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NASA SWOT Science Team Meeting 2022

# USING MACHINE LEARNING TO INTERPOLATE SSH

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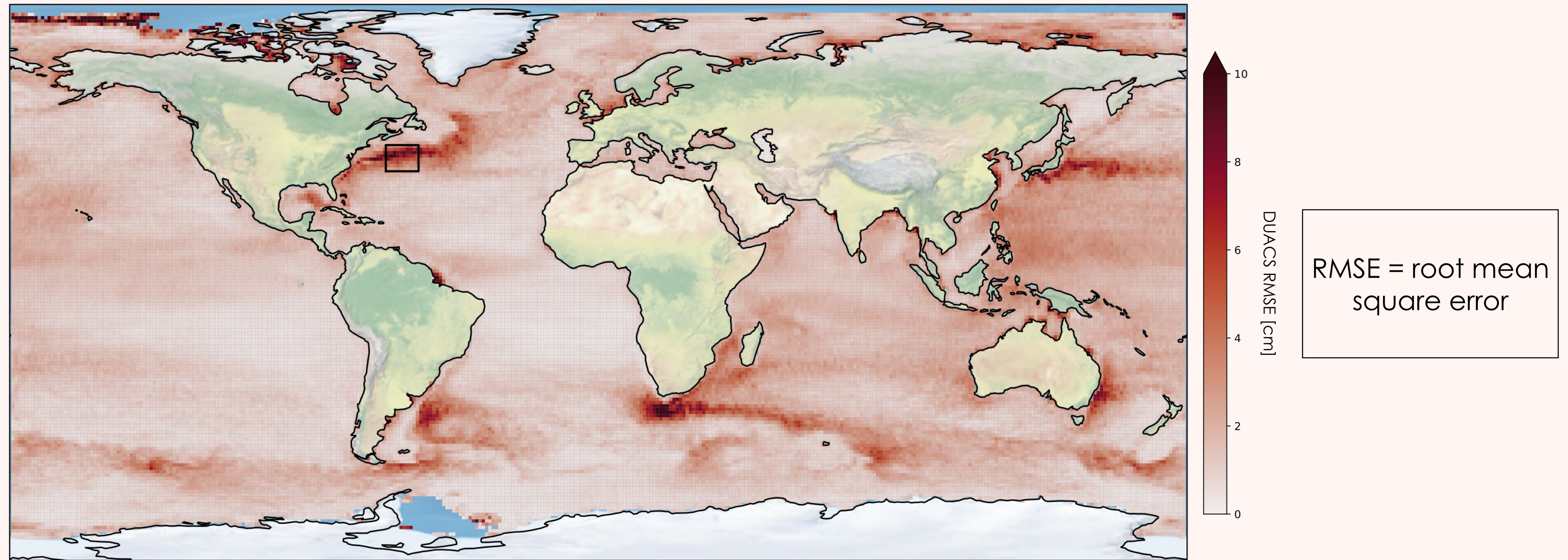
With thanks to Patrice Klein & Steve Brunton



# MOTIVATION

## SSH interpolation

- Nadir altimeters only sample SSH along 1D tracks which are widely spaced
- DUACS product uses 'optimal interpolation' to reconstruct 2D SSH field, leading to large errors in regions with energetic mesoscale turbulence:



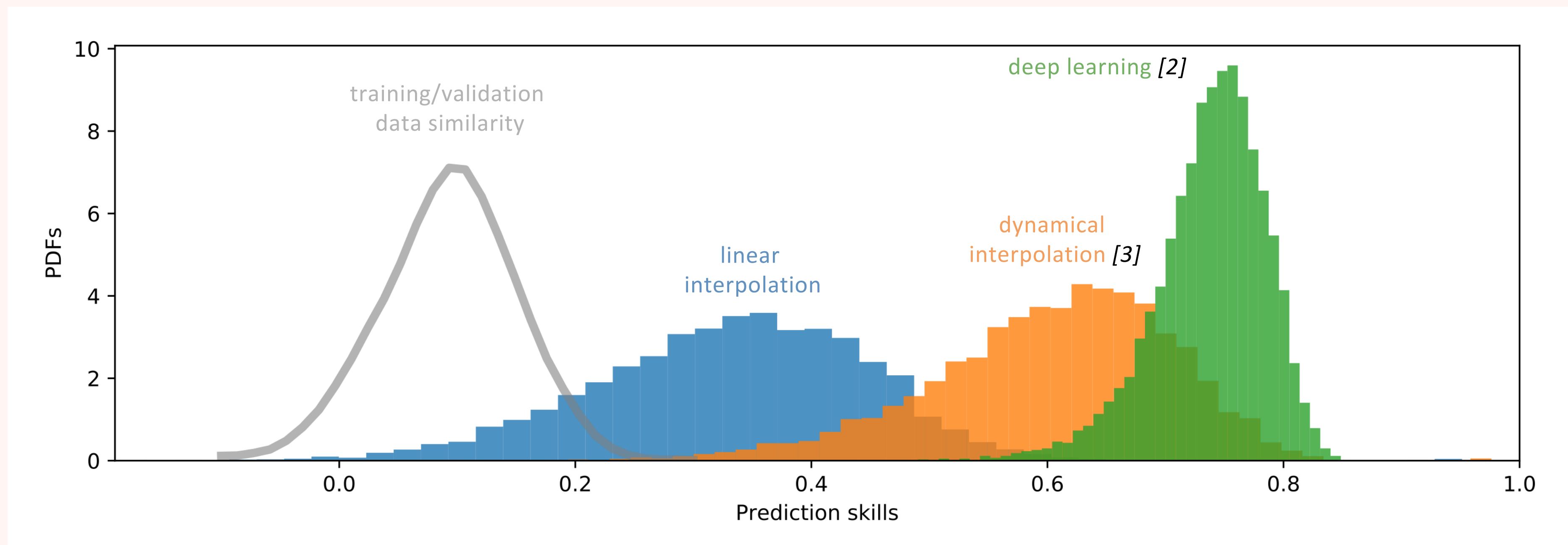
*DUACS RMSE against withheld Cryosat-2 observations (2015-2019) [1]*



# MOTIVATION

## Why use machine learning (ML)?

- Deep learning neural networks can learn non-linear mappings from inputs to outputs
- A neural network could be trained to learn the dynamics governing SSH evolution
- Previous work [2] showed a neural network could accurately interpolate SSH from a 2 layer QG model of ocean turbulence:



SSH prediction skill in QG turbulence for a deep learning, linear, and dynamical interpolation [2]

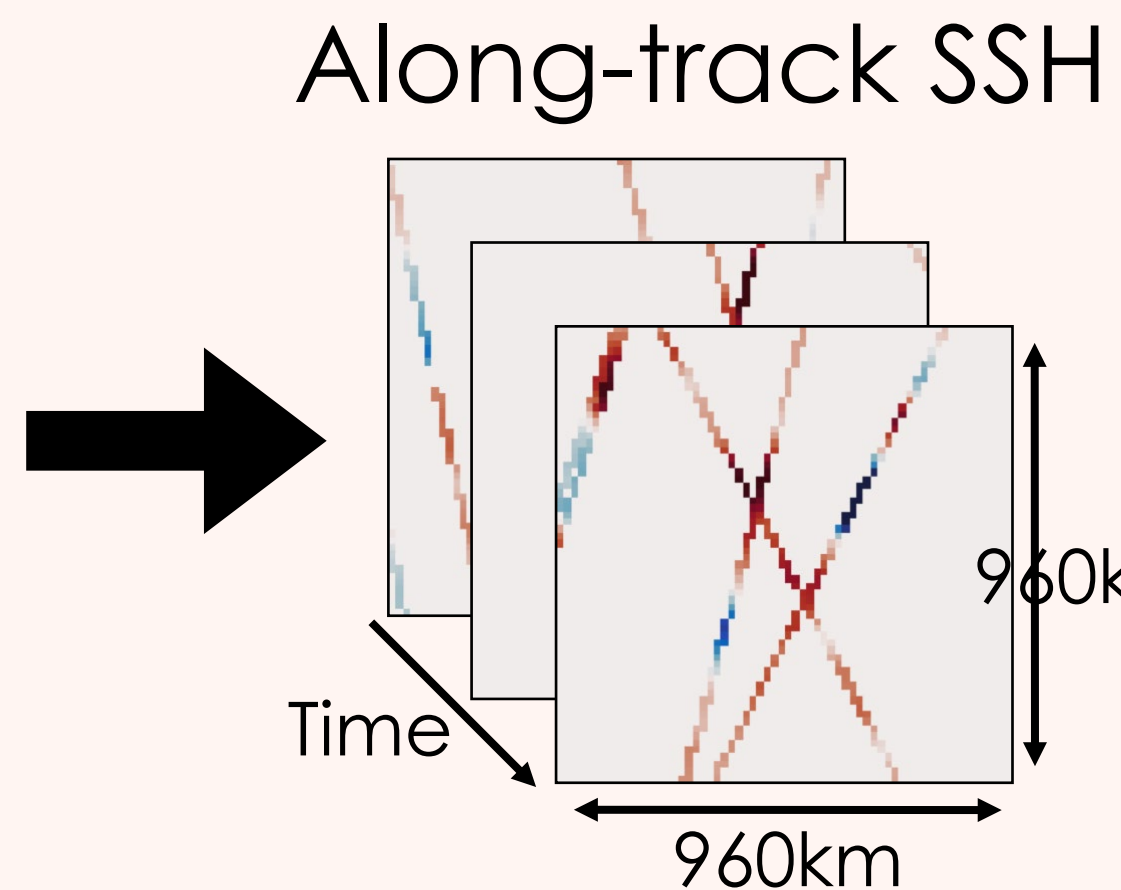
[2] Manucharyan, G., et al., 2021, *Journal of Advances in Modeling Earth Systems*.

