Triassic stratigraphic architecture, reservoir quality, and Machine Learning

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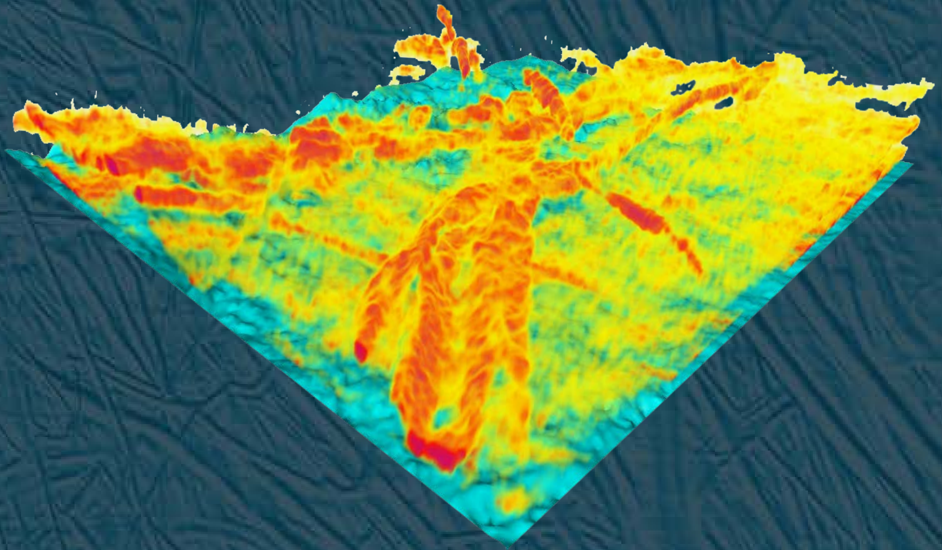


Can a computer learn to map stratigraphic architecture and reservoir quality…

by training on data?

Triassic plays in the Barents Sea

Low commercial success rate in

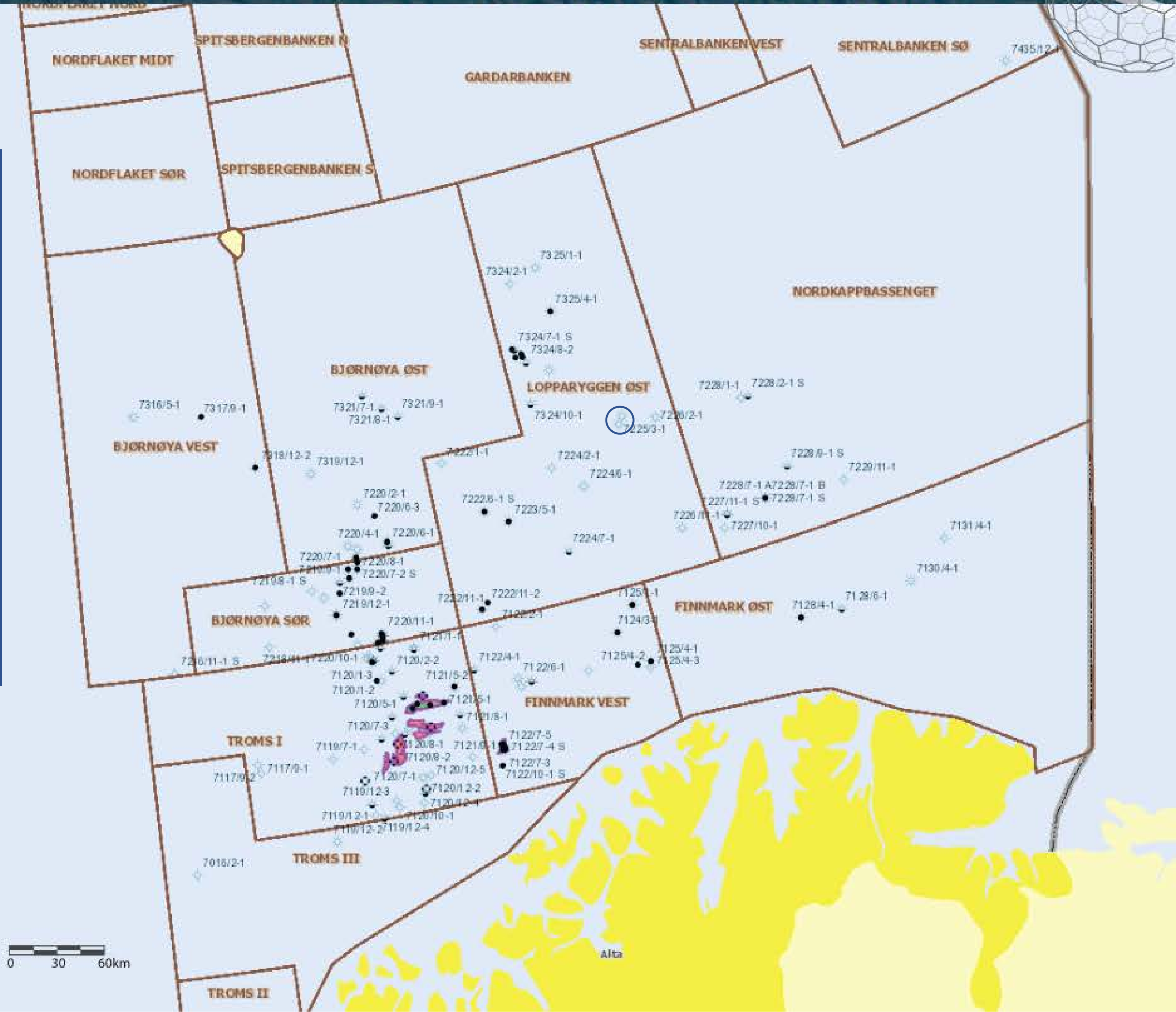
Barents Sea
116 exploration wells

↓

56 Technical / Comm. Discovery wells
3 potential development projects
2 Fields

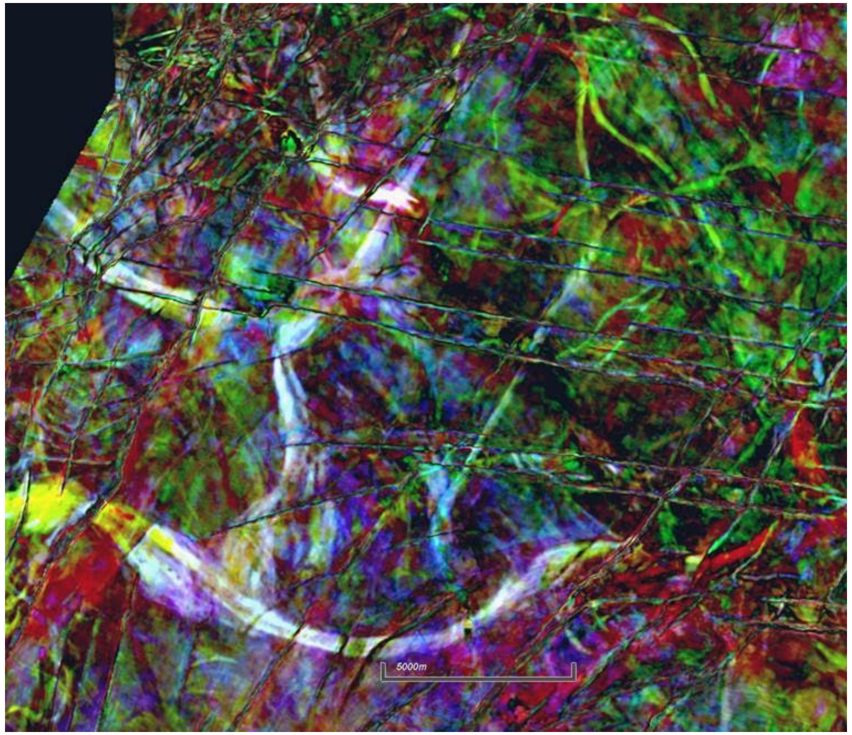
There are no simple rules that help us predict the location of the next big discovery

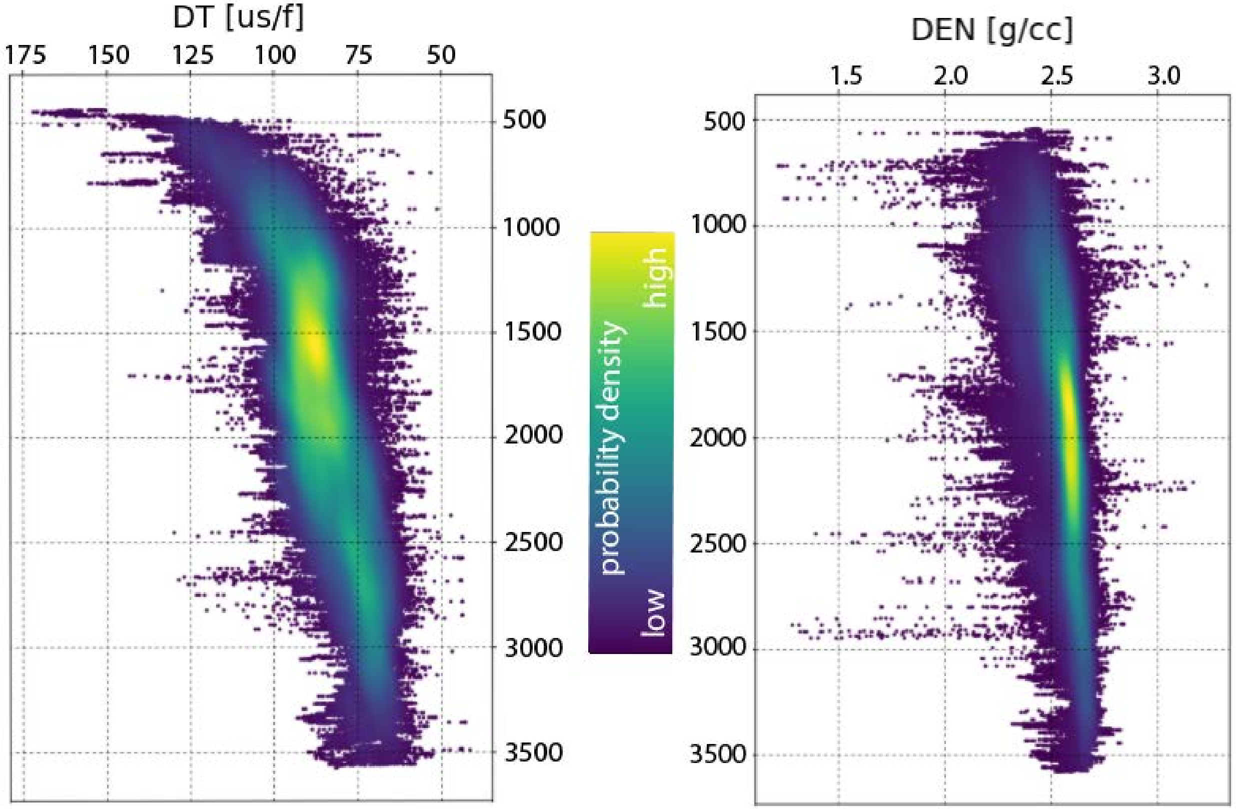
The prediction tasks petroleum geoscientists need to do are hard to codify



We have a lot of good data

- Excellent seismic imaging of sedimentary geology
- Abundant log and core data available





Can we use this data, and artificial intelligence, to improve reservoir prediction?

