

Estimating 4D differences in time-lapse using randomized sampling techniques

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Current challenges in 4D

- ▶ *Repeatability* of 4D seismic experiments
 - effort spent to repeat baseline and monitor surveys
 - processing decisions - should we apply similar or different processing to both data?
 - how do processing decisions depend on the data and the 4D signal?

- ▶ *Detectability* of 4D signal
 - very weak signals pose a challenge - hard to detect
 - 4D noise level impact on the signal quality

Motivation

- ▶ Need for repeatability ?
 - effort spent to repeat baseline and monitor surveys
 - processing decisions - should we apply similar or different processing to both data?
 - how do processing decisions depend on the data and the 4D signal?

- ▶ Resolution of 4D signals
 - how can we better *detect* and *improve* the signal-to-noise ratios of 4D signals ?

- ▶ Would like to *reduce* the acquisition *cost* of a 4D project

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- ▶ would like to reduce the acquisition cost of a 4D project

Big Question ???

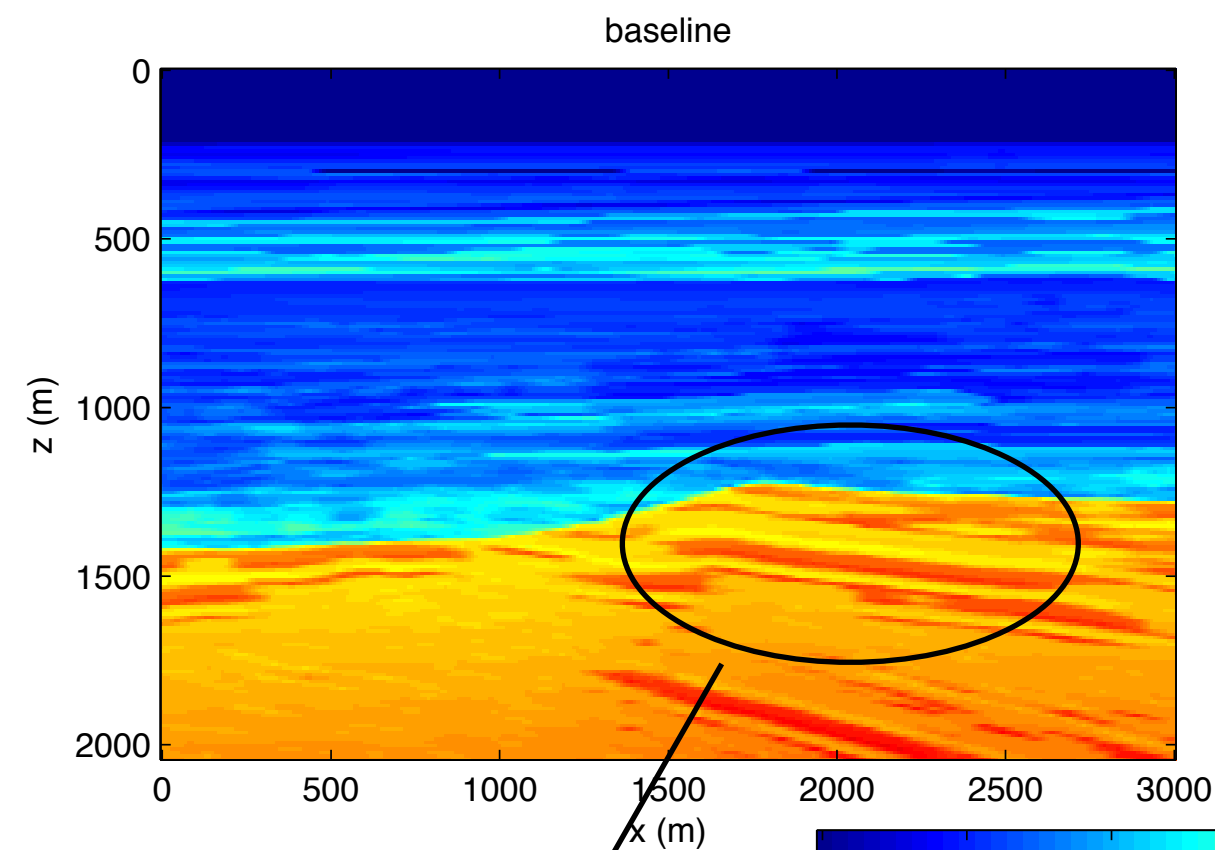
Motivation

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 - effort spent to repeat baseline and monitor surveys
 - processing decisions - should we apply similar or different processing to both data?
 - how do processing decisions depend on the data and the 4D signal?
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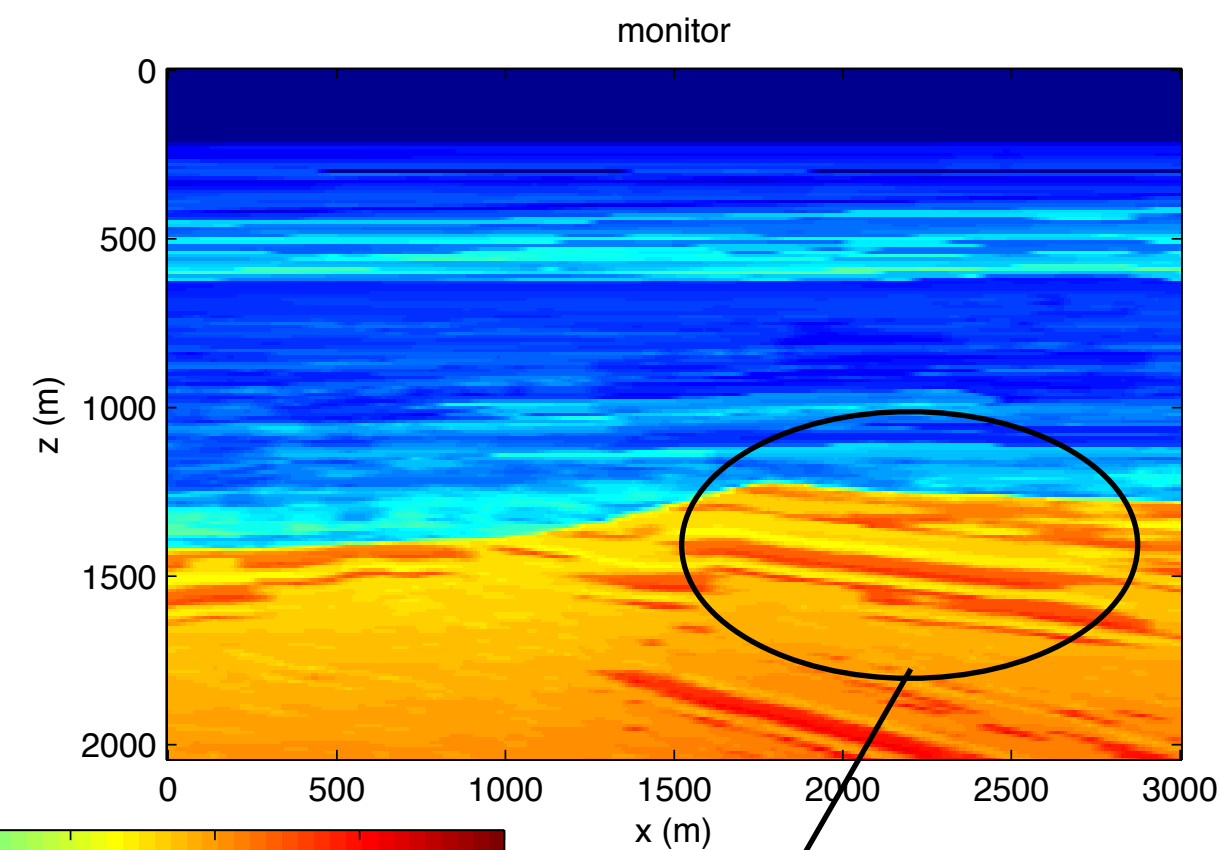
Big Question ???

- ▶ Should we perform **randomized** acquisition for a 4D project ?
- ▶ Should we **repeat** the acquisition or not ?
- ▶ What is the net effect on the 4D signal?

Baseline Model



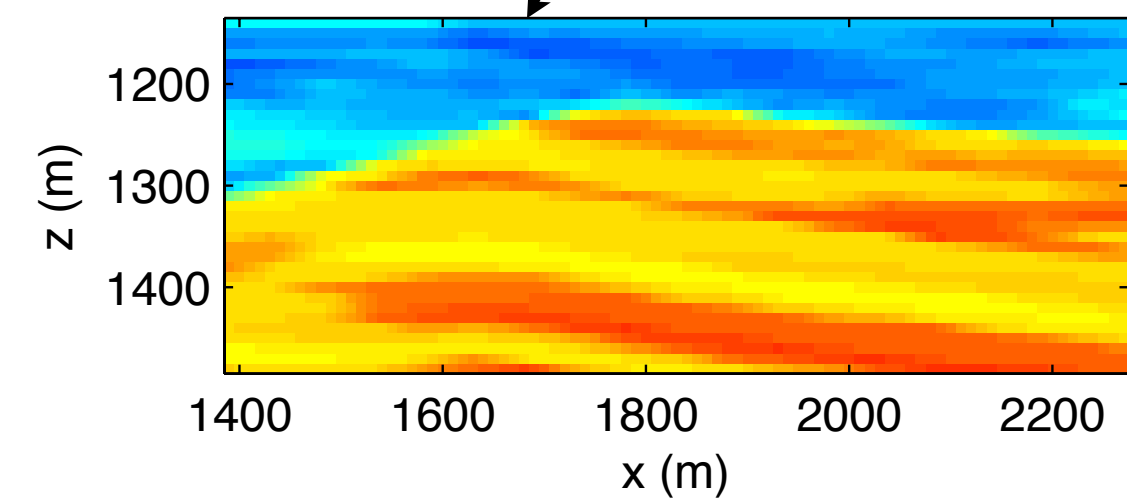
Monitor Model



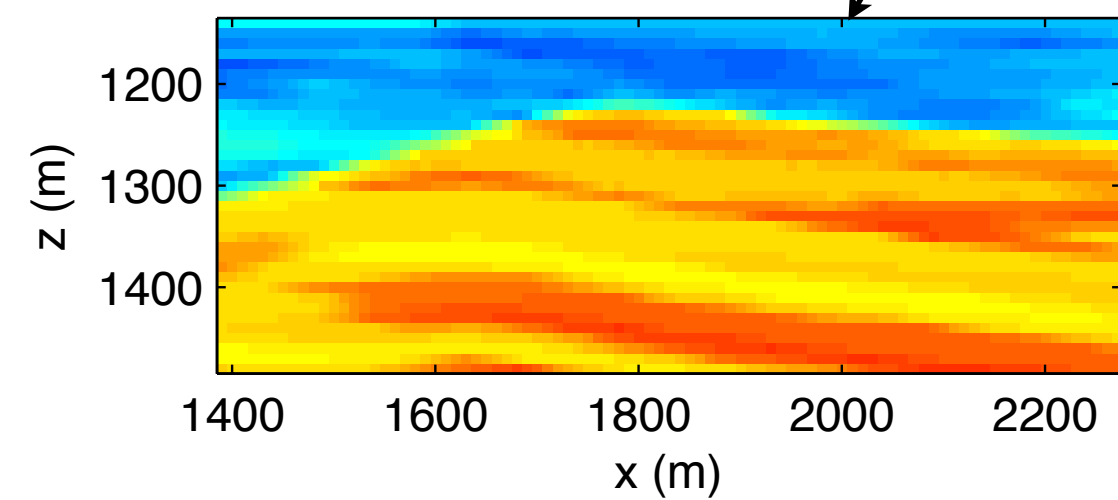
Current Practice

- Acquire data for ***baseline***
- Try to **repeat** acquisition geometry for ***monitor***
- Process baseline and monitor data
- Subtract to observe 4D signal

