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Shale Volume, Seismic Attributes, and Proper Data Preparation: Critical Components for Modelling Subsurface Lithology Distribution

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Abstract

The scarcity of well data and the inherent subjectivity of geological interpretations often leads to imprecise or oversimplified subsurface models. Traditional interpretation methods struggle with sparse datasets, necessitating the application of advanced machine learning techniques to enhance subsurface characterization. This study leverages artificial neural networks to predict lithology distribution using seismic attributes in the northern Croatian part of the Pannonian Basin System, an area with numerous exploratory wells. Seismic data, long employed as a supplementary interpretation tool, was used to generate a predictive lithological model, overcoming data limitations inherent to well-based methods. A key focus was the volume of shale, a lithological indicator, which was estimated using an extensive set of seismic attributes and processed through innovative data preparation techniques for artificial neural network analysis. A comprehensive artificial neural network based modelling approach was implemented over a 4365 km² 3D seismic dataset, targeting Pannonian (Late Miocene–Early Pliocene) sediments deposited in deltaic, turbiditic, and lacustrine environments. Results show that standardization of input data significantly improved model accuracy, particularly in capturing key geological features such as meandering sandstone-filled channels. In contrast, normalization led to unreliable predictions, while raw data substantially underestimated sandstone volumes. Despite its advantages, the method's limitations stem from the inherent uncertainty in the volume of shale estimation and interpreter subjectivity. The approach is well-suited for geological settings with two or three dominant lithologies distinguishable on geophysical well logs. While applicable to coal-bearing strata and shale-rich carbonates, its effectiveness in more complex geological settings requires further refinement. The findings highlight the untapped potential of legacy seismic data for geo-energy applications, including hydrocarbon exploration, geothermal studies, and carbon storage.

Keywords: volume of shale, artificial neural networks, lithology mapping, geo-energy exploration

1. INTRODUCTION

The lack of subsurface data and the inherent subjectivity of interpreters have been major contributors to imprecise or overly simplified interpretations and resulting geological models. Well data are often too sparse to enable meaningful interpretations using traditional methods, so the implementation of seismic data with advanced machine learning techniques is expected to yield better modelling results (SMIRNOFF et al., 2008; ZHOU et al., 2019; FENG et al., 2024; ZHOU & LIU, 2024). Machine learning techniques enable the combination of well and seismic derived properties in a time efficient way which can greatly improve the accuracy and the resolution of the resulting geological model.

Visualizing subsurface lithology, including the volume and spatial distribution of rock types, typically starts with well data. This generally refers to well logs and information about the lithology of well cuttings and core samples if available. However, in many regions worldwide, the number of wells is limited, they are either sparsely distributed, or the available data is old. The Croatian part of the Pannonian Basin System is characterized by a several hundred, old exploratory wells, some of which were drilled over 50 years ago. Therefore, seismic data has long been used as a supplementary tool to aid the geological interpretation process, offering valuable insights into subsurface characterization (NOVAK ZELENIKA et al., 2018; VUKADIN, 2022; XU & HAQ, 2022). In recent years, this type of study has increasingly relied on the application of artificial neural networks for various purposes: lithology prediction (BRCKOVIĆ et al., 2017; KAMENSKI et al., 2020), estimation of porosity and permeability (ITURRARÁN-VIVEROS & PARRA, 2014), seismic reservoir characterization (OTHMAN et al., 2021), shale volume prediction (TAHERI et al., 2021; MOHAMMADINIA et al., 2023), two-way-time prediction (KAMENSKI et al., 2024).

Recent studies in northern Croatia, specifically within the southwestern part of the Pannonian Basin System, have

explored the application of neural networks to enhance the independence and accuracy of subsurface interpretations based on various geophysical datasets (seismics, well logs), in combination with well data (BRCKOVIĆ et al., 2017; KAMENSKI et al., 2020; KAMENSKI et al., 2024). These studies demonstrated the effectiveness of neural networks, particularly in scenarios with limited data. For instance, the inevitable challenges of time-to-depth conversions were successfully surpassed using neural networks, which predicted two-way-time data from stratigraphical and petrophysical parameters in the depth domain, particularly in scenarios where conventional time-to-depth conversion data were unavailable (KAMENSKI et al., 2024). Efforts have also been made to predict lithology based on sparse well and seismic data (BRCKOVIĆ et al., 2017; KAMENSKI et al., 2020). These investigations provided valuable new insights into subsurface characterization in northern Croatia, while also highlighting challenges of lithology prediction, such as the inadequate upscaling of well logs (KAMENSKI et al., 2020).

To determine the lithology distribution in areas where only seismic data is available and well data is sparse, this study utilized an extensive set of seismic attributes to predict the volume of shale, a parameter that serves as an indicator of lithology distribution. Furthermore, this approach was tested with legacy data, as pre-stack seismic data, which can be utilized for lithology prediction, is often unavailable (ADEOTI et al., 2017; BORNARD et al., 2005). To achieve this, innovative data preparation processes were implemented.

This study highlights the successful application of available legacy data, revealing its substantial untapped potential that has yet to be fully utilized when processed by artificial neural network algorithms. Neural networks were chosen for lithology distribution prediction over other machine learning approaches for several key reasons. Primarily, neural networks represent an excellent tool for capturing complex, non-linear relationships inherent in geological data, which makes them well-suited for modelling intricate subsurface patterns. Additionally, they have proven successful in similar applications, such as predicting porosity and permeability (e.g., ITURRARÁN-VIVEROS & PARRA, 2014), further validating their effectiveness in geoscientific tasks. To demonstrate this approach, a study area with available 3D seismic data, covering 4365 km^2 in the northern part of Croatia was selected (Fig. 1) to investigate the possibility of predicting the general lithology distribution within the Pannonian stratigraphic interval based on seismic attributes.

