Using Deep Learning Model to Simulate Wind in Building Area

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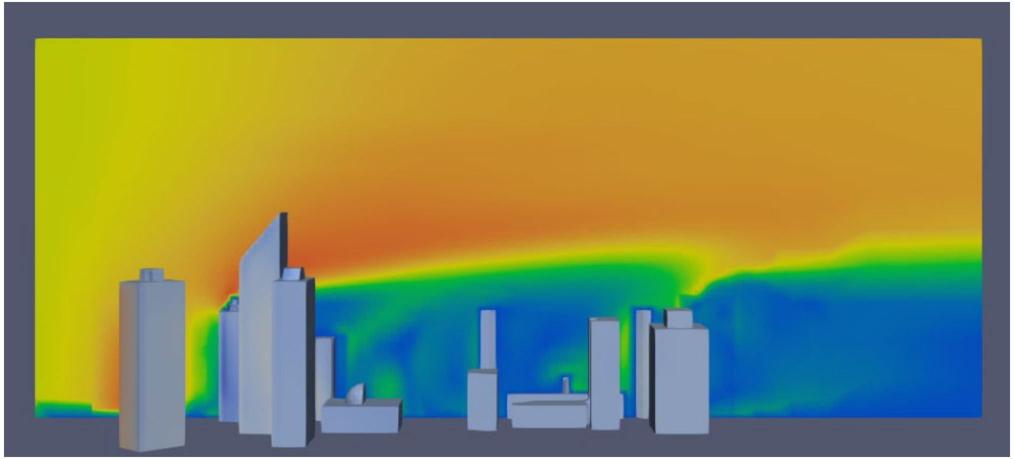
Urban Wind Flow



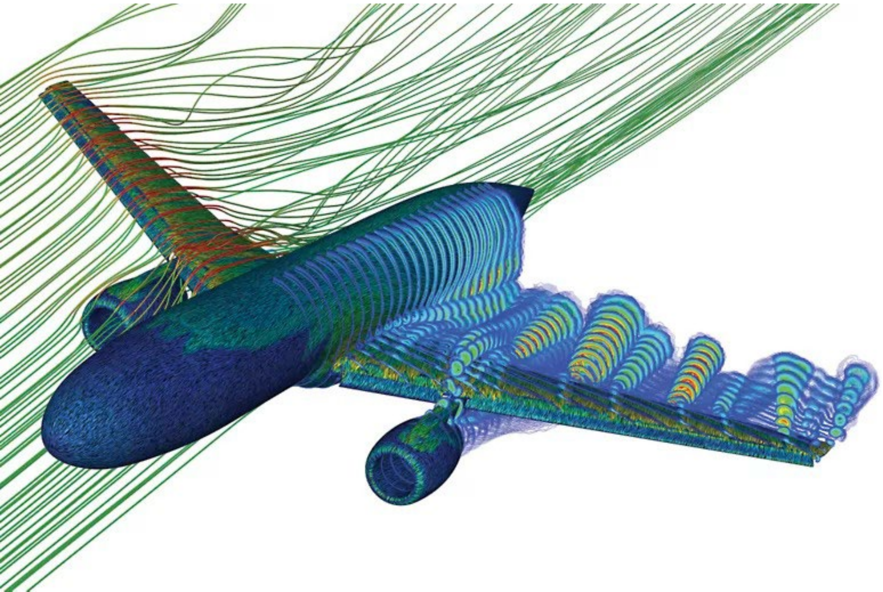
Pedestrian Comfort

Pollutant Dispersion

Building Design

Traditional Method

Computational Fluid Dynamics (CFD)



Based on three fundamental conservation laws:

1. Mass is conserved.
2. Momentum is conserved.
3. Energy is conserved.

These laws are expressed as a set of equations (Navier-Stokes) that are solved numerically.

A New Approach

- The high computational and time cost of CFD.
- Recent advancements in deep learning offer a promising alternative.
- Deep learning models has been proven can learn complex spatial patterns from data.

Opportunity: Can we use a deep learning model as a surrogate to approximate CFD results rapidly?

Research Questions

Main Research Question:

To what extent can a Swin-Transformer-based surrogate accurately simulate wind fields in urban environments under specific initial conditions?

