Determination of Multivariate Relationships between Petrophysical and Rock Mechanical Properties

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A geological model is one of the main inputs for the simulation process and geostatistical techniques are used widely to produce these models. Structural, facies and property models are included in each geostatistical realization. Petrophysical properties, i.e. porosity, permeability and saturations, are the only properties required for conventional flow simulation but in the case of coupled geomechanical-flow simulation process rock mechanical properties should be modeled stochastically as well. Spatial modeling of multiple variable is one of the most common challenges in the field of geostatistics. Conventional Gaussian techniques is the most common approach for cosimulation of multiple variable which is applicable only when multi-variate gaussianity assumption is confirmed. Alternative techniques such as stepwise conditional transformation should be considered if variables don't show gaussianity very well. Statistical analysis, i.e. univariate and bivariate analysis, is the primary step of each geostatistical modeling process to select the best work flow for geostatistical modeling in the case of dealing with multiple variables. In this paper, bivariate relationship between petrophysical, i.e. porosity, attributes used for determination of rock mechanical properties, i.e. dipole sonic logs and density log, and rock mechanical properties, i.e. poison ratio and young modulus, is investigated. Data set related to one of western Canadian oilsands basins is used for that purpose.

Introduction

Almost all natural soils are highly variable and rarely homogeneous. Lithological and inherent spatial variability of soils, are two categories of soil heterogeneity. To improve the accuracy of recovery performance predictions, detailed high-resolution geological models are built geostatistically, which are applied in numerical simulation process. Structural, facies and property modeling are three main parts of each geological models. Petrophysical and rock mechanical properties are two groups of properties which could be modeled stochastically. In the case of conventional flow simulation process, in which soil deformation has not significant effect on recovery performance, petrophysical properties, i.e. porosity, permeability and saturations, are the only properties which are modeled stochastically however, considering heterogeneous rock mechanical properties has a significant effect on predicted reservoir performance for the cases in which soil deformation could not be ignored and coupled geomechanical flow simulation process should be considered instead of flow simulation alone. A comprehensive geological model consisting of petrophysical and rock mechanical properties as well as the in-situ stress state is termed a Mechanical Earth Model (MEM).

Like petrophysical properties, log data is one of the main sources of data used for determination of rock mechanical properties. Dipole Sonic logs, i.e. compression and shear velocity logs, and density log are the main logs from which elastic properties could be determined. Equation 1 and 2 show the equations from which poison ratio (ν) and young modulus (E) are determined respectively.

$$\upsilon = \frac{0.5\left(\Delta t_s / \Delta t_c\right)^2 - 1}{\left(\Delta t_s / \Delta t_c\right)^2 - 1} \quad \textbf{(1)}$$

$$E = \frac{\rho_b}{\Delta t_c^{\,2}} \frac{(1-2\upsilon)(1+\upsilon)}{(1-\upsilon)} \quad \textbf{(2)}$$

where Δt_s is shear wave transformation time, Δt_c is compression wave transformation time and ρ_b is bulk density. The cosimulation of multiple properties remains a significant outstanding problem in reservoir characterization. Gaussian simulation techniques are the most common and simple simulation approaches used in reservoir property modeling. The use of Gaussian techniques require variables to be multivariate Gaussian; however, earth science phenomena are rarely Gaussian (Leuangthong and Deutsch, 2000). Transformation techniques are applied to make the model variables Gaussian. The conventional technique is the normal score transformation. This technique generates univariate Gaussian distributions but do not ensure bivariate or multivariate Gaussianity. Instead, the multivariate distributions may show signs of non-linearity, mineralogical constraints, and heteroscedasticity as shown in Figure 1.

