PGE 383 - Stochastic Methods for Reservoir Modeling - Spring 2019

Project Update #6 by Team 8, Uncertainty models and local uncertainty

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Executive Summary

The work included:

- Calculation of the uncertainty in facies proportions and average porosity by using the spatial bootstrap method
- Propagation of uncertainty in facies proportions and porosity average to porosity realizations
- Integration of the local uncertainty into the calculation of oil in place

The total OIP was estimated to be around 16.7 million barrels, and the estimated OIP from every scenario was within +/- 10 percent of this value. Considering multiple scenarios does significantly affect the result, therefore, the process of selecting different variable values for every scenario is important and checks must be in place to ensure removal of unrealistic values. For instance, the degree of variability in the facies proportion has a direct impact on the estimated OIP. The number of scenarios and the subsequent realizations do result in an improvement in the overall estimate of the OIP. Therefore, if more scenarios can be created and more realizations can be run, the more accurate our predictions of OIP would be.

Also, based on the generated map for the expected OIP, as expected, it was observed that there is a higher probability of finding more oil in place along the initially identified channel.

Description of Workflows and Methods

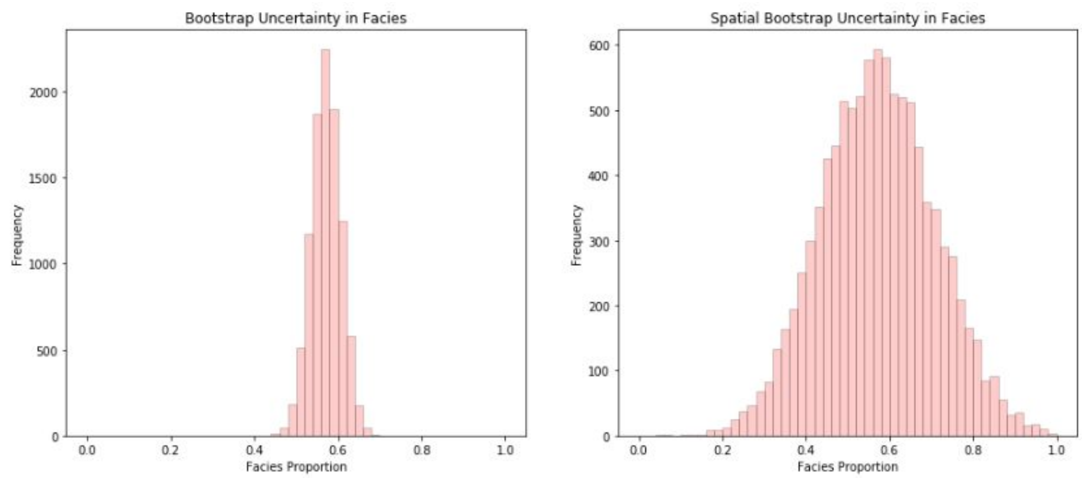
1. Estimation of ‘n effective’ to account for spatial continuity using the spatial bootstrap
2. Spatial bootstrap for average porosity and facies proportions to generate 10 scenarios
3. For the given mean porosity and variance values (for both shale and sand) for every scenario, performing the affine correction on the original declustered data
4. For every individual scenario calculating the trend for the affine corrected porosity (in both sand and shale independently) and the facies proportions.
5. Removing the trends to obtain residuals, and subsequently performing sequential gaussian(porosity) and indicator(facies) simulation on the residuals, to generate ten independent realizations. For the facies realizations, the proportions were adjusted according to the facies proportions in the scenario.
6. Adding the trend back after the simulation for each realization, and finally combining the porosity realizations for sand and shale using the cookie-cutter approach
7. Estimating the Oil In Place (OIP) for every cell over the entire area on interest, for the every realization.
8. Using post-simulation methods (e-type local expectation, conditional standard deviation and local percentile evaluation), maps for P10, P90, expectation and standard deviation for OIP, porosity and facies proportion were generated for every scenario.

