Closed-Loop Field Development Optimization under Uncertainty

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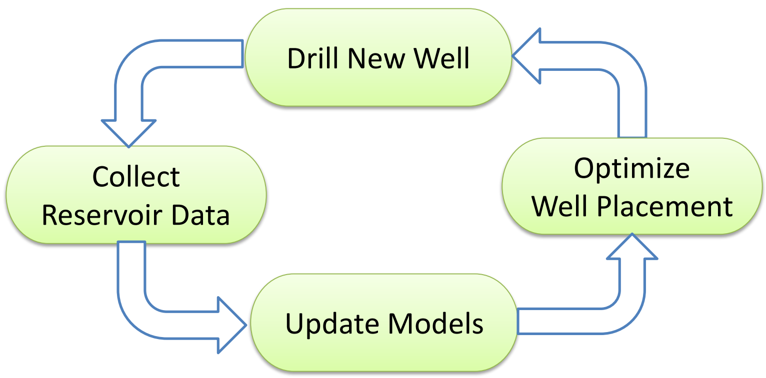
Closed-loop Field Development

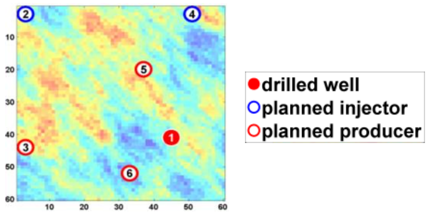


- Each new well is optimized with knowledge that it is one well in a sequence
- This is in contrast to optimizing each well independently

Closed-loop Field Development Optimization

t_1

Optimization

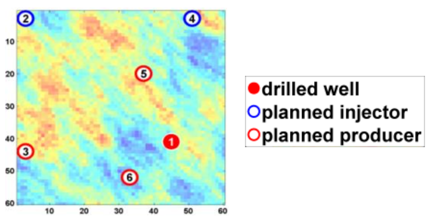


Closed-loop Field Development Optimization

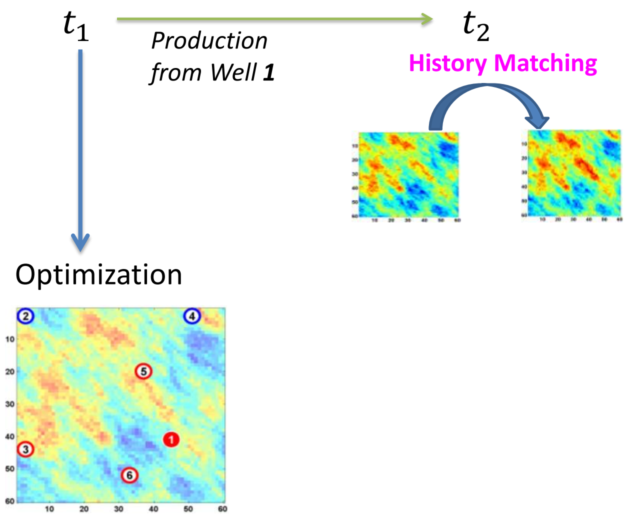
t_1 → t_2

Production from Well 1

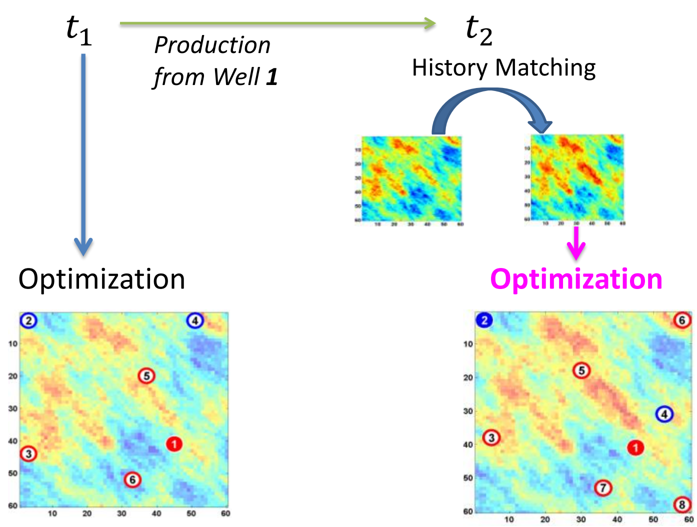
Optimization



Closed-loop Field Development Optimization



Closed-loop Field Development Optimization

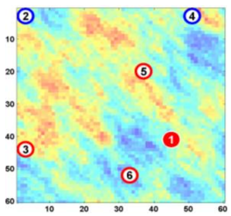


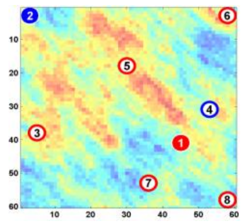
Closed-loop Field Development Optimization

t_1 → *Production from Well **1*** → t_2 → ***Prod / Inj from Wells 1 & 2*** → t_3

t_1 ↓ Optimization

t_2 ↓ History Matching ↓ Optimization

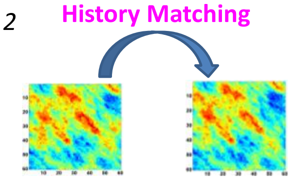




Closed-loop Field Development Optimization

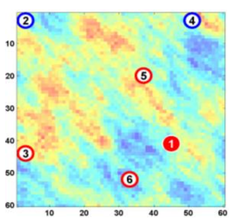
t_1 → *Production from Well **1*** → t_2 → *Prod / Inj from Wells 1 & 2* → t_3

