

Randomization & repeatability in time-lapse marine acquisition

Haneet Wason, Felix Oghenekohwo, and Felix J. Herrmann



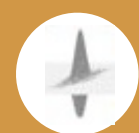
University of British Columbia

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SLIM



University of British Columbia

Randomization & repeatability in time-lapse marine acquisition

with help from Curt da Silva & Ernie Esser



SLIM



University of British Columbia

Motivation

Seemingly *innocent* remark by Craig J. Beasley at SBGf meeting:

“Should we repeat in randomized marine acquisition?”

Disclaimer

Assumptions:

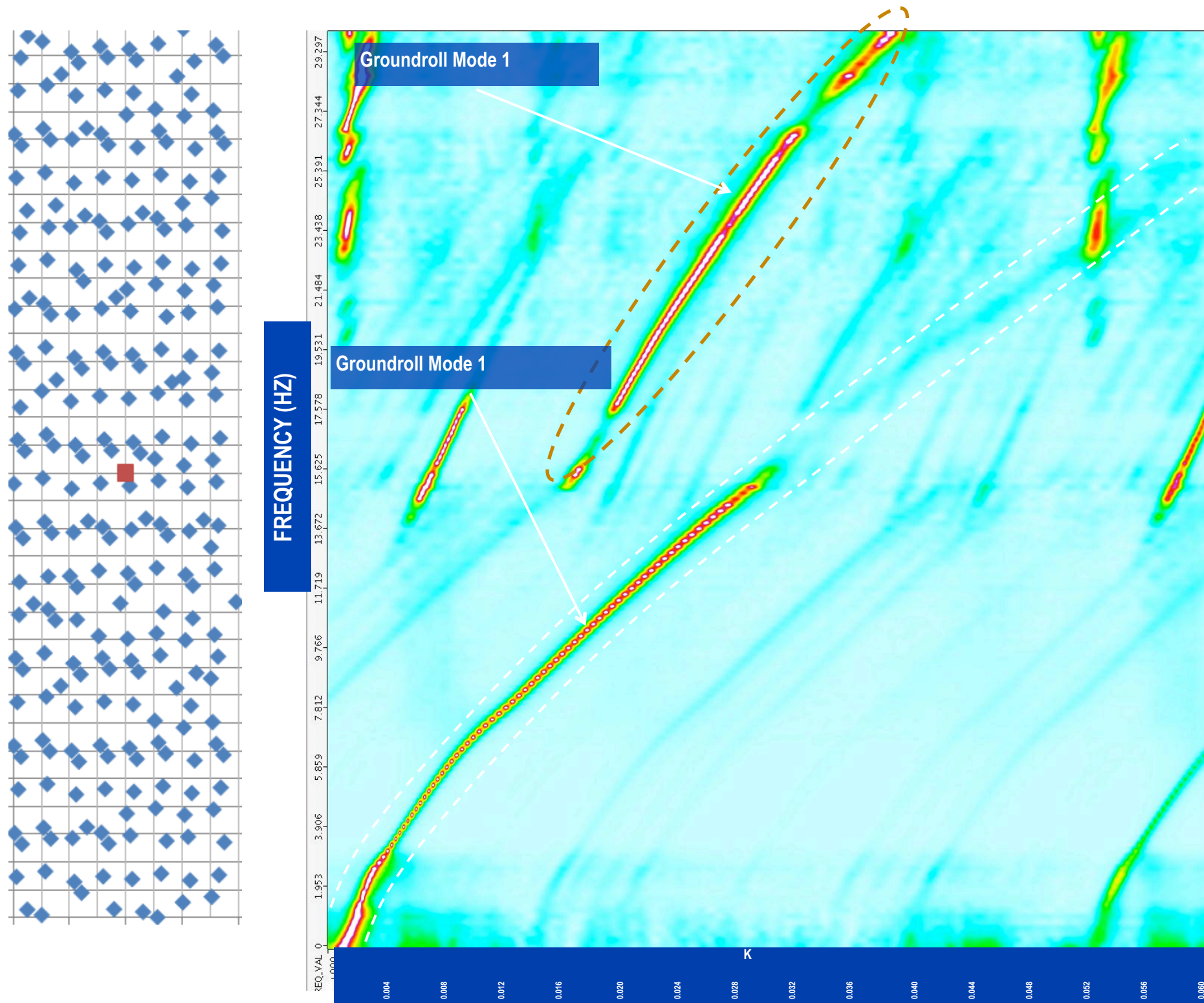
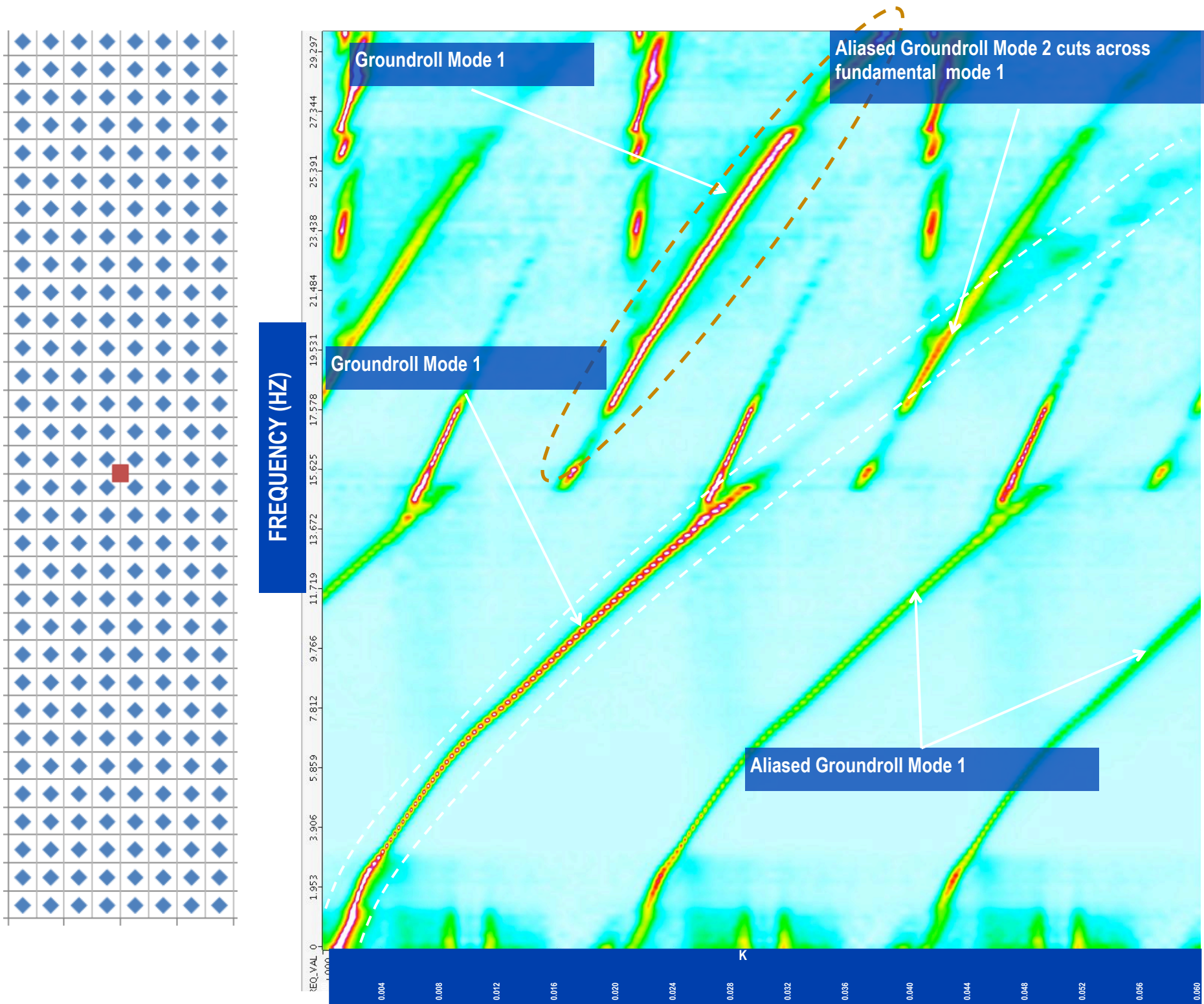
- ▶ you are a *believer* in *randomized* acquisition & *sparse* recovery
- ▶ *seismic* data & *time-lapse* signal *both* permit *sparse* representations
- ▶ there are *no* calibration *errors* *but* there can be *additive* noise
- ▶ *degree* repetition refers to *percentage* of a *survey* that is repeated *exactly*

All observations are based on *synthetic* ocean bottom data...

Randomized sampling

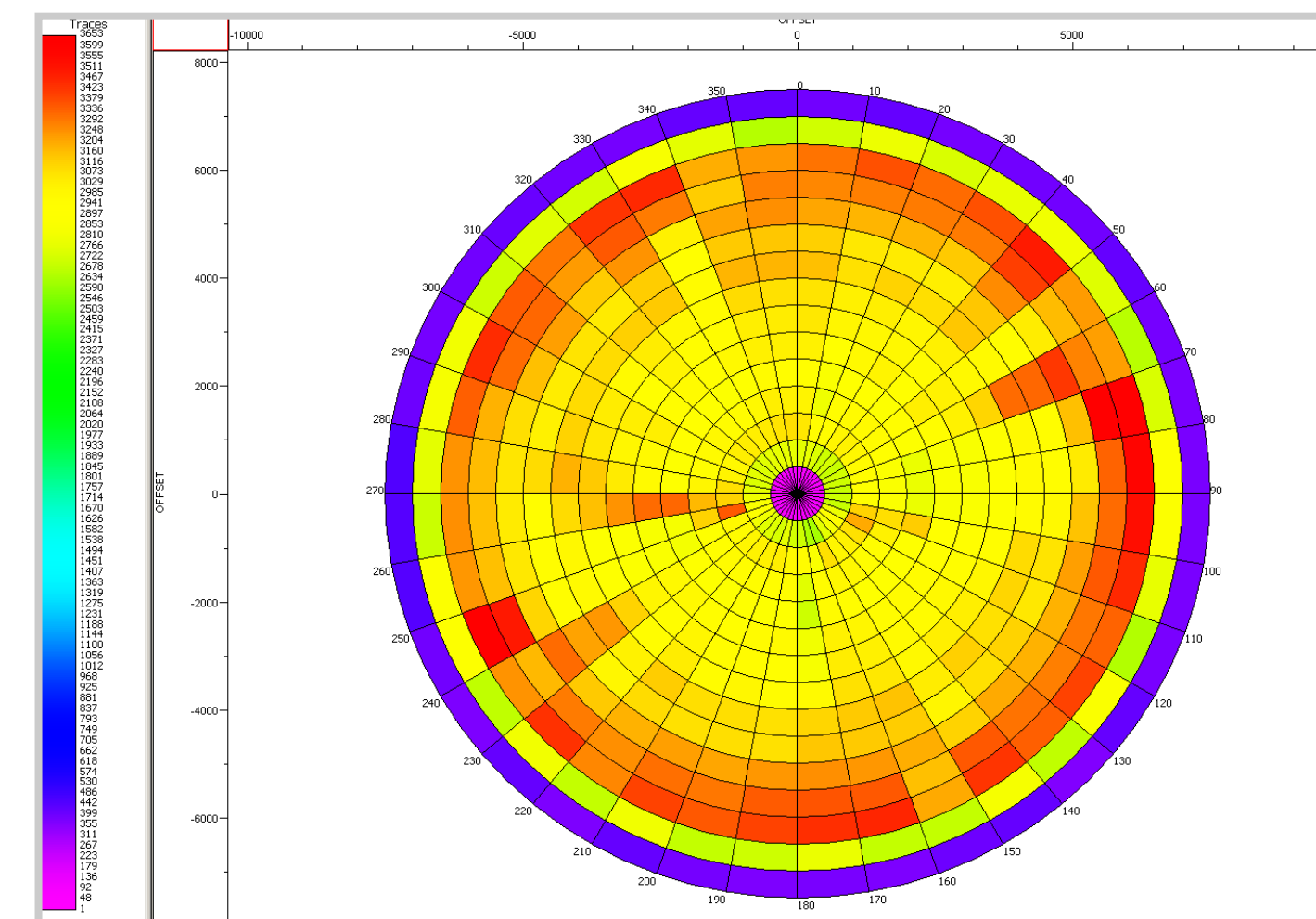
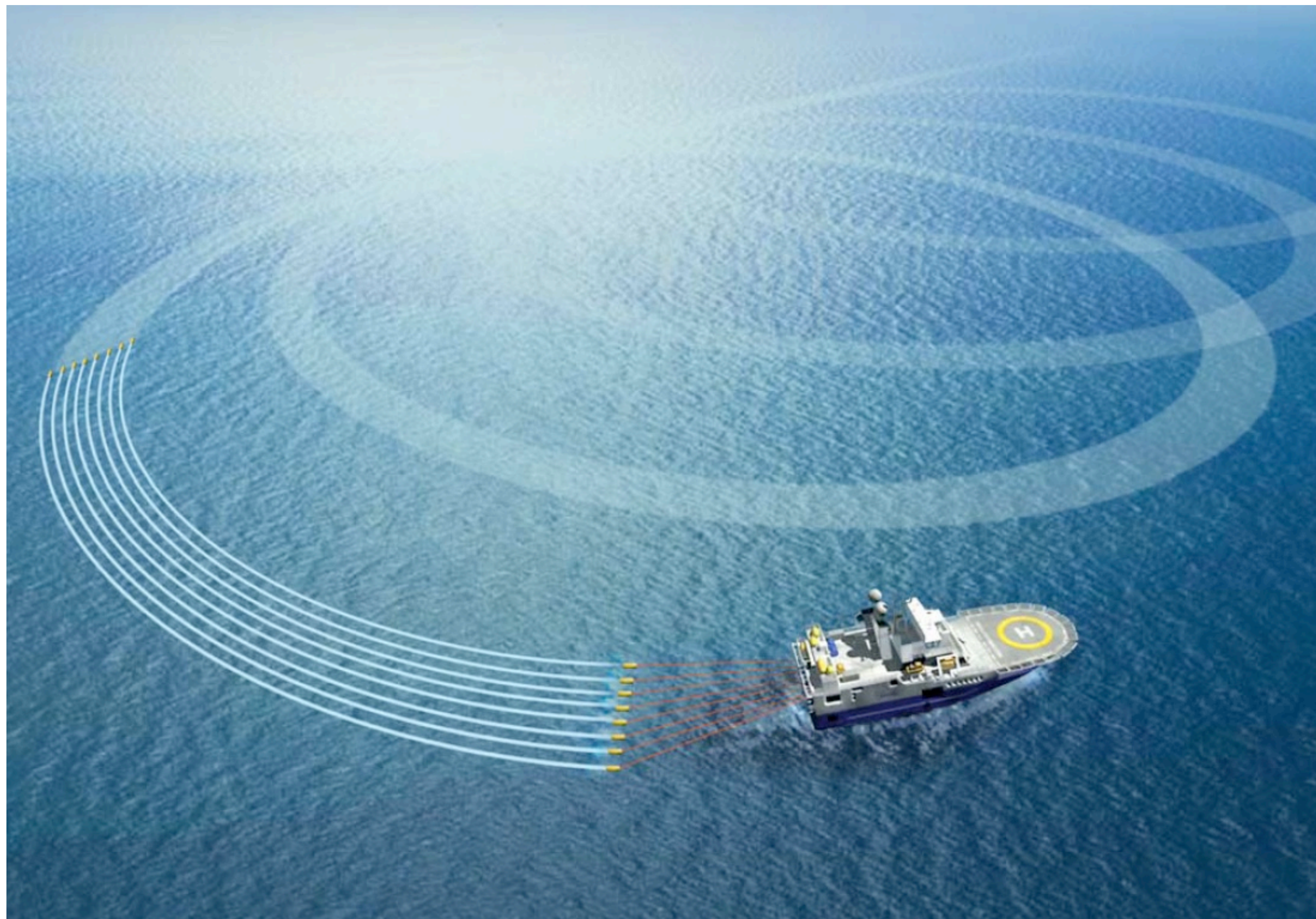
– examples from industry (WesternGeco)

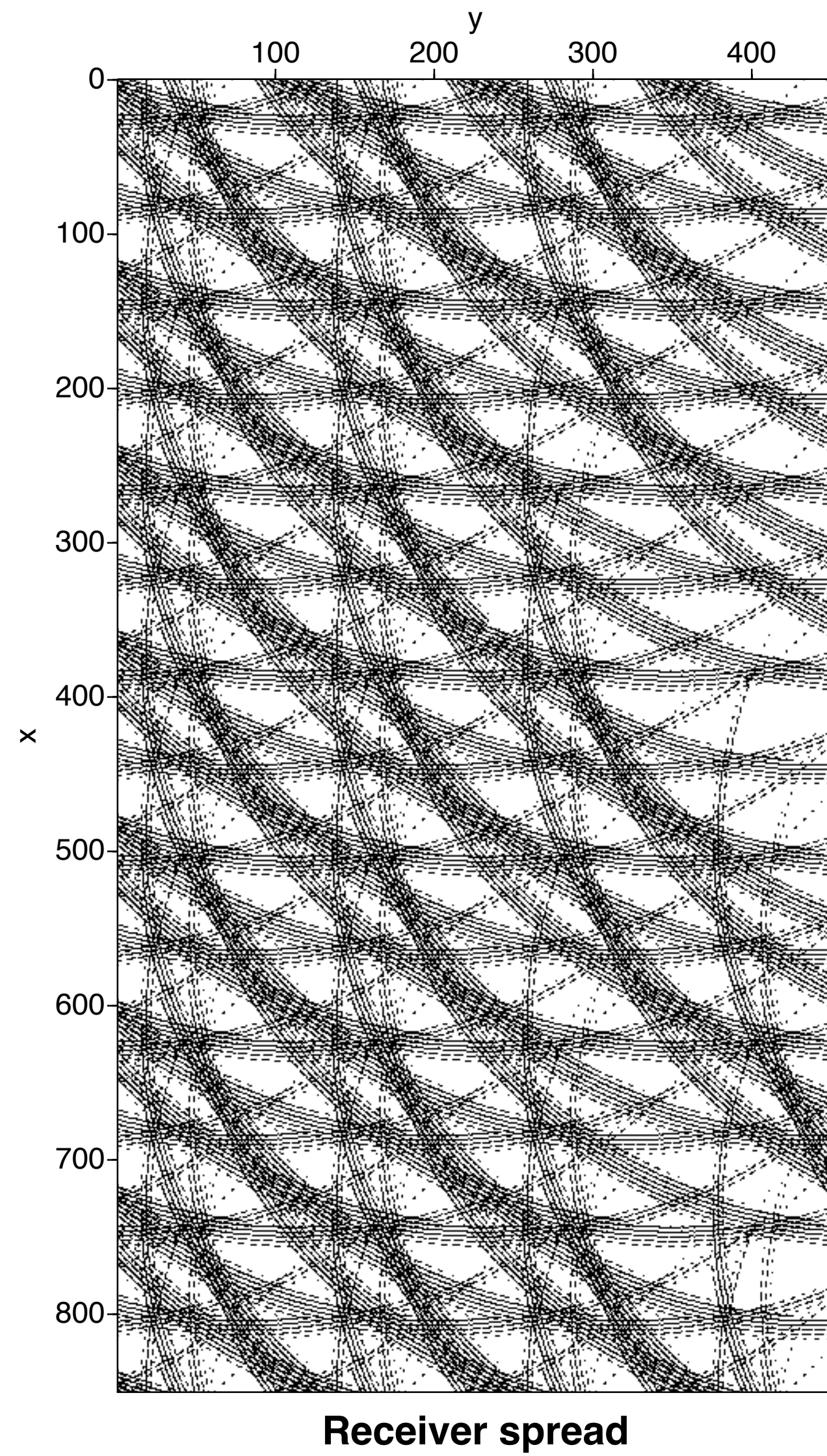
Random *source* locations
(thanks Nick Moldoveanu)



Coil sampling

– examples from industry (WesternGeco)





Courtesy Nick Moldoveanu

34 % of samples



Challenge

Starting SPGL1 recovery...

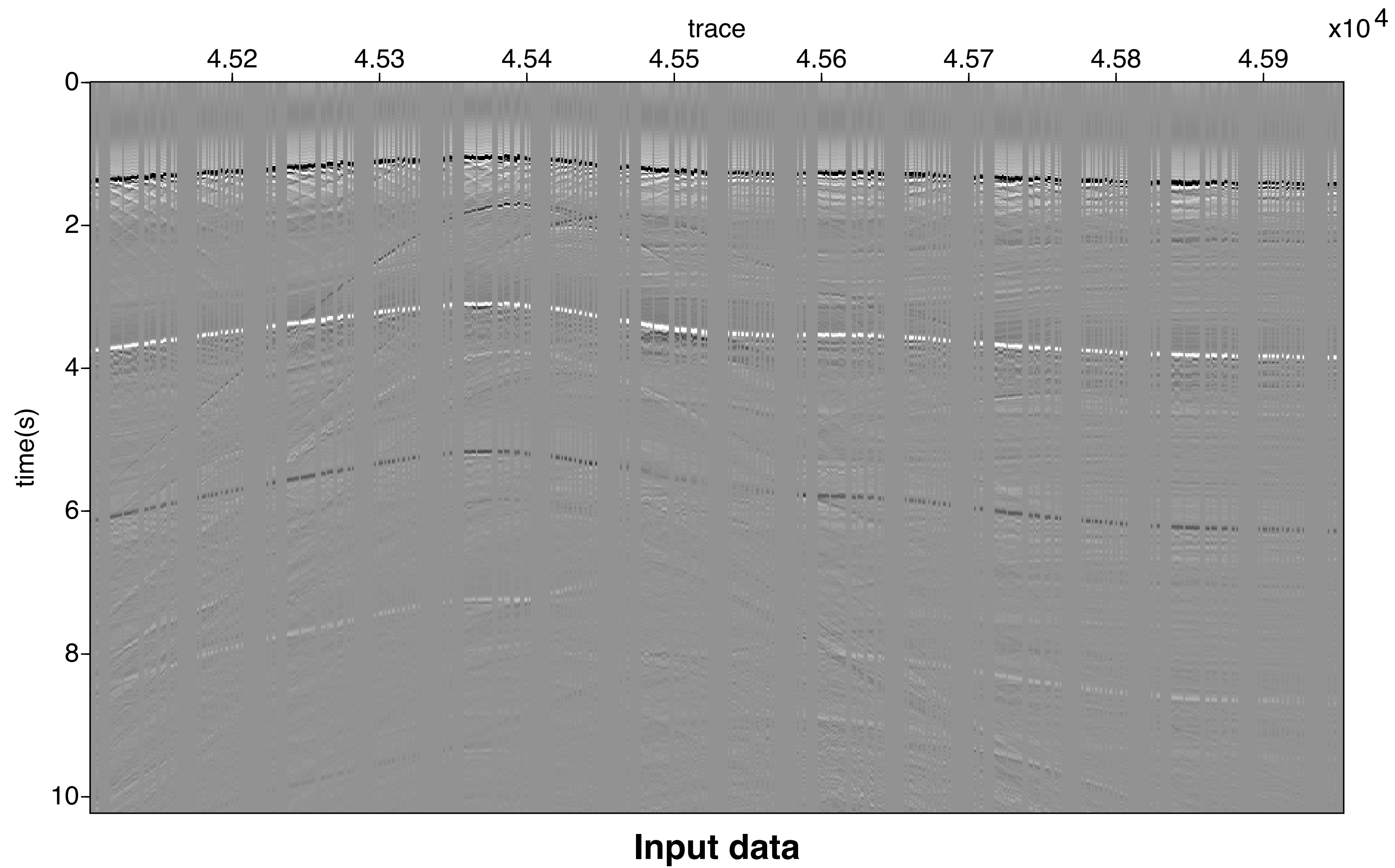
```
=====
SPGL1_SLIM v. 46  (Tue, 14 Jun 2011) based on v.1017
=====
No. rows           : 103672320      No. columns        : 1459253760
Initial tau        : 0.00e+00      Two-norm of b       : 3.92e+05
Optimality tol     : 1.00e-04      Target objective    : 0.00e+00
Basis pursuit tol  : 1.00e-06      Maximum iterations  :      110

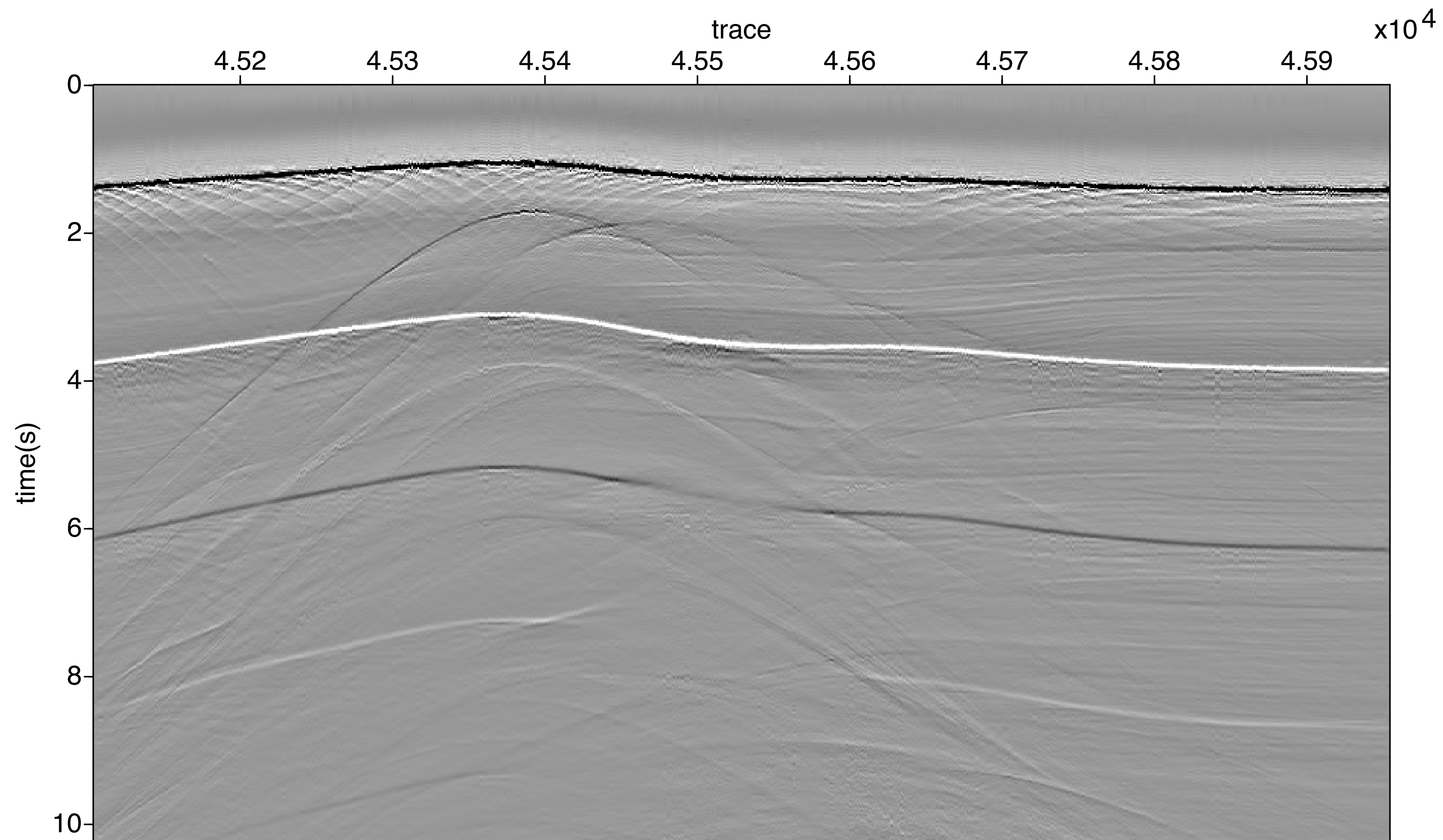
  Iter   Objective   Relative Gap   Rel Error   gNorm   stepG   nnzX   nnzG   tau
    0   3.9236638e+05  0.0000000e+00  1.00e+00  6.903e+03  0.0     0     0  2.2303101e+07
    1   3.9219958e+05  1.9364118e+00  1.00e+00  6.677e+03 -0.3     2     0
    2   3.4192692e+05  2.1884194e+00  1.00e+00  5.147e+03  0.0   14452     0
    3   3.2859582e+05  4.1722491e-01  1.00e+00  1.373e+03  0.0   48295     0

   108   1.5609476e+03  1.6347854e+04  1.00e+00  7.335e+00  0.0  356264726     0
   109   1.5850938e+03  9.3198454e+04  1.00e+00  4.283e+01  0.0  346355398     0
   110   1.5641524e+03  6.9308202e+04  1.00e+00  3.104e+01  0.0  345144021     0

ERROR EXIT -- Too many iterations

Products with A      :      125      Total time   (secs) : 34838.7
Products with A'     :      112      Project time (secs) : 2875.2
Newton iterations    :       26      Mat-vec time (secs) : 25882.1
Line search its      :       23      Subspace iterations :        0
```





Interpolation with 2D Curvelet

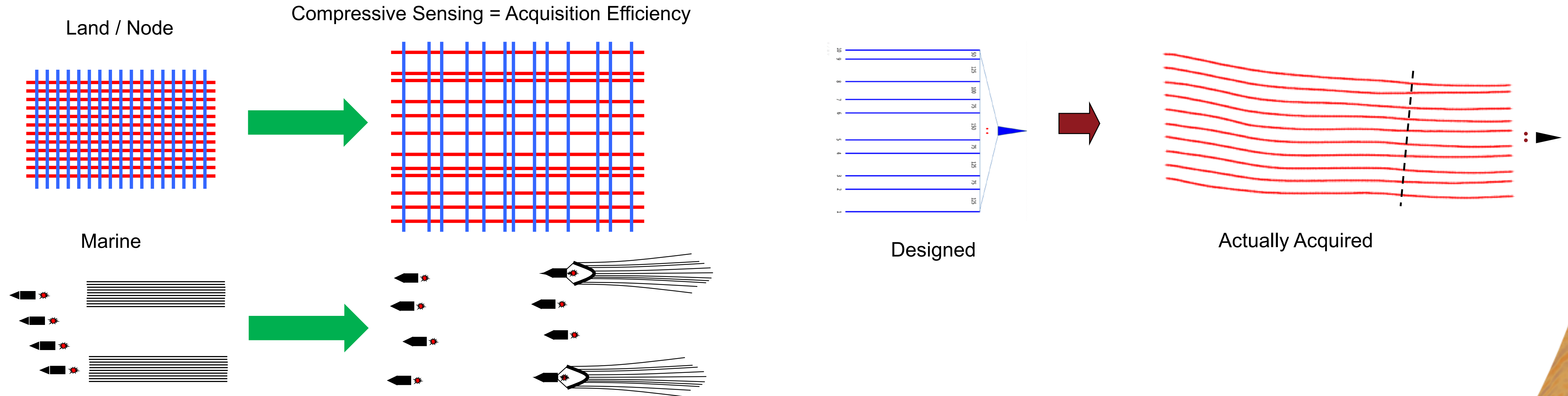
Mosher, C. C., Keskula, E., Kaplan, S. T., Keys, R. G., Li, C., Ata, E. Z., ... & Sood, S. (2012, November). Compressive Seismic Imaging. In *2012 SEG Annual Meeting*. Society of Exploration Geophysicists.

