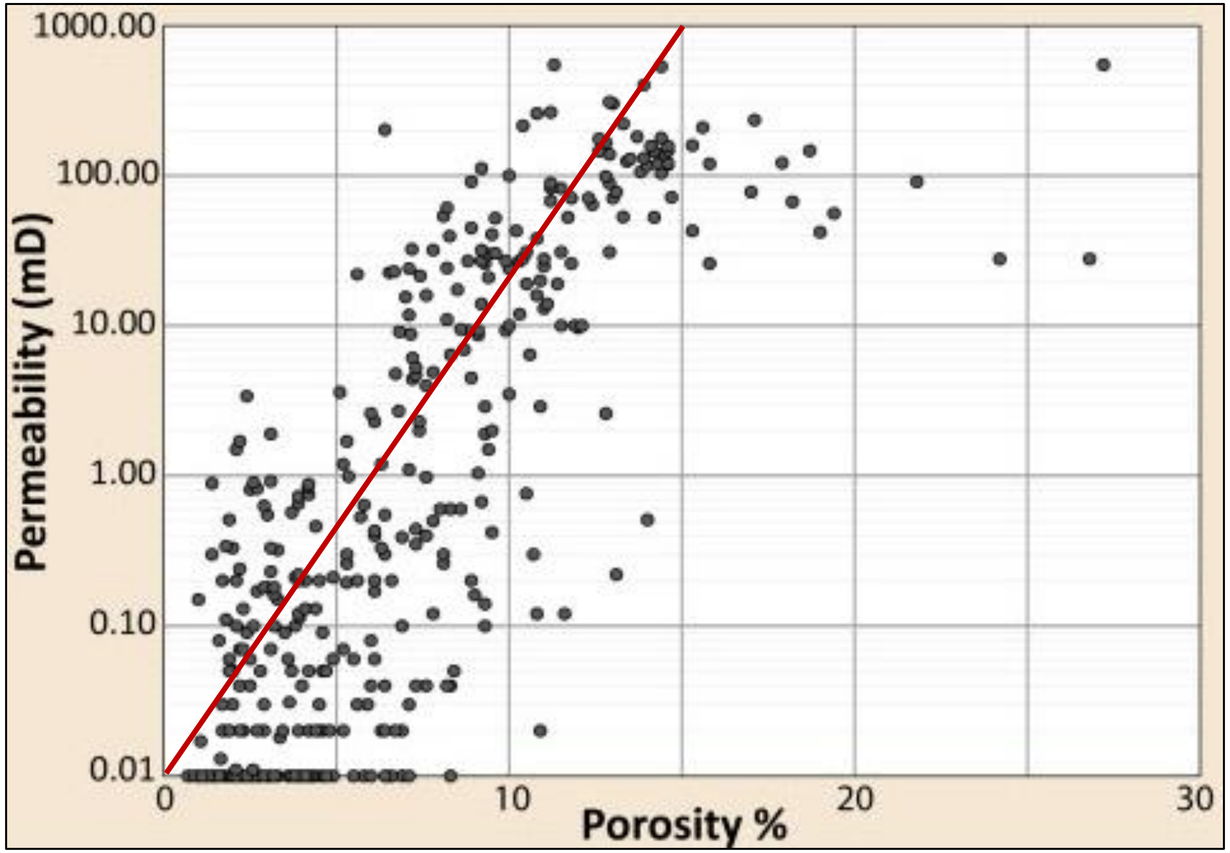


Porosity-permeability relationship

- Having predicted porosity, we then attempted to predict permeability, which is more difficult.
- Here is a log-linear cross-plot of Permeability versus Porosity from the Deadwood Formation, where the red line on the plot indicates the following relationship between permeability and porosity:

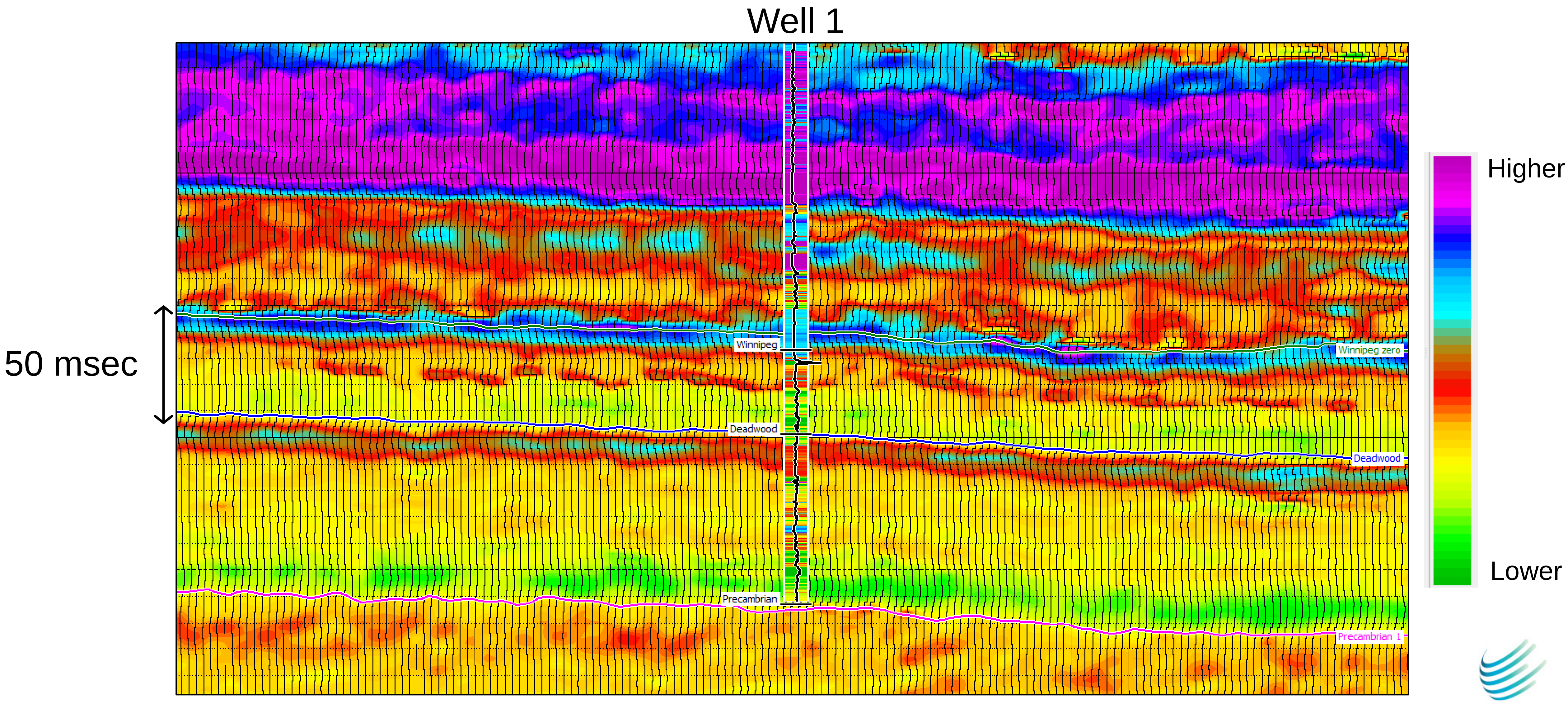
$$\log_{10} perm = -2 + \frac{porosity}{3}$$