[3] Ubelmann, C., et al., 2015, *J. Atmos. Ocean. Tech.*

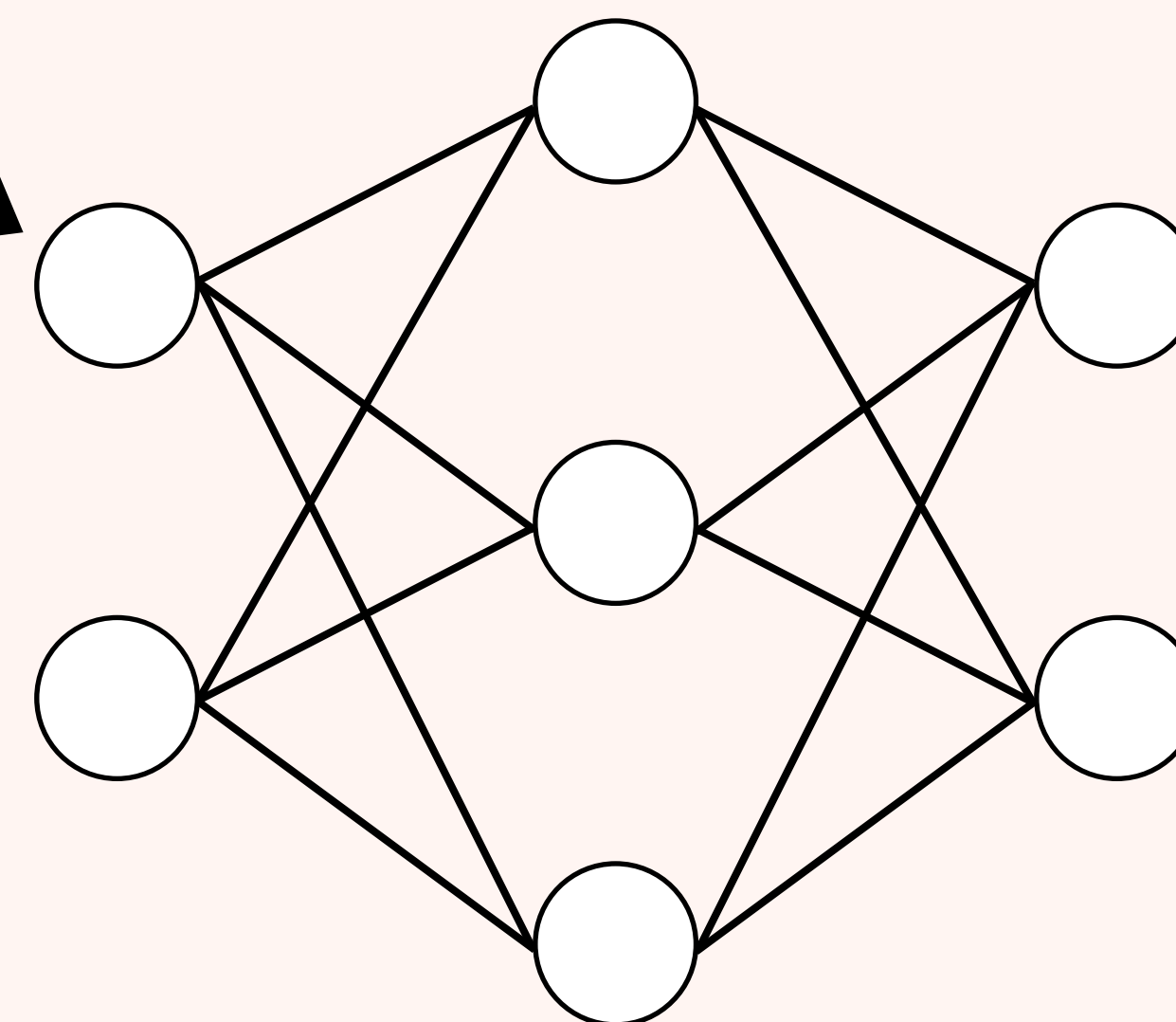
# METHODS



Satellite Altimeters



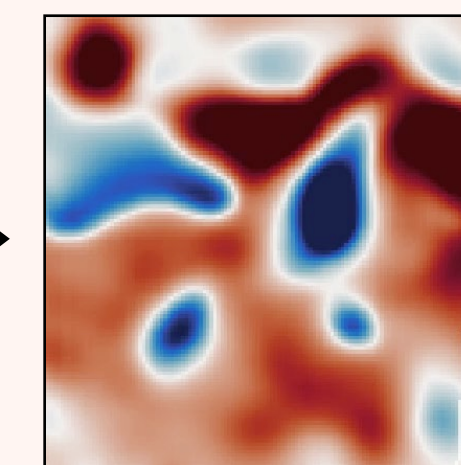
Neural Network  
(ConvLSTM)



adjust network  
parameters

ConvLSTM = Convolutional  
Long Short-Term Memory

2D SSH  
Reconstruction



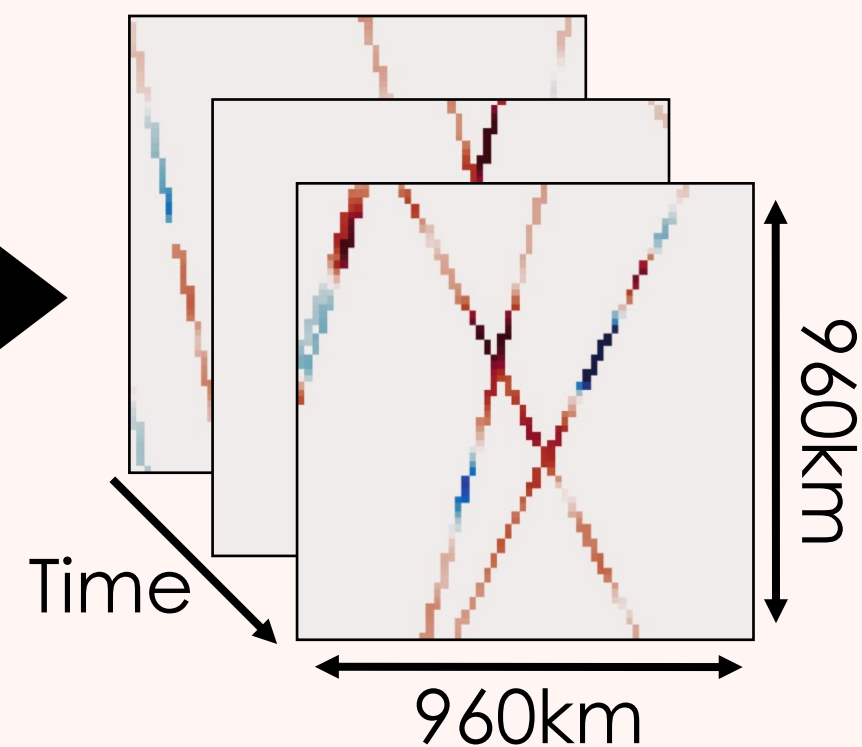
reconstruction  
error from withheld  
observations

# METHODS

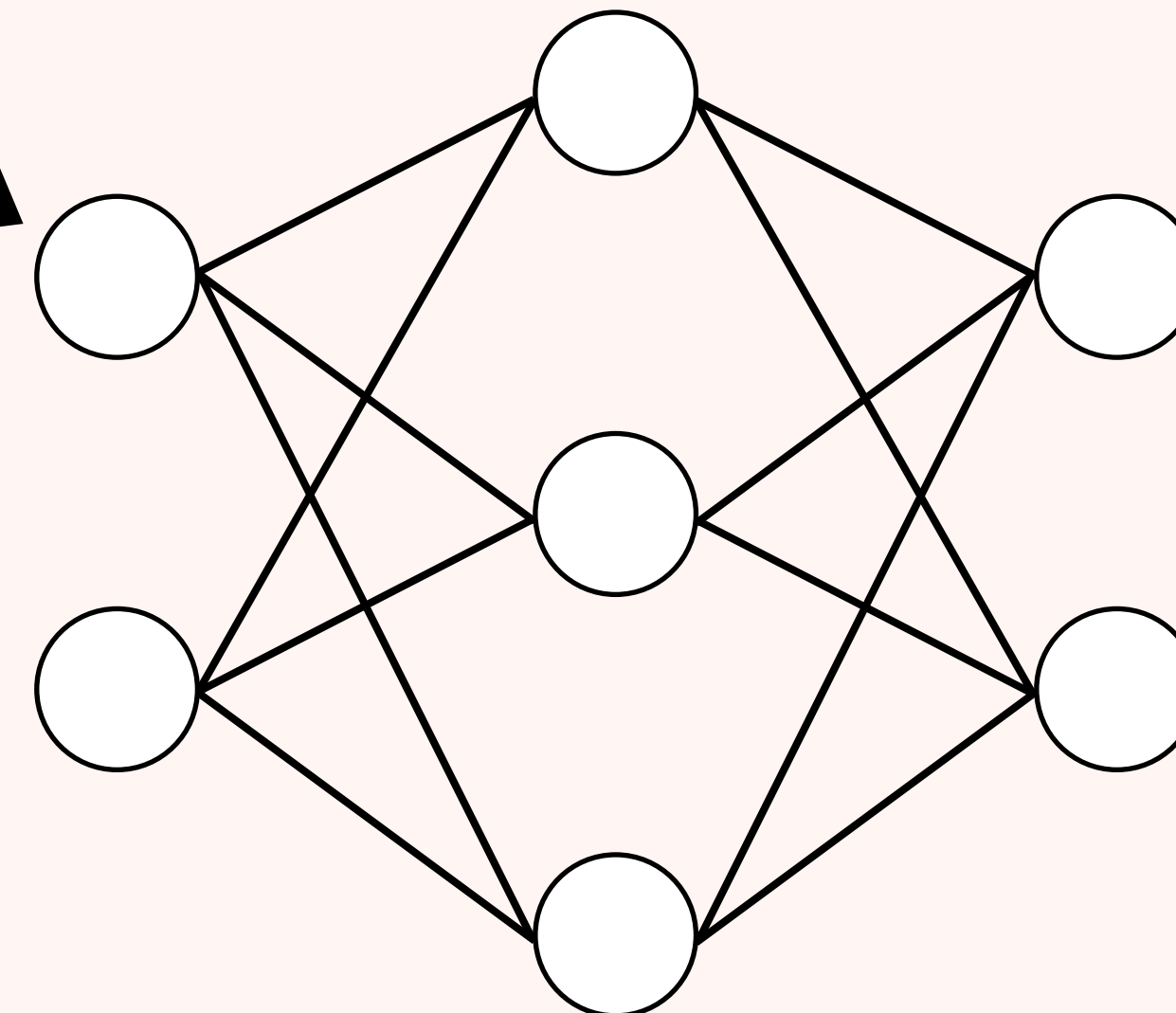


Satellite Altimeters

Along-track SSH



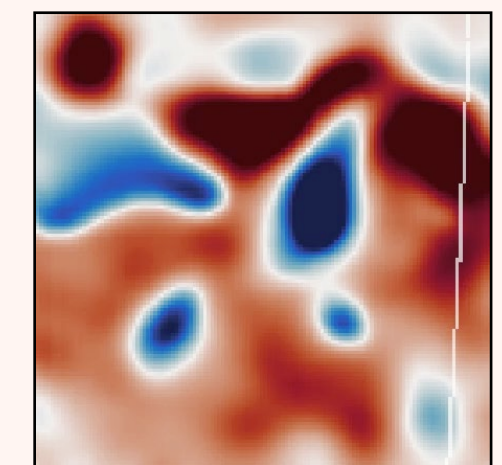
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2D SSH  
Reconstruction



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From SQG dynamics:

Surface geostrophic currents (and hence SSH) are related to surface buoyancy (and hence SST). [4]

So, SST observations could be used to help inform SSH reconstruction. [5]

[4] Lapeyre, G., 2017, *Fluids*.

[5] Isern-Fontanet, J., et al., 2006, *Geophysical Research Letters*.



