A new take on compressive time-lapse seismic acquisition, imaging and inversion

Felix Oghenekohwo and Felix J. Herrmann

PIMS Workshop on Advances in Seismic Imaging and Inversion May 20 to 22, 2015
University of Alberta, Edmonton, Canada

SLIM
University of British Columbia

A new take on compressive time-lapse seismic acquisition, imaging and inversion

Felix Oghenekohwo and Felix J. Herrmann

Team : Rajiv Kumar, Haneet Wason, Ernie Esser, Ning Tu

   

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Overview

- Introduction to CS
- Timelapse (4D) & CS
- Challenges for 4D
- Recent CS extensions
- Stylized examples
- Linearized Inversion
- Conclusions

Felix J. Herrmann, Michael P. Friedlander, and Ozgur Yilmaz, "Fighting the Curse of Dimensionality: Compressive Sensing in Exploration Seismology", *Signal Processing Magazine, IEEE*, vol. 29, p. 88-100, 2012
Felix J. Herrmann, "Randomized sampling and sparsity: Getting more information from fewer samples", *Geophysics*, vol. 75, p. WB173-WB187, 2010

Compressive sensing *paradigm*

Find **representations that reveal** ***structure***

- *transform*-domain *sparsity* (e.g., Fourier, curvelets, etc.)

Sample **to** ***break*** **the** ***structure***

- *randomized* acquisition (e.g., *jittered* sampling, time *dithering*, *encoding*, etc.)
- destroy *sparsity*

Recover ***structure*** **by promoting**

- *sparsity* via *one*-norm *minimization*

Mosher, C. C., Keskula, E., Kaplan, S. T., Keys, R. G., Li, C., Ata, E. Z., ... & Sood, S. (2012, November). Compressive Seismic Imaging. In *2012 SEG Annual Meeting*. Society of Exploration Geophysicists.

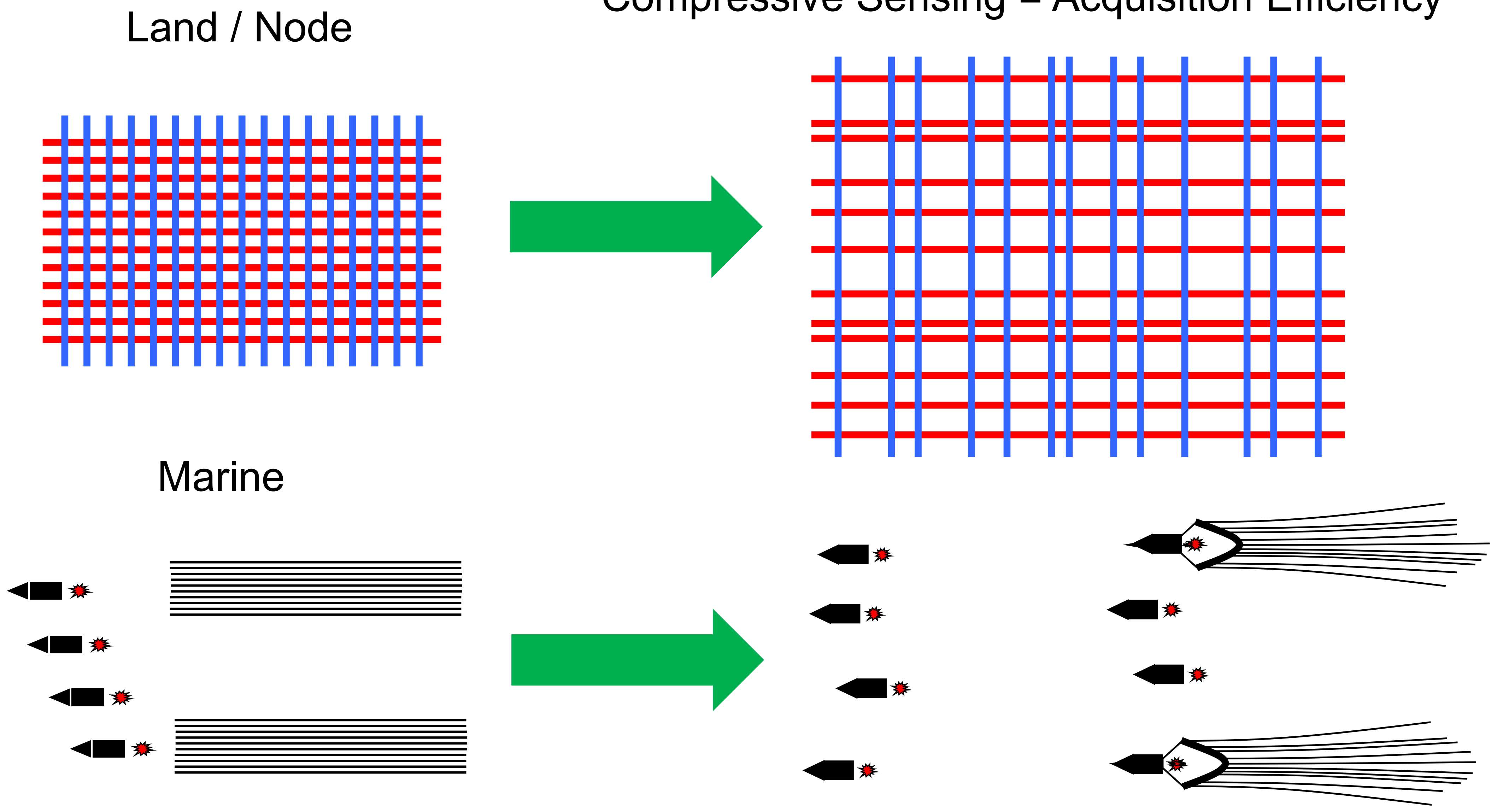
Randomized undersampling

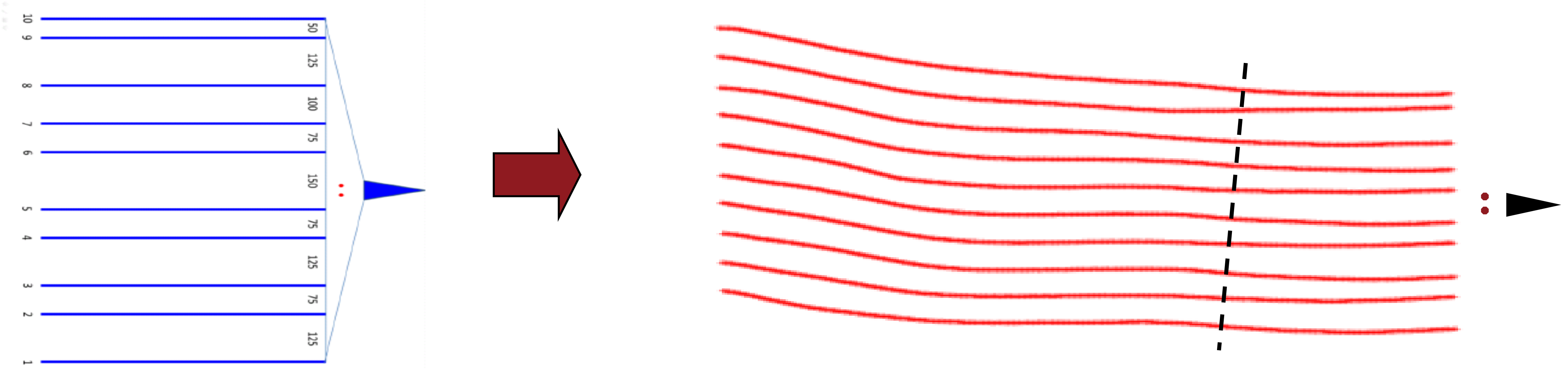
– examples from industry (ConocoPhilips)

Deliberate & natural randomness in acquisition

(thanks to Chuck Mosher)

Compressive Sensing = Acquisition Efficiency





Designed

Actually Acquired

Haneet Wason and Felix J. Herrmann, "Time-jittered ocean bottom seismic acquisition",
in *SEG Technical Program Expanded Abstracts*, 2013, vol. 32, p. 1-6.

Hassan Mansour, Haneet Wason, Tim T.Y. Lin, and Felix J. Herrmann, "Randomized marine acquisition with compressive sampling matrices",
Geophysical Prospecting, vol. 60, p. 648-662, 2012.

Time-lapse seismic

Current acquisition paradigm:

- *repeat* **expensive** dense acquisitions & *"independent"* processing
- compute *differences* between *baseline* & *monitor* survey(s)
- challenging to ensure *repetition*

New compressive sampling paradigm:

- cheap subsampled acquisition, e.g. via time-*jittered* marine *undersampling*
- exploits insights from distributed compressive sensing
- may offer possibility to *relax* insistence on *repeatability*

Compressive sensing in 4D

Sampling

$$\mathbf{A}_1\mathbf{x}_1 = \mathbf{b}_1$$

subsampled baseline data

$$\mathbf{A}_2\mathbf{x}_2 = \mathbf{b}_2$$

subsampled monitor data

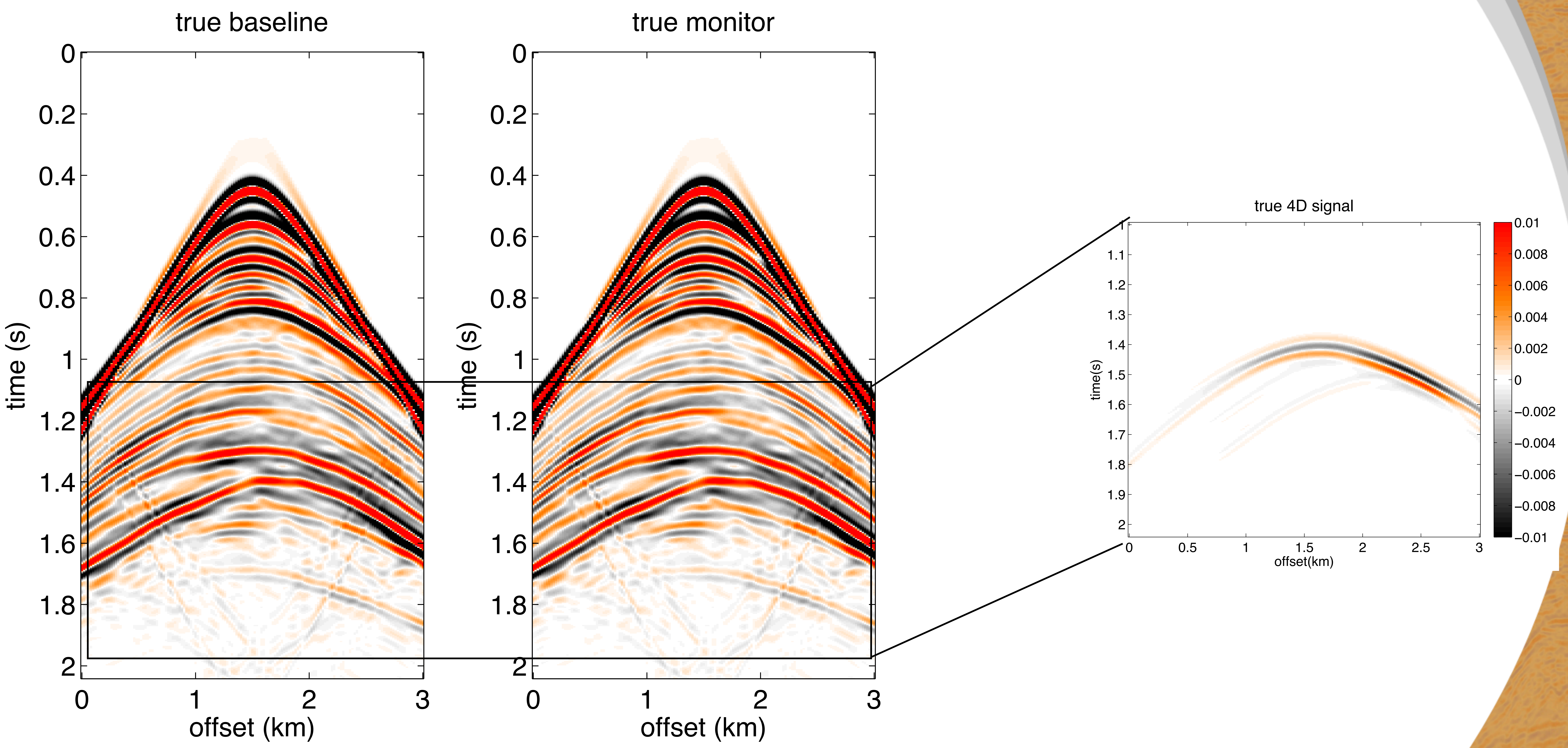
Sparsity-promoting recovery

$$\tilde{\mathbf{x}} = \arg\min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{subject to} \quad \mathbf{A}\mathbf{x} = \mathbf{b}$$

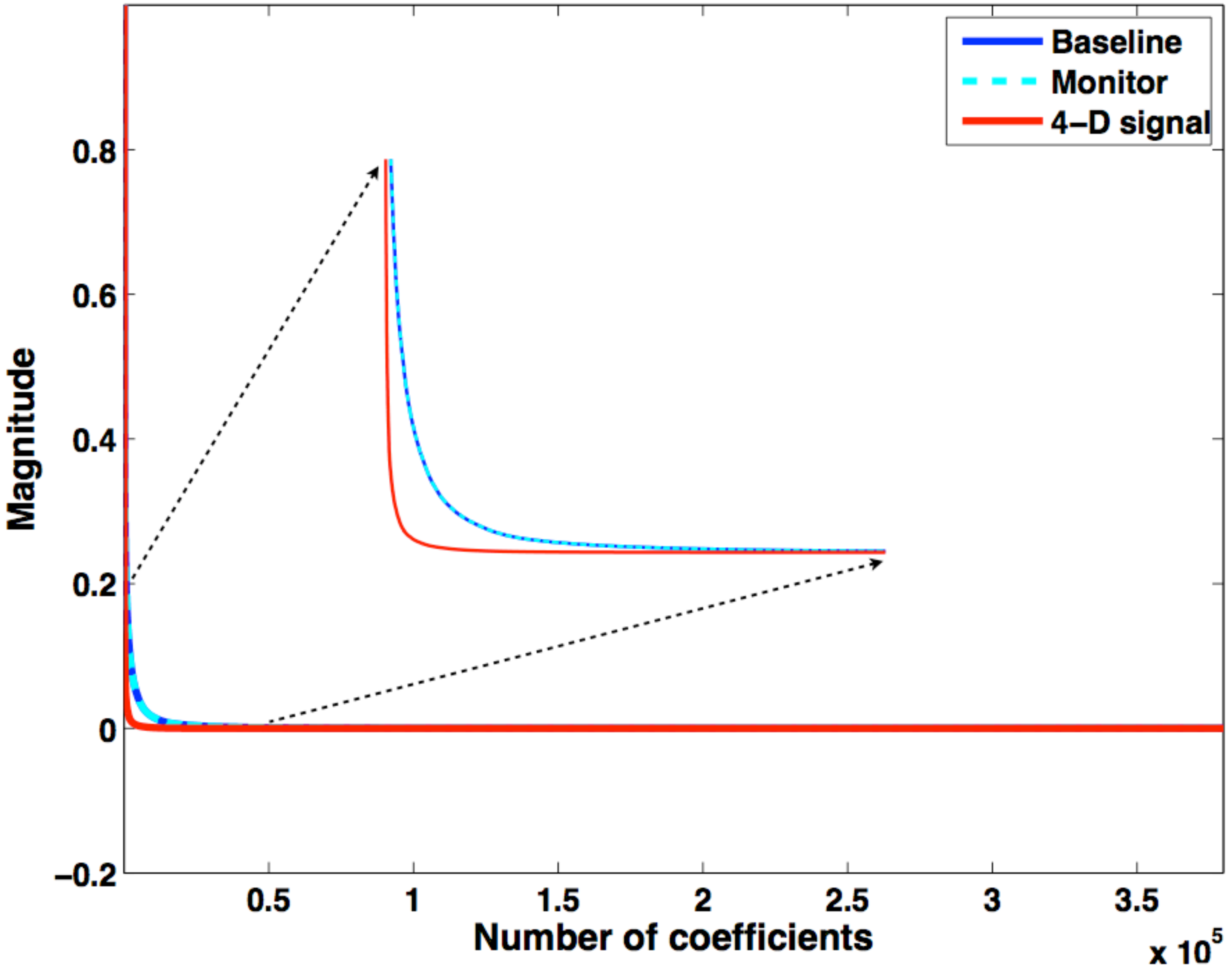
recovered data: $\tilde{\mathbf{d}} = \mathbf{S}^H\tilde{\mathbf{x}}$

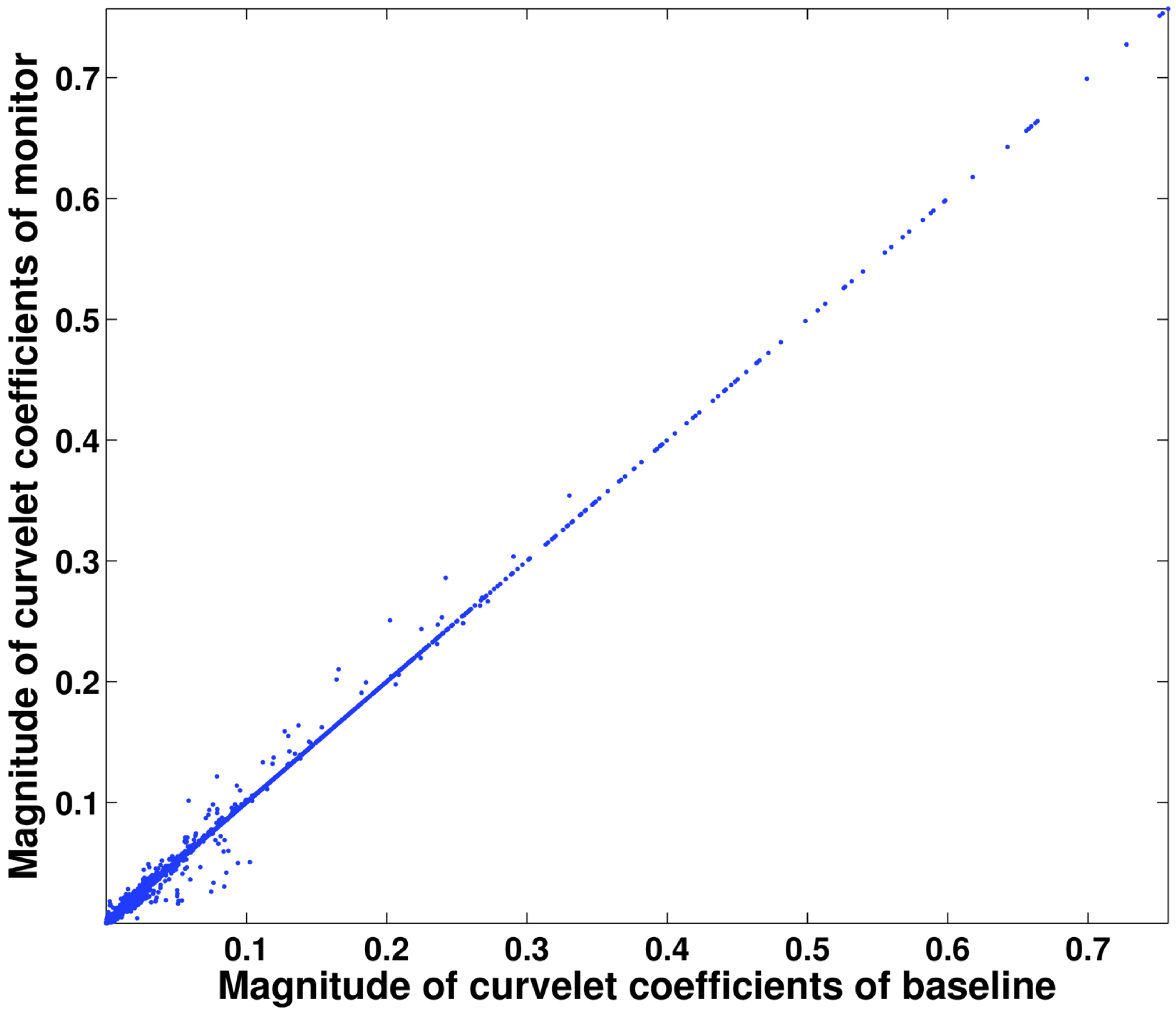
Probing time-lapse data ....

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



Structure - curvelet representation





Observations

- Compressible
  - few coefficients needed for reconstruction
- Correlations in different vintages
  -significant overlap along the diagonal
- Time-lapse signal
  -more compressible

Can we exploit the structure in the time-lapse data simultaneously ?

