ENHANCED DEEP LEARNING ARCHITECTURE FOR 3D AIR POLLUTION DISPERSION FORECASTING

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Context

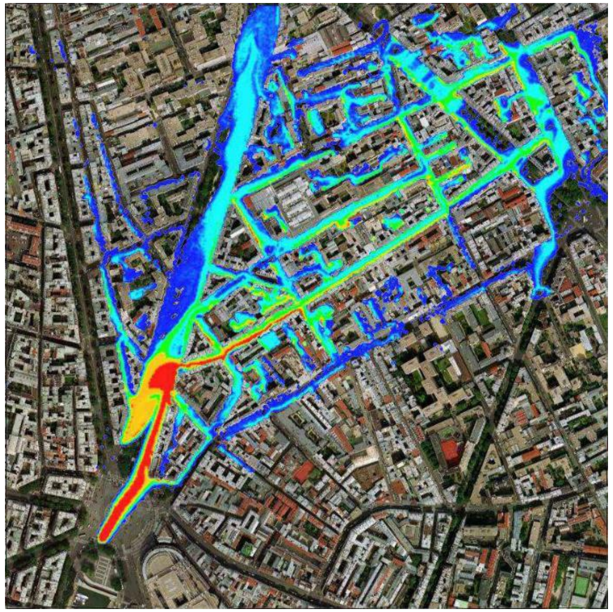
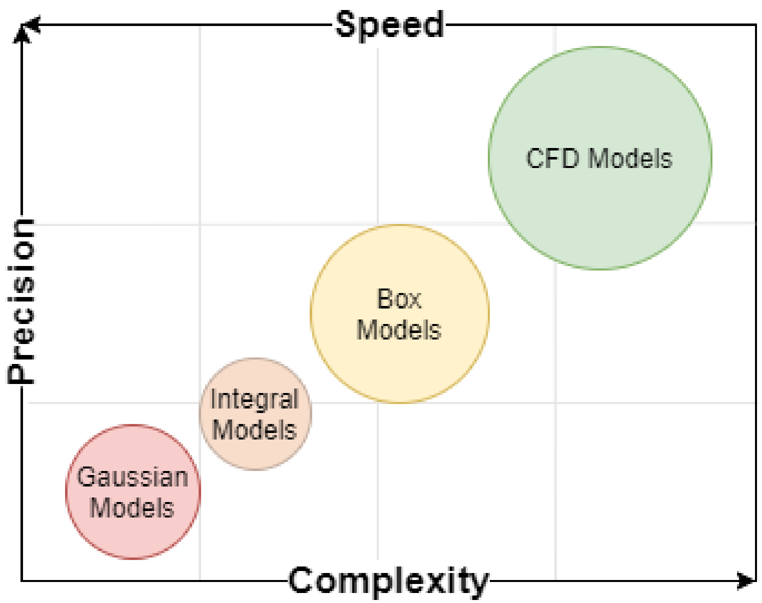


Figure from P. Armand et al. (2015)

- Unexpected pollution emissions in urban areas: accidental (e.g. chemical accidents) or malicious (e.g. hostile fire)
- Emergency crisis intervention to protect the population and the environment

Context



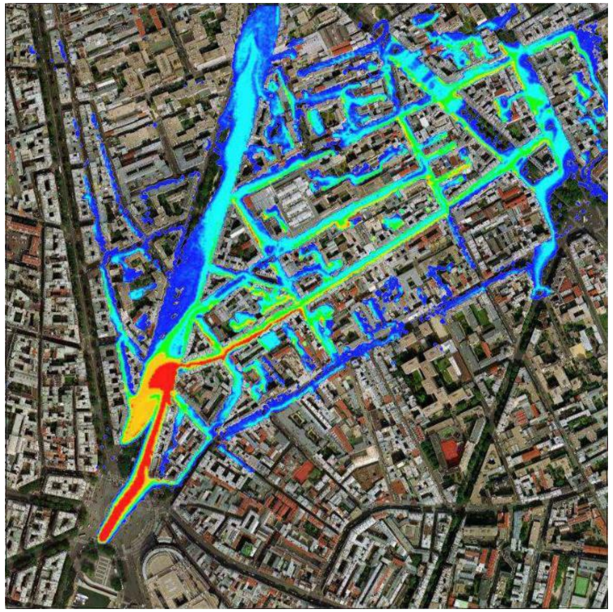


Figure from P. Armand et al. (2015)

