Approximation of high-resolution surface wind speed in the North Atlantic using discriminative and generative neural models based on RAS-NAAD 40-year hindcast

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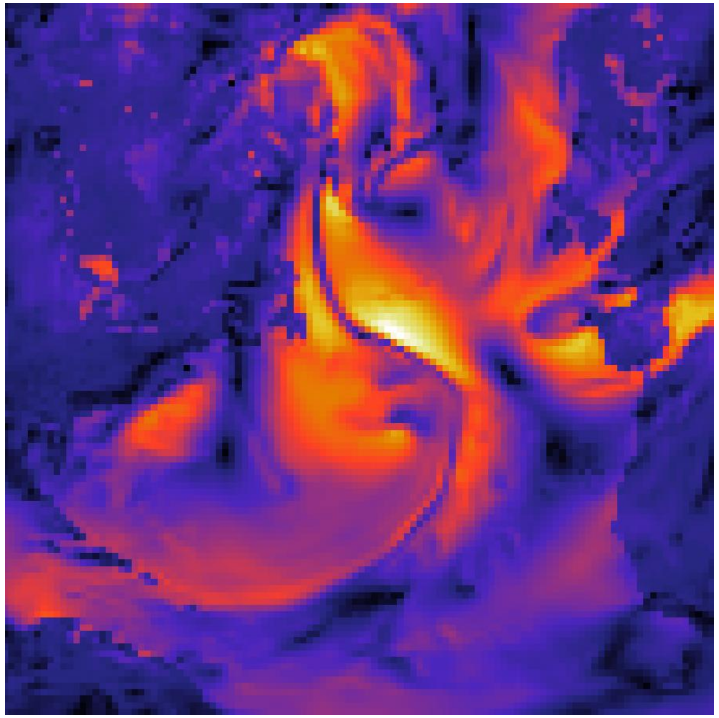
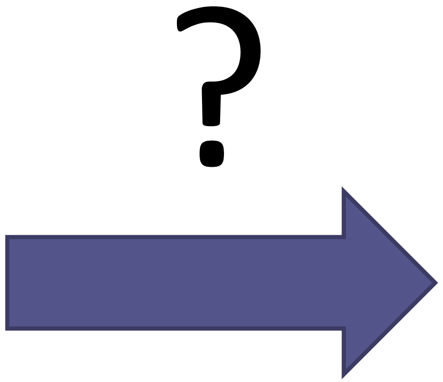
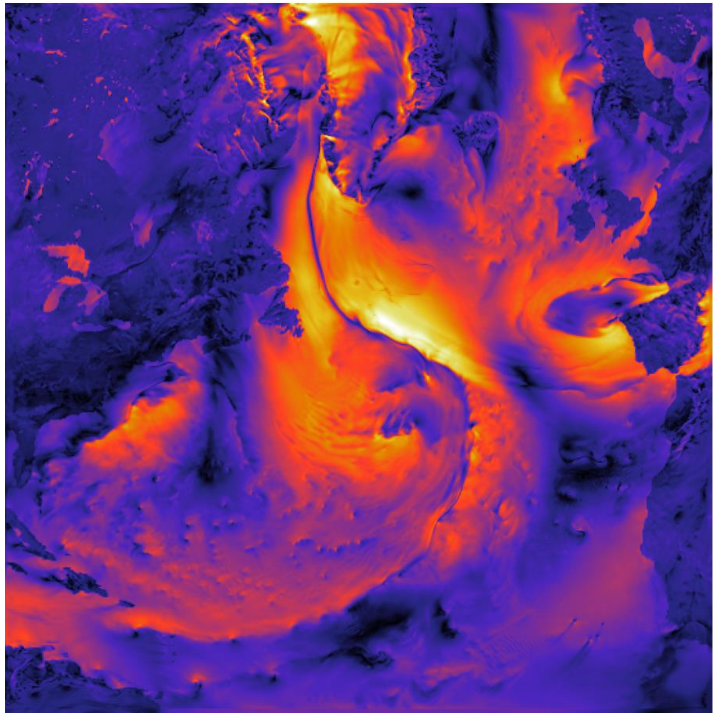
Problem review

- **Global warming** increases temperature and changes local precipitation and wind patterns.
- Global circulation models (**GCMs**) – low resolution.
- Numerical weather prediction (NWP) on a **global scale** in GCMs – computationally expensive.
- Solution is **downscaling.**
- Downscaling approximates values obtaining **high-resolution information** about physical variables **from low-resolution modeling outputs**.







Downscaling methods

1) Dynamical downscaling:

- Low-resolution numerical modeling – entire area of interest;
- Low-resolution outputs – **boundary conditions** for high-resolution modeling;
- High-resolution modeling – **in particular subareas** of the modeling area.

