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Application of Unsupervised Machine Learning Techniques in Detailed Recognition of Gas Producing Subtle Submarine Channel System

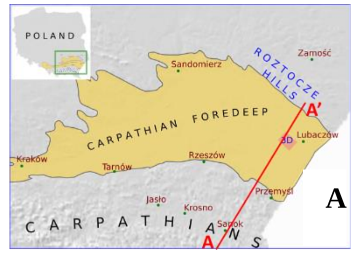
Mariusz Łukaszewski*[1, 2]; 1. Geofizyka Toruń S.A., Seismic Data Interpretation Department, Toruń, Poland, 2. AGH University of Science and Technology, Faculty of Geology, Geophysics and Environment Protection; Kraków, Poland.

Abstract

The Miocene age sediments filling the Polish part of the Carpathian Foredeep Basin are characterized by the lithological and facies diversity. This in turn provides an excellent opportunity for implementing Machine Learning techniques in search of hydrocarbon (HC) traps. Especially stratigraphic traps related to a subtle submarine channel system. The use of classic amplitude-based attributes has unveiled the shape and the extent of this subtle stratigraphic feature. Texture attributes (i.e. GLCM Energy and Entropy) have also proven to be helpful, as well as frequency RGB blending or use of alternative stratigraphic imaging technique. Despite the interesting interpretation results obtained, some questions still remained to be answered. For example, the amplitude-based attribute images did not exactly match the information from the wells with best production parameters, located within the main distributary channel. Hence the idea of using self-learning techniques in search for seismic facies information that is not provided by any conventional seismic approach. Two unsupervised classifying algorithms were used in the research: Neural Net 3D and Kohonen SOM 3D. The obtained results allowed for a geological interpretation consistent with the borehole data, revealing previously unnoticeable elements of the examined structural object. Moreover, in further research, the Principal Component Analysis (PCA) technique was applied to a frequency content of a thin seismic layer within which it is located a gas producing channel system. This led to interesting conclusions on the possible thickness evaluation of the channel system. Application of unsupervised Machine Learning techniques, as a complementary method to the classic interpreter approach, resulted in a detailed recognition of gas producing subtle submarine channel system, with the possibility of indicating optimal locations for further exploration.

Introduction

The seismic data used in the research comes from a modern 3D survey located in the NE part of the Carpathian Foredeep Basin, which belongs to the foreland basin system that surrounds the Carpathian orogenic belt (Figure 1). The basin here is filled with thick pelagic and turbidite formations which sedimentation process was influenced by its close proximity to the Roztocze Hills, forming part of the Carpathian forebulge zone. The main objective of the research was a fragment of sedimentation profile of Late-Badenian and Sarmatian age. There is a gas field here below horizon H, which, like most of the local commercial accumulations, is related to the structural trap (Figure 2). All boreholes shown are gas producing, except for well 6 which is negative. Well 9 was not tested for this interval.



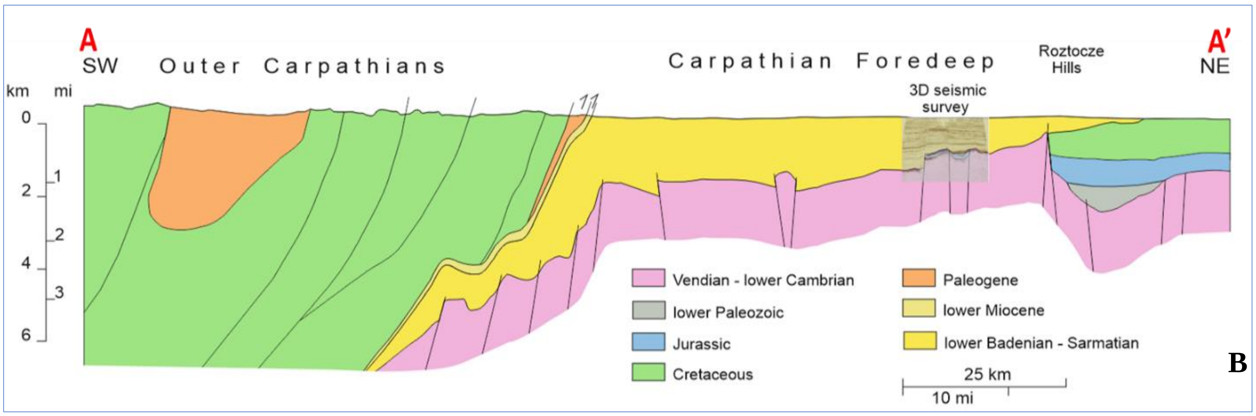


Figure 1. Location map of the study area: NE part of Polish Carpathian Foredeep and the 3D seismic survey (A). Geological cross section AA' through the eastern part of the Polish Outer Carpathians and their foreland (modified after Oszczypko et al. 2005) (B).