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Distributed compressive sensing
– *joint* recovery model (JRM)

vintages

$$\mathbf{x}_1 = \mathbf{z}_0 + \mathbf{z}_1$$
$$\mathbf{x}_2 = \mathbf{z}_0 + \mathbf{z}_2$$

differences

common component

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

baseline

monitor

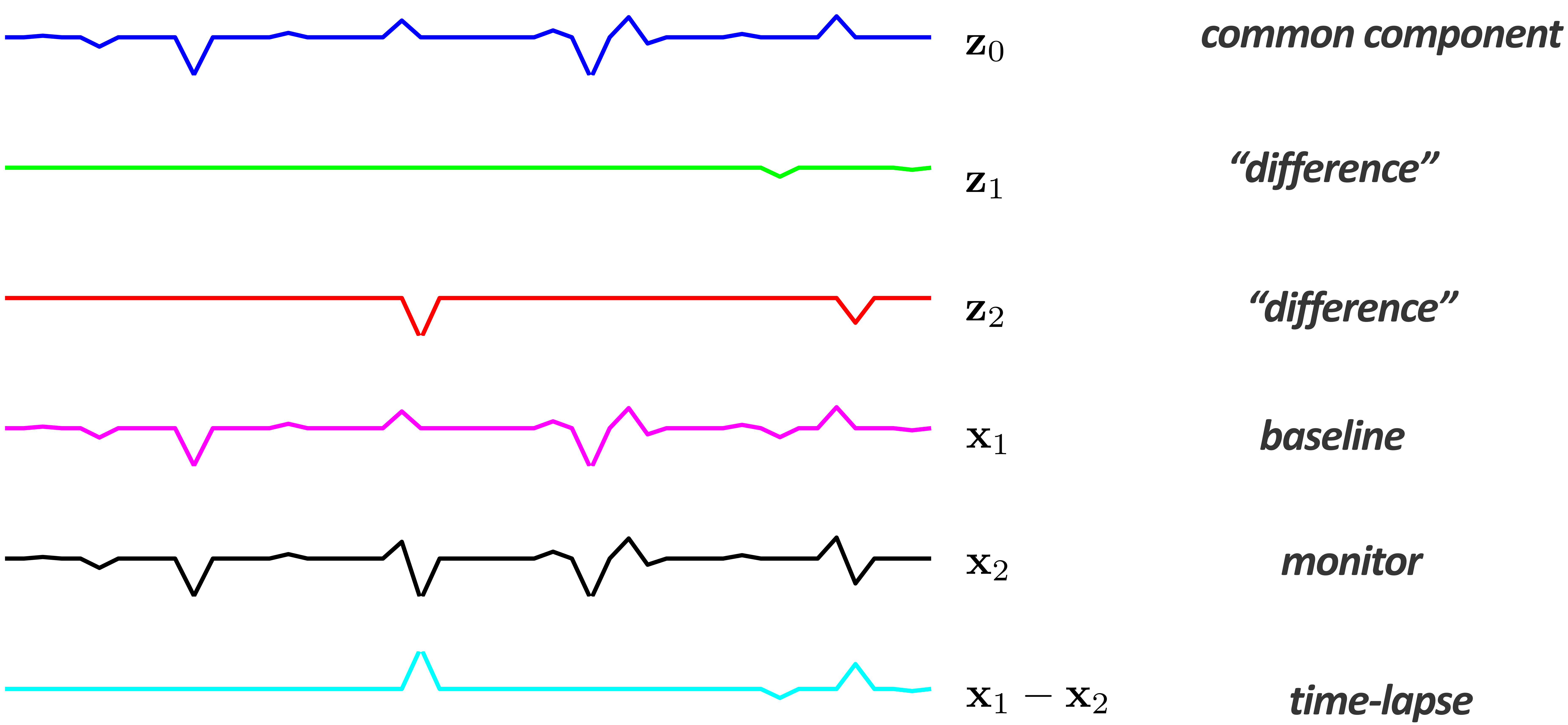
- **Key idea:**
  - use the fact that *different* vintages *share* common information
  - invert for *common* components & *differences* w.r.t. the *common* components with *sparse* recovery

Interpretation of the model
– w/ & w/o repetition

- **In an *ideal* world** $(\mathbf{A}_1 = \mathbf{A}_2)$
  - JRM *simplifies* to recovering the *difference* from $(\mathbf{b}_2 - \mathbf{b}_1) = \mathbf{A}_1(\mathbf{x}_2 - \mathbf{x}_1)$
  - expect *good* recovery when *difference* is *sparse*
  - ***but*** relies on "*exact*" repeatability...
- **In the *real* world** $(\mathbf{A}_1 \neq \mathbf{A}_2)$
  - no absolute *control* on *surveys*
  - *calibration* errors
  - noise...

Stylized examples

Sparse baseline, monitor and time-lapse signals



Signal length $N = 50$

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Stylized experiments

Conduct *many* CS experiments to compare

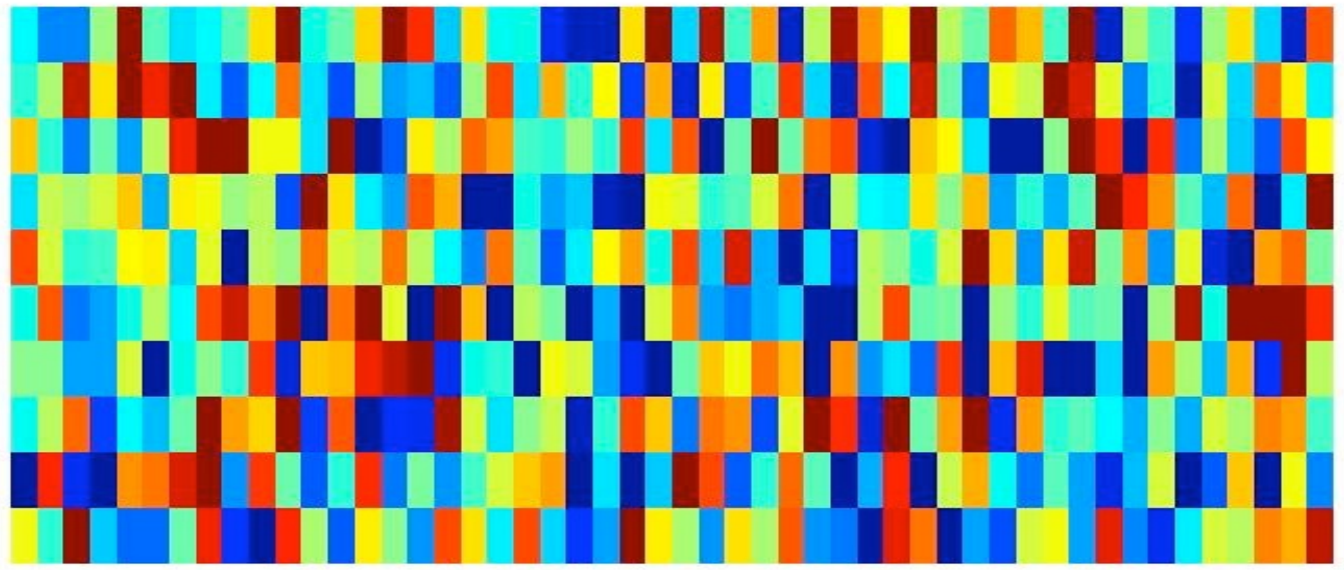
- *joint* vs *parallel* recovery of signals and the difference
- recovery with *completely* independent $\mathbf{A}_1,\ \mathbf{A}_2$
- *random* acquisition with different numbers of samples

Stylized experiments

Conduct *many* CS experiments to compare

- *joint* vs *parallel* recovery of signals and the difference
- recovery with *completely* independent $\mathbf{A}_1, \ \mathbf{A}_2$
- *random* acquisition with different numbers of samples

$\mathbf{A}_1$



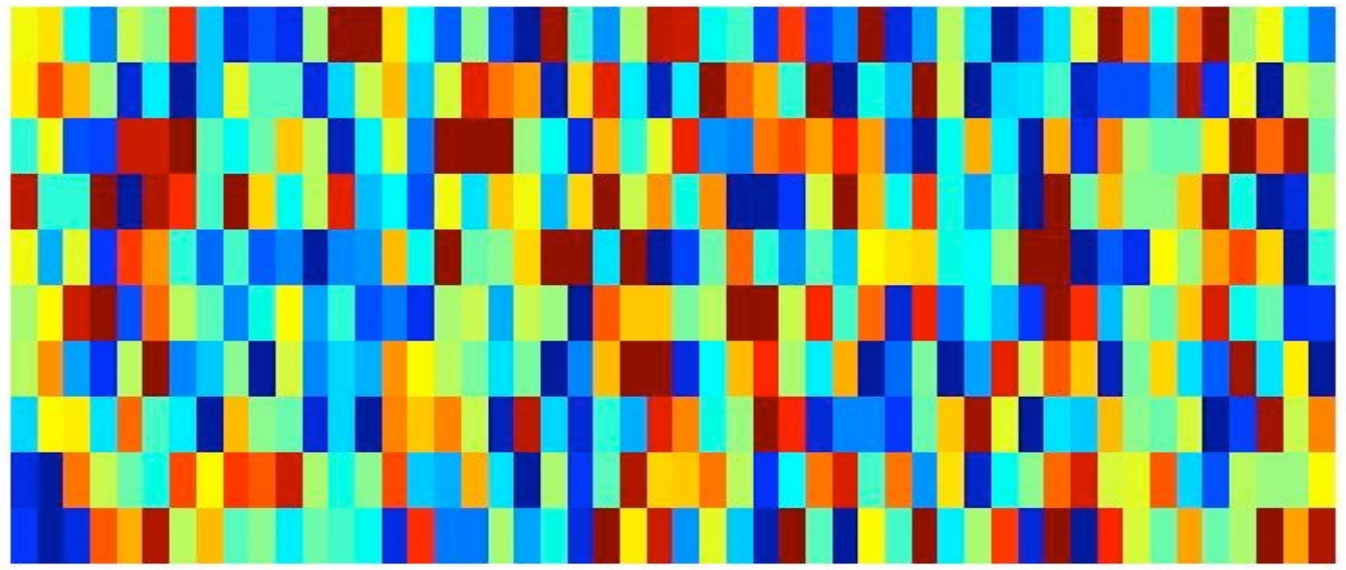
n

N

$\mathbf{b}_1 = \mathbf{A}_1\mathbf{x}_1$

$\mathrm{n} = 10$

$\mathbf{A}_2$



n

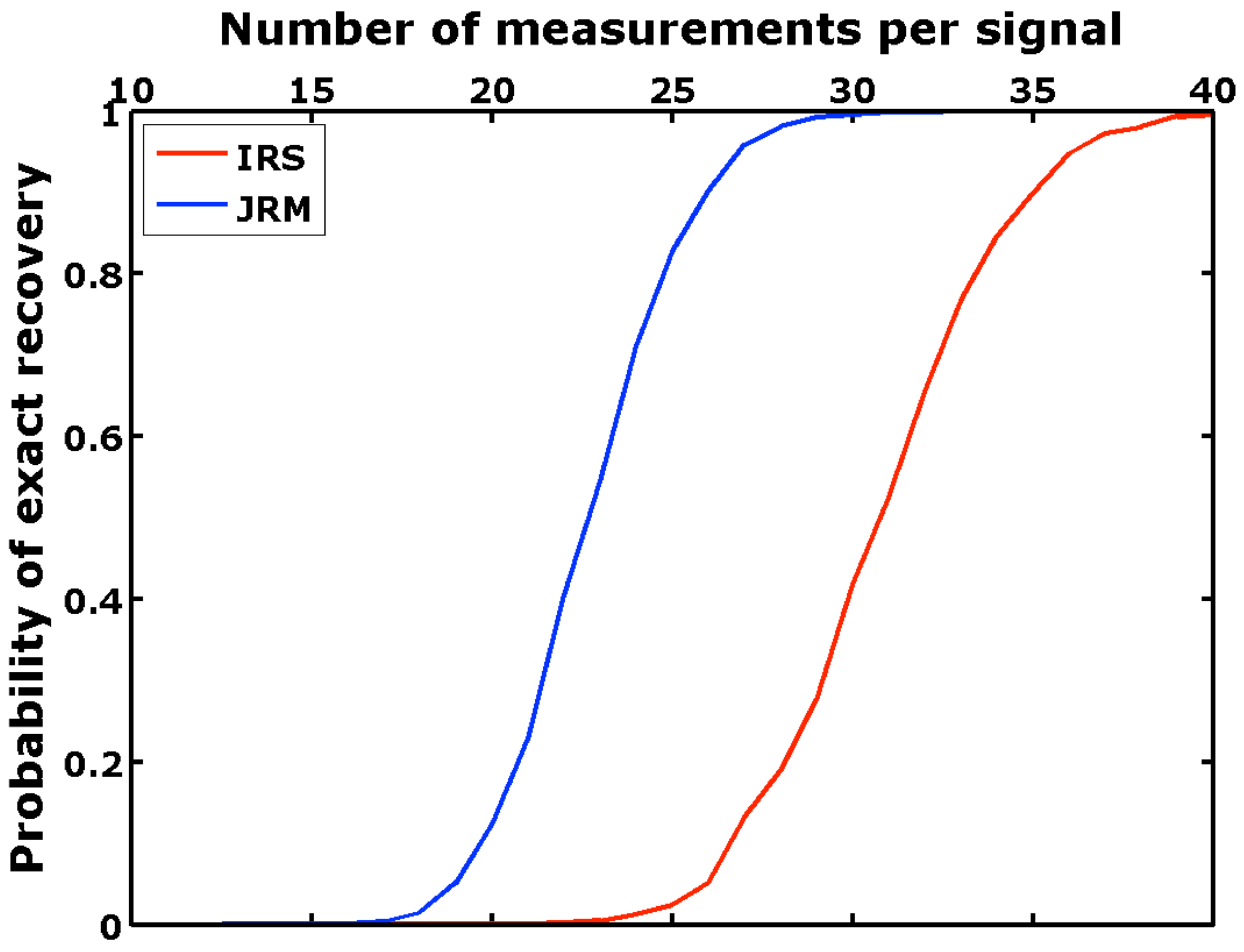
N

$\mathbf{b}_2 = \mathbf{A}_2\mathbf{x}_2$

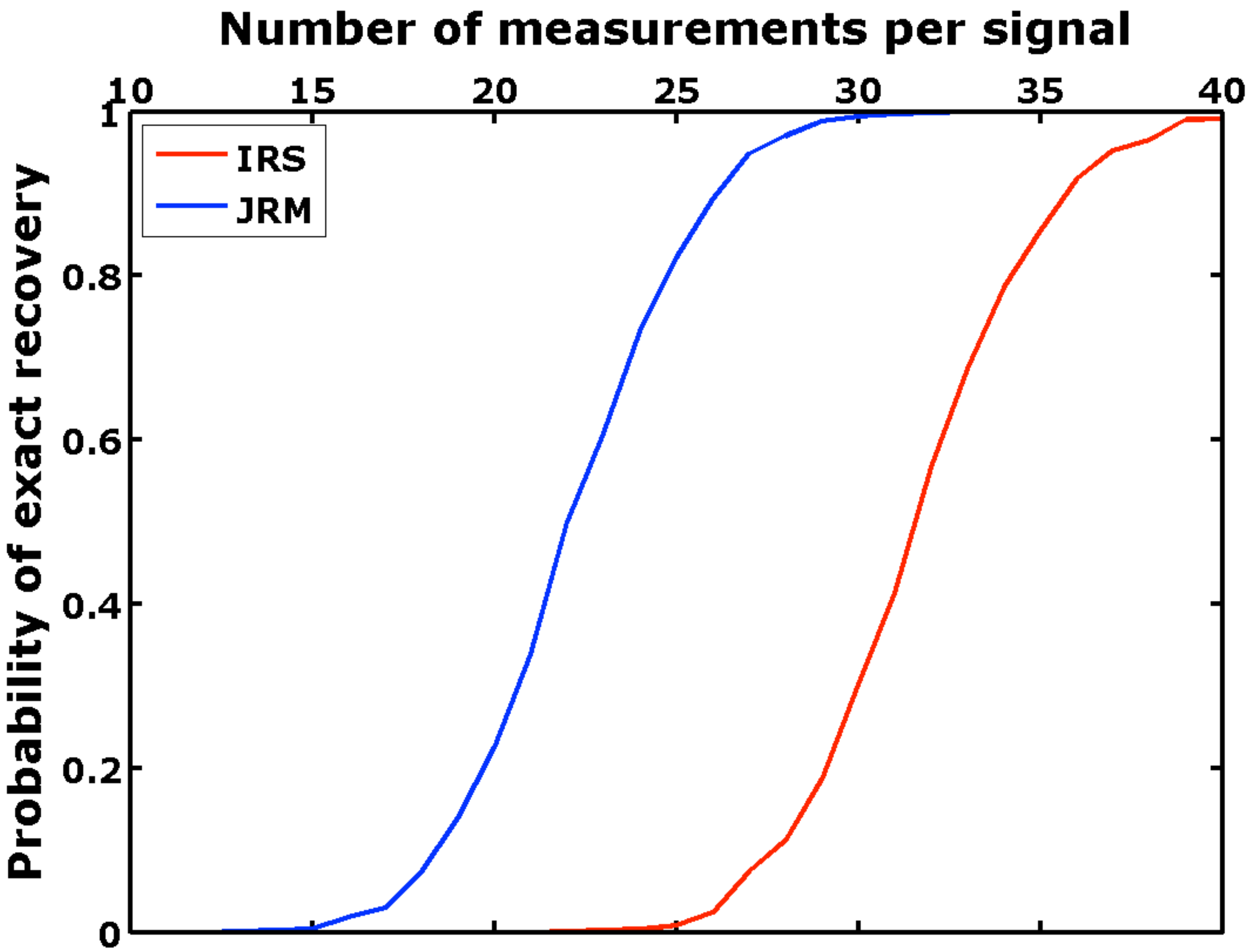
Run 2000 different experiments

Compute Probability of recovery

Results: *independent* versus *joint* recovery



Recovery of vintages



Recovery of difference

Observations

- Joint recovery (processing) is better than independent processing
- Improved recovery of vintages and difference
- Requires fewer samples (subsampled data)

Application to imaging

- credit to Ning Tu

Ning Tu and Felix J. Herrmann, "**Fast imaging with surface related multiples by sparse inversion**", *Geophysical Journal International*, vol. 201, p. 304-317, 2014.

Felix J. Herrmann and Xiang Li, "**Efficient least-squares imaging with sparsity promotion and compressive sensing**", *Geophysical Prospecting*, vol. 60, p. 696-712, 2012.

Migration

Problem formulation

$$\tilde{\mathbf{x}} = \arg\min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{subject to} \quad \|\mathbf{A}\mathbf{x} - \mathbf{b}\|_2 \leq \sigma$$

where

$$\mathbf{A} = \overbrace{\nabla \mathrm{F}[\mathbf{m}_0, q]}^{\textbf{Linearized Demigration operator}} \mathbf{C}^H$$

$$\mathbf{b} = \delta \mathbf{d}$$

$$\delta \tilde{\mathbf{m}} = \mathbf{C}^H \tilde{\mathbf{x}}$$

Migration

Dimensionality reduction

$$\tilde{\mathbf{x}} = \arg\min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{subject to} \quad \|\underline{\mathbf{A}}\mathbf{x} - \underline{\mathbf{b}}\|_2 \leq \sigma_k$$

