Adversarial image-to-image model to obtain highly detailed wind fields from mesoscale simulations in mountainous and urban areas

XIII JORNADA DE JÓVENES INVESTIGADORES/AS DEL I3A
June 2024

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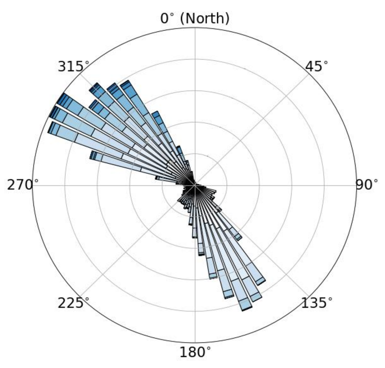
ABSTRACT The characterisation of wind is of great interest in multiple disciplines such as city planning, pedestrian comfort and energy generation. We propose a conditional Generative Adversarial Network (cGAN), based on the Pix2Pix model [1], that can generate detailed local wind fields in areas with complex orography or an urban layout, which are comparable in level of detail to those from Computational Fluid Dynamics (CFD) simulations, from coarser Numerical Weather Prediction (NWP) data.

MESOSCALE SIMULATIONS Numerical Weather Prediction (NWP). Coarse and hence cheaper. Resolutions of ~1 km. Hourly data for a whole year (8760 events).

EVENT SELECTION Too expensive to simulate all events in CFD. Selection of the characterizing events through binning a wind rose (more details in [2]).



CFD SIMULATIONS Highly detailed and more expensive. Resolutions of ~m. *SIMPLE* algorithm, *isothermal* flow, *Reynolds-averaged Navier-Stokes* equations of *continuity* and *momentum* and *Spalart-Allmaras* for turbulence.

Several hours or days of CPU time per simulation.

cGAN MODEL conditional Generative Adversarial Network is proposed to generate highly detailed wind fields based in the image-to-image Pix2Pix model [1]. *Inputs* are the mesoscale simulations and *targets* the CFD simulations.

Few hours of GPU time for training. Inference time of seconds.

SIMULATION DATA AS IMAGES We use a image-to-image model. To reconcile the data structure of the numerical simulations and the expected data of the deep-learning model, we arrange simulation data as square matrices that can be understood as images.

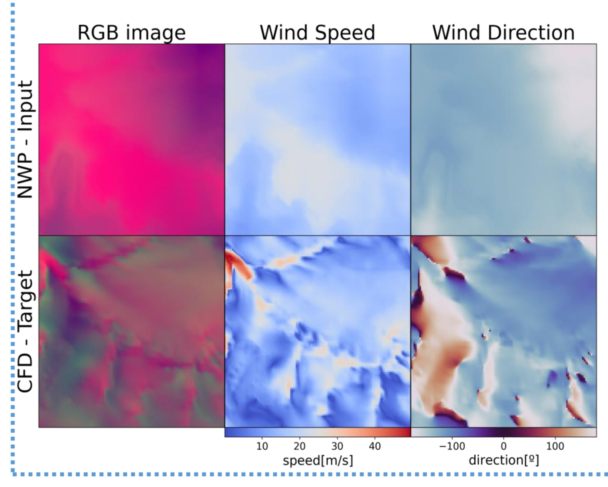


Figure 1. Model inputs and targets. *First row*: inputs (NWP); *second row*: targets (CFD). *First column*: RGB image representation (wind components as channels); *second column*: wind speed; *third column*: wind direction.

