Development of a daily gridded wind speed observation product using artificial intelligence in Spain

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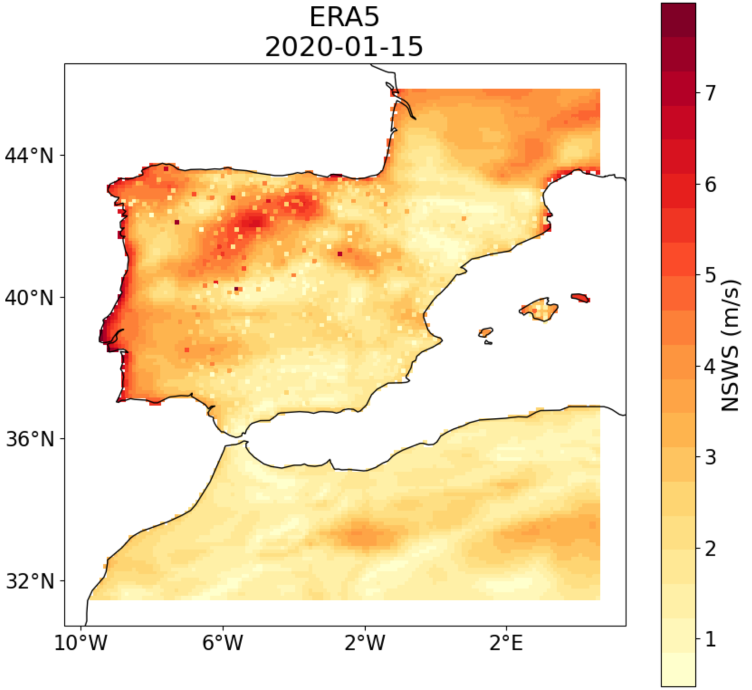
What we are going to see

- ERA 5 and NSWS* observations: disagreements
- Spatial interpolation techniques
- Pre-processing of data and Partial Convolution Neuronal Network model
- We have **first** results!
- Sensitivity to masks (random/constant) and training period
- What we have learnt
- Planned roadmaps

(*)NSWS: Near Surface Wind Speed

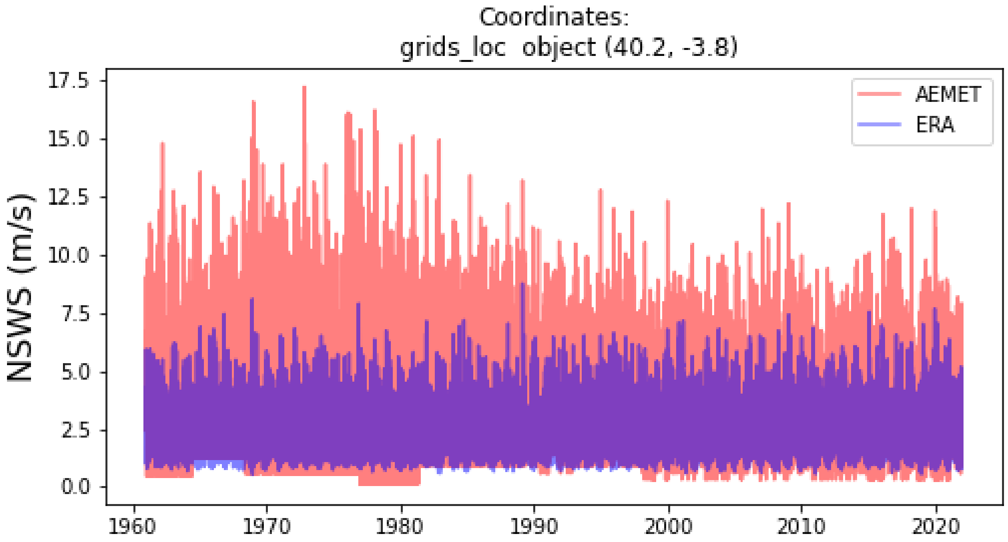
ERA 5 underestimates observed NSWS:



- ERA5 data resolution of 0.1º (~9km) **not sensitive** to **small-scale processes** (such as orography or land cover)

