Integrated Electromagnetic methods supported by Machine Learning for Risk Mitigation in Exploration Geosciences

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Summary of the presentation

In this presentation, we discuss a general method for supporting exploration with multidisciplinary data and Machine Learning methods. We explain the method directly using a real application as a significant case history. We explain how we obtained a suite of oil prediction maps in the Barents Sea combining seismic, electromagnetic and gravity data, and with the crucial support of a full Machine Learning workflow. We discuss data analysis and methods and show the results vs. the wells drilled in the area of study. The following are useful reference papers, including all the technical details of our approach:

1)*Paolo Dell'Aversana, Stefano Colombo, Barbara Ciurlo, Johan Leutscher and Jan Seldal, 2012.* CSEM data interpretation constrained by seismic and gravity data: an application in a complex geological setting. First Break.

2) *Paolo Dell'Aversana, Stefano Colombo, Barbara Ciurlo, 2018.* Integrated Geophysics and Machine Learning for Risk Mitigation in Exploration Geosciences. EAGE Conference Extended abstract.

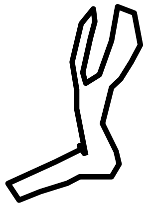
Summary slide: data, methods and results

Data	Methods
1) 2D seismic lines	1) Seismic interpretat.
2) 2D CSEM lines	2) CSEM-Grav. Interpr.
3) Satellite gravity data	3) Cooperat. Modelling
4) Well logs	4) Constrained invers.
5) Prior geological and structural info	5) Joint inversion
	6) Machine Learning

Wells used for calibration in the 2010-2017 study

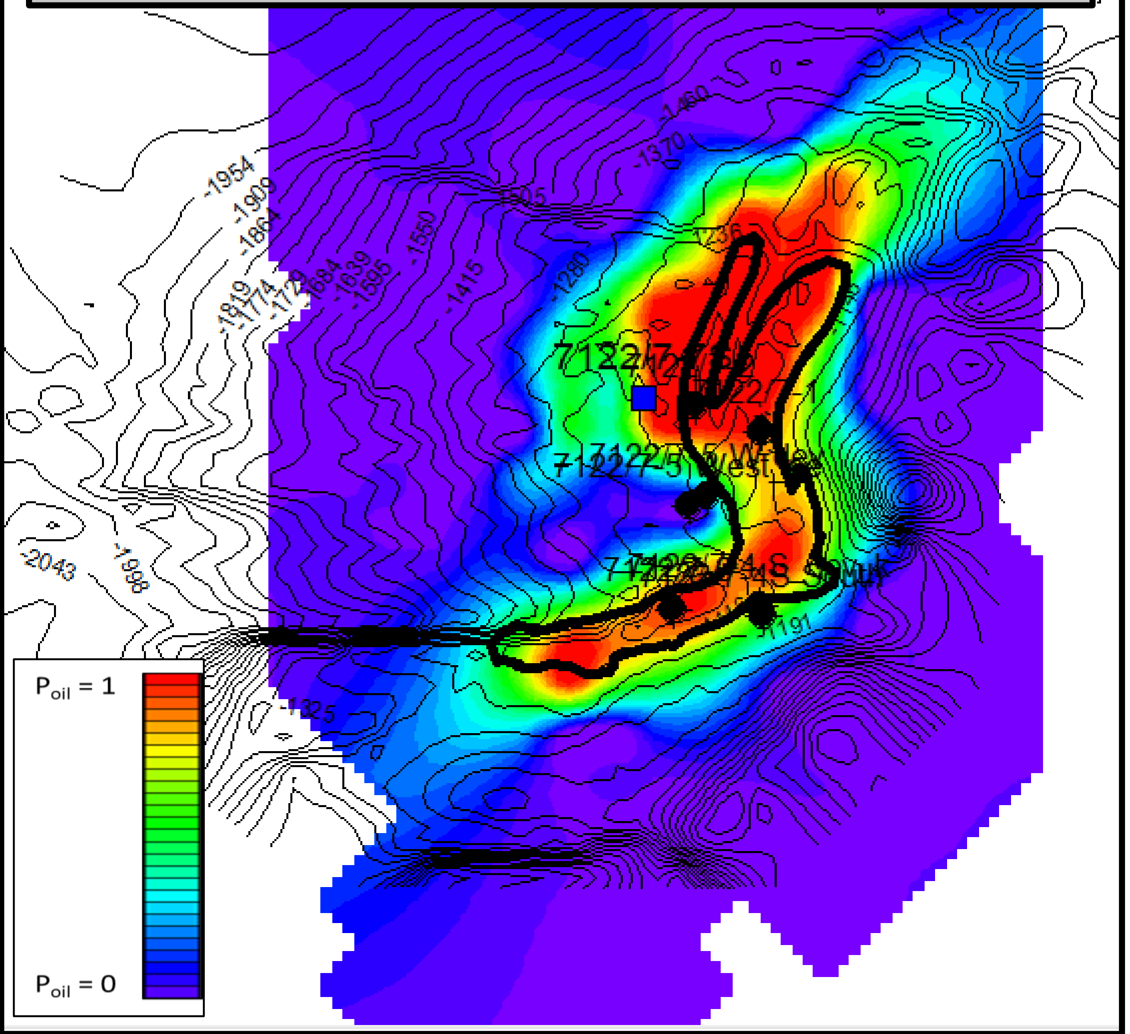
Appraisal well drilled in 2019

‘Old’ (2012) HC/W contact based on seismic data Interpretation and wells, provided in 2010-2012.

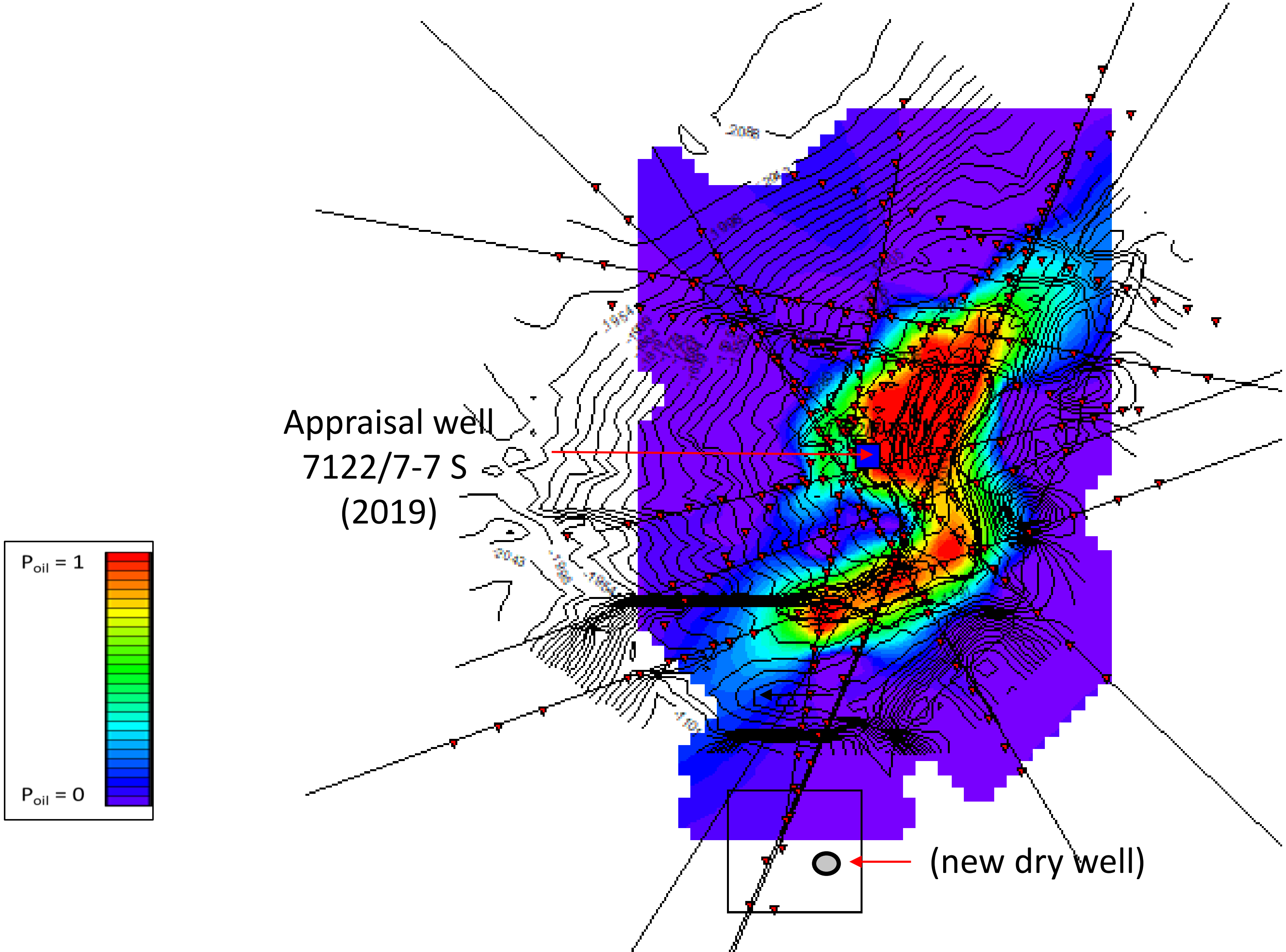


Oil prediction map for top reservoir

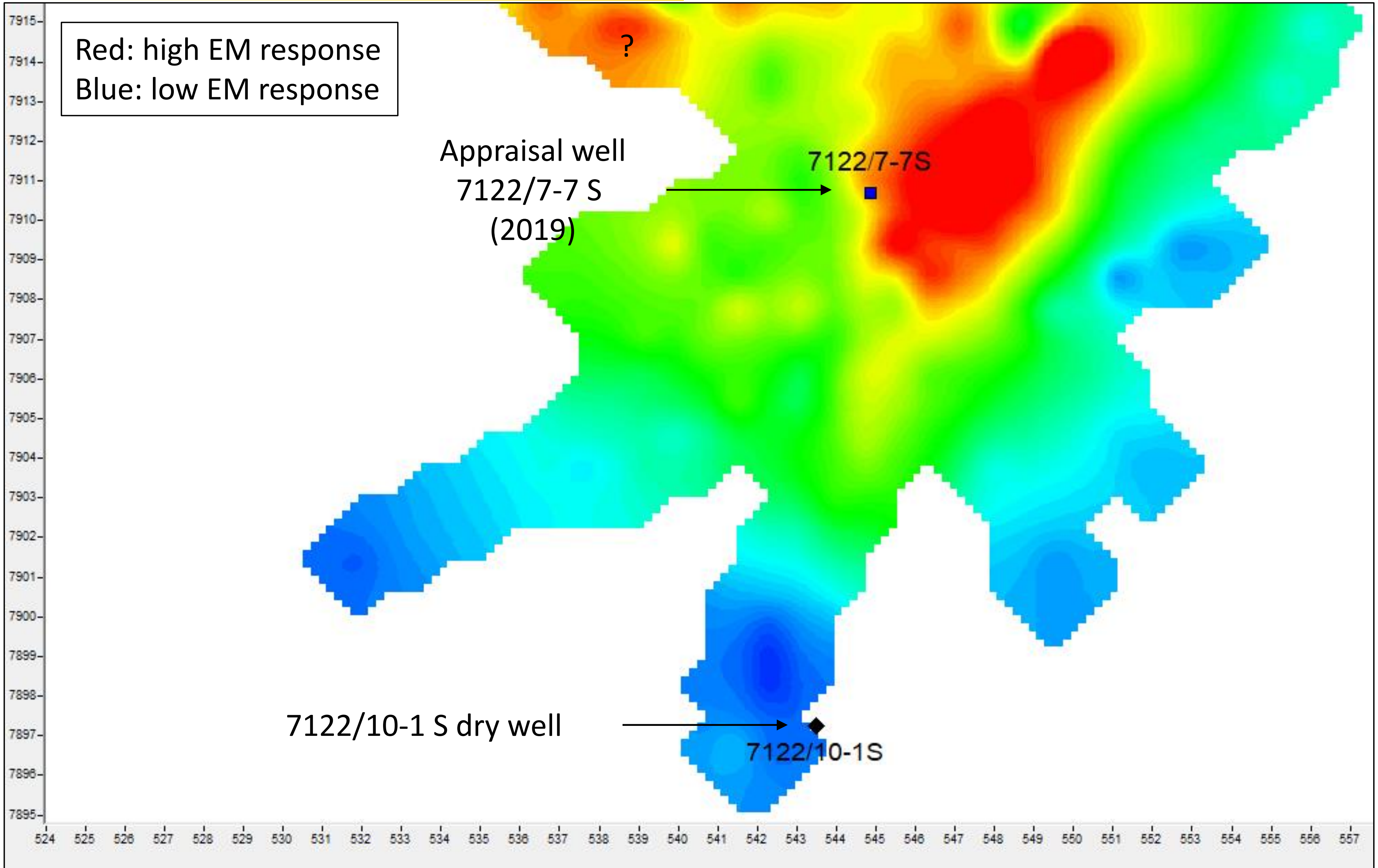
(published in 2012, confirmed and partially updated by following studies from 2013 to 2017)



CSEM layout vs oil prediction map, recent appraisal and exploration wells



Map of electric and magnetic response (normalized: 2005-2006)



The geological-geophysical problem

Defining the lateral extension of hydrocarbon distribution in stacked sand reservoirs, in a complex geological setting characterised by many fault systems, carbonate and sharp lateral geological variations.

Methodological scheme: Multi-physics and Machine Learning

Training Machine Learning algorithms with labelled data/models calibrated at well location

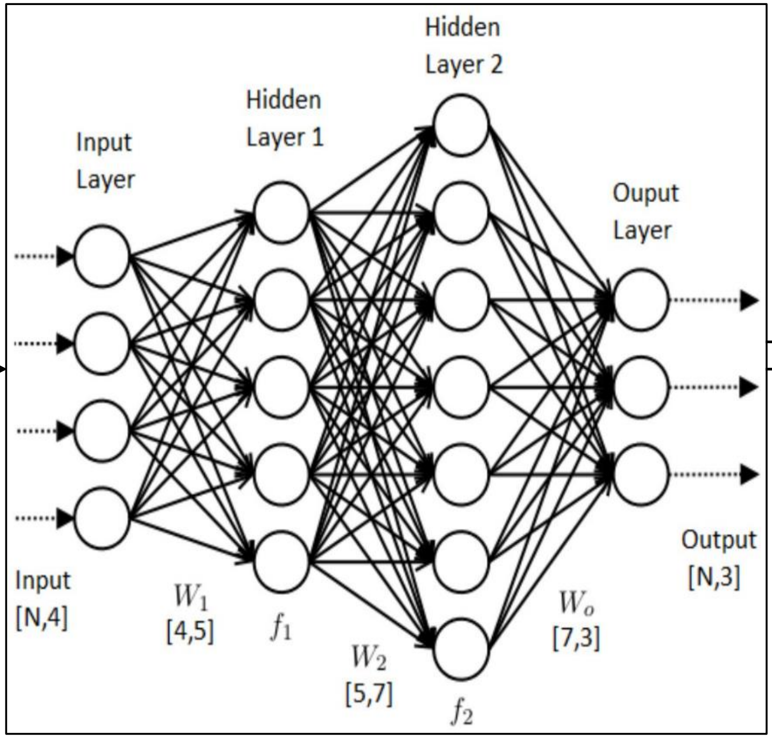
W E L L S

DATA

Seismic
CSEM
Gravity
Borehole

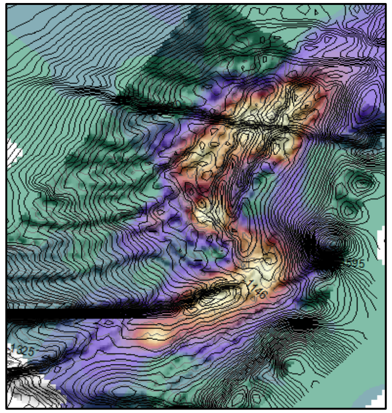
MODELS

Seismic
interpret.
Resistivity
Density

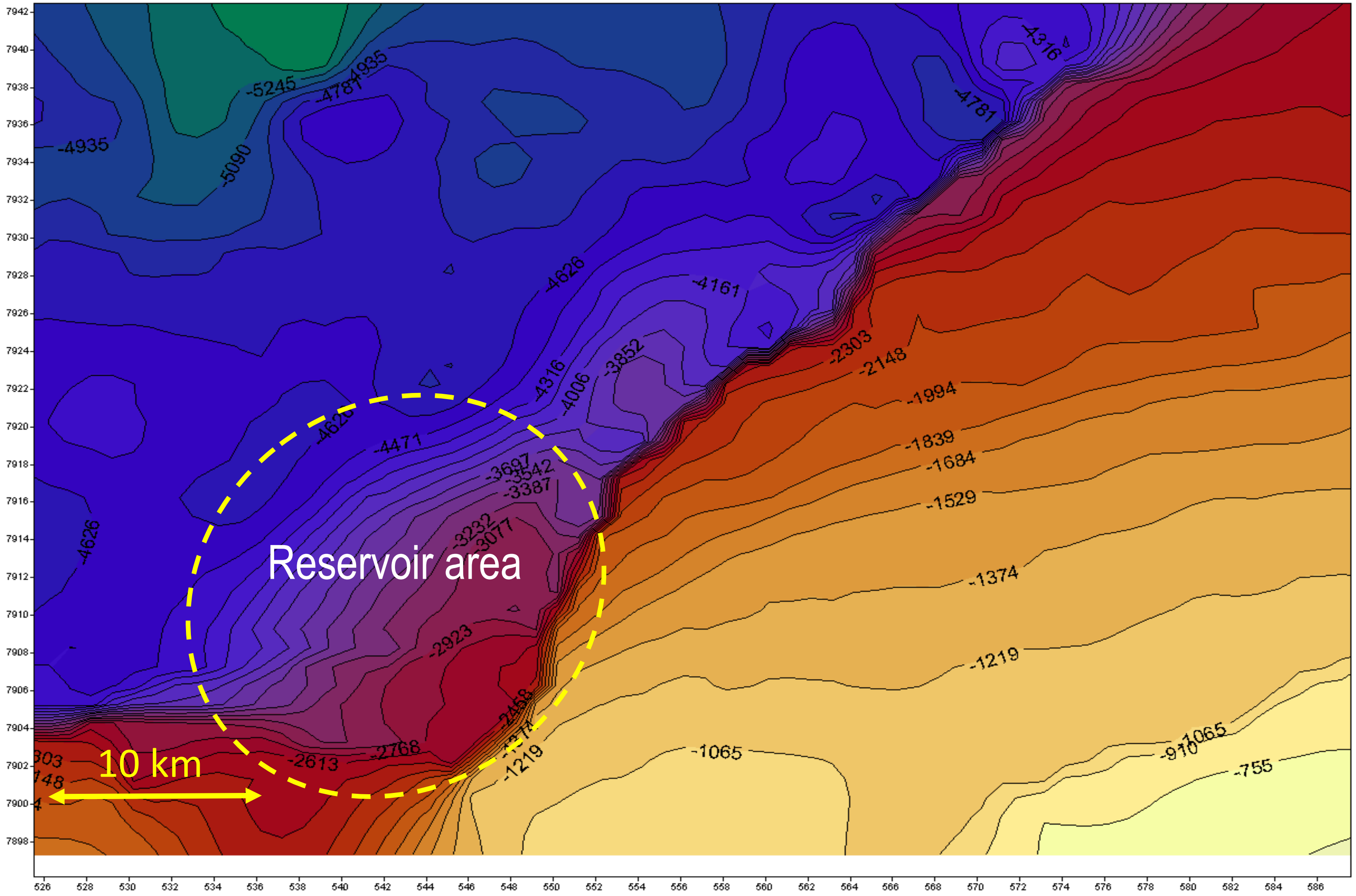


PREDICTIONS AWAY FROM THE WELLS

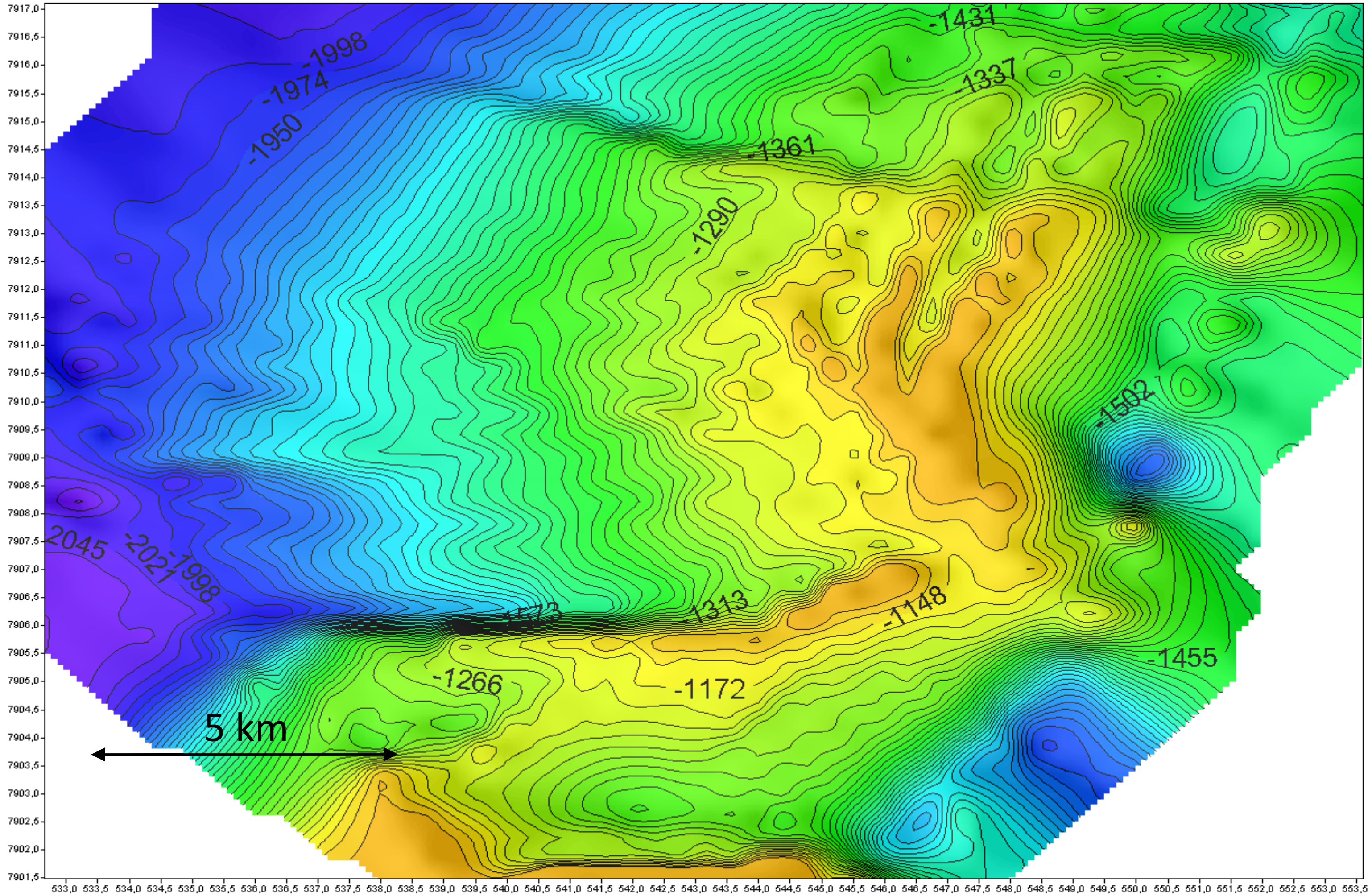
Brine or Oil in the reservoir?



