Reconstruction and analysis of QuikSCAT wind measurements with an EOF-based technique

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1. Summary

QuikSCAT wind products are often used to provide numerical model atmospheric forcing. However, due to the configuration of the satellite swaths, gaps are frequently observed in the daily wind maps.
We present a solution based on truncated EOF decomposition to fill these gaps.

2. Data & preprocessing

Level 2-swaths are downloaded from the NASA-JPL server at:
ftp://podaac-ftp.jpl.nasa.gov/allData/quikscat/L2B12/.
Each day, 14 swaths are available. Each swath file is 33M in HDF format, 7.9M in NetCDF. All the swaths are interpolated on a 0.25° × 0.25° grid and gathered for each day. In this work, we limit ourselves to three months of data and to North Atlantic Ocean.
Figure 1 shows that:

- images are affected by gaps, since the satellite orbits do not cover the whole ocean each day;
- they are discontinuities in the wind field due to the superimposition of the individual swaths.

These are the issues we try to solve with DINEOF.

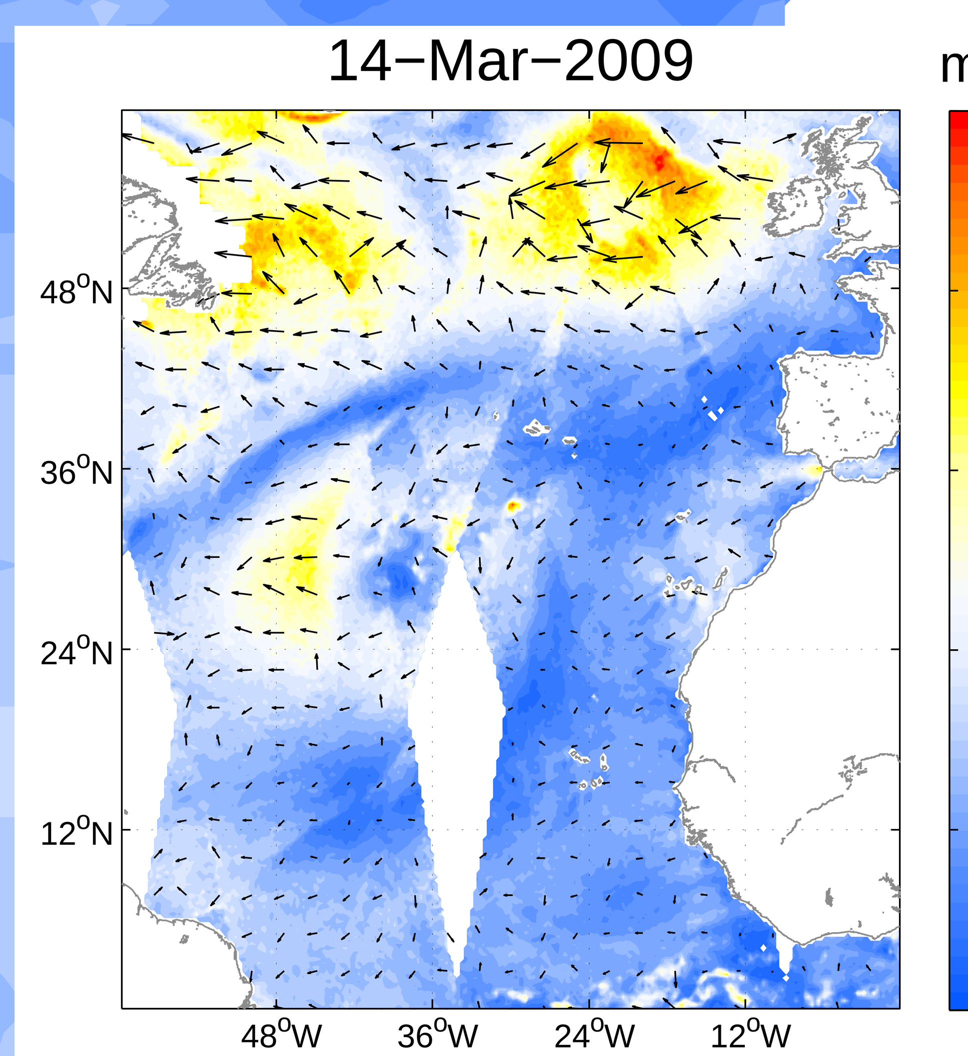

FIGURE 1: *Wind speed field obtained by combining the swaths of February 14, 2009.*

