PS Using Machine Learning Techniques for Mapping Dolomitic Facies in a Triple Porosity Calcareous Reservoir. Campeche Sound, Gulf of Mexico*

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Abstract

The Campeche Sound area is located southeast of the continental shelf in the Gulf of Mexico and represents about 80% of Mexico's national oil production. Two major oil fields are in the area, the Cantarell and Ku-Zaap-Maloob fields. They both produce from a Cretaceous carbonate with a complex porous system diagenetically altered through dolomitization, dissolution, and fracturing processes. This reservoir exhibits three main types of porosity: (1) matrix, (2) fracture, and (3) vuggy porosity. However, fracture and vuggy porosities are the main porosity types due to the connectivity of porous volume.

Mapping the associated facies to these porosities is challenging due to the heterogeneous distribution related to the dolomitization process. To characterize the spatial distribution of facies and related porosity of the dolomitic reservoir, analysis of high-resolution 3D seismic was performed on post-stack-time-migrated (PSTM) and post-stack-depth-migrated (PSDM) seismic data. This study includes an elastic inversion and generation of numerous geometrical attributes. The seismic products obtained from the inversion process were used along with the geometric seismic attributes to estimate seismic facies through machine learning techniques such as Artificial Neural Net (ANN), Generative Topographic Maps (GTM), Weighted Linear Combination (WLC), Self-organized maps (SOM), and K-Means. The results obtained were compared to the original facies description from wells in the area as blind-test. Differences between the approach using PSDM and PSTM seismic data were not significant, but, for the Lower Cretaceous interval the inversion performed using PSTM had a much better result.

Using machine learning techniques for mapping dolomitic facies in a triple porosity calcareous reservoir. Campeche Sound, Gulf of Mexico

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AASPI

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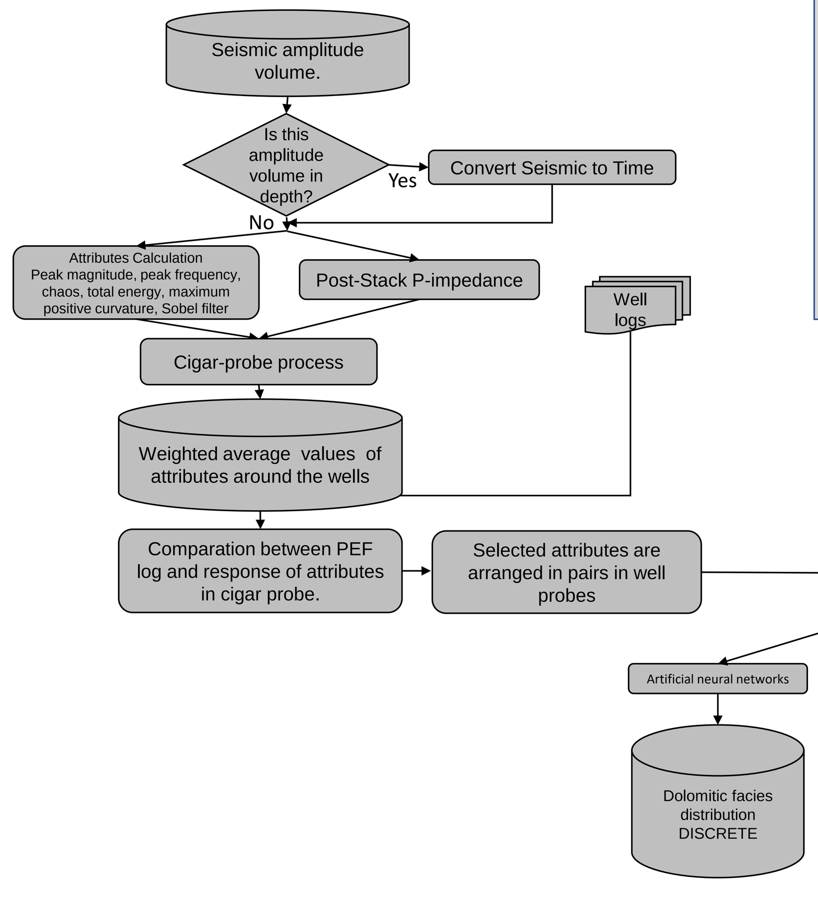
Mapping the associated facies to these porosities is challenging due to the heterogeneous distribution related to the dolomitization process. To characterize the spatial distribution of facies and related porosity of the dolomitic reservoir, analysis of high-resolution 3D seismic data was performed on post-stack-time-migrated (PSTM) and post-stack-depth-migrated (PSDM) seismic data. This study includes the products of an elastic inversion, and the generation of numerous geometrical attributes to predict the facies through machine learning techniques, such as Artificial Neural Net (ANN), Generative Topographic Maps (GTM), and Weighted Linear Combination (WLC). The results obtained were compared to the original facies description from a well in the area used as blind-test. Differences between the approach using PSDM and PSTM seismic data were highlighted showing important differences for the Lower Cretaceous interval where data for inversion of PSTM data had a much better result.

