MAGIC

Envisaging a world with greener cities

Managing Air for Green Inner Cities Partner Meeting

Numerical advances

Laetitia Mottet, Huw Woodward, Rossella Arcucci, Elsa Aristodemou and Chris Pain

08 December 2020

Introduction & Outline

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Envisaging a world with greener cities

- Accurate modelling of indoor environment
  - Indoor Geometry Generator (IGG)
  - Indoor simulations
- Optimising Numerical models (led by R. Arcucci)
  - Data Assimilation and Neural Network
  - Optimal sensors placement

Accurate modelling of indoor environment

Numerical Model

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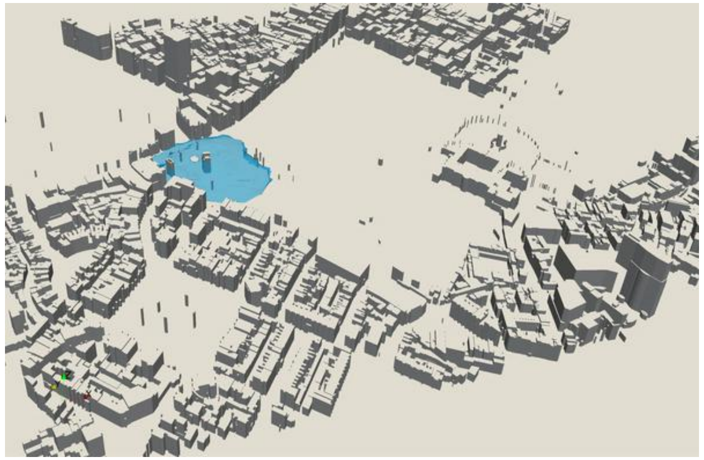
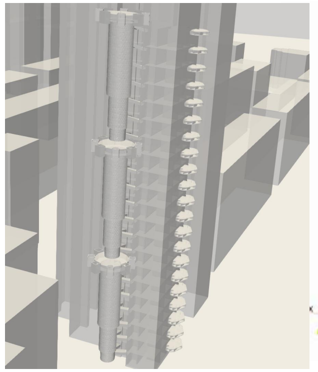
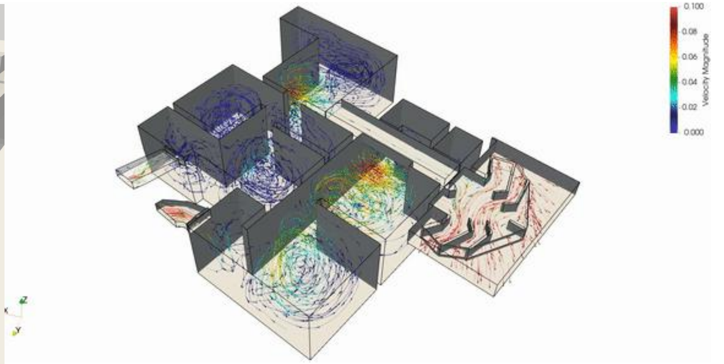
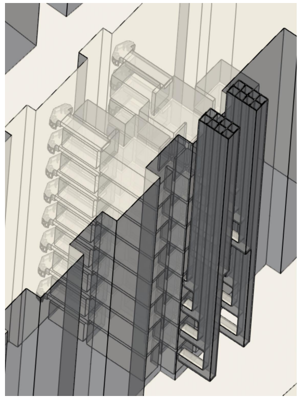
- CFD software Fluidity
  - Open-source - Imperial College London http://fluidityproject.github.io/
  - Finite-element method
  - Unstructured and adaptive mesh in GMSH format
  - LES

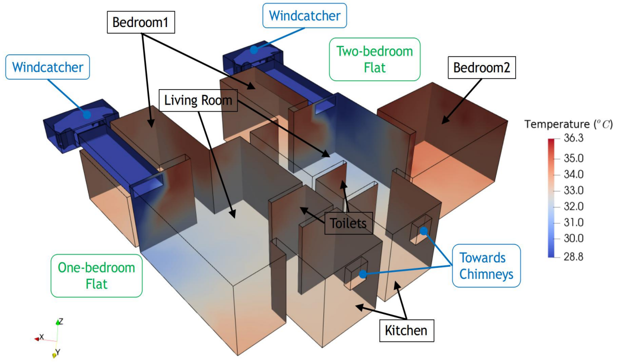
- Simulations
  - For outdoor urban environment simulations
  - For indoor space simulations











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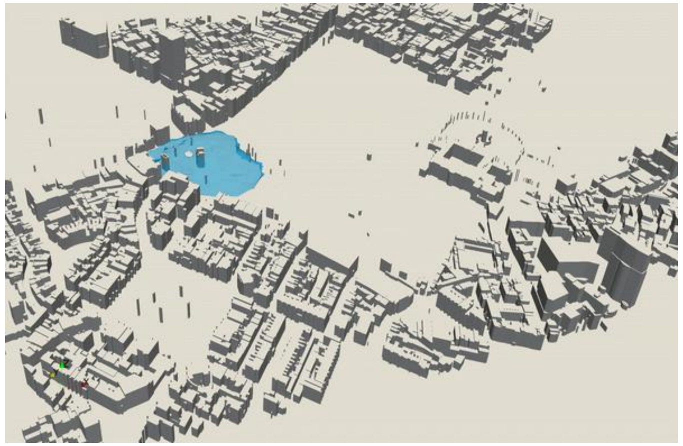
Indoor Geometry Generator (IGG)

- Geometry generation
  - Urban terreno
    - Automatically generate **urban environments** consistent with CFD



Indoor Geometry Generator (IGG)

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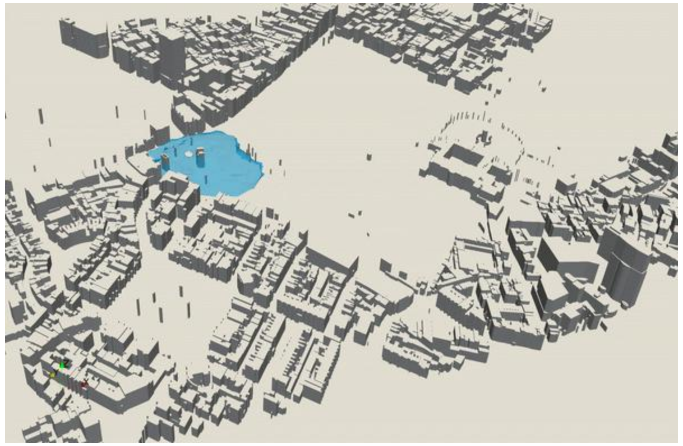
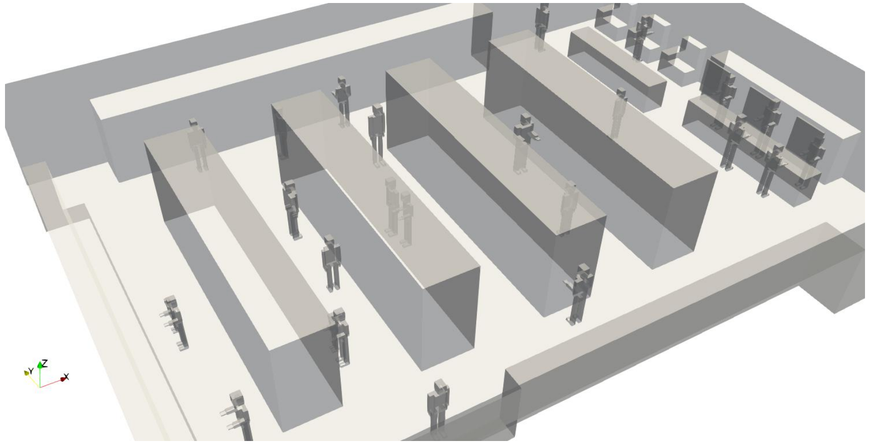
- Geometry generation
  - Urban terreno
    - Automatically generate **urban environments** consistent with CFD
  - Indoor Geometry Generator (IGG): novel capability
    - Automatically generate **indoor spaces** consistent with CFD
    - Easy, quick and friendly to use
      - Inlet and outlet of ventilation
      - Doors, windows
      - Various furniture (bed, table, chair, shelf...)
      - Various accessories (laptop, screen, computer...)
      - Static Humans
      - Different BCs can be assigned to features
      - Possibility for the user to coarsen/refined the mesh





