Reservoir Characterization and Monitoring: From Inversion to Reservoir Characterization*

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Abstract

A non-linear full-waveform inversion scheme (FWI-res) has been applied to a synthetic seismic dataset, which was obtained based on a high-resolution geological and petrophysical model (Book Cliffs, USA). Since the non-linear relationship between the data and the property values has been fully honoured by the inversion method, the retrieval of the rock properties and geological geometries is successful. Then the inversion results are used as an input for the prediction of lithology, in which the fuzzy logic method will be used. The property values from three well logs are firstly used to build the membership functions (MFC) of the 12 different lithologies in which the unnormalized double-Gaussian function is utilised in order to fit the possibility of the histogram. Because in the petrophysical modeling the lithology has been divided into the marine and non-marine parts, the membership function (MFC) has been separated accordingly. In order to qualify the performance of the classifier, both of the confusion matrix as a visual inspection and the Matthews Correlation Coefficient (MCC) as a quantity measurement are proposed. The biggest advantage of the confusion matrix is that not only the percentage of correct classifications can be analysed, but that also for the nearly correct classification can be analysed, as well as the wrong classifications. Instead of using the accuracy which is defined as the ratio of the correctly classified samples over the total number of samples, the MCC is used here a numerical discrimination of the misclassification distributions. The result of the classification shows that the main reservoir lithologies, such as the coarse and medium-grained sandstones, are well predicted. Wrong predictions do happen, in which medium-grained sandstone is misclassified as claystone, which is the non-reservoir lithology. However, this error only accounts for a very small percentage and does not influence our overall assessment of the performance of the fuzzy logic method.

References Cited

Cuddy, S. J., and P.W.J. Glover, 2002, The application of fuzzy logic and genetic algorithms to reservoir characterization and modelling: in P.M. Wong, F. Aminzadeh, and M. Nikravesh, eds., Soft computing for reservoir characterization and modeling, Studies in fuzziness and soft computing series, 80: Physica-Verlag, p. 219-242.

Feng, R. S.M. Luthi, A. Gisolf, and S. Sharma, 2017, Obtaining a high-resolution geological and petrophysical model from the results of reservoir-orientated elastic wave-equation-based seismic inversion: Petroleum Geoscience, DOI: 10.1144/petgeo2015-076.

Gisolf, A., and P.M van den Berg, 2010, Target oriented non-linear inversion of seismic data: P308, presented at the 72nd EAGE Annual Meeting, Barcelona, 14-17 June.

Haffinger, P.R., 2013, Seismic broadband full waveform inversion by shot/receiver refocusing: PhD thesis, TUDelft, Nederland.

Reservoir Characterization & Monitoring

From Inversion to Reservoir Characterization

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AAPG/SEG International Conference and Exhibition

Delphi Consortium

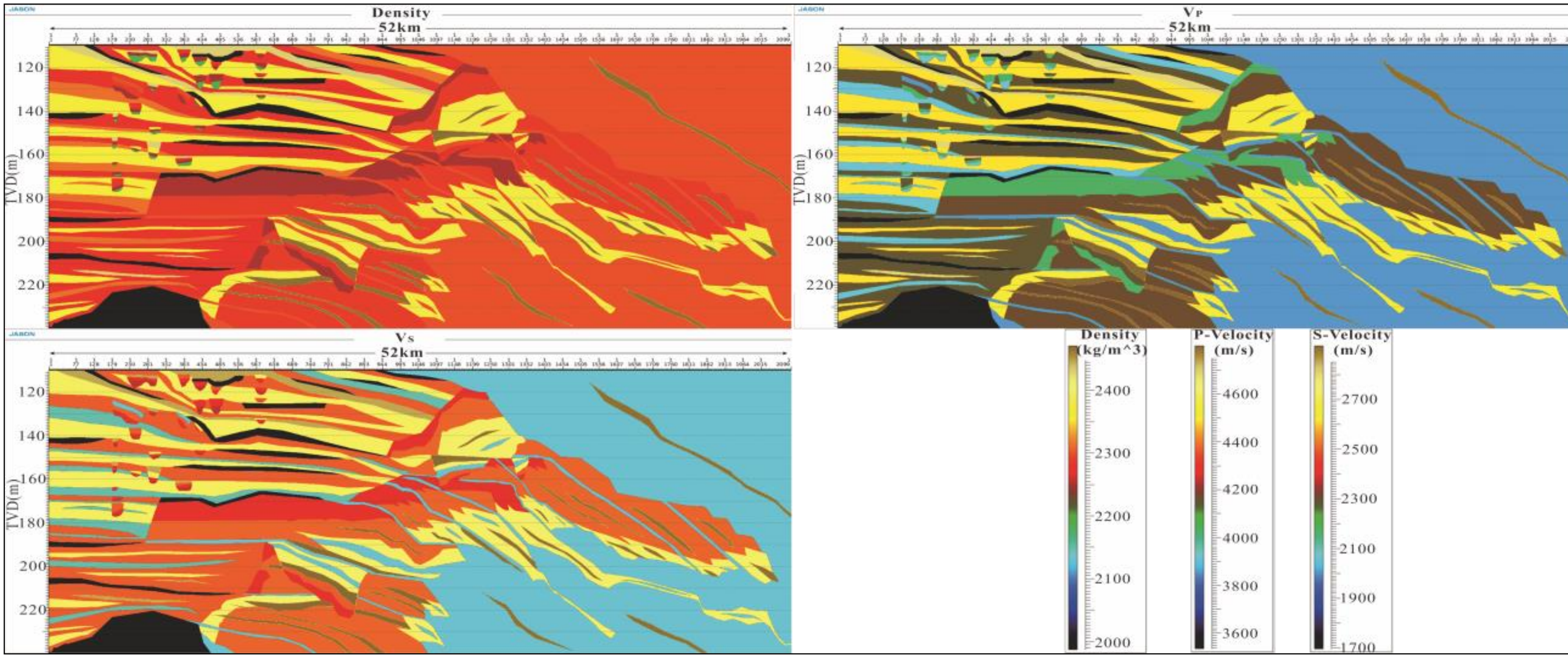
TU Delft
Delft University of Technology

Presenter's notes: Generally, the geophysical inverse problems are multidimensional and ill posed, and they are often strongly affected by noise and measurement uncertainty. Therefore, the inversion result is often non-unique. With the integration of prior information, the inversion result is expected to be more compact. What I am trying to do here is to build the geological model, which has been populated with the elastic parameters to derive the reservoir properties.

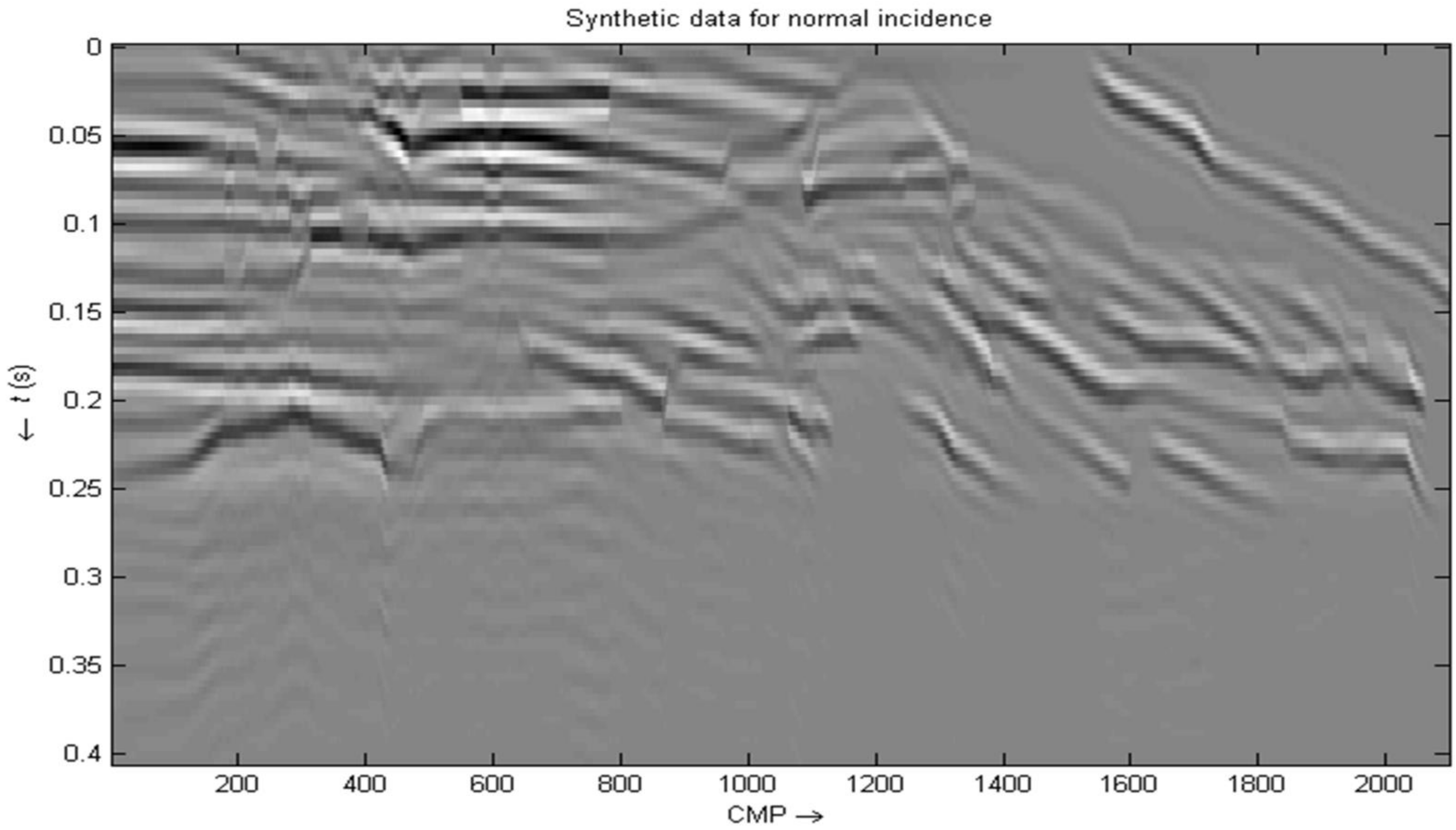
Objectives

- Extract rock properties by using elastic full-waveform inversion.
- Characterize reservoir units (lithology) based on the inversion results.