THE PYRENEES (SIERRA DE LA PARTACUA)

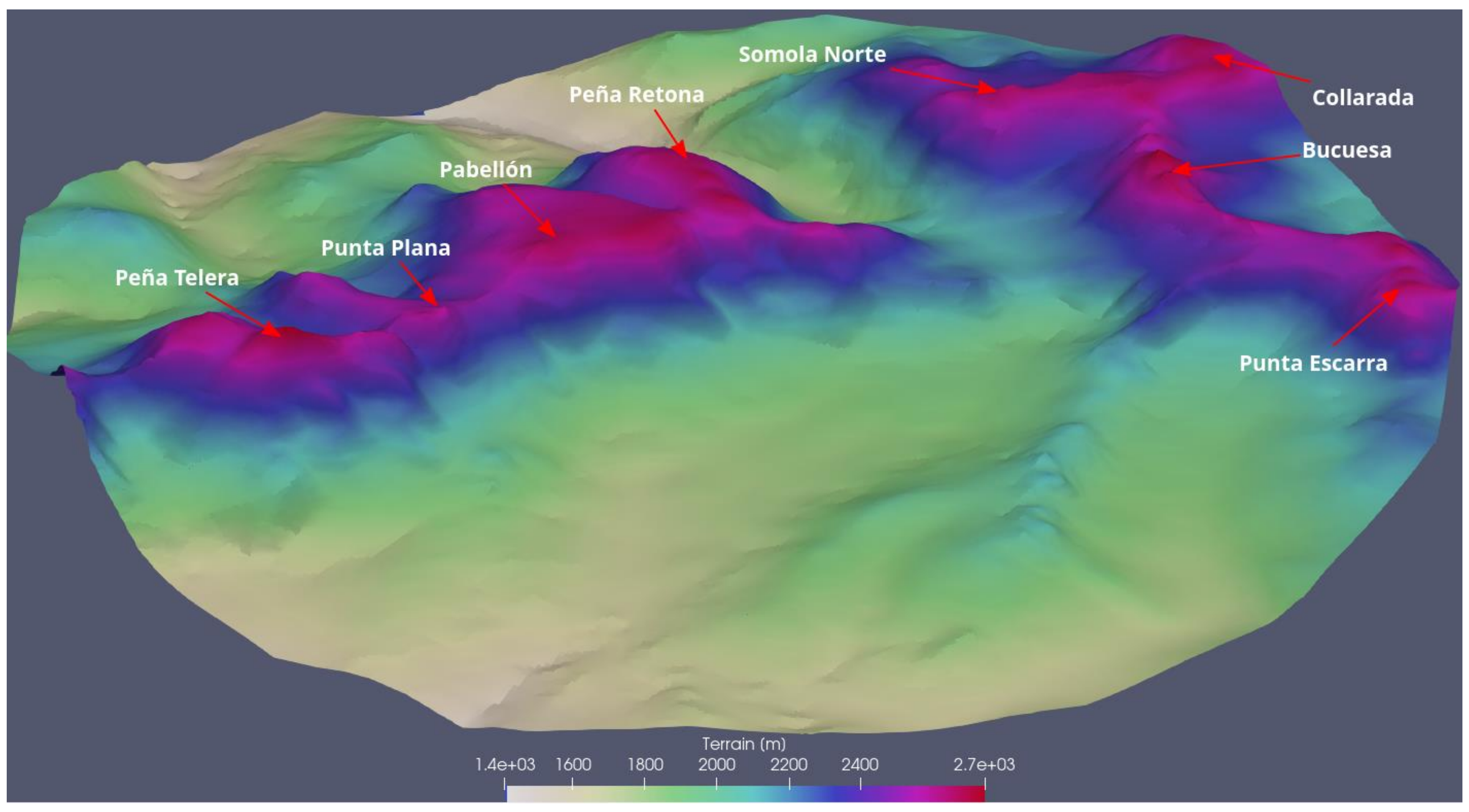


Figure 2. CFD mesh rendering of the Pyrenees (sierra de la Partacua) test case. It has 250k cells, with a resolution up to ~12m.

