

An inverse modelling technique for emergency response application

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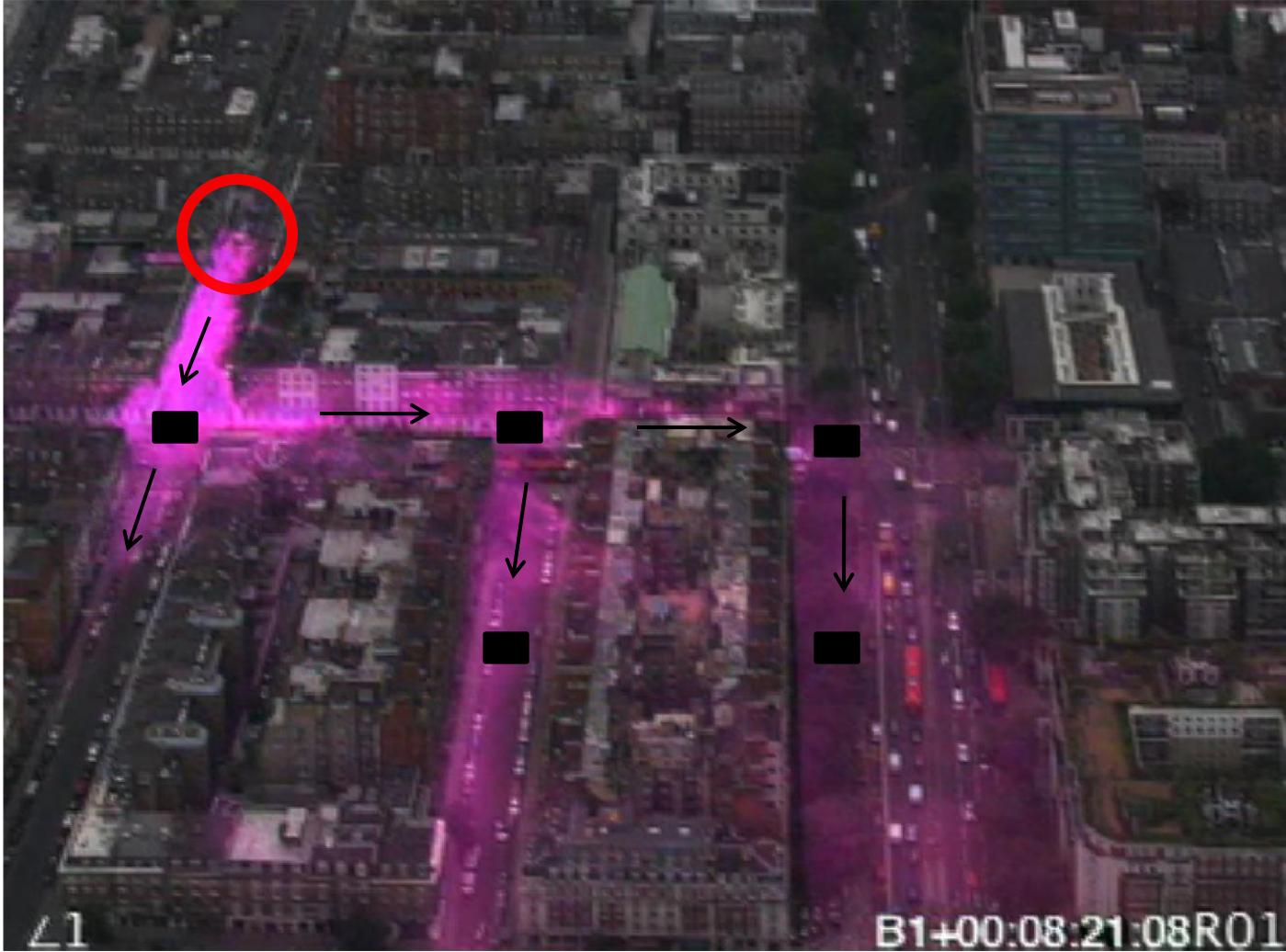


Malicious or accidental release in an urban area

What area should the first responders cordon off or evacuate?