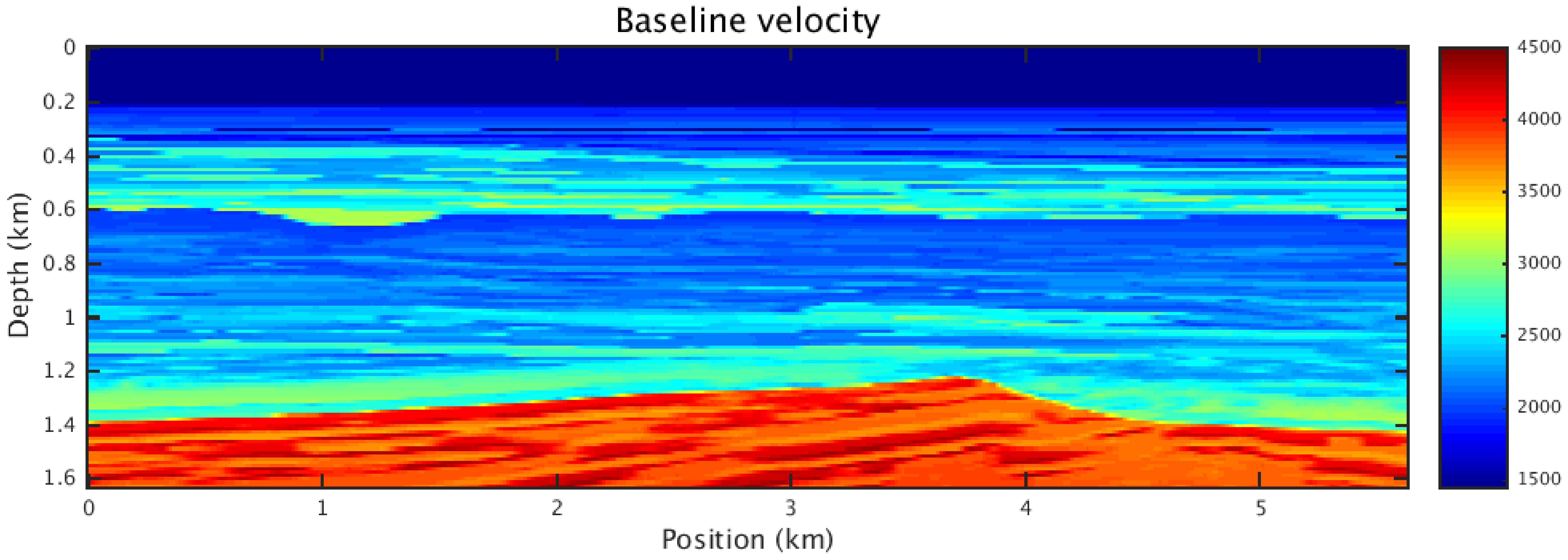
where

$$\underline{\mathbf{A}} = \mathrm{RM}\mathbf{A}$$

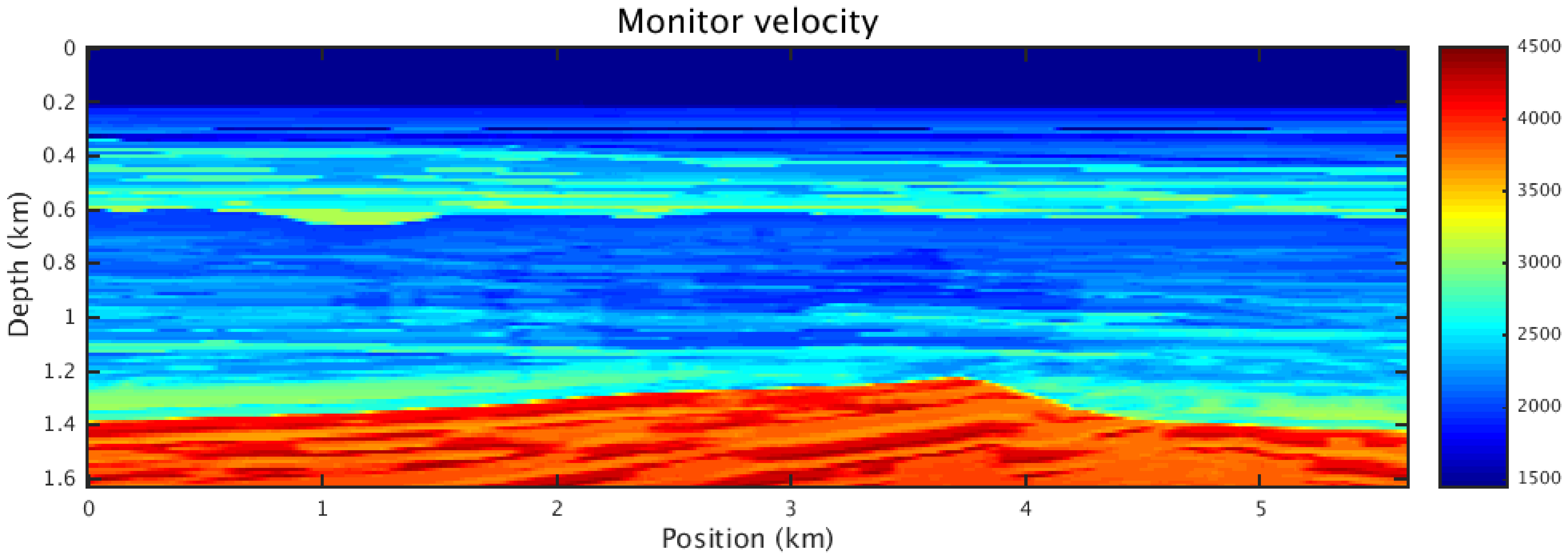
$$\underline{\mathbf{b}} = \mathrm{RM}\mathbf{b}$$

$$\delta\tilde{\mathbf{m}} = \mathbf{C}^H\tilde{\mathbf{x}}$$

Model

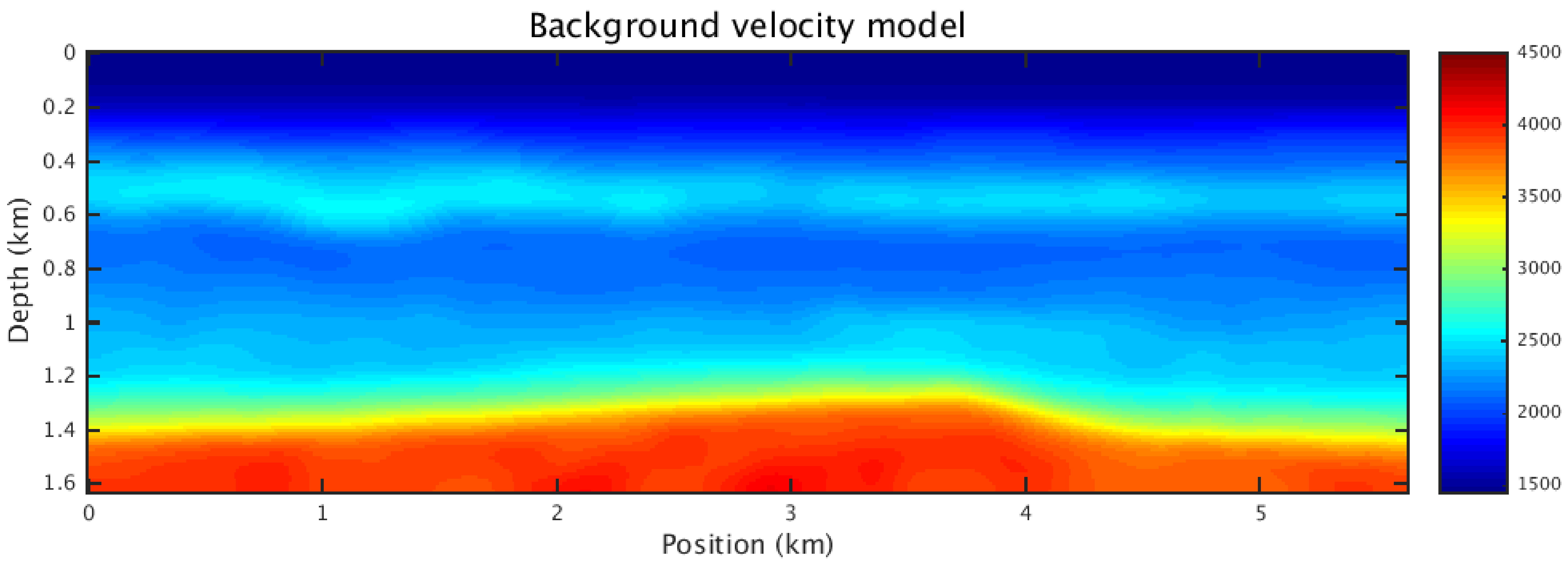


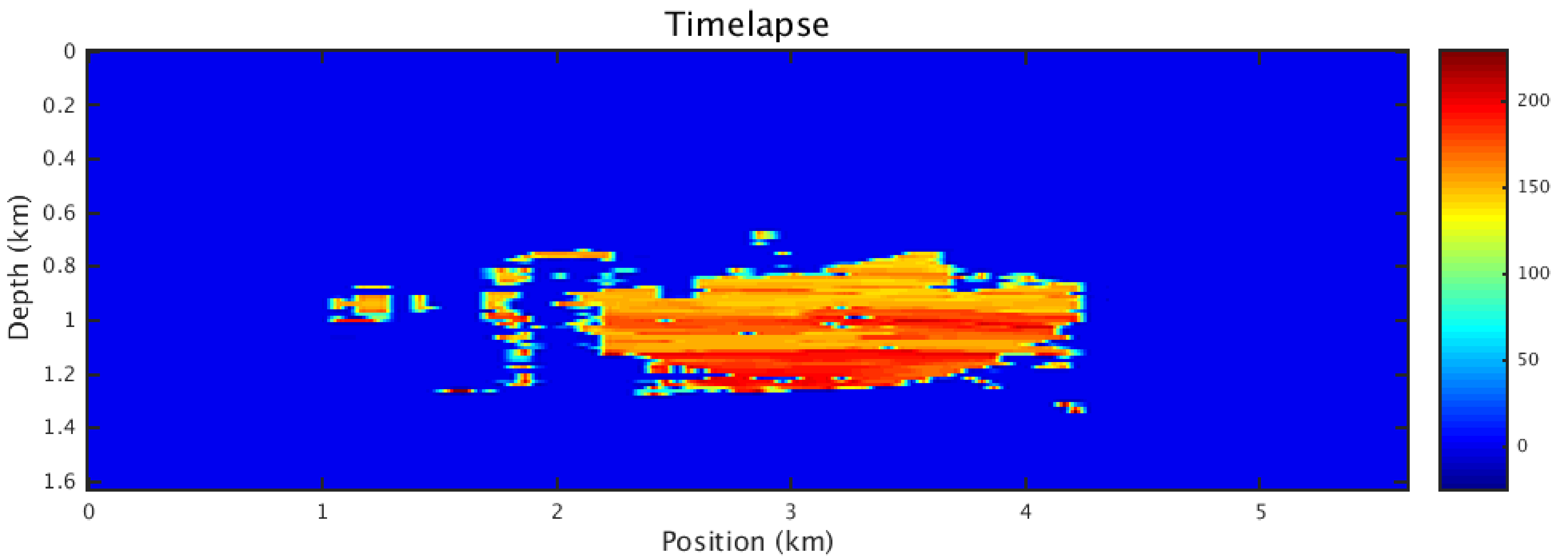
Baseline velocity
Depth (km)
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
0
1
2
3
4
5
Position (km)
4500
4000
3500
3000
2500
2000
1500



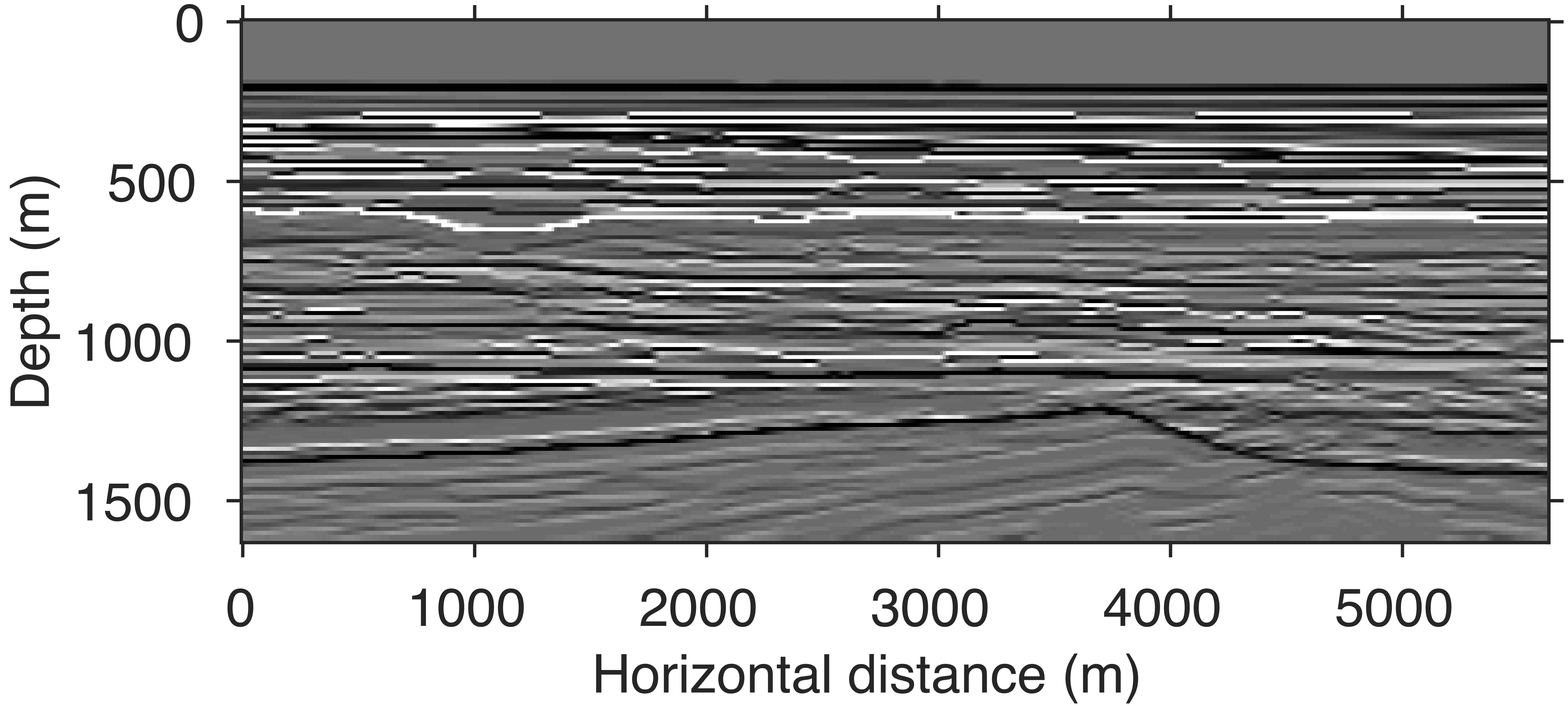
Monitor velocity
Depth (km)
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
0
1
2
3
4
5
Position (km)
4500
4000
3500
3000
2500
2000
1500

Initial/Difference

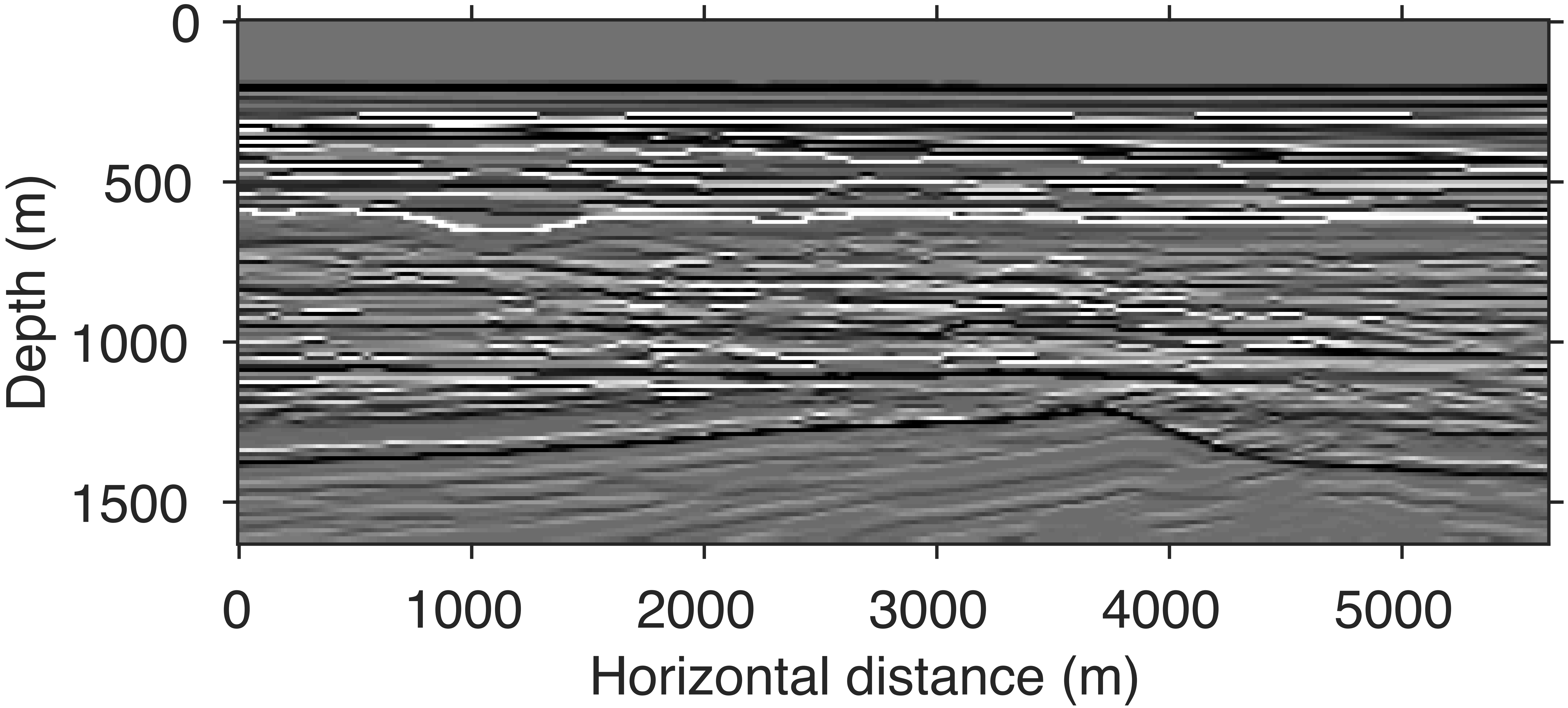




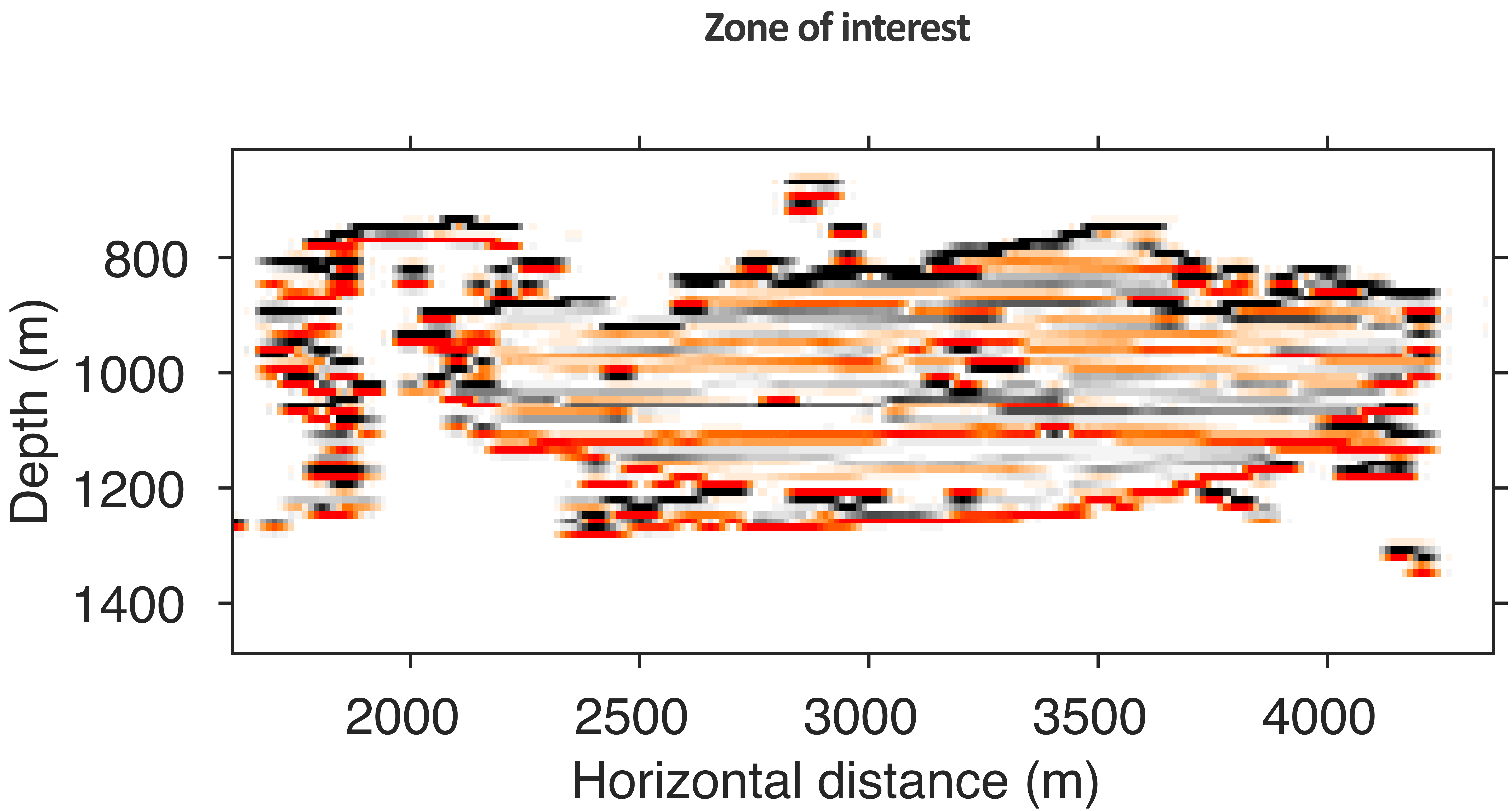
Baseline perturbation



Monitor perturbation



Time-lapse reflectivity



Migration

Modeling parameters

- 225 shots @ approx. 25m interval
- 225 receivers @ approx. 25m interval
- 120 frequencies between 5 & 35Hz for imaging
- Shot records of 4seconds
- Ricker wavelet @ 20.0Hz
- Baseline & Monitor with “different” source/receiver positions

Objective

- Imaging of baseline/monitor
- Observe and interpret changes in reflectivity
- Compare independent (IRS) and the joint method (JRM)

