



AI-Enhanced Urban Atmospheric Dispersion Modelling for Radiological Emergency Preparedness and Decision Support

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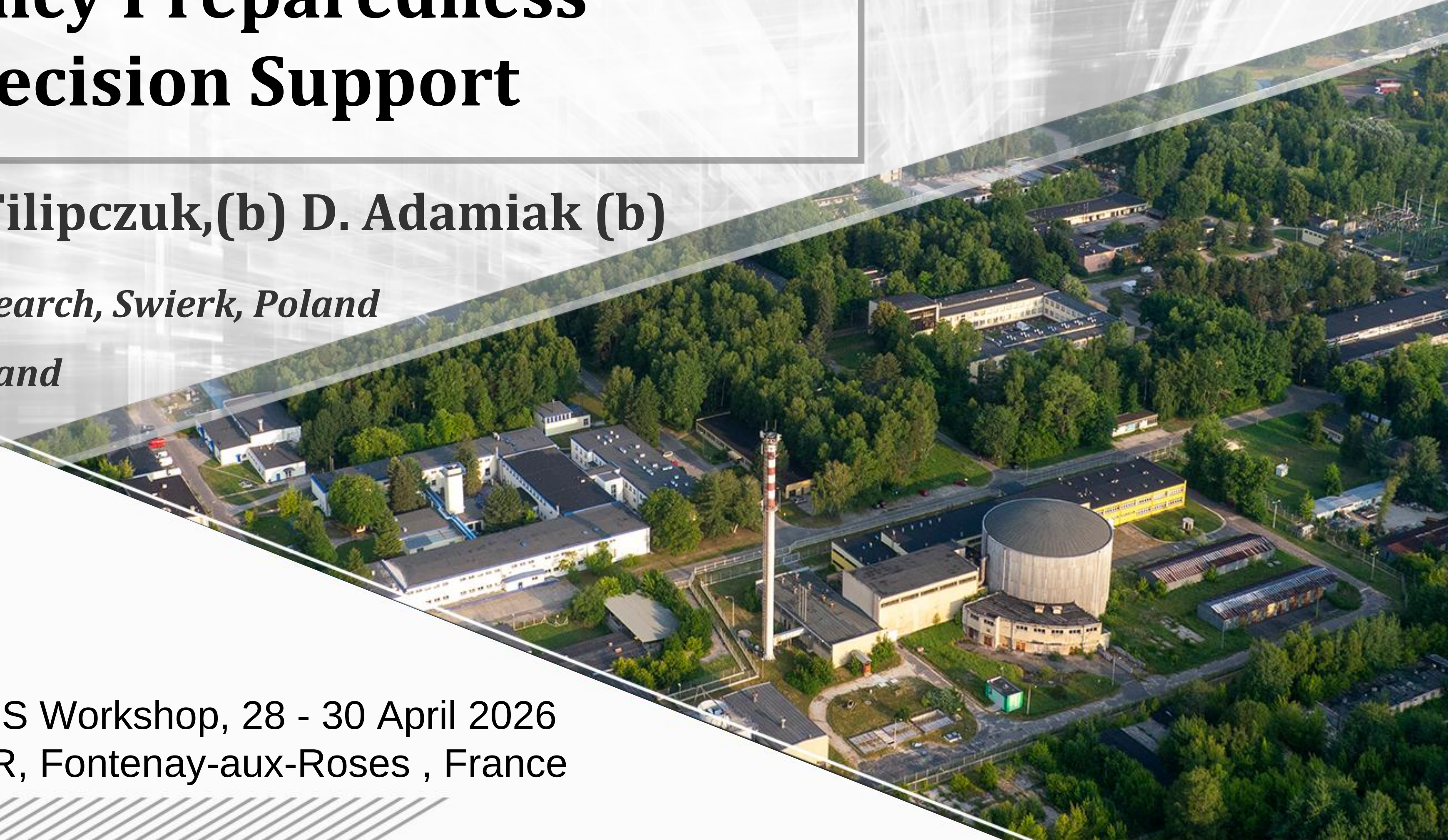
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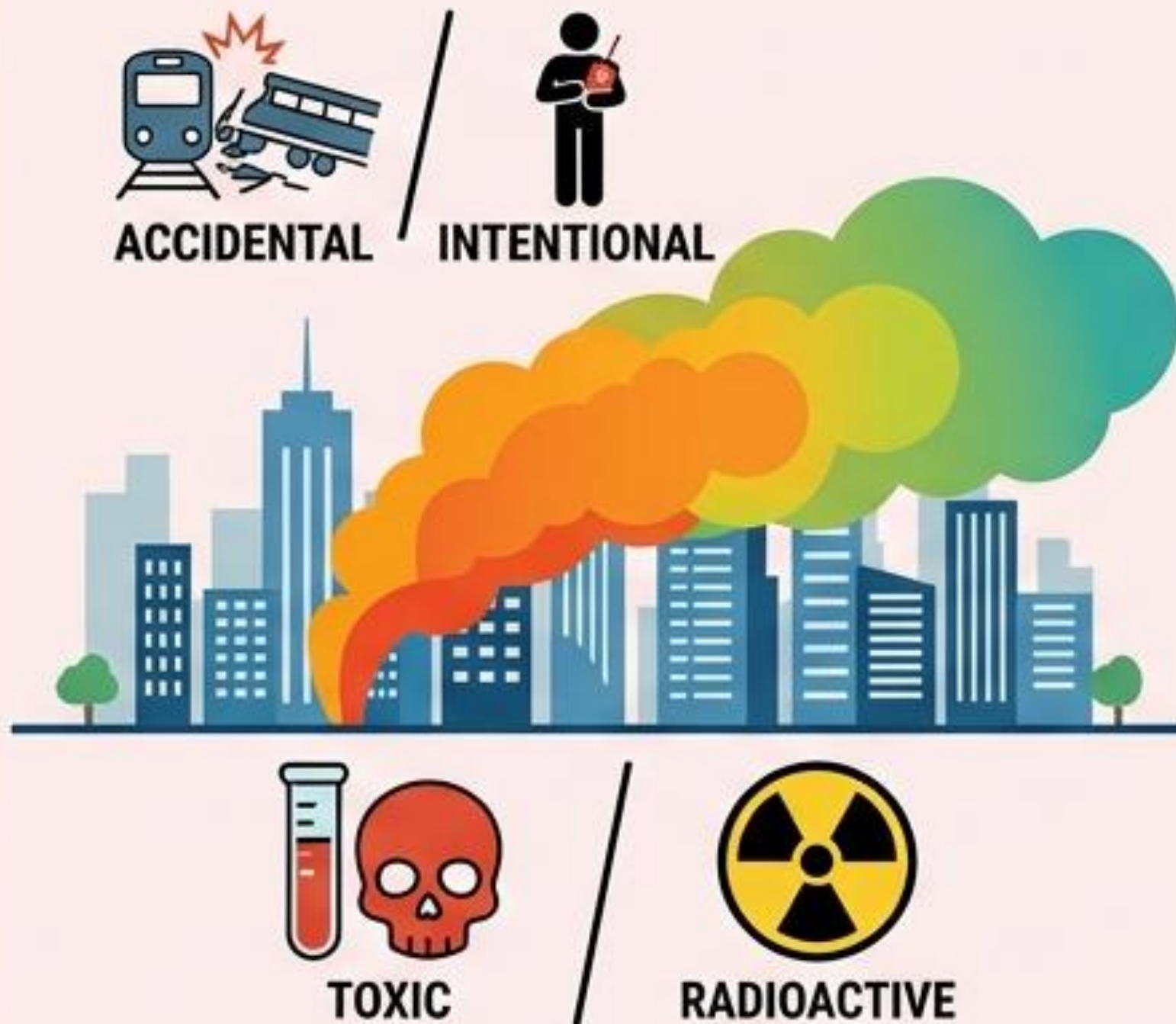


Outline

- Motivation
- Elements of the contaminant source localization system
- Why artificial deep neural networks (DNN)?
- DNN model training results
- Conclusions