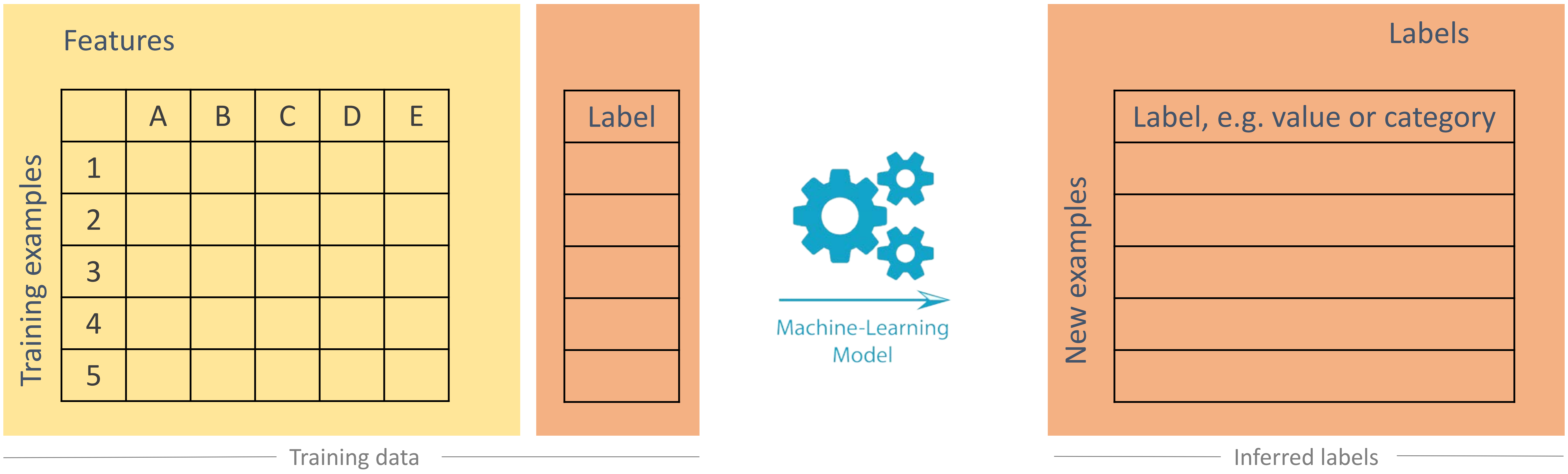
What is Machine Learning and Supervised Learning?

Machine learning: “gives computers the ability to learn without being explicitly programmed” Arthur Samuel, 1959

Supervised learning: “the machine learning task of inferring a function from labeled training data”

Input

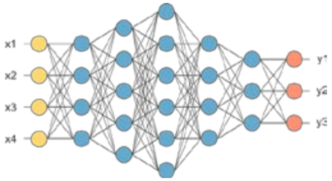
Output



How can we apply Machine Learning to reservoir quality studies?

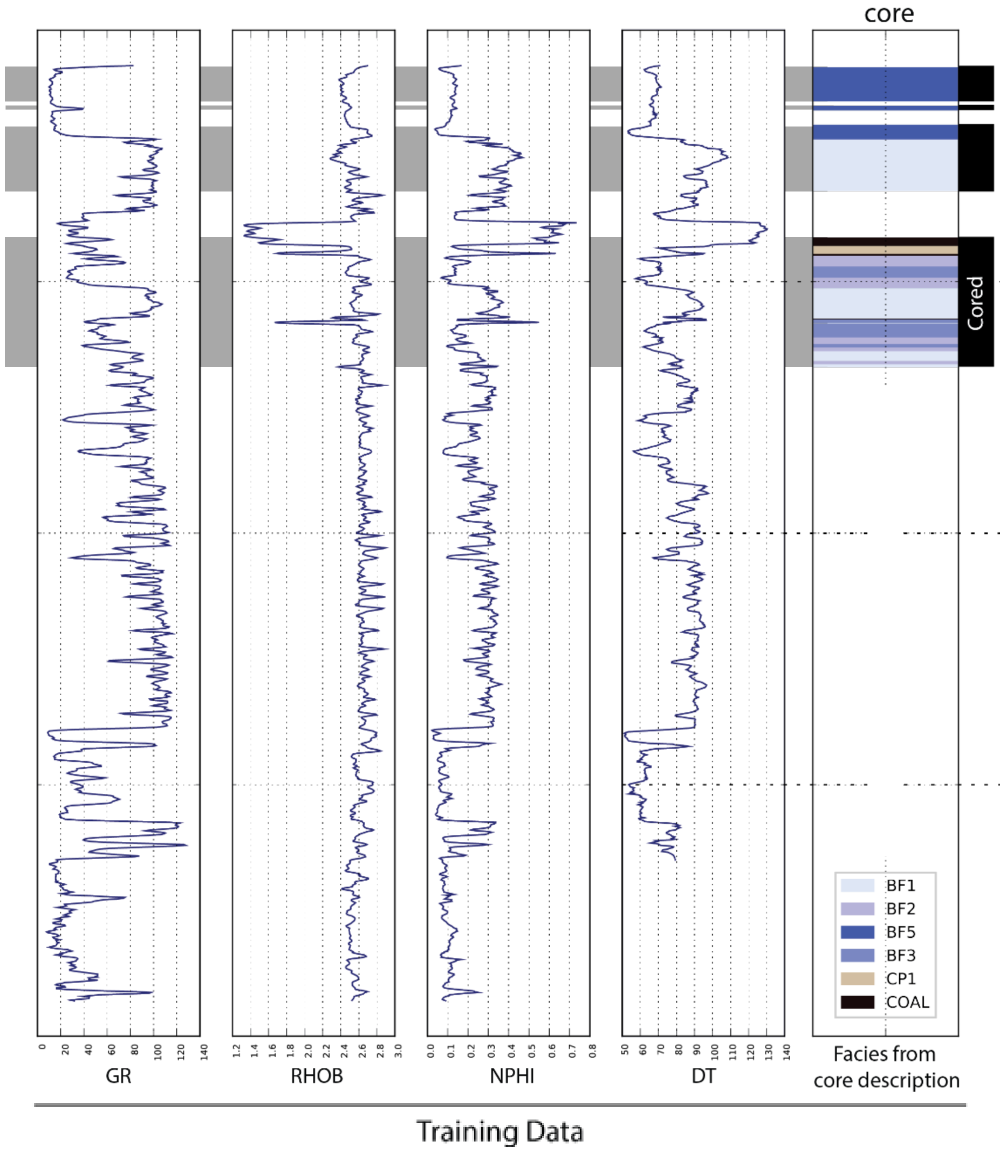
Input Features		**ML models**	**Output** Labels
Wireline logs	core data		Porosity, permeability, facies, and facies association **logs**
AI, Vp/Vs	logs, core data		Porosity, permeability, facies, and facies association **cubes**
Partial stacks	logs, core data		Porosity, permeability, facies, and facies association **cubes**

