Time-lapse imaging with multiples and distributed compressed sensing

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Time-lapse seismic imaging

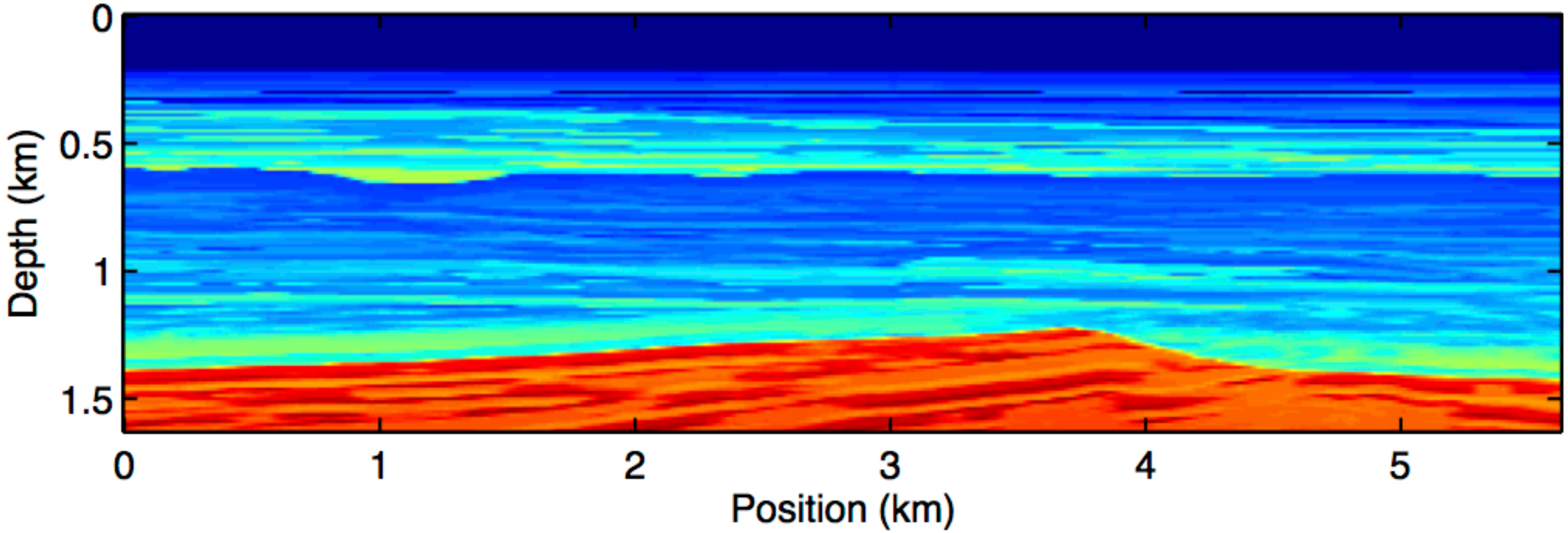
Why should we care ?

Time-lapse seismic

- Changes in a reservoir impact production decisions
- The changes are usually inferred from time-lapse seismic data
- Challenges related to acquisition (repeatability) and processing of time-lapse data still persist
- Seismic imaging of weak time-lapse changes remains a major challenge among many others.

