Exploring denoising and reconstruction methods for SWOT

Gómez-Navarro, L., Cosme, E., Le Sommer, J., Metref, S., Lguensat, R., N. Papadakis

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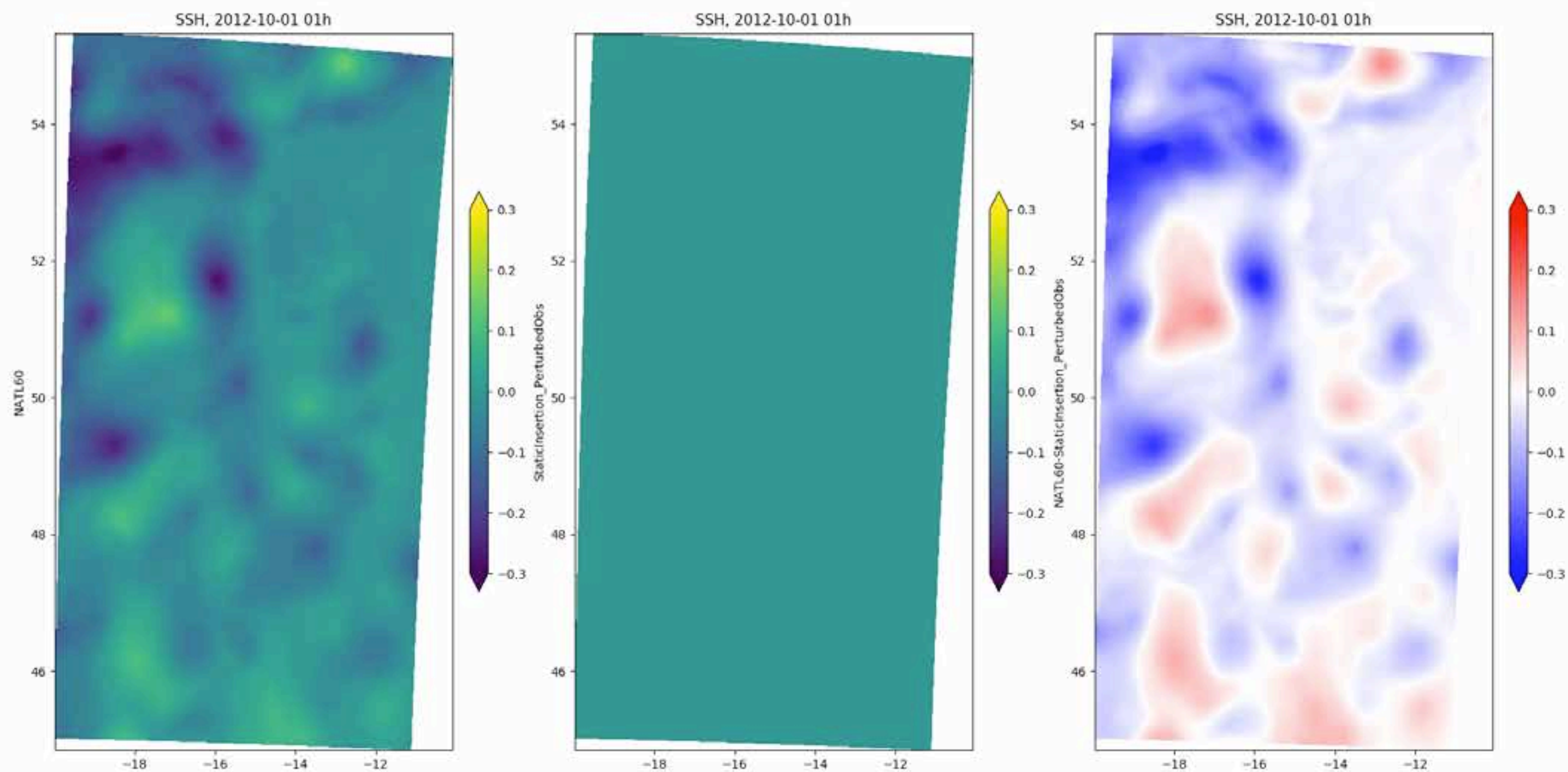
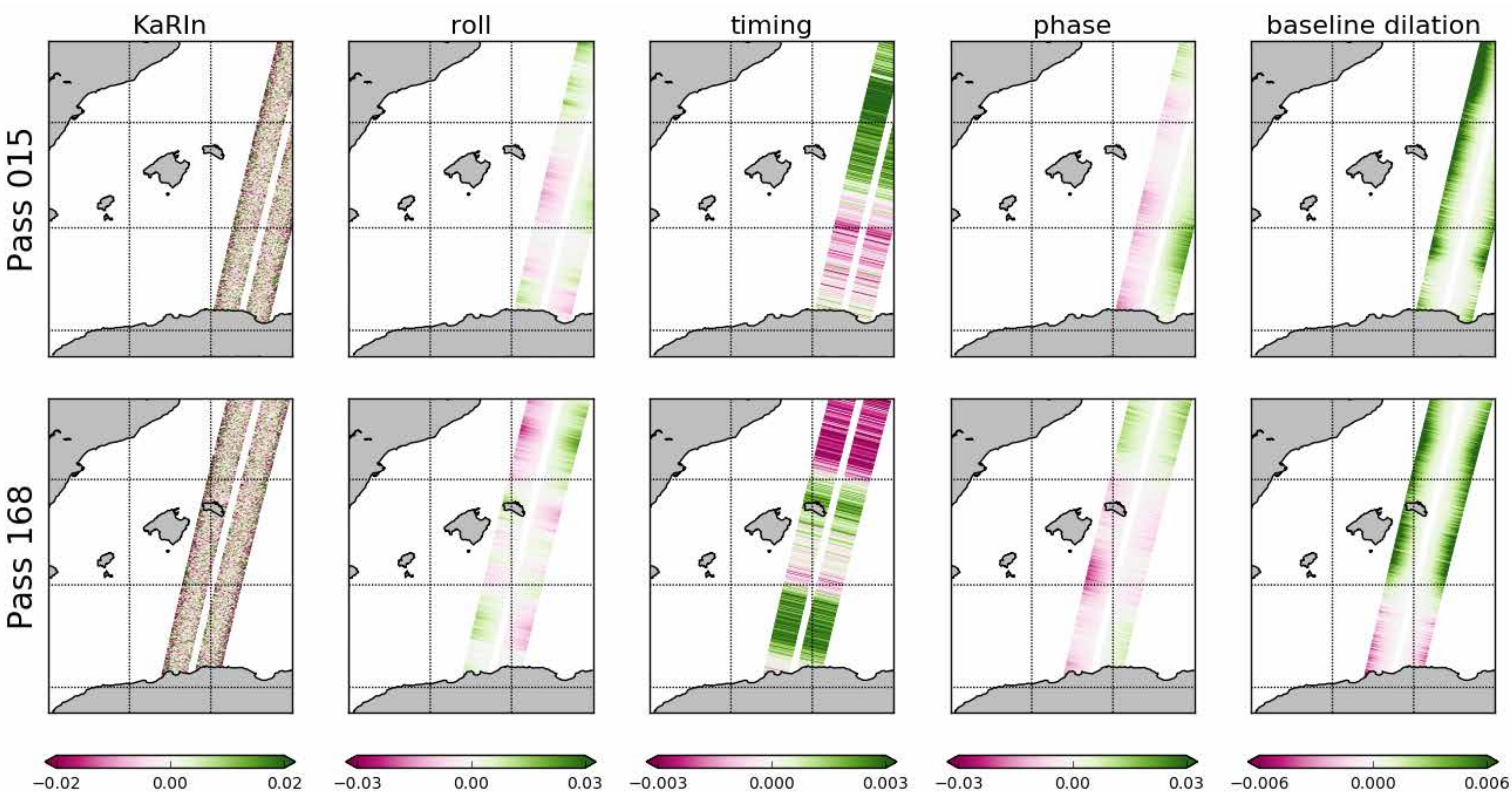
Special thanks to L. Gaultier for SWOT simulator support!

Introduction



Introduction

Spatially uncorrelated vs correlated **instrumental** noise (SSH [m])



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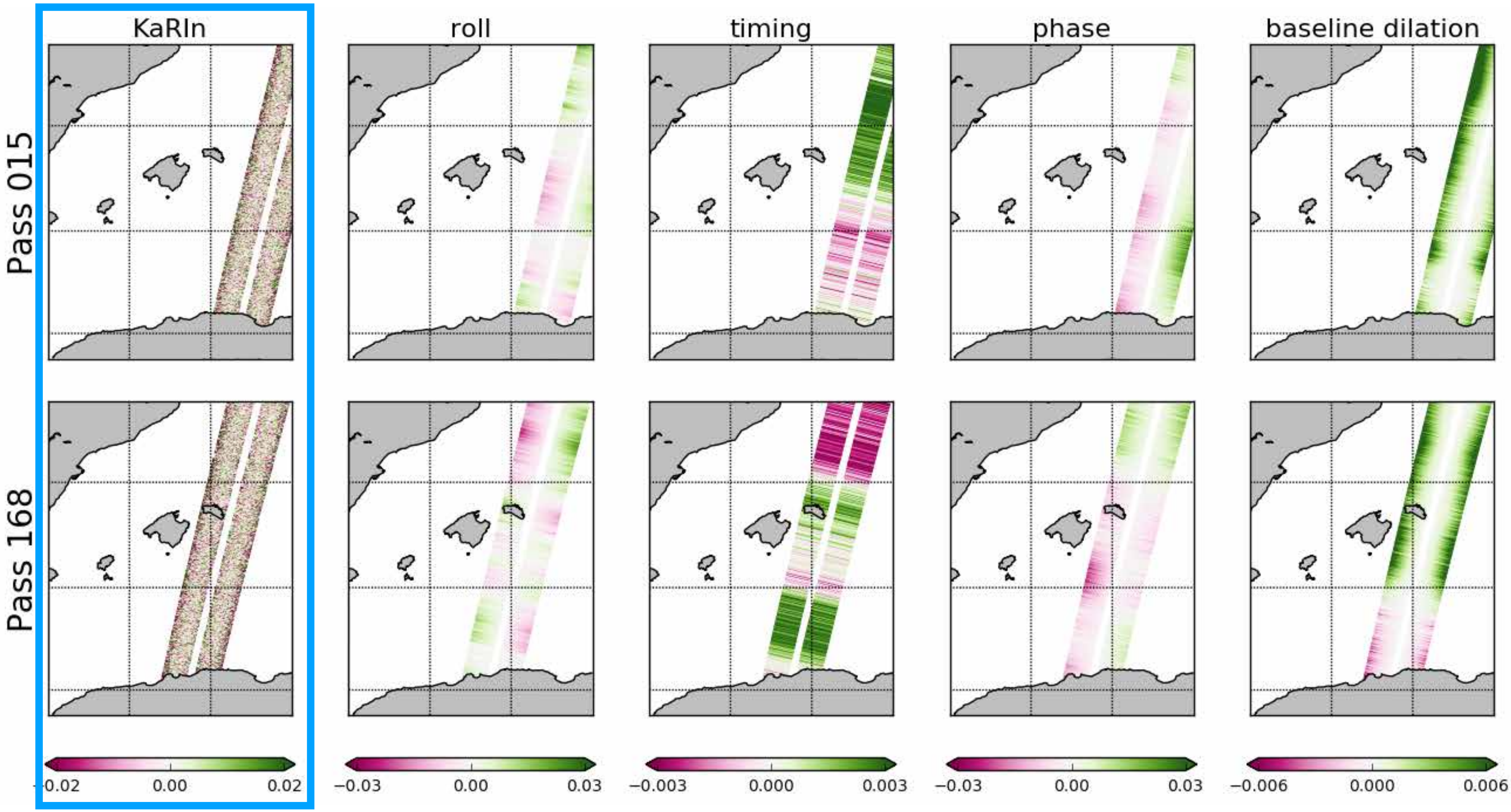

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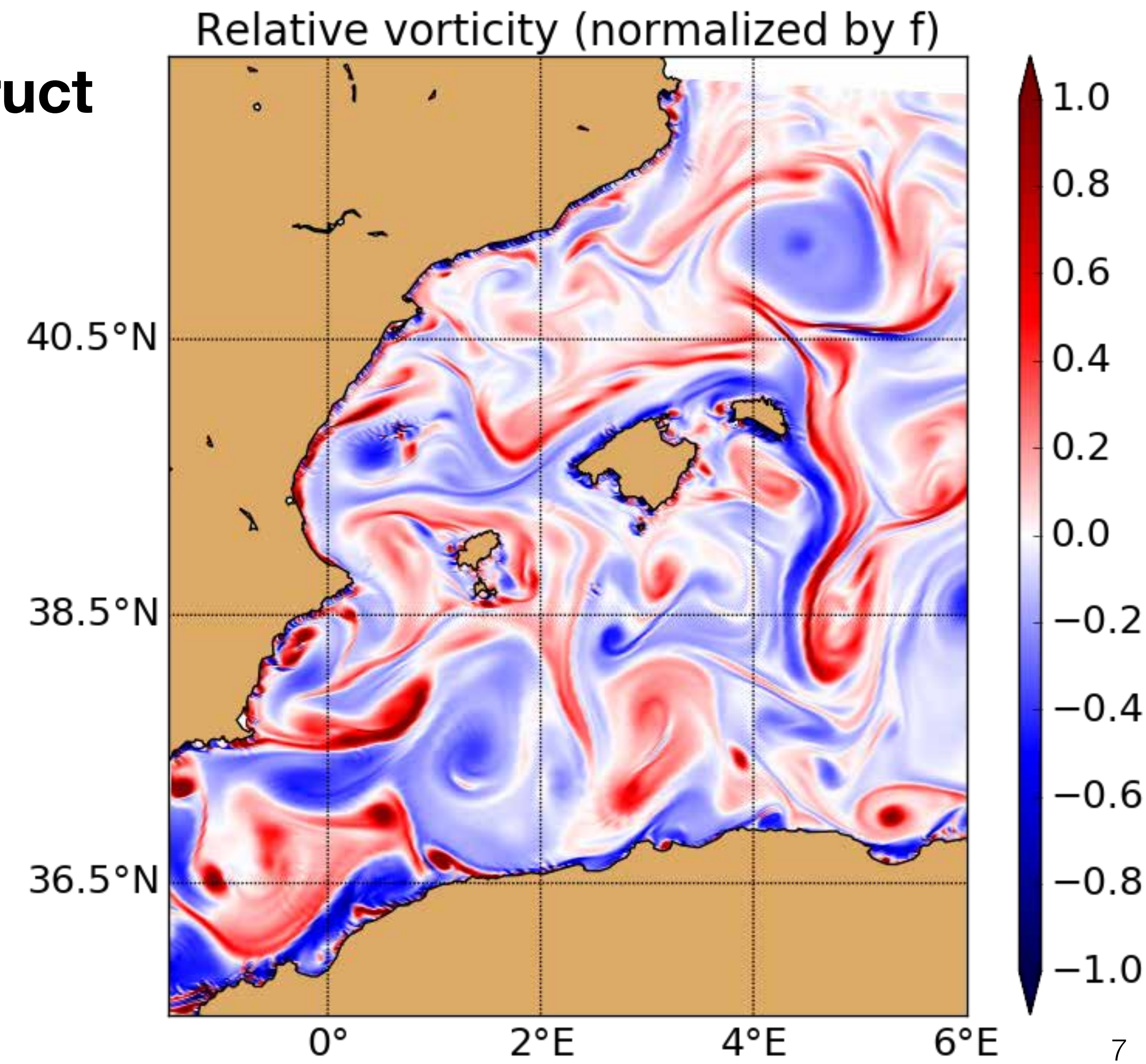
—> need to well reconstruct the SSH derivatives to:

- Obtain physical variables: geostrophic velocity and vorticity



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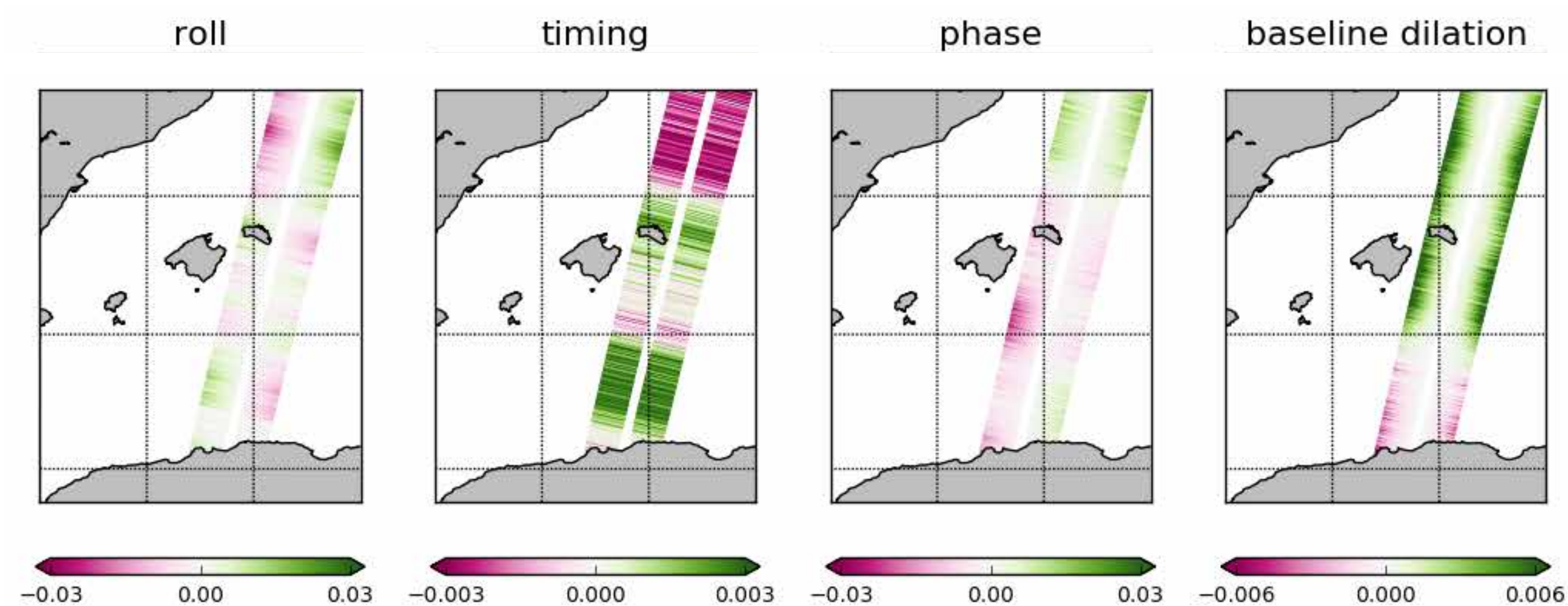
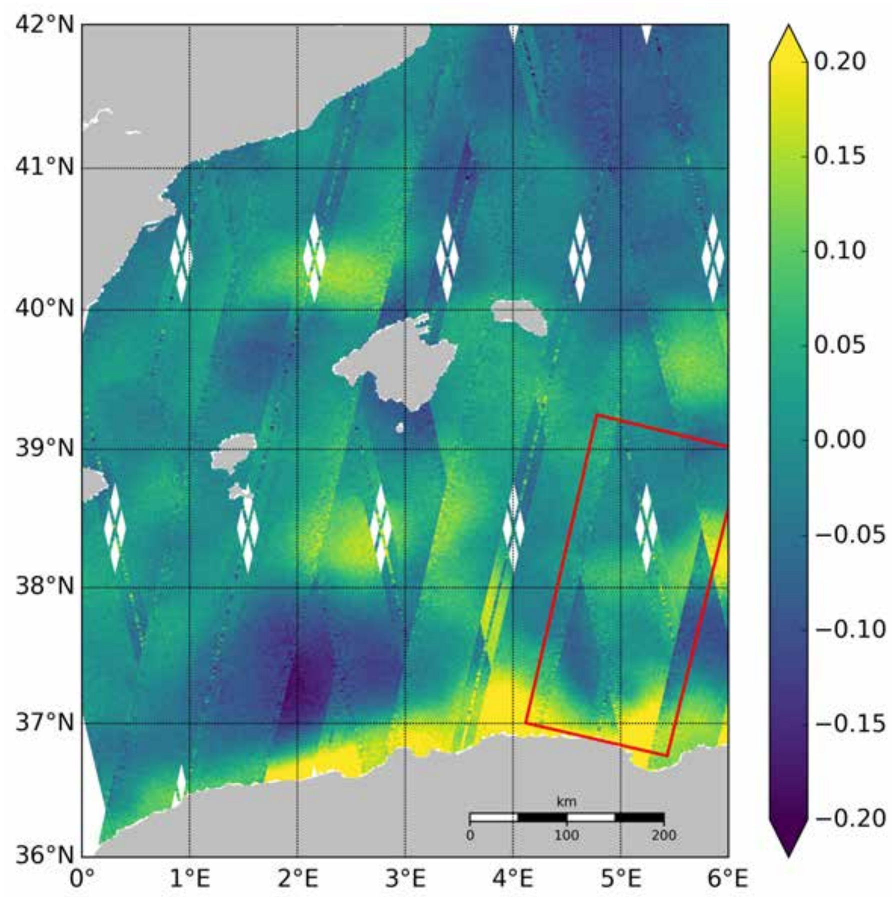
—> need to well reconstruct the SSH derivatives to:

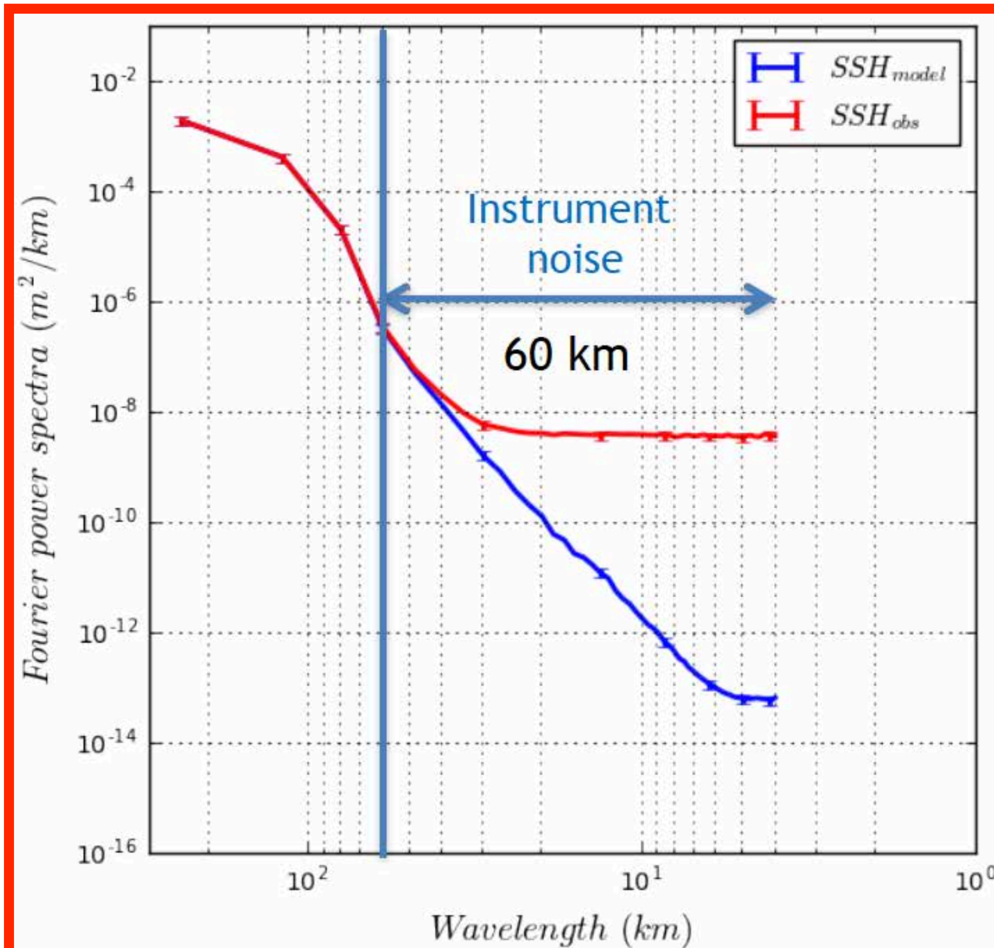
- **Data assimilation methods use the information on the derivatives** to remove correlated errors (Ruggiero *et al*., 2016)



Previous studies



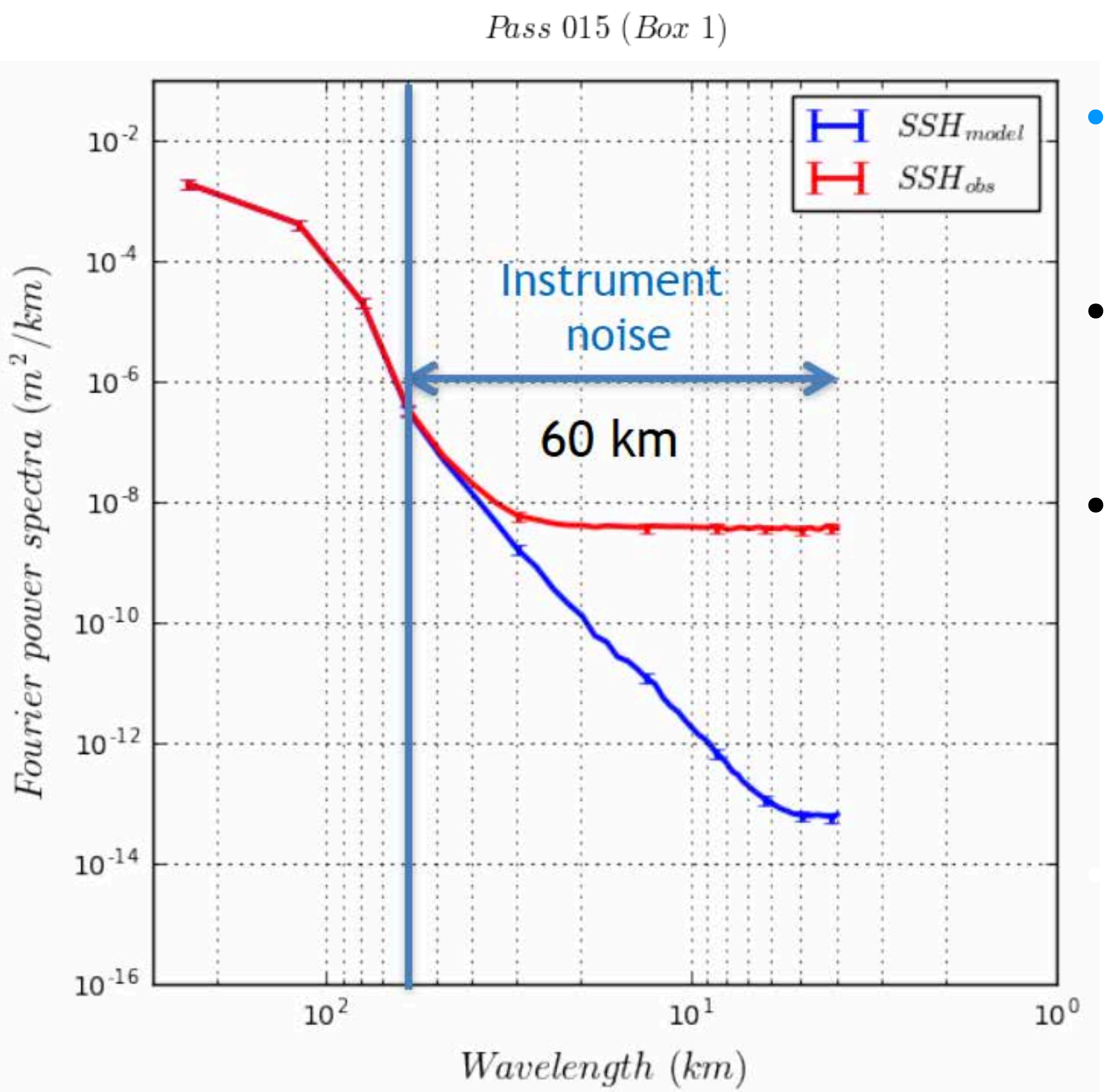
SSH_obs [m] (pseudo-SWOT data) of cycle 2



* Errorbars denote 95% confidence interval

Gómez-Navarro *et* al., 2018, *Remote Sensing*

Previous studies



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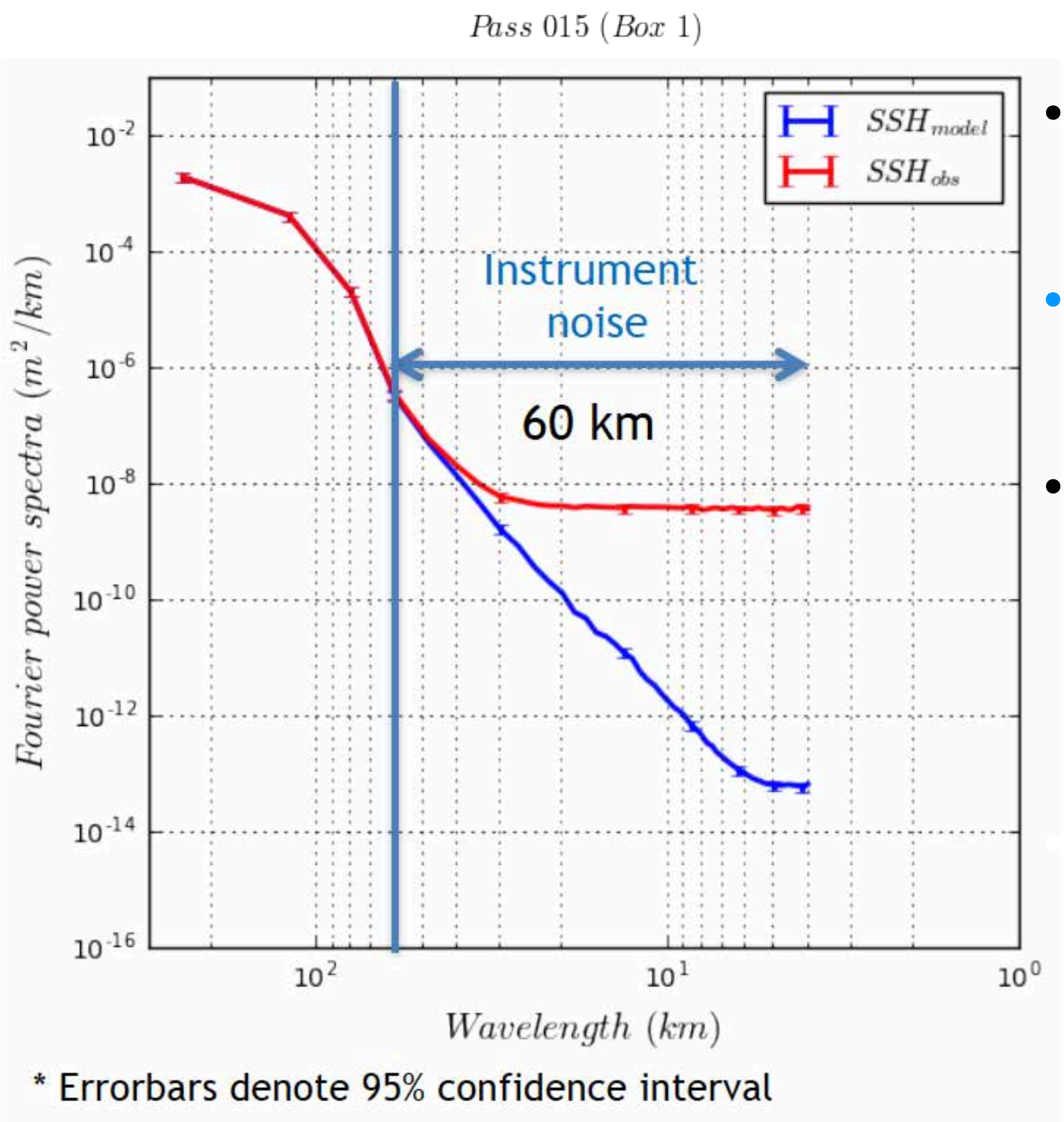
- **Pass 15 subdomain spatial spectra average of 117 cycles**
- SWOT simulated data resolve wavelengths > 60 km.
- Significant improvement compared to standard altimeter gridded fields that resolve wavelengths > 150-200 km (Chelton *et al*., 2007).

Previous studies



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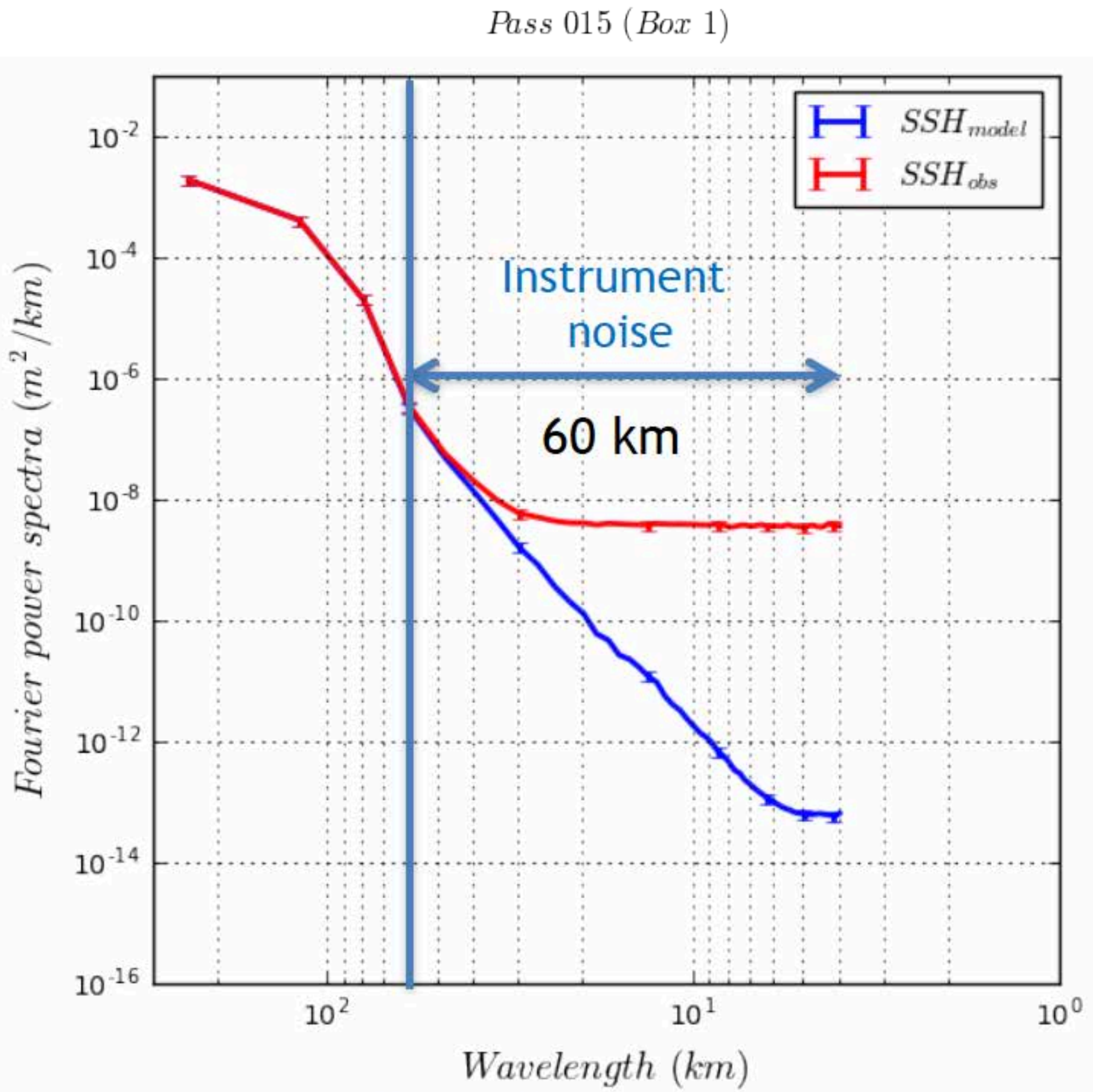

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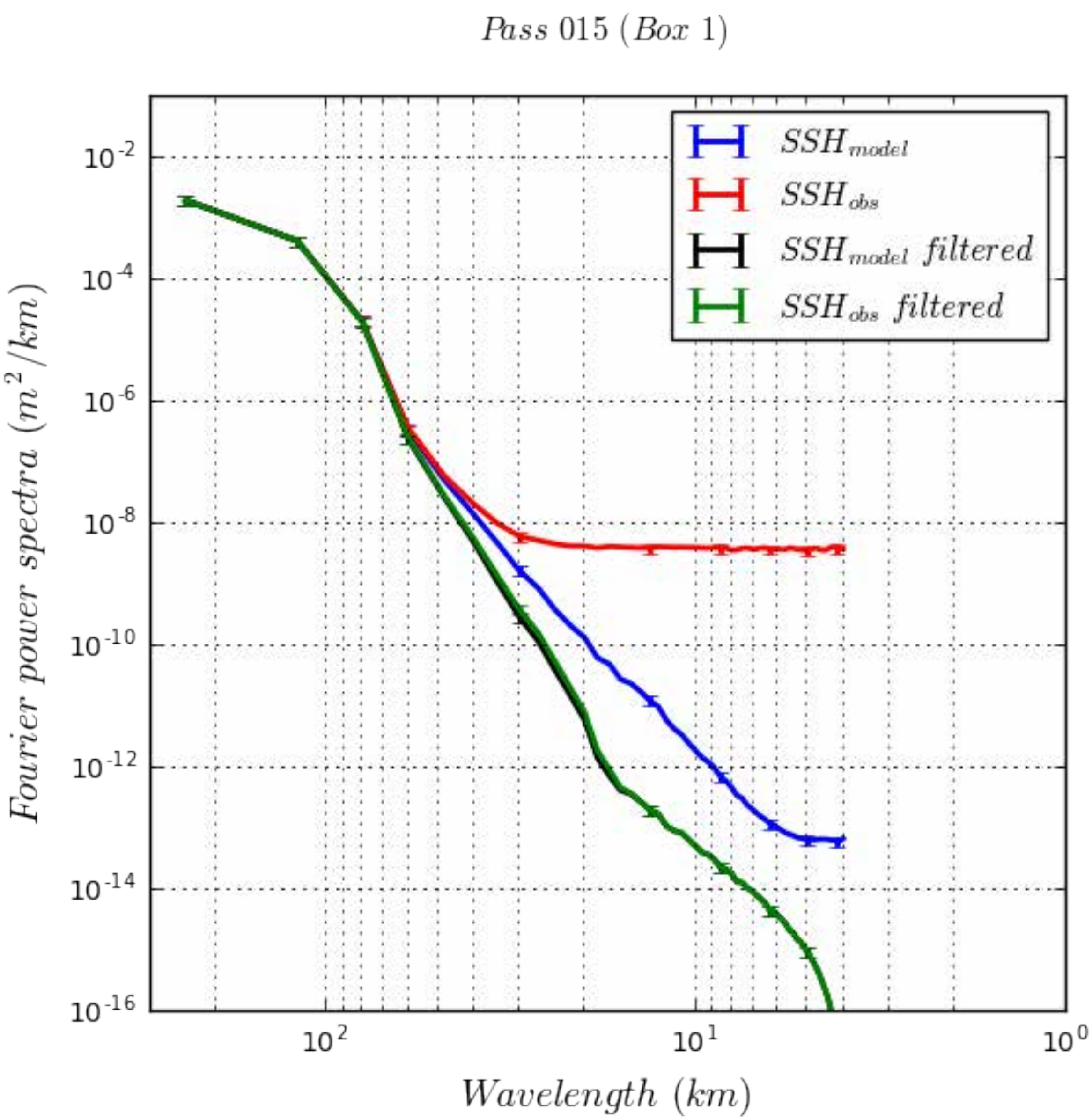