$$\Rightarrow perm = 0.01 * 10^{\frac{porosity}{3}}$$



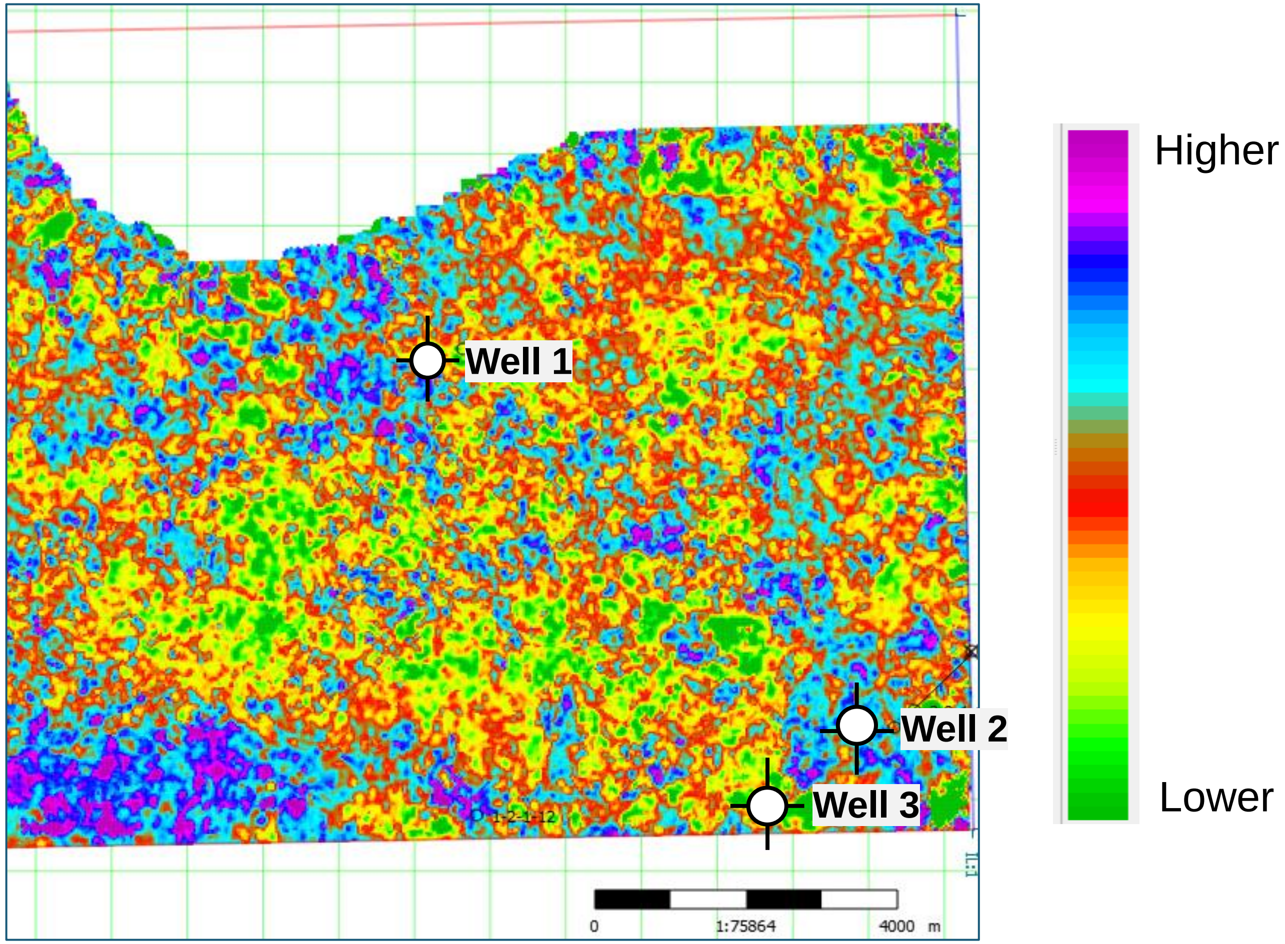
Nesheim, 2021

Permeability transform with PNN



Permeability map slice with PNN

- The predicted permeability map.
- The map is averaged over a 10 ms window picked 42 ms below the Deadwood.
- As with the porosity map, we see consistently high permeability throughout the zone of interest.
- An absolute scale has not been used because we estimated only relative permeability.



Geothermal Study Conclusions

- In this part of my talk, a 3D survey in the Western Canadian Sedimentary basin was utilized for the evaluation of a deep basal clastic geothermal target zone.
- Seismic pre-stack inversion and machine learning techniques were used to determine reservoir variability and extent from porosity and permeability.
- The key factors that control the quality of the results were the seismic processing and the well-to-seismic ties.
- Also, the choice of which machine learning technique to use and the parameter selection for this network are of utmost importance.
- Because of limited number of training wells, we found that the Probabilistic Neural Network gave the best results.

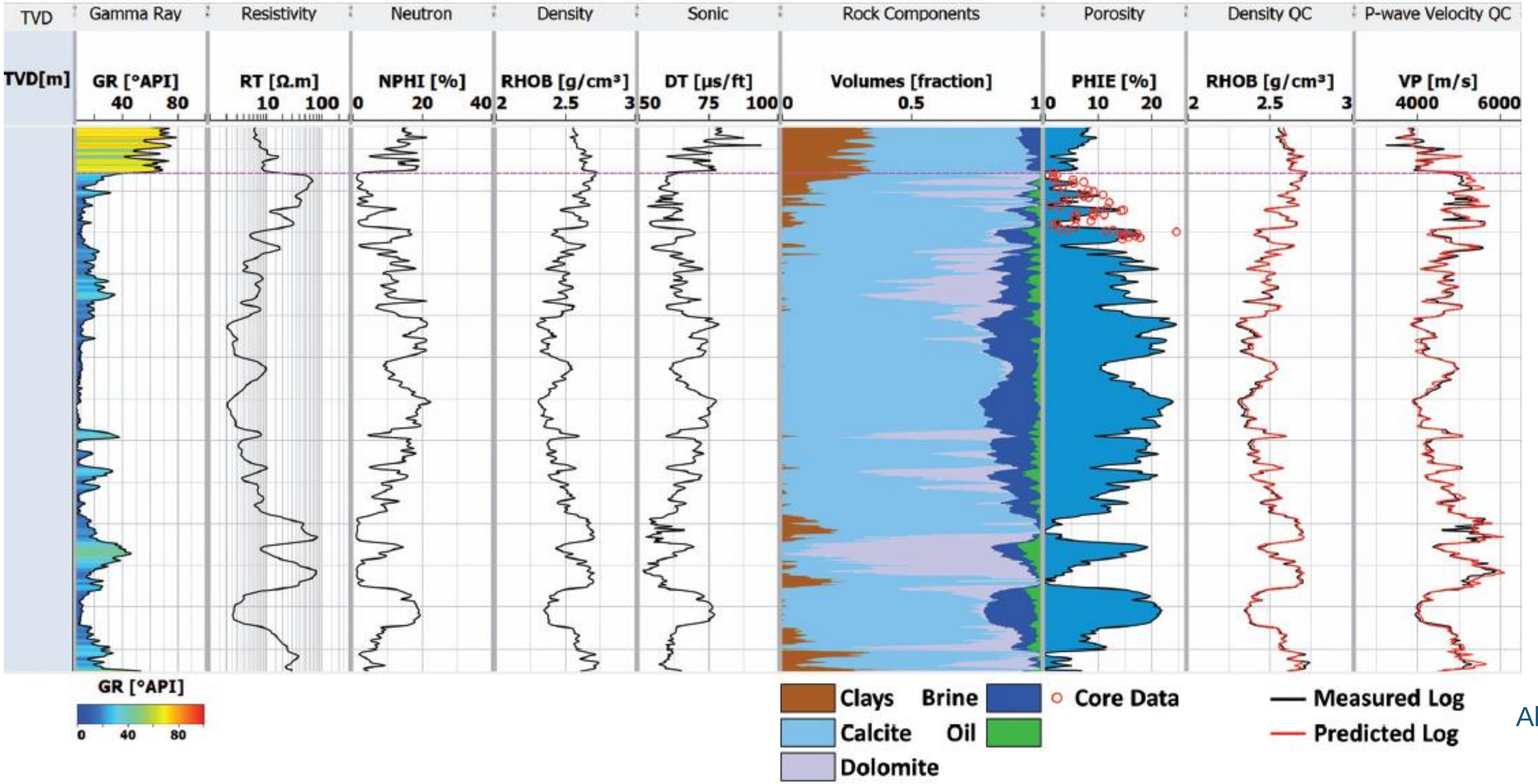
Case Study #2:

The Dogger Formation carbonate reservoir, France

Carbonate geothermal reservoir example

- The Dogger Formation is the main hot water and heat supplier for approximately 40 low-enthalpy geothermal plants currently operating in the Paris Basin.
- The success of such geothermal projects relies on the quality of the reservoir (i.e., temperature, porosity, and permeability).
- Sources of information from which to infer these key reservoir characteristics, such as wireline logs and cores and 2D seismic lines are unfortunately scarce.
- To address this issue, Downton et al. (2020) introduced a novel hybrid theory-guided approach to the generation of synthetic data, which combines the use of rock-physics models statistical simulations.
- This methodology is applied by Allo et al. (2021) to generate hundreds of pseudo-wells to train deep feed-forward neural networks (DFNNs) for deriving the total porosity and volume of clays in the Dogger Formation from recorded 2D full-stack seismic lines.
- These two rock properties are used to compute the effective porosity, from which an absolute permeability is derived based on laboratory measurements on core data.

