CERFACS

CENTRE EUROPÉEN DE RECHERCHE ET DE FORMATION AVANCÉE EN CALCUL SCIENTIFIQUE

GIS

Uncertainty Quantification @Paris-Saclay

Groupe de travail « Assimilation de données »

Inauguration October 18th, 2022

https://uq-at-paris-saclay.github.io/news/inauguration/

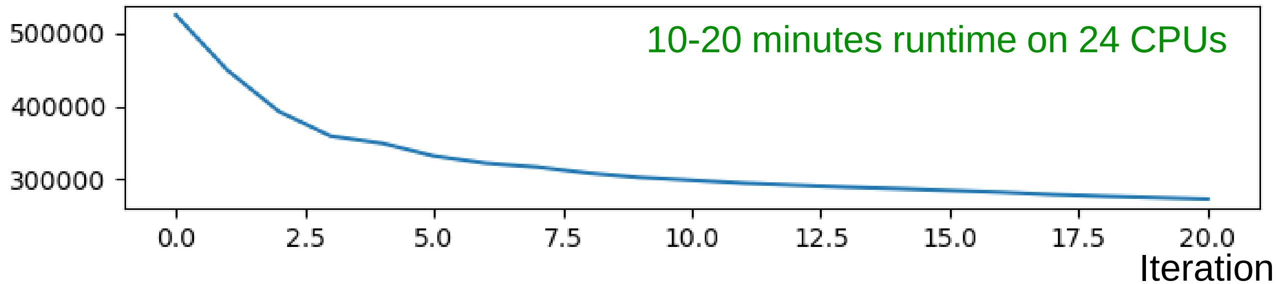
A brief overview of DA @CERFACS

Improve DA methods for Earth system and environmental applications in modelling and prediction mode

- Data assimilation algorithms: variational, ensemble-based and hybrid strategies
- Description of covariance matrices model and observations
- Strategies for the assimilation of heterogeneous and innovative data

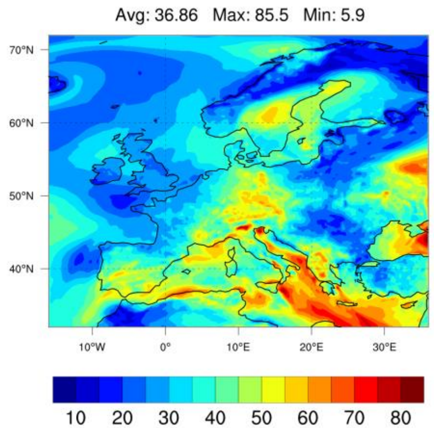
Ensemble-variational 4DEnVar for air quality forecasts (E. Emili@CERFACS) to deal with moderate resolutions (10-20 km over Europe) and multi-variate dimension (up to 100 chemical species)

4DEnVar cost function

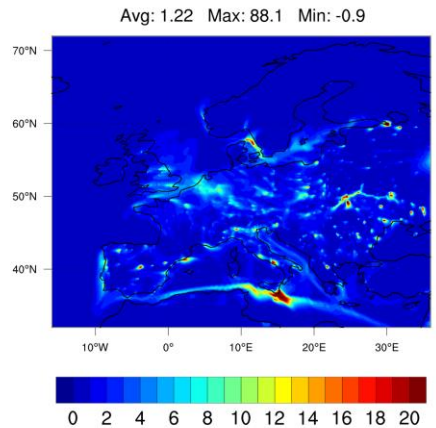


Analysis daily average

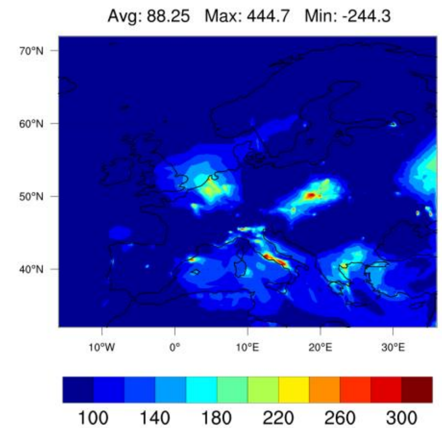
Ozone O_3 (ppb)



