

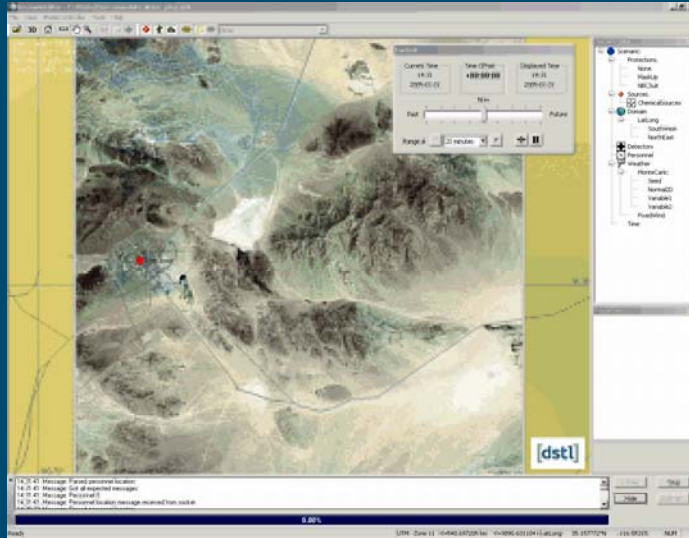
[dst]

CB Weapon Environment Prediction: **Source Term Estimation**

Paul Thomas,

Peter Robins, Ronni Rapley

Operational Need



- Operational strategy: base CBRN Hazard Estimates on **dispersion models**.
- Dispersion modelling is **dependent on Source Term** parameters
- For covert CBR releases, Source Terms will **not** be known
- **Fast** source term estimation needs to be performed
- An estimate of the **uncertainty** of the Source Term aids decision making

Introduction

Bayesian approach

- $P(D|H)$ is generally intractable, instead we calculate relative probabilities
- to calculate probabilities of hypotheses $P(x,y,Q,t,A|D)$, we need:
 - a prior: $P(x,y,Q,t,A)$
 - and a likelihood: $P(D|x,y,Q,t,A)$

$$P(H | \mathbf{D}) = \frac{P(\mathbf{D} | H)P(H)}{\sum_H P(\mathbf{D} | H)}$$

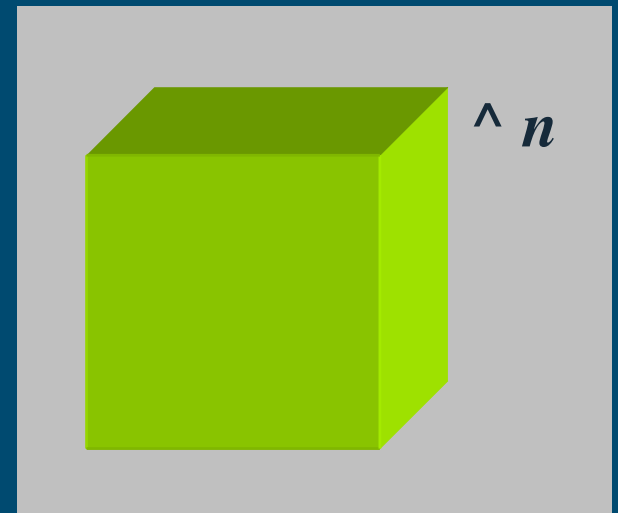
$$\frac{P(H_A | \mathbf{D})}{P(H_B | \mathbf{D})} = \frac{P(\mathbf{D} | H_A)P(H_A)}{P(\mathbf{D} | H_B)P(H_B)}$$

Likelihood calculation needs either:

- fast dispersion model
- inverse dispersion run

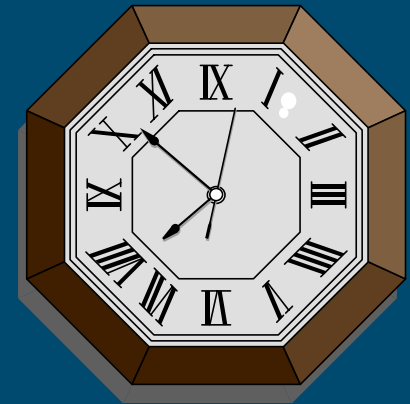
Technical Problems

- multidimensional search space;
 - sampling strategies to make efficient hypotheses in hypercube
- computational efficiency
- fixed / mobile sensors
- fusion of disparate data
- modelling sensor response
- biological source term estimation
- Evaluation of methodology



Technical Problems

- multidimensional search space;
- **computational efficiency**
 - target: source term estimation 5 minutes after first detection
- fixed / mobile sensors
- fusion of disparate data
- modelling sensor response
- biological source term estimation
- Evaluation of methodology



Technical Problems

- multidimensional search space;
- computational efficiency
- **fixed / mobile sensors**
 - fixed sensors → high data rate.
- fusion of disparate data
- modelling sensor response
- biological source term estimation
- Evaluation of methodology

