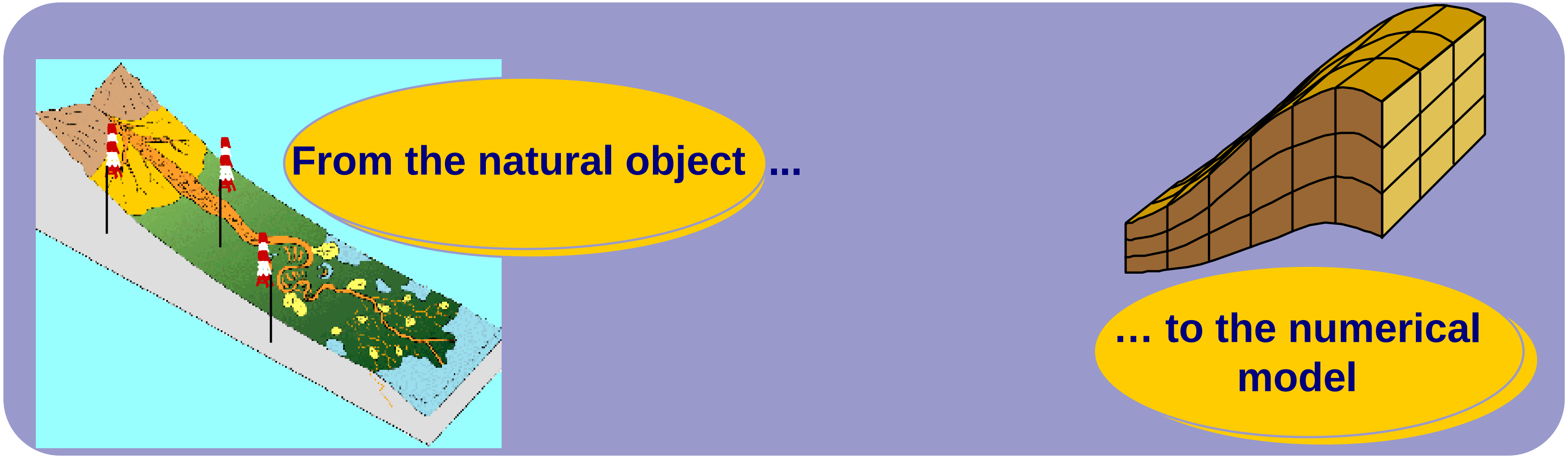
Caractérisation des réservoirs pétroliers par les données sismiques, avec l'aide de la géomodélisation

Thèse de doctorat présentée par Audrey Neau

Directeurs de thèse: B. De Voogd (Pr., UPPA) & P. Thore (Ingénieur, Total)

14 mai 2009



RESERVOIR CHARACTERIZATION :

The continuing process of integrating and interpreting geological, geophysical, petrophysical, fluid and performance data to form a unified, consistent description of a reservoir.

GEOMODELING :

Mathematical methods applied to the unified modeling of the topology, geometry, and physical properties of geological objects

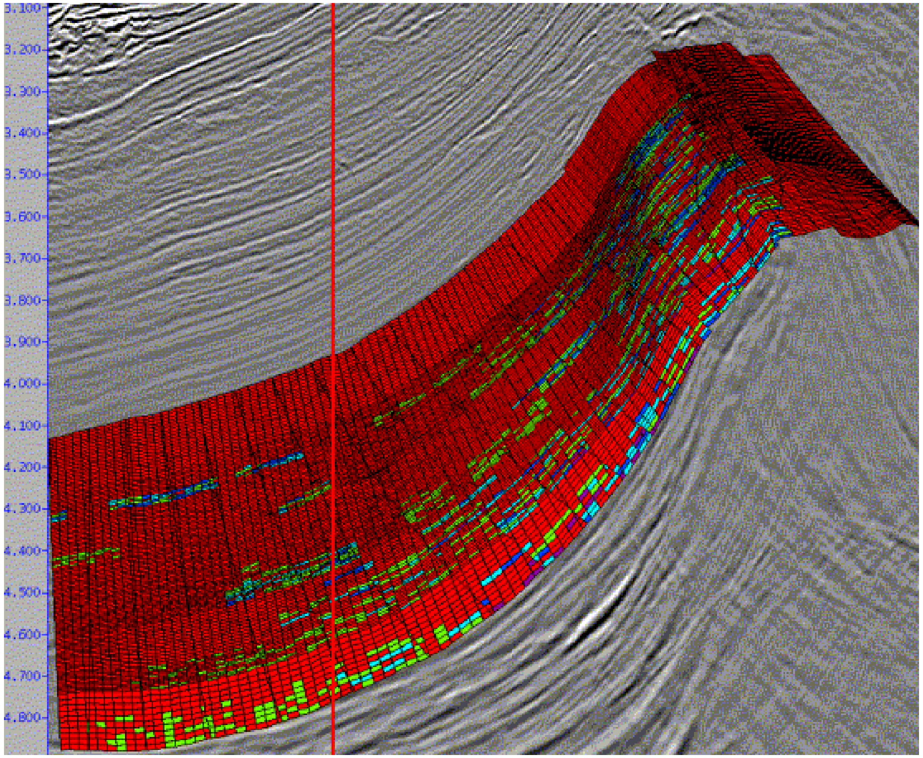
General scientific objectives : Reservoir characterization

-Problem : Different scales and types of data (reservoir, seismic , wells, …)

Added-Value of this Thesis

-Traditionnal reservoir characterization schemes use the geological grid.

-We developed methods directly based on the reservoir grid



NB: Seismic data are angle stacks in time domain

MODEL ⟷ DATA

MODEL
- •Grid
- •Hydrocarbon Reservoir

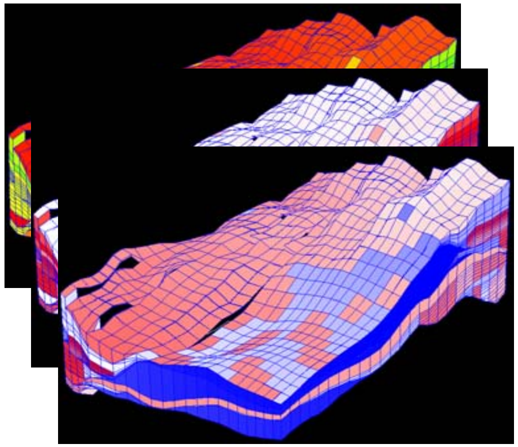
DATA
- •Seismic
- •Wells

- **Reservoir model validation**
  - Seismic modeling from reservoir grid
  - Structural uncertainty impact on reservoir infilling

- **Reservoir characterization alternatives**
  - Gradual Deformation based Inversion
  - Petrophysical inversion by neural supervised classification

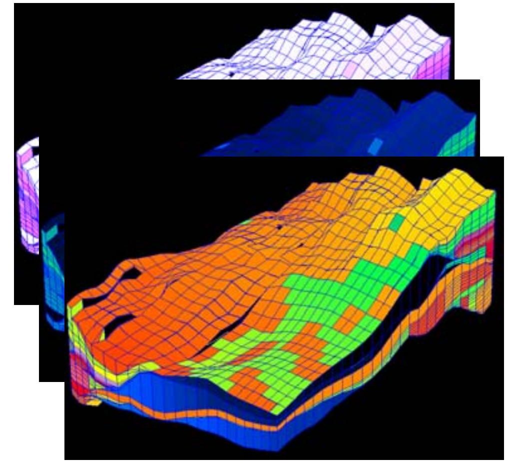
Seismic Modeling from Reservoir grids

Reservoir Simulations



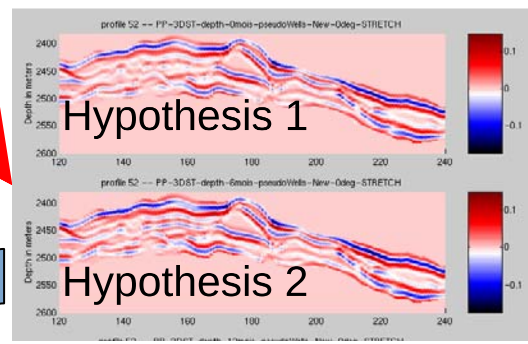
Reservoir parameters (phie, Vclay, Sw, Pressure …)

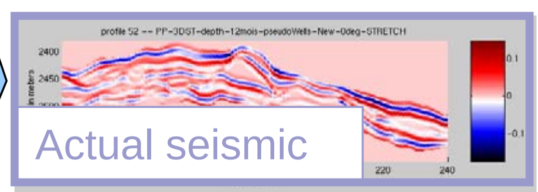
PEM



Elastic parameters (Rhob, Vp, Vs)

Analysis and updating:
Reservoir Simulations and seismic response vs. actual seismic



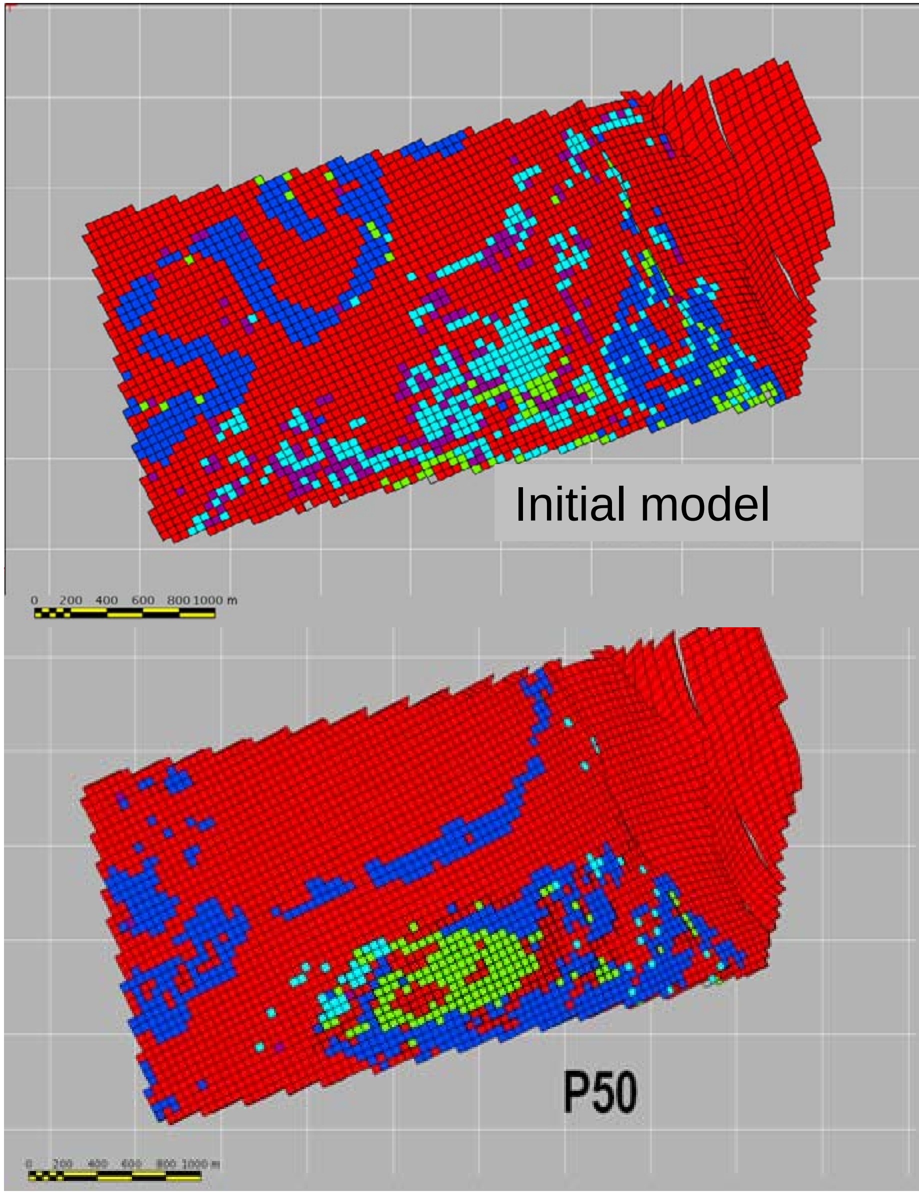


Seismic Modeling

Well Validation

Structural uncertainty impact on reservoir infilling

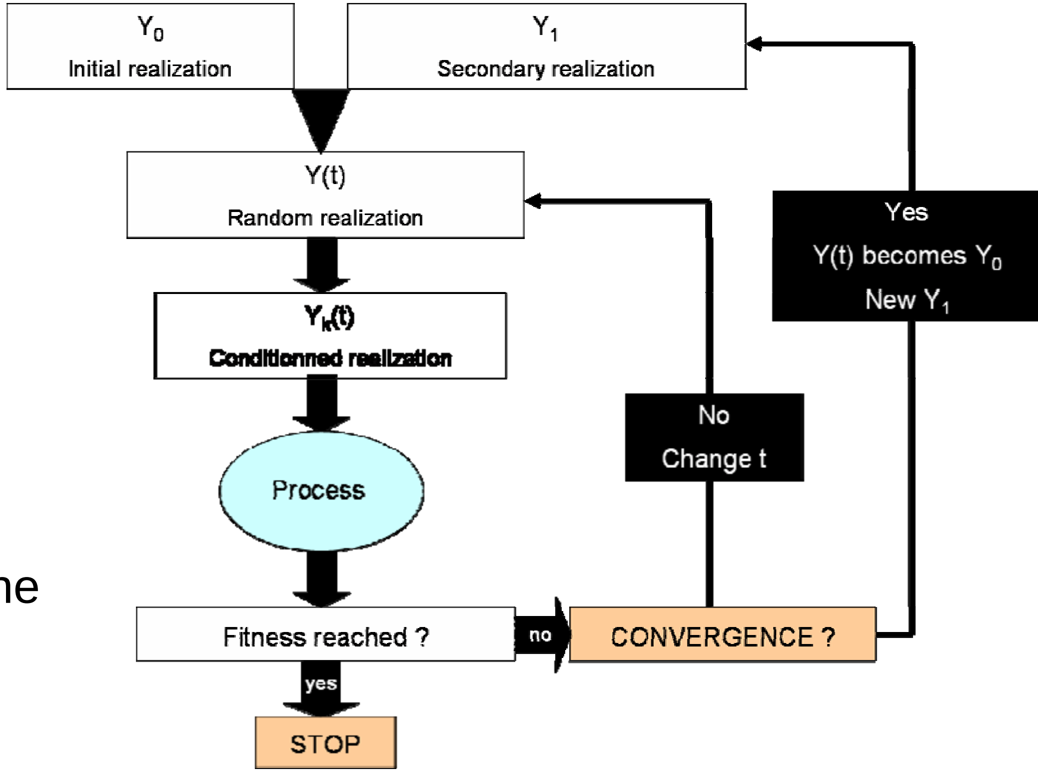
- Reservoir grid must be consistent with all available data
- Errors due to
  - Time to Depth conversion
  - Picking uncertainty
  - Seismic horizons transformation into a 3D grid



Gradual deformation based Inversion - 1/2

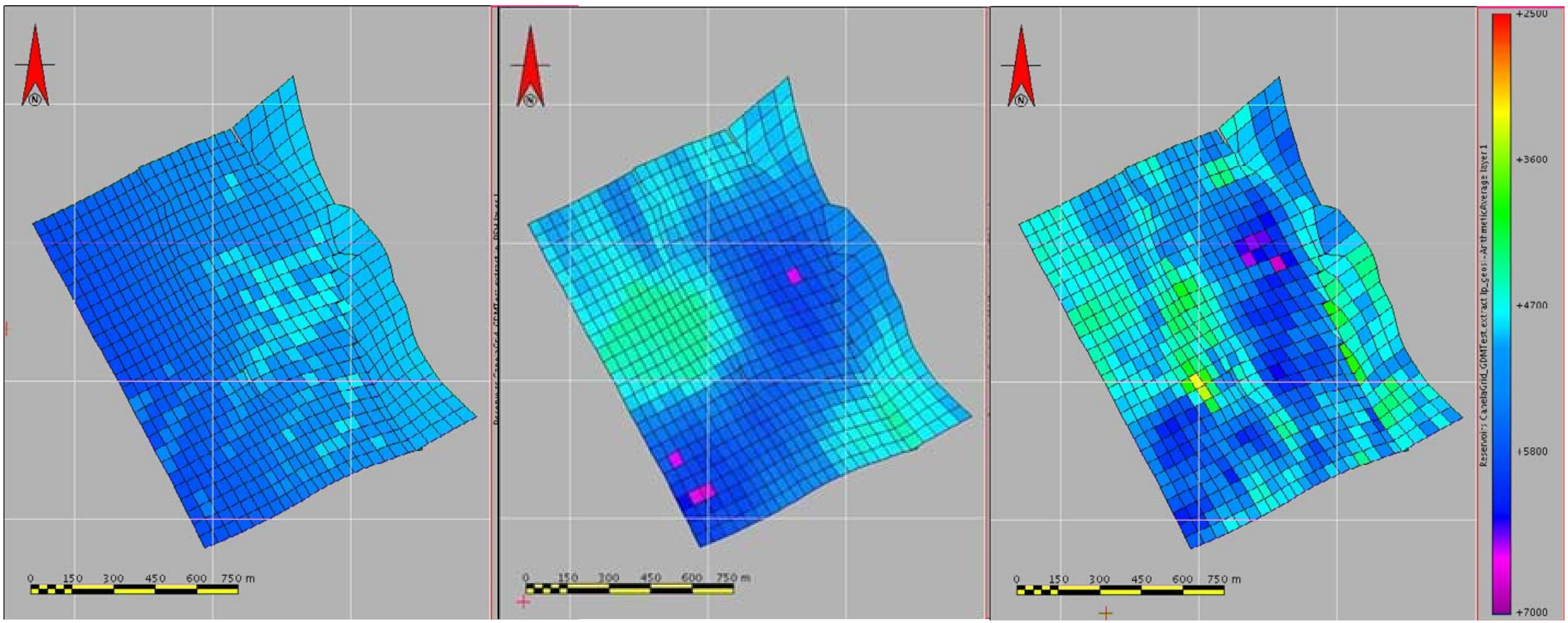
$$Y(t) = Y_0\cos(t) + Y_1\sin(t)$$

- Seismic data inversion at reservoir grid scale
- Geostatistical parameterization
- Traditionnal inversion methods : seismic scale is not compatible with reservoir scale
- This new method works directly in the reservoir grid, with a minimisation function



Gradual deformation based Inversion - 2/2

Initial Realization | Final Realization | Actual Realization



- **Supervised Neural Classification – Methodology**
  - Kohonen Self Organizing Maps
  - Data Preparation
- **The Massive Modeling Approach**
- **Application on a clastic case study: Beta Field**
  - Preliminary tests
  - Petrophysical Training
  - Seismic Training
  - Validation of results
- **Application on a carbonate case study: Gamma Field**
  - Preliminary tests
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- **Concluding Remarks & Perspectives**

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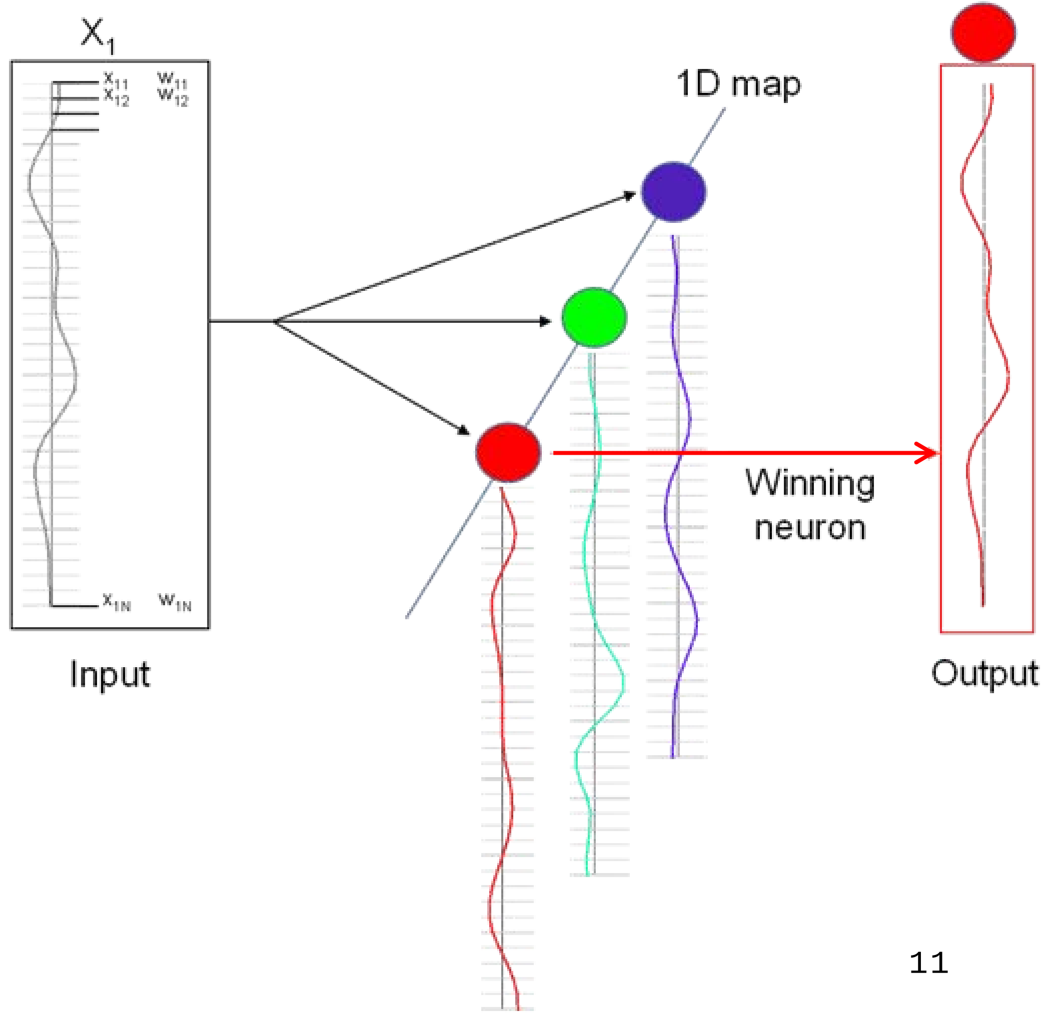
- KSOM : unsupervised neural network
- Looks for regularities and characteristics in a N-dimensionnal dataset
- Comparison between neurons and samples based on trace correlation

- 2 phases :
  - learning and classification

- A sample is given to the network
- The winning neuron is determined, then updated for a better match with the sample

- The output of the KSOM is
  - A model trace repartition map
  - A fitness map



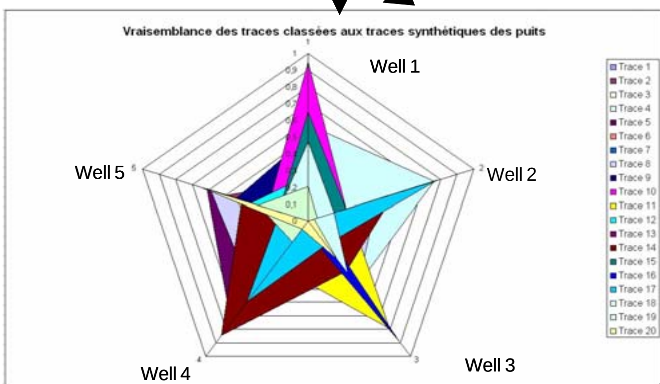
Problem : The training phase

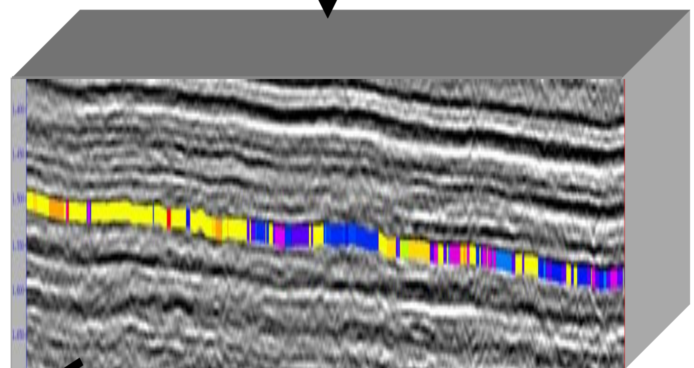
-Well Logs do not provide a sufficient database to train the neural networks.