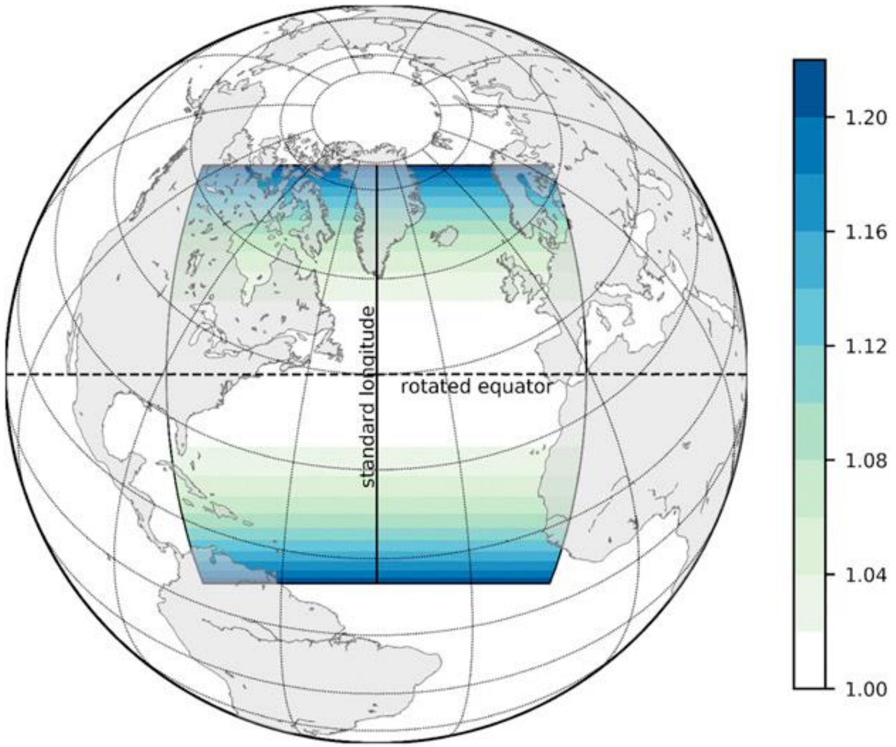
2) Statistical downscaling:

- **No** numerical modeling;
- **Functional relationship** between low- and high-resolution data is approximated by **training a statistical model** on dataset pairs;
- **Computational efficiency – functional relationship is** applied directly to low-resolution data;
- The downscaling **quality can be lower** than that obtained in dynamic downscaling;
- **Widely used** because of lower computational costs;
- Allows using **non-linear machine-learning methods (e.g., artificial neural networks, *ANN*)**.

Research purpose

High-resolution downscaling of surface wind speed in the North Atlantic region comparing discriminative and generative **neural networks** based on RAS-NAAD* 40-year hindcast

Materials



RAS-NAAD – retrospective NAAD dynamic model
(by Shirshov Institute of Oceanology, Russian Academy of Sciences)

January 1979 – December 2018:

Low resolution – RAS-NAAD LoRes (110 x 110 grid, resolution **≈ 77 km**)
High resolution – RAS-NAAD HiRes (550 x 550 grid, resolution **≈ 15 km**)

Time resolution – 3 hours

Variables – *U* and *V* components of 10m wind speed;
sea-level atmospheric pressure, *SLP*

Fig. The modeling area from 10º N to 80ºN and from 90ºW to 5ºE

* Gavrikov A. et al. RASNAAD: 40-yr High-Resolution North Atlantic Atmospheric Hindcast for Multipurpose Applications (New Dataset for the Regional Mesoscale Studies in the Atmosphere and the Ocean) //Journal of Applied Meteorology and Climatology. – 2020. –V. 59. – №. 5. – P. 793-817.

Quality metrics

- Root-mean-square error (RMSE)

$$RMSE = \sqrt{\frac{1}{550*550}\sum_{i=1}^{550}\sum_{j=1}^{550}\left(\sqrt{(U^*_{i,j})^2+(V^*_{i,j})^2}-\sqrt{(U_{i,j})^2+(V_{i,j})^2}\right)^2}$$

$U_{i,j}$ и $V_{i,j}$ – HiRes wind speed components, $U^*_{i,j}$ и $V^*_{i,j}$ – downscaled wind on 550 x 550 grid

- Root-mean-square error of extreme wind (RMSE-95):

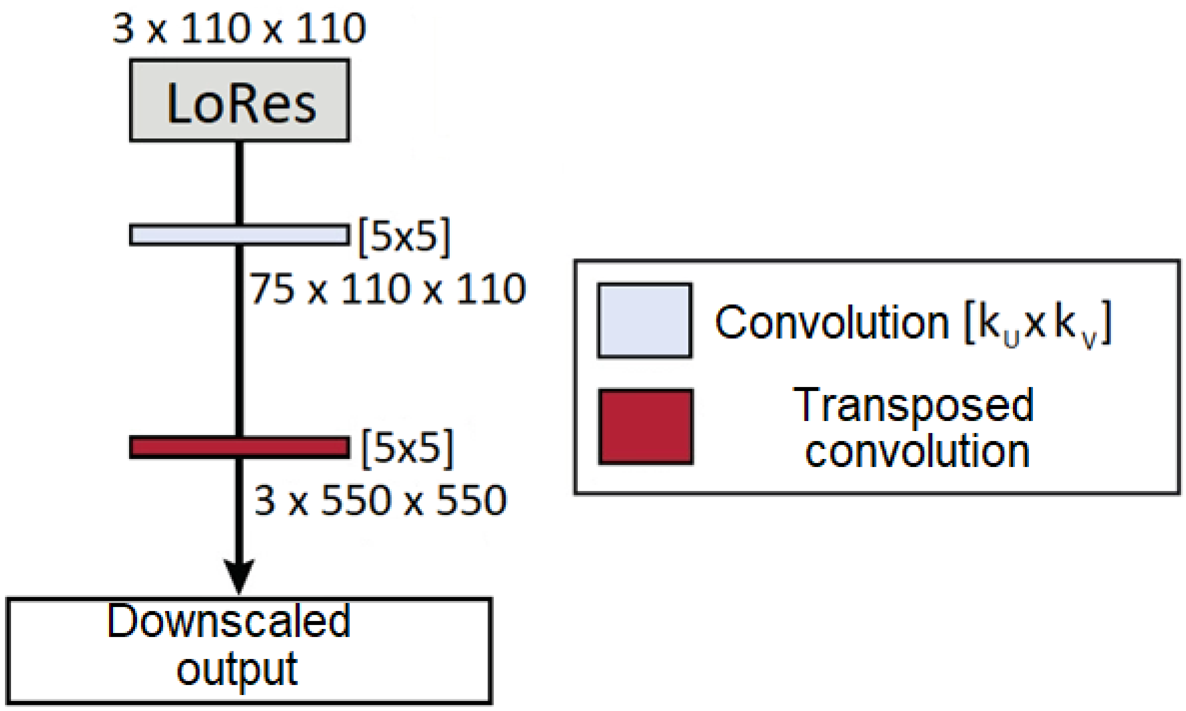
  RMSE for grid nodes where wind is higher than its 95th percentile