9. The OIP maps for every scenario were finally combined to generate one map for the OIP over the entire area of interest.

Results and Discussion

- **Uncertainty in facies proportion and average porosity using spatial bootstrap**
  To account for effect of spatial continuity on random sampling, spatial bootstrap is used to assess uncertainty. Generally, the uncertainty distributions of properties of interest derived by spatial bootstrap show higher variance while retain the mean compared to those of distributions derived by bootstrap

  - Sand facies proportions

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the effective n is  11.505025587287681
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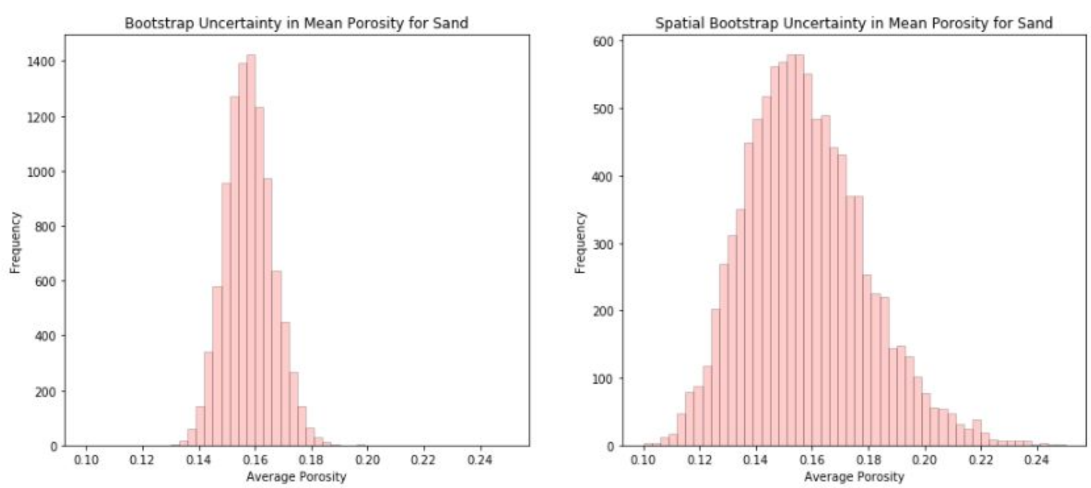
Figure 1. Bootstrap (left) and Spatial bootstrap (right) uncertainty of sand facies proportion

  - Mean porosity / sand facies

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the effective n is  17.250903565720446
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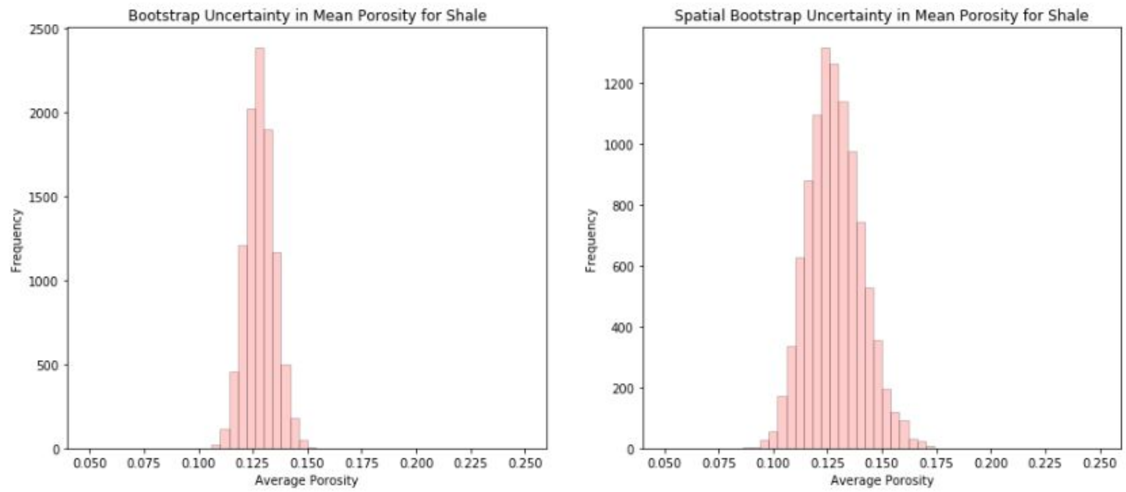
Figure 2. Bootstrap (left) and Spatial bootstrap (right) uncertainty of mean sand porosity