Results from this study can have application in geo-energy characterization for various purposes, from hydrocarbon exploration, geothermal investigations, carbon capture, utilization and storage, etc.

2. GEOLOGICAL OVERVIEW

The study area, located in the North Croatian Basin (NCB), lies within the southwestern part of the Pannonian Basin System (PBS). Base of the Neogene-Quaternary infill is represented by Palaeozoic crystalline and partially metamorphosed rocks, which are in places overlain by Mesozoic carbonates (PAMIĆ & LANPHERE, 1991; PAMIĆ, 1998; PAVELIĆ, 2001; VELIĆ, 2007; MALVIĆ & CVETKOVIĆ, 2013; PAVELIĆ & KOVAČIĆ, 2018). Basin evolution is associated with rifting, and syn-rift and post-rift sediments can be distinguished (LUČIĆ et al., 2001; SAFTIĆ et al., 2003; PAVELIĆ & KOVAČIĆ, 2018; RUKAVINA et al., 2023). The extension began during the Ottnangian and Carpathian and is believed to have been driven by the eastward extrusion of the Alps (FODOR et al., 1999). In these conditions, deposition of coarse-grained sediments (rock-fall breccias and conglomerates) interlayered with sandy and silty layers took place (PAVELIĆ & KOVAČIĆ, 2018). The extension was accompanied by a later marine transgression and volcanic activity in the Badenian (LUČIĆ et al., 2001; SAFTIĆ et al., 2003; ĆORIĆ et al., 2009; MARKOVIĆ et al., 2021). Depositional environments during the Badenian were very diverse. Locally, marsh-type fine-grained sediments can be found, which are overlain by carbonate deposits (BAKRAČ et al., 2010). Deepening of the depositional environment resulted in the lacustrine sedimentation of shales, and siltstones, together with thin, sandy turbidites and occasional conglomerates (PAVELIĆ & KOVAČIĆ, 2018), with sporadic occurrences of pyroclastics resulting from accompanying volcanism (PAVELIĆ, 2001; SAFTIĆ et al., 2003). A change of depositional environment from lacustrine to marine occurred during the Middle Badenian with deposition of shales interlayered with coarse grained clastics (PAVELIĆ & KOVAČIĆ, 2018). The Late Badenian is characterized by the end of the syn-rift phase and the beginning of the post-rift phase (PAVELIĆ, 2001; PAVELIĆ & KOVAČIĆ, 2018). During the Late Badenian, carbonate sedimentation on small carbonate platforms, formed around islands, was followed by marl deposition in the deeper parts of the sea (VRSALJKO et al., 2006; PAVELIĆ & KOVAČIĆ, 2018). By the latest Badenian, a general shallowing occurred, marked by deposition of biocalcarenites and conglomerates, reduced volcanic activity, and localized emersions. The breakup of central Paratethys started in the latest Badenian when it lost connection to the Indo-Pacific Ocean and the palaeo-Mediterranean Sea (RÖGL, 1999). The isolation of the basin and subsequent salinity fluctuations at the Badenian/Sarmatian boundary led to the extinction of most stenohaline marine organisms, while unique associations adapted to the new conditions, emerged or migrated from Eastern Paratethys, marking the Sarmatian age of the deposits (PAVELIĆ & KOVAČIĆ, 2018 and references therein). The final separation of the Pannonian Basin System from other surrounding marine environments took place at the end of the Middle Miocene (ĆORIĆ et al., 2009).

The post-rift phase of PBS development was characterized by a thermal subsidence due to lithospheric cooling (PAVELIĆ & KOVAČIĆ, 2018), resulting in the creation of significant accommodation space. This phase was characterized by the deposition of thick sand and marl sequences in brackish conditions within Lake Pannon (LUČIĆ et al., 2001; SAFTIĆ et al., 2003; PAVELIĆ & KOVAČIĆ, 2018). During the Pliocene and Quaternary, the stress regime turned to compressional, which resulted in activation of reverse faults and reactivation of normal faults with reverse displacement characteristics (HORVÁTH & CLOETINGH, 1996). Sedimentary environments were shallower than in the Pannonian with

