Assimilating Spatially Dense Data for Subsurface Applications—Balancing Information and Degrees of Freedom

Trond Mannseth and Kristian Fossum

Uni Research CIPR

Two Porous Media

with different fluid conductivity (permeability)

Sandstone sample

Sponge

Two Porous Media

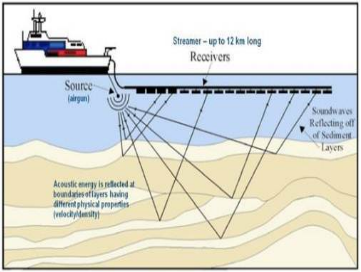
with different fluid conductivity (permeability)

Sandstone sample

Sponge

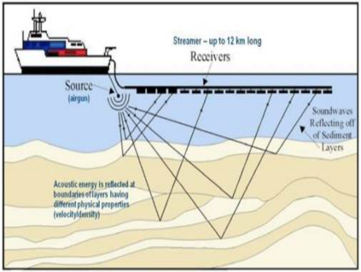
Task: estimate permeability, $k(x)$

Seismic Data



Offshore seismic data acquisition

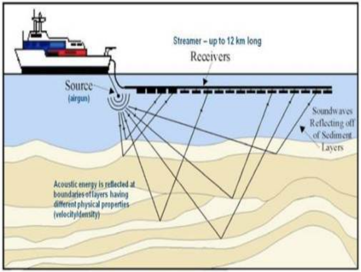
Seismic Data



Offshore seismic data acquisition

Seismic data are spatially dense

Seismic Data



Offshore seismic data acquisition

Seismic data are spatially dense

Link between seismic data and $k(x)$?

Link between Seismic Data and $k(x)$

Link between Seismic Data and $k(x)$

$k(x) \rightarrow$ flow modeling $\rightarrow$ fluid pressure and fluid content

Link between Seismic Data and $k(x)$

$k(x) \rightarrow$ flow modeling $\rightarrow$ fluid pressure and fluid content

F. pressure and f. content $\rightarrow$ petro-elastic modeling $\rightarrow$ elastic properties

Link between Seismic Data and $k(x)$

$k(x) \rightarrow$ flow modeling $\rightarrow$ fluid pressure and fluid content

F. pressure and f. content $\rightarrow$ petro-elastic modeling $\rightarrow$ elastic properties

Elastic properties $\rightarrow$ seismic modeling $\rightarrow$ simulated seismic data

Link between Seismic Data and $k(x)$

$k(x) \rightarrow$ flow modeling $\rightarrow$ fluid pressure and fluid content

F. pressure and f. content $\rightarrow$ petro-elastic modeling $\rightarrow$ elastic properties

Elastic properties $\rightarrow$ seismic modeling $\rightarrow$ simulated seismic data

We use elastic properties ('inverted seismic data') as 'seismic data' when estimating $k(x)$

Background

Inverted seismic data

Background

Inverted seismic data

Elastic properties: V_p, V_s, ρ, … are pixel fields

Background

Inverted seismic data

Elastic properties: V_p, V_s, ρ, ... are pixel fields

Spatially dense $\rightarrow$ high potential for estimating $k(x)$

Background

Inverted seismic data

Elastic properties: V_p, V_s, ρ, ... are pixel fields

Spatially dense $\rightarrow$ high potential for estimating $k(x)$

Signal masked by errors (acquisition, processing, inversion, ...)

Background

Inverted seismic data

Elastic properties: V_p, V_s, ρ, ... are pixel fields

Spatially dense $\rightarrow$ high potential for estimating $k(x)$

Signal masked by errors (acquisition, processing, inversion, ...)

$\Rightarrow$ Extract data *features* with enhanced 'signal-to-noise ratio'

Background

Inverted seismic data

Elastic properties: V_p, V_s, ρ, ... are pixel fields

Spatially dense $\rightarrow$ high potential for estimating $k(x)$

Signal masked by errors (acquisition, processing, inversion, ...)

