Downscaling of surface wind speed over the North Atlantic using conditional Generative Adversarial Networks

Mikhail Krinitskiy[1*], Svyatoslav Elizarov, Alexander Gavrikov[1], Sergey Gulev[1]

1 Shirshov Institute of Oceanology, Russian Academy of Sciences
Sea-Air Interactions Laboratory (SAIL)

* krinitsky@sail.msk.ru

This work was undertaken with financial support by the Russian Ministry of Science and Higher Education (agreement No 05.604.21.0210), project ID RFMEFI60419X0210)

Motivation

- **Dynamic downscaling** of geophysical fields is a ”gold standard”, though it is **computationally expensive**;
- Regional circulation models and global circulation models are good in modeling at large scale, however, there is a room for improvement in terms of the skills of representing **small-scale subgrid processes** and their computational costs;
- Nowadays we have access to several **fine-resolution modeling results** of the climate system, **concurrent and colocated with a low-resolution** ones (e.g., RAS-NAAD hindcast*) that may be a rich data source for **statistical trainable downscaling models**;
- In computer vision, there are several approaches for **denoising and downscaling** (super-resolution problem) blurry and noisy images;
- Geophysical fields are not images: they are not generated by the same distribution, and the numbers of “channels” are not necessary 1 or 3. Still, the **CV approaches may be adopted** in order to denoise and/or downscale geophysical fields;

THE GOAL OF OUR STUDY:

Downscaling of the wind speed field over Northern Atlantic using **Deep Learning** techniques established in computer vision field with **constraints** imposed motivated by the **physics** of the downscaled processes.

* Gavrikov et al. “RAS-NAAD: 40-yr High-Resolution North Atlantic Atmospheric Hindcast for Multipurpose Applications (New Dataset for the Regional Mesoscale Studies in the Atmosphere and the Ocean)”. *J. Appl. Meteor. Climatol.* **2020**, *59*, 793–817, doi:10.1175/JAMC-D-19-0190.1

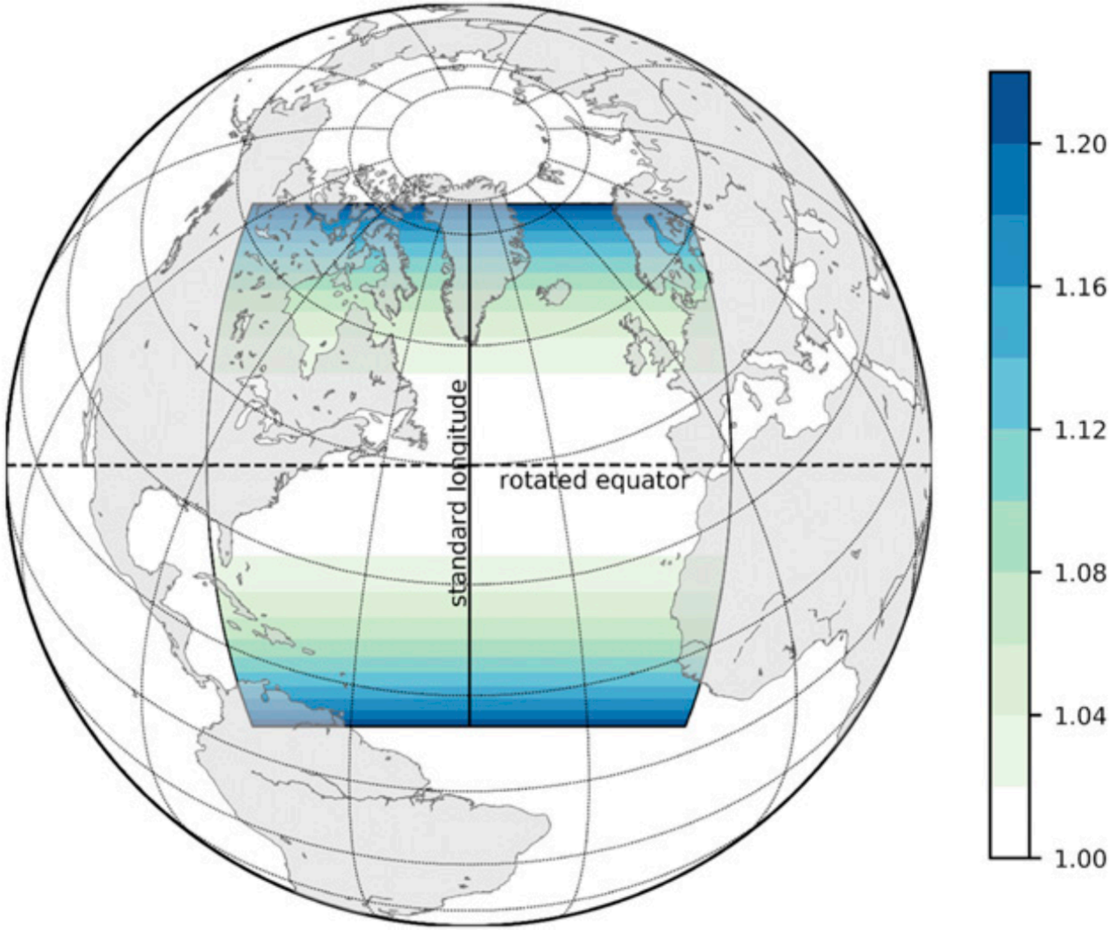
Data

RAS-NAAD hindcast* data is used.

