Economic time-lapse seismic acquisition and imaging - Reaping the benefits of randomized sampling with distributed compressive sensing

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Outline

Introduction:

- *basic concepts - seismic, time-lapse etc.*
- compressive sensing & impact
- motivation

Time-lapse seismic:

- *current challenges & existing solutions*
- overview of my contribution
- main message

Outline

Theory:

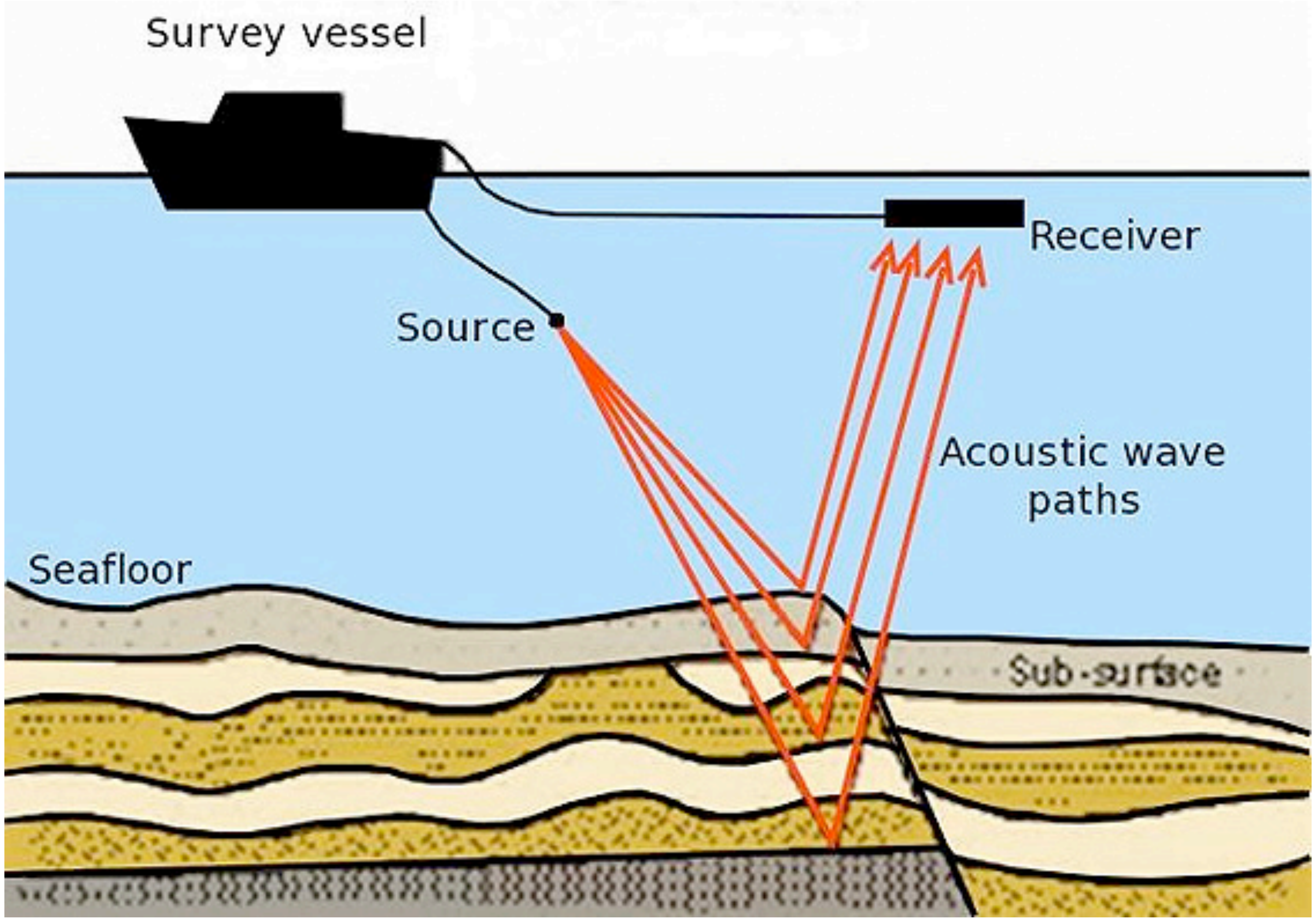
- *compressive sensing in seismic*
- *randomized acquisition in marine*
- *time-lapse formulation*
- DCS & joint recovery model

Applications:

- *time-lapse marine acquisition - Chapters 2, 3 & 4*
- time-lapse seismic imaging - Chapter 5

Conclusions

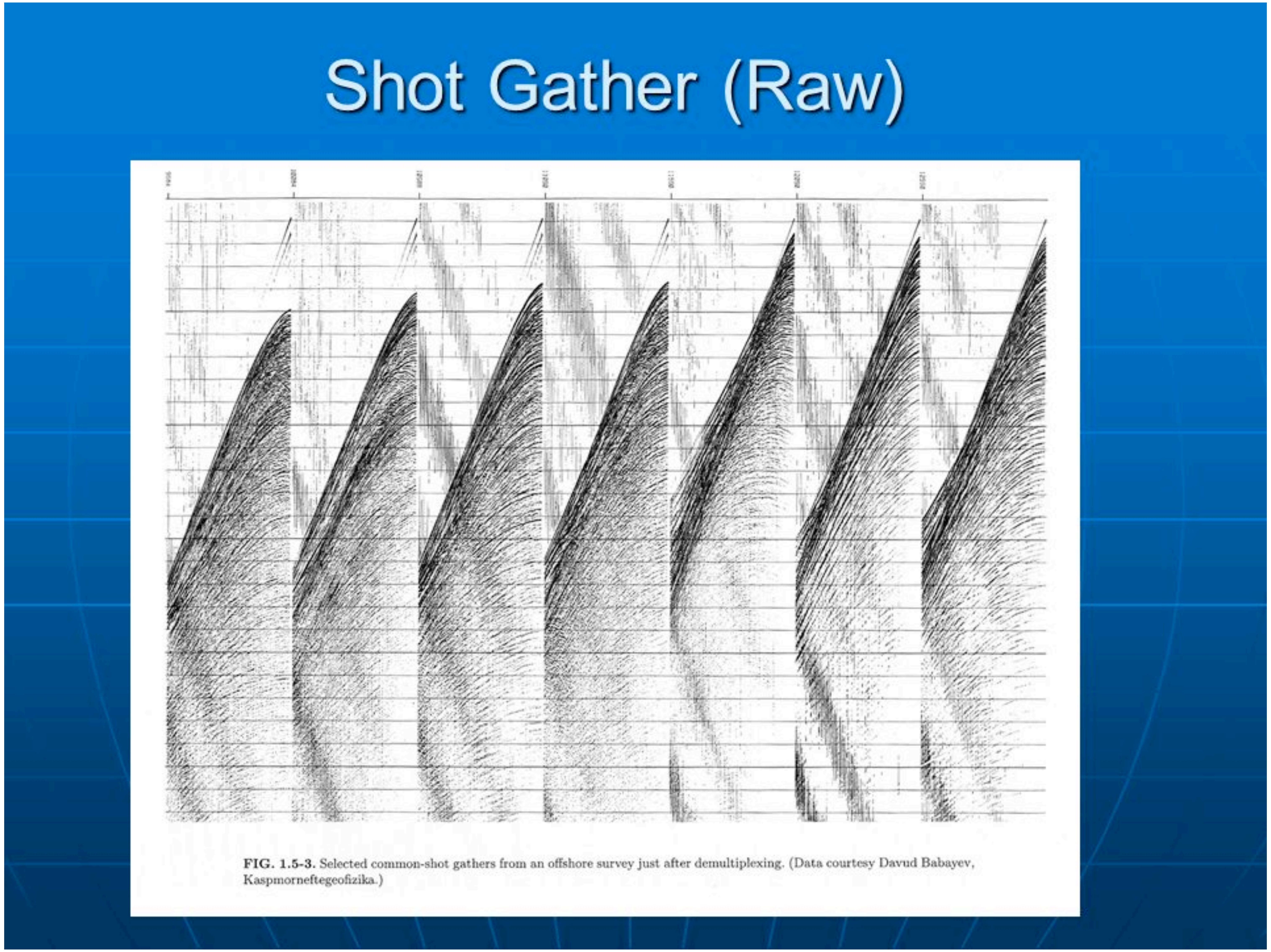
Marine seismic survey



Principle:

- *Airgun fires shot*
- Reflections from subsurface
- *Recorded by receivers*
- *Generates data (shot records)*
- *Repeat after "t" seconds*

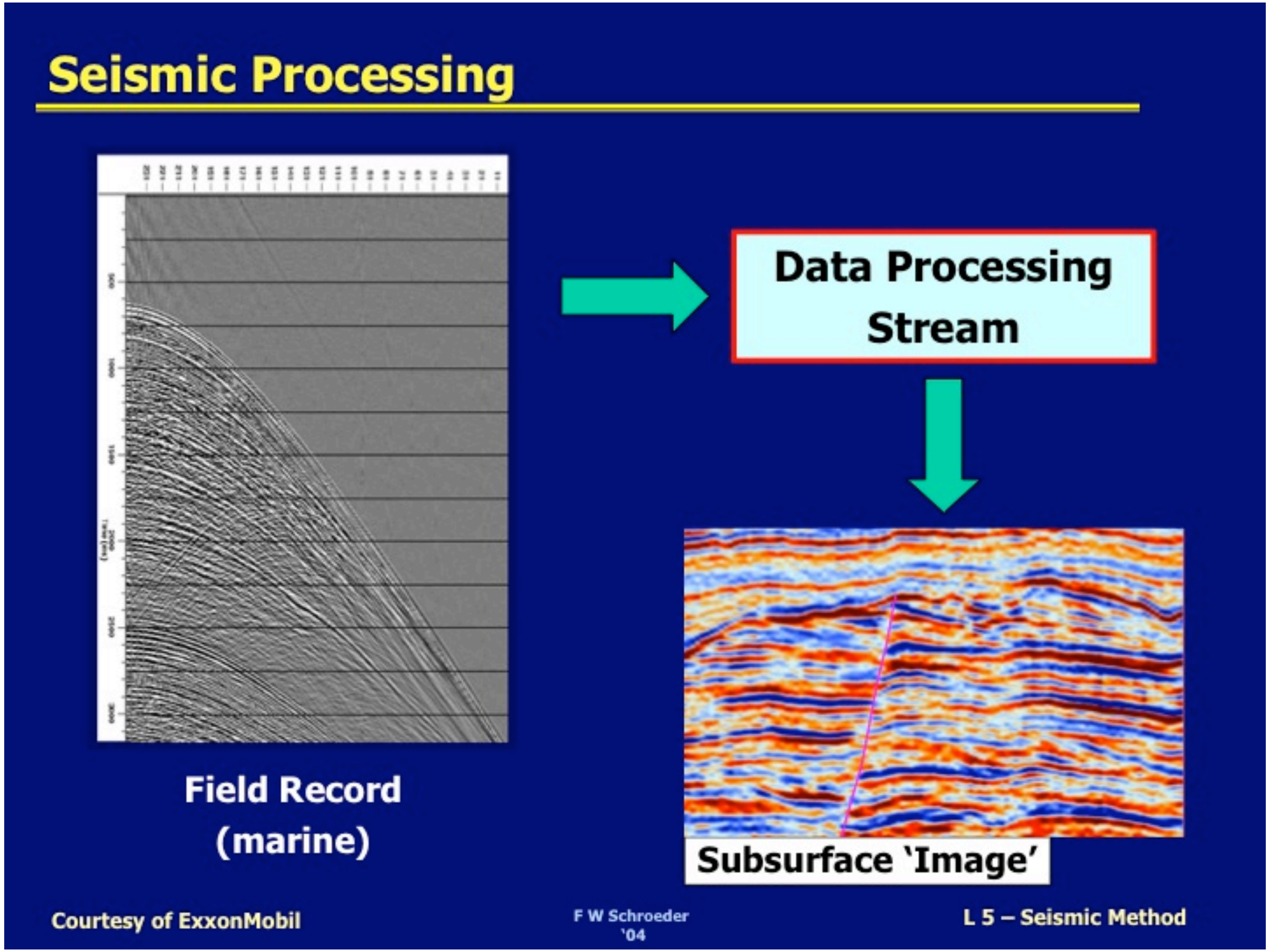
Marine seismic data



Shot records:

- *Non-overlapping*
- Contain coherent events
- *Reflections*
- *Function of time & offset*
- *Record many shots*

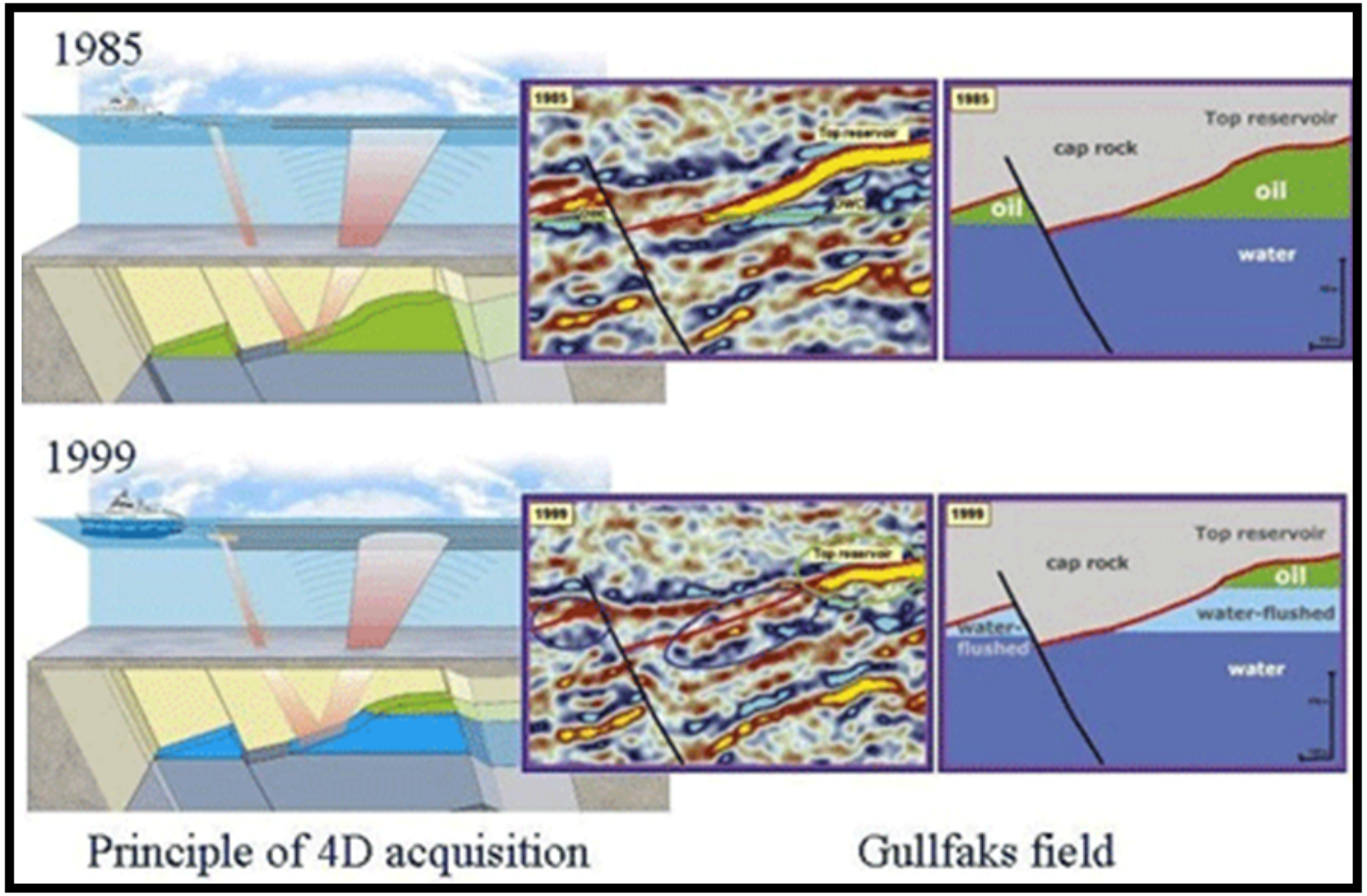
Seismic method



Workflow:

- *data acquisition*
- preprocessing
  - sorting, noise removal etc.
  - multiple removal
  - velocity analysis
  - NMO correction
- *postprocessing*
  - *stacking*
  - *noise suppression*
  - *migration (imaging)*
  - *other enhancements*

Principle of time-lapse



http://www.geoexpro.com/articles/2009/05/4d-geophysical-data

Principle:

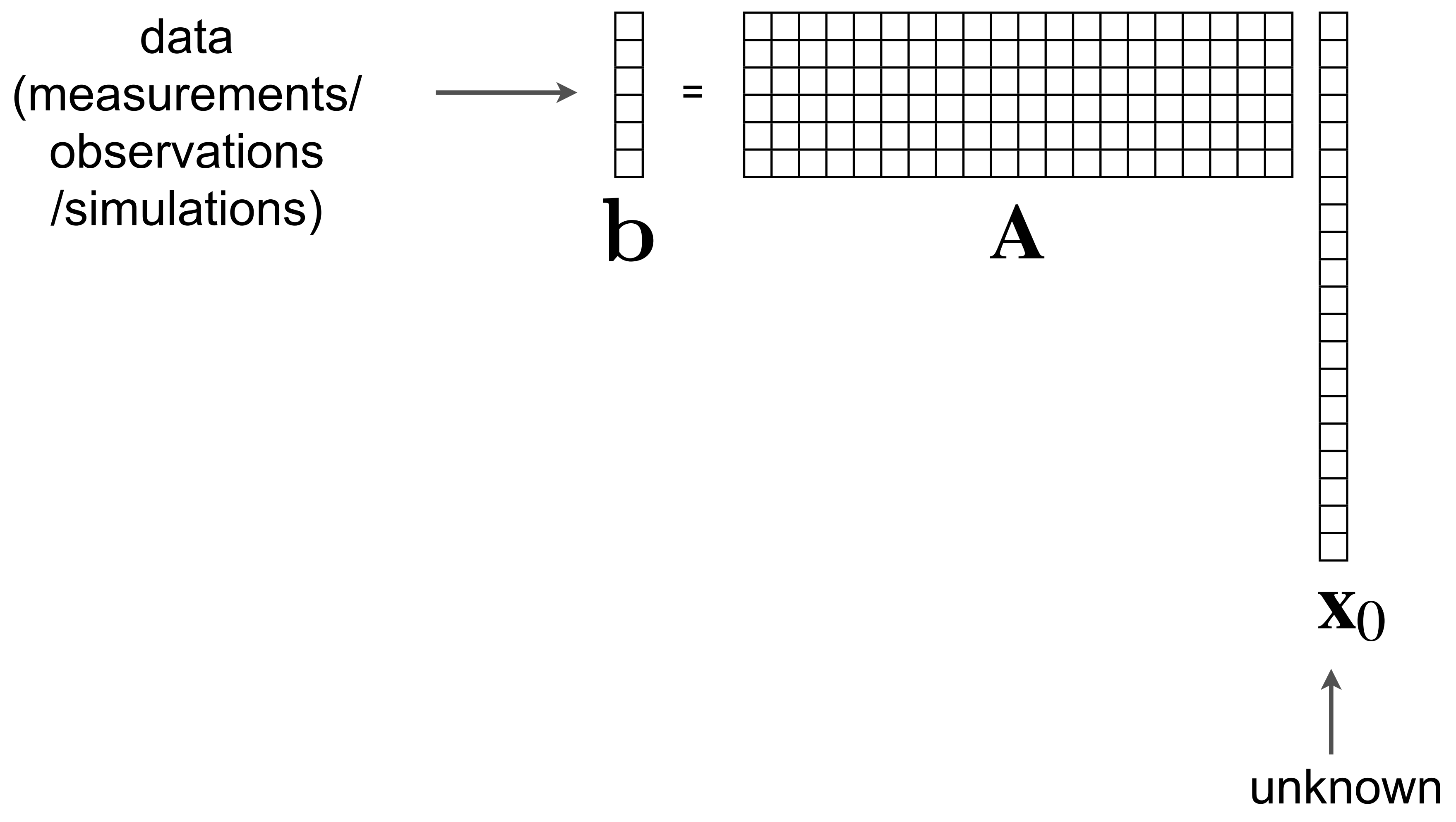
- *1st - Baseline*
- 2nd - Monitor
- *Difference = Baseline - Monitor*
- *Quantify changes*
- *Fluid sat., temp., pressure etc.*

Current acquisition *paradigm*:

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

Compressive sensing

Consider the following (severely) *underdetermined* system of *linear* equations:



Is it possible to recover $\mathbf{x}_0$ accurately from **b**?