- CFD-level accuracy is required for risk assessment
- CFD models are realistic but **slow**

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- Crisis management requires **fast** intervention

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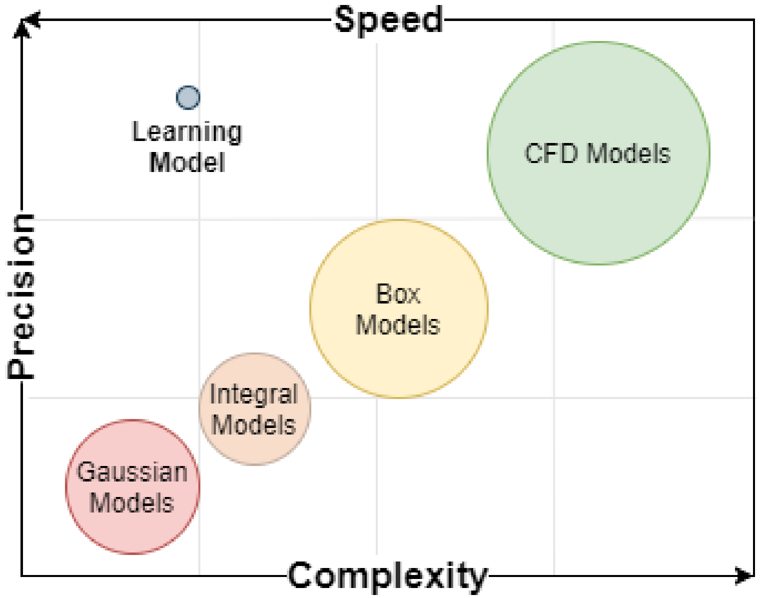

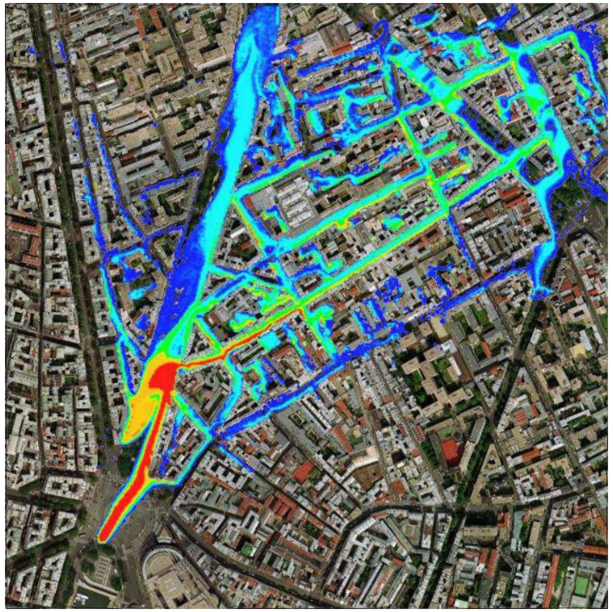

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Problem Definition

- **We want to predict 3D pollution dose field (integrated concentration) for an exposure duration of 2 hours following an accidental release**