The Book Cliffs model



Synthetic Data



Presenter's notes: For normal incidence synthetic data, it is seen that characteristics of channels and coals, and the position of the siltstone in the marine part. In addition, the original whole sand unit has been divided into smaller units. The predicted seismic response allows assessing the appearance of small-scale stratigraphic features in the seismic data.

Inversion: Parameterization

$$\kappa = \frac{1}{K} = \frac{1}{\lambda + \frac{2}{3}\mu}$$

$$M = \frac{1}{\mu}$$

Compressibility

Bulk modulus

Lame parameters

Shear compliance

Shear modulus

$$V_P = \sqrt{\frac{1}{\rho}\left(\frac{1}{\kappa} + \frac{4}{3M}\right)}$$

$$V_S = \sqrt{\frac{1}{M\rho}}$$

Presenter's notes: Lamé parameter (λ) and shear modulus (μ) are important, intrinsic, elastic properties of rocks. They relate stresses and strains in perpendicular directions. The *bulk modulus* of a substance measures the substance's resistance to uniform compression. It is defined as volumetric stress over volumetric strain. The shear modulus describes an object's tendency to shear (the deformation of shape at constant volume) when acted upon by opposing forces; it is defined as shear stress over shear strain.

Inversion: Parameterization

Instead of inverting for κ, M, ρ, the contrast functions based on the backgrounds(κ_0, M_0, ρ_0) are to be calculated:

$$\chi_\kappa(z) = \frac{\kappa(z) - \kappa_0(z)}{\kappa_0(z)}$$

$$\chi_M(z) = \frac{M(z) - M_0(z)}{M_0(z)}$$

$$\chi_\rho(z) = \frac{\rho(z) - \rho_0(z)}{\rho_0(z)}$$

Presenter's notes: The backgrounds are smooth non-reflecting media in which the incident field and Green's functions are calculated (Haffinger, 2013). They represent the prior knowledge before the inversion.

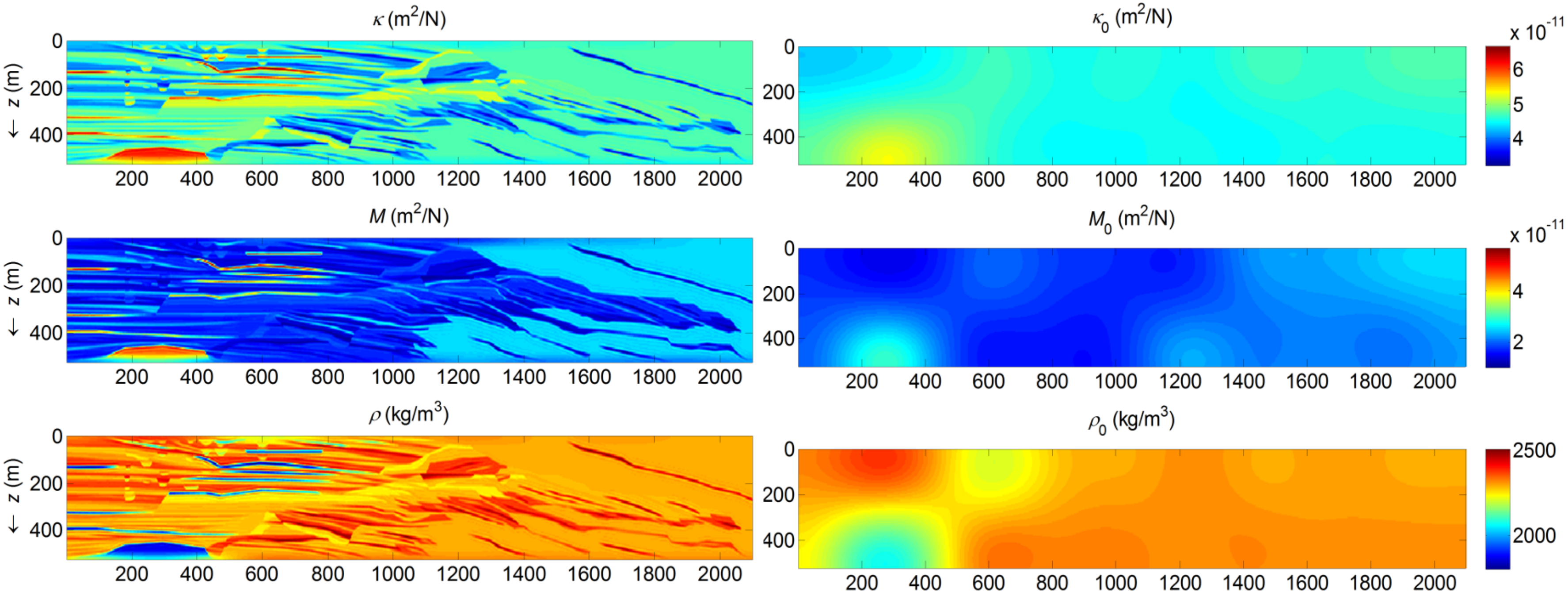
Inversion: Scheme

- Full elastic non-linear AVO（AVP）inversion
- Non-linearity means all internal scattering and mode conversion have been taken into consideration over the target interval
- 1.5D inversion.

