Recurrent application of pseudo ensemble smoother for calibration of channelized reservoirs using convolutional autoencoder

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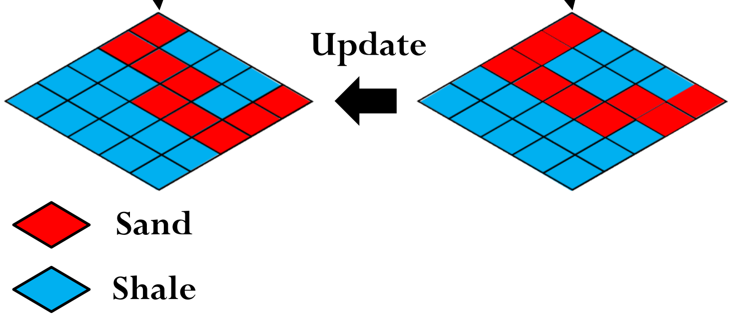
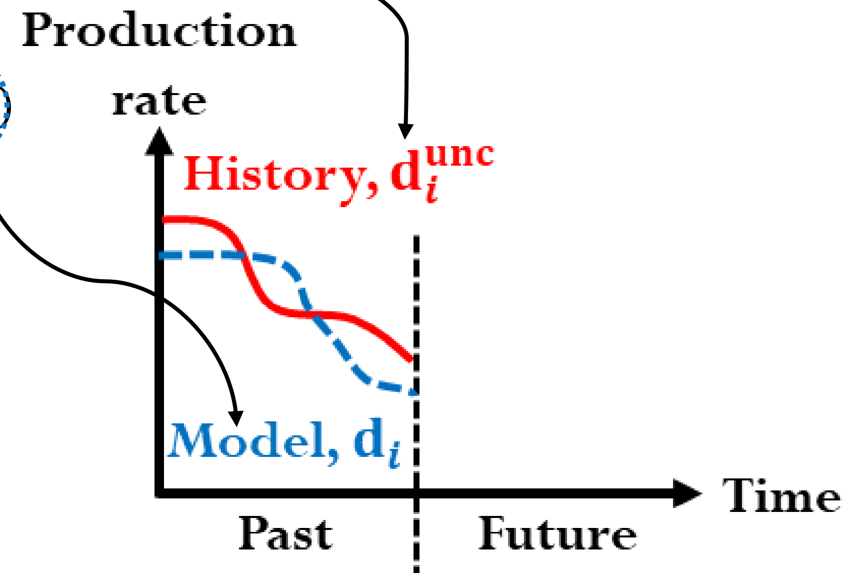
Contents

History matching by EBMs

- The equation of model update

$$\mathbf{m}_i = \mathbf{m}_i^{\mathrm{b}} + \mathbf{C}_{\mathrm{md}}\left(\mathbf{C}_{\mathrm{dd}} + \alpha_p \mathbf{C}_{\mathrm{D}}\right)^{-1}\left(\mathbf{d}_i^{\mathrm{unc}} - \mathbf{d}_i\right)$$





m: state vector (geological model realization)

$\mathbf{m}^{\mathrm{b}}$: state vector before update

d: simulated response

$\mathbf{d}^{\mathrm{unc}}$: perturbed observation data

$\mathbf{C}_{\mathrm{md}}$: cross-covariance matrix of **m** and **d**

$\mathbf{C}_{\mathrm{dd}}$: simulated response of a state vector

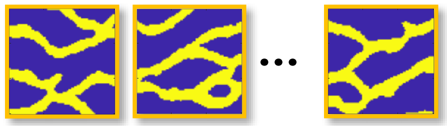
$\mathbf{C}_{\mathrm{D}}$: covariance matrix of the observed data measurement error

* Geological plausibility (reality)

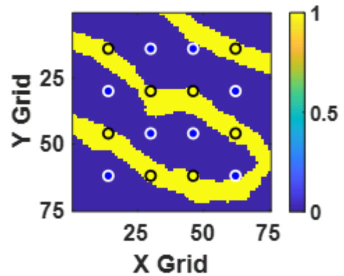
* Computational cost (simulation, matrix)

