



AVIATION TWIN TRANSITION CLUSTER

A EUROPEAN INITIATIVE FOR A SUSTAINABLE FUTURE

RefMap Clustering Event 2025

Advancing Sustainable Aviation & Urban Air Mobility

How does the turbulence affect the drone trajectory?

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Our partners



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Background and motivation

The overall objective of REFMAP is produce robust **real-time artificial intelligence** (AI) model that uses Deep Reinforcement Learning for the optimisation of environmental performance in multi-scale air traffic management (ATM);

The rising awareness of urban environmental issues in the last few decades motivated the increased interest in the analysis of the turbulent flow structures and statistics in urban areas in order to find the best compromise between trajectory and safety.

1. Study the flow field and analyse the most hazardour regions around buildings
2. Use this data to train and test the DRL algorithm



Turbulence around two obstacles in tandem: Effects of obstacle height and separation

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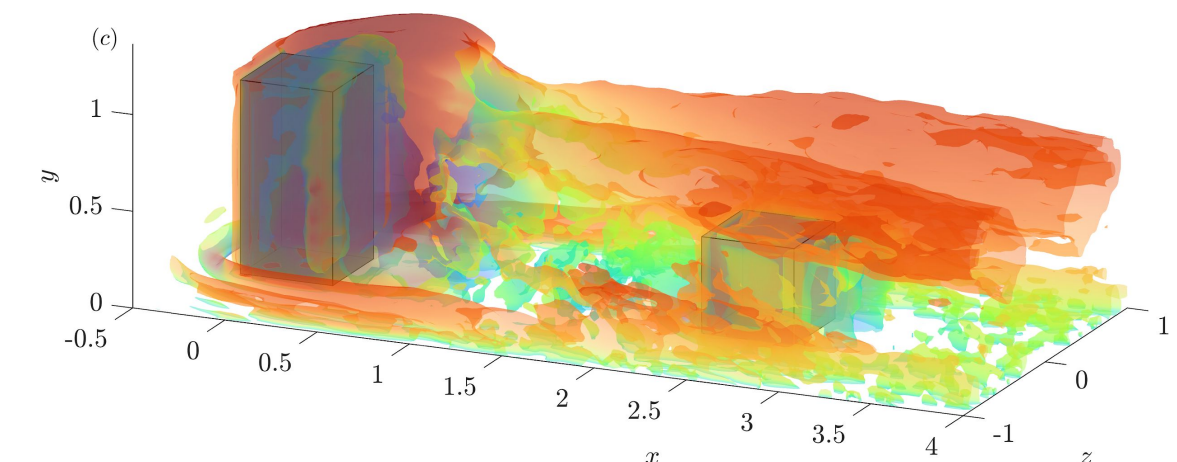
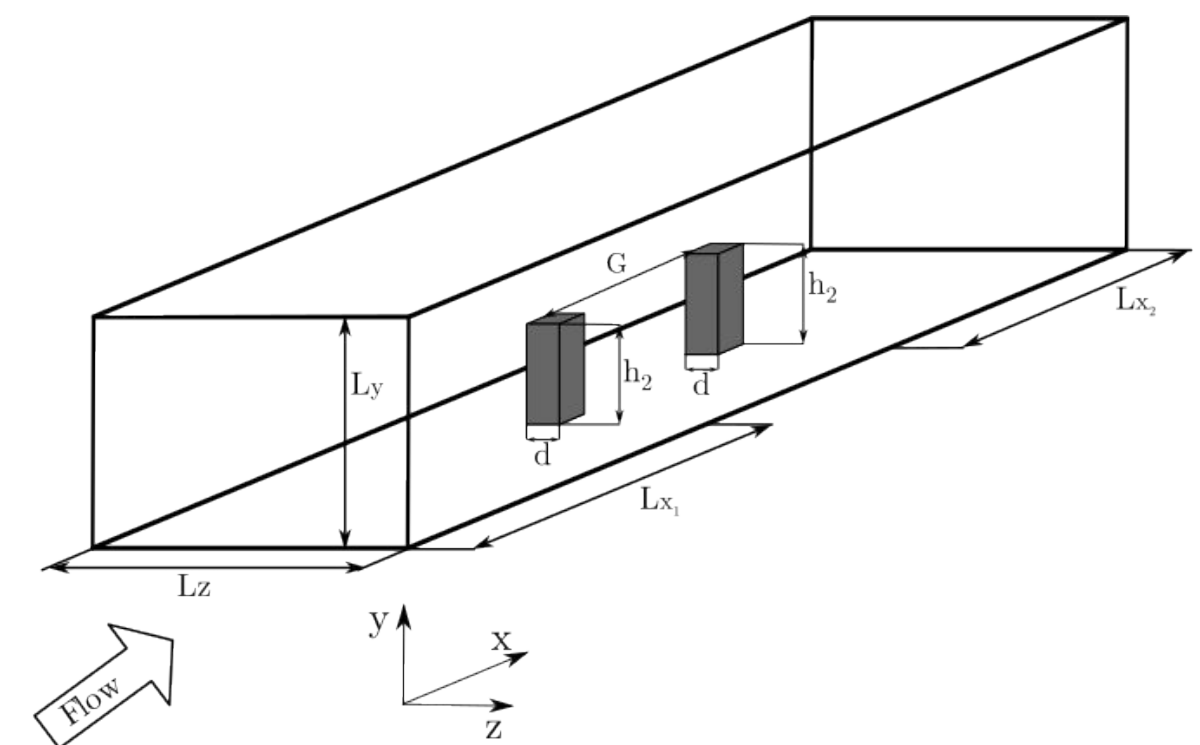
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Simulation setup