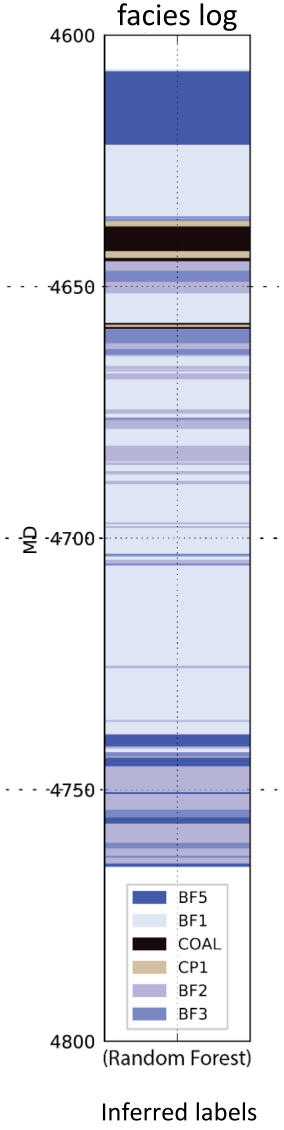
Training data



Inferred labels

AI-Assisted Facies Classification





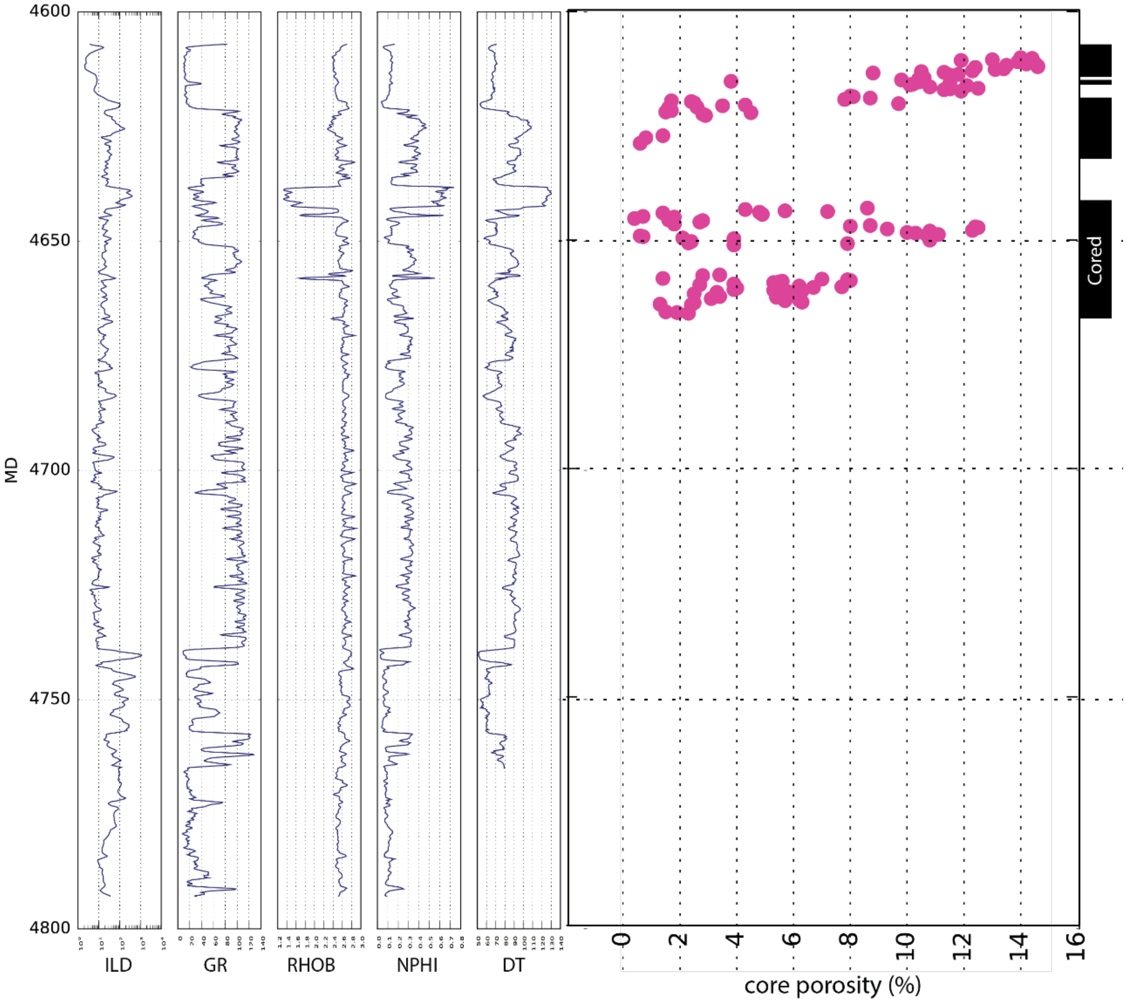
Supervised Learning

"learns a function from labeled training data"

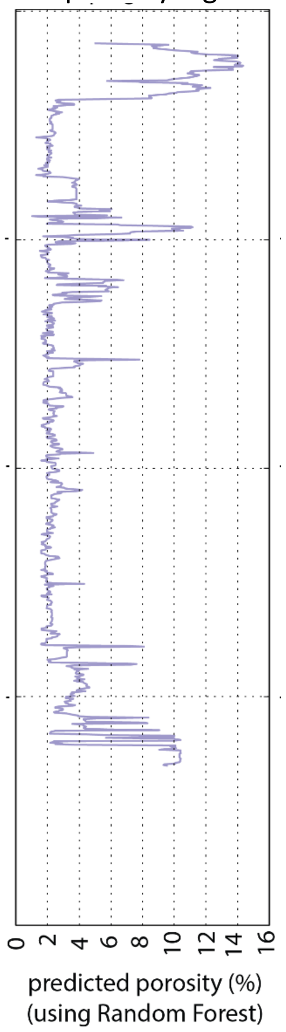
Inference

"the function can be used to label new data"

AI-Assisted Rock-Property Prediction



Training Data



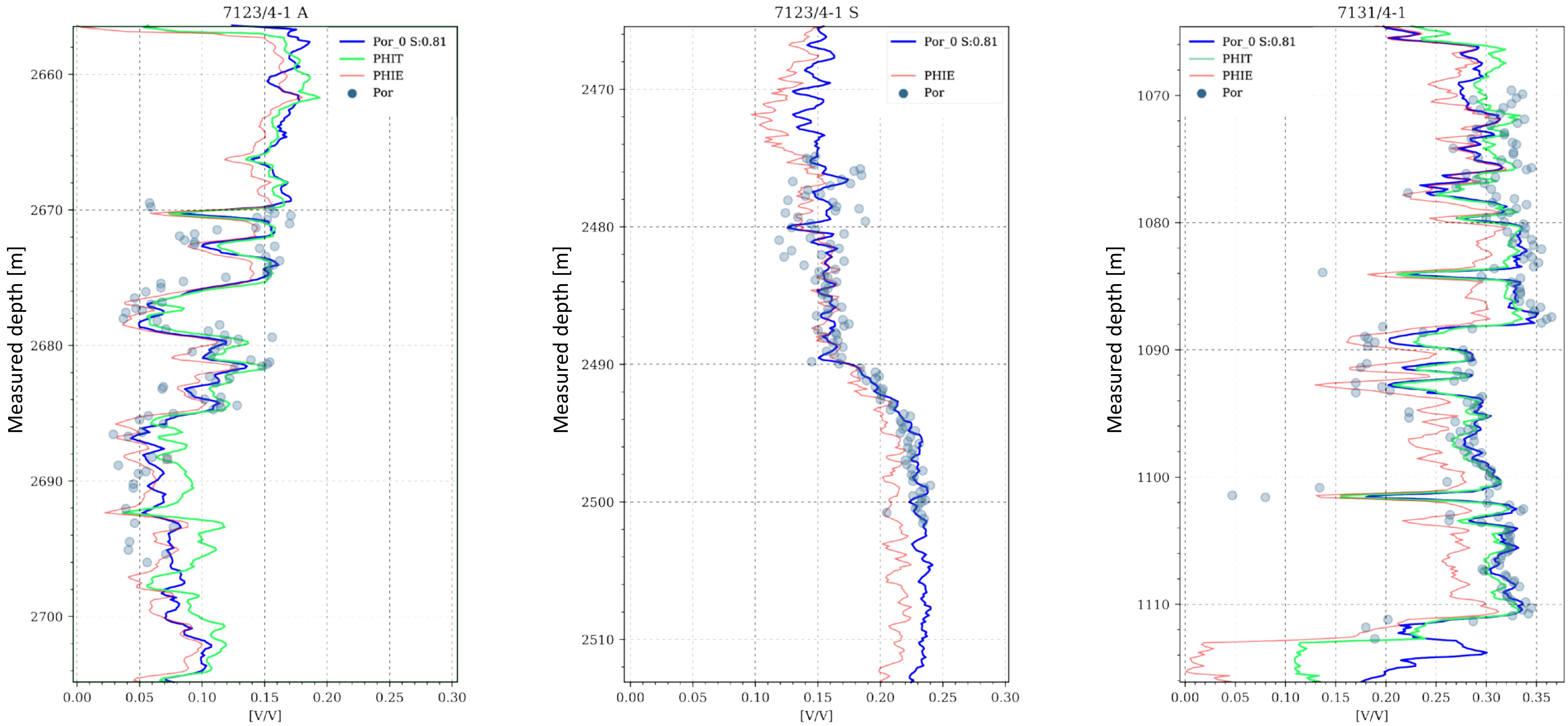
Inferred porosity

Supervised Learning can be applied to predict:

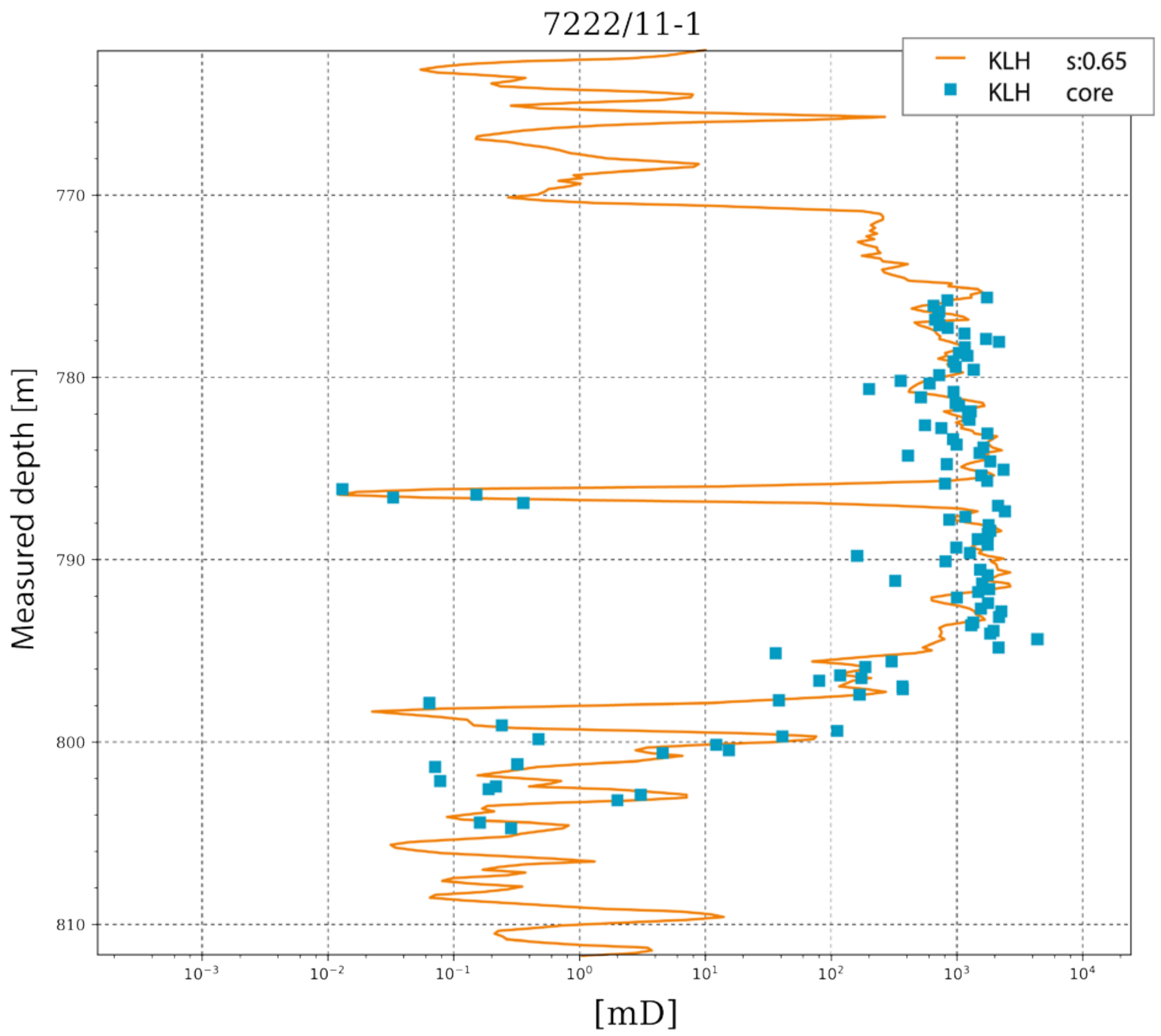
- Porosity
- Permeability
- Saturation
- Source Rock properties
- Or any property

« We simply need data to train on »