The field of *Compressive Sensing* attempts to answer this.

Compressive sensing

Signal model

$$\mathbf{b} = \mathbf{A}\mathbf{x}_0 \quad \text{where} \quad \mathbf{b} \in \mathbb{R}^n$$

and $\mathbf{x}_0$ *k*-sparse

Sparse one-norm recovery

$$\tilde{\mathbf{x}} = \arg\min_{\mathbf{x}} ||\mathbf{x}||_1 \stackrel{\text{def}}{=} \sum_{i=1}^{N} |x[i]| \quad \text{subject to} \quad \mathbf{b} = \mathbf{A}\mathbf{x}$$

with $\mathrm{n} \ll N$ where N is the *ambient dimension*

Impact of CS

THE LEADING EDGE

Table of Contents

Departments

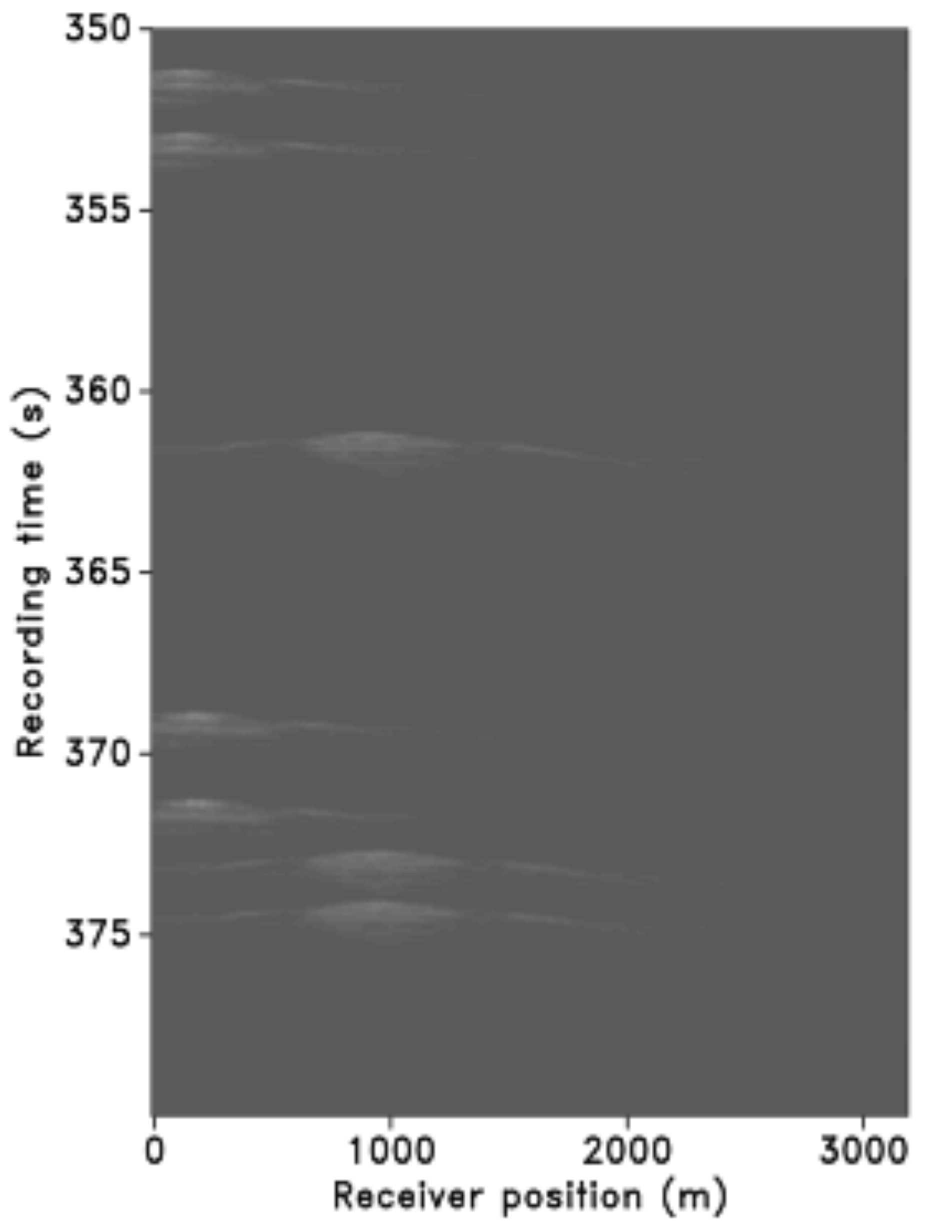
Cover image: Houston, Texas, USA downtown city skyline at dusk by Sean Pavone/Shutterstock.

Impact:

- *Industry uptake e.g. ConocoPhillips.*
- Reported improvement in efficiency & economics - up to 10-fold improvements
- *Planned time-lapse surveys*

Sim. src (jittered) blended shots
– instance of compressive sensing

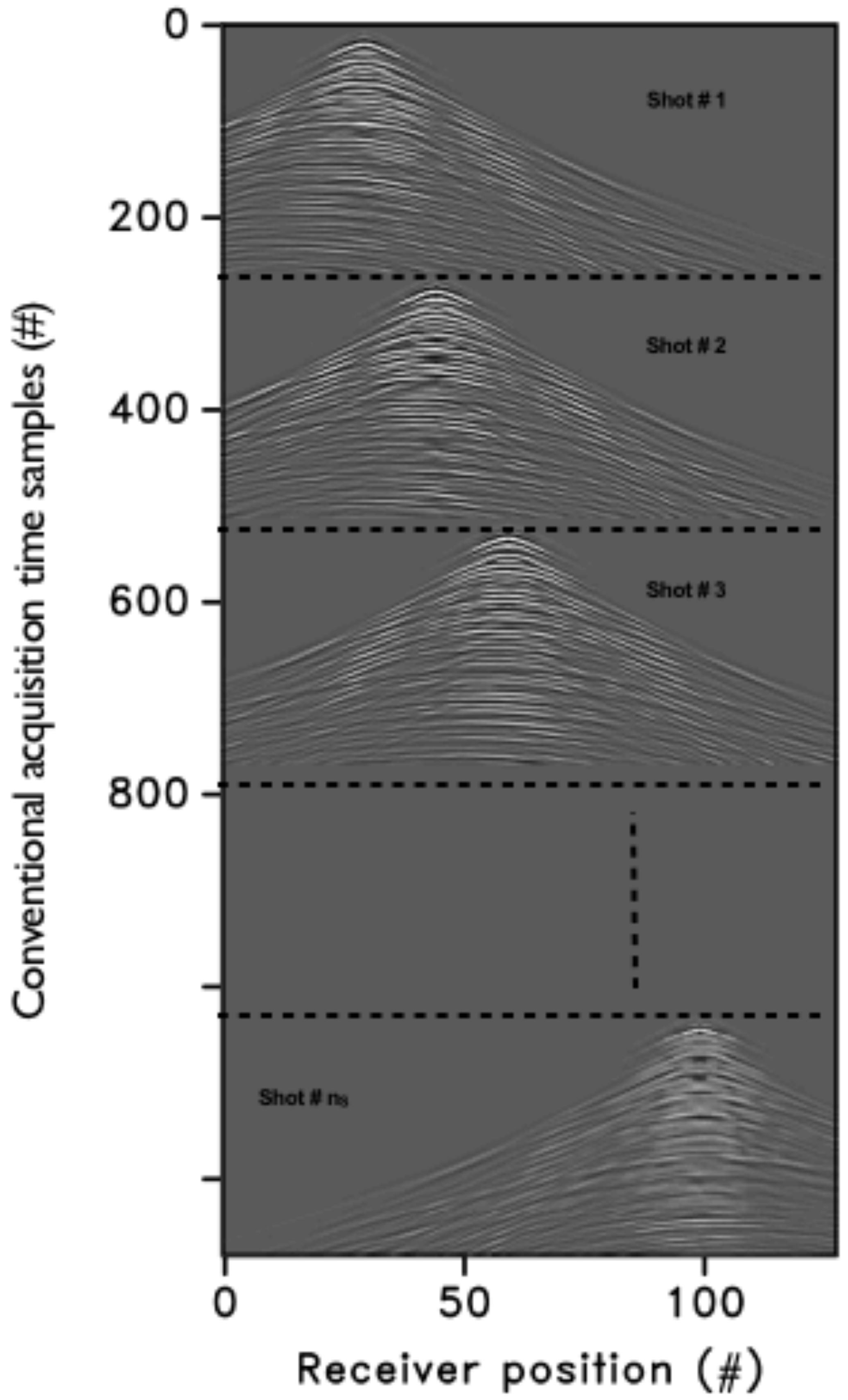
subsampled shots with overlap between shot records



source fires at jittered times and jittered positions

sum

all shots without overlap between shot records



Context

Time-lapse surveys

- are *expensive*
- require strict *repeat* surveys
- repetition of surveys is *difficult*

Solution:

- cheap surveys based on CS
- less reliance on survey repetition

Objective

- *Reduce cost of time-lapse surveys*
- Improve quality of the prestack vintages
- Less reliance on high degrees of survey replicability

Method:

- design low-cost surveys based on CS
- leverage the shared information in time-lapse recordings

Thesis contributions

Time-lapse & CS:

- *first* attempt *to investigate feasibility*
- focus on impact of survey *replication*
- implications for *repeatability*
- impact of *calibration errors*

Main message:

- Do not attempt to *replicate* time-lapse surveys
- Recover surveys “jointly” w/ the proposed JRM

Watanabe et al., 2004; Denli and Huang, 2009; Zheng et al., 2011;
Asnaashari et al., 2012; Raknes et al., 2013; Shragge et al., 2013;
Maharramov et al., 2014; Yang et al., 2014.

Time-lapse : current practice/methods

Acquisition/Processing:

- *effort to repeat* **expensive** *dense* acquisitions & "*independent*" processing
- mostly static receivers to minimize differences
- *"cross-equalization" to address some non-repeatability effects*

Imaging/Inversion:

- different methods (data/image domain) depending on non-repeatability effects
- *Parallel WI,* DDWI, SeqFWI, AltFWI, IDWT

CS formulation in time-lapse

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

SLIM

Aim

- *Reduce cost of time-lapse surveys*
- Improve quality of the prestack vintages
- Avoid repetition

Method:

- economic randomized sampling based on CS
- sparsity-promoting data recovery
- leverage the shared information in time-lapse recordings

Distributed compressed 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

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

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

Joint recovery model (JRM)

sparsity-promoting minimization:

$$\tilde{\mathbf{z}} = \arg\min_{\mathbf{z}} \underbrace{\|\mathbf{z}\|_1}_{\text{support detection}} \quad \text{subject to} \quad \underbrace{\mathbf{A}\mathbf{z} = \mathbf{b}}_{\text{data-consistent amplitude recovery}}$$

$$\tilde{\mathbf{z}} = \begin{bmatrix} \tilde{\mathbf{z}}_0 \\ \tilde{\mathbf{z}}_1 \\ \tilde{\mathbf{z}}_2 \end{bmatrix} \begin{matrix} \\ \left.\begin{matrix} \\ \\ \end{matrix}\right\} \text{time-lapse} \end{matrix}$$

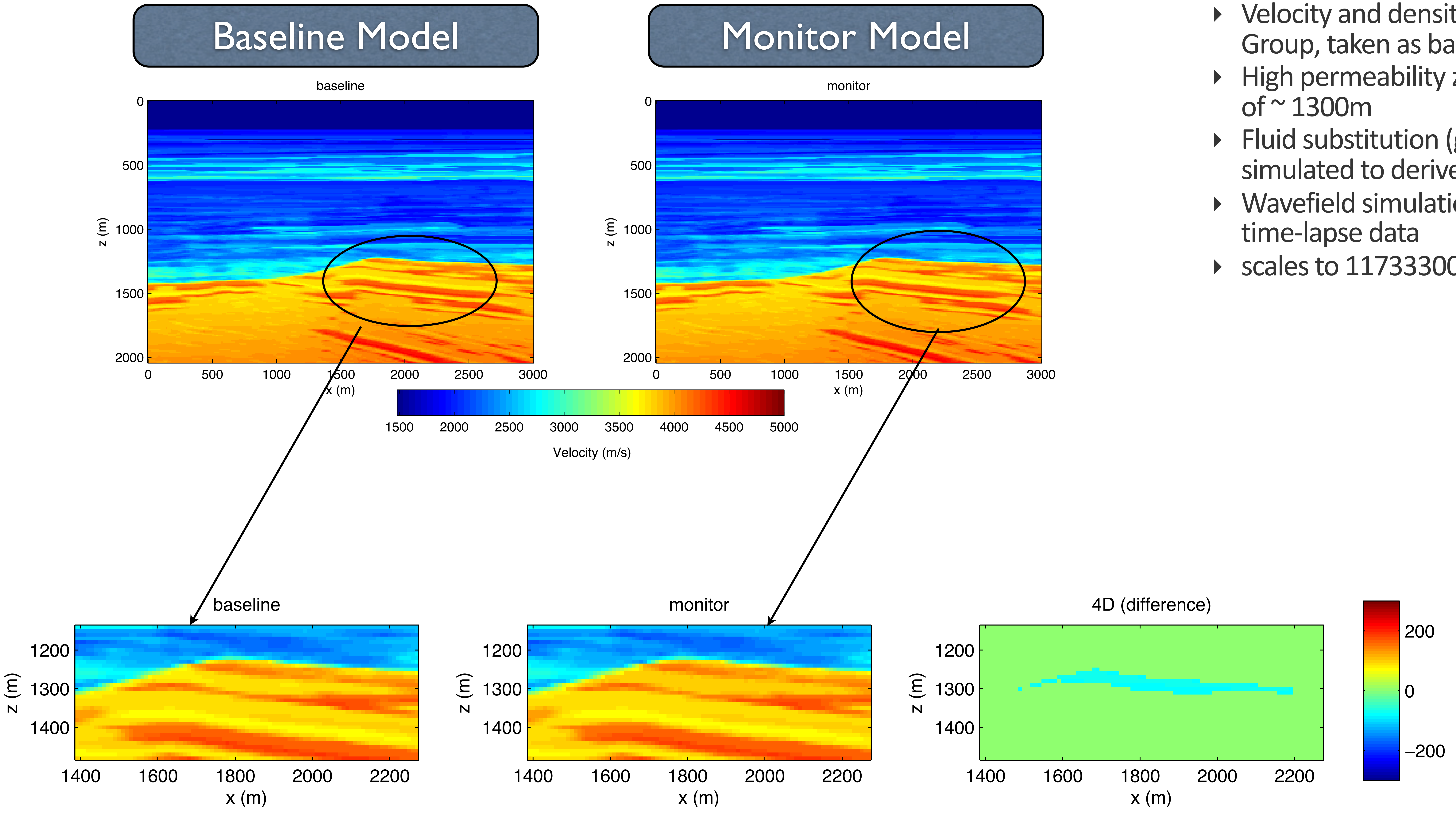
Key idea:

- invert for common components & innovation w.r.t. common components with sparse recovery
- common component observed by all surveys

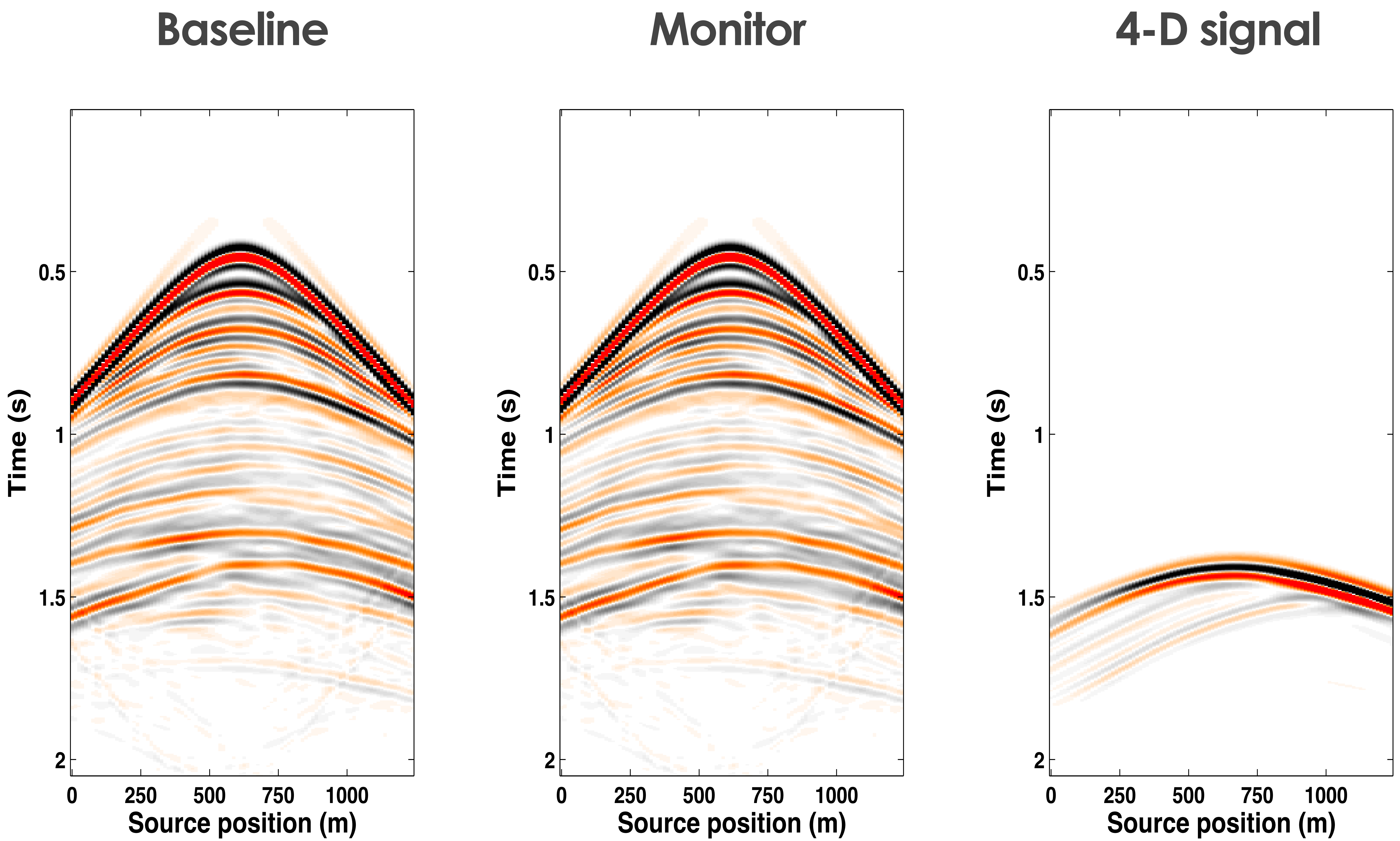
Seismic application

Method

- Velocity and density model provided by BG Group, taken as baseline
- High permeability zone identified at a depth of ~ 1300m
- Fluid substitution (gas/oil replaced with brine) simulated to derive monitor velocity model
- Wavefield simulation to generate synthetic time-lapse data
- scales to 11733300 x 114882048