Nitrogen dioxide NO_2 (ppb)



Carbone Monoxide CO (ppb)



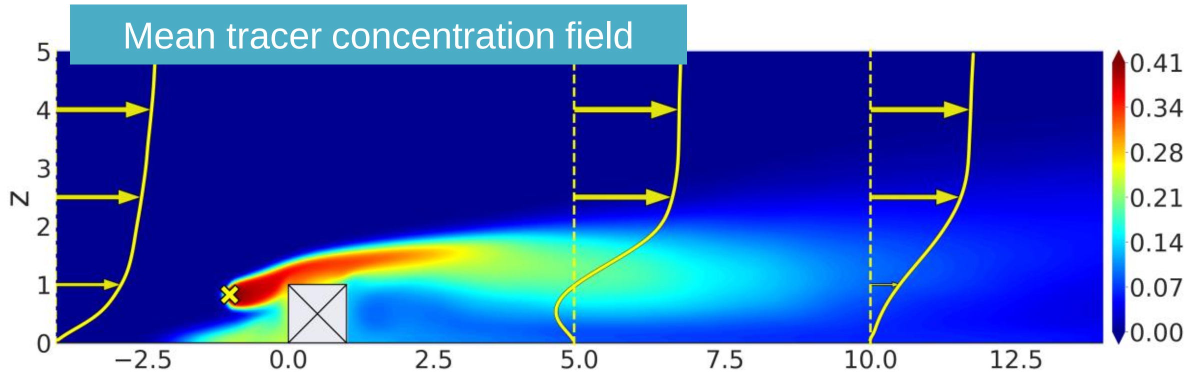
Parametric reduced-order modeling for atmospheric boundary layer flows for pollutant dispersion and micrometeorology (M. Rochoux@CERFACS)

4 parameters → **Parametric reduced-order model** →

$$K \equiv K(x, y, \boldsymbol{\theta}) = \sum_{m=1}^{N_{\text{modes}}} p_m(\boldsymbol{\theta})\, \psi_m(x, y)$$

GPR (Gaussian process regression) metamodel

POD (Proper Orthogonal Decomposition) reduced basis

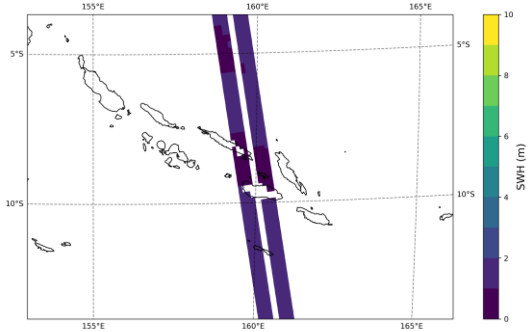


AVBP

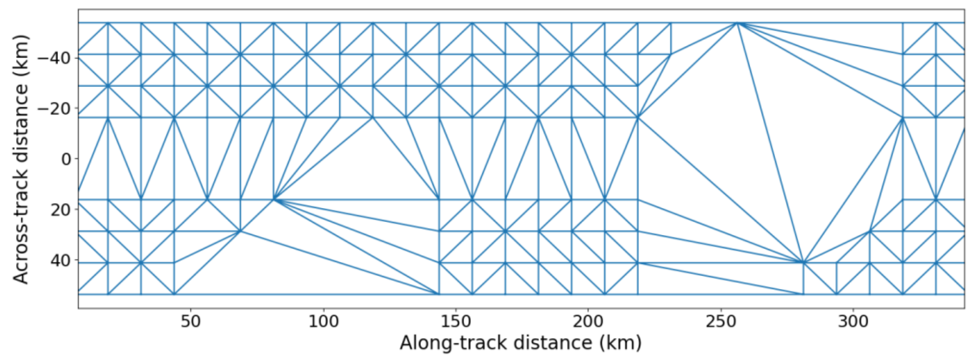
Description of covariance matrices model and observations

Represent the covariances of remote sensing observation errors for ocean data assimilation dynamics with a diffusion operator (A. Weaver@CERFACS)

