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Modelling pollution in the urban environment using neural networks

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CONTENTS

INTRODUCTIOIN

Topic

Air Pollution

Public Health Concern

Question

Prediction Accuracy

Limitations of Traditional Methods

Answer

Comprehensive Framework incorporating

- Neural Networks
- Computational Fluid Dynamic
- Data Assimilation

LITERATURE REVIEW

1

Neural Networks
&
Computational Fluid Dynamics

- NN-based Solver for PDEs
- Potential and Performance

Using ai libraries for incompressible computational fluid dynamics (Chen et al.)

2

Traditional Modelling
v.s.
Convolutional VAE

- Generation of Predictions
- Computational Resources
- Reducing Dimensionality

Bridging observations, theory and numerical simulation of the ocean using machine learning (Sonnewald et al.)

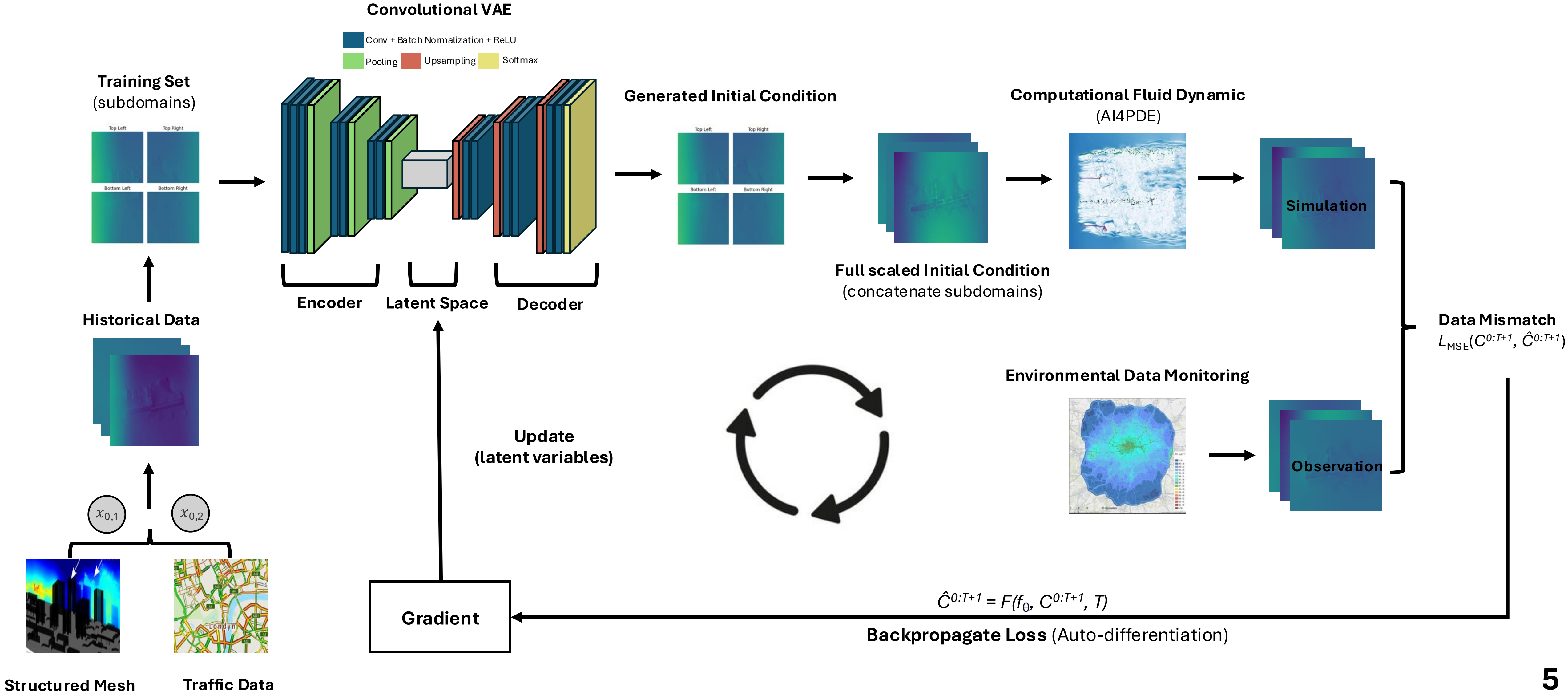
3

Assimilation
with
Observational Data

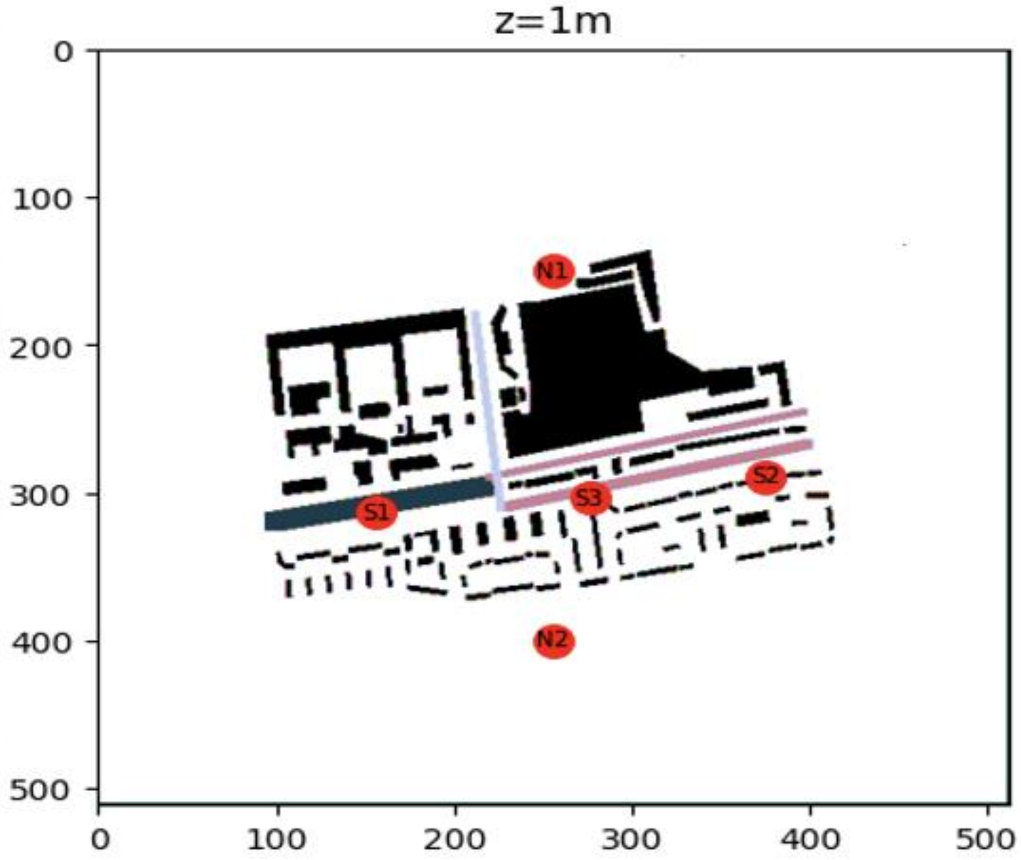
- Refining the Model
- Adjusting to Realistic Environment
- Accuracy of Predictions

Data assimilation in the latent space of a neural network (Amendola et al.)