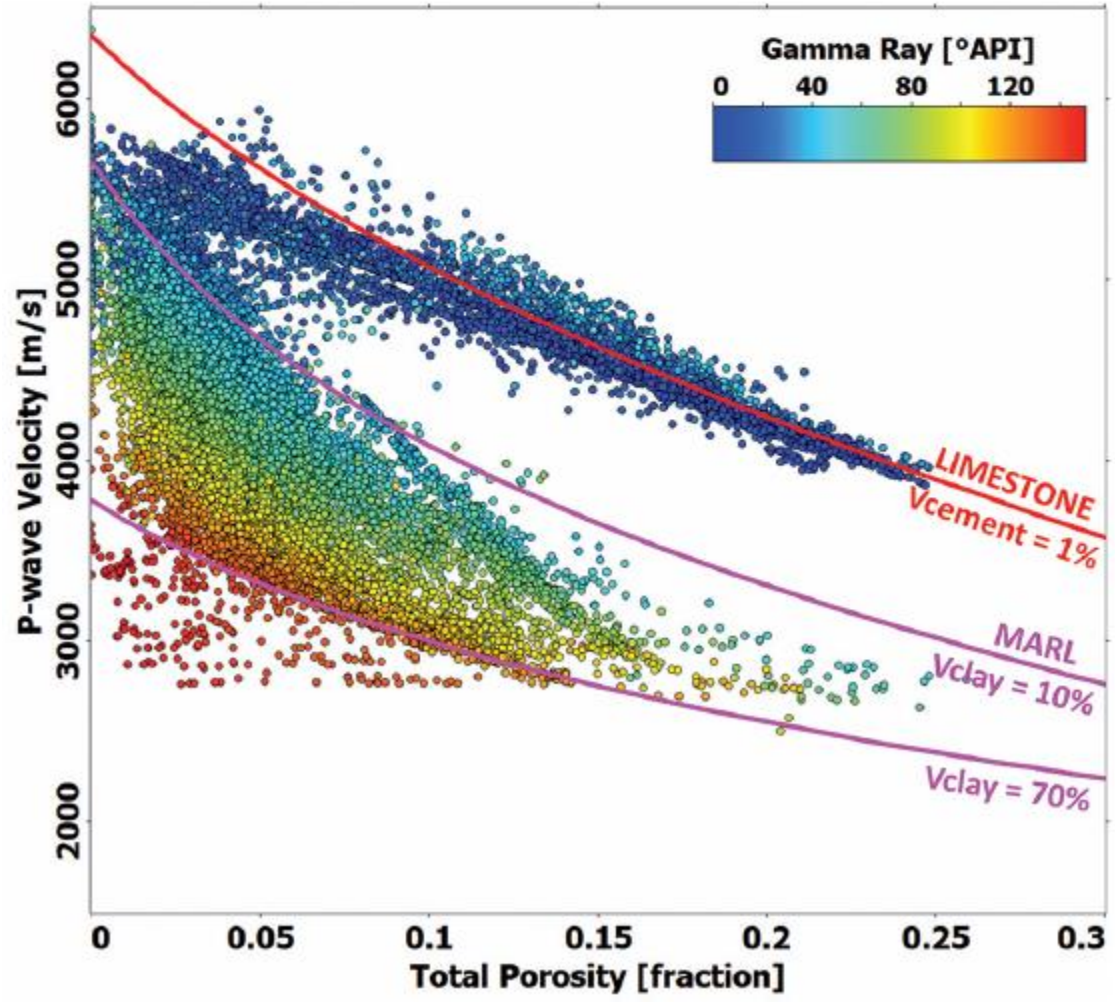
Petrophysical analysis



Allo et al. (2021)

Petrophysical analysis at one of the exploration wells, where mineral volumes (track 6) and porosity (track 7) are computed from a set of petrophysical logs (tracks 1 to 5) using multilinear regressions.

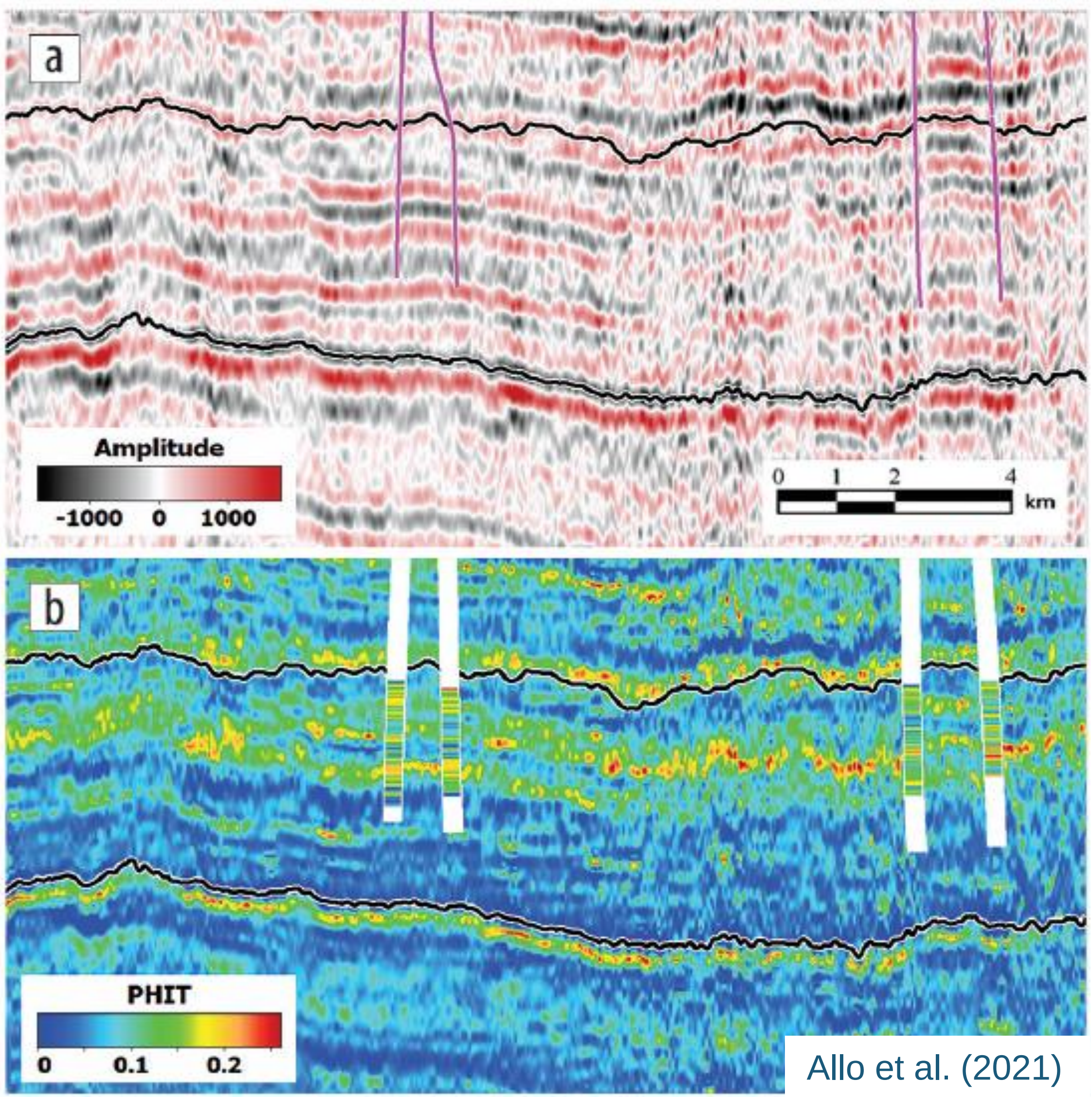
Rock Physics Template



Allo et al. (2021)

- Rock-physics template based on the cemented sandstone model superimposed on log data color coded by gamma ray.
- The red line, obtained with 1% of cement, fits the main trend observed in the clean cemented limestones.
- The pink lines, obtained with no cement, delimit marls with an increasing volume of clays (10% for the top line and 70% for the bottom line).

