Salient results from the Merging Ocean Models and Observations at the Meso and Sub-mesoscales (MOMOMS) project

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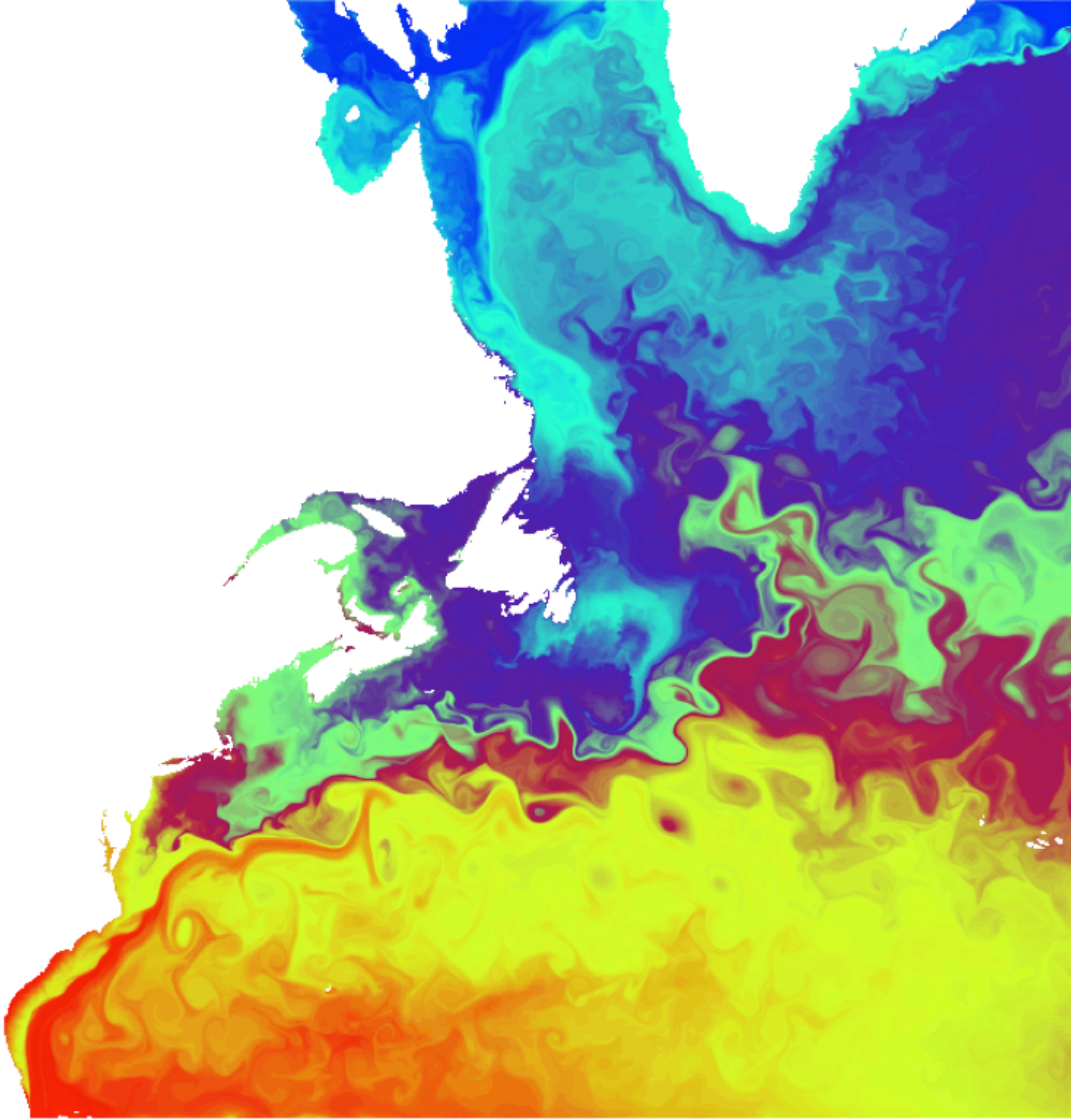
Abstract

This contribution highlights progresses made in the Merging Ocean Models and Observations at the Meso and Sub-mesoscales (MOMOMS) OSTST project. The project mainly focused on (i) Observability of mesoscale dynamics by altimetry, (ii) new, multi-scale algorithms for data inversion and assimilation, and (iii) multi-sensor based ocean reconstruction. Two new algorithms are presented to address the assimilation of non-local observations, i.e. observations possibly affected by geographically distant quantities, and the assimilation of observation sets containing non-local, large-scale signature. Both problems are rendered difficult in Ensemble data assimilation by the necessary use of analysis localization techniques. Applications with altimetry are presented. The presentation also introduces an algorithm combining the assimilation of altimetry, which adjusts the mesoscale dynamics, with the assimilation of SST images to adjust the finer scales. Finally, the benefit of assimilating (future) surface current observation in addition to altimetry is shortly illustrated.

3 axes of research

- Observability of mesoscale dynamics by altimetry
- New, multi-scale algorithms for data inversion and assimilation
- Multi-sensor based ocean reconstruction

Results from the last two items are shown in the following slides.