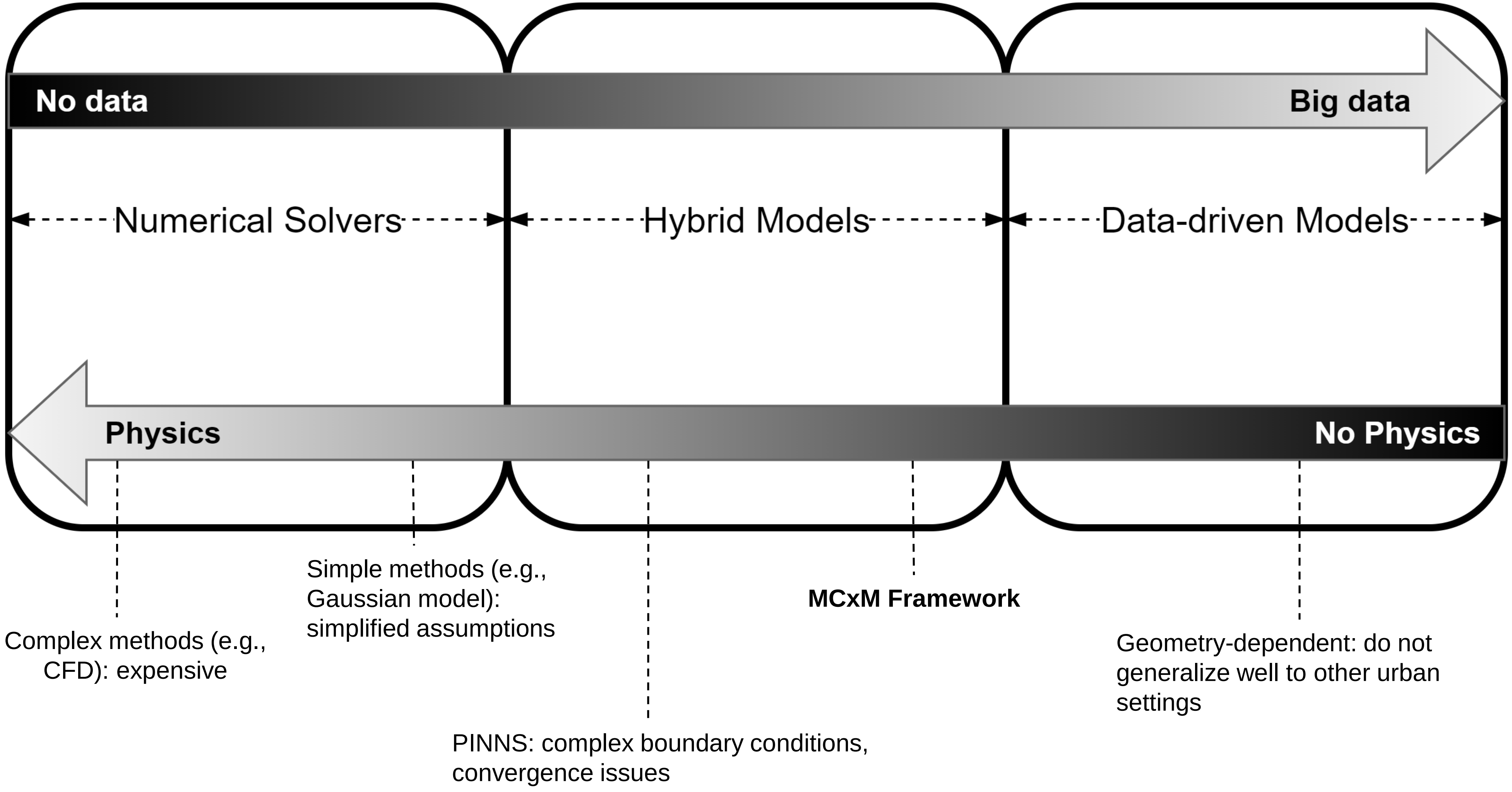
✓ Instantaneous point emission: location, quantity

✓ Urban 3D occupancy grid: binary mask showing the presence of buildings at every location of the grid