RAS-NAAD* is a 40-year (1979-2018) retrospective reconstruction of the North Atlantic atmosphere of 14km resolution made with WRF-ARW 3.8.1.
Time resolution is 3-hourly.

Source geophysical fields:
U10 – zonal wind component at 10m.
V10 – meridional wind component at 10m.
SLP – sea level pressure

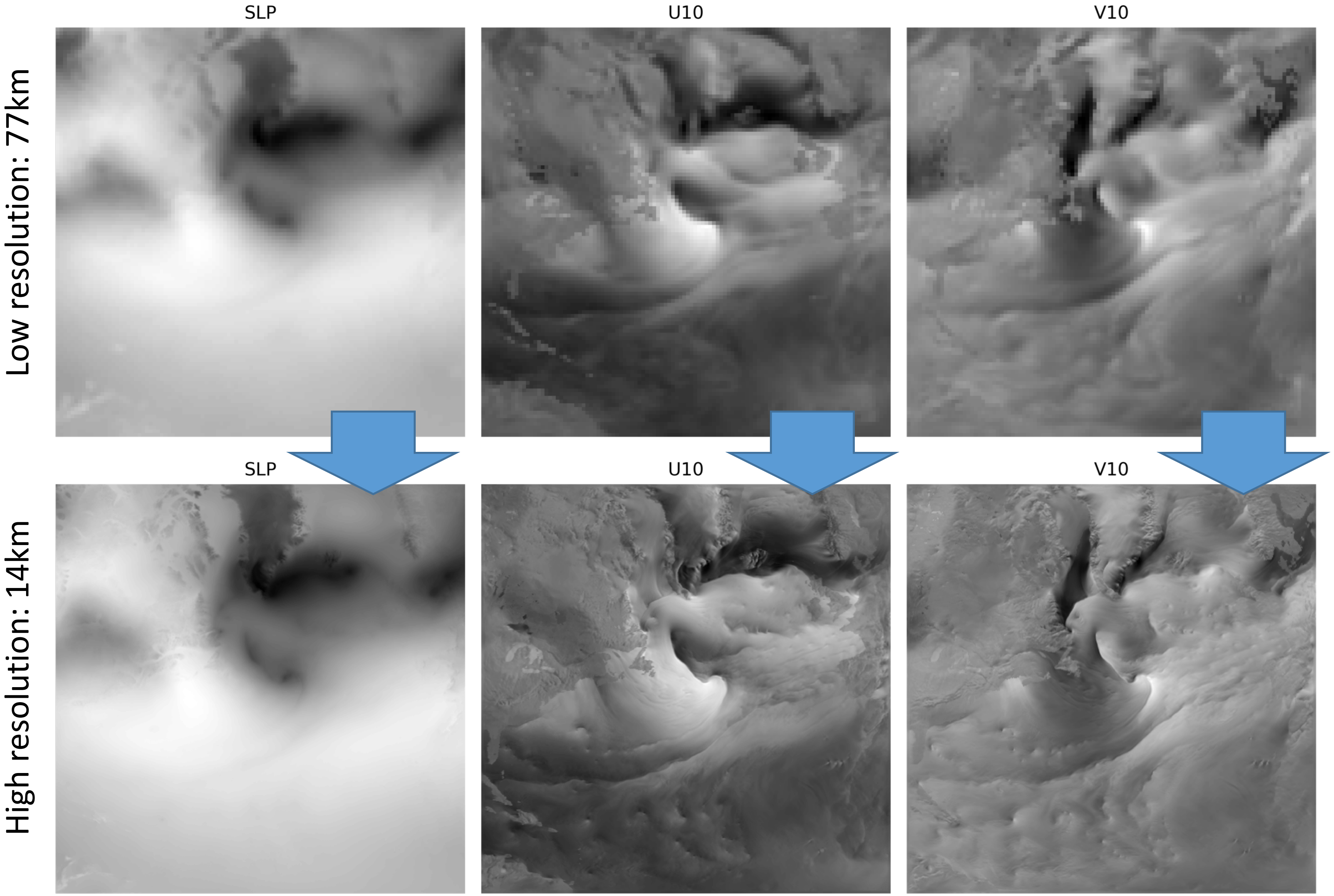
Low resolution: 77km (horizontal) – **110x110** grid points
High resolution: 14km (horizontal) – **550x550** grid points



RAS-NAAD computational domain and map-scale factor for the HiRes simulation (from Gavrikov et al. 2020)

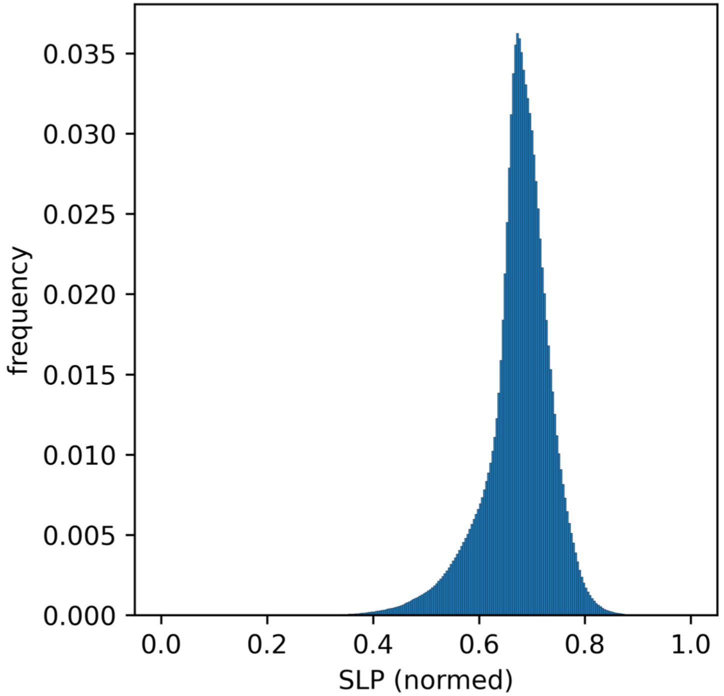
* Gavrikov et al. "RAS-NAAD: 40-yr High-Resolution North Atlantic Atmospheric Hindcast for Multipurpose Applications (New Dataset for the Regional Mesoscale Studies in the Atmosphere and the Ocean)". *J. Appl. Meteor. Climatol.* **2020**, *59*, 793–817, doi:10.1175/JAMC-D-19-0190.1

