Applications of deep learning to subgrid eddy parameterization in high- and low-resolution ocean model

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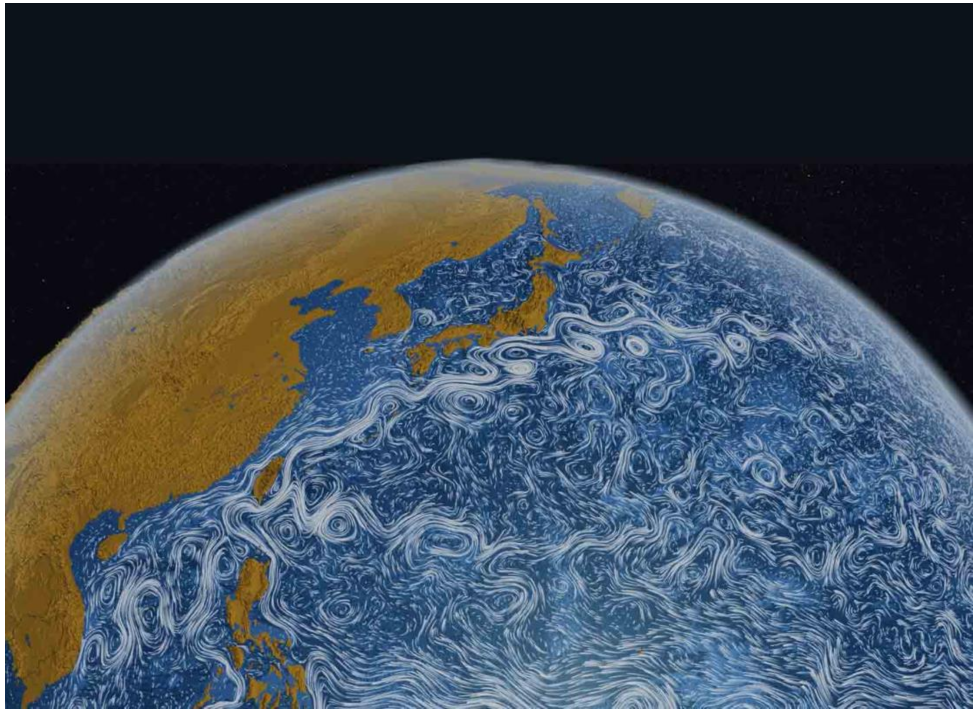
PART ONE

Introduction

Background



Interaction with large-scale flow

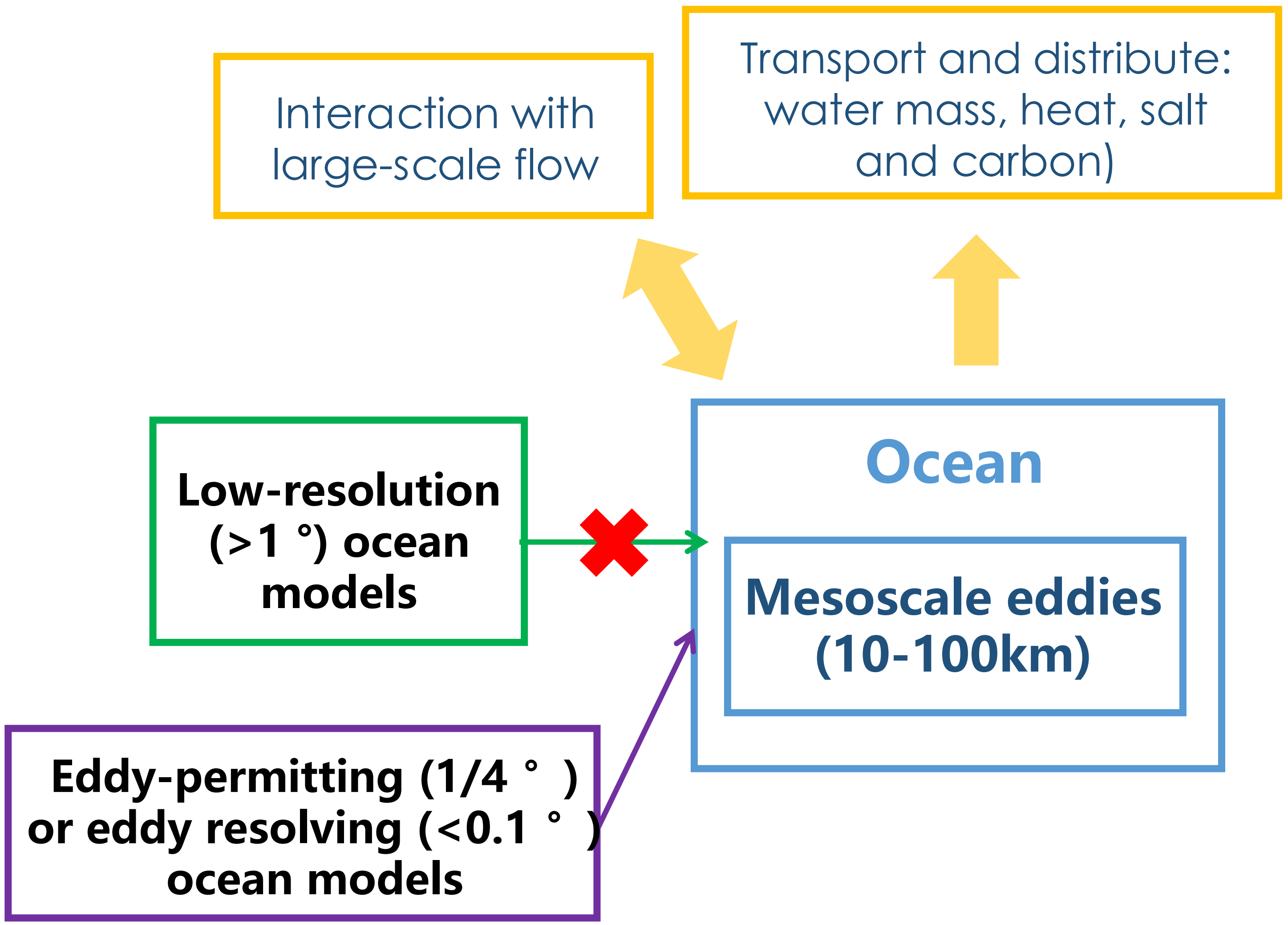
Transport and distribute: water mass, heat, salt and carbon)

Ocean

Mesoscale eddies (10-100km)

1.1 Introduction

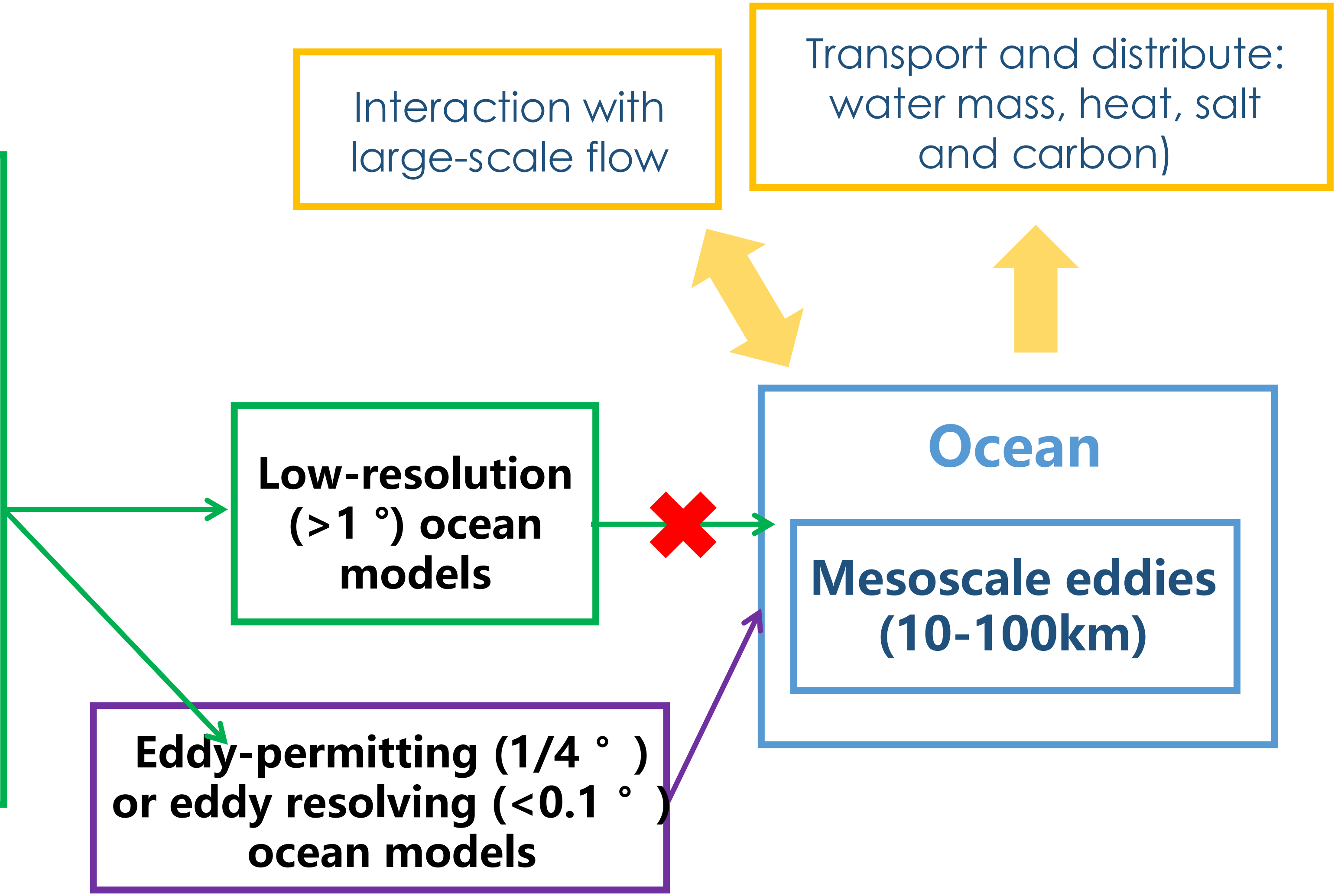
Background



Background

Eddy parameterization:

- **Deterministic:**
  - Gent-McWilliams (GM) [Gent and Mcwilliams, 1990]
  - Resolution function [Hallberg, 2013]
- **Stochastic :**
  - Probability distribution function [Zanna et al., 2017]



Machine Learning

Deep Learning :

- Popular in the field : image processing, language, etc.
- Extract information from data
- Data-driven approach, to approximate nonlinear relationship, without obey physical principles and conservation laws.

Applications:

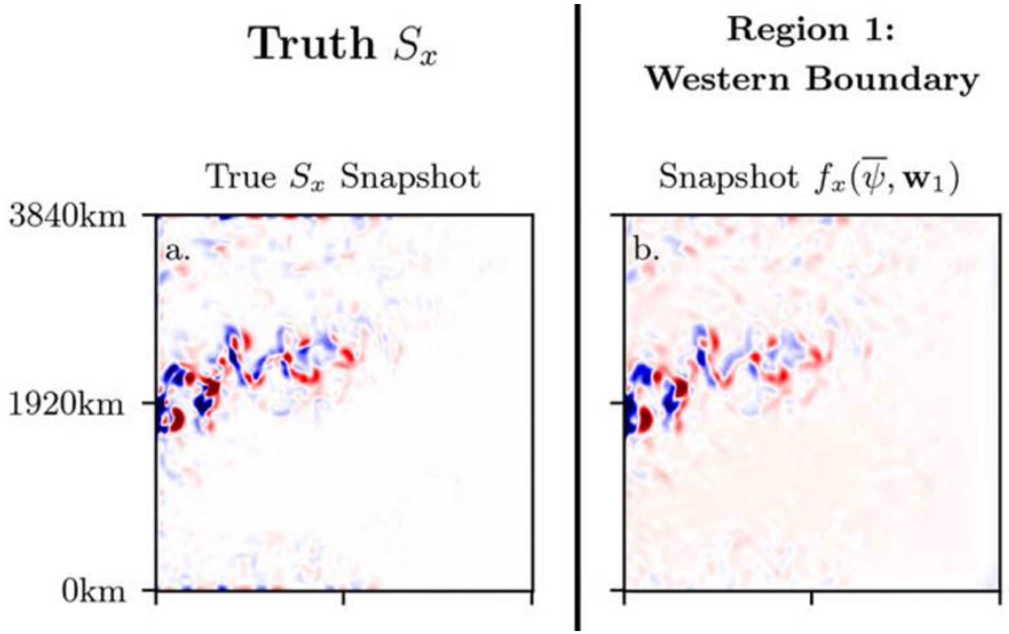
➢ Climate models:
- Typhoon Forecast [Jiang et al., 2018],
- representing unresolved moist convection [Gentine et al., 2018].

