Machine Learning Mineralogy Classification Comparison to Empirical Log Relationship and Implication for Physics Informed Modeling

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ABSTRACT

Determination of seismic lithology, porosity and pore fluid requires detailed modelling of petrophysical logs to improve the correlation with a seismic AVO response. Unfortunately, acquiring a complete set of logs for all wells in a seismic survey is unpractical, and estimating sonic, shear and density using empirical relationships is the standard approach. While these empirical relationships have worked for recon analysis, they have generally not given the details needed for accurate geophysical analysis. Machine Learning has given us a new way of investigating these relationships. By analyzing over 138 wells with DT, Vs & RHOB logs from the North Sea, Australia, and Canada, we could generate synthetic Vp, Vs, and RHOB using traditional and the XGBoost regressor, where the latter showed to work better in this data.

In the first part of this report, we intend to share our observation following log normalization & depth trend removal on DT, RHOB & DTS estimation using XGBoost (Chen & Guestrin, 2016), one of the few Machine Learning solutions that do not require completed dataset. In the second part of this report, we will look at using these empirical relationships to evaluate mineralogy. In the final part of the report, we will share some of the observations of Vp, Vs and RHOB's relationship with mineralogy

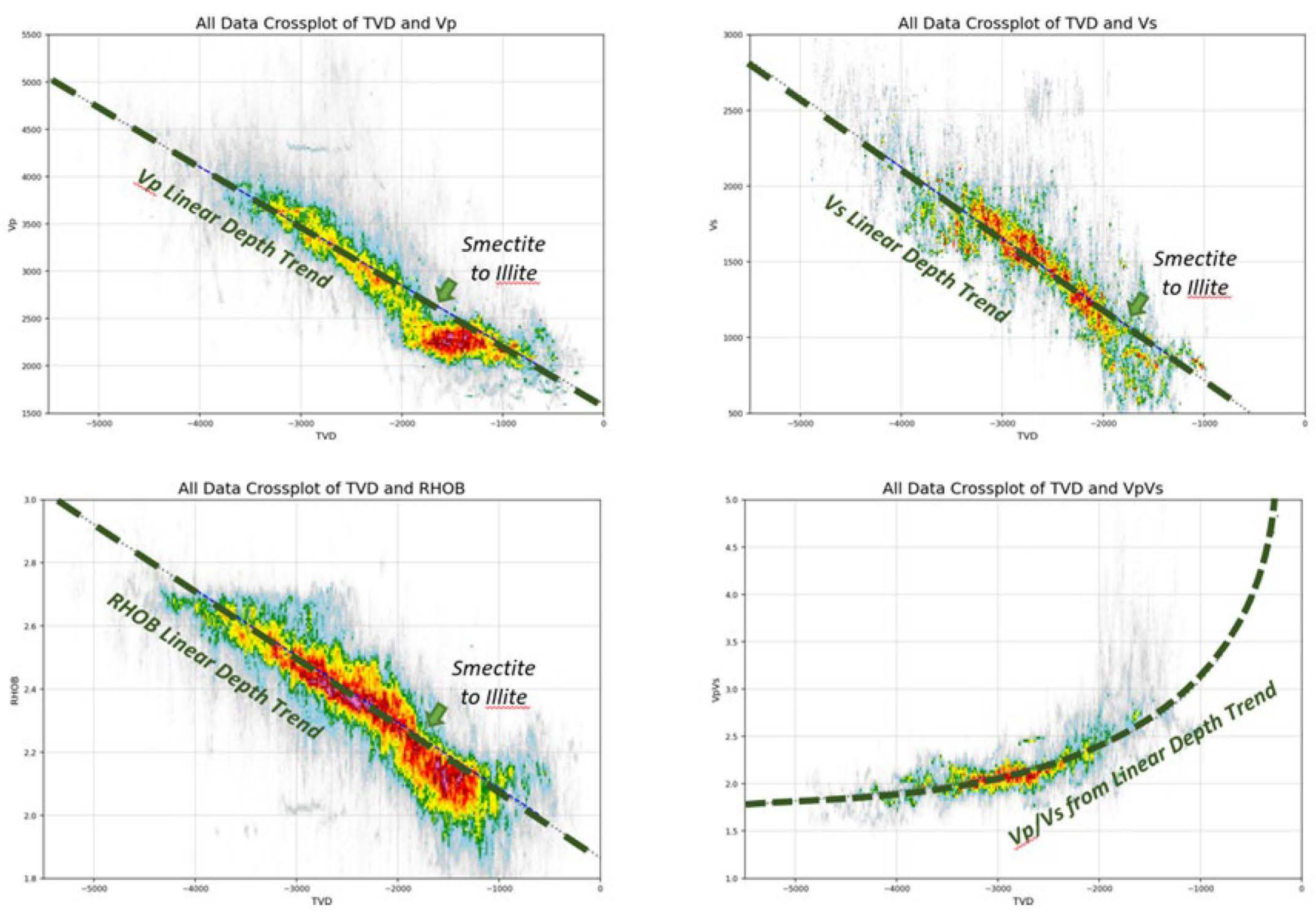
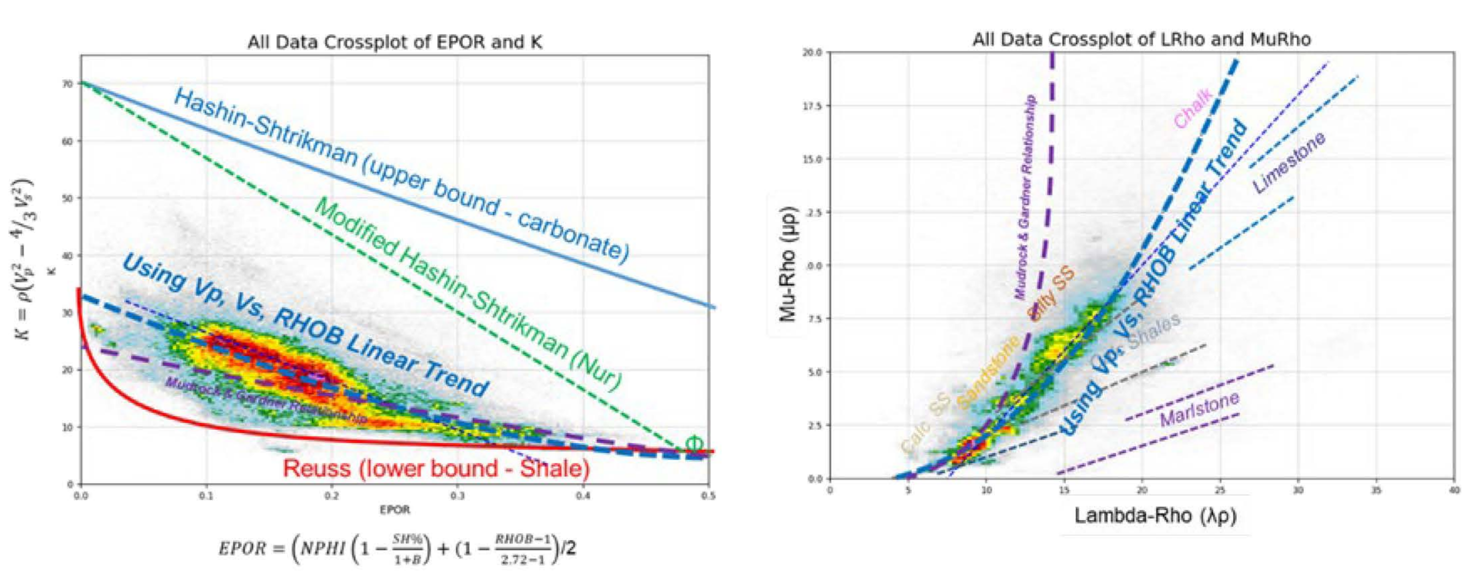


Figure1: Input data plotted against depth, strong discontinuity at -1800 m is assumed to be the location of smectite clay conversion into illite.



$$EPOR = \left(NPHI\left(1-\frac{VSH\%}{1+\beta}\right) + \left(1-\frac{RHOB-1}{2.72-1}\right)\right)/2$$

Figure 2 - Bulk Modulus (left) and Lambda-Rho/Mu-Rho (right) cross plots of input data