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Indoor Geometry Generator (IGG)

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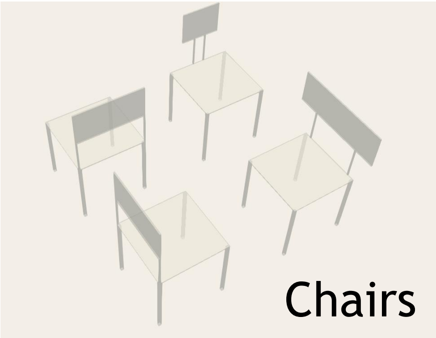
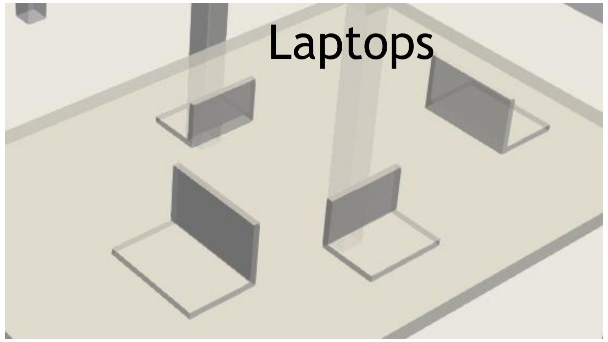
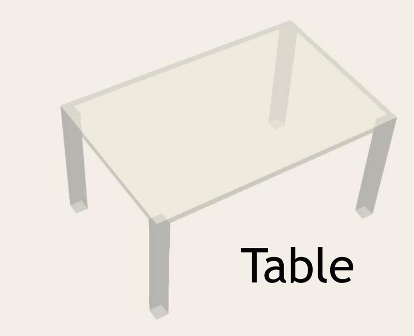
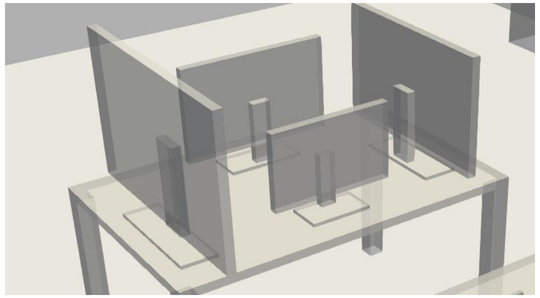
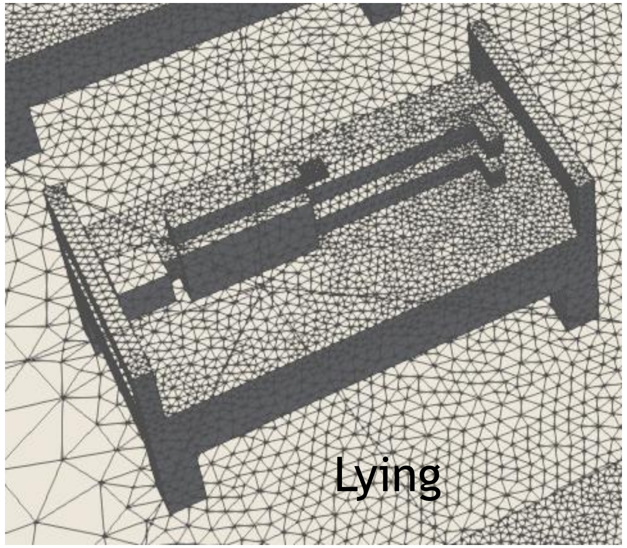