✓ Steady wind speed and direction above urban canopy

State of the Art

Figure inspired from NVIDIA Modulus Sym



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Previous Work: MCxM-2D

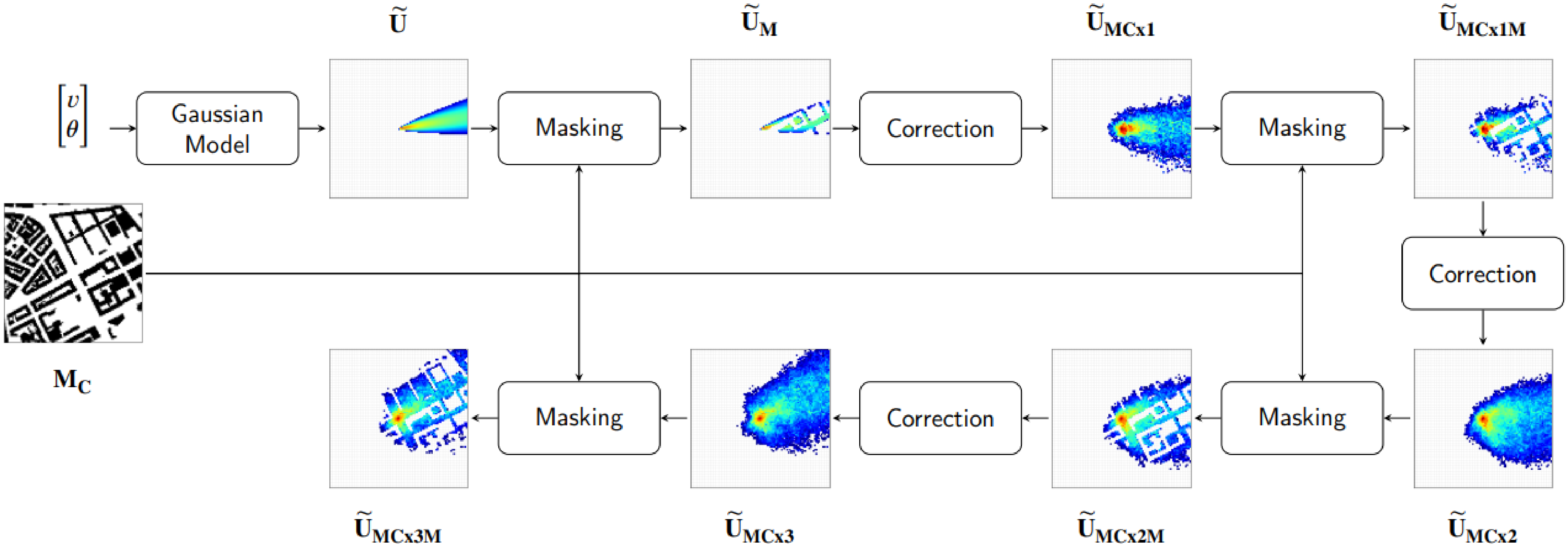
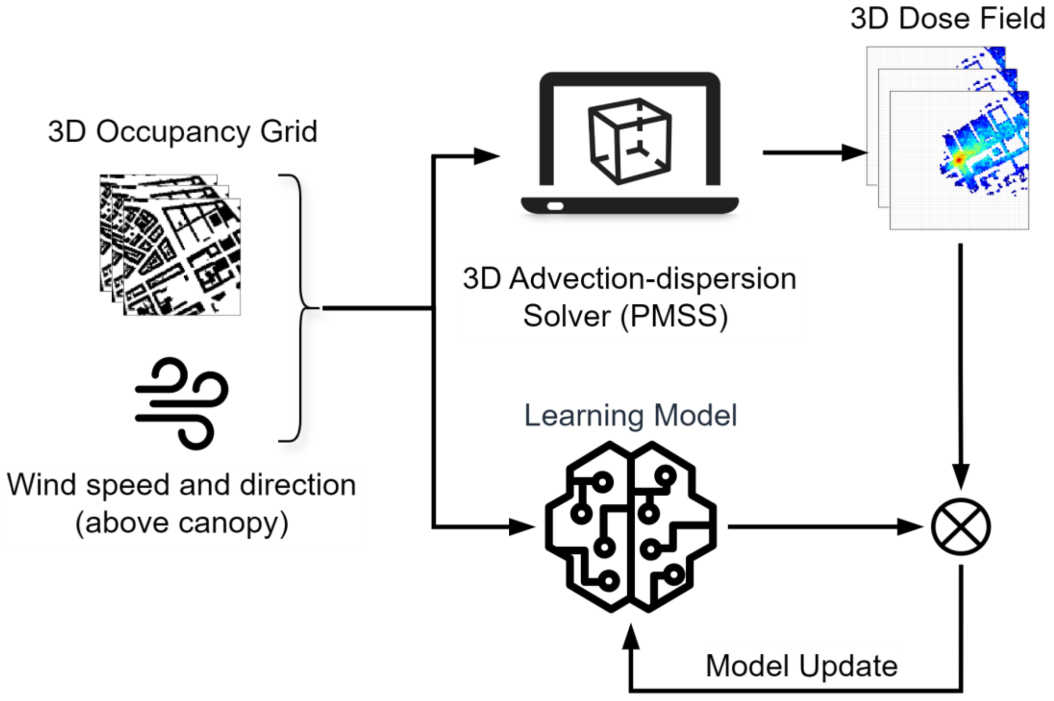


Figure from M. Mendil et al. (2022)

- **MCxM-2D:** fast **surrogate** model to estimate the **pollution exposure** within a given time period
- **Designed to learn from 2D slices of 3D dispersion data**