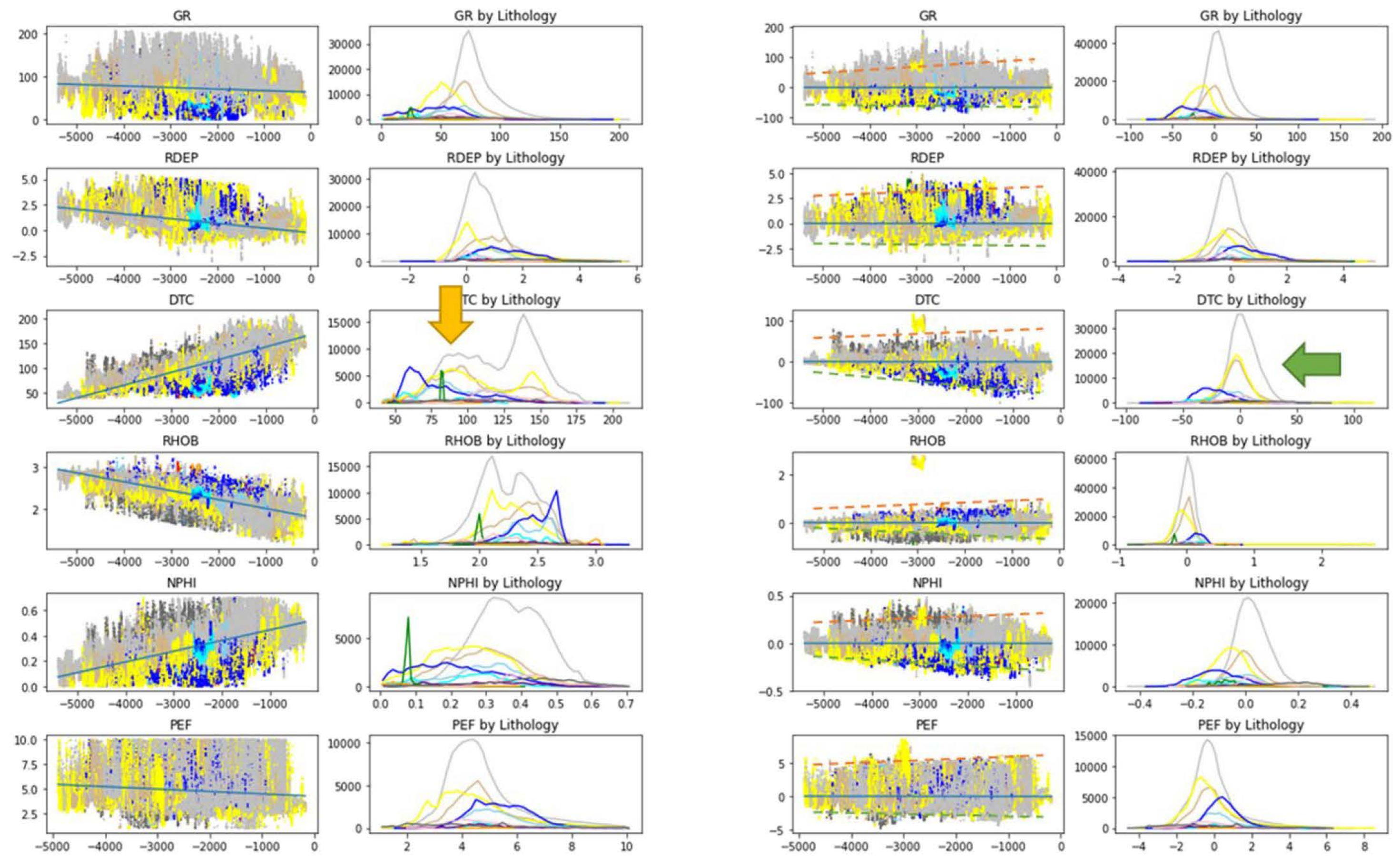


Figure 3 - Curve plot against depth: standard curve left and residual right. Histogram are by lithology