METHODOLOGY – Overview of the Workflow



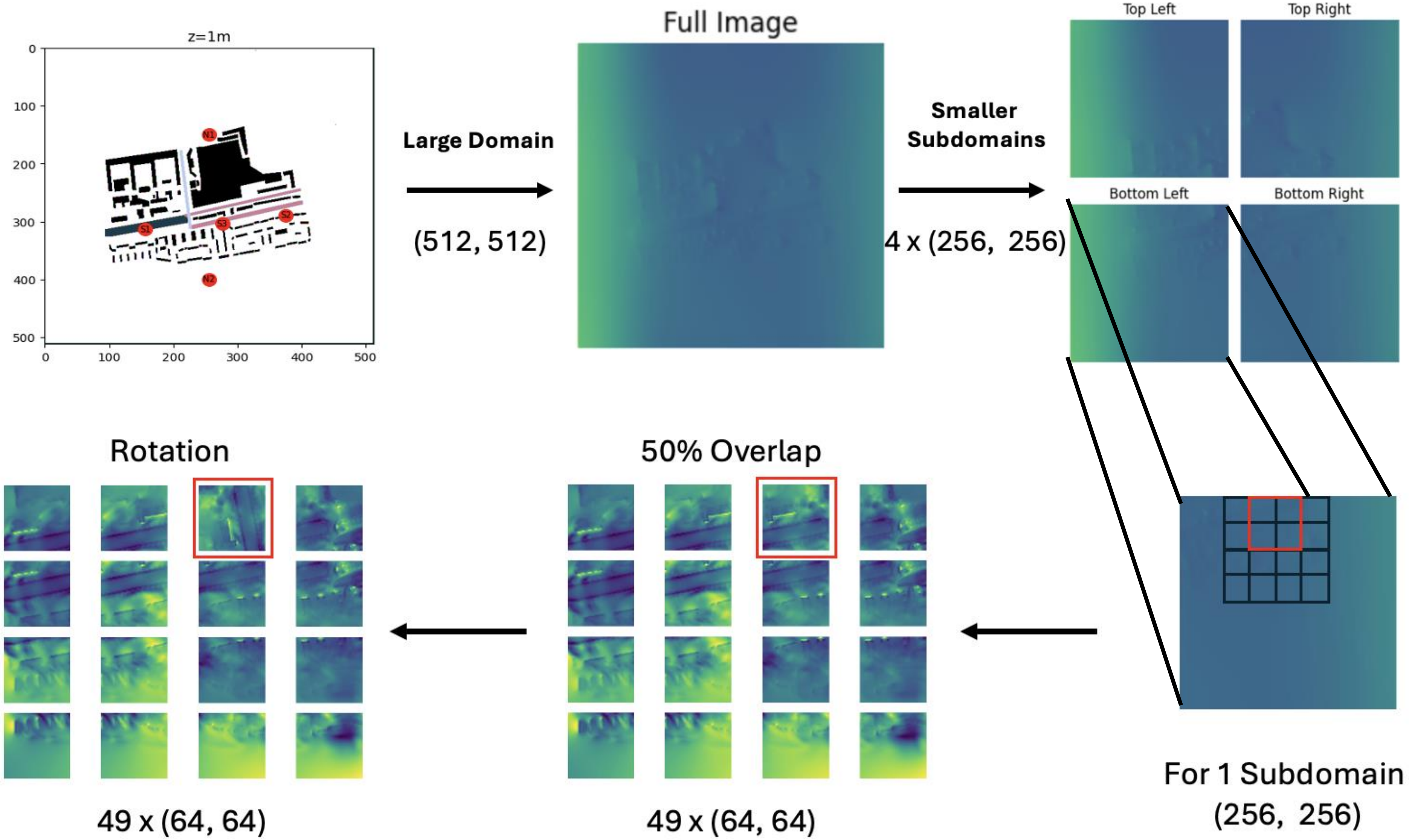
METHODOLOGY - Setup of a Test Case



(512, 512)

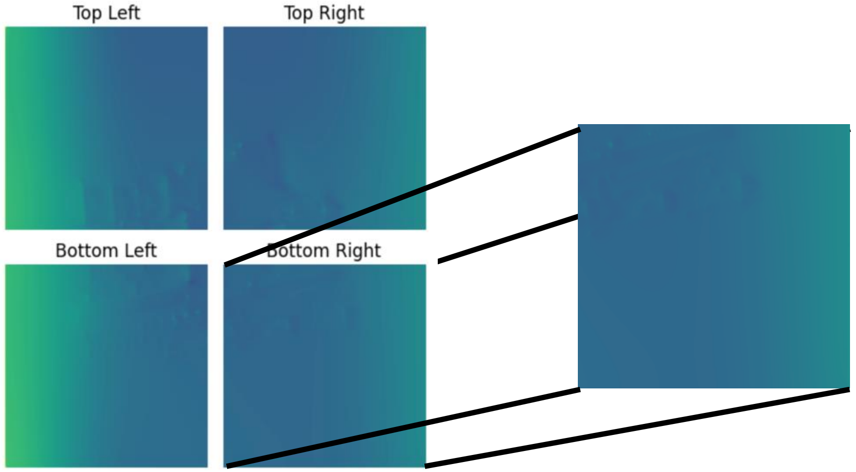
Sensor locations: Optimising sensor location using neural networks applied to air pollution (Zhan Xuan & Hong Xuan)

METHODOLOGY – Data Preprocessing



METHODOLOGY – Convolutional VAE

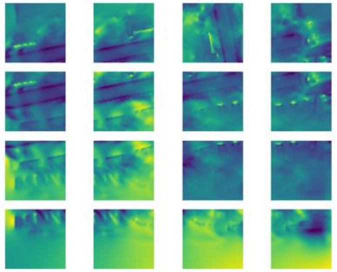
For Each Subdomain
(4 in total)



1 x (512, 512)

(256, 256)

