Correlation-Based Localization

Implementation and Analysis with a Reservoir Model

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NORCE

Background

- Anderson (2007); Bishop and Hodyss (2007); Fertig et al. (2007) The original papers on correlation-based localization.
- Evensen (2009) Correlation-based localization in EnKF for linear advection equation.
- Luo and Bhakta (2020); Luo et al. (2019) Digires using Luo-IES with Norne?
- Neto et al. (2021) Digires using subspace EnRML with field model from Petrobras.
- Soares et al. (2021) Digires using Luo-IES (from Luo) with Norne?
- Le et al. (2016) Adaptive ESMDA.

I find that these papers don't provide a very deep analysis.

Problem definition

- The Digires papers were positive to correlation-based localization.
- Remus wanted to test correlation-based localization in ERT.

→ Implementation project with Equinor.

Approach

ERT solves for the ensemble update

$$\mathbf{X}^{\mathrm{a}} = \mathbf{X}^{\mathrm{f}}\mathbf{T}. \tag{1}$$

- Local analysis computes the update one row at the time

$$\mathbf{X}_i^{\mathrm{a}} = \mathbf{X}_i^{\mathrm{f}}\mathbf{T}_i \tag{2}$$

- One parameter: **correlation trucation value**.
- No tapering (yet).
- https://github.com/equinor/iterative_ensemble_smoother
- https://github.com/equinor/ert

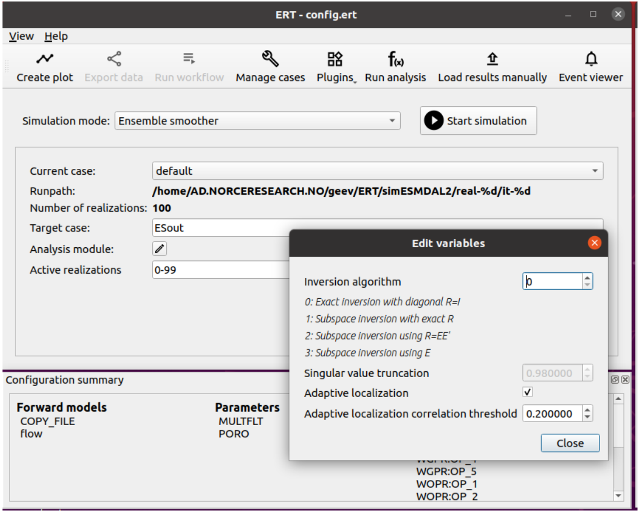
Why do we need localization?

- Everybody else uses localization, and Patrick says it is necessary.
- We cannot afford to run a sufficiently large ensemble.
- We need a larger ensemble space to fit all the information in the data.
- We need to reduce the impact of spurious correlations as they lead to underestimated variance.
- We will likely get better results with localization.

Why not distance-based localization?

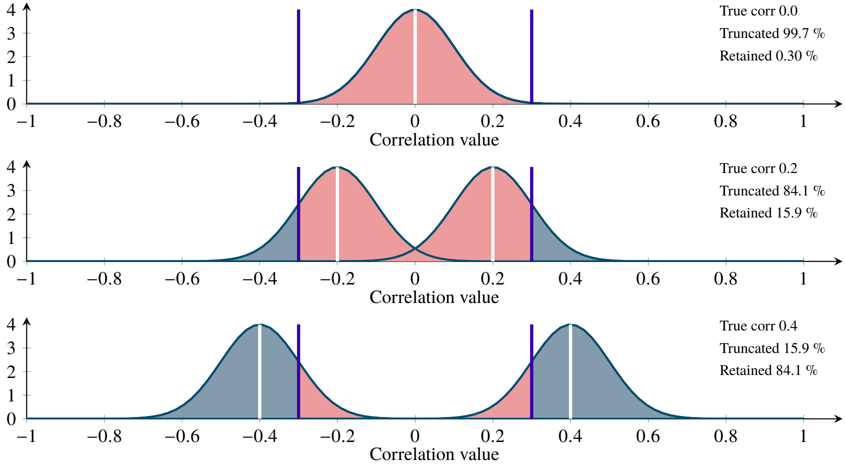
- ERT already has a distance-based localization scheme (it is intricate to use, though).
- Correlation-based localization would be easier to use if it works.