What are the source characteristics? - uncertainty

Where will the plume spread?



- Chemical sensor
- Source position

Malicious or accidental release in an urban area

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The DYCE consortium

DYnamic deployment planning for monitoring of
ChEmical leaks using an ad-hoc sensor network



Chemical sensors



Communications
& networking



Inverse modelling to estimate
the source characteristics

Wind tunnel & tracer trial
validation studies



Funding

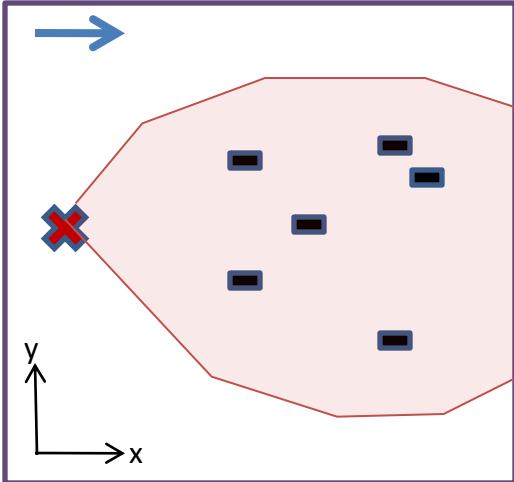


Engineering and Physical Sciences
Research Council

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Inverse modelling

Inverse problem: extracting source characteristics from a set of concentration measurements



1. Make a first guess of the source characteristics (Q, X_s, Y_s)
2. First guess → forward model → model-predicted concentrations
3. Model-predicted concentrations vs. measured concentrations → Minimisation algorithm → 'best' estimate of source characteristics.
4. 'Best' estimate → forward model → predicted plume.

Forward model

Forward model → model-predicted concentrations

Gaussian plume model - well known and understood

Inputs: source strength and position, wind speed and stability

We assume

- one continuous point source
- a ground level release, i.e. $Z_s = 0$
- concentration measurements at ground level

$$C = \frac{Q}{\pi u \sigma_Y \sigma_Z} \exp\left(\frac{-(Y - Y_s)^2}{2\sigma_Y^2}\right)$$