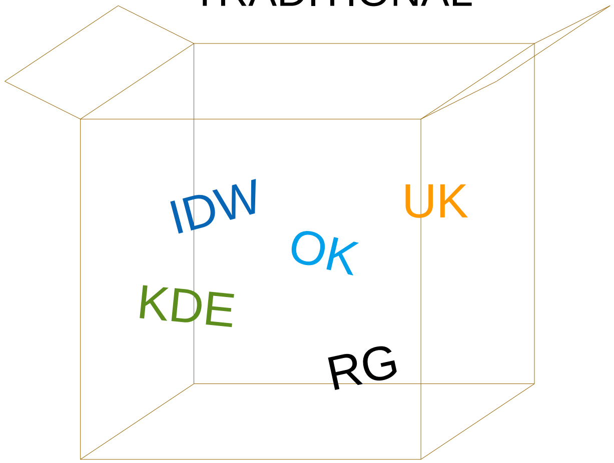
- Near-surface wind speed (NSWS, ~10m above the ground) observations registered by the National Spanish Meteorological Service (AEMET) provide **in situ** data of winds, being able to capture the effect of small-scale processes

Underesimation of ERA5 and NSWS is observed in **spatial** and **temporal** distributions of windspeed



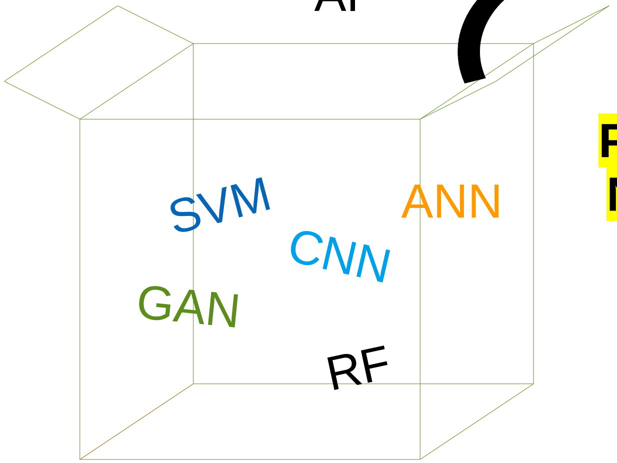
Spatial interpolation techniques

TRADITIONAL



- Statistic and geostatistical methods
- Problems in complex terrain and low density of stations