Seismic results

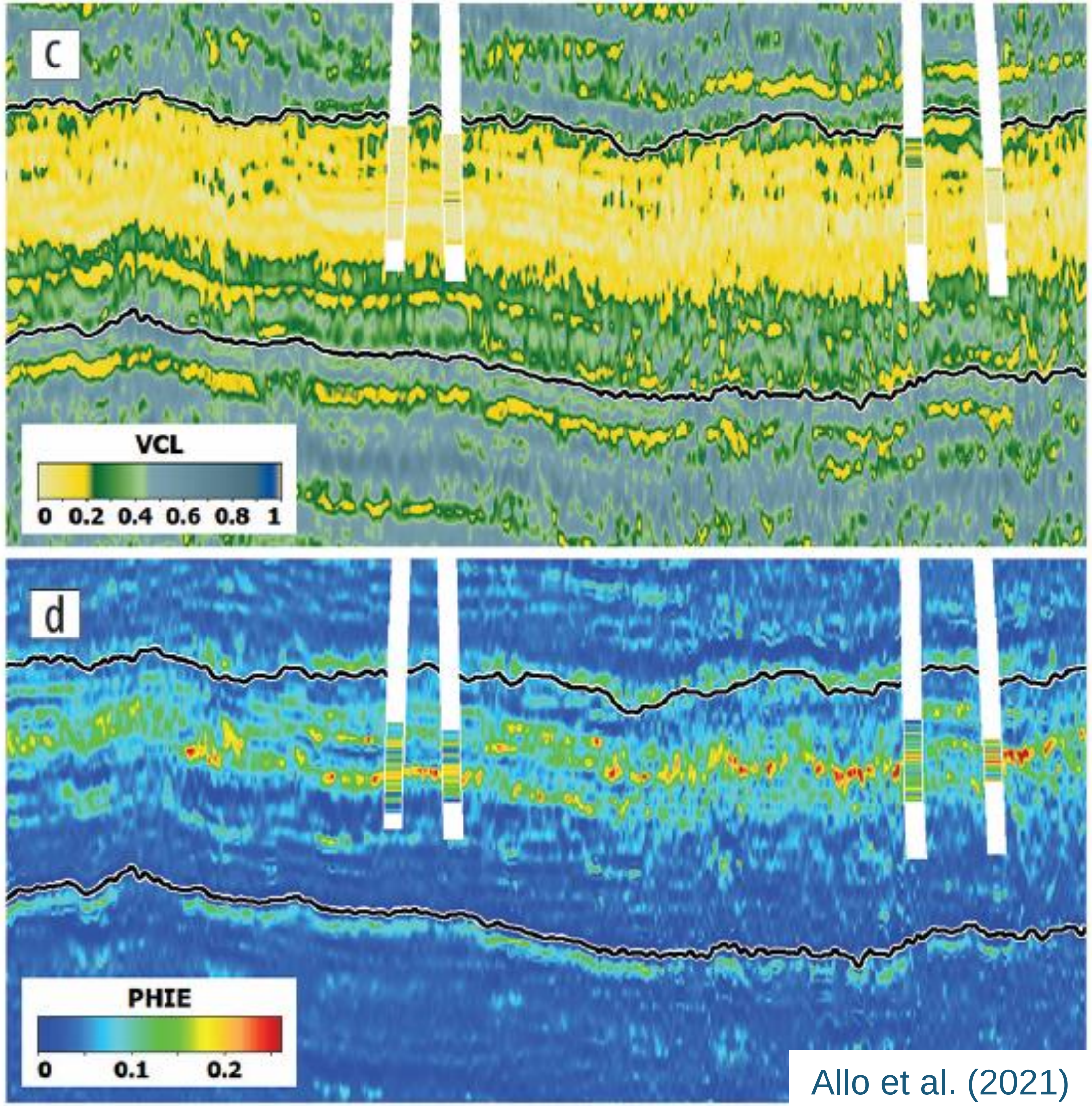


Allo et al. (2021)

a) Input seismic section crossing the study area from west to east. The top horizon represents the top of the Dogger Formation. The bottom horizon corresponds to the top of the marls with Ostrea acuminata (Middle Bajocian).

b) Estimated total porosity showing porous layers in the upper part of the Dogger Formation, which correlates with logs from nearby wells.

Seismic results

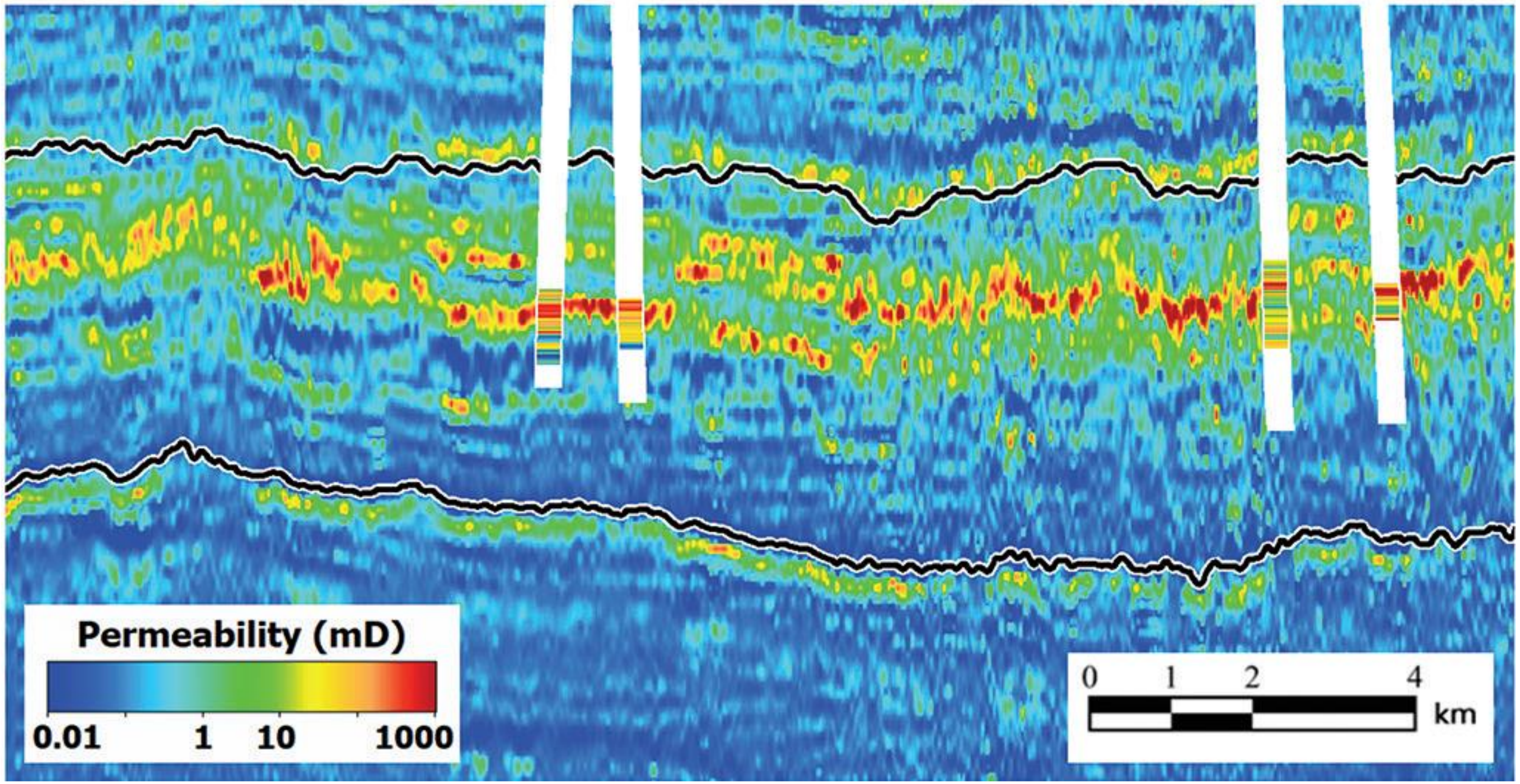


Allo et al. (2021)

c) Estimated clay volume confirming that most of the upper part of the Dogger Formation consists of clean limestones.