Simulated time-lapse data
– time-domain finite differences



time samples: **512**
receivers: **100**
sources: **100**

sampling
time: **4.0 ms**
receiver: **12.5 m**
source: **12.5 m**

Evaluation

Signal to noise ratio:

$$\mathrm{SNR}(\mathbf{d}, \tilde{\mathbf{d}}) = -20 \log_{10} \frac{\|\mathbf{d} - \tilde{\mathbf{d}}\|_2}{\|\mathbf{d}\|_2}$$

Repeatability as NRMS (normalized root mean square): [Kragh and Christie (2002)]

$$\mathrm{NRMS}(\tilde{\mathbf{d}}_\mathbf{1}, \tilde{\mathbf{d}}_\mathbf{2}) = \frac{200 \times \mathrm{RMS}(\tilde{\mathbf{d}}_\mathbf{1} - \tilde{\mathbf{d}}_\mathbf{2})}{\mathrm{RMS}(\tilde{\mathbf{d}}_\mathbf{1}) + \mathrm{RMS}(\tilde{\mathbf{d}}_\mathbf{2})}$$

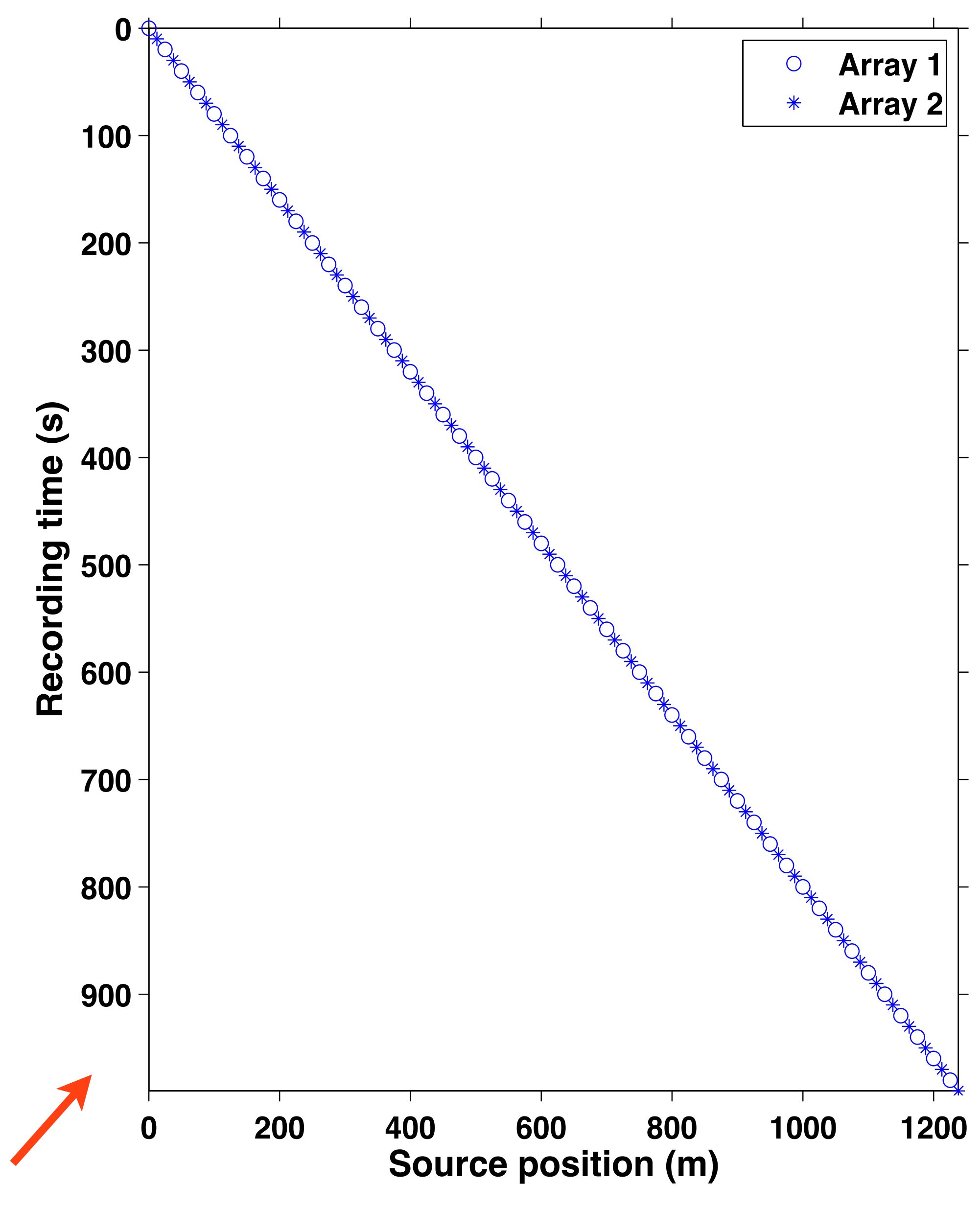
$$\mathrm{RMS}(\mathbf{d}) = \sqrt{\frac{\sum_{t=t_1}^{t_2} (\mathbf{d}[t])^2}{N}}$$

N is the number of samples in the interval t_1 to t_2

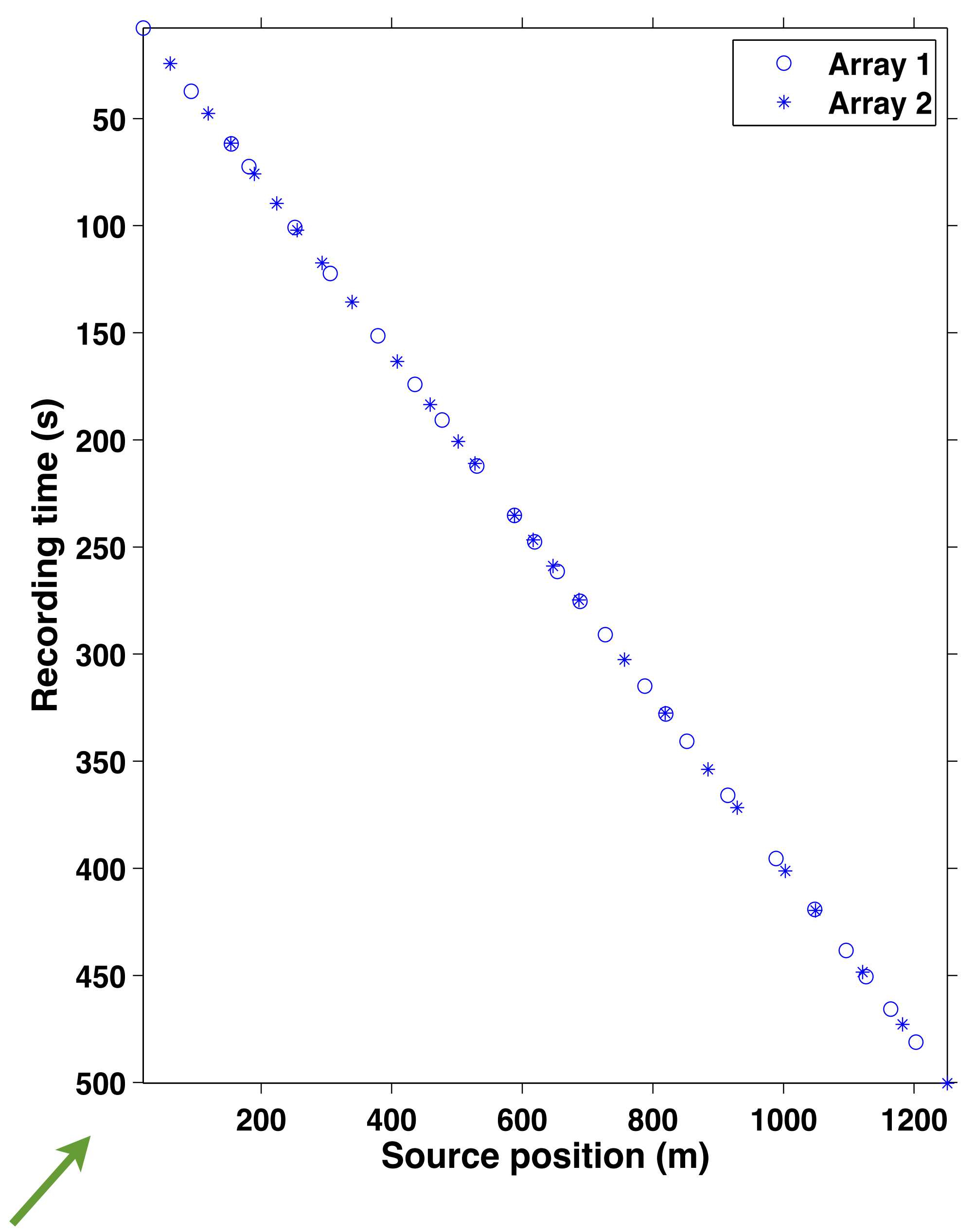
$\mathbf{d}[t]$ is a sample recorded at time t

Conventional vs. *time-jittered* sources
– *subsampling* ratio = 2, 2 source arrays

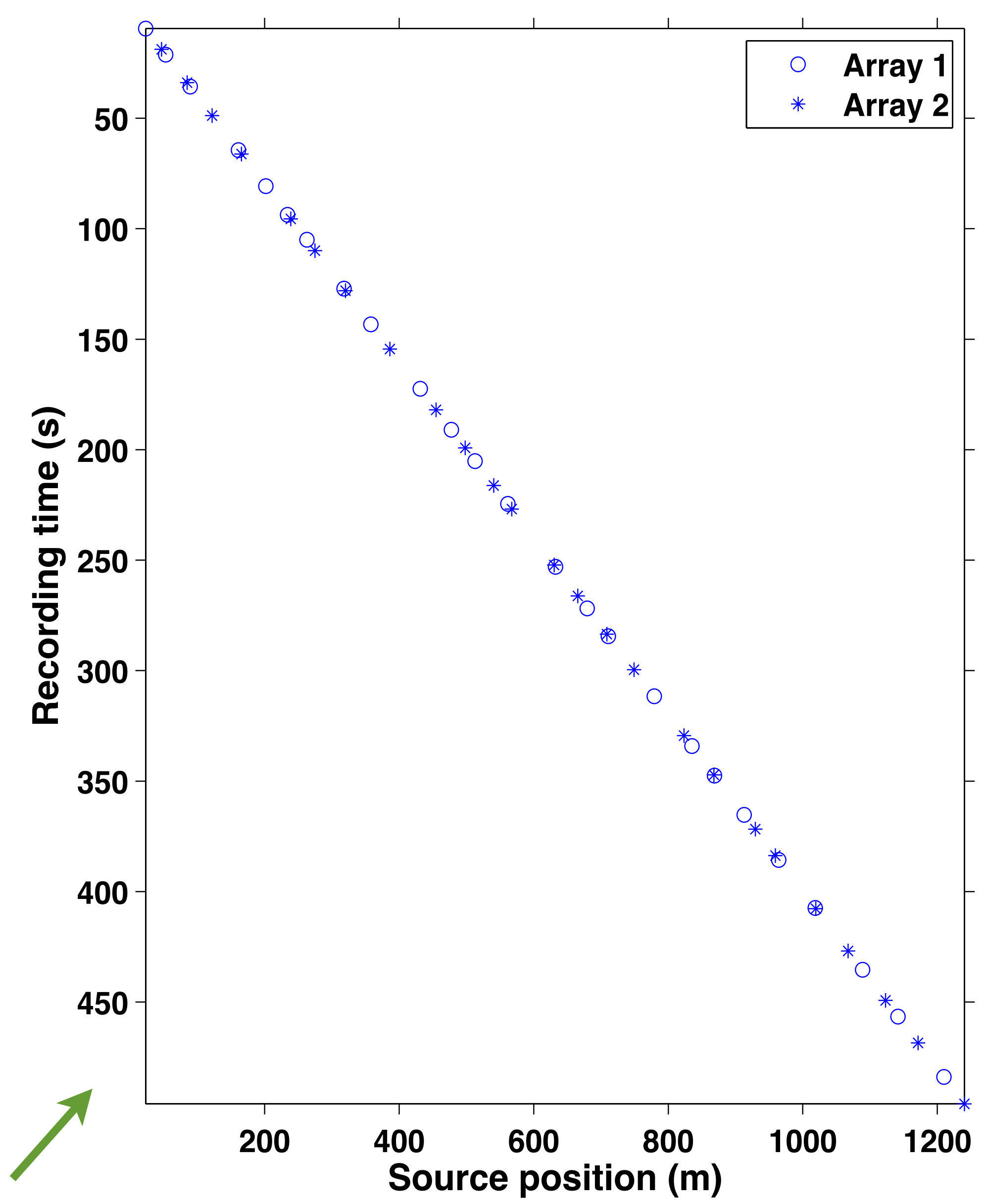
conventional



jittered acquisition 1 (baseline)



jittered acquisition 2 (monitor)



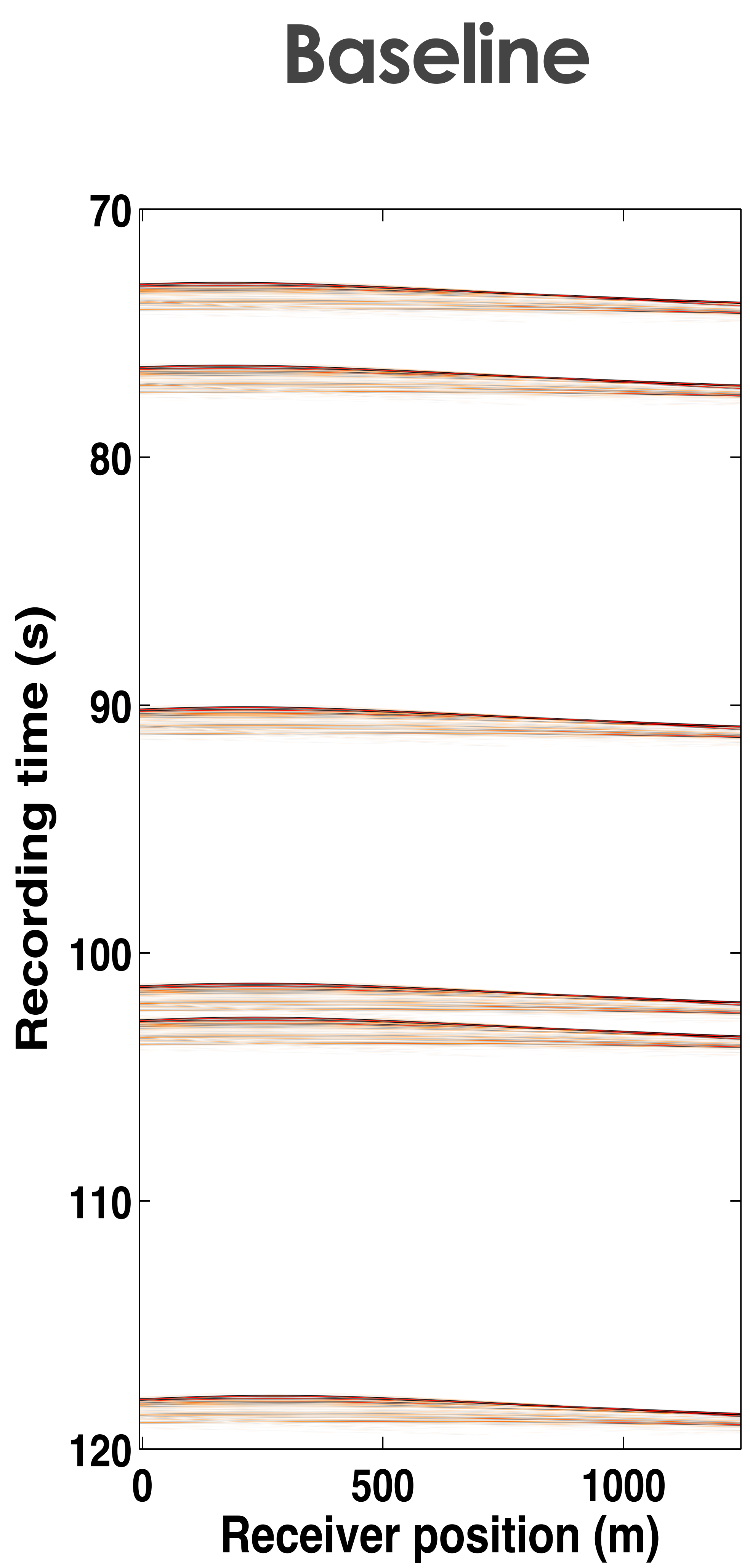
***"unblended"* shot gathers**
number of shots = **100** (per array)
shot record length: 10.0 s
spatial sampling: **12.5 m**
vessel speed: **1.25 m/s**
recording time = 100 x 10.0 = **1000.0 s**