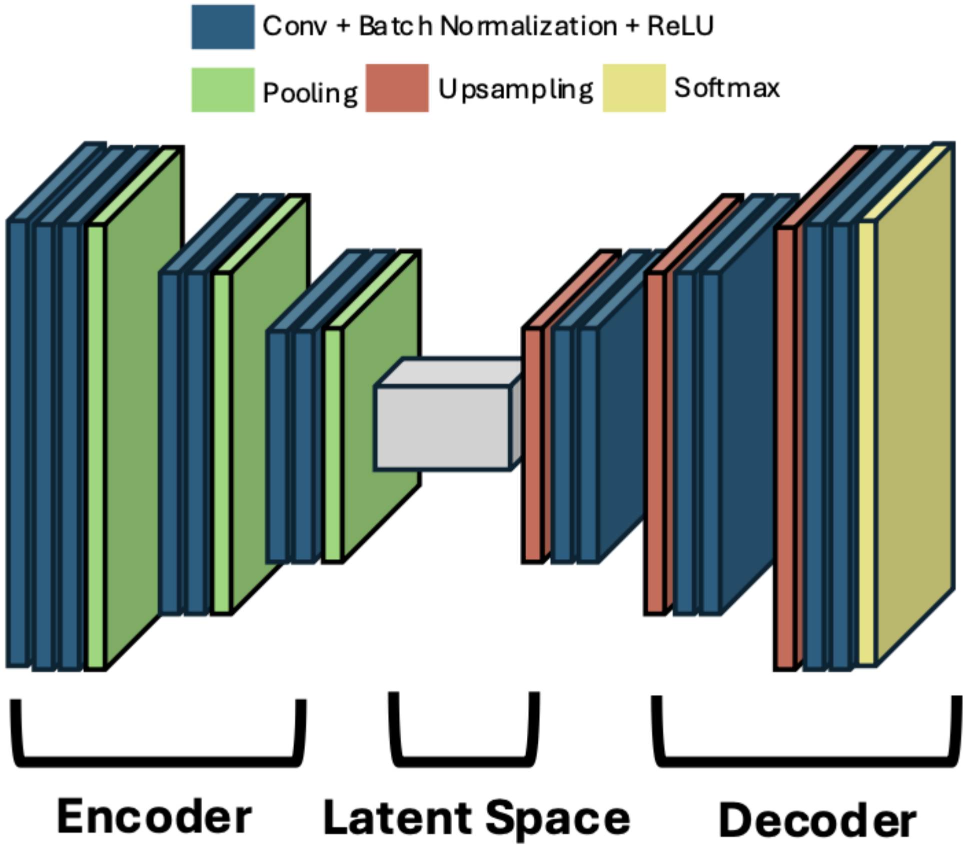
Priors
(Overlap, Rotation)



49 x (64, 64)

3x64x64x64=786,432

Convolutional VAE



64x8x8x8 = 32,768

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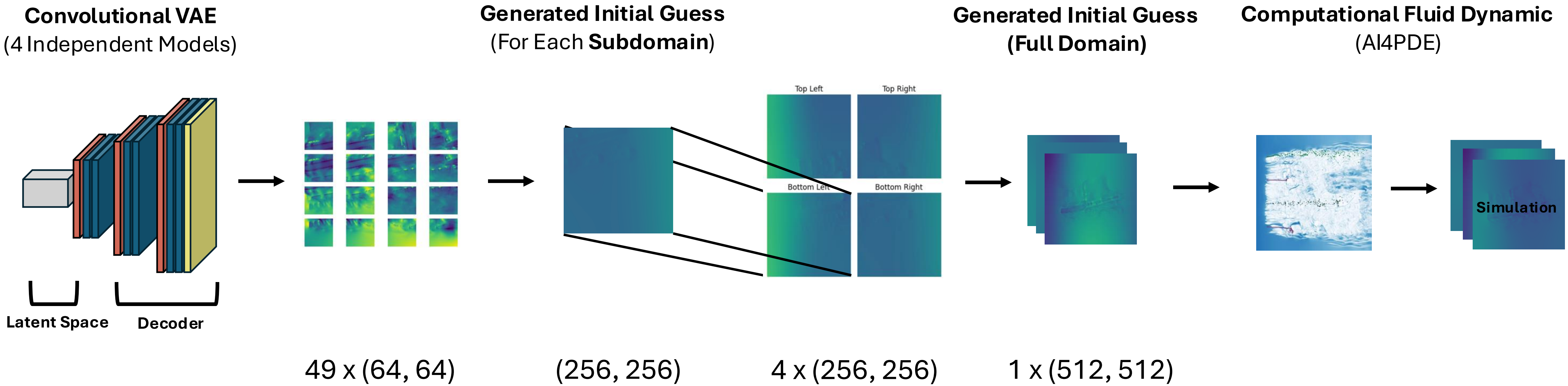
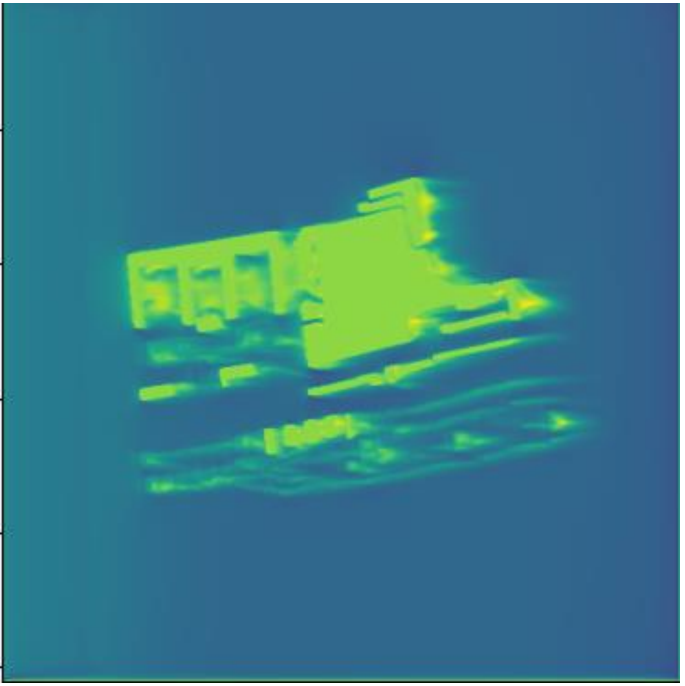
METHODOLOGY – Convolutional VAE