ERT Menu

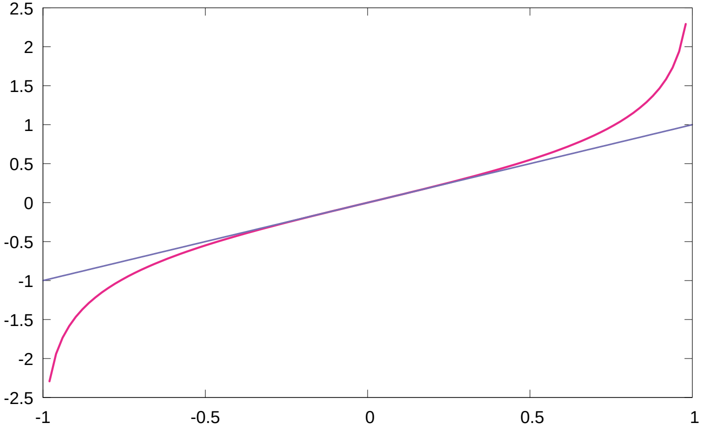


ERT - config.ert
View
Help
Create plot
Export data
Run workflow
Manage cases
Plugins
Run analysis
Load results manually
Event viewer
Simulation mode:
Ensemble smoother
Start simulation
Current case:
default
Runpath:
/home/AD.NORCERESEARCH.NO/geev/ERT/simESMDAL2/real-%d/it-%d
Number of realizations:
100
Target case:
ESout
Analysis module:
Active realizations
0-99
Edit variables
Inversion algorithm
0
0: Exact inversion with diagonal R=I
1: Subspace inversion with exact R
2: Subspace inversion using R=EE'
3: Subspace inversion using E
Singular value truncation
0.980000
Adaptive localization
Adaptive localization correlation threshold
0.200000
Close
Configuration summary
Forward models
COPY_FILE
flow
Parameters
MULTFLT
PORO
WGPR:OP_5
WOPR:OP_1
WOPR:OP_2

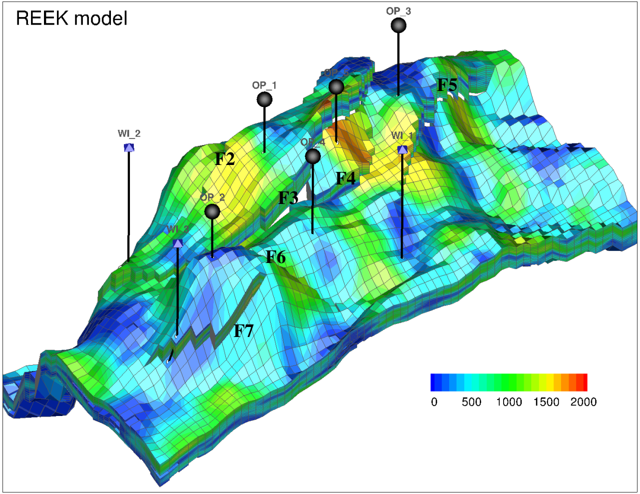
Truncation scheme (100 realizations)



