Geological Realism of Deep Water Channel Reservoir Models with Intelligent Priors*

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Search and Discovery Article #41011 (2012)**
Posted August 31, 2012

*Adapted from oral presentation at AAPG Annual Convention and Exhibition, Long Beach, California, April 22-25, 2012
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Abstract

The automation of history matching makes very difficult for modellers to preserve the geological realism of reservoir models. Automation incurs a risk of generating reservoir models with unrealistic geometries based on ad-hoc combination of the model parameter (e.g. channels that are 1 m wide and 200 m thick). Moreover, computational effectiveness of history-matching decreases, as the search for optimum extends to a wider domain. Furthermore, the use of geologically unrealistic reservoir models could mislead the development plan for a specific reservoir.

Use of geological prior information in reservoir models provides a way to control relations between geomodel parameters to ensure their realism. Geological prior information is usually obtained from sources like outcrops, seismic data, or modern depositional environments. Geological prior models quantitatively describe the natural relations among the geo-parameters (e.g. channel width, thickness, sinuosity, etc).

Current practice of modelling sand bodies in deepwater channels is based on deterministic or two-dimensional geological priors, which establish relationships between only two parameters at a time.

In this work we propose to tackle the problem of preserving realism in automated history matching by building robust prior models that describe the non-linear multivariate dependencies between geological parameters of the deep water channelized system. We built multi-dimensional realistic priors using intelligent techniques, specifically One-Class Support Vector Machine. OC-SVM allows capturing hidden relations of the deep water channel parameters (Channel Width and Thickness, Meander Amplitude, and

Wavelength). Furthermore, it is possible to predict realistic parameter combinations, not observed in the available data; but still plausible in nature.

In automated history matching we sample from these realistic priors in order to assure geological realism. A Multiple Point Statistics (MPS) algorithm SNESIM is used to model facies in a deep water channelized reservoir. Variability of the channel geometries are produced by SNESIM algorithm using the affinity parameter, which alters the geometry compared to the training image. We developed a technique to link the MPS affinity parameter with the observed geological characteristics described by the intelligent priors used in history matching. History-matched models produced under geological realistic constraints reduce uncertainty of the production prediction.

Selected References

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Geological Realism of Deep Water Reservoir Models with Intelligent Priors

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and D. Arnold
Heriot-Watt University

AAPG-2012 ACE
Long Beach, April 22-25

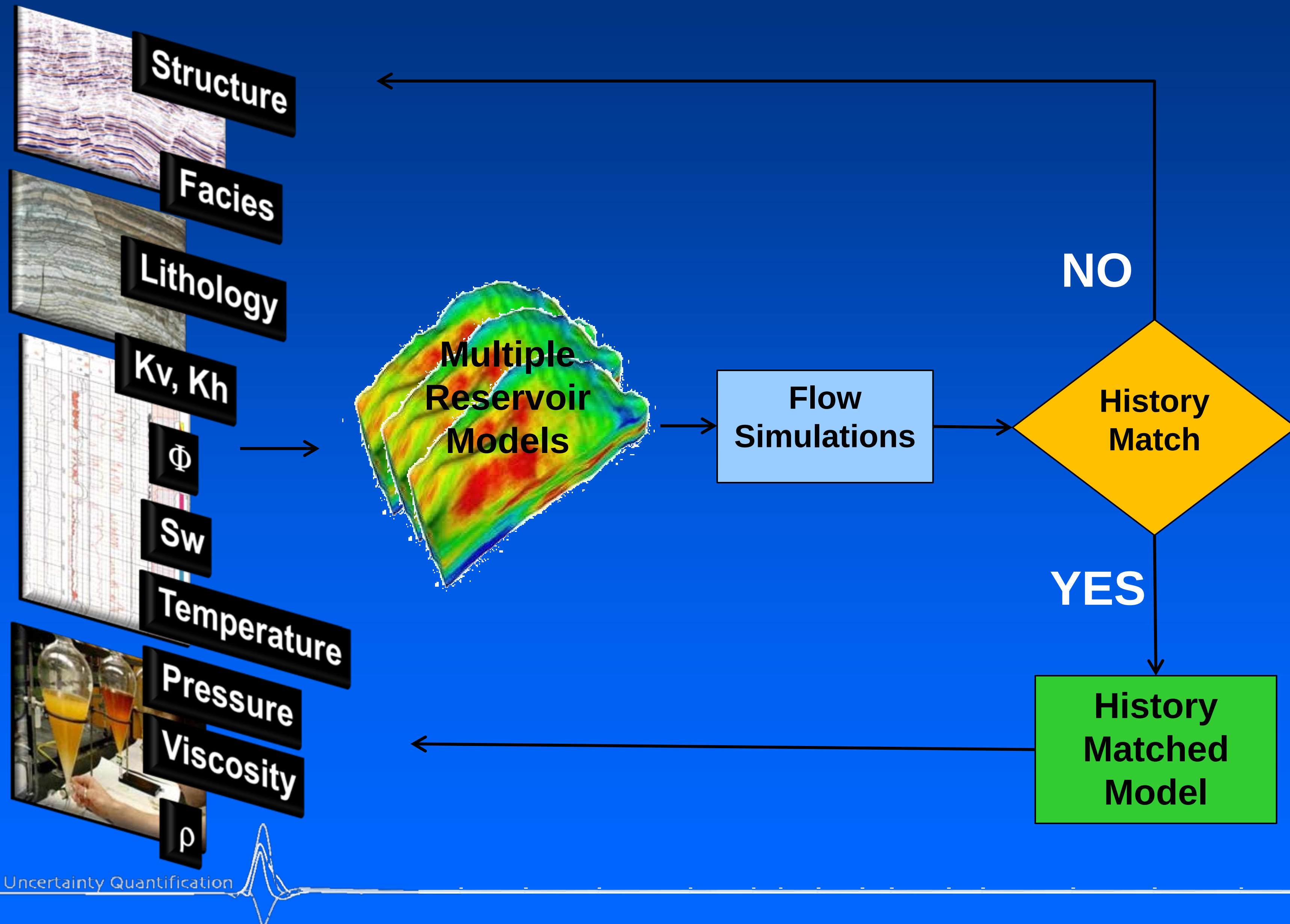
Outline

- Introduction
- Geological Prior Information
- One Class-SVM
- Automatic History Matching
- Conclusions

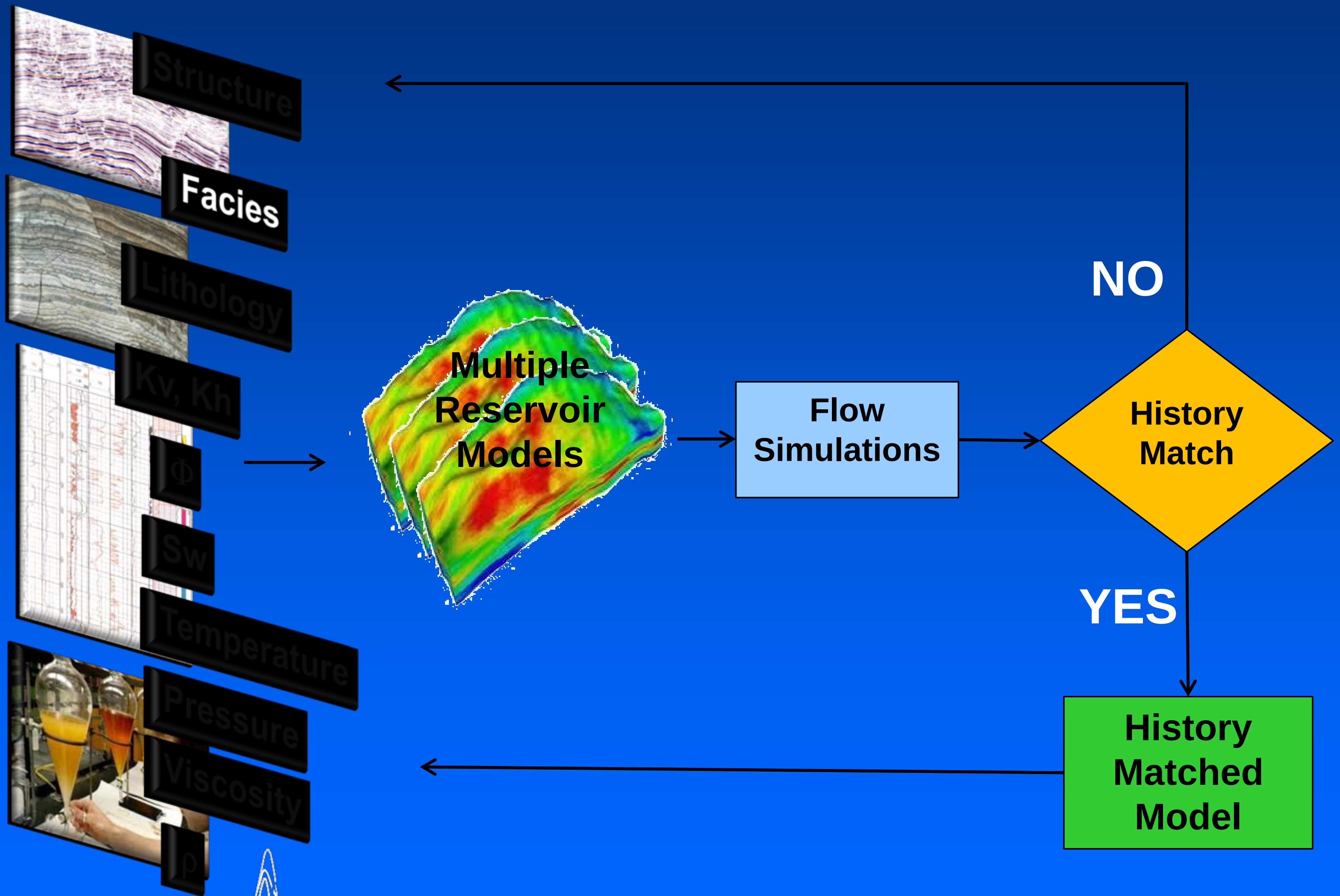
Aims

- Highlight the use of geological prior information to ensure realistic geology.
- Build realistic Geological Prior Models for simulating deep marine channels.
- Include these prior models into the automated history match framework.
- Reduce uncertainty of reservoir models using intelligent prior information.

Automatic History Matching



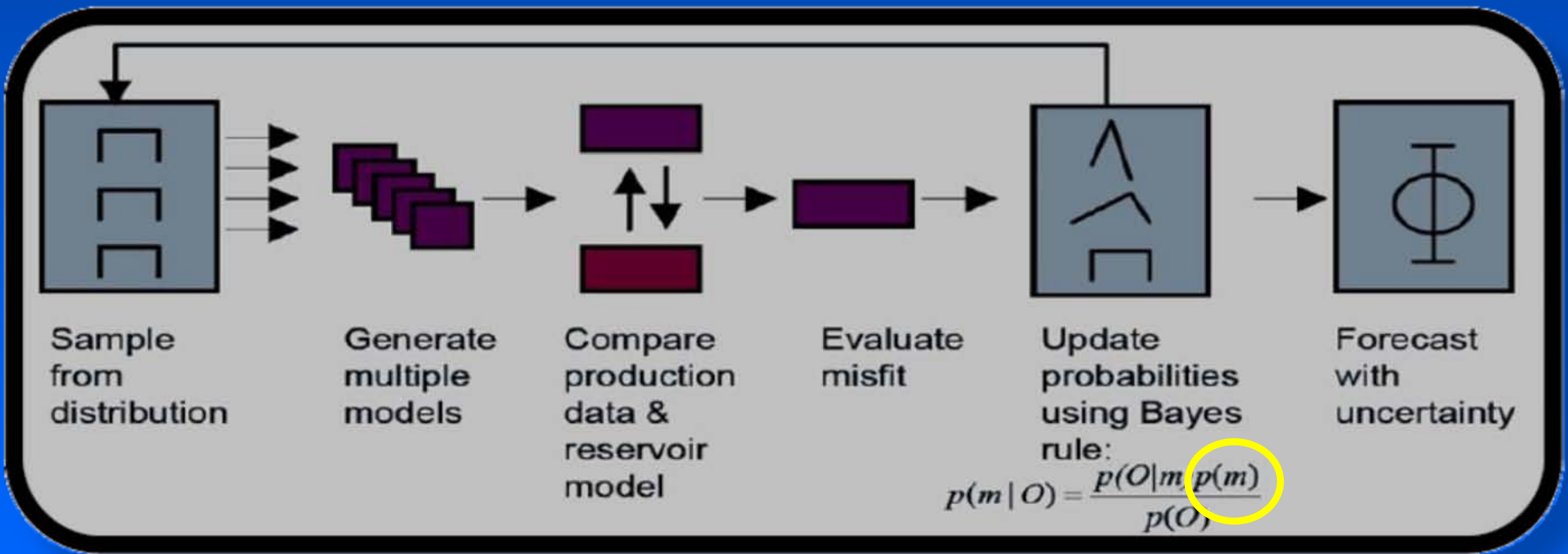
Automatic History Matching



Prior Probabilities

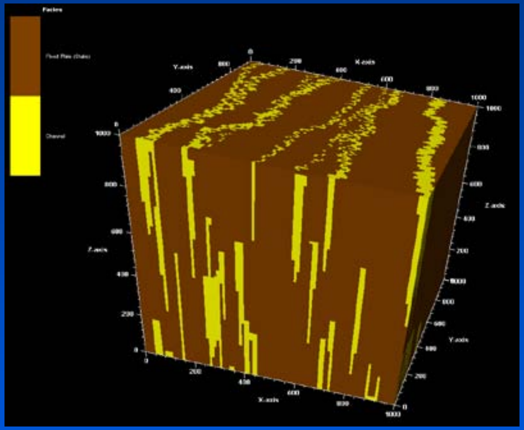
Prior probabilities are based on previous experience, and often used to predict outcomes before they actually happen.