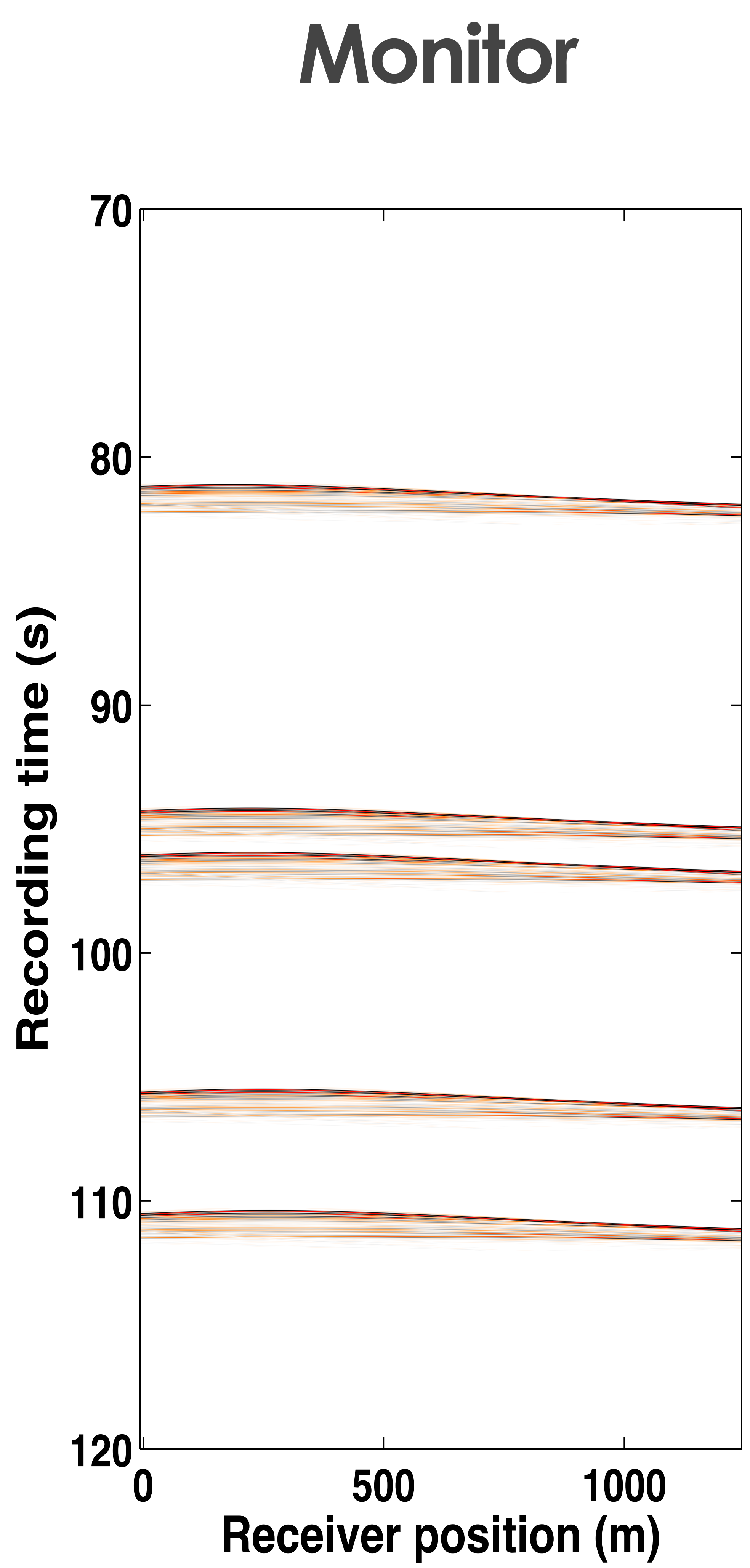
[BLENDING & SUBSAMPLING]
spatial subsampling factor = 2

spatial sampling ***increase*** factor = 2
[DEBLENDING & INTERPOLATION]

***"blended"* shot gathers**
number of shots = 100/2 = **50** (25 per array)
spatial sampling: **50.0 m (*jittered*)**
vessel speed: **2.50 m/s**
recording time ≈ 1000.0 s/2 = **500.0 s**

Measurements
– *subsampled* and *blended*





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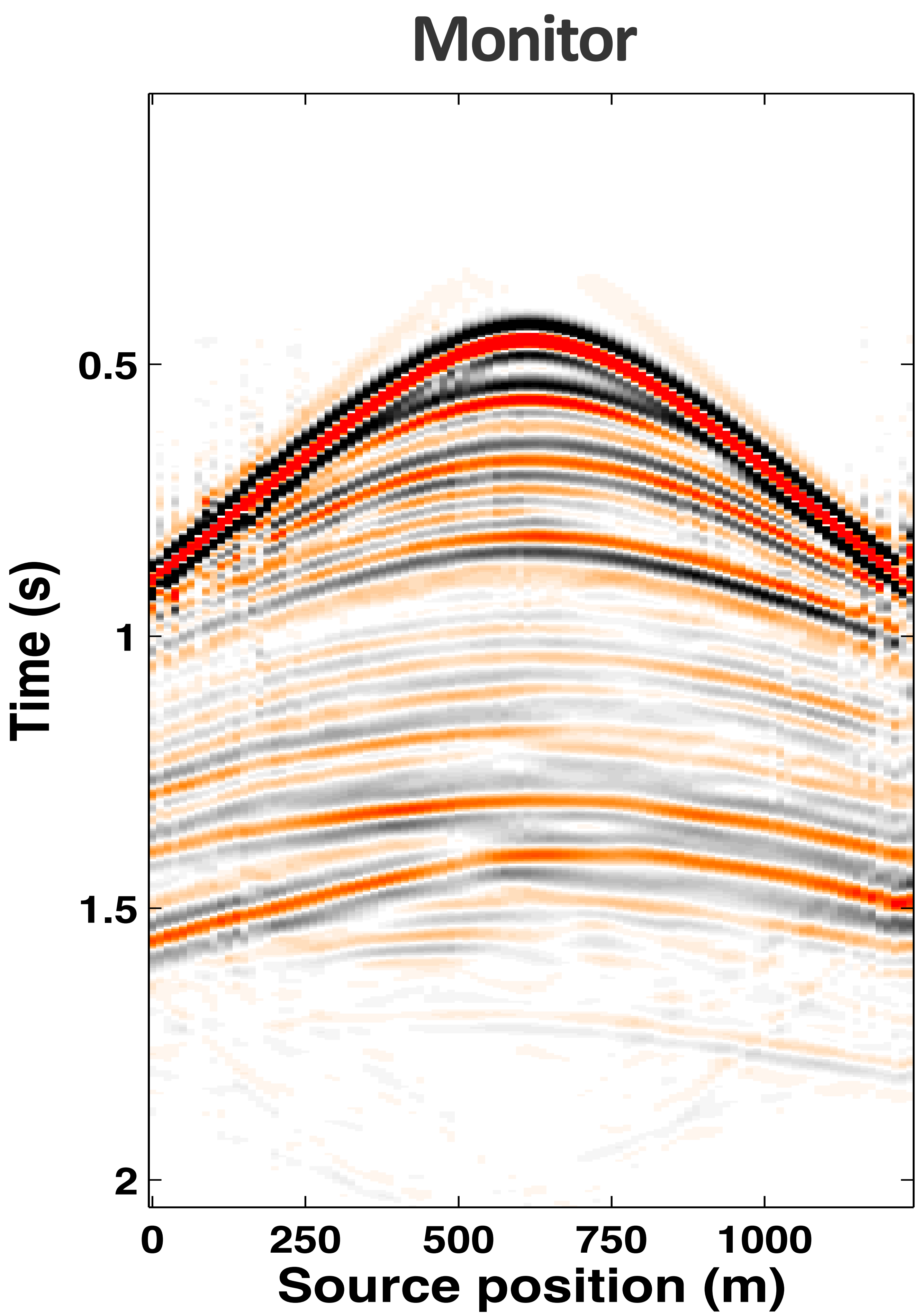
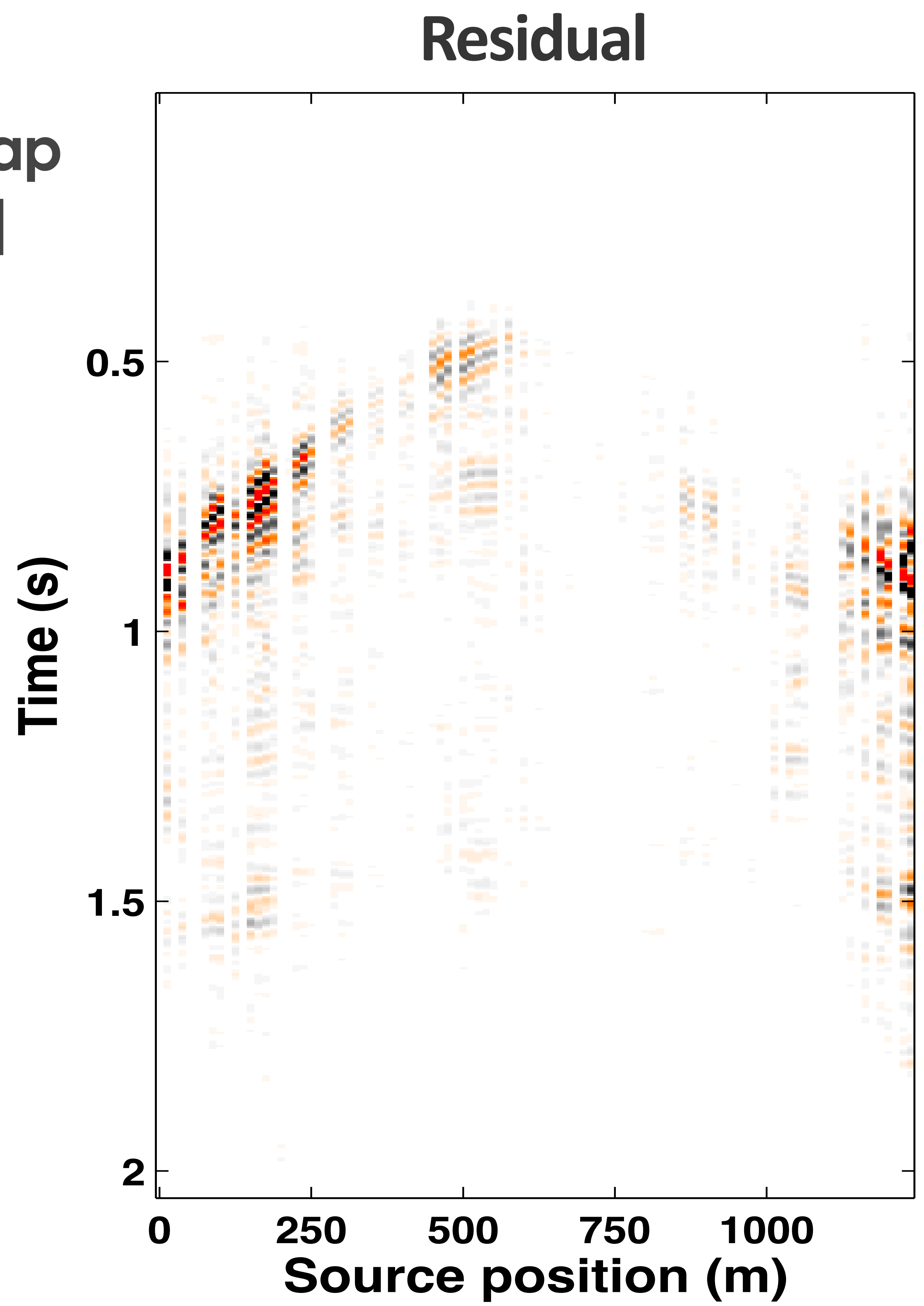
recovered data: $\tilde{\mathbf{d}} = \mathbf{S}^H \tilde{\mathbf{x}}$

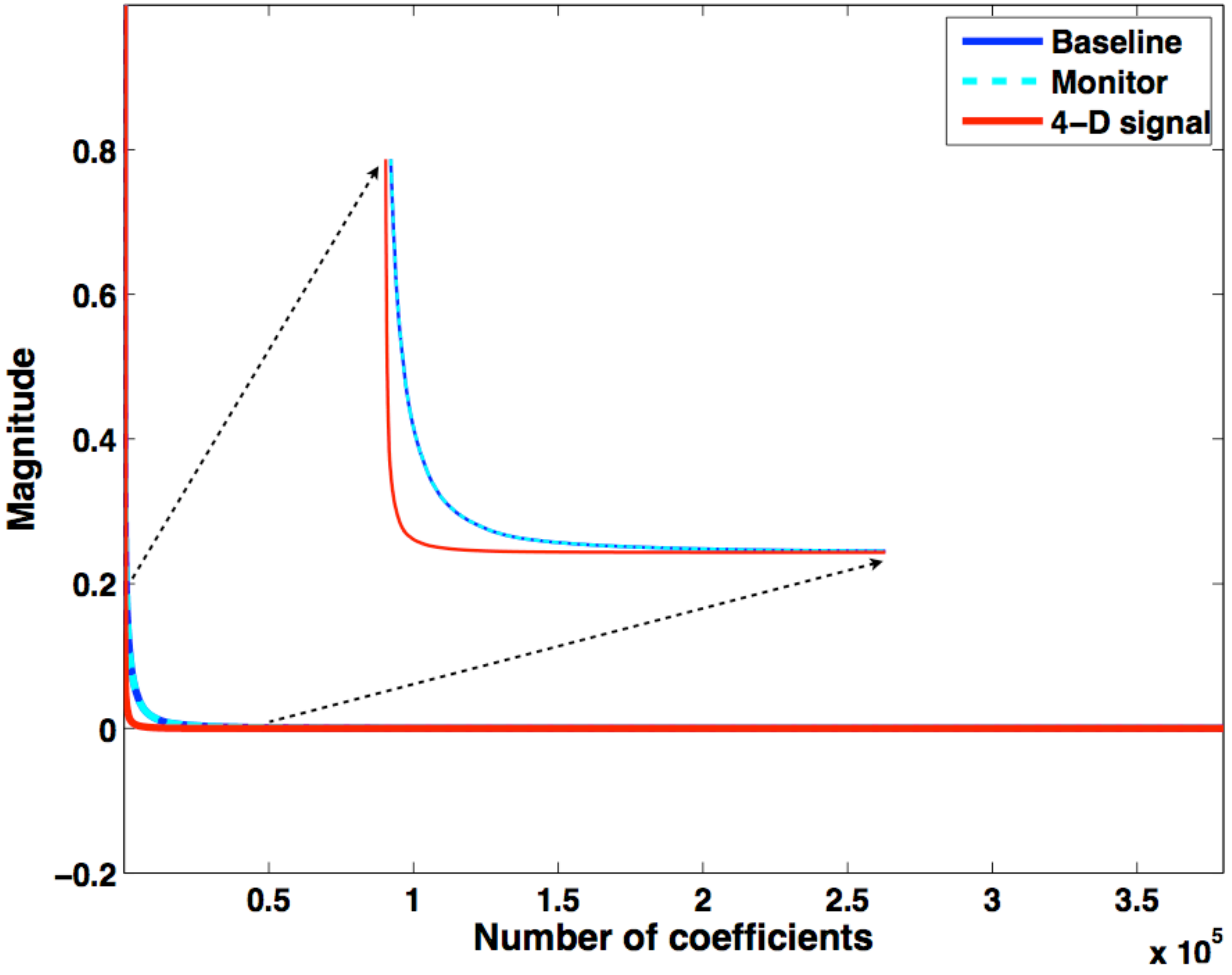
Recovery (independently)

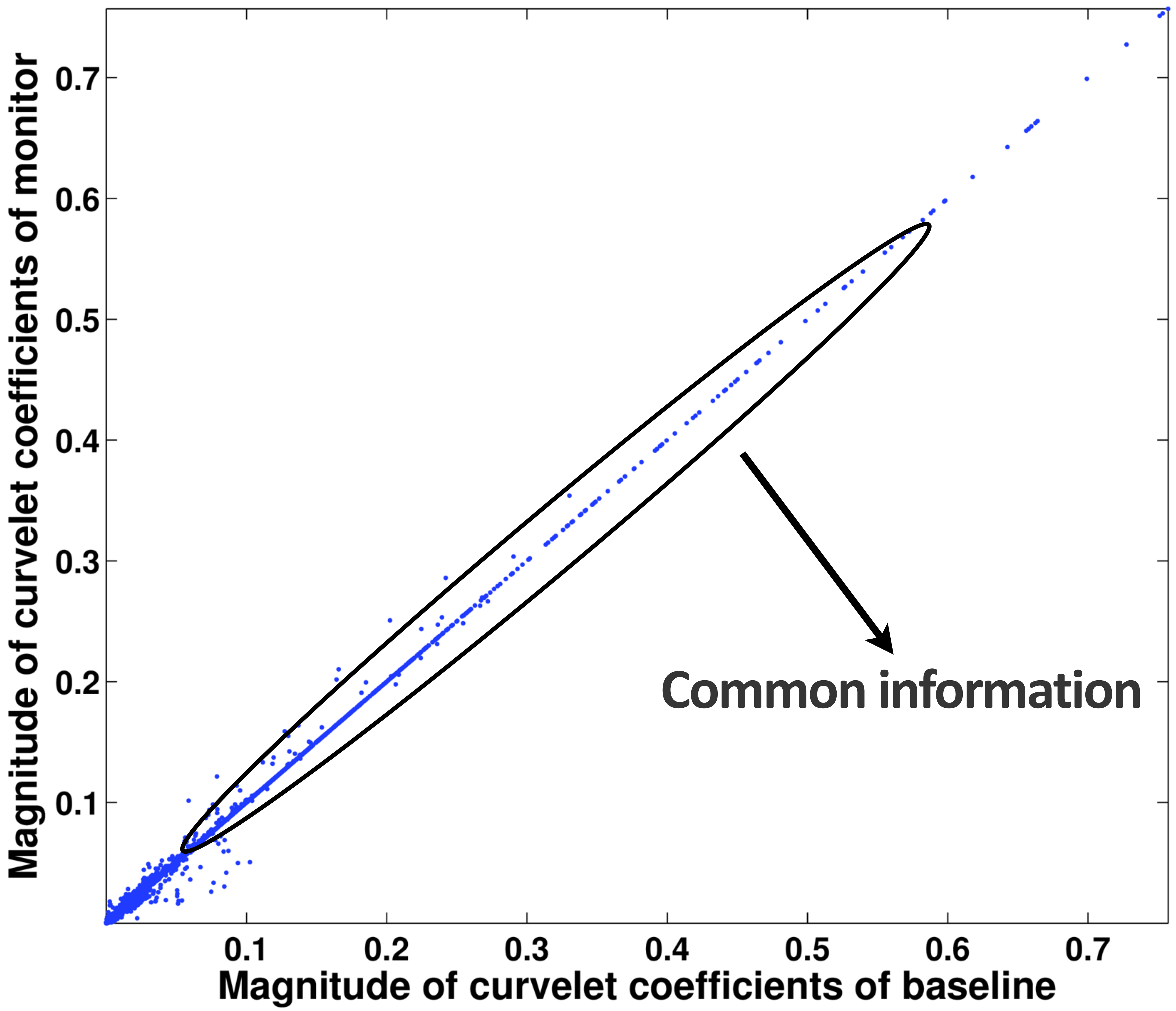


25% overlap
[10.3 dB]