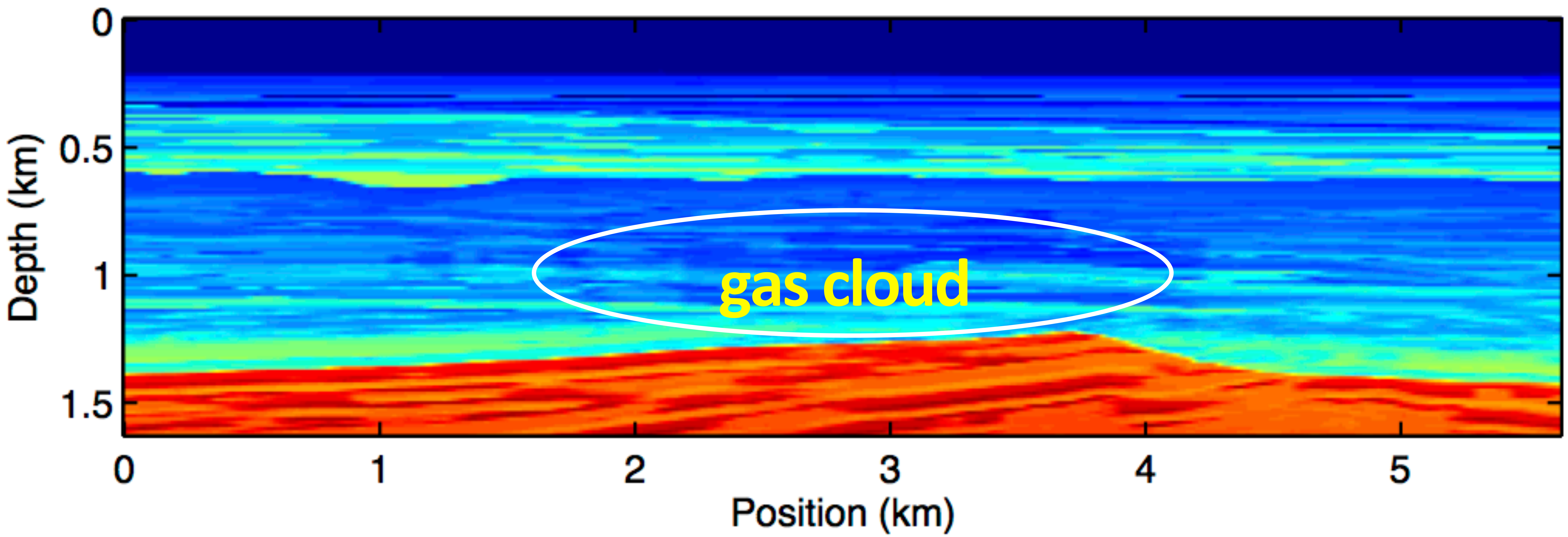
Time-lapse seismic

Baseline

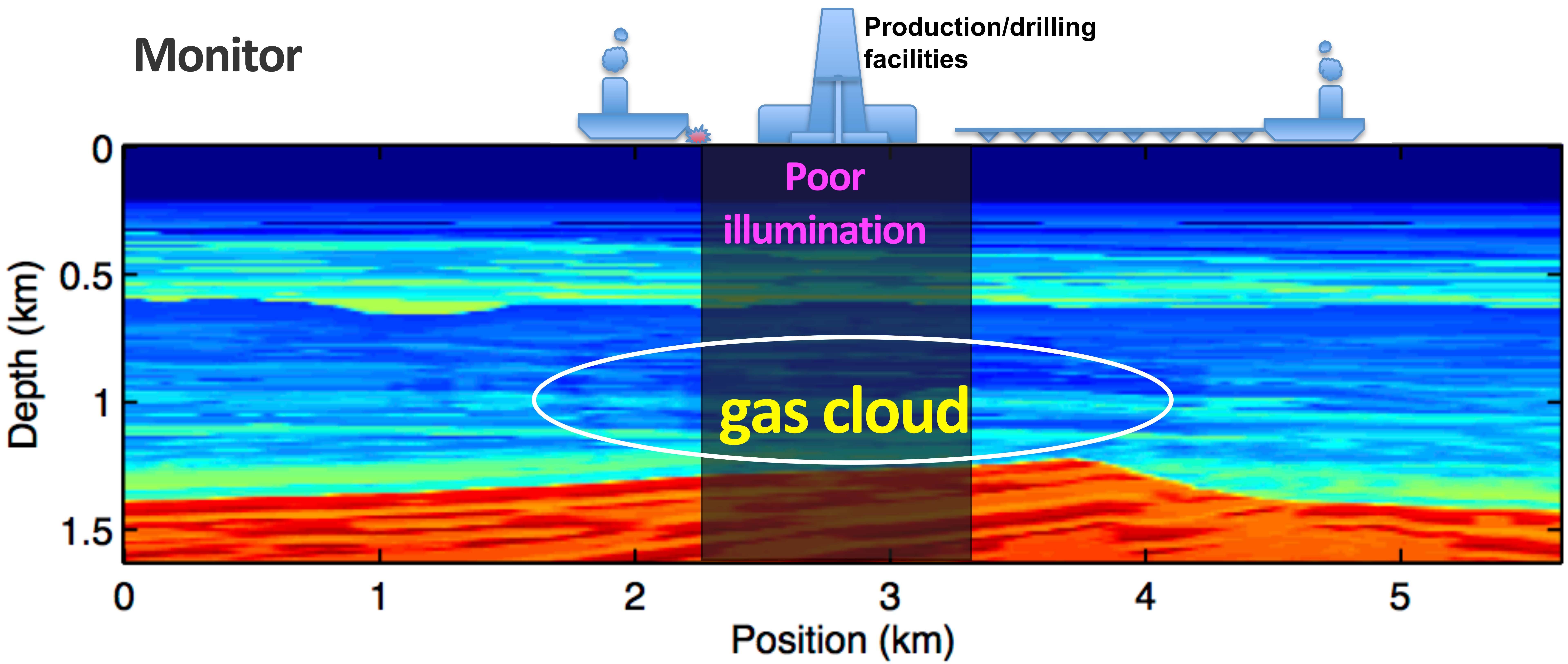


Time-lapse seismic

Monitor



Time-lapse seismic



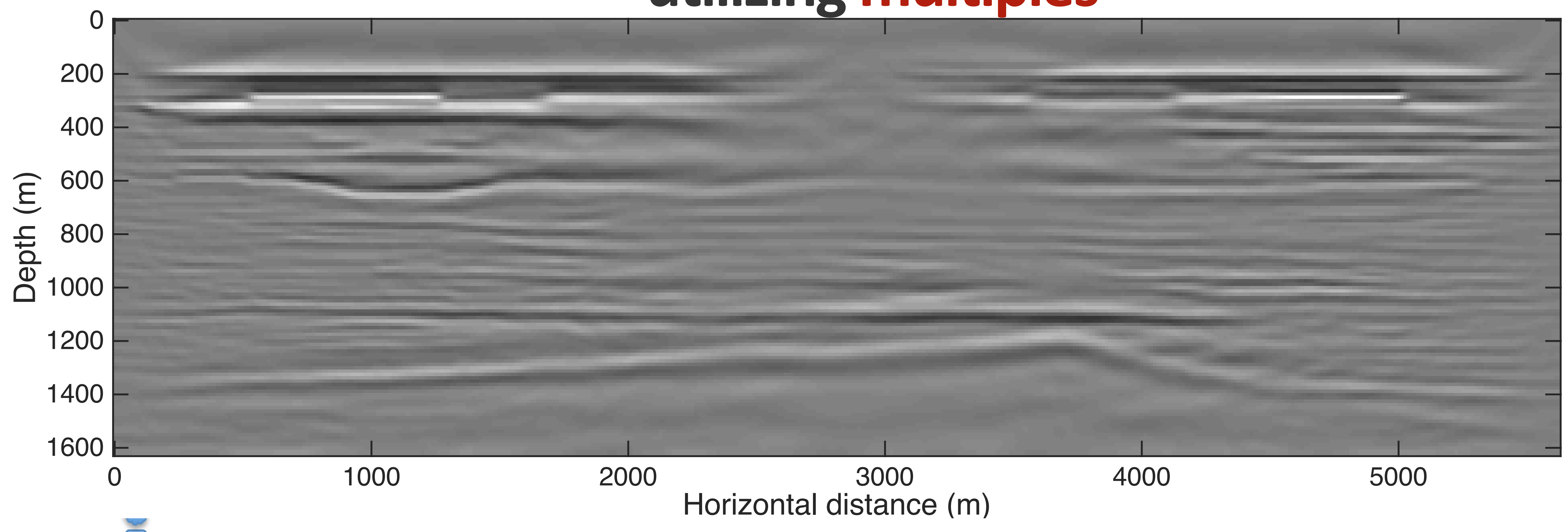
Challenges

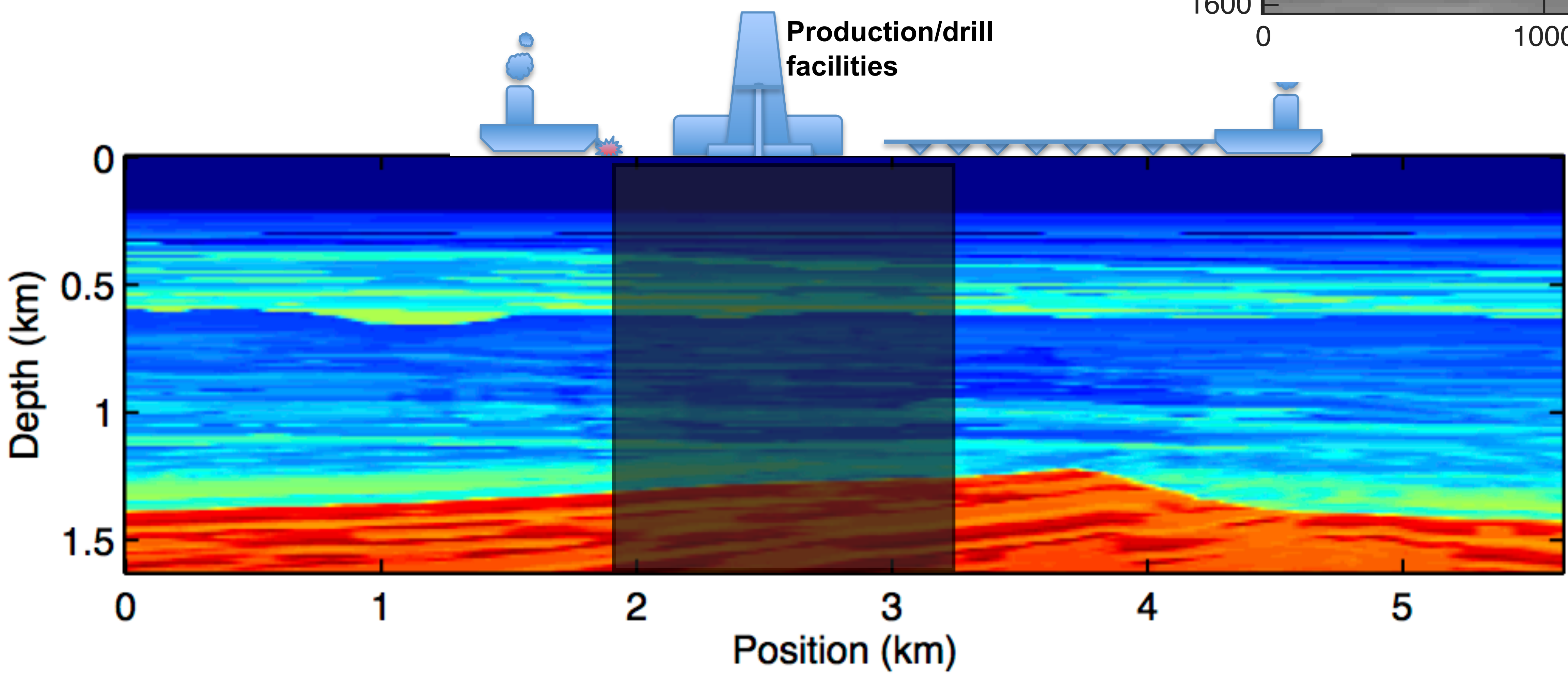
- Obstruction leads to poor source illumination of the subsurface
- Monitor image may be prone to errors/artifacts
- Inaccurate monitor image may construe false anomalies as actual time-lapse changes

How can we solve this seismic imaging problem in time-lapse?

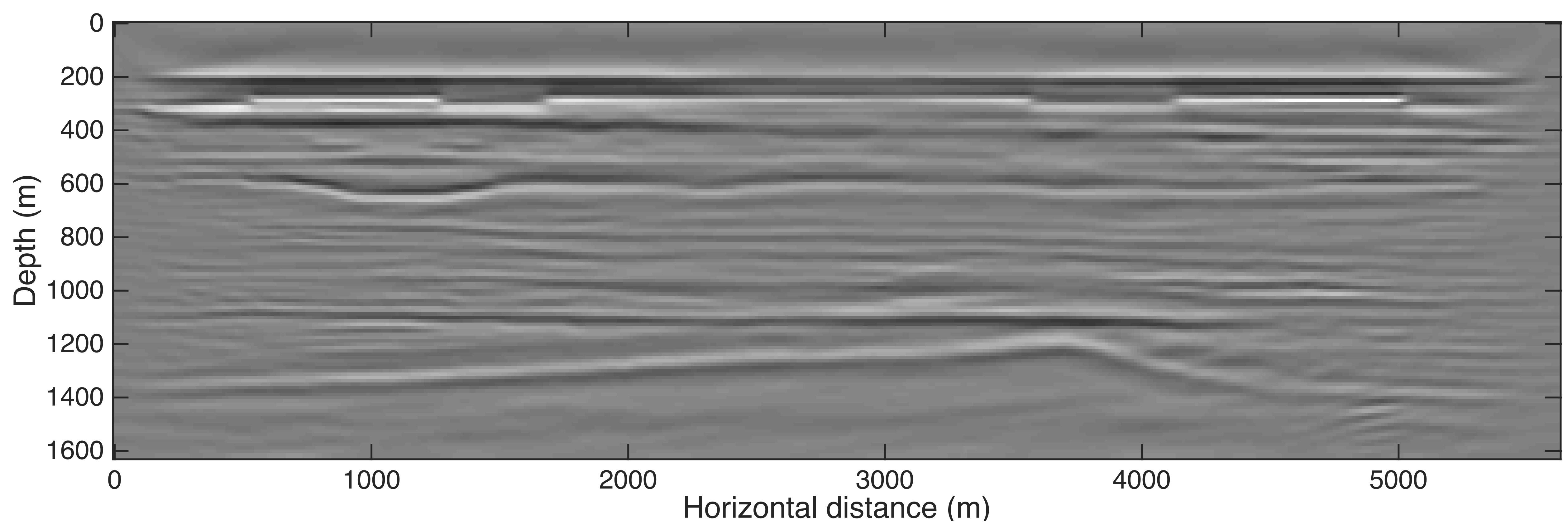
Large monitor acquisition gap

Sparsity-promoting migration utilizing multiples

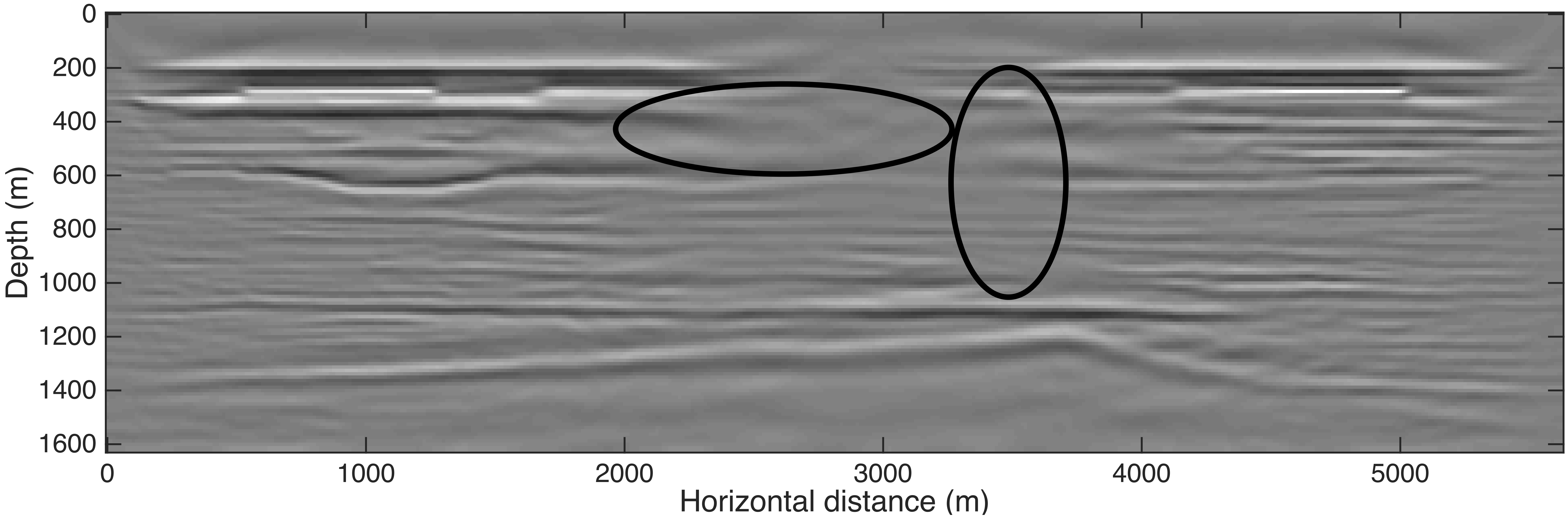




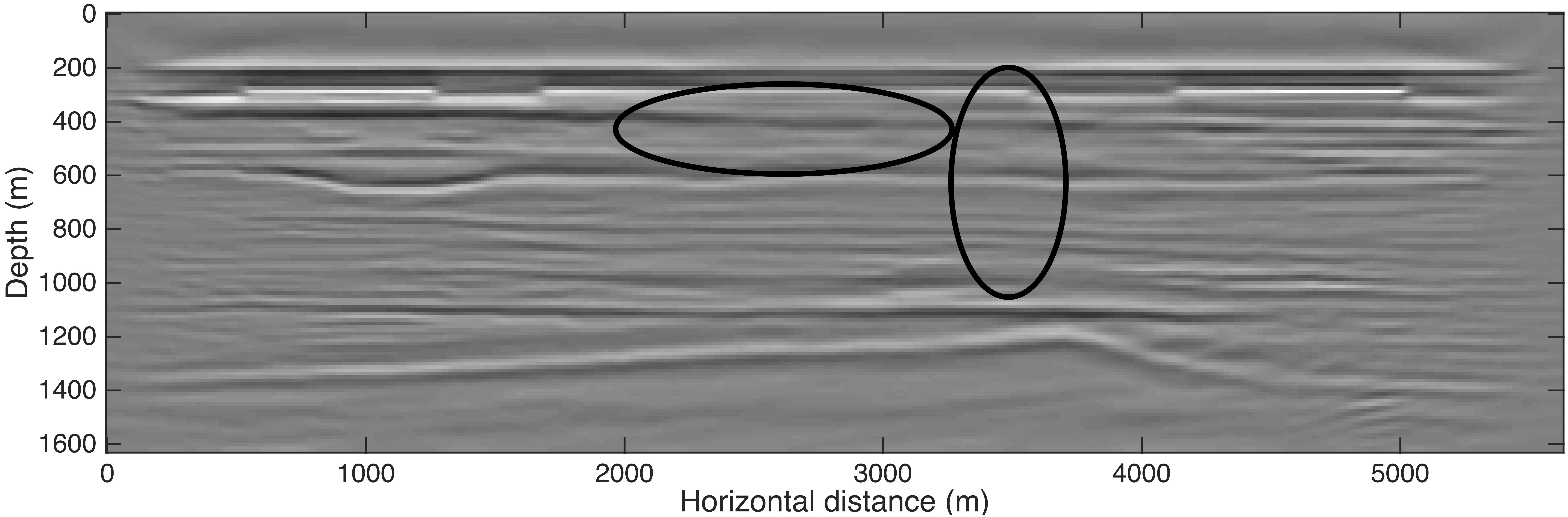
Joint sparsity-promoting migration utilizing multiples