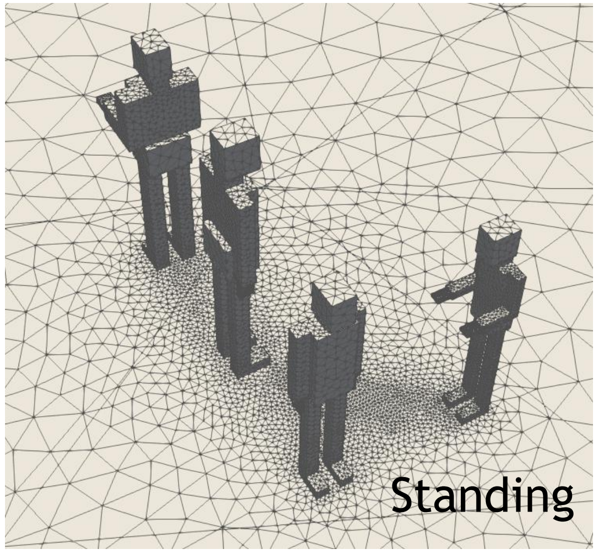


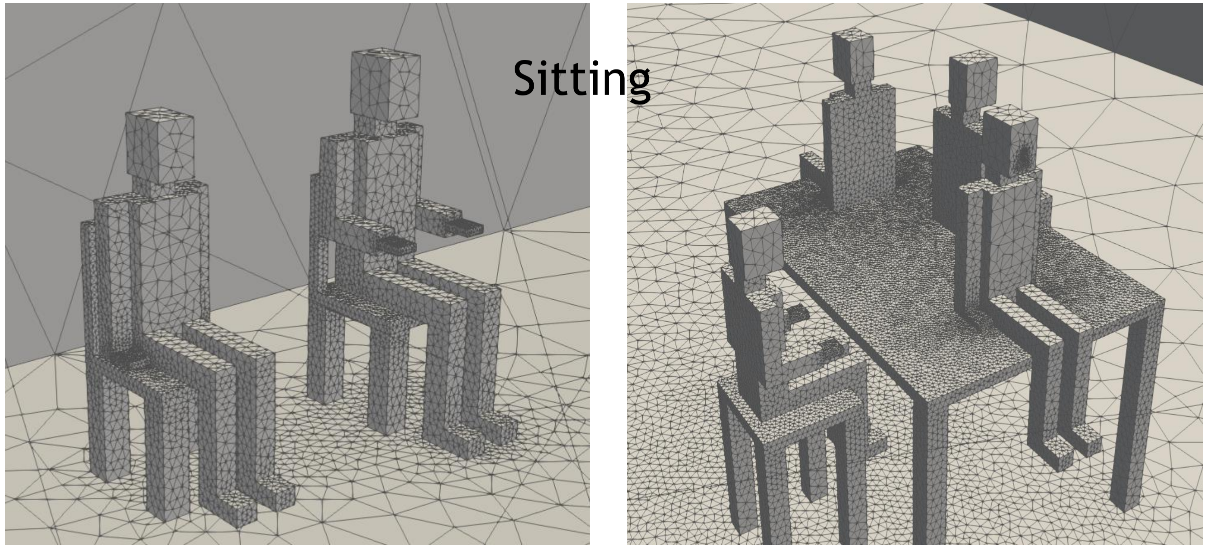


Screens









Indoor Geometry Generator (IGG)

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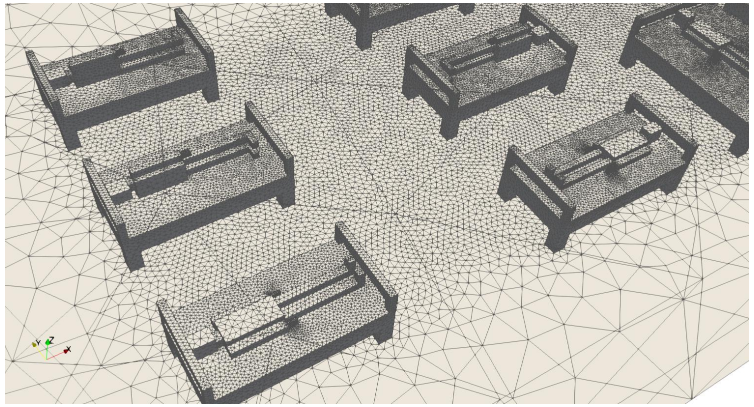
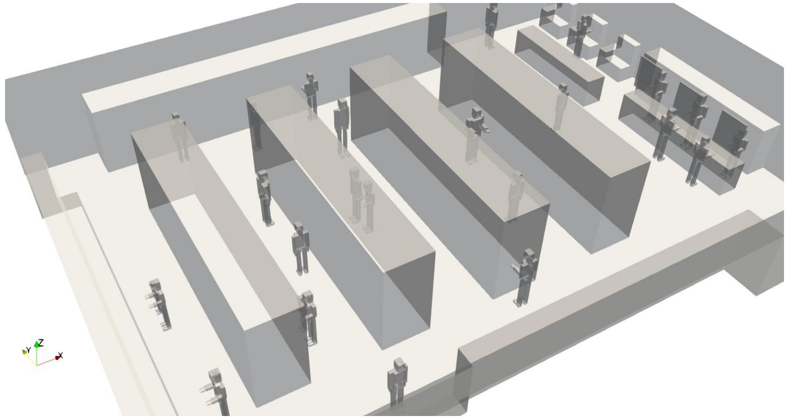
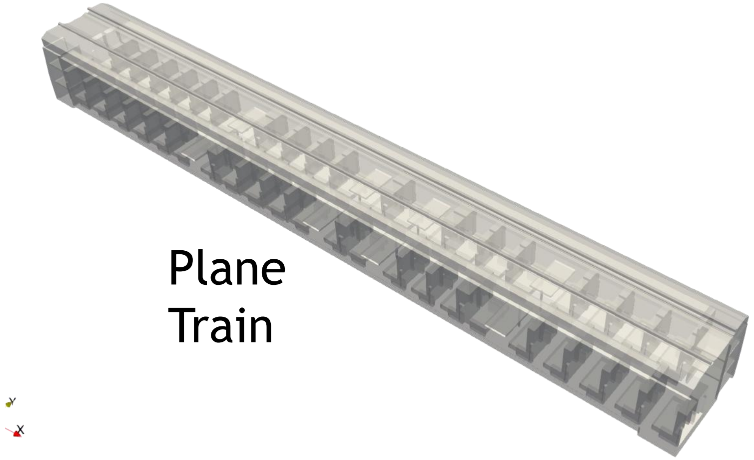


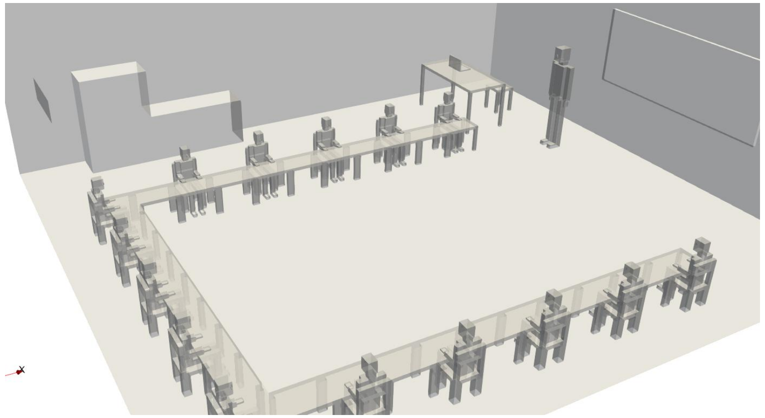
Hospital



Supermarket/Shop



Plane
Train



Schools

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Indoor simulations

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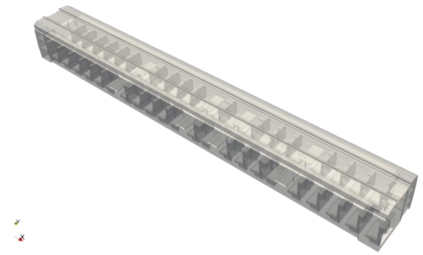
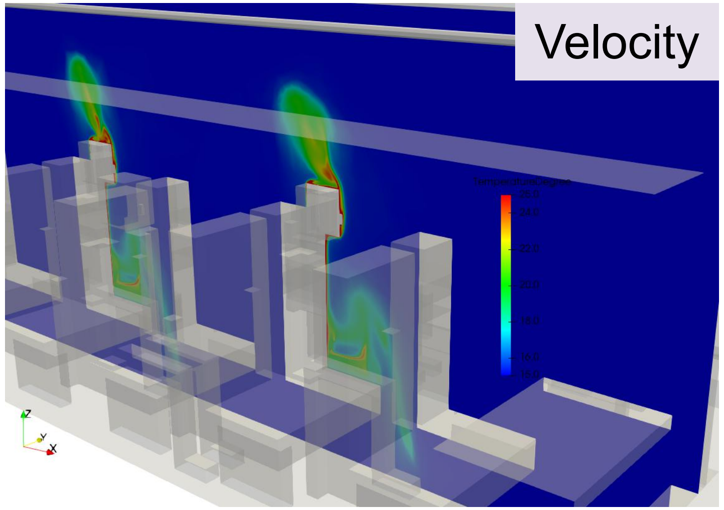
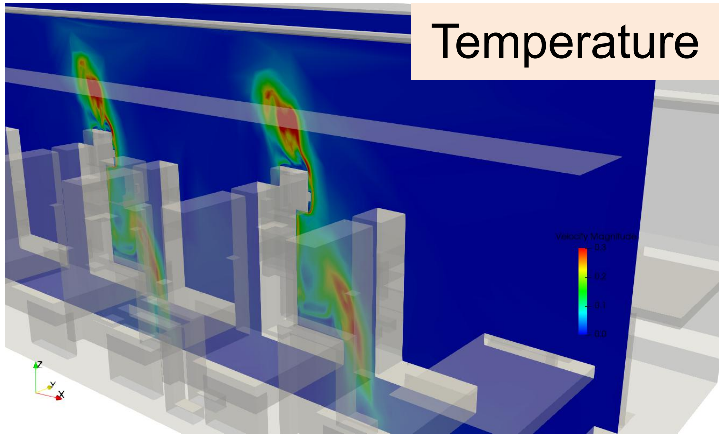