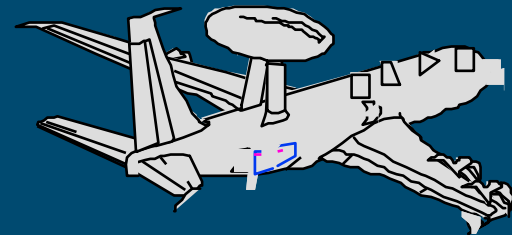


Mobile sensors → position unknown



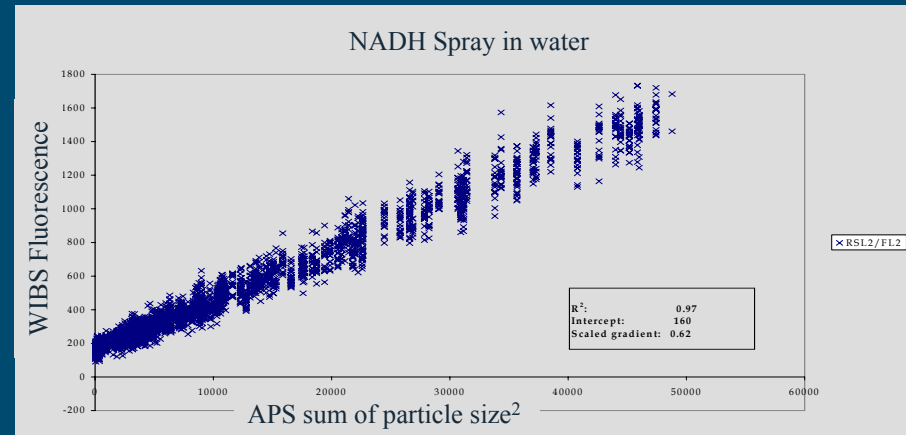
Technical Problems

- multidimensional search space;
- computational efficiency
- fixed / mobile sensors
- fusion of disparate data
 - e.g. human observations, ISTAR observations
- modelling sensor response
- biological source term estimation
- Evaluation of methodology



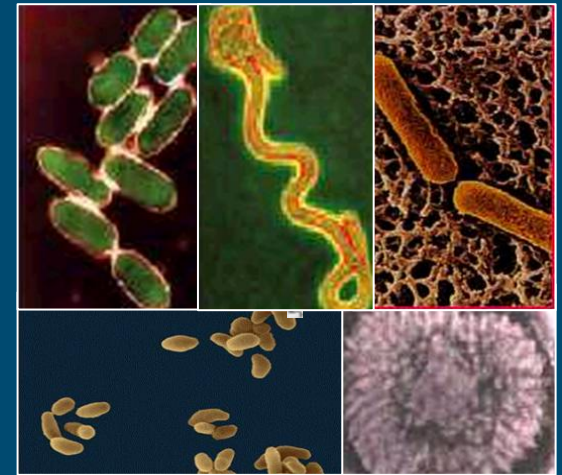
Technical Problems

- multidimensional search space;
- computational efficiency
- fixed / mobile sensors
- fusion of disparate data
- **modelling sensor response**
 - so that sensor uncertainty can be accounted for
- biological source term estimation
- Evaluation of methodology



Technical Problems

- multidimensional search space;
- computational efficiency
- fixed / mobile sensors
- fusion of disparate data
- modelling sensor response
- **biological source term estimation**
 - biological background leads to false alarms
- Evaluation of methodology



Technical Problems

- multidimensional search space;
- computational efficiency
- fixed / mobile sensors
- fusion of disparate data
- modelling sensor response
- biological source term estimation
- **Evaluation of methodology**
 - objective validation



Multidimensional Search Space

- **Differential Evolution - Markov Chain**
- On start-up several hypotheses, (we use 50) are distributed throughout the prior, these form the start of Markov Chains
- For each hypothesis, run the UDM to calculate the parameters of the clipped Gaussian (μ, σ)
- Then the probability/ weighting of each hypothesis can be calculated immediately data becomes available
- During ideal time, cycle through each Markov Chain in turn. New jumps are proposed from difference between chains

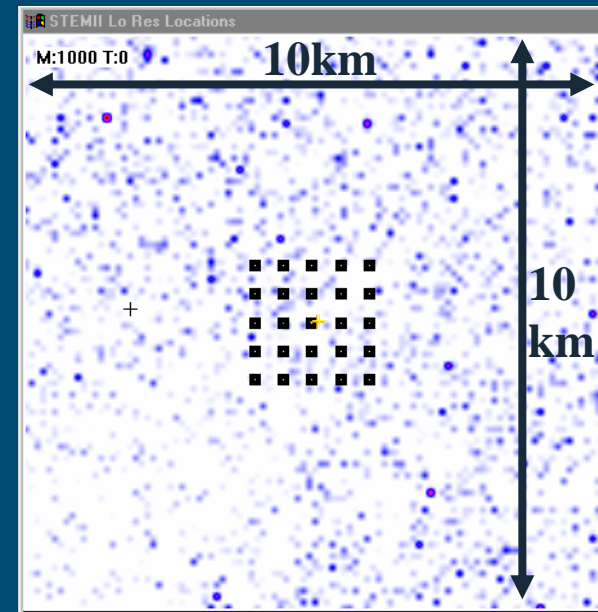
$$\mathbf{x}_{i,new} = \mathbf{x}_{i,old} + \gamma (\mathbf{x}_j - \mathbf{x}_k) + \epsilon, \quad i \neq j \neq k$$

- **Adaptive**: Population mimics distribution (inc. correlations).
- **Aggressive** expansion from degeneracy.