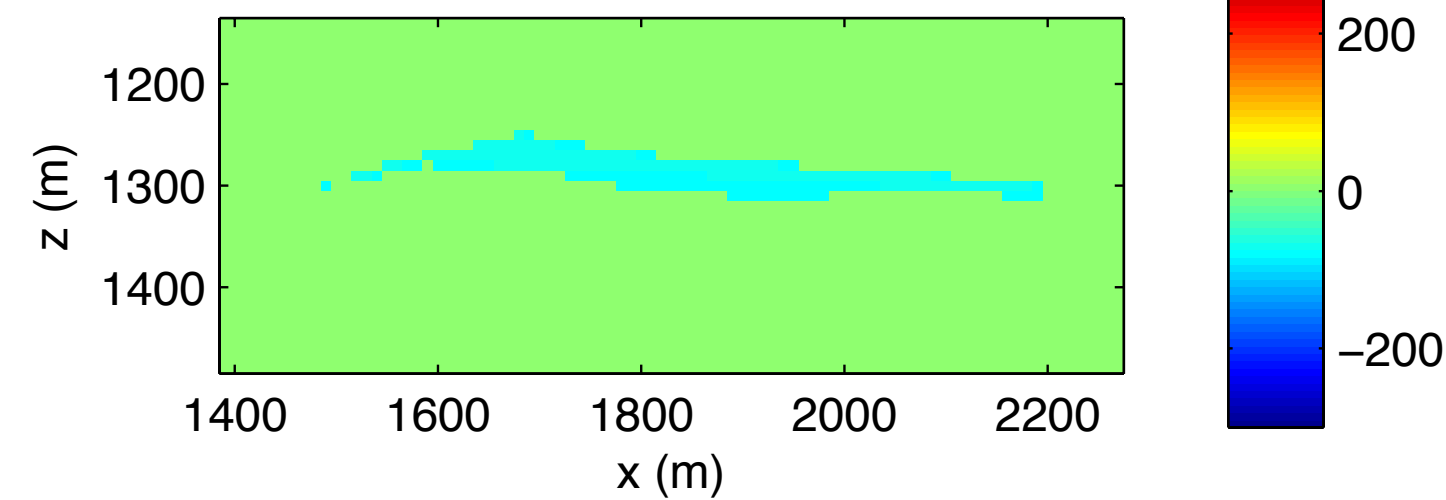
baseline



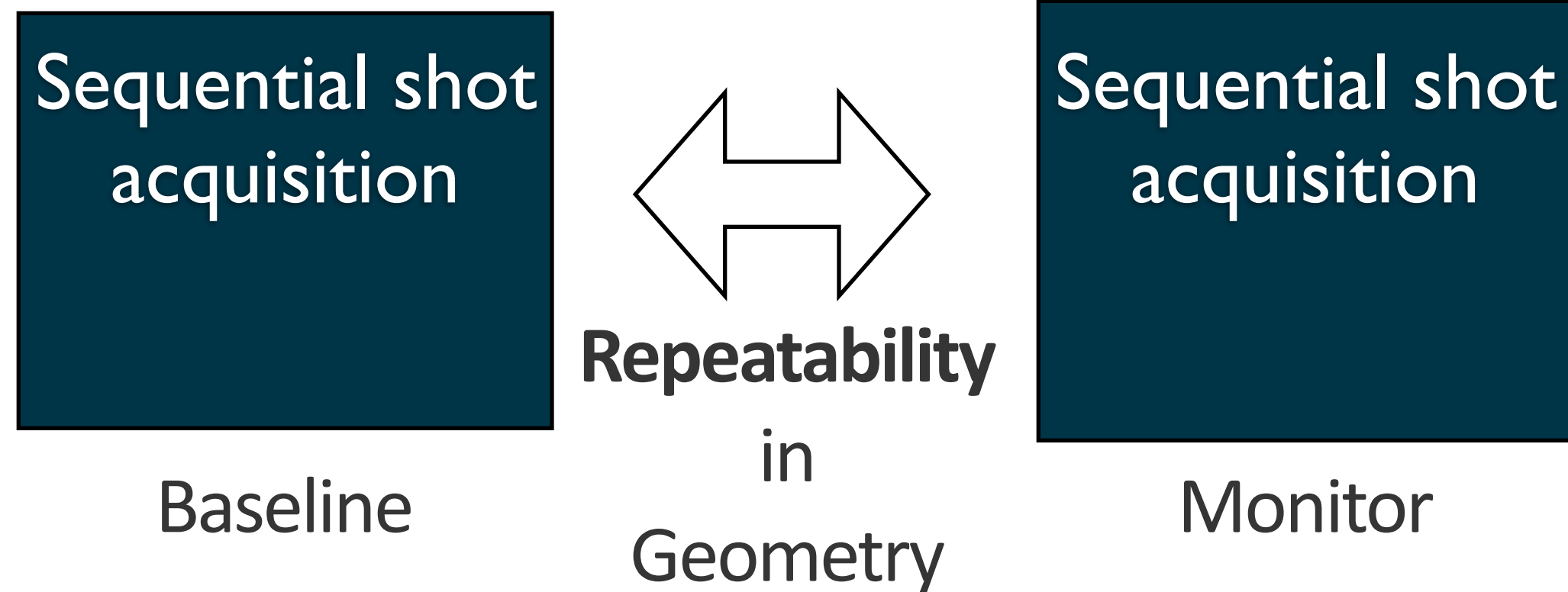
monitor



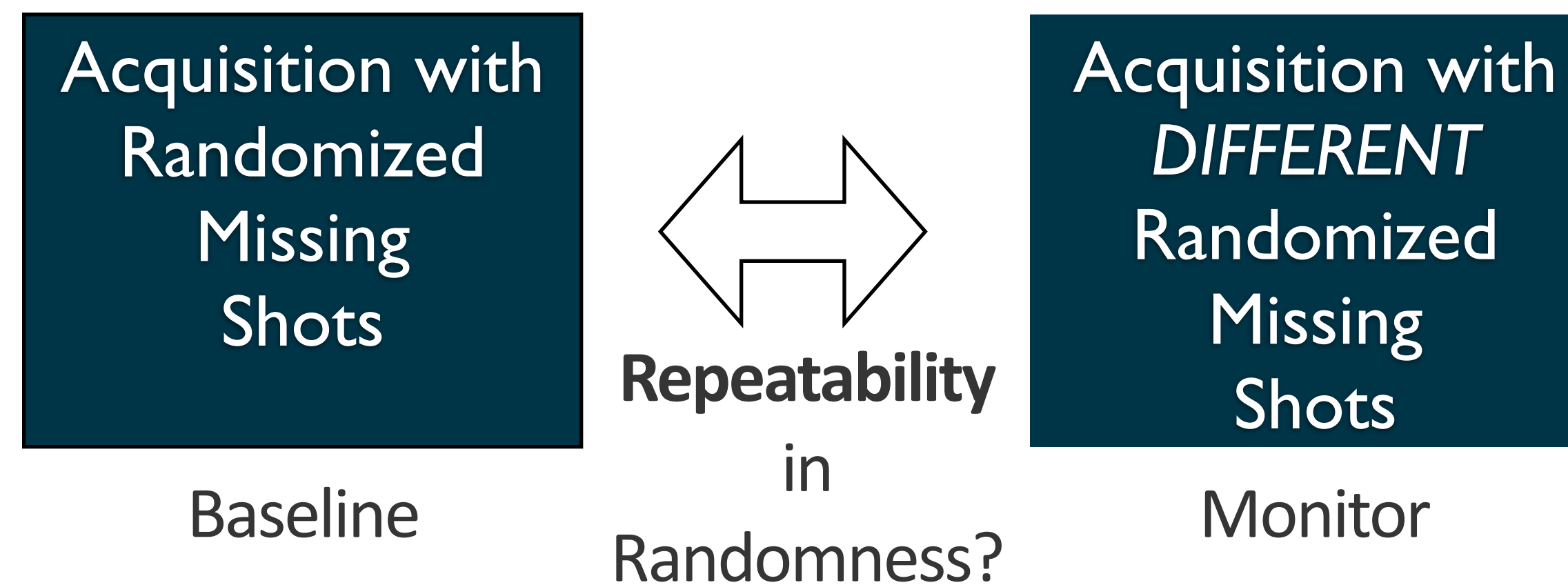
4D (difference)



Conventional acquisition



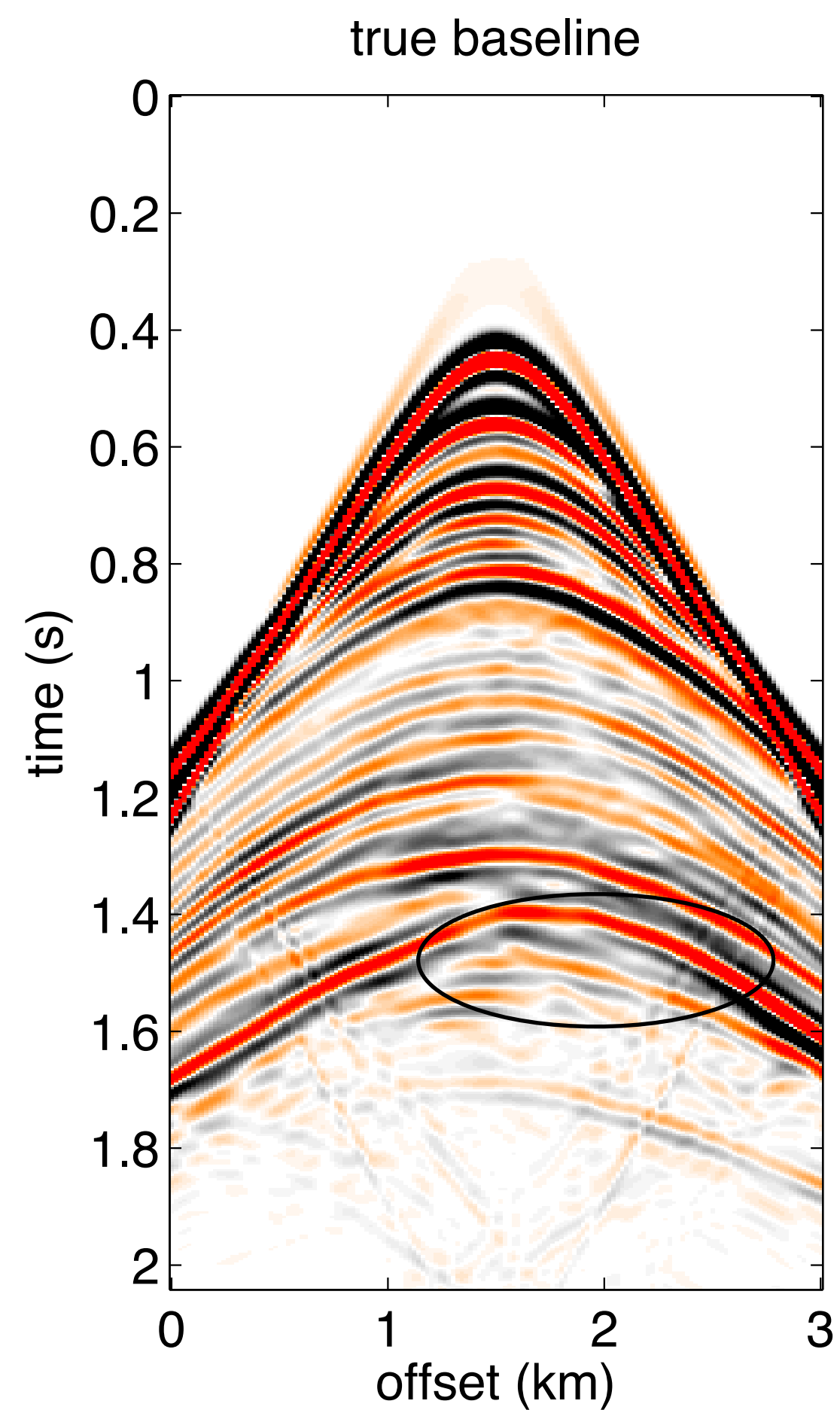
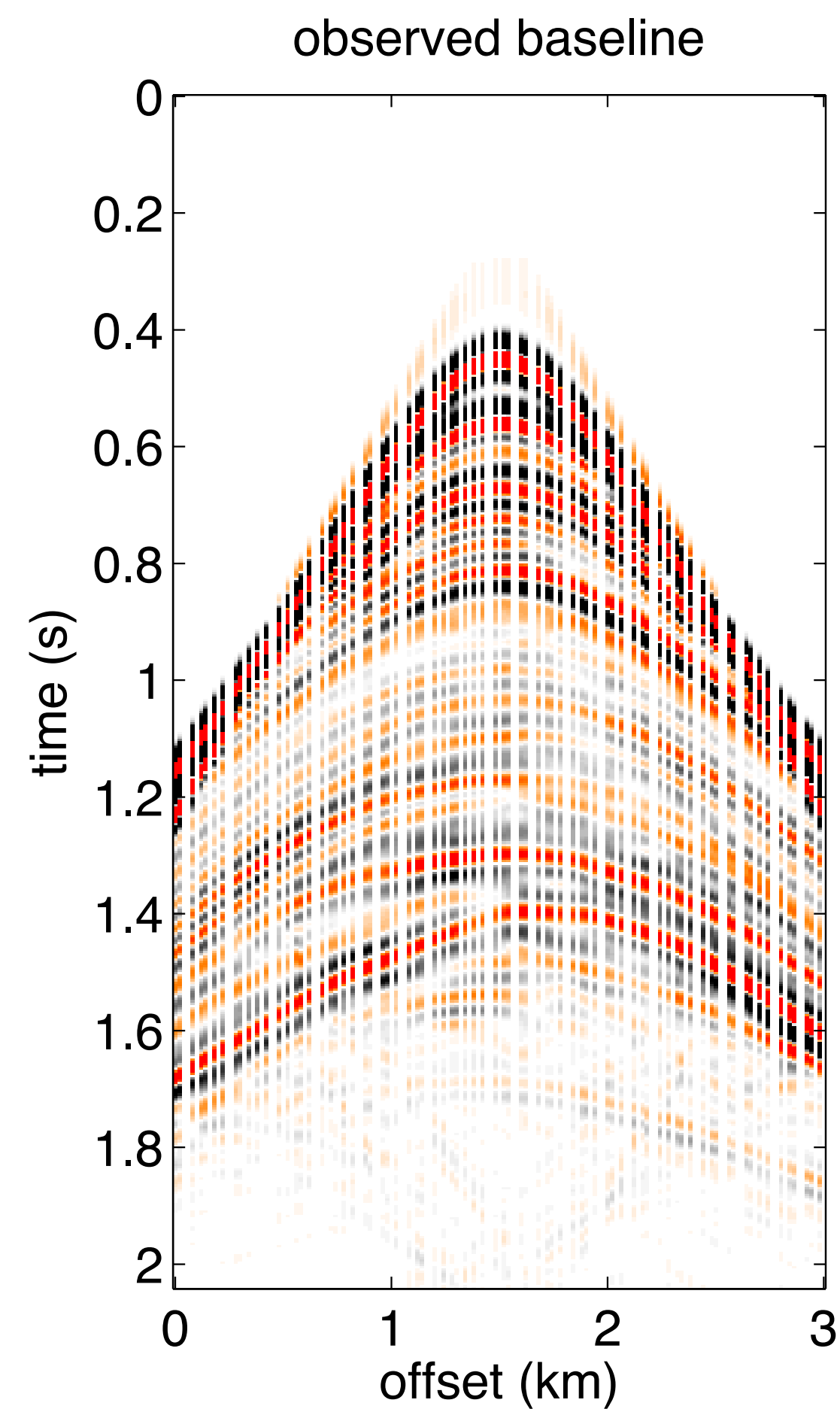
Proposed acquisition



Numerical Experiment

For Baseline model

- **(Proposed Setup)** randomized acquisition with missing shots
 - we require the fully and coarsely sampled data on a regular grid
 - apply Compressed Sensing (CS)



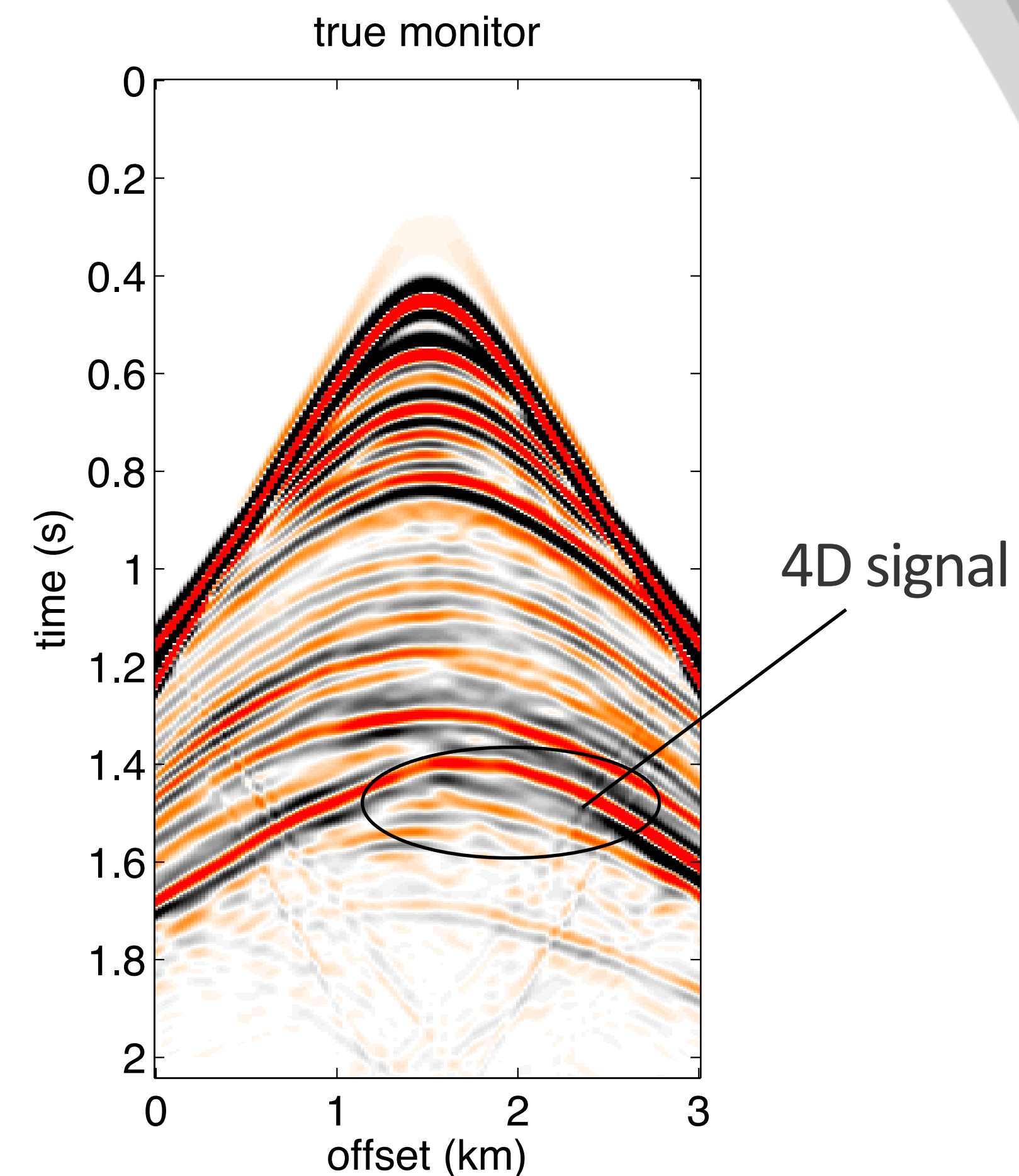
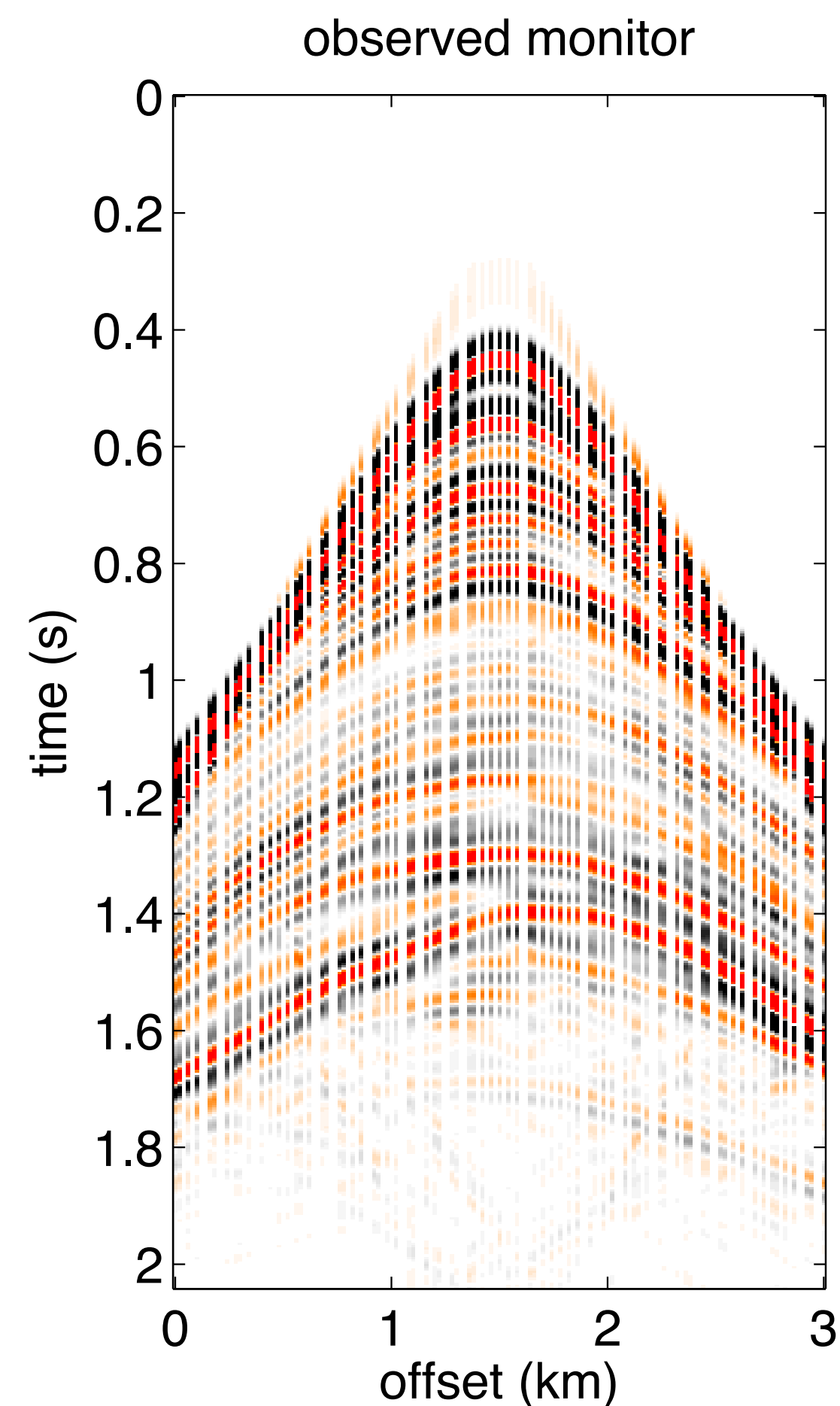
Numerical Experiment

