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

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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.

Numerical simulations

The aim of this study is to obtain detailed velocity data from coarser, and hence relatively inexpensive, meteorological data. Mesoscale simulations, using a NWP model, are used as boundary conditions for detailed wind field CFD simulations that are used to train the model.

Two scenarios are considered, a mountainous region in the Pyrenees and a built area in Zaragoza (Spain). In both cases, OpenFOAM v6 is used for the CFD, using the SIMPLE algorithm for pressure-velocity coupling, considering isothermal flow, solving the Reynolds-averaged Navier-Stokes equations of continuity and momentum and employing the Spalart-Allmaras model of turbulence. The mesh for the Pyrenees has about 250 thousand cells (Fig.1) and the one for Zaragoza about 2 million cells (Fig.2).

Image-to-image model

Inputs to and outputs from the AI model are images; to reconcile the data structures, simulation results are rearranged into a square 128×128 image format. These pseudo-images have two channels, which are the horizontal wind components u and v.

The proposed model is a cGAN, based on Pix2Pix [1] which is an image-to-image model. The model has two main components: a generator and a discriminator. The generator produces images that look as realistic as possible. The discriminator determines whether a given image is real (from the CFD training set) or fake (generated by the generator). These two elements are trained in tandem, using NWP results as inputs and CFD results as targets.

Training data selection

CFD simulations are more expensive than NWP, so only a few representative events are simulated in detail to train the AI model; those are selected by categorising the NWP data in bins by wind speed and direction at a central location. Events are chosen from the most populated bins, excluding adjacent bins. For training, 193 events are selected for the Pyrenees case and 214 for Zaragoza; for testing, 80 additional random events are simulated using CFD. See [2] for more details of the process.

Results

Two case studies are carried out: Sierra de la Partacua in the Pyrenees and the Actur neighbourhood in Zaragoza. A wind speed MAE of 1,36 m/s and 18,7º for wind direction is achieved for the Pyrenees (excluding points with wind speeds below 2 m/s), while for Zaragoza are 0,42 m/s and 33,8º. Results in Fig.3 and Fig.4 shows that the model is capable of successfully capturing the general flow trend and several wakes of the corresponding CFD true data.

Moreover, for the Zaragoza case, a feature engineering in the channels of the images achieve a further improvement in wind direction prediction of 7º; u and v are transformed into V, $\sin\theta$ and $\cos\theta$ where V is the wind speed and θ wind direction.

For the Pyrenees scenario, each CFD simulation takes 40 min, while the inference time for the AI model is less than 1 s. In the case of Zaragoza, this speed-up is greater, as each CFD simulation takes 8 h with the same inference time.

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 mountainous and urban regions. A substantial computational speed-up is obtained when comparing with traditional CFD simulations.

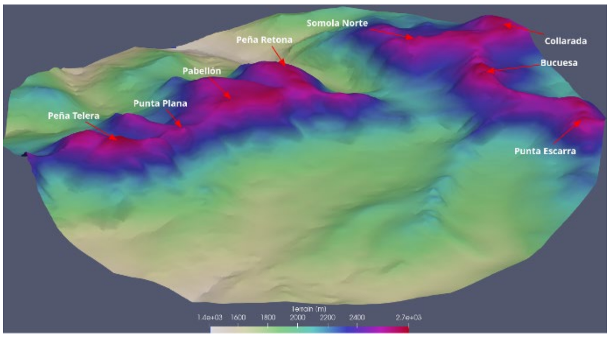

Figure 1. CFD mesh for the Pyrenees case.

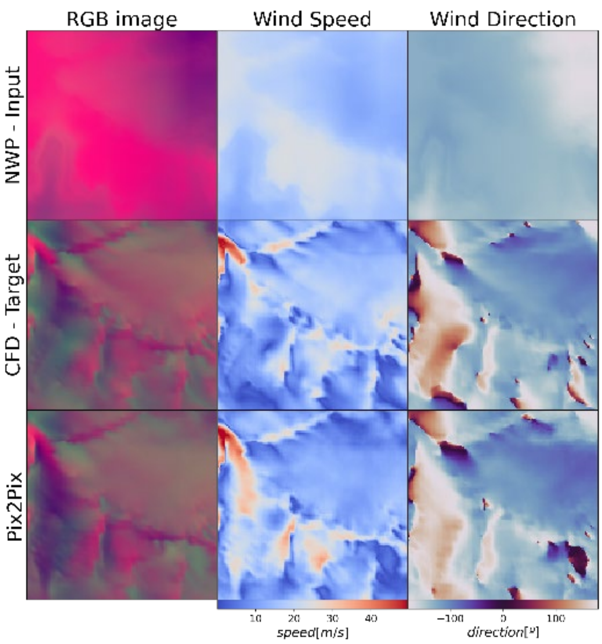

Figure 3. Results for 2018-01-01 at 03:00 in the Pyrenees.

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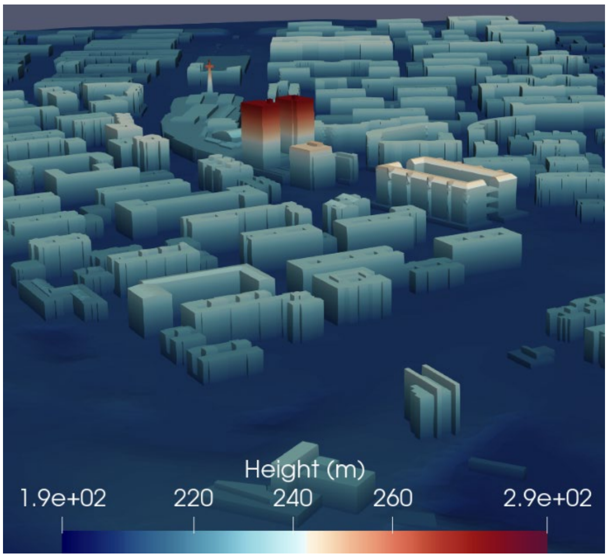

Figure 2. CFD mesh for the Zaragoza case.

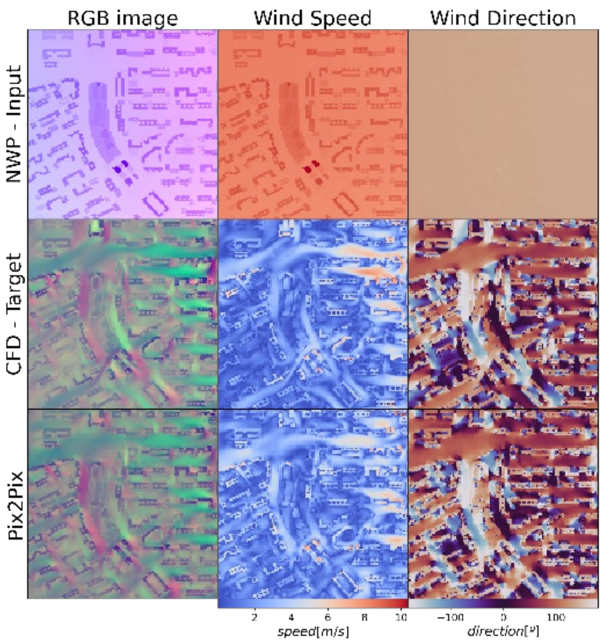

Figure 4. Results for 2018-05-06 at 19:00 in Zaragoza.