

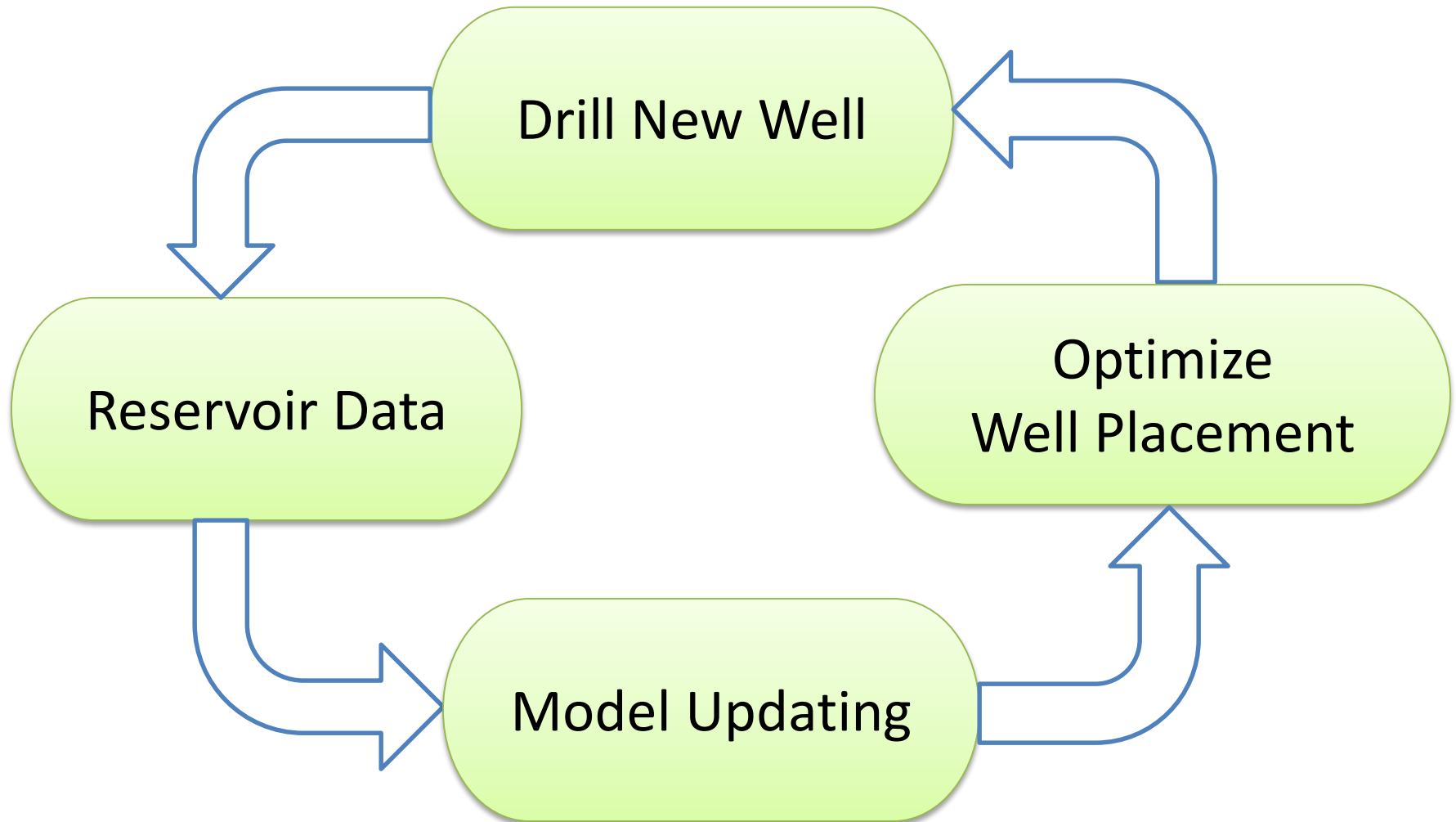
Closed-Loop Field Development Optimization

Mehrdad Shirangi Louis J. Durlofsky

Smart Fields Consortium Annual Meeting
November 14-15, 2013



Closed-loop Field Development

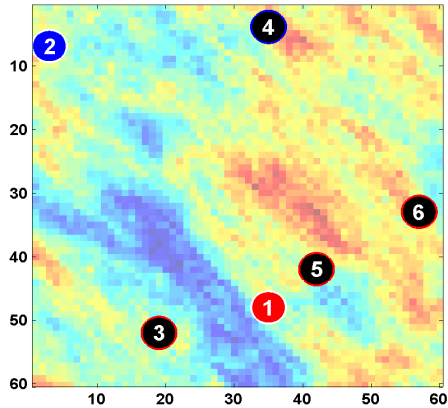


Closed-loop Field Development Optimization

t_0



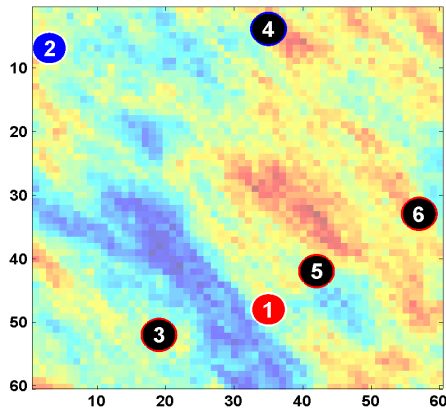
Optimization



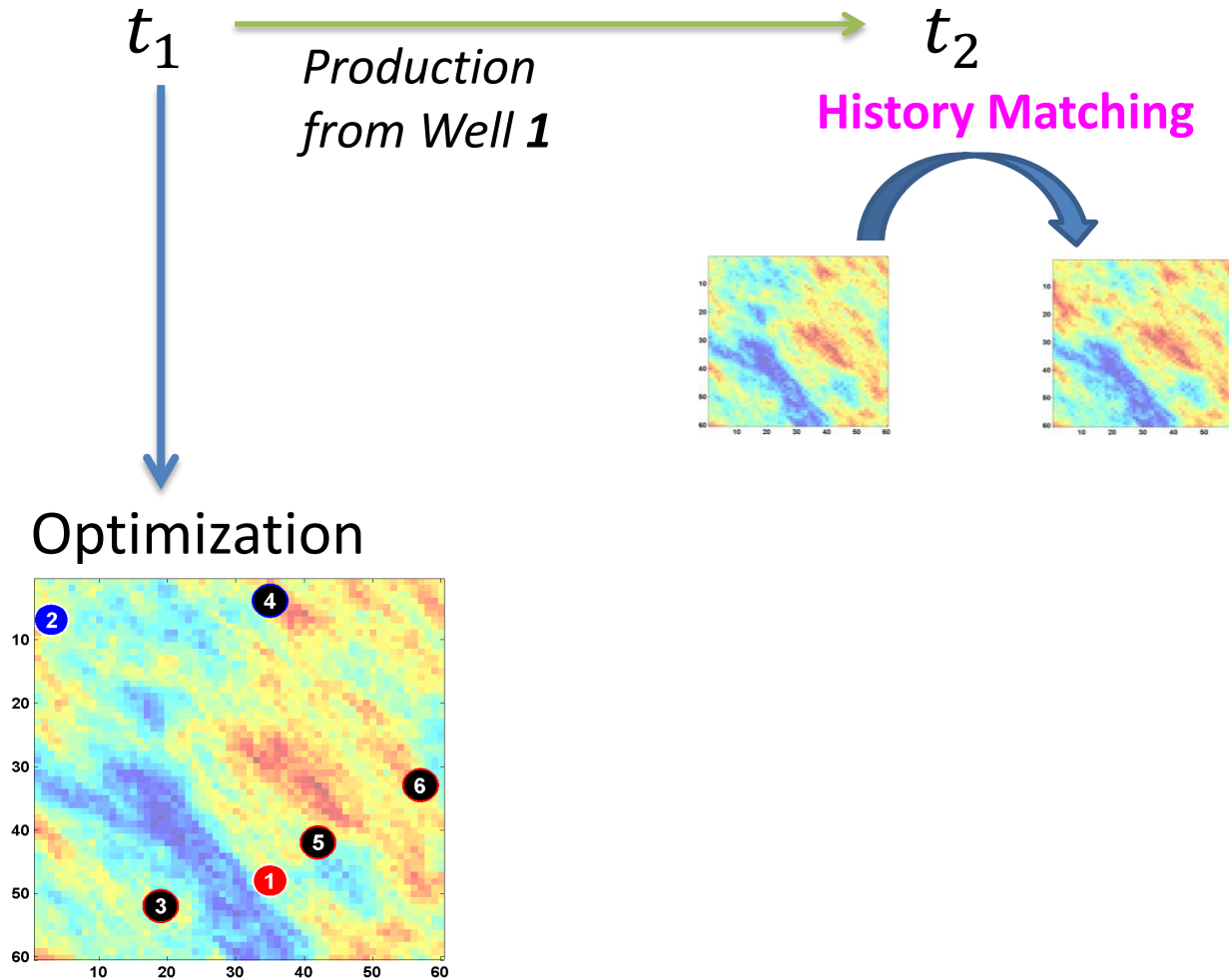
Closed-loop Field Development Optimization



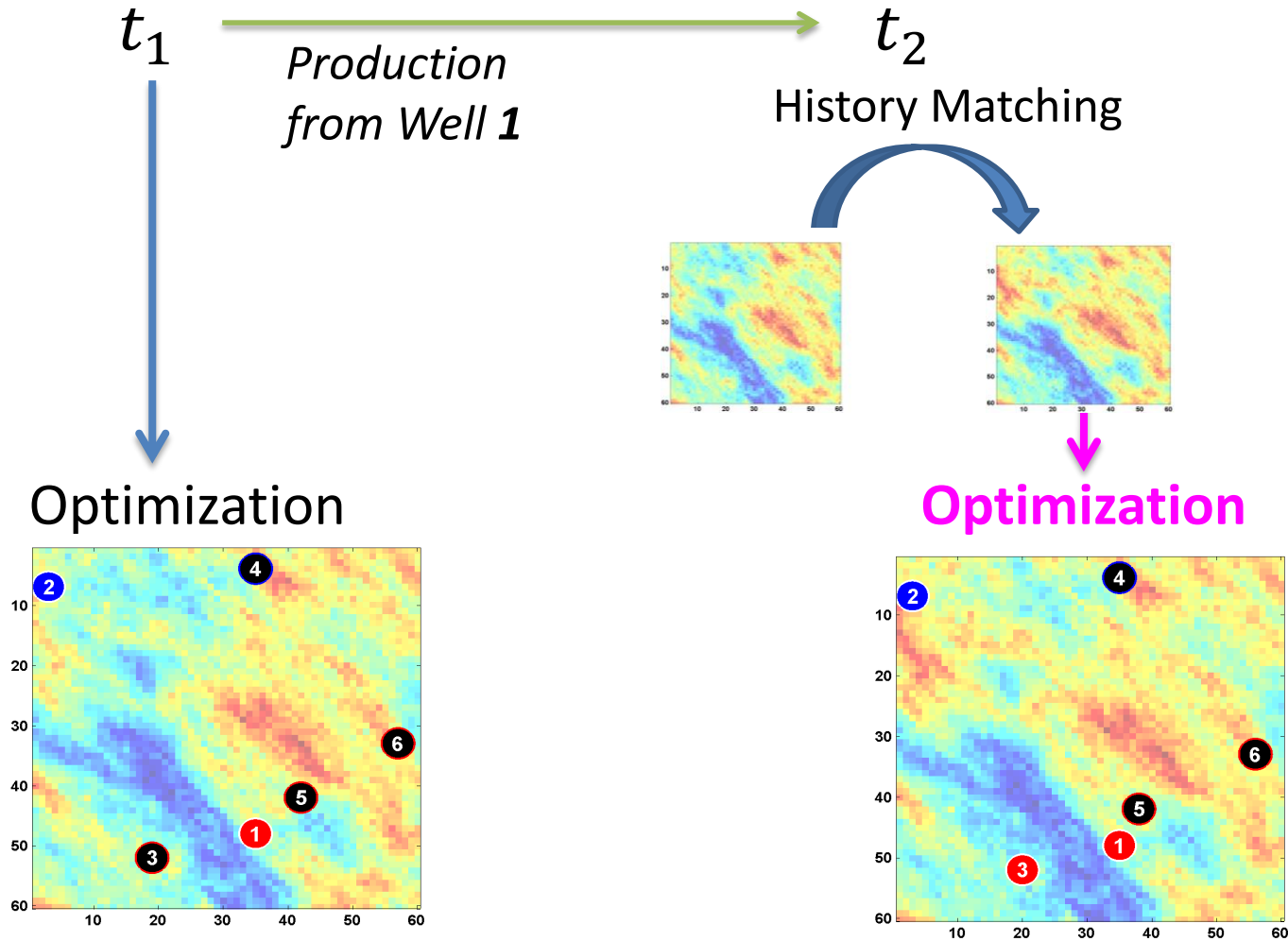
Optimization



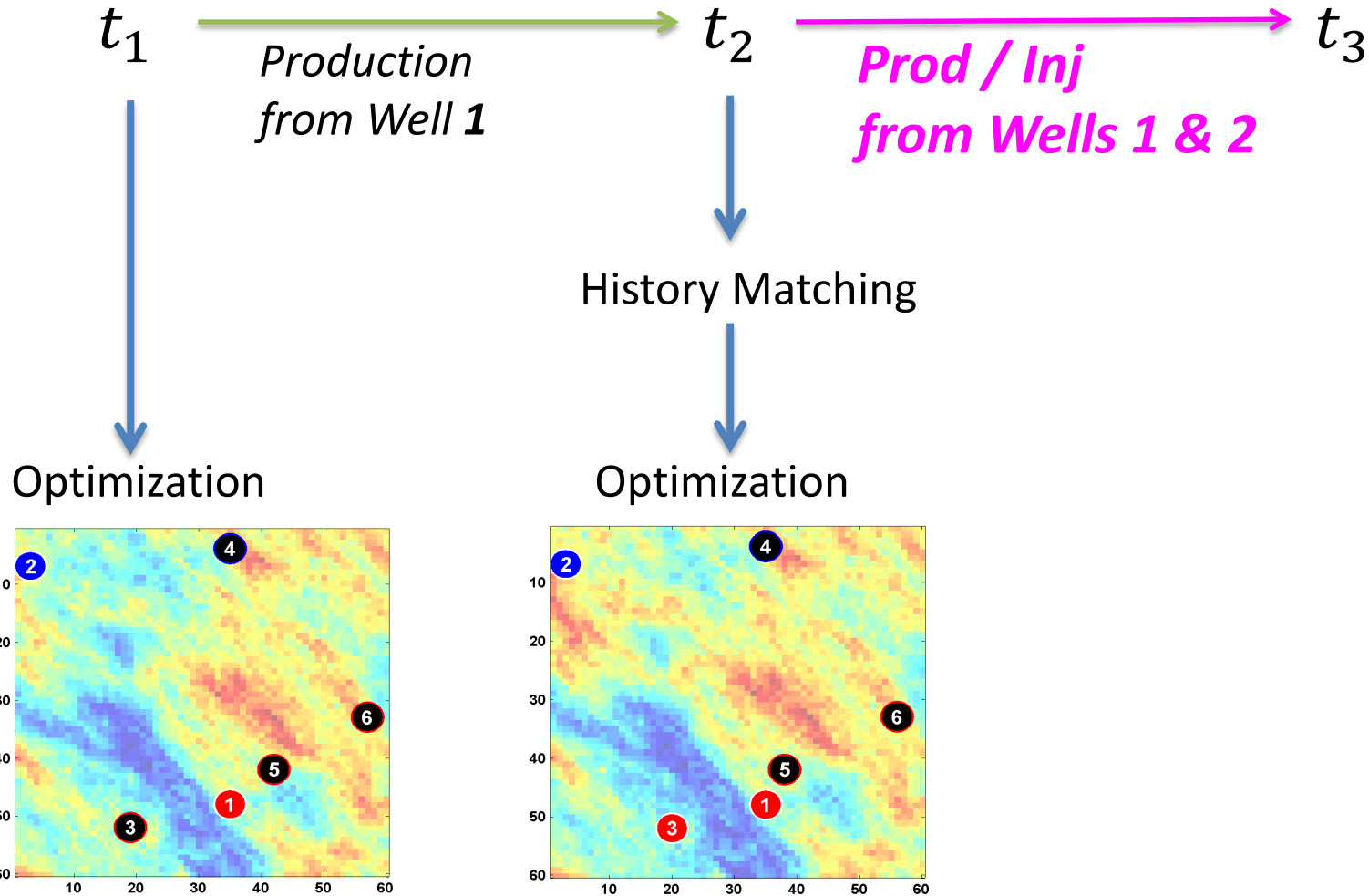
Closed-loop Field Development Optimization



