Time-lapse seismic without repetition: reaping the benefits from randomized sampling and joint recovery

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SLIM
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Current challenges in 4D

- *Repeatability* of 4D seismic experiments

  *- difficult to **repeat** baseline and monitor surveys*

  - identical or different processing to both data?

- *Detectability* of 4D signal

  - very weak signals below noise level

Objective

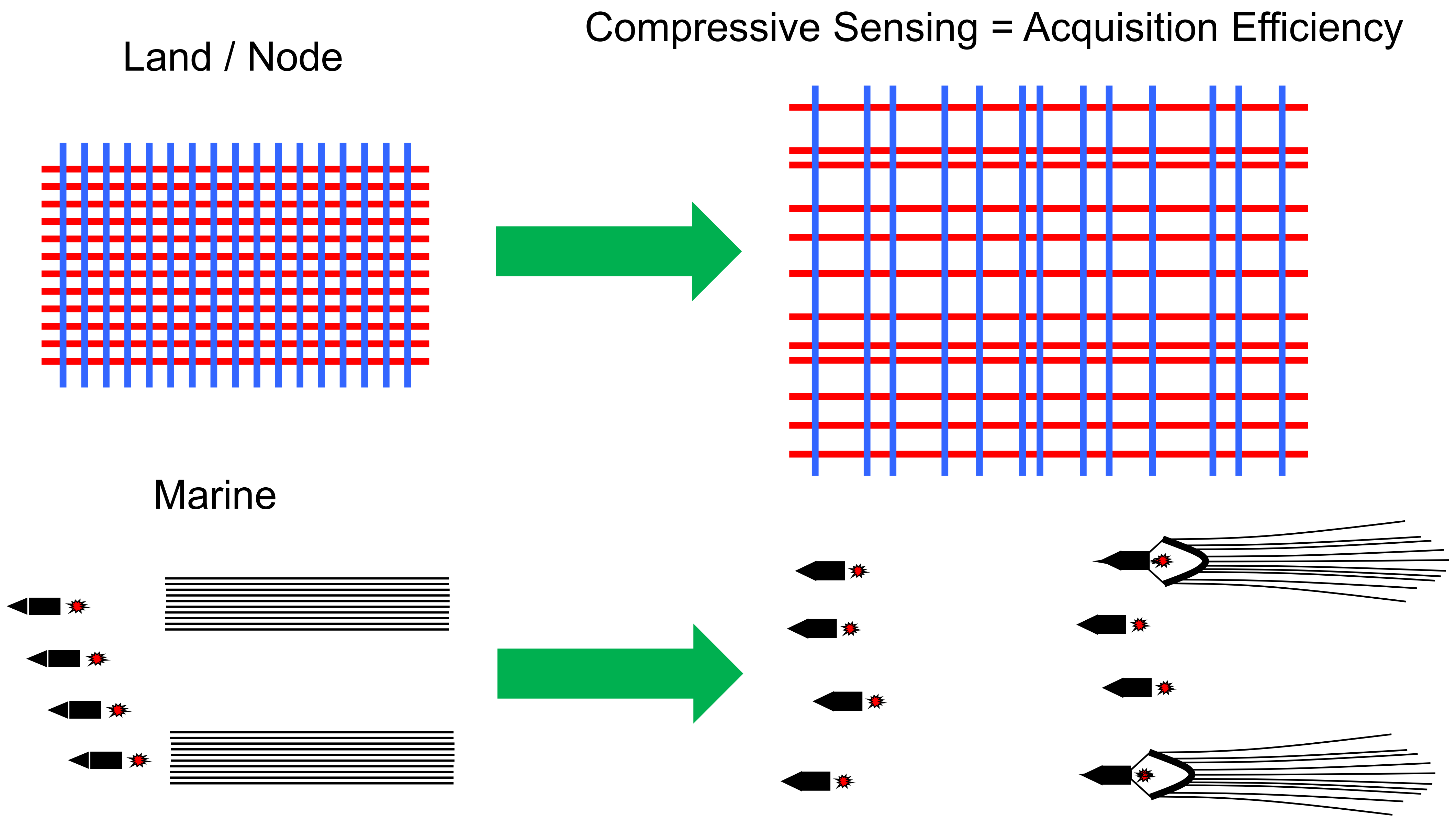
- *Reduce cost of data acquisition for a 4-D project*
  - *via randomized sampling techniques using compressed sensing ideas*
- *Design acquisition schemes to*
  - *investigate the requirement for repetition of surveys*
- *Improve quality of 4-D signal*
  - *via joint recovery method* (JRM)