# METHODS

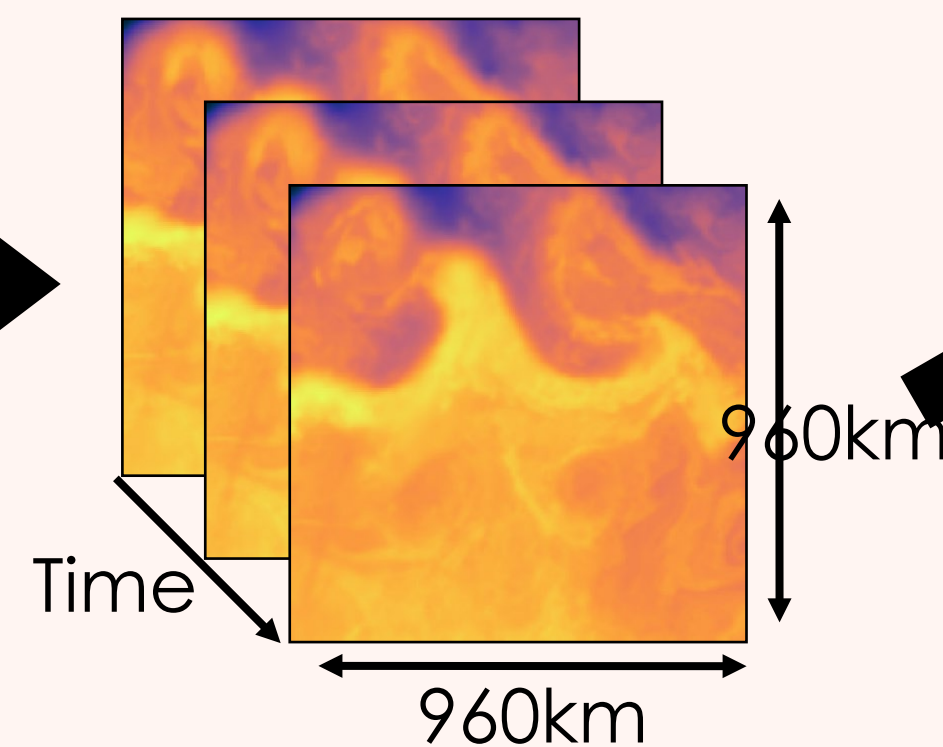
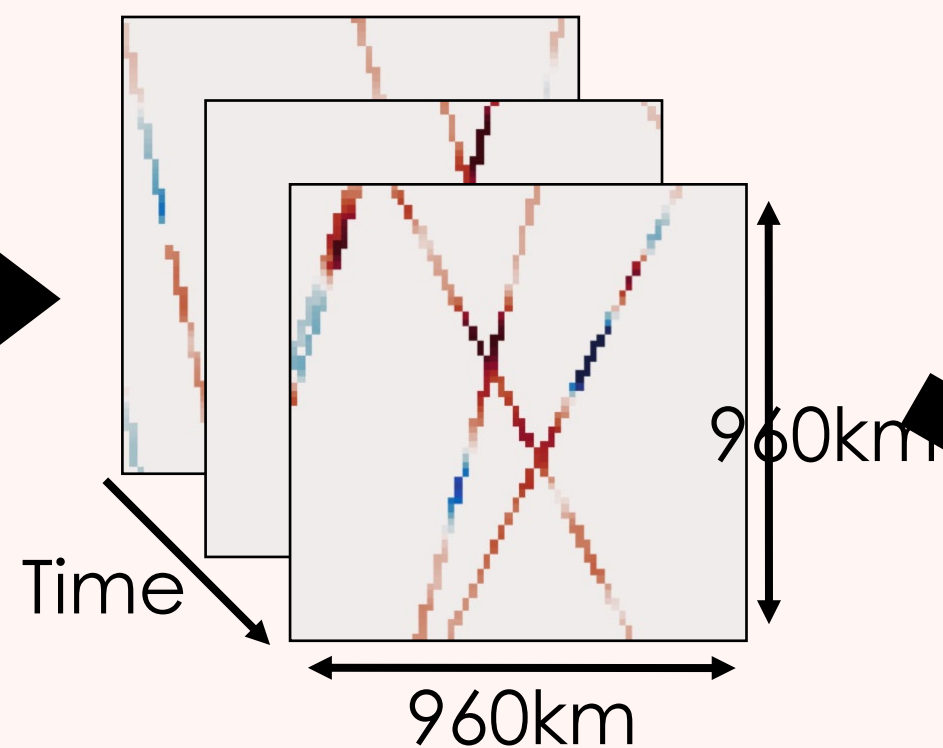


Satellite Altimeters



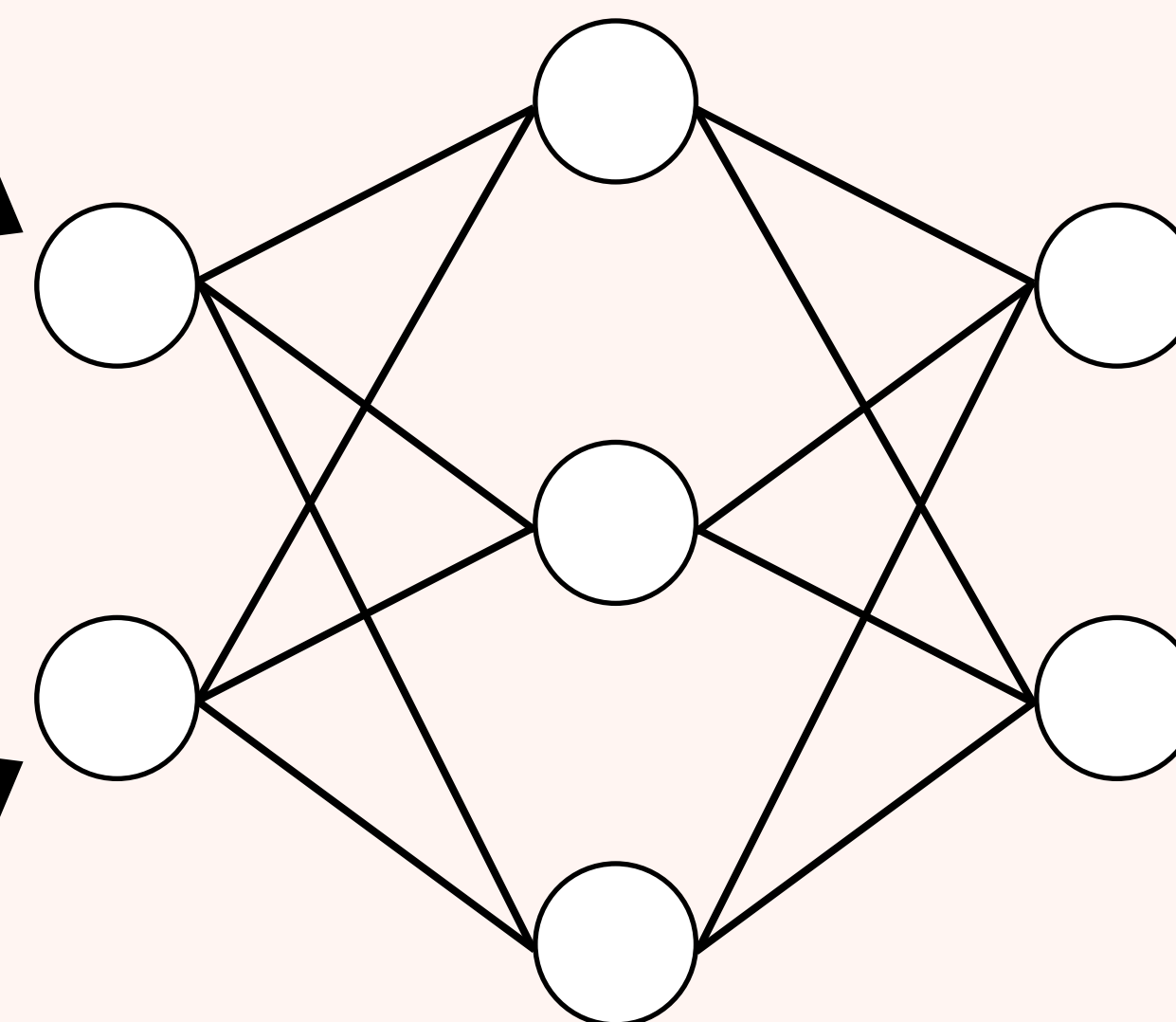
Satellite Radiometers  
+ in-situ obs

Along-track SSH



Gridded SST  
(GHR SST)

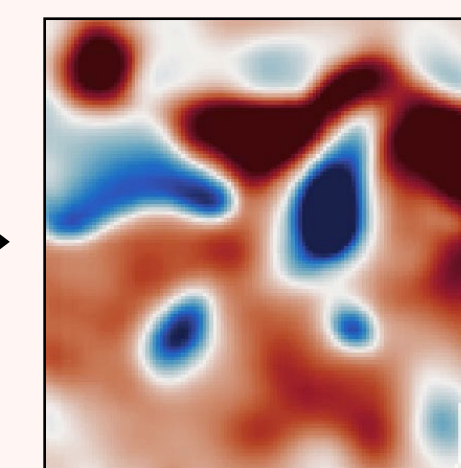
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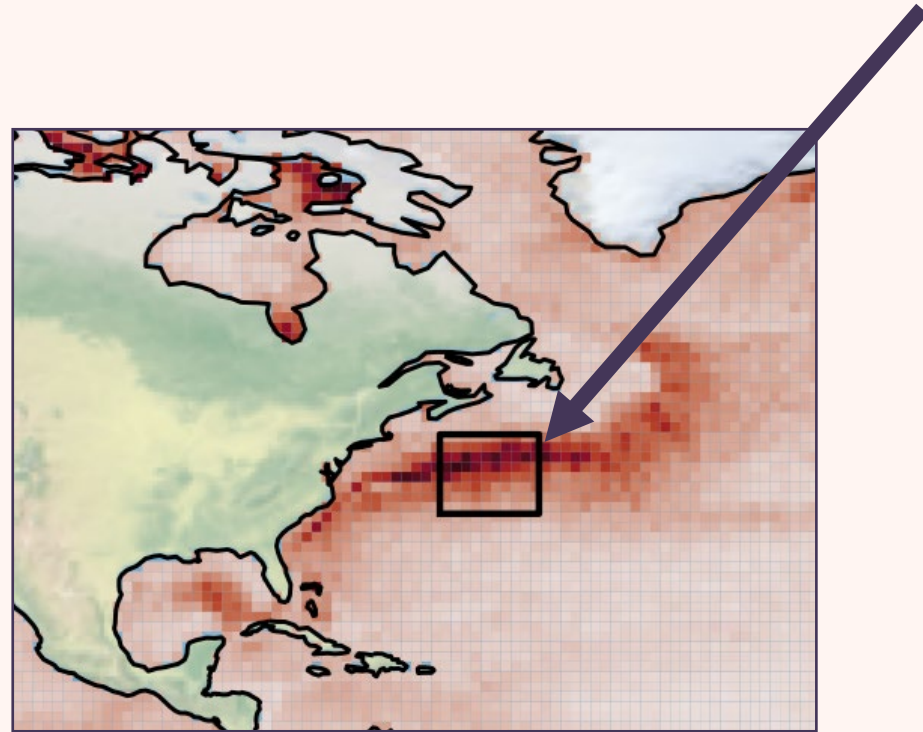
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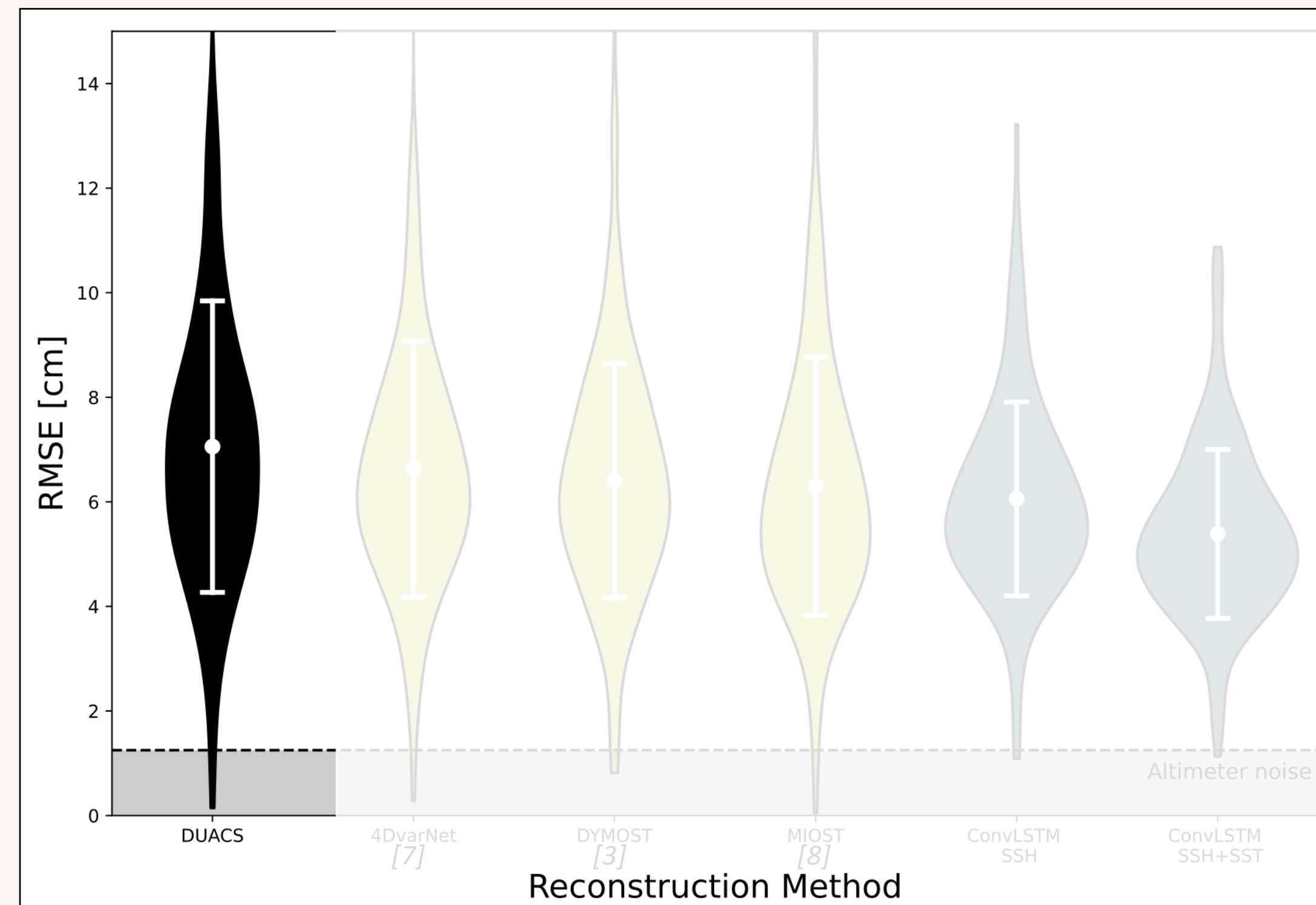
# RESULTS