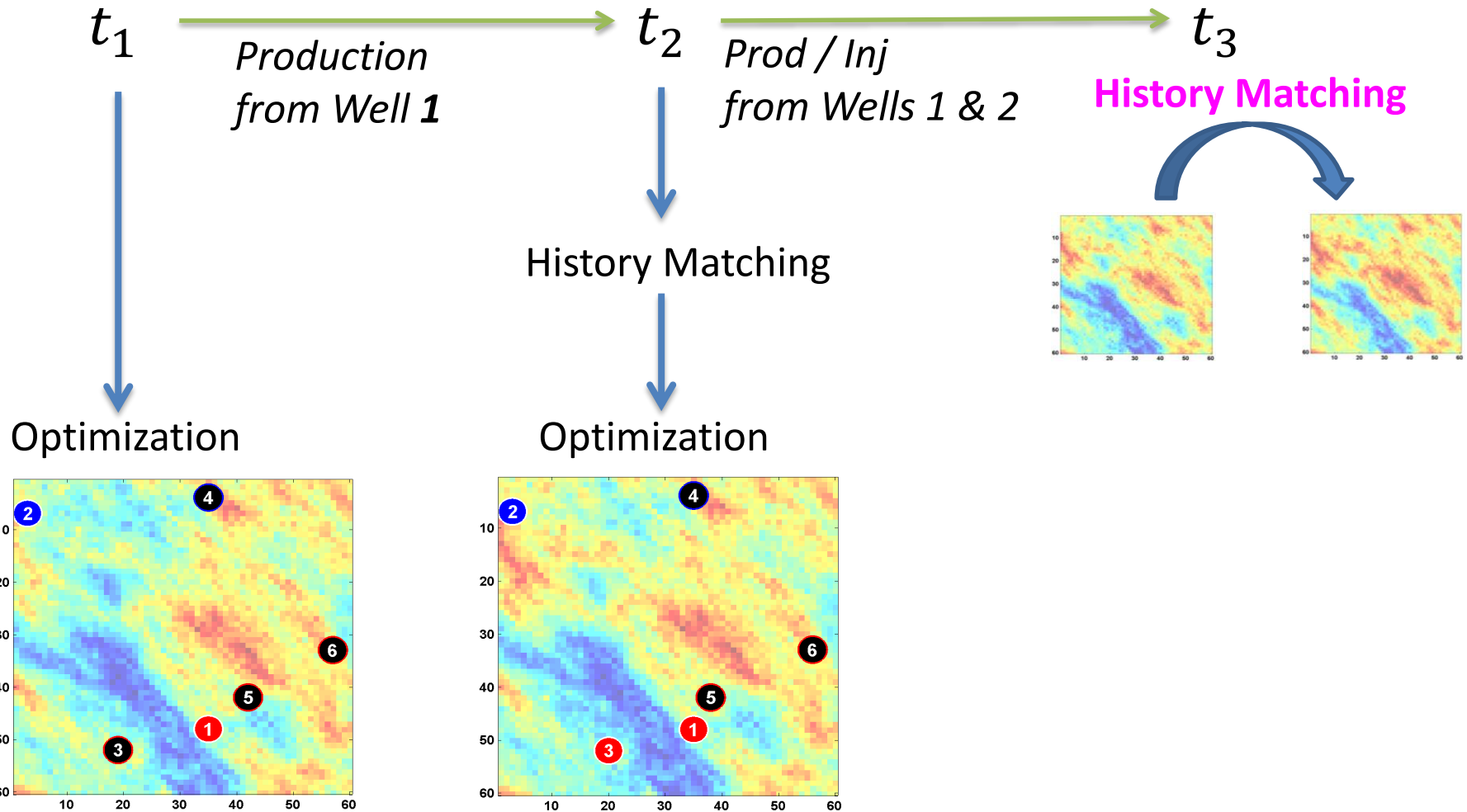
Closed-loop Field Development Optimization



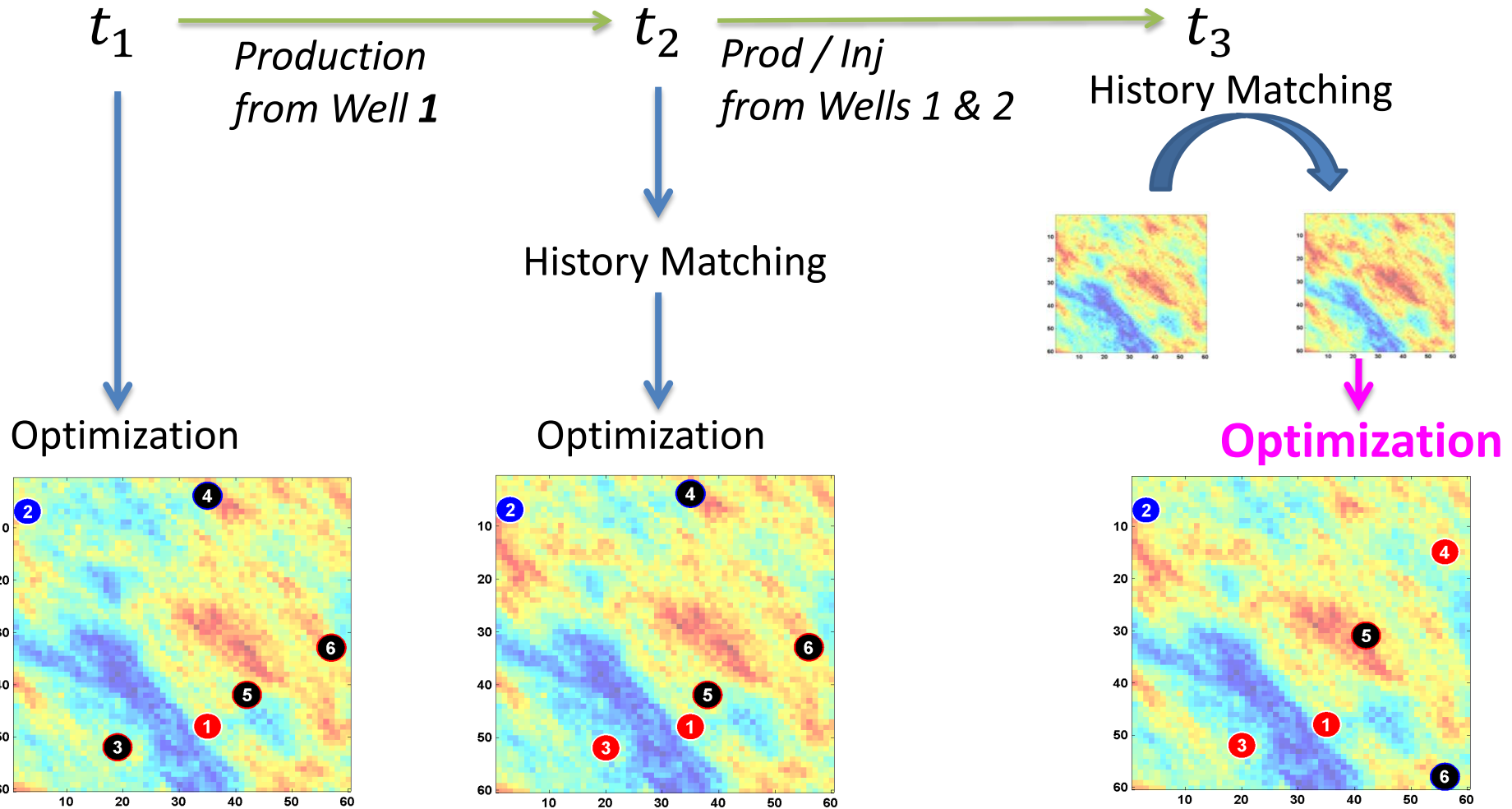
Closed-loop Field Development Optimization



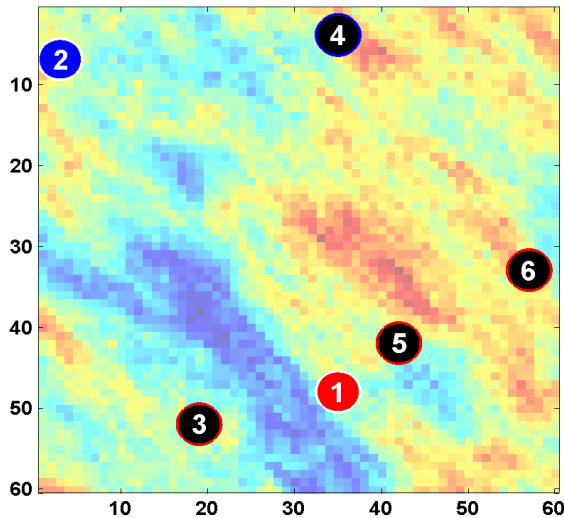
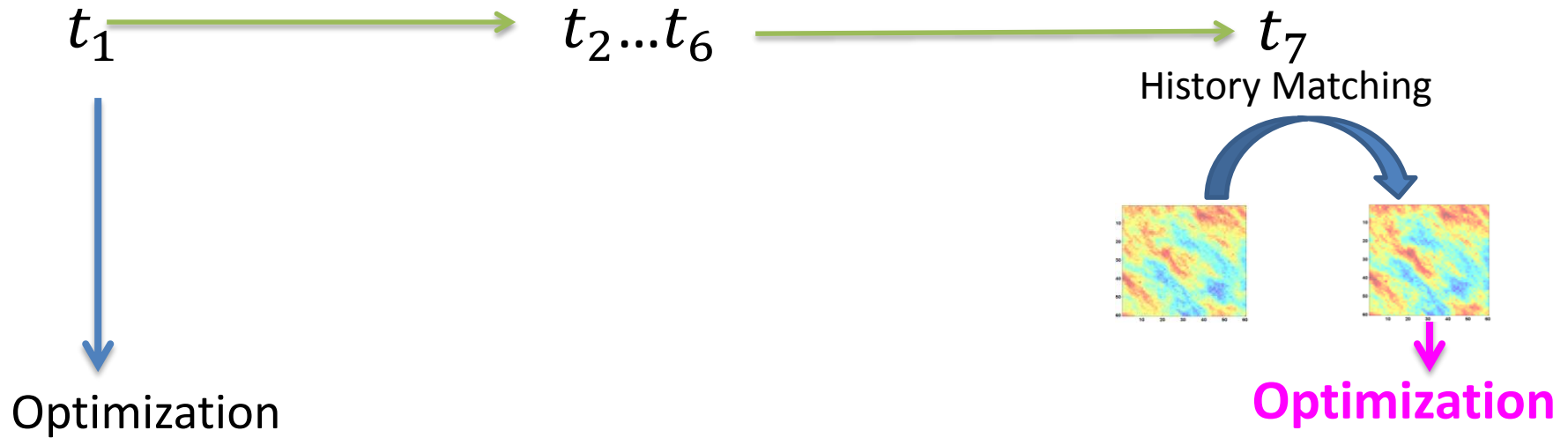
Closed-loop Field Development Optimization



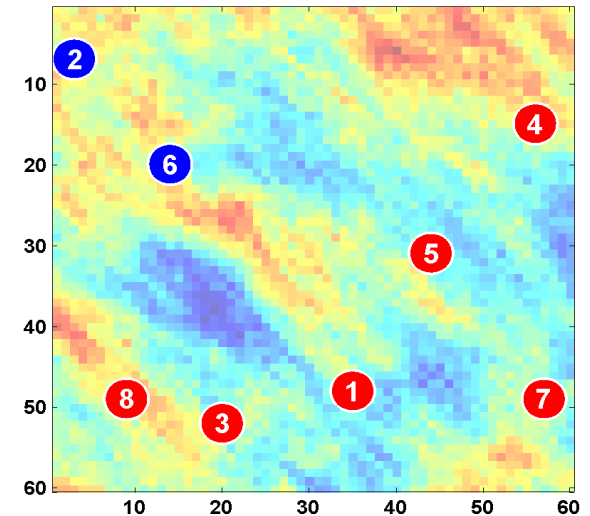
Closed-loop Field Development Optimization



Closed-loop Field Development Optimization



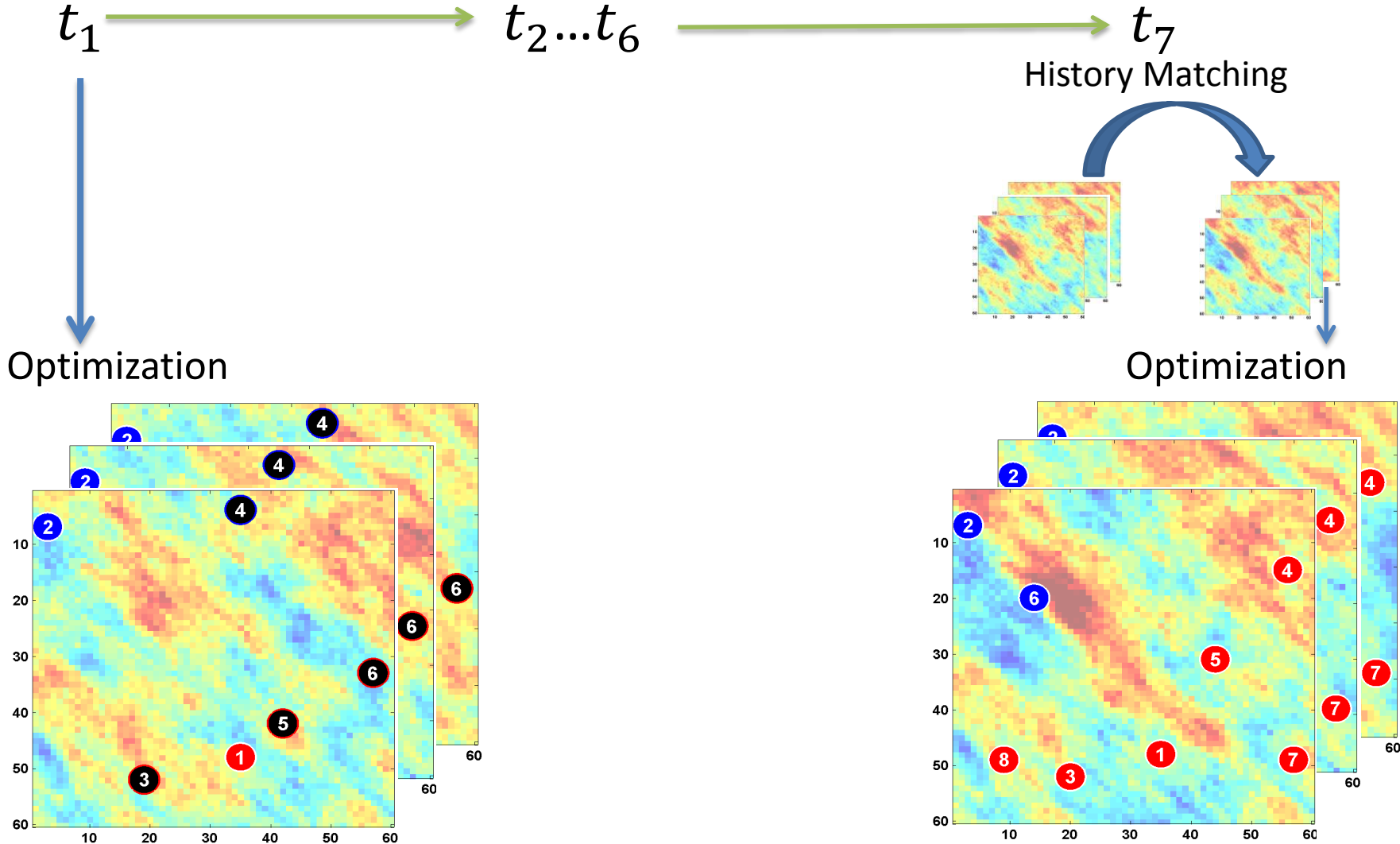
Nov 14-15, 2013



SFC

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CLFD with Multiple Realizations