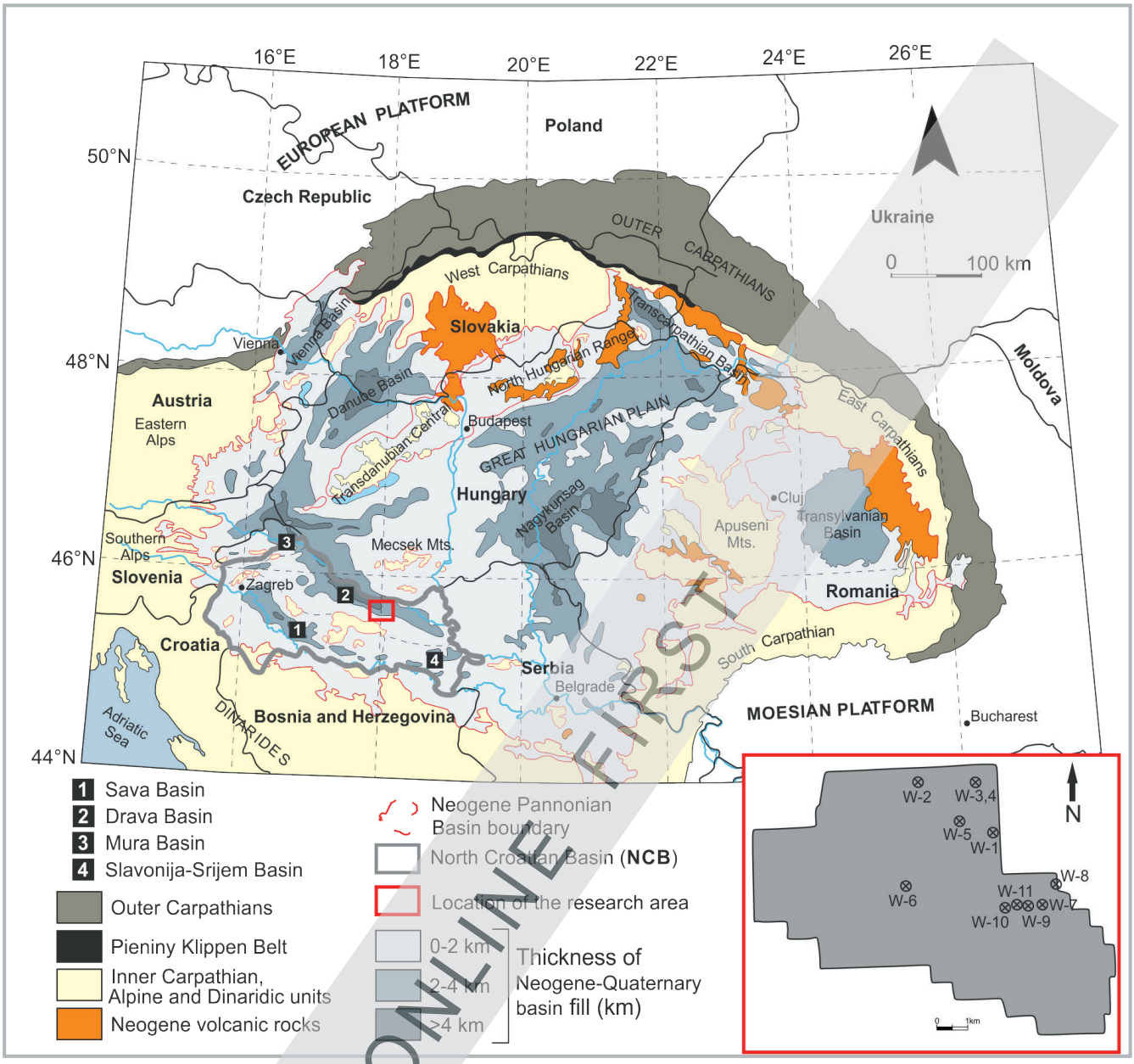

Figure 1. The Pannonian Basin System with the outline of the North Croatian Basin and the study area location. The red rectangle represents the extent of 3D seismic coverage of the "Donji Miholjac" 3D seismic block with the locations of 11 wells highlighted, enlarged in the inset at lower right corner (modified from Cvetković et al. (2019), after Dolton (2006) and Schmid et al. (2008)).

fluctuations from lacustrine and marsh to terrestrial (CVETKOVIĆ, 2013). Lithologically, they are represented by sands, clays and gravel with occasional coal seams or layers. As the tectonic regime shifted from extensional to compressional, basin inversion occurred which led to the formation of structural traps within the older Pannonian sediments.

The NCB's marginal position within the PBS results in generally thinner Neogene sedimentary sequences compared to the central part of the PBS, with the exception of the Drava Basin where the Neogene sedimentary sequence reaches a thickness of almost seven kilometres (SAFTIĆ et al., 2003; VELIĆ, 2007; CVETKOVIĆ et al., 2019).

The focus of this research is the sediments of the Pannonian (Late Miocene–Early Pliocene), that were deposited after the Central Paratethys Sea transitioned into the brackish Lake Pannon around 11.6 million years ago. Pannonian sediments, primarily derived from the Eastern Alps and the Western Carpathians, were deposited in a variety of environments, including deltaic, turbiditic, and lacustrine settings (KOVAČIĆ & GRIZELJ, 2006; PAVELIĆ & KOVAČIĆ, 2018; MATOŠEVIĆ et al., 2024a). The Pannonian deposits include lacustrine marls and limestones in the early stages, followed by sands and siltstones from deltaic environments as the lake progressively filled. These deposits serve as significant source rocks, reservoirs, and caprocks in the Croatian part of the PBS (LUČIĆ et al., 2001; SAFTIĆ et al., 2003).

3. METHODOLOGY

For the task of determining the spatial distribution of lithology throughout the study volume, a comprehensive workflow was implemented. This began with the definition of the model

boundaries. The top and bottom of the model were delineated based on regional well tops identified using resistivity well logs. For this study, focusing on the sediments of the Pannonian stratigraphic interval, the regional marker "α" was chosen as the model's top surface and "Rs_7" as its bottom, i.e. Top Pannonian and Base Pannonian surfaces respectively. Lateral boundaries were defined with the 3D seismic volume coverage.