## Root mean square error

- We tested our reconstruction's accuracy against independent altimeter observations in a region of the Gulf Stream (55-65°W, 34-42°N) and compared to other methods using data from [6]:



### EXISTING METHOD



[3] Ubelmann, C., et al., 2015, *J. Atmos. Ocean. Tech.*

[6] [https://github.com/ocean-data-challenges/2021a\\_SSH\\_mapping\\_OSE](https://github.com/ocean-data-challenges/2021a_SSH_mapping_OSE).

[7] Fablet, R., et al., 2021, *ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci.*

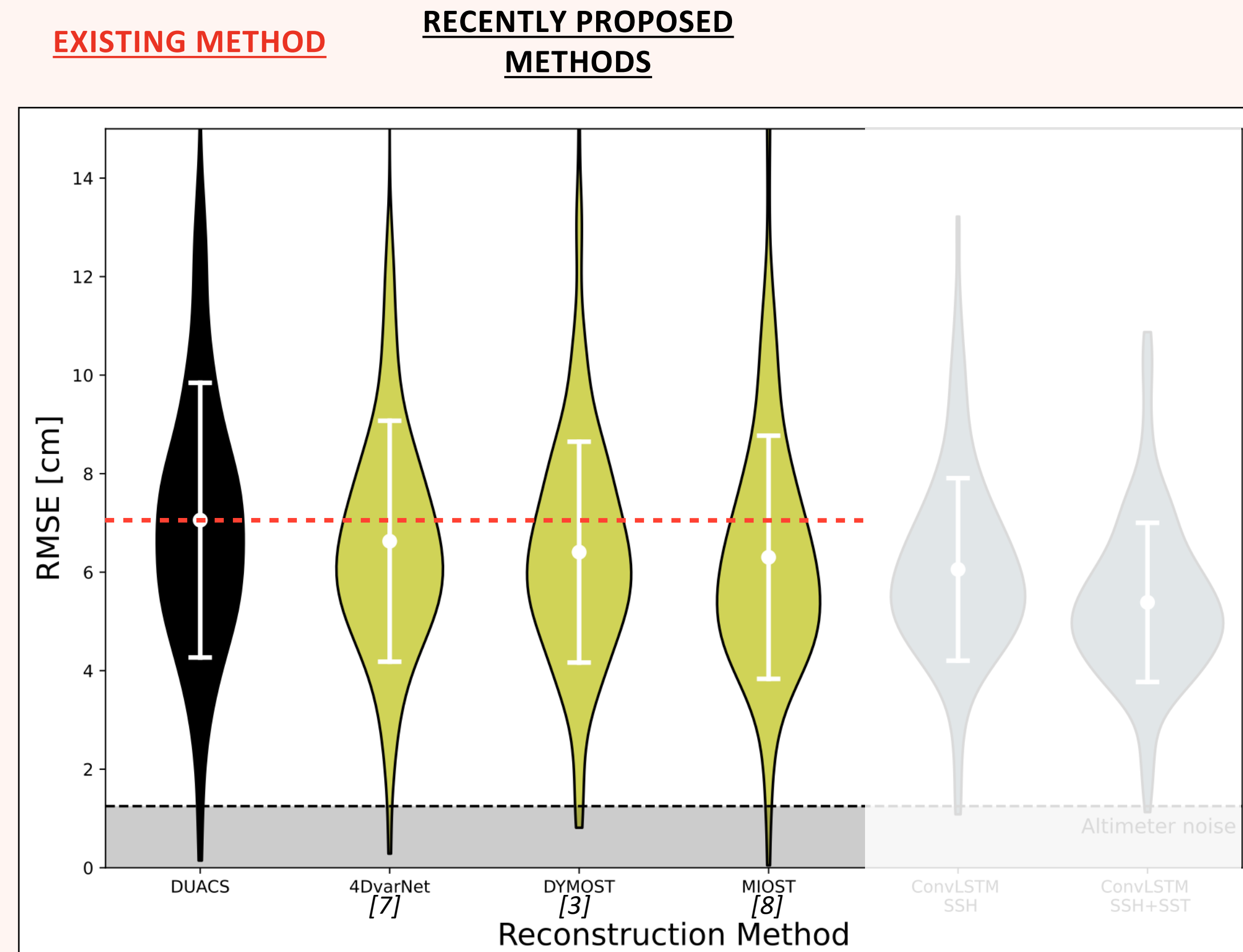
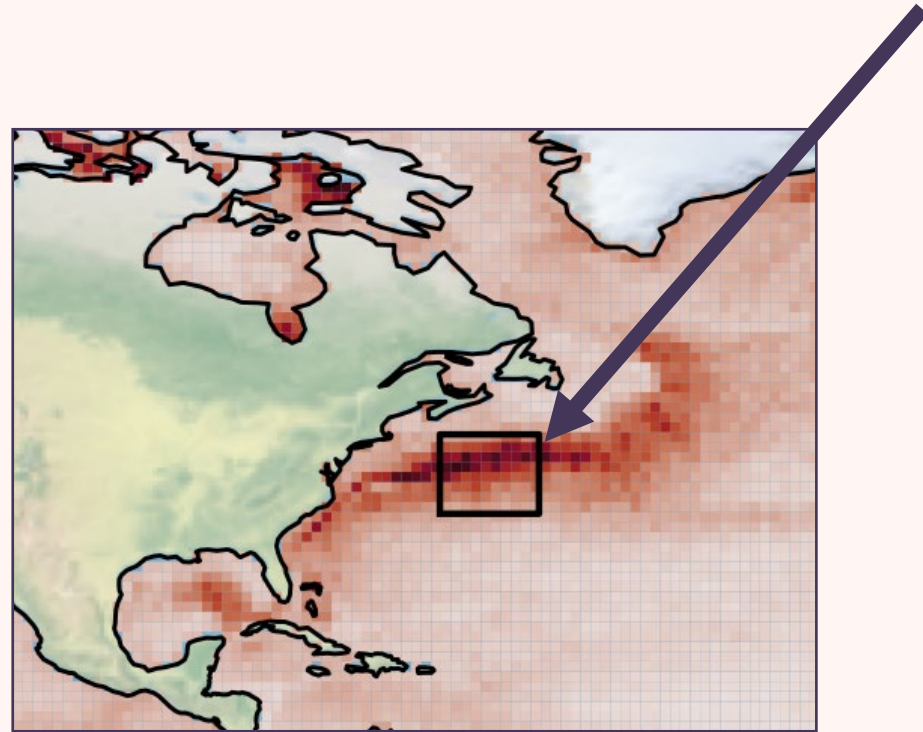
