

A FAST RELIABLE ALGORITHM FOR POINT SOURCE LOCALIZATION: APPLICATION TO A NEW KITFOX DATA SET

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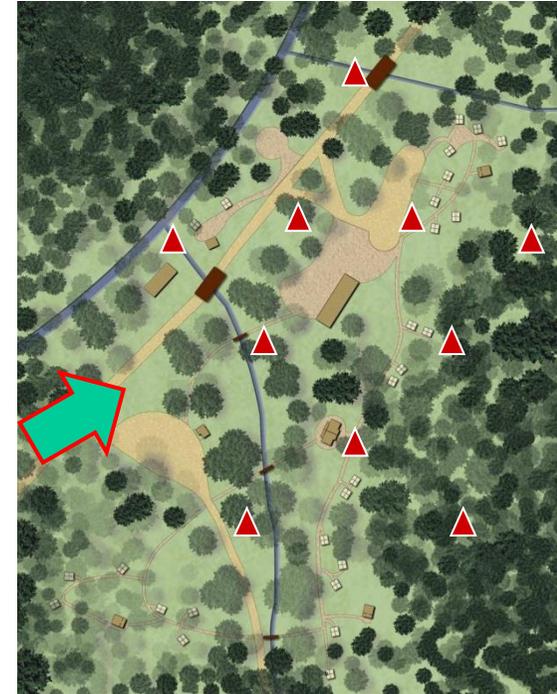
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□ Context

→ Accidental or intentional atmospheric contaminant release (local scale)

- Source estimation methods aim to estimate
 - source(s) location(s)
 - source type, strength, and number
 - release start time and duration
- Given :
 - site description (terrain, vegetation, building)
 - available meteorological information
 - m concentrations measured by a network

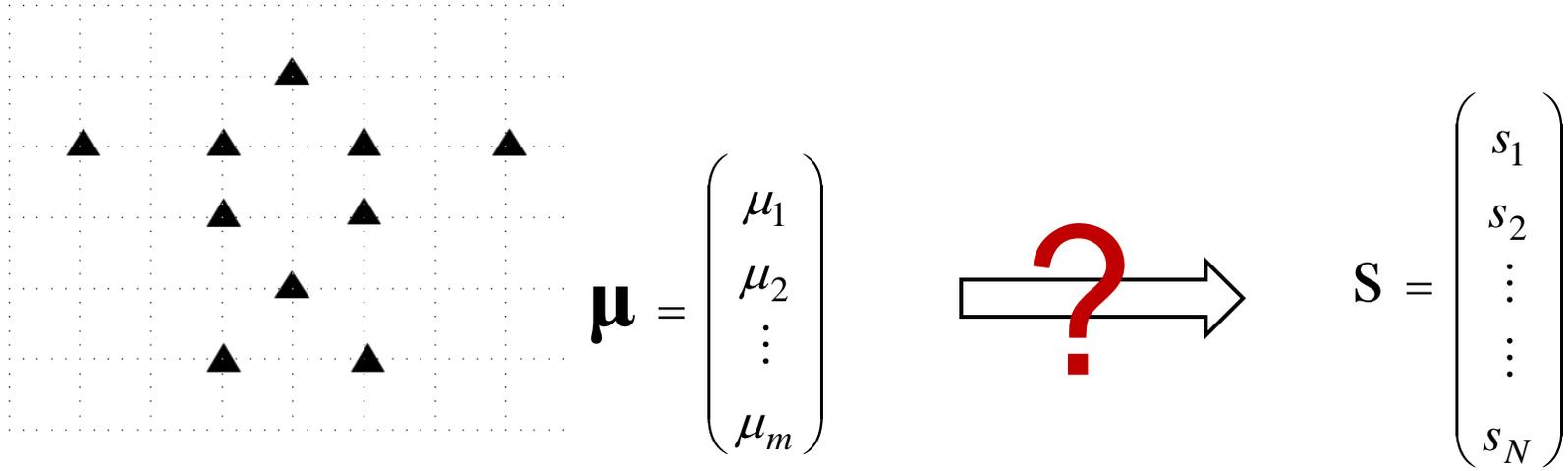


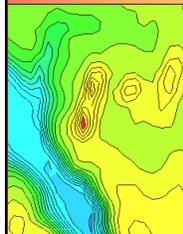
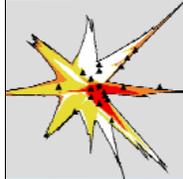
Several source estimation algorithms are currently being developed

