

Wind direction retrieval from SAR images using ResNet

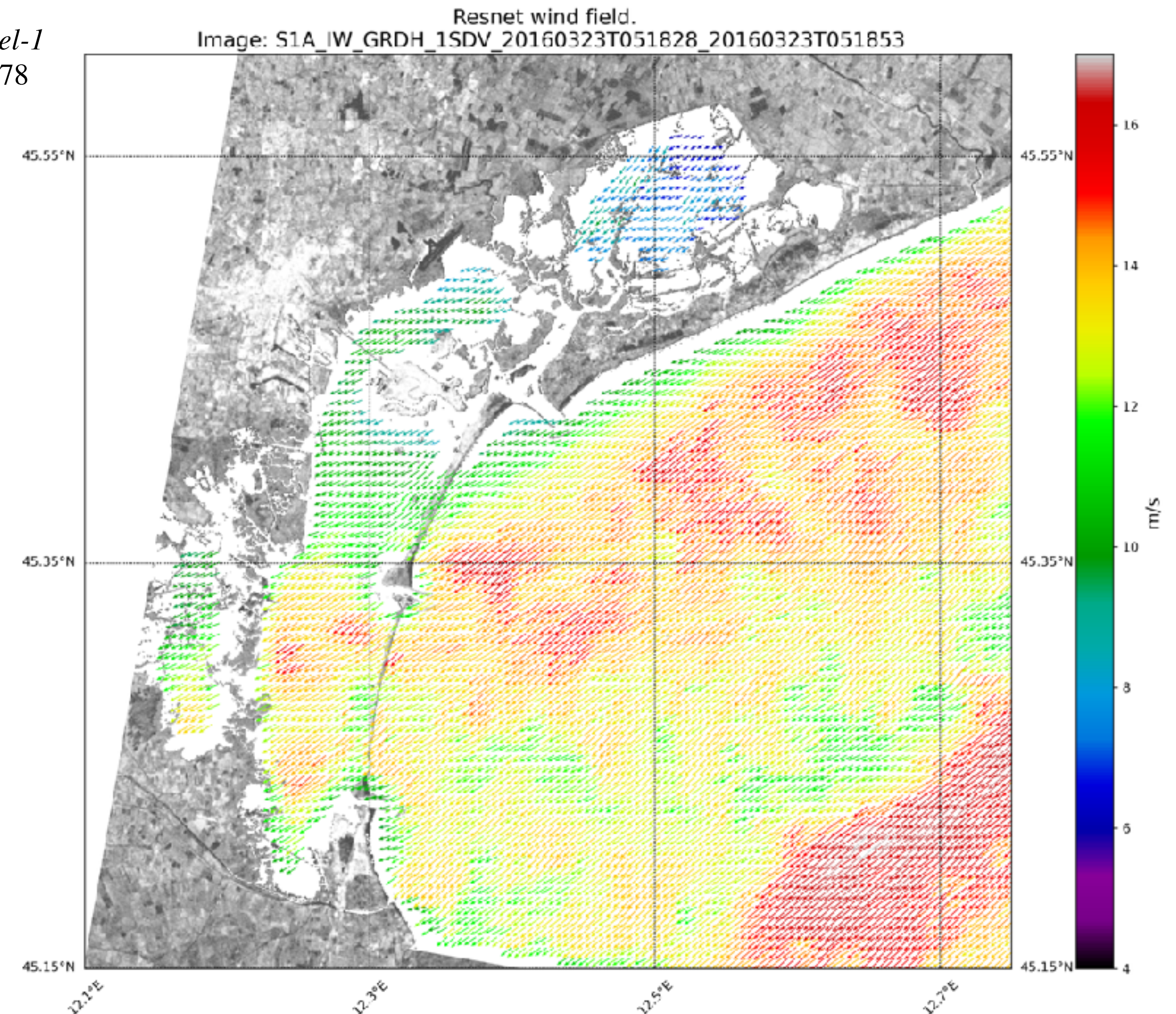
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Why using a deep learning technique as the ResNet to retrieve the wind direction from SAR images?

The results here presented comes from: **Zanchetta, A. and S. Zecchetto**: *Wind direction retrieval from Sentinel-1 SAR images using ResNet*, *Remote Sensing of Environment*, 253, February 2021, doi: 10.1016/j.rse.2020.112178

- The wind direction is required by the Geophysical Model Functions (GMF) to obtain the wind speed from the SAR backscatter.
- Retrieving the wind direction directly from the SAR image disentralls the wind field estimation from the dependancy on external wind direction.
- Obtaining the wind direction directly from the SAR images allows the investigation of the high resolution wind spatial variability which is not possible to obtain with other methods. Furthermore the high resolution (~500 m) wind direction may improve the reliability of the wind speed calculated with GMFs.
- New possibilities of investigation: estimation of the wind field very close to coastlines (distance < 500 m), showing the interaction of the wind with the local orography, in small enclose basins or under complex flow situations; unprecedented detailed retrieval of wind direction of tropical cyclones; analysis of the wakes of wind farms, etc..