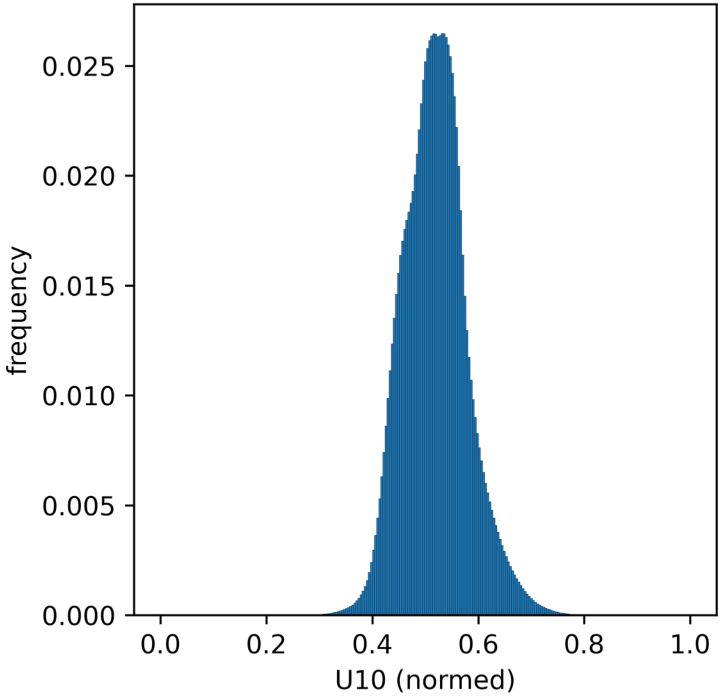
Data

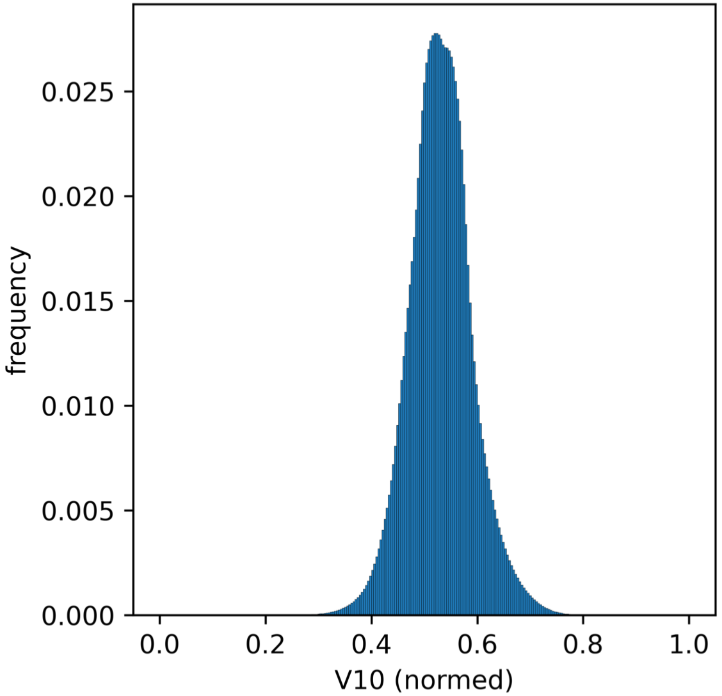

Low resolution: 77km
High resolution: 14km
SLP
U10
V10
SLP
U10
V10

Data preprocessing

(1) normalization to the range [0, 1]