□ The discrete inverse problem

- Source described, on a grid of N points, by a source vector \mathbf{s}
- It generates a field of concentrations only known through m observations $\mu_i = C(\mathbf{x}_i)$ at locations \mathbf{x}_i ($i=1 \dots m$)

The problem consists in determining the N unknown components of the source vector from the m measurements





□ The renormalization technique

→ Deterministic technique:

- use of a minimum of a priori information
- use of adjoint transport equations (receptors oriented modeling technique)
- computation of a renormalizing function

→ It returns a source estimate which is **linear** with respect to the observations

- Issartel et al. (2005, 2007): utility of the renormalization to minimize inversion artifacts
- Sharan et al. (2009): reconstruction of a single ground-level point source
- Singh et al. (2013): identification of multiple-point sources releasing similar tracer
- Turbelin et al. (2014): generalization for discrete inverse problems

For a matter of simplicity, this presentation only deals with continuous releases, for time varying releases see Issartel et al. (2007)

□ The linear model

- The concentrations measured at the captors locations are linear functions of the sources, the multiplicative factor being the retroplumes matrix **A**
 - **components obtained by solving adjoint equations**

$$A = \begin{pmatrix} a_1^1 & \dots & a_1^N \\ \vdots & \ddots & \vdots \\ a_m^1 & \dots & a_m^N \end{pmatrix}$$

Retroplumes matrix ($m \times N$)

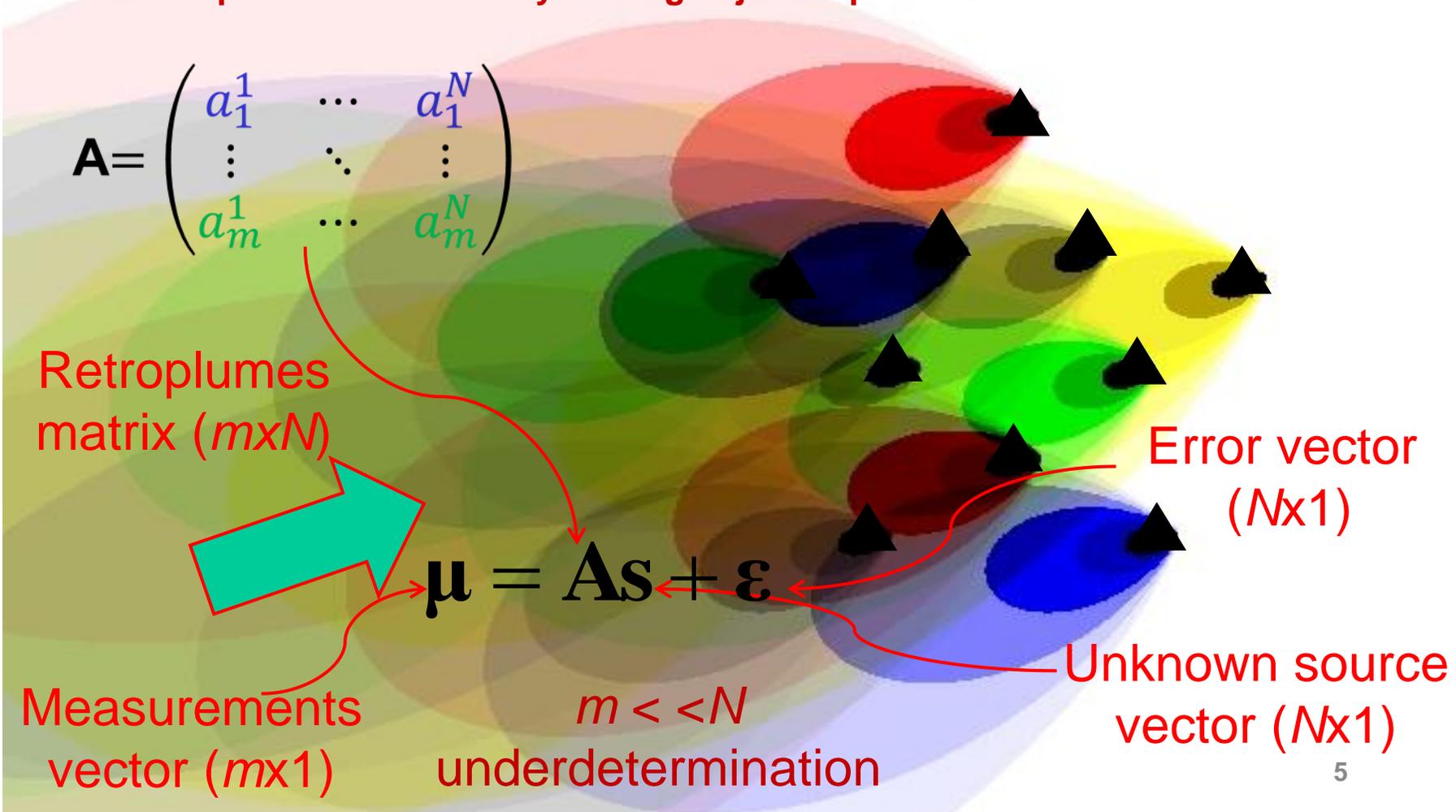
Measurements vector ($m \times 1$)

