Predicting Brittleness for Wolfcamp Shales Using Statistical Rock Physics and Machine Learning*

Jaewook Lee[1] and David Lumley[1]

Search and Discovery Article #42566 (2021)**
Posted February 8, 2021

*Adapted from oral presentation accepted for the 2020 AAPG Annual Convention and Exhibition online meeting, September 29 – October 1, 2020.
 DOI:10.1306/42566Lee2020

[1]Department of Geosciences, University of Texas at Dallas, Dallas, TX, United States (jaewook.lee@utdallas.edu)

Abstract

The ‘fracability’ for organic-rich shale formations is one of the important factors to identify shale production sweet spots. Since this property is not well understood, we utilize the mineralogical or elastic brittleness indices, as indirect indicators of fracability estimation. However, the elastic brittleness, directly calculated from Young’s modulus and Poisson’s ratio, has a weak correlation with the mineralogical index in practice. It can also give misleading results to determine well locations and optimize recovery. For this reason, we conduct statistical analyses and apply supervised machine learning to produce a more reliable brittleness prediction. Machine learning techniques can help to solve complex and nonlinear problems using large data sets. First, we conduct bivariate correlation analysis to define the most highly correlated association of rock physics properties to the mineralogical brittleness. Among the properties, we distinguish four influential factors, such as bulk density, Young's modulus, porosity, and overburden stress. Second, we derive a multi-linear regression model from four input variables based on the correlation analysis result. This regression model shows a better explanation than the traditional elastic brittleness, presenting lower RMSE and higher R_2 values. Third, we apply a supervised machine learning method to these variables for a more predictive model. In this study, we use the multi-layer feedforward neural network based on the Levenburg-Marquardt algorithm. The approach finds the optimal weights for the network and has a better fit to the data than the regression model, decreasing the RMSE and increasing the R_2. As a result, our combined statistical rock physics and machine learning approach can prevent the blind feeding and over-training of the networks. We conclude that machine learning techniques can provide a more accurate estimation of shale brittleness, compared to the traditional elastic brittleness method.

References Cited

Herwanger, J.V., A.D. Bottrill, and S.D. Mildren, 2015, Uses and abuses of the brittleness index with applications to hydraulic stimulation: in Unconventional Resources Technology Conference, San Antonio, Texas, 20-22 July 2015 (pp. 1215-1223). Society of Exploration Geophysicists, American Association of Petroleum Geologists, Society of Petroleum Engineers.

Jarvie, D.M., R.J. Hill, T.E. Ruble, and R.M. Pollastro, 2007, Unconventional shale-gas systems: The Mississippian Barnett Shale of north-central Texas as one model for thermogenic shale-gas assessment: AAPG Bulletin, v. 91/4, p. 475-499.

Rickman, R., M.J. Mullen, J.E. Petre, W.V. Grieser, and D. Kundert, 2008, A practical use of shale petrophysics for stimulation design optimization: All shale plays are not clones of the Barnett Shale: in SPE annual technical conference and exhibition. Society of Petroleum Engineers.

Vernik, L., 2016, Seismic petrophysics in quantitative interpretation. Society of Exploration Geophysicists.

Wang, F.P., and J.F. Gale, 2009, Screening criteria for shale-gas systems: Gulf Coast Association of Geological Societies Transactions, v. 59, p. 779-793.

ACE 2020 AAPG ANNUAL CONVENTION & EXHIBITION INCORPORATING SEPM & GCAGS
29 SEPT – 1 OCT ONLINE AND ON DEMAND

Predicting Brittleness for Wolfcamp Shales Using Statistical Rock Physics and Machine Learning