Optimisation

Minimise a cost function

$$J = \frac{1}{2} \sum_{i=1}^N \frac{(C_i^o - C_i^m)^2}{{\sigma_i}^2}$$

Concentration measurements C^o

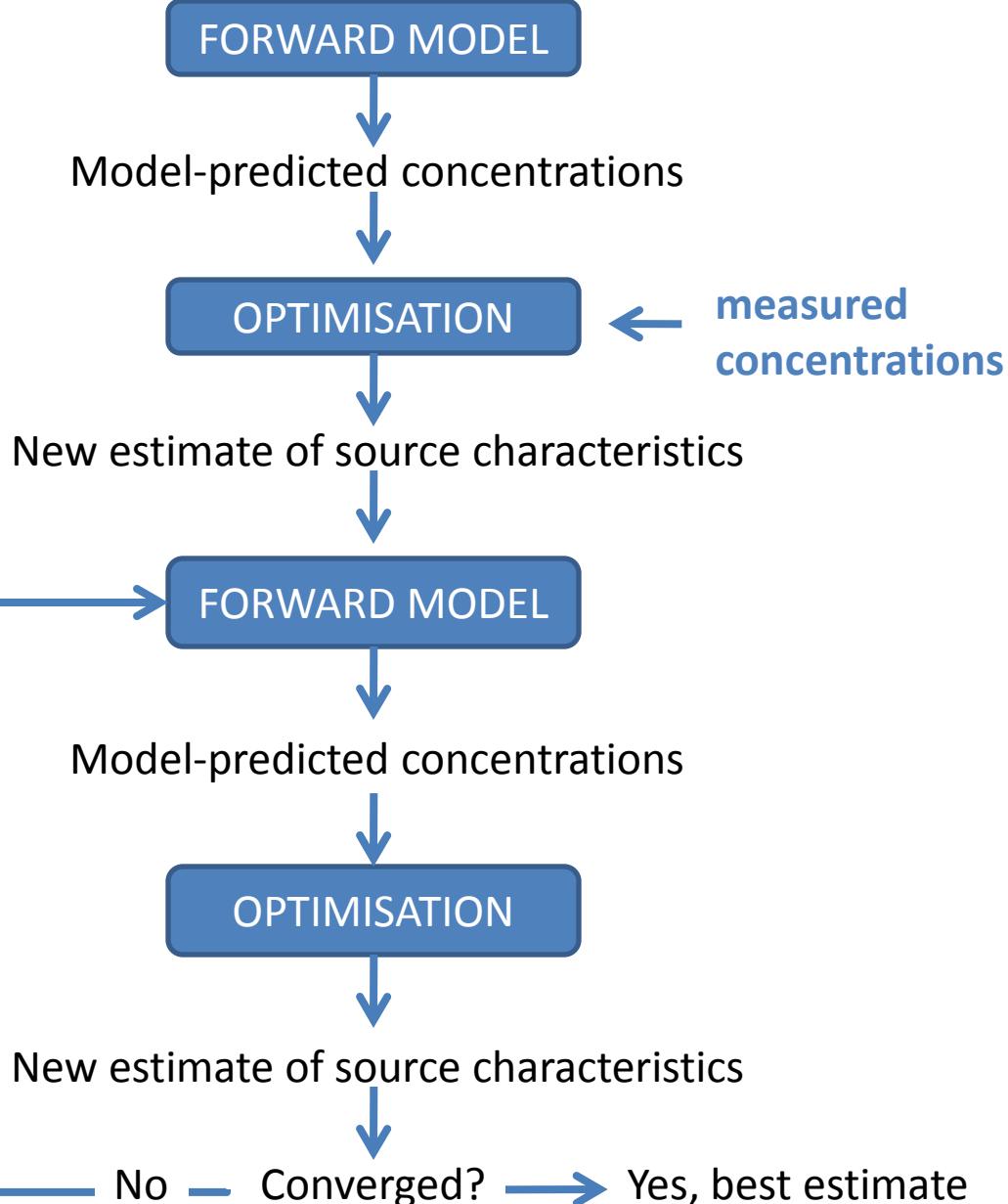
Model-predicted concentrations C^m

Measures the discrepancy between the measured and model-predicted concentrations

Minimise J , which is the same as finding the values of the source characteristics for which the gradient of J is zero. This is your ‘best’ estimate of the source characteristics.

Least squares fit plus error weighting which leads to an uncertainty estimate of the source characteristics.

First guess of source characteristics



Need a rapid algorithm

Time is important in emergency situations

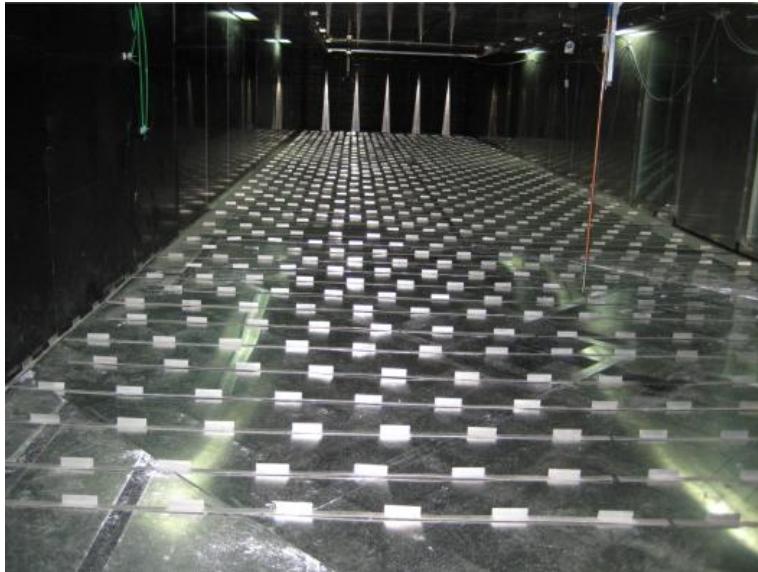
Estimate of uncertainty associated with the 'best' estimate from second derivative of the forward model w.r.t the source characteristics