Optimization Problem

- Objective function for field development optimization:

$$NPV = J = p_o Q_o - c_{wp} Q_{wp} - c_{wi} Q_{wi} - \sum c_{well}$$

$$J = J(\mathbf{u}, m_j^i)$$

- \mathbf{u} : vector of decision parameters (number of wells, well types, controls, locations, drilling sequence)
- m_j^i : j -th realization updated at time t_i
- Robust optimization:

$$\bar{J} = \frac{1}{N_e} \sum_{j=1}^{N_e} J(\mathbf{u}, m_j^i)$$

Optimization Problem

$$\bar{J} = \frac{1}{N_e} \sum_{j=1}^{N_e} J(u, m_j^i)$$

- $M_i = [m_1^i, m_2^i \dots m_{N_e}^i]$: is the set of realizations updated at t_i

$$\bar{J} = \bar{J}(u, M_i)$$

Optimization Problem

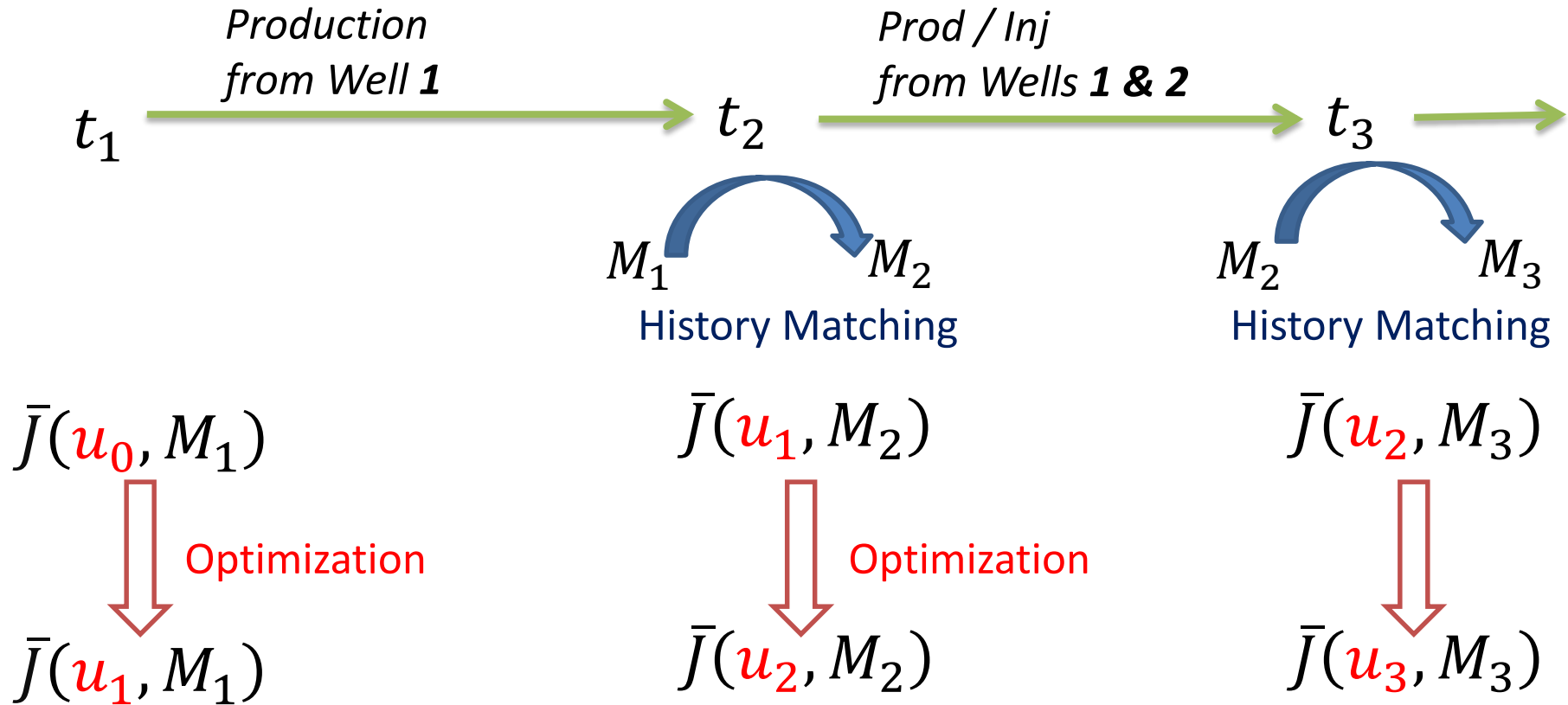
$$\bar{J} = \frac{1}{N_e} \sum_{j=1}^{N_e} J(u, m_j^i)$$

- $M_i = [m_1^i, m_2^i \dots m_{N_e}^i]$: is the set of realizations updated at t_i

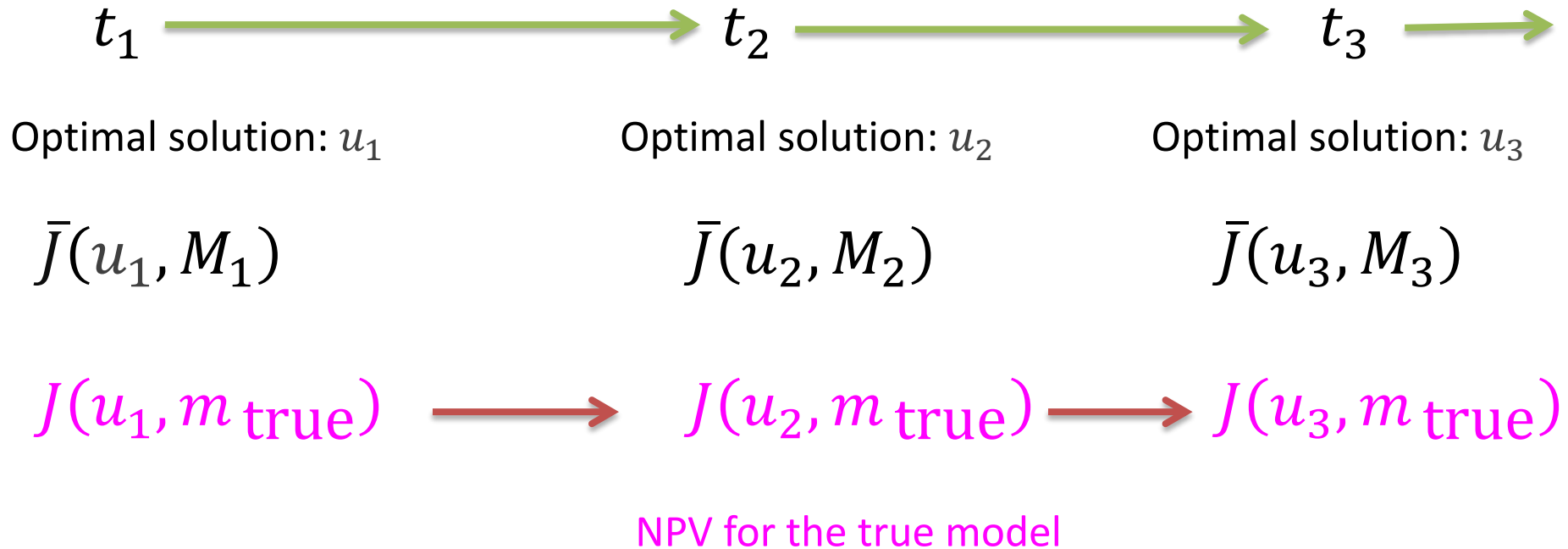
$$\bar{J} = \bar{J}(u, M_i)$$

- Optimal solution (at t_i) : $u_i = \operatorname{argmax} \bar{J}(u, M_i)$, using PSO-MADS (Isebor et al 2013)
- Use u_{i-1} as initial guess when optimizing at time t_i

Evolution of Solution in CLFD



Evolution of Solution in CLFD



- At each CLFD time-step, run the true model with the optimal solution to get the “NPV for the true model”

History Matching in the Bayesian Framework

- Minimize

$$O(m) = \frac{1}{2} (m - \bar{m}_{\text{prior}})^T C_M^{-1} (m - \bar{m}_{\text{prior}}) + \frac{1}{2} (g(m) - d_{\text{obs}})^T C_D^{-1} (g(m) - d_{\text{obs}})$$

← Model mismatch term (prior)
← Data mismatch term (likelihood)

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

$g(m)$: predicted data (vector), *BHP*, phase rates

C_D : (diagonal) covariance matrix for measurement errors

- Minimizing $O(m)$ gives the **m**aximum **a** posteriori estimate (MAP)

History Matching Production and Hard Data

- Minimize

$$\begin{aligned} O(m) = & \frac{1}{2} (m - \bar{m}_{prior})^T C_M^{-1} (m - \bar{m}_{prior}) && \leftarrow \text{Model mismatch term (prior)} \\ & + \frac{1}{2} (g(m) - d_{obs}^p)^T C_{D,p}^{-1} (g(m) - d_{obs}^p) && \leftarrow \text{Production data} \\ & + \frac{1}{2} (m^h - d_{obs}^h)^T C_{D,h}^{-1} (m^h - d_{obs}^h) && \leftarrow \text{Hard data} \end{aligned}$$

d_{obs}^h : vector of observed model parameters (hard data)

m^h : current estimate for observed model parameters

$C_{D,h}$: (diagonal) covariance matrix for measurement errors

RML for History Matching Production and Hard Data

- Generate N_e samples from the prior pdf

$$\mathbf{m}_{uc} \sim N(m_{prior}, C_M)$$

- Generate N_e samples as $\mathbf{d}_{uc}^p \sim N(d_{obs}^p, C_{D,p})$ and

$$\mathbf{d}_{uc}^h \sim N(d_{obs}^h, C_{D,h})$$

- Minimize N_e objective functions to generate N_e posterior samples using L-BFGS (Oliver et al, 1996)

$$\begin{aligned} O(m) = & \frac{1}{2} (m - \mathbf{m}_{uc})^T C_M^{-1} (m - \mathbf{m}_{uc}) \\ & + \frac{1}{2} (g(m) - \mathbf{d}_{uc}^p)^T C_{D,p}^{-1} (g(m) - \mathbf{d}_{uc}^p) \\ & + \frac{1}{2} (m^h - \mathbf{d}_{uc}^h)^T C_{D,h}^{-1} (m^h - \mathbf{d}_{uc}^h) \end{aligned}$$

Computational Cost of CLFD Experiments ($N_e = 6$)

PSO-MADS Optimization
(360 Cores)

- $N_e \times 15,000$ simulations
- 250 equivalent simulations

L-BFGS for History Matching
(N_e Nodes = $16 \times N_e$ Cores)

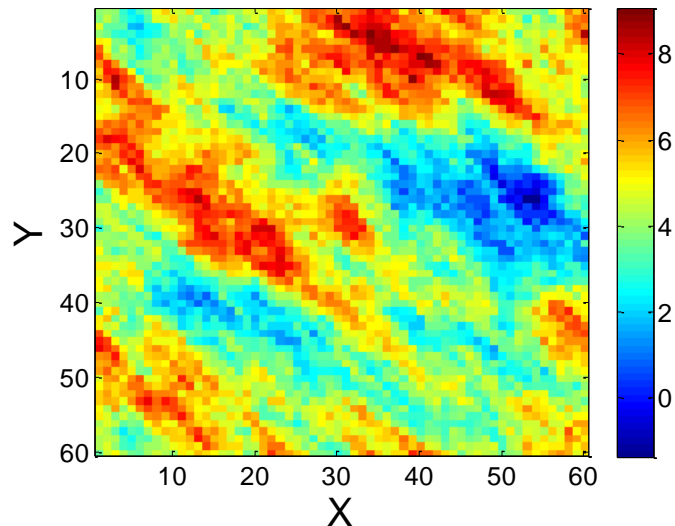
- $N_e \times 50$ simulations
- 5 equivalent simulations

Full CLFD
(8 wells - 1 well at a time)

- About 0.5 million simulations
- 1800 equivalent simulations

2D Example, 60×60

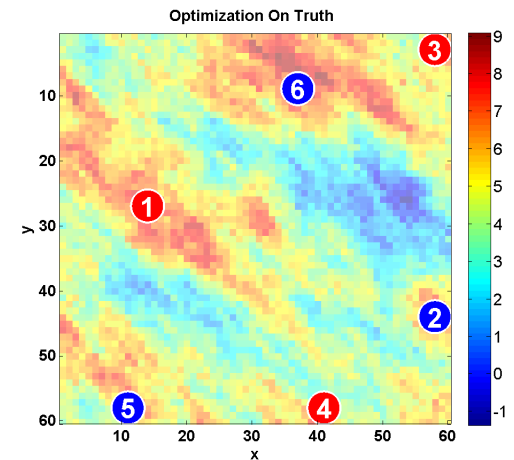
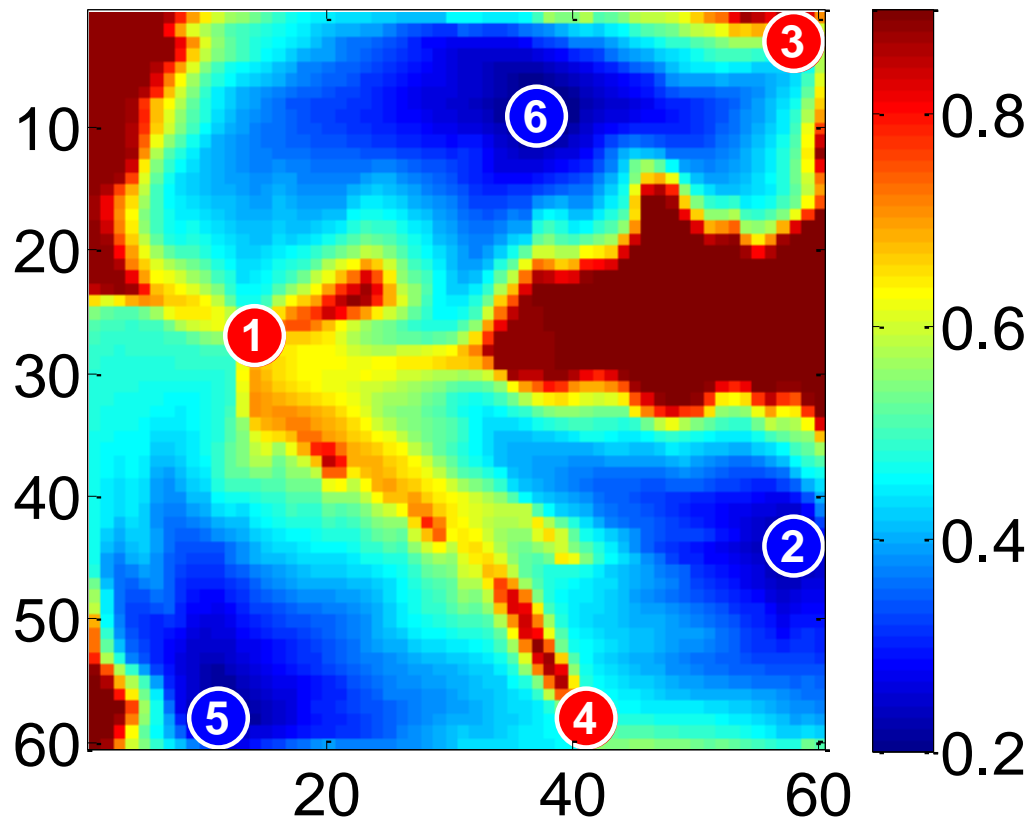
- Uncertain model parameters: $\ln(k)$
- Budget to drill maximum **8** wells (1 well at a time)
- Optimize over 6 realizations (BHP control)



parameter	value
well cost	\$ 25 million
oil price	\$ 90 / bbl
produced water	\$ 15 / bbl
injected water	\$ 15 / bbl
drilling lag-time	210 Days
reservoir Life	3000 Days