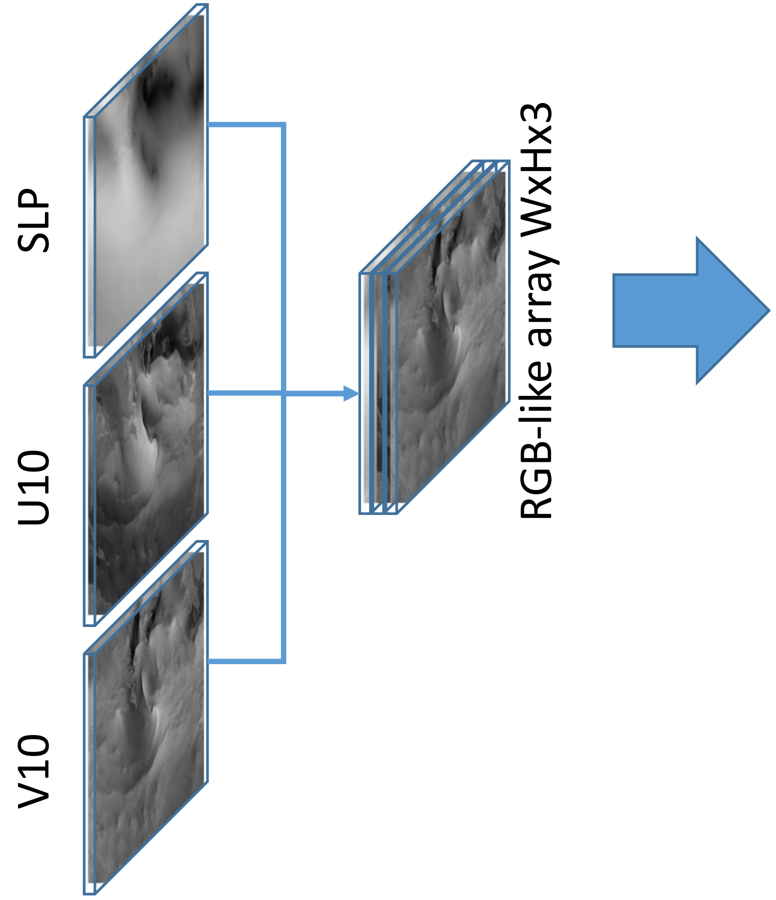




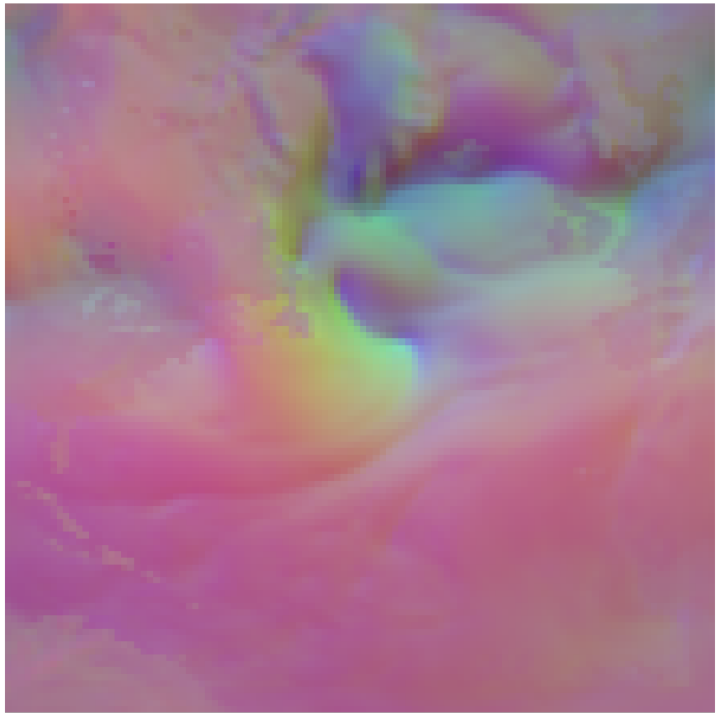
Normalized source data distributions (same for LoRes and HiRes)

Data preprocessing

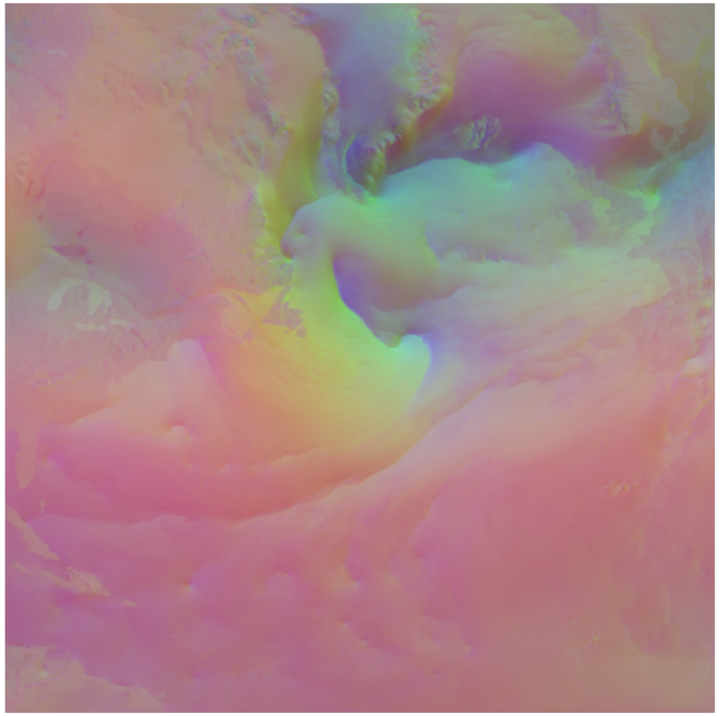
(2) SLP, U10, V10 -> 3-channel image-like array



