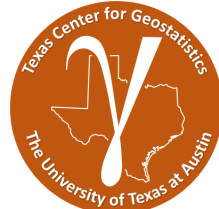




William C. Gussow 2018 Canadian Society of Petroleum Geoscience Advances in Applied Geomodeling for Hydrocarbons

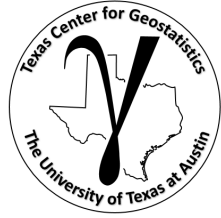


Geostatistical Workflows for Modeling Uncertainty for Unconventionals

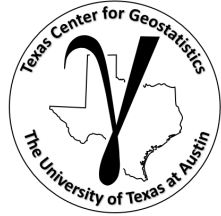
Michael J. Pyrcz, P.Eng., Associate Professor
Hildebrand Department of Petroleum and Geosystems Engineering
Bureau of Economic Geology, Jackson School of Geosciences
The University of Texas at Austin

WHAT STARTS HERE CHANGES THE WORLD

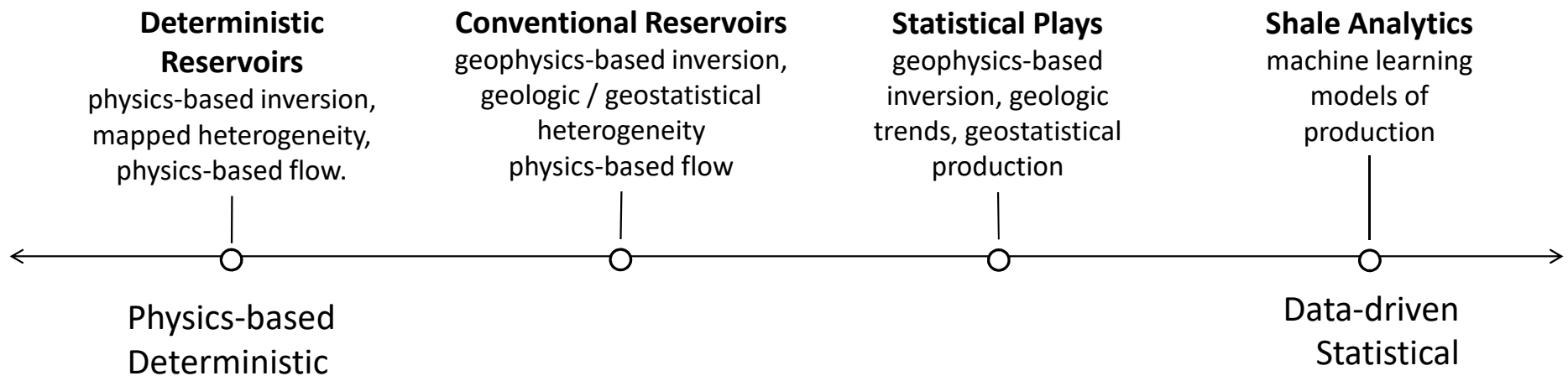
Conclusions



1. Due to increased data and transfer function uncertainties we are motivated to use the **statistical play approach**.
2. Statistical play approach is the **regionalization of production**.
3. As the geostatistics community, we need to reinforce the **need to account for spatial continuity, data conditioning, location and boundaries**.
4. We can do this with **model resampling workflows** to provide support for decision making in unconventional.



Overview



If we are going to work with the statistical play and shale analytics:

- Spatial continuity, conditioning data, location and boundaries

Let's start with the statistical play concept.

Overview

Traditional Play:

- Reservoir measurements and geologic regions to infer reservoir property spatial distributions
- Input to the transfer function for forecasting

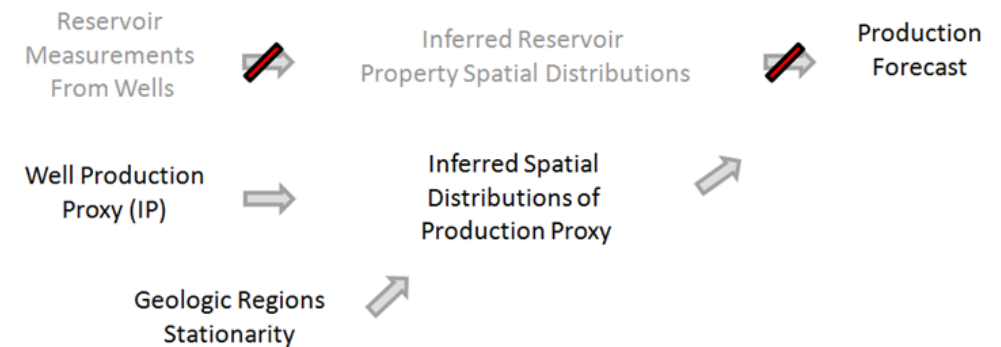
Traditional



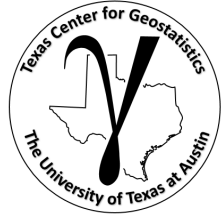
Statistical Play:

- Reservoir measures are more uncertainty
- Linkages from measures to performance is weakened.
- Treat production as the regionalized variable (*Schmoker, 1999; Olea, 2011*).

Statistical Play



Traditional vs. Statistical Play (Pyrz, Janele, Weaver and Strebelle, 2017)



Previous Work

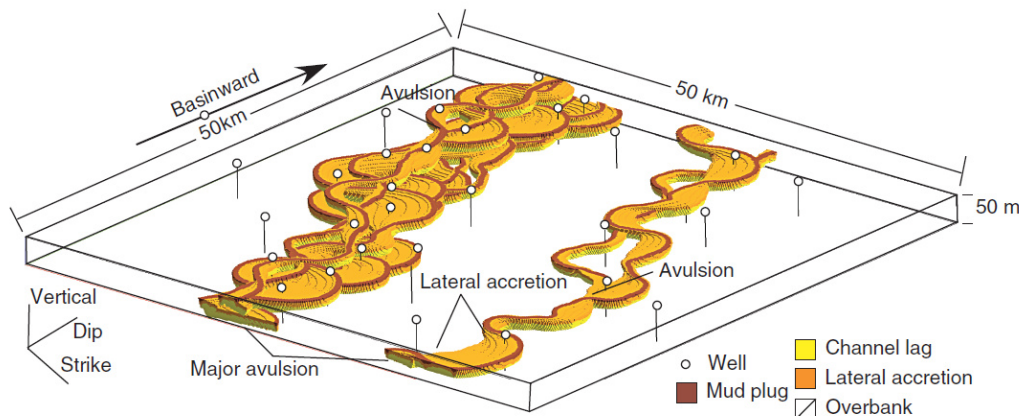
Statistical Play:

- Direct modeling of well production (Estimated Ultimate Recovery) or proxy (initial production) (*Schmoker, 1999*)
- Geostatistical simulation of production with secondary data (e.g. thickness and vitrinite reflectance) (*Olea et al., 2010 and 2011*)
- Uncertainty modeling based on bootstrap (*SPEE Monograph #3, 2010*)
- Uncertainty by well spacing (Wilde and Deutsch, 2013)

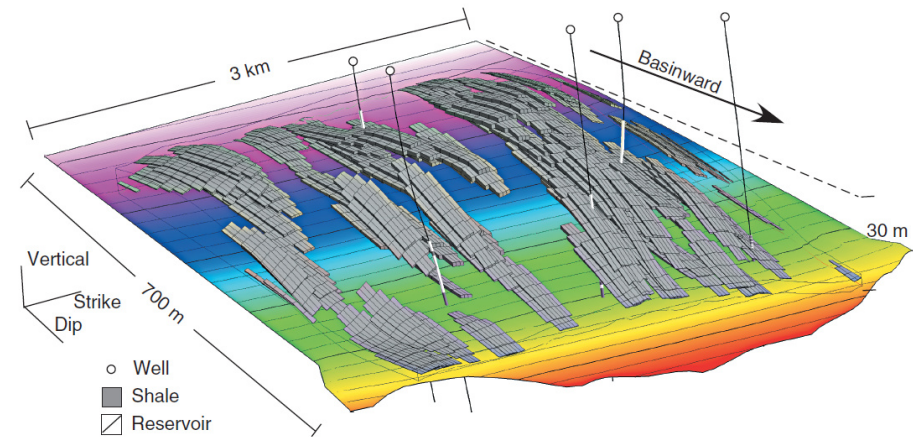
Model Resampling:

- Resampling from stochastic simulations with spatial bootstrap (*Journel, 1994*).
- Uncertainty in facies proportion from independent wells (*Hass and Formery, 2002*).
- Model resampling for early assessment (*Journel and Bitanov, 2004*).
- Synthetic well resampling from stochastic realizations for appraisal NTG uncertainty (*Maharaja, 2007*)

Previous Work



An Event-Based model with avulsion and meander migration (Pyrzcz and Deutsch, 2014).



An object-based mud drape model for a deltaic setting (Pyrzcz and Deutsch, 2014).

Model Resampling

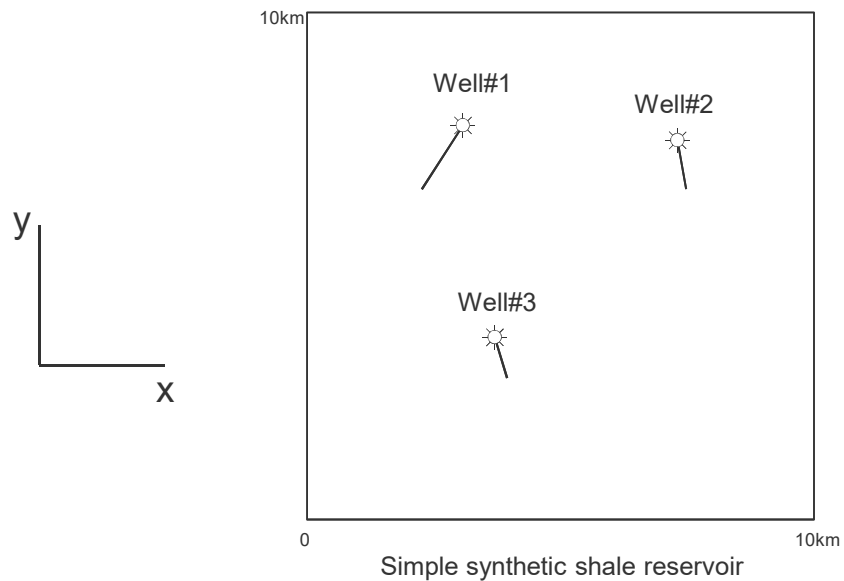
- Extracting samples from an ensemble of subsurface models to explore uncertainty, evaluate sampling strategy, value of information etc.
- Integrates all model decisions and conditioning
- Robust in the presence of nonstationarities, spatial continuity, boundaries



Previous Work

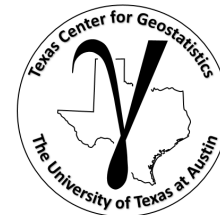


Geostatistical Simulation Approach (Olea et al., 2012)