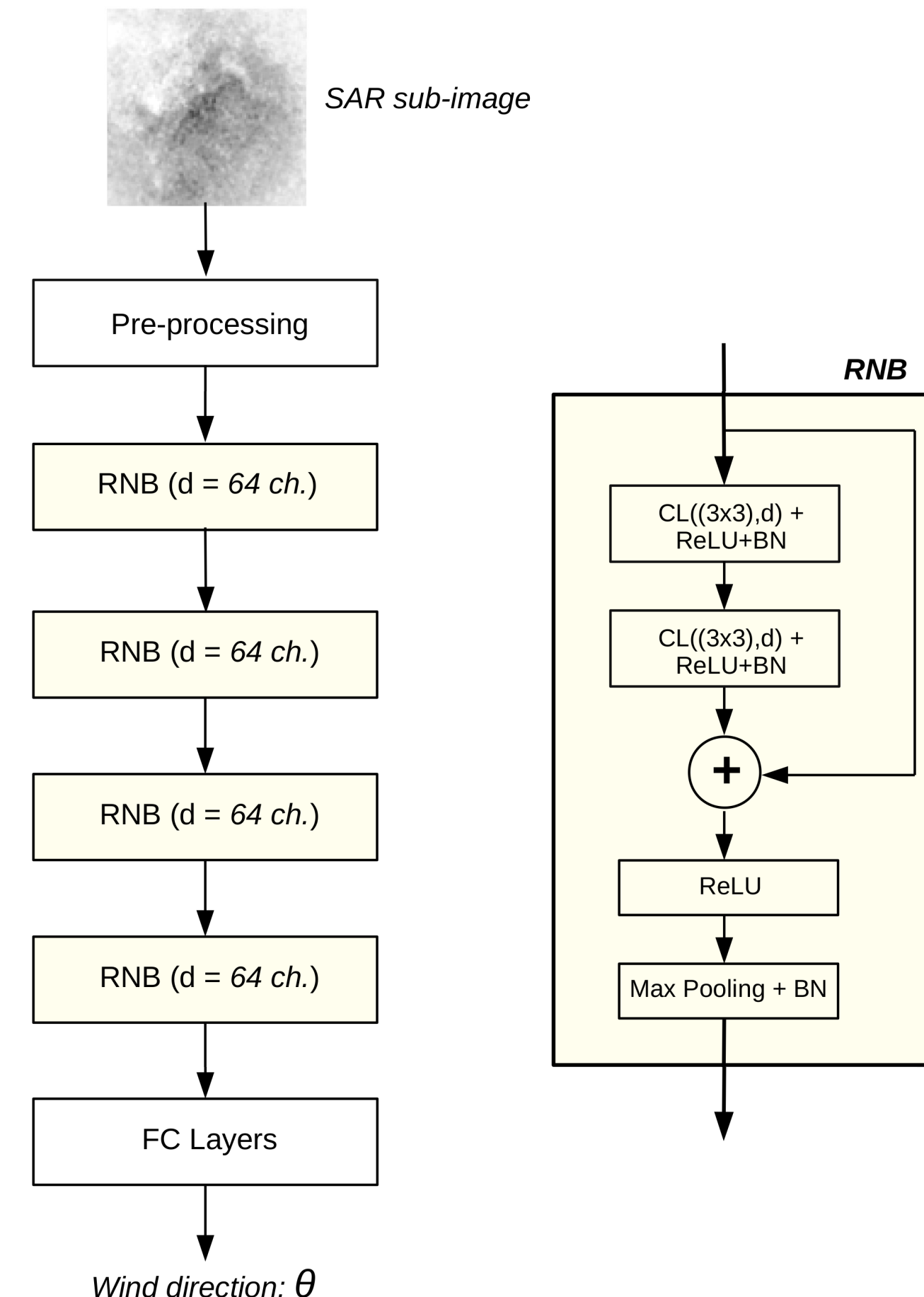


ResNet wind field over the Venice Lagoon at 500 m resolution.
Sentinel 1-A, 3 March 2016.

The ResNet

- Convolutional layers hierarchically extract abstract features from the SAR image spatial structure at different scales.
- Fully connected layers act as function approximators which map the features extracted by the CNN into a likely wind direction.
- The ResNet structure helps in solving a problem of degradation of the training accuracy that comes from stacking many convolutional layers (*He et al., 2016*).
- The training has been carried out on a million sub-images coming from 25 Sentinel-1 SAR whole images.
- Details about the model and its training procedure can be found in *Zanchetta and Zecchetto, 2021*.

He, K., Zhang, X., Ren, S., Sun, J., 2016. Deep residual learning for image recognition. In: *Proceedings of the IEEE conference on computer vision and pattern recognition*. pp. 770–778.