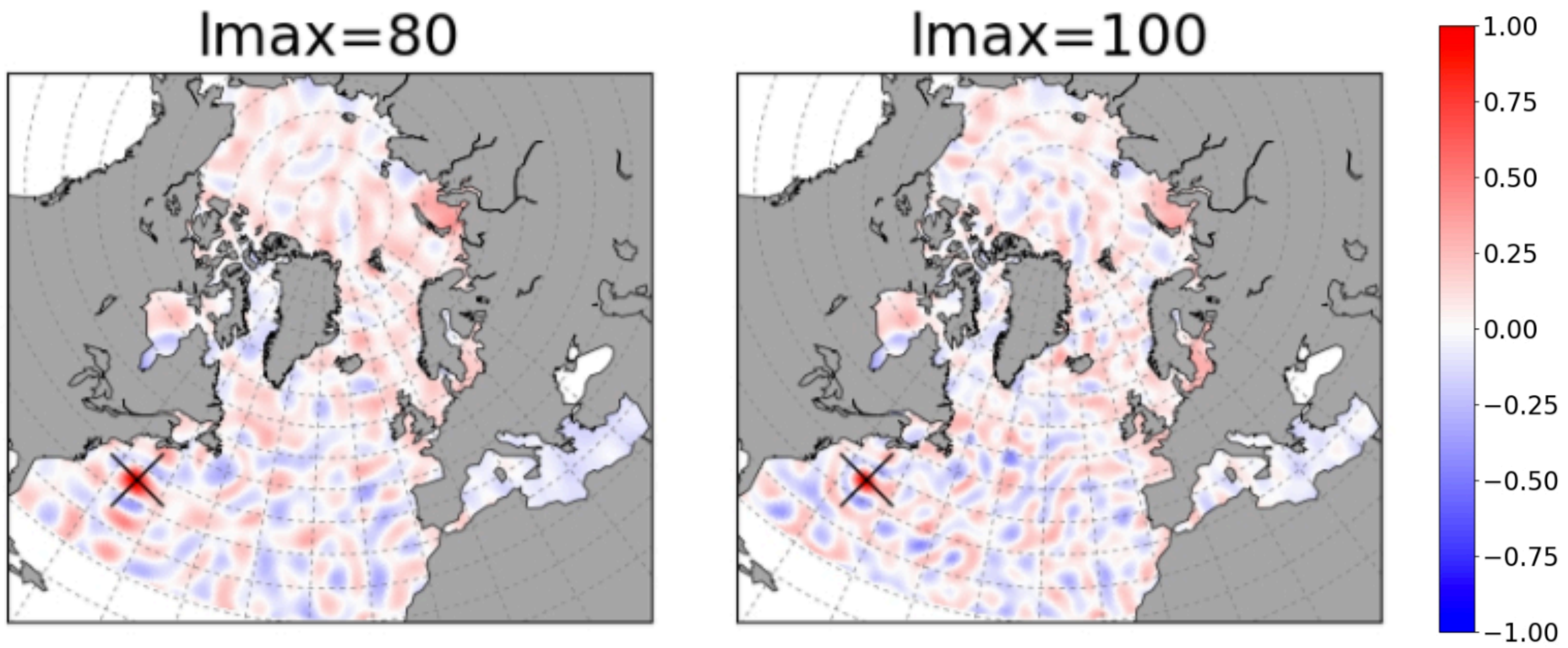


A multiscale ocean data assimilation approach combining spatial and spectral localisation

Background:

Data assimilation aims at correcting model variables using observations. In ensemble data assimilation, each single observation can affect distant variables based on ensemble correlations. Spurious correlations due to subsampling (small ensemble size) induce spurious corrections. This forces to localize the analysis, i.e. limit the impact of each observation to a short geographical radius. This process, called spatial localization, rules out the possible large scale signature of observations.

Figure: Correlations with SSH at gridpoint indicated by a cross, from a 69-members ensemble of NEMO 1/4° simulations of the Arctic Ocean. Small scales have been removed using a spherical harmonic decomposition and truncation of higher modes. Left and right figures result from 2 different truncations. Both display long-distance (and likely inadequate) correlations.



Tissier et al, www.ocean-sci.net/15/443/2019/

A multiscale ocean data assimilation approach combining spatial and spectral localisation

Strategy:

It is proposed to decompose the ensemble members on spherical harmonics, and perform the Ensemble Kalman Filter analysis with the spectral coefficients, with localization applied in the spectral space. An inverse transformation provides the analysis ensemble in the physical space.

Spatial and spectral localizations are combined to draw the maximum benefit from both (for small-scale processes and large-scale processes, respectively).

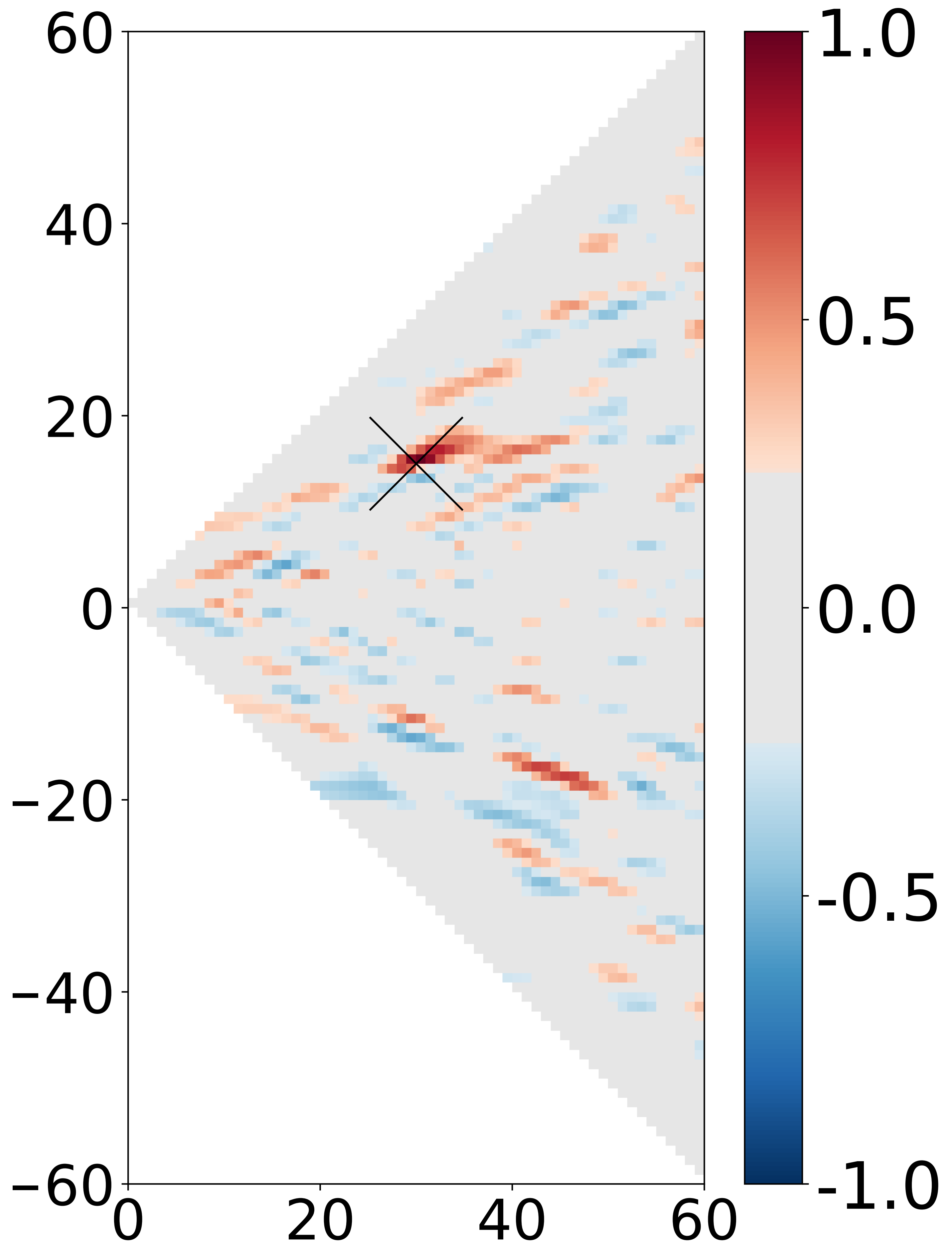


Figure: Ensemble correlations with the point indicated by the cross, in the spectral space. Abscissa and ordinate indicates the l and m degrees (standard notation for spherical harmonics) respectively. Distant correlations exist, but can be mitigated using localization in this spectral space.