AI

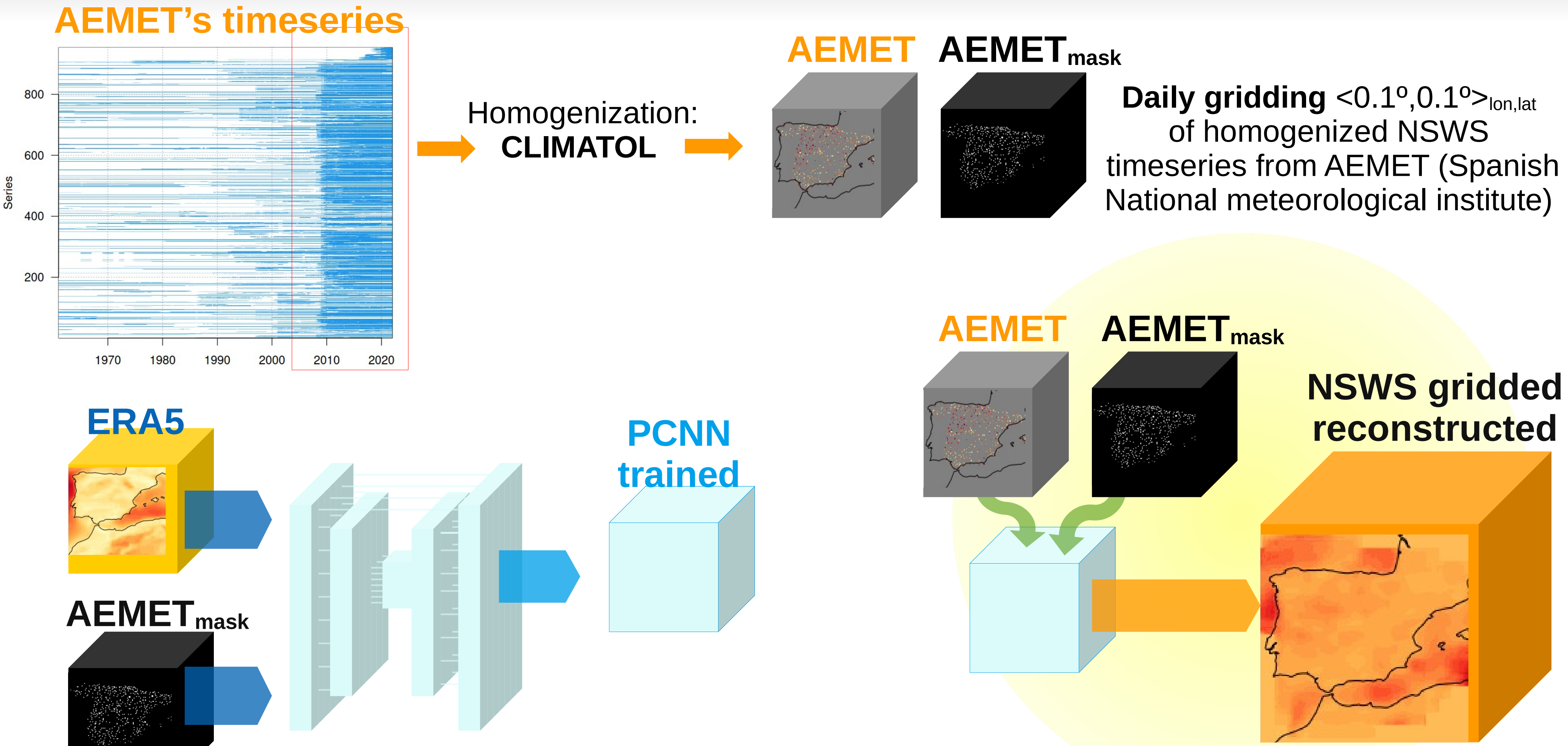


- Complex to implement due to their hyperparameter optimization
- Difficult interpretation of results
- Well-performance in non-linear context

Partial **C**onvolutive **N**euronal **N**etwork

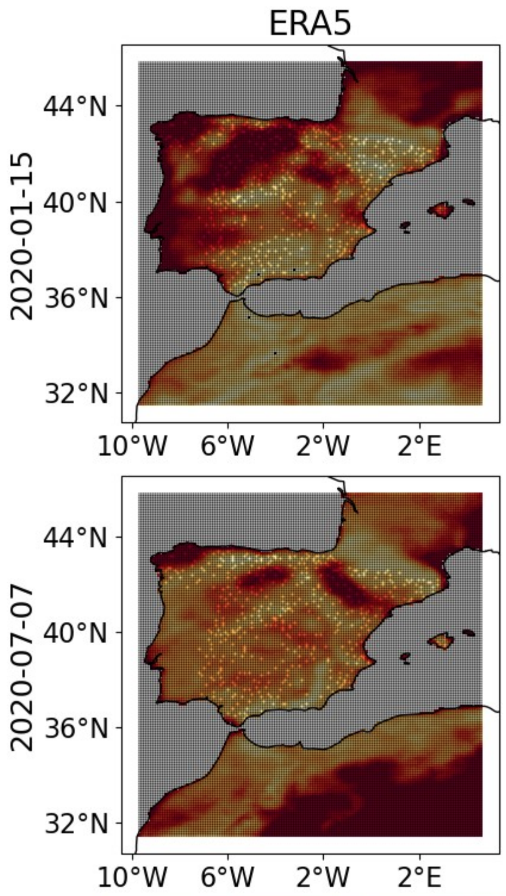
- Developed by Liu et al. (2018) based on a U-Net structure (Ronnenberger et al. 2015)
- Used to **reconstruct missing observational** data:
  → temperature (Kadow et al 2020)
  → remote sensing (Loops et al. 2021)
  → **global wind speed** HadISD's observations **(Zhou et al. 2022)**

Pre-processing of data and Partial Convolutive Neuronal Network (PCNN) model



(*) ERA5 data used here is a combination of ERA5-Land with interpolated NSWS values of $ERA5_{0.25º}$ at oceans grid points

