Supervised and Unsupervised Learning: How Machines Can Assist Quantitative Seismic Interpretation

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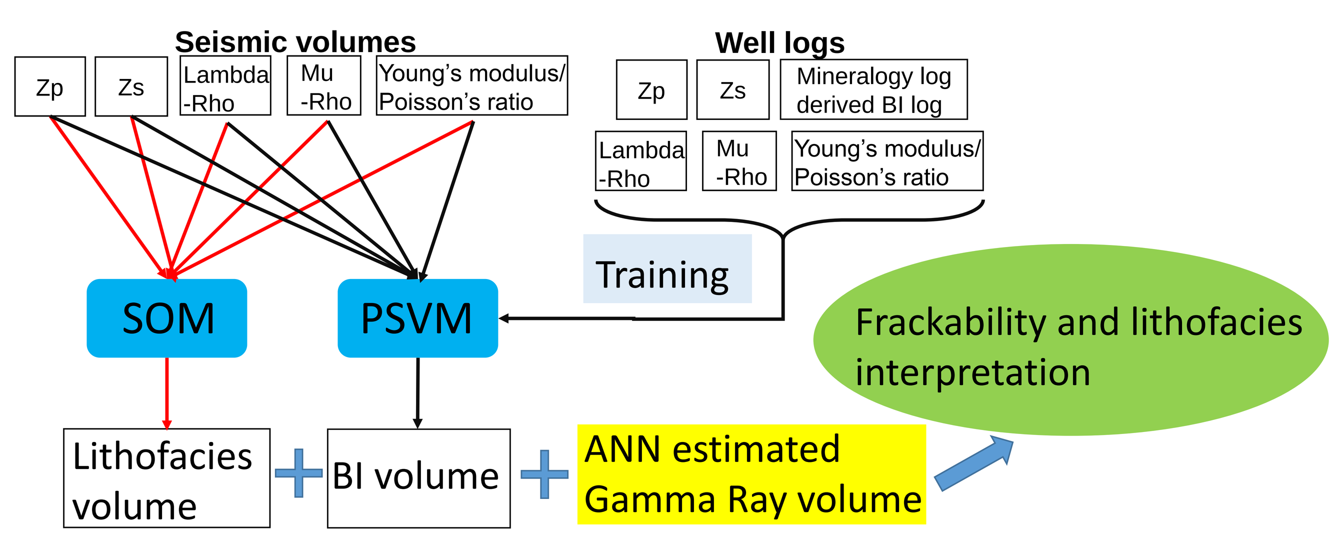
Summary

In this study, we use an example from the Barnett Shale to demonstrate how supervised and unsupervised machine learning techniques provide the right leverages for seismic interpreters. Combining automatic machine analysis and human interpretation helps understanding the extensive data interpreters have.

Introduction

Frackability is a key parameter of recovering unconventional shale reservoirs which can be measured by the brittleness index (BI) of reservoir rocks. In this study we used both unsupervised learning technique (self-organizing map or SOM) and supervised learning technique (proximal support vector machine or PSVM) to estimate BI using five petrophysical attributes. For SOM, we cannot directly get BI from the inputs, but can have clustered lithofacies, which need to be further interpreted based on well logs. For PSVM, we can directly calculate BI on seismic data based on the relation obtained from a training well. Because Gamma Ray is a good indicator of TOC as well as clay minerals which generally make a rock ductile, we also compared the estimated BI with a Gamma Ray volume estimated from artificial neural network (ANN).

Workflow



Discussion

By using the same input data for SOM and PSVM, we generated a SOM cluster volume and a BI volume, respectively. Being an unsupervised learning algorithm, SOM provides clusters which need to be further interpreted using other data, whereas PSVM gives us determined products, which in this study is BI. There is a virtual correlation between SOM clusters and BI; however, one cannot conclude the clusters represent BI values. In fact, SOM clusters contain all the information from five input volumes and recover natural relations within the data other than linking the inputs to a specific output (BI).

Conclusions and Future Work

Supervised and unsupervised machine learning techniques provide human guided classification as well as data driven clustering which help us better understand the data. Interpretation of unsupervised clusters requires correlating with other data and expert insight to interpret. Supervised training needs carefully chosen input data to insure its geologic meaningfulness.