- Peak signal-to-noise ratio (PSNR)

$$PSNR = 10\lg\left(\frac{MAX^2}{MSE}\right)$$

  MAX – maximum normalized value between 3 downscaled variables on 550 x 550 grid,
  MSE – mean-square error of 3 normalized downscaled variables

Linear CNN*

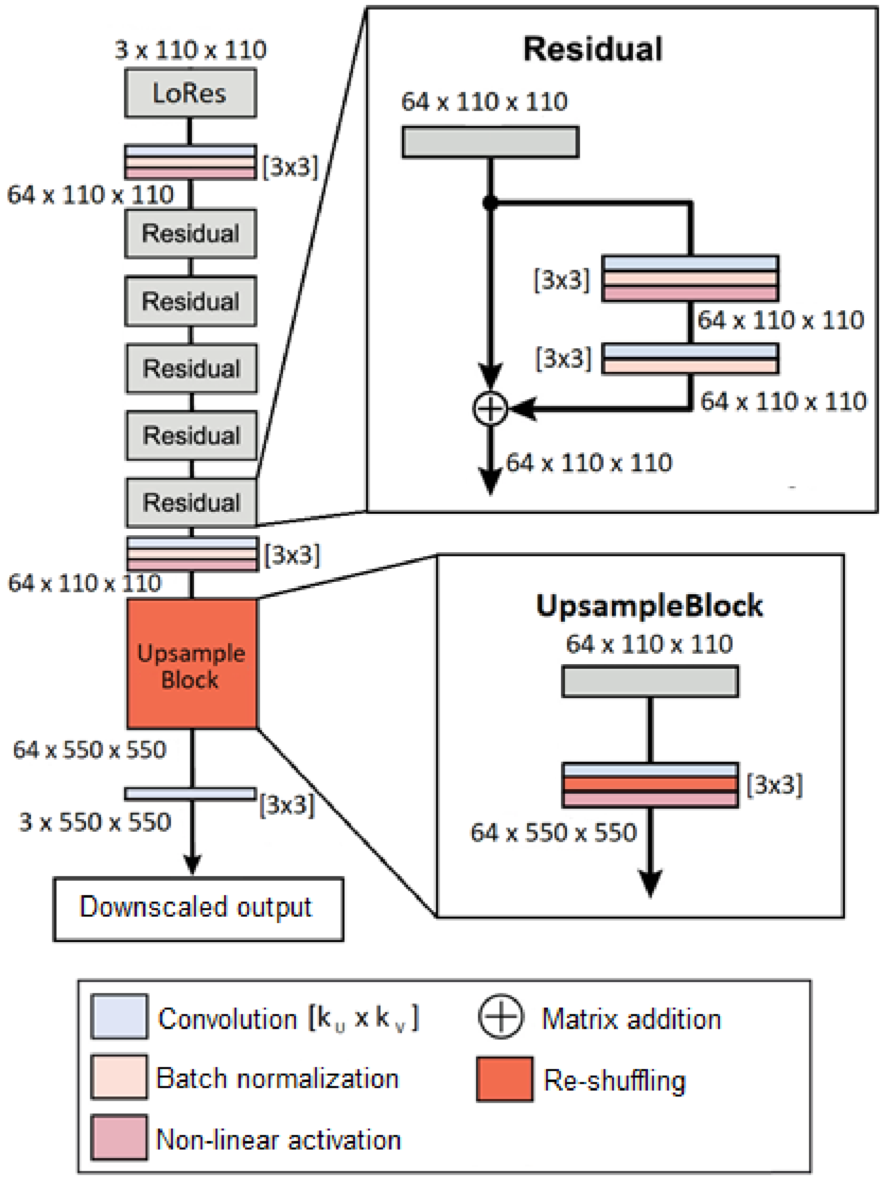


Simplest convolutional neural network (CNN) in this research

Linear downscaling of wind speed

* Höhlein K. et al. A comparative study of convolutional neural network models for wind field downscaling //Meteorological Applications. – 2020. – V. 27. – №. 6. – P. e1961.

