

## Authors

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## Partners



## References

[1] M. Lopez-Radcenco et al., "Locally-adapted convolution-based super-resolution of irregularly-sampled ocean remote sensing data", IEEE ICIP 2017, Beijing, China.

[2] R. Fablet et al., "Improving mesoscale altimetric data from a multi-tracer convolutional processing of standard satellite-derived products", IEEE TGRS, in press.

## Acknowledgements

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## 1. Abstract

Super-resolution is a classical problem in image processing, with numerous applications to remote sensing image enhancement. Here, we address the **super-resolution of irregularly-sampled remote sensing images**. Using an **optimal interpolation as the low-resolution reconstruction**, we explore **locally-adapted multimodal convolutional models** and investigate different **dictionary-based decompositions**. We consider an **application to the reconstruction of sea surface height (SSH) fields from two information sources**, along-track altimeter data and sea surface temperature (SST) data. The reported experiments demonstrate the relevance of the proposed model, especially **locally-adapted parametrizations with non-negativity constraints**, to **outperform optimally-interpolated reconstructions**.

## 3. Model

### Convolution-based model:

$$Y(t) = Y_{LR}(t) + H_Y * Y_{LR}(t) + H_X * X(t) + N(t)$$

- $H_Y$  and  $H_X$  are space-and-time-varying two-dimensional  $(2W_p+1) \times (2W_p+1)$  matricial operators.
- $N$  is a space-time noise process.

### Global unconstrained calibration:

- ▶ For any given space-time location  $(t_0, s_0)$ , the model is fitted using all observations  $\{Y^*(k), t^*(k), s^*(k)\}$  that verify:

$$t^*(k) \in [t_0 - D_t, t_0 + D_t] \\ \|s^*(k) - s_0\| \leq D_s$$

- ▶ Cost function to be minimized (mean square error criterion):  $\mathcal{E}(H_X, H_Y) = \sum_k \|dY^*(k) - \widehat{dY}^*(k)\|^2$

where  $dY^*(k) = Y^*(t^*(k), s^*(k)) - Y_{LR}(t^*(k), s^*(k))$

$$\widehat{dY}^*(k) = H_Y * Y_{LR}(t^*(k), s^*(k)) + H_X * X(t^*(k), s^*(k))$$

## 4. Results

### Remote sensing super-resolution application:

- ▶  $\{Y_{LR}(t)\}_t$  – Daily SSH (sea surface height) images
- ▶  $\{X(t)\}_t$  – Daily SST (sea surface temperature) images
- ▶  $\{Y^*(k)\}_k$  – Satellite along-track altimetry data (Fig. 1)