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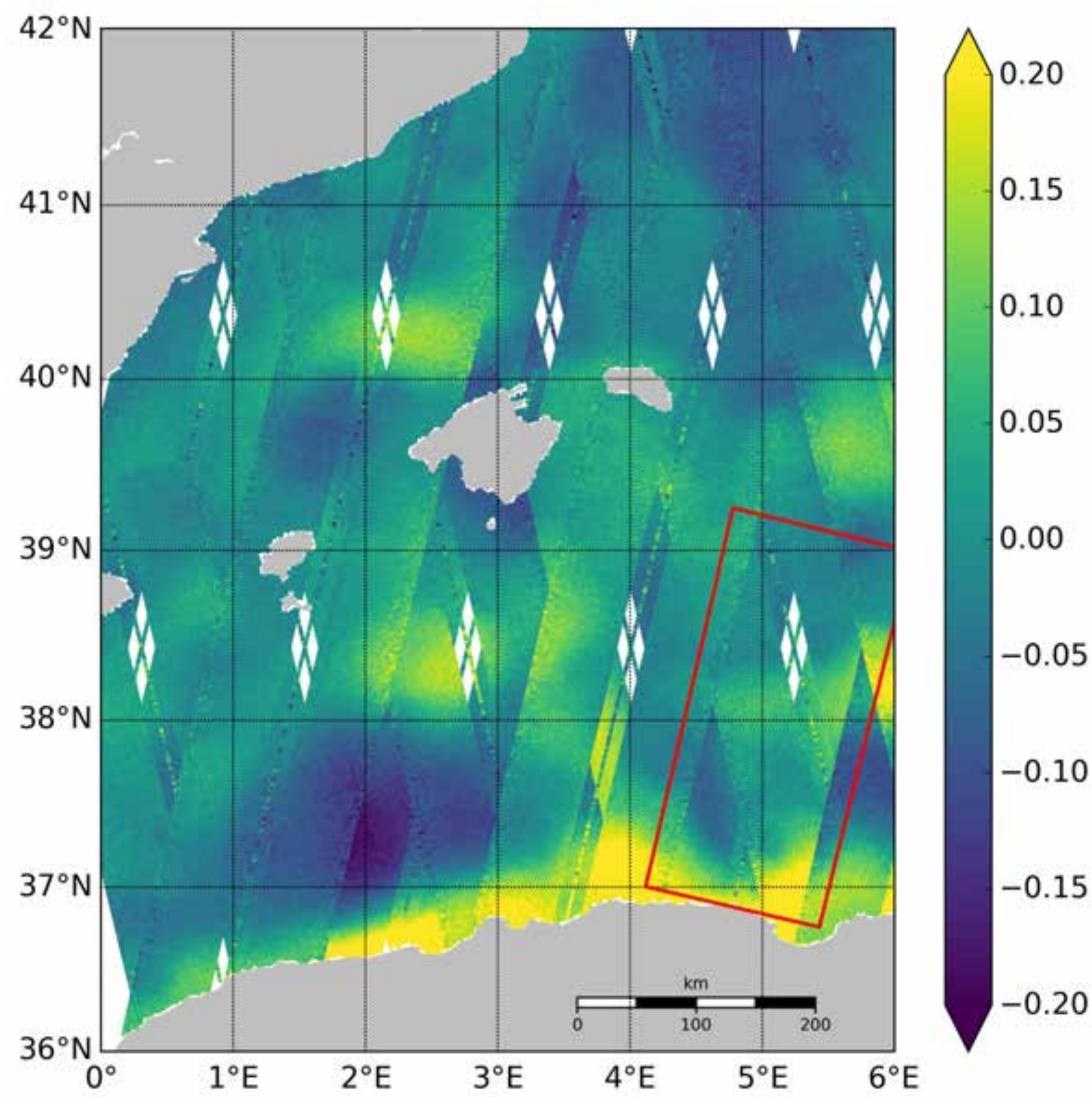
- **60 km cut-off wavelength Laplacian Diffusion filter**

Previous studies



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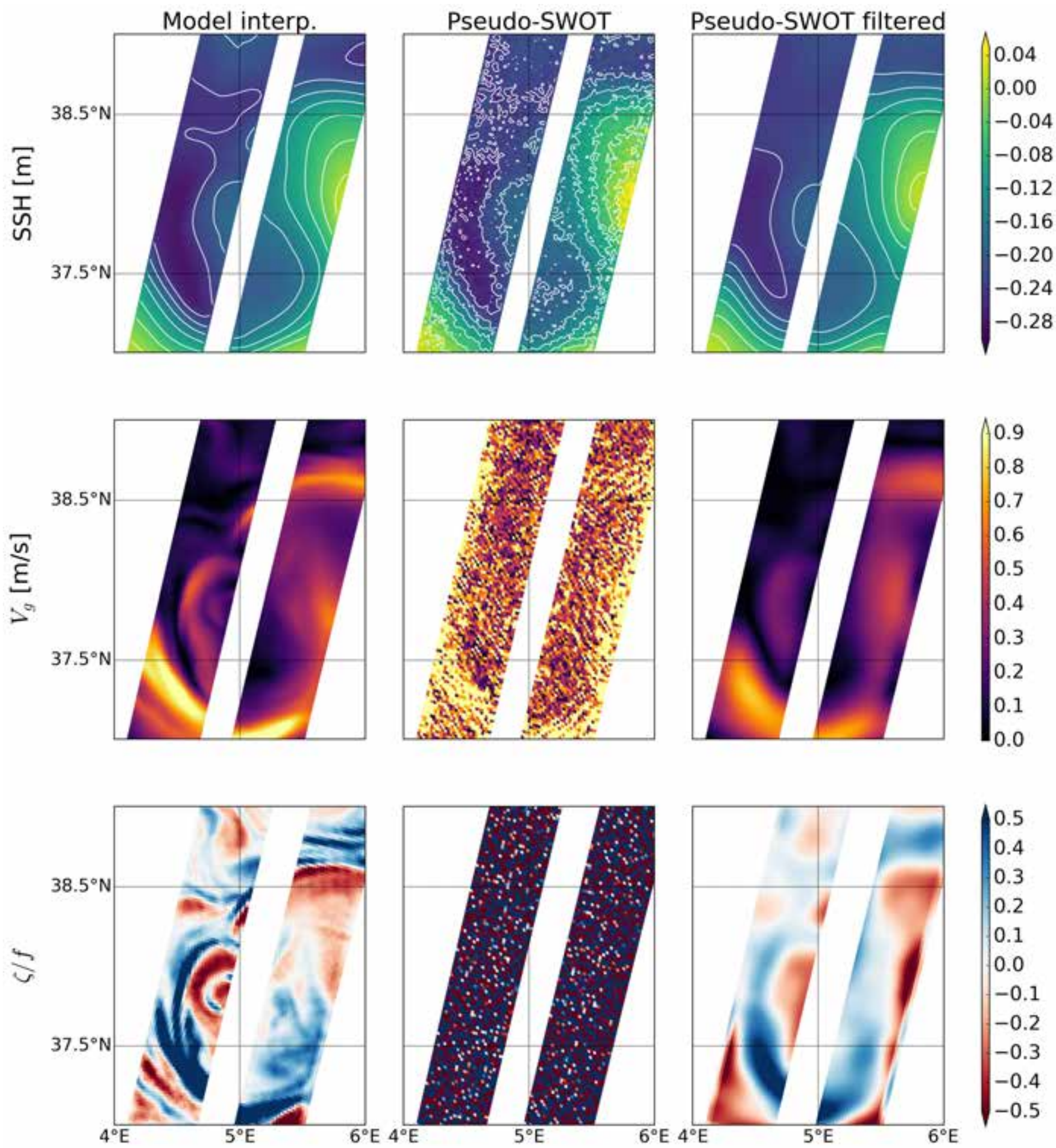
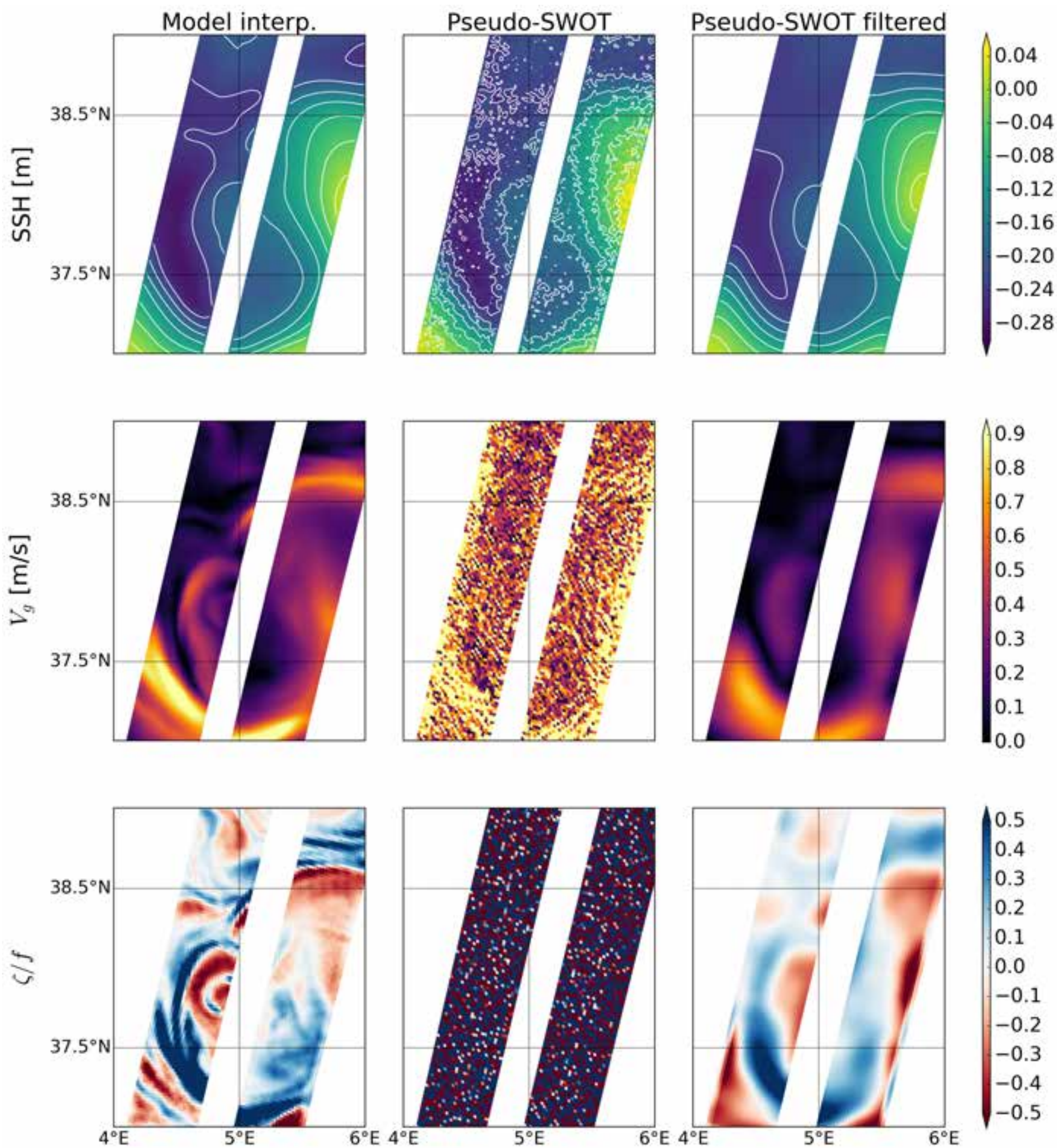


Model interp.
Pseudo-SWOT
Pseudo-SWOT filtered
SSH [m]
V_g [m/s]
ζ/f
38.5°N
37.5°N
4°E
5°E
6°E
0.04
0.00
−0.04
−0.08
−0.12
−0.16
−0.20
−0.24
−0.28
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
0.5
0.4
0.3
0.2
0.1
0.0
−0.1
−0.2
−0.3
−0.4
−0.5



—> need to investigate further:

Method that better preserves the gradients and their intensities.

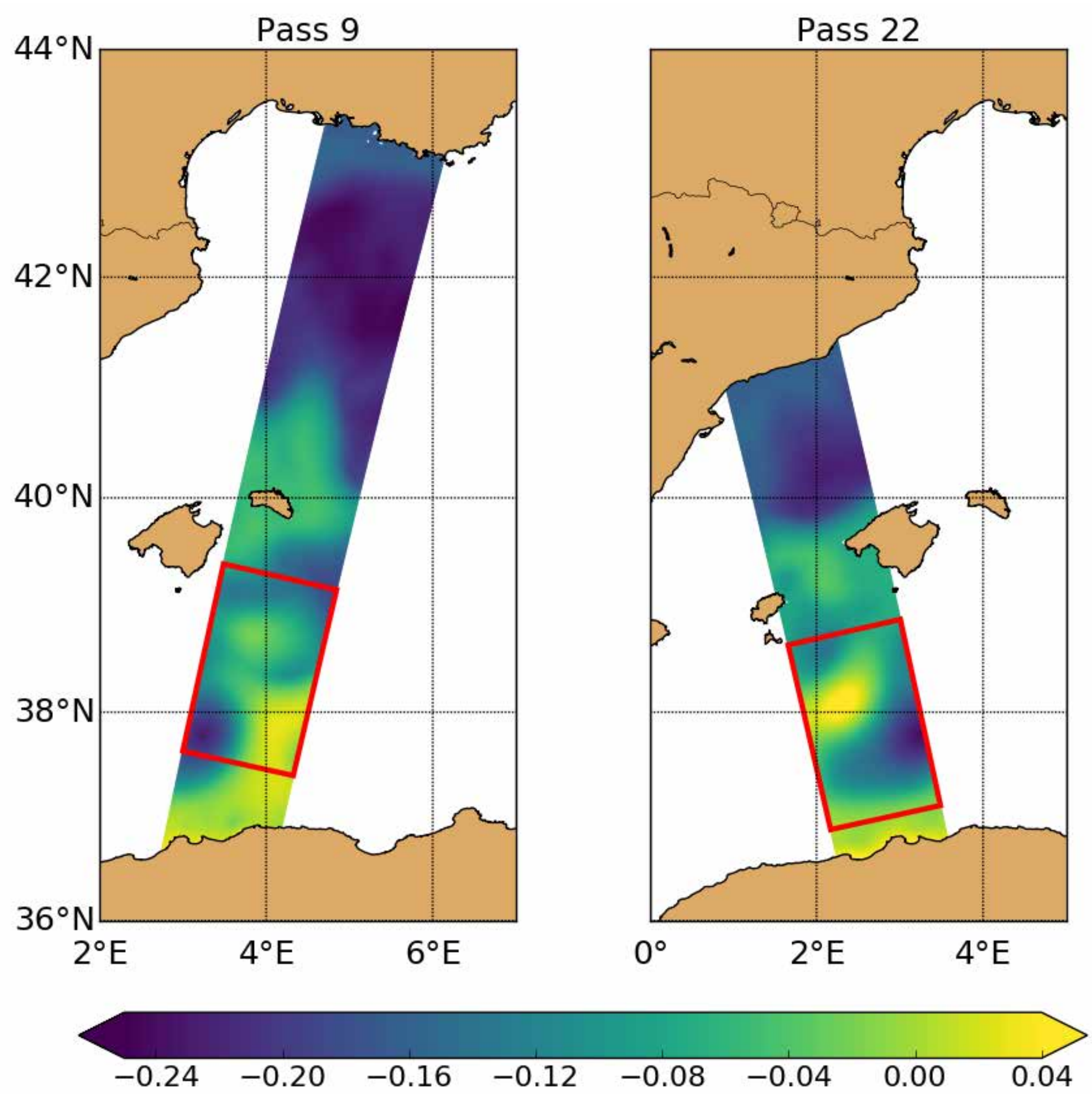
Filtering: Derivatives penalization

—> function we minimize:

$$\boxed{J(h) = \frac{1}{2}\|h - h_{obs}\|^2 + \frac{\lambda_1}{2}\|\nabla h\|^2 + \frac{\lambda_2}{2}\|\Delta h\|^2 + \frac{\lambda_3}{2}\|\nabla \Delta h\|^2}$$

—> can penalize order 1, 2 or 3 or a combination

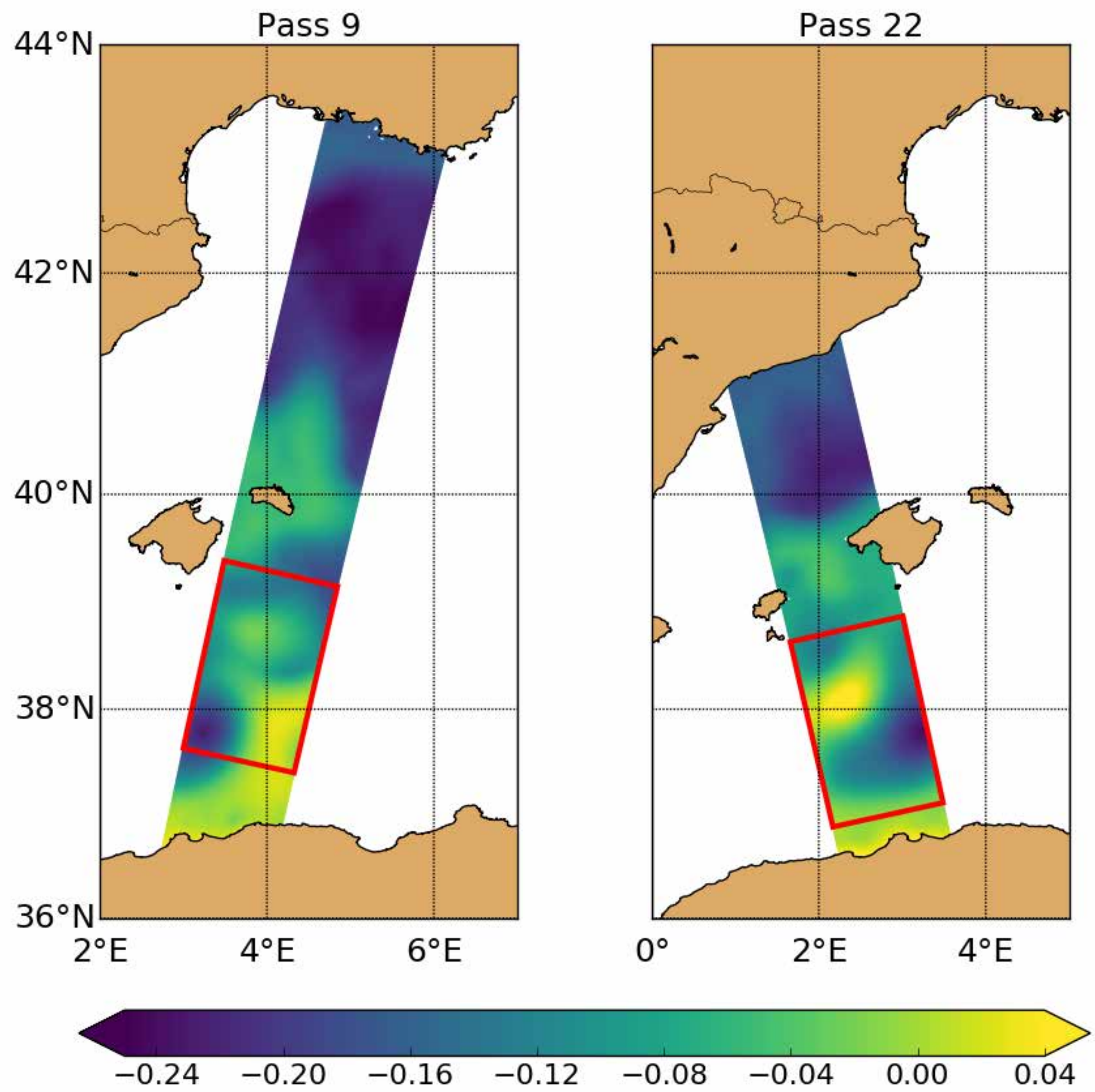
Filtering: dataset



SSH [m]