- Mean porosity / shale facies

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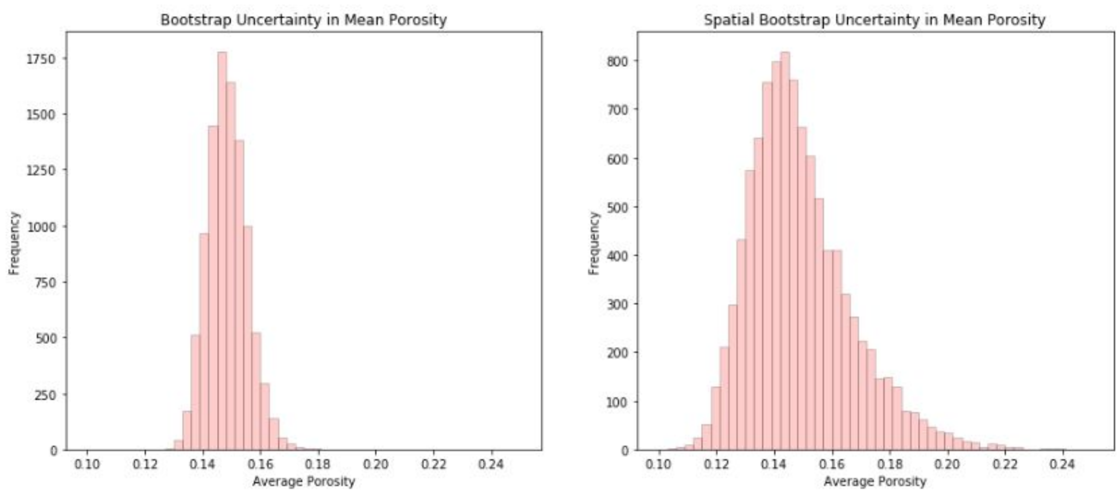
the effective n is  16.847669487186206
```

Figure 3. Bootstrap (left) and Spatial bootstrap (right) uncertainty of mean shale porosity

- Mean porosity / net

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the effective n is  25.01164655668339
```

Figure 4. Bootstrap (left) and Spatial bootstrap (right) uncertainty of mean porosity of all facies

- **Building uncertainty models from 10 randomly sampled facies proportion scenarios and 10 randomly sampled mean porosity scenarios**

Given uncertainty distributions from spatial bootstrap workflow, 10 sand facies proportion and 10 mean porosity values for sand and shale are randomly sampled. The assumption is that all realizations are equiprobable. However, while selecting the facies proportions, heuristics was

used to impose a condition on selecting realizations. The sand facies proportion could not be less than 40 percent and could not be more than 90 percent.
Based on the sampled values and their statistics, the affine correction is performed on the original declustered data. This helps generate the various scenarios.

- **Facies realizations with embedded uncertainty (10 scenarios)**

The proportion of facies for the 10 generated scenarios was:

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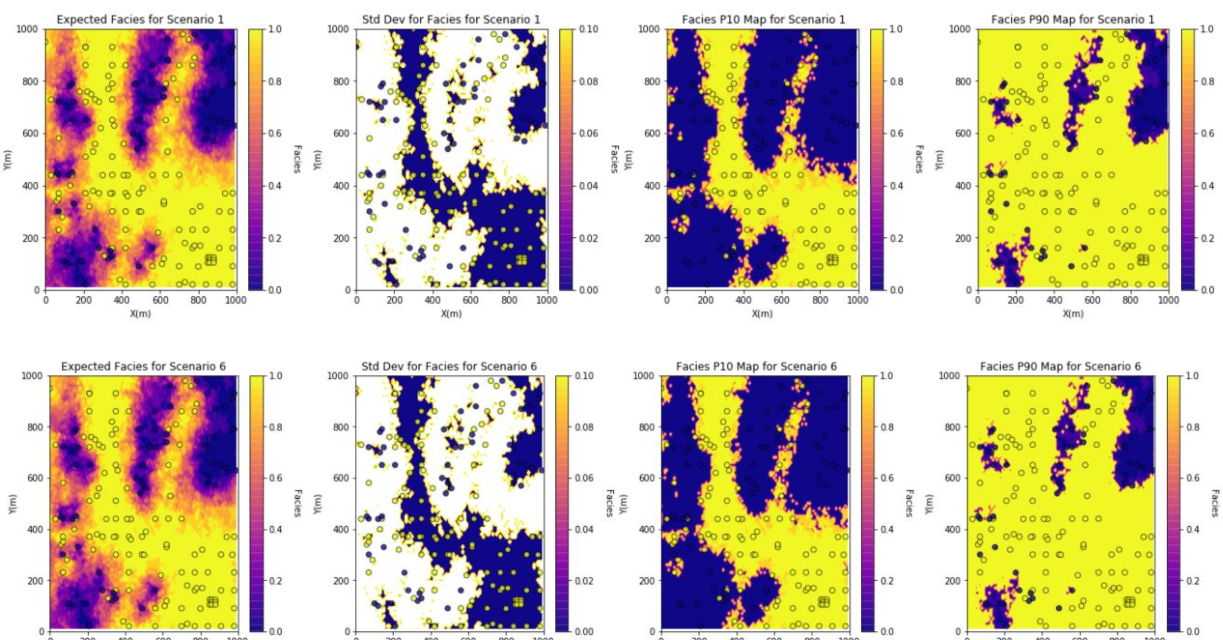
The proportion of facies for the various scenarios are