AI-Assisted Porosity Prediction; Snadd and Kobbe formations



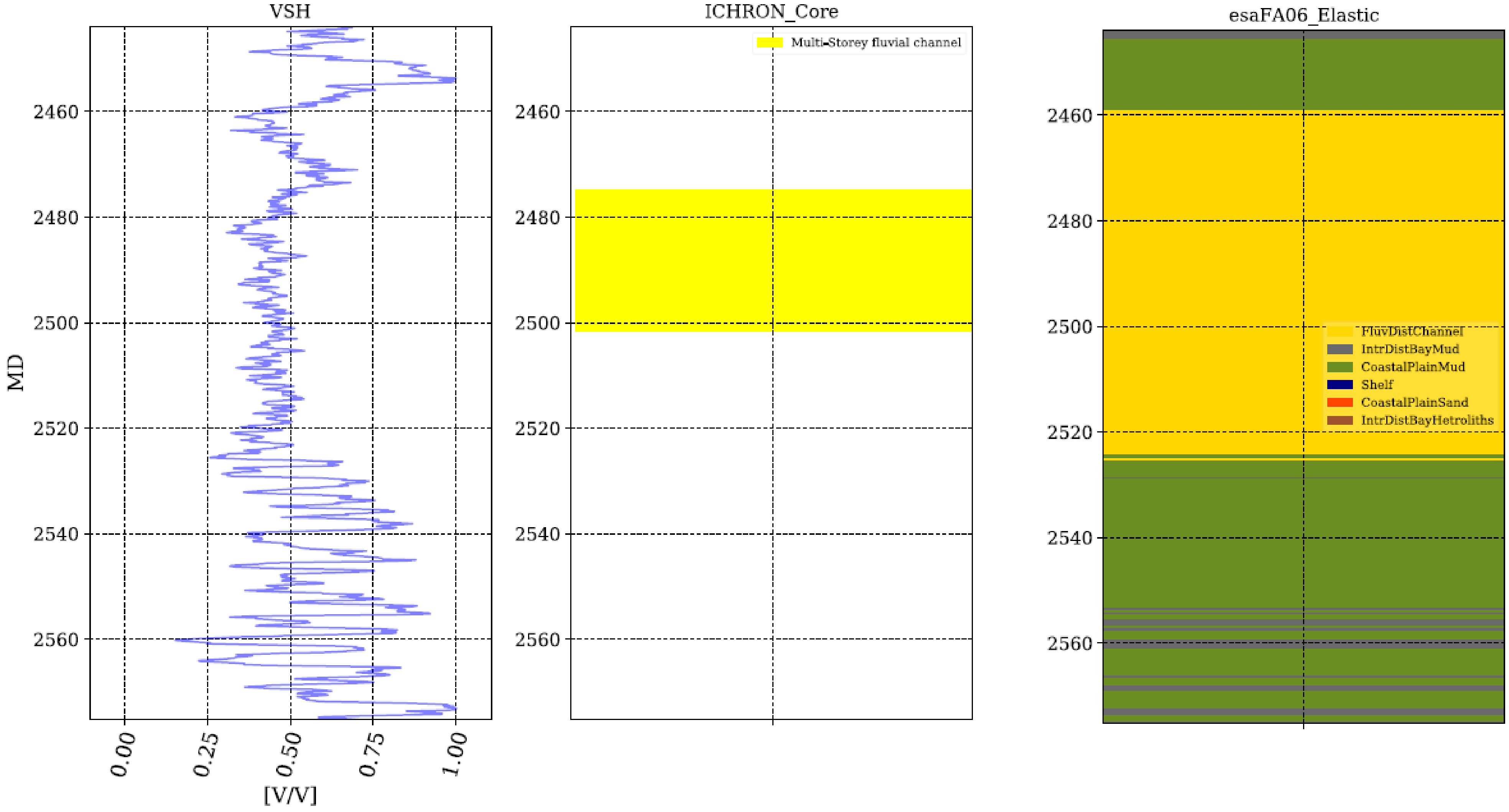
AI-Assisted Permeability Prediction; Snadd and Kobbe formations



Permeability is predicted from wireline logs and core data

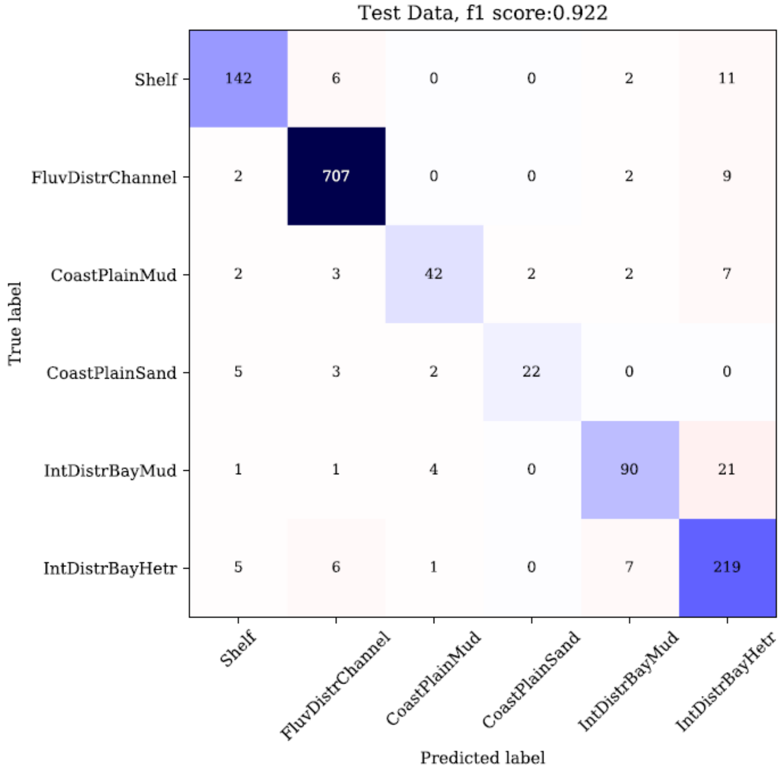
- Input logs: DEN, DT, DTS_mlFilled, NEU, RDEP, RMED, Formation, Depth, Relative position in formation
- Note that KLH is <u>not</u> estimated as a function of porosity

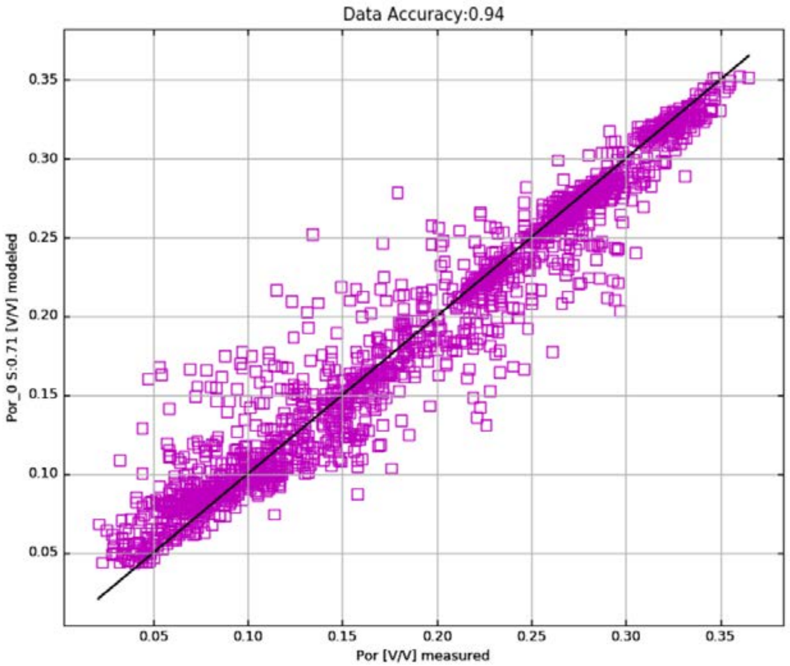
AI-Assisted Facies Prediction; Snadd Formation