➢ Turbulence modeling (e.g [Ling et al., 2016])

Machine Learning

Bolton et al.,2019 (BM18):

- An idealized high-resolution ocean model,
- Deep learning : Convolutional neural networks (CNNs)
- Represent both the spatial and temporal variability of the eddy momentum forcing



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Objectives

1. Apply the CNNs in a **realistic simulation**
2. Test the sensitivity of the neural networks

3. The main goal : Using sub-sample data from an eddy-resolving model, to represent unresolved eddies in low-resolution model as a **subgrid-scale parametrization**

contents

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PART TWO

Methodology

Subgrid eddy momentum forcing

The horizontal momentum equation :

$$\boxed{\frac{\partial \boldsymbol{u}}{\partial t} + (\boldsymbol{u} \cdot \nabla)\,\boldsymbol{u} = F + D}$$

Large-Eddy Simulation :

Large scale and eddy components

$$\boldsymbol{u} = \overline{\boldsymbol{u}} + \boldsymbol{u}'$$

Gaussian Filter

Subgrid eddy momentum forcing

The horizontal momentum equation :

$$\boxed{\frac{\partial \boldsymbol{u}}{\partial t} + (\boldsymbol{u} \cdot \nabla)\,\boldsymbol{u} = F + D}$$

Large-Eddy Simulation :

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Gaussian Filter

$$\frac{\partial \overline{\boldsymbol{u}}}{\partial t} + (\overline{\boldsymbol{u}} \cdot \nabla)\,\overline{\boldsymbol{u}} = \overline{F} + \overline{D} + (\overline{\boldsymbol{u}} \cdot \nabla)\,\overline{\boldsymbol{u}} - \overline{(\boldsymbol{u} \cdot \nabla)\,\boldsymbol{u}}$$

Subgrid eddy momentum forcing

The horizontal momentum equation :

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Large-Eddy Simulation :

Large scale and eddy components

$$\boldsymbol{u} = \overline{\boldsymbol{u}} + \boldsymbol{u}'$$

Gaussian Filter

$$\frac{\partial \overline{\boldsymbol{u}}}{\partial t} + (\overline{\boldsymbol{u}} \cdot \nabla)\overline{\boldsymbol{u}} = \overline{F} + \overline{D} + \boxed{(\overline{\boldsymbol{u}} \cdot \nabla)\overline{\boldsymbol{u}} - \overline{(\boldsymbol{u} \cdot \nabla)\boldsymbol{u}}}$$

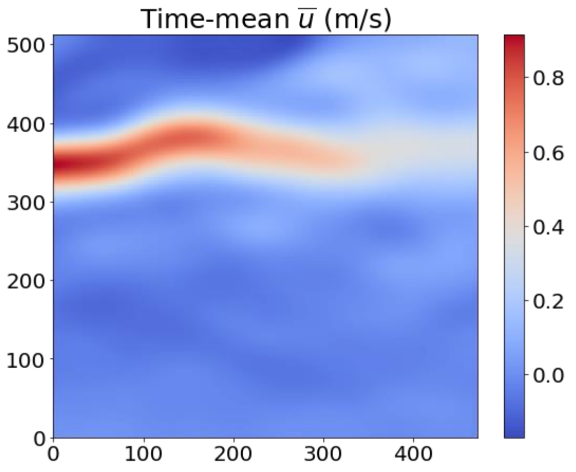
$$\boxed{\frac{\partial \overline{\boldsymbol{u}}}{\partial t} + (\overline{\boldsymbol{u}} \cdot \nabla)\overline{\boldsymbol{u}} = \overline{F} + \overline{D} + \boldsymbol{S}}$$

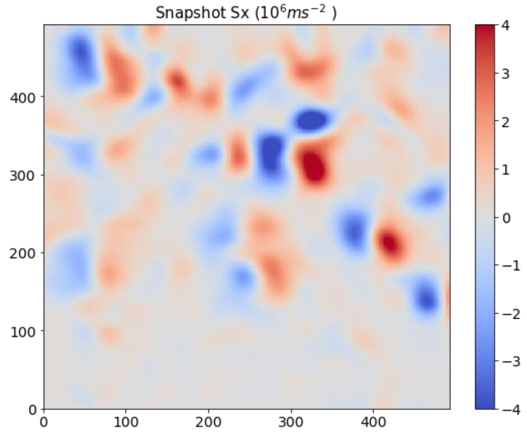
Filtered momentum forcing

Filtered Dissipation

Subgrid eddy momentum forcing

Subgrid eddy momentum forcing





$$(\overline{\boldsymbol{u}} \cdot \nabla)\,\overline{\boldsymbol{u}} - \overline{(\boldsymbol{u} \cdot \nabla)\,\boldsymbol{u}}$$

$$\frac{\partial \overline{\boldsymbol{u}}}{\partial t} + (\overline{\boldsymbol{u}} \cdot \nabla)\,\overline{\boldsymbol{u}} = \overline{F} + \overline{D} + \boldsymbol{S} = (Sx,\ Sy)$$

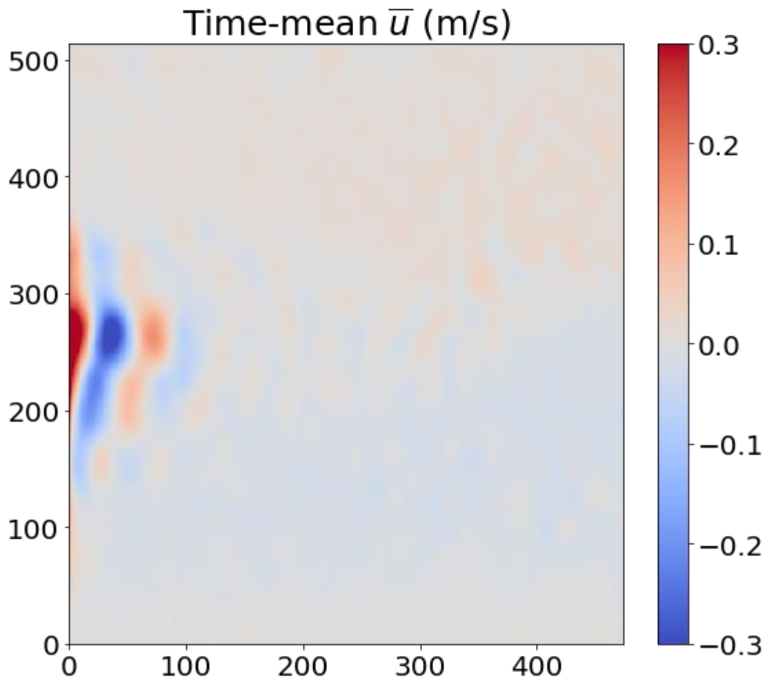
Filtered momentum forcing

Filtered Dissipation

Subgrid eddy momentum forcing

The Ocean model and data

1. Gyre case:
Coastal and Regional Ocean COmmunity (CROCO)

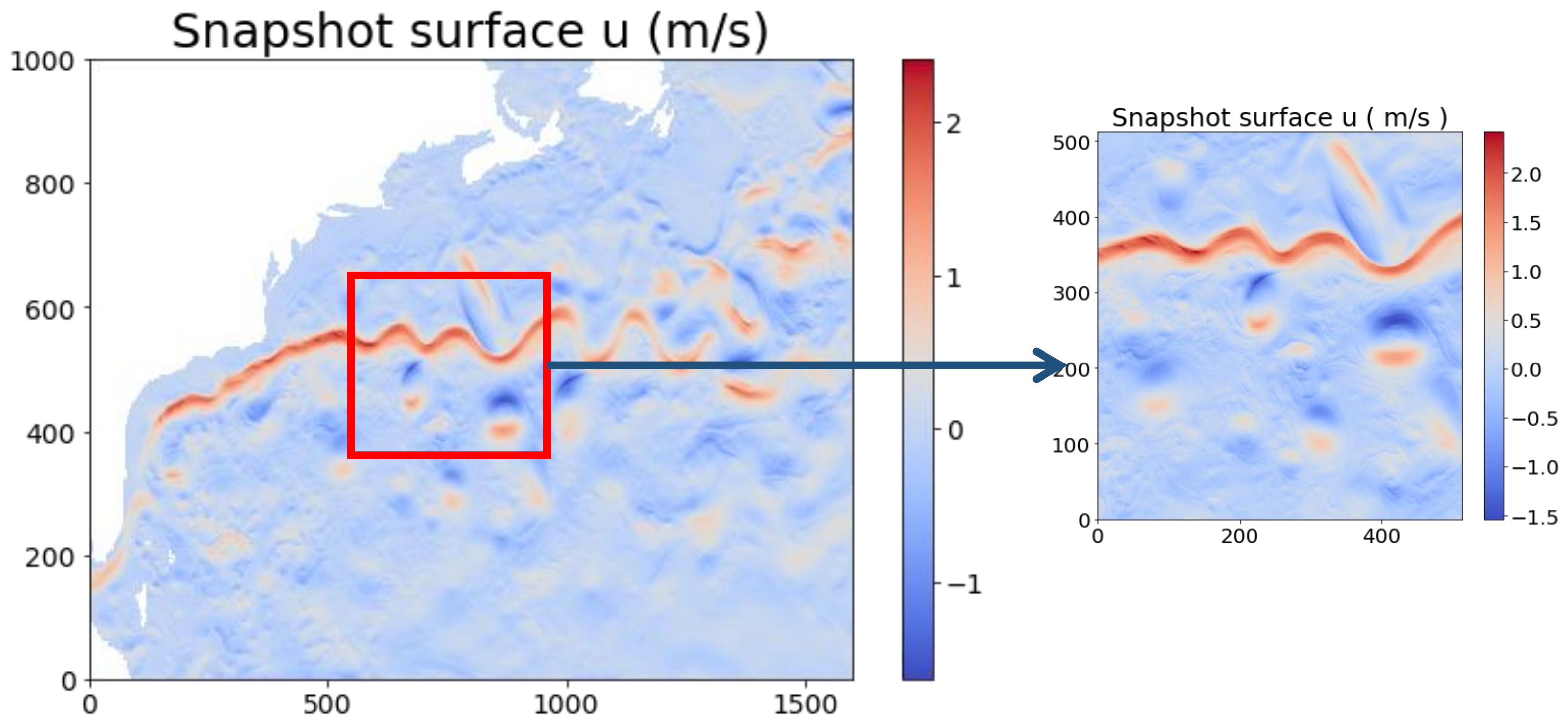


Study Region:

- Bounded-square basin
- Length L=3600km
- Flat bottom
- High-resolution 512 x 512, dx=7.0 km
- Constant wind stress forcing applied on surface
- 1000 daily data of velocity stored

The Ocean model and data

2. Realistic simulation in the Gulf Stream: Regional Ocean Modeling System (ROMS)



Study Region:

- Realistic simulation
  512 x 512, dx=2.5 km
- In the Gulf Stream
- Length L=1280km
- The effect of the topography is considered
- 5-day intervals , 1000 snapshots of velocity stored

From Gula et al. [2015]