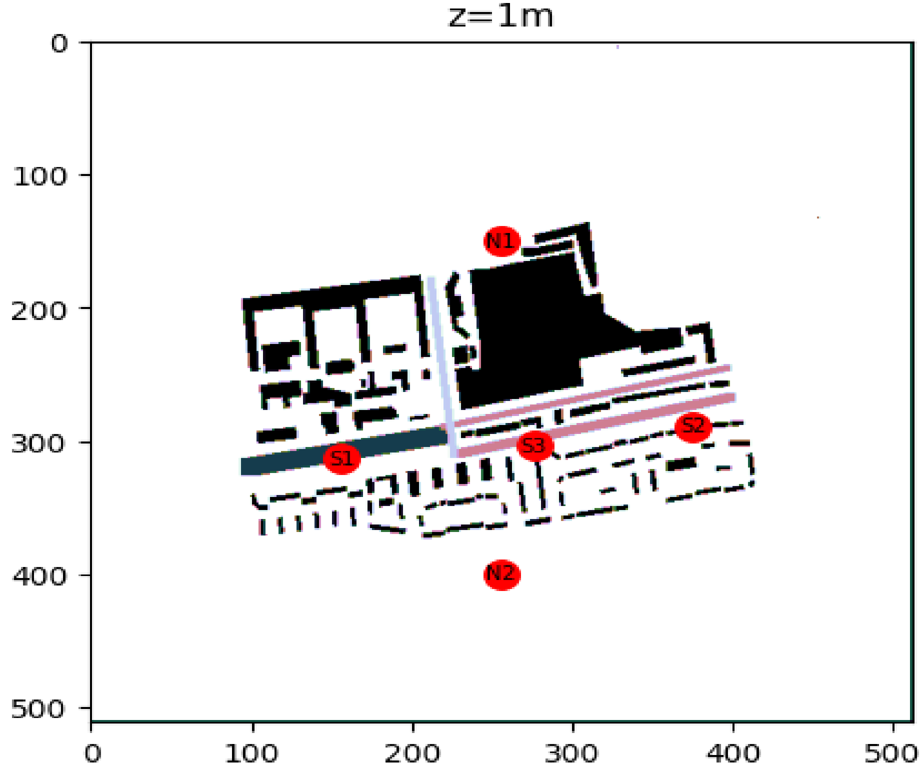


METHODOLOGY – CFD Simulation

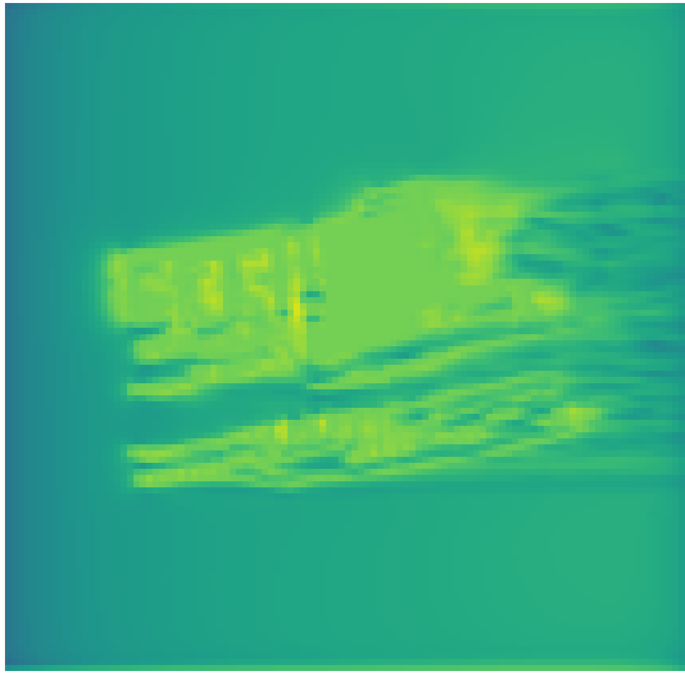
Generated Initial Condition



Computational Fluid Dynamic Model
(10000 timesteps)



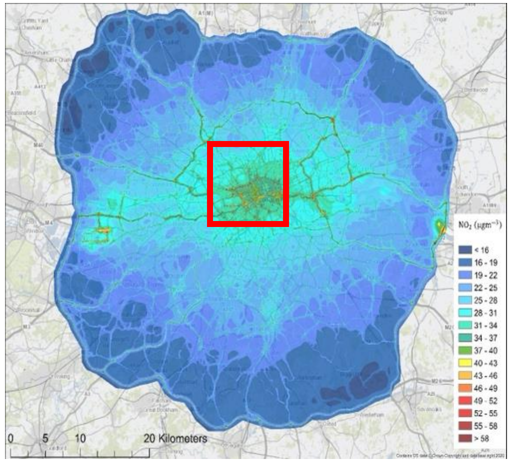
Simulation Result



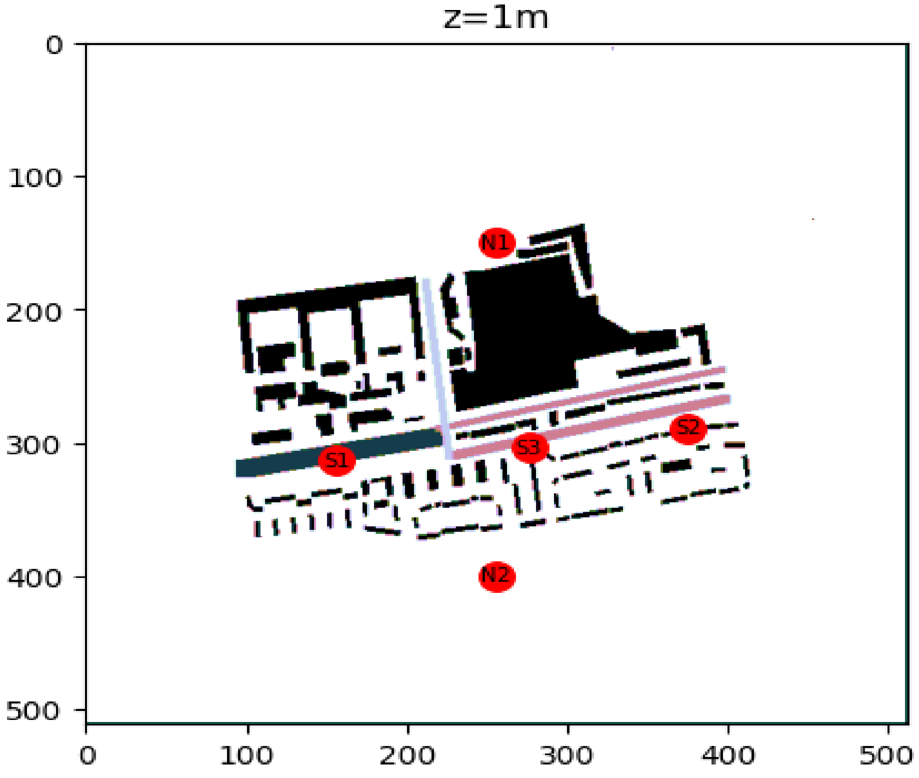
METHODOLOGY – Observational Data

Raw Data
(cleansing, missing values)

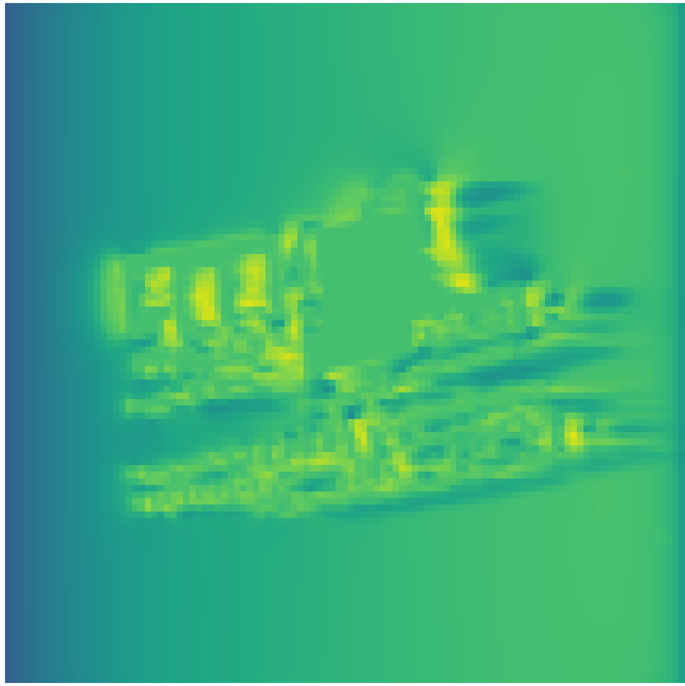
A4636	131	37	21	28		45
A2524	86	20	24	21	1	20
A3713	75	17	13	18		27
A4452	73	5	33	17		18
A4088	72	14	16	12	2	28
A2103	68	14	13	14	1	26
A2156	68	16	13	19	2	18
A3681	66	12	16	9	1	28
A1366	50	11	15	12		12
A2610	39	5	7	12		15