Sub-questions:

- How do different urban building layouts affect the accuracy of the surrogate in simulating wind fields?
- How do varying inflow speeds affect the accuracy of the surrogate in urban wind field simulation?
- How does introducing a flow-aware loss function influences the surrogate's accuracy?

Scope

Scope of the Thesis:

- **Scale**: 2D urban domains of 100m×100m.
- **Conditions**: Steady-state wind flow.
- **Representation**: Wind flow represented as 2D raster images.
- **Wind Direction**: A single, fixed inflow direction.
- **Exclusions**: Building height, terrain, vegetation, and thermal effects are not considered.

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2. Methodology

Methodology

- **Dataset Generation**:
  Create a large dataset of urban geometries.

- **CFD Simulation**:
  Use Ansys to simulate wind flow for each geometry.

- **Model Training**:
  Train the Swin Transformer surrogate model on the generated data.

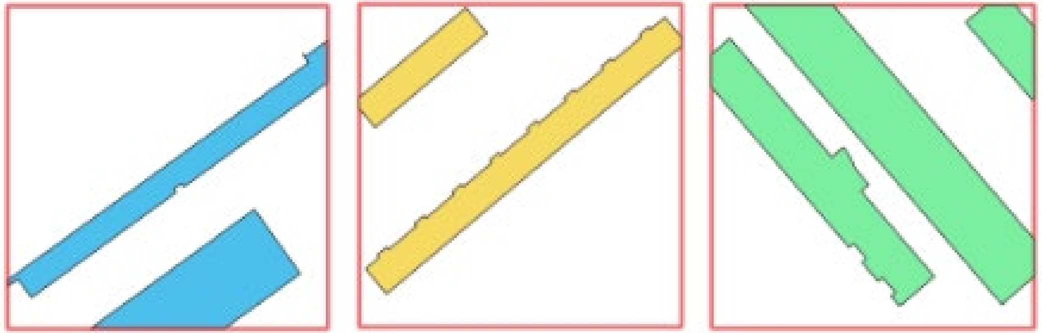
- **Evaluation**:
  Systematically test the model's performance based on the research questions.

Methodology

Dataset Generation

- **Source**: Building footprints were extracted from **3DBAG**.

- **Processing**:
  1. Partitioning
  2. Cleaning
  3. Visual Check



Methodology

Dataset Overview

- **Training & Validation Set**: 690 unique urban tiles.
- **Test Sets**:

  General: 60 uncategorized samples to test general performance.

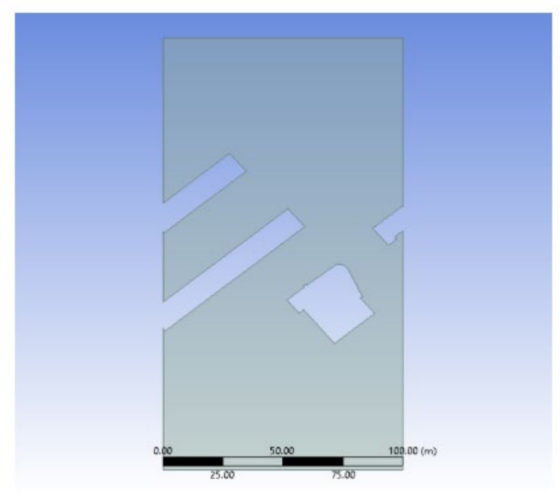
  Layout-Specific:

  - Attached (22)
  - Detached (30)
  - High-Rise (17)
  - Industrial (30)
  - Mixed (26)

Methodology

CFD Simulation with Ansys

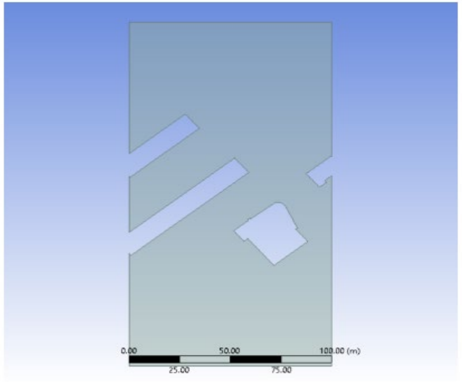
- **Software**: Ansys was chosen for its robust workflow and scripting capabilities for automation.
- **Turbulence Model**: The k-ϵ model.
- **Boundary Conditions**:
  - **Inlet**: Bottom boundary.
  - **Outlet**: Top boundary.
  - A 50m margin was added to the top and bottom to minimize boundary effects.



