Proceeding Series of the Brazilian Society of Computational and Applied Mathematics, v. 12, n. 1, 2026.

Trabalho apresentado no XLIV CNMAC, Fundação Getulio Vargas - Rio de Janeiro - RJ, 2025.

Proceeding Series of the Brazilian Society of Computational and Applied Mathematics

AI-Driven Short-Term Wind Speed Forecasting: Enhancing Accuracy and Interpretability

Marcos Martínez-Roig[1] Cesar Azorin-Molina[2]
CIDE (CSIC-UV-GVA), Moncada (Valencia), Spain
Leonardo B. L. Santos[3] José Marengo[4]
CEMADEN, São José dos Campos, SP

The generation of accurate and reliable short-term forecasts (<12 hours) of near-surface ($\sim$ 10m above ground level) wind speed fields, hereinafter called NSWS, are crucial for various socioeconomic and environmental applications. For example, in the face of climate change, accurate $\sim$ 50/100m wind speed predictions can contribute to the decarbonization of the electricity grid by optimizing the wind energy generation. However, monitoring and forecasting NSWS is challenging due to its inherent space-time variability, especially in regions with complex orography such as the Iberian Peninsula in Spain.

Traditional NSWS forecasting methods relies on Numerical Weather Prediction (NWP) models, which require significant computational resources, particularly when high spatial and temporal resolution is required. In addition, these NWP models often yield inaccurate results, especially in regions with complex orography. As a more efficient alternative to this constraint, here we explore the ability to Artificial Intelligence (AI) methods to enhance the efficiency and accuracy of short-term NSWS predictions. We propose the use of two deep learning methods:

1. A U-Net architecture based on Partial Convolutions to generate high-resolution hourly NSWS maps from station-based observations [3].

2. An encoder-decoder architecture based on mixed convolutional and recurrent (ConvLSTM) layers to predict short-term NSWS maps using the generated infilled data as input [4].

This real-time AI-based product, designed as an early warning system, generate high-resolution (3/9-km) short-term (12 h; 1-h resolution) NSWS forecasts in near real-time (seconds).

Measurements from meteorological station networks provide accurate and site-specific observations that capture local wind effects but have limited spatial coverage, being sparse and often absent in mountainous and remote areas. In contrast, reanalysis and simulation products offer complete spatial coverage at low resolution but fail to accurately reproduce local wind conditions. Our AI-based tool combines the strengths of both approaches using both observational and simulation data, achieving high correlation and low prediction errors. The inference process, however, relies solely on station-based data, making it a cost-effective alternative to NWP models. The observational data is provided by the Spanish Meteorological Agency (AEMET) [1], while the simulation data comes from reanalysis products like ERA5-Land (9 km) [2].

[1]marcos.martinez.roig@csic.es
[2]cesar.azorin@csic.es
[3]leonardo.santos@cemaden.gov.br
[4]jose.marengo@cemaden.gov.br

Beyond performance evaluation, we apply well-established interpretability techniques to analyze the model's decision-making process:

On one hand, Feature Importance methods were applied to assess the relevance of each input time step. Feature Permutation and Feature Ablation, which modify or remove features respectivelyto measure performance impact, showed an expected exponential decay in importance over time. However, both techniques highlight that time steps around 7 hours in the past are particularly relevant for accurate forecasting, emphasizing the importance of long-term information.

On the other hand, Pixel Attribution techniques were applied to identify key spatial regions in the input wind speed maps. Different methods were applied, all based on gradient calculations, highlighted different areas of interest. While Saliency Maps and Integrated Gradients focus on direct sensitivity to input changes, Guided Backpropagation enhances fine details by suppressing negative gradients. Grad-CAM provides a coarse localization of important regions by visualizing activations layers and Guided Grad-CAM combines both approaches, offering a sharper and more interpretable attribution. Despite differences, all methods consistently emphasized regions where unexpected wind patterns or extreme events occur, revealing the model's primary focus.

These interpretability analyses enhance trust in AI-driven forecasts while guiding improvements in model architecture and input selection. We tested this approach on the Iberian Peninsula, but it can be adapted to other regions, such as Brazil, by retraining the neural networks with region-specific data. This scalable AI-based method improves short-term NSWS forecasting for AEMET and other meteorological services, demonstrating AI's potential to enhance both forecast precision and operational efficiency in meteorology.

Acknowledgements

We thank AEMET for the observed wind speed data. This research was funded by: CNPq 46053/2023-6, MITECO and NextGenerationEU (Regulation EU 2020/2094), through CSIC'sPTI-Clima; the MICIU - NextGenerationEU (PRTR-C17.I1) and GVA - THINKINAZUL/2021/018; the GVA-CIPROM/2023/38; and the CSIC - LINCG24042.

Referências

[1] Agencia Estatal de Meteorología (AEMET). **AEMET - Agencia Estatal de Meteorología**. Accessed: 2025-03-11. 2025.

[2] Copernicus Climate Change Service (C3S). **ERA5-Land Reanalysis**. Accessed: 2025-03-11. 2025.

[3] G. Liu, F. A. Reda, K. J. Shih, T. Wang, A. Tao e B. Catanzaro. "Image Inpainting for Irregular Holes Using Partial Convolutions". Em: **European Conference on Computer Vision** (2018). DOI: 10.1007/978-3-030-11009-3.

[4] X. Shi, Z. Chen, H. Wang, D. Yeung, W. Wong e W. Woo. "Convolutional LSTM Network: A Machine Learning Approach for Precipitation Nowcasting". Em: **CoRR** abs/1506.04214 (2015). arXiv: 1506.04214.