Tissier et al, www.ocean-sci.net/15/443/2019/

A multiscale ocean data assimilation approach combining spatial and spectral localisation

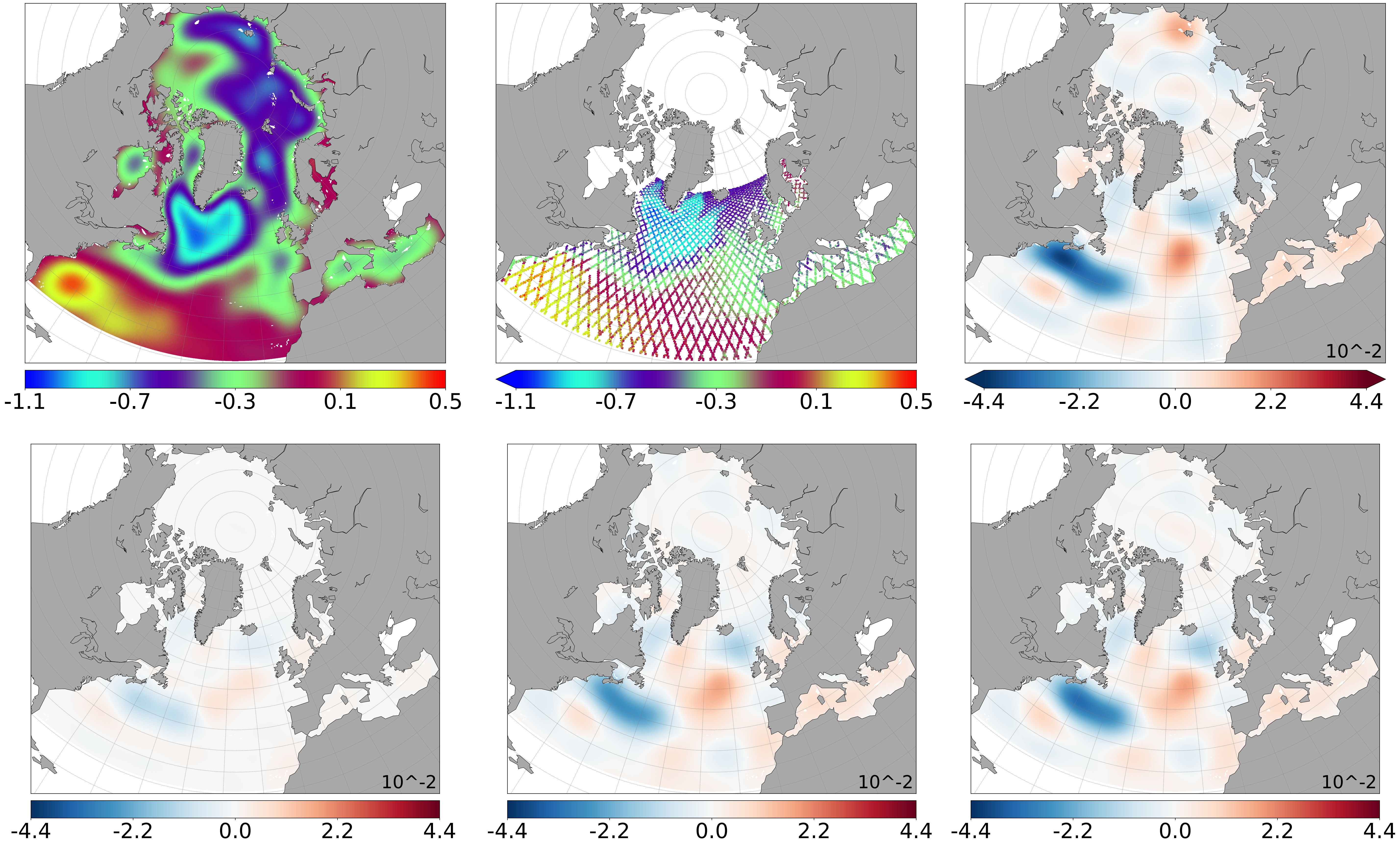


Figure:
Top, from left to right: Ensemble mean of SLA, simulated nadir observations, ensemble mean anomaly (difference with true SLA field, simulated with NEMO; target of the analysis).
Bottom, from left to right: Correction from the Ensemble Kalman Filter analysis with only spatial localization, only spectral localization, and the combination of both.
Only the large scales (> 200 km) are shown here.

Tissier et al, www.ocean-sci.net/15/443/2019/

Implicitly Localized MCMC Sampler to Cope With Non-local Data Constraints in Large-Size Inverse Problems

Background:
In high-dimensional inversion problems, sample-based Bayesian inversion methods are limited by the sample size. Ensemble assimilation of geophysical data is generally implemented with covariance localization techniques, which limit the geographical extent of the impact of each individual observation in the analysis. This is actually acceptable with local observations, but not with non-local observations. This work investigates a localized Monte Carlo Markov Chain (MCMC) sampling method that unifies the notions of covariance localization and non-local observations.

This work is exposed in more details in a thematic splinter.

Brankart 2020, https://www.frontiersin.org/articles/10.3389/fams.2019.00058

Implicitly Localized MCMC Sampler to Cope With Non-local Data Constraints in Large-Size Inverse Problems