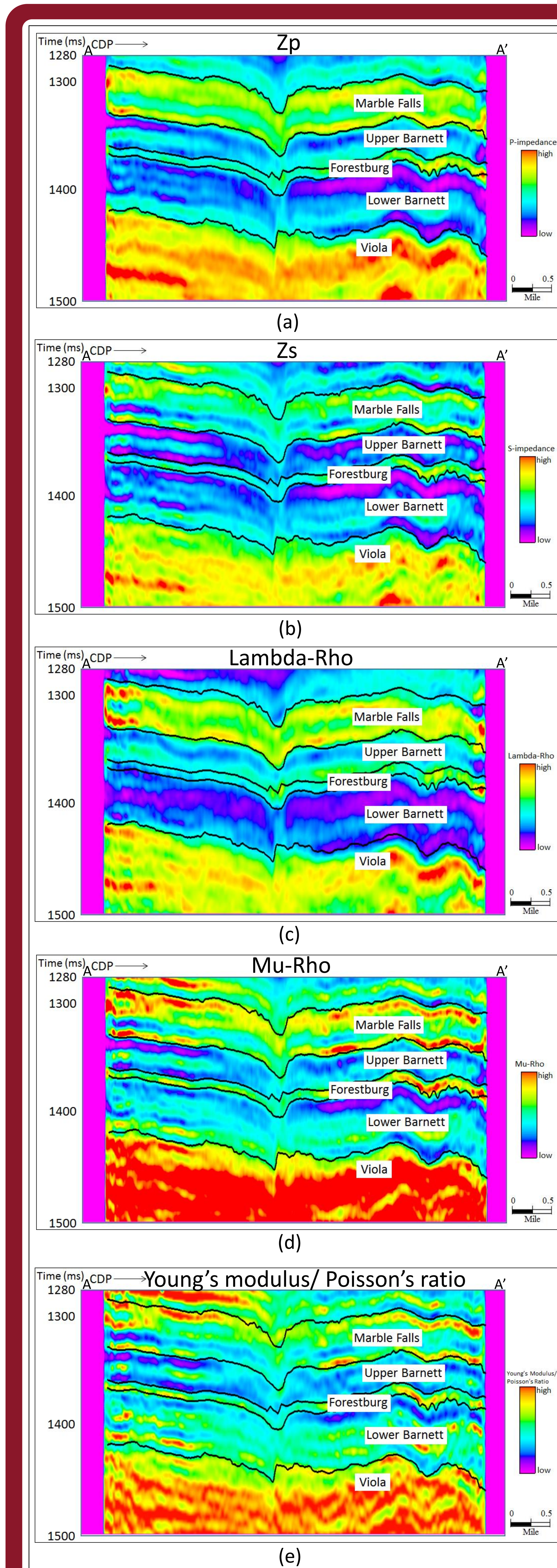


Figure 1. Five input seismic attribute volumes at line AA': (a) P-impedance; (b) S-impedance; (c) Lambda-Rho; (d) Mu-Rho; and (e) Ratio between Young's modulus and Poisson's ratio. All these volumes are either inverted or further calculated from prestack simultaneous inversion.