A training dataset is created from geostatistical simulation between wells.

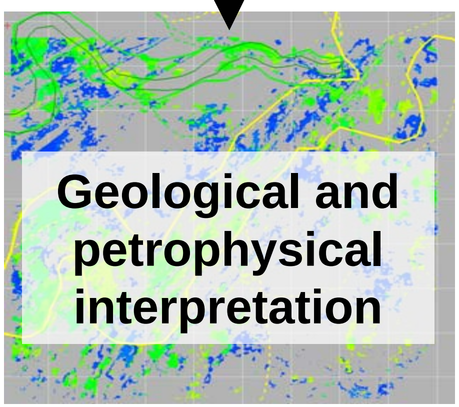
Neural Network applied to real data

PCA

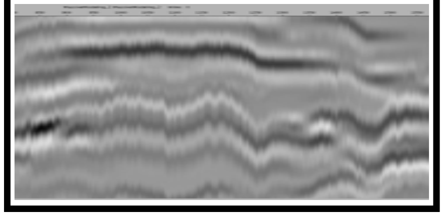




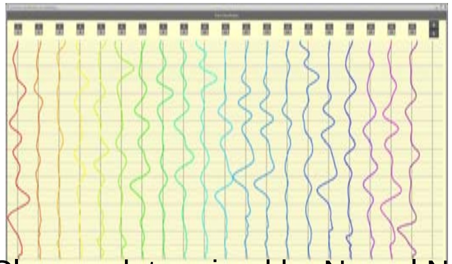
Petrophysical discrimination



Training set from Gradual Simulations Constrained to Wells

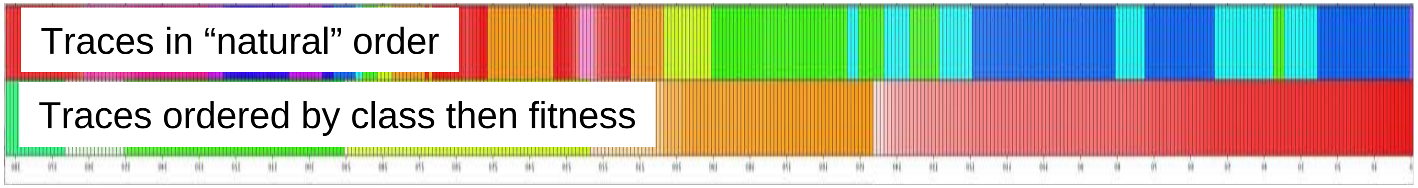


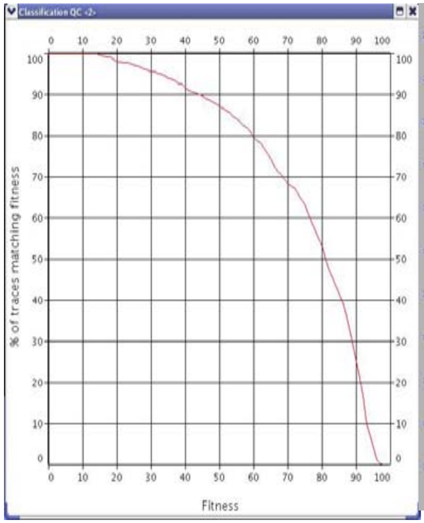
Neural Network Analysis

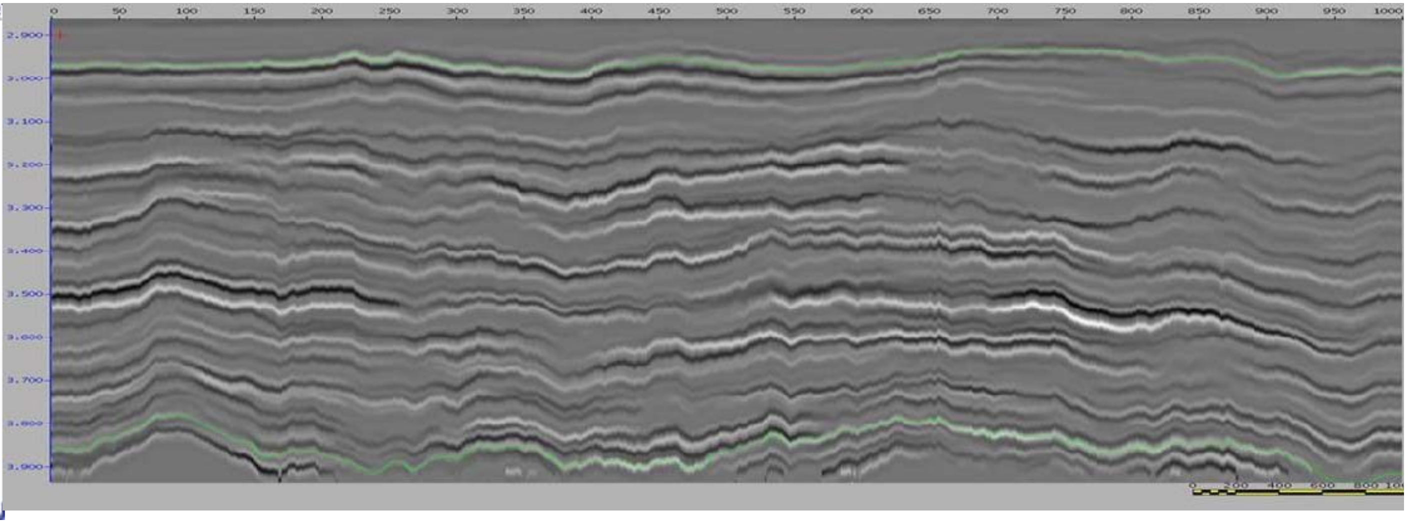


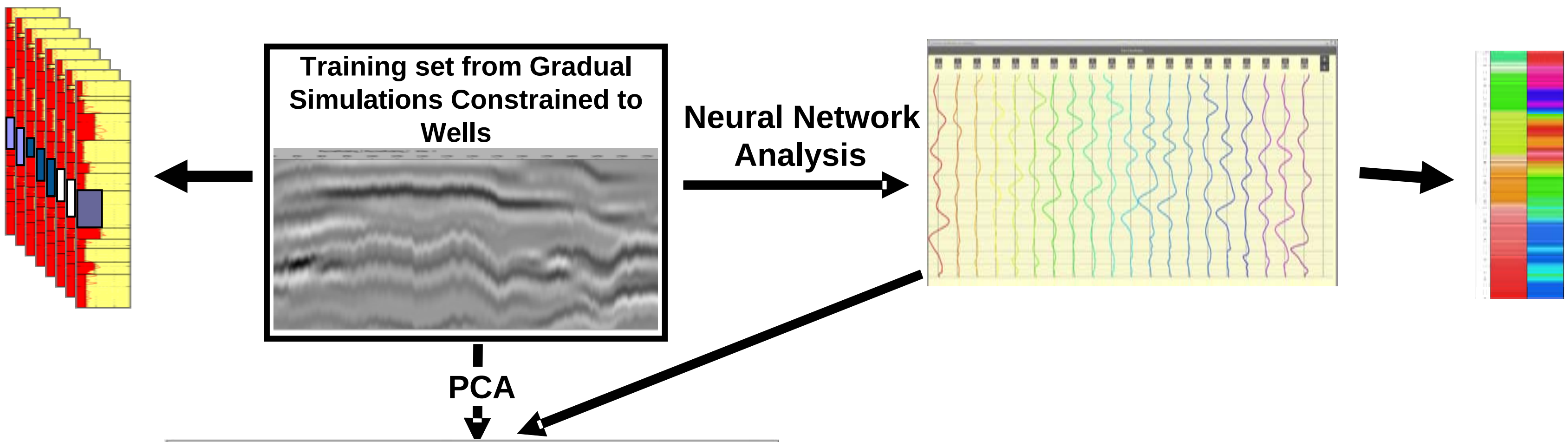
Classes determined by Neural Net

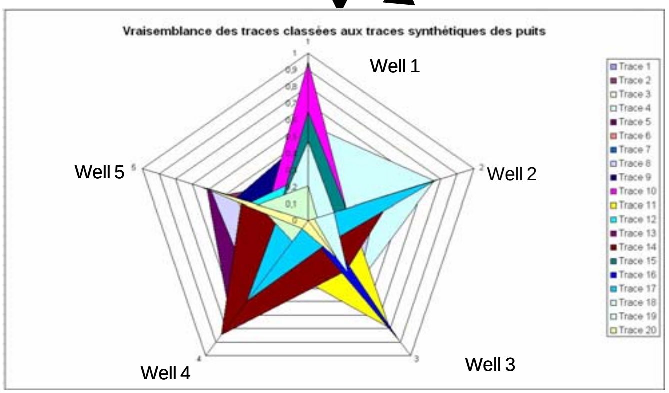
Cumulated Histogram of Correlation







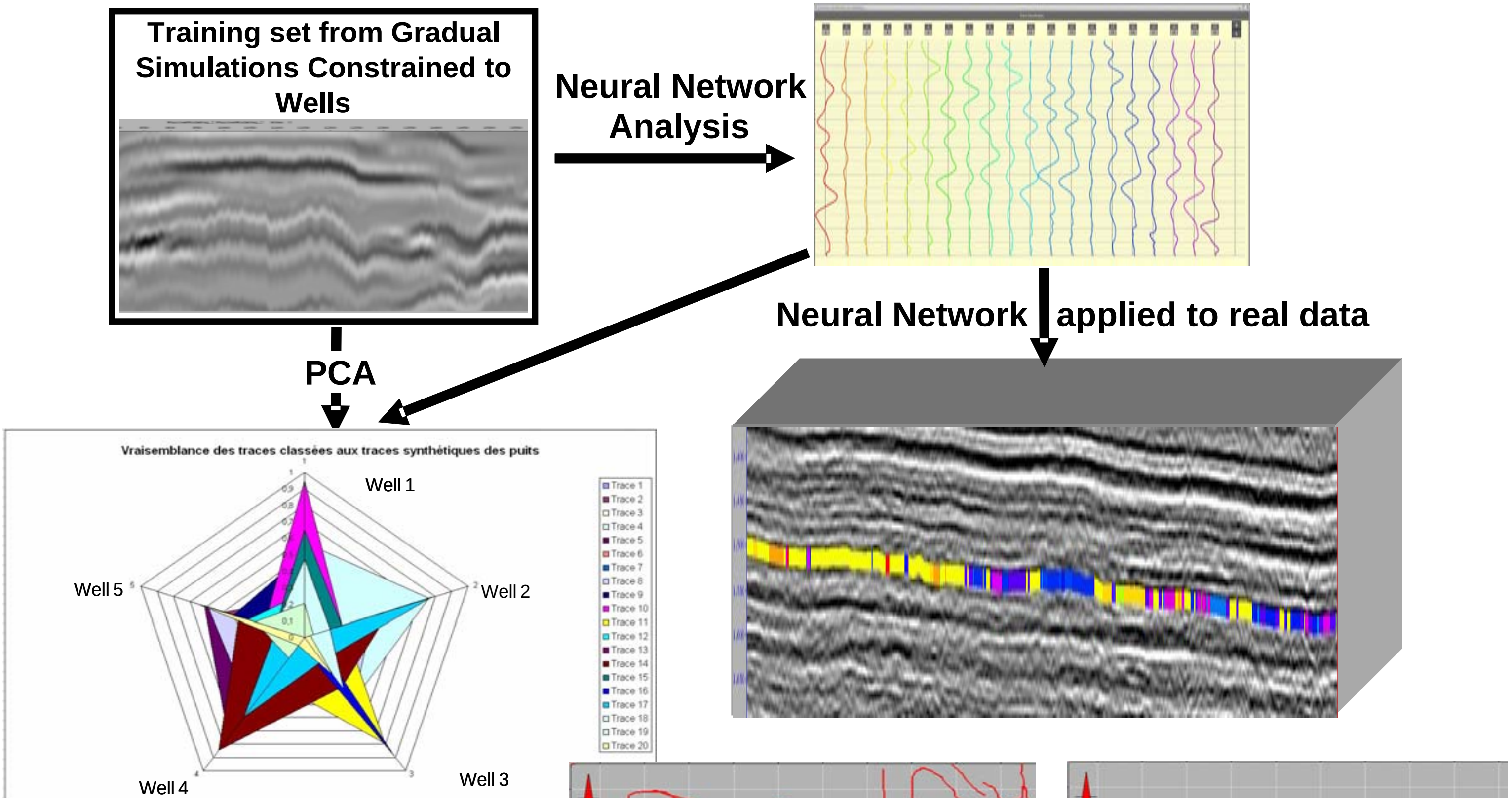


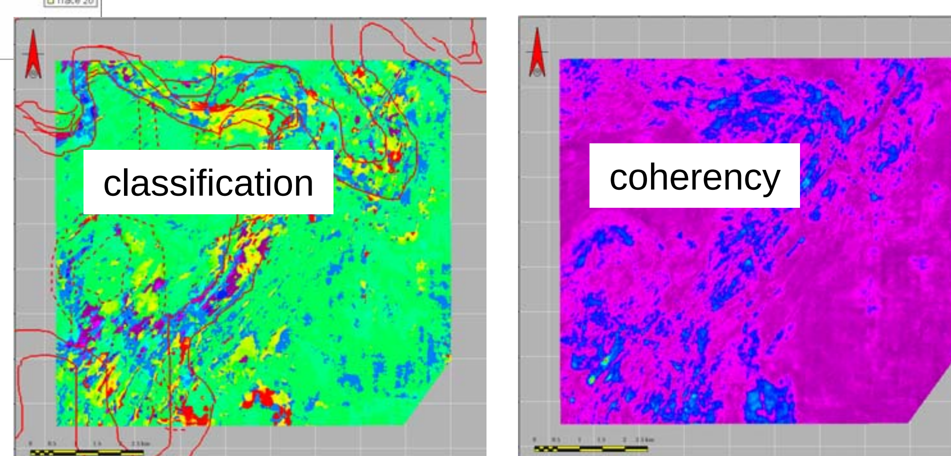


Are model traces related to the petrophysical parameters ?

Relationships between seismic training traces and pseudo wells are known

Supervised Classification of the actual data





Procedure

- Phase 1 : Data preparation

- Petroelastic logs for each well are blocked at geological scale while keeping coherency with actual seismic data
- These logs are used to generate pseudo-logs by geostatistical interpolation between wells

- Phase 2 : Training the neural network

- Unsupervised classification is applied on the pseudo-logs or on the actual seismic date
- Validation of the classification

- Phase 3 : Classification with the results from training

- Classes obtained in phase 2 are used to classify the other set of data
- Validation of the classification

Procedure

- Classical way: Petrophysical training
  - Training the network on the Massive Modeling dataset
  - Classifying the actual seismic data
  - Validation through explanation rate i.e. how well the synthetics represent the data

- Alternative: Seismic training
  - Training the network on the actual seismic data
  - Classifying the Massive Modeling dataset
  - Are all classes represented in the synthetics? (surjection)
  - Are there synthetics out of the seismic range? (injection)

<u>Ideally we would like to have a bijection</u>

Well Log Blocking & Optimization

Blocking :

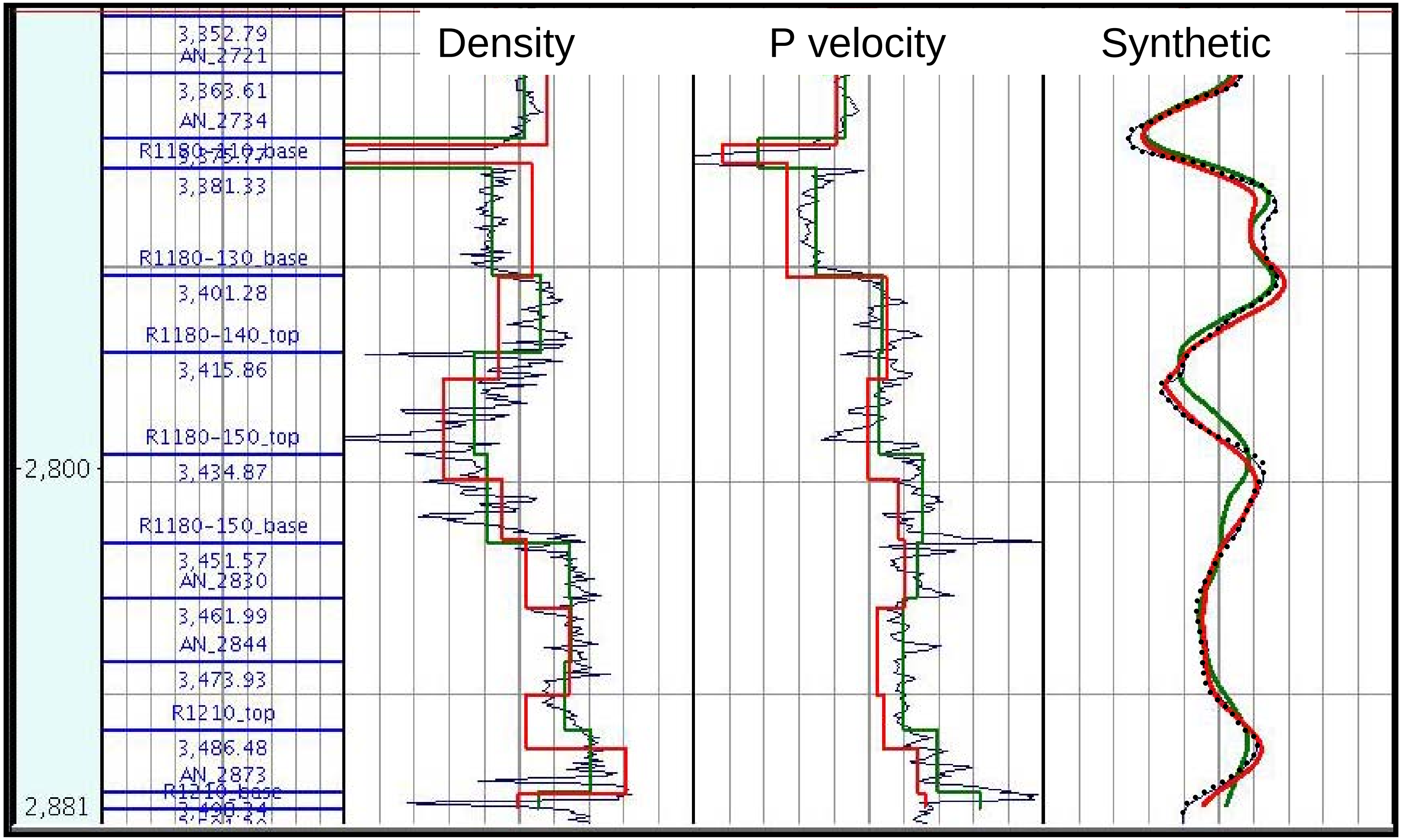
Decreasing the number of petrophysics parameters

Scale up to the stratigraphic resolution

Optimization with respect to seismic data:

Thickness and property perturbation

"Log Inversion" from initial blocking



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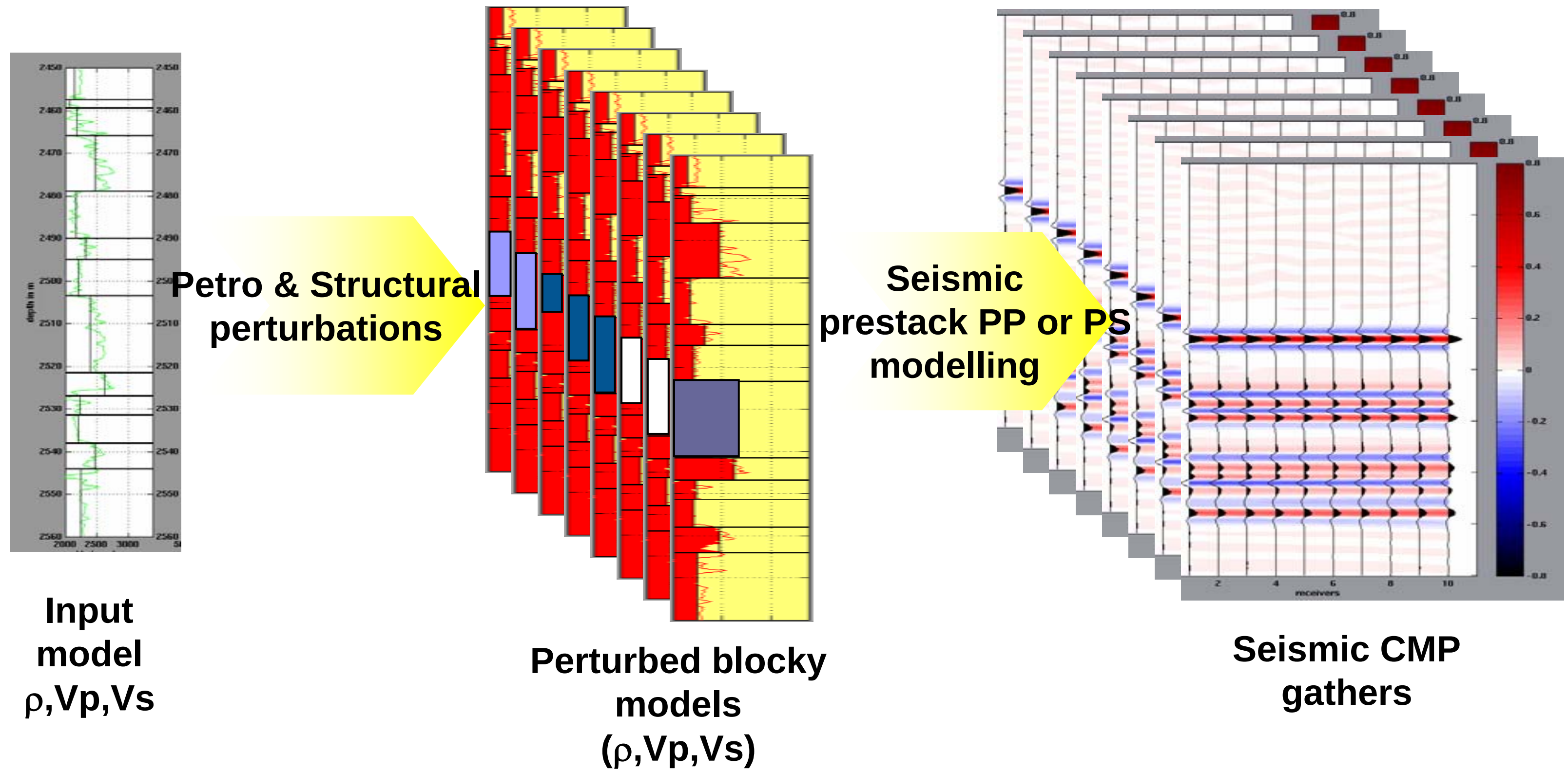
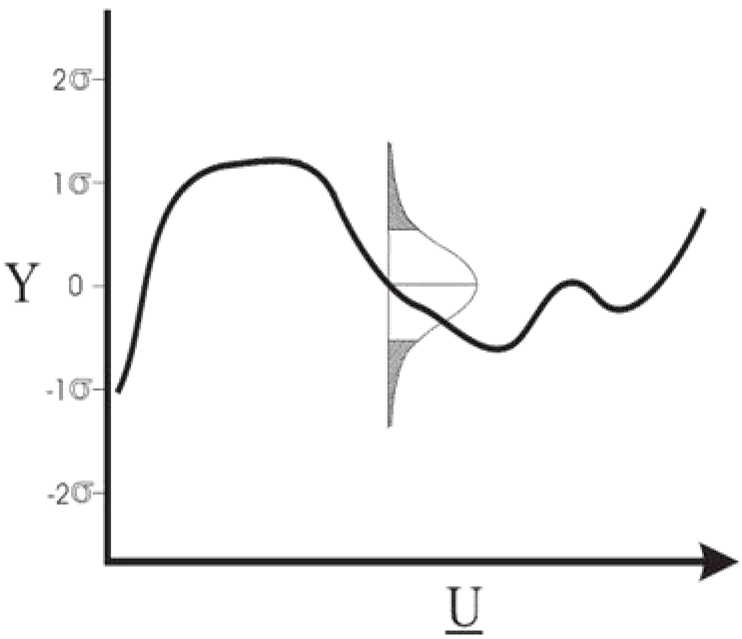
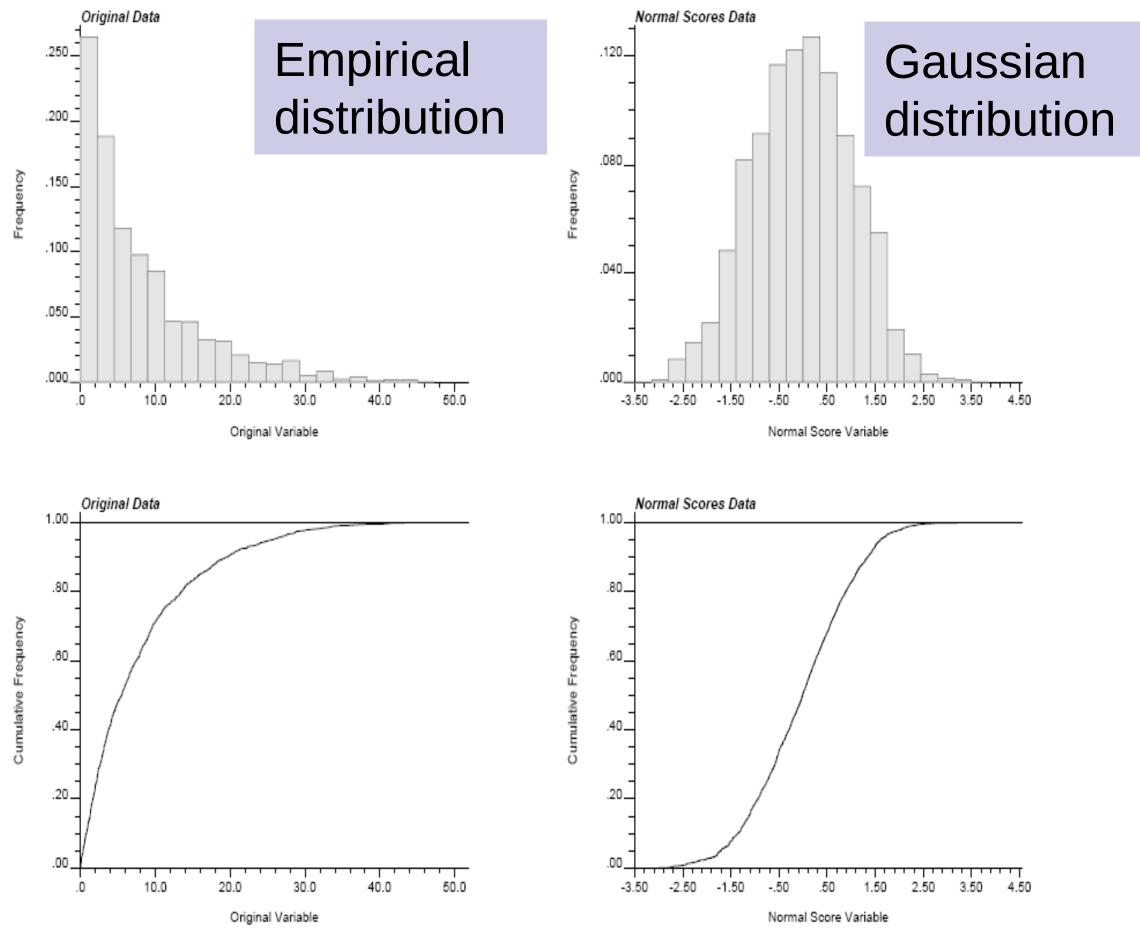


Perturbations are applied on layer thickness and properties to blocked (at the stratigraphic scale) wells in order to simulate the possible range of realizations of the reservoir geology/petrophysics.

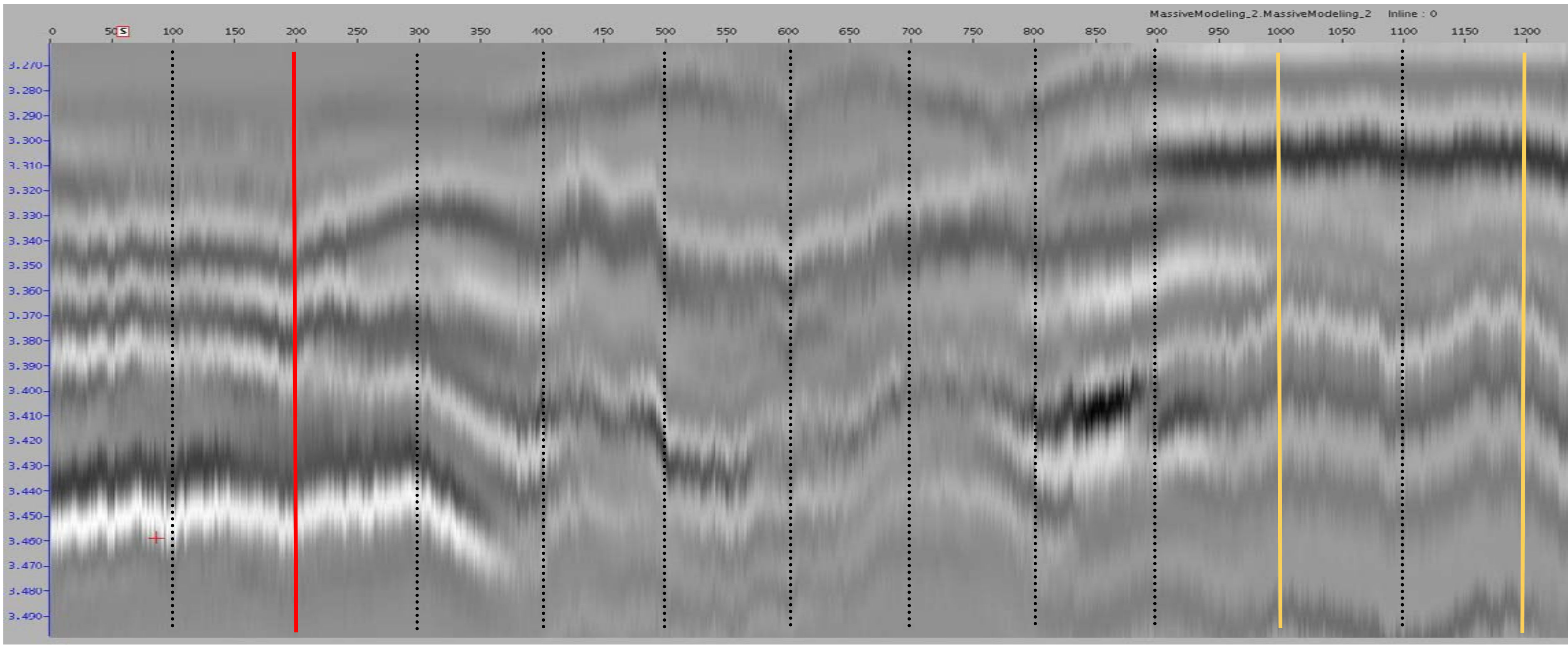
The importance of prestack massive seismic modeling for AVO calibration and seismic reservoir characterization P. Julien, F. Pivot, A. Douillard, Y. El‐Ouair, S. Toinet., SEG Expanded Abstracts 21, 1731(2002)

- 1D Sequential Gaussian Simulation
- Pseudo-spatial component
- 1D SGS for each parameter (layer 1 : thickness, Vp, Rho, …)



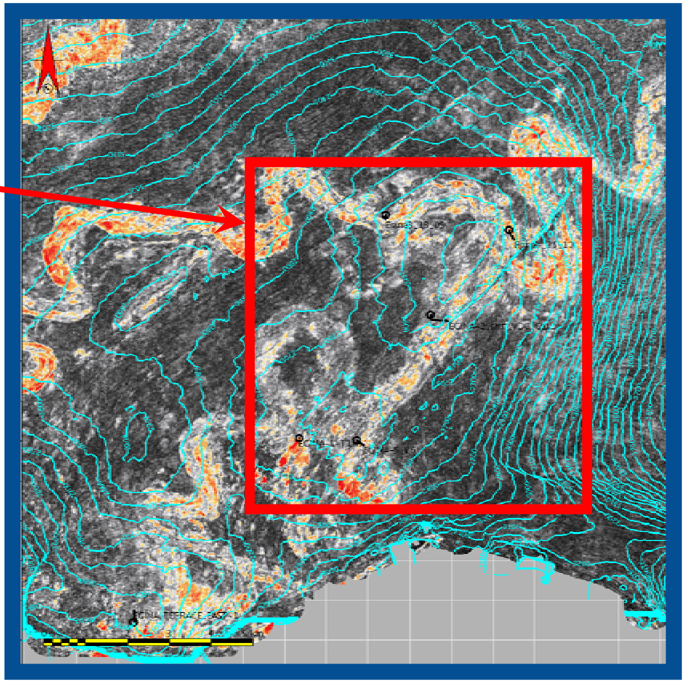


Pseudo-logs are generated using geostatistical interpolation (SGS) conditioned by actual wells. Thicknesses, velocities and densities are interpolated in a gradual way.

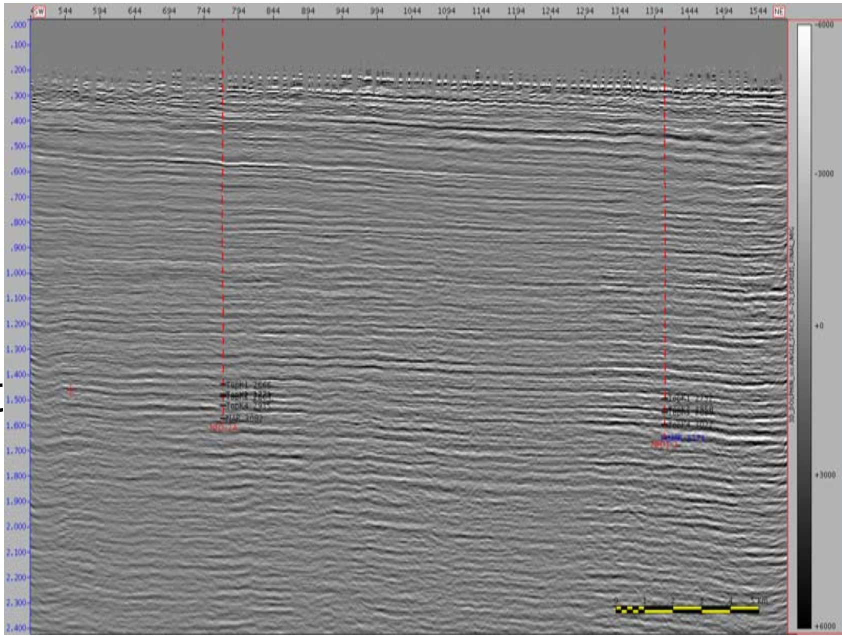


Well 1 Well 2 Well 2

Synthetics are computed on the pseudo-well population resulting in the training dataset.



- **Beta Field :**
  - Clastic model
  - Complex geology
  - Sandy channels, shaly overburden
  - Particularity : high petrophysical variability.



- **Gamma Field :**
  - Carbonate case
  - « Layer-cake » geology
  - Alternation limestone / dolomite / anhydrite
  - Particularities: small petrophysical variability ; multiple just above the target reservoir.

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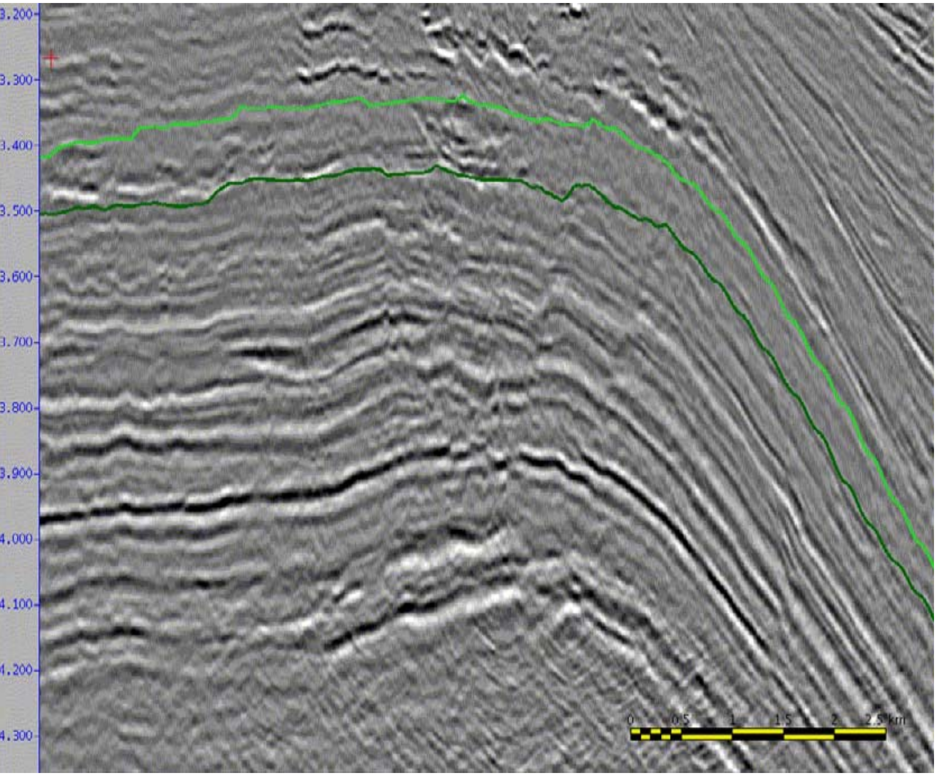
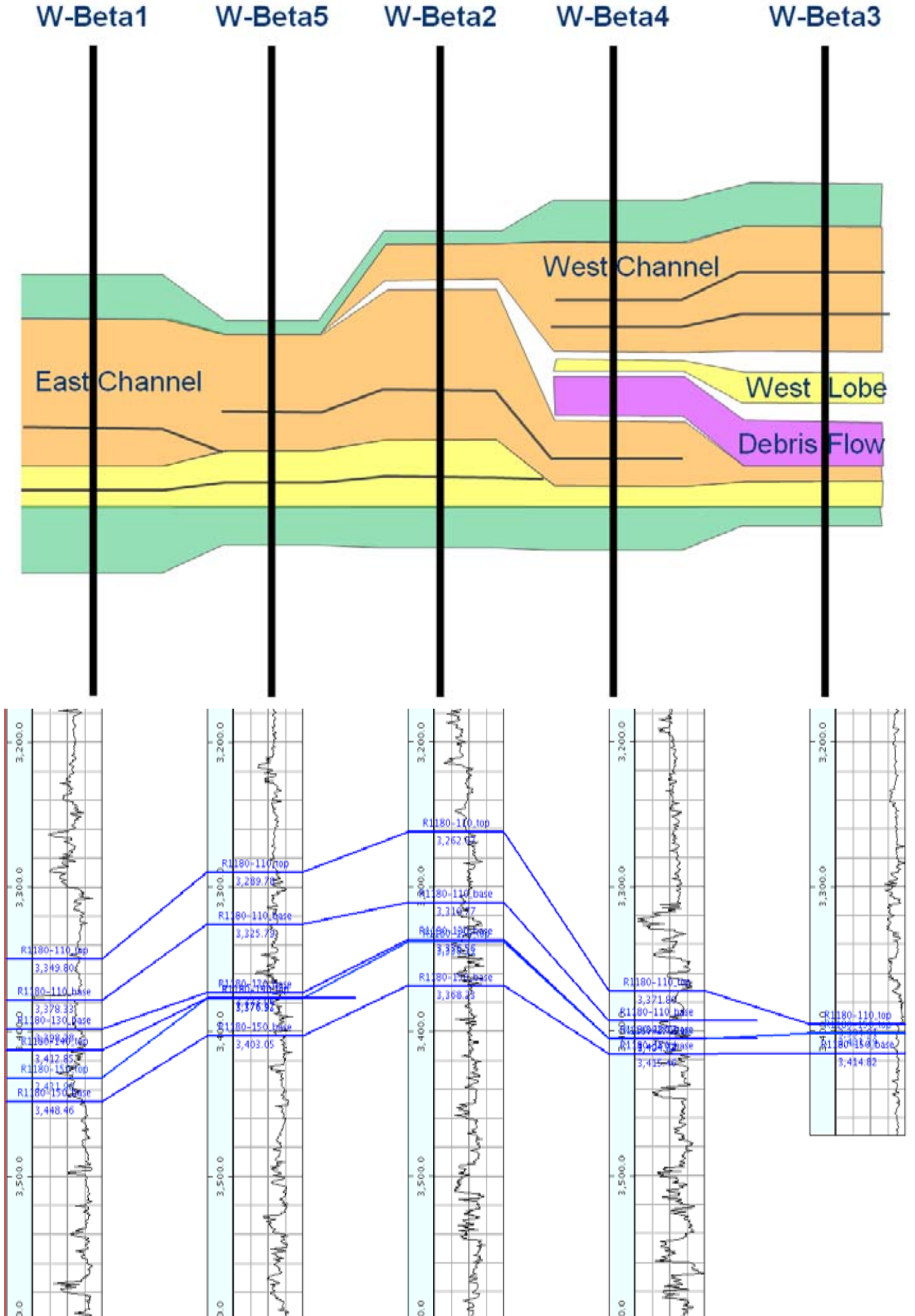
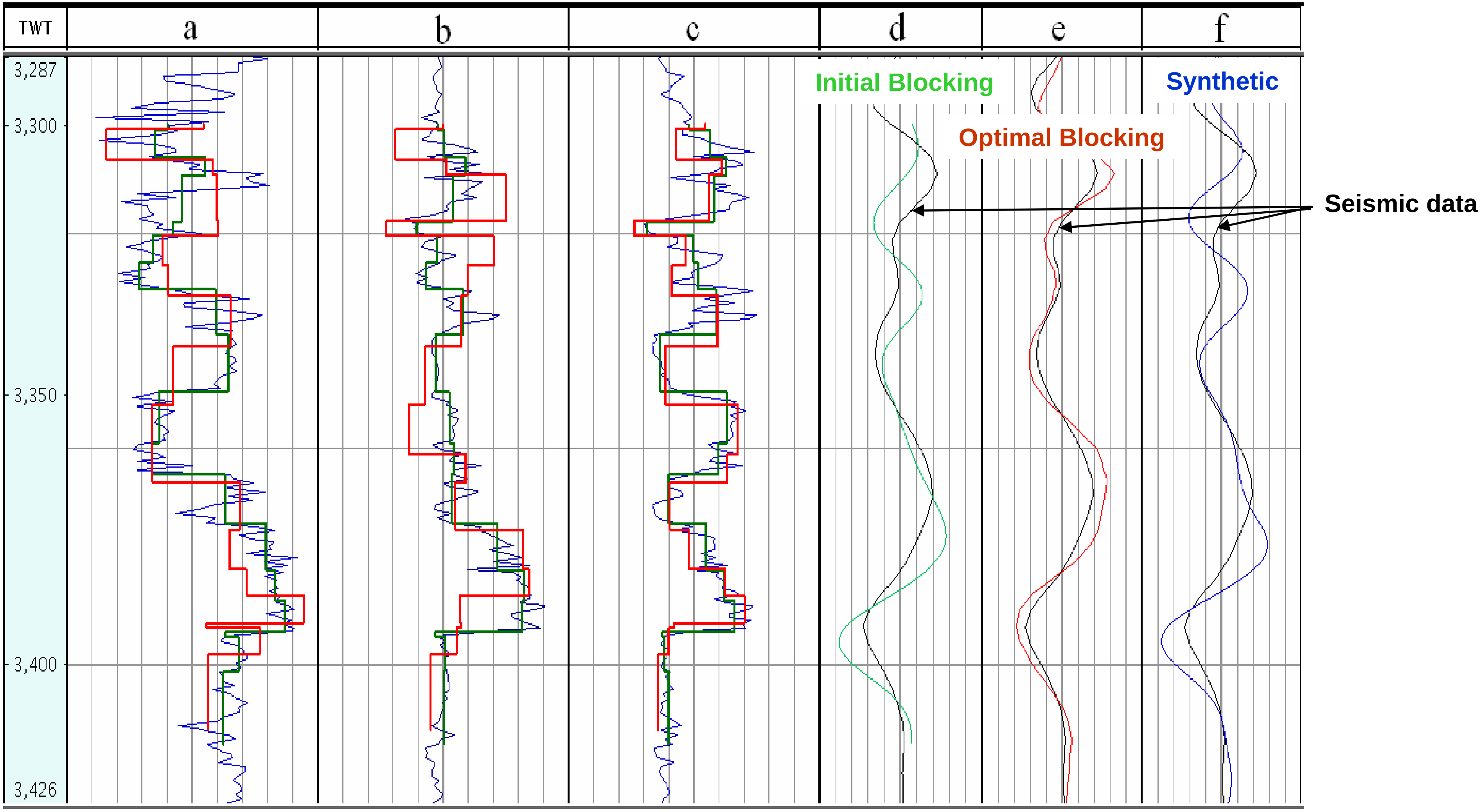
- **Concluding Remarks & Perspectives**