Low resolution: 77km



High resolution: 14km



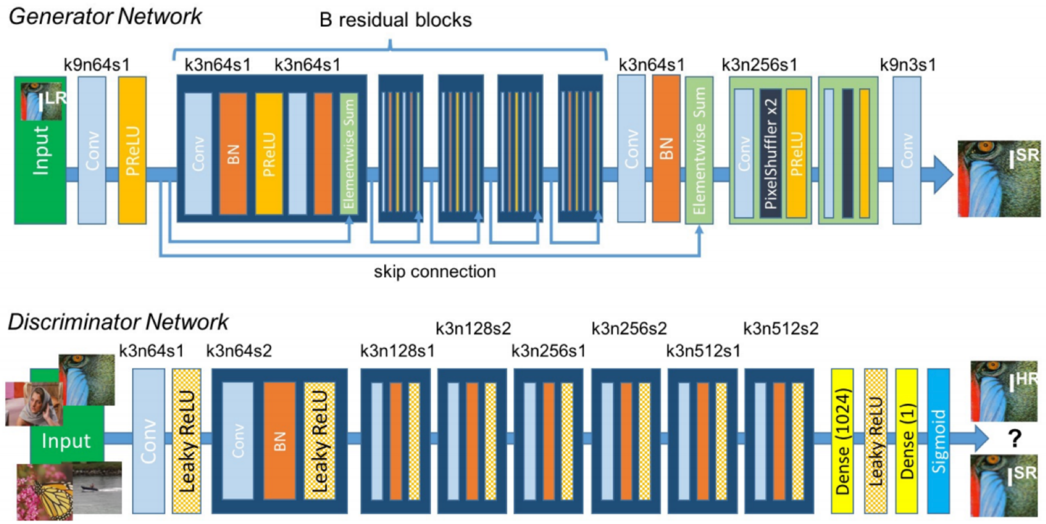
RGB-like representations of normalized source data
(SLP corresponds to red channel; U10 – green; V10 – blue)

Method

SRGAN[*] – generative adversarial network for super-resolution task

Main ideas:

- Use conditional Generative Adversarial Network (**cGAN**) to approximate a **joint distribution** $P(data_{hires}, data_{lores})$ instead of discriminative approach when fitting a conditional distribution $P(data_{hires}|data_{lores})$;
    - bonus: GANs outcome is inherently probabilistic so one may generate (draw) multiple downscaled results and treat them as **ensemble members**, thus estimating ensemble mean and **uncertainty**;
- Use content reconstruction loss (MSE) along with Perceptual Loss[*] which makes it posible to exploit the skill of VGG network to extract meaningful features of specific scales and certain levels of abstraction;
- Impose physics-guided constraints (in a form of the loss components) as regularizations while training an SRGAN;

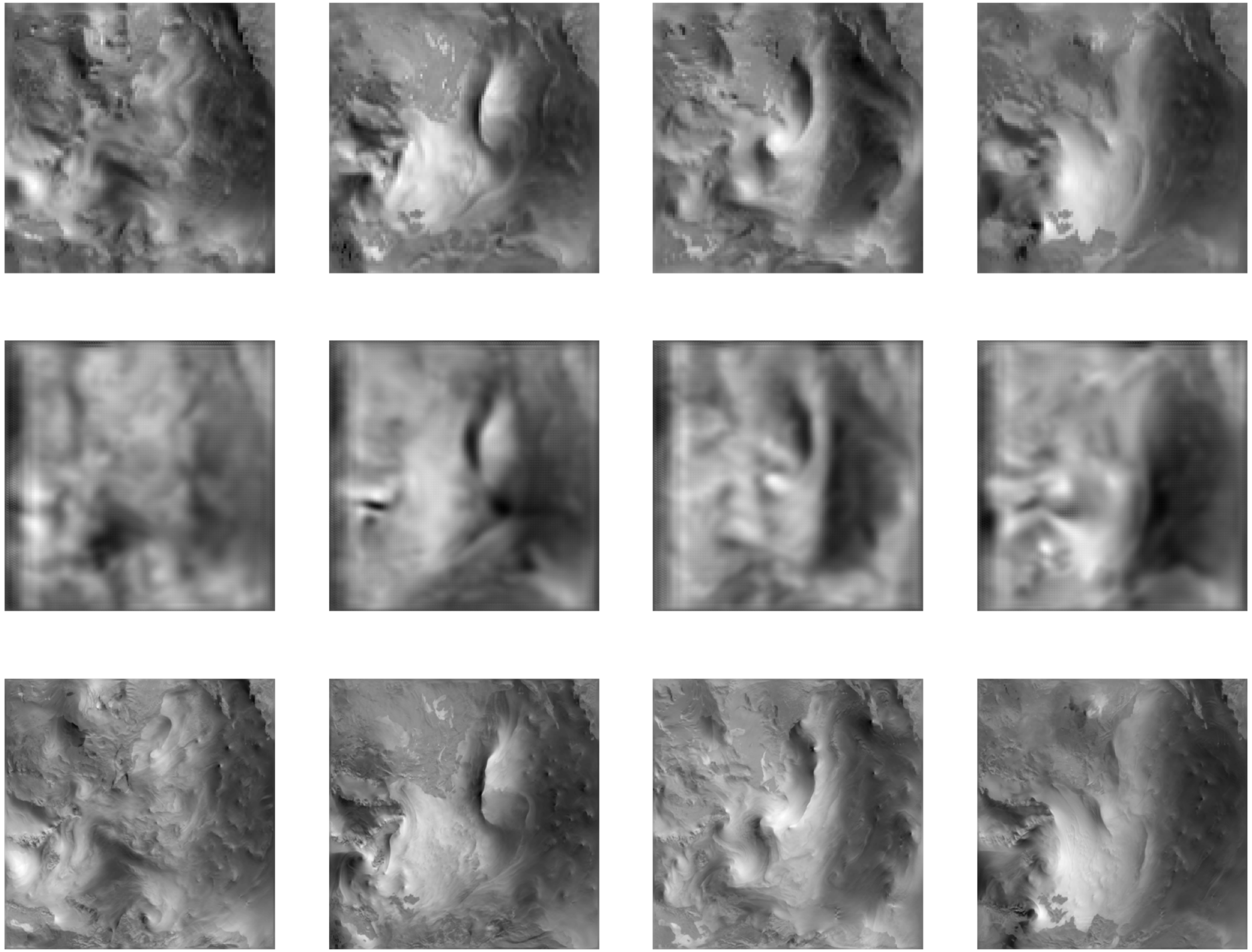


SRGAN structure, from Ledig et al. 2017[*]

[*] Ledig, C.; Theis, L.; Huszar, F.; Caballero, J.; Cunningham, A.; Acosta, A.; Aitken, A.; Tejani, A.; Totz, J.; Wang, Z.; et al. Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network. [arXiv:1609.04802](https://arxiv.org/abs/1609.04802) *[cs, stat]* **2017**.