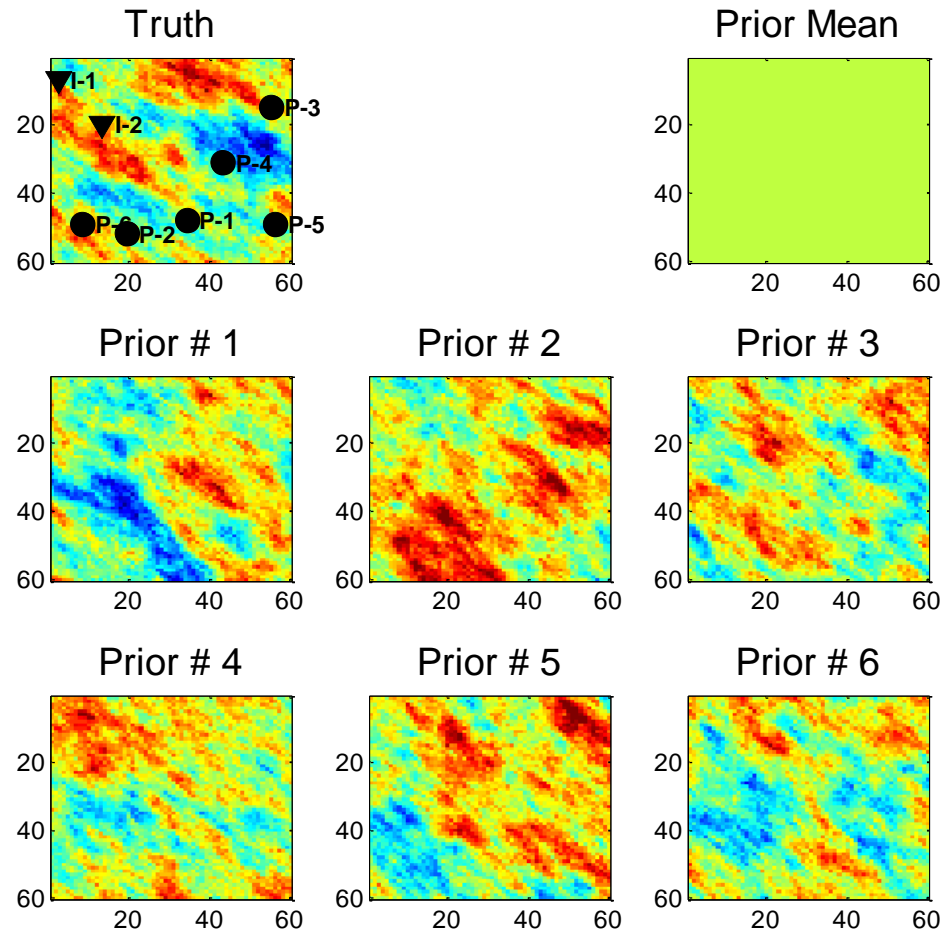
Optimization on the True Model

3000 Days

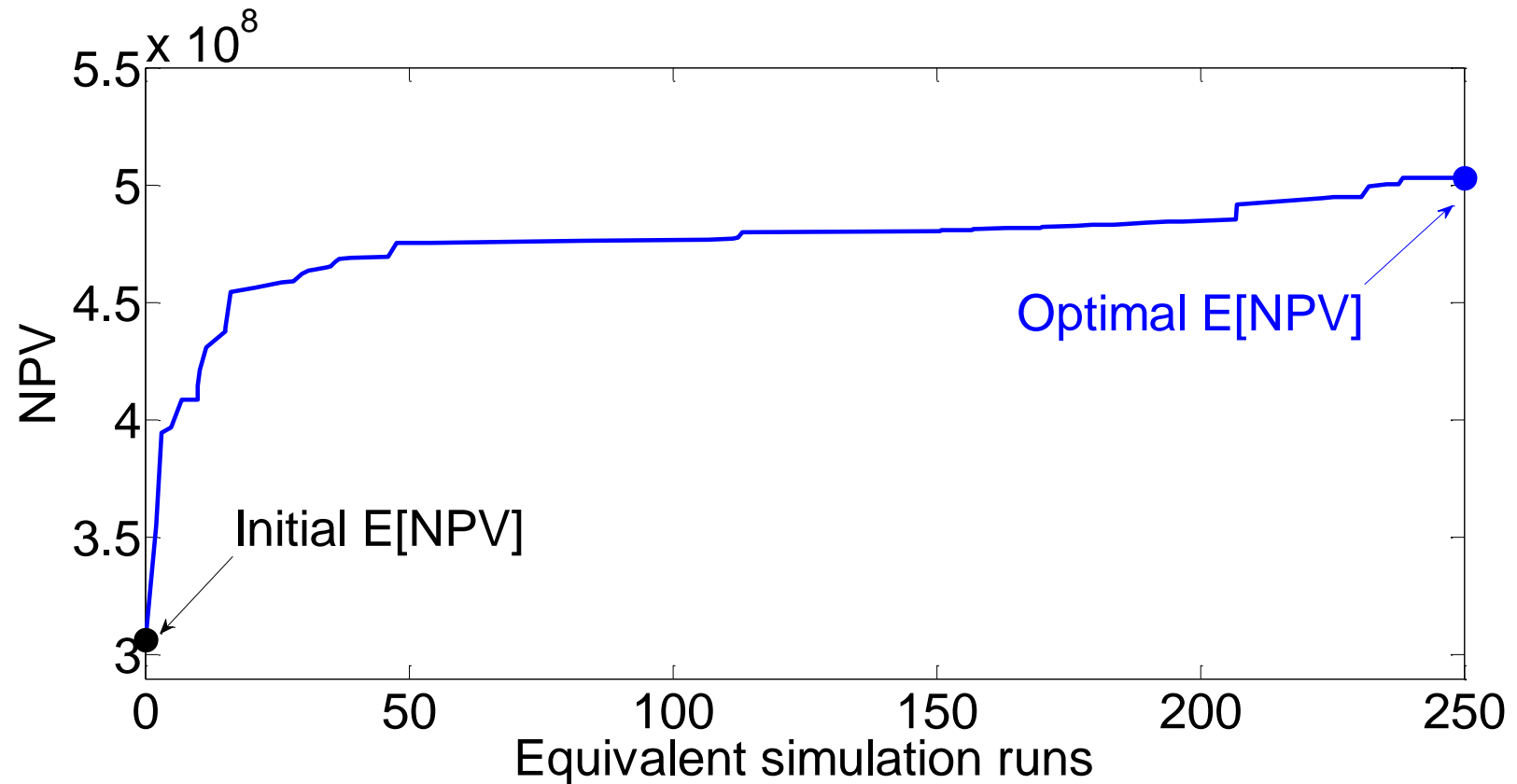


S_w distribution at the end of each optimization time-step

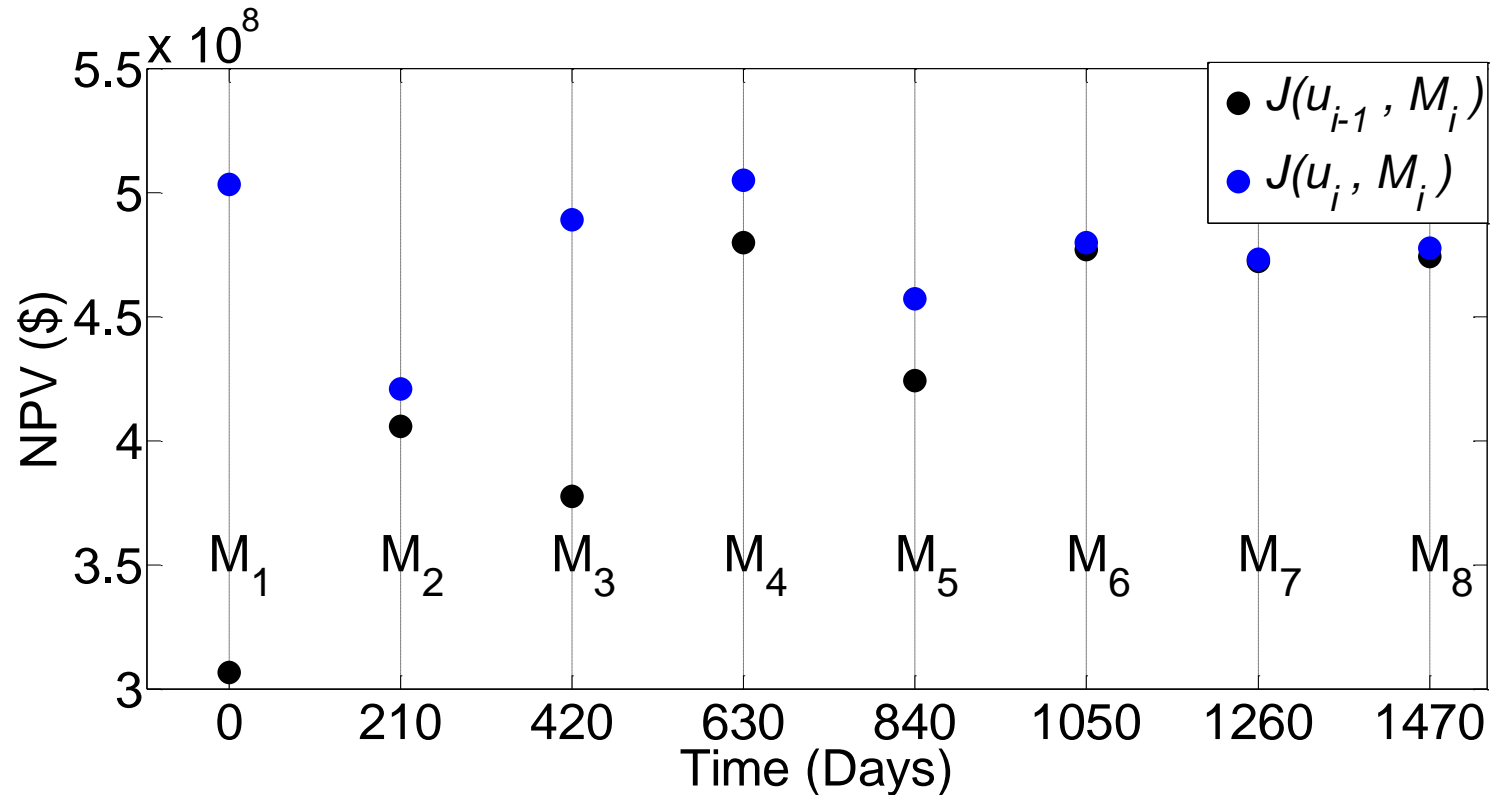
Unconditional Permeability Fields



Optimization Over Prior Realizations (1st Optimization Step of CLFD)

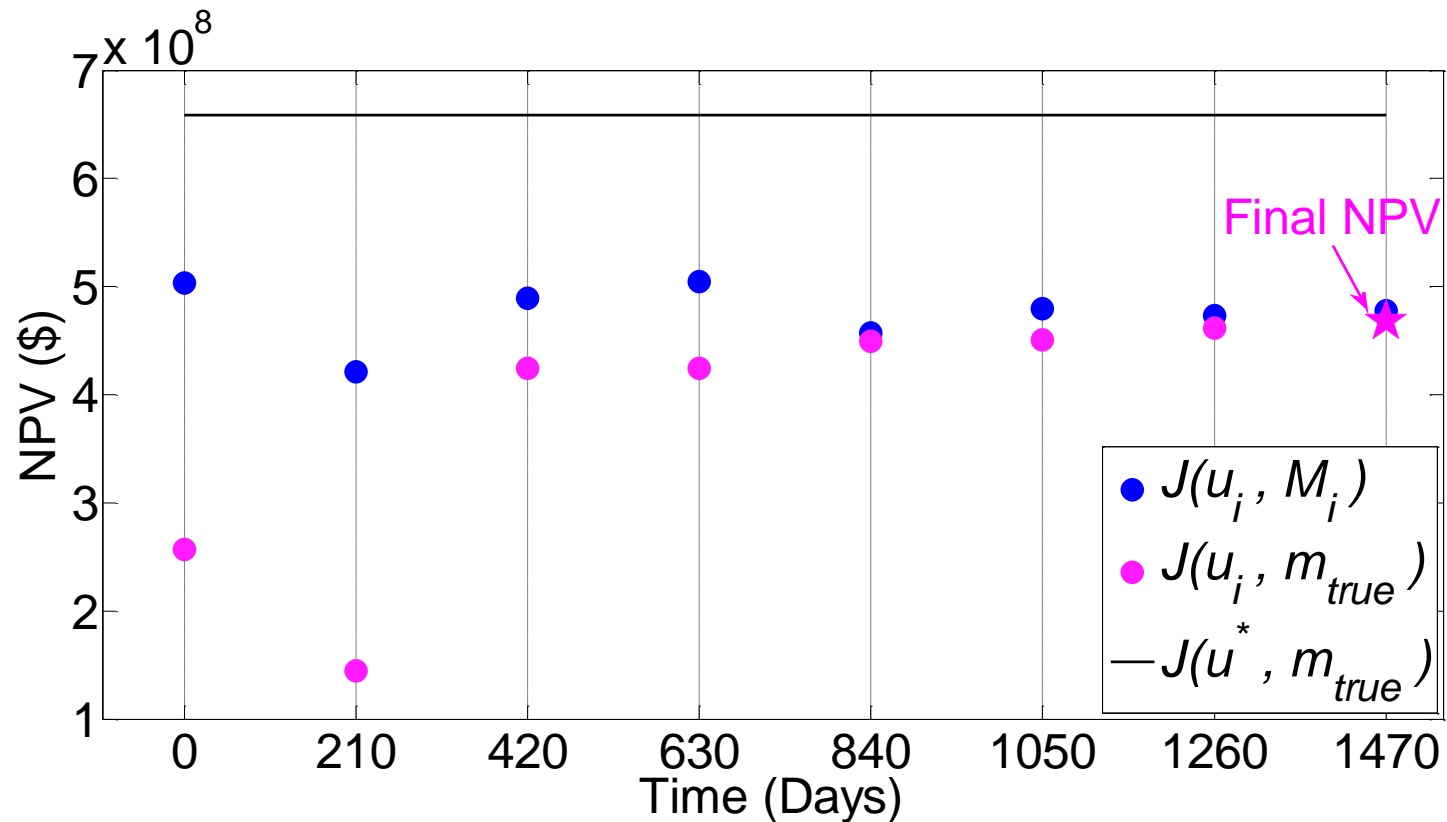


Optimal NPV & Corresponding Initial Guess



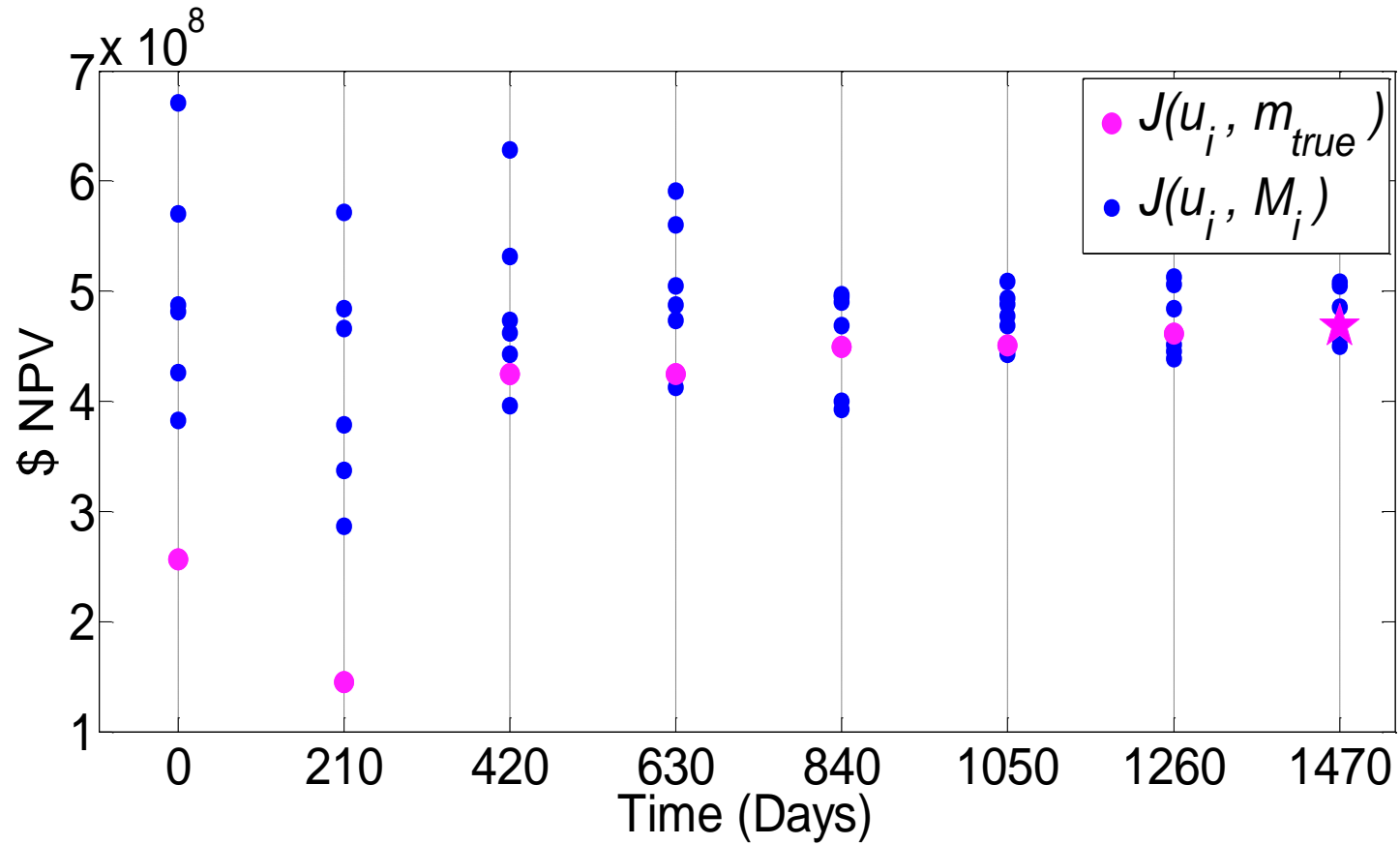
- $J(u_i, M_i)$: Optimal E[NPV] over 6 realizations updated at t_i
- $J(u_{i-1}, M_i)$: Initial E[NPV] over 6 realizations updated at t_i

Optimal NPV versus Update Steps of CLFD

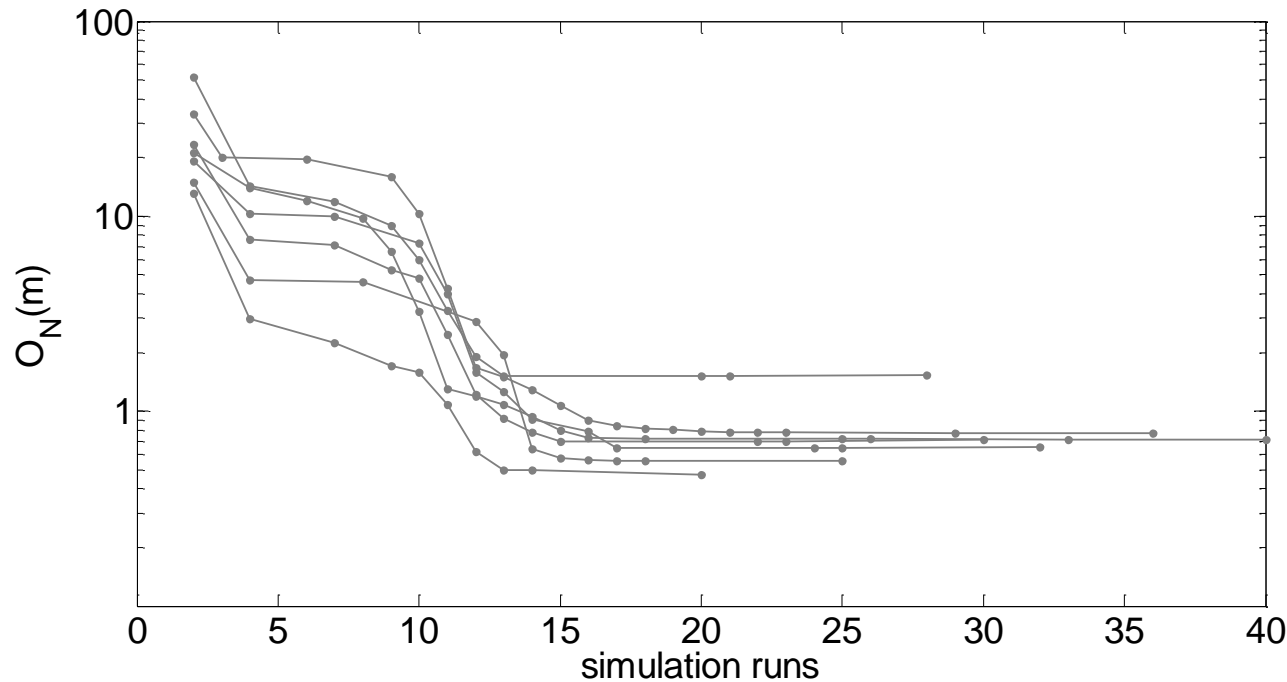


- $J(u_i, M_i)$: Optimal E[NPV] over 6 realizations updated at t_i
- $J(u_i, m_{true})$: NPV for the true model (run the true model with u_i)
- $J(u^*, m_{true})$: Optimization on the true model