- Beta Field :
  - 5 wells
  - Target reservoir = 100ms

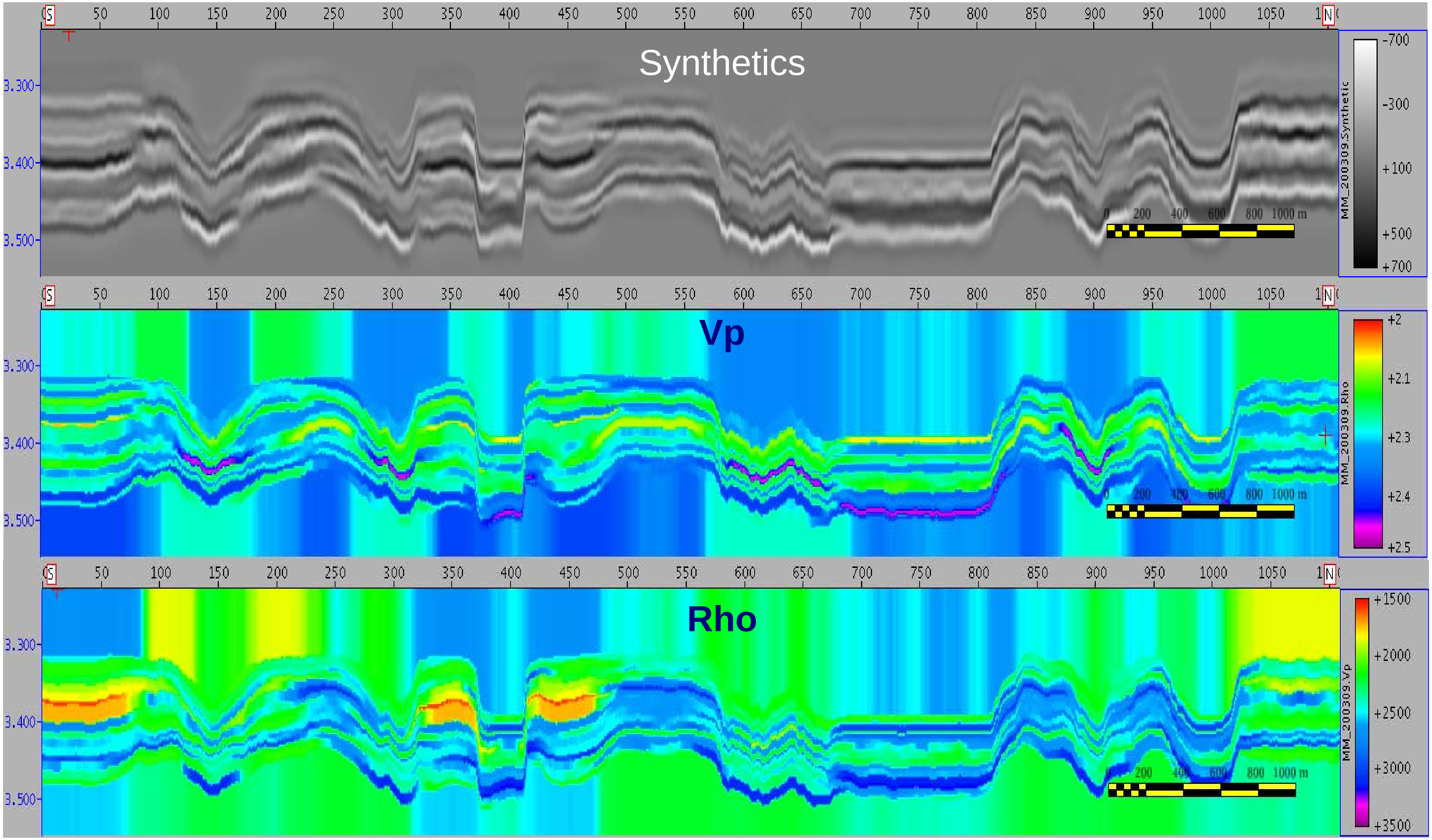




Beta Field: Well log blocking & optimization



Training set used more than 80000 traces



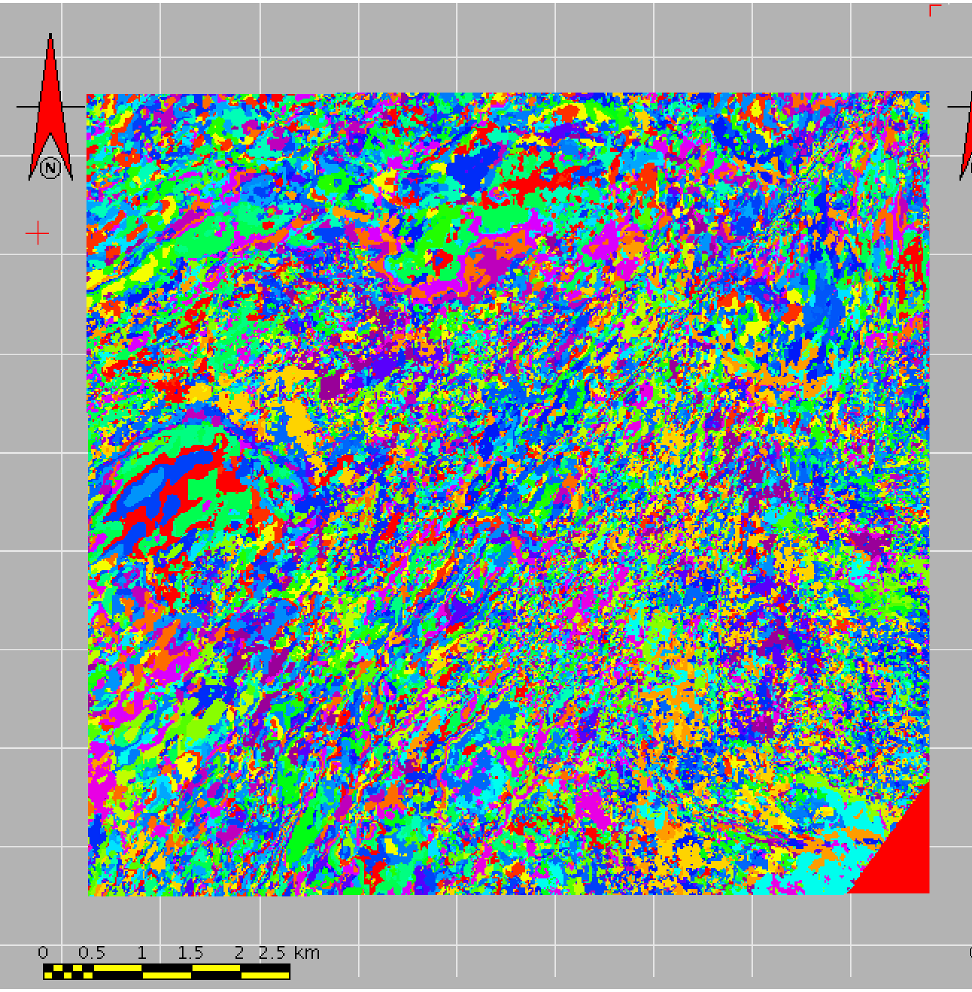
3 main parameters for the neural network:

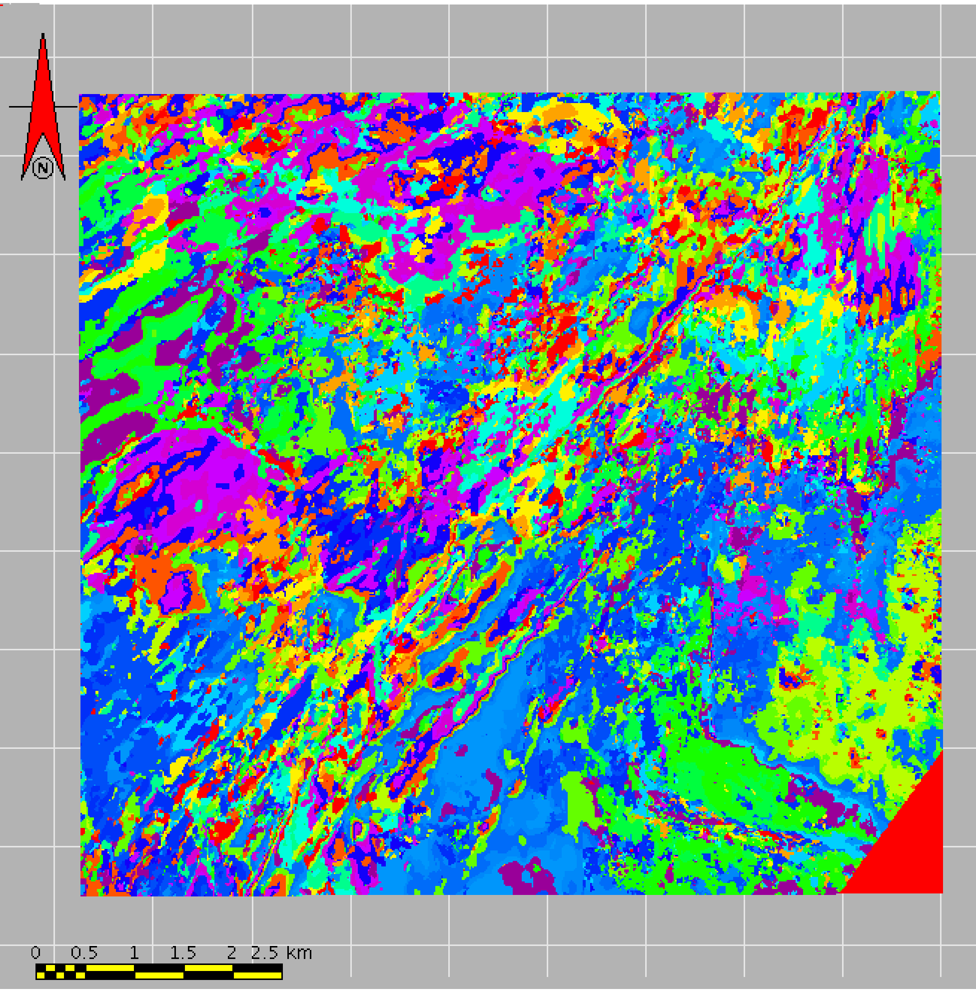
- **<u>Number of neurons constituting the map</u>**
  - **Underfitted: non identified signal**
  - **Overfitted: explain noise in the data**

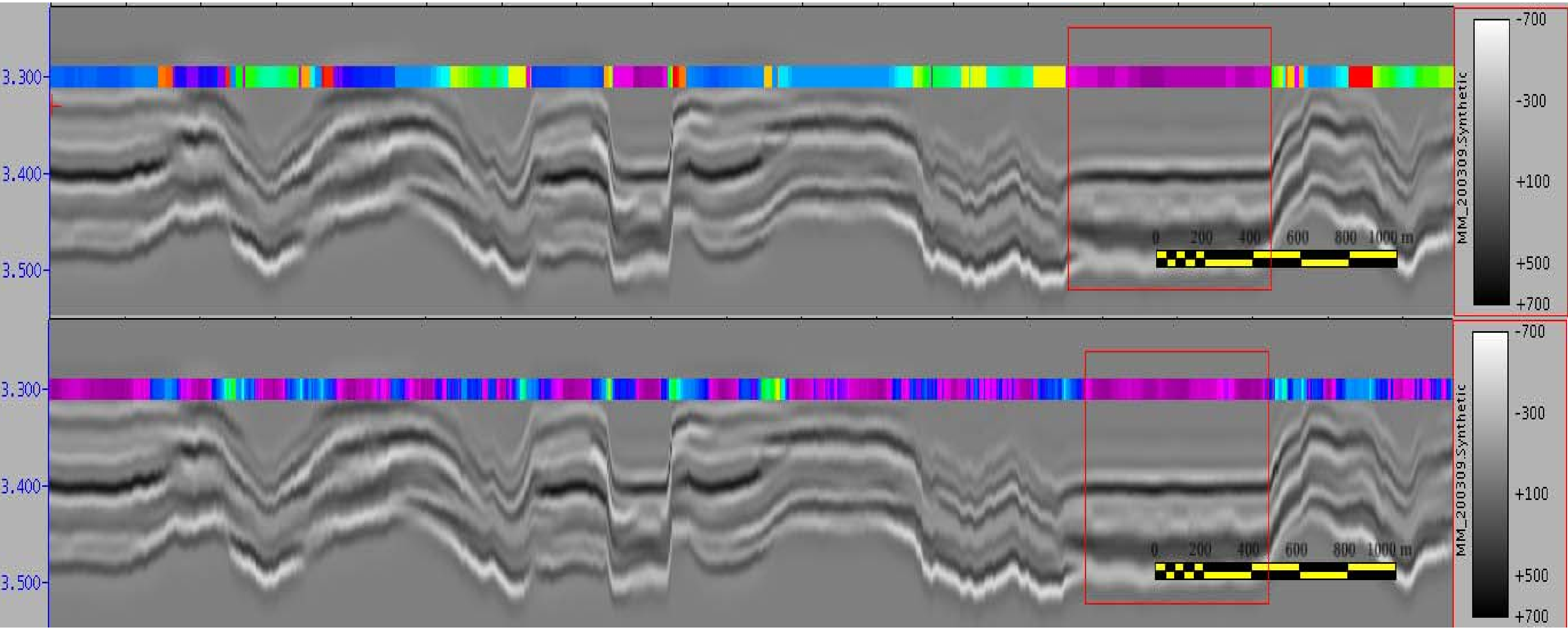
- **<u>Neighborhood radius</u>**
  - **Size of the active environment**
  - **At each iteration, neurons are updated within this radius**

- **<u>Interval thickness (in time)</u>**
  - **Will affect the stability of the network**
  - **Empirical determination**

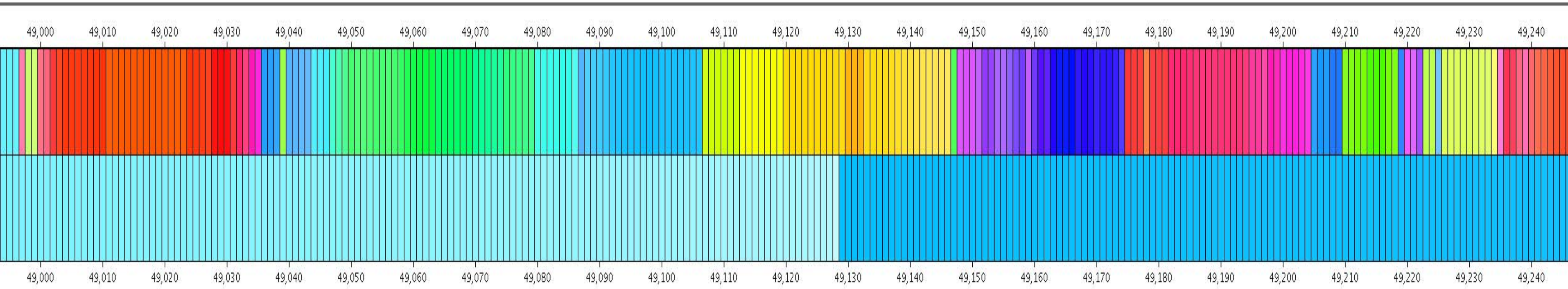
Non supervised Classification Maps with interval thickness of 50ms and 180 ms







3.300
3.400
3.500
0 200 400 600 800 1000 m
MM_200309.Synthetic
-700
-300
+100
+500
+700



49,000
49,010
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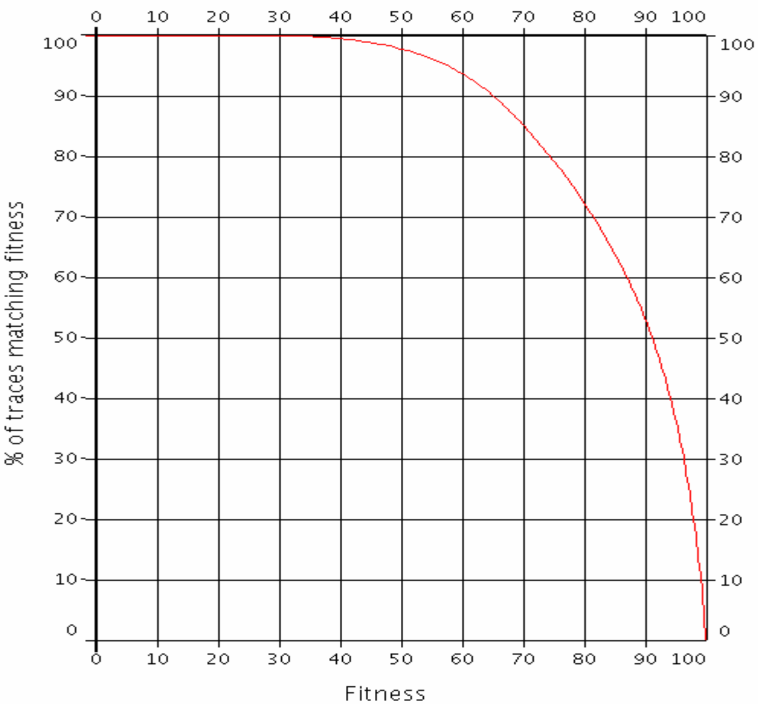
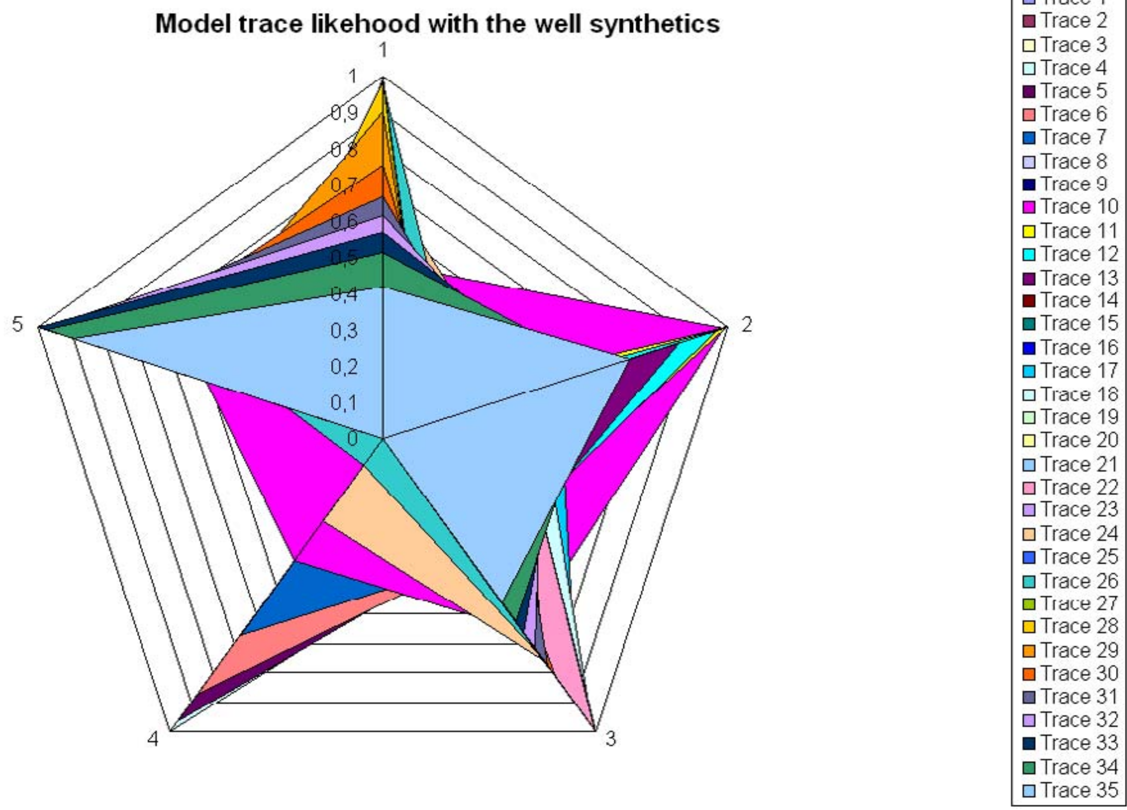
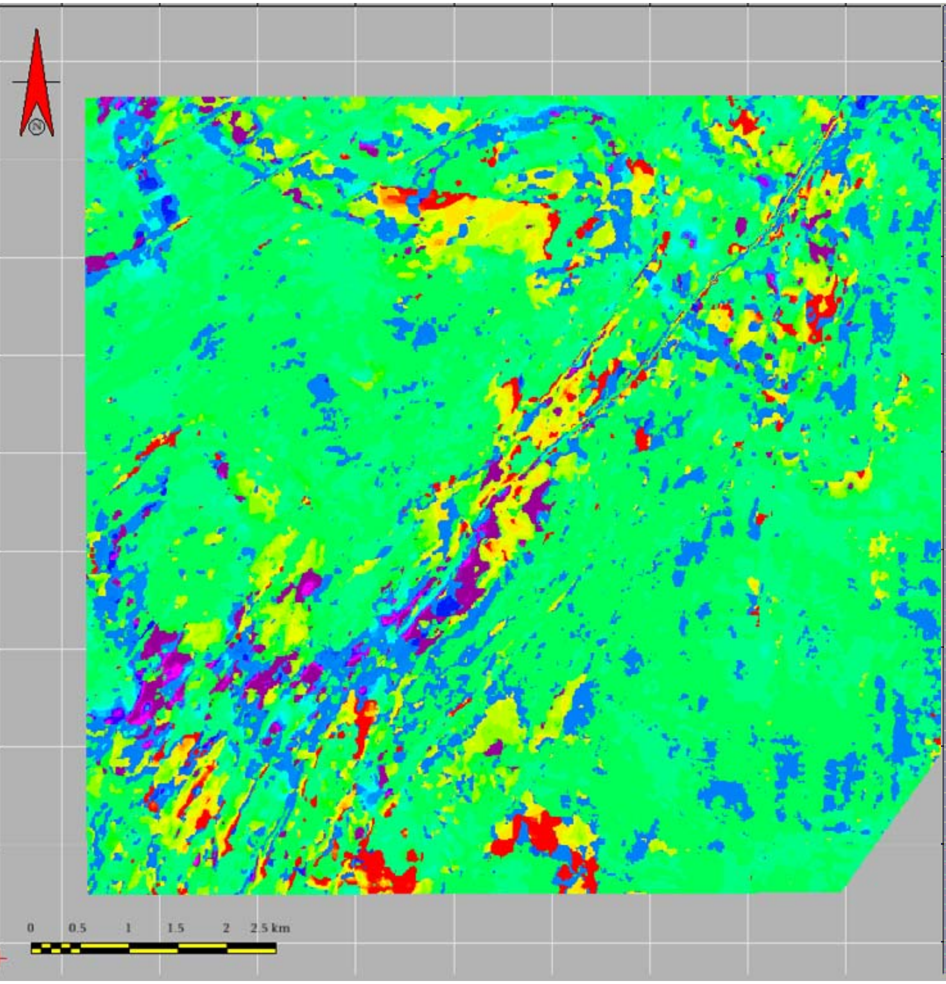