Train

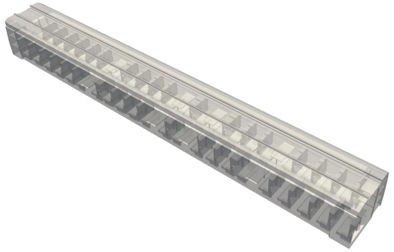


Velocity



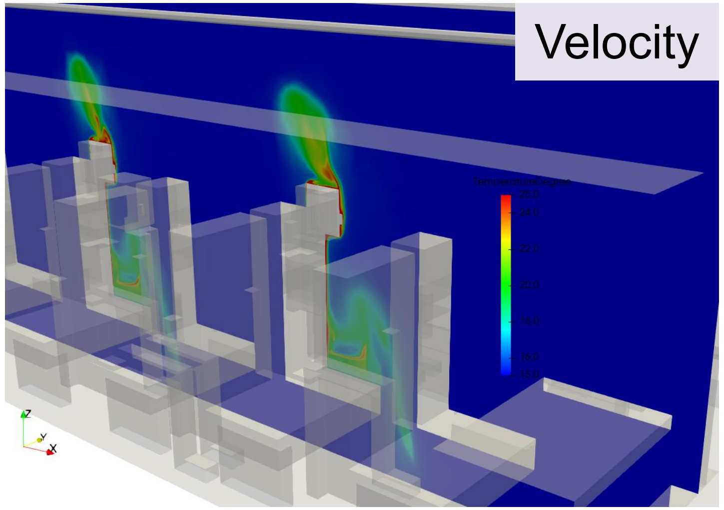
Temperature

Indoor simulations

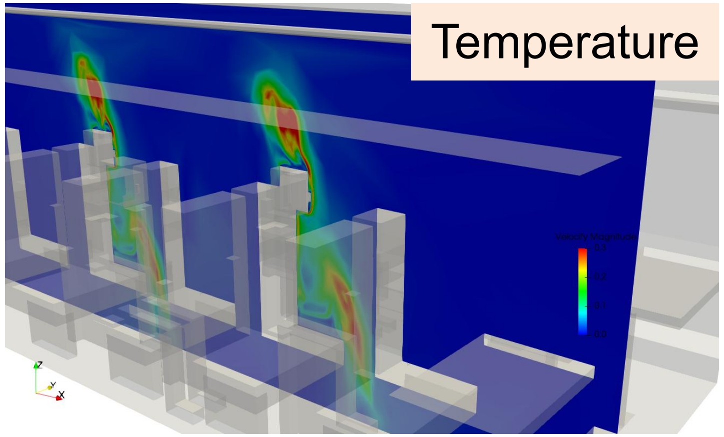


Train

Velocity



Temperature



Breathing and thermal plume models

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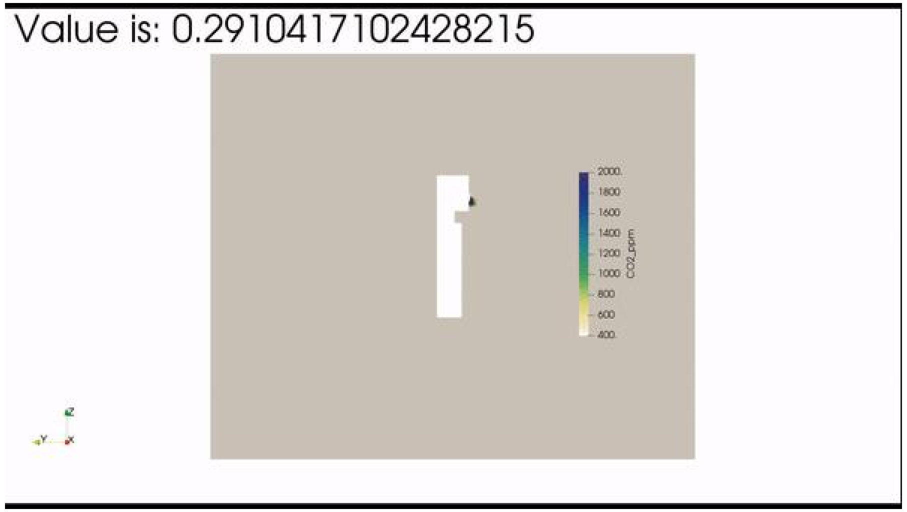
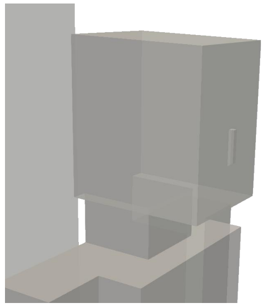
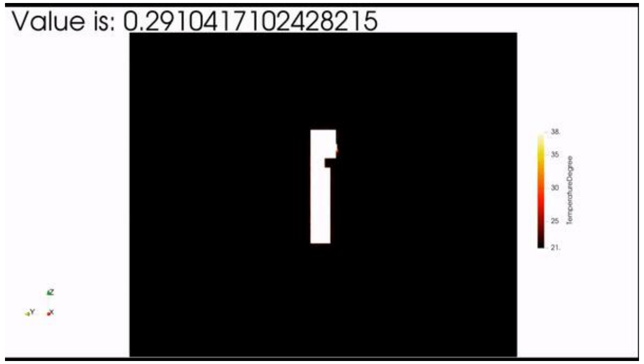


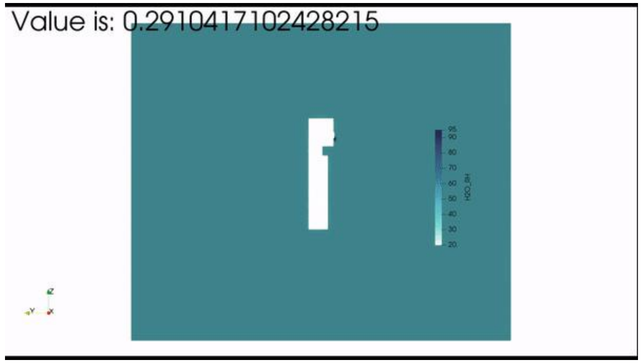
CO_2 (ppm)