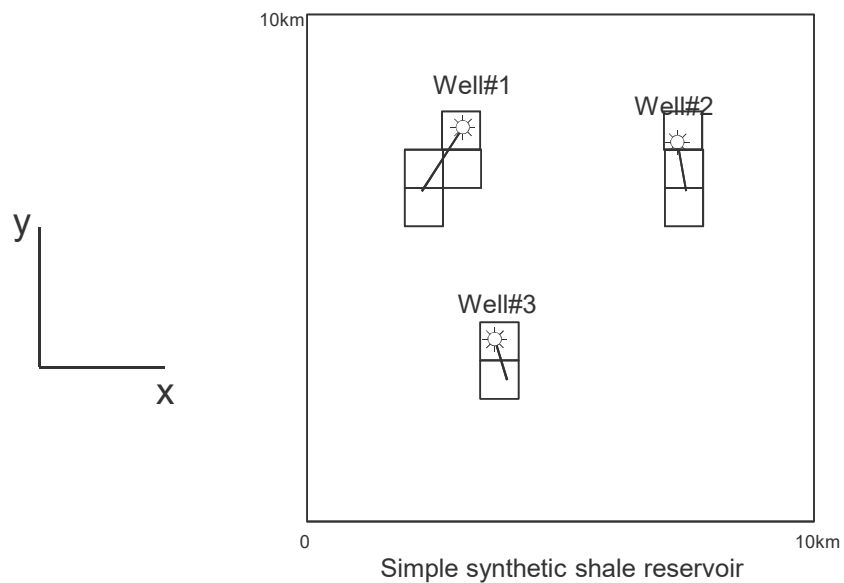


Previous Work



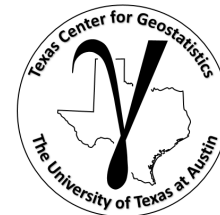
Geostatistical Simulation Approach (Olea et al., 2012)

1. Partition EUR over cells within drainage area.



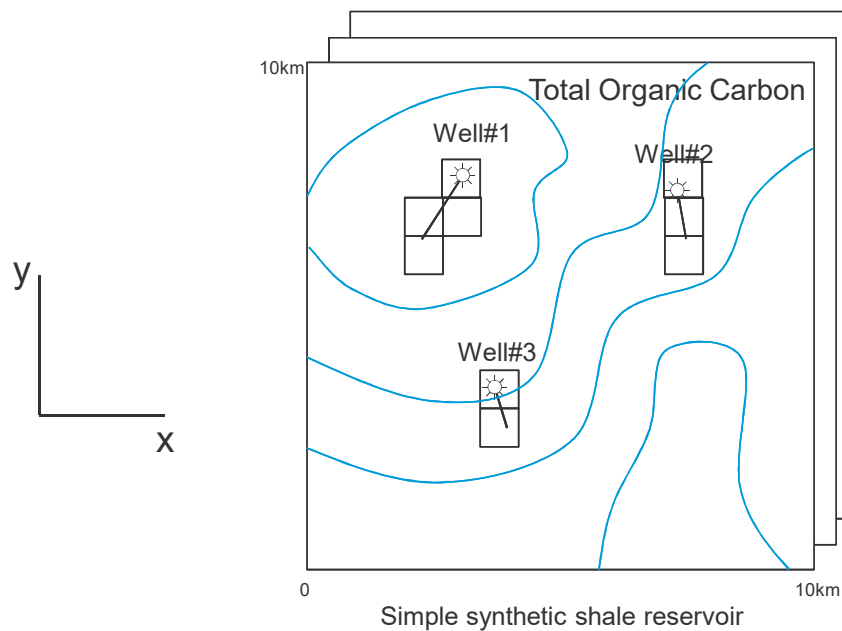


Previous Work



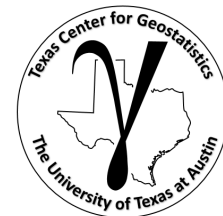
Geostatistical Simulation Approach (Olea et al., 2012)

1. Partition EUR over cells within drainage area.
2. Simulate secondary variables.



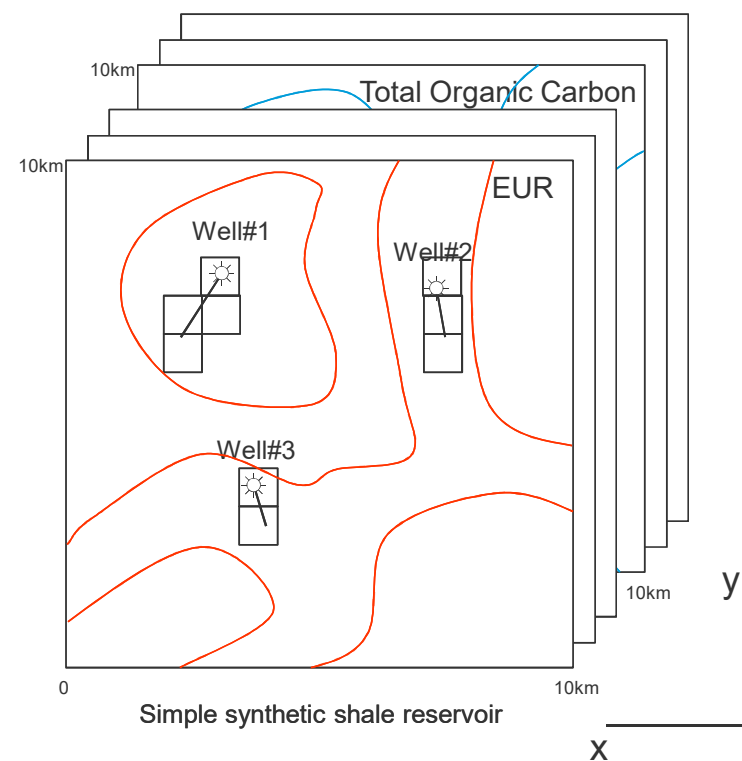


Previous Work



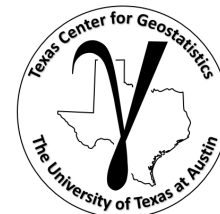
Geostatistical Simulation Approach (Olea et al., 2012)

1. Partition EUR over cells within drainage area.
2. Simulate secondary variable(s).
3. Cosimulate EUR constrained by secondary variable(s).



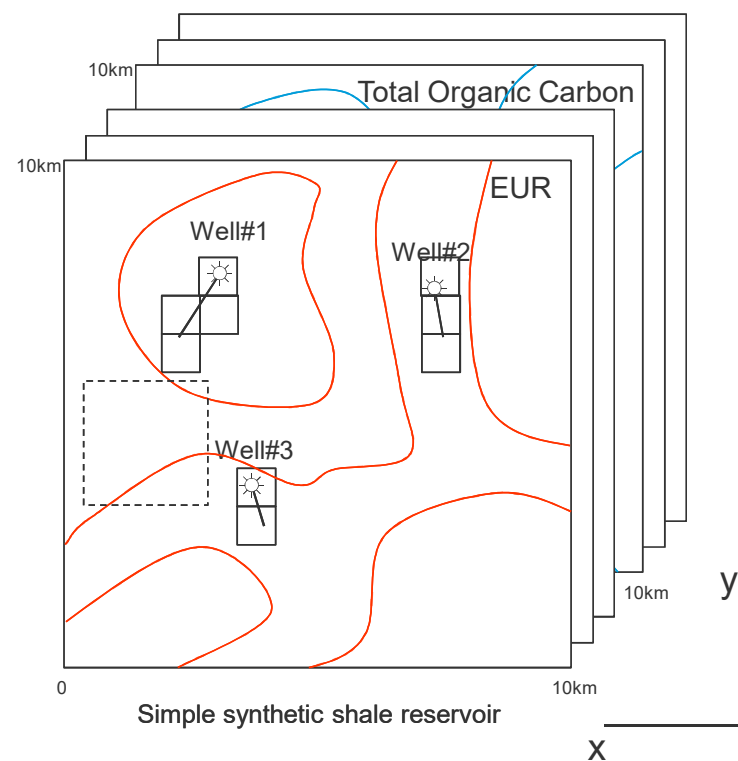
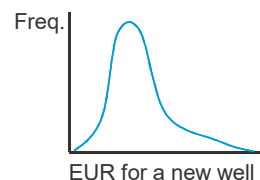


Previous Work



Geostatistical Simulation Approach (Olea et al., 2012)

1. Partition EUR over cells within drainage area.
2. Simulate secondary variable(s).
3. Cosimulate EUR constrained by secondary variable(s).
4. Summarize simulated EUR over assessment area.

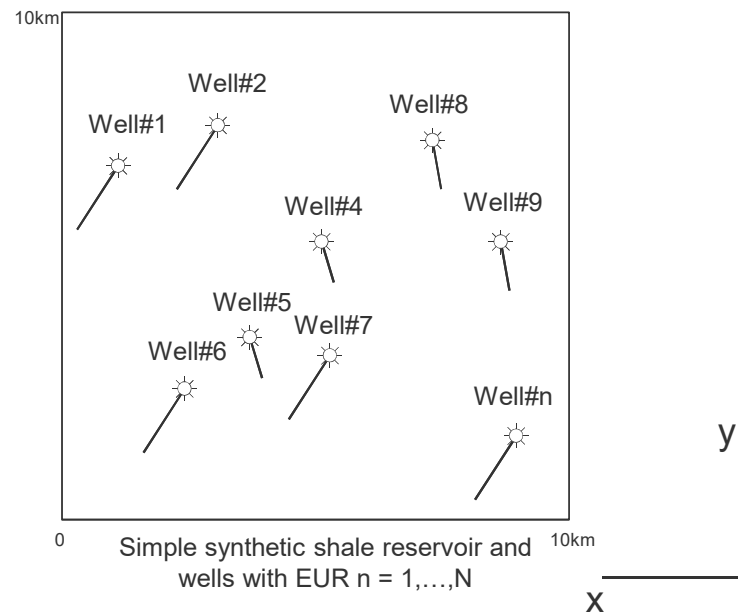




Previous Work

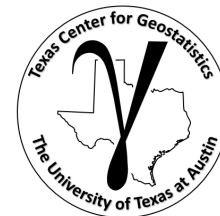


Bootstrap Approach (Efron, B., 1982; SPEE, 2010)