We have **first** results!
→Reconstruction of masked ERA5



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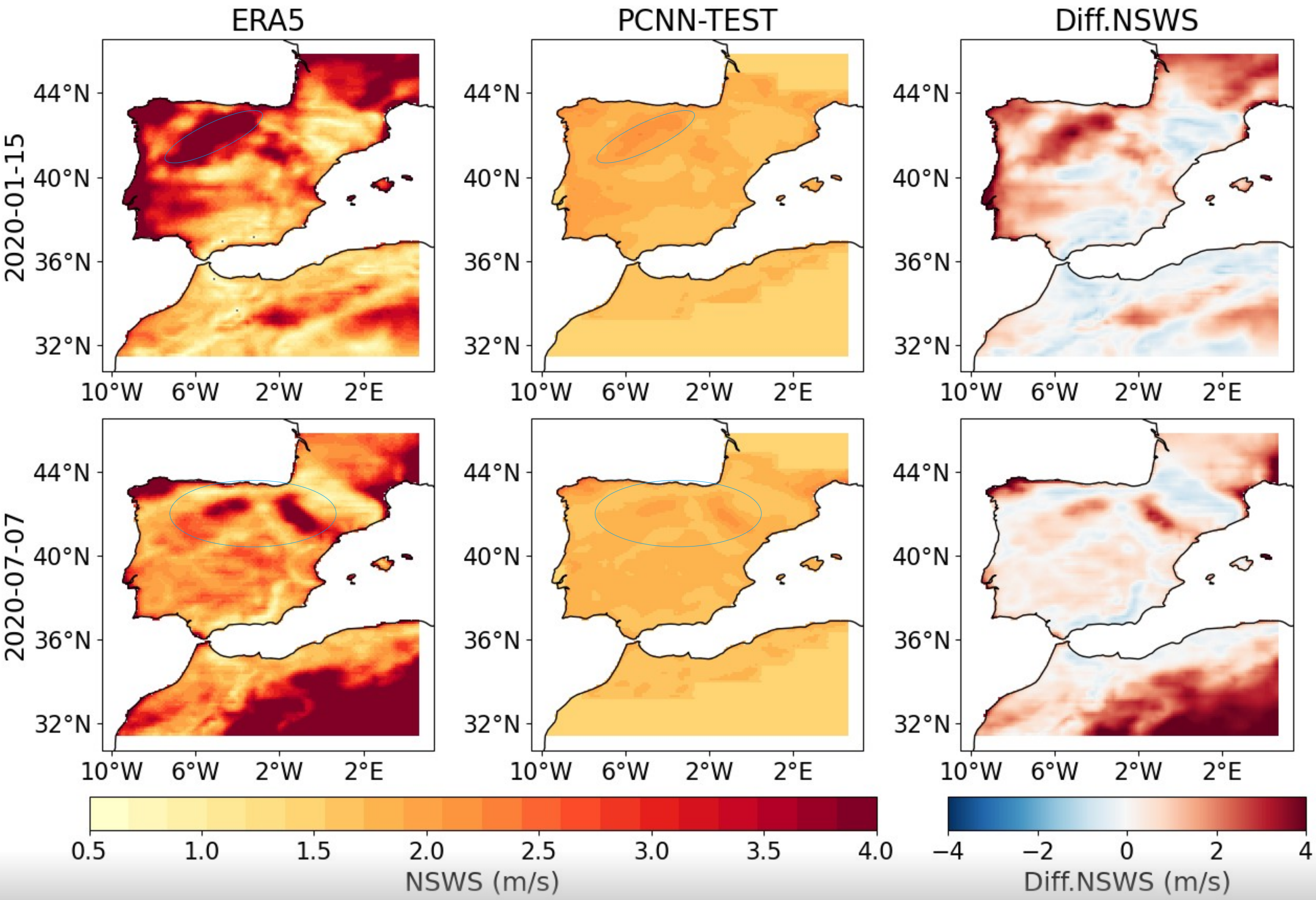
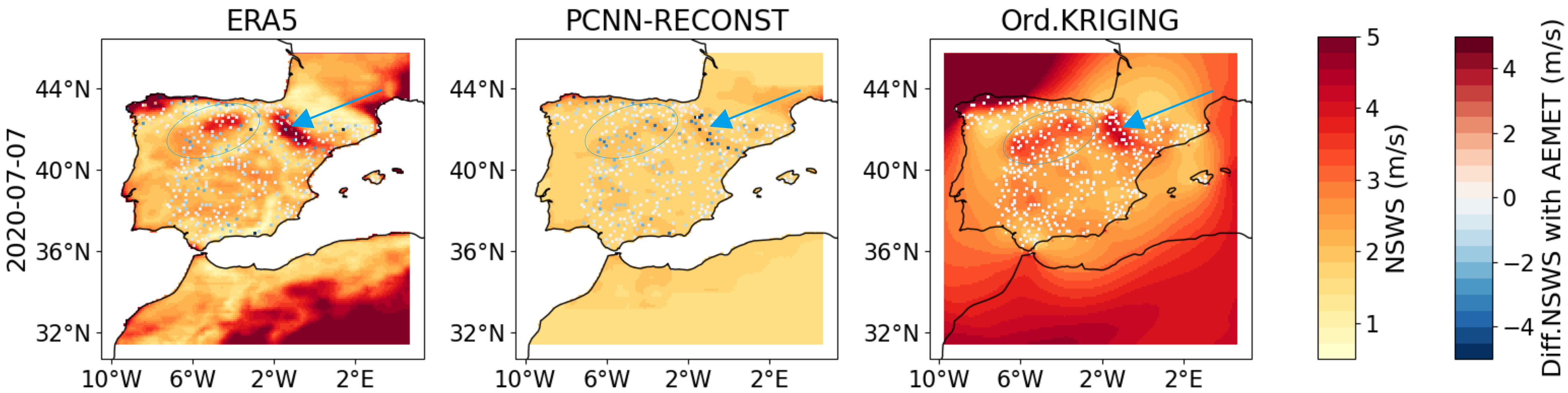
→Reconstruction of masked ERA5



When the PCNN is asked to predict windspeed values in the masked grid points of ERA5 data in the test phase, it is able to reproduce the spatial pattern of the NSWS in ERA5, achieving a RMSE~8.9 m/s

We have **first** results!

