2023 SPE EUROPE ENERGY GEOHACKATHON

#6 Seismic Inversion – Rock Physics/Reservoir Characterization

Kirill Siraev

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#DatafyingEnergy

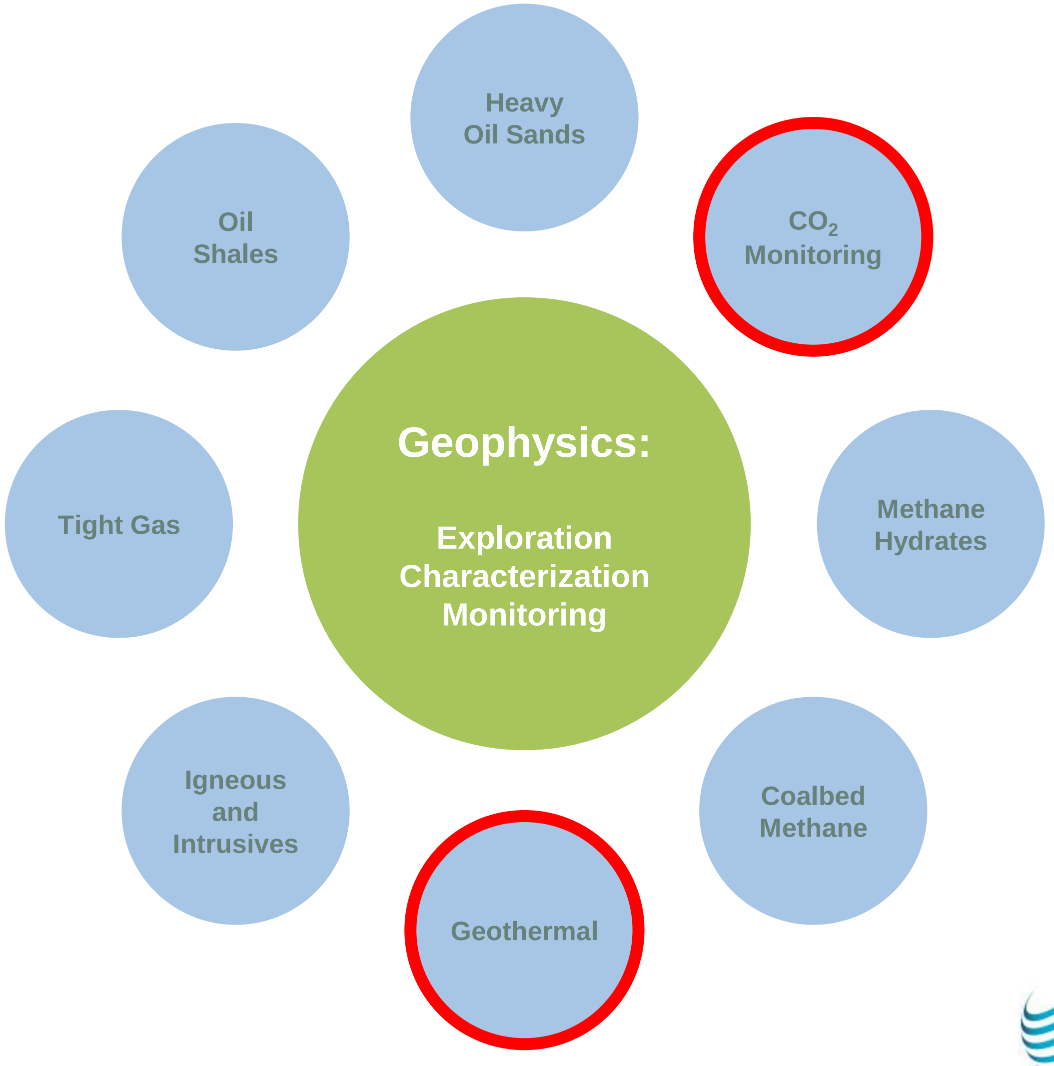
Outline

- Introduction
- Case study #1: The Cambrian Deadwood sandstone reservoir, Canada
    - Seismic inversion
    - Machine learning
- Case study #2: The Dogger Formation carbonate reservoir, France
    - Rock physics driven machine learning
- Conclusions

Introduction

- Since the 1980s, we have used the 3D seismic technique successfully in the search for hydrocarbons.
- Geothermal energy and CO2 monitoring are part of a broader spectrum of unconventional uses for geophysics.
- Well and seismic data acquired by the oil and gas industry can be used as the basis for both approaches.

Unconventional Resources & CO_2



Tura, Schuelke and Soldo, TLE, 2009

Available software tools

- Rock physics analysis.
- Basic seismic analysis and display.
- Seismic attribute analysis.
- AVO and pre-stack inversion.
- Seismic facies analysis.
- Time lapse analysis.
- Multi-component analysis.
- Azimuthal and fracture analysis.
- Machine Learning prediction of reservoir parameters.
- The Python Ecosystem.

PowerLog

HampsonRussell

Jason

Case Study #1:

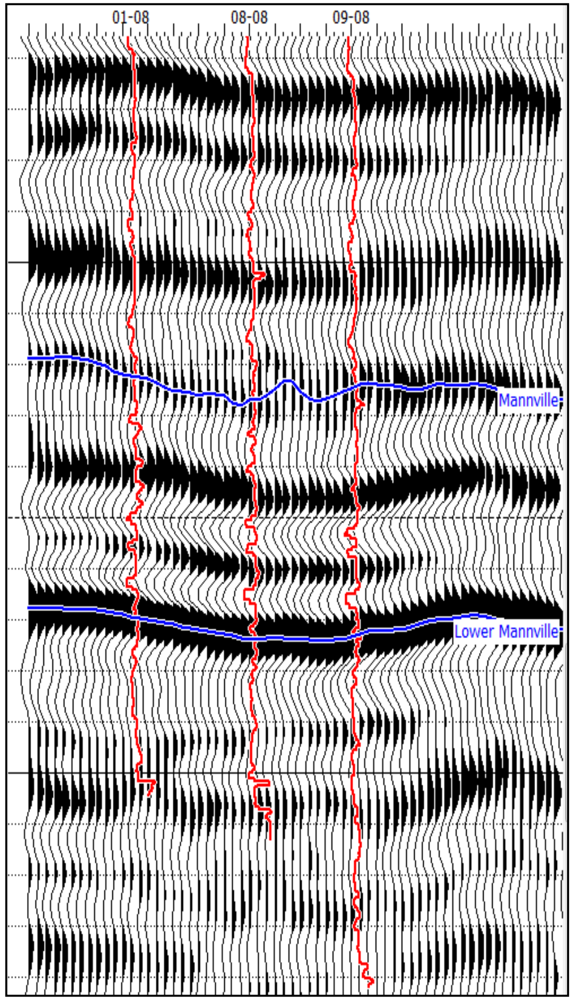
The Cambrian Deadwood sandstone reservoir, Canada

Geothermal project location

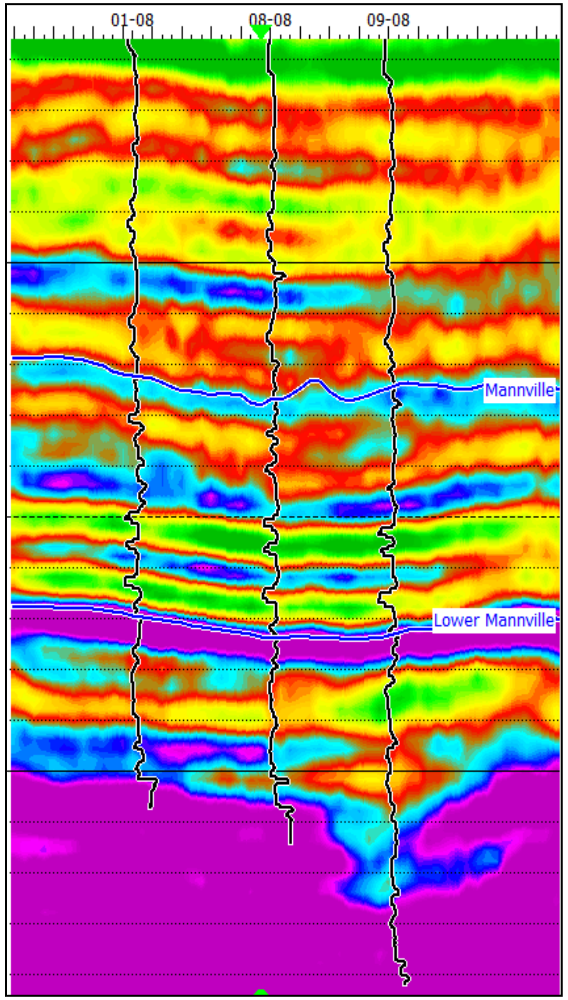
- DEEP (Deep Earth Energy Production) has targeted the Basal Sandstones of the Williston basin for geothermal production.
- The Cambrian Deadwood Sandstone reservoir will be exploited by an array of horizontal producer and injector wells.
- **Seismic inversion** and **machine learning** will be used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

Seismic inversion

Definition

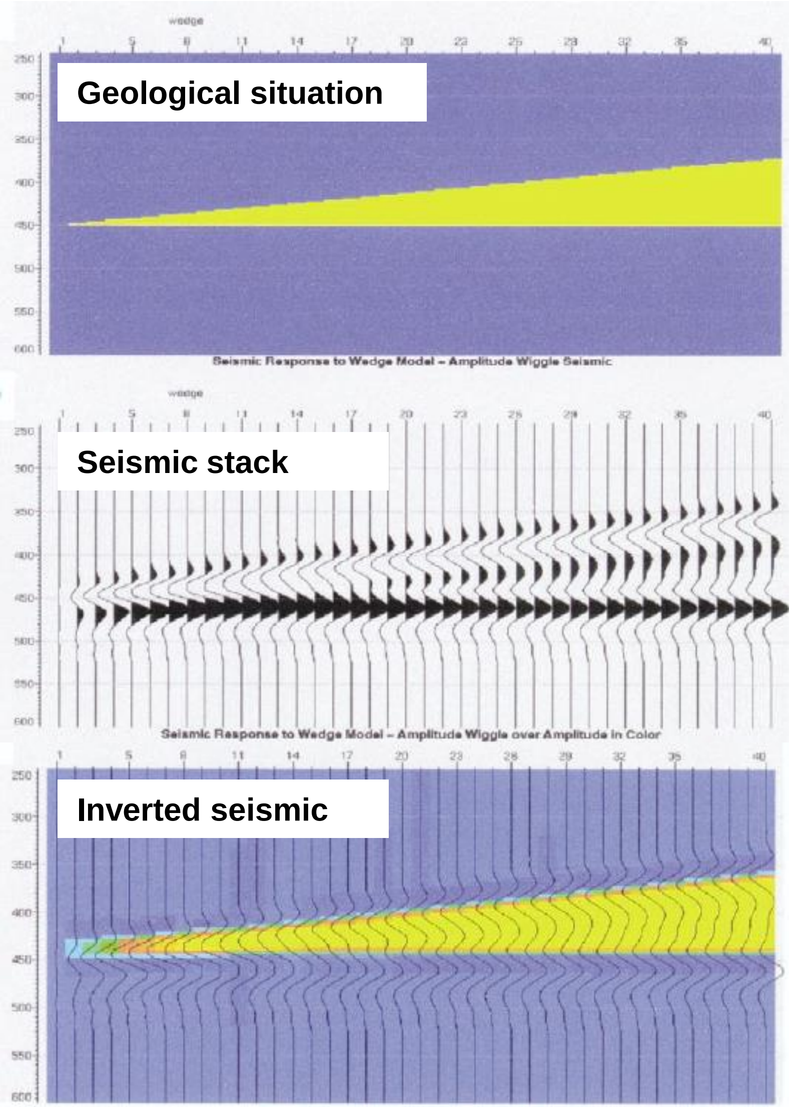


Inversion is the process of extracting from the seismic data, the underlying geology which gave rise to that seismic.

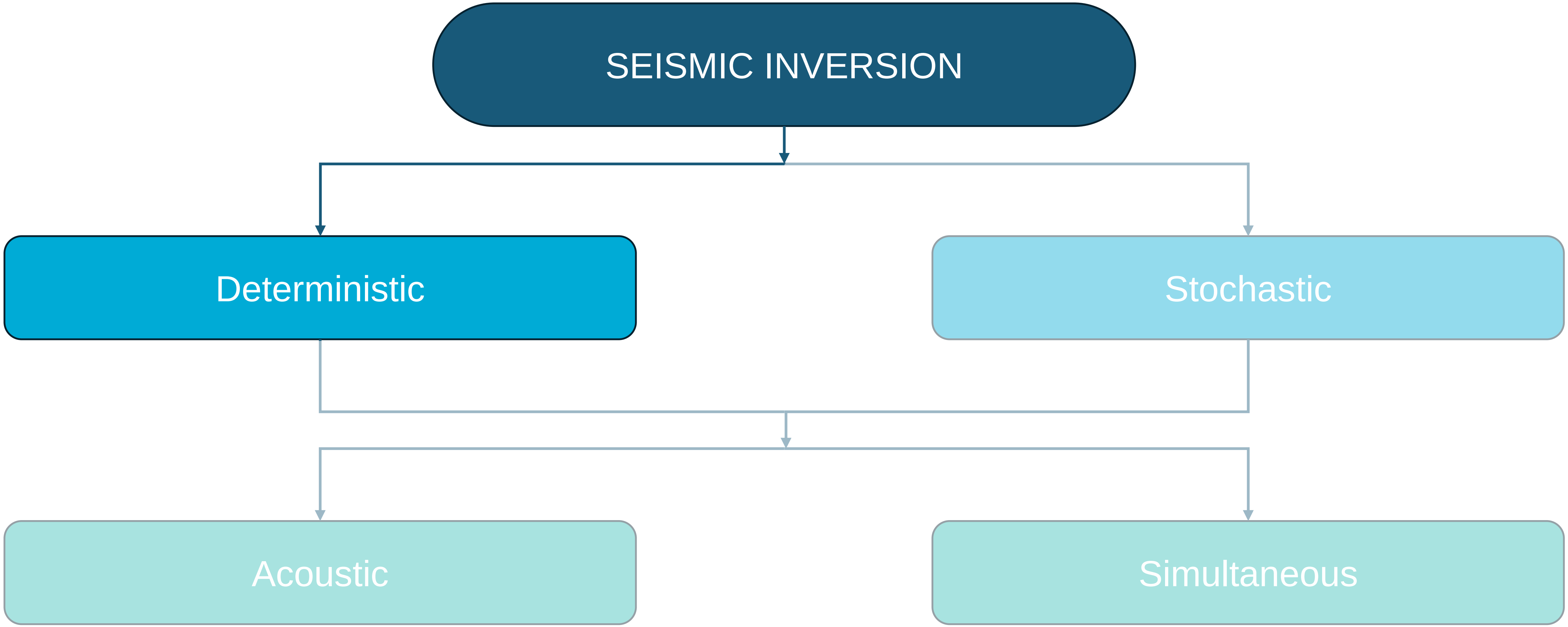


Why perform seismic inversion?

- Incorporate well log information into seismic volumes.
- Increase the bandwidth and therefore the resolution.
- Interval rather than boundary values.
- Remove wavelet effects.
- Understand phase effects.
- Identify lithology, pore-fill and porosity changes.
- Easier, more accurate interpretation.



Seismic inversion approaches



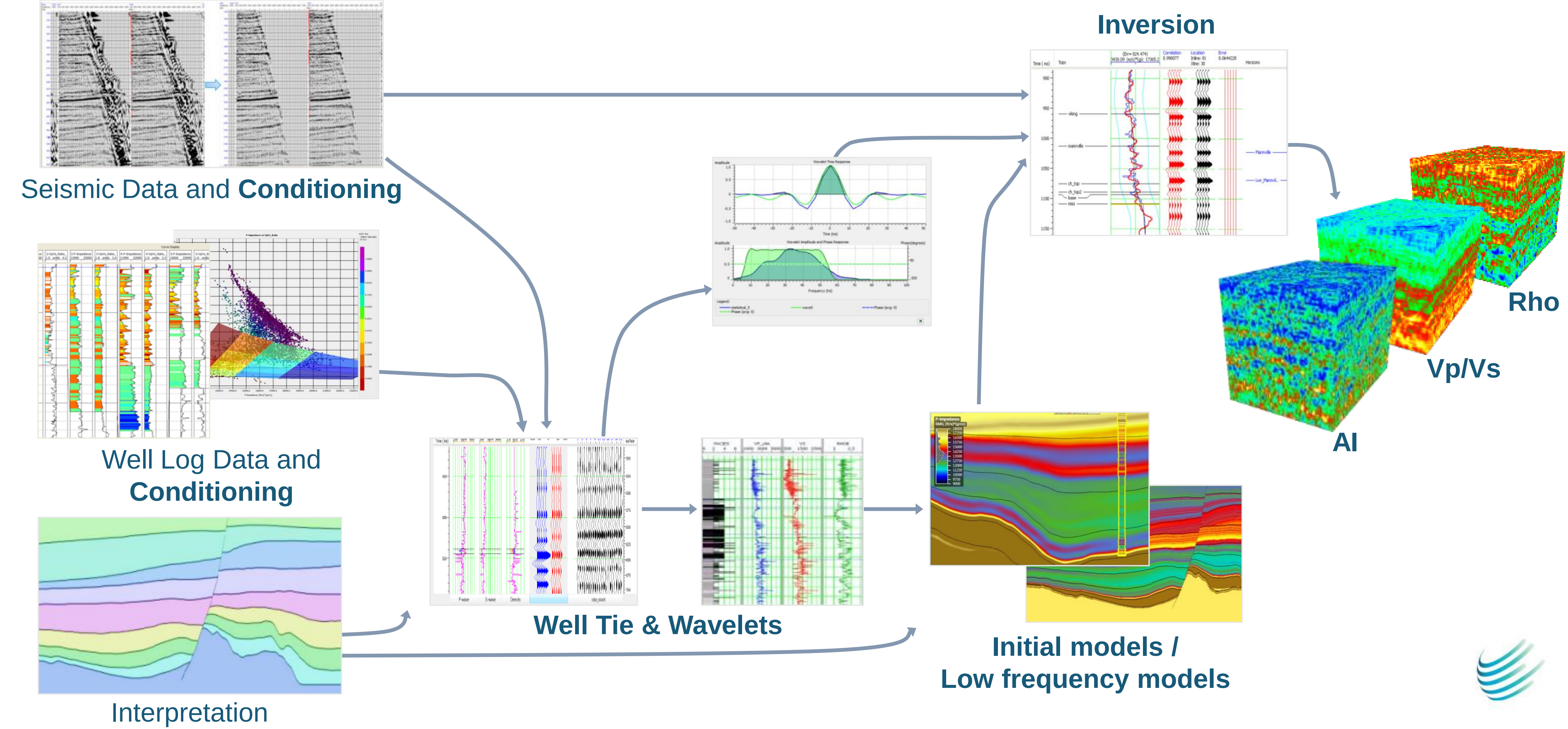
Deterministic inversion algorithms

- Bandlimited
- Colored
- Model-based
- Linear programming sparse spike
- Maximum likelihood sparse spike
- Sparse layer reflectivity
- Constrained sparse spike inversion

HampsonRussell

Jason

Deterministic model-based inversion workflow



Deterministic inversion: Pros and cons

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- Incorporate well log information into seismic volumes.
- Increase the bandwidth and therefore the resolution.
- Interval rather than boundary values.
- Remove wavelet effects.
- Understand phase effects.
- Identify lithology, pore-fill and porosity changes.
- Easier, more accurate interpretation.