Computational Efficiency

Idle time processing

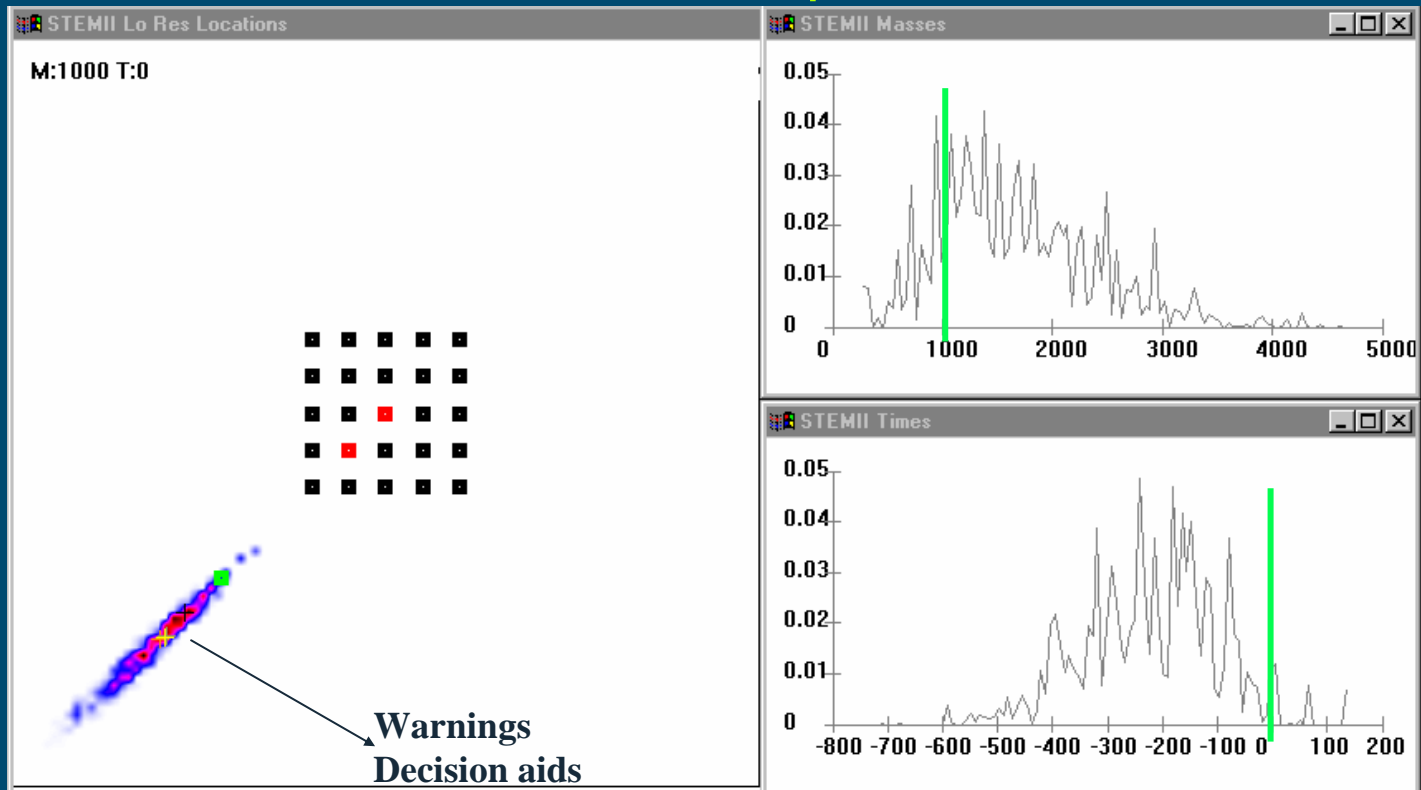
- Add new samples to map out posterior according to current data.
 - Propose new samples.
 - Differential Evolution – Markov Chain.
 - Two-Step Accept/reject.
- Check for data.
- Sample Importance Resample if:
 - Few hypotheses have significant weight.
 - Data process time rules out idle time.



Computational Efficiency

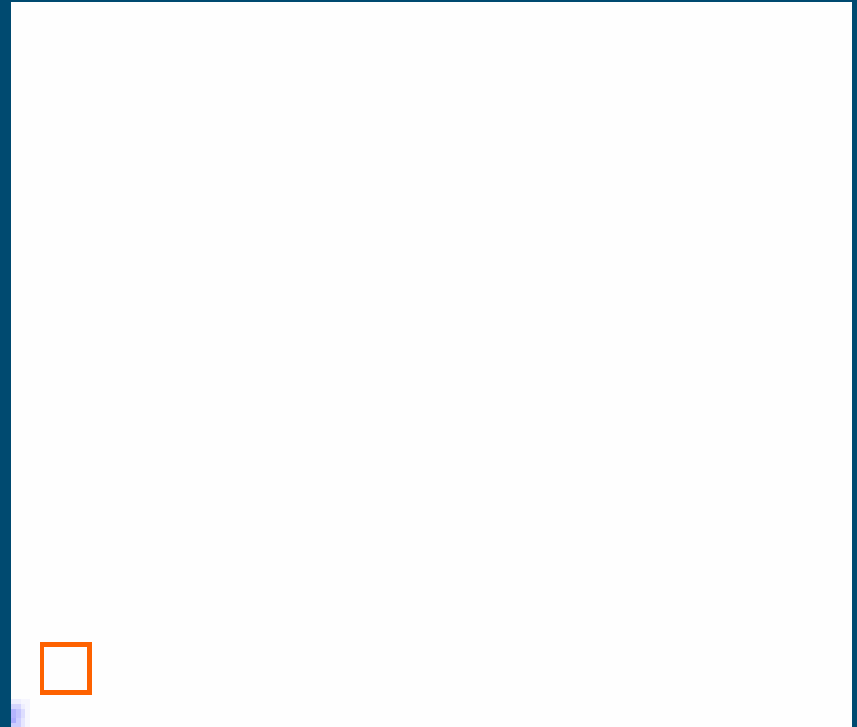
Chem scenario, fixed sensors

5 minutes after first sensor responds



Fixed / mobile sensors

- Fusion of data from mobile sensors
- Previously unreported sensors, e.g. with a manoeuvre unit
- No opportunity to perform pre-processing
- Alarm only (rather than bar reading or concentration)