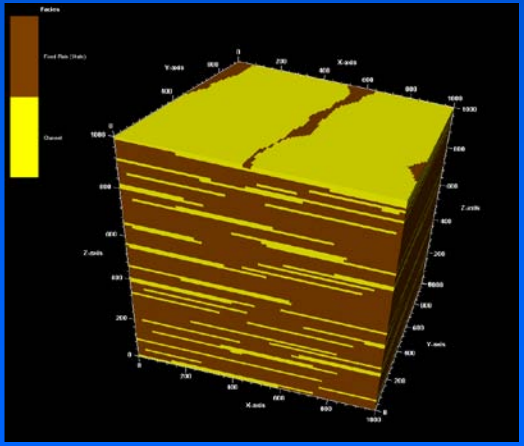
Scheme for the application of the Bayesian framework



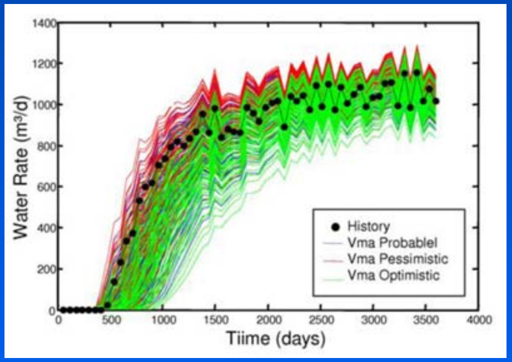
Unrealistic Models

Unrealistic Facies Models





History Matched Models



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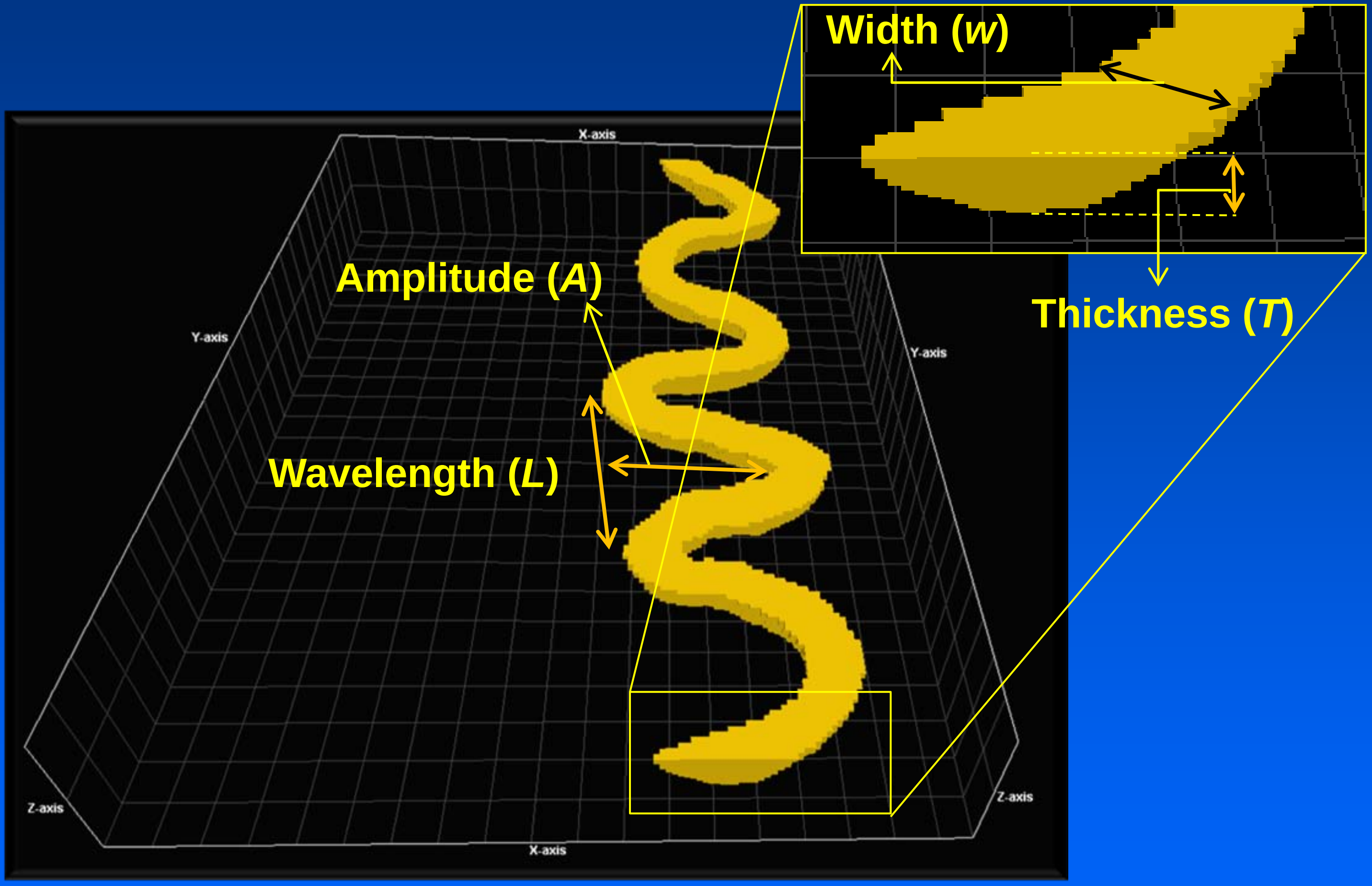
Geological Parameters

Wavelength (*L*)

Amplitude (*A*)

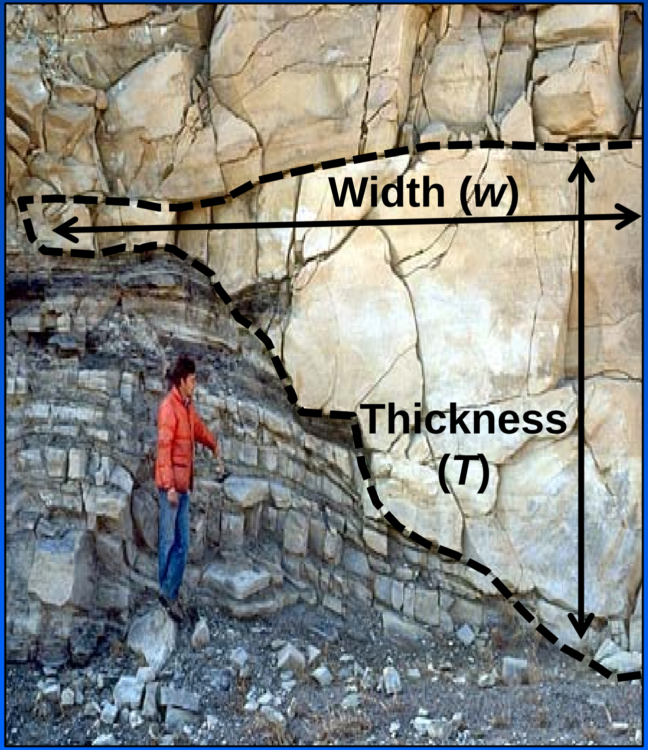
Thickness (*T*)

Width (*w*)



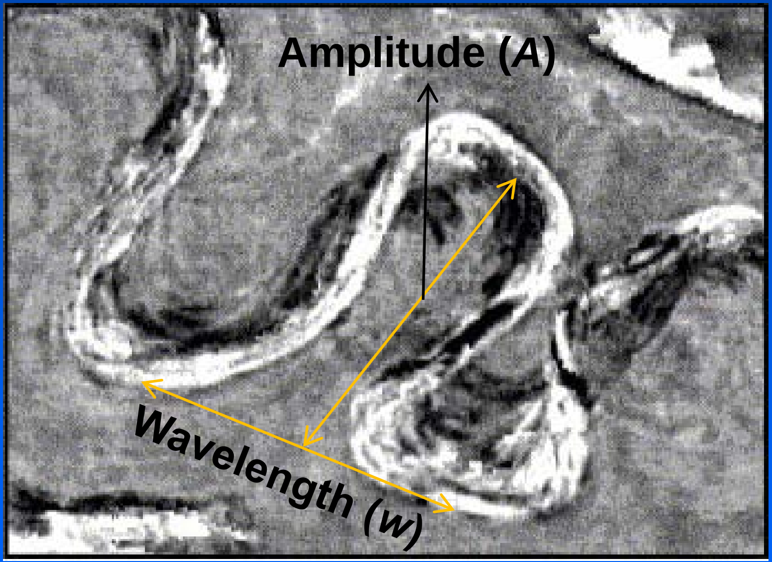
Sources of Data for Modeling Priors

Outcrop
Description



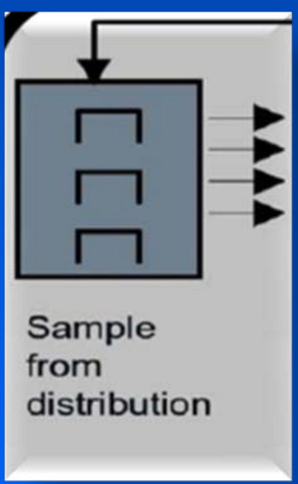
Modified from Scholle (1999)

Geophysical Data

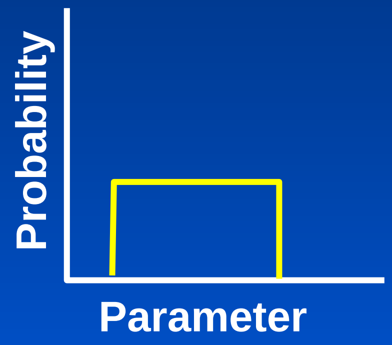


Modified from Posamentier (2003)