Randomized undersampling

– examples from industry (ConocoPhillips)

Deliberate & natural randomness in acquisition

(thanks to Chuck Mosher)



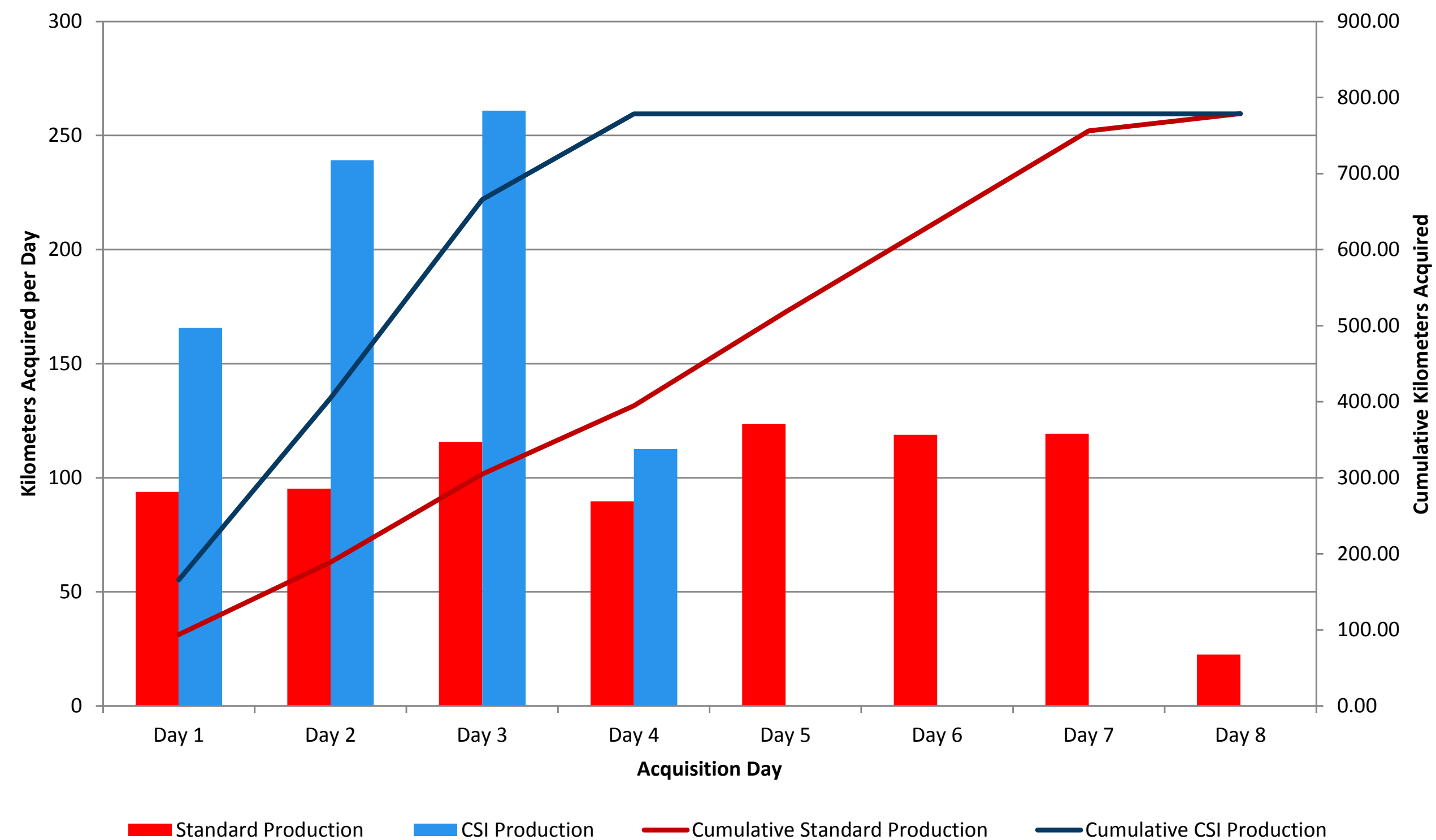
Bottom line

– examples from industry (ConocoPhillips)

Economics

(thanks to Chuck Mosher)

Standard Production vs. CSI Production



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*

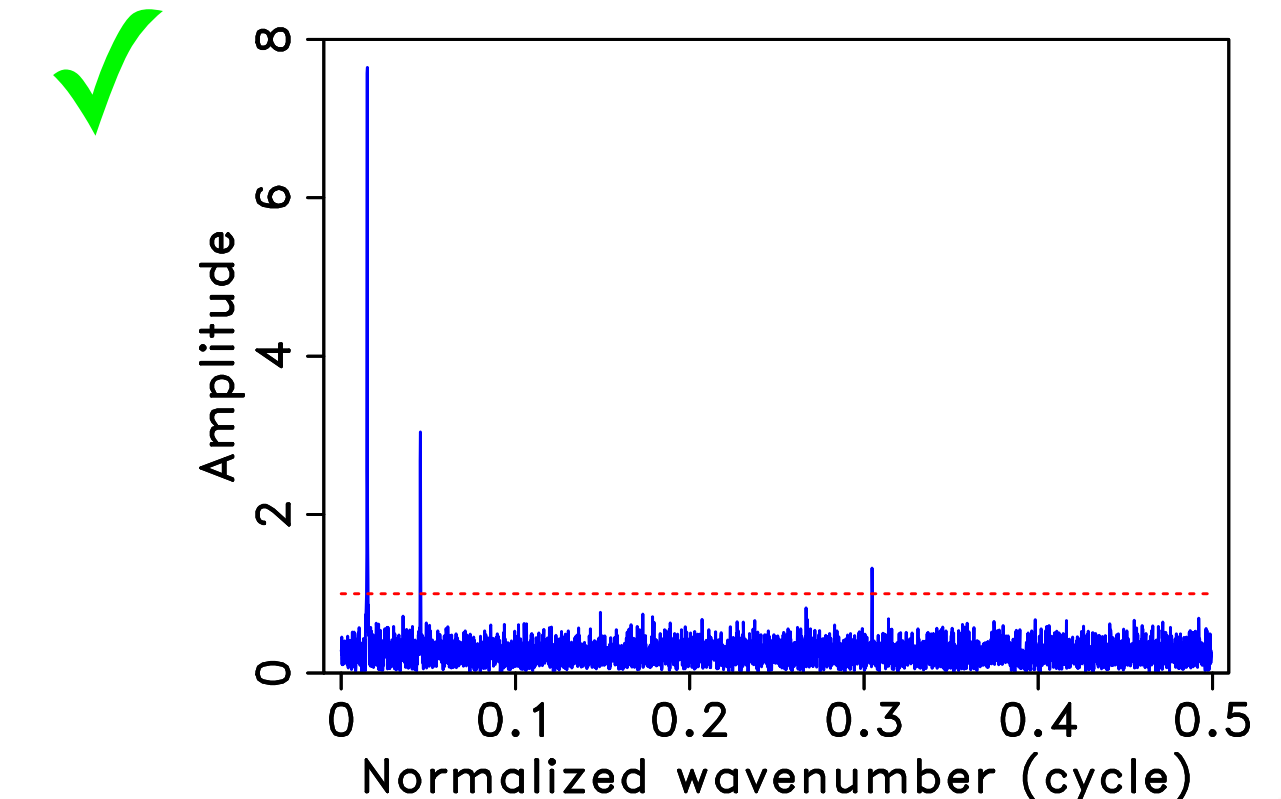
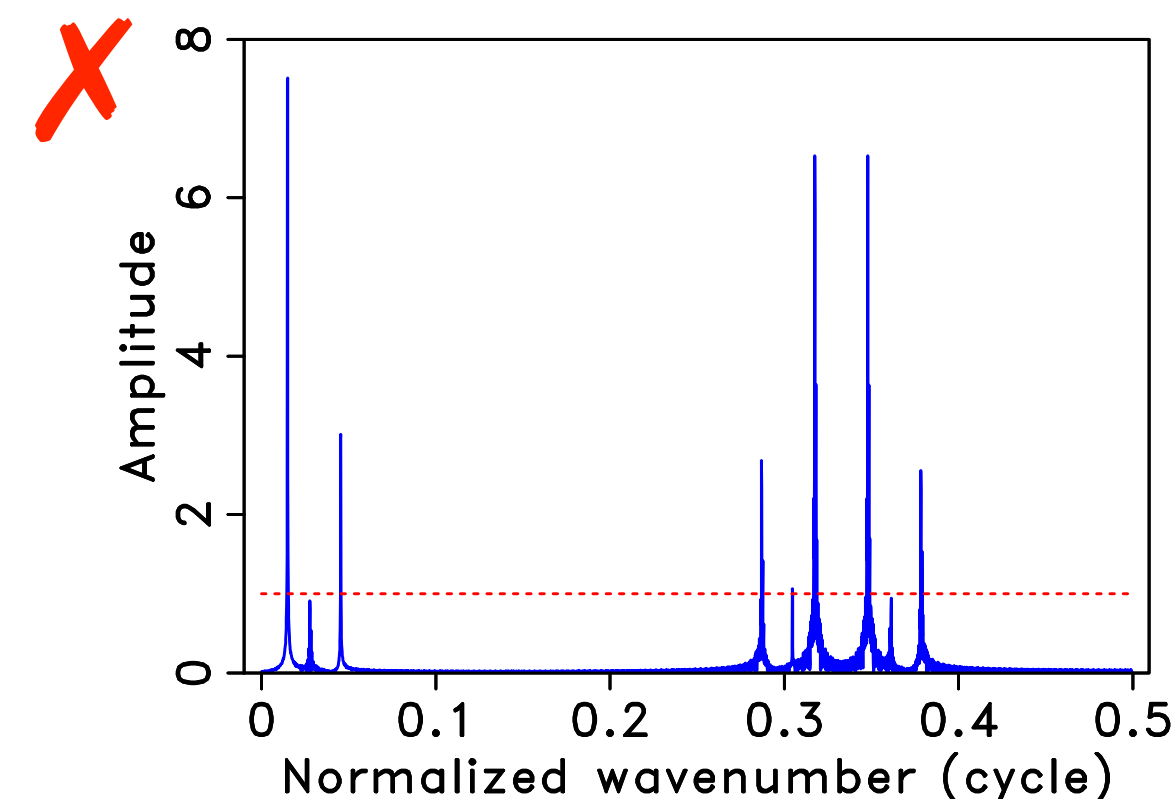
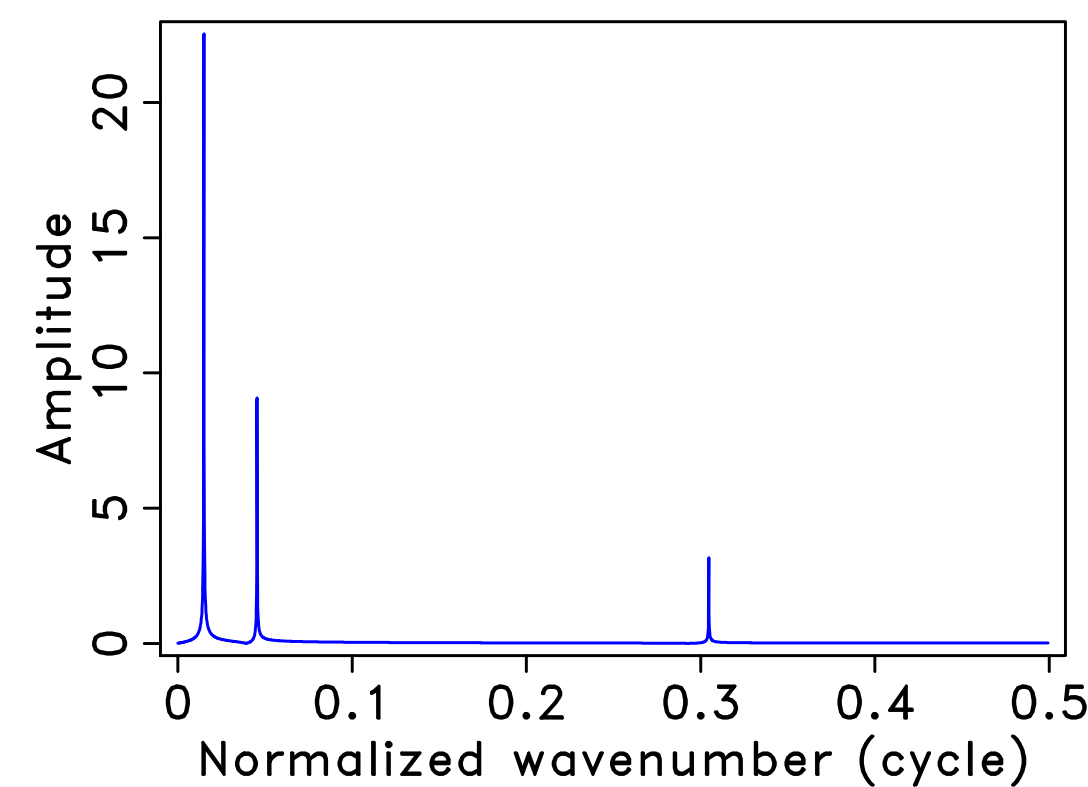
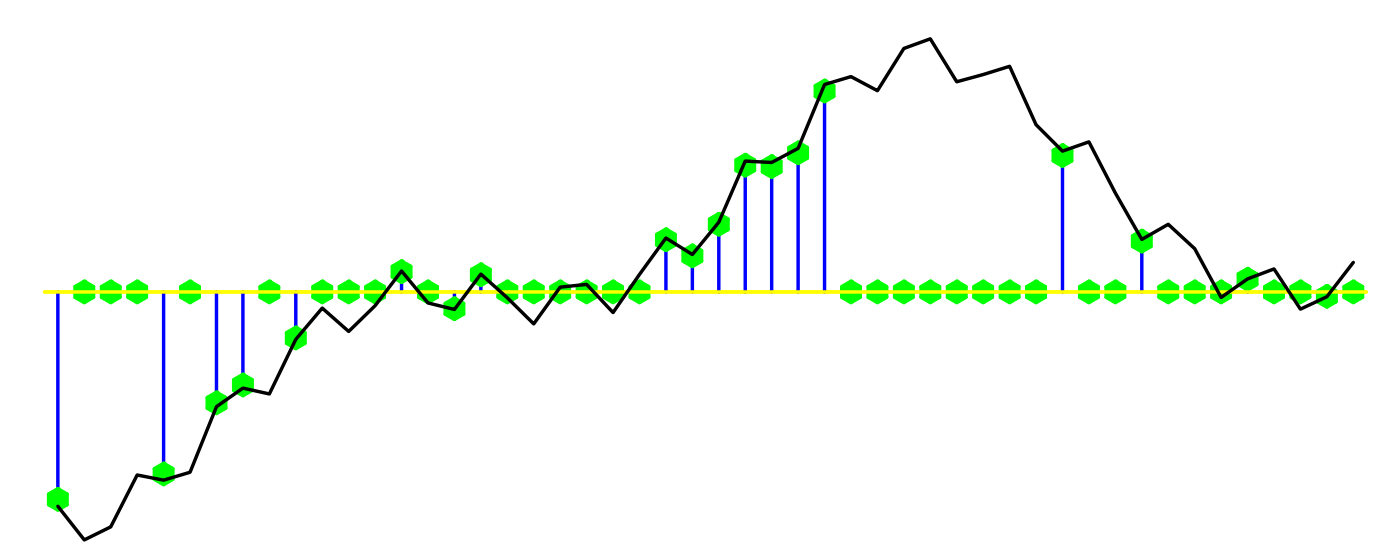
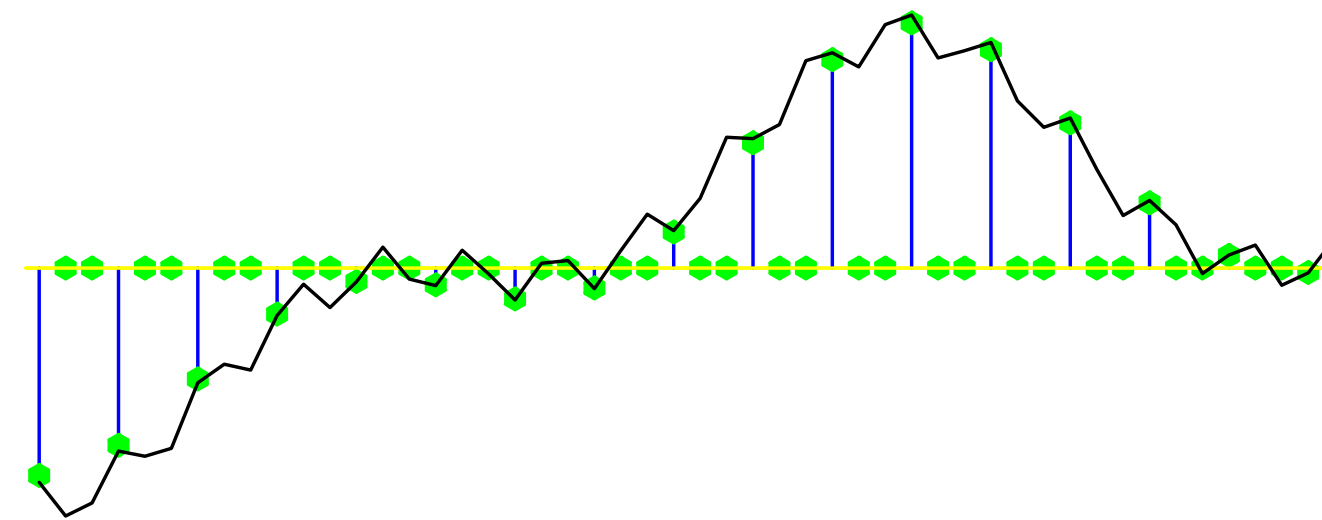
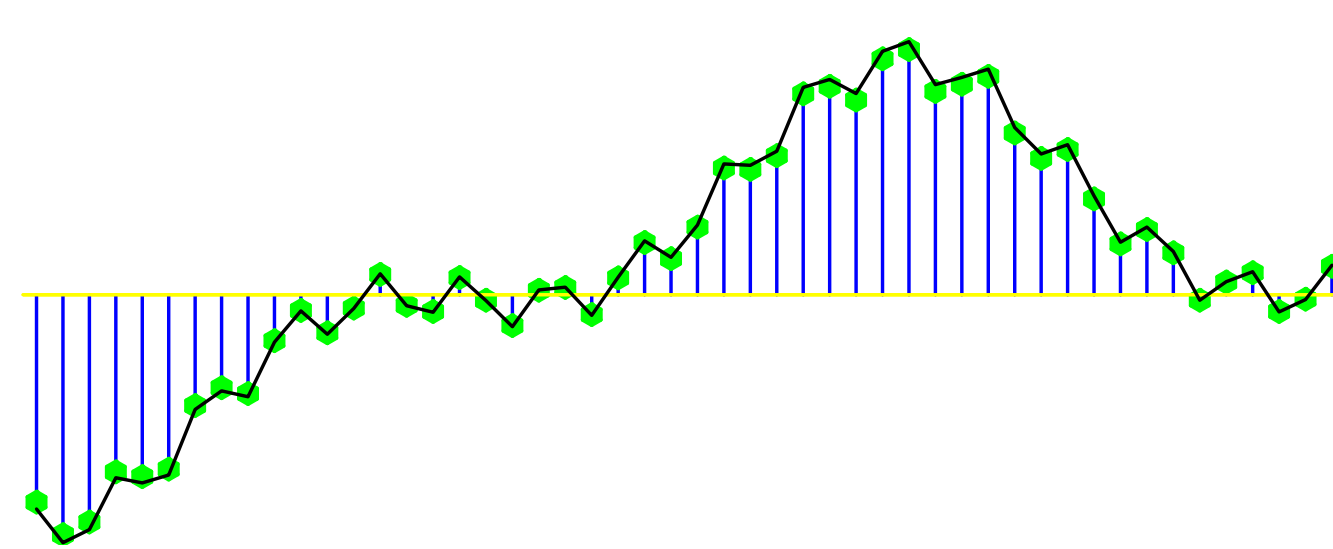
Felix J. Herrmann and Gilles Hennenfent, “[Non-parametric seismic data recovery with curvelet frames](#)”, *GJI*, vol. 173, p. 233-248, 2008.

Gilles Hennenfent and Felix J. Herrmann, “[Simply denoise: wavefield reconstruction via jittered undersampling](#)”, *Geophysics*, vol. 73, p. V19-V28, 2008.

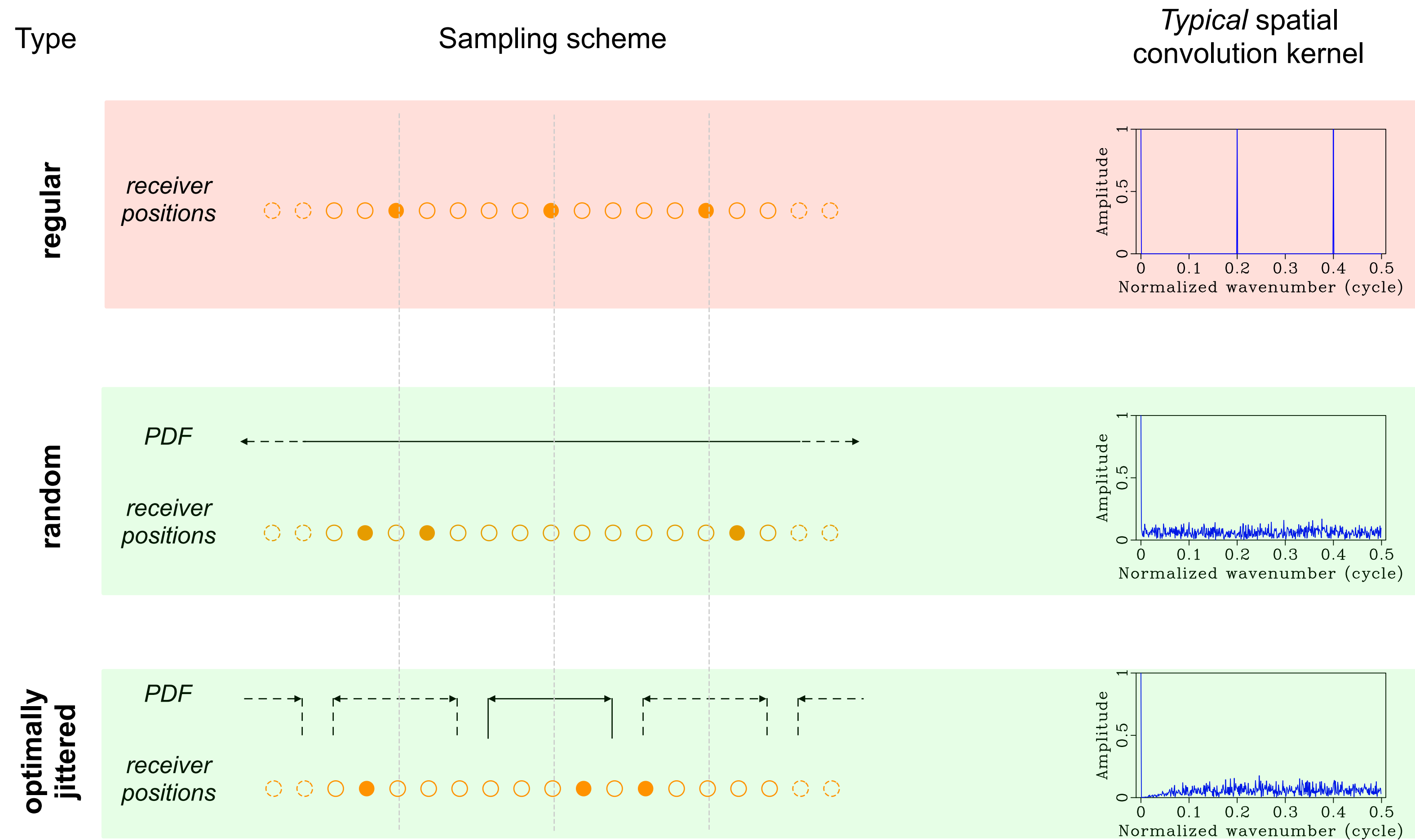
Felix J. Herrmann, “[Randomized sampling and sparsity: Getting more information from fewer samples](#)”, *Geophysics*, vol. 75, p. WB173-WB187, 2010.

Golden oldies

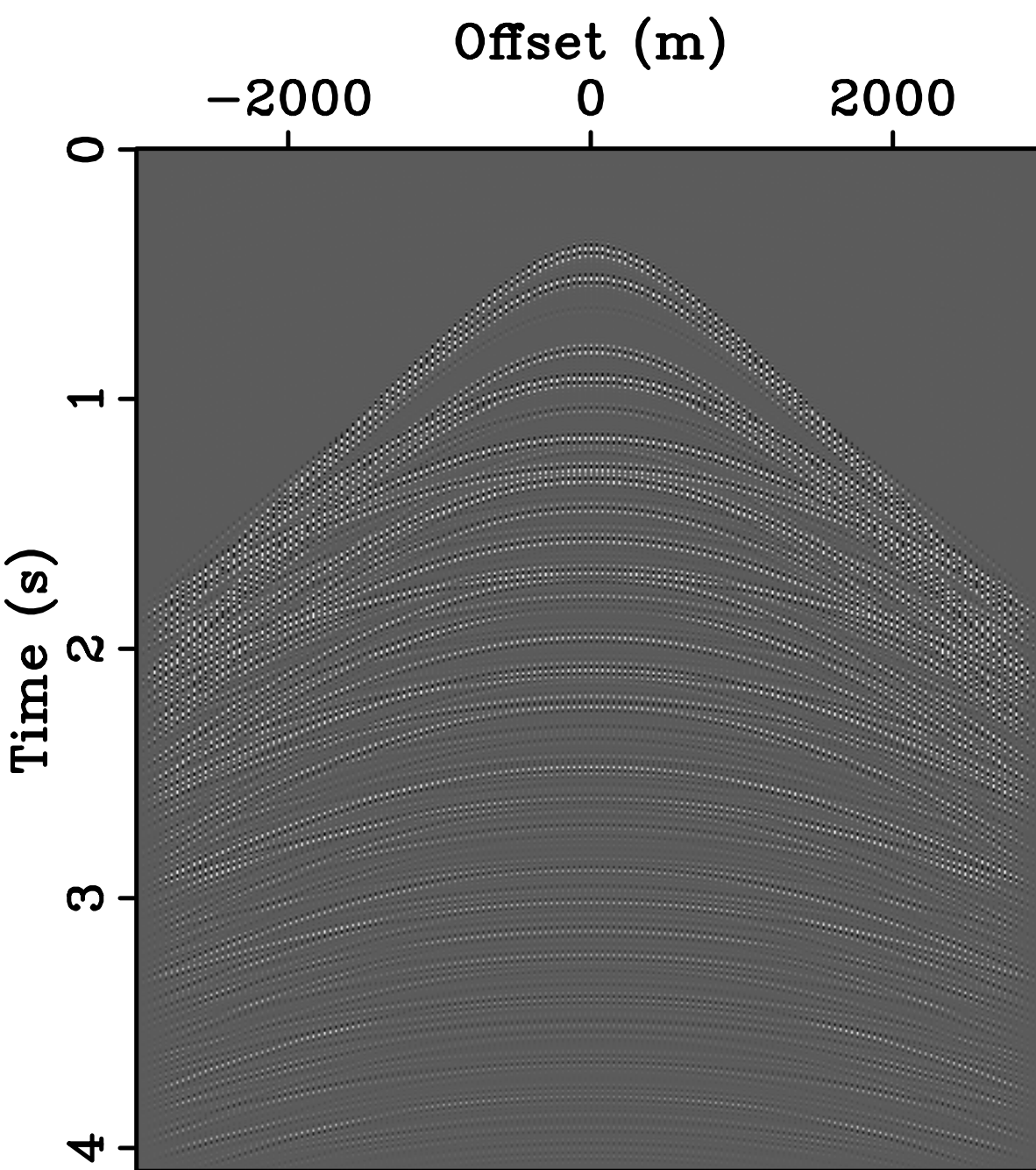
– sparse time-harmonic signals



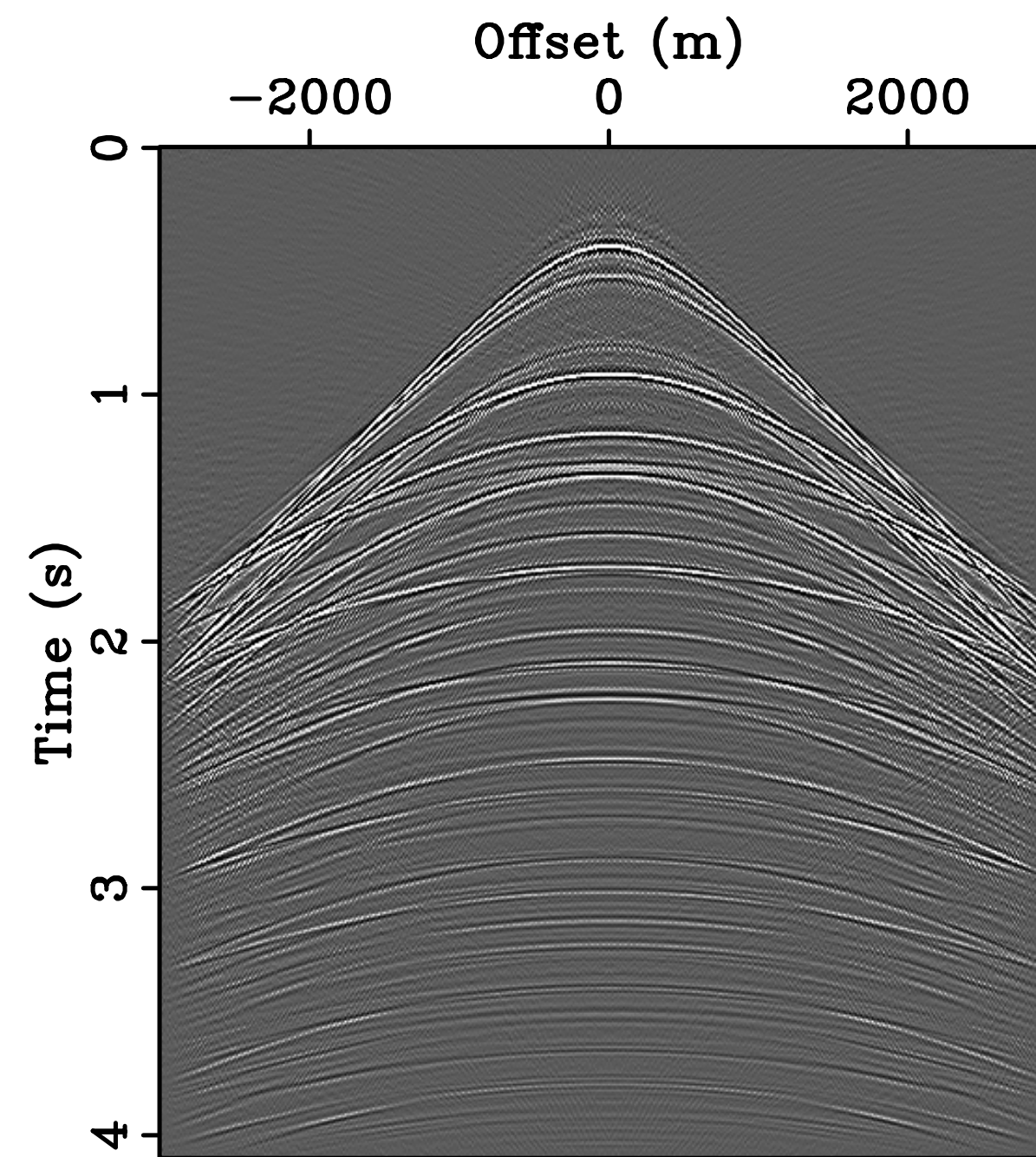
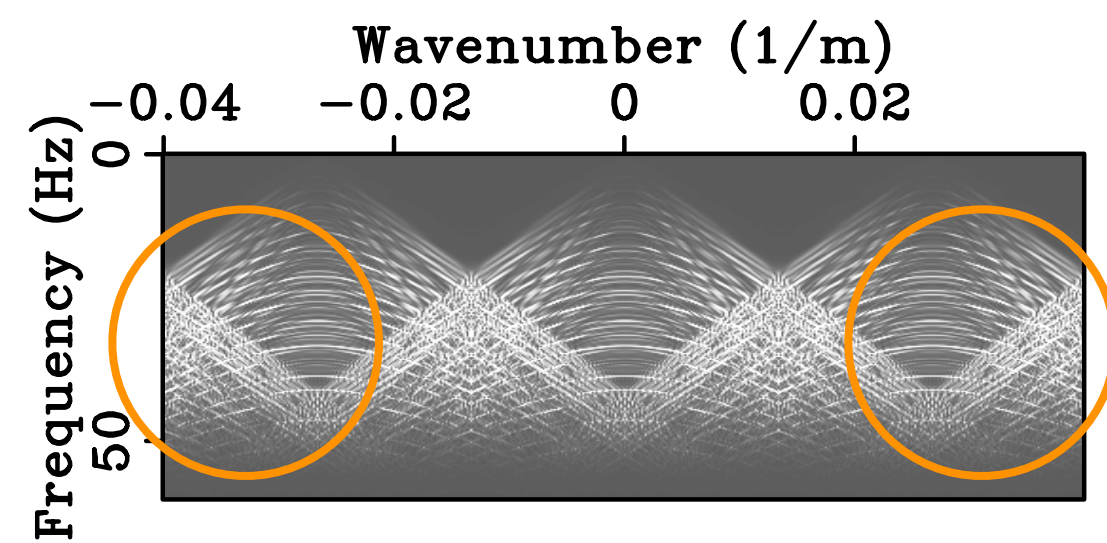
Jittered sampling



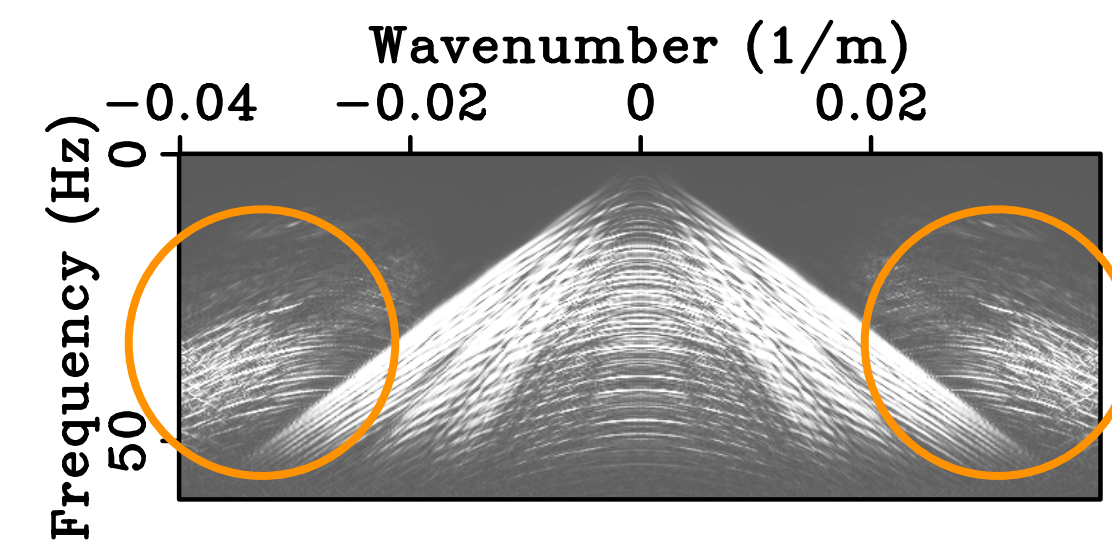
Periodic sampling



3-fold undersampled

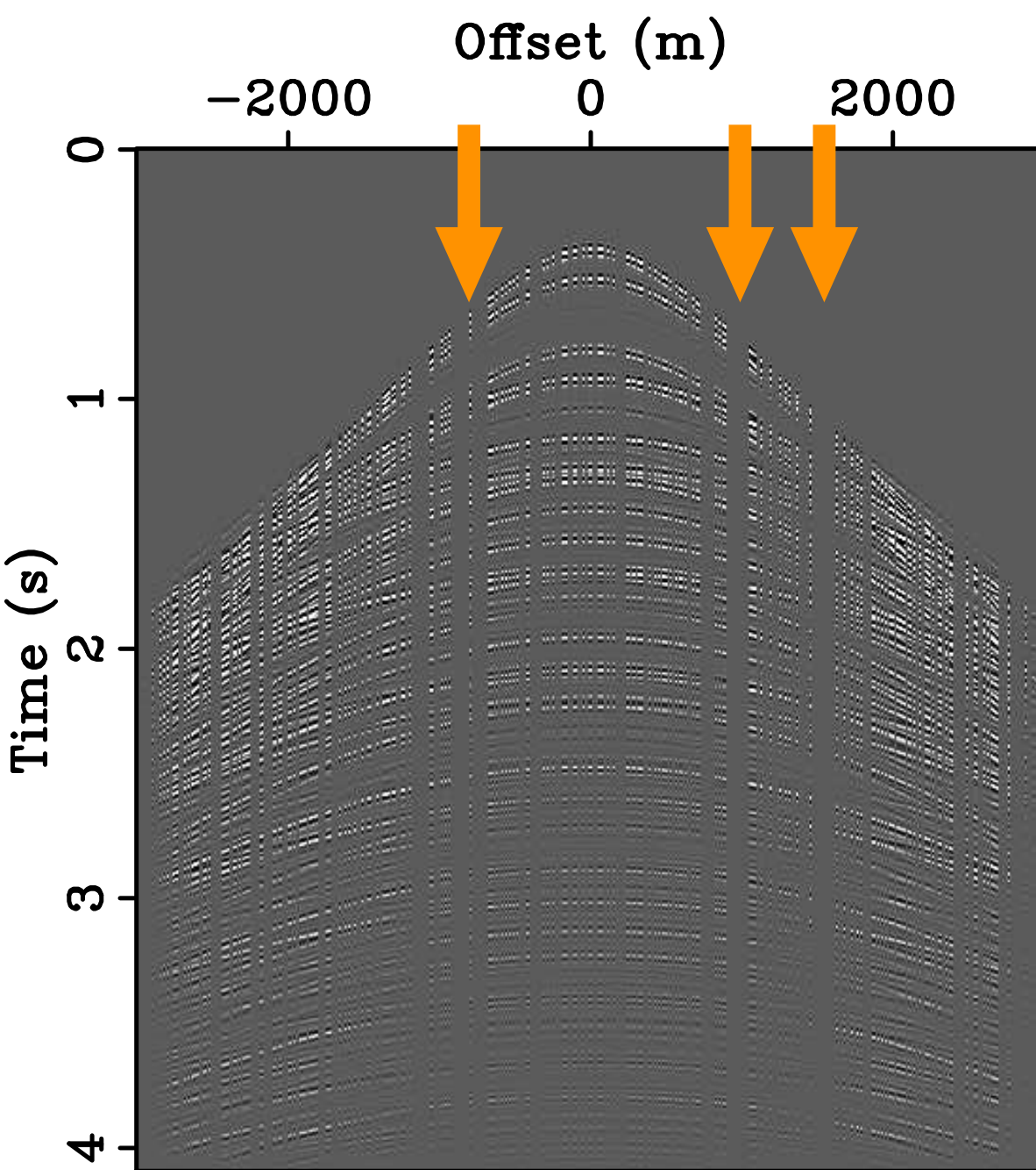


recovered

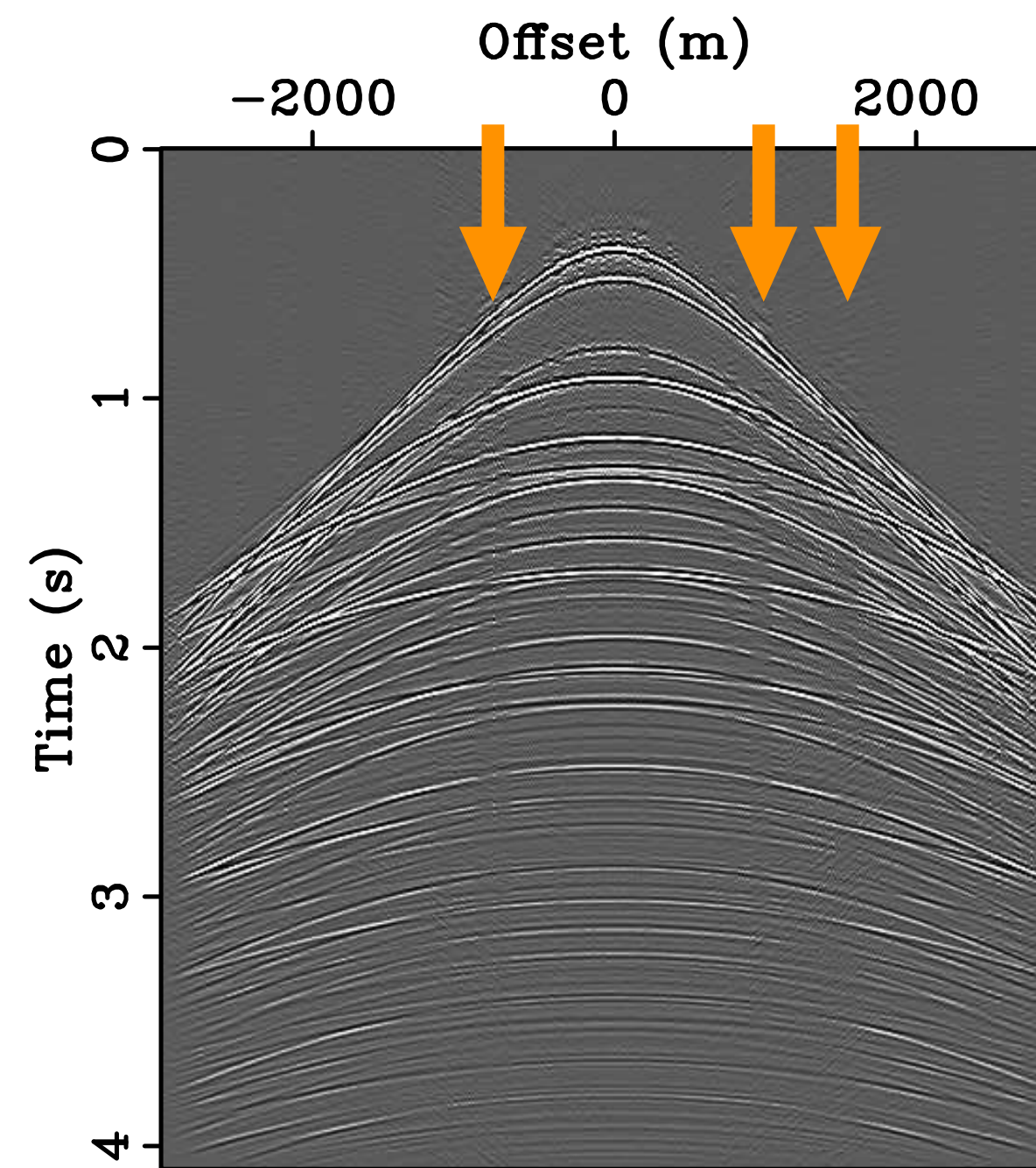
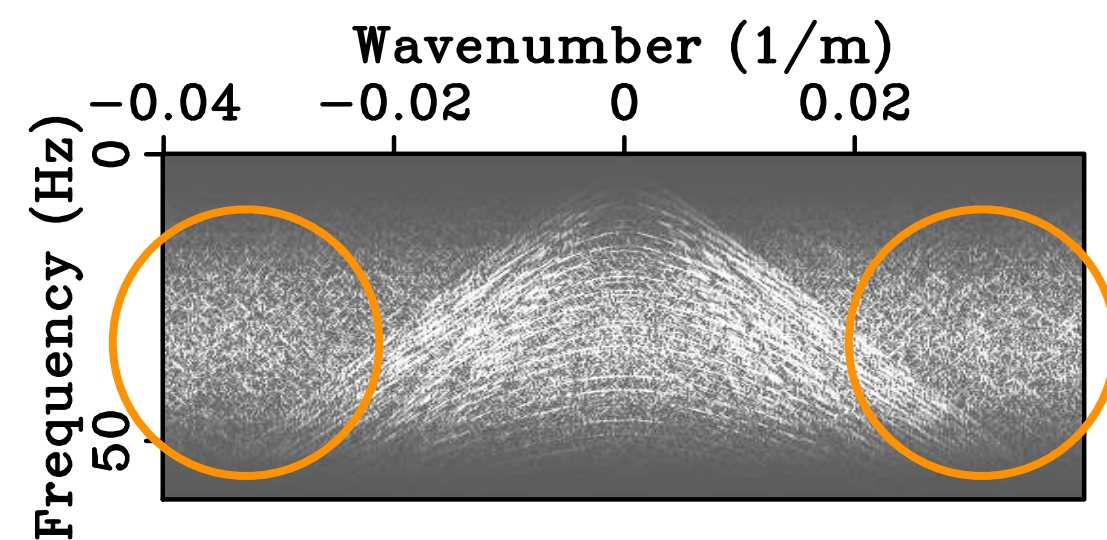


