Simplified Predictive Models for CO_2 Sequestration Performance Assessment

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Srikanta Mishra
Battelle Memorial Institute

Priya Ravi Ganesh,
Jared Schuetter, Doug Mooney
Battelle Memorial Institute

Louis Durlofsky
Jincong He, Larry Zhaoyang Jin
Stanford University

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Infrastructure for CCS
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Presentation Outline

- Benefit to the Program / Stakeholders
- Project Overview
- Technical Status
  - Reduced physics based modeling
  - Statistical learning based modeling
  - Reduced order method based modeling
- Accomplishments to Date
- Summary and Next Steps

Benefit to the Program

- Research will develop and validate a portfolio of simplified modeling approaches to predict the extent of CO_2 plume migration, pressure impact and brine movement for a semi-confined system with vertical layering
- These approaches will improve existing simplified models in their applicability, performance and cost
- The technology developed in this project supports the following programmatic goals: (1) estimating CO_2 storage capacity in geologic formations; (2) demonstrating that 99 percent of injected CO_2 remains in the injection zone(s); and (3) improving efficiency of storage operations

Benefit to Stakeholders

- Provide ***project developers*** with simple tools to screen sites and estimate monitoring needs
- Provide ***regulators*** with tools to assess geological storage projects quickly without running full-scale detailed numerical simulations
- Enable ***risk assessors*** to utilize robust, yet simple to implement, reservoir performance models
- Allow ***modelers*** to efficiently analyze various CO_2 injection plans for optimal well design/placement

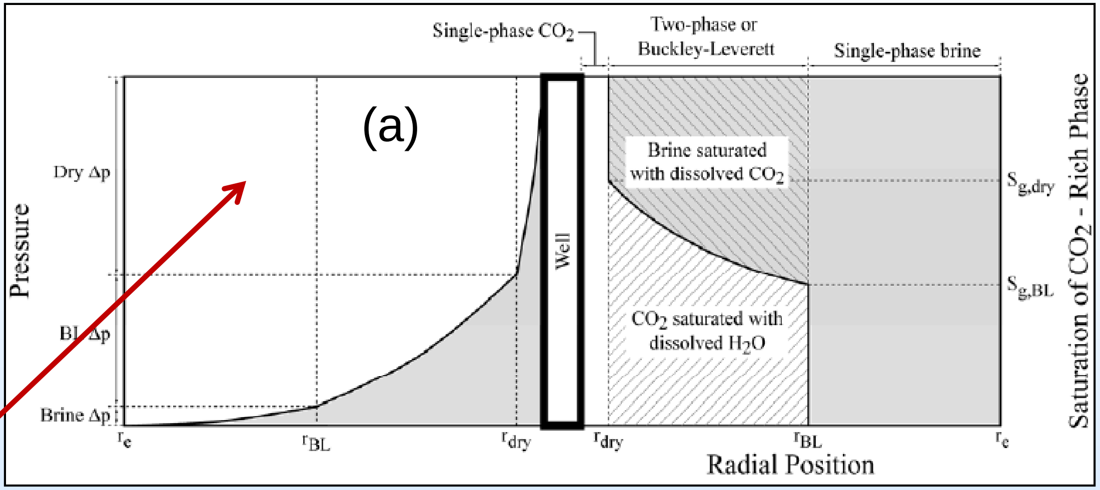
Project Overview

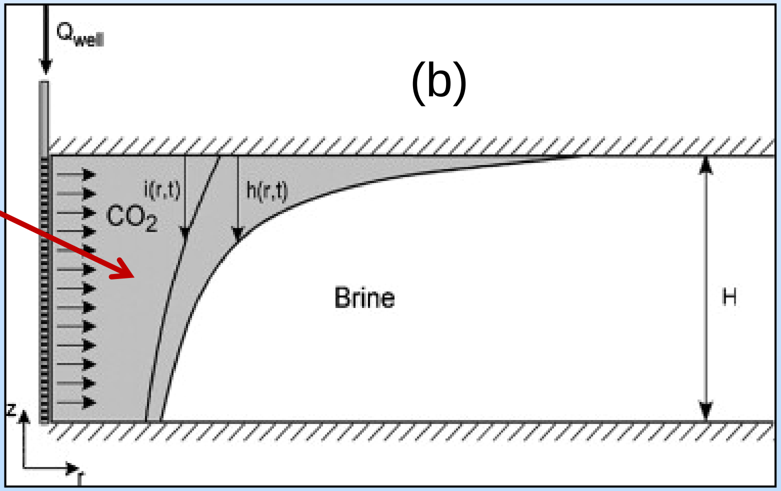
Goals and Objectives

- **Objective** ⇨ Develop and validate a portfolio of simplified modeling approaches for CO_2 sequestration in deep saline formations
  - **Reduced physics-based modeling** - where only the most relevant processes are represented
  - **Statistical-learning based modeling** - where the simulator is replaced with a “response surface”
  - **Reduced-order method based modeling** - where mathematical approximations reduce computational burden
  - **Uncertainty and sensitivity analysis** – to validate the simplified modeling approaches for probabilistic applications

Reduced Physics Based Models
Background

- Useful alternative to simulators if "macro" behavior is of interest
- Analytical models of radial injection of supercritical CO_2 into confined aquifers
  - **(a) Fractional flow** model (Burton et al., 2008; Oruganti & Mishra; 2013)
  - **(b) Sharp interface** model (Nordbotten & Celia, 2008)
- Require extension for semi-confined systems with vertical layering (based on detailed simulations)



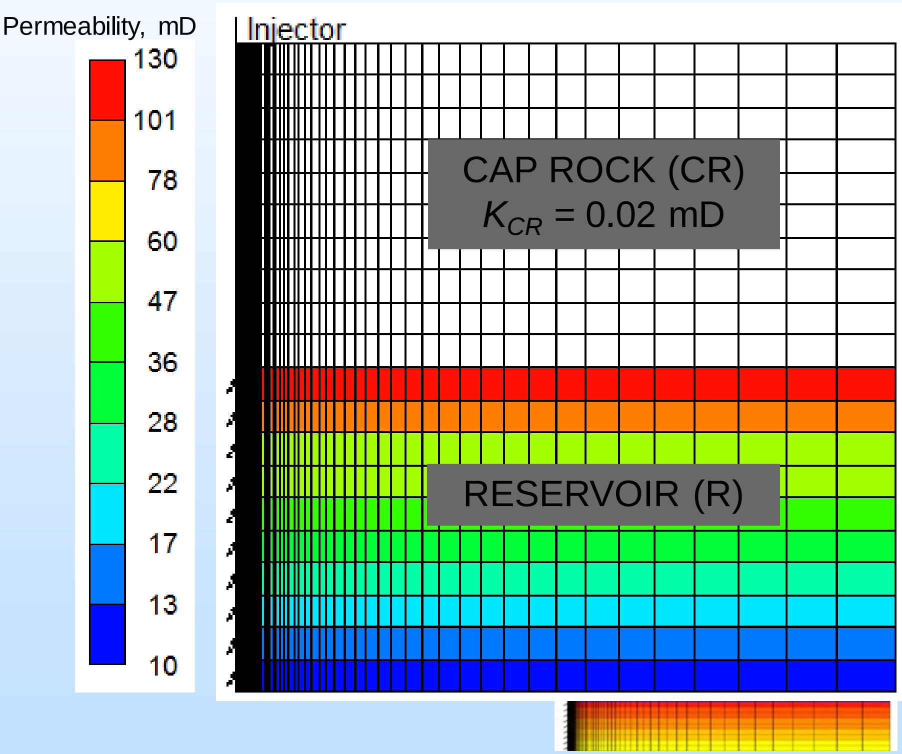


Reduced Physics Based Models

Approach (using GEM)