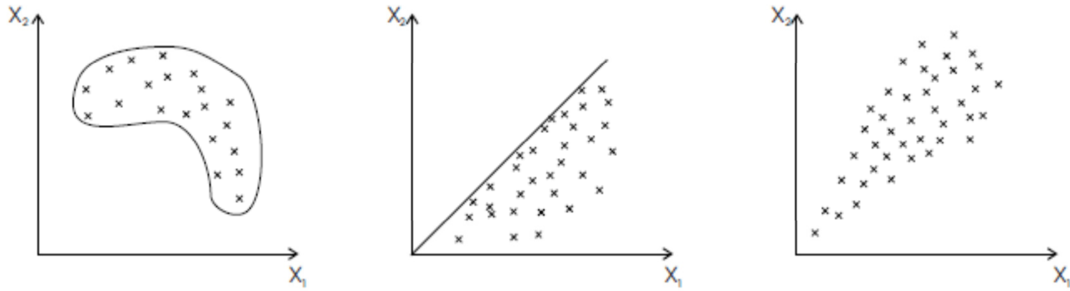

Figure 1: Examples of problematic bivariate distributions for Gaussian simulation: non-linear relations (left), constraints (centre) and heteroscedasticity (right) (Leuangthong 2003)

In the case of appearance of these features which confirm that data don't follow multi-variate Gaussianity assumption, alternative techniques such as stepwise conditional transformation technique should be used and applied instead of conventional Gaussian techniques for cosimulation of multiple variables. Univariate and multivariate statistical analysis are preliminary steps which should be performed before geostatistical modeling process. Investigating the results obtained from multivariate statistical analysis helps in selecting the most precise multivariate geostatistical modeling work flow.

In this work, univariate and bivariate statistical analysis is performed for petrophysical, i.e. porosity, attributes used for determination of rock mechanical properties, i.e. dipole sonic logs and density log, and also rock mechanical properties, i.e. poison ratio and young modulus, is investigated. Data set related to one of western Canadian oilsand reserves is used for that purpose. By defining simple cut-off on porosity, available data for this study is divided in two facies which is facies 1 (Φ<0.28) and facies 2 (Φ>0.28).

Results

Figure 2 and Figure 3 shows univariate statistical analysis of facies 1 and facies 2 respectively. Porosity, poison ratio, young modulus, compression wave velocity, shear wave velocity, compression to shear wave velocity ratio and density are 7 attributes which are considered for analysis in each facies. Differences in statistical information of each attribute could be seen by comparing corresponding histogram of each attribute in Figure 2 (facies 1) and Figure 3 (facies 2). To investigate bivariate statistical analysis, first data is transformed from original unit to normal score unit system and then scatter plot of each two variables has been plotted. Just as an example, in Figure 4 and 5 the scatter plot of porosity respect to other properties are shown. From this analysis the correlation coefficients existed between variables could be determined. In figure 6 and figure 7 correlation coefficient matrices of attributes are shown respectively for facies 1 and facies 2. As could be seen although for some bivariate correlation coefficients are almost the same in facies 1 and facies 2 but for some others, there is significant difference in correlation coefficients. The correlation coefficients existed between porosity and compression velocity could be mentioned as one set of bivariate in which there is considerable difference in correlation coefficient.

Discussion and Conclusions

In this study, multivariate relationships between petrophysical and rock mechanical properties was investigated. For that purpose the data set related to one of Canadian oilsand basin was considered and seven attributes, i.e. porosity, young modulus, poison ratio, compression velocity, shear velocity, compression/shear velocity and density, were considered. The correlation coefficient matrix obtained for each facies and it has been shown that for some set of bivariate there is considerable difference in the correlation coefficient existed between two attributes.

References

Leuangthong, O. and Deutsch, C. V. (2000). Stepwise Conditional Transformation for Simplified Cosimulation of Reservoir Properties. CCG Annual Report-Report No.2 .

Leuangthong, O. (2003). Stepwise Conditional Transformation, Ph.D. Thesis, University of Alberta.