$\Rightarrow$ Extract data *features* with enhanced 'signal-to-noise ratio'

Some information will, however, be lost

Background

Ensemble-based methods

Background

Ensemble-based methods

Degrees of freedom (DOF) is limited by ensemble size, E (assuming no localization)

Background

Ensemble-based methods

Degrees of freedom (DOF) is limited by ensemble size, E (assuming no localization)

E is usually moderately large ($\mathcal{O}(100)$)

Background

Ensemble-based methods

Degrees of freedom (DOF) is limited by ensemble size, E (assuming no localization)

E is usually moderatly large ($\mathcal{O}(100)$)

Spatially dense data may lead to unwarranted strong uncertainty reduction in estimation results

Background

Ensemble-based methods

Degrees of freedom (DOF) is limited by ensemble size, E (assuming no localization)

E is usually moderatly large ($\mathcal{O}(100)$)

Spatially dense data may lead to unwarranted strong uncertainty reduction in estimation results

Feature extraction may alleviate this problem

Background

Ensemble-based methods

Degrees of freedom (DOF) is limited by ensemble size, E (assuming no localization)

E is usually moderately large ($\mathcal{O}(100)$)

Spatially dense data may lead to unwarranted strong uncertainty reduction in estimation results

Feature extraction may alleviate this problem

Subspace pseudo inversion is another alternative

Background

Balancing information and DOF

Background

Balancing information and DOF

Both feature extraction and subspace pseudo inversion reduce data influence

Background

Balancing information and DOF

Both feature extraction and subspace pseudo inversion reduce data influence

Hence, some of the information available is not applied in the data assimilation

Background

Balancing information and DOF

Both feature extraction and subspace pseudo inversion reduce data influence

Hence, some of the information available is not applied in the data assimilation

Need to balance the applied information content against available DOF

Scope

Balancing information and DOF

Scope

Balancing information and DOF

How to reduce data influence sufficiently to avoid unwarranted strong uncertainty reduction without discarding important information?

Scope

Balancing information and DOF

How to reduce data influence sufficiently to avoid unwarranted strong uncertainty reduction without discarding important information?

Alternatively:
How to increase ensemble size sufficiently to handle spatially dense data without increasing computational cost?

Reduce Data Influence

Approaches

Reduce Data Influence

Approaches

Data coarsening

Reduce Data Influence

Approaches

Data coarsening

Structure extraction

Reduce Data Influence

Approaches

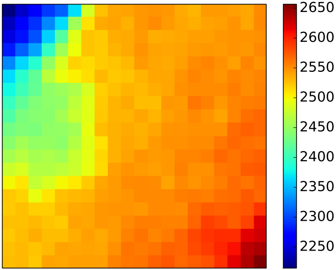
Data coarsening

Structure extraction

Subspace pseudo inversion

Reduce Data Influence–Approaches

Data coarsening

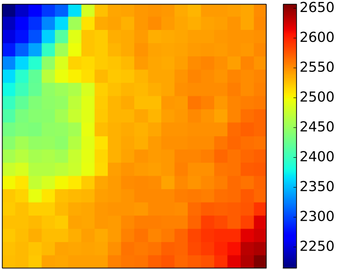


Data field

400 data

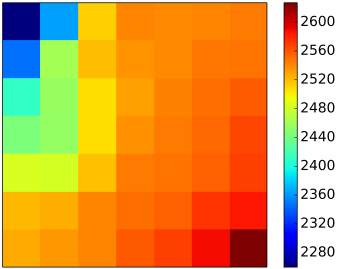
Reduce Data Influence–Approaches

Data coarsening



Data field

400 data

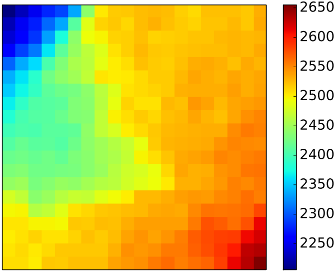


Coarsened data field

49 data

Reduce Data Influence–Approaches

Structure extraction

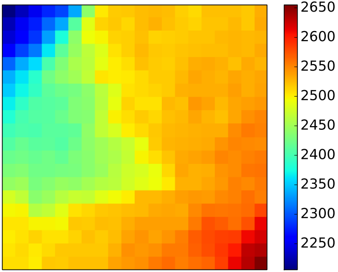


Data field

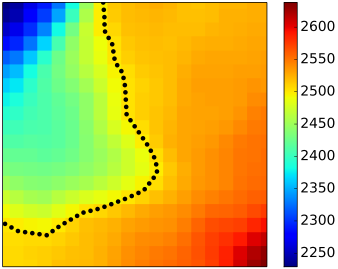
400 data

Reduce Data Influence–Approaches

Structure extraction



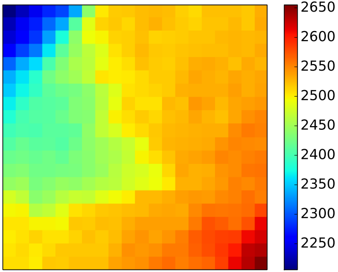
Data field
400 data



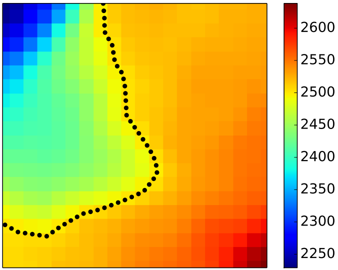
Smoothened field
with 60 data

Reduce Data Influence–Approaches

Structure extraction



Data field
400 data



Smoothened field
with 60 data

Structure data: point locations

Reduce Data Influence–Approaches

Subspace psudo inversion[1]