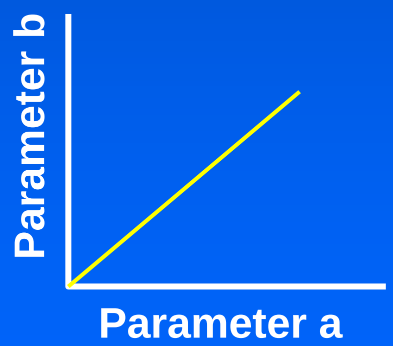
Prior Information for Facies Geometry

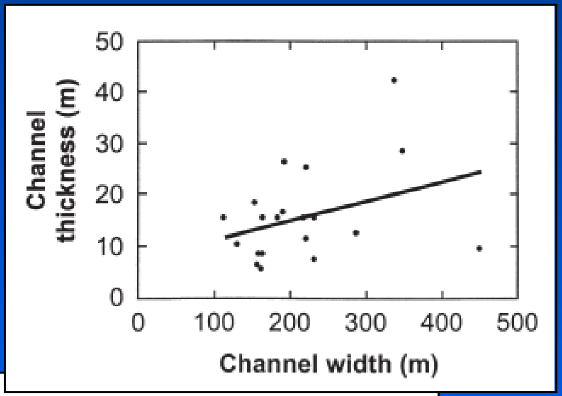


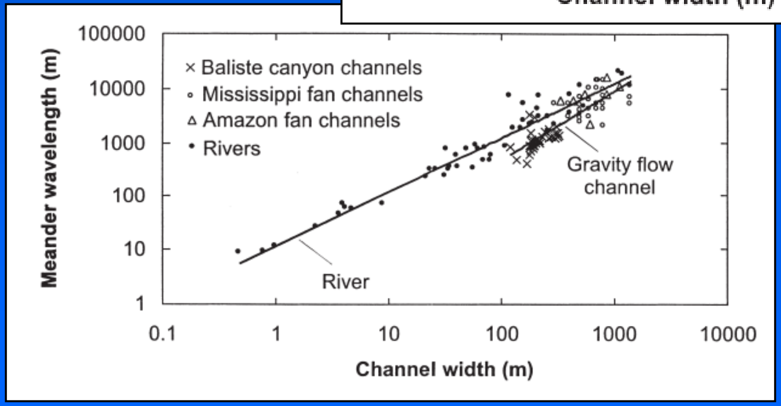
Uniform Priors



Empirical Equations

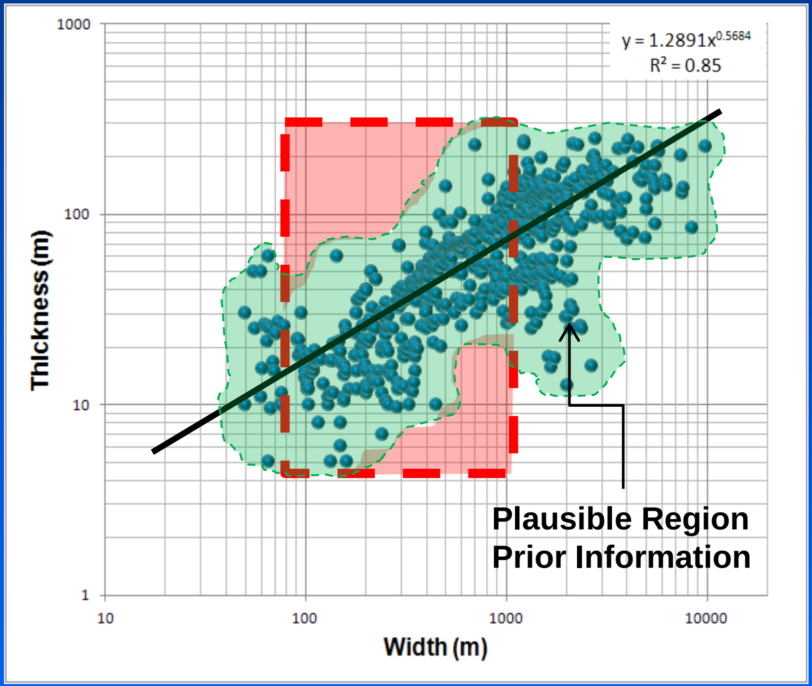




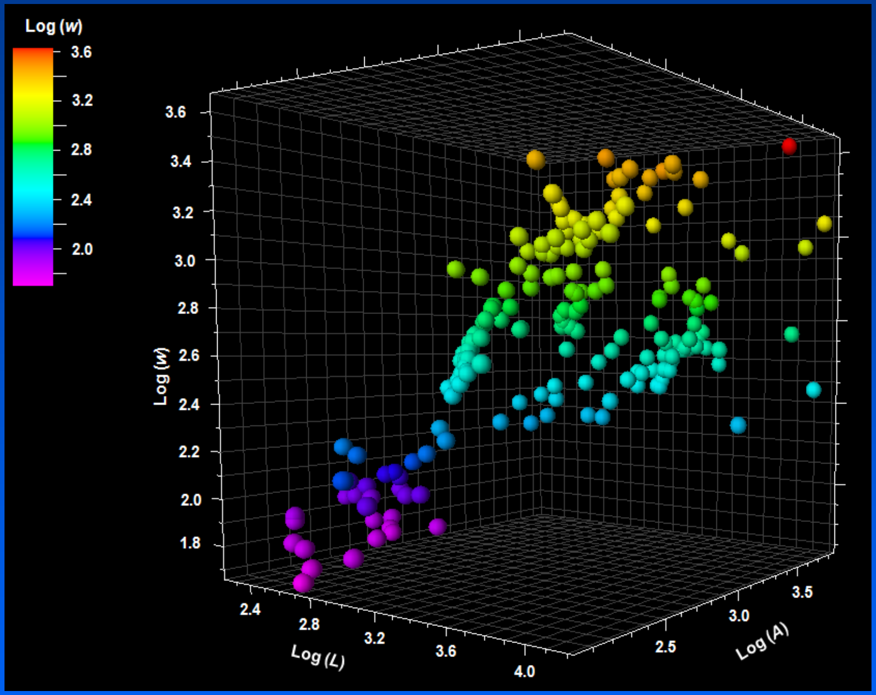


Modified from Wonham *et al*., (2000)

Existing Knowledge



657 Data-points

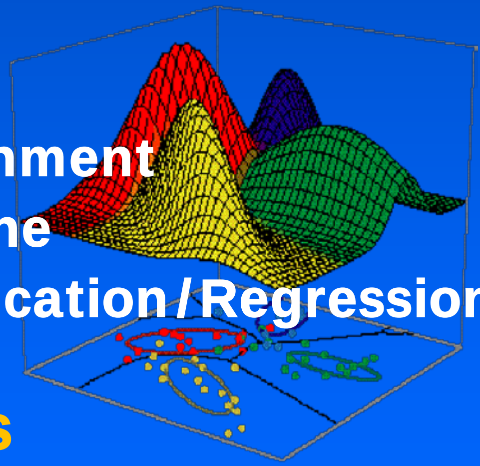


277 Data-points

Building Realistic Priors

- Multidimensional problem
- Avoid uniform ranges and linear regressions
- Predict between data points

Machine Learning Techniques ⇨ **Environment**
Medicine
Classification / Regression



Capture non-linear multivariate relations

Outline

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- One Class-SVM
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One-Class Support Vector Machine

- Extension of SVM to handle training with only positive examples ("one-class" classification).

(Schölkopf *et al*.,1999)

OC-SVM Toy example

Parameters

S - SVM type

t - Kernel type

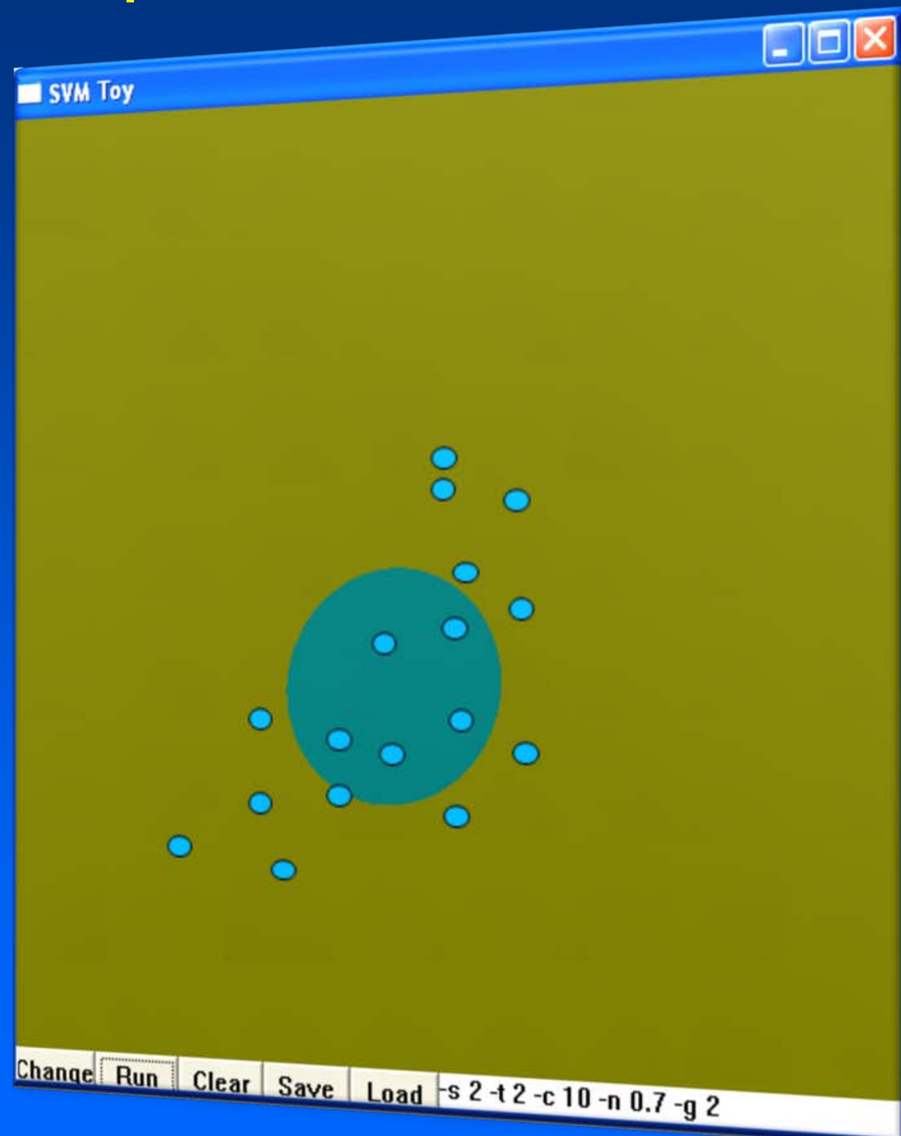
C - cost (SVR)

η - nu factor

g - gamma of the kernel function

Using libsvm from:
http://www.csie.ntu.edu.tw/~cjlin/libsvm/

OC-SVM Toy example



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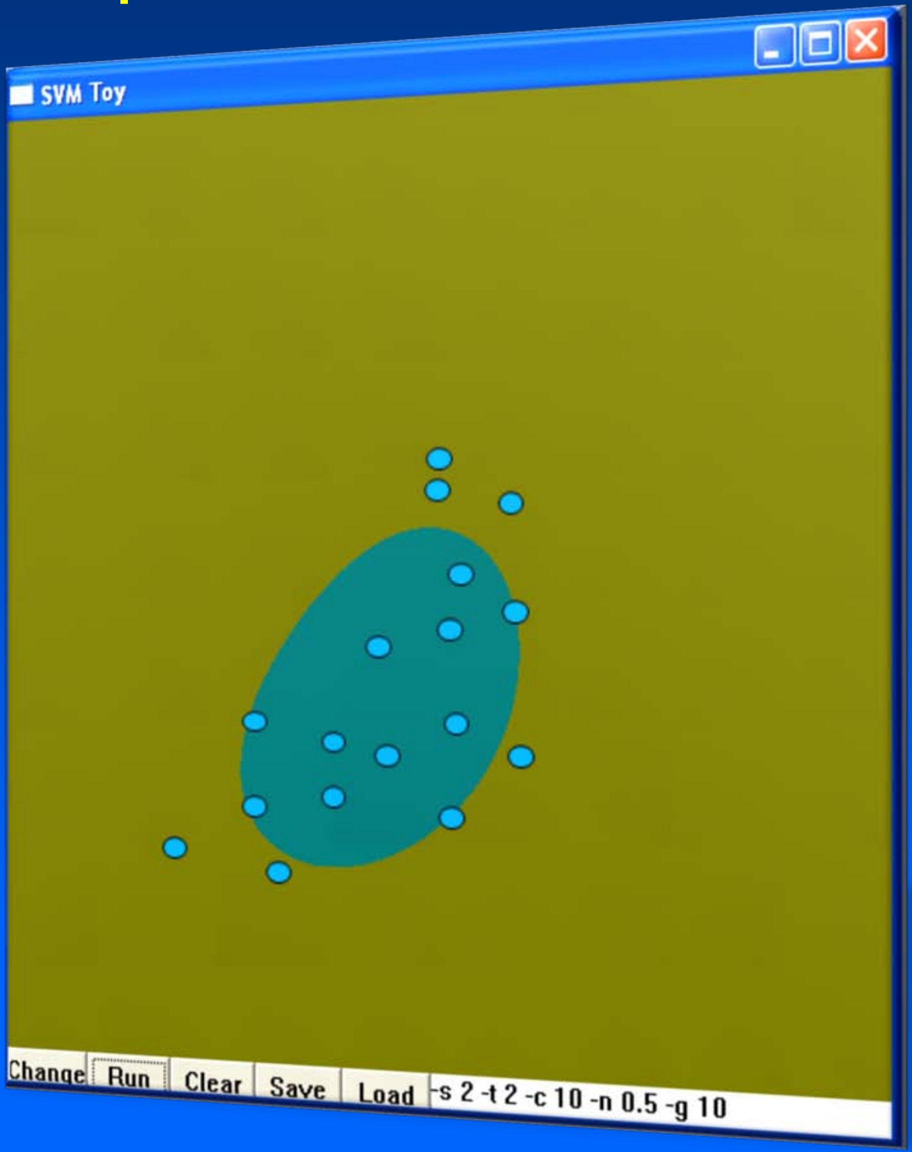