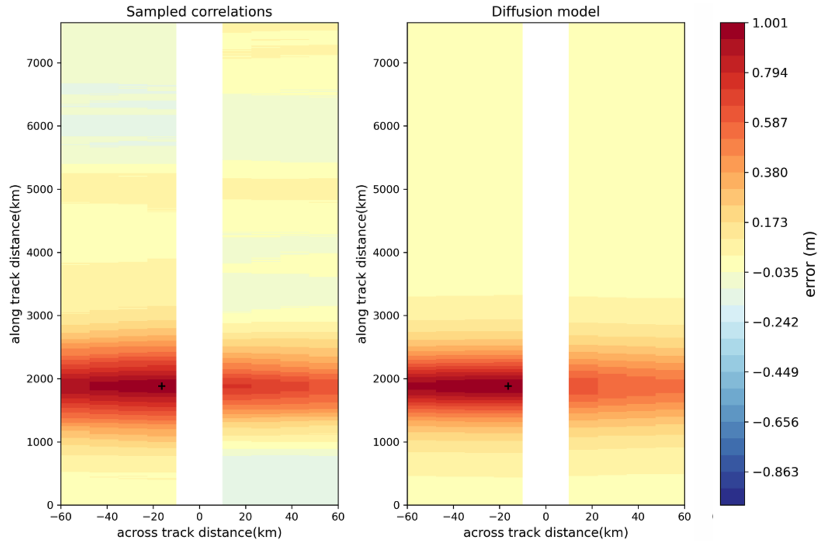
Simulated satellite track from SWOT



Gaps due to land, missing data and quality control



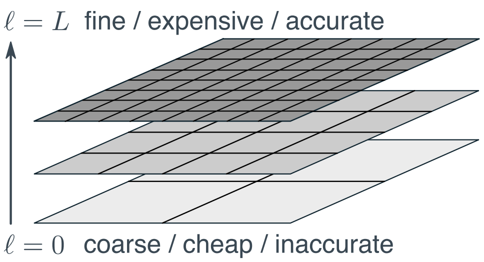
Estimated error correlations from the SWOT simulator (calibrated)