High variability of sedimentation environments during the temporal – spatial evolution of a basin fill makes the study area extremely interesting for testing modern tools and unconventional methods. And the main focus of these efforts was to estimate the exploration potential of structures within the basin. There are evidences to suggest that unconventional gas accumulations, related to non-structural types of traps, may occur in this region. Such exploration objects are, in particular, the external and internal elements of submarine channels and fans. The different seismic signatures of these geological forms and the small scale of amplitude variation along with limited visibility make the process of their identification time consuming and difficult.

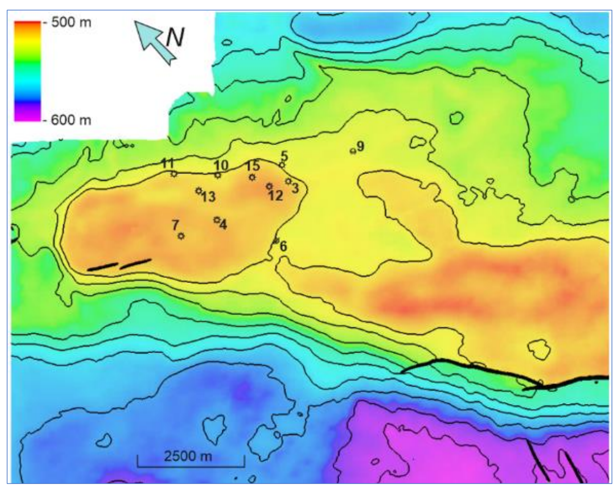


Figure 2. Depth structure map of horizon H.

The key stage of the interpretation workflow was the selection of seismic attributes that are highly sensitive to the presence of the objects sought. Interpretation work was carried out within a specific seismic layer, a target zone, covering only an interval of about 10 – 12 m thick, below the seismic horizon H (Figure 3). This cognitive process was performed in two ways: in a traditional way, through the conventional work of the interpreter and in an automated manner by the use of unsupervised Machine Learning (ML) techniques.

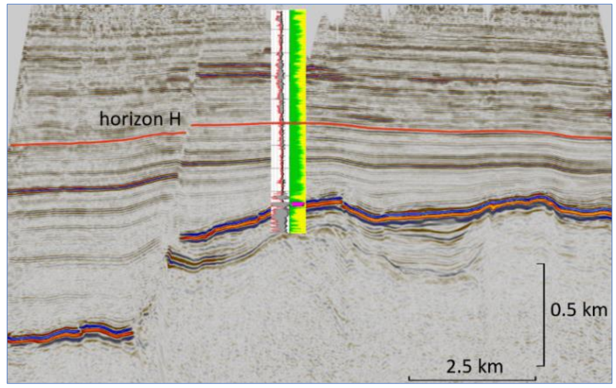


Figure 3. Depth seismic section.

The conventional approach to the interpretation of seismic data was based on the generation and analysis of seismic attributes. The attribute selection list was long including amplitude, frequency, seismic texture or geometric attributes. Most of them has provided a number of clues in the process of detecting potential prospecting objects. However, in the obtained attribute imaging, some inaccuracies were observed with respect to the borehole data. And so, e.g. the popular attribute of the distribution of mean square RMS amplitude values (Figure 4) allows to focus on the right seismic interval and capture potential zone that stands out from the seismic background. The observed amplitude anomaly did not yet allow to determine the genesis of the tested object. The lineaments highlighted in warmer colors suggested the possibility of the presence of channel-like elements. However, the location of producing wells 3, 12 and 13 (with the best reservoir parameters) was not clearly emphasized in this distribution of RMS values.