3. Method: DINEOF

Data INterpolating Empirical Orthogonal Functions (DINEOF, (Beckers and Rixen, 2003, Alvera-Azcárate et al., 2005) is a self-consistent and parameter-free method, based on the Singular Value Decomposition (SVD) of a matrix **X**. **X** has a dimension $m \times n$, where m is the spatial dimension and n is the temporal dimension.

$$\mathbf{X} = \mathbf{U}\mathbf{S}\mathbf{V}^T \tag{1}$$

with

U, the spatial EOFs, with a dimension $m \times r$,
V, the temporal EOFs, with a dimension $m \times r$ and
S, the singular values, with a dimension $r \times r$.

The optimal number of modes is determined with a cross-validation procedure: clusters of data with the shape of real clouds are set apart for validation.
The present version of DINEOF offers the filtering of the temporal covariance matrix as a way to ensure coherence between images that are close to each other in time (Alvera-Azcárate et al., 2009). Two parameters controls the filtering of the temporal covariance matrix:

- α specifies the strength of the filter,
- p the reach of the filter.

There is a condition to guarantee the filter stability is related to the minimal time interval between two consecutive images:

$$\alpha \leq \frac{\min(\Delta t)^2}{2}.$$

4. Results

For the analysis, we try several combinations between:

- the wind components u and v,
- the wind intensity $\|\mathbf{u}\|$,
- the wind direction θ.

The parameters for the filtering of the covariance matrix are the same as in (Alvera-Azcárate et al., 2009):

$$\alpha = 0.01\, d^2, \tag{2}$$
$$p = 3, \tag{3}$$

This means that periods $T < 2\alpha p = 1.1$ days are filtered out of the image time series.

- Wind norm only: the reconstruction seems to work well. However, as there is no physics in DINEOF, nothing implies that the reconstructed values will always be positive. Indeed, in some regions, we obtained a negative wind norm, which makes no sense.
- Wind norm and direction: the problem here is that the input direction θ is defined between 0 and 360°, but nothing implies that the reconstructed values will stay in this interval.

EOFs

We have represented the three most dominant modes with 26%, 11% and 5.7074% of the signal variance in the next figure.