ES vs. ES-MDA

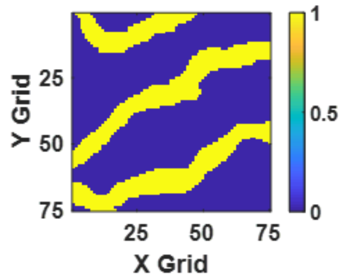
100 realizations



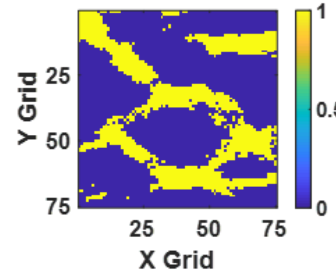
True field



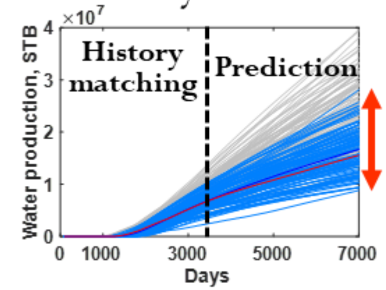
Initial model



Updated model by ES



Updated ensemble by ES

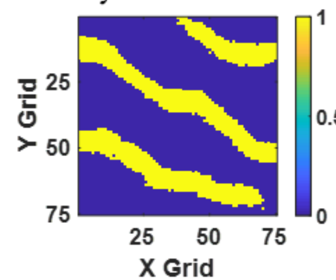


The number of reservoir simulation

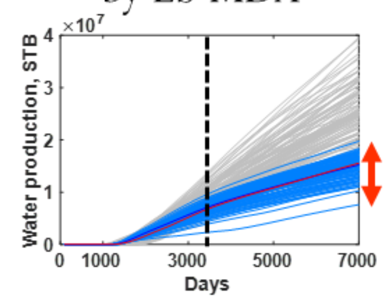
↓

200

Updated model by ES-MDA



Updated ensemble by ES-MDA



The number of reservoir simulation

↓

500

Grey line: initial ensemble

Blue line: updated ensemble

Dark blue line: mean of updated ensemble

Red line: true field

Research motivation

performance ↑ & simulation cost ↓

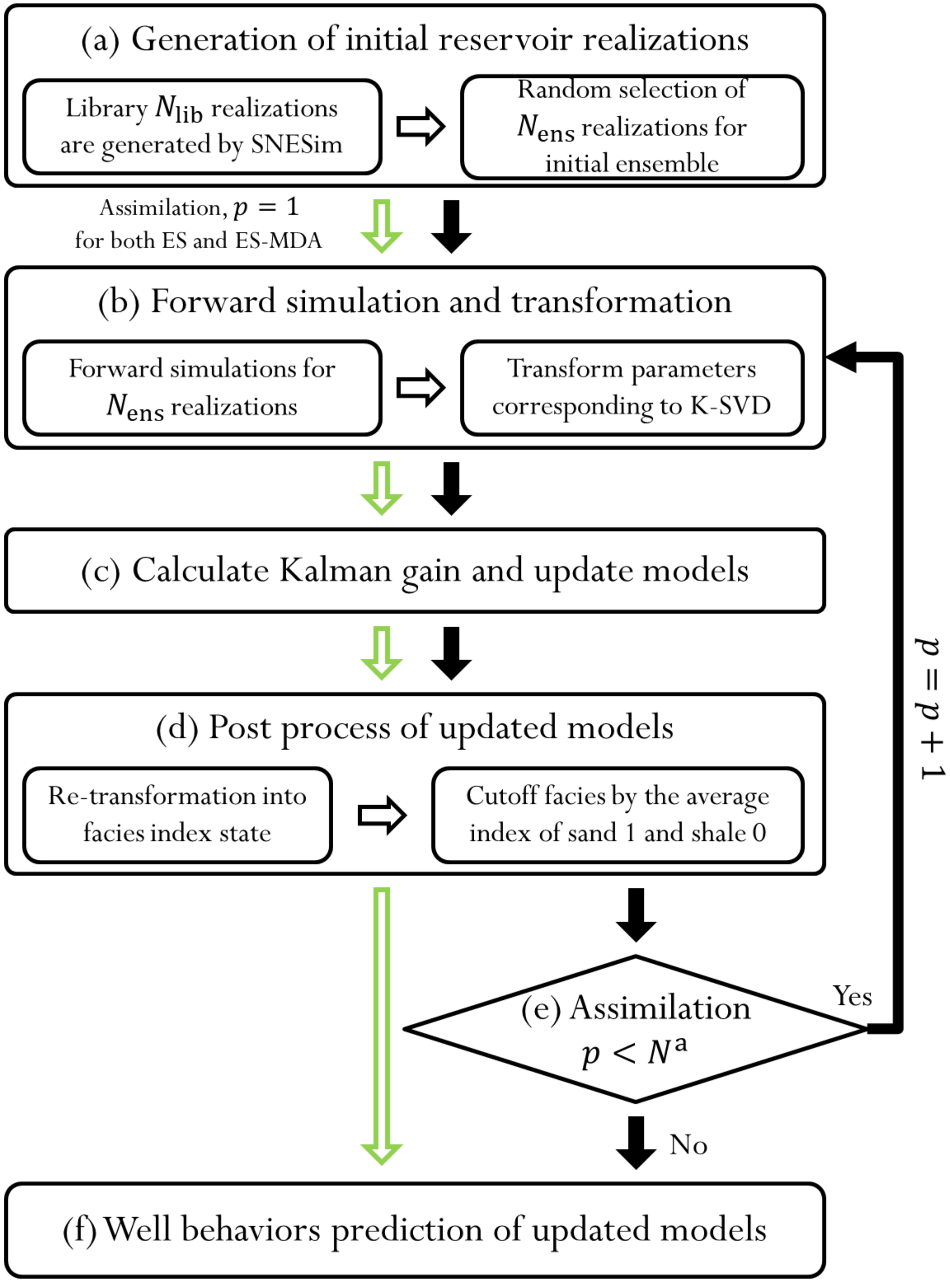
ES & ES-MDA

ES

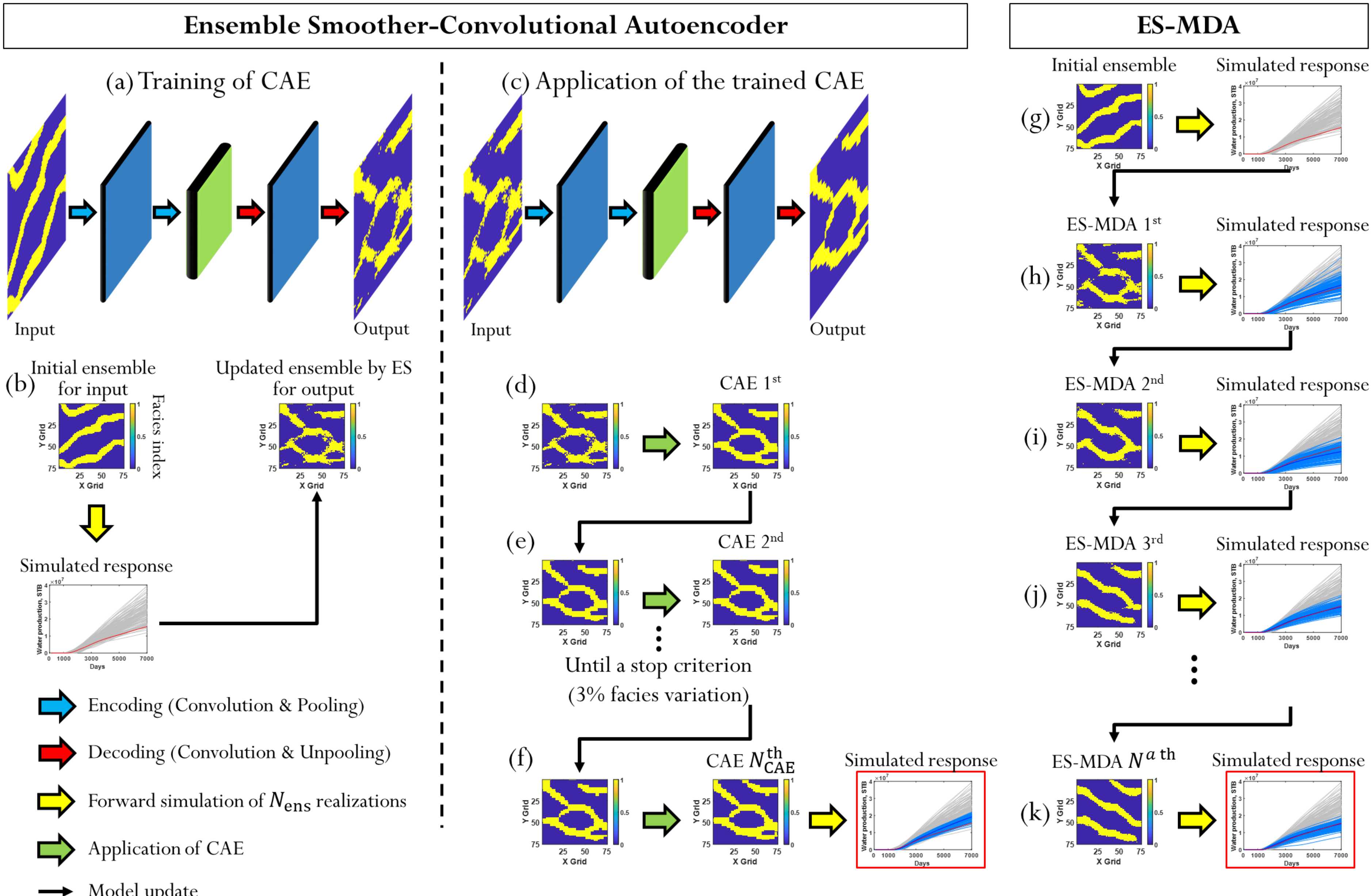
ES-MDA

N^a: number of assimilations for ES-MDA

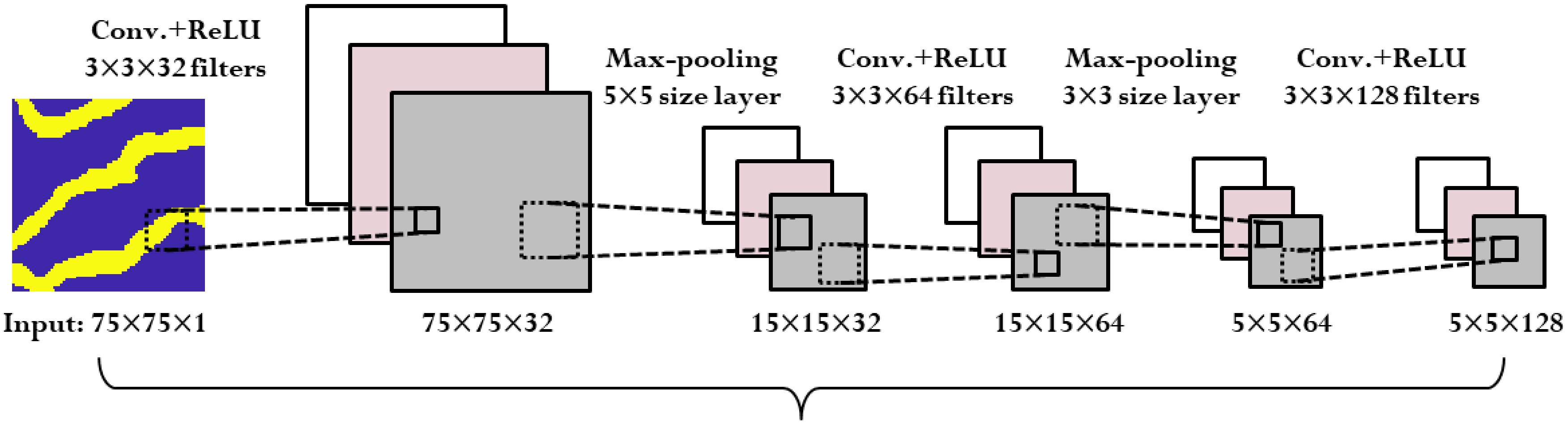
K-SVD: K-Singular Value Decomposition



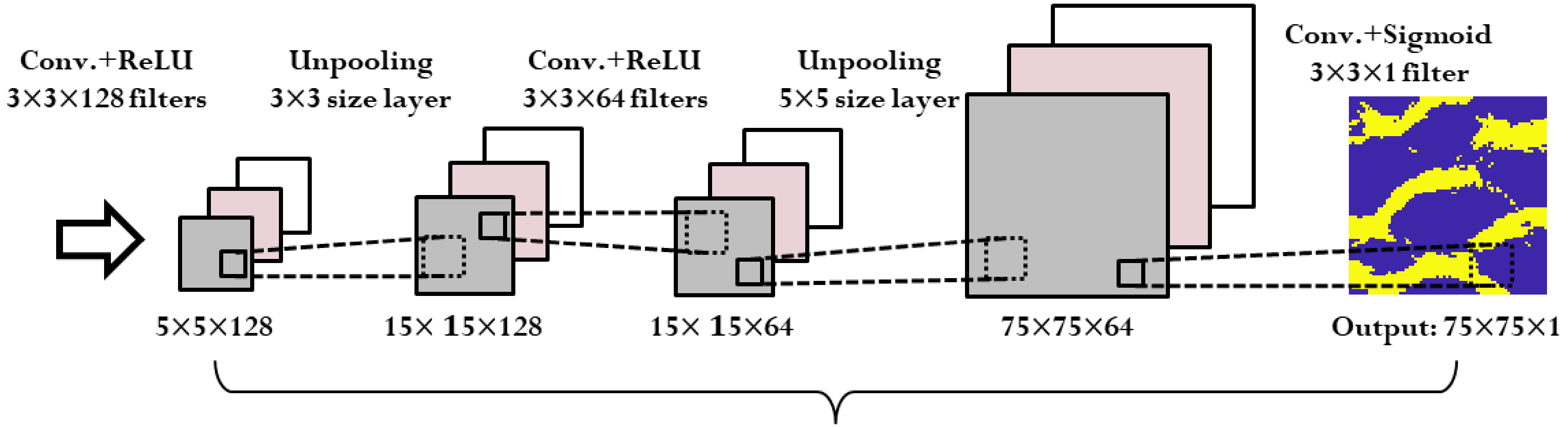
ES-CAE (pseudo ES) vs. ES-MDA



Convolutional Autoencoder (CAE)



(a) Encoding

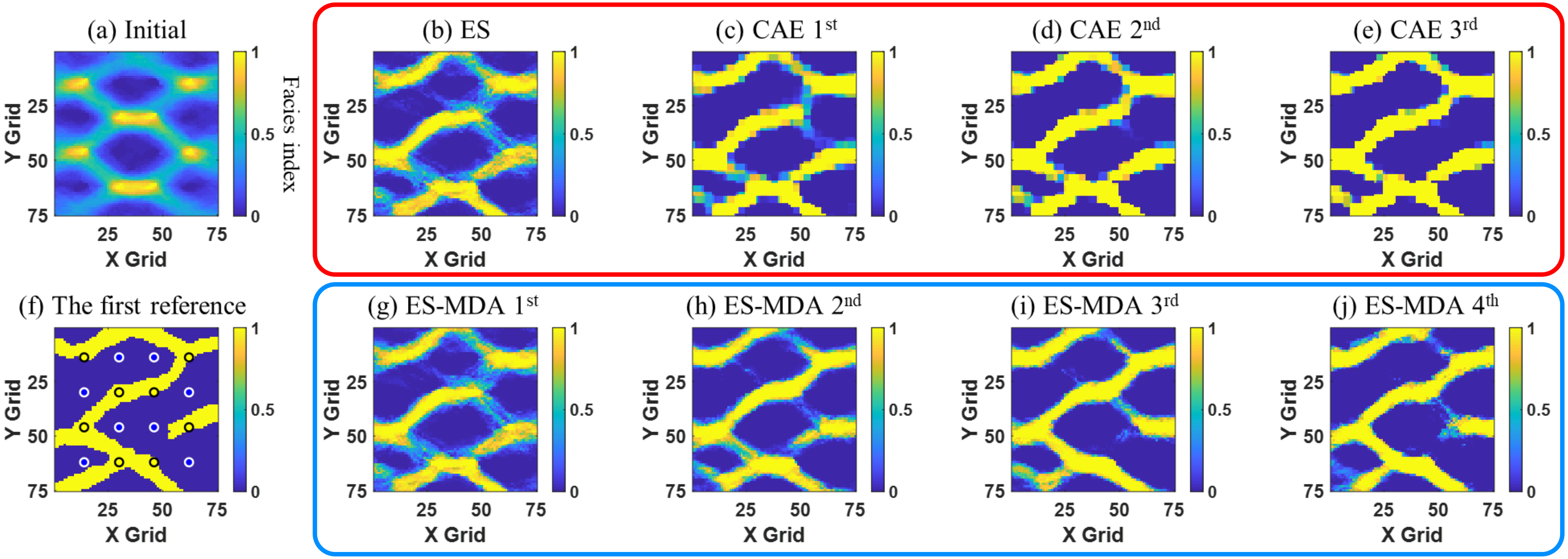


(b) Decoding

Facies distribution results (Case 1)