Spread of NPV of Realizations versus Update Steps of CLFD



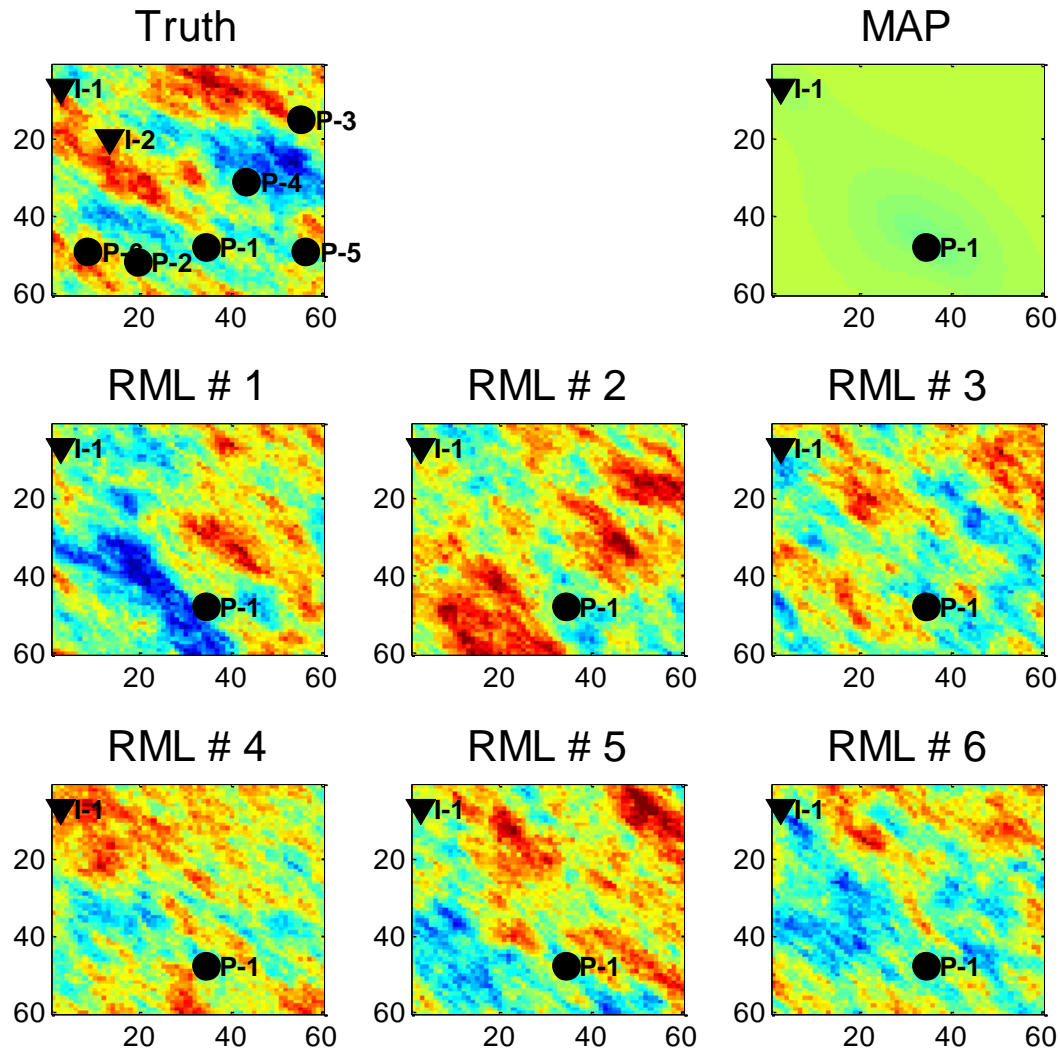
History Matching Objective Function Versus Simulation Runs (Step 3 of CLFD)



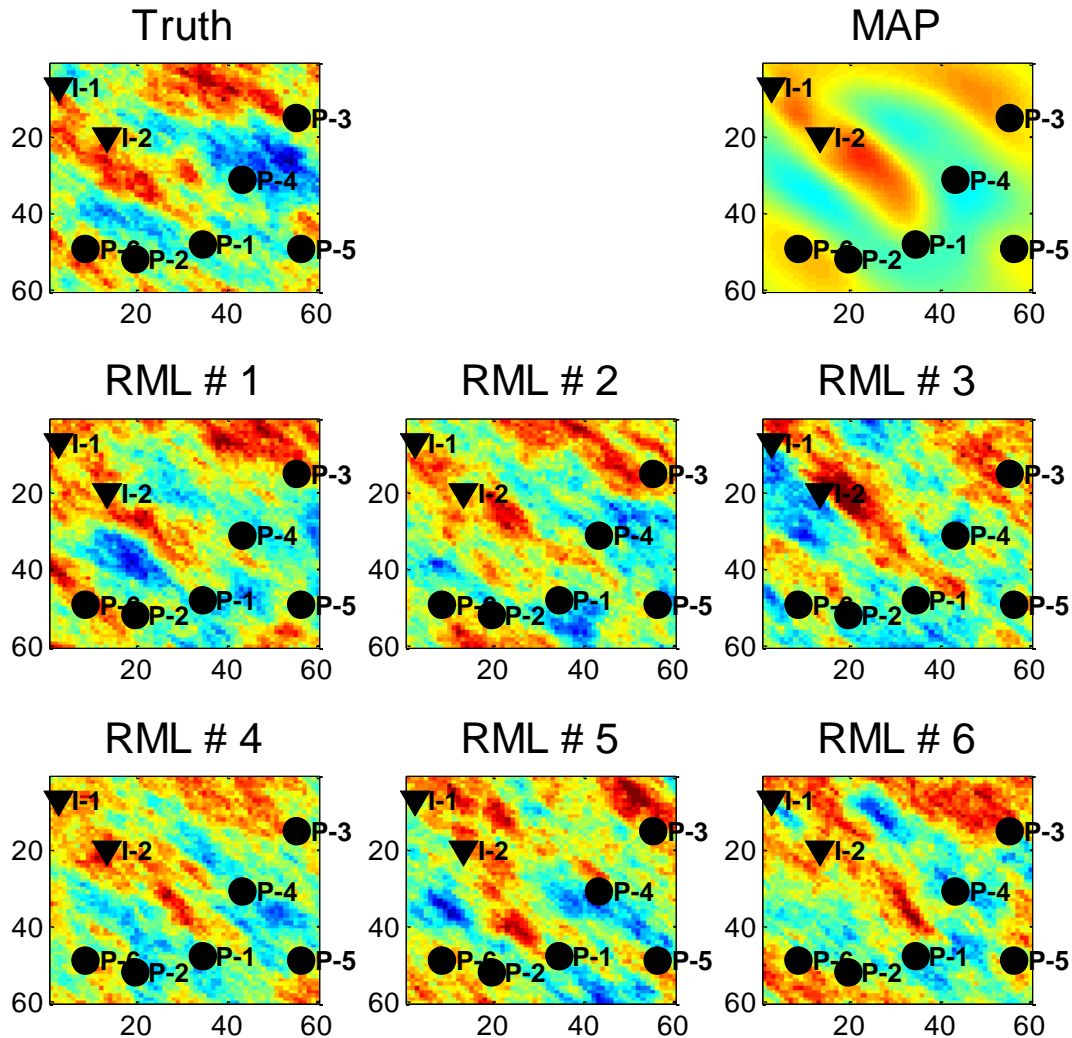
$$O_N(m) = O(m)/N_d$$

$$O(m) = \frac{1}{2}(m - m_{uc})^T C_M^{-1}(m - m_{uc}) + \frac{1}{2}(g(m) - d_{uc}^p)^T C_{D,p}^{-1}(g(m) - d_{uc}^p) + \frac{1}{2}(m^h - d_{uc}^h)^T C_{D,h}^{-1}(m^h - d_{uc}^h)$$

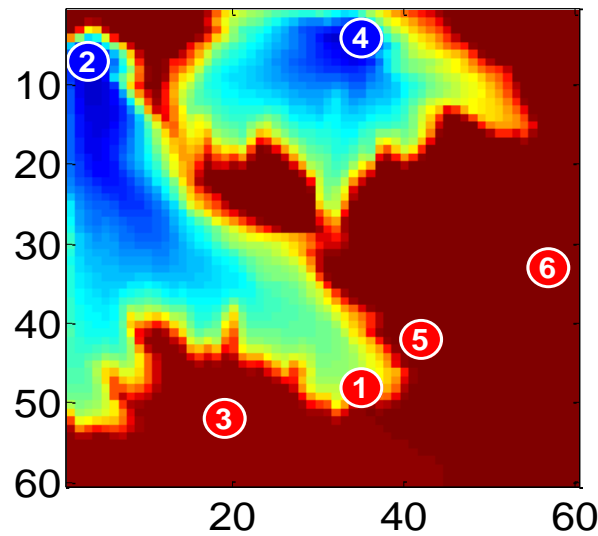
Log-Permeability Fields at $t_2 = 210$ Days



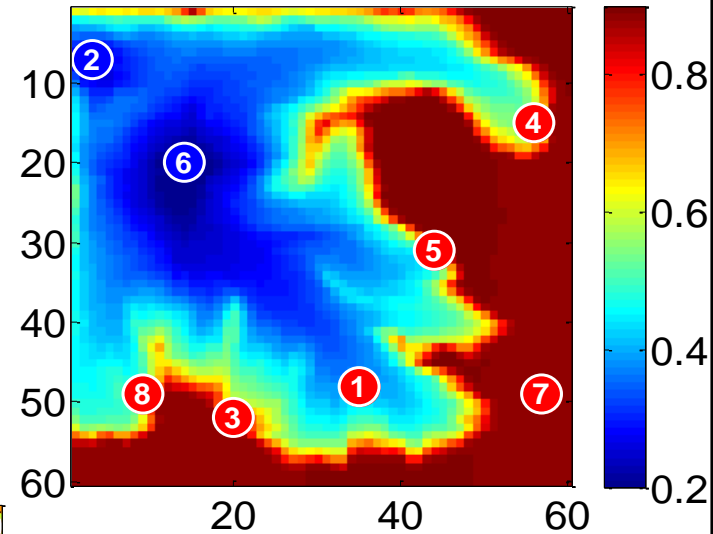
Log-Permeability Fields at $t_9 = 1680$ Days



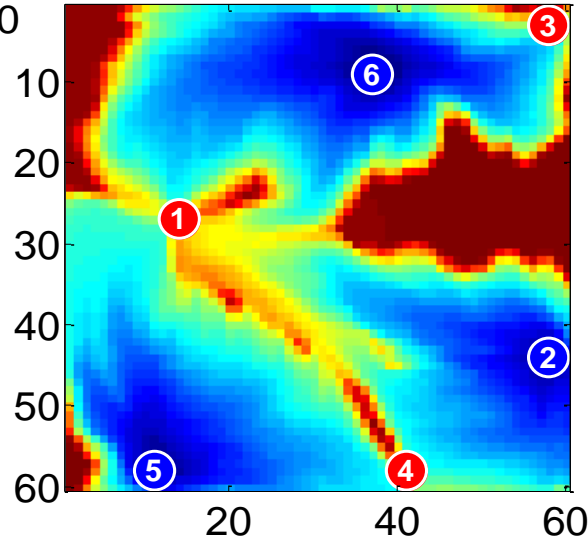
Final Oil Saturation on Truth for CLFD and "Opt on Prior"



Optimization on prior



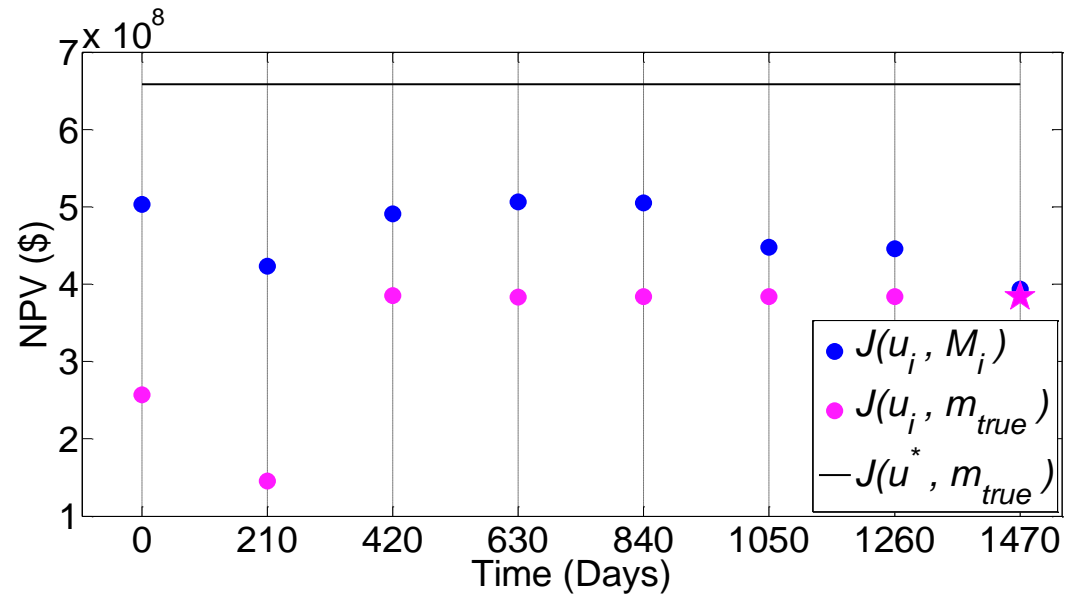
Final CLFD solution



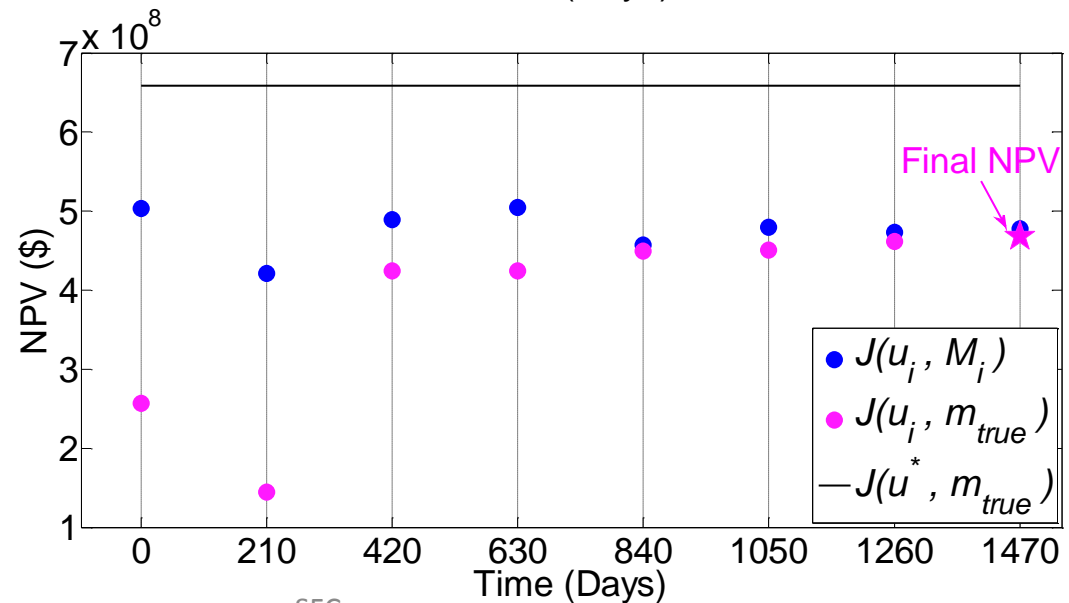
Optimization on the true model (perfect info)