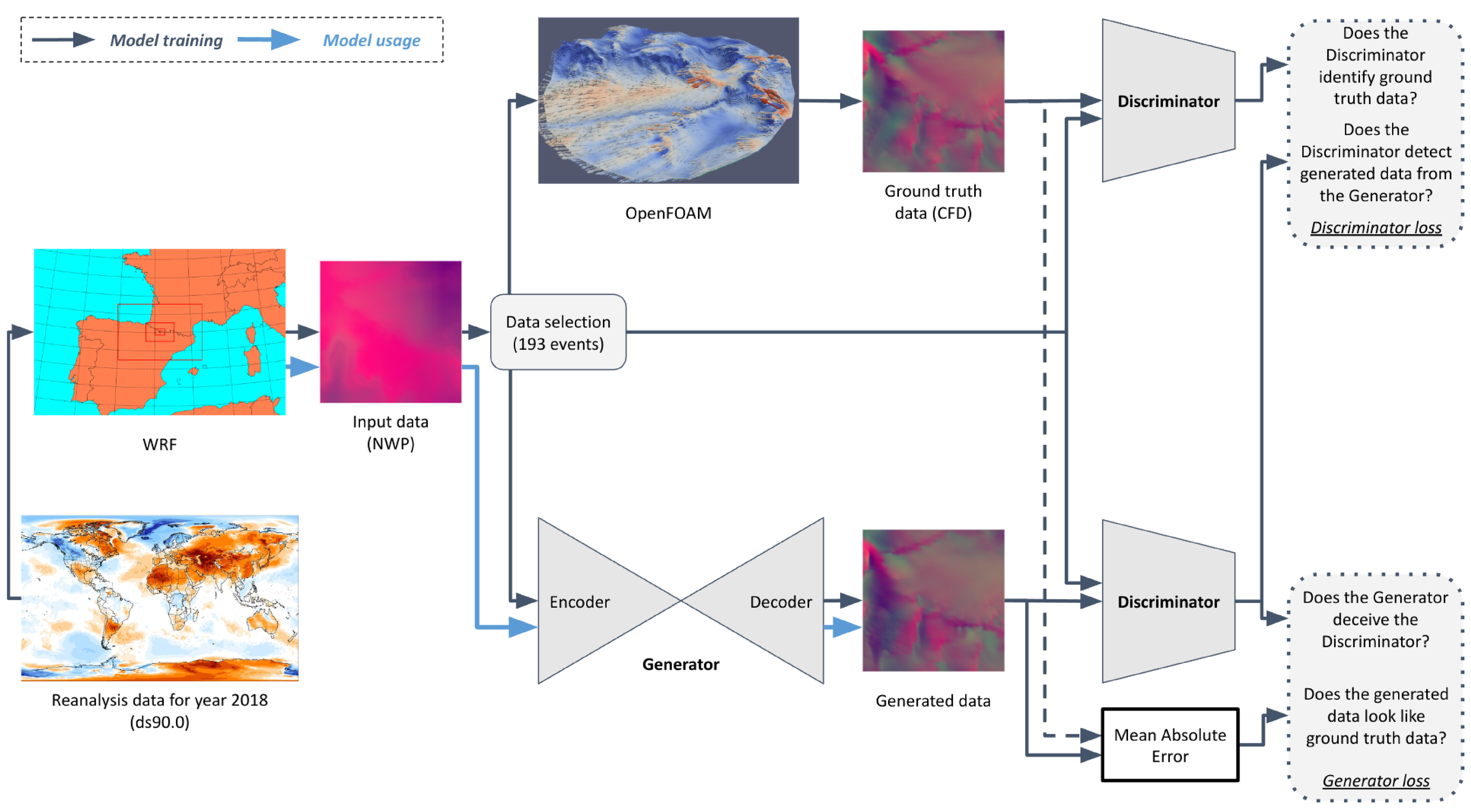