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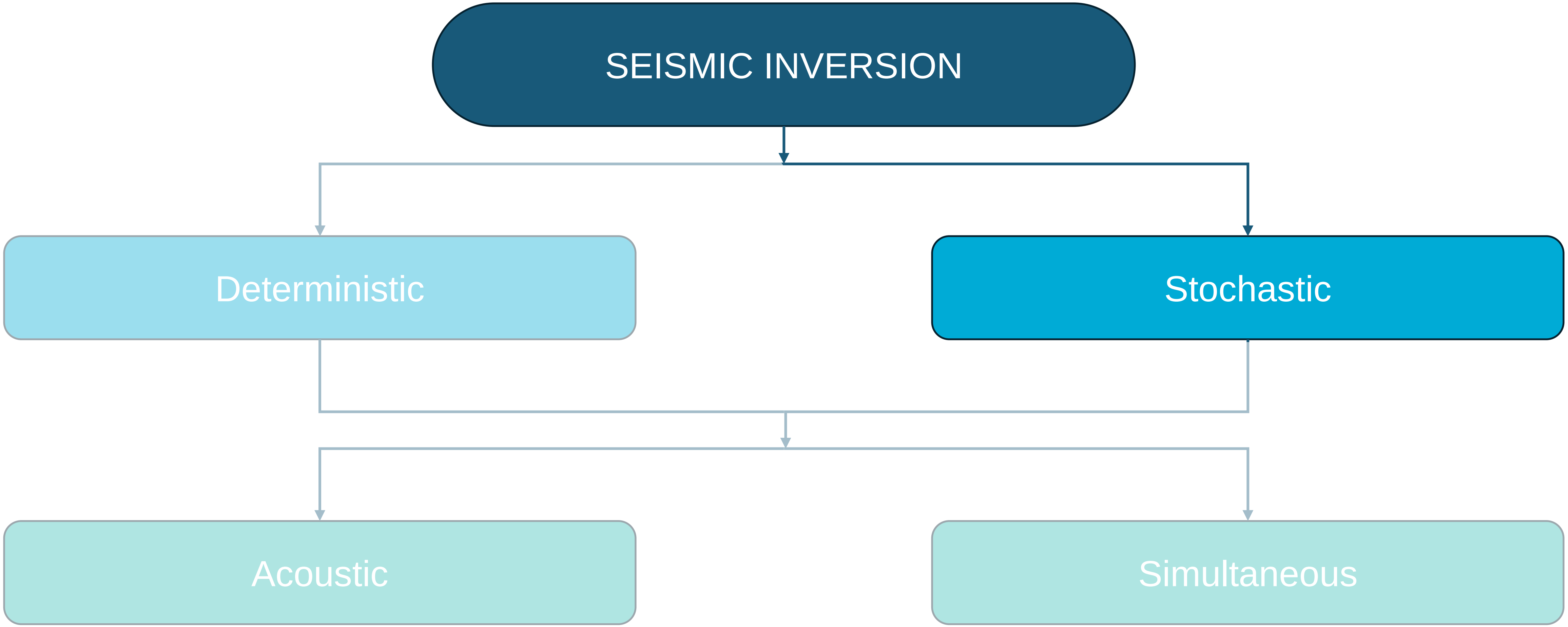
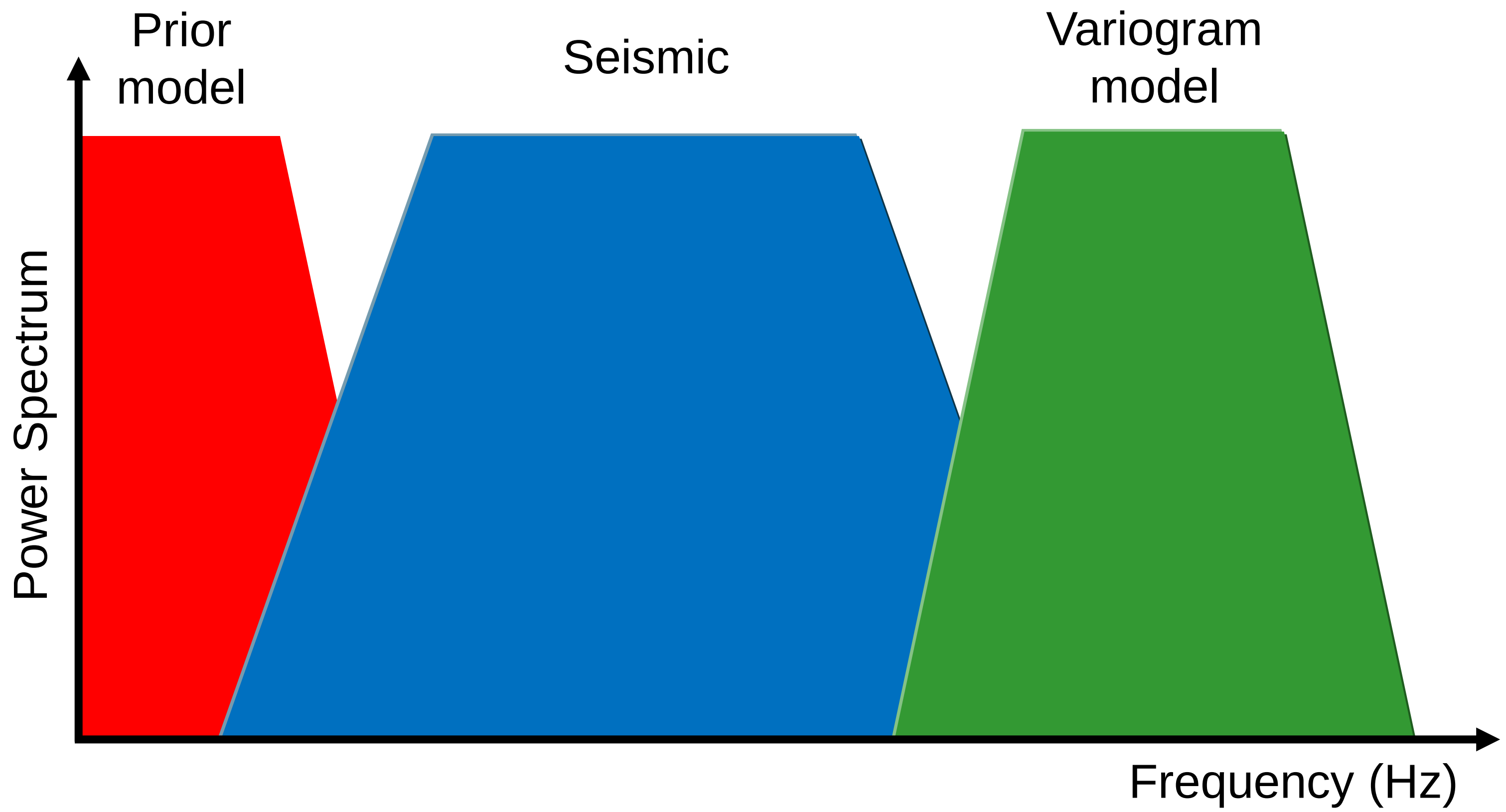
- The resolution of seismic data doesn’t allow one to solve for a thin reservoir.
- Single solution.

Seismic inversion approaches



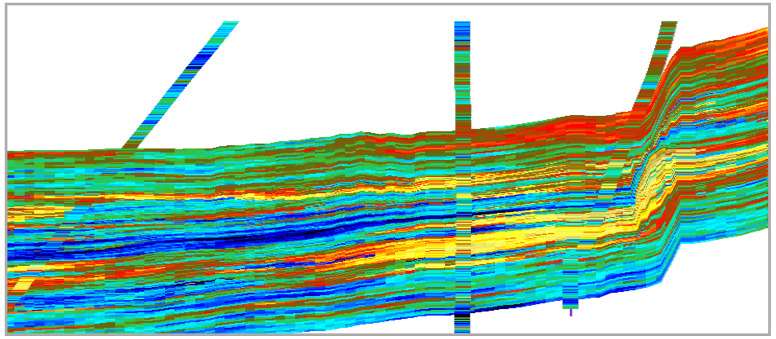
Stochastic inversion



Geological model building approaches

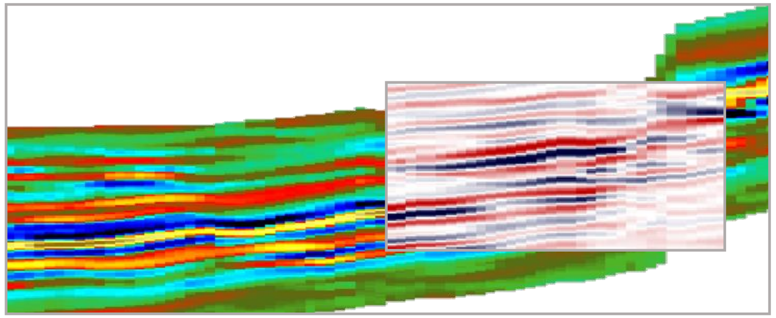
"Classic" geological modelling

- High vertical detalization
- Probability analysis capability
- Model is valid only in the area surrounding the wells
- Weak integration of seismic data



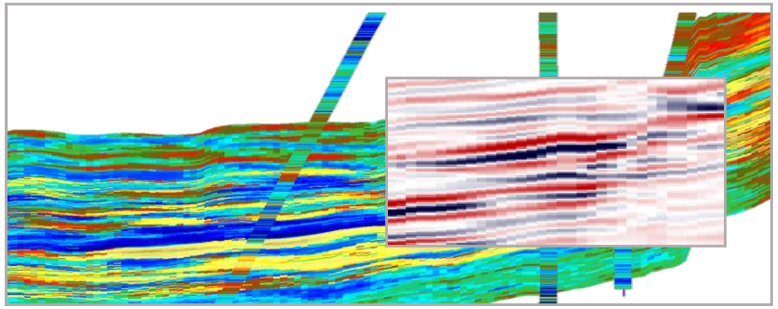
Deterministic inversion

- High lateral detalization
- Independent assessment of reservoir properties from seismic
- Low vertical detalization
- One optimal solution



Stochastic inversion

- High lateral&vertical detalization
- Reservoir properties evaluation from seismic data
- Model is aligned with drilling data
- Probability analysis capability

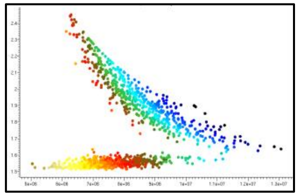


Stochastic inversion workflow

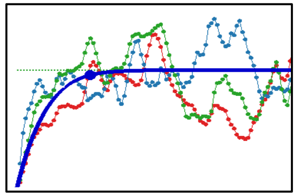
Hypotheses

Geology

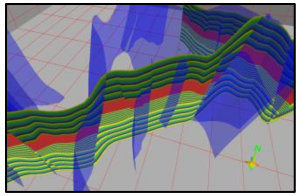
Rock physics



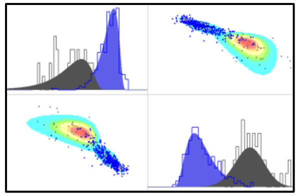
Variograms



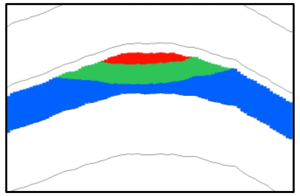
Geological grid



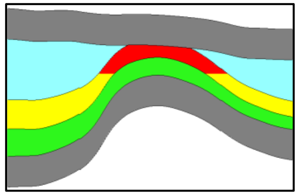
PDFs



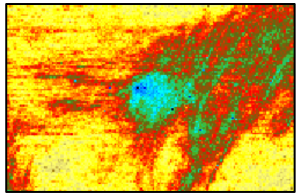
Fluid contacts

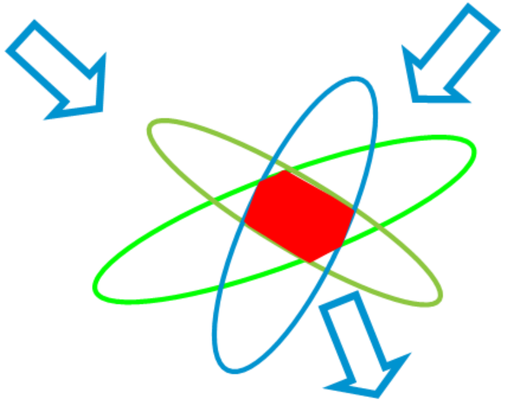


Facies proportions



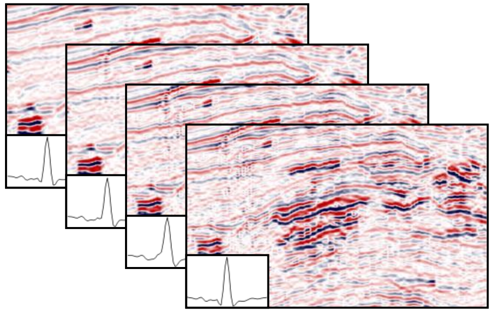
Signal/Noise ratio



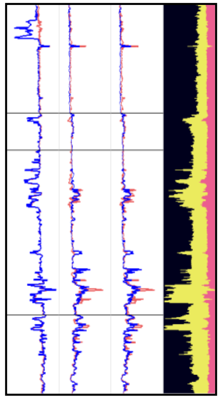


Field data

Seismic and wavelets

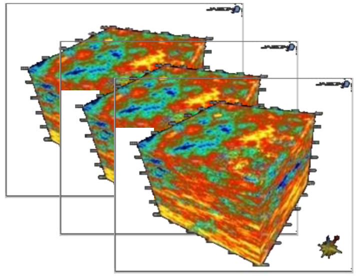


Wells

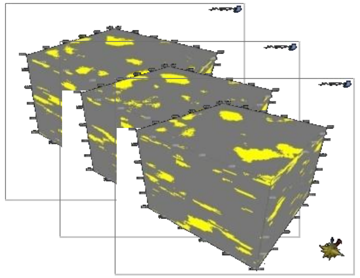


Reservoir models

Elastic properties

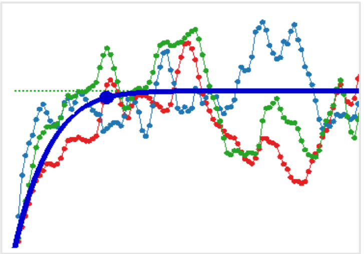


Lithofacies

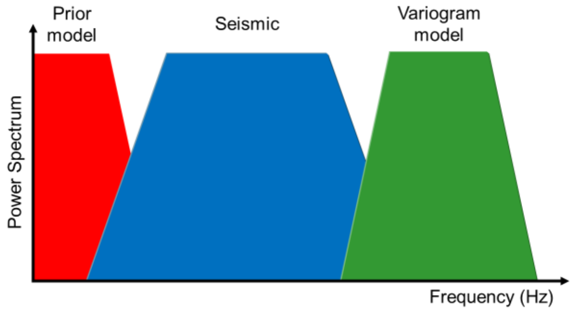


Advantages of stochastic inversion

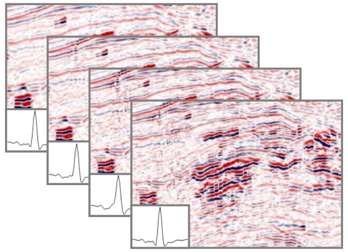
Vertical Variograms



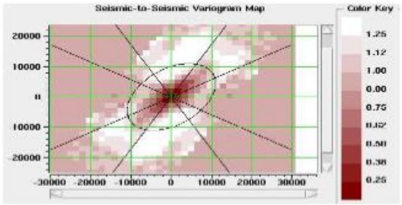
High vertical details



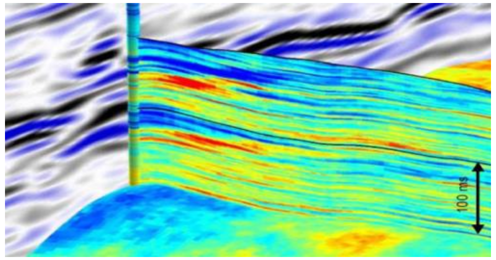
Seismic



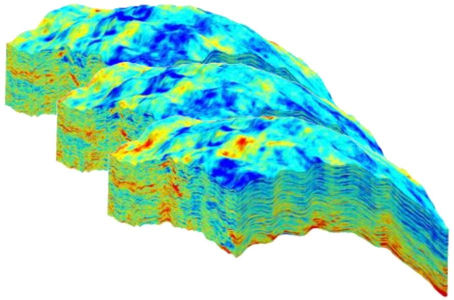
Horizontal Variograms



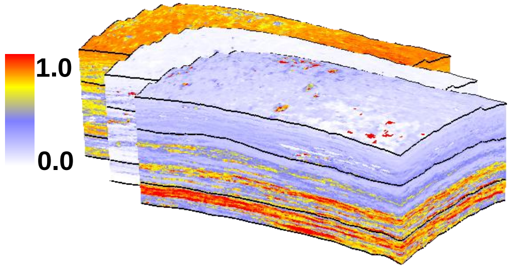
High lateral details



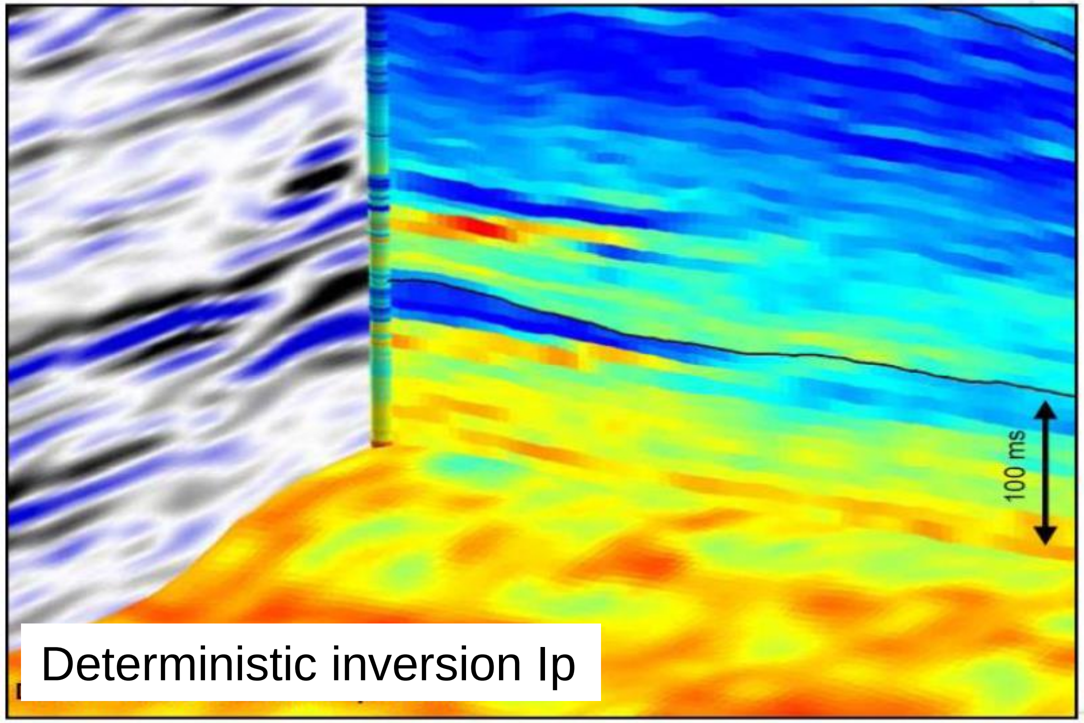
Multiple realisations

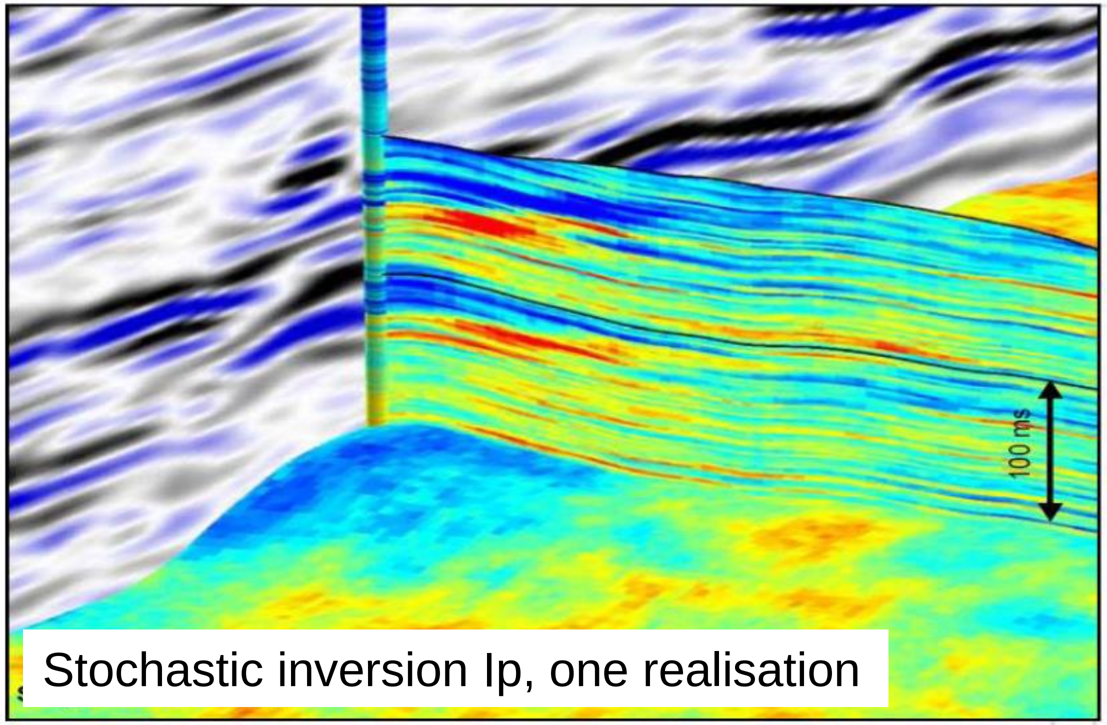


Probability analysis capability



Deterministic vs. stochastic inversion example





Seismic inversion results

Deterministic

- Models of elastic properties:
  - P-Impedance
  - S-Impedance
  - Density
  - Vp/Vs

Geostatistical

- Multiple realizations of elastic properties models:
  - P-Impedance
  - S-Impedance
  - Density
  - Vp/Vs
- Multiple realizations of lithofacies models

How to obtain porosity and permeability estimates, essential for the geothermal studies?