Fixed / mobile sensors

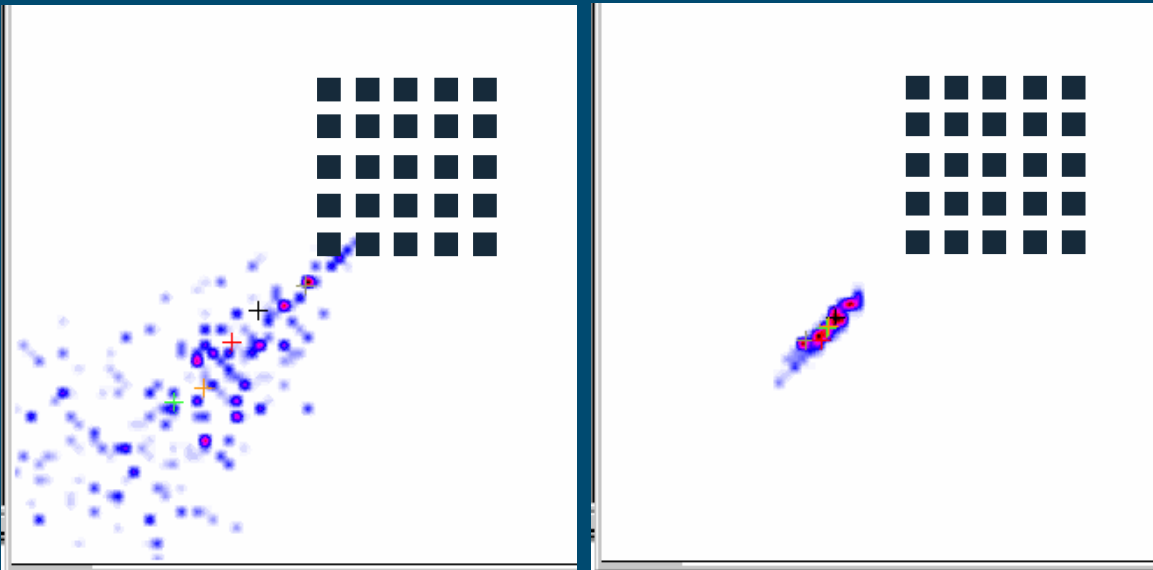
- Fusion of data from mobile sensors
- Previously unreported sensors, e.g. with a manoeuvre unit
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Solution:

- Dispersion model adjoint
- Current simplifying assumptions include spatially homogeneous wind flow and terrain - in this case, the reversal of wind and time form an exact adjoint

Human observations

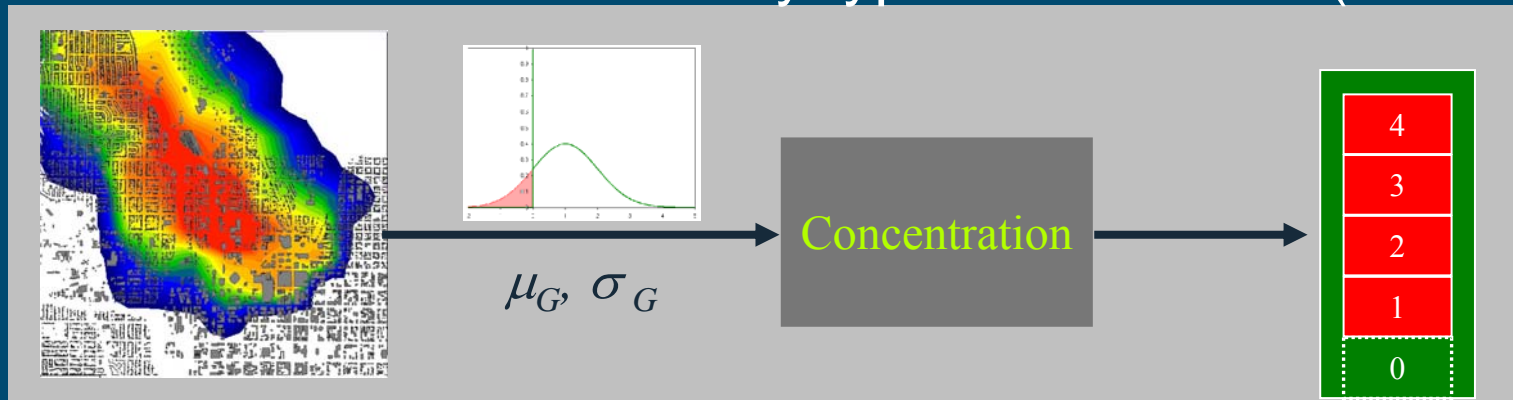
- Human observation fusion
- Either bearing-only or bearing and range



- Bearing uncertainty modelled as Gaussian
- Range uncertainty modelled as Log-normal

Sensor response models

- Probabilistic models of sensor response
- Chemical sensor: Ion Mobility type “bar” sensor (\equiv ACADA)