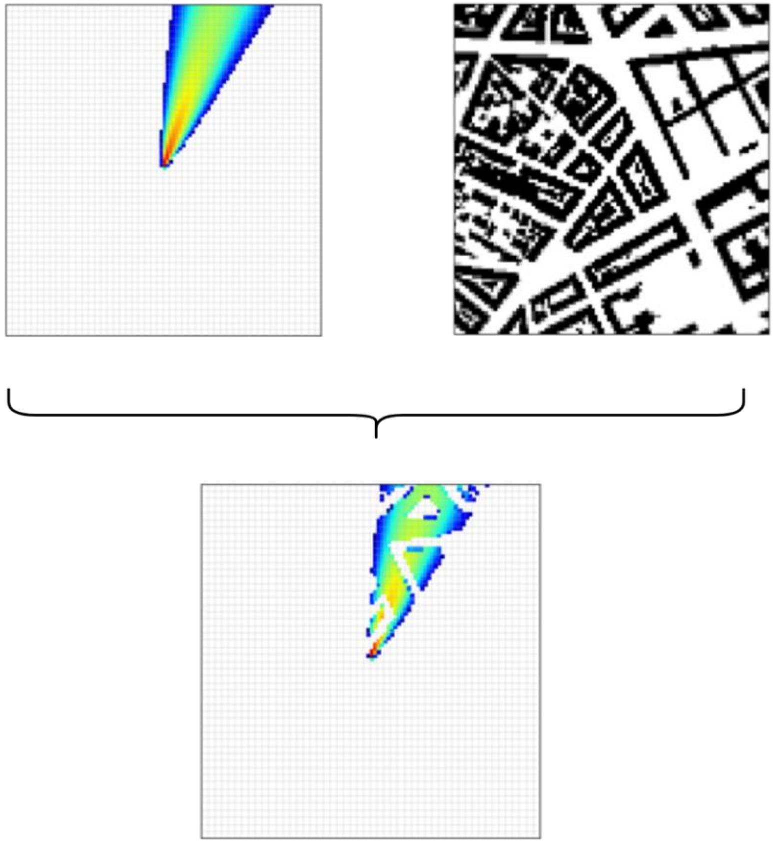
Current Learning Approach: MCxM-3D

- **Model inputs** : stationnary wind properties above urban canopy, 3D occupancy grid, emission source
- **Model prediction**: 3D dose field
- **Target**: synthetic 3D dose field, simulated with Parallel Micro-SWIFT-SPRAY (PMSS)
- **Learning model** : parametric function (neural network) and gradient-based optimization



Physics-based Prior

$$\int_0^{2h} \frac{Q}{2\pi\sigma_x\sigma_y} \exp\left(-\frac{(x-vt)^2}{2\sigma_x^2}\right) \exp\left(-\frac{y^2}{2\sigma_y^2}\right) dt$$



❖ Raw wind state variables not used directly as inputs

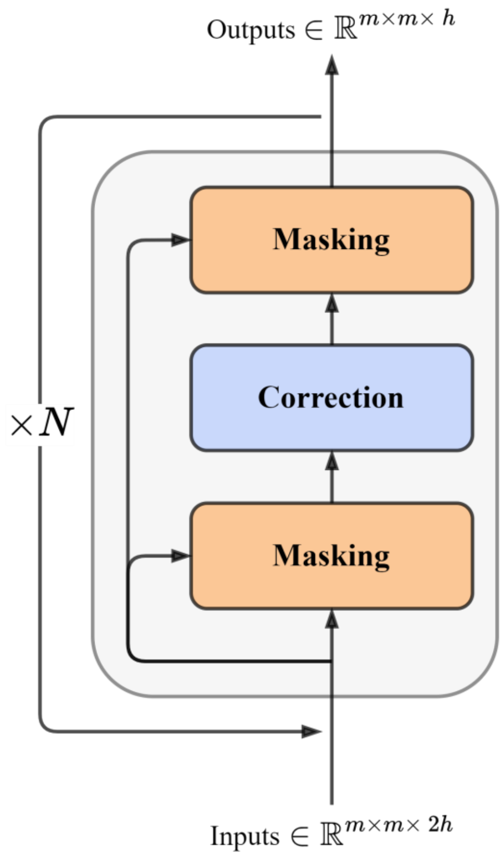
✓ Physics-based initialization: better guidance for the learning process