CLFD with and without Incorporating Hard Data

Only production data conditioning

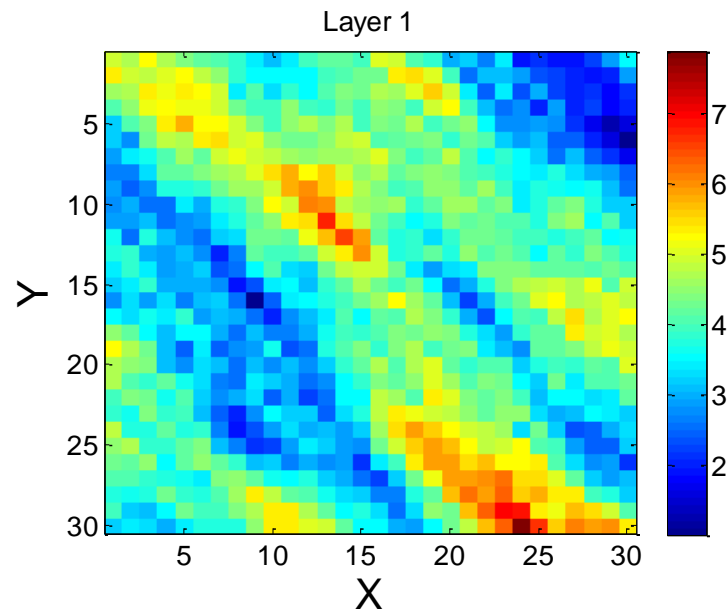


Production and hard data conditioning



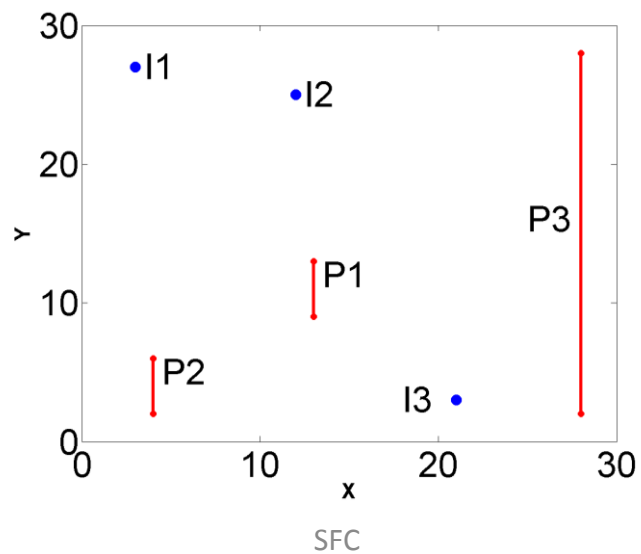
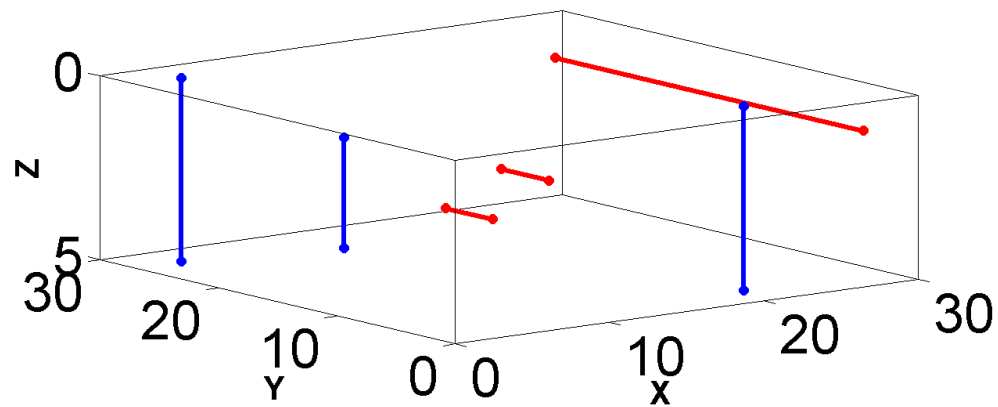
3D Example, $30 \times 30 \times 5$

- Uncertain model parameters: $\ln(k)$
- Drill **6** wells : 3 horizontal producers, 3 vertical injectors
- Optimize over 6 realizations (BHP control)

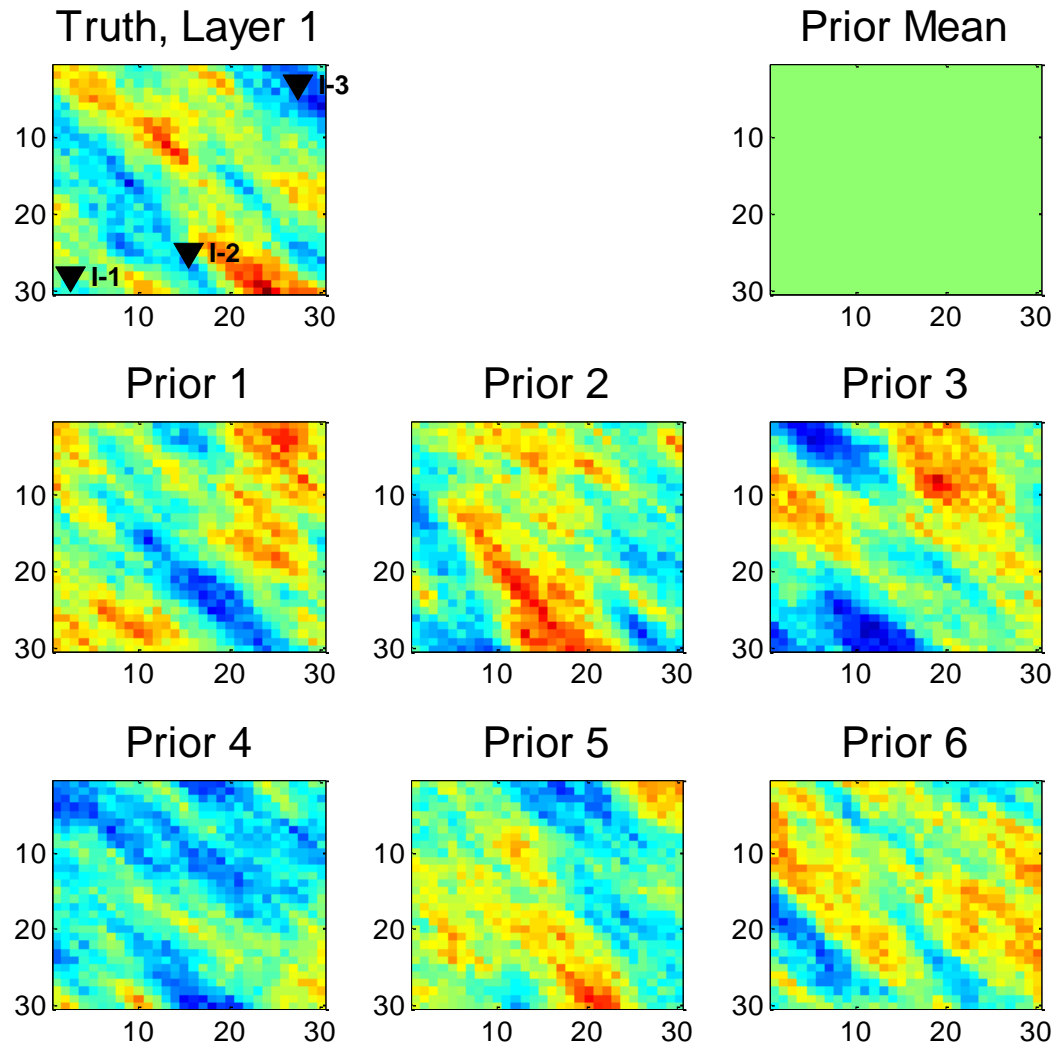


parameter	value
well cost	\$ 25 million
oil price	\$ 90 / bbl
produced water	\$ 10 / bbl
injected water	\$ 10 / bbl
drilling lag-time	210 Days
reservoir Life	2000 Days
perforation cost	\$ 1 million /gb

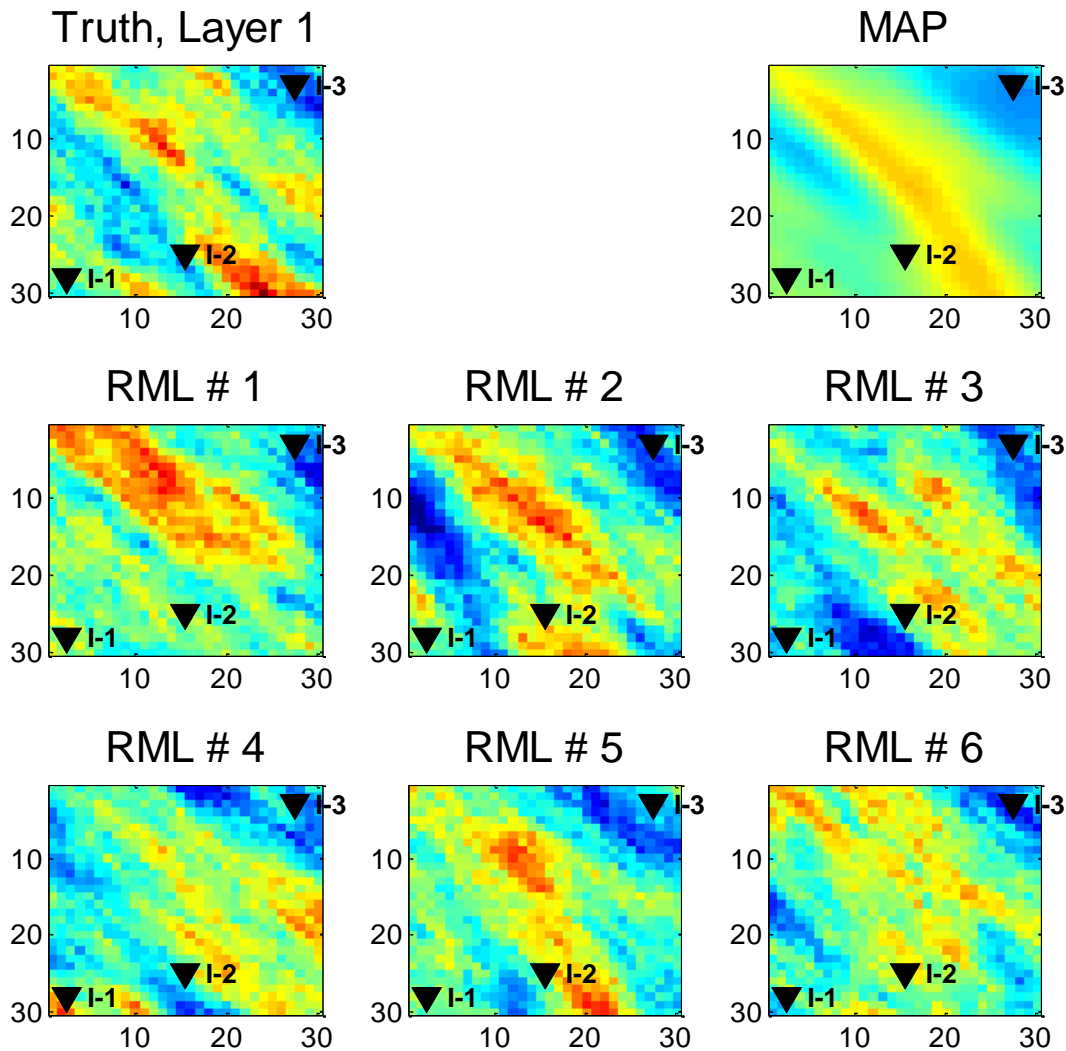
Optimization on the True Model



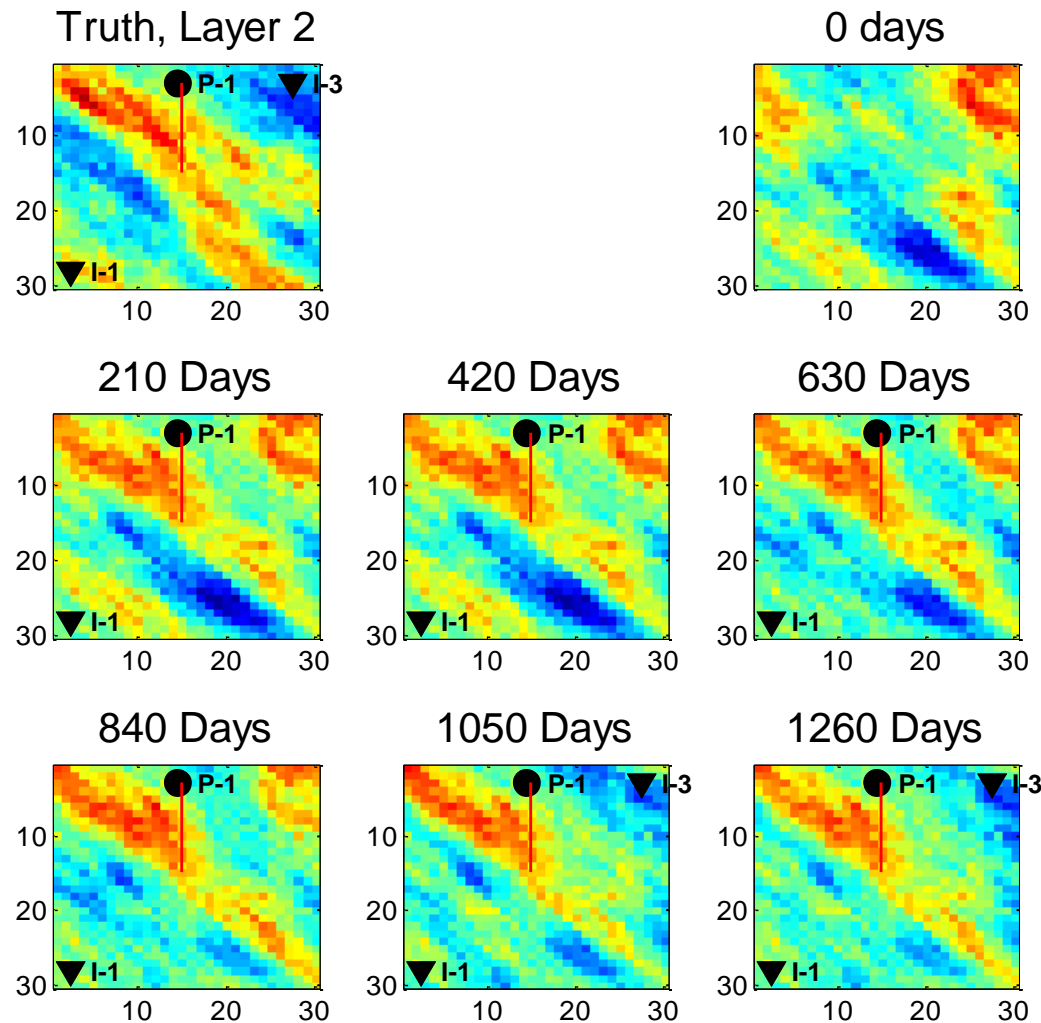
Unconditional Log-Permeability Fields (Layer 1)



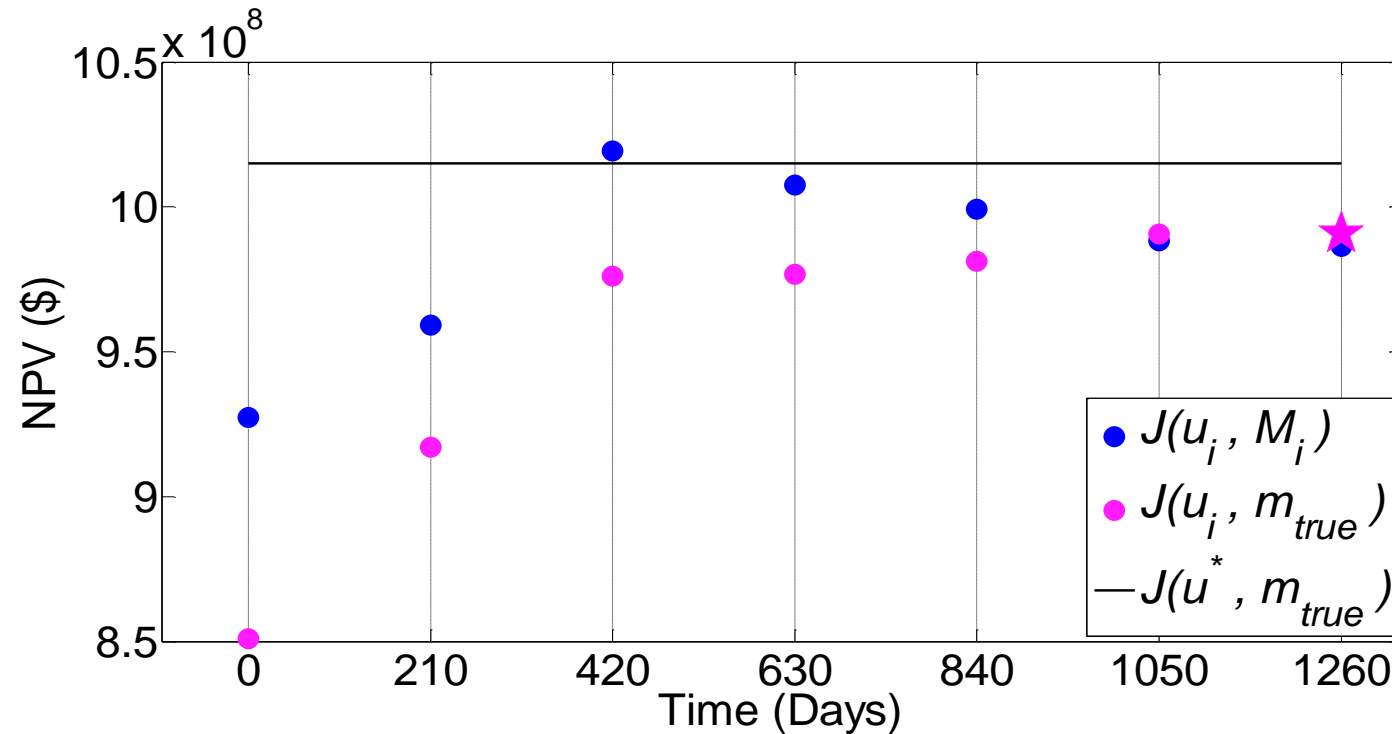
Log-Permeability Fields at $t_9 = 1260$ days (Layer 1)