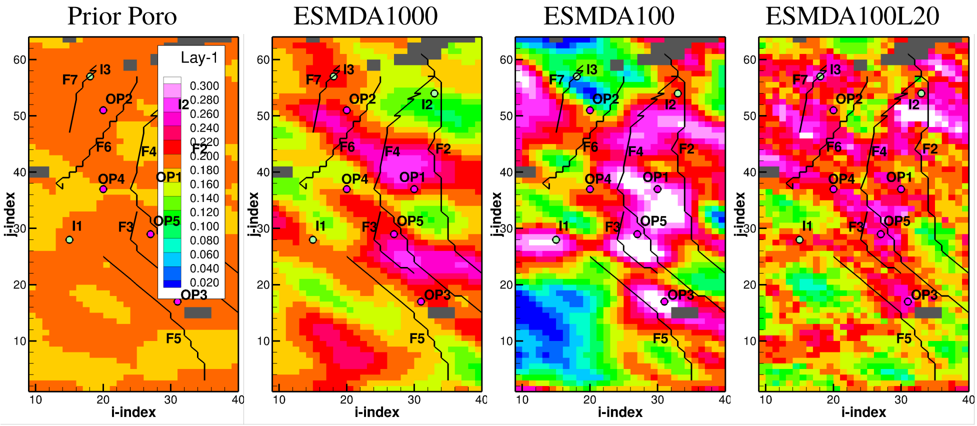
Fisher transformation



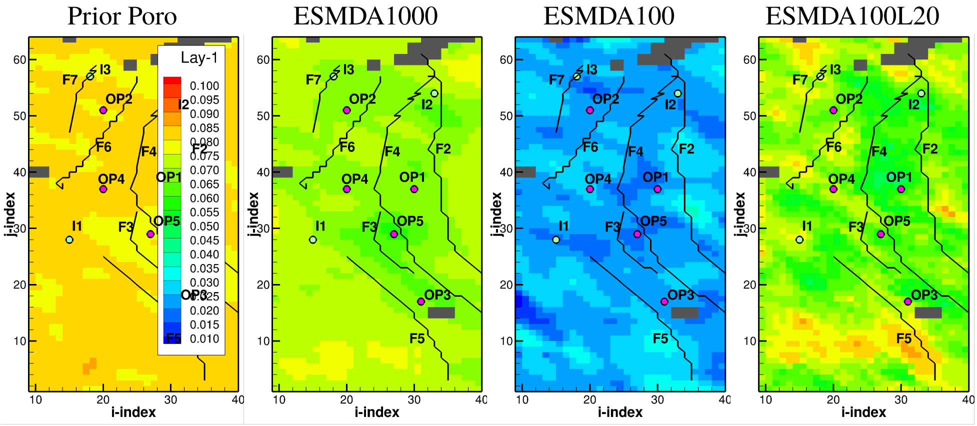
REEK



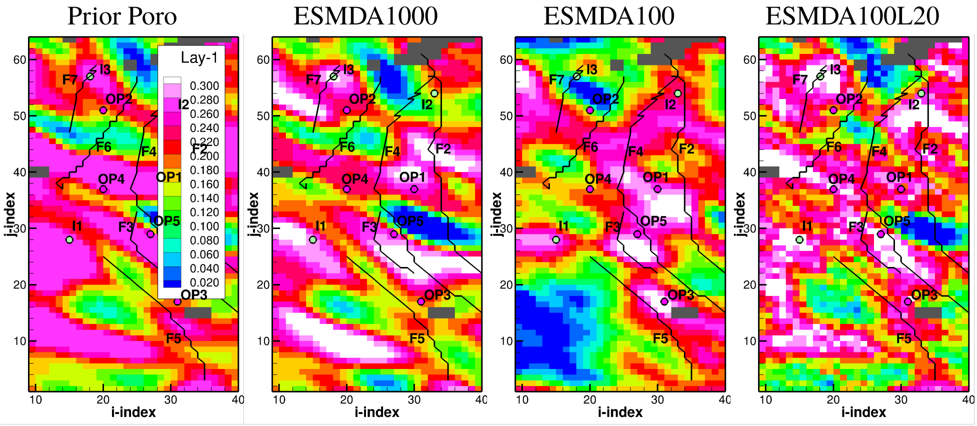
Example porosity mean, Layer 3



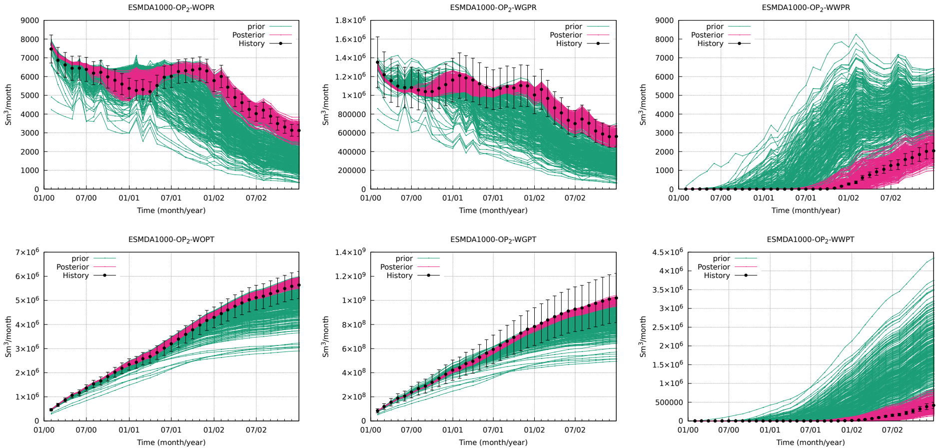
Example porosity std dev, Layer 3



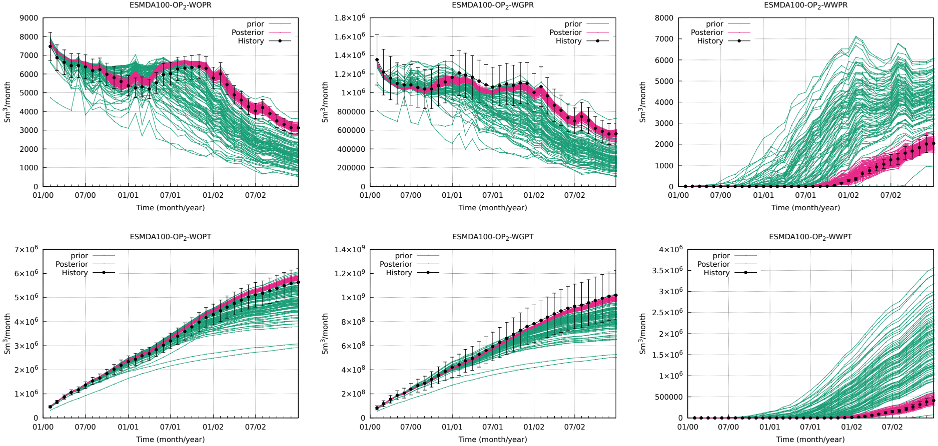