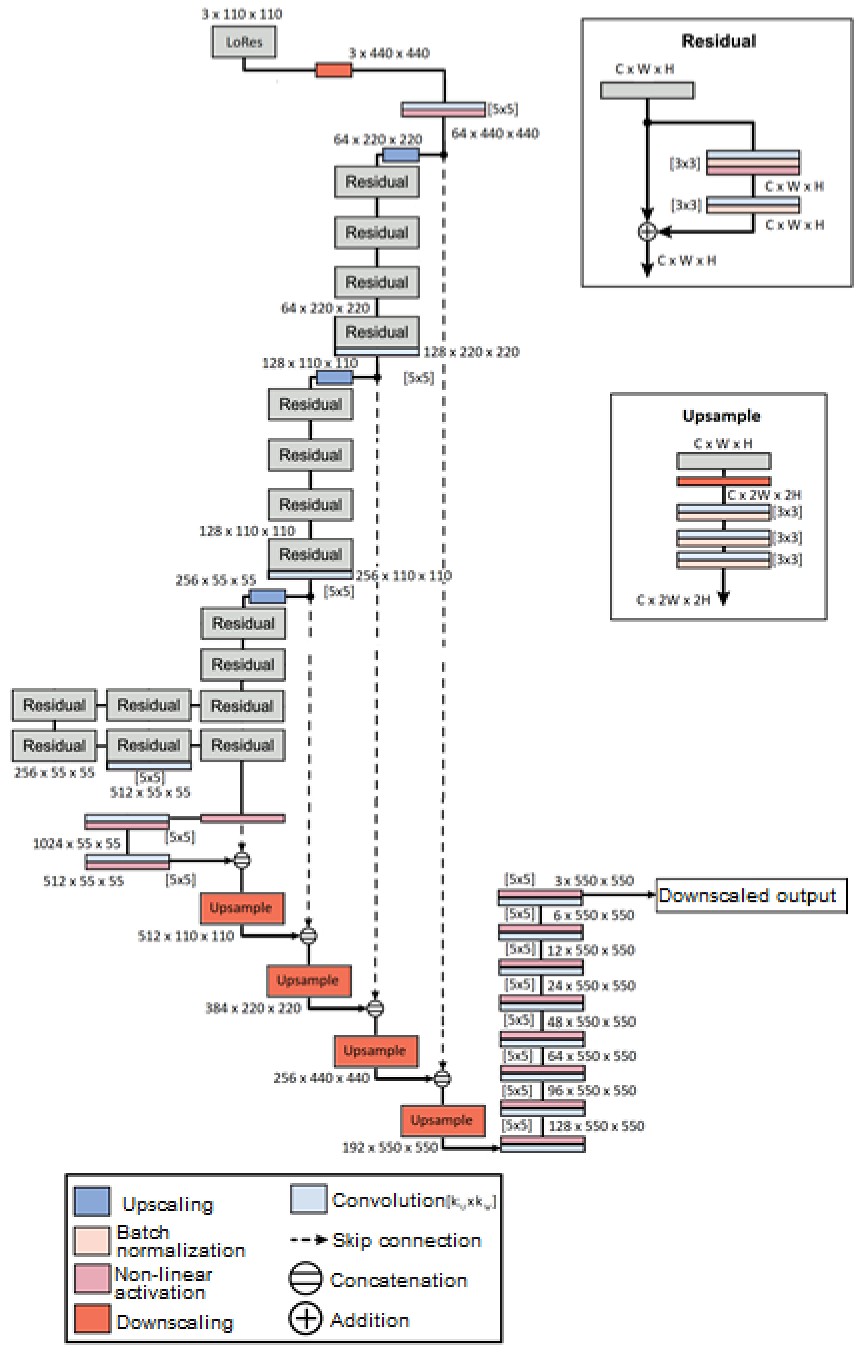
ResNet



<u>Increased depth</u> of convolutional neural networks

Increased learning stability <u>(residual connections)</u>

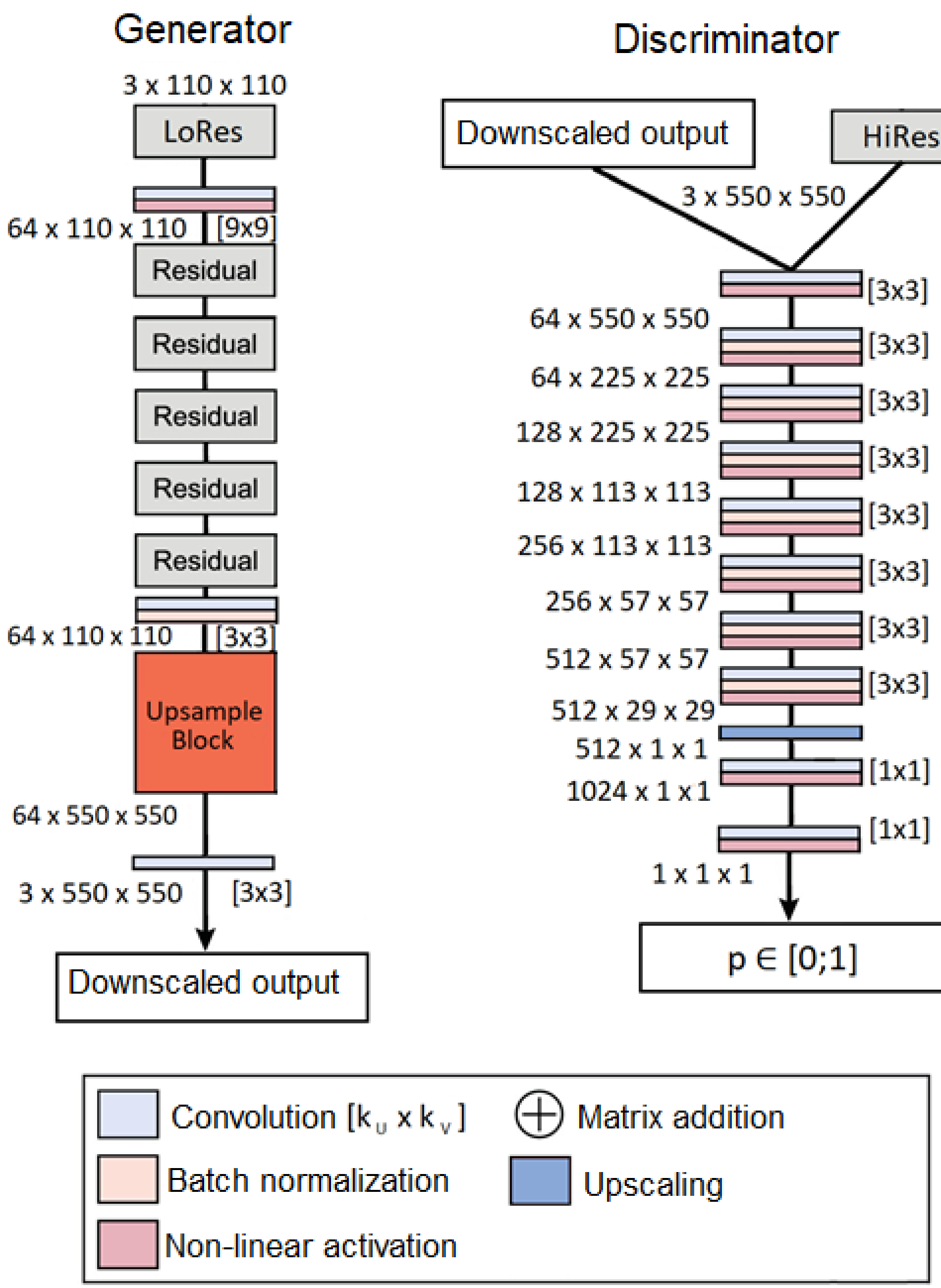
<u>Non-linear</u> activation functions



U-net (ResNet-based encoder)

Skip connections:

- Learning stability;
- Extracting of functional dependencies corresponding to different spatial scales;
- Initial features propagate closer to the output.



SR-GAN*

Two models are trained simultaneously