SNR = 6.92 dB

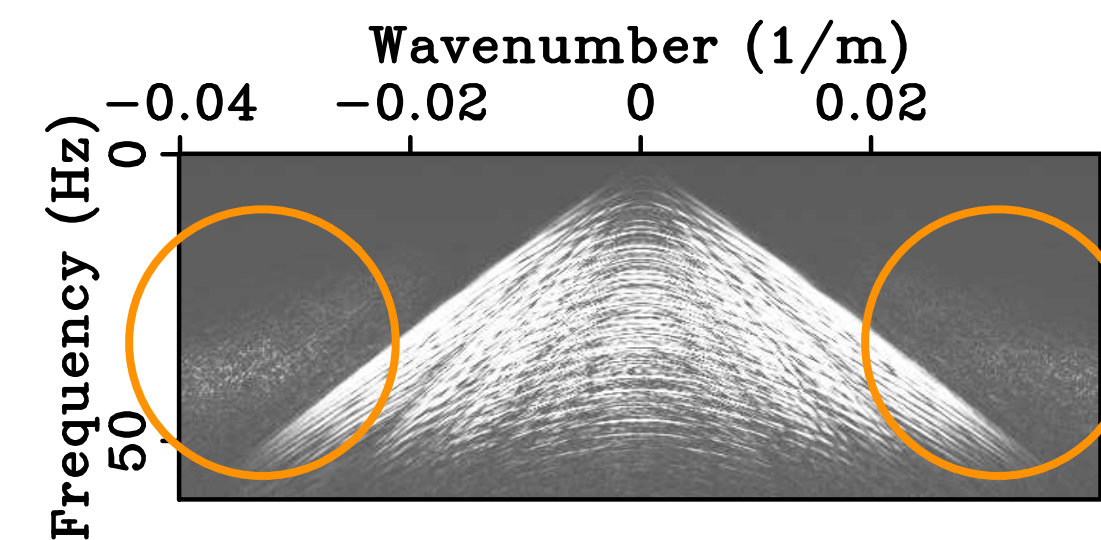
Uniform random sampling



3-fold undersampled

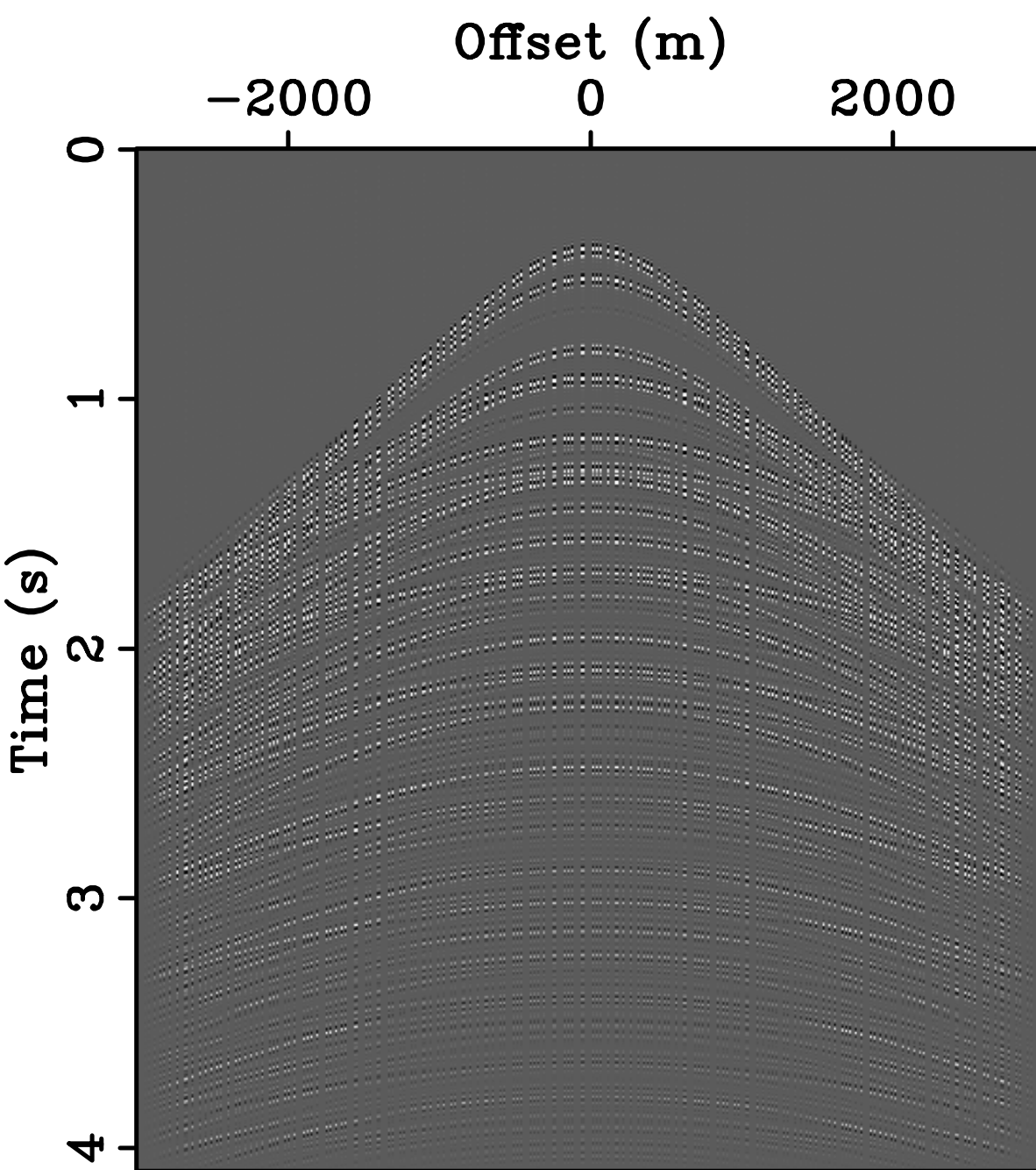


recovered

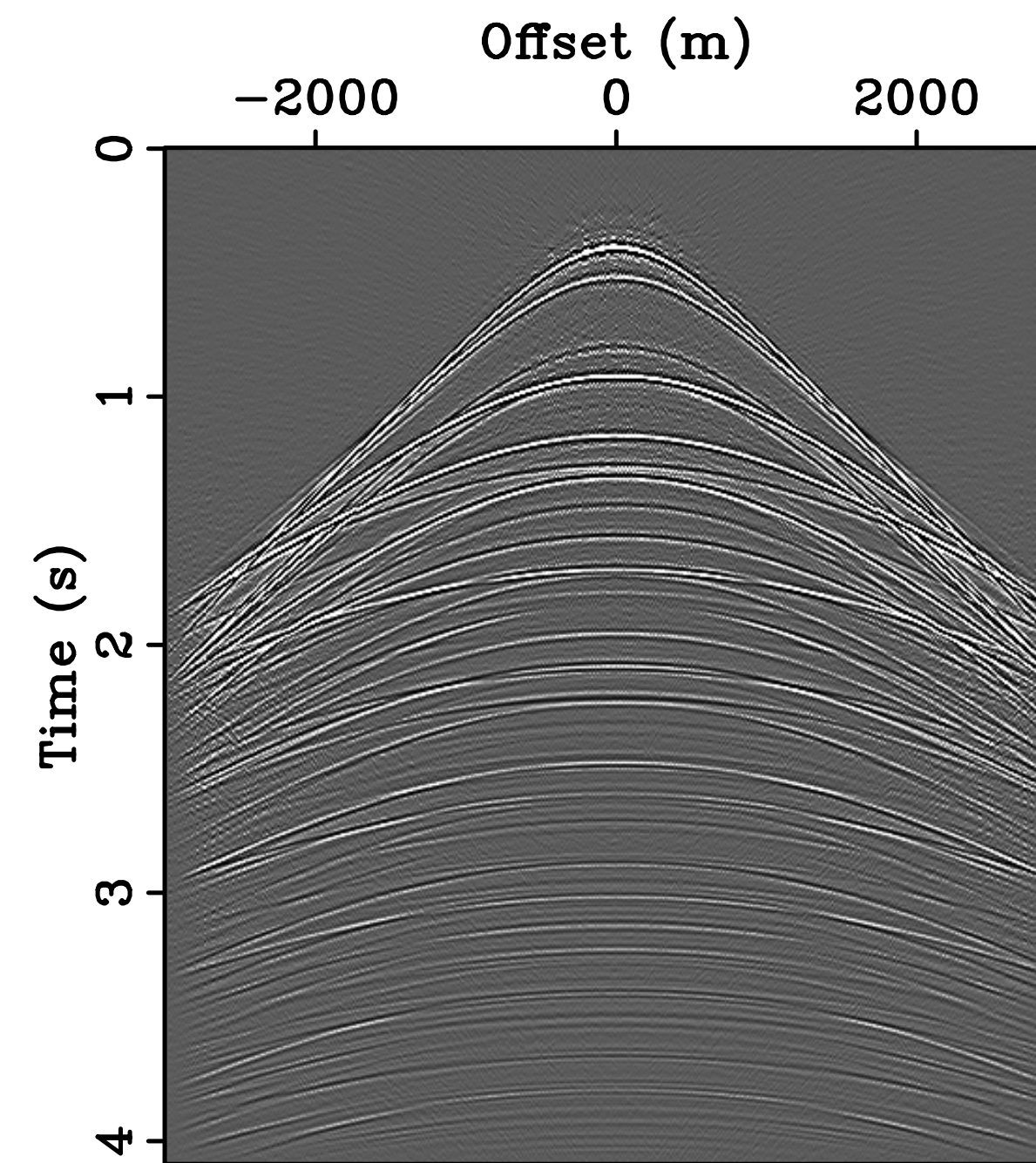
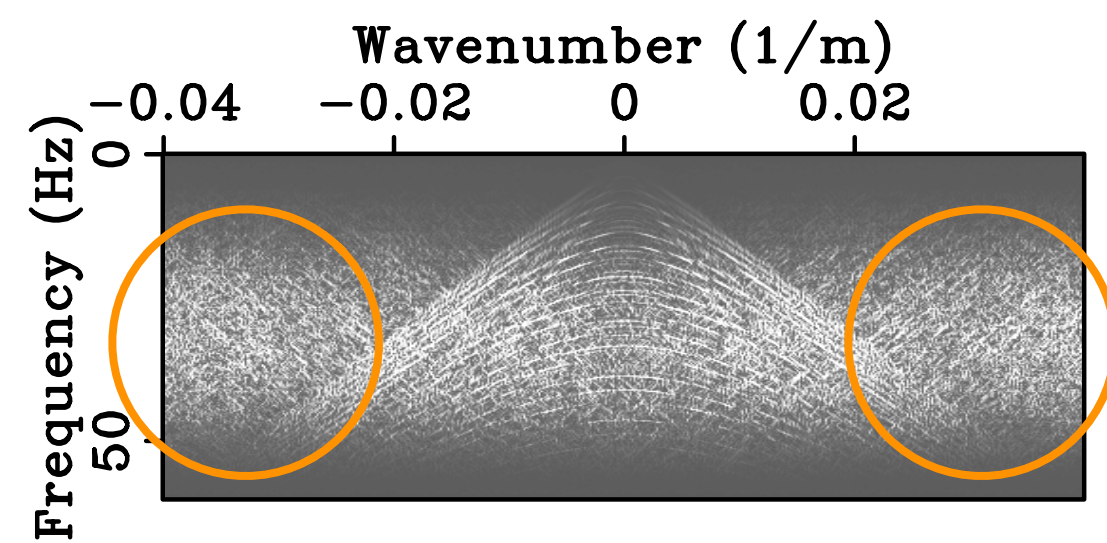


SNR = 9.72 dB

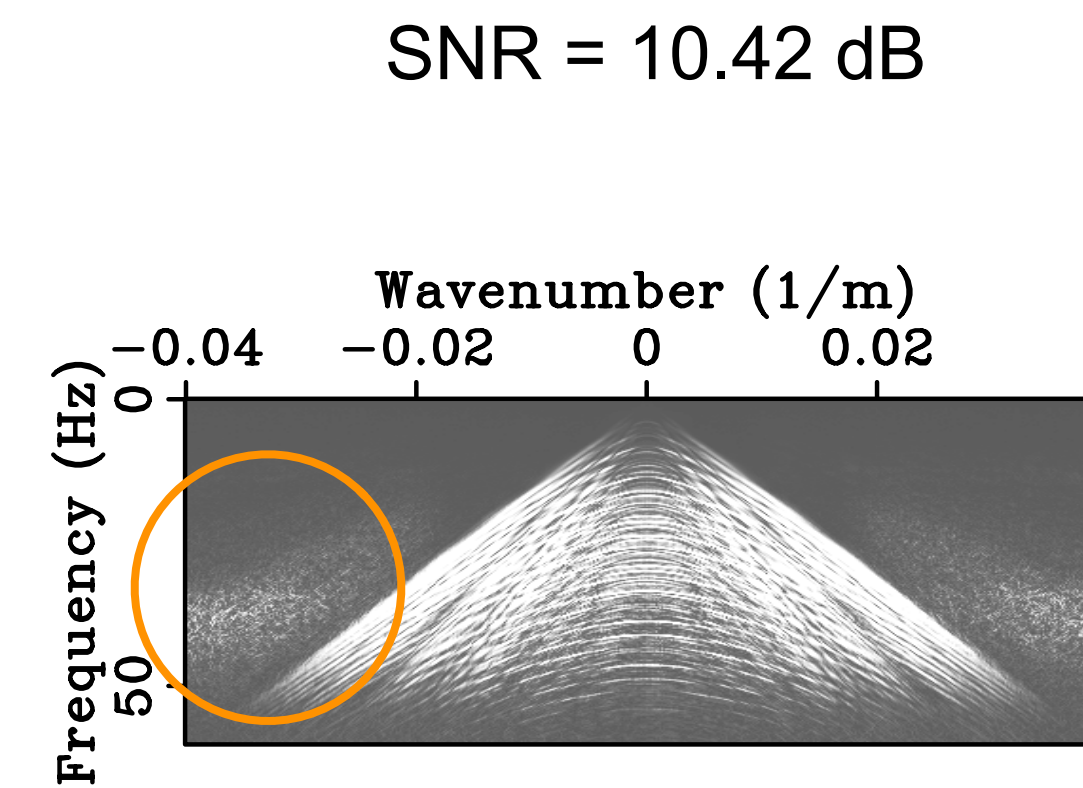
Jittered sampling



3-fold undersampled



recovered



Time-*jittered* marine acquisition

Objective

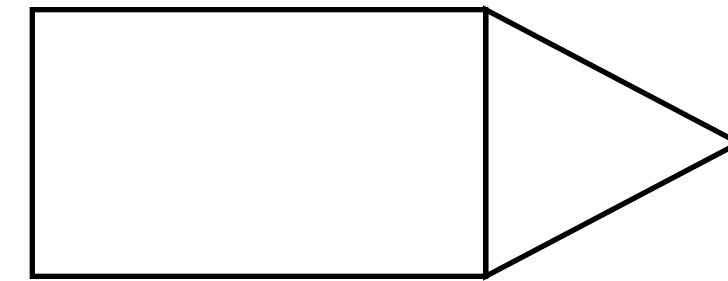
Shorten marine acquisition *times* & *increase* source sample *density*.

Question:

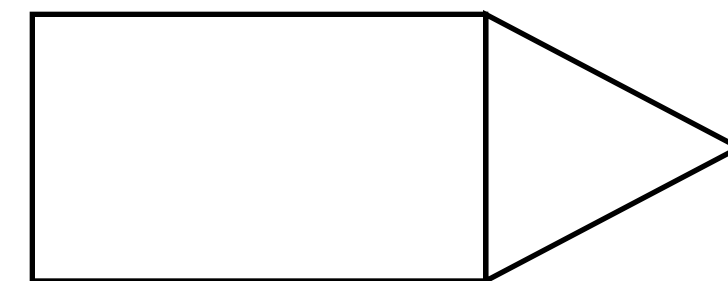
Does increased *variability* of *firing* times improve recovery?

Regular vs. *jittered* locations

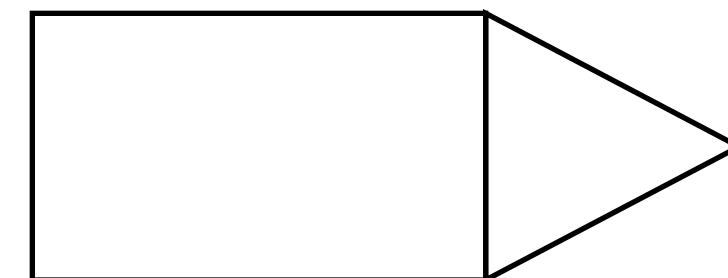
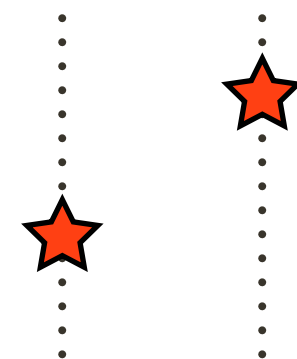
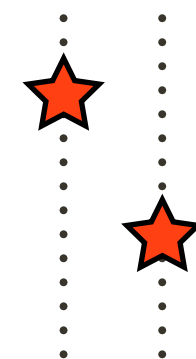
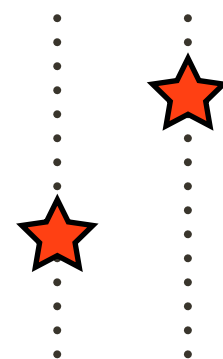
regularly sampled spatial grid



almost regularly sampled spatial grid
(low variability)

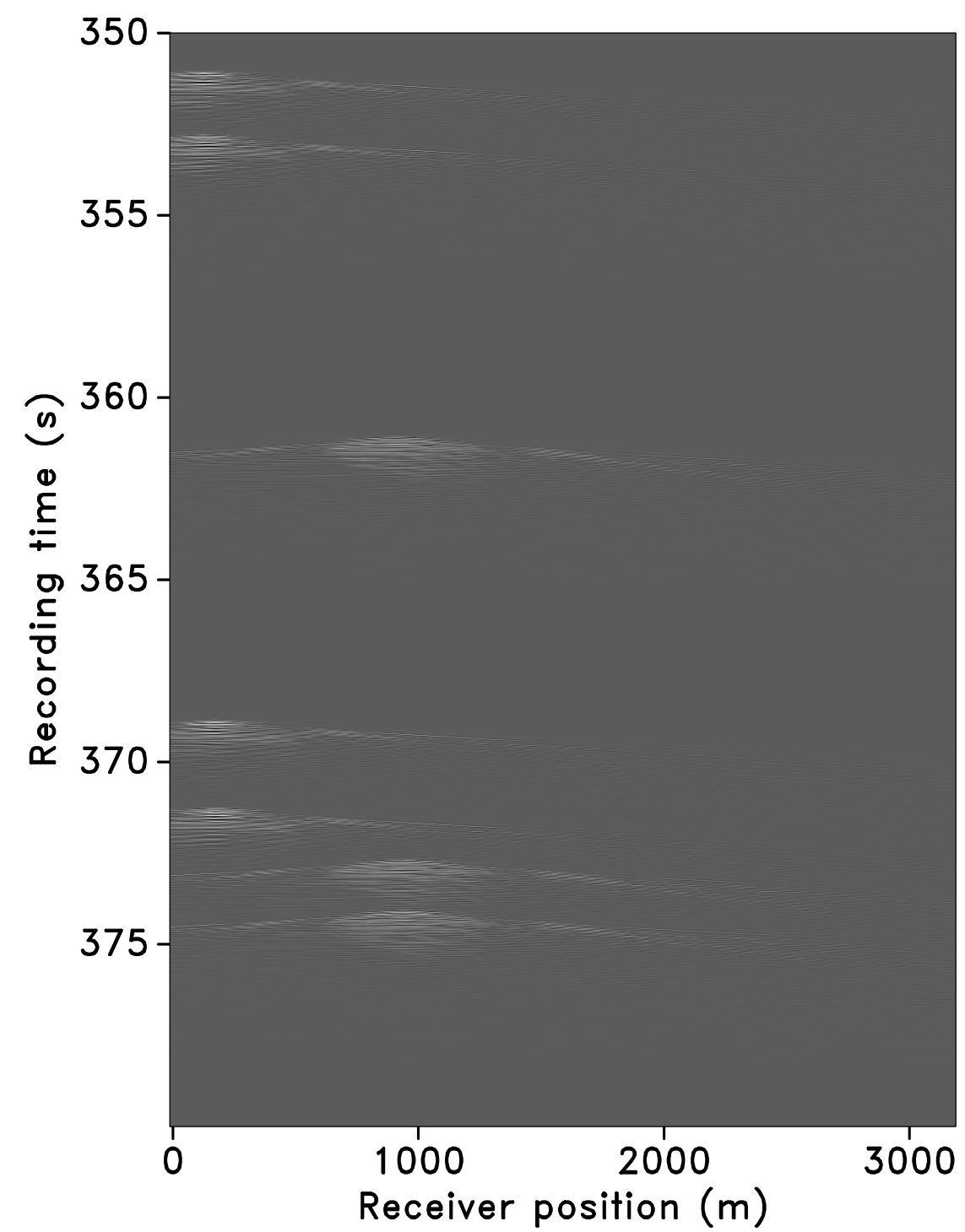


irregularly sampled spatial grid
(high variability)



acquire in the field on *irregular* grid
(*subsampling* shots *w/ overlap*
between shot records)

b

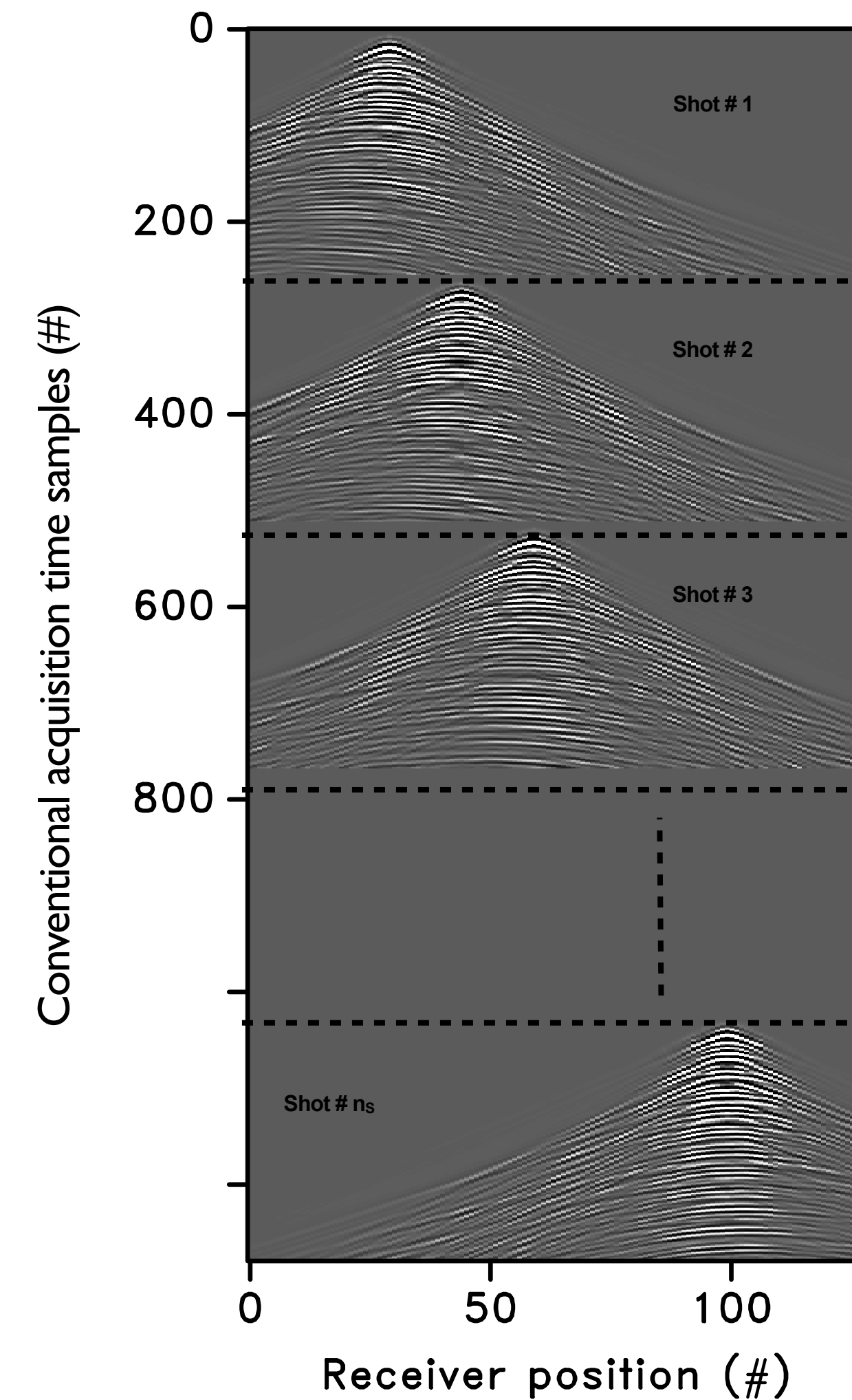


=

M

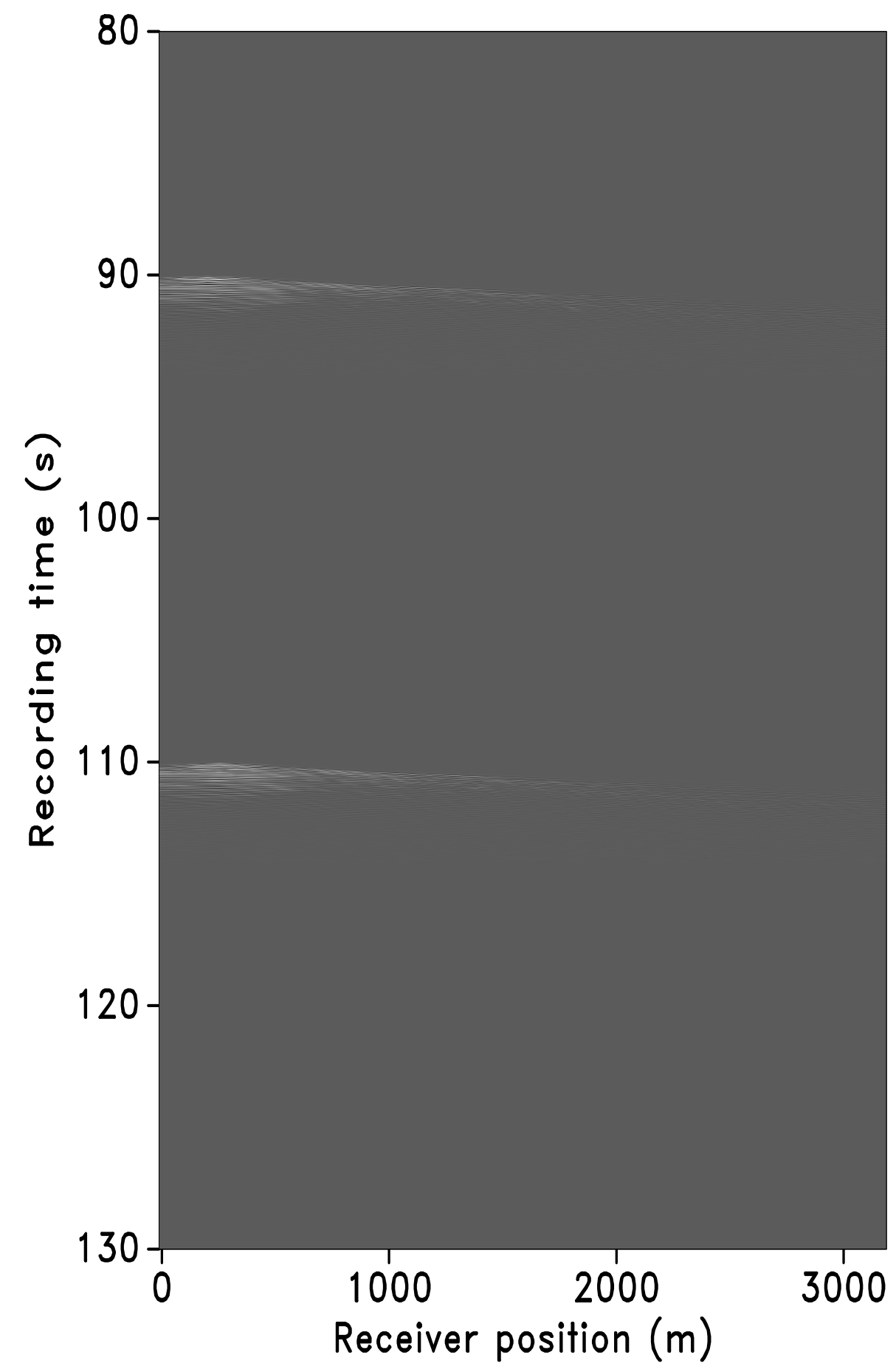
would like to have on *regular* grid
(*all* shots *w/o overlaps* between
shot records)

d

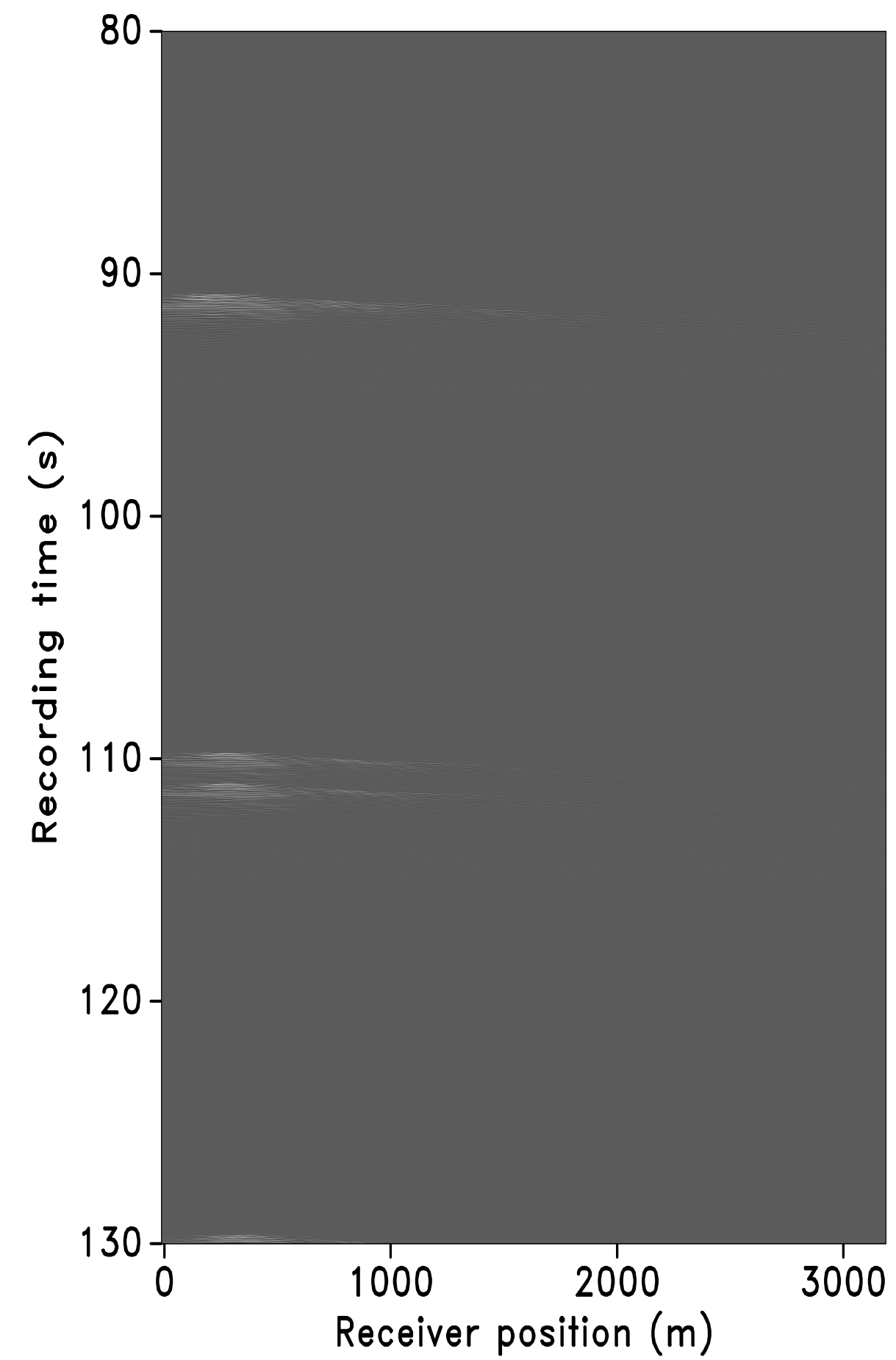


Measurements

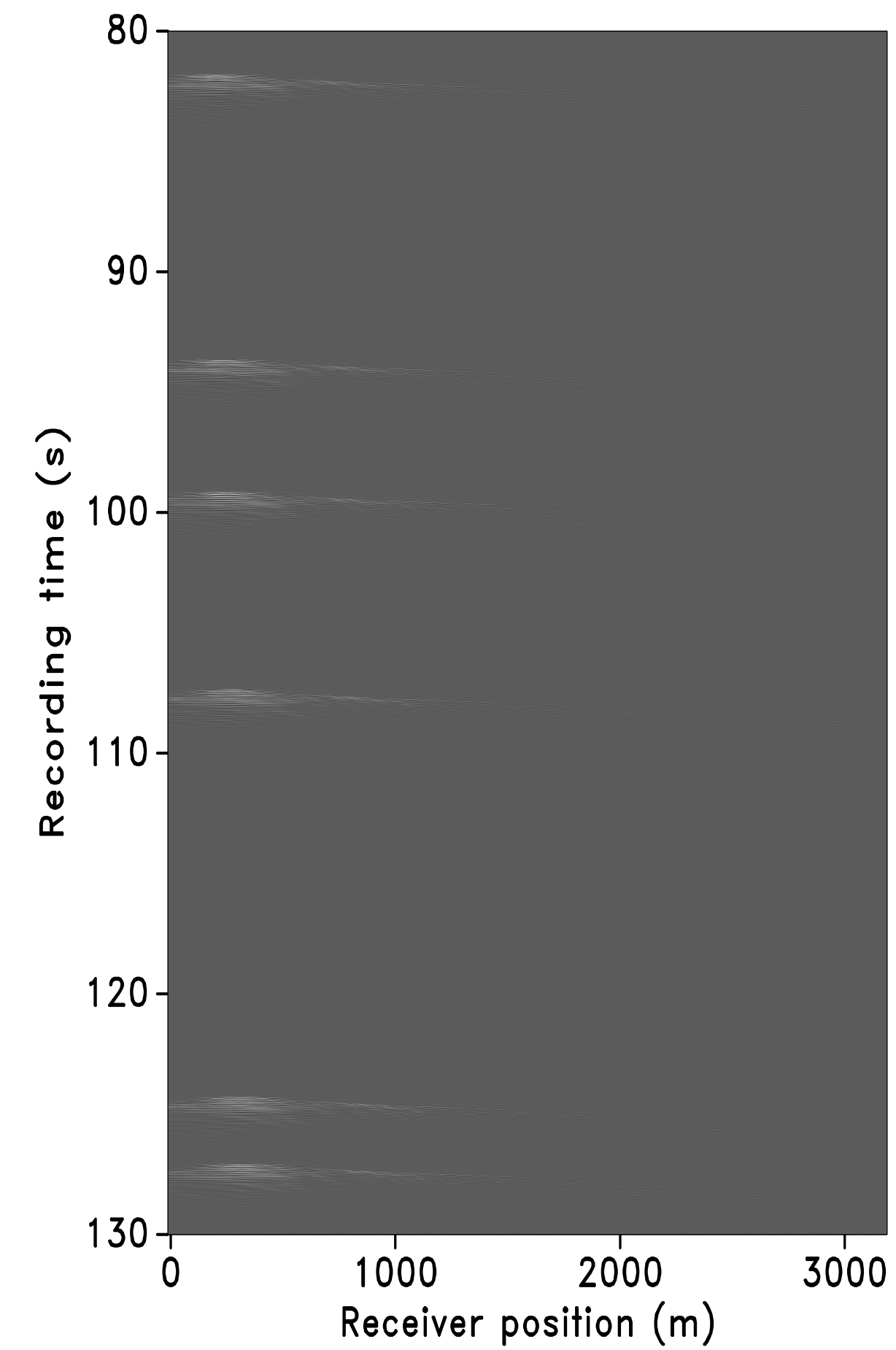
periodic



low variability



high variability



Sparsity-promoting recovery

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

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

\mathbf{S}^H

a *transform domain synthesis*

\mathbf{A}

measurement operator : $\mathbf{M}\mathbf{S}^H$, \mathbf{M} is a blending operator

