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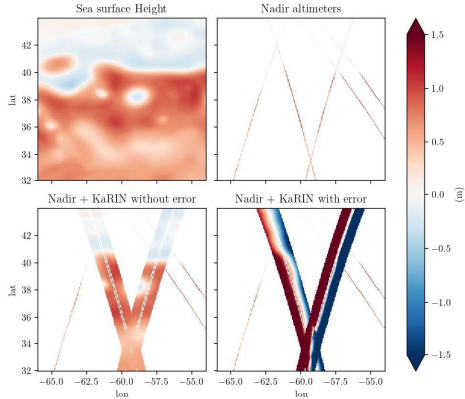
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Regional SWOT calibration using scale aware deep learning

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Introduction



Context

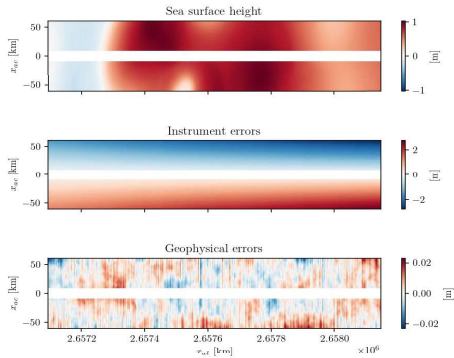
- Sea surface height (SSH) fluctuates with ocean currents
- Current altimeter satellites measure sea surface height at nadir
- Upcoming SWOT mission with new 2D KaRIN sensor
- Applications: climate monitoring, marine traffic, etc..

Problem

- From NADIR data, we achieve an estimation error of 2 cm on the swath
- >75% of uncalibrated observation energy made of errors (bottom right)

Can we separate the SSH from the errors in the uncalibrated observations?

Data (OSSE)



Observations

- Geophysical fields are simulated using the NEMO ocean model (NATL60)
- Pseudo observations are sampled from the simulation
- Acquisition errors are simulated using the Swot simulator

Gridded products

- Optimal interpolation based DUACS product (operational SOTA)
- Learning based 4DVarNet interpolation product (OSSE SOTA)

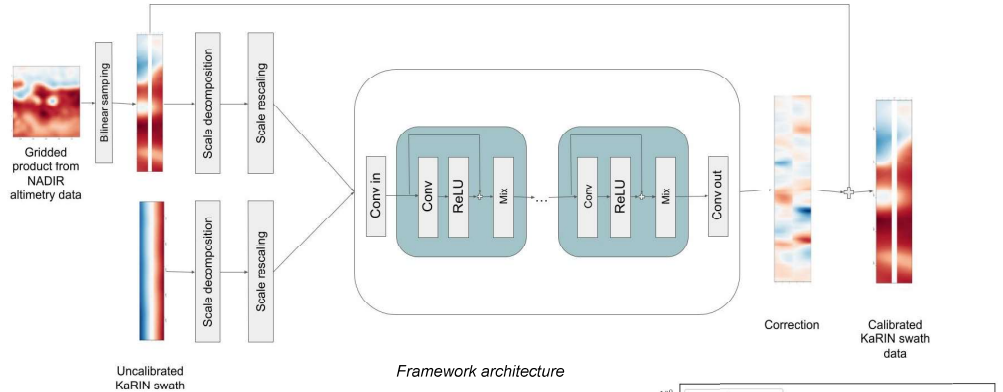
Key takeaways

- We propose a novel calibration approach based on a scale decomposition scheme that enable a trained neural network to separate the error signals from the SSH.