Generator (G): creates different outputs with the same dimensions as real high-resolution data

Discriminator (D): determines whether a certain element is taken from the distribution generated by *G* or from the true data distribution

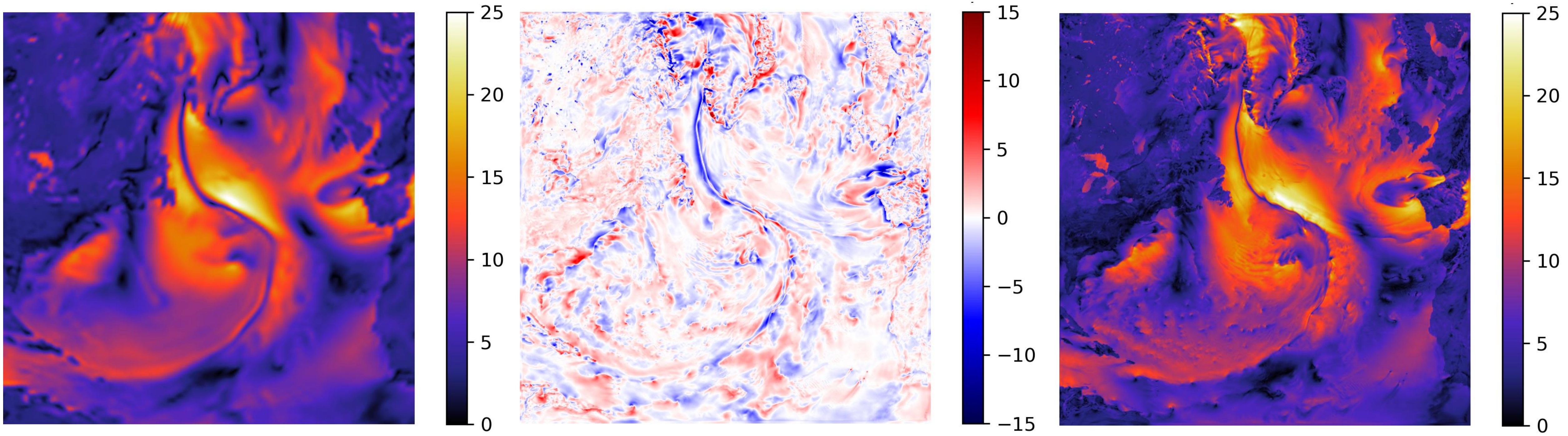
Learning – adversarial process:

G learns to make its output more plausible, similar to real data distribution.

D learns to define the plausibility of G outputs as 0 and that of real data as 1.