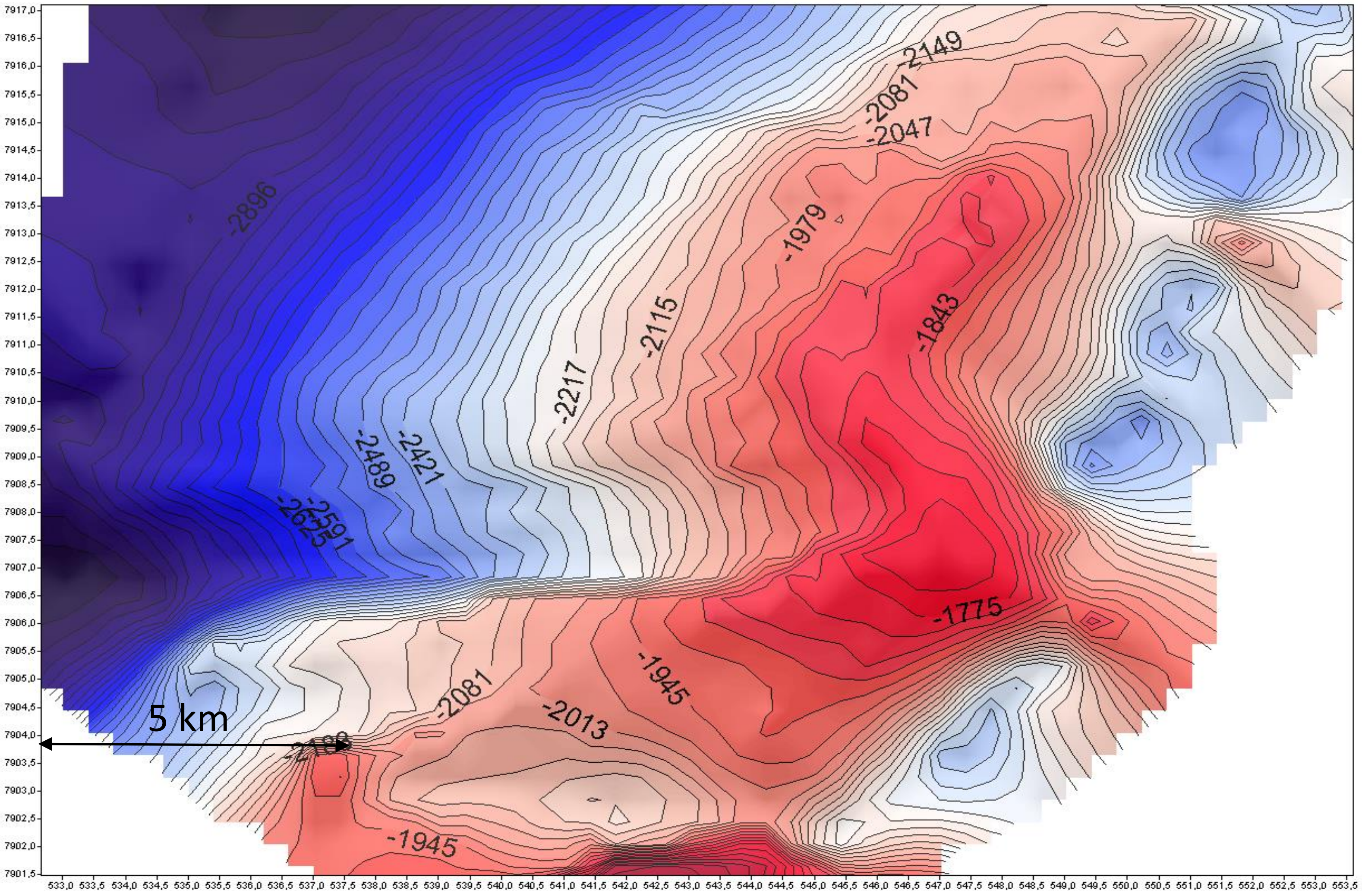
Location of the reservoir area, co-rendered with the map of top carbonates

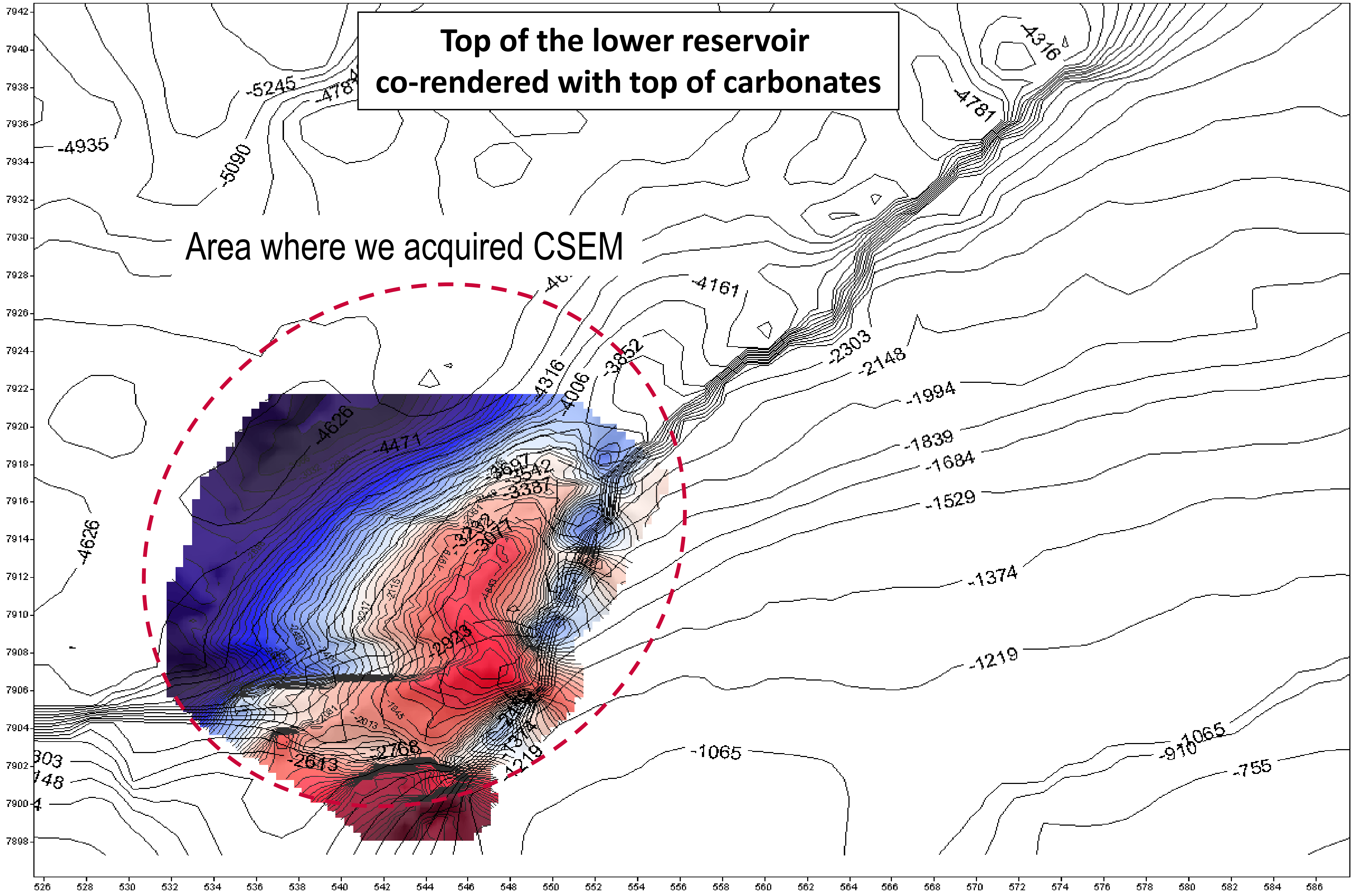


Upper reservoir

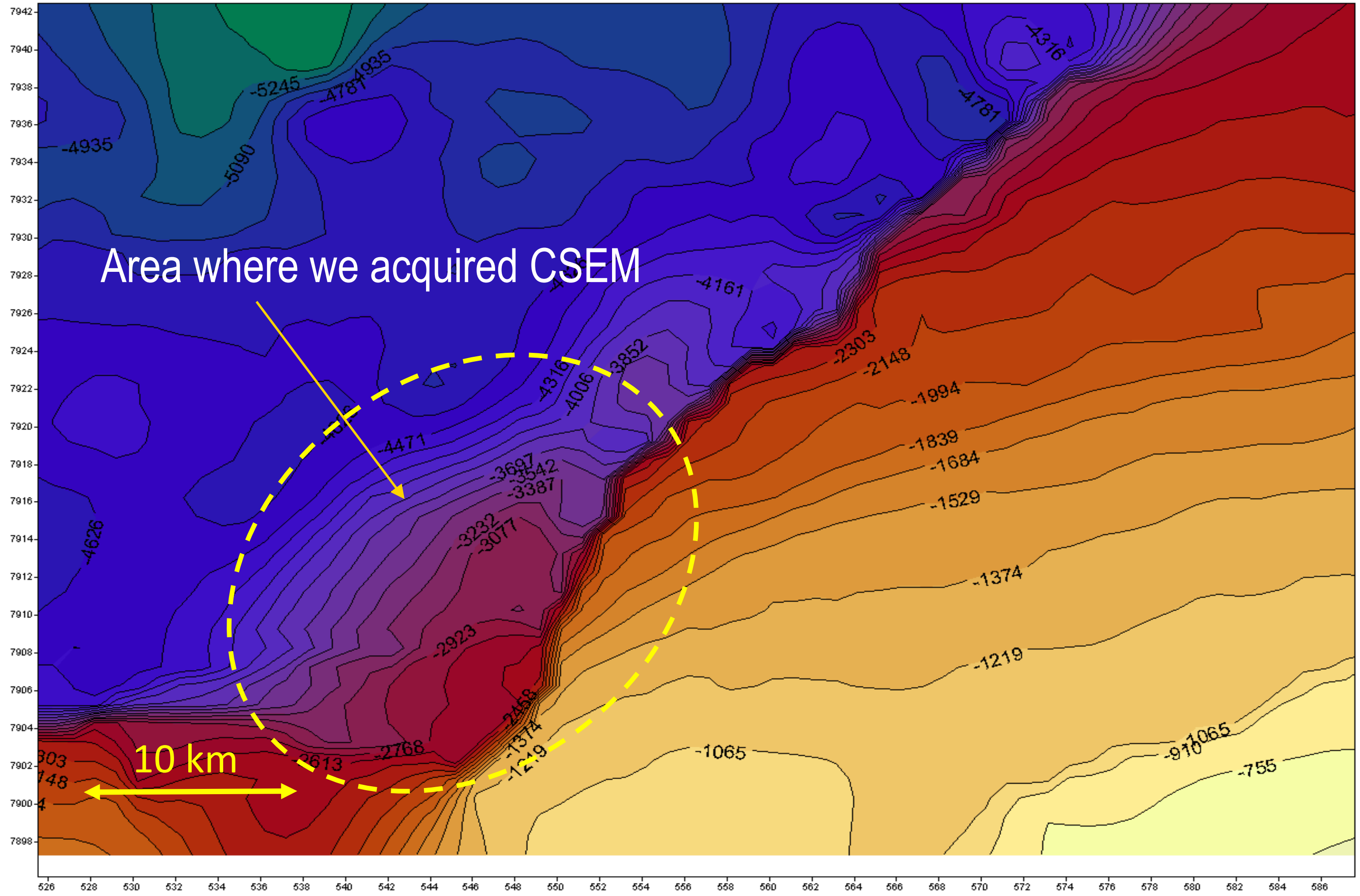


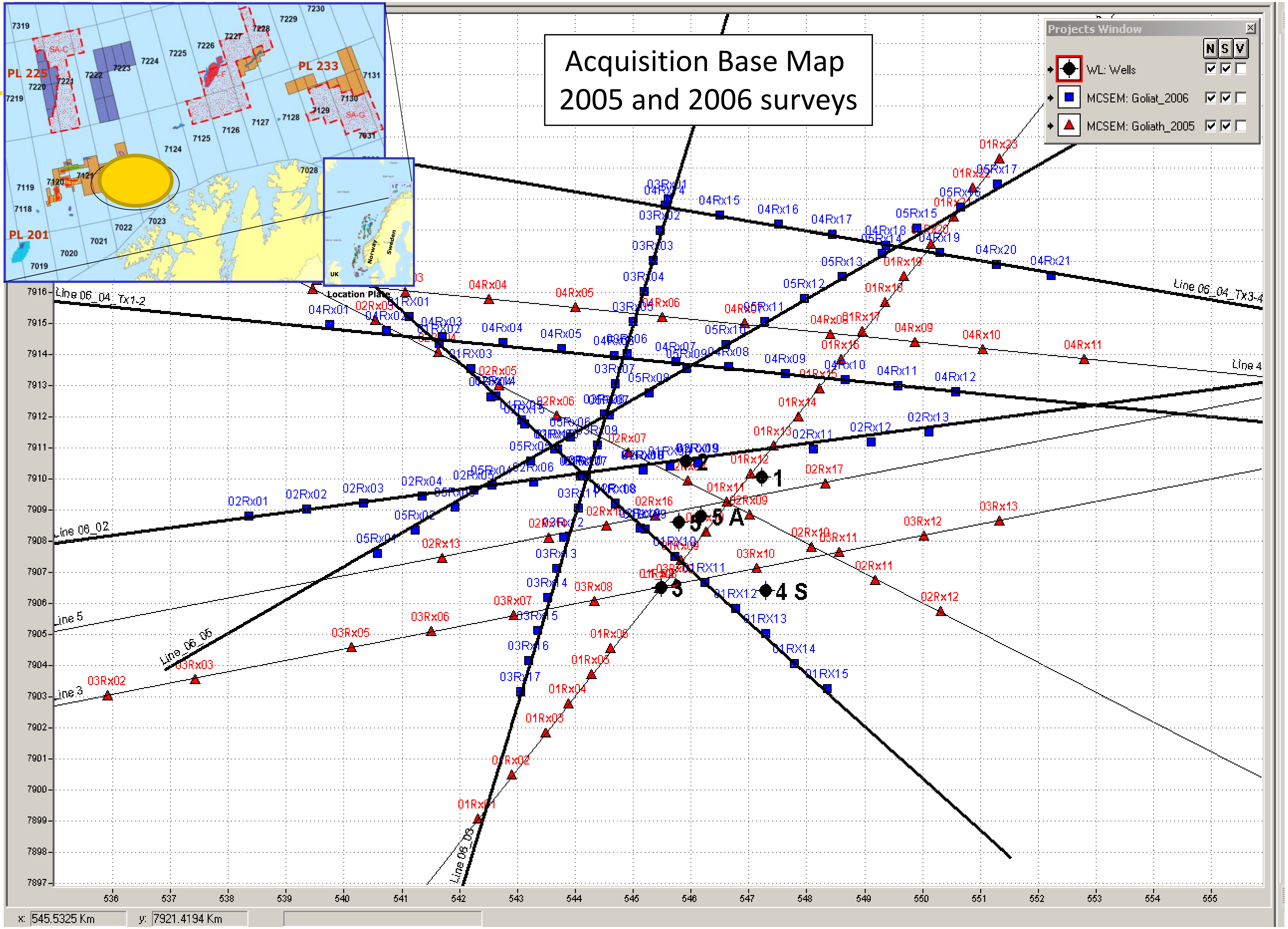
Lower reservoir




Top of the lower reservoir
co-rendered with top of carbonates
Area where we acquired CSEM
-5245
-4935
-5090
-4161
-4316
-4781
-2303
-2148
-1994
-1839
-1684
-1529
-1374
-1219
-1065
-755
-4626
-4471
-2613
-2768

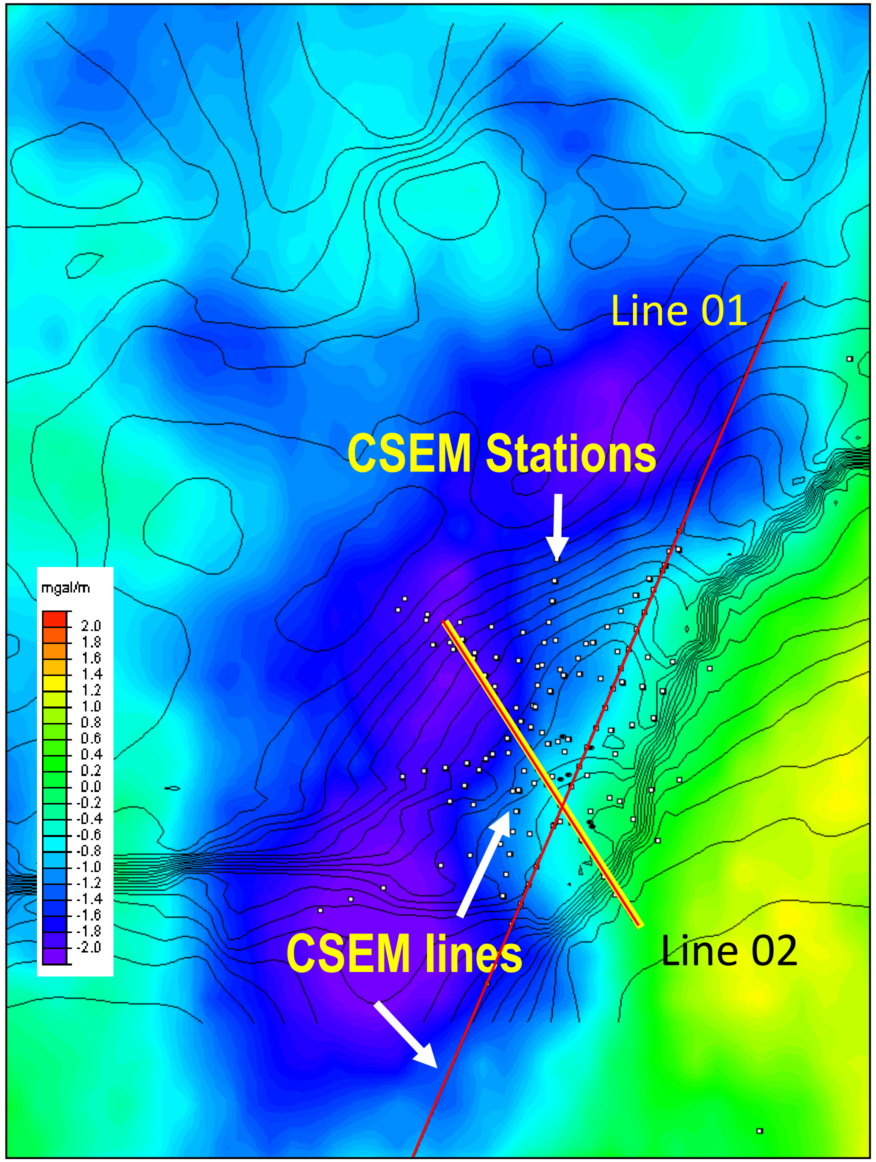
Top carbonates

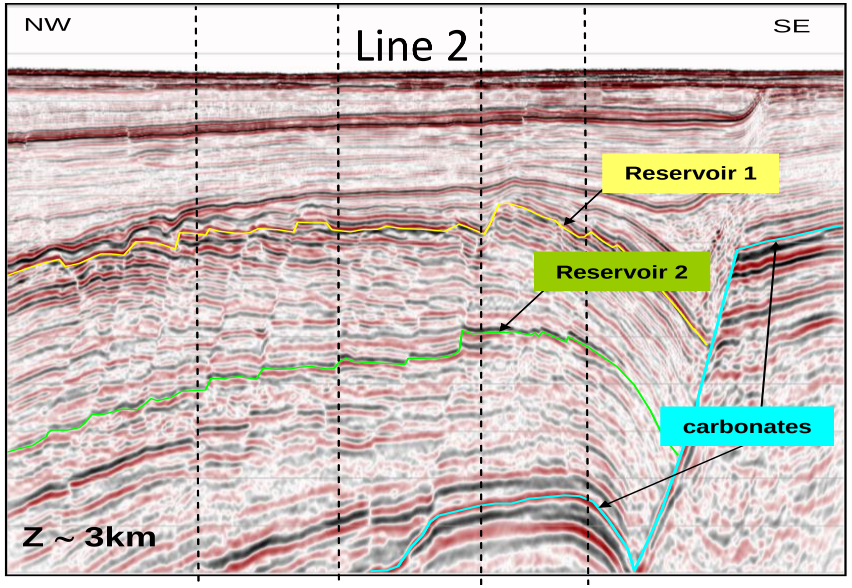


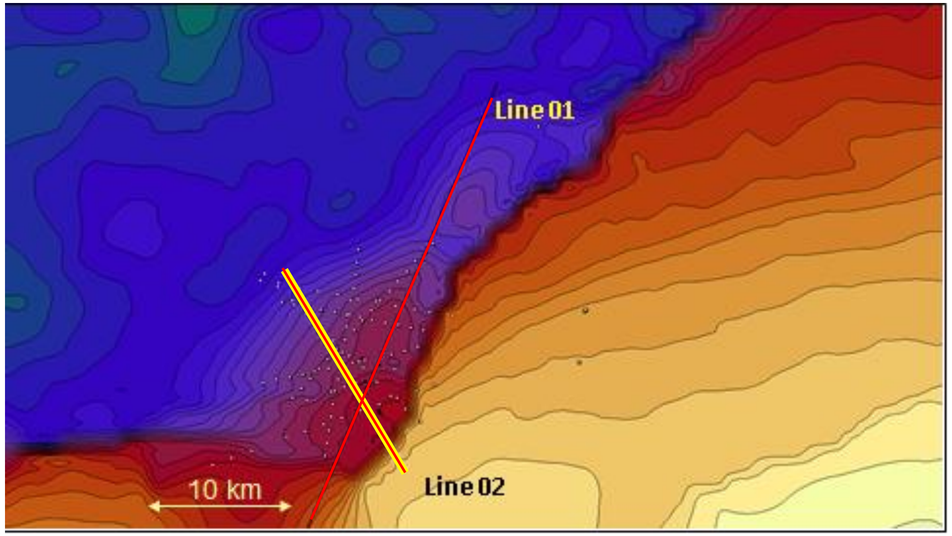

Acquisition Base Map
2005 and 2006 surveys
Projects Window
WL: Wells
MCSEM: Goliat_2006
MCSEM: Goliath_2005
PL 225
PL 233
PL 201
Location Plane
Line 06_04_Tx1-2
Line 06_04_Tx3-4
Line 06_02
Line 06_05
Line 06_03
Line 5
Line 3
Line 4
x: 545.5325 Km
y: 7921.4194 Km

Seismic, gravity and CSEM information, and map of gravity response.

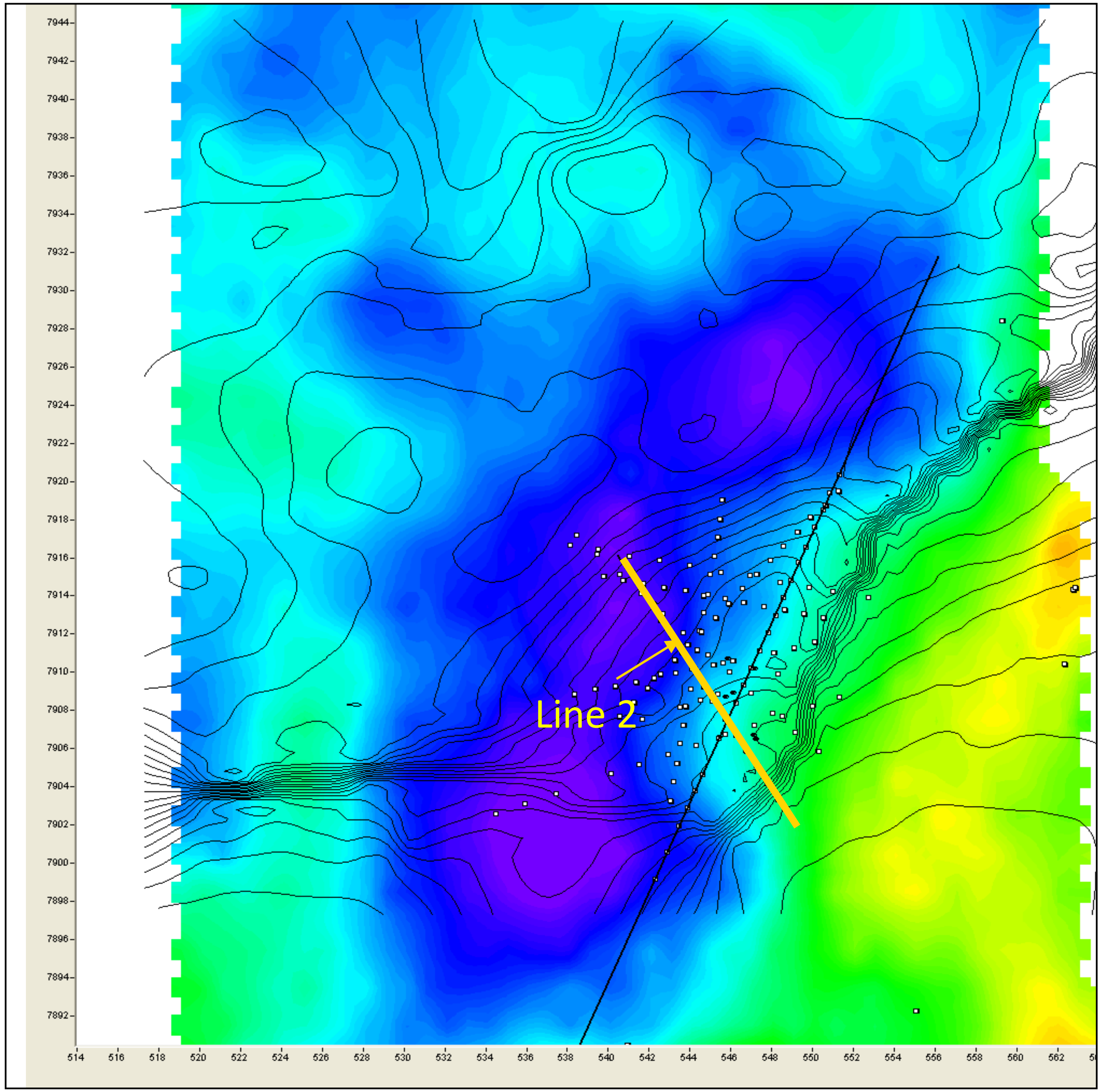
A couple of CSEM lines are shown and discussed in the following slides.