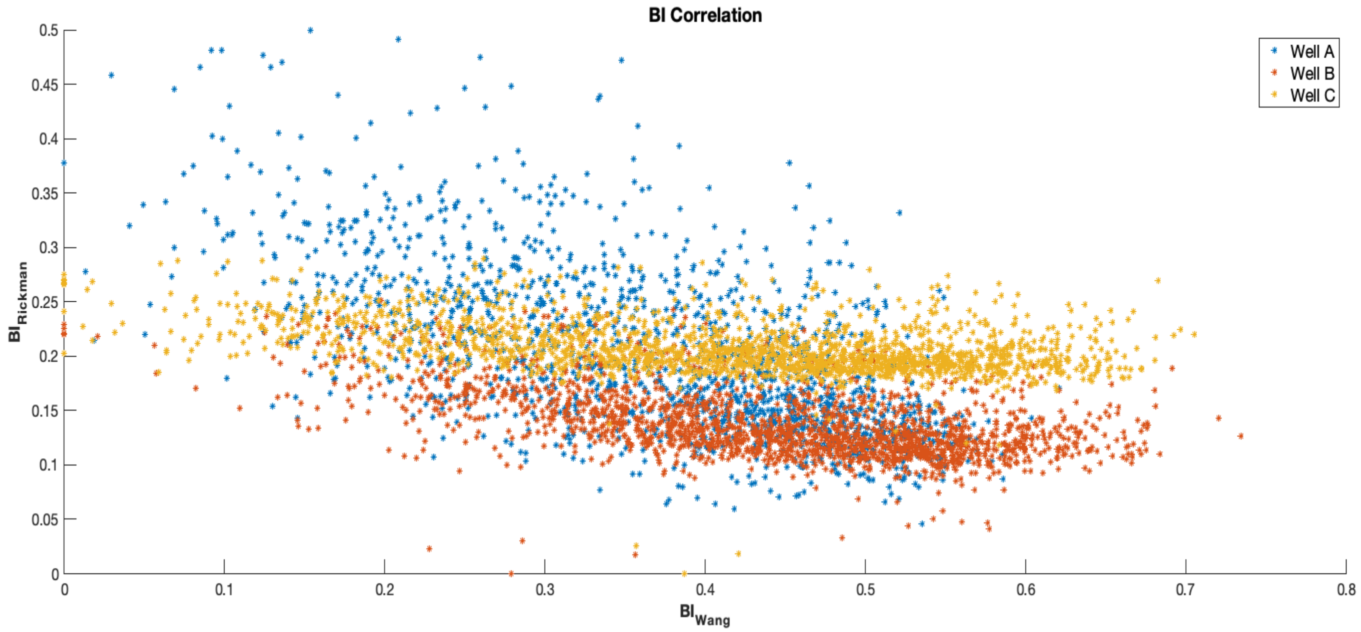
Jaewook Lee* and David Lumley

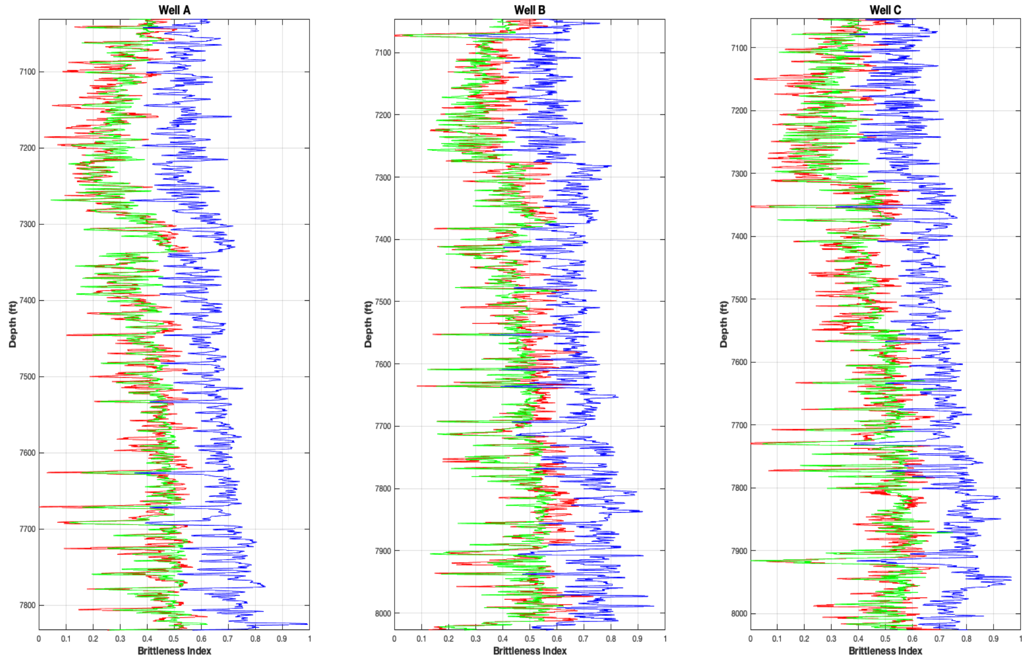
UTD 3D+4D Seismic FWI Research Consortium

Dept. of Geosciences, University of Texas at Dallas

Research Objective

- Our combined statistical rock physics and machine learning approach can provide a more accurate estimation of shale brittleness, compared to the traditional elastic brittleness method.