- Fast-sampling phase
  (SWOT simulator (Gaultier and Ubelmann, 2015))

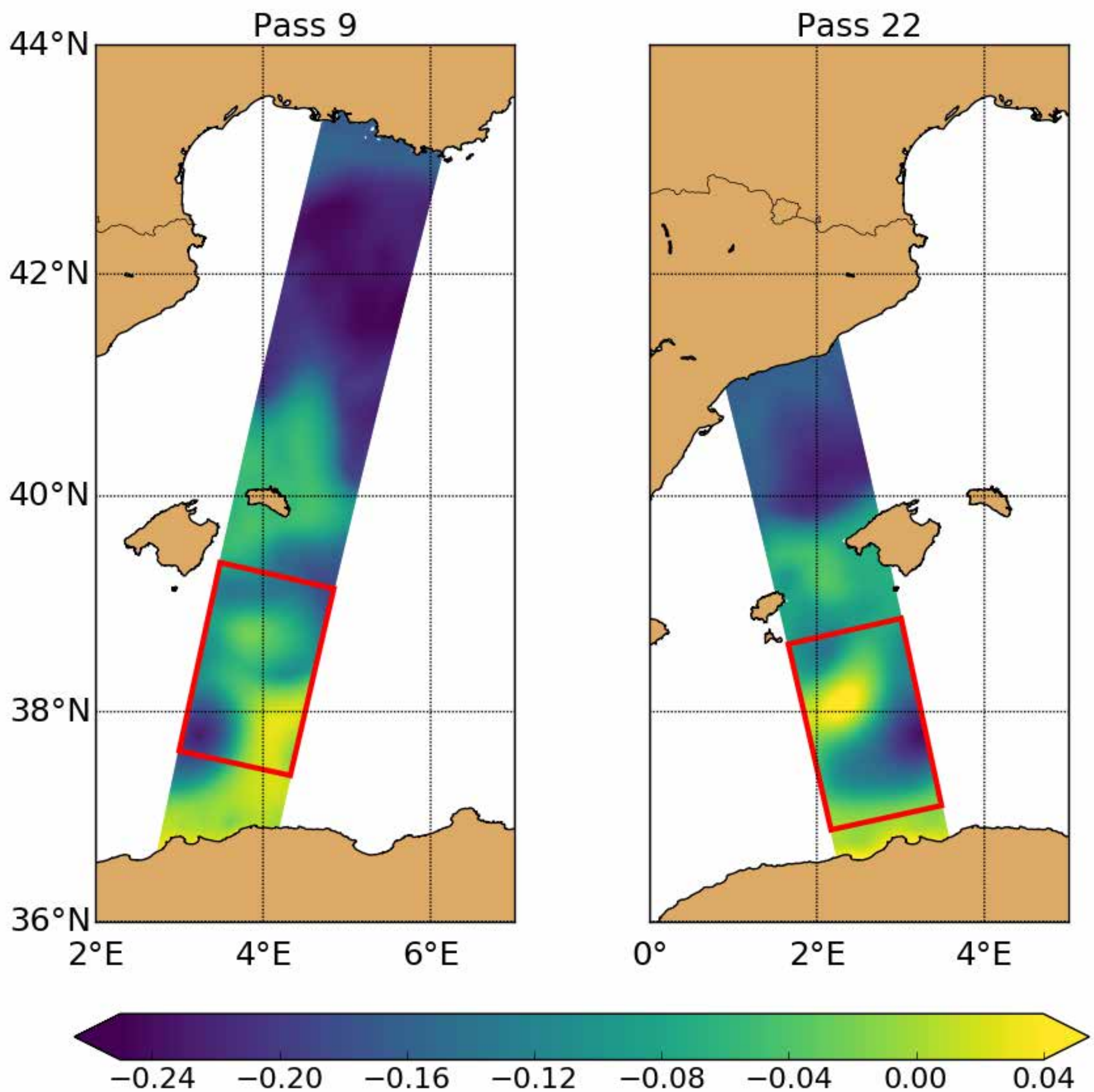
Filtering: dataset



SSH [m]

- Fast-sampling phase (SWOT simulator (Gaultier and Ubelmann, 2015))
- Season specific dataset

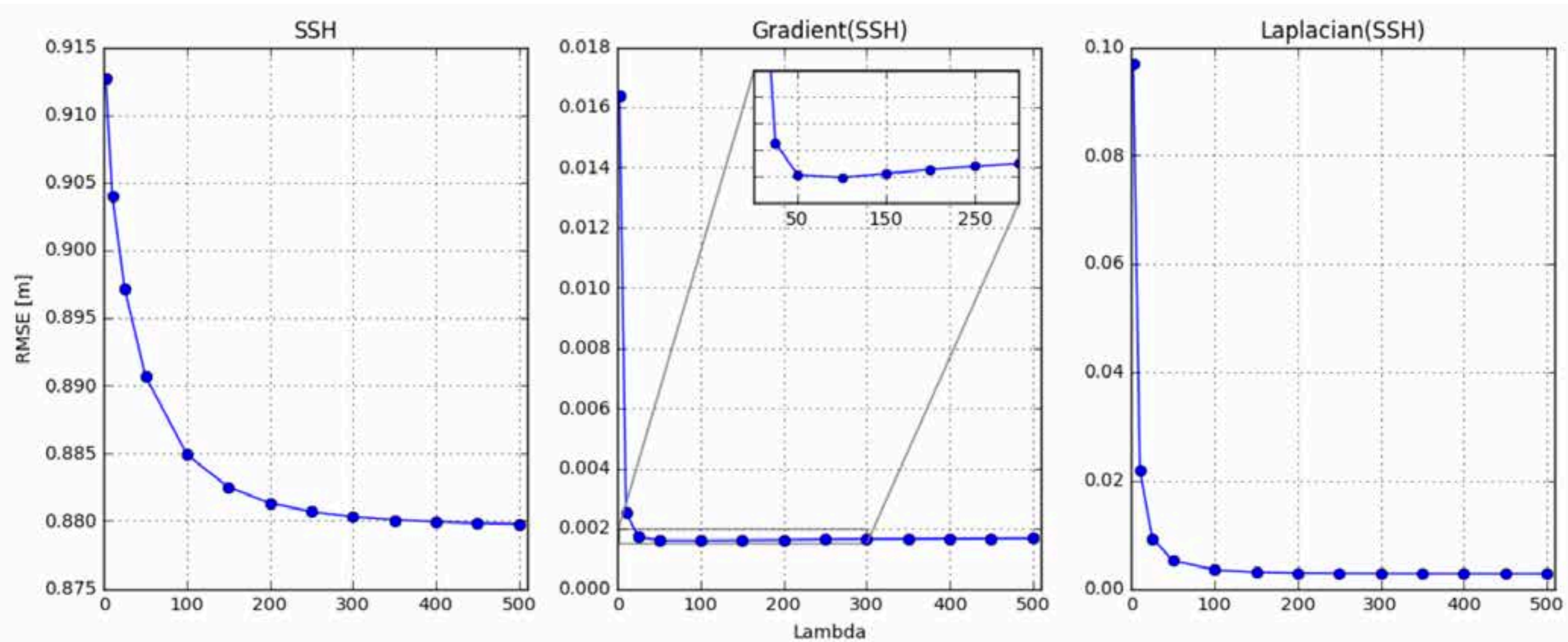
Filtering: dataset



SSH [m]

- Fast-sampling phase (SWOT simulator (Gaultier and Ubelmann, 2015))
- Season specific dataset **—> Summer 2012**

Filtering results: penalization order 1



(Normalized by RMSE of non-filtered SSH)

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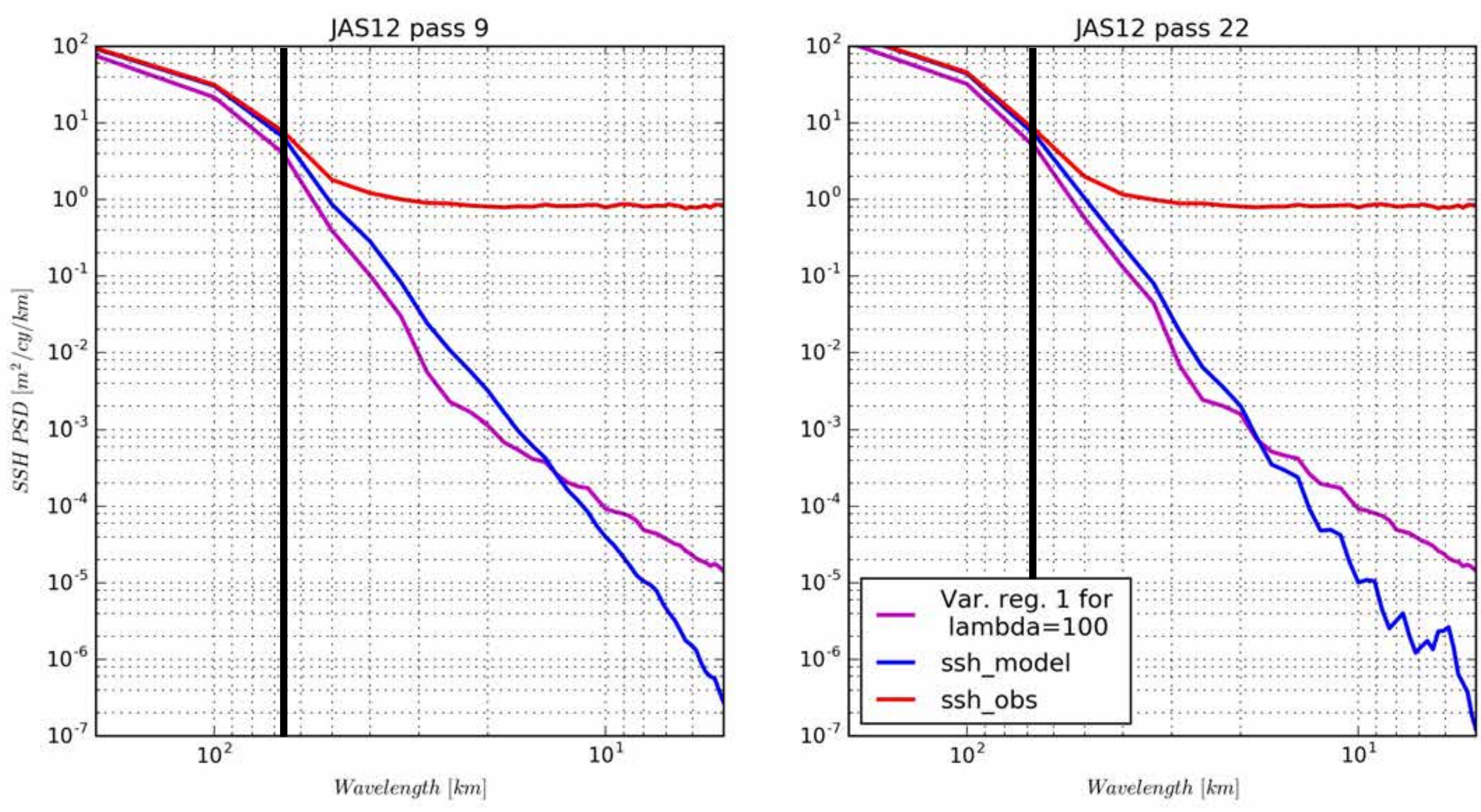

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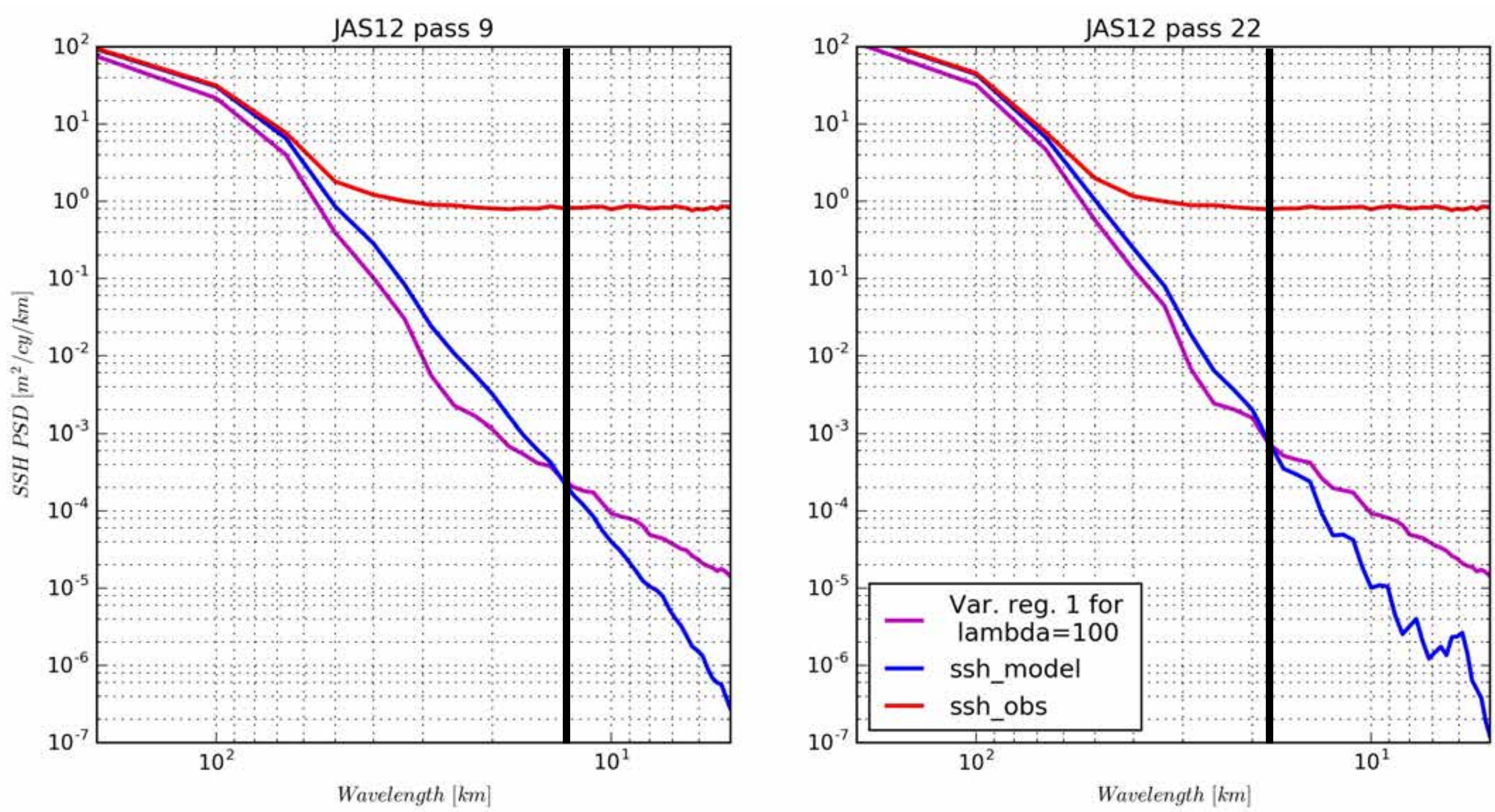

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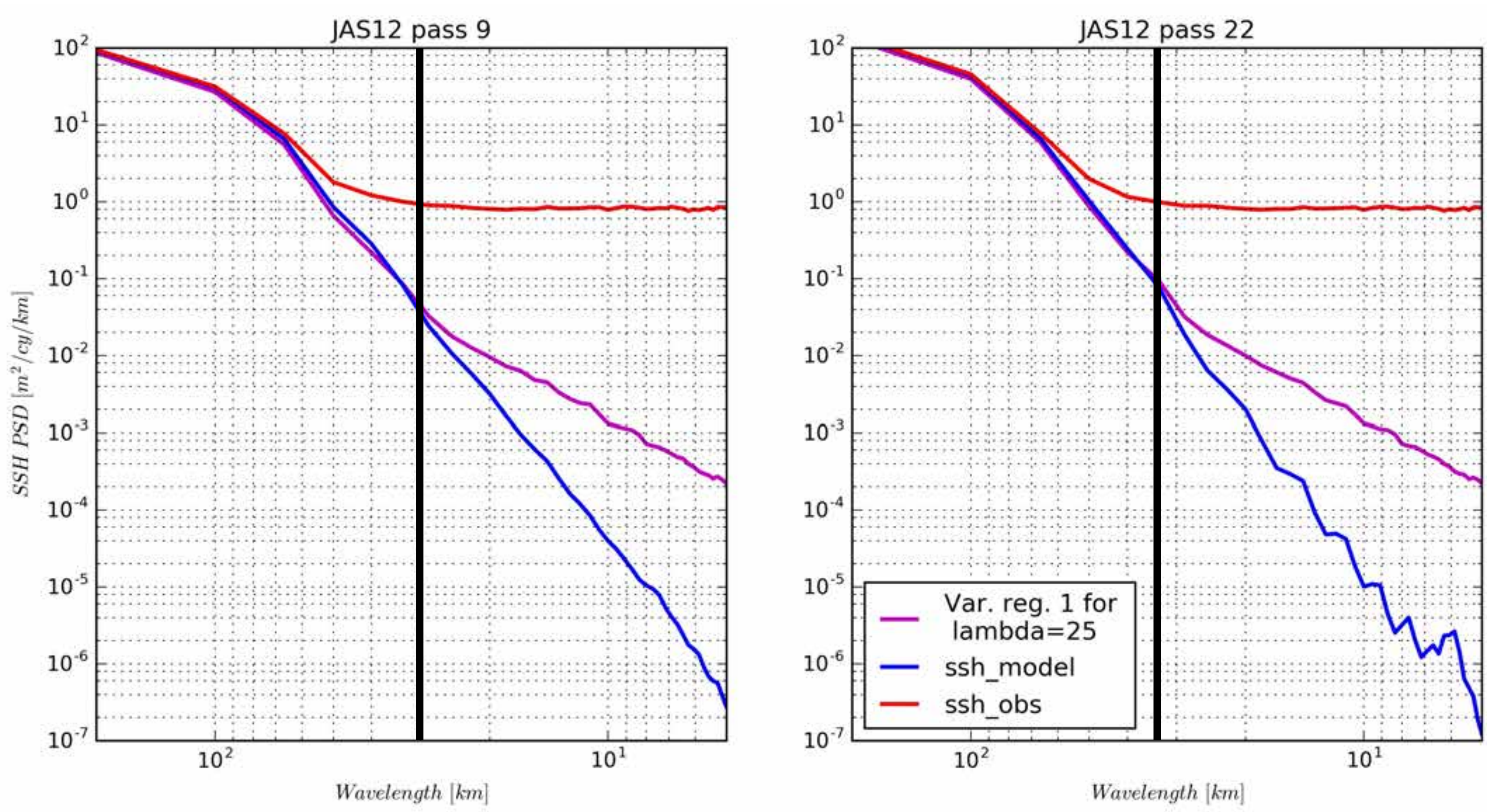