Motivation

1. THE THREAT & COMPLEXITY



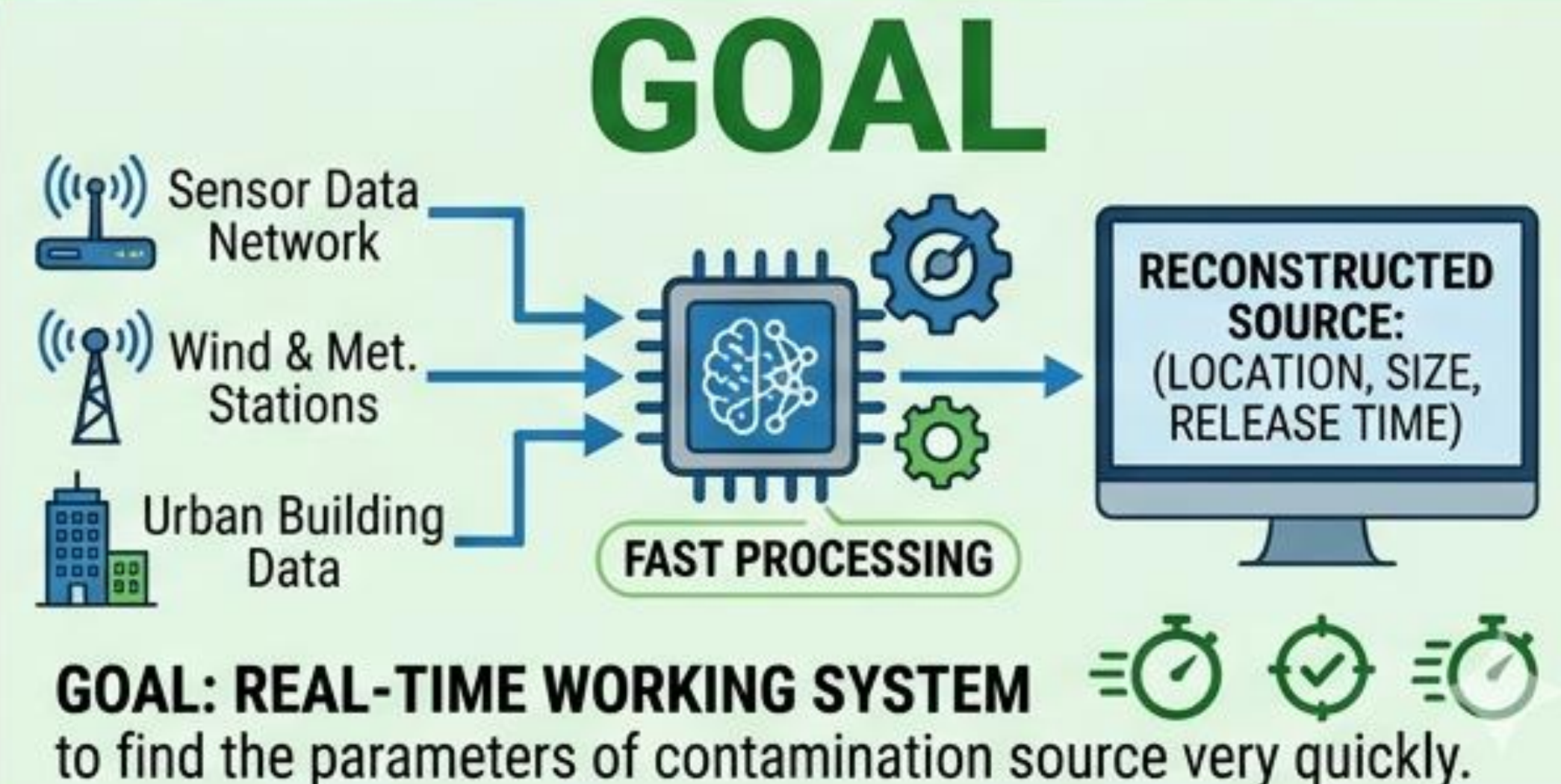
Predicting the transport and dispersion of the contaminant becomes a critical problem for homeland defense. Predicting the transport and dispersion of the contaminant becomes a critical problem for homeland defense. **EITHER ACCIDENTAL OR INTENTIONAL, EITHER TOXIC OR RADIOACTIVE, ETC.**

2. URGENT RESPONSE REQUIREMENT

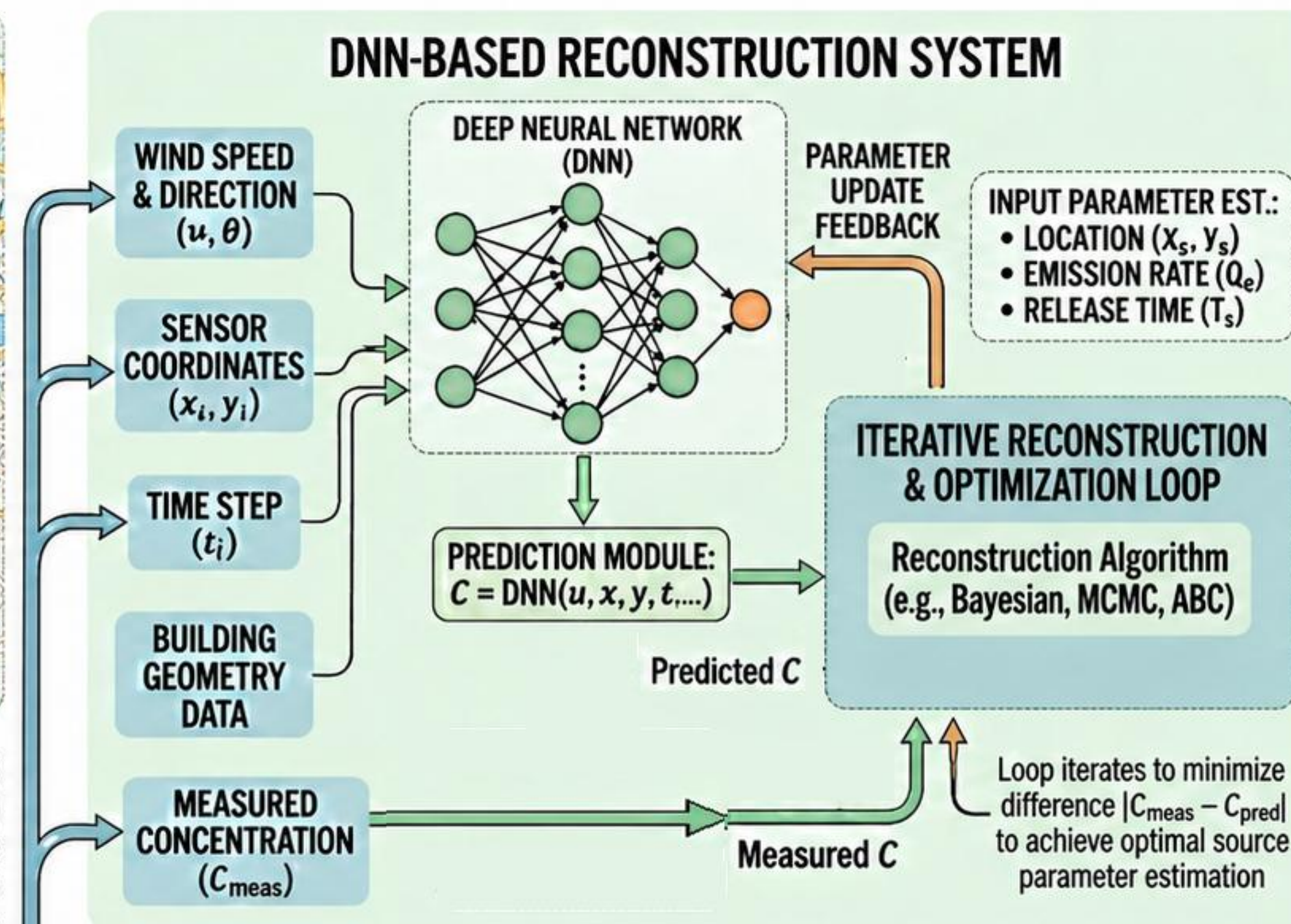
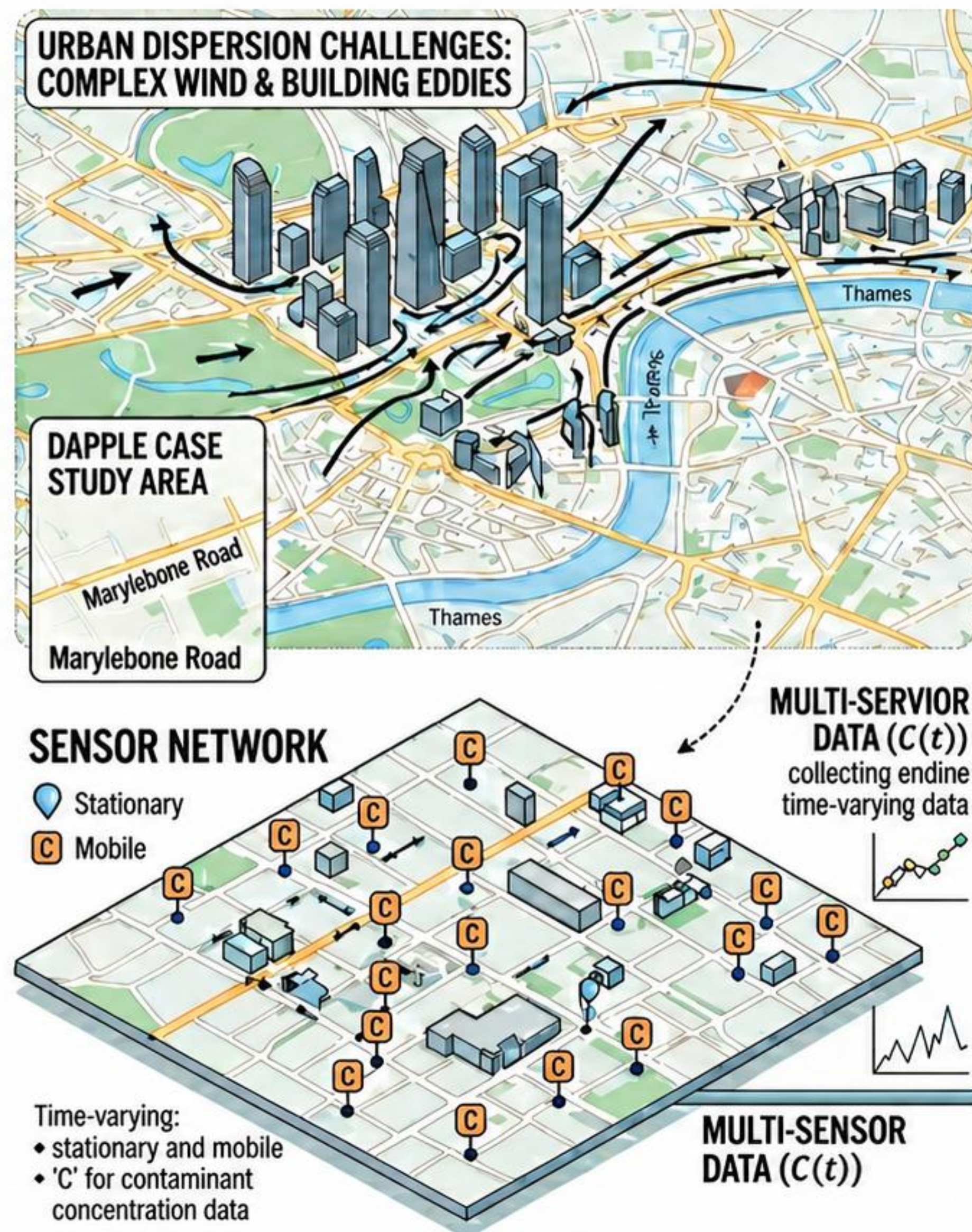