Evolution of Log-Permeability Field for Realization 1 (Layer 1)

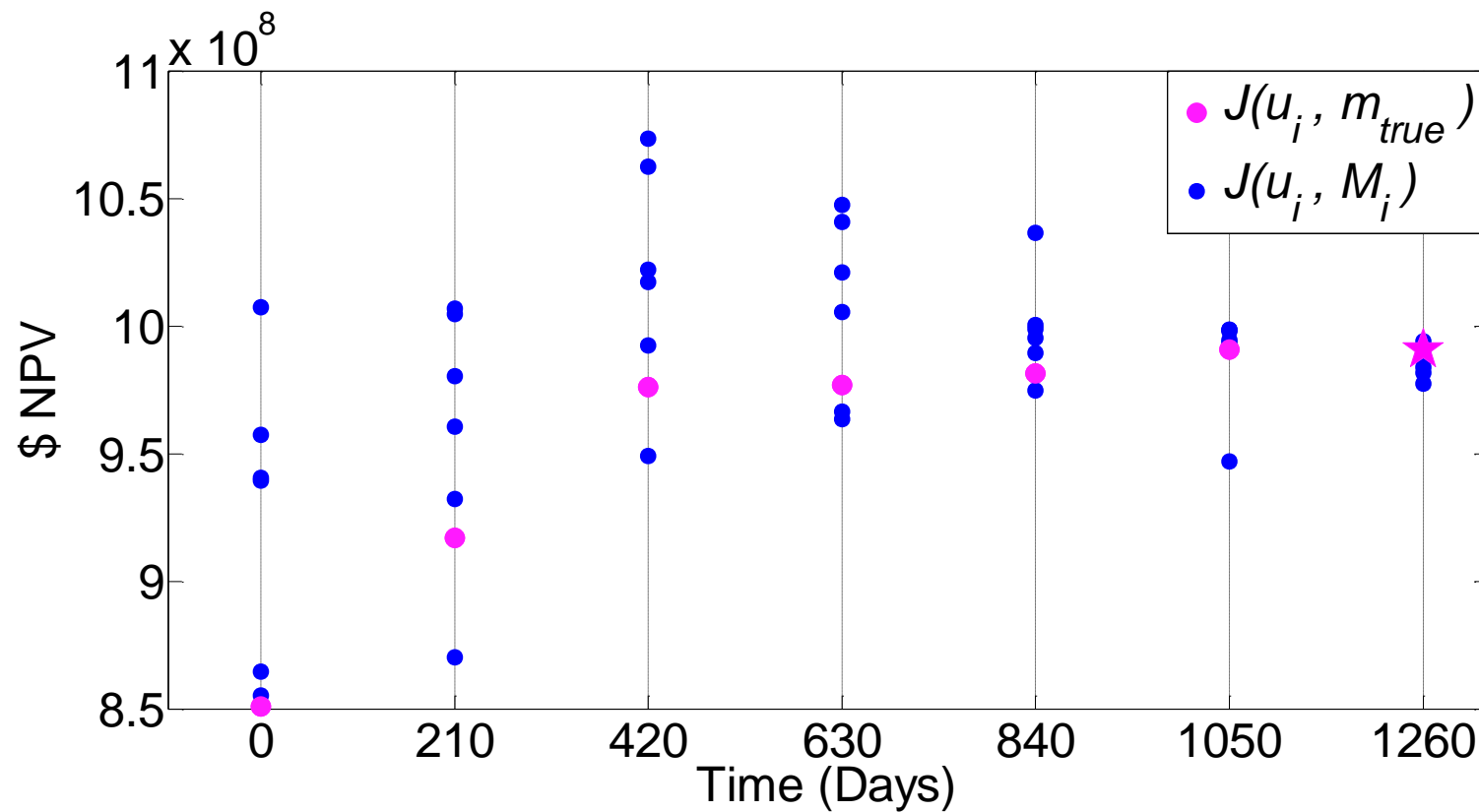


Optimal NPV versus Update Steps of CLFD



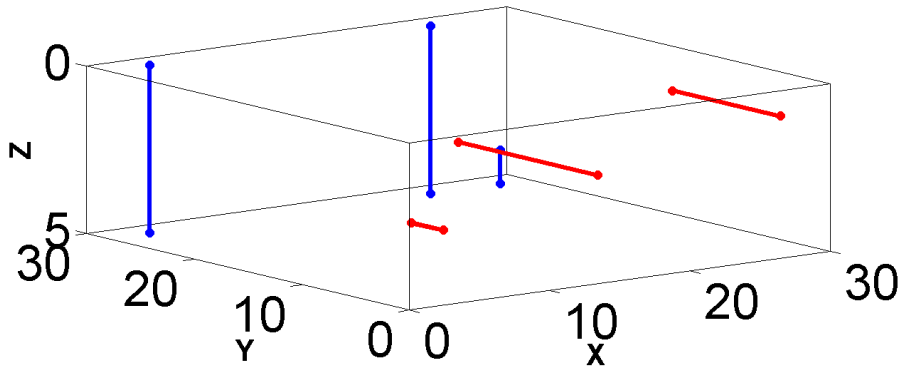
- $J(u_i, M_i)$: Optimal E[NPV] over 6 realizations updated at t_i
- $J(u_i, m_{true})$: NPV for the true model (run the true model with u_i)
- $J(u^*, m_{true})$: Optimization on the true model

Spread of NPV of all Realizations versus Update Steps of CLFD

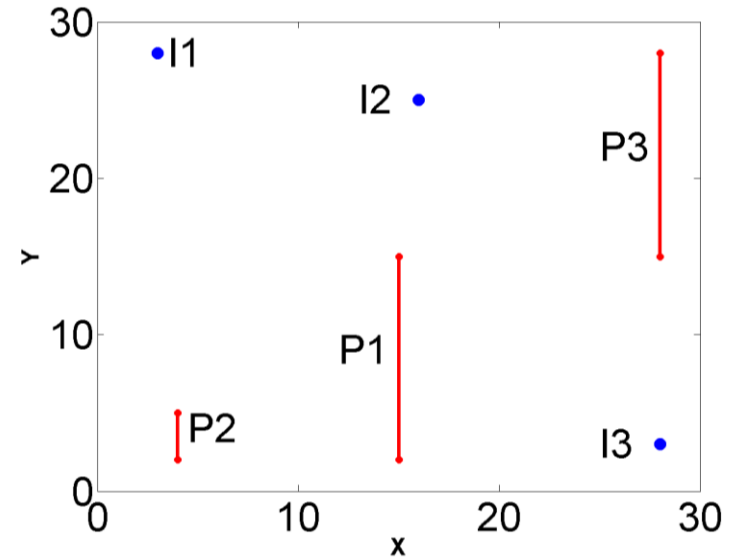
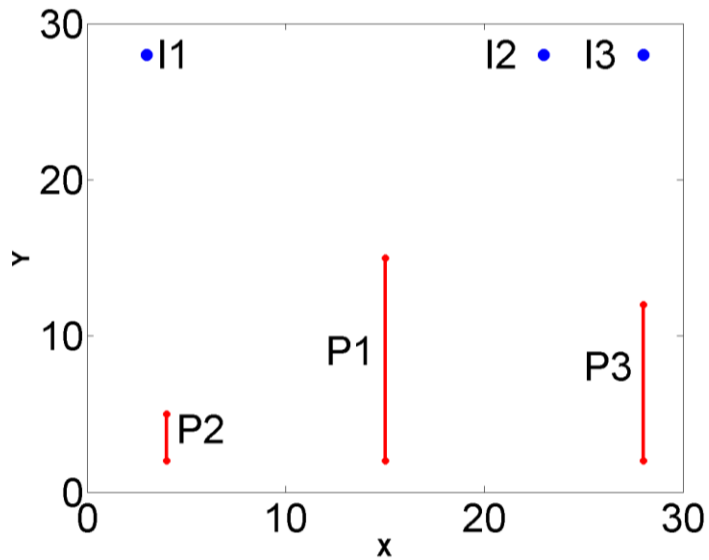
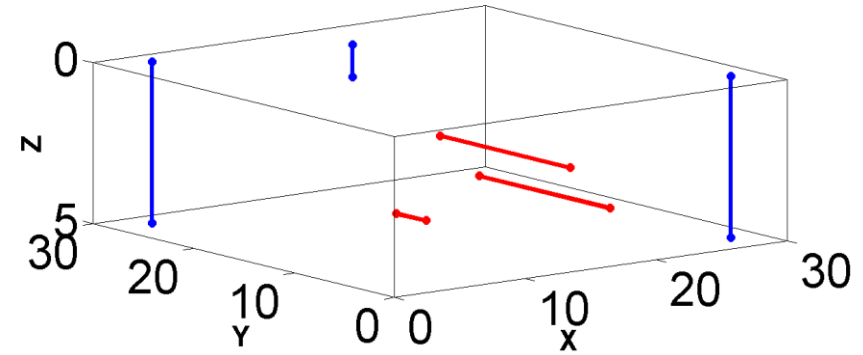


Evolution of Optimal Solution

Step # 1 of CLFD

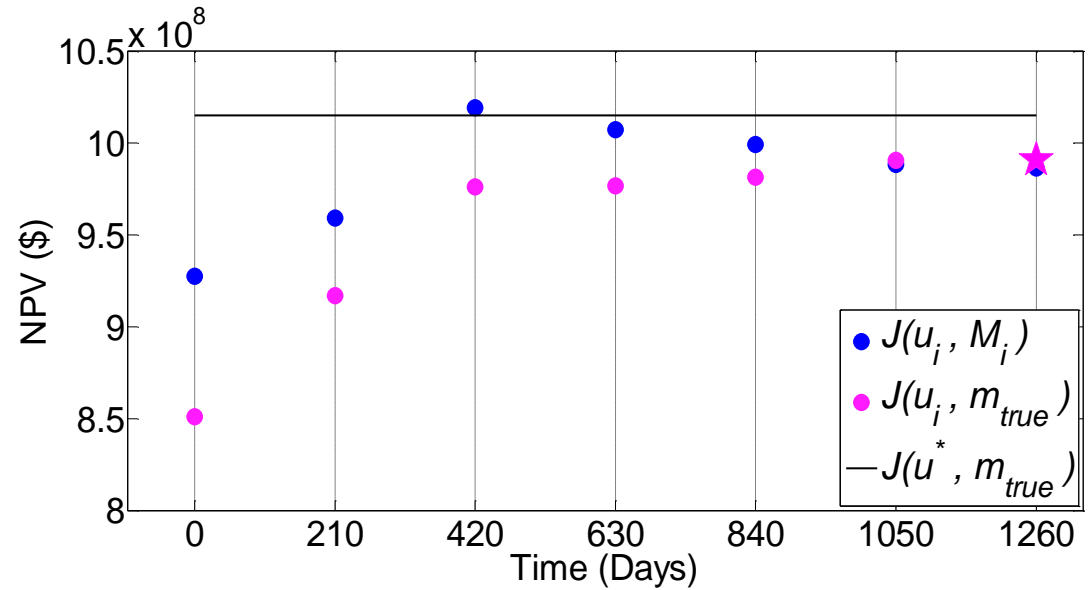


Step # 6 of CLFD

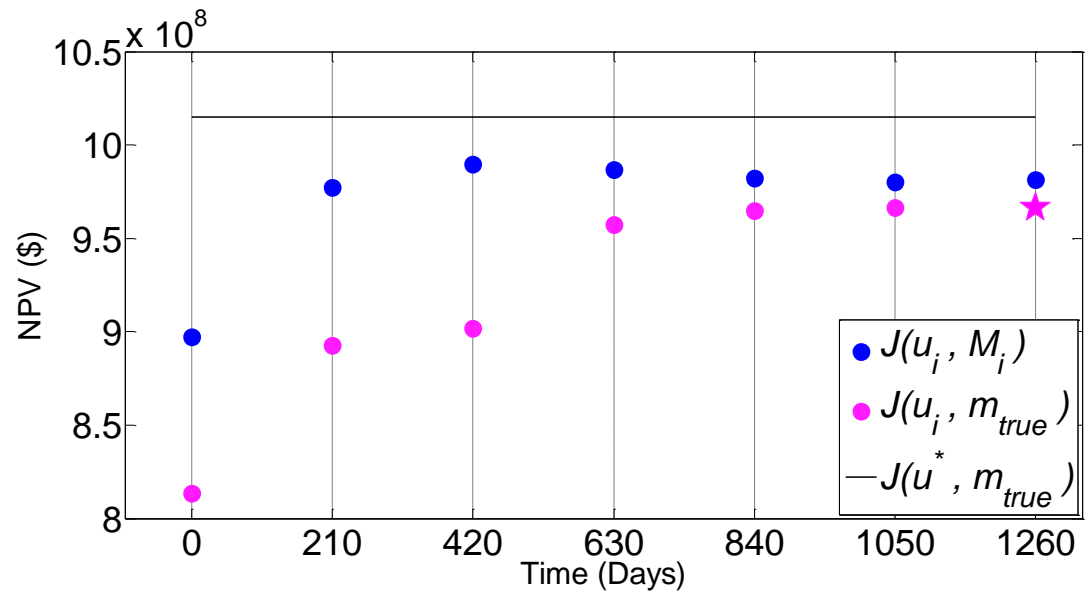


Sensitivity to Different Sets of Initial Realizations (6 Realizations)

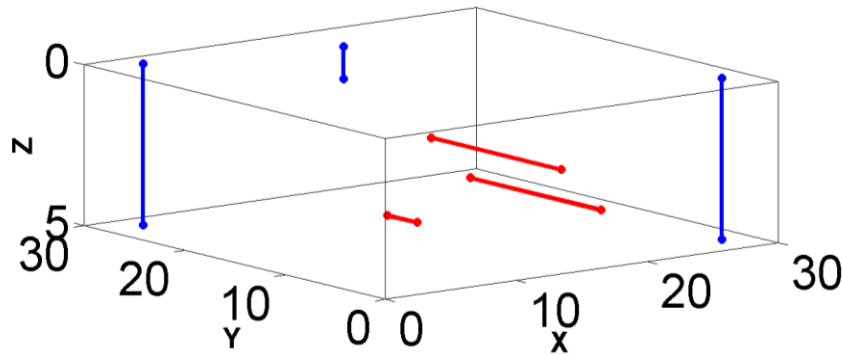
Set 1 of Initial Realizations



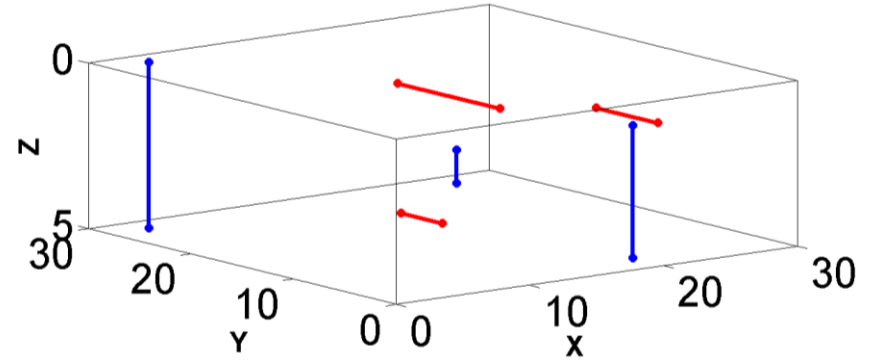
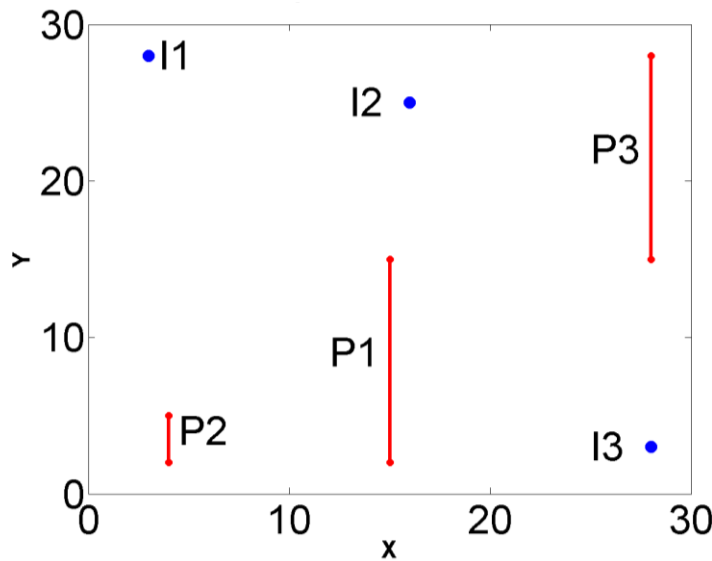
Set 2 of Initial Realizations