Deep Learning with the CNNs

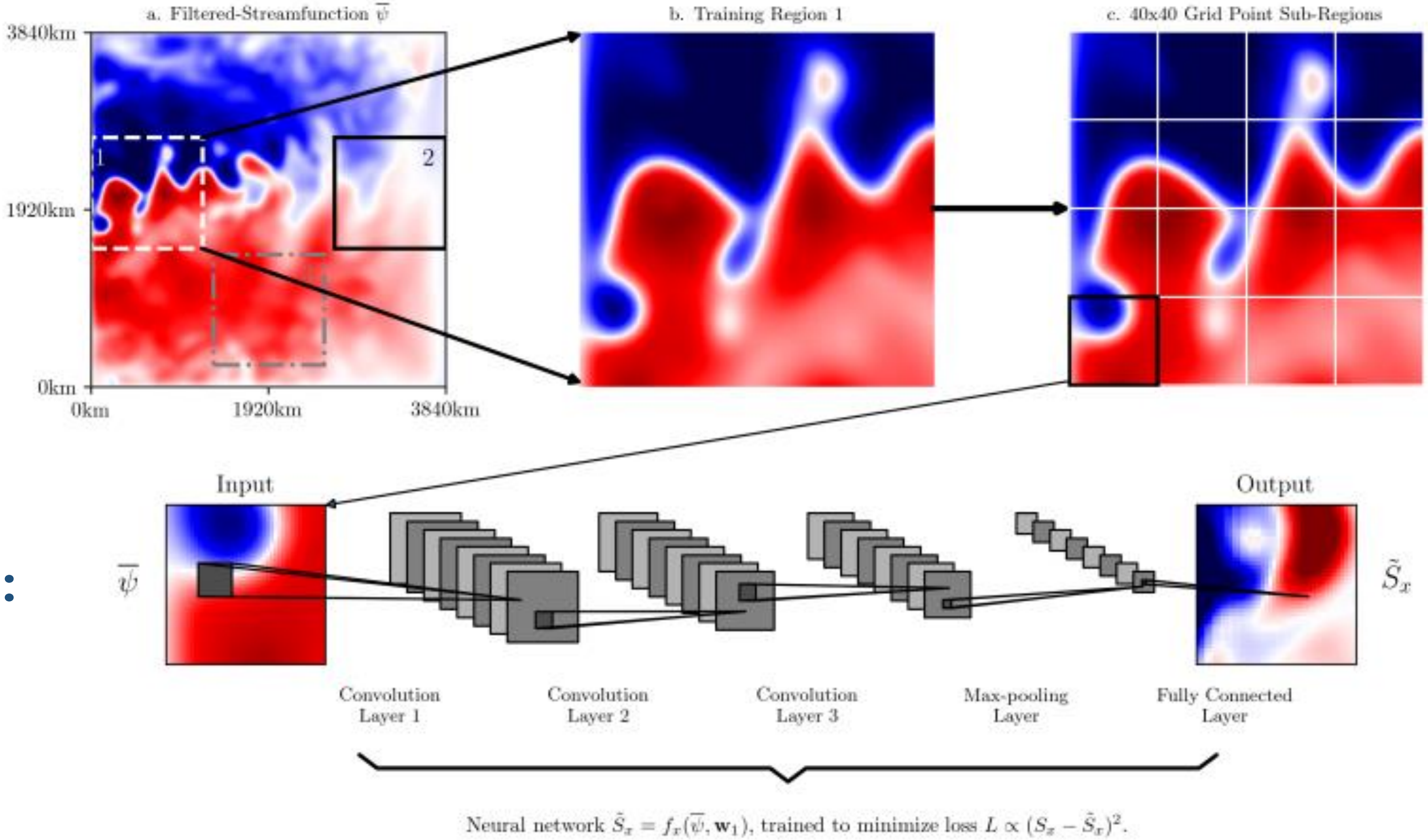
Training Strategy:
in BMI8

The full domain
(512 x 512)

Study Region
(160 x 160)

Training Sub-region
16 x (40 x 40)

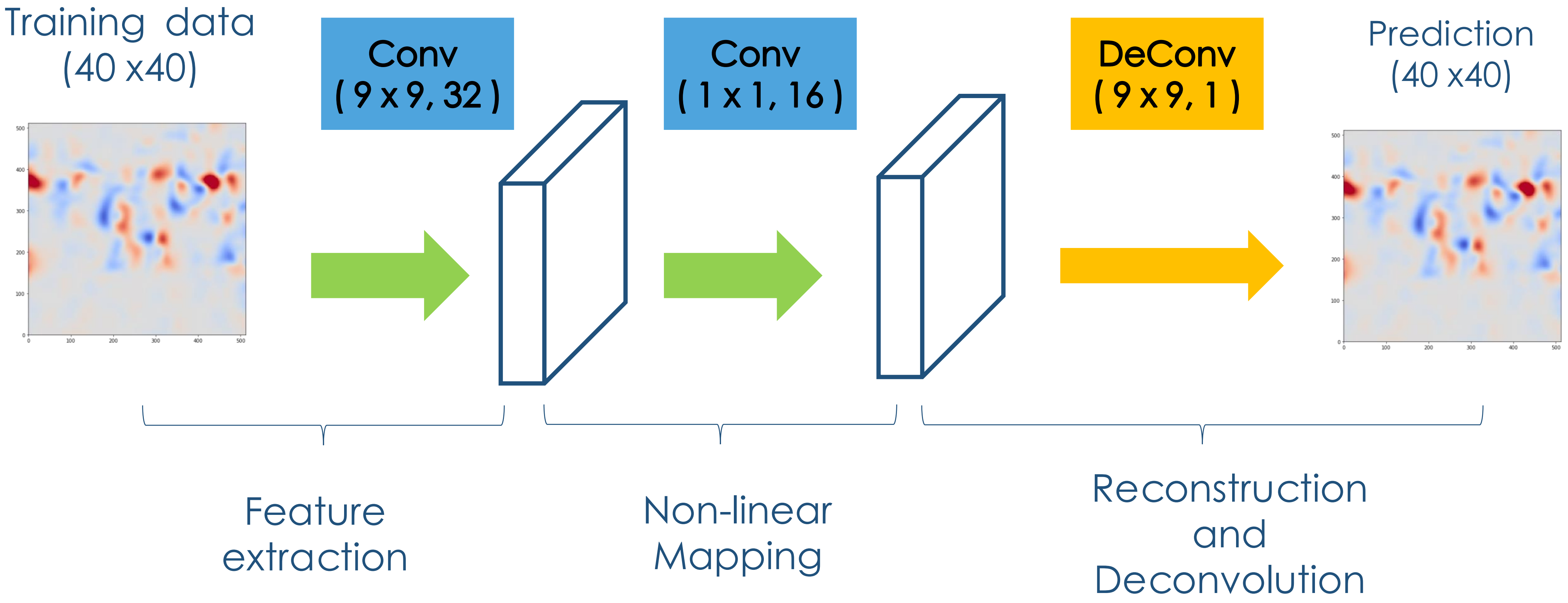
The architecture of CNNs :



2.3 Methodology

Deep Learning with the CNNs

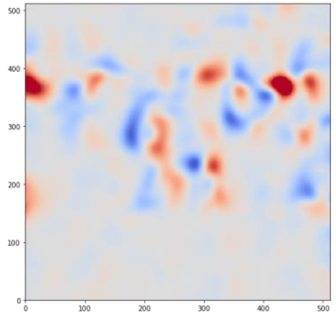
Another architecture of CNNs



Deep Learning with the CNNs

Another architecture of CNNs

Training data
(40 x40)

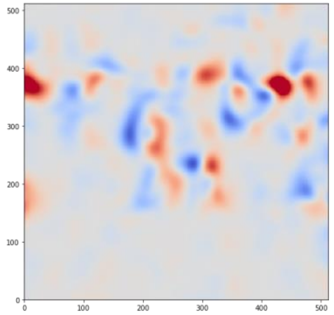


Conv
(9 x 9, 32)

Conv
(1 x 1, 16)

DeConv
(9 x 9, 1)

Prediction
(40 x40)



Feature extraction

Non-linear Mapping

Reconstruction and Deconvolution

Total training parameters: 4 449
In BM18 : 325 728

Fast speed to learn , maintain good performance

2.3 Methodology

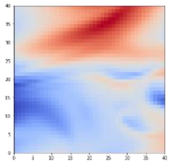
Training Strategy

Total Dataset :

Training dataset (80%)

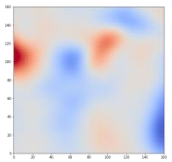
Validation dataset (20%)

Training data (40 x40)

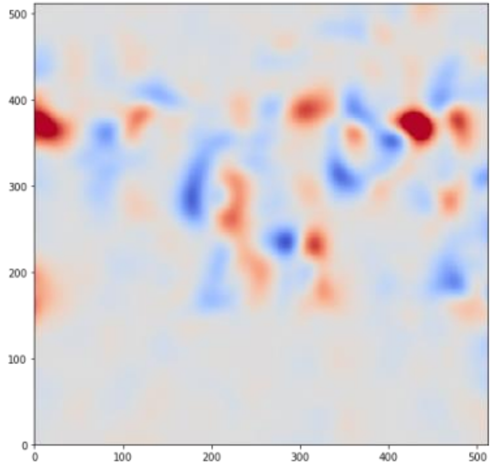


CNNs

Prediction (40 x40)

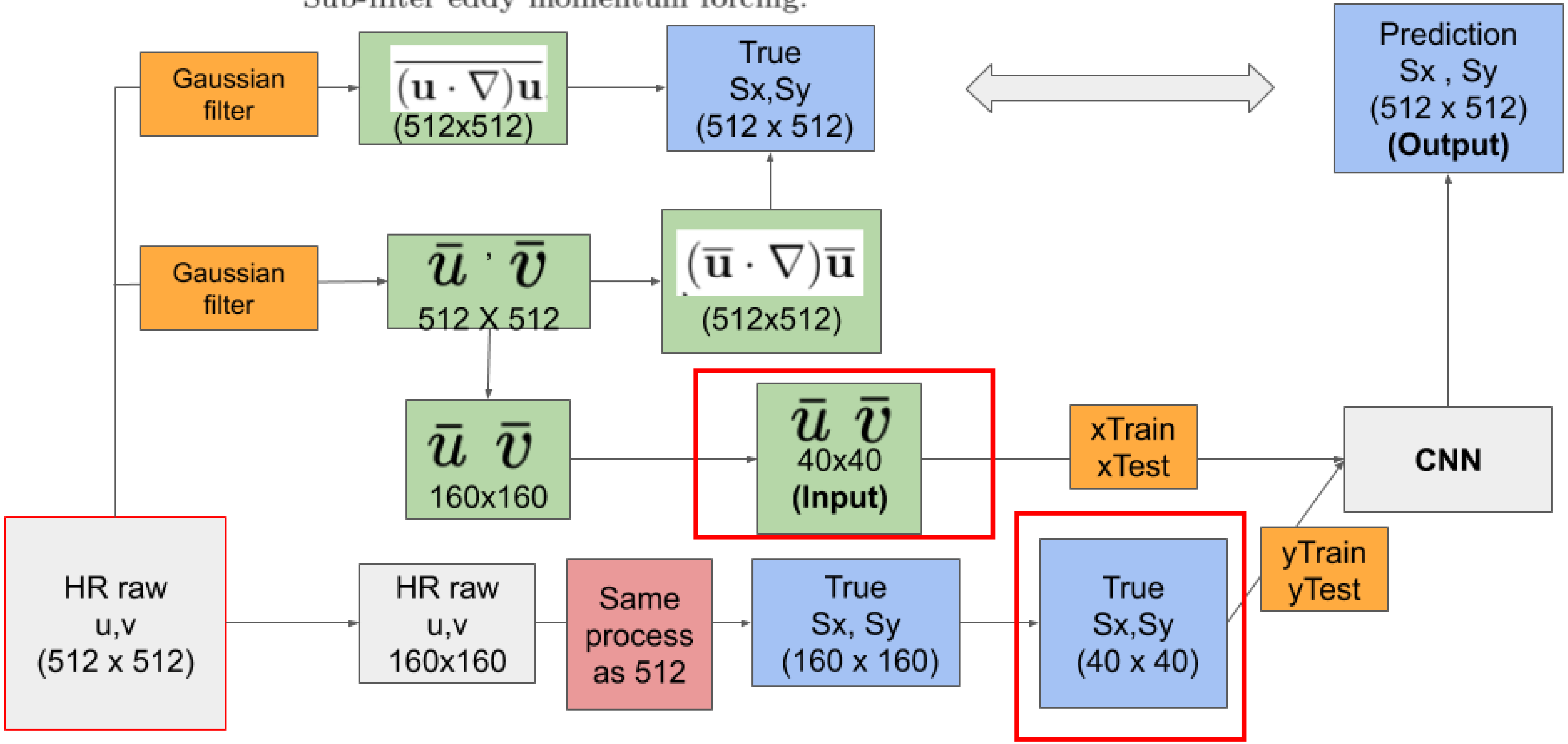


Prediction (512 x 512)