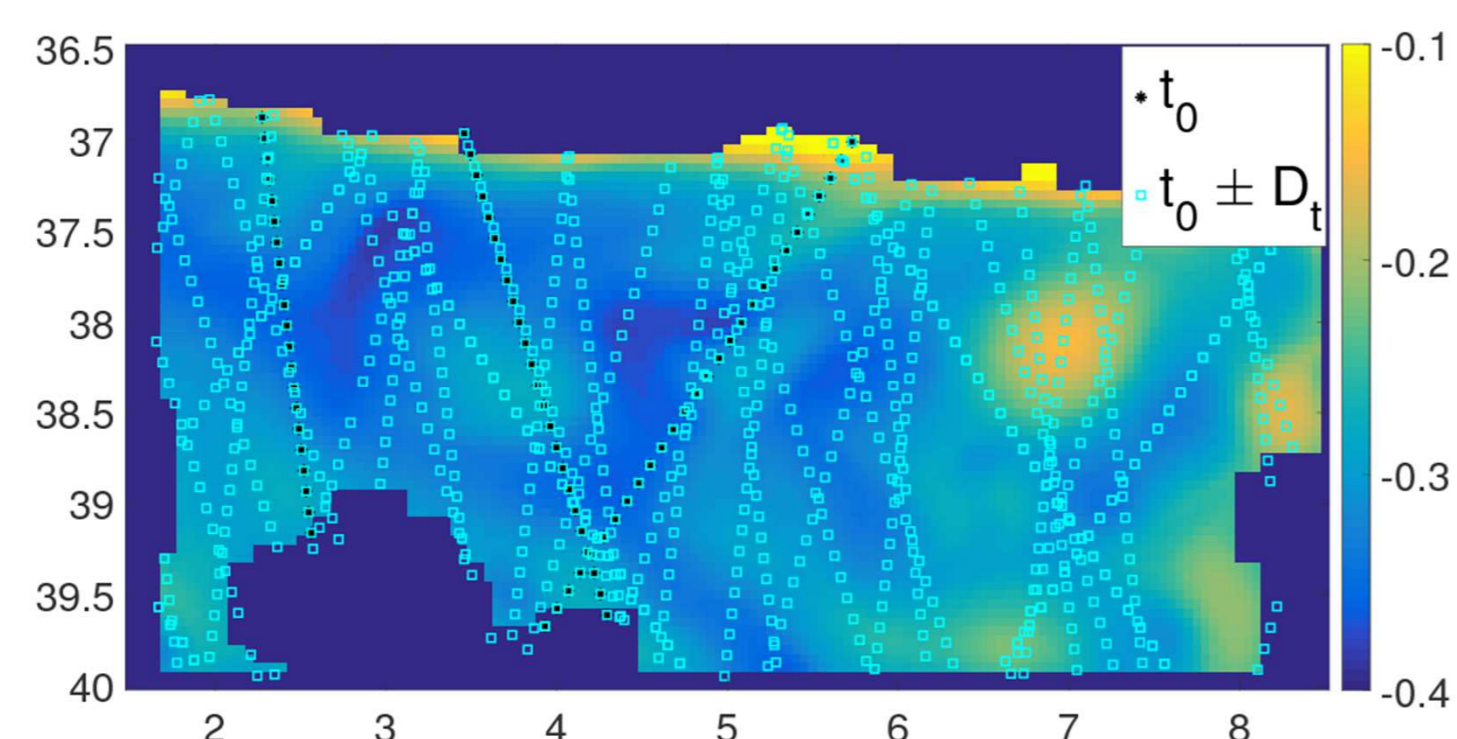


Fig. 2: Illustration of the irregular sampling of high-resolution observations associated with ocean remote sensing data: sea surface height image with the sampled along-track positions by satellite altimeters (cyan squares) in a  $\pm 10$ -day time window around April 20<sup>th</sup>, 2012.