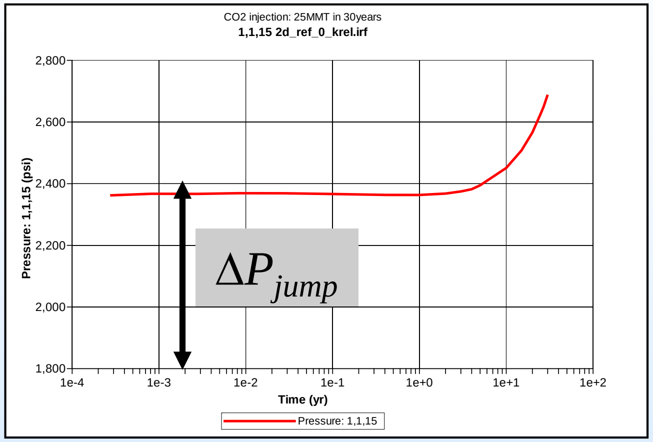
CAP ROCK PROPERTIES

ϕ, h, K, P_c

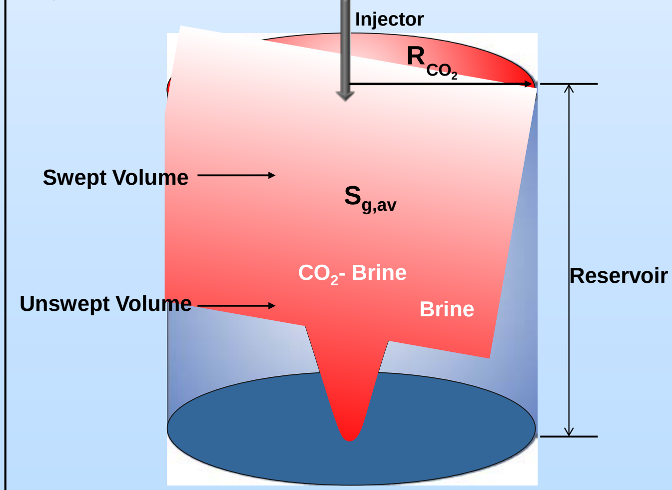


RESERVOIR PROPERTIES

ϕ, h, $<K>$, K_v/K_h, k_{rel}



$S_{g,av}$ = Average Gas Saturation in Swept Volume



$$E_v = \frac{\text{Swept Volume}}{\text{Swept Volume + Unswept Volume}}$$

Reduced Physics Based Models

Simulation Scenarios

	Parameter	Description	Units	Reference value	Low Value	High Value	Comments
1	h_R	Thickness of reservoir	m	150	50	250	
2	h_{CR}	Thickness of caprock	m	150	100	200	
3	$k_{avg,R}$	Average horizontal permeability of reservoir	mD	46	12	220	
	V_{DP}	Dykstra-Parson's coefficient	--	0.55	0.35	0.75	perfectly correlated with $k_{avg,R}$
4	$k_{avg,CR}$	Average horizontal permeability of caprock	mD	0.02	0.002	0.2	
5	k_V/k_H	Anisotropy ratio	--	0.1	0.01	1	
6	Q	CO_2 Injection rate	MMT/yr	0.83	0.33	1.33	
	L	Outer radius of reservoir	km	10	5	7	perfectly correlated with Q
7	ϕ_R	Porosity of reservoir	--	0.12	0.08	0.18	
8	ϕ_{CR}	Porosity of caprock	--	0.07	0.05	0.1	
9	$P_{C,CR}$	Capillary pressure model of caprock	--	reference	decrease P_c by 3X	increase P_c by 3X	
10	I_k	Indicator for permeability layering	--	random	Increasing from top	Increasing from bottom	

Reduced Physics Based Models

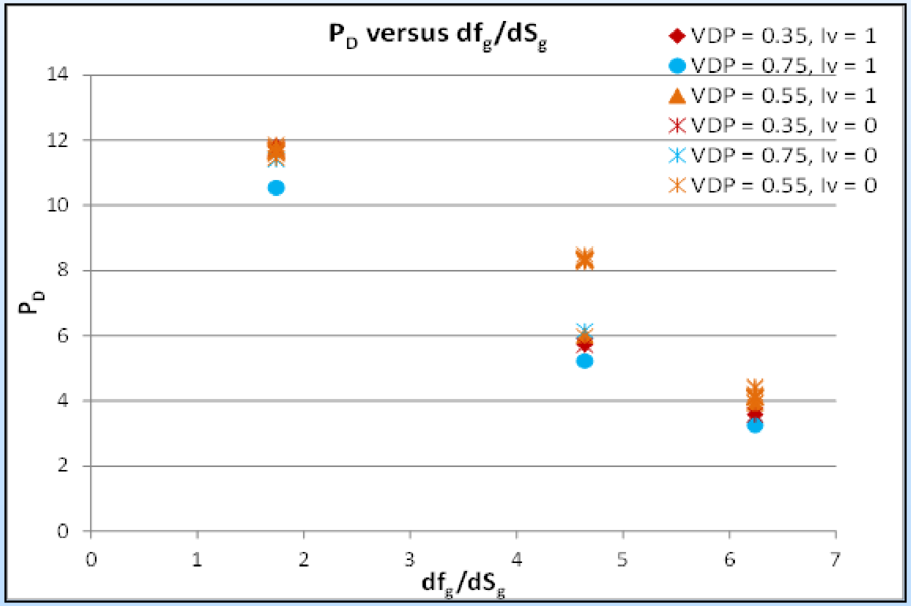
Insights on Injectivity and Storage Efficiency

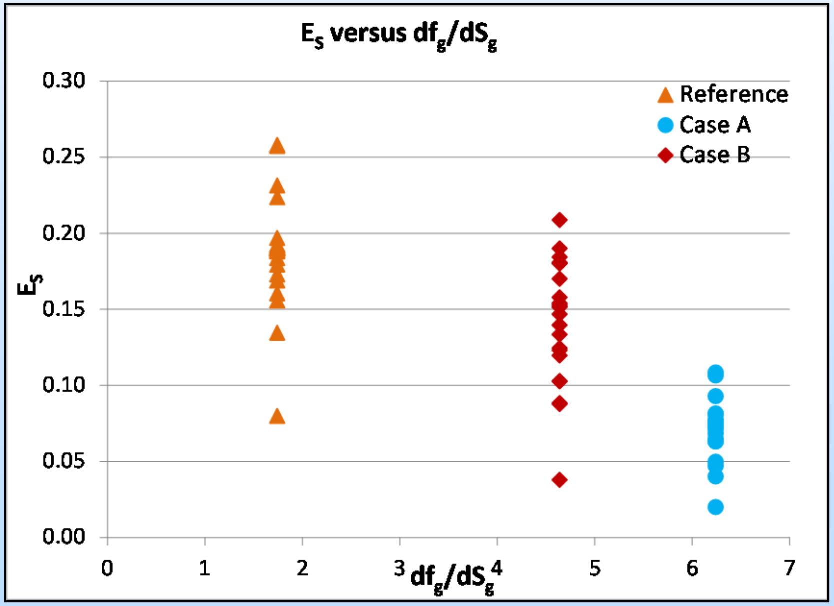
$$P_{D,jump} = \frac{2\pi kH}{q\mu_w}\Delta P_{jump}$$

$$R_{CO_2}^2 = \frac{Q}{\pi\phi H\bar{S}_g E_v} = \frac{Q}{\pi\phi H E_s}$$

If $\boldsymbol{P_D}$ can be predicted, then $\boldsymbol{q}$ v/s $\boldsymbol{\Delta P}$ can be estimated

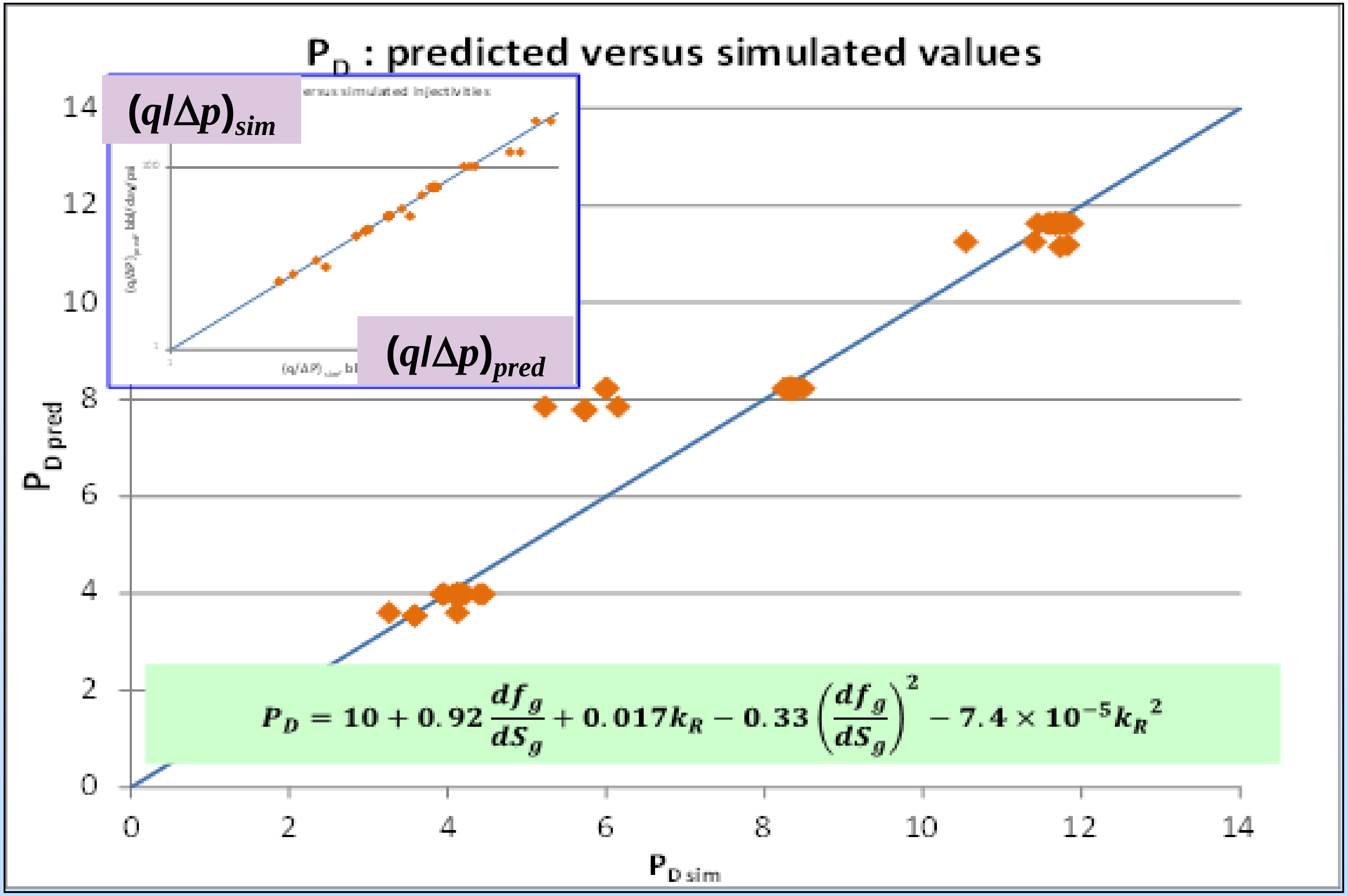
If $\boldsymbol{E_S}$ can be predicted, then $\boldsymbol{R_{CO2}}$ can be estimated