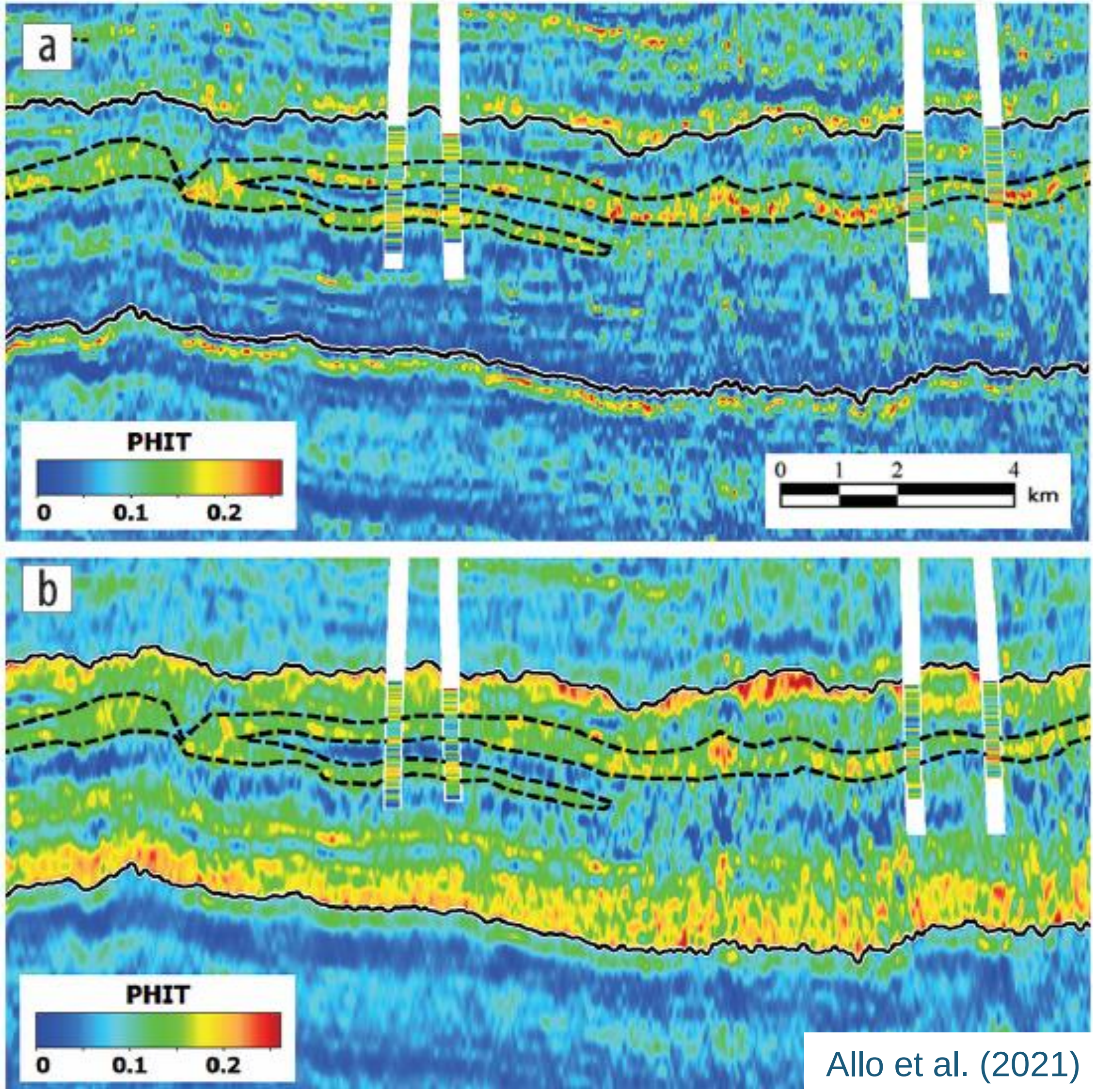
d) Effective porosity obtained by combining the estimated total porosity and clay volume highlighting layers with high connected porosity.

Seismic results

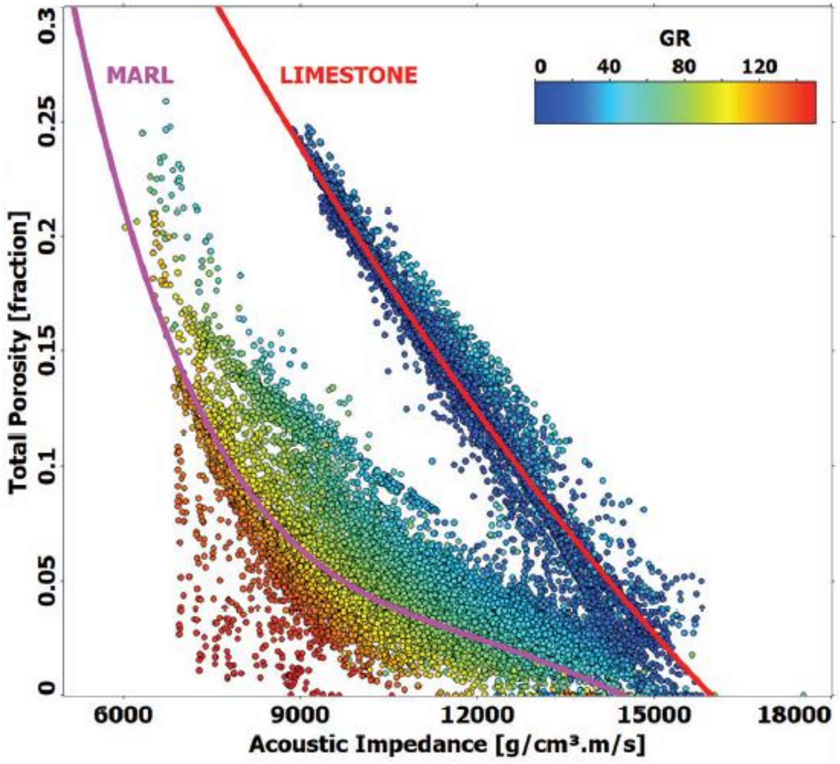


Absolute permeability derived from the estimated effective porosity. Several high-permeability layers are clearly visible in the upper part of the Dogger Formation and represent potential conduits for geothermal fluid circulation.

Seismic results



Allo et al. (2021)



a) Total porosity estimated with DFNN. The black dotted lines delimit the highly porous oolitic layers in the upper part of the Dogger Formation.

b) Total porosity derived from inverted acoustic impedance using statistical polynomial laws (bottom) for limestones (red line) and marls (pink line).