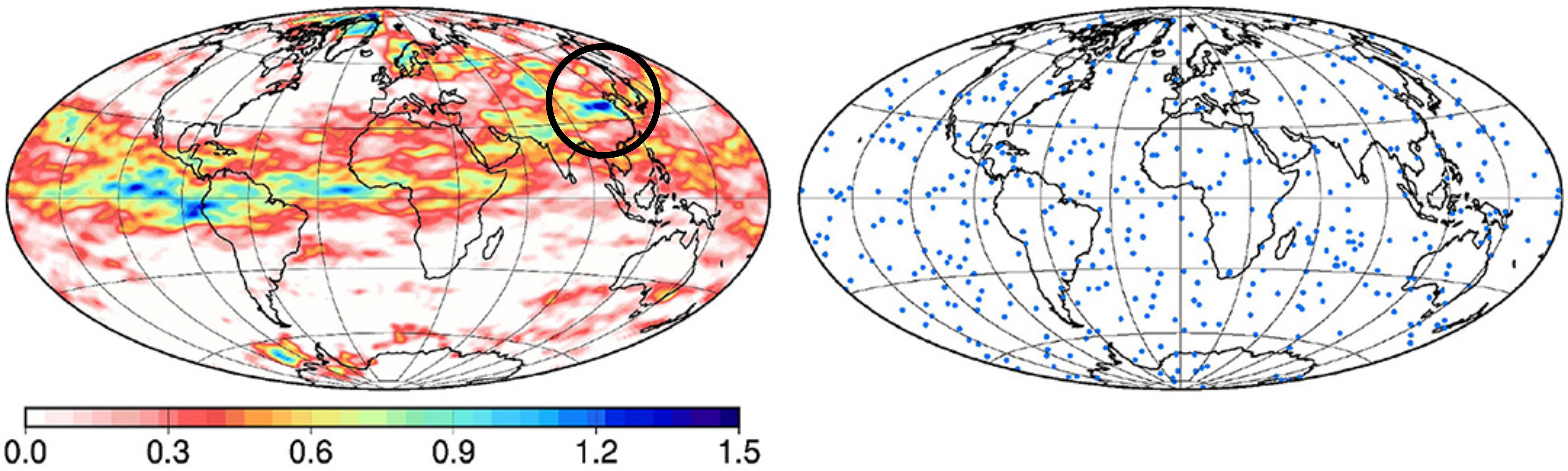


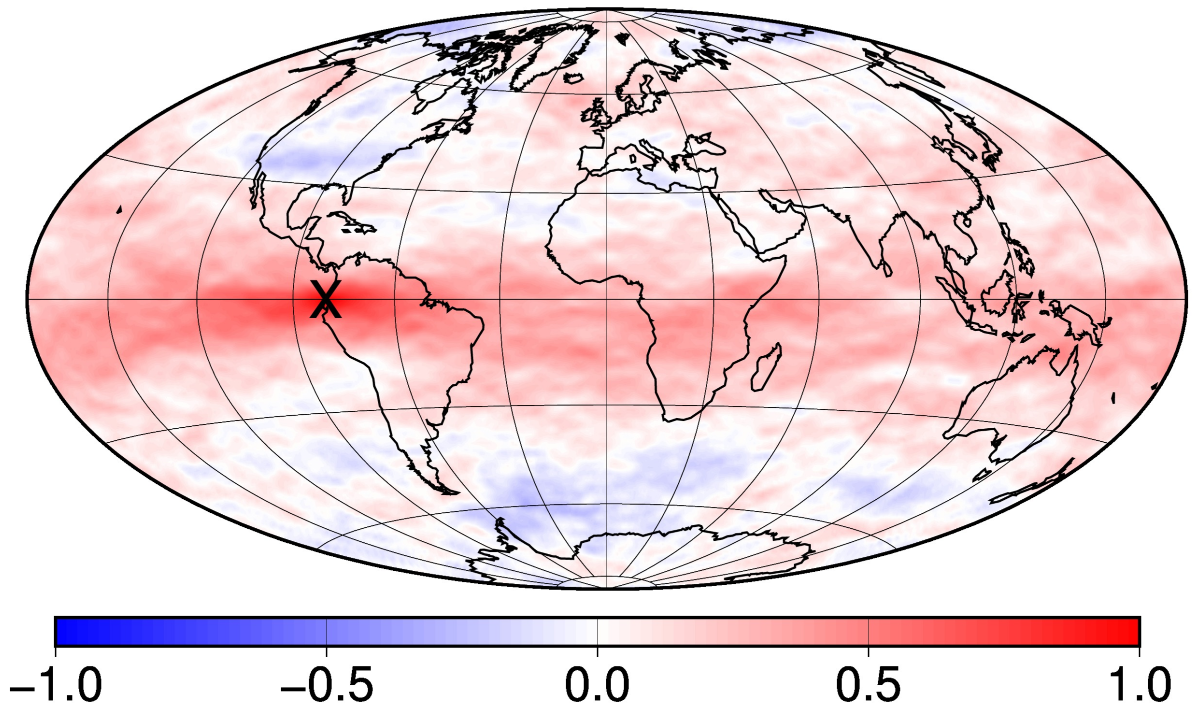
Figure: Left: A synthetic 2D field on the sphere, with finite probability (25%) to be 0. This field is considered as the unknown truth to be retrieved through observations located on the Right. Another observation considered is the location of the maximum, indicated with the black circle.

Brankart 2020, https://www.frontiersin.org/articles/10.3389/fams.2019.00058

Implicitly Localized MCMC Sampler to Cope With Non-local Data Constraints in Large-Size Inverse Problems

Localization is implemented with Schur products of each ensemble member with other, resolution-degraded ensemble members. The correlations in the resulting ensemble are equivalent to Schur-multiply the initial correlation matrices.

Fig 1: Correlations with location indicated with the cross, from the original ensemble, C



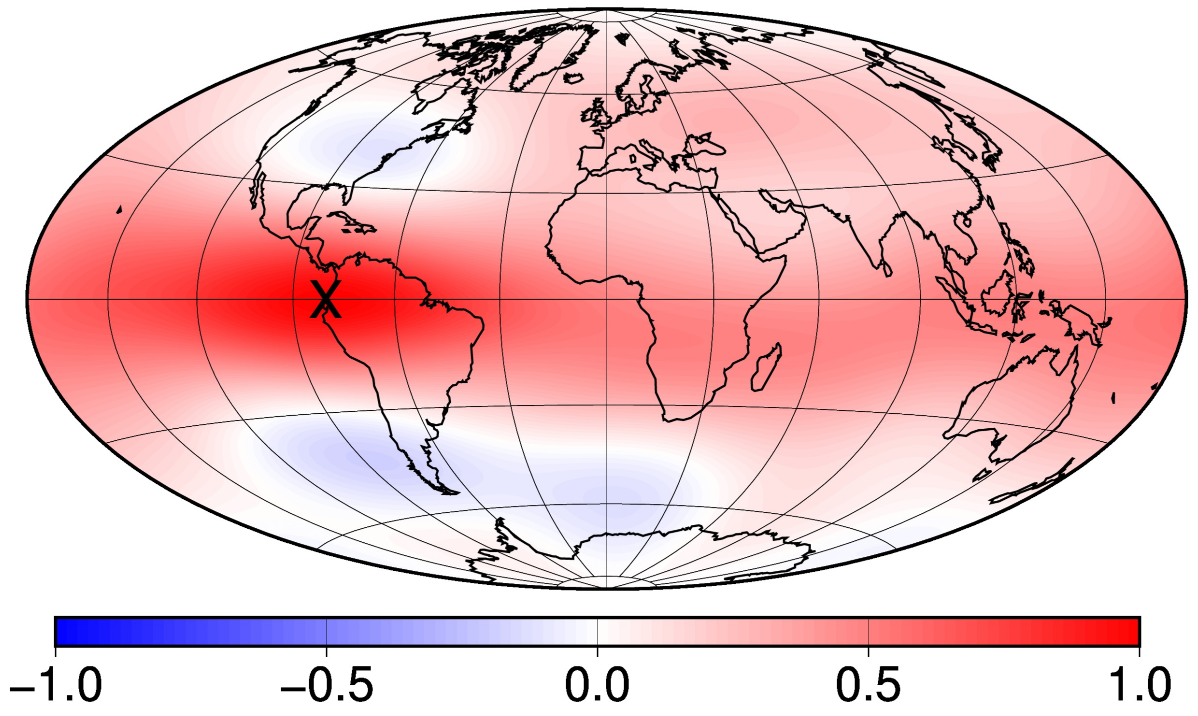
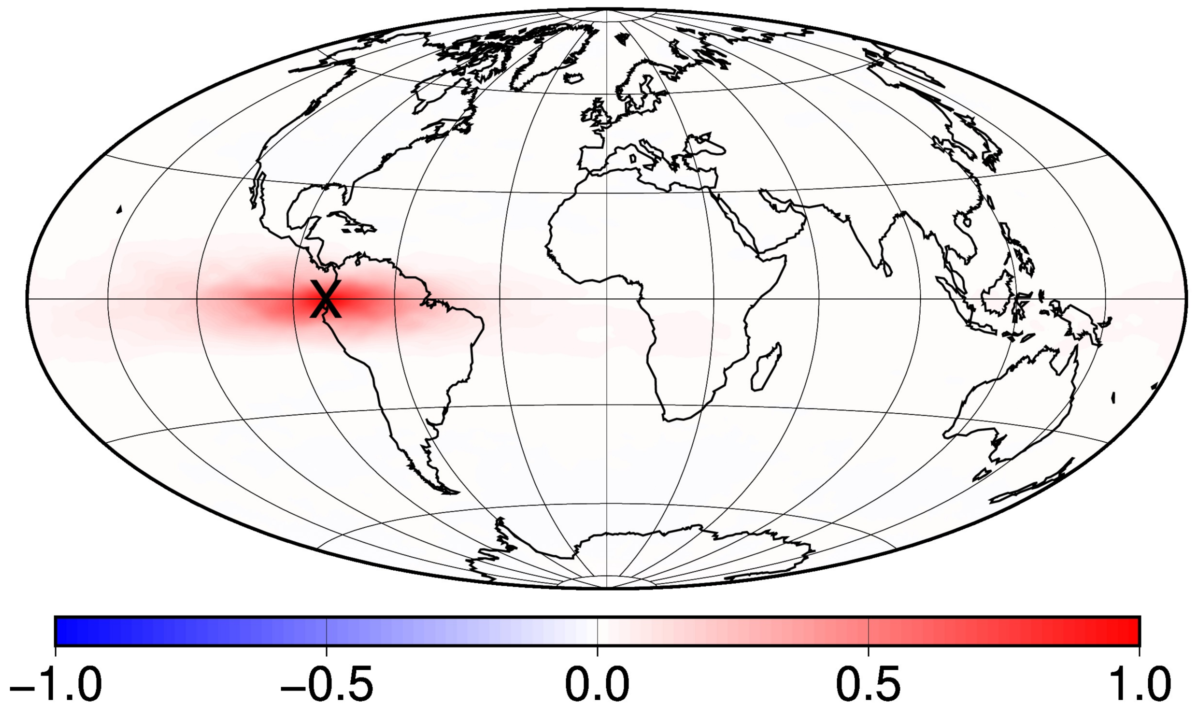