Monitor
-w/ missing sources/receivers



Monitor (Joint Inversion)
-w/ missing sources/receivers



Assumption: a *reasonably accurate* background velocity model is given

Main messages

Demonstrate how least-squares migration of time-lapse seismic data

- can be carried out **efficiently**
- uses the **common information** in the time-lapse vintages
- can make active use of **surface-related multiples** in the data to resolve issues related to large acquisition gaps

by sparsity-promotion accelerated by re-randomization

Theory

Seismic imaging

Baseline

$$\mathcal{F}[\mathbf{m}_1] = \mathbf{d}_1$$

$$\mathbf{J}_1 = \nabla\mathcal{F}[\mathbf{m}_0, \mathbf{S}_1]$$

$$\widetilde{\delta\mathbf{m}_1} = \mathbf{J}_1^*\mathbf{d}_1$$

migrated
baseline image

$\mathcal{F}$: forward modelling

$\mathbf{m}$: model parameters

$\mathbf{d}$: observed data

$\mathbf{m}_0$: background model

$\mathbf{S}$: source wavelet

$\mathbf{J}/\nabla\mathcal{F}$: Jacobian/Demigration

Seismic imaging

Monitor

$$\mathcal{F}[\mathbf{m}_2] = \mathbf{d}_2$$

$$\mathbf{J}_2 = \nabla\mathcal{F}[\mathbf{m}_0, \mathbf{S}_2]$$

$$\widetilde{\delta\mathbf{m}_2} = \mathbf{J}_2^{*}\mathbf{d}_2$$

migrated
monitor image

$\mathcal{F}$: forward modelling

$\mathbf{m}$: model parameters

$\mathbf{d}$: observed data

$\mathbf{m}_0$: background model

$\mathbf{S}$: source wavelet

$\mathbf{J}/\nabla\mathcal{F}$: Jacobian/Demigration

Move to inversion
instead of migration
to control source cross-talk

Seismic imaging as an inverse problem

$$\tilde{\mathbf{x}} = \arg\min_{\mathbf{x}} \|\mathbf{x}\|_1$$

$$\text{subject to } \|\mathbf{d} - \nabla\boldsymbol{\mathcal{F}}[\mathbf{m}_0, \mathbf{S}]\mathbf{C}^*\mathbf{x}\|_2 \leq \sigma$$

$$\mathbf{C}^* = \text{curvelet synthesis operator}$$

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

Inverted image

Seismic imaging as an **inverse problem**

$$\tilde{\mathbf{x}} = \arg\min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{subject to } \|\mathbf{d} - \nabla\boldsymbol{\mathcal{F}}[\mathbf{m}_0, \mathbf{S}]\mathbf{C}^*\mathbf{x}\|_2 \leq \sigma$$

$$\mathbf{C}^* = \text{curvelet synthesis operator}$$

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

Inverted image

Very expensive!!!

with all the data

From l1 minimization
to l1 constraint + re-randomization

From l1 minimization to l1 constraint

$$\tilde{\mathbf{x}} = \arg\min_{\mathbf{x}} \|\mathbf{x}\|_1$$

$$\text{subject to } \|\mathbf{d} - \nabla\boldsymbol{\mathcal{F}}[\mathbf{m}_0, \mathbf{S}]\mathbf{C}^*\mathbf{x}\|_2 \leq \sigma$$

$$\Downarrow$$

$$\min_{\mathbf{x}} \|\mathbf{d} - \nabla\boldsymbol{\mathcal{F}}[\mathbf{m}_0, \mathbf{S}]\mathbf{C}^*\mathbf{x}\|_2$$

$$\text{subject to } \|\mathbf{x}\|_1 \leq \tau$$

Reducing the computation

Virtue of source linearity

$$\mathbf{W}\nabla\boldsymbol{\mathcal{F}}[\mathbf{m}_0, \mathbf{S}] = \nabla\boldsymbol{\mathcal{F}}[\mathbf{m}_0, \mathbf{WS}]$$

$$\mathbf{WS} = \mathbf{S}$$

$$\mathbf{Wd} = \mathbf{d}$$

$\mathbf{W}$: gaussian entries

(randomized simultaneous sources)

: or subset of identity matrix

(randomly selected shots)

Reducing the computation

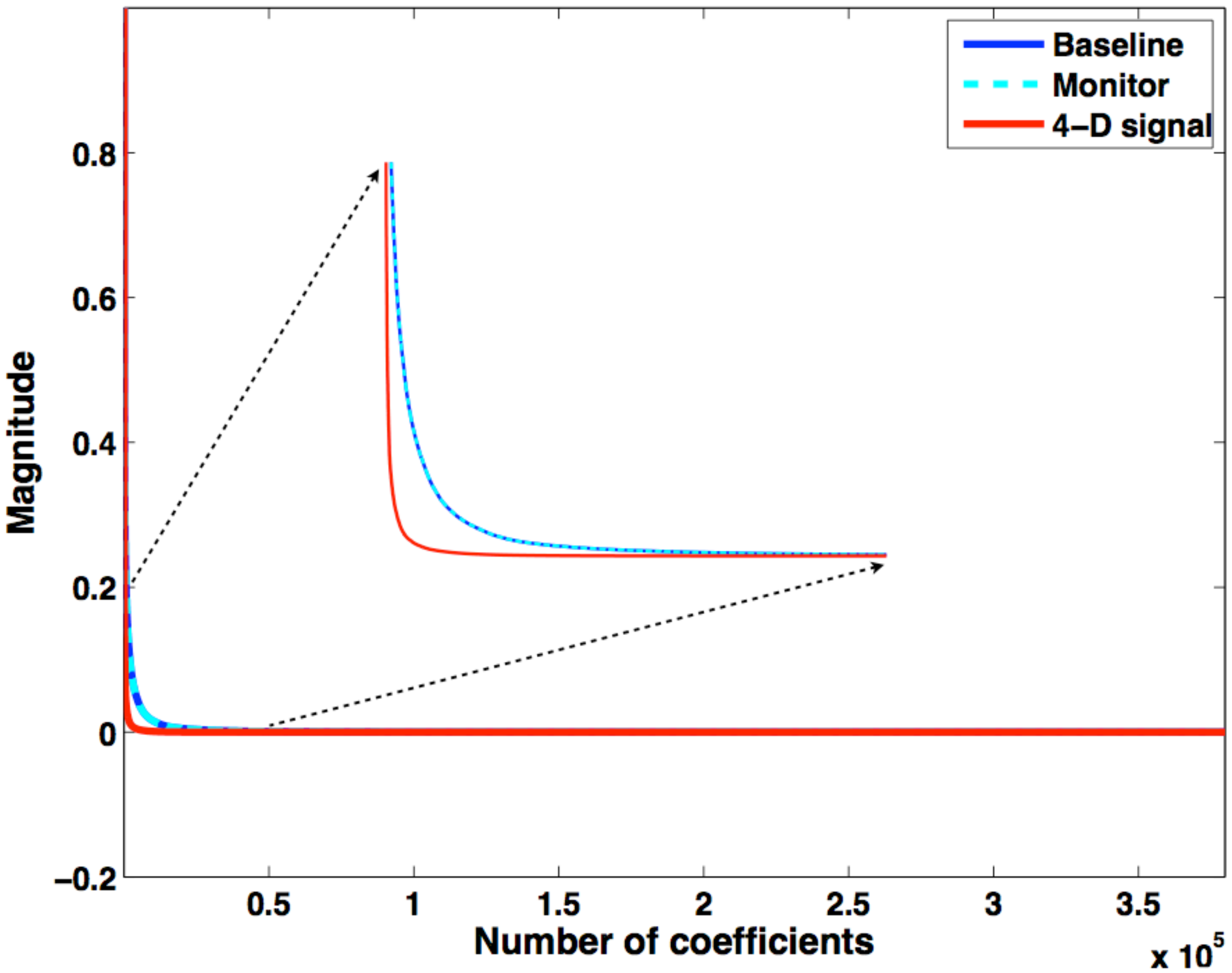
$$\min_{\mathbf{x}} \|\mathbf{d} - \nabla\boldsymbol{\mathcal{F}}[\mathbf{m}_0, \mathbf{S}]\mathbf{C}^*\mathbf{x}\|_2$$
$$\text{subject to } \|\mathbf{x}\|_1 \leq \tau$$