Workflow



This workflow explores the integration of seismic data with well-log data for facies definition. The seismic attributes are tested by extracting the traces nearby the borehole along the stratigraphic zone of interest. Then, this weighted average is compared to the well-log response of the lithologies in the well bore.

Study area and stratigraphy

A

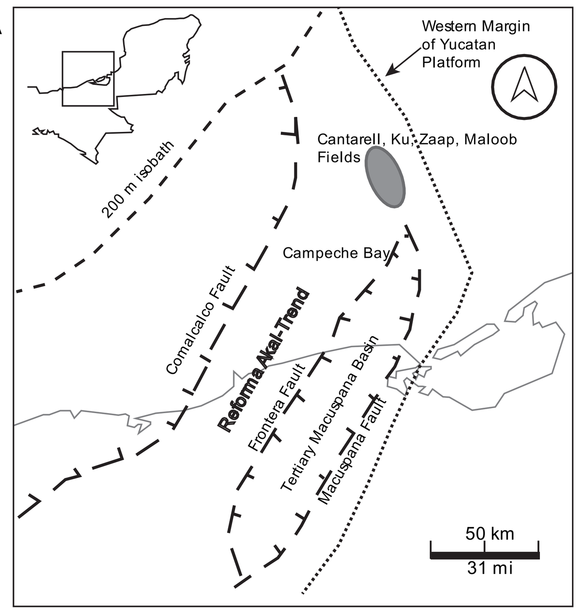
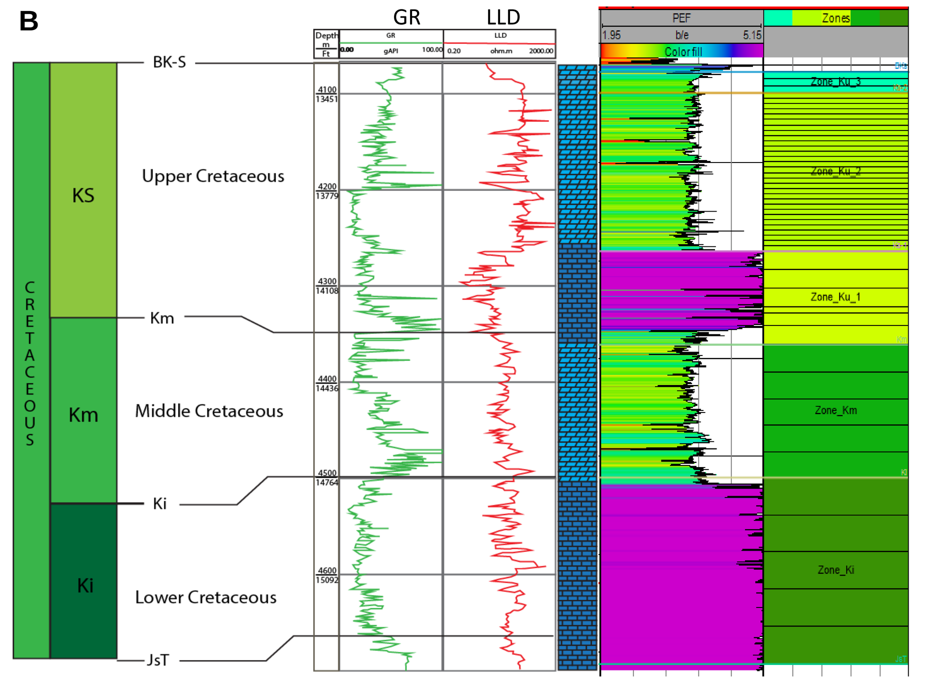
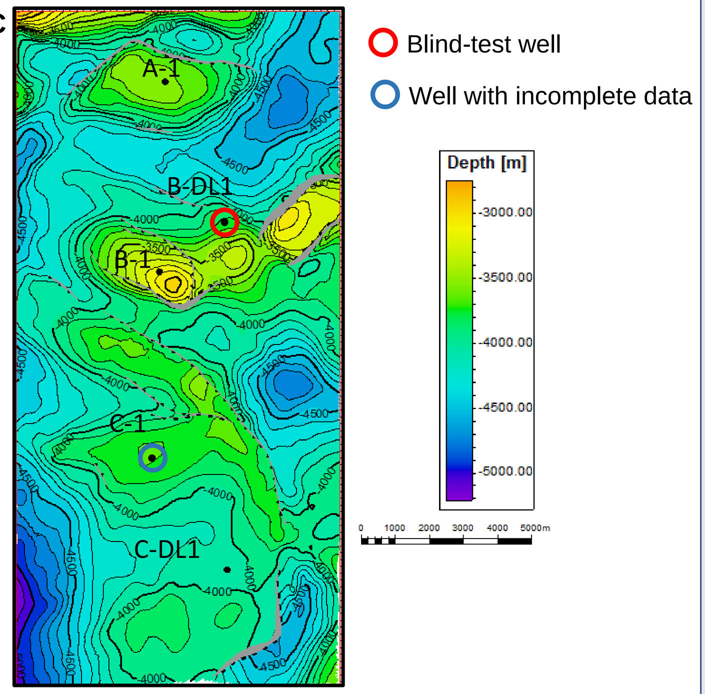