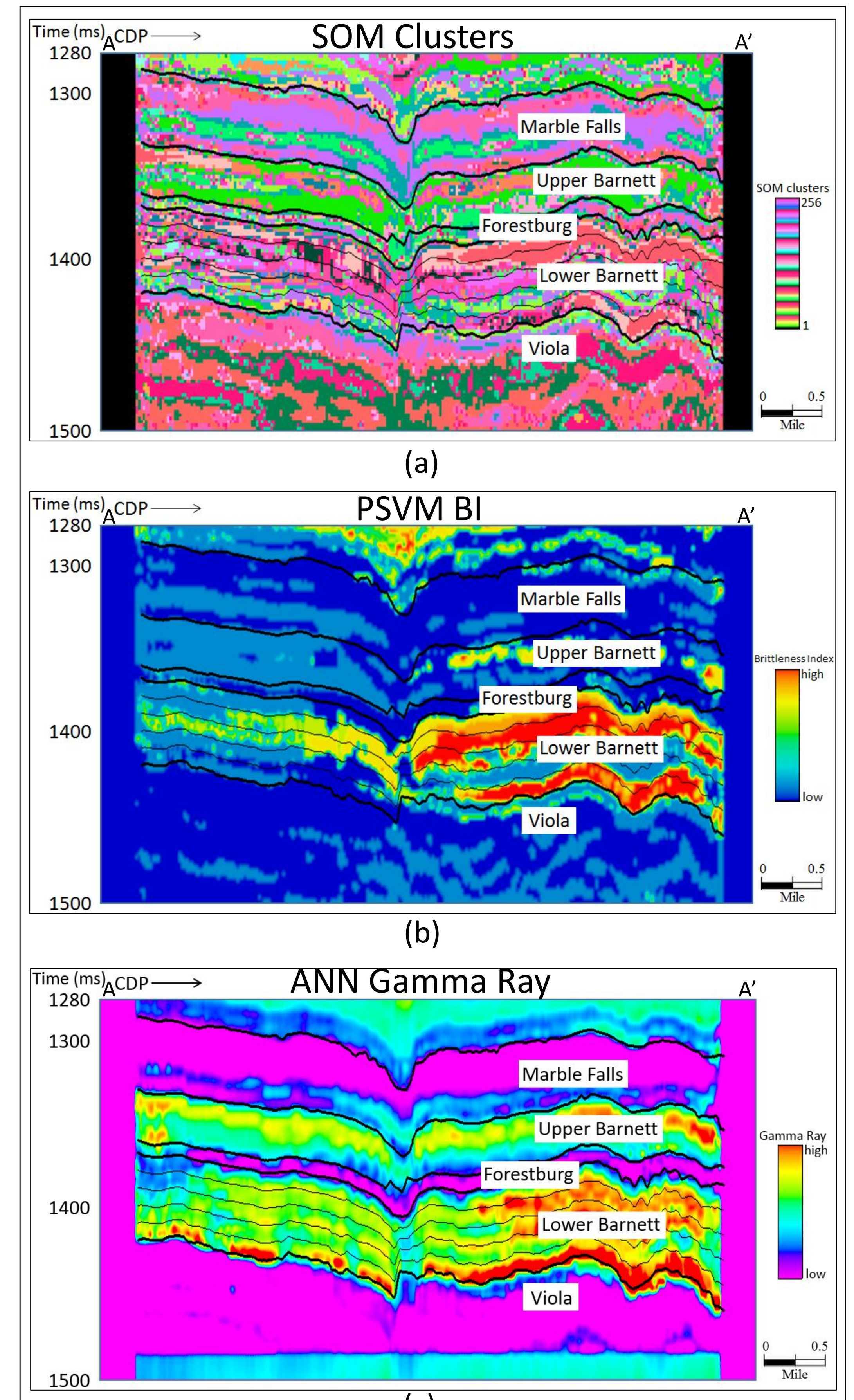


Figure 2. Cross sections at line AA' through: (a) SOM clusters using five inputs in Figure 1; (b) PSVM estimated BI from five inputs in Fig. 1 using one training well three miles northeast to the survey; and (c) ANN estimated Gamma Ray volume from impedances and spectral components derived attributes. Marble Falls, Forestburg and Viola are limestone formations, where Upper and Lower Barnett are shale reservoirs. One can identify the two main brittle formations within the Lower Barnett Shale in (b) correlate to high Gamma ray zones in (c), which confirms the argument that there exists zones with both high BI and high TOC in the Lower Barnett (Perez, 2013). Four stratal slices are generated between Lower Barnett and Viola horizons shown as thin black lines, which are further displayed in Figure 3.

