Fusion of Sensor and Model Data

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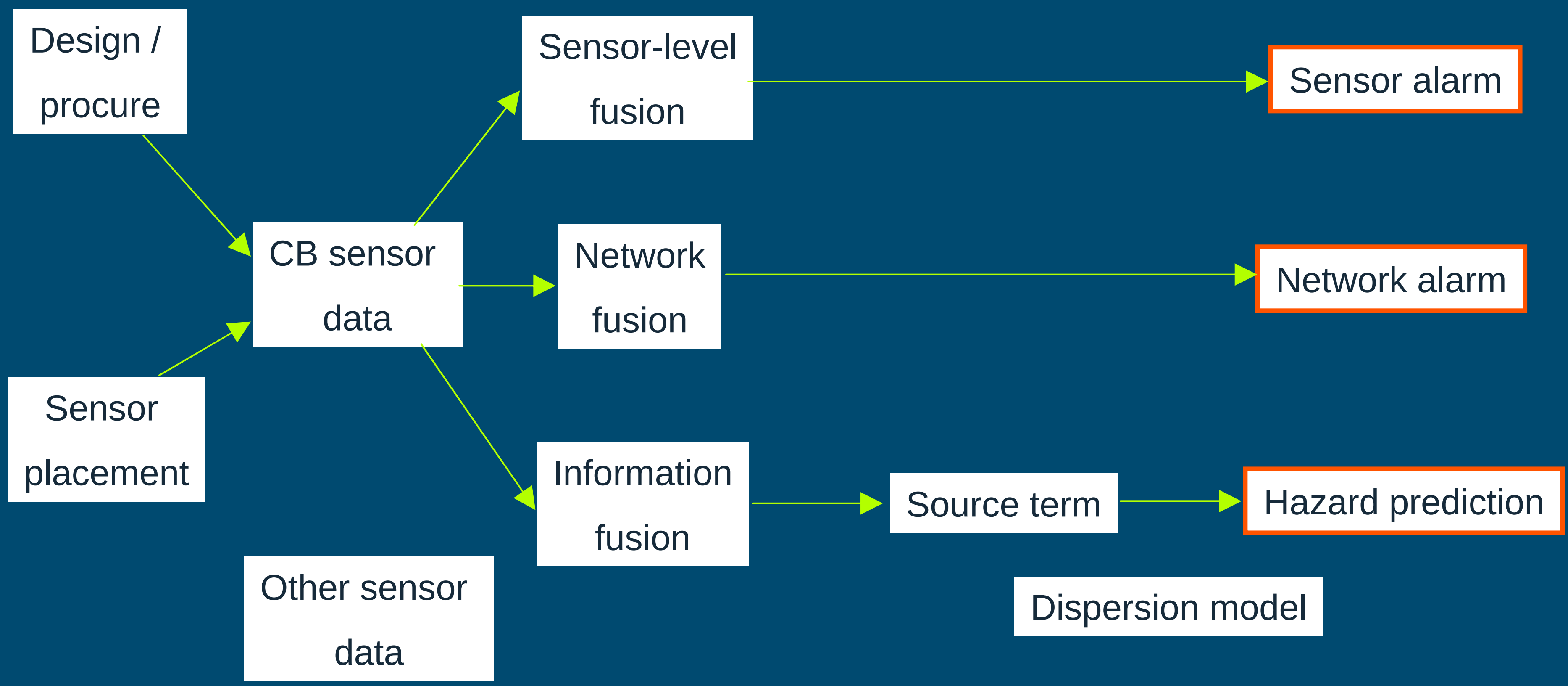
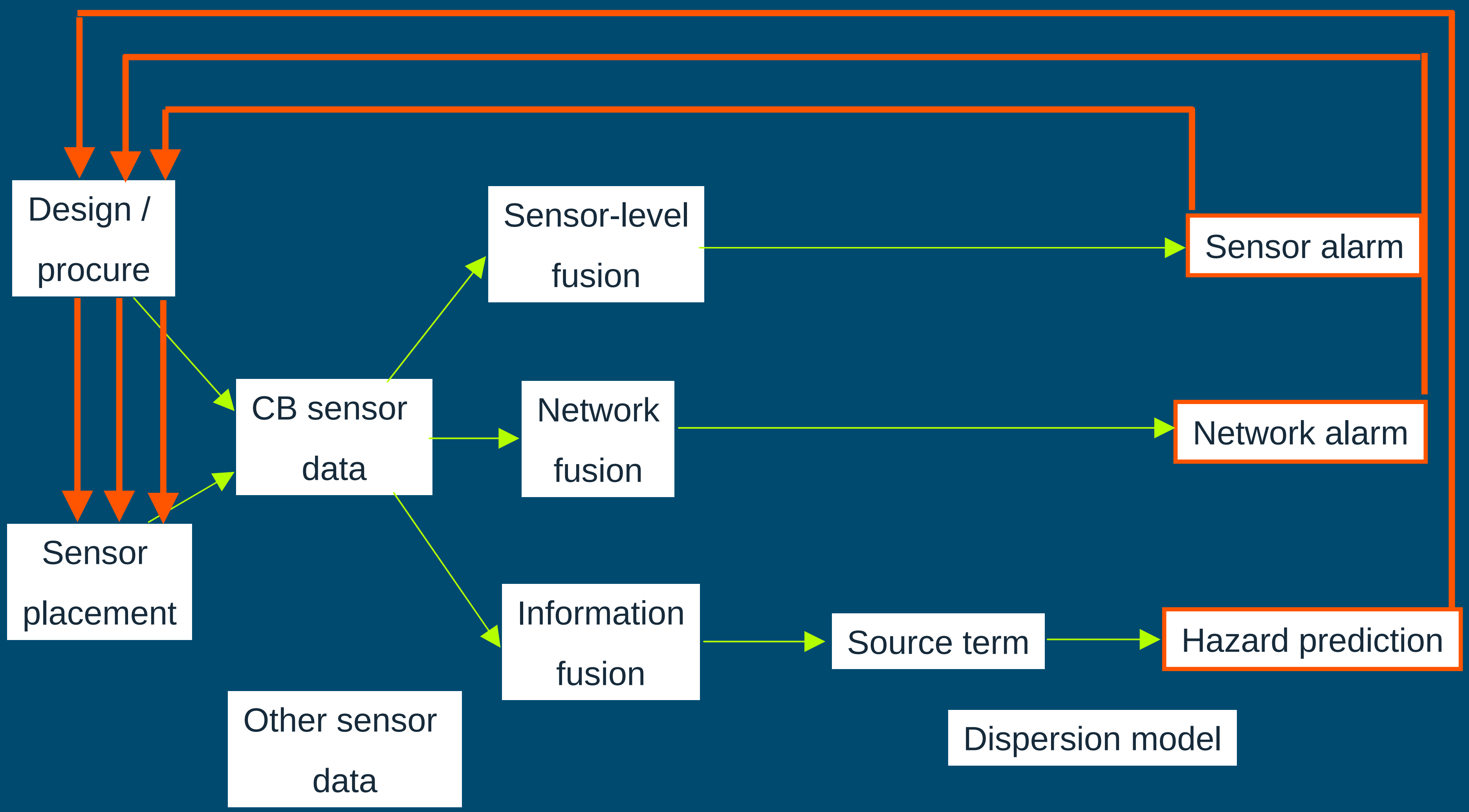
The big picture...

