Real-Time Estimation of Gas Emission Sources Using Particle Filters and Neural Networks

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1 | MOTIVATION

Real-time identification and quantification of greenhouse-gas emissions under transient atmospheric conditions is a critical challenge in environmental monitoring.

2 | AIM

We introduce a spatio-temporal inversion framework that embeds a deep-learning surrogate of computational fluid dynamics within a sequential Monte Carlo algorithm to perform Bayesian inference of emission rate and source location in dynamic flow fields.

3 | SURROGATE MODEL

- Training data:
  - fixed wind boundary conditions.
  - varying source location.
  - numerical solver spatio-temporal simulations:

$$C_{\mathrm{ns}}(\dot{x}, \dot{y} | \tilde{x}, \tilde{y}) = f_c\big(\tilde{x}, \tilde{y}, f_v(u_{\kappa:t}, p_{\kappa:t}, \omega, \Omega)\big)|_{\dot{x},\dot{y}}.$$

- Architecture: multilayer perceptron.
- Loss function:

$$L(\boldsymbol{\Theta}) = \frac{1}{N}\sum_{i=1}^{N} ||C_{\mathrm{MLP}}\big(\tilde{x}^{(i)}, \tilde{y}^{(i)}; \boldsymbol{\Theta}\big) - C_{\mathrm{ns}}(\dot{x}, \dot{y} | \tilde{x}^{(i)}, \tilde{y}^{(i)})\,||^2.$$

- Parameters:
  - weights and biases: $\boldsymbol{\Theta}$.
  - number of training data: N.
  - source location: $(\tilde{x}, \tilde{y})$.
  - sensor location: $(\dot{x}, \dot{y})$.

4 | INVERSION MODEL

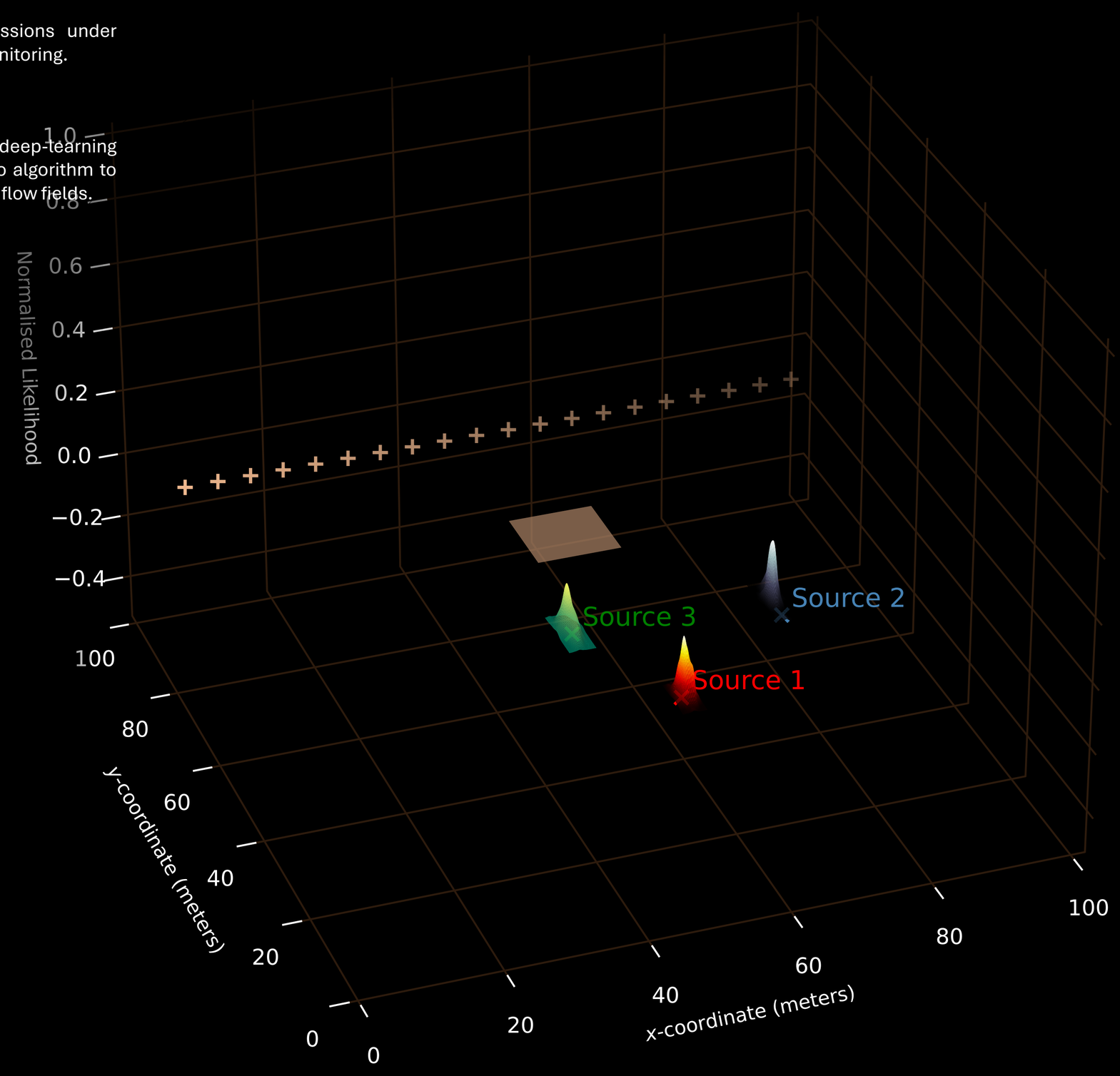
- Estimated parameters: $\boldsymbol{\theta_t} = \{\tilde{x_t}, \tilde{y_t}, s_t\}$
  - source location: $(\tilde{x_t}, \tilde{y_t})$.
  - emission rate: s_t.
- Model: Sequential Importance Resampling particle filter.
- State equation:

$$\boldsymbol{\theta}_t = \boldsymbol{\theta}_{t-1} + \boldsymbol{\zeta}_t.$$

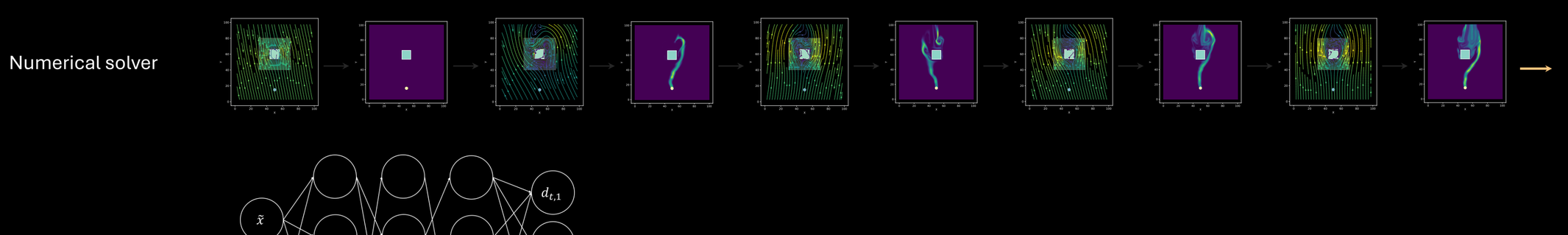
- Observation equation:

$$\boldsymbol{d}_t = C_{\mathrm{MLP}}(\dot{x}, \dot{y}, \dot{z} | \tilde{x}, \tilde{y}, \tilde{z}) \times \boldsymbol{s}_{\kappa:t} + \boldsymbol{\beta}_{\kappa:t} + \boldsymbol{\varepsilon}_t.$$

- Parameters:
  - time point: t.
  - sensors' observation: $\boldsymbol{d}$.
  - atmospheric gas transport model: C.
  - background concentration: β.
  - sensor error: $\boldsymbol{\varepsilon}$.