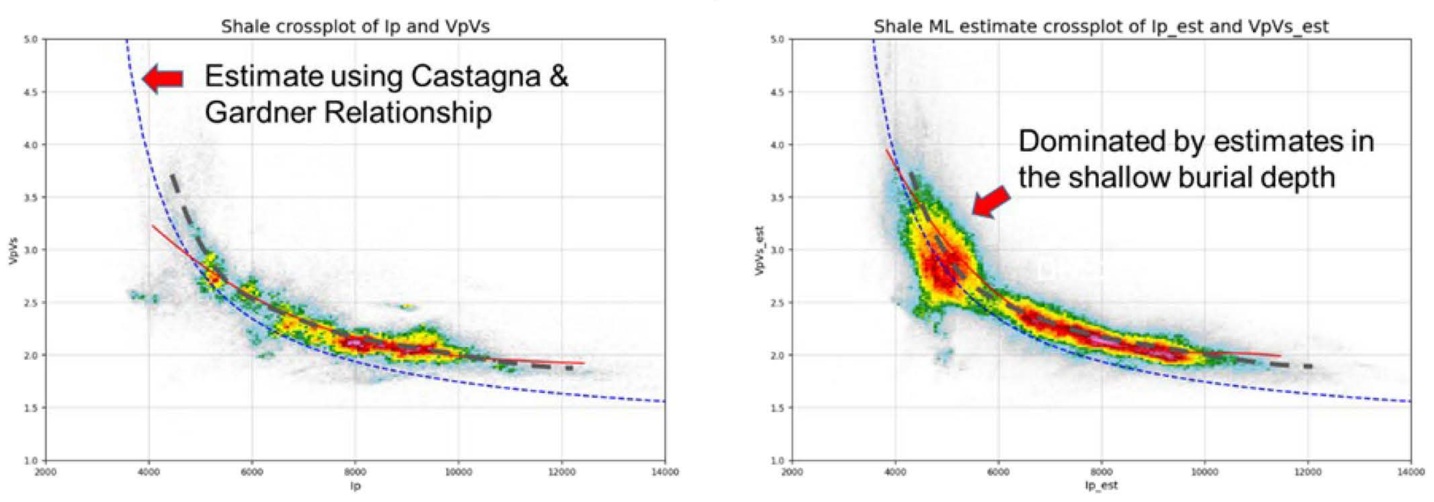


Figure 4 - Comparison of Empirical Relationship with input shale mineralogy (left) and XGBoost estimation (right). The large scatter centred around Ip=5000 results from the shortage of shallow input data (under 2000m burial depth) coupled with the uncertainty in mineralogy..