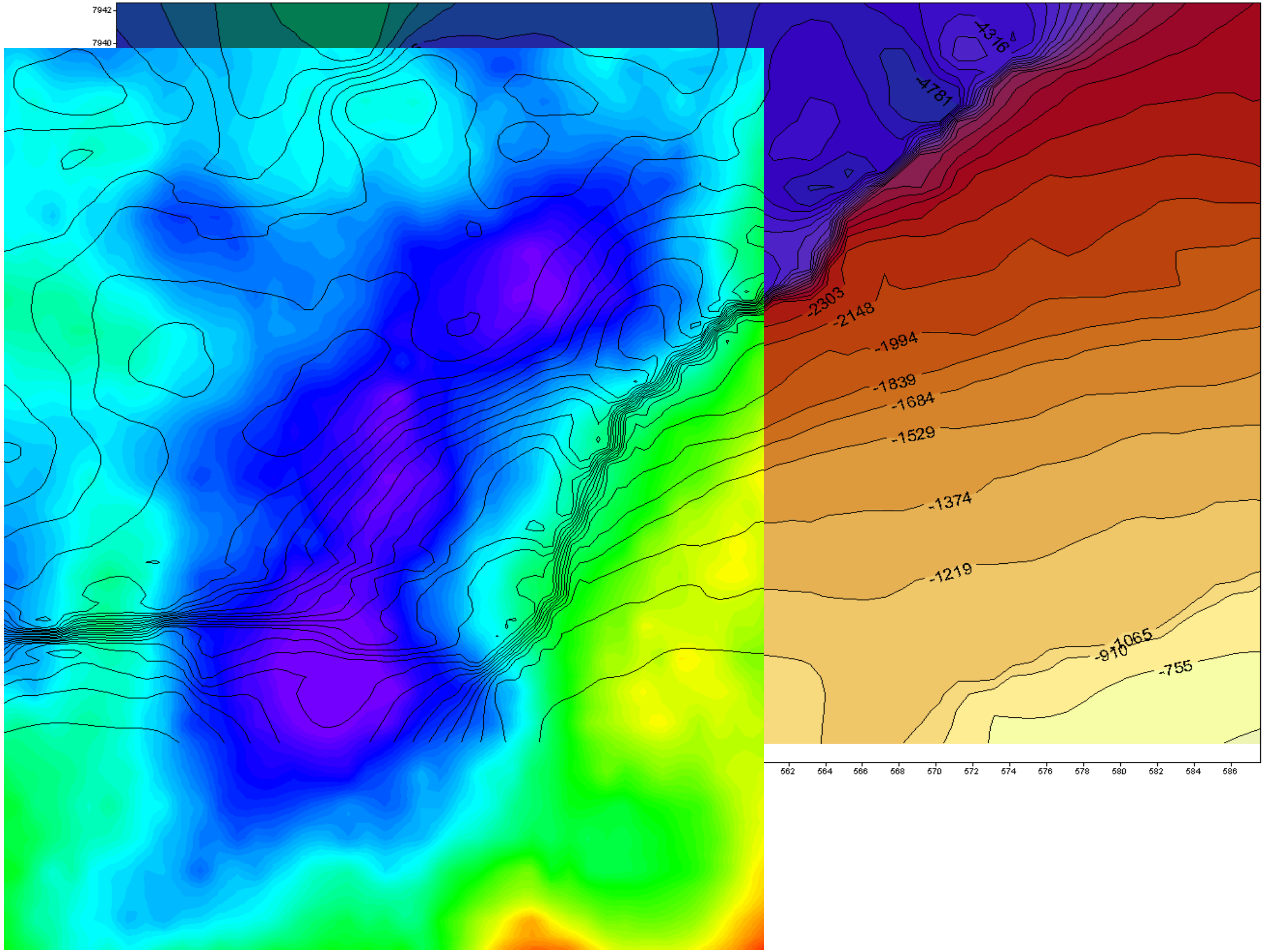


CSEM 3D forward modeling example

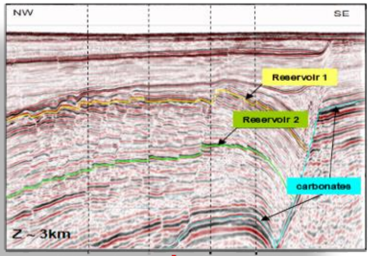


Line 2 (it corresponds with the first CSEM Line acquired in the 2006 CSEM survey)

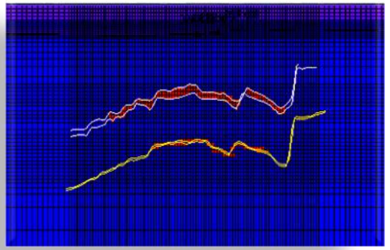
Top of carbonates vs. First Vertical Derivative (FVD) of Bouguer anomaly



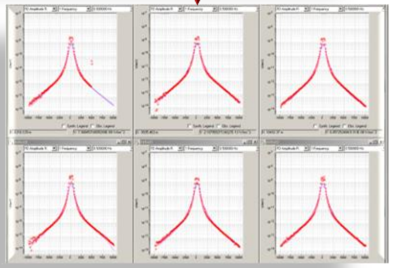
CSEM modelling constrained by seismic data



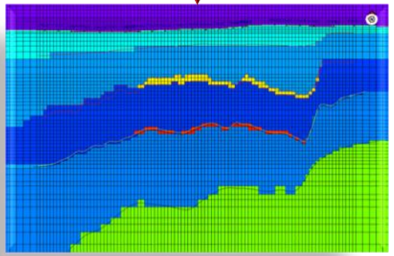
Import interpreted horizons from 3D seismic volume



Fill layers with resistivity values estimated from well logs



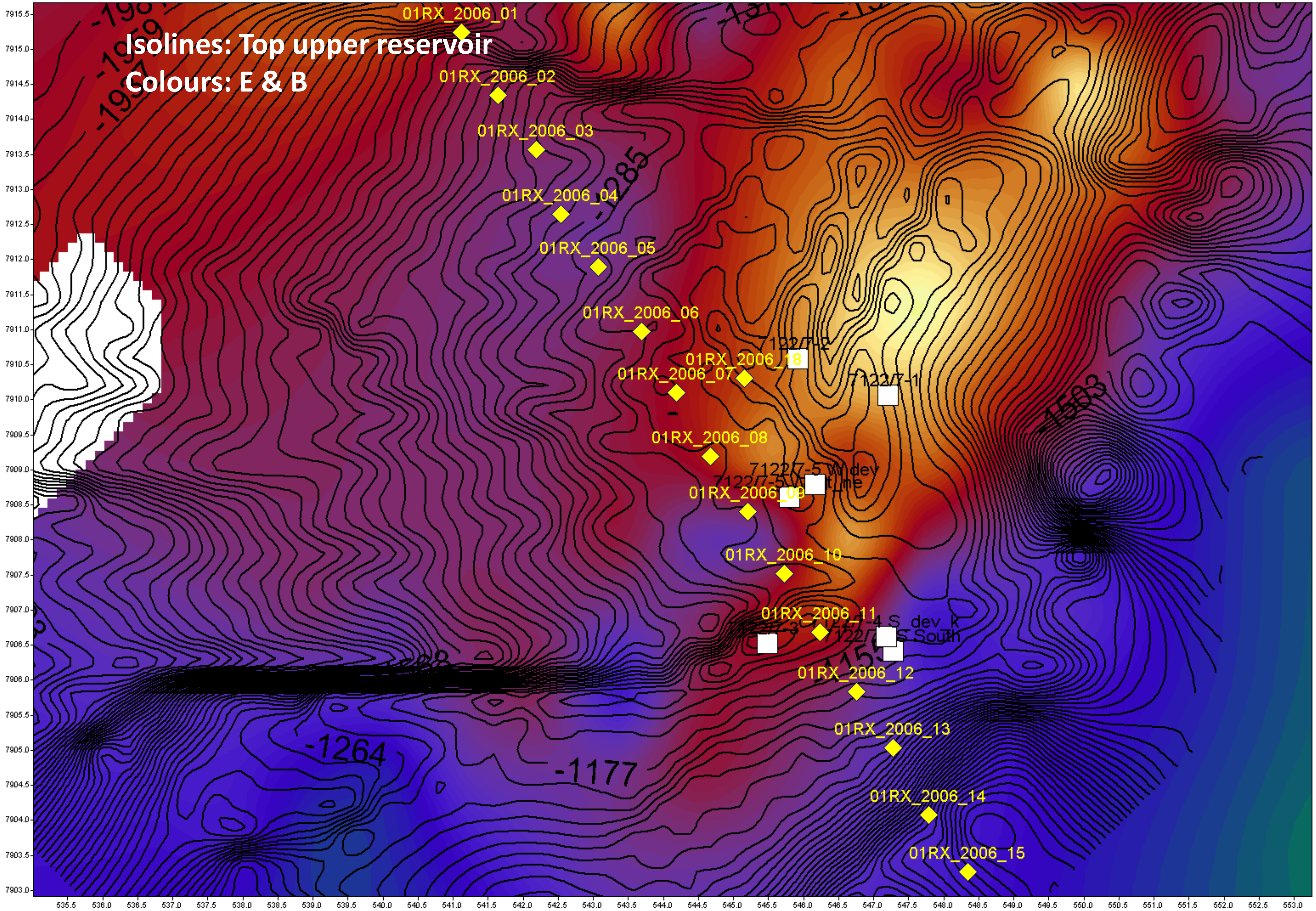
Run 3D CSEM FWD modelling and check the misfit at each receiver

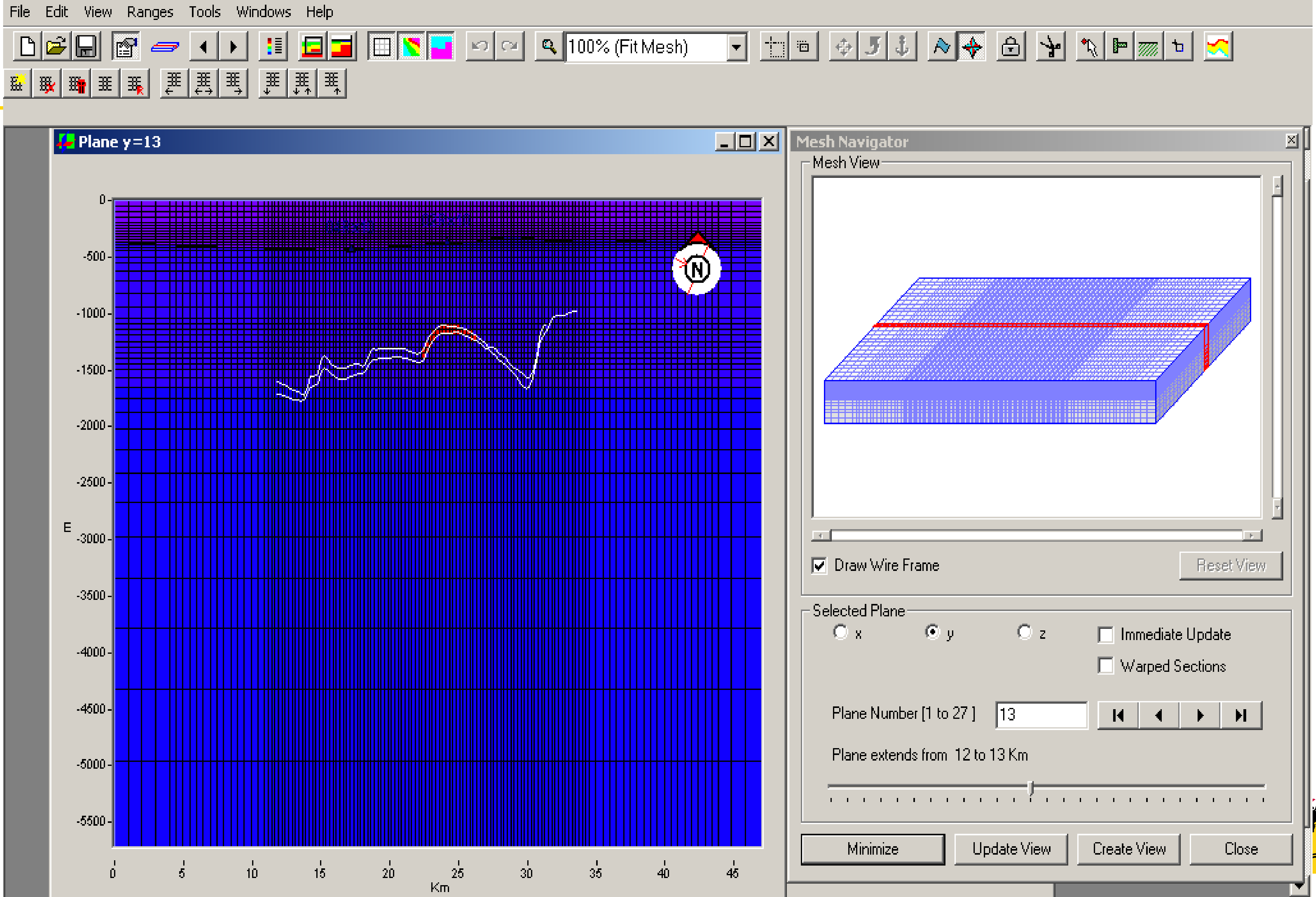


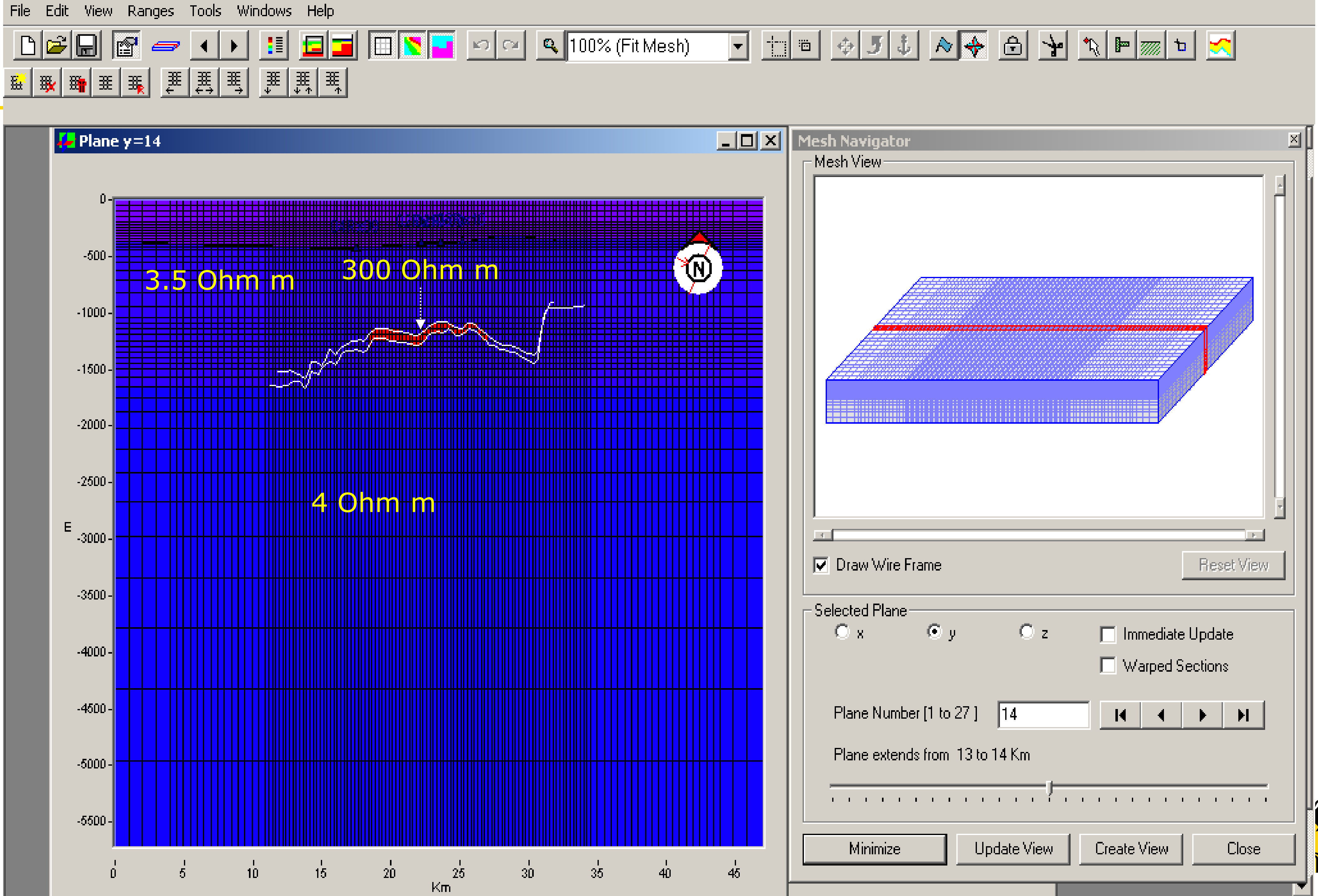
Update the model and iterate until a reasonable fit is obtained

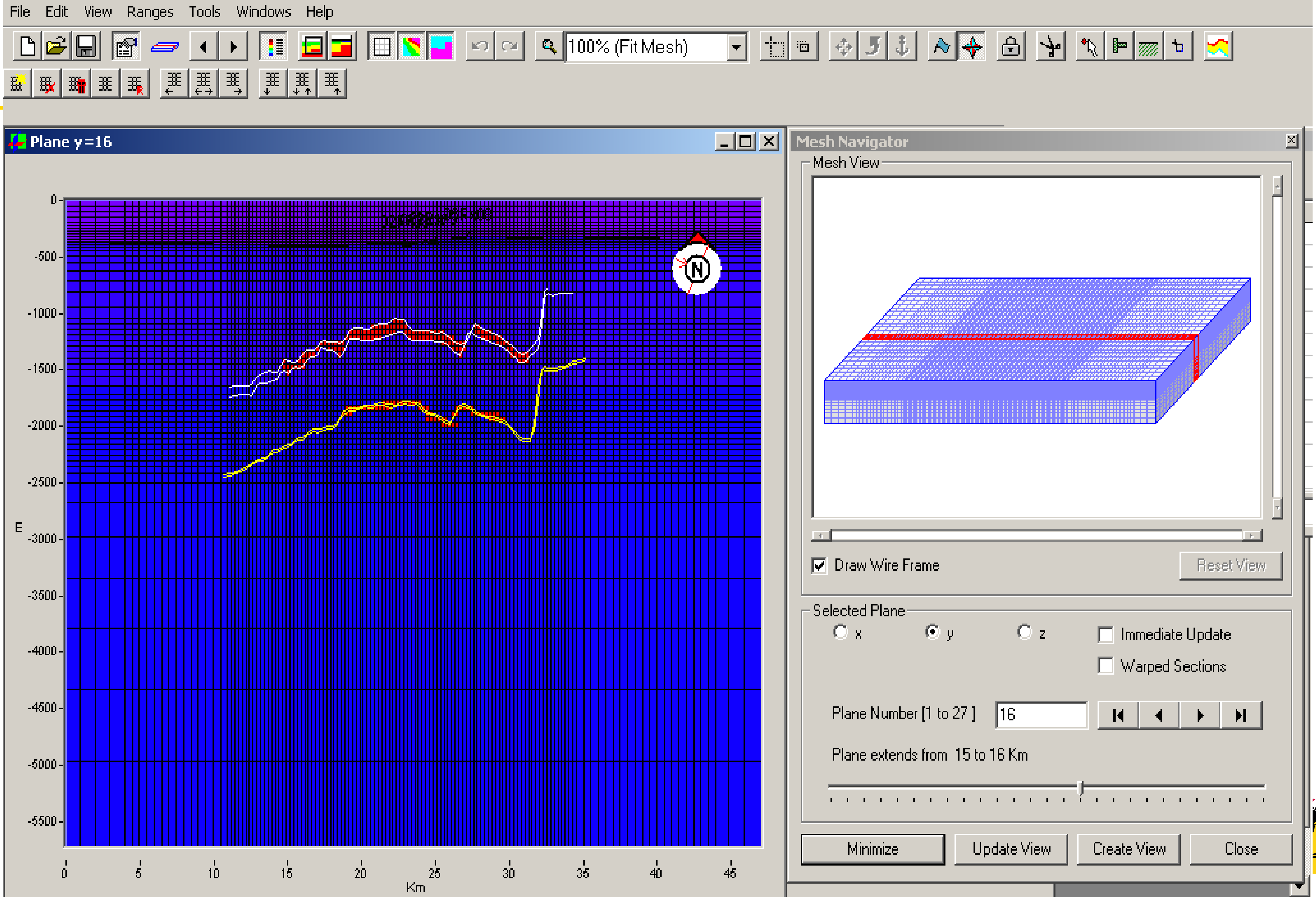
Isolines: Top upper reservoir

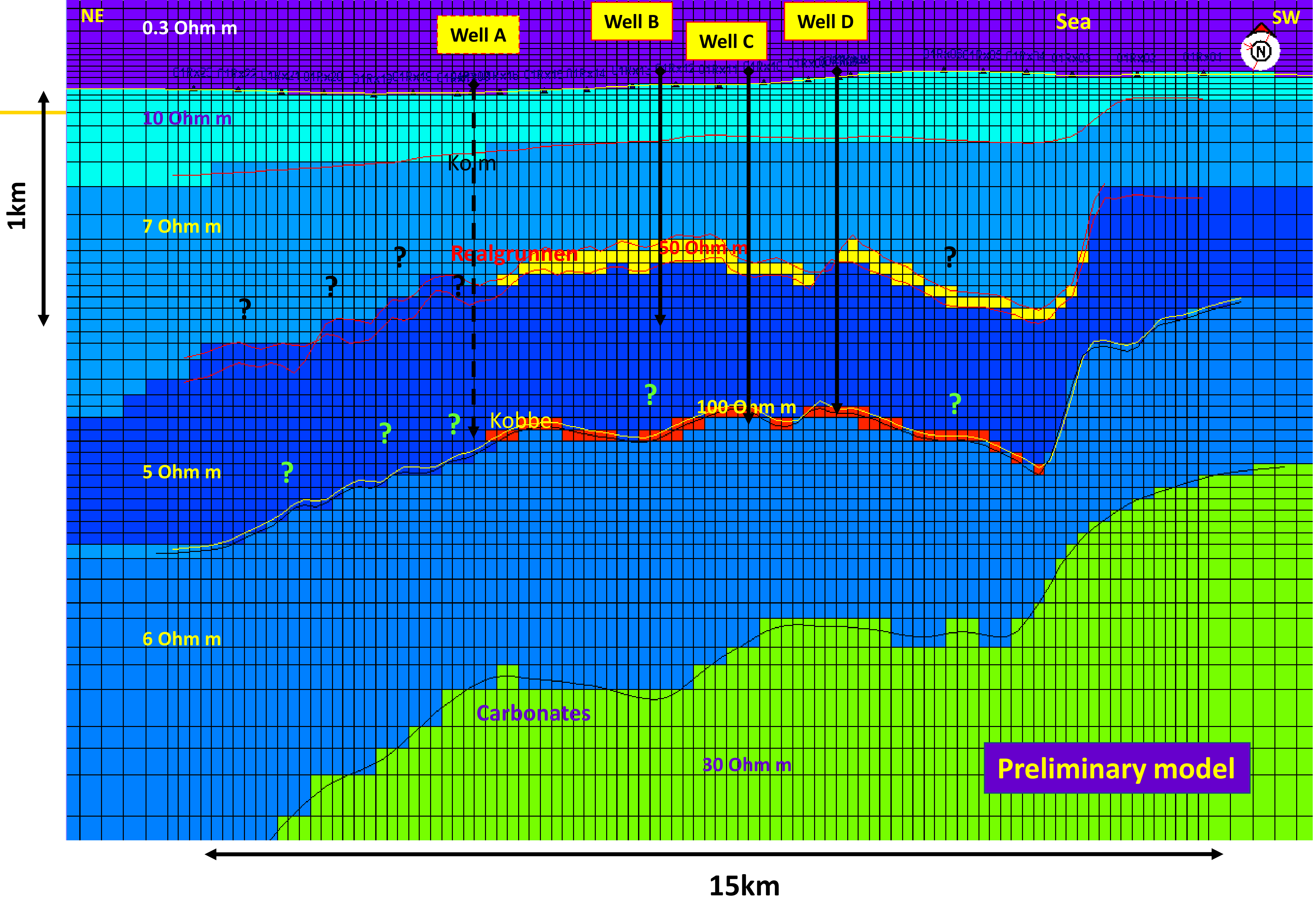
Colours: E & B



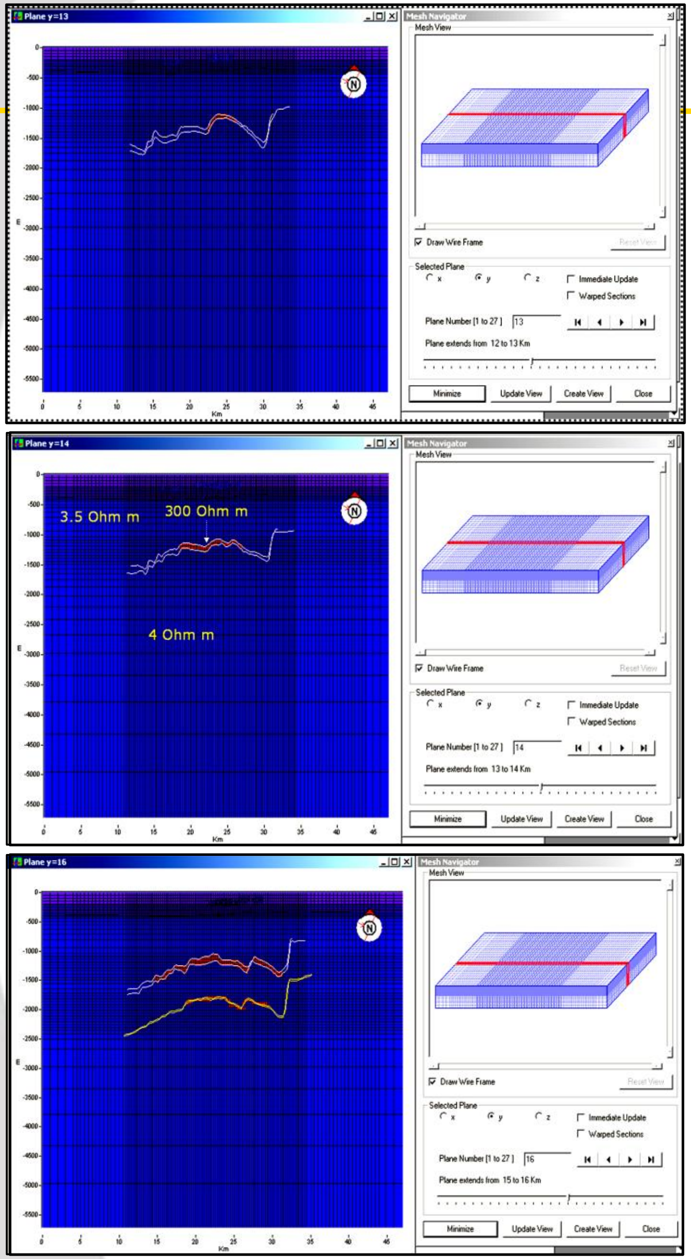

File Edit View Ranges Tools Windows Help
100% (Fit Mesh)
Plane y=13
0
-500
-1000
-1500
-2000
-2500
-3000
-3500
-4000
-4500
-5000
-5500
E
0 5 10 15 20 25 30 35 40 45
Km
N
Mesh Navigator
Mesh View
Draw Wire Frame
Reset View
Selected Plane
x
y
z
Immediate Update
Warped Sections
Plane Number [1 to 27]
13
Plane extends from 12 to 13 Km
Minimize
Update View
Create View
Close