Temperature (°C)



Water vapour (%)



Summary and future work

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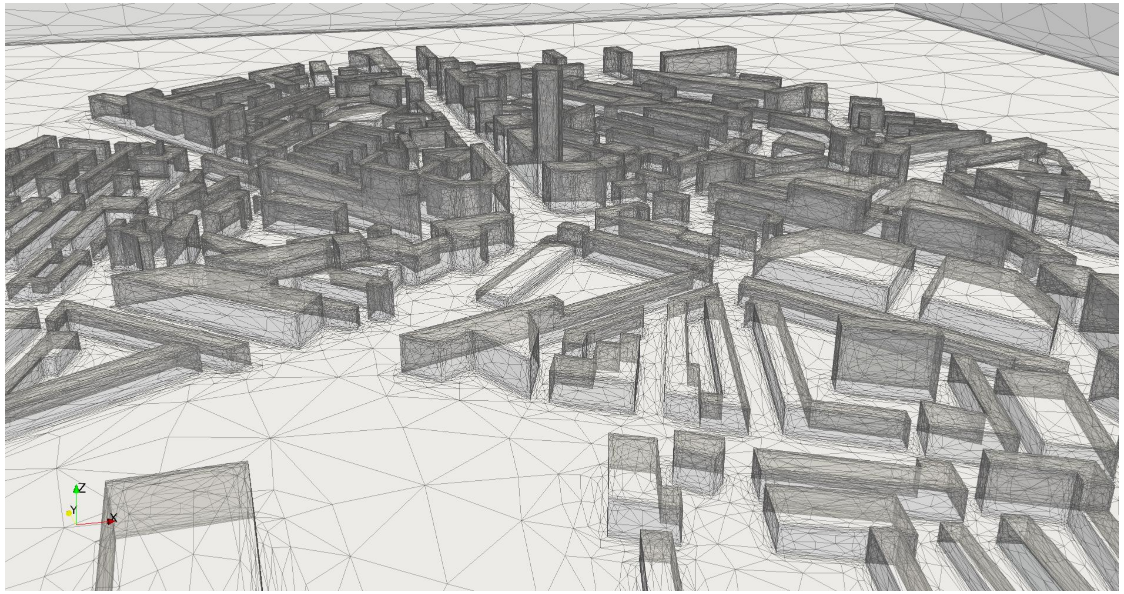
- Summary
  - Accurate representation of indoor spaces
  - Breathing and thermal plume models
- Future work
  - Indoor transport of pollutant
  - Single-sided ventilation
    - Buoyancy-driven vs wind-driven
    - Impact of wind direction

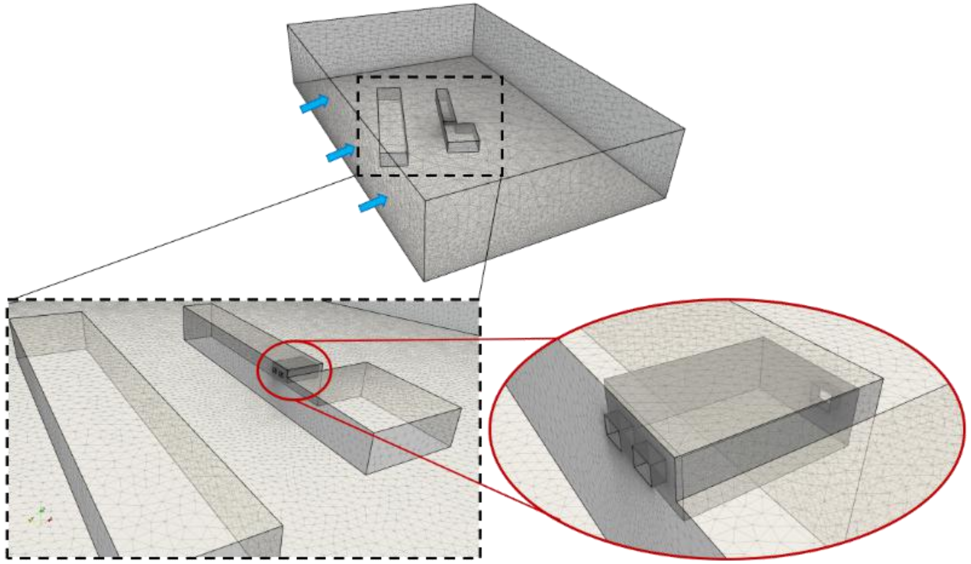
Optimising Numerical Models

MAGIC test cases

- Outdoor environment LSBU area
  - Wind tunnel data
  - Sensors data from field studies
  - CFD simulations



- Indoor space Clarence Centre
  - Sensors data from controlled experiment, cross ventilation
  - CFD simulation



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Optimising Numerical Models

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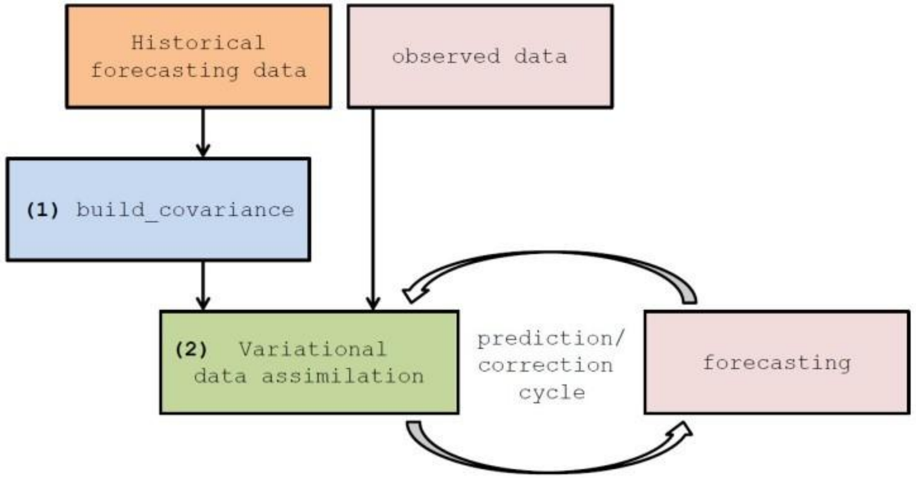
Data Assimilation (DA) is an uncertainty quantification technique used to **incorporate observational data into a prediction model** in order to **improve** numerical forecasted **results**.