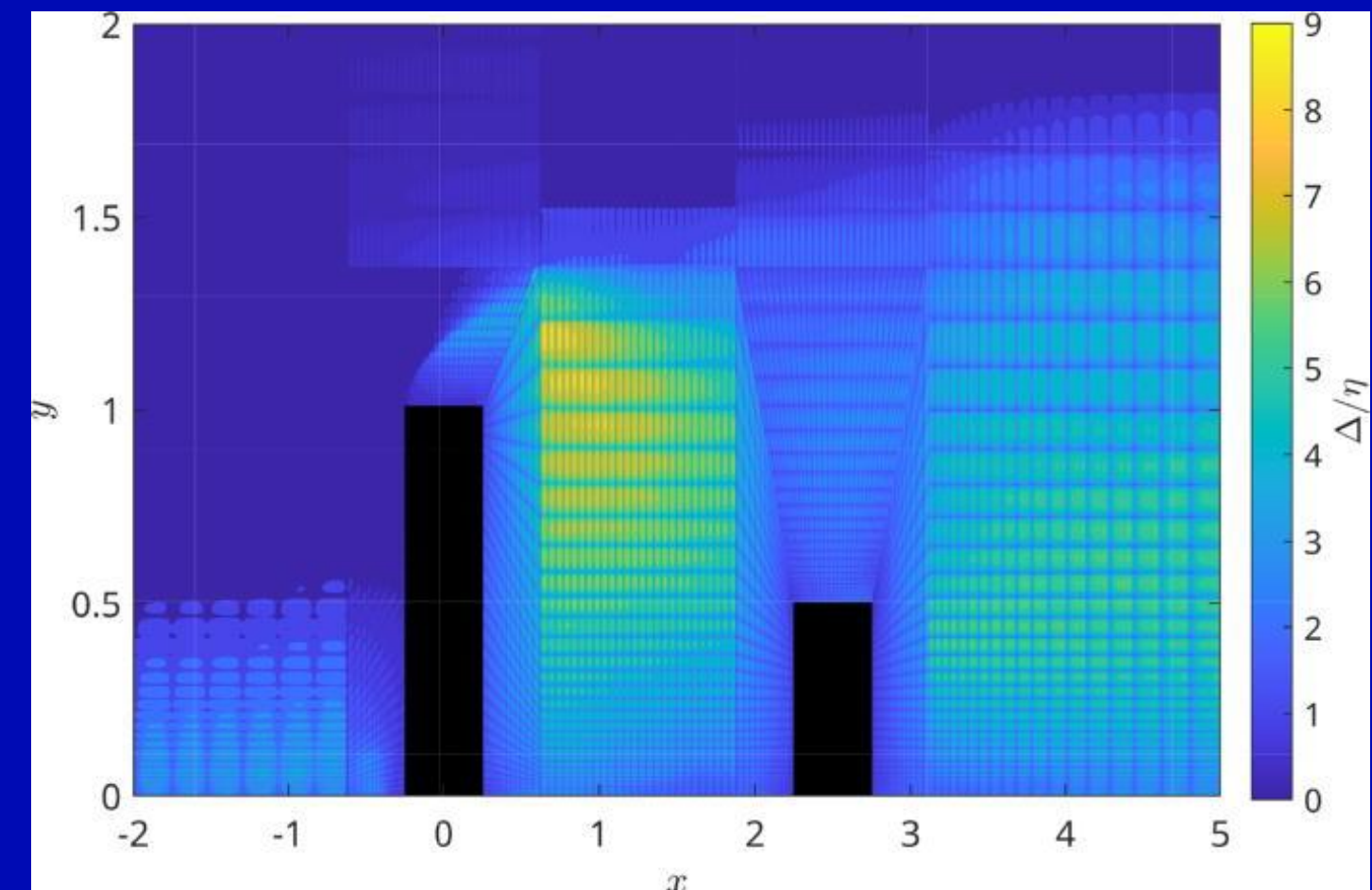
Nek5000 based on Spectral Element Methods[1].
LES with a high-resolution approximated
deconvolution model (ADM). The obstacles are
immerse into a turbulent boundary layer with
 $Re_d=10000$

For all cases considered, the mesh size satisfies
 $Dx^+ < 18$, $Dy^+ < 5$, and $Dz^+ < 9$, making the mesh
resolution comparable to that of a DNS.

We compared 3 cases with different heights and
gaps, namely Skimming Flow (SF), Wake
Interferenze (WI) and Isolated Roughness (IR).

Hereinafter “21” stands for the
the ratio between obstacle heights.