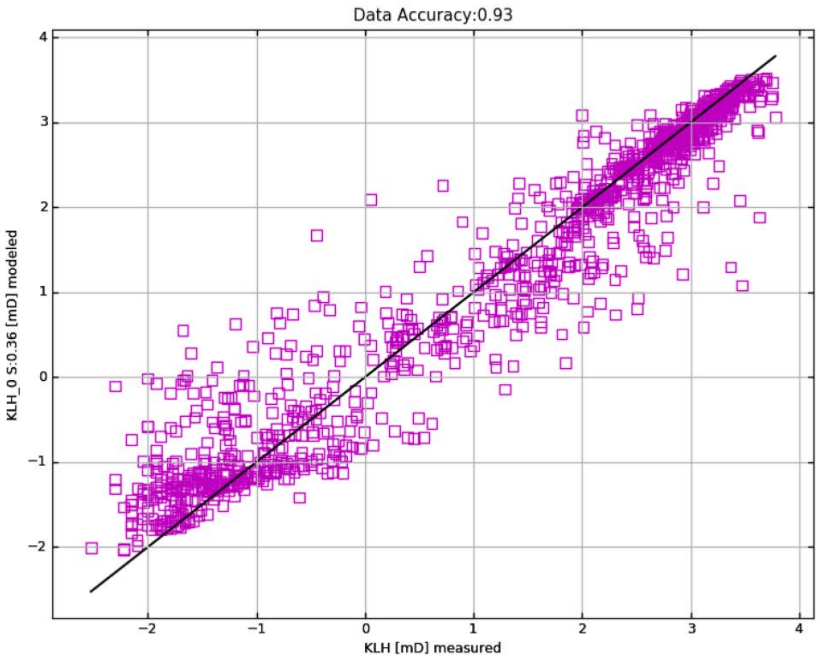


Measuring accuracy

By blind testing







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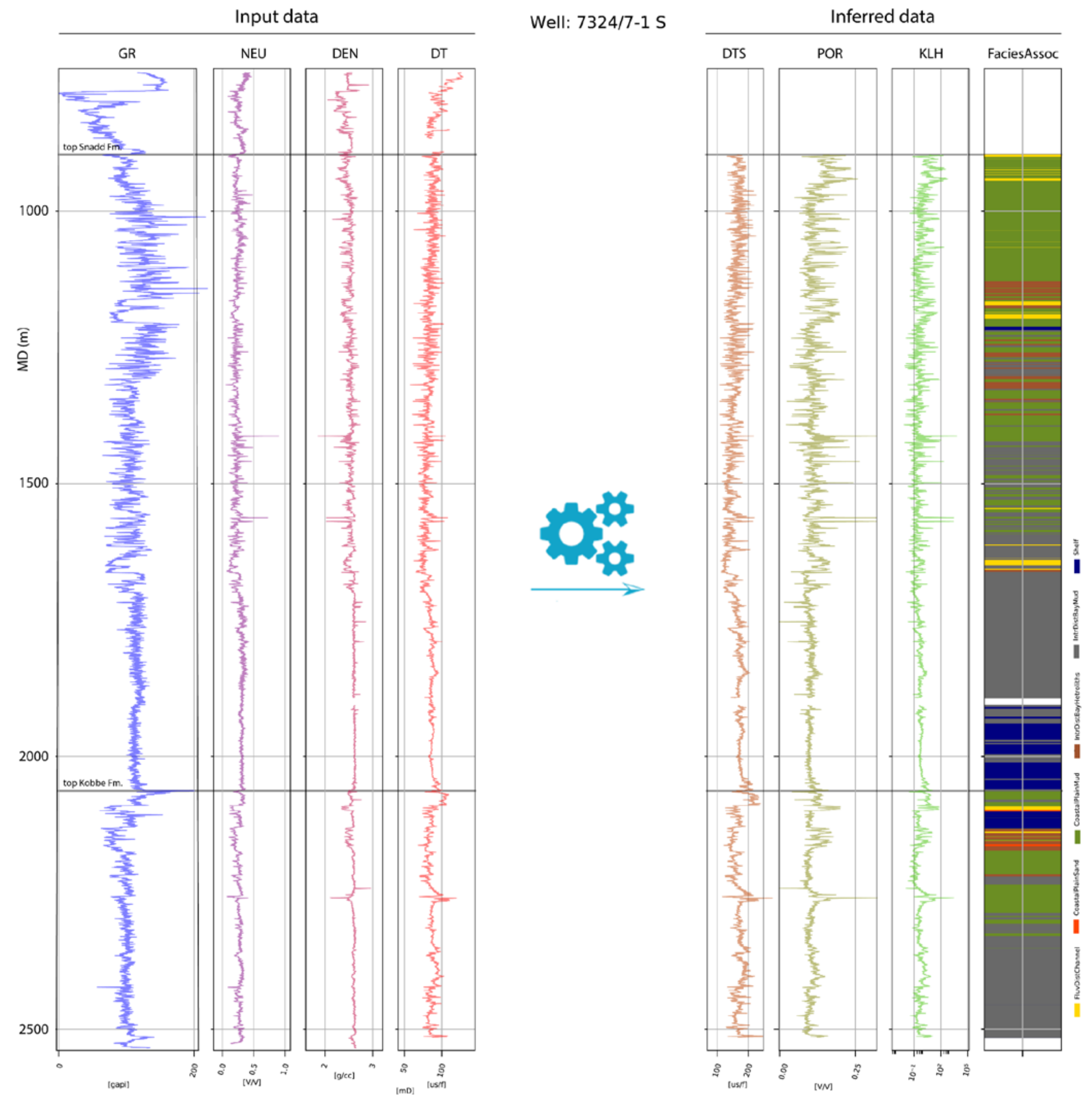
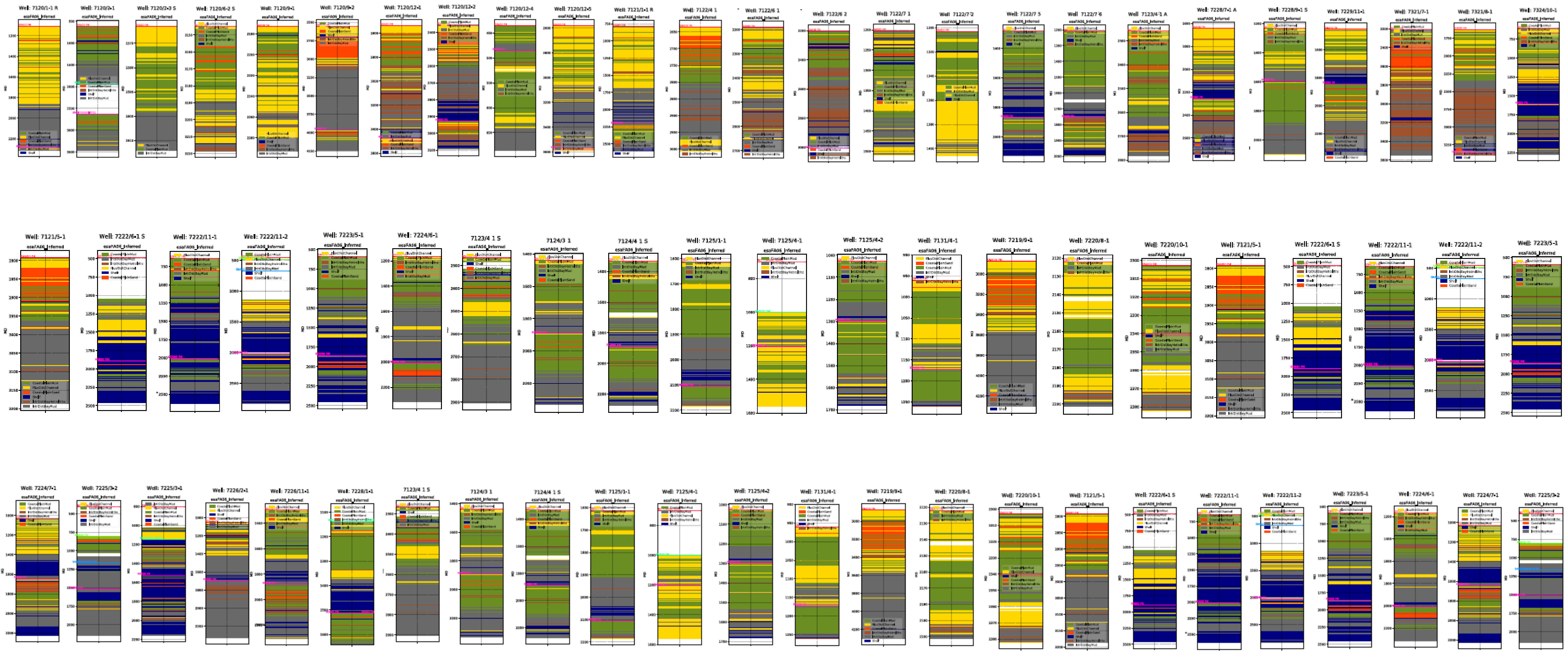
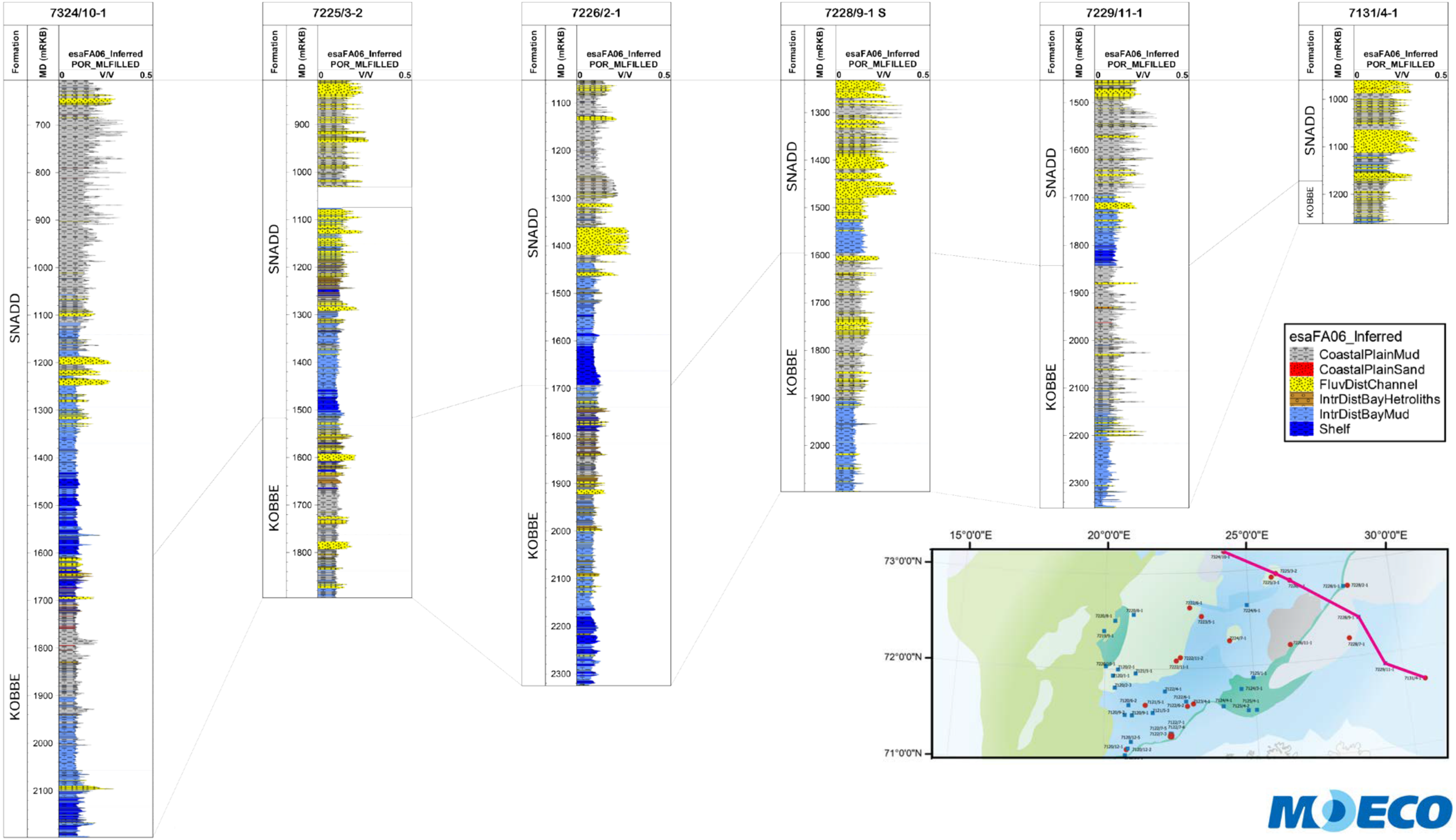
Rock properties are predicted for the Snadd and Kobbe formations in all available wells

		Blind test	60/40 split
Shear sonic	score:	93,4%	99%
Porosity	score:	71,4%	88%
Permeability	score:	35,9%	81,4%
Facies associations	score:	50,0%	92,2%



Orders of magnitude increase of data set





7324/10-1
7225/3-2
7226/2-1
7228/9-1 S
7229/11-1
7131/4-1
Formation
MD (mRKB)
esaFA06_Inferred
POR_MLFILLED
0 V/V 0.5
SNADD
KOBBE
esaFA06_Inferred
CoastalPlainMud
CoastalPlainSand
FluvDistChannel
IntrDistBayHetroliths
IntrDistBayMud
Shelf
15°0'0"E
20°0'0"E
25°0'0"E
30°0'0"E
73°0'0"N
72°0'0"N
71°0'0"N