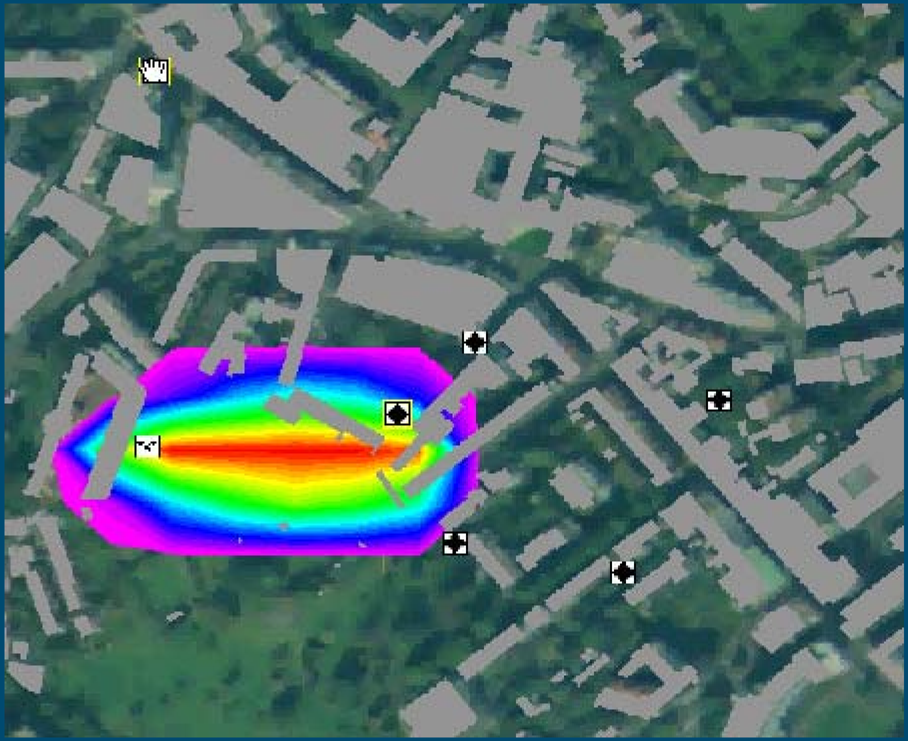


The big picture...



1) Sensor placement

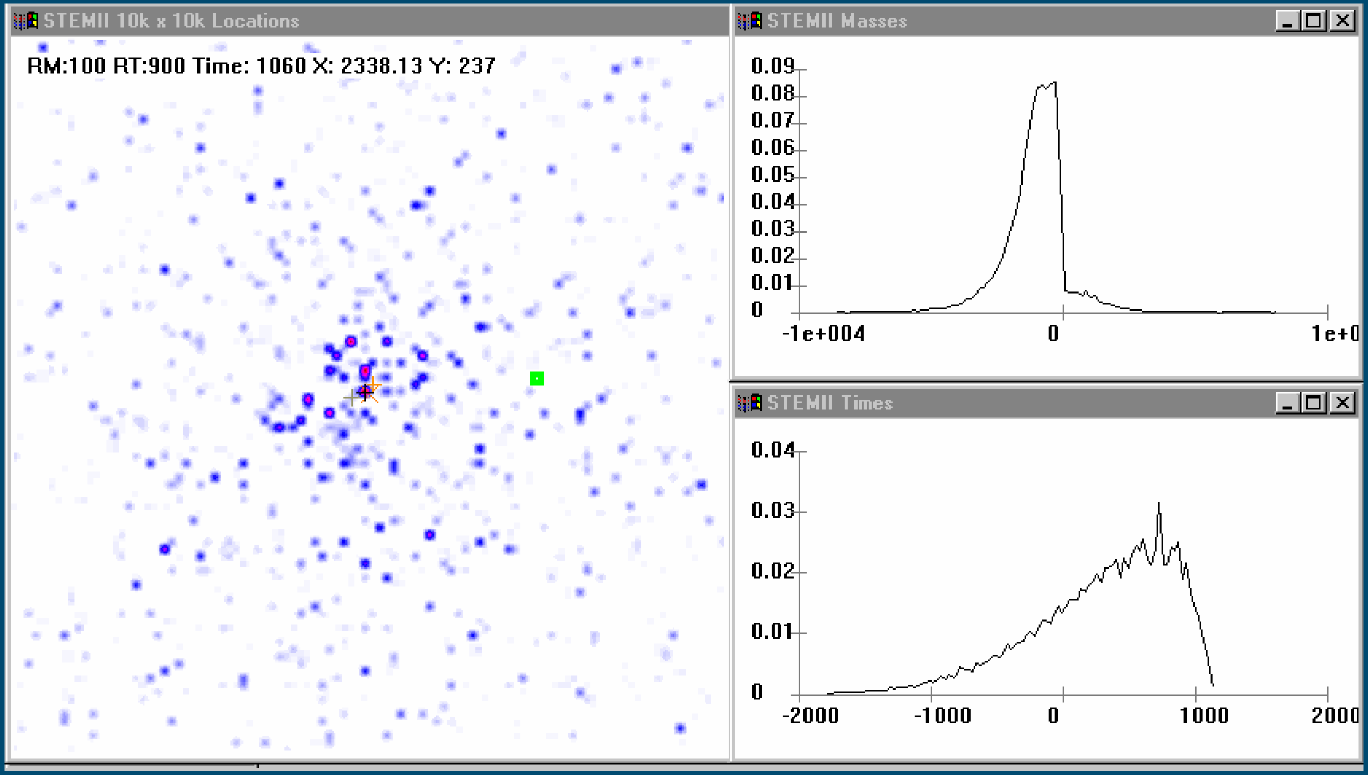
- 1) Place sensors to maximise probability of any sensor detecting a release
- 2) Place sensors to maximise detection capability of the sensor network
- 3) Place sensors for optimal hazard prediction
- 4) Target UAVs and other mobile sensors...