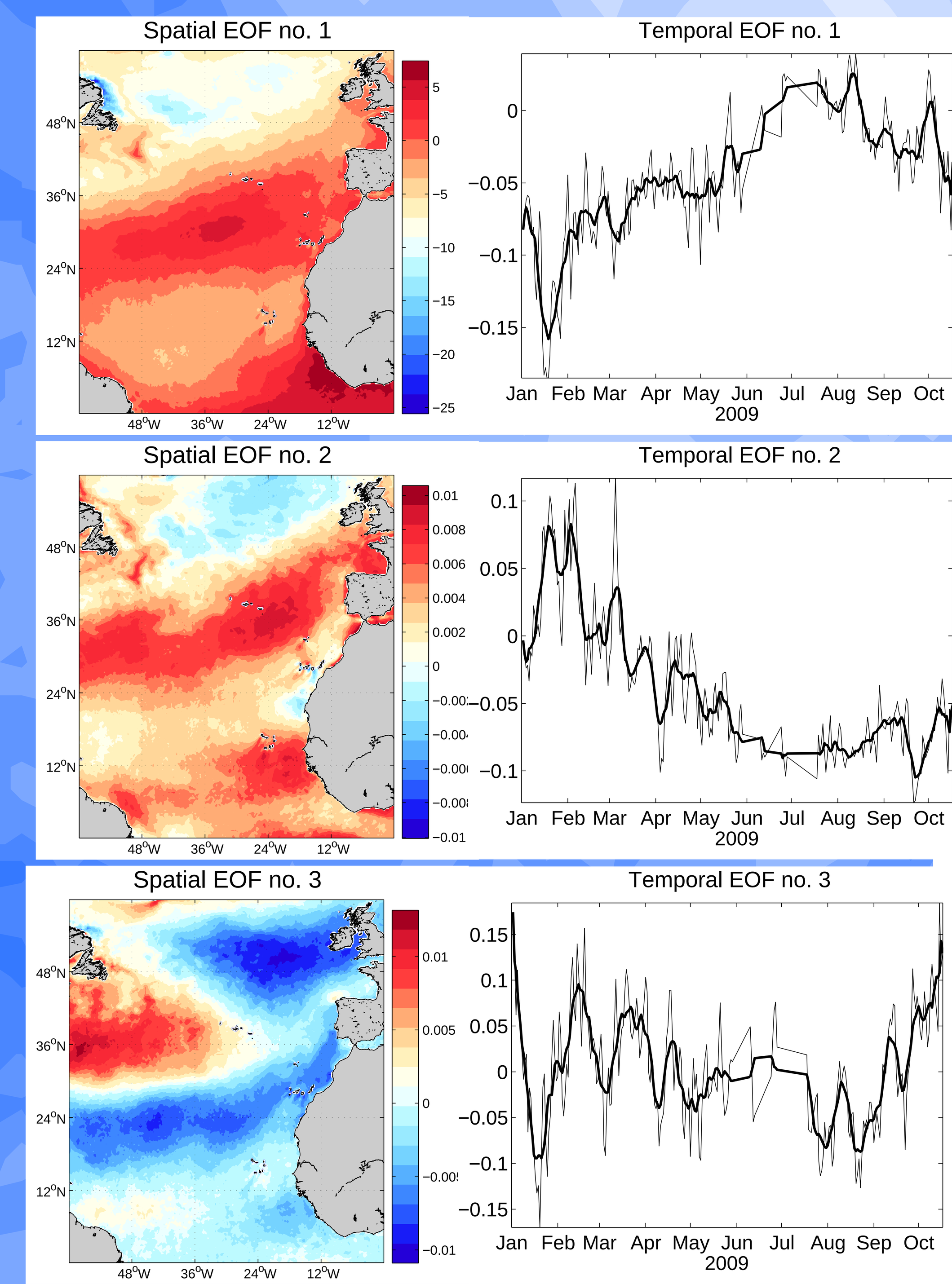

FIGURE 2: *First three EOFs corresponding to the reconstruction of the wind norm.*