Exploratory wells within the study area were very scarce, so all the wells which at least partially intersected the chosen interval were taken into the analysis. A total of 11 wells were included: eight that drilled trough both the Top Pannonian ("α") and Base Pannonian ("Rs_7") boundaries, and three which were terminated before reaching the Base of the Pannonian, i.e. intersecting only part of the interval of interest. The Top Pannonian well top ("α") is not identified by distinct patterns in the apparent electrical resistivity curve. Instead, it is defined as the transition point where the resistivity curve shifts from a shallower zone with high variability in resistivity to a deeper zone characterized by more stable resistivity values. This transition is the result of change in depositional conditions, specifically the shift from deeper-water lacustrine sedimentation during the Pannonian to shallow lacustrine and alluvial sedimentation in the Pliocene of the Drava Basin and also in the western part of the Sava Basin, which is characterized by more frequent vertical and lateral lithological variations, reflected on the resistivity curve (CVETKOVIĆ, 2017). Well top "Rs_7" was defined by an emphasized increase in resistivity values at the transition from the Lower Pannonian limey shales to the Middle Miocene limestone, due to pronounced resistivity differences between the limestones and shales (PALACKY, 1988). A well to seismic tie was performed either on the basis of available vertical seismic profiling measurements in the wells or with the artificial neural network approach as in KAMENSKI et al. (2024). These horizons were mapped across the "Donji Miholjac" 3D seismic block (Fig. 2), producing interpreted surfaces that defined a study area of 4,365 km² with a total volume of 11,660 km³.

A volume of shale (V_{sh}) analysis was performed by interpreting the Spontaneous Potential (SP) log (Fig. 3), as Neutron, Spectral Radioactivity, Resistivity, and Gamma ray logs were excluded from the analysis due to technological and/or geological constraints specific to the study area. This widely used procedure (SERRA, 1984; ASQUITH & KRYGOWSKI, 2004) is based on the assumption that the SP deflection between the static value of SP (SSP) in a clean sandstone and shale baseline (representing 100% shale) is proportional to the volume of shale (RIDER, 2002), i.e. it assumes that the volume of shale at any given point can be estimated by linear interpolation between the SP value having 0% of shale (SP_{clean}) and the shale baseline value (SP_{shale}) having 100% of shale (Equation 1):

$$V_{sh} = \frac{SP - SP_{clean}}{SP_{shale} - SP_{clean}} \cdot 100 \quad (1)$$

where SP represents reading of SP value in any point of interest.

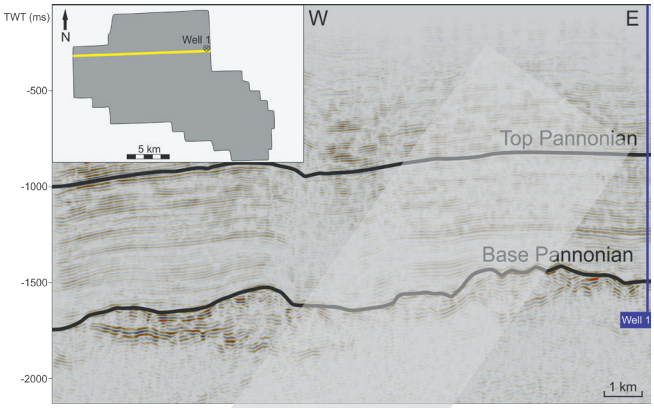

Figure 2. Inline seismic section highlighting the interpreted Top and Base Pannonian surfaces of the subsurface model. The inset indicates the location of the seismic section within the study area.

Once the volume of shale (V_{sh}) values were obtained for all 11 wells, upscaling was performed to firstly average the V_{sh} value within the corresponding model cell and to enable integration with the seismic data. This was performed for models with 20, 50, 100 and 200 layers. Based on the results and to mitigate overestimation of the predominant lithology, the selected model was the one stratified into 200 layers, maintaining an average cell height of 6.5 metres. This approach effectively prevented excessive layering thickness, ensuring that the upscaling process did not introduce biases in lithology distribution predictions by the artificial neural networks (ANNs). Overestimation of the predominant lithology had been a significant challenge in previous studies (KAMENSKI et al., 2020), but this refined layering strategy minimized such distortions.

Following the upscaling of the volume of shale (V_{sh}) values, selected seismic attributes were extracted at the upscaled data points, forming a comprehensive dataset for ANN training. This step ensured that the model retained both the geological resolution necessary for more realistic lithology prediction and the statistically valid dataset required for effective machine learning applications.

Seismic attributes contain a huge amount of data which holds significant relationships between the physical characteristics that remain undetectable through conventional seismic visualization techniques (TANER et al., 1976; TANER, 2001). These attributes, derived from seismic data, capture kinematic, dynamic, geometric, and statistical characteristics, play a fundamental role in structural, stratigraphic, and petrophysical interpretation. Their application significantly enhances subsurface analysis and reservoir characterization (DJEDDI, 2016).

In this study, the selection of seismic attributes was guided by their ability to emphasize lithological and morphological features, thereby aiding artificial neural networks in producing geologically coherent lithology distribution predictions. Seismic attributes that capture key lithological and morphological features were generated based on comprehensive reviews of seismic attribute application (CHOPRA & MARFURT, 2006; LIU & MARFURT, 2006; KER et al., 2014; BRCKOVIĆ et al., 2017; LI et al., 2019; OUMAROU et al., 2021). Twelve attributes were constructed: Sweetness, 3D Curvature, Vari-

