PGE 383 - Stochastic Methods for Reservoir Modeling - Spring 2019

Project Update #2 by Team 8, Univariate, Spatial Data Analysis

Name: Fernando A Apango, Gurtej S Saini, Tharit Tangkijwanichakul, Bochao Zhao

Executive Summary

The purpose of this update is to subject the data to further evaluation, by understanding its spatial distribution, identifying and correcting for sampling bias, then performing subsequent analysis on it. This update was built on top of the initial subsurface estimate formulated from the univariate analysis conducted for update 1.

The work included:

- Applying cell declustering technique to correct sampling bias in the data
- Statistical hypothesis testing for porosity and permeability values for each facies
- Heterogeneity assessment of porosity and permeability values using multiple metrics
- Preliminary uncertainty model for porosity and permeability based on facies
- An initial estimate of oil in place (in barrels)

Description of Workflows and Methods

These following steps were carried out in the IPython Jupyter notebook primarily by using the GSLIB module:

1. Corrected sampling bias in the data by cell declustering
2. Conducted t-test(mean) and F-test(variance)
3. Assessment of reservoir heterogeneity
4. Built uncertainty models for porosity and permeability (by facies) using confidence intervals and bootstrap
5. Built uncertainty models for facies proportions and oil in place using bootstrap
6. Assessment of the impact of data from 10 new wells on the uncertainty model

Results and Discussion

<u>Declustering</u>

As discussed in the previous report, based on the collected well data, there seems to be a sampling bias, i.e. some preferential sampling in the high porosity area. More data seems to have been collected around the 900m, 100m region in the south-east of the given area. Similarly, the sampling density is relatively high around the 100m, 410m region. On the other hand, very few samples are collected in the 800m, 500m region. This would result in a high bias in the estimated univariate statistics for the reservoir, therefore, the first step was to use the cell declustering technique to assign different weights to the different data points.

<u>Statistical Hypothesis Testing for Porosity and Permeability by Facies</u>

Hypothesis: Facies 0 and Facies 1 have the same average porosity

Pooled T-statistic is 6.16, and T-critical lower and upper values are [-1.97 1.97] using a confidence level of 95%. Therefore, we *reject the null hypothesis*, and we interpret that Facies 0 and Facies 1 are significantly different based on their porosity values.

Hypothesis: Facies 0 and Facies 1 have the same average permeability
Pooled T-statistic is 2.81, and T-critical lower and upper values are [-1.97 1.97] using a confidence level of 95%. Therefore, wer *reject the null hypothesis*, which means we consider the two facies have considerably different average permeability values.

Hypothesis: Facies 0 and 1 have same porosity variance
Pooled F-statistic is 1.84, F-critical lower and upper values are [-1.49 1.49] using a confidence level of 95%. Therefore, we reject the null hypothesis, as we interpret that the two facies have different porosity variance.

Hypothesis: Facies 0 and 1 have same permeability variance
Pooled F-statistic is 56.03, lower and upper values are [-1.49 1.49] using a confidence level of 95%. Therefore, we reject the null hypothesis as we interpret that the two facies have different permeability variance.

<u>Assessment of Heterogeneity</u>
To determine heterogeneity of the given data the following were calculated independently for the two different facies:
- Coefficient of Variance for both porosity and permeability
- Dykstra-Parsons coefficient of variation for assessment of permeability variation
- Lorenz Coefficient

The tables below summarize the results and the interpretations:

Coefficient of Variation		
	Facies 0	**Facies 1**
Porosity	0.44	0.68
Permeability	2.1	2.4
Permeability/ Porosity	2.47	2.44

Coefficient of Variation		
	Facies 0	**Facies 1**
Porosity	Homogeneous	Heterogeneous
Permeability	Very Heterogeneous	Very Heterogeneous
Permeability/ Porosity	Very Heterogeneous	Very Heterogeneous

Dykstra-Parsons Coefficient		
	Facies 0	**Facies 1**
Porosity	0.28	0.23
Permeability	0.94	0.89

Dykstra-Parsons Coefficient		
	Facies 0	**Facies 1**
Porosity	Homogenous	Homogeneous
Permeability	Very Heterogeneous	Very Heterogeneous