Scenario 1 :  0.753
Scenario 2 :  0.511
Scenario 3 :  0.535
Scenario 4 :  0.647
Scenario 5 :  0.582
Scenario 6 :  0.664
Scenario 7 :  0.432
Scenario 8 :  0.844
Scenario 9 :  0.473
Scenario 10 :  0.433
```

Figure 5. Monte Carlo simulated sand proportion from spatial bootstrap uncertainty model

Facies realizations were simulated (10 realizations for every scenario) using sequential indicator simulation, on the affined-corrected data. The following figures show the e-type expectation, conditional standard deviation and the 10 and 90 percentiles summarized over all the realizations for three scenarios.



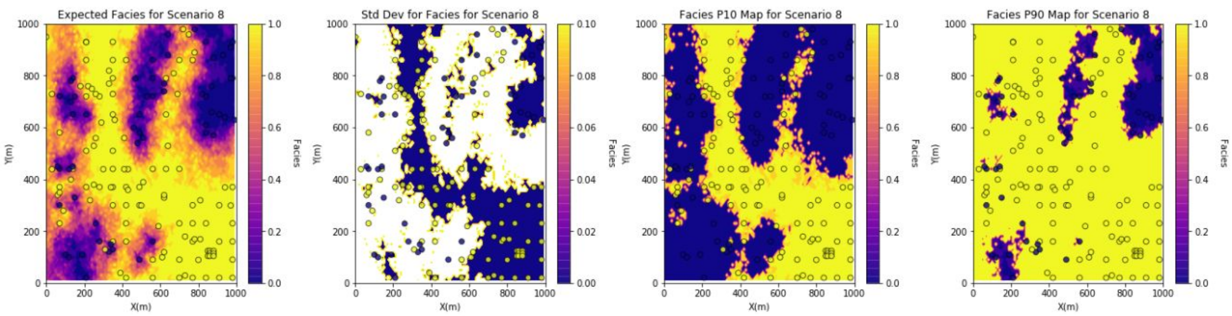


Figure 6. Examples of simulated facies maps from different MCS sand facies proportion

- **Porosity realizations with embedded uncertainty (10 scenarios)**
  Both sand and shale porosity are simulated (10times) separately using sequential gaussian simulation and their corresponding affine-corrected data. Then overall porosity maps are generated by the cookie-cutter approach, where the facies maps are based on 10 different simulated facies scenarios.

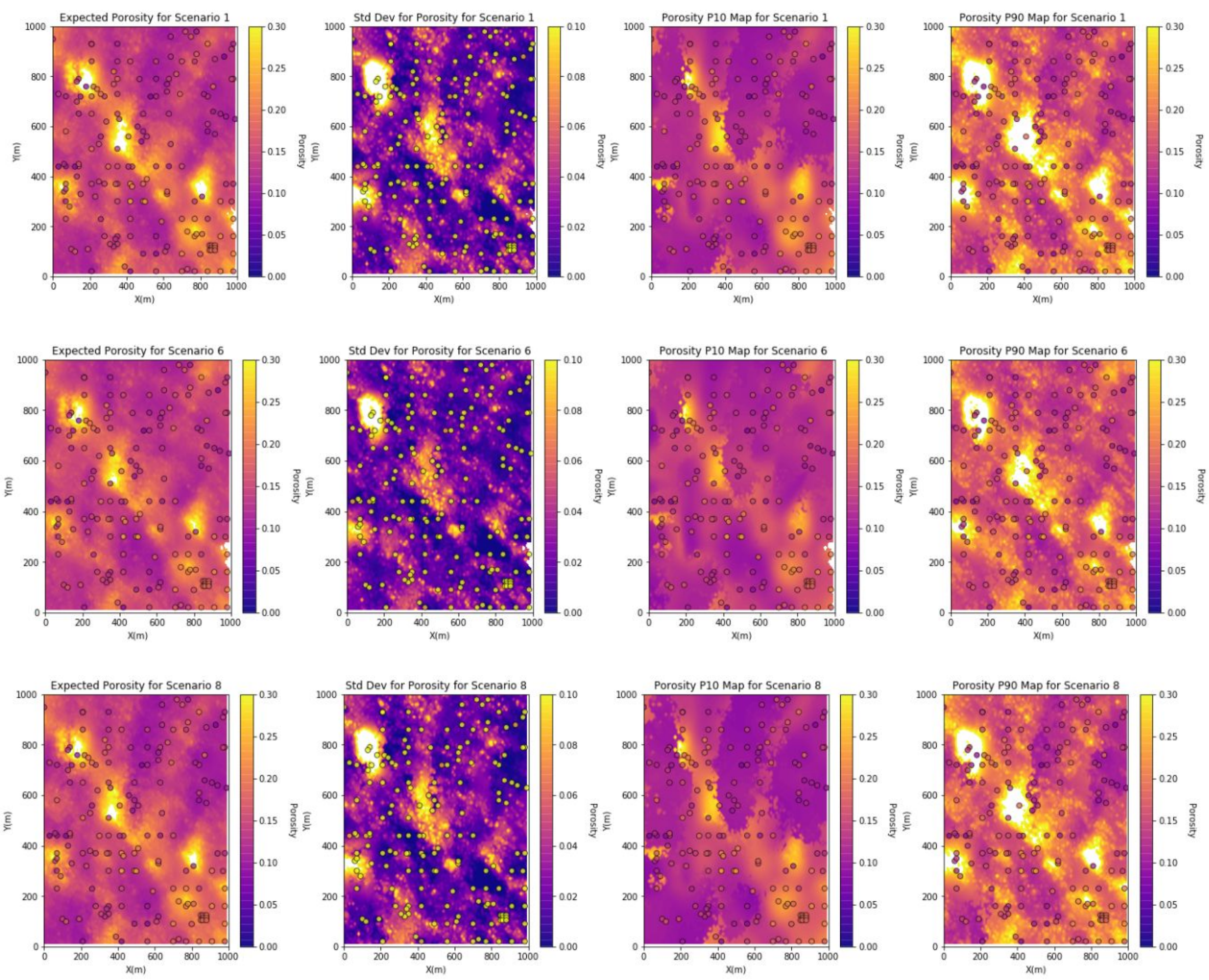


Figure 7. Examples of simulated porosity maps from different scenarios - MCS mean sand porosity, mean shale porosity, and sand facies proportion.