**How the changes in the geometry affects
the flow around the buildings?**



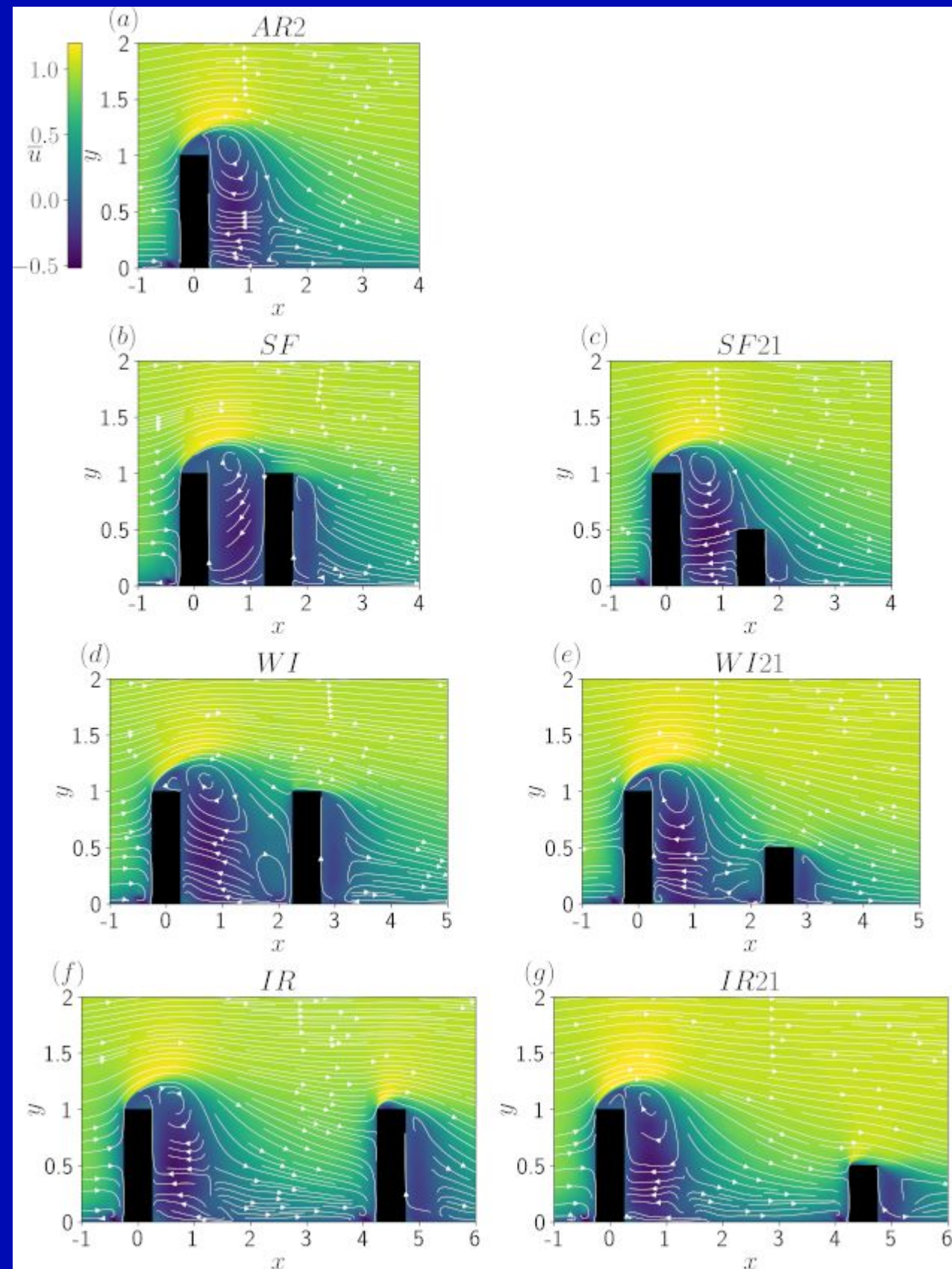


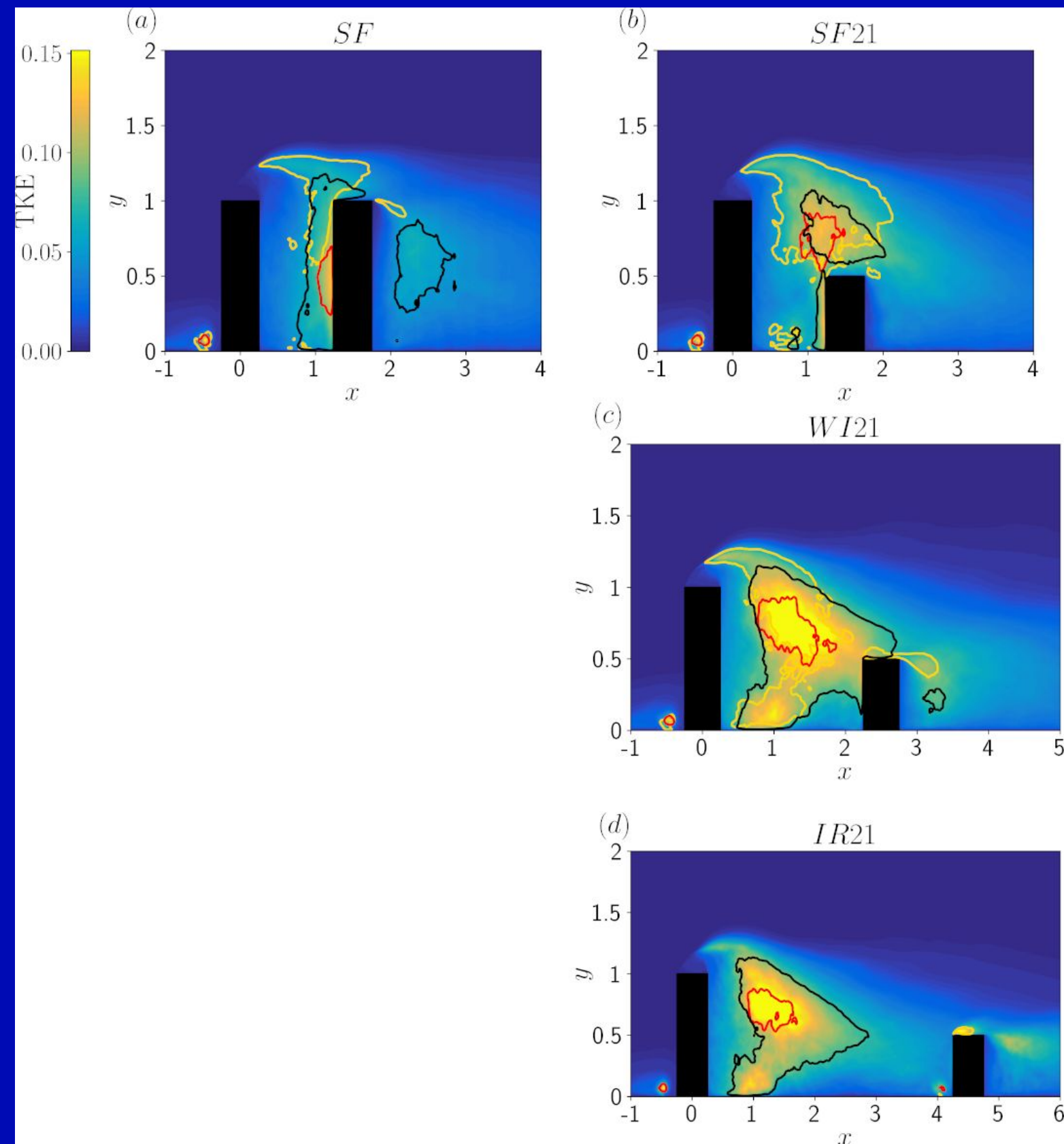
Flow field

The comparison with other cases shows that the shorter obstacle affects only the bottom portion of the wake.

The flow attaches at the upper surface and we can distinguish **two recirculation regions**.