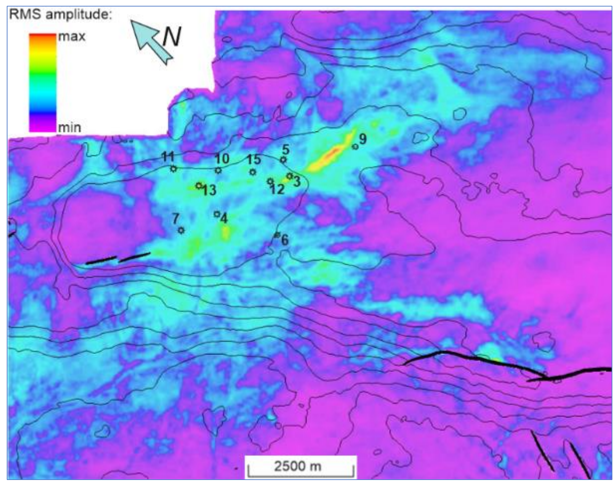


Figure 4. RMS seismic amplitude values distribution map.

In turn, the use of texture attributes (derived by the use of the Grey Level Co-occurrence Matrix method, GLCM) resulted in obtaining a more unambiguous geometry of the examined object (Figure 5). The use of the GLCM method texture attributes in the described case was one of the important elements of the preliminary exploration phase of the seismic data interpretation work (Łukaszewski 2021). These attributes highlighted the internal elements of this object and provided a lot of information about the complexity of the channel system present here. The gas-bearing sand thickness here is about 8 m thick. The other wells, located outside the channel, most probably within the channel fans, have reported lower sand thickness ranges from 2 to 6 m.

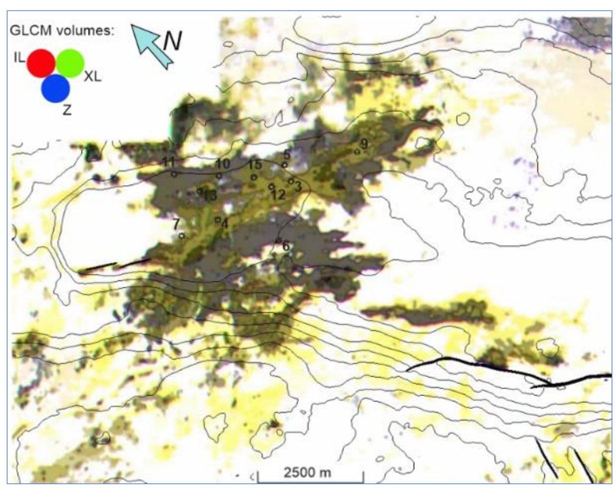


Figure 5. GLCM Energy, a box probe with manipulated transparency.

Hence both: the low thickness along with the low acoustic impedance between channel system and surrounding clastic environment, influenced by gas saturation, most probably caused a barrier for amplitude-based method in this feature detection. Therefore, in further analysis, seismic attributes were used which use the frequency content. For example, it has been shown the Sweetness attribute (Figure 6), as a combination of amplitude and frequency, which is used to emphasize the HC filled reservoir (Hart 2008). Excellent results in the imaging of the examined object were also obtained by selecting iso-frequencies compositions within the chosen interval (Figure 7A).

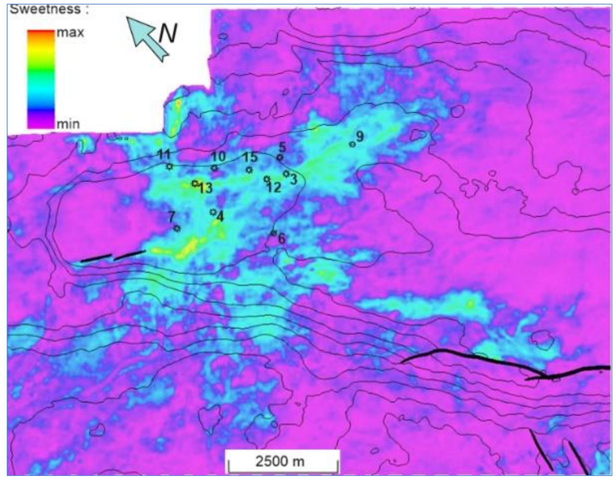


Figure 6. Seismic attribute Sweetness.