Porosity and permeability prediction

- Porosity prediction based on inversion results:
  - Based on rock physics modeling
  - Based on P-Impedance vs. Porosity relationship
  - Multilinear regression
  - Co-simulation
  - Machine leaning

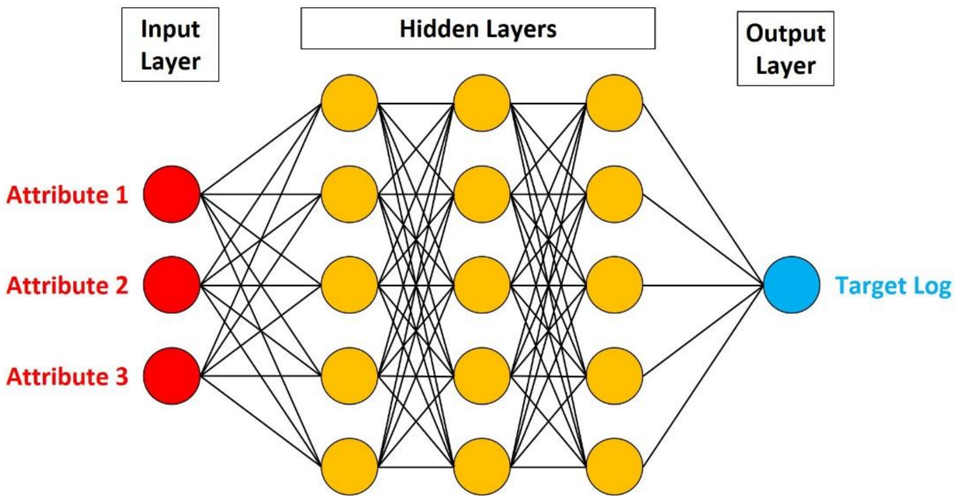
- Permeability prediction:
  - Based on rock physics modeling
  - Based on Porosity vs. Permeability relationship
  - Based on laboratory measurements on core data

Machine learning

Deep neural networks in HampsonRussell

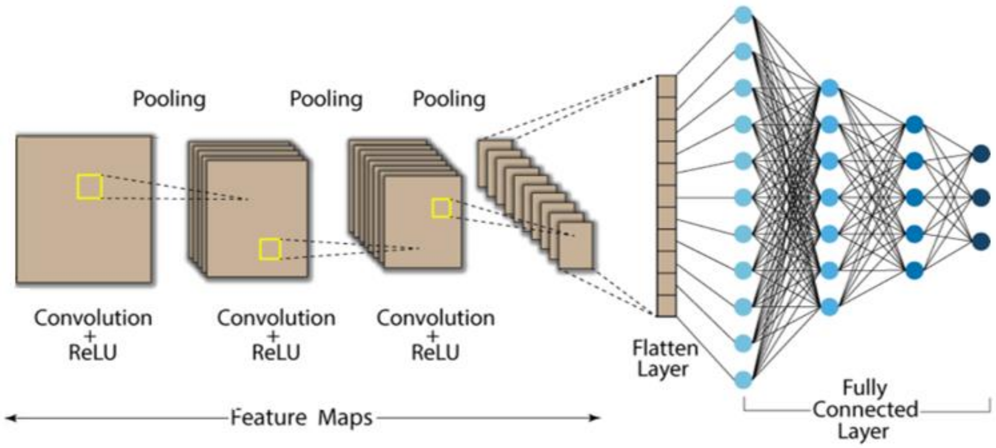
Emerge DFNN

- 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



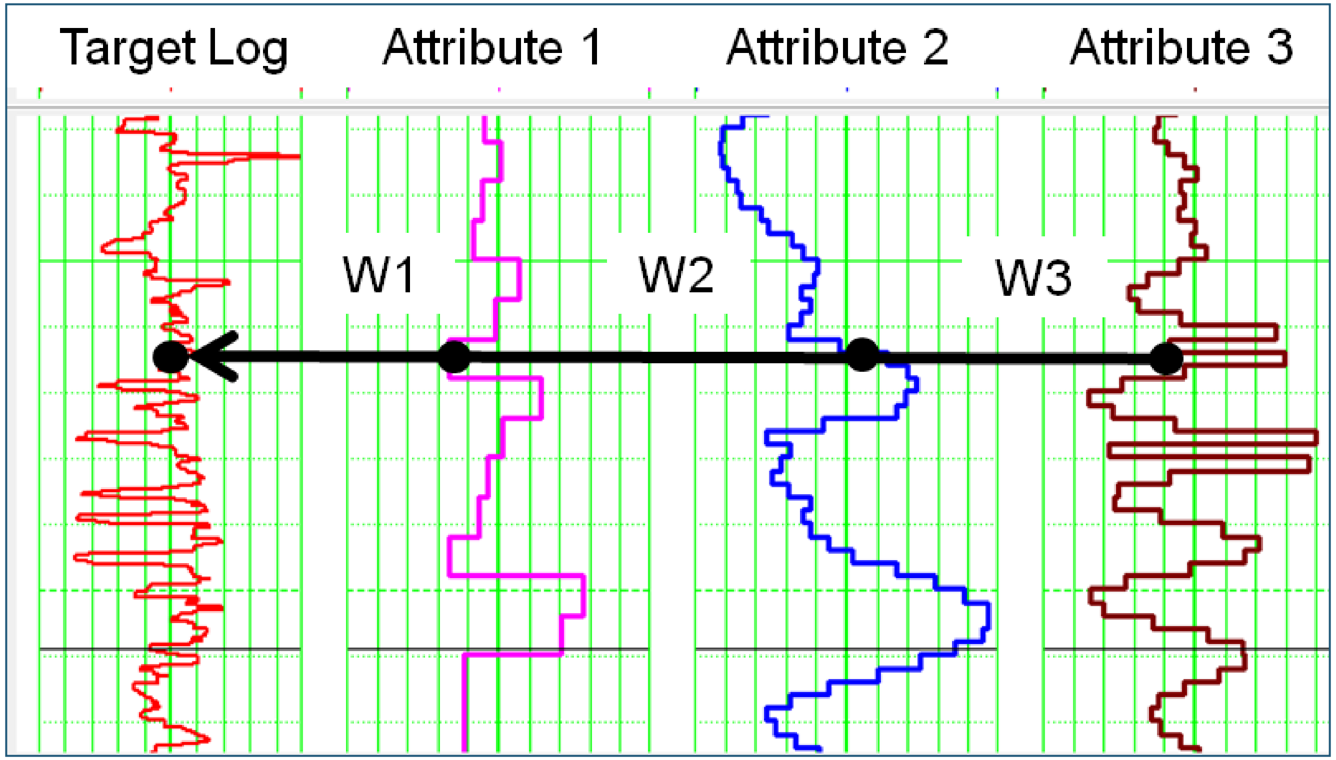
GeoAI CNN

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



Predicting log properties with seismic attributes

- Emerge is a program that analyses well log and seismic attributes at well locations.
- It finds a relationship between the log and seismic attributes at the well locations.
- It uses this relationship to “predict” a volume of the log property at all the other locations of the seismic volume.

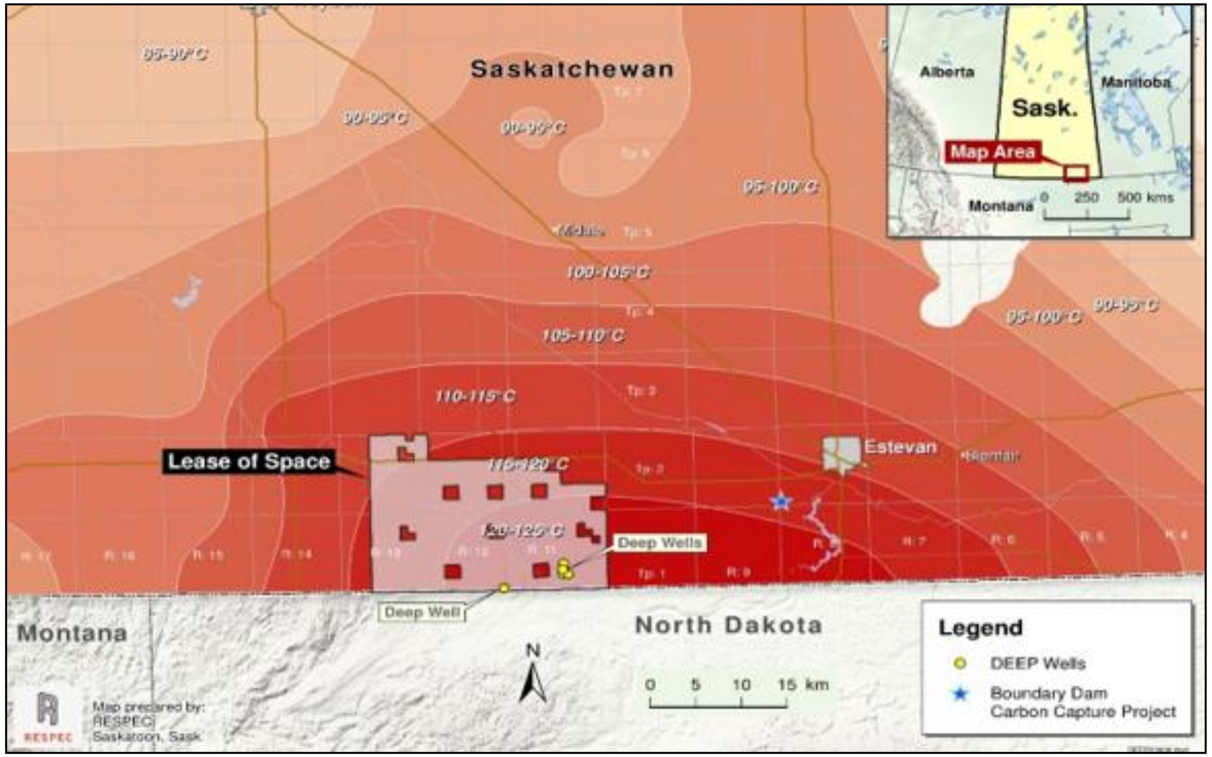


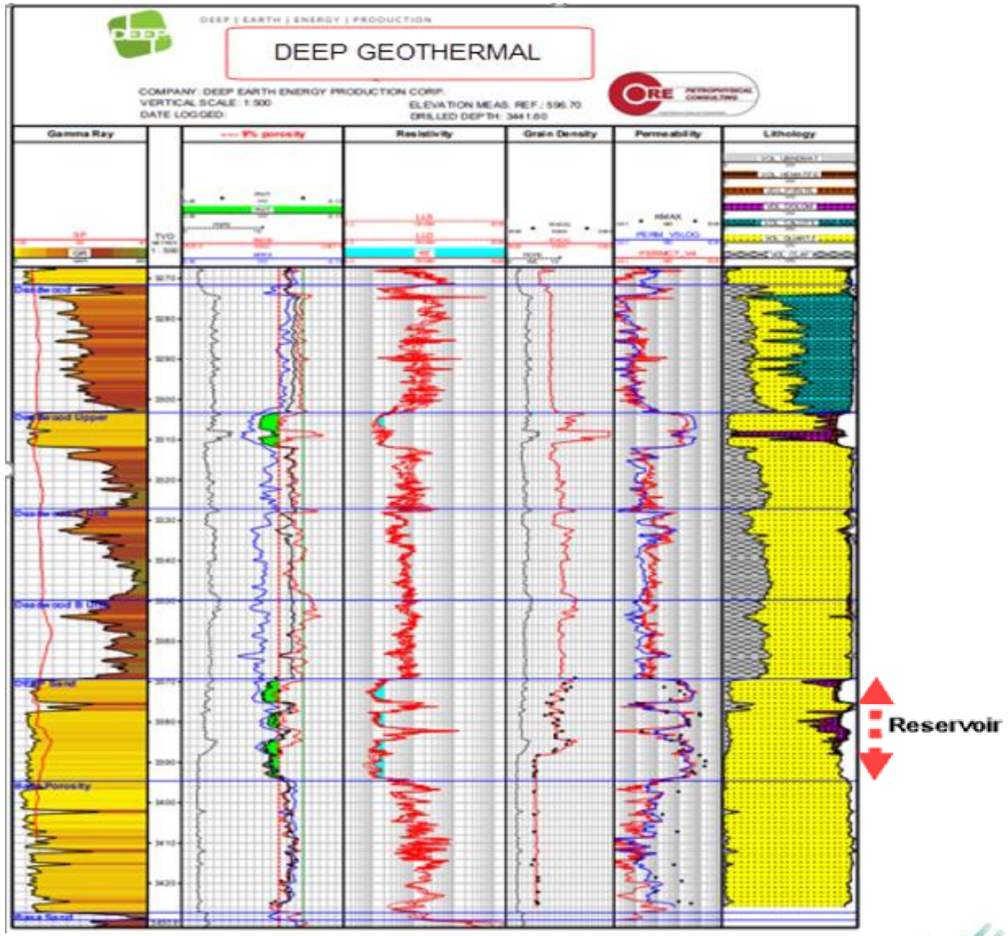
Geothermal project location

- DEEP (Deep Earth Energy Production) has targeted the Basal Sandstones of the Williston basin for geothermal production.
- 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.

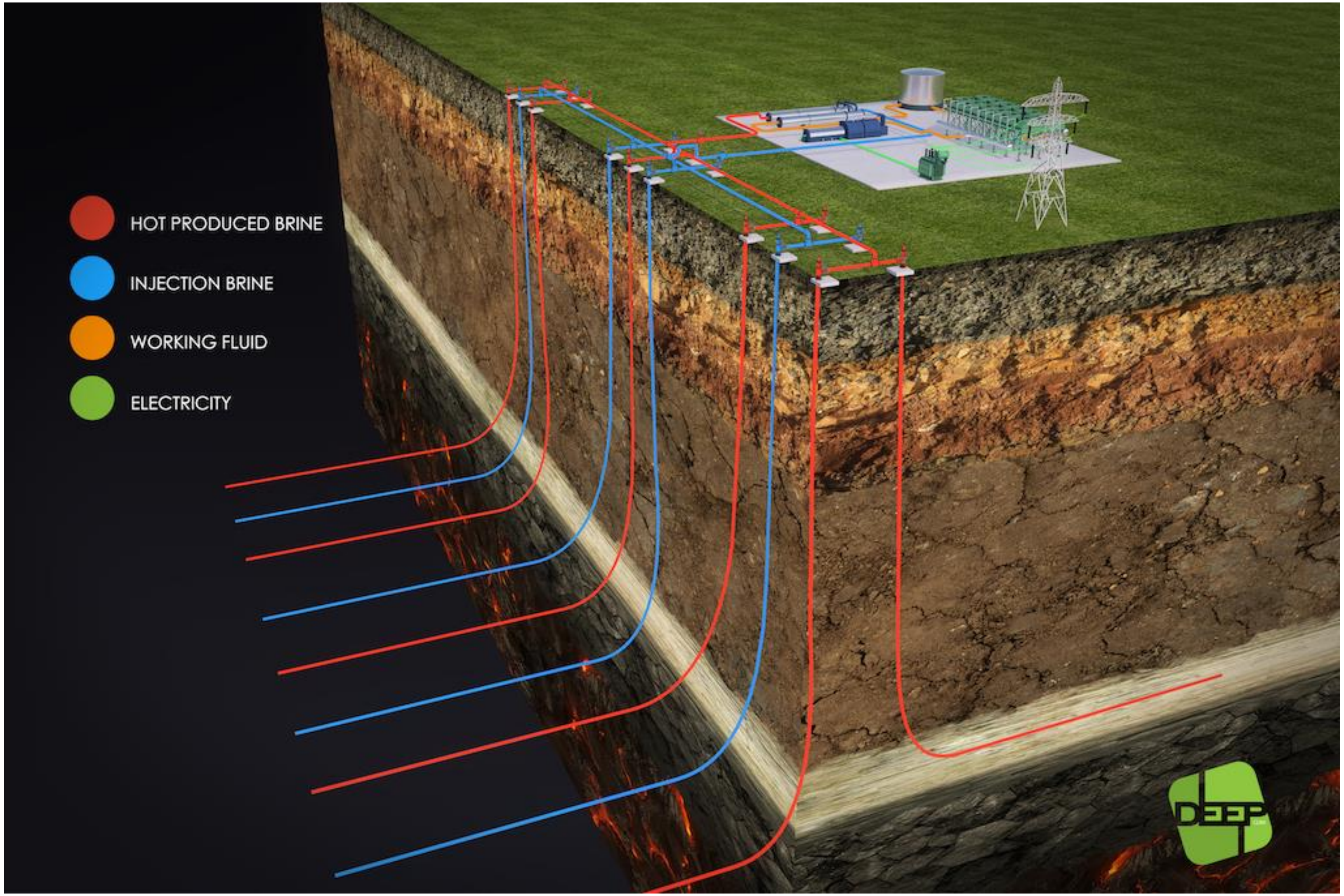
Basal Cambrian temperature and reservoirs