EMERGENCY RESPONSE GROUP should have a system to find the parameters of contamination source **VERY QUICKLY**.

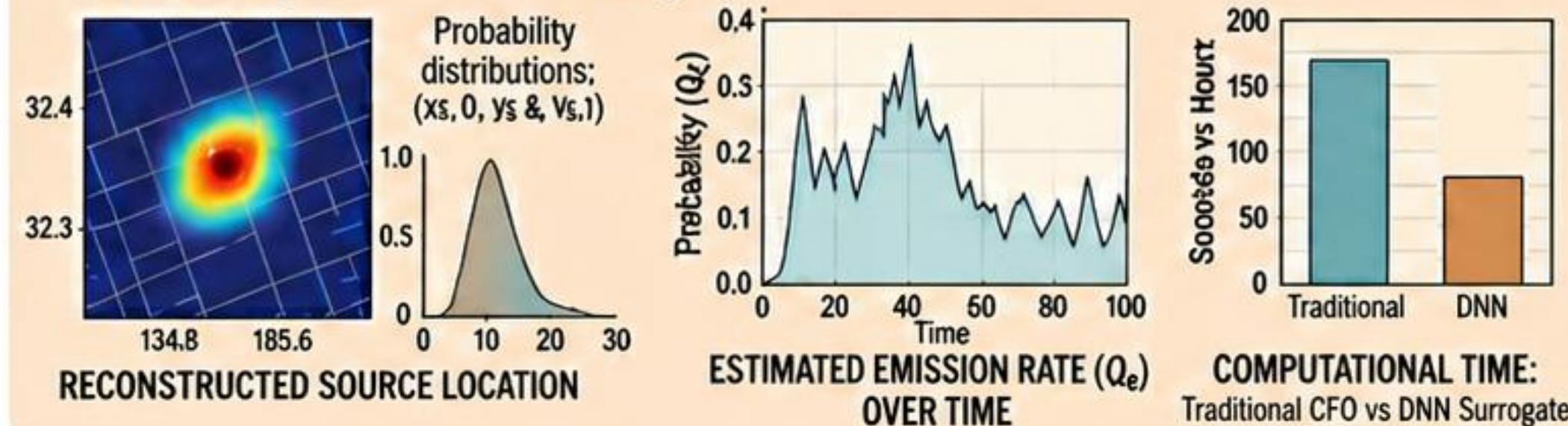
3. THE SOLUTION & GOAL



DYNAMIC CONTAMINANT SOURCE RECONSTRUCTION IN URBAN ENVIRONMENT: SENSOR DATA & DNN



OUTPUTS (OPTIMIZED STATE)