\mathbf{b}

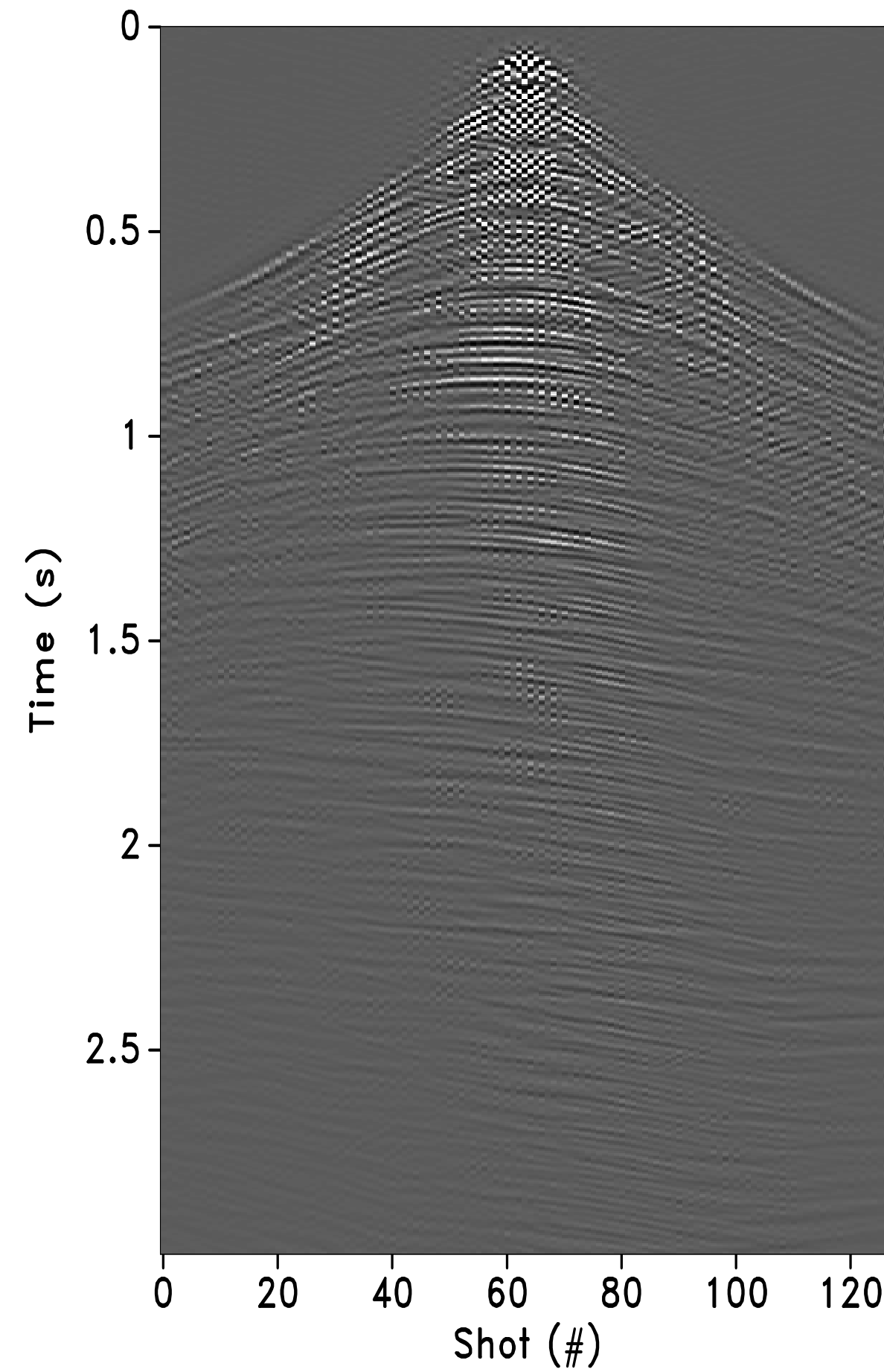
blended data

$\tilde{\mathbf{x}}$

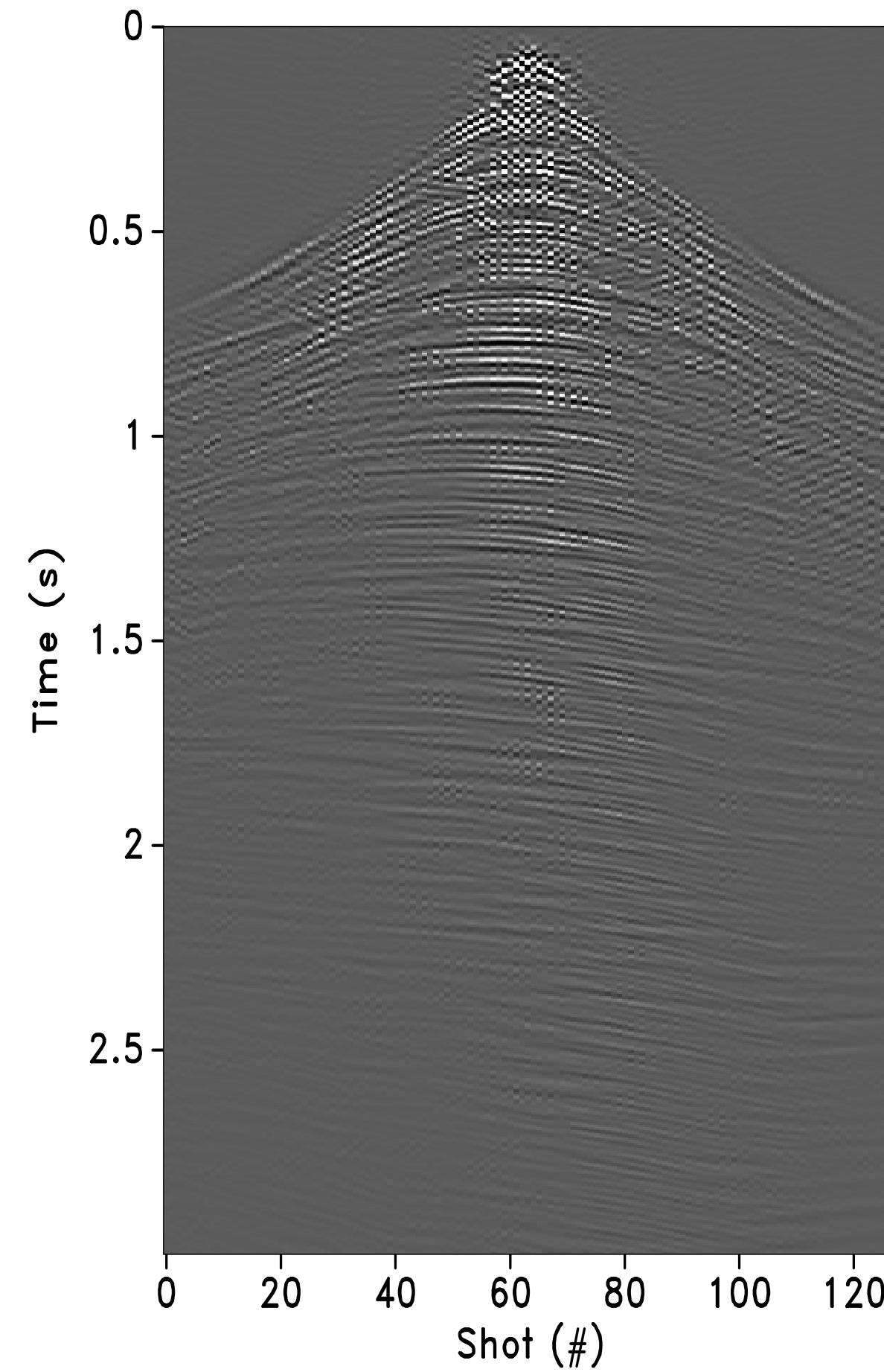
estimated curvelet coefficients for source separated wavefield

Recovery ["deblending" from 50 m grid to 25 m grid]

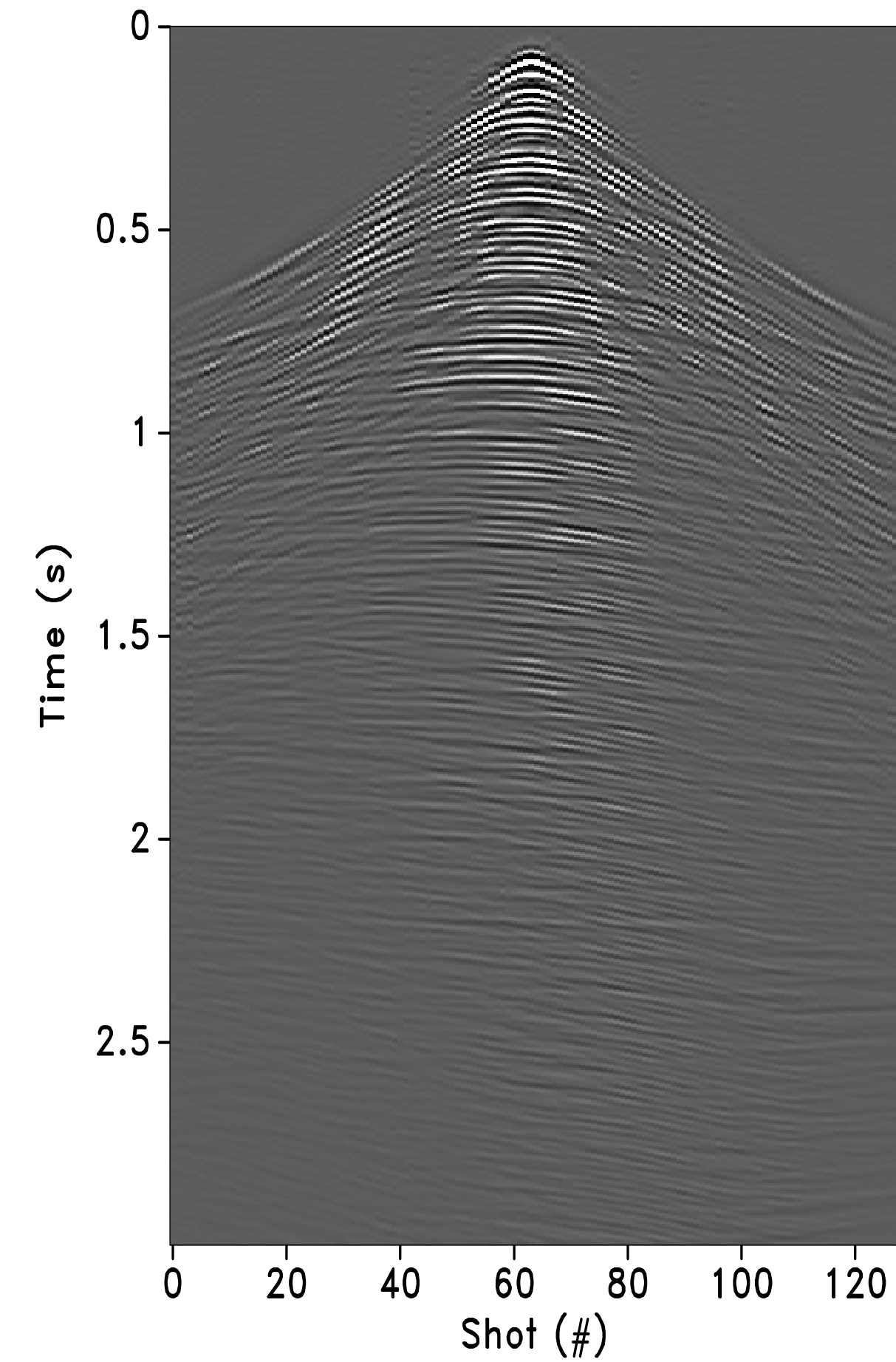
periodic
(1.6 dB)



low variability
(3.2 dB)

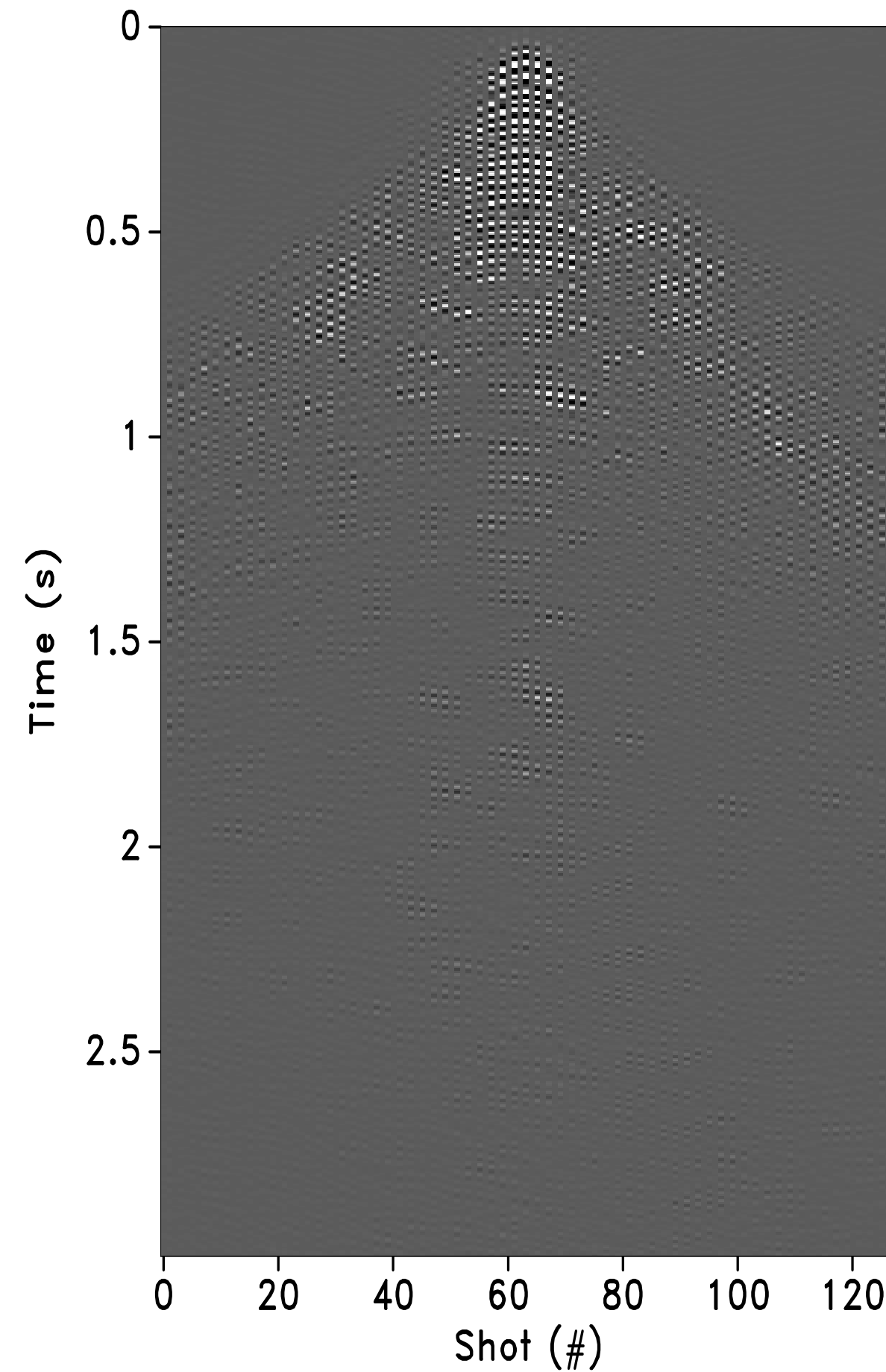


high variability
(16.5 dB)

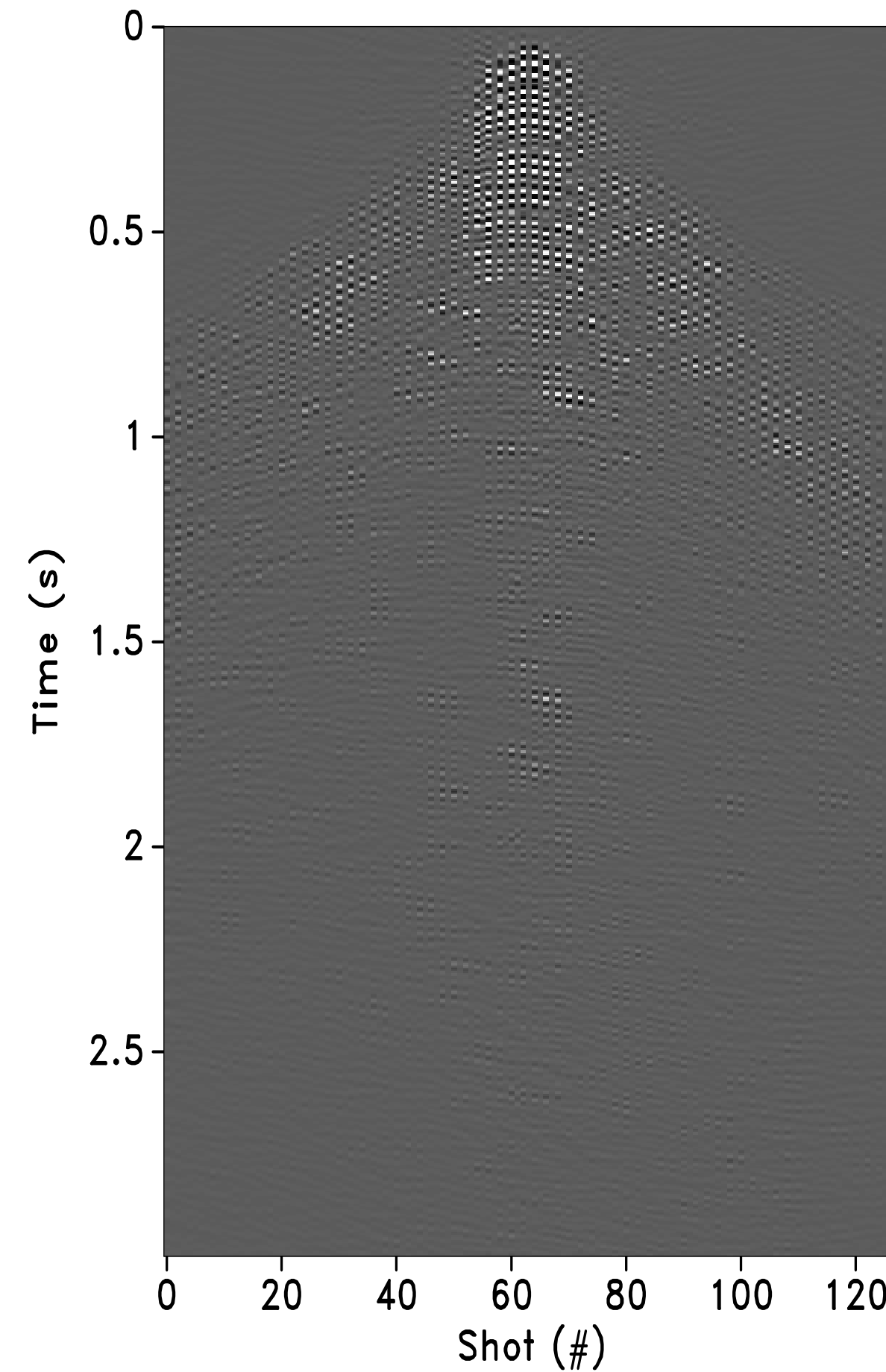


Difference [“deblending” from 50 m grid to 25 m grid]

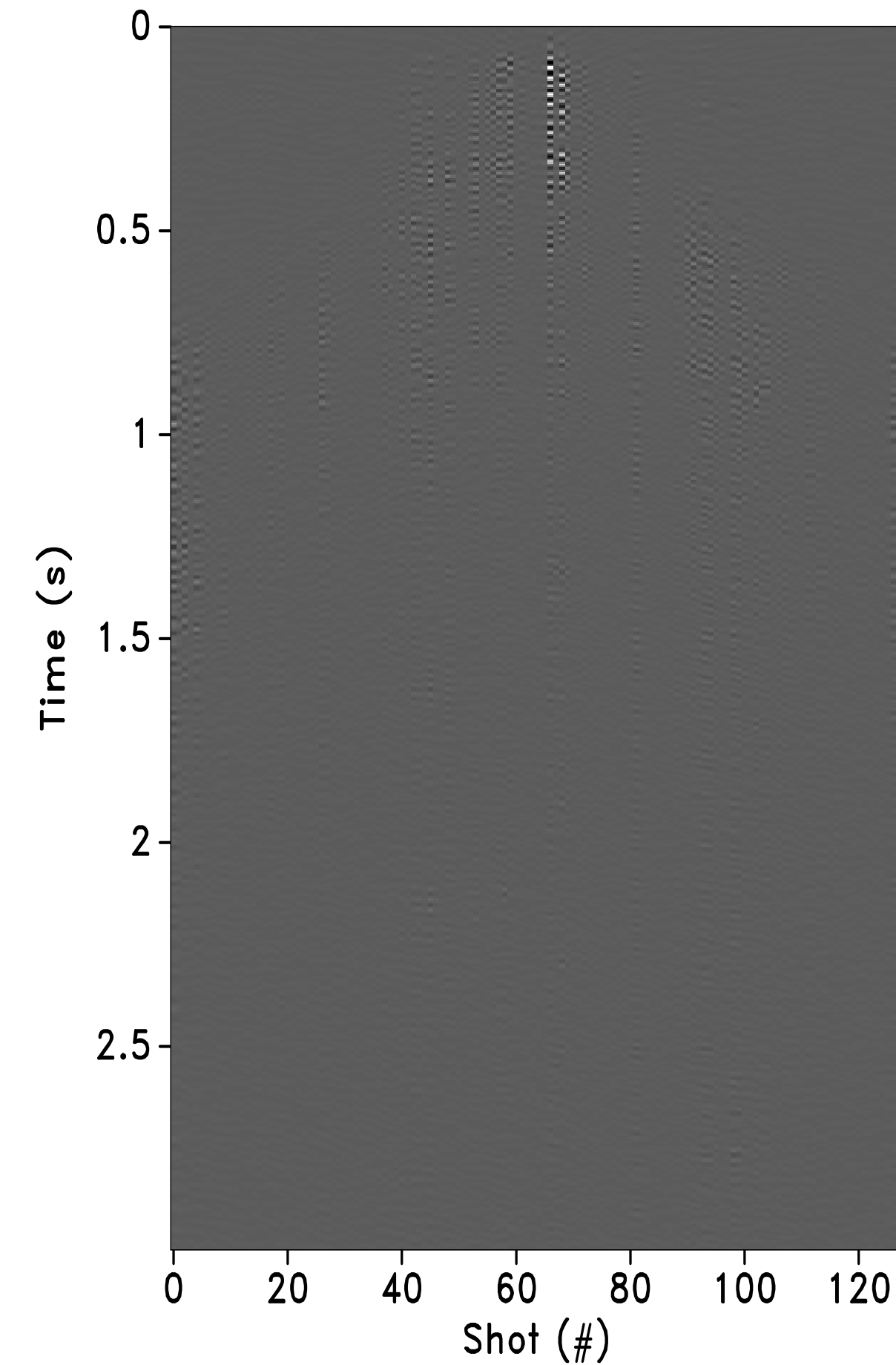
periodic
(1.6 dB)



low variability
(3.2 dB)



high variability
(16.5 dB)



Haneet Wason and Felix J. Herrmann, "[Time-jittered ocean bottom seismic acquisition](#)", *SEG*, 2013
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

Observations

Recoveries entail *joint* interpolations & deblendings/source separations

Question:

Does increased *variability* of firing times improve curvelet recovery?

- ✓ yes, but only for ocean bottom acquisition – towed arrays are more challenging

Randomized time-lapse seismic

Objective

Acquire *high-fidelity wide-azimuth long-offset time-lapse*

Questions:

Process/recover *independently* or *jointly* – to exploit *common* features of *surveys*?

Should we *repeat* the *surveys* when doing *randomized undersampling*?

Haneet Wason, Felix Oghenekohwo, and Felix J. Herrmann, "[Randomization and repeatability in time-lapse marine acquisition](#)". 2014.
Felix Oghenekohwo, Ernie Esser, and Felix J. Herrmann, "[Time-lapse seismic without repetition: reaping the benefits from randomized sampling and joint recovery](#)", in *EAGE*, 2014.

Time-lapse seismic

Current acquisition paradigm:

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

New compressive sampling paradigm:

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

Distributed compressive sensing

– joint recovery model (JRM)

vintages

$$\begin{aligned} \mathbf{x}_1 &= \mathbf{z}_0 + \mathbf{z}_1 \\ \mathbf{x}_2 &= \mathbf{z}_0 + \mathbf{z}_2 \end{aligned} \rightarrow \text{differences}$$

\downarrow

common component

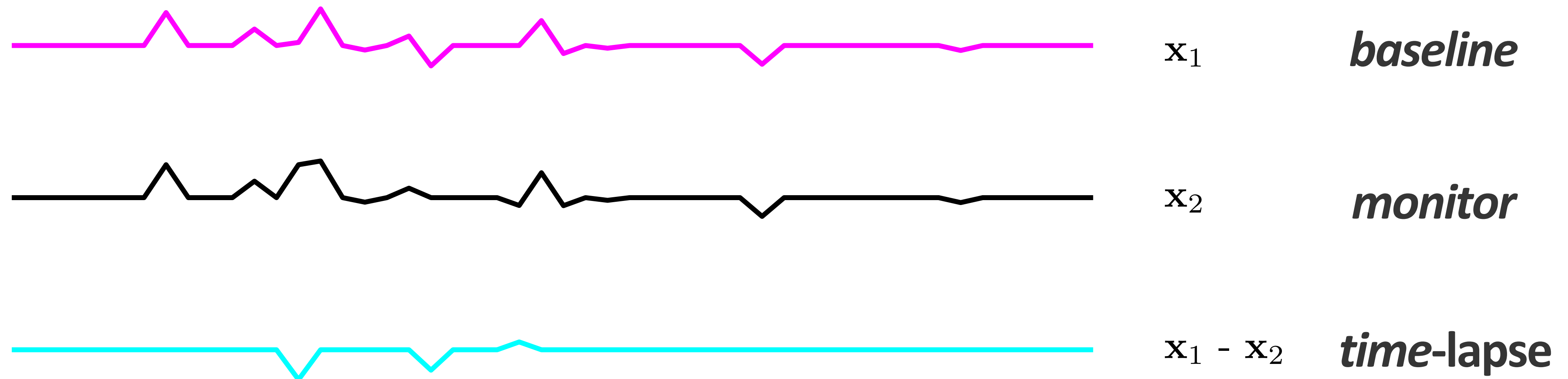
$$\overbrace{\begin{bmatrix} \mathbf{A}_1 & \mathbf{A}_1 & \mathbf{0} \\ \mathbf{A}_2 & \mathbf{0} & \mathbf{A}_2 \end{bmatrix}}^{\mathbf{A}} \overbrace{\begin{bmatrix} \mathbf{z}_0 \\ \mathbf{z}_1 \\ \mathbf{z}_2 \end{bmatrix}}^{\mathbf{z}} = \overbrace{\begin{bmatrix} \mathbf{b}_1 \\ \mathbf{b}_2 \end{bmatrix}}^{\mathbf{b}}$$

baseline
monitor

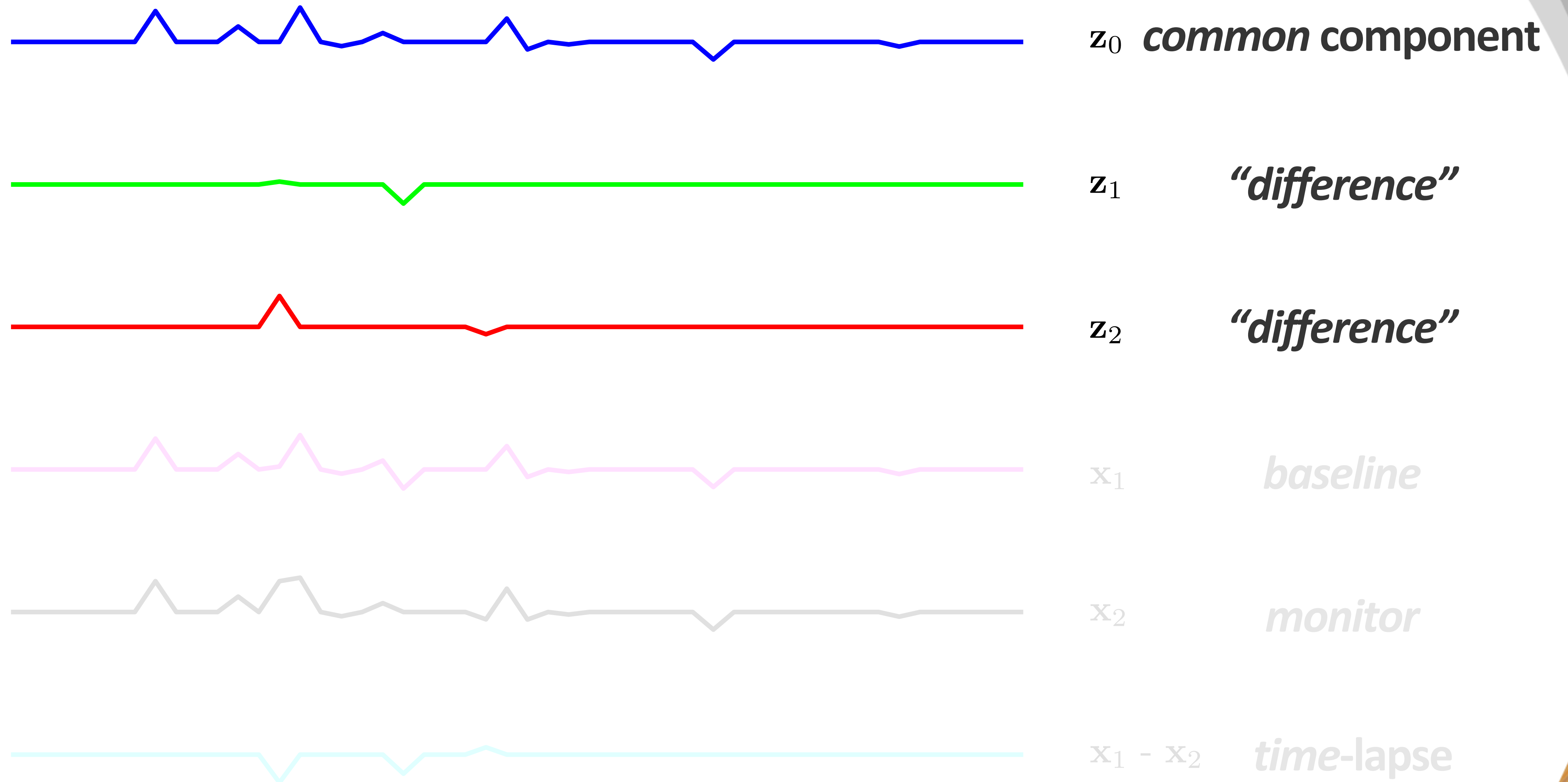
Key idea:

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

Sparse baseline, monitor & time-lapse signals



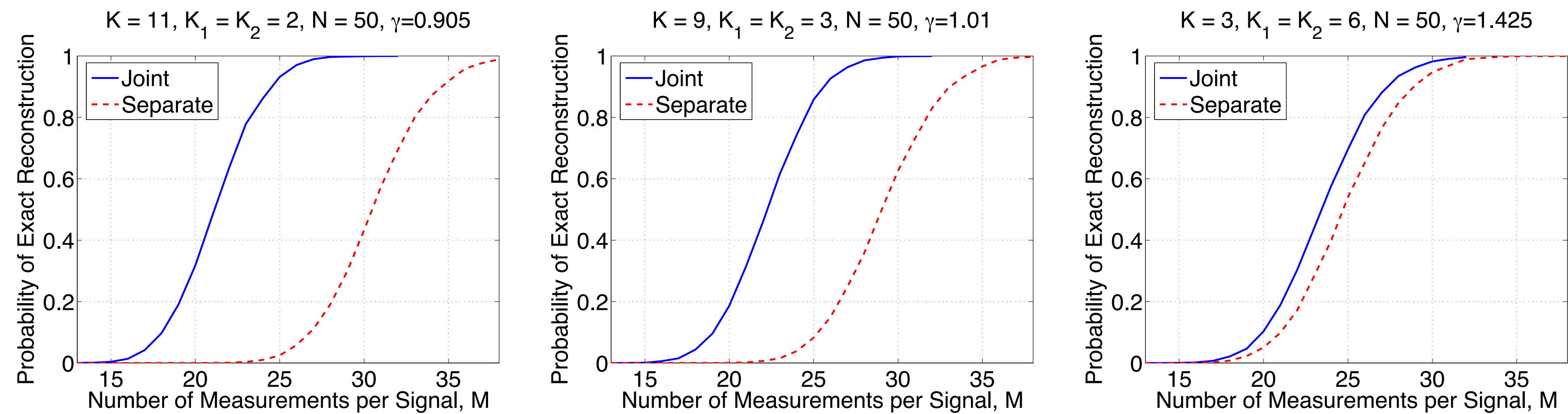
Sparse Joint Recovery Model (JRM)



Sparse recovery

– w/ & w/o JRM (1000 experiments)

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



decreasing *common* sparsity

Observations

Joint recovery model (JRM):

- ▶ improves *recovery* results for *both* vintages *significantly* compared to *independent* recovery strategy (IRS)
- ▶ when there is *common* sparsity
- ▶ quality *decreases* for *decreasing* common *sparsity*

Is this the *end* of the *story* for *time-lapse* where we are interested in *differences* between the *vintages*...?

Time-lapse

– 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...

To *repeat* or *not* repeat that’s the question...