Implementation details

$$\mathbf{S} = \underbrace{(\bar{\mathbf{u}}\cdot\nabla)\bar{\mathbf{u}} - \overline{(\mathbf{u}\cdot\nabla)\mathbf{u}}.}_{\text{Sub-filter eddy momentum forcing.}}$$



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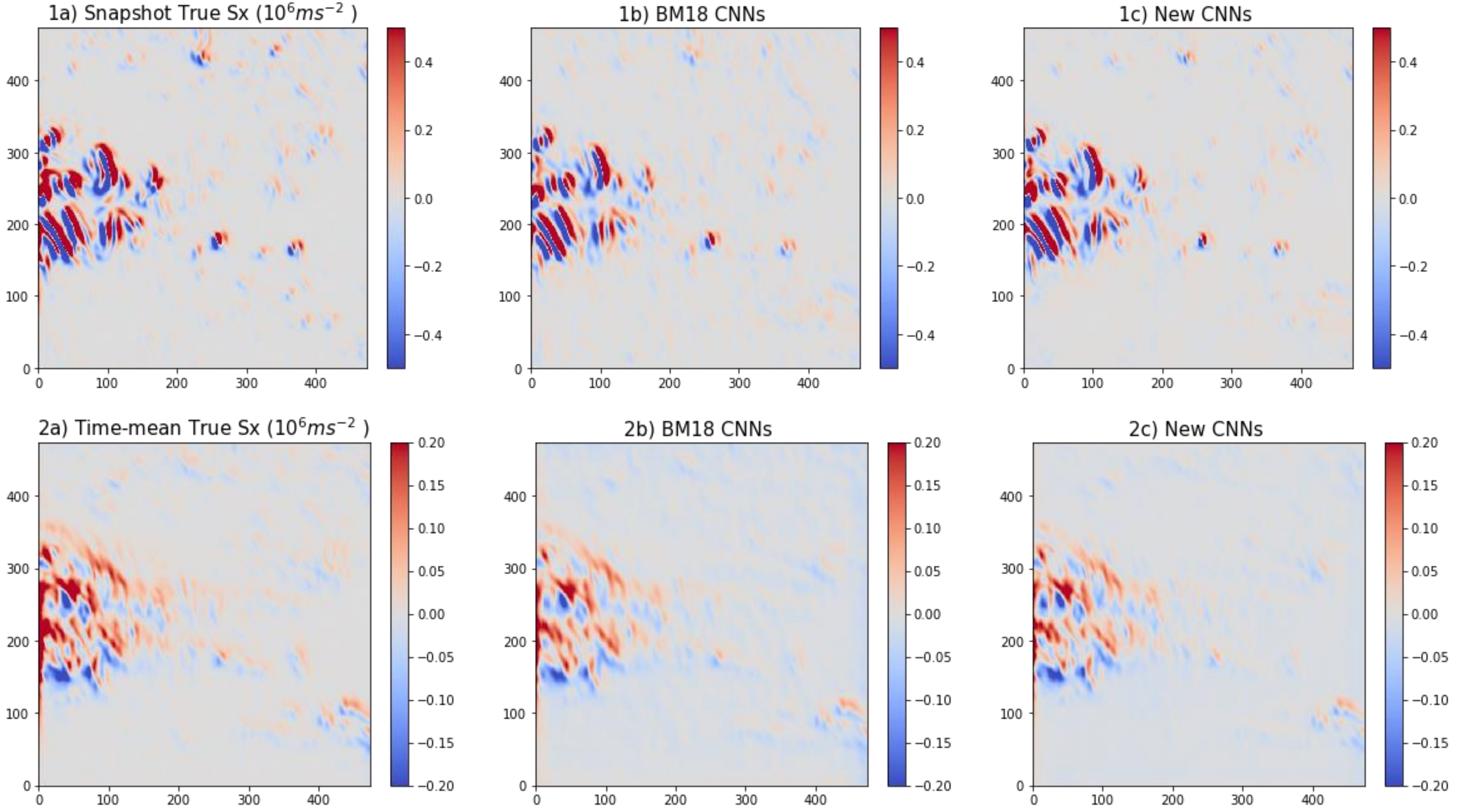
PART THREE