Reduced Physics Based Models

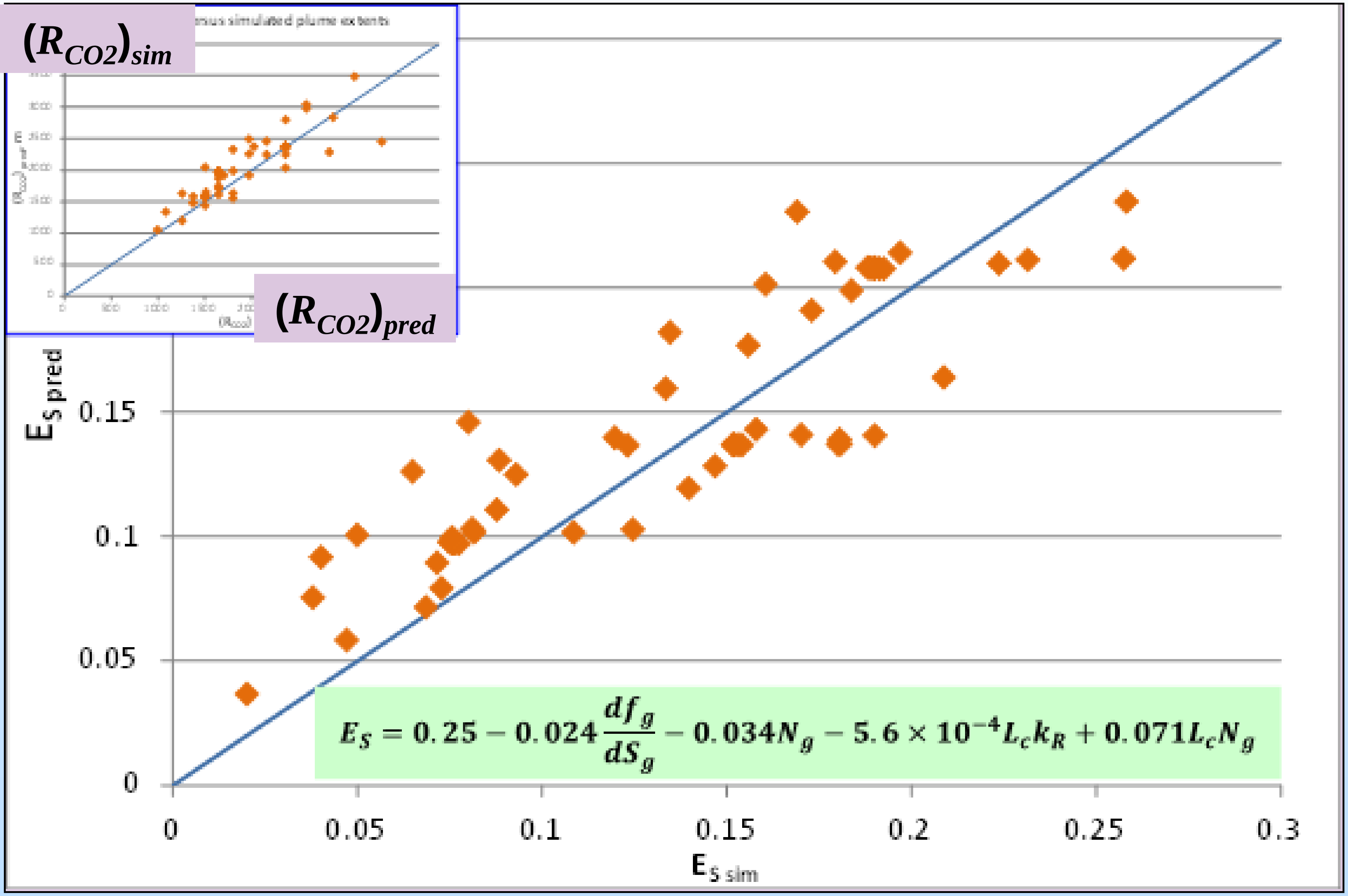
Dimensionless Injectivity – Predictive Model



$$P_D = 10 + 0.92\frac{df_g}{dS_g} + 0.017k_R - 0.33\left(\frac{df_g}{dS_g}\right)^2 - 7.4\times10^{-5}{k_R}^2$$

Reduced Physics Based Models

Storage Efficiency – Predictive Model



Reduced Physics Based Models

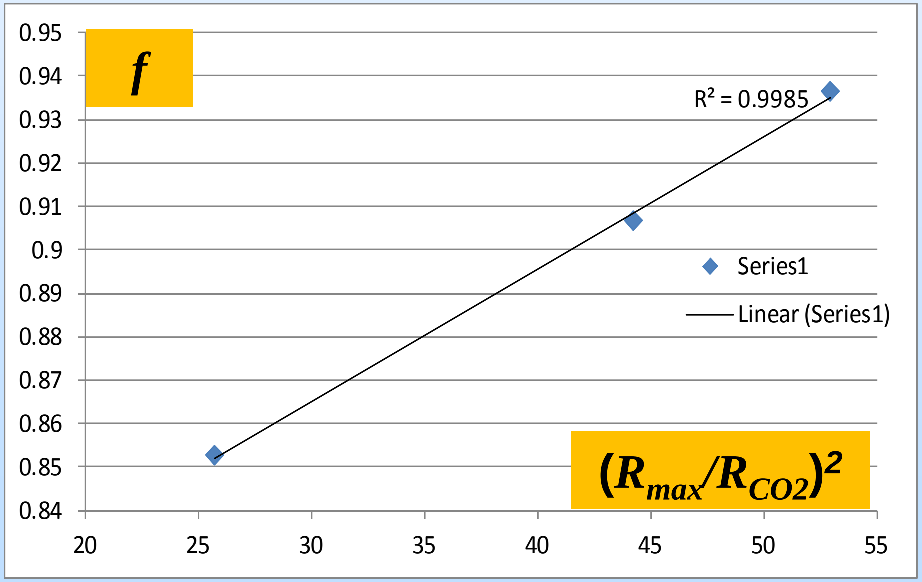
Average Pressure in Reservoir

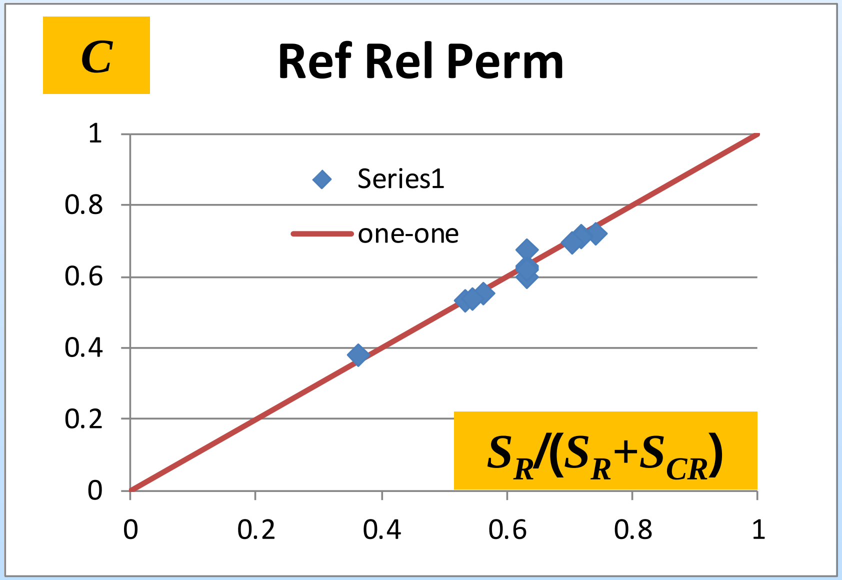
$$\boxed{\overline{P}_D = f\, 2\pi t_{DA}}$$