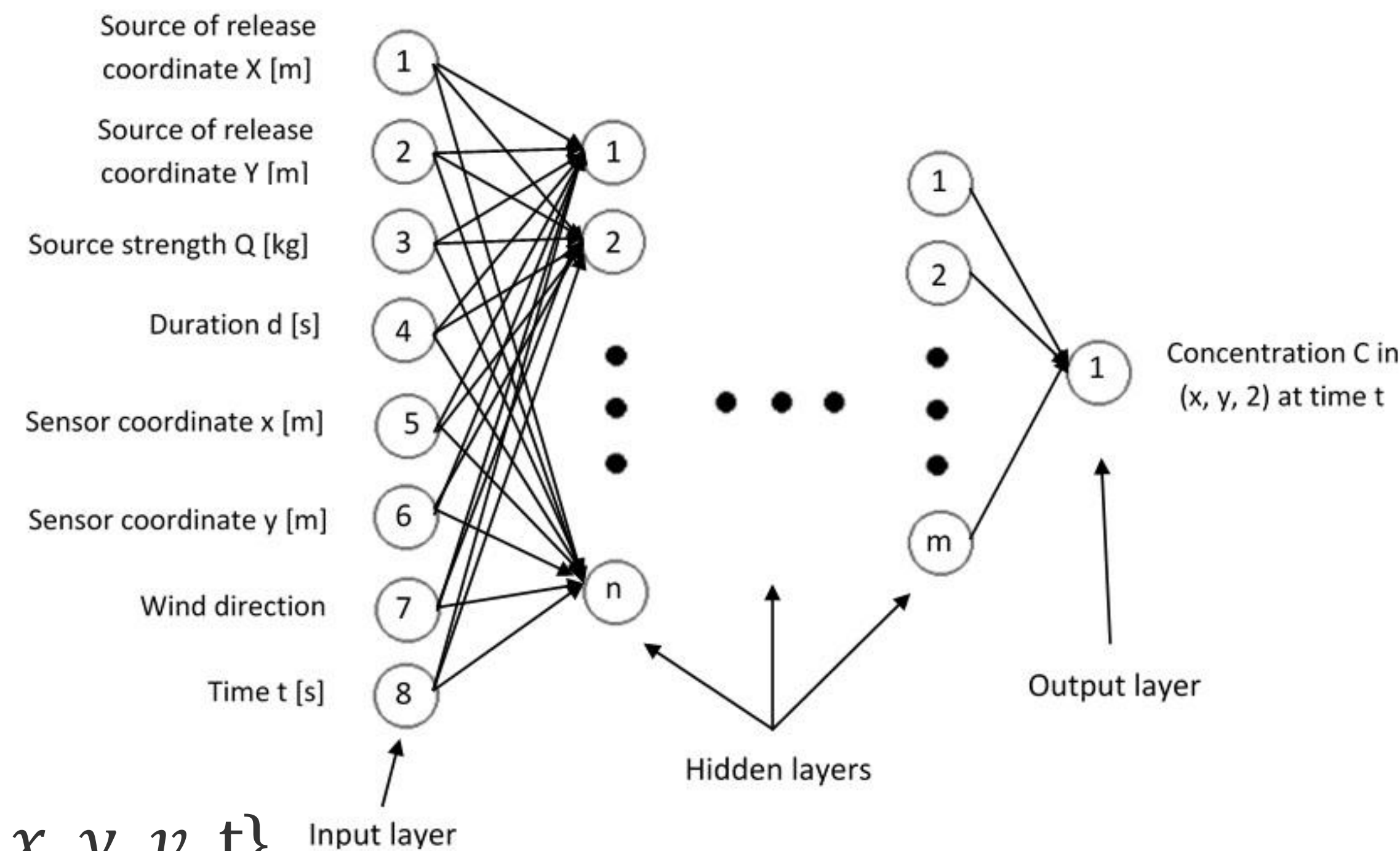


SOURCE CHARACTERISTICS

- FAST INVERSE MODELING
- REAL-TIME CAPABILITY
- ROBUST OPERATION
- HANDLES COMPLEX TOPOGRAPHY

DNN training goal & topology

- **Objective:** Train DNN to serve as a fast dispersion model that can be applied in a contaminant source localization system
- Thus, the structure of the input vector is as follows
 - $Input_i \equiv \{X_s, Y_s, Q, d, x, y, v, t\}$.
- Based on the input vector for the contamination source located at the coordinates $(X_s, Y_s, 2)$ (in meters within the domain), Q is the release rate, d is the duration of the release (in seconds), v is the wind and release lasting through d seconds the trained network should return the output neuron
 - $Output_i = C_i^{S_j(x,y)}(t)$
- denoting the concentration C at sensor S_j with coordinates (x, y) in t -minutes after the onset of the release.



DNN Training Data-City London

-DAPPLE site

- We decided to check the possibility of training the DNN to simulate the airborne toxin transport in the area of central London, where the DAPPLE experiment was conducted [www.dapple.org.uk].
- From four Trials run in March and Jun 2007, we have concentrations at 15 receptor positions for 30 minutes with 3-minute intervals. This gives us, in sum, about **600 point-concentrations** for four various source positions and release rates.
This amount of data is **not enough** to properly train the ANN.
- The only solution is to use the verified and well-recognized dispersion model to generate the dataset utilized to train, test, and validate the DNN