The second obstacle delimits the development of the wake.





Stresses

The comparison with other cases shows that the shorter obstacle affects only the bottom portion of the wake.

The flow attaches at the upper surface and we can distinguish **two recirculation regions**.

The second obstacle delimits the development of the wake, more evident when considering the turbulent kinetic energy used to identify the hazardous regions.

Here the high k is released to more intense velocity fluctuations that can damage the drones or it can lose control.

Deep Reinforcement Learning

Development of deep-reinforcement-learning (DRL) method on 2D snapshots.

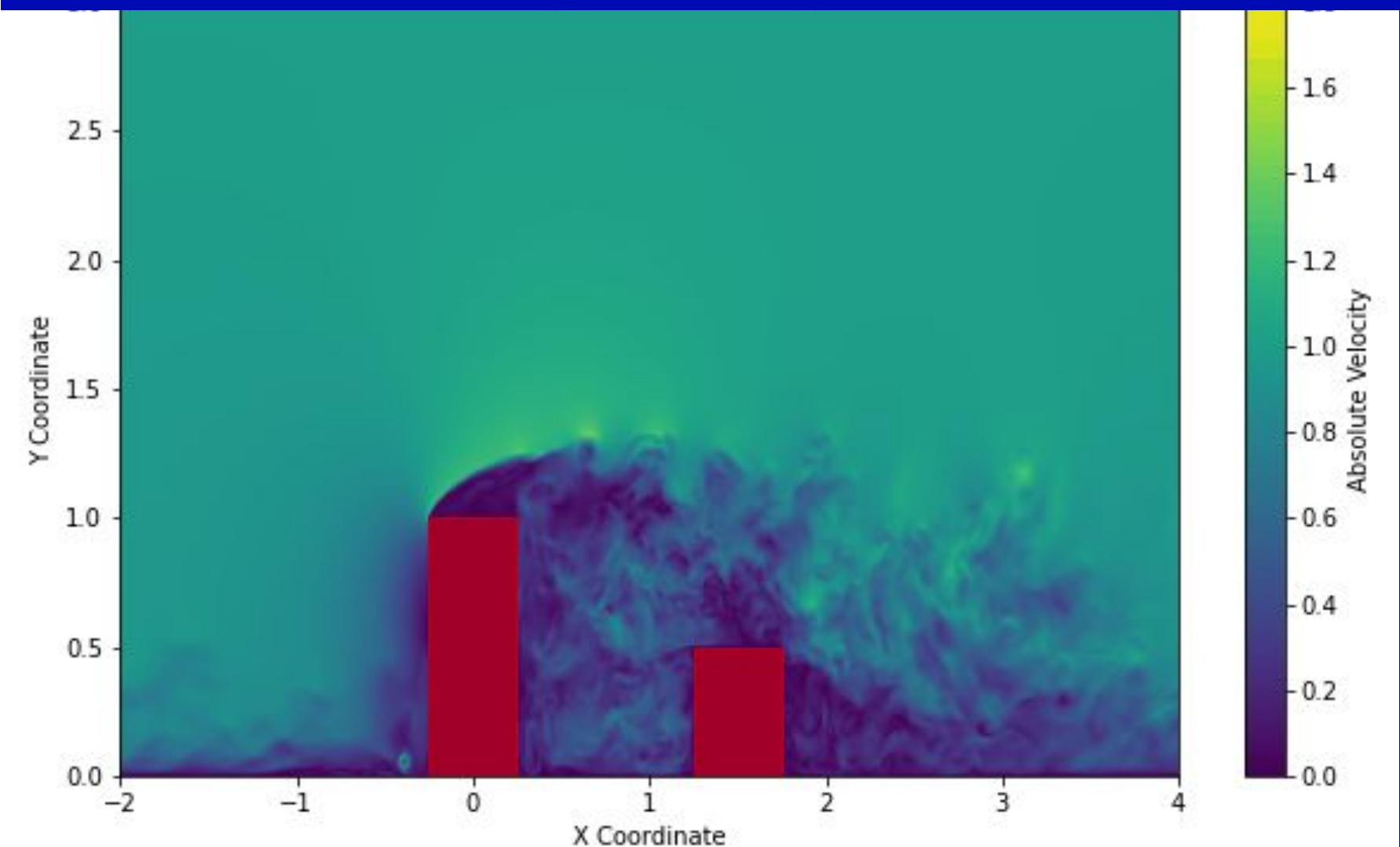
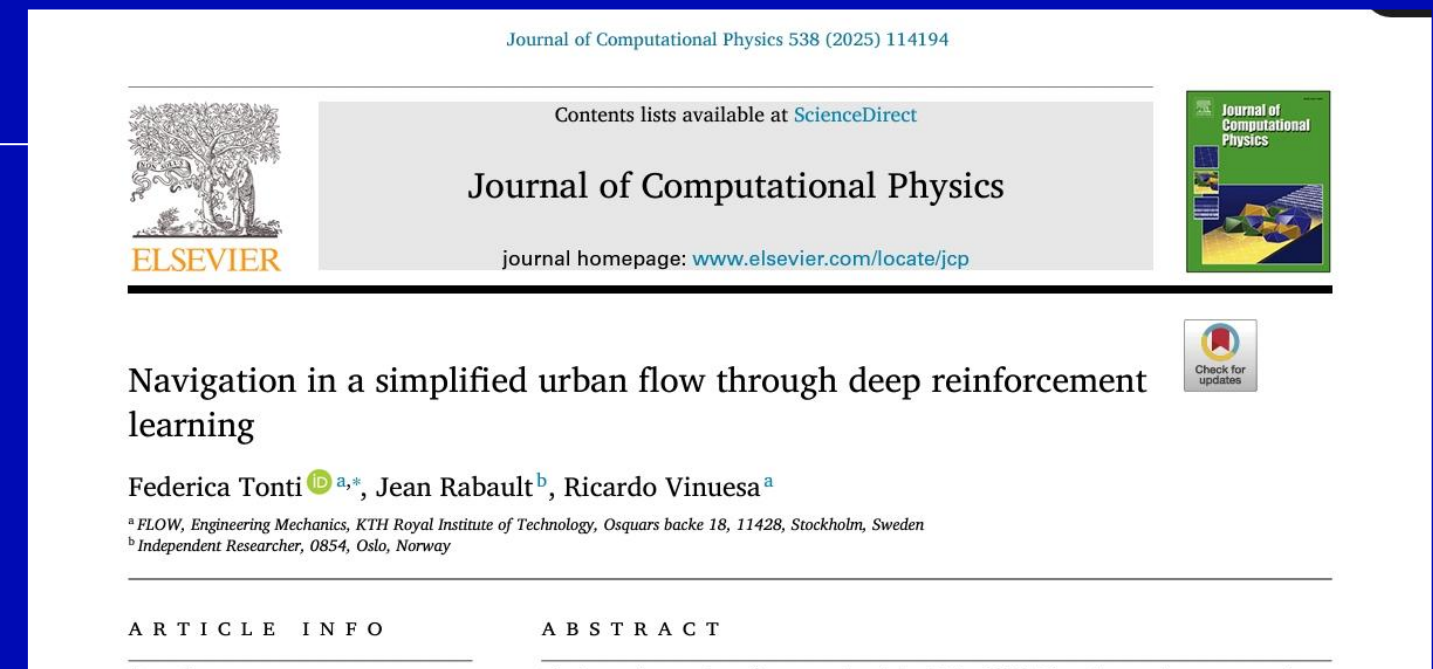
Combination of PPO and LSTM (proximal-policy optimization and long short-term memory networks).