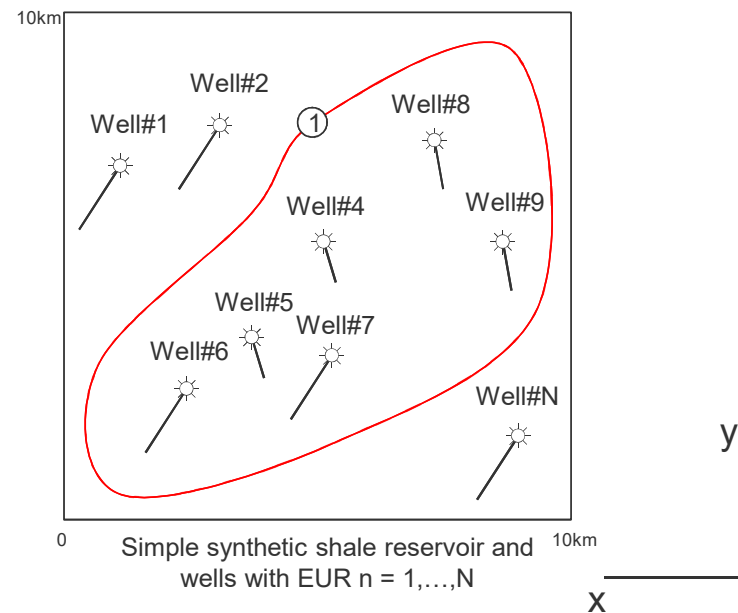


Previous Work



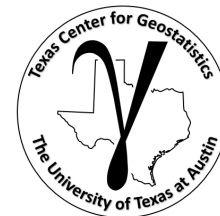
Bootstrap Approach (Efron, B., 1982; SPEE, 2010)

1. Identify analogous wells





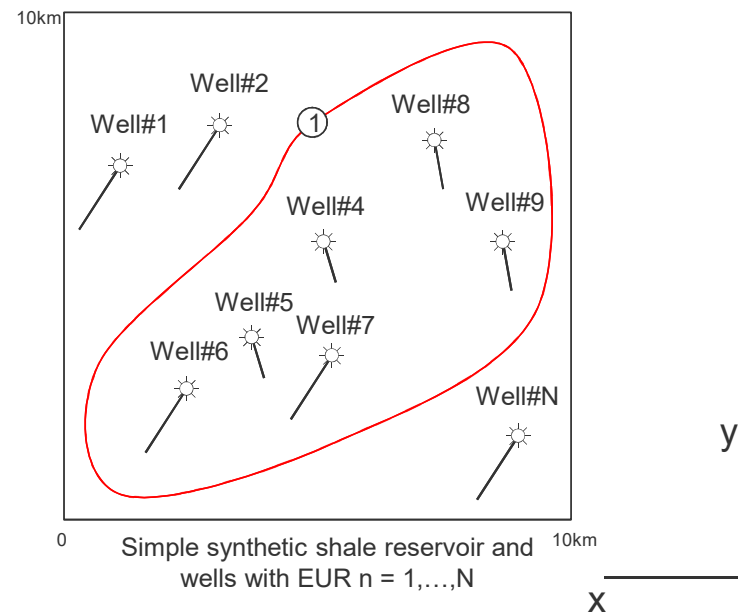
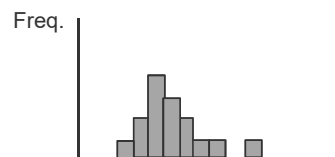
Previous Work



Bootstrap Approach (Efron, B., 1982; SPEE, 2010)

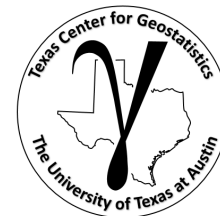
1. Identify analogous wells
2. Model the EUR distribution

② EUR Distribution



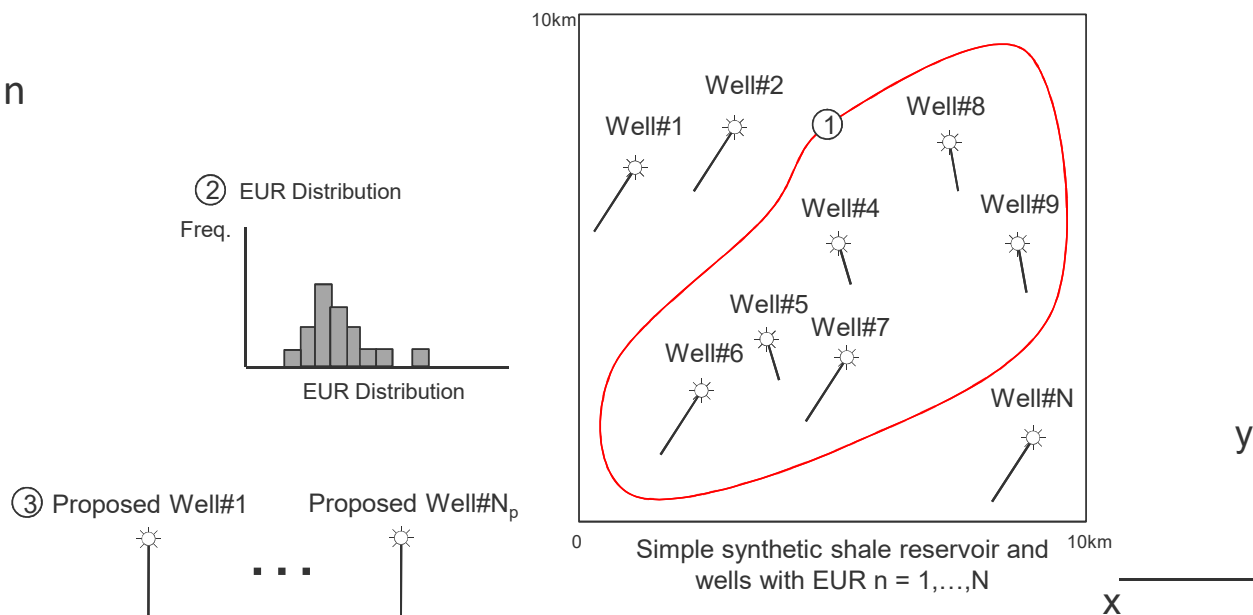


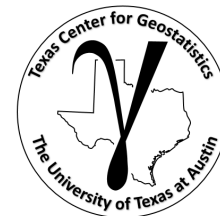
Previous Work



Bootstrap Approach (Efron, B., 1982; SPEE, 2010)

1. Identify analogous wells
2. Model the EUR distribution
3. Determine number of wells in plan

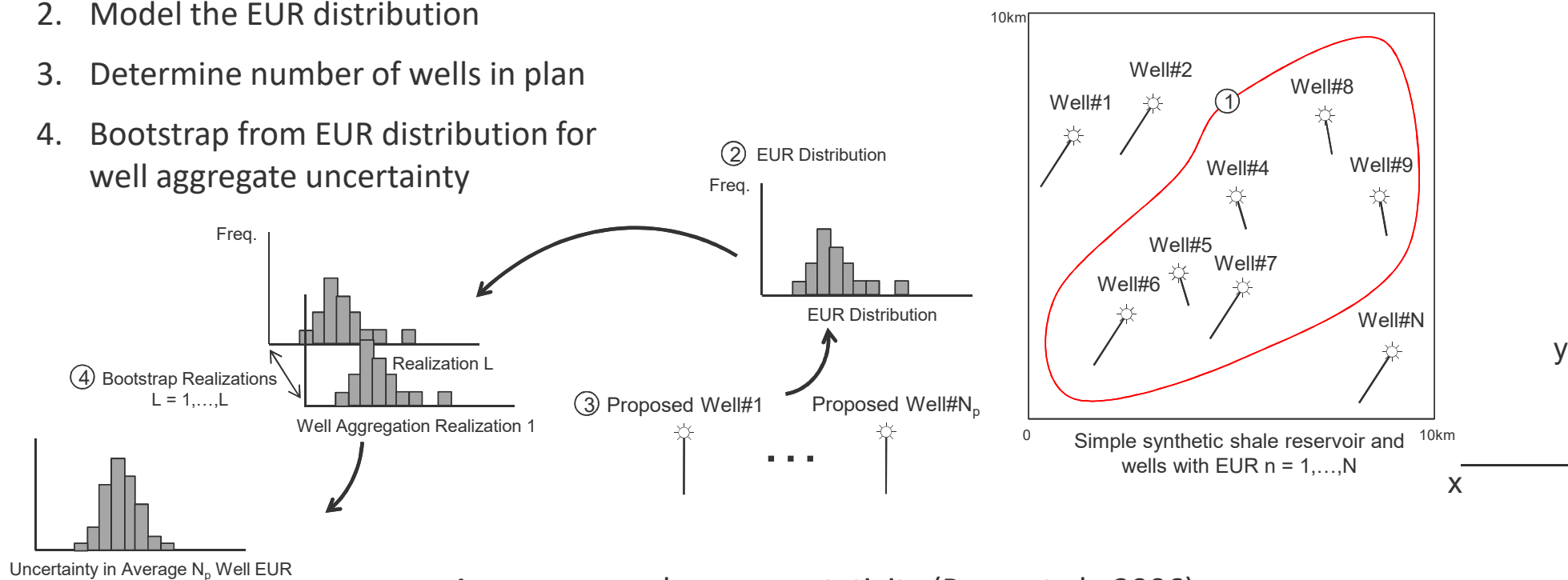




Previous Work

Bootstrap Approach (Efron, B., 1982; SPEE, 2010)

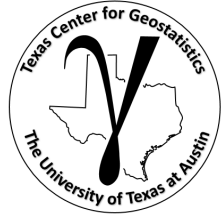
1. Identify analogous wells
2. Model the EUR distribution
3. Determine number of wells in plan
4. Bootstrap from EUR distribution for well aggregate uncertainty



Assumes sample representativity (Pyrzcz et al., 2006).

SPEE Monograph #3

Assumptions

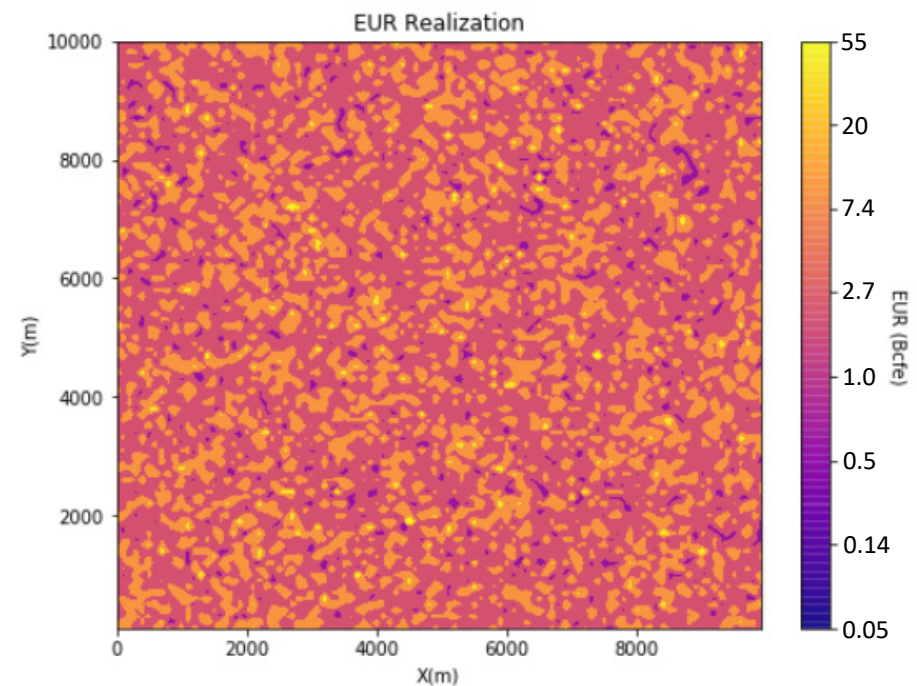


Conservative with Regard to Stationarity / Extrapolation:

1. Analog selection
2. Allowable offsets
3. Number samples

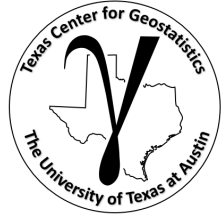
Spatial continuity:

- All bootstrap sampled wells are treated independent identically distribution
- No spatial location
- EUR / EUR proxy has no spatial correlation



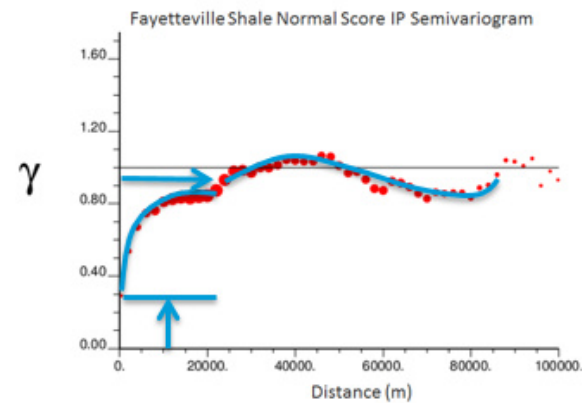
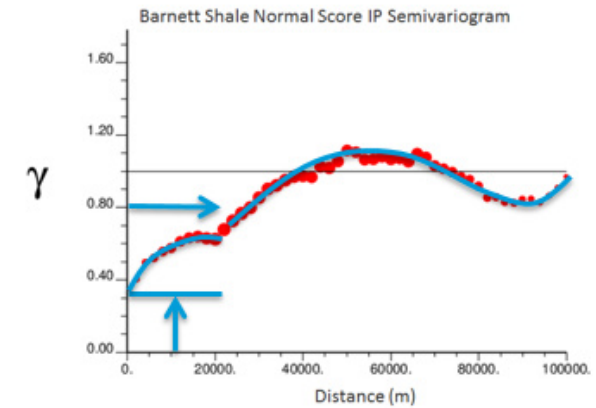
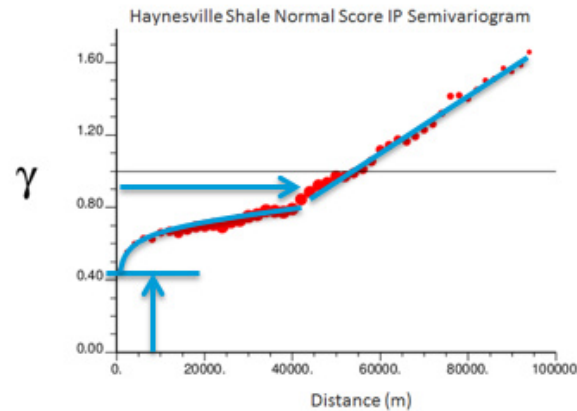
EUR for a field without spatial correlation.

Resampling With Spatial Correlation



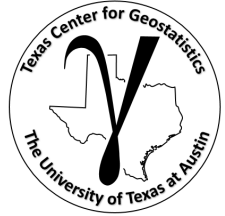
EUR / EUR proxy spatial continuity include multiple spatial frequencies:

1. 30-40% nugget effect
2. 30-40% medium scale continuity
3. 20-30% long range trend / cyclicity



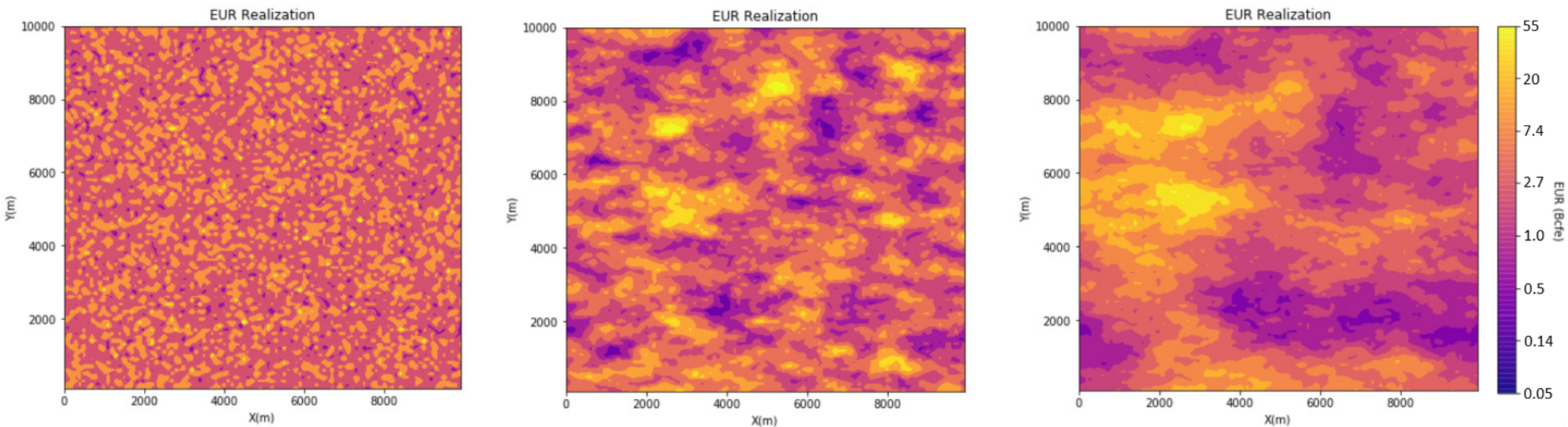
Experimental semivariograms for domestic shale IP (Pyrzcz et al., 2016)

Resampling With Spatial Correlation



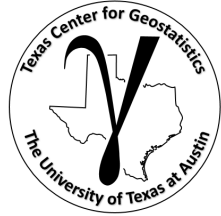
EUR / EUR proxy spatial continuity include multiple spatial frequencies:

1. 30-40% nugget effect
2. 30-40% medium scale continuity
3. 20-30% long range trend / cyclicity



Three distinct EUR models with Nugget, Medium and Long Range Cyclicity.

Does Spatial Context Matter?



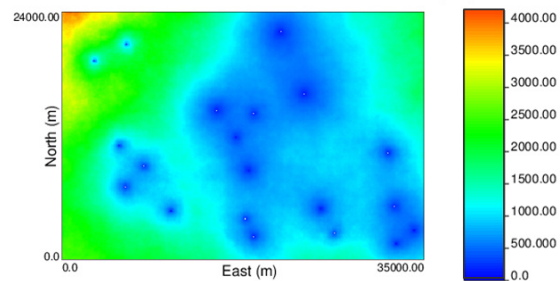
Spatial Bootstrap applied to 3 distinct drilling strategies:

1. Pad in low uncertainty region
2. Pad in high uncertainty region
3. Infill drilling

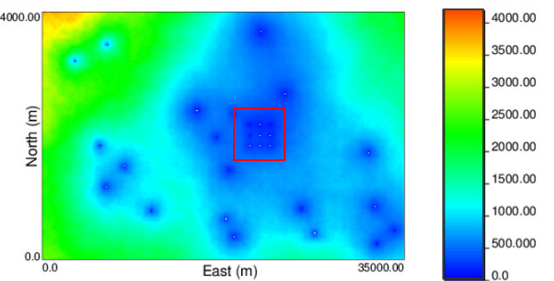
SPEE Monograph #3 Prediction

- The same uncertainty model

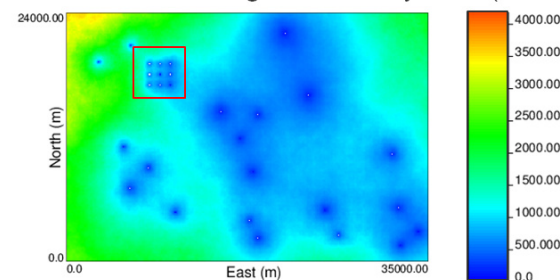
Available Data and Local Uncertainty (MCFPD)



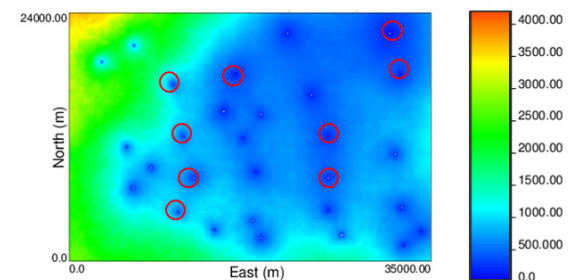
Scenario 1: Pad in Low Uncertainty Area (MCFPD)



Scenario 2: Pad in High Uncertainty Area (MCFPD)



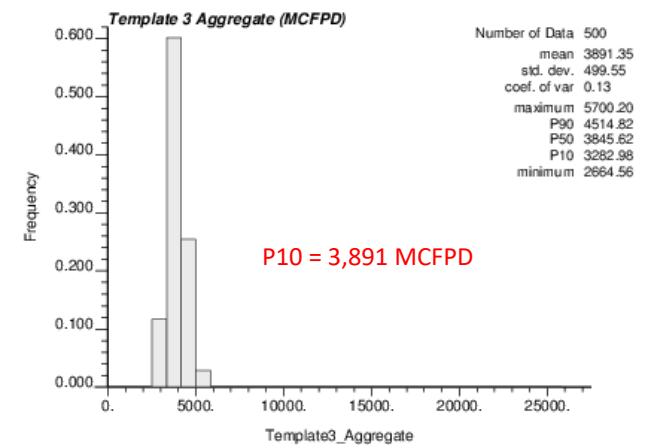
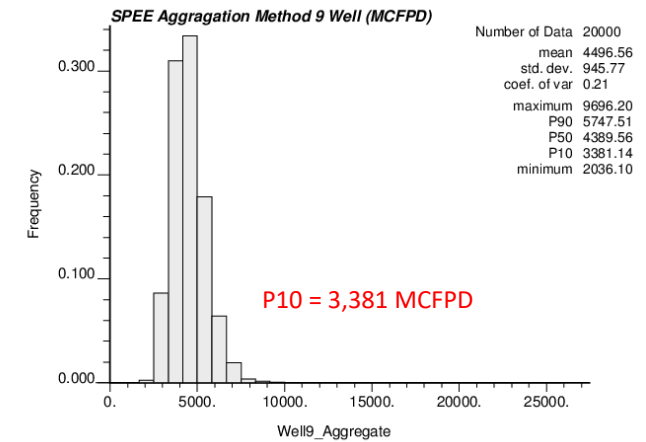
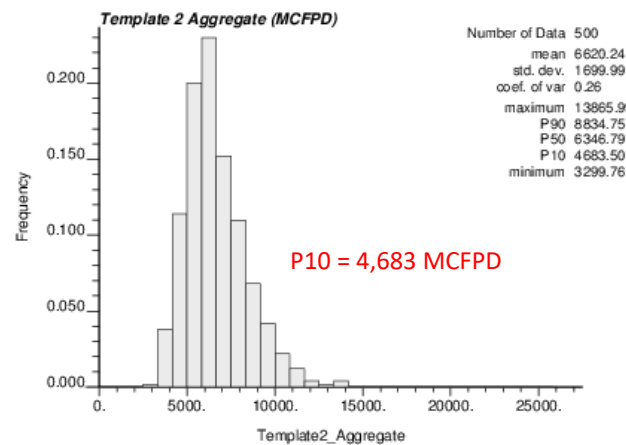
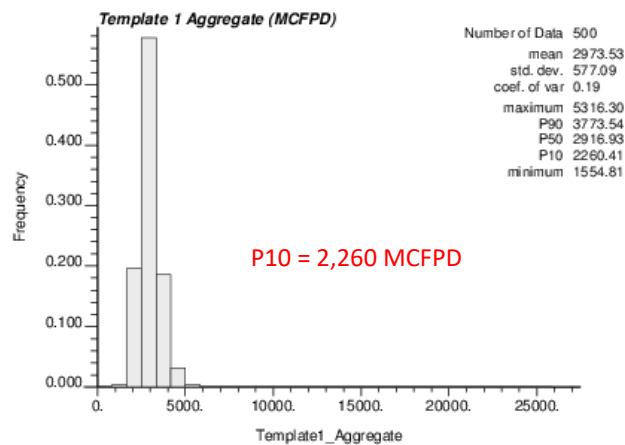
Scenario 3: Drilling to Reduce Uncertainty (MCFPD)