* Ledig C. et al. Photo-realistic single image super-resolution using a generative adversarial network // Proceedings of the IEEE conference on computer vision and pattern recognition. – 2017. – P. 4681-4690.

Bicubic interpolation



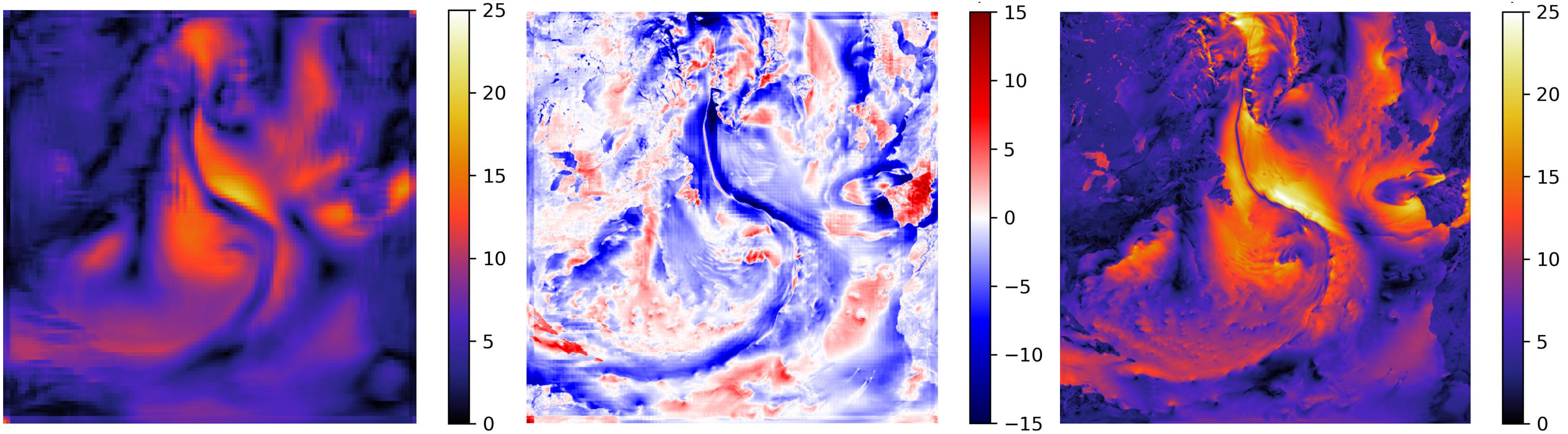
a

b

c

Fig. Wind speed (00:00, 1 Jan 2010), m/s:
(a) Bicubic interpolation;
(b) Difference between bicubic interpolation and NAAD HiRes;
(c) NAAD HiRes

Linear CNN



a b c

Fig. Wind speed (00:00, 1 Jan 2010), m/s:
(a) Linear CNN downscaling;
(b) Difference between downscaled wind and NAAD HiRes;
(c) NAAD HiRes

ResNet

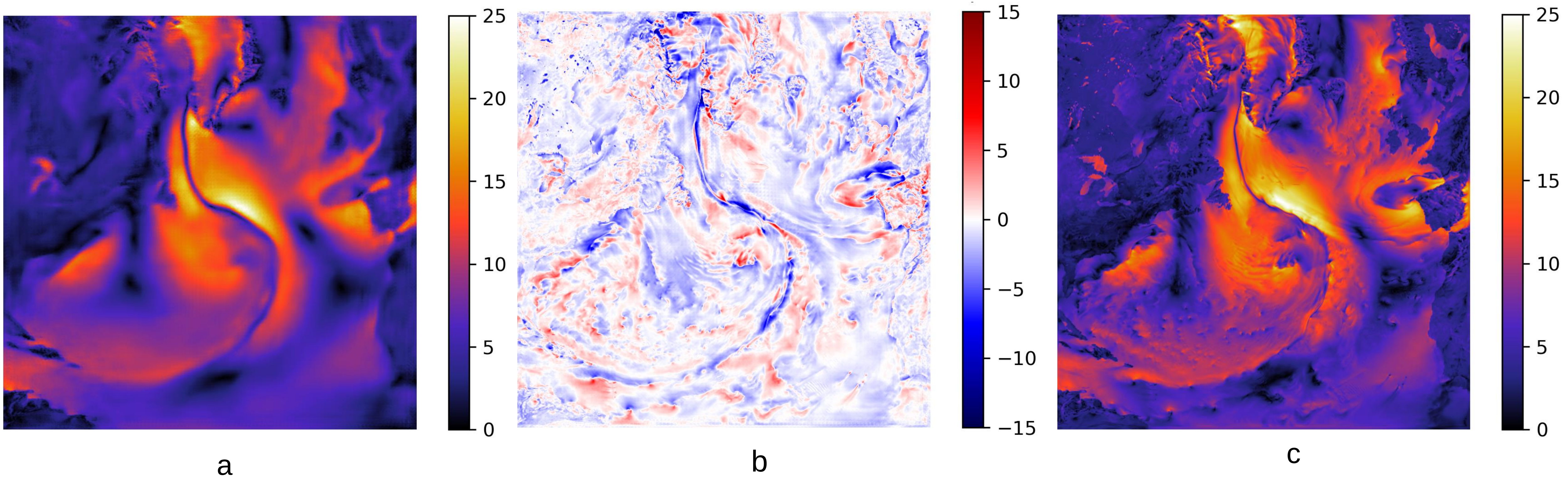


Fig. Wind speed (00:00, 1 Jan 2010), m/s:
(a) ResNet downscaling;
(b) Difference between downscaled wind and NAAD HiRes;
(c) NAAD HiRes