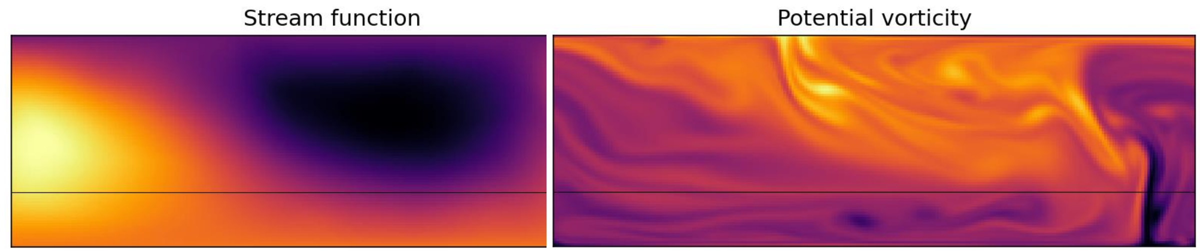


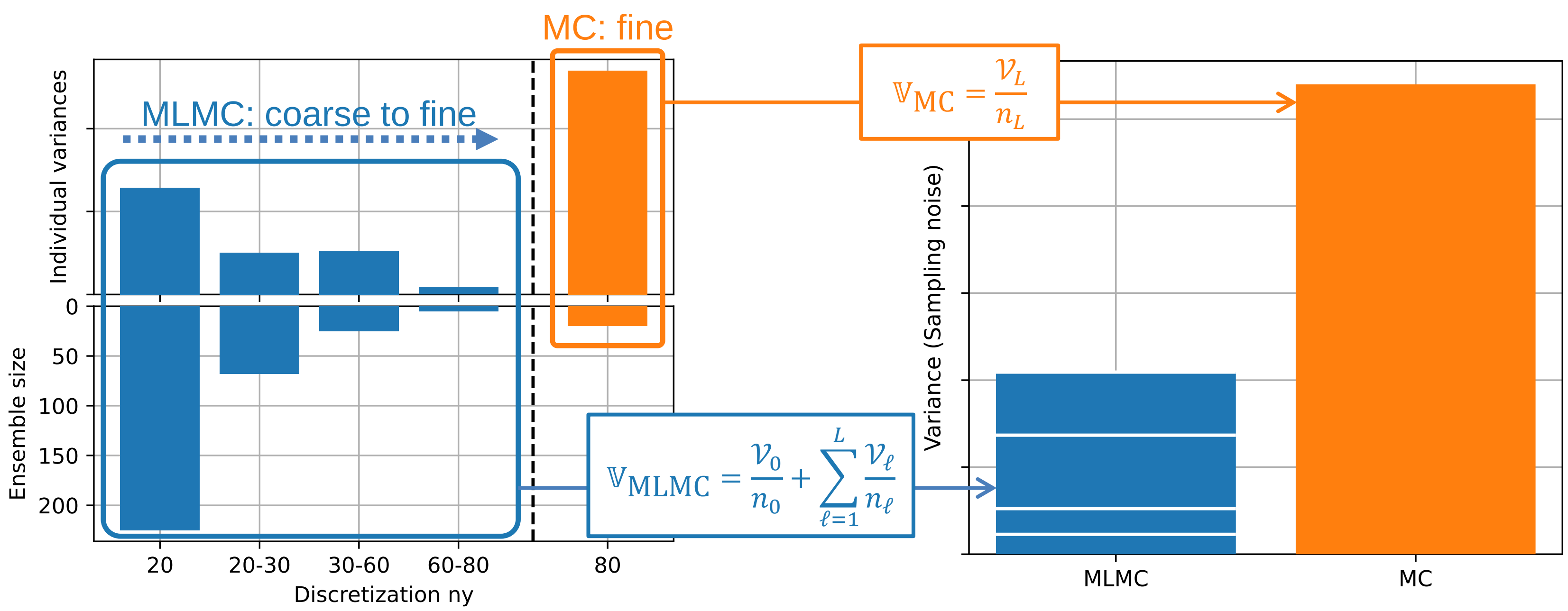
SWOT error correlations modelled with a diffusion operator

Description of covariance matrices model and observations

Multifidelity estimation of the background covariance matrix for ensemble variational DA with a quasi-geostrophic model (P. Mycek@CERFACS)

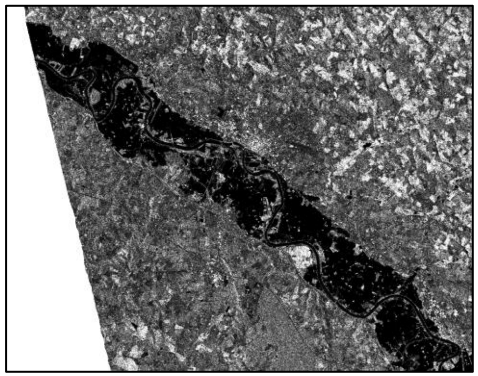


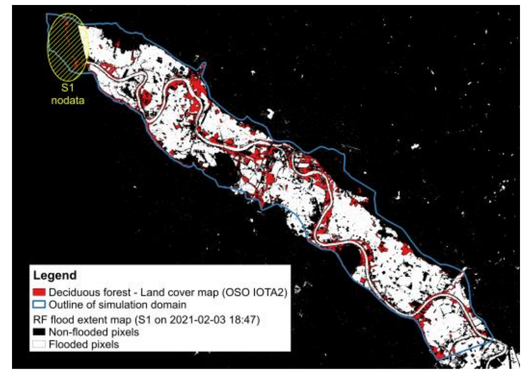




Strategies for the assimilation of heterogeneous and innovative data

Assimilation of remote sensing data for flood forecasting complementary with in-situ data, dealing with non-gaussianity in ensemble based algorithms (S. Ricci@CERFACS)