An alternative stratigraphic imaging technique such as ExChroma was also used (without using any seismic attribute), obtaining information with

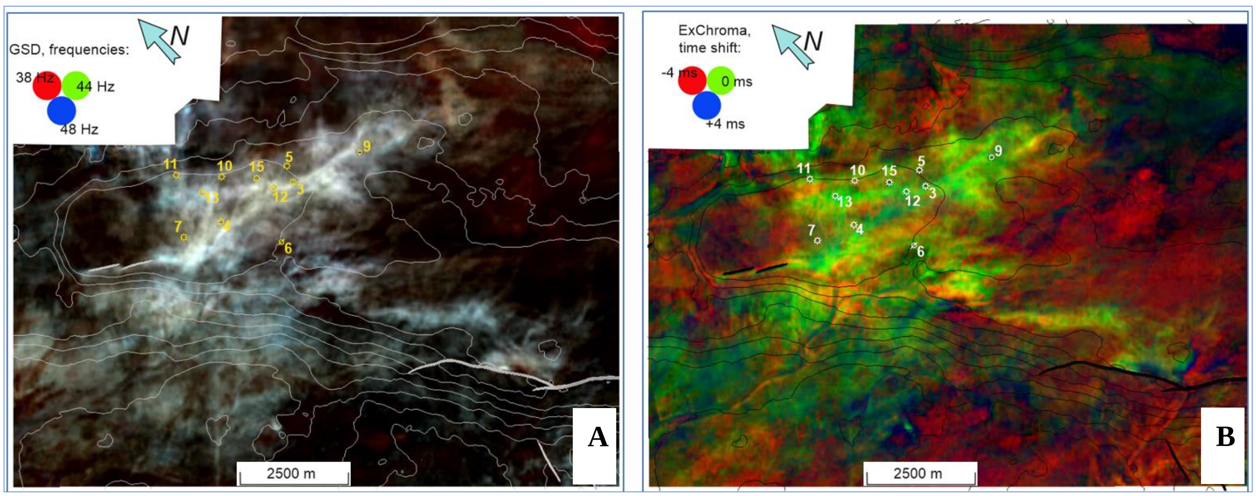


Figure 7. Composite of iso-frequencies 38, 44 and 48 Hz within the chosen interval (A). ExChroma, seismic amplitude volume (B).

a similar level of detail (Figure 7B). In the latter case, new and important information was the perfect imaging of the main channel, now visible in the SW part of the studied area.

All the seismic attributes used provided a lot of information about the tested object. The result of the conventional approach to the interpretation of 3D seismic data is imaged complex of channels with frontal splays and leveed channel (Figure 8). However, it would be difficult to conclude on their basis as to the causes of the negative borehole 6. Also, the quite random location of the boreholes at the northern boundary of this object, 11, 10, 15 and 5 is puzzling given the good reservoir parameters encountered here. Many of the questions posed seem to have been answered by the results of the applied unsupervised ML as described in the next chapter.

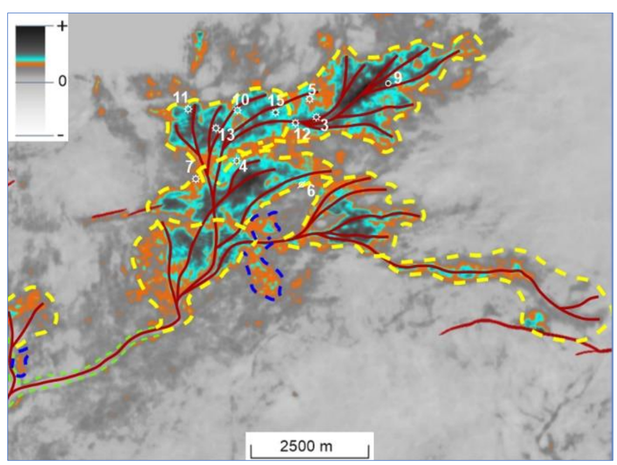


Figure 8. Interpreted distributary channels along with levees, probable crevasse splays and fans. Horizon slice, amplitude seismic volume, dedicated color bar.

Machine Learning technique application methodology

The applied workflow can be described in four main stages:

- selection of long list of seismic attributes,
- Principal Component Analysis (PCA) to reduce the attribute space,
- selection algorithms and parameters testing for unsupervised classification,
- ML application to derived frequency data.

The first stage was largely implemented during the classic approach to facies interpretation of seismic data, described in more detail in the previous chapter. The list of seismic attributes applicable to the fulfillment of prospecting targets was quite long. Hence, in order to select only those carrying the most important information about the analyzed geological object, dedicated tools were used. Principal Component Analysis technique has proven to be an appropriate one for understanding which seismic attribute (or their combination) has interpretive significance (Roden et al. 2015). Seismic attributes with highest percentage contributing to largest variation in the data for first principal component were: Sweetness, Envelope, Intensity and GLCM Energy. In the next stage, the seismic attributes defined by the PCA were the input data for the unsupervised classification. Two classification algorithms were used: simple Neural Net 3D and Kohonen SOM 3D. In the case of the first algorithm, Neural Net 3D, the resulting 10-class volume was found interesting. On the other hand, using the Kohonen SOM 3D algorithm, the resulting volumes with a higher class combination were considered. Finally, the 5×5×5 and 8×8×8 matrices were selected as providing the most informative result. Obtained seismic volumes of Kohonen SOM 3D classification to 125 as well as to 512 classes were subject to a detailed analysis of the observed geobodies within a box probe.