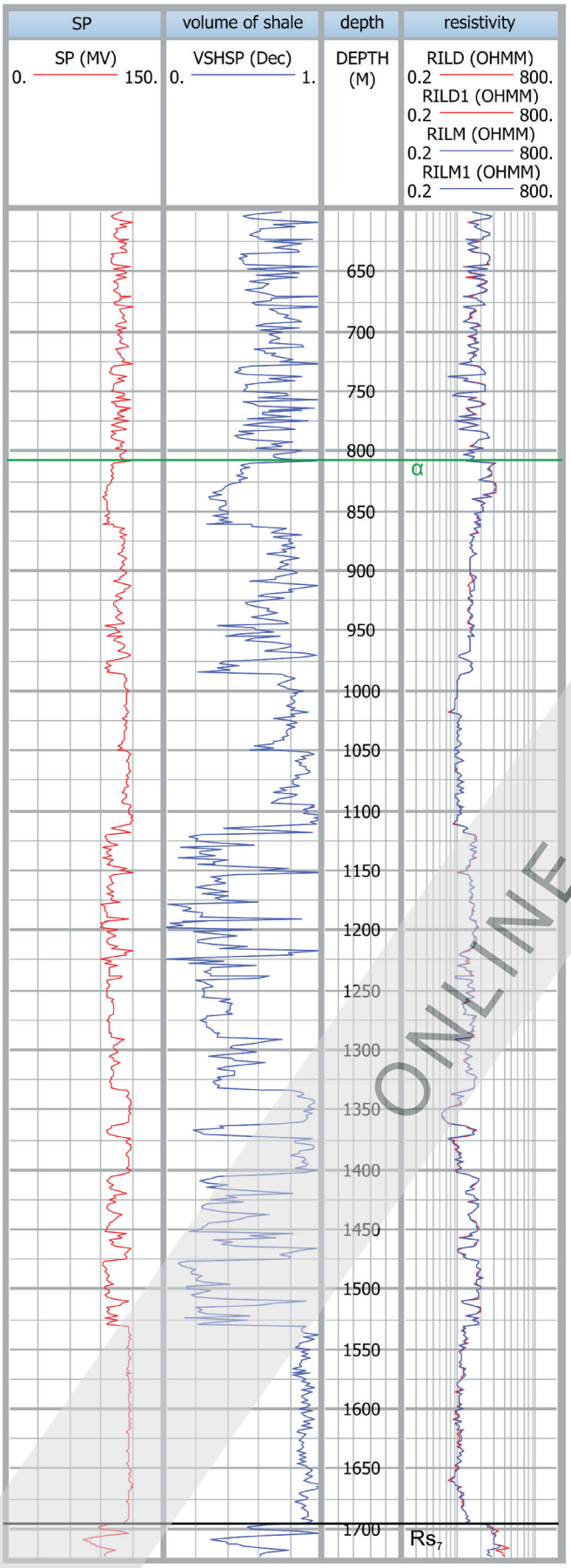

Figure 3. Well logs for Well-1: the SP log is shown in red, the calculated volume of shale is represented in blue, and resistivity logs in both red and blue. Green and black horizontal lines indicate the regional markers "α" and "Rs_7".

ance, Original Amplitude, Instantaneous Frequency, Envelope, Instantaneous Phase, Generalized Spectral Decomposition, Apparent Polarity, Reflection Intensity, Root-Mean-Square (RMS) Amplitude and Relative Acoustic Impedance.

Sweetness and RMS Amplitude effectively detect and display coarse-grained intervals and compaction features (SUBRAHMANYAM & RAO, 2008; KOSON et al., 2014). Variance (edge) and Reflection Intensity serve as reliable indicators of lithology variations (PIGOTT et al., 2013; KOSON et al., 2014), while Original Amplitude provides a clear representation of sediment continuity and discontinuity (BRCKOVIĆ et al., 2017 and references therein). Additionally, Apparent Polarity is mostly related to the useful detection of gas-charged layers (KER et al., 2014).

OUMAROU et al. (2021, and references therein) demonstrated that Instantaneous Frequency aids in seismic facies recognition, while 3D Curvature is crucial for identifying structural features such as channels, faults, anticlines, synclines, and salt domes. Instantaneous Phase delineates subsurface layering, whereas Instantaneous Frequency and Generalized Spectral Decomposition assist in layer thickness estimation and seismic geomorphology analysis (LIU & MARFURT, 2006; LI et al., 2019). Furthermore, Envelope and Relative Acoustic Impedance (RAI) provide insights into lithology, thickness estimation, and sequence delineation, and offer valuable information regarding porosity and permeability (OUMAROU et al., 2021; PIGOTT et al., 2013; KOSON et al., 2014).

Input data for ANN analysis consisted of data points created along well paths, each containing X, Y, Z coordinates, 12 seismic attributes and shale volume values (Fig. 4a, b). Data was statistically processed before the ANN training process. Feature scaling was applied to mitigate the significant scale differences among seismic attributes. Three input versions were prepared: Raw data, Normalized data (rescaled between 0 and 1), and Standardized data (centered at a mean of 0 with a standard deviation of 1). Normalization and standardization processes ensured uniform scaling across all features, including seismic attributes and volume of shale values, which inherently range from 0 to 1.