Introduction

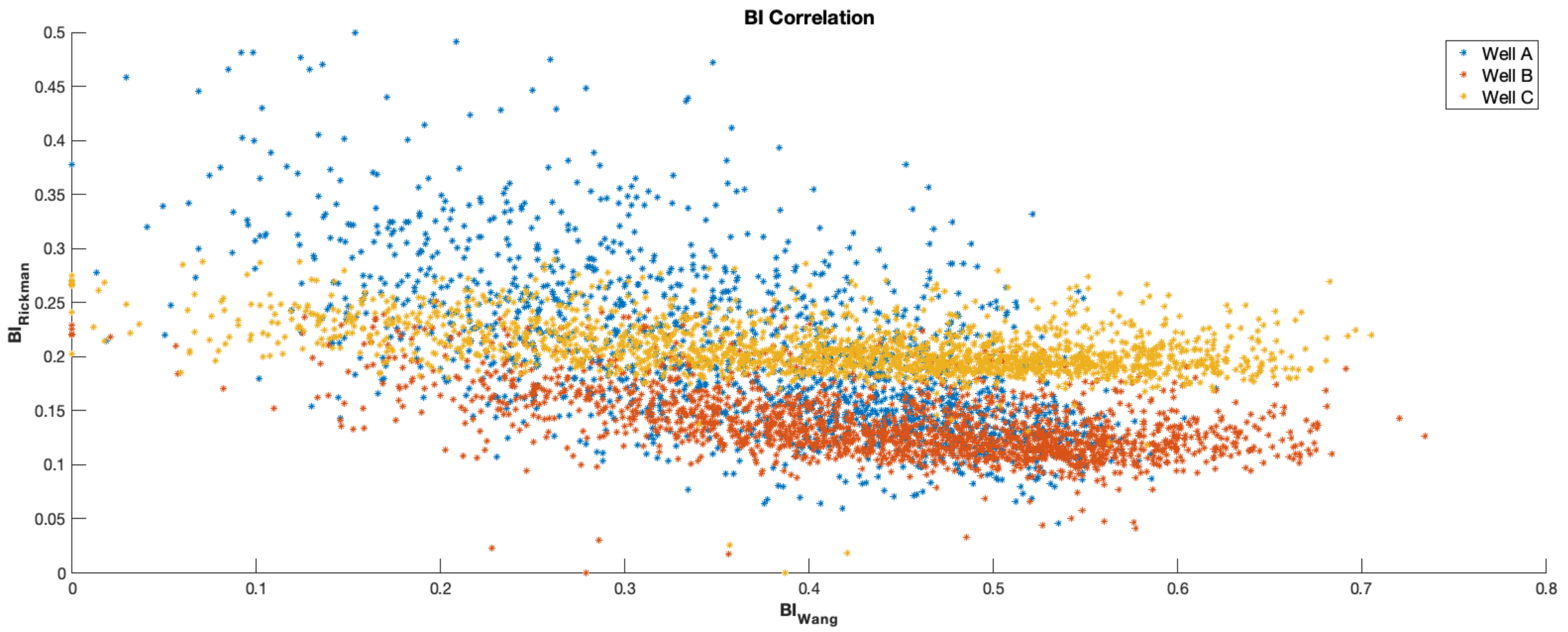
- Brittleness indices (BI) based on **mineral content of rocks**
  - Jarvie et al., 2007: $BI_{Jarvie} = \frac{Qz}{Qz+Ca+Cl}$
  - Wang and Gale, 2009: $BI_{Wang} = \frac{Qz+Dol}{Qz+Ca+Cl+Dol+TOC}$
  - Both definitions are the fraction of stiff minerals in the matrix volume. Quartz-rich lithologies have a higher Young's modulus and a lower Poisson's ratio than clay-rich lithologies (Herwanger et al., 2015).
  - How can we predict this parameter from seismic and rock physics properties?

Introduction

- Elastic brittleness based on <u>**Young's modulus and Poisson's ratio**</u>
  - Rickman et al., 2008: $BI_R = 50\% \times \left(\frac{E - E_{min}}{E_{max} - E_{min}} + \frac{\nu_{max} - \upsilon}{\nu_{max} - \nu_{min}}\right)$
  - However, these two elastic moduli have nothing to do with rock failure. (ex. Cast iron vs. Wrought iron)
  - For this reason, this brittleness index is not physically meaningful and can be misleading in organic shale reservoirs (Vernik, 2016).

Introduction

- Besides, the correlation between the mineralogic BI and the elastic BI from the well data is significantly low. (**R = -0.4738**).



Introduction

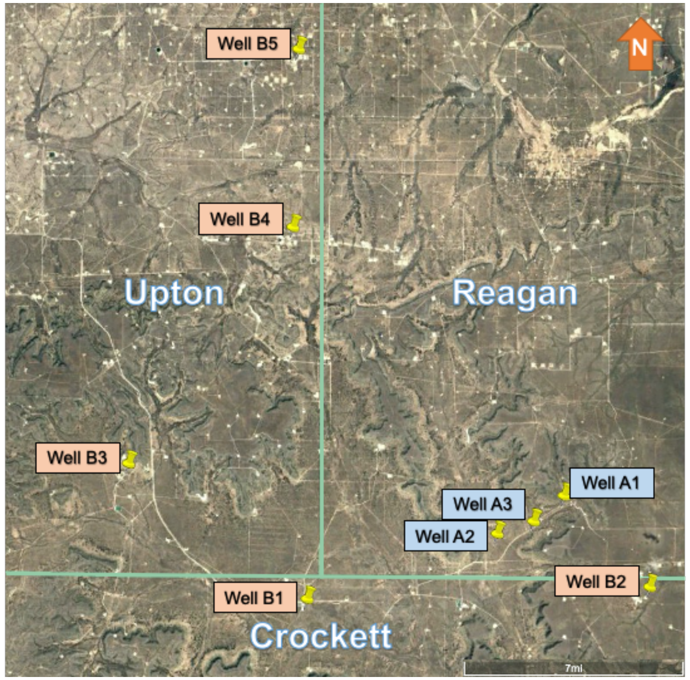
- Brittleness indices based on **mineral content of rocks**
  - Wang and Gale, 2009: $BI_{Wang} = \frac{Qz+Dol}{Qz+Ca+Cl+Dol+TOC}$
- Analytic approach has a clear physical meaning, but the nature of organic-rich shales has not been well understood.
- In this study, we perform the statistical analysis for the rock physics properties to the mineralogic brittleness index and predict the modeled index from the well logs with the supervised machine learning method.