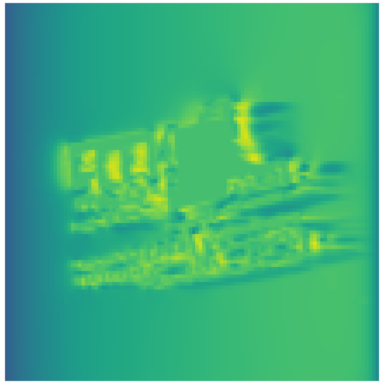
Computational Fluid Dynamic Model
(1 timesteps to create structured mesh)

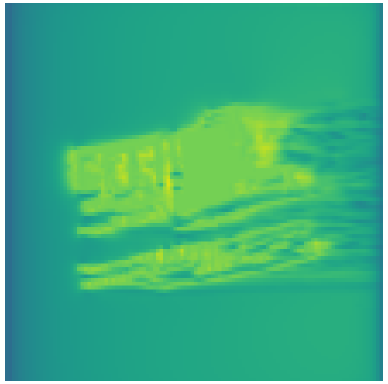


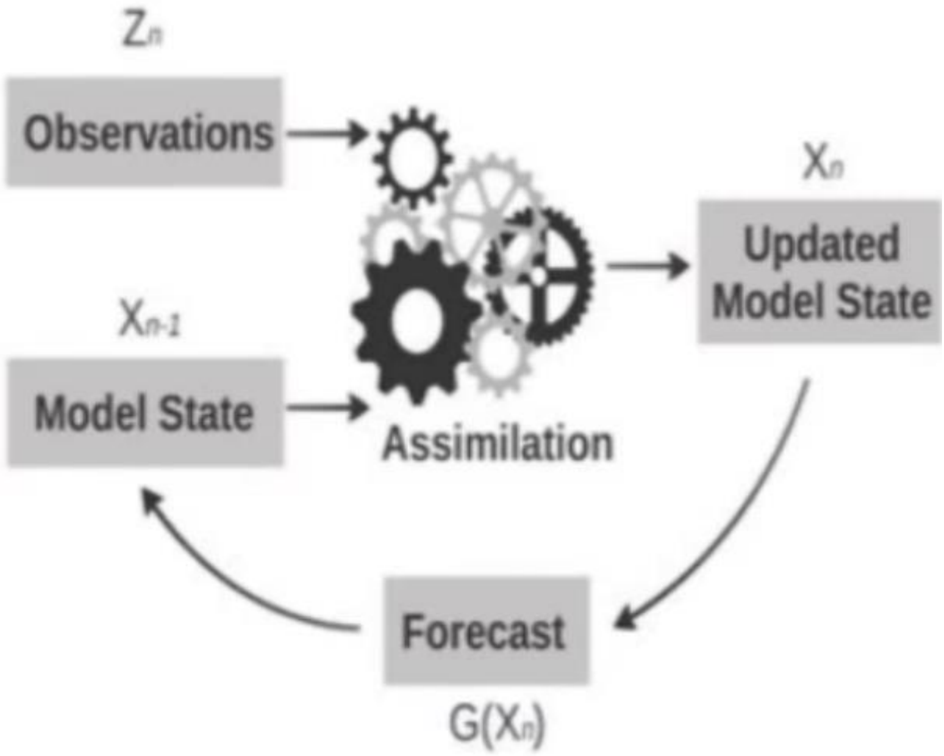
Observational Data

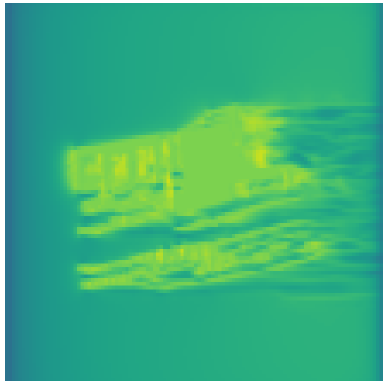