Stylized experiments

Conduct *many* CS experiments to compare

- ▶ *joint vs independent* recovery
- ▶ recovery w/ the *same, partly* or *completely* independent \mathbf{A}_1 , \mathbf{A}_2

for *baseline & monitor* surveys that

- ▶ *share a common* sparse component & have sparse *time-lapse* components
- ▶ are *randomly* acquired w/ *different* numbers of *samples*

Stylized experiment setup

Time-lapse signal:

$N = 50$ (is the total length of the time-lapse signal)

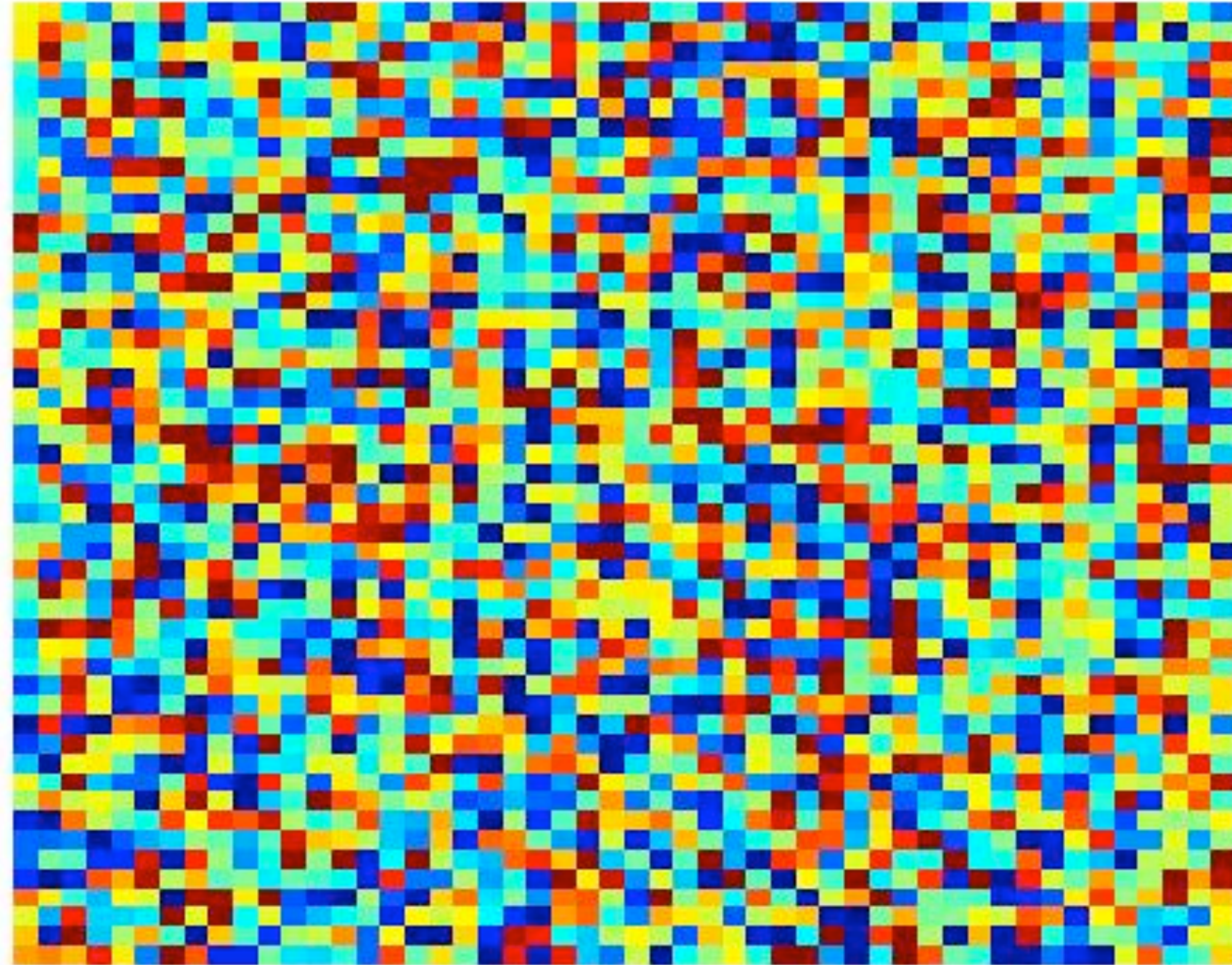
$K = 11$ (is the number of non-zeros in the common part of x_1 and x_2)

$K_1, K_2 = 2$ (is the number of non-zeros which is not common to x_1 and x_2)

Randomized undersamples:

- ▶ rows from a Gaussian matrix
- ▶ $n = \{5, 10, 15, 20, 25, 30, 35, 40\}$
- ▶ $\{0, 20, 40, 60, 80, 100\}$ % overlap

Underlying *Gaussian* sensing matrix



Randomized sensing matrices w/ varying overlap

Overlap

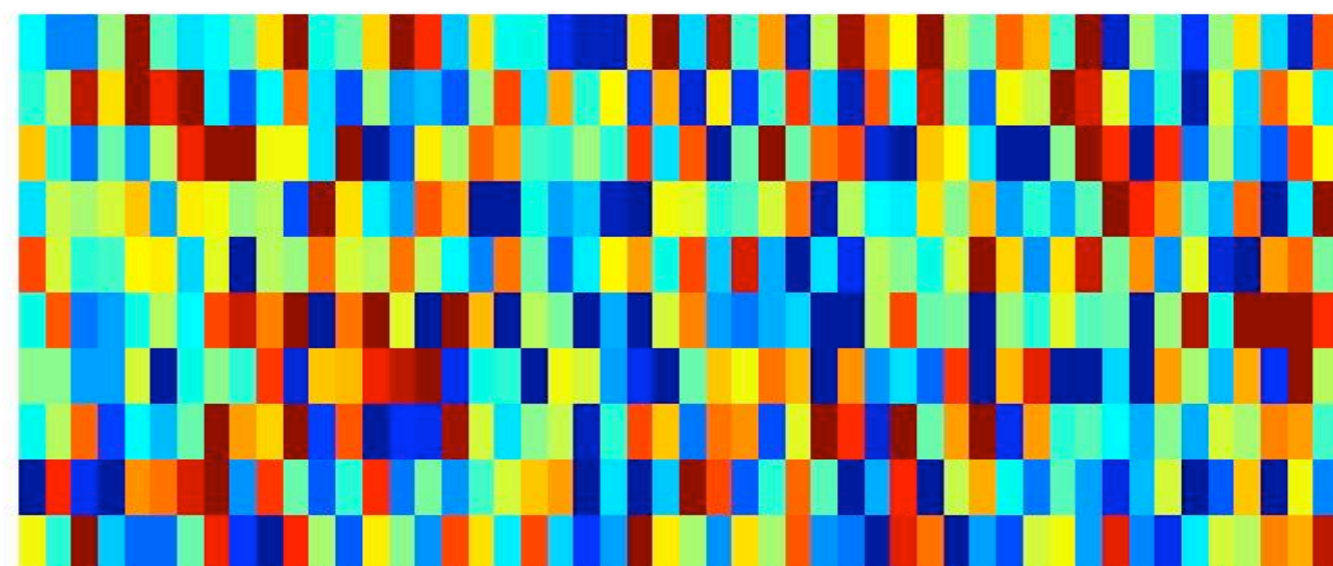
A_1

$n = 10$

A_2

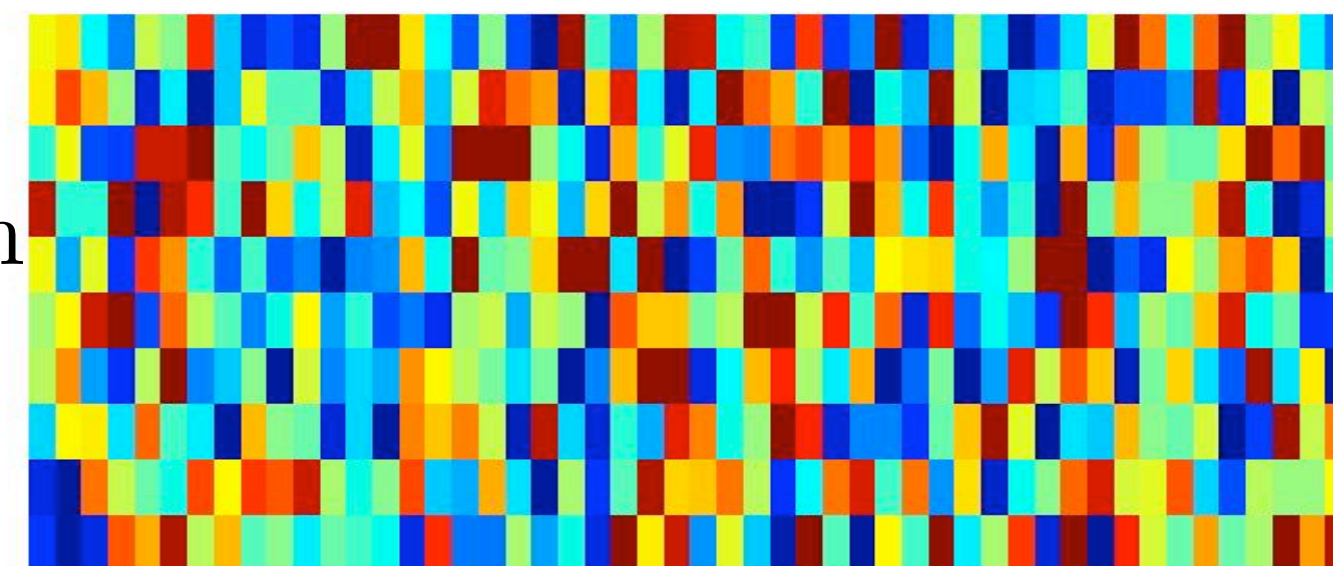
0%

n



N

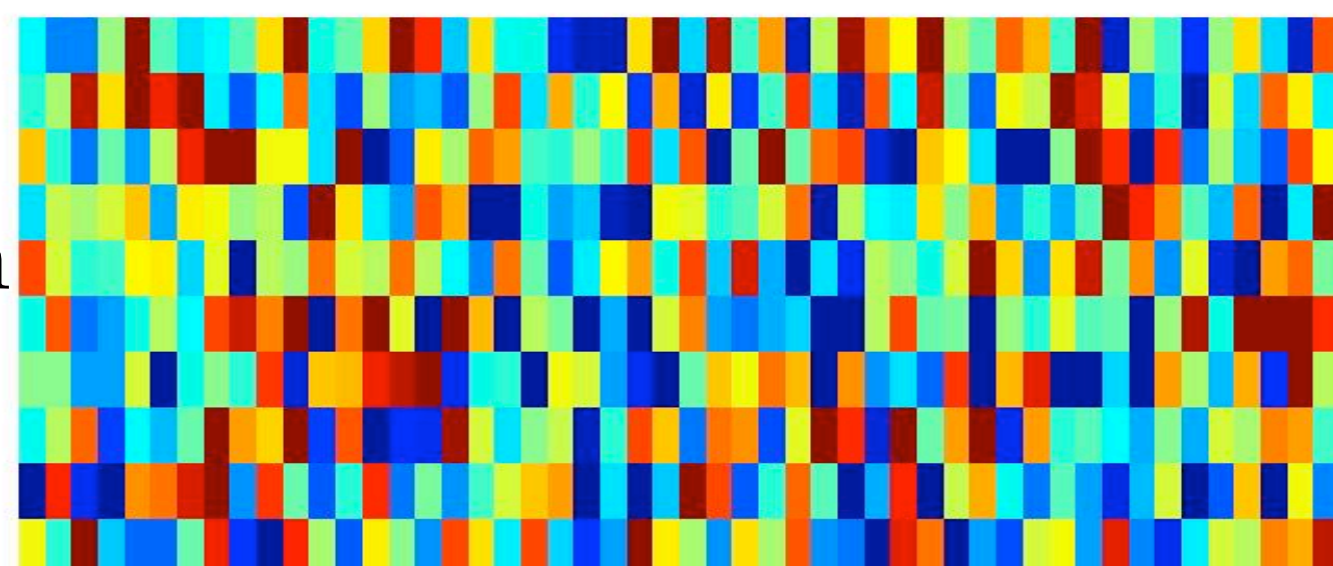
n



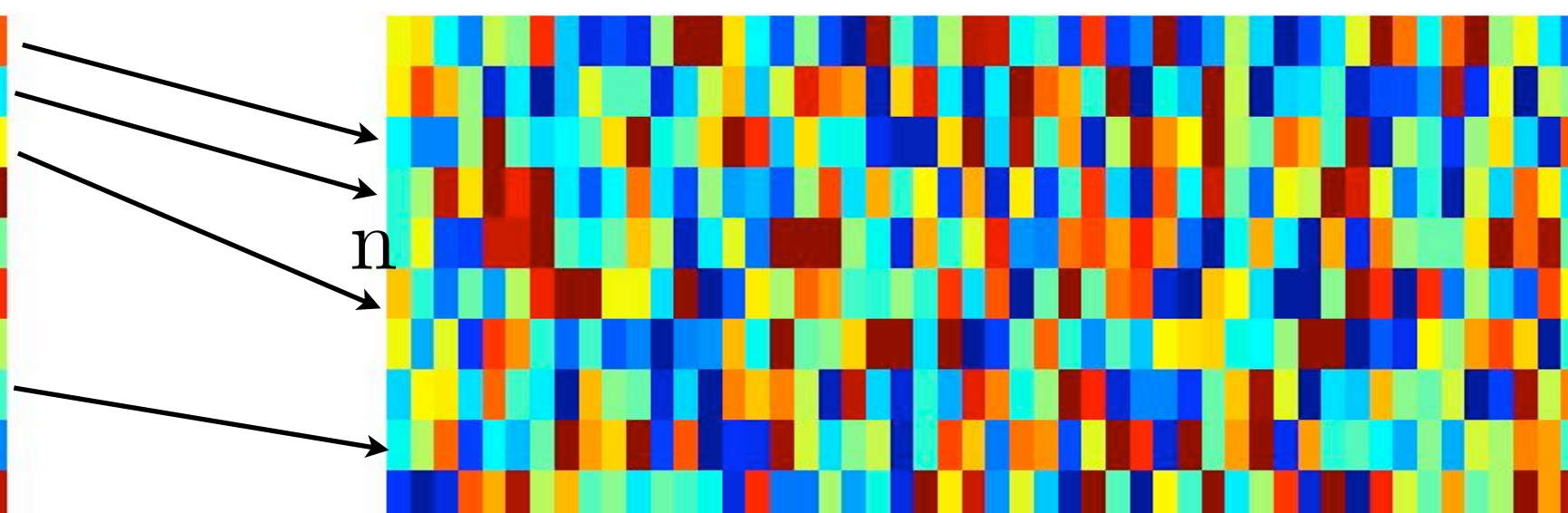
N

40%

n



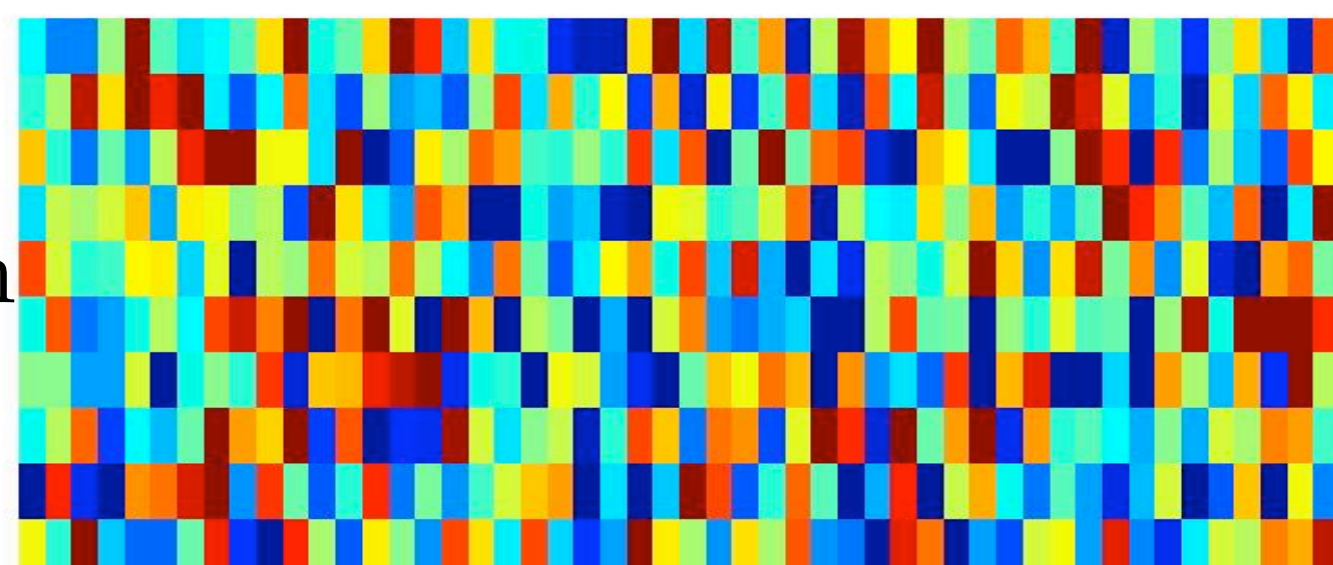
N



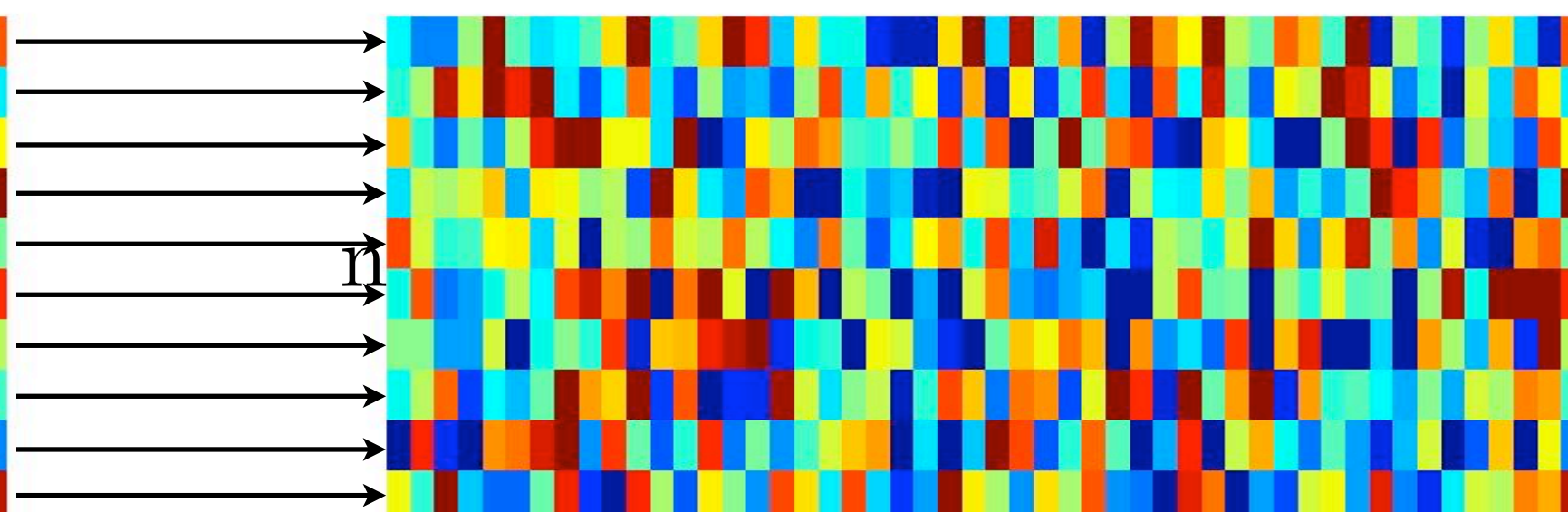
N

100%

n



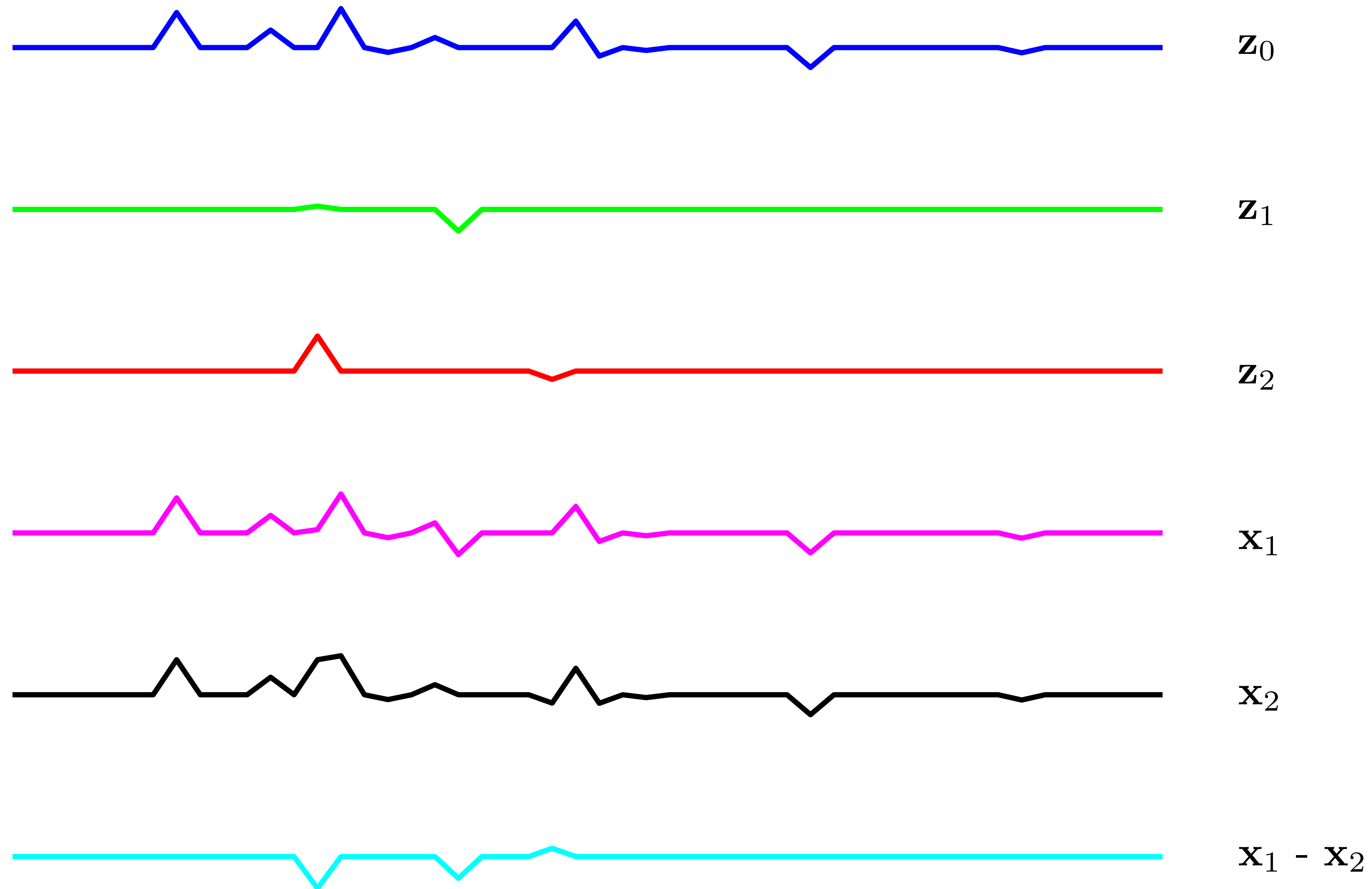
N



N

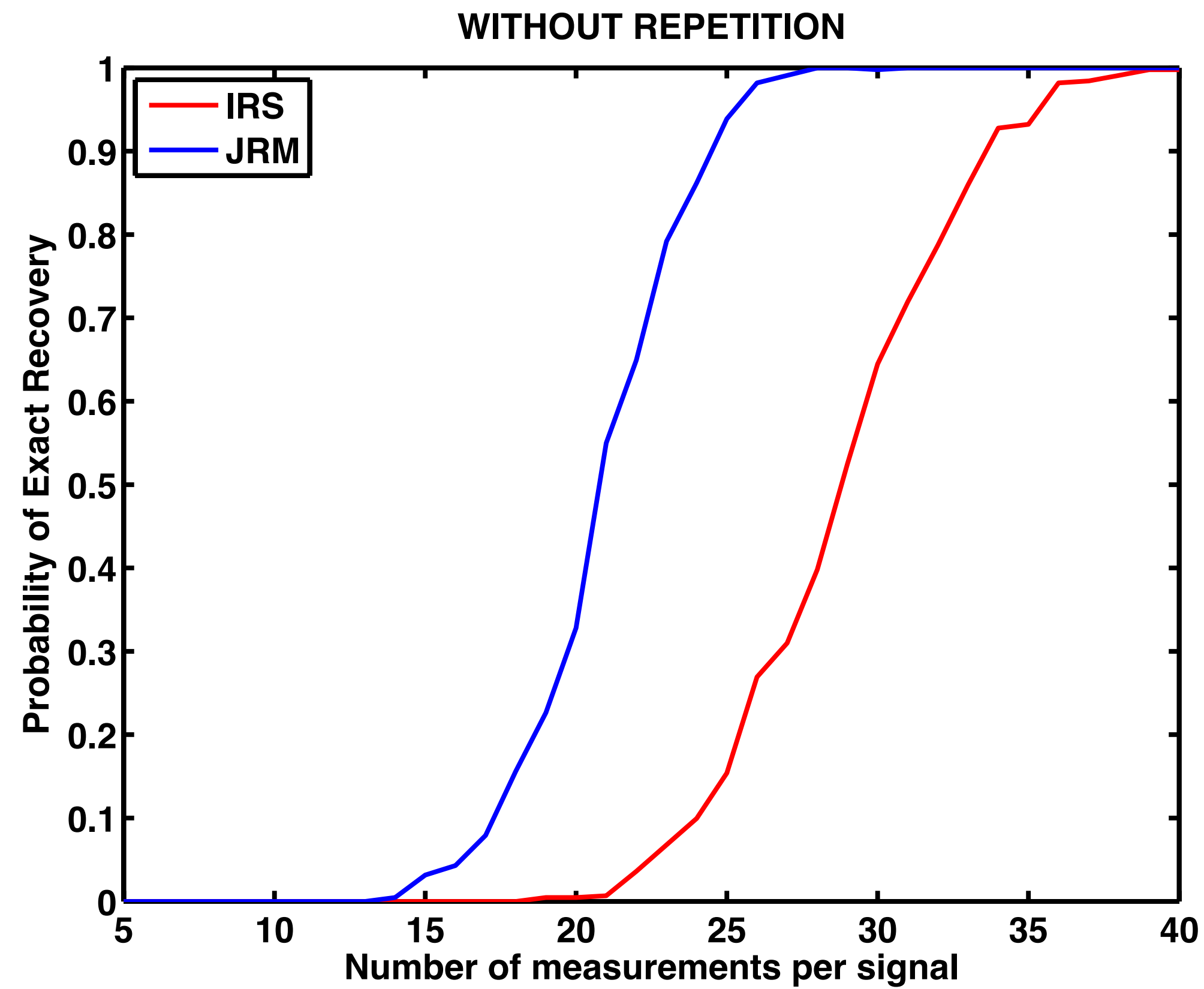
Random *sparse* vectors

– 250 experiments



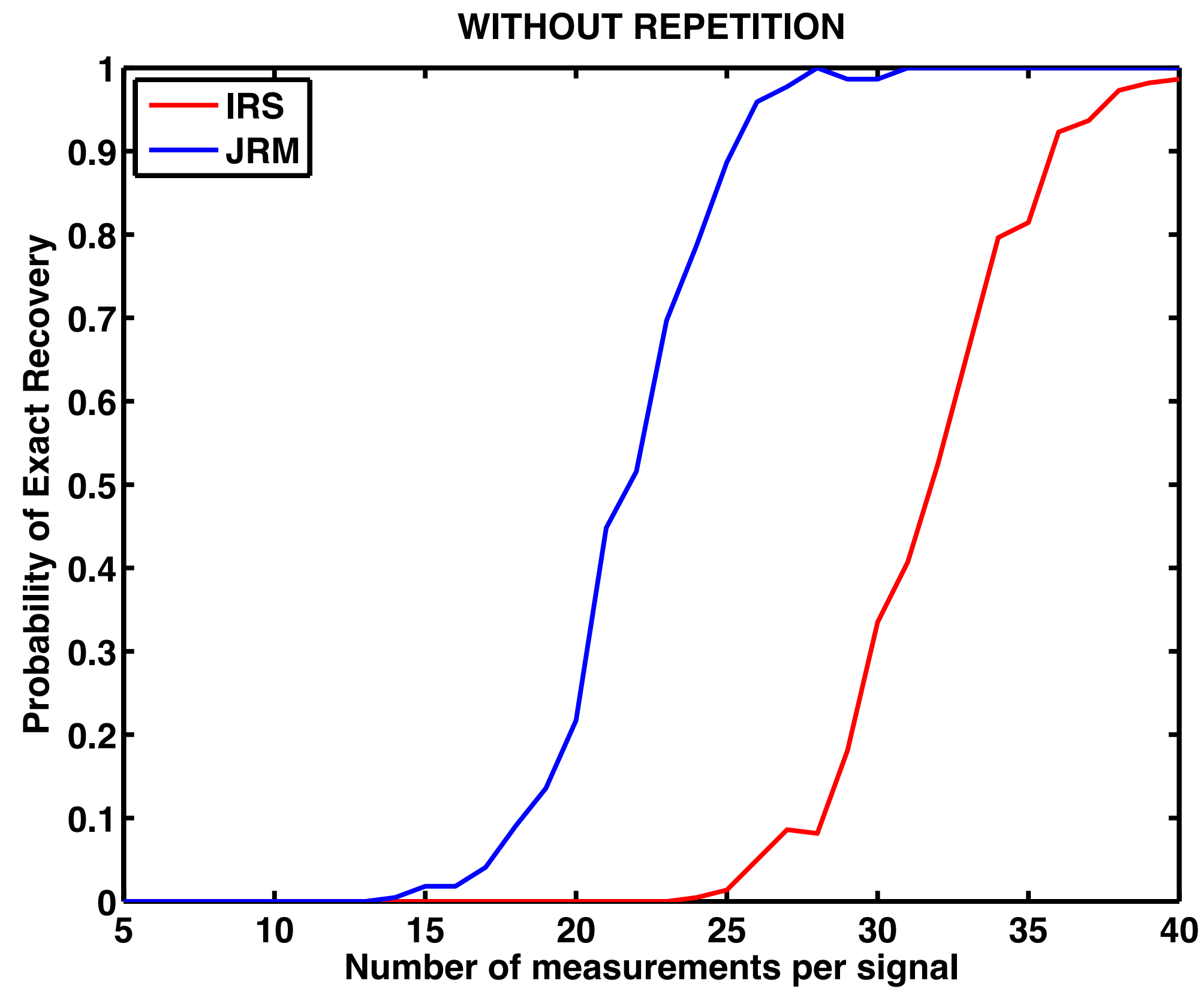
Recovery probability of vintages

– w/o repetition



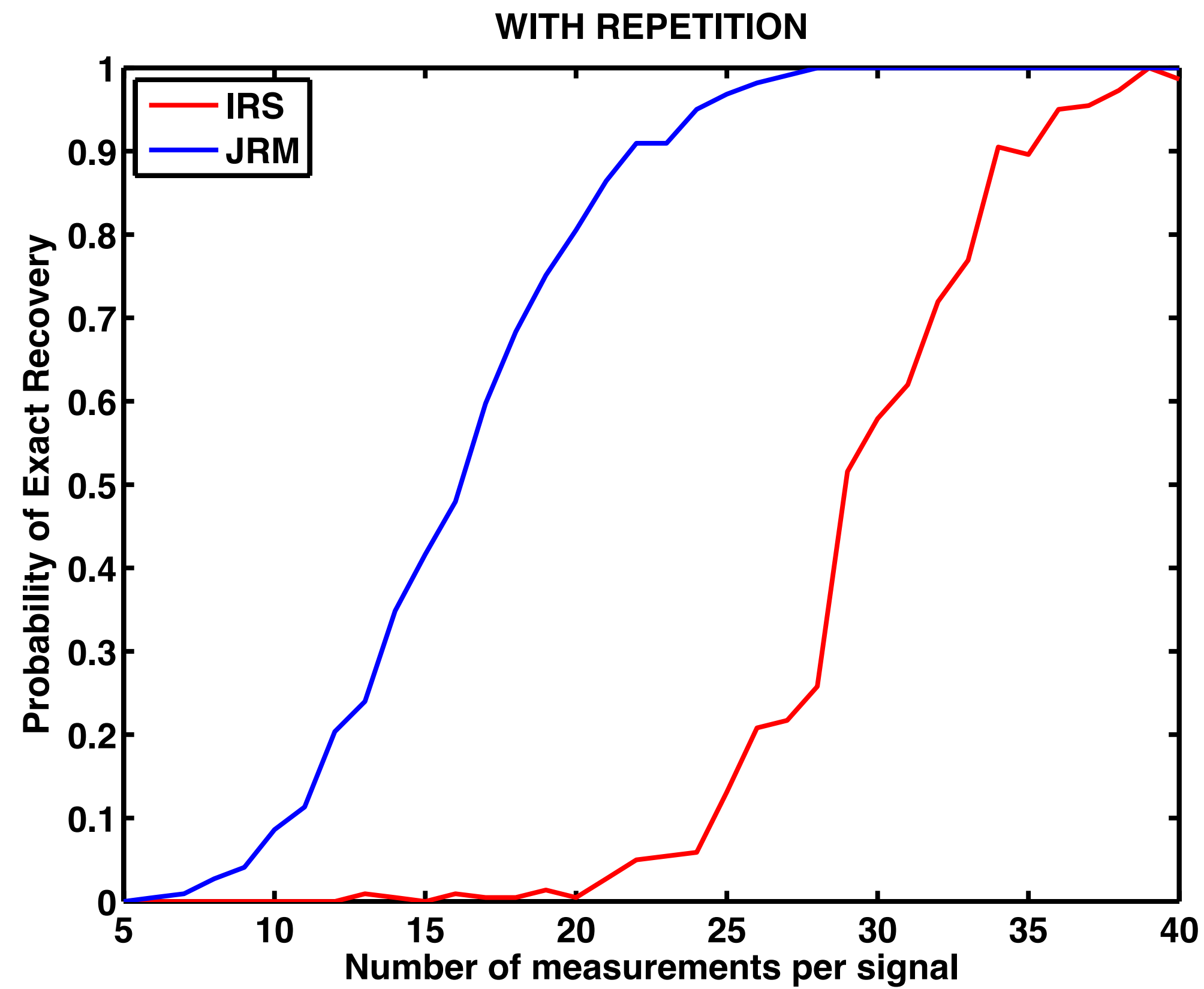
Recovery probability of *time-lapse difference*

– w/o repetition



Recovery probability of *time-lapse difference*

– w/ repetition



Observations

Recovery of *vintages* themselves *improves without repetition*

Recovery of *difference* improves **with** *repetition* because

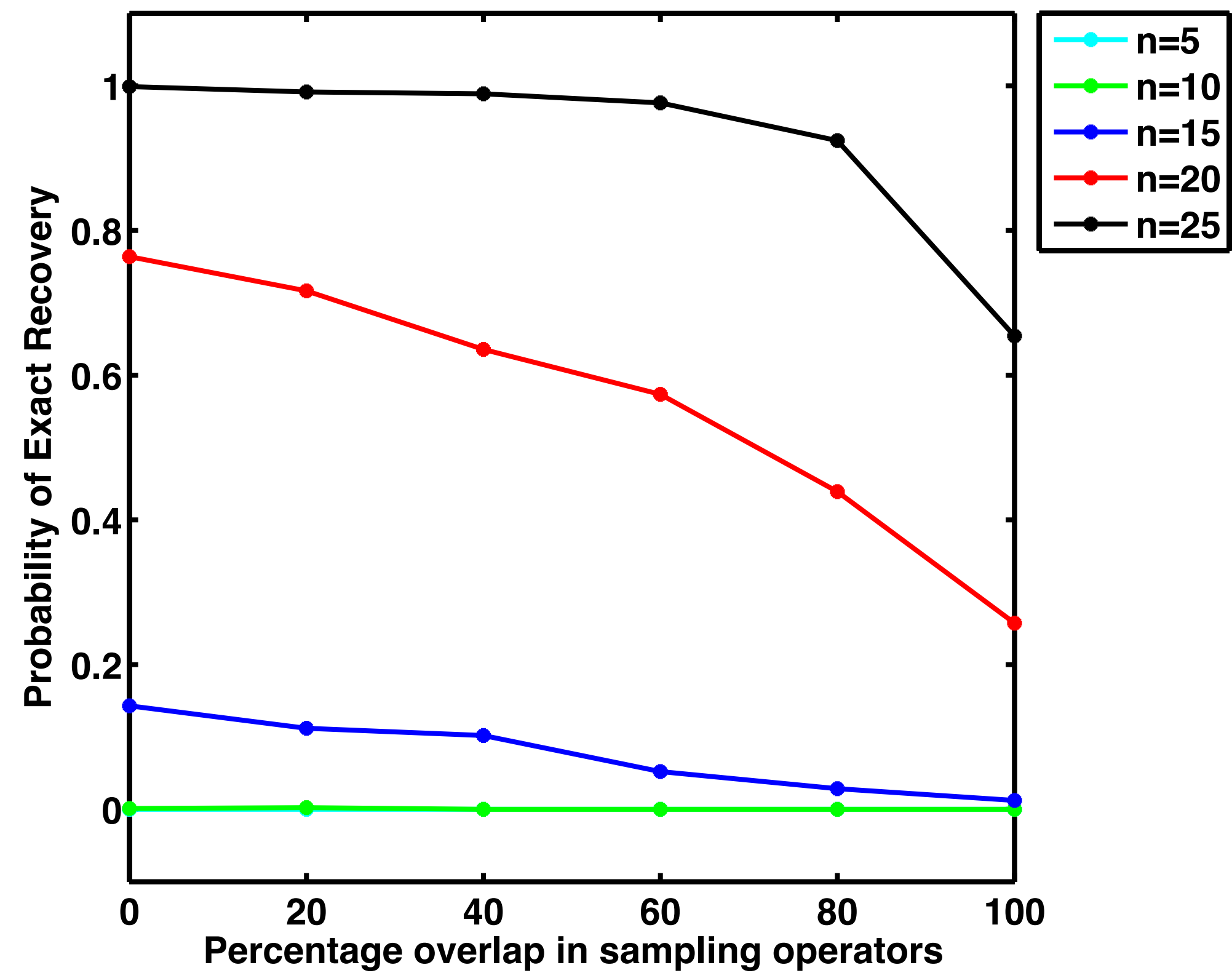
- ▶ *difference* is *sparse* compared to *sparsity* of *vintages*
- ▶ does **not** recover the *vintages* themselves... *dangerous*

Do the acquisitions really have to overlap?