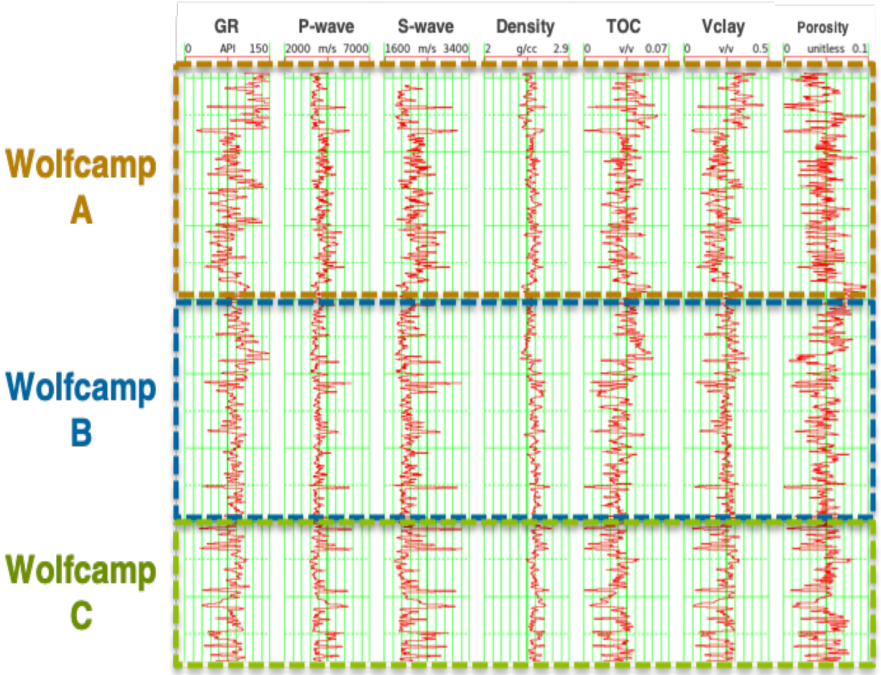
Research Strategies

- **Statistical rock physics analysis (modeling)**
  - **Bivariate correlation analysis**
    - To find properties which can be effective indicator to the BI
  - **Multivariate linear regression analysis**
    - To find the simplest model using the selected properties
- **Supervised machine learning**
  - To improve the modeled BI with a higher R^2 and lower RMSE values

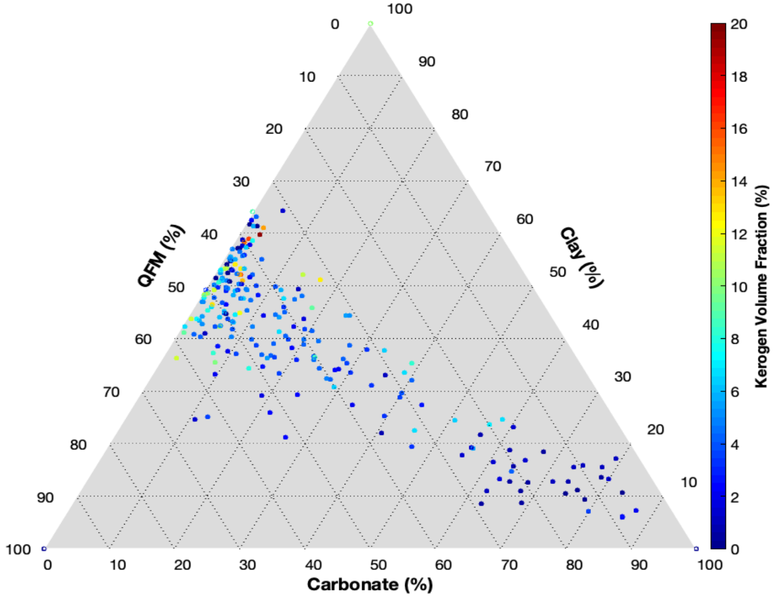
Study Area and Datasets

- We use wireline logs and core measurements obtained in Wolfcamp shales in the Midland Basin, eastern part of the Permian Basin, West Texas.