Background models

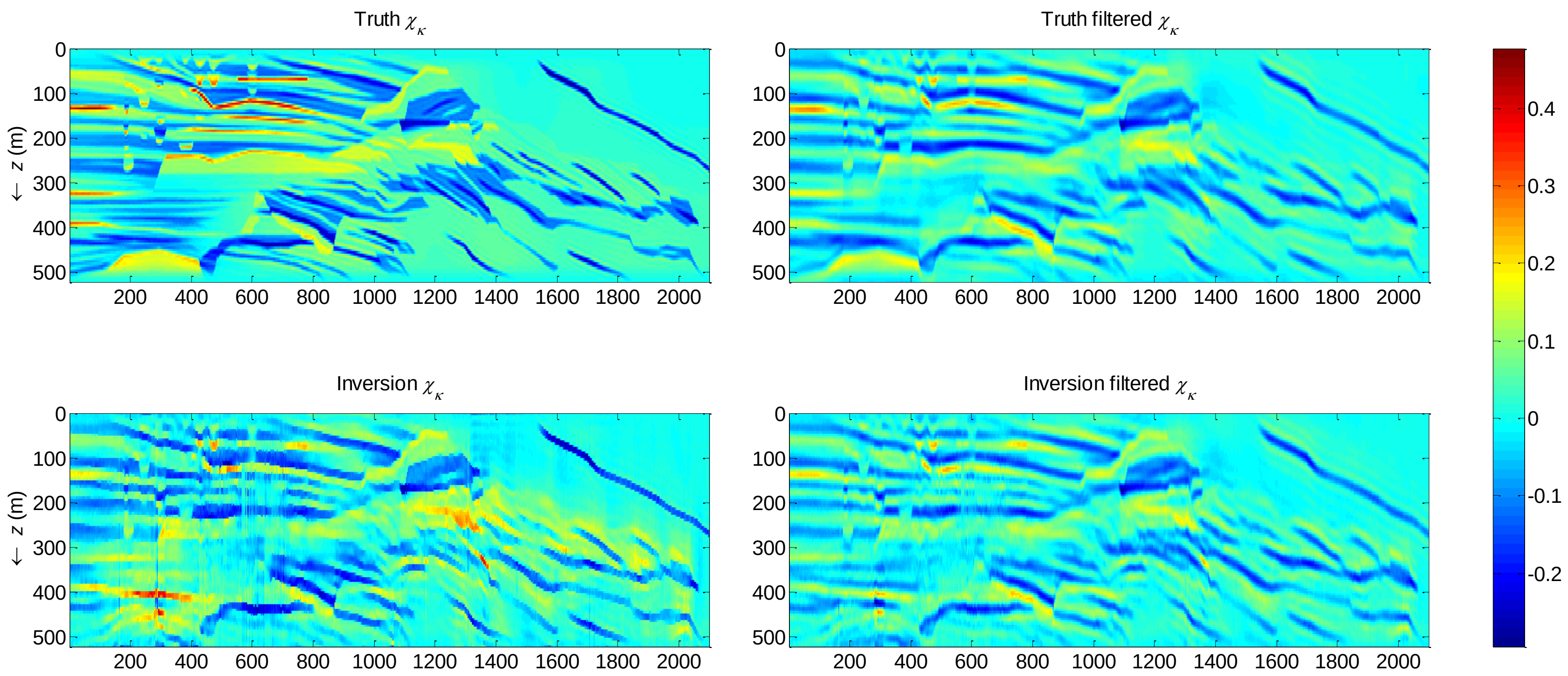
True models

Very smooth background models

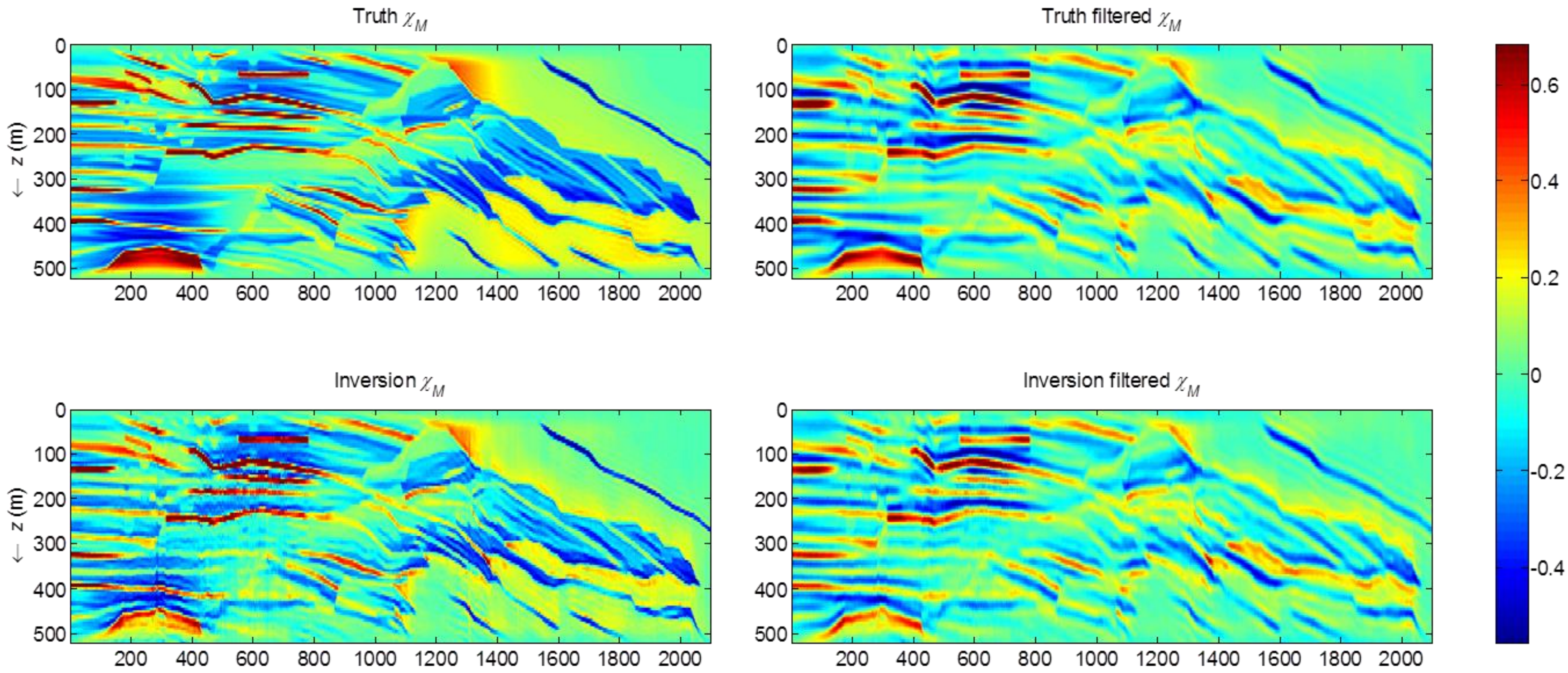


Presenter's notes: The background model is obtained by highly smoothing of the truth. In real inversion studies, backgrounds can be determined at well locations, or by using the migration velocity and invoking *rho* / v_P and v_S / v_P rock-physics relationships.