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

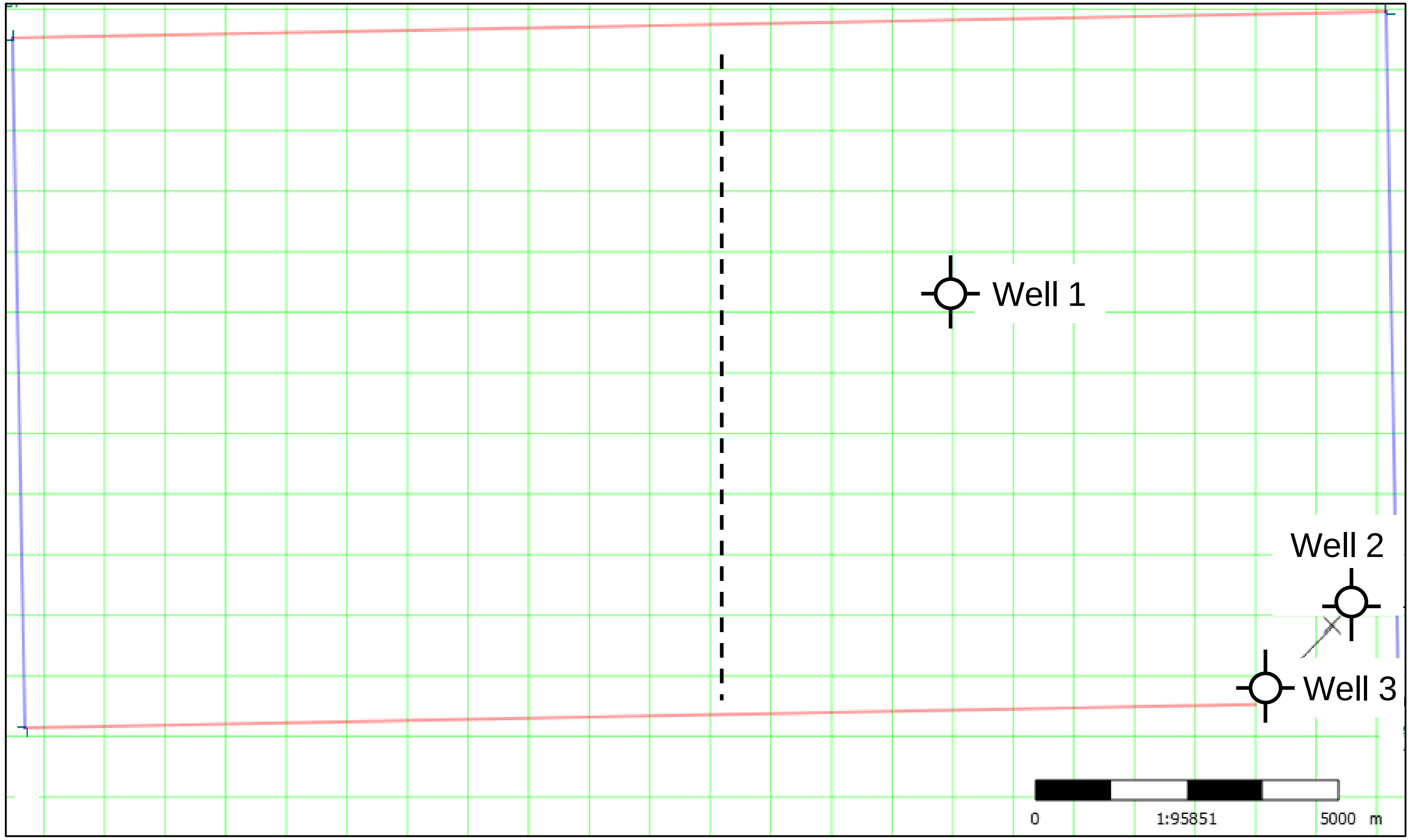




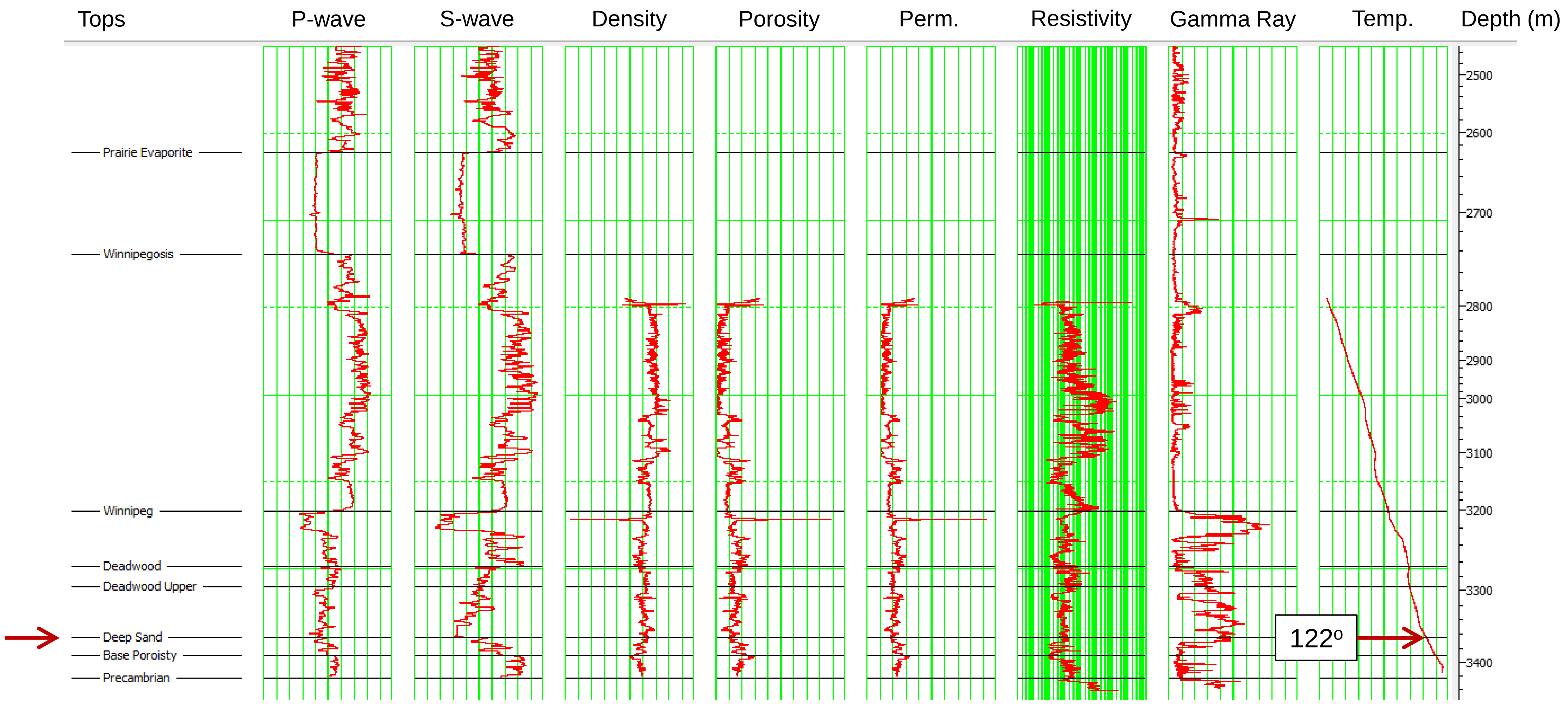
DEEP proposed well array layout



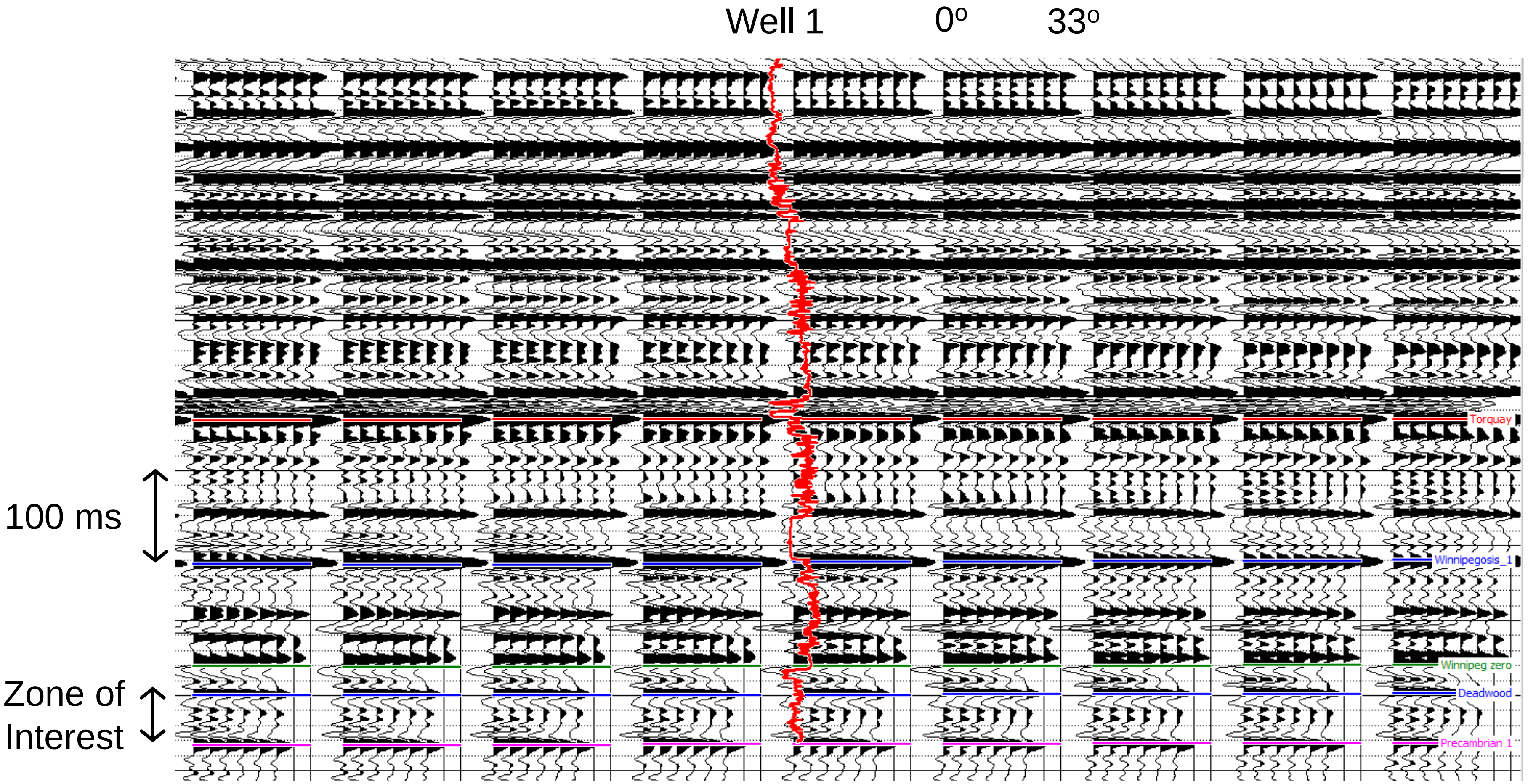
Seismic coverage



Well log curves for Well 1



Angle gathers near Well 1



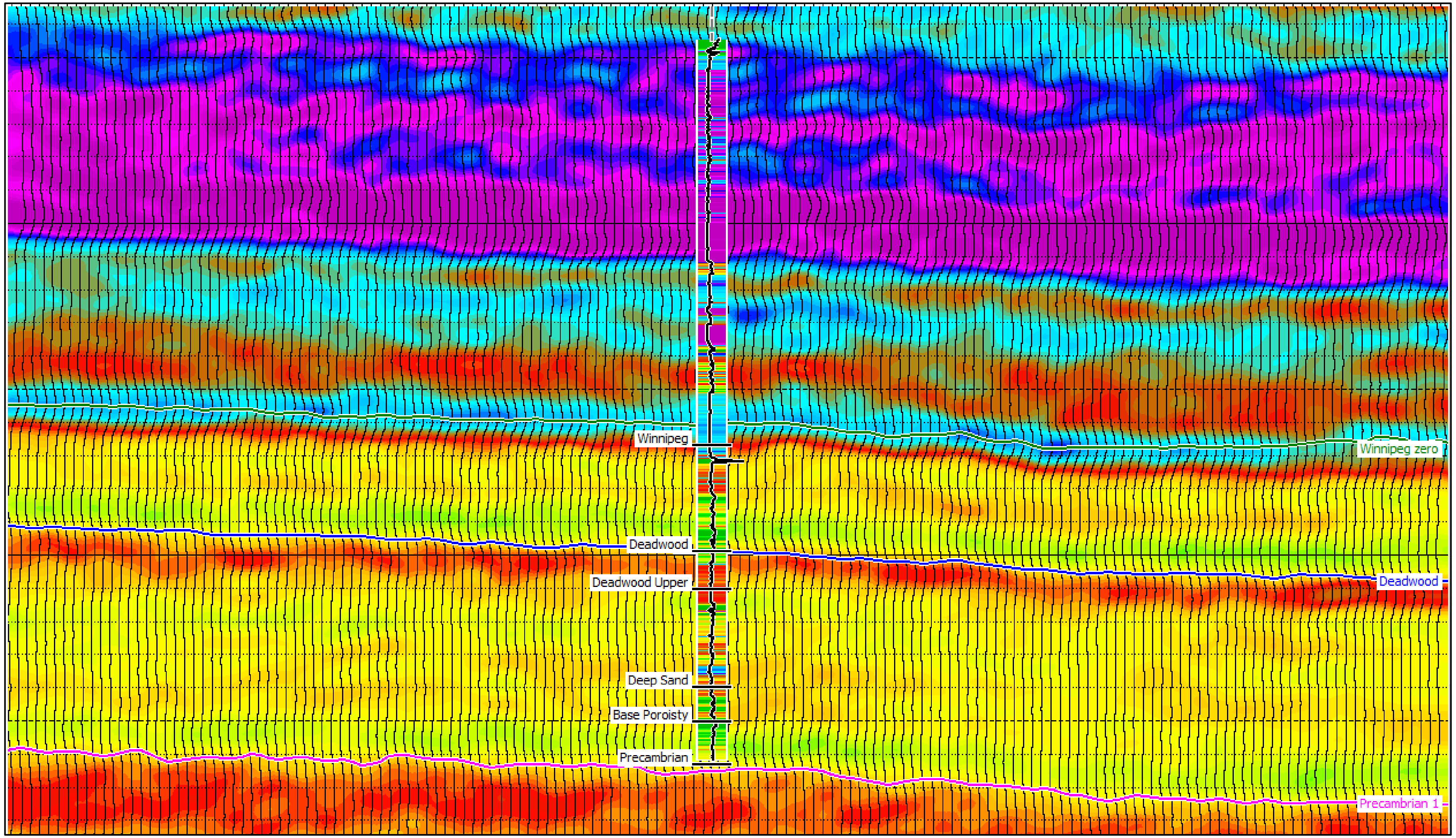
Seismic pre-stack inversion

- Pre-stack inversion using model-based approach was then performed with the following flow:
  - Extract a seismic wavelet and use it to correlate each well.
  - Build a starting P-impedance model by interpolating the correlated logs, guided by the picked seismic horizons.
  - Create logarithmic relationships between P-impedance and S-impedance, and P-impedance and density, to create S-impedance and density models.
  - Apply a low pass filter to all three starting models.
  - Use the Aki-Richards equation to iteratively update the starting models to obtain the best fit between the modeled and real data angle gathers.