Sources of error

- **Measurement error** the accuracy of the concentration measurement from the sensor
may be known
- **Model error** how good is the model at representing reality?
can only estimate
- **Sampling error** this is dependent on the averaging time of the data due to the natural variability of the concentrations
likely to dominate

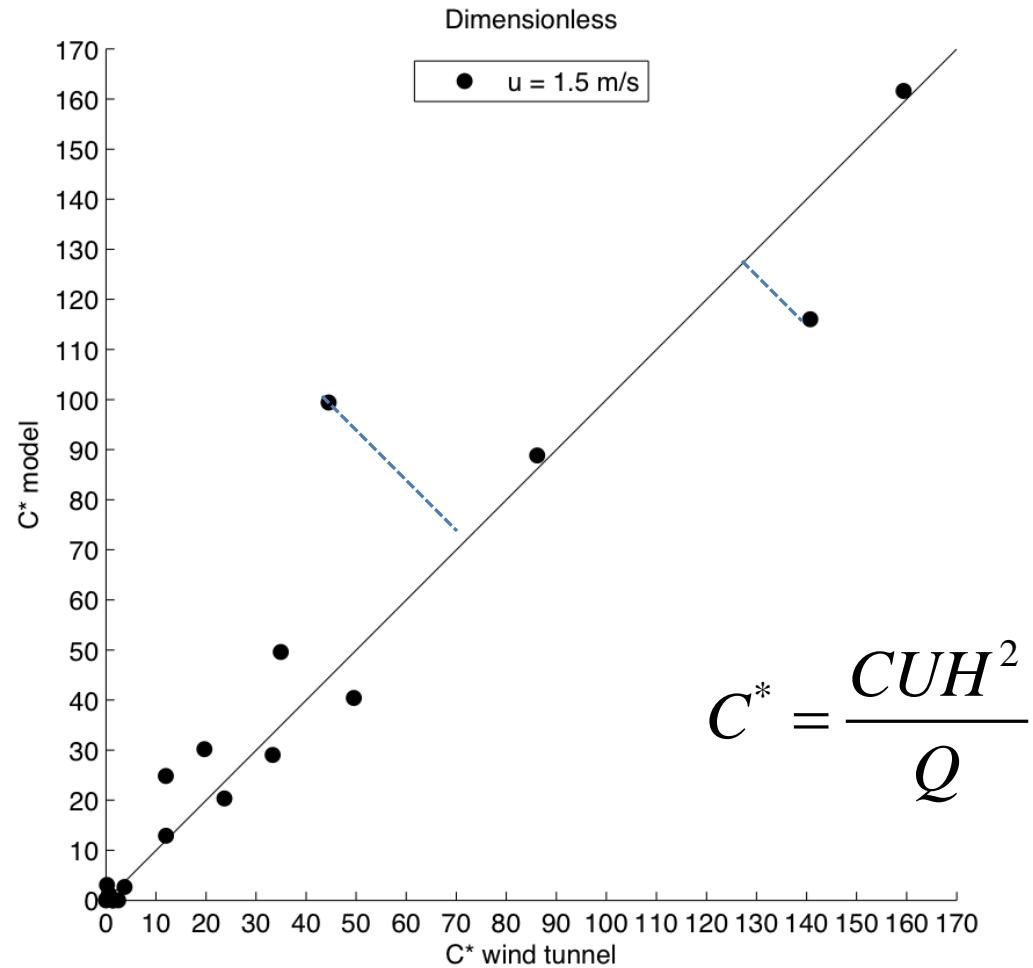
Could prevent the inverse algorithm from making a good estimate of the source characteristics

Wind tunnel data



Gaussian plume model tuned
to the wind tunnel data

Difference due to model
error and instrument
error?