Migration

Use 15 randomly selected sources and all the frequencies

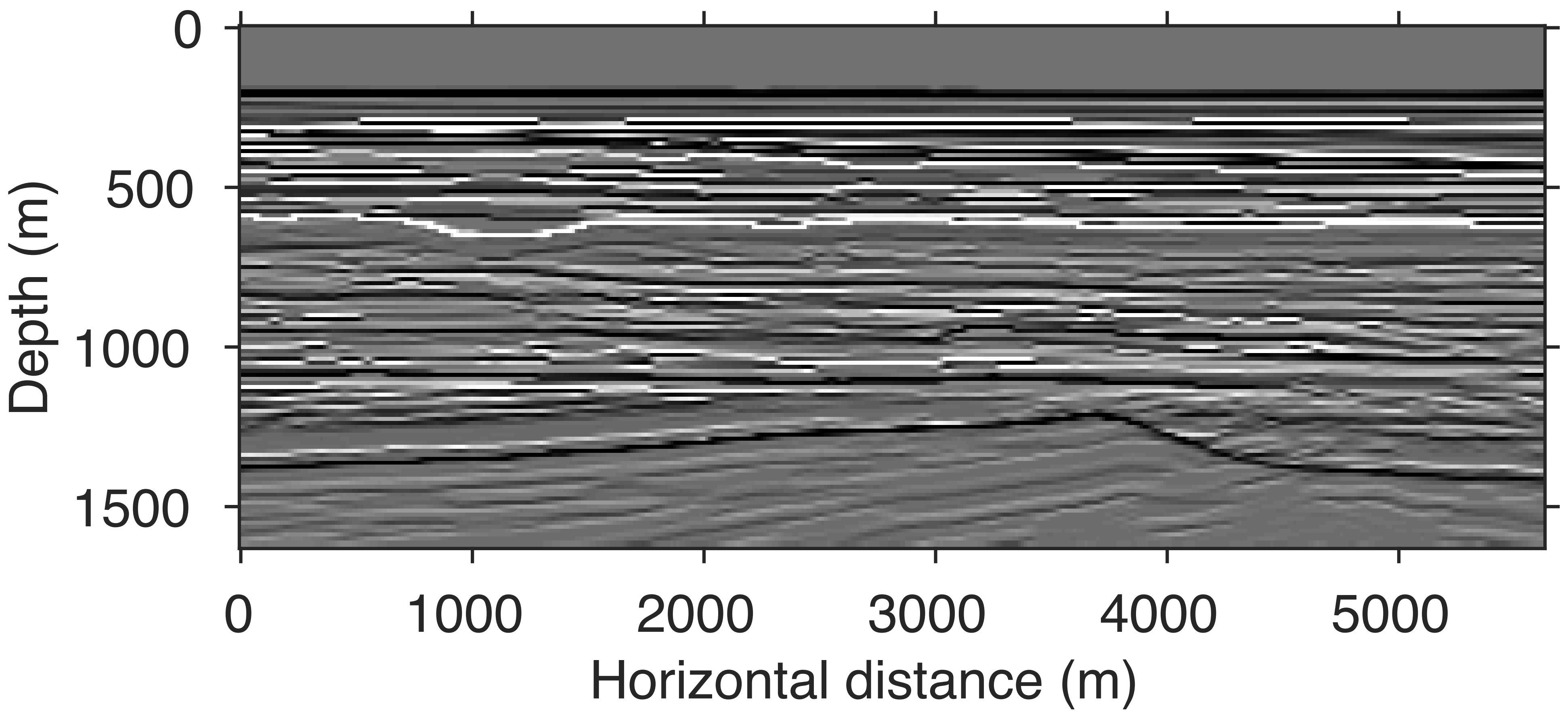
(1) Conventional RTM with data

(2) Least squares RTM

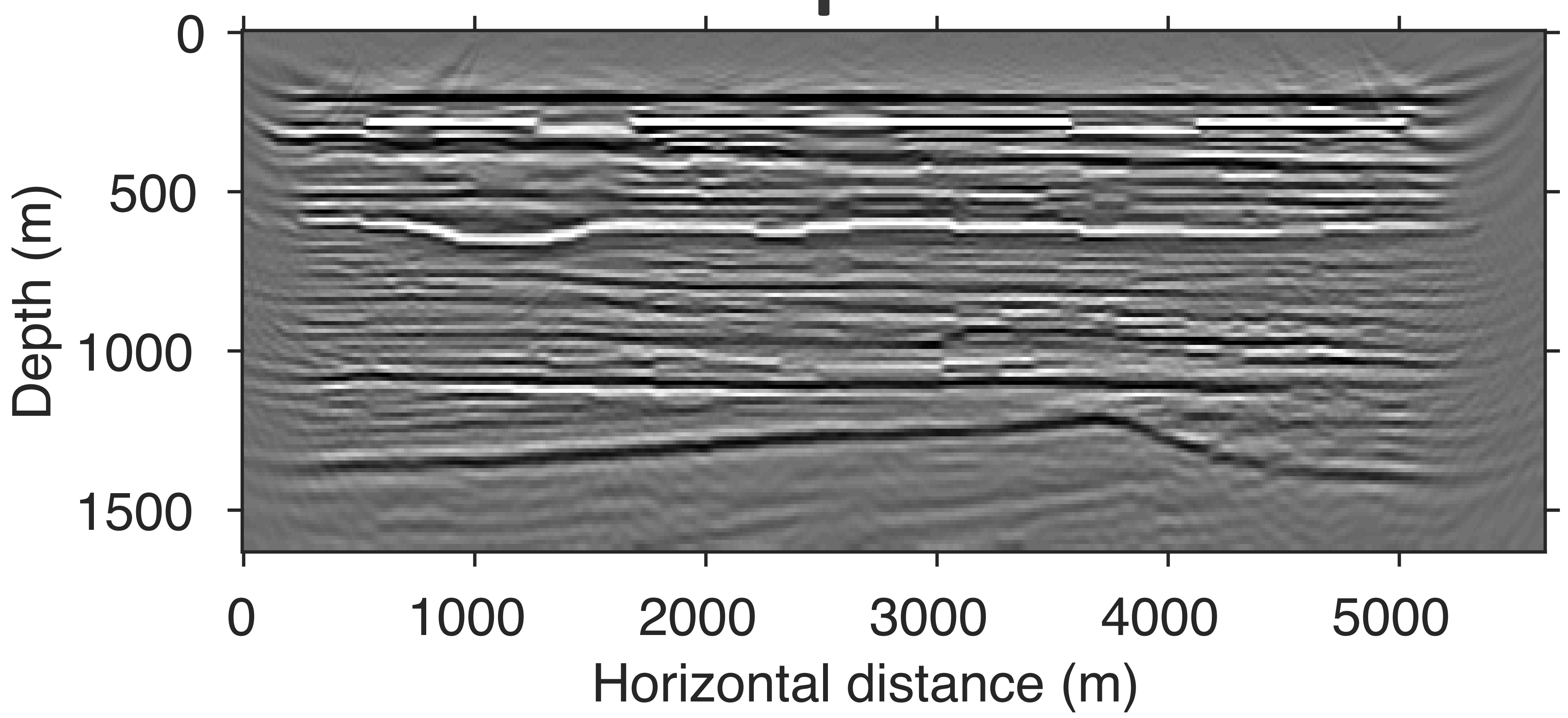
- Randomly select 15 sources and 16 frequencies at each iteration
- No renewal of sources, but frequency redraw at each iteration
- Exploit sparsity (in curvelet domain) of reflectivity
- Ricker wavelet @ 20Hz
- Fairly accurate background velocity model