$$\mu = As + \epsilon$$

$m \ll N$
underdetermination

Error vector ($N \times 1$)

Unknown source vector ($N \times 1$)



□ A minimum weighted norm solution

→ Any solution to the problem can be written as $\hat{\mathbf{s}} = \mathbf{G}\boldsymbol{\mu}$
 – \mathbf{G} ($N \times m$): some generalized inverse of \mathbf{A}

→ Discrete renormalized solution given by

$$\mathbf{s}_{//\mathbf{W}} = \mathbf{A}_{\mathbf{W}}^T \mathbf{H}_{\mathbf{W}}^{-1} \boldsymbol{\mu} = \mathbf{W}^{-1} \mathbf{A}^T (\mathbf{A} \mathbf{W}^{-1} \mathbf{A}^T)^{-1} \boldsymbol{\mu}$$

– unique minimum **W-weighted norm solution** of the problem, i.e.

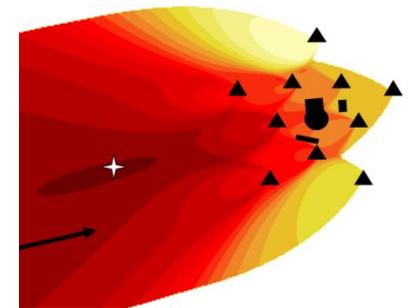
$$\mathbf{s}_{//\mathbf{W}} \text{ minimizes } \|\mathbf{s}\|_{\mathbf{W}} = \sqrt{\mathbf{s}^T \mathbf{W} \mathbf{s}}$$

→ Optimal diagonal weight matrix \mathbf{W} ($N \times N$), in case of a **single point source**

– the **maximum value** of the estimate corresponds to the location of the source

– the release intensity of the source is given by

$$\text{Intensity} = \frac{s_{//\mathbf{W}}(\mathbf{x}_0)}{w(\mathbf{x}_0)}$$



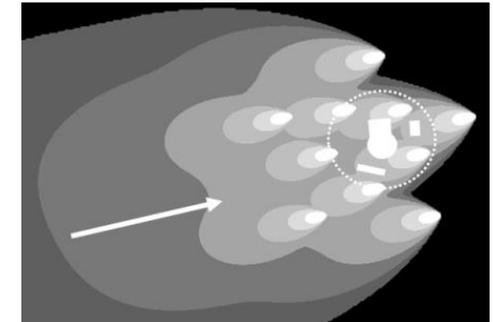
□ The renormalization condition

- Optimal reconstruction of position and intensity of all single sources, when (**renormalization condition**)

$$\text{diag}(\mathbf{A}_w^T \mathbf{H}_w^{-1} \mathbf{A}_w) \equiv 1 \quad \text{with } w_{jj} > 0 \quad \text{and} \quad \sum_{j=1}^N w_{jj} = m$$

- The components of the optimal weight function are the discrete values of the **visibility function**

- characterizes the regions well or poorly monitored by the network
 - focus at the detectors locations
 - decreases with increasing downwind distance



It has been interpreted as the prior distribution of the emissions apparent to the monitoring system