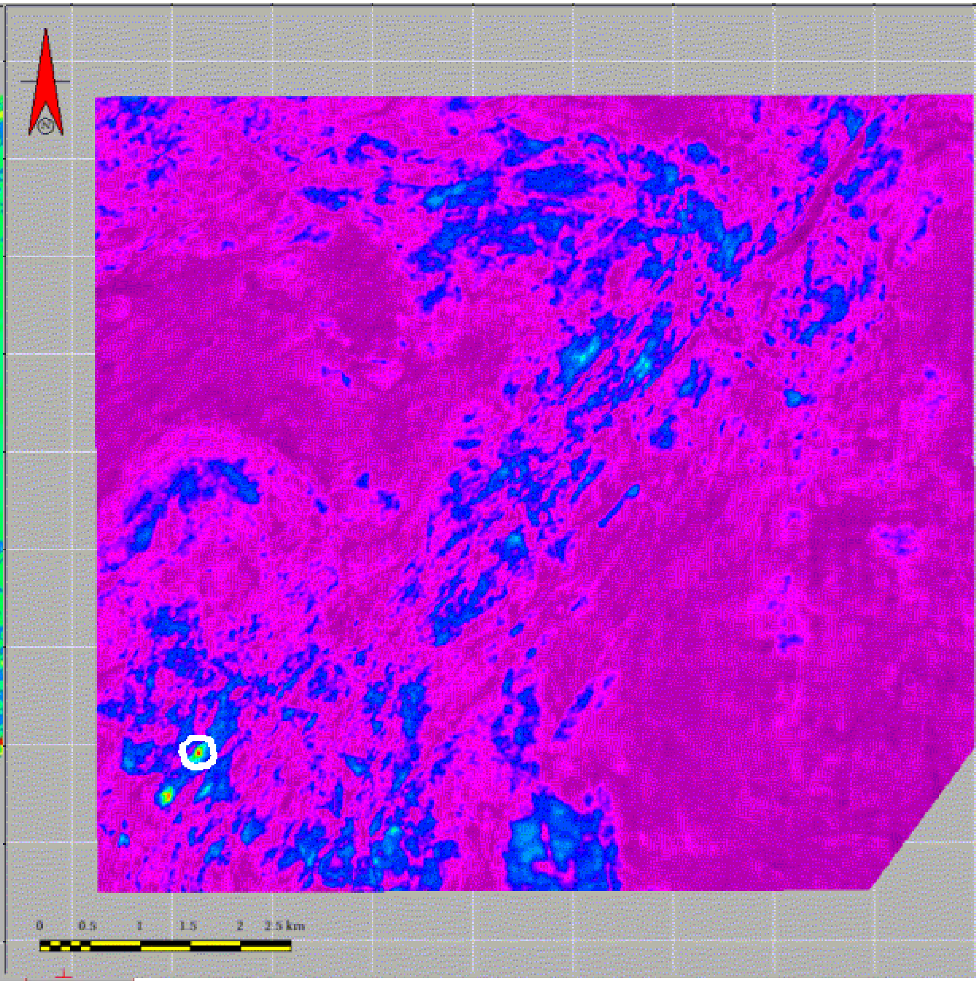


Parameter	Layer	T0 avg	T0 std dev	T1 avg	T1 std dev	T2 avg	T2 std dev
Thickness	1	5.625	3.586	5.408	3.635	5.589	3.637
Thickness	2	8.224	4.82	8.47	4.986	8.358	4.846
RHOB_resampled_blocked2_best	1	2.263	0.05	2.262	0.05	2.263	0.049
RHOB_resampled_blocked2_best	2	2.244	0.09	2.234	0.092	2.238	0.092
VP_resampled_blocked2_best	1	2,303.646	258.515	2,282.568	266.702	2,307.944	256.789
VP_resampled_blocked2_best	2	2,255.442	163.553	2,239.616	156.02	2,256.437	163.371