Example porosity real-1, Layer 3



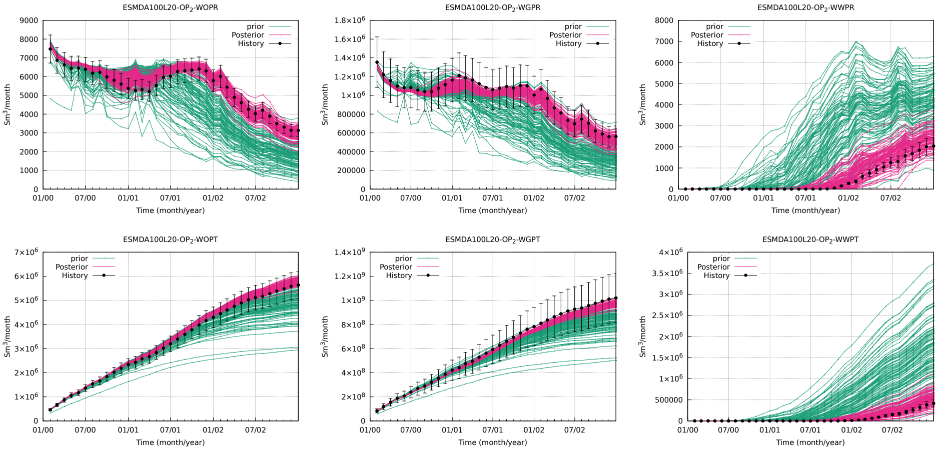
ESMDA1000


ESMDA1000-OP2-WOPR
ESMDA1000-OP2-WGPR
ESMDA1000-OP2-WWPR
ESMDA1000-OP2-WOPT
ESMDA1000-OP2-WGPT
ESMDA1000-OP2-WWPT
prior
Posterior
History
Sm3/month
Time (month/year)
01/00
07/00
01/01
07/01
01/02
07/02