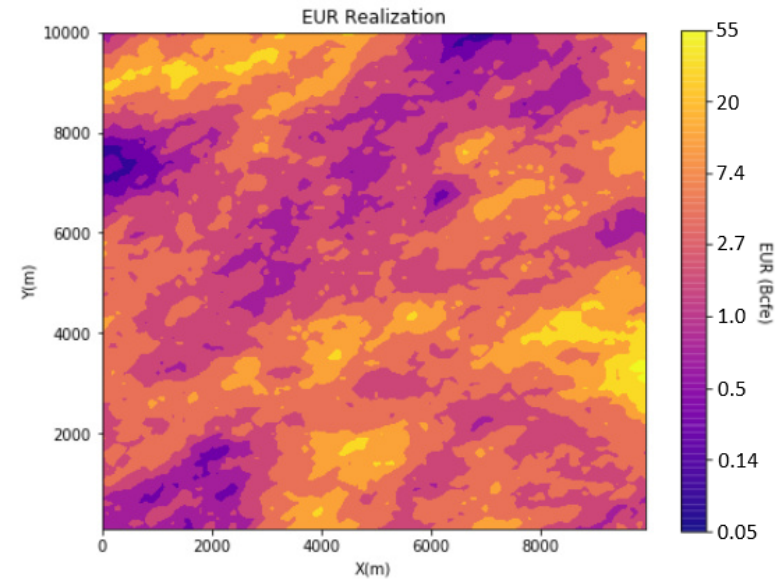
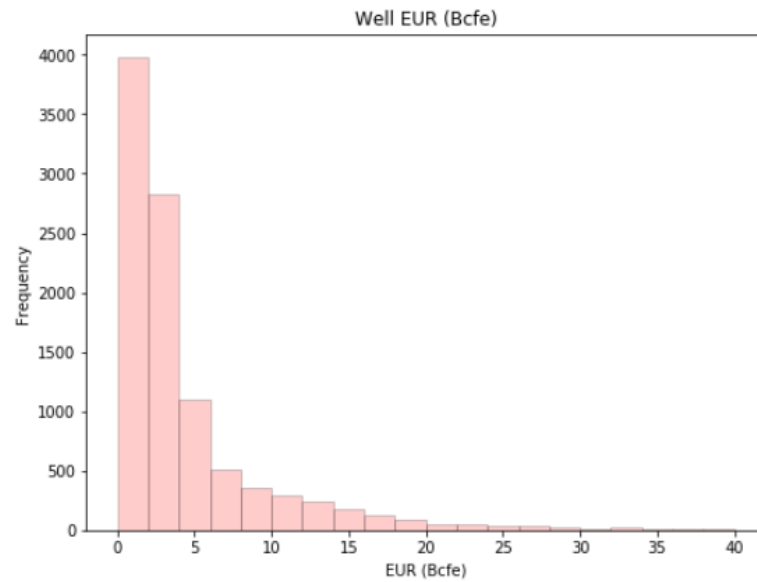
Does Spatial Context Matter?

Spatial bootstrap well aggregate uncertainty distributions:

- Significant difference in expectation / estimate, variance
- Spatial correlation increases uncertainty
- Local data decreases uncertainty



Problem Setting



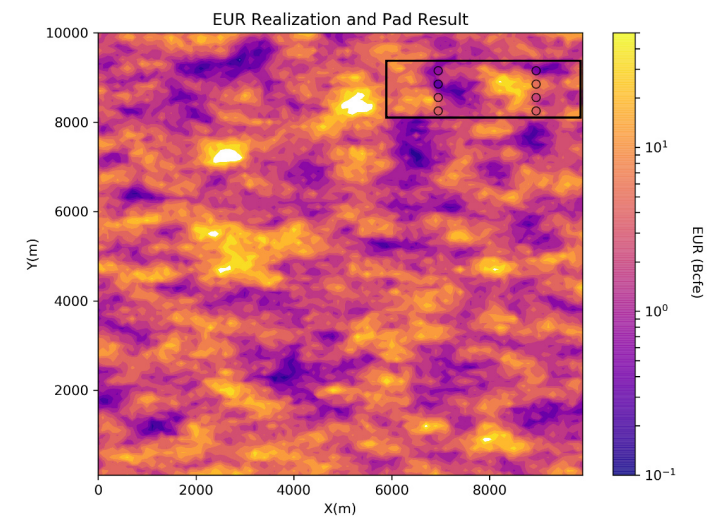
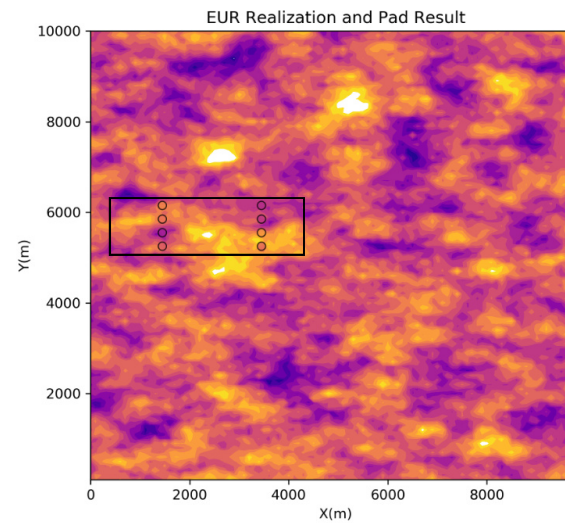
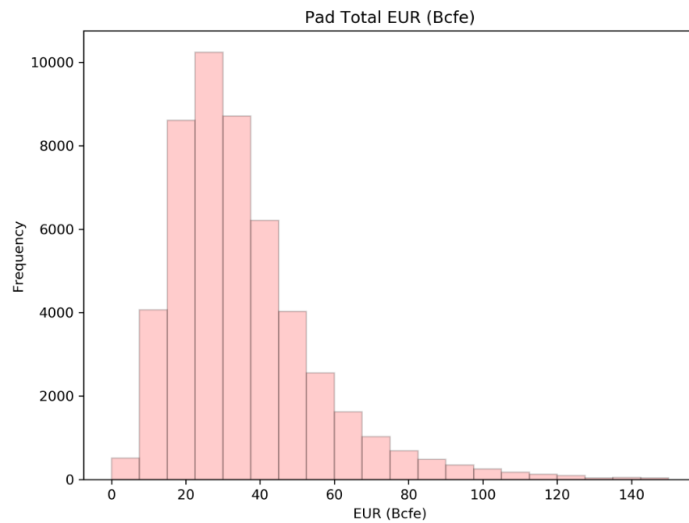
Utica-Point Shale Play Analog:

- Well EUR distribution and well spacing
- Variable EUR spatial continuity

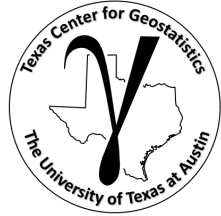
Problem Setting

Variability in the results:

- Within Pads: variability between wells in the same pad
- Between Pads: variability between pad aggregates
- These are balanced given a constant global variance



Question 1: What is the variability within a pad?



Under the assumption of stationarity we may apply dispersion variance (Journel and Huijbregts, 1978; Frykman and Deutsch, 1999).

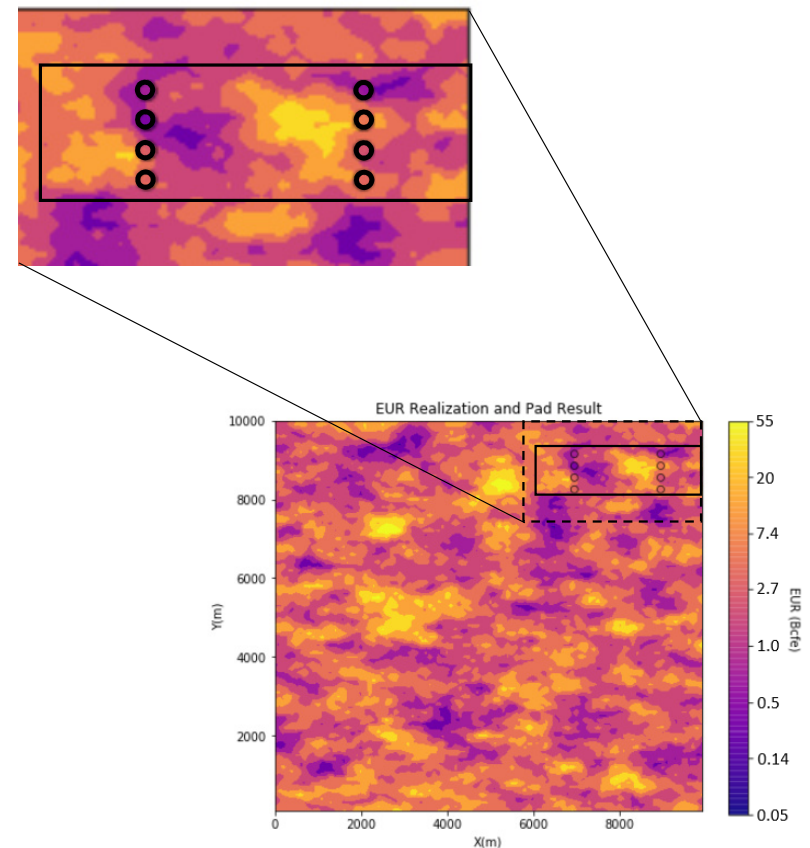
$$D^2(\text{well}, \text{pad}) = \bar{\gamma}(\text{pad}, \text{pad}) - \bar{\gamma}(\text{well}, \text{well})$$

Given an assumption of no spatial continuity,
 $\bar{\gamma}(\text{pad}, \text{pad}) \approx \text{sill}, \sigma_{\text{wells}}^2$

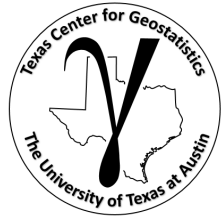
$$D^2(\text{well}, \text{pad}) = \bar{\gamma}(\cancel{\text{pad}}, \cancel{\text{pad}})^{\sigma_{\text{wells}}^2} - \bar{\gamma}(\cancel{\text{well}}, \cancel{\text{well}})$$

$$D^2(\text{well}, \text{pad}) \rightarrow \sigma_{\text{wells}}^2$$

All variability is observed within the pad.