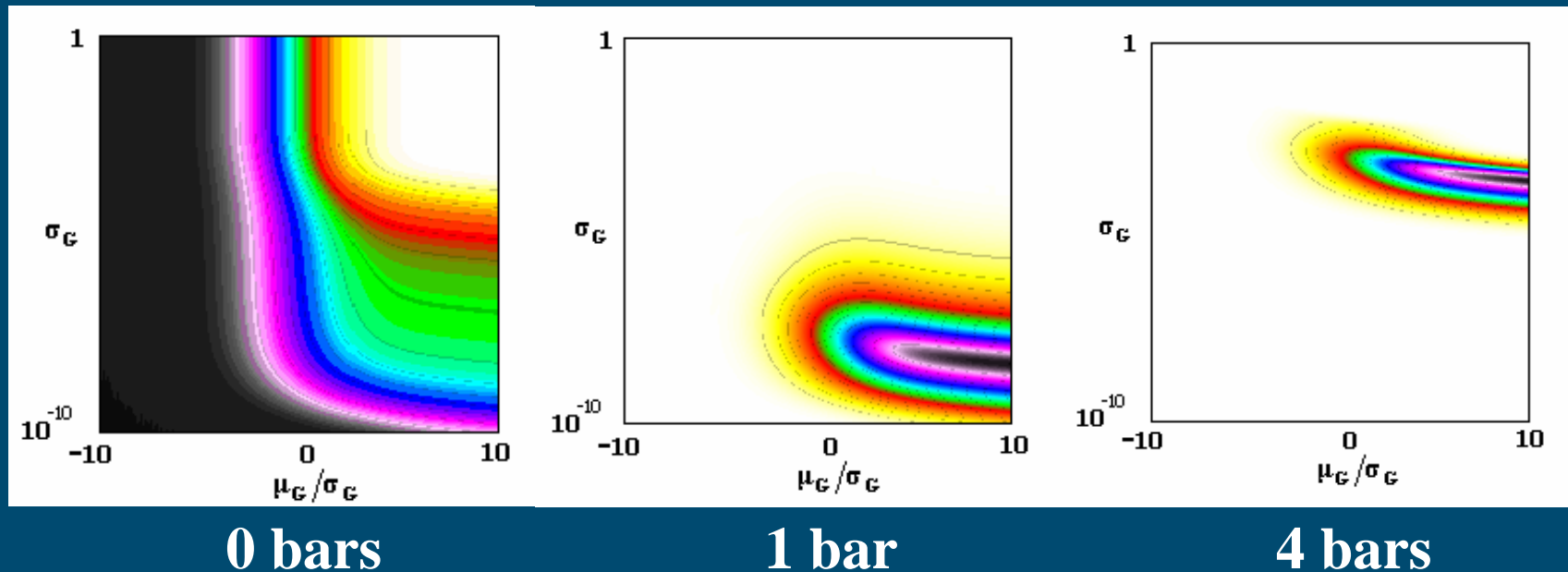
- model $P(\text{bar}_i | \text{dispersion code output})$.

$$P(\text{bar}_i | \mu_G, \sigma_G) = \int_0^{\infty} P(\text{bar}_i | c) P(c | \mu_G, \sigma_G) dc$$

$$P(\text{bar}_i | \mu_N, \sigma_N^2) = \int_0^{\infty} \frac{1}{\sqrt{2\pi(\alpha c + J)}} \int_{T_{i-1}}^{T_i} e^{-\frac{1}{2} \frac{(v-c)^2}{(\alpha c + J)}} dV \left[\frac{1}{2} \left(1 - \text{erf} \left(\frac{\mu_N}{\sigma_N \sqrt{2}} \right) \right) \delta(c) + \frac{1}{\sigma_N \sqrt{2\pi}} e^{-\frac{1}{2} \left(\frac{c - \mu_N}{\sigma_N} \right)^2} \right] dc$$

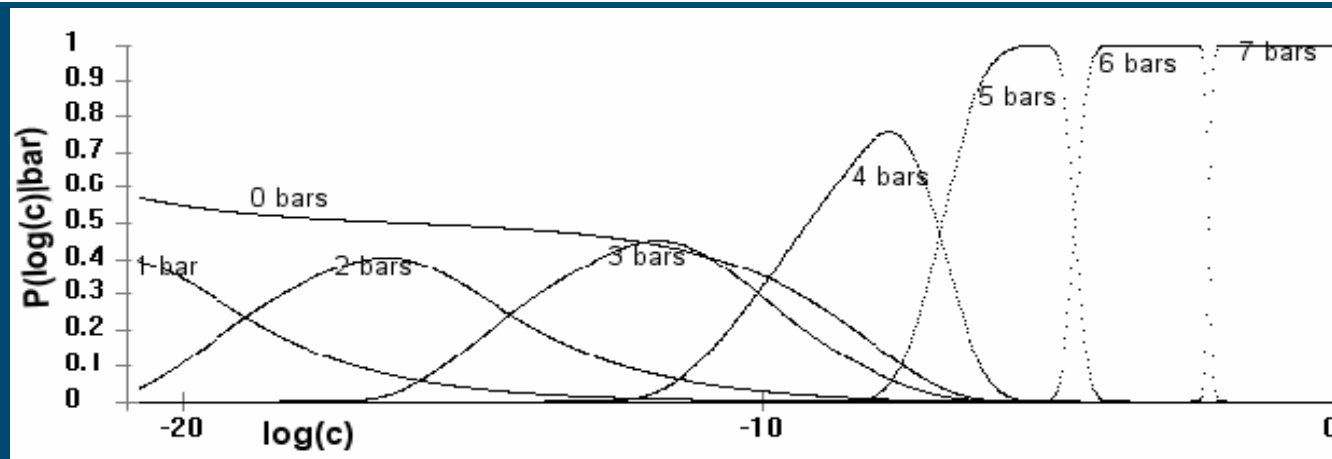
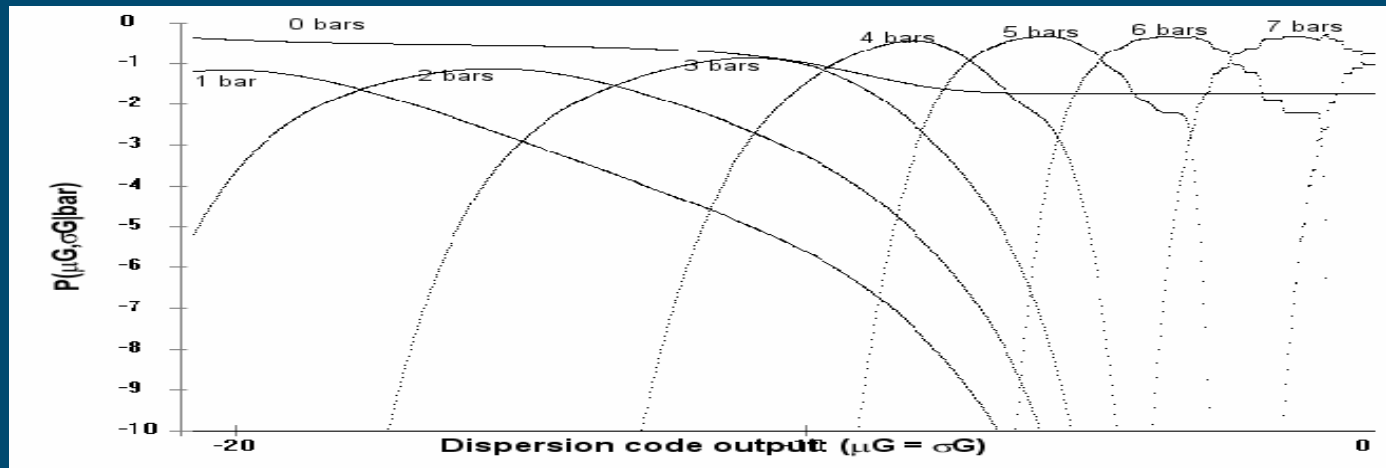
Sensor response models