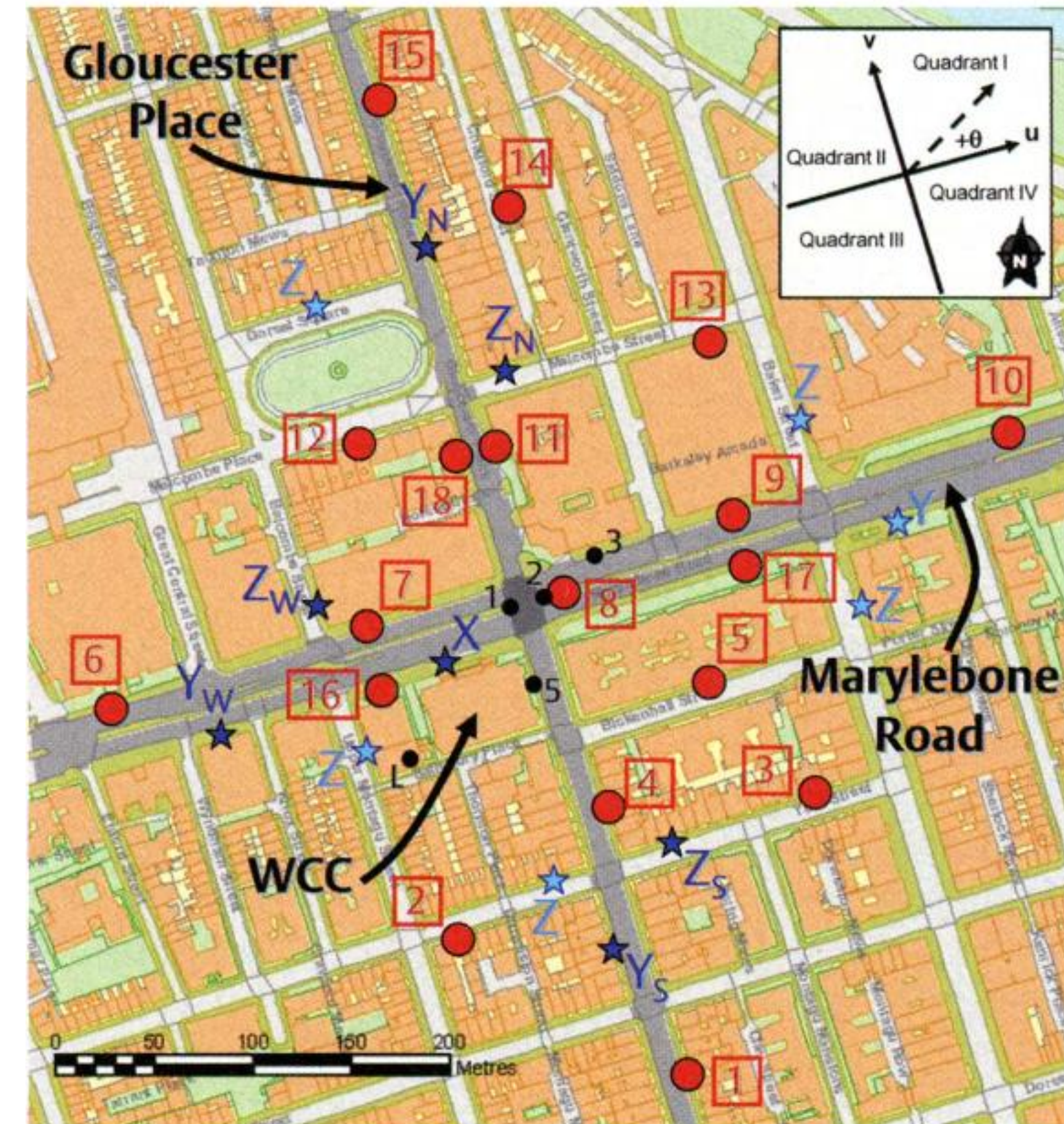
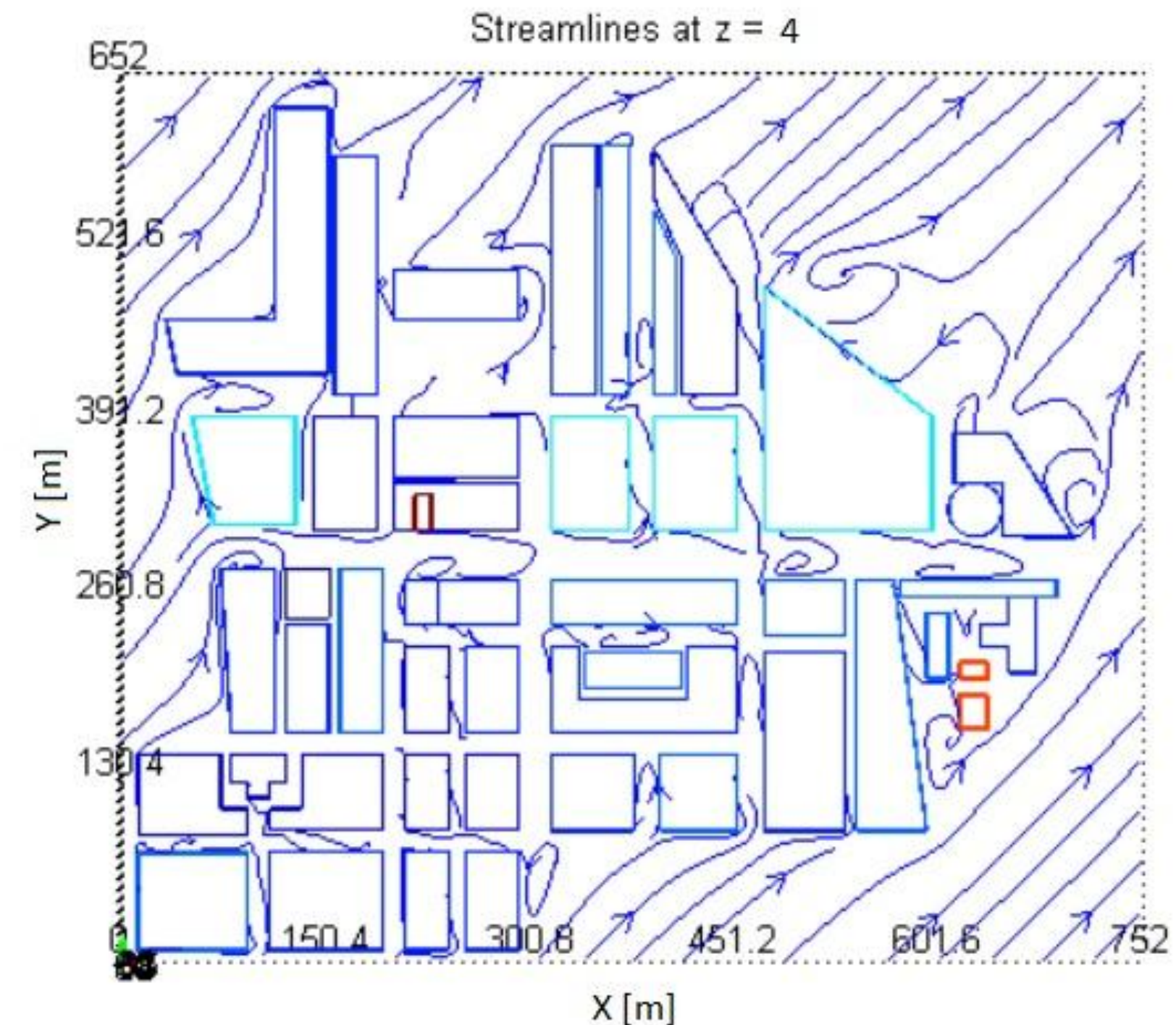
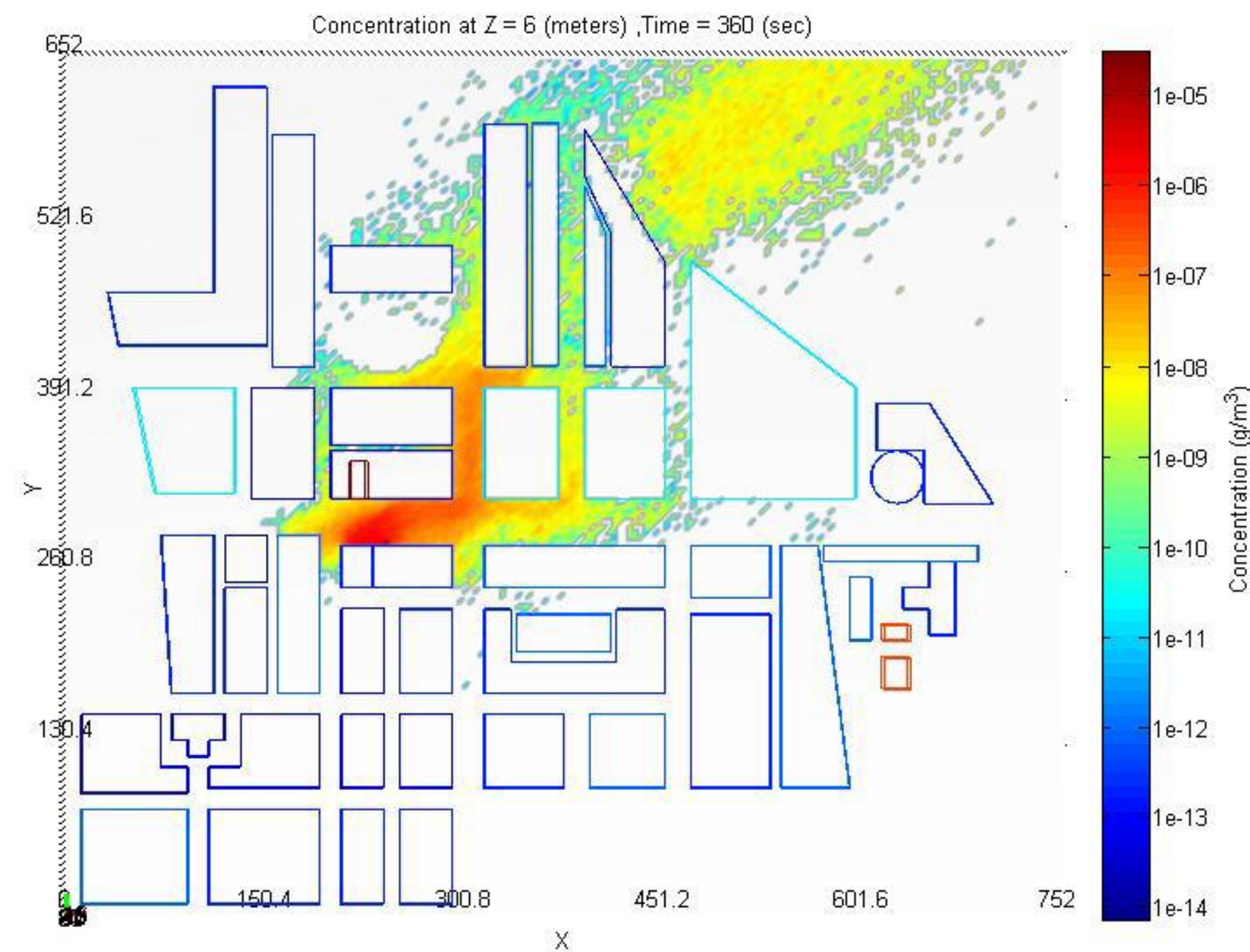


FIG. 1. The map shows the DAPPLE area of central London, and is centered at the focal intersection, that of Marylebone Road and Gloucester Place (at 51.5218°N, 0.1597°W). Also shown are the locations used in the summer 2007 campaign.

www.dapple.org.uk

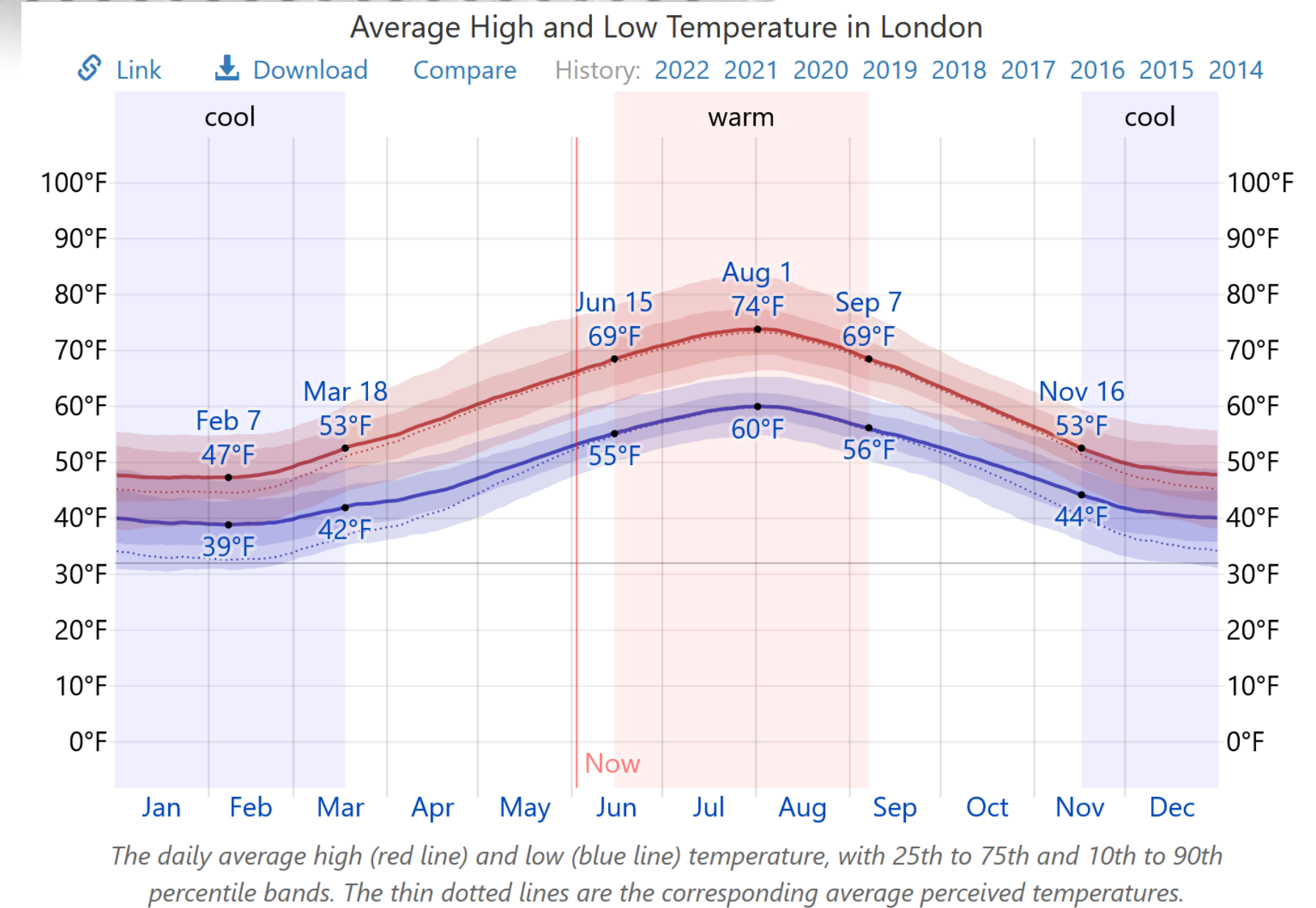
DNN Training Data-City of London -DAPPLE site