Question 1: What is the variability within a pad?



We expect spatial continuity. Consider the case with spatial continuity:

$$D^2(\text{well}, \text{pad}) = \bar{\gamma}(\text{pad}, \text{pad}) - \bar{\gamma}(\text{well}, \text{well})$$

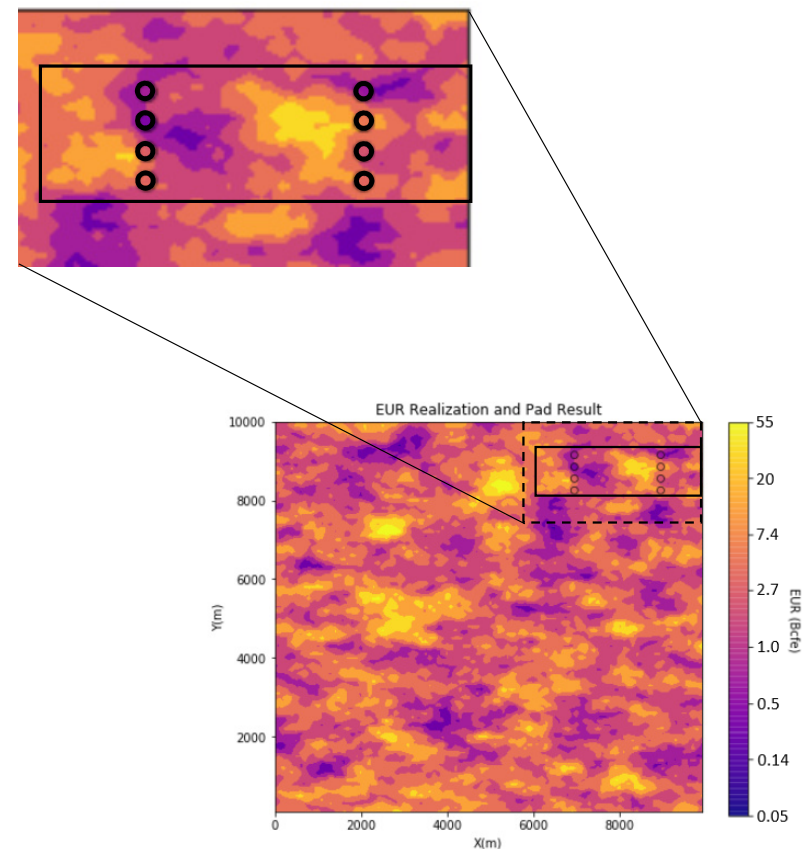
Given an assumption of spatial continuity:

$$D^2(\text{well}, \text{pad}) = \bar{\gamma}(\text{pad}, \text{pad}) - \bar{\gamma}(\text{well}, \text{well})$$

$$\bar{\gamma}(\text{pad}, \text{pad}) \leq \sigma_{\text{wells}}^2 \therefore D^2(\text{well}, \text{pad}) \leq \sigma_{\text{wells}}^2$$

There is consistency / correlation between wells within the pad.

This information sharing indicates that a single well may be informative of pad performance.



Question 2: What is the variability between pads?

Under the assumption of stationarity we may apply dispersion variance.

$$D^2(pad, AOI) = \bar{\gamma}(AOI, AOI) - \bar{\gamma}(pad, pad)$$

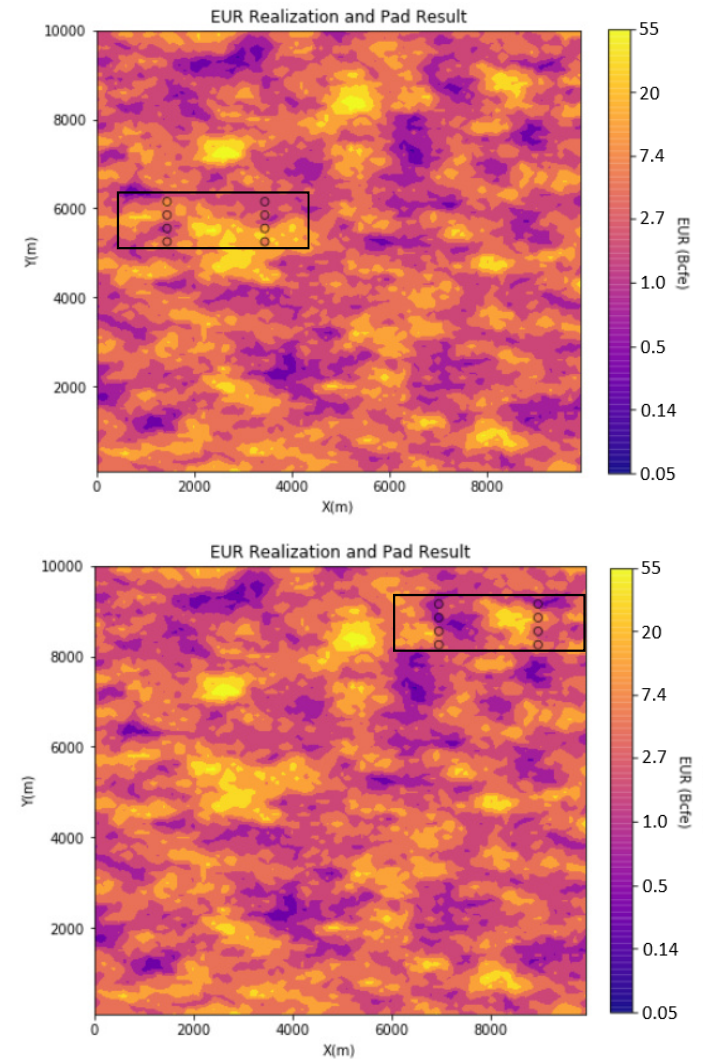
Given an assumption of no spatial continuity, both $\bar{\gamma}$ reach the sill, σ_{wells}^2

$$D^2(pad, AOI) = \cancel{\bar{\gamma}(AOI, AOI)}^{\sigma_{wells}^2} - \cancel{\bar{\gamma}(pad, pad)}^{\sigma_{wells}^2}$$

$$D^2(pad, AOI) \rightarrow 0$$

Pad variability is an issue of limited sampling from the population.

$$\sigma_{pad}^2 = \frac{s_{wells}^2}{n_{wells}}$$



Question 2: What is the variability between pads?

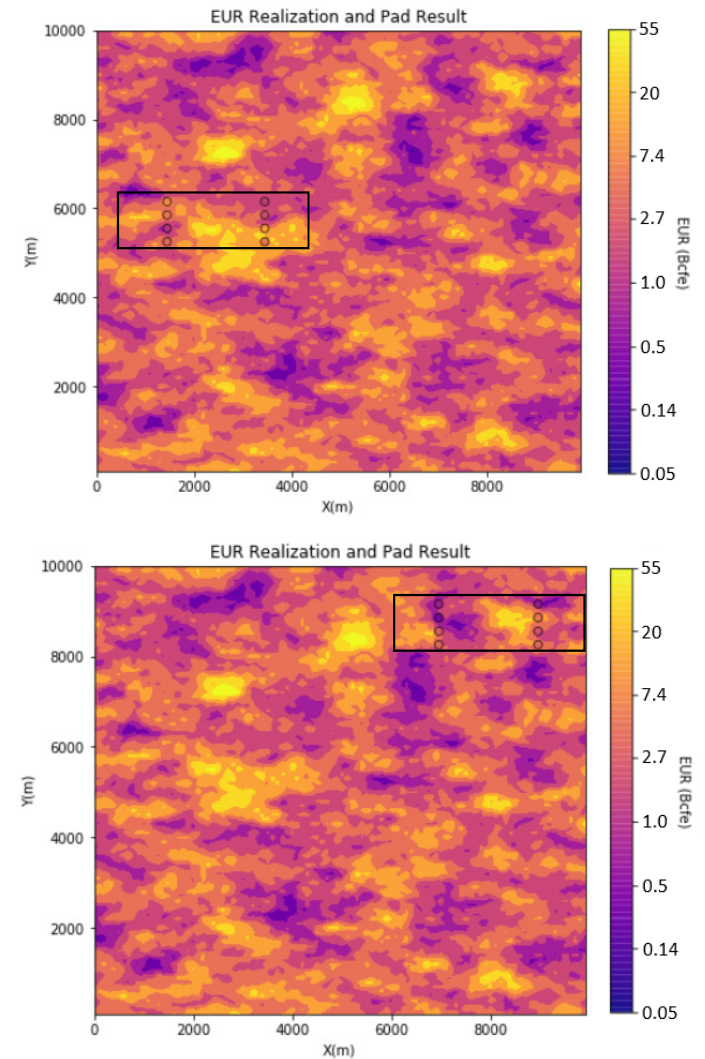
We expect spatial continuity. Consider the case with spatial continuity:

$$D^2(pad, AOI) = \bar{\gamma}(AOI, AOI) - \bar{\gamma}(pad, pad)$$

Given an assumption of spatial continuity:

$$D^2(pad, AOI) = \bar{\gamma}(AOI, AOI) - \bar{\gamma}(pad, pad)$$

Pad variability is dependent on the size of the pad, well spacing and number of wells, *volume sampled by the pad*.



Why Use Model Resampling?