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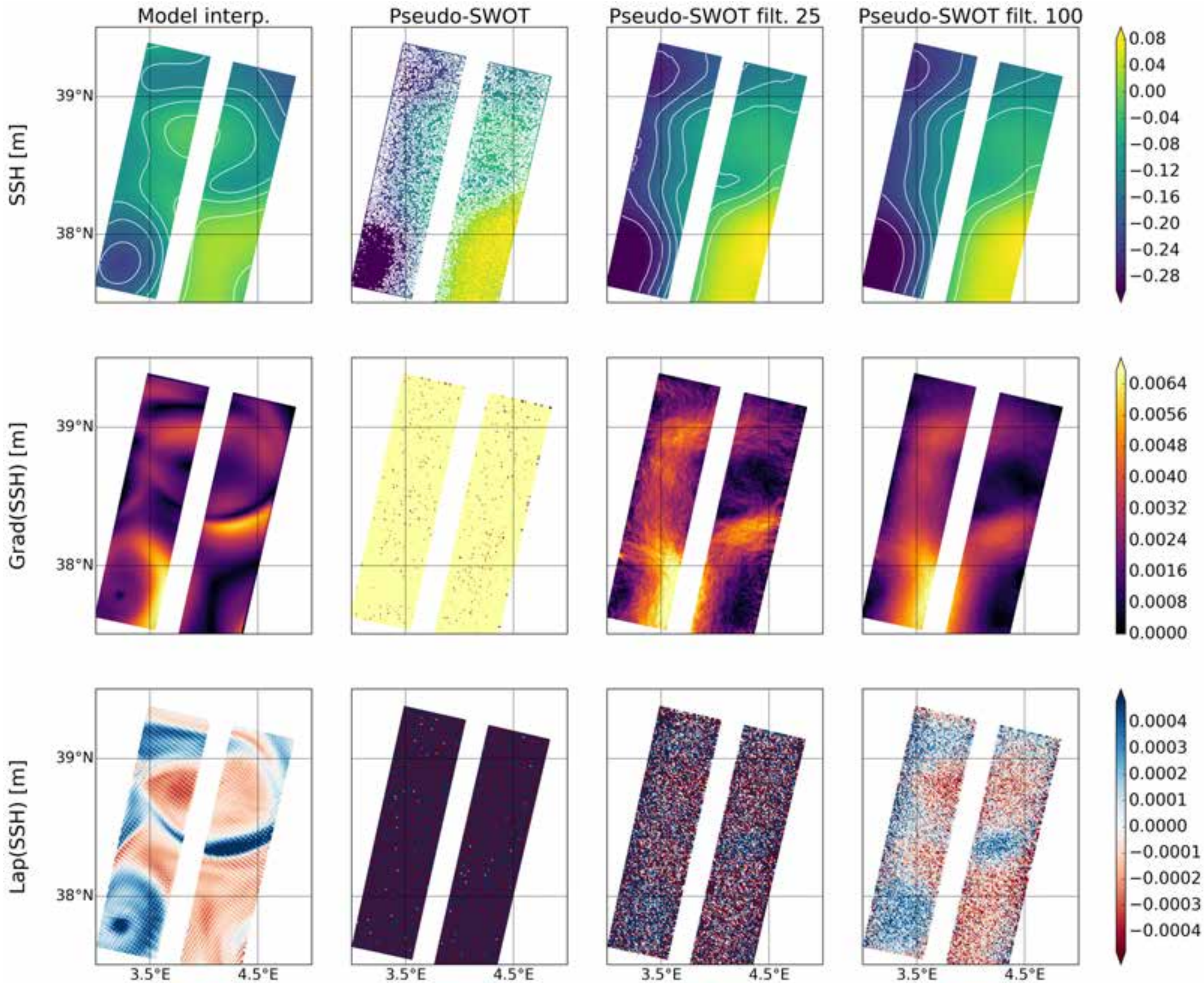

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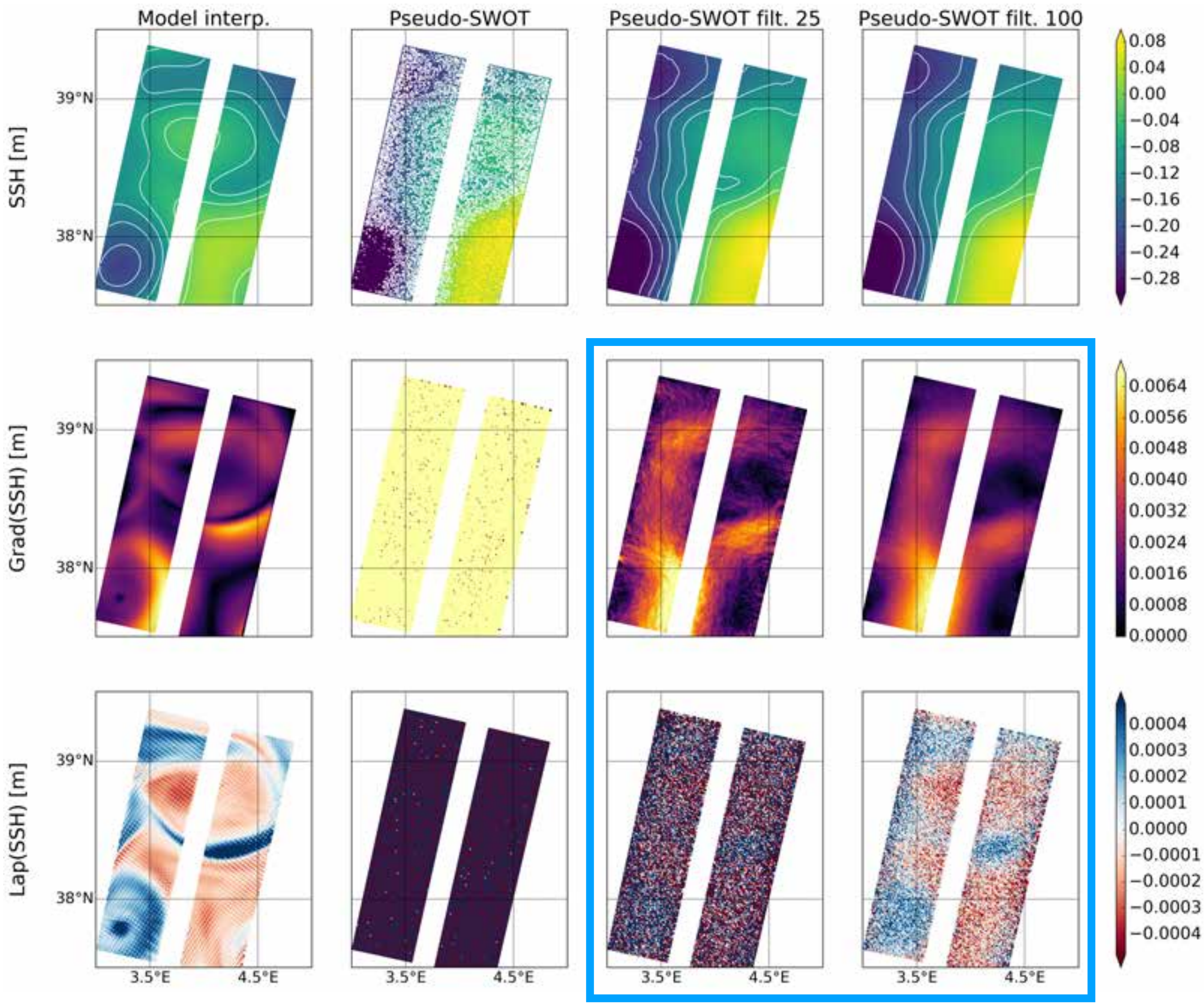
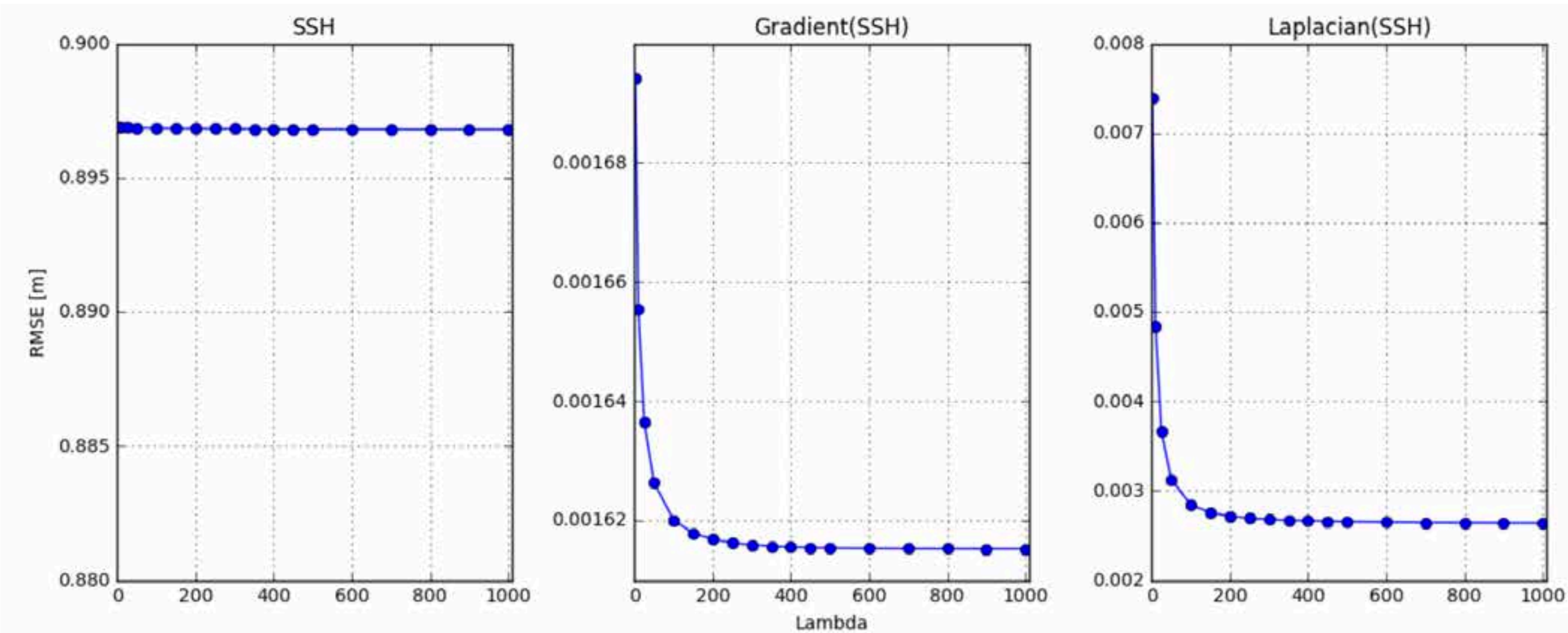


Filtering results: penalization order 1 + 2

Lambda 1 = 25



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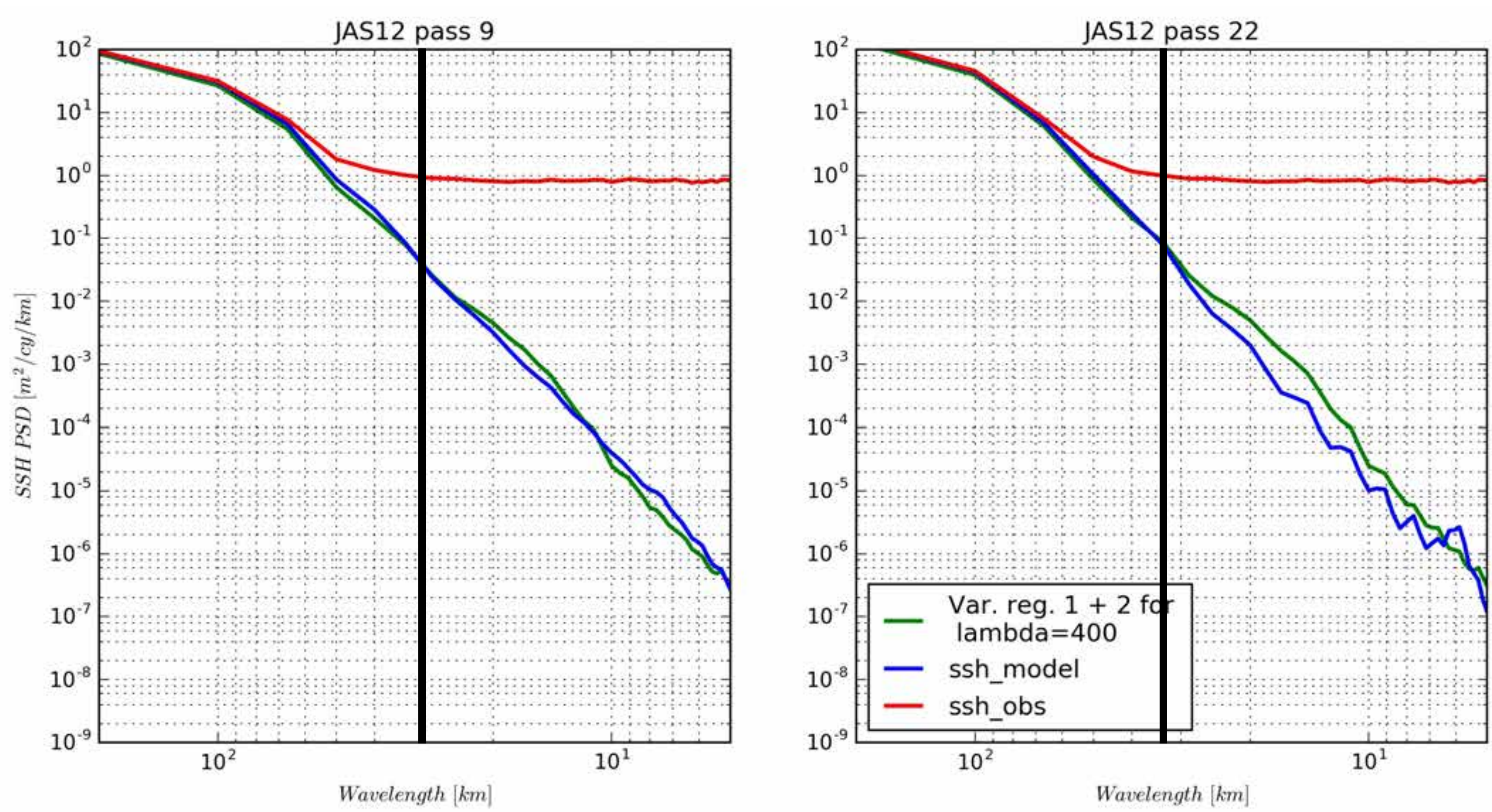

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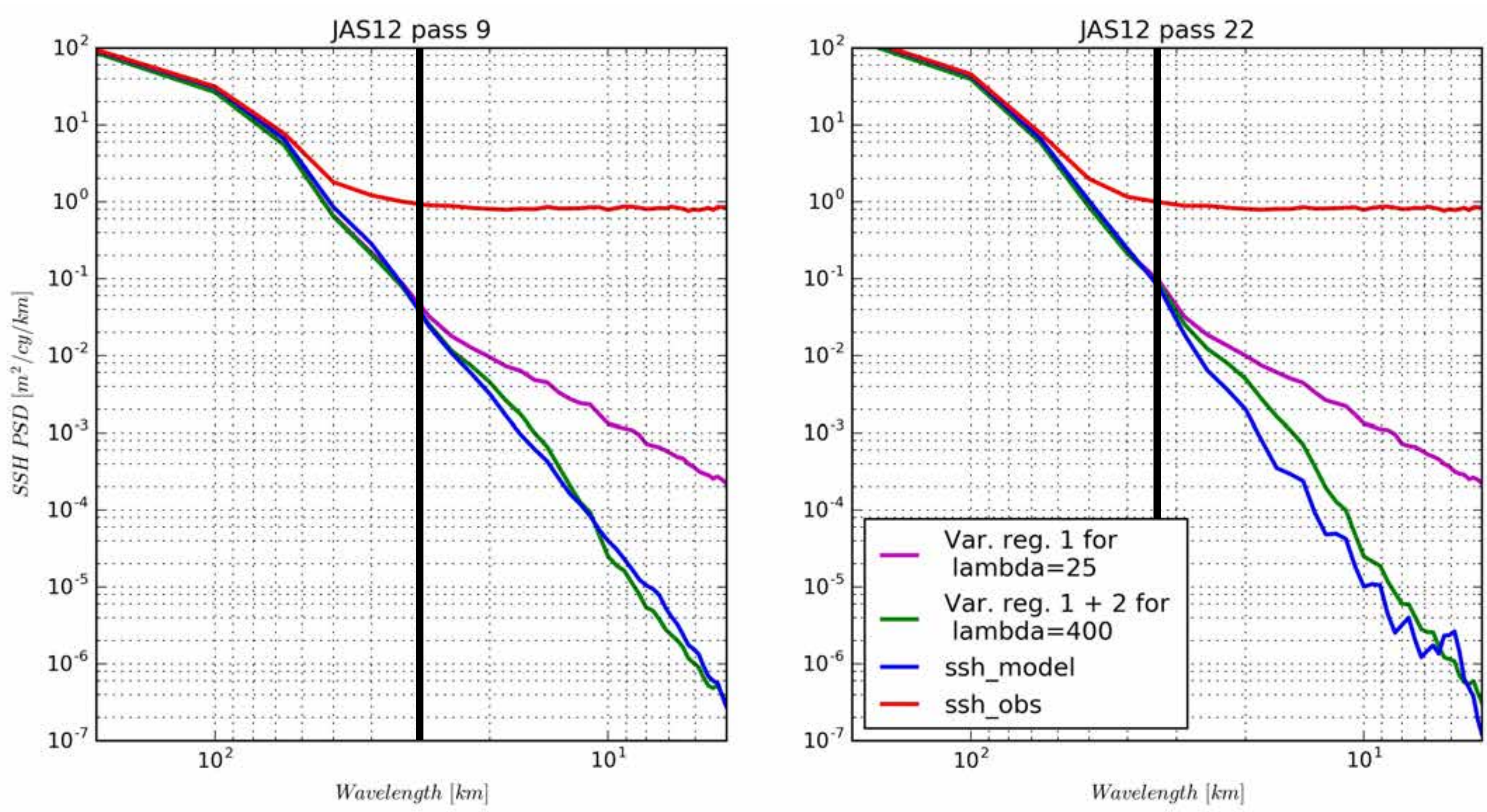