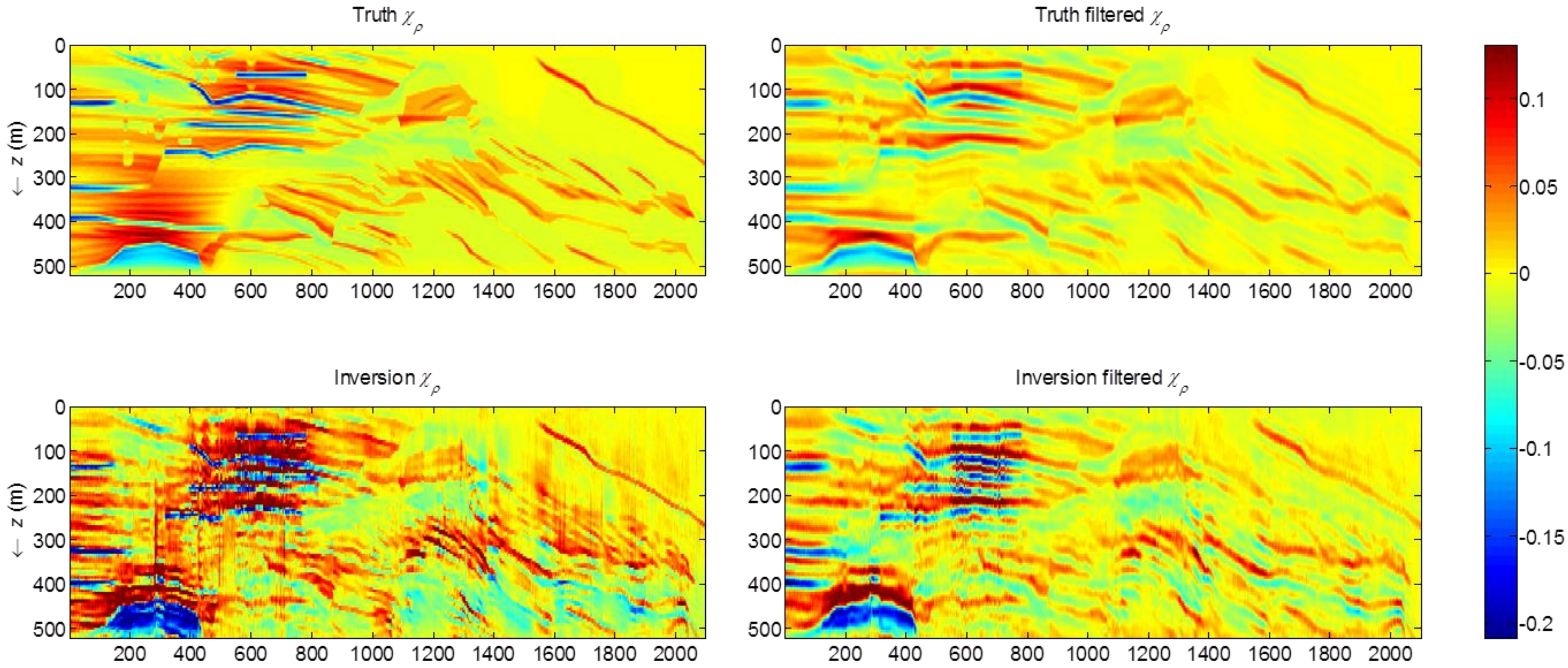
Inversion results



Inversion results



Inversion results

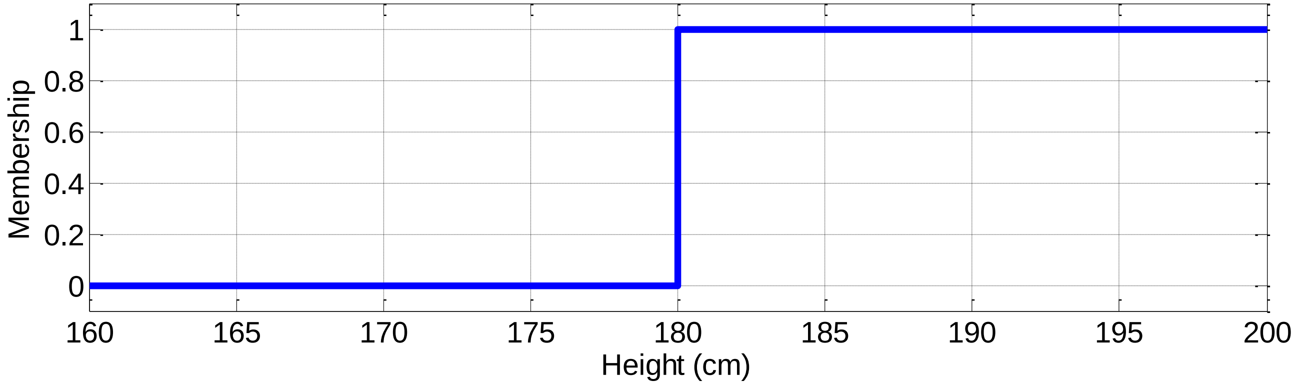


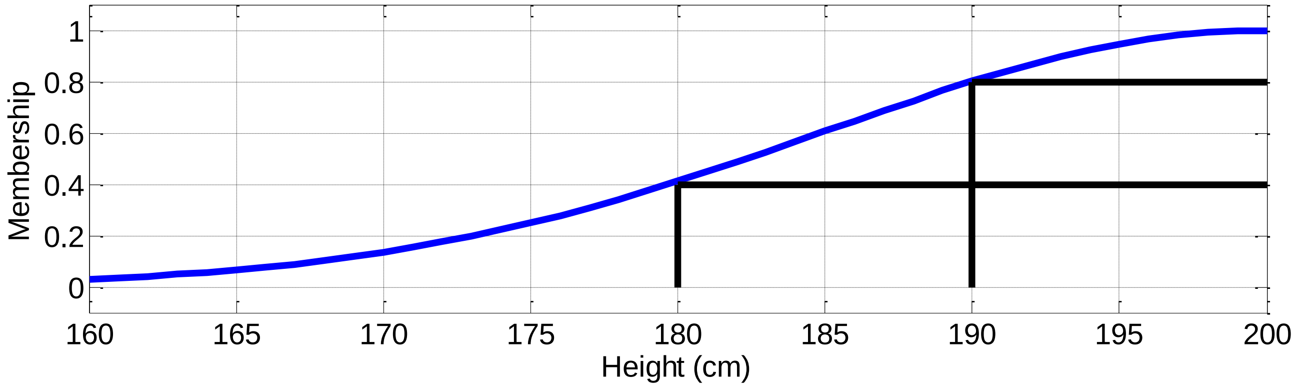
Fuzzy Logic Interpretation

- A normal extension of conventional binary logic (zeros and ones) developed to handle the concept of "partial truth" – truth values between "completely true" and "completely false". (Cuddy and Glover, 2002)
- Rather, assign a grayness, or possibility, to the quality of the prediction on each parameters of the rock, whether in type, porosity or permeability. Characterized by membership function.
- Simple, easily to train, non-iterative and more computer efficient.
- Bring in the geological prior information easily.

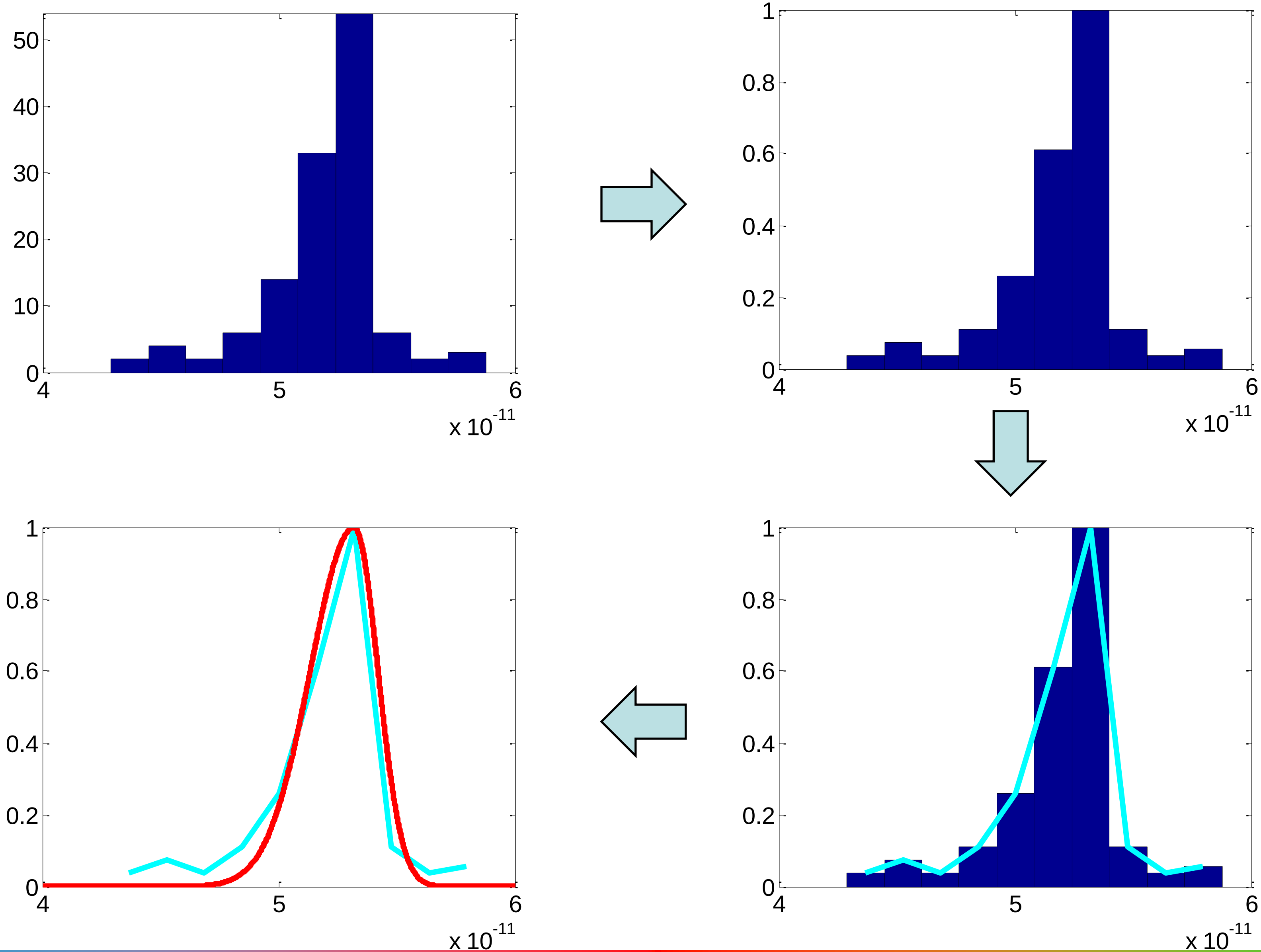
Membership Function (MFC)
(Tall People Club)

- Interval is in [0 1]
- Measures the degree of fit
- Being called Possibility instead of Probability



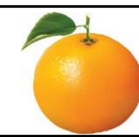


From Histogram to MFC



Confusion Matrix

- A table layout which visualizes classifier's performance.
- Each column means the instances of a predicted class.
- Each row represents the instances of a true class.

		The Predicted Class		
				
The True Class		11	5	2
		4	10	1
		0	3	15

Qualification of Confusion Matrix

Matthews Correlation Coefficient (MCC):

$$MCC = \frac{\sum_{k,l,m=1}^{N} C_{kk}C_{ml} - C_{lk}C_{km}}{\sqrt{\sum_{k=1}^{N}\left[\left(\sum_{l=1}^{N} C_{lk}\right)\left(\sum_{f,g=1,f\neq k}^{N} C_{gf}\right)\right]}\sqrt{\sum_{k=1}^{N}\left[\left(\sum_{l=1}^{N} C_{kl}\right)\left(\sum_{f,g=1,f\neq k}^{N} C_{fg}\right)\right]}}$$

Where:

C : Confusion Matrix

C_{ij} : The element from the i^{th} row and j^{th} column of C

N : The total number of classes in Confusion Matrix

MCC is in the range of [-1 1]. 1 means a perfect classification while -1 represents the extreme misclassification asymptotically when C is all zeros except for two symmetric elements $C_{i,j}$ and $C_{j,i}$. 0 is reached when all elements of C are equal or when all of C are zeros except for one column.

Examples of C and MCC

$$C = \begin{pmatrix} 6 & 0 & 0 \\ 0 & 6 & 0 \\ 0 & 0 & 6 \end{pmatrix}$$

$MCC = 1$

$$C = \begin{pmatrix} 0 & 0 & 9 \\ 0 & 0 & 0 \\ 9 & 0 & 0 \end{pmatrix}$$

$MCC = -1$

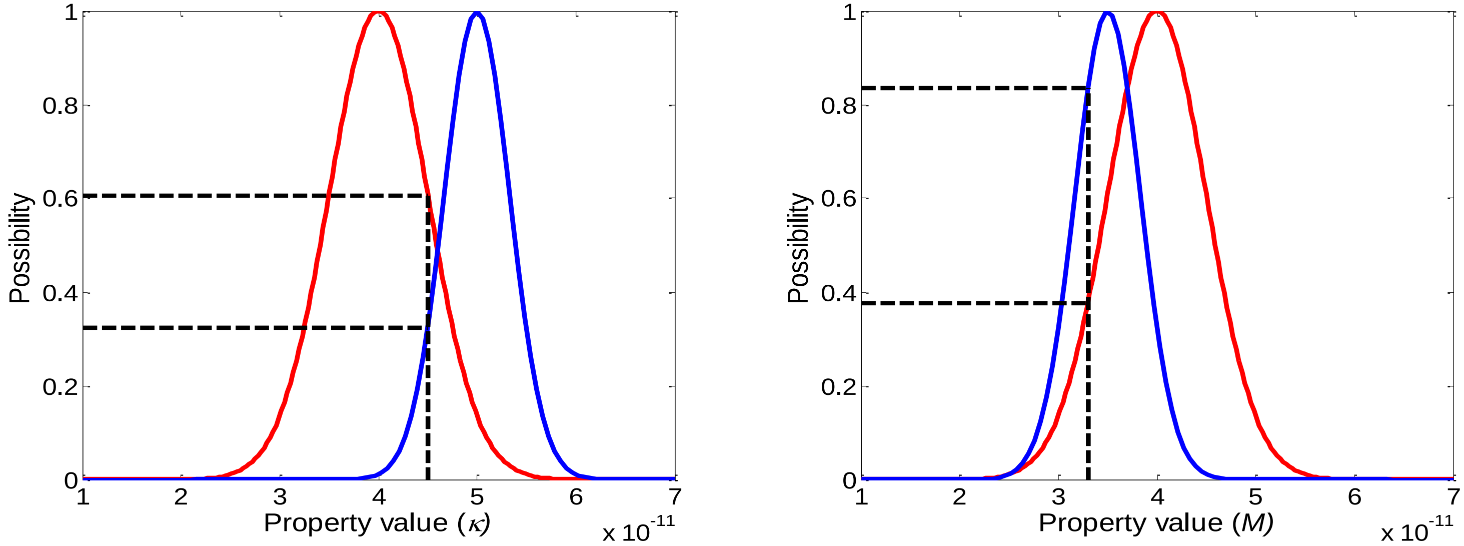
$$C = \begin{pmatrix} 2 & 2 & 2 \\ 2 & 2 & 2 \\ 2 & 2 & 2 \end{pmatrix}$$