*Fig 2: Correlations from the ensemble of resolution-degraded members of the original ensemble, C**

Fig 4: Correlations C localized by Schur-multiplying with C4



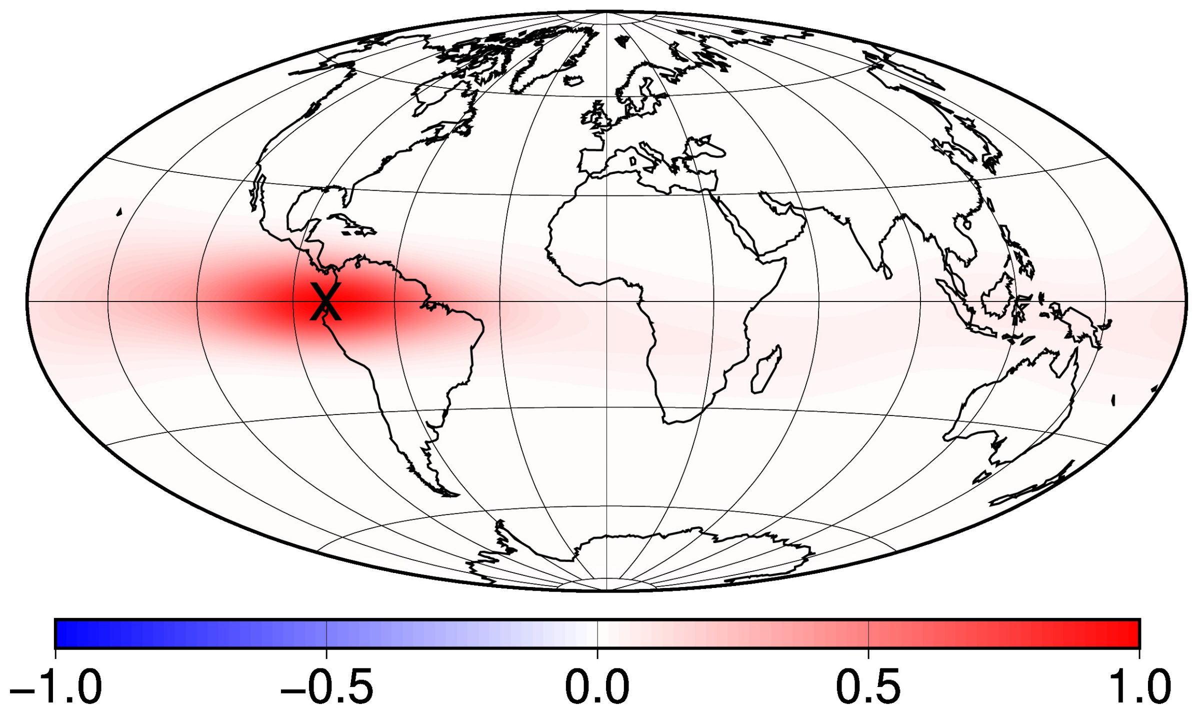


Fig 3: 4-wise Schur product $C4 = C^* \cdot C^* \cdot C^* \cdot C^*$

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Implicitly Localized MCMC Sampler to Cope With Non-local Data Constraints in Large-Size Inverse Problems

Schur products → Markov Chain → Acceptance/rejection

$$\mathbf{x}_i^{(0)} = 0\,; \quad \mathbf{x}_i^{(K+1)} = \alpha_K\, \mathbf{x}_i^{(K)} + \beta_K\, w_i^{(K)}\, \tilde{\mathbf{x}}_{\boldsymbol{\pi}_i(K)}$$