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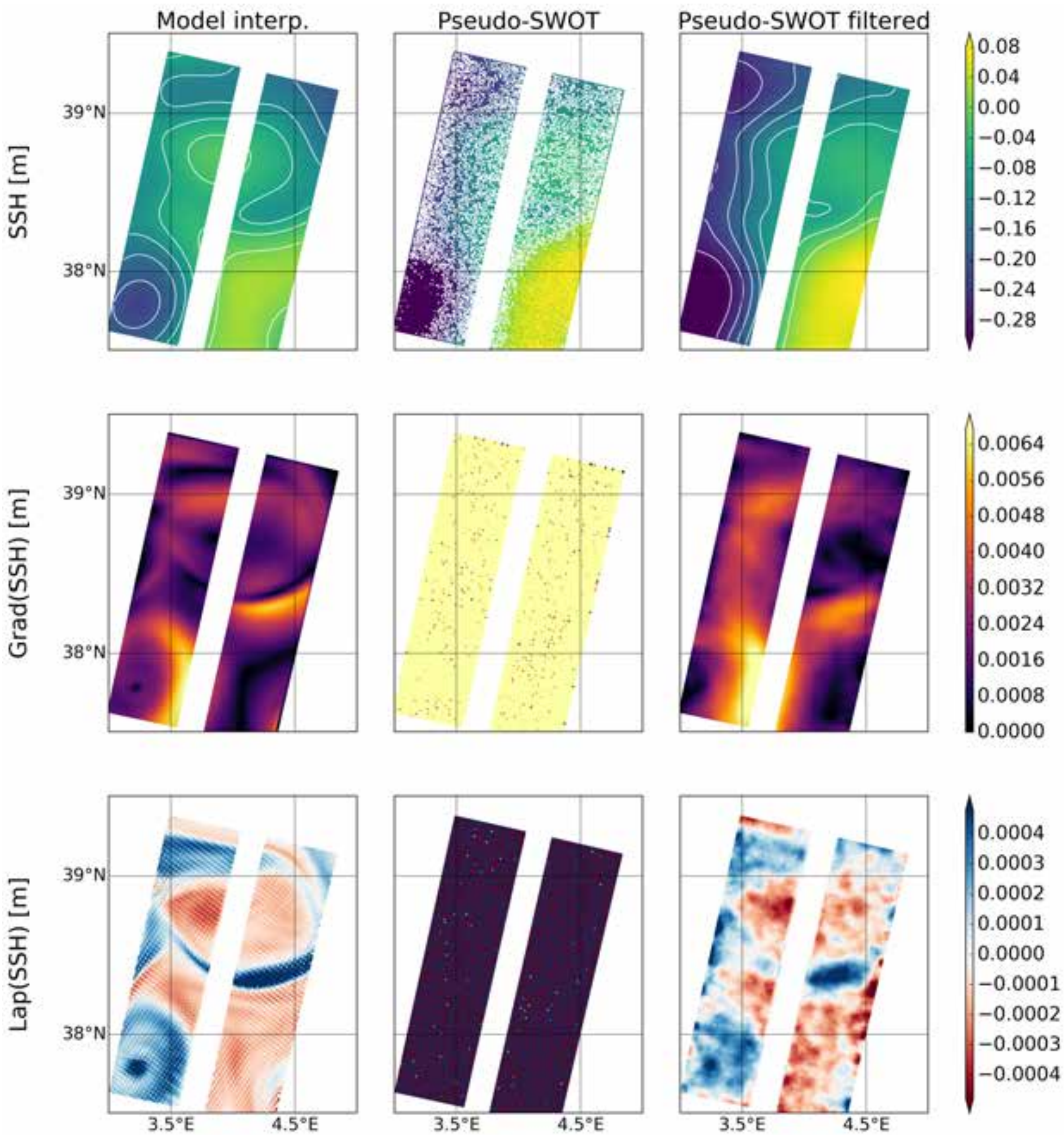

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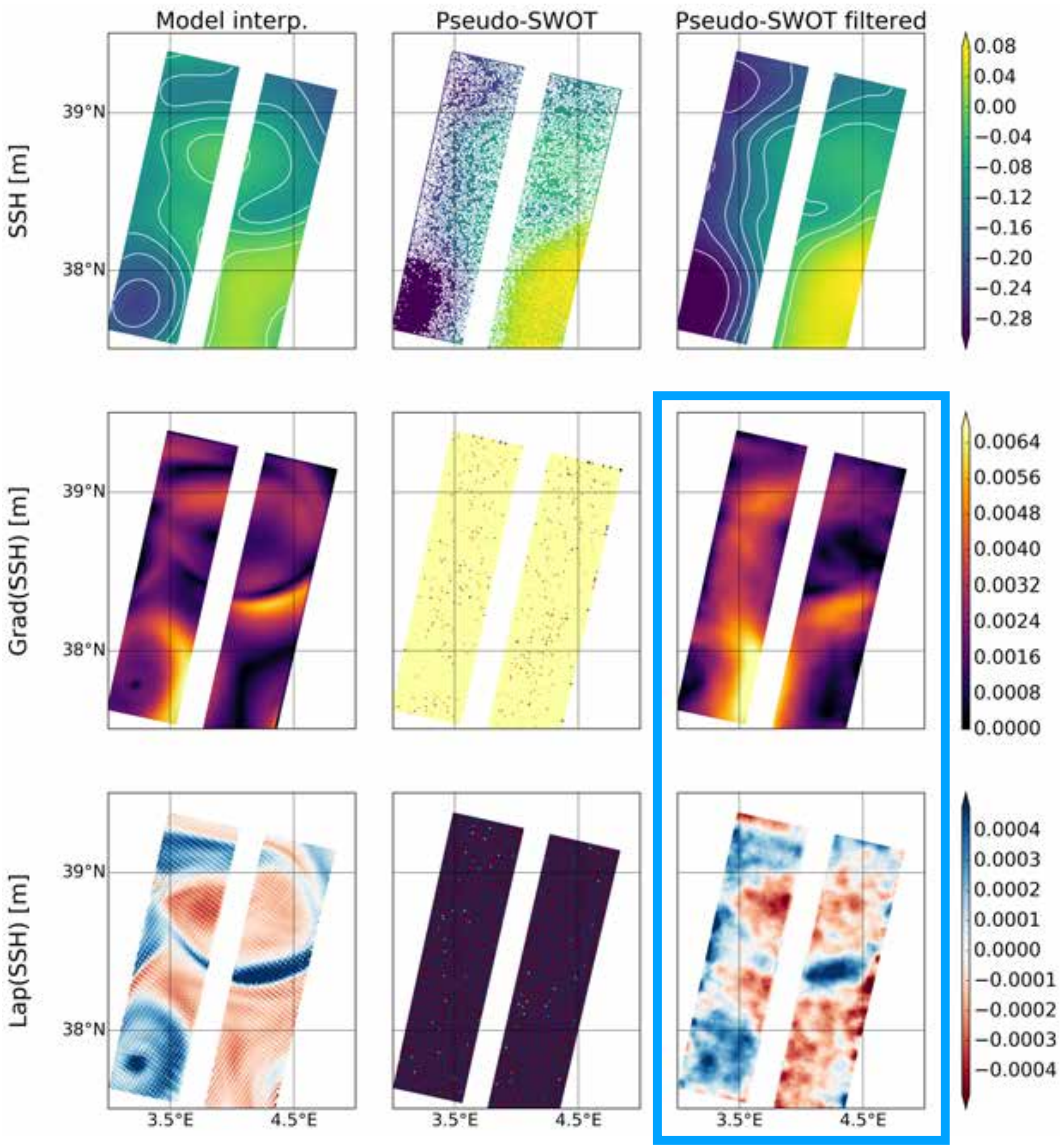

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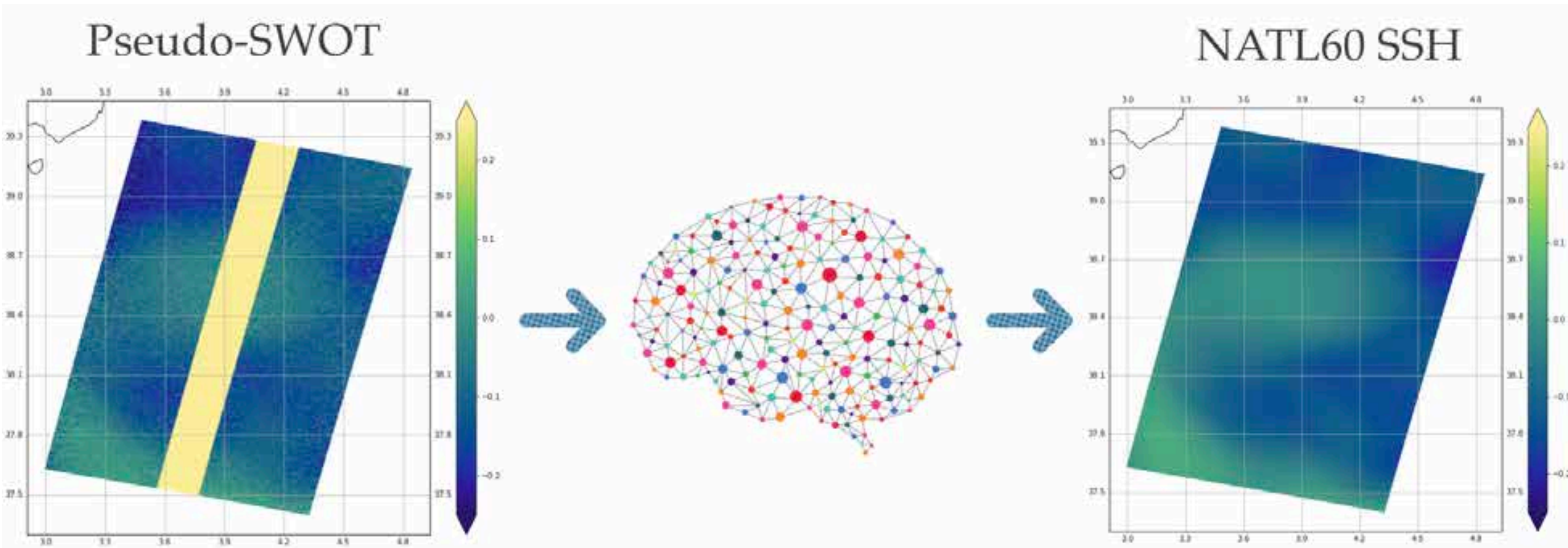
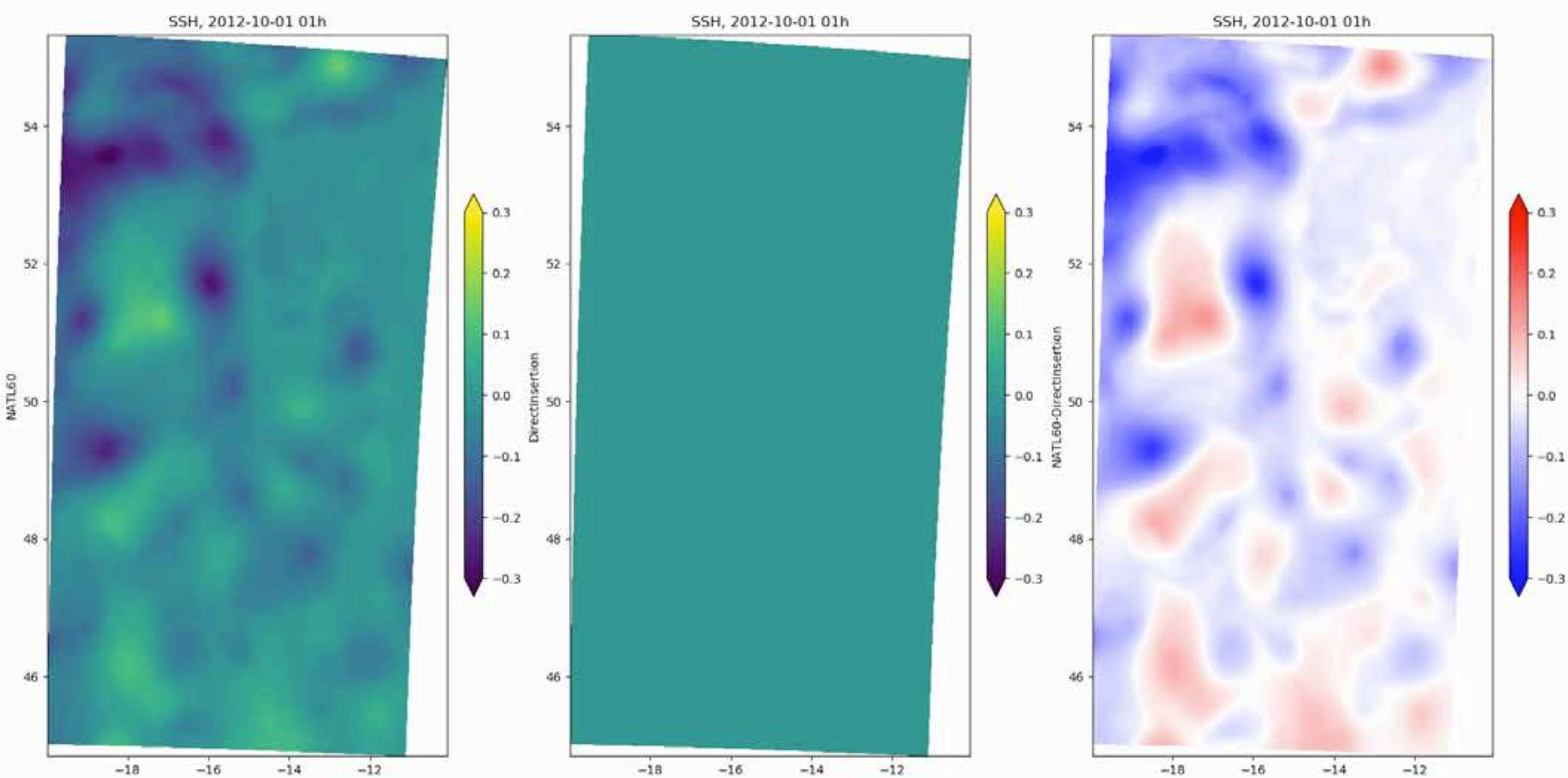
Alternative method: Convolutional Neural Networks for restoring SWOT



Machine Learning methods are getting an increasing interest thanks to deep learning techniques

(R. Lguensat)

Preliminary data assimilation results: (QG model)
From 1st October 2012 to 1st January 2013



(S. Metref)

Conclusions

- **KaRIn (uncorrelated) noise filtering important!**
  - **Filtered pseudo-SWOT resolves wavelengths of 60 km in the western Mediterranean and lower!**
- CNN: alternative method to remove noise
- Data assimilation methods:
  - Remove correlated errors
  - Obtention of 2D gridded maps
- Open source: Denoising tools will be shared with the submitted paper. https://github.com/LauraGomezNavarro

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Thank you!

Stay tuned for youtube videos!

https://tinyurl.com/MEOM-IGE

Additional information

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$$h^{k+1} = h^k + \tau_3(h_{obs} - h^k + \lambda_1 \Delta h^k + \lambda_2 \Delta\Delta h^k + \lambda_3 \Delta\Delta\Delta h^k)$$

- ; hobs = SSH_obs (Pseudo-SWOT dat to be filtered)
  h => pre-conditioning —> Gaussian-filtered image

- Other info.??

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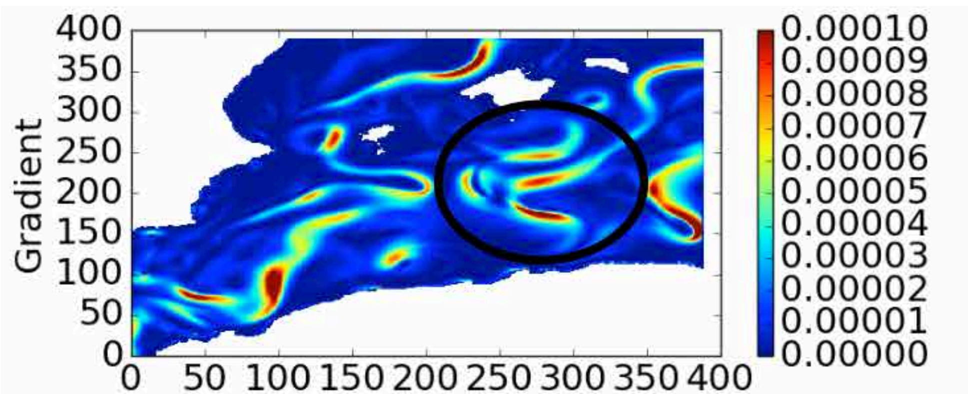
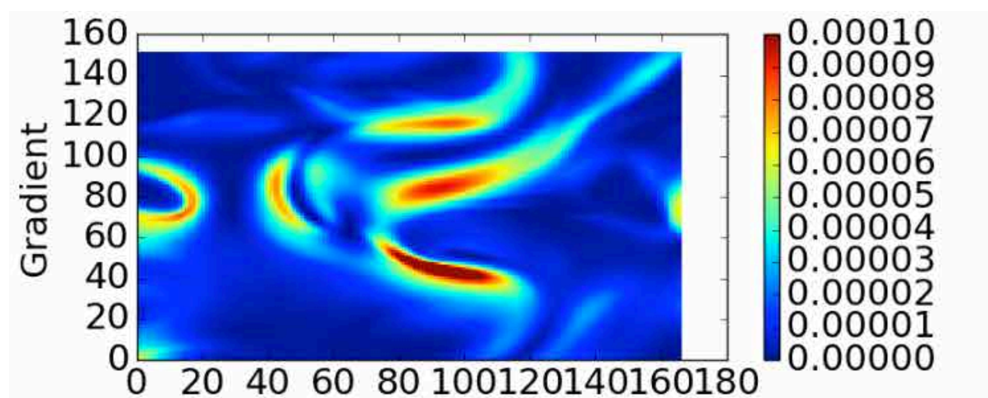
- Choice of parameters