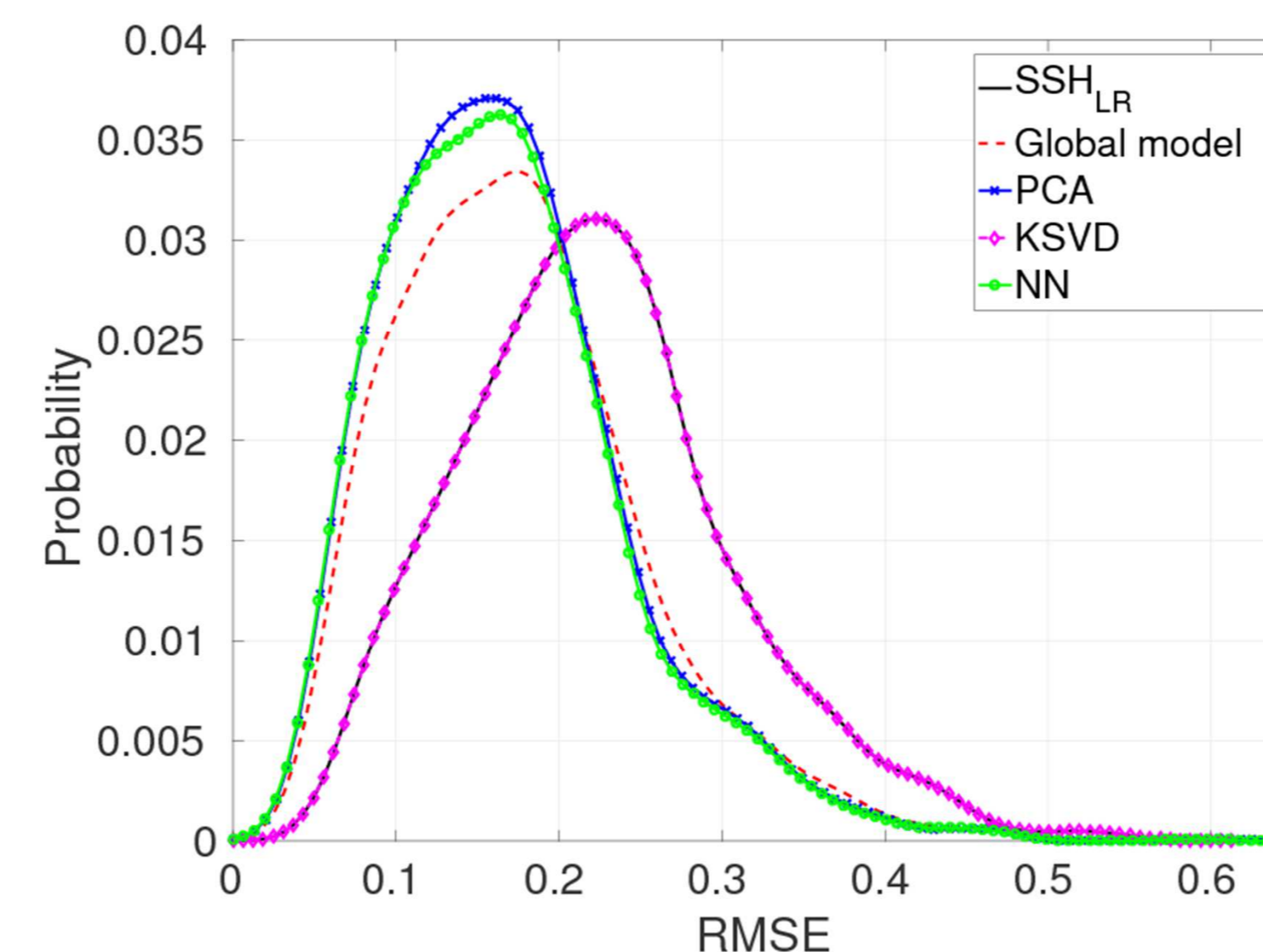


Fig. 3: Daily high-resolution images  $\{Y(t)\}_t$  reconstruction error (RMSE) distribution for a global convolutional model and for locally-adapted decompositions of the global convolutional model using  $K=10$  classes. The probability distribution of the RMSE for daily low-resolution SSH images  $\{Y_{LR}(t)\}_t$  is given as reference (noted as  $SSH_{LR}$ ).

## 6. Conclusion

We addressed the **multimodal super-resolution of irregularly-sampled high-resolution images**, using a **complementary high-resolution image source** and **dictionary-based decompositions** as a means to **better account for spatio-temporal variabilities** through more **locally-adapted model calibrations**. Numerical experiments for the **reconstruction of high-resolution sea surface height (SSH) images** support the selection of **non-negativity constraints** to achieve a **better local adaptation** and a **better reconstruction of higher-resolution details**. Future work includes **non-local extensions** of the proposed model to **combine spatio-temporal and similarity-based neighborhoods**, **non-linear dictionary-based decompositions** to **combine non-linear mapping and locally-adapted models**, and **applications to different sampling patterns**, for instance along-track narrow-swath satellite data vs. wide-swath satellite data.

## 2. Problem statement

### Problem:

Reconstruct a series of high-resolution images  $\{Y(t)\}_t$  at different times  $\{t_1, \dots, t_T\}$  from the corresponding series of low-resolution images  $\{Y_{LR}(t)\}_t$ .

### Sources of information:

- ▶ Low-resolution images  $\{Y_{LR}(t)\}_t$ .
- ▶ Complementary source of high-resolution images  $\{X(t)\}_t$ , correlated to  $\{Y(t)\}_t$ .
- ▶ Irregularly-sampled dataset of high-resolution point-wise observations  $\{Y^*(k)\}_k$  at times  $\{t^*(k)\}_k$  and locations  $\{s^*(k)\}_k$ .

### Locally-adapted dictionary-based convolutional models:

Operators  $H_X$  and  $H_Y$  are decomposed using a dictionary-based approach:

$$H_{\{X, Y\}} = \sum_{k=1}^K \alpha_k D_k^{\{X, Y\}}$$

- ▶  $D_k^X$  (resp.  $D_k^Y$ ) is the  $k^{\text{th}}$  component of the dictionary of operators for operator  $H_X$  (resp.  $H_Y$ ).
- ▶ Decomposition scalar coefficients  $\alpha_k$  are shared by operators  $H_X$  and  $H_Y$ .

- ▶ Different constraints are considered:

- Orthogonality (PCA).
- Sparsity (K-SVD).
- Non-negativity (NN).