METHODOLOGY – Data Assimilation

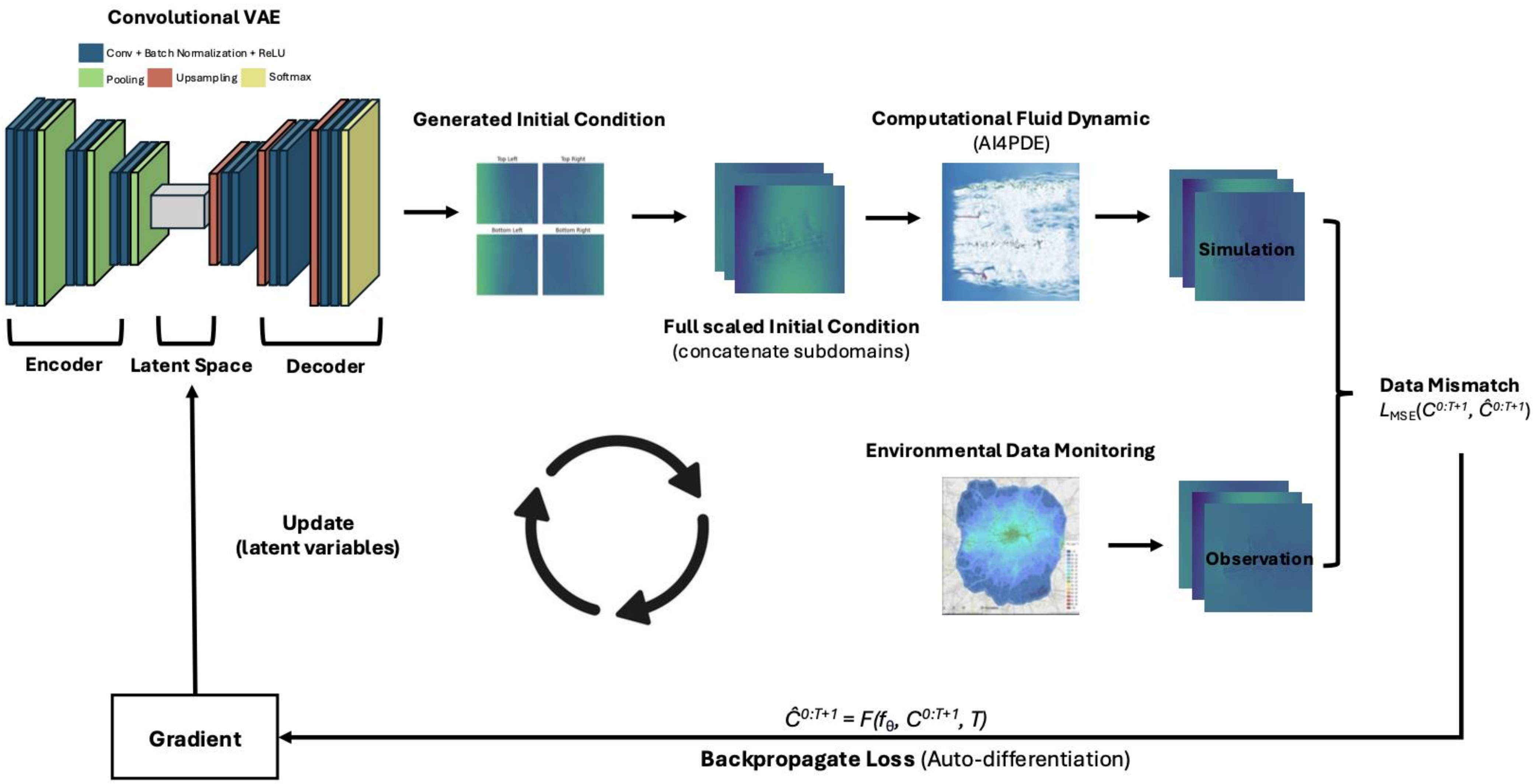






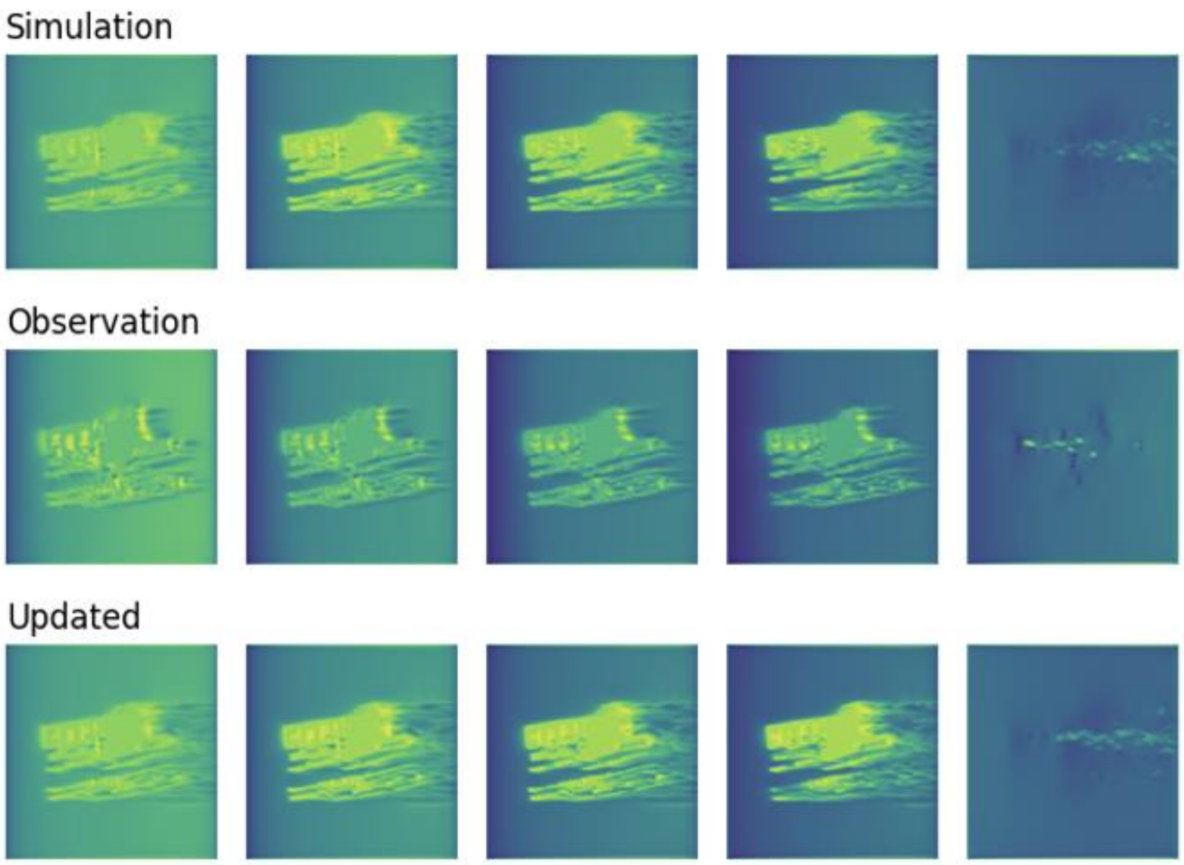


METHODOLOGY – Data Assimilation Loop

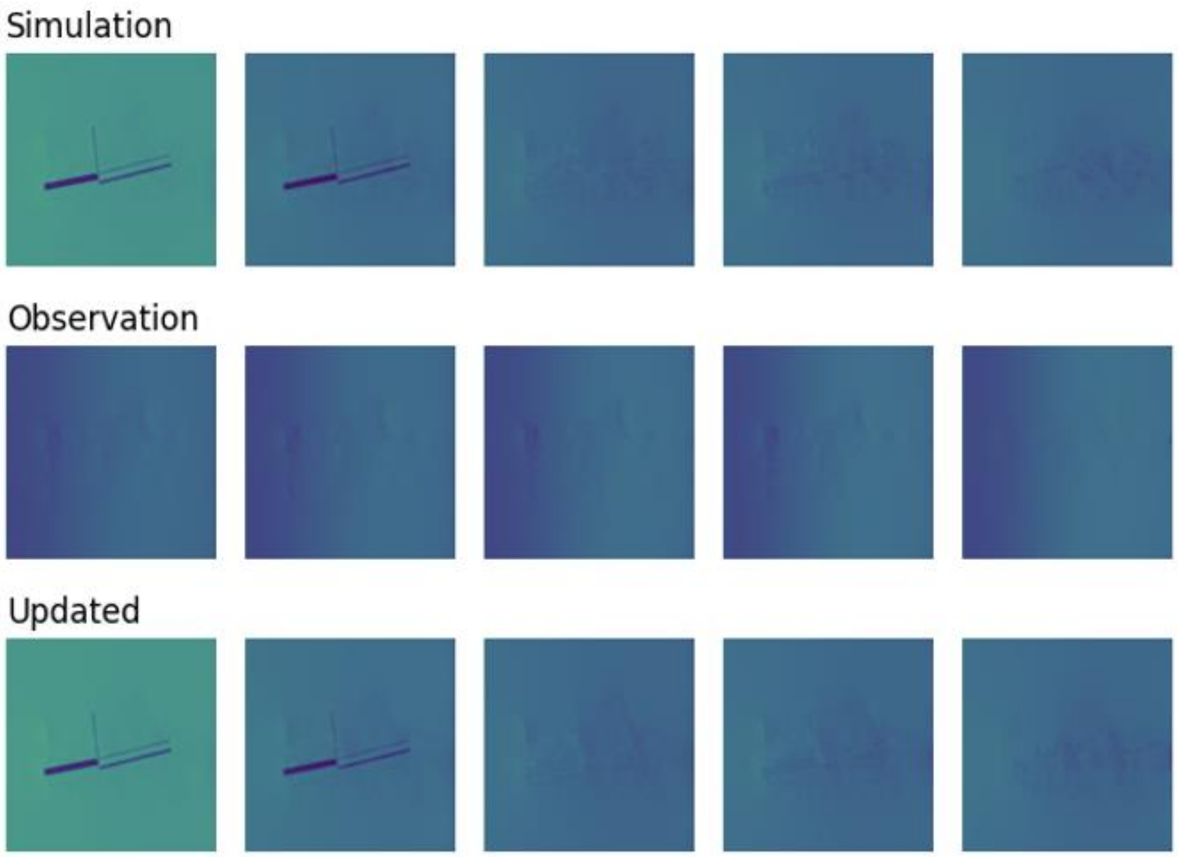


RESULTS - Velocity and Pollution Field