[1] Evensen G, Data Assimilation; the Ensemble Kalman Filter

Reduce Data Influence–Approaches

Subspace psudo inversion[1]

Matrix to be inverted in Kalman gain, $W = SS^T + (E-1)C_D$, may be (numerically) singular

[1] Evensen G, Data Assimilation; the Ensemble Kalman Filter

Reduce Data Influence–Approaches

Subspace psudo inversion[1]

Matrix to be inverted in Kalman gain, $W = SS^T + (E-1)C_D$, may be (numerically) singular

Use pseudo inverse, W^+, but this is costly for large no. of data

[1] Evensen G, Data Assimilation; the Ensemble Kalman Filter

Reduce Data Influence–Approaches

Subspace psudo inversion[1]

Matrix to be inverted in Kalman gain, $W = SS^T + (E-1)C_D$, may be (numerically) singular

Use pseudo inverse, W^+, but this is costly for large no. of data

Aproximate W by $B = SS^T + (E-1)SS^+C_D(SS^+)^T$, and use B^+ in Kalman gain

[1] Evensen G, Data Assimilation; the Ensemble Kalman Filter

Increase ensemble size without increasing cost

Approach–Upscaled simulations[2]

[2]Fossum K and Mannseth T, Coarse-scale data assimilation as a generic alternative to localization, Comput Geosci **21**(1) (2017)

Increase ensemble size without increasing cost

Approach–Upscaled simulations[2]

Standard forward model: $k(x) \rightarrow f(k(x))$

[2]Fossum K and Mannseth T, Coarse-scale data assimilation as a generic alternative to localization, Comput Geosci **21**(1) (2017)

Increase ensemble size without increasing cost

Approach–Upscaled simulations[2]

Standard forward model: $k(x) \to f(k(x))$

Upscaled forward model: $k(x) \to u(k(x)) \to f(u(k(x)))$

[2] Fossum K and Mannseth T, Coarse-scale data assimilation as a generic alternative to localization, Comput Geosci **21**(1) (2017)

Increase ensemble size without increasing cost

Approach–Upscaled simulations[2]

Standard forward model: $k(x) \rightarrow f(k(x))$

Upscaled forward model: $k(x) \rightarrow u(k(x)) \rightarrow f(u(k(x)))$

Computational cost $\sim$ solving linear system $\sim \mathcal{O}(G^{\beta})$; $\beta \in (1.25, 1.5)$

[2] Fossum K and Mannseth T, Coarse-scale data assimilation as a generic alternative to localization, Comput Geosci **21**(1) (2017)

Increase ensemble size without increasing cost

Approach–Upscaled simulations[2]

Standard forward model: $k(x) \to f(k(x))$

Upscaled forward model: $k(x) \to u(k(x)) \to f(u(k(x)))$

Computational cost $\sim$ solving linear system $\sim \mathcal{O}(G^\beta)$; $\beta \in (1.25, 1.5)$

Ensemble computational cost $\sim G^\beta E = G_u^\beta E_u \Rightarrow E_u = \left(\frac{G}{G_u}\right)^\beta E$

[2] Fossum K and Mannseth T, Coarse-scale data assimilation as a generic alternative to localization, Comput Geosci **21**(1) (2017)

Increase ensemble size without increasing cost

Approach–Upscaled simulations[2]

Standard forward model: $k(x) \rightarrow f(k(x))$

Upscaled forward model: $k(x) \rightarrow u(k(x)) \rightarrow f(u(k(x)))$

Computational cost $\sim$ solving linear system $\sim \mathcal{O}(G^{\beta})$; $\beta \in (1.25, 1.5)$

Ensemble computational cost $\sim G^{\beta}E = G_u^{\beta}E_u \Rightarrow E_u = \left(\frac{G}{G_u}\right)^{\beta} E$

Cost of E_u upscaled simulations equals that of E standard simulations

[2] Fossum K and Mannseth T, Coarse-scale data assimilation as a generic alternative to localization, Comput Geosci **21**(1) (2017)

Examples

Setup

Examples

Setup

Original data: bulk-velocity (V_p) pixel field

Examples

Setup

Original data: bulk-velocity (V_p) pixel field

Notation for labelling plots:

Original data: bulk-velocity (V_p) pixel field

Notation for labelling plots:

True: results obtained with pixel data and $E = 4800$

Examples

Setup

Original data: bulk-velocity (V_p) pixel field

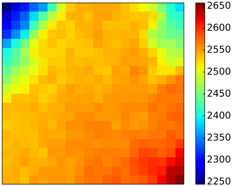
Notation for labelling plots:

True: results obtained with pixel data and $E = 4800$

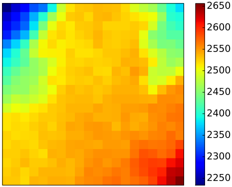
Estimate: results obtained with any type of data and computational cost corresponding to $E = 100$ standard simulations

Examples

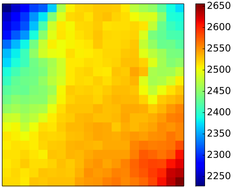
Pixel data



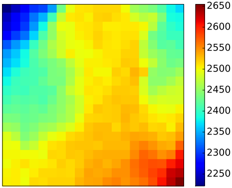
$t = t_1$



$t = t_2$



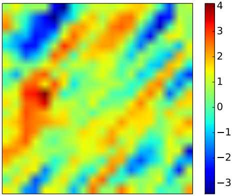
$t = t_3$



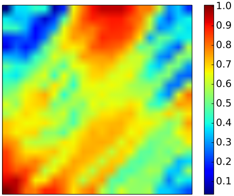
$t = t_4$

Examples

$k(x)$ estimate with pixel data on 20x20 grid



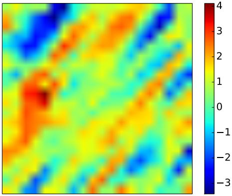
True mean



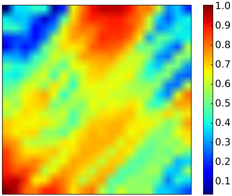
True stdv

Examples

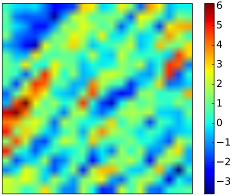
$k(x)$ estimate with pixel data on 20x20 grid



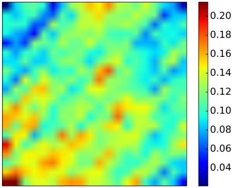
True mean



True stdv



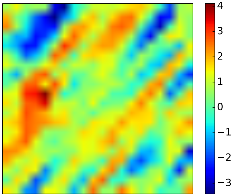
Estimate mean



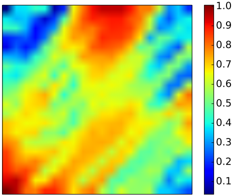
Estimate stdv

Examples

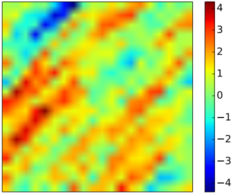
$k(x)$ estimate with data coarsening to 7x7 grid



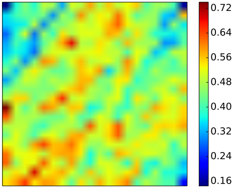
True mean



True stdv



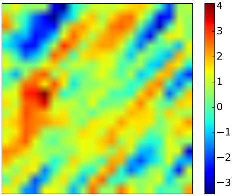
Estimate mean



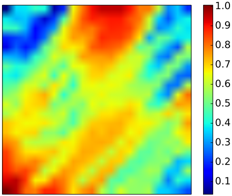
Estimate stdv

Examples

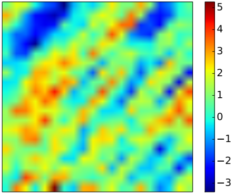
$k(x)$ estimate with 98% energy subspace pseudo inversion



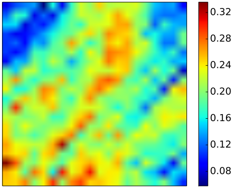
True mean



True stdv



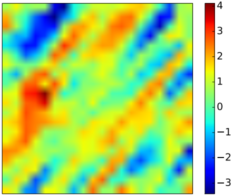
Estimate mean



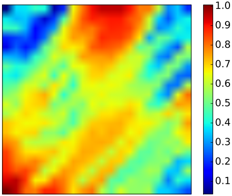
Estimate stdv

Examples

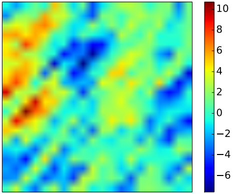
$k(x)$ estimate with 10x10 upscaled simulations