Methodology

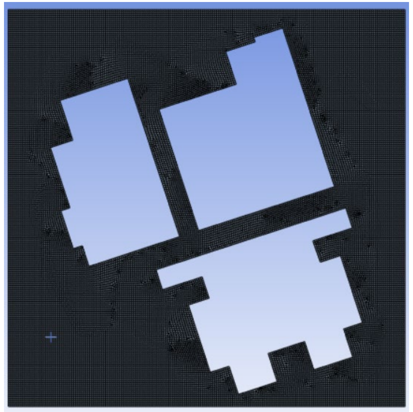
CFD Simulation with Ansys

Geometry



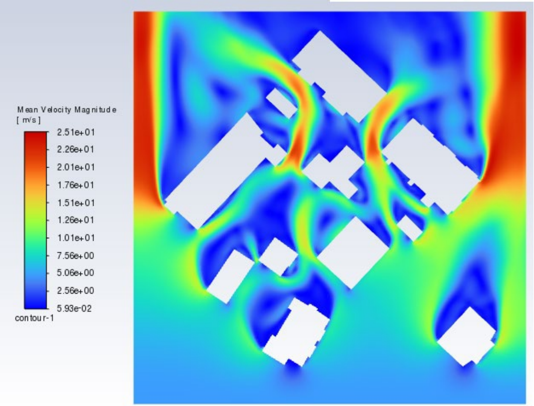
DesignModeler

Mesh



Ansys Mesh

Wind

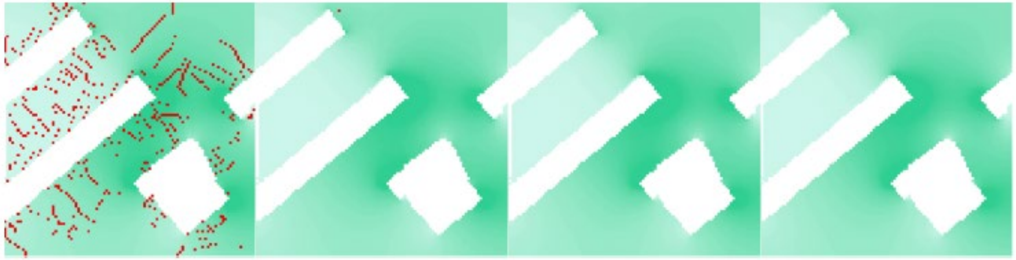


Ansys Fluent

Methodology

Mesh Resolution Study

- **Challenge**: Find the optimal balance between computational cost and simulation accuracy.
- **Experiment**: Tested mesh element sizes from 1.0m down to 0.3m.
- **Decision**: An element size of **0.5m** was chosen.