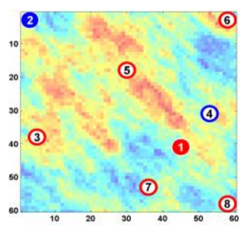
History Matching



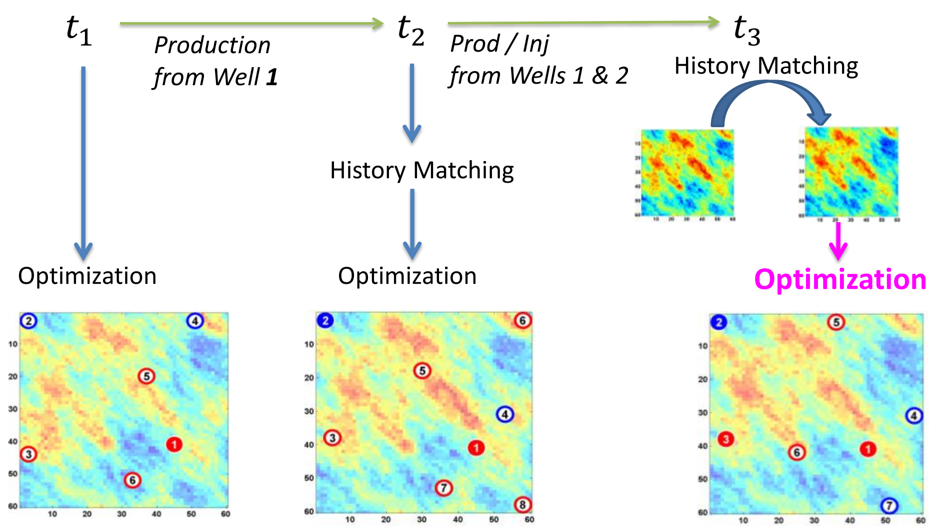
t_1 ↓ Optimization

t_2 ↓ History Matching ↓ Optimization

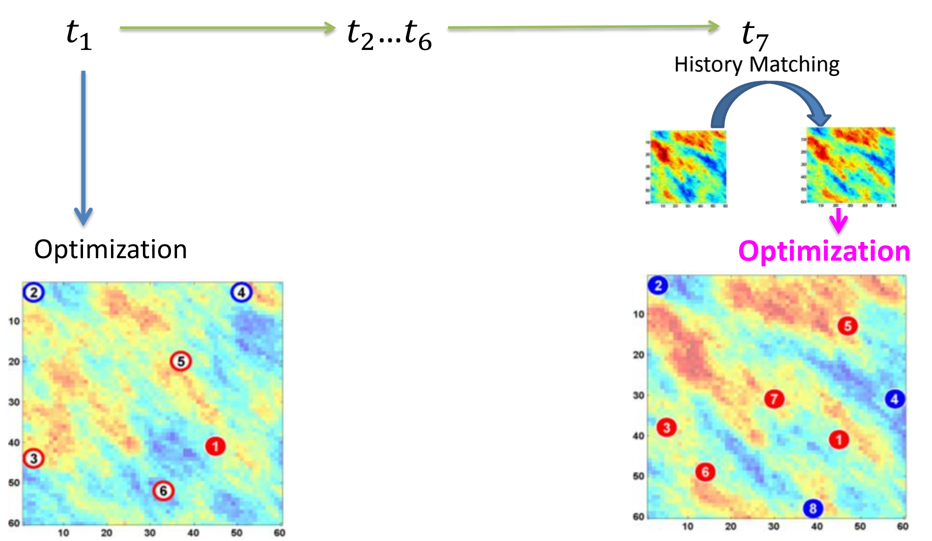




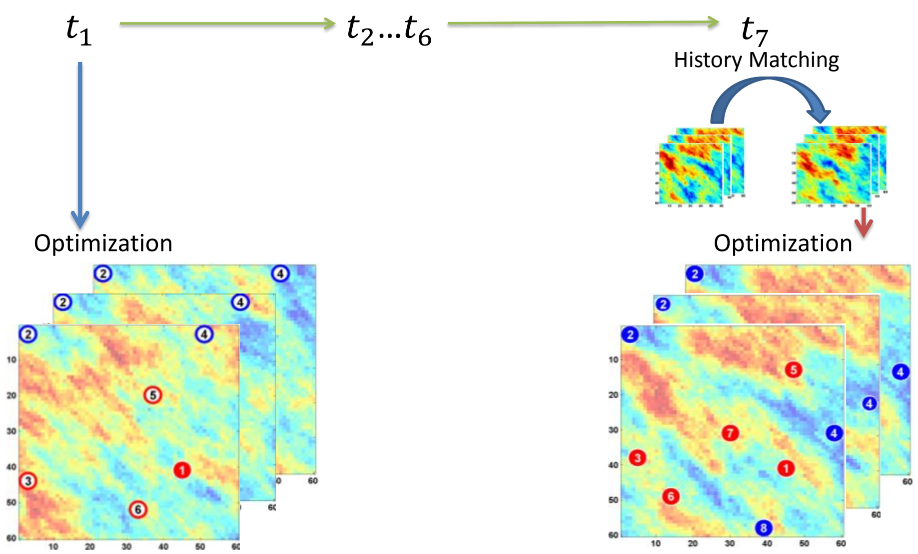
Closed-loop Field Development Optimization



Closed-loop Field Development Optimization



CLFD with Multiple Realizations



Optimization Problem in CLFD

- NPV objective for field development optimization:

$$J(x, m) = p_o Q_o - c_{wp} Q_{wp} - c_{wi} Q_{wi} - \sum c_{well}$$

- $\boldsymbol{x}$: vector of decision parameters (number of wells, well types, locations, controls, drilling sequence)
- $\boldsymbol{m}$: a “current” (updated) realization at time t_i
- Maximize expected NPV:

$$\bar{J}(\boldsymbol{x}) = \frac{1}{N} \sum_{j=1}^{N} J(\boldsymbol{x}, m_j)$$

Optimization Problem in CLFD

$$\bar{J} = \frac{1}{N} \sum_{j=1}^{N} J\left(x, m_j^i\right)$$

- $\boldsymbol{M^i} = [m_1^i, m_2^i \dots m_N^i]$: set of current realizations (updated at t_i)

$$\bar{J} = \bar{J}(x, \boldsymbol{M^i})$$

Optimization Problem in CLFD

$$\bar{J} = \frac{1}{N} \sum_{j=1}^{N} J\left(x, m_j^i\right)$$

- $M^i = [m_1^i, m_2^i \dots m_N^i]$: set of current realizations (updated at t_i)

$$\bar{J} = \bar{J}(x, M^i)$$

- Optimal solution (at t_i) : $\boldsymbol{x^i} = \operatorname{argmax}_x \bar{J}(x, M^i)$, using PSO-MADS (Isebor et al. 2014 a, b)
- Use x^{i-1} as initial guess for optimization at time t_i

Evolution of Solution in CLFD

t_1 → *Production from Well **1*** → t_2 → *Prod / Inj from Wells **1 & 2*** → t_3 →