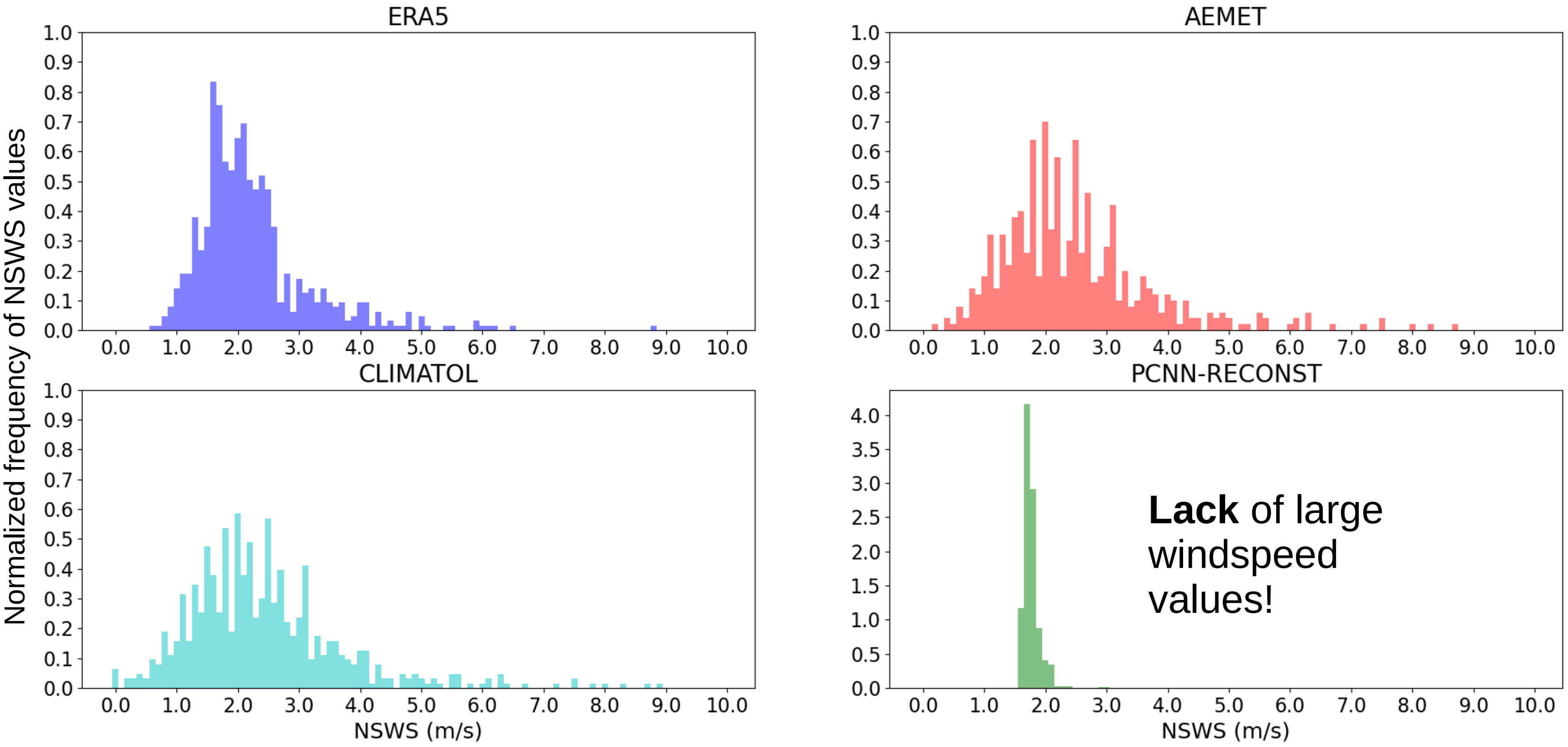
→Comparison of PCNN with O.K.



PCNN's reconstruction **enhances windspeed** in regions where several stations show higher windspeed values, but it **fails to reproduce the extreme values**. In fact, it underestimates the NSWS against observations even more than ERA5.