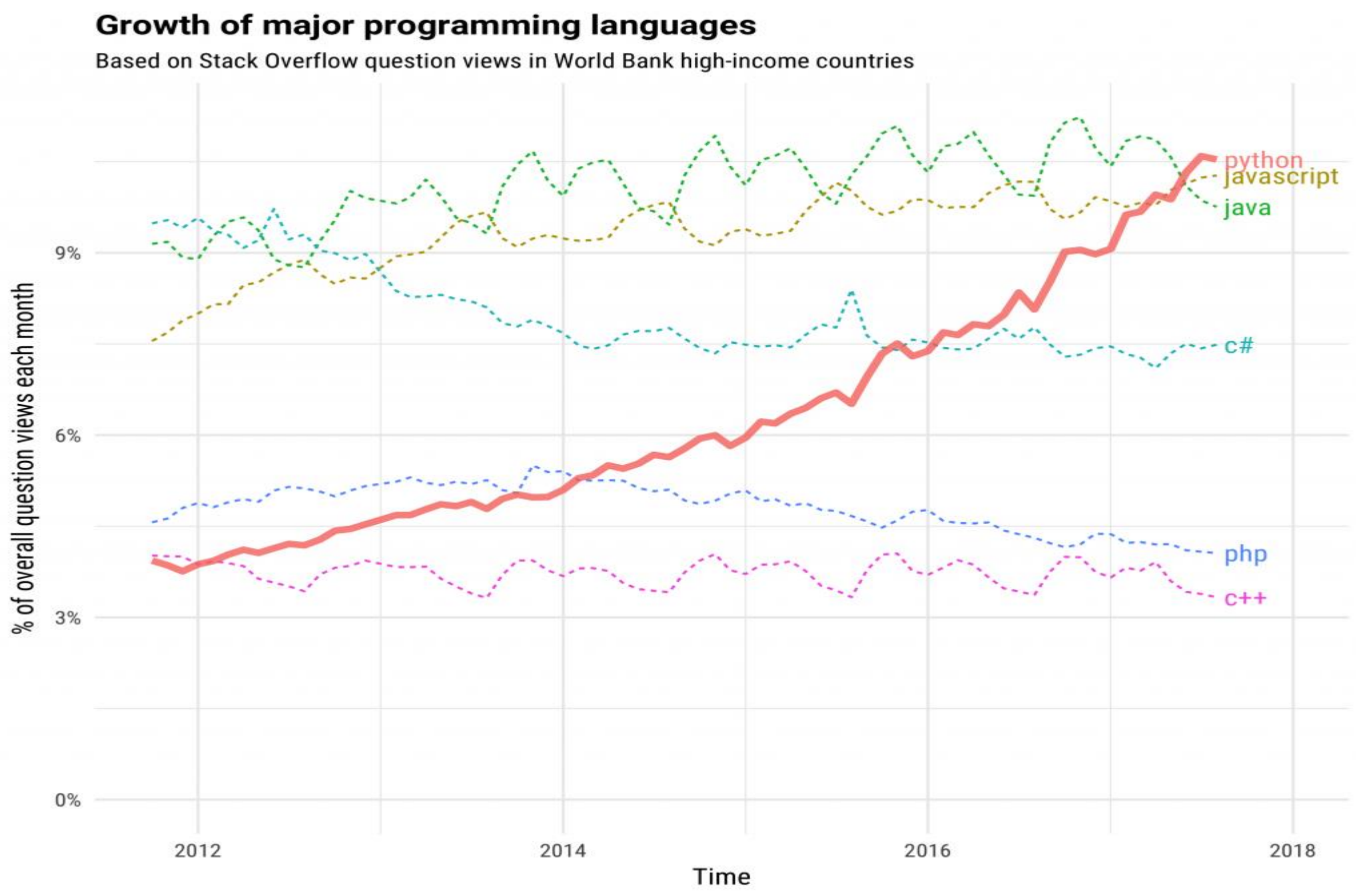
Why Python?

One of the fastest growing programming language

Adopted widely by the scientific community

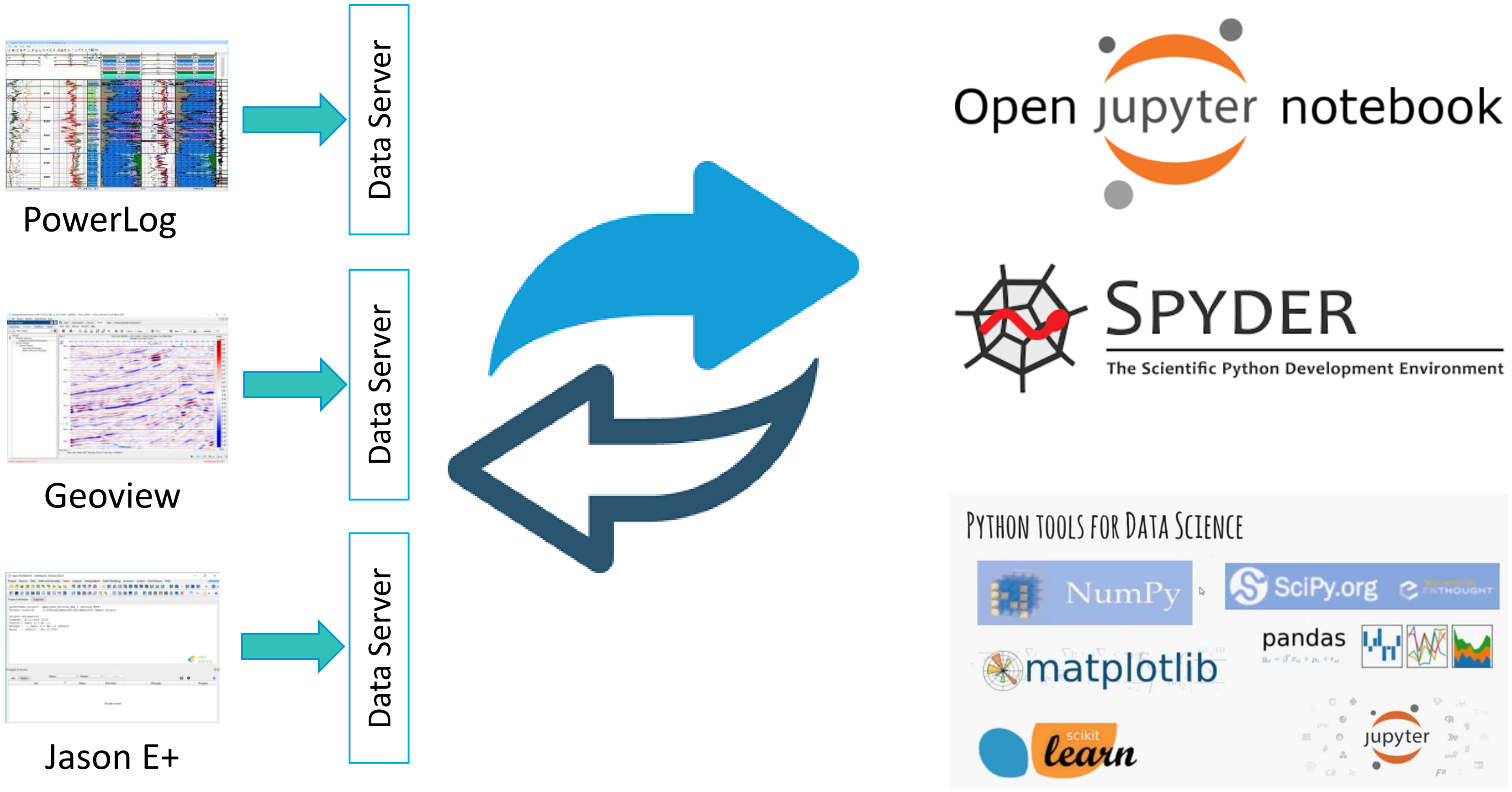
Excellent packages for visualization, statistics, numerical analysis, data analysis, machine learning

Example : pandas, numpy, scipy, keras, tensorflow



Source: https://stackoverflow.blog/2017/09/06/incredible-growth-python/

Python Ecosystems – how it works?