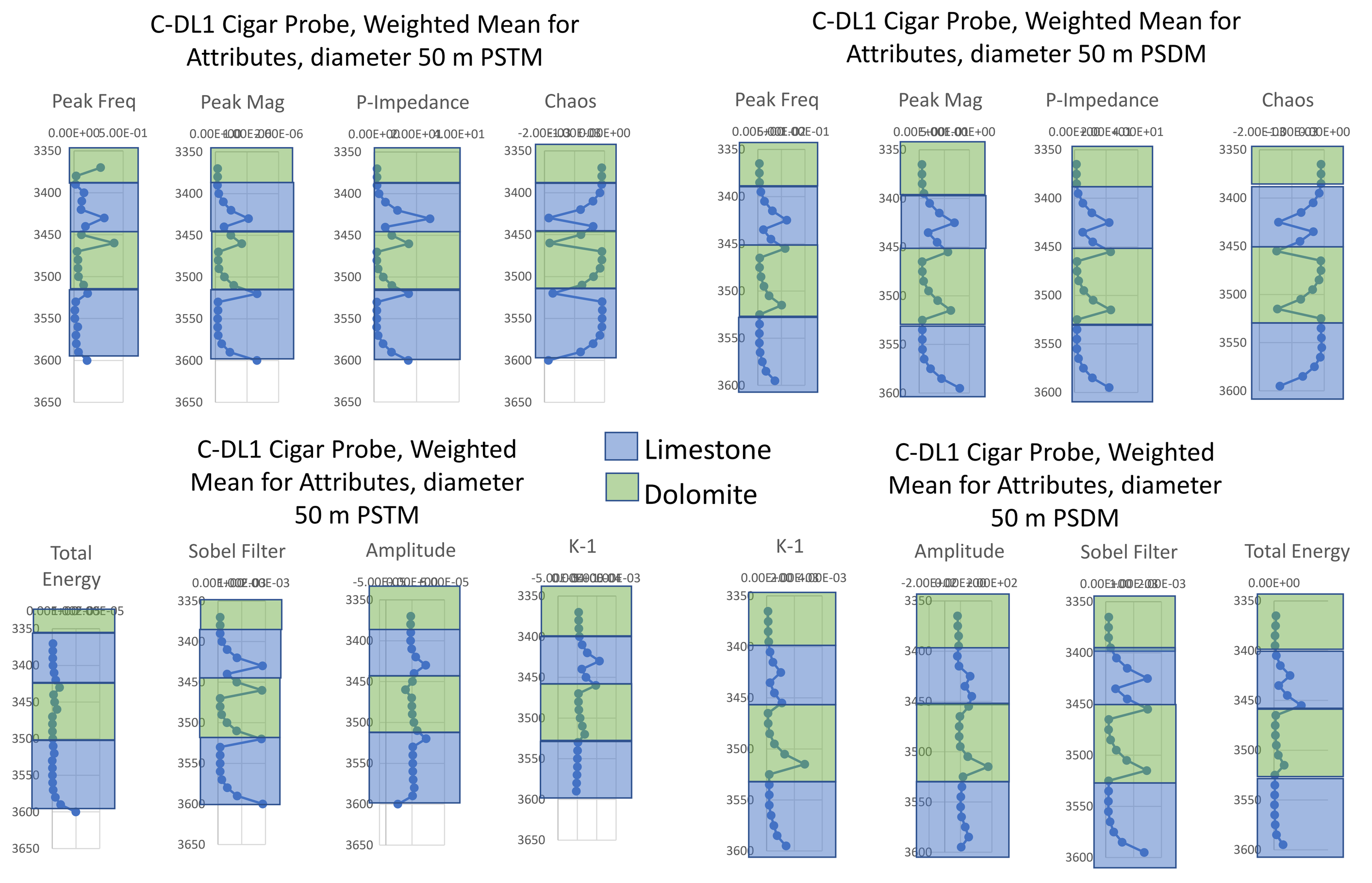
Figure 1: A) The location of the study area and the main structural features in the zone. Study area shares the geological history and some features with the major fields in the Gulf of Mexico, Cantarell, Ku, Maloob and, Zaap. B) Stratigraphic column for the study area and the type well log response. Dolomites generally exhibit better porosity and permeability than limestones. More intense dolomitization occurs in the breccias of the Upper Cretaceous upper zone. C) Map of the top of