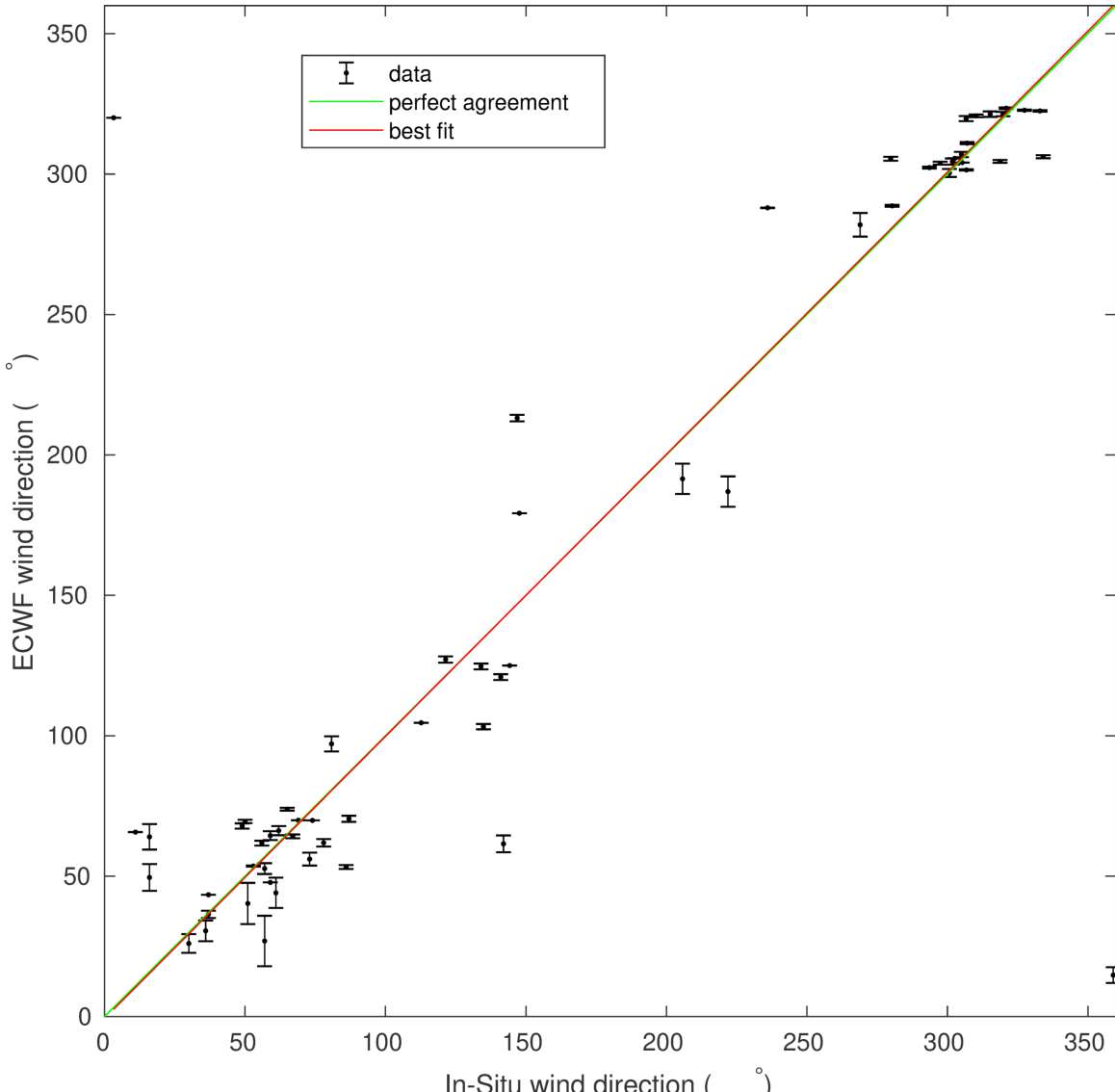
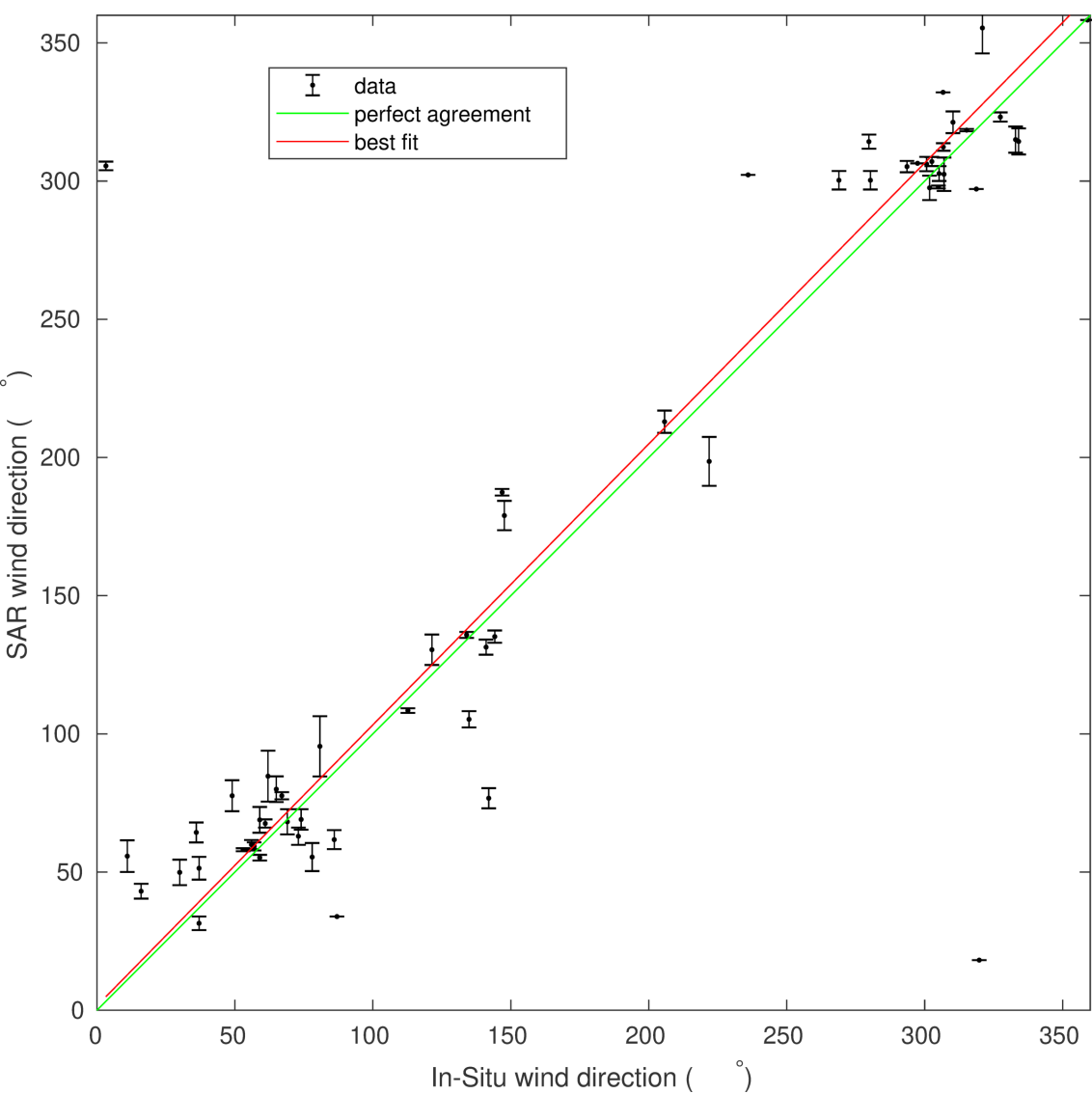
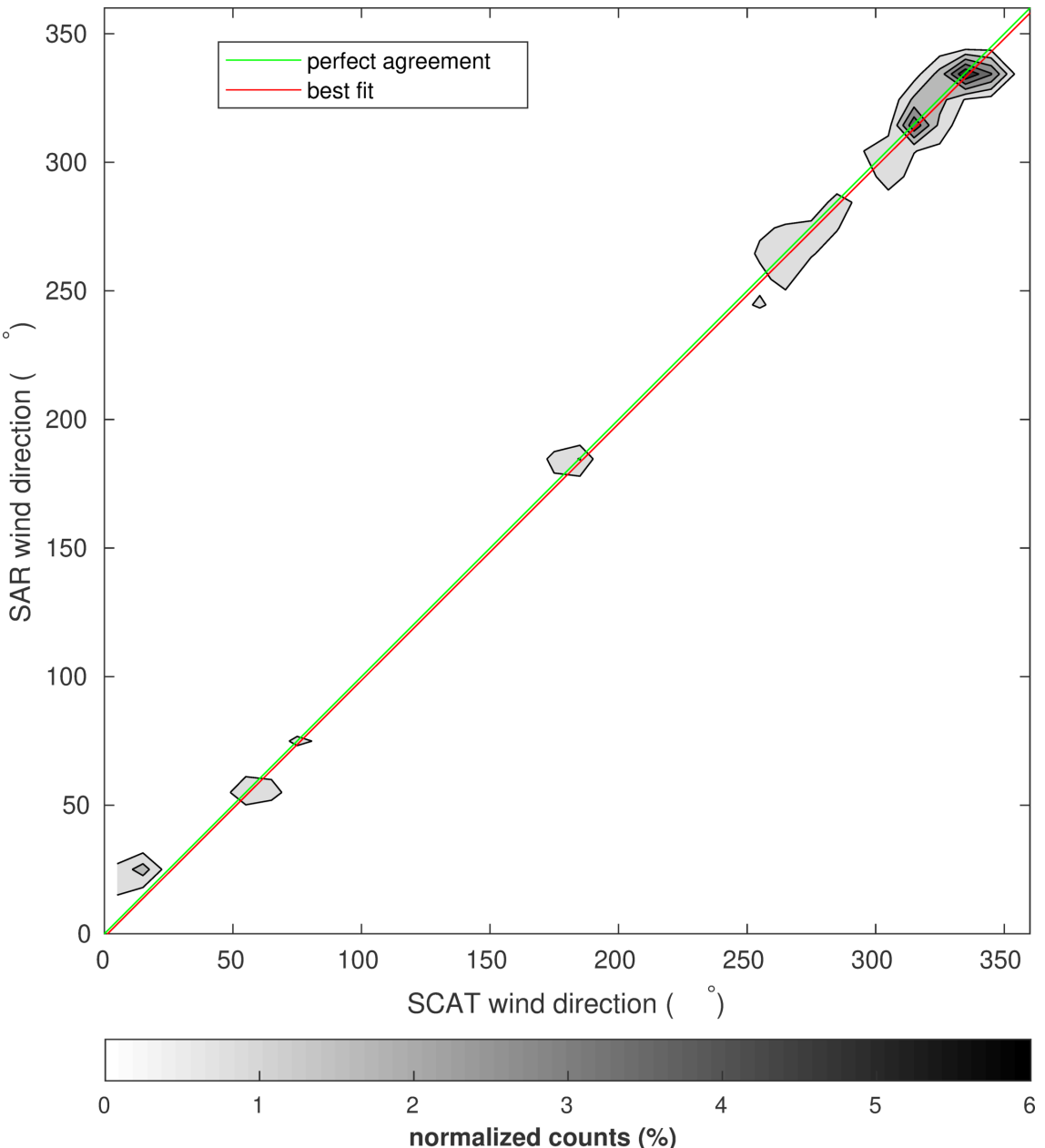
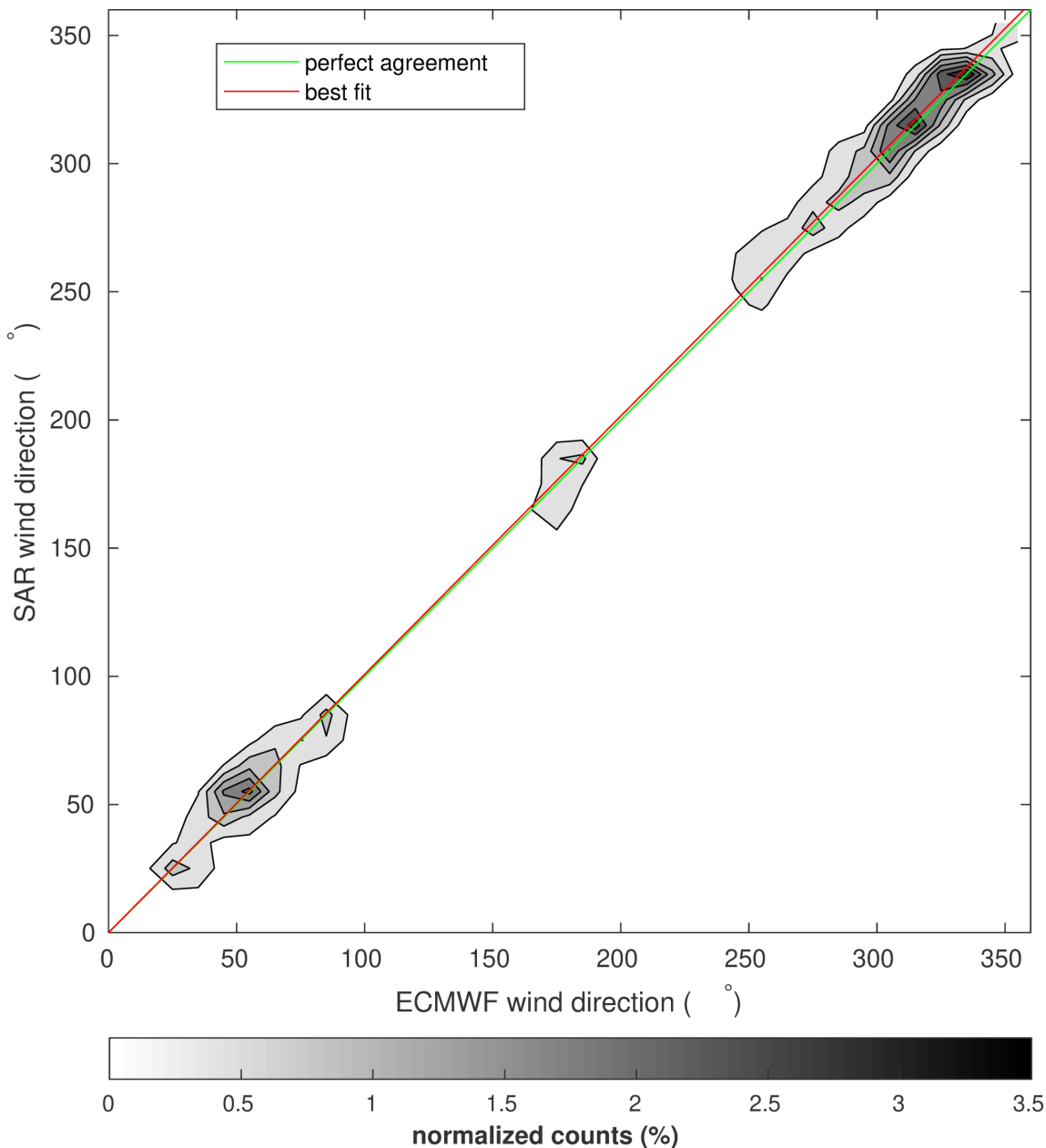
The structure of the chosen ResNet (M64RN4). The right diagram shows the building blocks structure (RNB), comprising a shortcut connection which propagates the input and adds it to the output of two stacked convolutional layers, consisting of d channels with filter size of 3×3 , which are indicated with $CL((3 \times 3), d)$; ReLU is the Rectified Linear Unit, BN the Batch Normalization. The left diagram shows the chosen model structure, consisting of four RNBs of 64 channels, followed by the fully connected layers (FC) as described in the text. Each layer of the FC is followed by ReLU and Batch Normalization, here not shown for the sake of clarity. (From *Zanchetta and Zecchetto, 2021*)