U-net

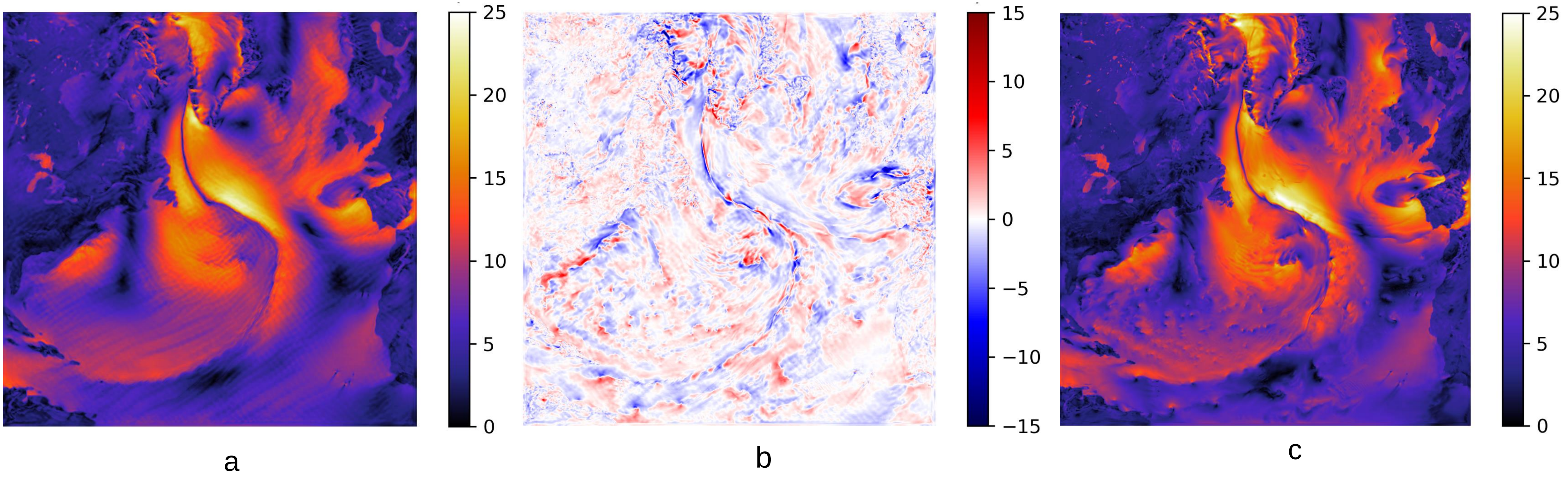
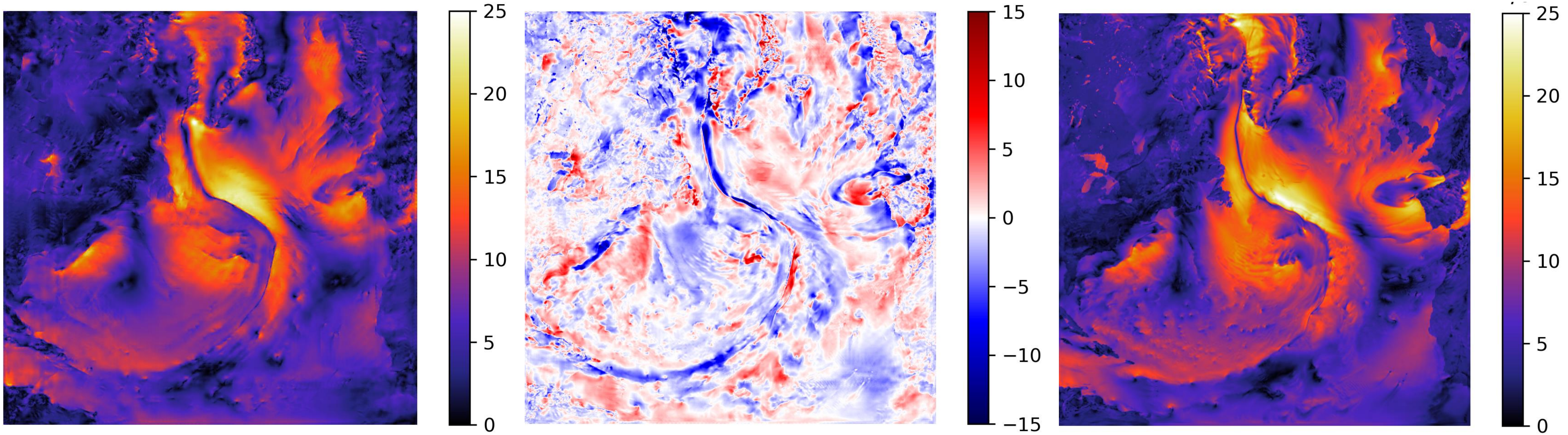


Fig. Wind speed (00:00, 1 Jan 2010), m/s:
(a) U-net downscaling;
(b) Difference between downscaled wind and NAAD HiRes;
(c) NAAD HiRes