5 | RESULTS



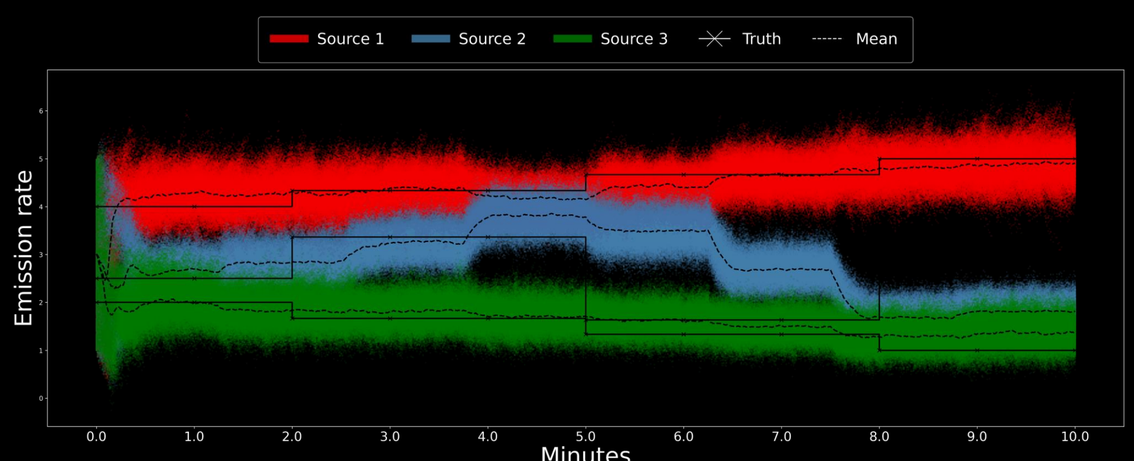


Fig 1 | Case study results for temporally varying emission rate estimation. The surrogate-based particle filter successfully tracks increasing, decreasing and fluctuating emission rates. The delayed adjustment after Source 2's emission rate shape drop at minute 5 highlights a limitation – such scenarios may require a more responsive two-layered particle filter.

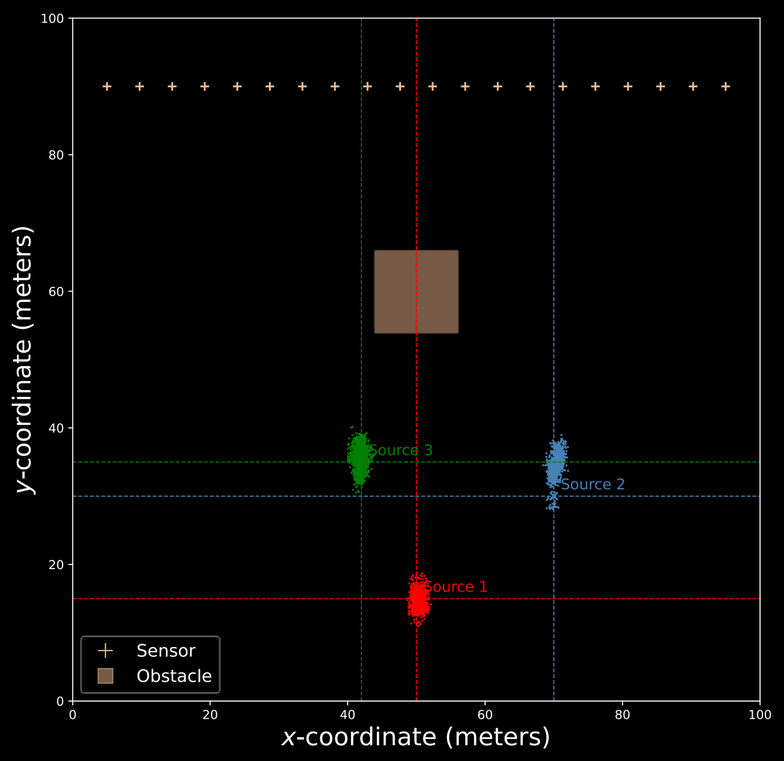


Fig 2 | Case study results for surrogate-based particle filter source location estimation in unsteady and obstructed flow fields. Data is collected using a line of 20 point-sensors. The three location posterior samples show location estimation at the end of the 10 minutes of gas release.

6 | CONCLUSION

We have introduced a real-time Bayesian inversion framework for estimating gas emission source location and emission rate in unsteady atmospheric flow fields. By embedding a multilayer perceptron surrogate for high-fidelity computational fluid dynamic models within a sequential importance resampling particle filter, we enable accurate and computationally efficient inference in complex environments. This combination allows for rapid, data-driven updates as new observations arrive, making the method suitable for time-critical spatio-temporal environmental monitoring tasks.

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