Filtering: Derivatives penalization

Choice of parameters: lambda

—> L2 norm calculation





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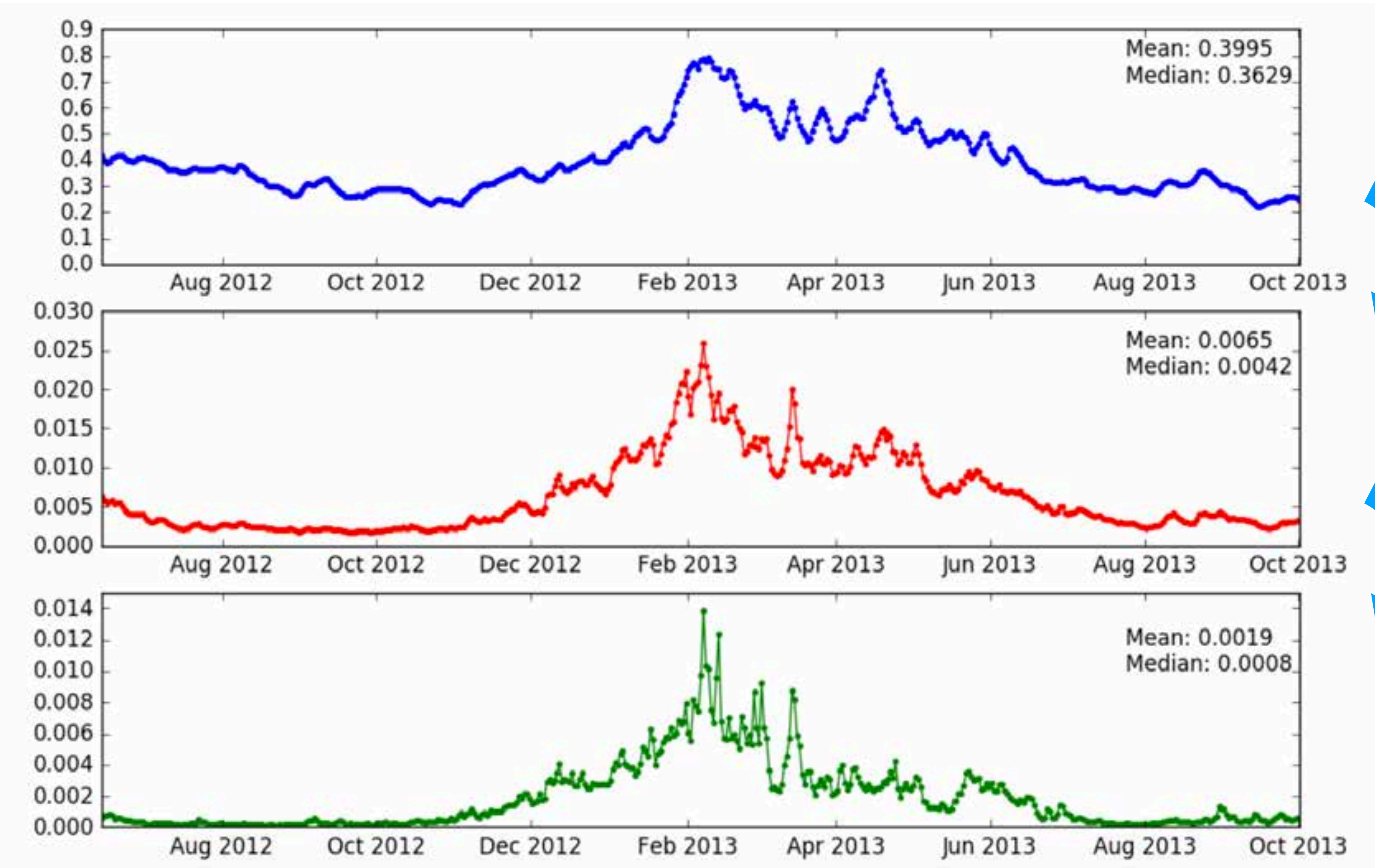
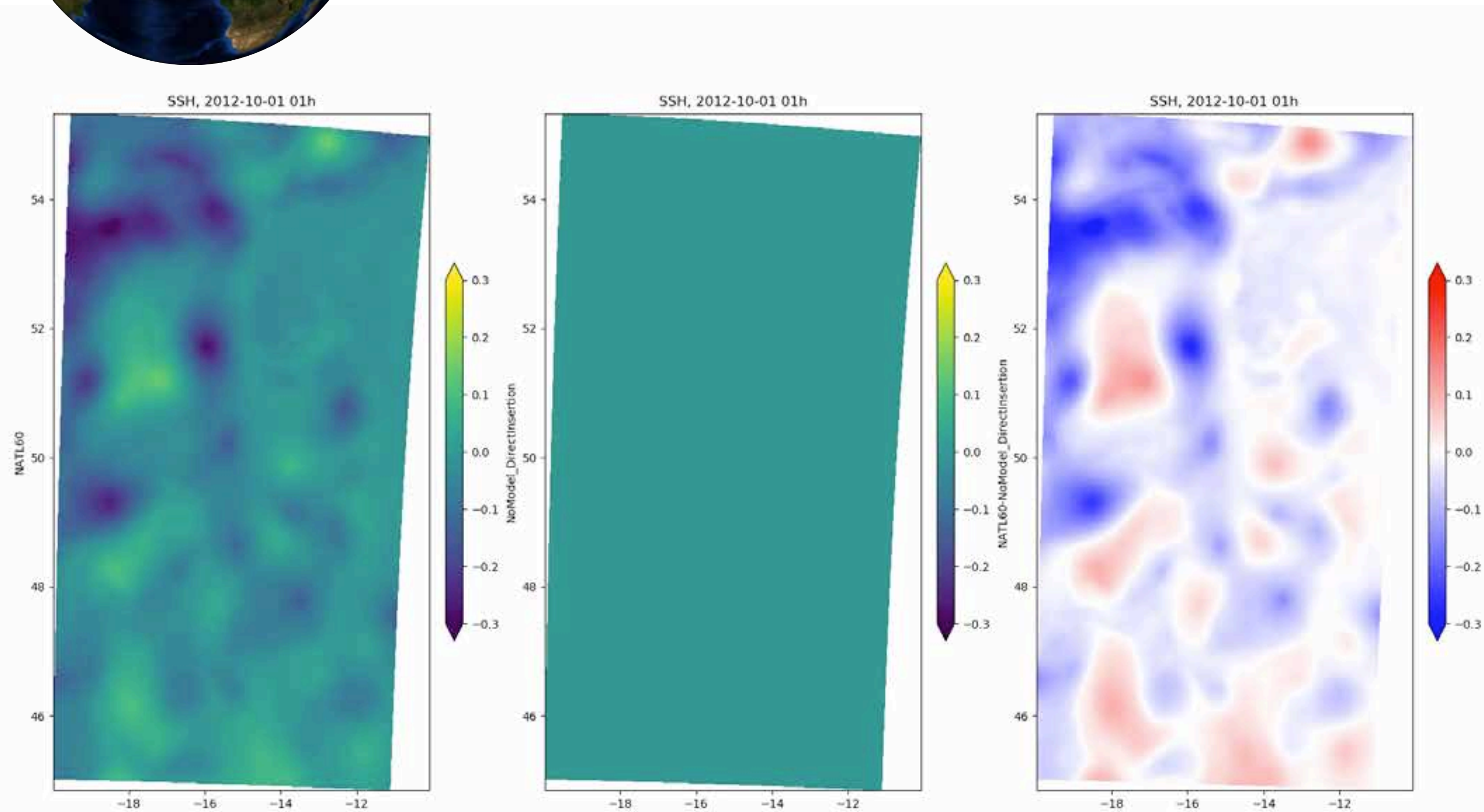
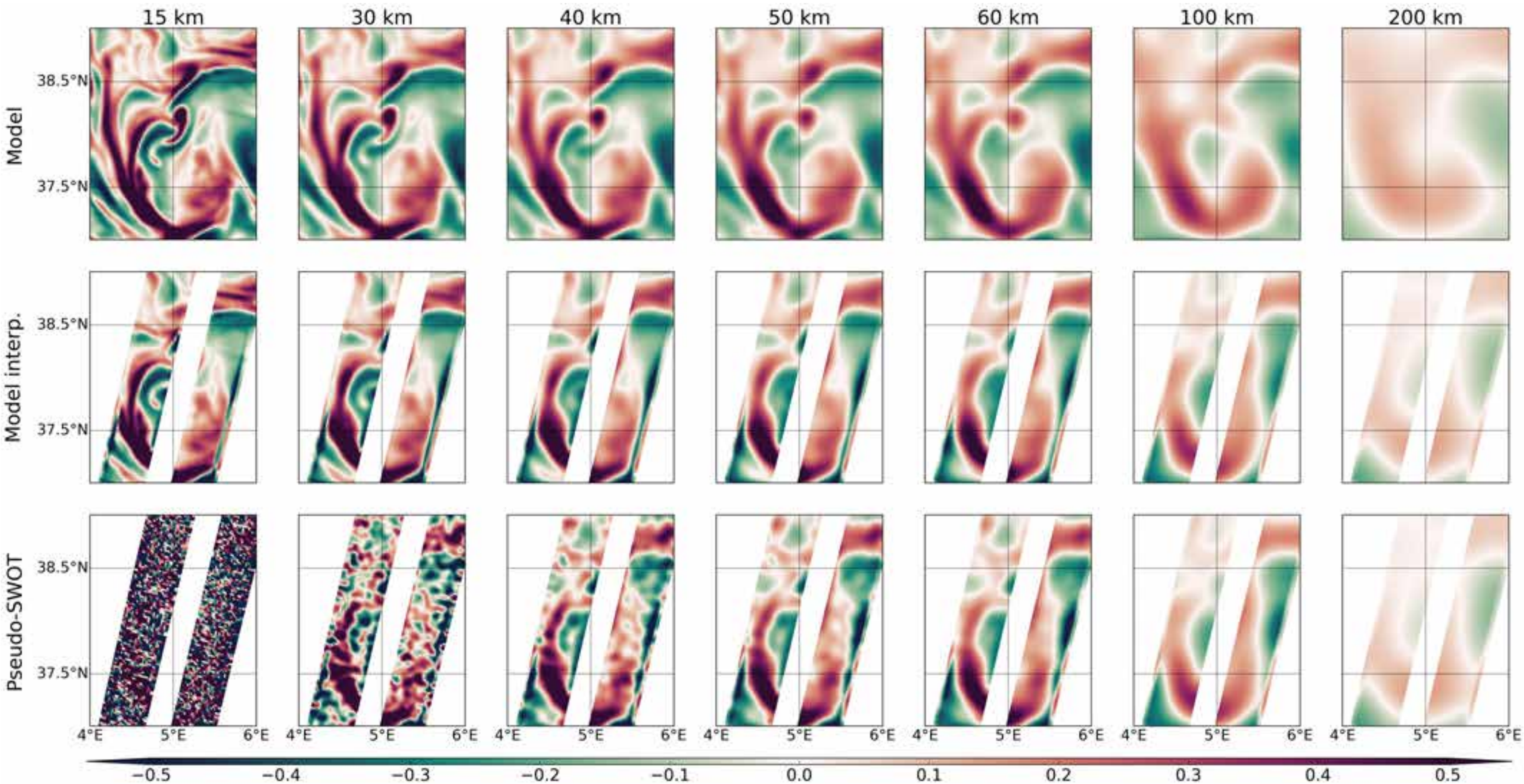


2 orders of magnitude

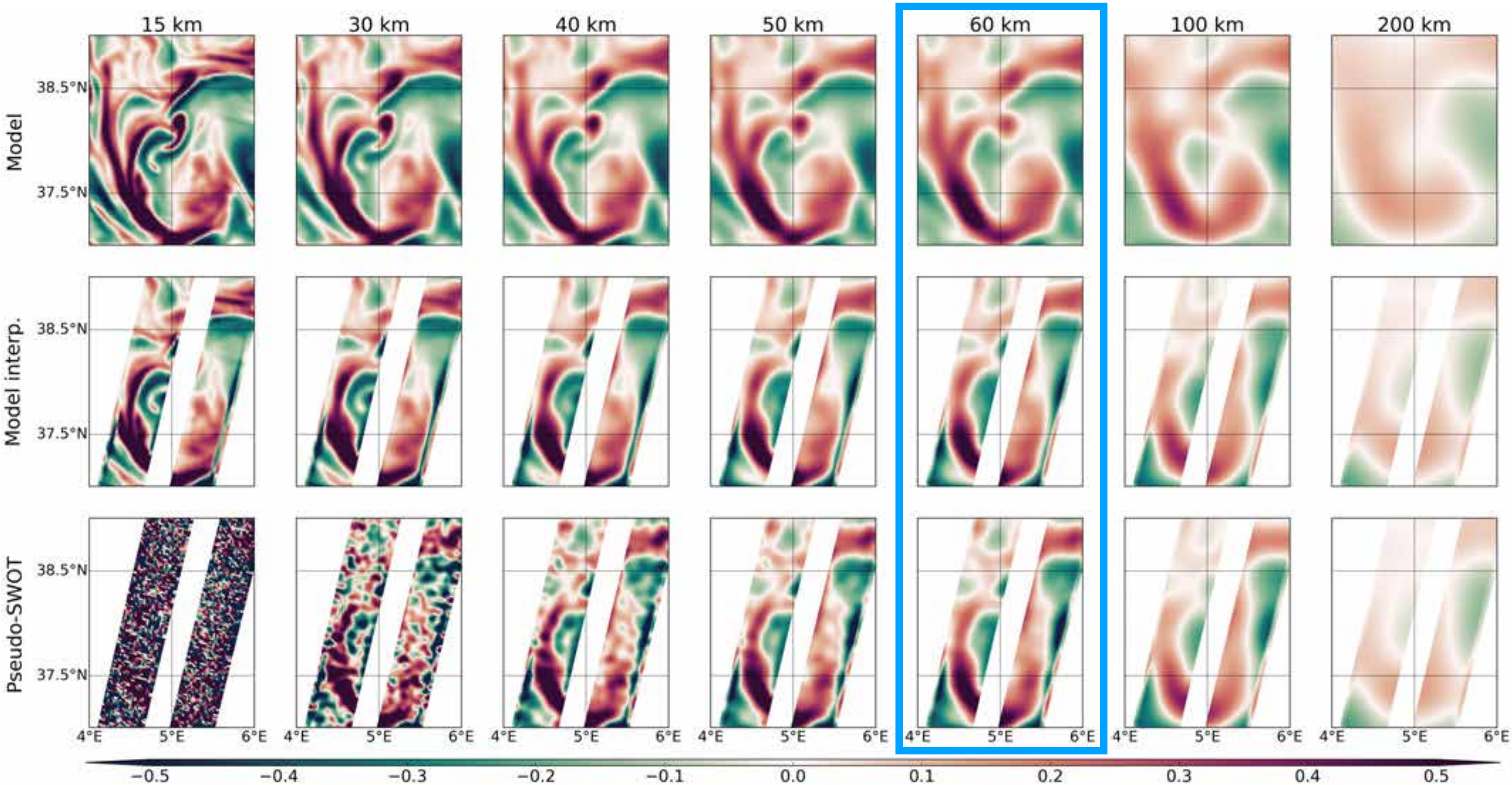
1 order of magnitude

Introduction





Relative vorticity (normalized by f)



Relative vorticity (normalized by f)

Summary

Part 2

- SWOT multi-platform experiments prior to launch are required to prepare CAL/VAL and better characterize the area(s) of study

- Pseudo-SWOT data:
  - SWOT-swath filter
  - Internal waves signal: new SWOT simulations with a global HYCOM simulation including tides. (B. Arbic)

- Joint experiment in 2018 (SW Mediterranean Sea): Spain (PRE-SWOT, MINECO) and France (BIO-SWOT, CNES) + others?. Integrate competences (ship, ADCP, gliders, drifters, underway CTD, underway phytoplankton community, remote sensing, modelling…)

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- **Data assimilation methods use the information on the derivatives**

$$\mathbf{R}^{+} = \begin{pmatrix} \mathbf{D}_0 & 0 & 0 & 0 & 0 \\ 0 & \mathbf{D}_{1a} & 0 & 0 & 0 \\ 0 & 0 & \mathbf{D}_{1c} & 0 & 0 \\ 0 & 0 & 0 & \mathbf{D}_{2a} & 0 \\ 0 & 0 & 0 & 0 & \mathbf{D}_{2c} \end{pmatrix}$$

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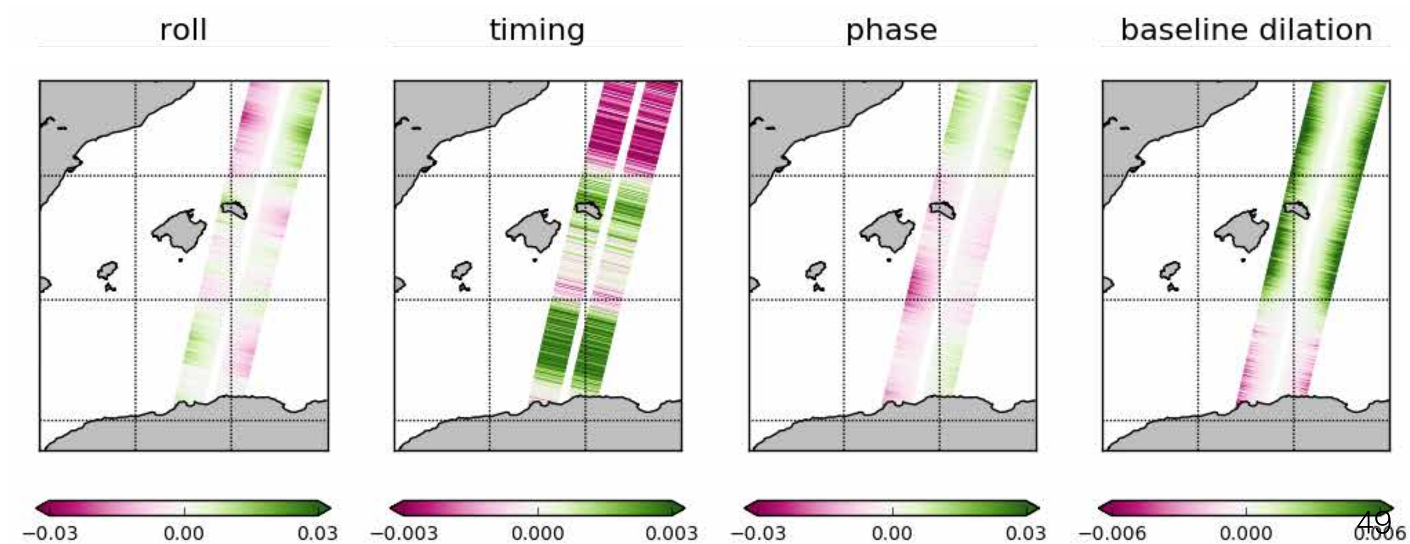
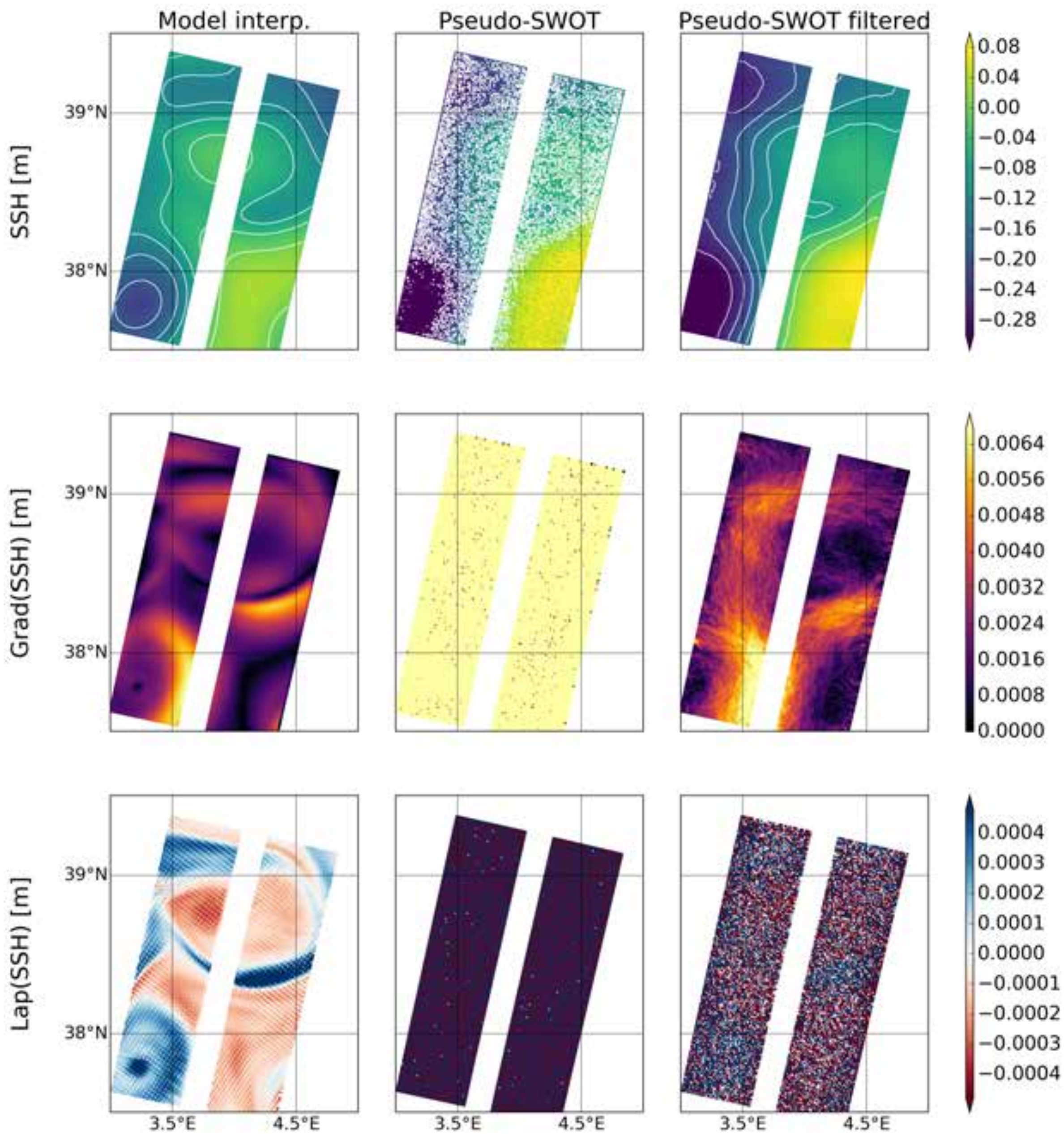