M^1 → M^2 History Matching

M^2 → M^3 History Matching

$\bar{J}(x^0, M^1)$ ⇓ Optimization $\bar{J}(x^1, M^1)$

$\bar{J}(x^1, M^2)$ ⇓ Optimization $\bar{J}(x^2, M^2)$

$\bar{J}(x^2, M^3)$ ⇓ $\bar{J}(x^3, M^3)$

Evolution of Solution in CLFD

t_1 → t_2 → t_3 →

Optimal solution: x^1 | Optimal solution: x^2 | Optimal solution: x^3

$\bar{J}(x^1, M^1)$ | $\bar{J}(x^2, M^2)$ | $\bar{J}(x^3, M^3)$

$J(x^1, m_{\text{true}})$ → $J(x^2, m_{\text{true}})$ → $J(x^3, m_{\text{true}})$

- Our interest is to investigate how "NPV for the true model" changes with update steps of CLFD

History Matching in Bayesian Framework

- Minimize

$$S(m) = \left(m - \bar{m}_{prior}\right)^T C_M^{-1}\left(m - \bar{m}_{prior}\right) \quad \leftarrow \text{Model mismatch term (prior)}$$
$$+ \left(g(m) - d_{obs}\right)^T C_D^{-1}\left(g(m) - d_{obs}\right) \quad \leftarrow \text{Data mismatch term (likelihood)}$$

d_{obs}: observed data (vector), *BHP*, phase rates, or hard data

$g(m)$: predicted data (vector)

C_D: (diagonal) covariance matrix for measurement errors

- Minimizing $S(m)$ gives the **m**aximum **a** **p**osteriori (MAP) estimate

Randomized Maximum Likelihood (RML) for Generating Multiple History Matched Models

- Generate samples from the prior pdf

$$\boldsymbol{m_{uc}} \sim N\left(m_{prior}, C_M\right)$$

- Generate perturbed observation samples

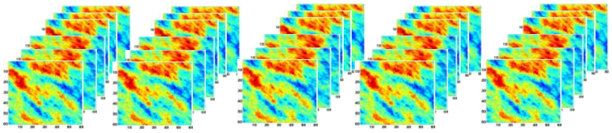
$$\boldsymbol{d_{uc}} \sim N\left(d_{obs}, C_D\right)$$

- Minimize N_R objective functions to generate N_R posterior samples using L-BFGS

$$S(m) = \left(m - \boldsymbol{m_{uc}}\right)^T C_M^{-1}\left(m - \boldsymbol{m_{uc}}\right)$$
$$+ \left(g(m) - \boldsymbol{d_{uc}}\right)^T C_D^{-1}\left(g(m) - \boldsymbol{d_{uc}}\right)$$

Optimization under Geological Uncertainty

- A large number of realizations (N_R) are used to capture uncertainty



- How many realizations to use in optimization?
- Sample validation: optimize for $N \ll N_R$ representative realizations, then **validate** representativity

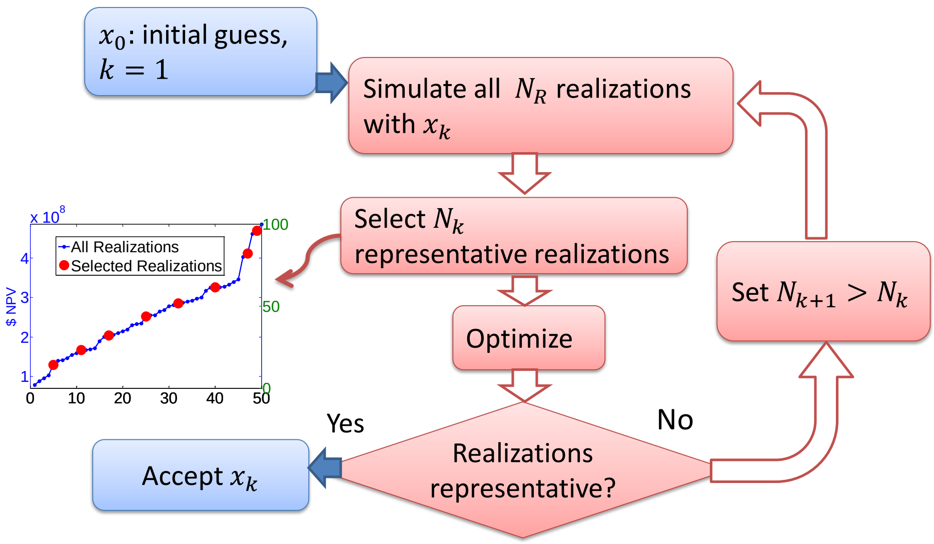
Sample Validation for Optimization under Uncertainty

- **R**elative **I**mprovement:

$$RI = \frac{\bar{J}(x_{opt}, M) - \bar{J}(x_0, M)}{\bar{J}(x_{opt}, \boldsymbol{M_{rep}}) - \bar{J}(x_0, \boldsymbol{M_{rep}})}$$

  - RI: Ratio of improvement for the entire set over that for the representative set
  - M : set of all realizations of size N_R
  - $\boldsymbol{M_{rep}}$: representative set of size N
  - x_{opt}, x_0: optimal solution & initial guess
- We require $RI \geq 0.5$ to accept x_{opt} as optimal solution

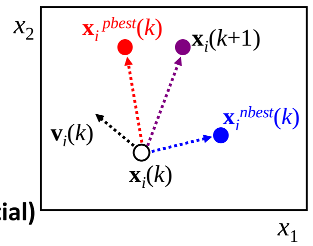
Sample Validation for Optimization under Uncertainty



Particle Swarm Optimization (PSO)

(Eberhart and Kennedy, 1995)

- Global stochastic search
- Solutions are particles in a swarm
- Solution update given by:



$$\mathbf{x}_i(k+1) = \mathbf{x}_i(k) + \mathbf{v}_i(k+1) \cdot \Delta t$$

$$\mathbf{v}_i(k+1) = \omega \cdot \mathbf{v}_i(k) \quad \textbf{(inertial)}$$

$$+ c_1 \cdot D_1(k) \cdot (\mathbf{x}_i^{pbest}(k) - \mathbf{x}_i(k)) \quad \textbf{(cognitive)}$$

$$+ c_2 \cdot D_2(k) \cdot (\mathbf{x}_i^{nbest}(k) - \mathbf{x}_i(k)) \quad \textbf{(social)}$$

(from Isebor 2013)

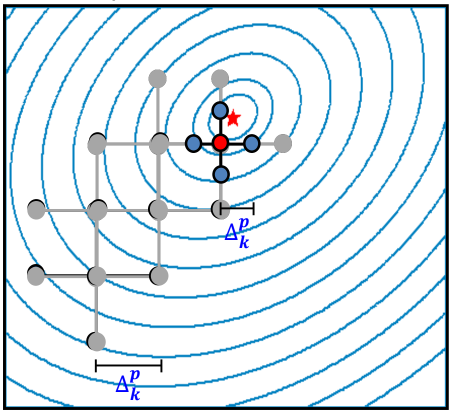
PSO parameters: $\omega, c_1, c_2; \quad D_1(k), D_2(k) \sim U(0,1)$