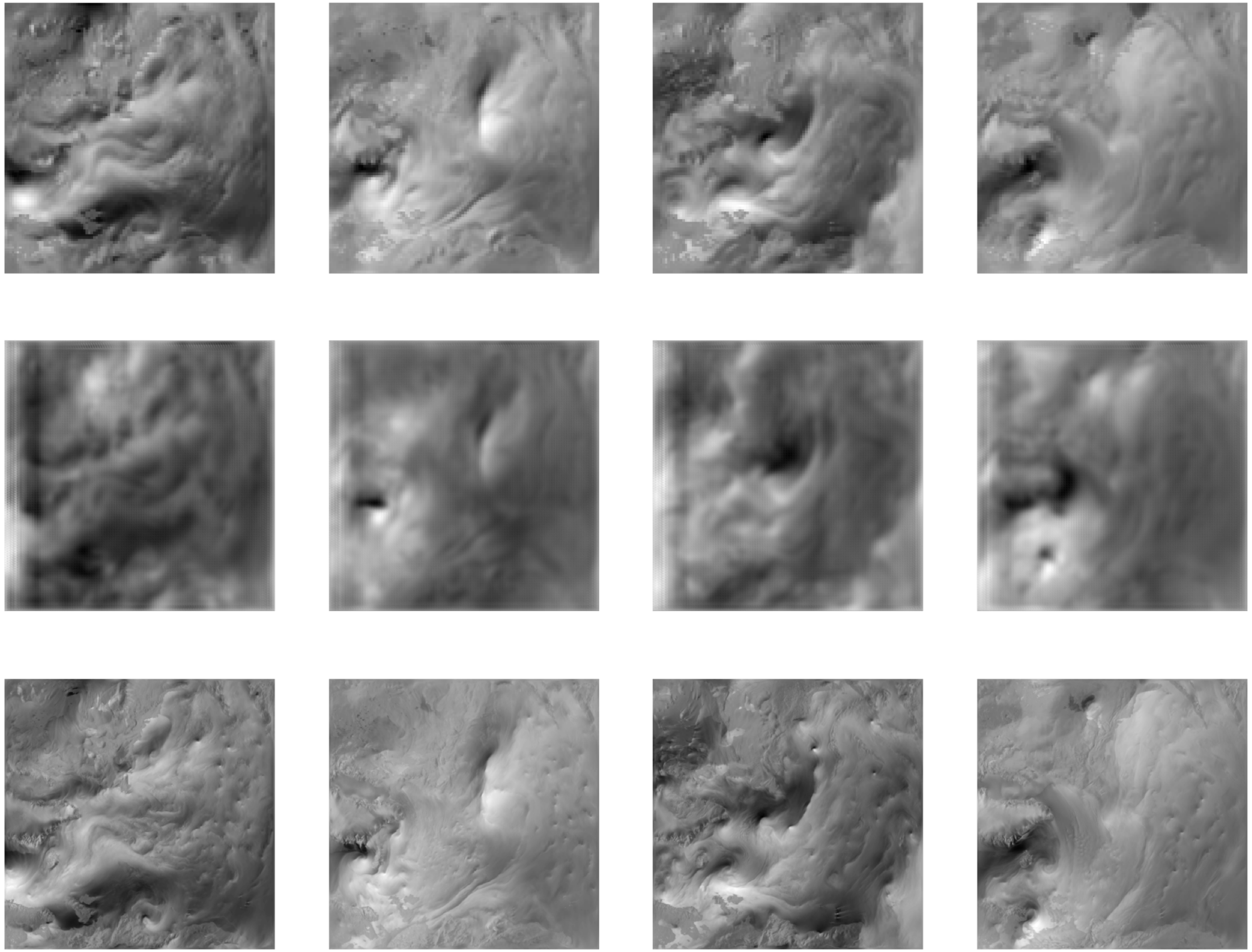
Results (preliminary, qualitative)

U10



Results (preliminary, qualitative)