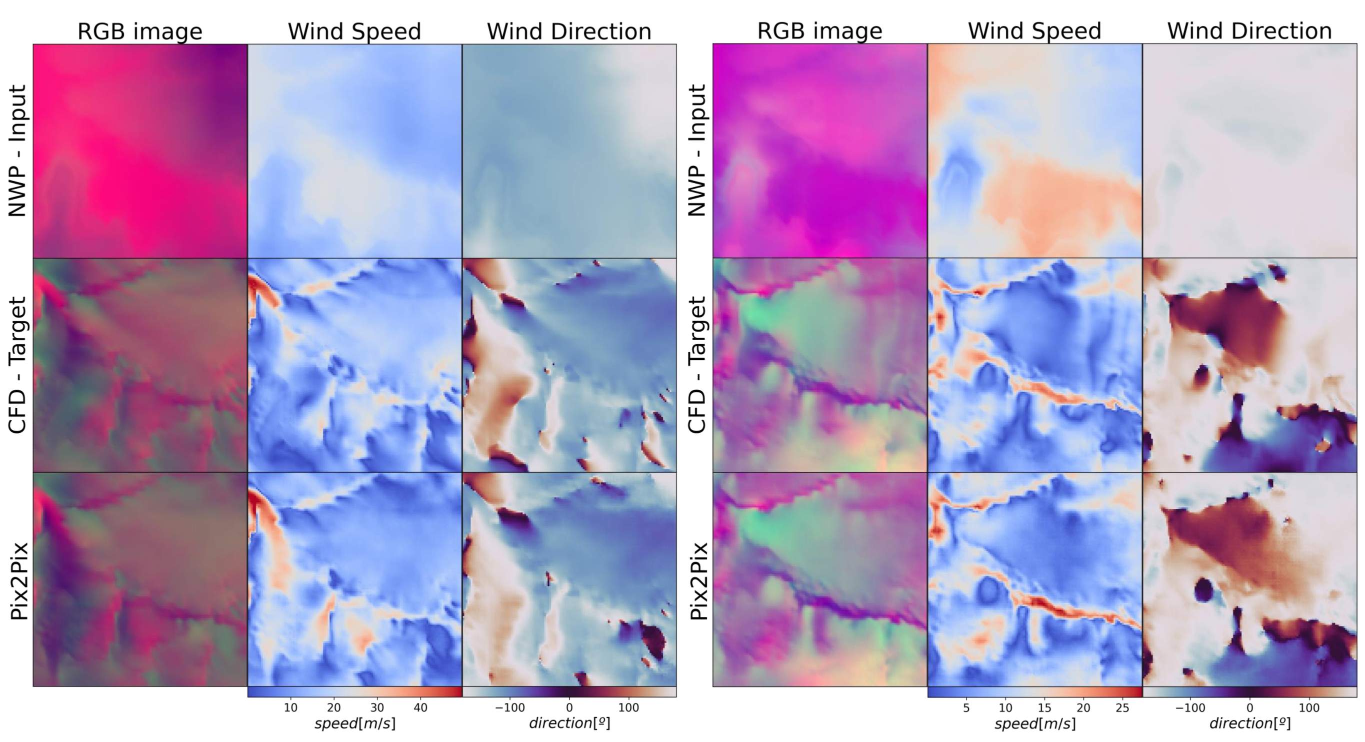