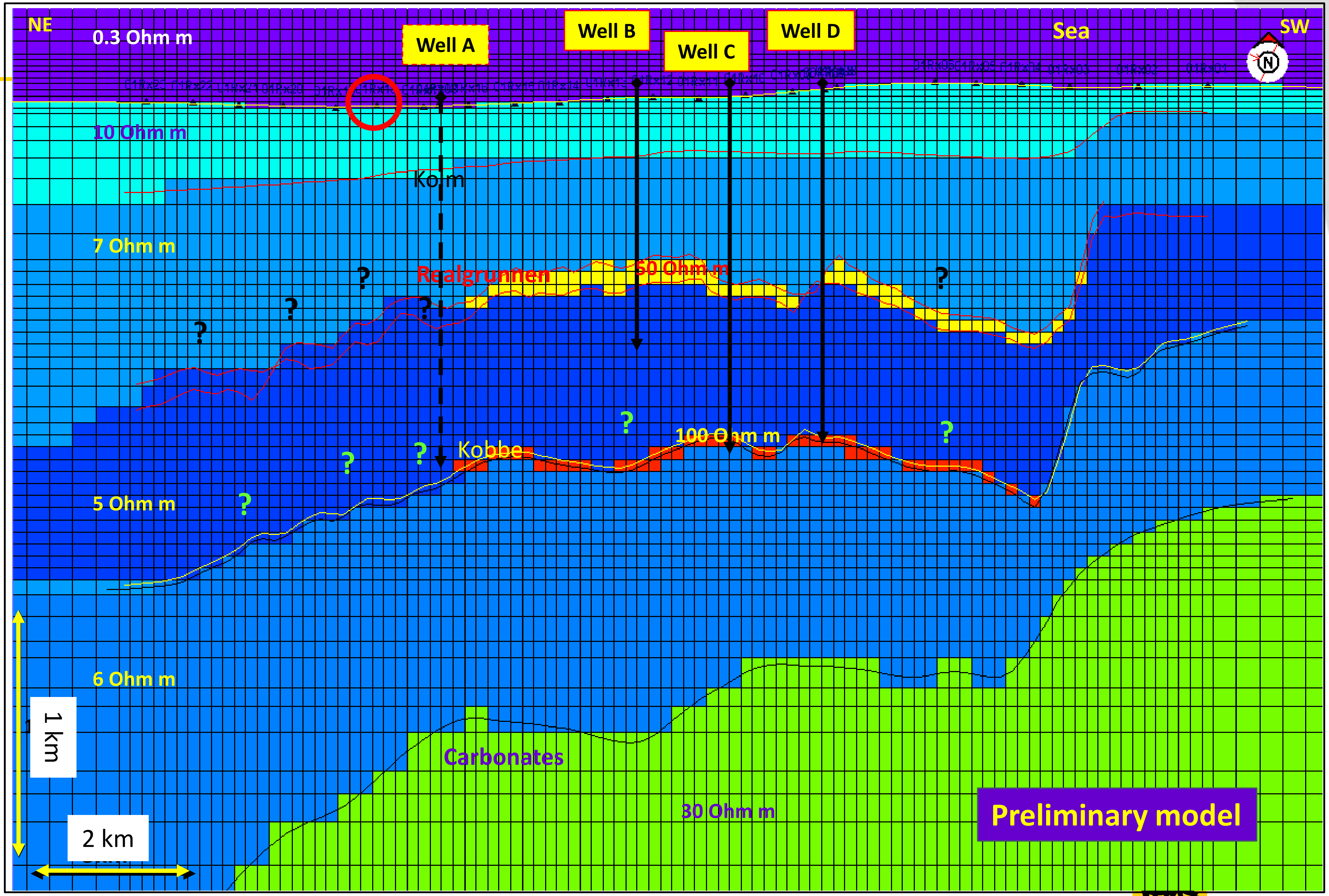

File Edit View Ranges Tools Windows Help
100% (Fit Mesh)
Plane y=14
3.5 Ohm m
300 Ohm m
4 Ohm m
N
E
Km
0
-500
-1000
-1500
-2000
-2500
-3000
-3500
-4000
-4500
-5000
-5500
0 5 10 15 20 25 30 35 40 45
Mesh Navigator
Mesh View
Draw Wire Frame
Reset View
Selected Plane
x
y
z
Immediate Update
Warped Sections
Plane Number [1 to 27]
14
Plane extends from 13 to 14 Km
Minimize
Update View
Create View
Close

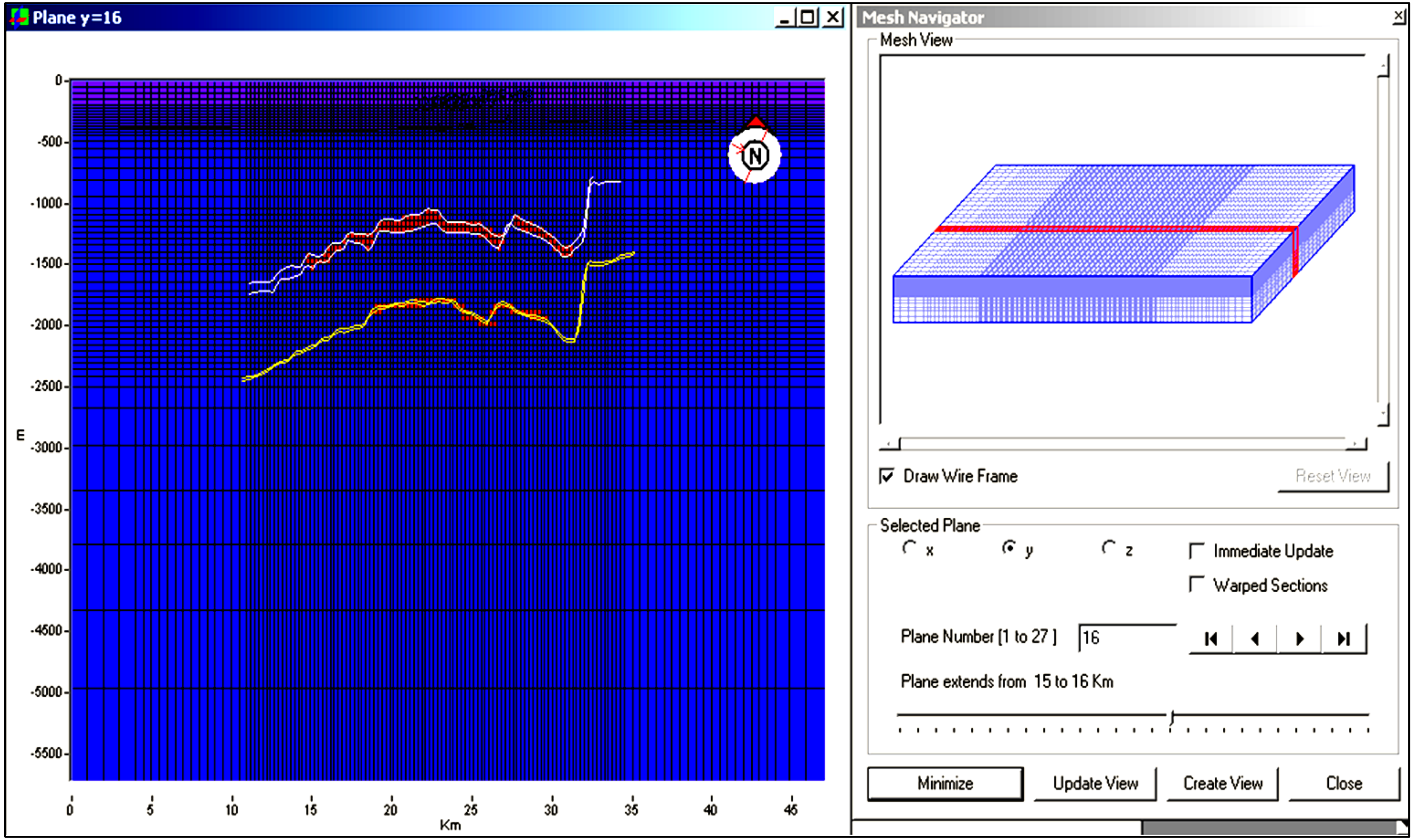

File
Edit
View
Ranges
Tools
Windows
Help
100% (Fit Mesh)
Plane y=16
0
-500
-1000
-1500
-2000
-2500
-3000
-3500
-4000
-4500
-5000
-5500
E
0
5
10
15
20
25
30
35
40
45
Km
N
Mesh Navigator
Mesh View
Draw Wire Frame
Reset View
Selected Plane
x
y
z
Immediate Update
Warped Sections
Plane Number [1 to 27]
16
Plane extends from 15 to 16 Km
Minimize
Update View
Create View
Close



NE
0.3 Ohm m
Well A
Well B
Well C
Well D
Sea
SW
10 Ohm m
Kolm
7 Ohm m
Realgrunnen
50 Ohm m
100 Ohm m
Kobbe
5 Ohm m
6 Ohm m
Carbonates
30 Ohm m
Preliminary model
1km
15km

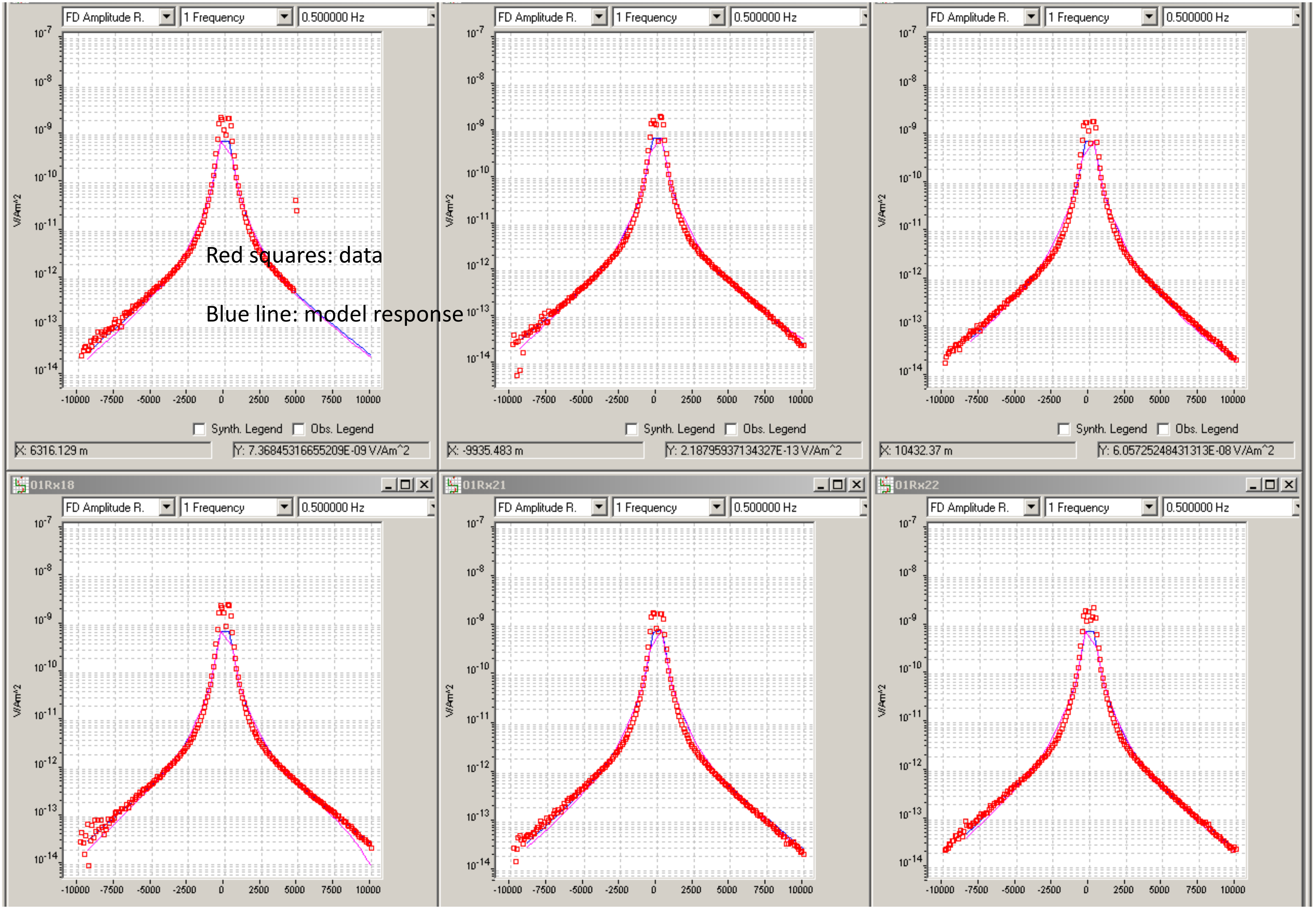

3.5 Ohm m
300 Ohm m
4 Ohm m


NE
0.3 Ohm m
Well A
Well B
Well C
Well D
Sea
SW
10 Ohm m
Kolm
7 Ohm m
Realgrunnen
50 Ohm m
100 Ohm m
Kobbe
5 Ohm m
6 Ohm m
1 km
Carbonates
30 Ohm m
2 km
Preliminary model

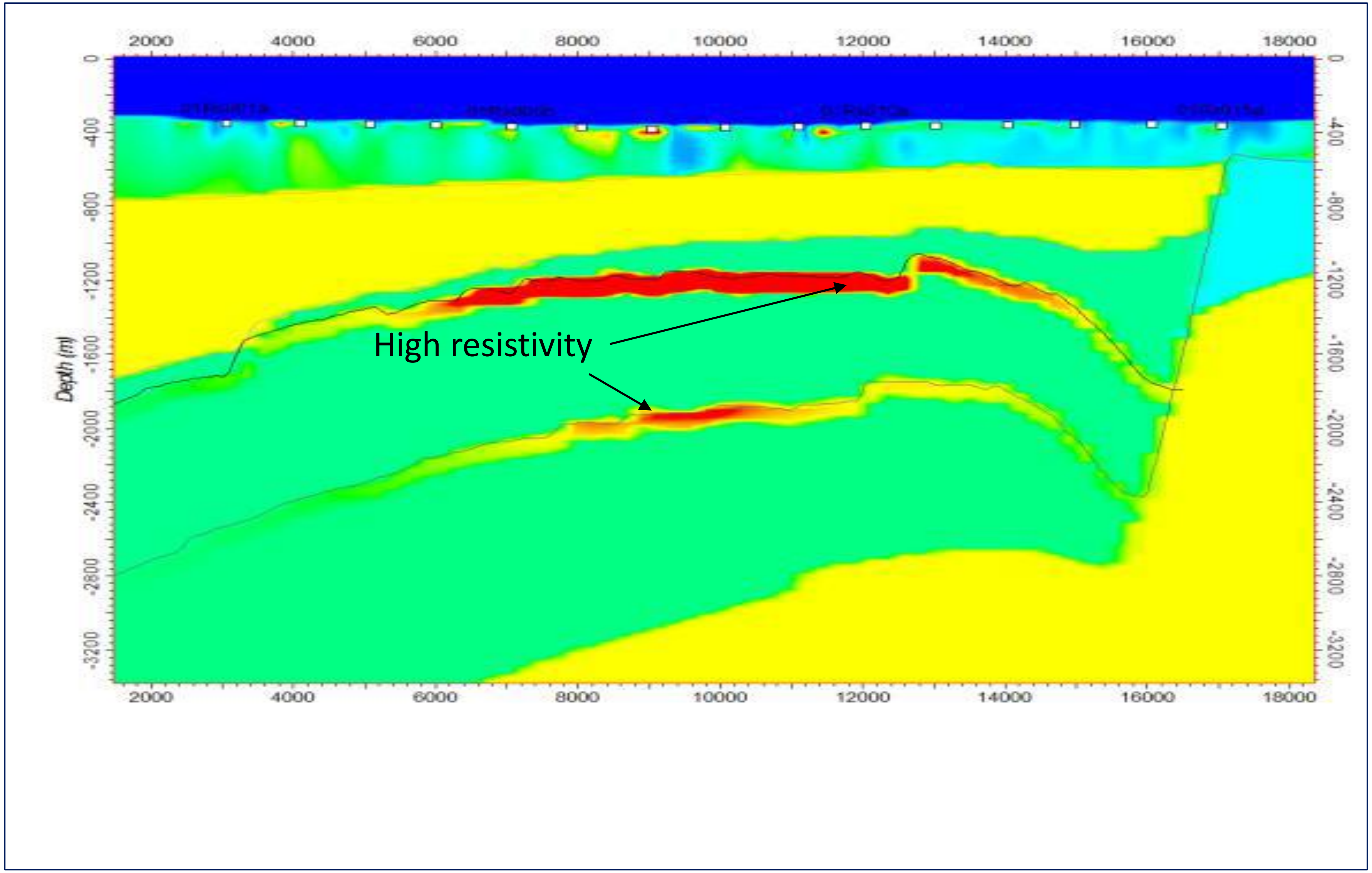


Plane y=16
0
-500
-1000
-1500
-2000
-2500
-3000
-3500
-4000
-4500
-5000
-5500
m
0
5
10
15
20
25
30
35
40
45
Km
N
Mesh Navigator
Mesh View
Draw Wire Frame
Reset View
Selected Plane
x
y
z
Immediate Update
Warped Sections
Plane Number [1 to 27]
16
Plane extends from 15 to 16 Km
Minimize
Update View
Create View
Close

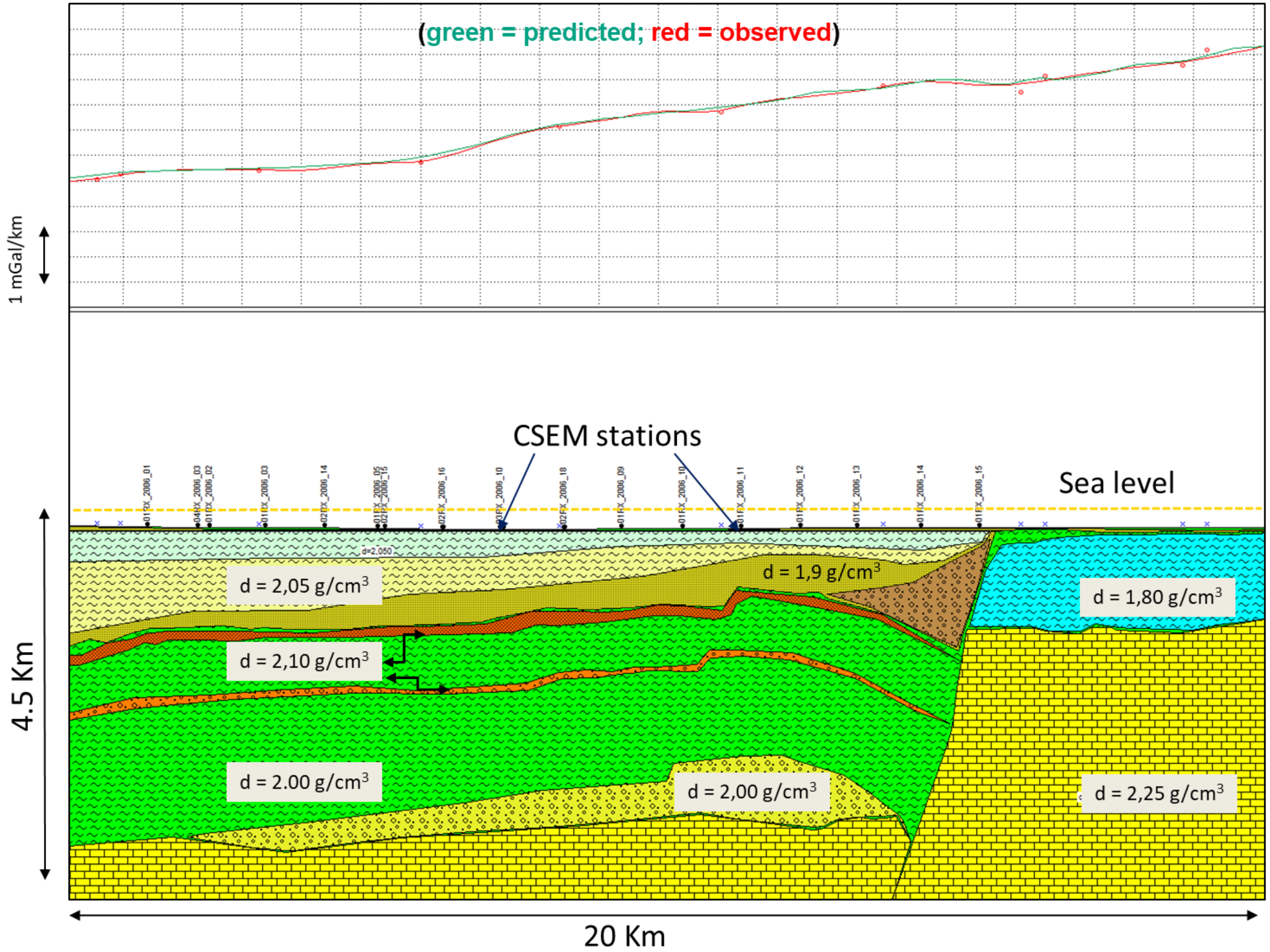
Examples of misfit analysis



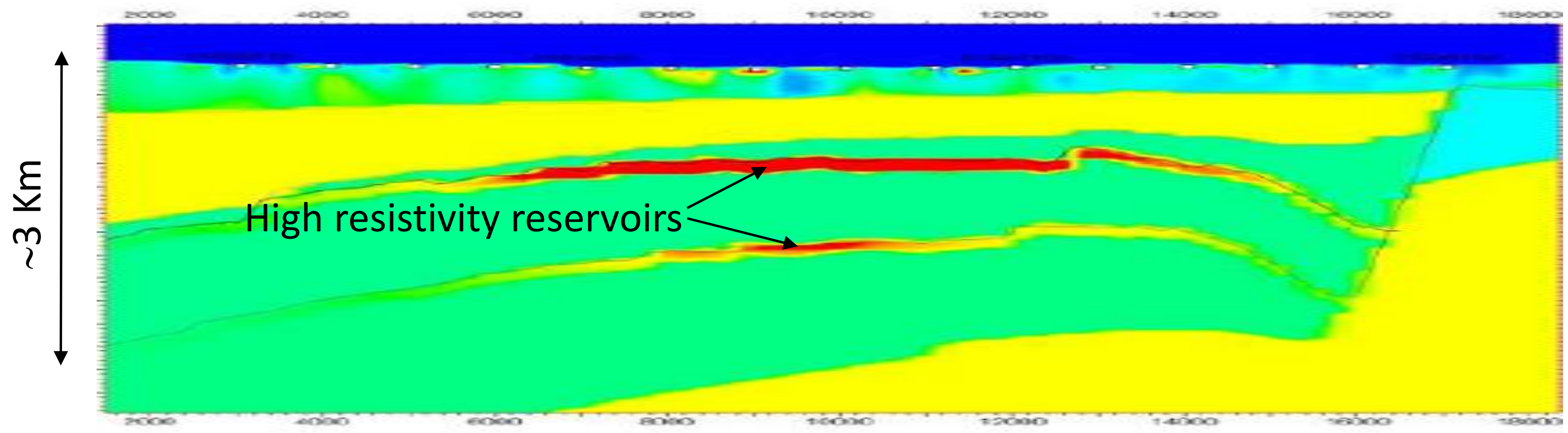
Constrained joint inversion of electric and magnetic CSEM data