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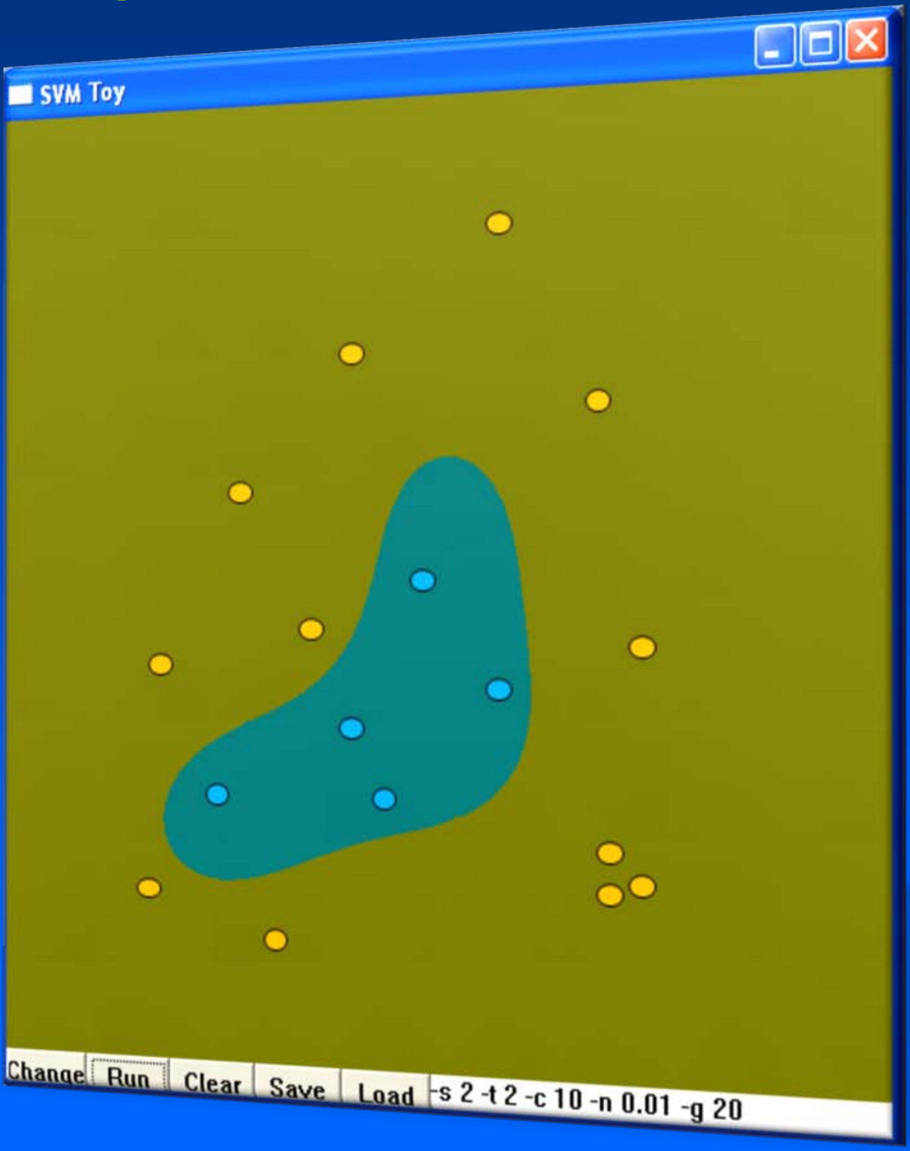
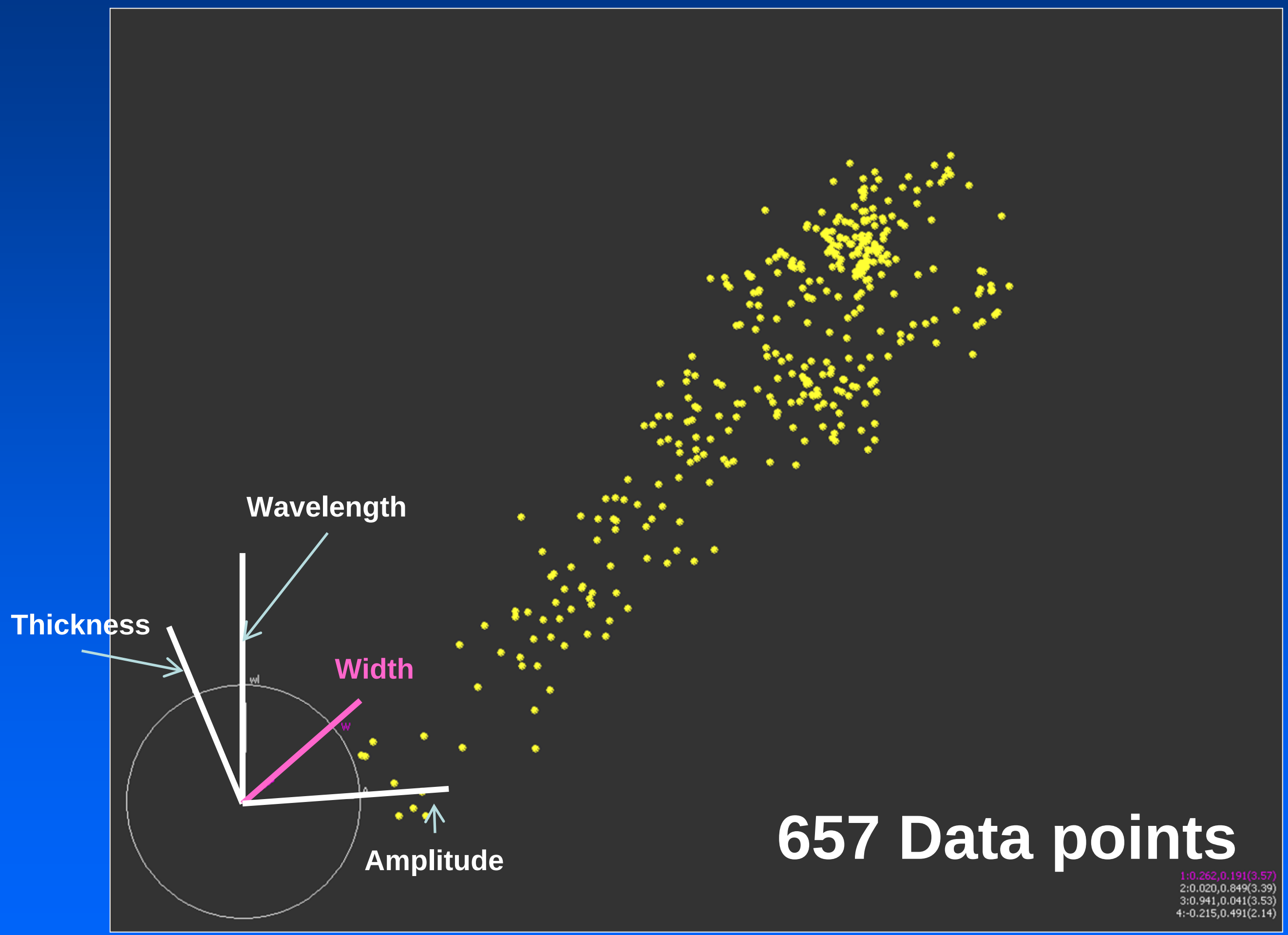
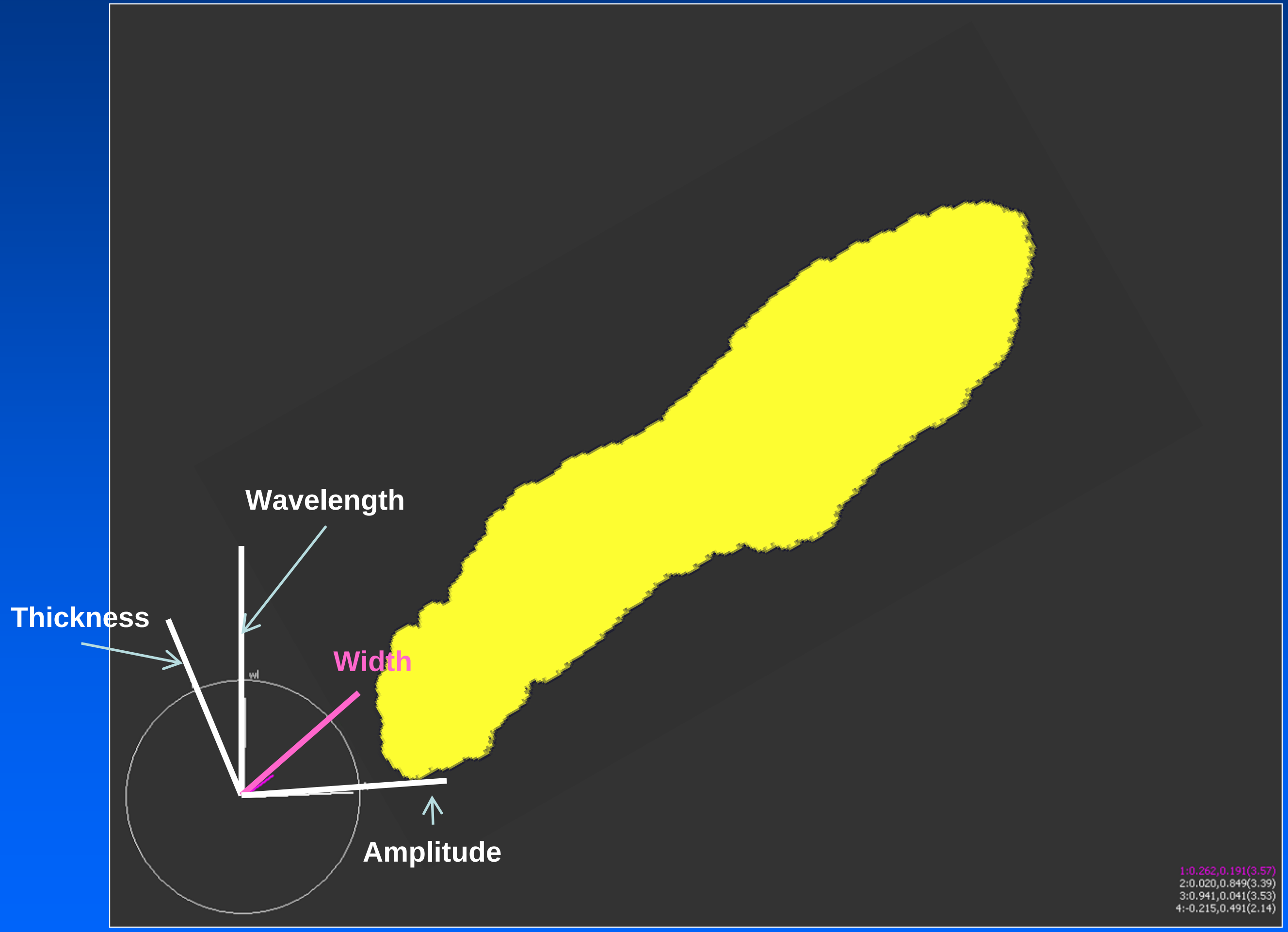


Using libsvm from:
http://www.csie.ntu.edu.tw/~cjlin/libsvm/

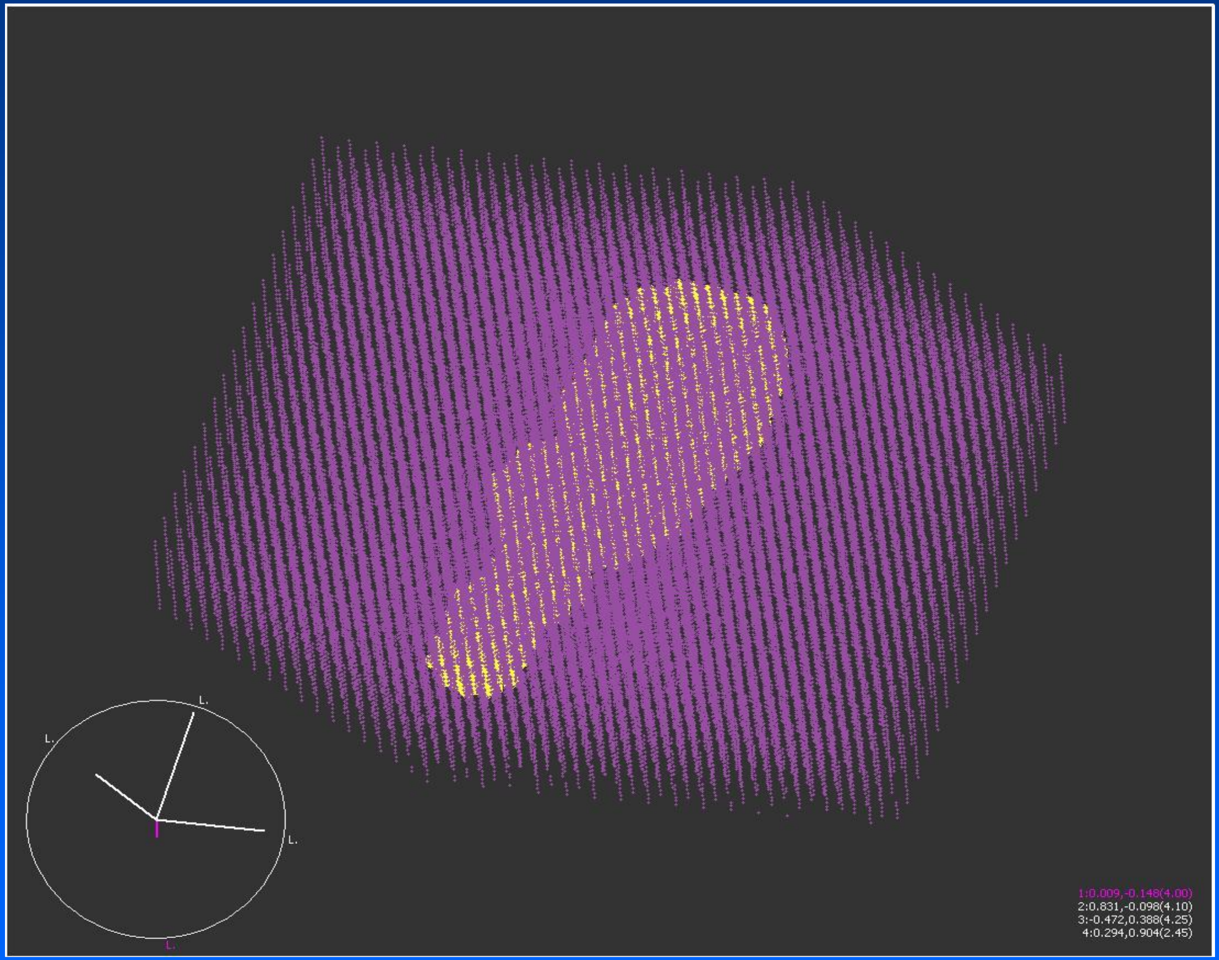
OC-SVM in 4-D


Wavelength
Thickness
Width
Amplitude
657 Data points
1:0.262,0.191(3.57)
2:0.020,0.849(3.39)
3:0.941,0.041(3.53)
4:-0.215,0.491(2.14)