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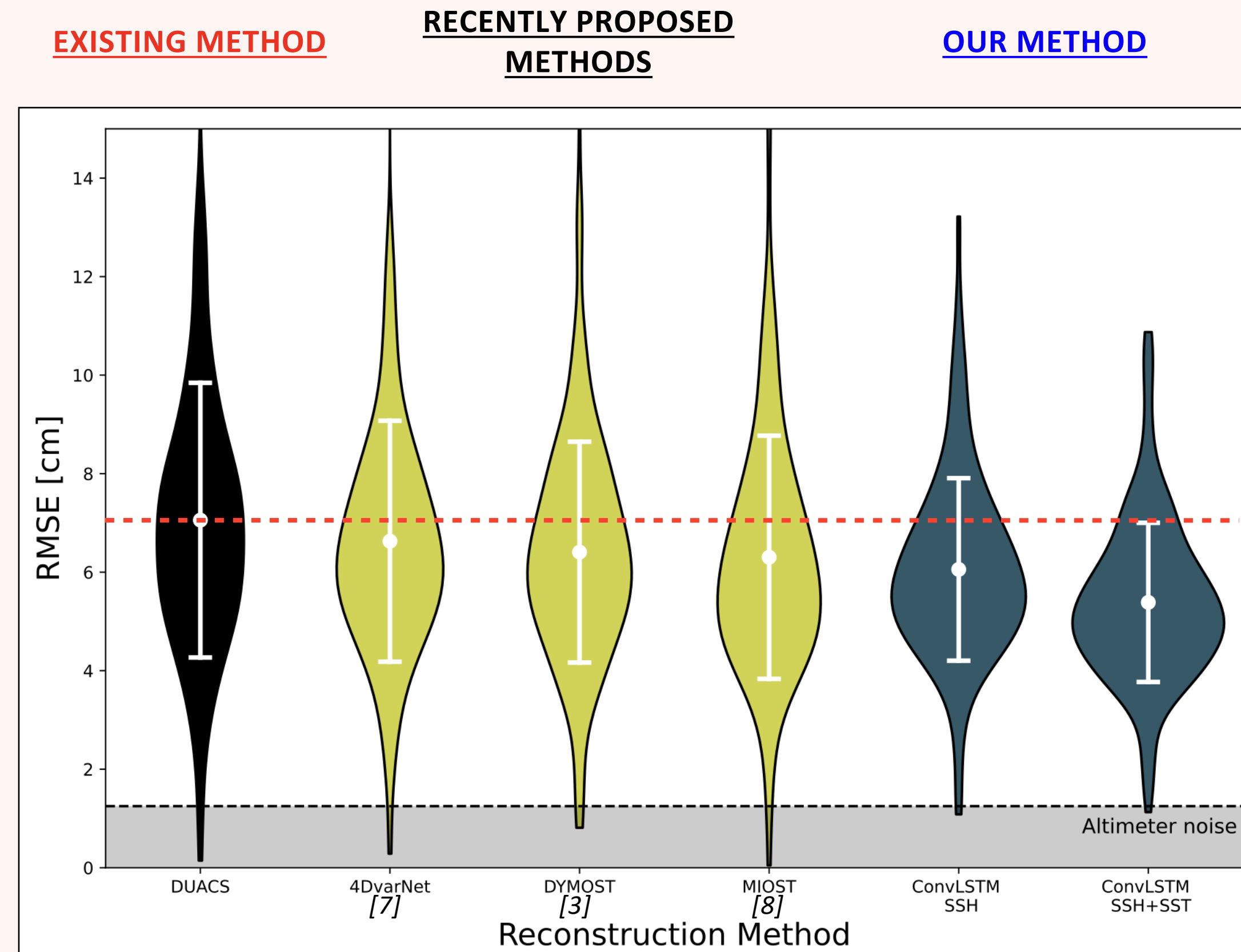
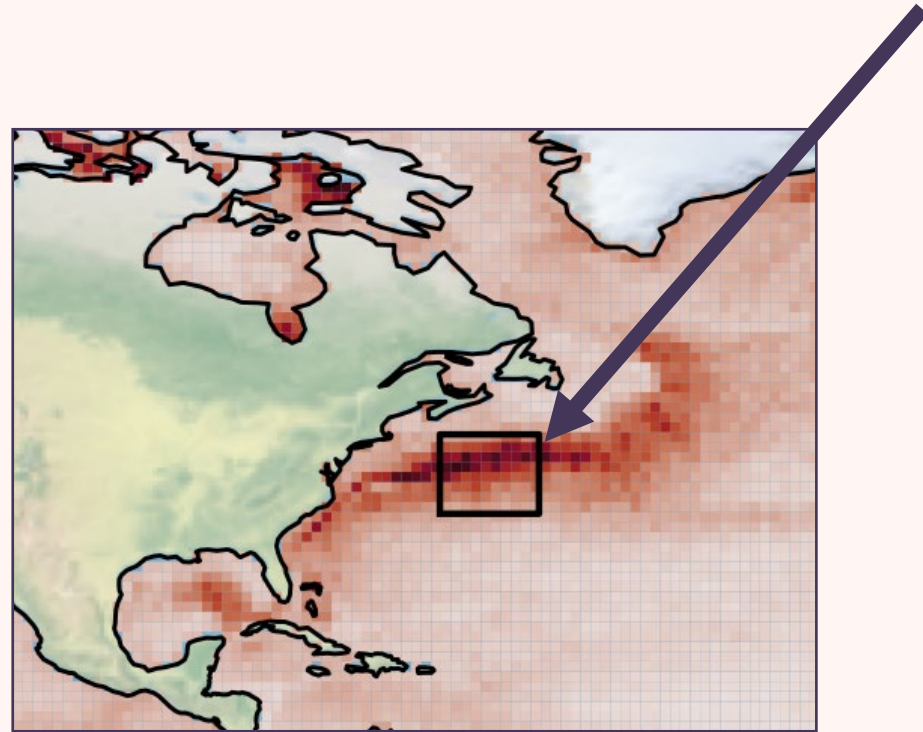
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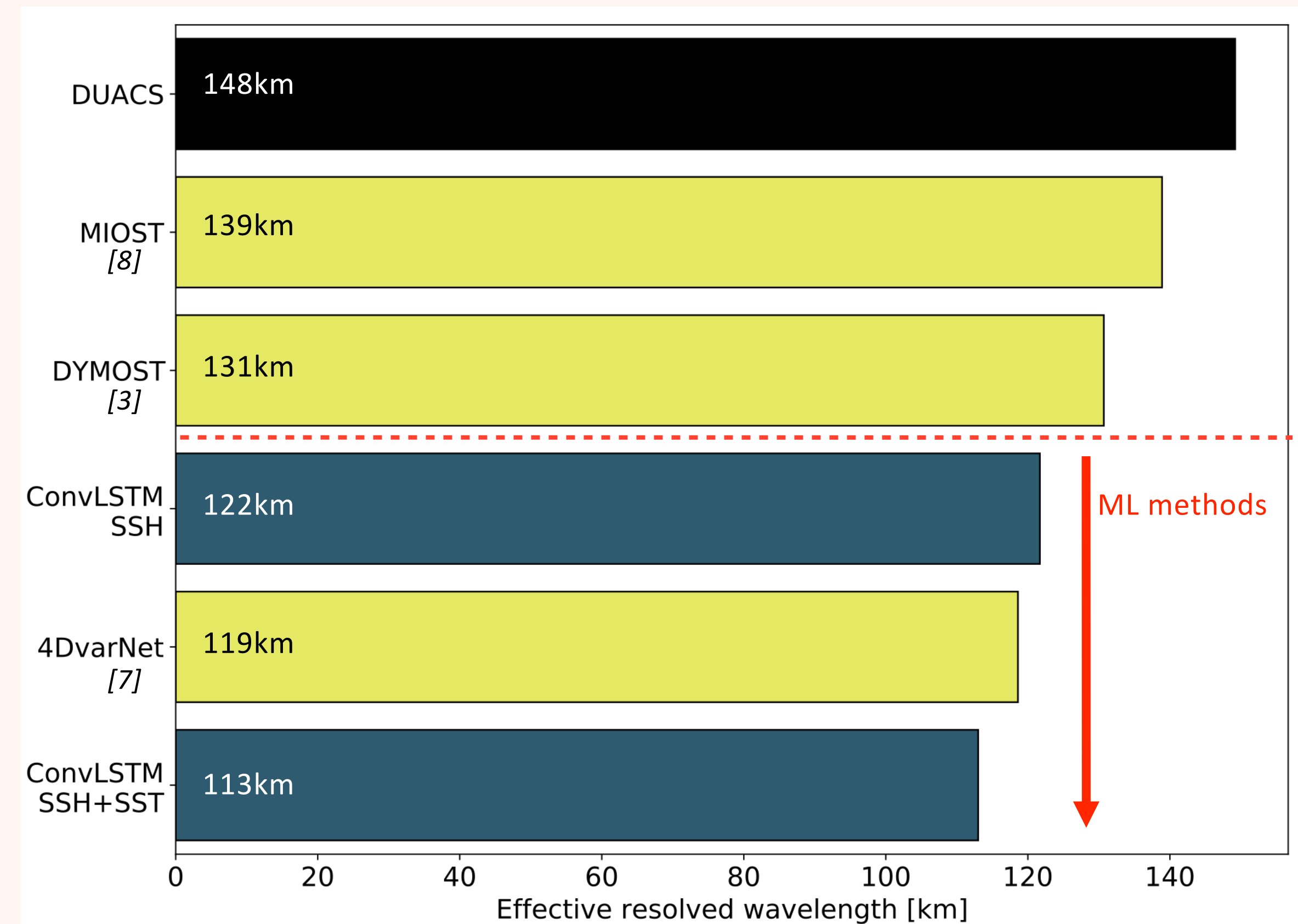
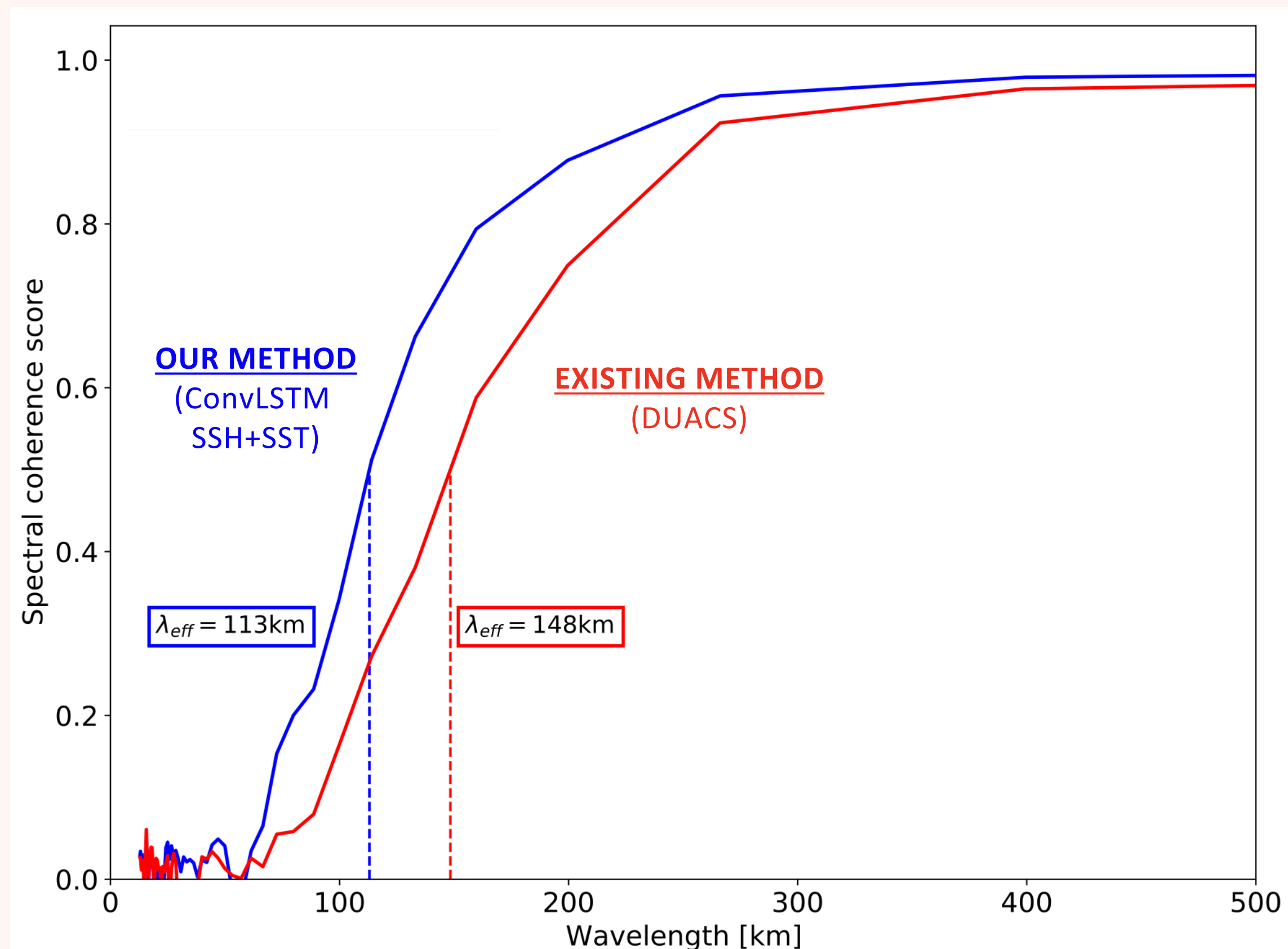
[8] Ubelmann, C., et al., 2021, *JGR Oceans*.

# RESULTS

## Effective resolution

- **Our method accurately resolves smaller scale SSH features:**

$$\text{Spectral coherence score} = 1 - \frac{\text{PSD}(\text{reconstruction} - \text{observations})}{\text{PSD}(\text{observations})}$$



[3] Ubelmann, C., et al., 2015, J. Atmos. Ocean. Tech.

[7] Fablet, R., et al., 2021, ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci.