✓ Masked Gaussian plume prior

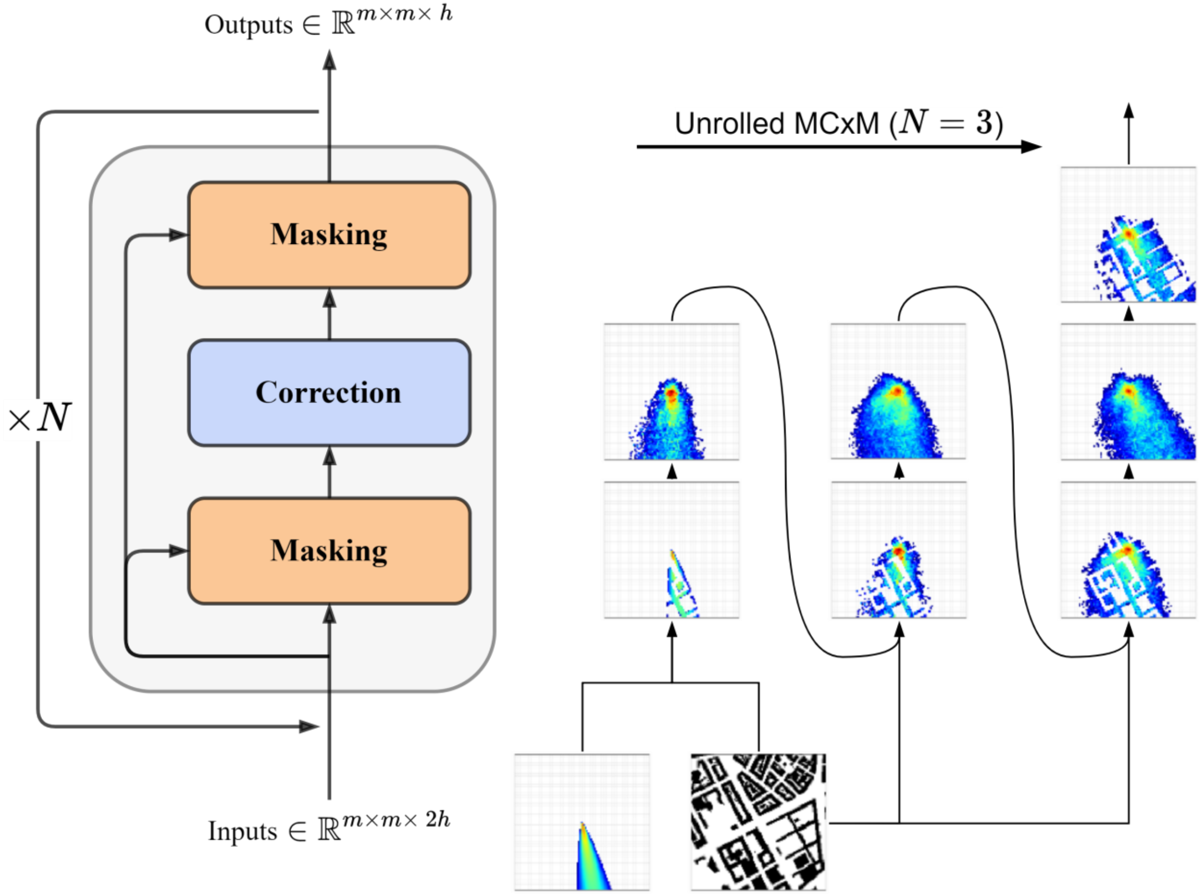
✗ Missing physics (trajectory changes, turbulence, etc.)

Discrepancy Correction

- Discrepancy correction: refines the prior by accounting for physical interactions with buildings
- 3D correction operator is learnt from data
- Sequence of N masking and correction to progressively model the impact of obstacles