$$\theta^a = \min\left[\exp(\delta J^o), 1\right]$$

with

$$\delta J^o = J^o(\mathbf{x}^{(K+1)}) - J^o(\mathbf{x}^{(K)})$$

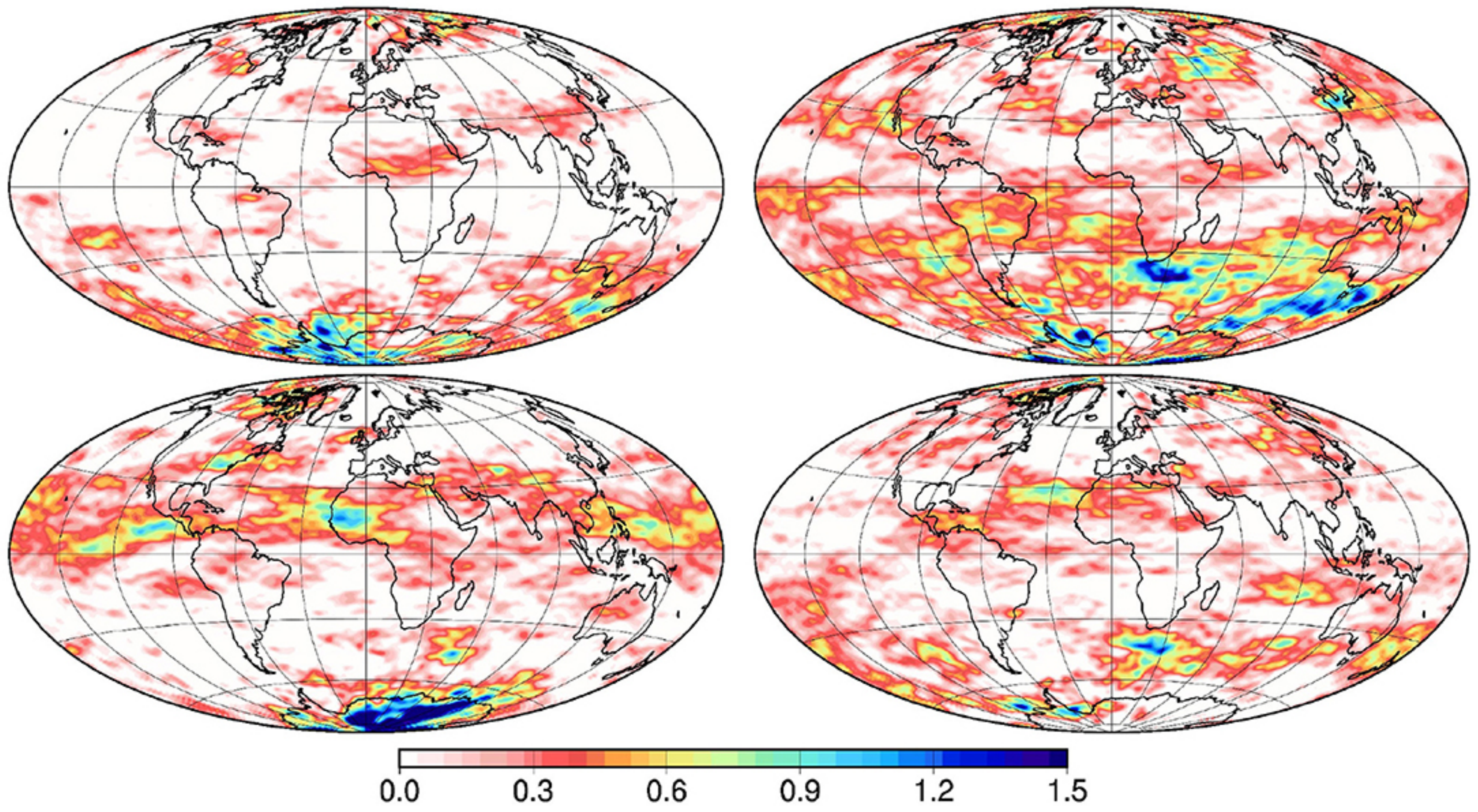

Fig 1: 4 members of the prior ensemble, randomly chosen

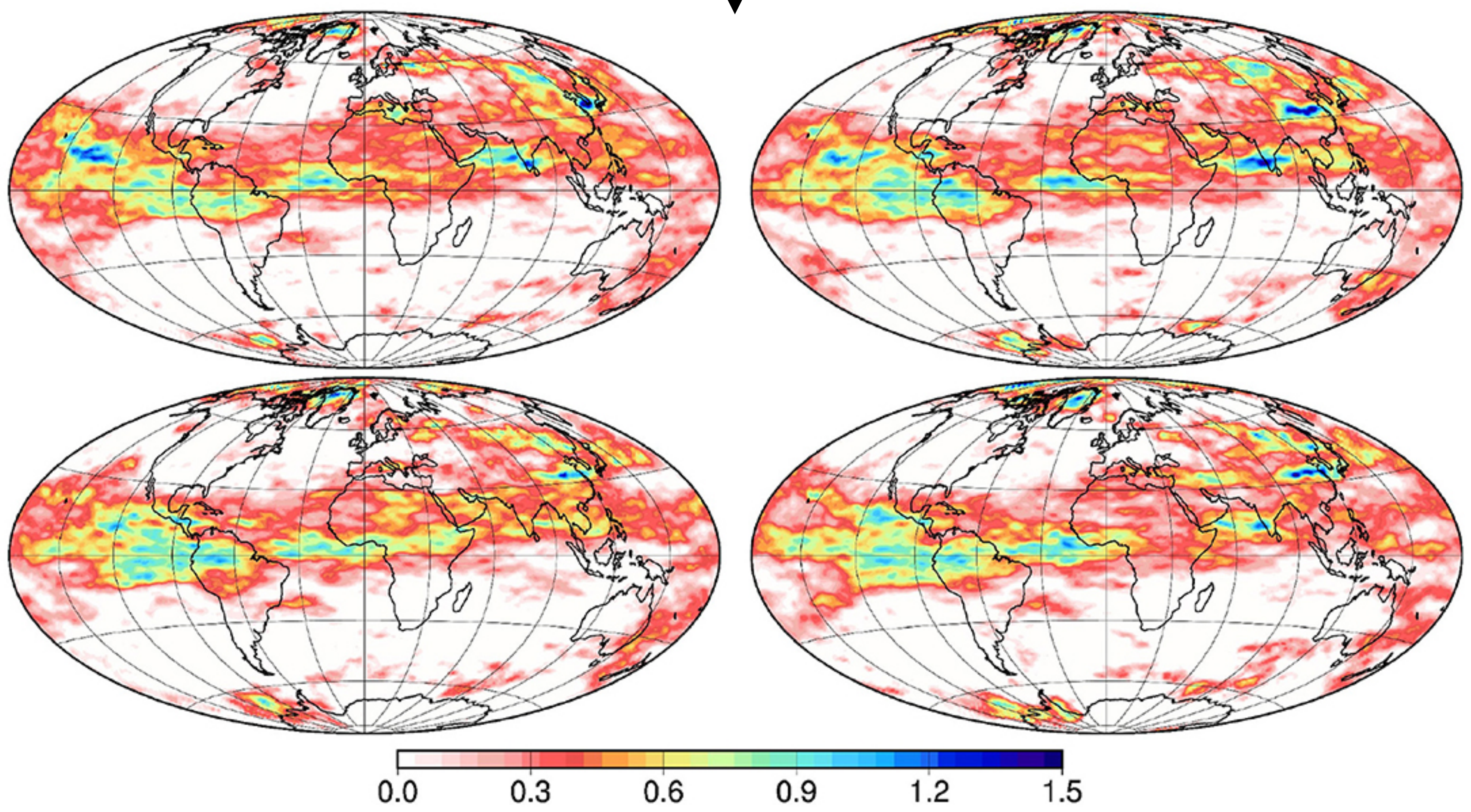

Fig 2: 4 members of the posterior ensemble, randomly chosen (to be compared with the true field)