1.0 m 0.7 m 0.5 m 0.3 m

Element Size (m)	Time Cost (s)
1.0	12
0.7	25
0.5	55
0.3	201

Methodology

Data Processing for Model Input

- Point-to-Raster Conversion
- Normalization
- Mask Generation

```
nodenumber,    x-coordinate,    y-coordinate,      x-velocity,      y-velocity,velocity-magnitude
         1, 4.745040894E+01, 1.076950760E+02,-4.606513023E+00, 1.130503845E+01, 1.220760059E+01
         2, 4.744303513E+01, 1.071796341E+02,-4.676264763E+00, 1.135389900E+01, 1.227925682E+01
         3, 4.793317795E+01, 1.071626434E+02,-4.630705833E+00, 1.142044640E+01, 1.232362175E+01
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         8, 2.501681137E+01, 9.365110397E+00, 3.460210800E+00, 9.420621872E+00, 1.003611469E+01
         9, 2.507768440E+01, 8.878129959E+00, 3.369159698E+00, 9.417509079E+00, 1.000214577E+01
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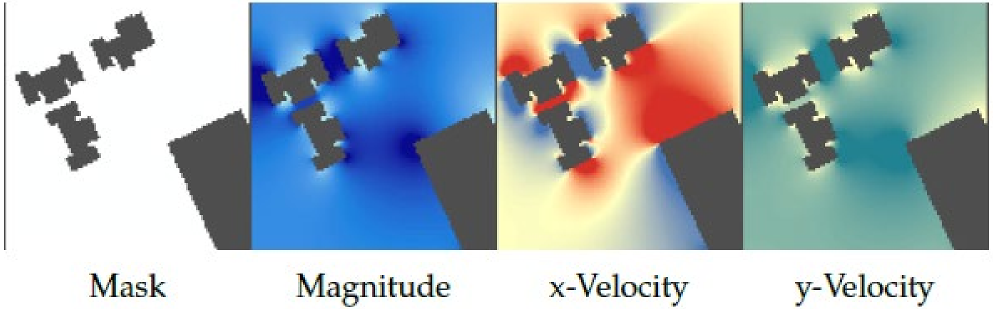


Methodology

The Swin Transformer Surrogate Model

- The original Swin Transformer architecture was preserved.
- Adapted for per-pixel regression.

Baseline Loss function: **RMSE**

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2}$$

Custom Loss Functions:

- **Buffer Loss**:

  L = Outer RMSE + ω · Inner RMSE

- **Divergence Penalty**:

$$\text{Divergence} = \frac{\partial u}{\partial x} + \frac{\partial v}{\partial y}$$

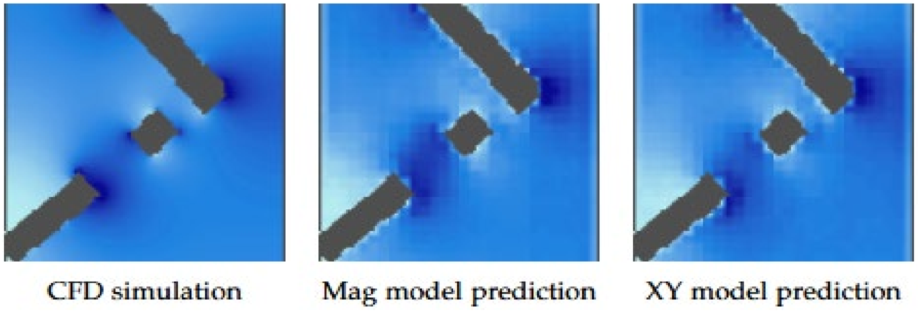
3. Results & Analysis

Results & Analysis

Target Format

Experiment: Trained two models—one predicting only wind magnitude, the other predicting x and y velocity components separately.

- The **XY-based model consistently outperformed** the magnitude-only model across all inflow speeds.
- The XY model better preserves sharp gradients and avoids the "blurry" predictions seen in the magnitude model, especially in narrow passages.



Inflow (m/s)	Mag MAE	XY MAE	Mag RMSE	XY RMSE
10.0	2.2663	2.1085	4.3963	4.1628

Results & Analysis

Inflow Speed

- Prediction error (RMSE) **scales linearly with inflow speed**.
- As inflow speed increases, velocity gradients near building walls become sharper.