$$\boxed{\overline{P}_D = fC 2\pi t_{DA}}$$

For a no-caprock system
f depends on relative permeability

C depends on ratio of reservoir storativity to total storativity

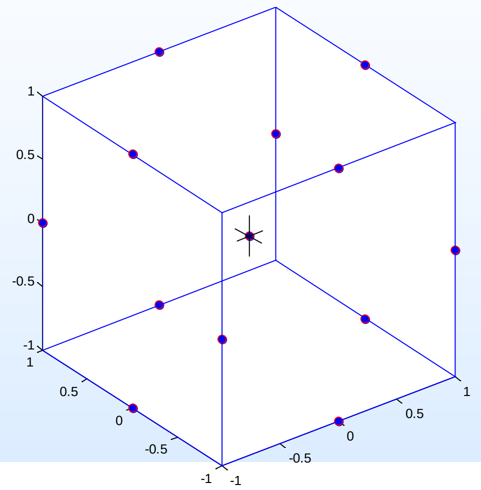




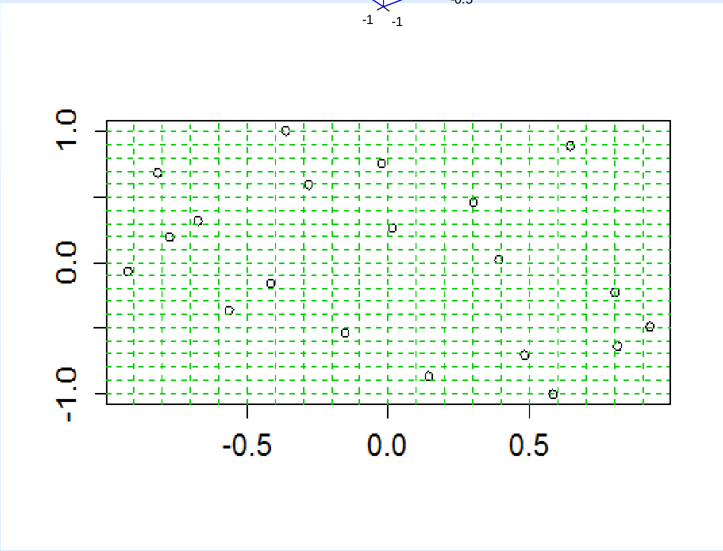
Statistical Learning Based Models

Background

- **Goal** ⇨ replace physics-based model with statistical equivalent
- **Experimental design** ⇨ selection of points in parameter space to run limited # of computer experiments
- **Response surface** ⇨ functional fit to input-output data to produce "proxy" model
- Two common options
  - Box-Behnken (BB) design
    3-pt + quadratic response surface
  - Latin Hypercube sampling (LHS)
    multi-point + higher-order model



BB



LHS

Statistical Learning Based Models

Metamodels Evaluated

2nd Order Polynomial

$$\hat{f}(\mathbf{x}) = b_0 + \sum_{i=1}^{p} b_i x_i + \sum_{i=1}^{p} \sum_{j>i} b_{ij} x_i x_j + \sum_{i=1}^{p} b_{ii} x_i^2$$

Multiple Adaptive Regression Spline (MARS)

$$\hat{f}(\mathbf{x}) = \sum_{i=1}^{k} c_i B_i(\mathbf{x})$$

Additive Regression (AREG)

$$g_0\left(f(\mathbf{x})\right) = \sum_{i=1}^{p} g_i\left(x_i\right)$$

Kriging with Matérn correlation

$$\hat{f}(\mathbf{x}) = \mu(\mathbf{x}) + Z(\mathbf{x})$$

$$Cov(Z(\mathbf{x})) = \sigma^2 \mathbf{R}$$

$$R(\mathbf{x}^i, \mathbf{x}^j) = \prod_{k=1}^{p} \left[1 + \frac{d_k\sqrt{5}}{\theta_k} + \frac{5d_k^2}{\theta_k^2}\right] \exp\left(-\frac{d_k\sqrt{5}}{\theta_k}\right)$$

Ordinary Kriging

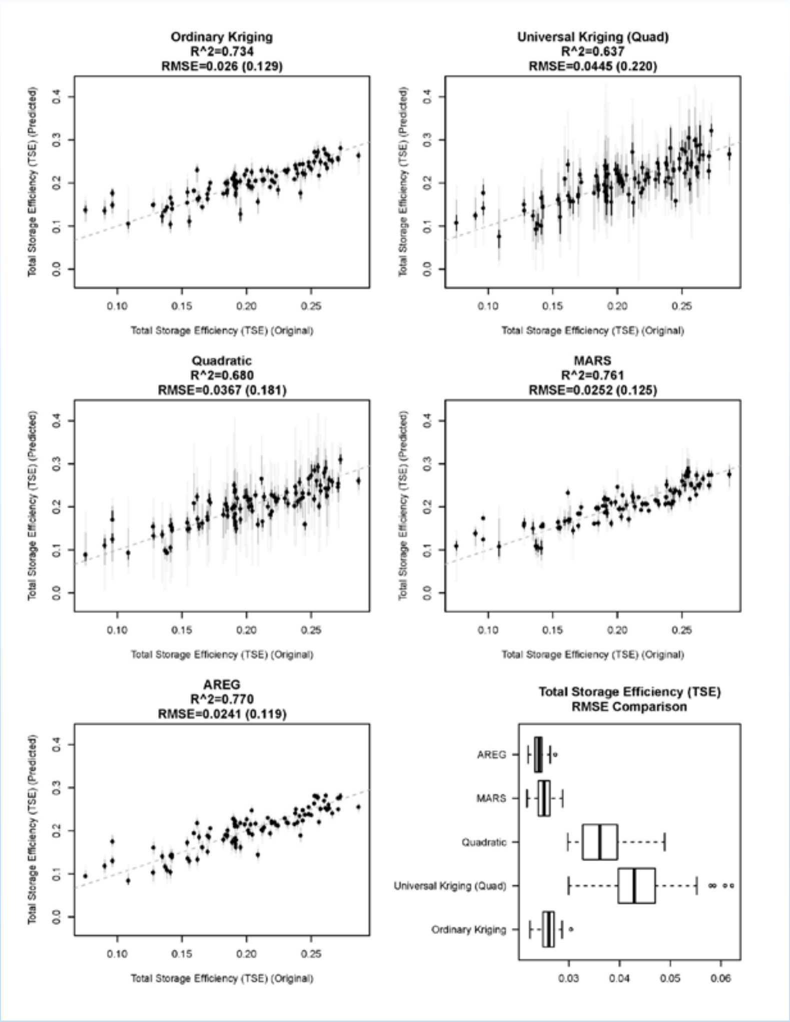
$$\mu(\mathbf{x}) = \mathbf{m}$$

Universal Kriging

$$\mu(\mathbf{x}) = b_0 + \sum_{i=1}^{p} b_i x_i + \sum_{i=1}^{p} \sum_{j>i} b_{ij} x_i x_j + \sum_{i=1}^{p} b_{ii} x_i^2$$