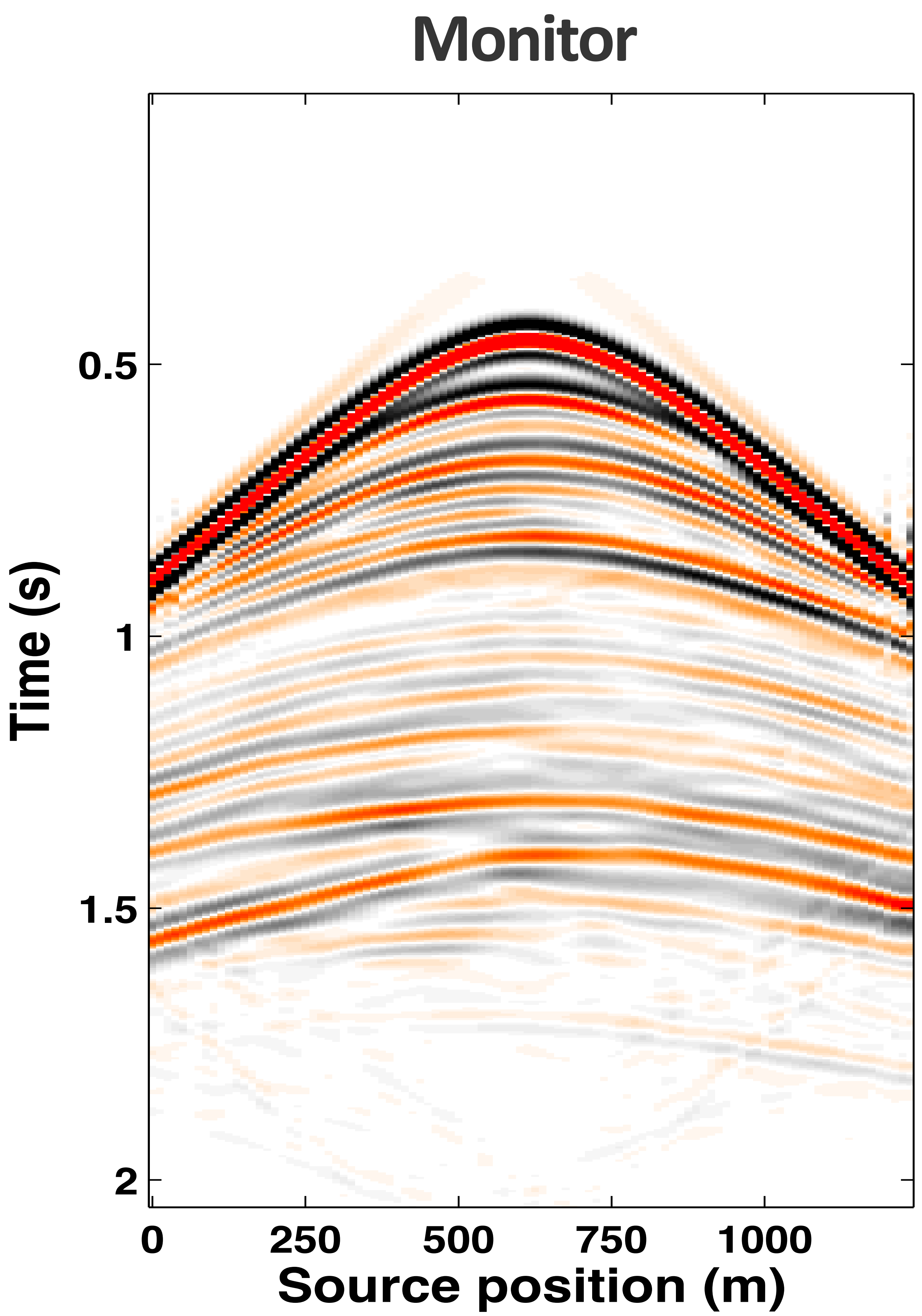


Structure - curvelet representation

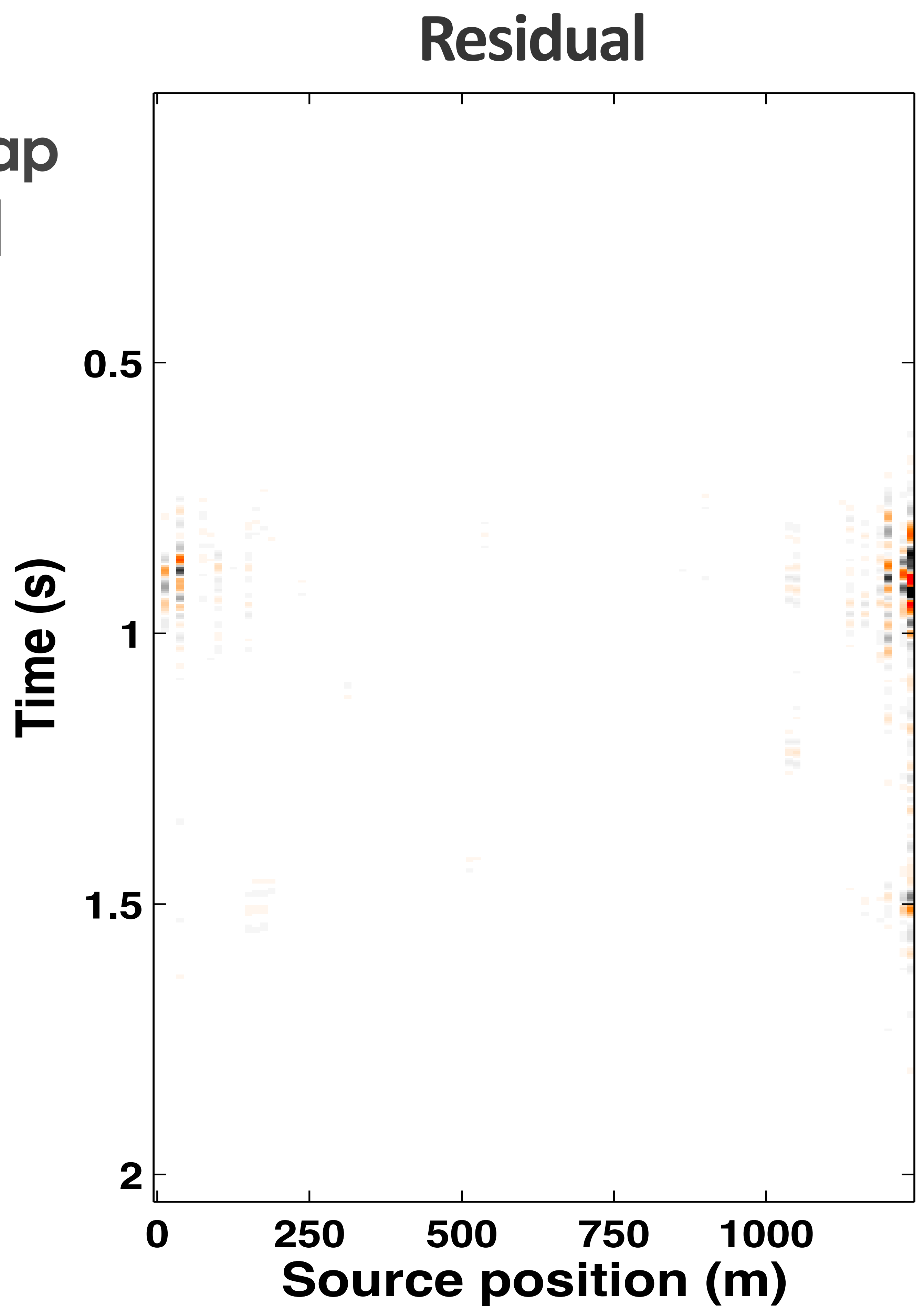




Recovery (jointly) via JRM

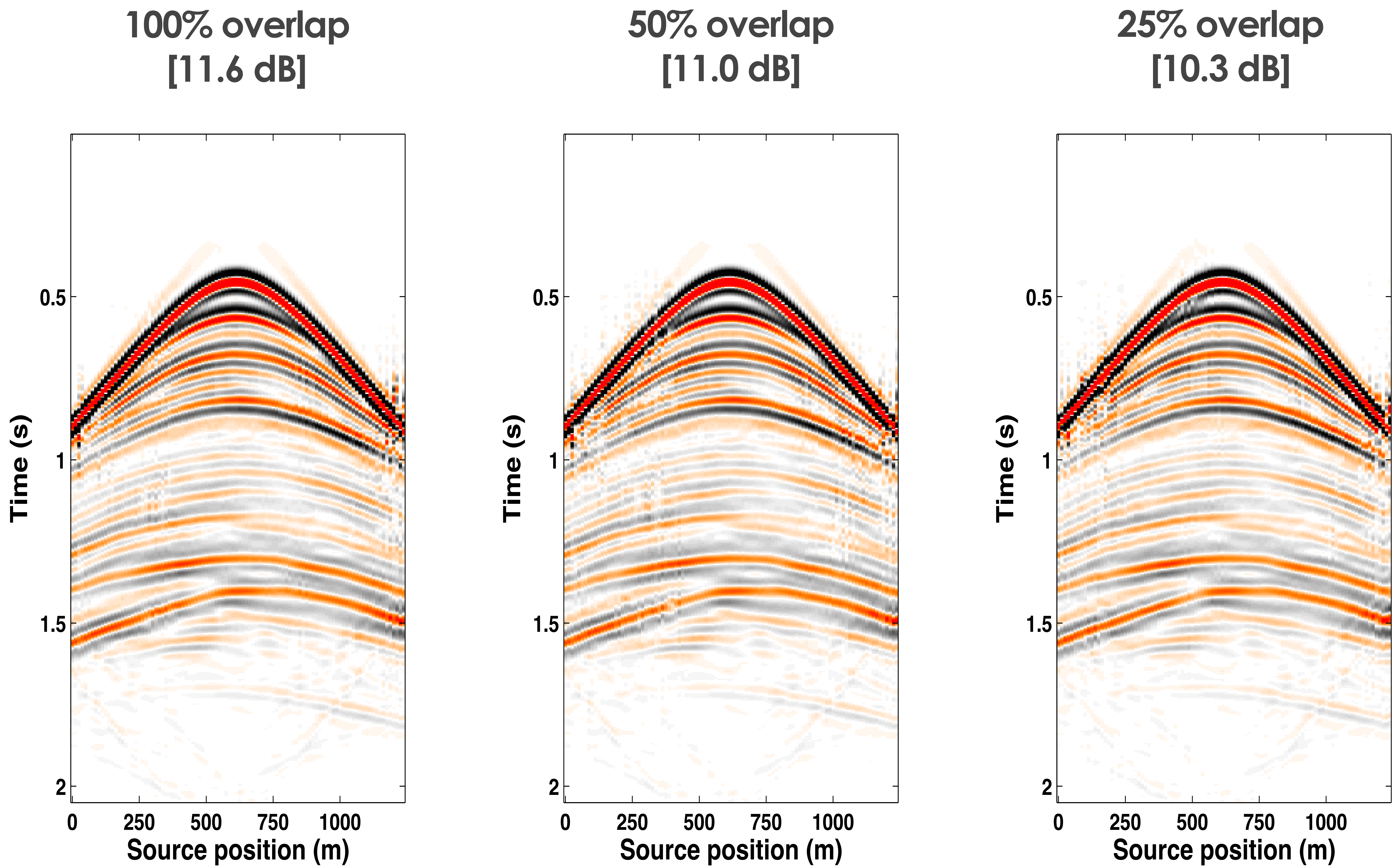


25% overlap
[18.6 dB]



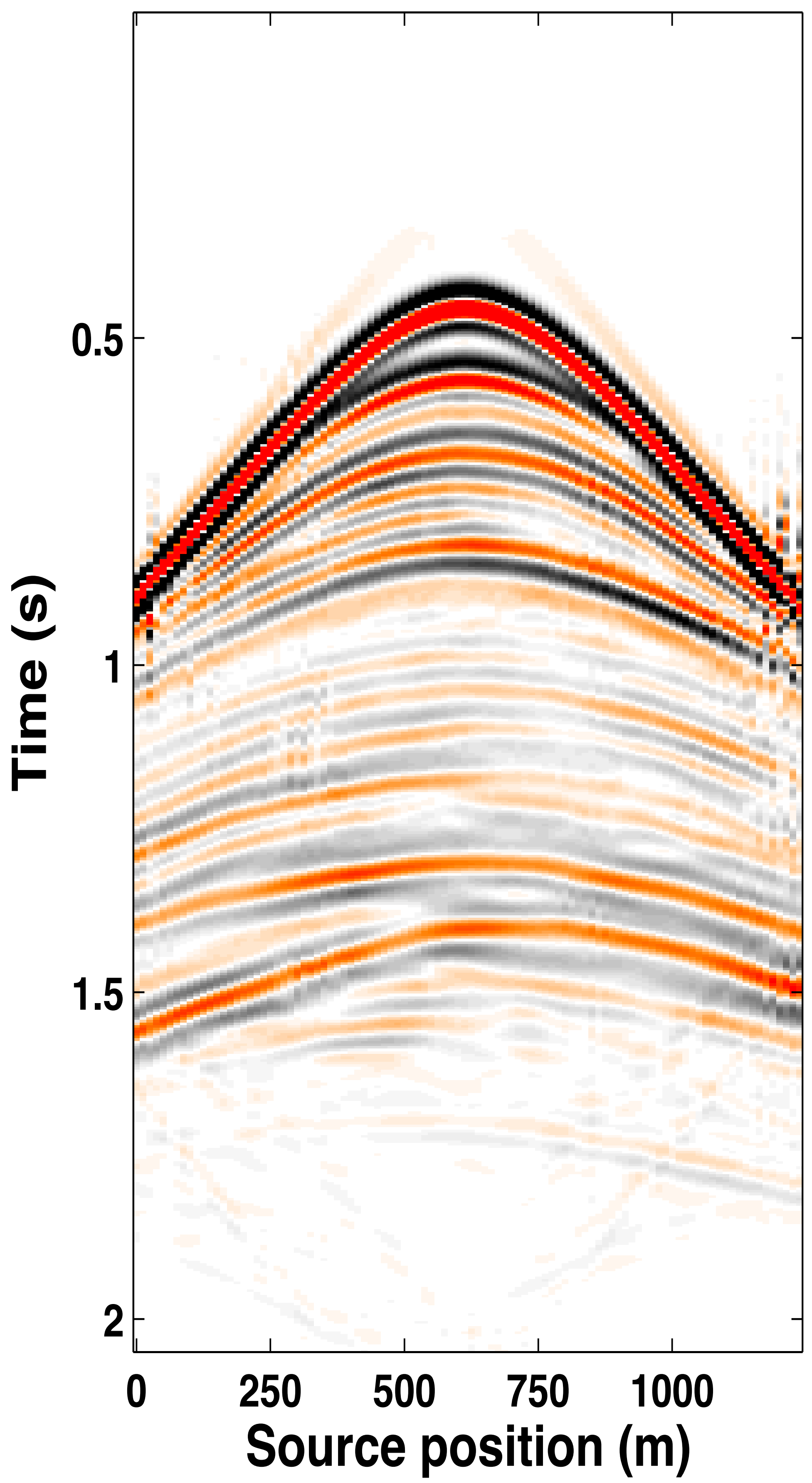
Monitor recovery

– Independent recovery

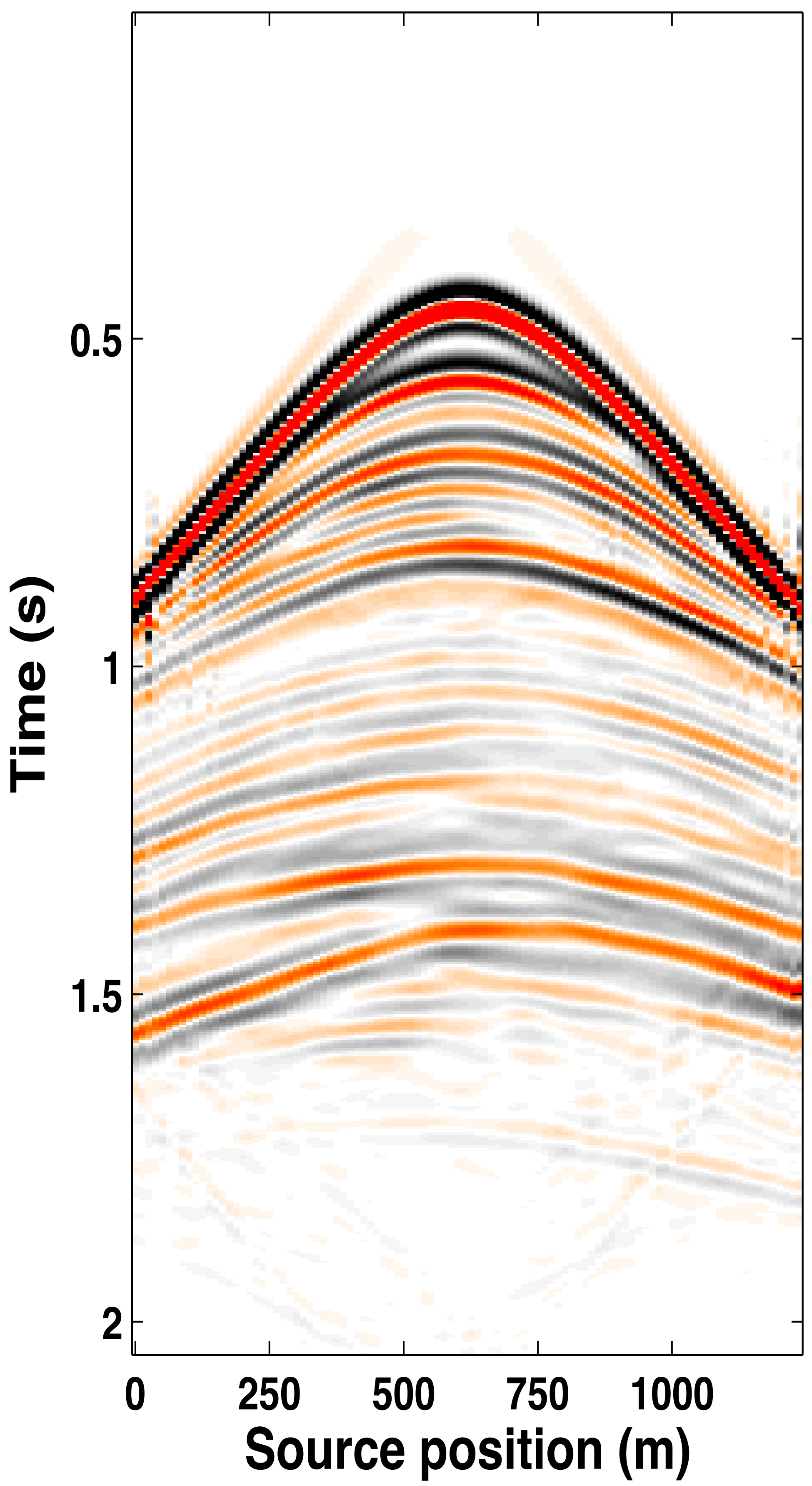


Monitor recovery
– Joint recovery

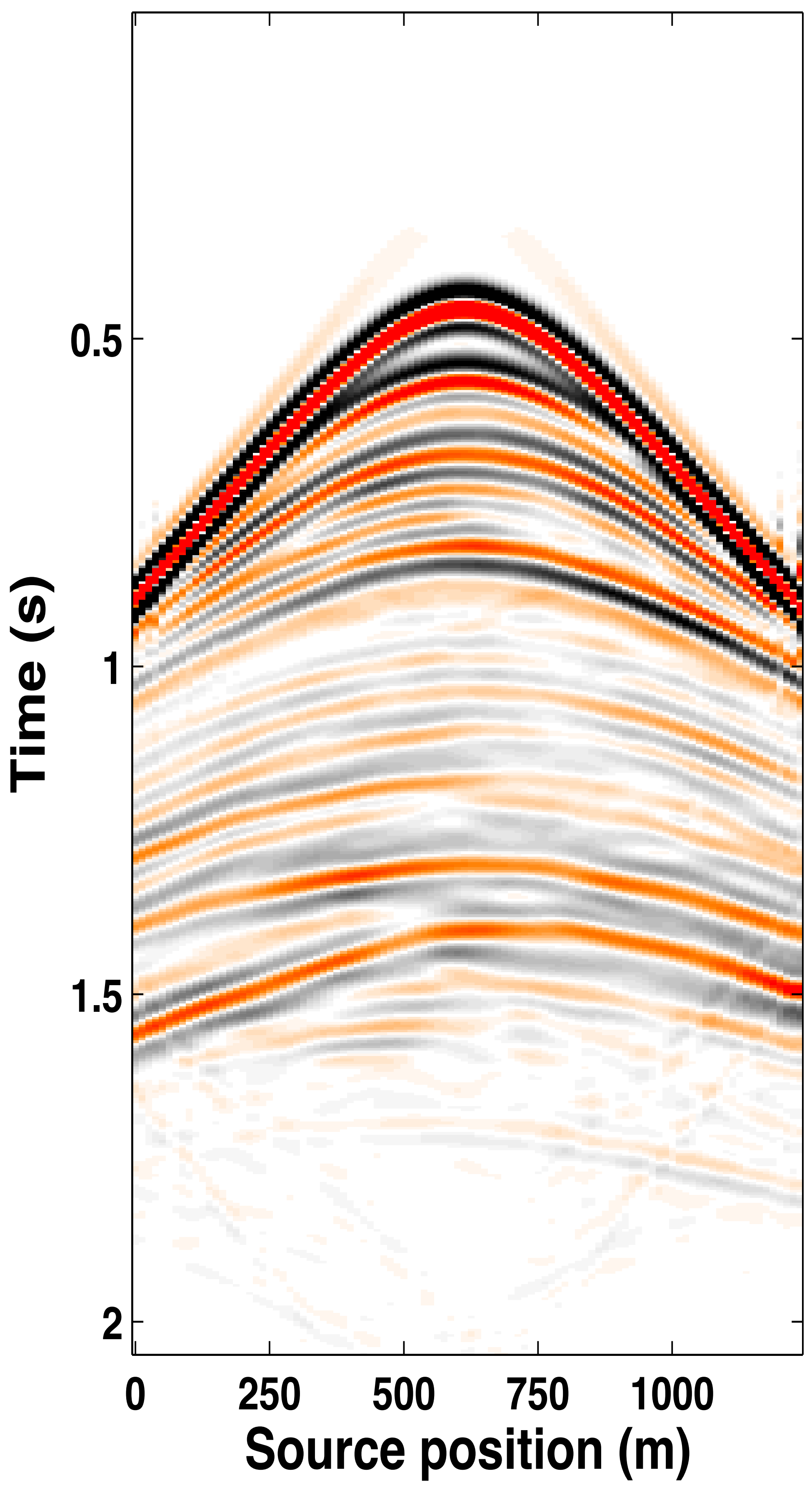
100% overlap
[11.6 dB]