For Baseline model

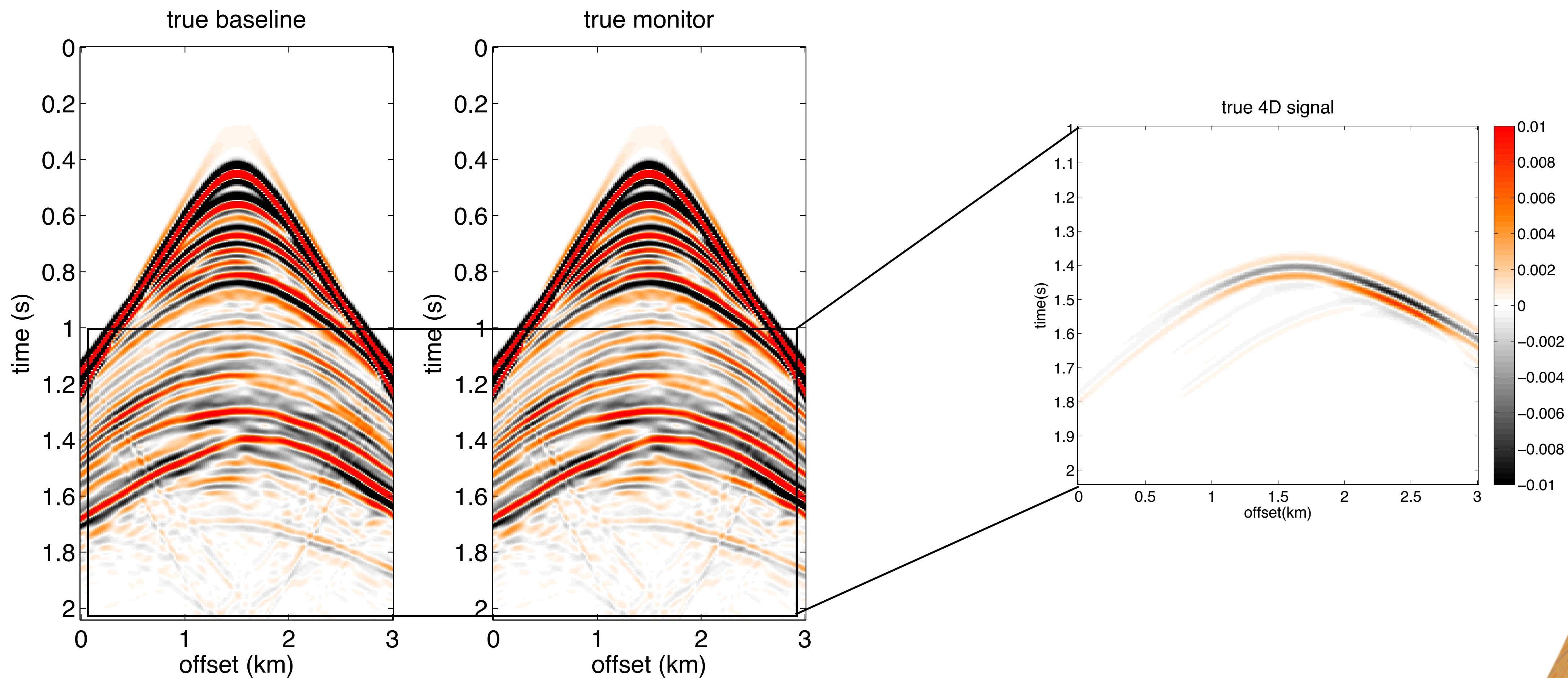
- **(Proposed Setup)** randomized acquisition with missing shots
 - we require the fully and coarsely sampled data on a regular grid
 - apply Compressed Sensing (CS)

For Monitor

- use a *different* randomized acquisition geometry?
 - we require the fully and coarsely sampled data on a regular grid
 - apply CS

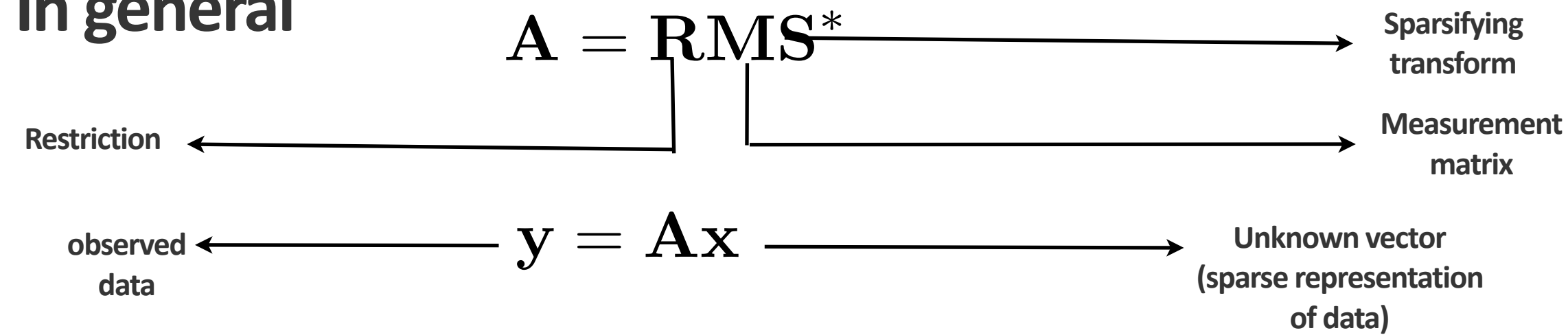


100% Repeated Seismic = Same Acquisition Geometry Regularly and Densely Sampled



CS in 4D – first approach

In general



Solve $\tilde{\mathbf{x}} = \arg \min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{s.t.} \quad \mathbf{y} = \mathbf{Ax}$

In 4D

let \mathbf{M} be the identity basis

$$\mathbf{A}_1 = \mathbf{R}_1 \mathbf{MS}^* \quad \text{and} \quad \mathbf{A}_2 = \mathbf{R}_2 \mathbf{MS}^*$$

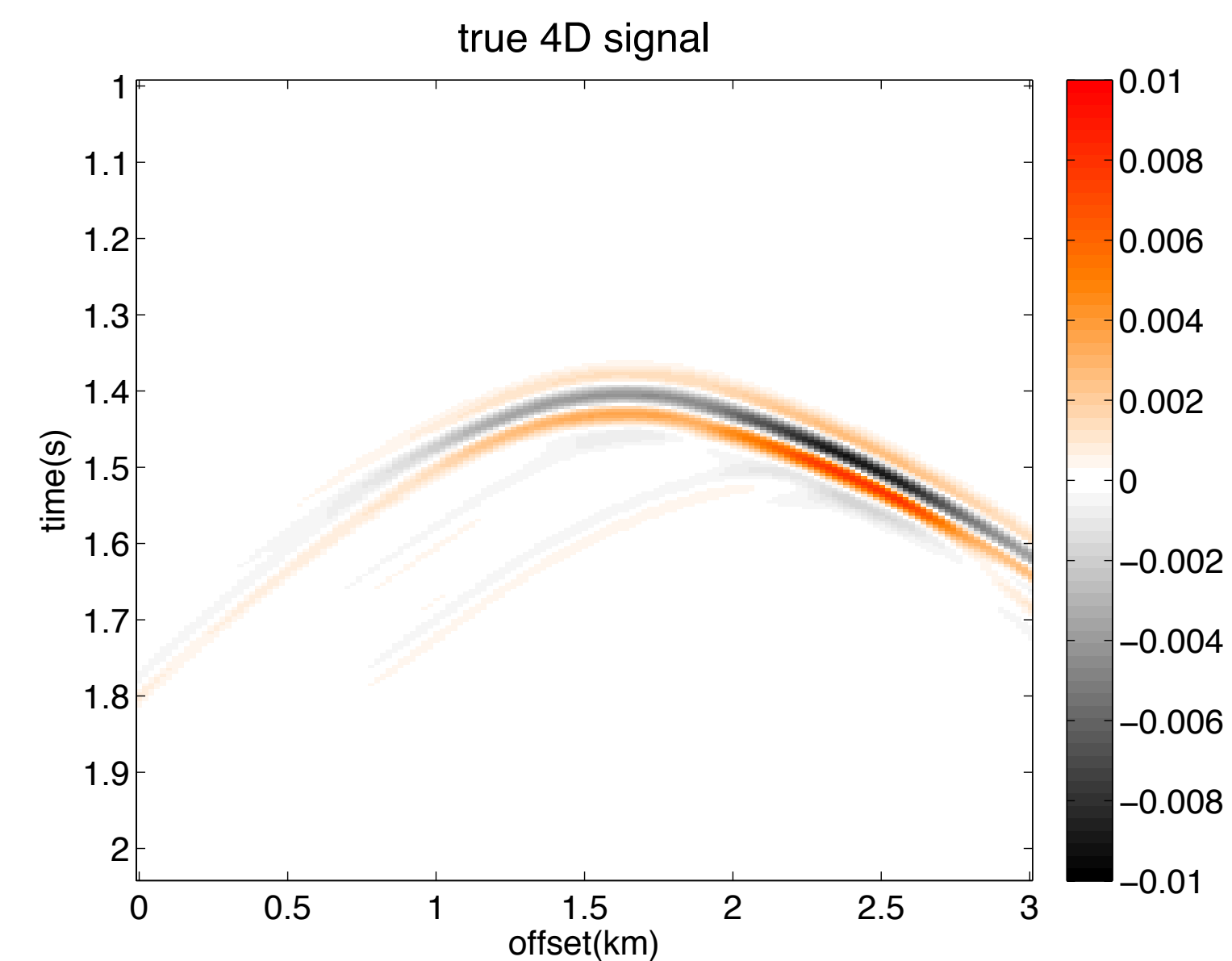
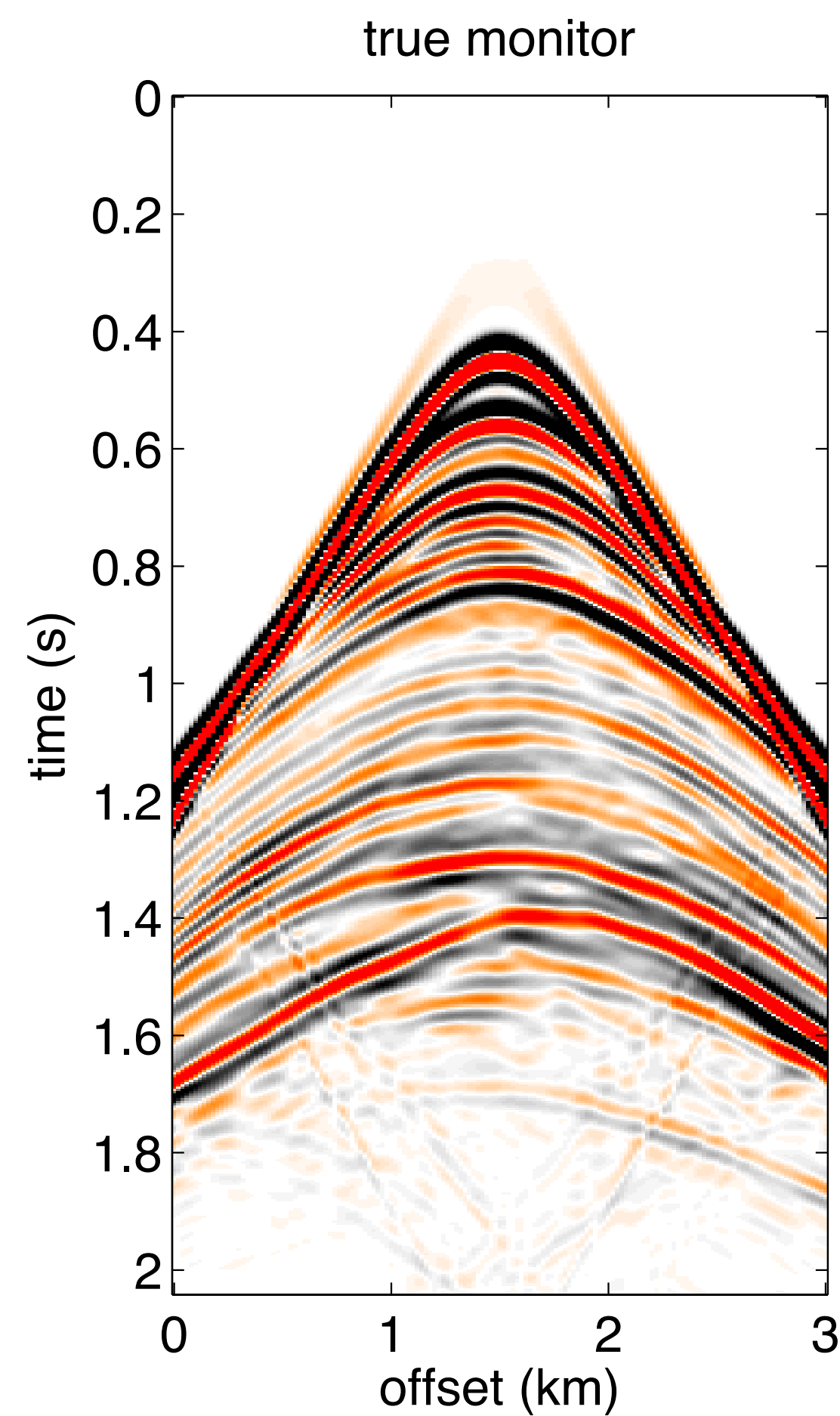
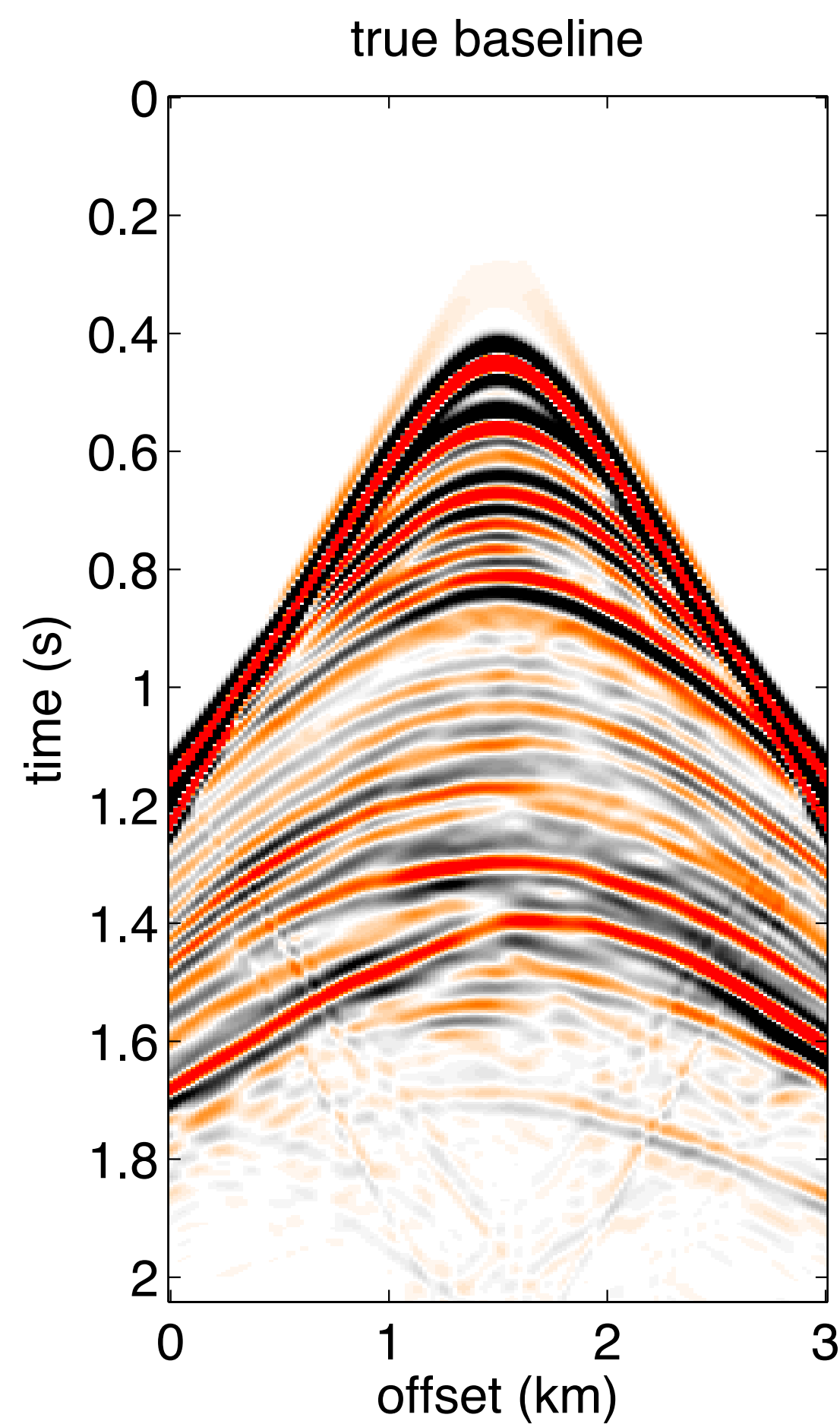
measure $\mathbf{y}_1 = \mathbf{A}_1 \mathbf{x}_1 \quad \text{and} \quad \mathbf{y}_2 = \mathbf{A}_2 \mathbf{x}_2$