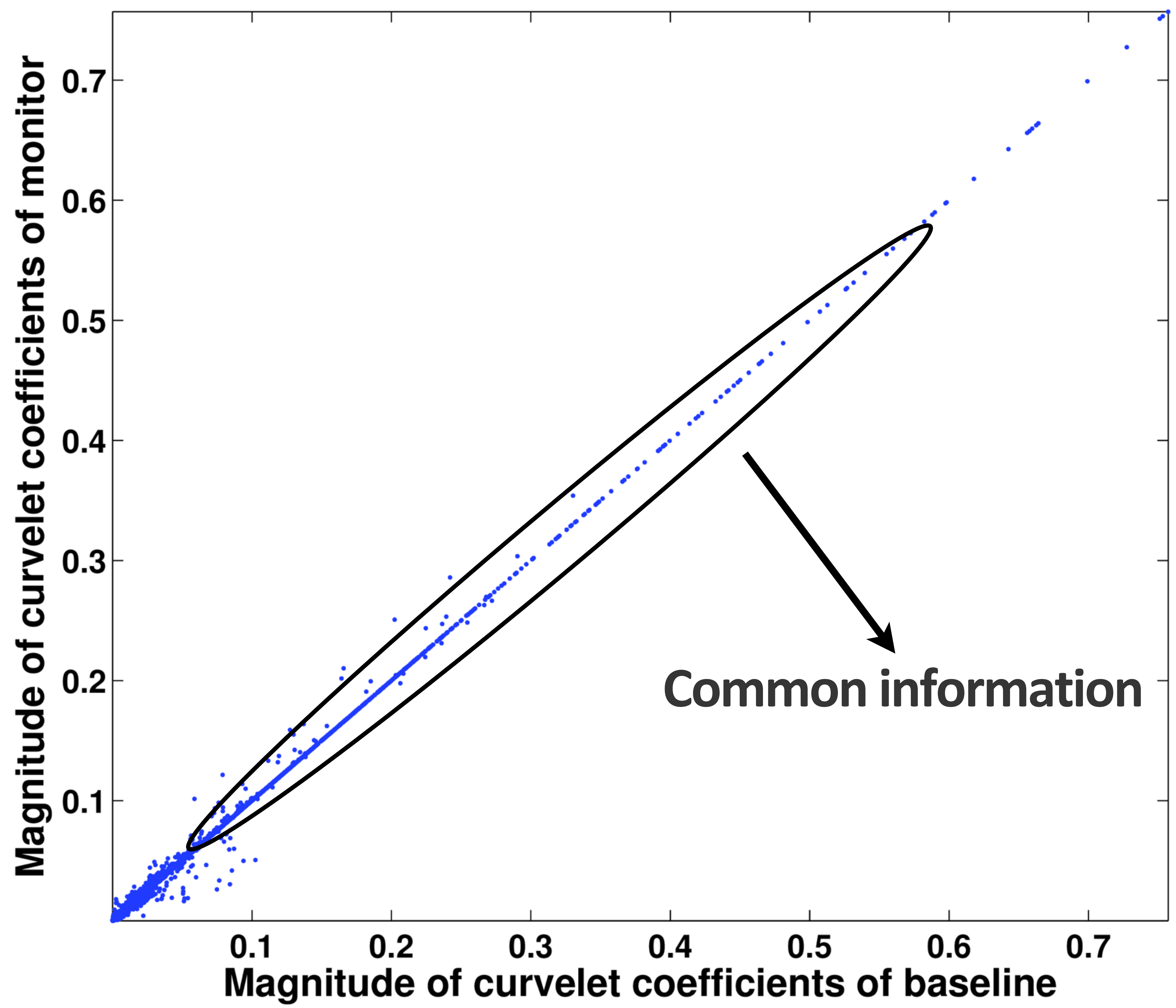
Reduced problem

$$\min_{\mathbf{x}} \|\mathbf{d} - \nabla\boldsymbol{\mathcal{F}}[\mathbf{m}_0, \mathbf{S}]\mathbf{C}^*\mathbf{x}\|_2$$
$$\text{subject to } \|\mathbf{x}\|_1 \leq \tau_k$$

Time-lapse seismic imaging as a joint linear inverse problem

Structure - curvelet representation





Wednesday, 28 October, 15

*Exploiting the **shared/common** information*

Dror Baron , Marco F. Duarte , Shriram Sarvotham , Michael B. Wakin , Richard G. Baraniuk. An Information-Theoretic Approach to Distributed Compressed Sensing (2005)