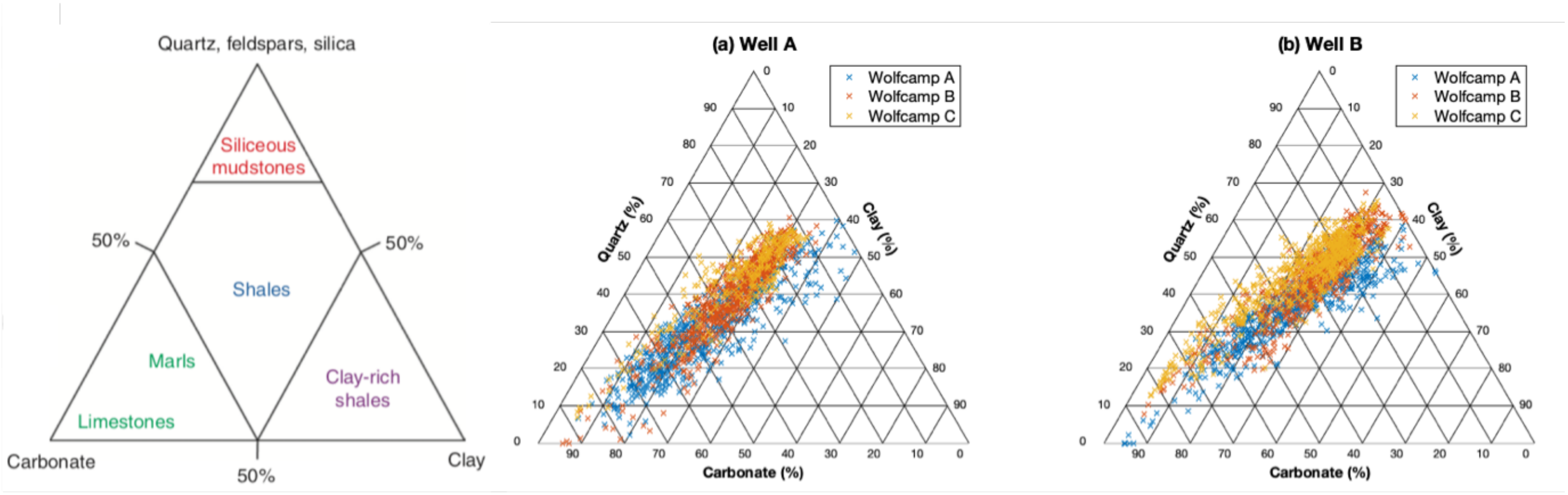
Well logs



Core measurements

Study Area and Datasets

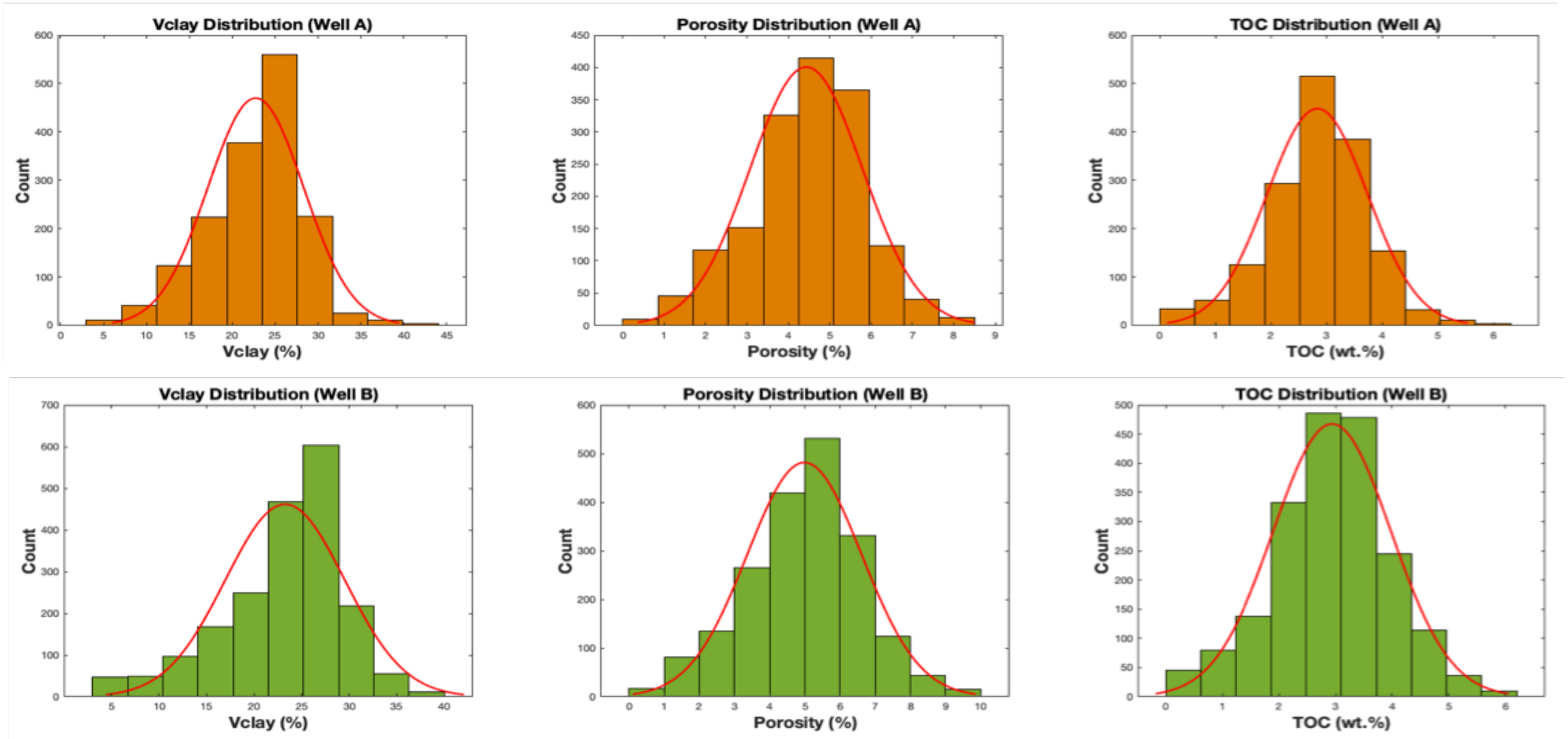
- Mineral composition of Wolfcamp shales
  - Shales with a few of interbedded limestone and marls



(Vernik, 2016)

Study Area and Datasets

- Rock properties of Wolfcamp shales
  - V_{clay}: 0-45%, Porosity: 0-10%, TOC: 0-6%