- Probabilistic models of sensor response
- Look-up table of pre-computed integrals



Sensor response models

- Probabilistic models of sensor response

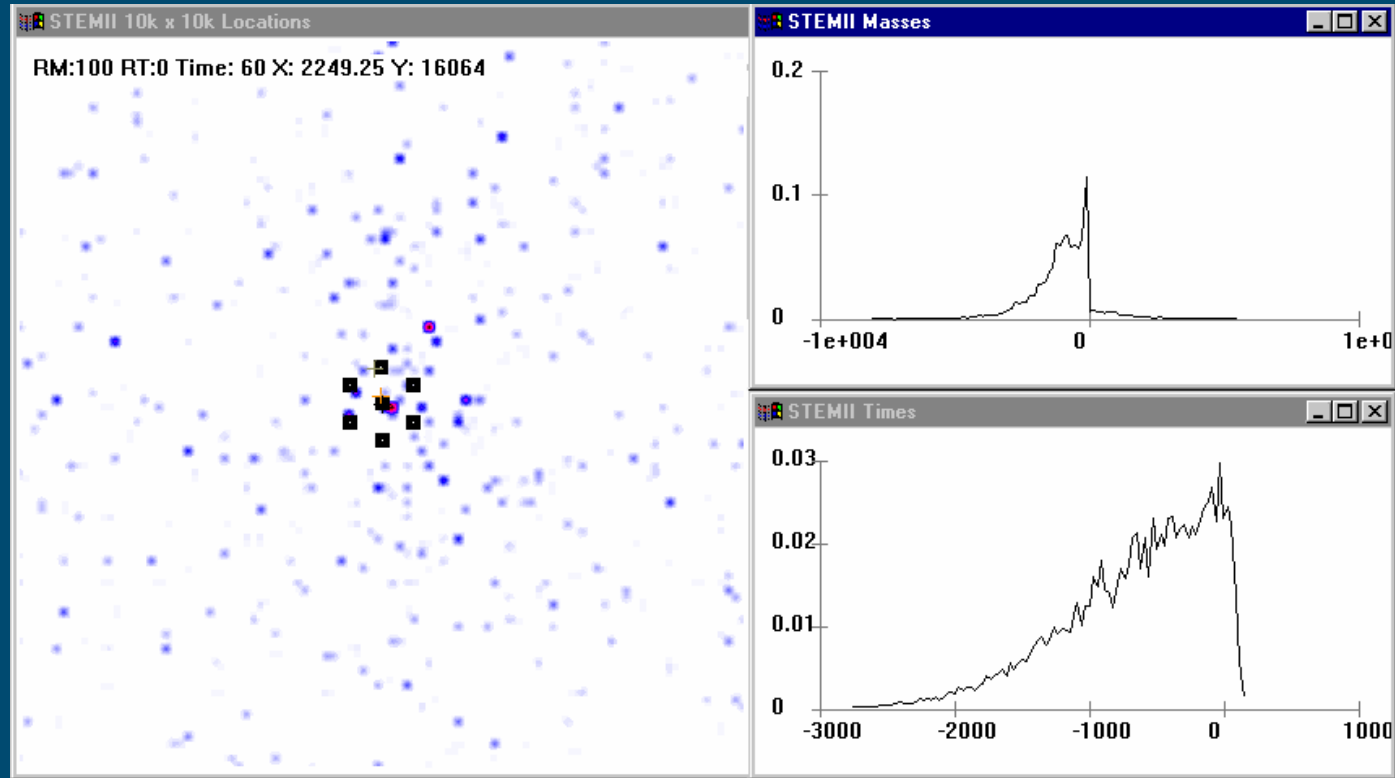


Source Term Estimation video

Chemical scenario

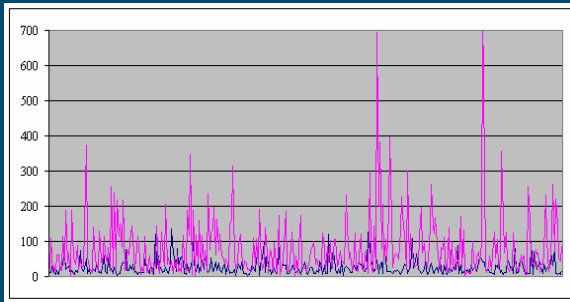
(faster than real time 1s = 1m)