True 4D signal : $\mathbf{S}^* (\mathbf{x}_1 - \mathbf{x}_2)$ (baseline - monitor)

Estimated 4D signal : $\mathbf{S}^* (\tilde{\mathbf{x}}_1 - \tilde{\mathbf{x}}_2)$

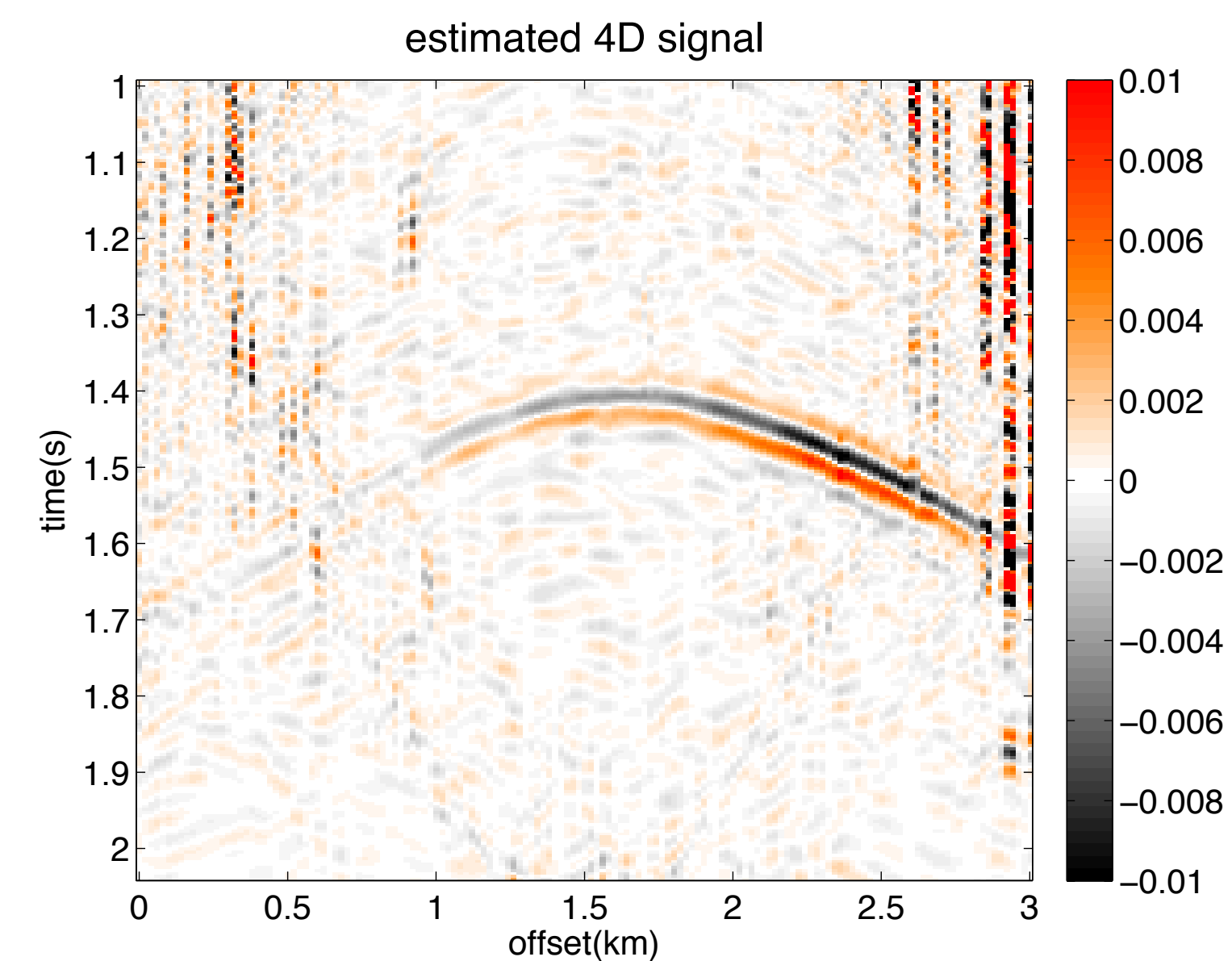
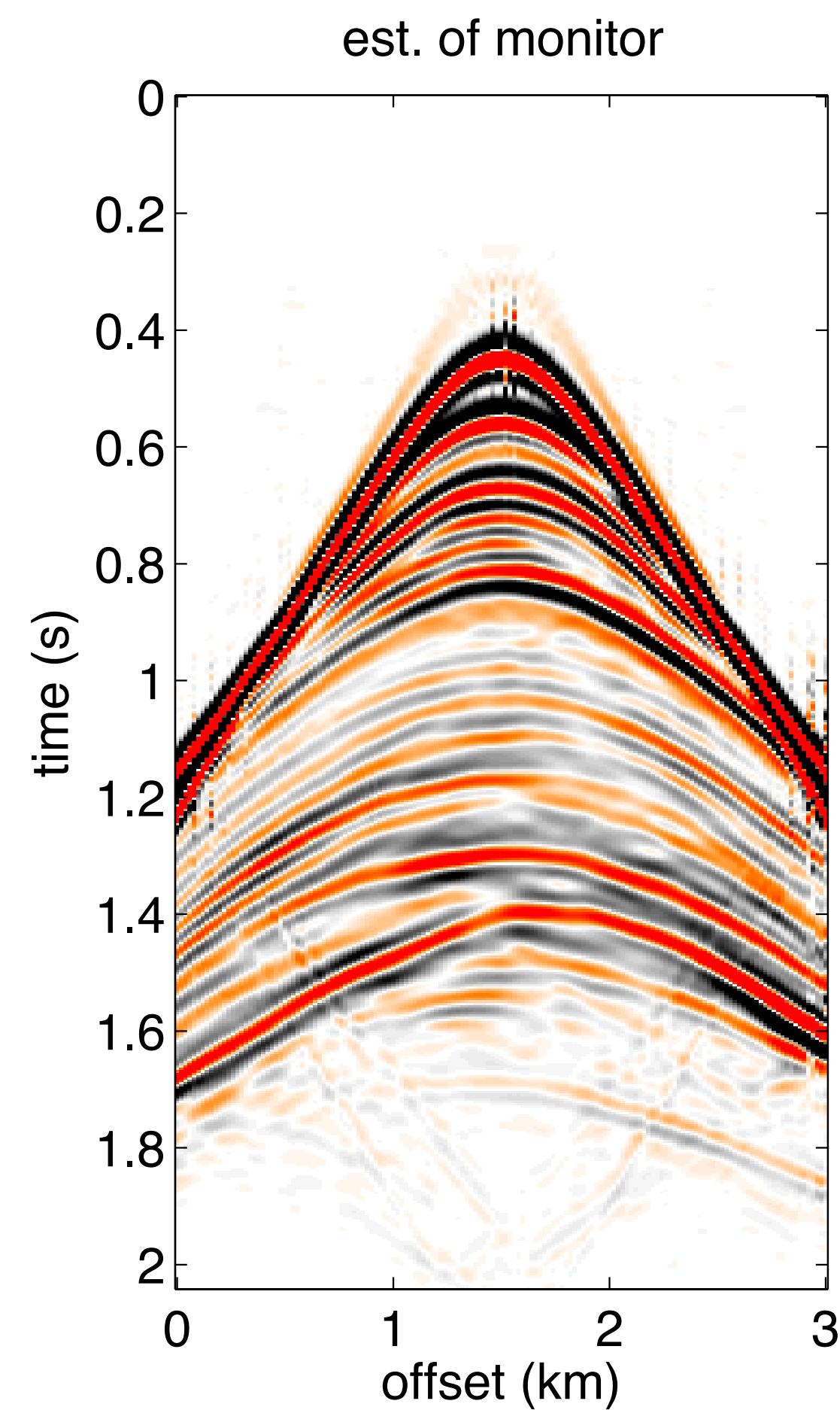
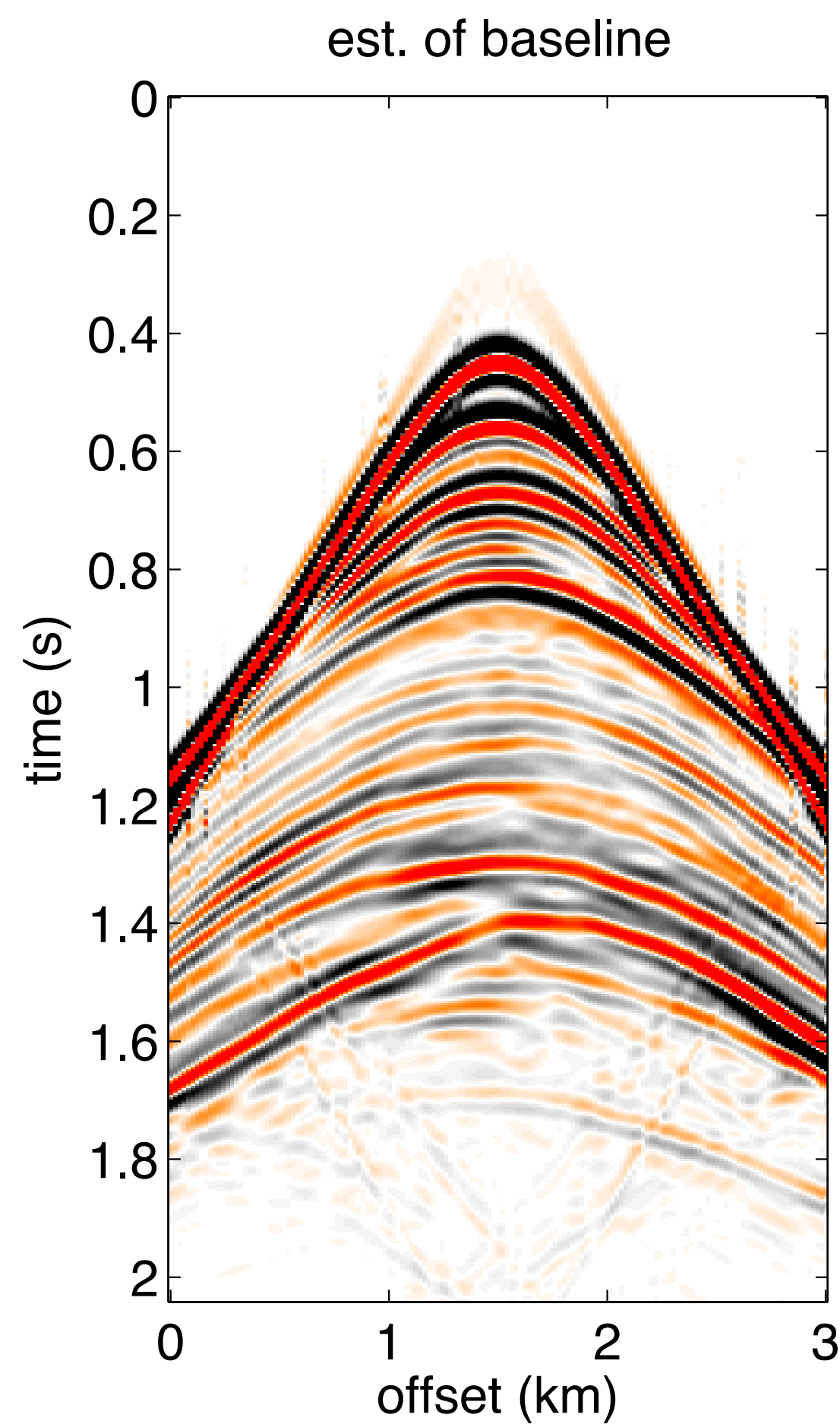
- observe random measurements for **baseline**
- observe a *different* random set of measurements for **monitor**
- reconstruct for each independently by using the sparsity recovery algorithm
- 4D signal is the difference of the reconstructed signals