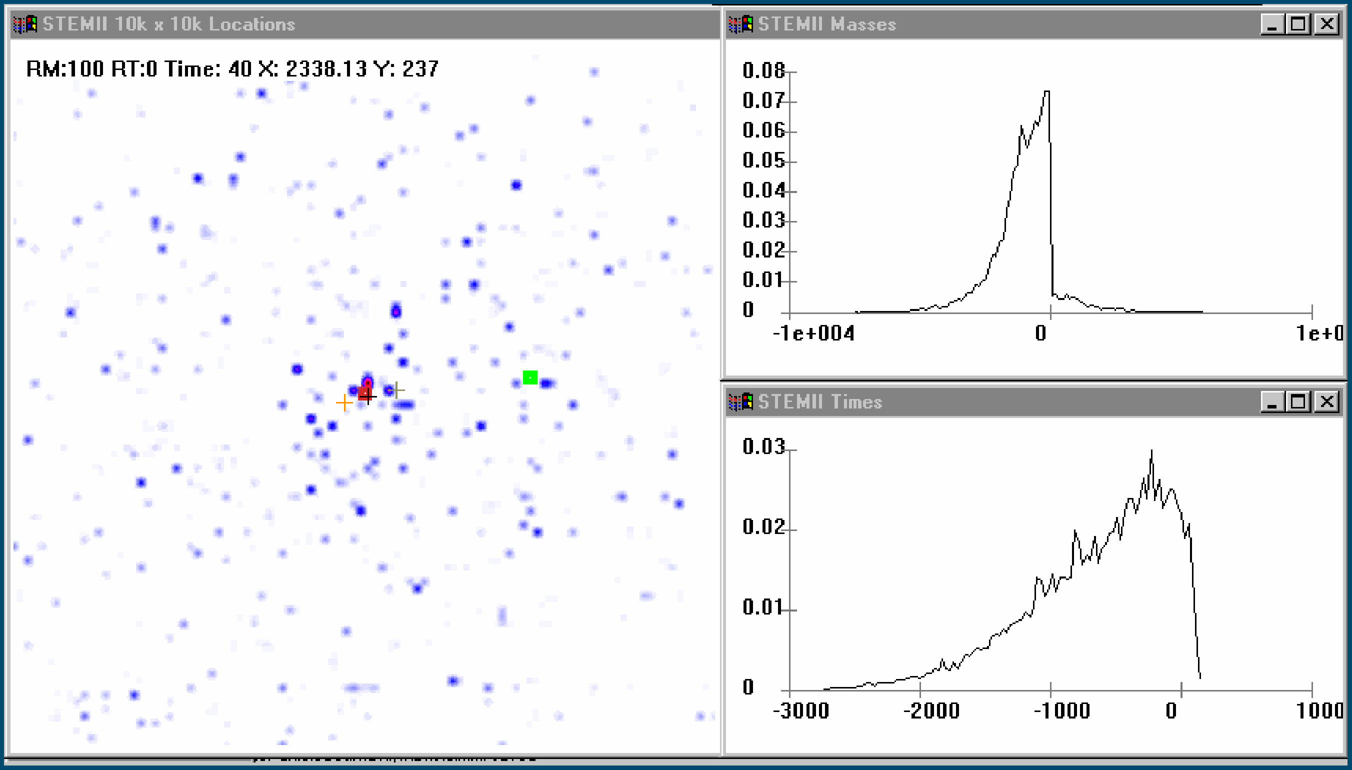
2) Sensor procurement

- 1) Design individual sensors based on key metrics
  - sensitivity
  - probability of detection
  - false positive rate
  - response time
- 2) Procure heterogeneous network of sensors to optimise key metrics at the *system level*, for the area to be protected
- 3) Design sensor network to optimise quality of hazard prediction