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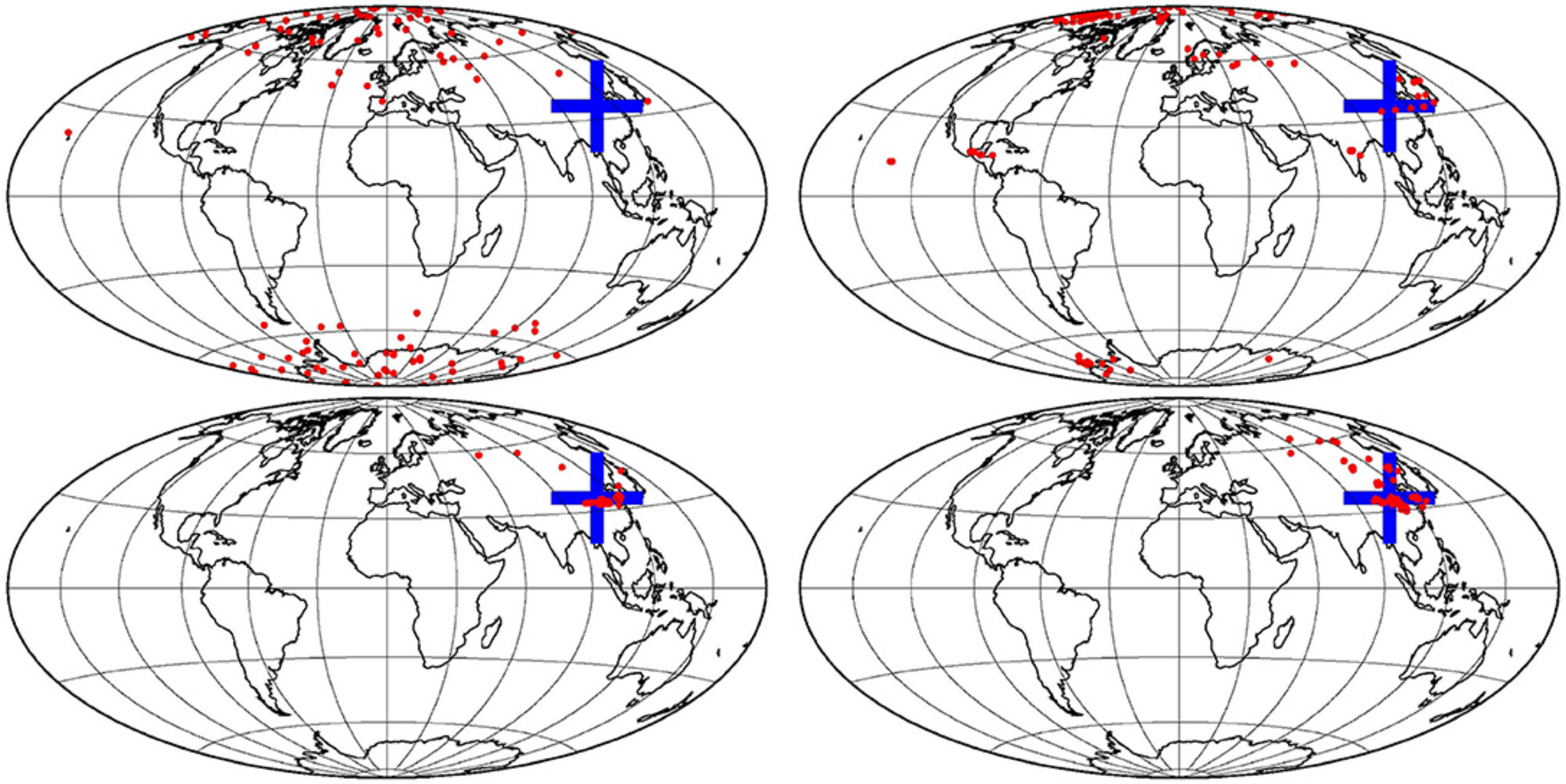
Implicitly Localized MCMC Sampler to Cope With Non-local Data Constraints in Large-Size Inverse Problems

Prior ensemble

Posterior ensemble with local observations only



Posterior ensemble with local and maximum location observations

Posterior ensemble with observation of maximum location only

Figure: Blue cross: location of maximum in the true field. Red dots: ensemble members. This experiment illustrates the capability of the algorithm to deal with the non-local observation of the maximum location.

Brankart 2020, https://www.frontiersin.org/articles/10.3389/fams.2019.00058

Multisensor assimilation: Combining assimilation of satellite altimetry and tracer images

Background:

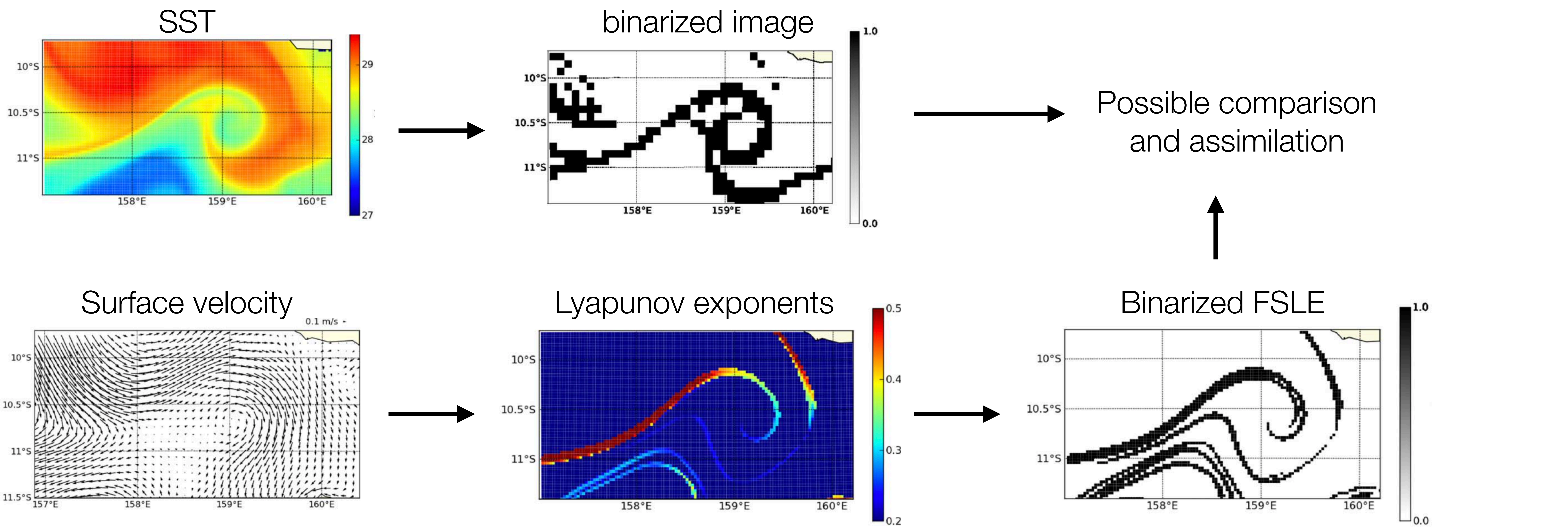
The background idea of tracer image assimilation here is illustrated on the next slide: an SST image can be binarized by thresholding the spatial gradient intensity. The velocity field from the assimilative model is used to compute Finite-Size Lyapunov Exponents (FSLEs). Those FSLEs are also binarized with thresholding considerations to be comparable with the binarized image. This makes it possible to adjust a high-resolution model velocity field based on the high-resolution image, and access to an observation-constrained estimation of the fine-scale (<50 km) surface dynamics.

The algorithm is based on a MCMC sampler characterized by slow (or no) convergence. The purpose of the persent work is to investigate the use of satellite altimetry assimilation as a preconditionner to image assimilation.