Wind Velocity in X-Direction



Pollution Concentration Field



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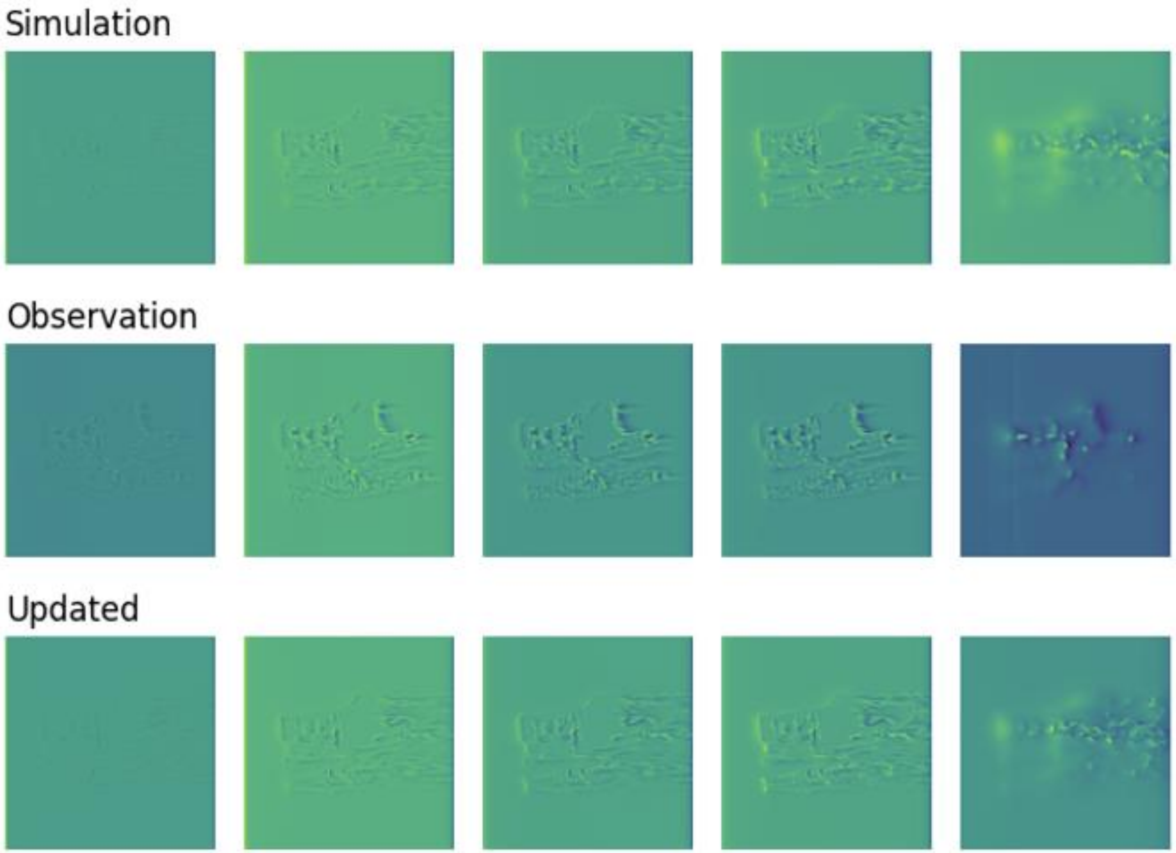
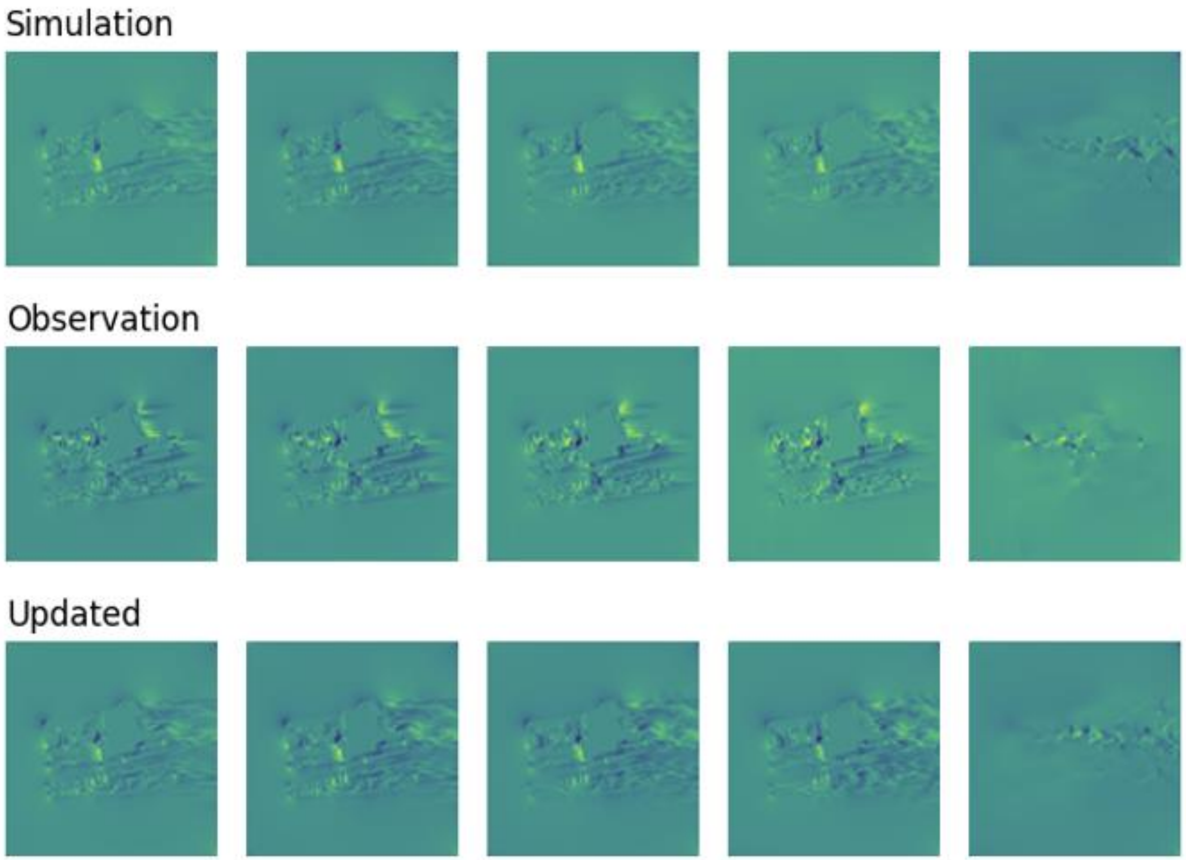
RESULTS - Velocity and Pollution Field