Optimal biosensor for identification - resonant mirror

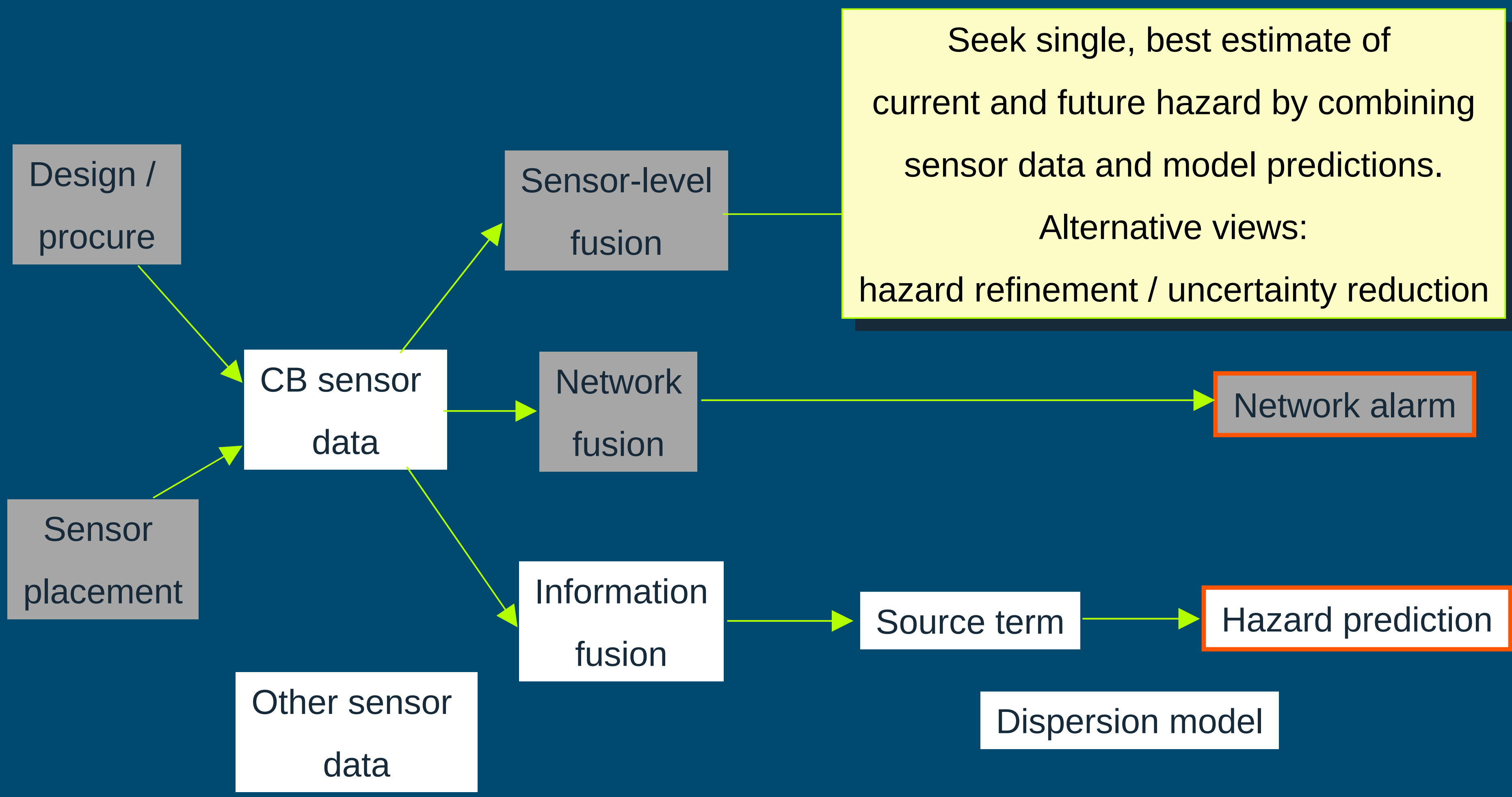


Better biosensor for hazard prediction - particle counter?



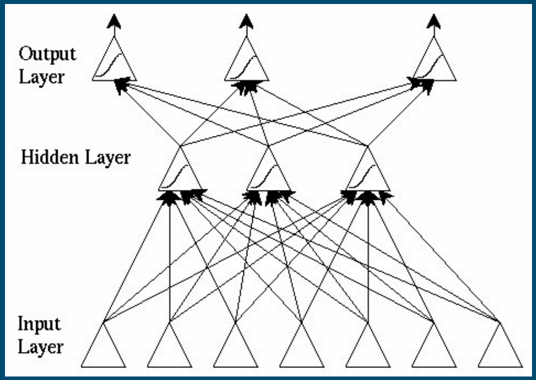
Impact of single sensor on source term estimation only - conclusions are limited!

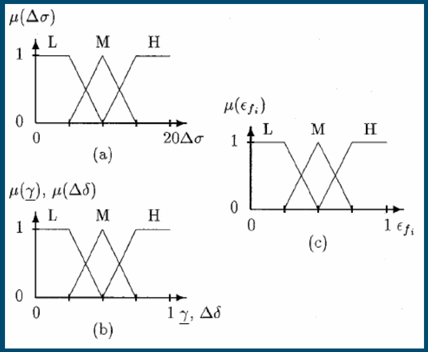
3) Fusion of sensor and model data

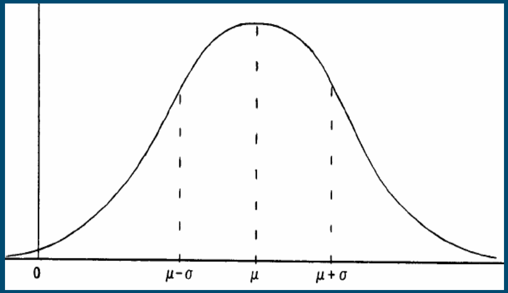


3a) Literature Review

- Investigated wide variety of possible methods
  - Bayes theory
  - Kalman Filter
  - Fuzzy Logic
  - Genetic Algorithms
  - Neural Networks
  - Variational Assimilation
  - Optimal Interpolation







- Chosen short list of suitable techniques for implementation into a synthetic environment

Bayesian fusion

$$p\left(H \mid D\right) = \frac{p\left(D \mid H\right) p\left(H\right)}{p\left(D\right)}$$

- ✓ Mathematically rigorous
  - ✓ incorporates uncertainty
- ✓ Simple in concept
- ✓ Incorporates prior knowledge
- ✓ Can be extended to incorporate any information
  - ✓ observer range and bearing

- × No absolute probabilities
- × Difficult to implement (complex integrals)
- × Computationally demanding

Kalman filter

$$\mathbf{x} = \mathbf{x}^{\mathrm{b}} + \mathbf{K}\left(\mathbf{y} - \mathbf{H}\,\mathbf{x}\right)$$

$$\mathbf{K} = \left(\mathbf{B}^{-1} + \mathbf{H}^{T}\mathbf{R}^{-1}\mathbf{H}\right)^{-1}\mathbf{H}^{T}\mathbf{R}^{-1}$$

- ✓ Sequential predictor-corrector data fusion method
  - ✓ incorporates uncertainty
- ✓ Provides prediction of the error covariances
- ✓ Incorporates prior knowledge

- × KF only for linear models
  - × Use extended or ensemble KF for non-linear models
- × Can be computationally demanding