Main Results

3.1 Gyre case : comparison with BM18

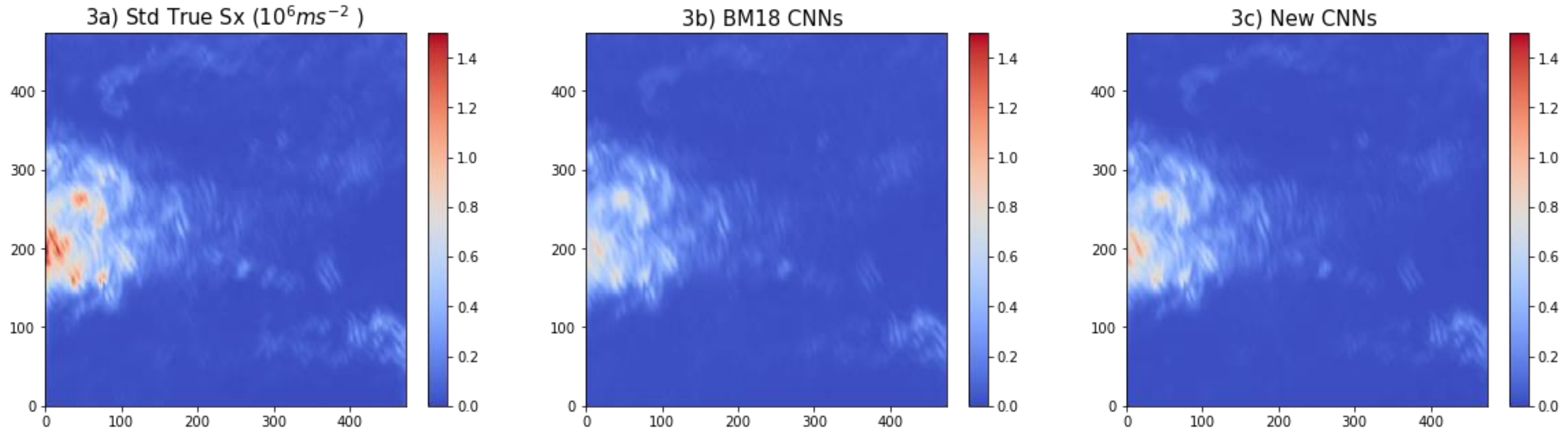
Snapshot of Sx

Time-mean Sx

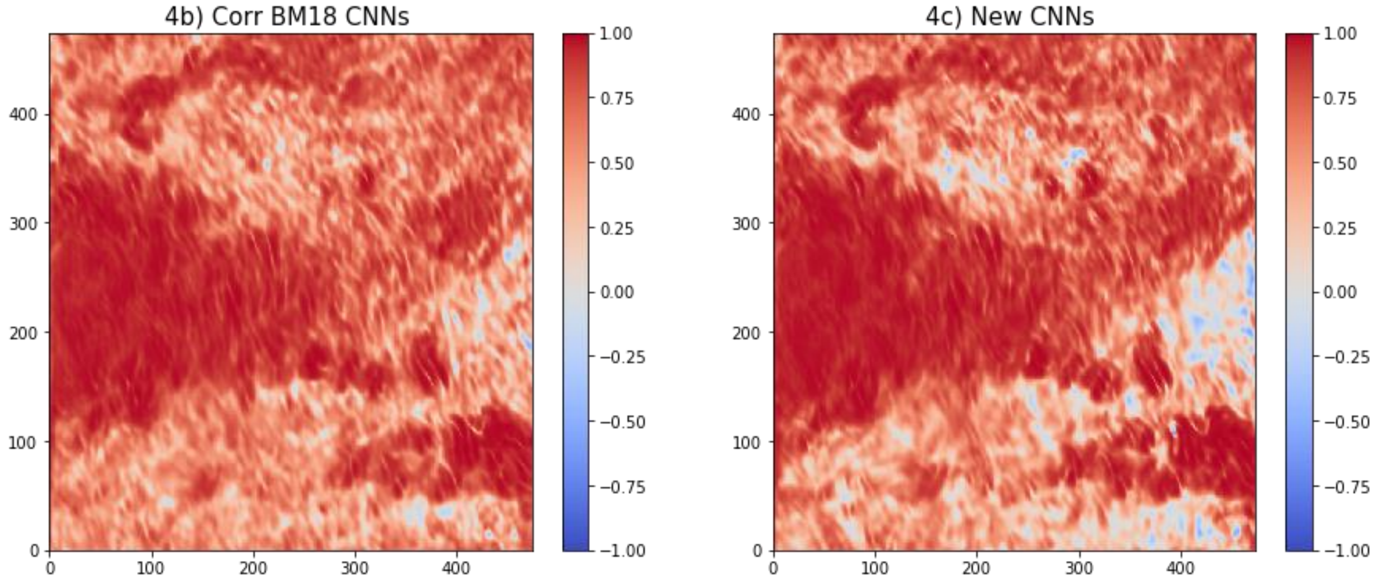


3.1 Gyre case : comparison with BM18

Standard deviation of Sx



Correlation between Sx and prediction



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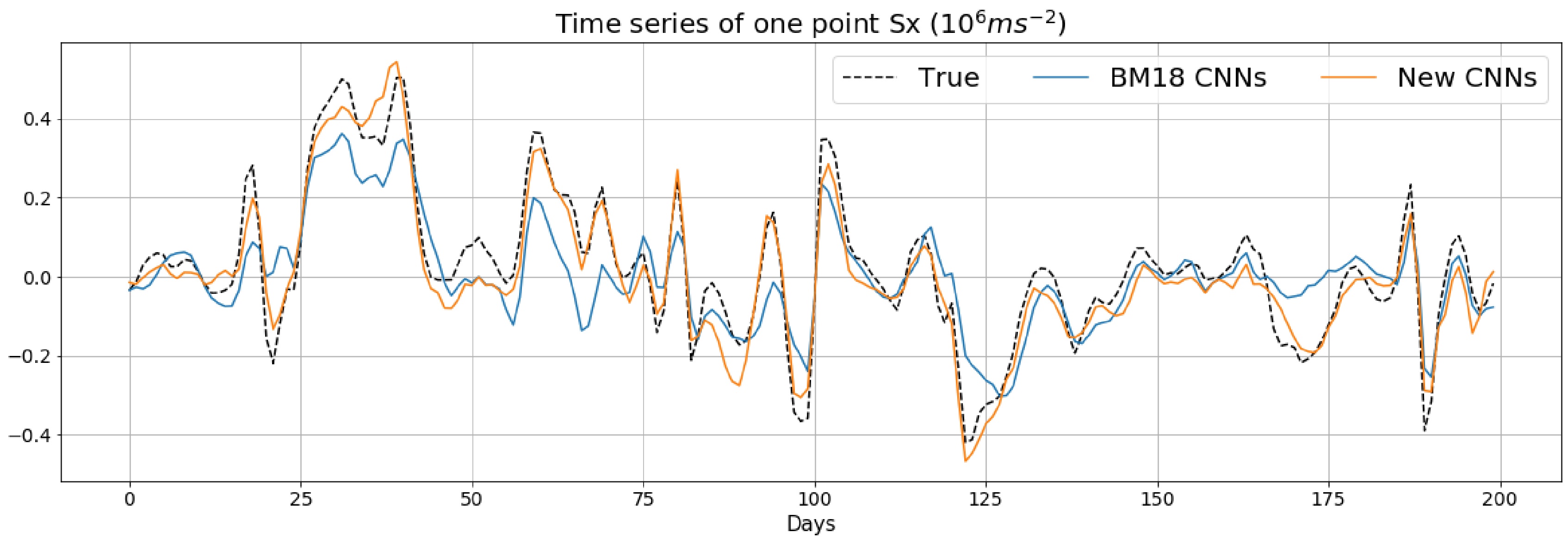
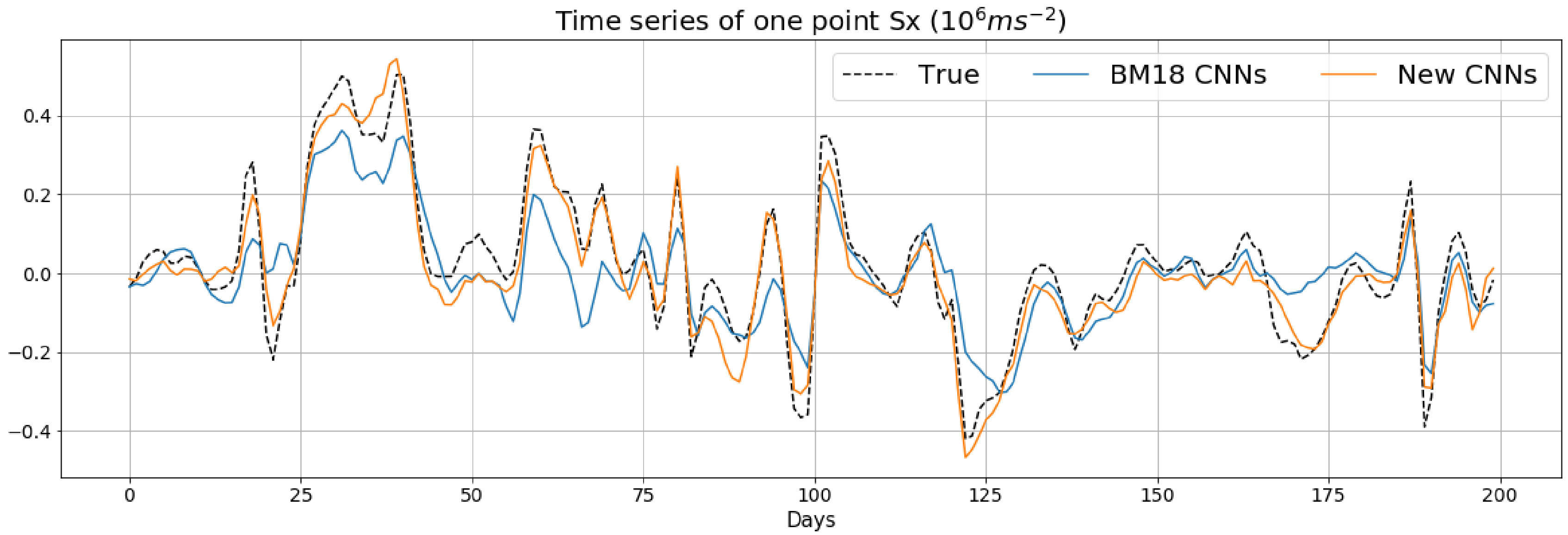


- The two time series of predictions generally match the fluctuation of true Sx,
- New CNNs have better performance in amplitude most parts.

3.1 Gyre case : comparison with BM18

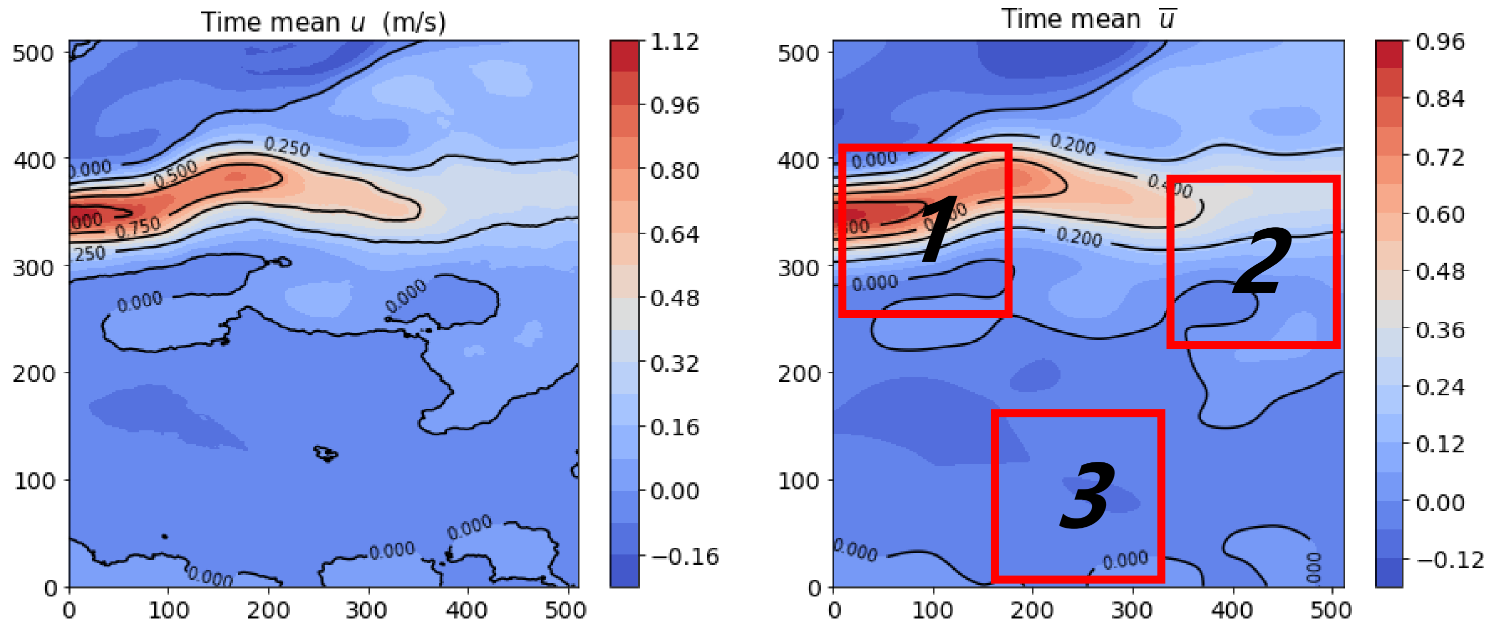


- Both good performance
- Both High correlation in the Western boundary

- New CNNs:

Fewer parameters to train, much less time to compute

Study Regions



Study Regions(160 x 160):

Region 1
Region 2
Region 3

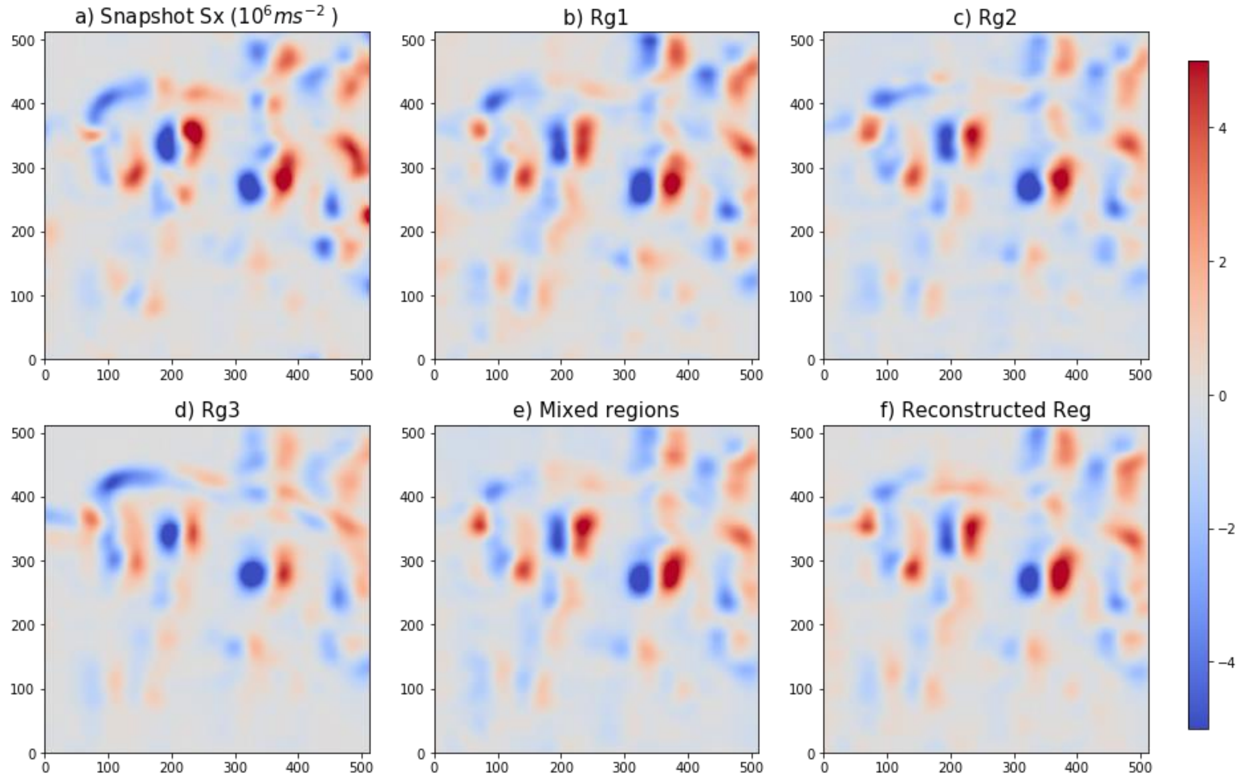
Region 4 : mixed three regions (33%,33%,34%)

Region 5 : random region

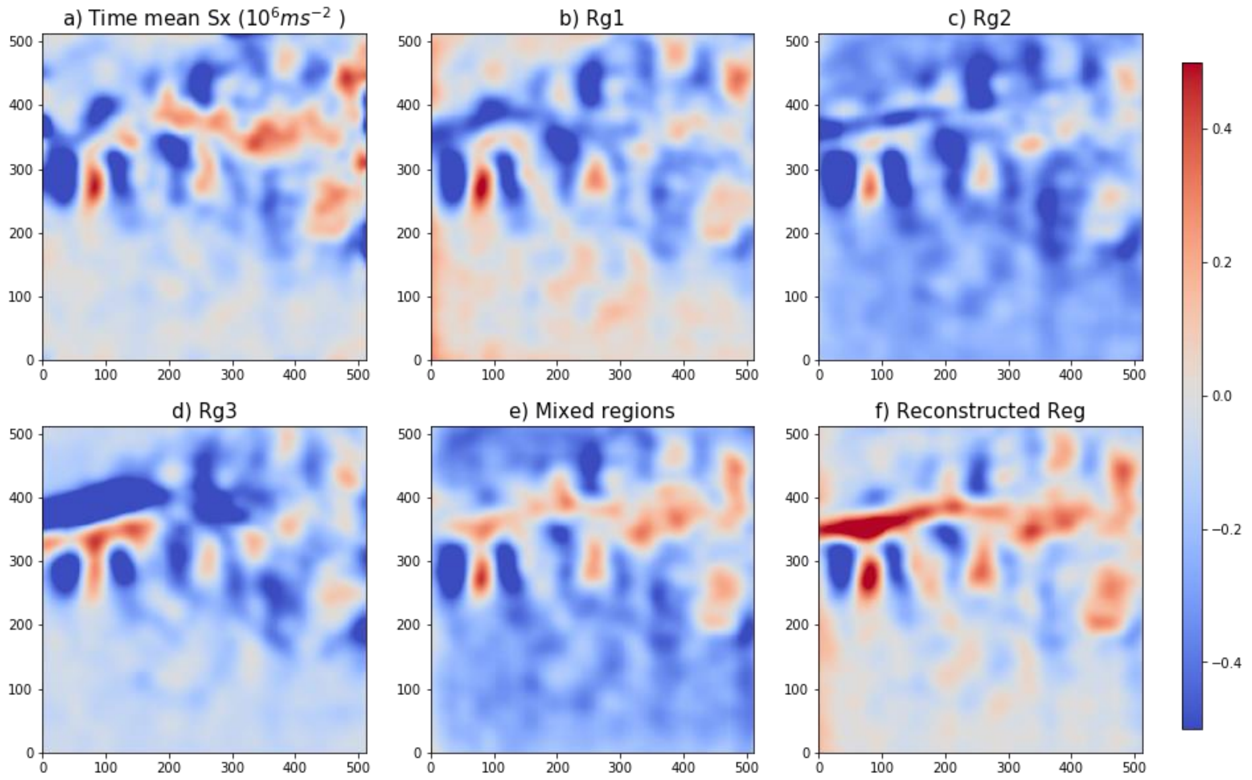
3.2 The Realistic simulation: the GS region