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

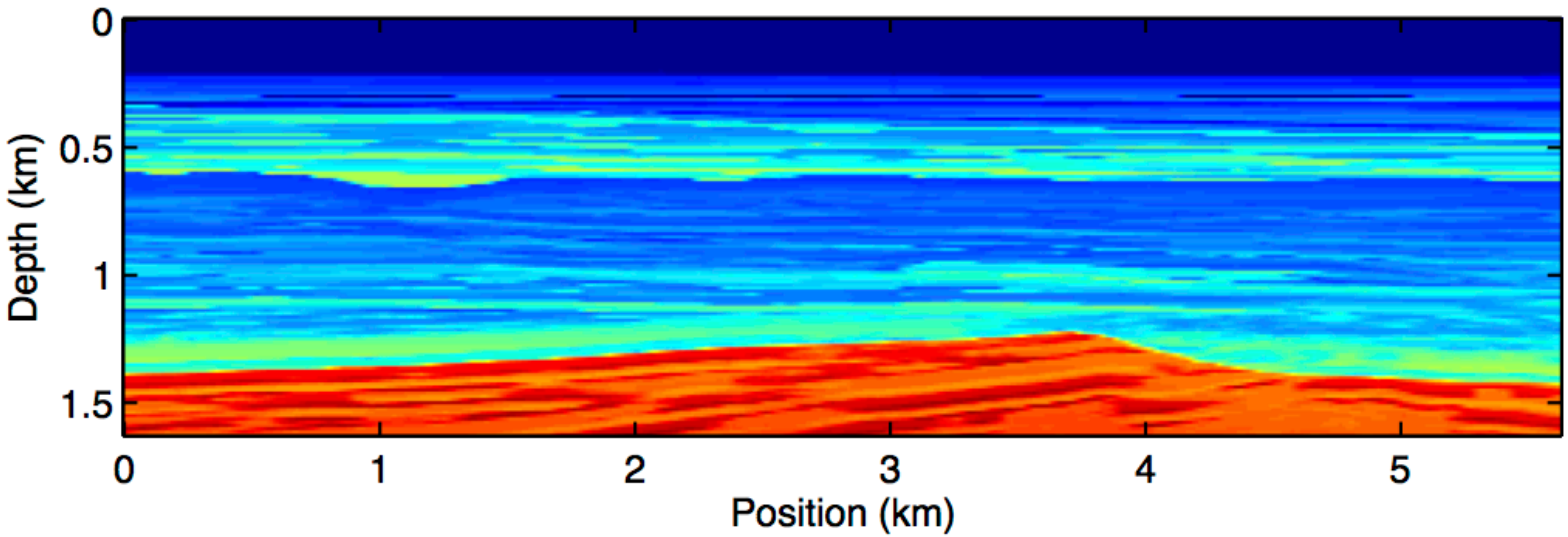
monitor

- **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

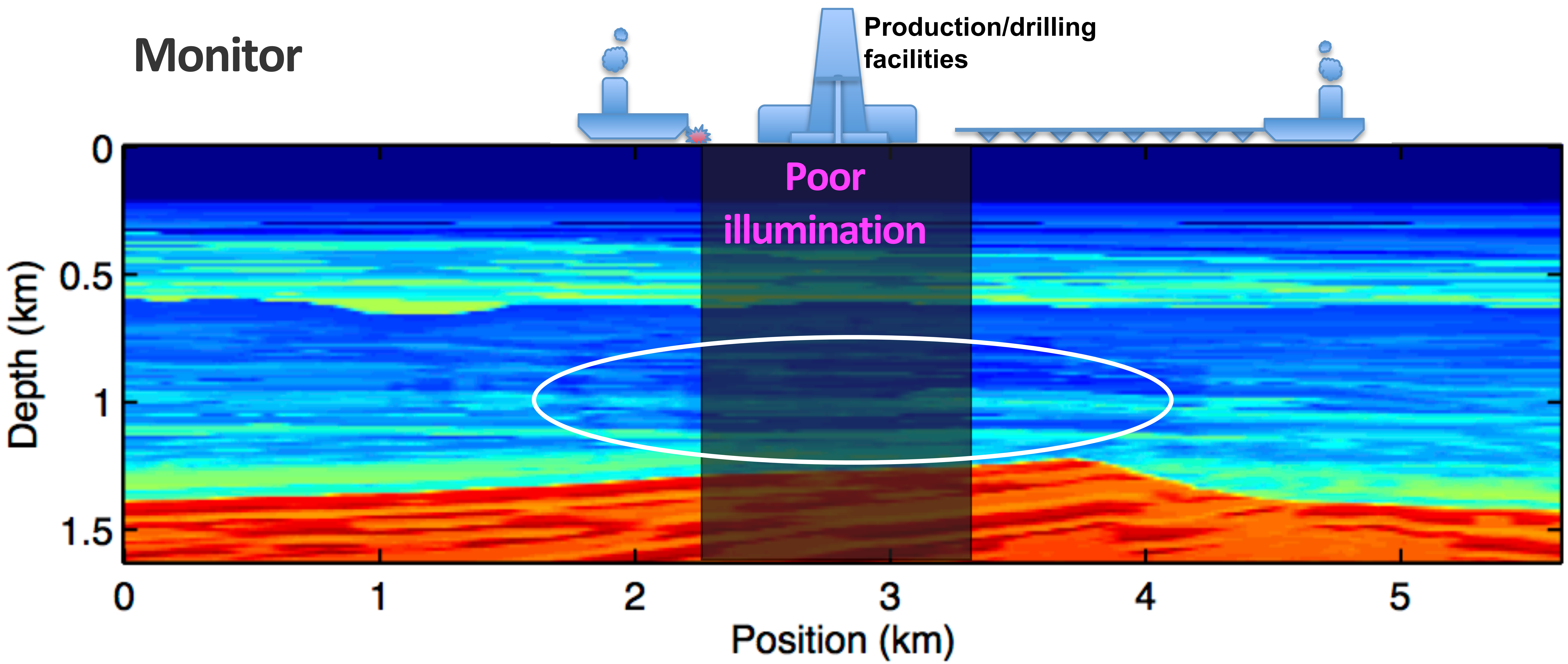
Application

BG time-lapse model

Baseline

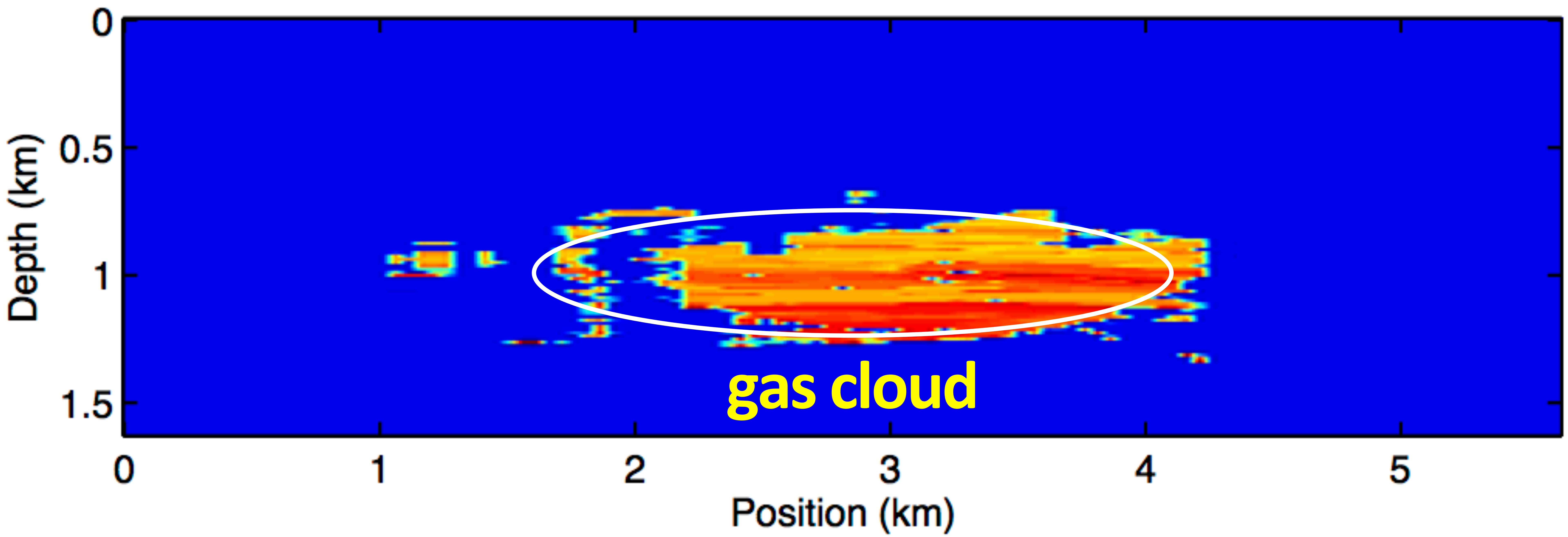


BG time-lapse model



BG time-lapse model

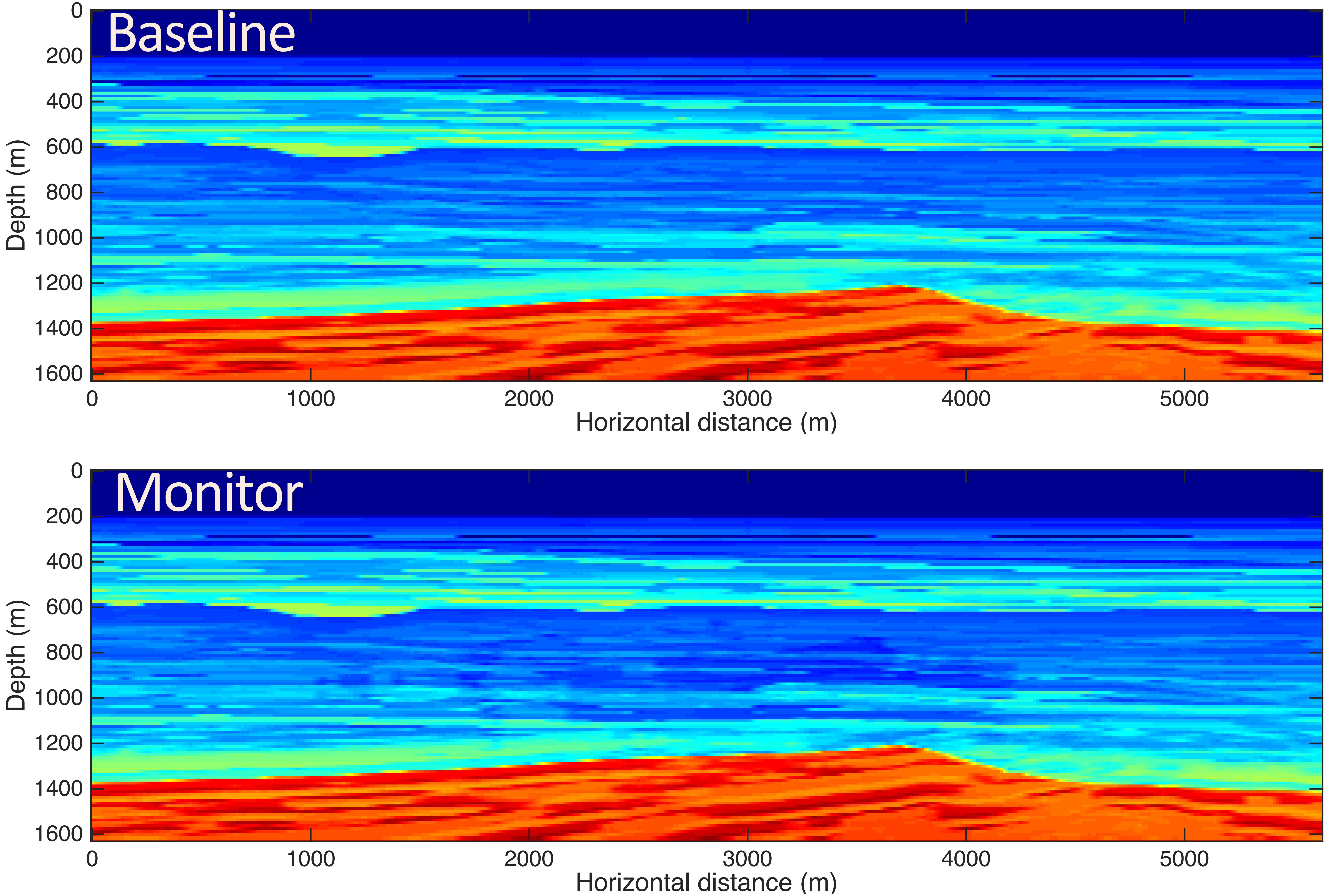
Difference



Experiment setup

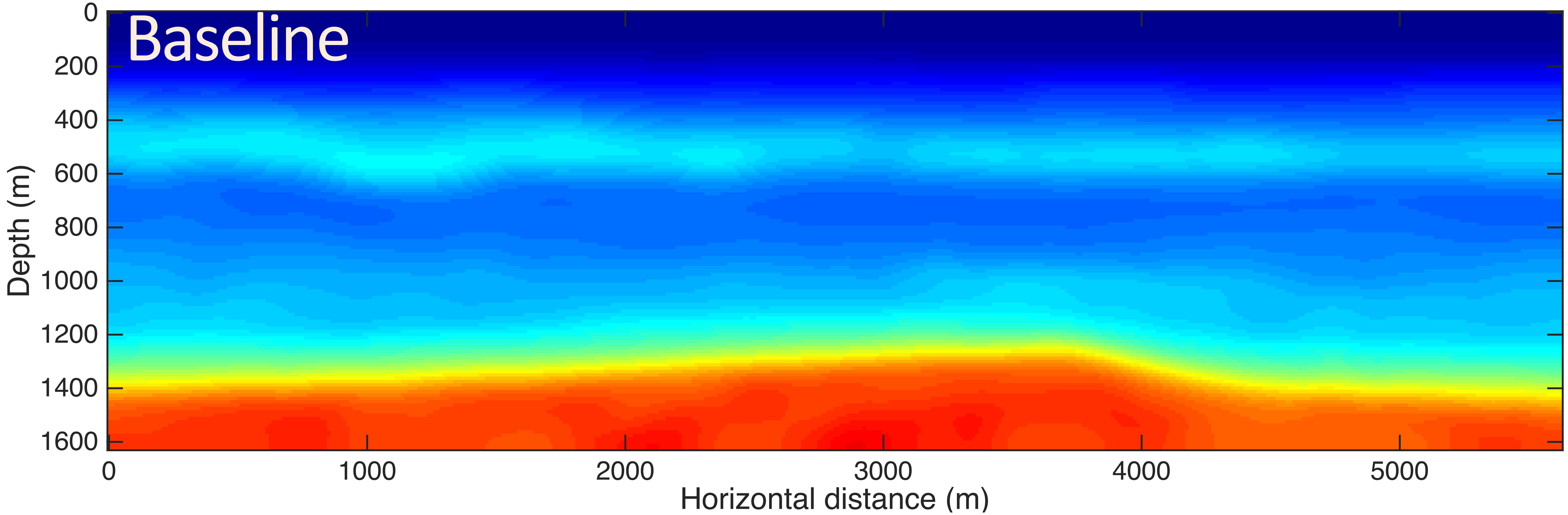
- a 2D slice of the BG model (w/ and w/o the gas cloud), 1.62 km deep, 5.63 km wide, 12.5m grid spacing
- *smoothed* baseline/monitor used as background model
- data simulated using Ricker wavelet w/ peak frequency of 20Hz
- 451 sources and receivers @ 12.5m spacing
- 160 frequency samples up to 40Hz
- forward modeling and inversion using same kernel
- using the ***true*** wavelet for inversion
- optimization solved with spgl1
- using 16 frequencies and 10 randomly selected shots with redraws

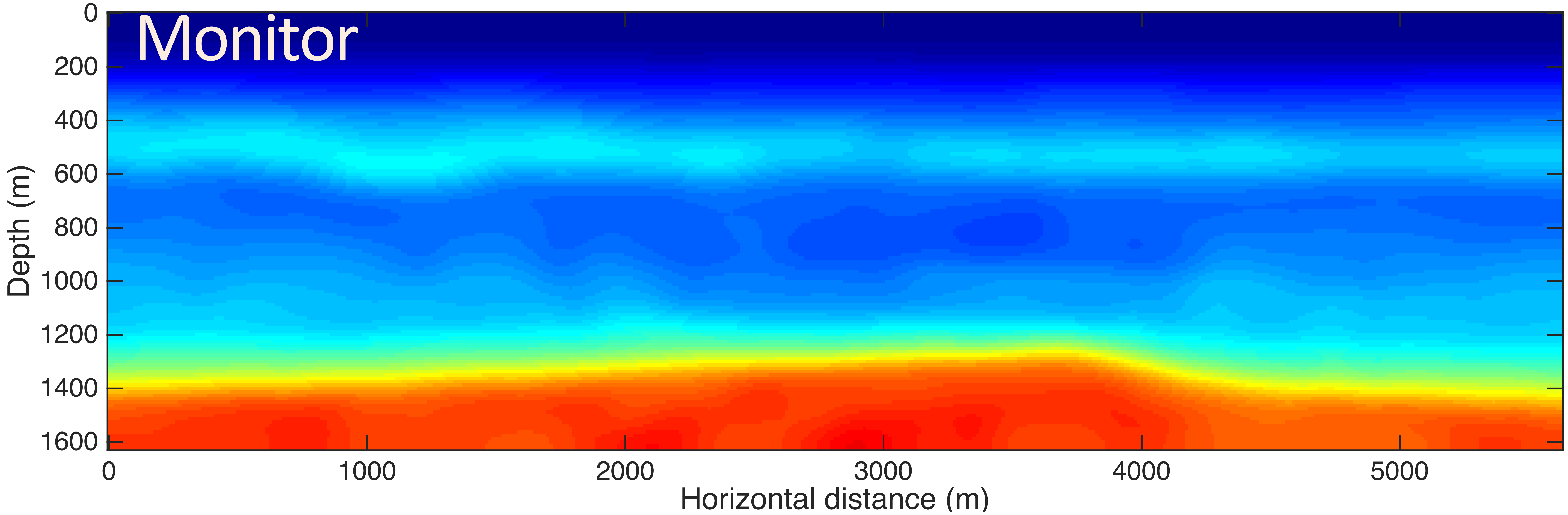
True model



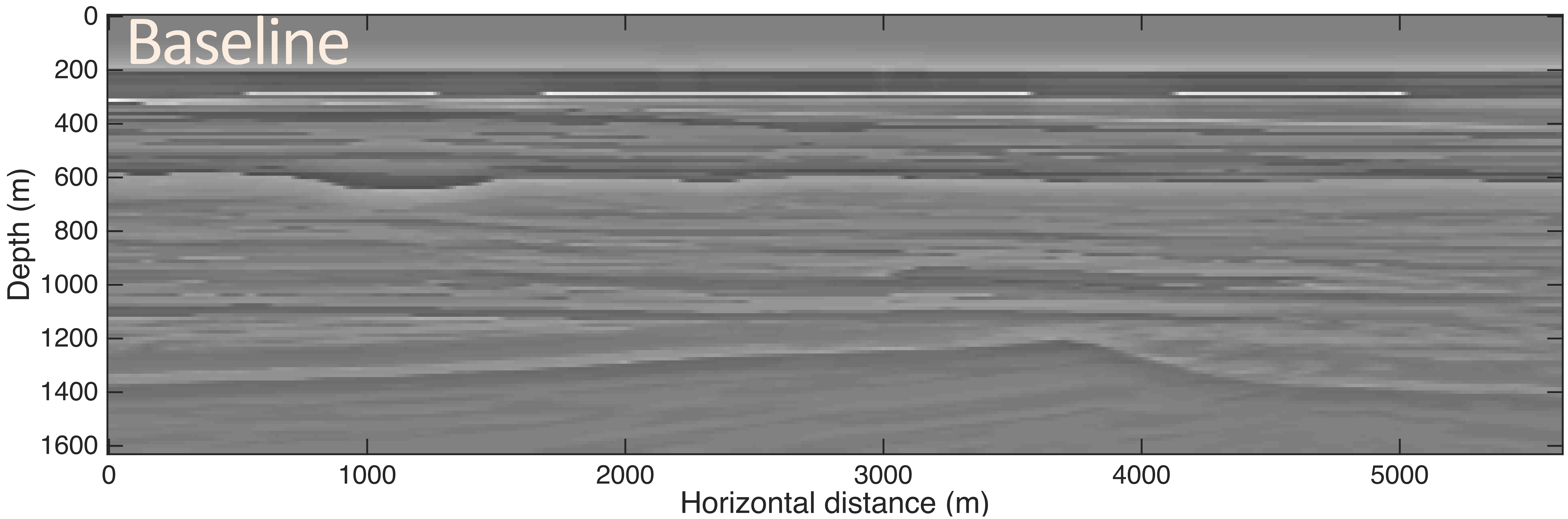
Baseline
Depth (m)
0
200
400
600
800
1000
1200
1400
1600
0
1000
2000
3000
4000
5000
Horizontal distance (m)
Monitor
Depth (m)
0
200
400
600
800
1000
1200
1400
1600
0
1000
2000
3000
4000
5000
Horizontal distance (m)

