AI-based Prediction of Short-Term Wind Speed in Spain

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Motivation

- Accurate forecasts of gridded near surface wind speed (NSWS) impact numerous socioeconomic and environmental fields. For instance, wind power is a leading source of renewable energy in several European countries: Denmark (50%), Ireland (40%) and Spain(23%).
- Current limitations:
  - Meteorological Stations: While they provide realistic observations, showing local or extreme events, they are not gridded data.
  - NWP models: They provide gridded data but often fail to capture local or extreme events, particularly in complex orographic areas (e.g., Valencia region). Additionally, they require substantial computational resources, specially at high spatial/temporal resolutions.

Objectives

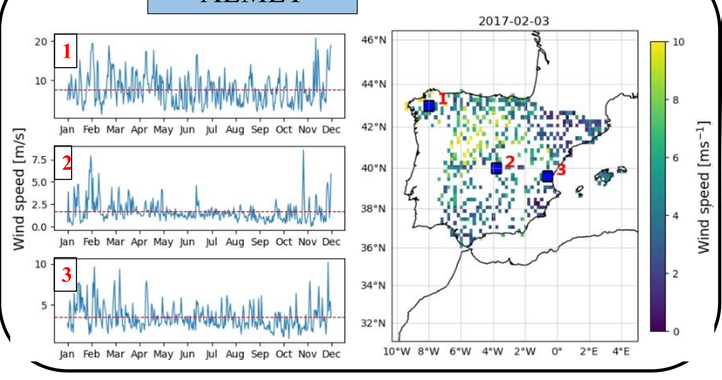
- To develop an AI-based tool for short-term forecasting (<12h, σ=1h) of gridded NSWS data using meteorological observations. The tool utilizes a two-stage deep learning approach, which should be developed and tested:
  - Infilling: To employ a UNet NN for infilling NSWS maps from met. observations.
  - Prediction: To use a Conv-LSTM NN for predicting NSWS maps from infilled maps.
- To build a model capable of generating fast predictions (just a few seconds), combining the strengths of both approaches, reanalysis and observational data.
- The future goal will be to provide a high resolution **Early Warning System** ([km, h] or less, depending on the data used) providing near real-time predictions.

Methodology

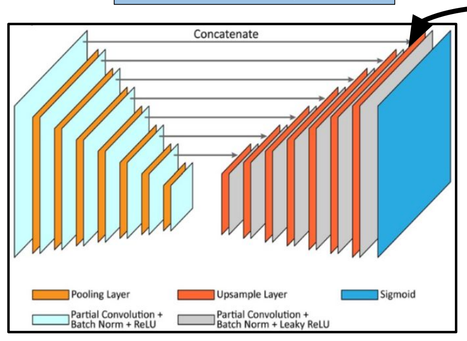
PREPROCESSING

- Quality Control:
  - Remove duplicates
  - Remove outliers
- Spatial consistency (TitanLib).
- ERA5-L grid projection.
- Normalization per coords

AEMET ~1000 obs. estations

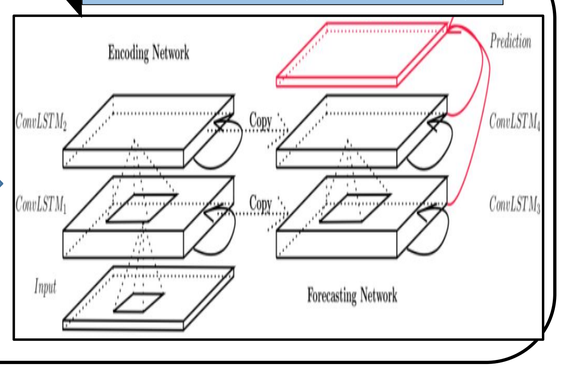


INFILLING (U-Net)