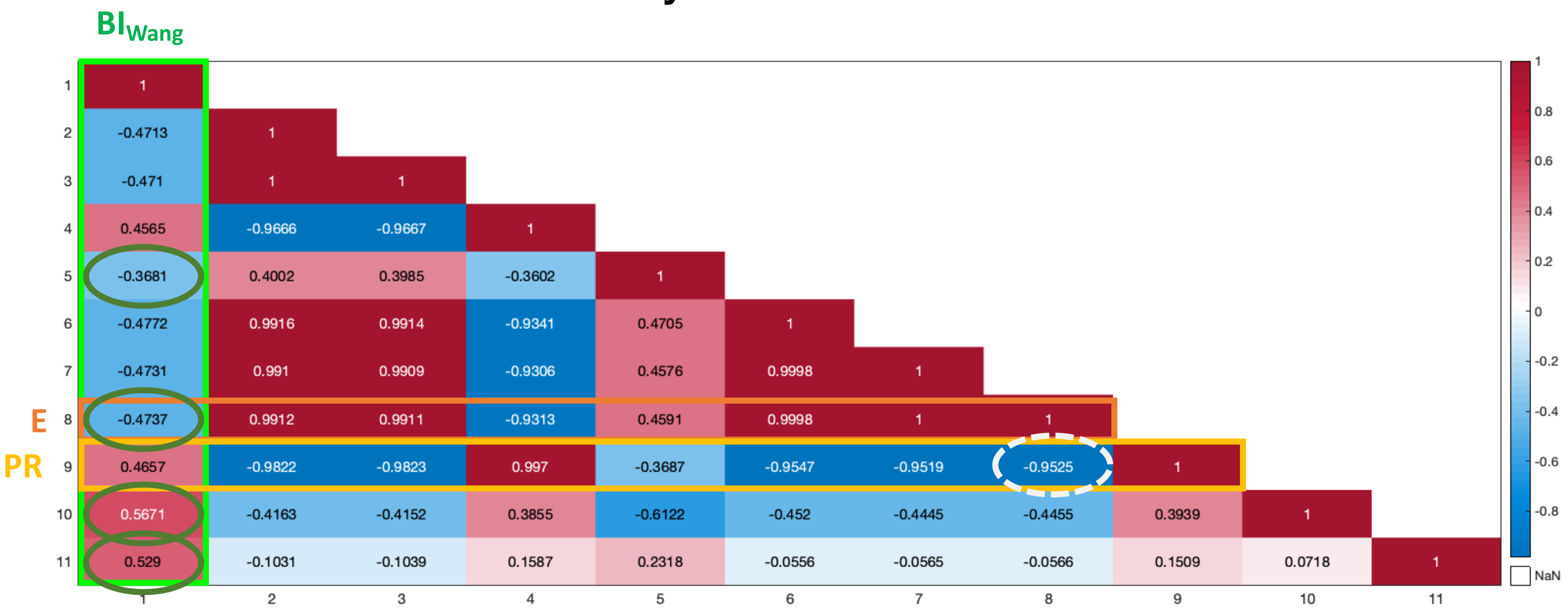
Statistical Rock Physics Analysis

- Output: Brittleness index (Wang and Gale's mineralogic BI)
  - $BI_{Wang} = \frac{Qz+Dol}{Qz+Ca+Cl+Dol+TOC}$
  - We calculate the BI values by conducting multi-mineral inversion from well logs and calibrate the inversion results with the core XRD data.

- Input: Rock physics properties (10 variables)
  - Seismic properties: V_P, V_S, V_P/V_S, ρ
  - Elastic properties: K, G, Young's modulus (E), Poisson's ratio (PR)
  - Rock properties: Porosity, Overburden stress (σ)
  - Variables directly related to mineralogy are **excluded** (e.g. V_{clay}, TOC).

Statistical Rock Physics Analysis

- Bivariate Correlation Analysis



(1) BI_{Wang}, (2) V_p, (3) V_s, (4) V_p/V_s ratio, (5) Bulk density, (6) Bulk modulus, (7) Shear modulus, (8) Young's modulus, (9) Poisson's ratio, (10) Porosity, (11) Overburden stress

Statistical Rock Physics Analysis

- We perform the bivariate correlation analysis to figure out the highly correlated association of rock physics properties to the mineralogical brittleness.
- Among the properties, we choose **four influential factors** as inputs for a multivariate linear regression model.
  - **Bulk density (ρ)**
  - **Young's modulus (E)**
  - **Porosity (ϕ)**
  - **Overburden stress (σ)**
- $\boldsymbol{BI = \beta_1 \rho + \beta_2 E + \beta_3 \phi + \beta_4 \sigma + \beta_5}$

Statistical Rock Physics Analysis

- Model 1: Modified elastic BI
  - $BI = \beta_1 E + \beta_2 \nu + \beta_3$

	Young's modulus (GPa)	Poisson's ratio (unitless)	Constant	R^2	RMSE
BI_{Wang}	-0.0048*** (β: -0.2758)	3.5287*** (β: 0.4442)	-0.5330	0.2267	0.1146

- Model 2: Multivariate linear regression model
  - $\boldsymbol{BI = \beta_1 \rho + \beta_2 E + \beta_3 \phi + \beta_4 \sigma + \beta_5}$

	Bulk density (g/cc)	Young's modulus (GPa)	Porosity (v/v)	Overburden stress (psi)	Constant	R^2	RMSE
BI_{Wang}	-0.5234*** (β: -0.2108)	-0.0031*** (β: -0.2101)	2.3695*** (β: 0.3054)	0.0003*** (β: 0.5441)	0.3613	0.6381	0.0784

Note that '*' sign indicates the degree of significance of the rock property effect based on p-value (*: $p<0.05$, **: $p<0.01$, ***: $p<0.001$).