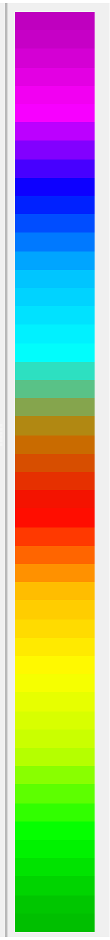
Inverted P-Impedance

Well 1

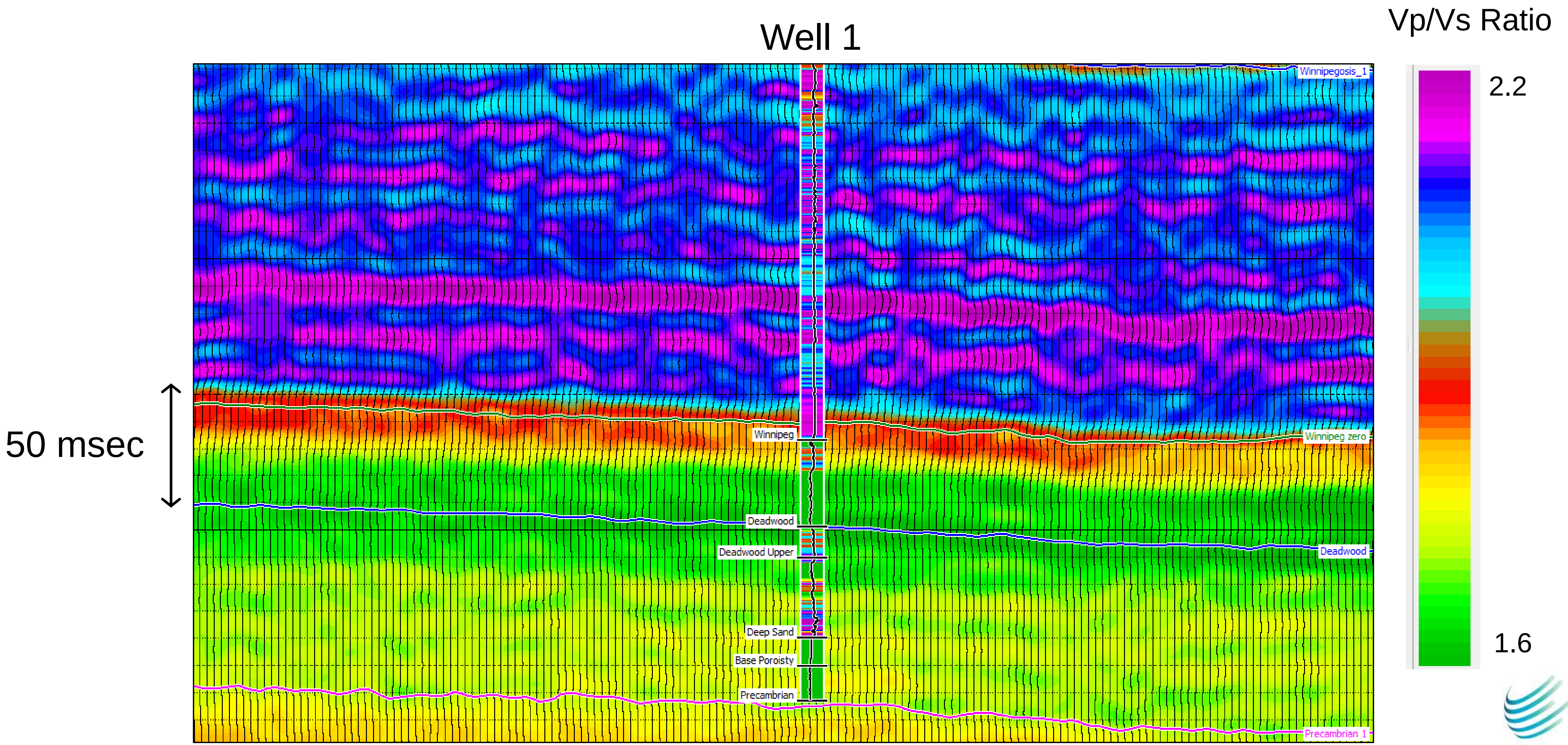
50 msec



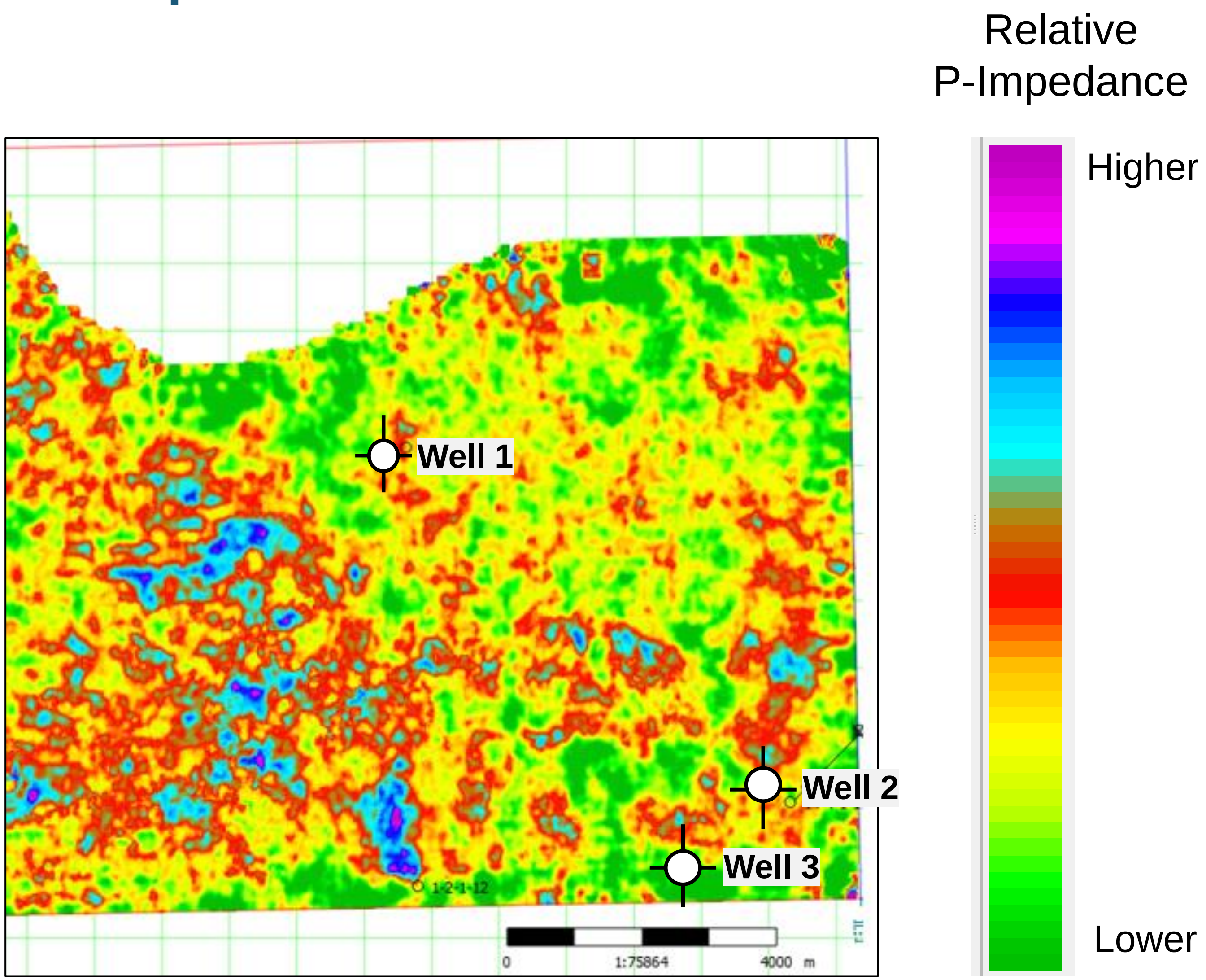
Relative
P-Impedance



Inverted Vp/Vs ratio

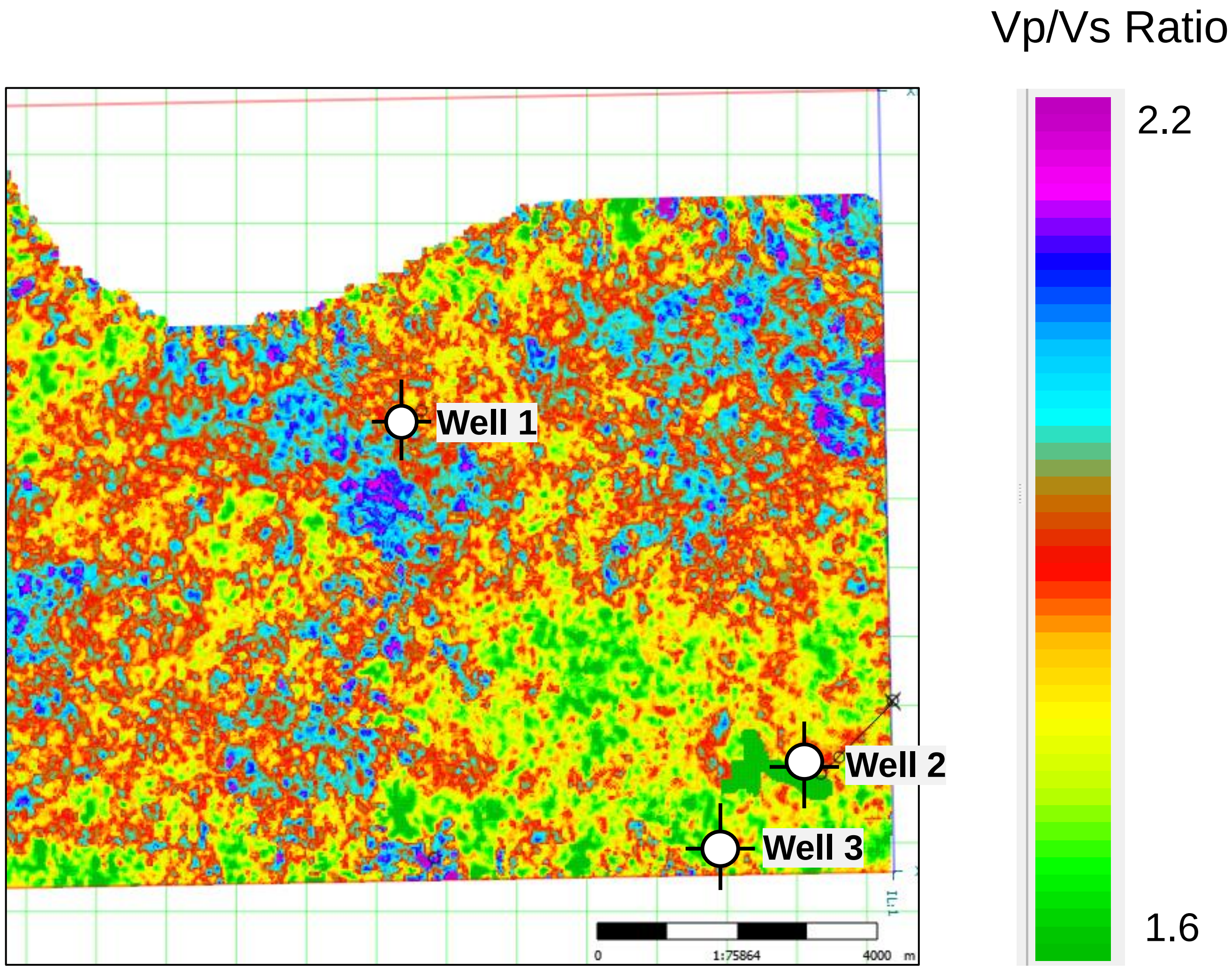


P-Impedance map slice



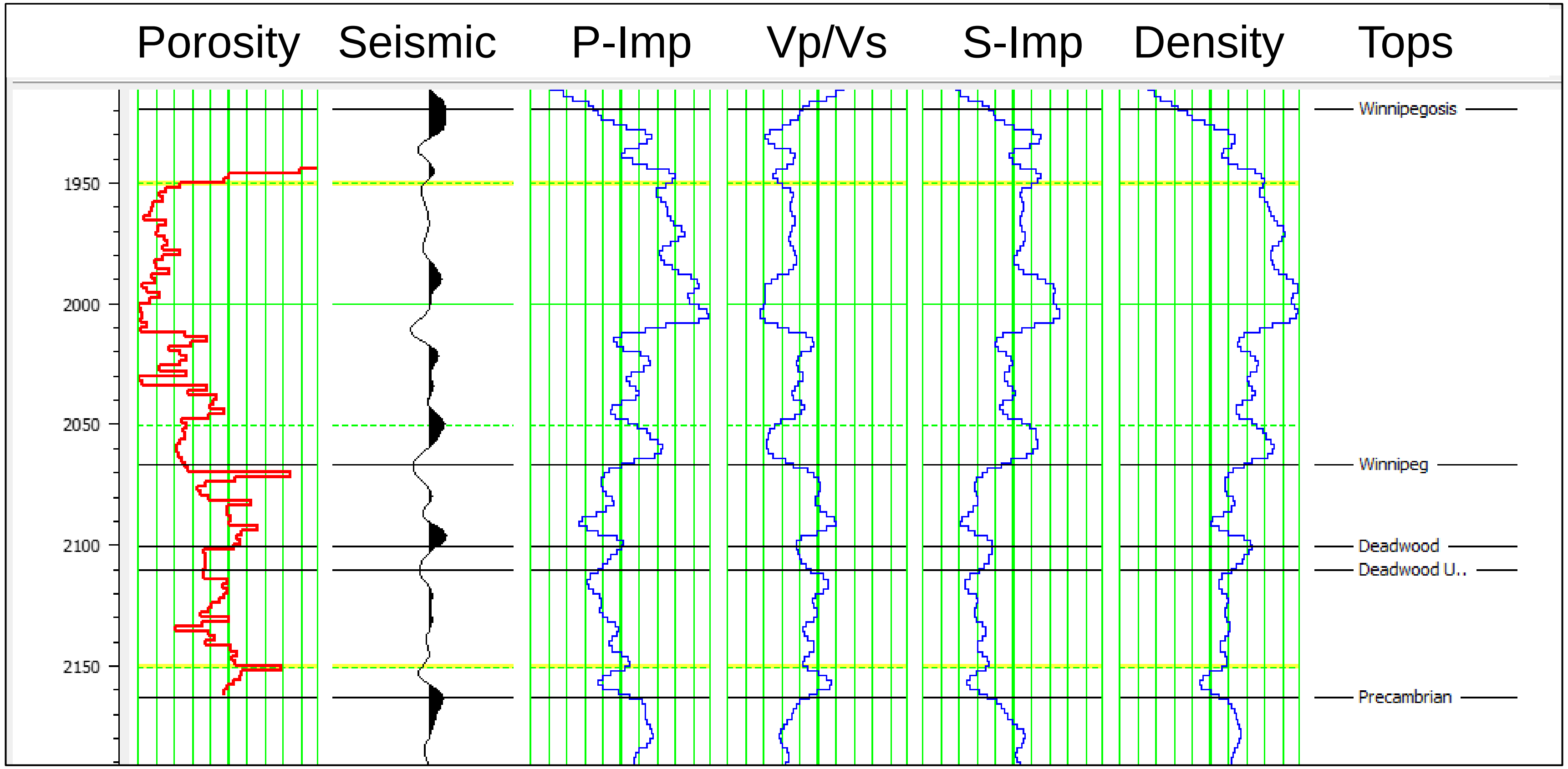
Vp/Vs ratio map slice

- 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.

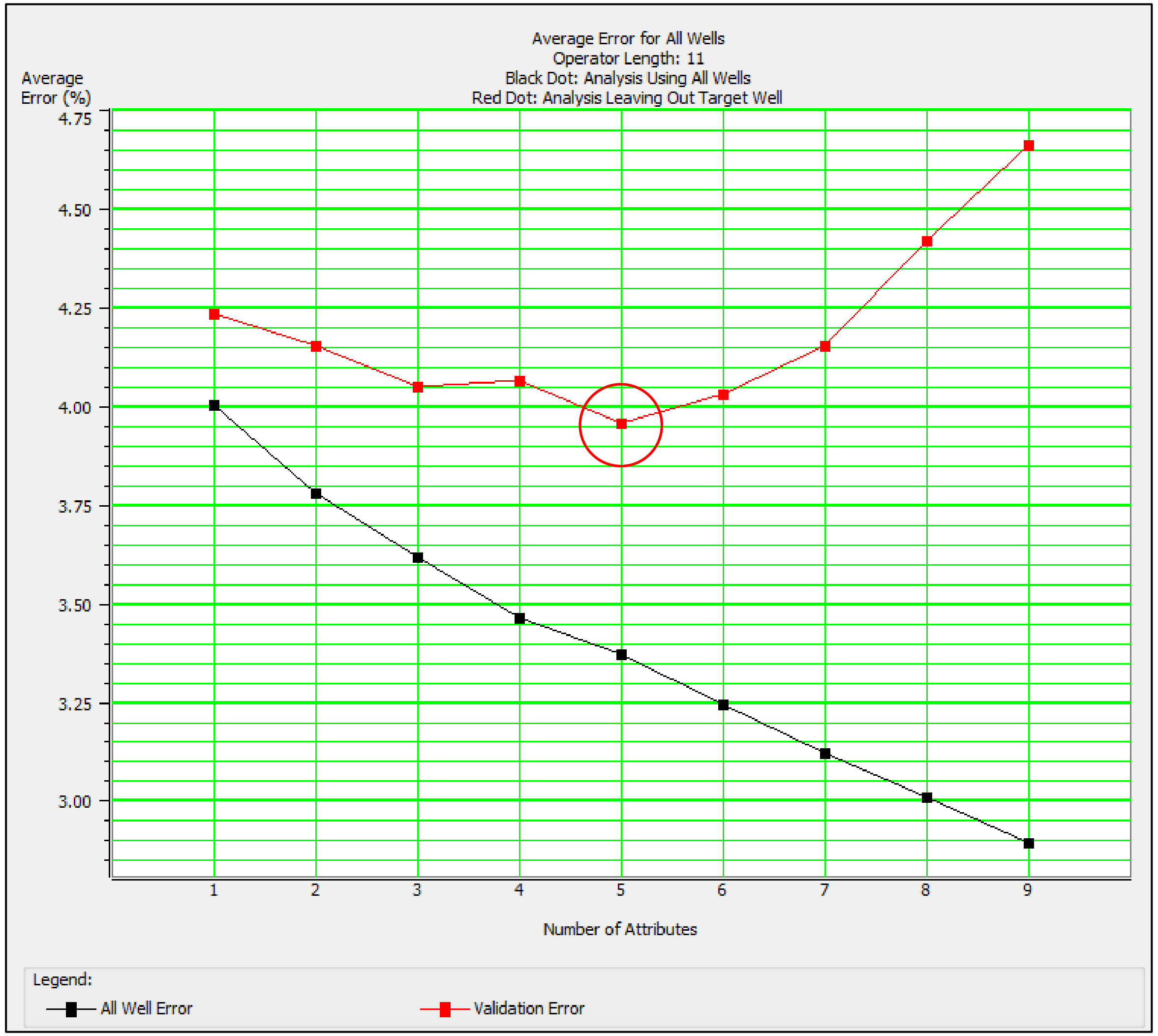


Emerge training data for Well 1

Emerge training data – Well 1



Training versus cross-validation error

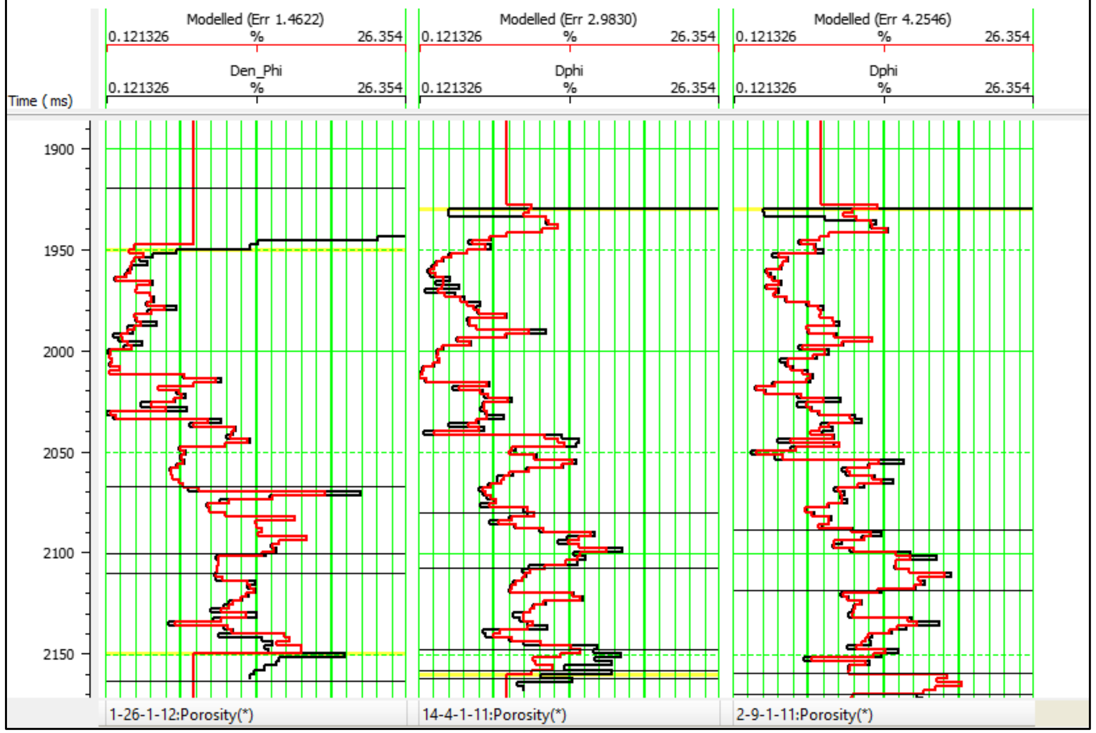


Emerge training attributes

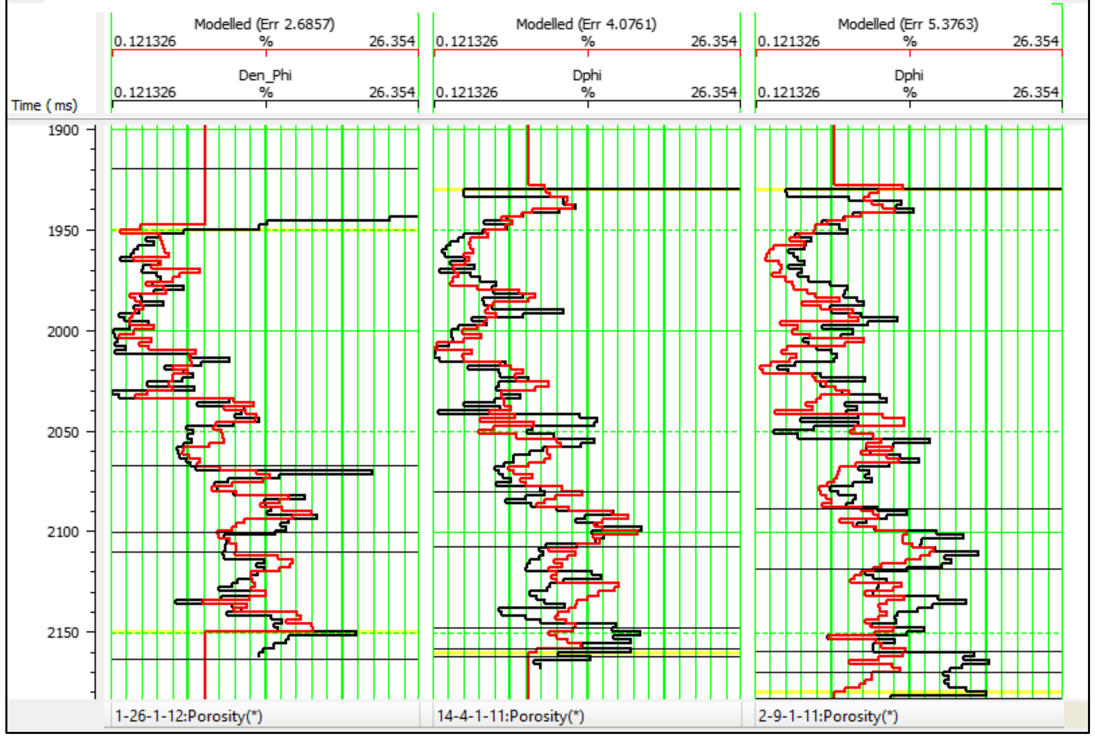
	Target	Final Attribute	Training Error	Validation Error
1	Sqrt(Porosity)	1/(Prestack_Inversion__2_Zs)	4.006055	4.237843
2	Sqrt(Porosity)	Filter 15/20-25/30	3.785451	4.159208
3	Sqrt(Porosity)	(Prestack_Inversion__2_Dn)**2	3.622563	4.054750
4	Sqrt(Porosity)	Apparent Polarity	3.469089	4.070477
5	Sqrt(Porosity)	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

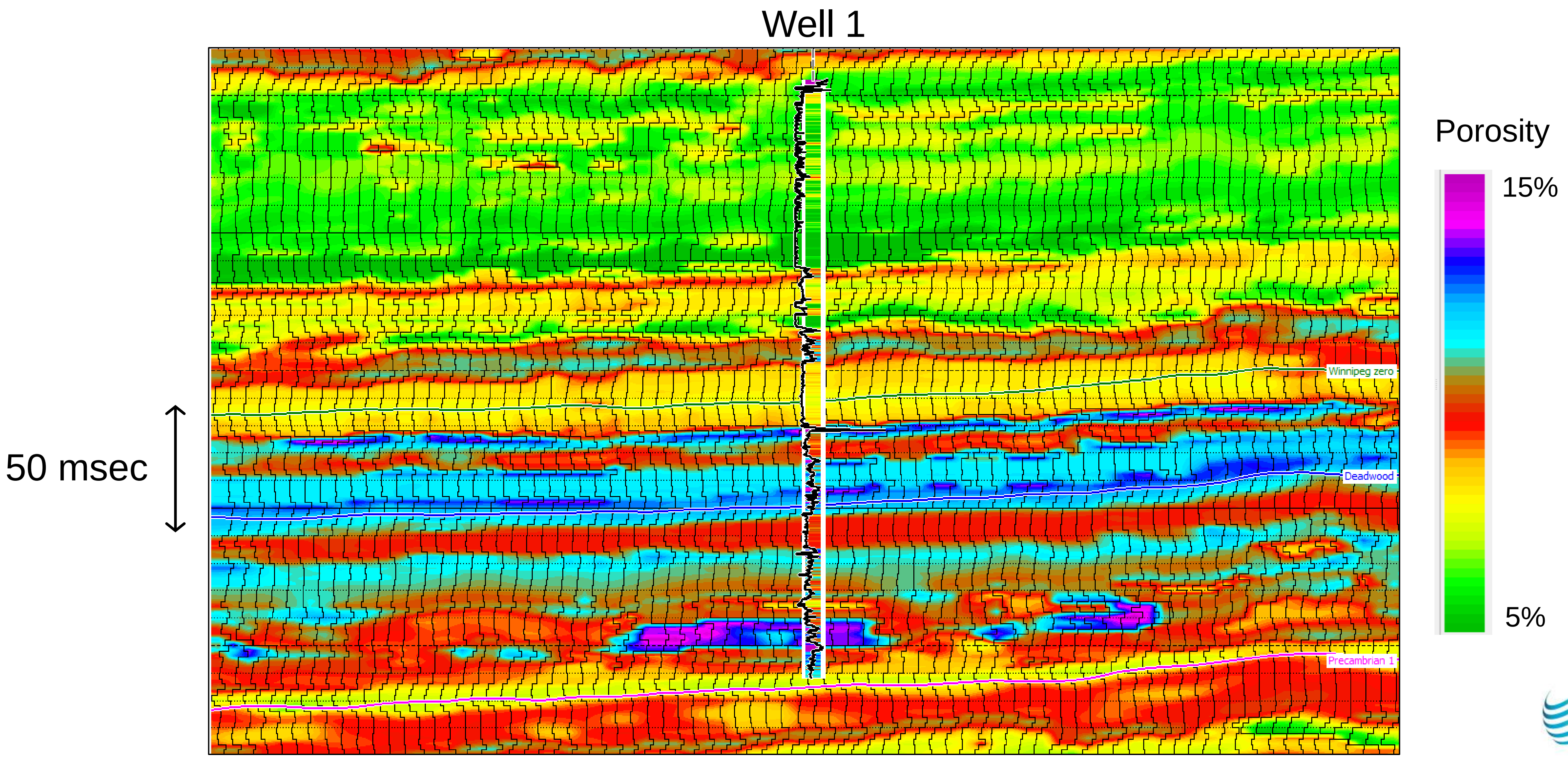
PNN Training Error: Correlation = 0.8210