V10



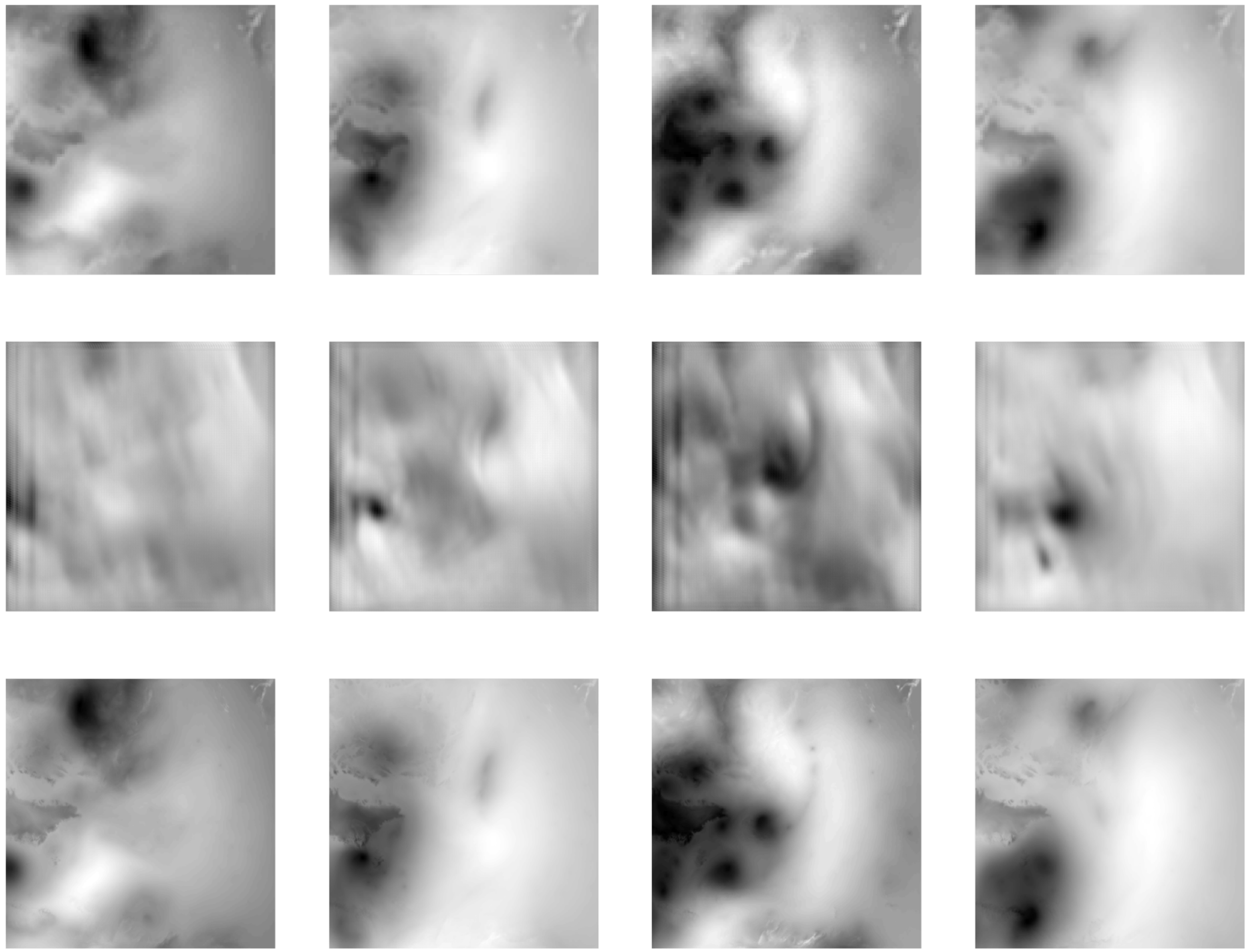
LoRes

Generated by cGAN

HiRes

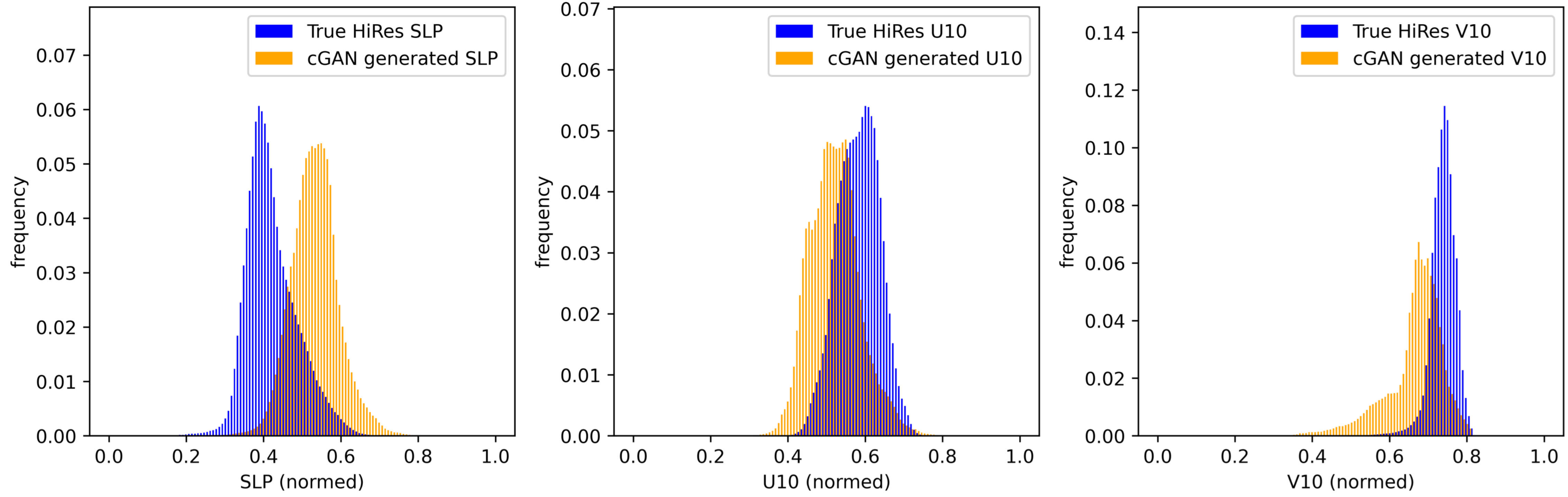
Results (preliminary, qualitative)