- Using Quick Urban Industrial Complex (QUIC) Dispersion Modelling System we have randomly drawn the ~ 500 contamination source locations, release rate within the interval $Q \in \langle 100\text{mg}, 999\text{mg} \rangle$ and its duration within interval $\langle 5\text{min}, 30\text{min} \rangle$ per single release.
- As a result, the training dataset covered about 5×10^7 vectors, including the release source's coordinates, the source strength, the release duration, and the output concentration in a given time and domain point. [Wawrzynczak&Berendt, 2020, 2023]

DNN Model-DAPPLE site

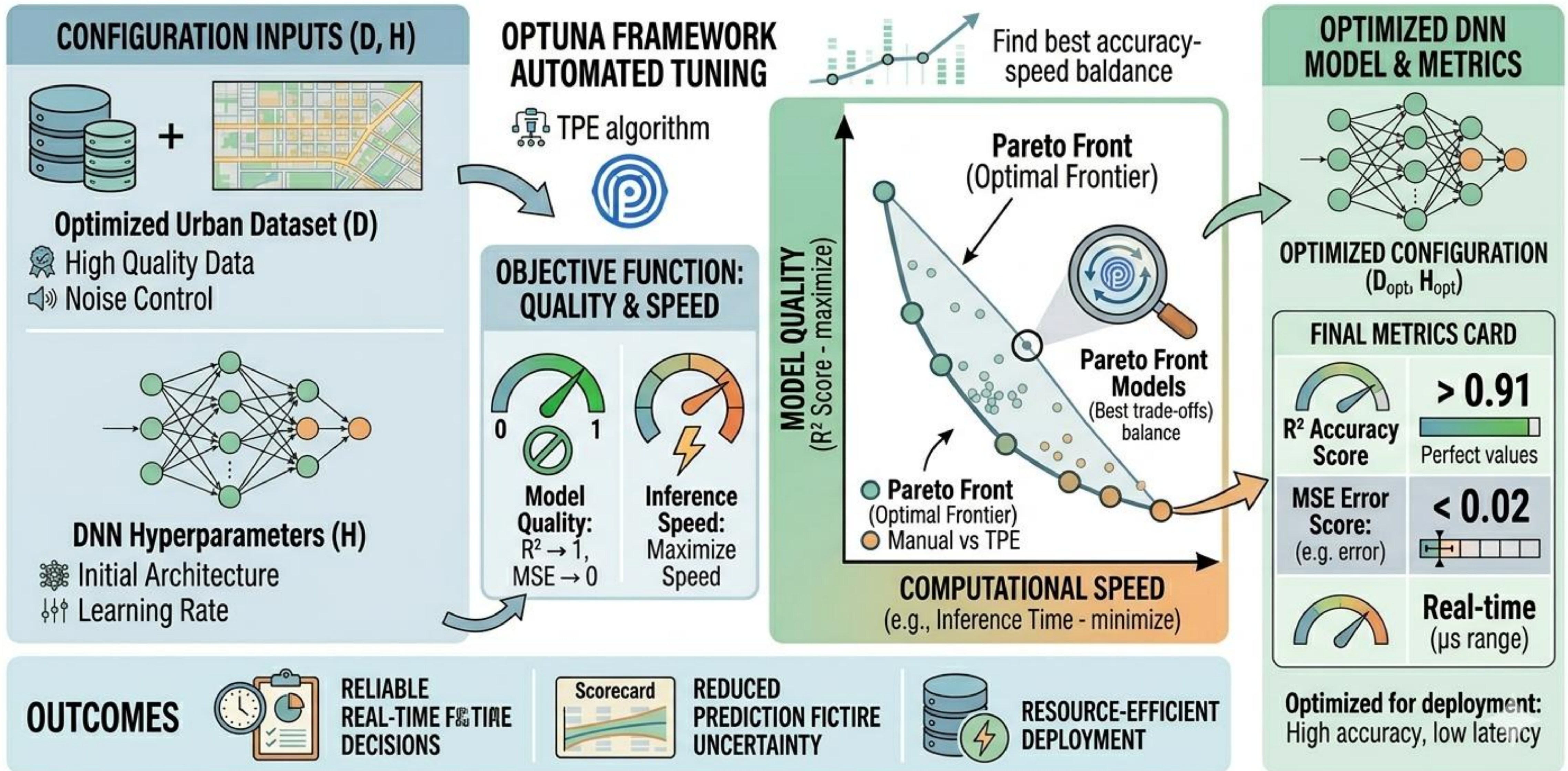
- The meteorological data were included accordingly to the statistics observed for the summer season in London during the years 2014-2021.
- Consequently, the average temperature in the selected season of the year was $\sim 18^{\circ}\text{C}$, and the average wind speed was 5m/s.
- Additionally, the percentage share of each of the eight main wind directions was taken into account (N - 10%, S - 10%, W - 20%, E - 10%, NW - 10%, NE - 11%, SE - 4%, SW - 25%).



<https://weatherspark.com/y/45062/Average-Weather-in-London-United-Kingdom-Year-Round>



DNN QUALITY OPTIMIZATION WITH OPTUNA FRAMEWORK: IMPACT OF TRAINING DATA & HYPERPARAMETERS



Results

Table 3. Hyperparameter configuration of the selected compromise model (Trial 5) chosen from the Pareto front.

Parameter	Value
Hidden layers L	10
Neurons per layer	513, 588, 549, 537, 275, 498, 584, 409, 525, 393
Learning rate η	2.11×10^{-5}

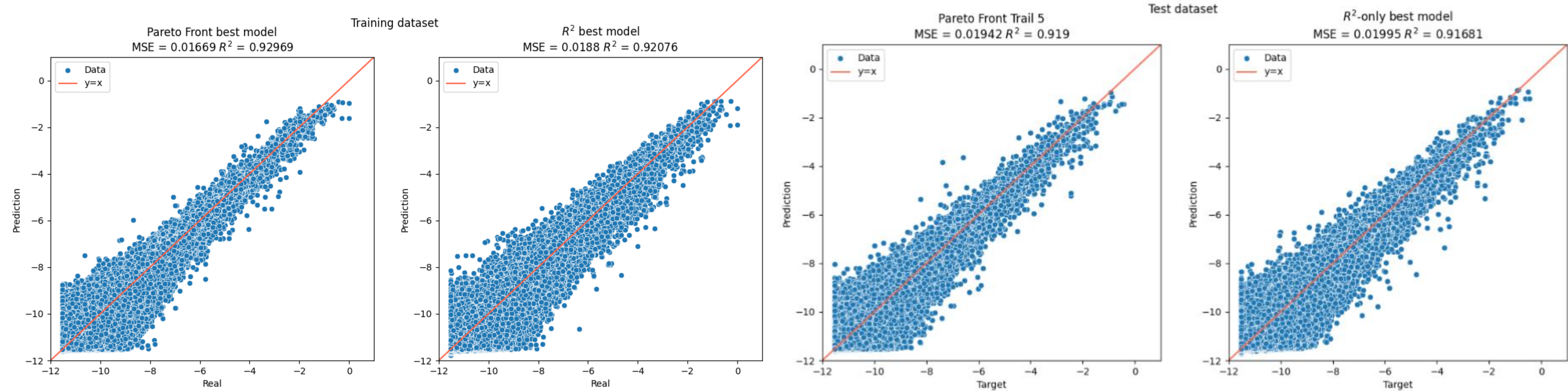


Fig. 6. Prediction versus reference concentration values for the Pareto-selected model (left) and the best single-objective (R^2 -only) configuration (right), evaluated on the independent test dataset.