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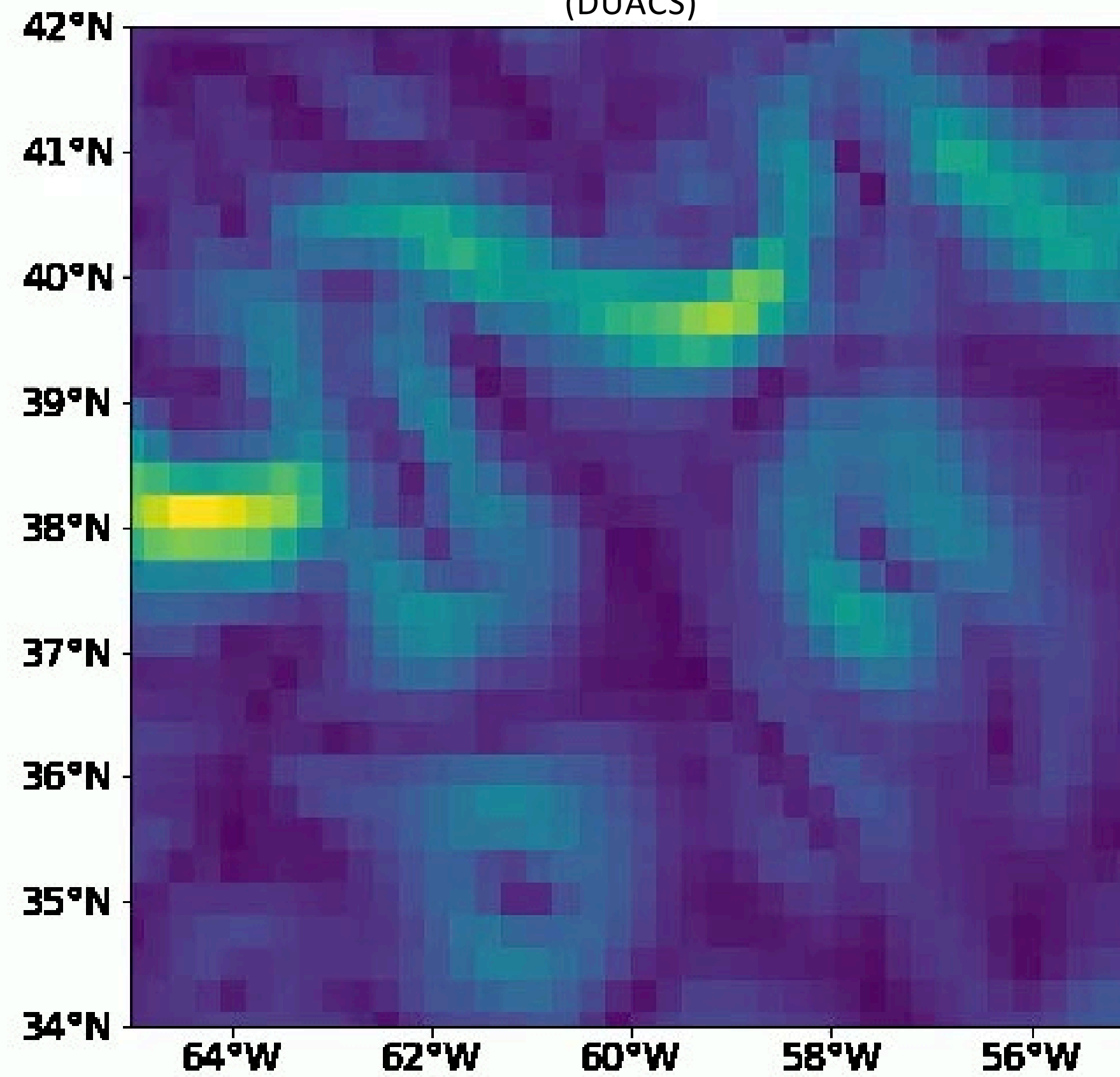


# RESULTS

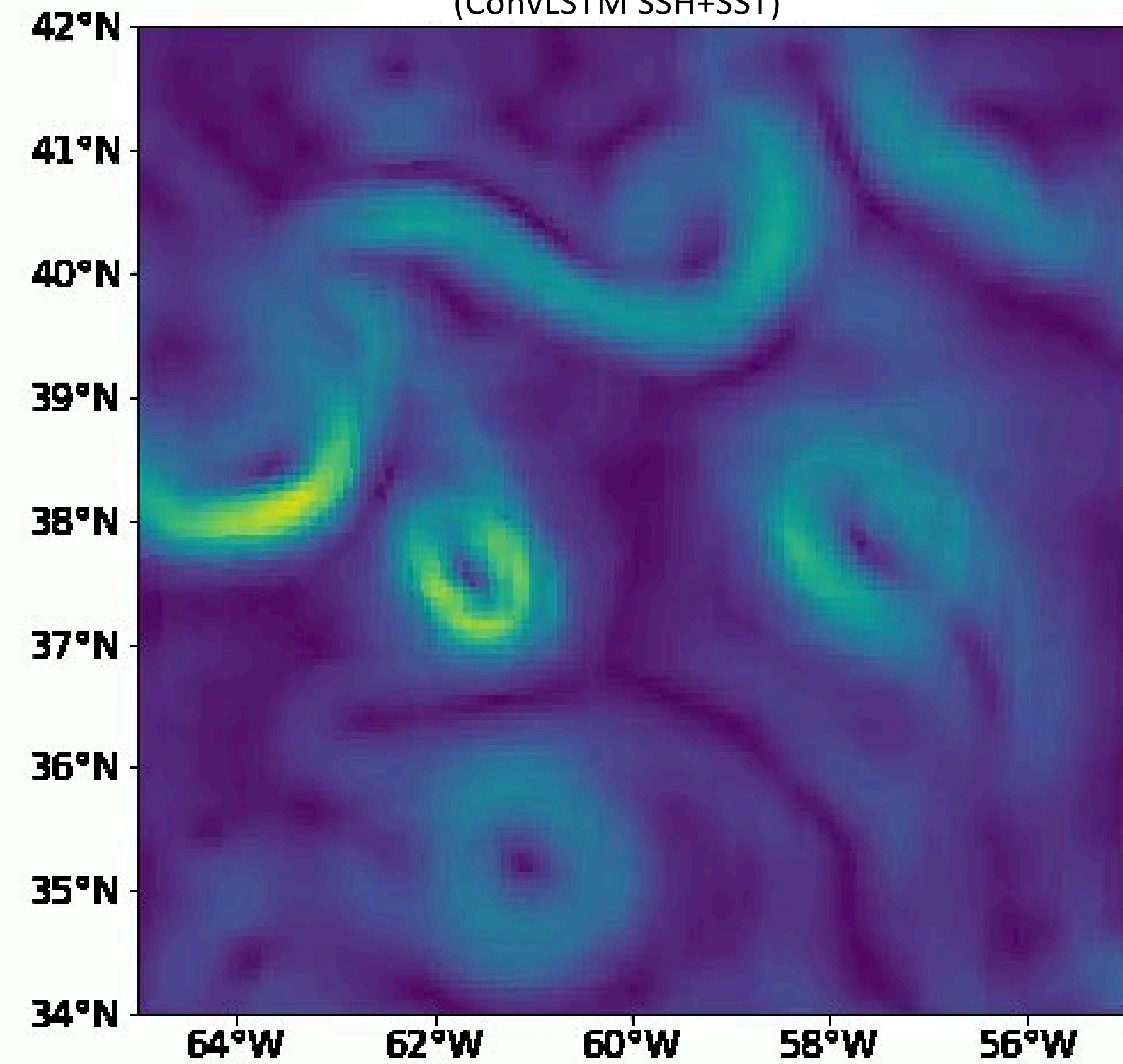
Surface geostrophic current speed

2017-01-01

EXISTING METHOD  
(DUACS)



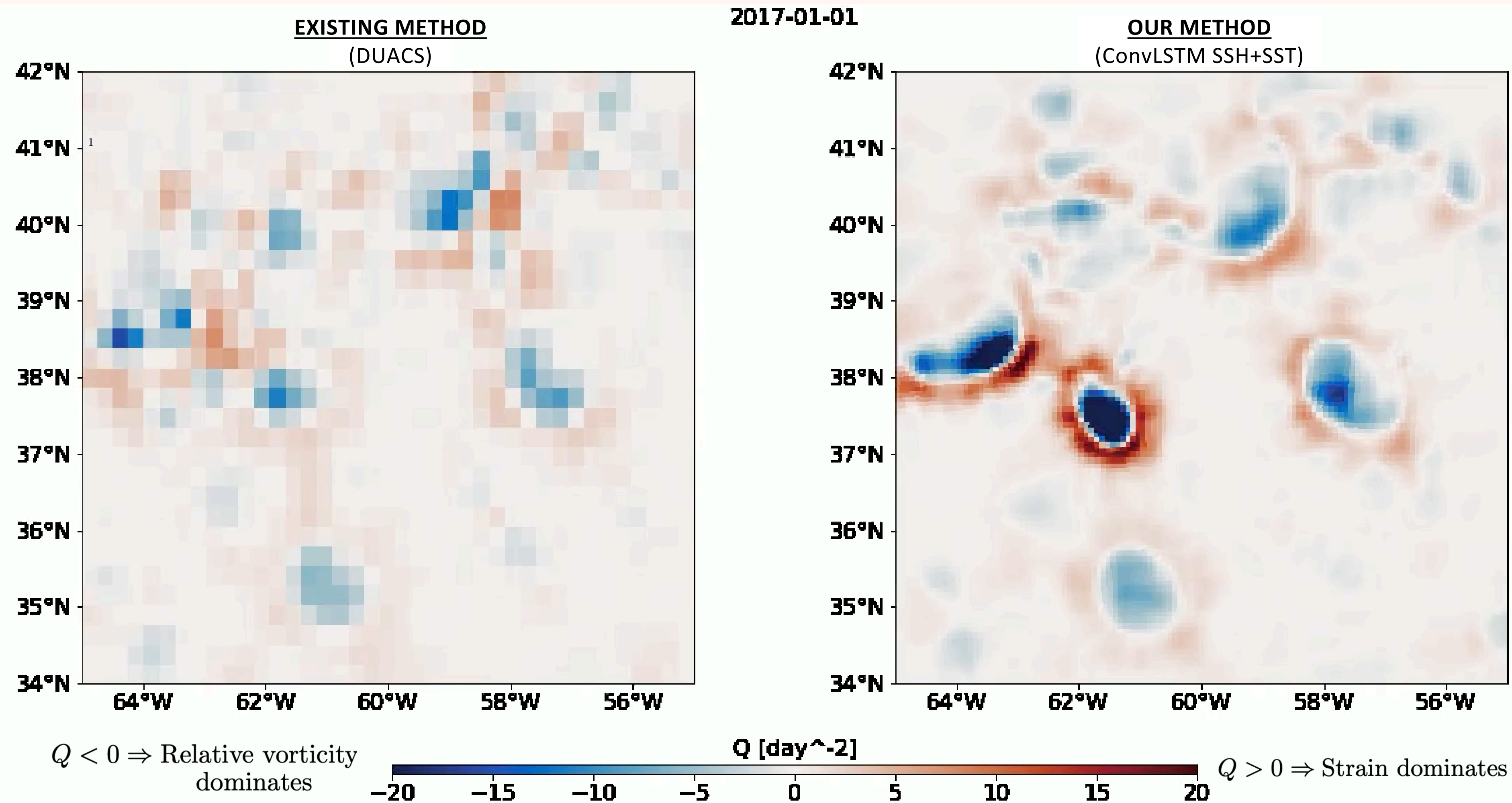
OUR METHOD  
(ConvLSTM SSH+SST)