SR-GAN



a b c

Fig. Wind speed (00:00, 1 Jan 2010), m/s:
(a) SR-GAN generator downscaling;
(b) Difference between downscaled wind and NAAD HiRes;
(c) NAAD HiRes

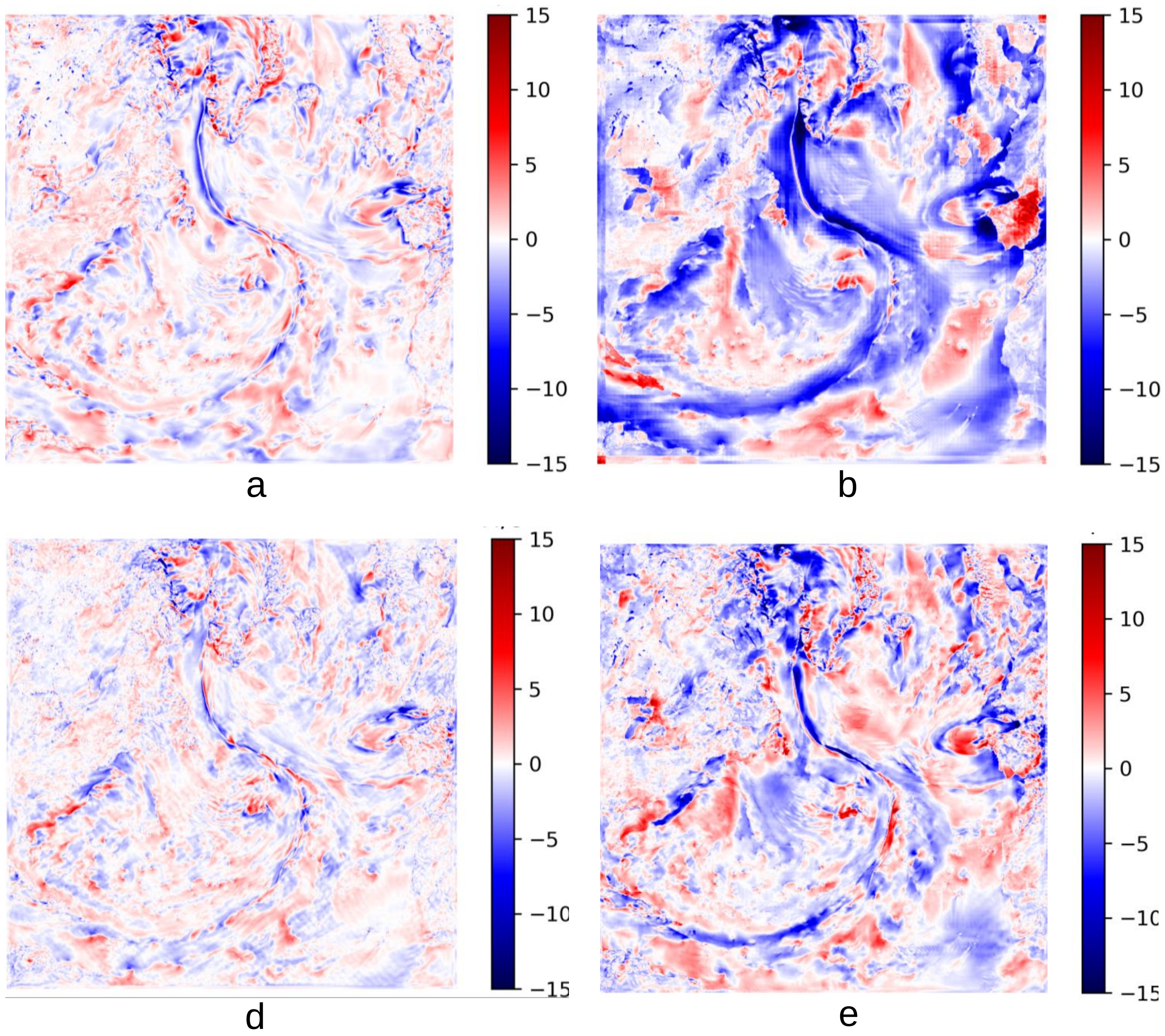


Fig. Wind speed (00:00, 1 Jan 2010), m/s – difference between downscaled wind and NAAD HiRes:

(a) Bicubic interpolation;

(b) Linear CNN;

(c) ResNet;

(d) U-net;

(e) SR-GAN

Results

Method	RMSE, m/s	RMSE-95, m/s	PSNR
Bicubic interpolation	1,44	**1,90**	**35,16**
Linear CNN	2,85	5,32	27,68
ResNet	1,42	2,21	32,87
U-net	**1,32**	1,97	34,46
SR-GAN	1,88	3,30	33,99

Table. Downscaling quality on validation dataset.
Bold – the best value for a particular quality metric

Summary

- Neural networks don’t outperform bicubic interpolation in RMSE-95 and PSNR.
- Based on RMSE, the best method is U-net.
- However, U-net learns to reproduce wind patterns over land, not meeting the purpose of the research.
- In the research, **SR-GAN** is the only method where learning is aimed at **improving the reproduction of wind patterns over the ocean**.
- SR-GAN <u>does not outperform</u> other methods in chosen quality metrics (incl. cubic interpolation)
- However, we consider SR-GAN to show the **most promising results** for further improvement and development.
- **GAN downscaling** is able to have <u>a wide variety of applications</u>, such as renewable energy and extreme weather forecasts.

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