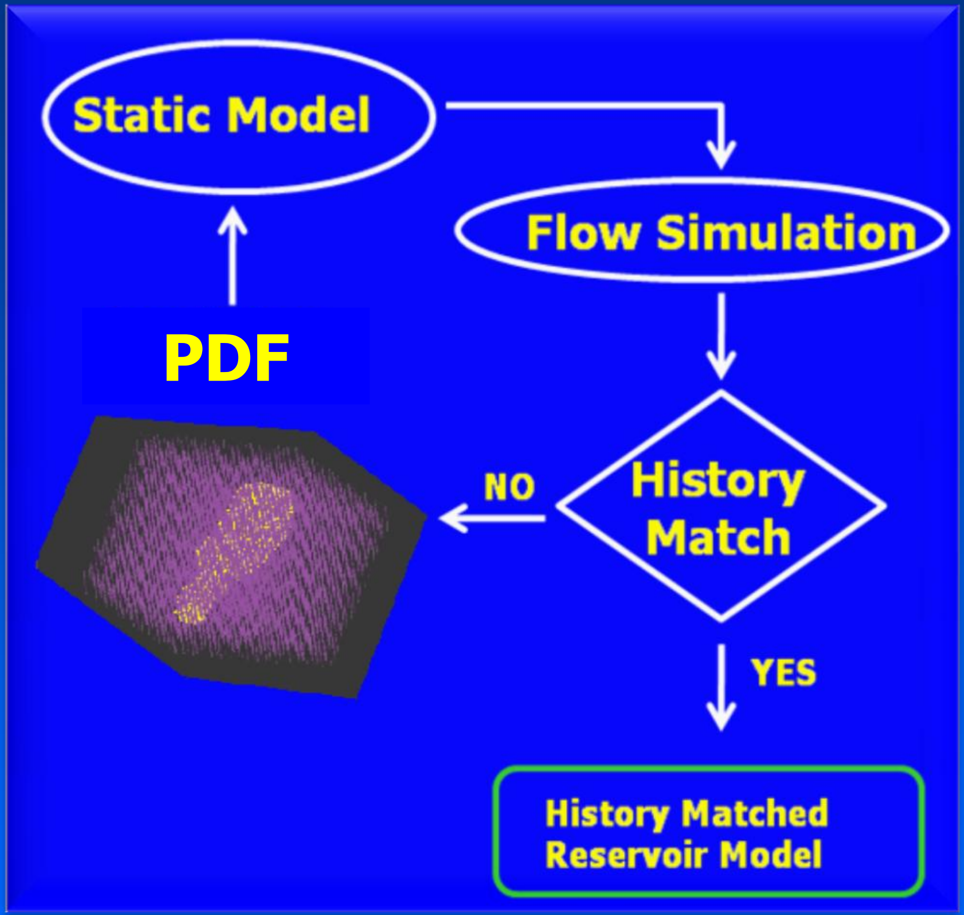
OC-SVM in 4-D Cloud



OC-SVM in 4-D Cloud



History Match Workflow



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Truth Case

Oil Reservoir

Deep Marine

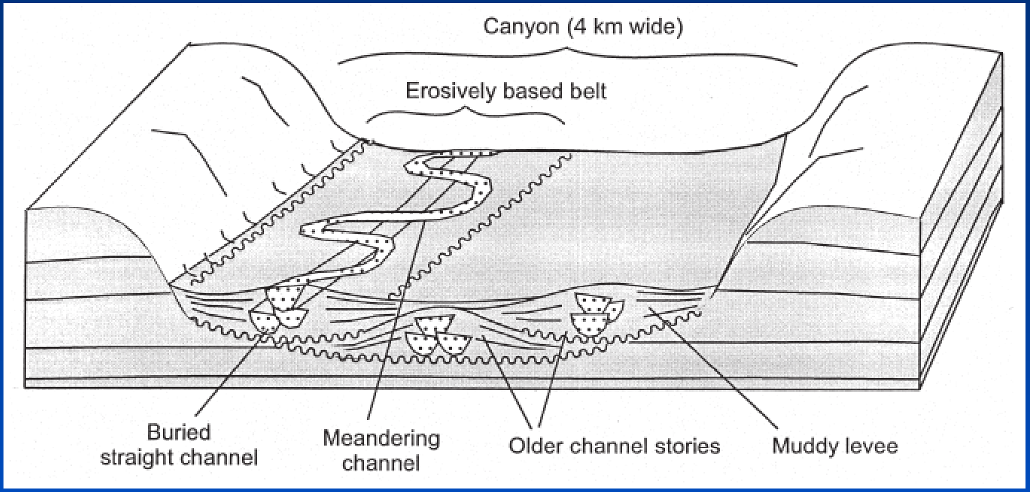
Facies	Poro (%)	Perm (mD)
Sand	20	500
Shale	0.001	0.001

Grid Cells
80140x25
280000

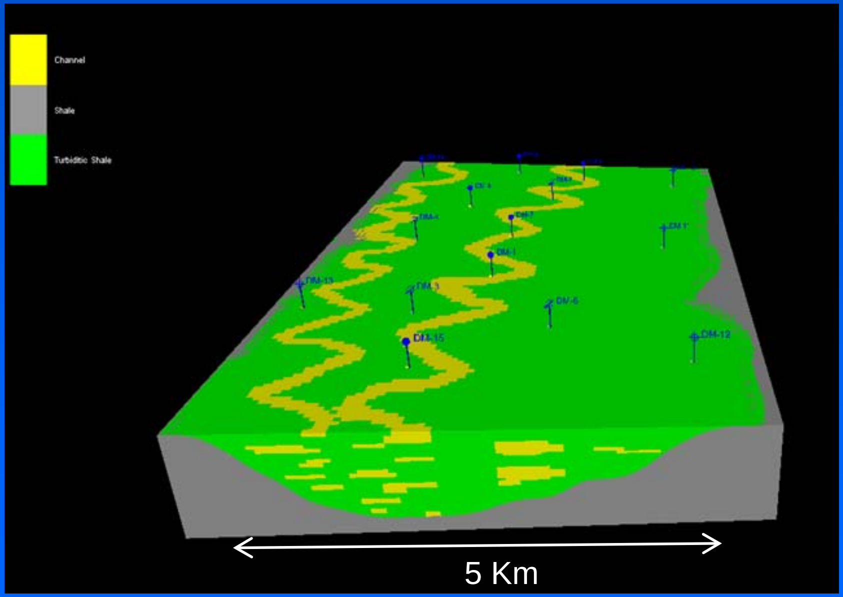
Fluid Properties: Stanford VI

Castro *et al*., 2005

Facies Model Baliste-Crécerelle Canyon Fill



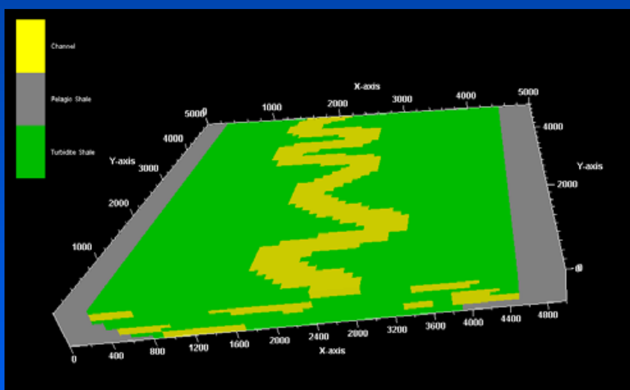
Modified from Wonham *et al*., (2000)



Facies Simulation

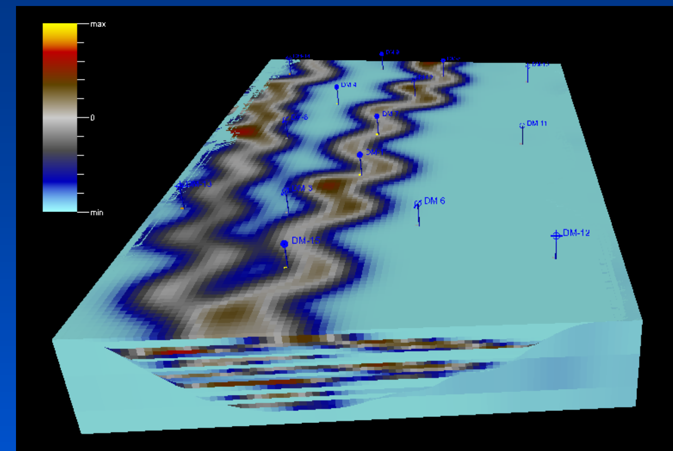
Multiple Point Statistics

Training Image



Width: 500 m
Thickness: 30m
Amplitude: 1000 m
Wavelength : 2000 m

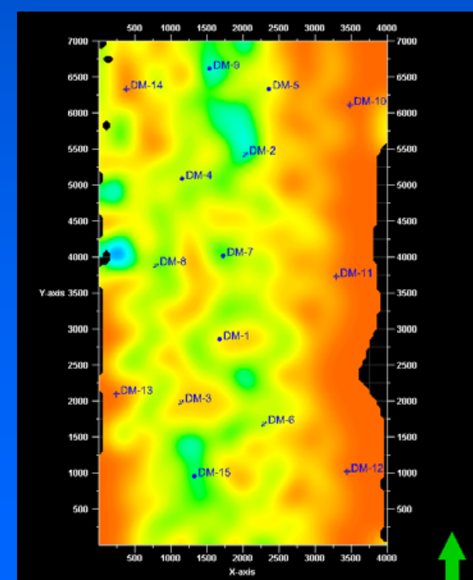
Conditioning:
Seismic attributes



Hard Data:

15 Wells

6 Producers
4 Injectors
5 Exploration



History Match Parameters

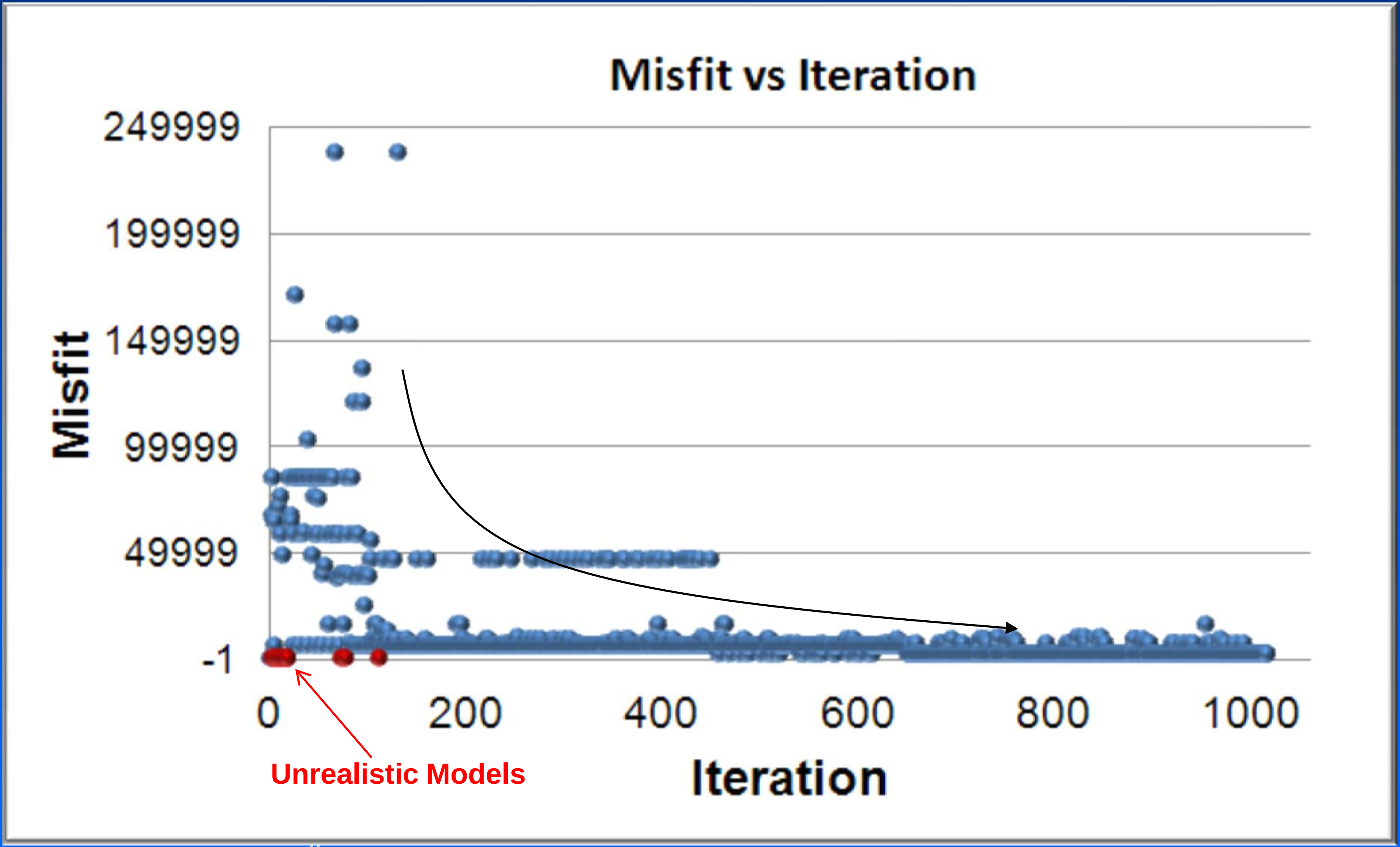
- **Misfit Definition**

$$M = \sum_{t=1}^{T} \frac{(q^{obs} - q^{sim})_t^2}{2\sigma^2}$$

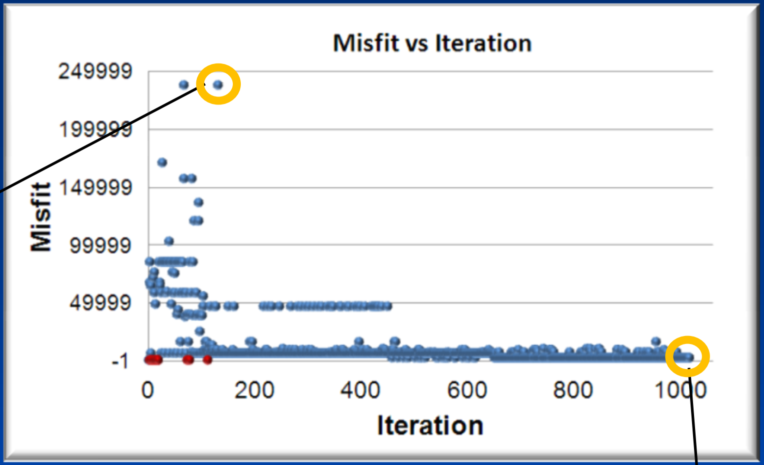
σ: 10% of the Truth case data
50 time-steps (600 days)
6 Producing wells
WWCT, WOPR, WBHP

- **Sampling Algorithm Definition**
  Particle Swarm Optimization
  15 Particles
  1116 Iterations

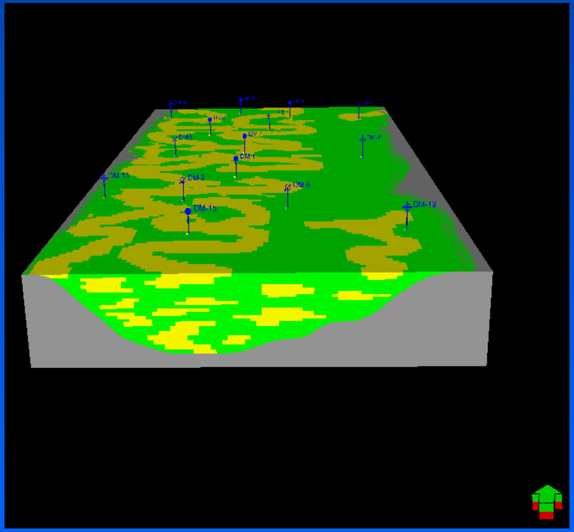
Misfit vs Iteration



Facies Models

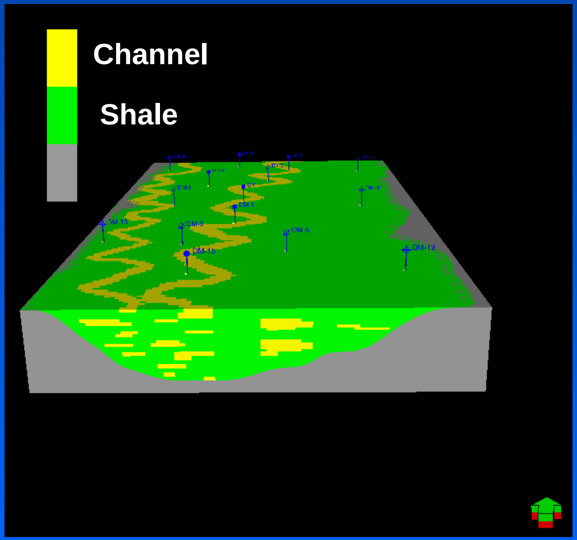


Model 132



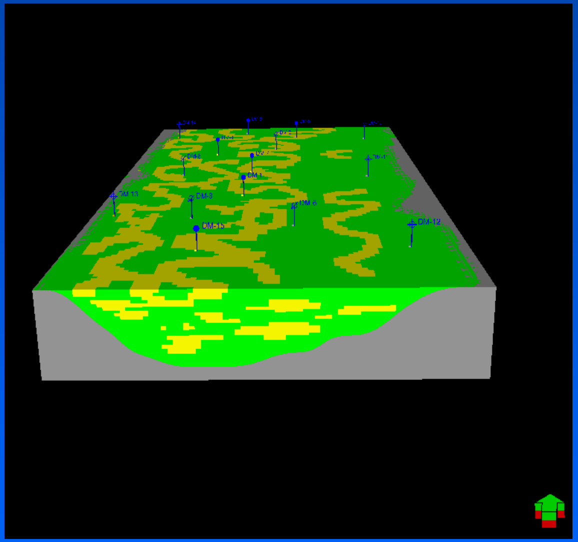
Misfit: 238171
***A*: 1635 m**
***L*: 921 m**
***W*: 585**
***T*: 41 m**

Truth Case



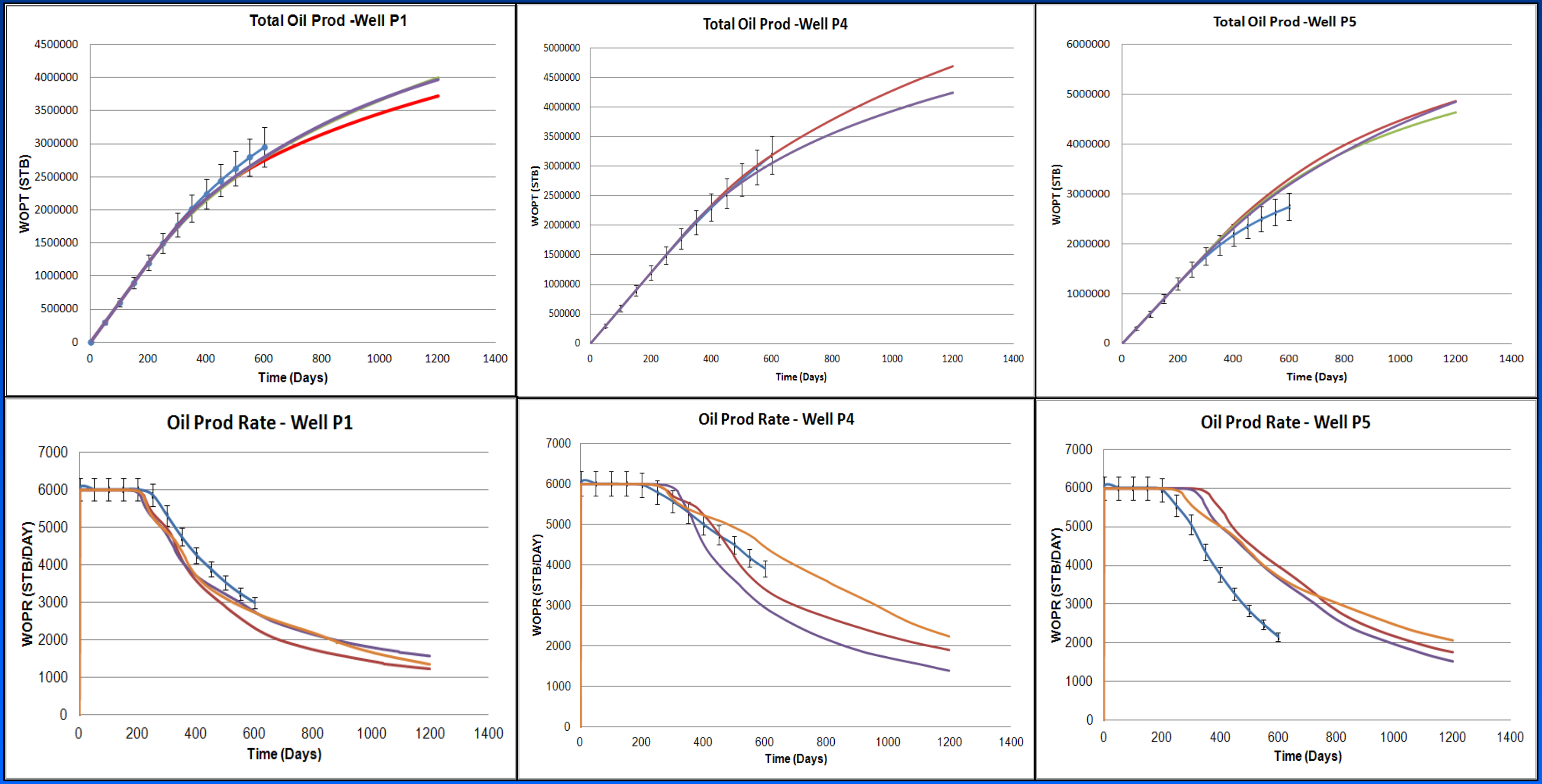
***A*: 950 m**
***L*: 1550 m**
***W*: 400**
***T*: 40 m**

Model 1015

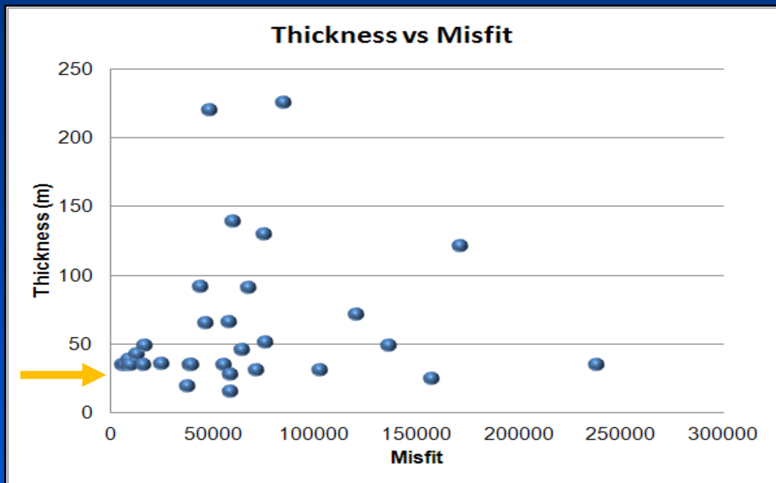


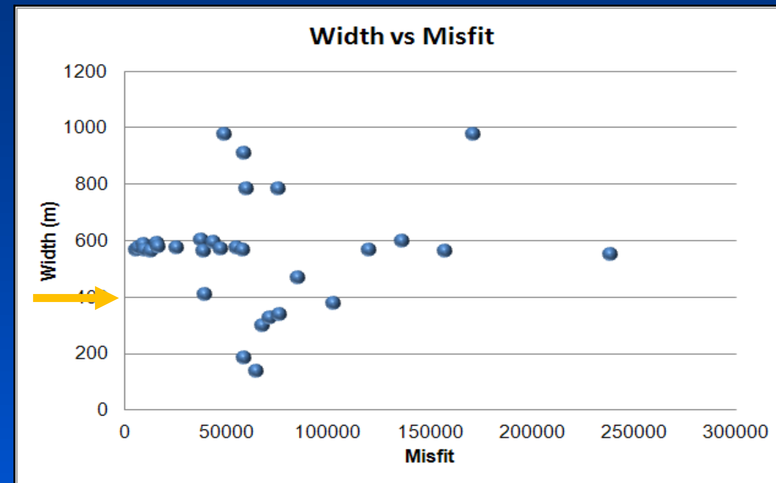
Misfit: 2498
***A*: 829 m**
***L*: 1453 m**
***W*: 565**
***T*: 35 m**