Duran Moro et al 2017, https://doi.org/10.1007/s10236-017-1062-3

Multisensor assimilation: Combining assimilation of satellite altimetry and tracer images

Figure: Principle of SST image assimilation to reconstruct fine-scale surface dynamics. Figure from Gaultier et al, 2013 (https://doi.org/10.1002/ 2013JC009660)



Duran Moro et al 2017, https://doi.org/10.1007/s10236-017-1062-3

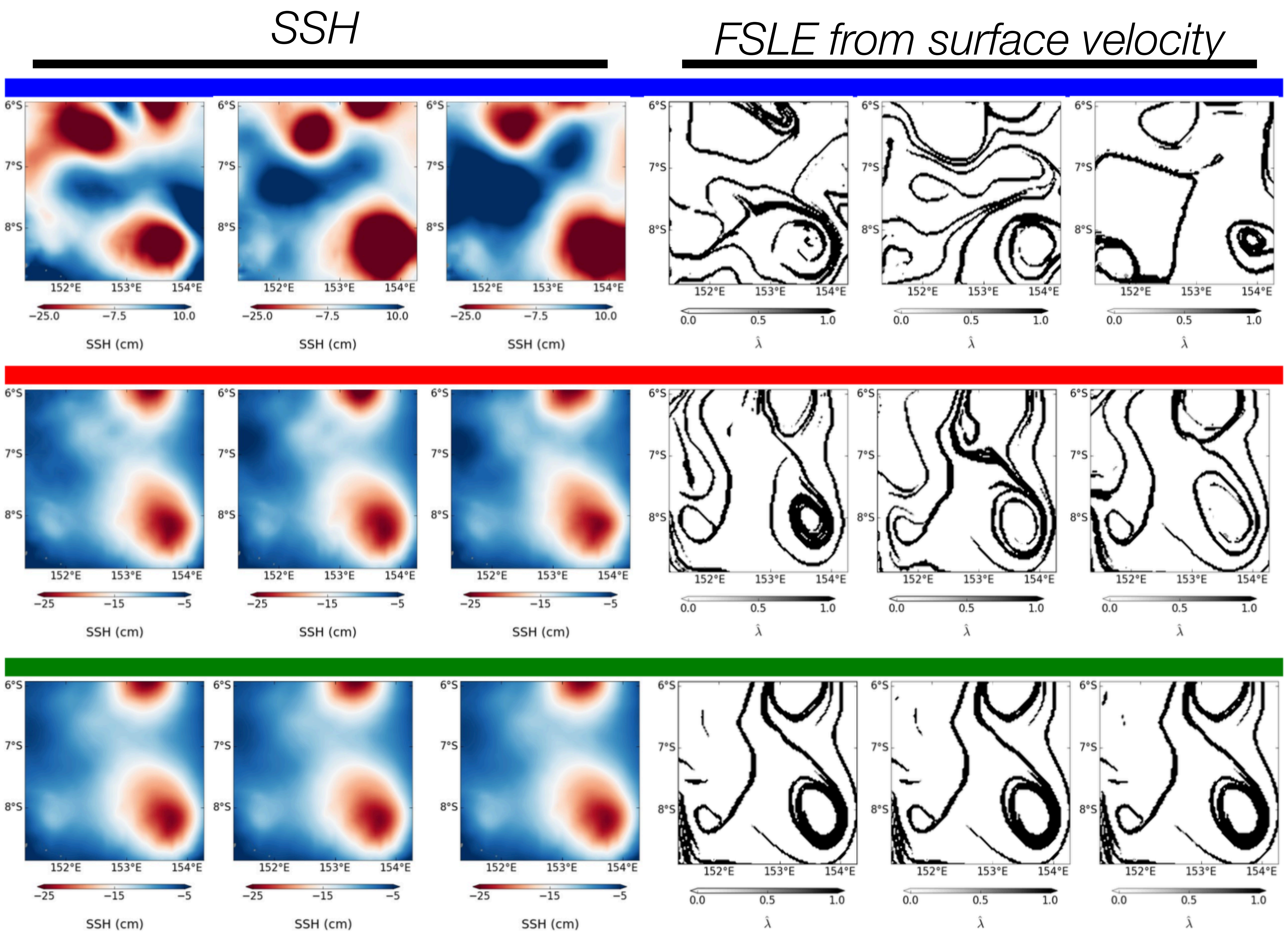
Multisensor assimilation: Combining assimilation of satellite altimetry and tracer images

Figure: 3 ensemble members

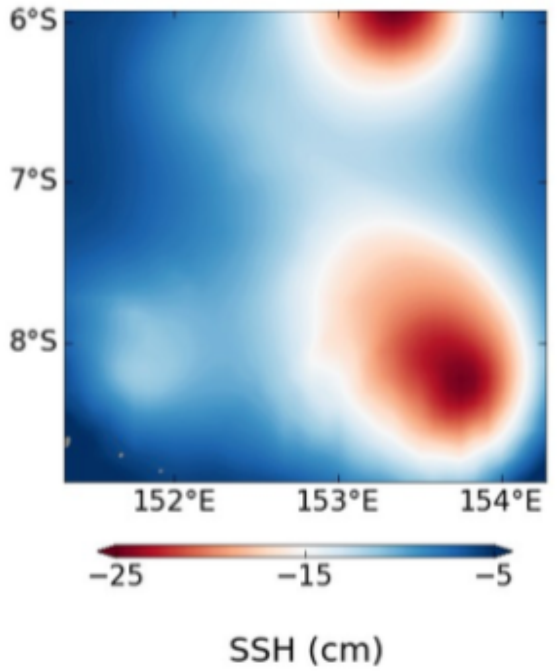
Before any assimilation

After assimilation of altimetry (note that FSLE are well preconditionned)

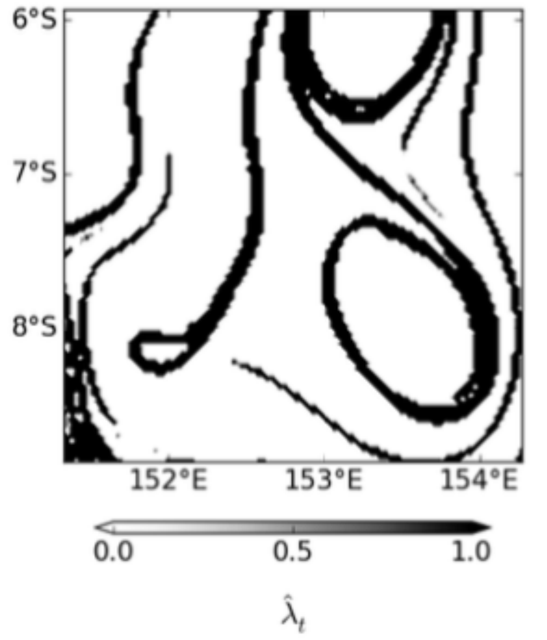
After assimilation of altimetry and FSLE



True SSH



True FSLE



Duran Moro et al 2017, https://doi.org/10.1007/s10236-017-1062-3

Multisensor assimilation: Combined assimilation of satellite altimetry and satellite observations of surface currents

Background:

Satellite altimetry provides information on geostrophic velocity. Future missions of wide-swath observation of surface velocity are being considered, which would complement altimetry w.r.t. ageostrophic surface velocity. This unpublished work investigated the combined assimilation of altimetry (nadir, SWOT) with wide-swath surface current observations (in prospect).

Multisensor assimilation: Combined assimilation of satellite altimetry and satellite observations of surface currents

Figure: Satellite altimetry observations (nadir, SWOT) and surface current observations (ESA/EE9 SKIM project) are simulated from the NEMO/NATL60 1/60° simulation, in a 10°x10° box in the Gulf Stream region, with realistic spatial and temporal sampling. These simulated observations are assimilated into a 1.5-layer QG model using a Back-and-Forth nudging technique.
Left: true vorticity snapshot from the OGCM simulation. Then, from left to right: simultaneous snapshots from the assimilation of nadir altimetry, SWOT, and SWOT+SKIM, respectively. Assimilating SKIM improves the representation of vorticity.