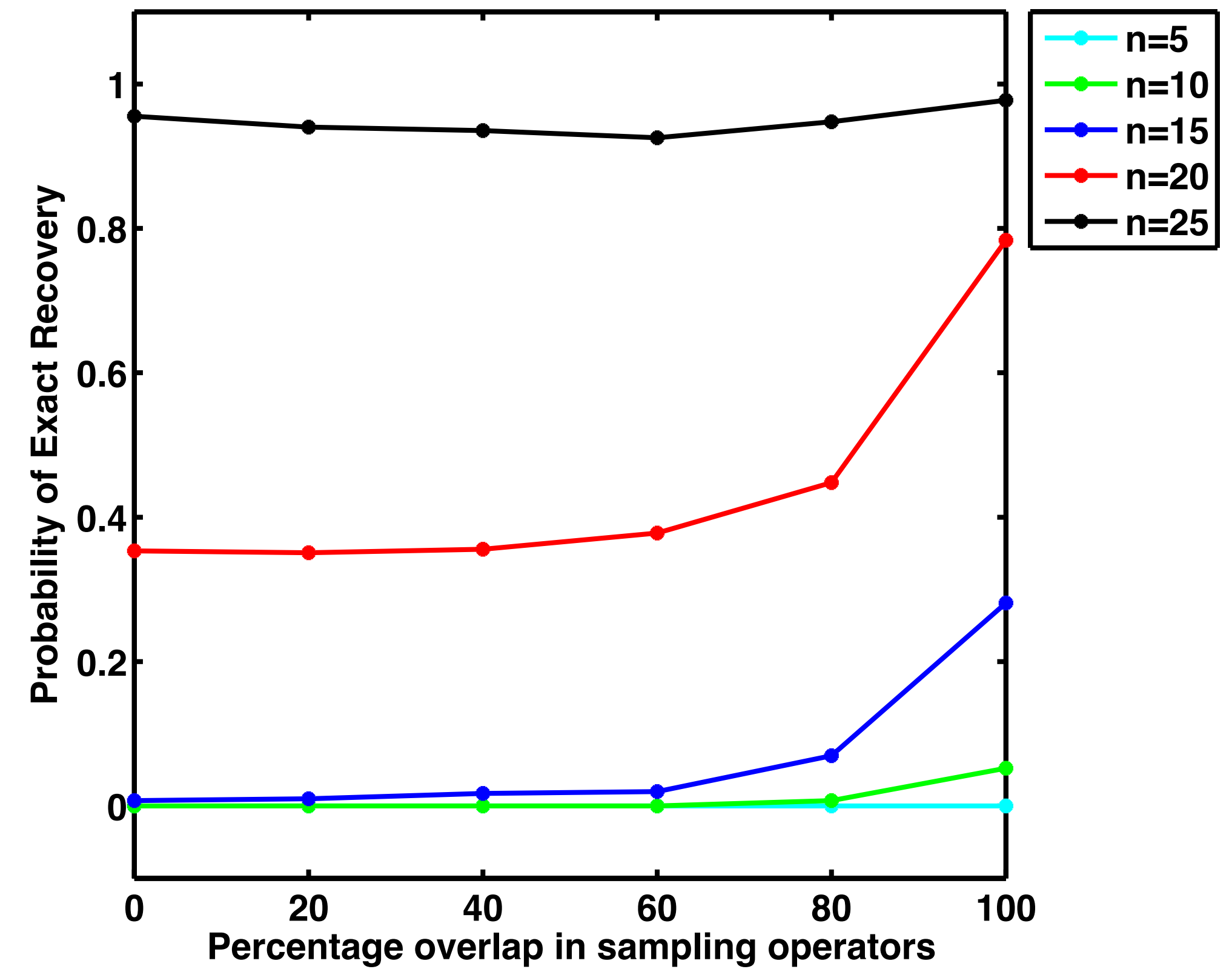
Recovery probabilities

– varying degrees of repetition

vintages



time-lapse



Observations

Recovery w/ *joint*-recovery model is ***always superior***

- ▶ recovery *quality* of vintages *decreases* when *repeating* time-lapse experiments

When *joint* recovery *fails*:

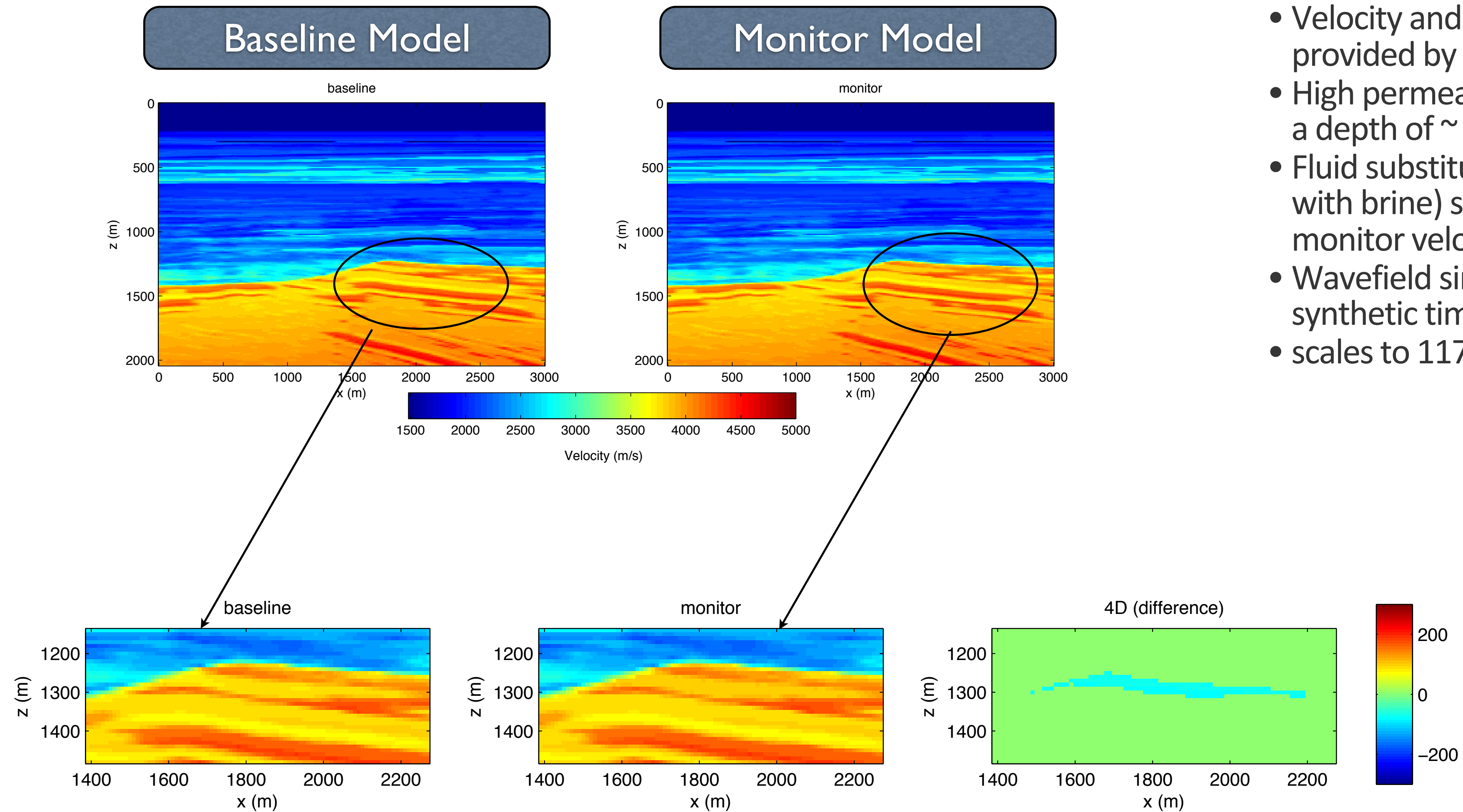
- ▶ *repetition* is *required* to obtain *time-lapse* signal
- ▶ *degree* of repetition needs to *increase* for *increased* subsampling

When *joint* recovery *succeeds*:

- ▶ *repetition* is **not** *required*
- ▶ recovery *quality time-lapse* does *not strongly* depend on *degree* of *repeatability*

Method

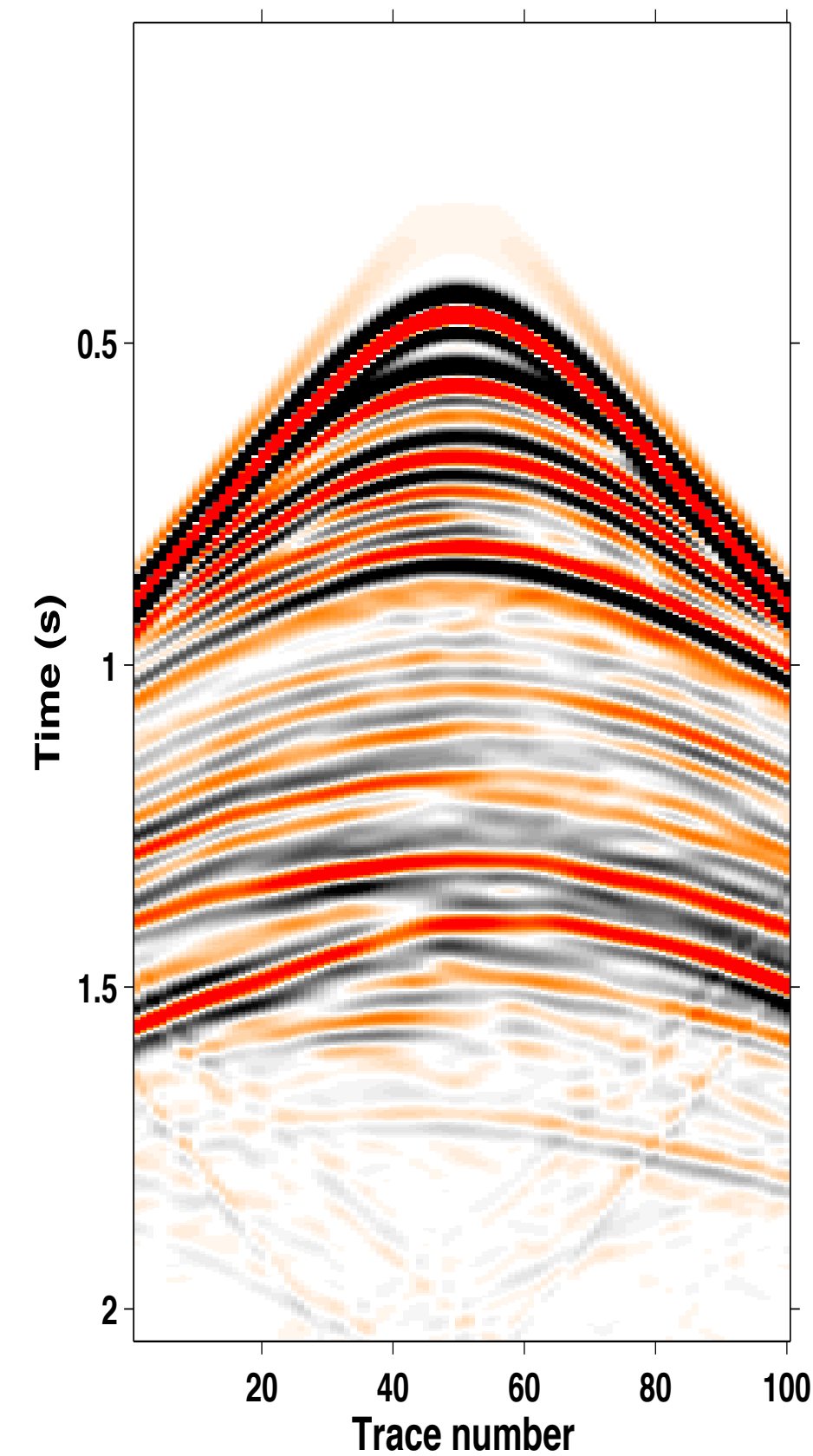
- Velocity and density model provided by BG, taken as baseline
- High permeability zone identified at a depth of $\sim 1300\text{m}$
- Fluid substitution (gas/oil replaced with brine) simulated to derive monitor velocity model
- Wavefield simulation to generate synthetic time-lapse data
- scales to $11733300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



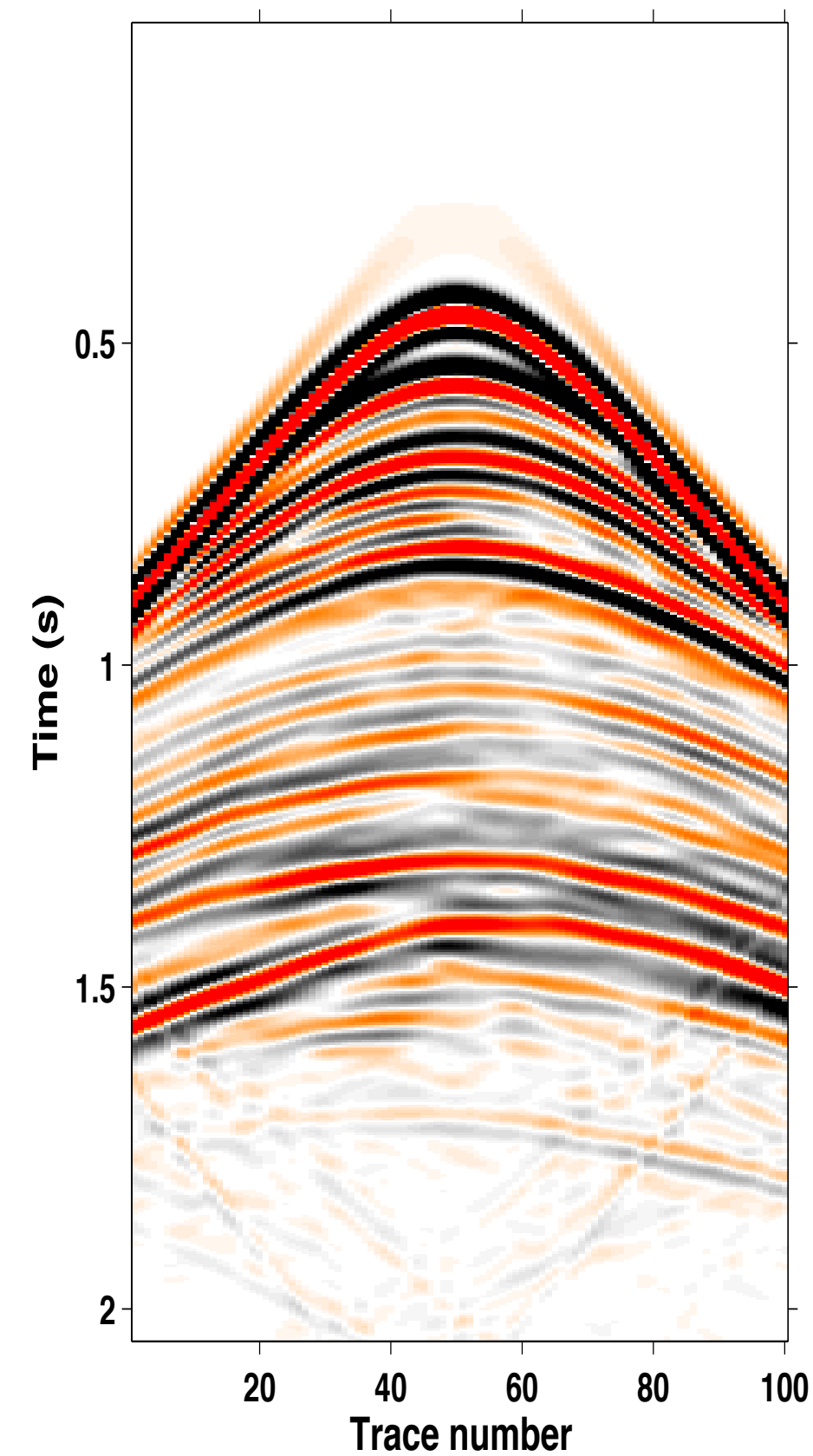
Simulated original data

– time-domain finite differences

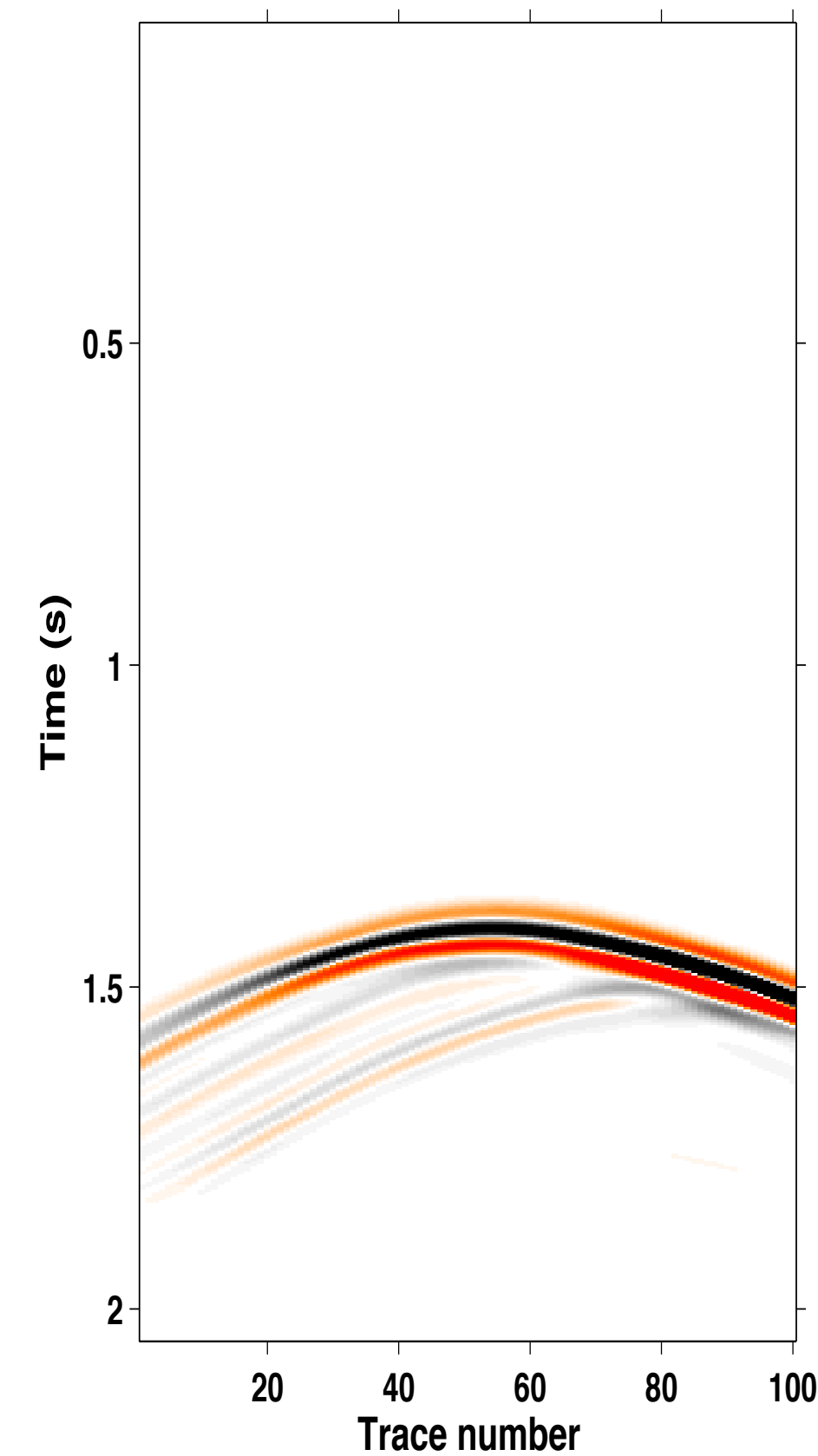
Baseline



Monitor



4-D signal



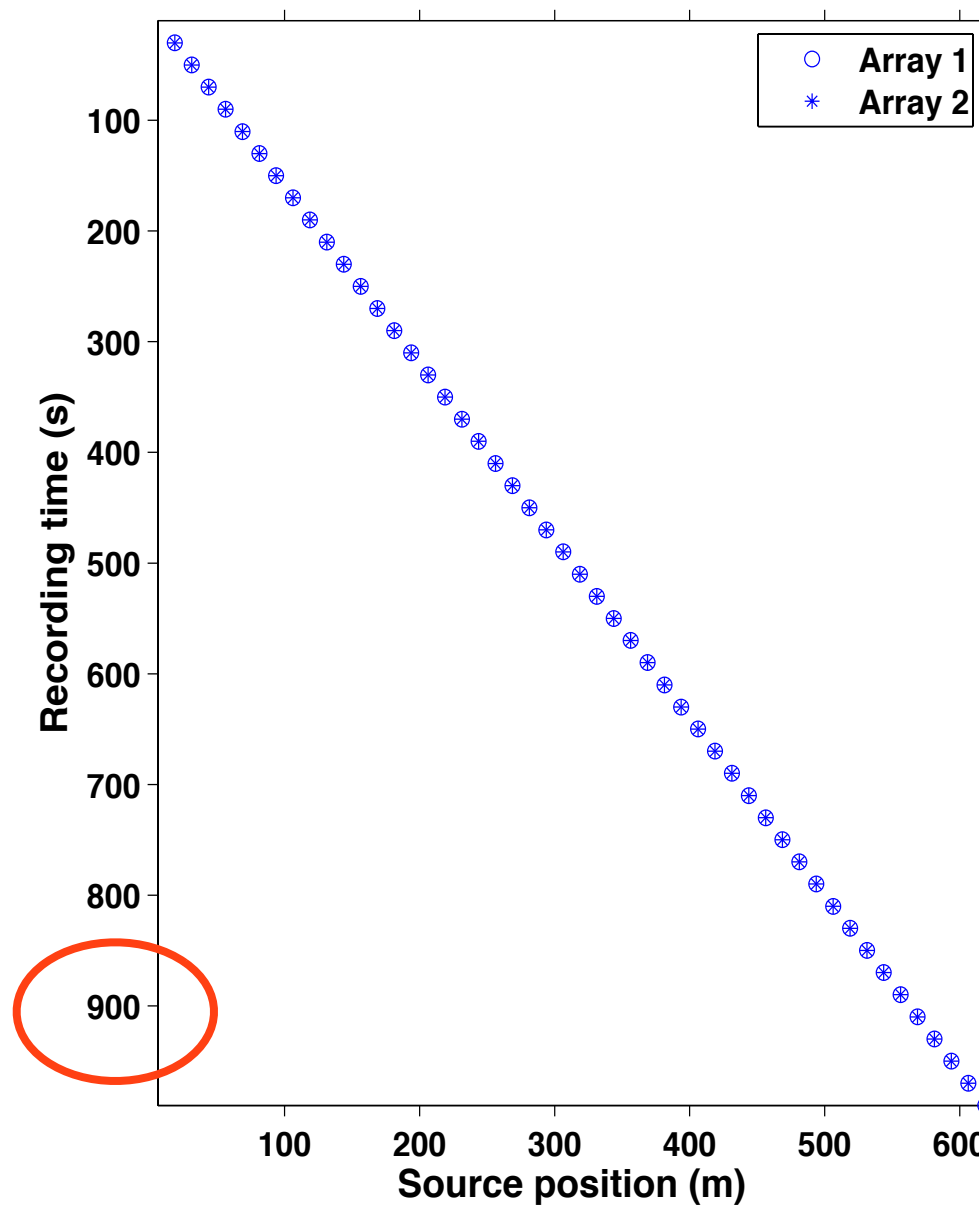
time samples: **512**
receivers: **100**
sources: **100**

sampling
time: **4.0 ms**
receiver: **25.0 m**
source: **25.0 m**

Conventional vs. *time-jittered* sources

– undersampling ratio = 4, 2 source arrays

conventional



“unblended” shot gathers

number of shots = **100** (per array)

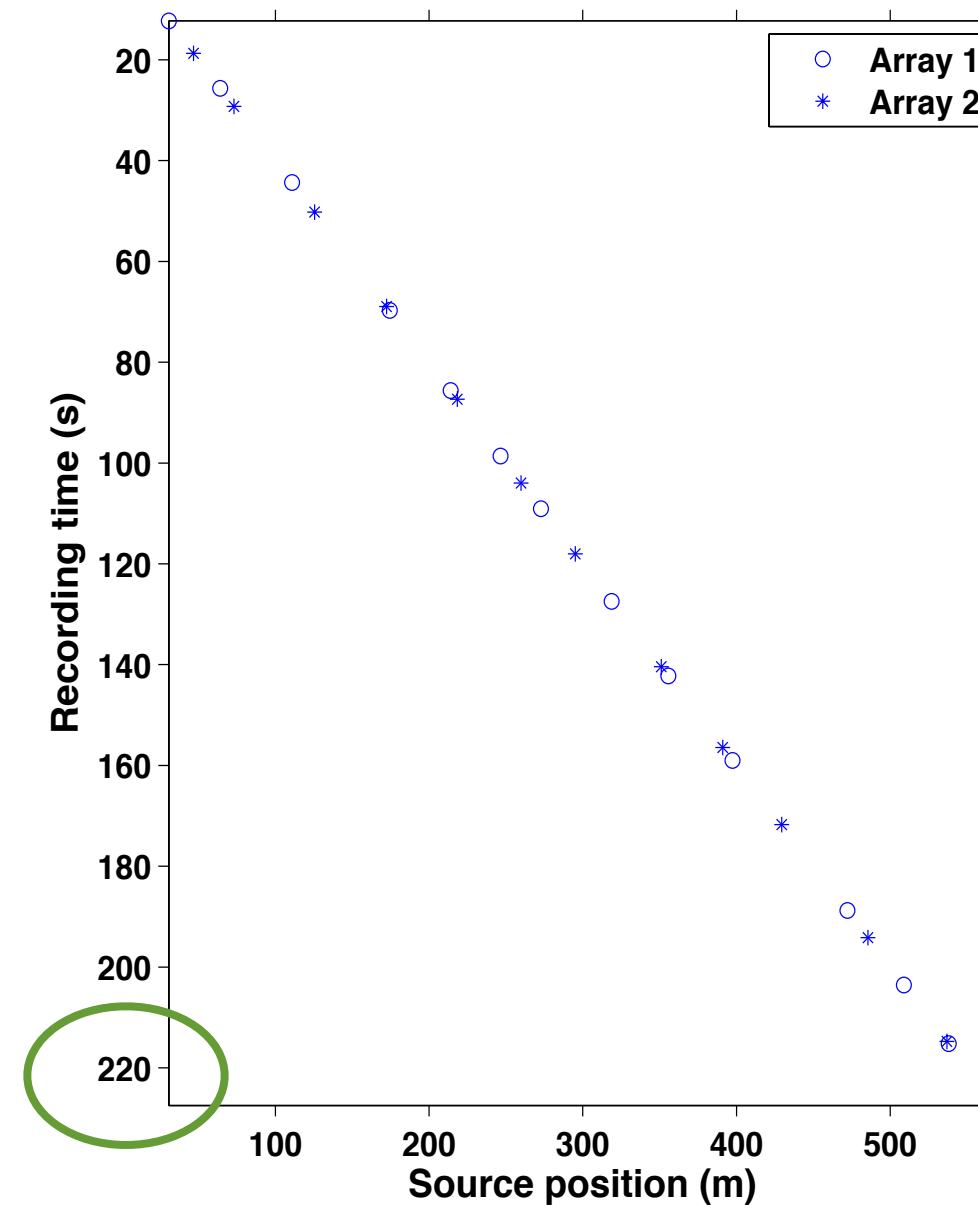
shot record length: 10.0 s

spatial sampling: **6.25 m**

vessel speed: **0.625 m/s**

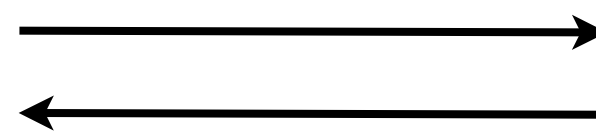
recording time = $100 \times 10.0 =$ **1000.0 s**

jittered acquisition 1
(for baseline)



[BLENDING & UNDERSAMPLING]

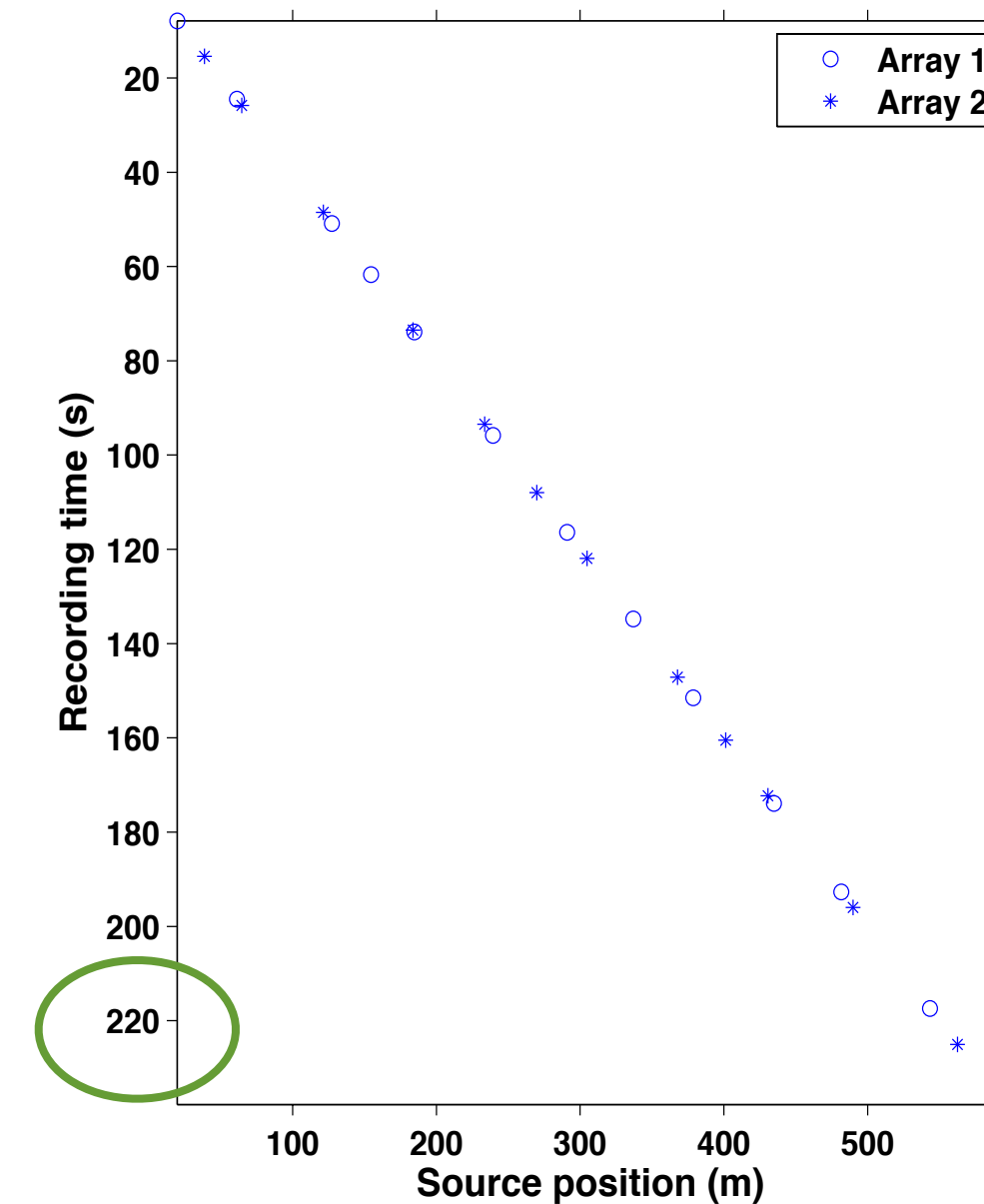
spatial undersampling factor = 4



spatial sampling **increase** factor = 4

[DEBLENDING & INTERPOLATION]

jittered acquisition 2
(for monitor)



“blended” shot gathers

number of shots = $100/4 =$ **25** (12-13 per array)

