SSH Super-Resolution using high resolution SST with a Subpixel Convolutional Residual Network

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Introduction

Ocean remote sensing:

▷ Ocean: important role in **climate regulation**

▷ Satellite observations are sparse, noisy, and **multi resolution**

▷ Case study: **Sea Surface Height** (SSH) downscaling using Sea Surface Temperature (SST) information

- SSH: low resolution ($\backsim 1/4°$)
- SST: high resolution contextual information ($\backsim 1/100°$)

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Downscale SSH: a Super-resolution task:

▹ Ill-posed **inverse problem**

▹ **Deep Neural Network** (DNN) to generate a solution
- proposed method : **multi input subpixel residual network**

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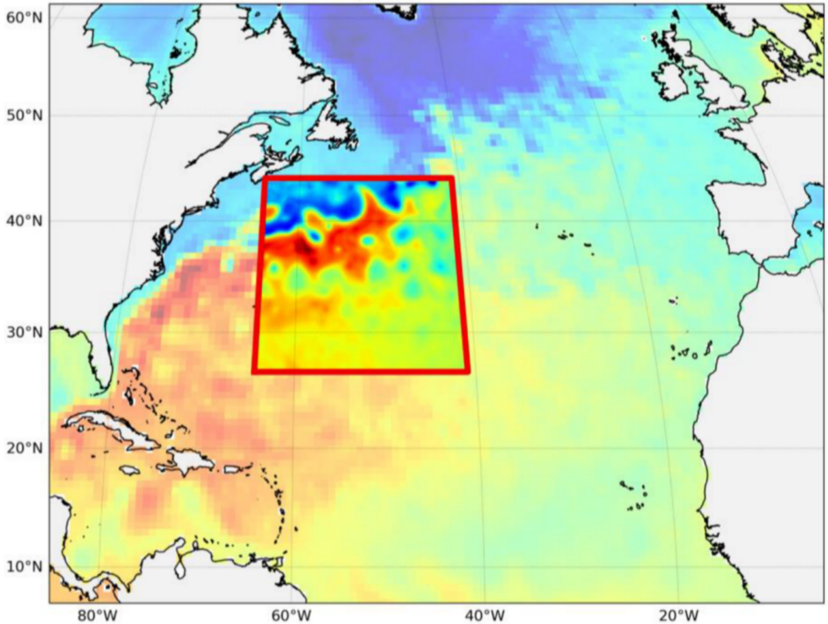
Motivations:

▷ Useful in ocean currents recovery
- geostrophic approximation

NATL60 model:

- High resolution: 1/60° (R01)
- Based on Nemo code
- Golf Stream (lat 25° to 45°, long 40° to 65°)

Studied Area:



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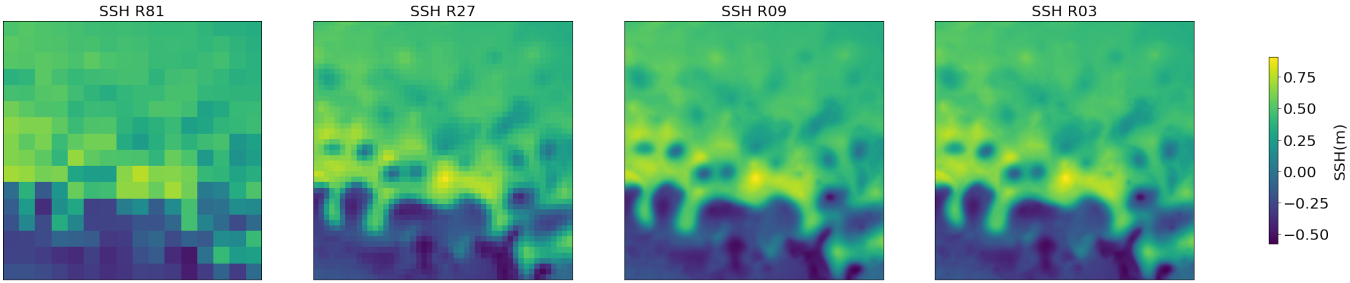
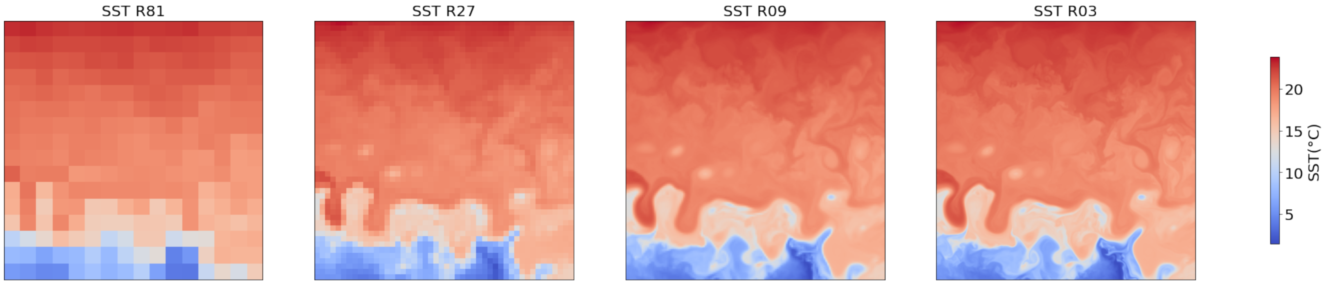
SSH:



SST:



Method

Super-resolution framework:

- $\mathbf{X}_{lr} = d(\mathbf{X}_{hr})$ where d is a decimation operator. We average the pixels in a square 27×27
  - ill posed inverse problem (d not injective)
- We aim to generate a solution to this inverse problem $\mathbf{X}_{sr}$
  - minimizing the MSE between $\mathbf{X}_{sr}$ and $\mathbf{X}_{hr}$

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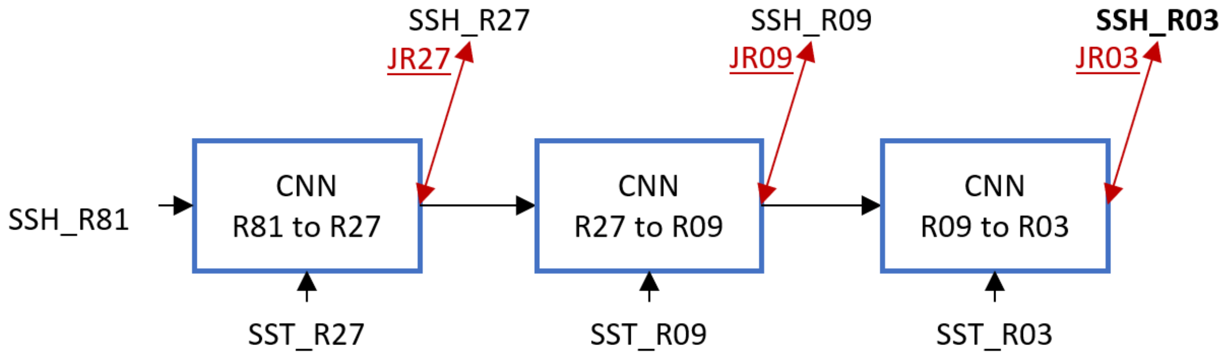
Deep Neural Network:

- Generate $\mathbf{X}_{sr}$ from $\mathbf{X}_{lr}$
  - Super-Resolution Convolutionnal Neural Network (SRCNN, 2014)
- In the literature :
  - Focus on natural images
  - Focus on lower up-scaling factor
  - Mostly single image Super Resolution (no cross input)