Variational Data Assimilation

$$J(\mathbf{x}) = \frac{1}{2}\left(\mathbf{x}-\mathbf{x}^{\mathbf{b}}\right)^{T}\mathbf{B}^{-1}\left(\mathbf{x}-\mathbf{x}^{\mathbf{b}}\right) + \frac{1}{2}\sum_{i=1}^{N}\left(\mathbf{y}_i - \mathbf{H}\mathbf{x}_i\right)^{T}\mathbf{R}^{-1}\left(\mathbf{y}_i - \mathbf{H}\mathbf{x}_i\right)$$

- ✓ Variational method
  - ✓ Assimilates all sensor data simultaneously
- ✓ Determines optimal analysis by solving the cost function
  - ✓ Provides gradient of analysis

- × Can be very computationally demanding
- × Does not determine the analysis directly

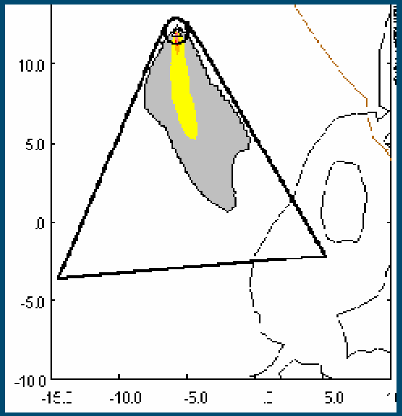
Overview of optimal techniques

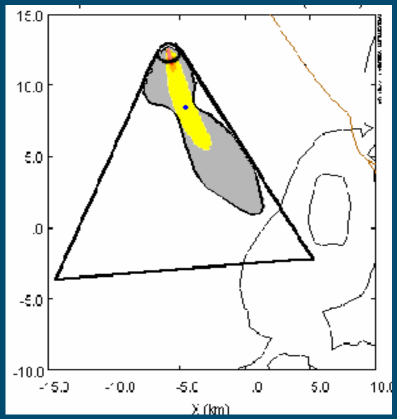
	Use observations at the same time	Use a time sequence of observations
Sequential	Optimal Interpolation	Kalman Filter, Bayes
Variational	3DVAR	4DVAR

- Most interested in techniques that use a time sequence of observations
  - Assumption that observations occur at the same time introduces additional error
- Comparison of sequential and variational methods

3b) Uncertainty propagation

- Crucial to quantify uncertainty in model predictions, as well as sensor data
  - source magnitude, time and location (x,y,z)
  - number of sources
  - meteorology (in complex environments) and turbulence
  - effects (e.g. casualties)
  - is data representative?
- MOD-funded uncertainty project





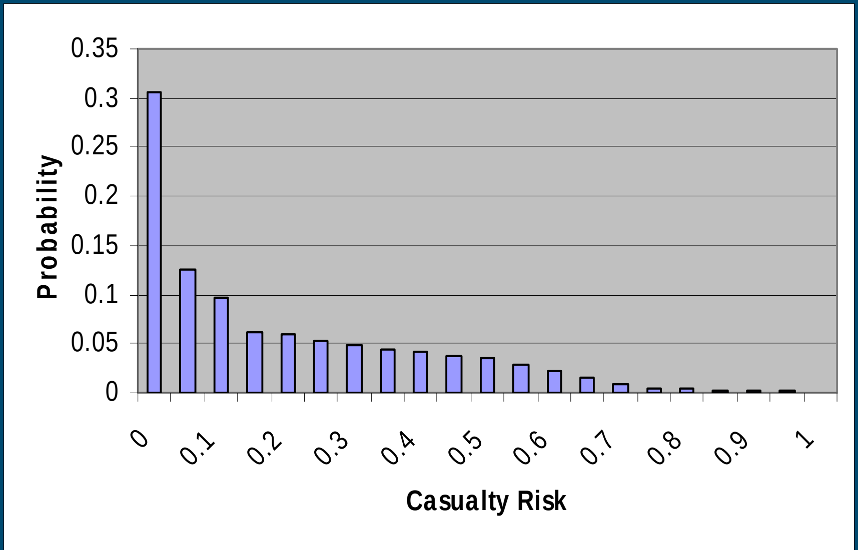
Reduce uncertainty, refine hazard

Uncertainty propagation

Course of Action	Without IPE	With IPE	Different Location
Casualty Risk	100%	0%	0%

- Dstl have developed an uncertainty propagation framework:
  - takes probabilistic output from SCIPUFF / UDM
  - propagates uncertainty in casualties due to
    - respirator
    - breathing rate
    - toxicology
    - medical counter measures