Statistical Rock Physics Analysis

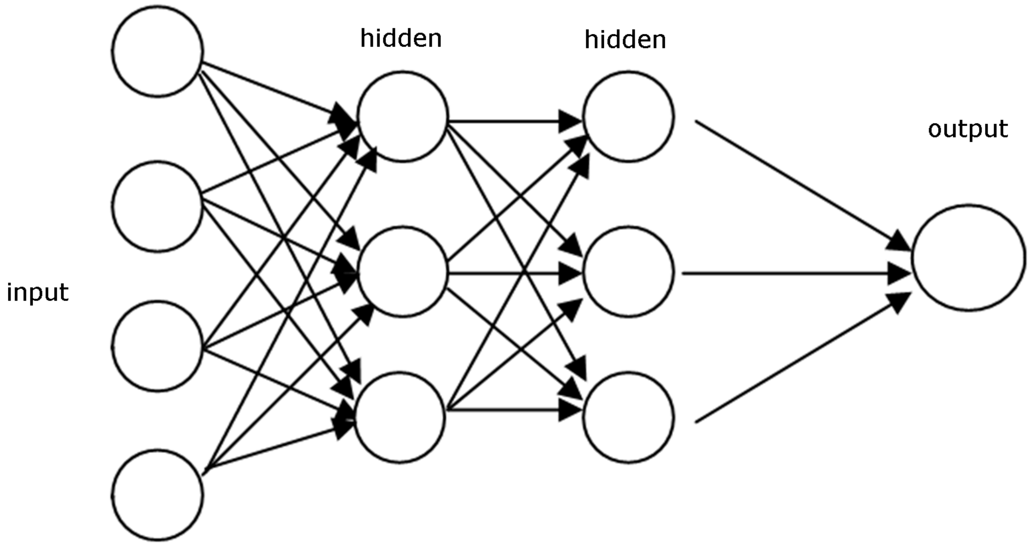
- The Model 2 can explain the variation in mineralogic BI better than the Model 1, according to the higher R^2 value and smaller RMSE.
- Therefore, using rock physics properties can enhance the prediction of this brittleness index, better than using two elastic properties.
- Furthermore, we can also use 'supervised machine learning' method to design a nonlinear model with a better prediction than the simple linear regression.

Supervised Machine Learning

- **Input**
  - Bulk density (ρ)
  - Young's modulus (E)
  - Porosity (ϕ)
  - Overburden stress (σ)
- **Output**
  - Brittleness index (BI_{Wang})
- **Methods**
  - Multivariate linear regression (MLR)
  - Probabilistic neural network (PNN)
  - Deep feed-forward neural network (DFNN)

Supervised Machine Learning

- Test 1: MLR vs. PNN vs. DFNN
- MLR
  - Number of hidden layers = 0
- PNN
  - Number of hidden layers = 1
- DFNN
  - Number of hidden layers = 5
  - Levenberg-Marquardt algorithm
  - Training: 70%, Validation: 20%, Testing: 10%



Supervised Machine Learning

- DFNN is a more effective method which shows the better prediction than MLR and PNN.

Method	Samples	RMSE	R^2
MLR	5513	0.0784	0.6379
PNN	3859 (Training)	0.0748	0.6706
	1103 (Validation)	0.0781	0.6365
	551 (Testing)	0.0787	0.6197
DFNN	3859 (Training)	0.0707	0.7067
	1103 (Validation)	0.0671	0.7380
	551 (Testing)	0.0663	0.7306