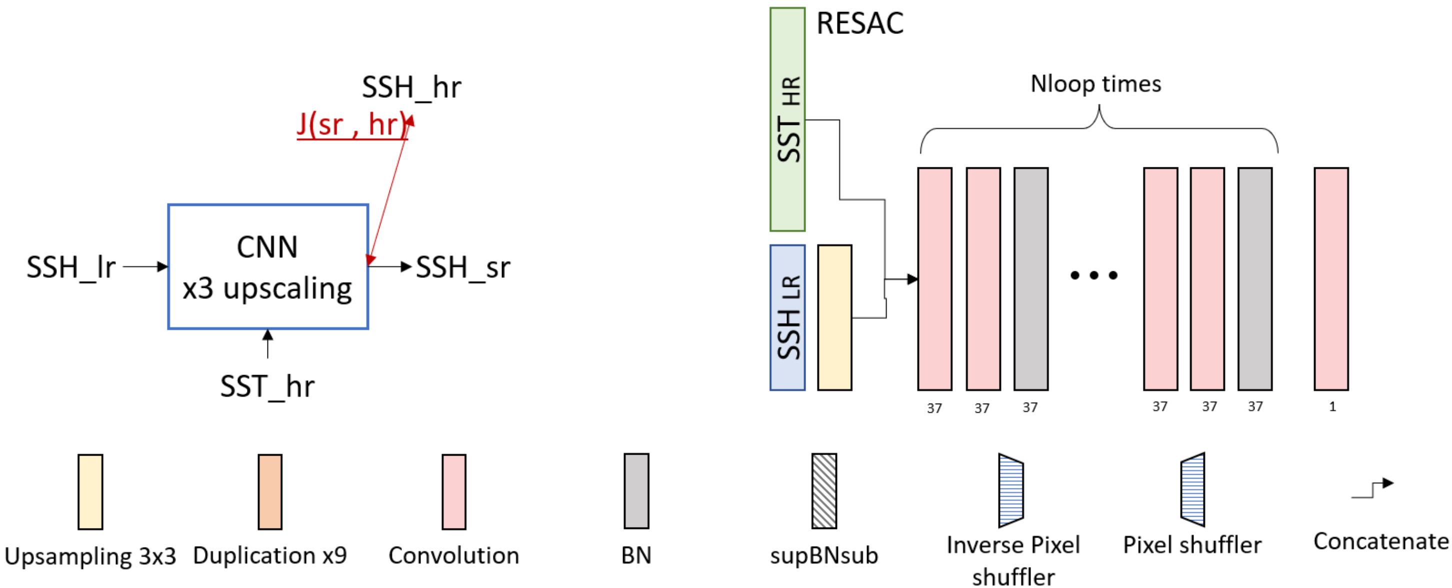
RESAC Method:

- ▷ Use SST High resolution data as an input
- ▷ Very large upscaling factor (x27) from R81 to R03
  - progressive downscaling 3 CNN block
  - control at 3 resolution



RESAC Architecture of one CNN block:

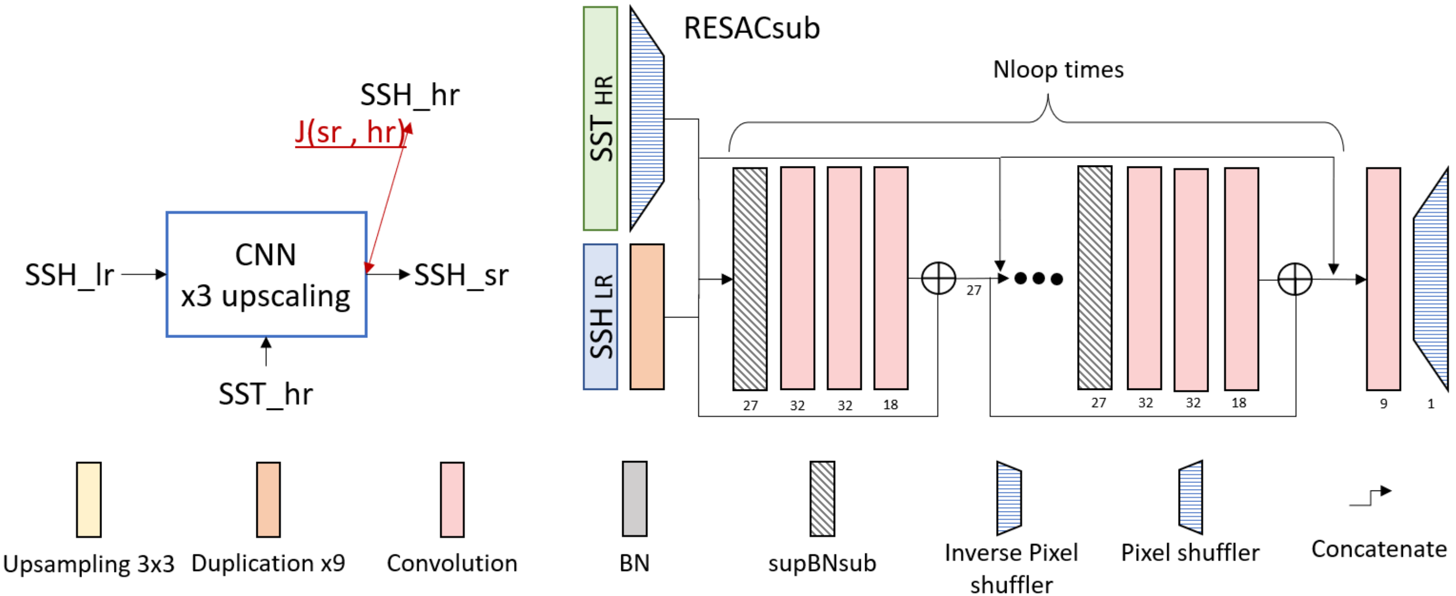
- ▷ Fully convolutionnal
- ▷ Bilinear upsampling (front)