Comparisons with ECMWF and scatterometer data

Statistical analysis has been carried out comparing the SAR-derived wind directions with those from ECMWF atmospheric model, ASCAT scatterometer and in-situ gauges, reporting very good results, as seen from the table.

Biases β are of the order of a few degrees, and centered root mean square difference* $cRMSd < 21^\circ$, consistent with the benchmark obtained comparing scatterometer with ECMWF wind directions over the areas imaged by SAR ($\beta = 2.1^\circ$, $cRMSd = 19^\circ$).

These results are relevant because they include the coastal data, not accounted in the benchmark.

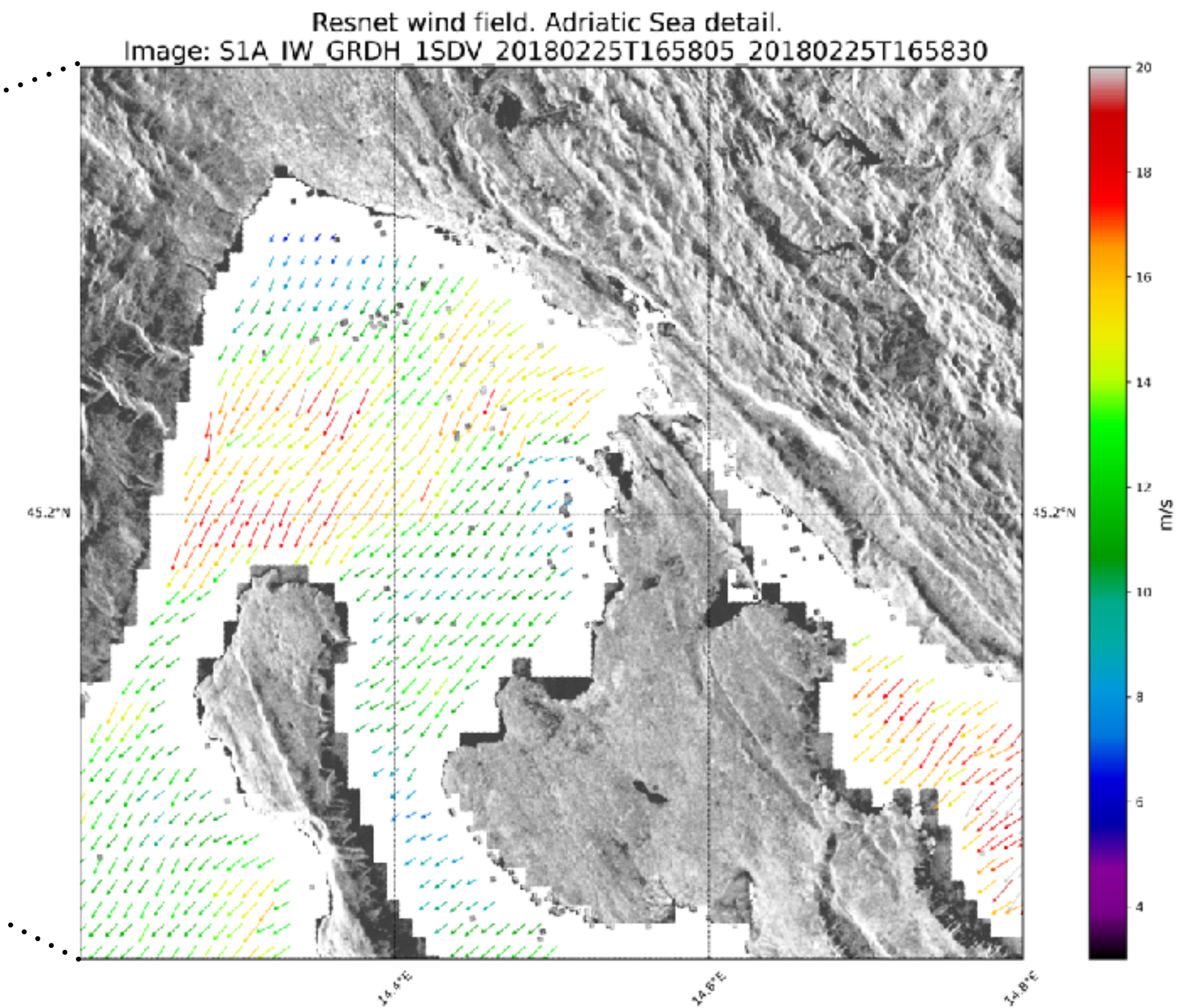
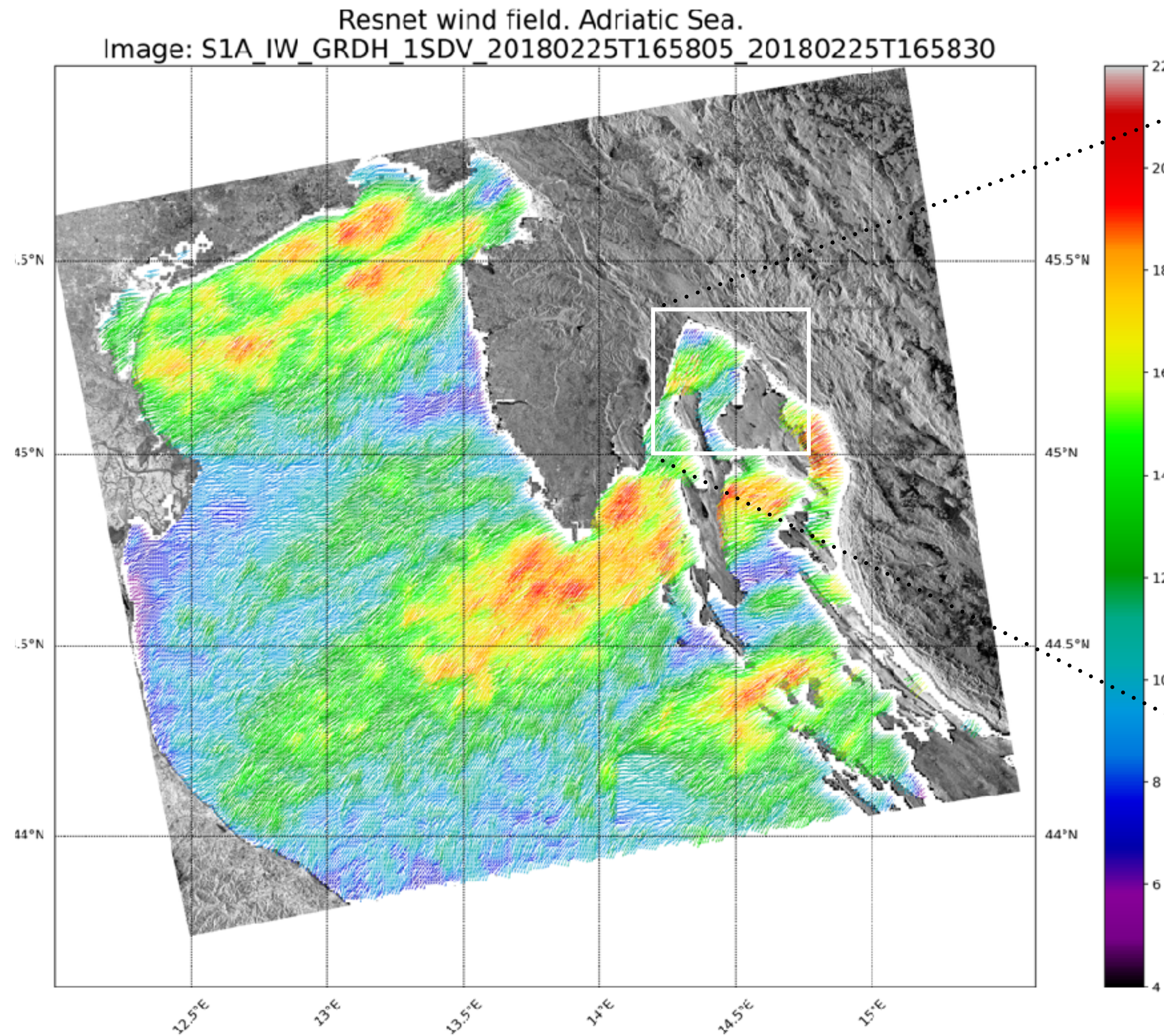