In the last phase of the work, an attempt was made to use ML techniques for derived frequency data (after spectral decomposition transformation). This idea arose as a result of the observed high sensitivity of frequency attributes in the process of detecting subtle geological forms.

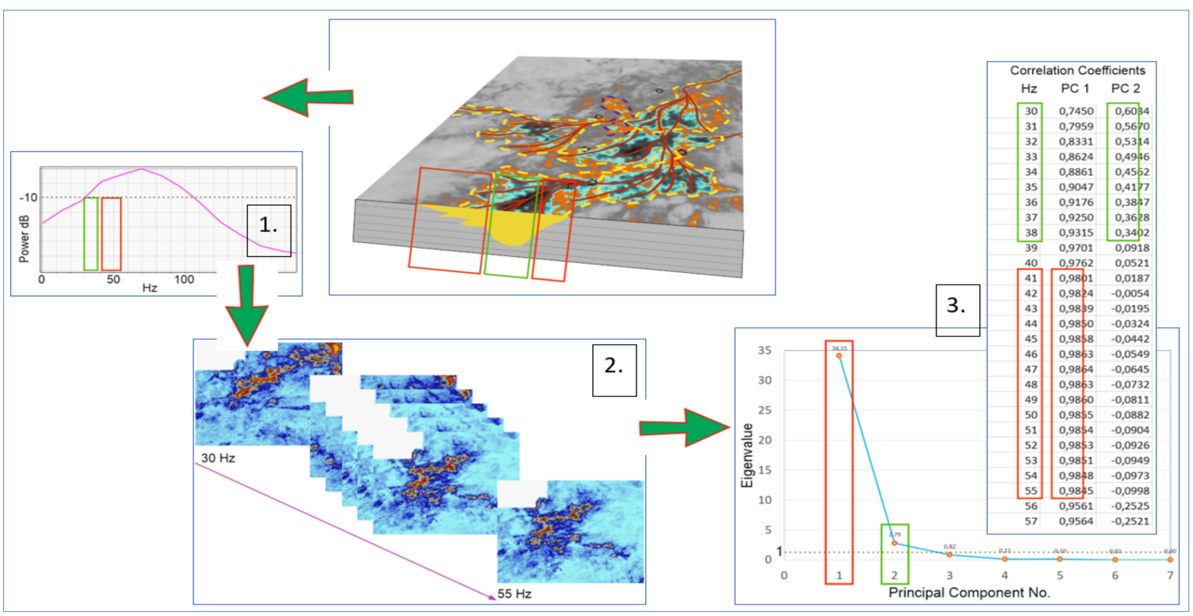


Figure 9. Generalized workflow for frequency data analysis.

Therefore it was required to reuse of frequency-based attributes, but in other way this time (Figure 9). Having frequency spectrum analyzed, a set of 2D amplitude images for chosen frequencies was generated. Attributes were captured from the flattened seismic amplitude volume, along time slice close to the base of the examined channel system. The collection of 28 amplitude maps, for frequency ranges from 30 – 57 Hz, was the input for PCA analysis. As a result, two eigenvectors were selected and the limited number of frequency maps was identified. The first principal component (PC1) revealed the importance of 15 attribute maps, for frequency ranges from 41 to 55 Hz, with their coefficients values above 0.95. The second principal component (PC2) consisted of 9 attribute maps (for frequency ranges from 30 to 38 Hz), with coefficients values around 0.5 – relatively small, but significantly different from the rest of the values. The set of 2D attribute maps, for both PC1 and PC2 (higher and lower frequencies respectively), were the input data for the unsupervised classification using simple Neural Net 2D algorithm.

Results

The resulting 10-class volume after using the Neural Net 3D algorithm very clearly illustrates probably the most sandy elements of the submarine channel complex (Figure 10A). They are described with selected classes 1, 2, 3 and 9 as shown in Figure 10B. Borehole 6 is clearly outside the above-mentioned classes, which is consistent with its negative status.