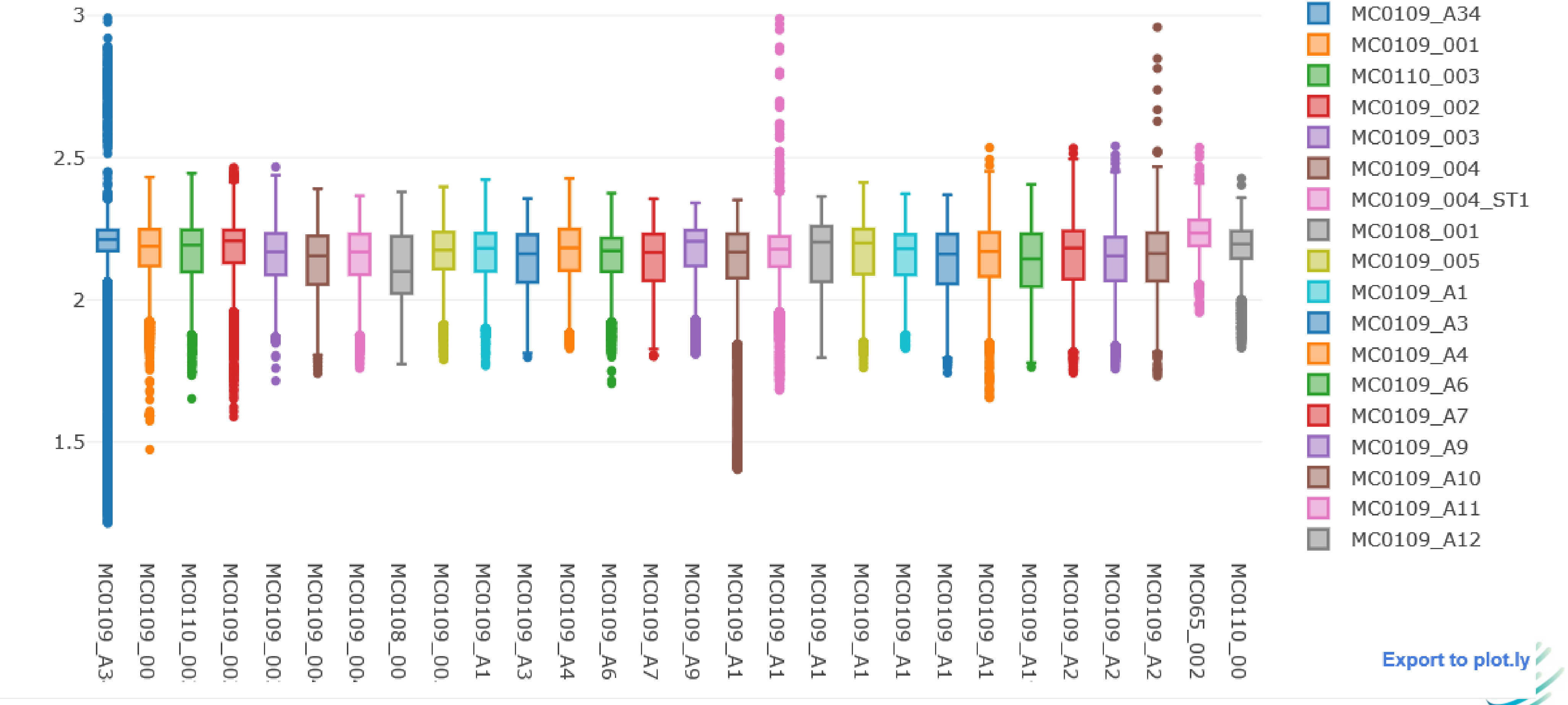


ML Workflows for Data Analysis: Anomaly Detection

Multi-Well B

```
%matplotlib inline
import plconnect.fu
import seaborn as s
import matplotlib.p
import numpy as np
import pandas as pd
import plconnect.fu
```

```
uwi_list = plf.get_
all_frames = []
all_uwis = []
all_wellnames = []

curve_name =  "&RHO
outlier_flag = "Box

zone = "WorkingInte
grid = "Default"
```



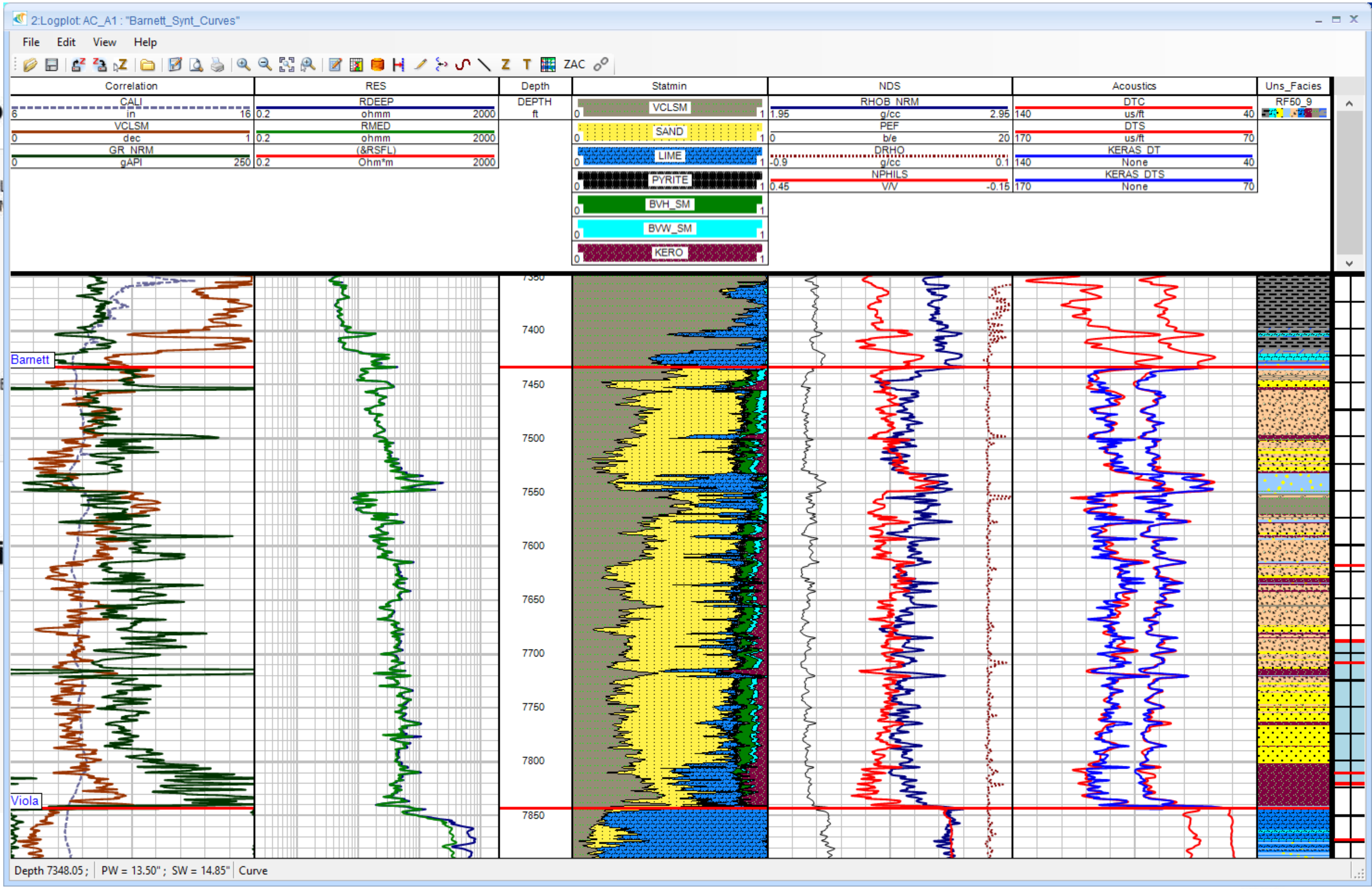
ML Workflows for Data Augmentation: Synthetic Curves

Predictions Step 1: Load the model to

```
In [17]: from keras.models import load_model, model_from_json
         regressor_path = os.path.join(MODEL_SAVE_DIRECTORY, DNN_MODEL
         weights_path = os.path.join(MODEL_SAVE_DIRECTORY, DNN_MODEL_N

         dl_model_json = None
         with open(regressor_path,"r") as f:
             dl_model_json = f.read()

         model_loaded = model_from_json(dl_model_json)
         model_loaded.load_weights(weights_path)

         sc_X_path = os.path.join(MODEL_SAVE_DIRECTORY, DNN_MODEL_NAME
         sc_X = pickle.load(open(sc_X_path, 'rb'))

         print("Model loaded")

         Model loaded
```