▷

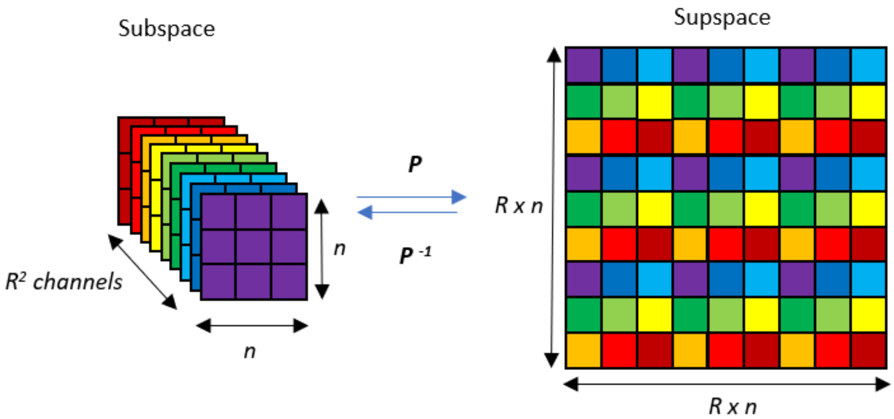
RESACsub Architecture of one CNN block:

- ▷ Residual network: $\mathbf{SSH}_{l+1} = \mathbf{SSH}_l + F_l^\theta(\mathbf{SSH}_l, \mathbf{SST})$
- ▷ Subpixel convolution
- ▷ Adapted Batch Normalization



Subpixel convolution layer:

- ▷ Convolution in a smaller deeper space
- ▷ Pixel shuffling operator P (bijective)



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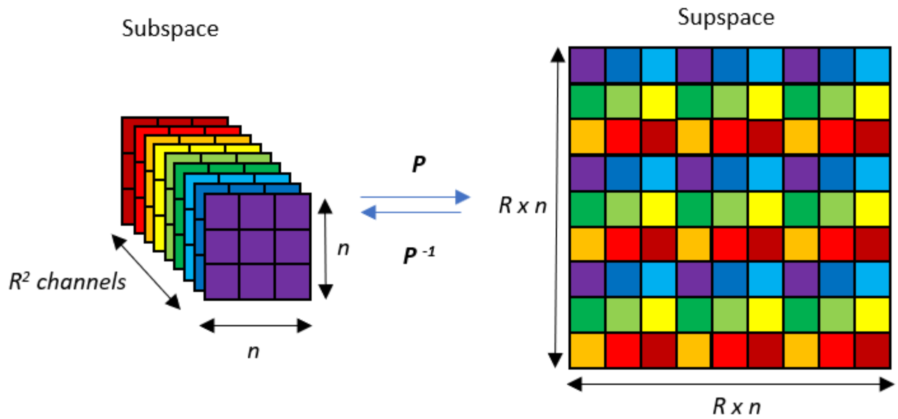

Advantages:

- ▷ Can be used as a **trainable upsampling**
- ▷ Less computatively expensive
- ▷ Higher perceptive field

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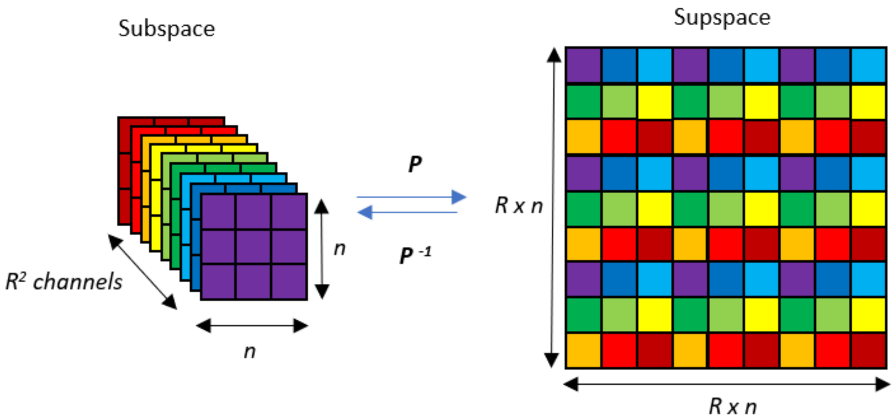