Sampling error

How to quantify the sampling error associated with taking a short time average to estimate the true mean in a turbulent flow

Standard deviation of the shorter time mean estimate of the true mean concentration

$$\sigma_{\bar{C}^t} = \left(\frac{1}{n} \sum_{i=1}^n \left(\bar{C}_i^t - \bar{C}^T \right)^2 \right)^{\frac{1}{2}}$$

t is the shorter averaging time

T is the total time length

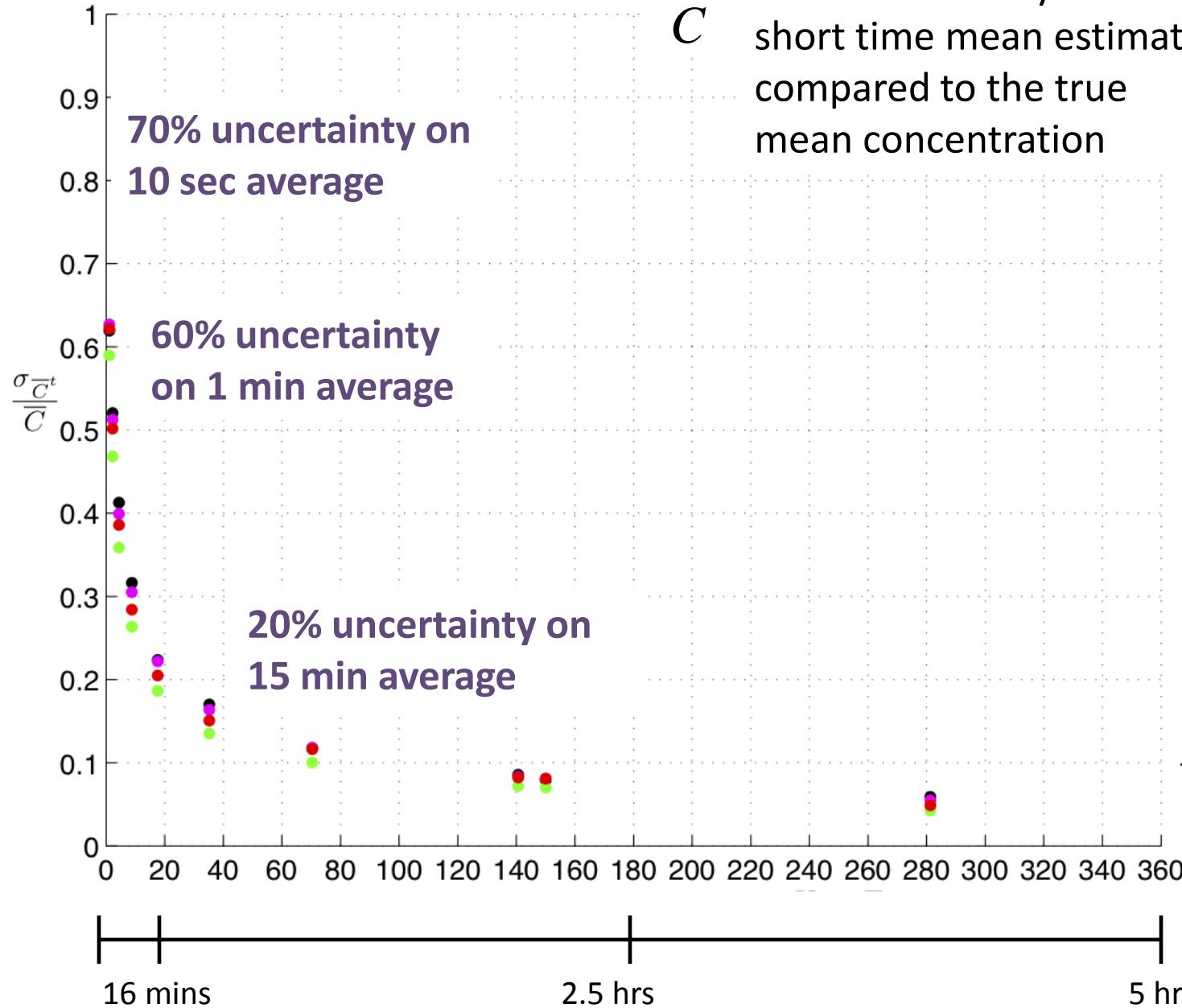
n is the n° of shorter averaging time samples