Figure 3. General schema and data workflow for the Pyrenees case. Explicit interactions between the Generator and Discriminator of the cGAN.



Figures 4 & 5. Event examples for the results obtained with the cGAN model for the complex terrain case. *First row*: input image (NWP); *second row*: target image (CFD); *third row*: predictions. *First column*: RGB representation; *second column*: wind speed; *third column*: wind direction.

RESULTS Mean Absolute Error of 1,36 m/s and 18,7º compared to CFD.

ZARAGOZA (ACTUR DISTRICT)

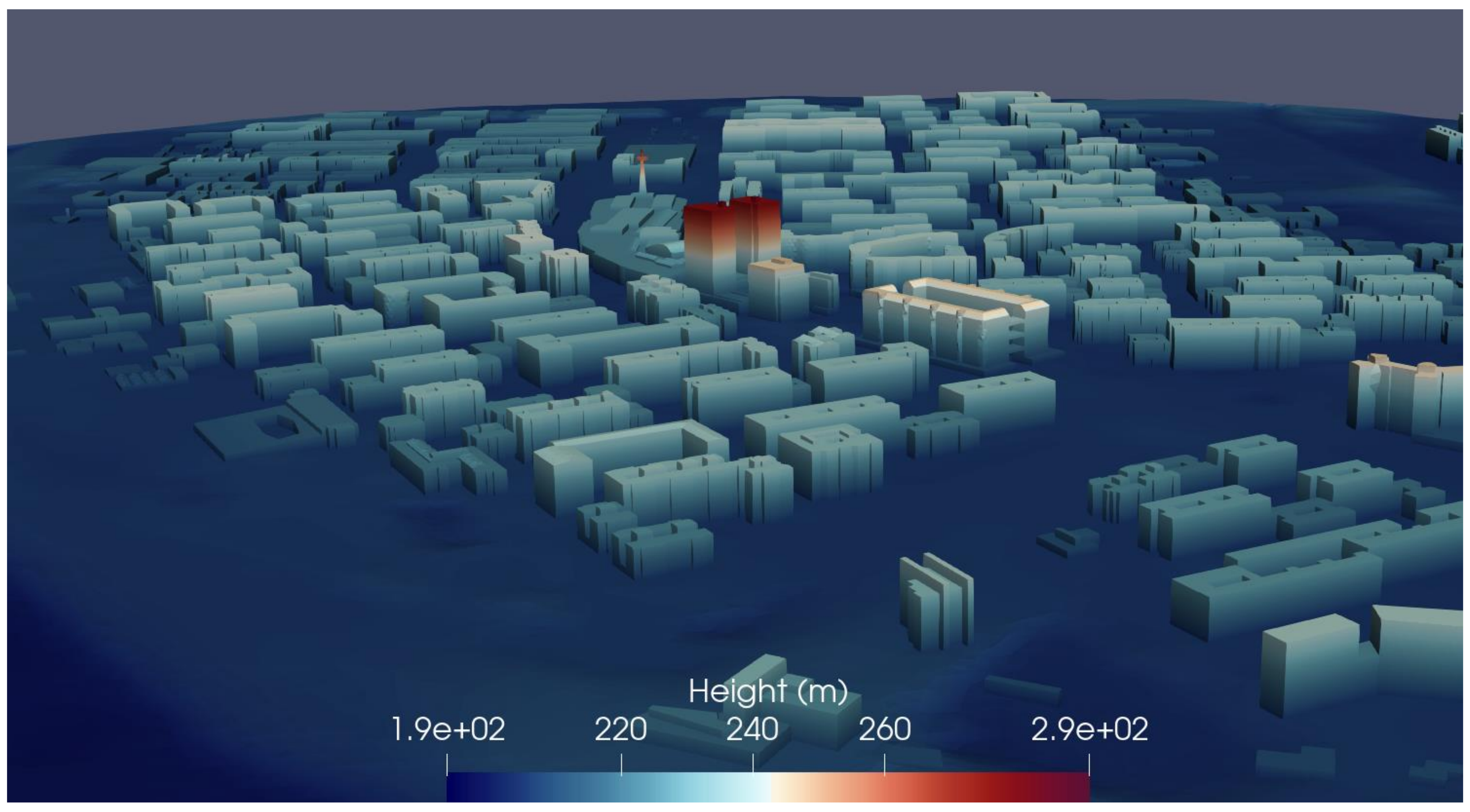


Figure 6. CFD mesh rendering of the Zaragoza (Actur district) test case. It has 2M cells, with a resolution up to ~2m.