Statistical Learning Based Models

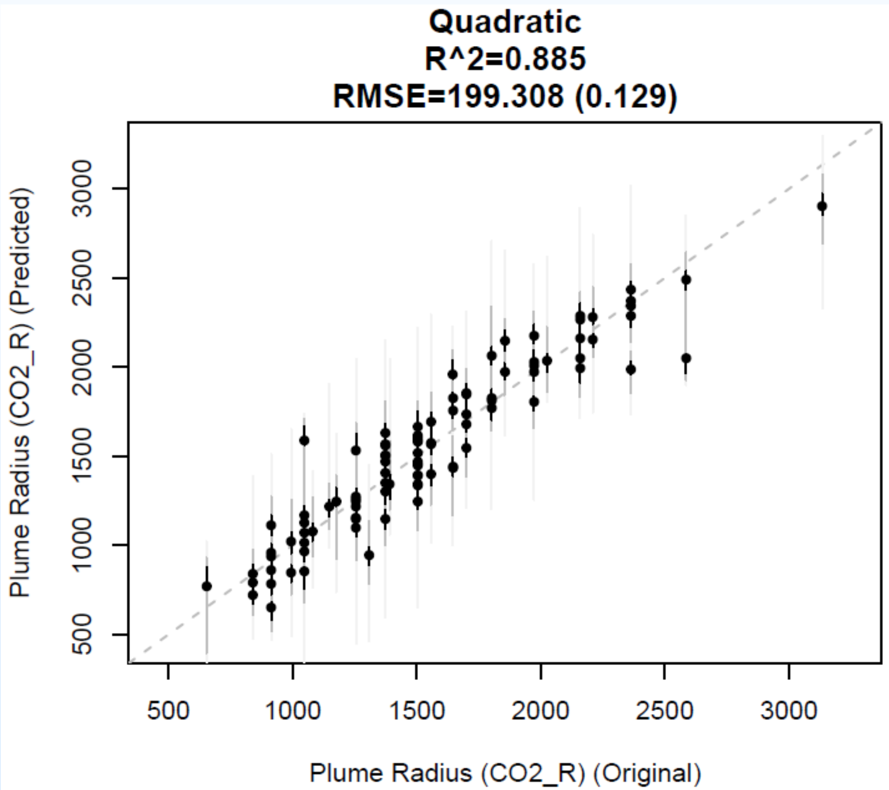
Box Behnken Design – Metamodeling

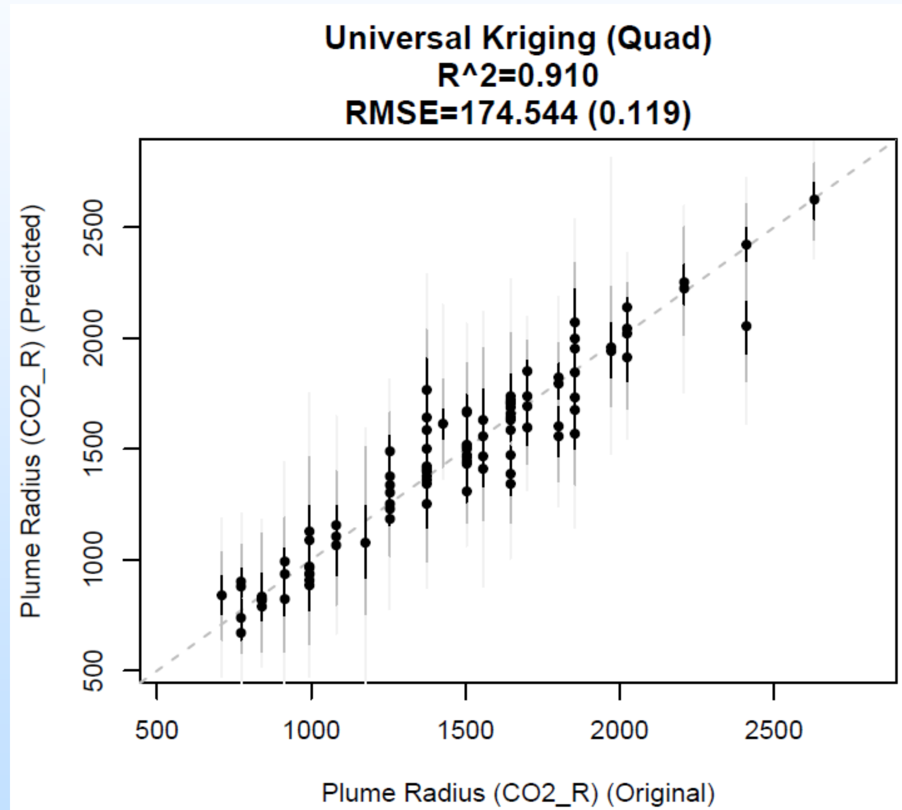


- Data from 2-D GEM simulations of CO_2 injection into closed volume
- 97 run Box-Behnken design with 9 factors
- 4 different meta-models
  - Quadratic
  - Kriging
  - MARS
  - Adaptive regression
- **Cross validation using 5 mutually exclusive subsets (78 training + 19 test data points) with 100 replicates**