50% overlap
[15.7 dB]



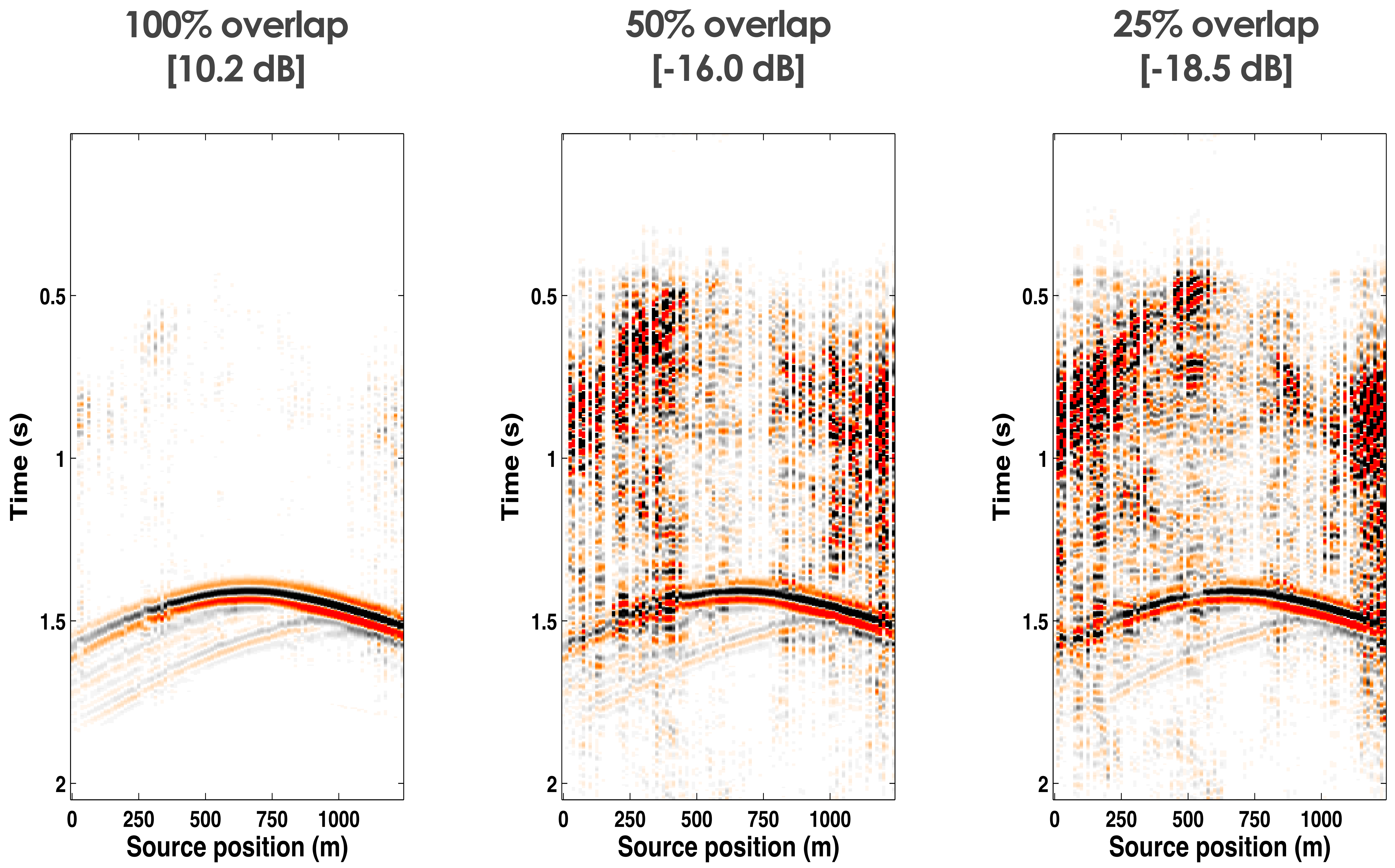
25% overlap
[18.6 dB]



4-D recovery

– Independent recovery

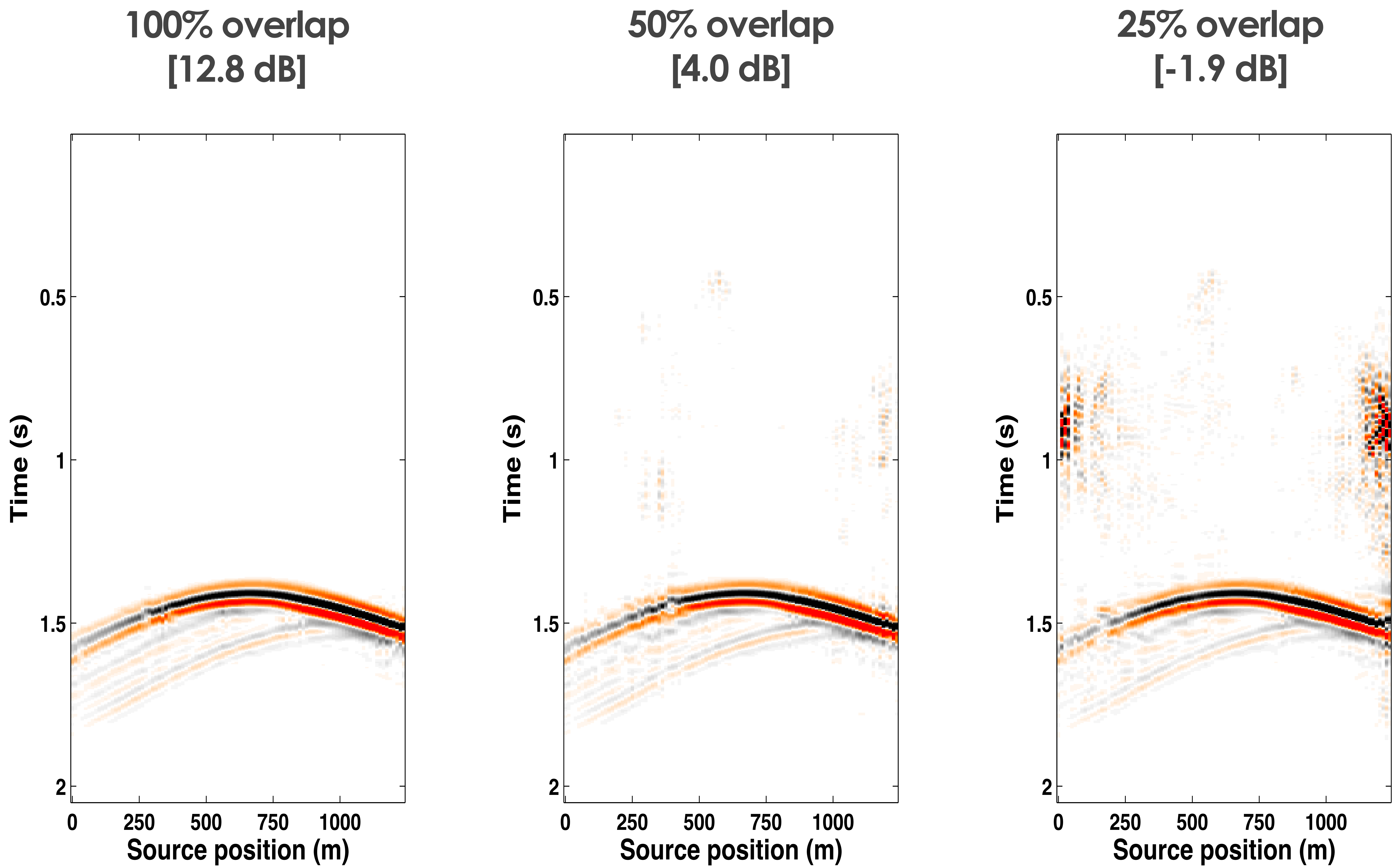
[colormap scale: 10 X]



4-D recovery

– Joint recovery

[colormap scale: 10 X]



Observations

In the given context of randomized subsampling,

- *Independent surveys bring extra information*
- *"Exactly" repeated surveys do not add any new information*
- *For different surveys, independent processing degrades recovery quality of vintages and time-lapse difference*
- *With joint recovery, we observe improvement in recovery quality of the vintages for completely independent surveys*

*Our joint recovery model exploits the shared information in time-lapse data, improving the **repeatability** of the vintages.*

"Exact" replicability of the surveys seems essential for good recovery of the time-lapse signal

Summary

With decrease in survey replication i.e. overlap in shot positions,

- *quality of recovered vintages improves significantly*
- *small variability in quality of the recovered time-lapse signal*

Recovered prestack vintages can serve as input to poststack processes.

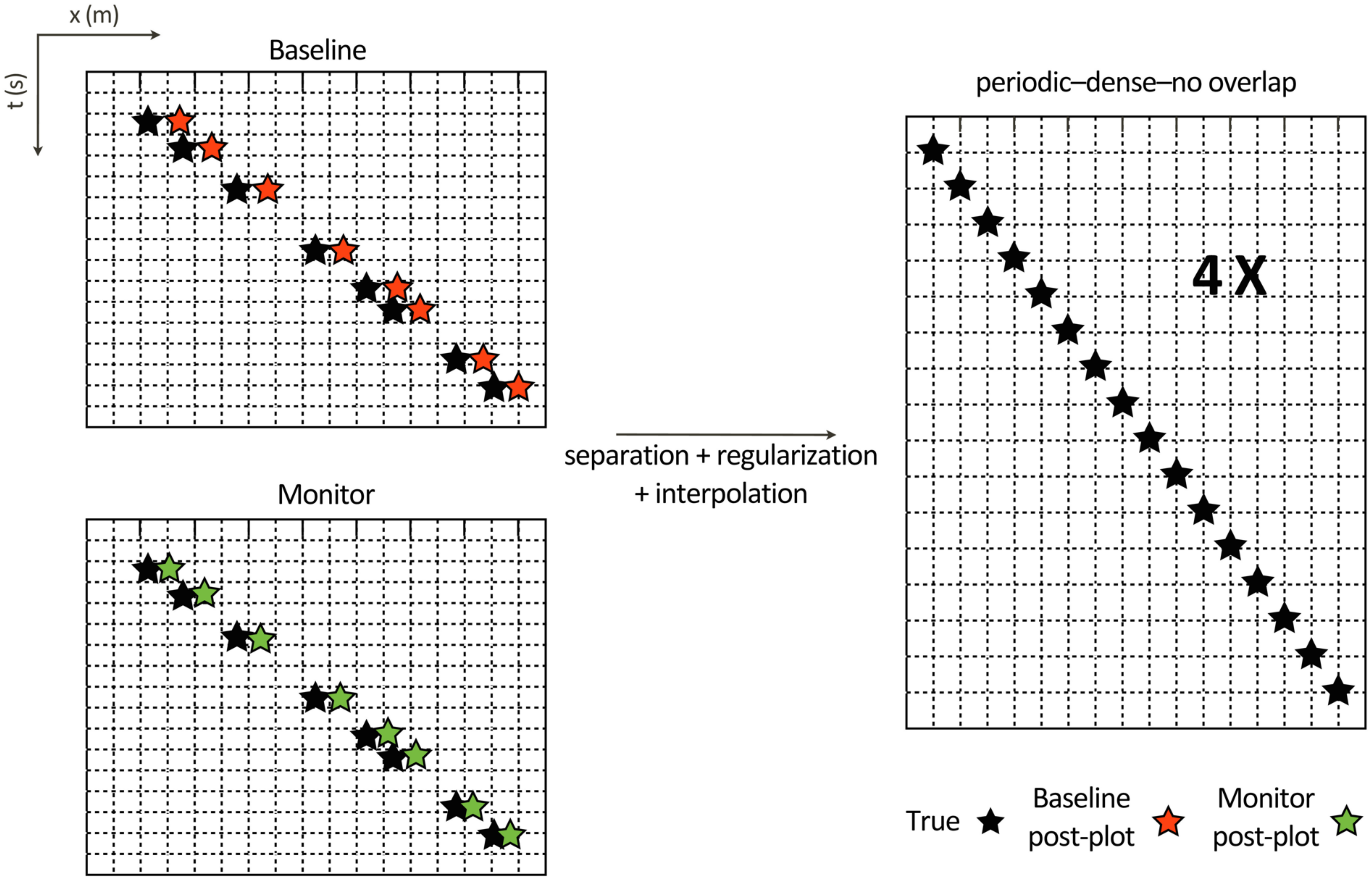
Results hold for processes with/without regularization (Chapter 2 & 3)

Focus on knowing the exact shot positions i.e. postplots, rather than striving to replicate the time-lapse surveys.

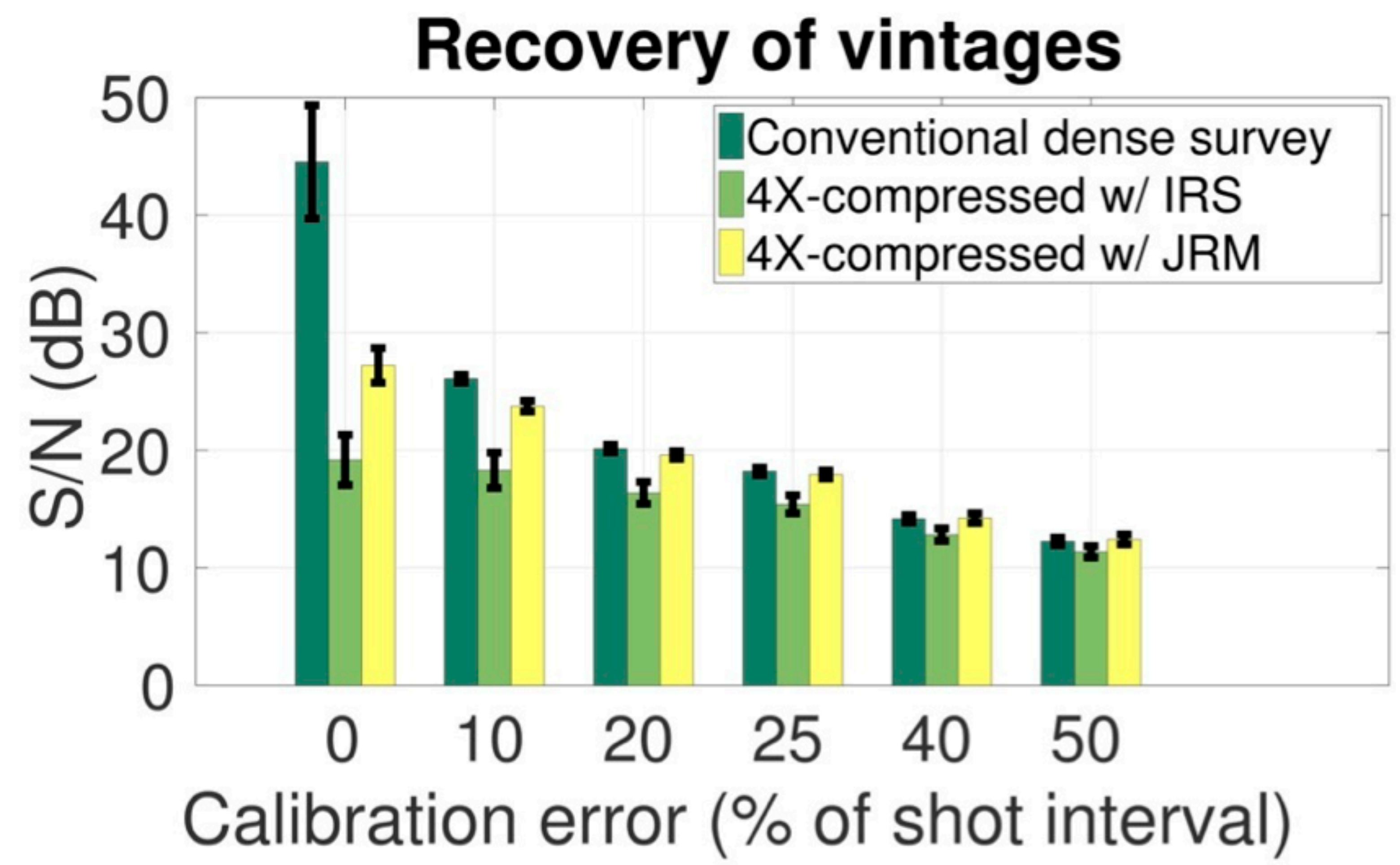
What is the impact of calibration errors?