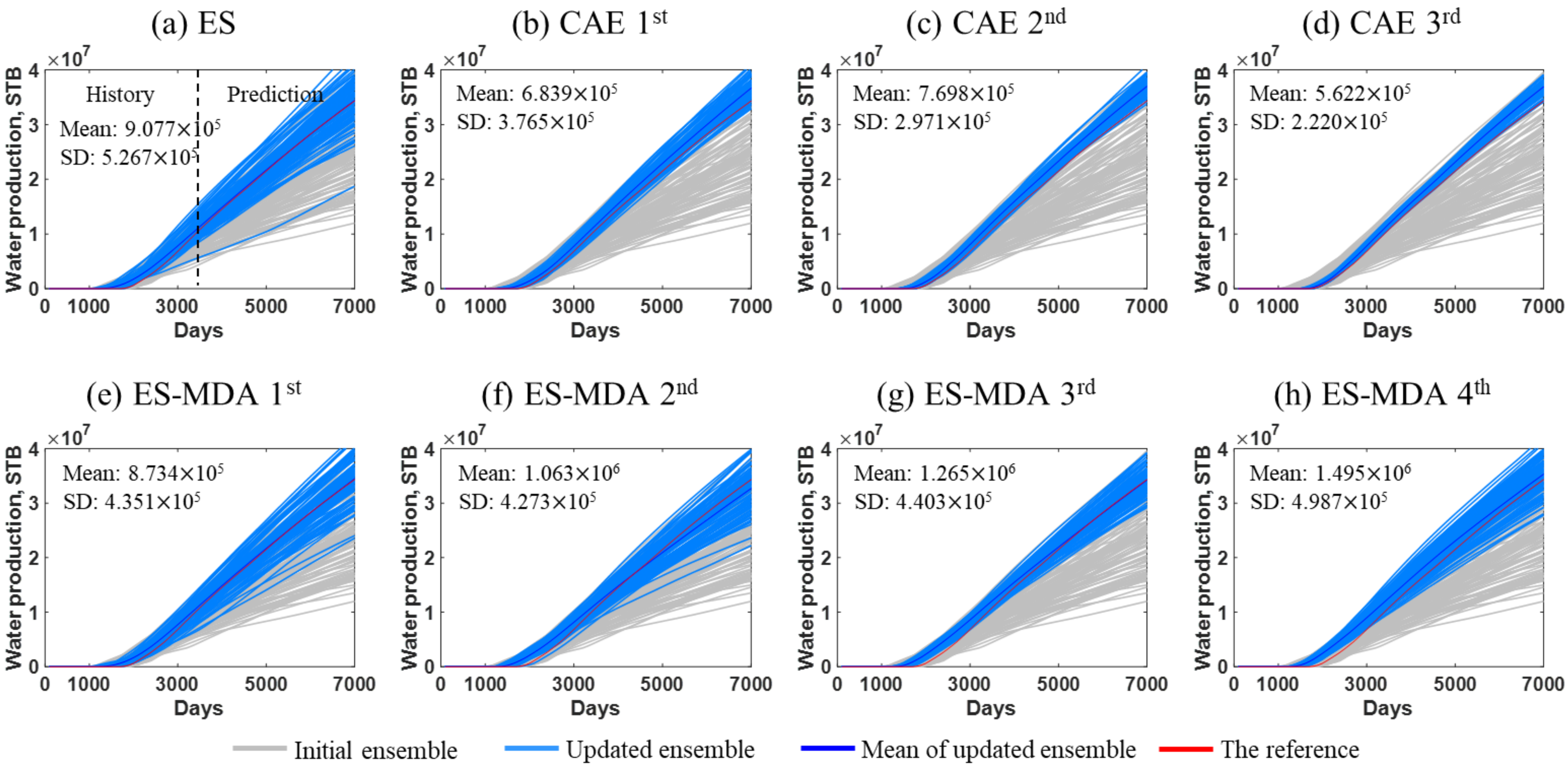
Parameter	Value
Number of grid blocks	75×75×1
Grid size (ft^3)	200×200×100
Initial gas saturation (fraction)	**0.75**
Initial water saturation (fraction)	**0.25**
Initial reservoir pressure (psia)	3,000
Index of sand and shale facies	1, 0
Permeability of sand and shale facies	300, 0.1

Parameter	Value
Observed well data	WGPR and WBHP
Max. WGPR (Mscf/day)	15,000
Min. WBHP (psia)	1,000
Total simulation period (day)	7,000
History matching period (day)	3,500
Prediction period (day)	3,500

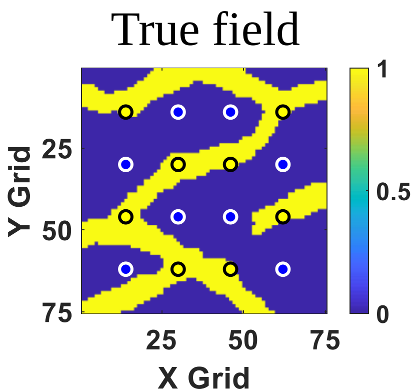


Cumulative water production results (Case 1)

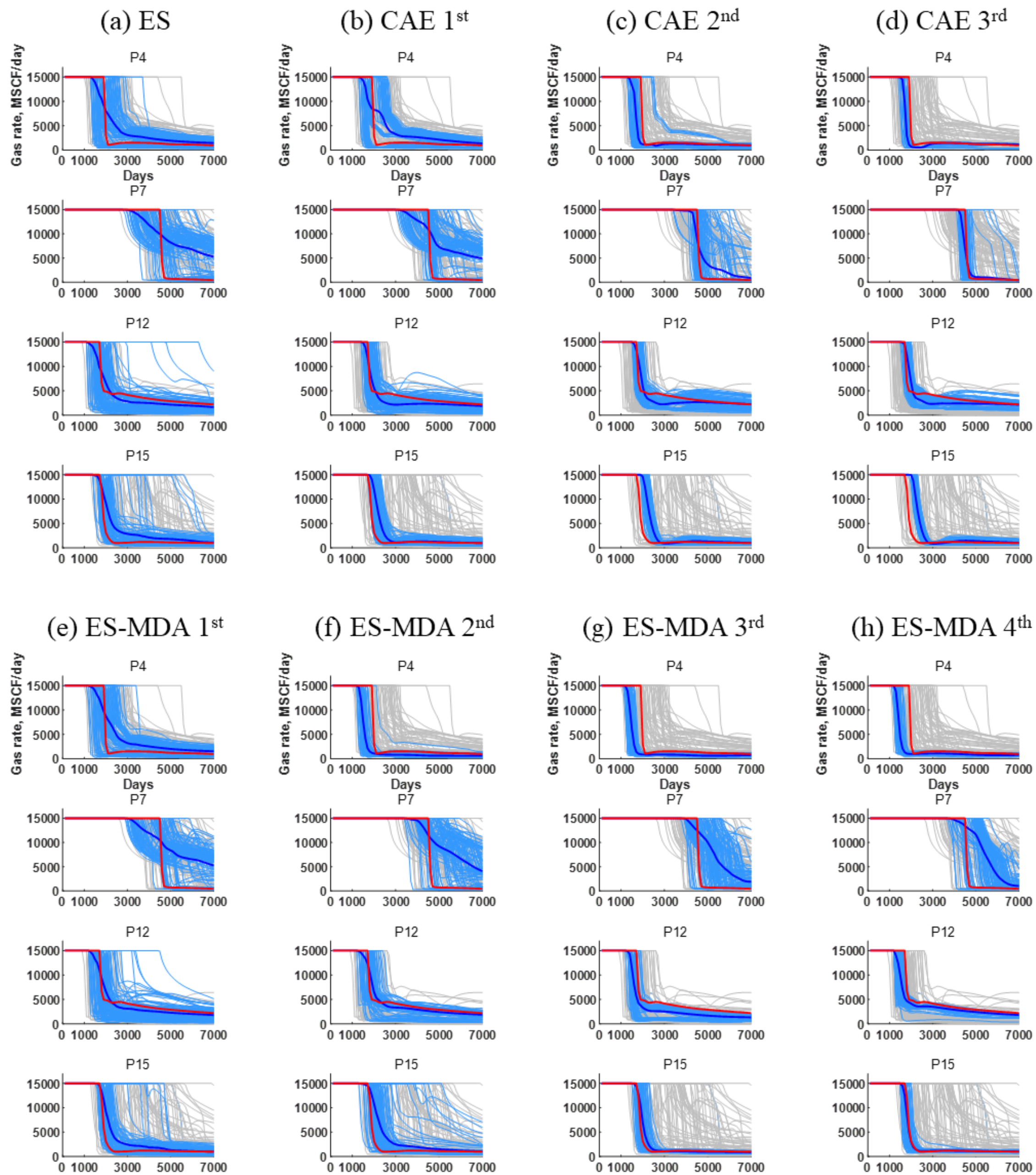
Mean and standard deviation of RMSE



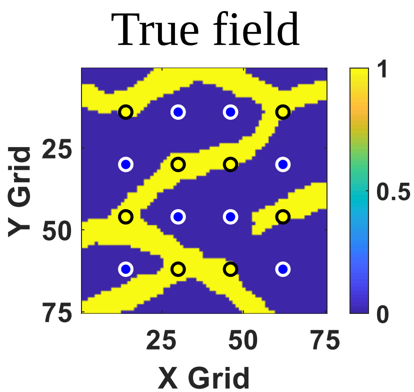
WGPR results (Case 1)