the reservoir. The study area is composed of three fields, named from North to South as A, B, and C. The field A was discovered by the well A-1. The field B has two wells. The discovery well B-1 and an appraisal well B-DL1 that was used as a blind test. The C field has two wells the discovery well C-1 only drilled 120 m inside the reservoir and the appraisal well C-DL1

B

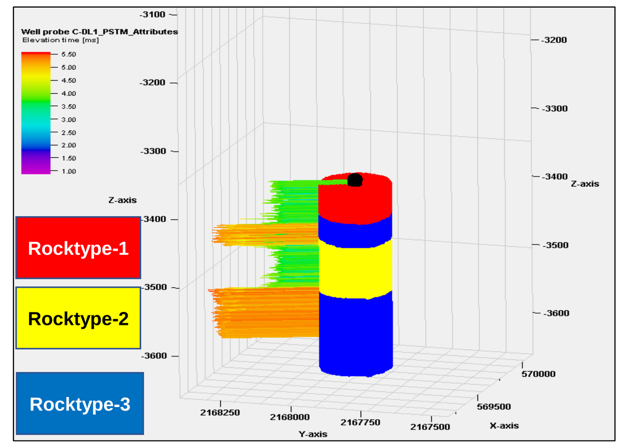


C





Well-probe extracted from Well C-DL1 PSTM



Values assigned to the analysis of the well-probe C-DL1

A)