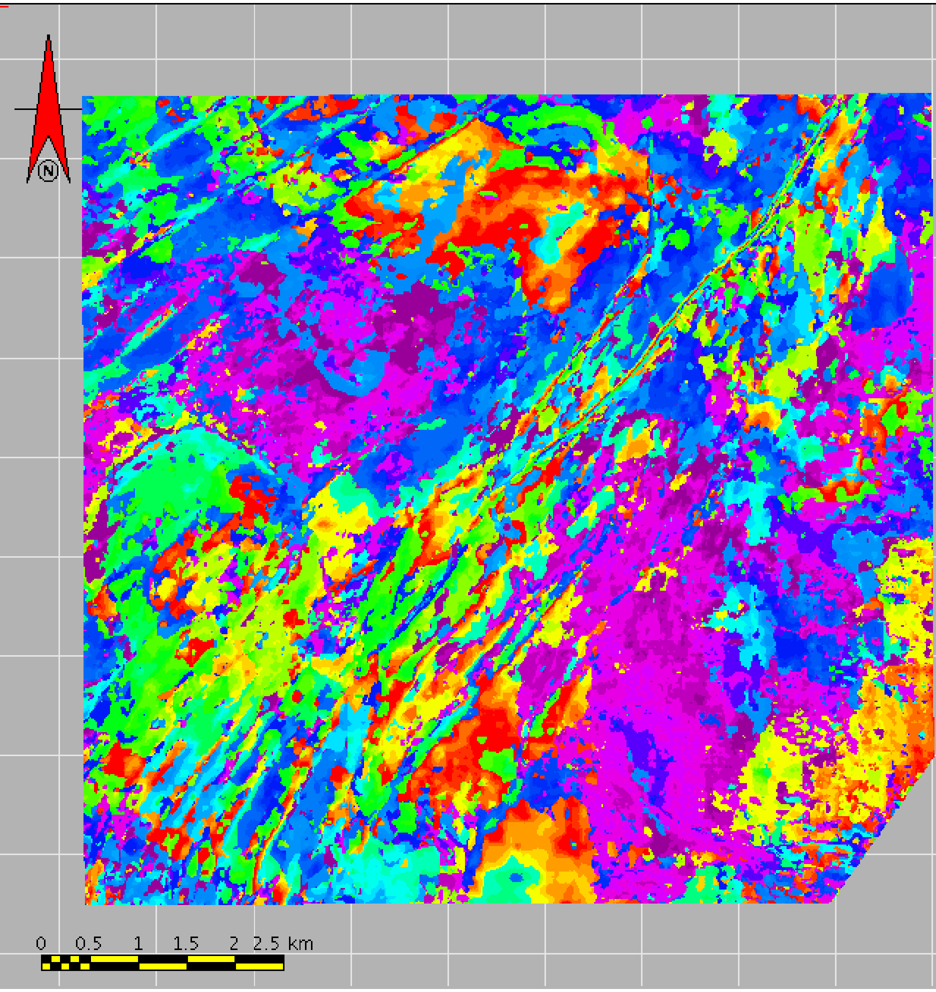
Beta Field: Petrophysical training



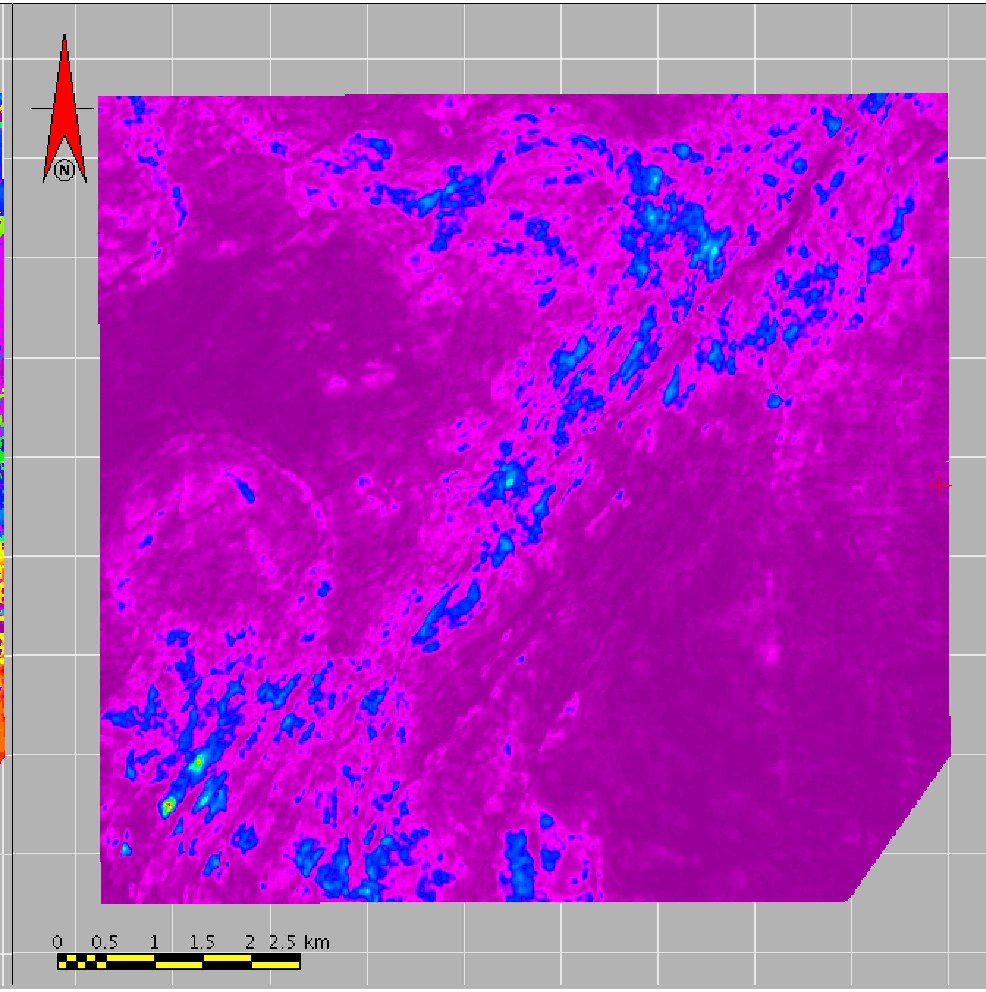
Neural Map



Fitness

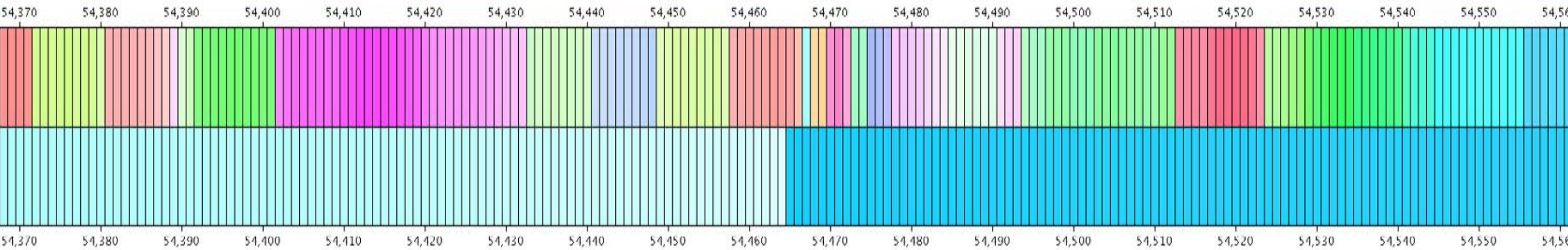


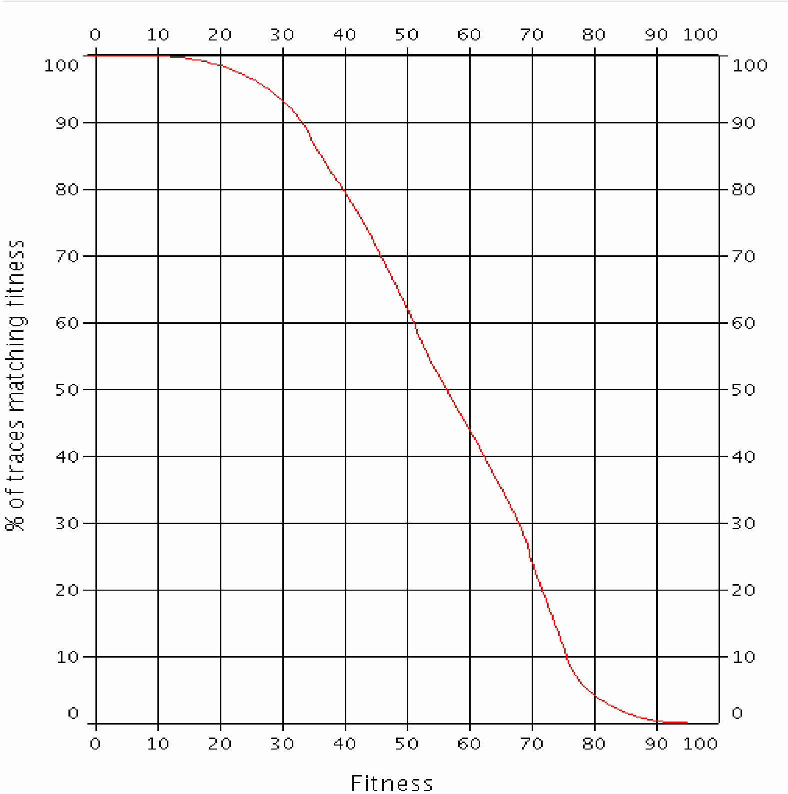
Neural Map

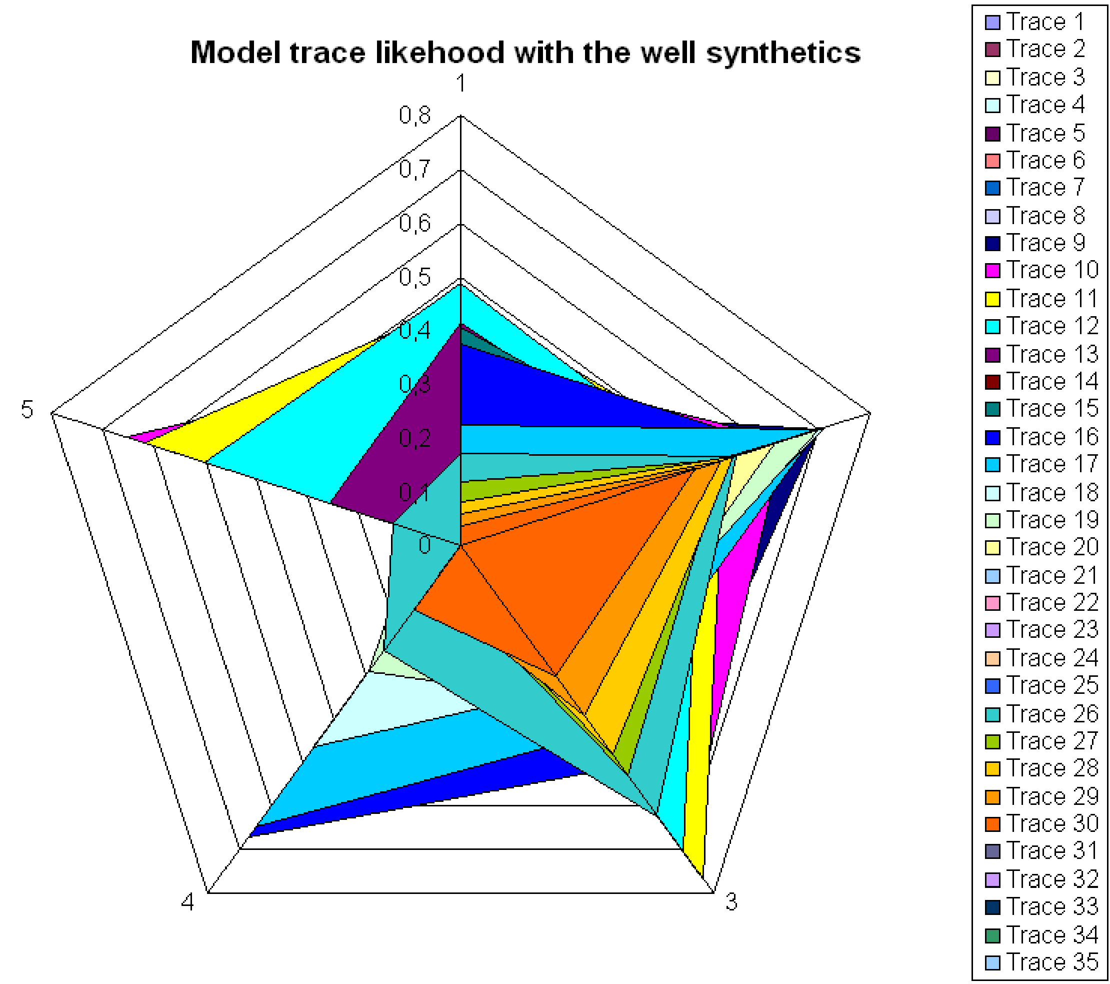


Fitness

Beta Field: Seismic training

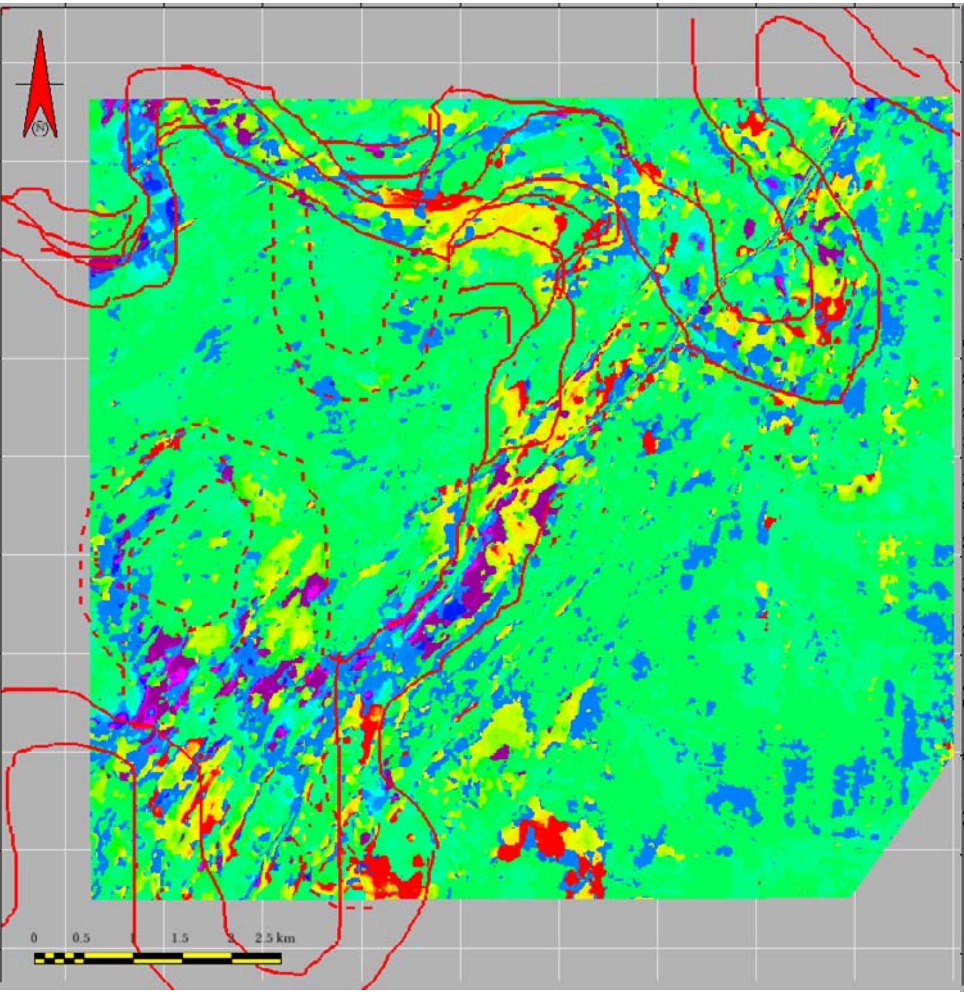




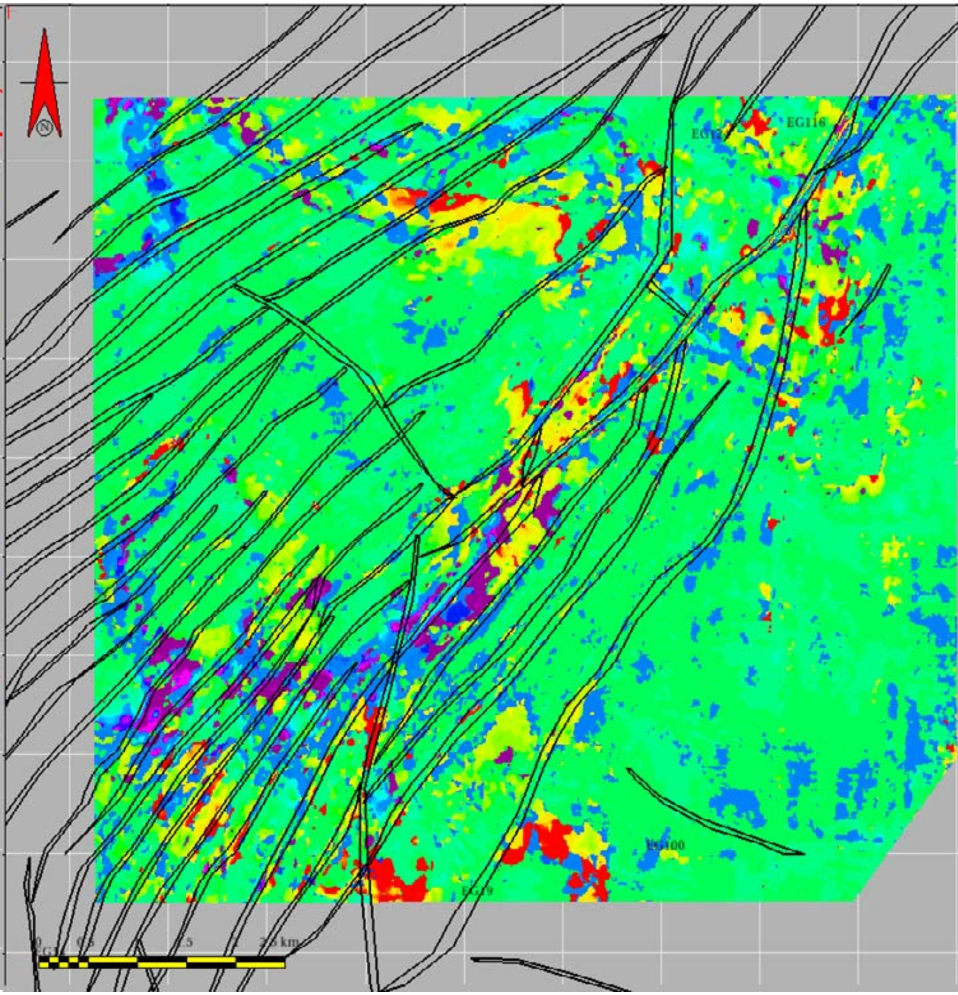


Supervised map interpretation for the petrophysical training

Sedimentary shape recognition

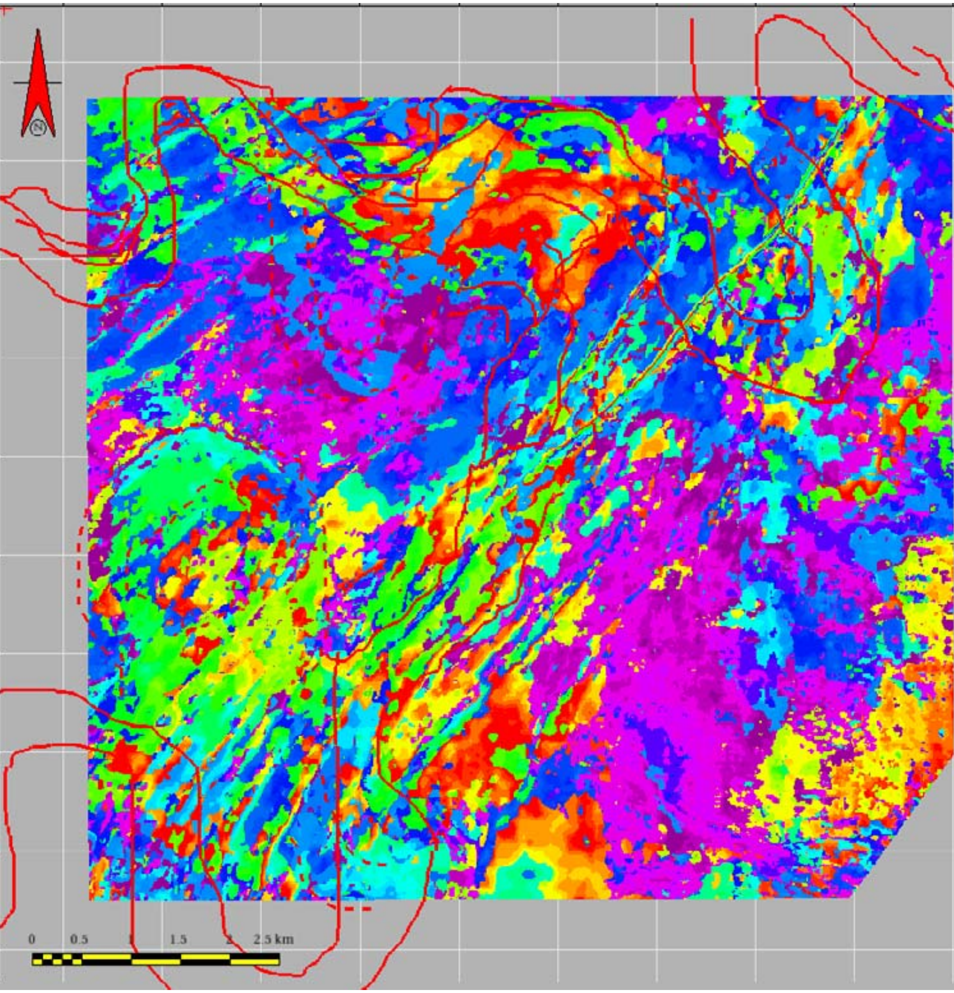


Structural content recognition

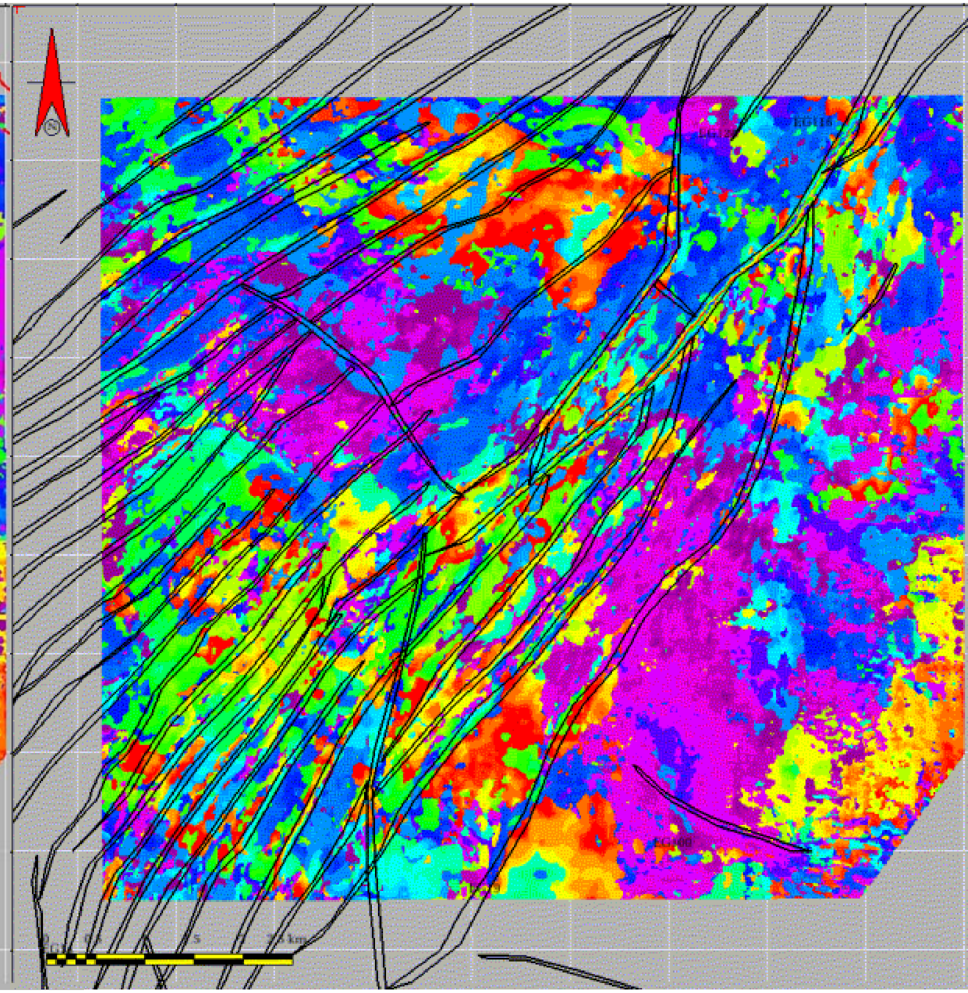


Supervised map interpretation for the seismic training

Sedimentary shape recognition



Structural content recognition



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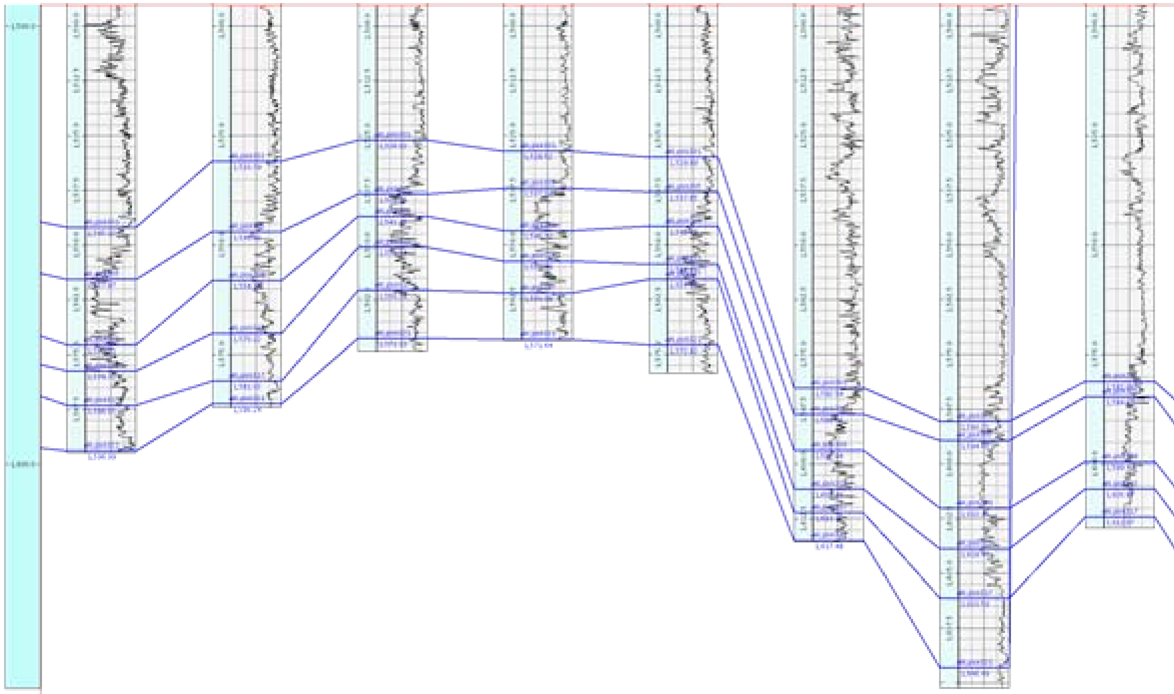
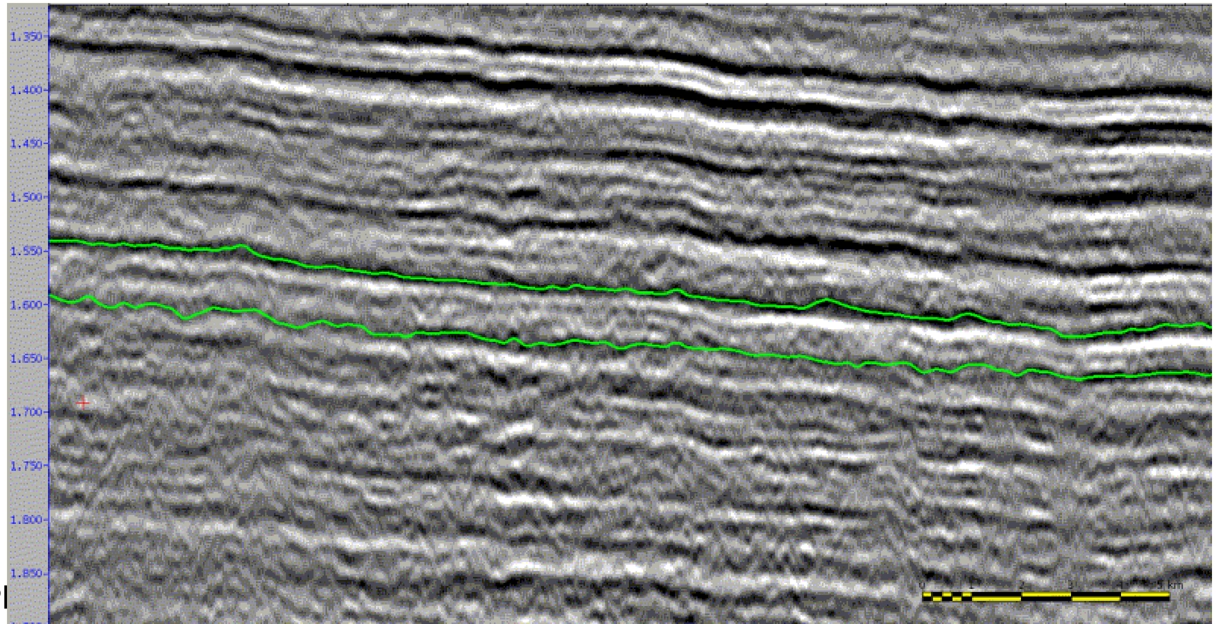
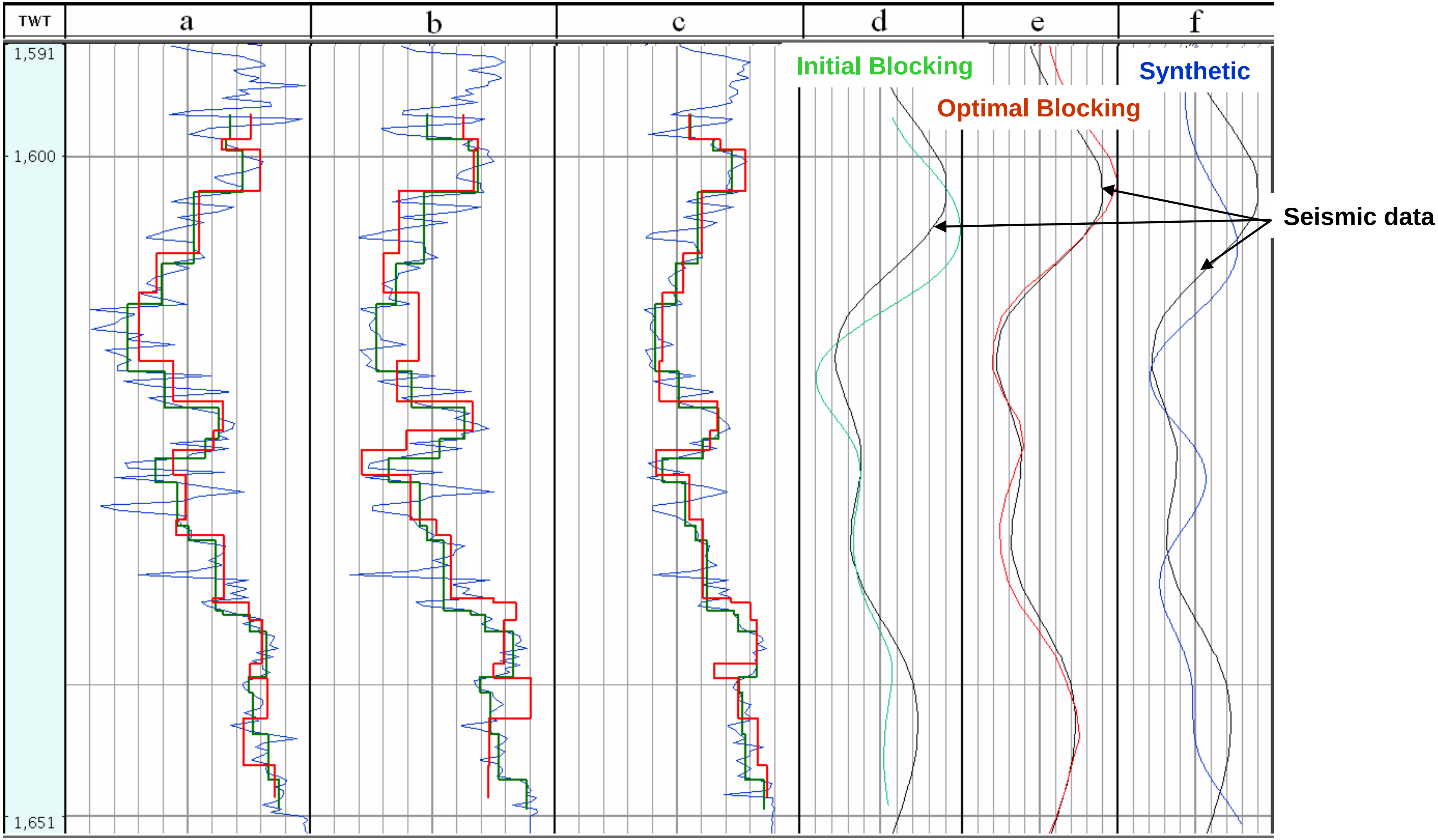
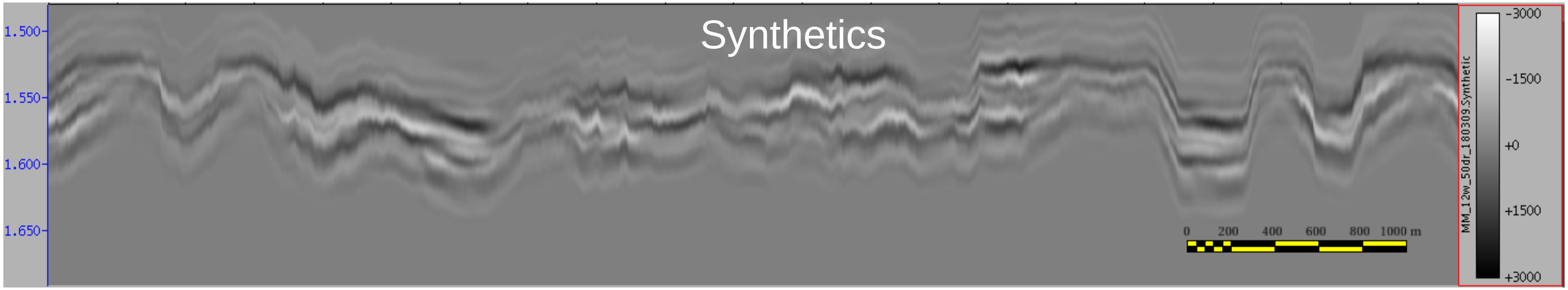
- Gamma Field :
  - 12 wells
  - Target reservoir = 70ms

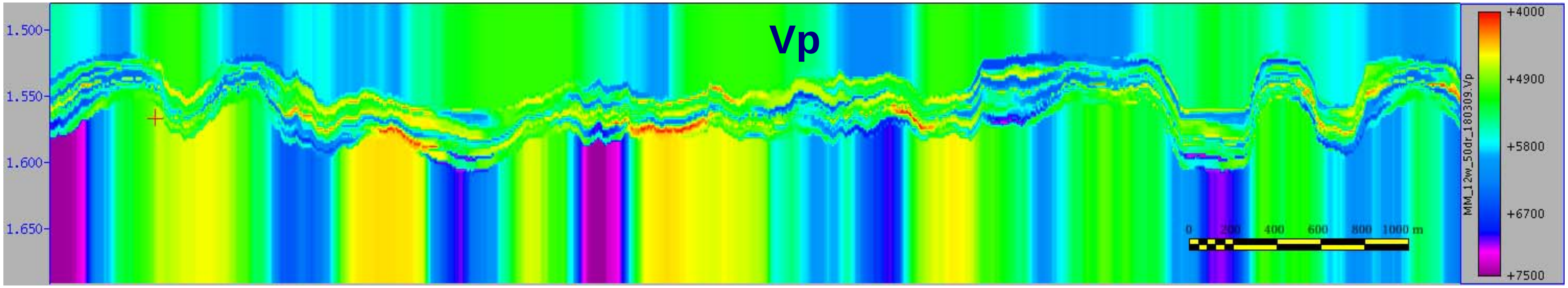


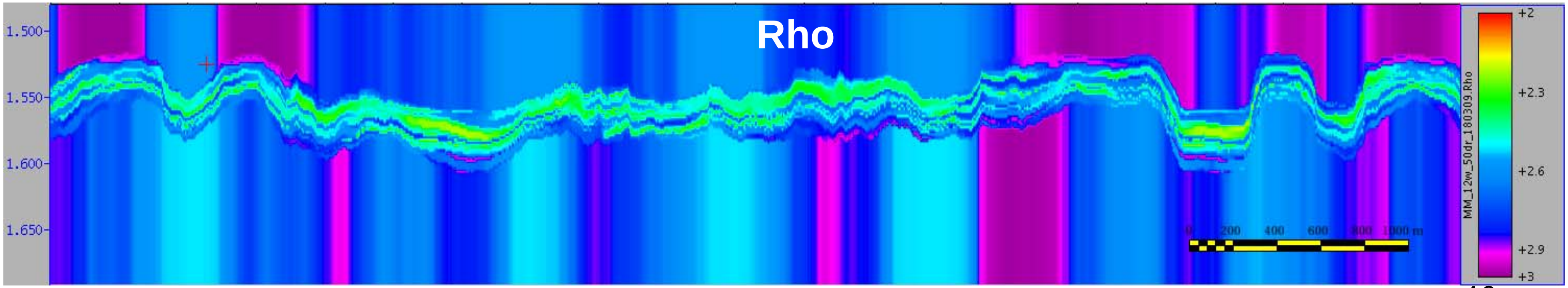



TWT
a
b
c
d
e
f
1,591
1,600
1,651
Initial Blocking
Optimal Blocking
Synthetic
Seismic data