Error reduction

MSE(c^M) error between CFD and sensors

MSE(c^{DA}) error between corrected results and sensors



- Data Assimilation
  - **Standard Data Assimilation** wind tunnel sensors DA in physical space
  - **Latent Assimilation** CO_2 sensors DA in the latent space of a neural network applied to Clarence Centre

- Optimal sensors placement for DA
  - **Weak Constraint Gaussian Process** applied to LSBU area
  - **Variational Gaussian Process** applied to Clarence Centre

Standard Data Assimilation

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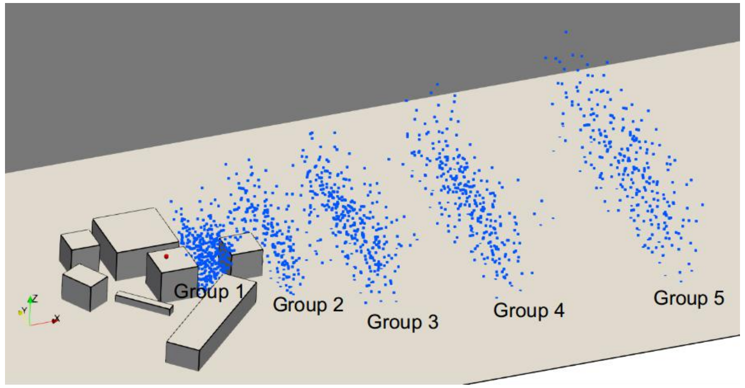
Enhancing CFD-LES air pollution prediction accuracy using data assimilation. *E. Aristodemou, R. Arcucci, L. Mottet, A. Robins, C. Pain and Y. Guo. Building and Environment, 165:106383,* ***2019****.*

WT data

Fluidity ... → 3DVarDA → *... Fluidity*

Goal

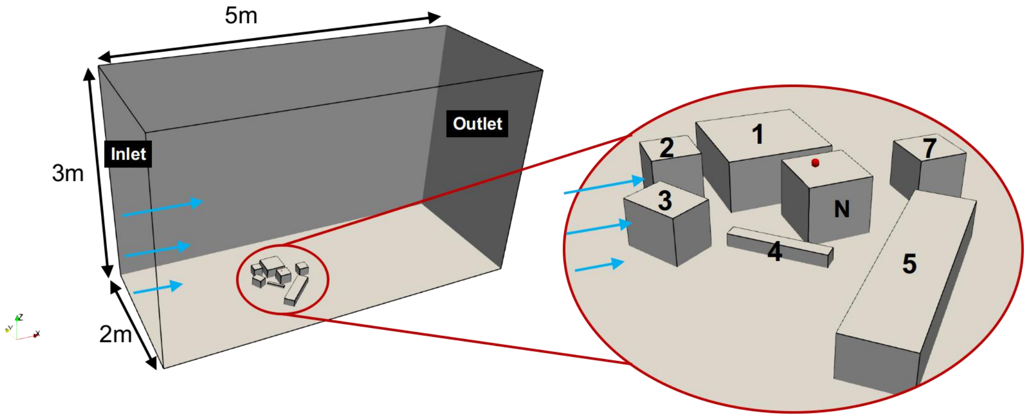
Develop a data assimilation method coupled with Fluidity able to improve accuracy using sensors data.



Technology

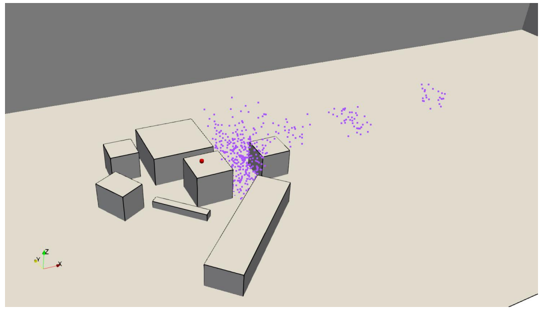
3D Variational Data Assimilation

Novelty Assimilation of wind tunnel sensor data for air pollution



Results

Assimilating sensors **located in high concentration zone** - whatever the distance from the source - and **close to the source** - whatever the concentration level - give an optimal error reduction.



Only 14 % of wind tunnel sensors data needed

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Latent Assimilation

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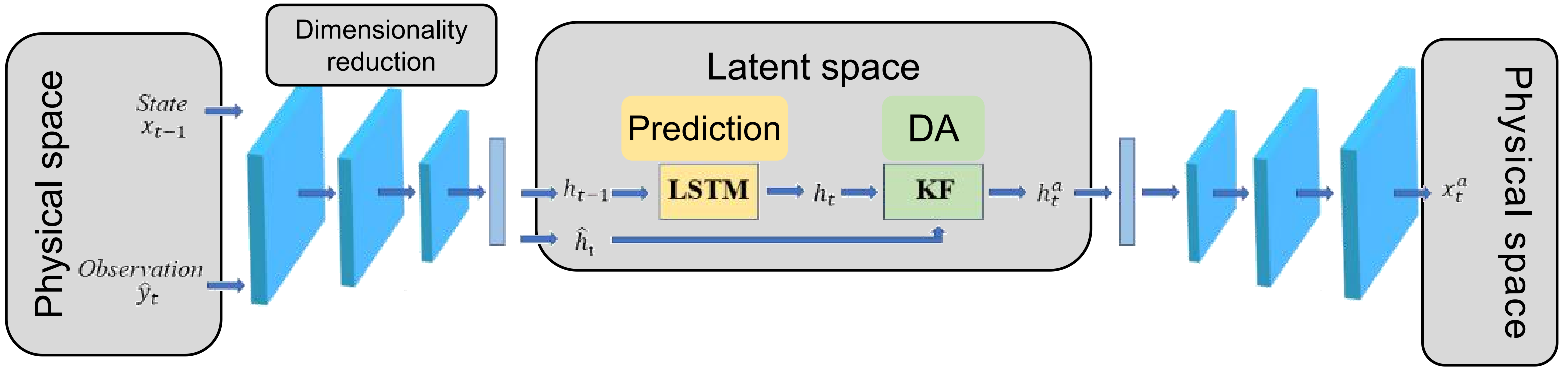
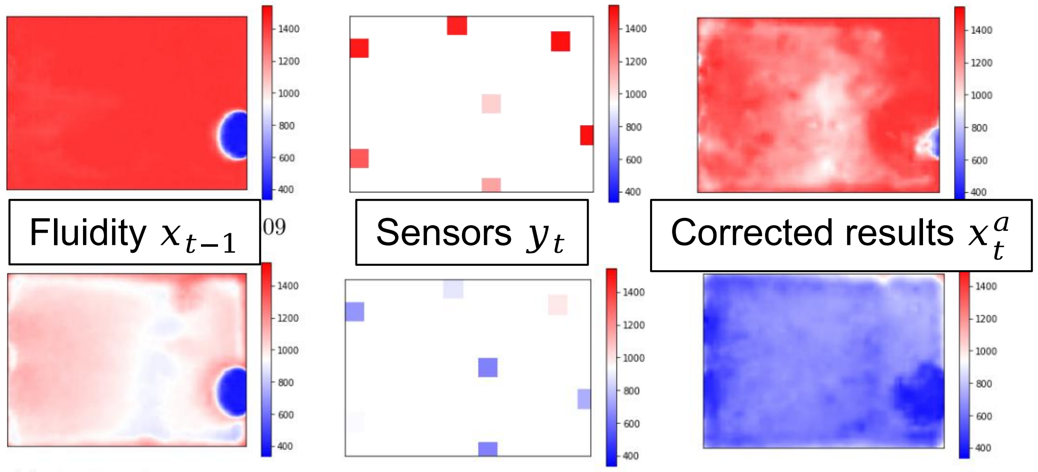
Data Assimilation in the Latent Space of a Neural Network. *M. Amendola, R. Arcucci, L. Mottet, C. Quilodran Casas, S. Fan, C. Pain, P. Linden and Y. Guo. Environmental Modelling & Software,* ***Submitted****.*

Goal
Develop a coupled machine learning and data assimilation model to be used for real-time air quality prediction.