Wind Velocity in Z-Direction

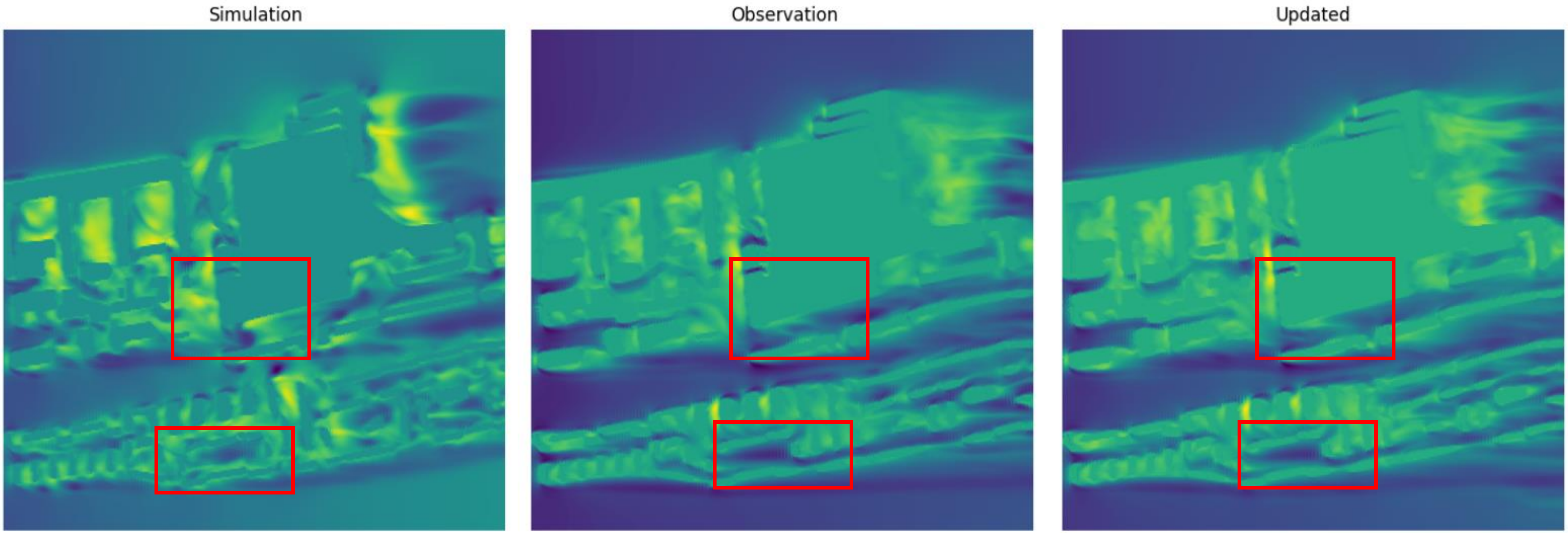


Wind Velocity in Y-Direction

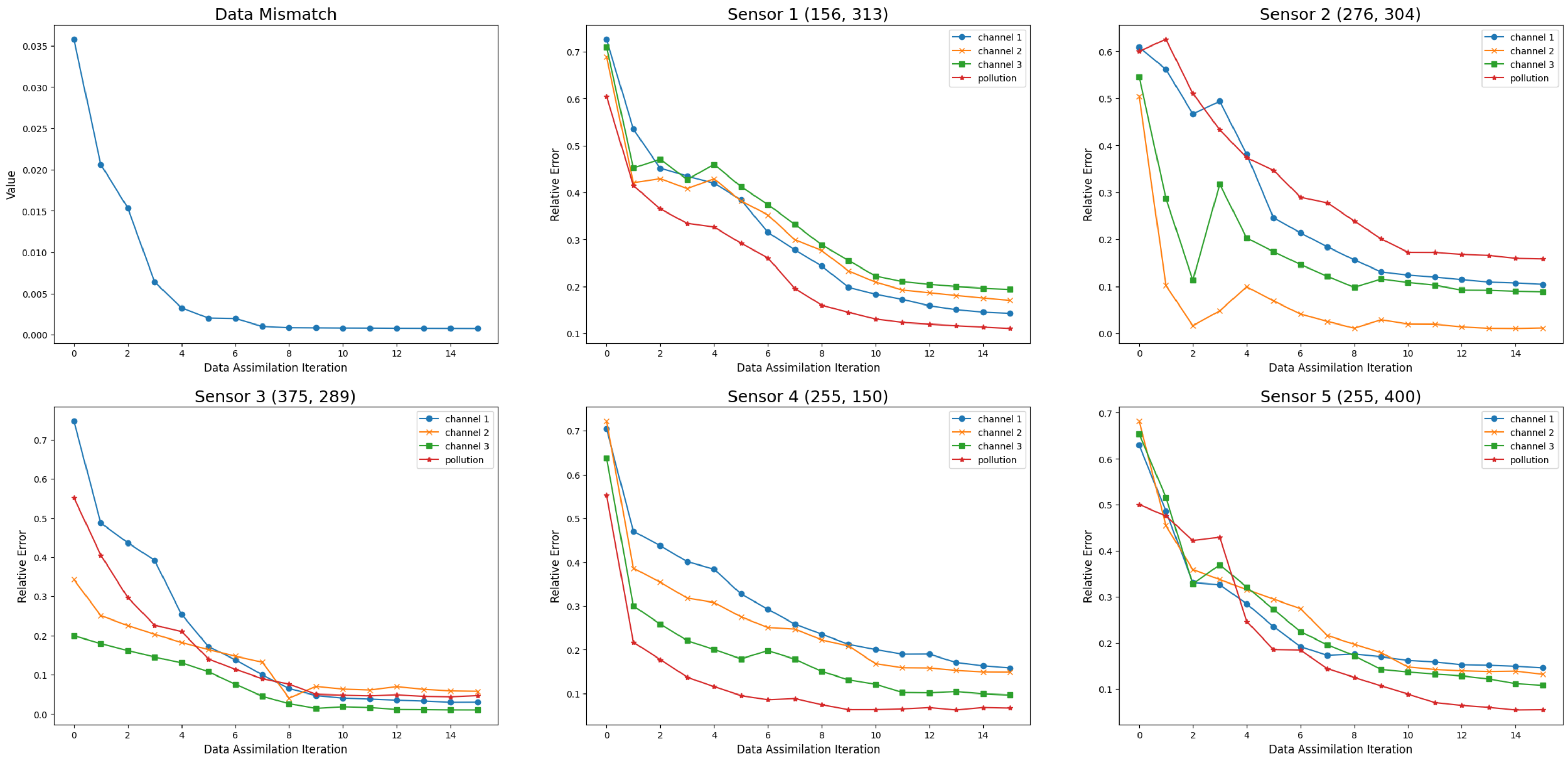


RESULTS - Detailed Analysis

(Velocity Field in x-direction at 1-Meter Height)



RESULTS – Data Mismatch & Sensor Performance



CONCLUSION & DISCUSSION

1

Novel Framework

- Neural Networks
- Computational Fluid Dynamic
- Data Assimilation

2

Large-Scale Predictions

- Feasibility for a smaller domain
- Relative Error < 10%
- Environmental Policy

3

Moving Window Strategy

- Memory Issue
- Stored and Reloaded
- In terms of Time

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