# RESULTS

## Okubo-Weiss Parameter (Q)

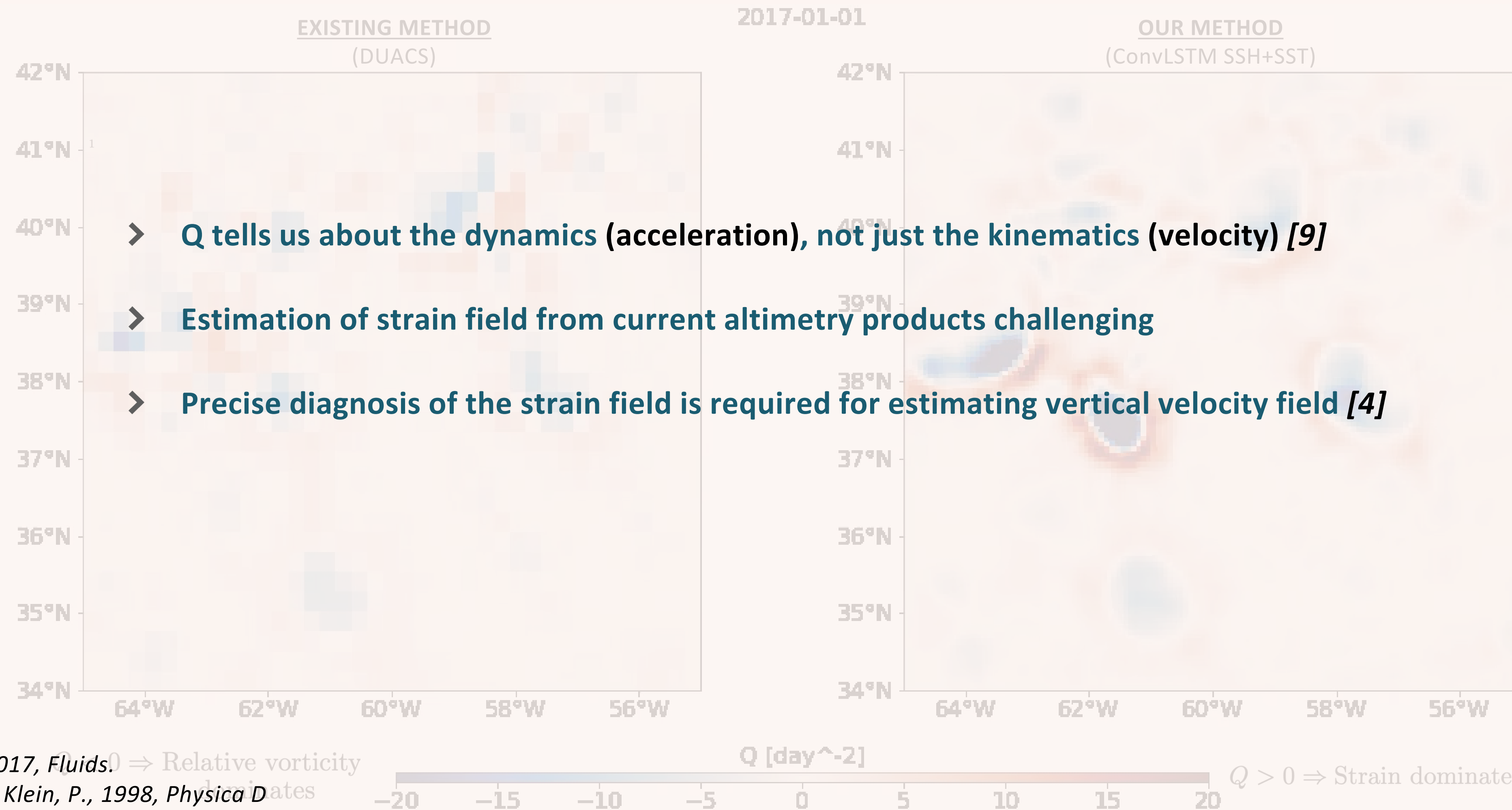
$$Q = \gamma^2 - \omega^2 = \underbrace{\left(\frac{\partial u}{\partial x} - \frac{\partial v}{\partial y}\right)^2}_{\text{strain rate}} + \left(\frac{\partial v}{\partial x} + \frac{\partial u}{\partial y}\right)^2 - \underbrace{\left(\frac{\partial v}{\partial x} - \frac{\partial u}{\partial y}\right)^2}_{\text{relative vorticity}}$$





# WHY DO WE NEED TO ACCESS THE OKUBO-WEISS PARAMETER?

$$Q = \gamma^2 - \omega^2 = \underbrace{\left( \frac{\partial u}{\partial x} - \frac{\partial v}{\partial y} \right)^2 + \left( \frac{\partial v}{\partial x} + \frac{\partial u}{\partial y} \right)^2}_{\text{strain rate}} - \underbrace{\left( \frac{\partial v}{\partial x} - \frac{\partial u}{\partial y} \right)^2}_{\text{relative vorticity}}$$



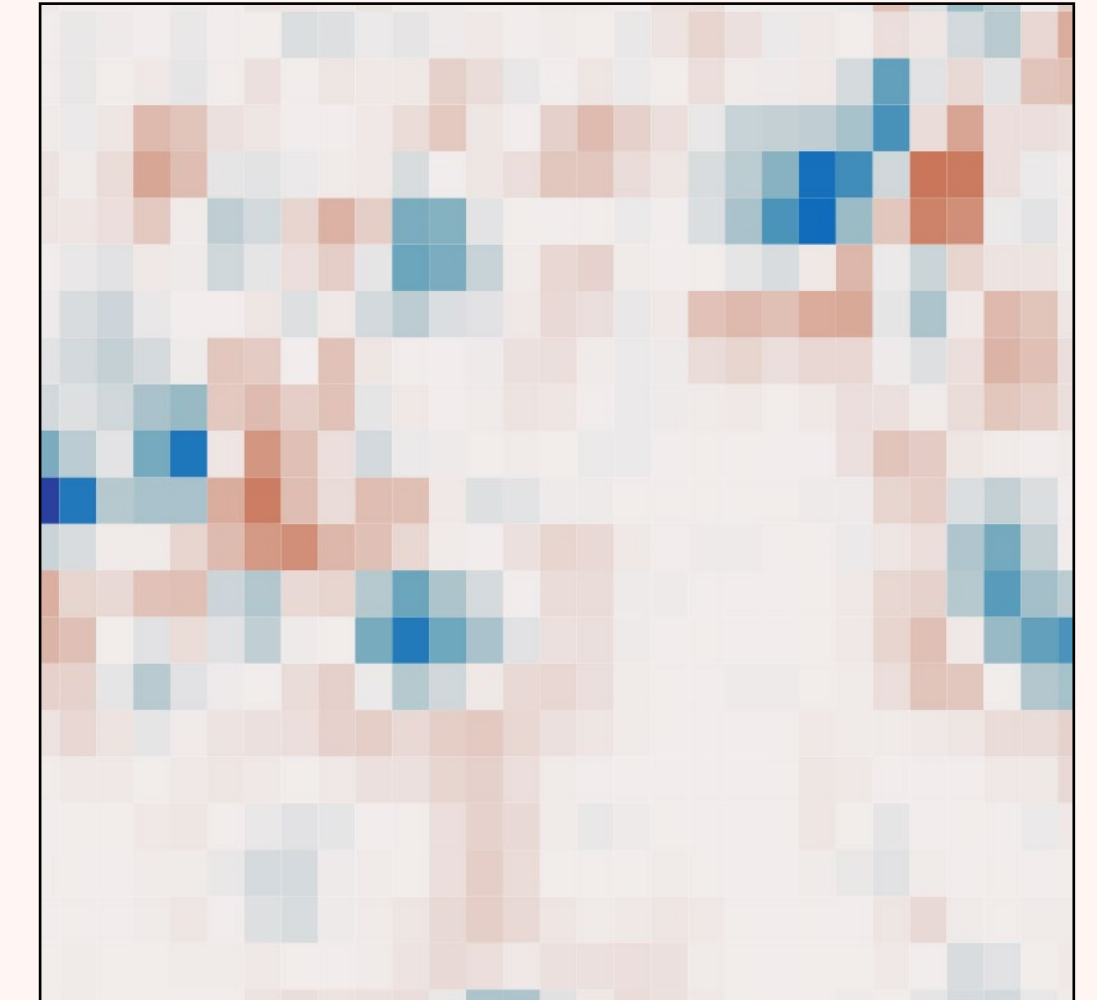
[4] Lapeyre, G., 2017, *Fluids*.

[9] Hua, B.L., and Klein, P., 1998, *Physica D*.

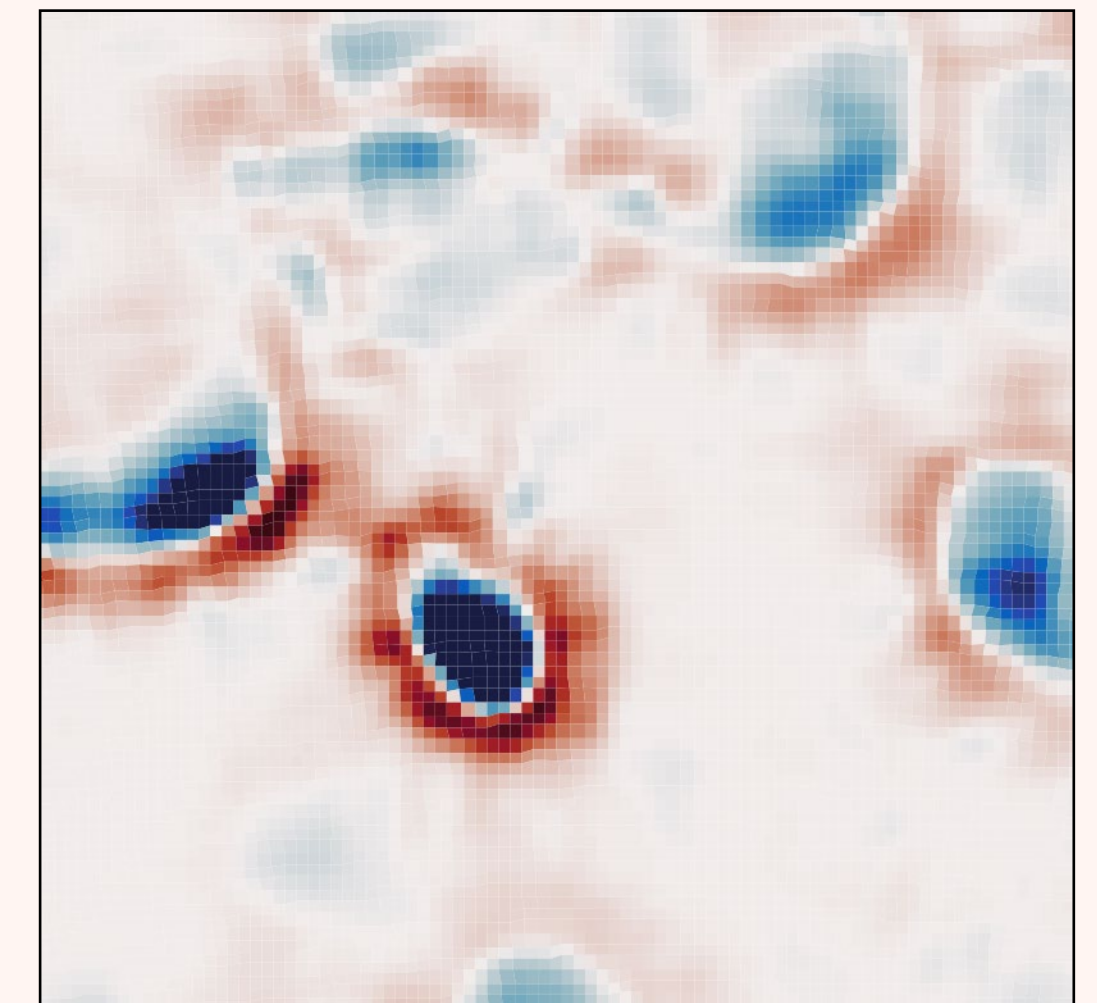
# NEXT STEPS

- Scale up to whole world - publish an improved global mesoscale SSH dataset from nadir altimeters and SST