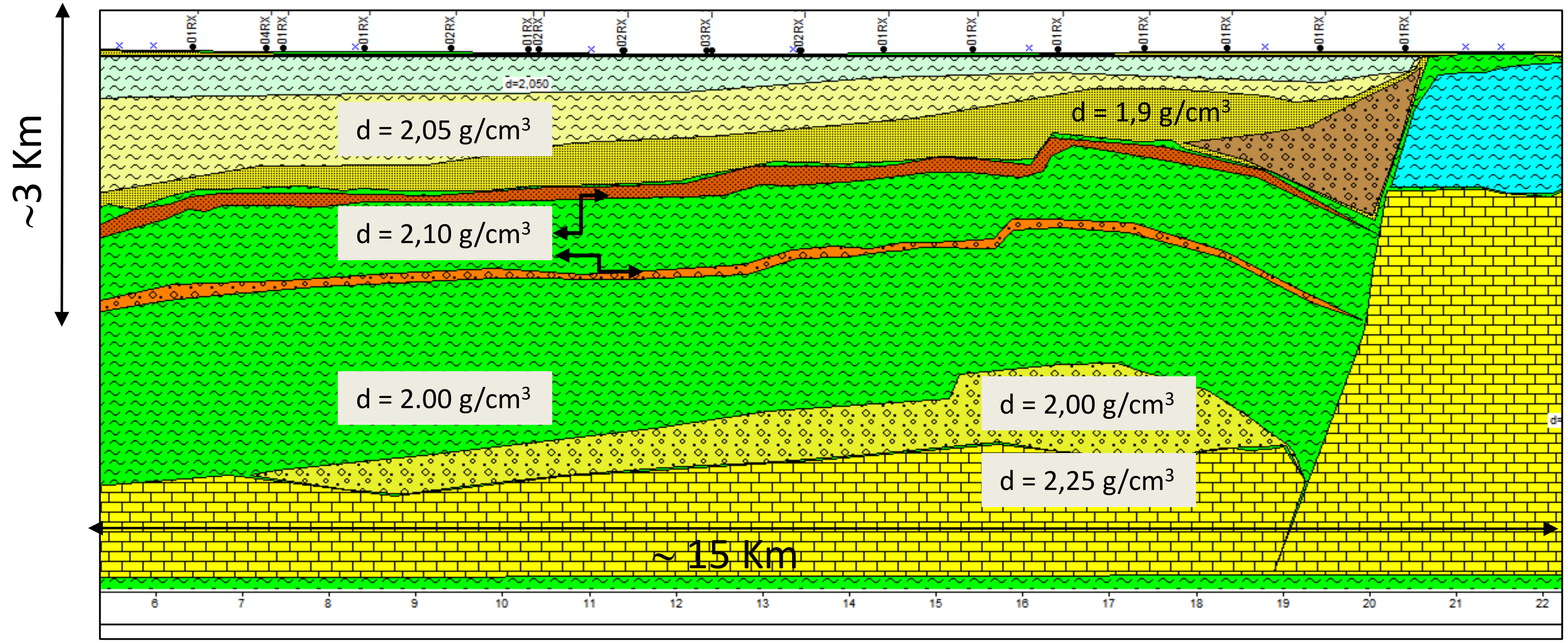


Gravity modelling constrained by seismic data



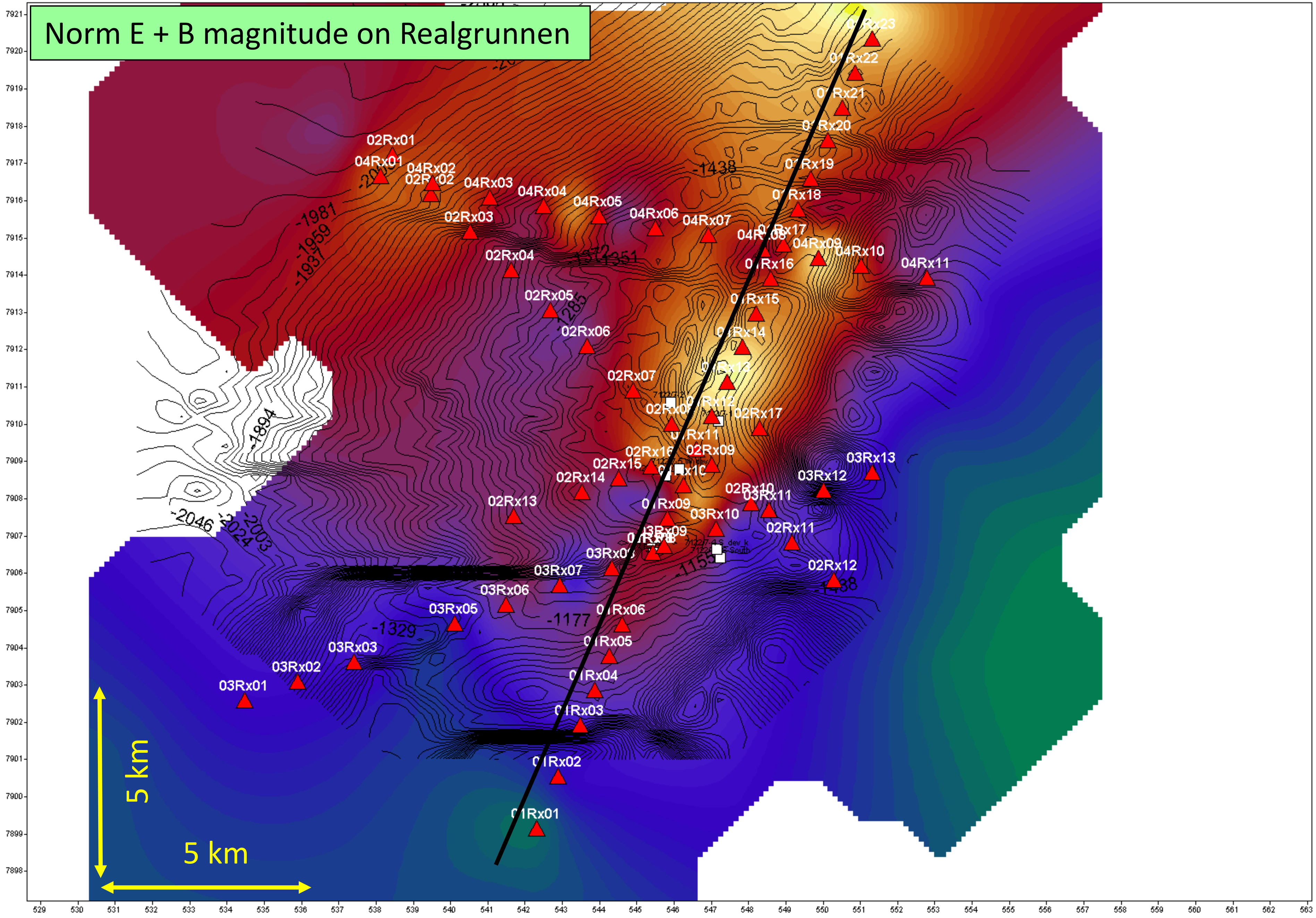
CSEM and gravity models comparison



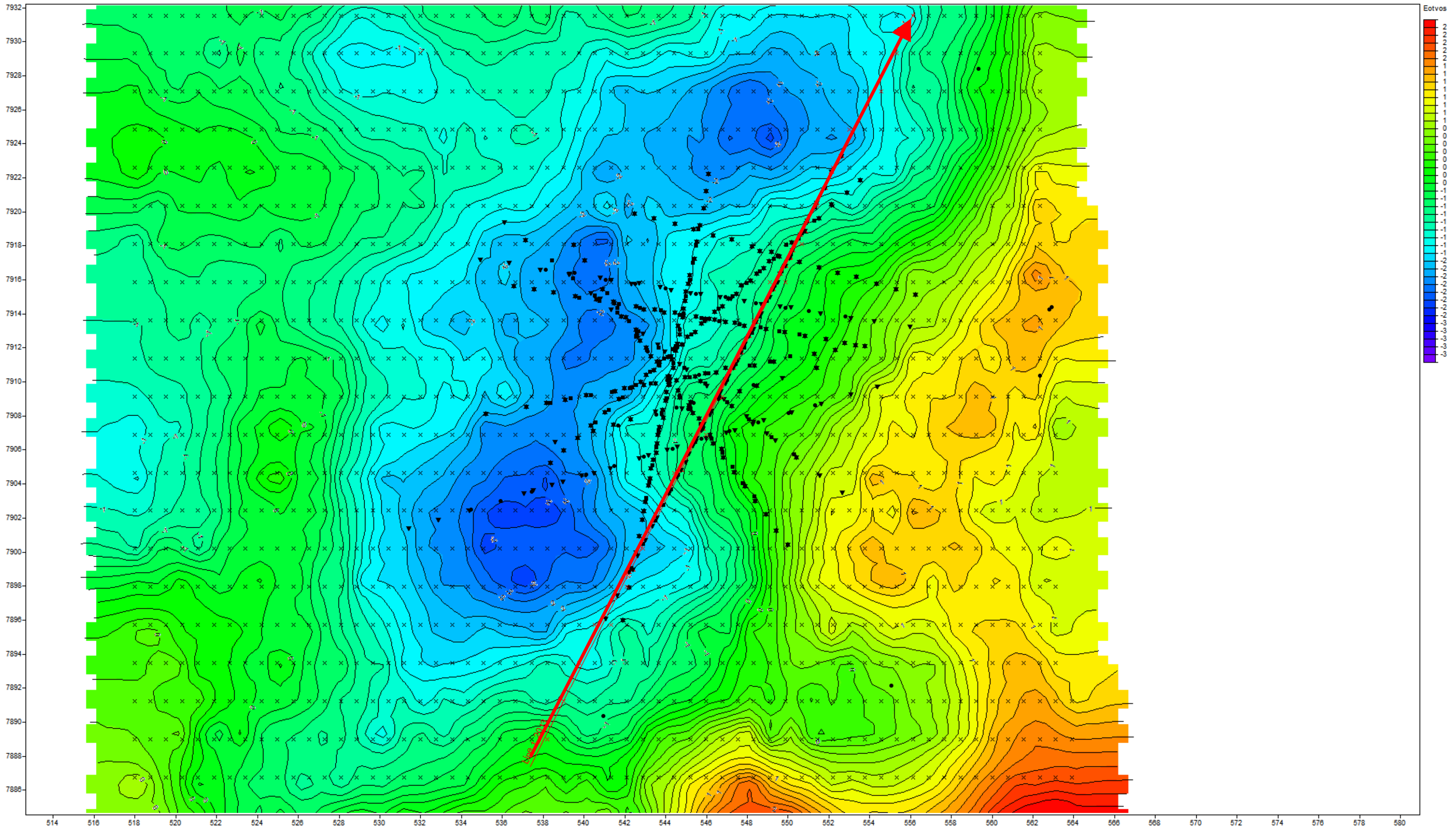


Integrated interpretation along another line: Line 01 - 2005

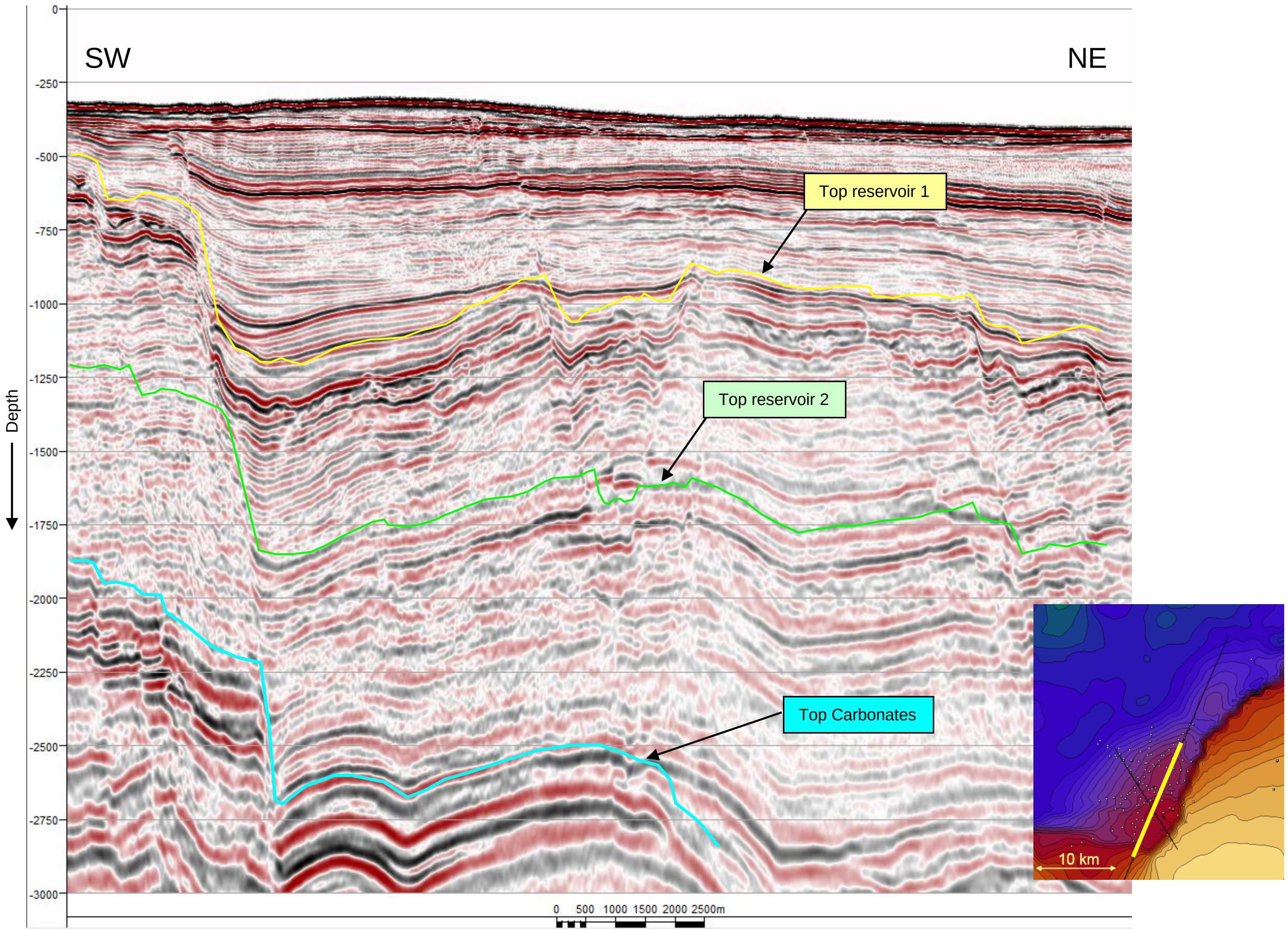
Norm E + B magnitude on Realgrunnen



First Derivative of the Bouguer anomaly

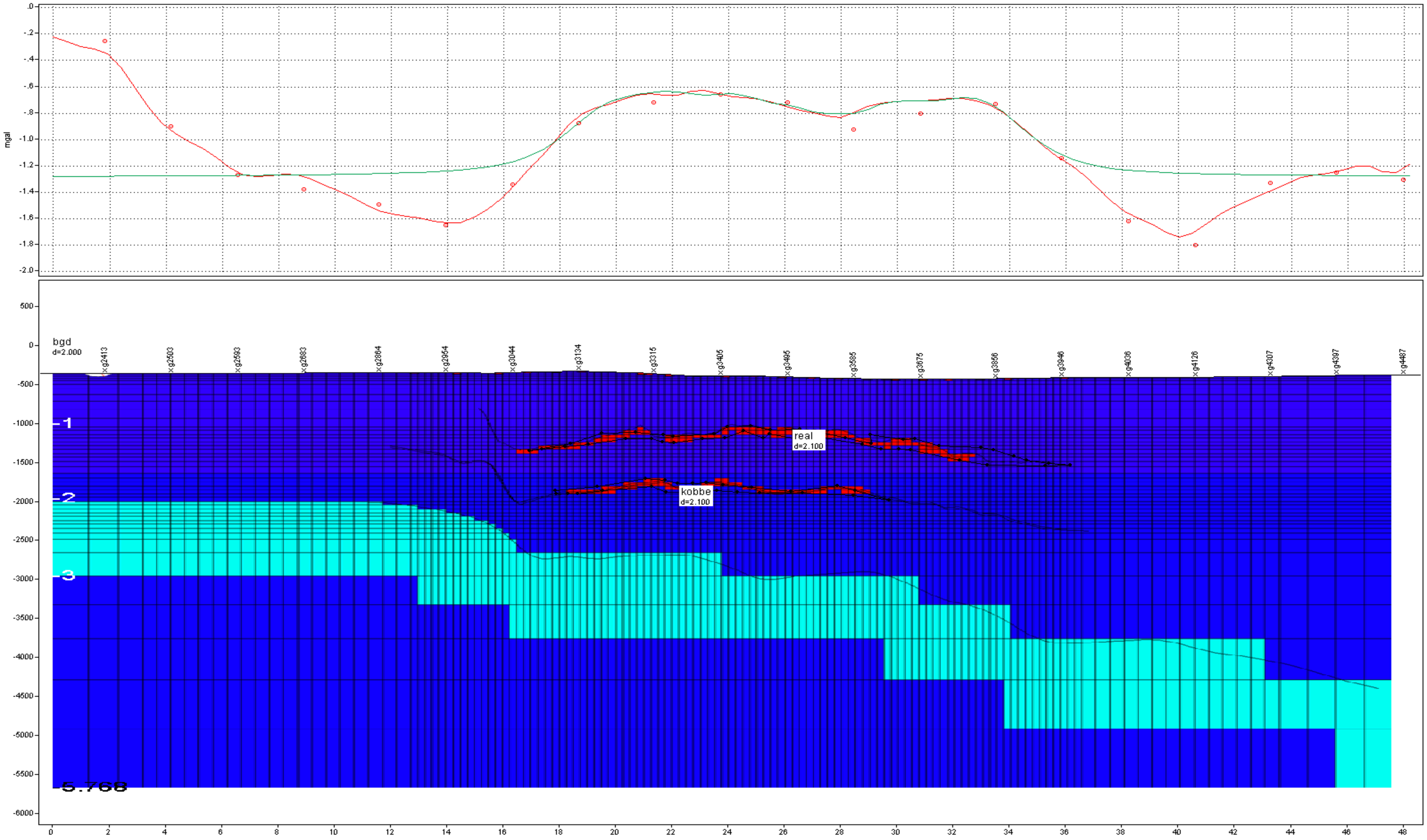


PSDM seismic section

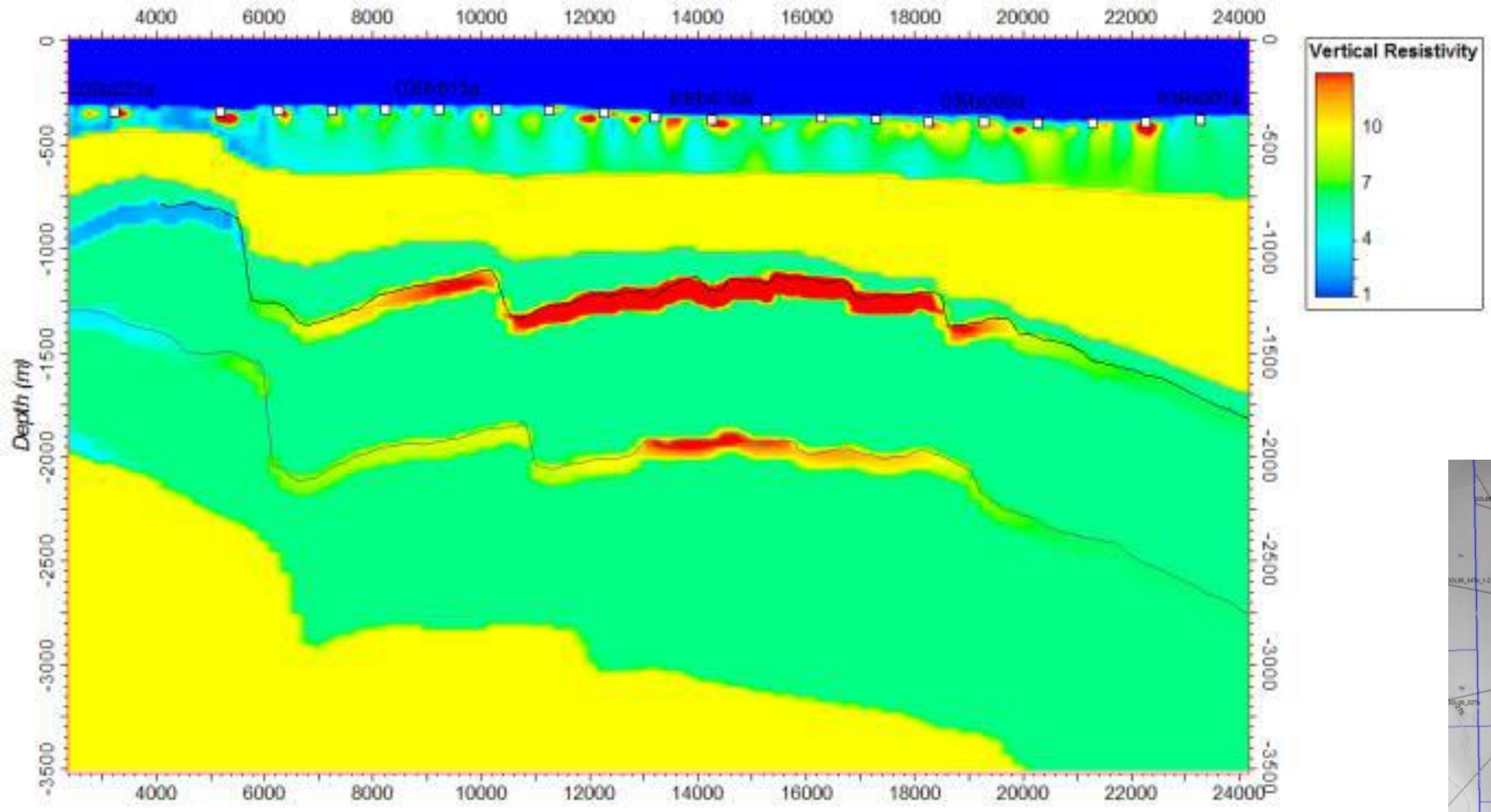


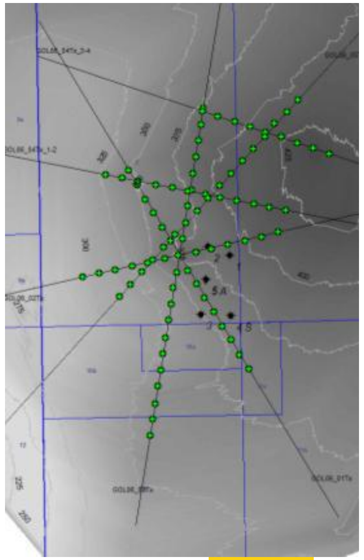
PSDM

Gravity modelling on resistivity model in background

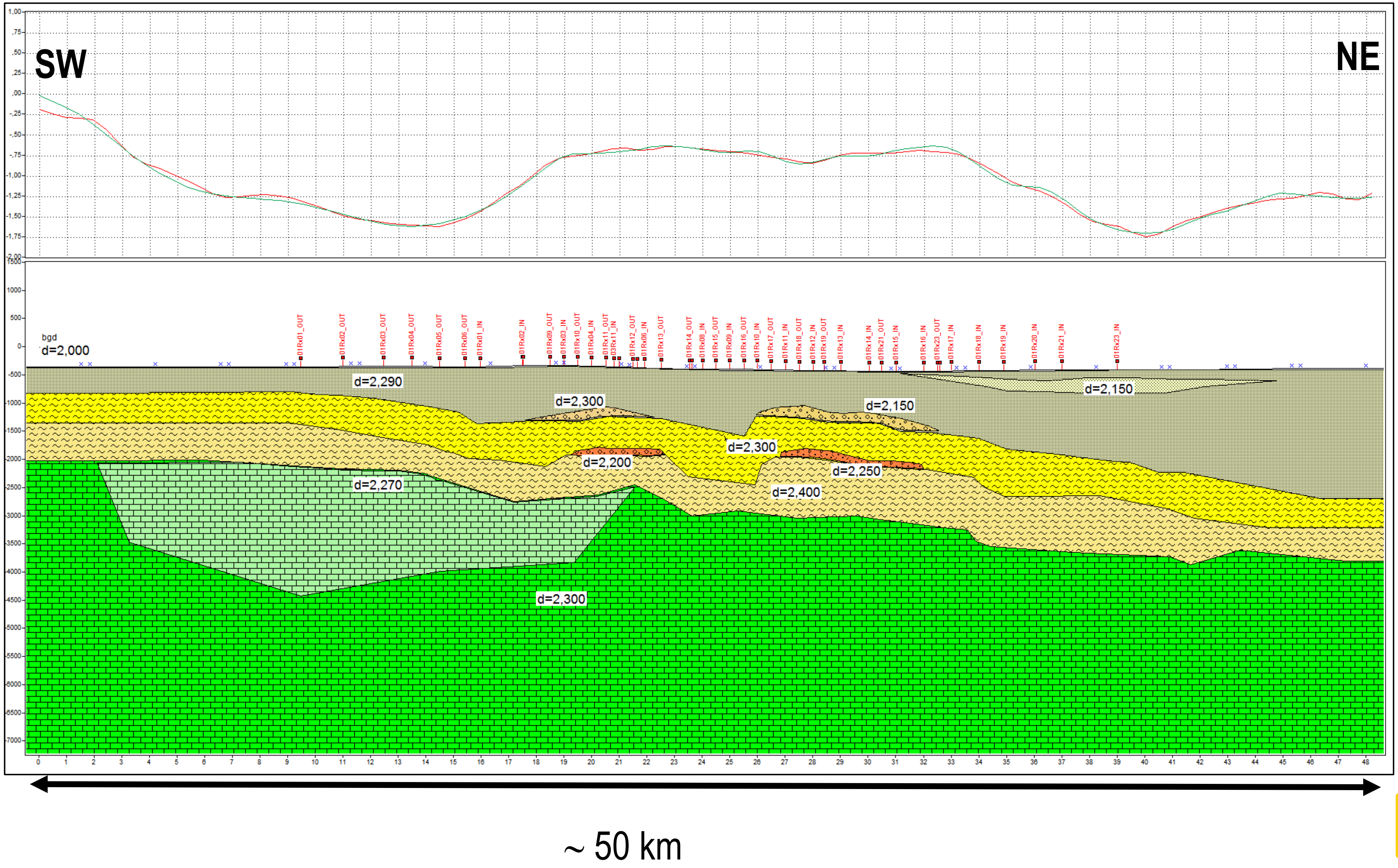


CSEM inversion [Line 03TX001 (running near)]





Gravity model line 1 CSEM 2005: First Vertical Derivative



Data analytics and Machine Learning

1) Definition of a feature matrix including all the observations (data space) and all the model parameters extracted from modelling, inversion, interpretation model/interpretation space).