SAME Geometry – regularly & densely sampled – IDEAL but *UNREALISTIC CASE*



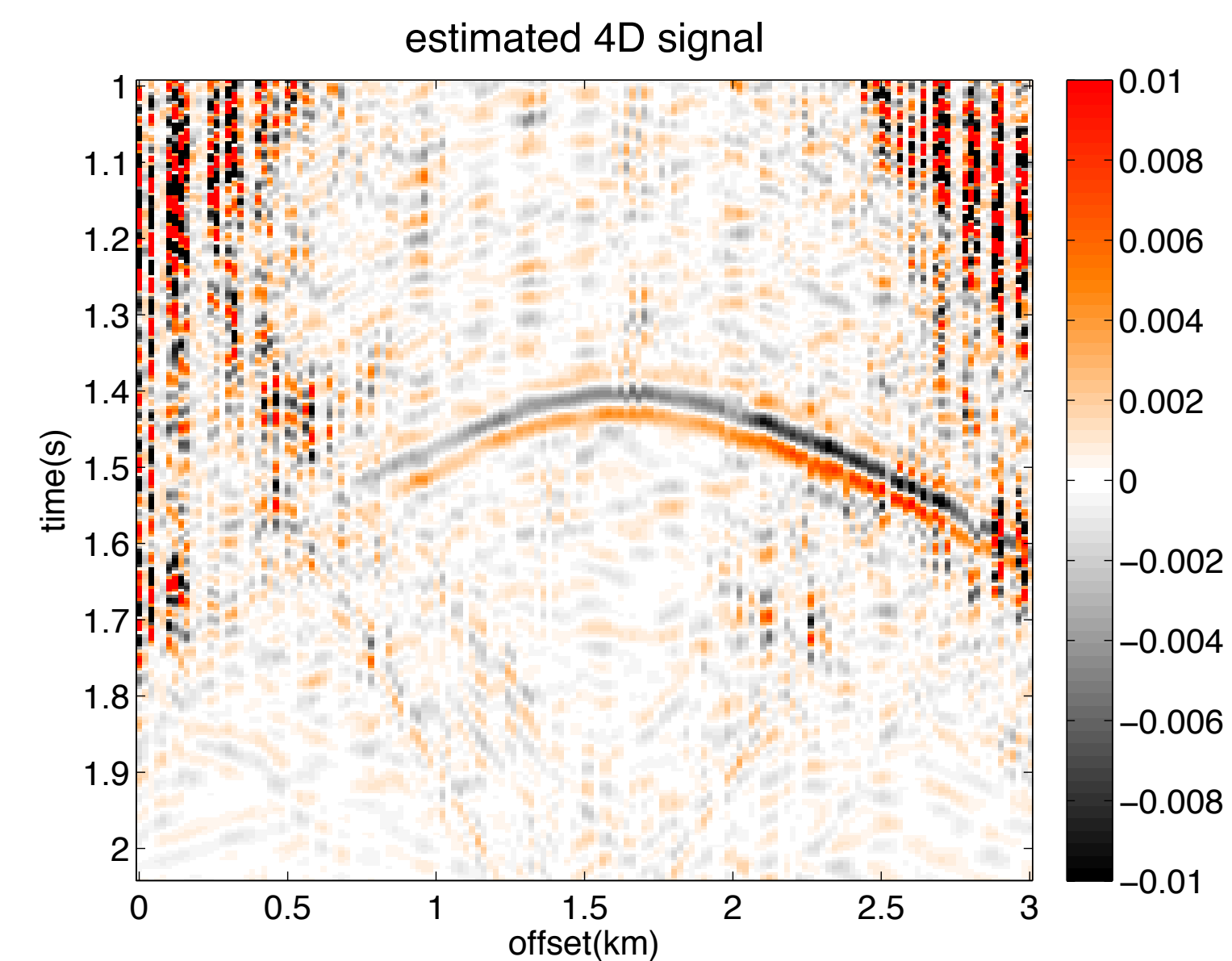
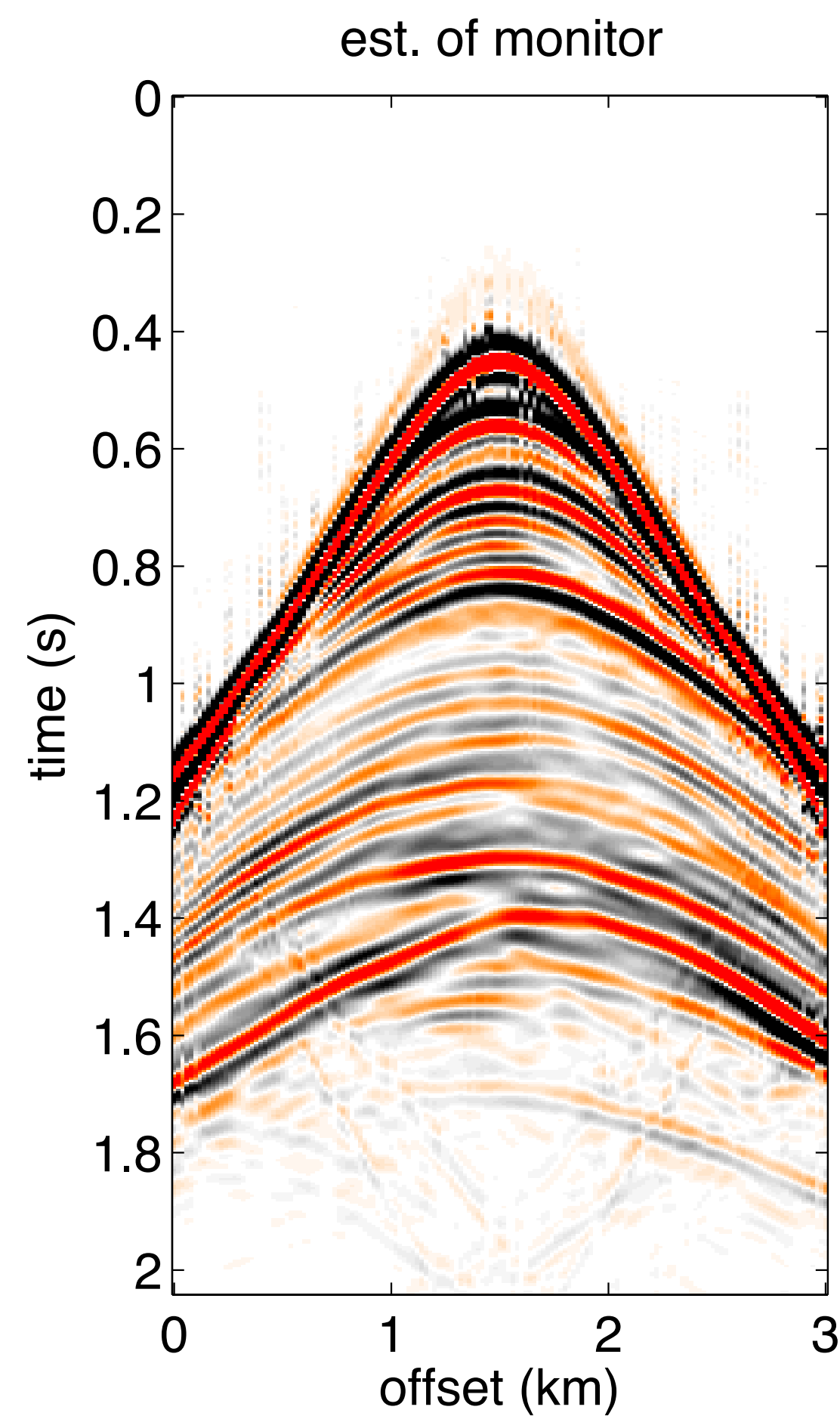
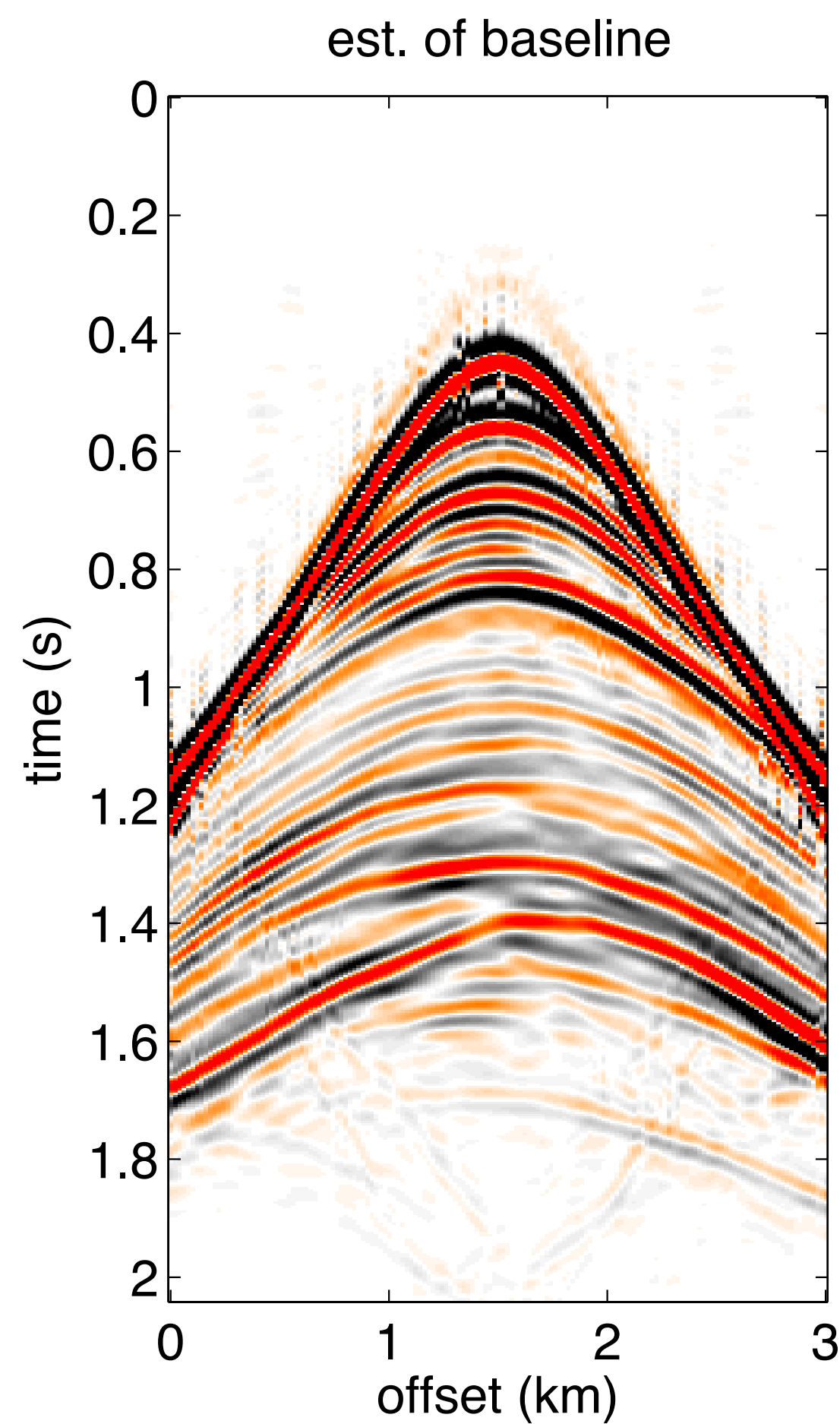
Result: 25% *INDEPENDENT* missing shots from each vintage

Result: OK



Result: 40% *INDEPENDENT* missing shots from each vintage

Result: Not OK



Motivation

- *Time*-lapse wavefields are compressible in the curvelet domain
- They have a lot of *information in common*

- Can we *exploit* this common **shared** information to make more *efficient* use of measurements?
- Can we use a model that *jointly* represents the wavefields.

Joint reconstruction model (JRM)

- ▶ Reconstruction of two or more signals
- ▶ *Each* of the signal is *compressible*
- ▶ The *joint* representation of the signals is *compressible*

$$\mathbf{A}_1 = \mathbf{R}_1 \mathbf{M} \mathbf{S}^* \quad \text{and} \quad \mathbf{A}_2 = \mathbf{R}_2 \mathbf{M} \mathbf{S}^*$$

$$\mathbf{y}_1 = \mathbf{A}_1 \mathbf{x}_1 \quad \text{and} \quad \mathbf{y}_2 = \mathbf{A}_2 \mathbf{x}_2$$

Rewrite

$$\begin{array}{l} \mathbf{x}_1 = \mathbf{z}_0 + \mathbf{z}_1 \\ \mathbf{x}_2 = \mathbf{z}_0 + \mathbf{z}_2 \end{array} \left. \vphantom{\begin{array}{l} \mathbf{x}_1 \\ \mathbf{x}_2 \end{array}} \right\} \text{unique part}$$

\downarrow
common shared support

Joint reconstruction model

$$\mathbf{x}_1 = \mathbf{z}_0 + \mathbf{z}_1$$

$$\mathbf{x}_2 = \mathbf{z}_0 + \mathbf{z}_2$$

$$\overbrace{\begin{bmatrix} \mathbf{A}_1 & \mathbf{A}_1 & \mathbf{0} \\ \mathbf{A}_2 & \mathbf{0} & \mathbf{A}_2 \end{bmatrix}}^{\mathbf{A}} \overbrace{\begin{bmatrix} \mathbf{z}_0 \\ \mathbf{z}_1 \\ \mathbf{z}_2 \end{bmatrix}}^{\mathbf{z}} = \overbrace{\begin{bmatrix} \mathbf{y}_1 \\ \mathbf{y}_2 \end{bmatrix}}^{\mathbf{y}}$$

$$\tilde{\mathbf{z}} = \arg \min_{\mathbf{z}} \|\mathbf{z}\|_1 \quad \text{s.t.} \quad \mathbf{y} = \mathbf{A}\mathbf{z}$$