O.K. is **more sensitive to extreme wind values** registered at individual stations. However, it shows important desviations from the NSWS pattern in ERA5.

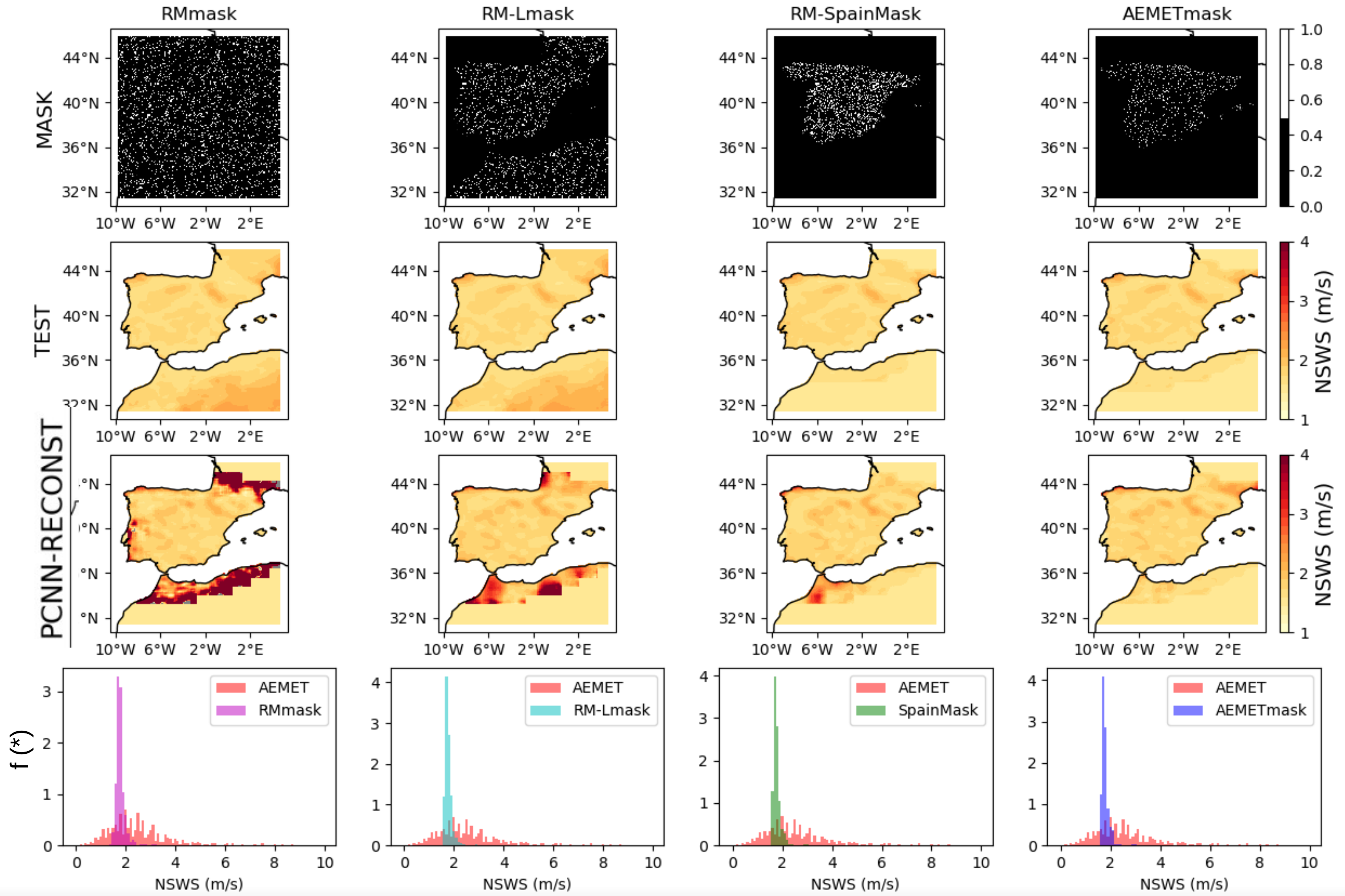
We have **first** results!
→Windspeed histograms



Lack of large windspeed values!

2020-07-07

Will our results improve with different types of masks?