Uncertainty propagation



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    - respirator
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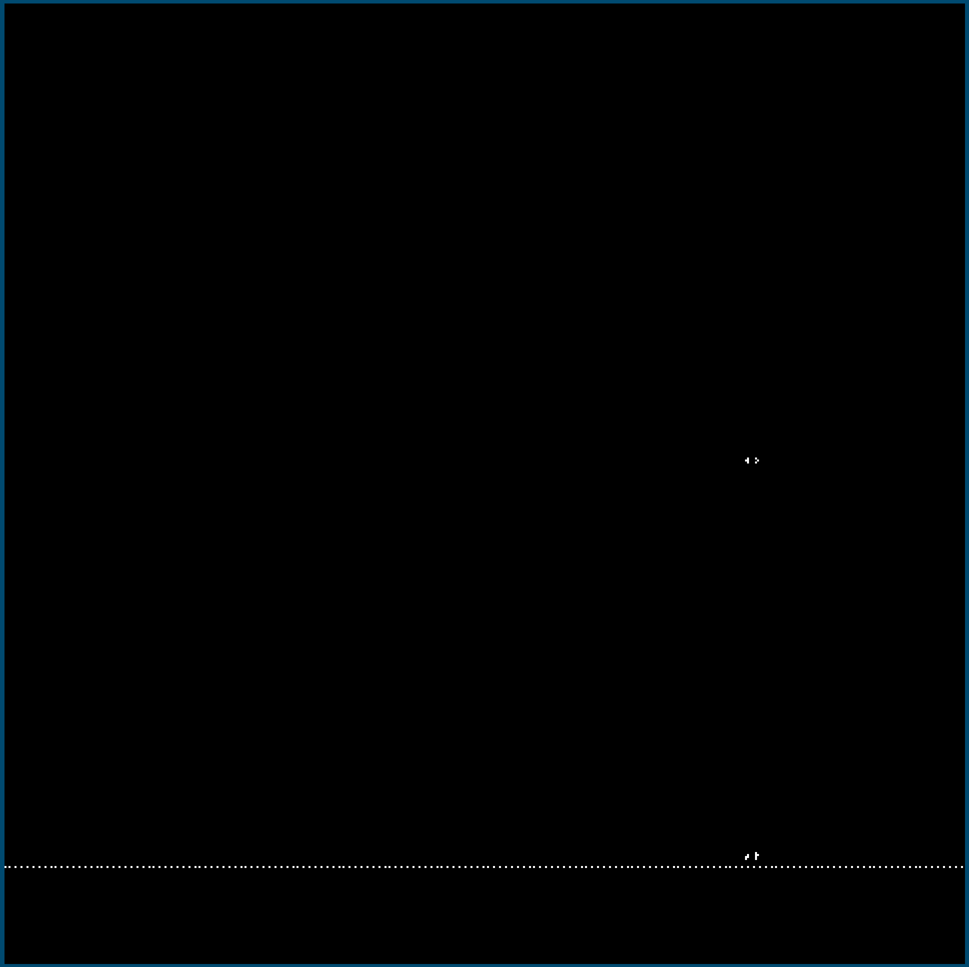
Course of Action	Without IPE	With IPE	Different Location
Casualty Risk	100%	0%	0%
Confidence Interval	90-100%	0-55%	0%

3c) Sensitivity study

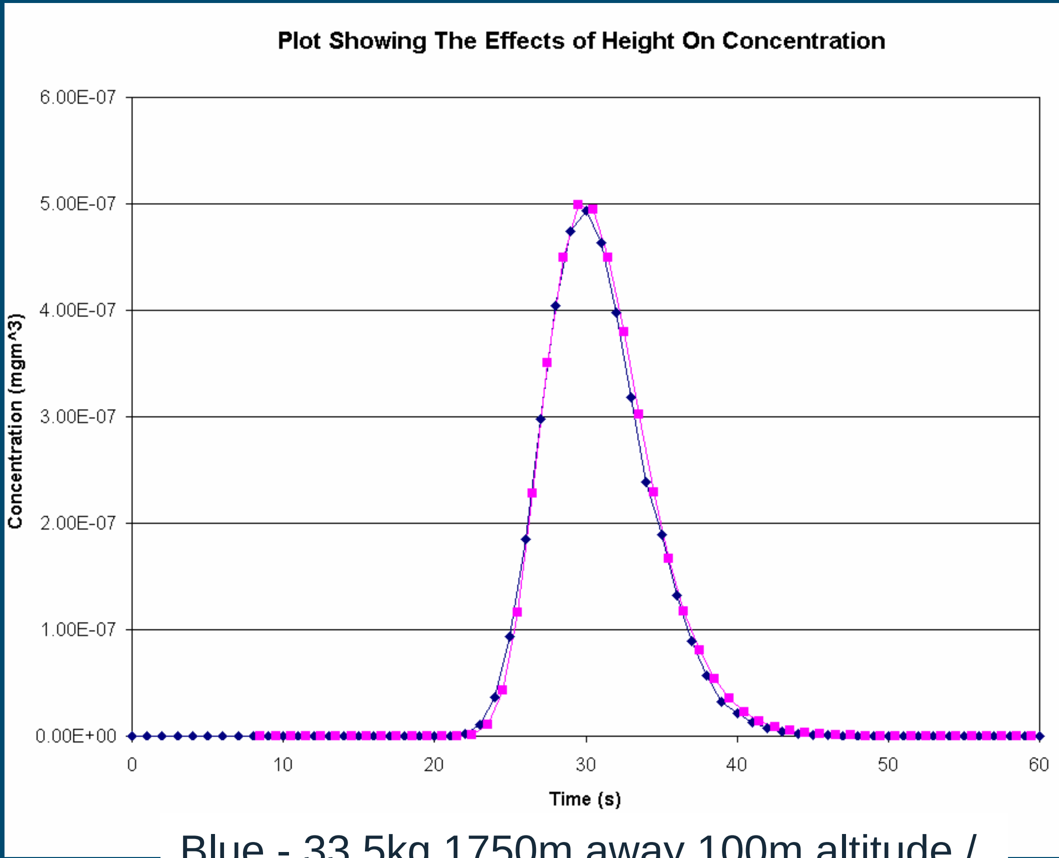
- Vary each input parameter in turn
  - source m,x,y,z,t
  - meteorology
  - turbulence
- Use synthetic environment to determine effect on output from range of possible sensors
  - CB sensors
  - meteorological sensors



3c) Sensitivity study

Identify inputs that have

- little effect on sensor output
  - neglect ⇒ simplify problem
- correlations with other inputs
  - retrieve dominant input
  - use knowledge of correlations to understand / estimate uncertainty in hazard prediction
- large effect on sensor output
  - apply short-listed techniques to retrieve these inputs