Lorenz Coefficient	
Facies 0	**Facies 1**
0.74	0.77

Lorenz Coefficient	
Facies 0	**Facies 1**
High heterogeneity	High heterogeneity

Based on the coefficient of variation for the permeability to porosity ratio, we can interpret that analyzed reservoir is very heterogeneous. In addition, if we were to use the chart (Figure 1) provided by Jensen et al. (2000) to compliment our analysis based on the estimated coefficients of variation of the reservoir facies, the depositional environment of our reservoir would have to be either crevasse splay, shallow marine rippled micaceous, or S.North Sea Rotliegendes Fm. However, this chart does not include any deep-water paleoenvironments, and therefore, there's no evidence to reject our initial interpretation of a deep-water channel system based on the geometry and distribution of the low acoustic impedance values which are the ones associated to the reservoir facies.

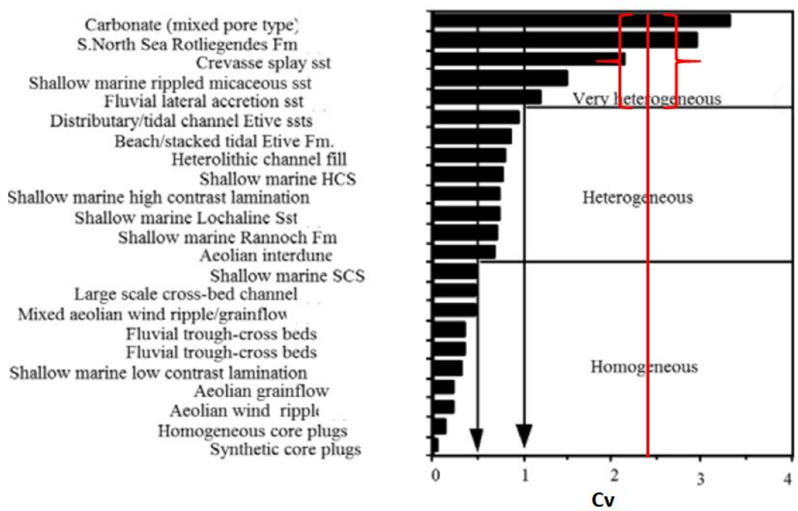

Figure 1: Relationship of the coefficient of variation with reservoir types (adapted from Jensen, J. R., Lake, L. W., Corbett P. M. W., and Goggin, D. J., 2000, Statistics for Petroleum Engineers and Geoscientists, Elsevier)

To evaluate the Lorenz coefficient, cumulative flow was plotted against cumulative storage capacity for the wells based on the facies types. These plots were generated for both the sorted data (based on the permeability to porosity ratio - in blue color), as well as the unsorted data (orange), as shown in the figure below, and compared against the line of equality (green). The heterogeneity is quite evident based on the shape of the blue curve and the variable slope in the orange curve.

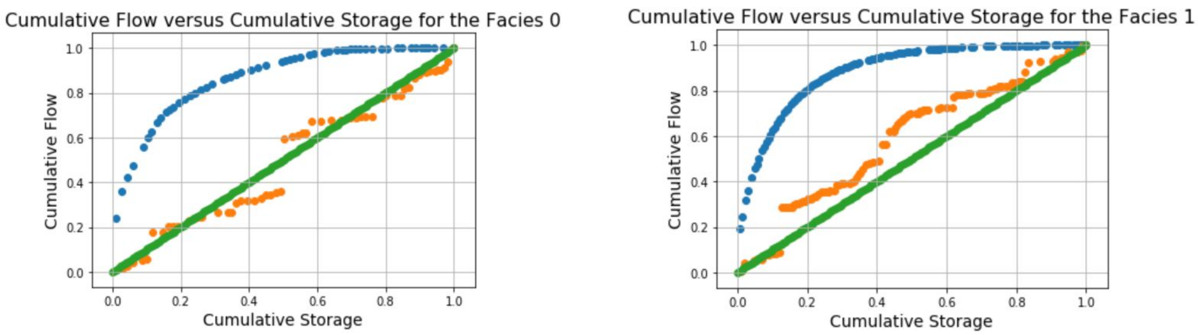

Figure 2: Plots of cumulative flow versus cumulative storage for the two facies types