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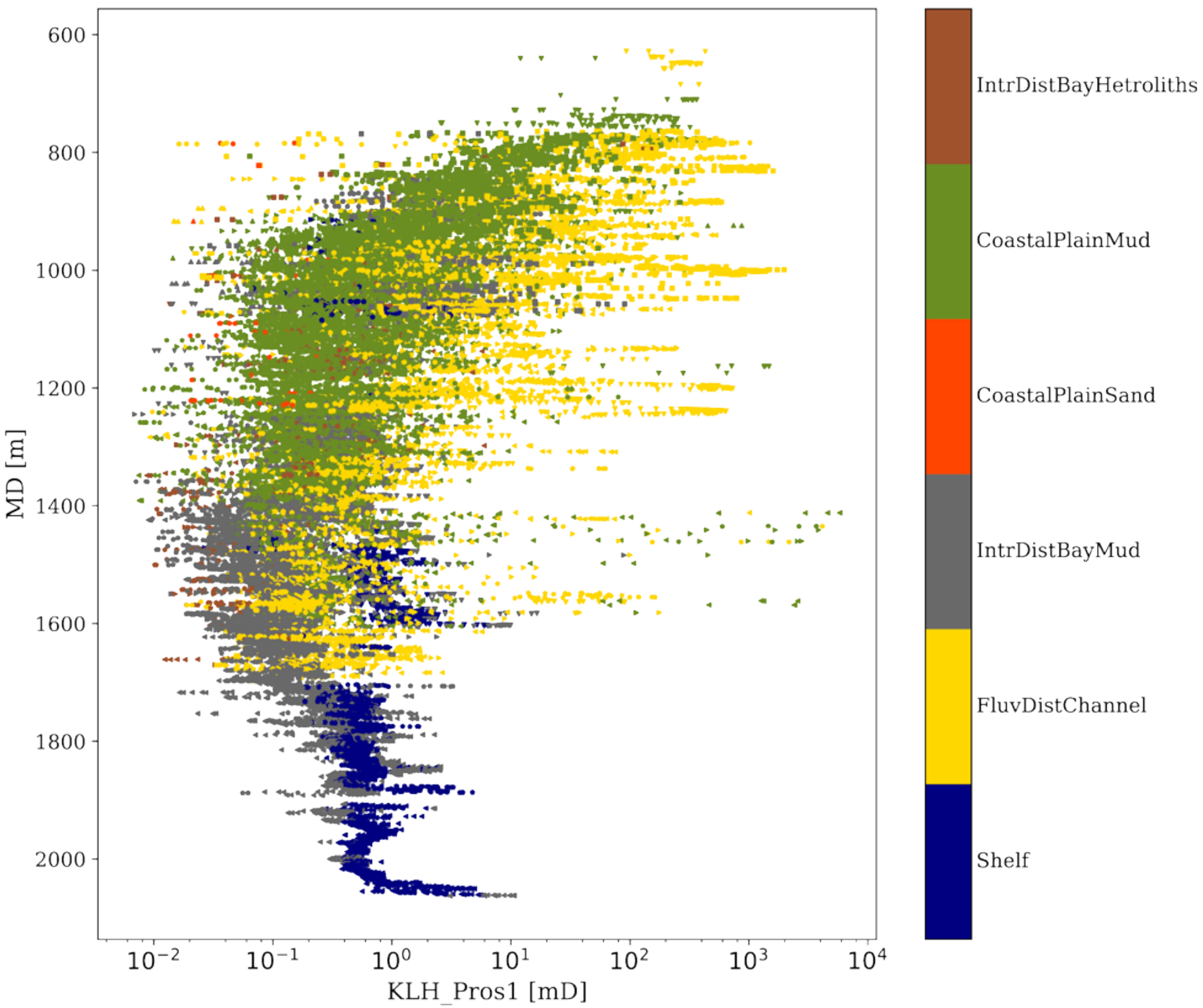
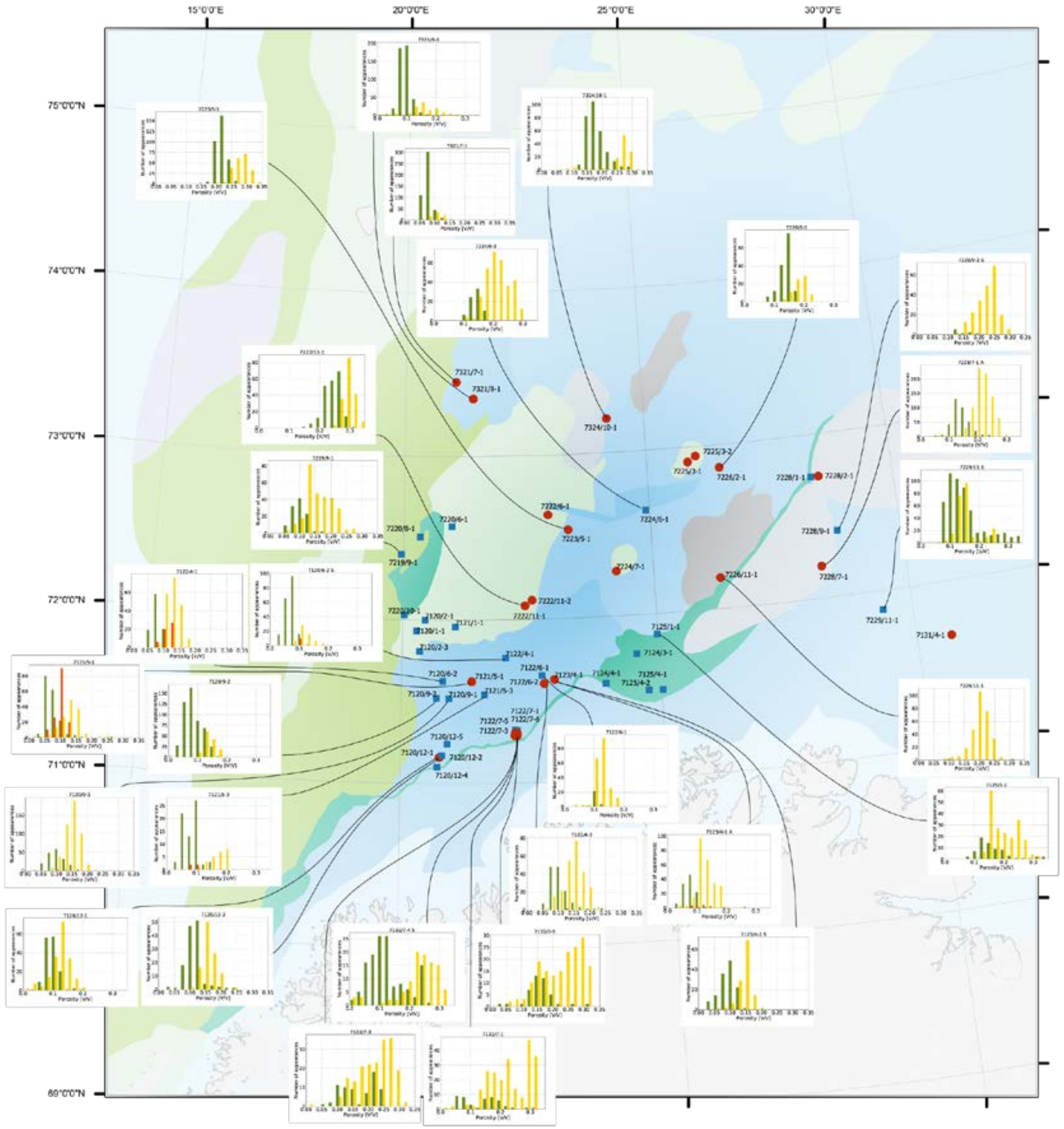
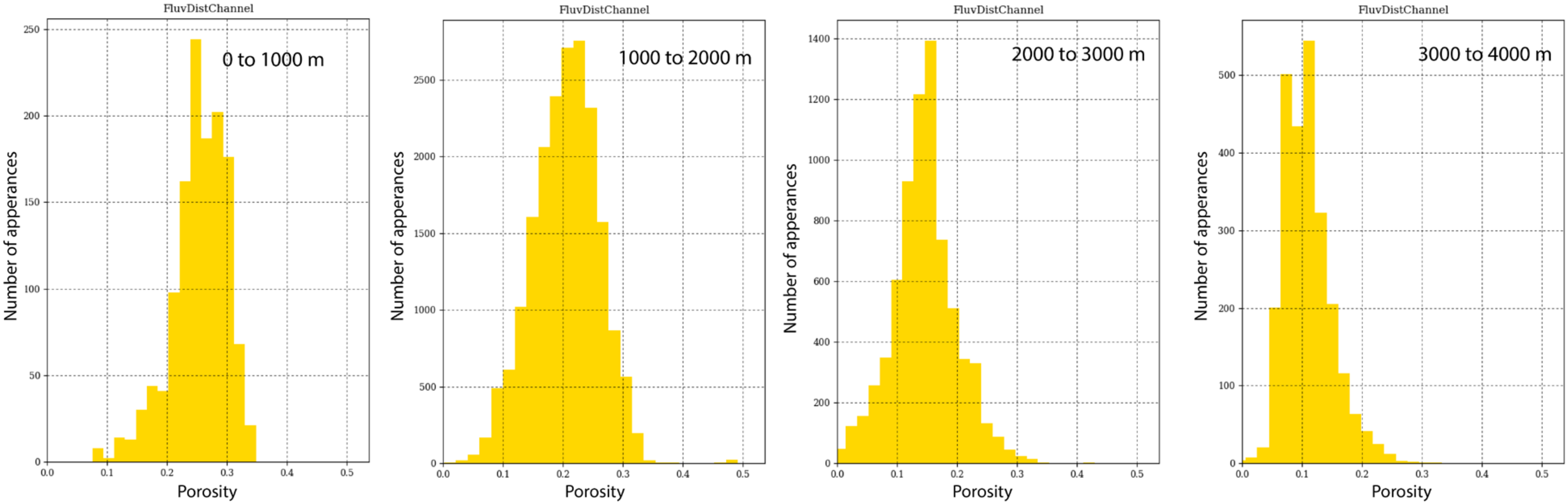
Regional reservoir-quality distribution studies