- **OIP realizations with embedded uncertainty (10 scenarios)**

The following procedure was followed to estimate the expected value of OIP:

- For every individual realization, for every individual cell (of 100 m2 area, with 10m by 10m dimensions), the OIP was estimated.
- The results over all the 10 realizations were then averaged by using the e-type combination to obtain the local expectation, to generate a map for the expected OIP for the individual scenario
- The total OIP over all the individual cells was then summed, for every scenario, to obtain the OIP over the entire area

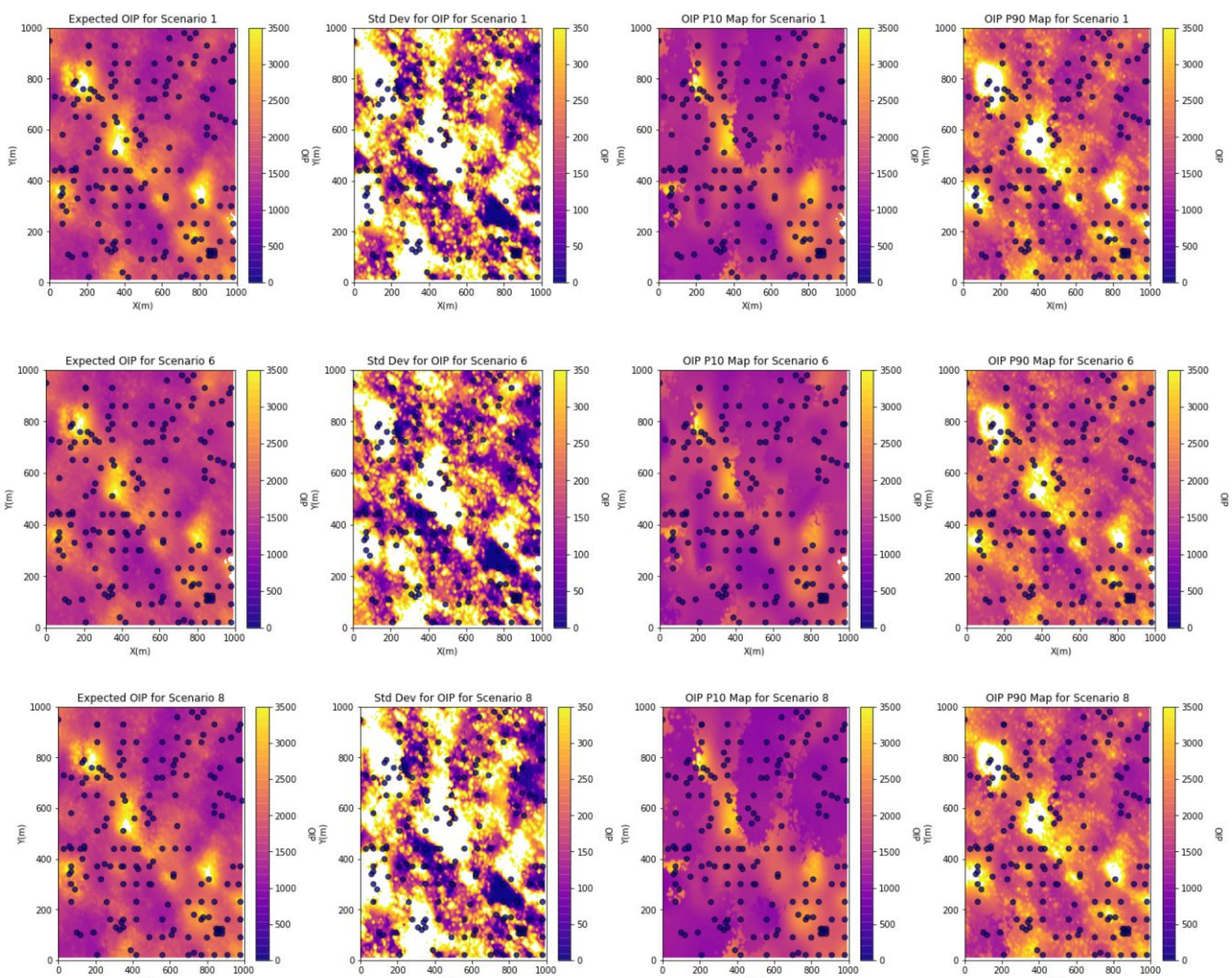


Figure 8. Examples of OIP maps from different scenarios - MCS mean sand porosity, mean shale porosity, and sand facies proportion.

The OIP for the 10 scenarios is shown below. As can be seen the degree of variability in the facies proportion has a direct impact on the estimated OIP.

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The total expected oil in million barrels for different scenarios is

Scenario 1 :  18.273
Scenario 2 :  17.465
Scenario 3 :  15.446
Scenario 4 :  15.921
Scenario 5 :  15.656
Scenario 6 :  17.545
Scenario 7 :  17.827