Baseline Image

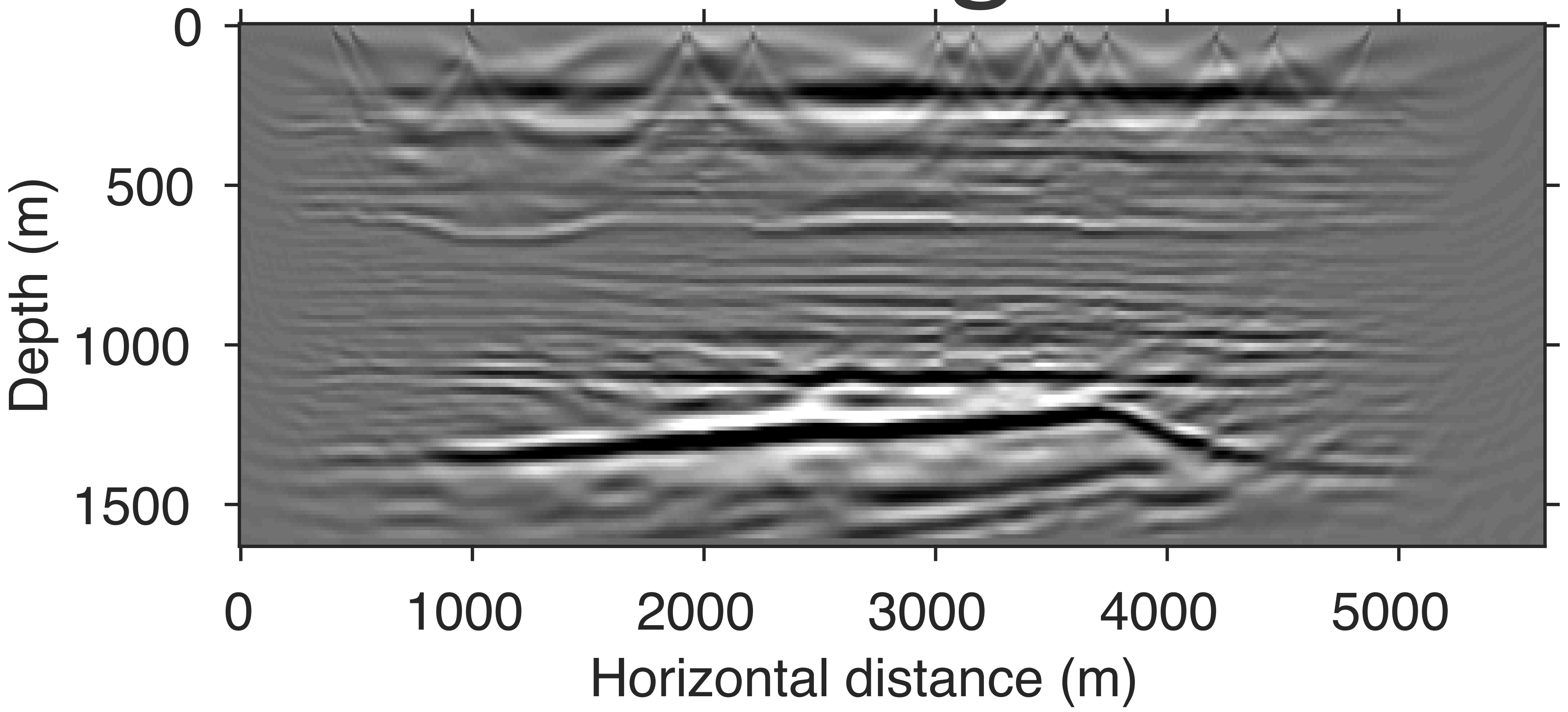
Baseline Image



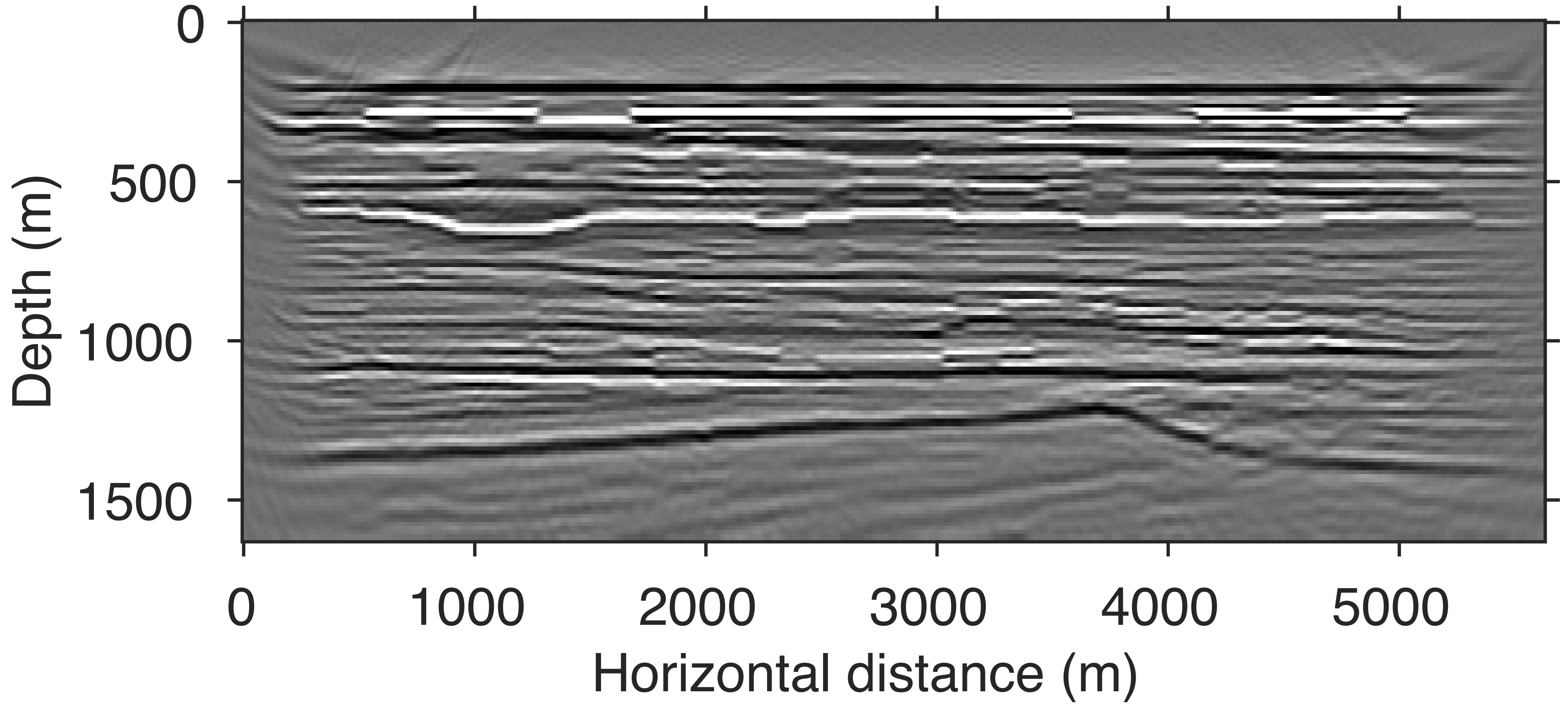
Indept. LSM



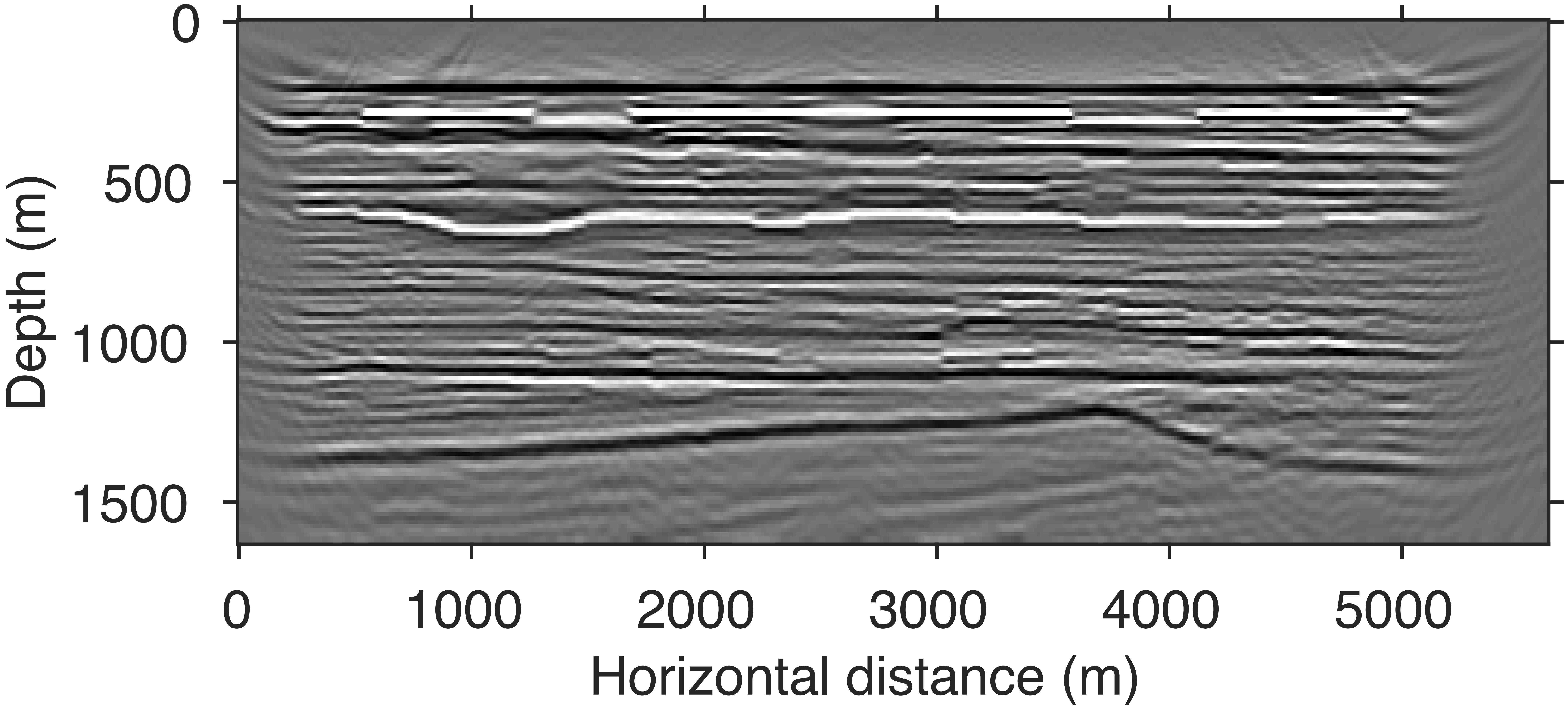
RTM Image



Joint LSM

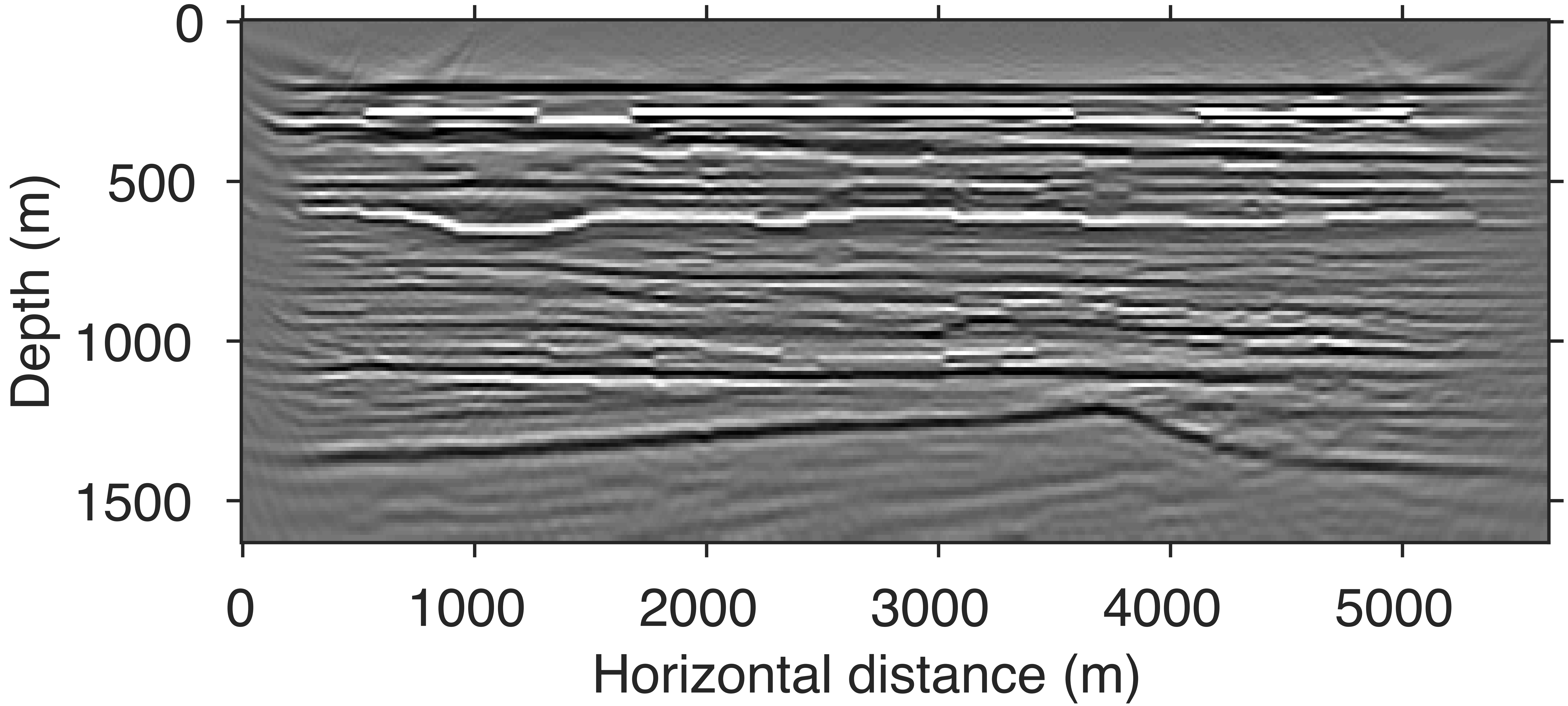


Baseline Image



Independent
LSM

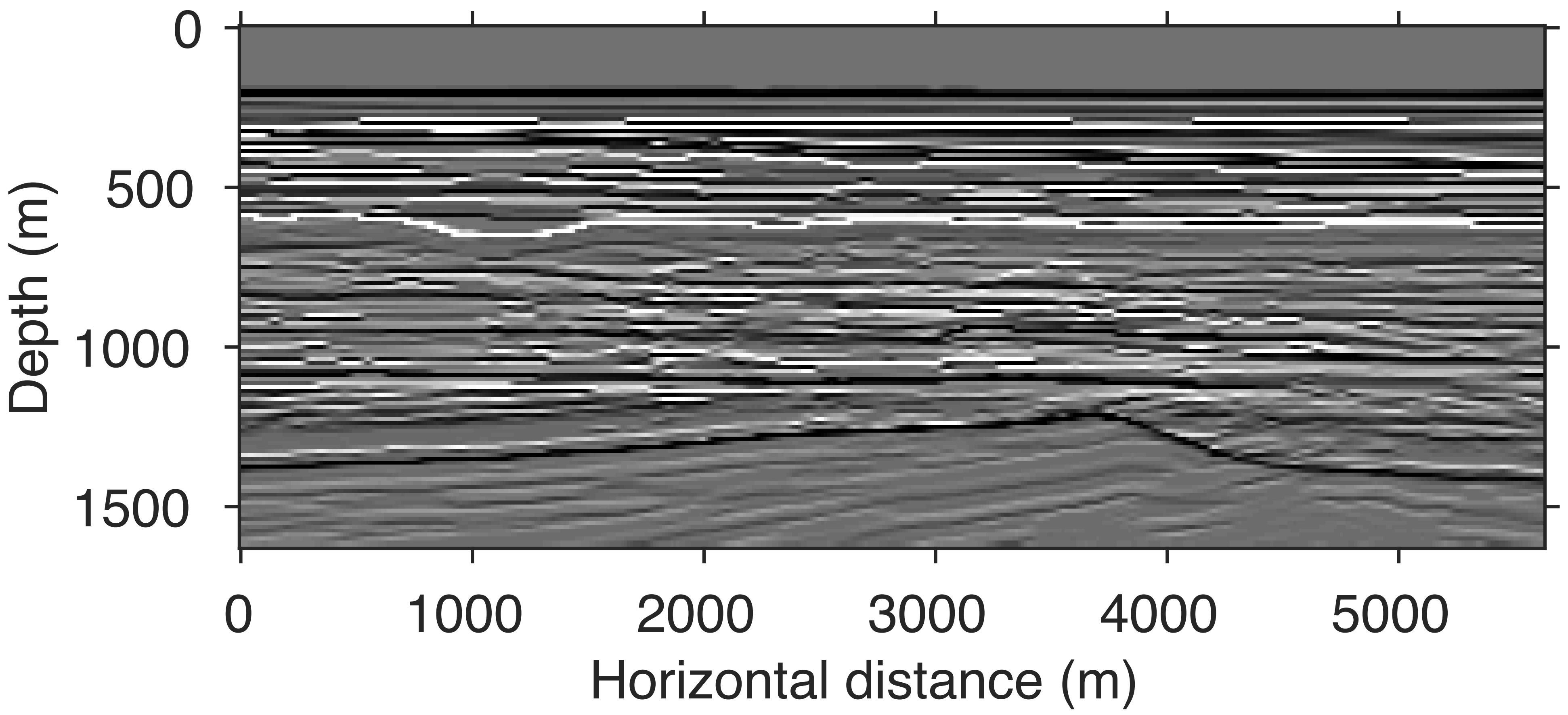
Baseline Image



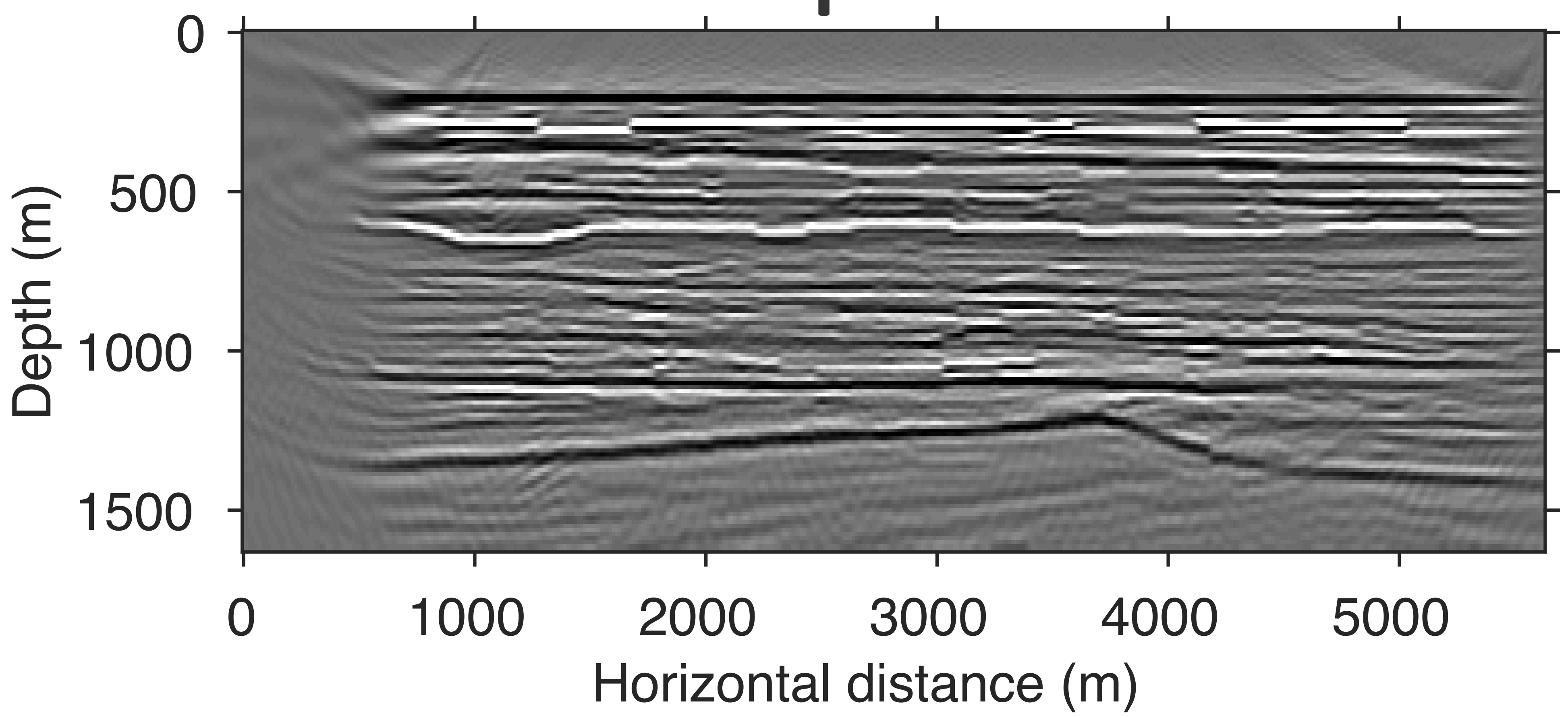
Joint
LSM

Monitor Image