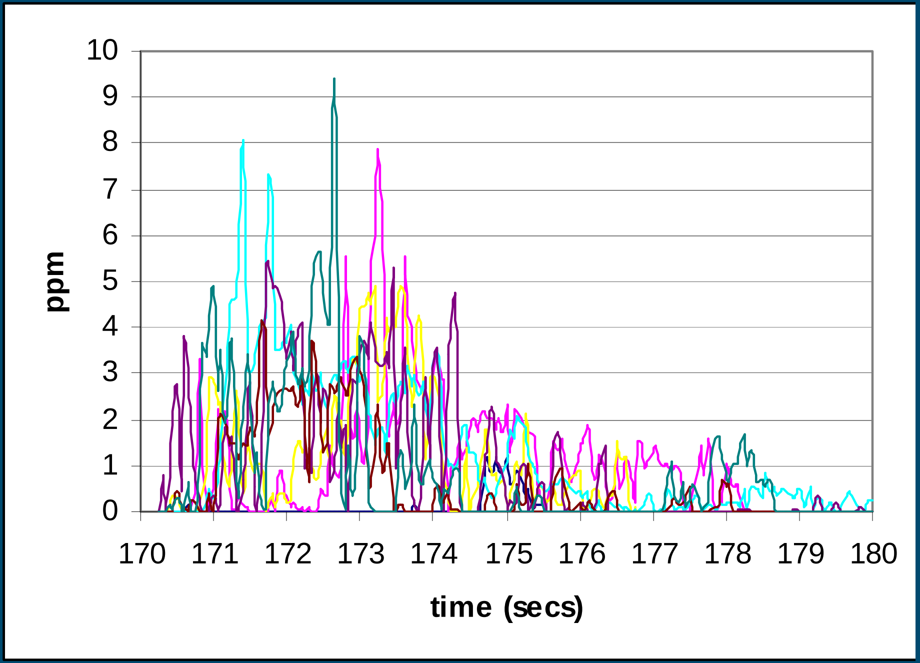


Blue - 33.5kg 1750m away 100m altitude /

Pink - 6 kg 1000m away 10m altitude

3d) Implementation in synthetic environment

- It is essential to test the short-listed techniques in a realistic synthetic environment
  – meteorological forecasts subject to significant error
    - 30° error common
  – experimental concentration profiles show strong effects of turbulence
  – no sensor is perfect



Measured effects of turbulence

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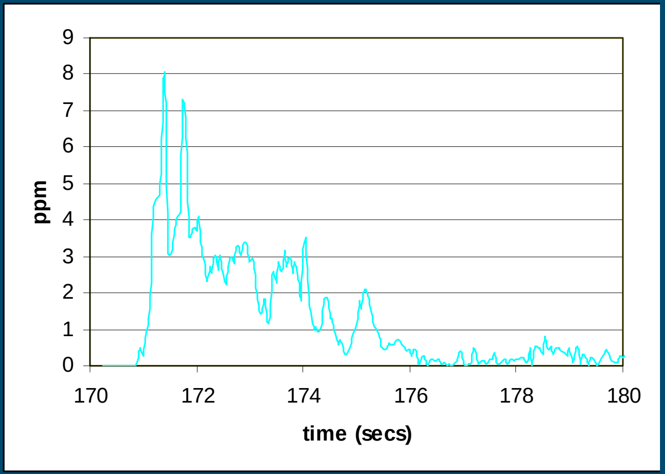
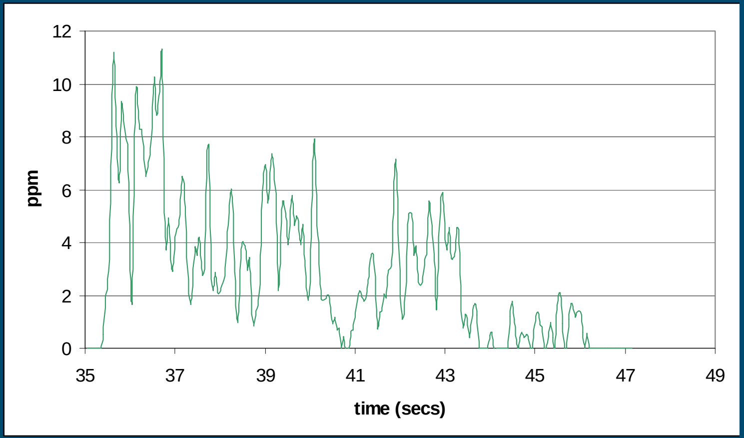