$$(\mathbf{A}_1 \neq \mathbf{A}_2)$$

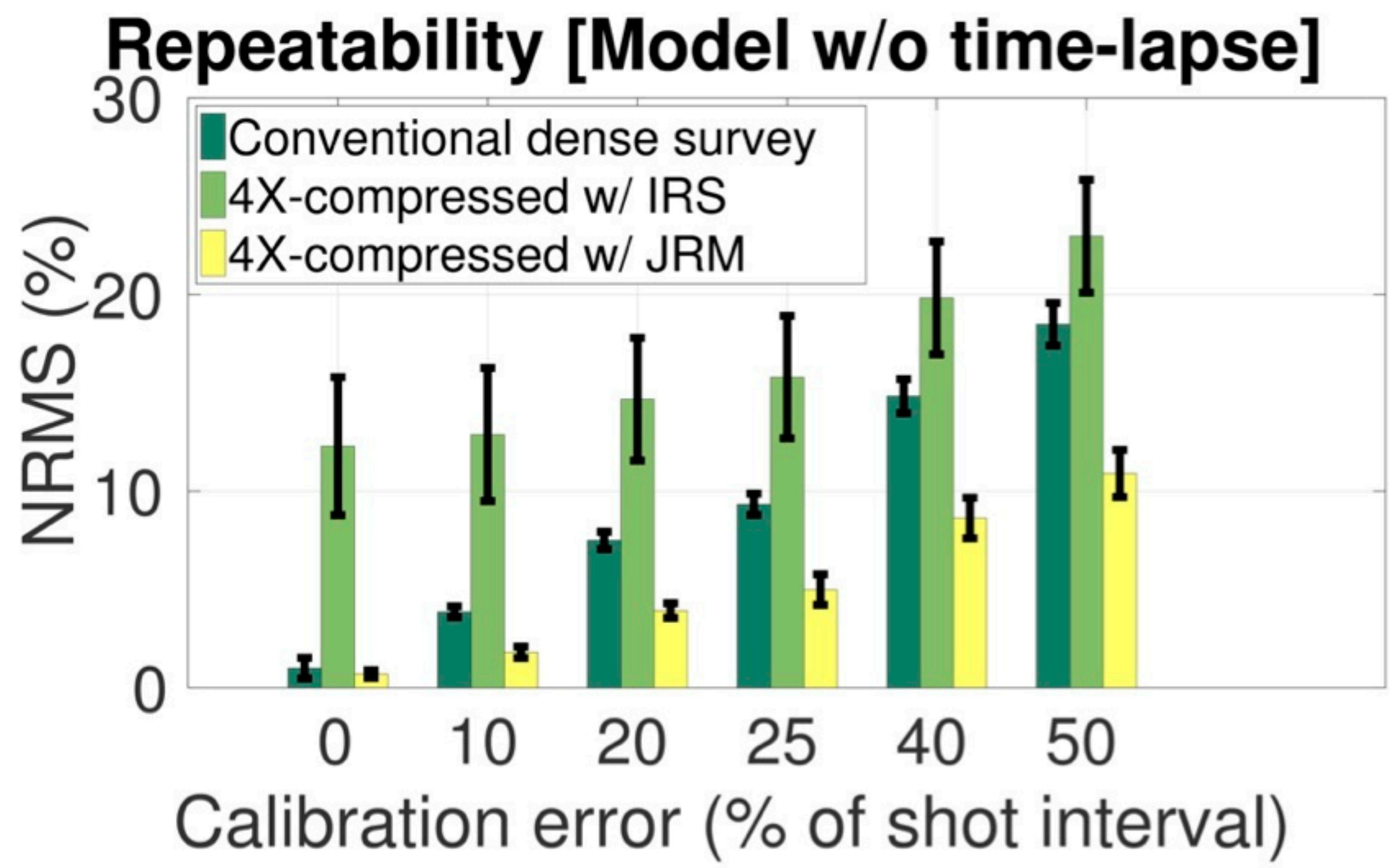
4-D time-jittered marine acquisition



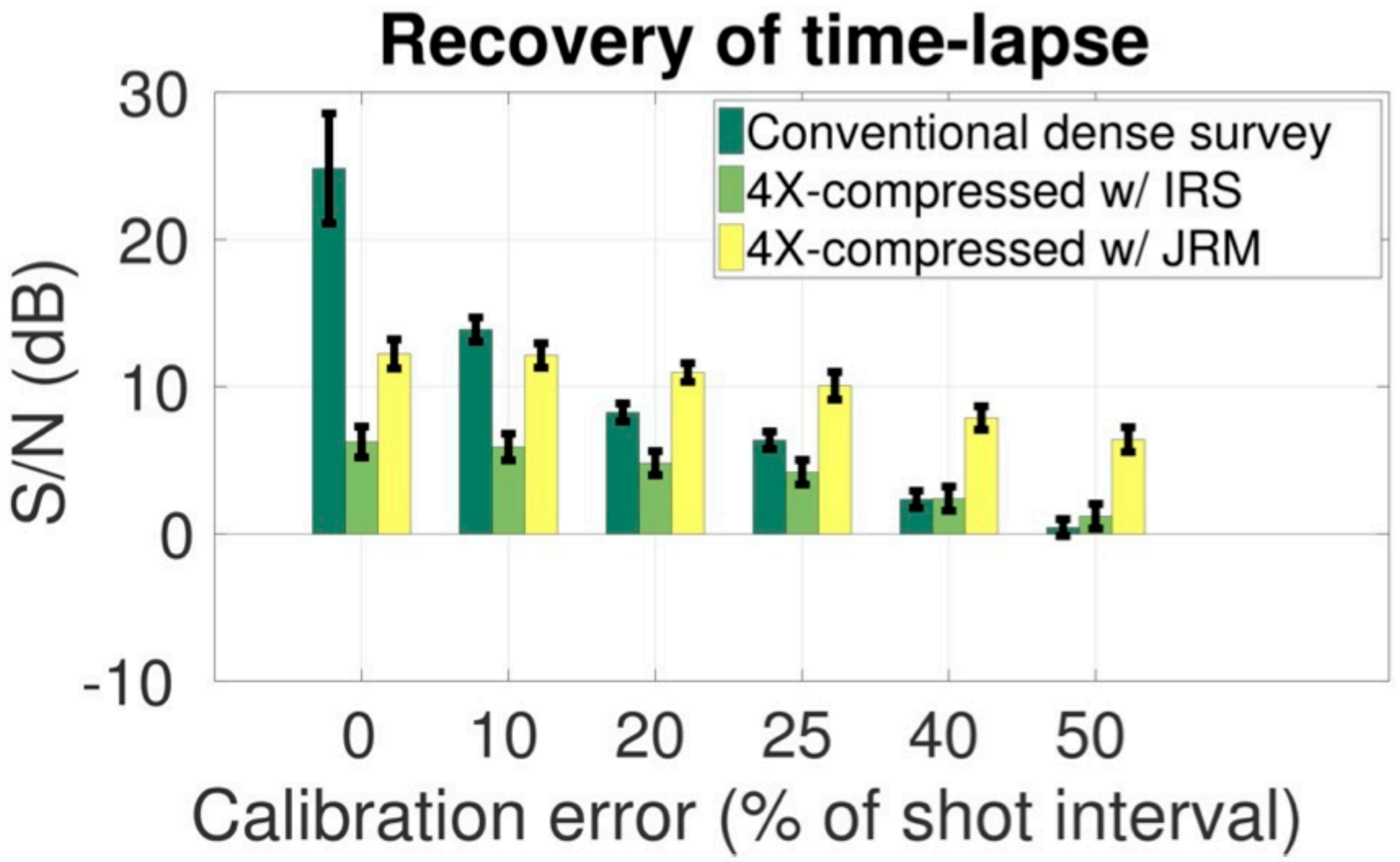
Recovery & repeatability



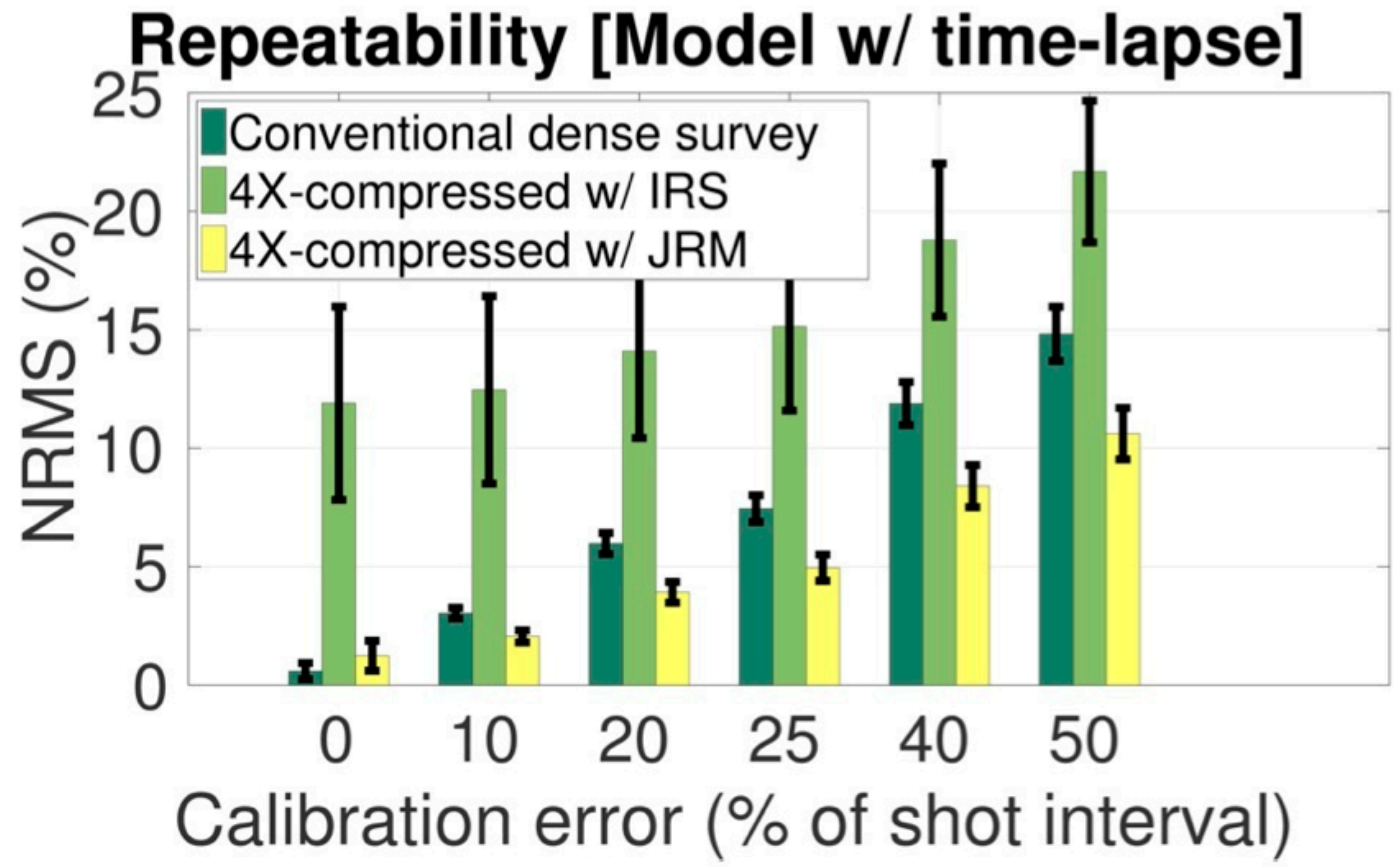
(a)



(b)



(c)



(d)

Summary

- *High-cost densely sampled surveys give best quality & repeatability in the absence of calibration errors*
- *Quality of dense surveys decay rapidly in presence of small errors*
- *Independently recovering the CS-based surveys leads to the worst recovery quality and repeatability*
- *Low-cost randomized surveys show modest decay in quality and repeatability when recovered with the joint recovery model*

Recovery with the JRM is stable with respect to calibration errors.

Time-lapse seismic imaging

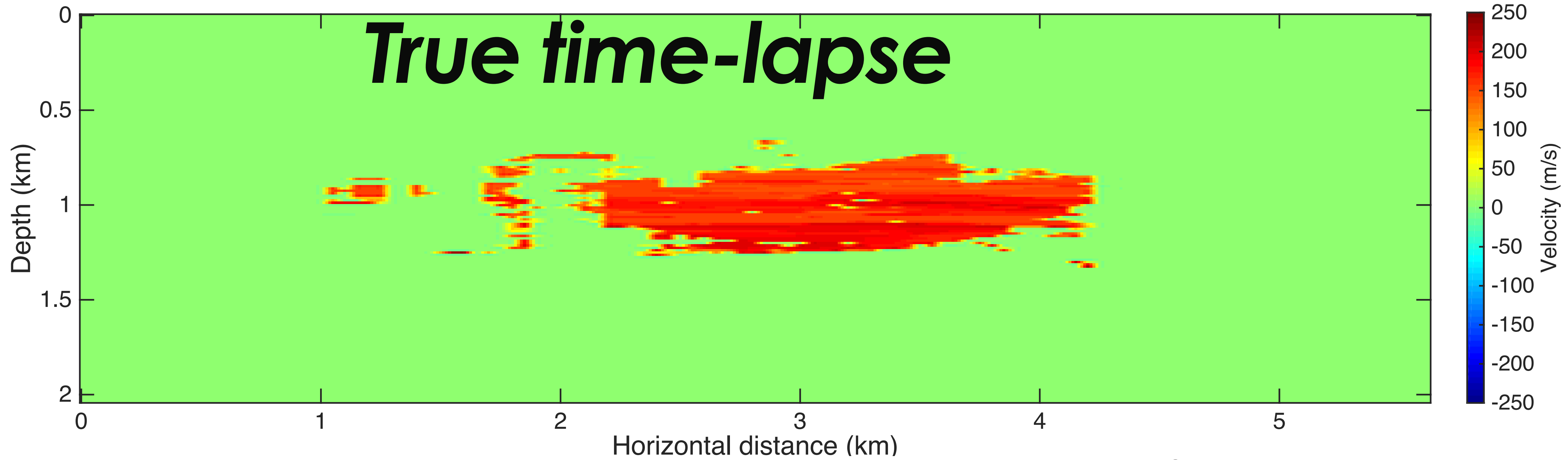
Challenges:

- *non-repeatability effects e.g. via acquisition differences*
- overburden complexity
- *weak 4D signal in complex areas*

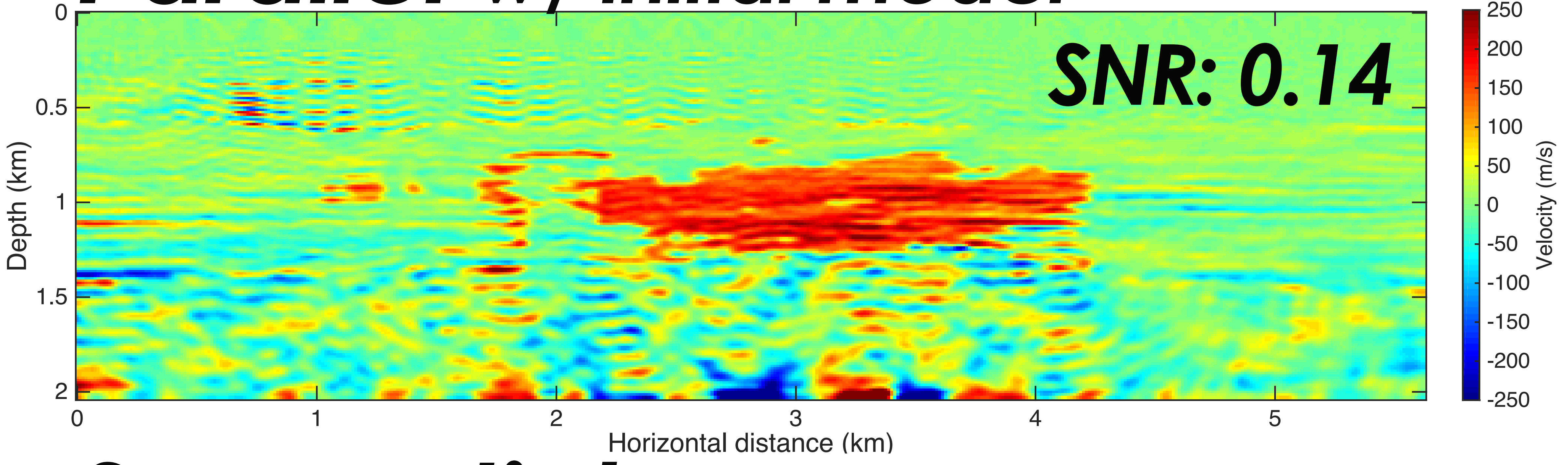
Objectives:

- *investigate the role of DCS & the JRM*
- compare data-domain versus image-domain
- *migration & FWI*

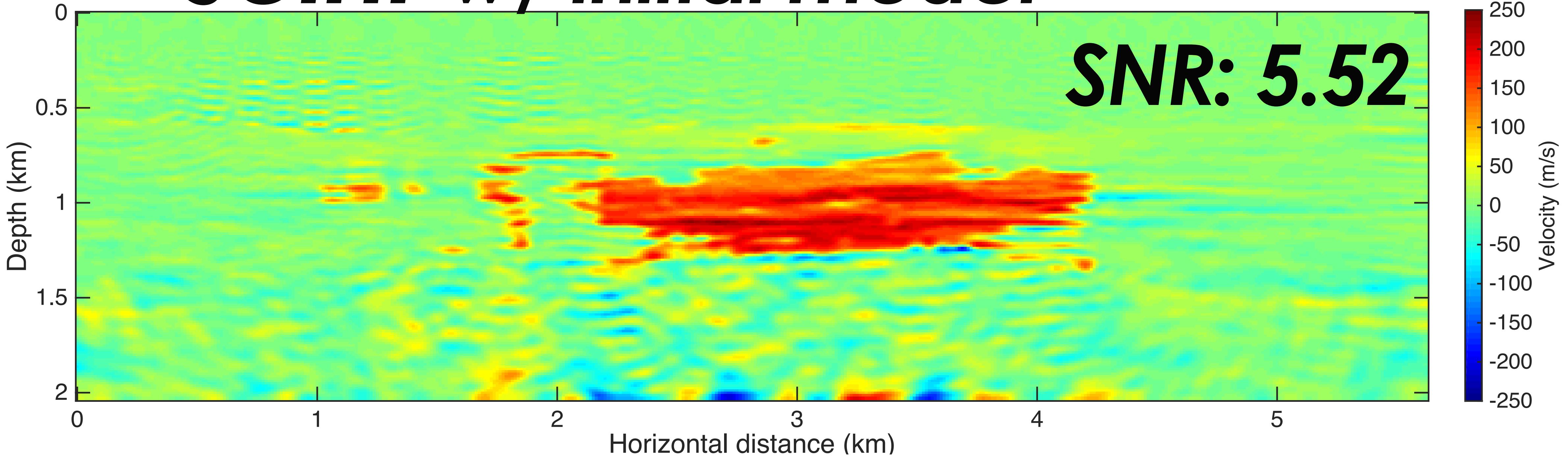
Assuming similar geometry, “good” starting model