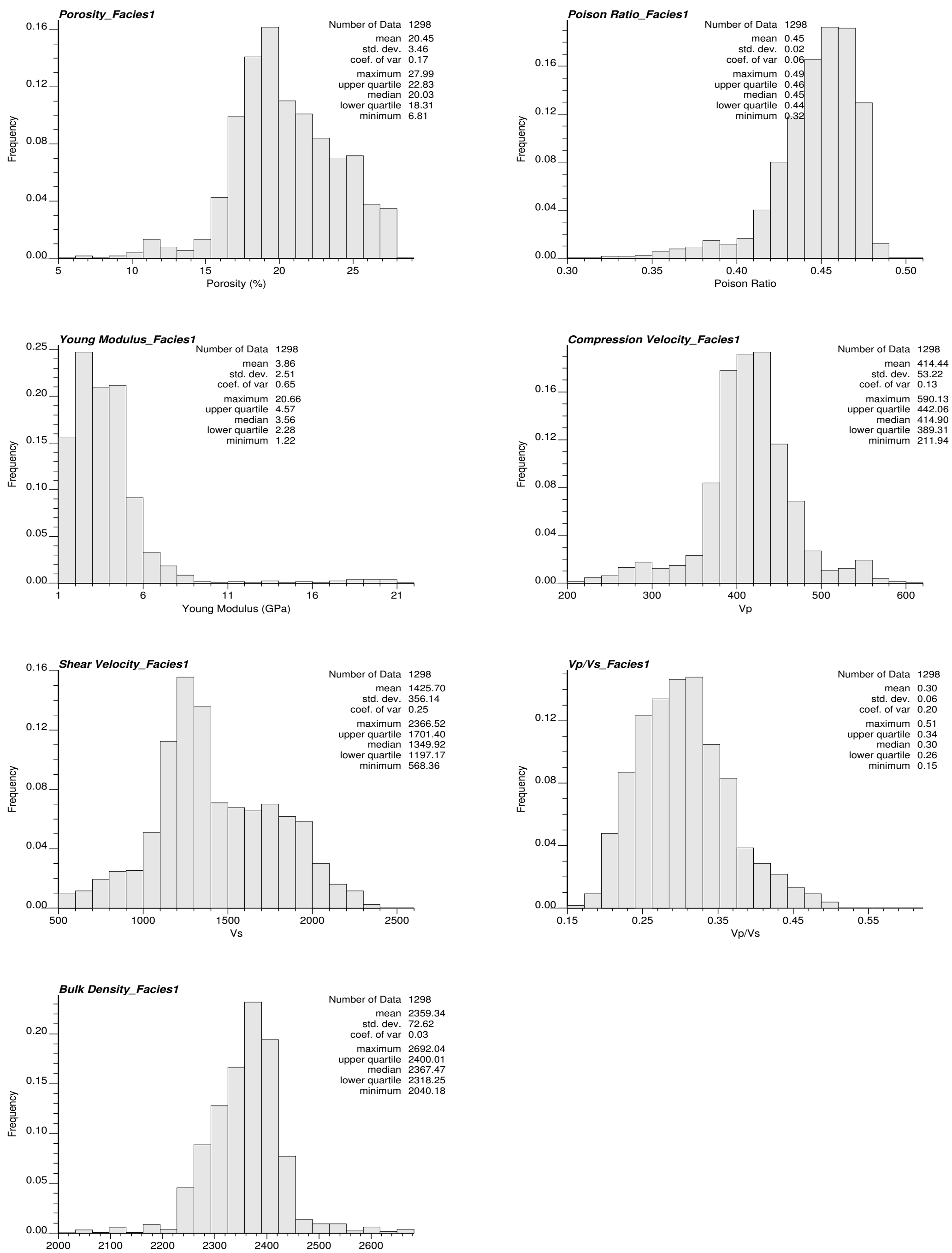

Figure 2: Histograms of attributes (facies1)