data sets	β (°)	$cRMSd$ (°)	linear correlation
ResNet-InSitu	-4.6	20.2	0.94
ResNet-ECMWF	-1.1	16.5	0.97
ResNet-Scatterometer	2.4	20.9	0.95
ECMWF-InSitu	-3.4	19.4	0.97
ECMWF-Scatterometer	2.1	19.0	0.96
OCN-ResNet	0.1	20.8	0.94
OCN-ECMWF	-1.8	17.1	0.95
OCN-Scatterometer	2.6	24.0	0.91

* The $cRMSd$ is the Root Mean Square difference, i.e. the bias-corrected root mean square deviation, i.e. $cRMSd^2 = RMSd^2 - \beta^2$, where $RMSd$ is the ordinary root mean square difference.

(From: **A. Zanchetta and S. Zecchetto**: “Wind direction retrieval from Sentinel-1 SAR images using ResNet”, *Remote Sensing of Environment*, 253, February 2021, doi: 10.1016/j.rse.2020.112178)

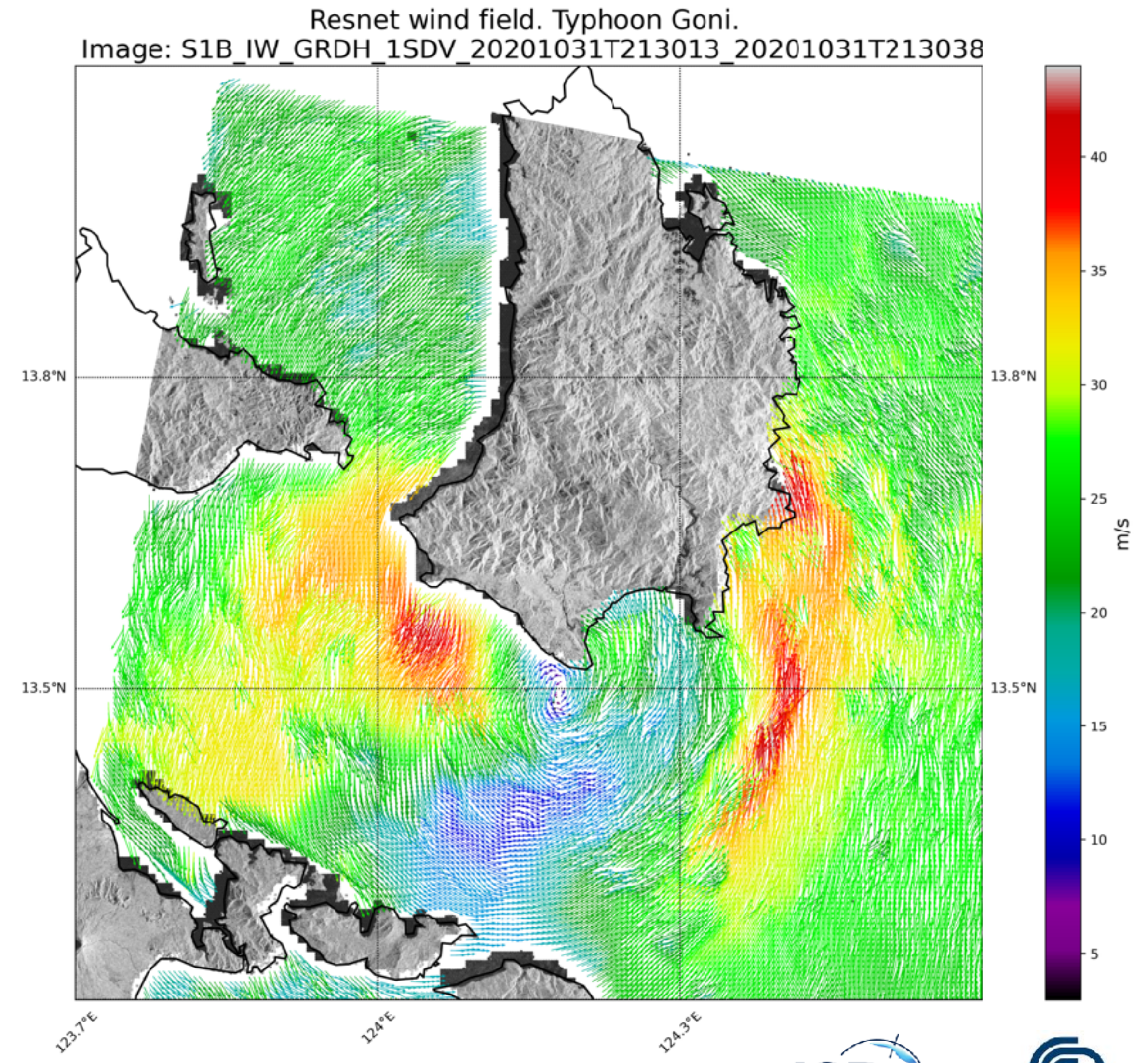
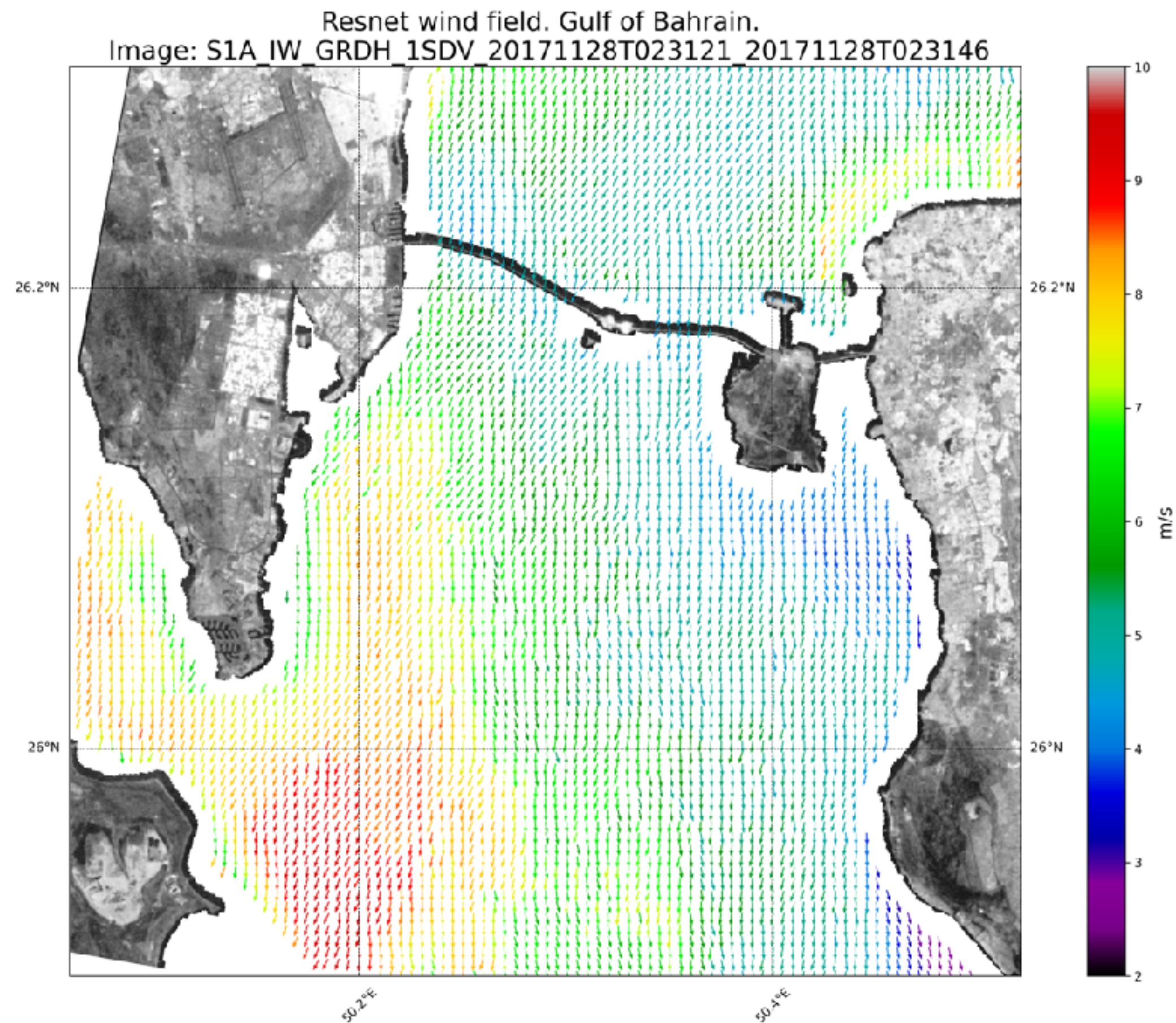
An example of SAR-derived wind field



The ResNet successfully retrieves the wind direction all over the area imaged by SAR.
The wind speed is computed with the CMOD-5, using the wind direction obtained from the ResNet.
Northern Adriatic Sea, grid spacing 500 m.

Hi-res retrieval of complex flow conditions

The ResNet allows to retrieve the wind direction even in complex flow situations. Here two examples of application on an image are presented, illustrating the retrieved wind field on the Gulf of Bahrain, and the typhoon Goni over the Philippines. Grid spacing 500 m.



Conclusions and work in progress

- ResNet is able to reliably retrieve the wind direction at a very high resolution (~ 500 m), showing the natural variability of the wind that at present cannot be resolved with other datasets.
 - The ResNet methodology has shown very good results also in situations characterised by strong divergence, independently on atmospheric stability conditions and, remarkably, even in the absence of wind streaks on the SAR images. Atmospheric fronts and tropical cyclones are retrieved with an unprecedented level of detail.
 - The high spatial resolution SAR-derived wind fields allow the description of the wind in close proximity of the coastlines, in enclosed basins like lagoons and lakes, where the wind field structure is often triggered by the surrounding orography.
 - The results are not affected by atmospheric lee waves, convective turbulence structures, presence of ships and platforms, surface long sea waves.
- ➡ Developing: a methodology to define the uncertainty on the wind direction estimation; analysis of the failed cases to understand their causes and attempt to further improve the methodology; automatic 180° dealiasing directly from the SAR images.



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