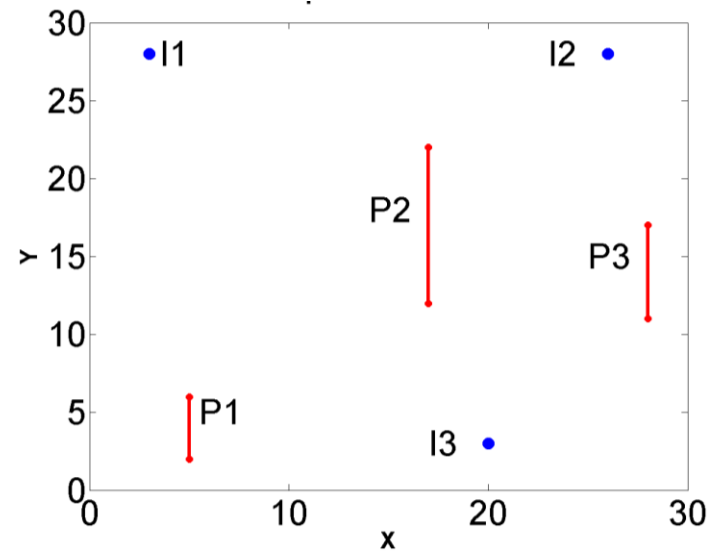
Optimal Solution for the Two Different Sets of Initial Realizations



Set 1 of initial realizations



Set 2 of initial realizations



Summary

- Closed-loop field development (CLFD) framework implemented
- Applied RML for history matching and PSO-MADS for field development optimization
- Demonstrated CLFD results for 2D and 3D examples with optimization over multiple realizations
- With CLFD, NPV for the true model, increased by 82% in 2D example, and by 20% for 3D example with horizontal producers

Future Work

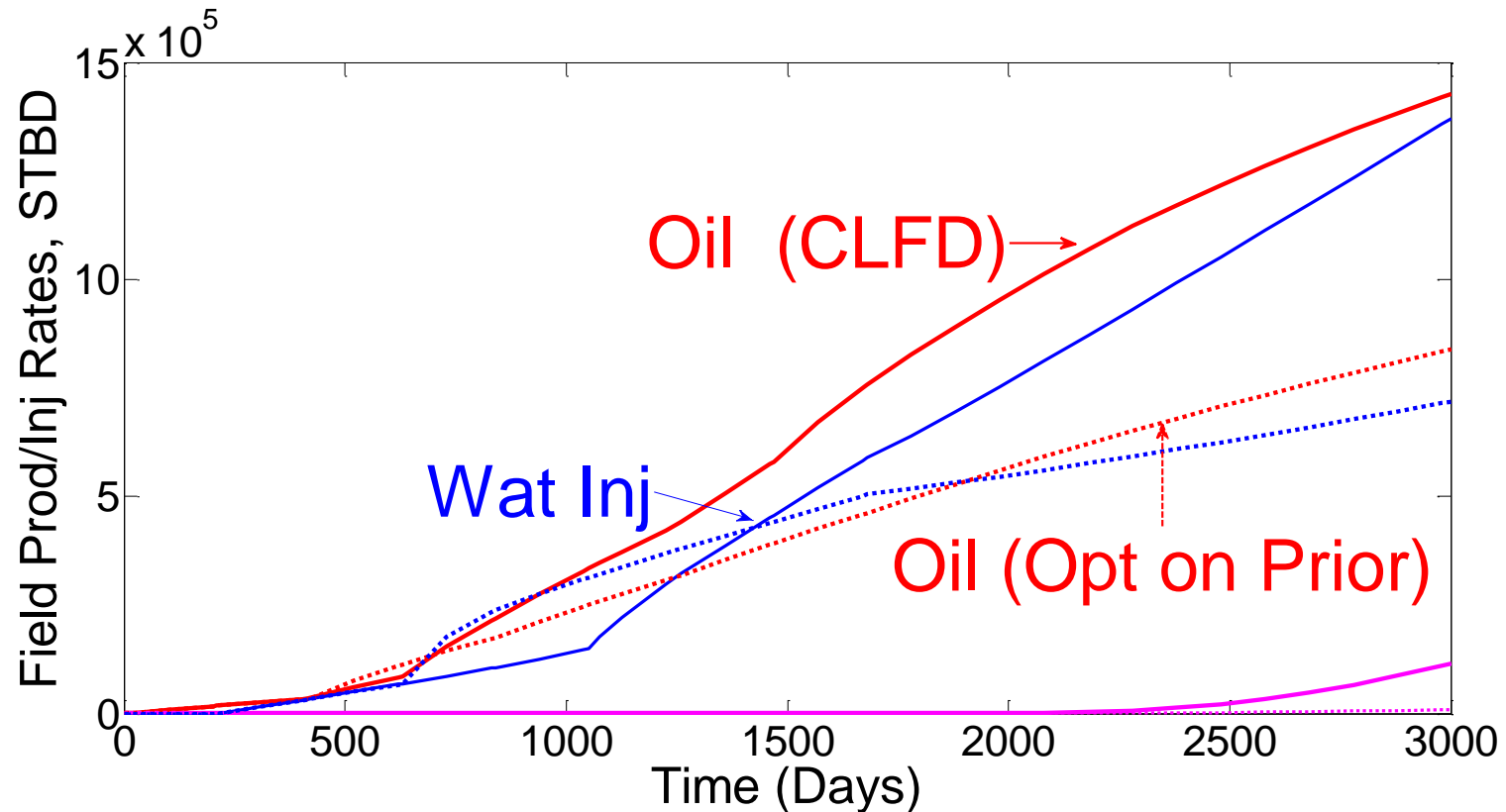
- Compare ensemble-based data assimilation with gradient-based history matching for CLFD optimization
- Assimilate seismic data in closed-loop field development
- Reduce computational effort required in CLFD framework
- Investigate approaches for selecting realizations

Acknowledgments

- Oleg Volkov
- Obi Isebor

Thank you!

True Field Production/Injection Rate from Step 1 and Step 8 of CLFD

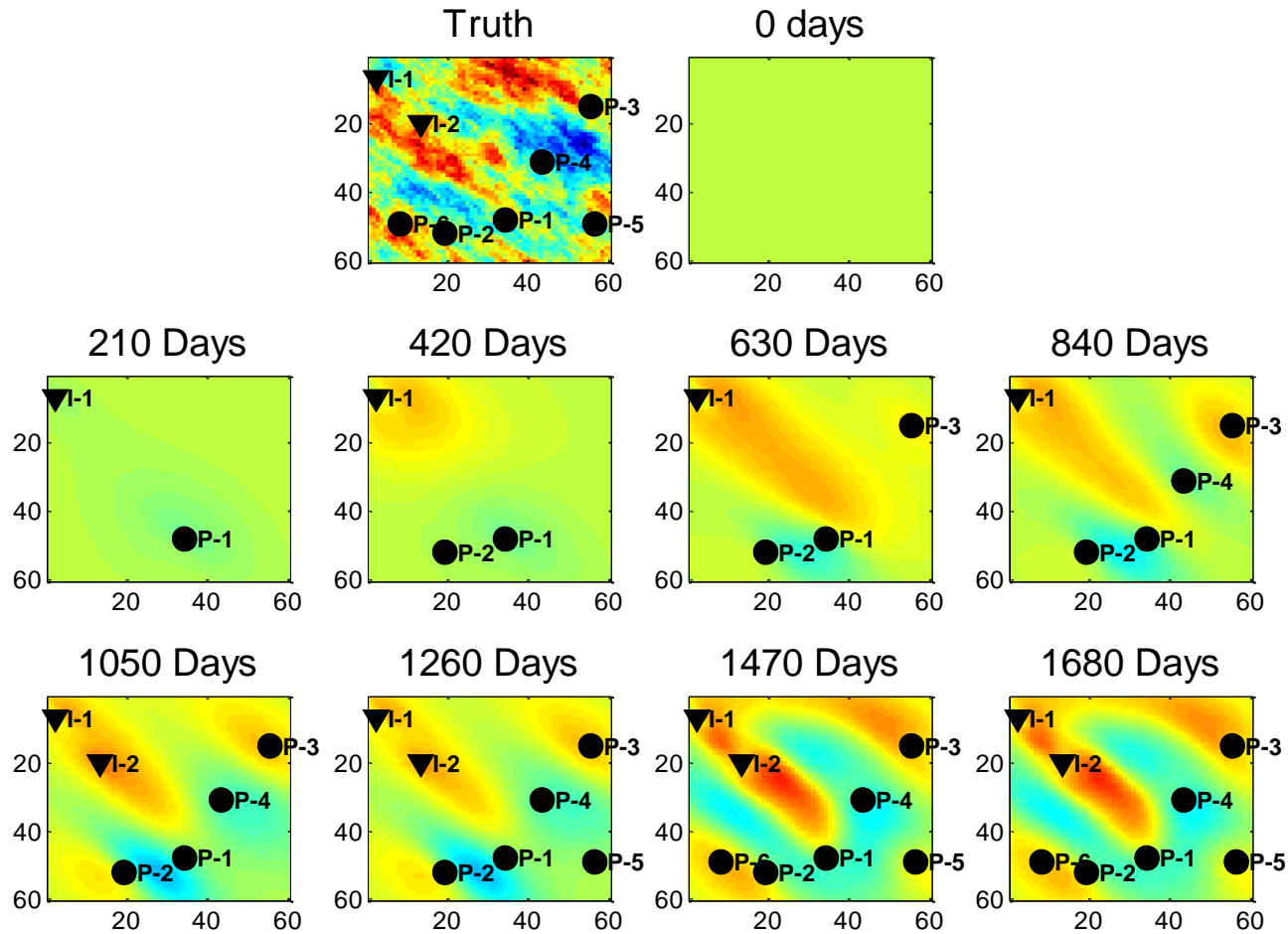


Solid curves: True field rates from optimal solution at final step of CLFD (1470 Days)

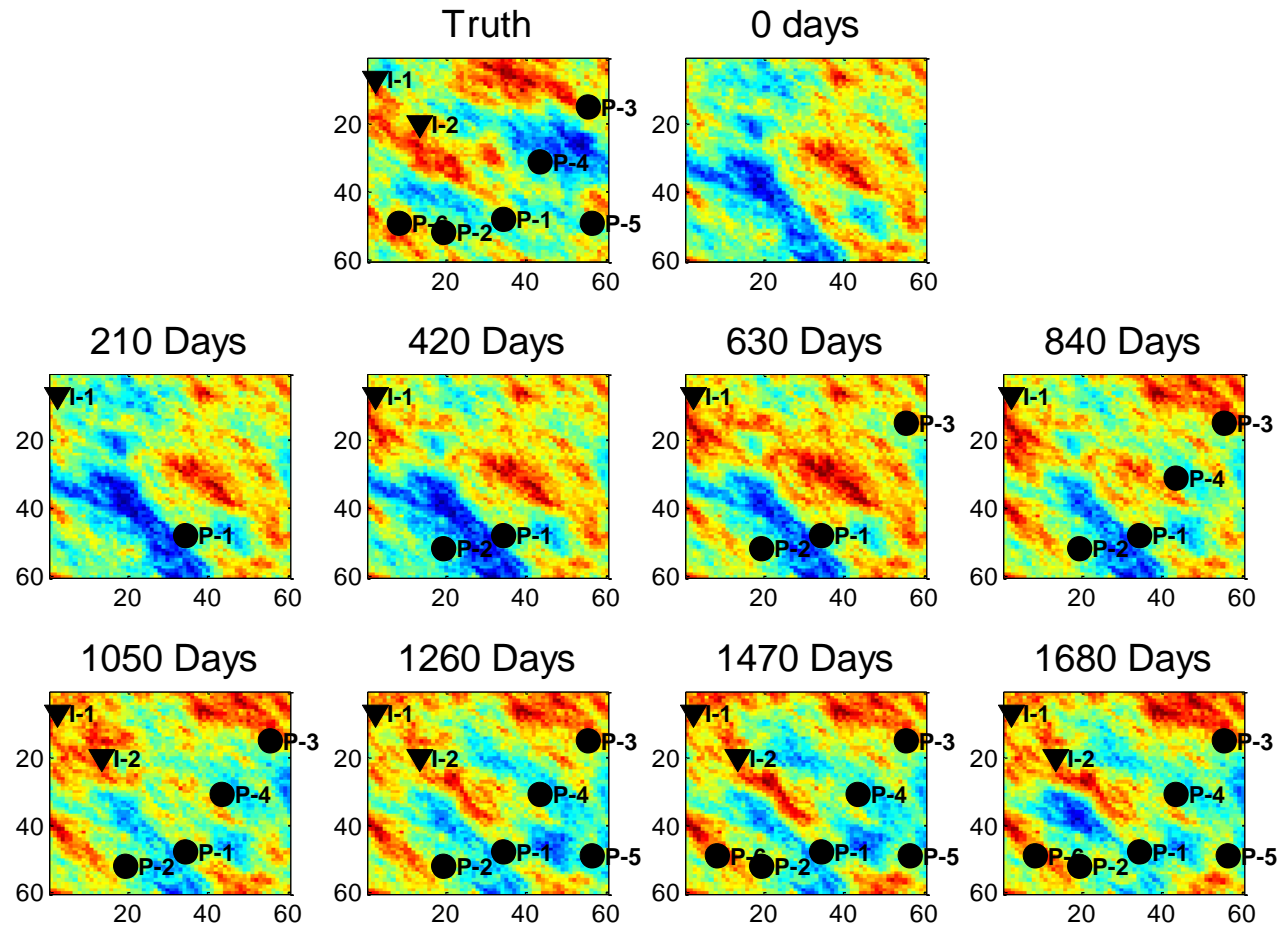
Dotted curves: True field rates from optimization on prior realizations (0 Days)

Red: oil, **Blue:** water injection, **Pink:** water production

Evolution of the MAP Estimate

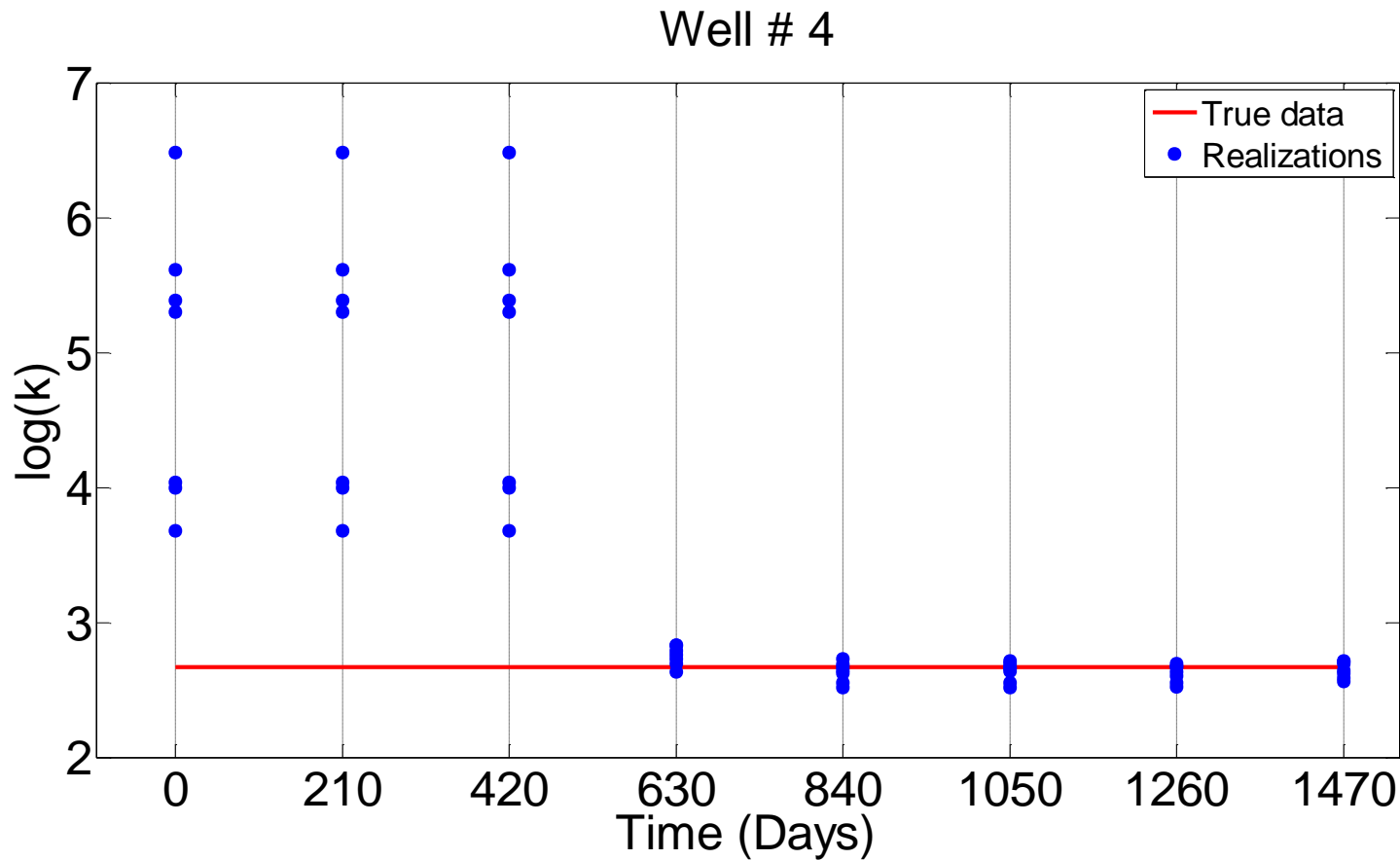


Evolution of Permeability Field for realization 1



Data Matches for log-perm of well # 4 versus Update Steps of CLFD

(History matching both hard data and production data)



$\log(k)$ of Well 4 is included as a hard data from Step 4 on