- The model struggles to resolve these sharp transitions, leading to increased underestimation of velocity at higher speeds.

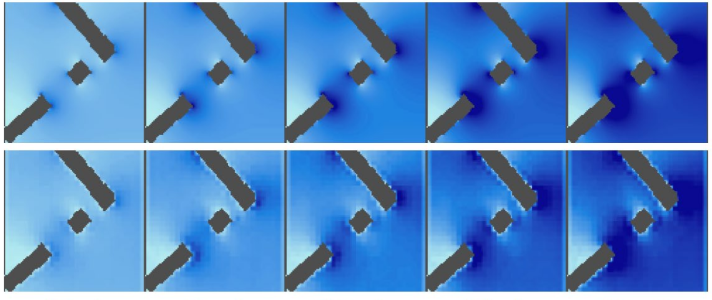
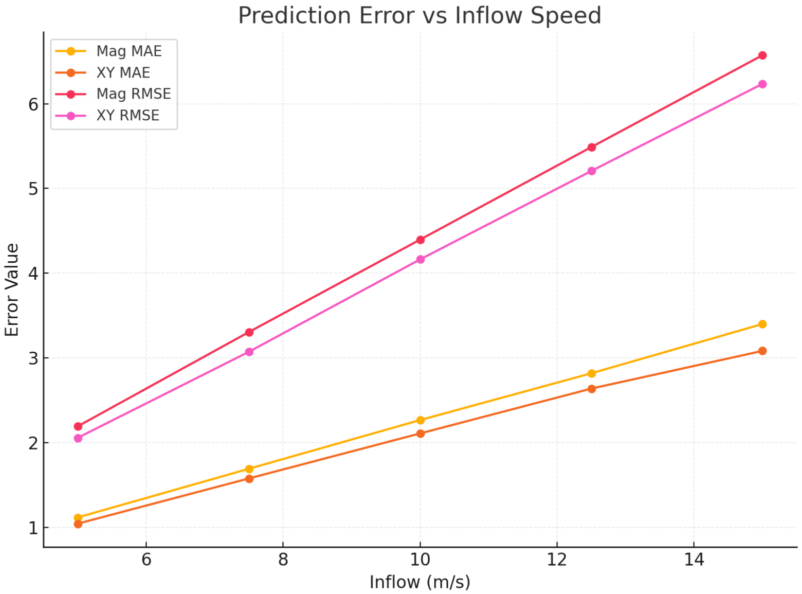


Figure 3.3: *Comparison of ground truth (top) and predicted magnitude fields (bottom) at five inflow speeds.*

Inflow (m/s)	XY MAE	XY RMSE
5.0	1.0434	2.0568
7.5	1.5772	3.0724
10.0	2.1085	4.1628
12.5	2.6378	5.2062
15.0	3.0828	6.2352



Results & Analysis Layout

Experiment: The XY-based model was tested on five categorized urban layouts at a fixed inflow speed of 10.0 m/s.

- **Mixed** and **Attached** layouts produced the highest errors, while the **Detached** layout had the lowest.
- Urban morphology is a primary driver of model error.
- Irregular street canyons and complex building shapes pose a significant challenge.

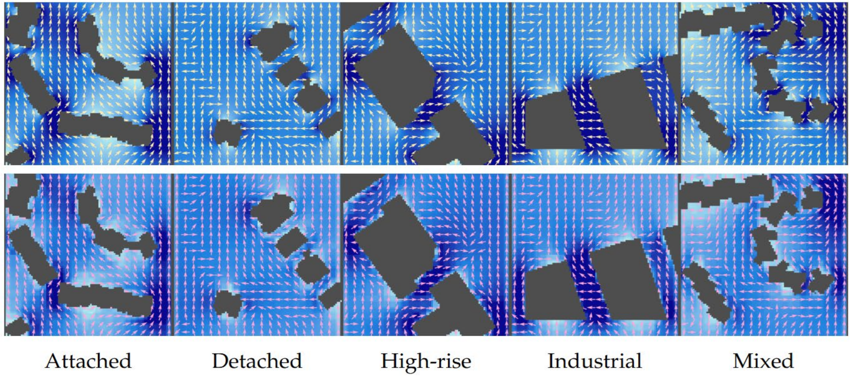
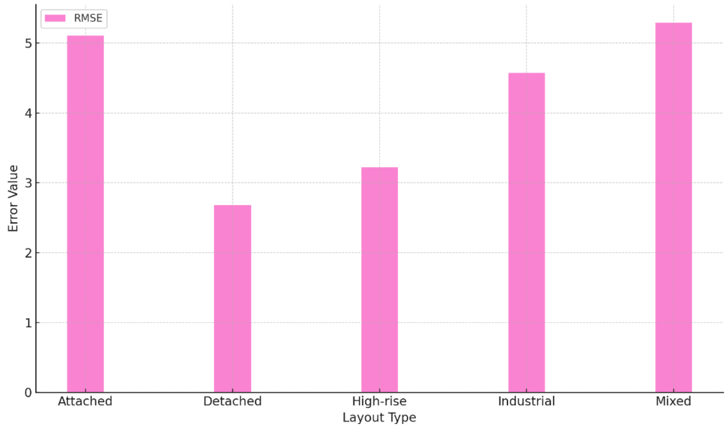


Figure 3.5: *Predicted wind magnitude fields and directions (bottom row) and corresponding ground truth (top row) for each layout type. All cases use the XY-based model at 10.0 m/s.*

Layout Type	Prediction MAE	Prediction RMSE
Attached	2.8163	5.1063
Detached	1.5176	2.6771
High-rise	1.8168	3.2231
Industrial	2.1914	4.5721
Mixed	2.5982	5.2886



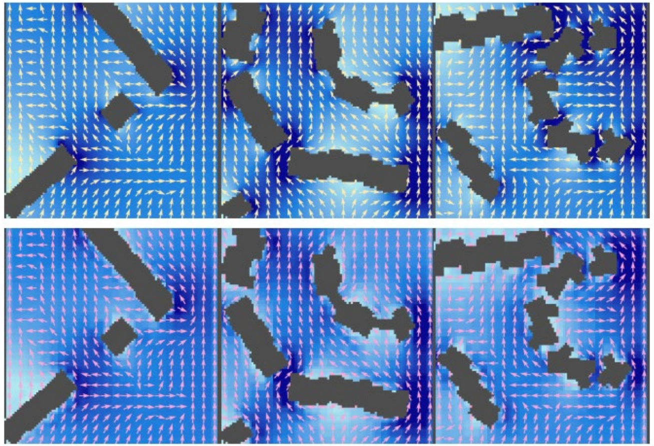
Results & Analysis

Buffer Loss

Goal: To improve accuracy in near-building regions.

- Adding the buffer loss resulted in only a marginal improvement.
- RMSE Reduction: 4.1628 → 4.1315 (a decrease of only 0.03).
- While some localized improvements were seen, persistent issues like directional errors and magnitude underestimation remained largely unsolved.

Ground Truth



Prediction

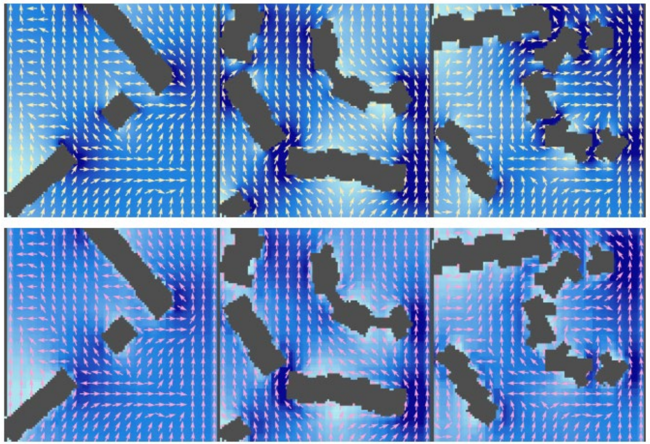
Model	Prediction MAE	Prediction RMSE
Baseline	2.1085	4.1628
With Buffer	2.0860	4.1315

Results & Analysis   Divergence Loss

Goal: To enforce physical consistency in the flow field.

- The divergence penalty also offered only a **marginal global improvement**.