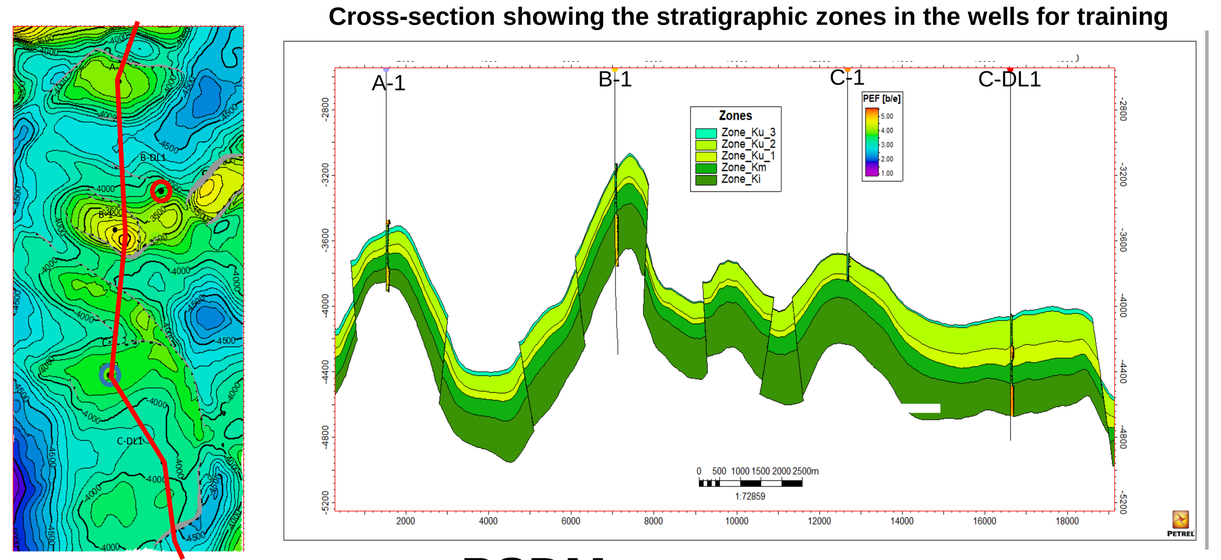
	Spectral Attributes		Geometric Attributes				Seismic Inversion	
Well	Peak Freq	Peak Mag	Chaos	Total Energy	Maximum positive Curvature	Sobel Filter	P-Impedance	Amplitude
A-1	0.5	1	1	0.5	0	1	1	0.5
B-1	0	0	0	1	1	0	0	1
C-DL1	1	1	1	0.5	1	1	1	1
Total	1.5	2	2	2	2	2	2	2.5

B)