□ Computation of the solution

→ The inverse operator is the **W-weighted generalized inverse** of **A**

$$\mathbf{S}_{//\mathbf{W}} = \mathbf{W}^{-1} \mathbf{A}^T (\mathbf{A} \mathbf{W}^{-1} \mathbf{A}^T)^{-1} \boldsymbol{\mu} = \mathbf{A}_{\mathbf{W}}^+ \boldsymbol{\mu}$$

- computed by “classical” matrix operations
- or by making use of the pseudo inverse concept

$$\mathbf{A}_{\mathbf{W}}^+ = \mathbf{W}^{-1/2} (\mathbf{A} \mathbf{W}^{-1/2})^+$$

- “(.)⁺”: **Moore–Penrose inverse** of a matrix

→ Several efficient algorithms to obtain a pseudo-inverse

- the most reliable one is based on the **Singular Value Decomposition** method

But the optimal matrix **W has first to be computed**

□ Computation of the optimal weights

- “The components of \mathbf{W} are the diagonal elements of the resolution matrix \mathbf{R} when the diagonal elements of the symmetric matrix \mathbf{R}_w are equal to one”

$$\mathbf{R} = \mathbf{A}_w^T \mathbf{H}_w^{-1} \mathbf{A} \qquad \mathbf{R}_w = \mathbf{A}_w^T \mathbf{H}_w^{-1} \mathbf{A}_w$$

$$w_{jj} = R_{jj} = w_{jj}^{-1} \mathbf{a}_j^T \mathbf{H}_w^{-1} \mathbf{a}_j \quad \text{when} \quad R_{wjj} = w_{jj}^{-2} \mathbf{a}_j^T \mathbf{H}_w^{-1} \mathbf{a}_j = 1$$

- This algorithm converges uniformly to the optimal weights matrix \mathbf{W}

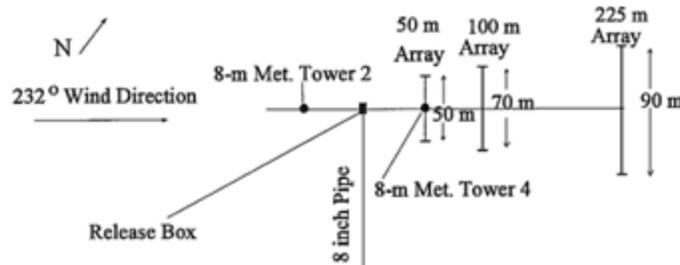
Algorithm 1. Computing the optimal weighted matrix \mathbf{W}

Require: Let $\mathbf{A} \in \mathbb{R}^{N \times m}$.

- 1: $N = \text{columns}[\mathbf{A}]$
- 2: $m = \text{rows}[\mathbf{A}]$
- 3: $\mathbf{W} = m/N * \mathbf{I}_N$ (initialization of \mathbf{W})
- 4: while $d_{\min} \leq 0.99$ (definition of the convergence criteria)
- 5: $\mathbf{H}^{-1} = (\mathbf{A}\mathbf{W}^{-1}\mathbf{A}^T)^{-1}$ (computation and inversion of the weighted Gram matrix)
- 6: For $j=1$ to N
- 7: $\mathbf{a}_j = \mathbf{A}(j)$ (writing the j columns of the matrices \mathbf{A} as vectors)
- 8: $\mathbf{d}_j = \mathbf{a}_j^T \mathbf{H}^{-1} \mathbf{a}_j * w_{jj}^{-2}$ (computation of the diagonal elements of \mathbf{R}_w , stored in a vector \mathbf{d})
- 9: End for
- 10: $d_{\min} = \min(\mathbf{d})$ (convergence verification)
- 11: $\mathbf{W} = \mathbf{W} * (\text{diag}[\mathbf{d}])^{1/2}$ (definition of a new weight matrix)
- 12: end while
- 13: return \mathbf{W}

□ The smooth desert kitfox experiments

➔ Sensors on 3 arrays oriented perpendicular to the centreline of the predicted transport course of the cloud



➔ 30 releases under neutral to extremely stable conditions

- 22 short duration releases (1.5 kg/s over 20s)
- 8 continuous releases (1-1.5 kg/s over 150-360s)

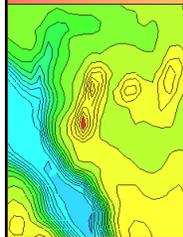
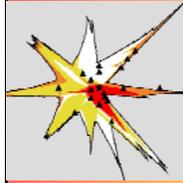
Table 1: Characteristics of the continuous release experiments