Results

- While the Pareto front provides a set of optimal trade-off solutions, a single model must be selected for deployment
- For set of Pareto-optimal configuration i , the Euclidean distance to the utopia point was computed as

$$d_i = \sqrt{(\tilde{R}_i^2 - 1)^2 + (\tilde{\text{MSE}}_i)^2}$$

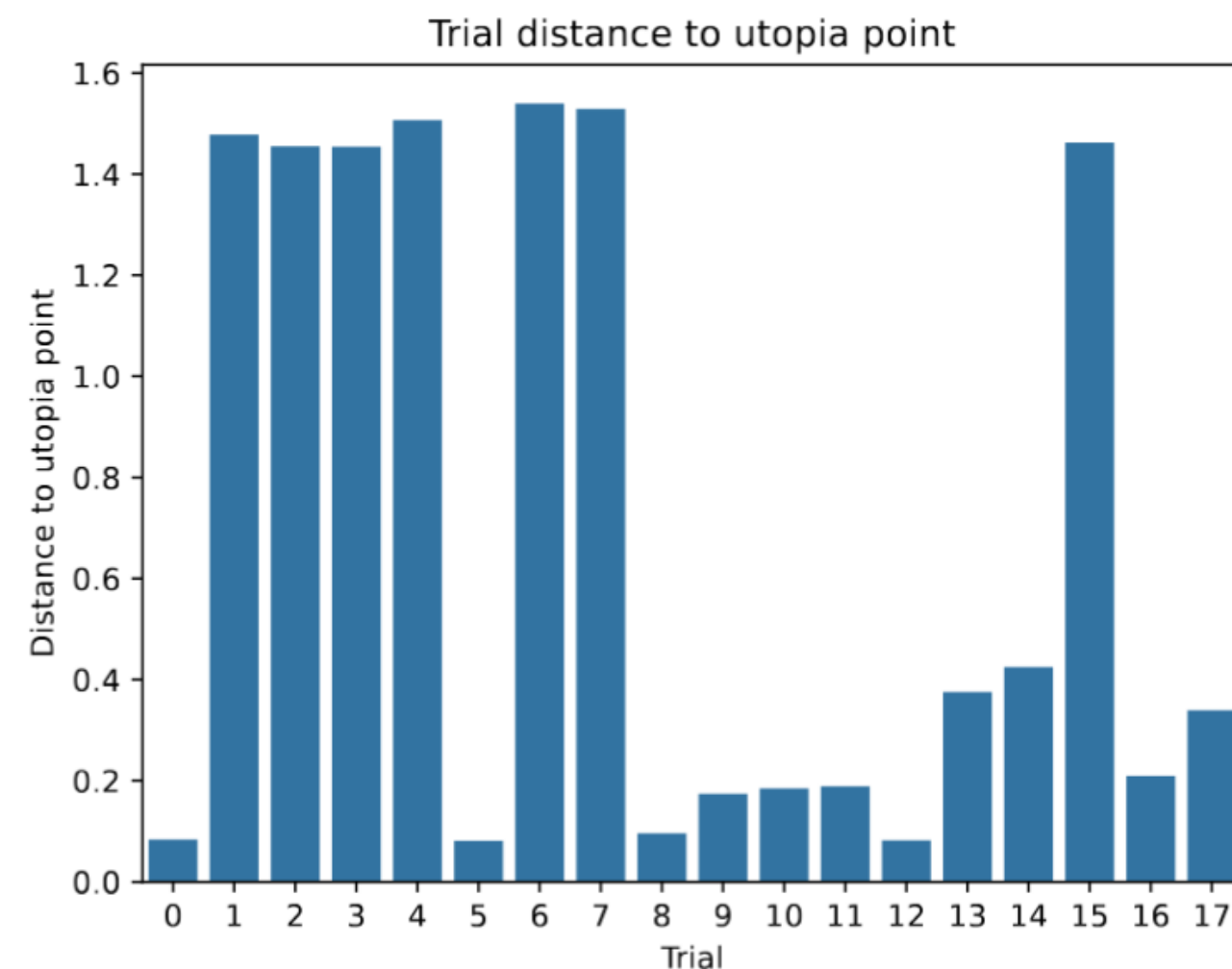


Fig. 5. Euclidean distance of Pareto-optimal configurations to the utopia point in the normalised objective space. Smaller values indicate more balanced trade-offs between R^2 and MSE.

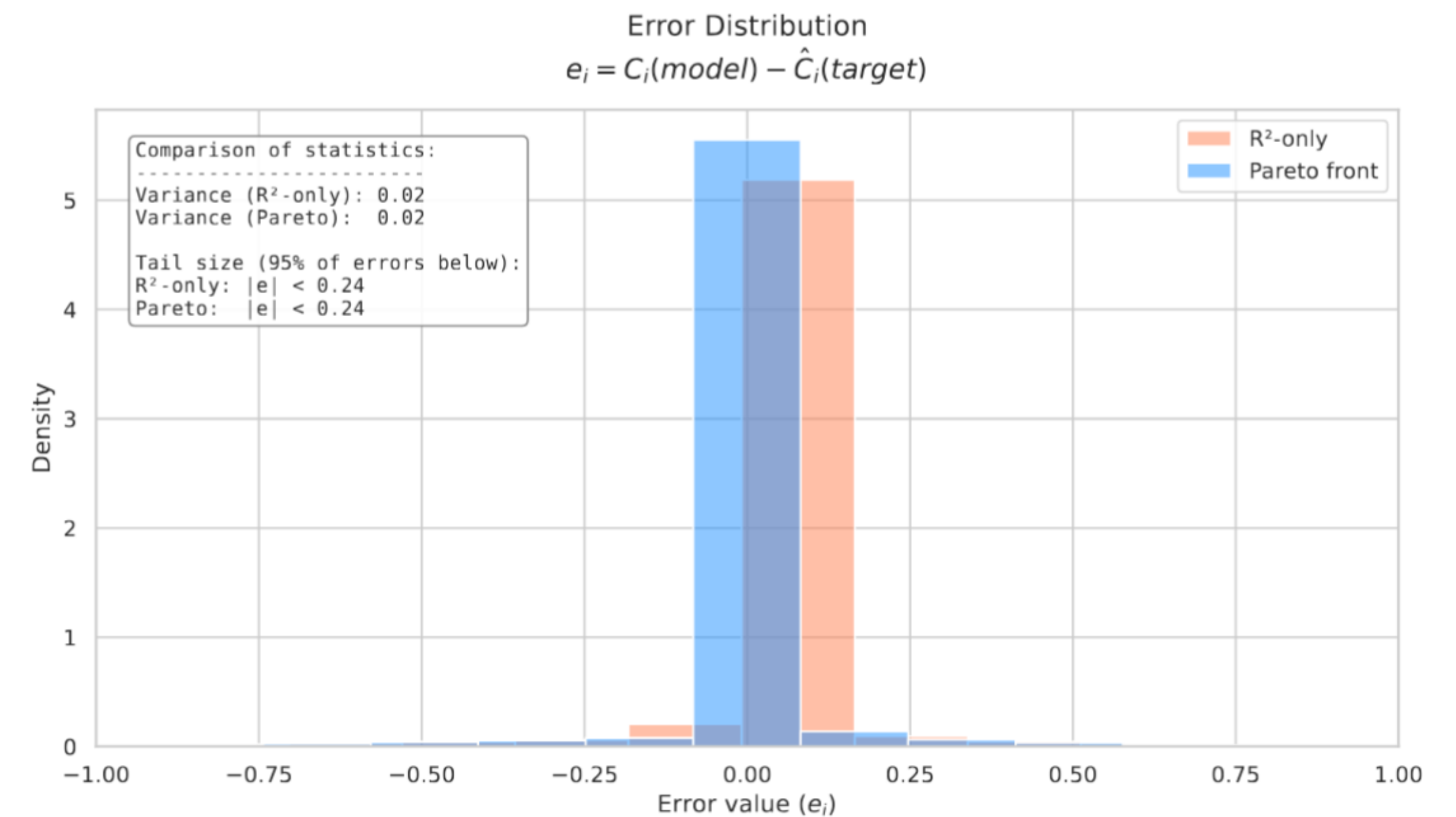


Fig. 7. Absolute error distributions on the test dataset for the Pareto-selected model (Trial 5) and the best configuration obtained by maximising R^2 only.