Non-Local Predictions

- **Snapshot of Sx**

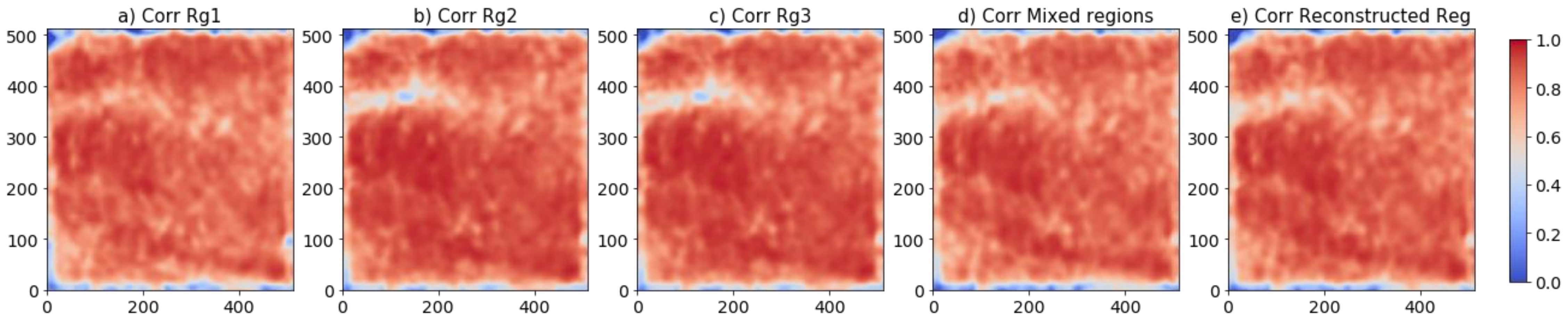


- **Time mean of Sx**



Non-Local Predictions

- **Correlation between true Sx and prediction**



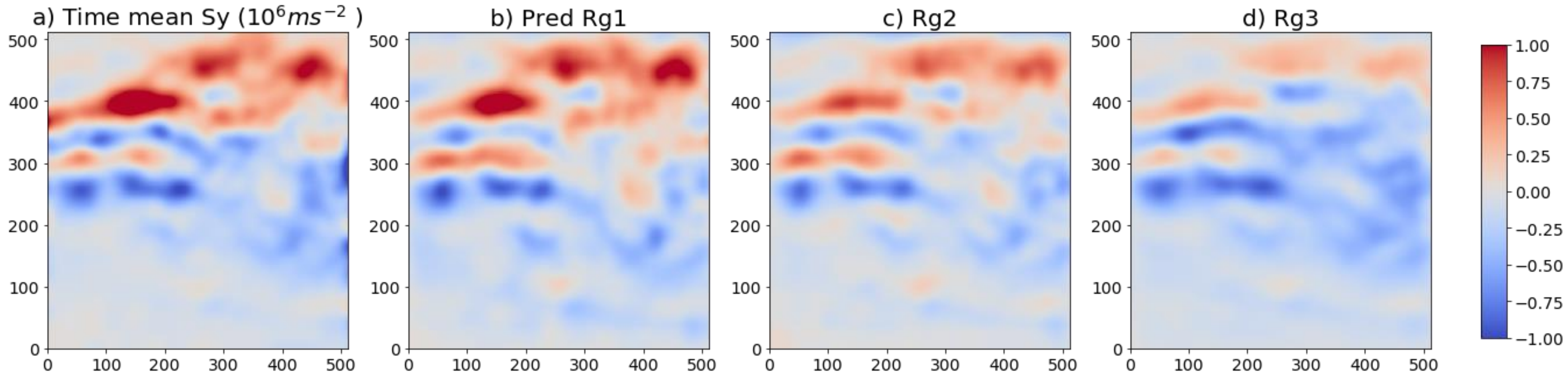
Overall averaged:

a) Corr Rg1	b) Corr Rg2	c) Corr Rg3	d) Corr Mixed regions	e) Corr Reconstructed Reg
0.86	0.85	0.73	0.85	0.84

- Correlation decreases visibly along the path of the jet near the western boundary.
- Better prediction in the Southern in Region 2, 3

Non-Local Predictions

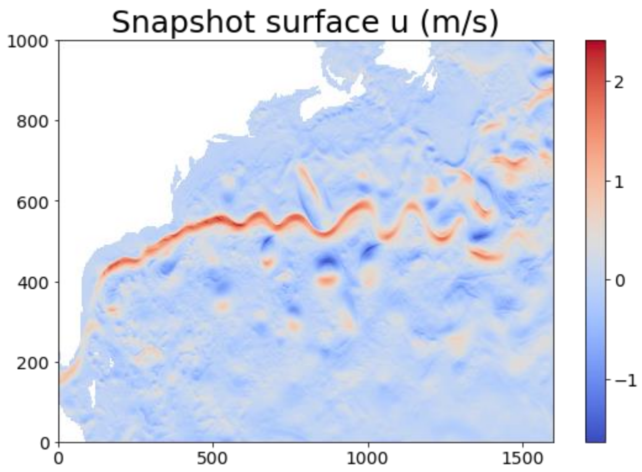
- **Time mean of Sy**

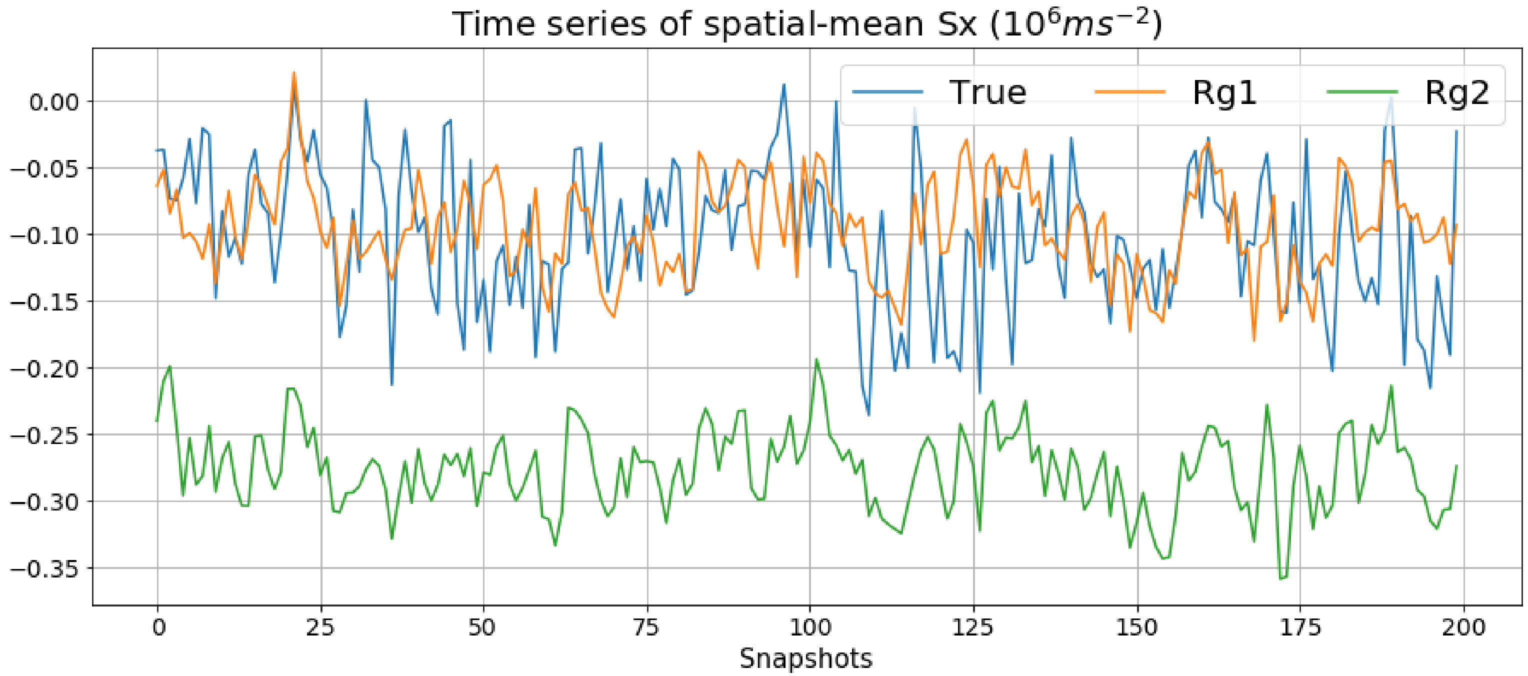


3.2 The Realistic simulation: the GS region

Conservation of energy

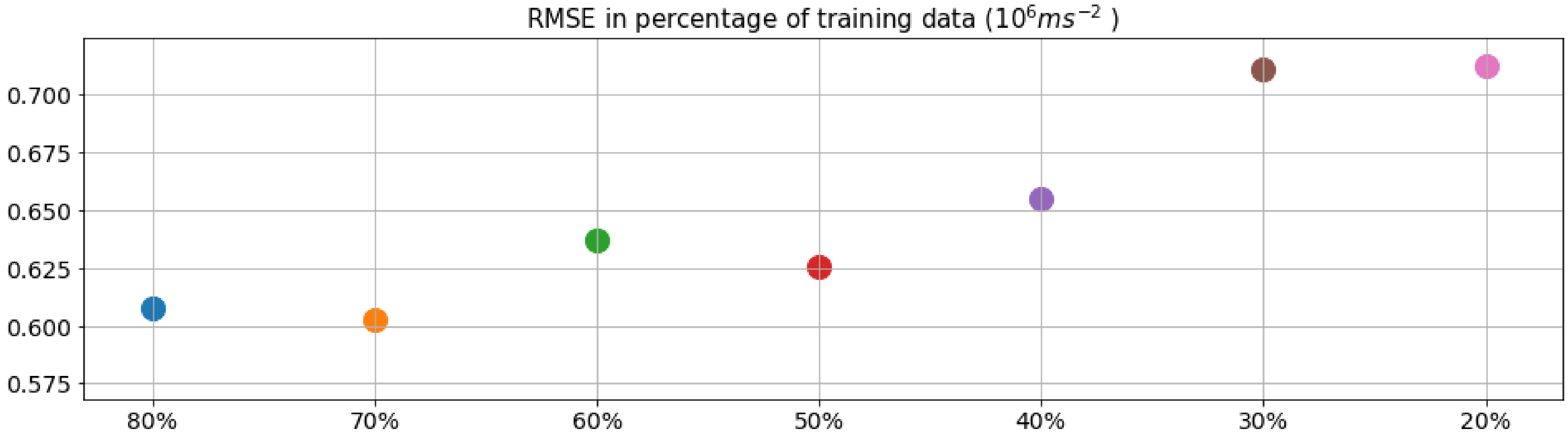
- For a whole simulation domain:
  a zero spatially-integrated momentum tendency
- In extracted region here:
  Small amount of negative momentum