PNN Validation Error: Correlation = 0.6512

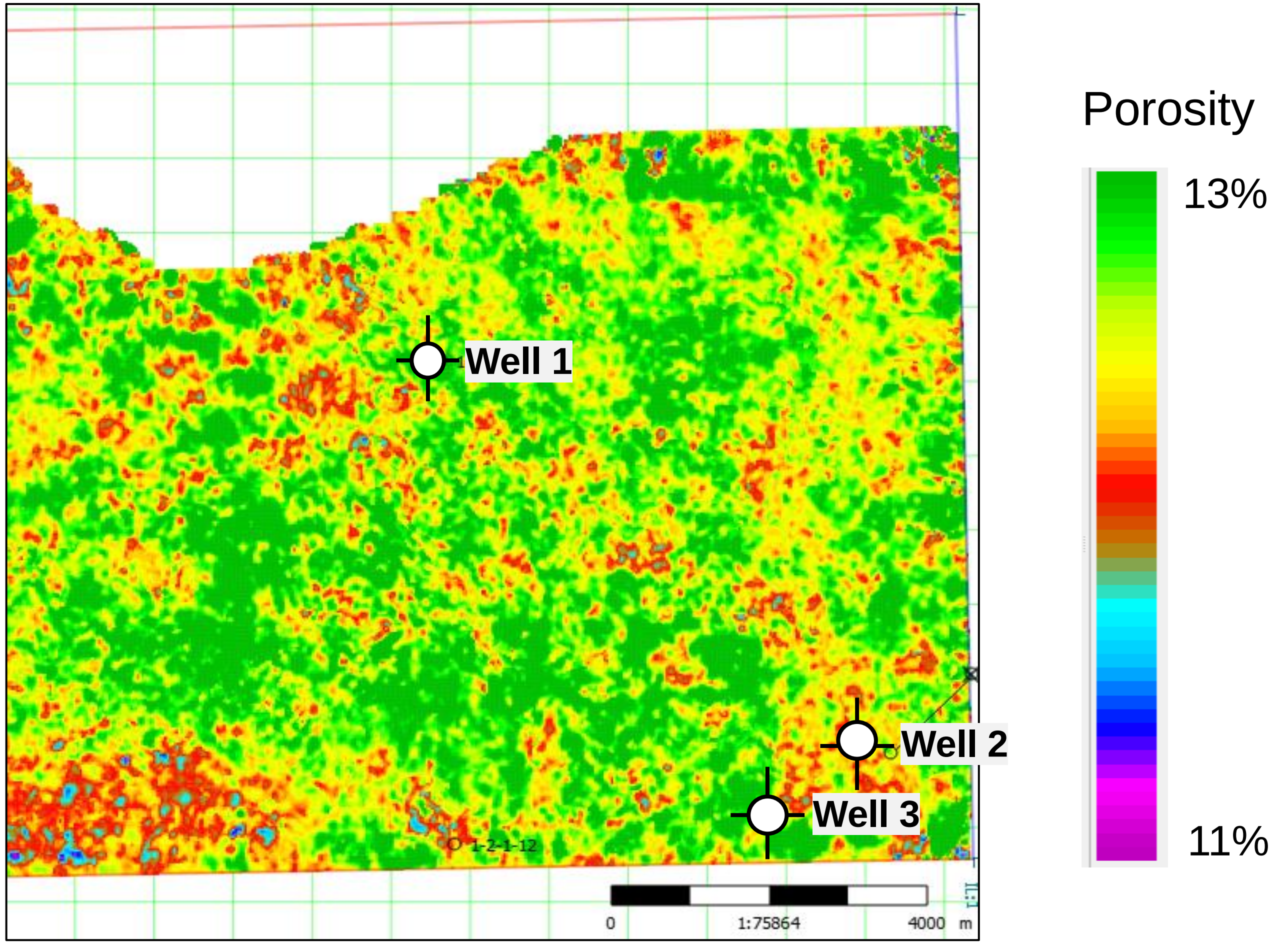


Porosity transform with PNN

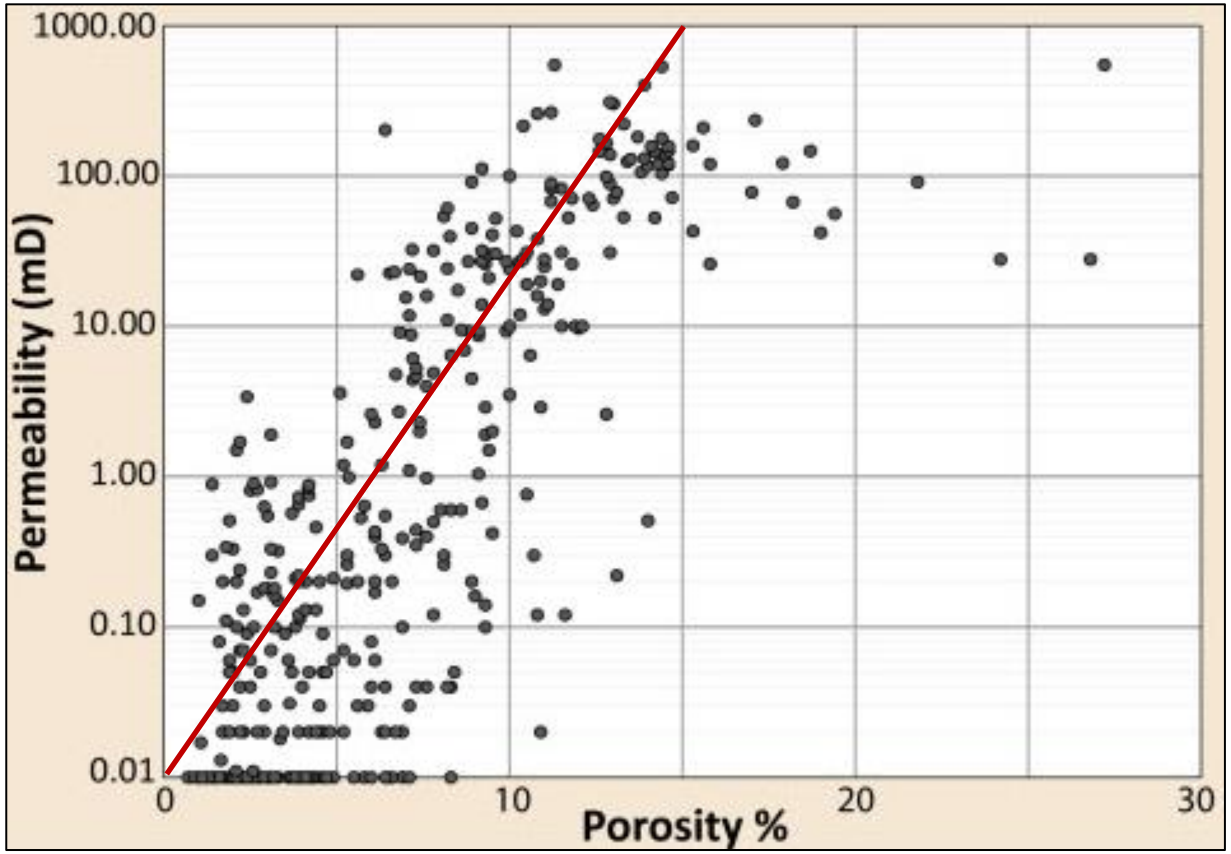


Porosity transform with PNN

- The map is averaged over a 10 ms window picked 42 ms below the Deadwood.



Porosity-permeability relationship

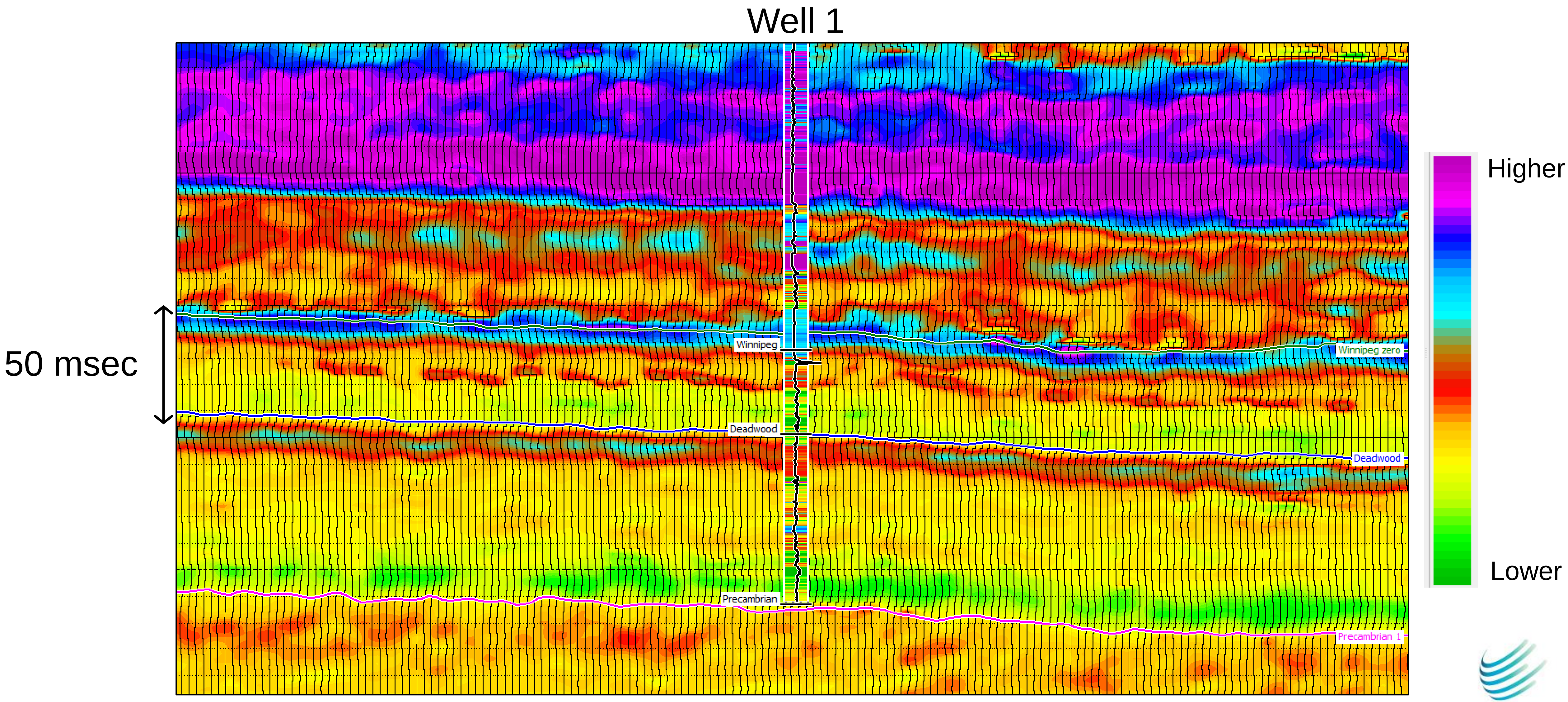


Nesheim, 2021

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

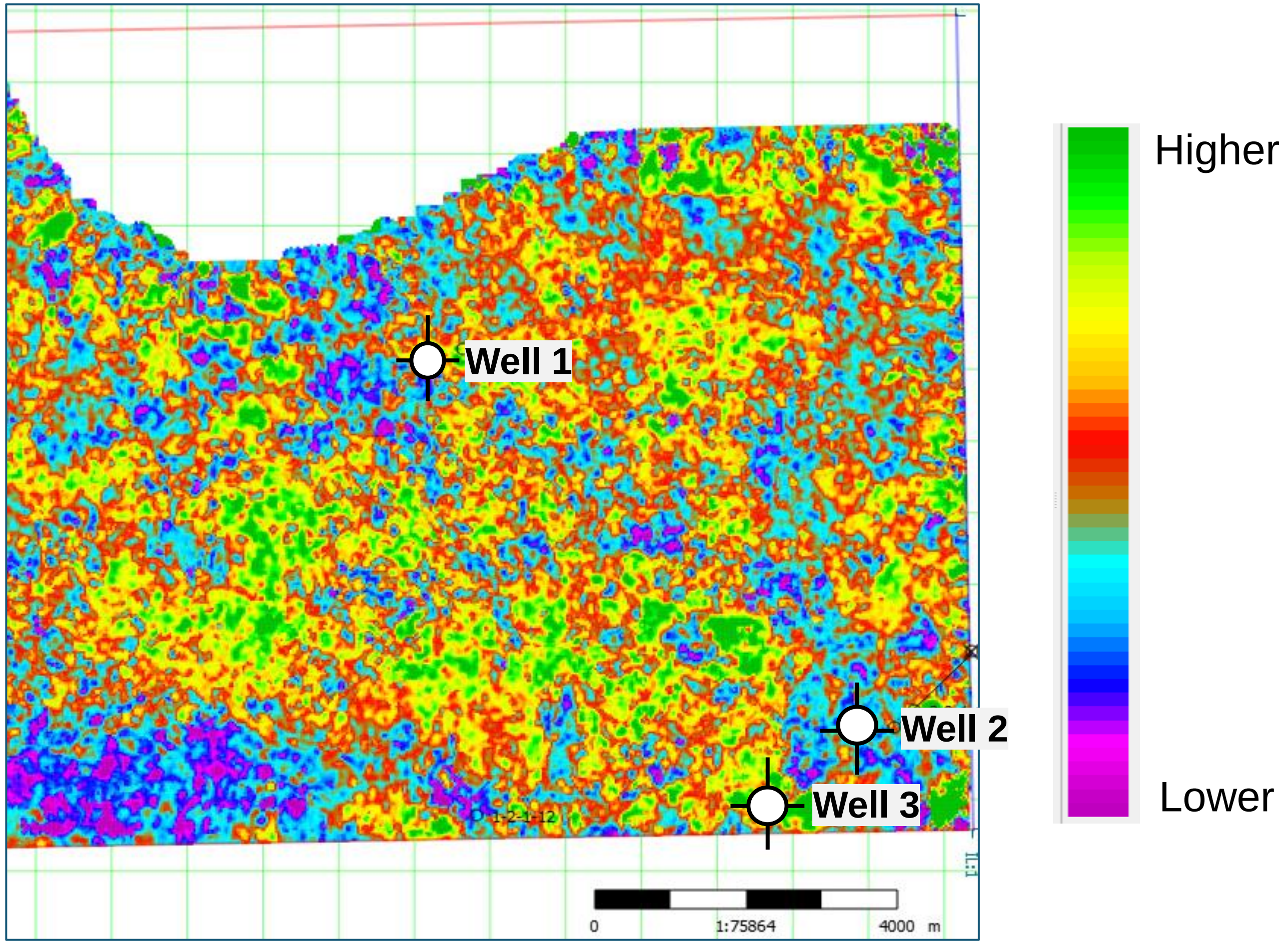
$$\Rightarrow perm = 0.01 * 10^{\frac{porosity}{3}}$$

Permeability transform with PNN



Permeability transform with PNN

- The map is averaged over a 10 ms window picked 42 ms below the Deadwood.



Summary

- 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 to porosity and permeability.
- The choice of which machine learning technique to use and the parameter selection are crucial.
- 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.
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- This methodology is applied by Allo et al. (2021) to generate hundreds of pseudo-wells to train deep feed-forward neural network (DFNN) for deriving the total porosity and volume of clays in the Dogger Formation from recorded 2D full-stack seismic lines.

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

↓

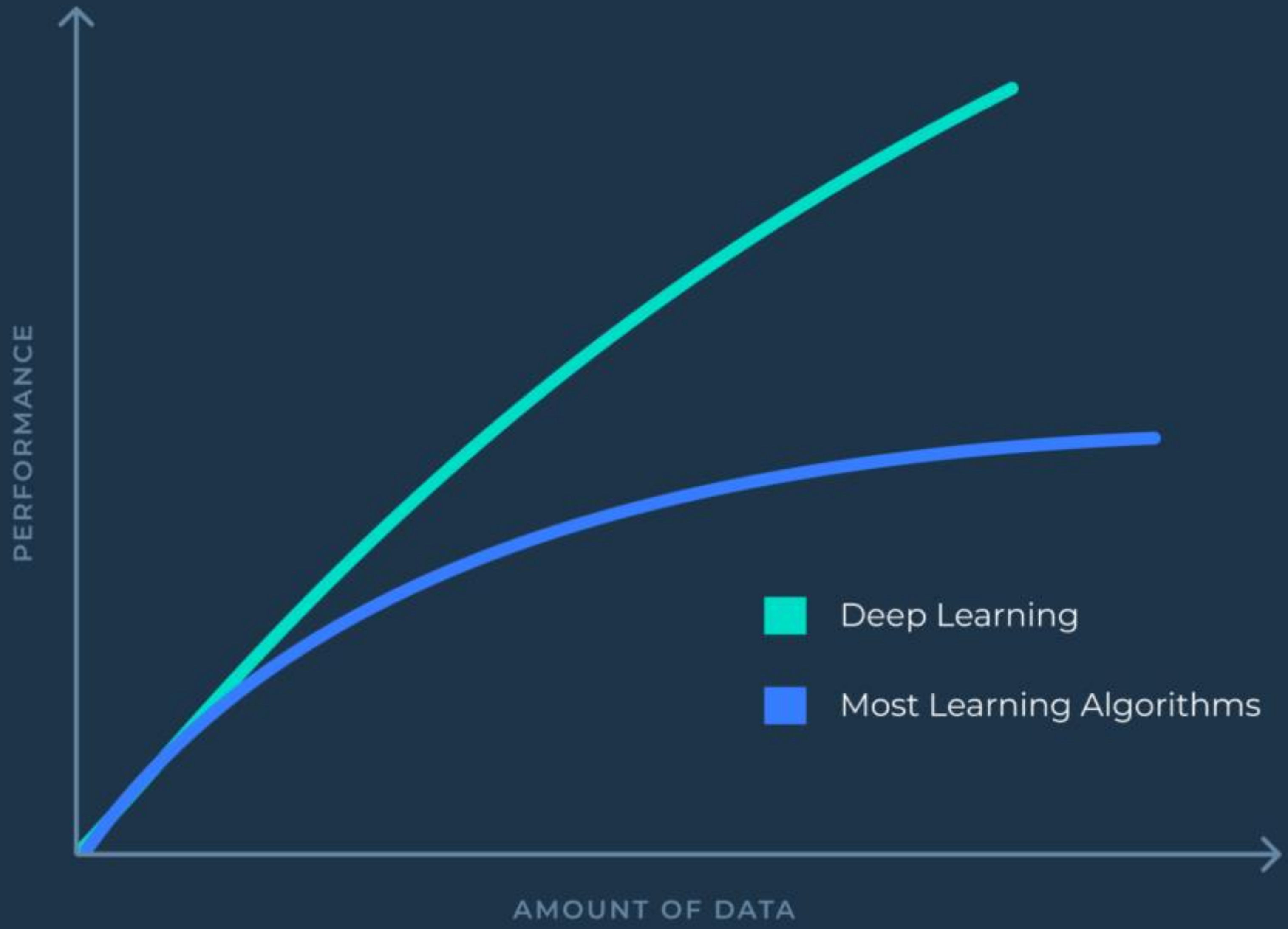
DIRECT RESERVOIR PROPERTIES PREDICTION

TIME-CONSUMING

↓

SPEED-UP RESERVOIR CHARACTERIZATION

Deep Learning benefits from extensive amounts of data



https://www.cloudapps.com

Proposed solution

HampsonRussell

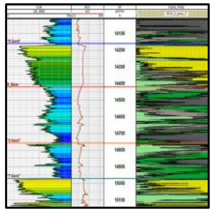
- Generate **synthetic catalog**, consisting of well log and seismic data, based on **rock physics modeling** and **statistical analysis**!