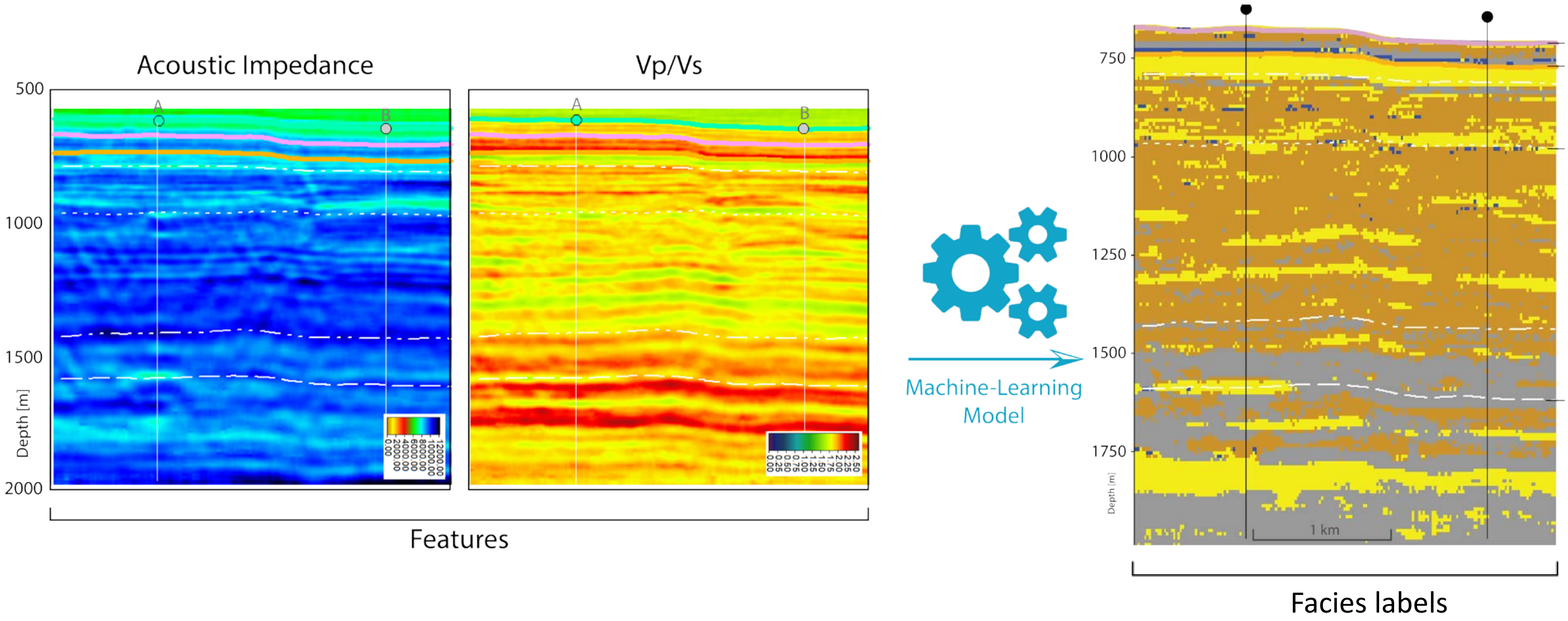
Probabilistic analysis

The high efficiency of Machine-Learning methods make them suitable for generating input to probabilistic predictions (Monte Carlo Simulation)



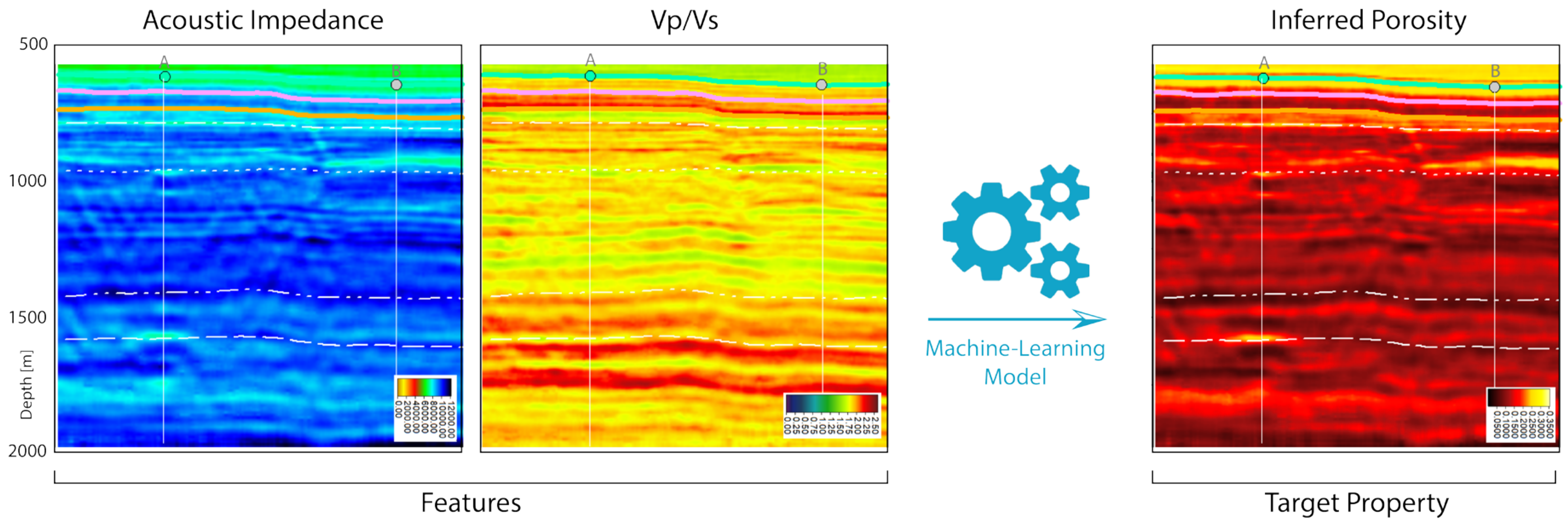
Useful when rock properties can not be derived directly from seismic

Facies prediction from seismic
Rock property prediction between wells

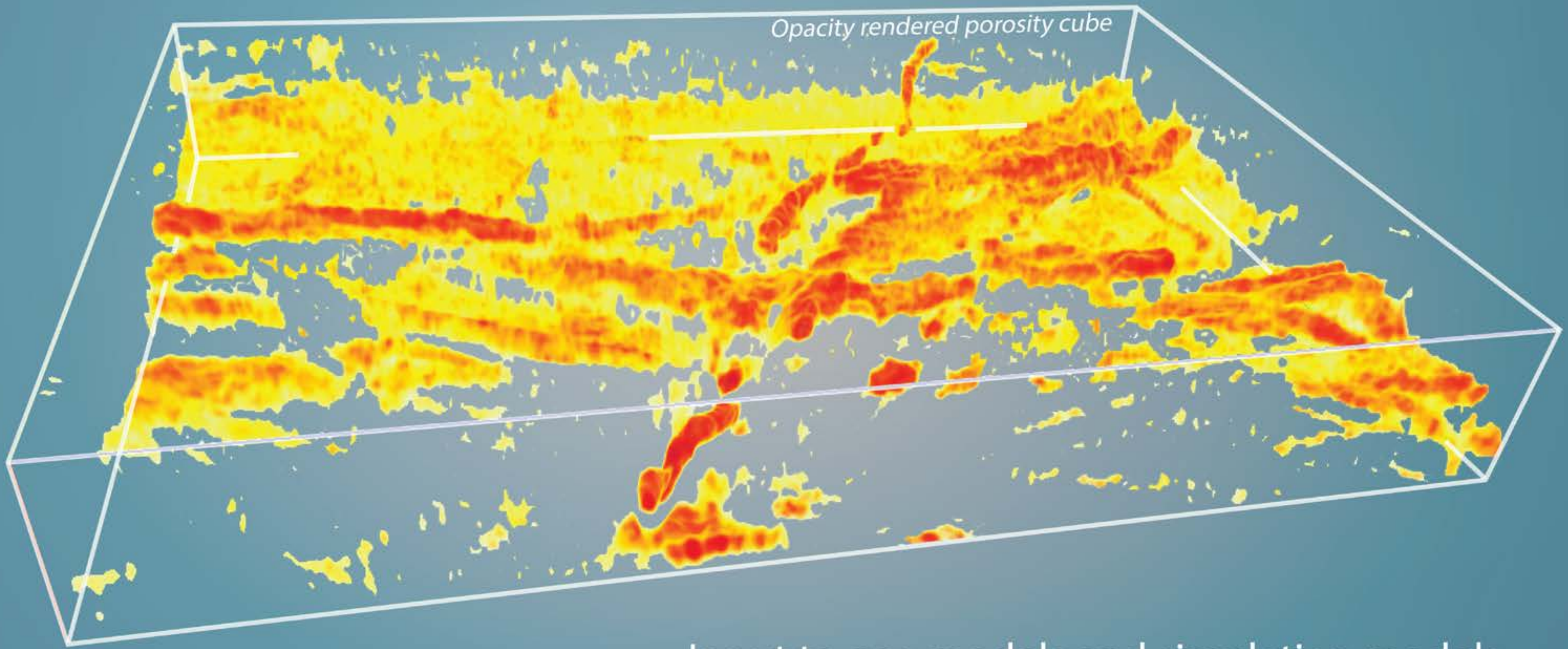


Porosity Prediction from seismic

Rock property prediction between wells



3D rock and fluid property cubes from well and seismic data



Input to geo models and simulation models

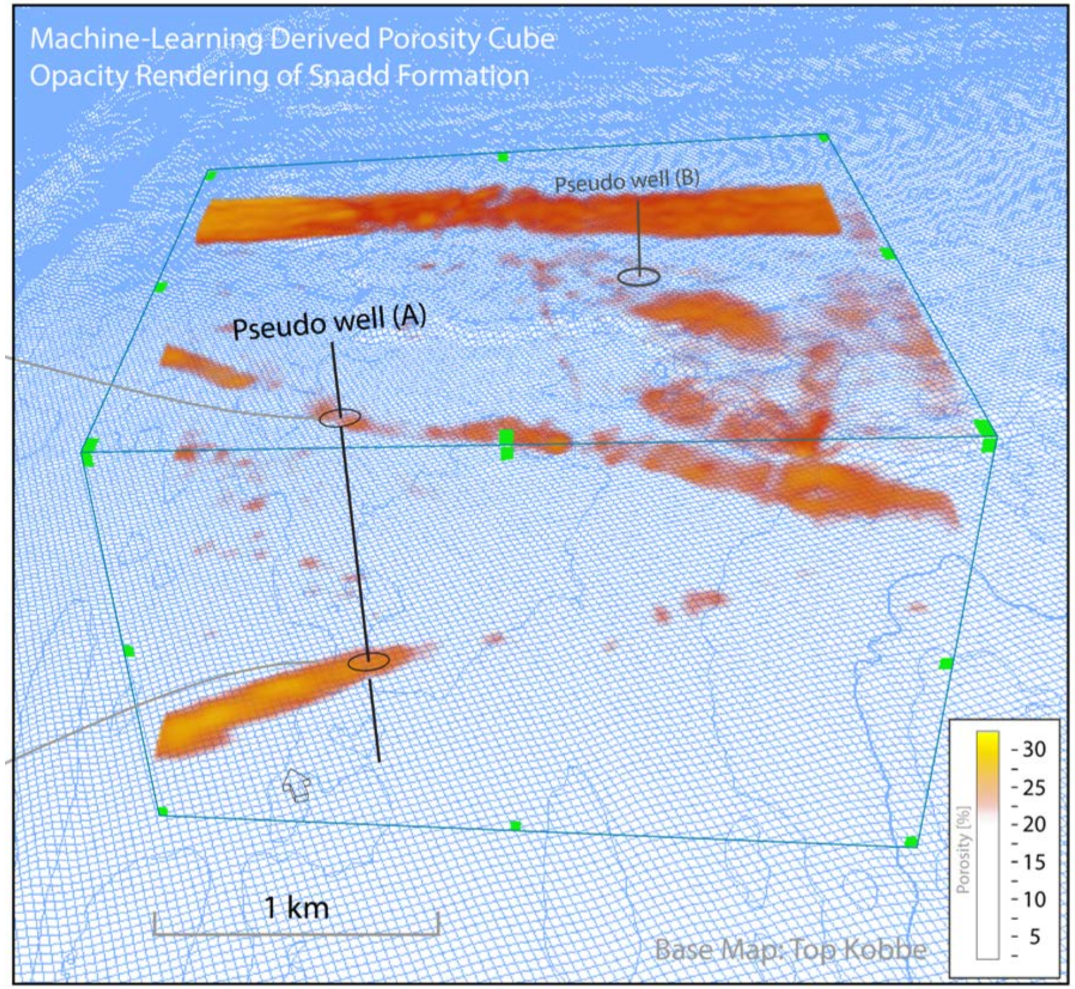
Knowledge transfer from data-rich to data-poor areas