- Actual releases:
 - Mass 100kg.
 - Time 0s.
 - 7 x bar detectors



Biological sensor fusion

- Biological background



Real background

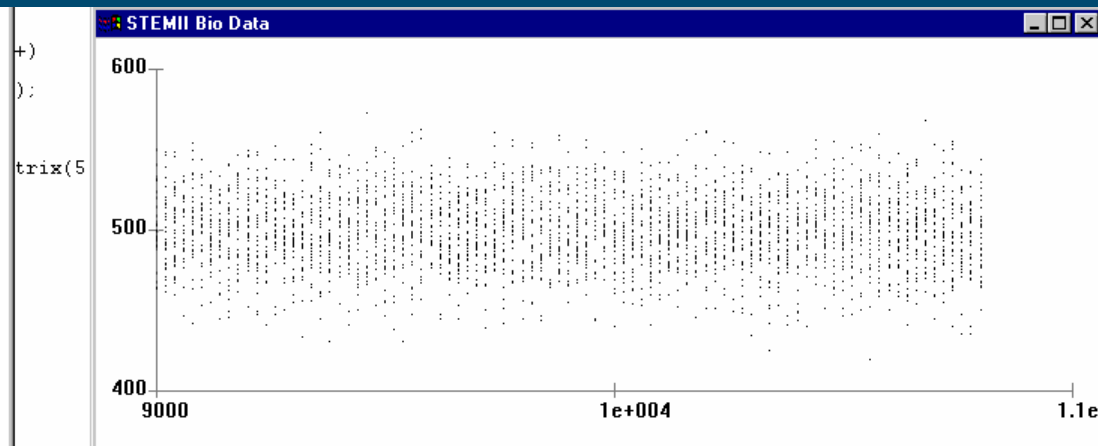
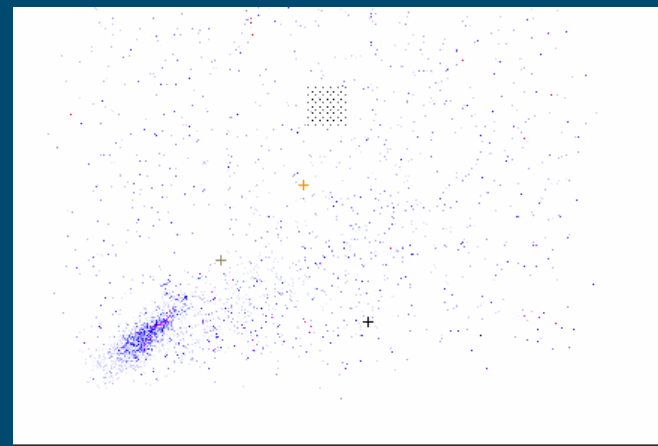
Exponentially weighted moving av. of Poisson distributed background
$$\mu_t = \alpha\mu_{t-1} + (1-\alpha)s_{t-1}.$$

i.e. mean = variance

STEM's internal model of background

Source Term Estimation

bkgrd subtracted sensor reading



Video of EWMA background discrimination (inc. simplistic background model)