- RMSE Reduction: 4.1628 → 4.1195 (a decrease of ~0.04)
- The model produced fields with slightly lower divergence, but the overall velocity prediction quality was not significantly enhanced.

Ground Truth



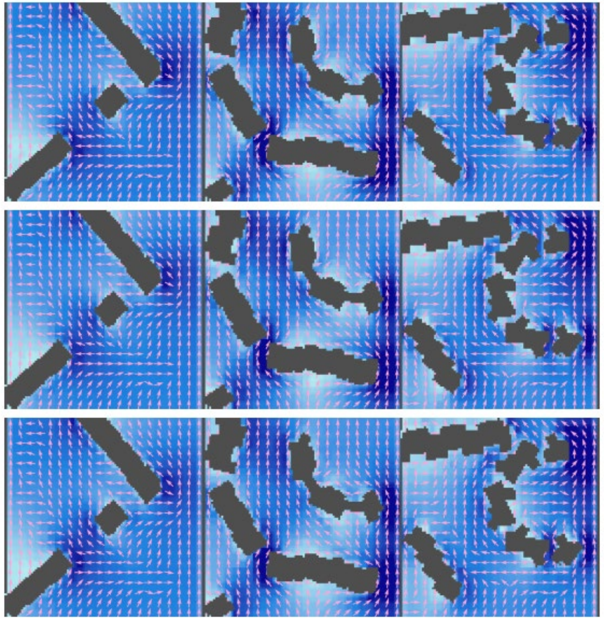
Prediction

Model	Prediction MAE	Prediction RMSE
Baseline	2.1085	4.1628
With Divergence	2.0559	4.1195

Combining Buffer and Divergence Loss

Hypothesis: Combining both loss terms could leverage their complementary strengths.

- The combined-loss model **did not produce a cumulative improvement**.
- RMSE: 4.1199, comparable to the divergence-only model.
- The model's predictive capacity seems to be constrained by factors other than the loss function design.



Buffer

Divergence

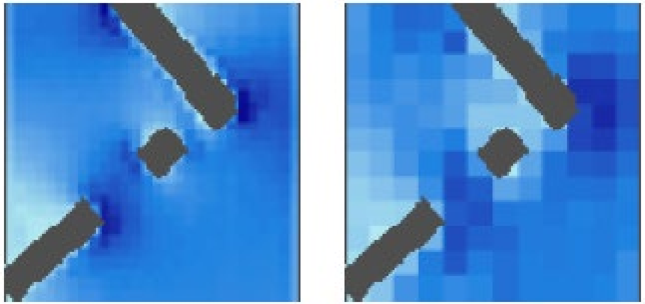
Buffer&
Divergence

Model	Prediction MAE	Prediction RMSE
Baseline	2.1085	4.1628
With Buffer	2.0860	4.1315
With Divergence	2.0559	4.1195
With Buffer & Divergence	2.0939	4.1199

Results & Analysis Architectural Resolution

Experiment: Compared the baseline model (patch size 2) with a model using a larger patch size of 5.

- Increasing the patch size from 2 to 5 caused a **massive increase in error.**
- RMSE Increase: 4.16 → 4.91. This change was far more significant.
- A larger patch size results in visibly less detailed predictions, confirming that the model's structural resolution is critical.



Patch Size	Window Size	Prediction MAE	Prediction RMSE
2	10	2.1085	4.1628
5	10	2.6494	4.9148

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4. Discussion & Conclusions

Discussion

- **Input Format is Key**: Training on XY-components is superior. It provides directional information and presents smoother gradients for the model to learn.
- **Error Correlates with Complexity**: Errors rise with both inflow speed and geometric irregularity (e.g., Mixed layouts) because both create sharper, harder-to-predict gradients.
- **Error is Concentrated Near Buildings**: The proportion of pixels adjacent to buildings strongly correlates with overall RMSE, highlighting that these high-gradient zones are the primary source of error.