We studied a UAV navigating in the 2D vertical plane of the case SF21 that is 3D.

As action space we considered the linear and angular acceleration of UAV modelled as a mass point.



Partially Observable Markov Decision Process, where only scarce information about the environment are passed to the network.



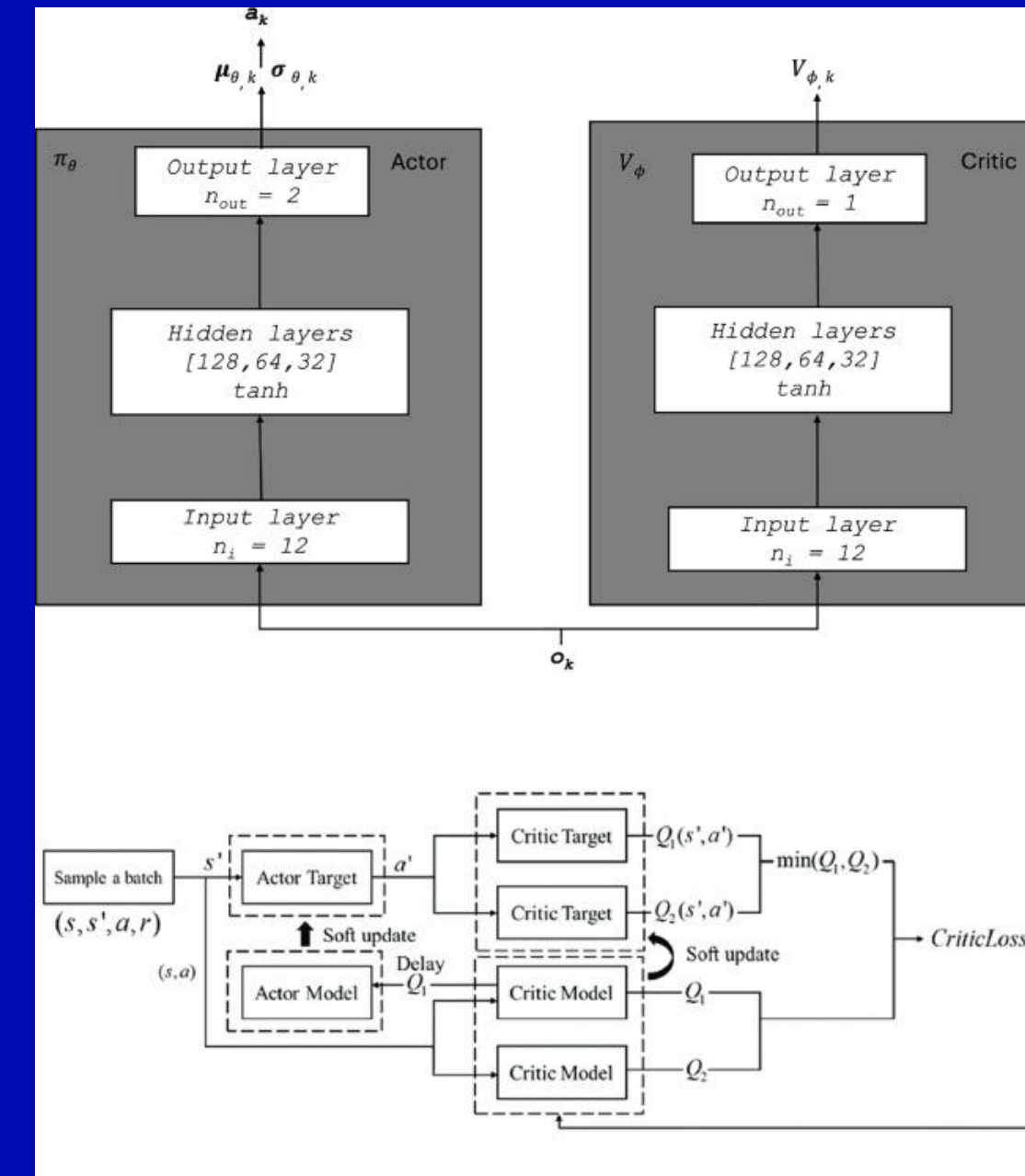
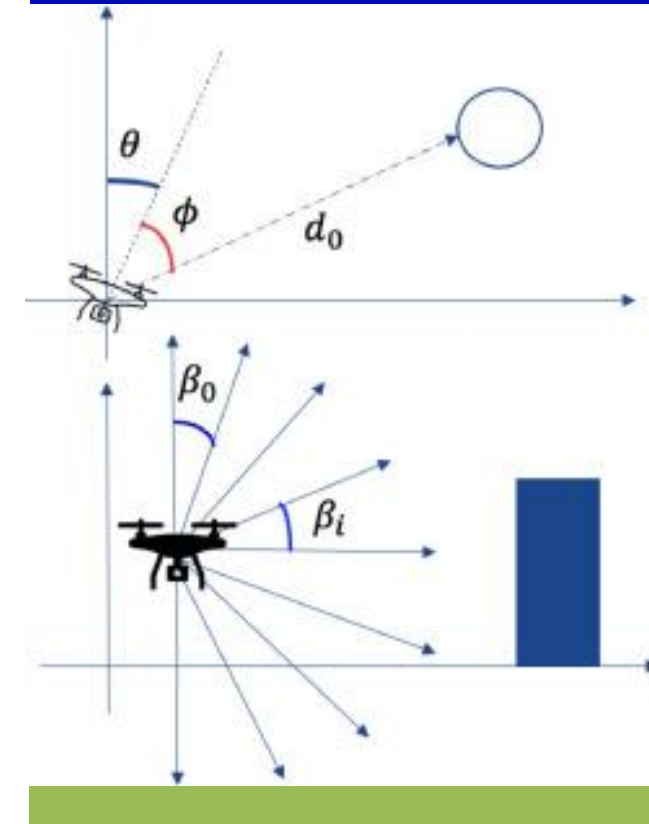
DRL setup

The drone does not know the flow field but only the puntual velocity. Both observation and action spaces are continuous.

The observation space is $\{\theta, \phi, d_0\} + \{\beta_i\}$, where θ is the heading angle of the UAV, ϕ is the relative angle of the UAV with respect to the target, d_0 is the distance between the UAV and the target, and $\{\beta_i\}$ are the angles associated with the sensors for obstacle detection, with $i \in [0, 8]$ spanning the angles between $-\pi$ and π .

As PPO, we have two NN The total reward is then given by

$$R_{\text{tot}} = \sum_{i=0, m} r_{i \text{ trans}} + r_{i \text{ obs}} + r_{i \text{ free}} + r_{i \text{ best}} + r_{i \text{ step}} + r_{i \text{ energ}}$$