<u>Uncertainty Models for Porosity and Permeability by Facies using Confidence Intervals and Bootstrapping</u>

The confidence intervals of both porosity and permeability are built using 95% confidence level. The results are the following:

Facies 1 (sand) mean porosity is 0.149 +/- 0.017, ranging [0.132, 0.167]

Facies 0 (shale) mean porosity is 0.147 +/- 0.021, ranging [0.126, 0.168]

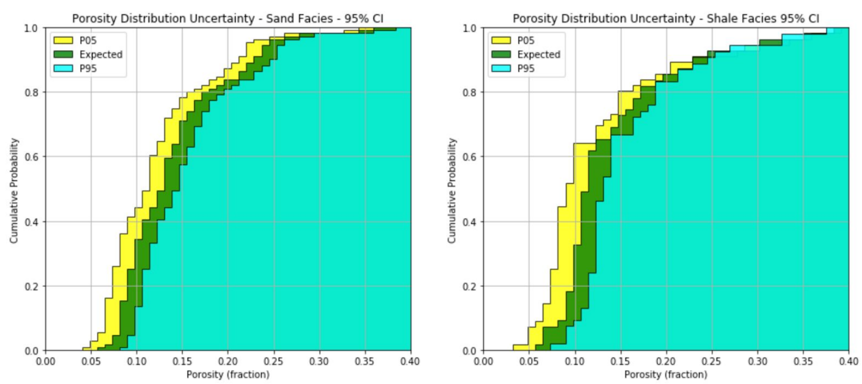

Figure 3. Porosity distribution uncertainty by facies with 3 different scenarios of porosity means using 95% confidence interval

Facies 1 (sand) mean permeability is 87.531 +/- 36.846 mD, ranging [50.686, 124.377] mD

Facies 0 (shale) mean permeability is 13.542 +/- 11.165 mD, ranging [2.377, 24.707] mD

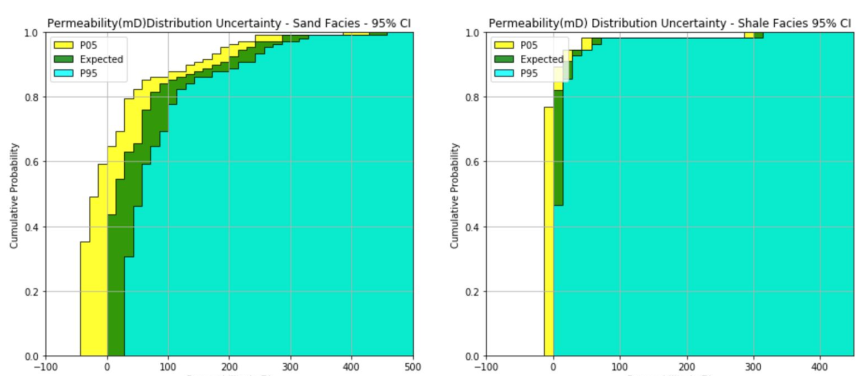

Figure 4. Permeability distribution uncertainty by facies with 3 different scenarios of permeability means using 95% confidence interval

For further investigation, bootstrap is used to build uncertainty models for mean porosity and mean permeability values for each facies. The results we obtained are the following:

Facies	Porosity				Permeability (mD)			
	P10	Mean	P90	S.D	P10	Mean	P90	S.D. (mD)
1 (sand)	0.156	0.16	0.164	0.0021	73.04	98.31	125.5	72.17
0 (shale)	0.126	0.13	0.134	0.0027	6.165	11.23	16.61	11.01