Data normalization was performed using following Equation 2:

$$x_{normalized} = \frac{(x - x_{\min})}{(x_{max} - x_{\min})} \quad (2)$$

Data standardization was performed using following Equation 3:

$$x_{standardized} = \frac{(x - \text{mean } of \text{ } range)}{\text{standard deviation of range}} \quad (3)$$

ANN analysis was performed in Tibco Statistica within the Statistica (Neural Nets) module. The process consists of the general selection of the ANN architecture constraints (minimum and maximum number of neurons in the hidden layer, activation functions and number of networks to be trained and retained), and the distribution of data into training, test and validation datasets. In this study, 80% of the cases were used for the training dataset, while the remaining 20%

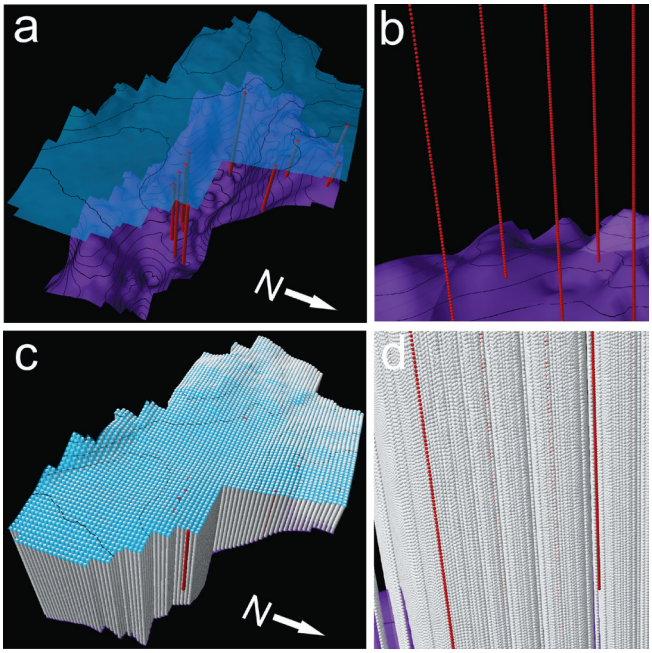

Figure 4. a, b) The blue surface represents the Top Pannonian surface, while the purple surface denotes the Base Pannonian surface. Red points indicate cells containing values for 12 seismic attributes and volume of shale (V_{sh}), which served as training input data for the artificial neural networks (ANNs); **c, d)** White points represent the data points where ANN predicted the volume of shale (V_{sh}) based on assigned seismic attribute values.

was evenly split between testing and validation. The number of iterations of the learning process is not strictly defined but is in the function of the prediction error decay. The learning process stops when the error on the training dataset does not significantly change or the error value is extremely variable for 20 consecutive iterations. The workflow follows three possible end conditions. The first occurs when optimal parameters are achieved, ensuring accurate predictions. The second arises when the ANN algorithm fails to predict the target variable, resulting in random output values. The third end condition is triggered when error values in the test and validation dataset begin to rise, indicating overtraining of the ANN. In all cases, the final network parameters are determined based on their optimal performance across the training, test, and validation datasets.

For prediction, 747,800 cells were generated within the geological model (Fig. 4c, d), with appended seismic attribute values. The trained ANNs (using Raw, Standardized, and Normalized datasets) were applied to predict shale volume for each cell.

Well-log interpretation was performed using Interactive Petrophysics (IP 2021) software, Petrel Schlumberger software package was used for seismic interpretation, attribute extraction, and model construction, and Statistica Tibco for ANN analysis. Additional calculations were performed in Excel.

4. RESULTS

Four subsurface models were constructed to determine the optimal layer thickness for the training and prediction process. These models varied only in the number of layers, which were set to 20, 100 and 200. The corresponding vertical point spacings for these models were an average of 79 m, 16 m and 8 m, respectively. The layering itself has an impact on the analysis in two ways. First, the layer height has a direct effect on the upscaling of the V_{sh} and seismic attribute values. As the layer thickness increases, more values will be averaged representing one data point in the well trajectory (Fig. 4b). Secondly, the number of cases for the ANN analysis significantly decreases from 1888 for the 200-layer case to 193 for the 20-layer case. This has a significant impact on the degree of success of the ANNs training process as it is sensitive to the number of cases for analysis (ALWOSHEEL et al., 2018).

Numerous iterations of the ANN parameters were tested to obtain the best output, as determined by correlation coefficients. The optimal neural network architecture was achieved with a learning rate of 80%, using a neural architecture search as the optimizer and the correlation coefficient as the error metric. Regarding predictions based on standardized and normalized data, the logistic sigmoid function proved to be the best activation function for both the hidden and output layers. In contrast, for raw data, best performance was obtained using the logistic sigmoid function for the hidden layer and the sinusoidal function for the output layer. The predictive performance of ANNs for the volume of shale values was evaluated using correlation coefficients of the target (interpreted V_{sh} value) and the predicted value of V_{sh} (Table 1), with the correlation coefficient serving as the primary metric for distinguishing between high- and low-efficient neural networks. The highest predictive accuracy was achieved in the model with most layers (Table 1, Model 200 layers). Among the tested models, the ANN trained on input data from the 200-layer model demonstrated to be the most successful and was therefore selected for further investigation (Table 1). ANNs trained on models with less than 100 layers had poorer performance (20-layer model) or were completely unable to predict the V_{sh} data (50-layer model which was omitted from the study).

To predict the volume of shale across the entire 3D seismic coverage, a model with 747,800 cells was generated (Fig. 4c, d), each containing values from 12 selected seismic attributes. These input data were processed using the same methodology as the training dataset. The most effective ANN architecture was then deployed to predict the volume of shale values across

Table 1. Correlation coefficients representing the performance of artificial neural networks for the three differently layered models. Bold results represent the model which is selected for artificial neural network analysis to predict the volume of shale values throughout the investigated area. The network architecture is represented by the number of neurons in the input, hidden and output layer, while the number in brackets indicates the number of learning iterations.