DNN prediction quality vs time

- Additionally verified the trained DNNs on the training dataset by the additional measure based on the fractional bias as was proposed in [Wawrzynczak, A., Berendt-Marchel, 2023, ICCS]

$$\rho(d_{ANN}^{1:t}, d_{target}^{1:t}) = \frac{1}{SN} \sum_{j=1}^{SN} \left[\frac{1}{t} \sum_{i=1}^t \frac{|D_i^{Sj} - \hat{D}_i^{Sj}|}{D_i^{Sj} + \hat{D}_i^{Sj}} \right]$$

- The measure ρ fits into the interval $[0, 1]$. If the ANN model prediction is ideal, then $\rho = 0$, and if the model predictions are completely wrong, it equals 1.
- **This measure reflects how well the DNN predicts the dose in all sensors at a given time.**

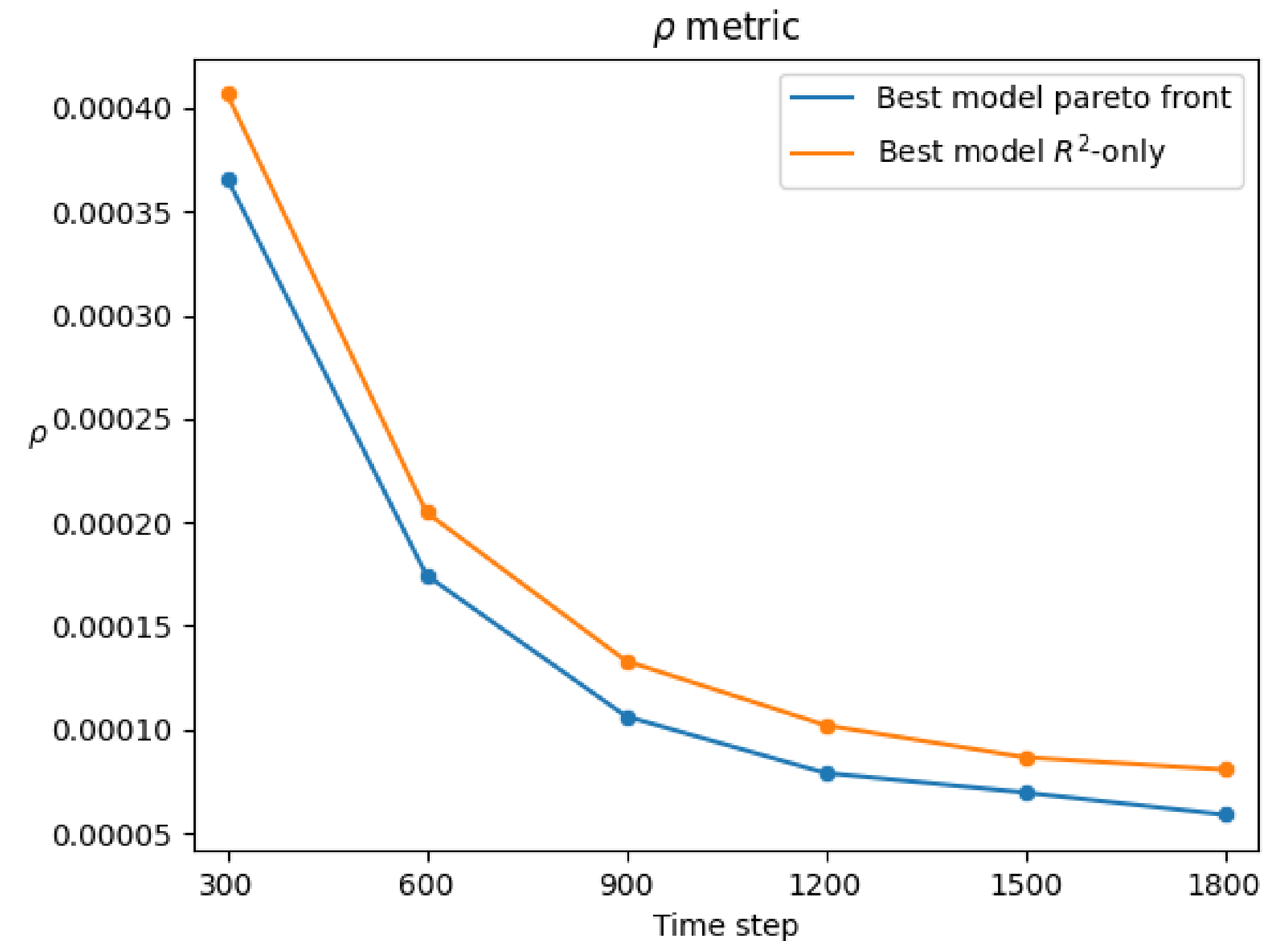
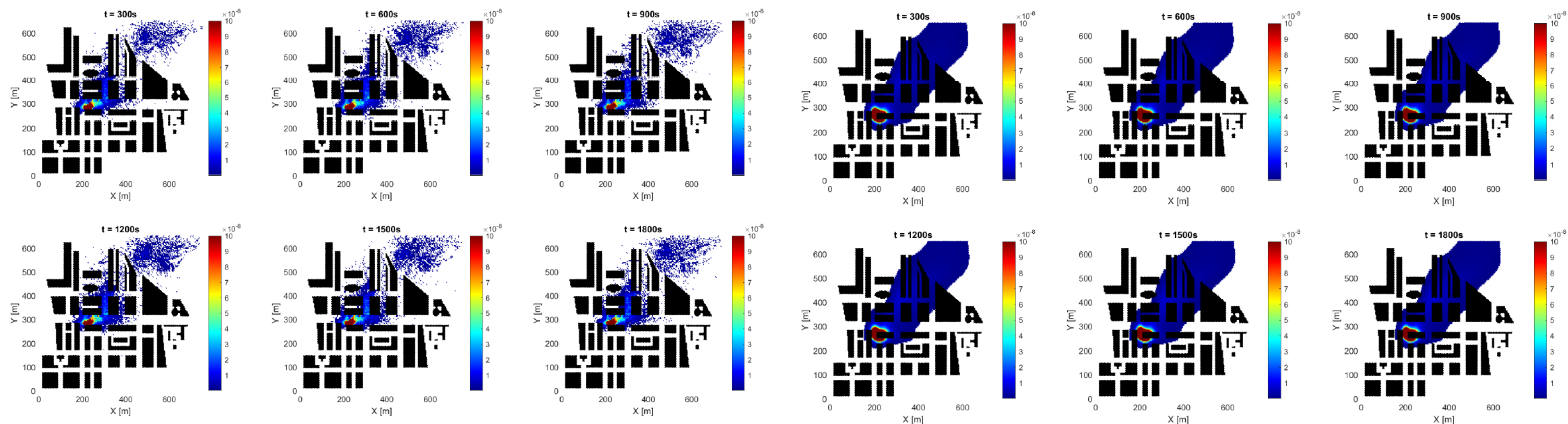


Figure 3: The ρ measure in the subsequent time steps for two selected DNNs (for testing dataset).

Did the DNN learn the physics standing behind the gas dispersion over the highly urbanized area?



QUIC

**(~300 seconds
for 1 point
concentration
estimation)**

DNN

**(~3 seconds for 1
point
concentration
estimation)**

Fig. The dispersion of the contaminant simulated by QUIC (left) vs. DNN (right) , Scenario 2

Conclusions

- The DNN can work well as a surrogate model for the atmospheric dispersion
 - ... when answer time is more important than precision
- Application of the DNN model in the emergency localization system make possible to achieve the real-time response, but...
 - it requires site-specific, well-trained DNN ->
 - Lots of data, both from models and field experiments in various weather conditions
 - **Open question:** to what extent can trained DNNs be applied to other urbanized terrains?



If You have any question, ideas, remarks, write ...☺ !

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