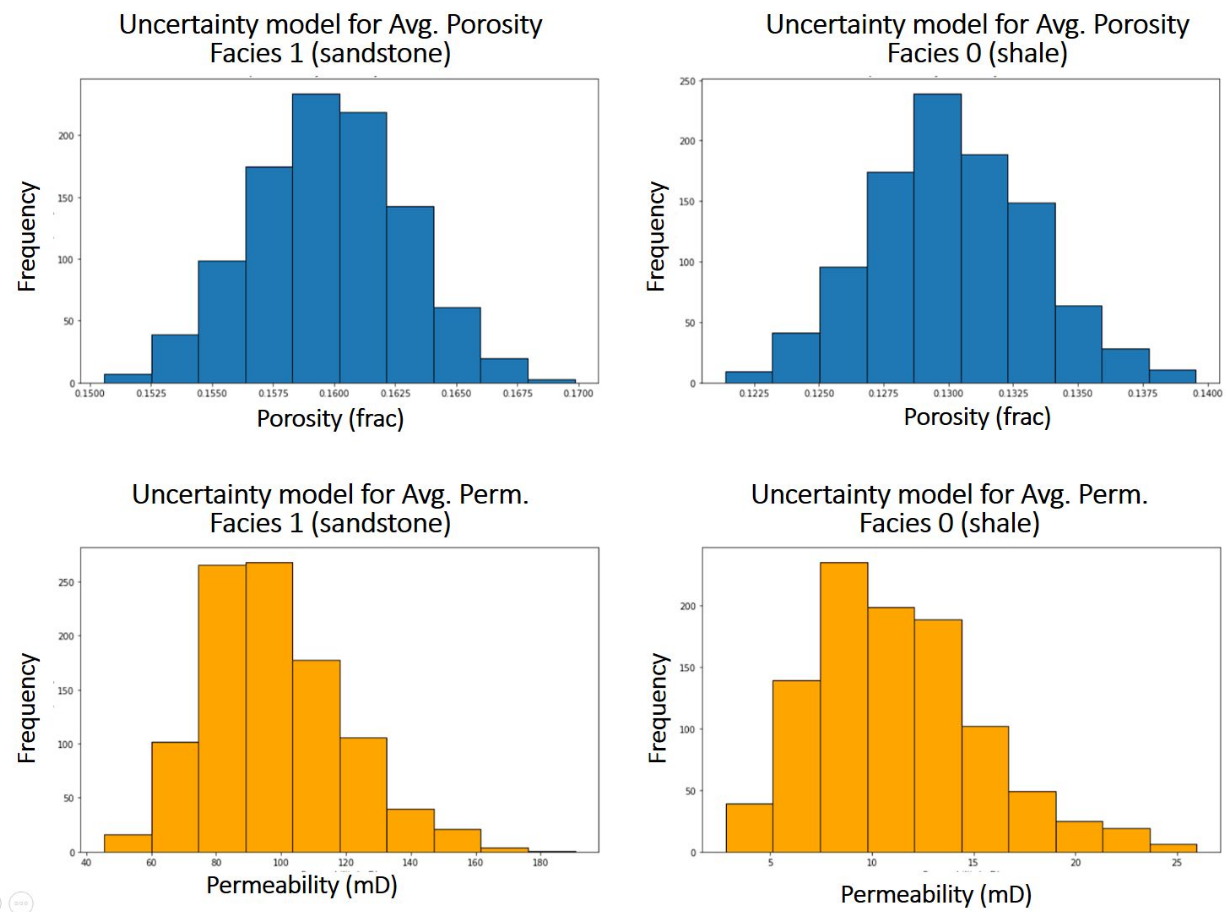

Figure 5. Bootstrap uncertainty models of porosity and permeability by facies

<u>Uncertainty Models for Facies Proportions and Oil in Place(barrels)</u>

To determine facies 1 (sand) proportion and OIP, bootstrap was also implemented. The result are the following: Facies 1 proportion mean is 0.62 with standard deviation 0.0483. 10th percentile is 0.577 and 90th percentile is 0.667.

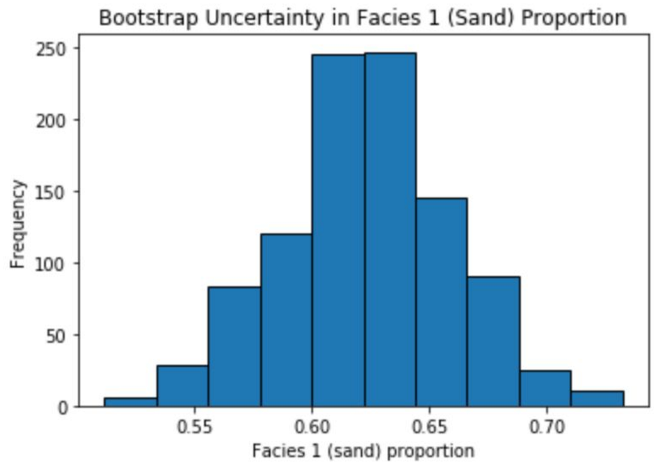

Figure 6. Bootstrap uncertainty models of facies 1 (sand) proportion in a reservoir