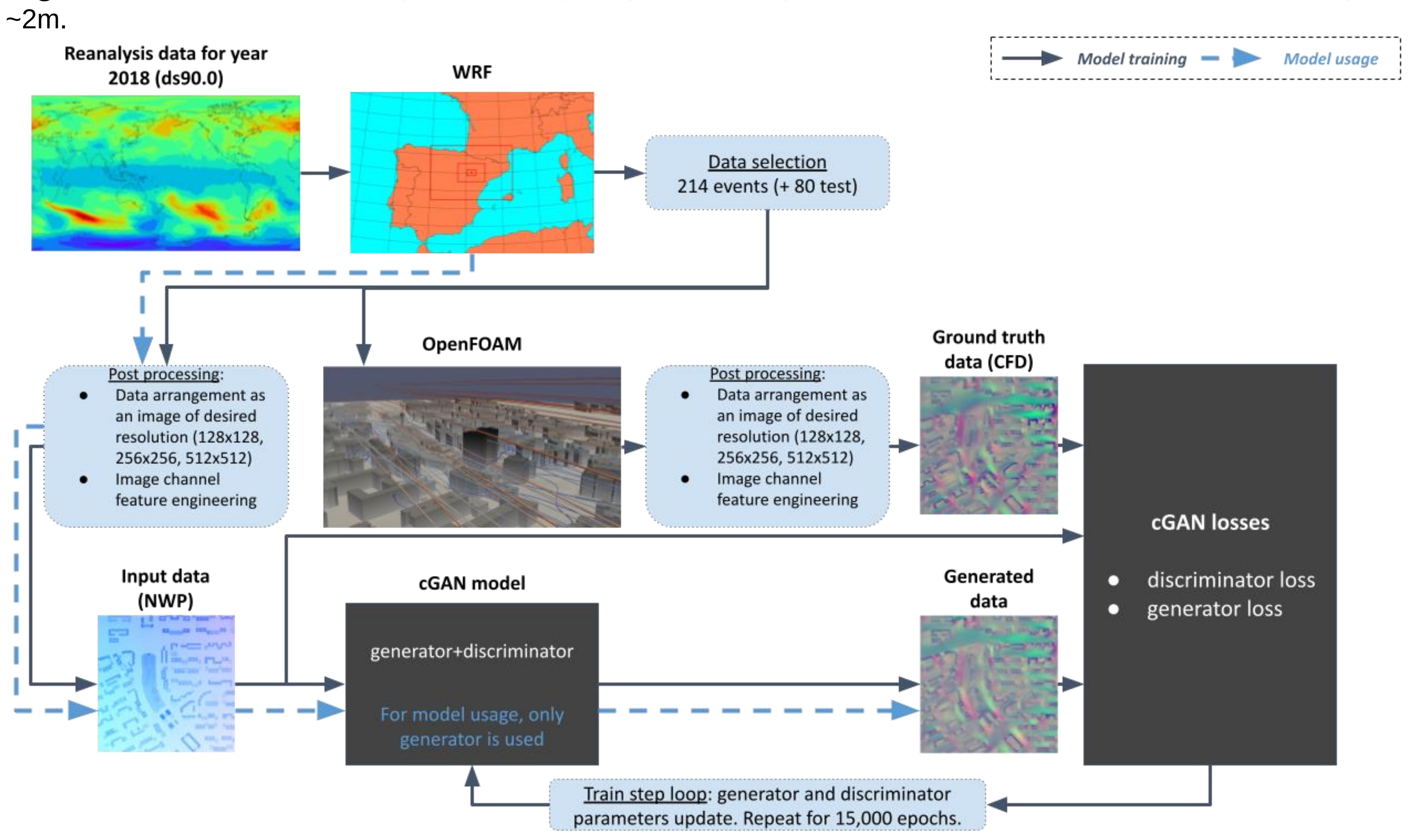
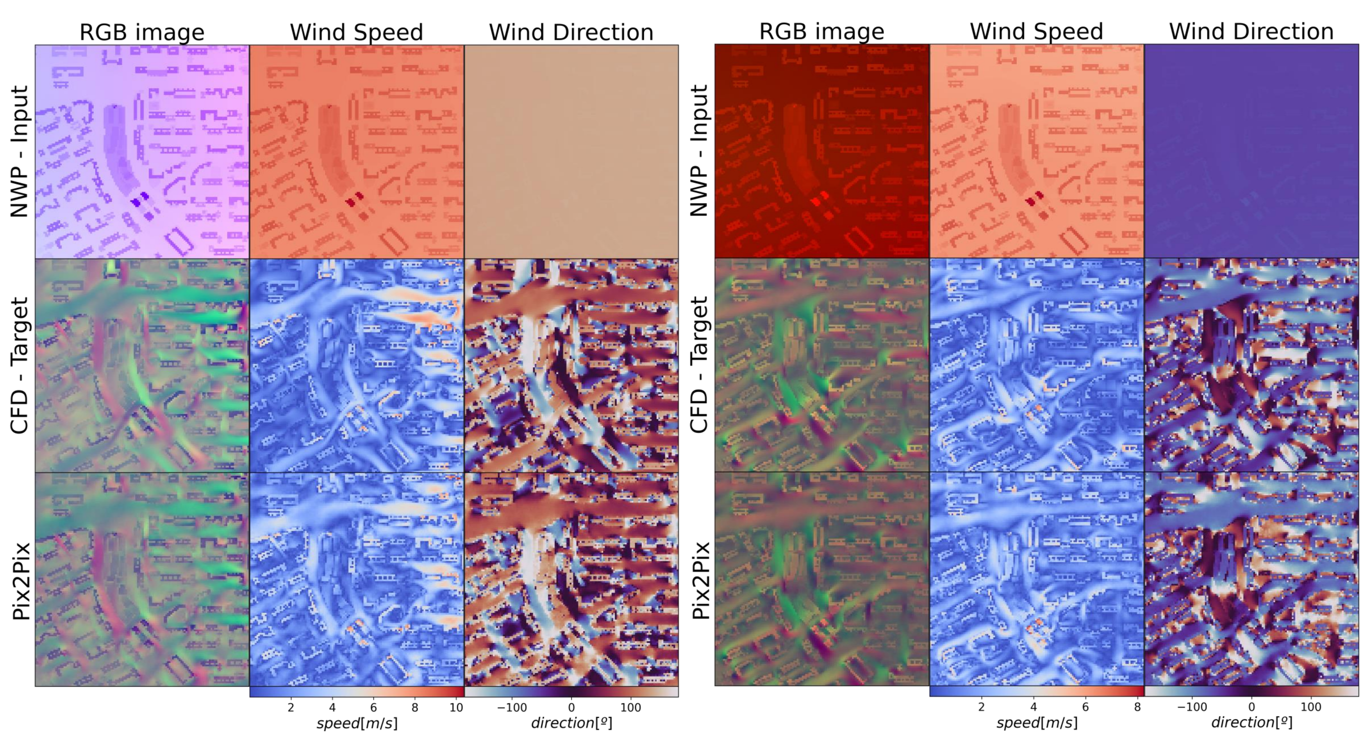