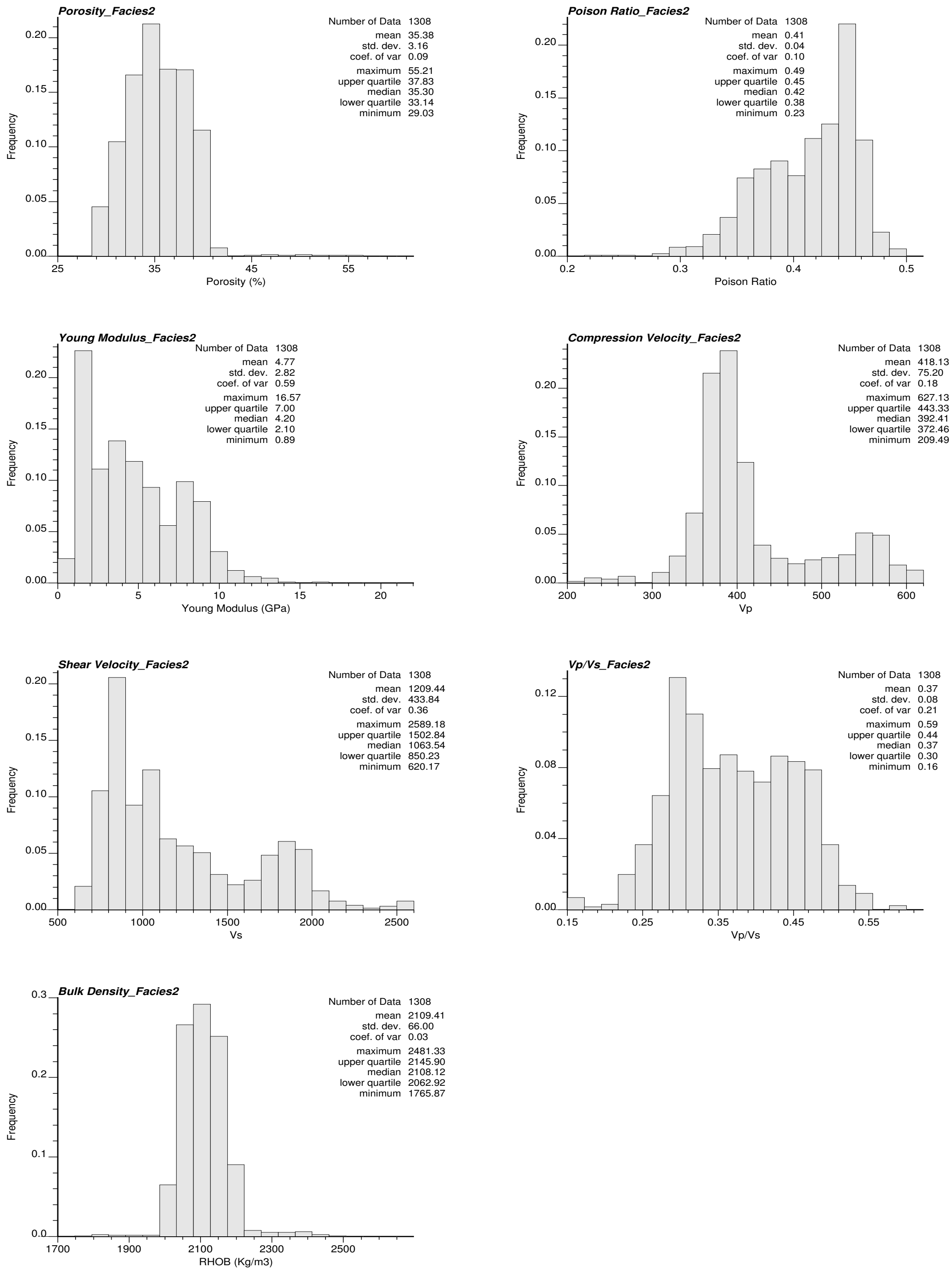

Figure 2: Histograms of attributes (facies 2)