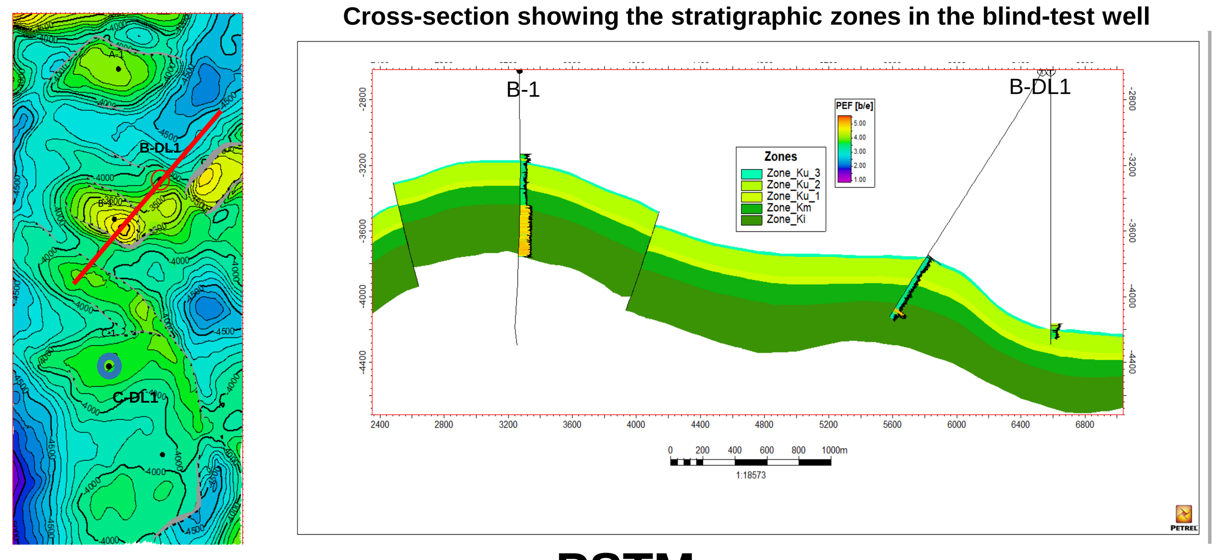
	Spectral Attributes		Geometric Attributes				Seismic Inversion	
Well	Peak Freq	Peak Mag	Chaos	Total Energy	Maximum positive Curvature	Sobel Filter	P-Impedance	Amplitude
A-1	1	1	1	0.5	1	1	1	1
B-1	0.5	0.5	0.5	0.5	0.5	0	1	1
C-DL1	1	1	1	1	1	1	1	1
Total	2.5	2.5	2.5	2	2.5	2	3	3