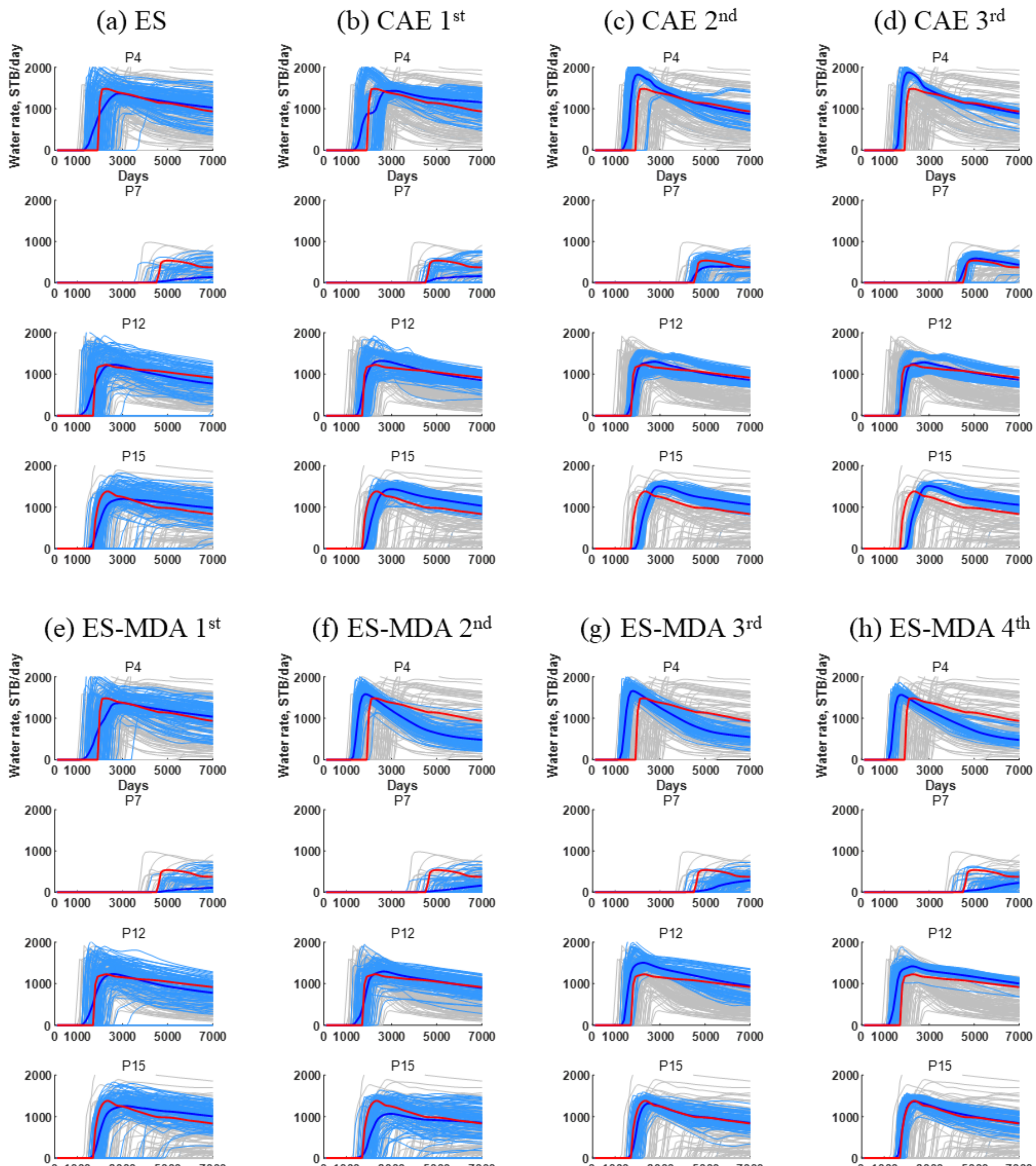
P1	P2	P3	P4
P5	P6	P7	P8
P9	P10	P11	P12
P13	P14	P15	P16



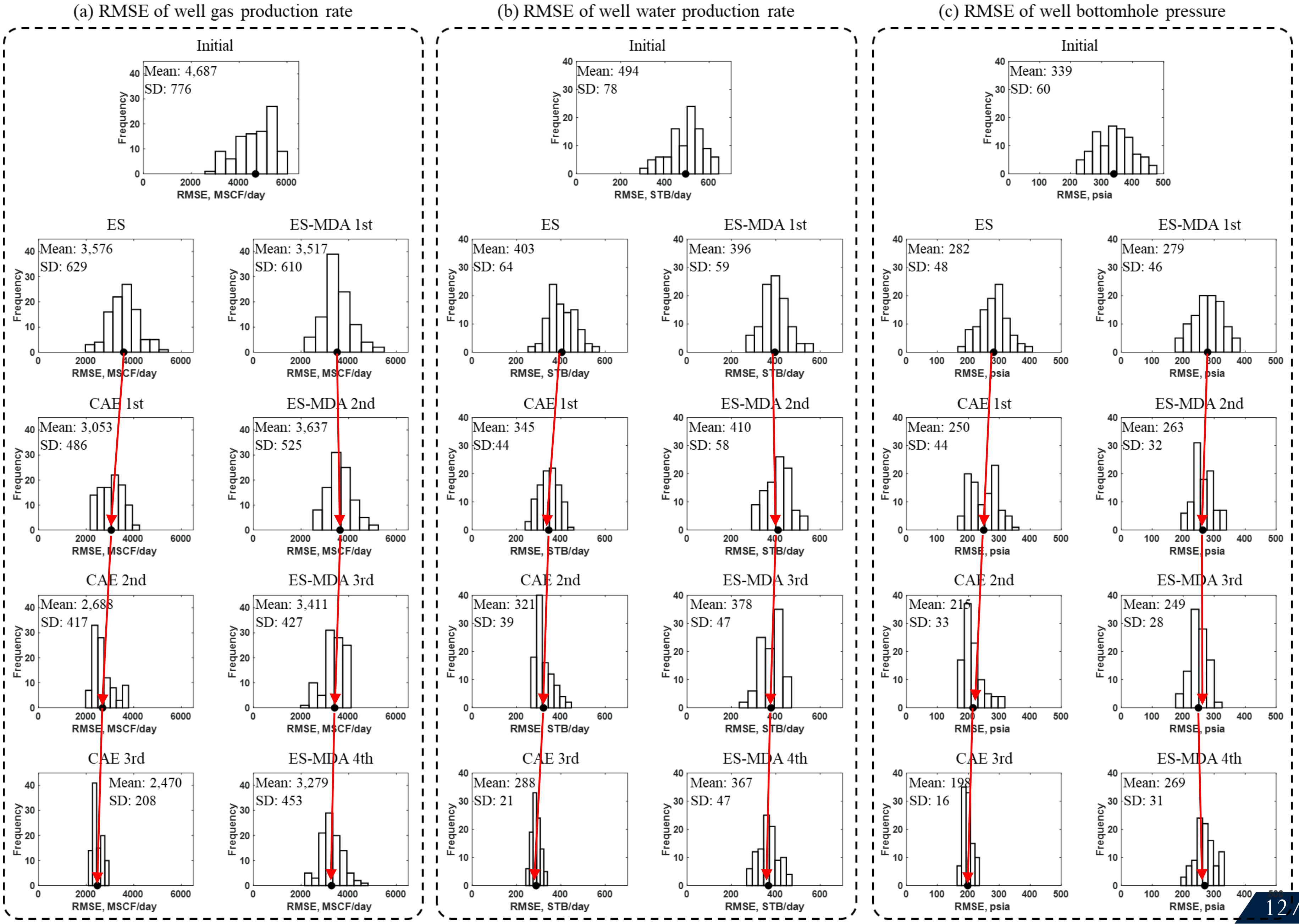
WWPR results (Case 1)