American / Canadian shale consistently production spatial continuity with:

- 30-40% nugget effect
- 30-40% medium range structure
- 20-30% trend structures

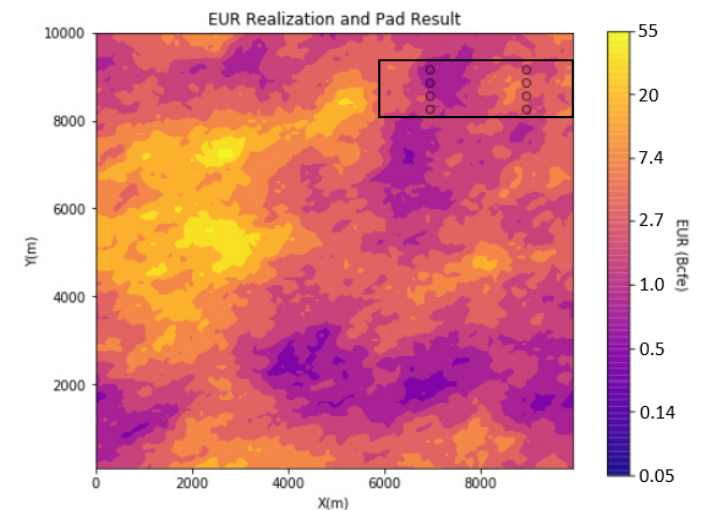
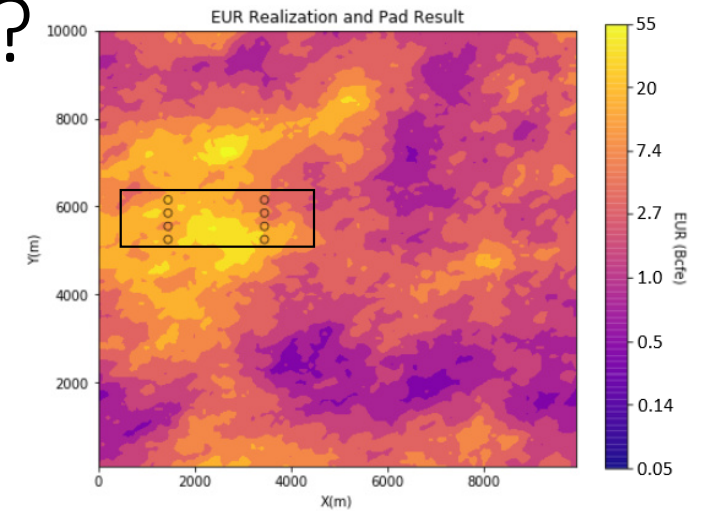
In addition there are various forms of secondary information

- Local information varies and nonstationarity

Accounting for boundary and conditioning.

We are also concerned with multiple wells correlated with each other

Model resampling is a good avenue.



Numerical Analogs

Design of Experiment

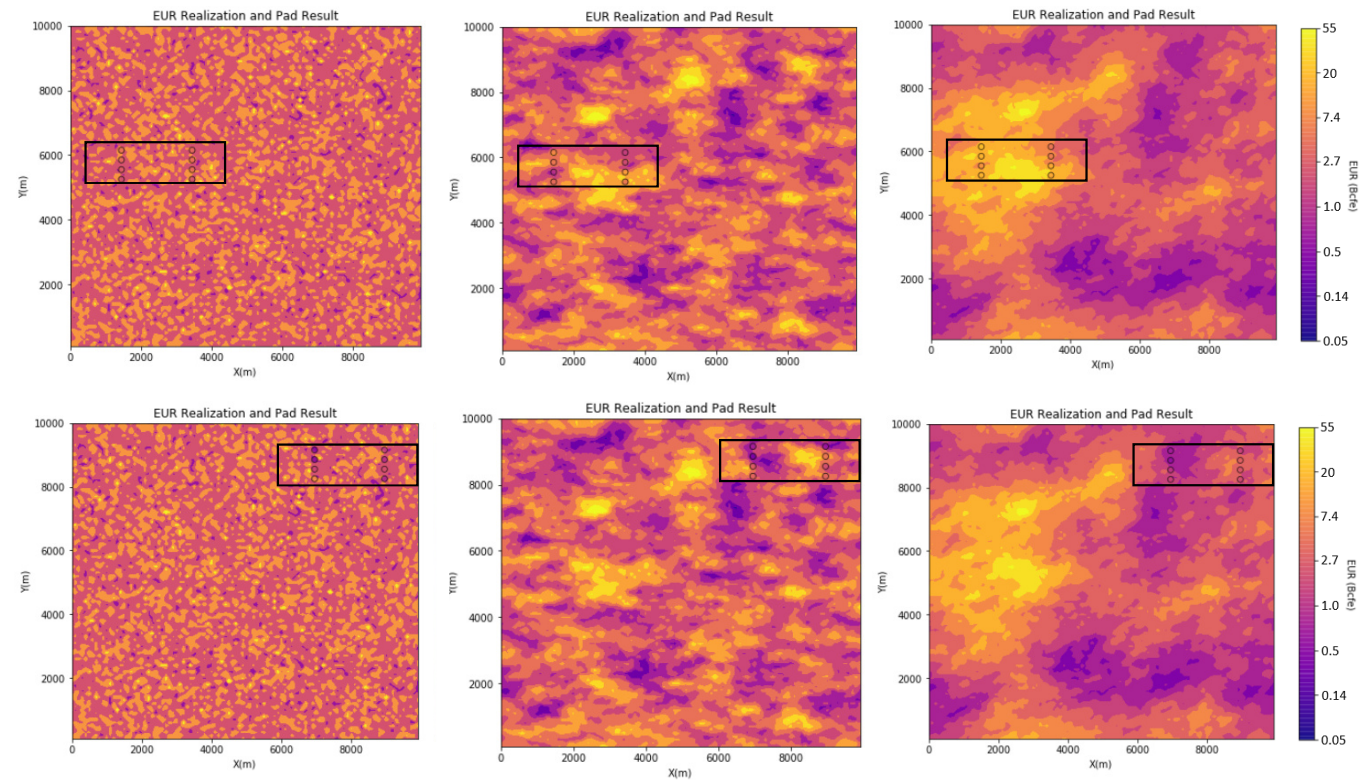
1000 realizations

Range:

- 100m
- 500m
- 1000m
- 2500m
- 5000m

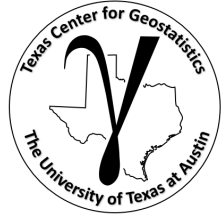
Pad Locations:

- 1000



Analog EUR distribution and well pad template based on Utica Shale and a range of EUR spatial continuities.

Question 1: What is the variability within a pad?



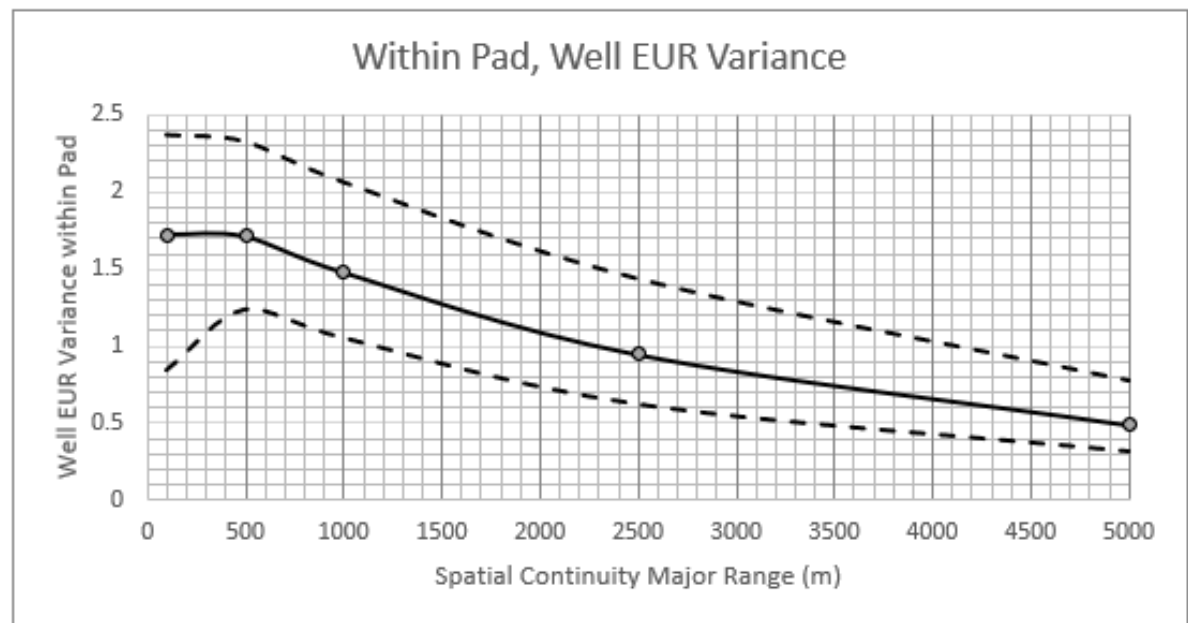
What is the impact of EUR spatial continuity on within pad variability?

From 500m to 5000m EUR major continuity range:

- the variance of wells within a pad reduces by greater than 70%

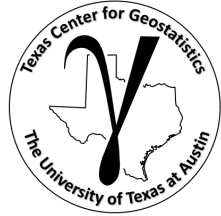
Predictive model?

- Could first well be early indicator?
- Why so much spread?



Within pad, well EUR variance vs. spatial continuity.

Question 1: What is the variability within a pad?



What is the impact of EUR spatial continuity on within pad variability?

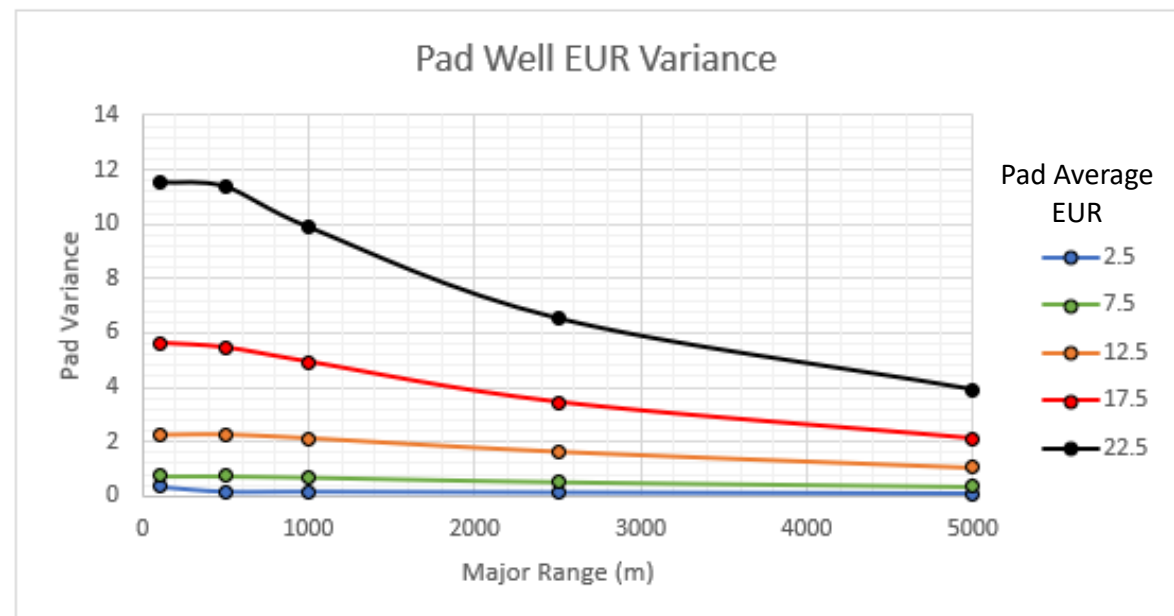
- Why so much spread?