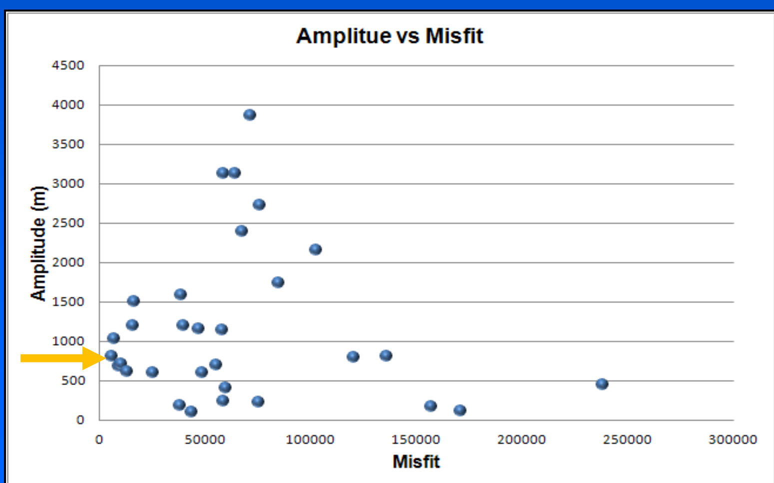
History Match

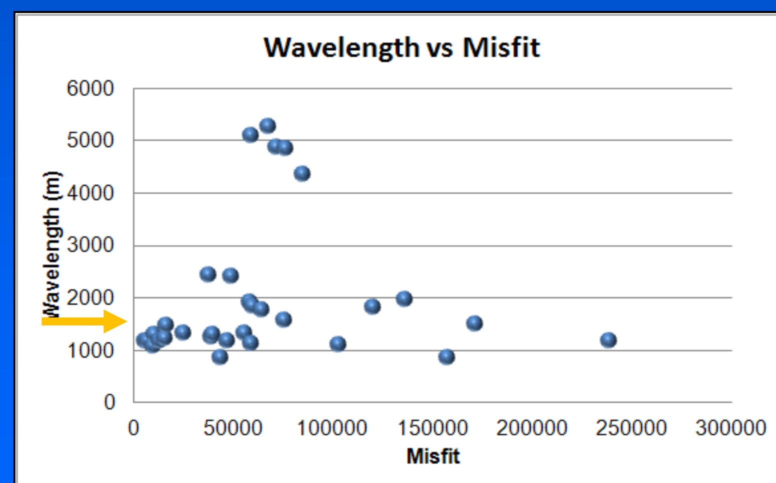


Analysis of the Generated Models



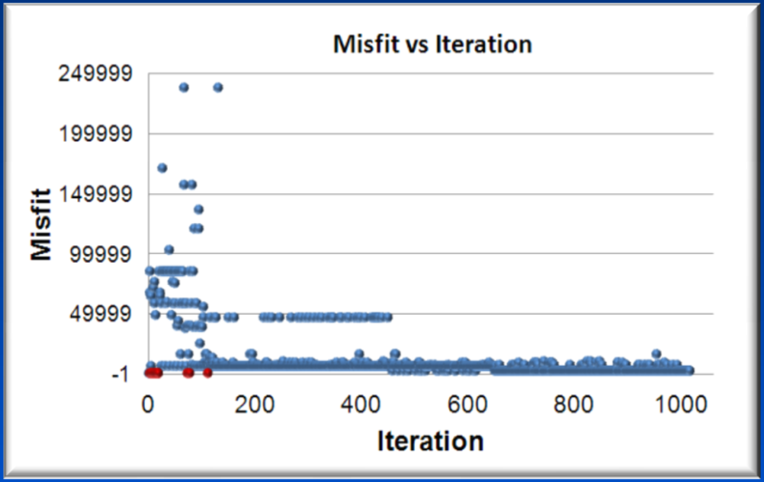


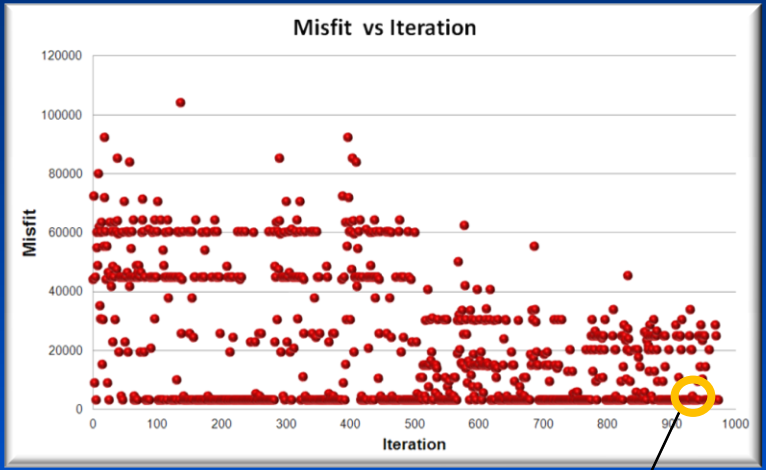


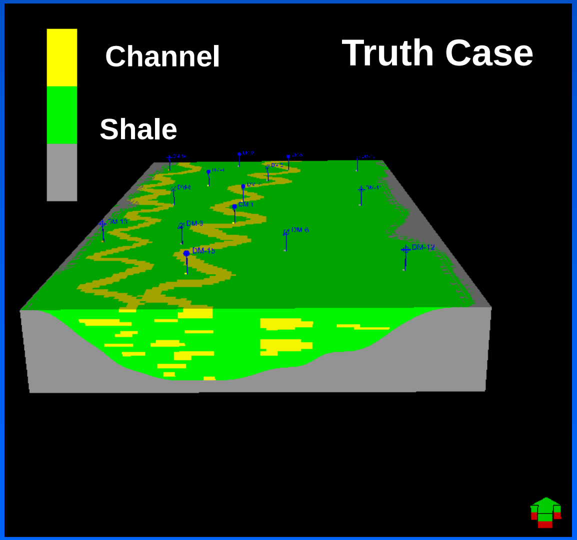


→ Truth Case

History Match using Uniform Priors

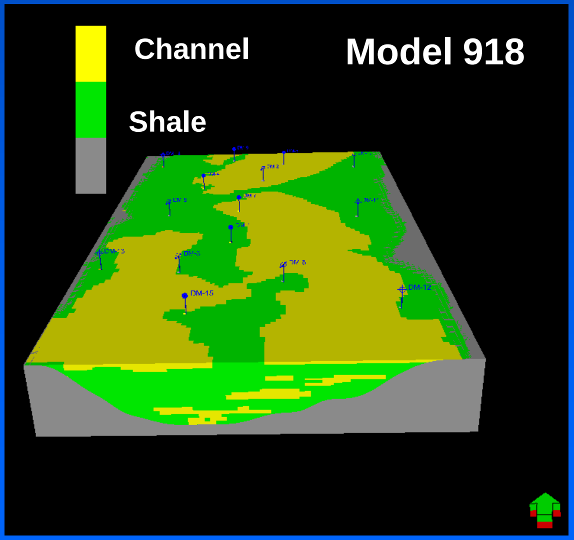






A: 950 m
L: 1550 m
W: 400
T: 40 m

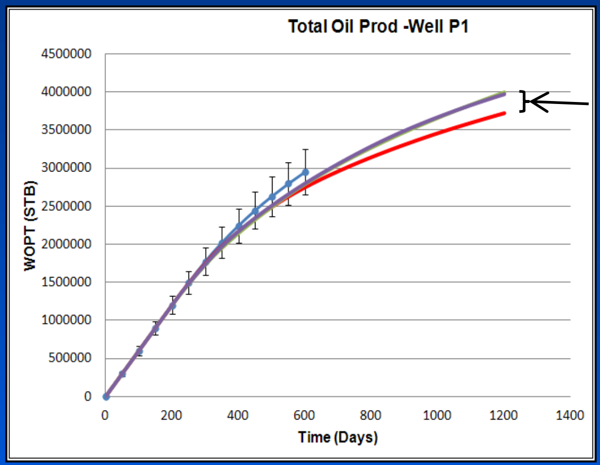
Misfit: 3125
A: 444 m
L: 6948 m
W: 1586
T: 47 m



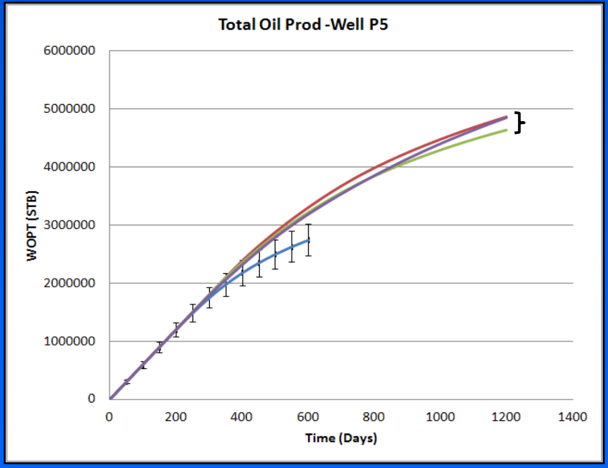
UNIFORM PRIORS

History Match using Uniform Priors

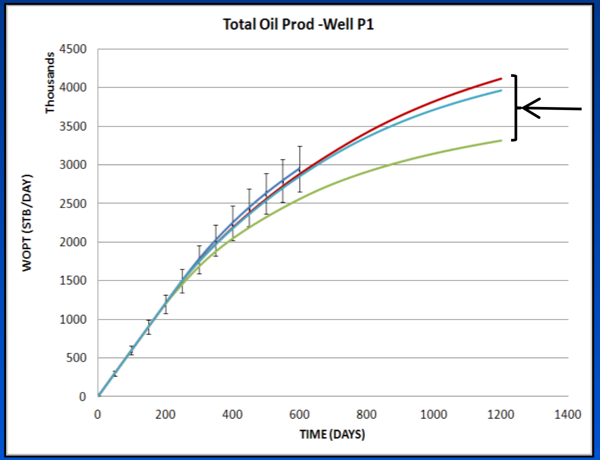
INTELLIGENT PRIORS



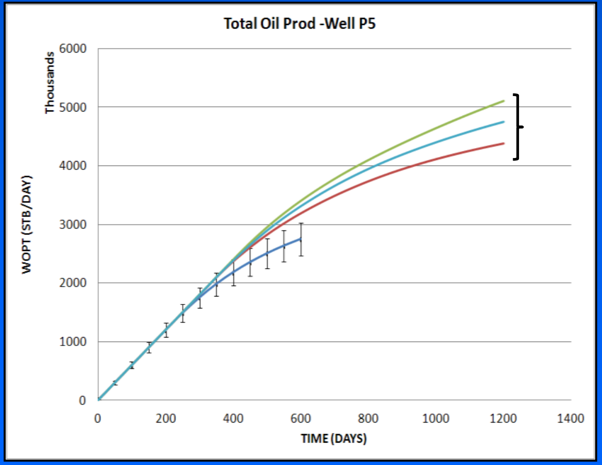
200000 STB



UNIFORM PRIORS



600000 STB



Conclusions

- Intelligent priors ensure realism of geological models.
- Reduce uncertainty in reservoir prediction.
- Reduce the number of models and computing time.
- Check for realism in geological models is essential, because unrealistic models may produce good history match as well.

Future work

- Generate intelligent prior models for:
  - other depositional environments
  - other geological properties
  - petrophysical properties
- Include improvements on continuity using MPS
- Include multiple training images

Acknowledgements

- Sponsors of Heriot-Watt Uncertainty JIP:

ConocoPhillips

bp

BG GROUP

JOGMEC

- Schlumberger to allow us using Eclipse

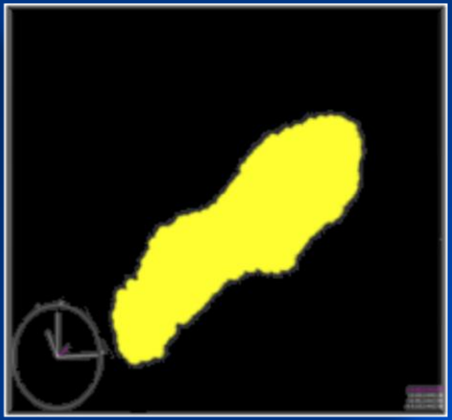
- Stanford University for the use of SGemS


HERIOT
WATT
UNIVERSITY
Institute of
Petroleum
Engineering
The Institute of Petroleum Engineering (IPE) is a specialised centre in teaching,
training and research with the largest PE research programme in the UK.