EXISTING METHOD  
(DUACS)



OUR METHOD  
(ConvLSTM SSH+SST)

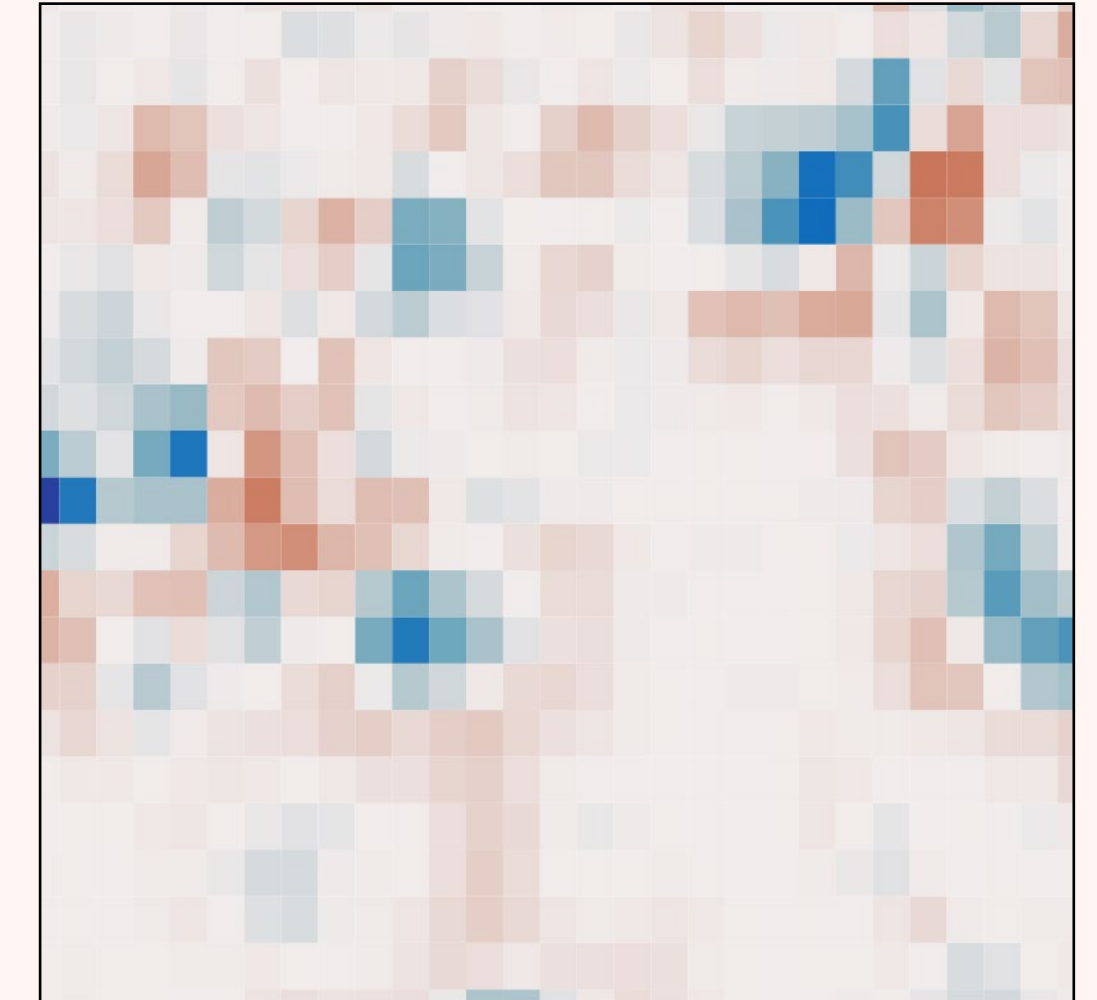




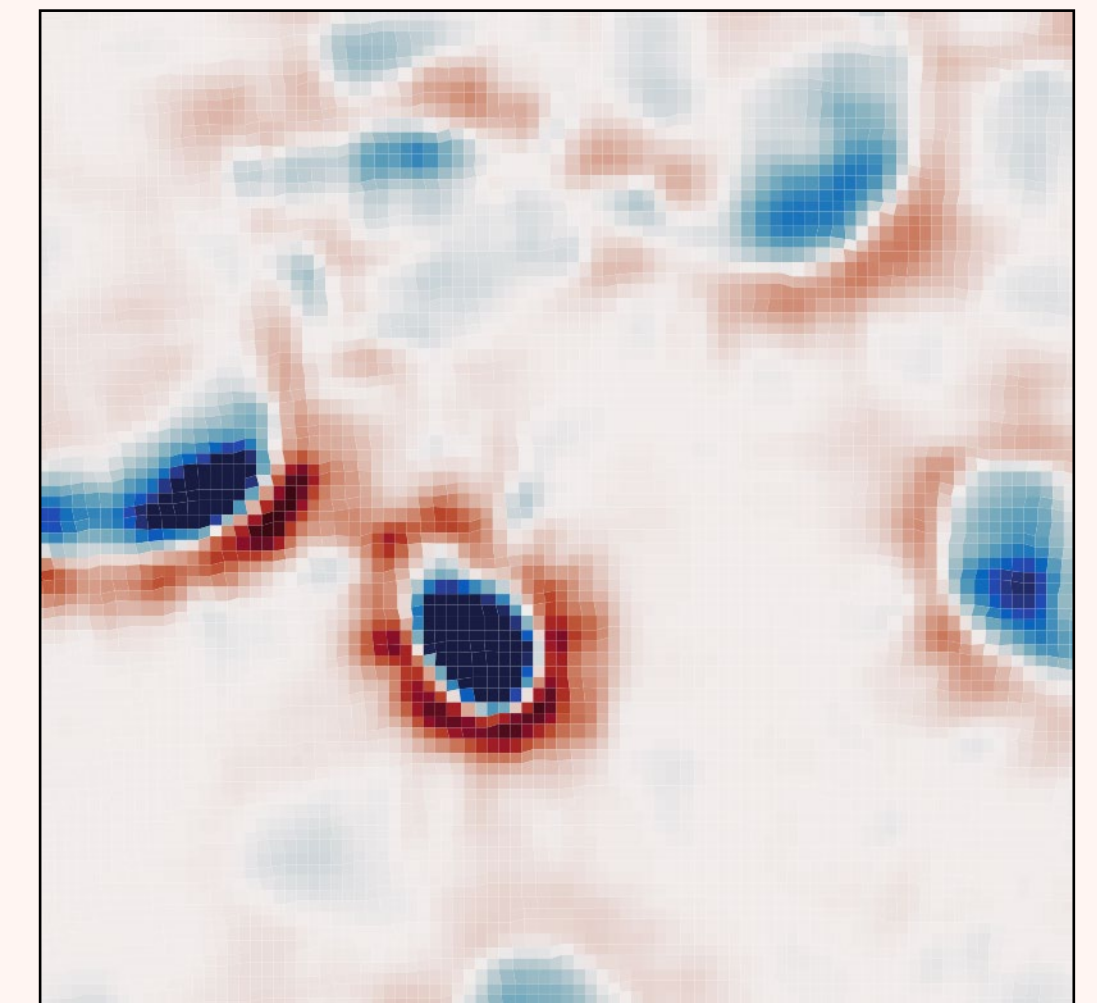
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- Explore using high resolution ocean models for training via transfer learning

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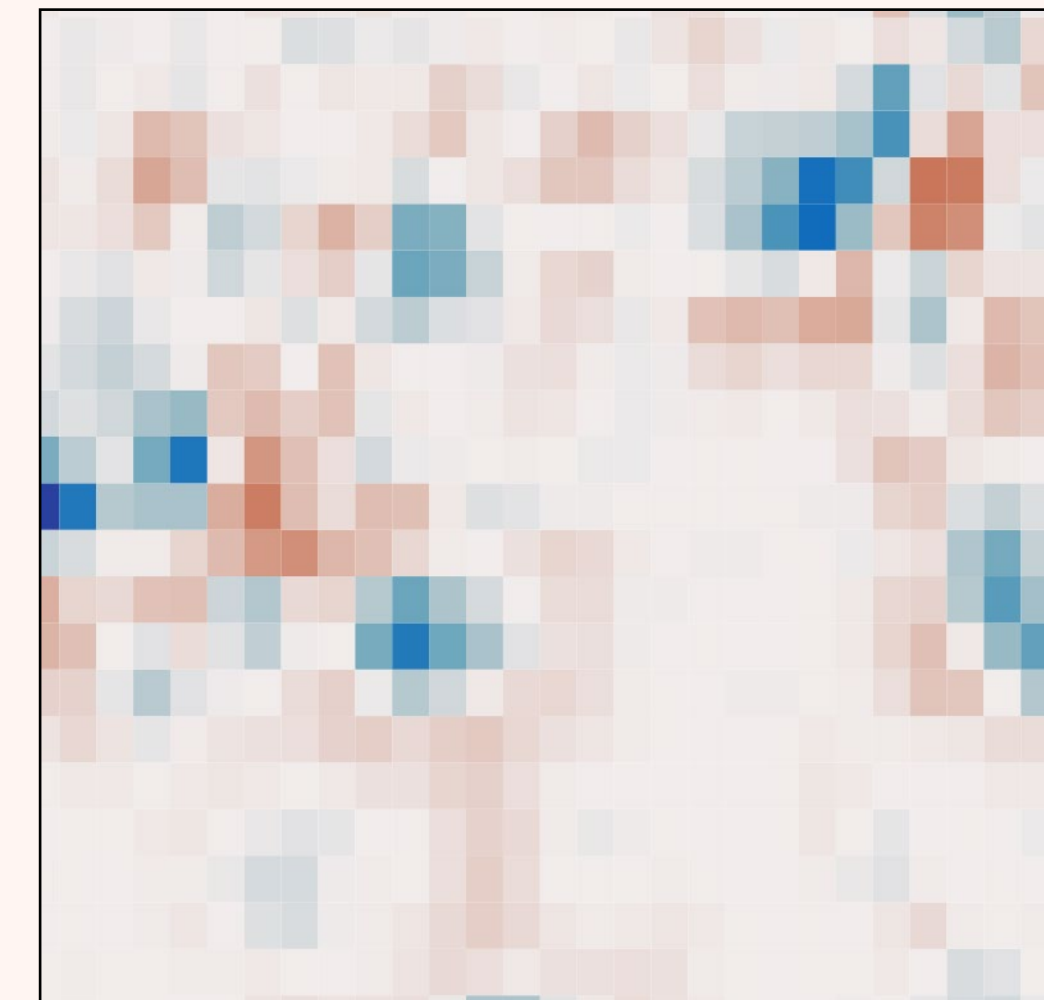
OUR METHOD  
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# NEXT STEPS

- Scale up to whole world - publish an improved global mesoscale SSH dataset from nadir altimeters and SST
- Explore using high resolution ocean models for training via transfer learning
- Opportunities and challenges for incorporating SWOT data:
  - High spatial resolution but low time resolution
  - Fast sampling phase offers unique opportunities for training ML interpolators

EXISTING METHOD  
(DUACS)



OUR METHOD  
(ConvLSTM SSH+SST)