Results

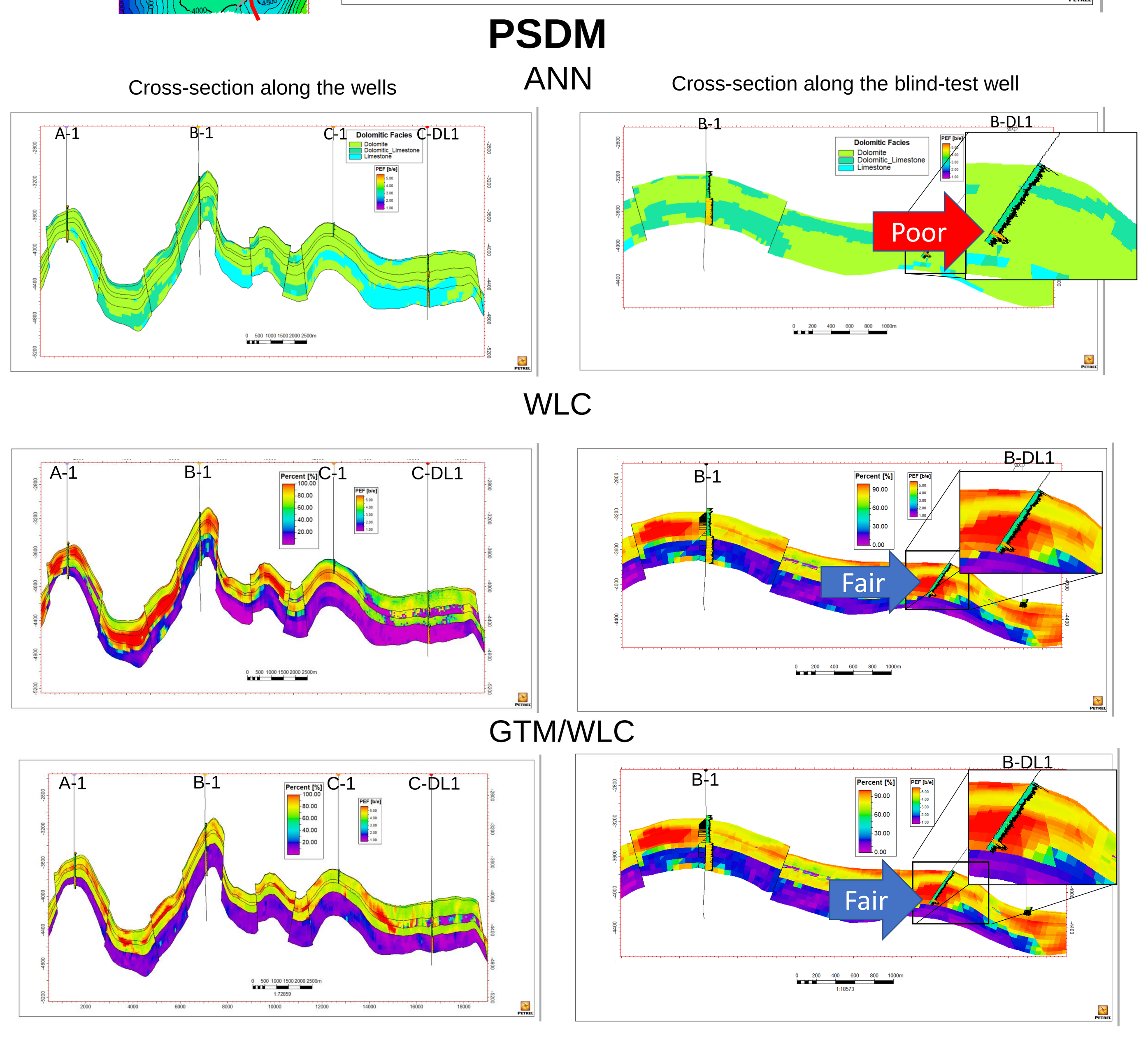
Cross-section showing the stratigraphic zones in the wells for training