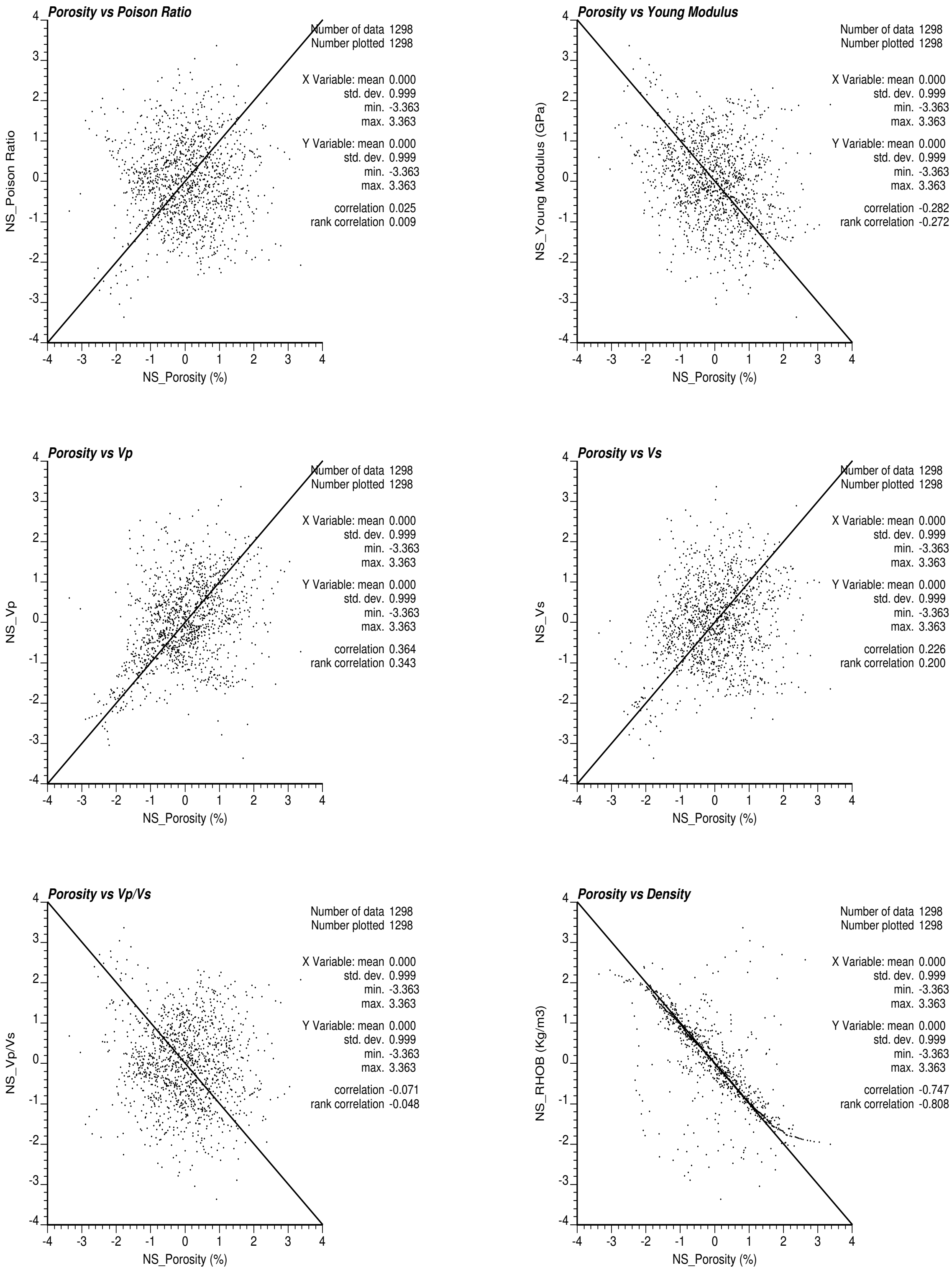

Figure 3: Scatter plots of porosity respect to other attributes (facies 1)