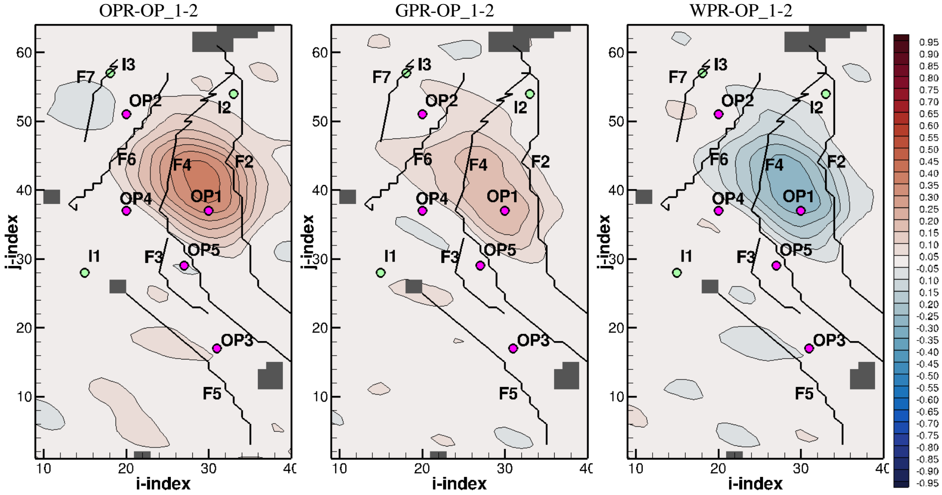
ESMDA100


ESMDA100-OP$_2$-WOPR
ESMDA100-OP$_2$-WGPR
ESMDA100-OP$_2$-WWPR
ESMDA100-OP$_2$-WOPT
ESMDA100-OP$_2$-WGPT
ESMDA100-OP$_2$-WWPT
prior
Posterior
History
Sm^3/month
Time (month/year)
01/00
07/00
01/01
07/01
01/02
07/02