Wells 13, 12 and 3, with the best reservoir parameters, are located centrally in the element described by class 3, interpreted as one of the channels. However, the obtained results do not explain the situation of producing wells 11, 10, 15 and 5, which seem to be located outside the classes defined in this way. The result of the analysis also indicates several other areas classified in a similar way, which are likely locations for further exploitation works. Figure 11A and Figure 11B show Kohonen SOM 3D classification to 125 classes and to 512 classes respectively. In both cases, only the class range that

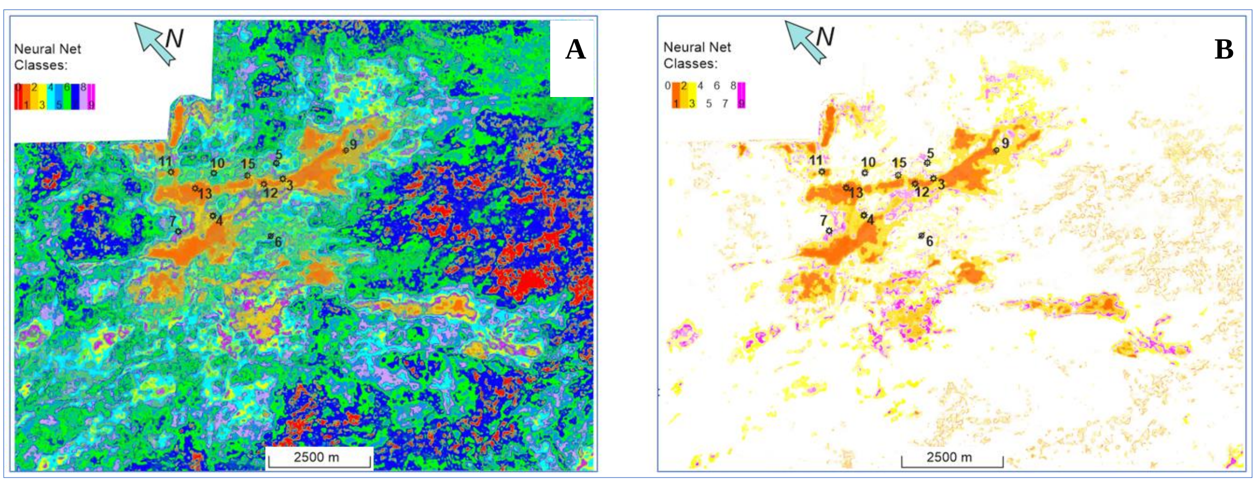


Figure 10. A box probe with manipulated transparency: resulting 10-class volume after applying Neural Net 3D algorithm (A), the selected classes well define the main channels of the studied complex (B).

defines the environment of the submarine channel complex is displayed. The obtained images are very similar to the results of Neural Net 3D, however, due to the much greater number of classes describing them, they are characterized by a greater degree of detail. What has not been achieved in previous analyzes, and appears in the Kohonen SOM 3D results, is one element forming the lineament between wells 11, 10, 15 and 5. It is described in the same class as the already known channels and has been interpreted as most likely an abandoned channel.

Such an interpretation seems to be consistent with the facial situation described in these producing wells.