Supervised Machine Learning

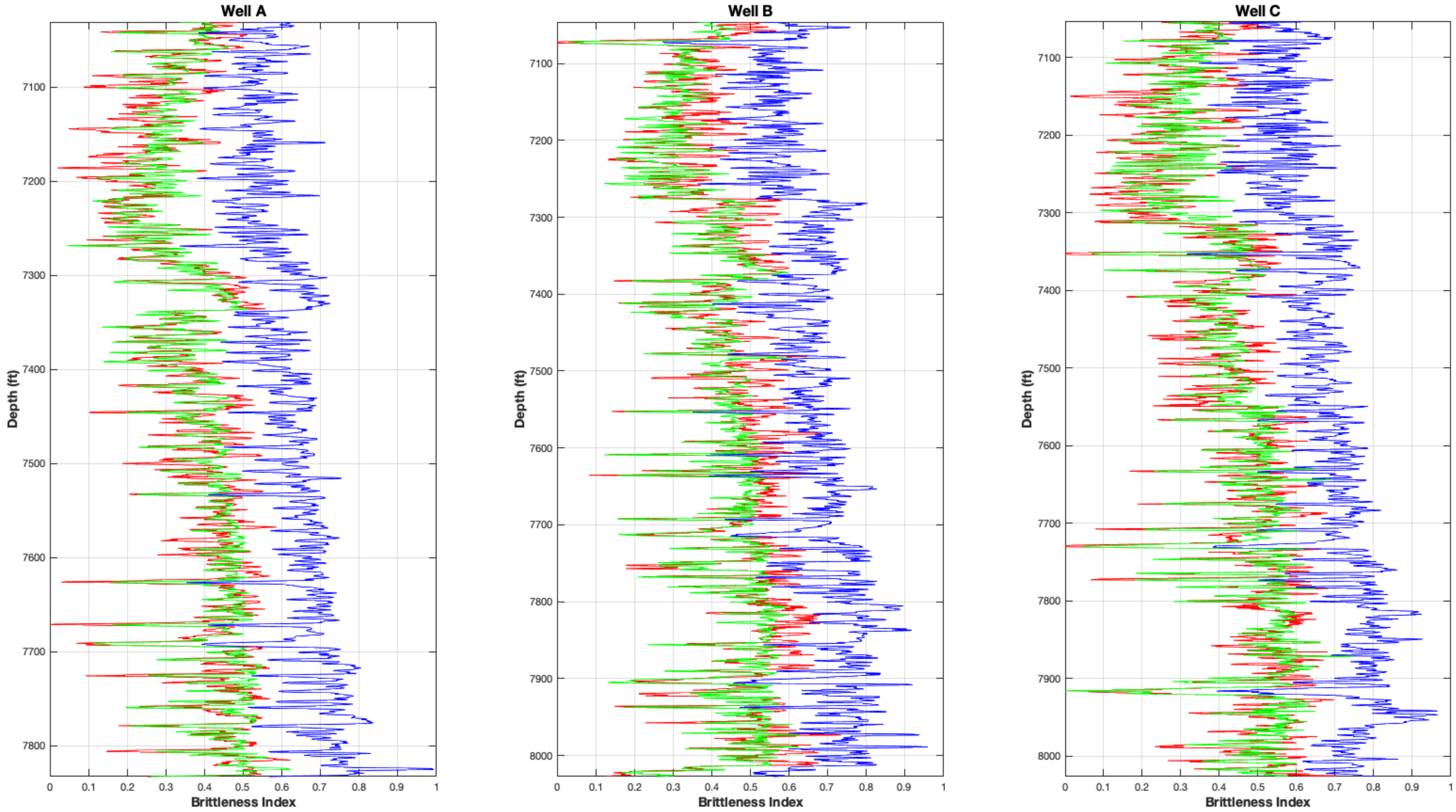
- Test 2: The number of hidden layers
- More layers allow the network to model transforms such as higher-order polynomials. They can also approximate the training data more accurately.
- As the number of hidden layers increases, this method can model more complexity by simulating any nonlinear functions.
- The greater the number of hidden layers, the greater the amount of training data required.

Supervised Machine Learning

- The result when using more hidden layers shows better prediction with lower RMSE and higher R^2 values.

Hidden layers	Samples	RMSE	R^2
5	3859 (Training)	0.0707	0.7067
	1103 (Validation)	0.0671	0.7380
	551 (Testing)	0.0663	0.7306
8	3859 (Training)	0.0684	0.7210
	1103 (Validation)	0.0689	0.7325
	551 (Testing)	0.0667	0.7355
10	3859 (Training)	0.0665	0.7372
	1103 (Validation)	0.0701	0.7211
	551 (Testing)	0.0646	0.7497

Supervised Machine Learning



Red: BI_{Wang}
Blue: BI_{MLR}
Green: BI_{DFNN}

Conclusions

- In this study, we apply the statistical rock physics modeling and supervised machine learning method to the prediction of BI.
- First, we conduct the statistical analysis to choose the best association of input properties such as density, Young's modulus, porosity, and overburden stress.
- Second, we improve the prediction model by using the DFNN, better than those by MLR and PNN. This result shows that the DFNN can provide a more accurate estimation of the BI, better than the traditional elastic brittleness.

Acknowledgements

- UT Dallas 3D+4D Seismic FWI Research Consortium sponsors
- Society of Exploration Geophysicists (SEG) Scholarships
  - DGS/Karen Kellogg Shaw Memorial Scholarship
  - SEG/Thomas A. Mazza Memorial Scholarship

References

- Herwanger*, J. V., Bottrill, A. D., & Mildren, S. D. (2015, July). Uses and abuses of the brittleness index with applications to hydraulic stimulation. In Unconventional Resources Technology Conference, San Antonio, Texas, 20-22 July 2015 (pp. 1215-1223). Society of Exploration Geophysicists, American Association of Petroleum Geologists, Society of Petroleum Engineers.
- Jarvie, D. M., Hill, R. J., Ruble, T. E., & Pollastro, R. M. (2007). Unconventional shale-gas systems: The Mississippian Barnett Shale of north-central Texas as one model for thermogenic shale-gas assessment. AAPG bulletin, 91(4), 475-499.
- Rickman, R., Mullen, M. J., Petre, J. E., Grieser, W. V., & Kundert, D. (2008, January). A practical use of shale petrophysics for stimulation design optimization: All shale plays are not clones of the Barnett Shale. In SPE annual technical conference and exhibition. Society of Petroleum Engineers.
- Vernik, L. (2016). Seismic petrophysics in quantitative interpretation. Society of Exploration Geophysicists.
- Wang, F. P., & Gale, J. F. (2009). Screening criteria for shale-gas systems.

Thank You for Your Attention!

Jaewook Lee
jaewook.lee@utdallas.edu
UTD 3D+4D Seismic FWI Research Consortium
Dept. of Geosciences, University of Texas at Dallas