Can globally explore solution space, but no guarantees of convergence

Pattern Search & Mesh Adaptive Direct Search

- Local search
- Naturally parallelizable
- Rigorous convergence theory based on stencil reduction
- Mesh Adaptive Direct Search (**MADS**): an advanced pattern search optimizer (Audet and Dennis Jr., 2006)

Optimization in $\mathbb{R}^2$

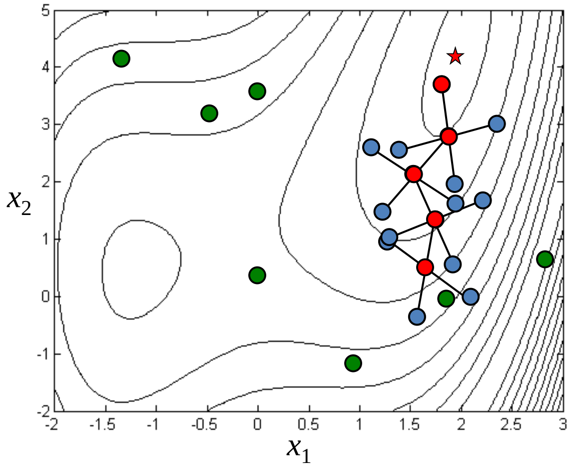


Basic pattern search (Kolda et al., 2003)

(from Isebor 2013)

PSO-MADS hybrid algorithm

- Developed by Isebor et al (2014 a, b)



Computational Cost of CLFD Runs ($N = 5$)

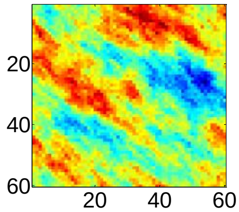
PSO-MADS Optimization (300 cores)	• $N \times 10{,}000$ simulations • ~ 200 equivalent simulations
L-BFGS for History Matching (Each node has 16 cores)	• N_R nodes $\times$ 50 simulations • ~ 10 equivalent simulations
Full CLFD (for 1 run) (8 wells - 1 well at a time)	• ~ 0.5 million simulations • ~ 1800 equivalent simulations

Computational Results

- Example 1: Simultaneous versus "well by well" optimization
- Example 2: CLFD for a 2D reservoir
- Example 3: CLFD for a 3D reservoir

Example 1:
Simultaneous versus Well-by-Well Optimization

- Deterministic reservoir description
- Simultaneous optimization: optimize the locations, controls and types of 4 wells drilled at 210 day intervals
- Well by well: optimize Well 1; then optimize Well 2 (drilled at 210 days), etc.

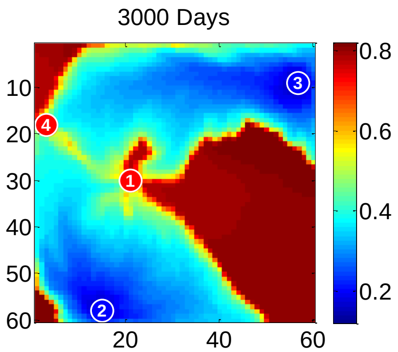


log-permeability

parameter	value
well cost	$ 25 MM
oil price	$ 90 / bbl
produced water	$ 10 / bbl
injected water	$ 10 / bbl
reservoir life	3000 days
Porosity	0.2

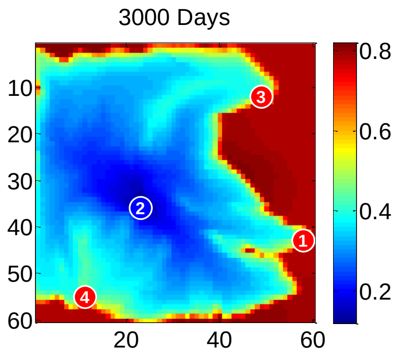
Final Saturation from Optimal Solutions

Well-by-Well



NPV = $**625** MM

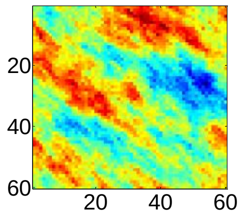
Simultaneous



NPV = $**708** MM

Example 2: CLFD for a 60 × 60 Reservoir

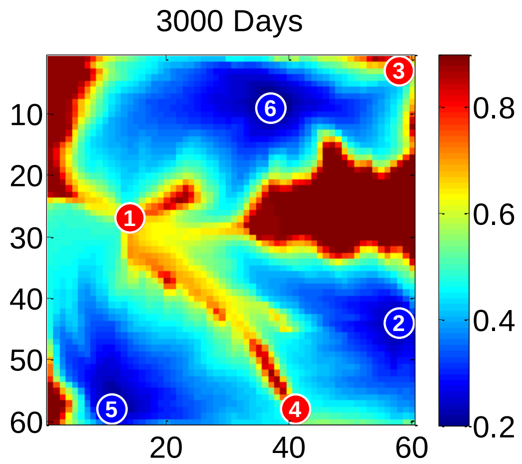
- Uncertain permeability field
- Budget to drill maximum **8** wells
- Case 1: $N = 3$
- Case 2: $N = 5$
- Case 3: $N = 10$
- Case 4: Optimization with sample validation step



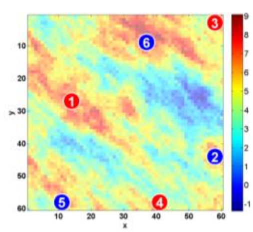
True log-perm

parameter	value
well cost	$ 25 MM
oil price	$ 90 / bbl
produced water	$ 10 / bbl
injected water	$ 10 / bbl
drilling lag-time	210 days
reservoir life	3000 days

Optimization on True Model (Deterministic)