Figure 7. General schema and data workflow for the Zaragoza case. Special attention in the post processing step, where different image resolution can be obtained or image channel feature cam be articulated.



Figures 8 & 9. Event examples for the results obtained with the cGAN model for the urban area case. *First row*: input image (NWP); *second row*: target image (CFD); *third row*: predictions. *First column*: RGB representation; *second column*: wind speed; *third column*: wind direction.

RESULTS Mean Absolute Error of 0,35 m/s and 27º compared to CFD.

CONCLUSIONS The proposed Machine-Learning model achieved very good agreement with the highly detailed CFD data capturing the main features of the flow in both the mountainous and the urban region. A substantial computational speed-up is obtained when comparing with traditional CFD simulations.

FUNDING This work was partly funded by Grant DIN2019-010452 from MCIN/AEI/10.13039/501100011033, Spain; by the Departamento de Ciencia, Universidad y Sociedad del Conocimiento del Gobierno de Aragón, Spain, as Group T32_23R Tecnologías Fluidodinámicas; and by Project TED2021-131861B-I00, financed by MCIN/AEI/10.13039/501100011033 (Spain) and by the European Union "Next-GenerationEU"/PRTR.

References

[1] P. Isola, J. -Y. Zhu, T. Zhou and A. A. Efros, "Image-to-Image Translation with Conditional Adversarial Networks," 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA, 2017, pp. 5967-5976, doi: https://doi.org/10.1109/CVPR.2017.632
[2] Milla-Val, J., Montañés, C. & Fueyo, N. Economical microscale predictions of wind over complex terrain from mesoscale simulations using machine learning. Model. Earth Syst. Environ. 10, 1407–1421 (2024). https://doi.org/10.1007/s40808-023-01851-x