Rock physics modeling

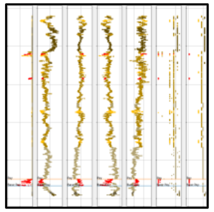
Synthetic catalog generation

Convolutional Neural Network

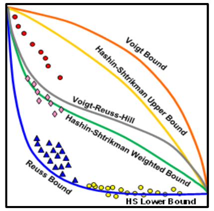
WORKFLOW



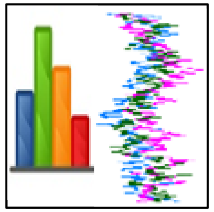
PETROPHYSICAL ANALYSIS



LITHOLAYER CLASSIFICATION

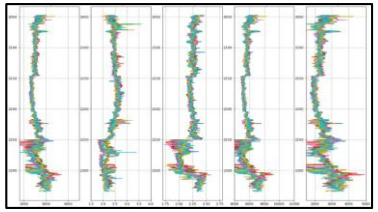


ROCK PHYSICS

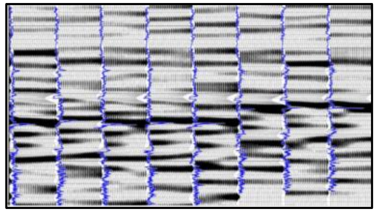


STATISTICAL ANALYSIS

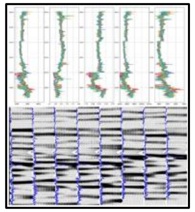
PSEUDO-WELLS SIMULATION



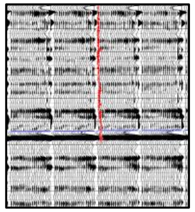
SYNTHETIC MODELING



CONVOLUTIONAL NEURAL NETWORK

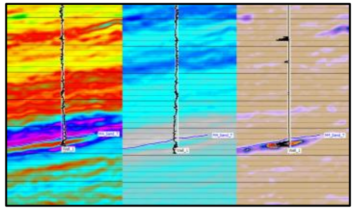


TRAINING



TRANSFER LEARNING

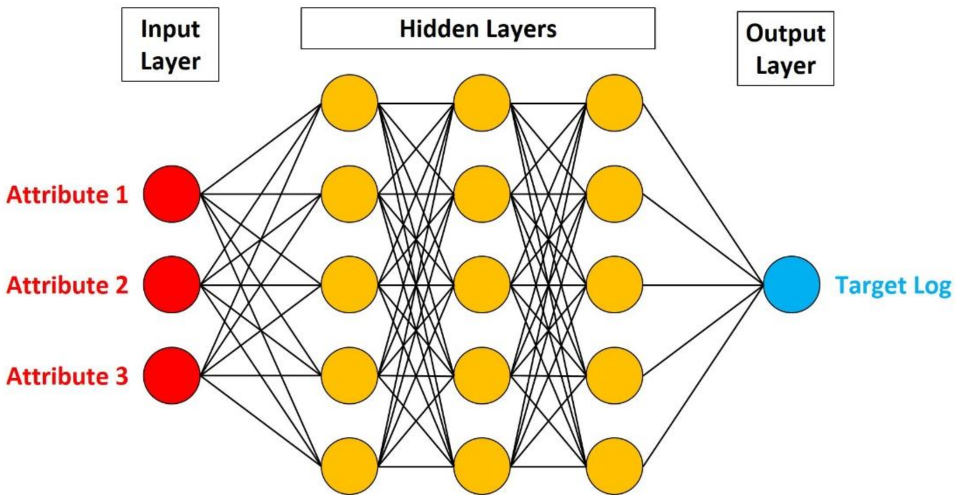
APPLYING



Deep neural networks in HampsonRussell

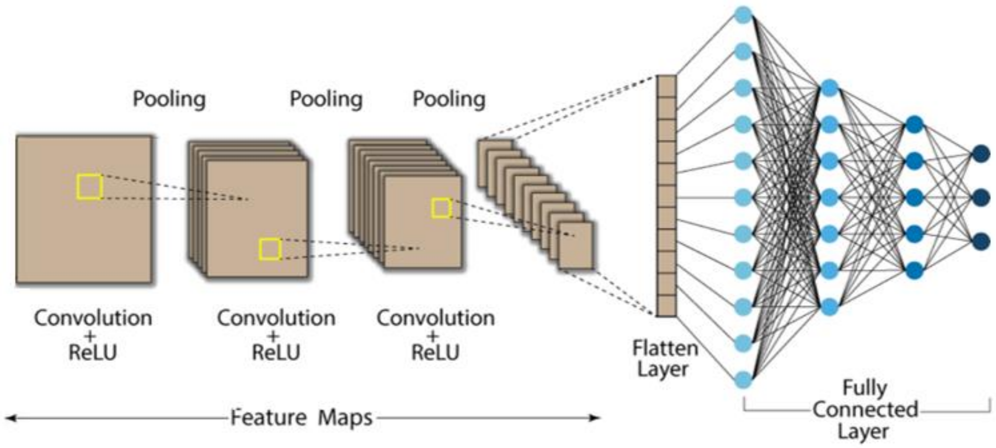
Emerge DFNN

- 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

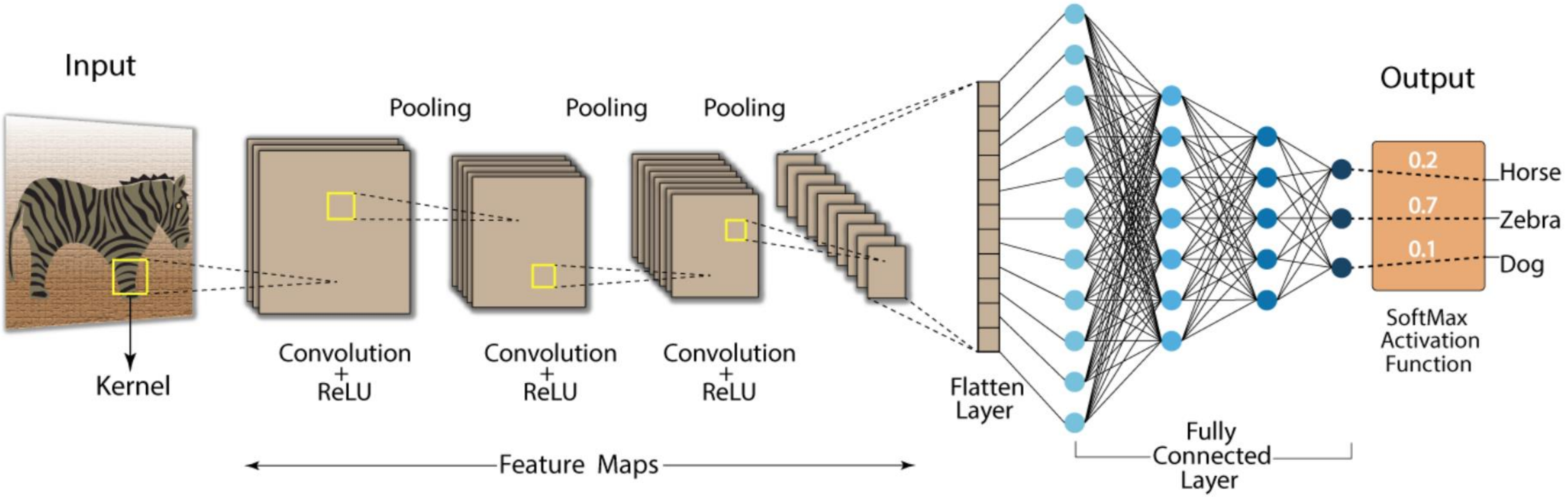


GeoAI CNN

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

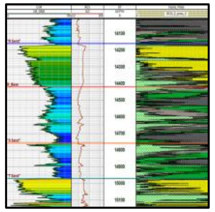


CNN

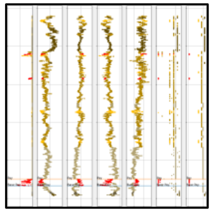


- Used in image classification
- The input consists of three sets of pixel maps (Red, Green and Blue)
- Two main steps: convolution and pooling
- The output is then flattened and input into an FC NN
- The output of the CNN can either be categories or continuous variables

WORKFLOW



PETROPHYSICAL ANALYSIS



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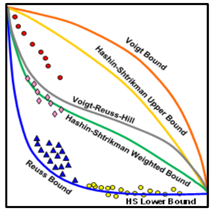
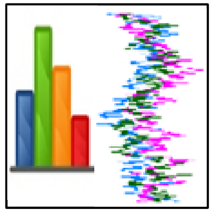


ROCK PHYSICS



STATISTICAL ANALYSIS

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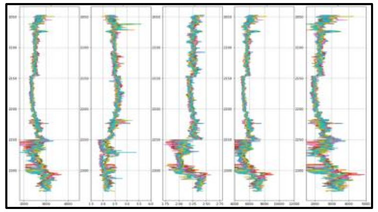
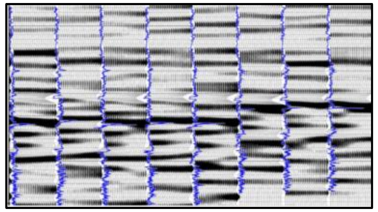


SYNTHETIC MODELING



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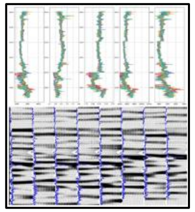
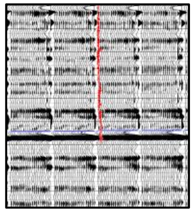
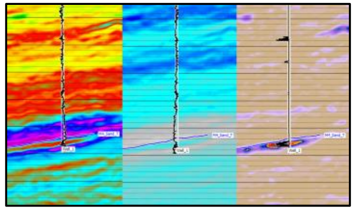


TRAINING

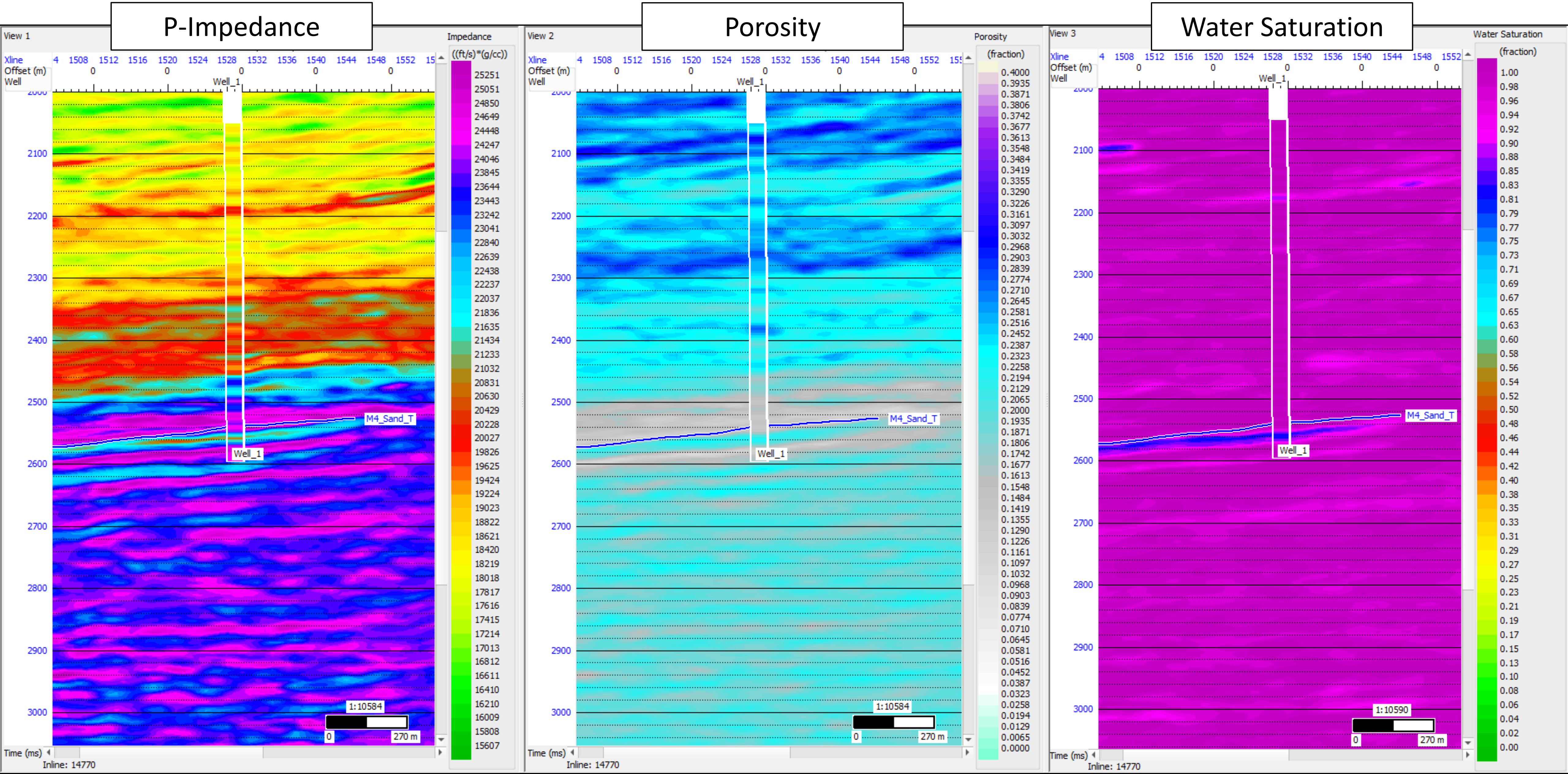


TRANSFER LEARNING

APPLYING



CNN PREDICTION RESULTS



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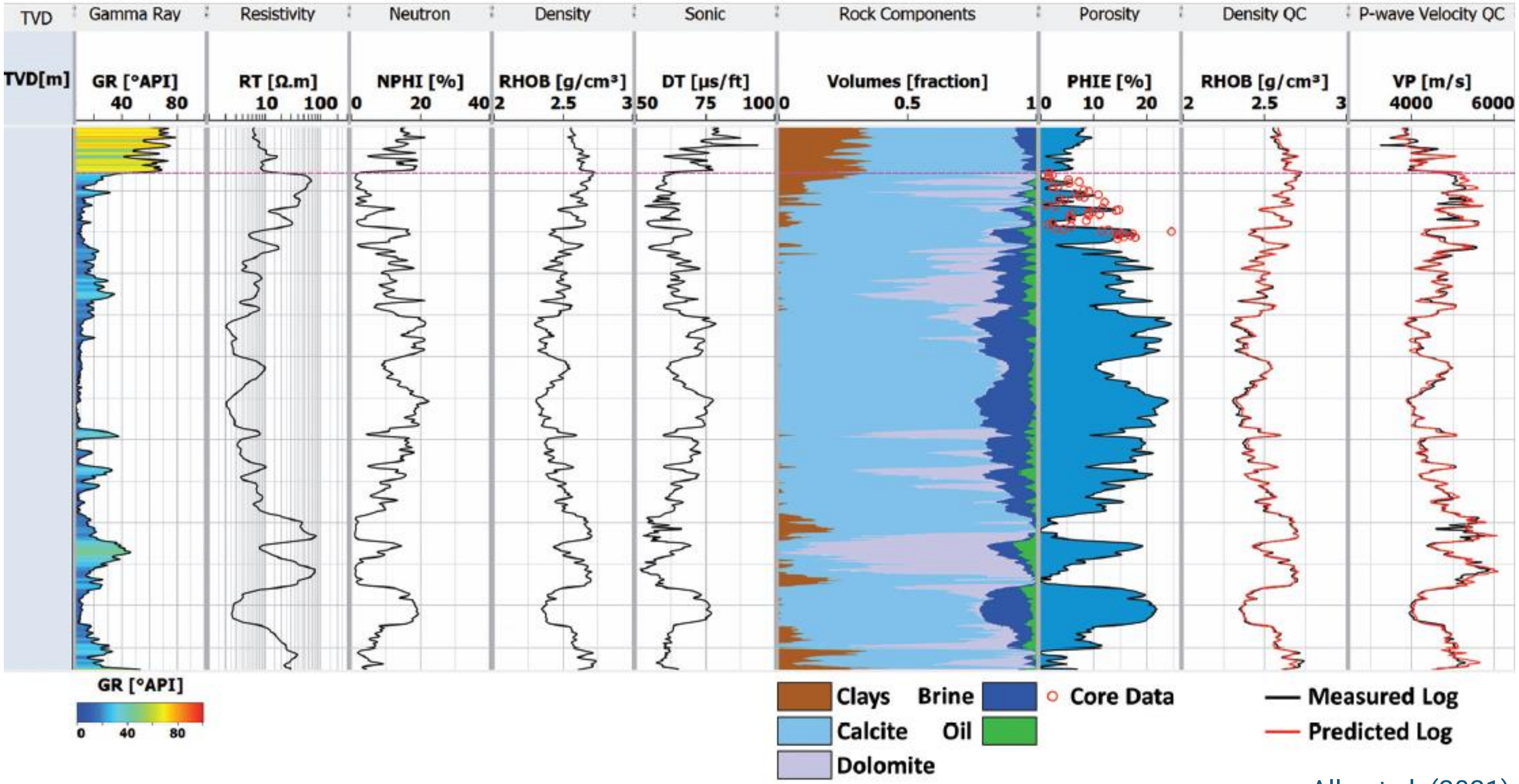
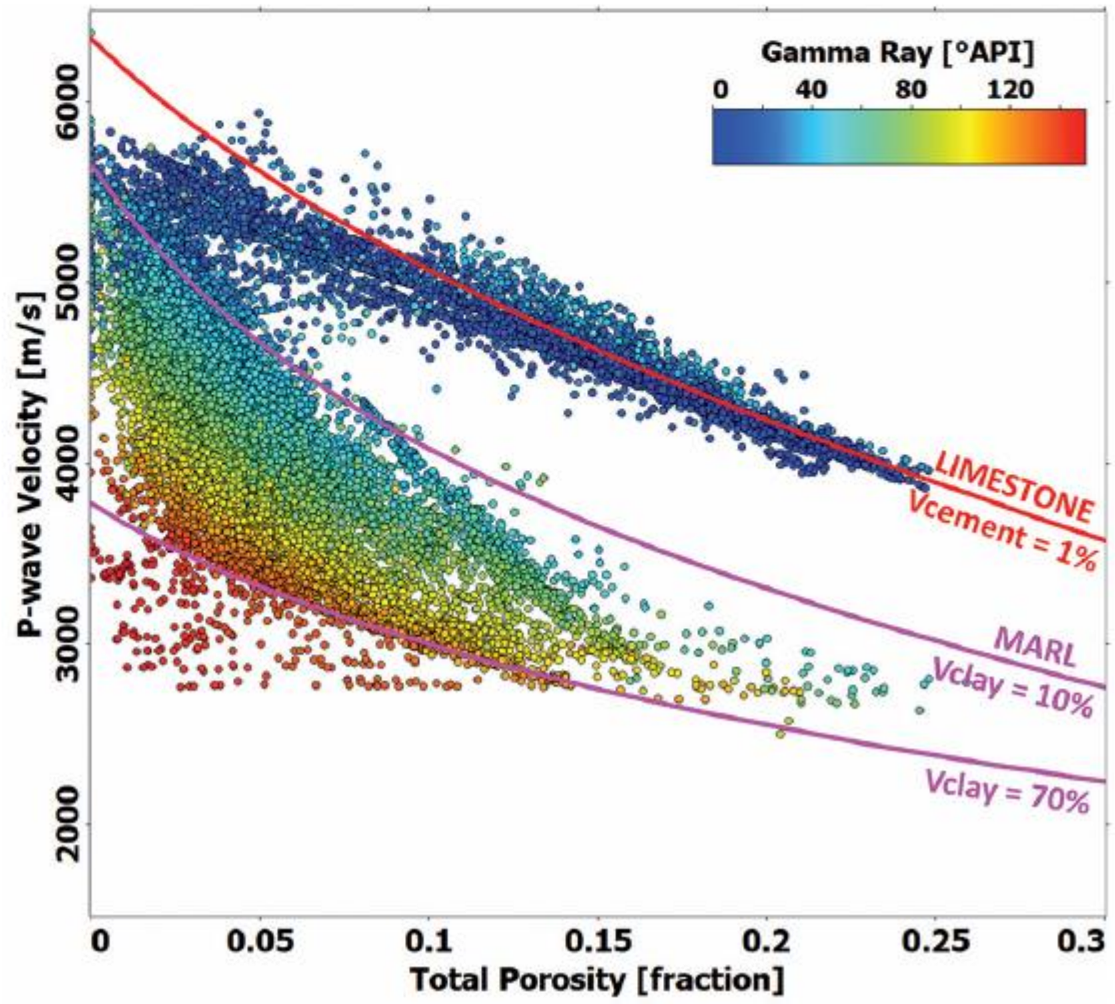
Petrophysical analysis