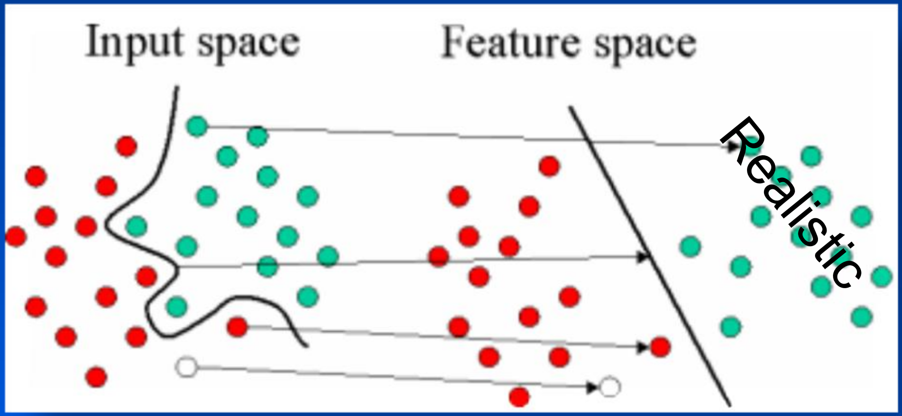
Thank you…

Back up

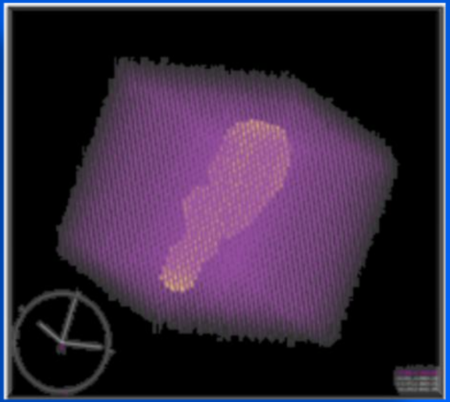
Probability Estimation



New Grid = OCSVM grid + Unrealistic points



OC-SVM

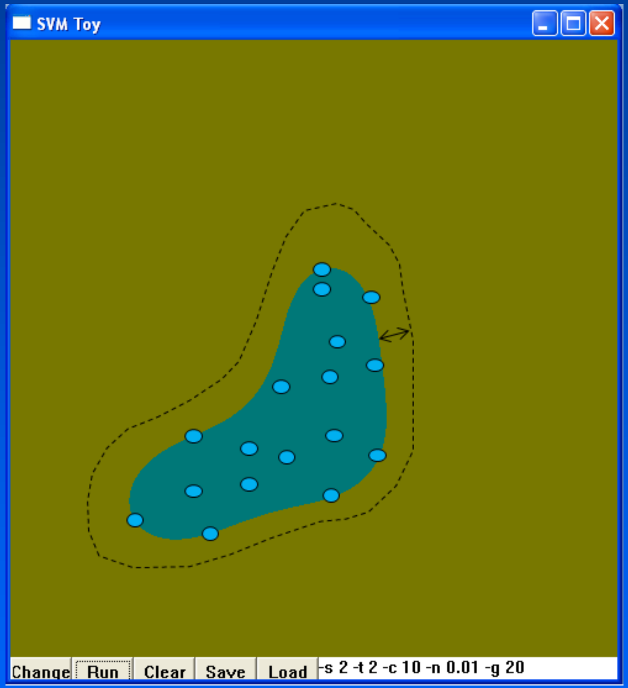


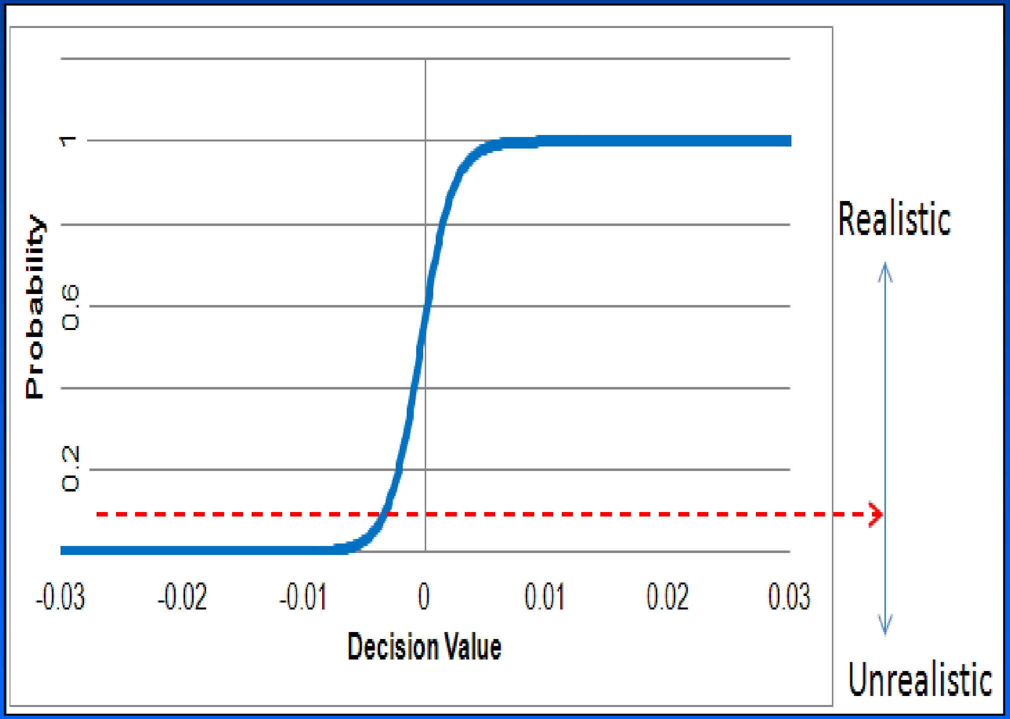
$$P(x)=(1+\exp(A\,x+B))^{-1}$$

x **: Decision Values obtained from oc-svm**

Probability Estimation

$$P(x) = (1 + \exp(A\,x + B))^{-1}$$

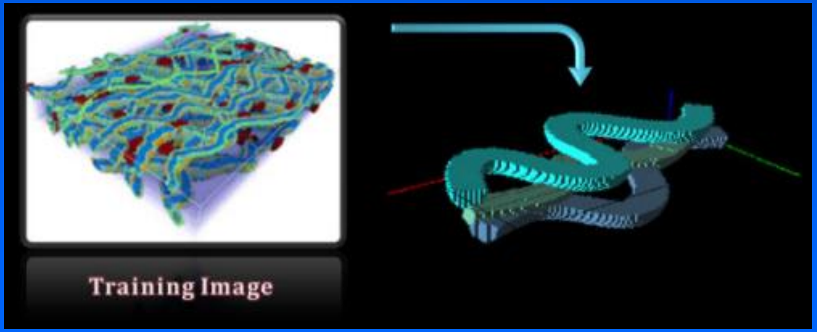




Facies Modelling

- Increase Geological Realism
- Potentially more complex patterns than those modelled by variogram.
- Incorporate realistic geological prior information.
- Easy incorporation of well and seismic data.

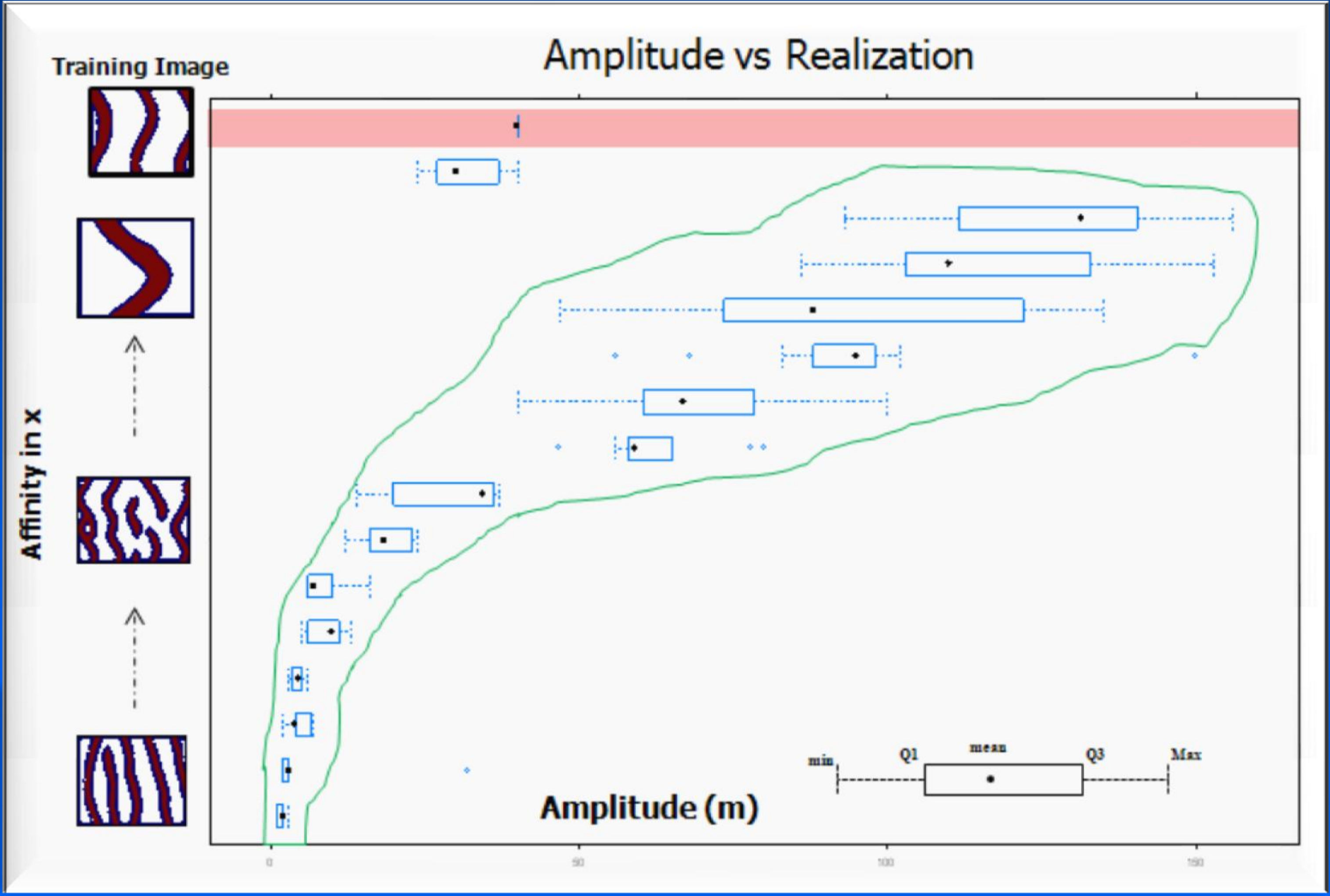
Multiple Point Statistics (MPS)



Channel Geometry in MPS

- Affinity parameters are difficult to interpret

Channel Geometry in MPS

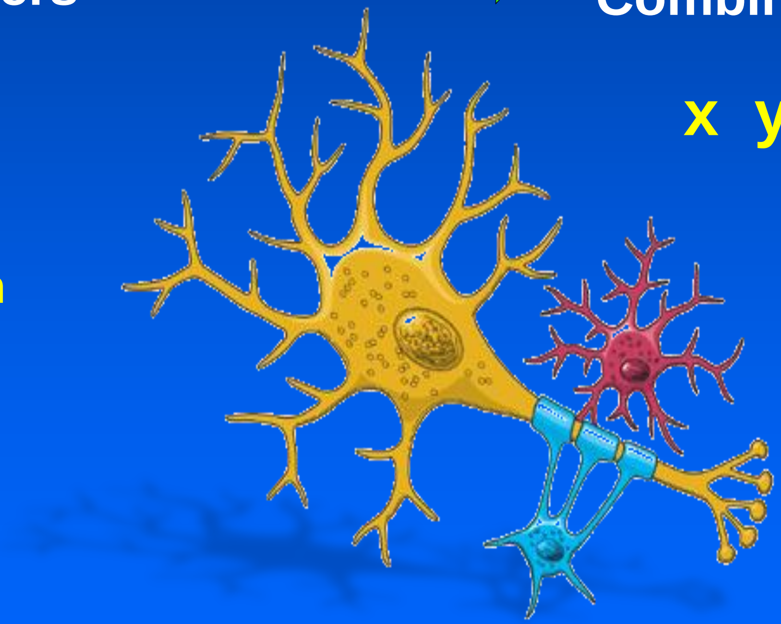


Geological vs Model Algorithm Parameters

ANN

Realistic Geological Parameters

- **Width**
- **Thickness**
- **Wavelength**
- **Amplitude**



Affinity Combination

x y z

MPS
SNESIM