Reconstruction

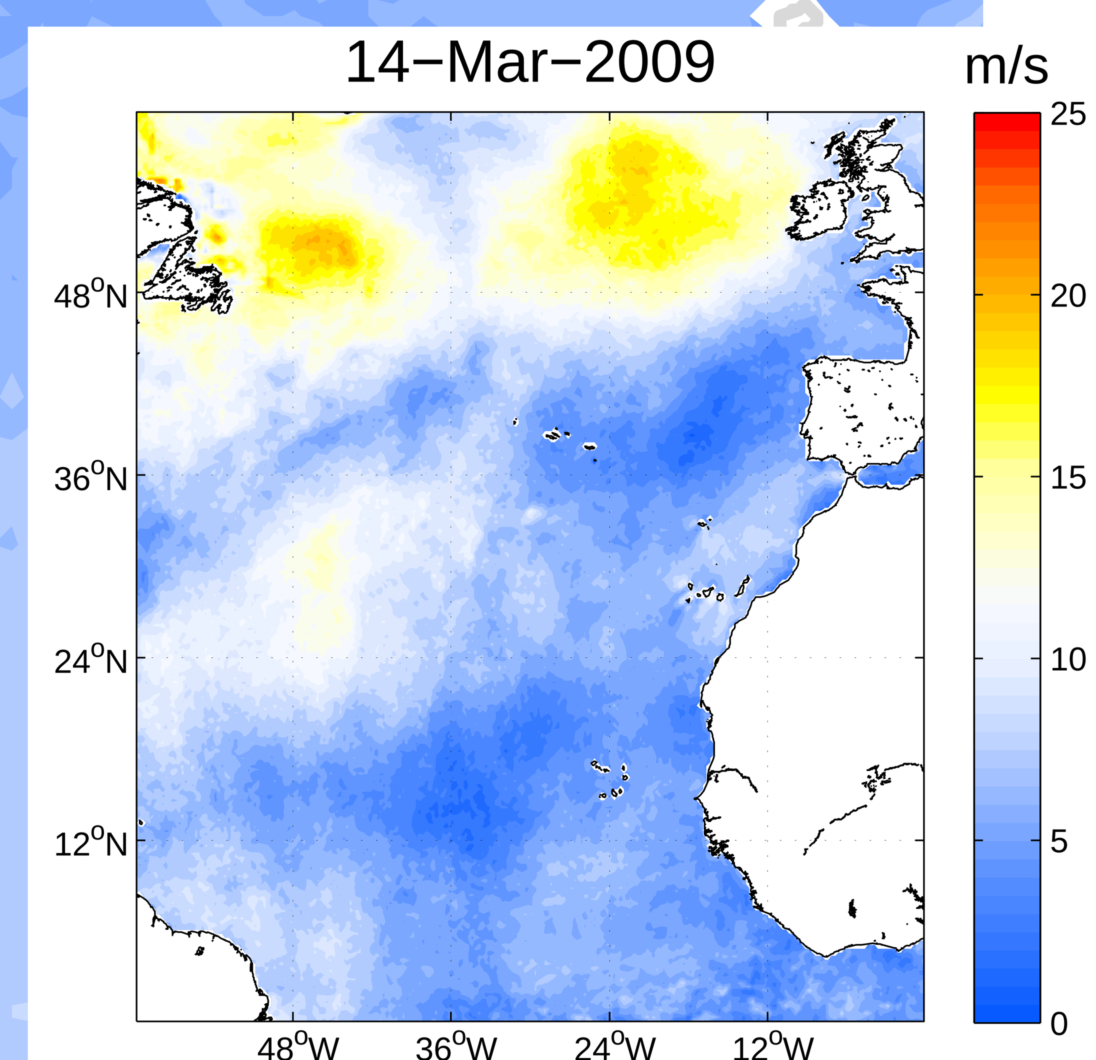

FIGURE 3: *Reconstructions of the wind norm for March 14.*

Conclusions & future work

The reconstruction of the incomplete wind fields show promising results. The main drawback is that some of the features of the fields are less marked in the reconstruction.
In the next experiments, two directions will be followed:

1. make reconstructions using different combinations for the parameters (α, p) relative to the filtering of the time covariance matrix. As the values used here are based on a work dealing with SST in the Black Sea, it is reasonable to think that the reconstruction of wind data in the North Atlantic Ocean will provide better results with another combination (α, p).
2. use SST data to further improve the quality of the reconstruction: the SST and the wind are intimately related, for instance in the regions of coastal upwelling. If we had SST data in regions where the wind was not measured, then the reconstruction could be improved, thanks to the covariance between wind and SST.
3. change the interval step for the reconstruction: here we have constructed initial images using 1 day of data (14 swaths). Another option would be to use 12, 6, or even less hours to prepare the images to be reconstructed. Doing so, we will lose the coverage, but on the other hand, we will improve the time resolution, and maybe avoid the smoothing of the wind features.

Main references

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Alvera-Azcárate, A.; Barth, A.; Sirjacobs, D. & Beckers, J.-M. (2009), Enhancing temporal correlations in EOF expansions for the reconstruction of missing data using DINEOF, *Ocean Sci.*, **5**, 475-485, doi:10.5194/osd-6-1547-2009.

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