Heteroscedasticity, pads with higher average EUR have:

- Higher variance
- Larger reductions in variance

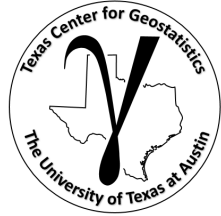
Accounting for heteroscedasticity we have a informative predictive model.

- With pad variance reduction due to spatial continuity



Within pad, well EUR variance vs. spatial continuity, by pad average EUR.

Question 2: What is the variability between pads?

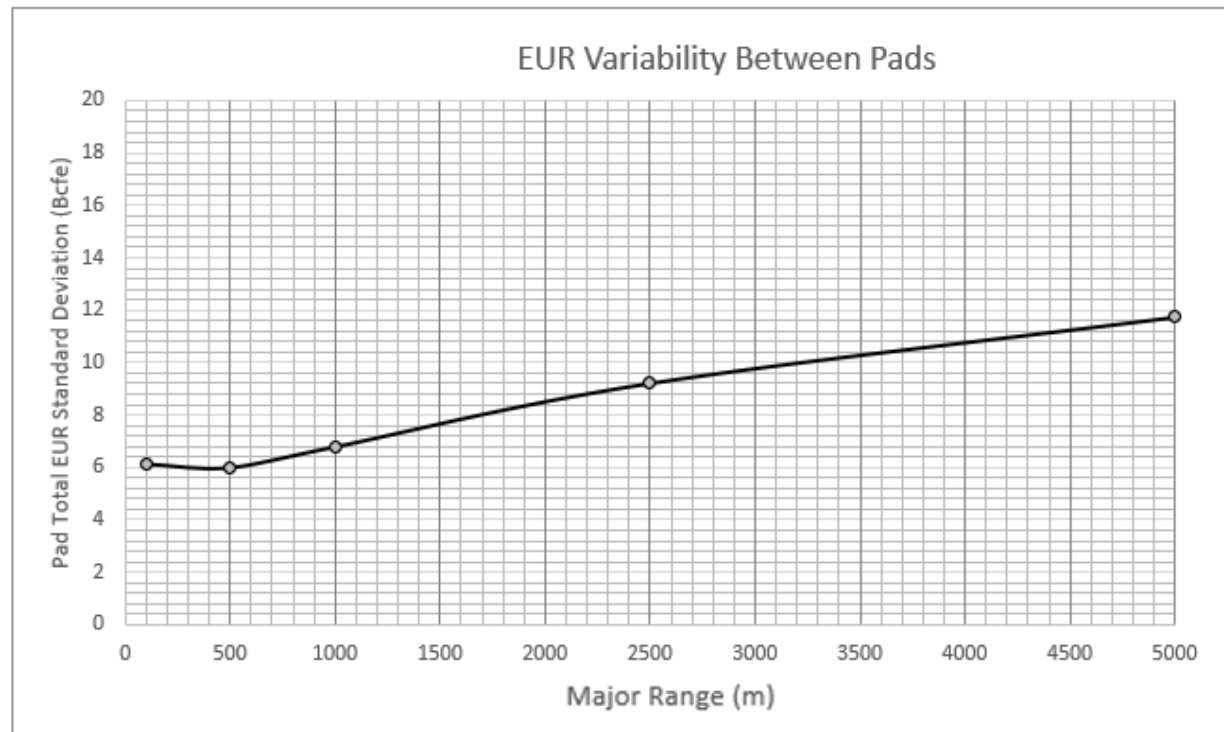


What is the impact of EUR spatial continuity on between pad variability?

- sensitivity of pad to location

Increase in spatial continuity increases variability between pads.

- more consistency within the pad
- all low or all high EUR wells



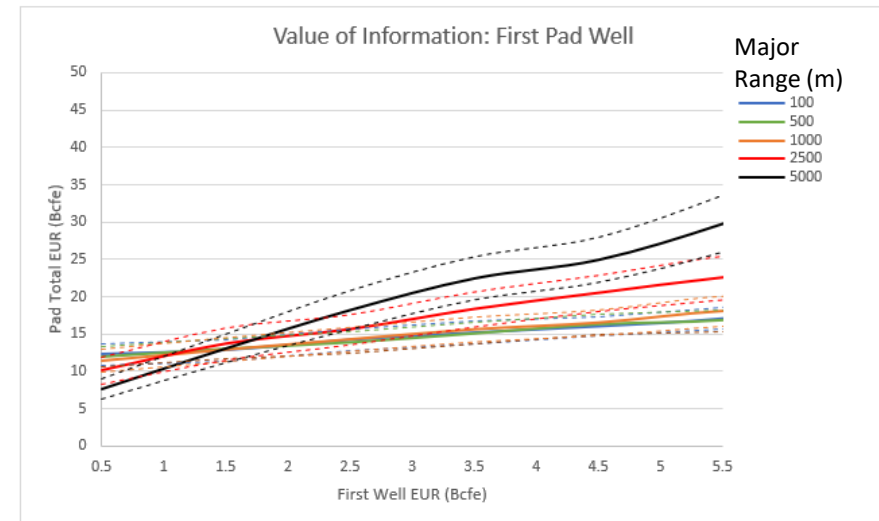
Between pad aggregate EUR variance vs. spatial continuity.

Question 3: How much information does a single well provide about the pad?

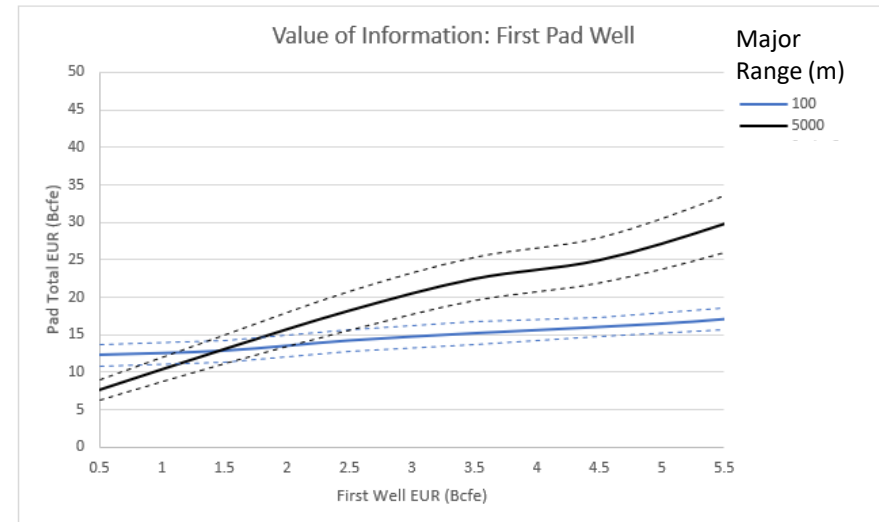
Is there an opportunity to use the first well as an early indicator to reduce well pad total EUR uncertainty?

For a low spatial continuity case the first well provides a poor early indicator of total pad performance.

For a high spatial continuity case the first well provides a good early indicator of total pad performance.

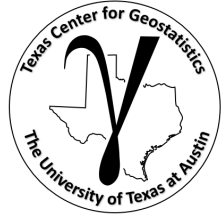


Pad aggregated EUR vs. first well EUR for each major continuity range.



Pad aggregated EUR vs. first well EUR for 100 m and 5000m major range.

Question 4: When is it best to abandon a pad?



Is there an opportunity to provide decision criteria for when to move on to a new pad?

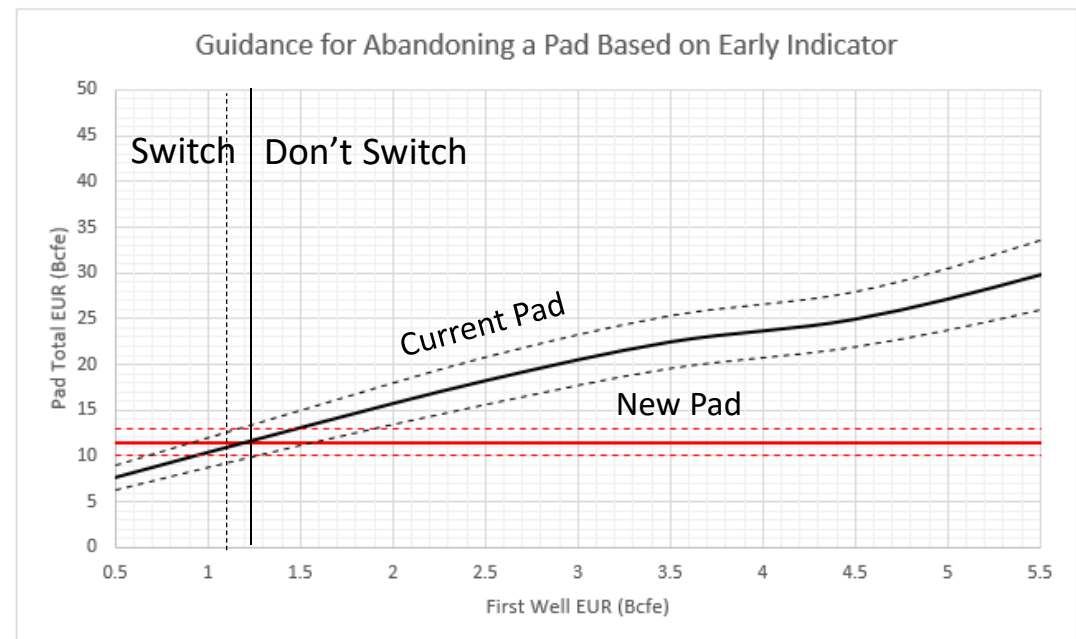
Note: no effort to account for associated costs, lost opportunities related to facilities.

Compare:

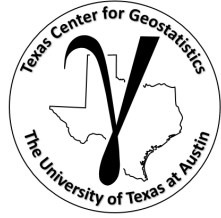
- the early indicator based pad performance uncertainty model
- global distribution for pad total EUR

Opportunity:

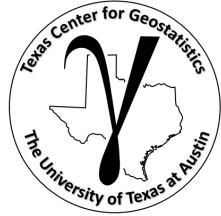
- Assign first well threshold for abandoning the pad.



Conclusions



1. Due to increased data and transfer function uncertainties we are motivated to use the **statistical play approach**.
2. Statistical play approach is the **regionalization of production**.
3. As the geostatistics community, we need to reinforce the **need to account for spatial continuity, data conditioning, location and boundaries**.
4. We can do this with **model resampling workflows** to provide support for decision making in unconventional.



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