Input data	Correlation coefficients		
	Model 20 layers	Model 100 layers	**Model 200 layers**
Raw	0.34	0.49	**0.68**
Normalized (Norm)	0.31	0.60	**0.70**
Standardized (STD)	0.33	0.43	**0.72**
	Network architecture		
Raw	12-123-1 (23)	12-161-1 (83)	**12-128-1 (270)**
Normalized (Norm)	12-181-1 (22)	12-138-1 (124)	**12-145-1 (208)**
Standardized (STD)	12-132-1 (21)	12-168-1 (92)	**12-80-1 (209)**

the target dataset, which consisted solely of 3D seismic attribute values. Table 1 demonstrates that standardized data produced the most efficient ANN predictions, whereas raw datasets yielded the least accurate predictions (Table 1, Model 200 layers).

Predicted shale volume values were categorized as follows: ≤0.5 as Sandstone, 0.5–0.7 as Sandstone-Shale, and ≥0.7 as Shale. These classifications were upscaled for lithology modelling, resulting in three distinct models corresponding to Raw, Standardized, and Normalized input data (Fig. 5).

The predicted lithology distribution for the model constructed from standardized (STD) input data suggests 52.17% Shale, 29.89% Sandstone-Shale and 17.94% Sandstone. For the model based on normalized (Norm) input data, the distribution was 55.14% Shale, 42.59% Sandstone-Shale, and 2.27% Sandstone. Predictions from raw (Raw) input data resulted in 38.12% Shale, 48.57% Sandstone-Shale, 13.31% Sandstone.

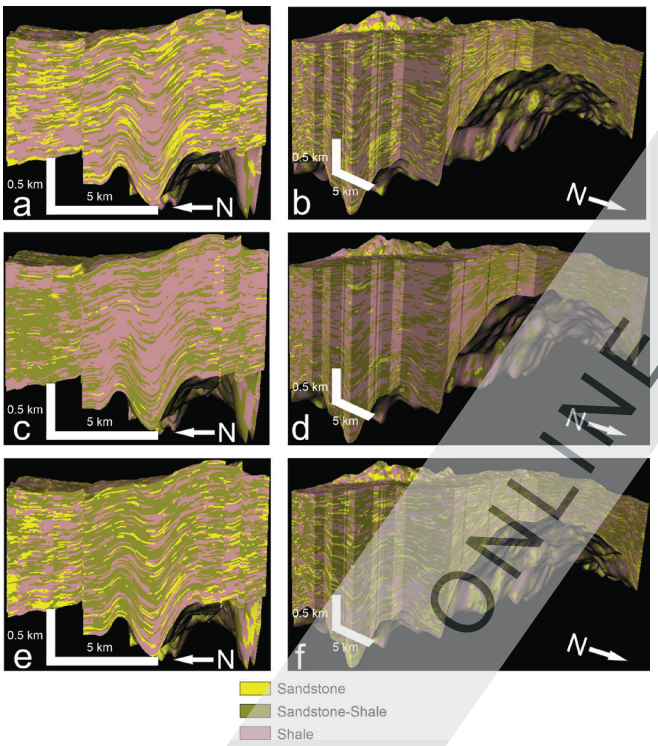

Figure 5. Lithology models developed using predicted volumes of shale values derived from: **a, b)** Standardized (STD) input data; **c, d)** Normalized (Norm) input data; and **e, f)** Raw input data.

5. DISCUSSION

The volume of shale (V_{sh}) was calculated from the Spontaneous Potential (SP) log. The Neutron log was not used due to the simple fact that only small intervals in the wells had a neutron log recorded, so in order to preserve consistency across the investigated interval, the electrolog was expected to be a better solution. Also, the Neutron log is, due to its shallow depth of penetration and consequential effect of wellbore conditions caused by the increased well diameter in clayey rocks, prone to misleading volume of shale estimates (KAMAYOU et al., 2021). The Resistivity log was not used because of the mineral composition of the Pannonian sandstones, which are lithic arenites with significant content of calcite, feldspars and micas (MATOŠEVIĆ et al., 2023, 2024a, 2024b). Namely, PIMIENTA et al. (2019) indicate significant differences in the resistivities of quartz-rich sandstones and feldspar rich sandstones, the latter showing significantly lower resistivities which could result in overestimated values of shale volume. Gamma ray (GR) cannot be used in the studied settings for the same reason – the significant content of feldspars and micas in the Upper Miocene sandstones, i.e. their potassium content, affects the GR readings (IMAM & TREWIN, 1991) leading to overestimated volume of clay/shale values (KAMEL & MABROUK, 2003). The thorium content from the Spectral Radioactivity log could be considered (RIDER, 2002) in a given setting, but the problem was the availability of Spectral Radioactivity logs that are very rare for the study area.

SP should not be used to estimate shale volume in areas where formation water resistivity (R_w) is not much different from mud filtrate resistivity (R_{mf}) (KAMEL & MABROUK, 2003), but that was not a limiting factor in the study area where the mud filtrate generally shows significantly different resistivity compared to the formation water. However, the shallower parts of the investigated unit/intervals could be affected by this limitation, due to the lower total dissolved solids (TDS) of the formation water, but short intervals of formation water salinity change mostly coincided with the upper boundary of the model – well top "α", Top Pannonian surface.

The upscaled volume of shale values served as the input variable for modelling, ensuring continuity rather than discrete categorization, as seen in previous studies (BRCKOVIĆ et al., 2017; KAMENSKI et al., 2020). This approach demonstrated the successful application of continuous input data in artificial neural networks, a methodology not commonly adopted in earlier research. Additionally, the upscaling process was carefully managed by implementing thin layering, effectively preventing overestimation of the predominant lithology. This was evident by the network performance increase with the increase of the number of layers within the geological model. Oversimplification in geological models with layers thicker than 16 metres led to poor performance or the complete inability of the ANN processing the input data to predict the V_{sh}.