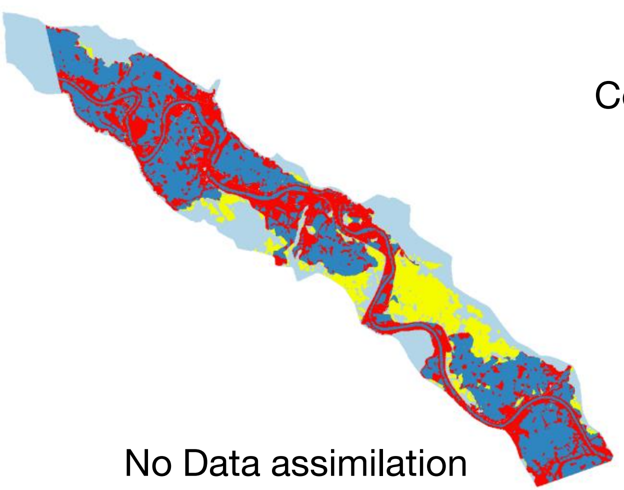


Flood extents derived from Sentinel-1 images

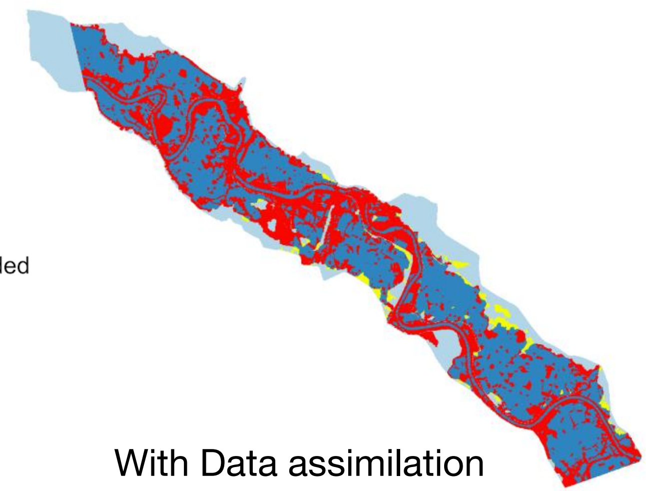
Contigency maps

2021/02/03 19:00

Legend
- Correctly predicted - Non flooded
- Correctly predicted - Flooded
- Underprediction
- Overprediction



No Data assimilation



With Data assimilation

Challenges in Data Assimilation

- Sensitivity analysis for control vector definition

- Estimation of model error
- Optimization for large dimension, non-linear models in variational algorithms

- Deal with large dimension (methods for dimension reduction)
- Deal with expensive solvers (methods for surrogate models)
- Deal with non-linear solvers (preconditioning),

- Modelling and/or stochastic estimation for error covariances
- Enhance DA methods with UQ and Machine/Deep Learning techniques

- Deal with non-gaussian errors for model state and observations (advanced algo, anamorphosis, …)

- Assimilation of novel forms, heterogeneous, (i.e. remote sensing) data with associated obs. operators

Challenges in Data Assimilation

- Sensitivity analysis for control vector definition

Compute SA (Sobol, Shapley indices), for dependant variables, large dimension reduction, surrogate model with mixture of experts
Collab. EDF, ISAE, Airbus, Météo-France, ENAC, ONERA , IRT

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Statistical strategies for bias removal with random forest algorithm
Collab. with Météo-France, EDF, CEREMA

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Formulate surrogates for non stationary flows in reduced dimension
Collab. EDF, LISN

- Deal with non-linear solvers (preconditioning),

Transform non quadratic cost function into quadratic with preconditioning, reduce dimension to most important error growth directions,…
Collab. ECMWF, IRIT

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Collab. ANITI, ECMWF, IRIT, …

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Advanced algorithm with particular filters, Anamorphosis with EnKF to move to gaussian space
Collab. CNES, IRIT, IRD

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- Assimilation of novel forms, heterogeneous data with associated obs. operators

Assimilate remote sensing data, 2D maps, along track data, with non gaussian errors, front-like data with associated metrics, integrated data, …
Collab. Météo France, CNES, CLS, …

Challenges in Data Assimilation

Working group in Data Assimilation

- As of today, ONERA, EDF, IFPEN, CEA are part of the GT-DA
- ONERA shared some interest on these topics, especially on data inversion, bayesian inversion and optimization, machine learning for DA.

How to get started with the GT

- Suggest internships in collaboration between GIS-LARTISSTE members
- Elaborate on existing applications as much as possible
- Share interest on your won applications
- Share knowledge and code on existing (on going) work