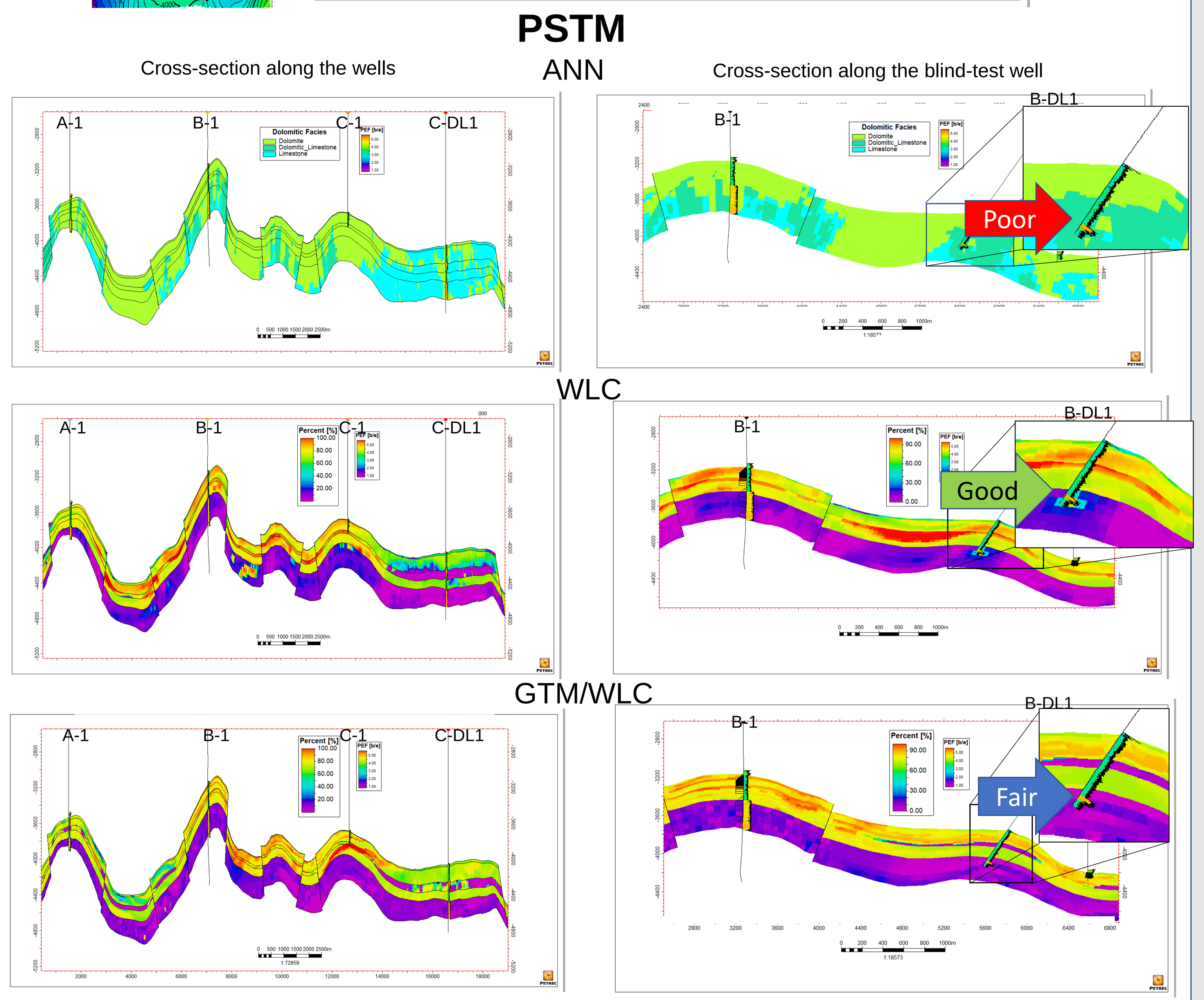
Cross-section showing the stratigraphic zones in the blind-test well



PSDM



PSTM



Cross-sections and profiles with the results in PSDM:
For the ANN model in the PSDM attributes the zones Ku-3 and Ku-2 are successfully predicted as dolomized. However, the zone K-1 is predicted as mainly dolomized missing the prediction of the limestone interval in the C-DL1 well. The results obtained in the blind test well were poor with the ANN prediction of only dolomized zones.
The WLC model was the most accurate to predict the expected lithologies. The limestone interval zone around the well C-DL1 was predicted successfully. The results obtained in the blind test well were fair failing to predict the limestone in the lower interval.
The GTM/WLC combination show fair results. The limestone in the unit Ku-1 was not successfully predicted. For the blind test well, the transition between the dolomite from Km and the limestone from Ki was well delimited. However, the model failed to predict the limestone in the lower part of the well.

Cross- sections and profiles with the results in PSTM:
For the ANN model in the PSTM volume the classification show poor results. Dolomitic lithologies were poorly predicted in the Ki zone. The results of the blind-test well show successful results using ANN. Classification of dolomitic lithologies and limestone intervals are accurately predicted.
The WLC the results were the most accurate. This method predicted successfully the units Ku-3 Ku-2 as dolomitic lithologies. Additionally, the Ku-1 unit was predicted as not dolomized in the area nearby the C-DL1 well. The unit Ki was successfully predicted as dolomitic lithologies only in the syncline between the field B and field C. The results shown in the blind test are accurate in the prediction predicting the limestone interval at the base of the well.
The GTM/WLC model shows fair results. However, the model failed to predict complete limestone within the zone Ku-1 around the well C-DL1. The area of the blind-test well was not predicted as limestone in the lower part of the well.

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