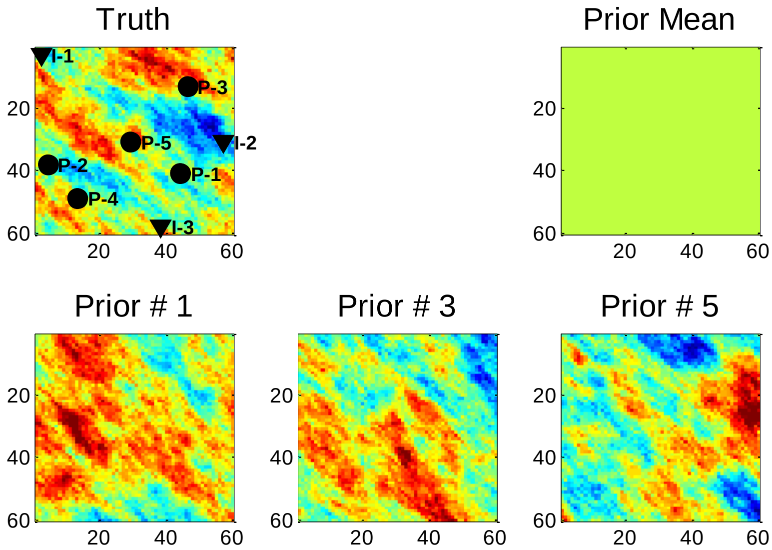


Optimal solution on True $\log(k)$

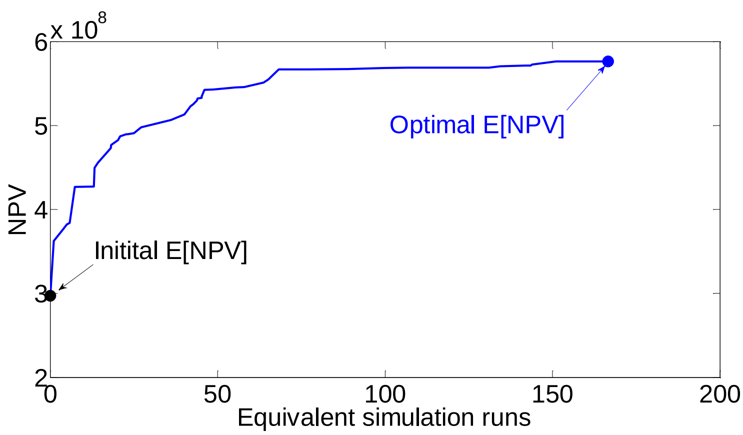


S_w distribution at each optimization control-step (NPV = $ 717 MM)

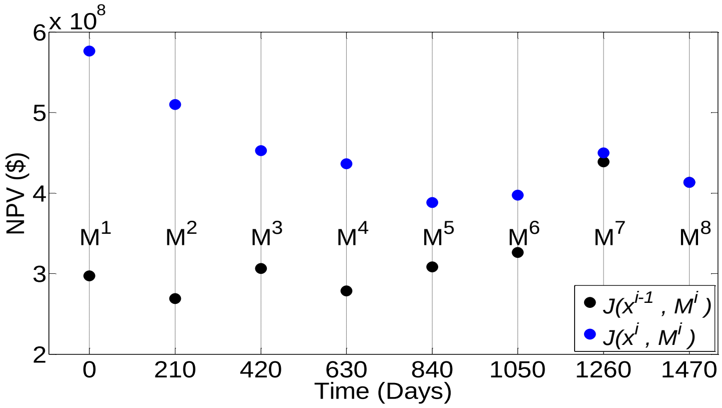
Unconditional Permeability Fields



Optimization over 3 Prior Realizations (1st Optimization Step of CLFD)



Optimal E[NPV] for CLFD with $(N = 3)$



- $J(x^i, M^i)$: **Optimal** E[NPV] at t_i
- $J(x^{i-1}, M^i)$: **Initial** E[NPV] at t_i

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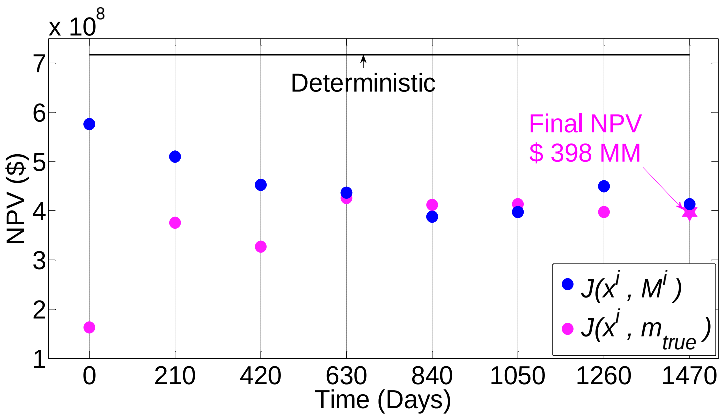
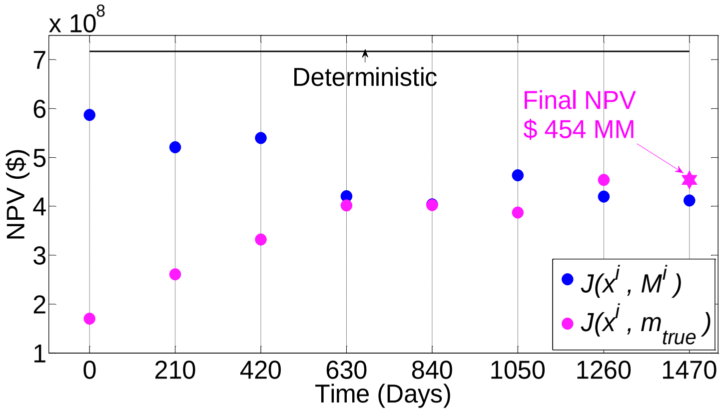
Optimal NPV versus Update Steps of CLFD $(N = 3)$



- $J(x^i, M^i)$: Optimal E[NPV] updated at t_i
- $J(x^i, m_{true})$: NPV for the true model (run the true model with x^i)