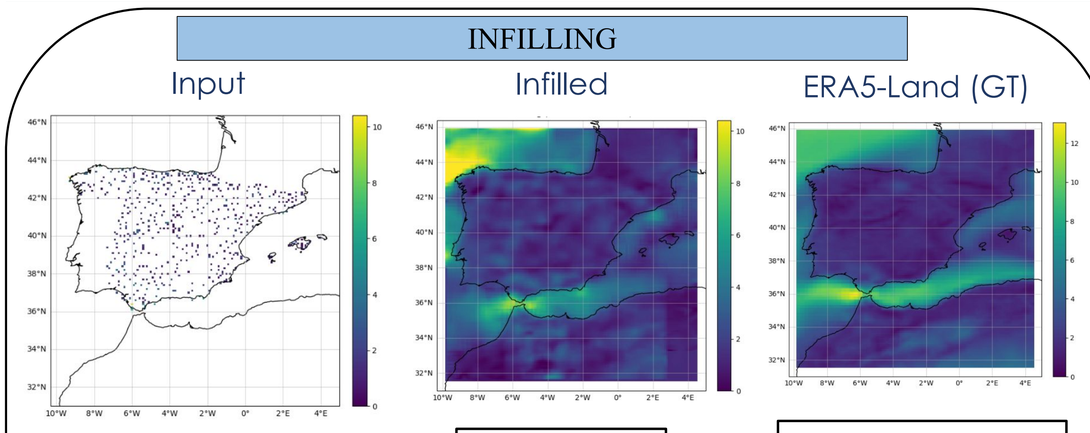
- Trained with masked ERA5-Land
- Inferred with AEMET obs.

PREDICTION (Conv-LSTM)



Results

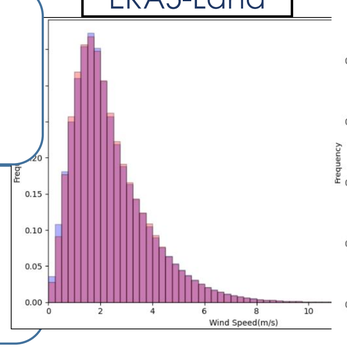
INFILLING



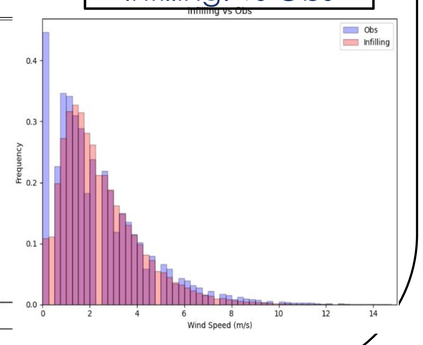
ERA5-Land:
Corr: 0.873 ± 0.073
RMSE: 1,219 ± 0.267 m/s

Met stations:
Corr: 0.773 ± 0.045
RMSE: 1.098± 0.272 m/s

ERA5-Land

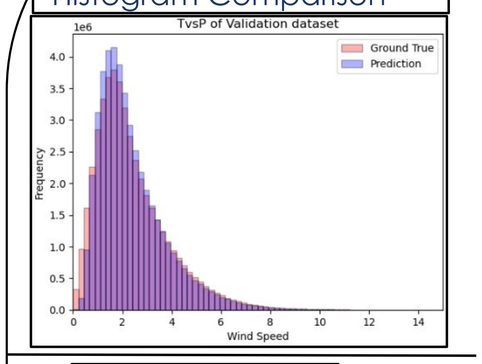


Infilling. vs Obs

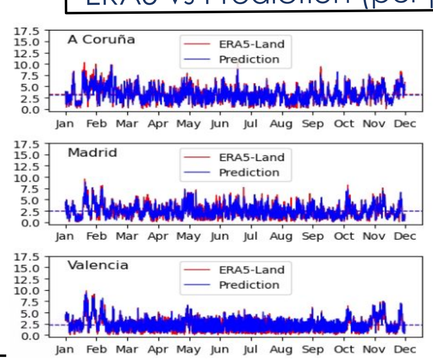


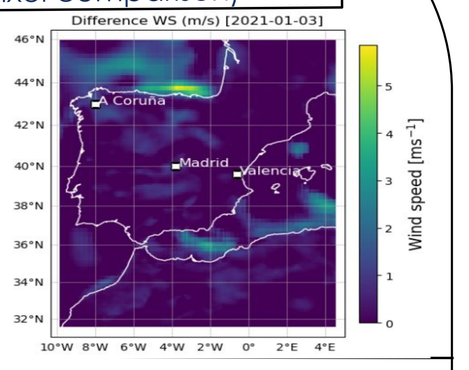
PREDICTION (12h ahead, σ=1h) — ERA5 validation