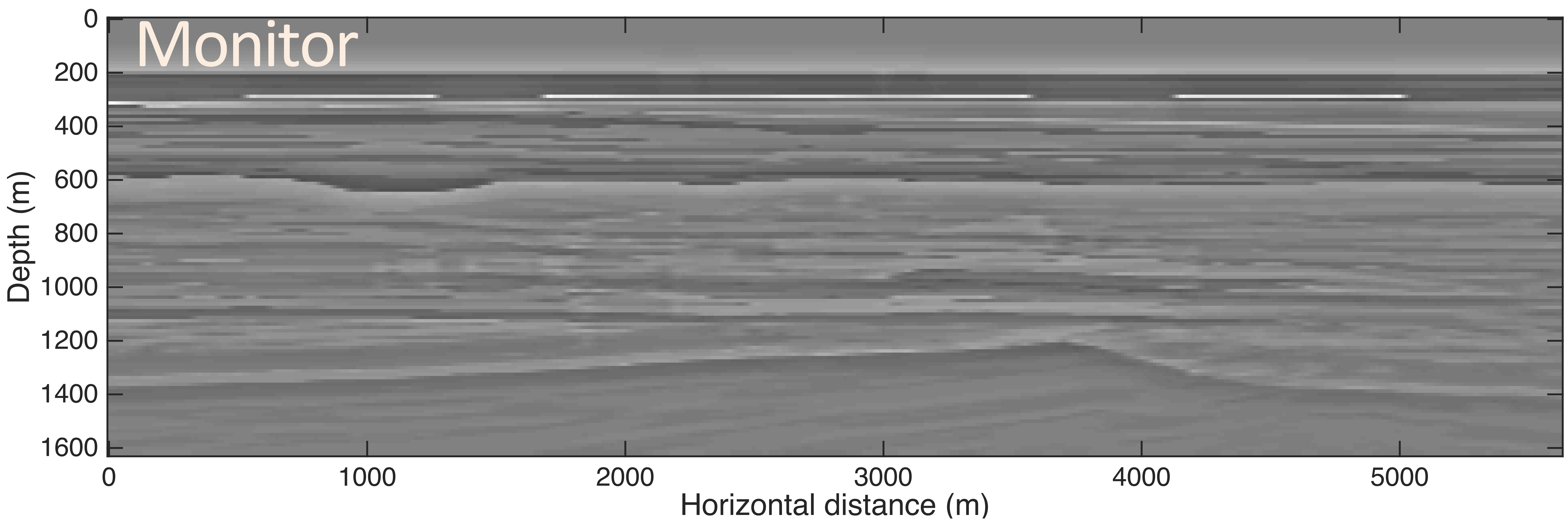
Background model



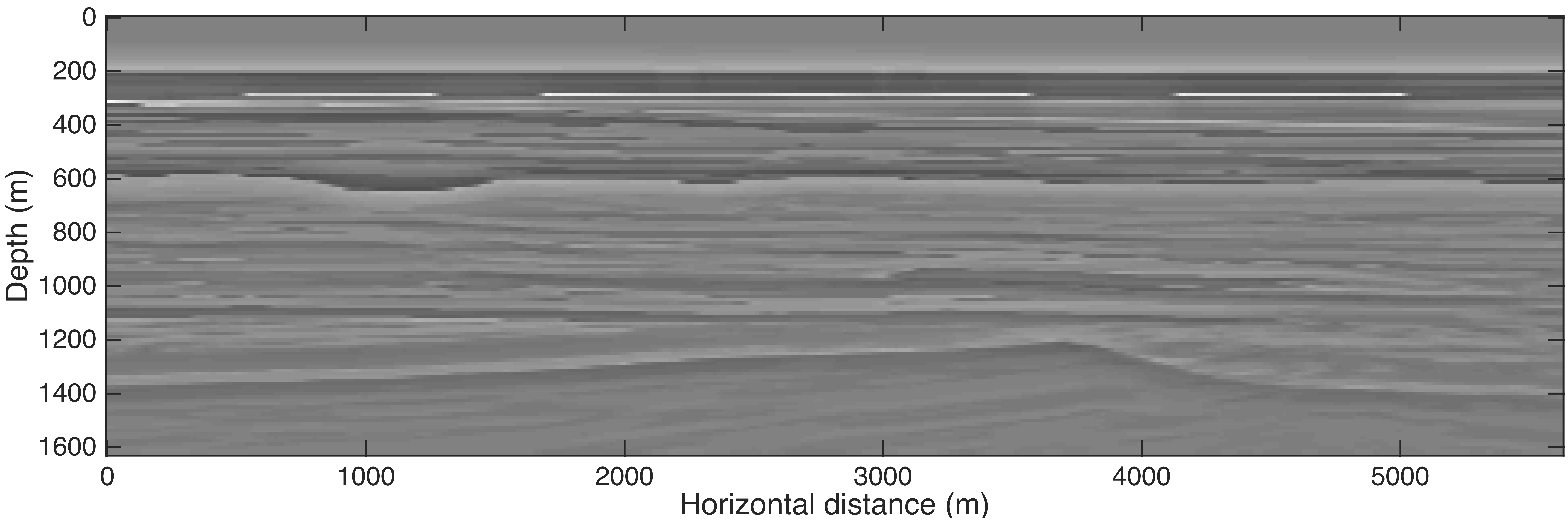


Model perturbations

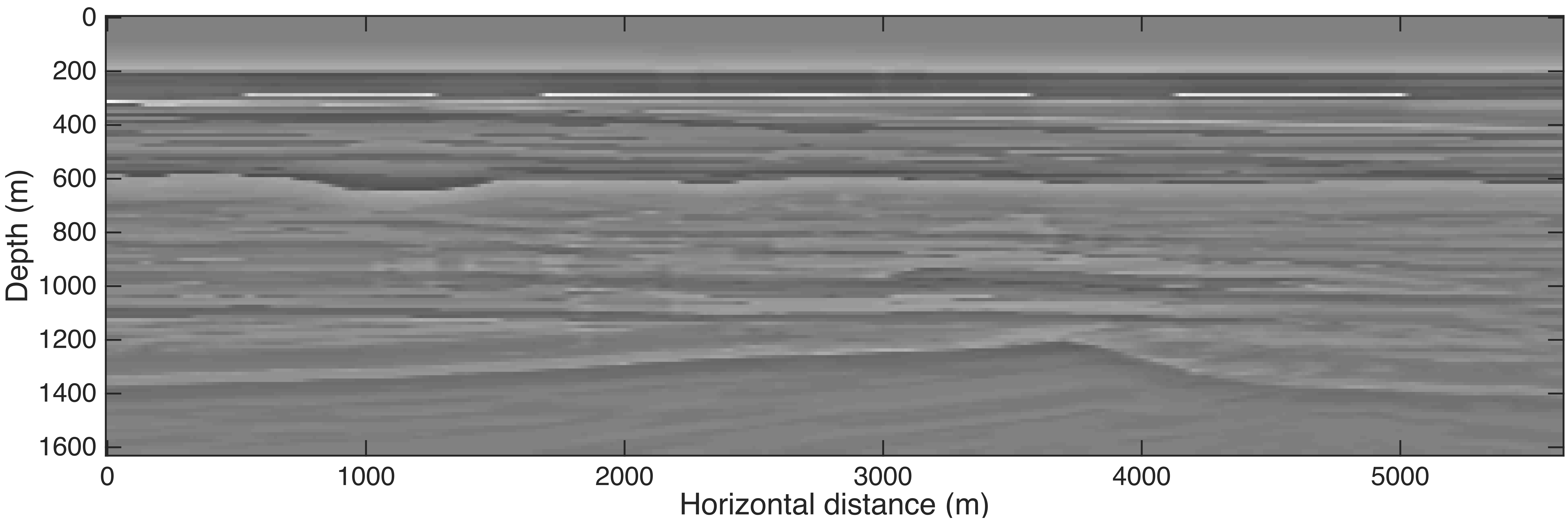




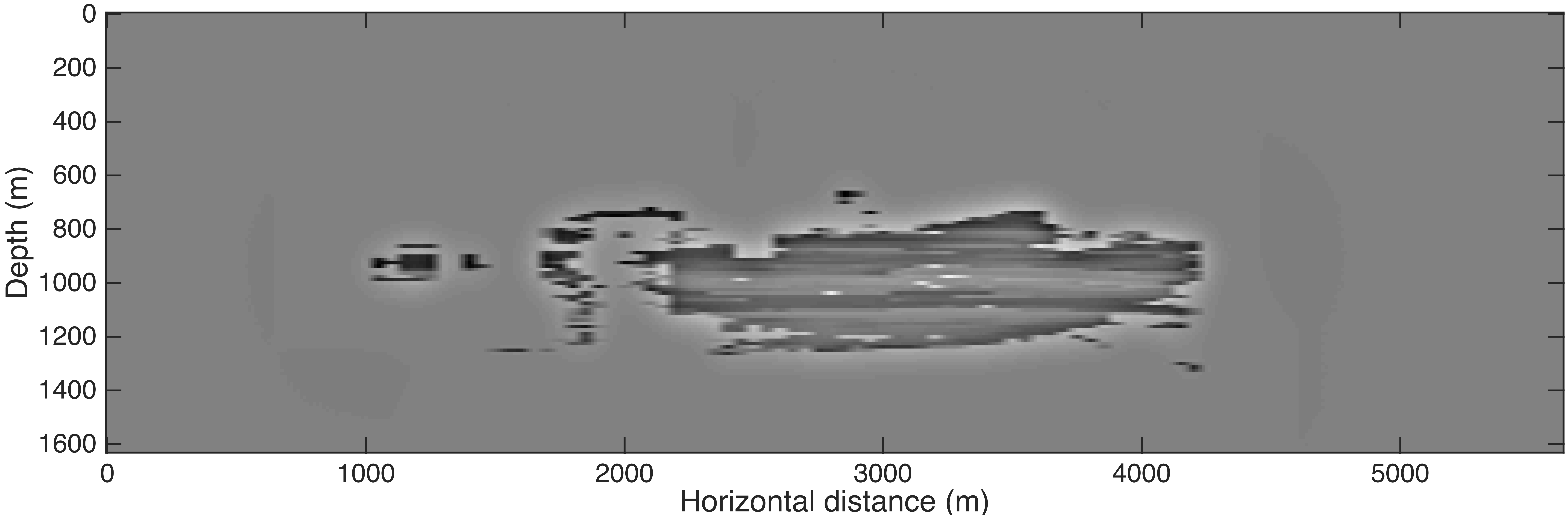
True baseline perturbation



True monitor perturbation



True time-lapse perturbation



Order of experiments

- Baseline inversion w/o acquisition gap
- Monitor inversion w/o acquisition gap
- Monitor inversion w/ acquisition gap due to missing sources only
- Monitor inversion w/ acquisition gap due to missing sources/receivers