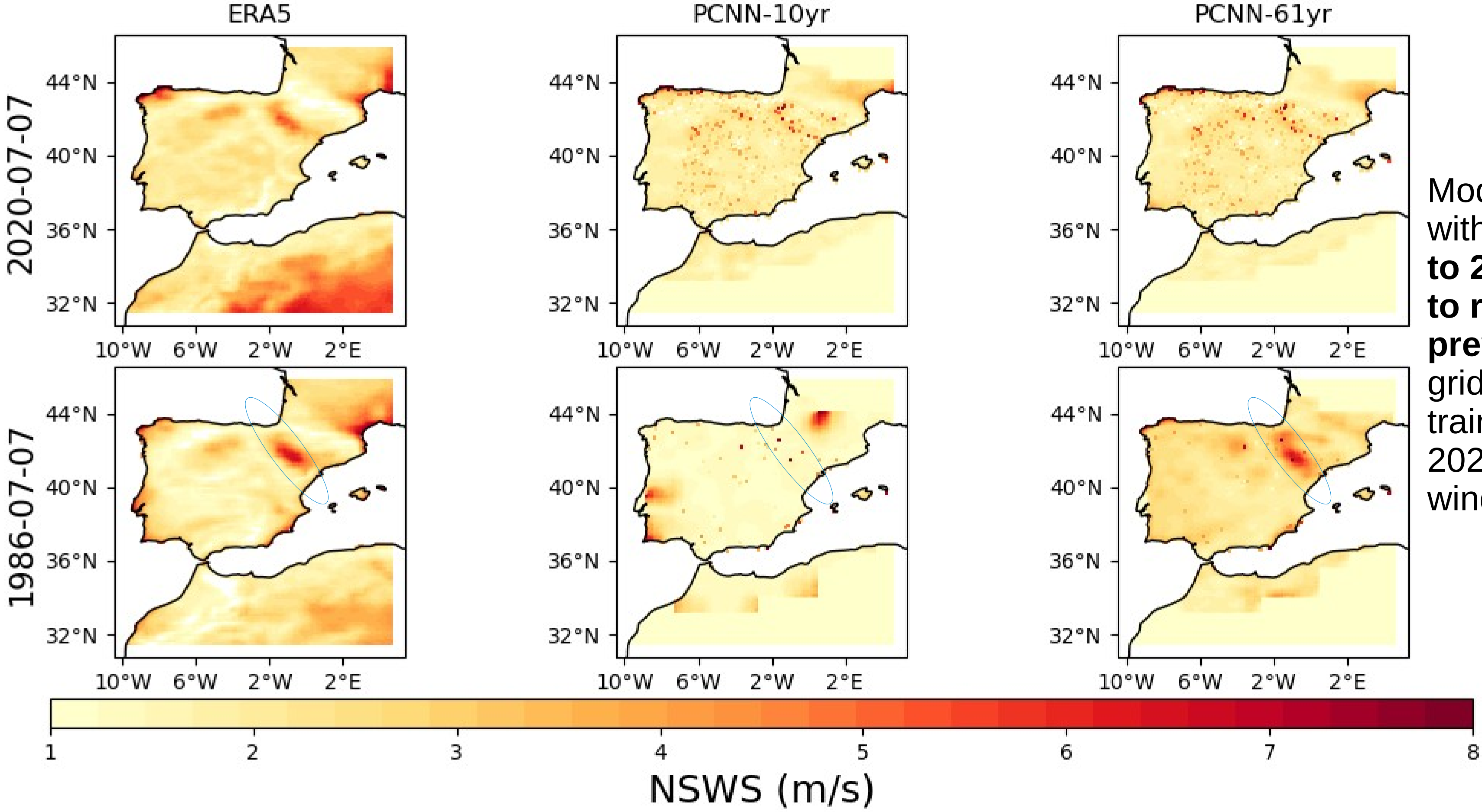


- **Differences in reconstruction of windspeed** in areas, such as North Africa and South of France, between models due to the **difference in valid pixels density** in those regions.

- Both **random mask** (Kadow et al. 2020) and **constant mask** (Zhou et al. 2022) lead to **same results** in Spain, with the same **lack of variance** in their histograms.