Statistical Learning Based Models

Proxy Models – Plume Radius





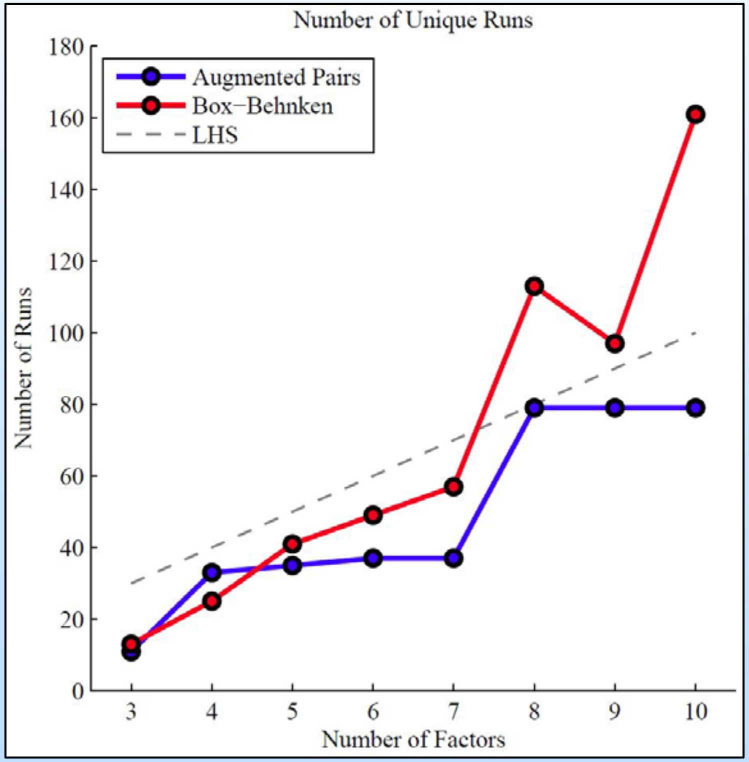
Box-Behnken Design

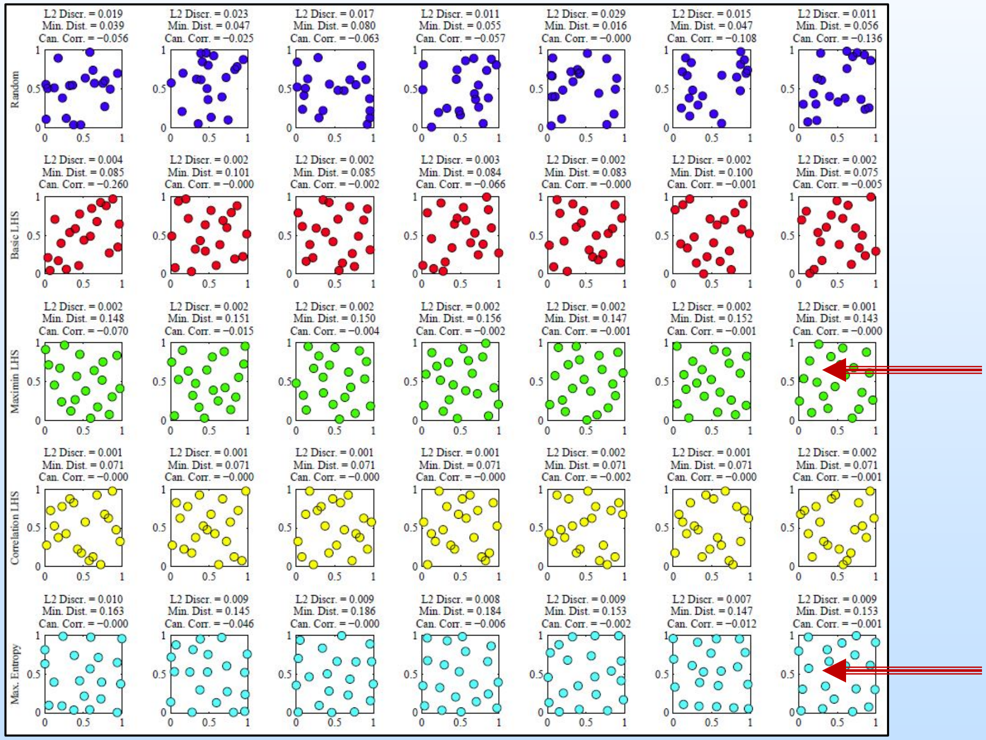
LHS Design

Statistical Learning Based Models

Generating Designs

Box-Behnken Alternative

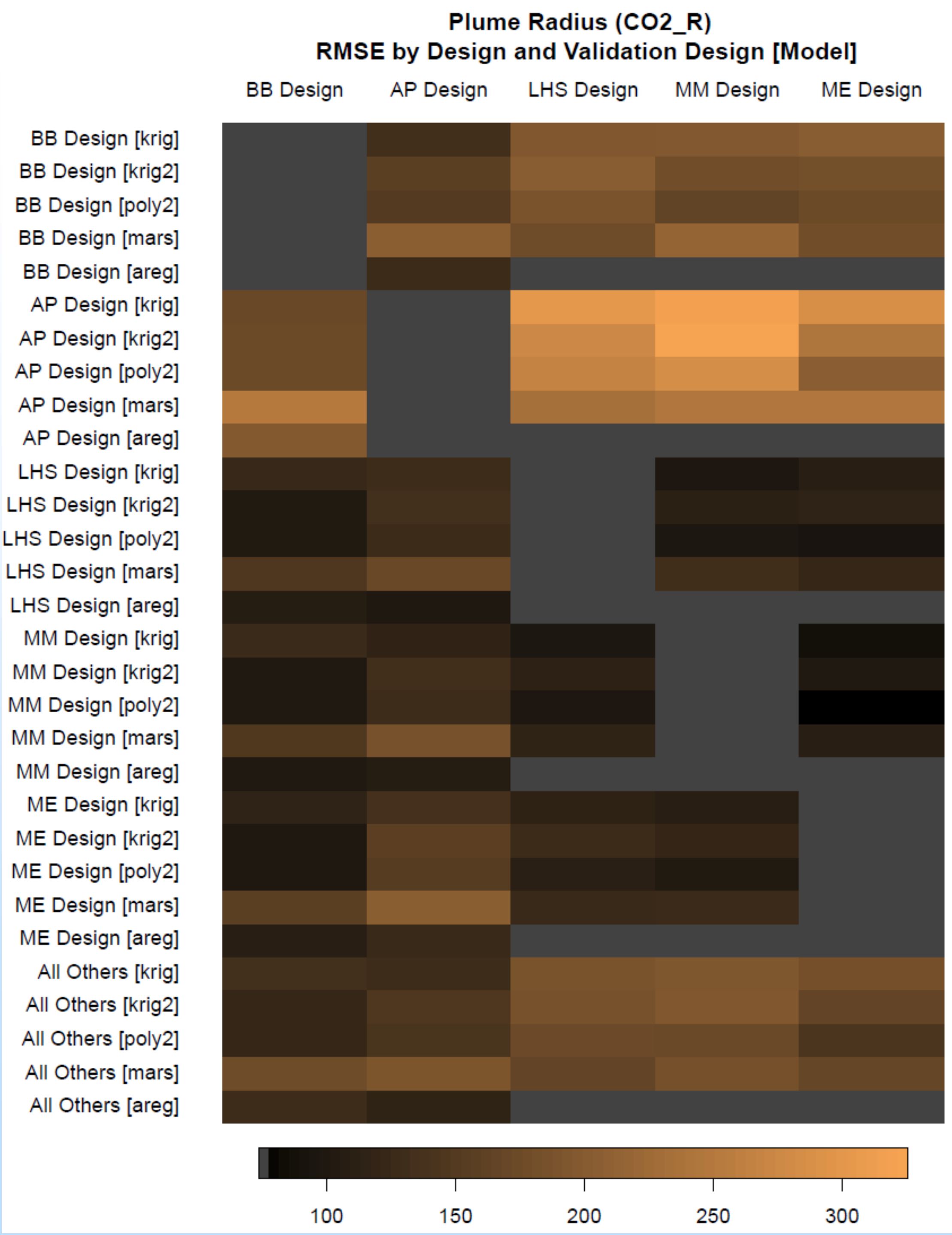




Alternative Space-Filling Designs

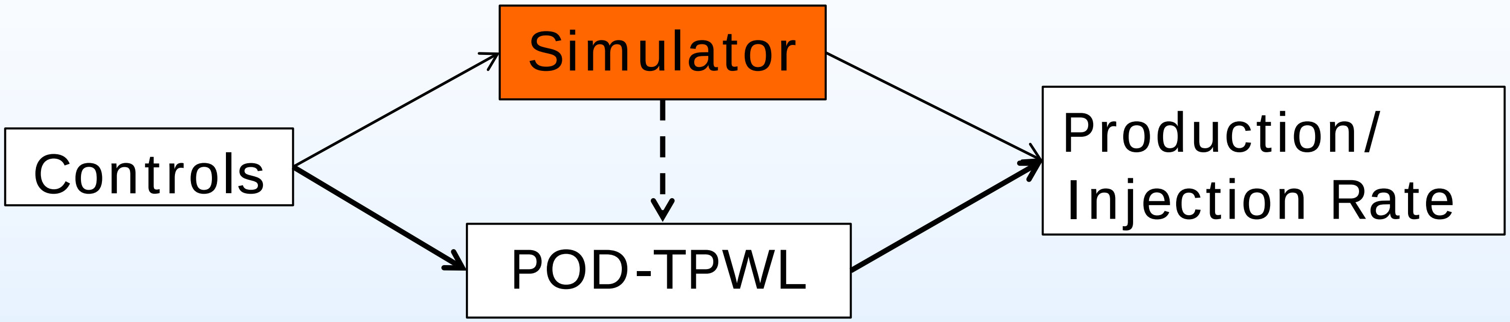
Statistical Learning Based Models

Evaluating Designs



Reduced Order Method Based Models

Background (1)



- Proper Orthogonal Decomposition (POD)
  - Represent high-dimensional state vectors (e.g., pressure & saturation in every grid block) with small number of variables by feature extraction
- Trajectory Piecewise Linearization (TPWL)
  - Predict results for new simulations by linearizing around previous (training) simulations

Reduced Order Method Based Models

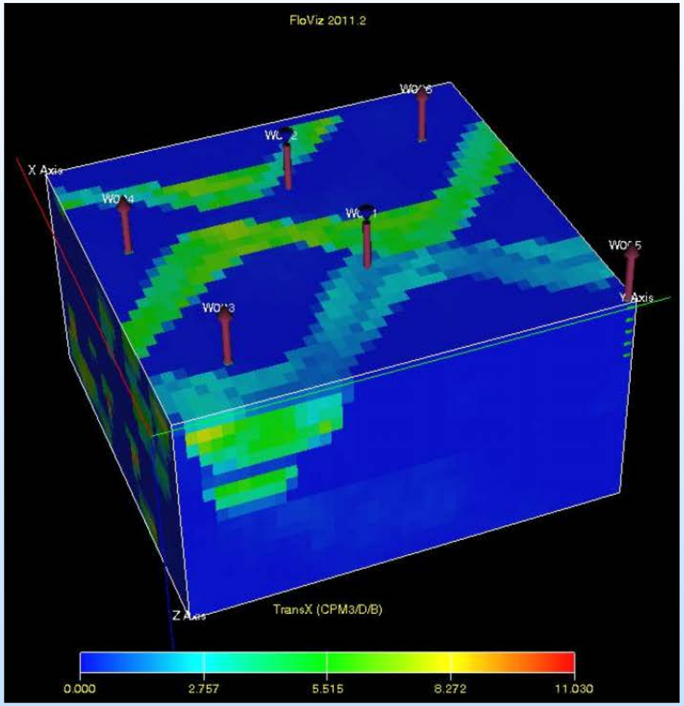
Background (2)

Order reduction		Nonlinearity treatment		Linear expressions w/ 100s of variables
⇩		⇩		⇩
POD	+	TPWL	=	POD-TPWL

- Retain the physics of the original problem
- Overhead is required to build the POD-TPWL model
- Evaluation of POD-TPWL model takes only seconds
- Applied previously to oil-water problems for optimization and history matching (Cardoso and Durlofsky 2010, 2011; He et al. 2011, 2013)

Reduced Order Method Based Models

Stanford VI Problem (CO_2 Storage+EOR)



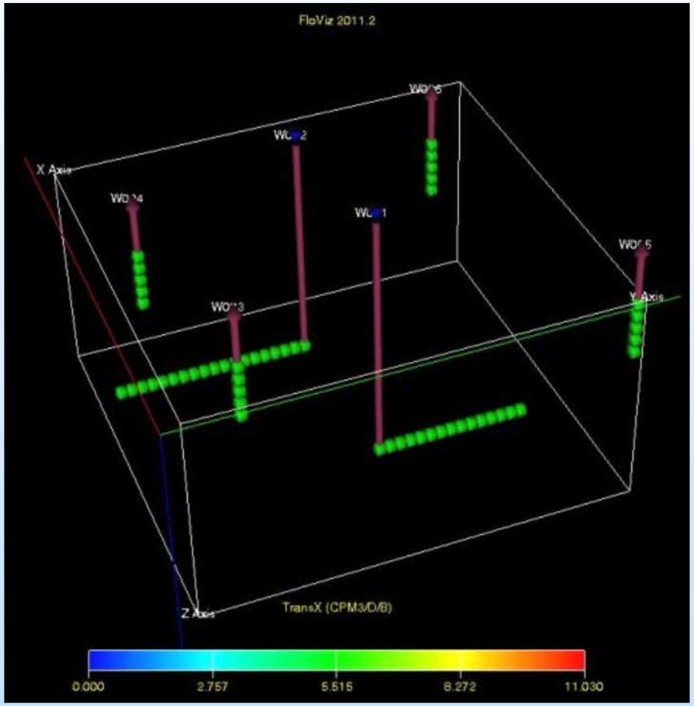
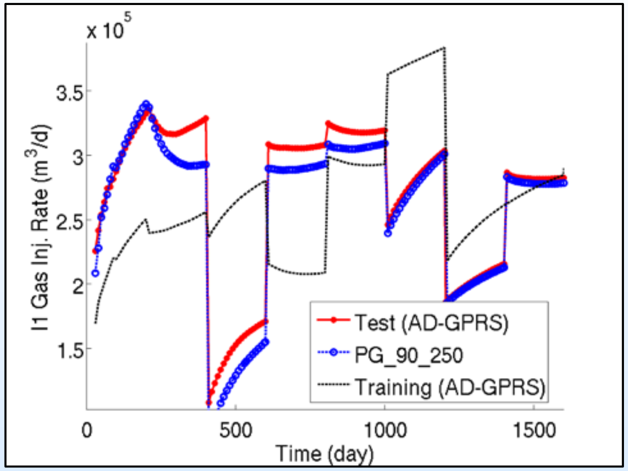
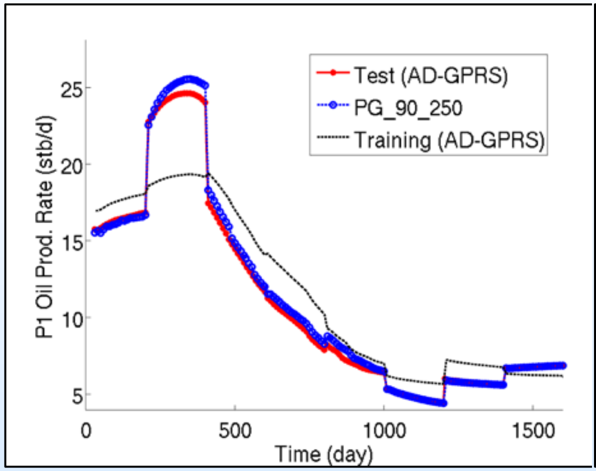