- This approach applies a correction at all scales

- This method allows for training a calibration operator on a regional domain

Proposed method

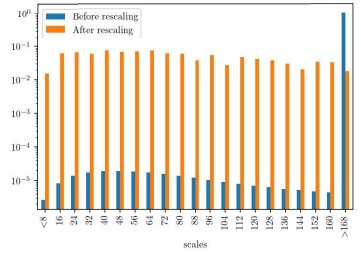


- We introduce a scale decomposition and renormalization scheme to facilitate the separation of SSH from errors signals in the observation
- We use the uncalibrated observation as well as a gridded product made from the NADIR altimeter data as inputs
- We train a convolutional neural network to output a correction of the gridded product on the swath

Scale decomposition scheme

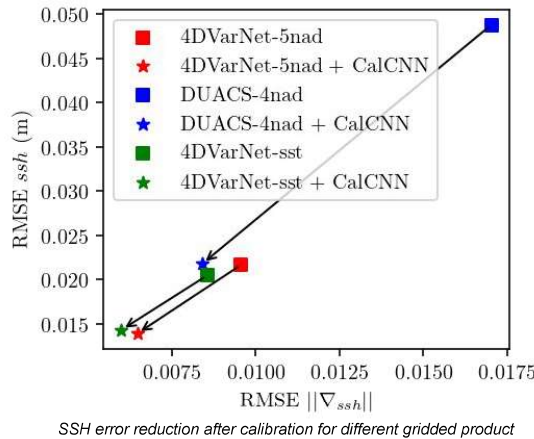
$$\mathcal{D}(f, [\sigma_0, \sigma_1, \dots, \sigma_N]) = [\mathcal{H}_{\sigma_0}(f), \mathcal{H}_{\sigma_1}(f) - \mathcal{H}_{\sigma_0}(f), \dots, \mathcal{H}_{\sigma_{N-1}}(f) - \mathcal{H}_{\sigma_{N-2}}(f), f - \mathcal{H}_{\sigma_N}(f)]$$

$$\mathcal{H}_{\sigma}(f(x_{ac}, x_{al})) = f(x_{ac}, x_{al}) - \sum_{k=1}^{k=[\frac{100\sigma^2}{\lambda^2}]} Ke^{-\frac{100k^2}{\sigma^2}} f(x_{ac}, x_{al} + k\delta x)$$

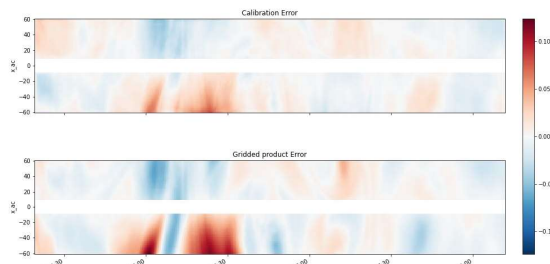


Scale-wise variance of the uncalibrated observation before and after rescaling

Results

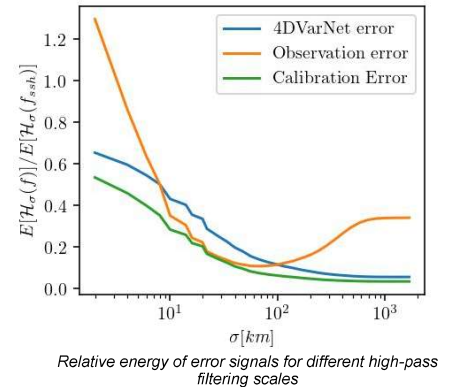


SSH error reduction after calibration for different gridded product



SSH error of 4DVarNet product before and after calibration

- We reach a residual error of less than 1.4 cm
- We can see the impact of the gridded product on the calibration performance on the figure on the left. Overall, a better gridded product will produce a better calibrated product.
- We can see in the bottom right figure how the interpolation error of the gridded product and the observation error behave at different scales. We can see the scales for which the observation has smaller errors than the gridded product. Note how the calibration error is lower than both inputs' errors at all scales.
- In the bottom left figure we can look at the impact of the calibration network on the gridded product estimation



Relative energy of error signals for different high-pass filtering scales

Experimental setup:

- 1 year simulation
- Focus on a 12°x12° Gulfstream region (34:46;-66;-54)
- 40 days evaluation period