Biological sensor fusion

- Biological sensor model

Simple particle counter sensor



Immuno-Assay detector

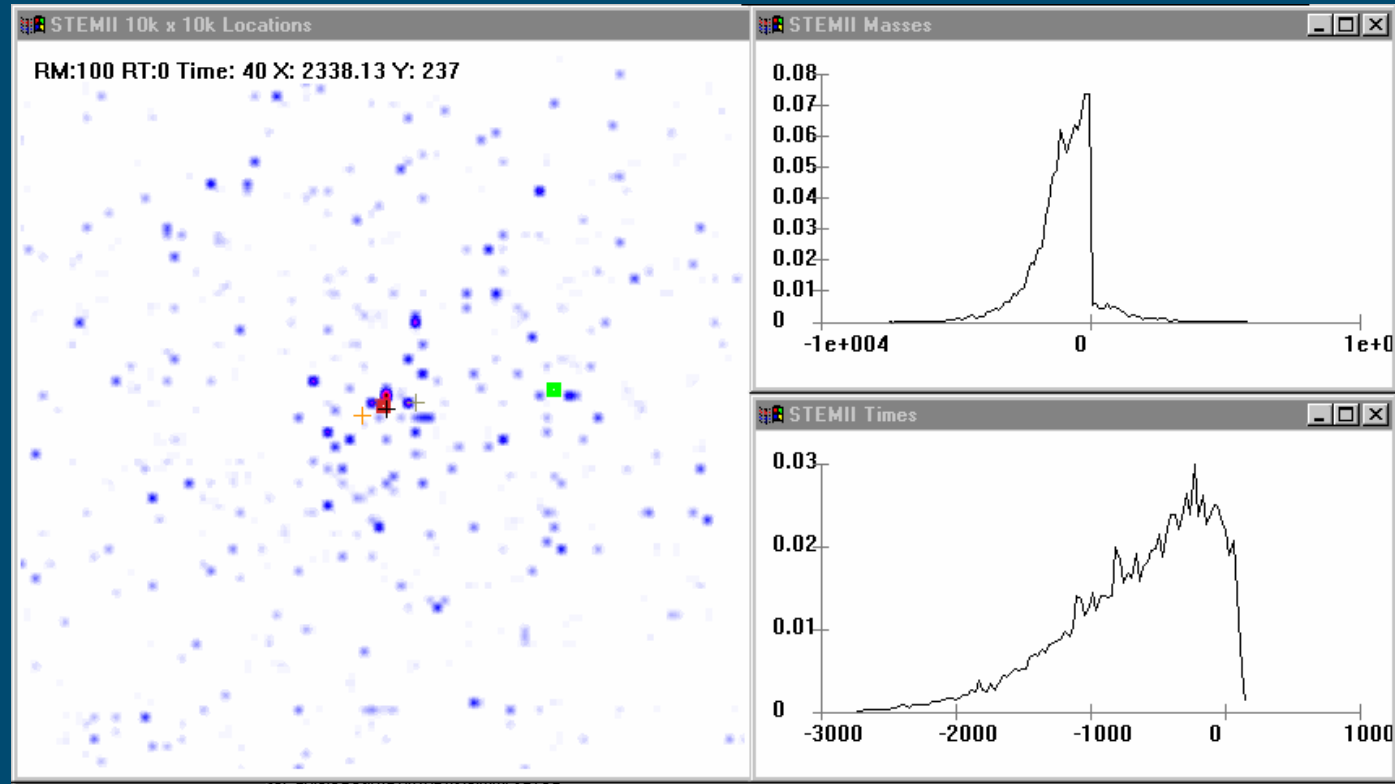


Source Term Estimation video

Biological scenario

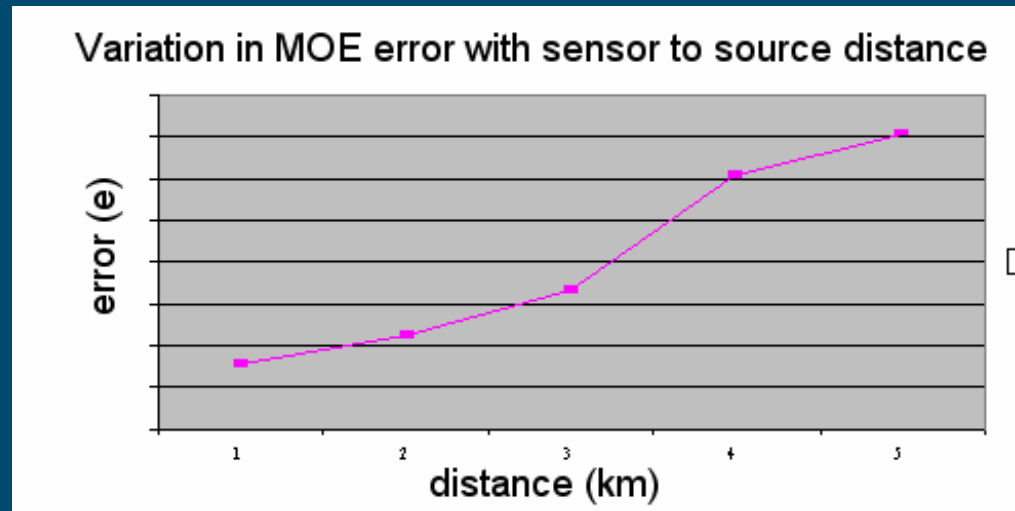
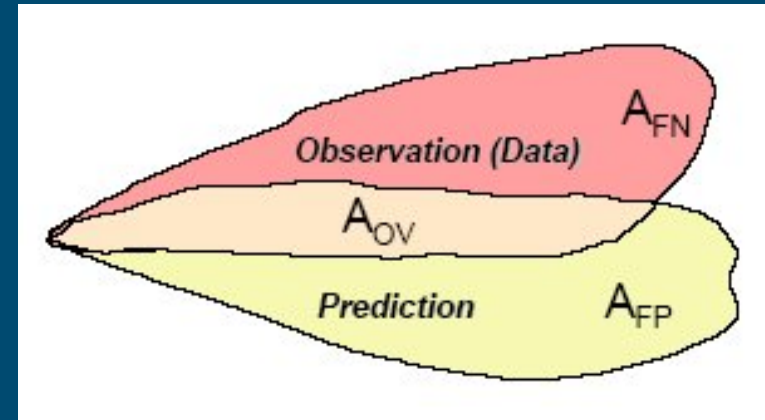
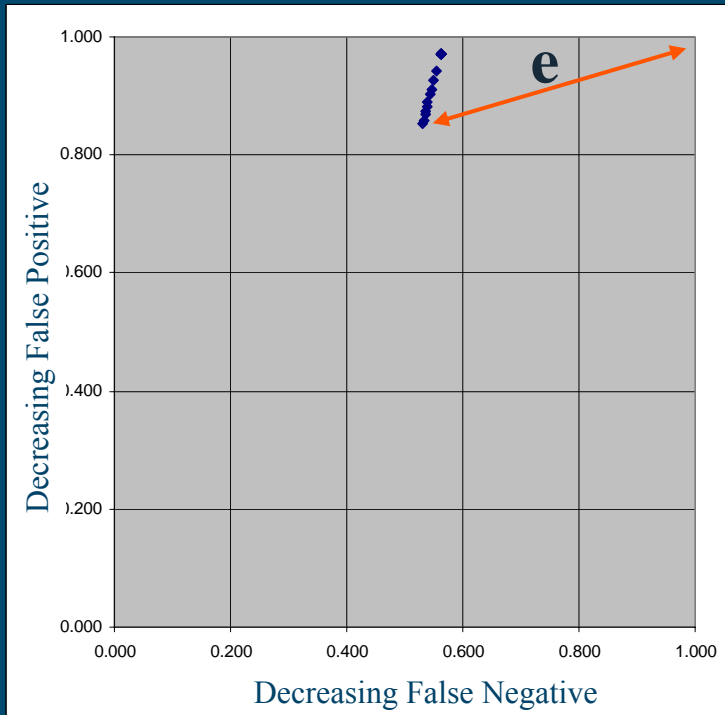
(faster than real time 1s = 1m)

- Actual releases:
 - Mass 100kg.
 - Time 0s.
 - 1 x particle counter



Evaluation of methodology

- Evaluation system built
- Measure of effectiveness – compares the areas of overlap, over and under-prediction between an the observed and predicted.



Peer Review

- Two papers presented at Fusion 2005 conference
- (Philadelphia, USA. July 25 - 29, 2005)

- **“Non-Linear Bayesian CBRN Source Term Estimation”**. Peter Robins and Paul Thomas
- **“A Probabilistic Chemical Sensor Model for Data Fusion”**. Peter Robins , Veronica Rapley and Paul Thomas

Future Research FY05 & FY06

- Extensive **evaluation** of STEM II will be carried out to determine performance in a synthetic environment
- More probabilistic **models of sensor response** will be built
- Extending the techniques developed for chemical releases to work for **biological releases**, in the presence of the natural background.
- Research will be carried out in order to speed up some of the more difficult mathematical calculations to make the system suitable for operational use in **complex terrain** and **urban areas**.
- Research will be carried out to allow modelling of **multiple source** terms and line strikes.



Questions?