$MCC = 0$

$$C = \begin{pmatrix} 6 & 0 & 0 \\ 6 & 0 & 0 \\ 6 & 0 & 0 \end{pmatrix}$$

$MCC = 0$

Combination Operator



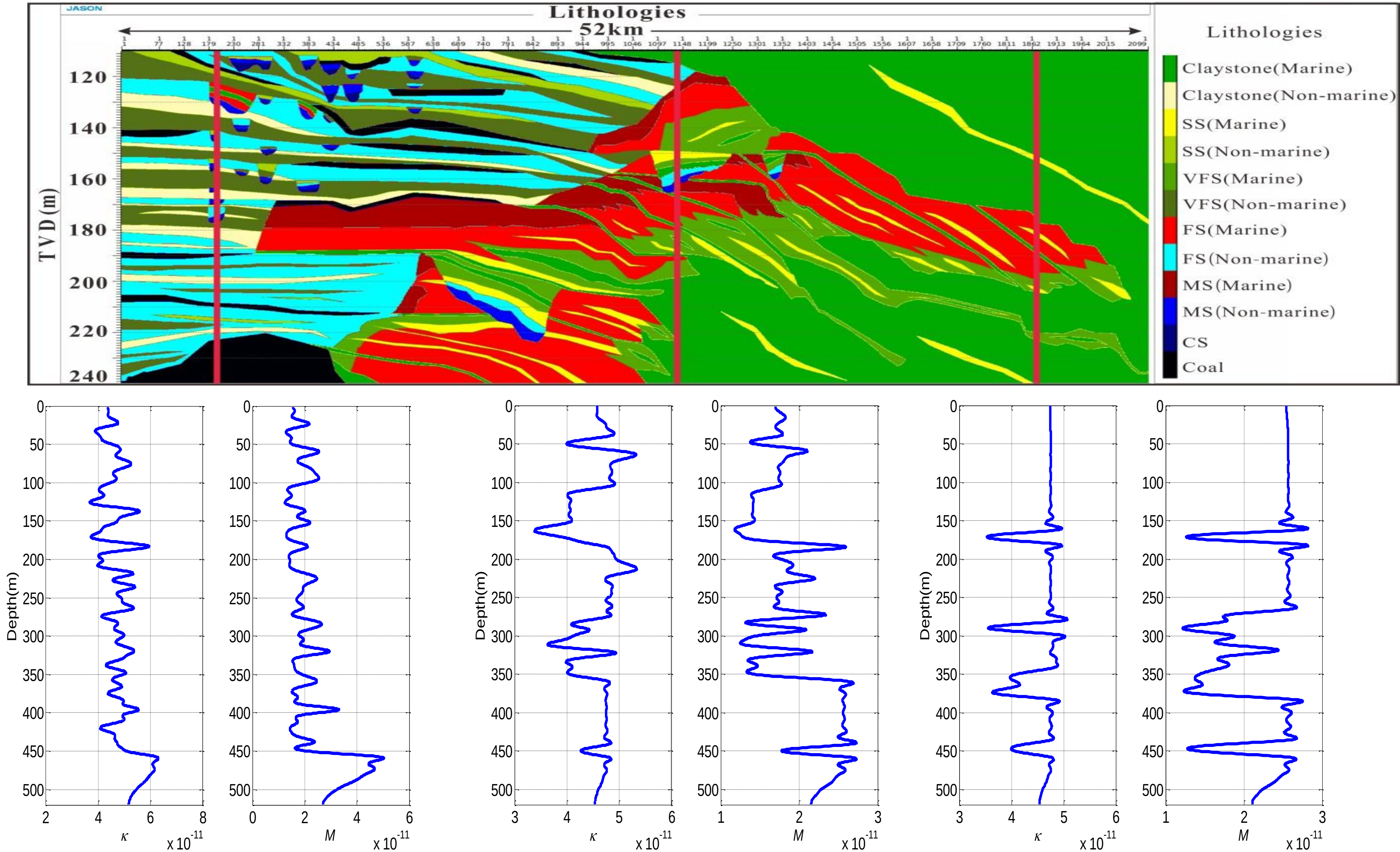
Red: lithology A; Blue: lithology B

The Fuzzy Gamma operator is proposed:

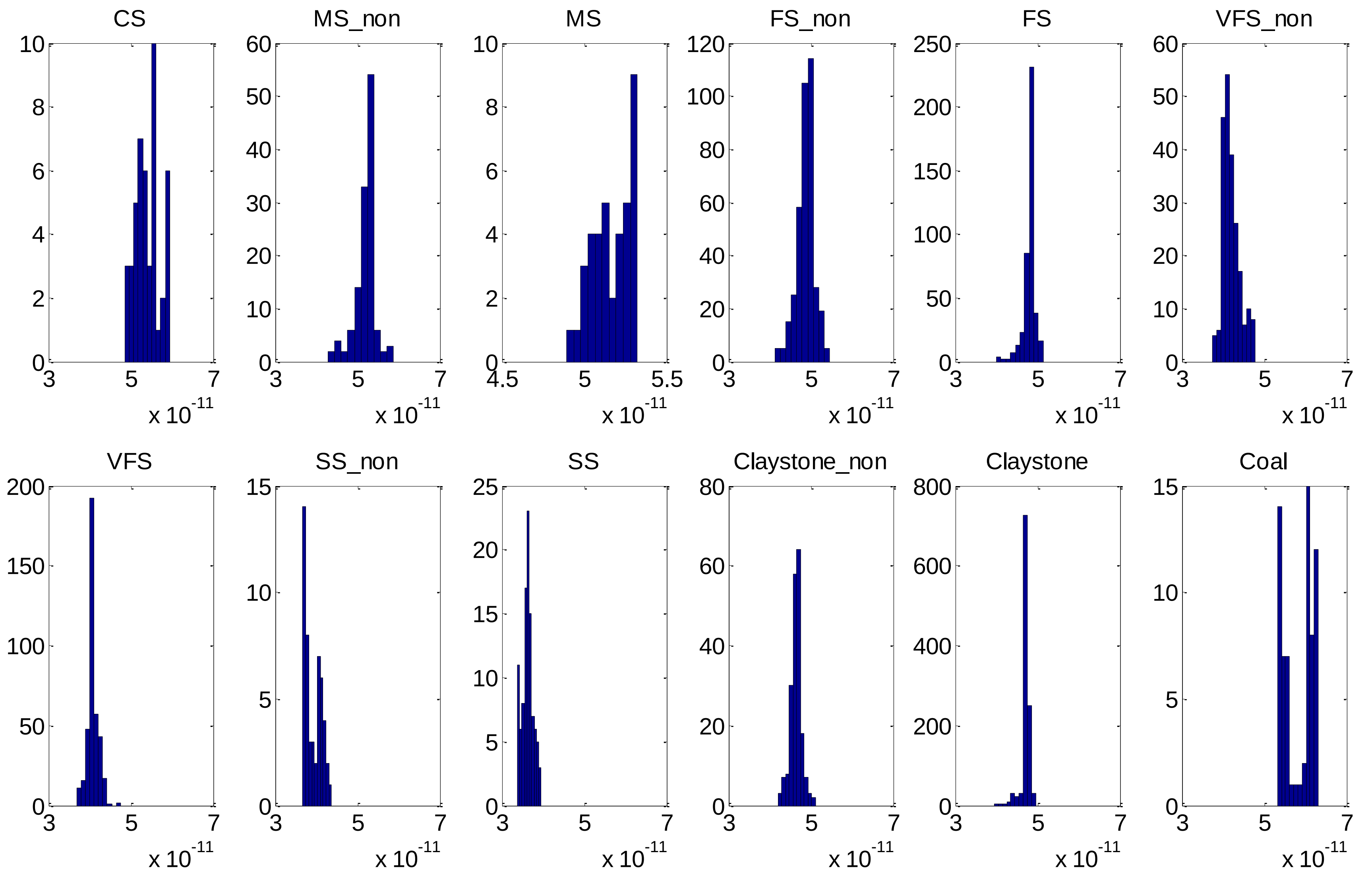
$$Lith = \left[1 - \prod_{i=1}^{N}(1-\mu_i)\right]^{\gamma} \cdot \left[\prod_{i=1}^{N}\mu_i\right]^{1-\gamma}$$

N is number of input datasets; μ_i is the possibility corresponding to the input data sample; γ is the Fuzzy Gamma operator and can be chosen between 0 and 1. Here it is to be 0.9 .