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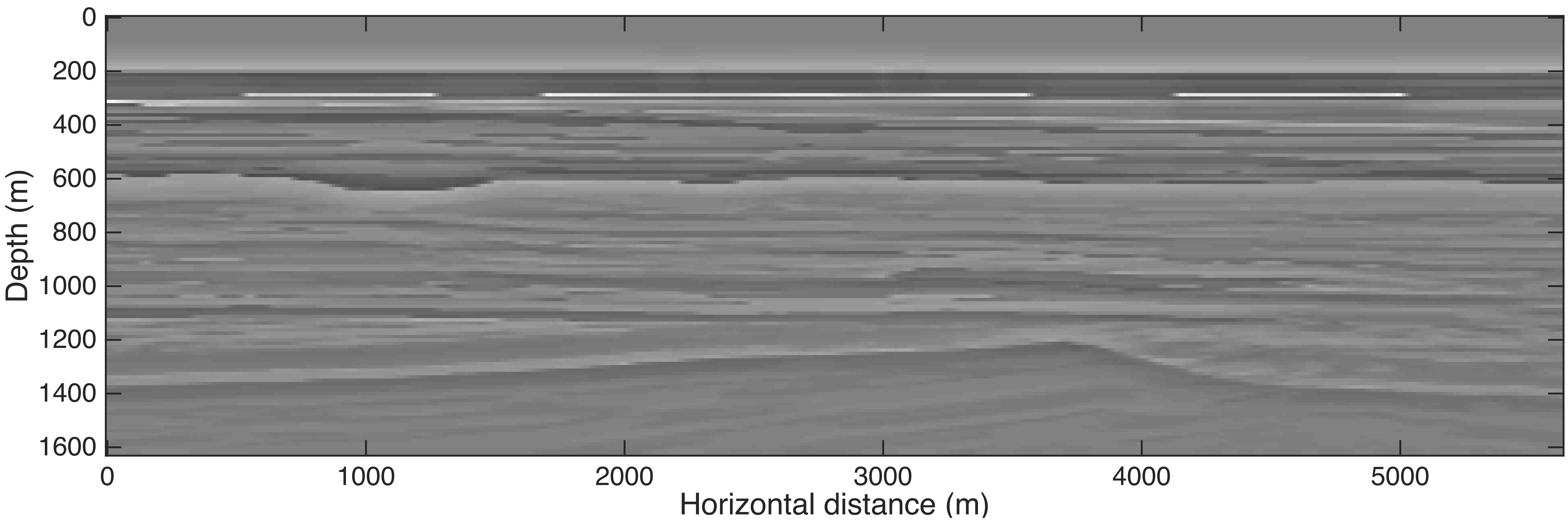
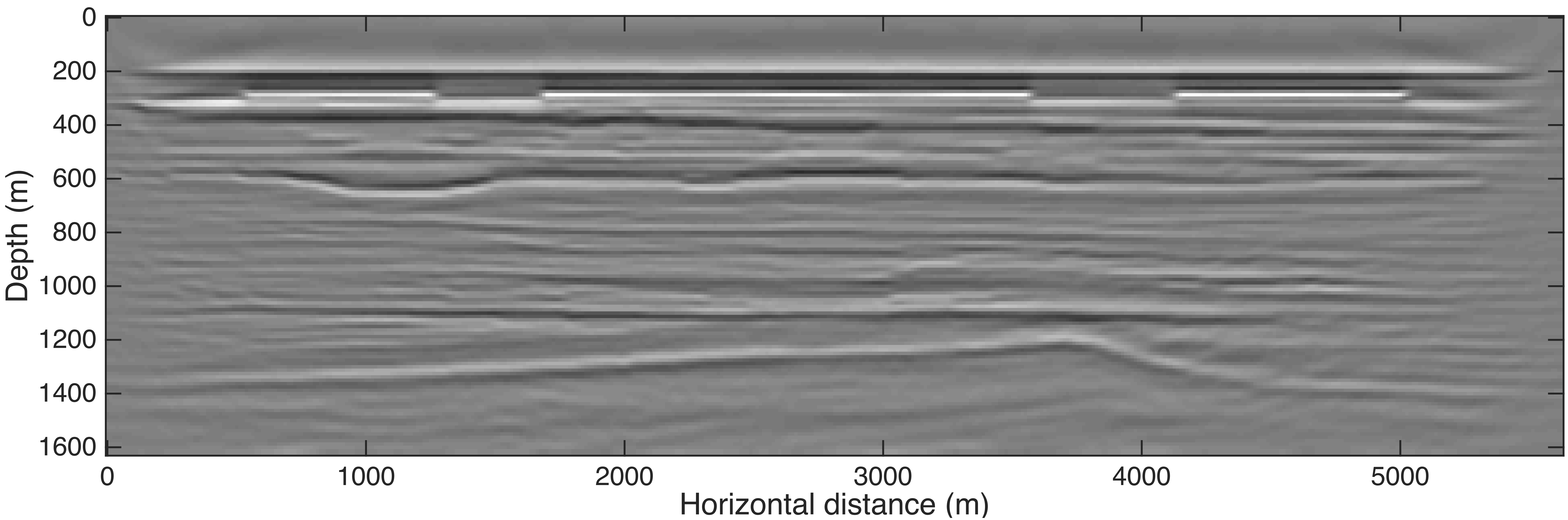
Baseline inversion results (w/o acquisition gap)

True baseline



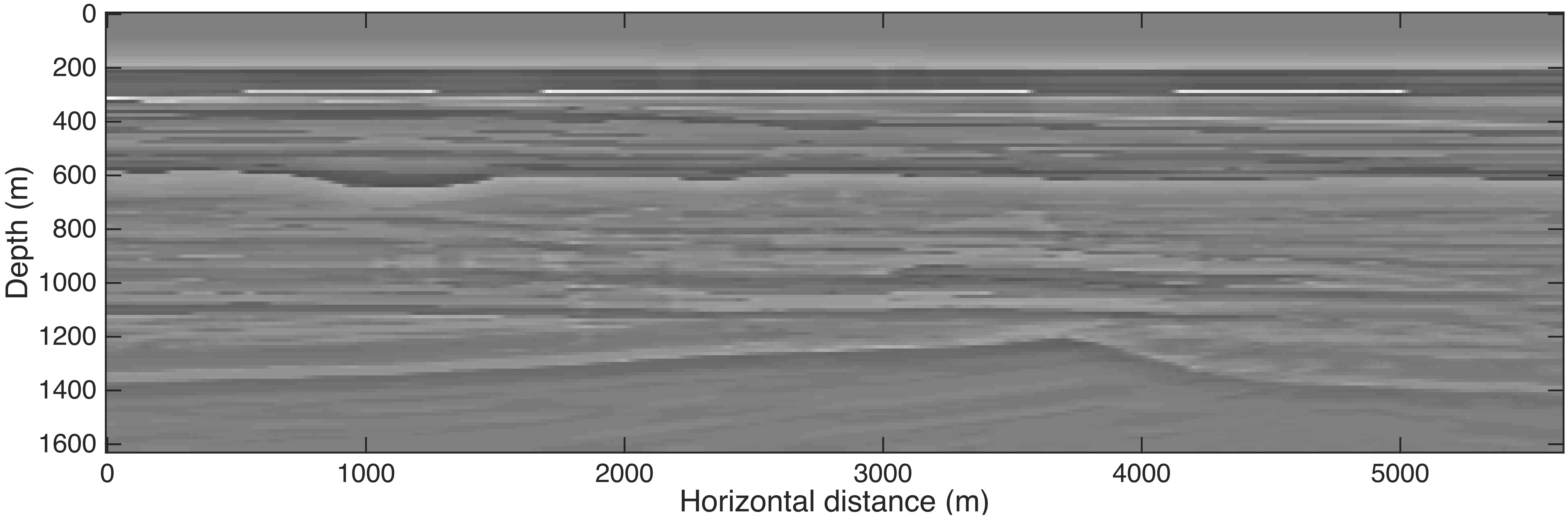
Inverted baseline

-without missing sources/receivers



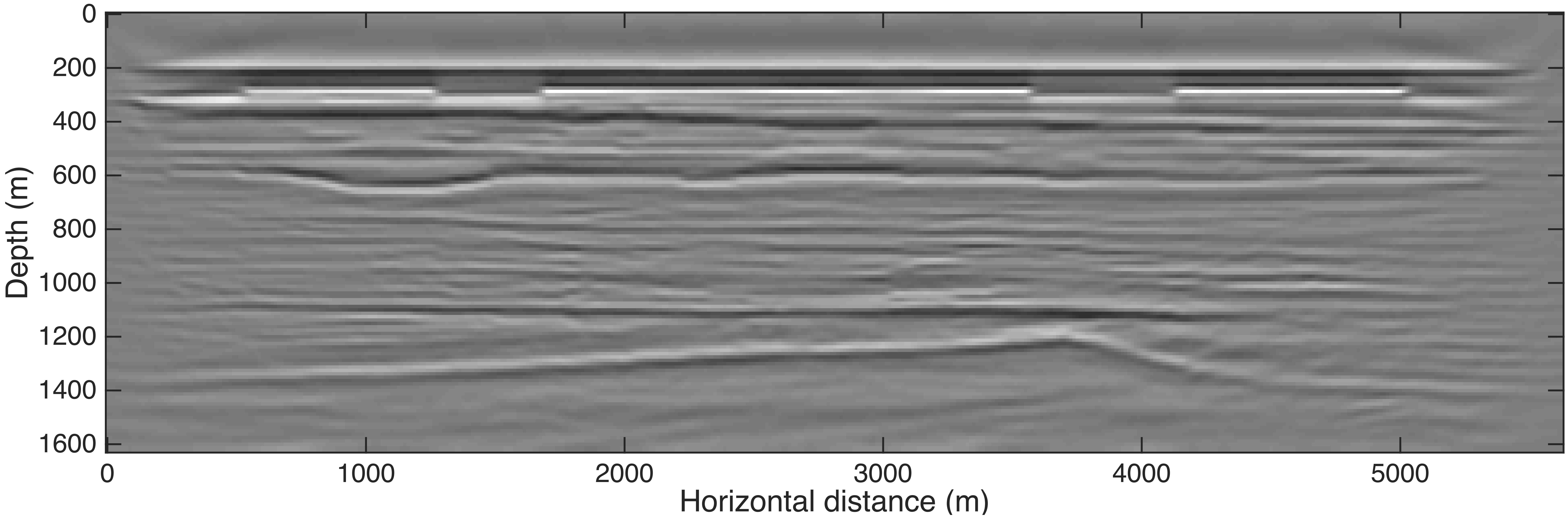
Monitor inversion results
(w/o acquisition gap)