2) Feature analytics (statistical distribution), Normalization, Pre-processing, Ranking …

3) Training using data near the wells

4) Selection of various learning algorithms

5) Classification and mapping

Features

DATA SPACE

Seismic: TWT at target depth

CSEM: EM amplitudes/phase at multiple frequencies and offsets; derived CSEM attributes; symmetry attributes.

Gravity: Observed gravity (and/or Bouguer), spatial filters, derivatives

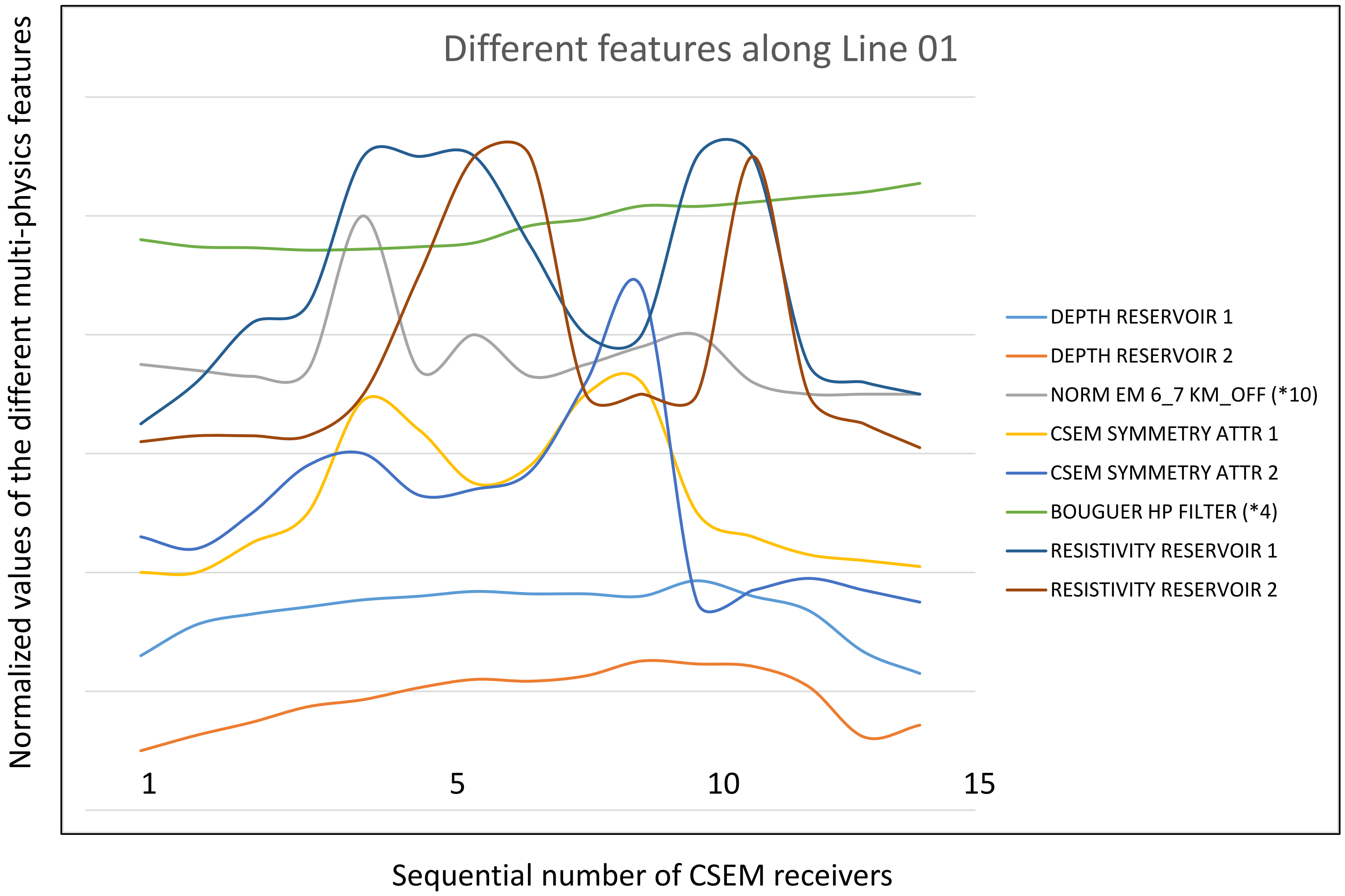
MODEL SPACE

Seismic: interpreted horizons in depth …

CSEM: resistivity models (at target depth)

Gravity: density models (at target depth)

Features



Different features along Line 01
Normalized values of the different multi-physics features
1
5
10
15
DEPTH RESERVOIR 1
DEPTH RESERVOIR 2
NORM EM 6_7 KM_OFF (*10)
CSEM SYMMETRY ATTR 1
CSEM SYMMETRY ATTR 2
BOUGUER HP FILTER (*4)
RESISTIVITY RESERVOIR 1
RESISTIVITY RESERVOIR 2
Sequential number of CSEM receivers

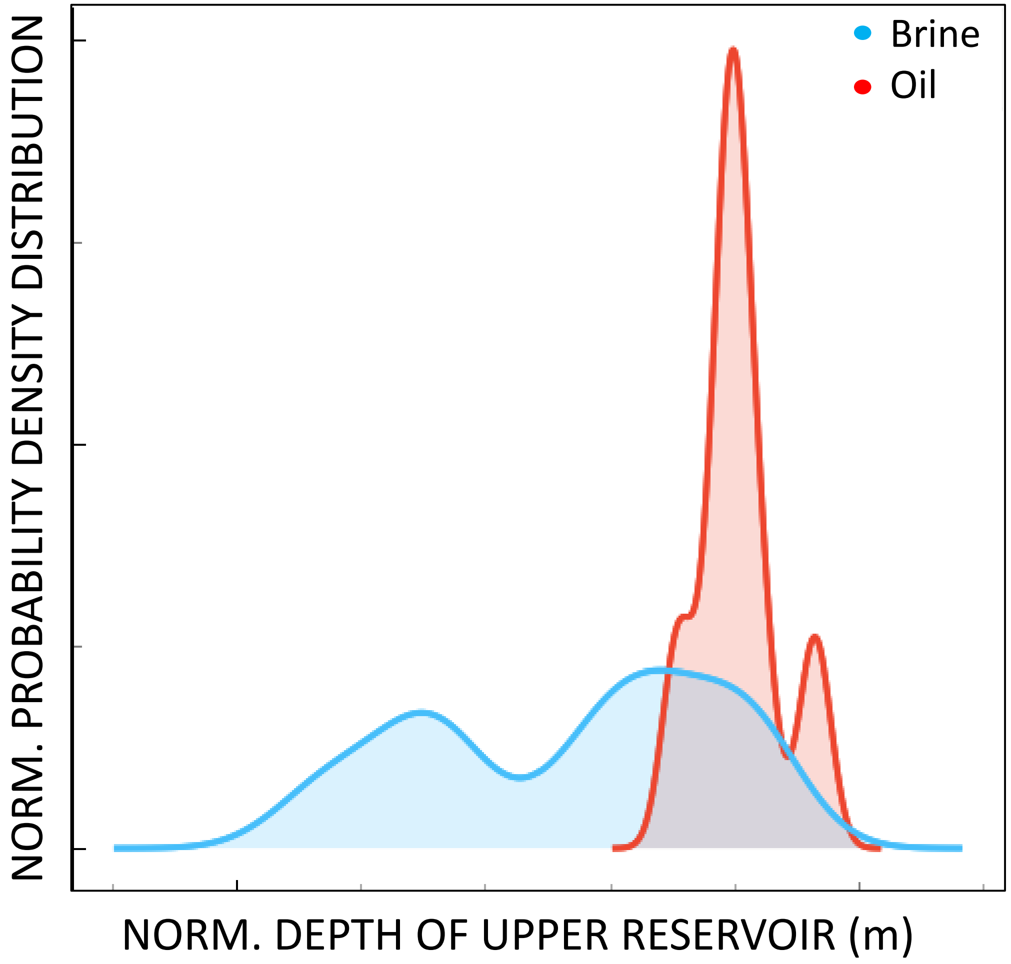
Ranking of features

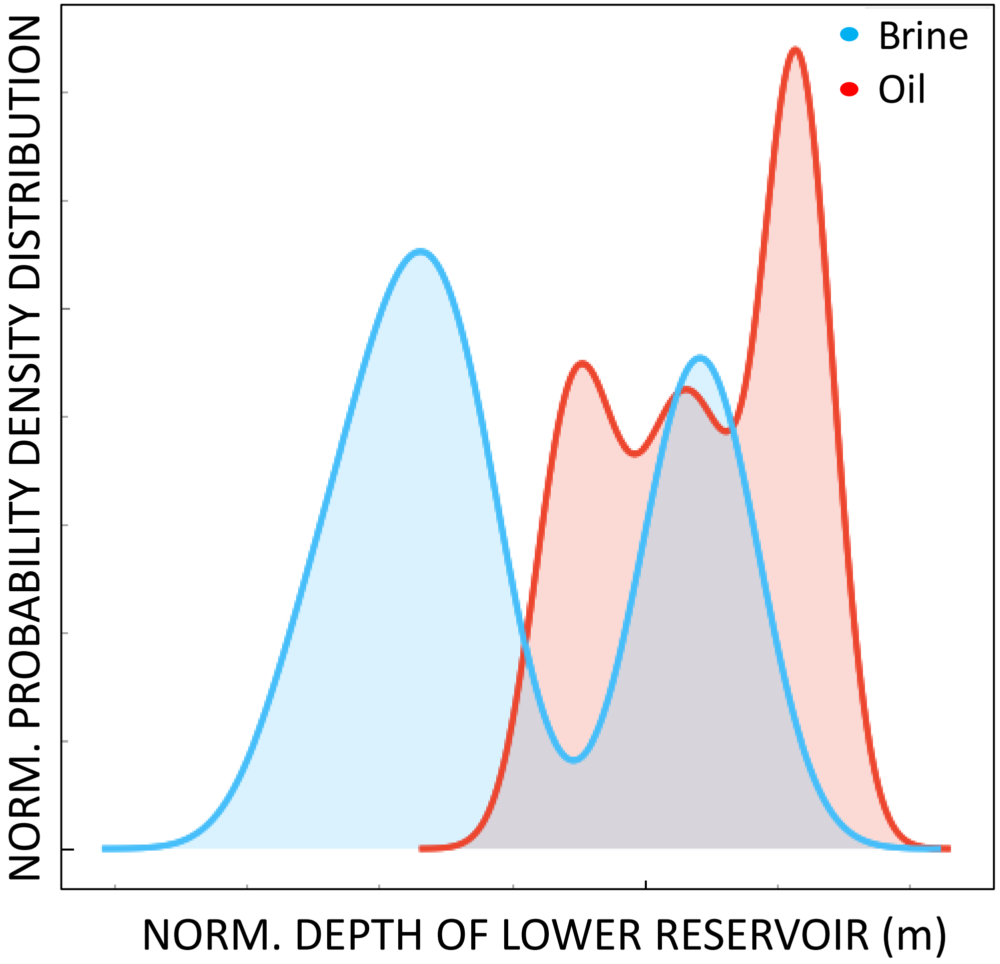
	#	Info. gain	Gain ratio	Gini	ANOVA	χ^2	ReliefF
RESISTIVITY RESERVOIR 1		0.647	0.335	0.331	19.015	9.224	0.343
DEPTH RESERVOIR 1		0.463	0.233	0.231	7.441	2.545	0.129
CSEM SYMMETRY ATTR 1		0.380	0.191	0.209	3.748	4.845	0.113
DEPTH RESERVOIR 2		0.380	0.191	0.209	7.035	2.545	0.148
CSEM SYMMETRY ATTR 2		0.330	0.166	0.176	0.941	1.364	0.018
NORM EM 6_7 KM_OFF (*10)		0.273	0.139	0.149	4.405	2.701	0.052
NORMALIZED EM 6_7KM_OFF		0.273	0.139	0.149	4.405	2.701	0.052
RESISTIVITY RESERVOIR 2		0.216	0.118	0.131	1.854	3.180	0.100
BOUGUER HP FILTER (*4)		0.063	0.032	0.042	0.650	0.810	0.021

Ranking of classifiers

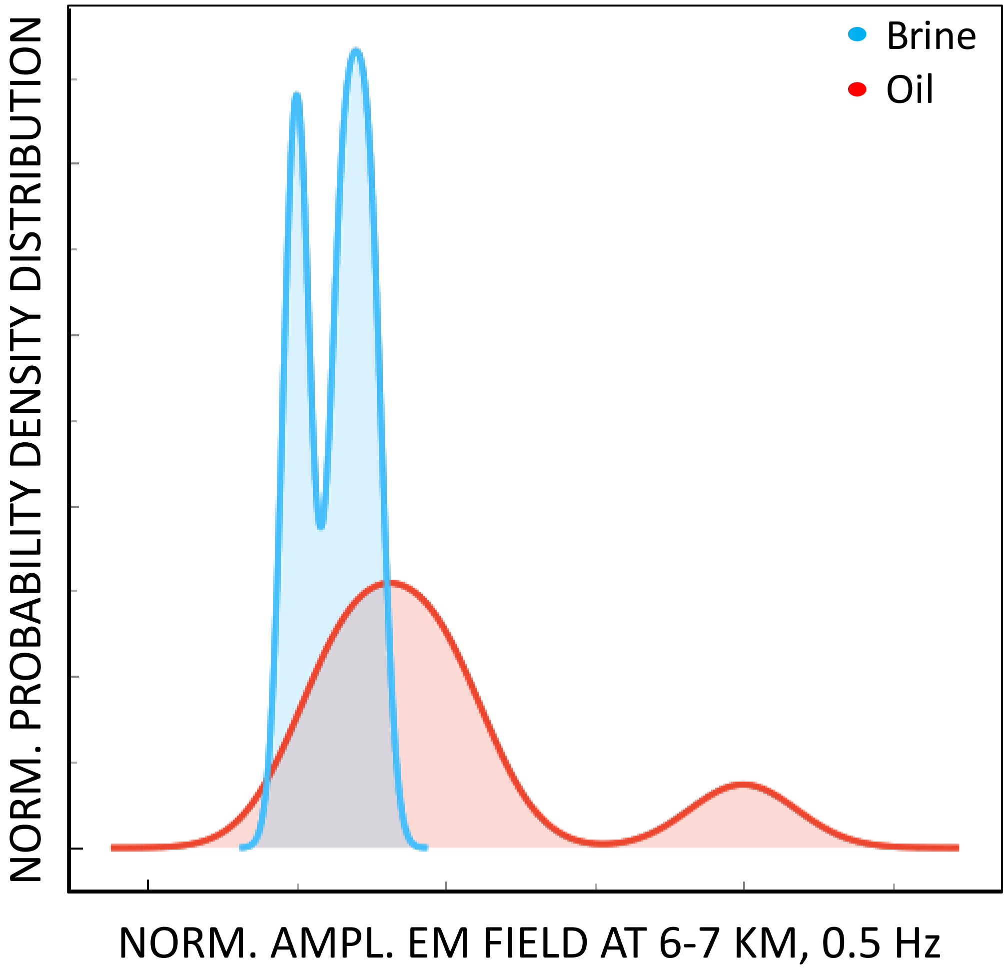
Method	AUC	CA	F1	Precision	Recall
Tree	0.825	0.733	0.726	0.747	0.733
Random Forest	0.825	0.733	0.733	0.733	0.733
Neural Network	0.750	0.600	0.600	0.600	0.600
Naive Bayes	0.900	0.000	0.000	0.000	0.000
CN2 rule inducer	0.650	0.667	0.664	0.667	0.667
AdaBoost	0.700	0.733	0.733	0.733	0.733

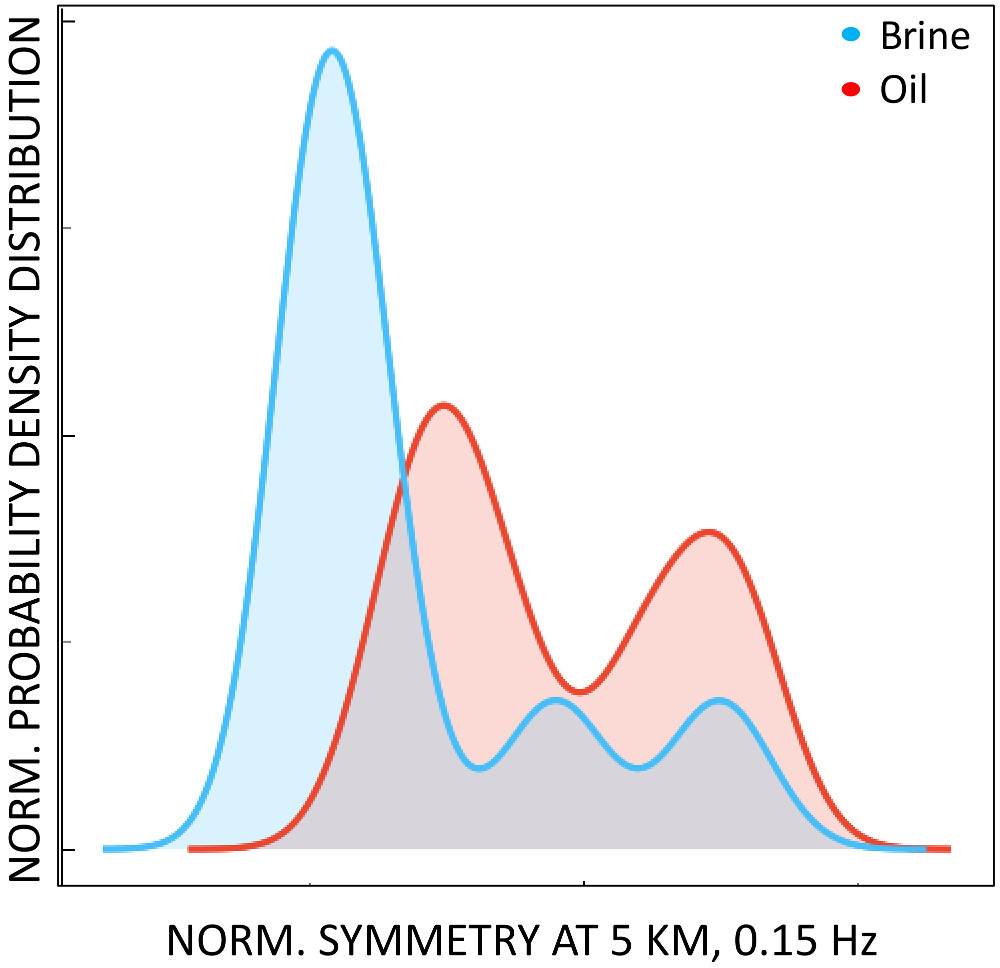
Examples of statistical distributions (L1 – 2006)



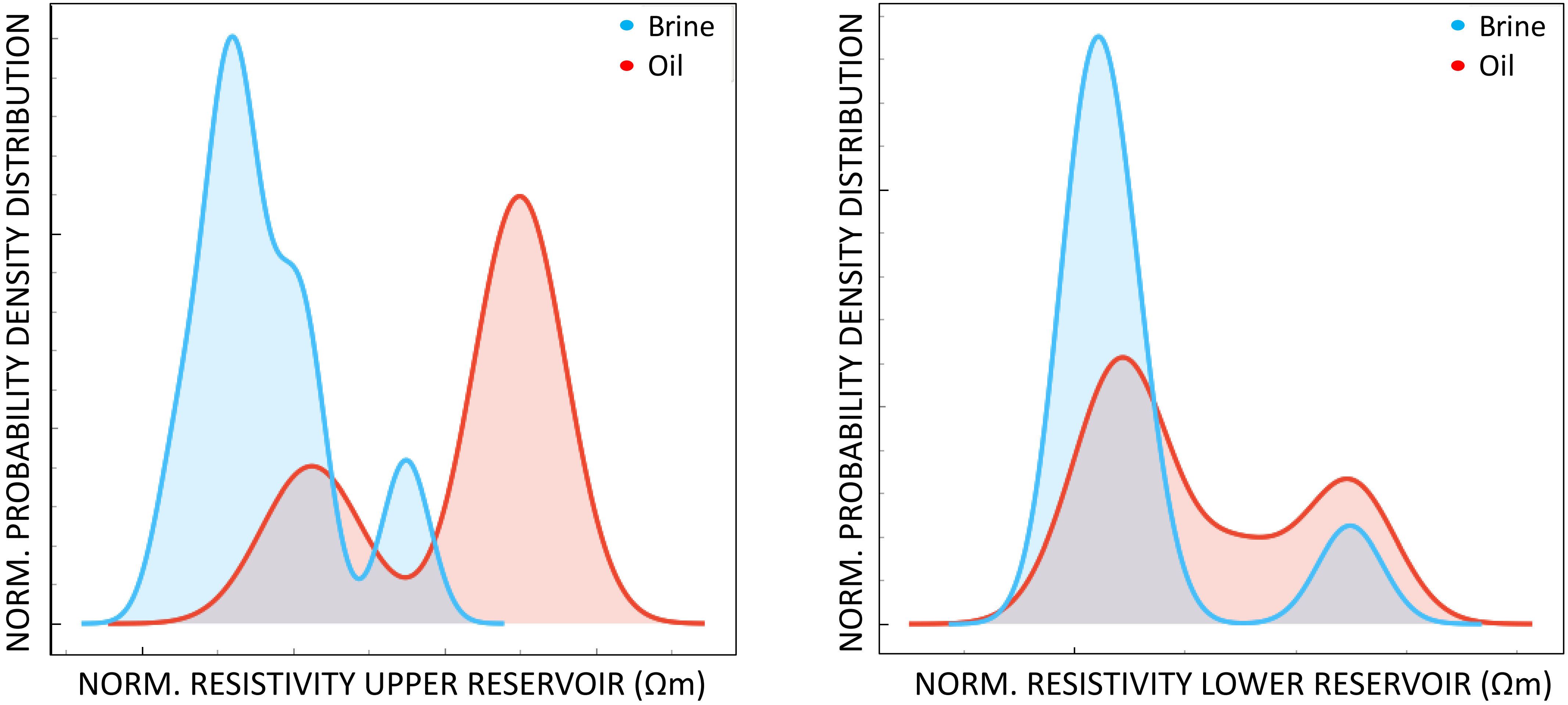


Examples of statistical distributions (L1 – 2006)