Figure 11. Geological model and well locations

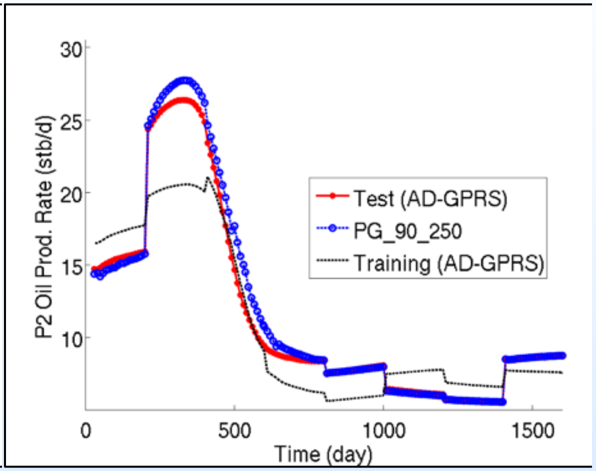
Reduced Order Method Based Models

POD-TPWL Performance

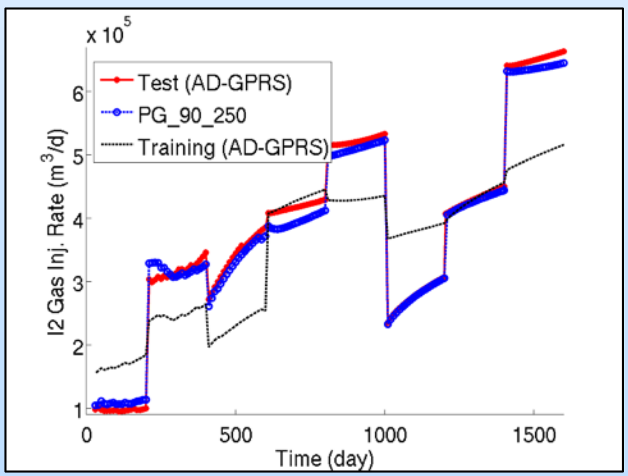


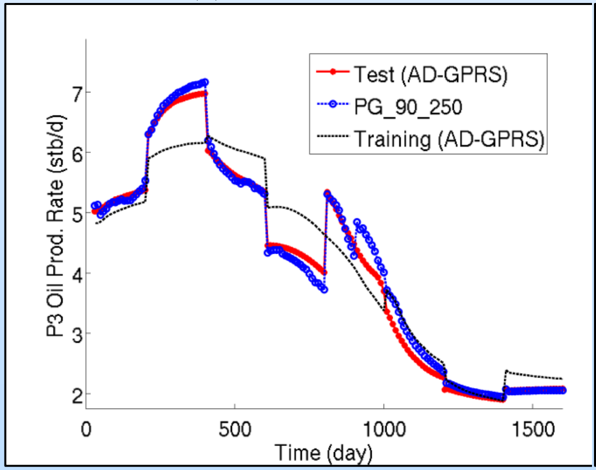


(a) Producer 1

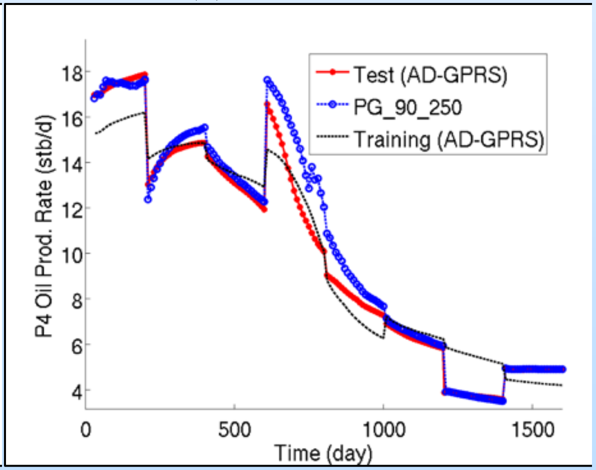


(b) Producer 2





(c) Producer 3



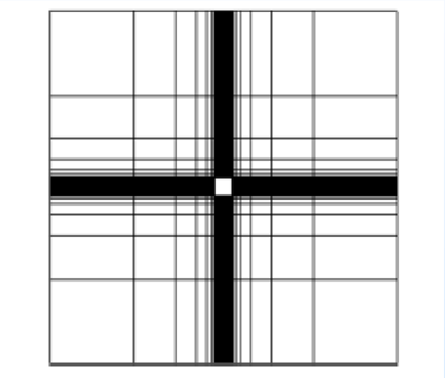
(d) Producer 4

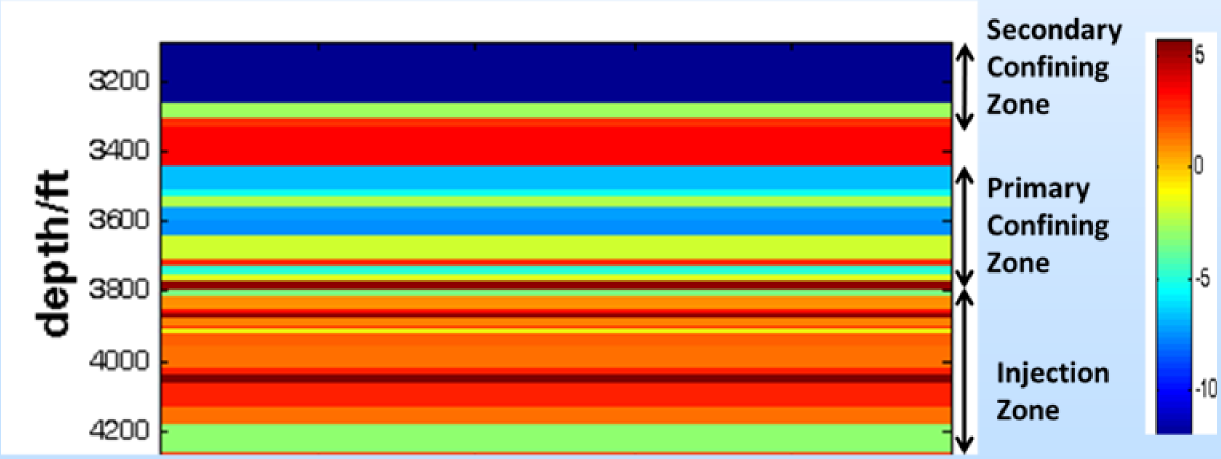
Figure 16. Oil production rates

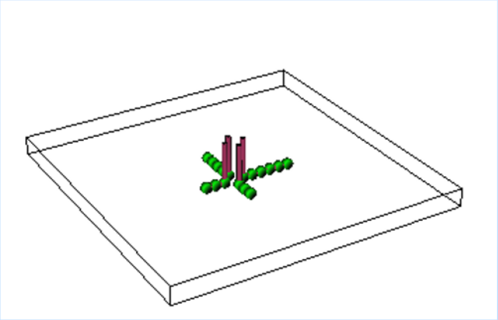
Reduced Order Method Based Models

4-Horizontal Well Problem (CO_2 Storage)

Idealized problem based on CO2 Storage in Mt Simon sandstone planned for the FutureGen 2.0 site