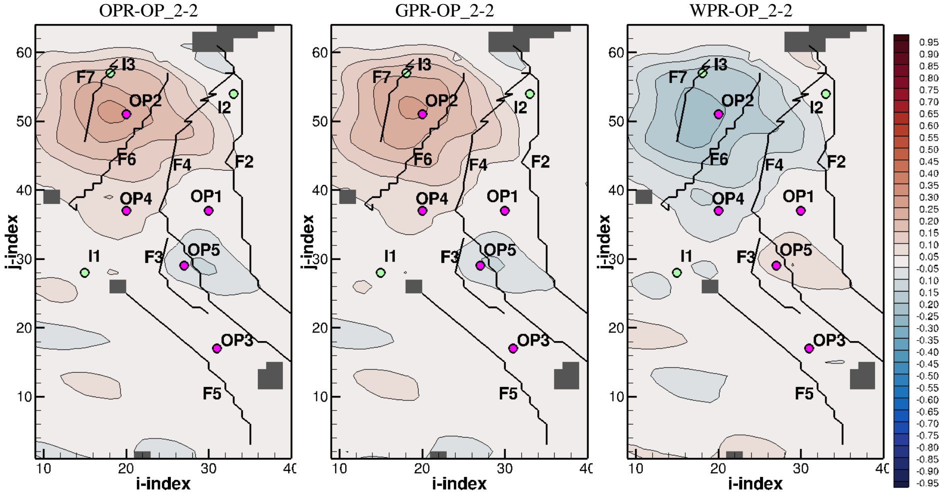
ESMDA100L20



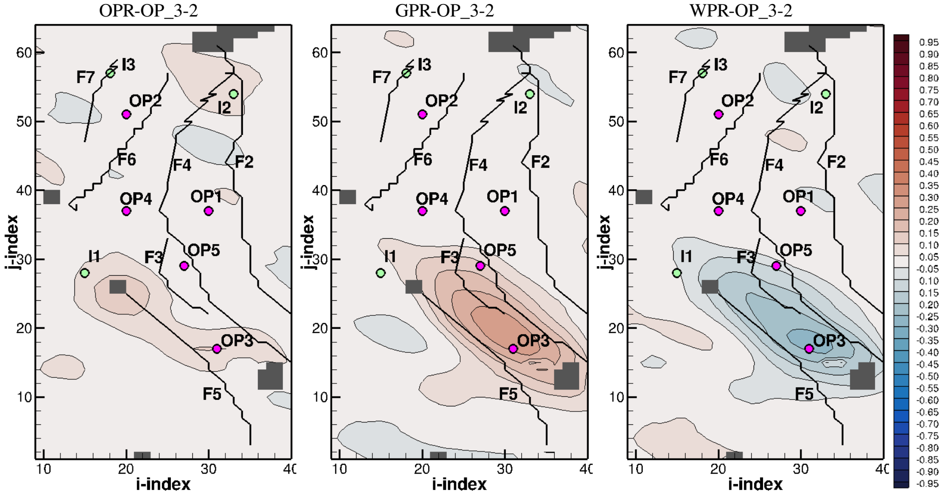
ESMDA1000-OP_1



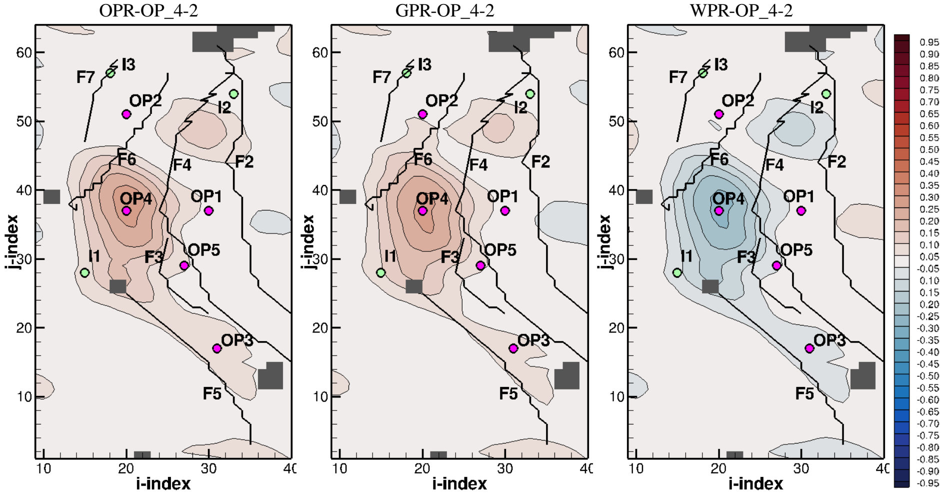
ESMDA1000-OP_2



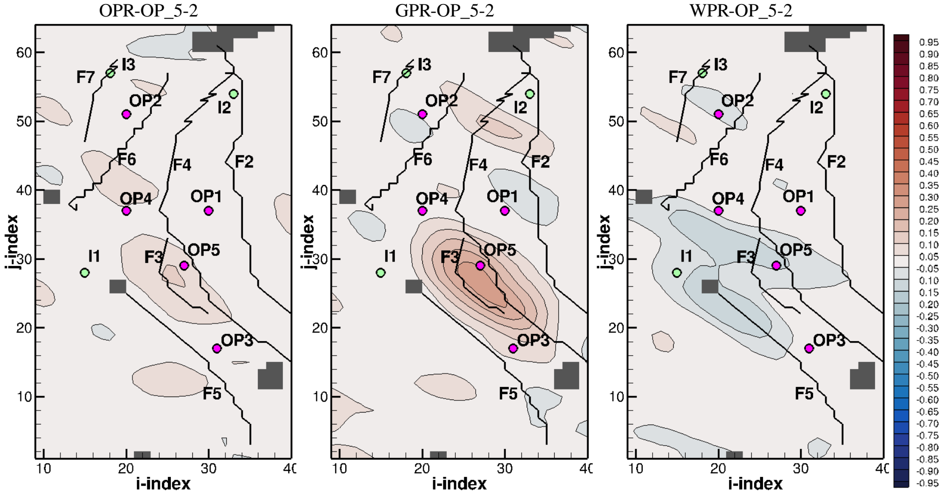
ESMDA1000-OP_3



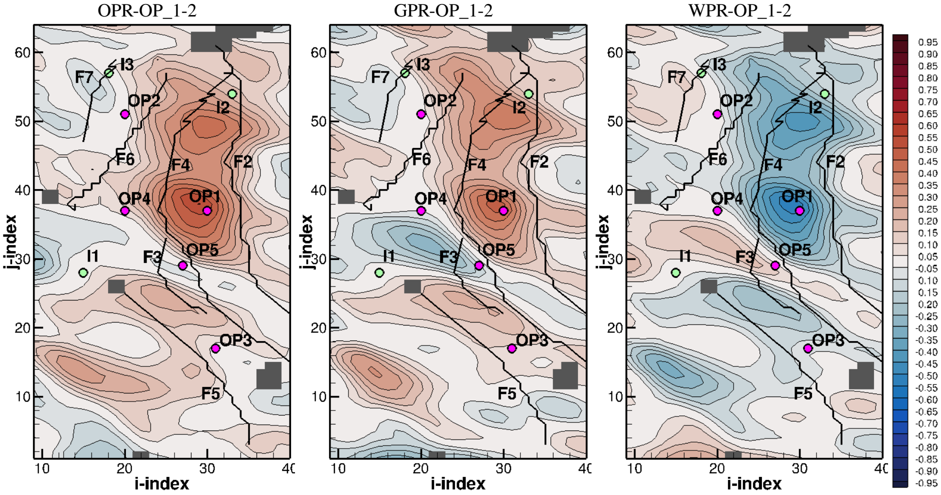
ESMDA1000-OP_4



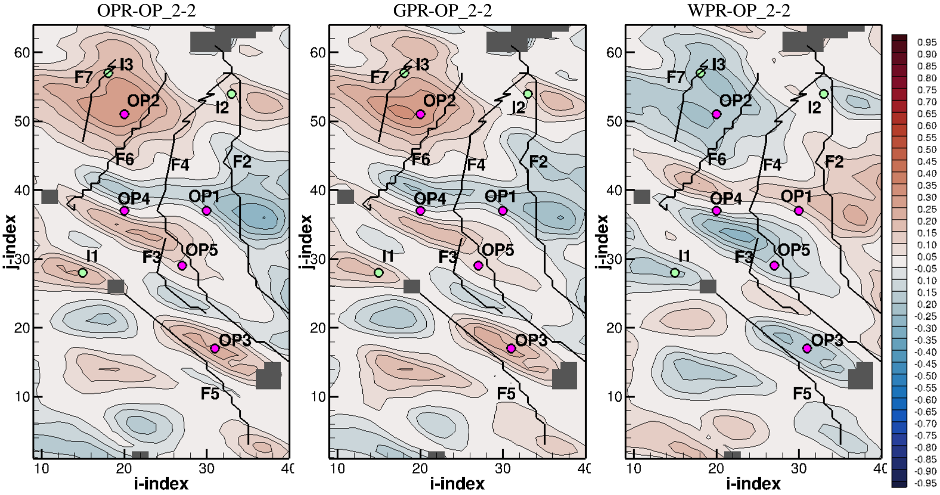
ESMDA1000-OP_5



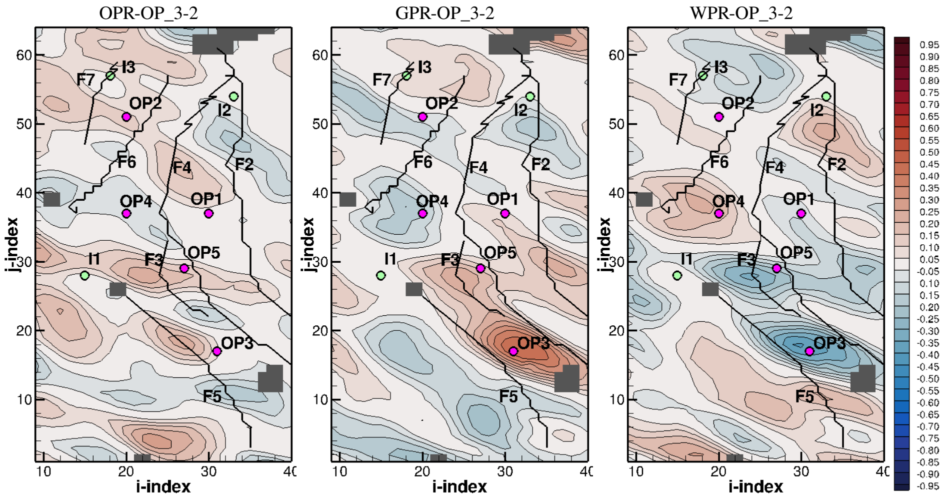