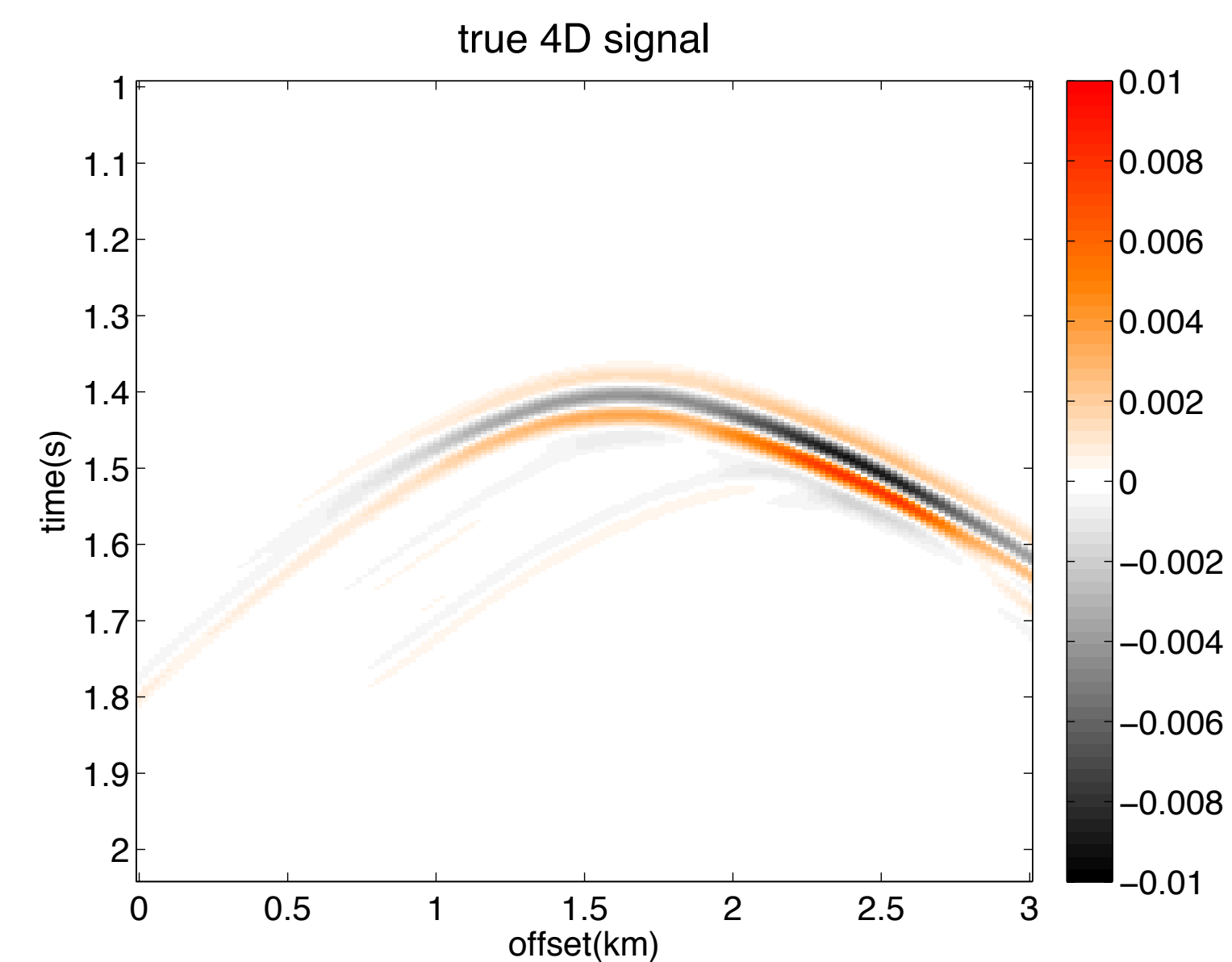
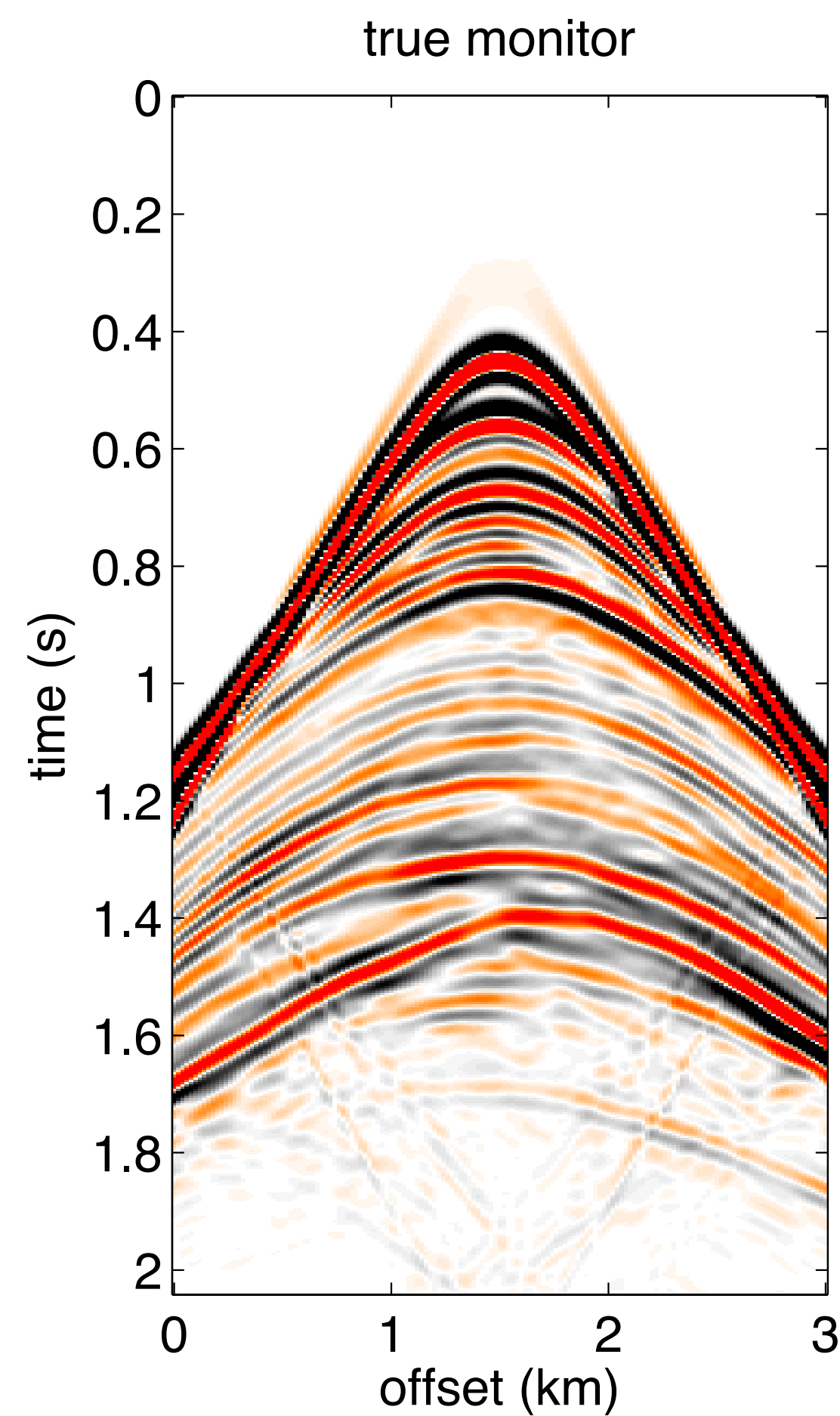
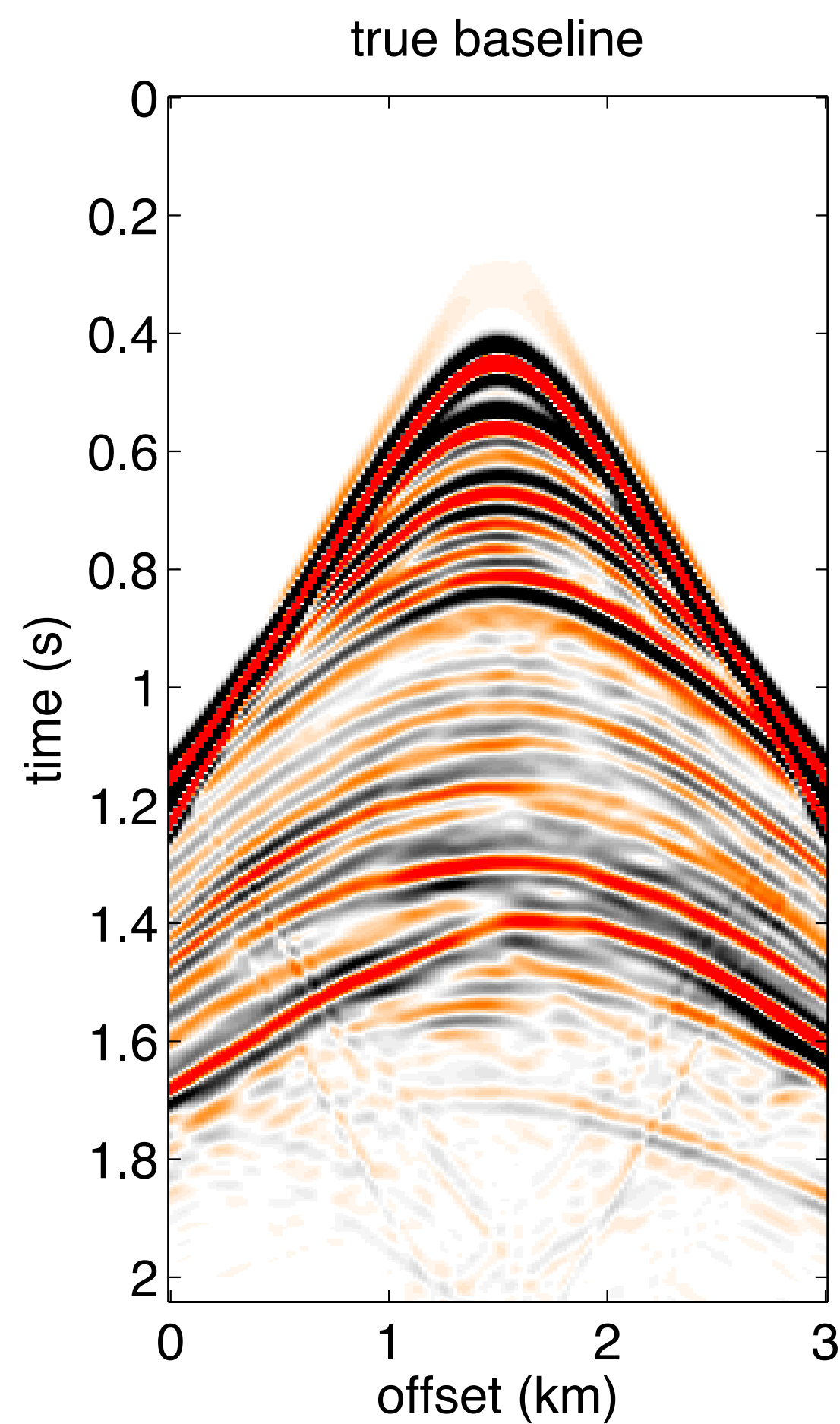
$$\tilde{\mathbf{z}} = \begin{bmatrix} \tilde{\mathbf{z}}_0 \\ \tilde{\mathbf{z}}_1 \\ \tilde{\mathbf{z}}_2 \end{bmatrix}$$

$$\tilde{\mathbf{x}}_1 = \tilde{\mathbf{z}}_0 + \tilde{\mathbf{z}}_1$$

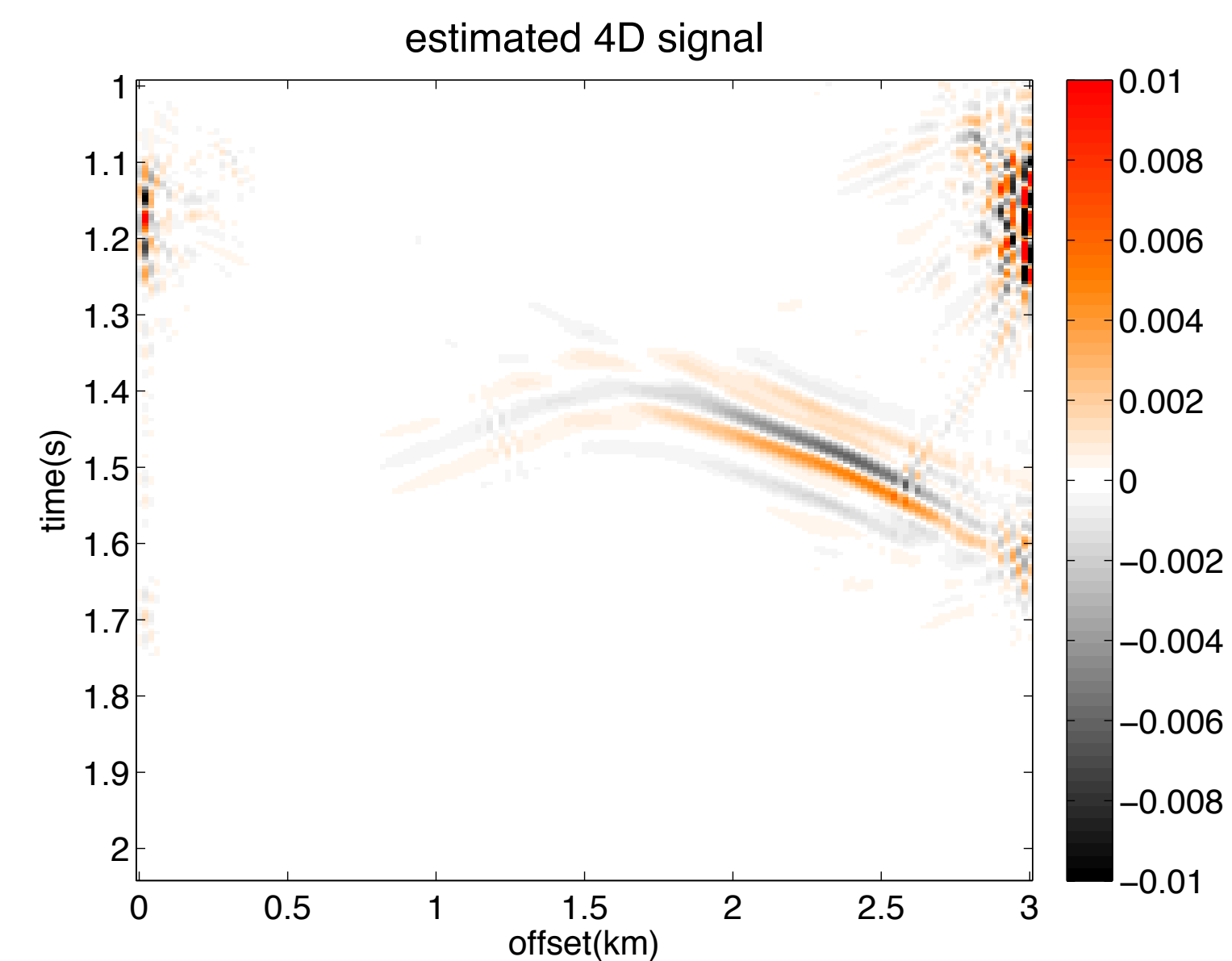
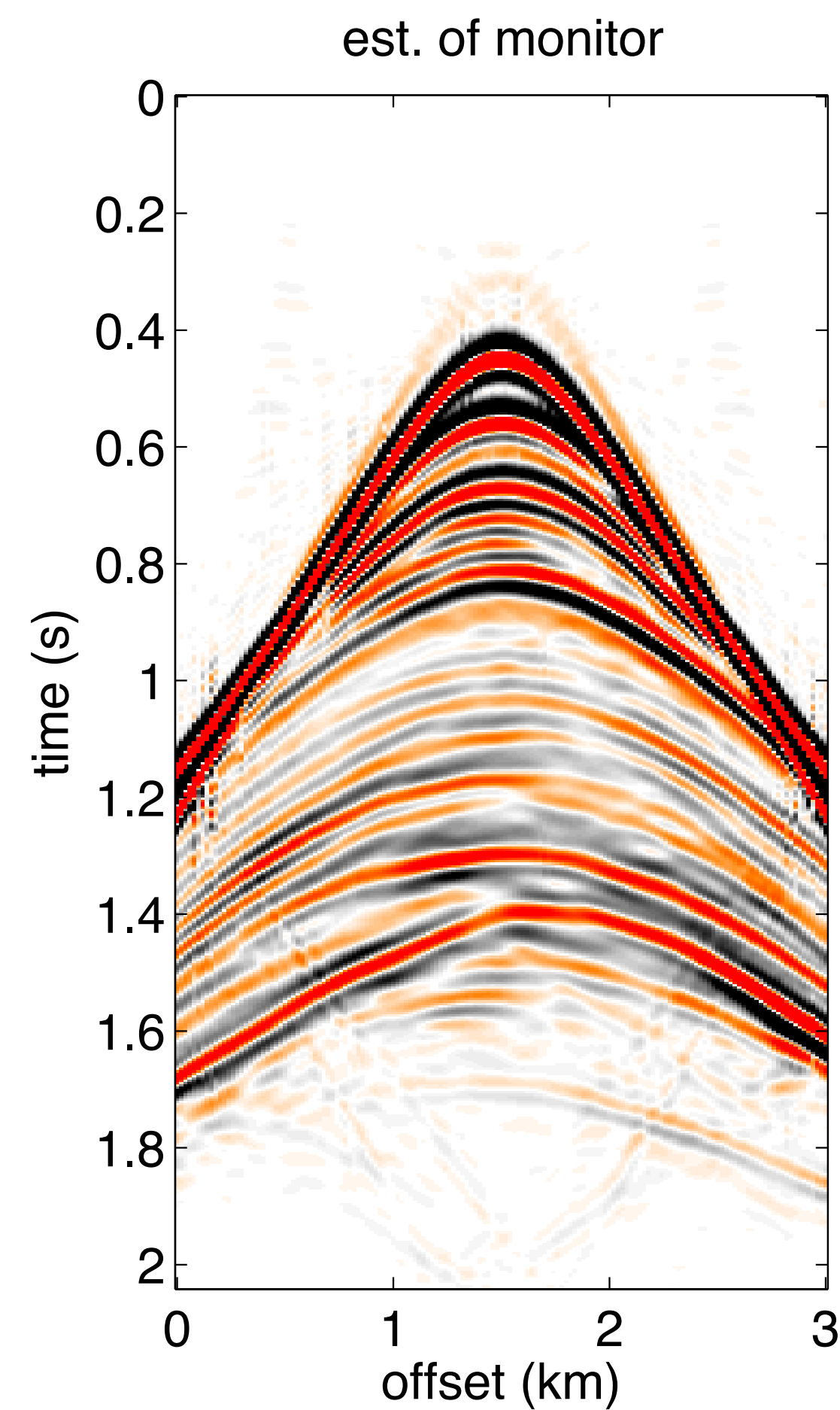
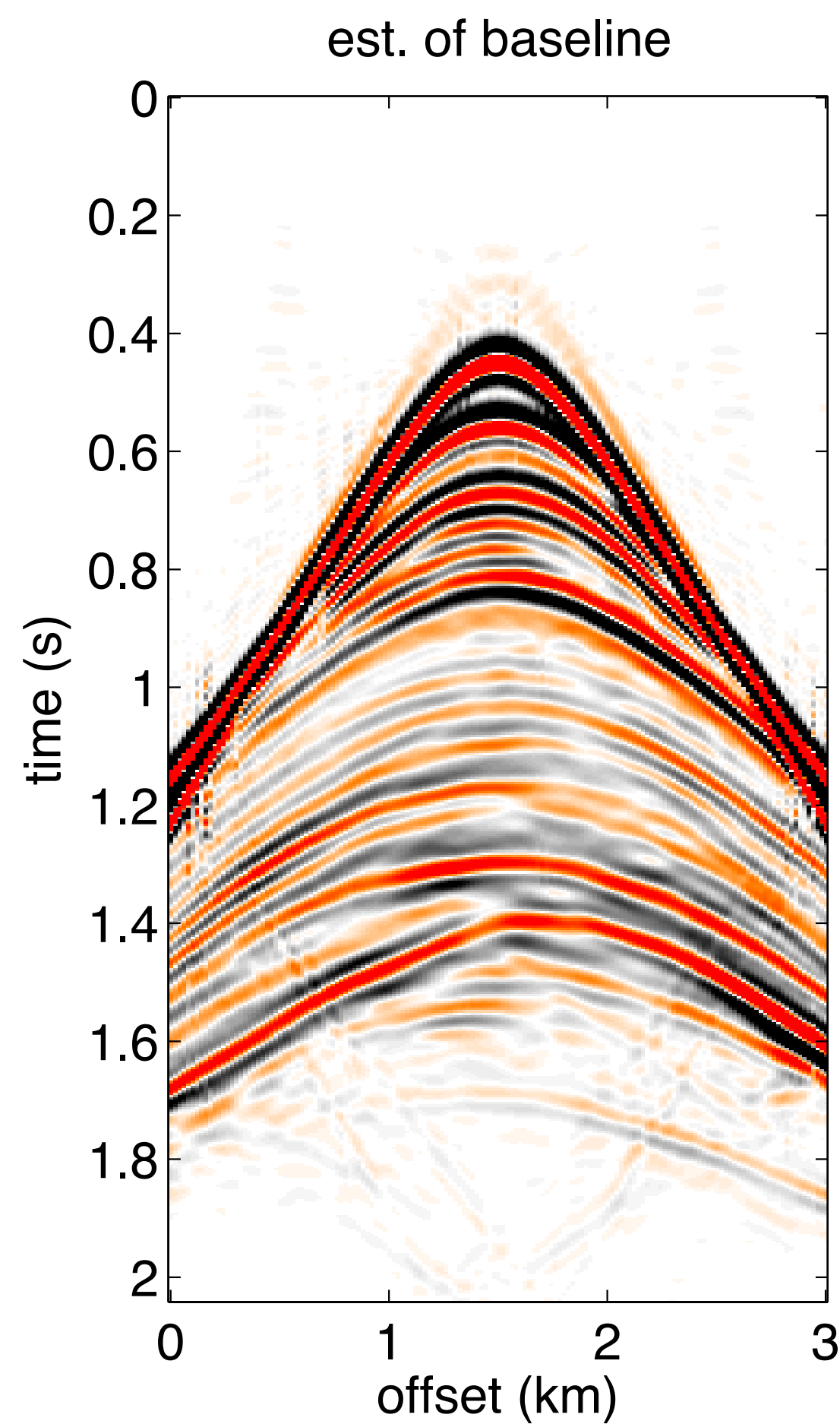
$$\tilde{\mathbf{x}}_2 = \tilde{\mathbf{z}}_0 + \tilde{\mathbf{z}}_2$$