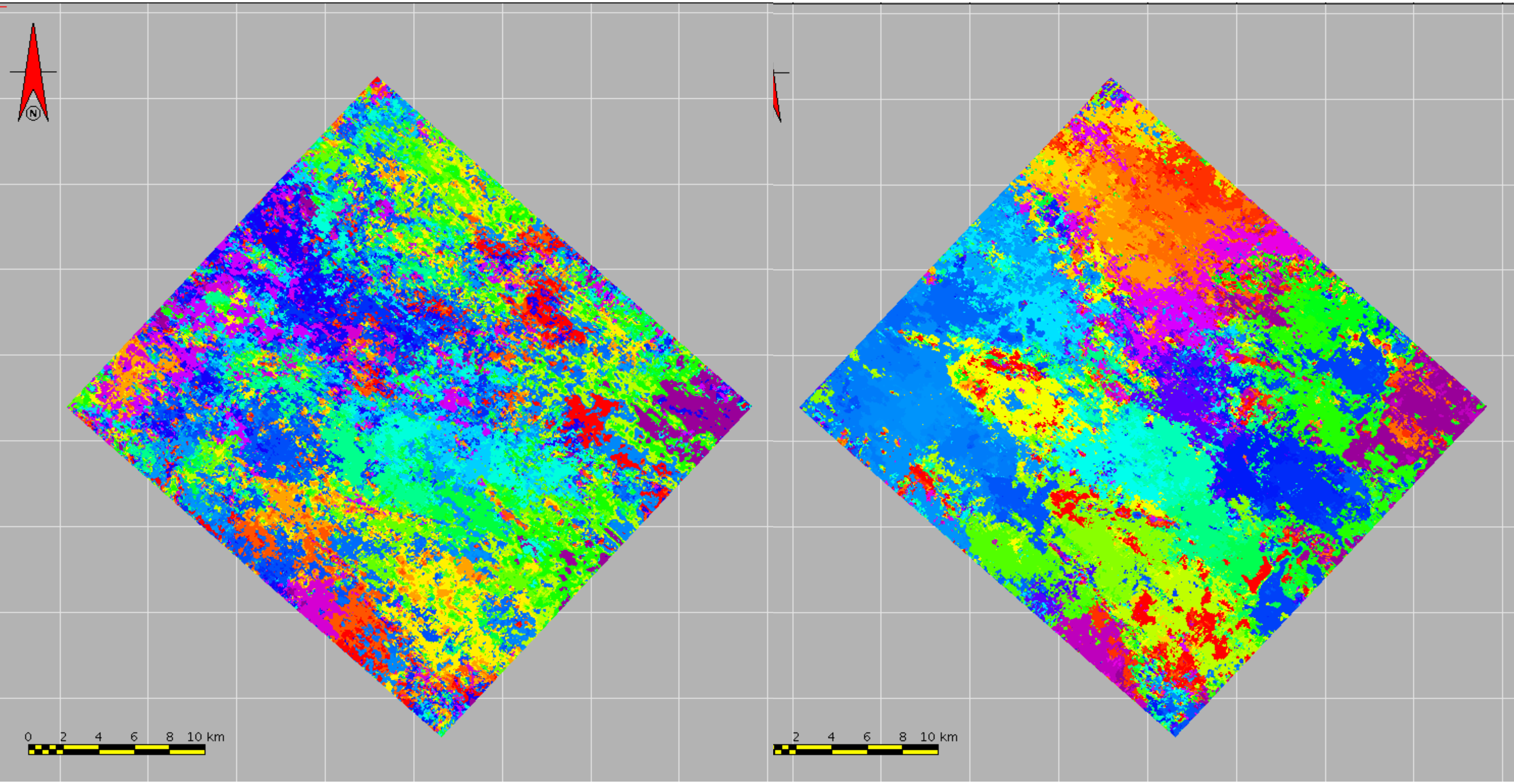
Training set used more than 80000 traces



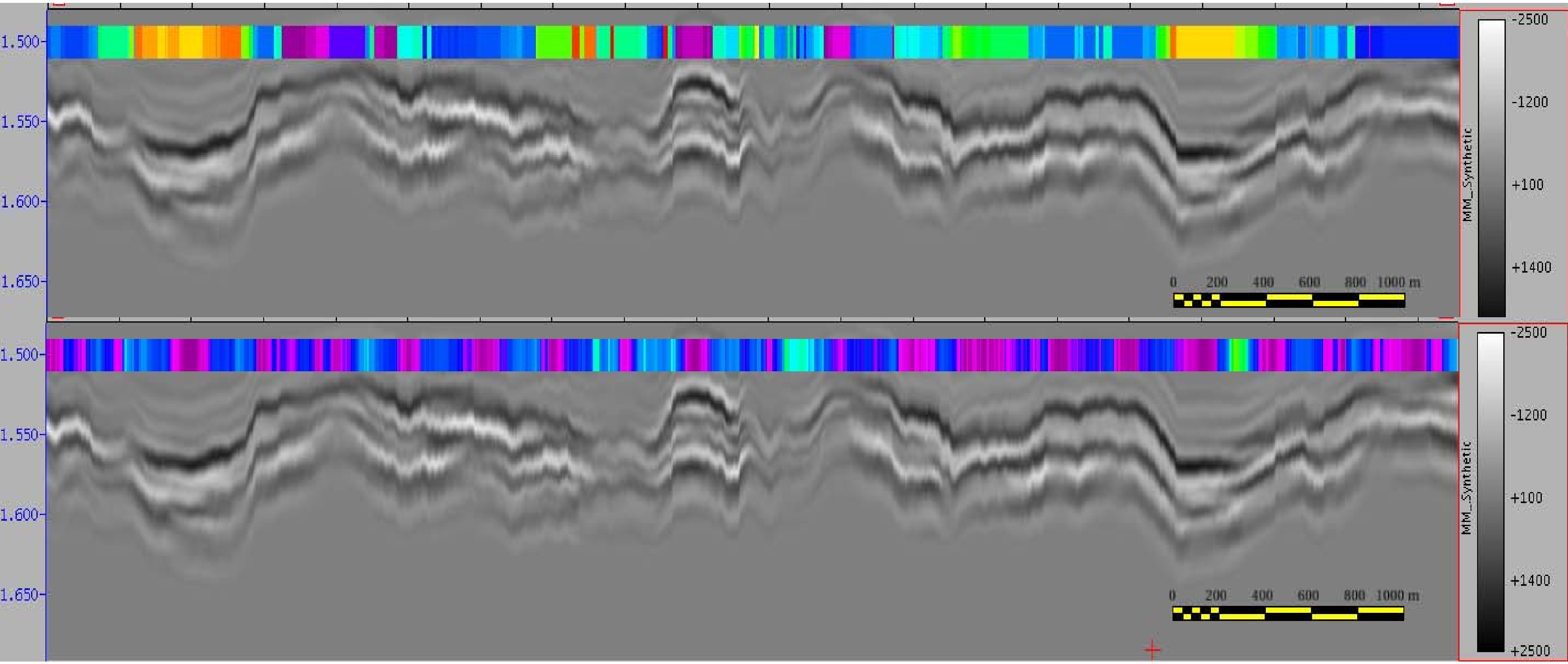


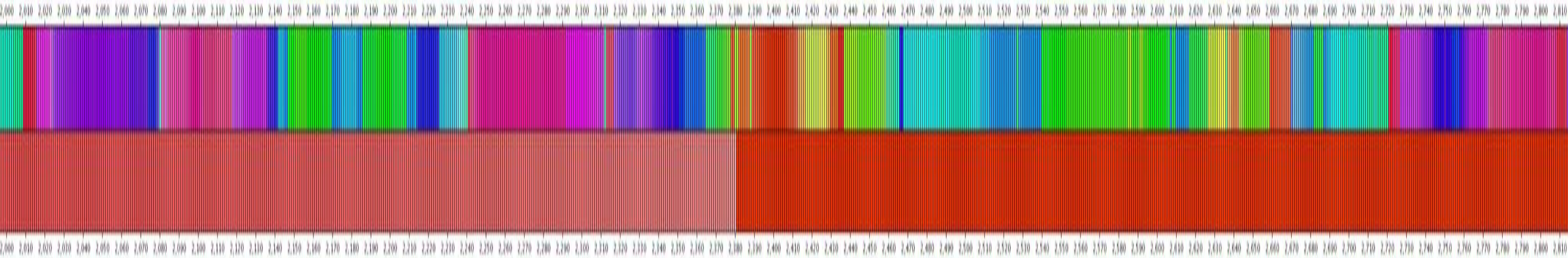


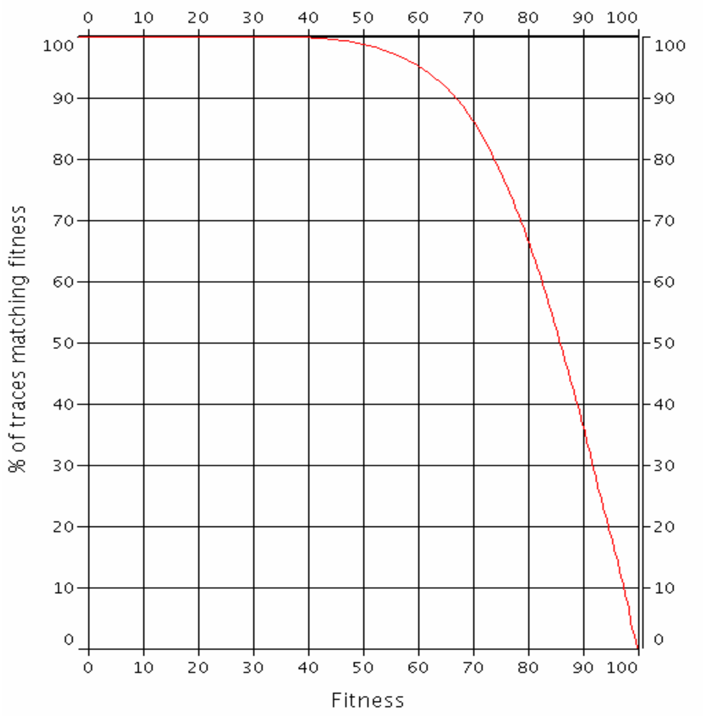
Non supervised Classification Maps with interval thickness of 50ms and 100 ms

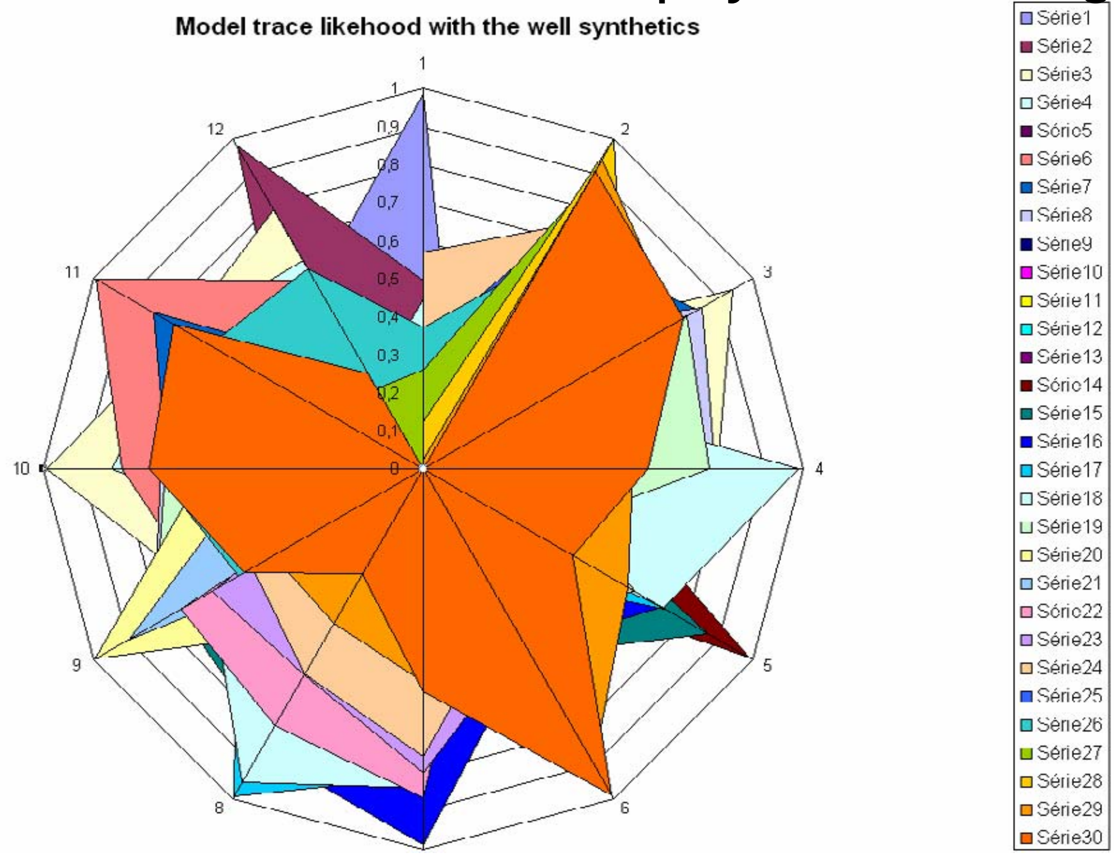


Gamma Field: Petrophysical training



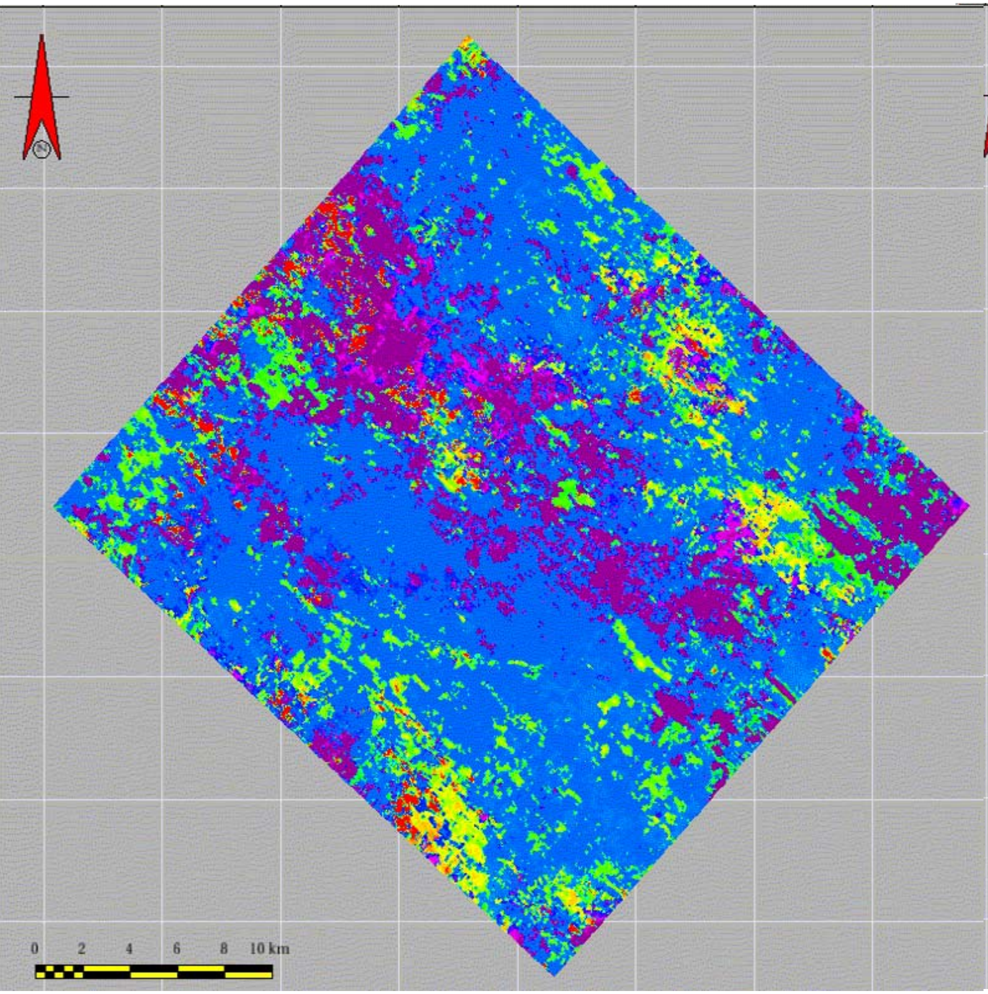




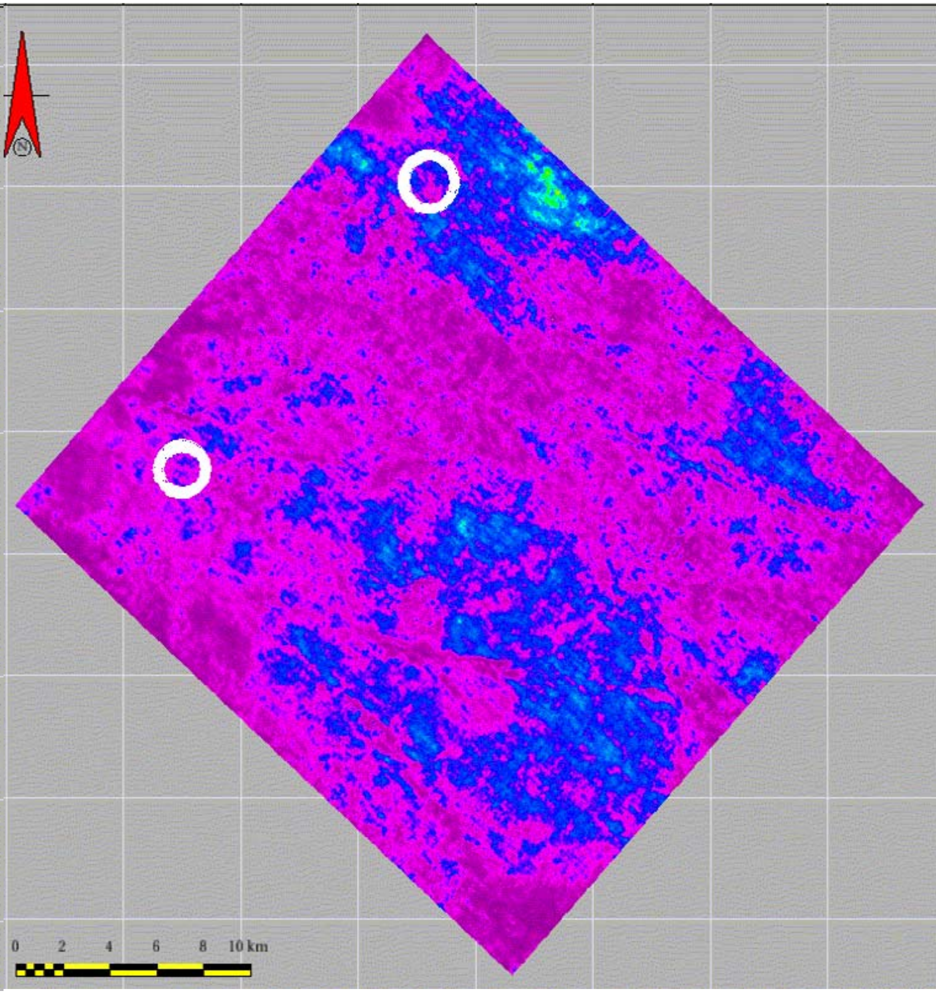


Parameter	Layer	T0 avg	T0 std dev	T1 avg	T1 std dev	T2 avg	T2 std dev	T3 avg	T3 std dev
Thickness	1	7.887	6.887	6.024	4.2	14.395	9.276	6.612	5.503
Thickness	2	4.755	4.848	2.906	2.453	6.218	5.675	1.953	2.519
RHO_resam...	1	2.765	0.082	2.756	0.05	2.755	0.078	2.738	0.076
RHO_resam...	2	2.682	0.073	2.653	0.041	2.683	0.06	2.645	0.064
Vp_resampl...	1	5,700.421	245.757	5,687.309	150.244	5,586.66	262.739	5,385.271	248.571
Vp_resampl...	2	5,847.324	322.966	5,901.429	197.275	5,994.325	293.835	5,808.403	297.603