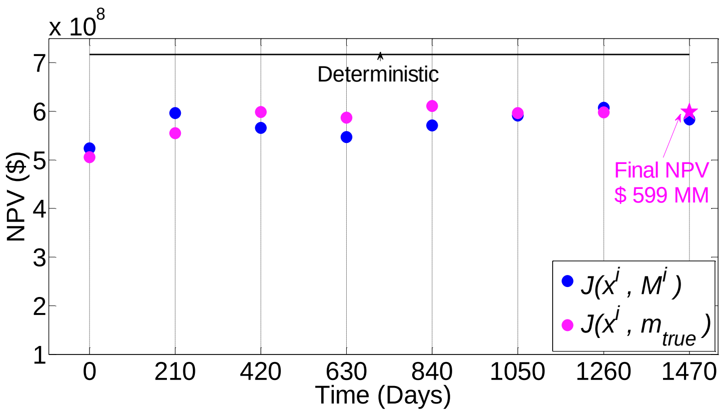
Nov 13-14, 2014 SFC 34

Optimal NPV versus Update Steps of CLFD $(N = 5)$



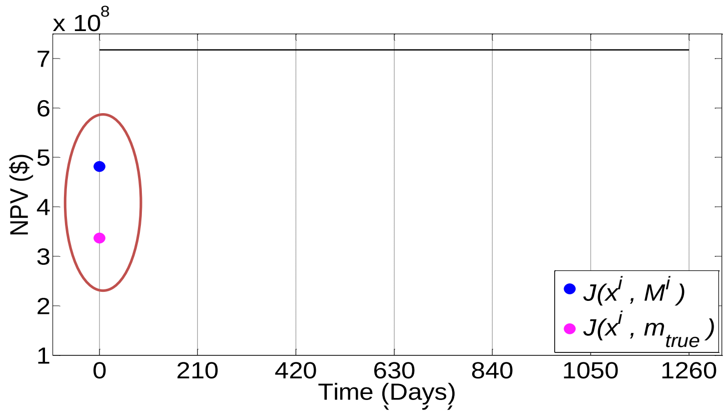
- $J(x^i, M^i)$: Optimal E[NPV] updated at t_i
- $J(x^i, m_{true})$: NPV for the true model (run the true model with x^i)

Optimal NPV versus Update Steps of CLFD $(N = 10)$



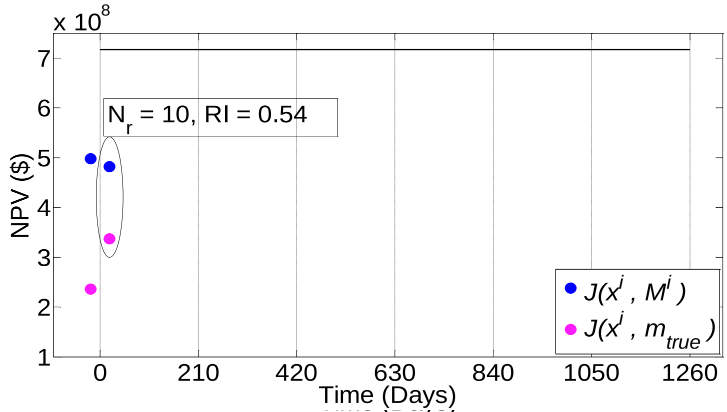
- Clear improvement in true NPV using $N = 10$ realizations
- How could we know that 3 or 5 realizations were not enough?

Optimal NPV versus Update Steps of CLFD **with Validation**



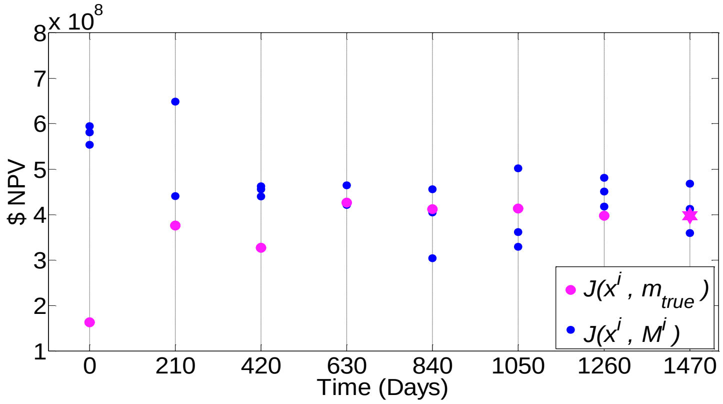
- First optimize based on $N = 6$ realizations
- Optimization is repeated for $N = 10$ (or higher) if validation not satisfied

Validation Step for Optimization over Multiple Realizations

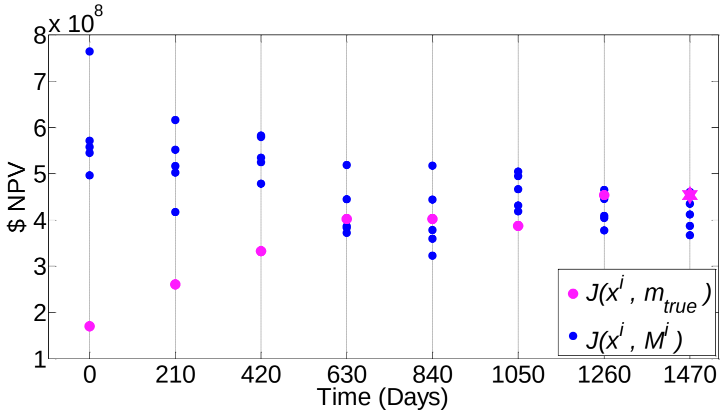


- Validation of relative improvement ($RI > 0.5$) improves the NPV for true model

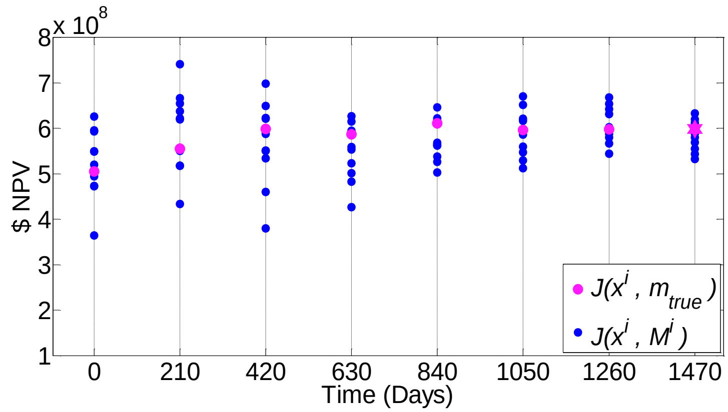
Optimal NPV for Realizations in CLFD ($N = 3$)



Optimal NPV for Realizations in CLFD ($N = 5$)