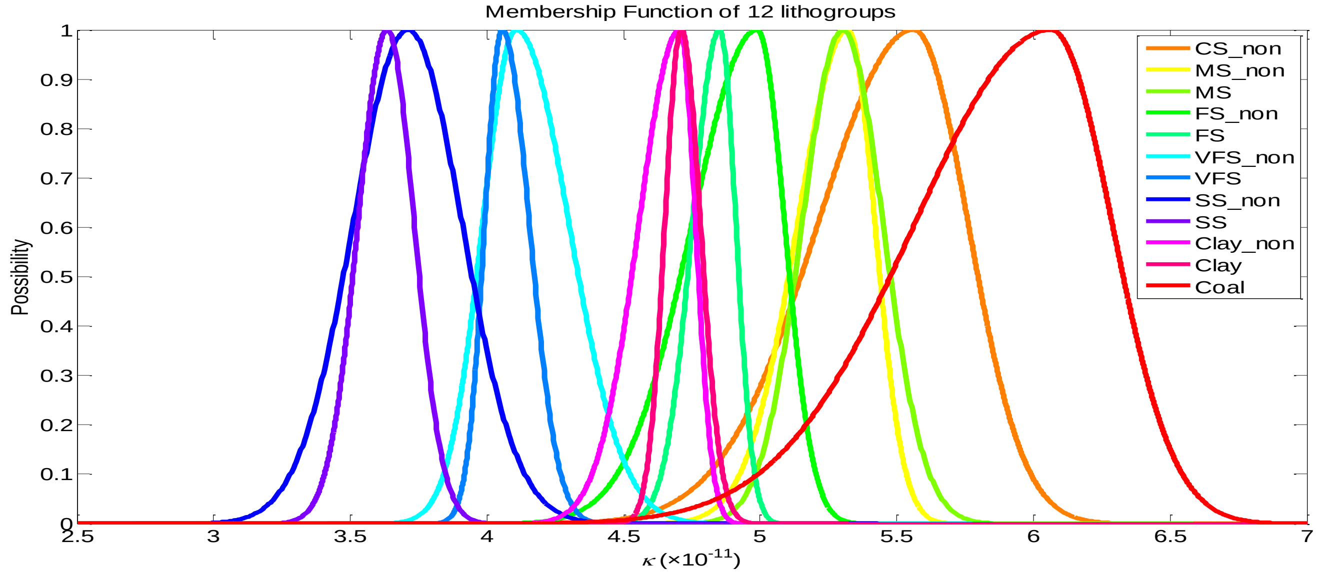
Well Locations (CMPs=185,1130,1880)

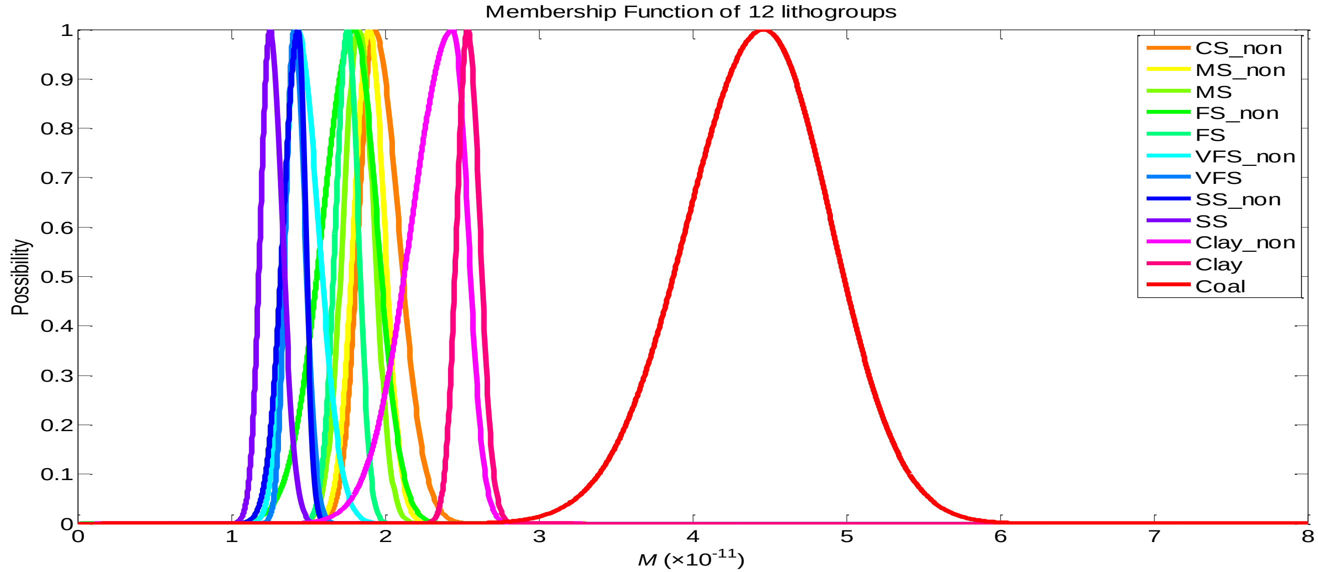


Training (Histograms in terms of κ)

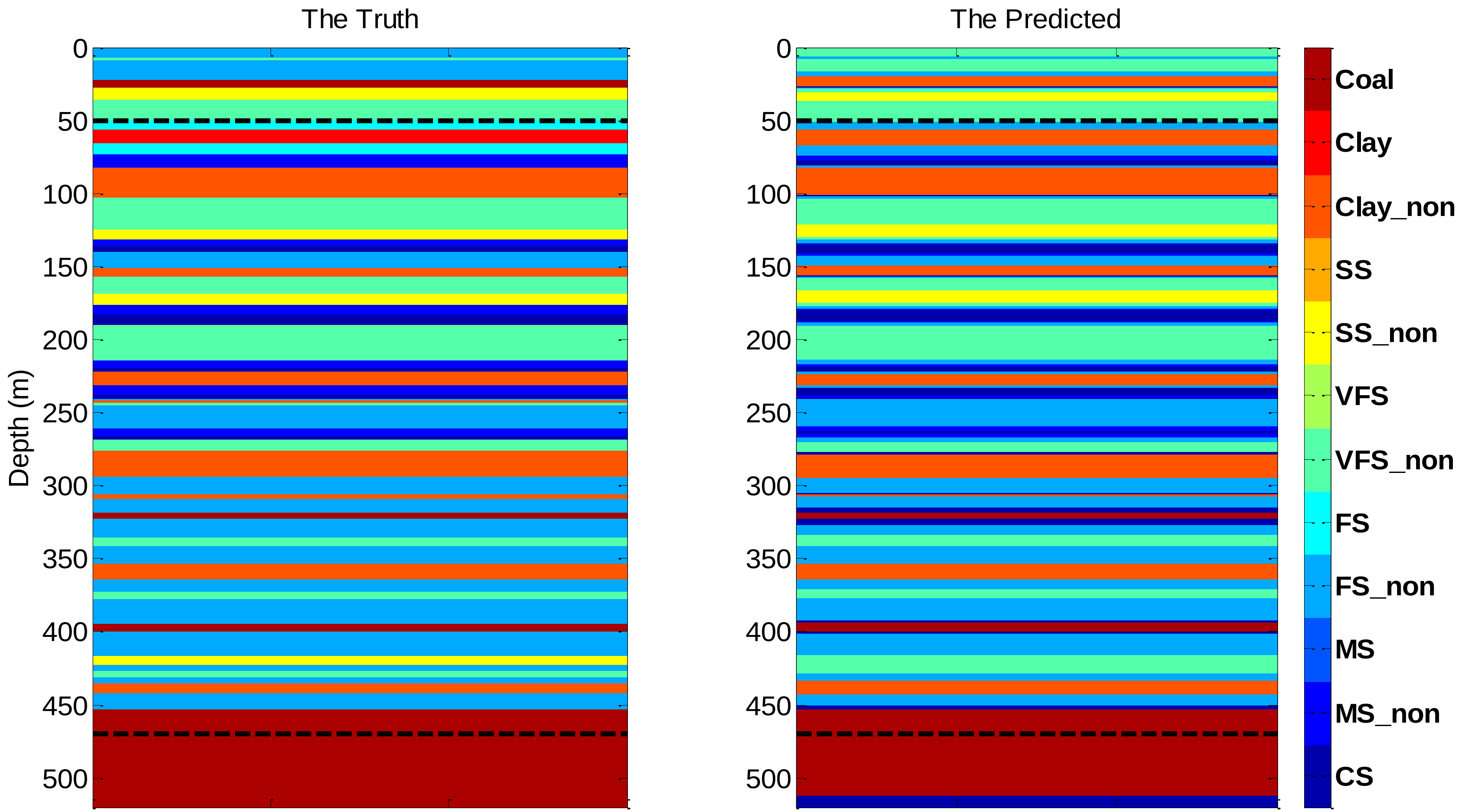


Training (MFC of 12 Lithologies)