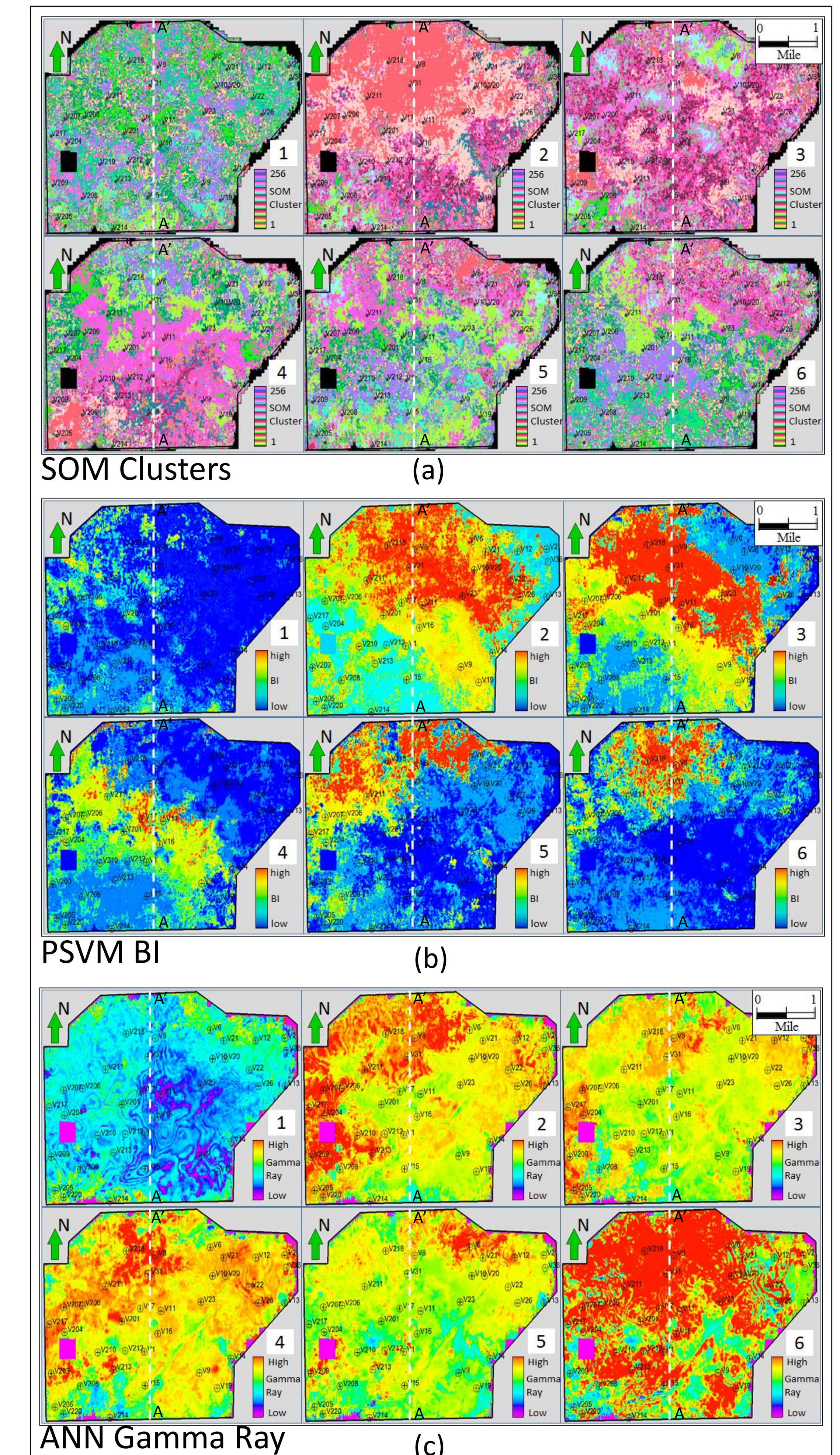


Figure 3. Horizons and stratal slices from Lower Barnett to Viola through: (a) SOM clusters as in Fig. 2(a); (b) PSVM estimated BI as in Fig. 2(b); and (c) ANN estimated Gamma Ray as in Fig 2(c). Position of stratal slices are marked in Fig. 2. White dashed lines indicate the location of line AA' in Fig. 1 and Fig. 2. Note the correlation of quartz-rich SOM clusters in pink and magenta with the high BI zones in the upper part of Lower Barnett Shale. Also note in the lower part of Lower Barnett Shale we have green and purple SOM clusters, low BI and high Gamma Ray which indicate clay-rich or TOC-rich shale.

Acknowledgements

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References

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Verma, S., A. Roy, R. Perez and K. J. Marfurt, 2012, Mapping high frackability and high TOC zones in the Barnett Shale: supervised probabilistic neural network vs. unsupervised multi-attribute Kohonen SOM: SEG Technical Program Expanded Abstracts 2012, pp. 1-5.

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