Estimated 4D signal : $\mathbf{S}^* (\tilde{\mathbf{x}}_1 - \tilde{\mathbf{x}}_2)$

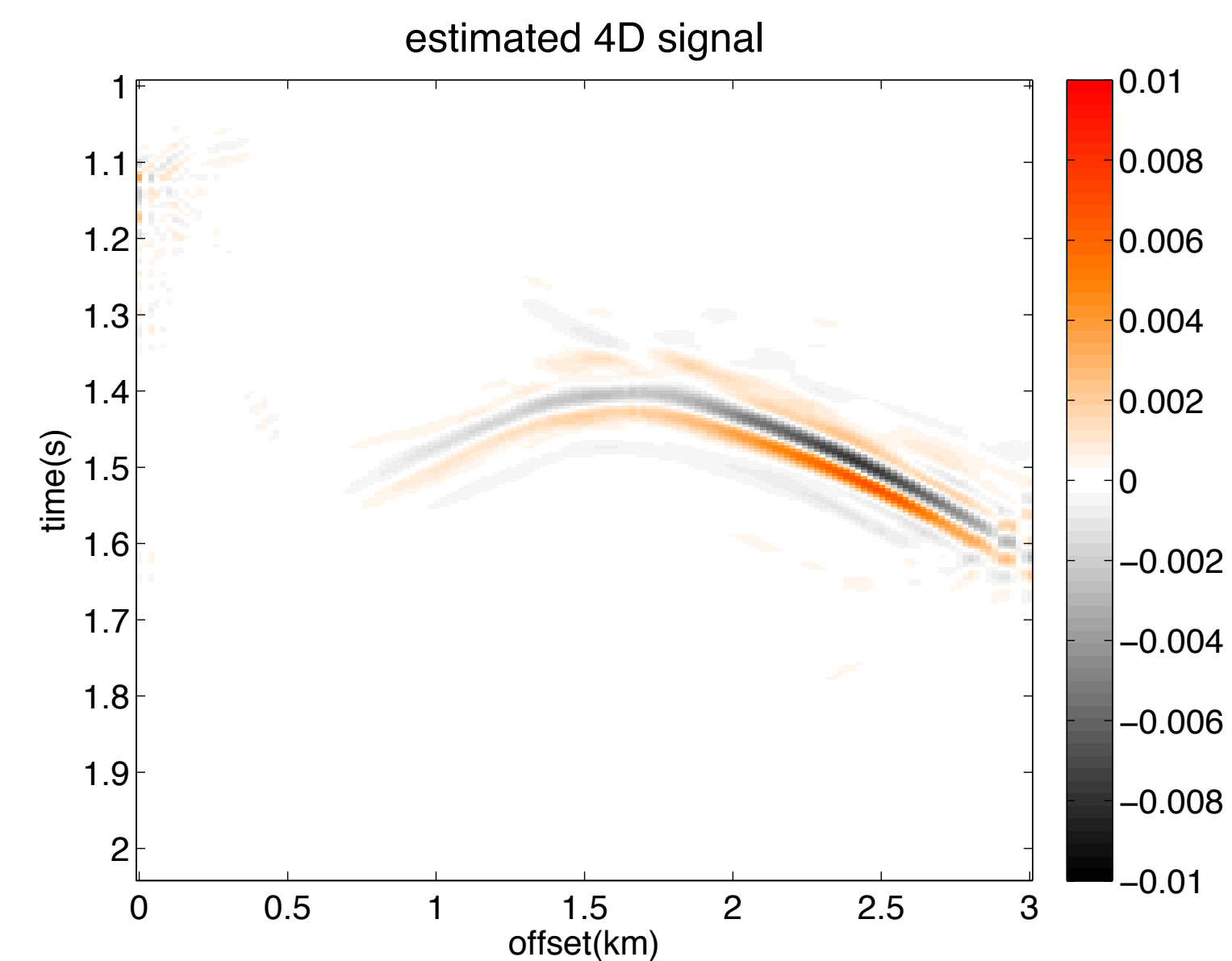
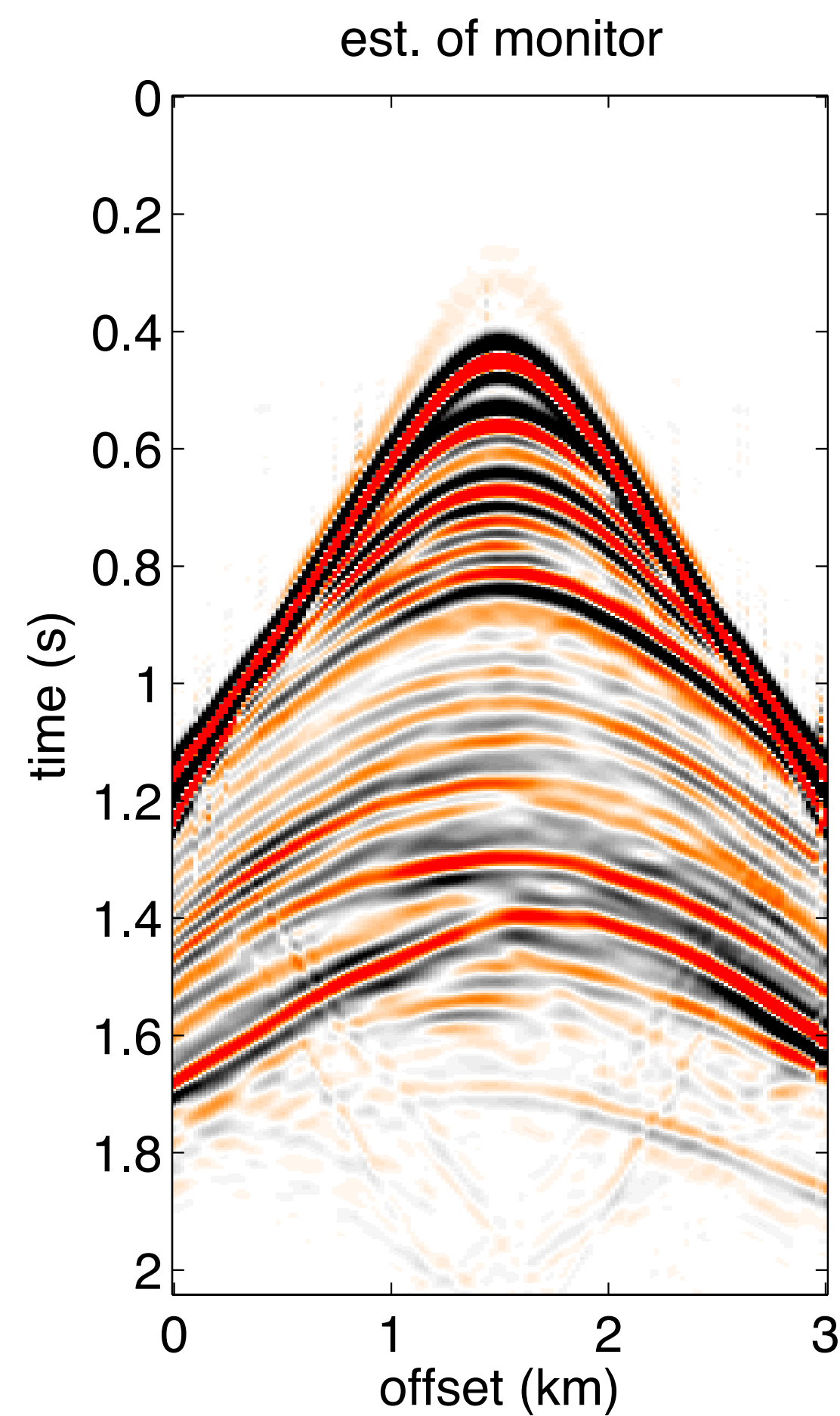
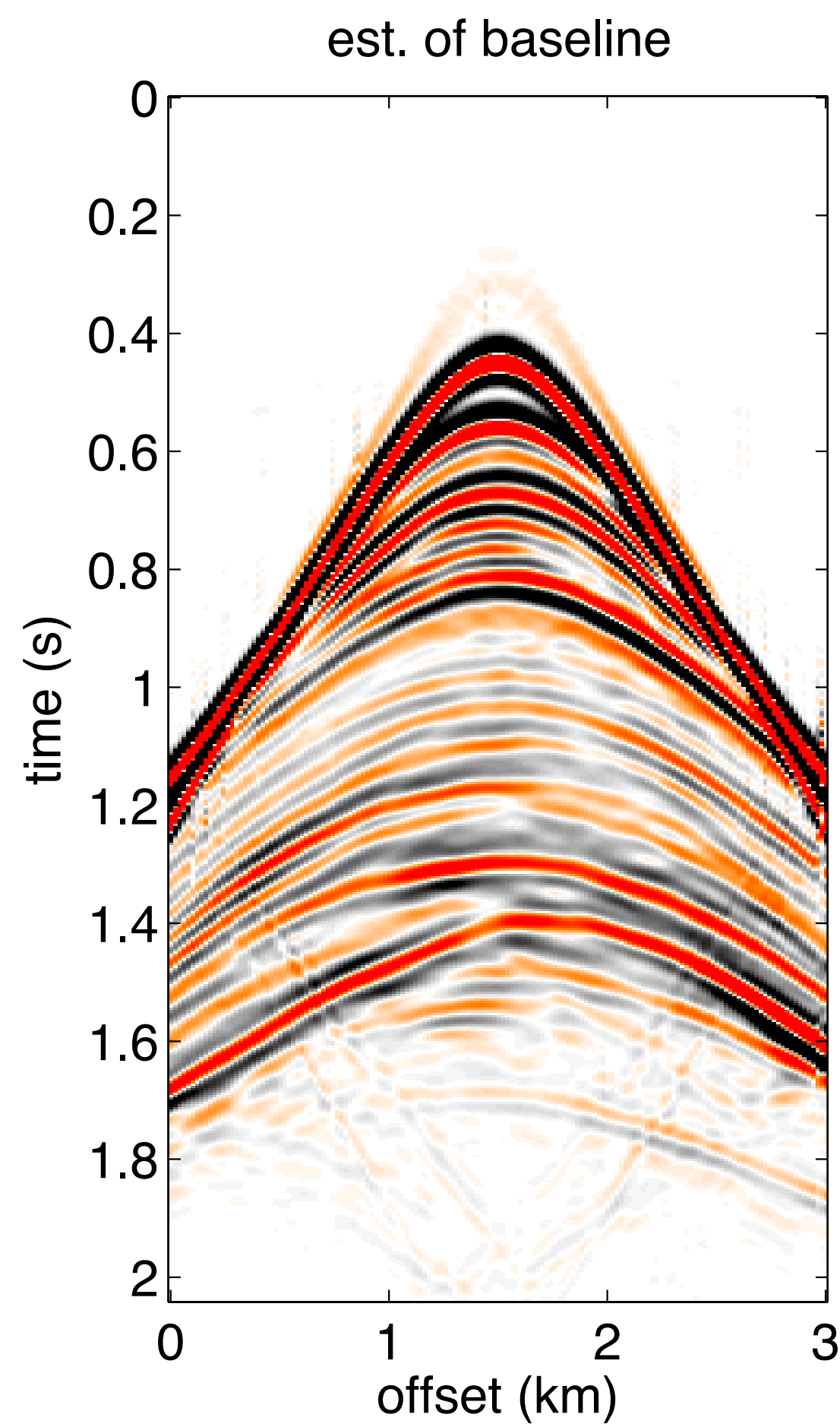
SAME geometry – regularly & densely sampled – IDEAL CASE



Result: 50% *INDEPENDENT* missing shots from each vintage (JRM)