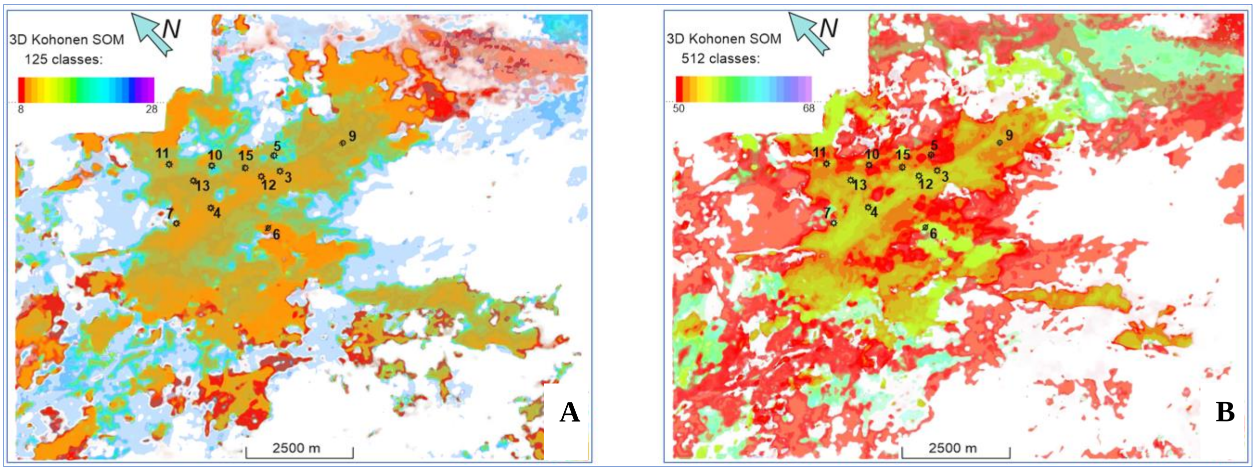


Figure 11. Box probe with manipulated transparency. Kohonen SOM 3D classification to 125 classes, classes 8 to 28 displayed (A). Kohonen SOM 3D classification to 512 classes, classes 50 to 68 displayed (B).

Since different channel thickness will tune with different frequencies (Partyka et al. 1999), the resulting 12-class maps (for both: higher and lower frequencies) constituted an interesting supplement to the analyzes performed, as a source of information on the relative thickness relations. Figure 12 shows the selected classes for both cases.

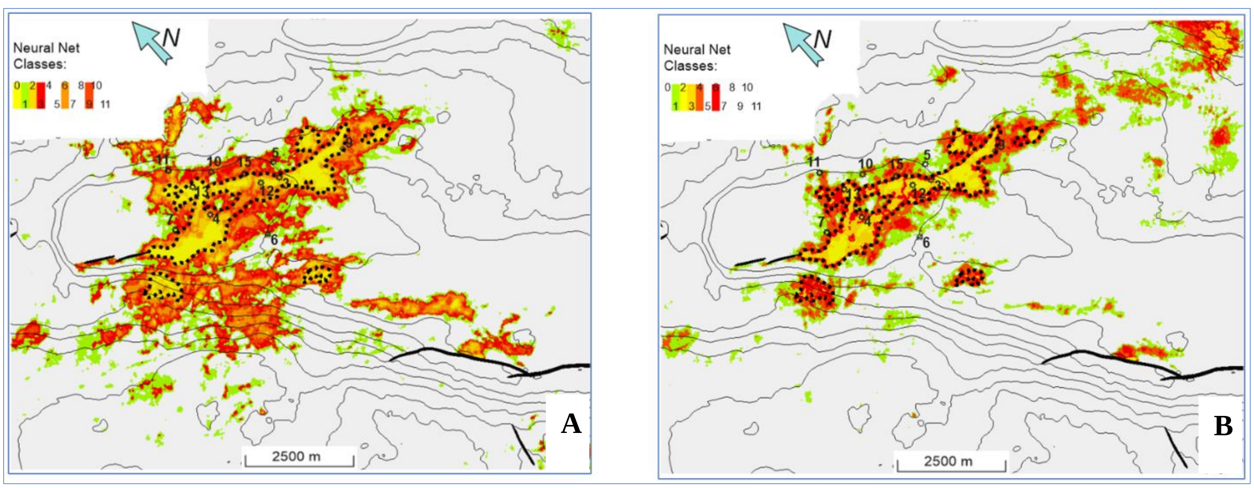


Figure 12. Resulting map after applying Neural Net 2D algorithm for PC1, higher frequencies (A) and PC2, lower frequencies (B). The selected classes (for both cases) show the relative thickness differences within the studied complex.

A black dotted polygon was superimposed on both maps, which is an interpretation of the zones with the highest thickness of sandy channels (based on the Neural Net 2D result for PC2). The resulting image for PC1 (higher frequencies) reveals less thick elements as well as a network of smaller distribution channels from the seismic background. Despite the fact that we are dealing with small thicknesses of sandy sediments (4 - 8 m), the proposed approach to relative thickness analyzes with the use of ML for frequency data brought good results.

The resulting classification image is consistent with the reservoir thickness found in the boreholes (Figure 13).