\bar{C}_i^t = mean concentration averaged over time t

\bar{C}^T = true mean concentration

Sampling error

$\frac{\sigma_{\bar{C}^t}}{C}$ = the uncertainty in the short time mean estimate compared to the true mean concentration



Wind tunnel
 $U_{ref} = 2.5 \text{ m/s}$
 $H = 1\text{m}$

$$\frac{U_{ref} T_{AV}}{H}$$

Equivalent
full scale
 $U_{ref} = 10 \text{ m/s}$
 $H = 500\text{m}$ 12

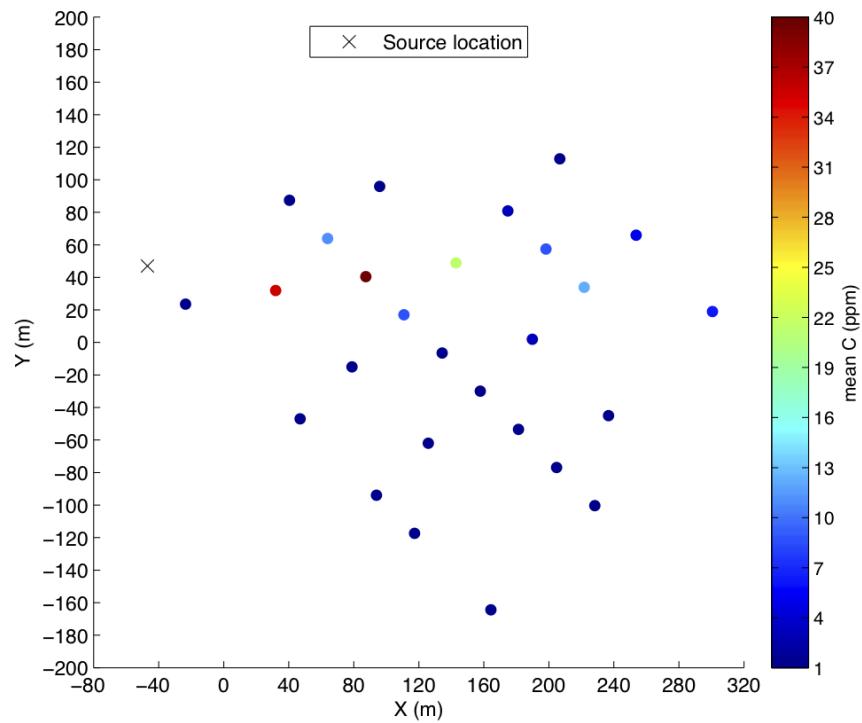
Inverse modelling - WT data

Source parameter	True value	First guess	units
Q	0.1	1	$\text{m}^3 \text{s}^{-1}$
X _s	-47	-24	m
Y _s	47	22	m

Source parameter	Estimate	Uncertainty	units
Q	0.075	0.002	$\text{m}^3 \text{s}^{-1}$
X _s	-30.37	1.54	m
Y _s	43.70	0.20	m

The true values of (Q , X_s , Y_s) do not lie within the uncertainty range of the estimates.