Training
Select data that are relevant for area of interest

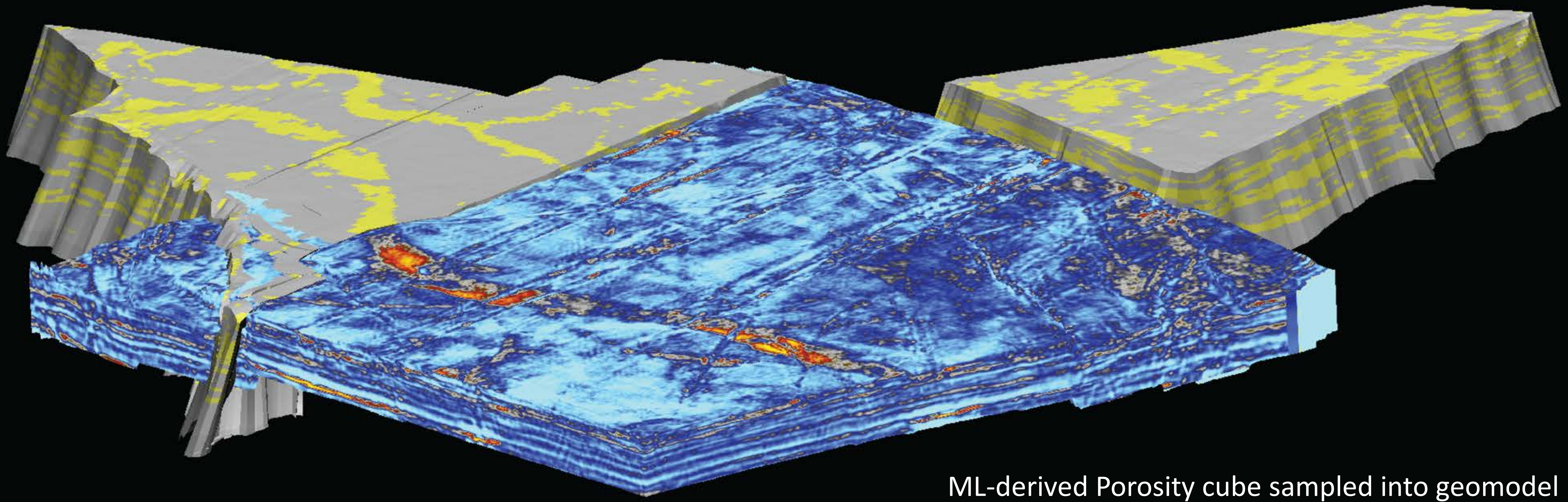
Inference
Can also be done in areas without well data

Uncertainty estimation
The efficiency of Machine Learning methods enables us to run multiple scenarios quickly

Scenario analysis with multiple analogs

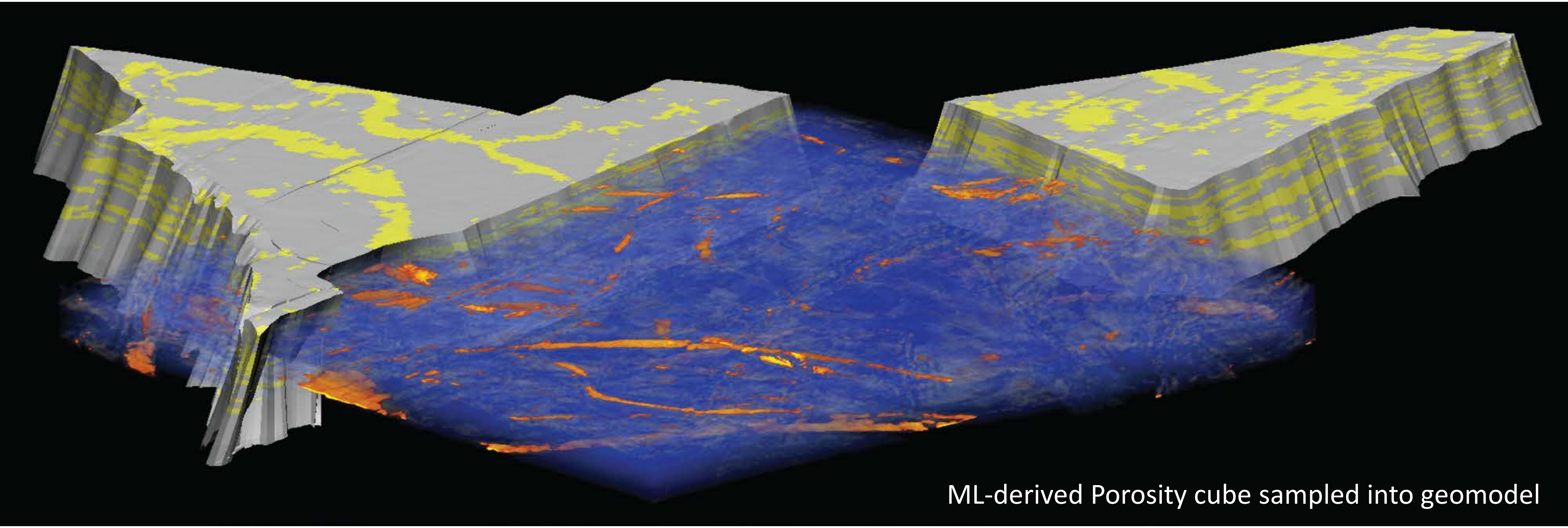


Machine-Learning assisted reservoir characterization



ML-derived Porosity cube sampled into geomodel

Machine-Learning assisted reservoir characterization



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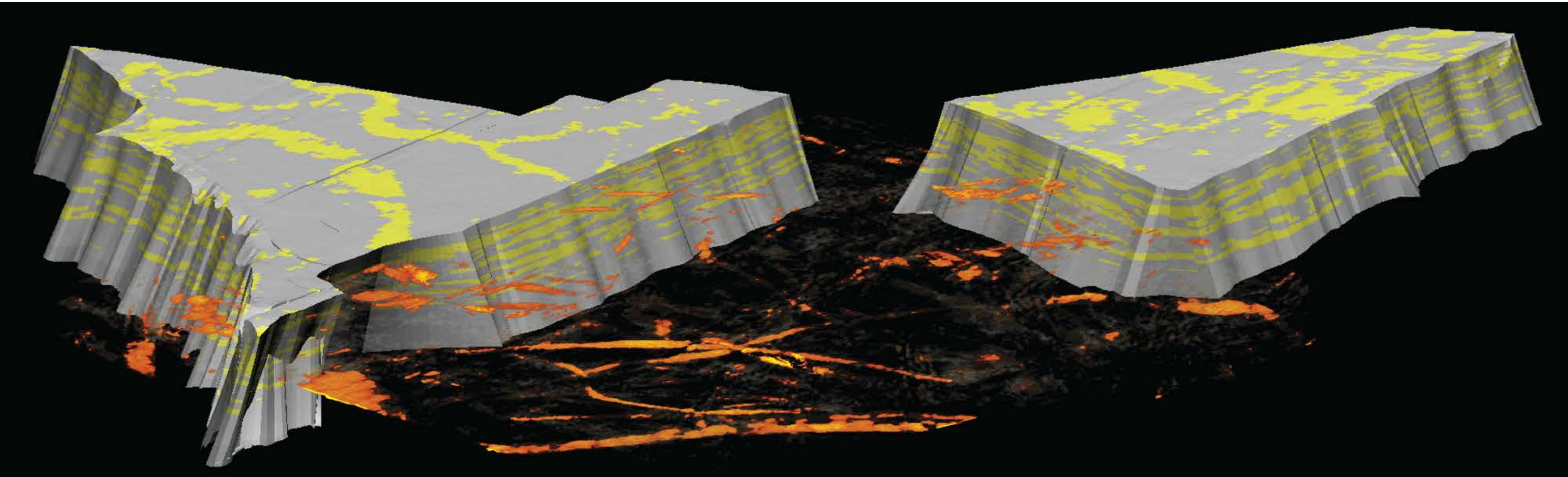
Machine-Learning assisted reservoir characterization



ML-derived Porosity cube sampled into geomodel

What have we learned about Triassic stratigraphic architecture and reservoir quality?

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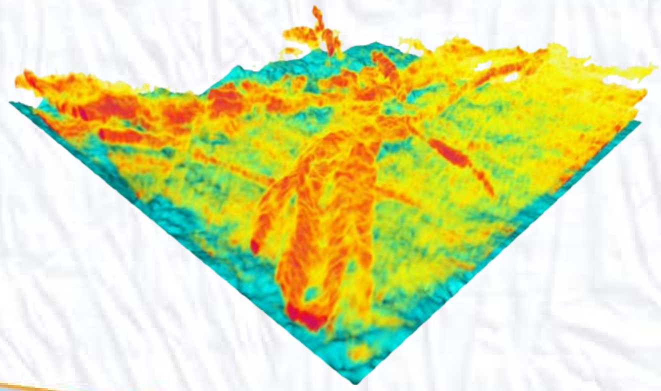

The ML approach enables us to:

- Quantify reservoir architecture
- Quantify porosity and permeability distribution
- Estimate reliability of empirical functions
- Estimate uncertainty of reservoir-quality predictions
- Improve workflow efficiency
- Utilize the large volume of data available

and not least, this novel approach gave us:

More freedom and time to be creative and collaborate across disciplines