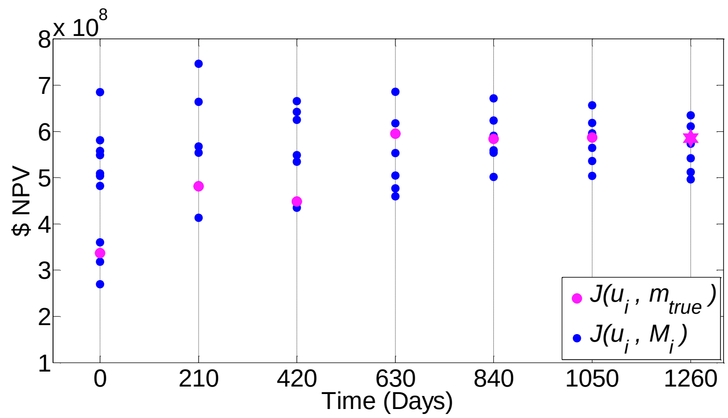


Optimal NPV for Realizations in CLFD $(\boldsymbol{N} = \mathbf{10})$



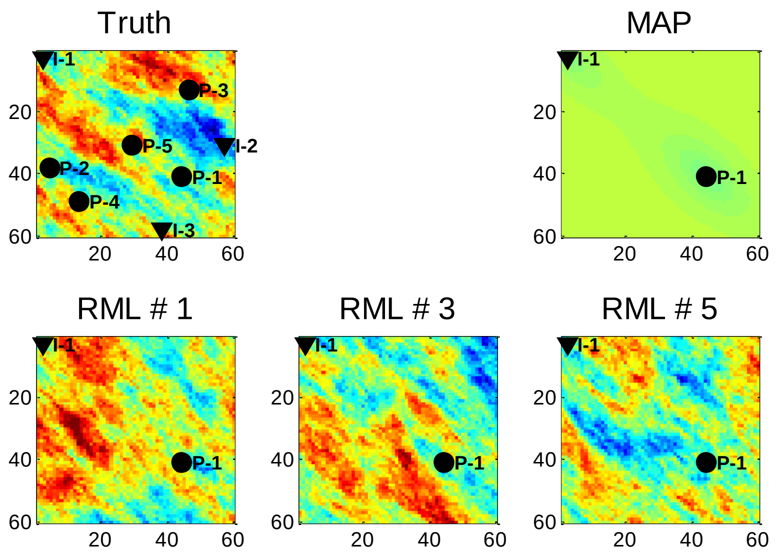
- NPV for truth is captured in the spread of realizations $(N = 10)$
- In reality, this information is not accessible during field development

Optimal NPV for Realizations in CLFD **with Validation**

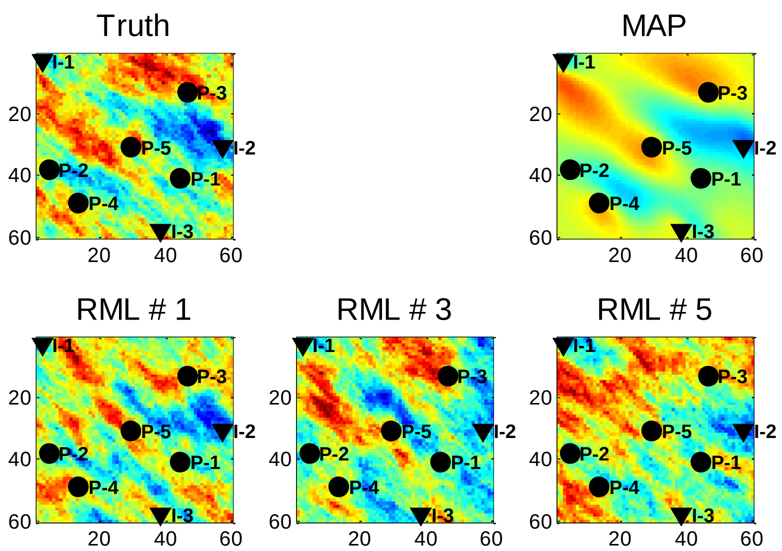


- NPV for truth falls within the spread of realizations NPV when sample validation is used

Log-Permeability Fields at $t_2 = 210$ Days

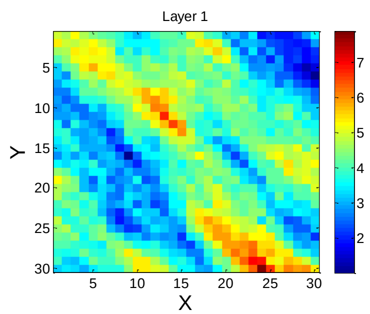


Log-Permeability Fields at $t_9 = 1680$ Days



Example 3: CLFD for a $30 \times 30 \times 5$ Reservoir

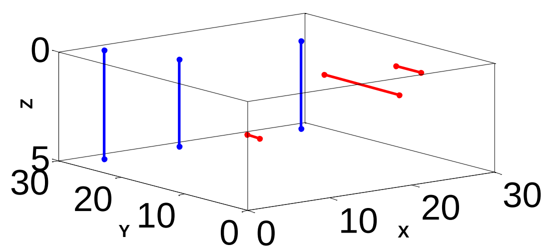
- Uncertain model parameters: $\ln(k)$
- Wells operated on BHP with maximum rate constraint
- Drill **6** wells : 3 horizontal producers, 3 vertical injectors
- Apply CLFD with Sample Validation

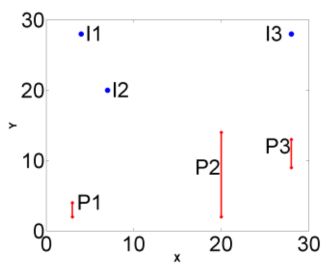


True log-perm

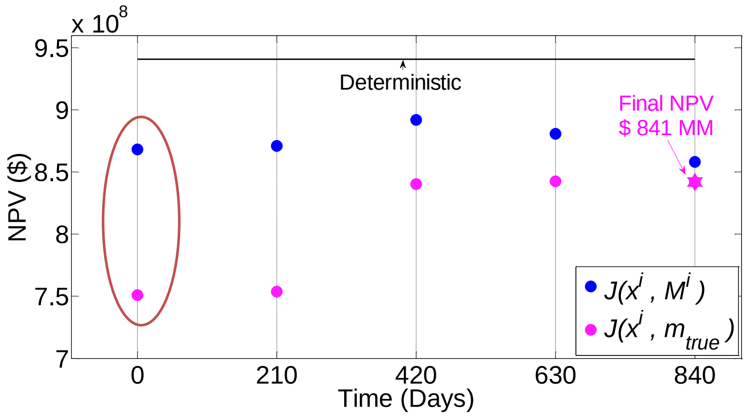
parameter	value
well cost	$ 25 MM
oil price	$ 90 / bbl
produced water	$ 10 / bbl
injected water	$ 10 / bbl
drilling lag-time	210 days
reservoir life	2000 days
perforation cost	$ 2 MM /blk