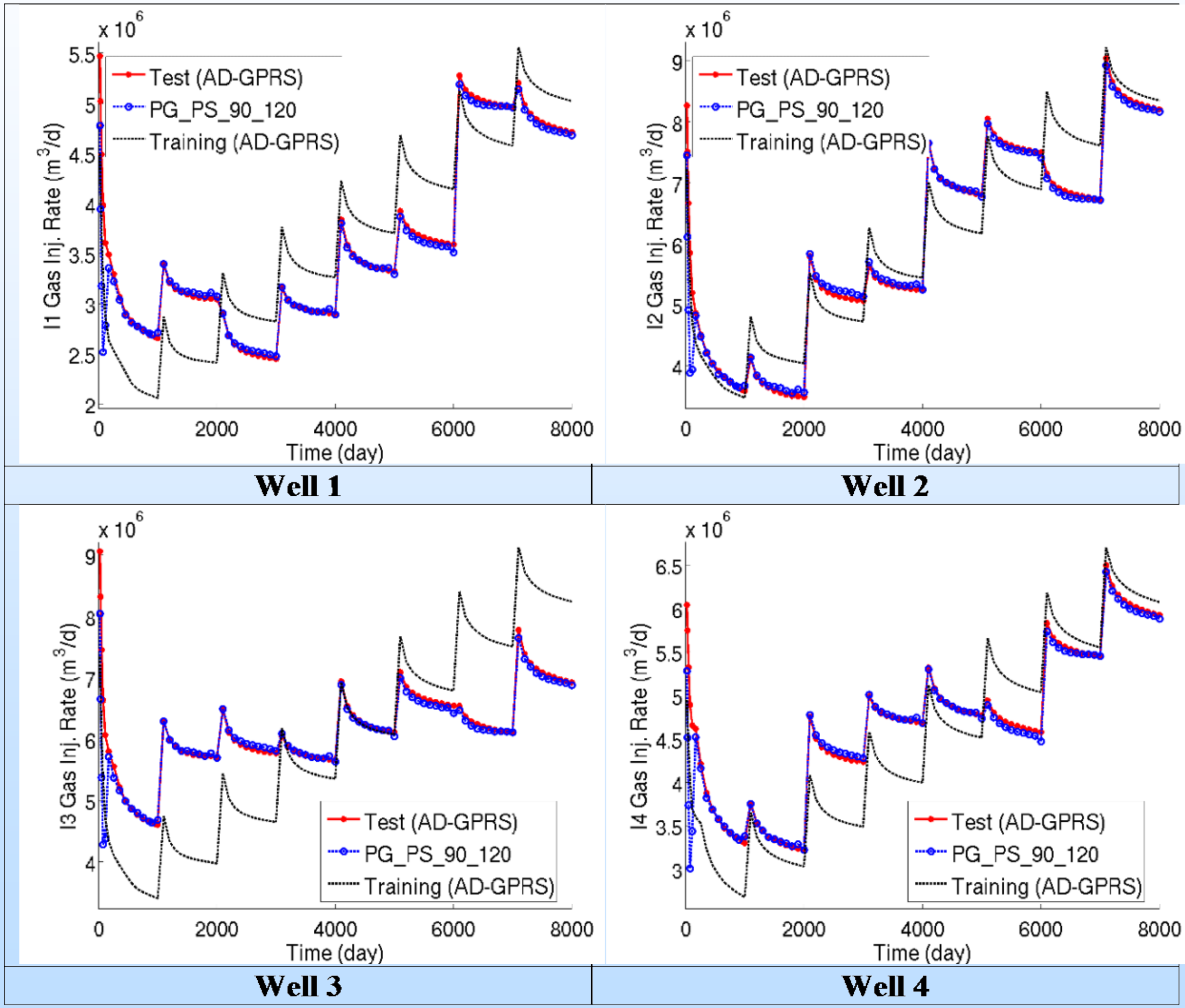






Reduced Order Method Based Models

POD-TPWL Performance



	Run Time
AD-GPRS	~720s
POD-TPWL construction	~1200s
POD-TPWL (test)	~5s

Summary

- Progress in developing simplified predictive models for layered reservoir-caprock systems
  - Reduced physics models for injectivity and plume radius
  - Improved proxy modeling workflow using BB/LHS designs
  - Application of POD-TPWL scheme to CO_2-brine systems
- Benefits to stakeholders
  - Site developers, regulators ⇨ simplicity, limited data
  - Modelers, risk assessors ⇨ computational efficiency

Accomplishments to Date

RPBM

- Developed simplified predictive models for dimensionless injectivity and CO_2 plume migration
- Made progress towards predictive modeling of average pressure behavior within injection reservoir

SLBM

- Compared performance of different metamodeling approaches for building proxy models
- Evaluated alternatives to commonly used sample designs (Box-Behnken and Latin Hypercube sampling)

ROMBM

- Demonstrated applicability of POD-TPWL for CO_2 injection into saline aquifers using a compositional simulator
- Evaluated different constraint reduction approaches

Summary and Next Steps

RPBM

- Reduced physics based modeling appraches for injectivity, plume migration and pressure buildup developed
- Topical report in preparation for current FY deliverable
- Models to be validated using uncertainty/sensitivity analysis

SLBM

- Statistical learning based proxy modeling approaches – combining sampling and metamodeling - developed
- Topical report in preparation for current FY deliverable
- Models to be validated using uncertainty/sensitivity analysis

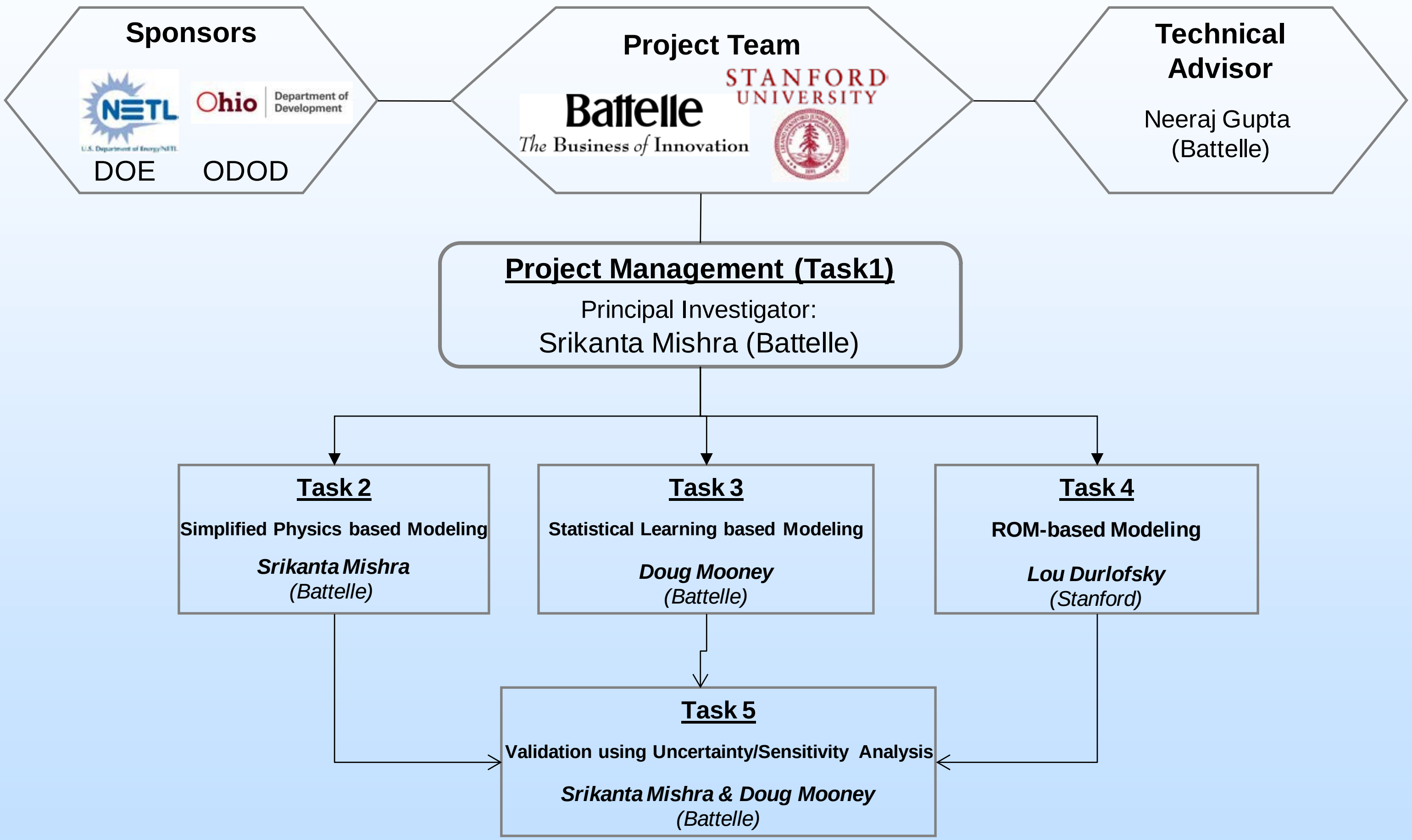
ROMBM

- POD-TPWL schemes to be tested for black-oil and heterogeneous geology models
- Models to be validated using uncertainty/sensitivity analysis

Appendix

These slides will not be discussed during the presentation, but are mandatory

Organization Chart



Project Manager – William O'Dowd (DOE)

Gantt Chart

	BP1				BP2				BP3			
	10/2012-09/2013				10/2013-09/2014				10/2014-09/2015			
Task Name	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Task 1: Project Management												
1.1 Project Management & Planning												
1.2 Update Project Mgmt. Plan	X											
1.3 Progress Reporting	X	X	X	X	X	X	X	☐	☐	☐	☐	☐
1.4 Project Controls												
1.5 Deliverables and Reporting				☐				☐		☐		☐
Task 2: Simplified physics based modeling												
2.1 Numerical experiments												
2.2 Models for two-phase region behavior												
2.3 Models for pressure buildup								☐				
Task 3: Statistical learning based modeling												
3.1 Design matrix generation												
3.2 Computer simulations												
3.3 Analysis of computer experiments								☐				
Task 4: ROM-based modeling												
4.1 Black-oil ROM procedures												
4.2 Compositional ROM procedures										☐		
Task 5: Validation using UA/SA												
5.1 Problem definition												
5.2 Probabilistic simulation												
5.3 Analysis of results												☐

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- <u>Journals, multiple authors</u>

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