- ▶ Given the trained dictionaries  $D_k^X$  and  $D_k^Y$ , the model decomposition is readjusted locally:

- Decomposition coefficients  $\alpha_k$  are readjusted locally for smaller, overlapping spatio-temporal neighbourhoods.

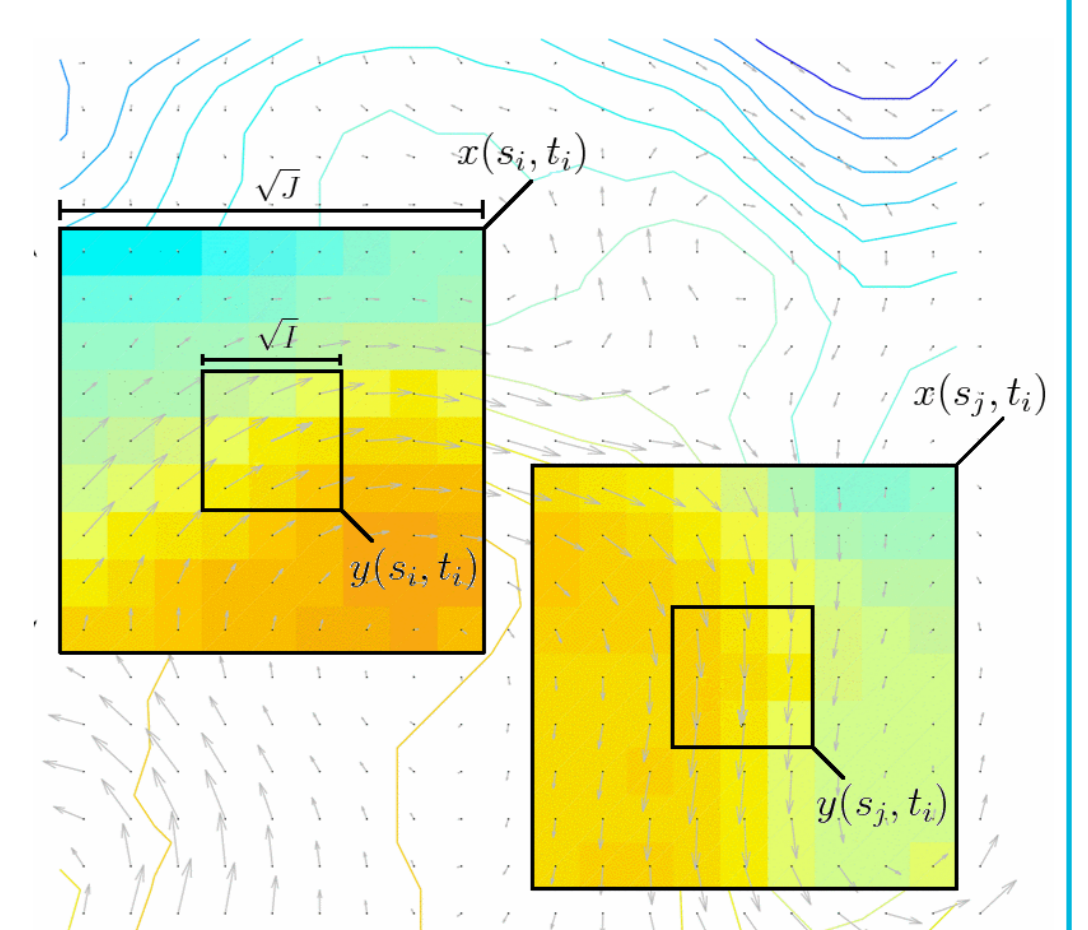


Fig. 1: Patch-based approach. Patch extraction for convolutional-based model learning.

	$K=2$	$K=5$	$K=10$
PCA	<b>0.1807</b>	<u>0.1734</u>	0.1680
KSVD	0.2228	0.2228	0.2228
NN	<b>0.1807</b>	<u>0.1734</u>	<b>0.1666</b>
Global model			0.1755
$SSH_{LR}$			0.2228

Tab. 1: Relative root mean square reconstruction error (RMSE) for daily high-resolution SSH images  $\{Y(t)\}_t$ , for a global convolutional model and for locally-adapted decompositions of a global convolutional model, considering  $K=2$ ,  $K=5$  and  $K=10$  classes. The RMSE value for daily low-resolution SSH images  $\{Y_{LR}(t)\}_t$  is given as reference (noted as  $SSH_{LR}$ ). Best results for each number of classes  $K$  considered are presented in **bold**. Results that outperform a global convolutional model are underlined.