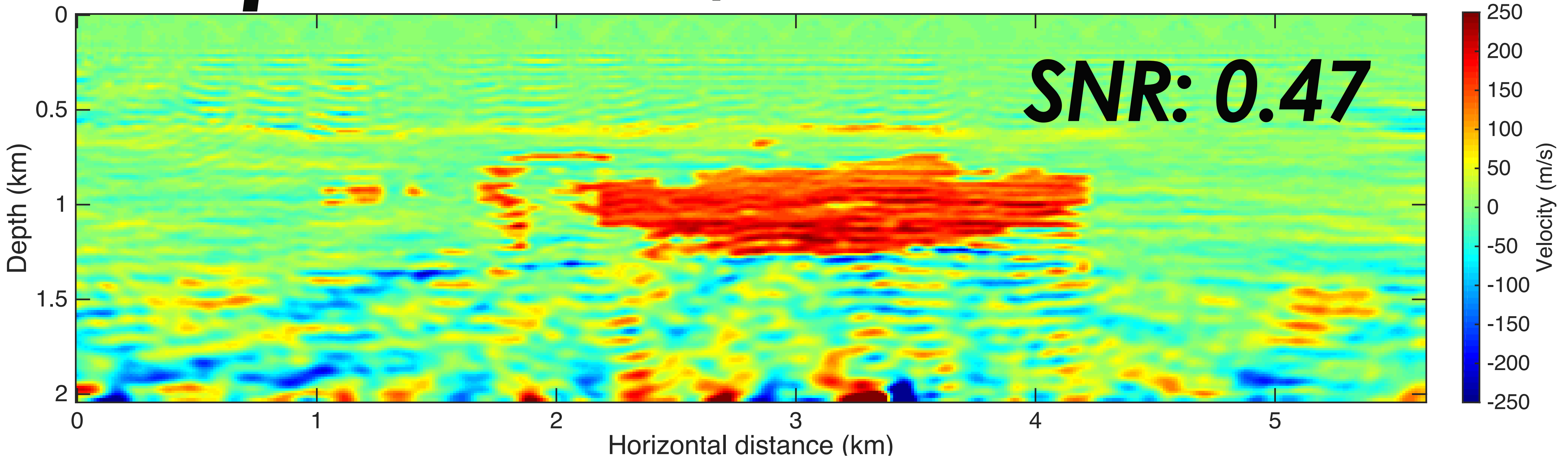
Parallel w/ initial model



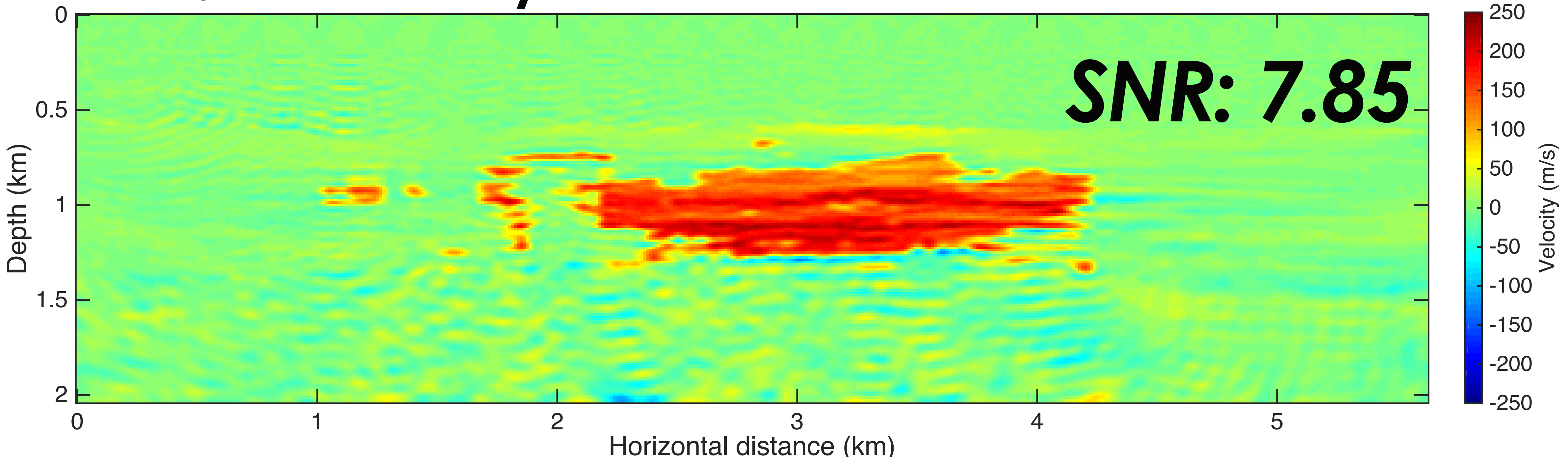
Joint w/ initial model



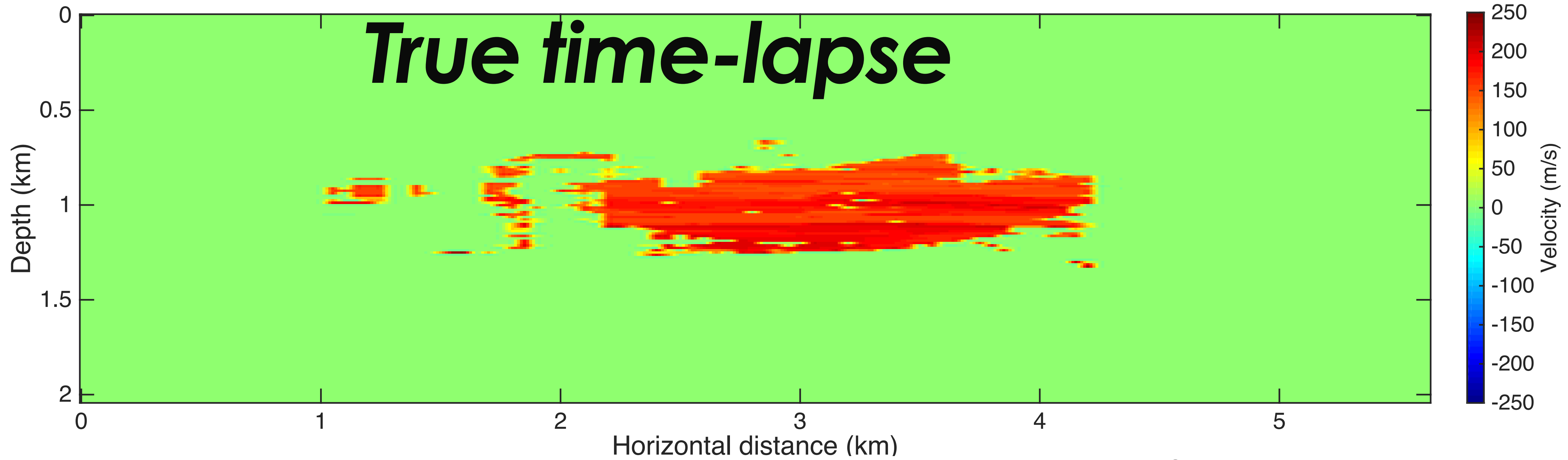
Sequential w/ inverted base



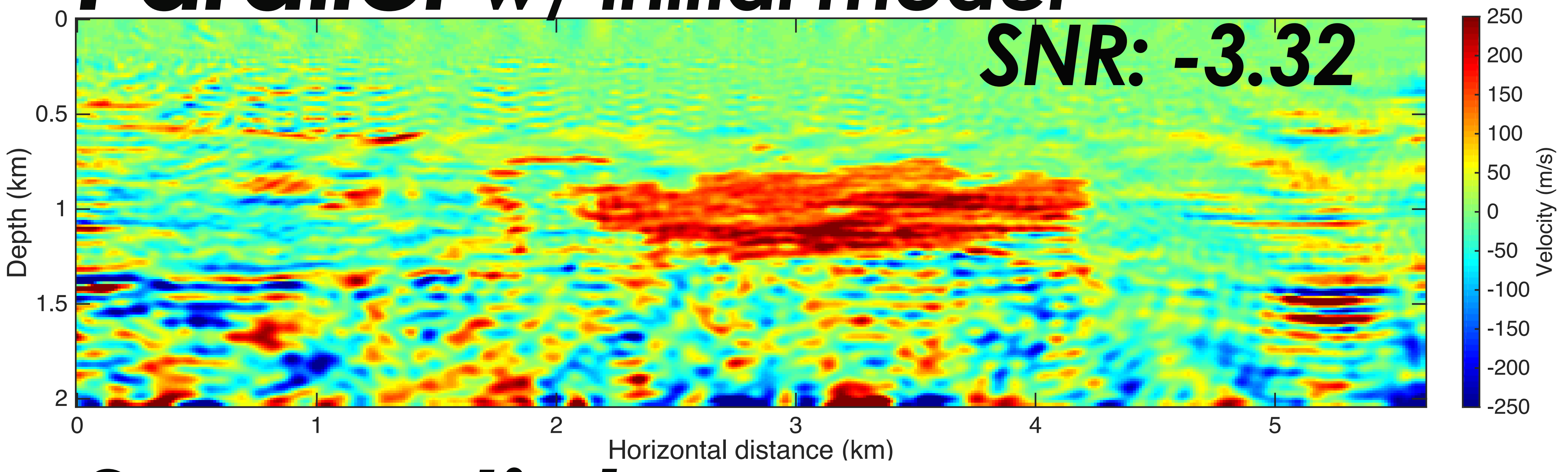
Joint w/ inverted base



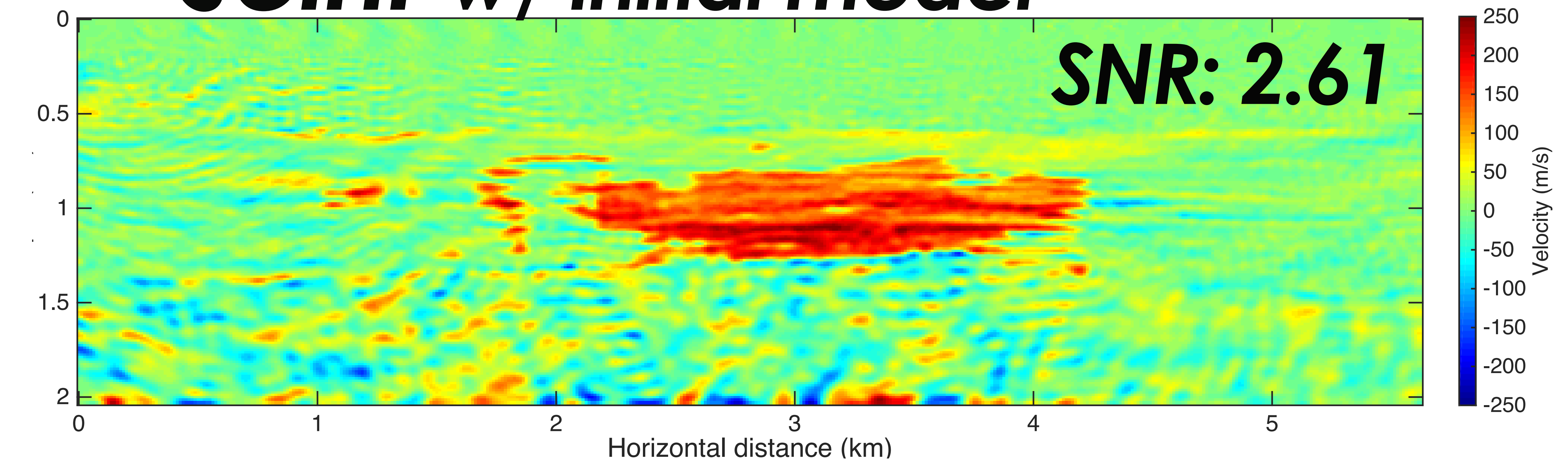
Assuming similar geometry, “poor” starting model



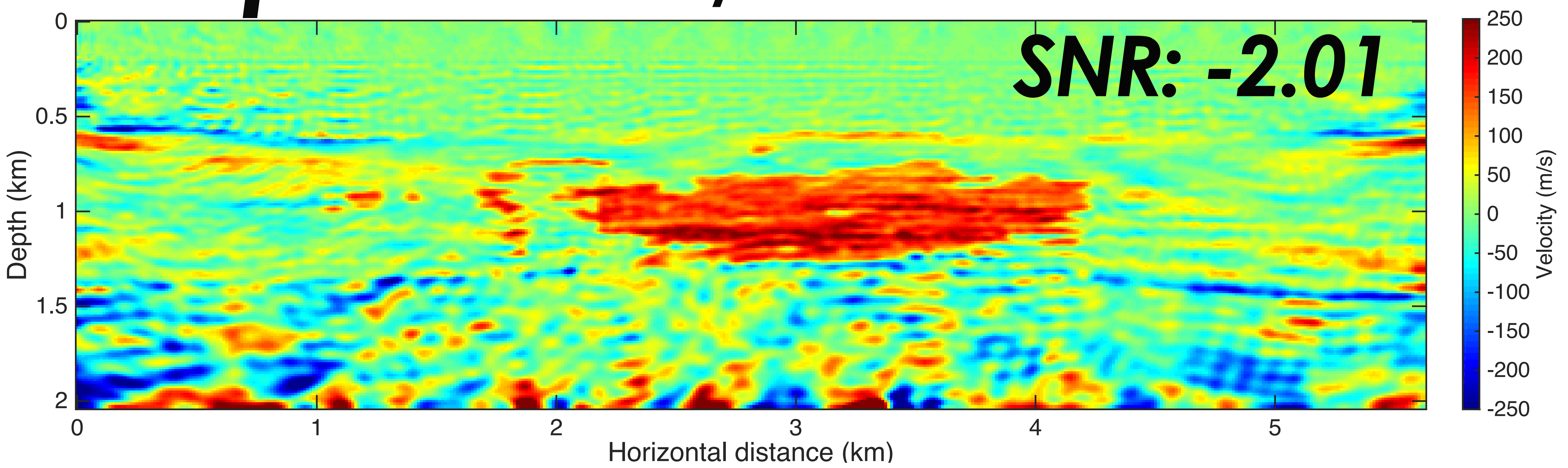
Parallel *w/ initial model*



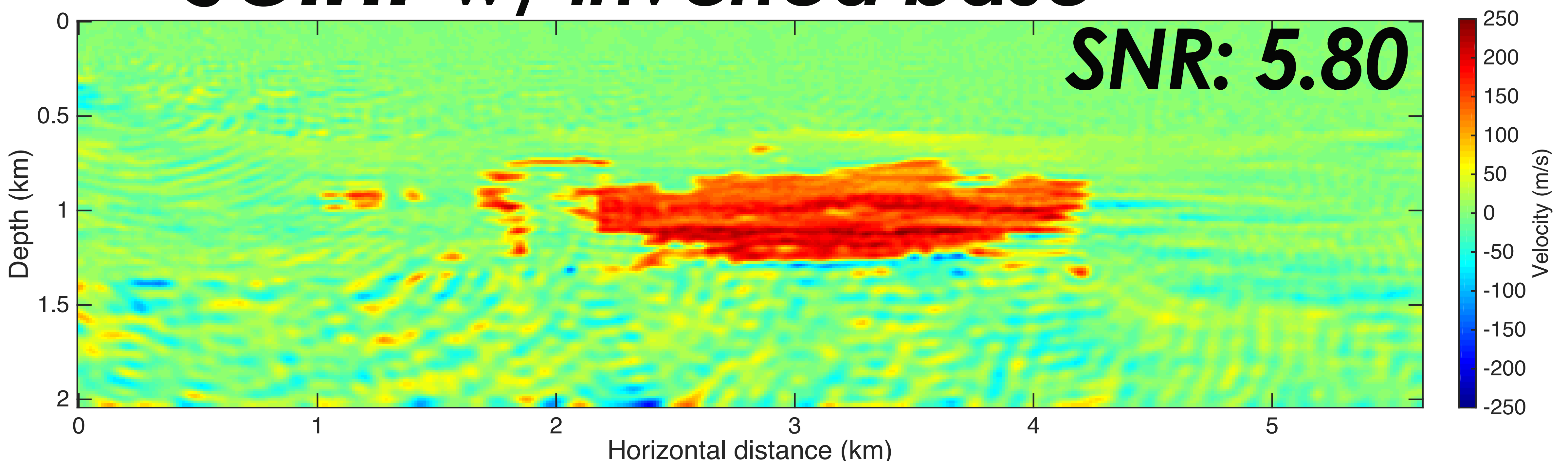
Joint *w/ initial model*



Sequential *w/ inverted base*



Joint *w/ inverted base*



Observations

A good initial model drives the inversion results for the vintages and time-lapse model

Sequential FWI is better than parallel FWI, however joint inversion with JRM is better than both approaches

Significant attenuation of the artifacts in the time-lapse model using JRM, which exploits the shared information in time-lapse

General conclusions

Time-lapse seismic acquisition:

- *Randomize acquisition & do not bother with "exact" repetition*
- Processing : recover high-quality vintages & time-lapse using the joint-recovery model (JRM)
- *Advantageous to have precise information on acquisition specs.*

Impact of calibration error in (time-lapse) CS:

- *Robust recovery using the JRM*
- Avoid independent processing & expensive conventional dense surveys
- *Shot timing errors need to be minimized, less so for spatial errors.*

General conclusions

Time-lapse seismic imaging with DCS:

- *Independent time-lapse inversions do not exploit the common information in the vintages*
- *Model differences due to different inversions can mask true time-lapse changes*
- Inversions leveraging the JRM yield images (or models) with better quality for both the vintages and time-lapse difference.
- *Inversions with JRM attenuates artifacts observed with separate inversions, minimizing the risk of false time-lapse changes*

Publications

- **Felix Oghenekohwo** and Felix J. Herrmann, “Improved time-lapse data repeatability with randomized sampling and distributed compressive sensing”, in *EAGE Annual Conference Proceedings*, 2017.
- Haneet Wason, **Felix Oghenekohwo**, and Felix J. Herrmann, “Low-cost time-lapse seismic with distributed compressive sensing–-Part 2: impact on repeatability”, *Geophysics*, vol. 82, p. P15-P30, 2017.
- **Felix Oghenekohwo**, Haneet Wason, Ernie Esser, and Felix J. Herrmann, “Low-cost time-lapse seismic with distributed compressive sensing–-Part 1: exploiting common information among the vintages”, *Geophysics*, vol. 82, p. P1-P13, 2017.
- **Felix Oghenekohwo** and Felix J. Herrmann, “Highly repeatable time-lapse seismic with distributed Compressive Sensing–-mitigating effects of calibration errors”. 2017.
- Felix J. Herrmann, Rajiv Kumar, **Felix Oghenekohwo**, Shashin Sharan, and Haneet Wason, “Compressive time-lapse marine acquisition”, in *SEG Workshop on Low cost geophysics: How to be creative in a cost-challenged environment; Dallas*, 2016.
- **Felix Oghenekohwo**, Rajiv Kumar, Ernie Esser, and Felix J. Herrmann, “Time-lapse FWI with distributed compressed sensing”, in *Inaugural Full-Waveform Inversion Workshop*, 2015.
- Haneet Wason, **Felix Oghenekohwo**, and Felix J. Herrmann, “Compressed sensing in 4-D marine–-recovery of dense time-lapse data from subsampled data without repetition”, in *EAGE Annual Conference Proceedings*, 2015.
- **Felix Oghenekohwo**, Rajiv Kumar, Ernie Esser, and Felix J. Herrmann, “Using common information in compressive time-lapse full-waveform inversion”, in *EAGE Annual Conference Proceedings*, 2015.
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- **Felix Oghenekohwo** and Felix J. Herrmann, “A new take on compressive time-lapse seismic acquisition, imaging and inversion”, in *PIMS Workshop on Advances in Seismic Imaging and Inversion*, 2015.
- Haneet Wason, **Felix Oghenekohwo**, and Felix J. Herrmann, “Randomization and repeatability in time-lapse marine acquisition”, in *SEG Technical Program Expanded Abstracts*, 2014, p. 46-51.
- **Felix Oghenekohwo**, Rajiv Kumar, and Felix J. Herrmann, “Randomized sampling without repetition in time-lapse surveys”, in *SEG Technical Program Expanded Abstracts*, 2014, p. 4848-4852.
- **Felix Oghenekohwo**, Ernie Esser, and Felix J. Herrmann, “Time-lapse seismic without repetition: reaping the benefits from randomized sampling and joint recovery”, in *EAGE Annual Conference Proceedings*, 2014.

Thank you!!!

To:

- *my advisor*
- committee
- sponsors of SLIM
- members of SLIM

To:

- *family*
- *friends*