Test No.	Average wind speed 2m a.g.l. (ms ⁻¹)	Average wind direction 2m a.g.l. (degree)	Release rate (kgs ⁻¹)	Release duration mm:ss	Stability Class
9-4	3.5	234	1.527	2:31	D-E
9-7	2.5	229	1.497	3:31	F
9-9	1.9	235	1.438	5:31	F-G
10-5	2.0	232	1.037	5:58	G+
10-6	1.9	198	0.995	5:00	F-G
12-7	1.6	211	1.019	4:59	F-G
13-6	3.0	227	1.114	3:32	E
13-7	2.3	213	1.028	3:00	F

□ Inputs for the renormalization method

- Components of **A** computed from an **analytical Gaussian dispersion model** (Sharan et al., 1996) used in a **backward mode**
 - use of Briggs' model for dispersion parameters
- Concentrations from 24 captors of the 50m and 100m arrays **averaged** to obtain the measured concentrations vector μ (i.e. $m=24$)
- Technique implemented on a discretized domain of 300×300 points (i.e. $N=90000$) with $\Delta x = \Delta y = 1\text{m}$

On a machine Intel® Core™ i5-3427U CPU 1.80GHz, 8Go RAM, the CPU time involved in estimating the components of **A**, **W** and $\mathbf{s}_{//w}$ was approximately <30 seconds



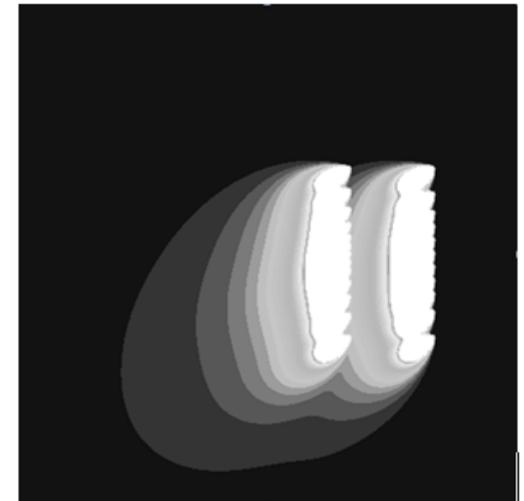
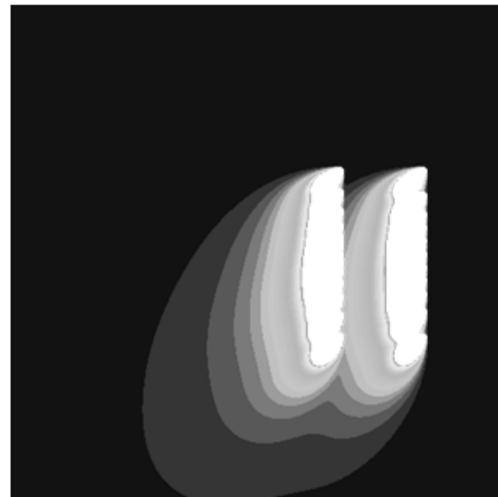
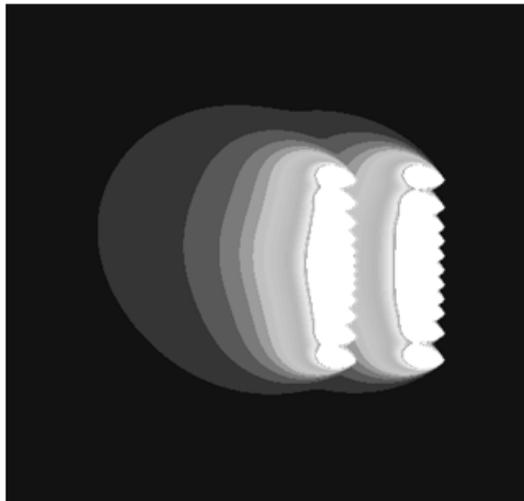
□ Results and discussion

→ Regions

- well monitored by the network: white
- poorly monitored by the network: black

The source location (middle of the domain) lies in a well monitored region of the network