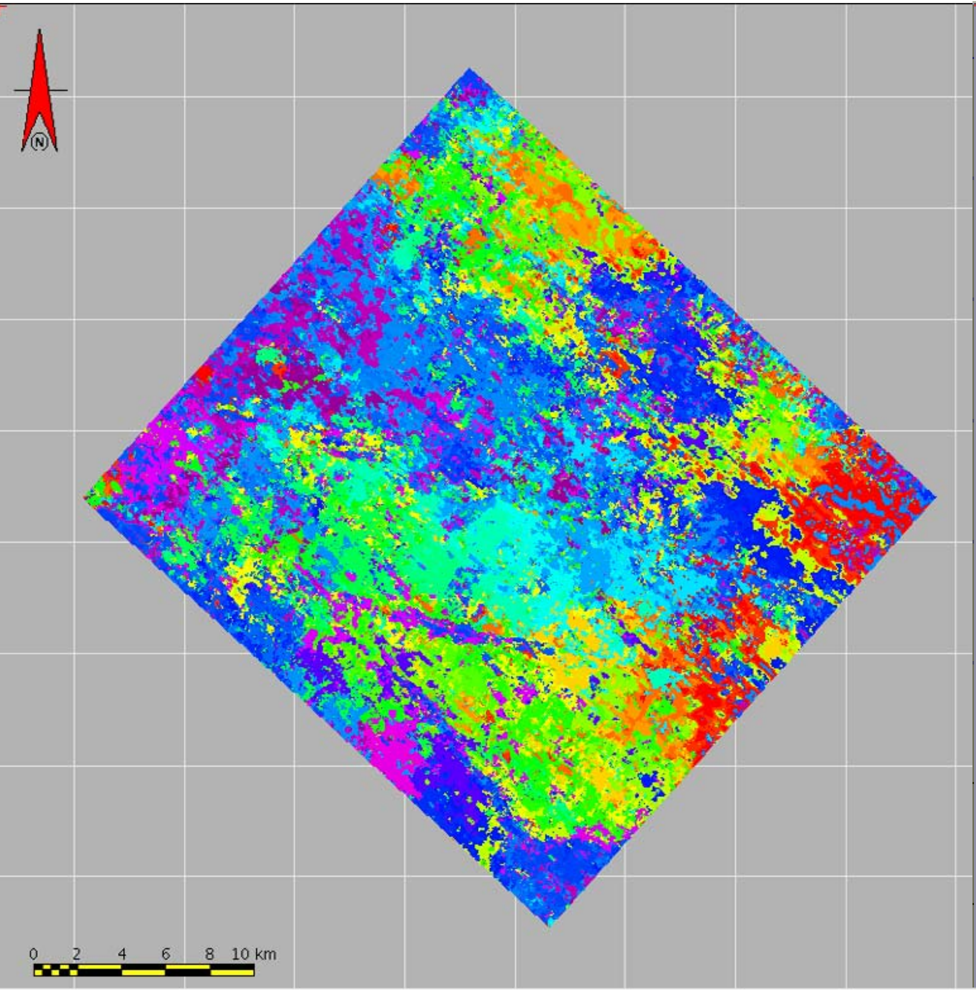
Gamma Field: Petrophysical training



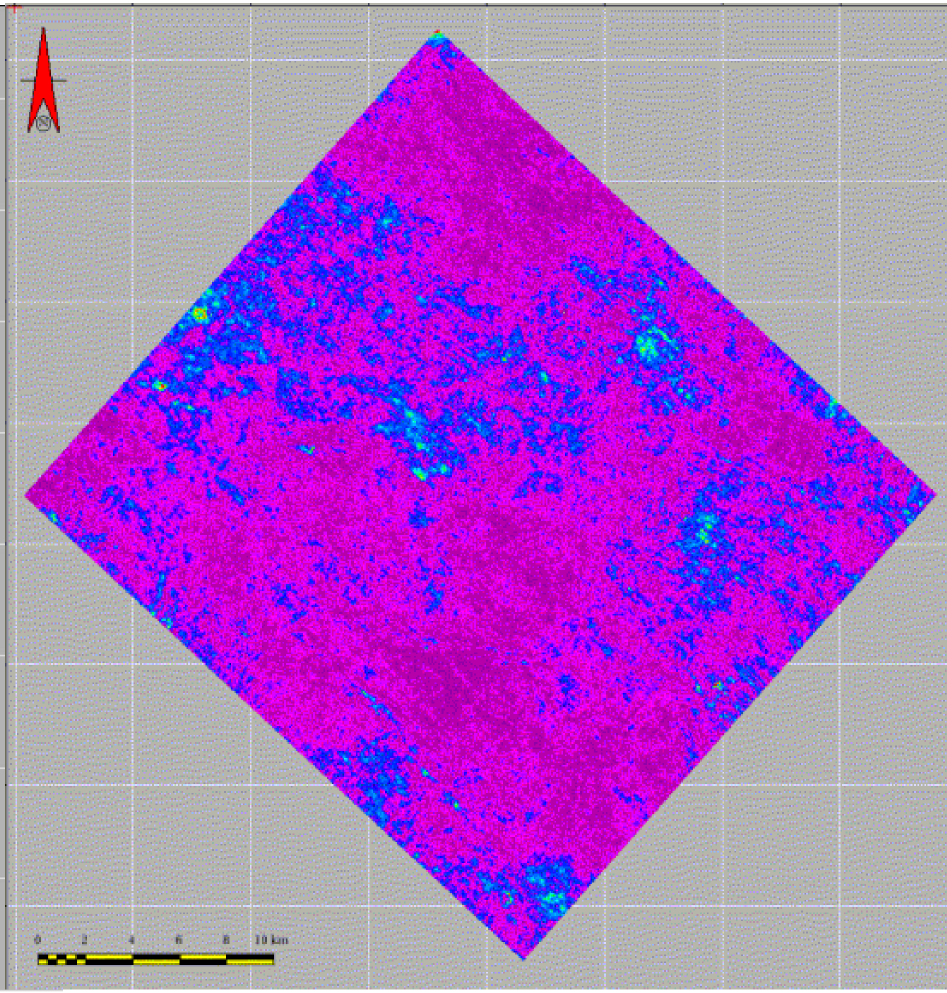
Neural Map



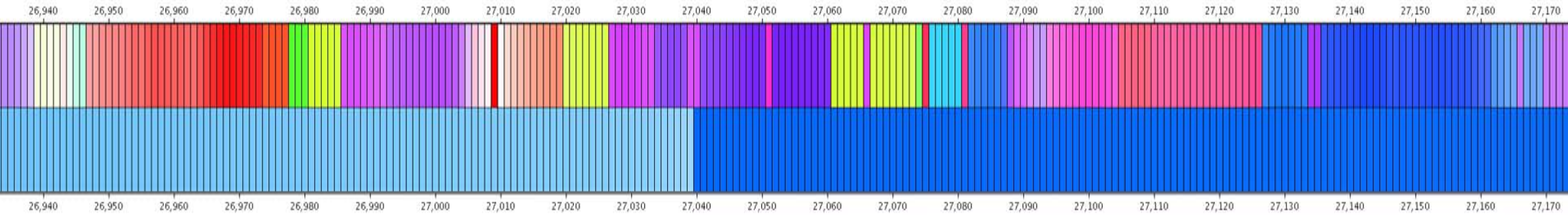
Fitness

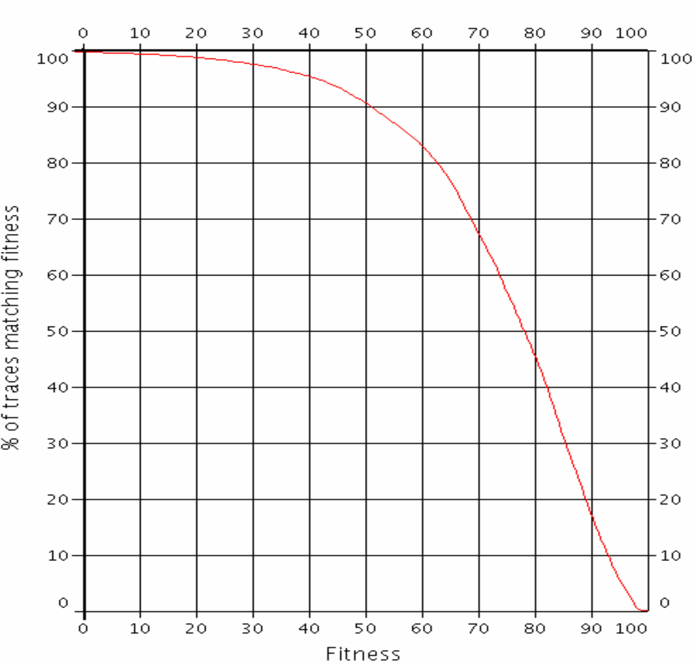


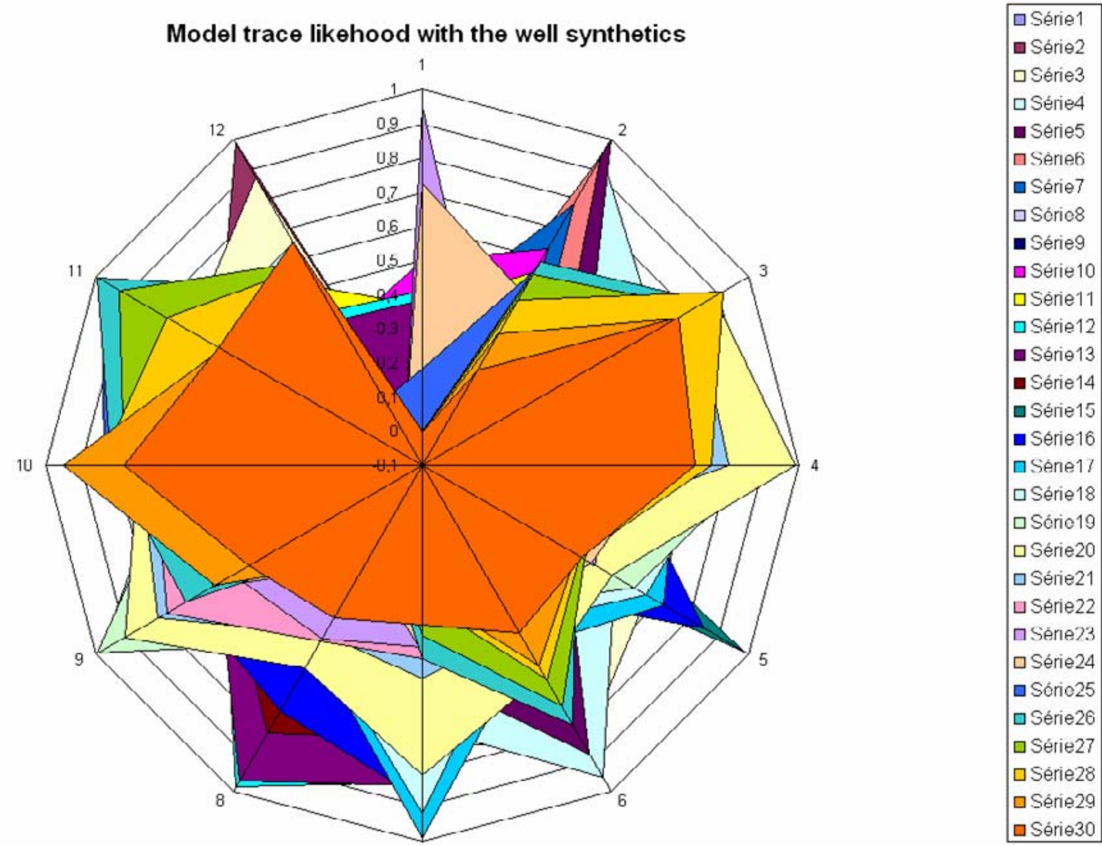
Neural Map



Fitness

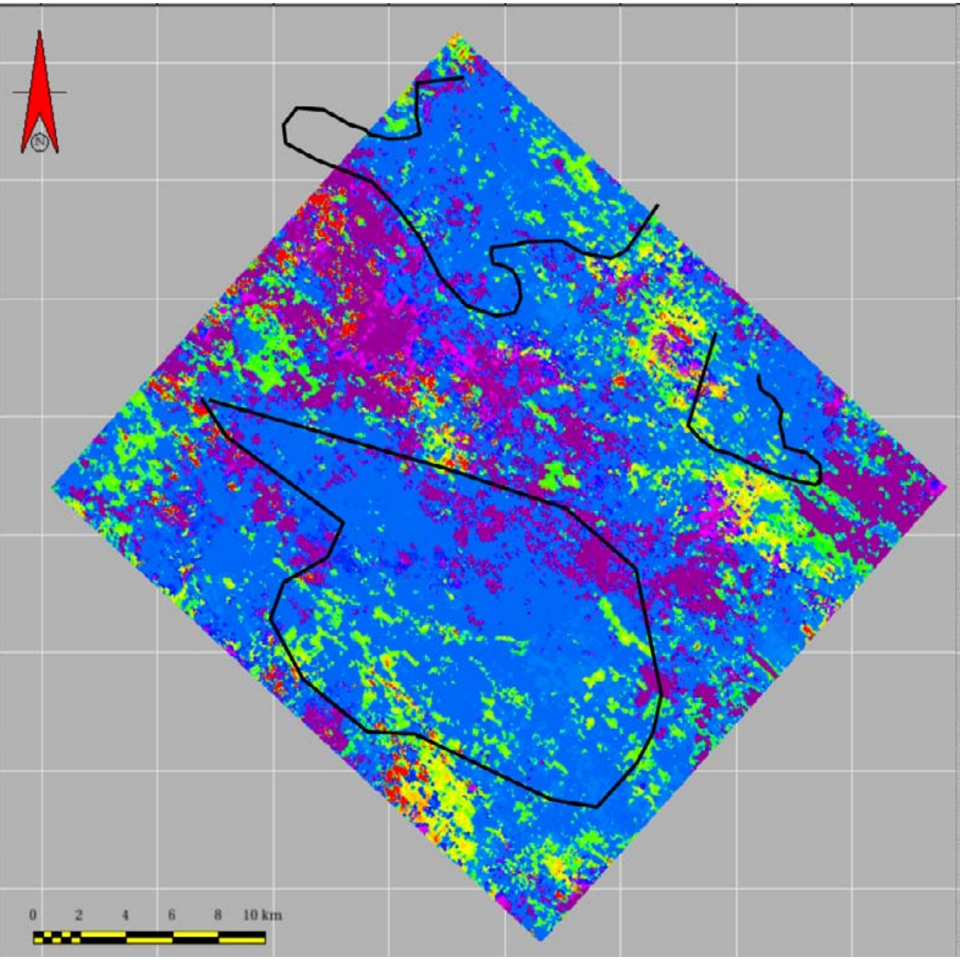



% of traces matching fitness
Fitness

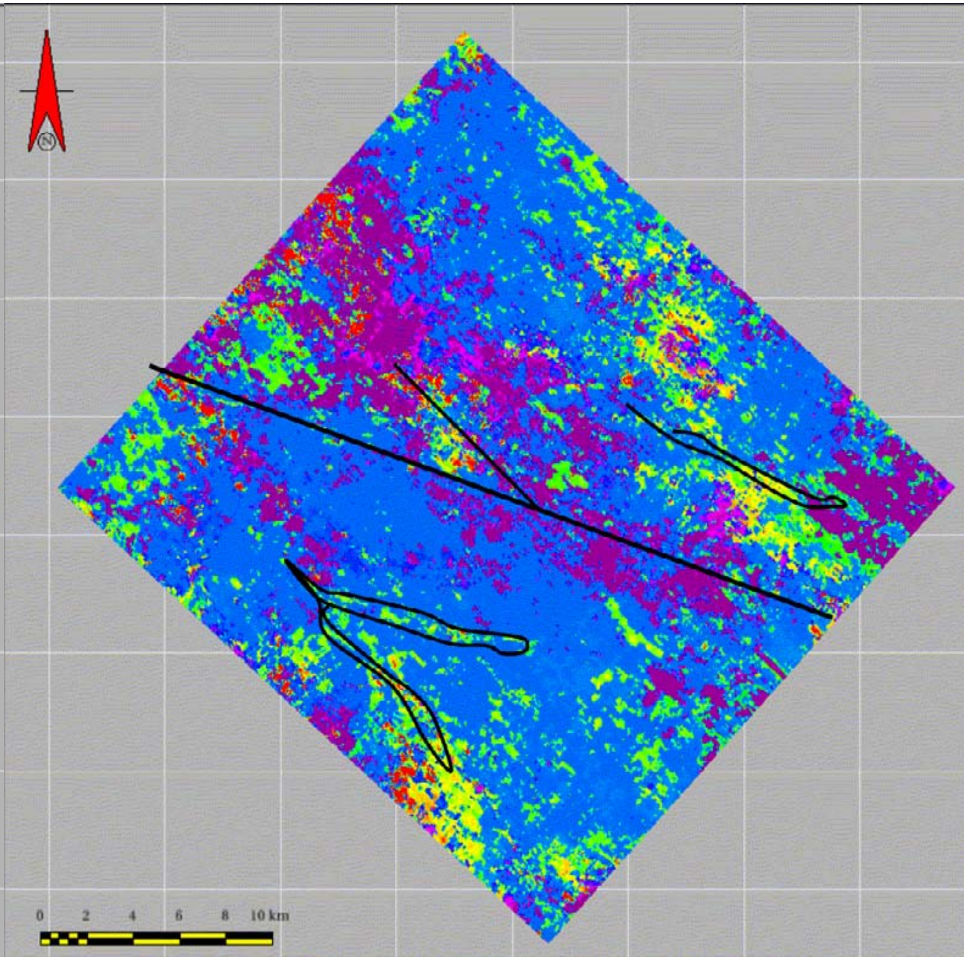

Model trace likehood with the well synthetics
Série1
Série2
Série3
Série4
Série5
Série6
Série7
Série8
Série9
Série10
Série11
Série12
Série13
Série14
Série15
Série16
Série17
Série18
Série19
Série20
Série21
Série22
Série23
Série24
Série25
Série26
Série27
Série28
Série29
Série30

Supervised map interpretation for the petrophysical training

Sedimentary shape recognition

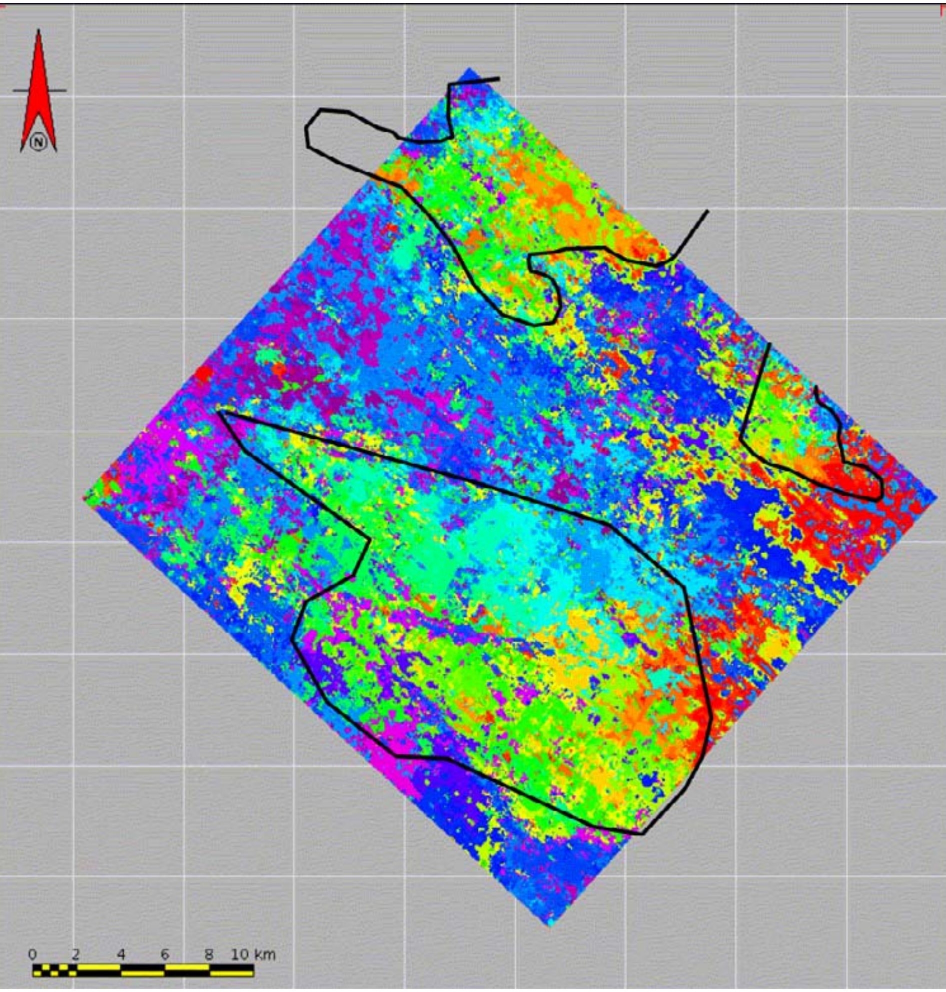


Structural content recognition

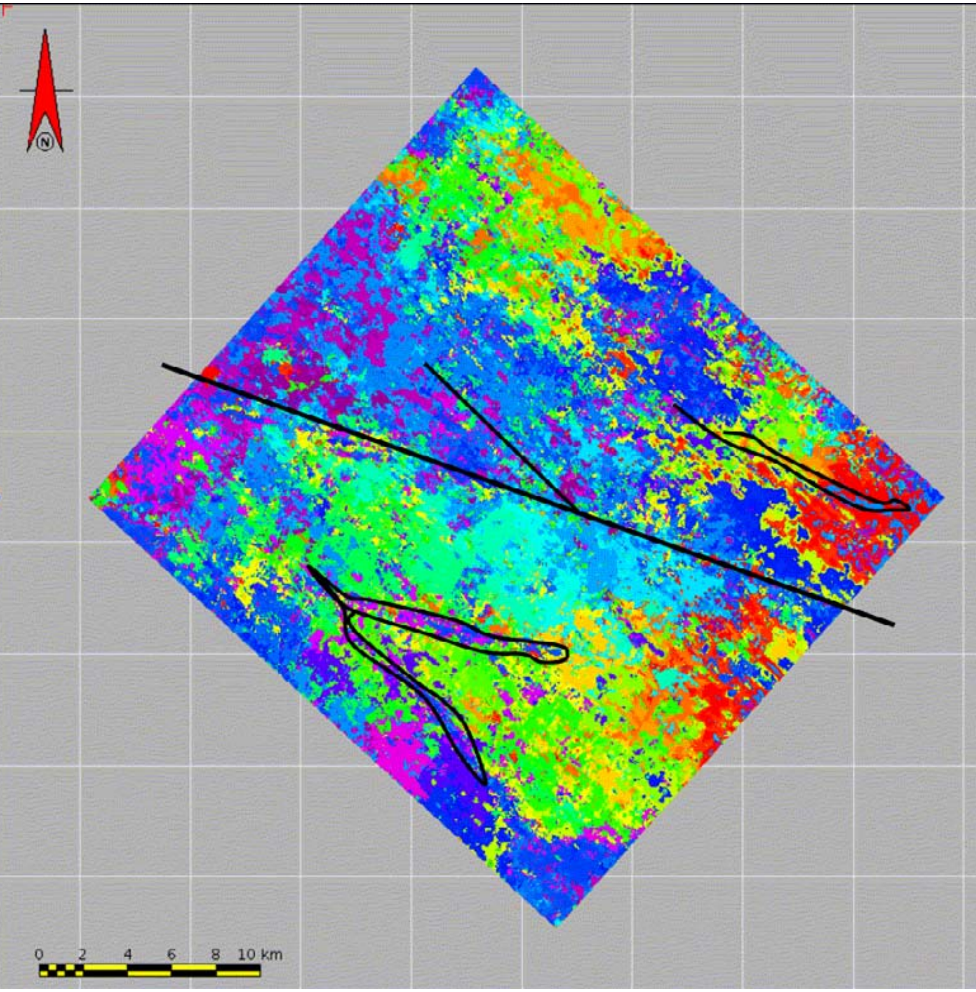


Supervised map interpretation for the seismic training

Sedimentary shape recognition



Structural content recognition



- **Supervised Neural Classification – Methodology**
  - Kohonen Self Organizing Maps
  - Data Preparation
- **The Massive Modeling Approach**
- **Application on a clastic case study: Beta Field**
  - Preliminary tests
  - Petrophysical Training
  - Seismic Training
  - Validation of results
- **Application on a carbonate case study: Gamma field**
  - Preliminary tests
  - Petrophysical Training
  - Seismic Training
  - Validation of results
- **Conclusion on Neural Network Inversion**

Conclusion on Neural Network Inversion

Methodology:

- We have described a new approach for supervised classification of seismic data for reservoir characterization
- Main difficulty of supervised classification : sparseness of the training population:
- Solution: massive synthetic data created by geostatistical interpolation of well log data.
- Choice of parameters is data-dependent
- Tools are available to guide the user

Case studies:

- Clastic case : success in petrophysical training to delineate geological bodies
- Carbonate case : success in seismic training to delinate main facies

Perspectives:

- Better representation of the geology in the training set
- Automatic discrimination of classes according to reservoir properties
- Working with seismic attributes instead of seismic amplitudes

Main contributions :

Reconcile the Reservoir grid with the Seismic data

- Evaluation of the reservoir grid
  - Compatibility Reservoir grid / seismic data
  - Impact of reservoir uncertainties

- Inversion of seismic data
  - Inversion based on Gradual Deformation
    - Need more work, a lot of improvement are possible

    \- Slow, works on a part of the reservoir, one composant variogram

    \+ No upscaling of the attributes is required
  - Conditional waveform recognition
    - Integrate the reservoir grid in the process

    \- Last step still missing (assigning petrophysical models to seismic traces)

    \+ Get the seismic information at the reservoir scale