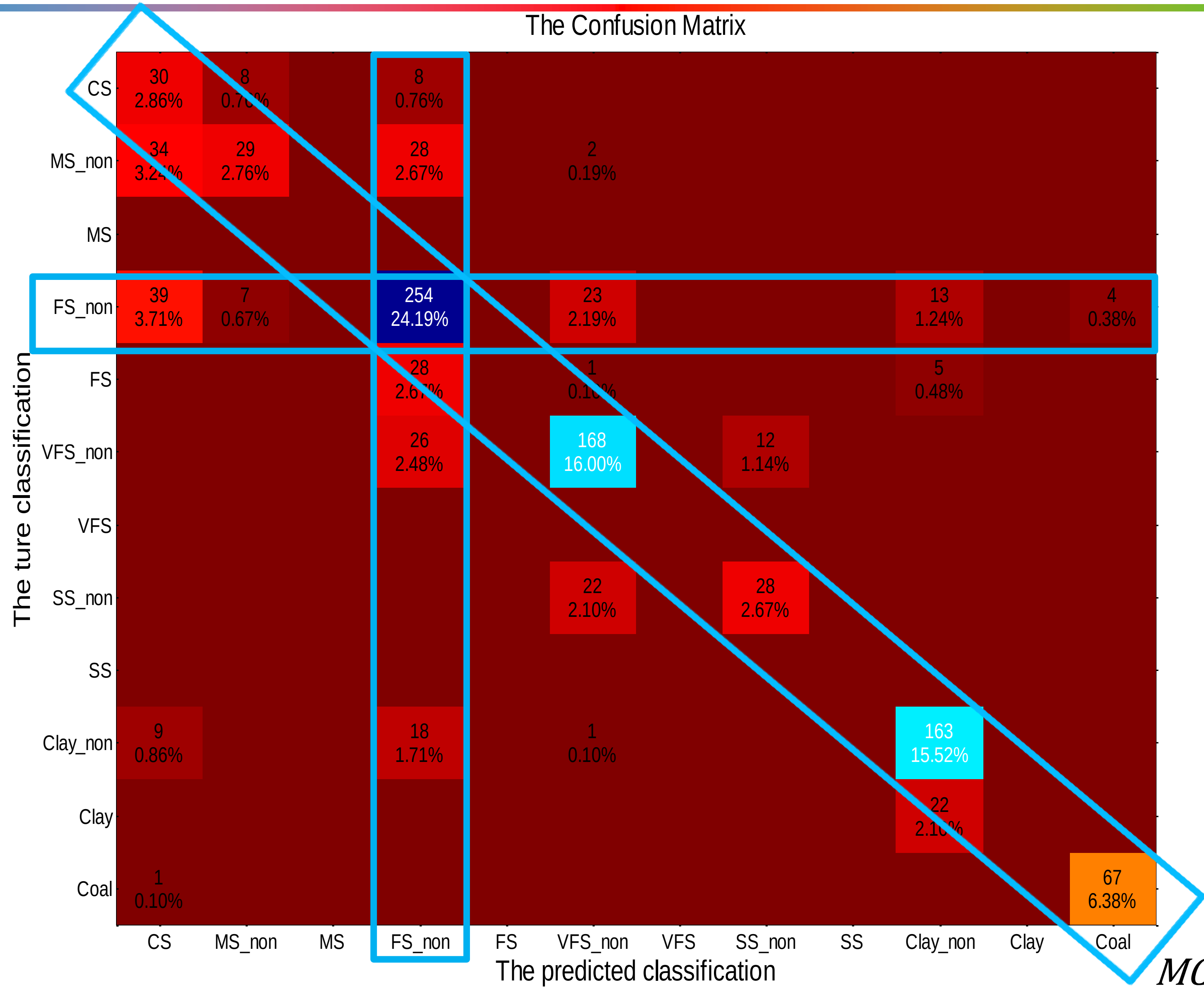




Validation
(CMP = 185,unsampled truth)



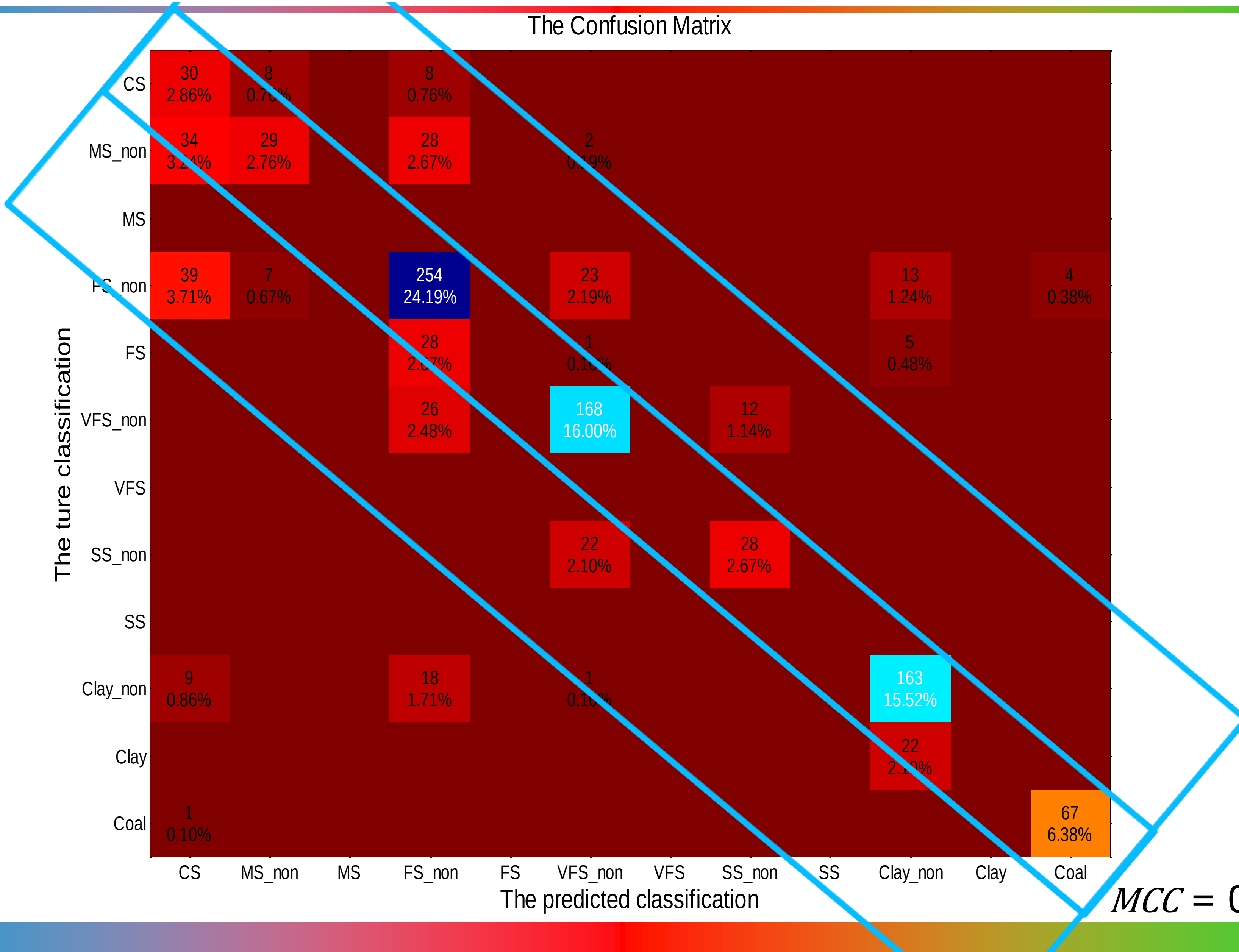
Validation
(CMP = 185,unsampled truth)



$MCC = 0.6323$

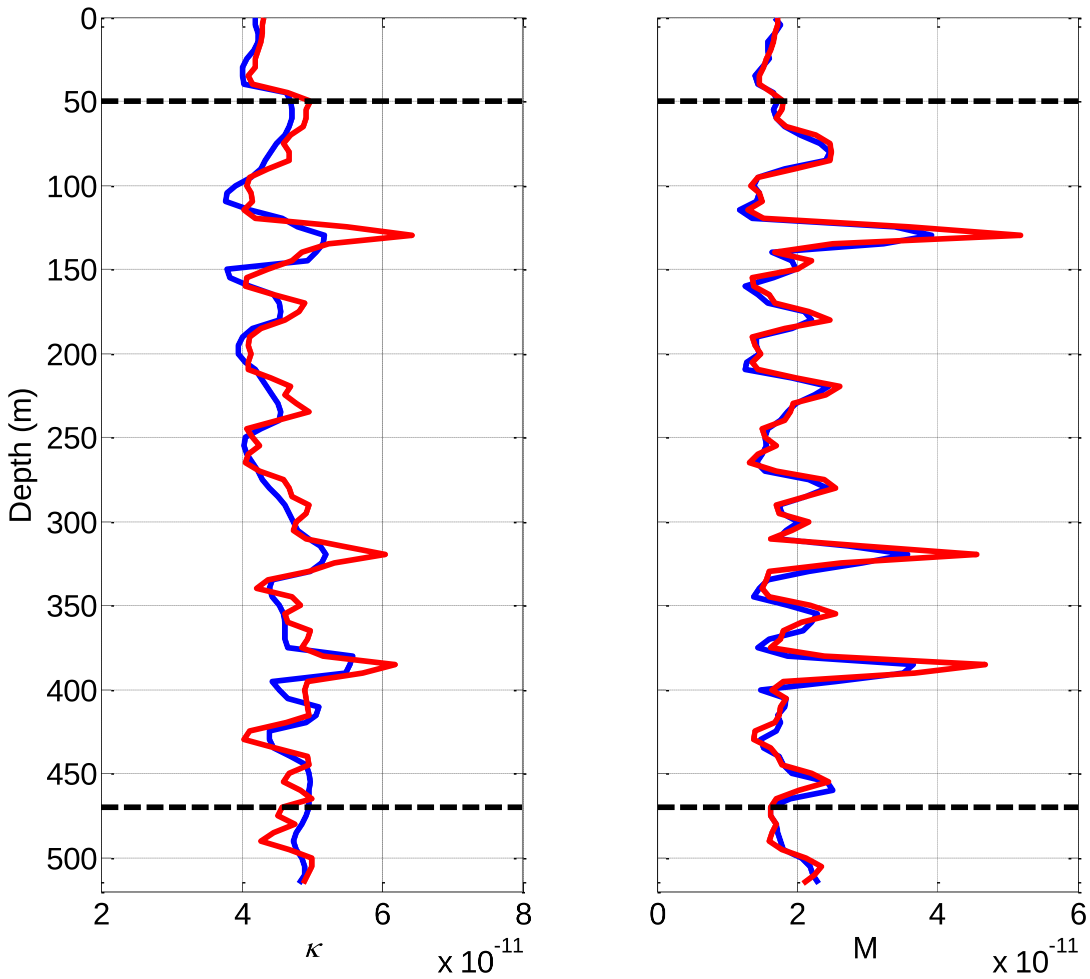
Validation

(CMP = 185,unsampled truth)