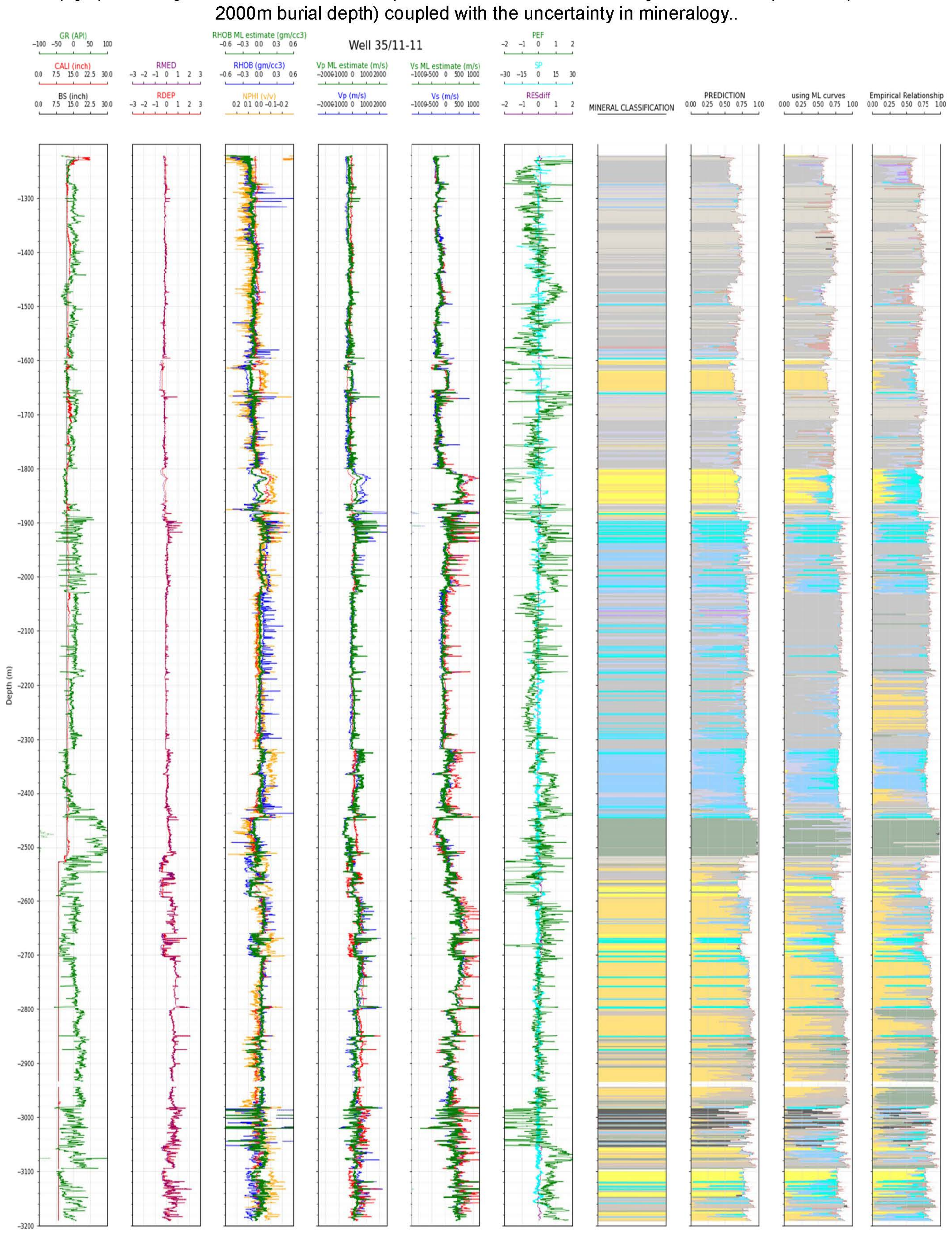


Figure 5 - Mineralogy estimation using petrophysical logs (Log), machine learn estimated logs (ML) and empirical relationship (ER).

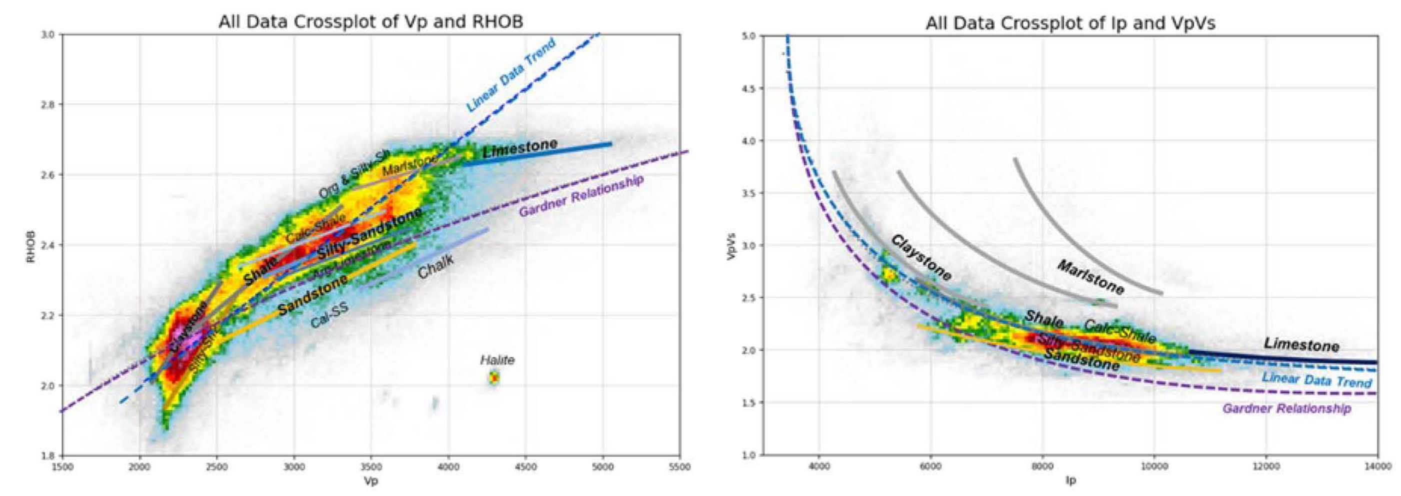


Figure 6 - Vp vs RHOB with Gardner line (left) and Vp/Vs vs Ip (right). Lines represent the most common profile for selective mineralogizes.