Based on the performance of the ANN training (Table 1, Model 200 layers), the best results were achieved using Standardized input data, followed by Normalized data and, lastly, Raw data. It is anticipated that Normalized or Standardized input data would yield better predictions, as Raw data contains original seismic attribute values that show significant variations and difference in magnitude. For example, the range of 3D Curvature spans from -0.56 to 2.33, Original Amplitude units range from -63,668.92 to 52,227.58, and Envelope values range from 459.39 to 73,946.72, while the volume of shale (V_{sh}) values range from 0 to 1. This high inconsistency in scale poses substantial challenges for ANNs to accurately predict V_{sh} from seismic attributes. The normalization and standardization processes enable a more balanced representation of the features, improving model performance.

Better performance of standardization compared to normalization can be attributed to the original data being more accurately characterized by mean and standard deviation, resulting in a standardized value range of -10.53 to 14.13, as opposed to the constrained normalization range of 0 to 1. These findings strongly suggest that preprocessing data, either by standardization or normalization, is essential for accurately predicting the volume of shale values from seismic attributes.

However, the results from lithology modelling offer distinct insights into the impact of data preprocessing on model accuracy and geological consistency. While preprocessing input data generally improves model performance, this study confirms that the benefits are particularly pronounced when using Standardized input data. The lithological model generated with STD data produced results that align closely with geological expectations, exhibiting features such as well-developed meander channels filled with sandstones. These results are not only statistically reliable but also geologically meaningful, as they are supported by numerous independent geological studies (ŠPELIĆ et al., 2023; PAVELIĆ & KOVAČIĆ, 2018 and references therein). The enhanced accuracy of this model suggests that standardization effectively preserves and enhances key lithological trends within the dataset.

In contrast, models constructed using Normalized (Norm) input data produced less reliable predictions. In some cases, their performance was even inferior to models developed using Raw (unprocessed) data. This suggests that normalization may distort the original statistical relationships between variables, leading to a loss of critical geological information. Notably, the model derived from Raw input data exhibited a significant underestimation of the total volume of sandstones, highlighting the risks associated with inadequate preprocessing. The omission or misrepresentation of such key geological features could lead to inaccurate interpretations of reservoir quality, depositional environments, or resource potential.

These findings underscore the crucial role of data preprocessing in artificial neural network (ANN)-based lithology distribution modelling. Proper standardization of the input data has resulted in geologically accurate and statistically reliable models, reinforcing the importance of preprocessing in machine learning applications within geosciences. However, normalization appears to compromise model reliability, making it an unsuitable preprocessing method for lithological modelling. As a result, careful selection of preprocessing techniques is essential for ensuring reliable, geologically consistent predictions in lithology modelling. This study proved that combining machine learning with traditional geological methods holds great potential for improving predictive capabilities in the geosciences.

The approach presented here is applicable in geological settings characterized by the relative uniformity of lithological composition, i.e. in settings with two to three main distinctive lithologies that can be distinguished based on the geophysical exploration data from wells. This approach is therefore expected to be applicable in constructing the model of coal bearing strata, where the Density log could be used to identify different lithological categories. It could also be used for the characterization of shale-rich carbonates, i.e. the spatial zonation of carbonate reservoirs with respect to shale volume. Modelling the spatial distribution of lithological composition prior to porosity modelling can be beneficial, as each lithological category can be associated with a specific porosity range (KOLENKOVIĆ MOČILAC et al., 2022). This approach allows the lithological model to control the porosity model, therefore representing a significant improvement over a simple sandstone-shale system. Additionally, the methodology offers potential for various geo-energy explorations, including hydrocarbon and geothermal explorations, as well as CO_2 storage assessments. However, in more complex lithological settings, this methodology would require further refinement and development to achieve optimal accuracy.

The transfer of this methodology to other settings is conditioned not only by geological characteristics but also by differences in the input data set. The presented methodology is limited to 3D seismic data due to the usage of a large number of attributes, some of which are not at all suited for calculation on 2D seismic data. Furthermore, the effectiveness of standardization over normalization is linked to the specific numerical value ranges of the seismic attributes in this study. These ranges are not necessarily the same for all 3D volumes, meaning that in other cases, normalization may yield better results. Therefore, the transferability of direct ANN parameters to other regions with different input data is not expected to be as successful; however, the developed methodology concept has high potential to improve lithology prediction across diverse geological settings.

6. CONCLUSION

This study presents an ANN approach for determining the subsurface lithology distribution based on well log and 3D seismic data. The importance of data preprocessing in ANN-based lithology modelling is highlighted. Standardized input data produced geologically consistent results, accurately representing key features including fluvial meander channels filled with sandstones. In contrast, models using Normalized data were less reliable, sometimes even underperforming compared to those using Raw data, which significantly underestimated sandstone volume. These findings emphasize that standardization enhances model accuracy, while normalization should be avoided as it can compromise lithology predictions.

The limitations of the approach presented in this work are mainly related to the estimation of the volume of shale, since the volume of shale represents a key input parameter, and its estimate is influenced by the available dataset as well as specific geological settings. Furthermore, there is a certain amount of subjectivity of the interpreter affecting the final result, but these issues are inherent to all analyses which are influenced by the volume of shale parameter.

The approach is suitable for geological settings with two to three main lithologies, distinguishable through geophysical well data. It can be applied to coal-bearing strata using Density logs or to shale-rich carbonates for reservoir zonation. However, for geologically complex settings, it requires significant refinement.

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