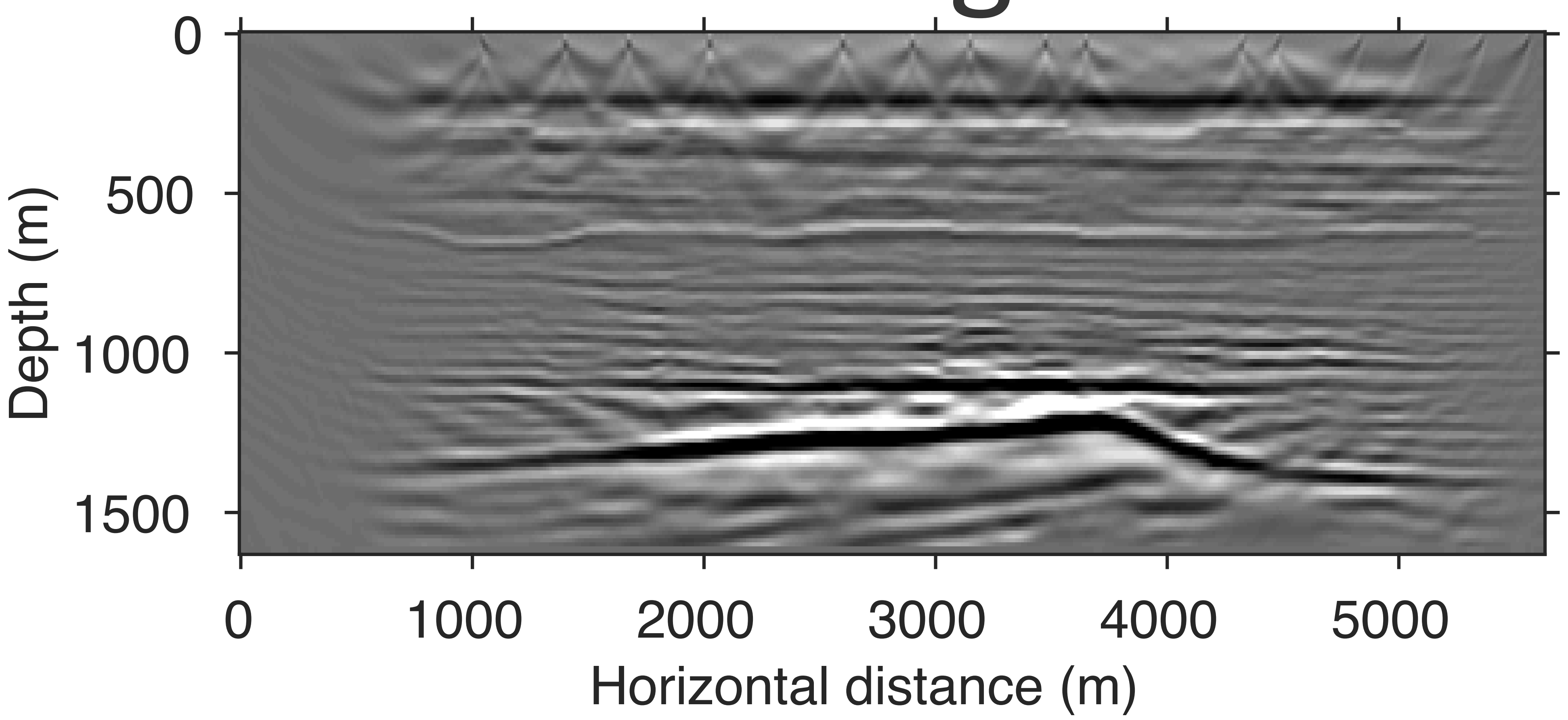
Monitor Image



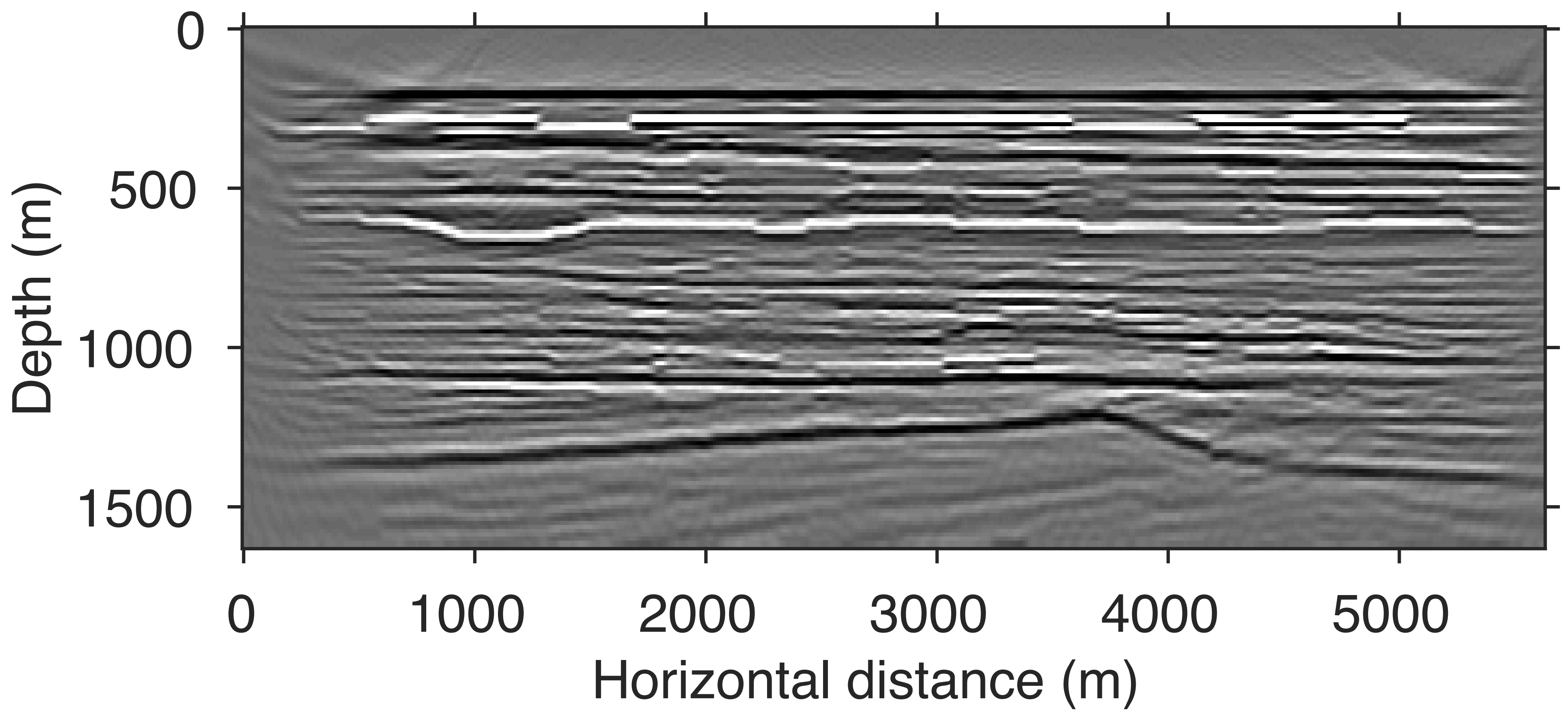
Indept. LSM



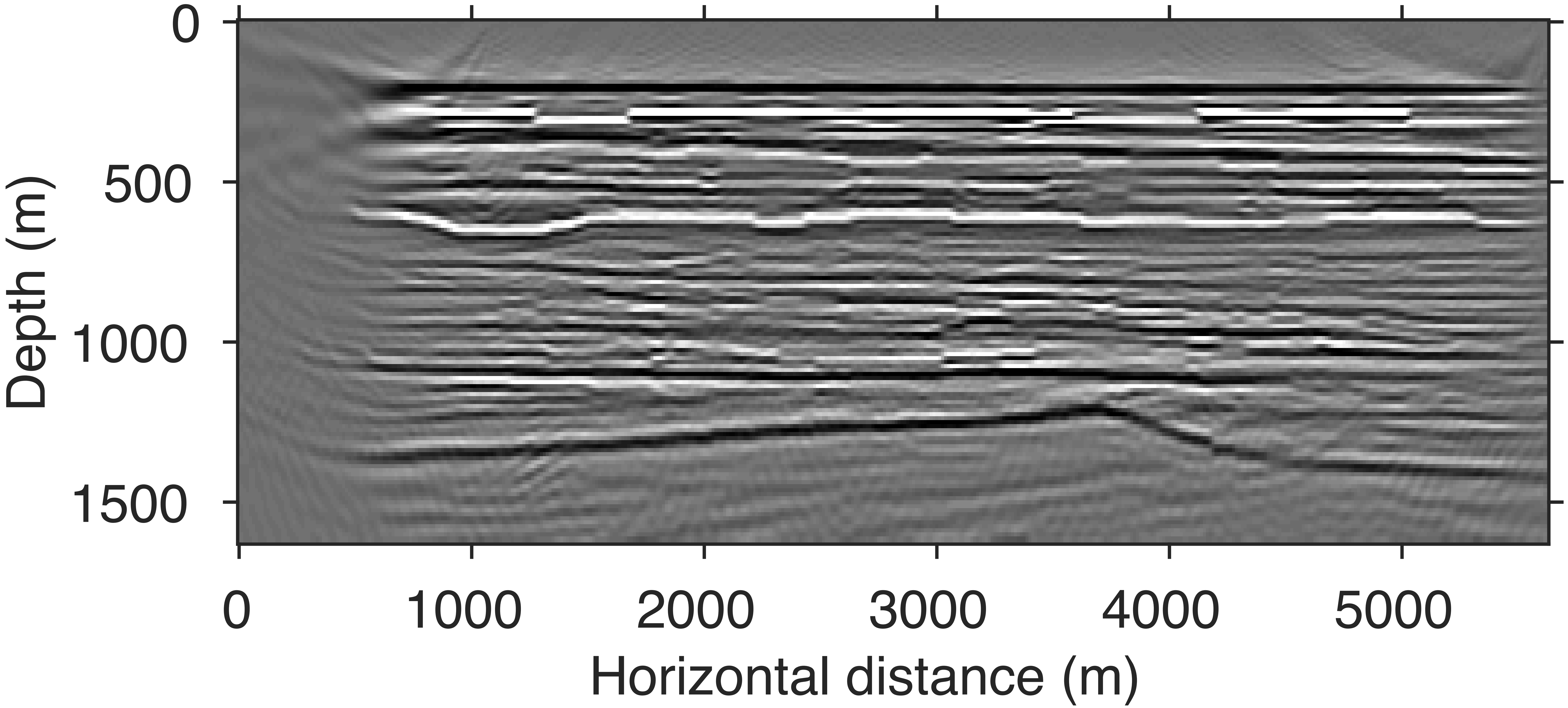
RTM Image



Joint LSM

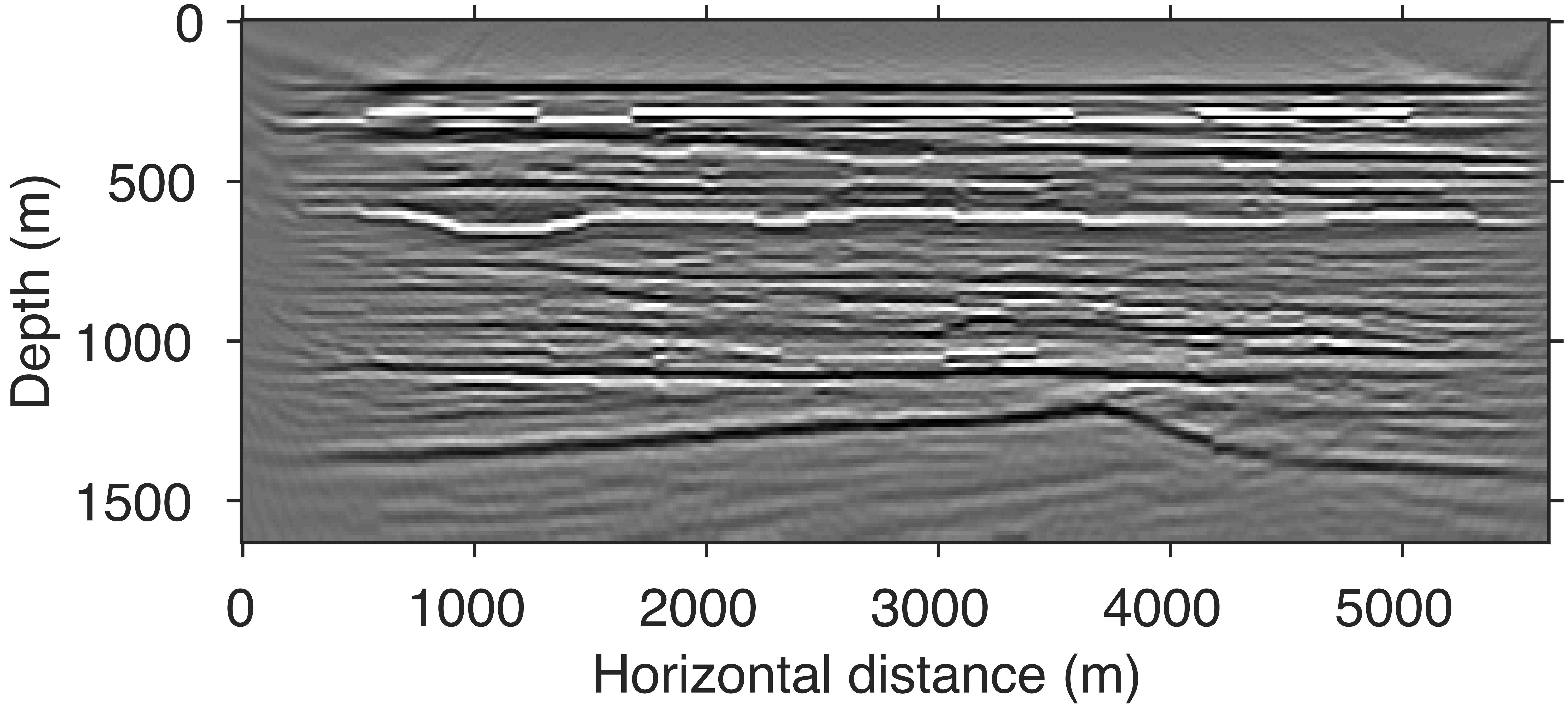


Monitor Image



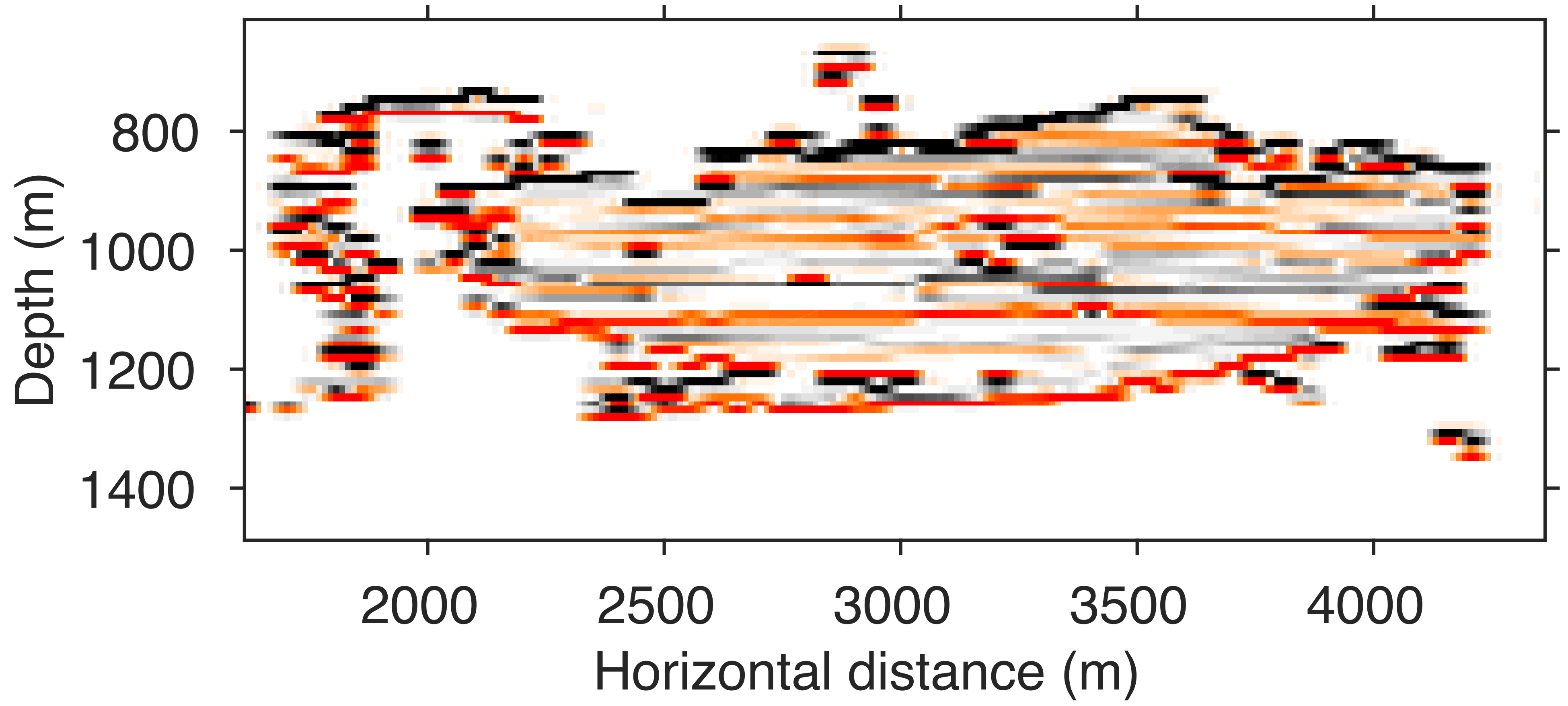
Independent LSM

Monitor Image

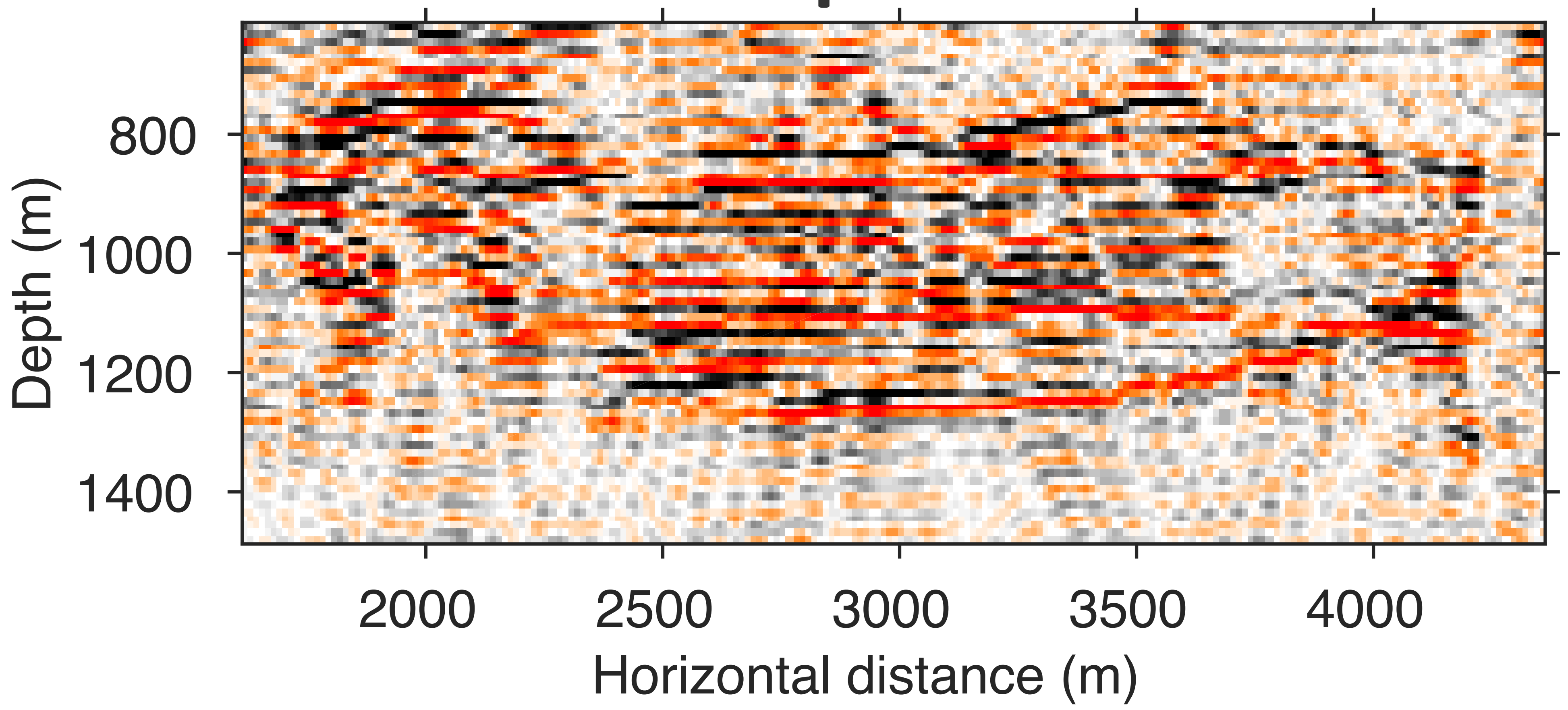


Joint
LSM

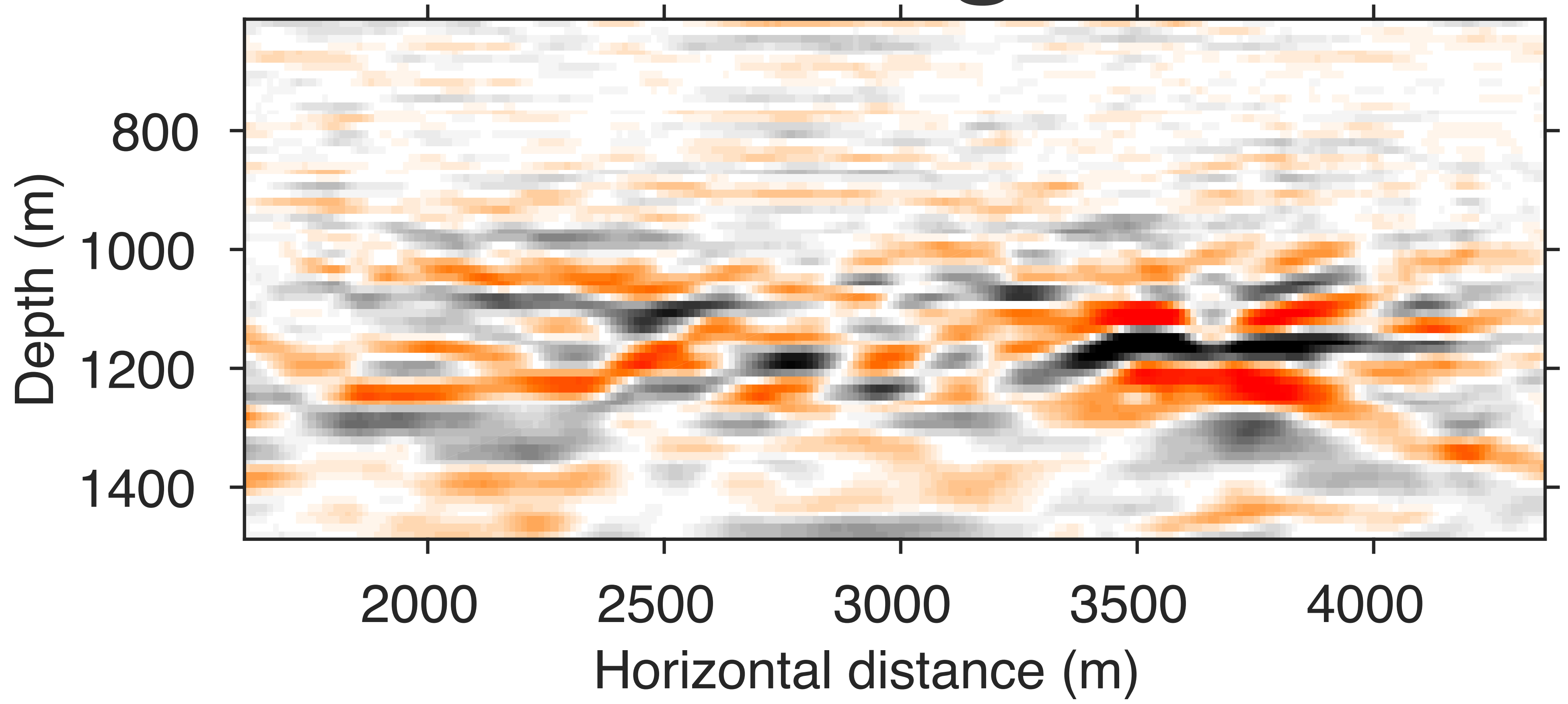
Time-lapse Image