Sensitivity of CNNs

- **The amount of training data :**
  - BM 18 : 9-years daily training data, and 1-year validation
  - Here, 800-snapshots training and 200 for validation



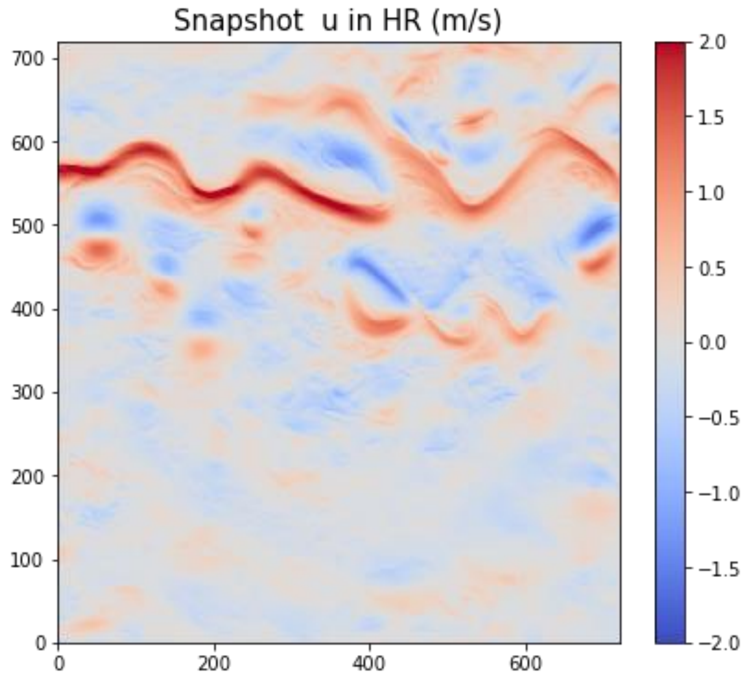
3.3. Implementation in low-resolution

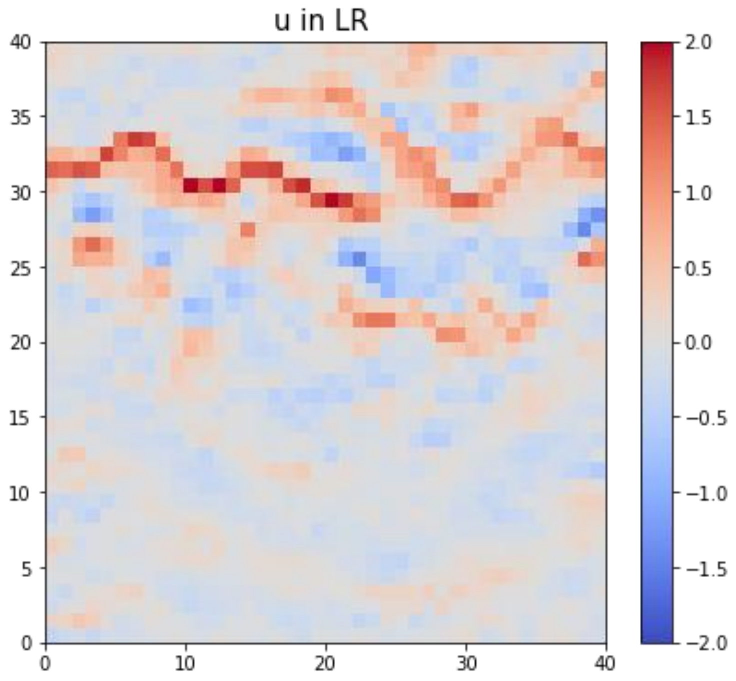
Training Strategy

High-resolution
720 x 720

Sub-sampled by a factor 18

Coarse-grid
40 x 40

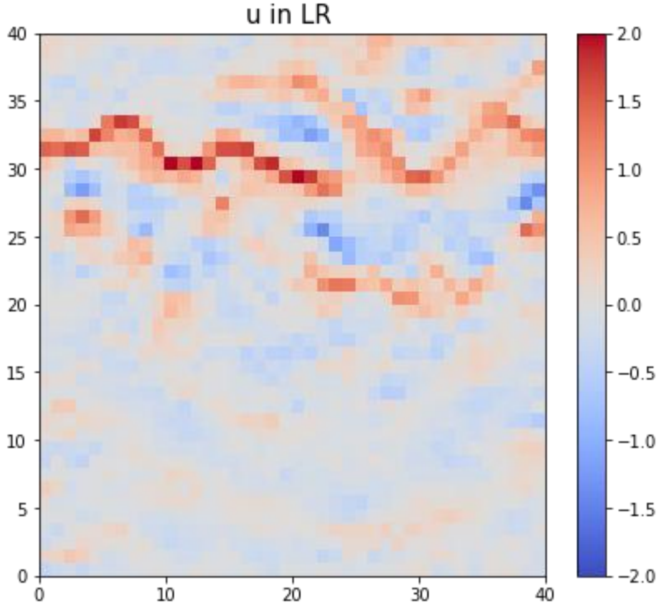


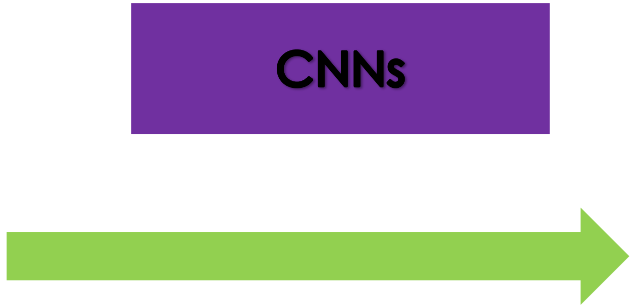


Training Strategy

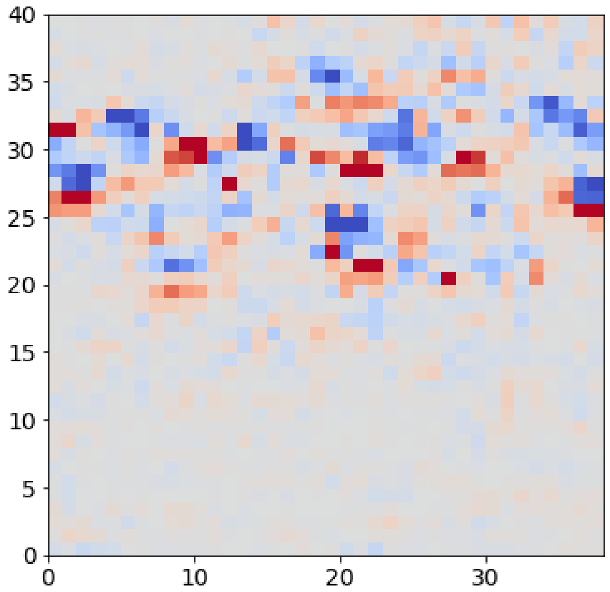
Total Dataset : Training dataset (60%) | Validation (20%) | Test dataset (20%)

Training data : u
(40 x40)



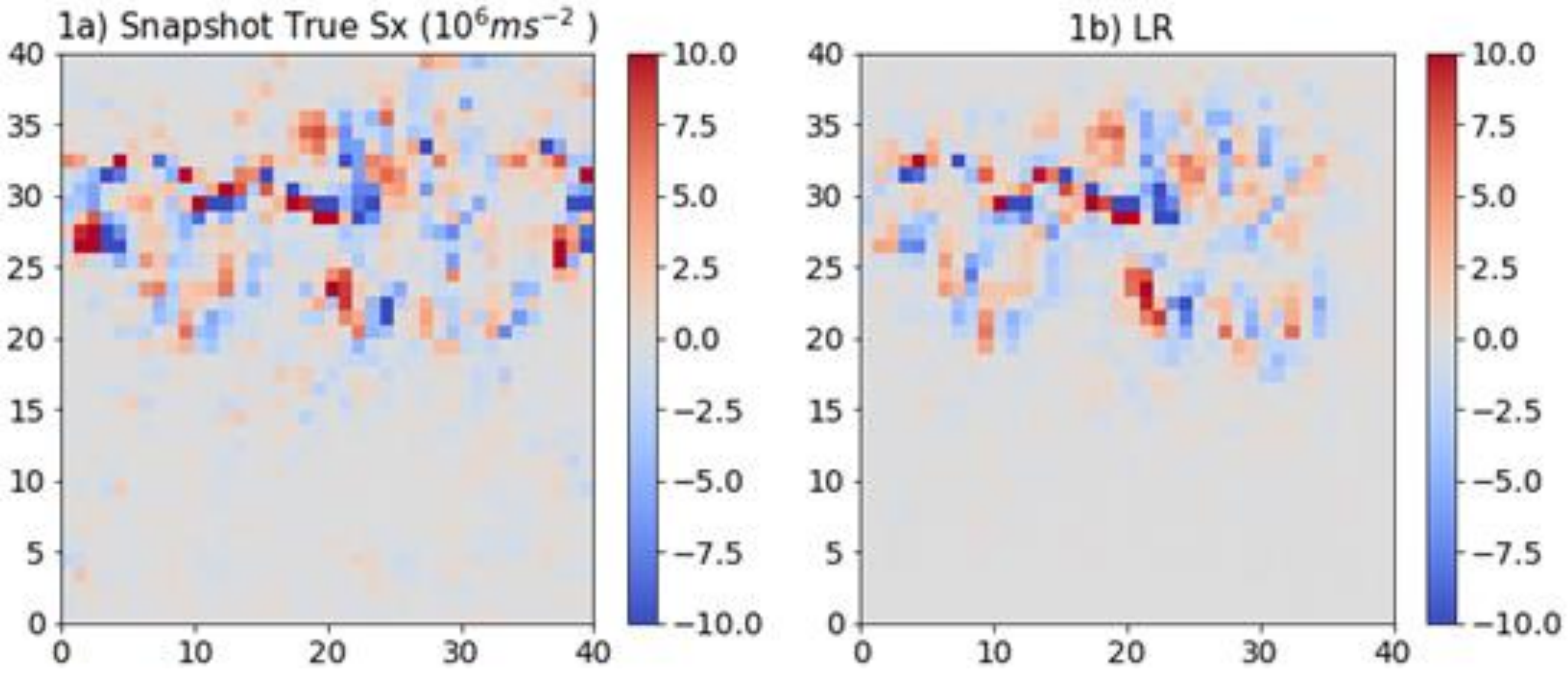


Prediction: Sx
(40 x 40)