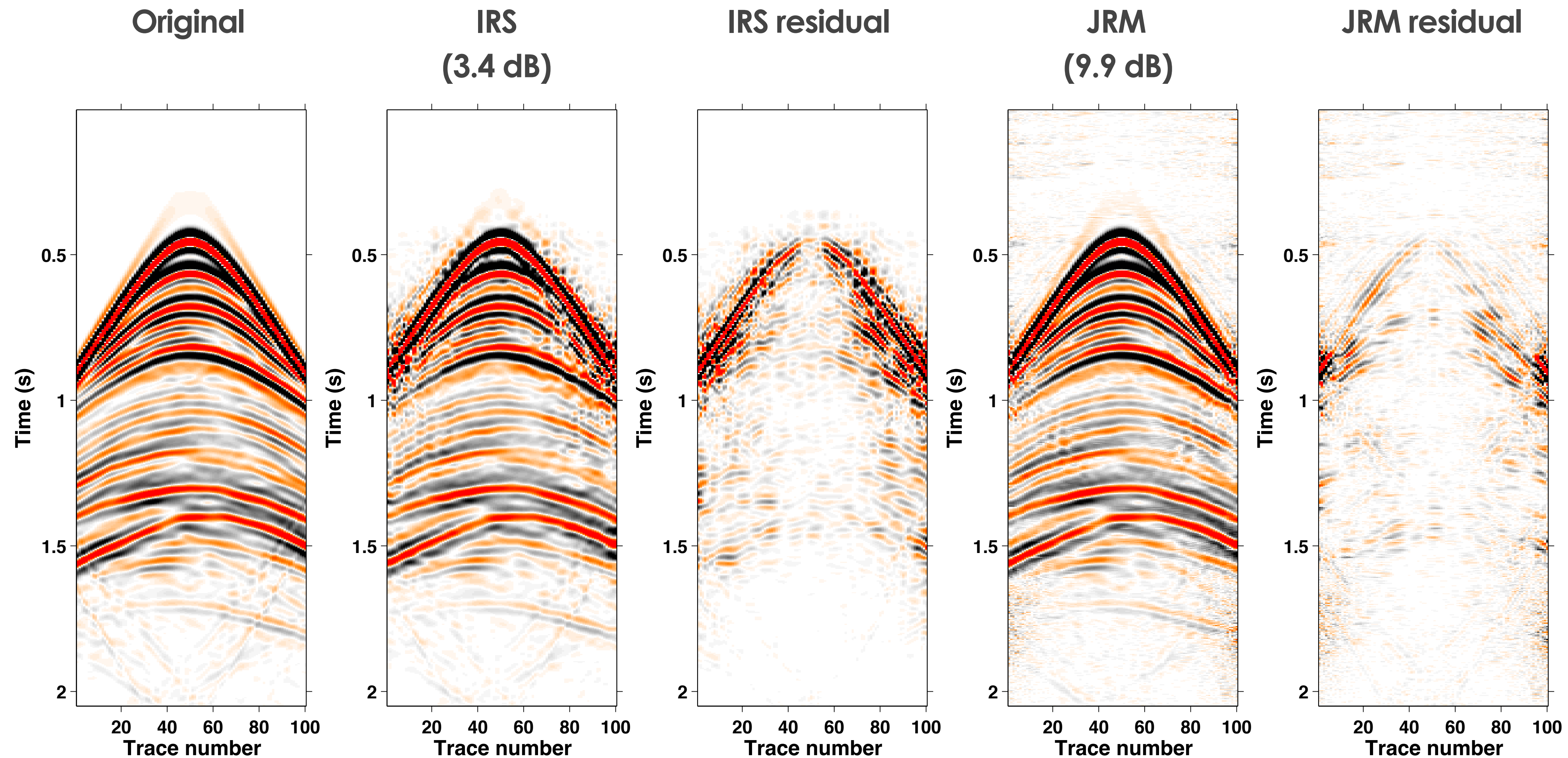
spatial sampling: **50.0 m (jittered)**

vessel speed: **2.50 m/s**

recording time $\approx 1000.0 \text{ s} / 4 =$ **250.0 s**

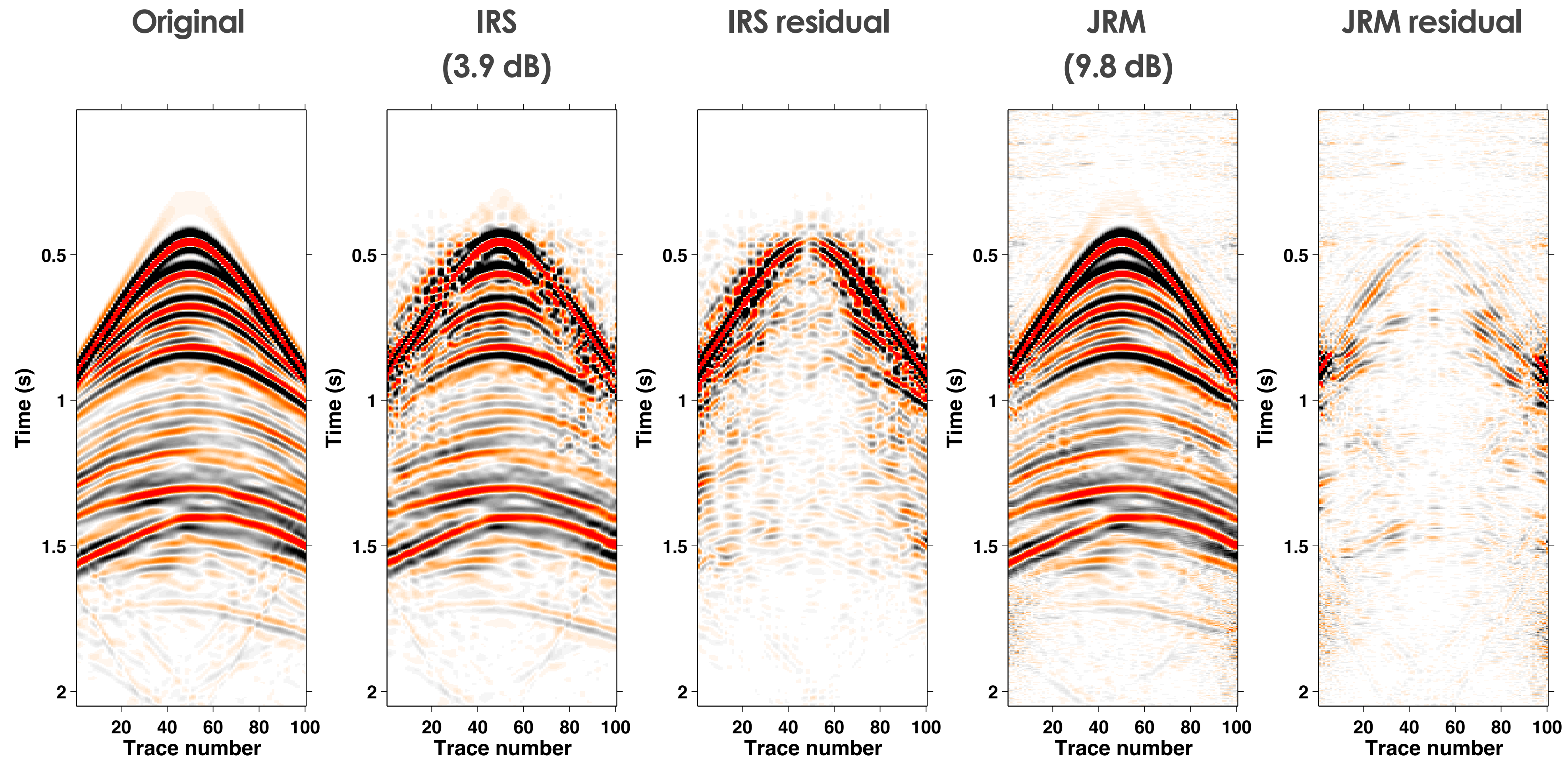
Baseline recovery

–“small” overlap (25%) in acquisition matrices



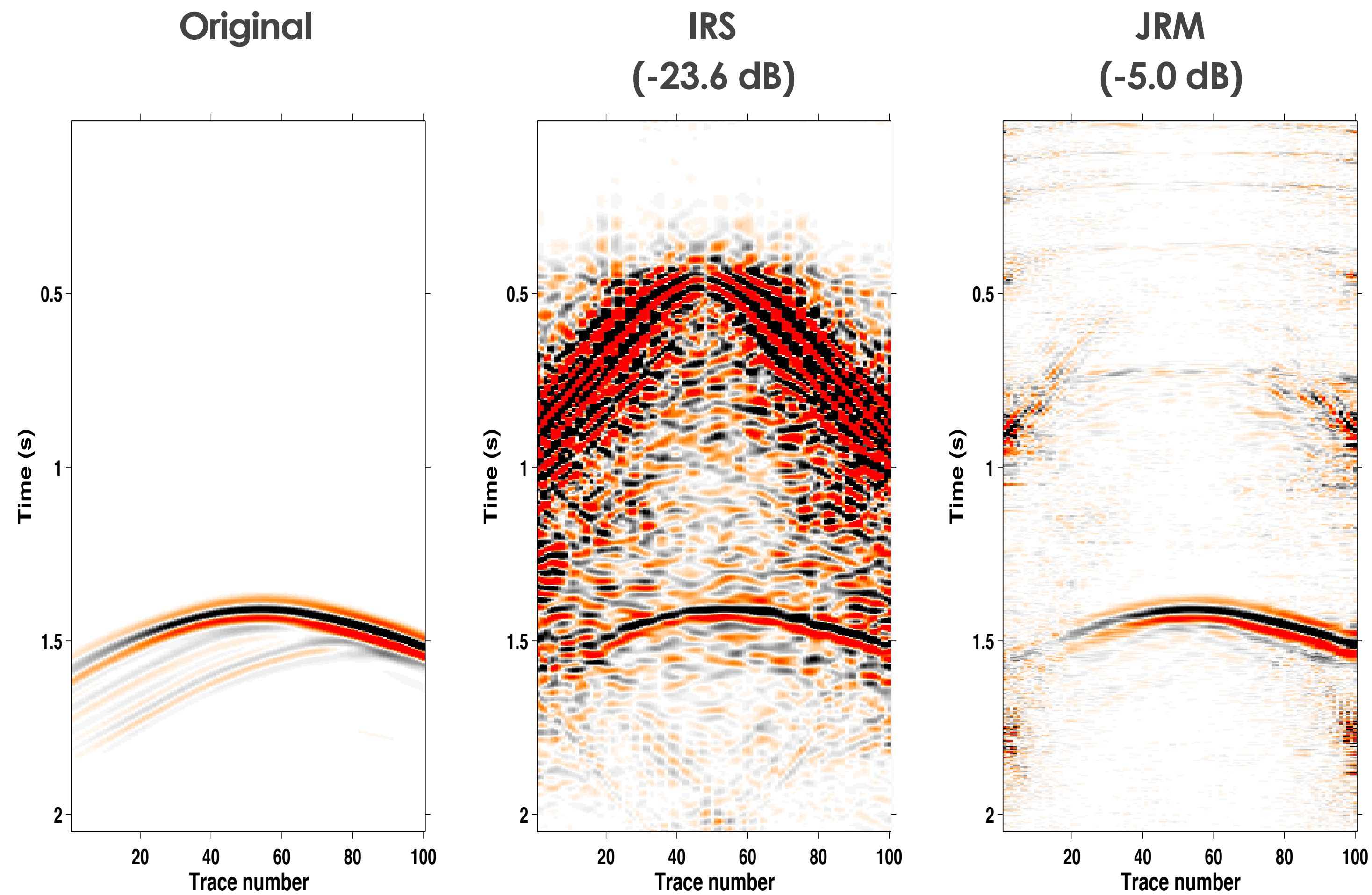
Monitor recovery

–“small” overlap (25%) in acquisition matrices



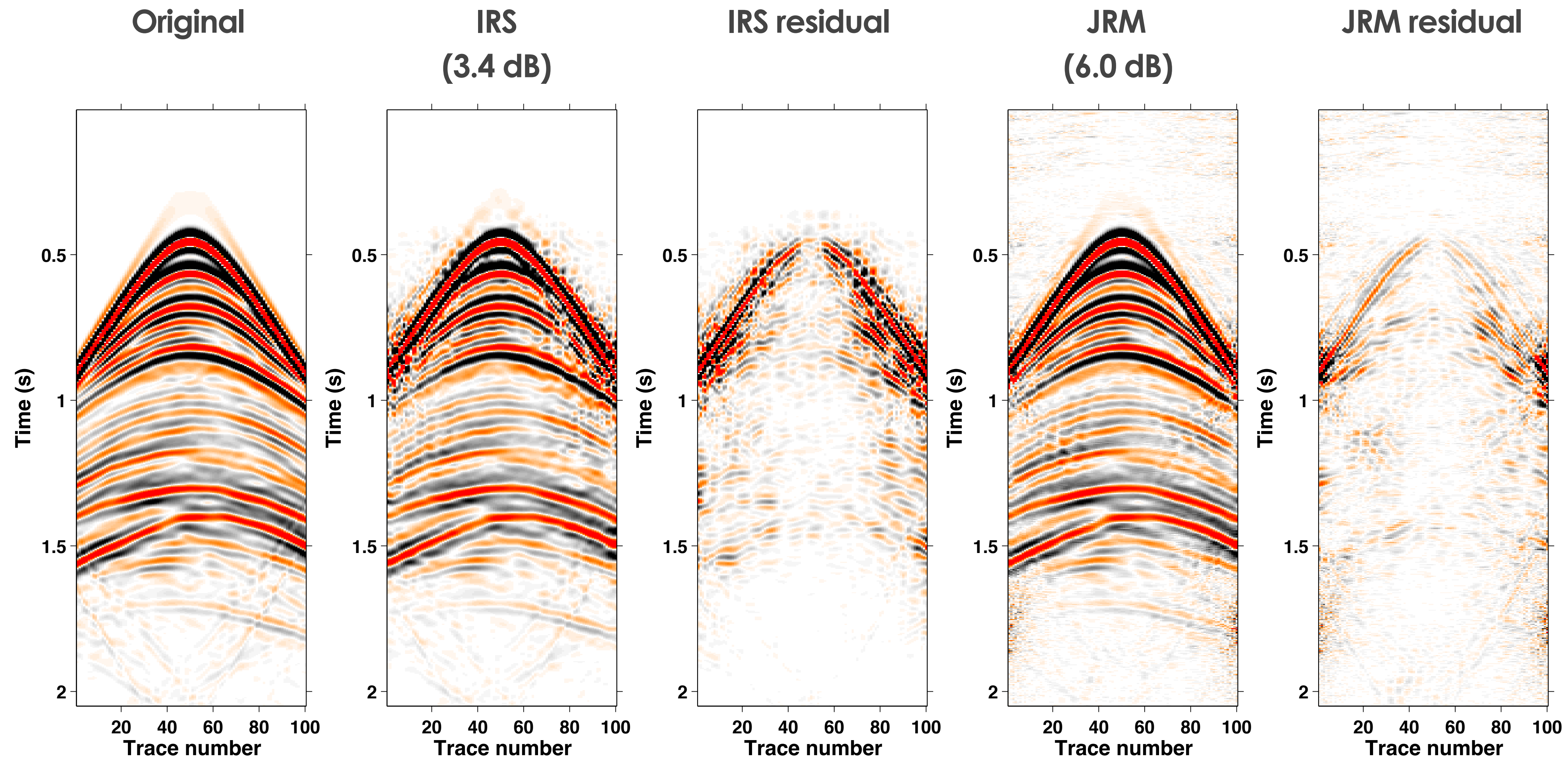
4-D recovery

- “small” overlap (25%) in acquisition matrices



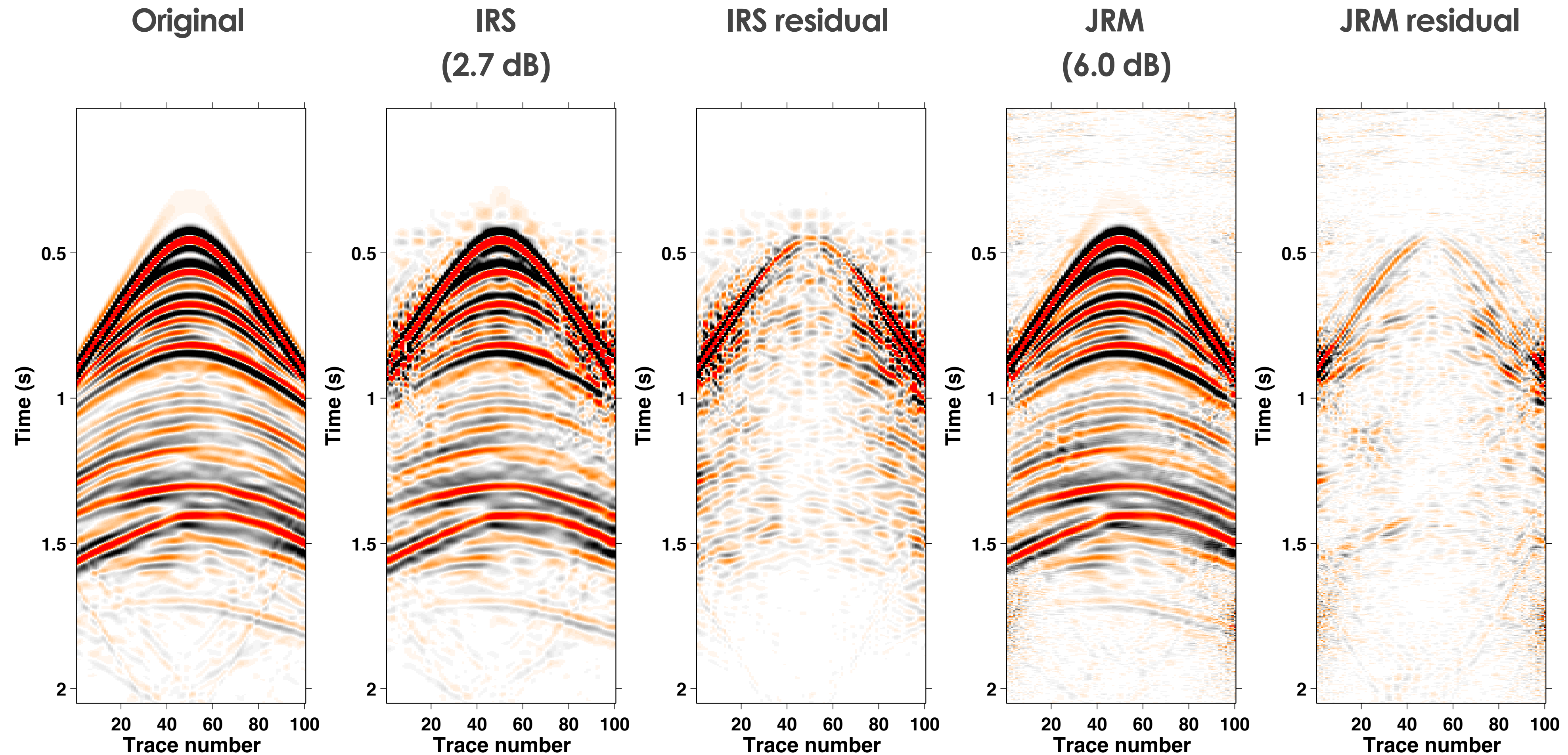
Baseline recovery

–“*large*” overlap (50%) in acquisition matrices



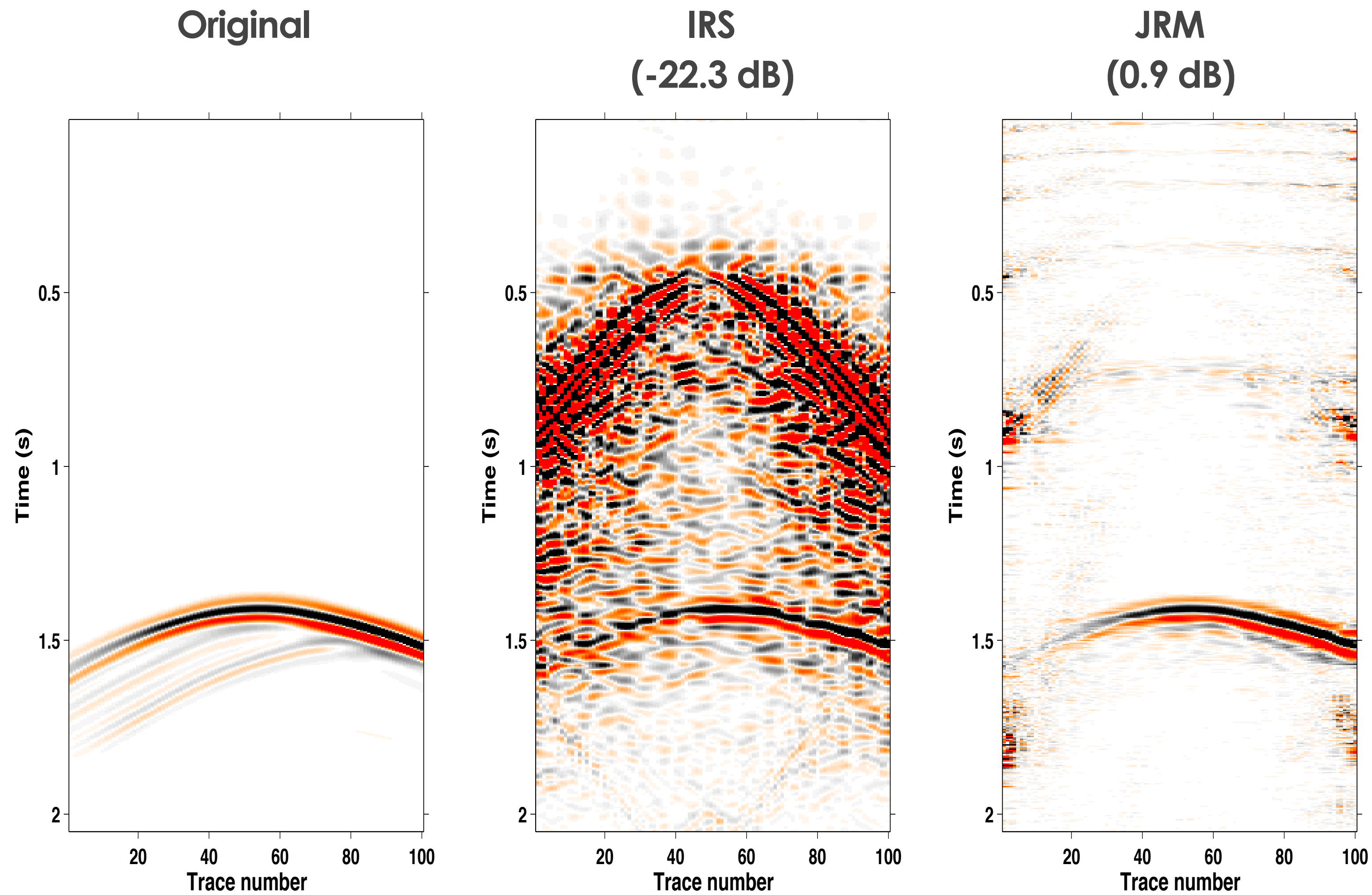
Monitor recovery

–“large” overlap (50%) in acquisition matrices



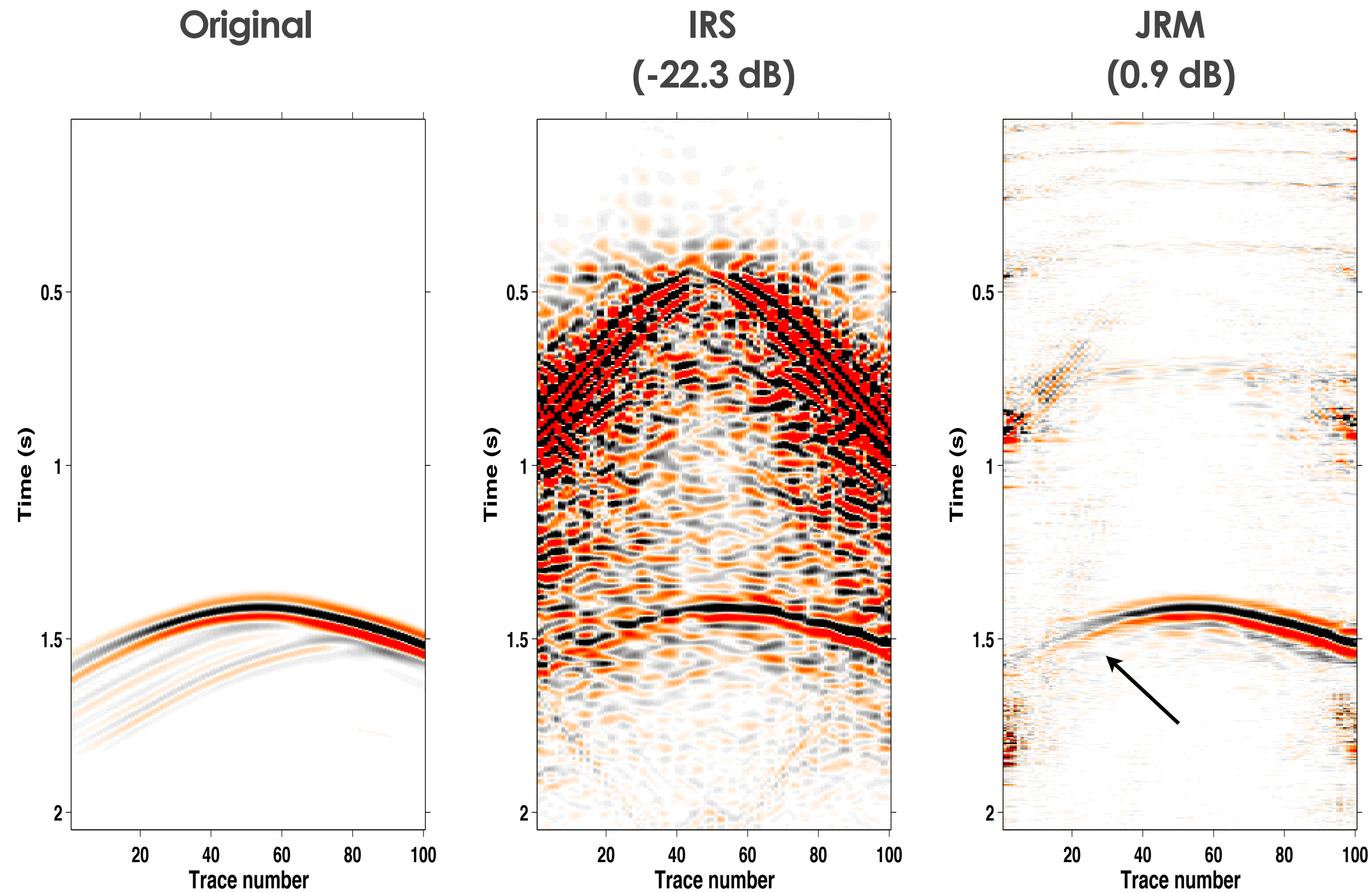
4-D recovery

–“large” overlap (50%) in acquisition matrices



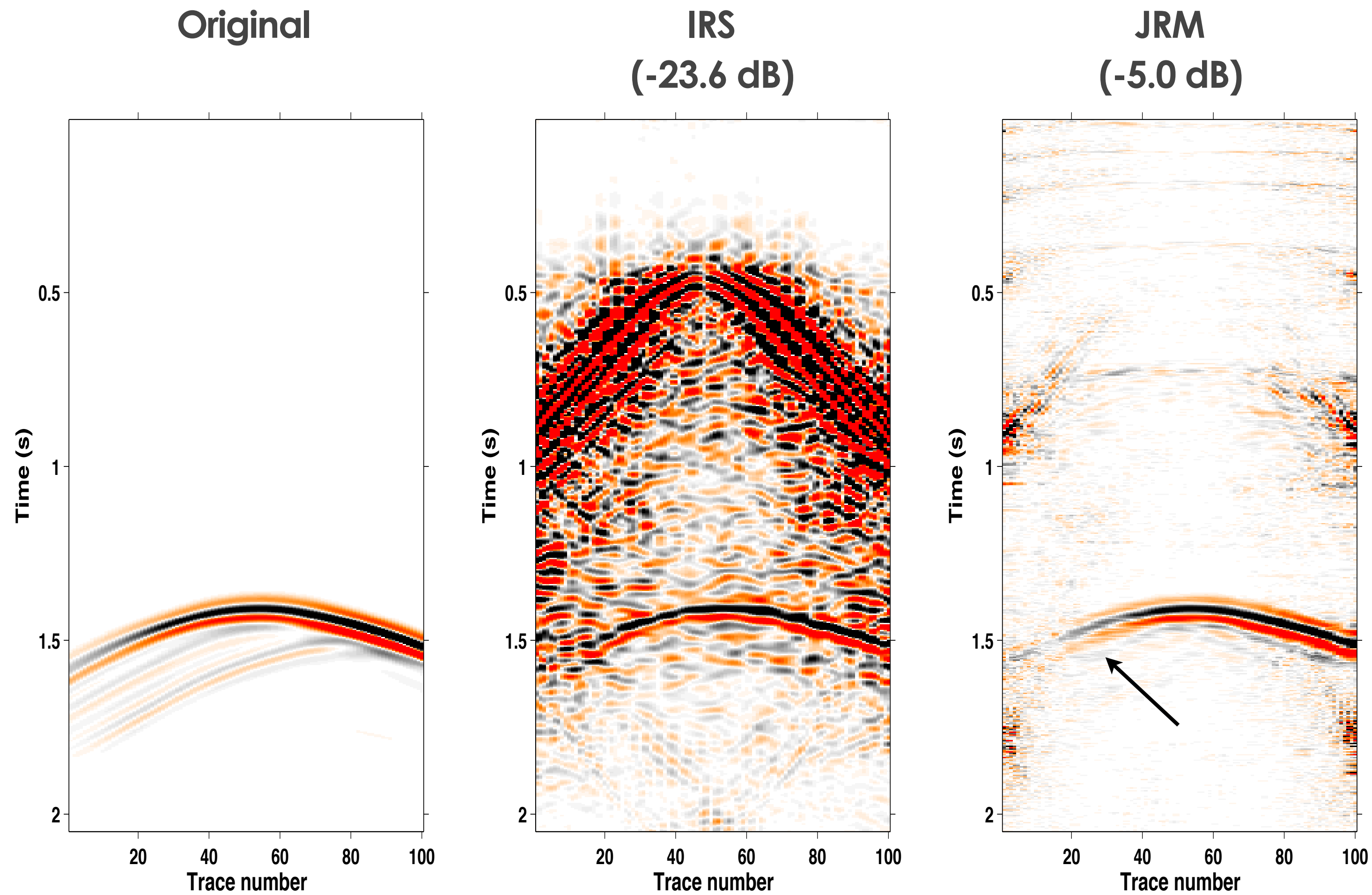
4-D recovery

–“large” overlap (50%) in acquisition matrices



4-D recovery

–“*small*” overlap (25%) in acquisition matrices



Observations

Stylized synthetics give *fundamental* insights when recovering 4-D seismic

Seismic synthetics are somewhat *inconclusive* but show that we do **not** necessarily have to insist on full *repetition* depending on the *recovery* of the *vintages*

Approach is *trivially* extendable to *multiple* vintages & *image* space

Questions:

Process/recover *independently* or *jointly* to exploit *common* features of *surveys*?

- ✓ process *jointly* leads to *improved* recovery of **both** vintages & time-lapse

Should we *repeat* the *surveys* when doing *randomized undersampling*?

- ✓ no, as long as one samples *sufficiently* to recover **both** vintages jointly

- ✓ yes, if recovery of vintages *fails* and *one* has a *high* degree of *repetition* then the *only* hope is to recover the *difference*, *not* recommended

Recommendations

The *Joint Recovery Model* always give superior results

- ▶ avoid *independent* recovery/processing *not* to miss *shared* structure
- ▶ while *large* degrees of *repetition* may allow for *recovery* of *sparse time-lapse* there is **no** guaranteed *recovery* of the *vintages* themselves

Aim for guaranteed *recovery* of the *vintages* instead

- ▶ *improves* recovery of *vintages* for *lower* degrees of *repetition*
- ▶ while *recovery* quality of *time-lapse* remains more or less the *same*

Lower *subsampling* rates instead of increasing *degrees of repetition*!

Acknowledgements

We need 4-D data!

Thank you for your attention !

<https://www.slim.eos.ubc.ca/>



SINBAD

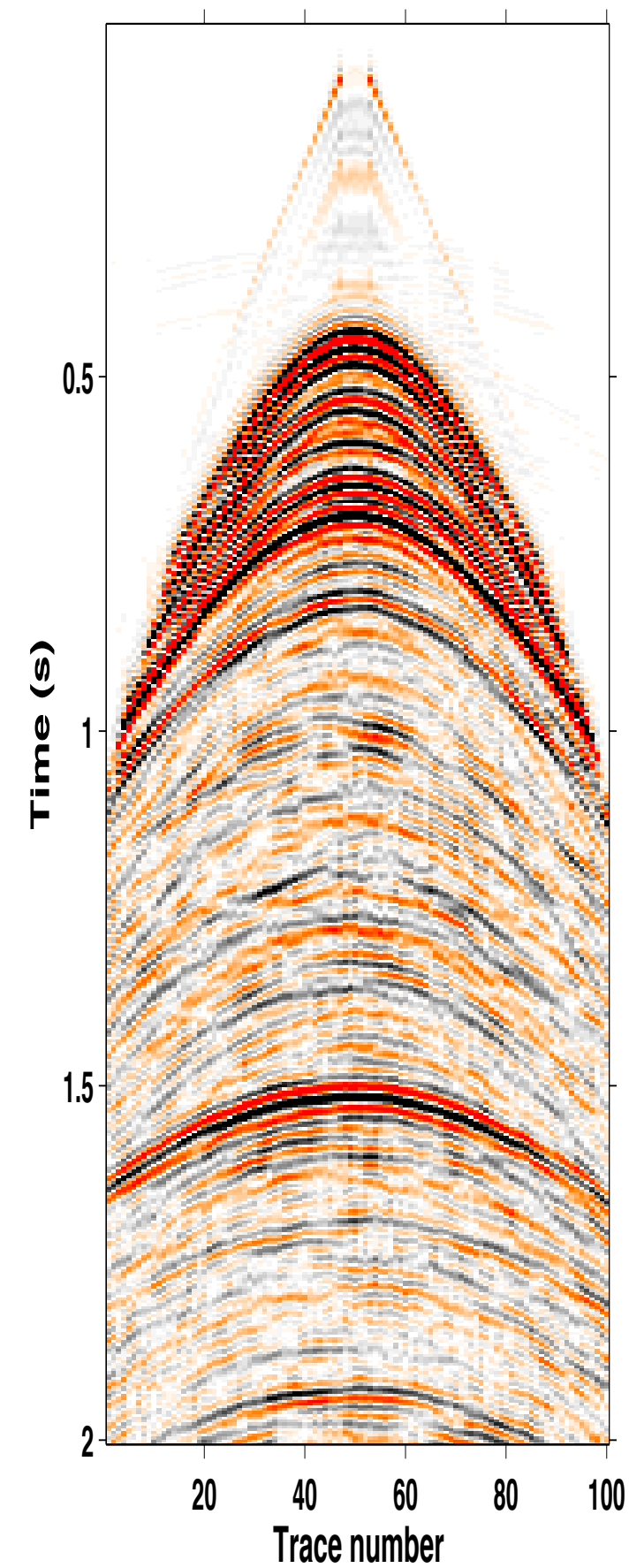


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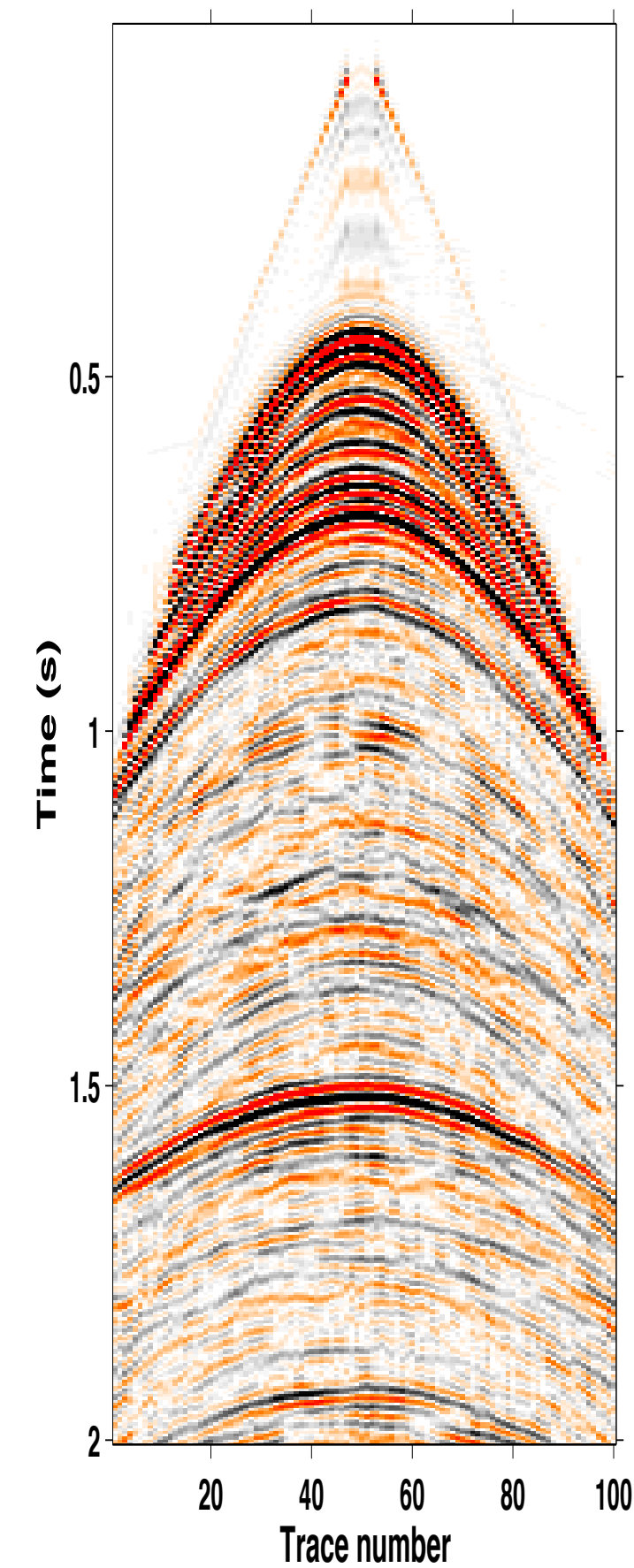
Real field-data example (from SEG abstract)