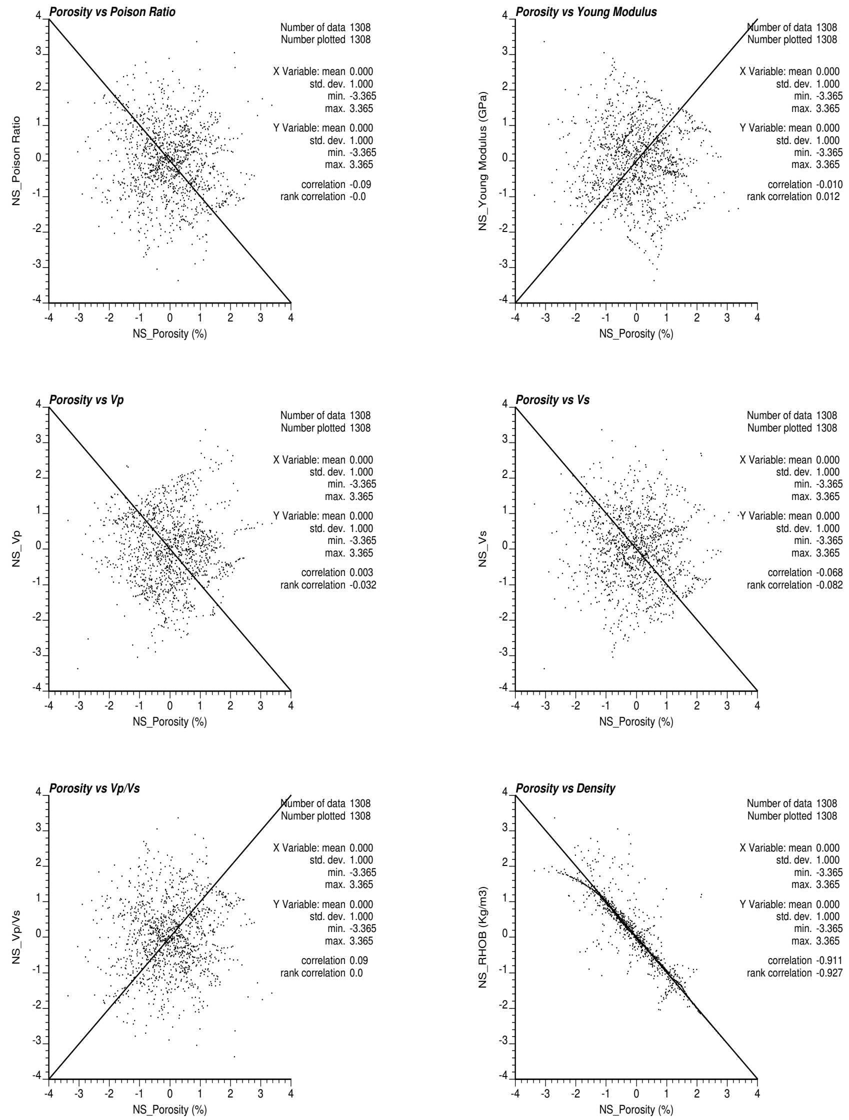

Figure 4: Scatter plots of porosity respect to other attributes (facies 2)

Correlation Matrix (Facies1)

	Porosity	Poison Ratio	Young Modulus	Vp	Vs	Vp/Vs	Density
Density	-0.75	-0.01	0.21	-0.36	-0.18	0.02	1.00
Vp/Vs	-0.07	-0.97	0.71	-0.23	-0.87	1.00	0.02
Vs	0.23	0.81	-0.80	0.65	1.00	-0.87	-0.18
Vp	0.36	0.17	-0.49	1.00	0.65	-0.23	-0.36
Young Modulus	-0.28	-0.71	1.00	-0.49	-0.80	0.71	0.21
Poison Ratio	0.02	1.00	-0.71	0.17	0.81	-0.97	-0.01
Porosity	1.00	0.02	-0.28	0.36	0.23	-0.07	-0.75

Figure 5: Correlation Coefficients (facies1)

Correlation Matrix (Facies2)

	Porosity	Poison Ratio	Young Modulus	Vp	Vs	Vp/Vs	Density
Density	-0.91	0.13	0.01	-0.01	0.08	-0.13	1.00
Vp/Vs	0.09	-1.00	0.65	-0.44	-0.88	1.00	-0.13
Vs	-0.07	0.88	-0.68	0.75	1.00	-0.88	0.08
Vp	0.00	0.44	-0.51	1.00	0.75	-0.44	-0.01
Young Modulus	-0.01	-0.65	1.00	-0.51	-0.68	0.65	0.01
Poison Ratio	-0.09	1.00	-0.65	0.44	0.88	-1.00	0.13
Porosity	1.00	-0.09	-0.01	0.00	-0.07	0.09	-0.91

Figure 6: Correlation Coefficient (facies2)