Novelty Assimilation in the latent space of a Neural Network

Technologies
AutoEncoder for **dimensionality reduction**
Long-Short-Term-Memory for **prediction**
Kalman Filter for **Data Assimilation**



(g) Predicted state t=1485 (i) Updated state t=1485

Results
Latent Assimilation improves **accuracy** and **efficiency** compared to standard DA.

MSE	LA	2.691e-06	$\div 10^3$
	sDA	6.997e-03	
Time	LA	4.823e-04	$\div 10^7$
	sDA	2.159e+03	

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Optimal sensor placement

Goal
Develop an optimal sensor placement model for air pollution.

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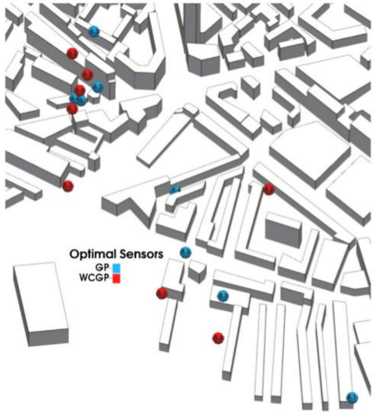
Weak Gaussian Process

Weak constraint Gaussian processes for optimal sensor placement. T. H. Dur, R. Arcucci, L. Mottet, M. Molina Solana, C. Pain and Y. Guo. Journal of Computational Science, 42:101110, **2020**.



Novelties
Domain decompostion for **big data problem**: fully parallel and scalable implementation
Noisy inputs are integrated into the GP through a DA approach.

Technologies
Spatial Model Weak constraint GP; *Sensor placement* Mutual Information

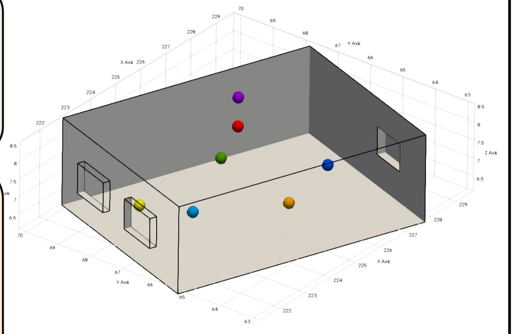
Error reduction after DA
3 order of magnitude lower compare to random placement.

Variational Gaussian Process

Variational Gaussian Process for Optimal Sensor Placement. G. Tajnafoi, R. Arcucci, L. Mottet, C. Vouriot, M. Molina Solana, C. Pain and Y. Guo. Applied Mathematics, 66:In Press, **2021**.

Novelties
Coupling of technologies; Reduction of time complexity; Extension to **3D**; Parallel and scalable implementation

Technologies
Spatial Model Variational GP preprocessed with Masked Autoregressive Flow
Sensor placement Mutual Information with Markov-Chain Monte Carlo wrapper to fine tune



Error reduction after DA
Optimal: 86%; Field study: 43%;
Random: 75% (mean), 27% (min)

Results
1. Improve the **accuracy, efficiency** and **stability** compared to standard GP.
2. **Improve the error reduction** compared to random sensor placement.

- Low → Accuracy → + High

+ Low ← Execution time ← - High

How to choose which model? Trade-off between accuracy and efficiency
It all depends the size of your initial data and the accuracy required.

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Data Assimilation can do even more...

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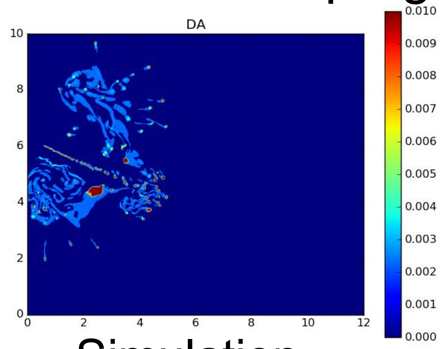
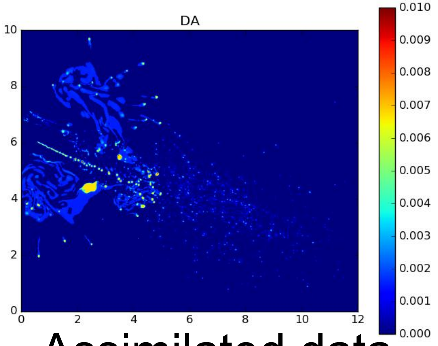
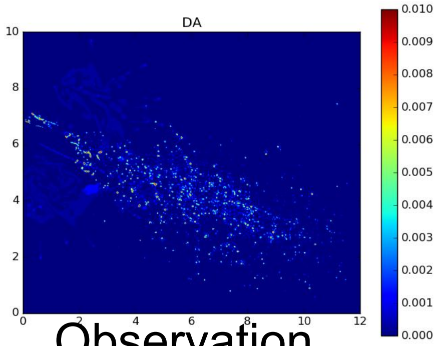
- Work in progress: Data Assimilation of coughing/sneezing/breathing from image/videos