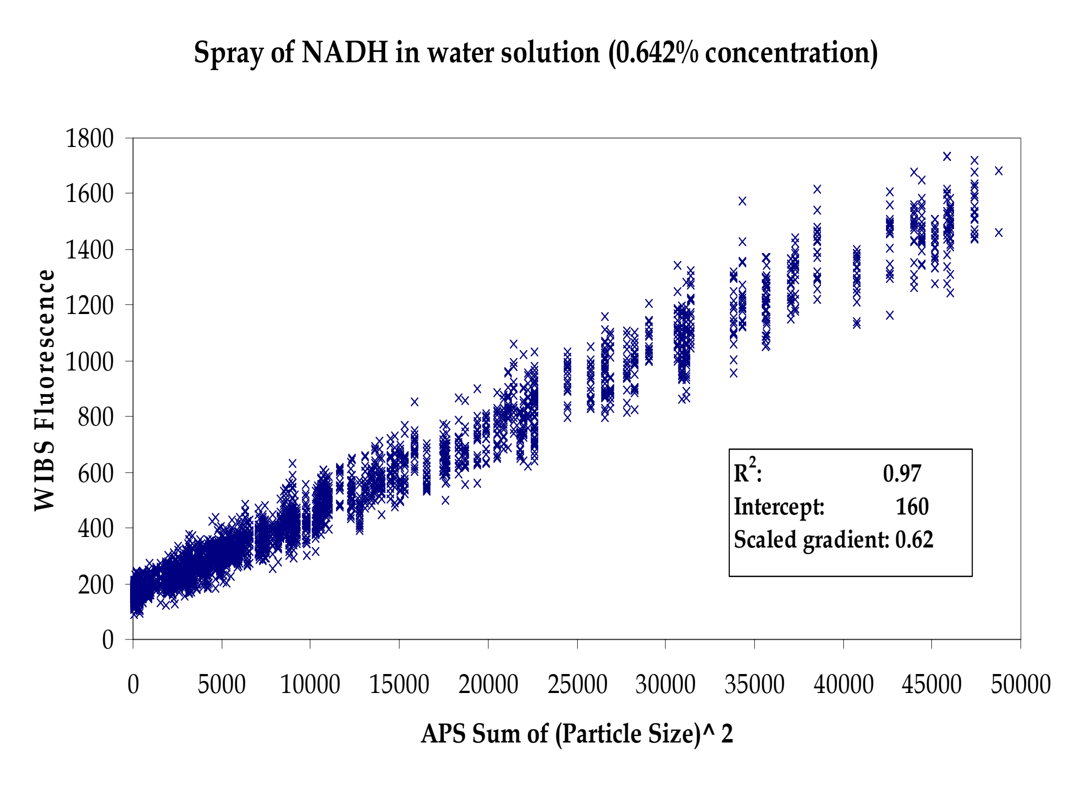
Data



Model

Synthetic environment

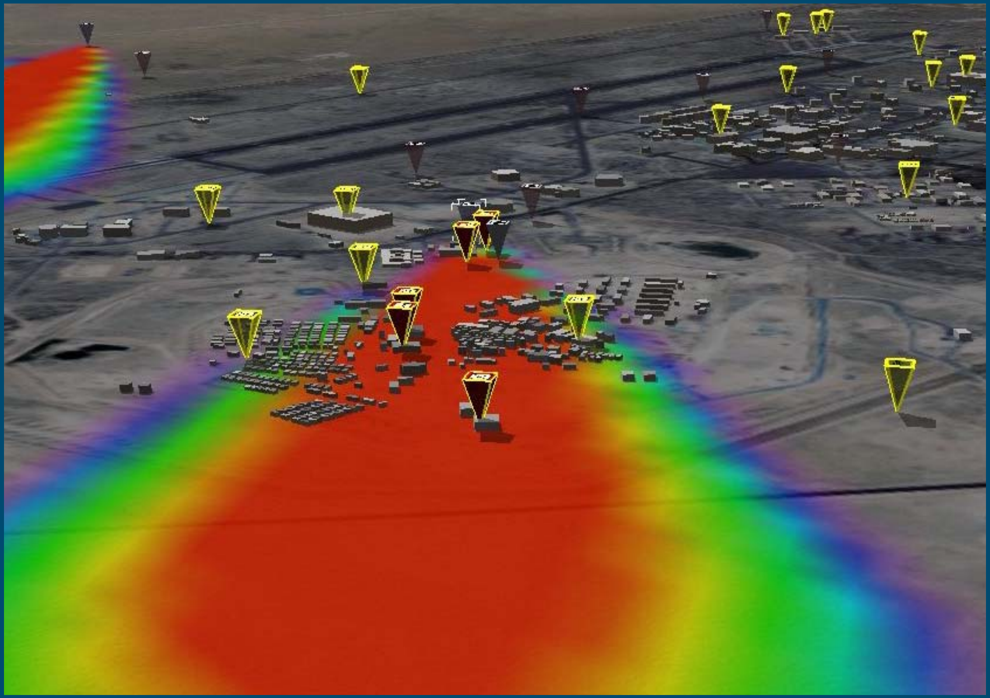
- Dstl's synthetic environment includes
  - model of meandering puffs
  - UDM
  - model of turbulence within puff
  - realistic sensor models
  - biological background model
  - Monte Carlo variation of model parameters



Analysis of data for biological sensor model

Future plans

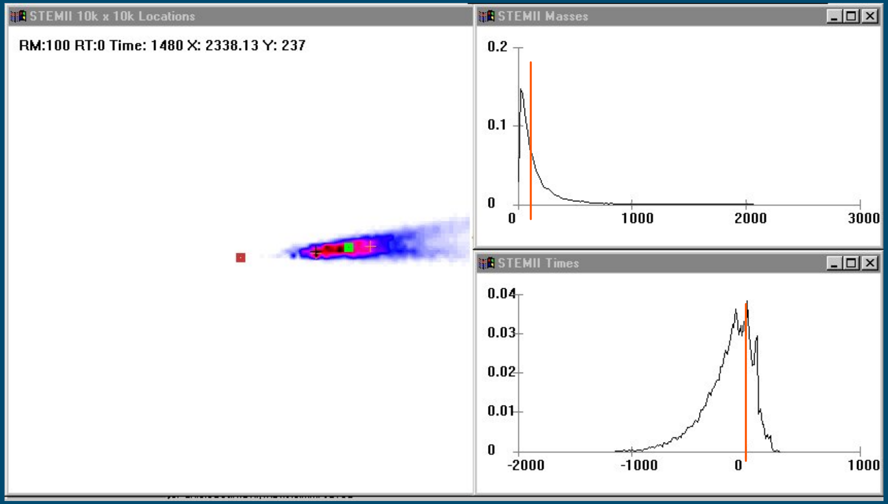
- Completion of sensitivity study
  - what information do we attempt to retrieve?
- Test short-listed techniques in synthetic environment for chemical, then biological releases
  - Biological data fusion complicated by fluctuating biological background
  - quantitative metrics (A_{FN}, A_{FP})



Biological sensor fusion

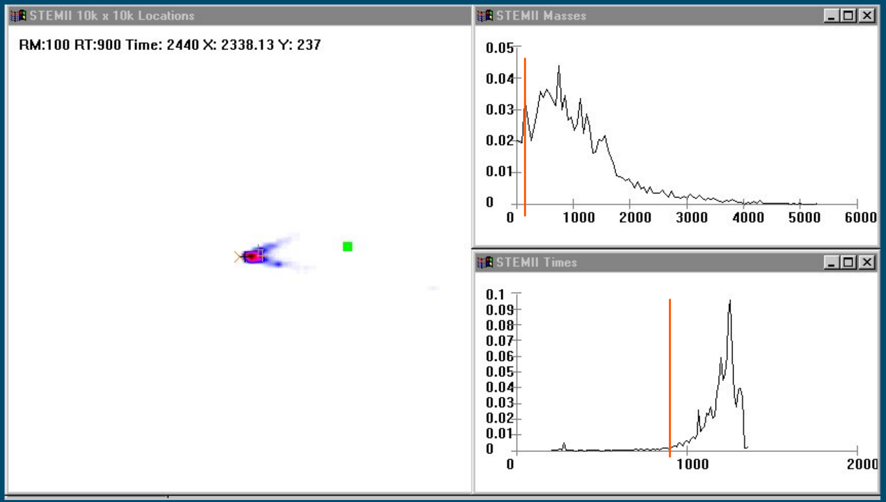
- Biological sensor model

Simple particle counter sensor



Low fidelity, analogue signal

Immuno-Assay detector



High fidelity, digital (2 state) signal

Try to explain better

sion: Information requirements differ depending on decision to be made