By using reservoir thickness of 20m, area size of 1000m by 1000m, 0.9 Oil saturation the estimated average reservoir OIP is **16.81 million barrels** with standard deviation 0.19 million barrels.10th Percentile is 16.42 million barrels and 90th Percentile is 17.21 million barrels.

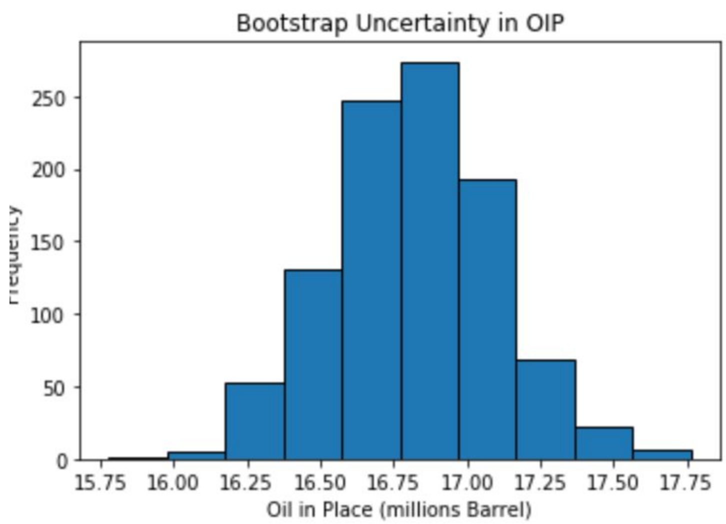

Figure 7. Bootstrap uncertainty models of Oil in Place (millions Barrel)

<u>Impact on Uncertainty Models if new 10 wells are drilled</u>

To estimate the impact of having data from 10 additional wells (178 instead of 168) we added 10 more random samples in the resampling stage of the bootstrap analysis process. The X and Y coordinates are also shifted by 50.5 (if one coordinate exceeds 1000 then the coordinate is reduced by 50.5 instead). By shifting a non-integer value, which ensures that a new sample's coordinates do not coincide with the coordinates in the original dataset.

We compared the results of this new declustering and bootstrapping process, with the uncertainty model we had previously built. The results are the following:

Facies	Porosity mean			Permeability mean (mD)		
	Before	After	Change(%)	Before	After	Change(%)
1 (sand)	0.160	0.158	1.250	98.310	95.070	3.296
0 (shale)	0.130	0.131	0.769	11.230	10.840	3.473

Facies	Porosity S.D			Permeability S.D (mD)		
	Before	After	Change(%)	Before	After	Change(%)
1 (sand)	0.0021	0.0021	1.5238	72.1700	69.8500	3.2146
0 (shale)	0.0027	0.0028	2.9259	11.0100	11.0700	0.5450

Conclusions

- Although the well samples are reasonably spatially spaced, there was some sampling bias, which was taken care of by using cell declustering.
- The two types of facies, facies 0 and facies 1, have very different porosity and permeability properties, and thus need to be treated independently.
- Based on the different heterogeneity measures (porosity and permeability) we estimated, the reservoir seems to be very heterogeneous.
- There is still uncertainty about the reservoir depositional paleoenvironment.
- From our uncertainty model, we consider 10 additional wells would not have a strong impact (max. Variation was of +/- 3%) in the estimation of the mean values of the different properties we were analyzing. Therefore, to significantly improve our estimations we would need data from more than 10 wells.
- A bivariate analysis of porosity, permeability, and acoustic impedance (by facies) is highly recommended to understand how these properties correlate with each other.

Future Work

- Conduct multivariate analysis independently for the two facies to further understand the distribution and correlations between different properties.
- Generate joint probability of different variables such as between porosity and permeability.