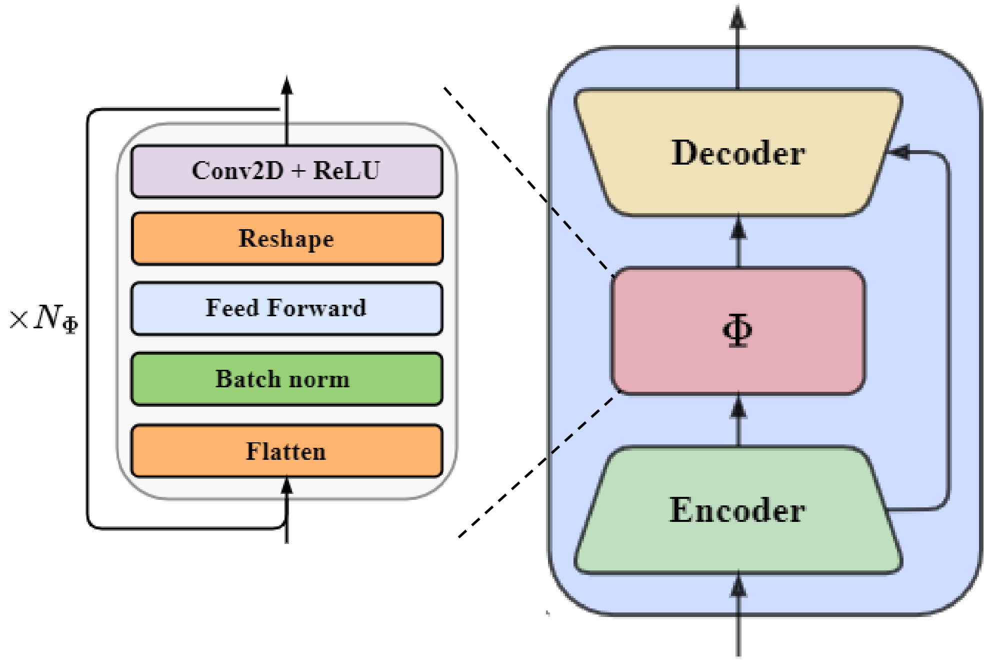
Discrepancy Correction



Architecture of Correction Block

- Dimensionality reduction:
  - Unet-based encoder/decoder
  - Residual connection

- Non-linear transformation ϕ:
  - Stack linear and non-linear operations to approximate a neural operator (N. Kovachki et al. 2023)
  - Solution operator aims to capture physical structures and symmetries
  - Enhance the ability to generalize to various boundary conditions (without retraining)



Composition of a correction block

Design of Experiment

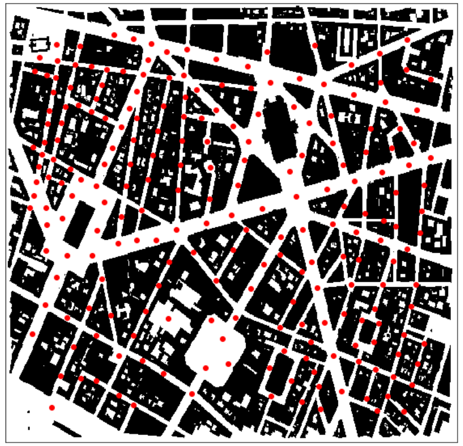
- Training/validation area: Grenoble City, France
  - $100 \times 100 \times 6$ grid ($4m$ horizontal resolution, varying vertical spacing)

- Test area: Paris City, France
  - $100 \times 100 \times 6$ grid ($4m$ horizontal resolution, varying vertical spacing)

- Instantaneous emission source:
  - Unit mass of the pollutant
  - Constant emission height $h_s = 2m$
  - Regularly sampled locations

- 108 stationary weather conditions:
  - 36 wind directions $\theta\ [°] \in \{0, 10, 20, \cdots, 350\}$
  - 3 wind speed $v\ [ms^{-1}] \in \{1.5, 3.5, 6\}$

- For given initialization, PMSS simulates the steady 3D wind field and the unsteady 3D concentration fields for two hours