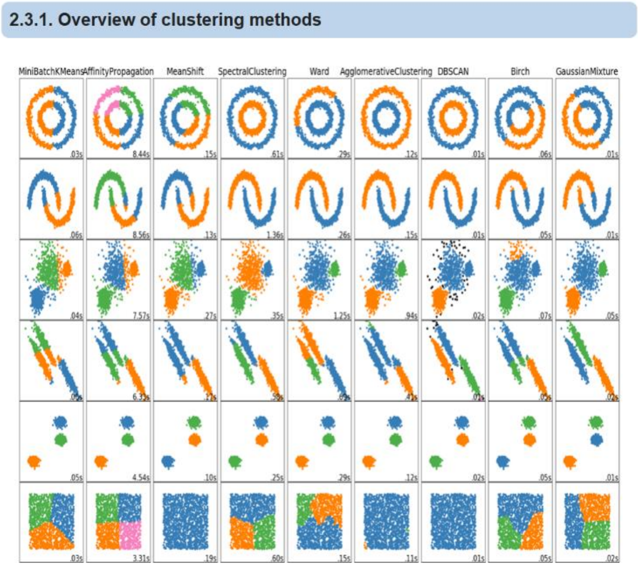
Predictions Step 2 :Select the well(s) i

```
In [18]:
         prediction_wells = plf.get_current_selected_wells()
         print(prediction_wells)

         from plconnect.exceptions import ExtensionException

         OUTCURVENAME = "KERAS_DT"

         prediction_zone  = "WorkingInterval"
         prediction_grid = "Default"
```

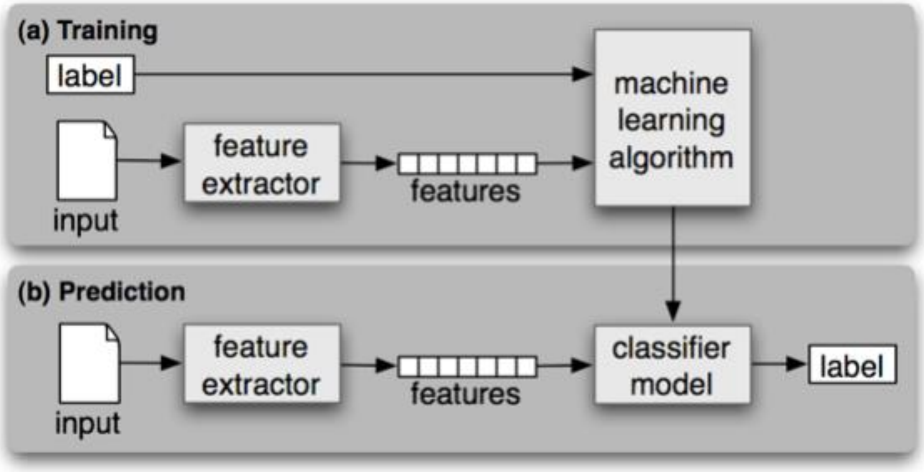


ML Workflows for Data Classification: Clustering Analysis Example

Unsupervised Clustering Algorithms seek to learn, from the properties of the data, an optimal division or discrete labeling of groups of points.



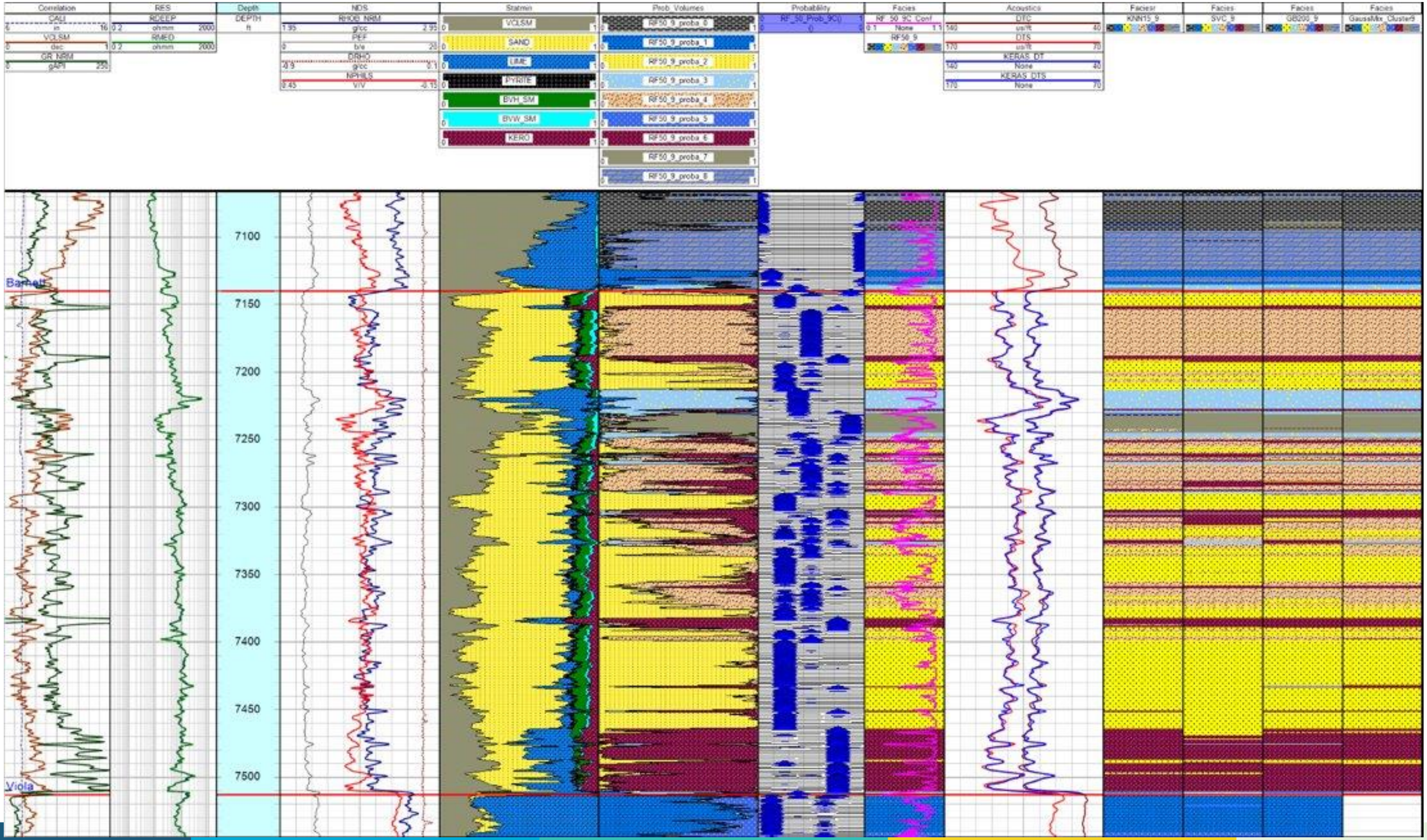
A comparison of the clustering algorithms in scikit-learn



In supervised learning, we start with importing dataset containing training attributes and the target attributes. The Supervised Learning algorithm will learn the relation between training examples and their associated target variables and apply that learned relationship to classify entirely new inputs (without targets).

Scikit-learn: Machine Learning in Python, Pedregosa *et al.*, JMLR 12, pp. 2825-2830, 2011.

ML Workflows for Data Classification: Facies with Probabilities



Conclusions

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Conclusions

- Machine Learning is a tool that augments the capabilities of geoscience specialists, not a replacement.
- The fusion of traditional geosciences with Machine Learning is crucial for modern geothermal studies.
- Embracing these advancements provides a deeper understanding and more efficient use of our data in geothermal exploration.

- Pavel.didenko@geosoftware.com

Q&A

Italian Section

Netherlands Section

London Section

Romanian Section

Croatian Section

Central Ukraine Section

Geothermal Technical Section

Data Science and Engineering Analytics Technical Section

ENERGY GeO Hackathon

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SPE Europe Region