True monitor



Inverted monitor

-without missing sources/receivers

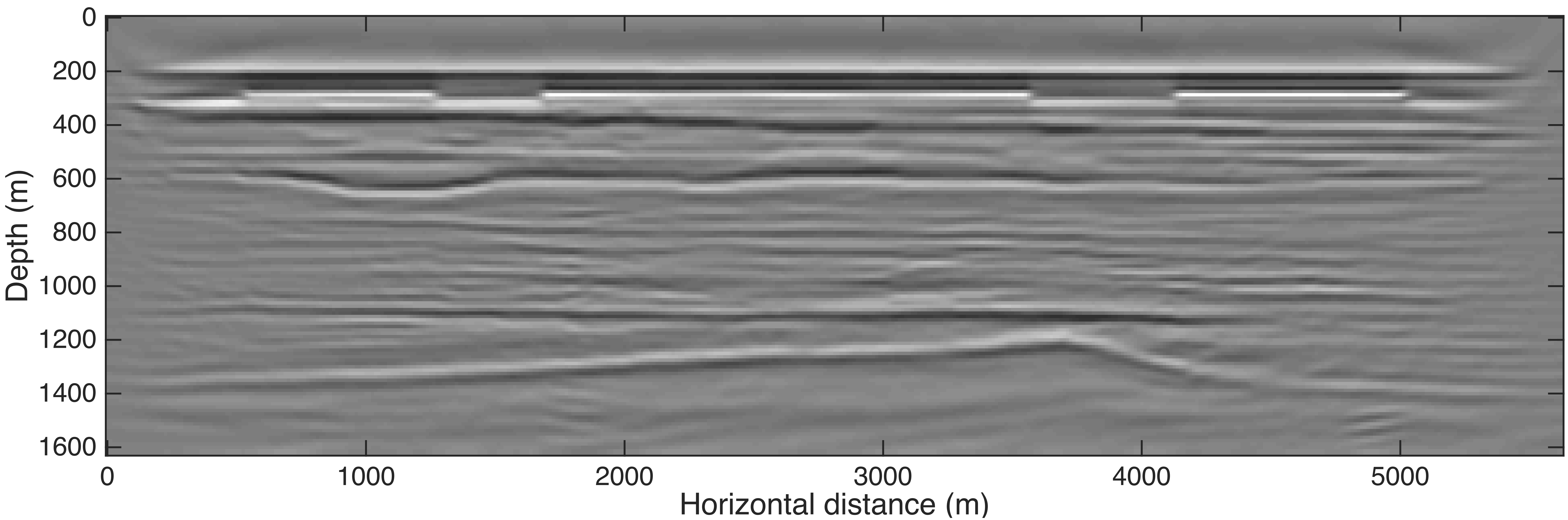


Monitor inversion results
(w/ acquisition gap)

With only sources missing in the monitor survey

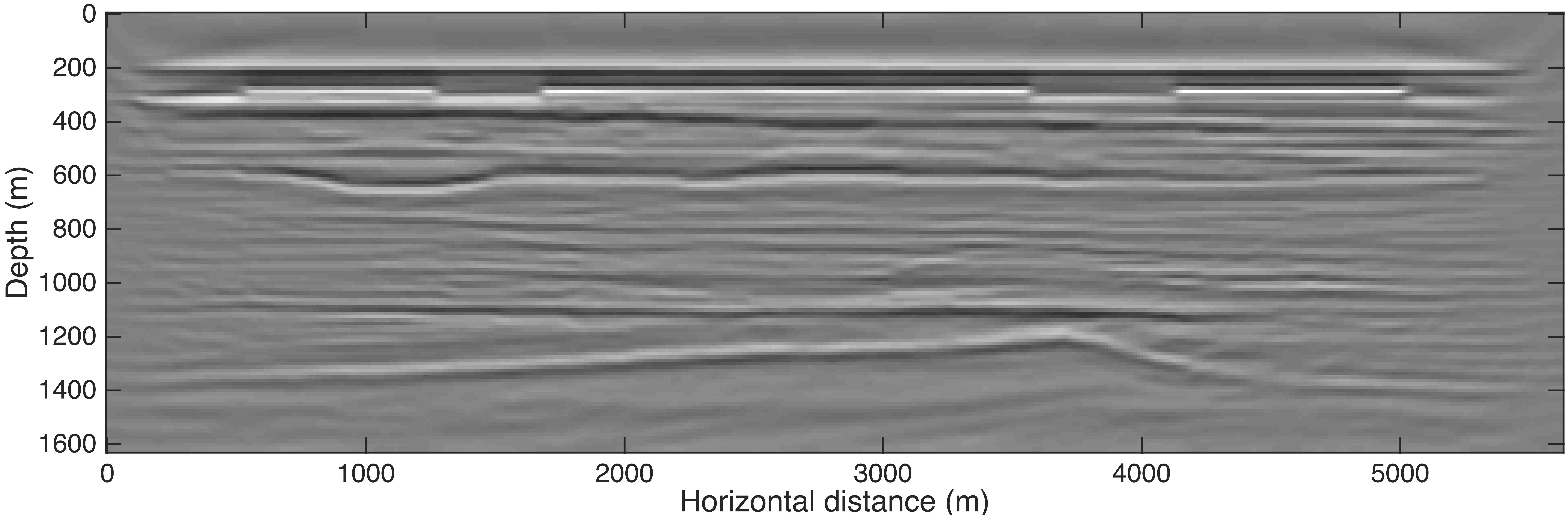
Inverted monitor

-with missing sources (1500m gap)



Inverted monitor (Joint inversion)

-with missing sources (1500m gap)



With both sources/receivers missing in the monitor survey

Expected challenges

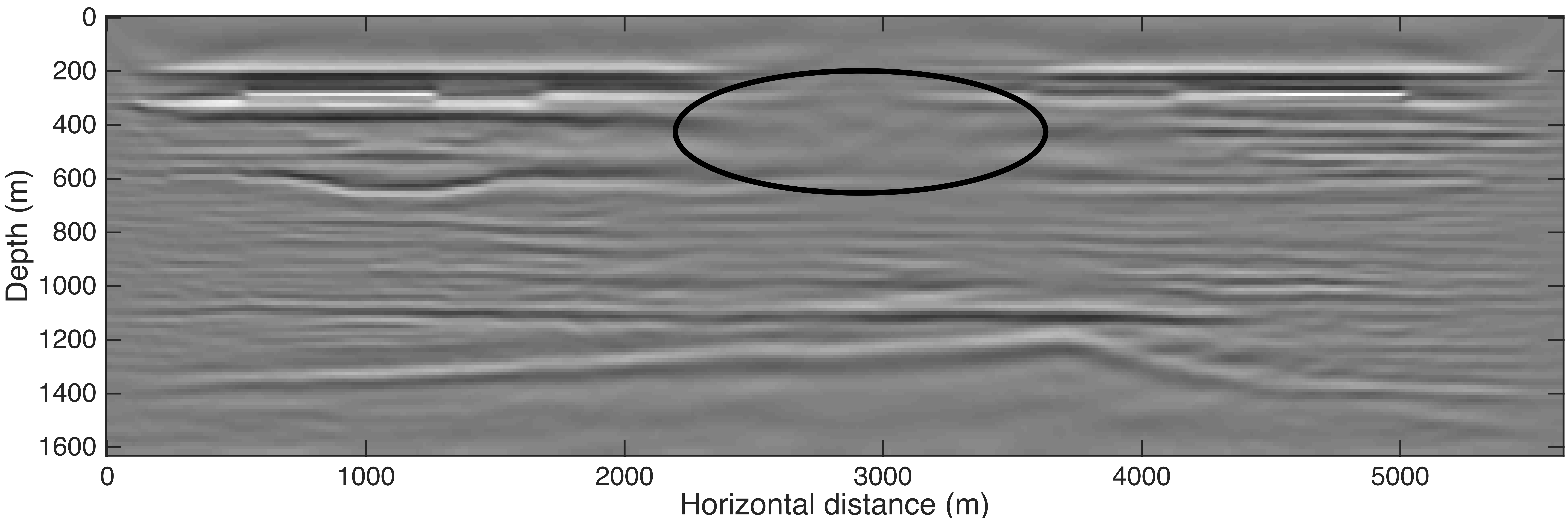
- Missing receivers implies absence of virtual sources

- Expected illumination of gaps by multiples therefore suffers

- Imaging of area beneath gap susceptible to errors

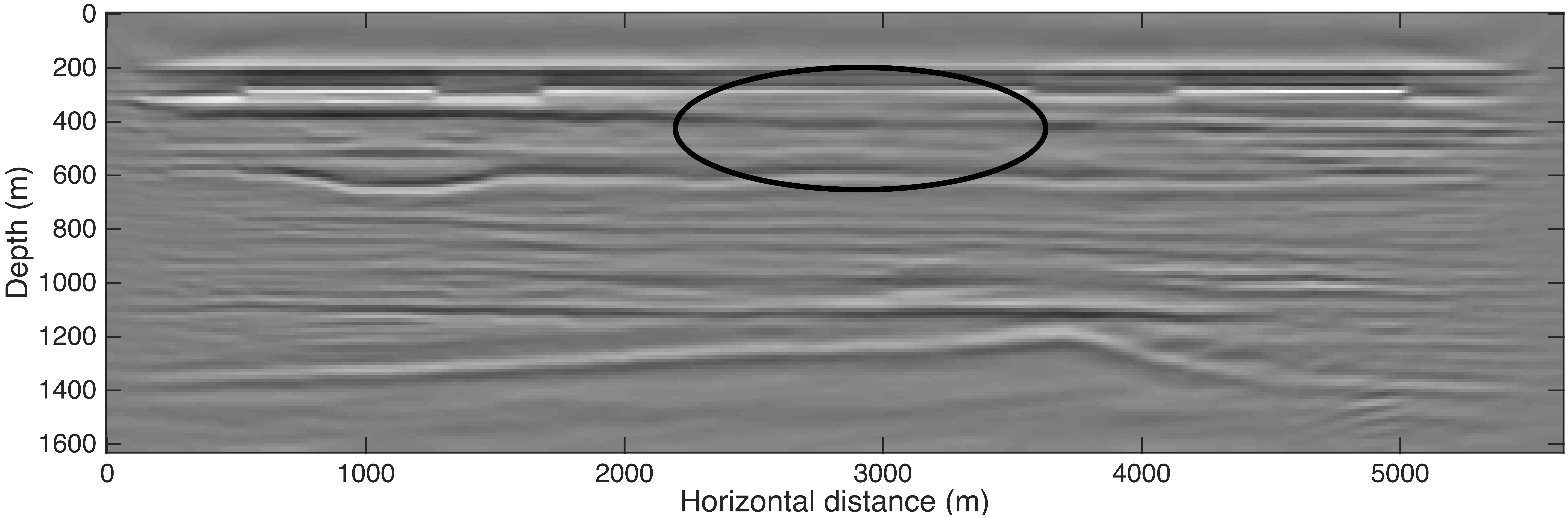
Inverted monitor

-with missing sources/receivers (>2000m gap)



Inverted monitor (Joint inversion)

-with missing sources/receivers (>2000m gap)



SLIM

Conclusions

- Surface-related multiples carry extra information that can be useful for time-lapse seismic imaging
- Combined with the joint recovery model that uses information from the vintages, issues related to poor illumination of subsurface can be mitigated
- The joint imaging can be extended to multiple vintages

Acknowledgements

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