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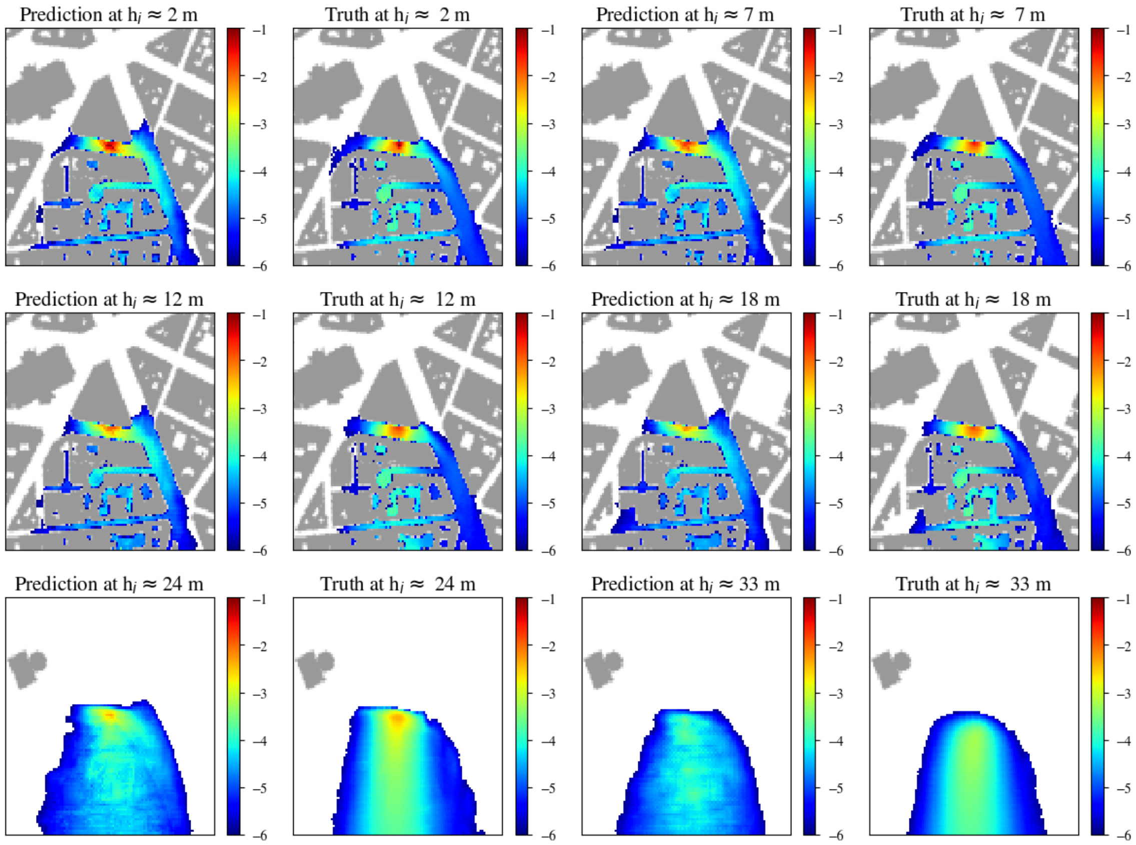
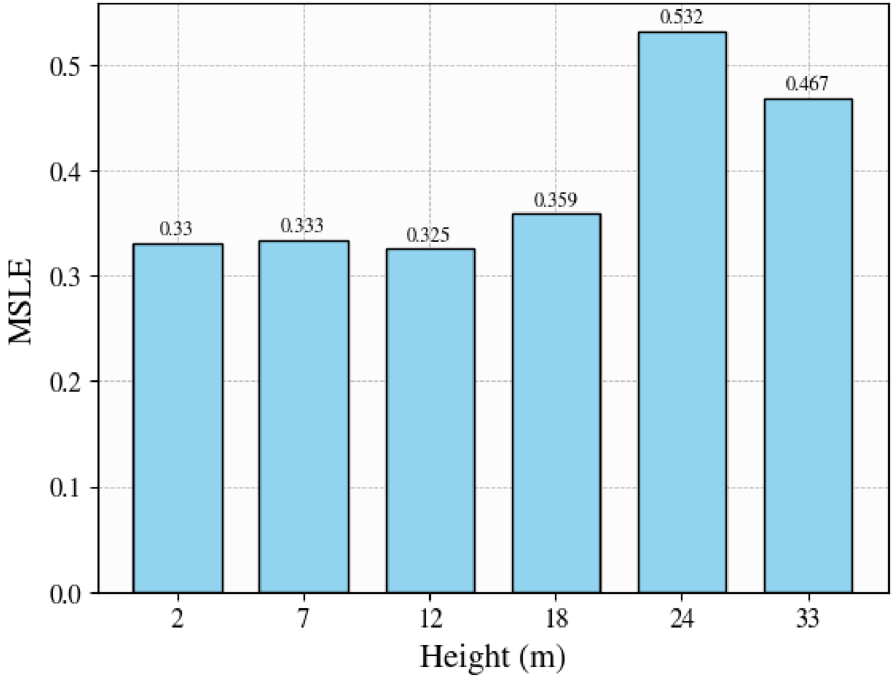
Results on Paris





- **Higher accuracy**: MSLE reduced by factor 3 compared to previous work (at height ~ 2m)
- Learning from **comprehensive spatial data** significantly improved the correction operator
- Accuracy diminishes at higher altitudes

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Conclusion

- ❑ Goal: fast and reliable surrogate model of dispersion in urban areas

- ✓ MCxM framework: combination of physics-based prior and discrepancy correction
- ✓ Extension to learn from comprehensive 3D spatial data
- ✓ Improved predictive performance, especially near-ground (human height)

- ❑ Future works: improve the predictive accuracy at higher altitudes and reliability (mass consistency)