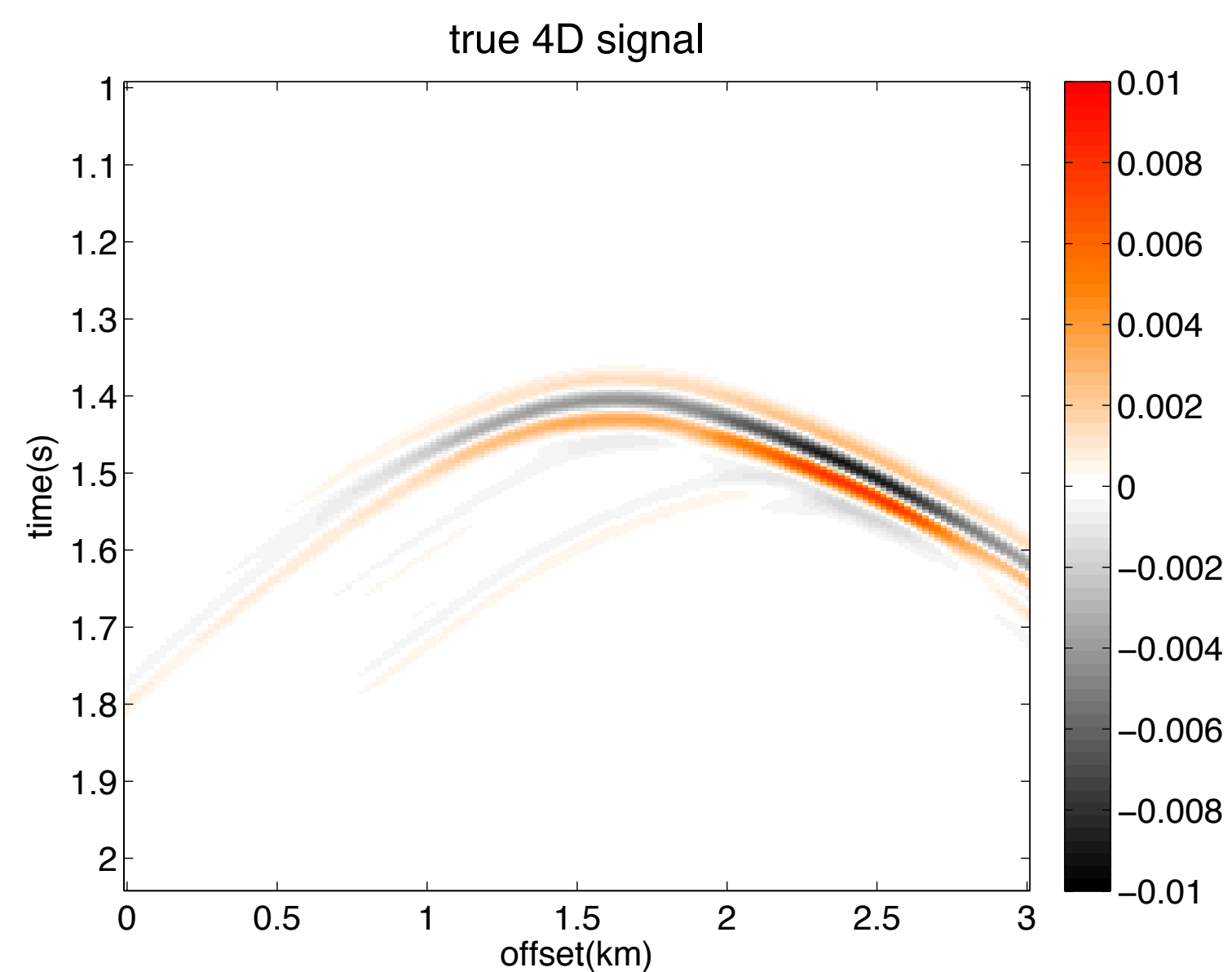


Result: 40% INDEPENDENT missing shots from each vintage (JRM)



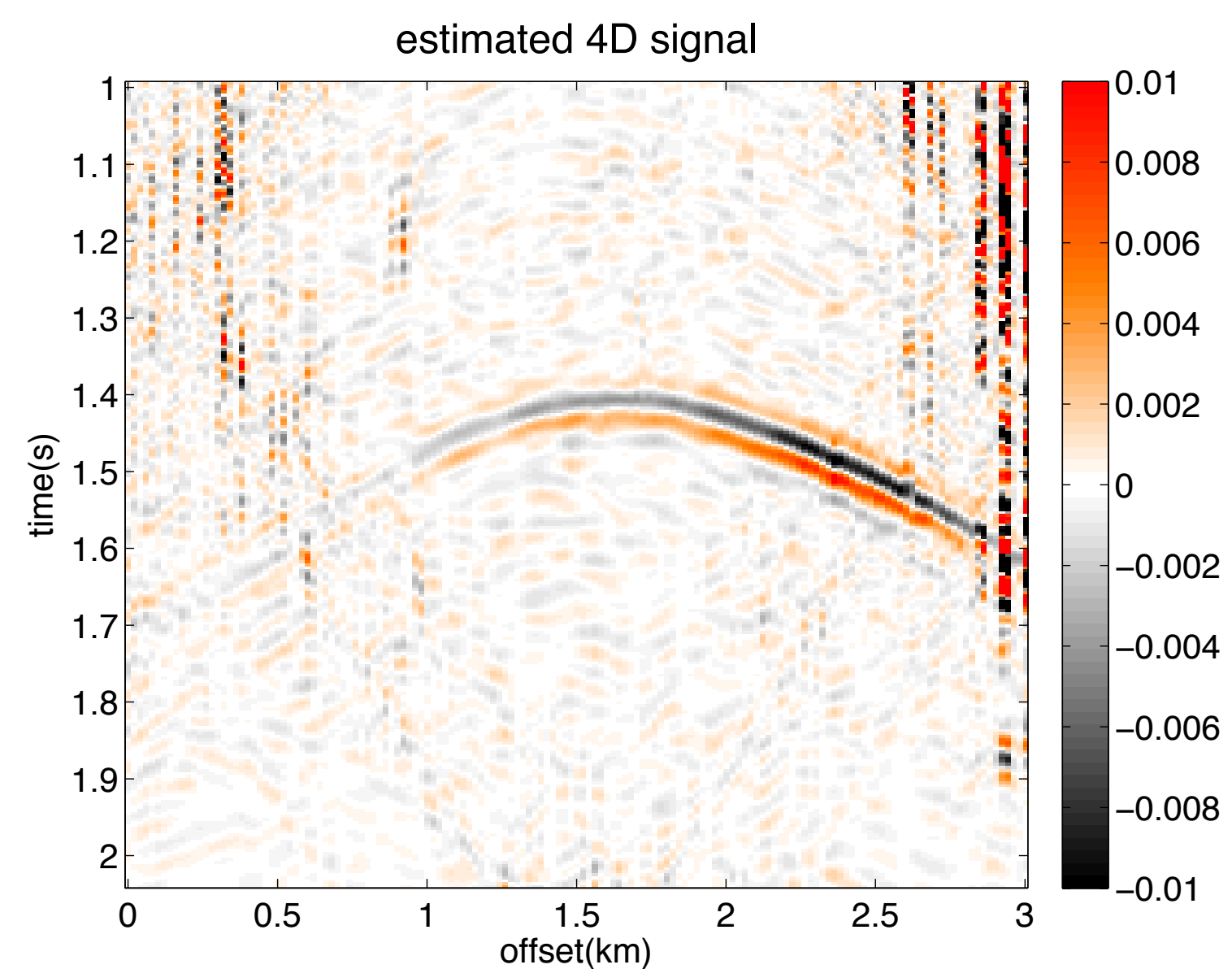
Independent vs *joint* reconstruction

“ideal 4D signal”



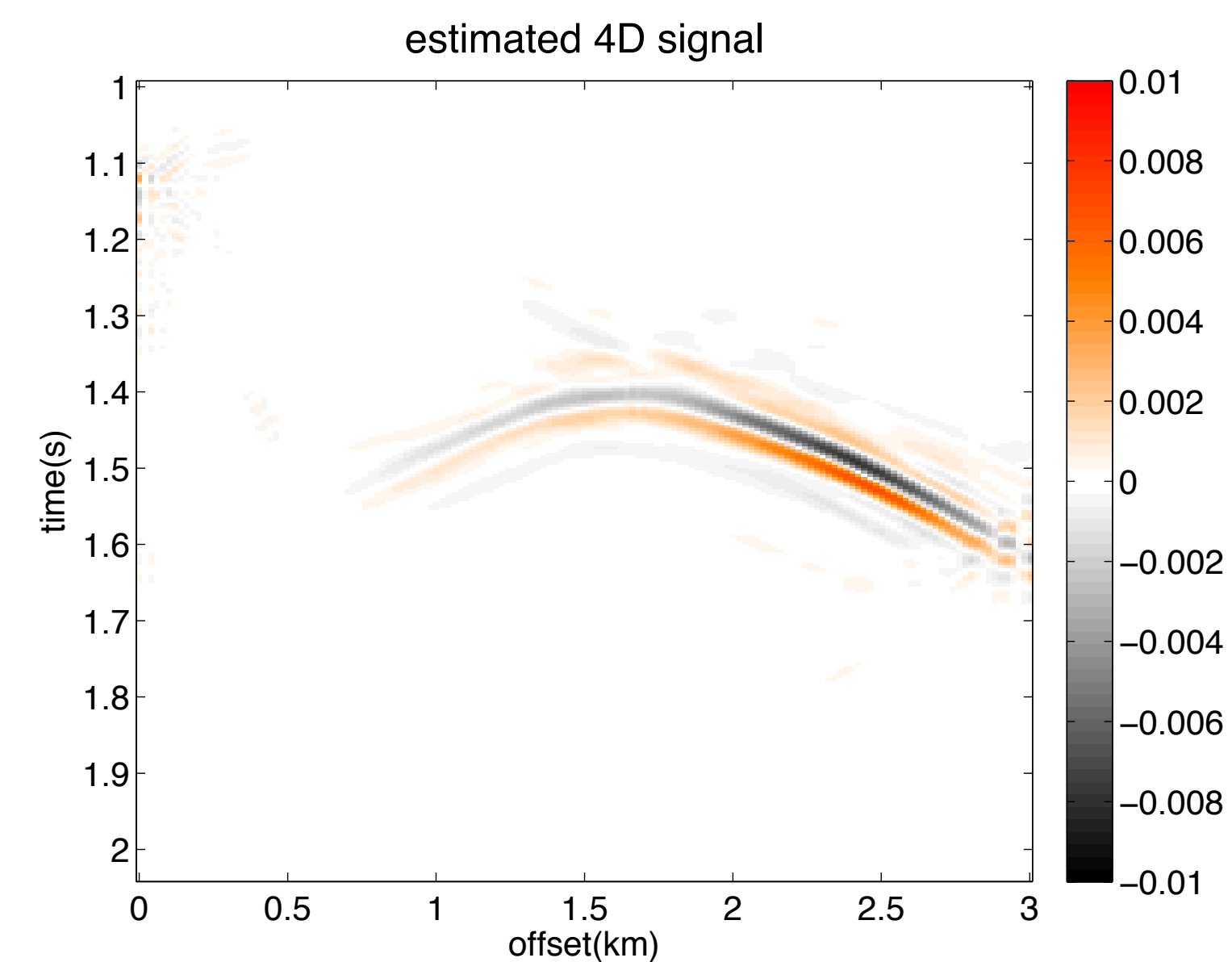
“independent CS recovery”

25% missing
from each vintage



“joint CS recovery”

40% missing
from each vintage



Generalization to more than 2 vintages

- Improvement in reconstruction quality for each signal
- Improved 4D signal reconstruction
- Joint representation enables reconstruction of each wavefield with fewer measurements from each survey

Conclusions

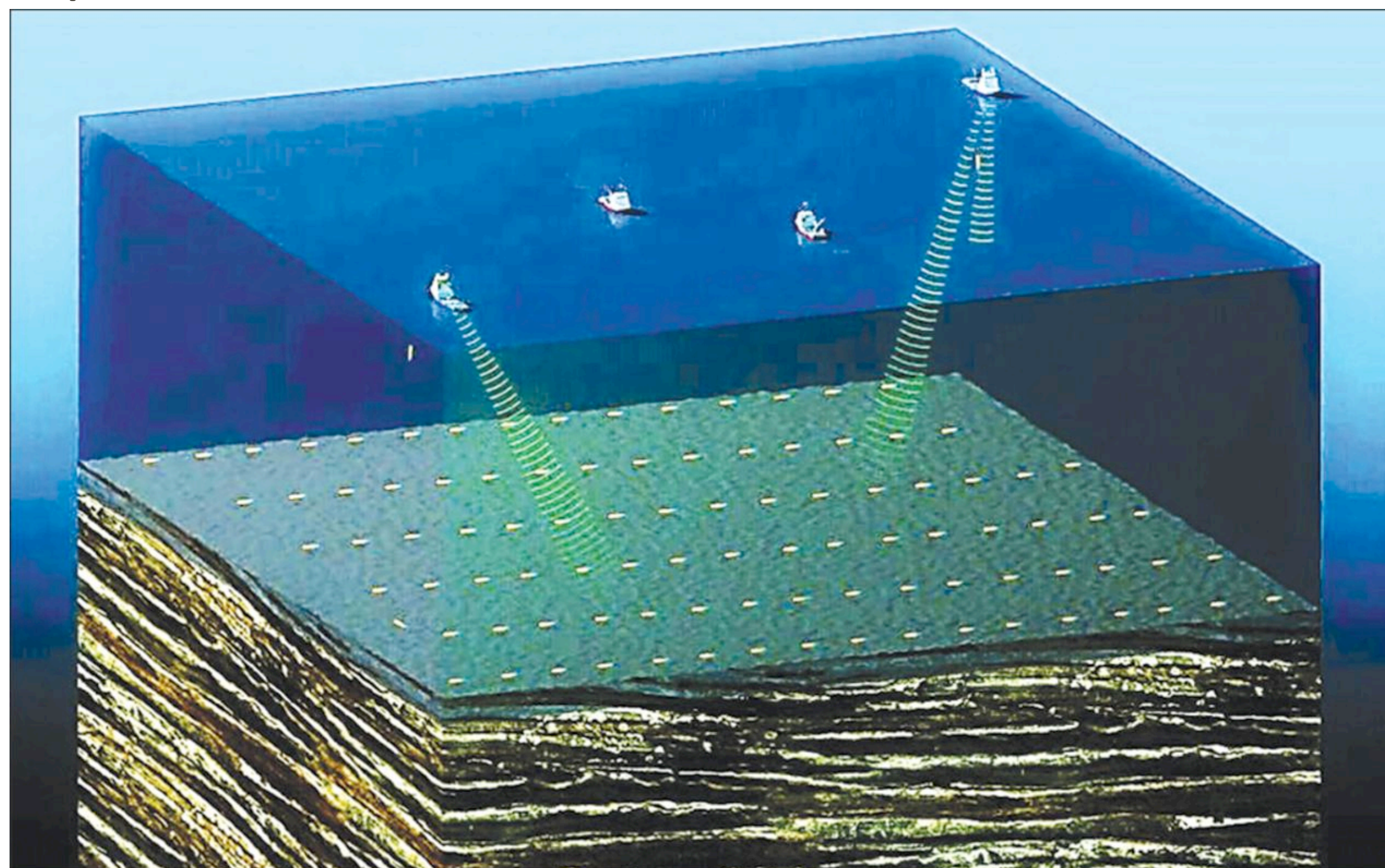
- resolving 4D changes depends on the *subsampling* ratio during *randomized* sampling
- careful planning of 4D project in mind, with *randomized* sampling, can save cost
- we can reconstruct 4D differences accurately without having to take the *same* set of *measurements* - we don't necessarily have to spend efforts *repeating* the surveys

Future Plan

- Detection of *weak* and *strong* 4D changes in *noisy* environments with *high* subsampling ratios
- Understand different sampling scenarios
 - we chose the subsampling ratios to be the same
- Incorporate joint reconstruction into wave-equation based inversion
- Extension to other realistic acquisitions including marine

Future Work - where are we going with this?

- Extension to other randomized acquisition scenarios- simultaneous shot acquisition for marine, with OBNs or OBCs



Acknowledgements

- Thanks to the following people
 - ▶ Felix Herrmann
 - ▶ Haneet Wason
 - ▶ Ernie Esser
- And Finally,

Acknowledgements

- Thank you for your attention!

MERCI!!!

SIYANBONGA!!!

DANKIE!!!!



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