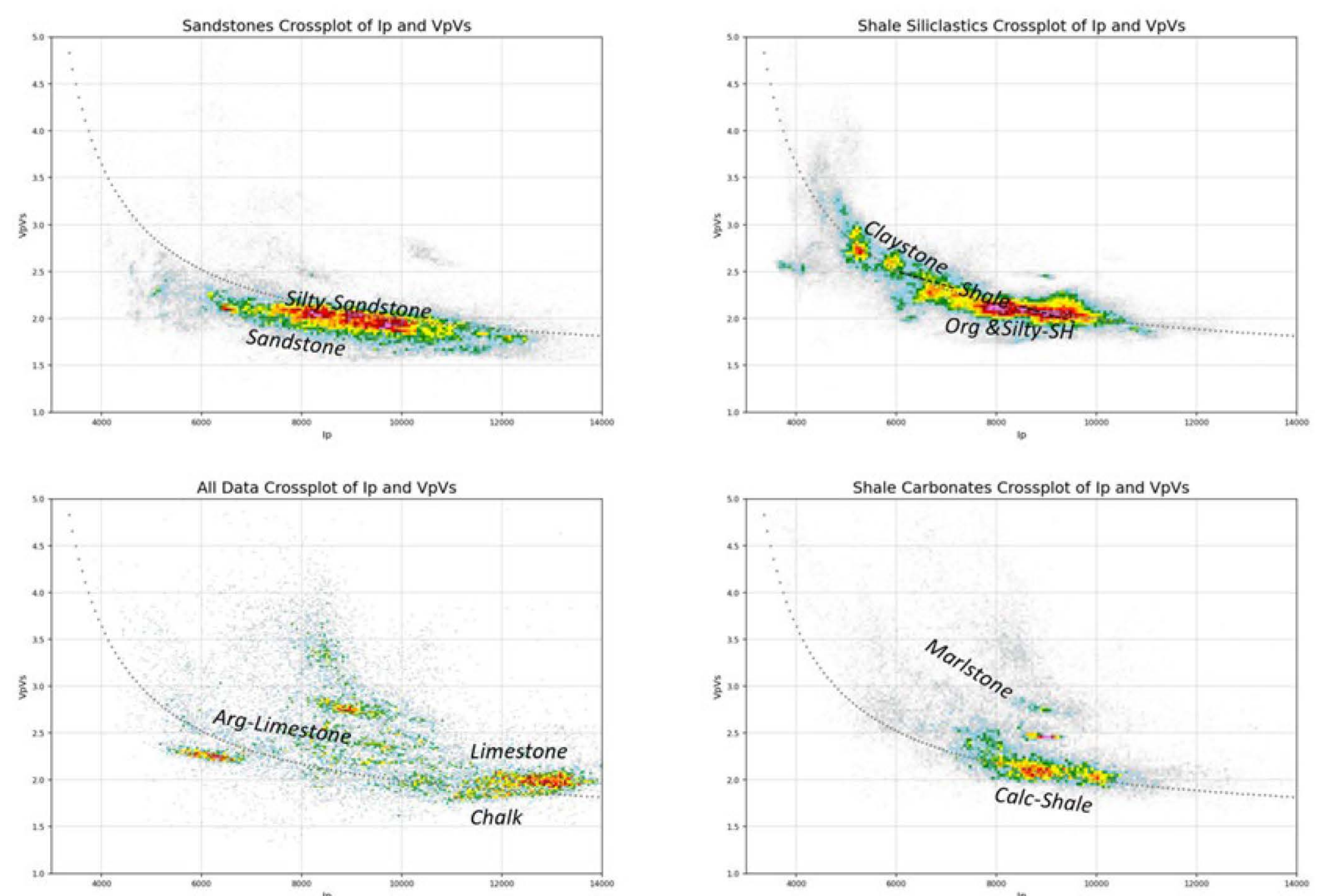
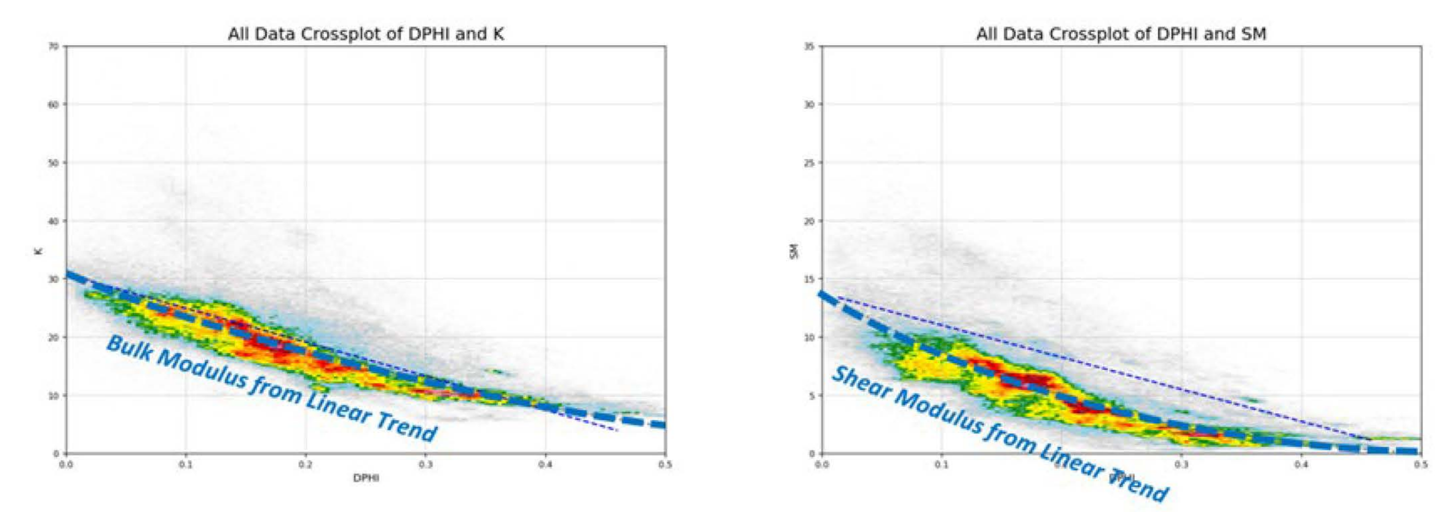
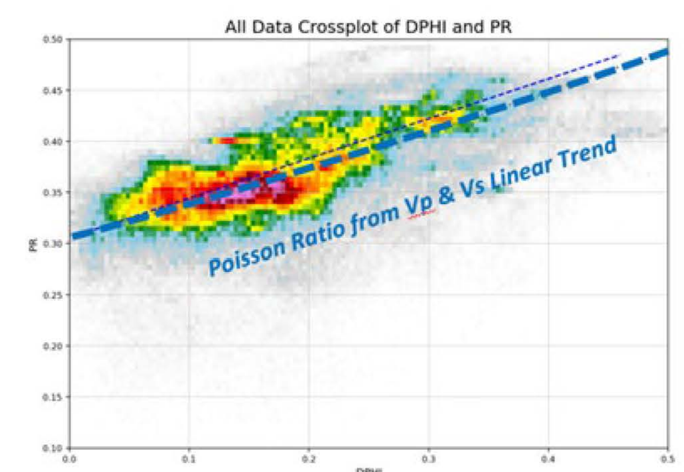


Figure 7 - Vp/Vs versus Ip for sandstone (upper-left), siliciclastic shales (upper-right), calc-shales (lower-right) and limestone (lower-left) mineralogy. Line fit to the 100% data.





Bulk & Shear modulus estimated using isotropic relationship to Vp, Vs and RHOB. Poisson Ratio estimate using Vp & Vs.

$$K = \rho\left(V_p^2 - {}^4\!/_3\, V_s^2\right) \qquad \mu = \rho V_s^2$$

$$\sigma = \frac{V_p^2 - 2V_s^2}{2\left(V_p^2 - 2V_s^2\right)}$$

Figure 8 - Rock-Physics Parameters of all input data (estimated from Vp, Vs and RHOB) plotted against DPHI estimate using Limestone density (2.72 gm/cc3).

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