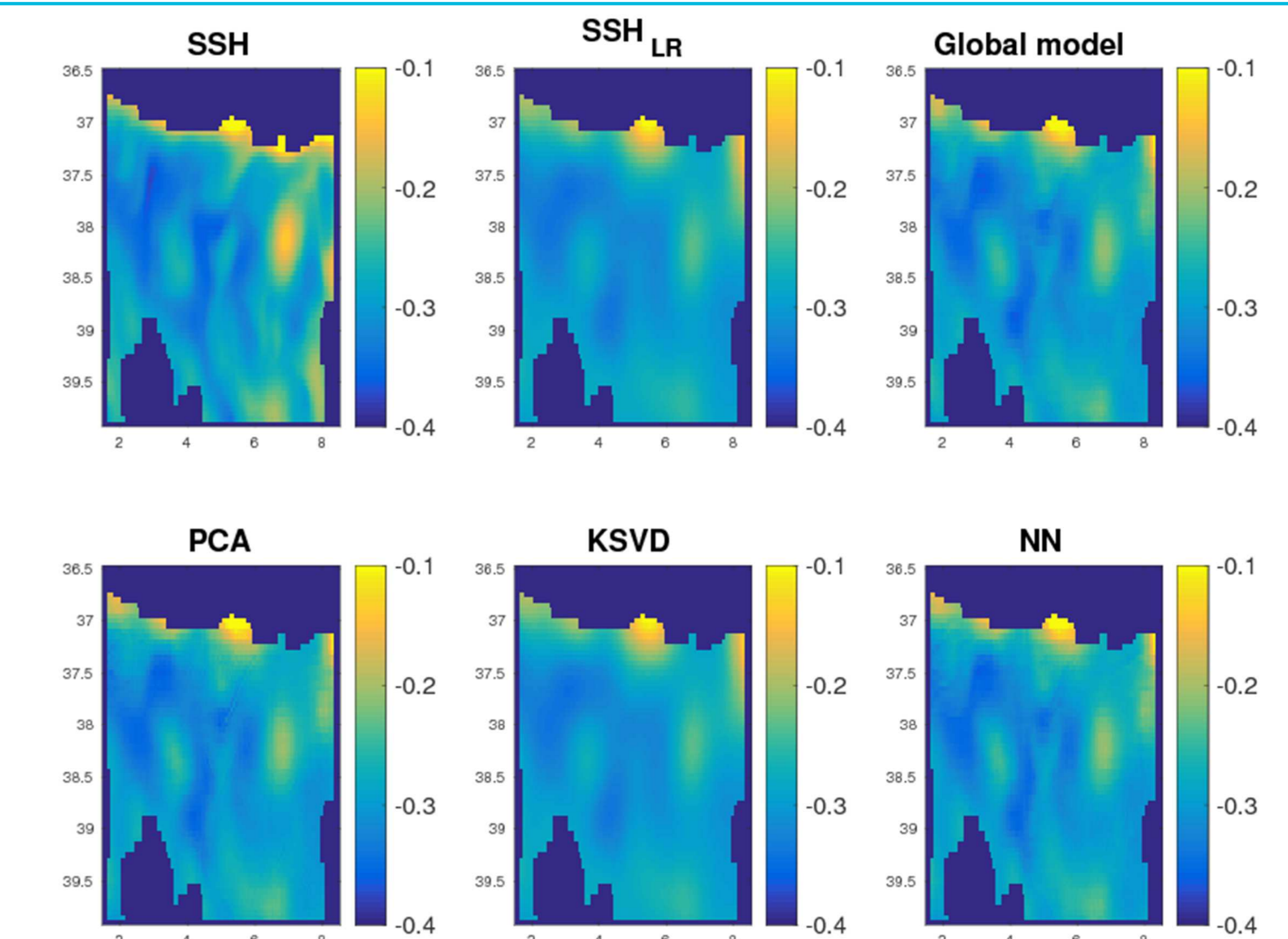


Fig. 4: Example of high-resolution SSH image reconstruction on April 20<sup>th</sup>, 2012, for a global convolutional model and for locally-adapted decompositions of the global convolutional model using  $K=10$  classes.