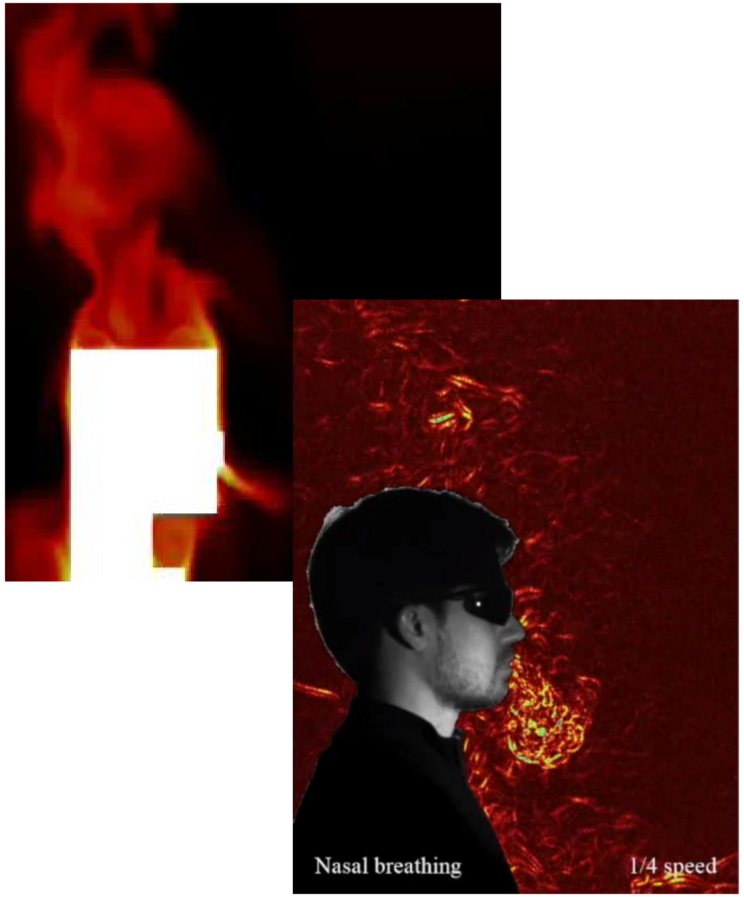
Simulation

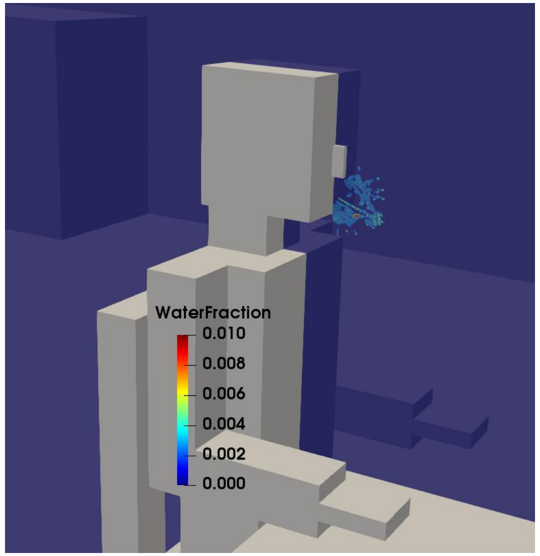


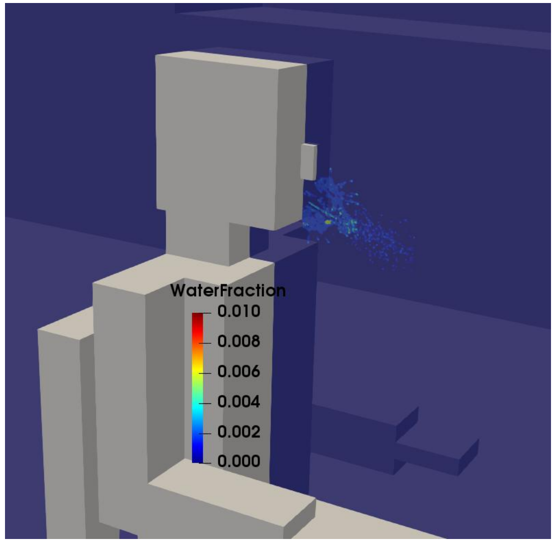
Assimilated data

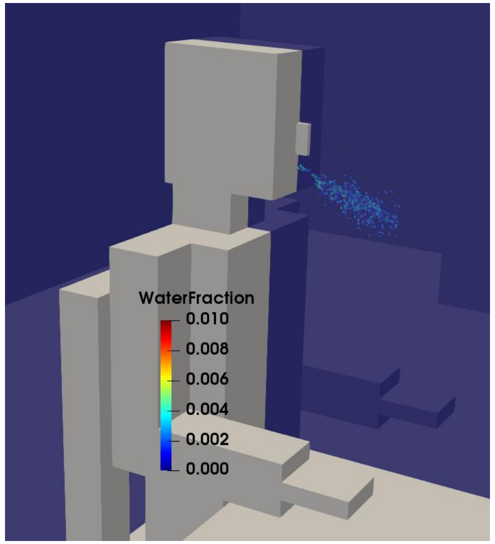


Observation









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To go further...

other papers of the MAGIC team on DA/ROM/ML/NN...

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*14. **Data Assimilation in the Latent Space of a Neural Network.** M. Amendola, R. Arcucci, L. Mottet, C. Quilodran Casas, S. Fan, C. Pain, P. Linden and Y. Guo. Environmental Modelling & Software,* **Submitted**.

*13. **Variational Gaussian Process for Optimal Sensor Placement.** G. Tajnafoi, R. Arcucci, L. Mottet, C. Vouriot, M. Molina Solana, C. Pain and Y. Guo. Applied Mathematics, 66:In Press,* **2021.**

*12. **Weak constraint Gaussian processes for optimal sensor placement.** T. H. Dur, R. Arcucci, L. Mottet, M. Molina Solana, C. Pain and Y. Guo. Journal of Computational Science, 42:101110,* **2020**.

11. Attention-based Convolutional Autoencoders for 3D-Variational Data Assimilation. J. Mack, R. Arcucci, M. Molina-Solana and Y. Guo, Yi-Ke. Computer Methods in Applied Mechanics and Engineering, 372:113291, **2020**.

10. Neural Assimilation. R. Arcucci, L. Moutiq and Y. Guo. International Conference on Computational Science, 155-168, **2020**.

9. A Reduced Order Deep Data Assimilation model. C. Q. Casas, R. Arcucci, P. Wu, C. Pain and Y. Guo. Physica D: Nonlinear Phenomena, 412:132615, **2020**.

8. Data-driven reduced order model with temporal convolutional neural network. P. Wu, J. Sun, X. Chang, W. Zhang, R. Arcucci, Y. Guo and C. Pain. Computer Methods in Applied Mechanics and Engineering, 360:112766, **2020**.

7. Adaptive Domain Decomposition for Effective Data Assimilation. R. Arcucci and L. Mottet and C. A. Quilodran Casas and F. Guitton and C. Pain and Y. Guo. Euro-Par 2019: Parallel Processing Workshops, 583-595, **2020**.

6. A Domain Decomposition Reduced Order Model with Data Assimilation (DD-RODA). R. Arcucci and C. Quilodran Casas and D. Xiao and L. Mottet and F. Fang and P. Wu and C. Pain and Y. Guo. Advances in Parallel Computing, 36:189-198, **2020**.

*5. **Enhancing CFD-LES air pollution prediction accuracy using data assimilation.** E. Aristodemou, R. Arcucci, L. Mottet, A. Robins, C. Pain and Y. Guo. Building and Environment, 165:106383,* **2019**.

4. Model error correction in data assimilation by integrating neural networks. J. Zhu, S. Hu, R. Arcucci, C. Xu, J. Zhu and Y. Guo. Big Data Mining and Analytics, 2(2):83-91, **2019**.

3. Optimal reduced space for variational data assimilation. R. Arcucci and L. Mottet and C. Pain and Y.-K. Guo.Journal of Computational Physics, 379:51-69, **2019.**

2. A domain decomposition non-intrusive reduced order model for turbulent flows. D. Xiao, C.E. Heaney, F. Fang, L. Mottet, R. Hu, D.A. Bistrian, E. Aristodemou, I.M. Navon and C.C. Pain. Computers & Fluids, 182:15-27, **2019**.

1. A reduced order model for turbulent flows in the urban environment using machine learning. D. Xiao, C.E. Heaney, L. Mottet, F. Fang, W. Lin, I.M. Navon, Y. Guo, O.K. Matar, A.G. Robins and C.C. Pain. Building and Environment, 148:323-337, **2019**.

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Thank you!
Any questions?

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