SLP



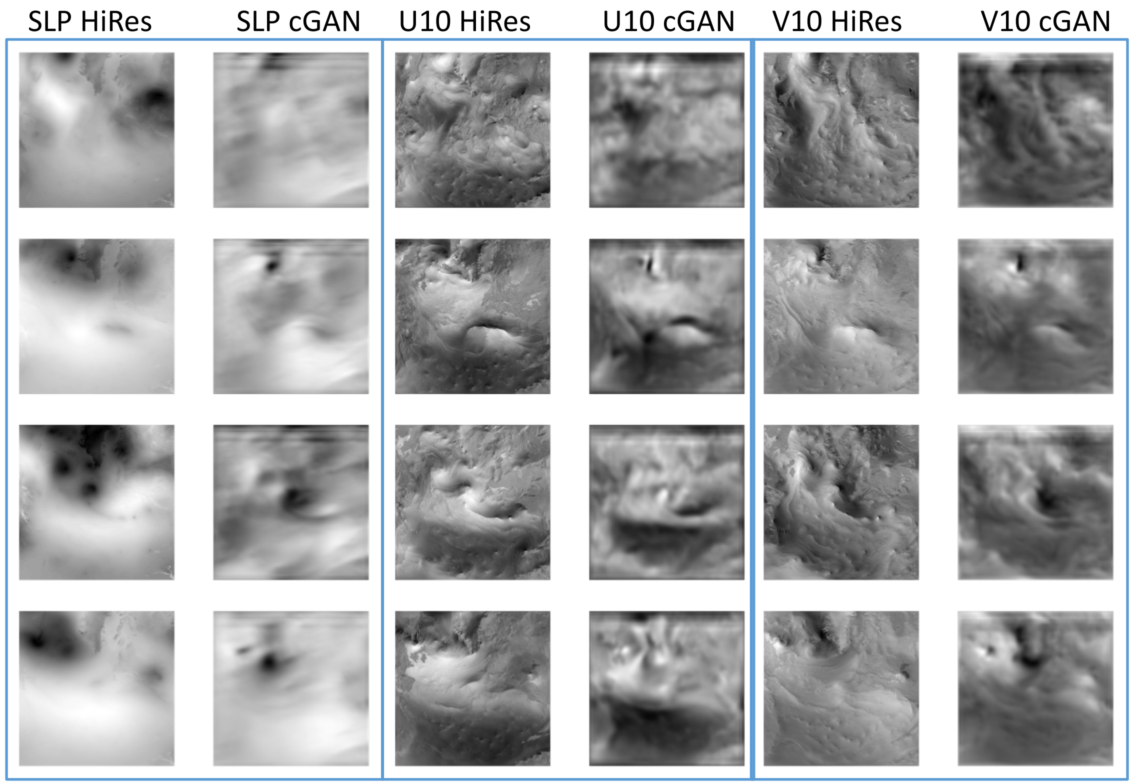
Results (preliminary, qualitative)

HiRes examples distribution vs. SRGAN generated examples distribution

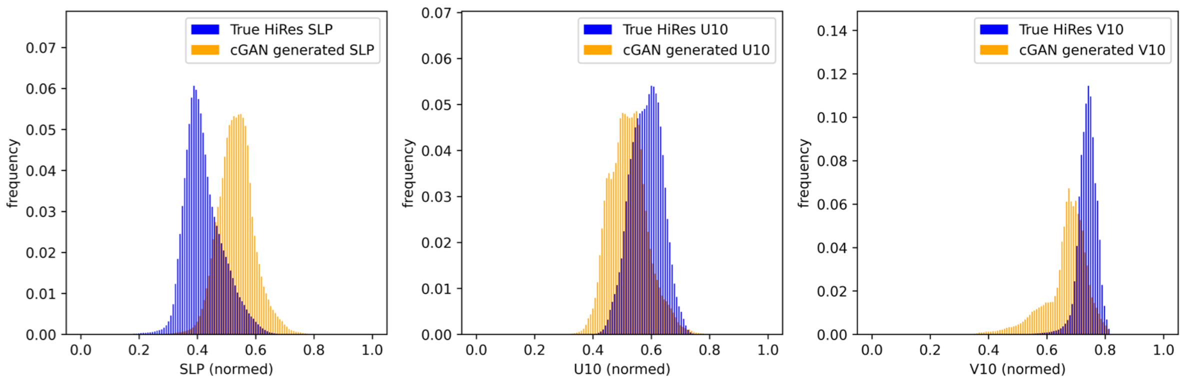


Conclusions and open questions

- cGAN approach does work in general. Note: the network does not have a corresponding ”true” HiRes example for LoRes conditioning examples, so the cGAN is forced to learn the distribution of HiRes data instead of direct mapping “LoRes -> HiRes”;
- Surprisingly, fine-structured field examples (U10, V10) are generated with stronger correspondence with the true examples compared to smooth and low-detailed field (SLP);
- Surprisingly, the distribution of the low-detailed field (SLP) differs more with the target distribution compared to fine-structured fields (U10, V10);
- U10 and V10 are generated with somewhat good distribution correspondence with the target (HiRes) distributions
- There is a room for improvement of the approach presumably within the scope of various levels of abstraction (scales of features) extracted from the VGG sub-network activation maps;
- There is also a room for improvement of the presented approach within the scope of physics-based regularization terms of the loss function.



HiRes examples distribution vs. SRGAN generated examples distribution



THANK YOU!

krinitsky@sail.msk.ru