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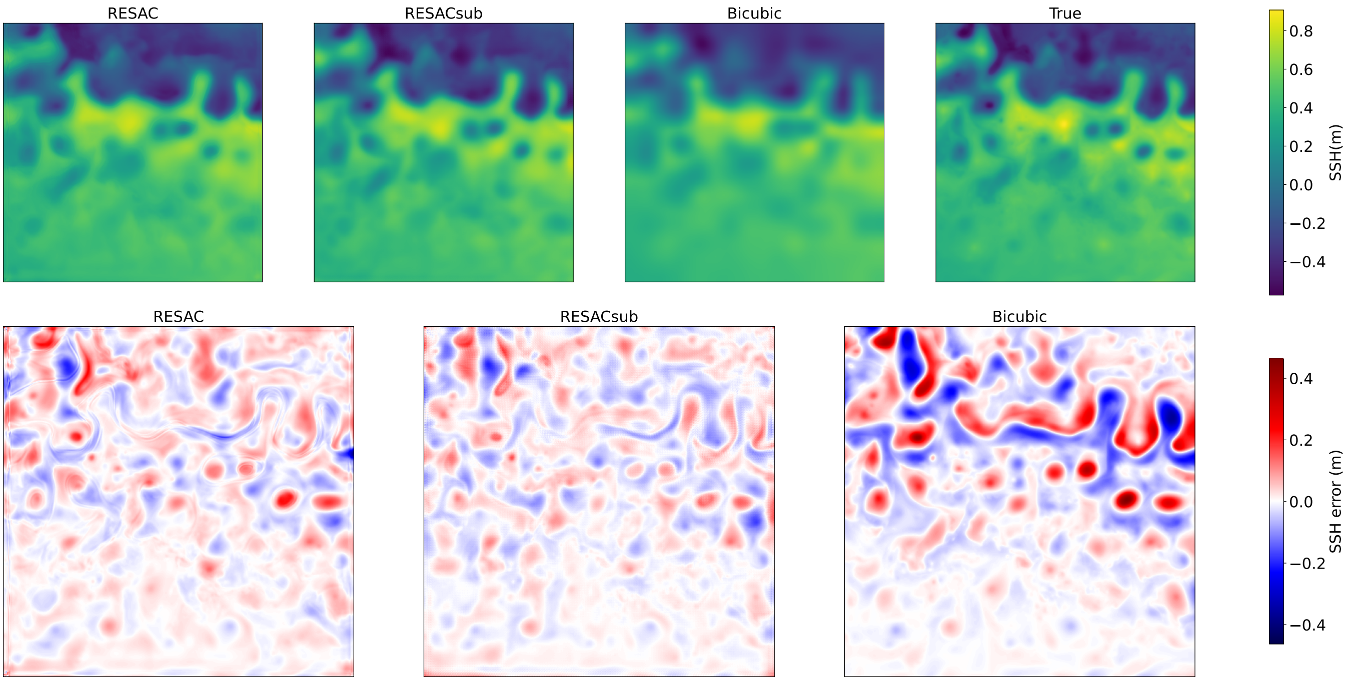
Drawbacks:

- ▷ Strong checkerboard artifacts
- ▷ Batch Normalization issue

Results - comparison between the methods

Predictions of the methods:



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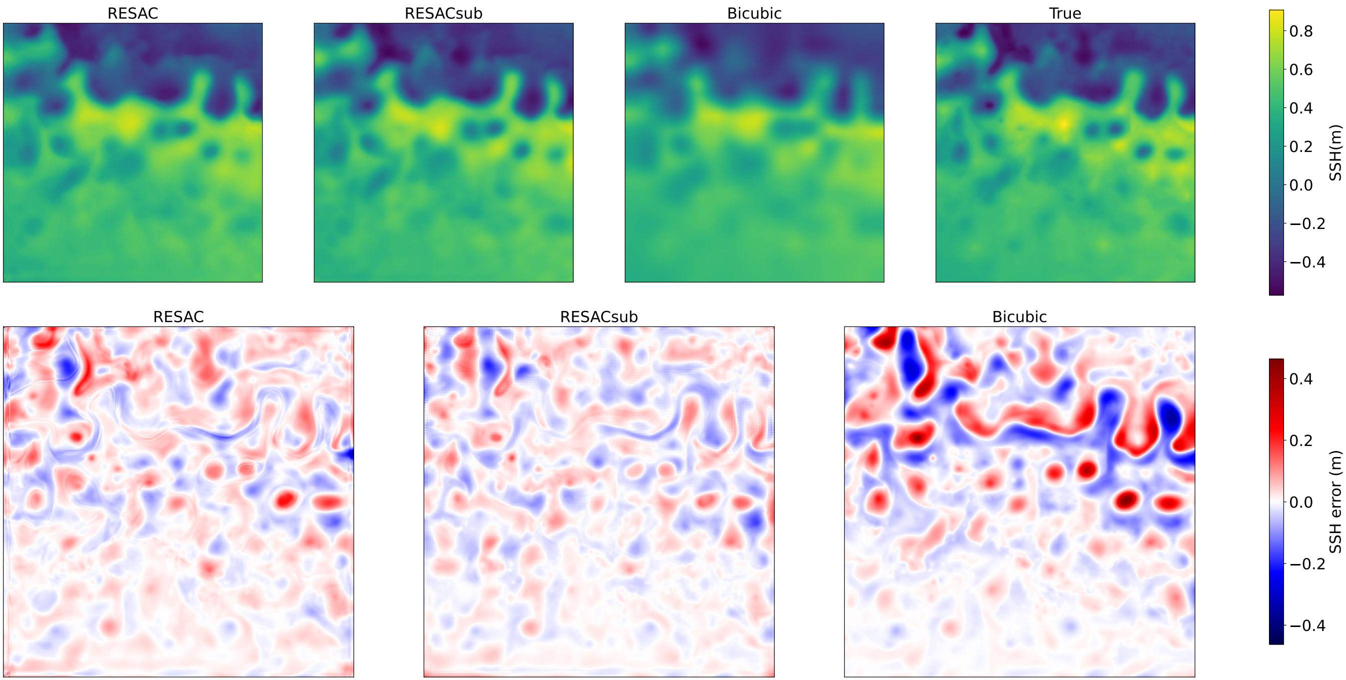
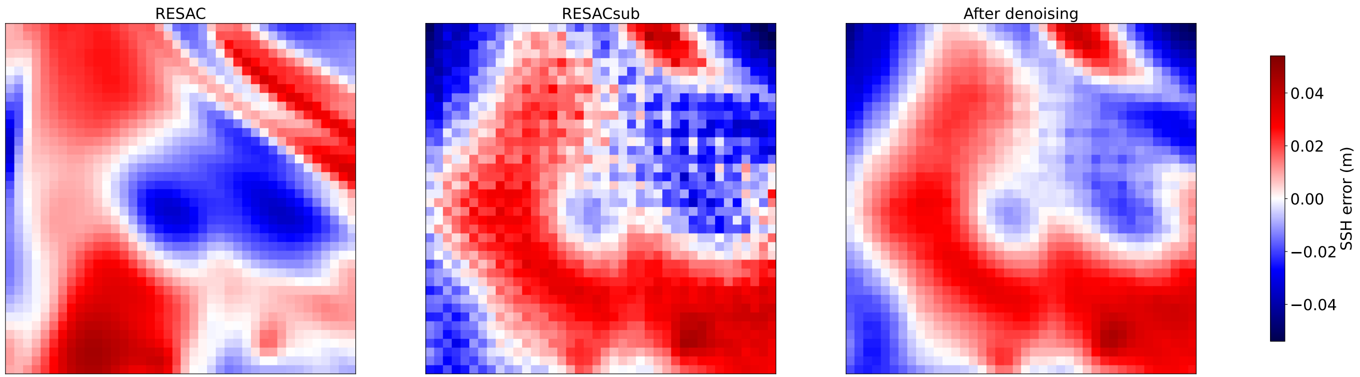


- ▷ Performances: RESACsub > RESAC >> Bicubic interpolation
- ▷ Bicubic interpolation is too smooth

Checkerboard artifacts:



- ▷ Subpixel convolution introduces **checkerboard artifacts**
- ▷ We use 2 convolution layers as a **denoiser**