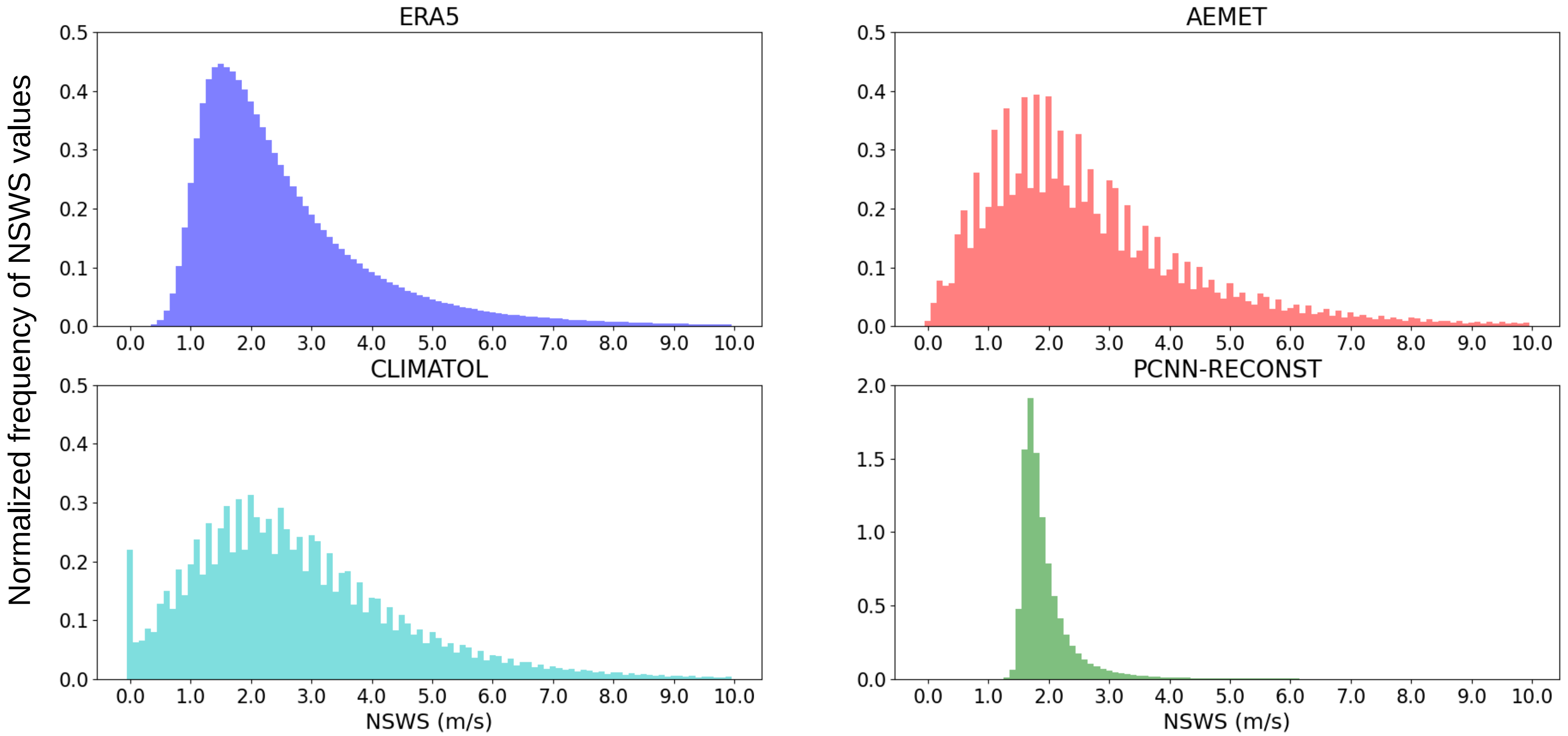
(*) Normalized frequency of NSWS values

How does the model reconstruct the NSWS grid before 2010?



Model trained only with data **from 2010 to 2022 is not able to reconstruct previous NSWS** grids, while PCNN trained from 1961-2021 captures the wind pattern.

Histograms of NSWS values at grid points with observations of ERA5, AEMET, reconstruction proposed by CLIMATOL and PCNN, during 1961-2021



What we have learnt:

1) PCNN has a relative **good performance** reconstructing **masked ERA5** datasets

2) It is able to reconstruct **spatial structures** from AEMET data input

3) Compared with **Ordinary Kriging**, PCNN leads to a **smoother wind field** because its **unrealistic histogram**.

4) PCNN reconstruction **fails** to reproduce **high NSWS values**, not preserving the variance of either ERA5 or AEMET data.

5) The use of **different types of mask**, constant/random, has **no impact** on results.

6) **Reconstruction is improved** when the model has been trained **with a longer time range**.

Planned roadmaps

- To tune in the loss function:

$$\mathcal{L}_{total} = \mathcal{L}_{valid} + 6\mathcal{L}_{hole} + 0.05\mathcal{L}_{perceptual} + 120(\mathcal{L}_{style_{out}} + \mathcal{L}_{style_{comp}}) + 0.1\mathcal{L}_{tv}$$

- To study the effects of perceptual losses against preserving variance loss.
- To compare with other AI models (such as GAN used by Miralles et al. 2022)
- To alter ERA5 training data so it looks like closer to NSWS’s observations.

Thanks for your attention!

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