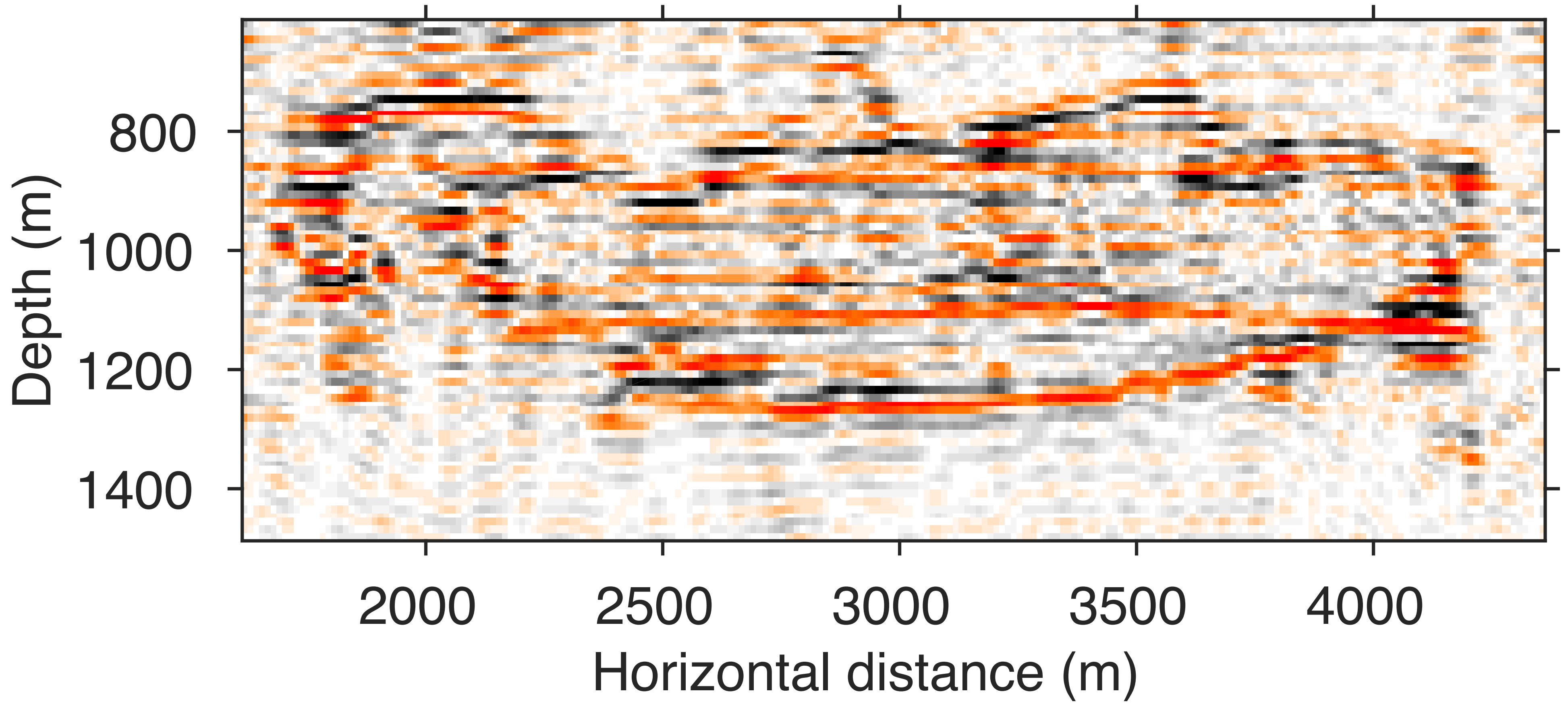
Indept. LSM



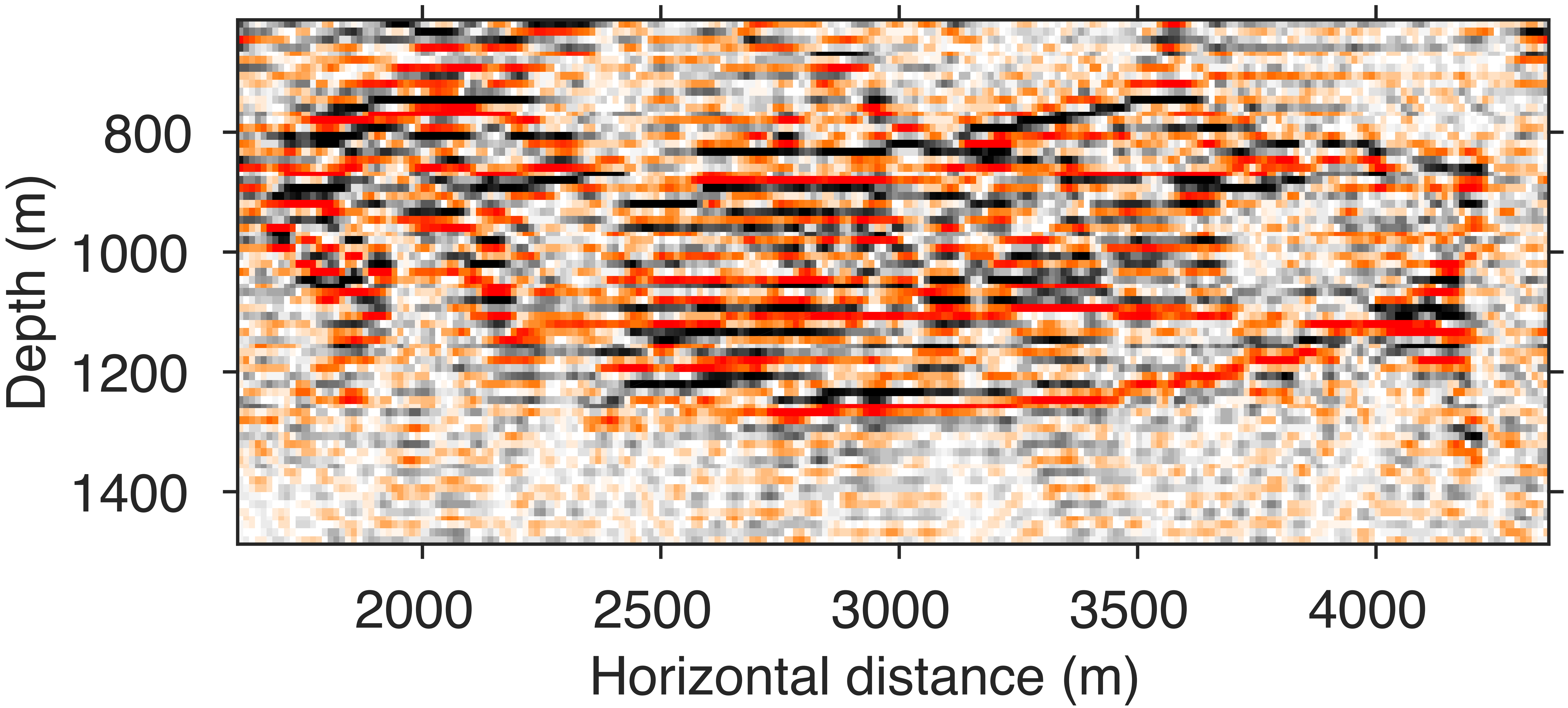
RTM Image



Joint LSM

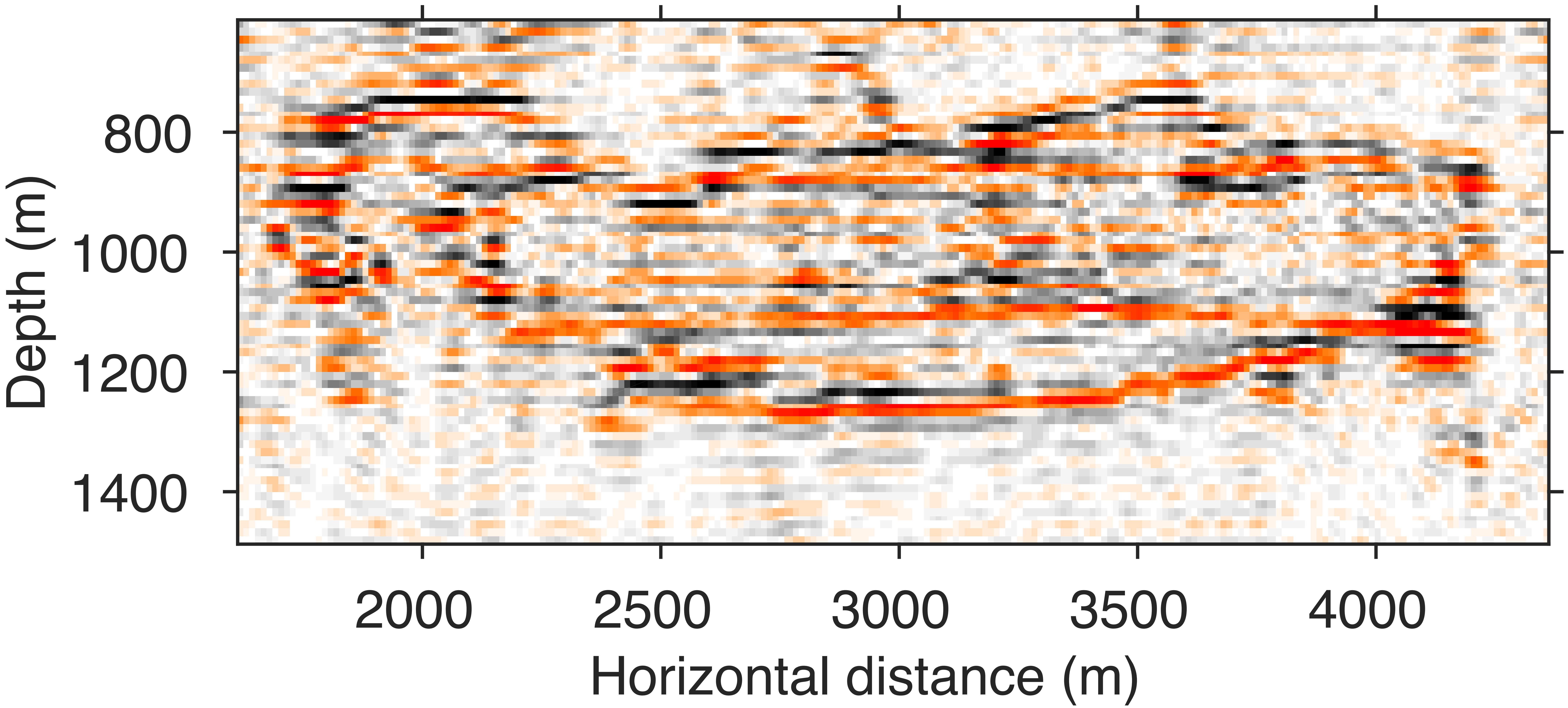


Time-lapse Image



Independent LSM

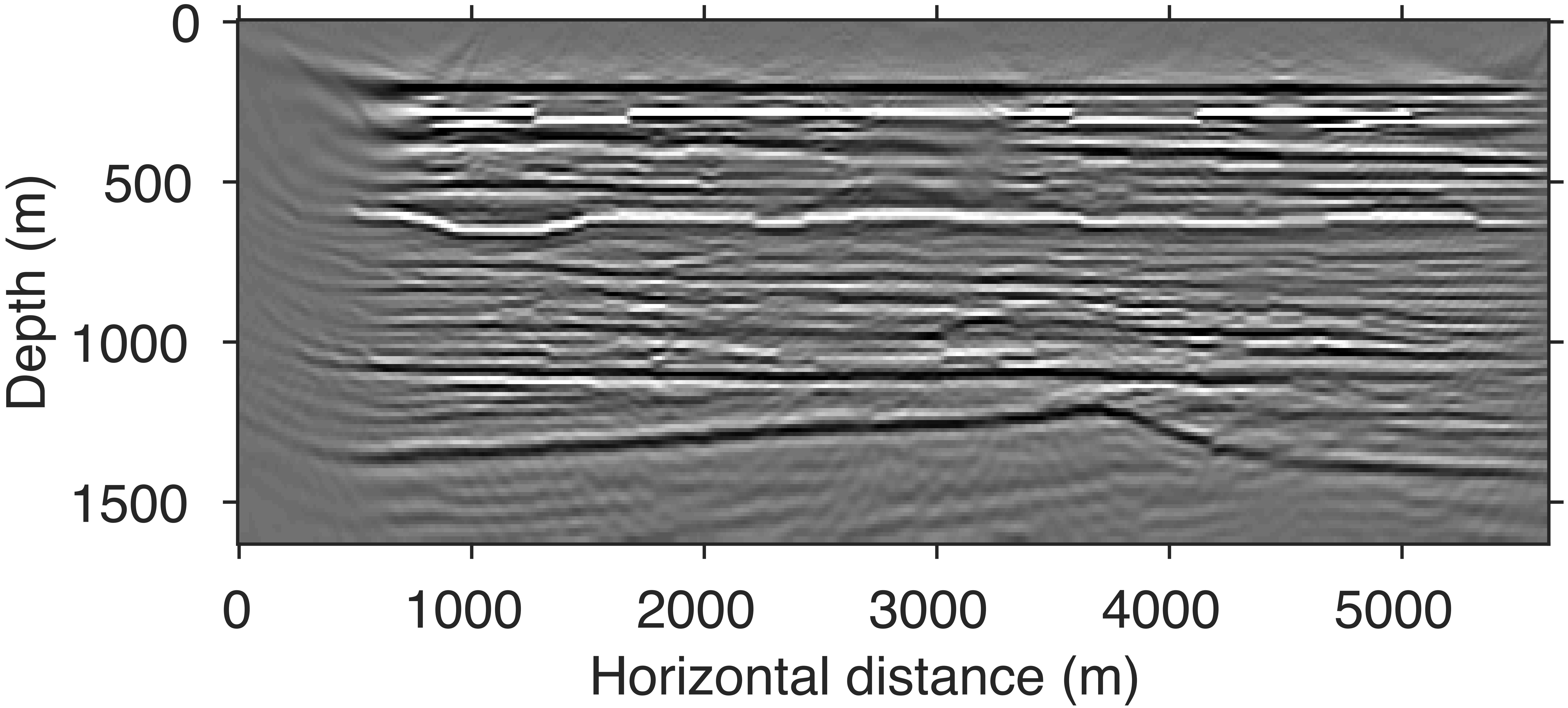
Time-lapse Image



Joint LSM

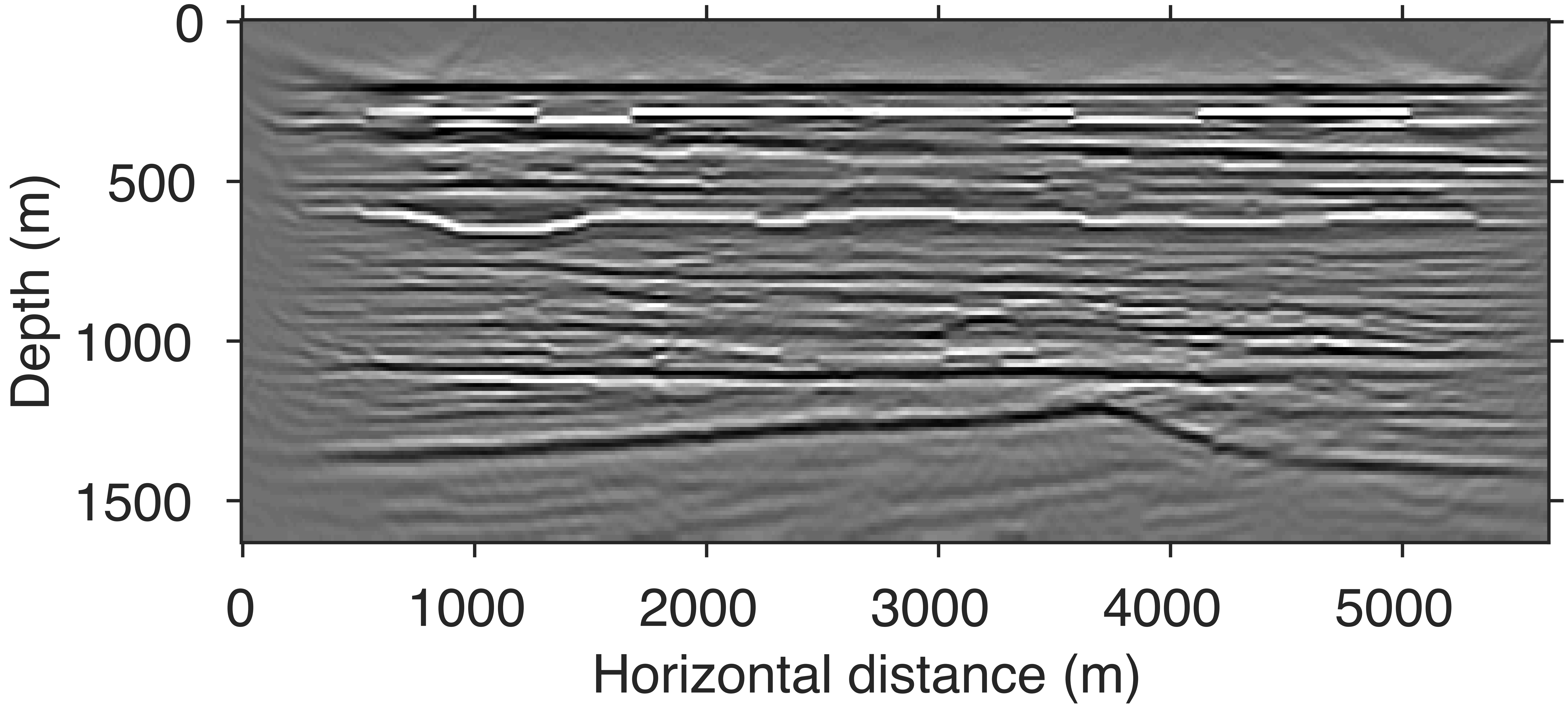
What happens when there is a gap in the monitor data?
How do we deal with the acquisition footprint?