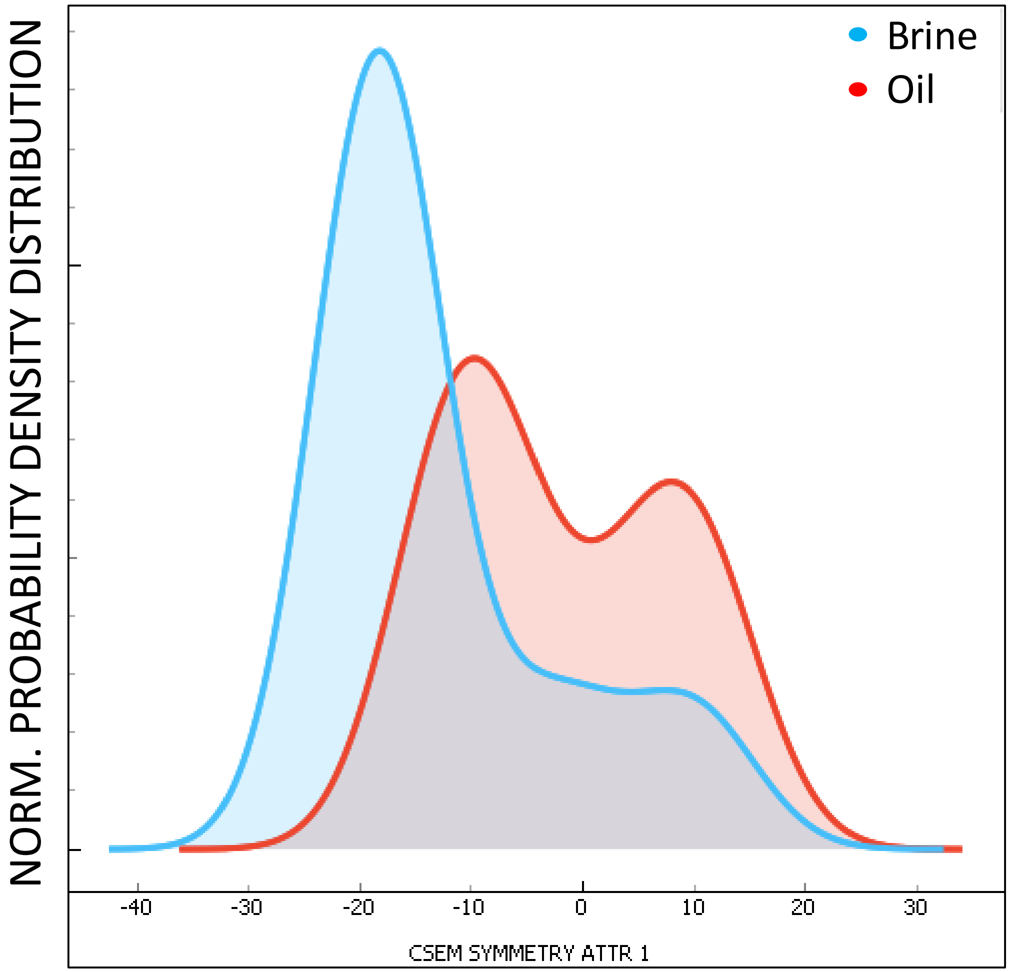


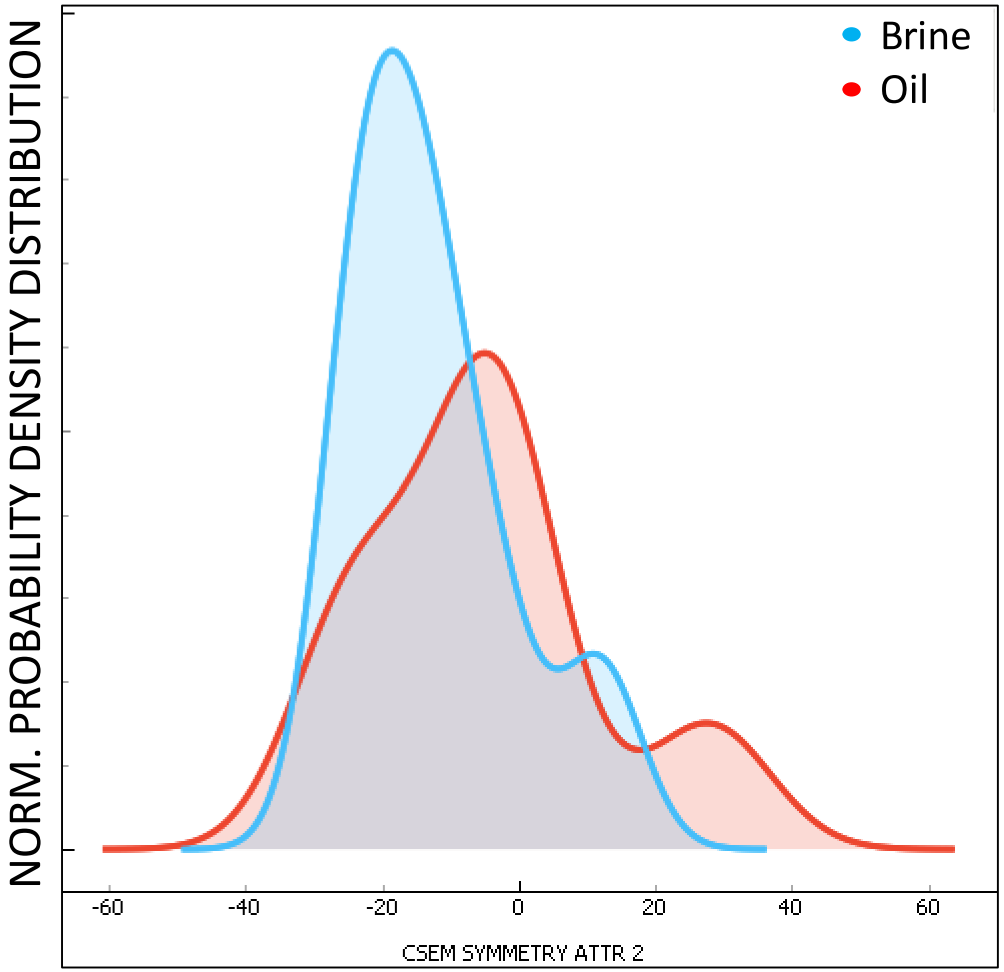


Examples of statistical distributions (L1 – 2006)

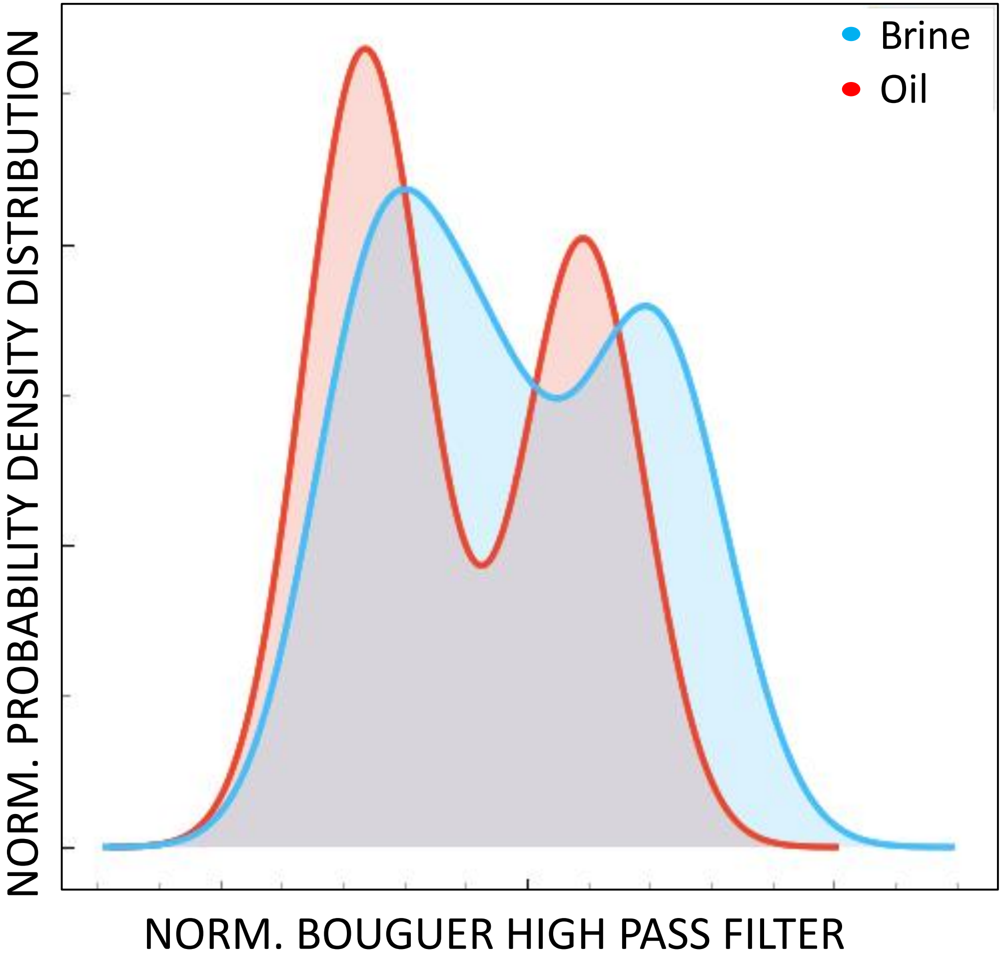


Examples of statistical distributions (L1 – 2006)





Examples of statistical distributions (L1 – 2006)



Multi-physics and Machine Learning

Training Machine Learning algorithms with labelled data/models calibrated at well location

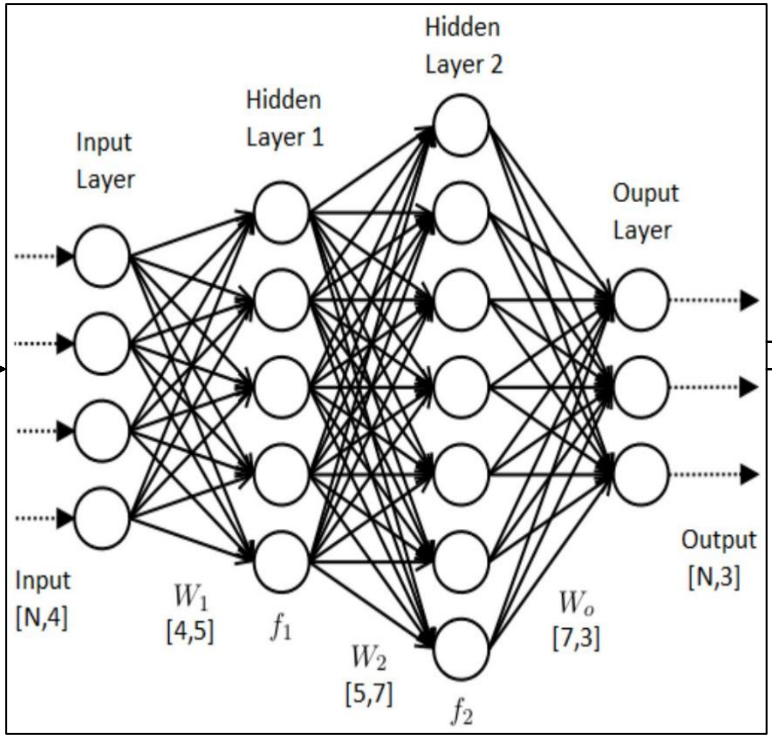
WELLS

DATA

Seismic
CSEM
Gravity
Borehole

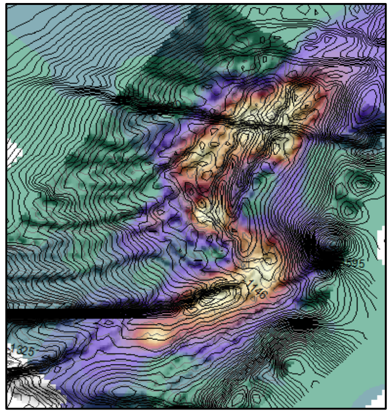
MODELS

Velocity
[AVO t.b.d.]
Resistivity
Density

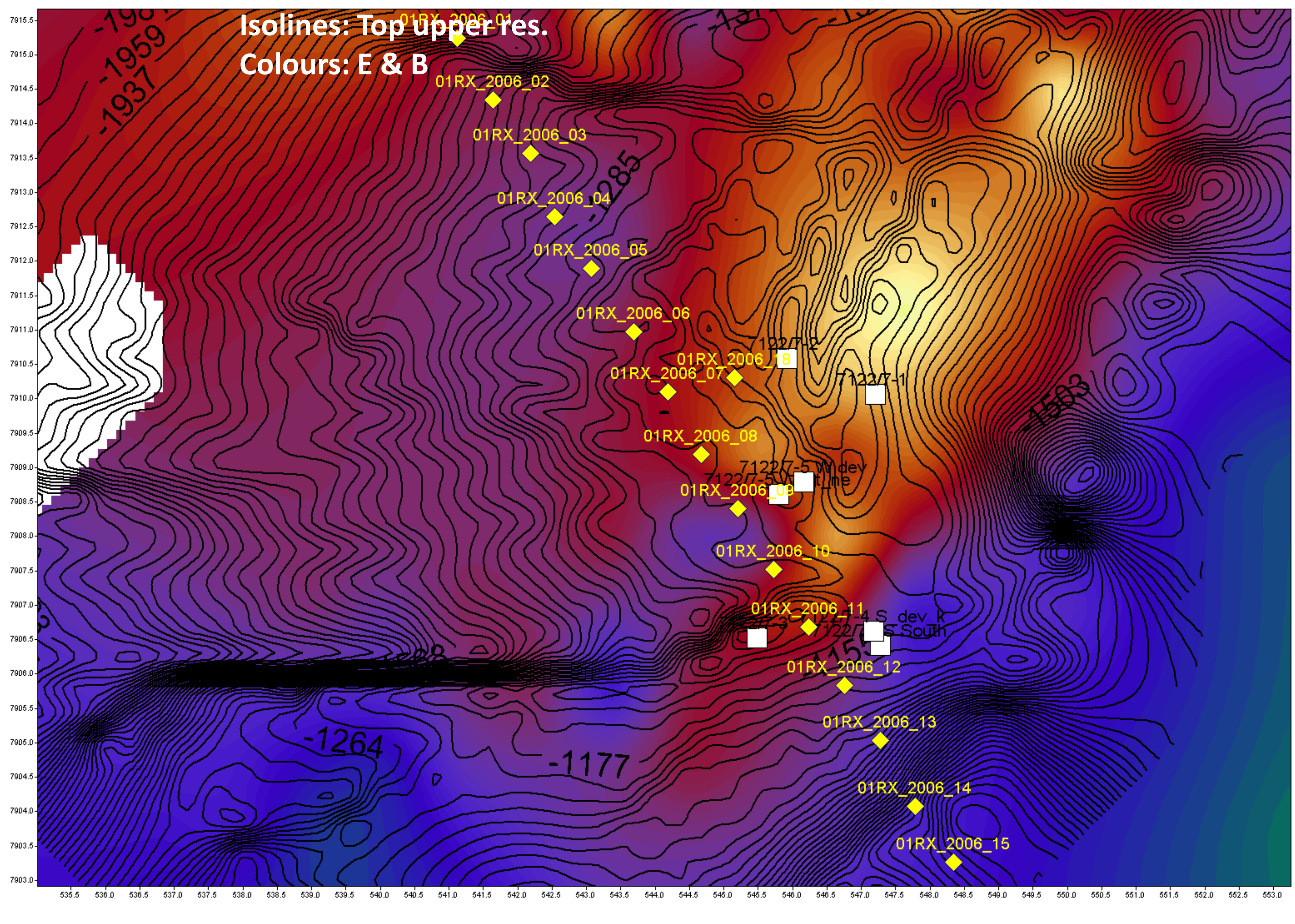


PREDICTIONS AWAY FROM THE WELLS

Brine or Oil in the reservoir?



Isolines: Top upper res.
Colours: E & B

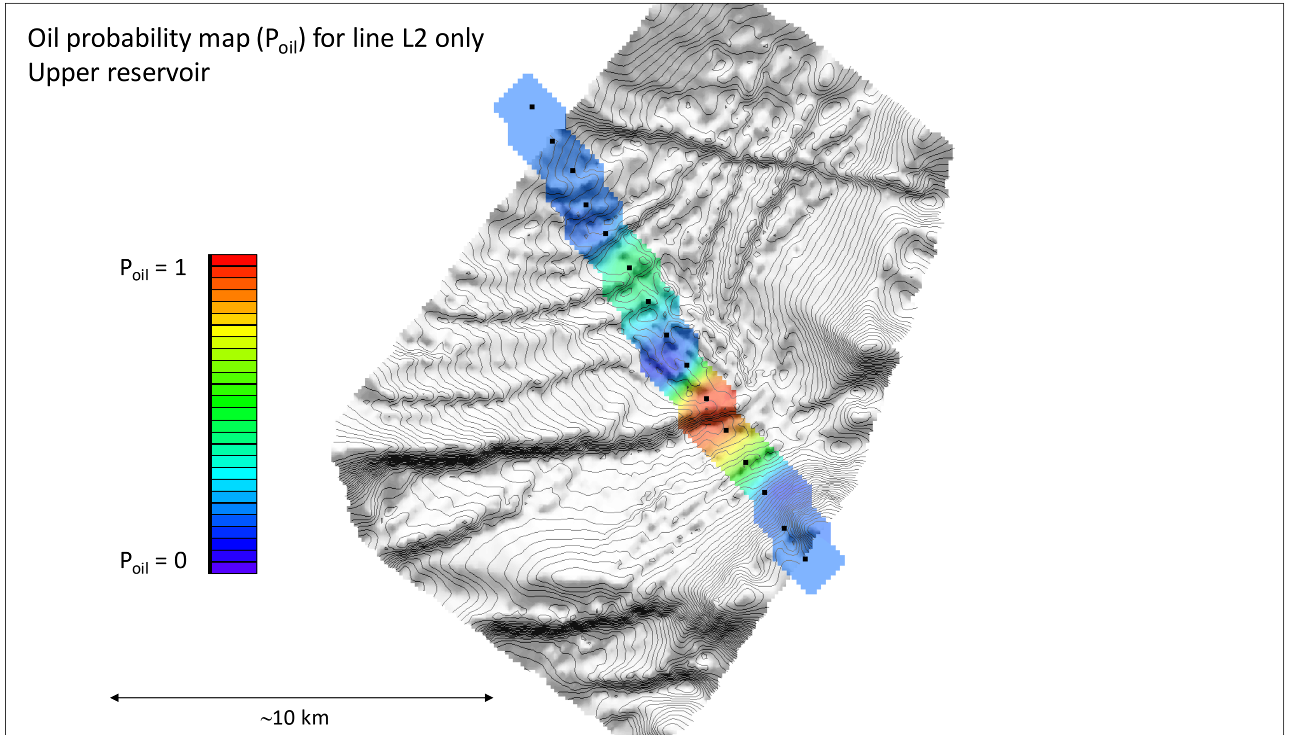


Many machine learning algorithms … many maps

We used a suite of machine learning methods that produced a suite of probability maps.

All the maps are similar, sometimes showing minor differences, depending on the different performances of the predictive algorithm.

Oil probability map for one individual line (L1 – 2006) for upper reservoir



Other maps and additional results

vs. recent appraisal well 7122/7-7 S

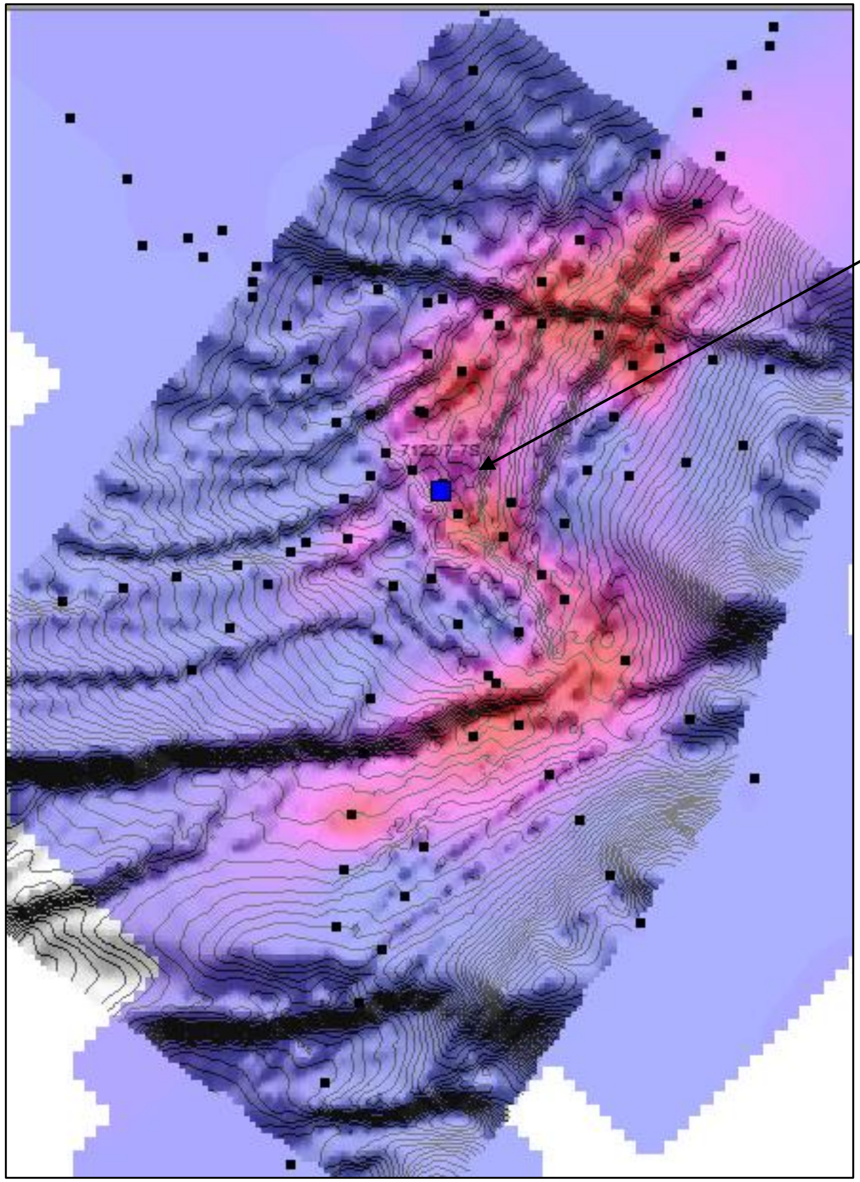
Many machine learning algorithms … many maps

The map on the right has been obtained using Deep Neural Networks (Dell'Aversana et Al., 2018).

It fully confirmed the results anticipated In our publication of 2012 (Dell'Aversana et Al., 2012; see next slide).

This map, as well as the other predictive maps, show high (80-90%) probability of oil in the western sector of the field, in agreement with the appraisal well 7122/7-7S completed in 2019.

Purple: high oil probability (90-100%).



Appraisal well 7122/7-7 S

Oil probability map in Realgrunnen (purple: oil probability > 90%).

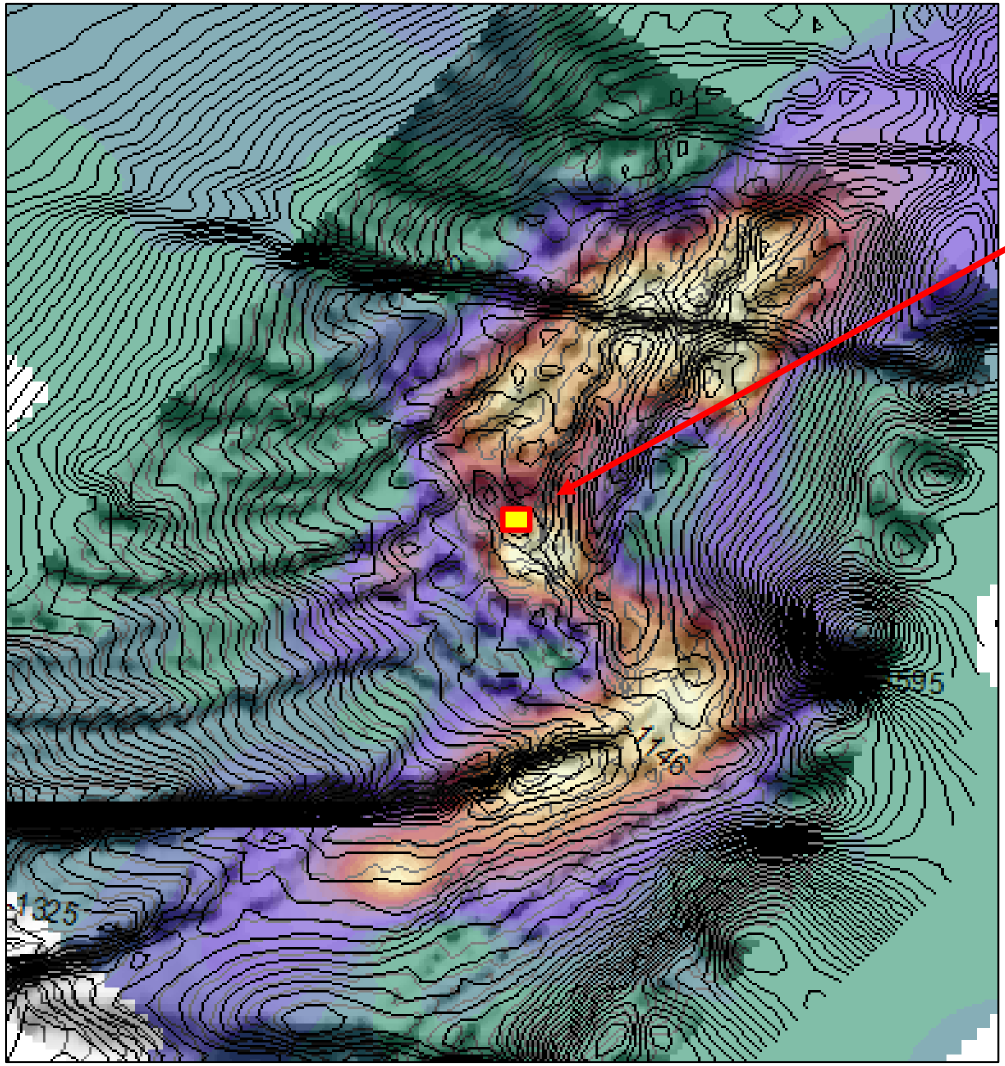
Many machine learning algorithms … many maps

The map on the right has been obtained using Deep Neural Networks (Dell'Aversana et Al., 2018).

It fully confirmed the results anticipated in our publication of 2012 (Dell'Aversana et Al., 2012; see next slide).

It shows high (80-90%) probability of oil in the western sector of the field, in agreement with the appraisal well 7122/7-7S completed in 2019.

Yellow: high oil probability (90-100%).



Appraisal well
7122/7-7 S

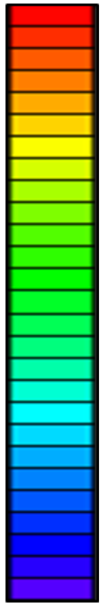
Oil probability map in Realgrunnen (yellow: oil probability > 90%).

Oil probability map (P_{oil}) – Using all data

Upper reservoir.