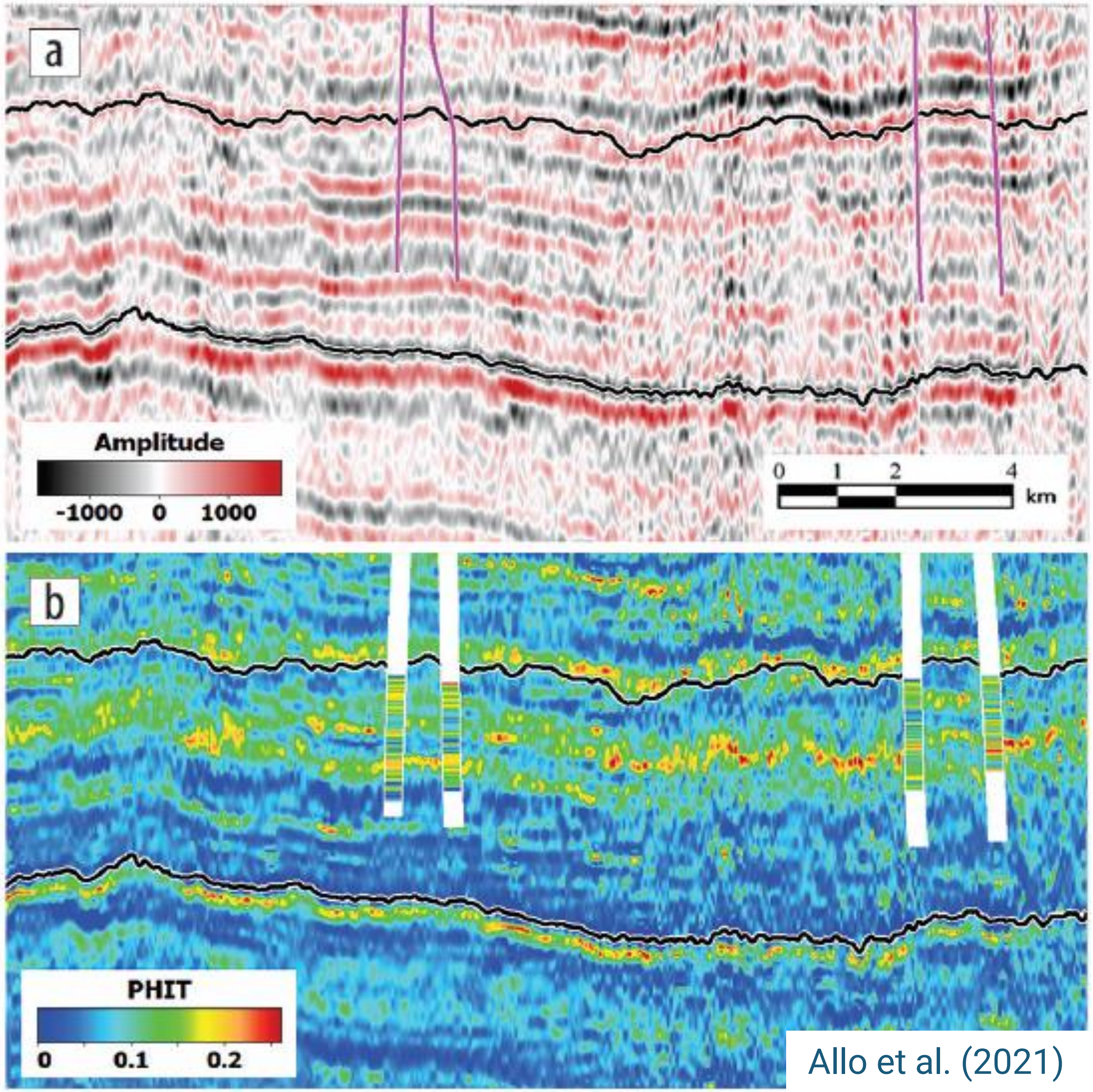
Allo et al. (2021)

Rock physics template



Allo et al. (2021)

Initial seismic and estimated total porosity

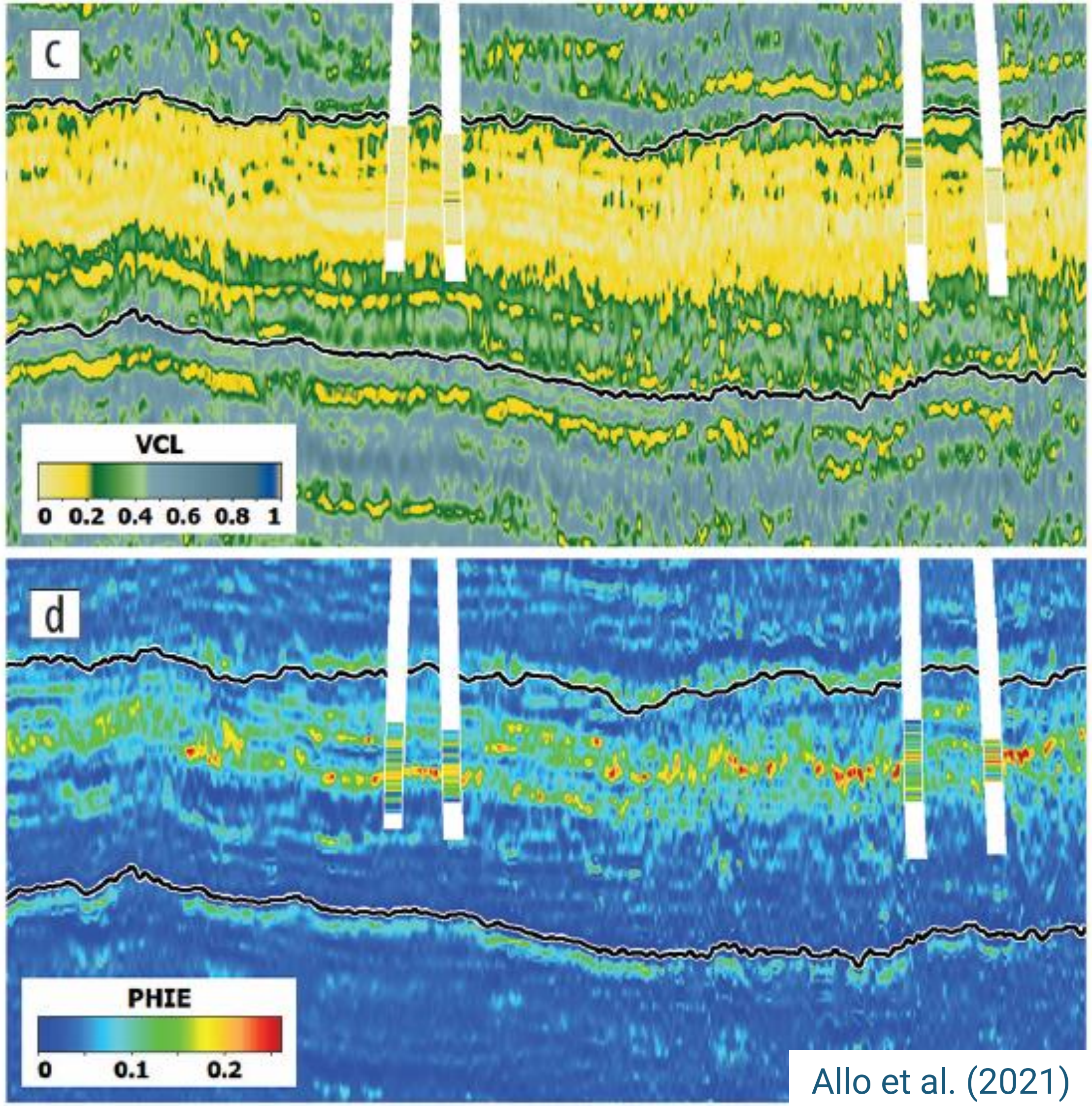


Allo et al. (2021)

a) Input seismic section.

b) Estimated total porosity.

Estimated clay volume and effective porosity

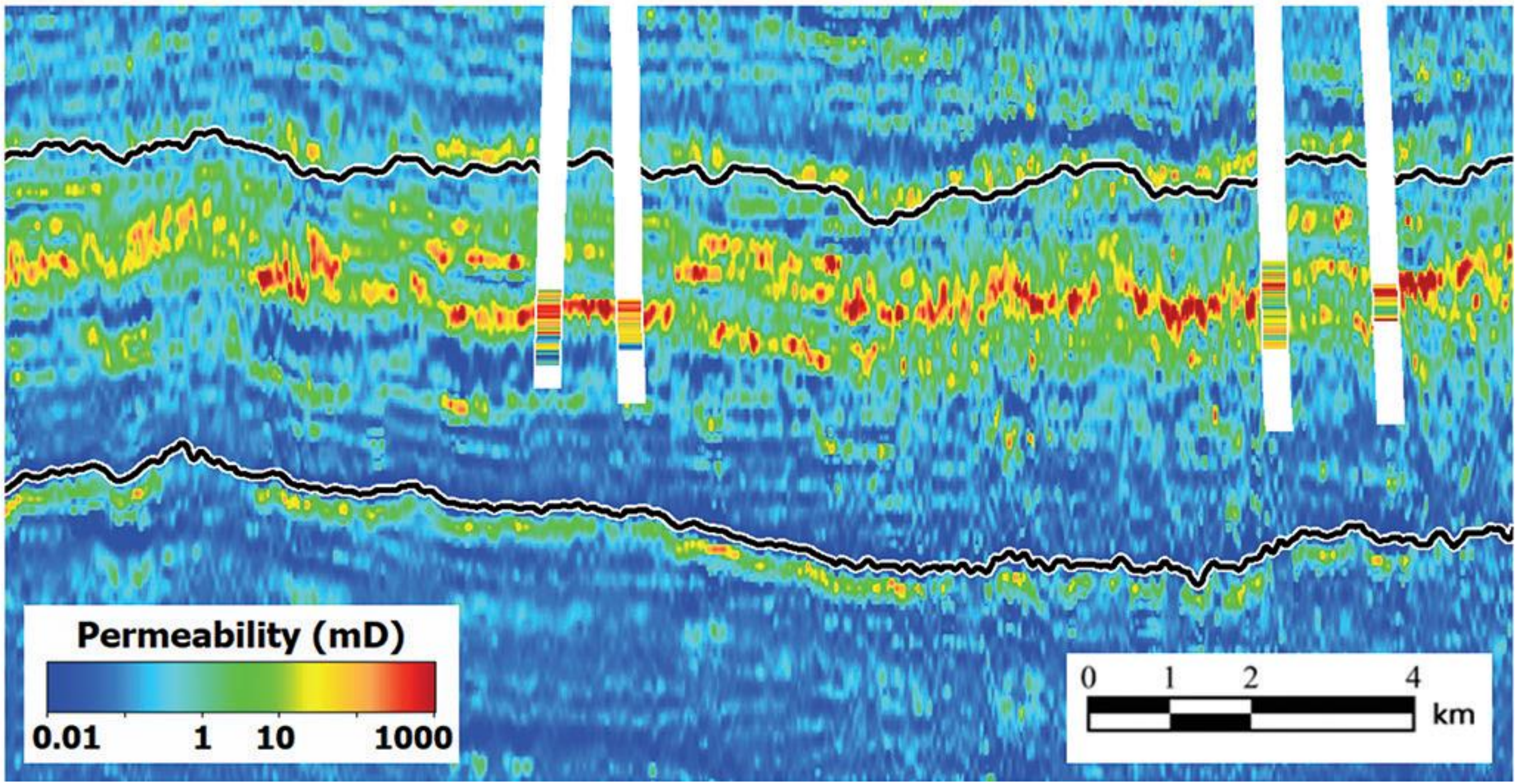


Allo et al. (2021)

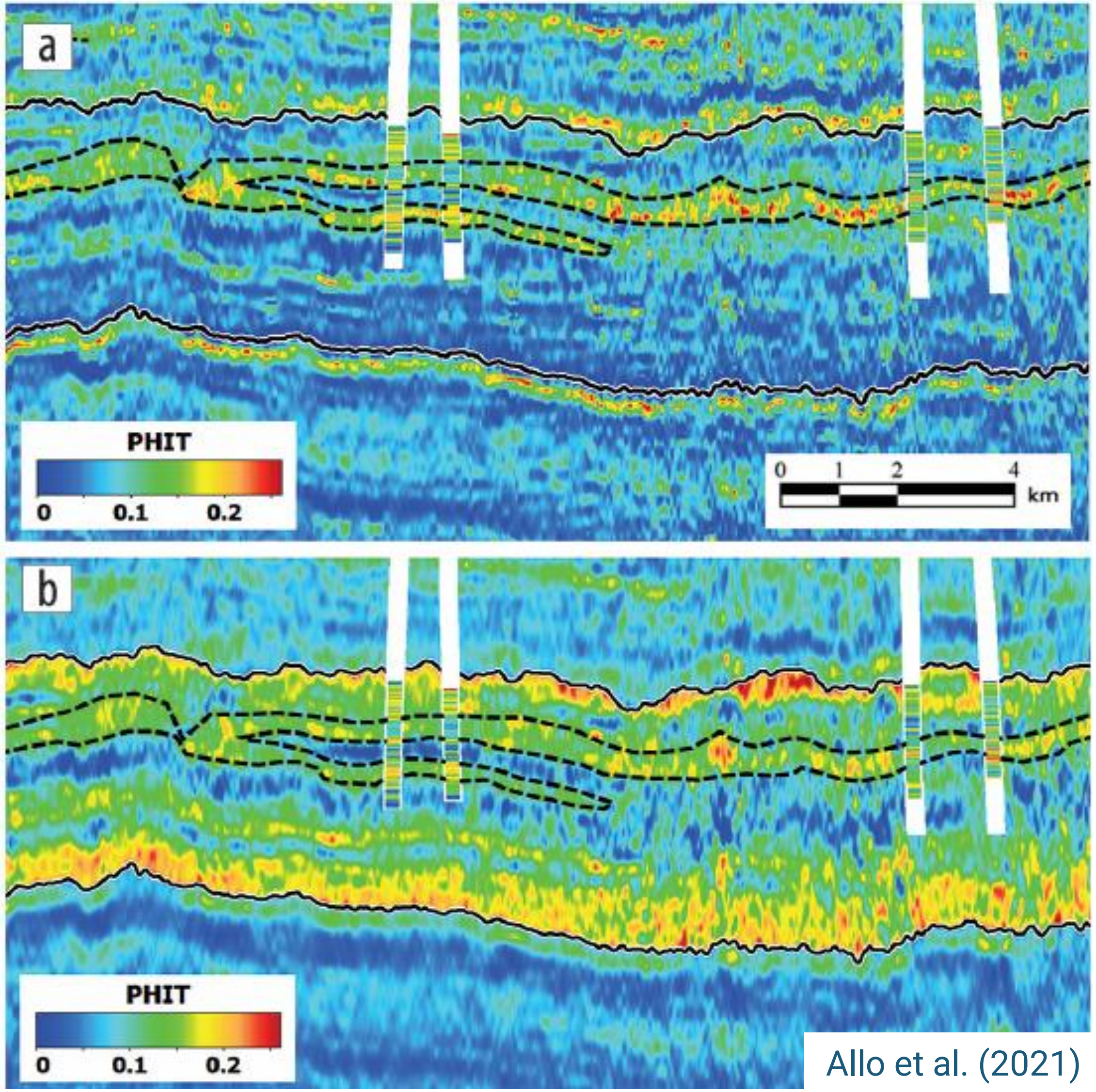
c) Estimated clay volume.

d) Estimated effective porosity.

Estimated absolute permeability



Inversion vs. Machine learning



Allo et al. (2021)

a) Total porosity estimated with DFNN.

b) Total porosity derived from inverted acoustic impedance using statistical polynomial laws.

Conclusions

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Innovative workflows for "Energy Transition"

- Geothermal reservoir
- CO_2 storage
- Soil characterization (windfarm)

Netherlands Journal of Geosciences

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Original Article

Cite this article: Boersma QD, Bruna PO, de Hoop S, Vinci F, Tehrani AM, and Bertotti G. The impact of natural fractures on heat extraction from tight Triassic sandstones in the West Netherlands Basin: a case study combining well, seismic and numerical data.

The impact of natural fractures on heat extraction from tight Triassic sandstones in the West Netherlands Basin: a case study combining well, seismic and numerical data

Quinten D. Boersma[1], Pierre Olivier Bruna[1], Stephan de Hoop[1], Francesco Vinci[2], Ali Moradi Tehrani[3] and Giovanni Bertotti[1]

[1]TU Delft, Stevinweg 1, 2628 CN, Delft, the Netherlands; [2]PanTerra, Leiderdorp, the Netherlands and [3]CGG, The Hague, the Netherlands

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Seismic reservoir characterization of potential CO_2 storage reservoir sandstones in Smeaheia area, Northern North Sea

hr

Manzar Fawad[a,*], MD Jamilur Rahman[a], Nazmul Haque Mondol[a,b]

[a] University of Oslo, Norway
[b] Norwegian Geotechnical Institute, Norway

The Leading Edge

hr

Characterization of a carbonate geothermal reservoir using rock-physics-guided deep neural networks

By Fabien Allo, Jean-Philippe Coulon, Jean-Luc Formento, Romain Reboul, CGG, and Laure Capar, Mathieu Darnet, Benoit Issautier, Stephane Marc, Alexandre Stopin, BRGM

hr

MADRID 2015

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Time-lapse AVO Analysis of 3D Surface Seismic Data Sets from the Ketzin CO2 Storage Pilot Site, Germany

M. Ivandic* (Uppsala University), C. Juhlin (Uppsala University) & S. Lüth (GFZ German Research Centre for Geosciences)

Geophysical Prospecting

EAGE EUROPEAN ASSOCIATION OF GEOSCIENTISTS & ENGINEERS

Geophysical Prospecting, 2018 doi: 10.1111/1365-2478.12666

Monitoring CO_2 saturation using time-lapse amplitude versus offset analysis of 3D seismic data from the Ketzin CO_2 storage pilot site, Germany

hr

Monika Ivandic[1*], Peter Bergmann[2,3], Juliane Kummerow[2], Fei Huang[1], Christopher Juhlin[1] and Stefan Lueth[2]

[1]Department of Earth Sciences, Uppsala University, Villavägen 16, 75236, Uppsala, Sweden, [2]GFZ German Research Centre for Geosciences, Helmholtz Centre Potsdam, Telegrafenberg, 14473, Potsdam, Germany, and [3]SINTEF Petroleum Research, Trondheim, Norway

Received February 2017, revision accepted June 2018

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July-August 2009
10.1190/1.3167784

The Leading Edge

Seismic characterization of a CO_2 flood in the Ardley coals, Alberta, Canada

jw hr

Jason McCrank and Don C. Lawton

Conclusions

- In this presentation, I discussed how GeoSoftware tools can be used to map possible geothermal reservoirs sites.
- There are two recommended workflows:
  - Inversion followed by machine learning.
  - Rock physics driven machine learning.

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↓

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SPEED-UP RESERVOIR CHARACTERIZATION

Q&A

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