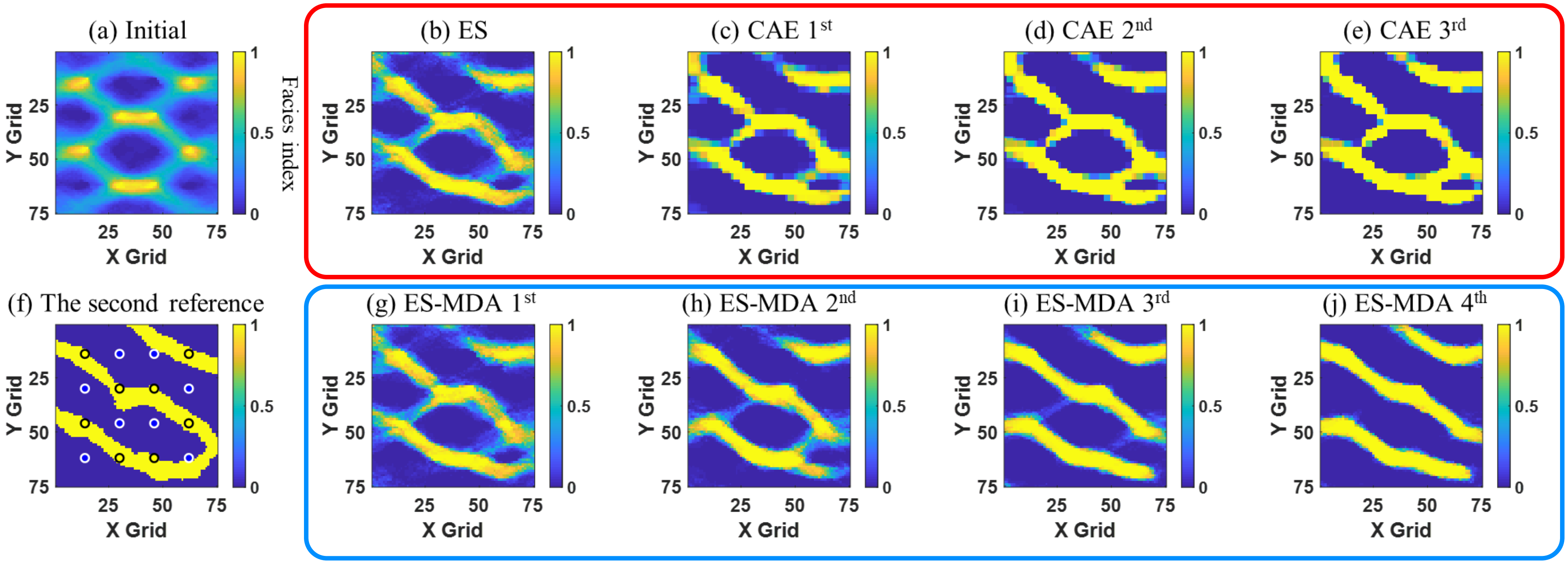
P1 P2 P3 **P4**
P5 P6 **P7** P8
P9 P10 P11 **P12**
P13 P14 **P15** P16



RMSE of WGPR, WWPR, WBHP (Case 1)

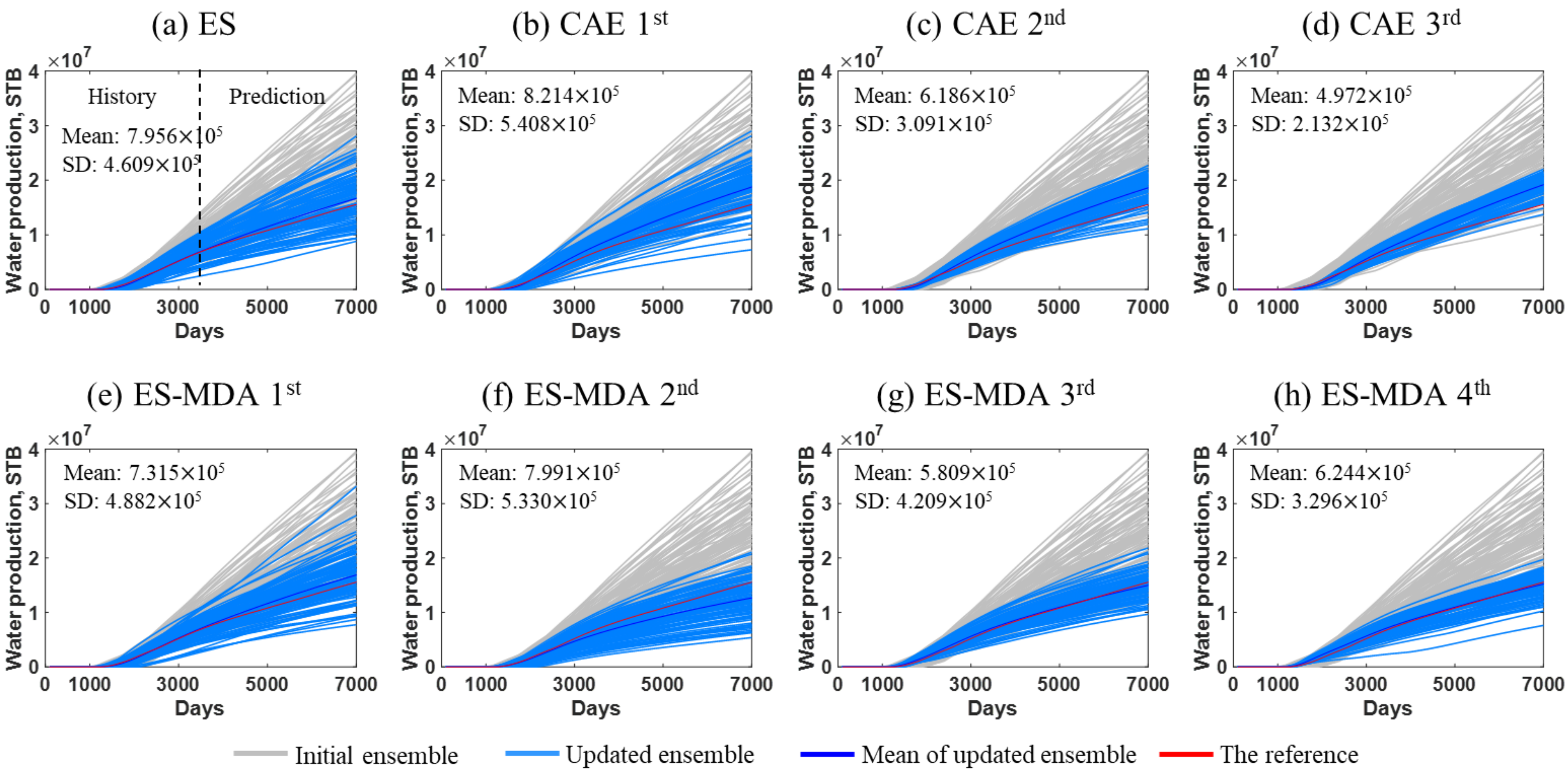


Facies distribution results (Case 2)



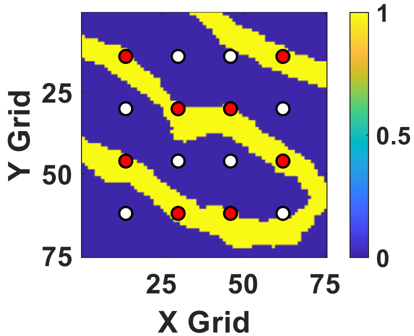
Cumulative water production results (Case 2)

Mean and standard deviation of RMSE

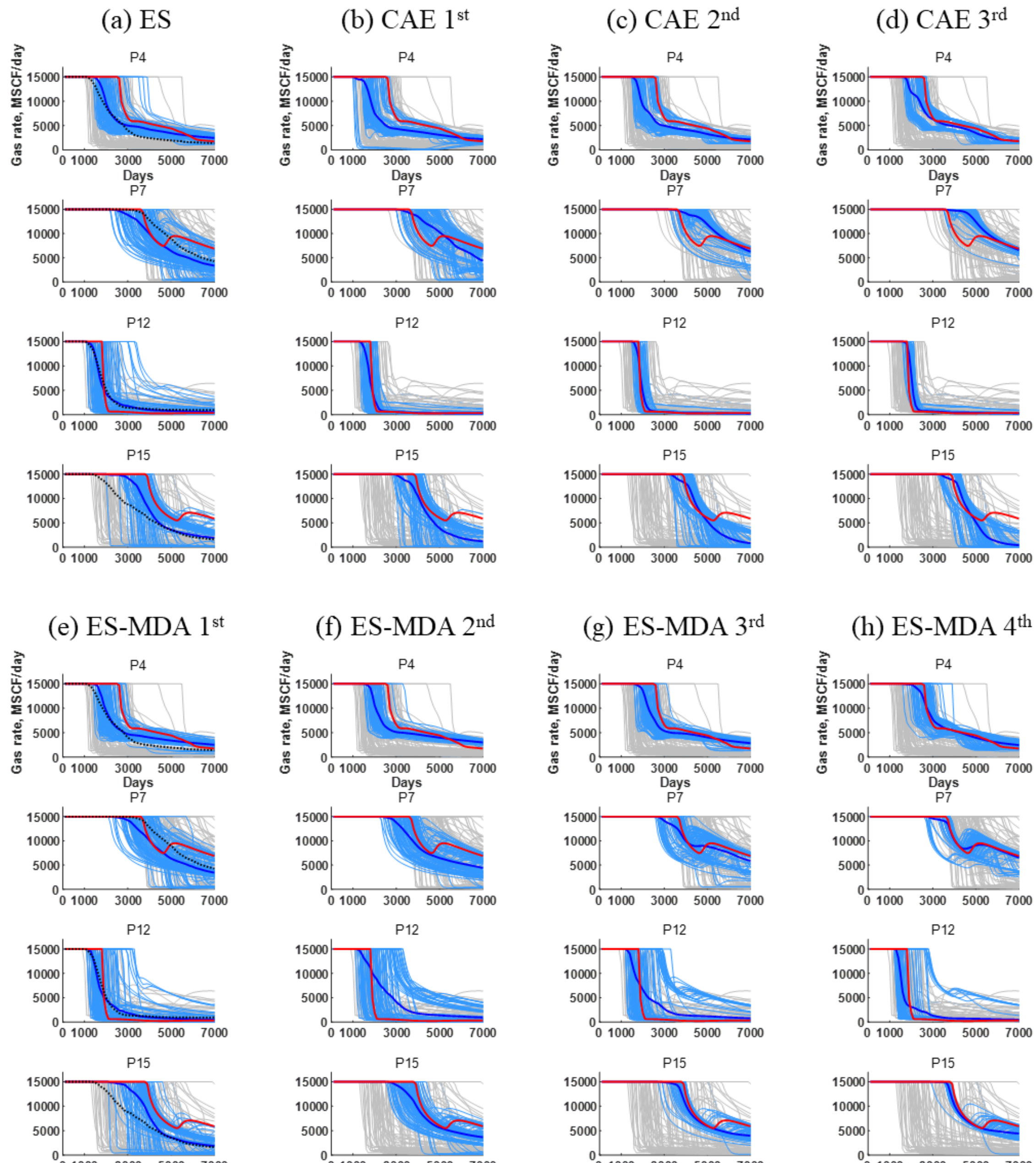


WGPR results (Case 2)