Visibility of the monitoring network for cases 9-9, 12-7 and 13-7

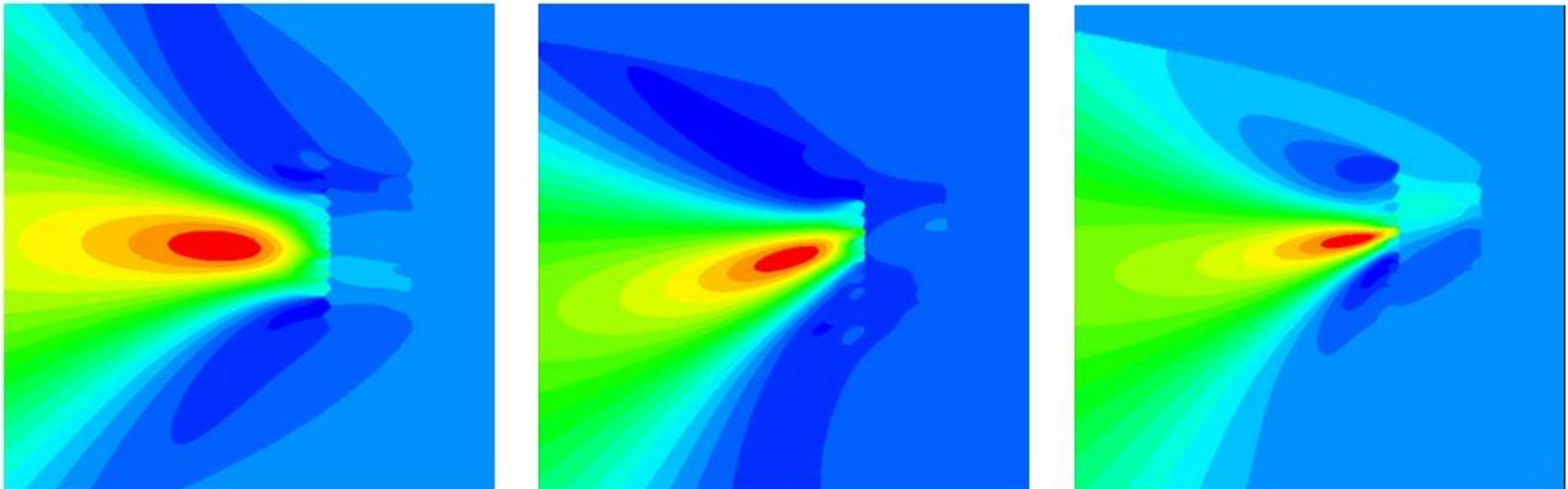


□ Results and discussion

→ The maxima of $s_{//w}$ is unique and sharp at position (x_s, y_s)

- lateral direction: $0 \leq \Delta y_s / x_m \leq 0.08$
- longitudinal direction: $0 \leq \Delta x_s / x_m \leq 0.2$
 - x_s is placed upstream of the true position, basically because \mathbf{A} has been derived from a Gaussian model with constant mean wind speed, direction and empirical dispersion parameters

$s_{//w}$ for cases 9-9, 12-7 and 13-7



□ Conclusions

→ The discrete source estimate given by the renormalization technique is

$$\mathbf{s}_{//\mathbf{w}} = \mathbf{W}^{-1} \mathbf{A}^T (\mathbf{A} \mathbf{W}^{-1} \mathbf{A}^T)^{-1} \boldsymbol{\mu} \quad \text{with } \mathbf{W} = \text{diag}(w_1, w_2, \dots, w_N)$$

- corresponds with the minimum \mathbf{W} -norm solution of the underdetermined linear inverse problem

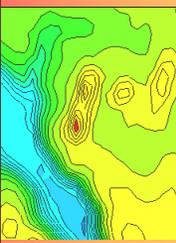
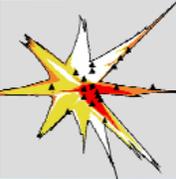
→ It can be expressed by making use of the concept of generalized inverse

$$\mathbf{s}_{//\mathbf{w}} = \mathbf{A}_{\mathbf{w}}^+ \boldsymbol{\mu}$$

- a computationally reliable way to compute the pseudo inverse is by using the Singular Value Decomposition (SVD)
- **but a specific algorithm must be used to compute the optimal weight matrix**

→ Applied to a new KITFOX data set, the source is observed to be distinctly located and converges onto reasonable estimates

- new results needed with a more appropriate dispersion model



Thank you for your attention

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