Optimization on True Model



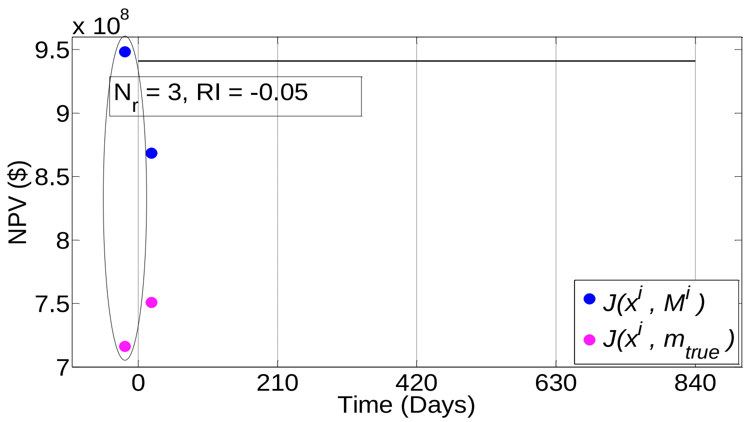


Optimal NPV in CLFD

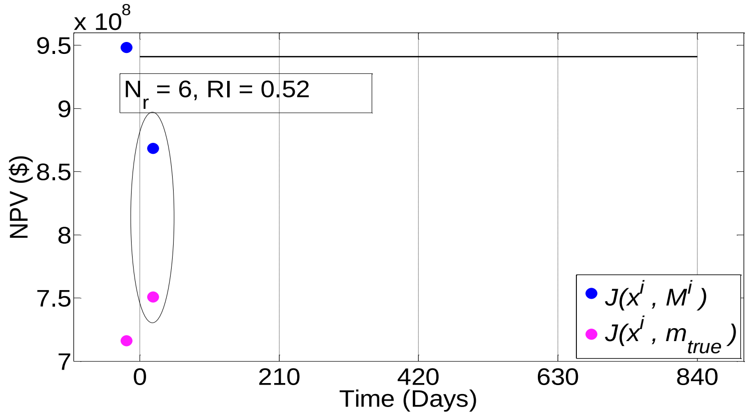


- $J(x^i, M^i)$: Optimal E[NPV] updated at t_i
- $J(x^i, m_{true})$: NPV for the true model (run the true model with x^i)

Optimal NPV in CLFD with Validation

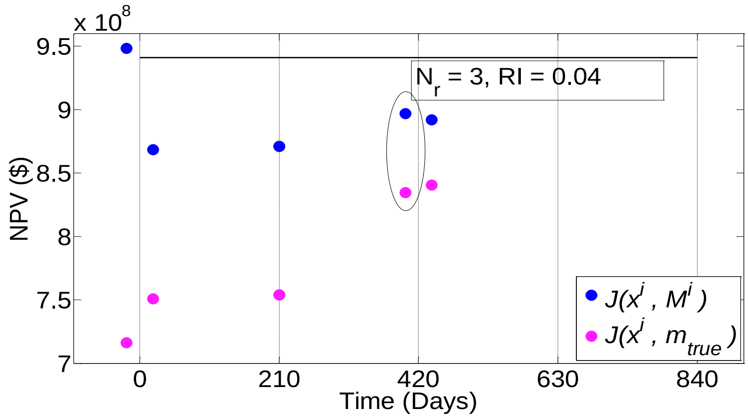


Optimal NPV in CLFD with Validation



- Clear improvement in NPV for truth using sample validation
- Optimal E[NPV] becomes closer to the NPV for truth

Optimal NPV in CLFD with Validation



- $J(x^i, M^i)$: Optimal E[NPV] updated at t_i
- $J(x^i, m_{true})$: NPV for the true model (run the true model with x^i)

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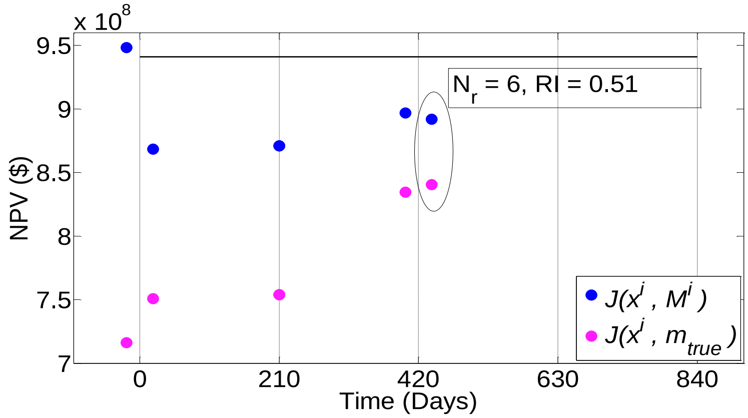

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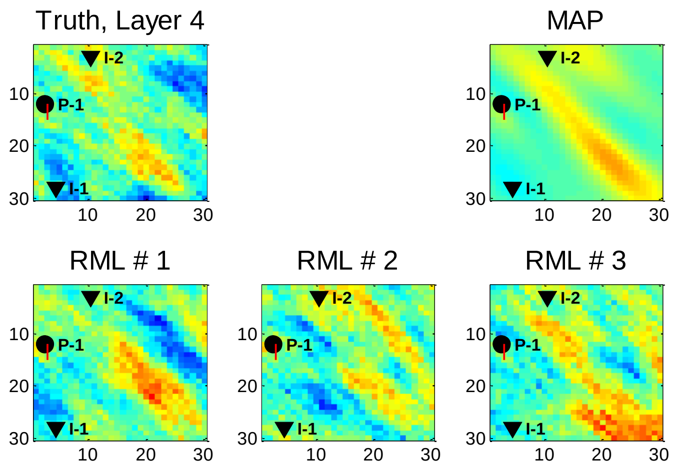
Log-Permeability Fields at $t_5 = 840$ days (Layer 4)



Summary

- Closed-loop field development (CLFD) framework refined and enhanced
- Results show that the use of too few realizations leads to lower NPV values for true model
- A sample validation procedure was developed and tested
- Significant improvements in NPV for true model are achieved using sample validation in CLFD

Future Work

- Apply CLFD to multipoint geostatistical models using O-PCA history matching from Hai Vo (Vo and Durlofsky, 2014)
- Apply bi-objective optimization for minimizing risk of geological uncertainty while maximizing expected NPV in CLFD
- Investigate other approaches for choosing a set of representative models
- Apply CLFD to more realistic cases
- Assimilate 4D seismic data in CLFD

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Thank you!