Prediction

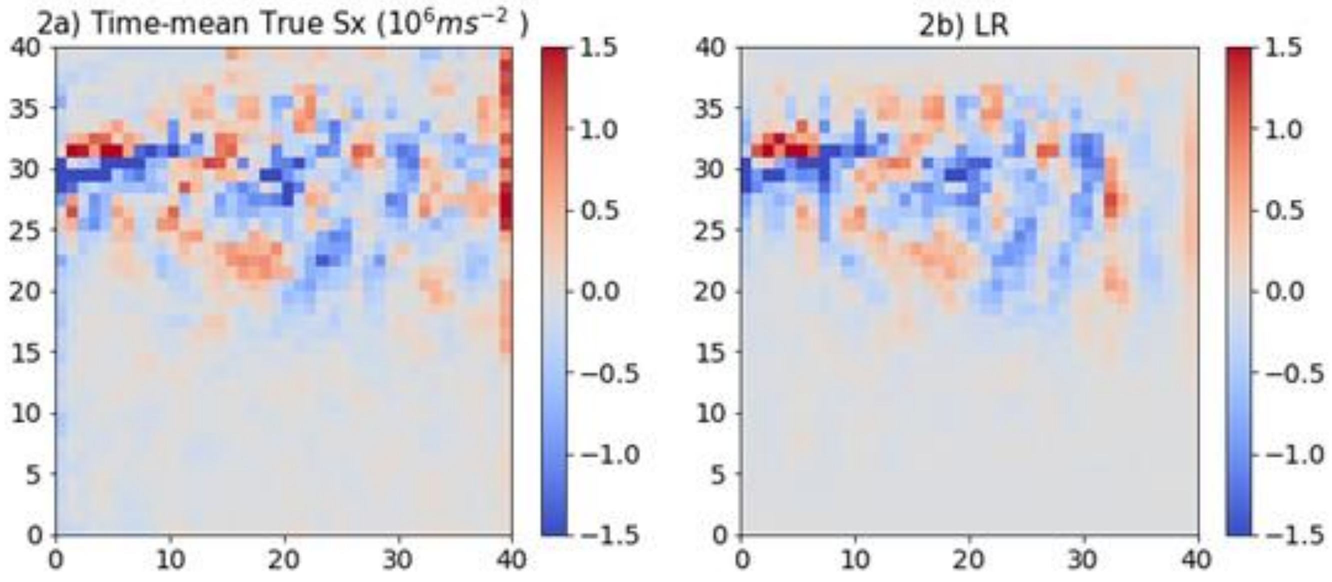
- **Snapshot of Sx**

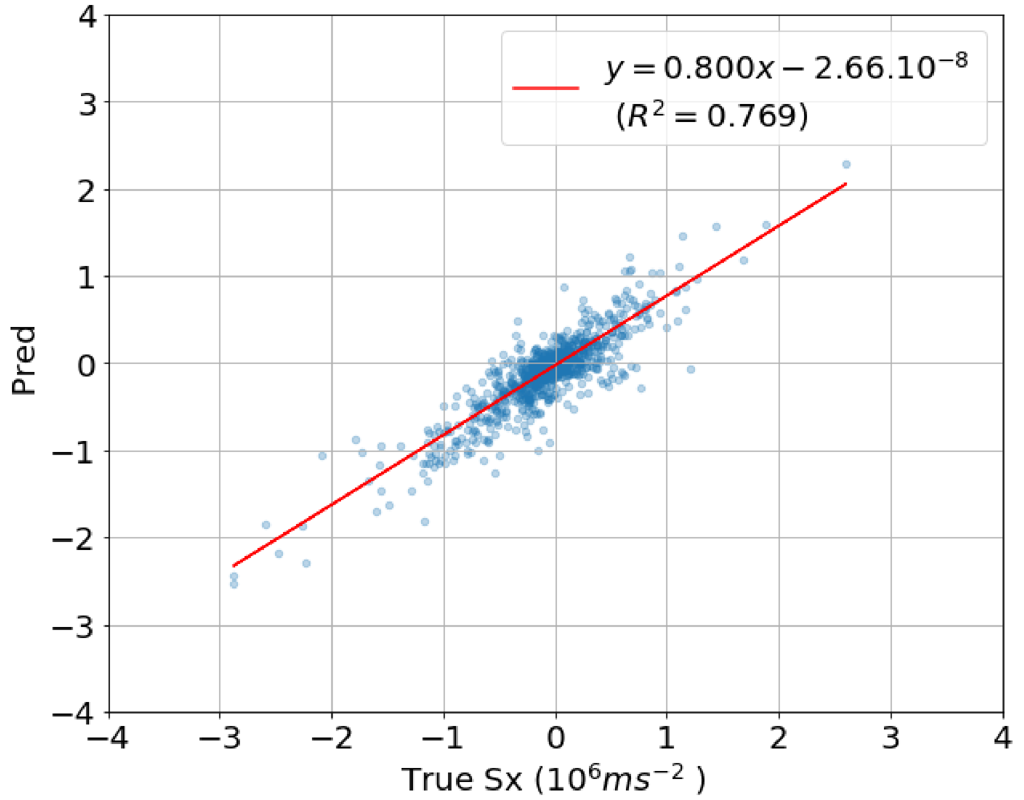


3.3. Implementation in low-resolution

Prediction

Time-mean of Sx



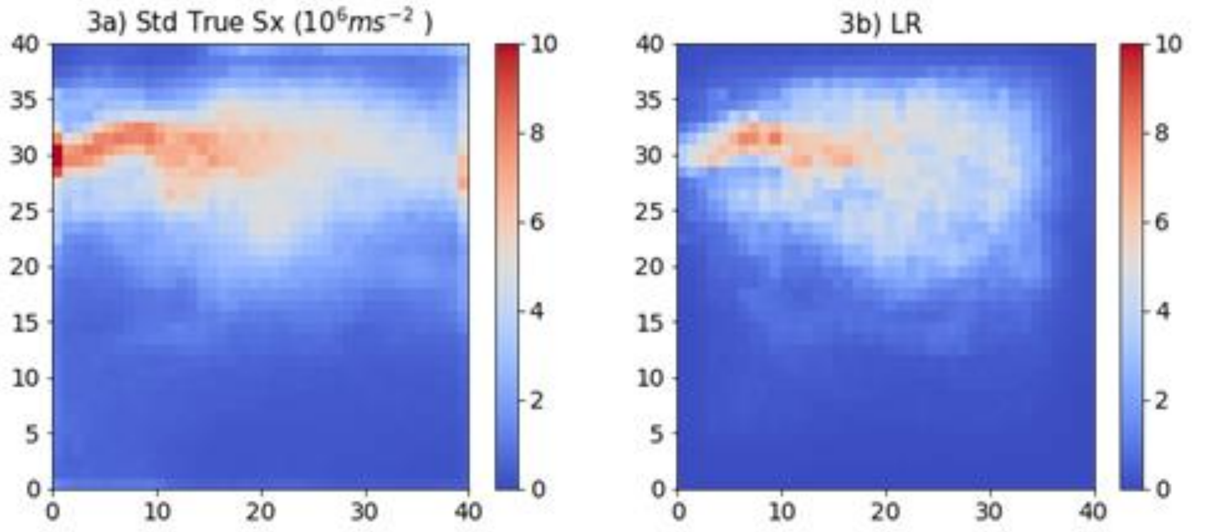


Scatterplot between time-averaged true Sx and corresponding prediction

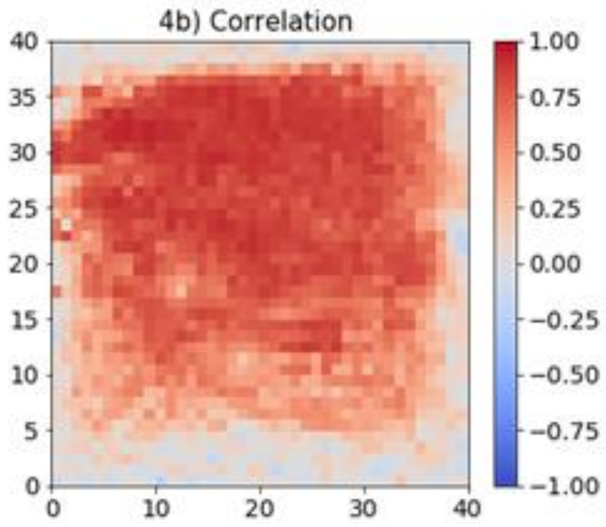
3.3. Implementation in low-resolution

Prediction

- **Standard deviation of Sx**

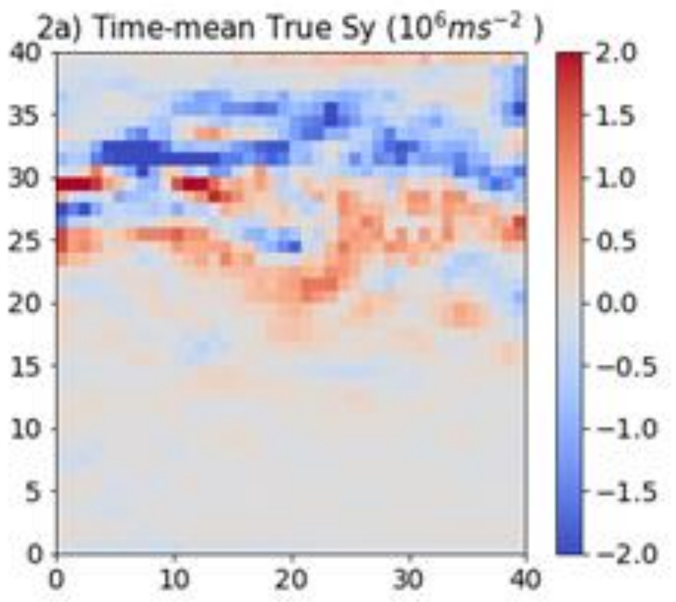


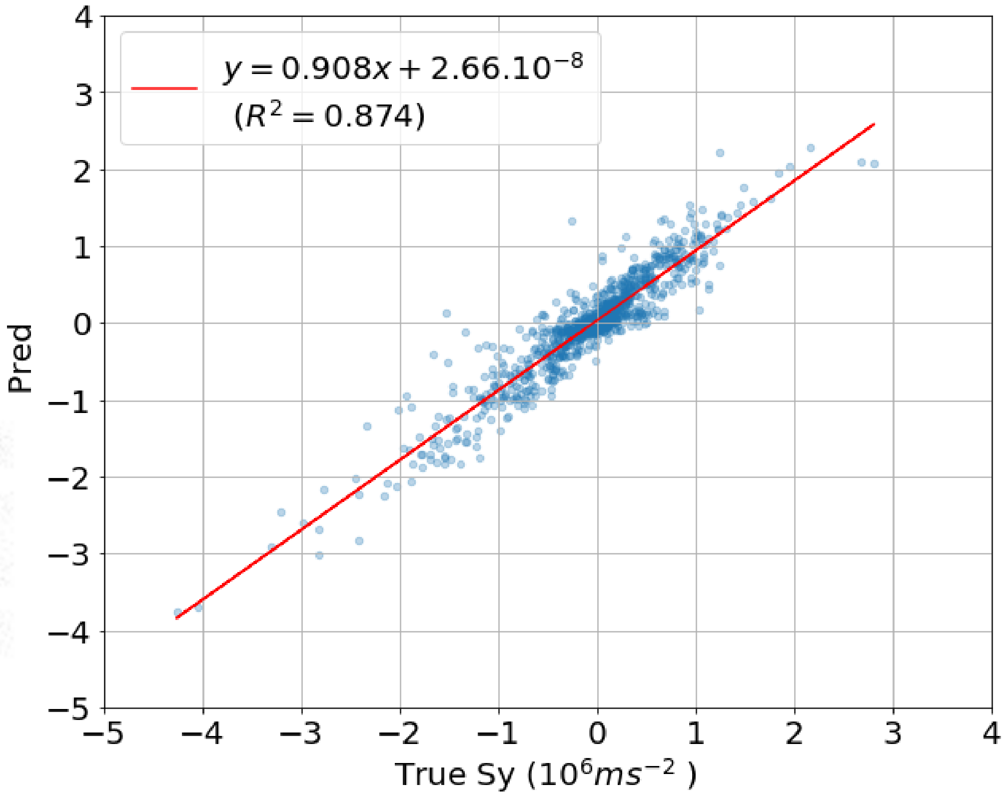
- **Correlation between true Sx and prediction**



Prediction

Time-mean of Sy





Scatterplot between time-averaged true Sy and corresponding prediction

04

PART Four

Conclusion

4. Conclusion

1. CNNs can predict the spatial and temporal variability of the eddy momentum forcing in high-resolution. A limited amount of data is sufficient for good performance.

2. Using sub-sampled data from high-resolution, CNNs can accurately represent both the spatial and temporal variability of the eddy momentum forcing comparable to the high-resolution model.

3. Potential in using machine learning as an eddy parameterization to augment the low-resolution ocean models in the future.