Filtering results: penalization order 1



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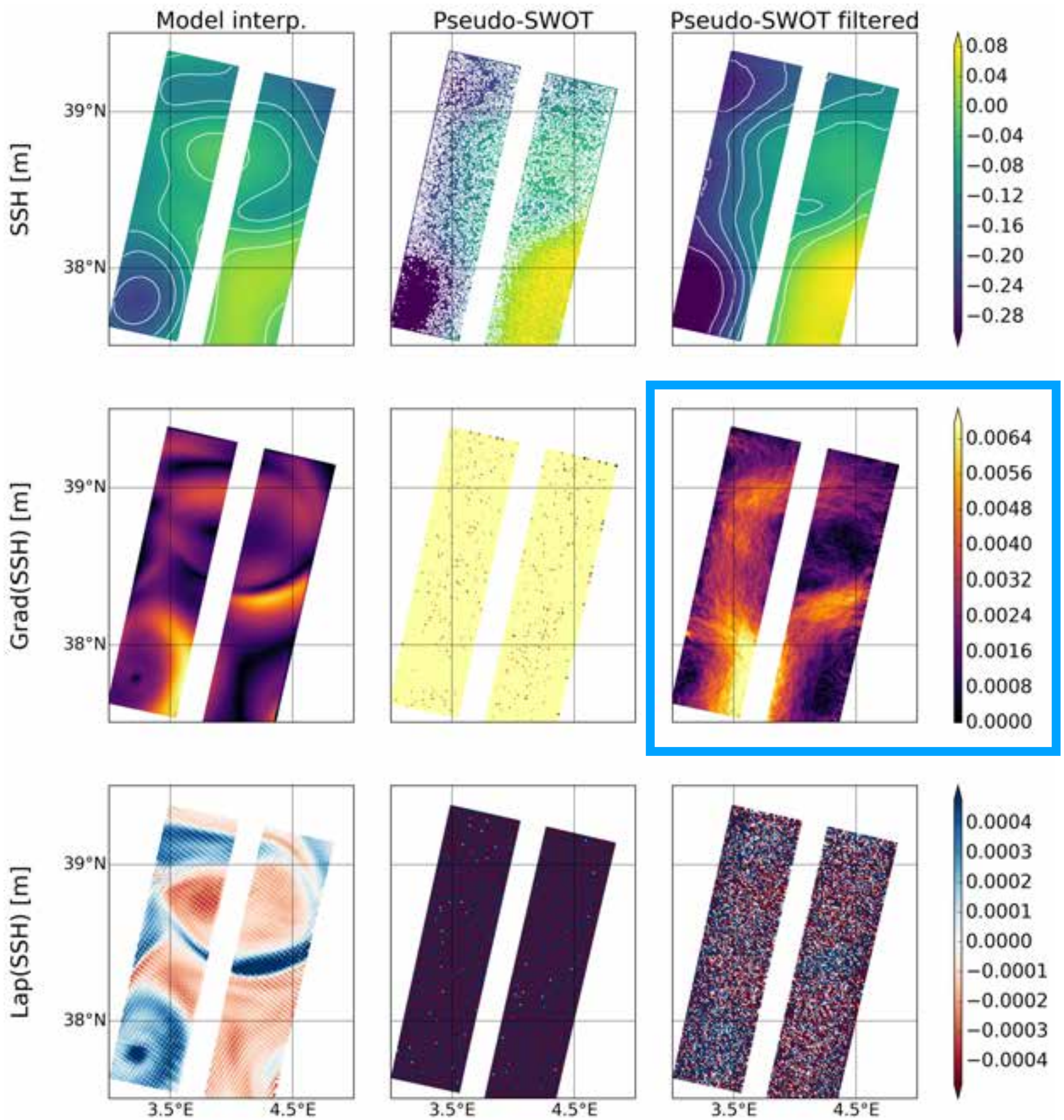

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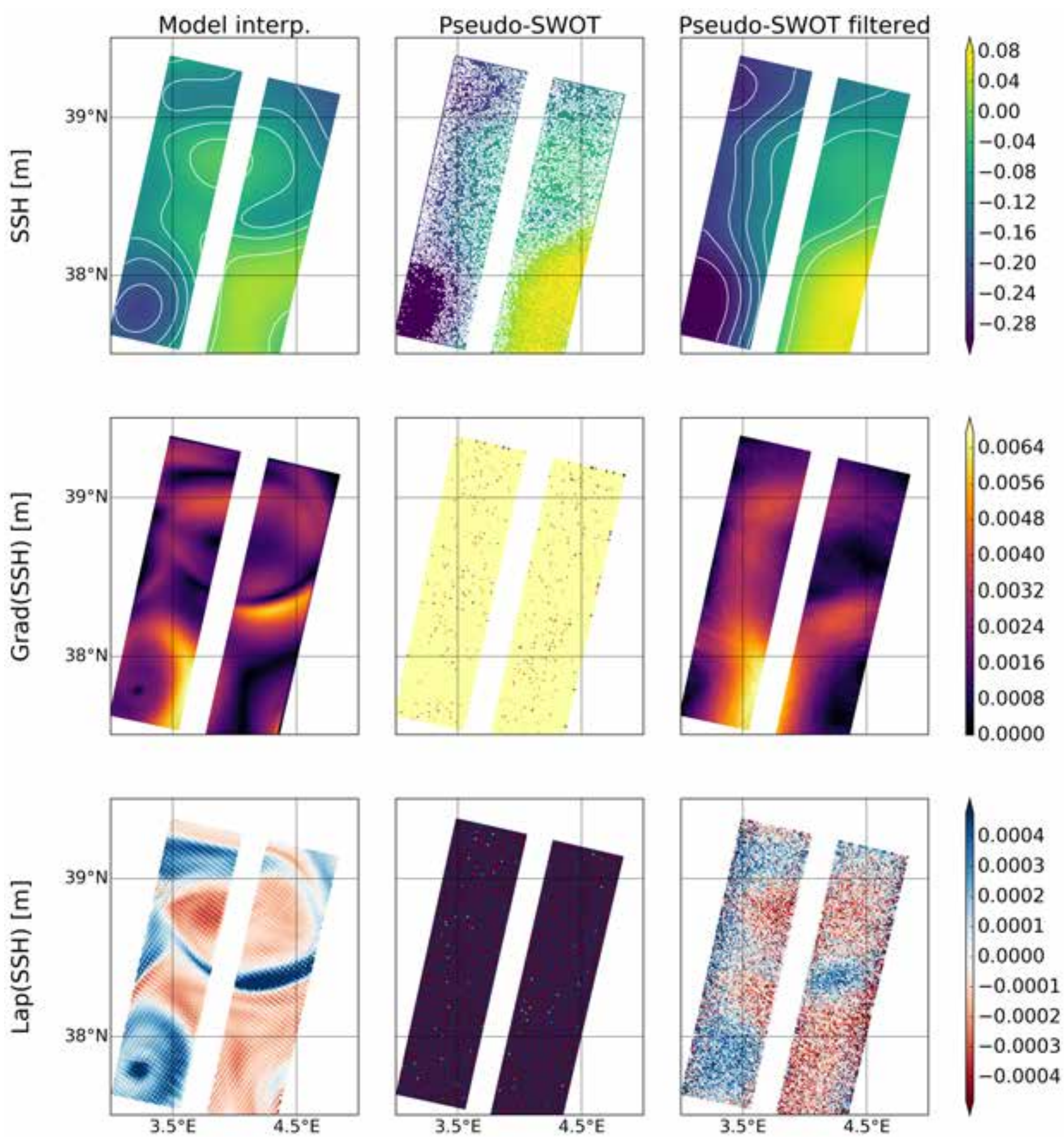
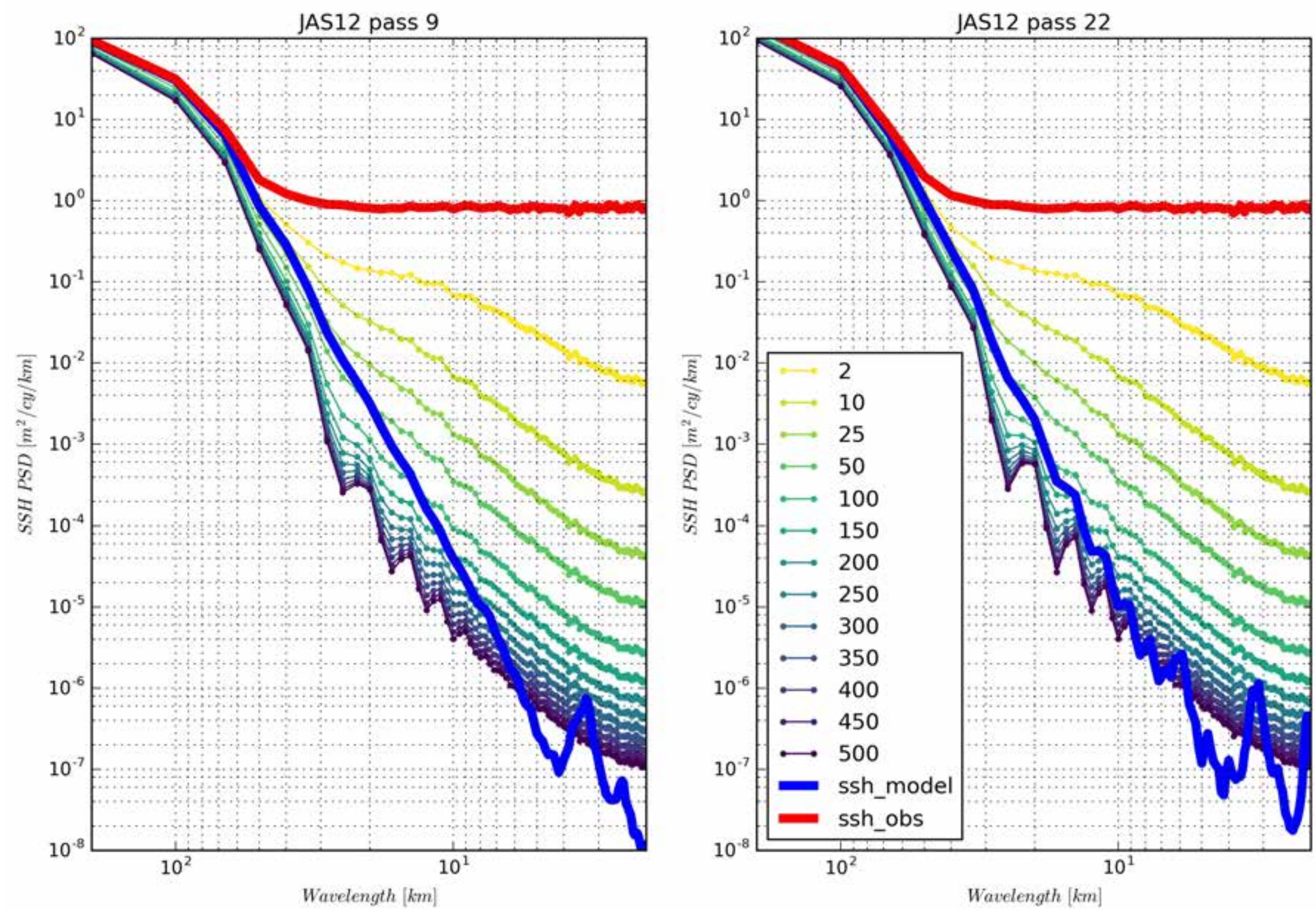
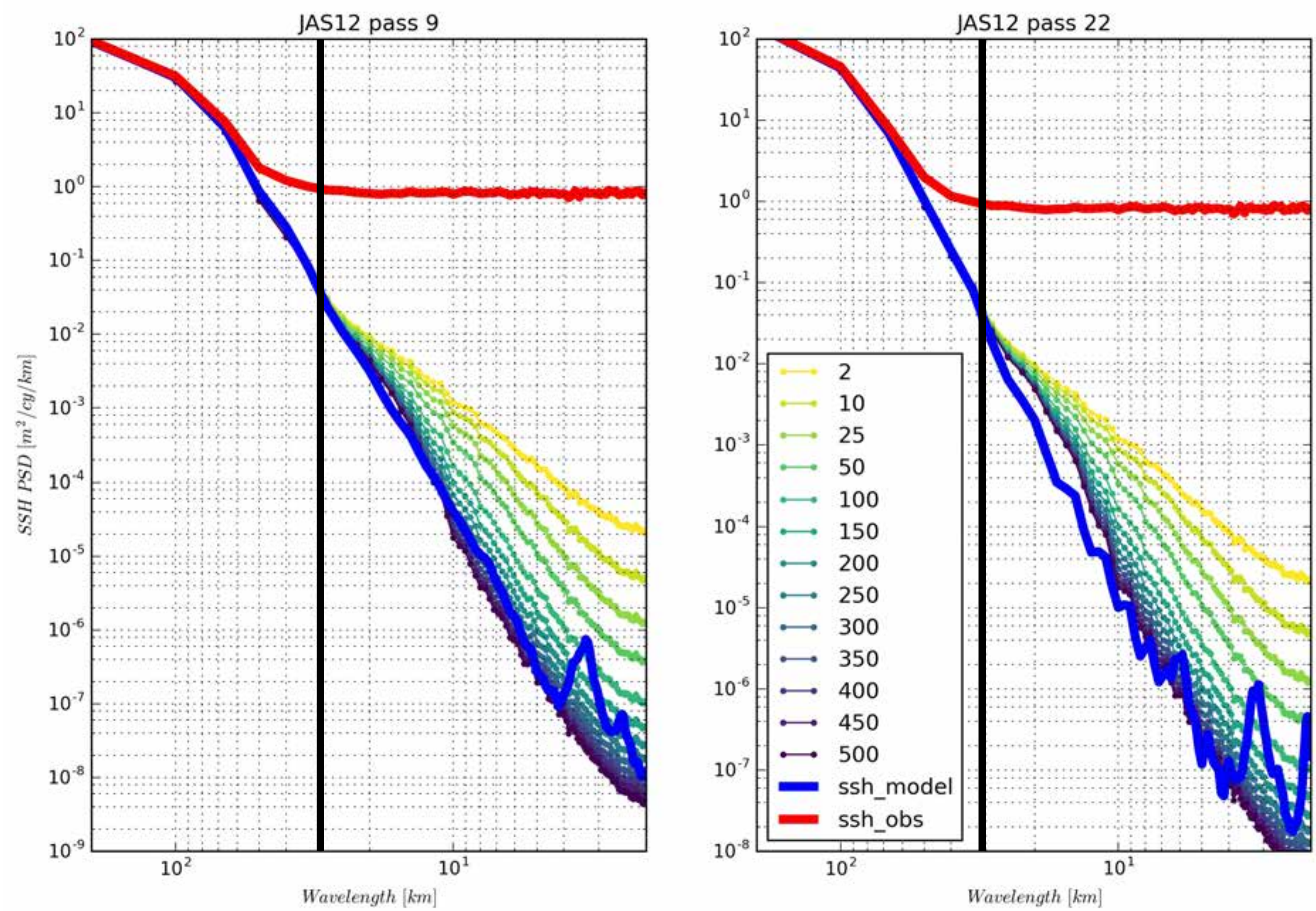


Lambda 1 = 100

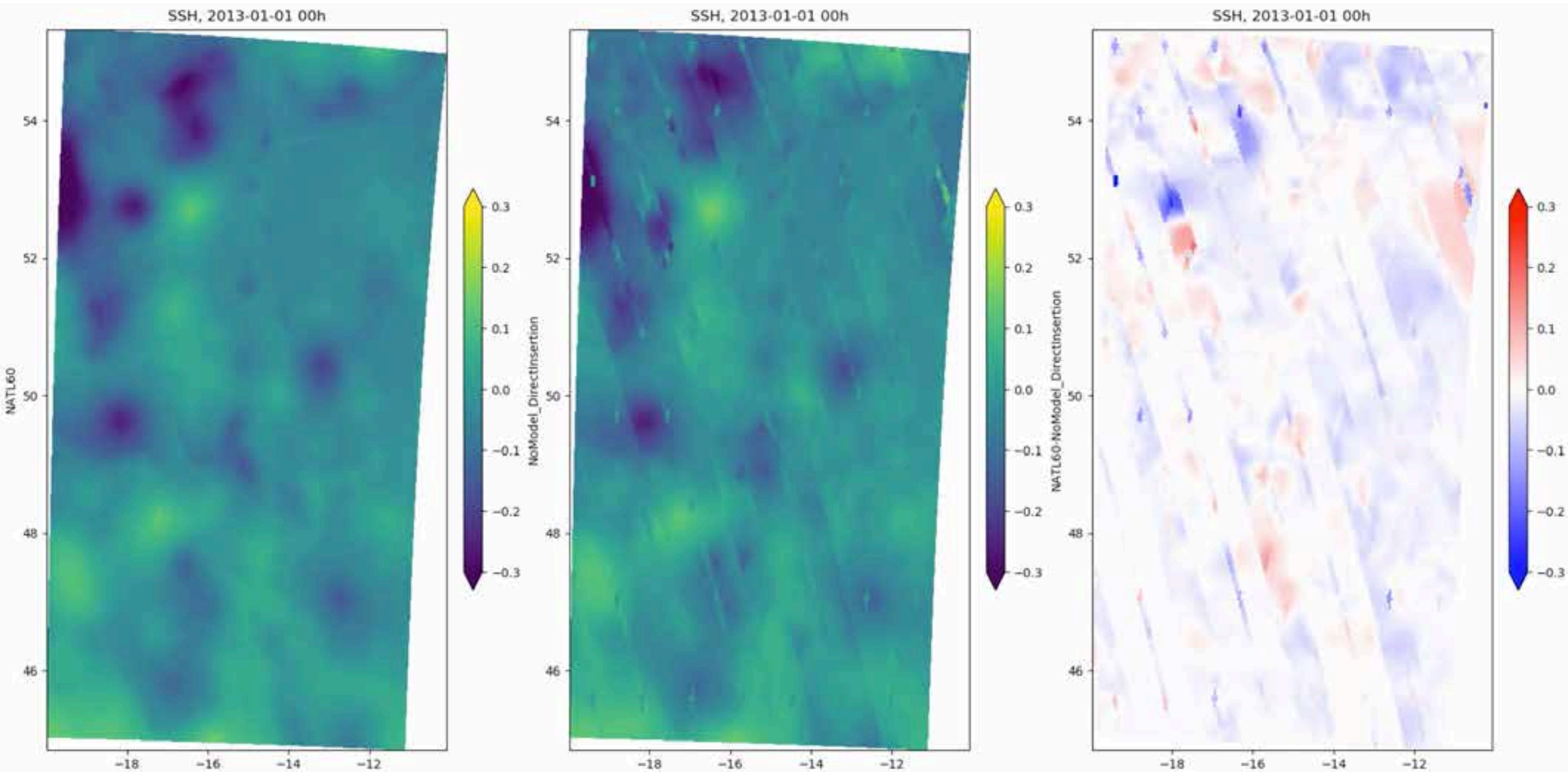
Filtering results: penalization order 1



Filtering results: penalization order 1 + 2



No assimilation



Assimilation