- **Soft Constraints are Insufficient**: Buffer and divergence losses offered only minor fixes. The model prioritizes minimizing average pixel error over enforcing physical behavior, revealing the limitations of using them as "soft" constraints.
- **Architecture is Paramount**: The model's ability to capture fine detail (set by patch size) is the most dominant factor influencing performance.

Discussion

The Main Advantage: Computational Efficiency

Despite its limitations, the surrogate model offers a massive advantage in speed.

CFD Simulation: ~4 minutes 20 seconds per sample.

ML Surrogate: ~4 seconds per sample on the same hardware.

Step	CFD	ML surrogate
Ansys DesignModeler	3 min	–
Ansys Mesh	1 min 10 s	–
Ansys Fluent	10 s	–
Total per sample	**4 min 20 s**	**4 s**

Conclusion

Conclusion 1: Answering the Sub-Questions

- **Urban Layouts:** Densely packed and irregular layouts lead to higher error because they contain more high-gradient, near-building zones.
- **Inflow Speeds:** Error increases linearly with inflow speed because higher speeds create sharper, harder-to-resolve gradients.
- **Flow-Aware Loss:** Custom loss functions provide only negligible improvements to overall RMSE. They cannot overcome the model's fundamental architectural limitations.

Conclusion

Conclusion 2: Answering the Main Research Question

- The surrogate is capable of **approximating the general structure** of the wind field but consistently fails in high-gradient zones near buildings.
- Its accuracy is decisively governed by **architectural factors**.
- For **rapid, preliminary flow estimation** on open area where speed is more important than precision.

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5. Future Work

Future work

Based on the findings and limitations, future research could explore:

1. **Geometric Scale**:
   3D Voxel Input
   Larger Coverage

2. **Transient Inflow**

3. **Model Modification**
   Physics-Informed Loss
   Architecture with better performance

Thanks for your listening!