27 data points from wind tunnel data



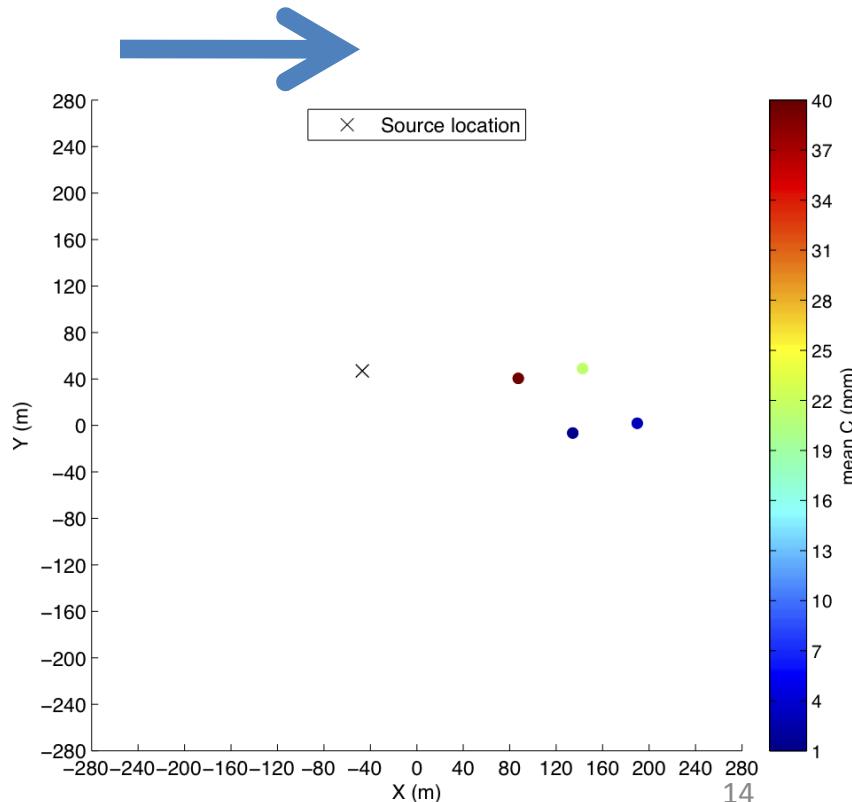
Inverse modelling - WT data

Source parameter	True value	First guess	units
Q	0.1	1	$\text{m}^3 \text{s}^{-1}$
X _s	-47	-24	m
Y _s	47	22	m

Source parameter	Estimate	Uncertainty	units
Q	0.097	0.010	$\text{m}^3 \text{s}^{-1}$
X _s	-46.57	7.84	m
Y _s	46.51	1.37	m

The true values of (Q , X_s , Y_s) lie within the uncertainty range of the estimates.

Sub set of 4 data points where the data values were accurately predicted by the Gaussian plume model



Conclusions

- Characterising the errors is essential for inverse modelling
 - can quantify the measurement error
 - can estimate the model error for the wind tunnel data
 - however, it is sampling error that appears to be the most important, it could potentially hamper the inverse algorithm from finding the ‘best’ estimate.
- We have a method for estimating the uncertainty due to sampling error that can feed into the inverse algorithm – need to test it.
- Other studies we have done with synthetic data showed that measurements scattered about the plume in a square configuration lead to better estimates of the source characteristics because they contain direct information on the lateral spread of the plume.

Further work

- Test the inverse algorithm with a different forward model – the network model approach for urban dispersion.
- Use wind tunnel data collected using rectangular blocks to represent buildings in an urban area for validation.

Thank you for your attention