Original data

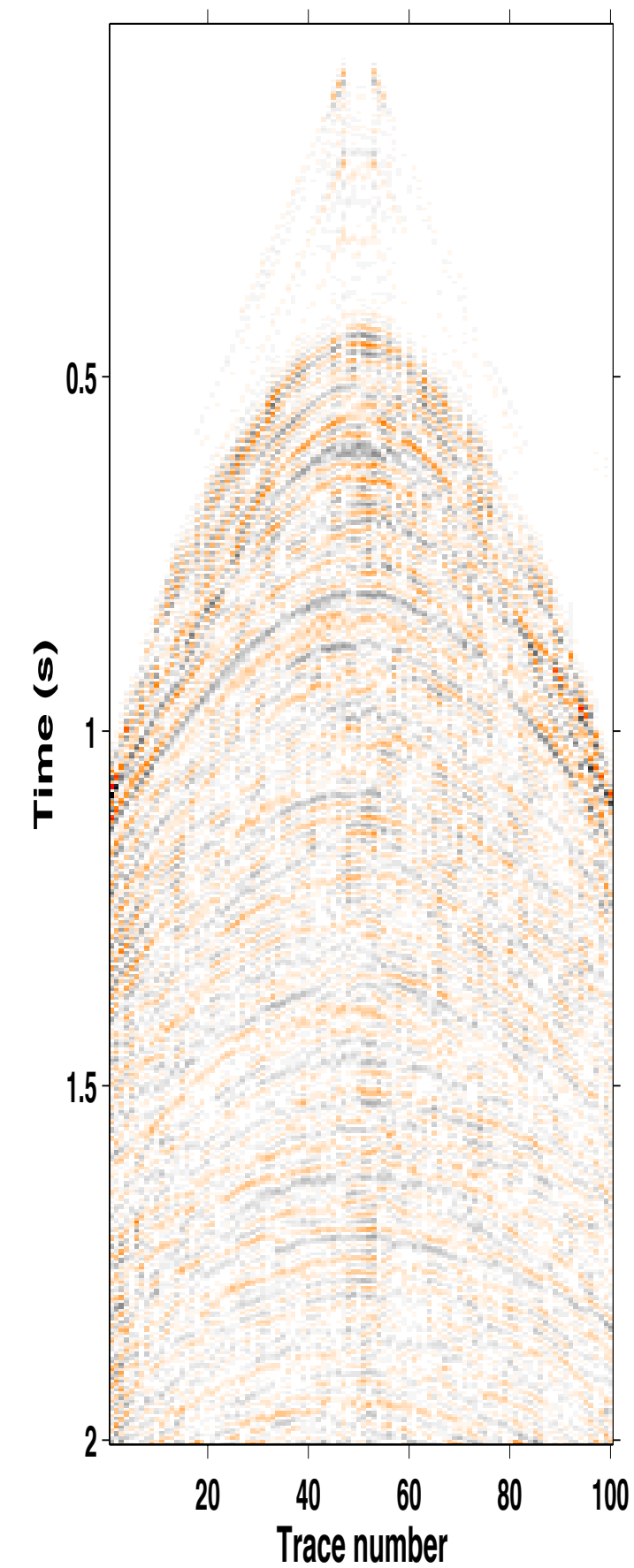
Baseline



Monitor



4-D signal

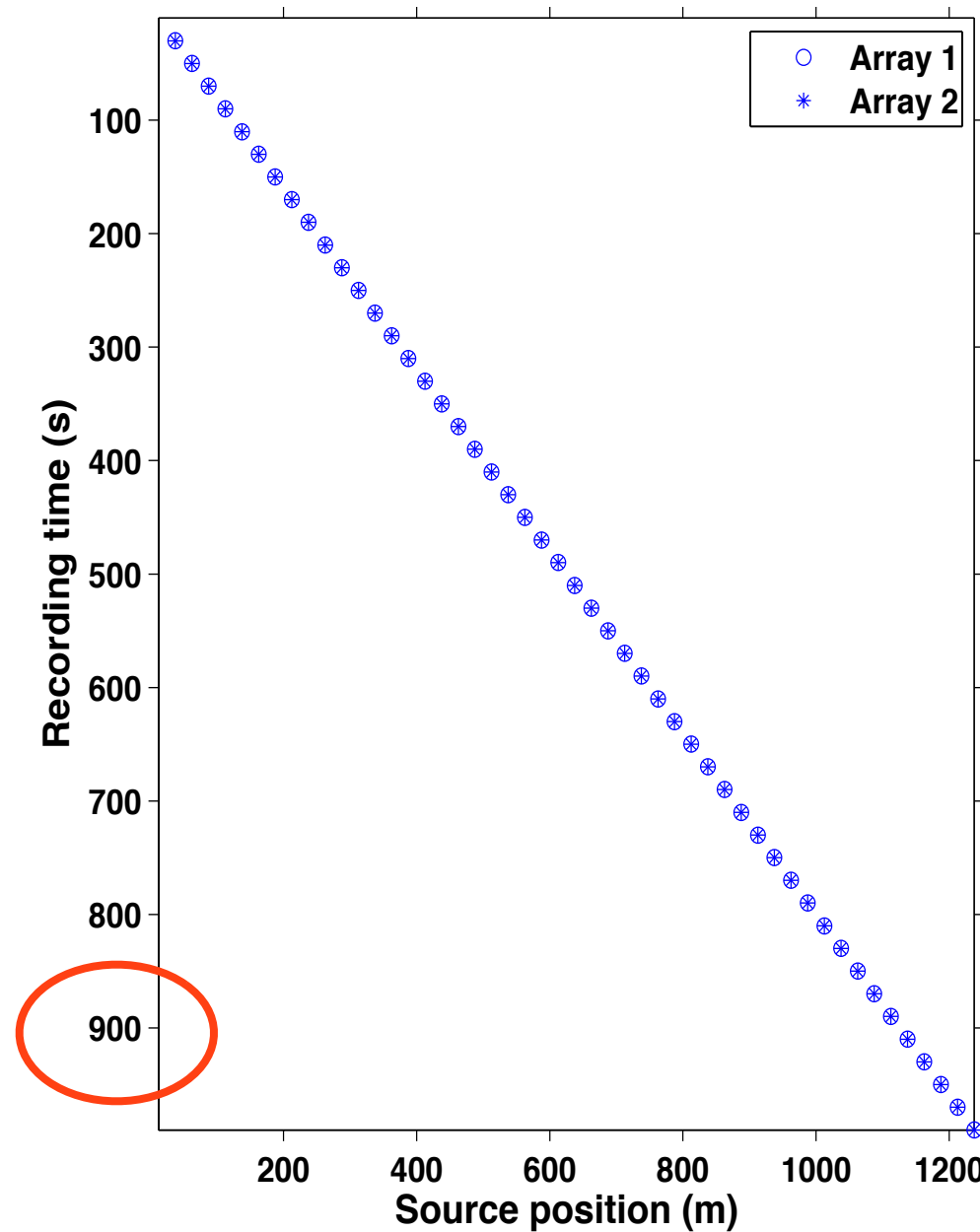


time samples: **501**
receivers: **100**
sources: **100**

sampling
time: **4.0 ms**
receiver: **25.0 m**
source: **25.0 m**

Conventional vs. *time-jittered* sources

conventional



“unblended” shot gathers

number of shots = **100** (per array)

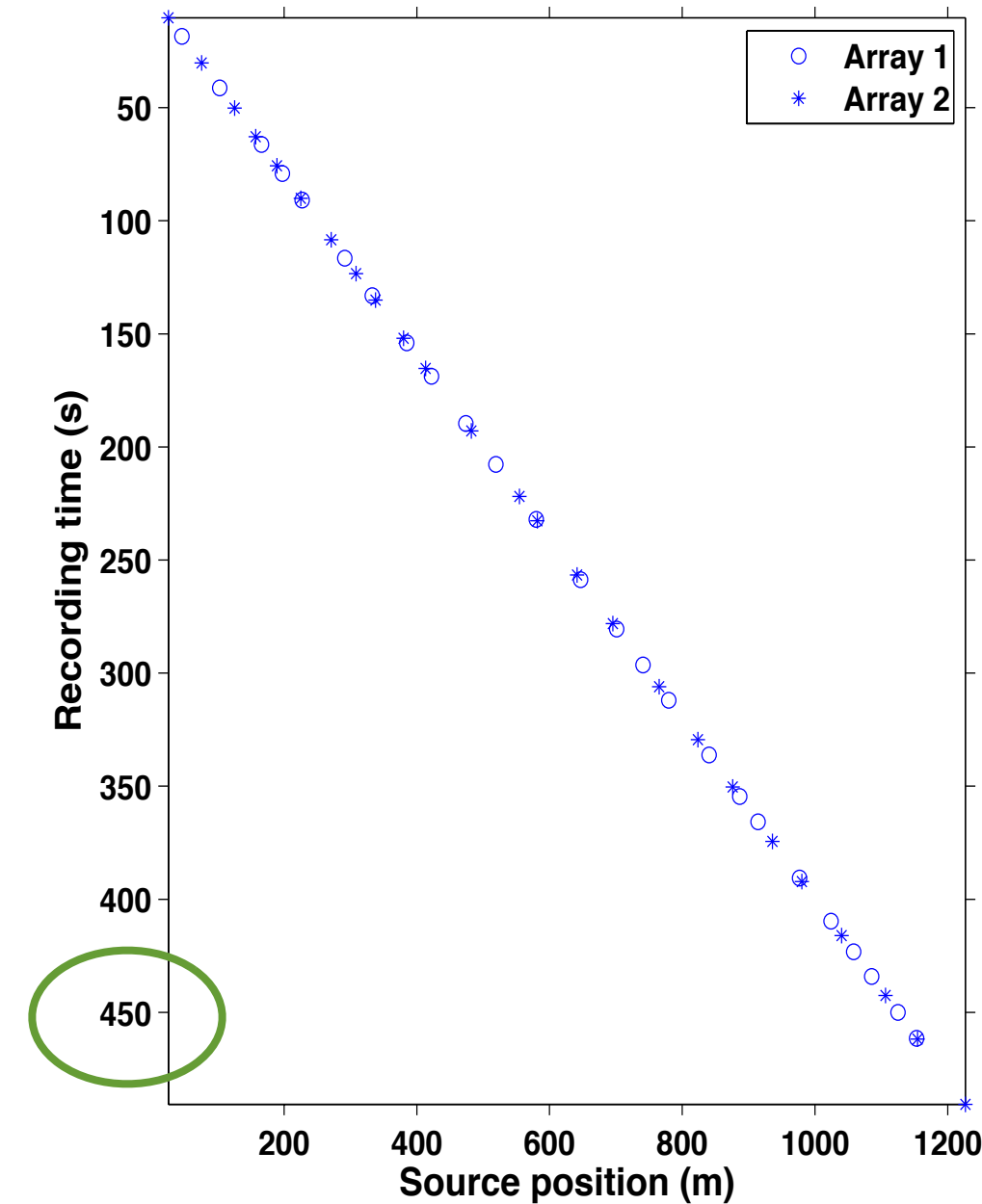
shot record length: 10.0 s

spatial sampling: **12.5 m**

vessel speed: **1.25 m/s**

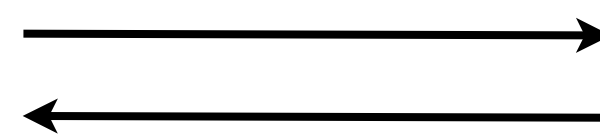
recording time = $100 \times 10.0 =$ **1000.0 s**

jittered acquisition 1
(for baseline)



[BLENDING & UNDERSAMPLING]

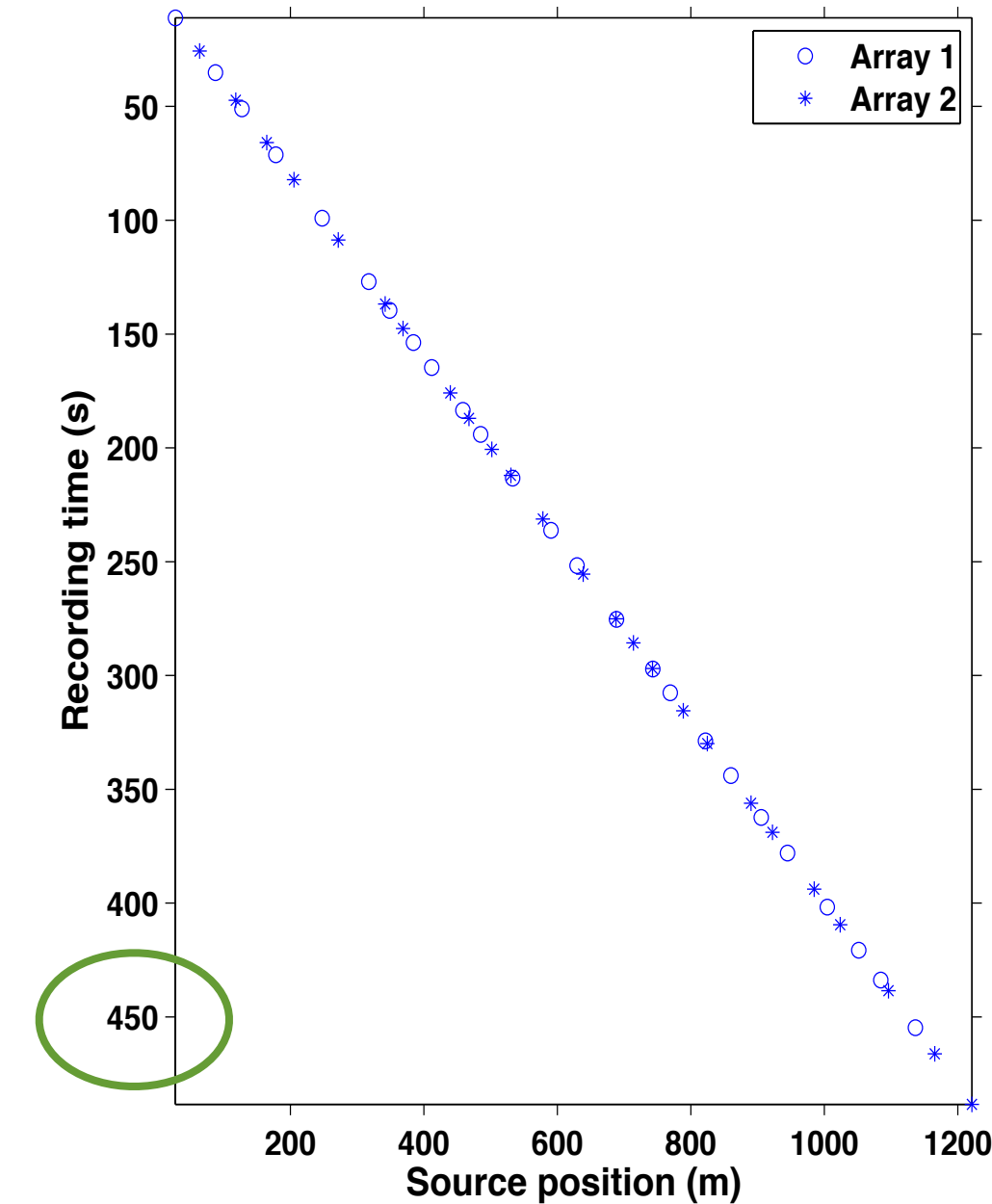
spatial undersampling factor = 2



spatial sampling **increase** factor = 2

[DEBLENDING & INTERPOLATION]

jittered acquisition 2
(for monitor)



“blended” shot gathers

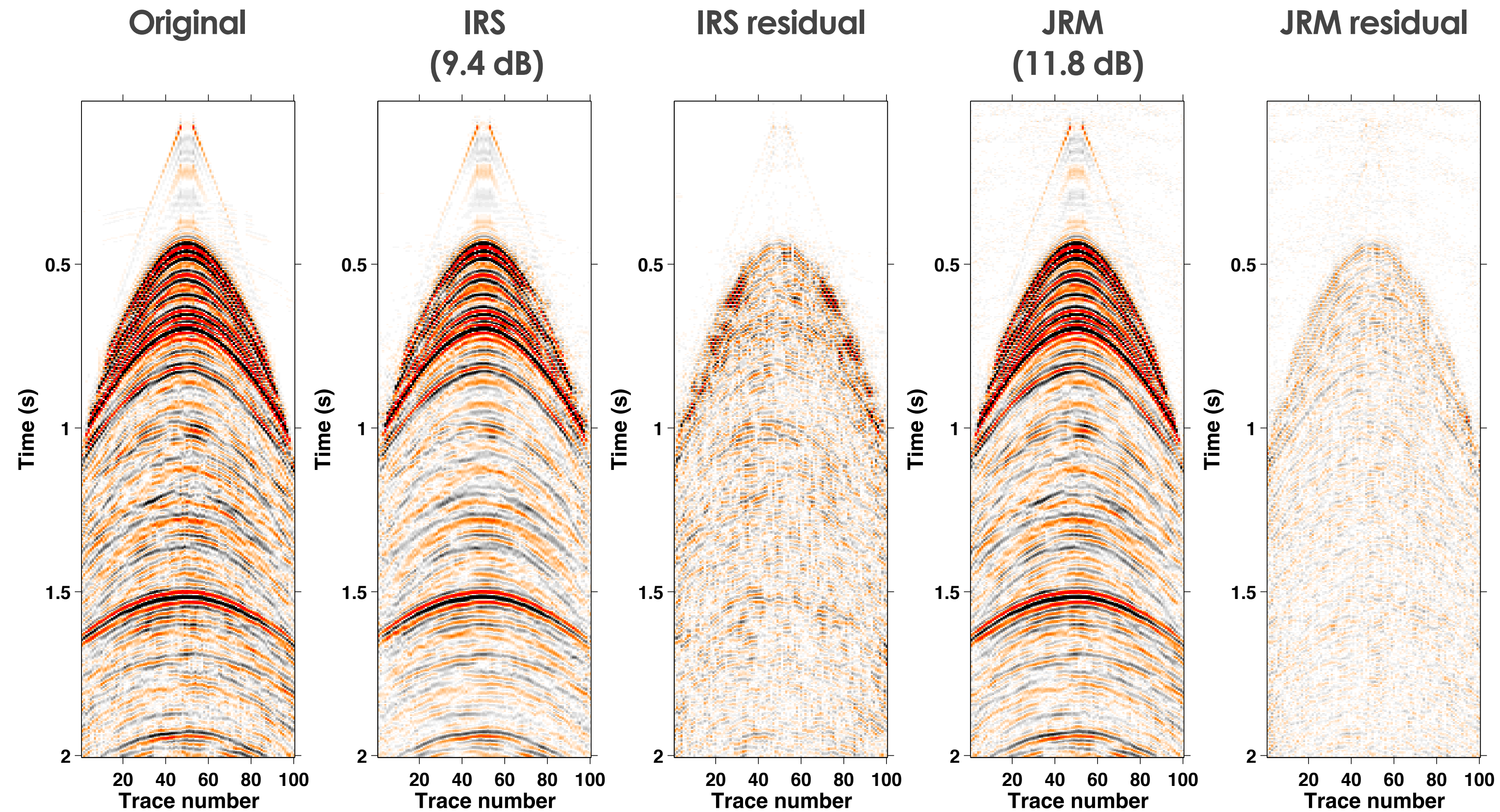
number of shots = $100/2 =$ **50** (25 per array)

spatial sampling: **50.0 m (jittered)**

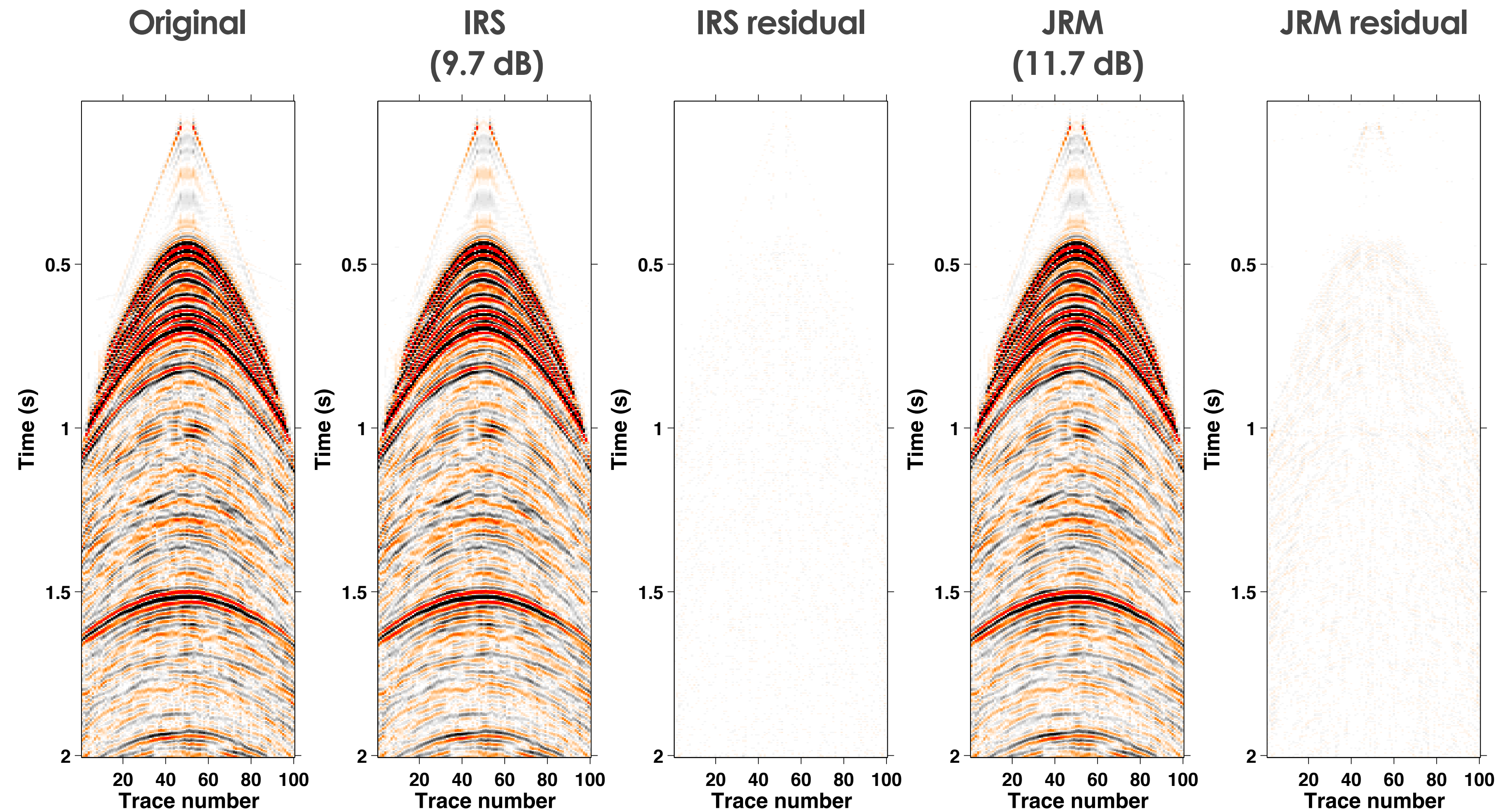
vessel speed: **2.50 m/s**

recording time $\approx 1000.0 \text{ s} / 2 =$ **500.0 s**

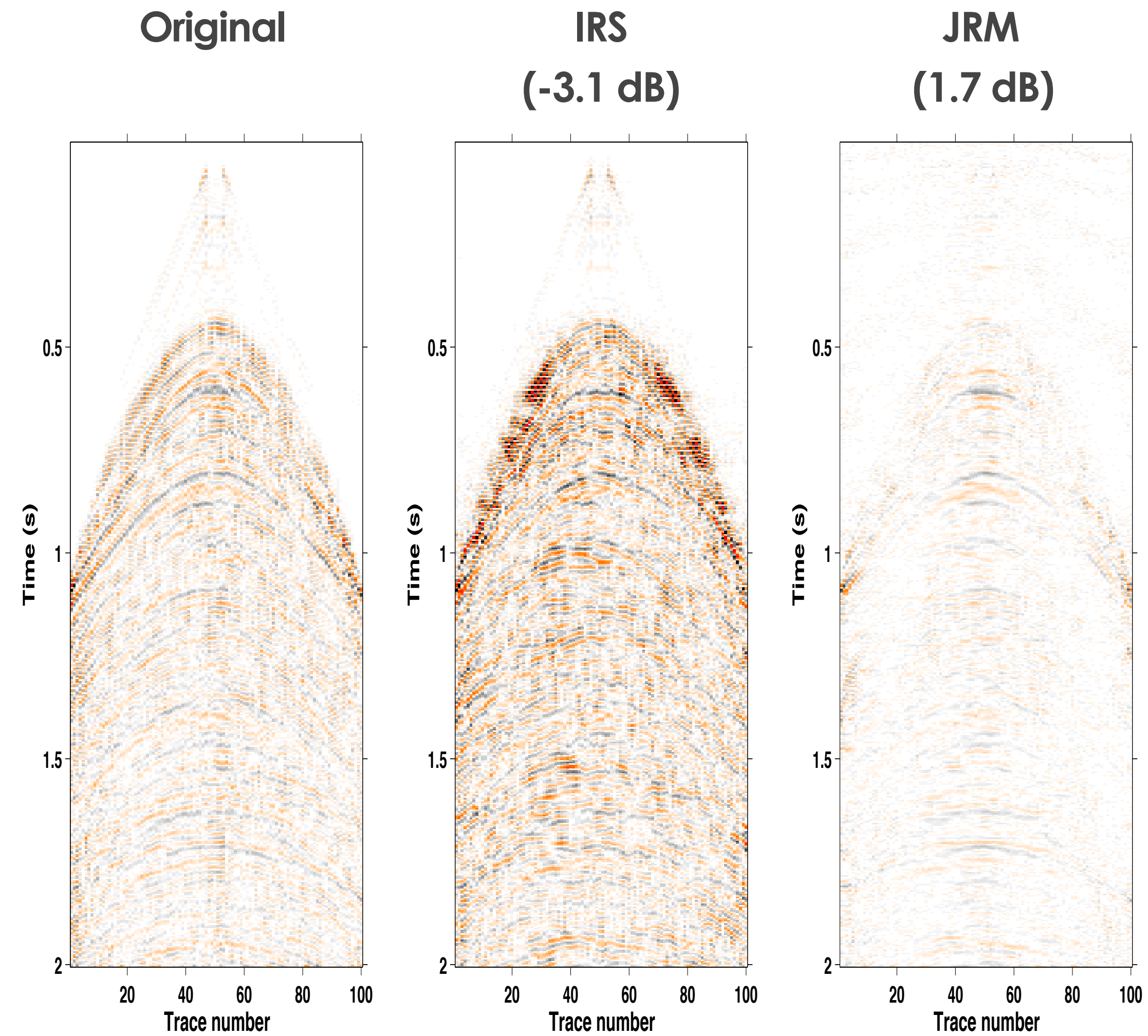
Baseline recovery



Monitor recovery

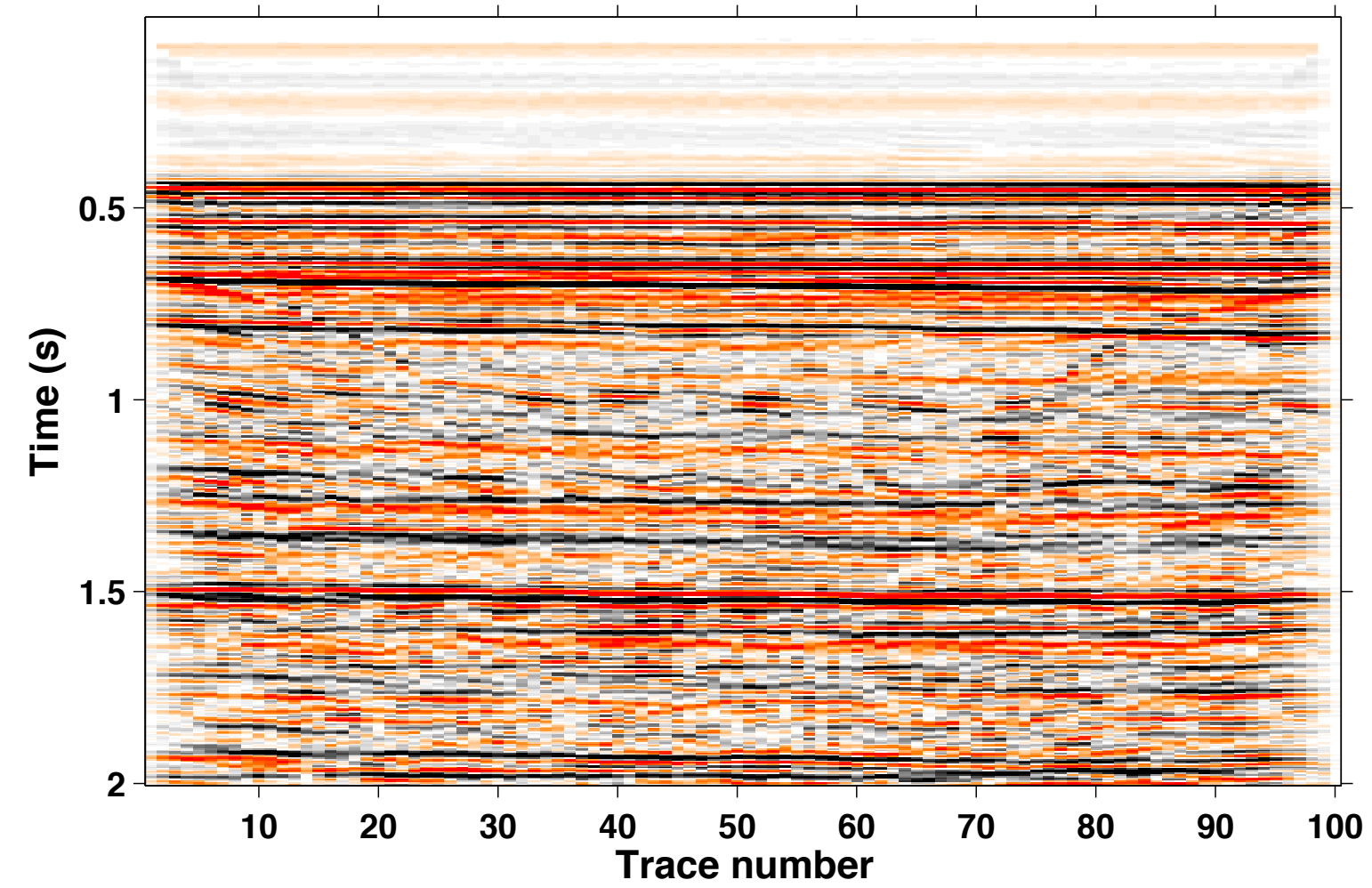


4-D signal recovery

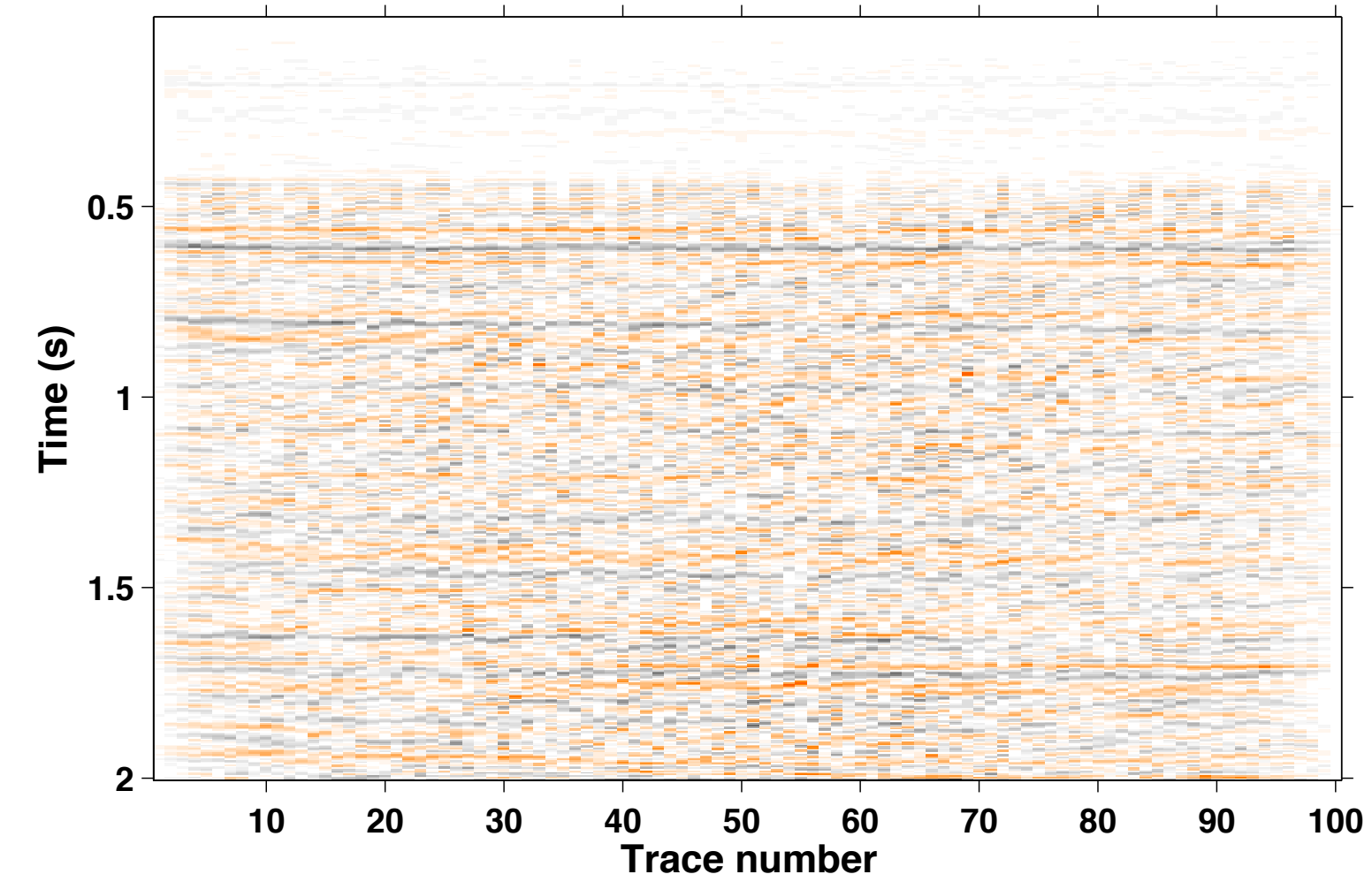


Stacked sections

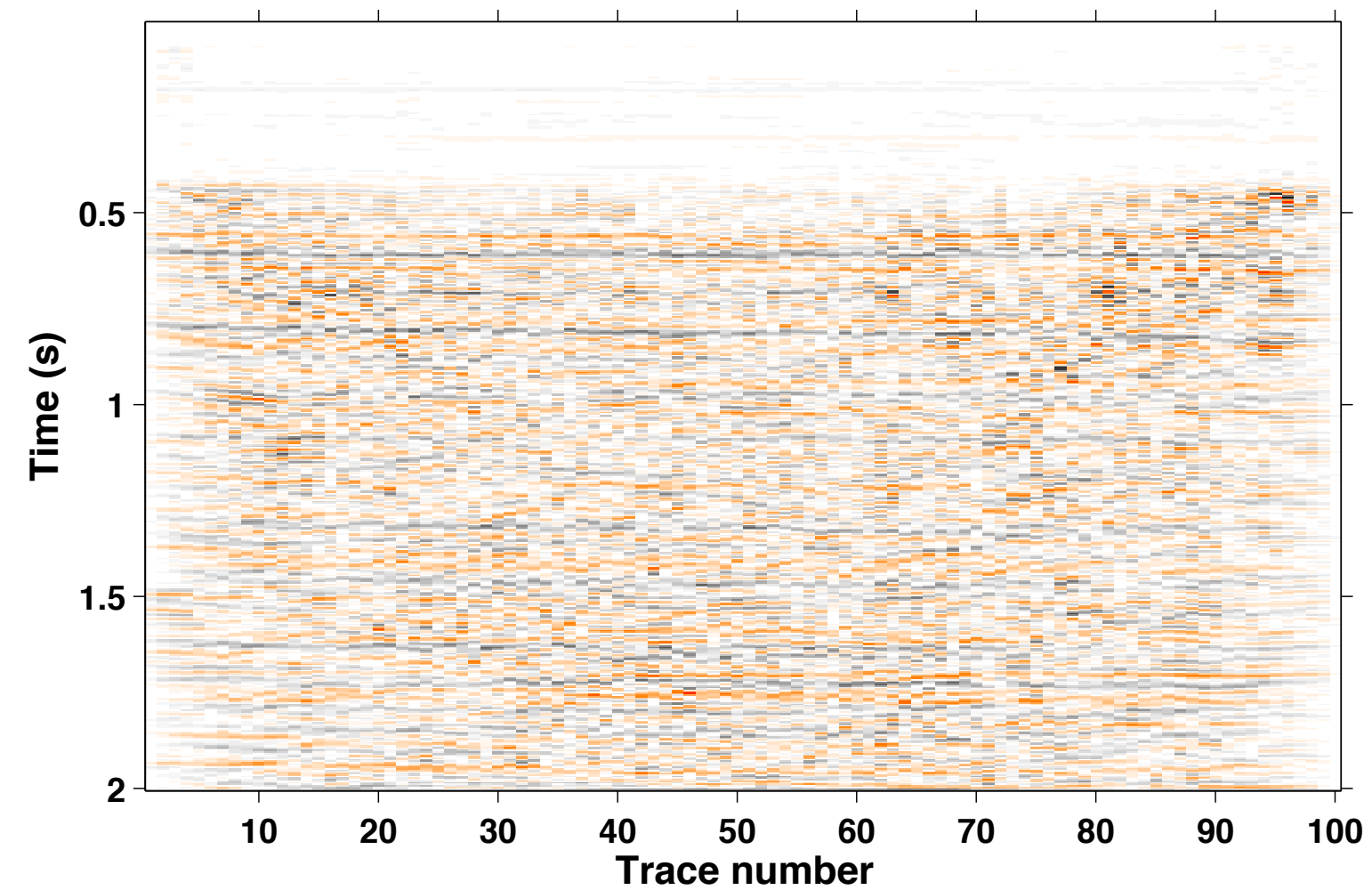
**Original
baseline**



**Original
4-D**



**IRS
recovered
4-D**



**JRM
recovered
4-D**