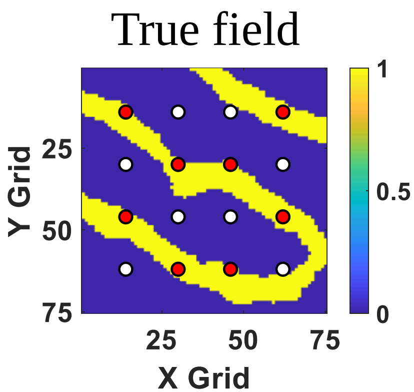
True field



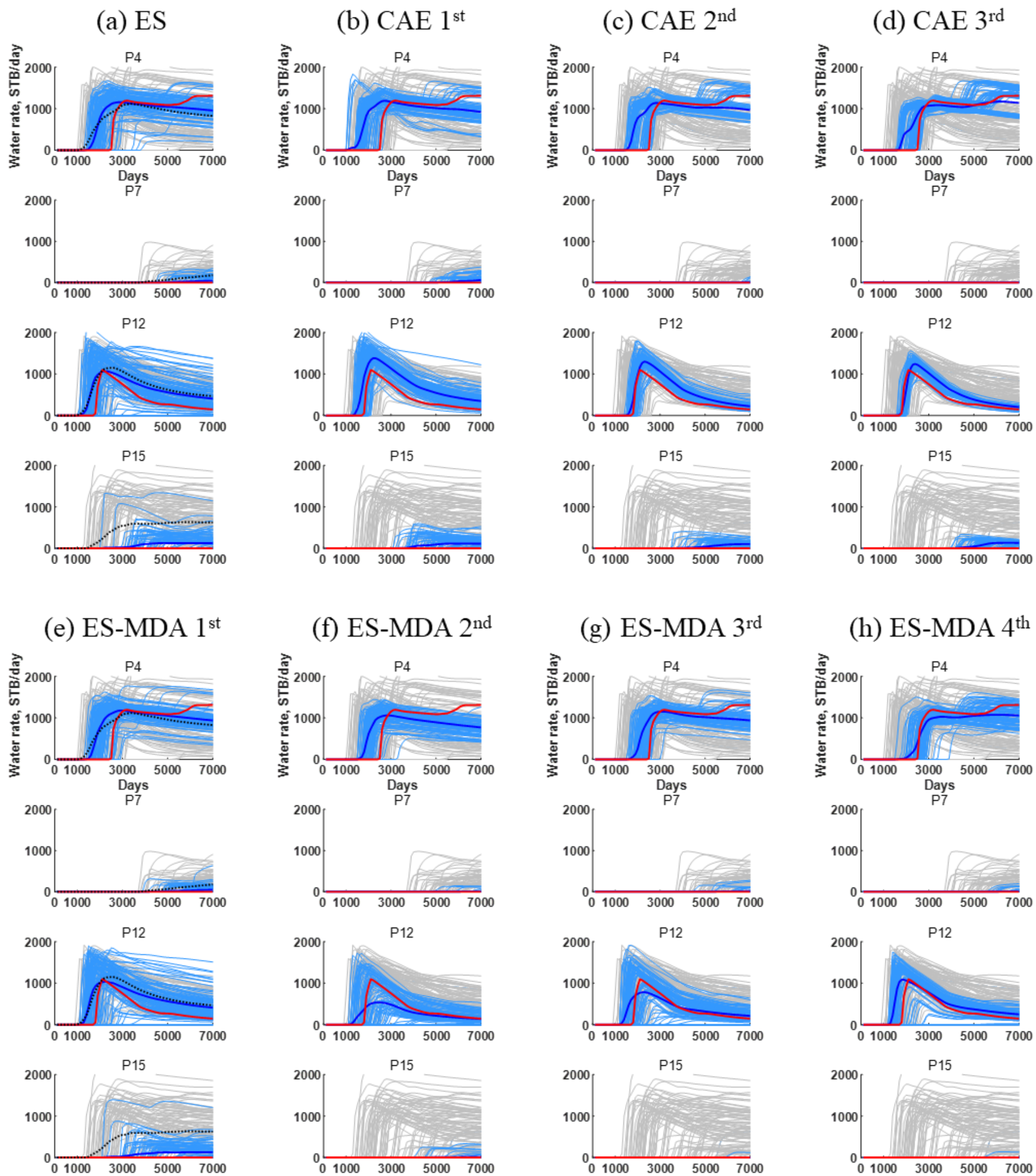
P1	P2	P3	**P4**
P5	P6	**P7**	P8
P9	P10	P11	**P12**
P13	P14	**P15**	P16



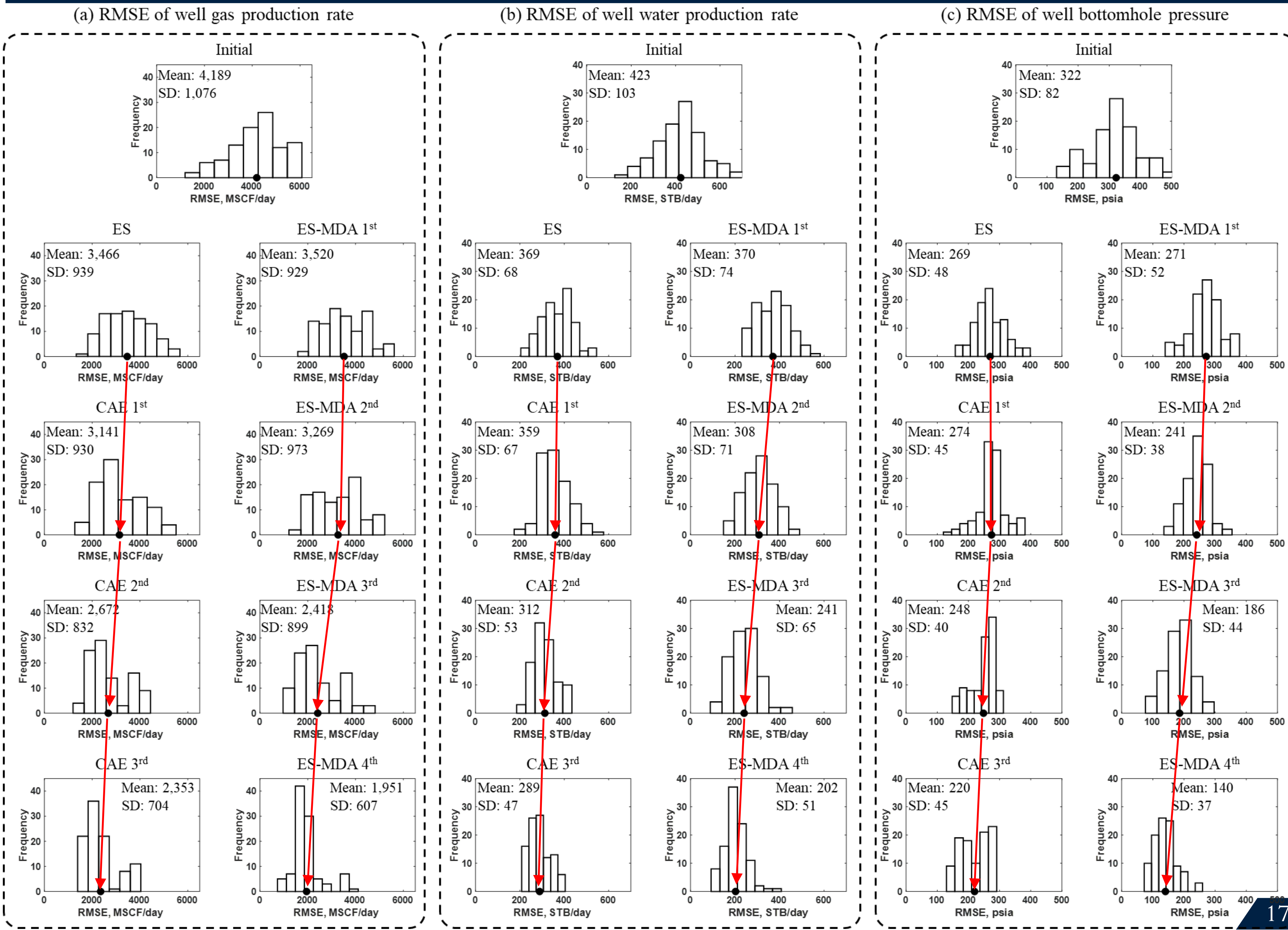
WWPR results (Case 2)



P1	P2	P3	P4
P5	P6	P7	P8
P9	P10	P11	P12
P13	P14	P15	P16



RMSE of WGPR, WWPR, WBHP (Case 2)



RMSEs of the updated ensembles (Case 1 & 2)

Data type	WGPR, MSCF/day				WWPR, STB/day				WBHP, psia			
Algorithm	ES-CAE		ES-MDA		ES-CAE		ES-MDA		ES-CAE		ES-MDA	
	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
Case 1	2,470	208	3,279	453	288	21	367	47	198	16	269	31
Case 2	2,353	704	1,951	607	289	47	202	51	220	45	140	37
μ_{diff} (Case 1)	-25%				-22%				-26%			
μ_{diff} (Case 2)	21%				43%				57%			

Conclusions

1. It showed the potential of ES-CAE to boost ES according to comparable history matching performance saving forward simulation cost compared to ES-MDA.