Inversion results with 500m gap



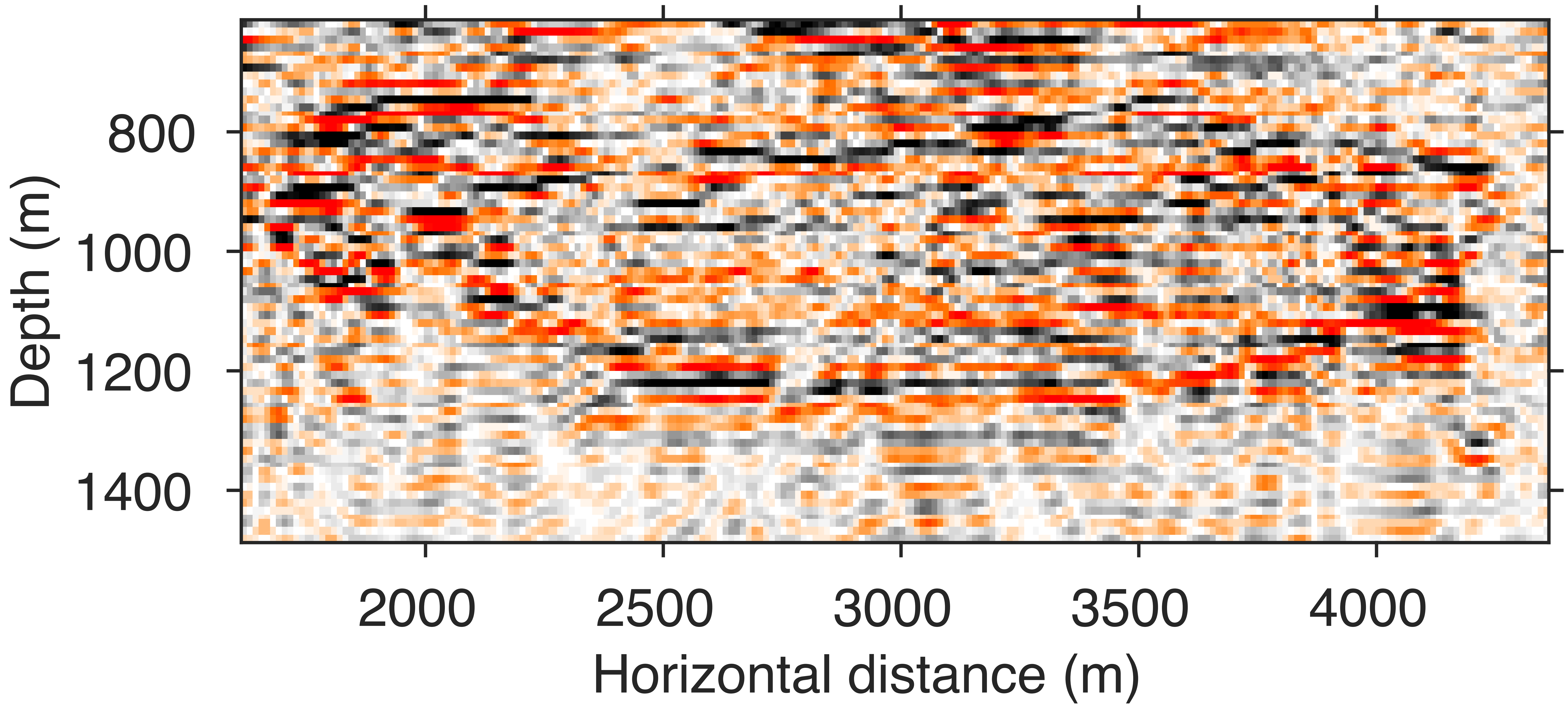
Independent LSM

Inversion results with 500m gap



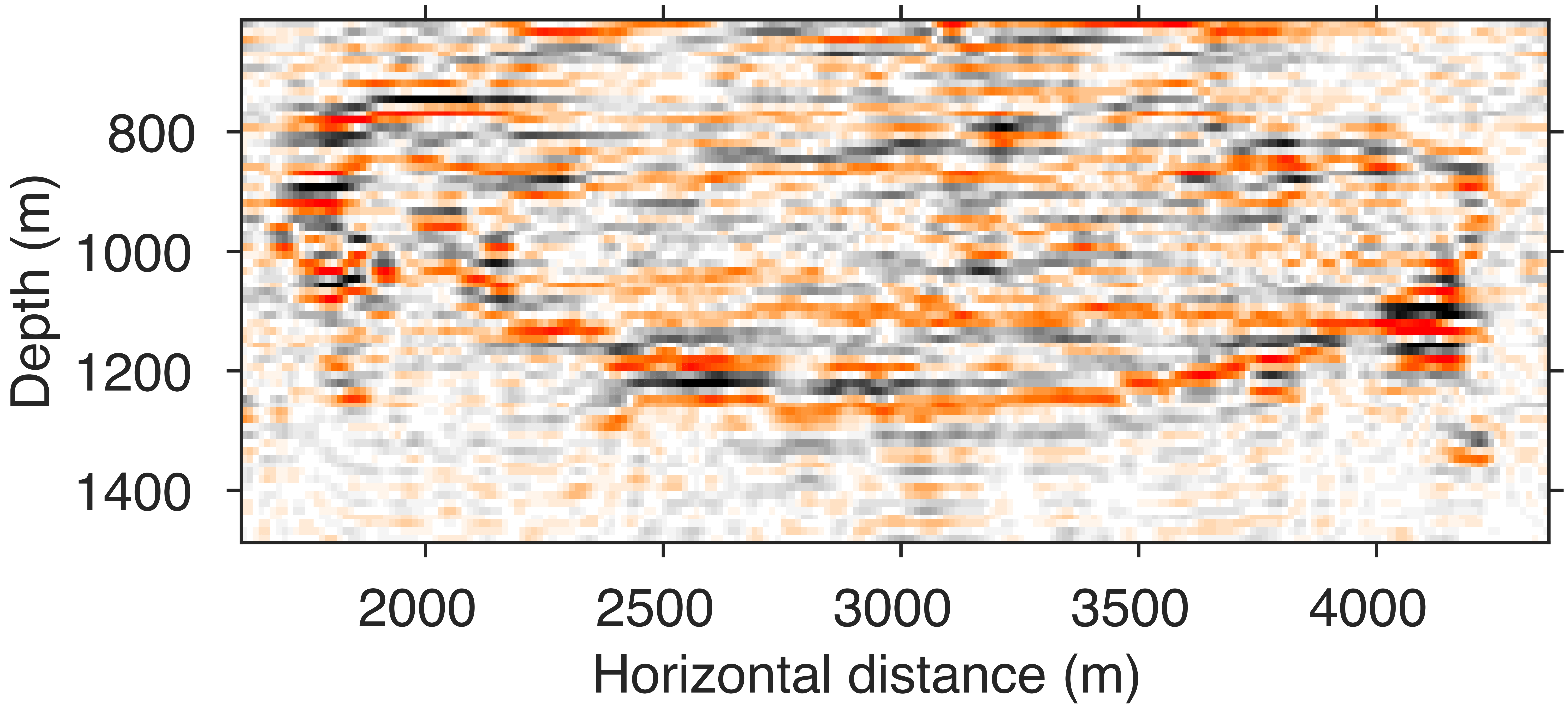
Joint
LSM

Inversion results with 500m gap



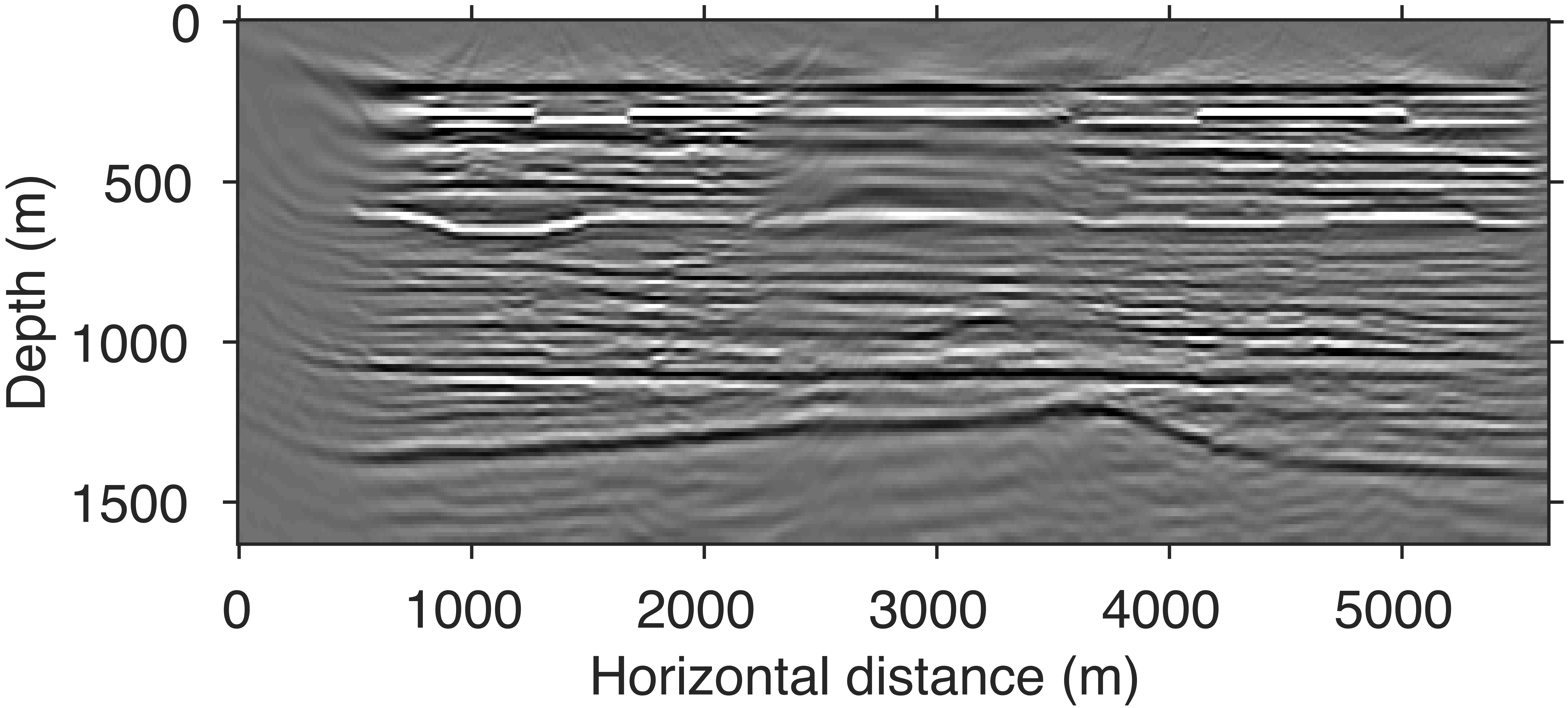
Independent LSM

Inversion results with 500m gap



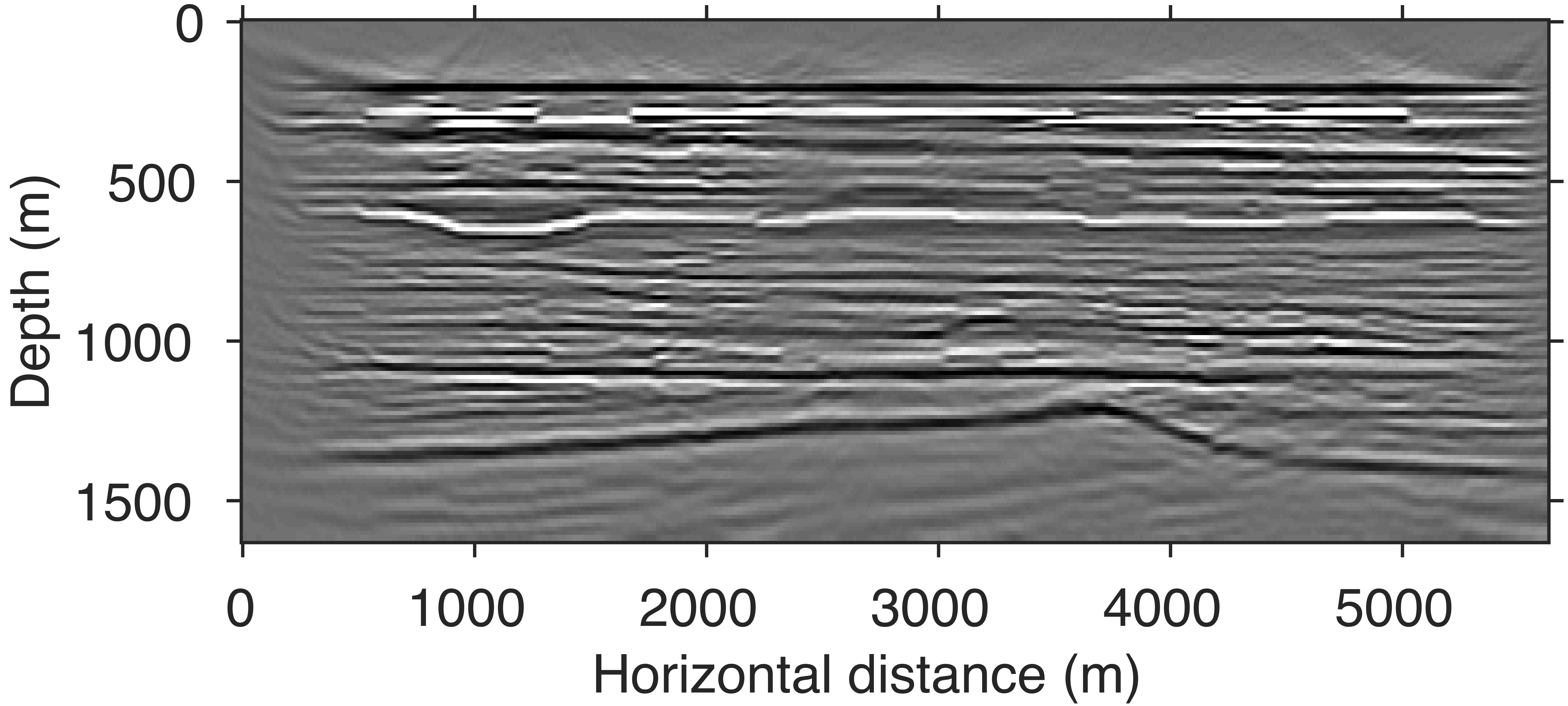
Joint
LSM

Inversion results with 1000m gap



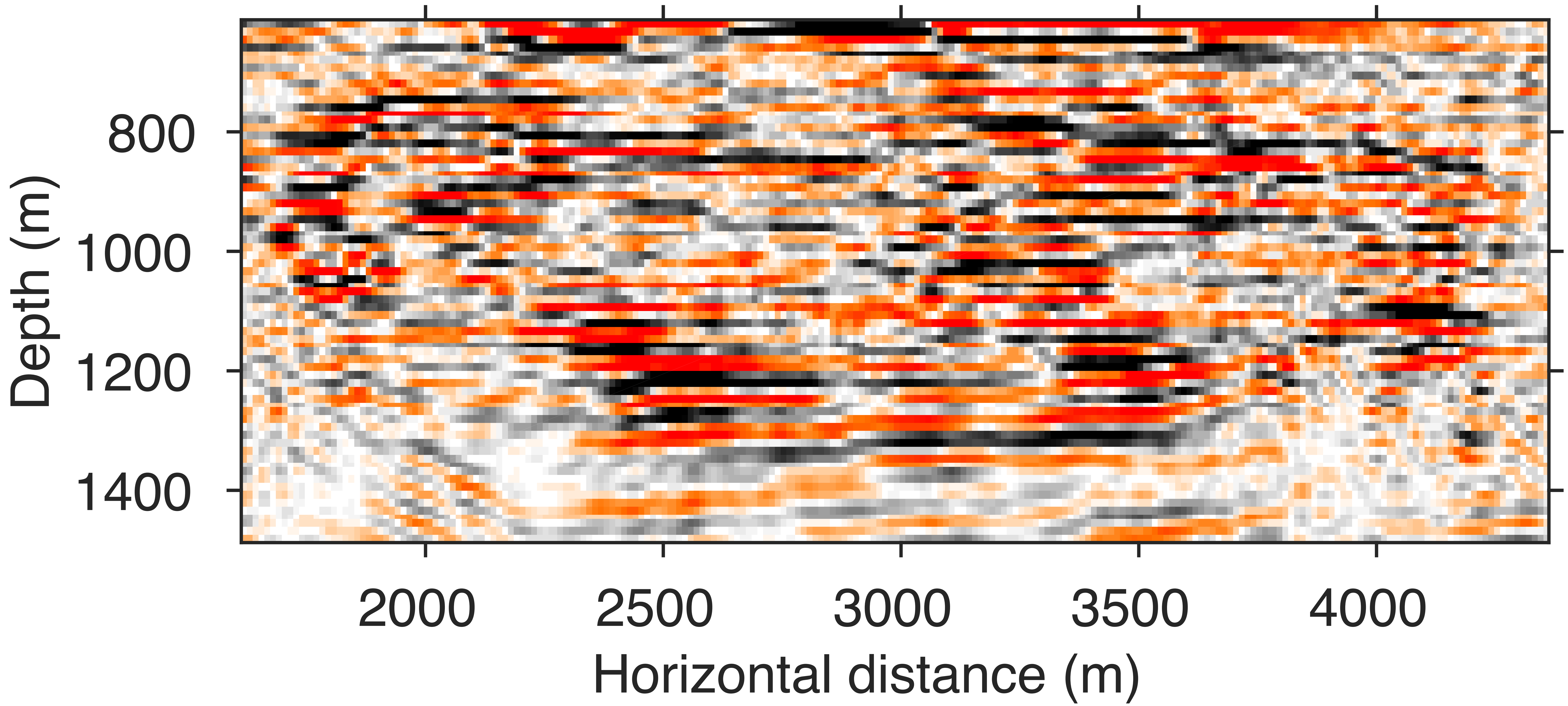
Independent LSM

Inversion results with 1000m gap



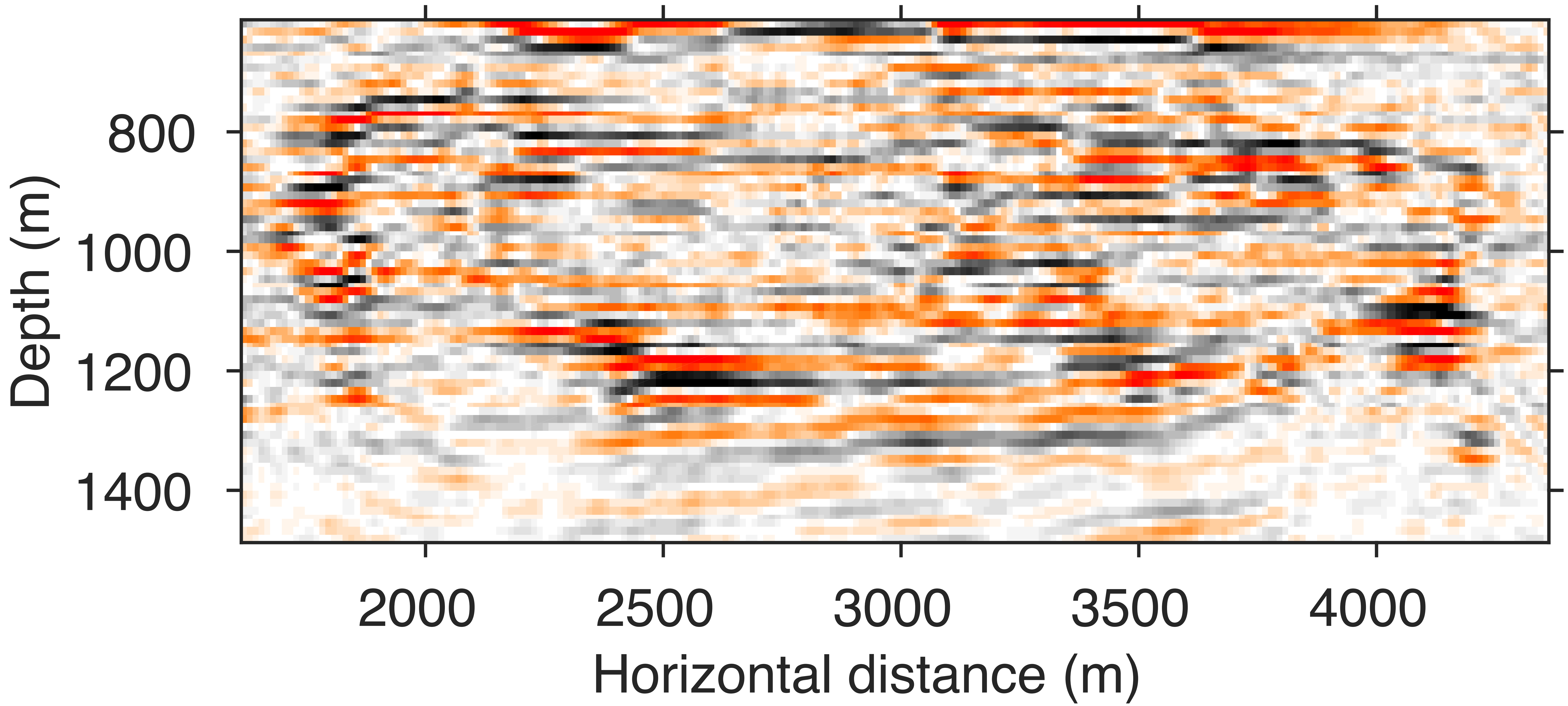
Joint
LSM

Inversion results with 1000m gap



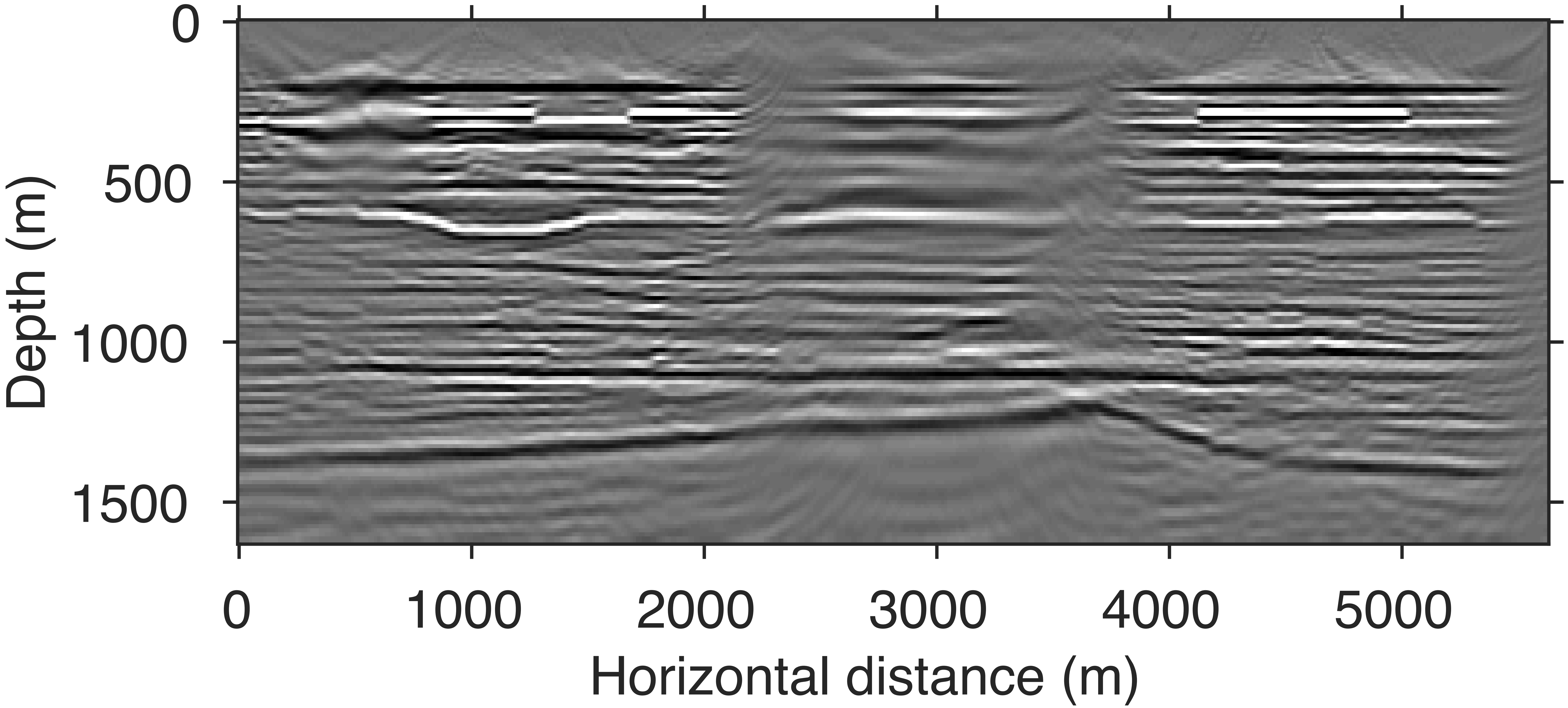
Independent LSM

Inversion results with 1000m gap



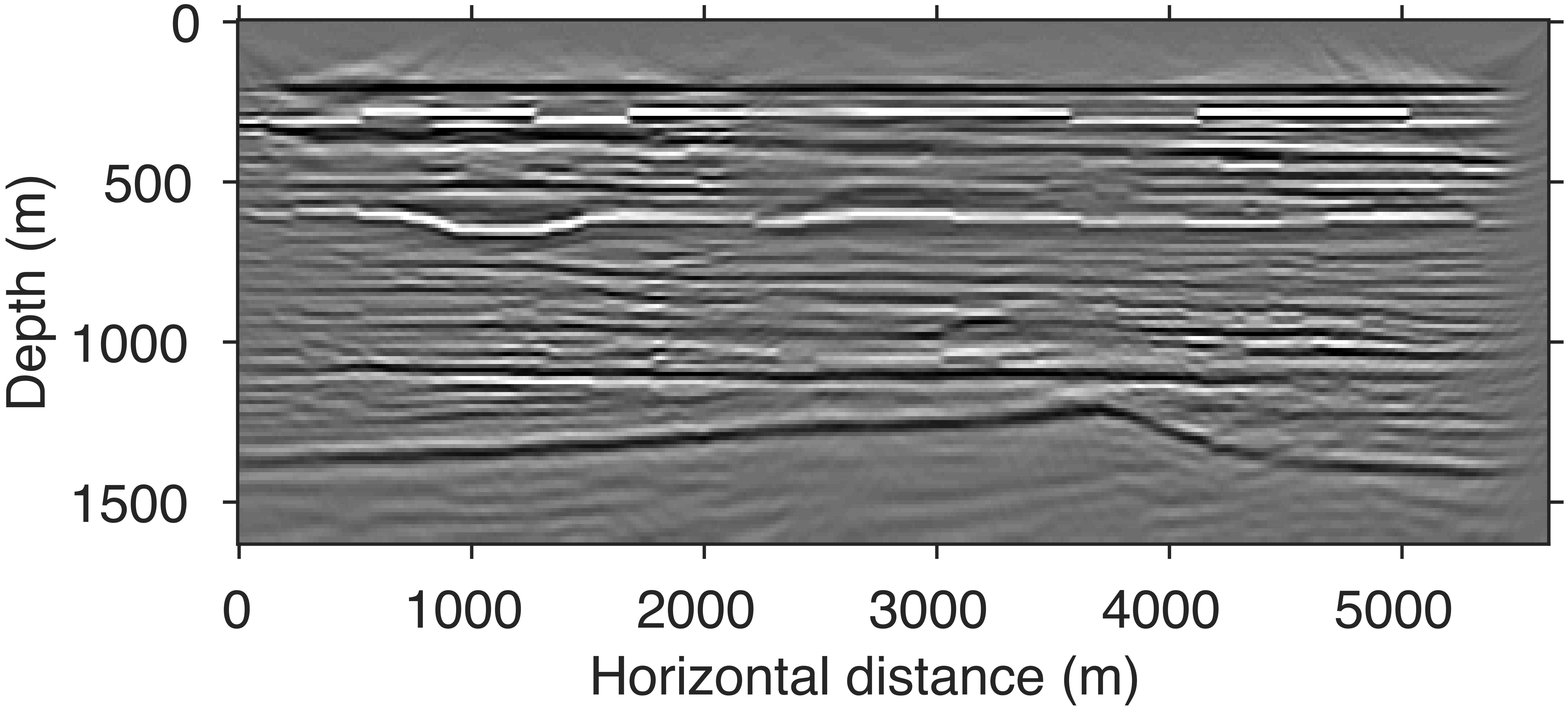
Joint
LSM

Inversion results with 1500m gap



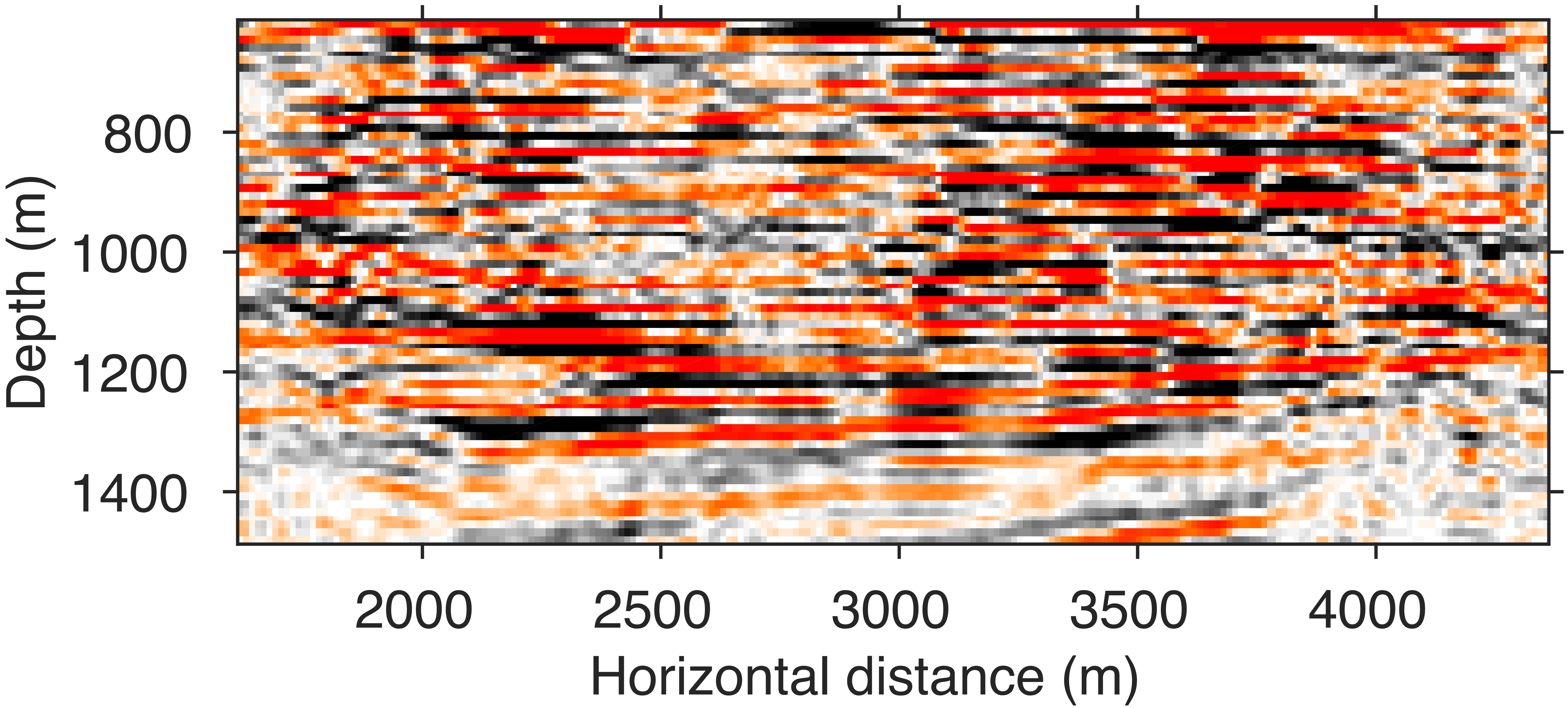
Independent LSM

Inversion results with 1500m gap



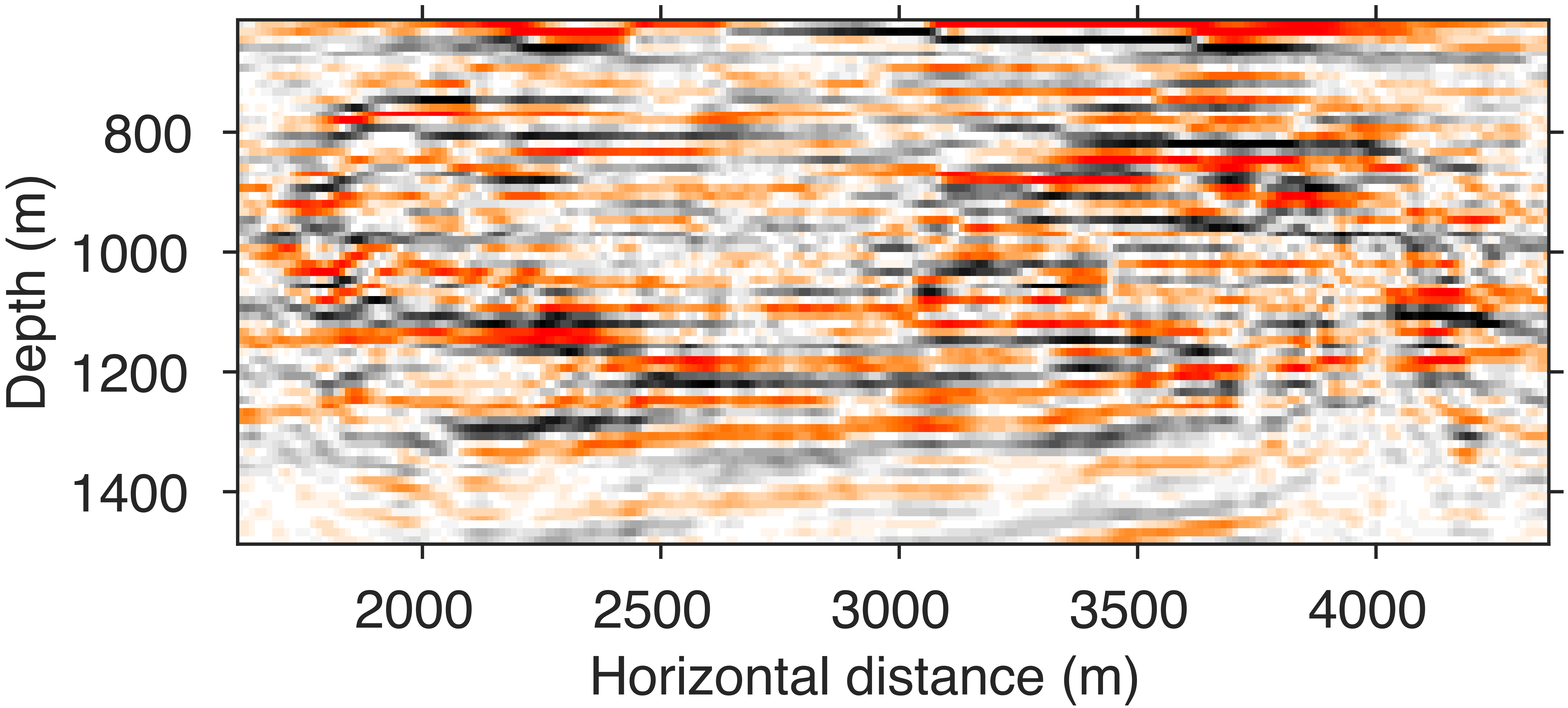
Joint
LSM

Inversion results with 1500m gap



Independent
LSM

Inversion results with 1500m gap



Joint
LSM

Conclusions

Randomized sampling techniques may be extended to time-lapse seismic surveys and processing.

Speed-up imaging using random subsets (compressively sampled) of data via sparsity-promotion.

Process time-lapse data jointly, not independently, in order to exploit the *shared* information.

Joint recovery method still fairly stable with respect to large acquisition gaps.

Provided we understand the *physics* of our model, we can reconstruct, process and interpret time-lapse vintages accurately.

Acknowledgements

SINBAD

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