ESMDA100-OP_1



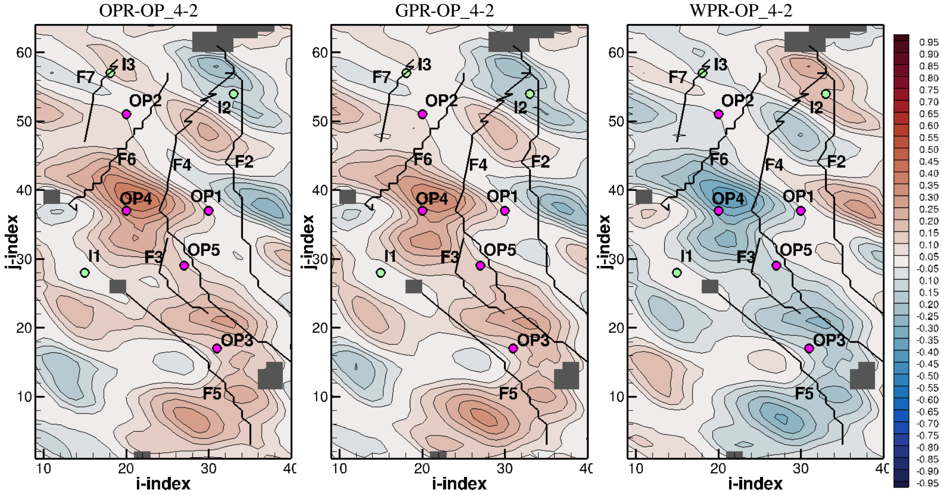
ESMDA100-OP_2



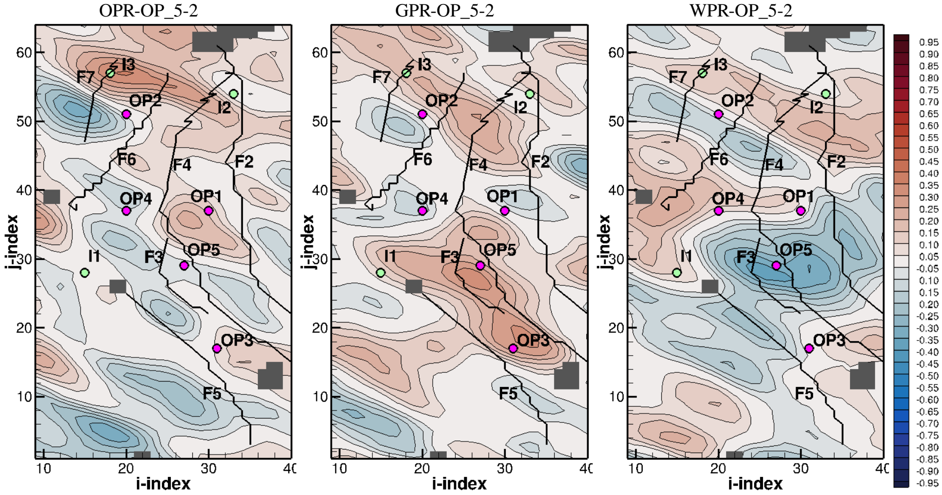
ESMDA100-OP_3



ESMDA100-OP_4



ESMDA100-OP_5



Conclusion

- Correlation-based localization results in a good fit to the data.
- It retains more of the ensemble variance.
- Minimal update to the prior that leads to a history match.
- I would be more comfortable by increasing the ensemble size.
- The physical correlations have a magnitude similar to the sampling errors (100 realizations).
- Ongoing work and we need to analyze more.

Anderson, J. L. Exploring the need for localization in the ensemble data assimilation using a hierarchical ensemble filter. *Physica D*, 230:99–111, 2007. doi:10.1016/j.physd.2006.02.011.

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