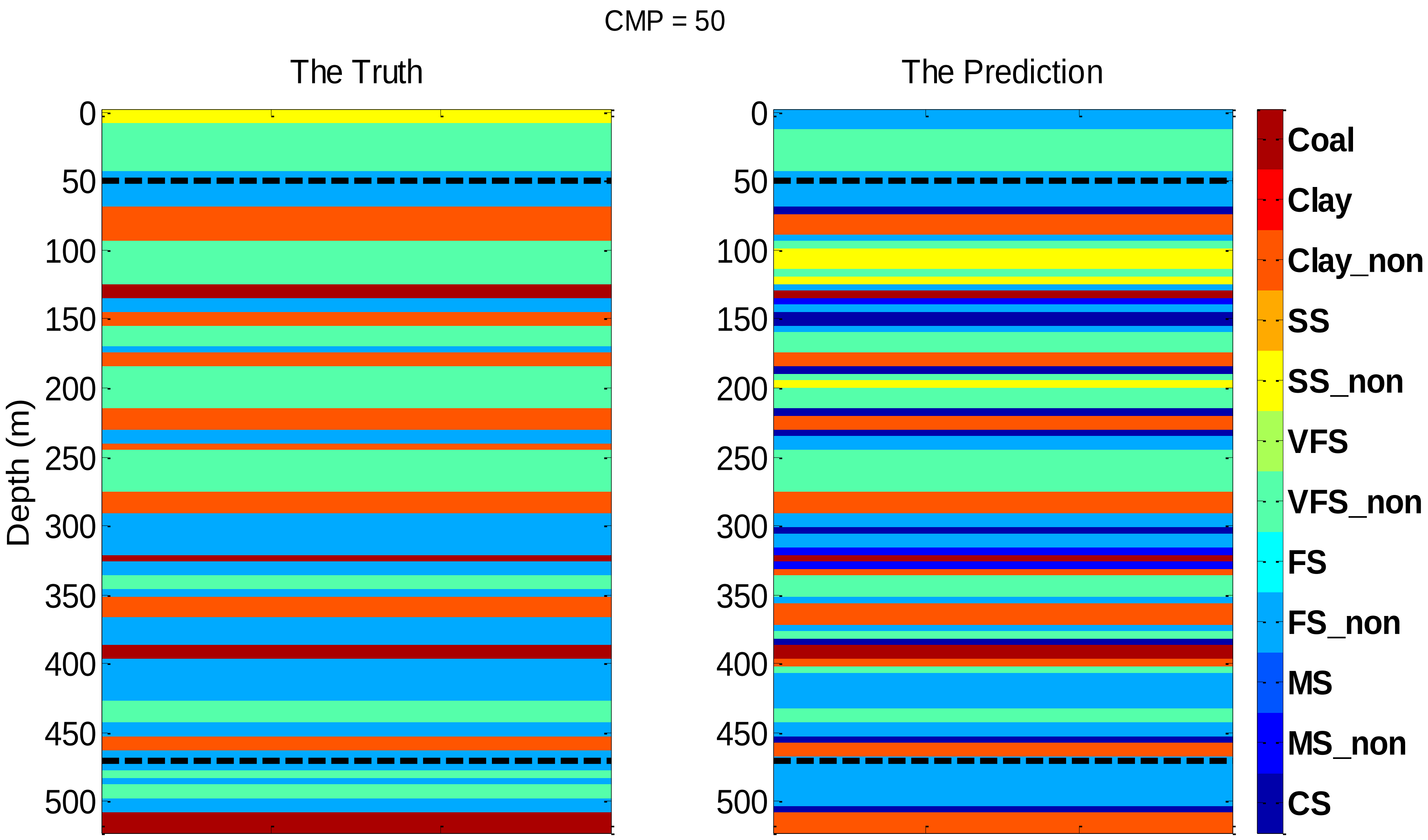


$MCC = 0.6323$

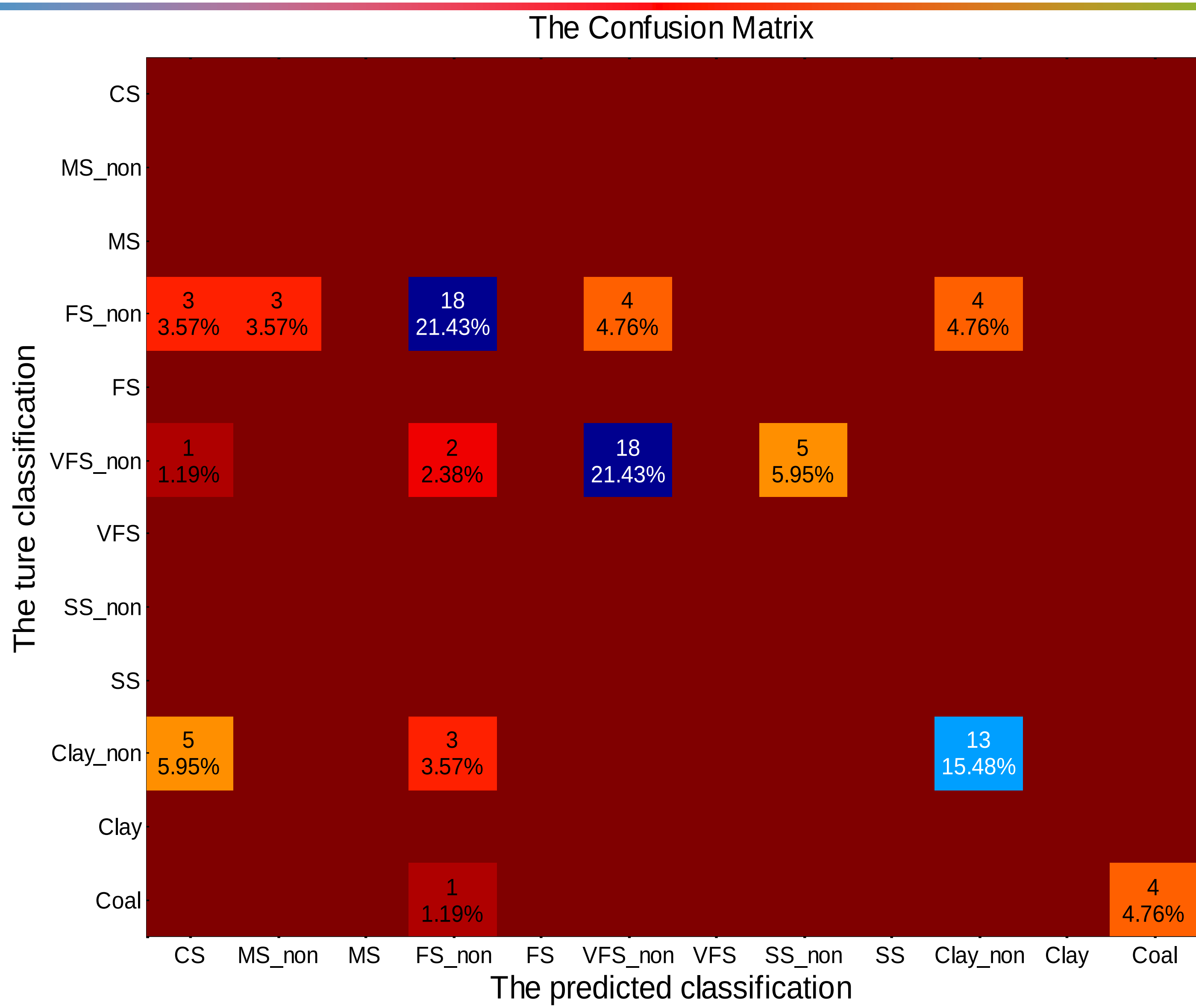
Testing
(CMP = 50,sampled inversion)



Testing
(CMP = 50,sampled inversion)



Testing
(CMP = 50,sampled inversion)



$MCC = 0{,}5238$

Conclusions

- The elastic non-linear full wave form inversion technique was applied on a realistic high-resolution geological model, giving accurate quantitative reconstruction of all sedimentological features.
- Two main elastic parameters (κ and M) together with the density information were successfully retrieved from synthetic seismic dataset using elastic non-linear inversion.
- The fuzzy logic inference scheme has been applied for lithological interpretation with the inversion results as the input.
- The lithology prediction is satisfactory even though there are some misclassified lithologies.

Thank you for your attention

References:

Feng, R. Luthi, S.M. Gisolf, A. and Sharma, S. 2017. *Obtaining a high-resolution geological and petrophysical model from the results of reservoir-orientated elastic wave-equation-based seismic inversion*. Petroleum Geoscience, DOI: 10.1144/petgeo2015-076.

Gisolf, A. & van den Berg, P.M. 2010. *Target oriented non-linear inversion of seismic data*. P308, presented at the 72nd EAGE Annual Meeting, Barcelona, 14-17 June.