2. The CAE learns the principle to calibrate reservoir realizations by ES and it took only 15 seconds with GPU.

3. With the same simulation capacity, ES-CAE gives better history matching than the first update of ES-MDA.

4. We expect that ES-CAE can complement ES-MDA at cheaper computational cost.

Thank you for listening

Q & A

Inverse modeling

● In petroleum engineering

$G(m) = d$

m: reservoir parameters like k or ϕ

d: well behaviors and seismic data

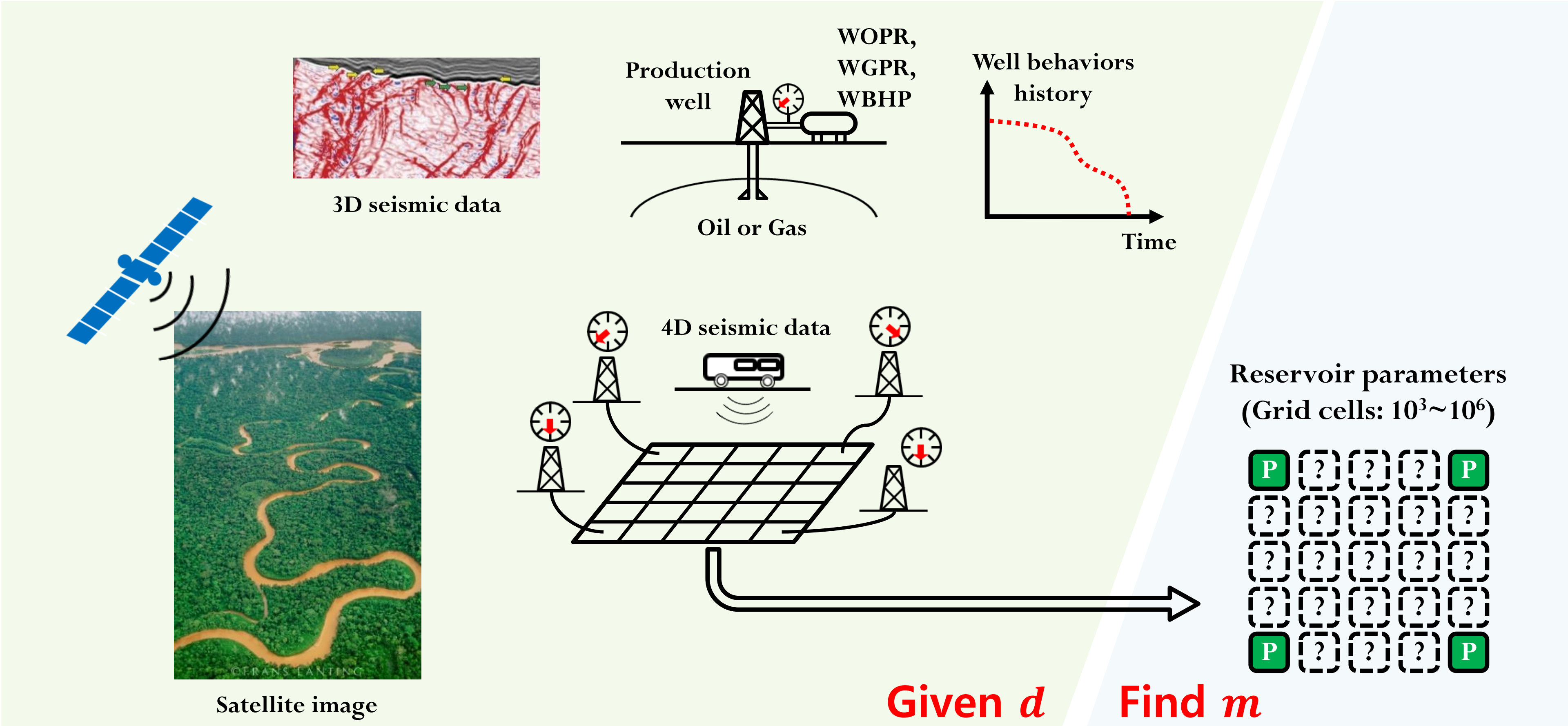
G: a reservoir simulator like Eclipse

-Limited information

-Expensive cost

-Measurement error

Reliable inverse modeling to make a proper decision

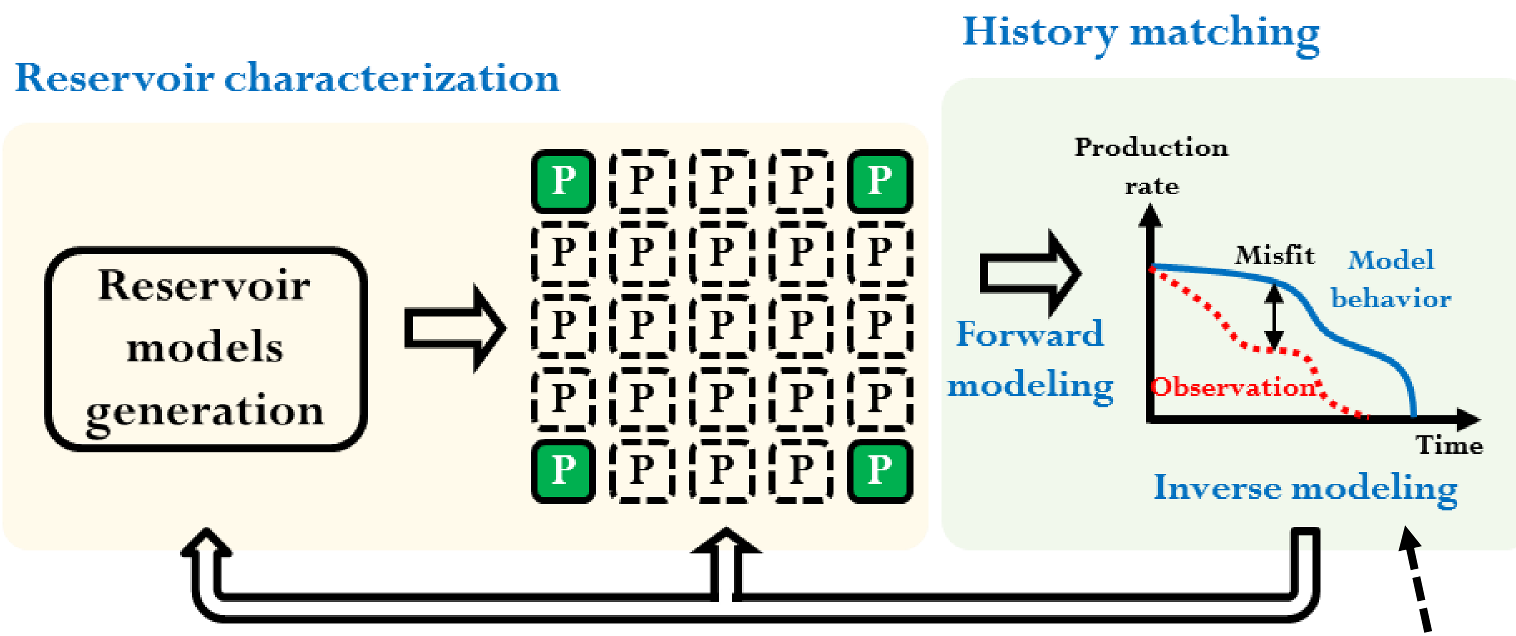


*In Meteorological models, Parameters: 10^7, Observation 10^5

Inverse modeling

Reservoir characterization & History matching

- History matching: to adjust a reservoir model according to the given history
- Reservoir characterization: to generate new reservoir models or modify previous ones



Ensemble based methods

- EnKF, ES, and ES-MDA

History matching

The forward and inverse modeling

- The forward modeling is to find d given m
- The inverse modeling is to find m given d