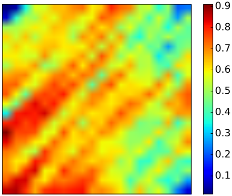
True mean



True stdv



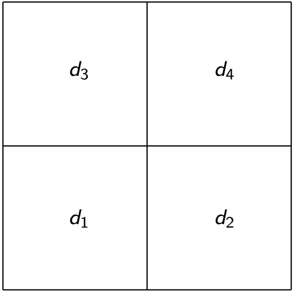
Estimate mean



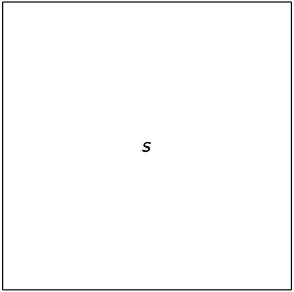
Estimate stdv

Grid Mismatch

Coarser simulation grid



Data-grid detail



Simulation-grid detail

Grid Mismatch

Coarser simulation grid

d_3	d_4
d_1	d_2

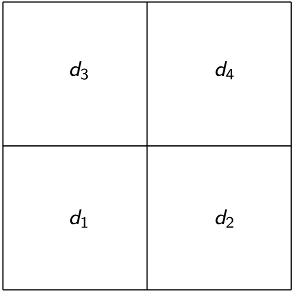
Data-grid detail

s	s
s	s

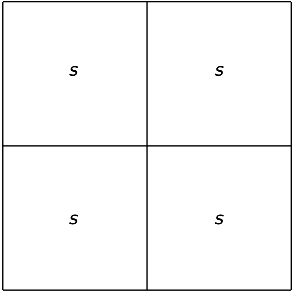
Simulation-grid detail after downscaling to data grid

Grid Mismatch

Coarser simulation grid



Data-grid detail



Simulation-grid detail after downscaling to data grid

s cannot match four different values

Grid Mismatch

Coarser simulation grid

d_3	d_4
d_1	d_2

Data-grid detail

s	s
s	s

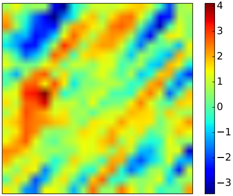
Simulation-grid detail after downscaling to data grid

s cannot match four different values

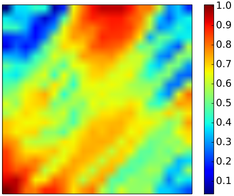
Not a problem with upscaled simulations and well data

Examples

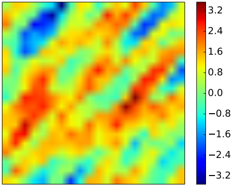
$k(x)$ estimate with 10x10 upscaled simulations and 10x10 data coarsening



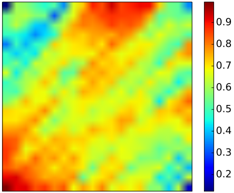
True mean



True stdv



Estimate mean



Estimate stdv

Summary

Summary

Investigated how to balance information against available DOF

Summary

Investigated how to balance information against available DOF

Three ways of reduction of data-space influence (data coarsening, structure extraction, subspace pseudo inversion) and one way of increasing ensemble size without increasing cost (upscaled simulations) have been considered

Summary

Investigated how to balance information against available DOF

Three ways of reduction of data-space influence (data coarsening, structure extraction, subspace pseudo inversion) and one way of increasing ensemble size without increasing cost (upscaled simulations) have been considered

Reduction of data-space influence (all three ways) gave some improvement, with structure extraction as the least successful

Summary

Investigated how to balance information against available DOF

Three ways of reduction of data-space influence (data coarsening, structure extraction, subspace pseudo inversion) and one way of increasing ensemble size without increasing cost (upscaled simulations) have been considered

Reduction of data-space influence (all three ways) gave some improvement, with structure extraction as the least successful

Upscaled simulations did not give good results

Summary

Investigated how to balance information against available DOF

Three ways of reduction of data-space influence (data coarsening, structure extraction, subspace pseudo inversion) and one way of increasing ensemble size without increasing cost (upscaled simulations) have been considered

Reduction of data-space influence (all three ways) gave some improvement, with structure extraction as the least successful

Upscaled simulations did not give good results

Upscaled simulations combined with data coarsening gave good results, particularly when scales of simulation grid and data grid were similar

Acknowledgements

Partial financial support was provided by the CIPR/IRIS cooperative project '4D Seismic History Matching', which is funded by industry partners Eni, Petrobras and Total, as well as the Research Council of Norway (PETROMAKS II)