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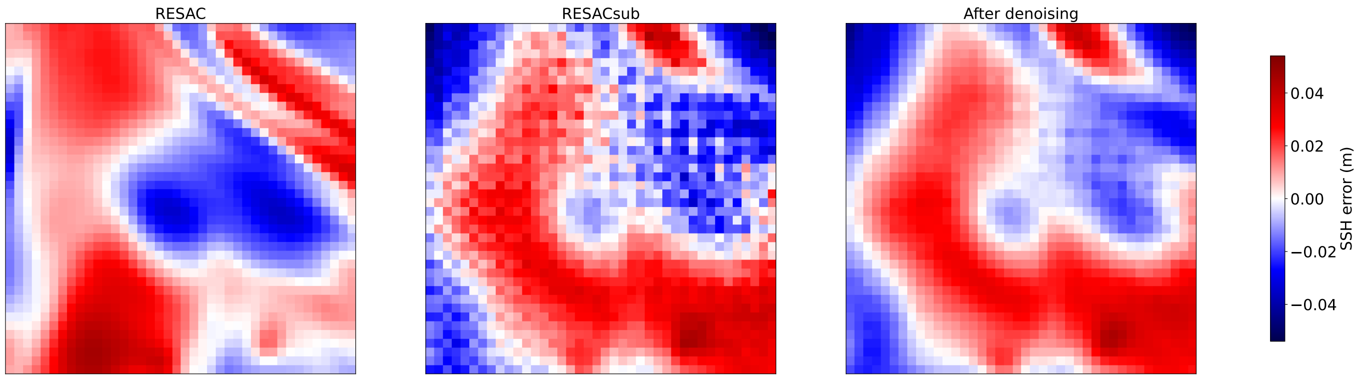

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Scores:

Model	RESAC	RESACsub	After Denoising	Bicubic
weights	344,976	334,722	51,841	unsupervised
RMSE (cm)	5.50	4.00	**3.94**	6.94

- Small improvement with the denoising network

Conclusion

RESACsub architecture:

▷ Subpixel Convolution

- improves performances with lesser numerical cost
- but introduces checkerboard artifacts

▷ Adapted form of Batch Normalization

▷ Denoising with large filter CNN

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▷ Adapted form of Batch Normalization

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Performances:

▷ Very large upscaling factor (x27)

▷ RESACsub outperform bicubic and RESAC :
- after denoising we achieve a RMSE of 3.94 cm (5.50cm for RESAC and 6.94 for Bicubic)

Perspectives

Improvement:

- ▷ Using temporal information of SST
  - Passive tracker
  - More information about currents
- ▷ Other architectures : SRGAN

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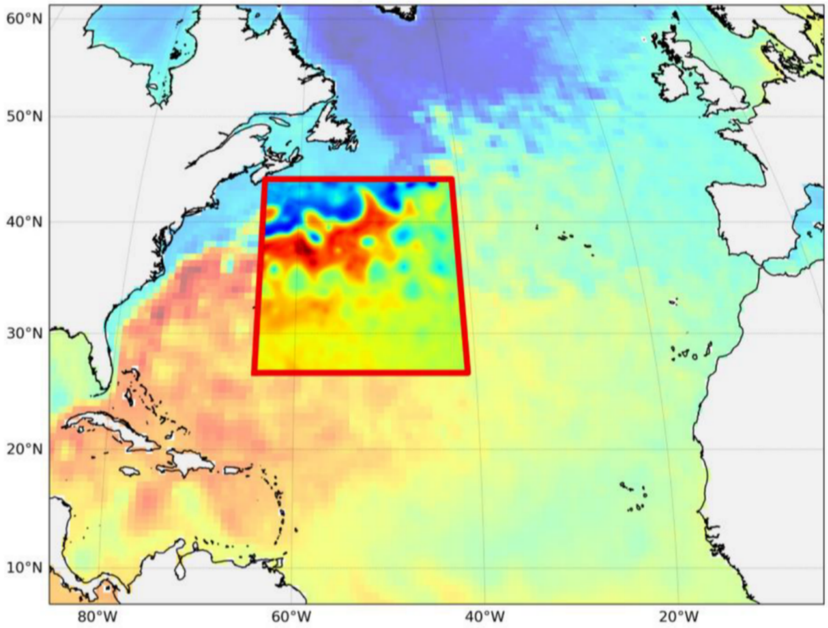
Perspectives:

- ▷ Application to other geophysical data : Salinity
- ▷ Transfer Learning to real world data
  - Using the satellite along track measures

Thank you!



For details:

- my email : theo.archambault@lip6.fr
- article with code : https://gitlab.lip6.fr/archambault/resacsub