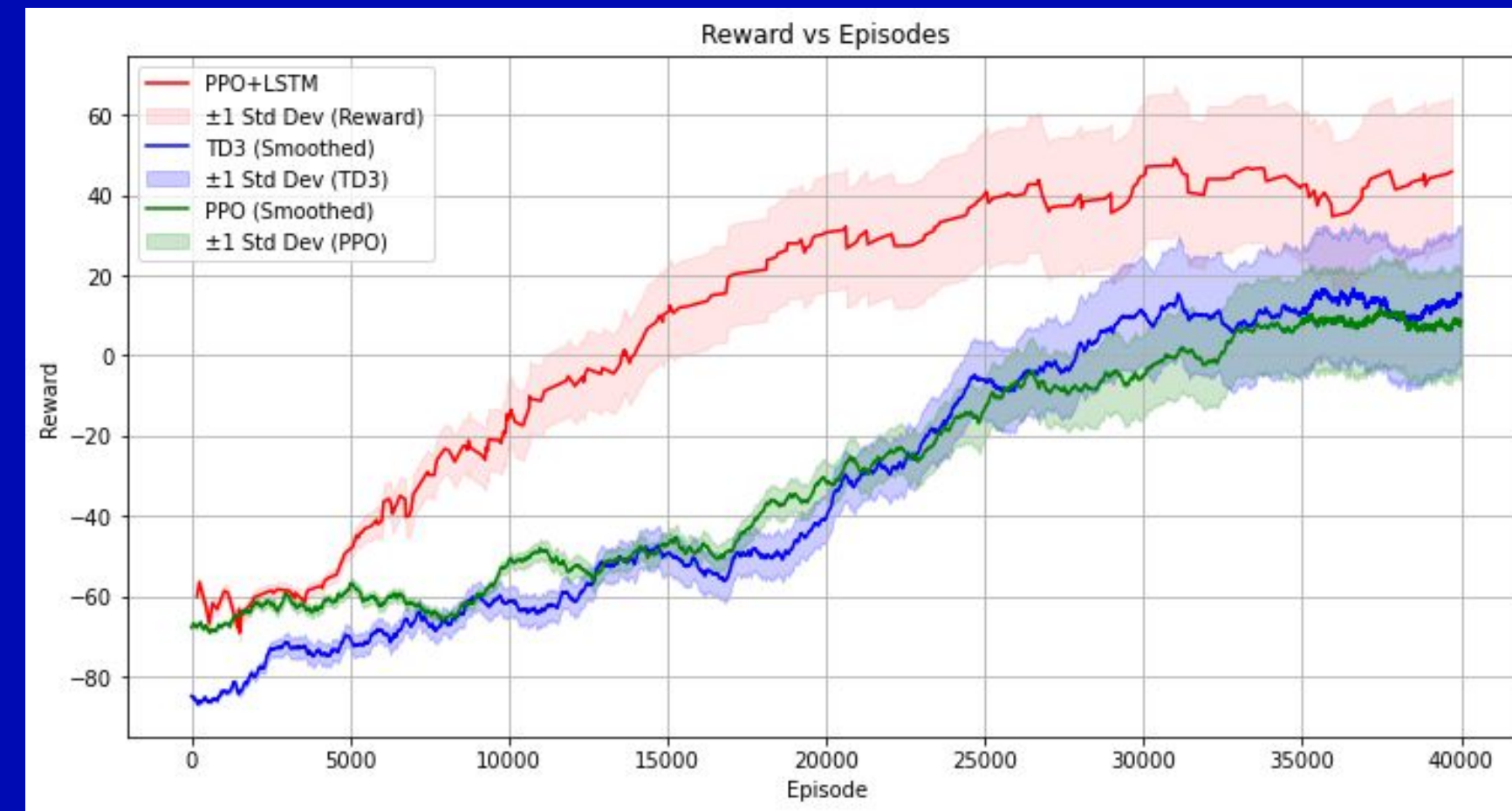
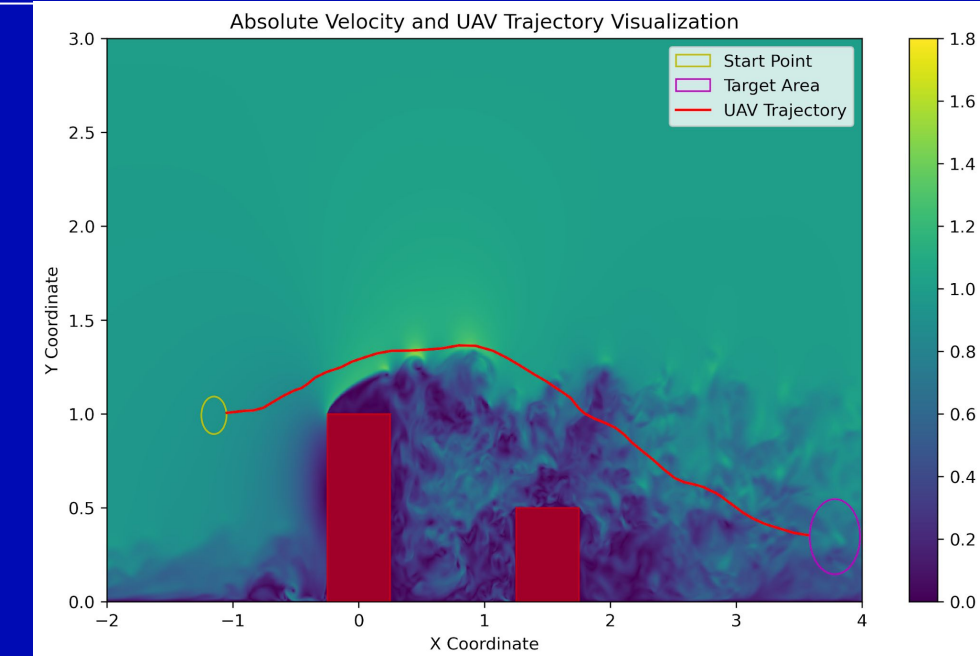
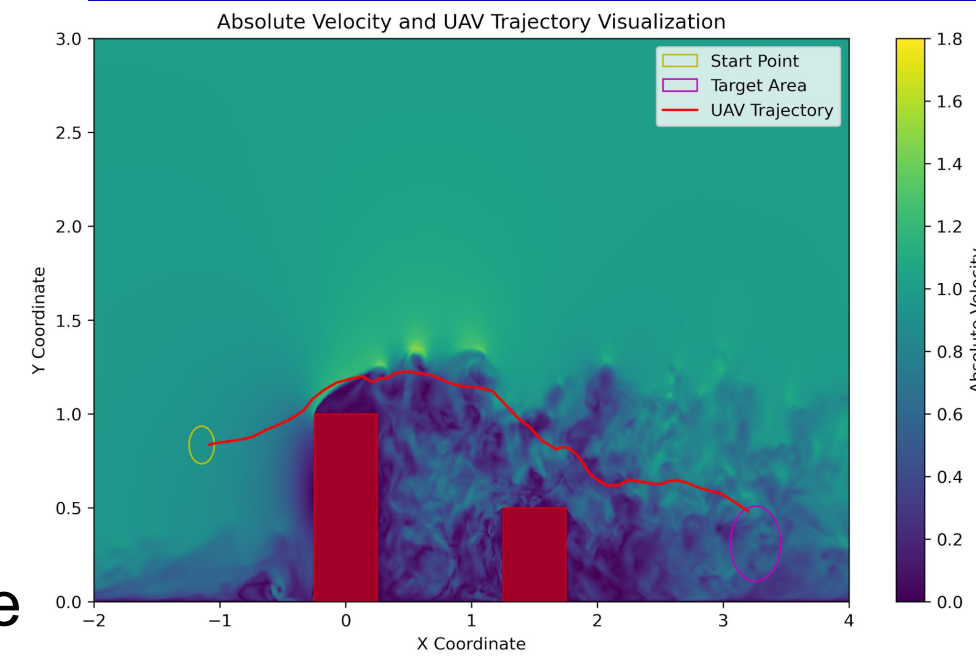