Scenario 8 :  17.664
Scenario 9 :  16.868
Scenario 10 :  15.441
```
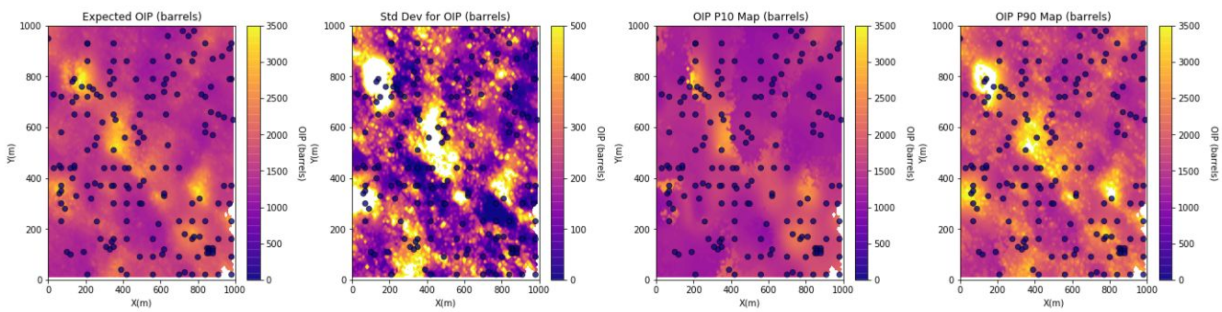

Figure 9. Simulated total expected OIP for 10 scenarios

Finally the OIP maps over all the various scenarios were combined to generate one map over the entire area:

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The expected OIP (million barrels) for the combination of the scenarios and subsequent realizations is  16.7633
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Figure 10. Total expected OIP map and its standard deviation, P10, and P90 map

Conclusions

- Variance expands significantly when we account for spatial continuity (bootstrap with 'n effective')
- By including the local uncertainty into our simulations we're more confident about the areas with greater potential for drilling. An under-explored region was identified in the central-eastern portion of our study area that shows consistent high OIP even in the P10 generated maps.

Future Work

- There is a possibility to incorporate more heuristics and expert-based knowledge while generating scenarios. This would help improve the overall estimates of the OIP.
- Develop a loss function to determine the cost of underestimating or overestimating the OIP