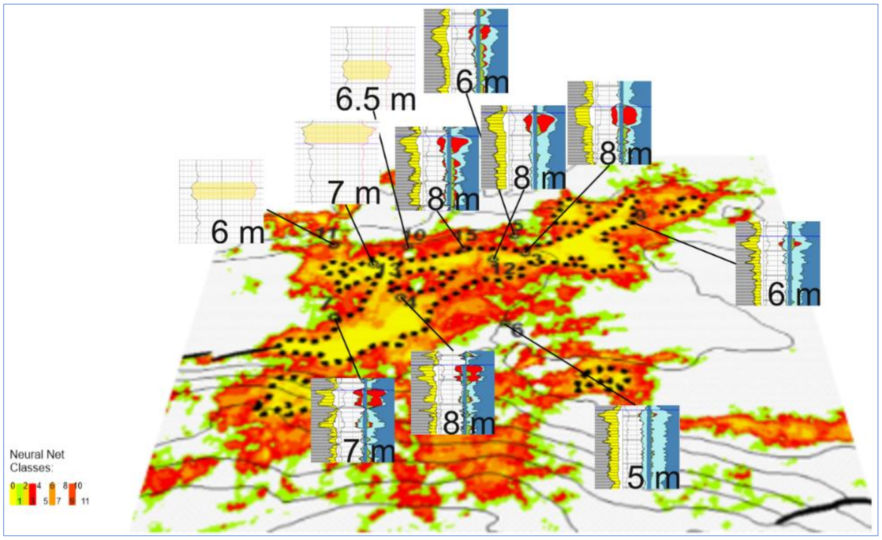


Figure 13. The obtained classification image (Neural Net 2D classification map for PC1) is consistent with the reservoir thickness found in the boreholes.

Conclusions

The obtained images, as a result of the attempts to use ML techniques for detailed recognition of the subtle submarine channel system, provided a lot of information about this stratigraphic feature. The shape of the main producing channel is clearly imaged now and consistent with the available well control. Moreover, the channel has its eastern, unexplored extension. A new object with similar geometric characteristics emerges from the background in a undrilled zone to the south. Apart from the channels, interesting areas highlighted by other classes are also noticed, which would represents other system features, like fans or crevasse splays. The interesting conclusions could be drown also on the possible thickness evaluation of the channel system. Performing the described detailed analysis for this interesting interval of Miocene sediments also has important implications for the gas field with which the studied geological object is undoubtedly related. Figure 14 shows the concept of hybrid hydrocarbon accumulation as would now be considered the gas field mentioned herein. All gas producing wells are located within the 4-way closure structure. The trap in the current interpretation can be extended to the limits of the examined stratigraphic feature, obtaining a new, hybrid closure. Application of unsupervised Machine Learning techniques as a complementary method to the classic interpreter approach, resulted in tangible benefits. It has led to detailed recognition of gas producing subtle submarine channel system, with the possibility of indicating optimal locations for further exploration.

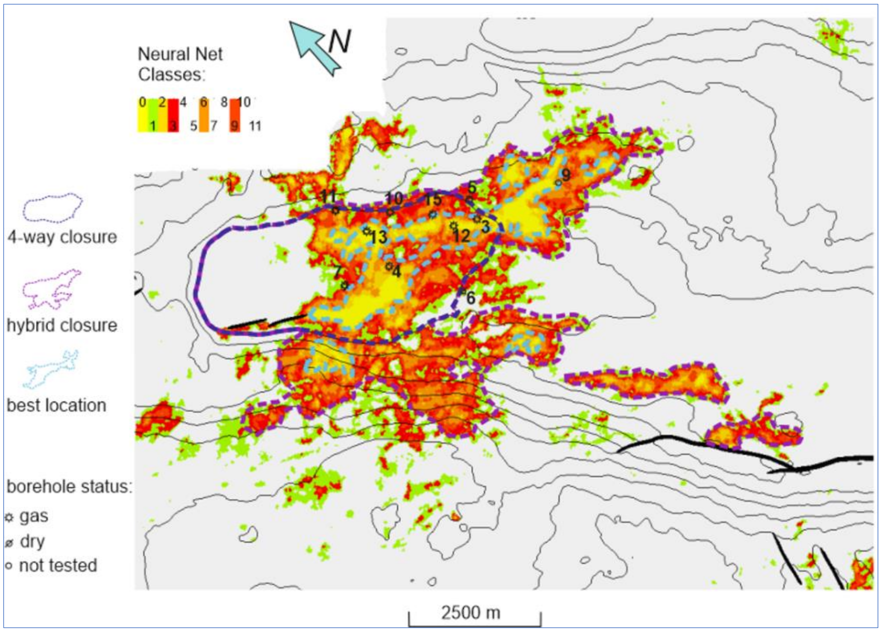


Figure 14. The concept of hybrid hydrocarbon accumulation with optimal locations for further exploration.

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