Trajectory optimisation for drones

The PPO + LSTM method **significantly outperforms** the state of the art.

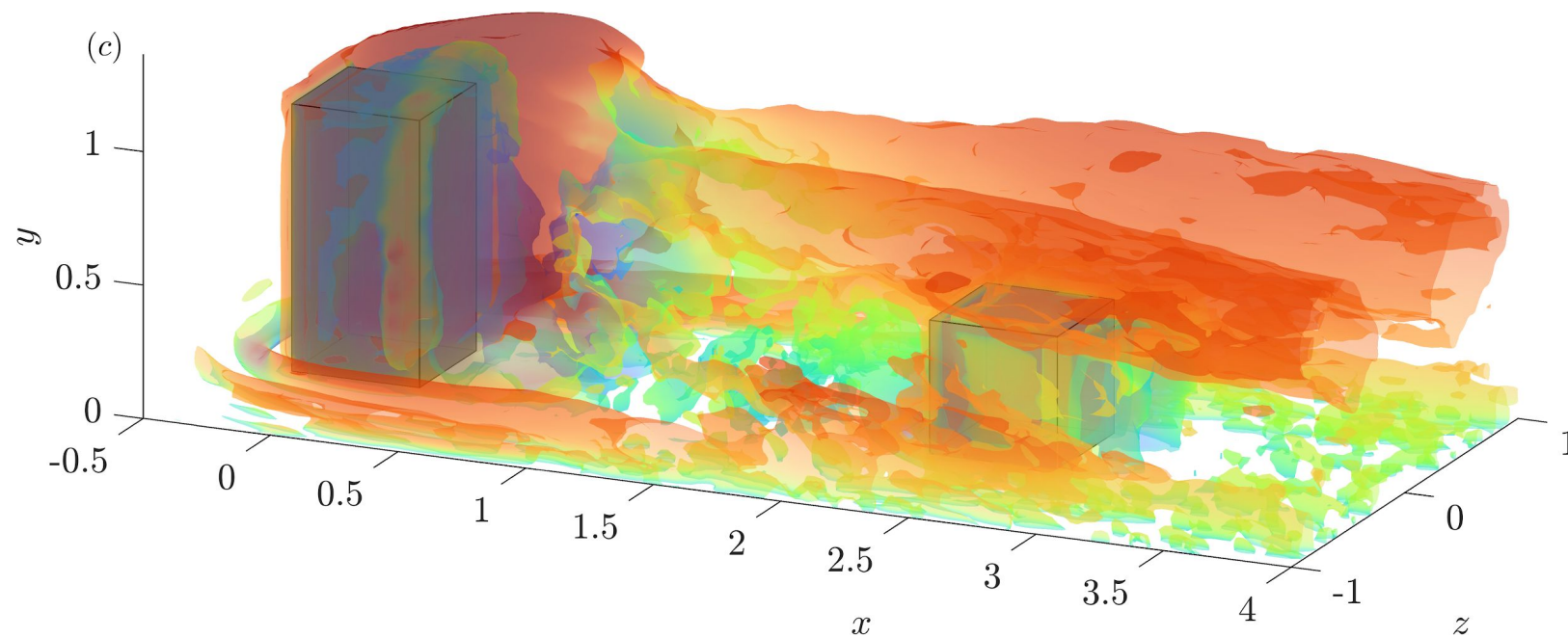
The UAV not only avoids the obstacles, but also manages to properly exploit the flow-field regions where the velocity is higher, and avoids getting trapped in regions with high recirculation.

These regions are the same highlighted by the numerical exploitation.



Conclusions

1. The study of the flow field in a urban environment is a preliminare analysis of the most hazardous areas to avoid for drones.
2. The high risks is linked to the high turbulent fluctuations
3. DRL with PPO and LSTM algorithm is performing in almost realtime and the long training is bilance by high performance
4. **The 3D case adds many complexity and still ongoing**



**thank you
for your attention!**

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**Q&A /
Closing**





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