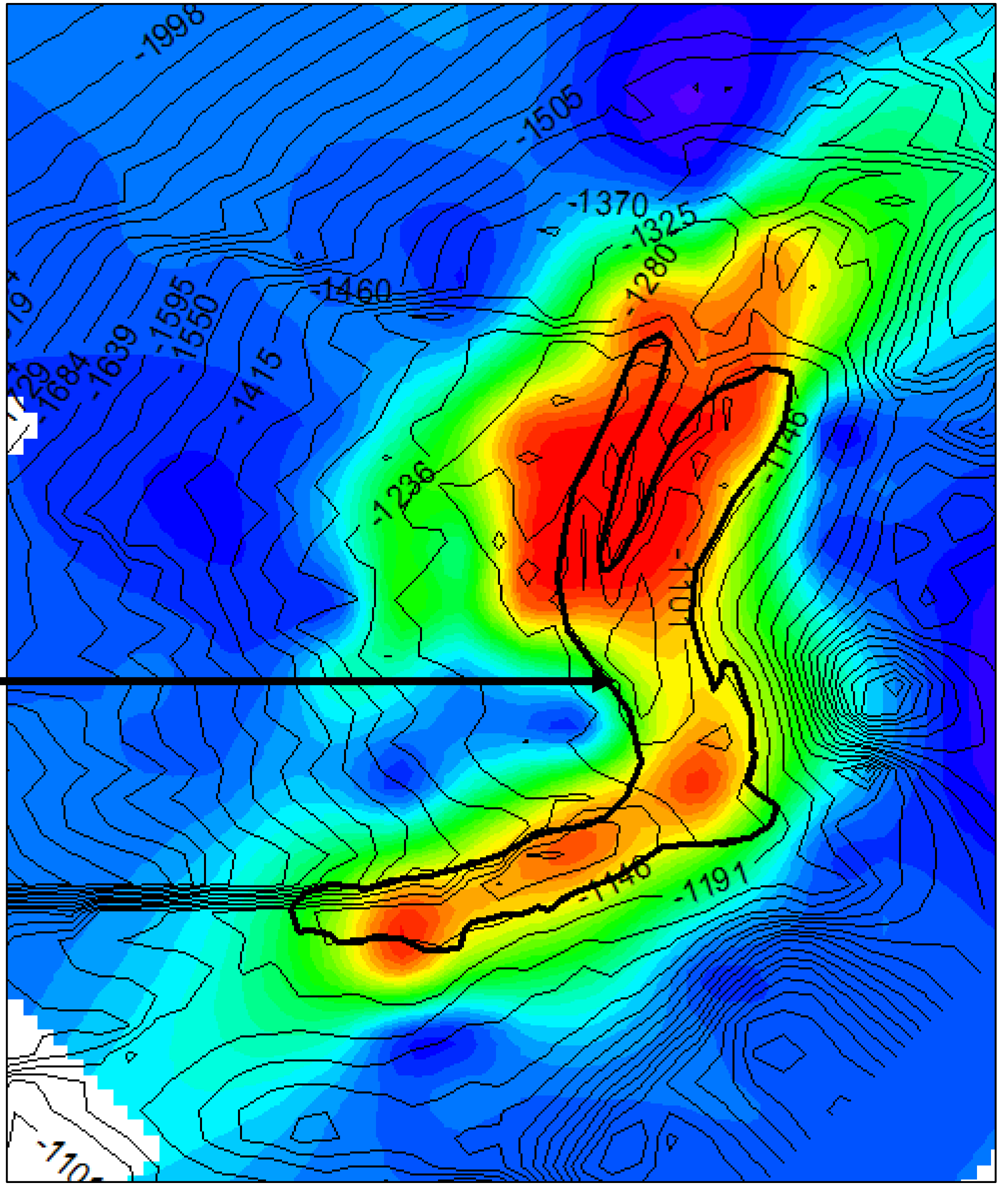
Map obtained in May 2010 and published in 2012, confirmed, with minor changes, using Machine Learning.

$P_{oil} = 1$



$P_{oil} = 0$

'Old' (2012) HC/W contact based on seismic data Interpretation and wells, provided by Eni Norge in 2010.



This map has been published in our First Break paper in 2012:
'CSEM data interpretation constrained by seismic and gravity data: an application in a complex geological setting'
Paolo Dell'Aversana, Stefano Colombo, Barbara Ciurlo, Johan Leutscher and Jan Seldal

Paper published by Eni - First Break (2012)

first break volume 30, November 2012

technical article

CSEM data interpretation constrained by seismic and gravity data: an application in a complex geological setting

Paolo Dell'Aversana,[1*] Stefano Colombo,[1] Barbara Ciurlo,[1] Johan Leutscher[2] and Jan Seldal[2]

Abstract

We describe a novel approach to the interpretation of marine controlled source electromagnetic (CSEM) data based on electromagnetic attributes in combination with gravity and seismic data. This integrated approach involves a new electromagnetic attribute of resistor probability, and has been applied in a complex exploration area in the Barents Sea adjacent to an extensive carbonate platform. We used the data recorded by a total of 172 CSEM receivers from two different surveys. Gravity data were also used to highlight large-scale geological features. Integrating seismic, electromagnetic, and gravity information helped to distinguish resistivity anomalies caused by geological variations from those caused by hydrocarbons. Finally, the hydrocarbon distributions in two stacked reservoirs were accurately mapped. Our integrated approach significantly improved the appraisal of the field, reducing the exploration risk in the surrounding area and facilitating the placement of future wells.

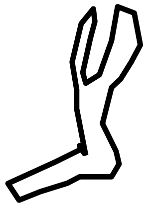
Info summary: data and predictions

Data	Methods
1) 2D seismic lines	1) Seismic interpretat.
2) 2D CSEM lines	2) CSEM-Grav. Interpr.
3) Satellite gravity data	3) Cooperat. Modelling
4) Well logs	4) Constrained invers.
5) Prior geological and structural info	5) Joint inversion
	6) Machine Learning

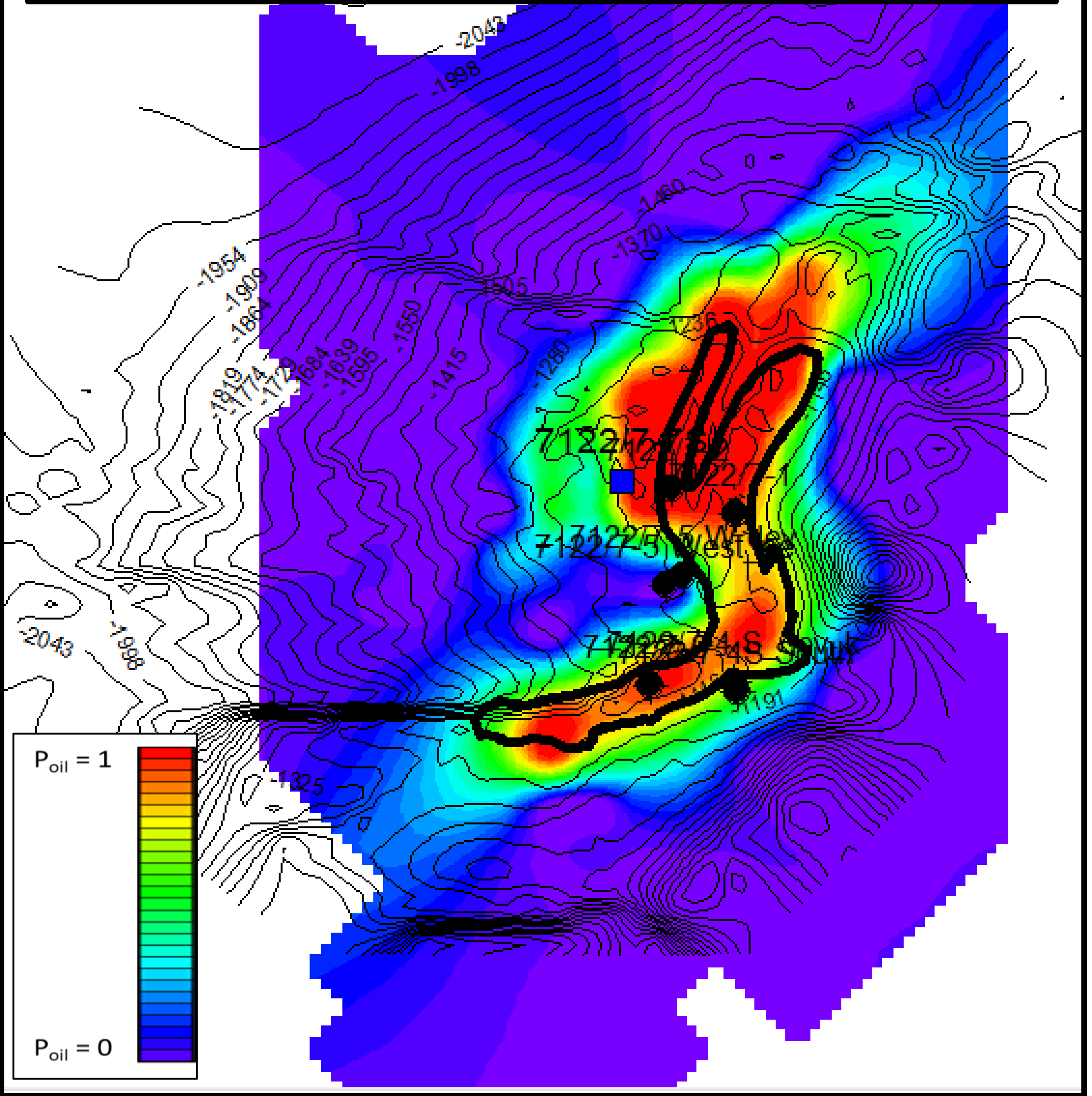
● Wells used for calibration in the 2010-2017 study

■ Appraisal well drilled in 2019

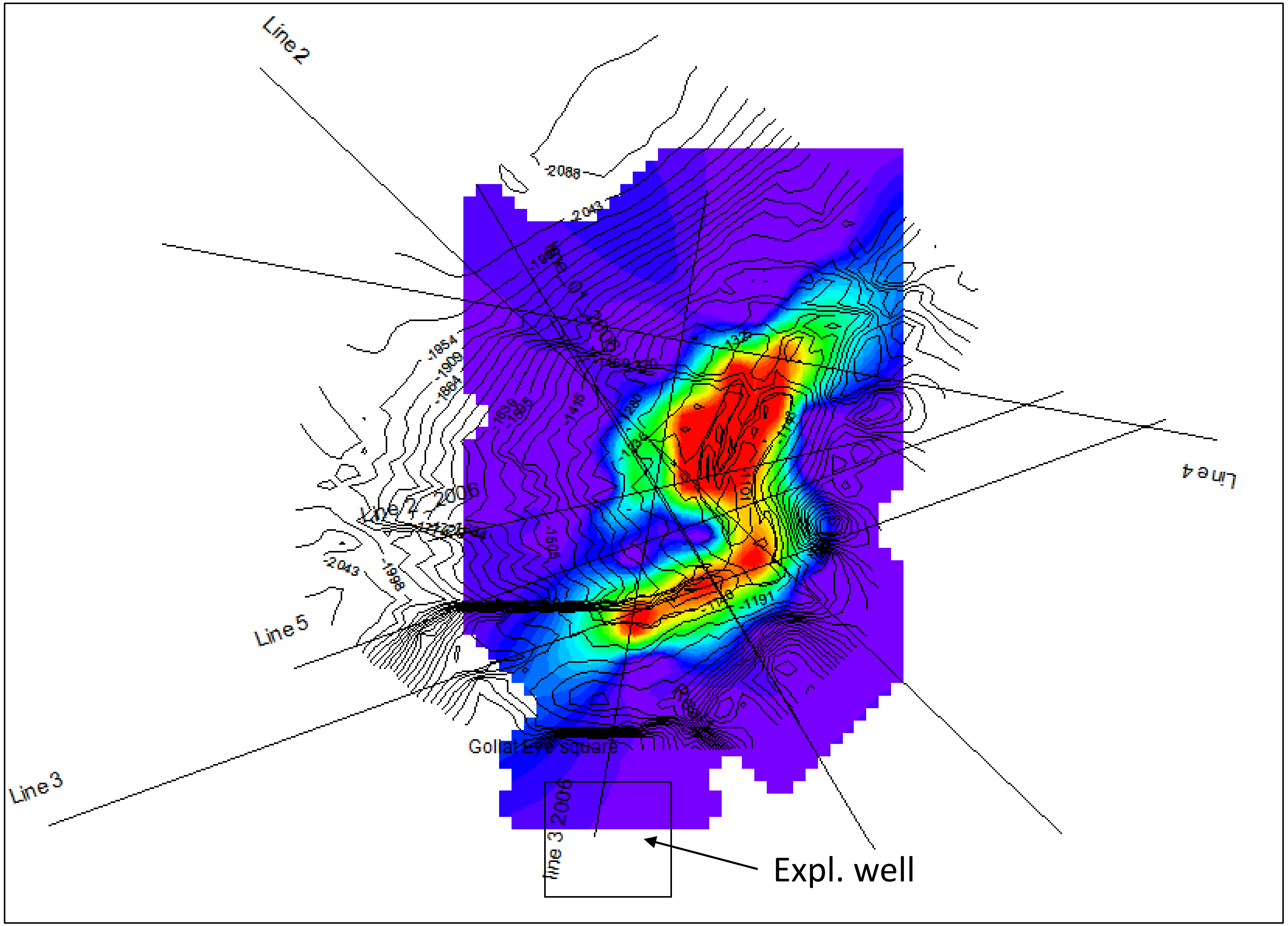
‘Old’ (2012) HC/W contact based on seismic data Interpretation and wells, provided in 2010-2012.



Oil prediction map for top res. (2012)



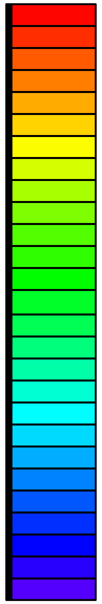
Top reservoir probability map expanded



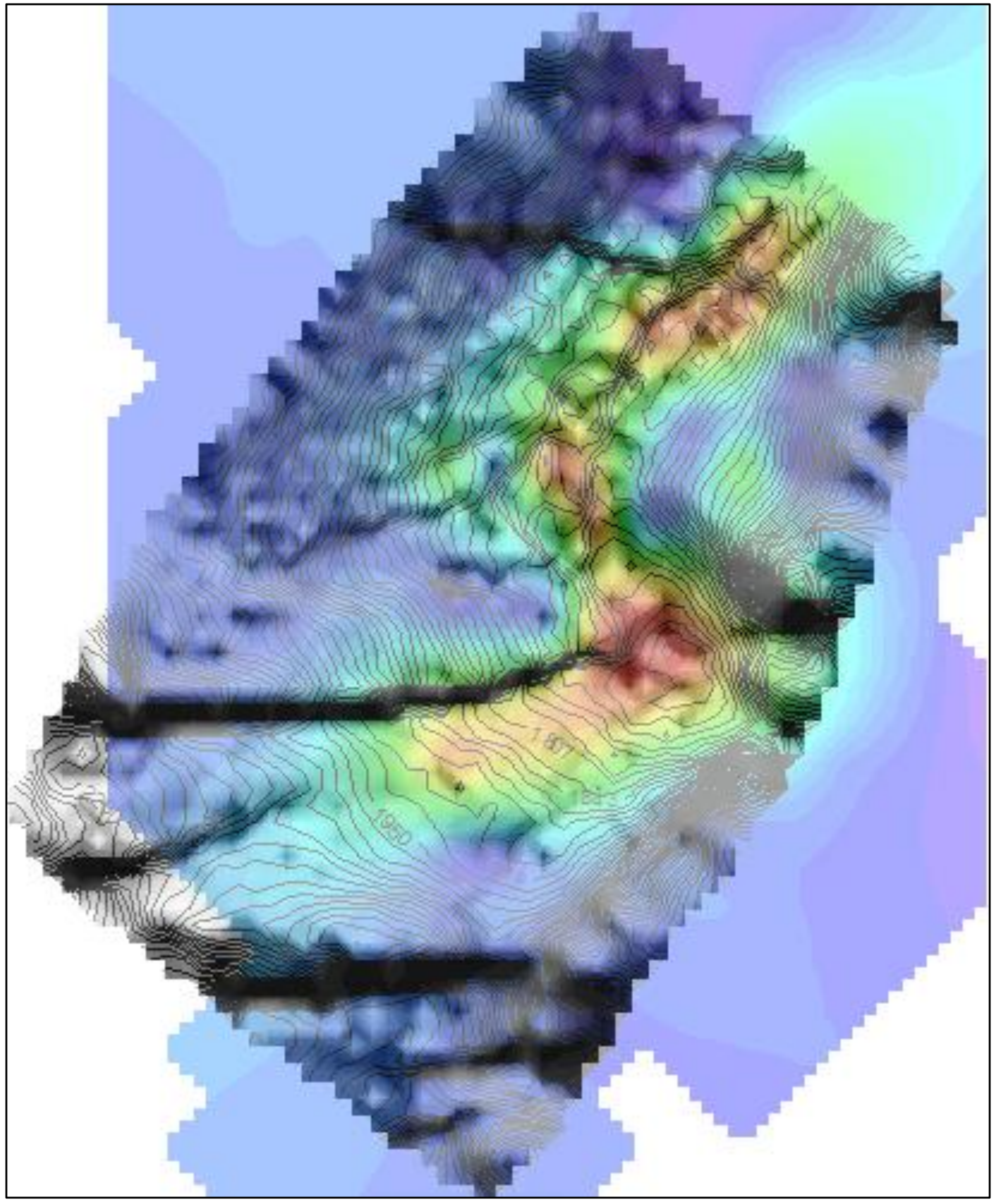
Map for the lower reservoir

Oil probability map (P_{oil}) – All data
Lower reservoir

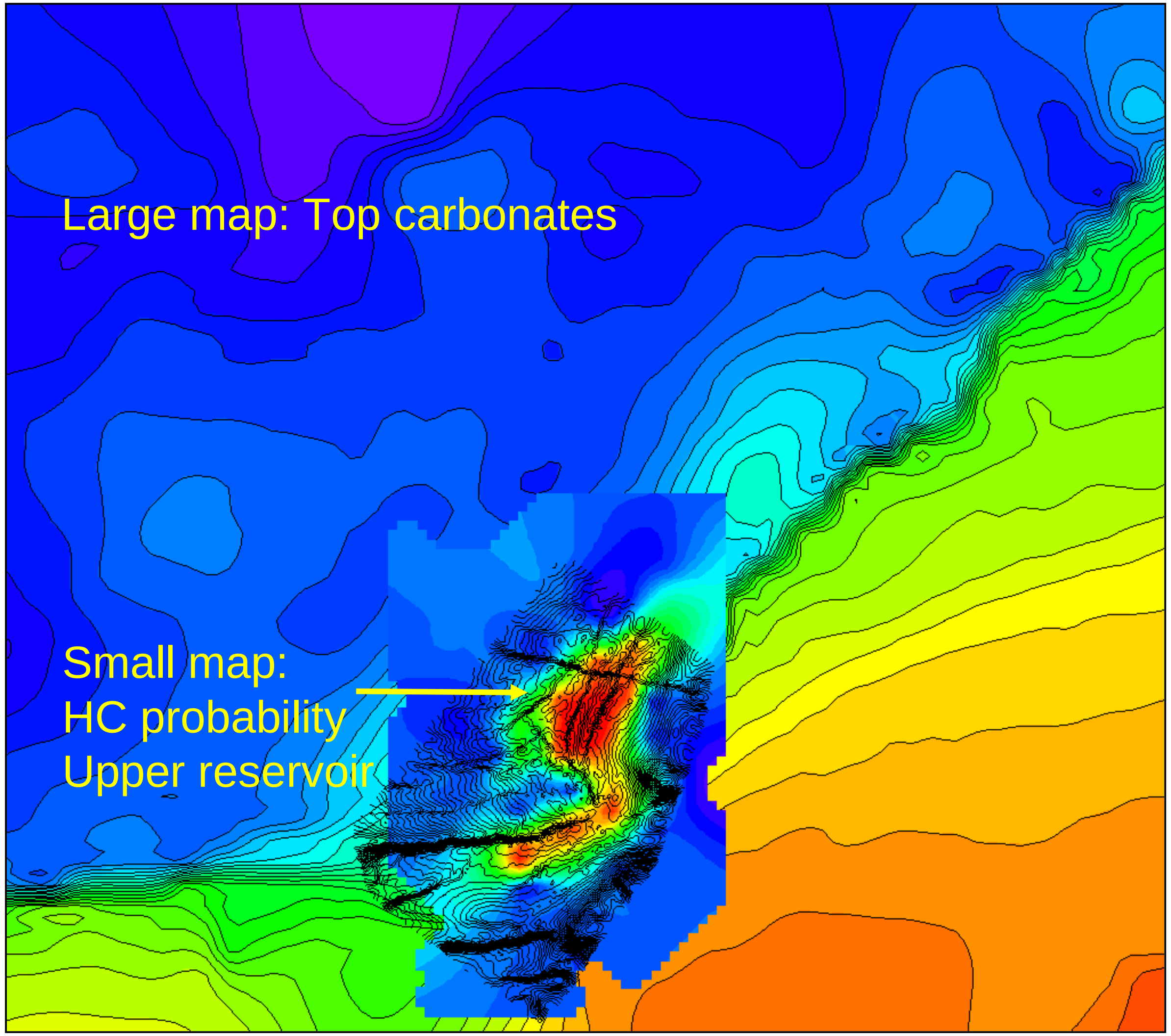
$P_{oil} = 1$

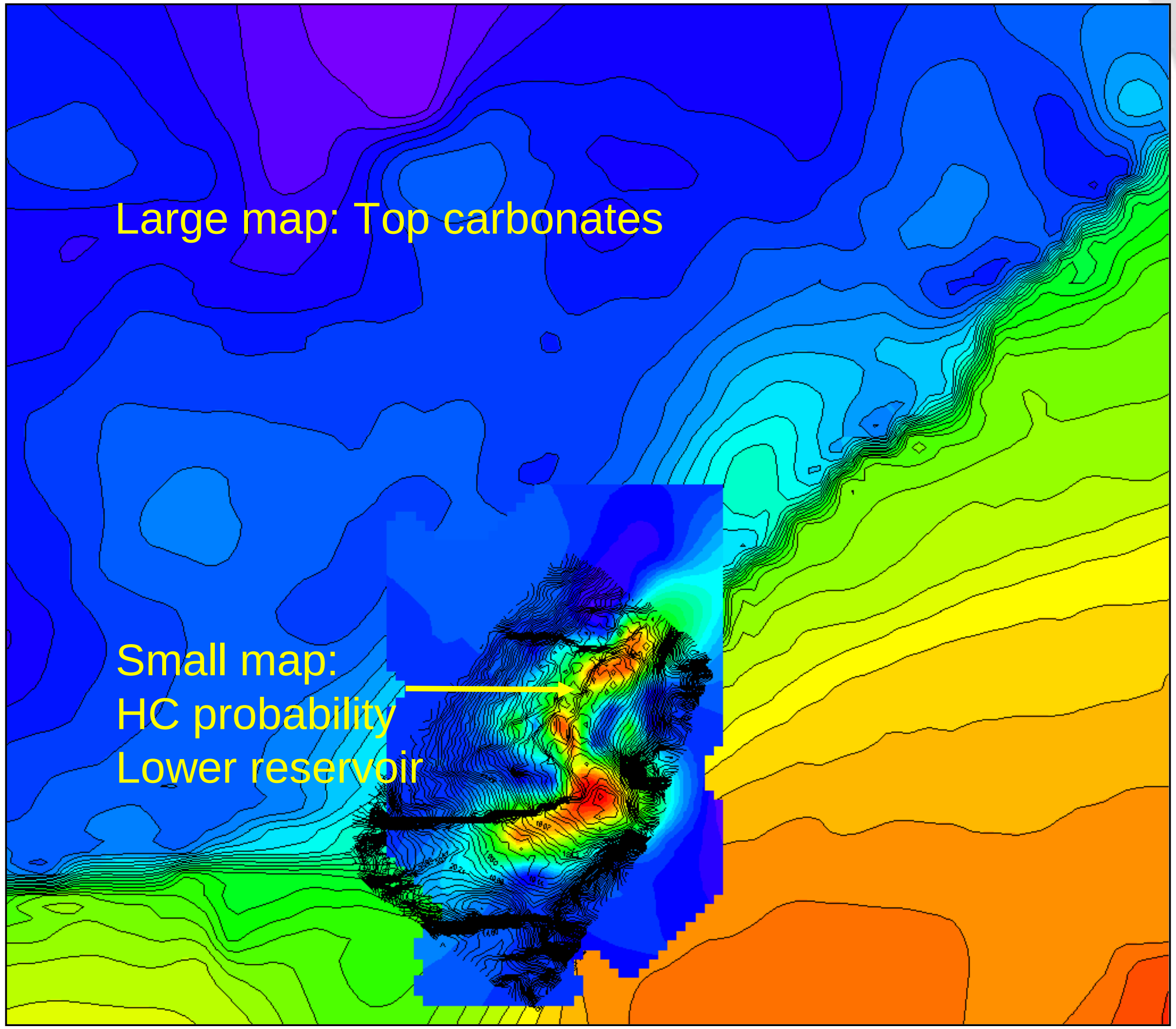


$P_{oil} = 0$



'Summary maps' of oil probability map for all 11 lines (interpolated) for both reservoirs





Conclusions

All the maps produced (and published) with the integrated approach (CSEM + multi-physics + machine learning) from 2012 to 2017 show high (80-90%) probability of oil in the western sector of the field, in agreement with the appraisal well 7122/7-7S completed in 2019.

Finally, our prediction maps show a clear trend of low (or even zero) probability to find oil in the southernmost sector, where the exploration well 7122/10-1 S was effectively dry in the top reservoir formation.