Histogram Comparison

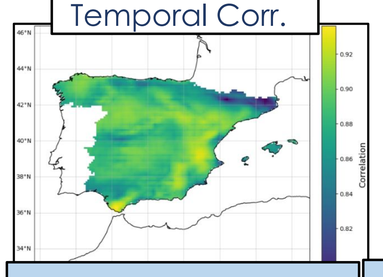


ERA5 vs Prediction (per pixel comparison)



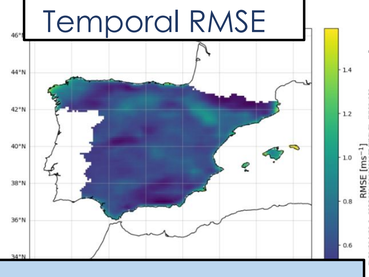


Temporal Corr.



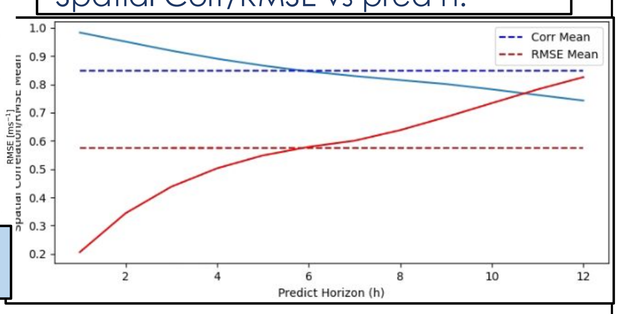
Corr: 0.8771 ± 0.0264

Temporal RMSE

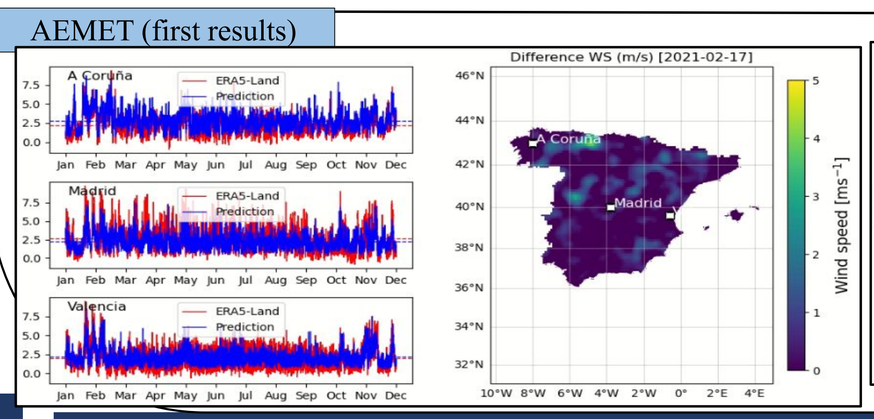


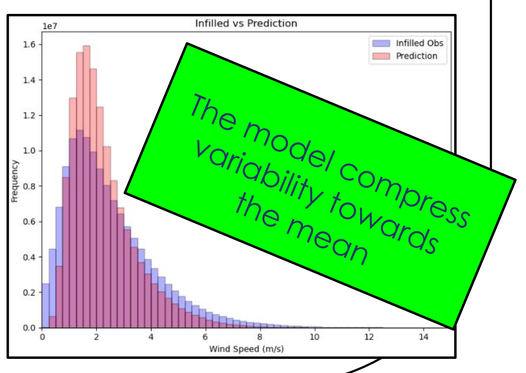
RMSE: 0.573 ± 0.271 m/s

Spatial Corr/RMSE vs pred h.



AEMET (first results)





Conclusions

1. This AI-tool, including both Infilling and Prediction, demonstrates a very good performance with the ERA5-Land validation dataset, showing strong correlations and small errors.
2. The initial tests show the feasibility of using this product as an Early Warning System working in near real-time.
3. The initial tests with AEMET obs are encouraging, showing realistic wind speed maps and capturing the temporal NSWS variation at each location relatively well.

Next steps:

1. A **new training strategy** will be implemented in which the AEMET obs alongside ERA5-Land data are incorporated so that the model outputs are better aligned with AEMET obs, making it more representative of station-measured wind patterns.
2. Test higher spatial res datasets: NEWA (σ~3km) or WRF (σ~1km).
3. Denser met. stations in small regions (AVAMET in Valencia).
4. Test other **NN architectures** like GraphNN and transformers.

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