$$G(m) = d$$

m: model parameters

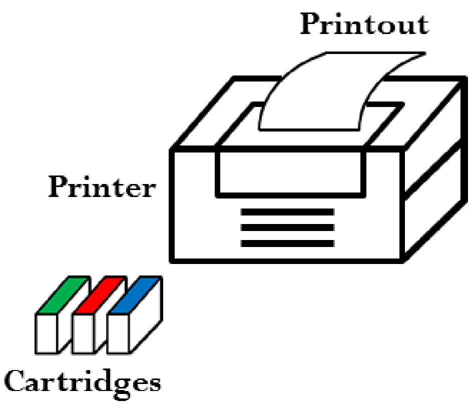
d: observed data

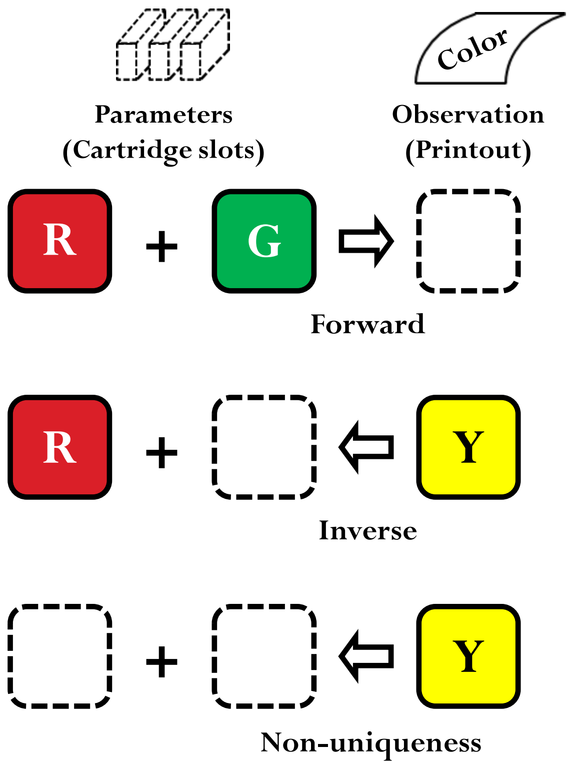
G: a function physically understood

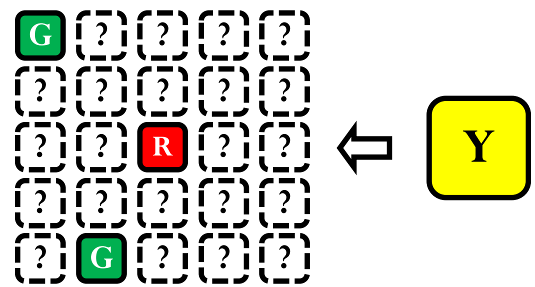
m: colors in cartridges

d: a color in printout

G: a printer that we understand its principle







In complicated problem

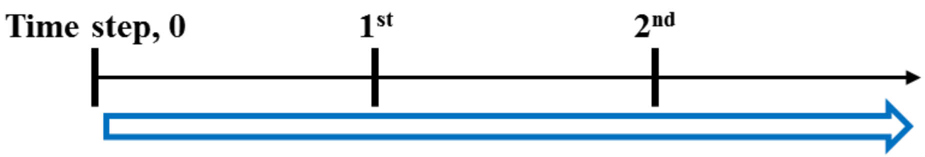
- Many unknowns compared to clues

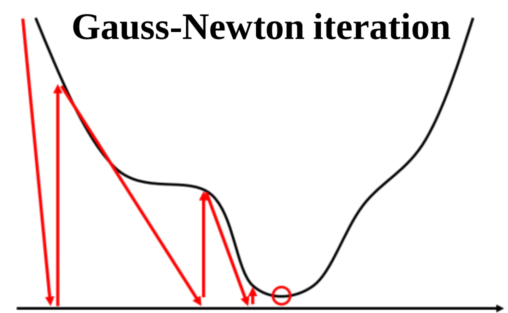
- Likewise in petroleum engineering

Ensemble based methods

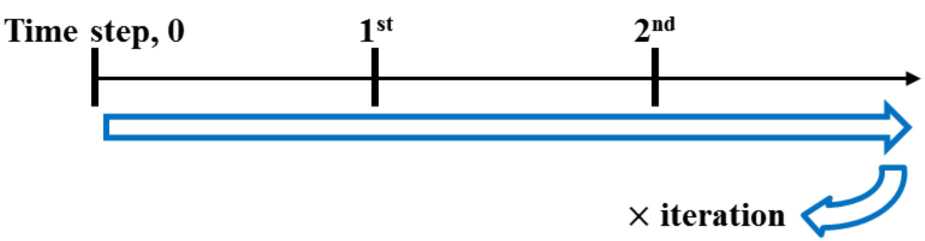
- Ensemble Kalman Filter (EnKF): update in each step

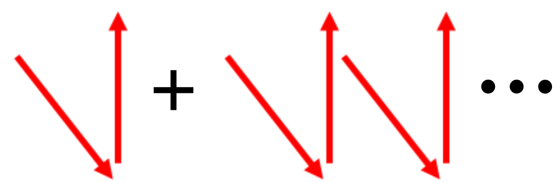
- Ensemble Smoother (ES): update at once



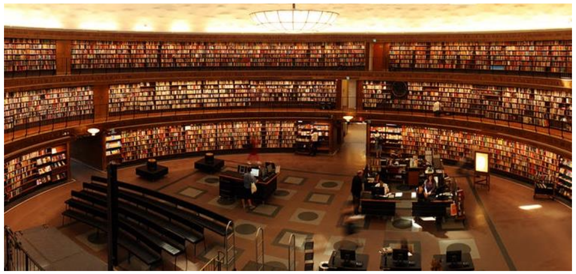


- Ensemble Smoother with Multiple Data Assimilation (ES-MDA)

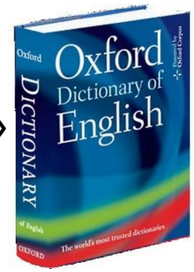




K-Singular Value Decomposition



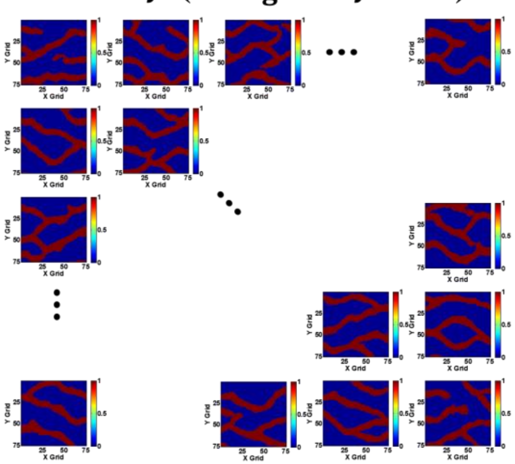
Extract



Words selection

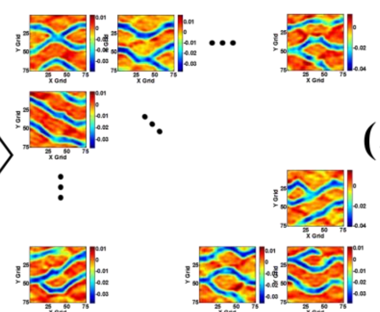
A sentence
“I love cookies”
Or the book
‘Romeo & Juliet’
Or even every books
of library

Library (Y, N_{grid} by N_{lib})



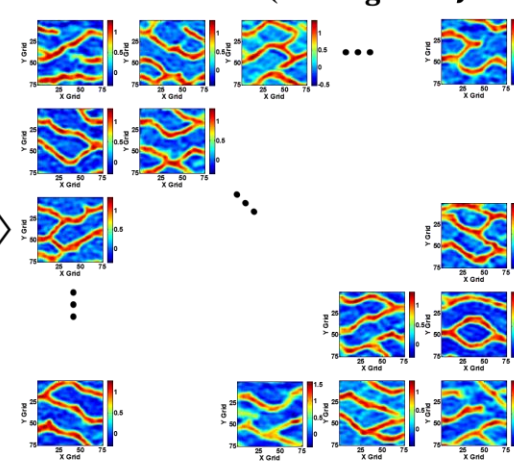
K-SVD

Dictionary (D, N_{grid} by N_{dict})

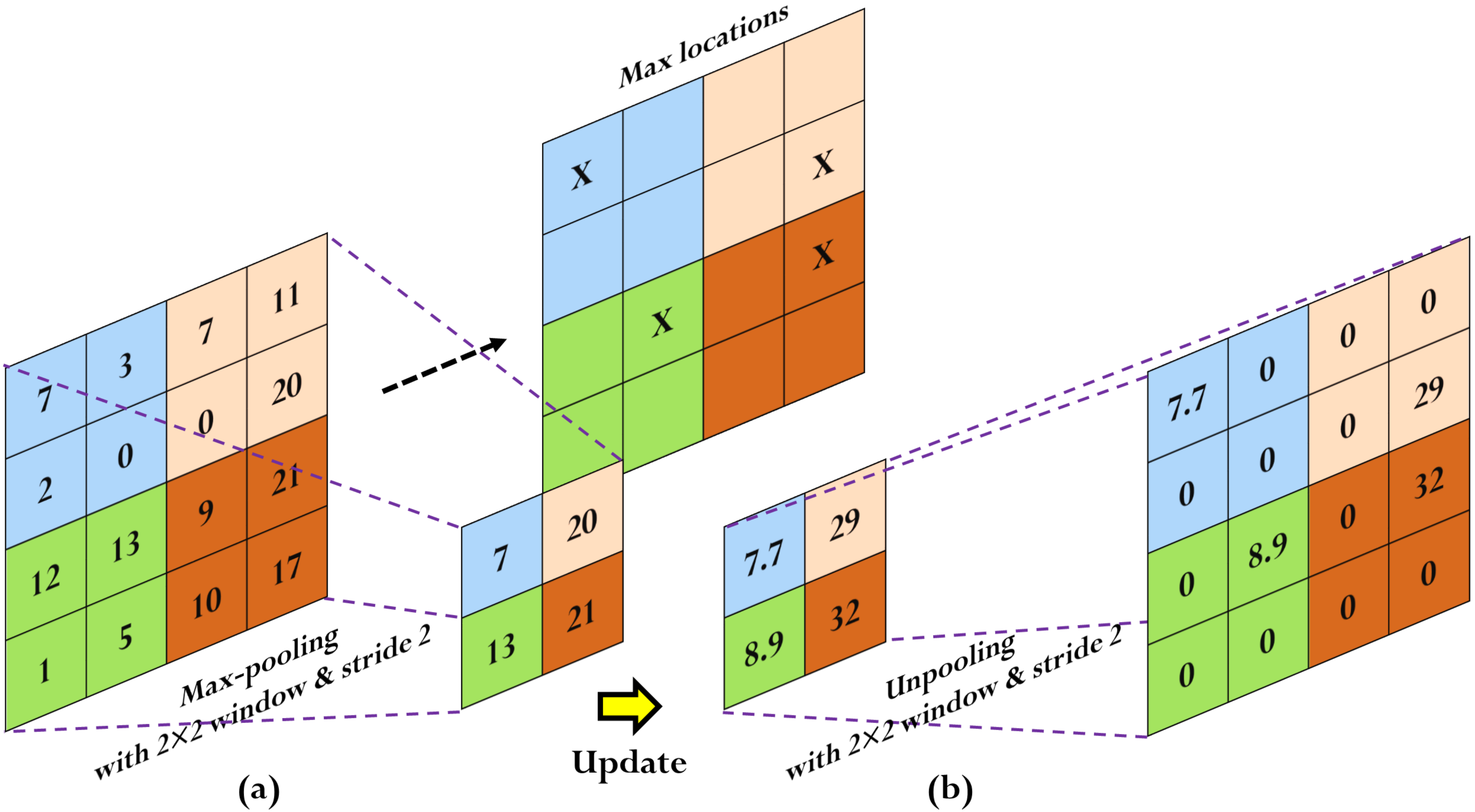


Weight
coefficients
(N_{dict} by N_{lib})
X

Reconstruction (Y’, N_{grid} by N_{lib})



Max pooling & Unpooling (CAE)



Parameter	Value
Ratio of training data (%)	72
Ratio of validation data (%)	18
Ratio of test data (%)	10
Batch size	16
Maximum number of epochs	50
Optimizer for training	Adam

Standard deviation of facies distribution

Facies variation between	Case 1 Variation, %	Case 2 Variation, %
Initial vs 1st	18.24	18.11
1st vs 2nd	9.38	9.05
2nd vs 3rd	3.61	3.68
3rd vs 4th	1.90	2.26

$$M_{\text{var}} = \frac{1}{N_{\text{grid}}}\frac{1}{N_{\text{ens}}}\sum_{i=1}^{N_{\text{grid}}}\sum_{j=1}^{N_{\text{ens}}}\left|\hat{x}_i^j - \text{NN}(\hat{x}_i^j)\right| \times 100\ (\%)$$

x_i: facies index of ith grid-block

N_{grid}: number of grid-blocks

N_{ens}: number of ensemble members

NN: trained neural network model, CAE