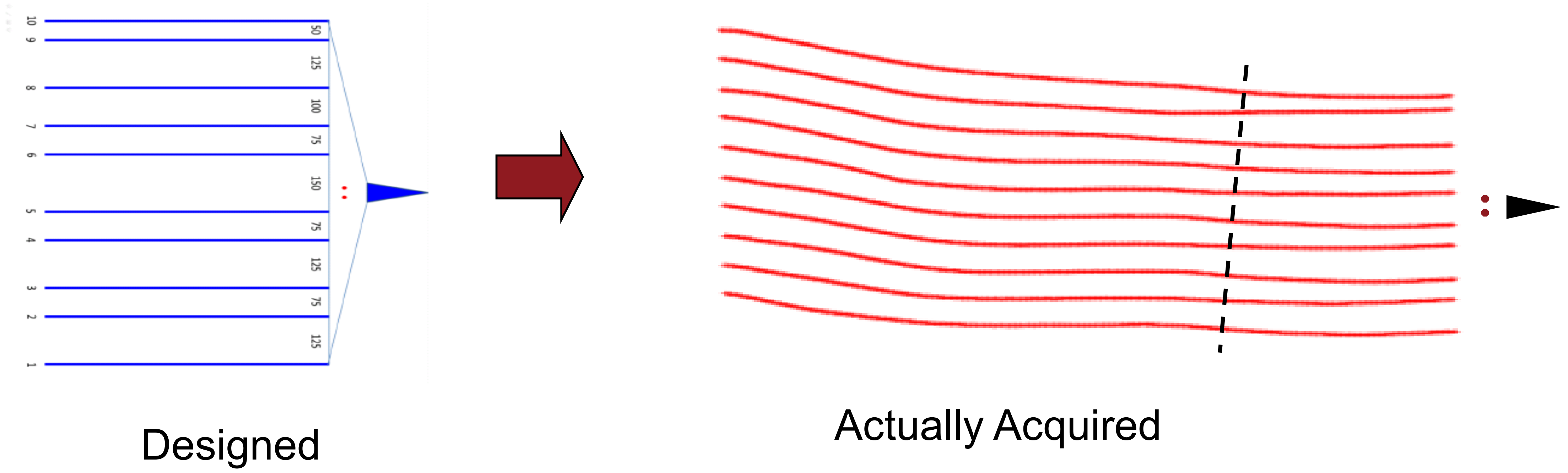
Mosher, C. C., Keskula, E., Kaplan, S. T., Keys, R. G., Li, C., Ata, E. Z., ... & Sood, S. (2012, November). Compressive Seismic Imaging. In *2012 SEG Annual Meeting*. Society of Exploration Geophysicists.

Randomized undersampling
– examples from industry (ConocoPhilips)

Deliberate & natural randomness in acquisition

(thanks to Chuck Mosher)





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Premise

- *randomized acquisition works*
- *use insights from compressed sensing*
- *sparse recovery/reconstruction of seismic data and time-lapse signal*

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Premise

- *there are no calibration errors but there can be additive noise*
- *no static effects arising from variation of water column properties*

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

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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*

Question

How does compressive sensing and ***randomized*** *acquisition affect* ***time-lapse*** *data in terms degree of* ***repeatability*** *of the surveys?*

Haneet Wason and Felix J. Herrmann, “Time-jittered ocean bottom seismic acquisition”, in *SEG Technical Program Expanded Abstracts*, 2013, 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. Abstract BibTex Tagged

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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** *sub*sampled acquisition, e.g. via time-*jittered* marine *under*sampling
- may offer *possibility* to *relax* insistence on *repeatability*
- *exploits* insights from *distributed* compressive sensing

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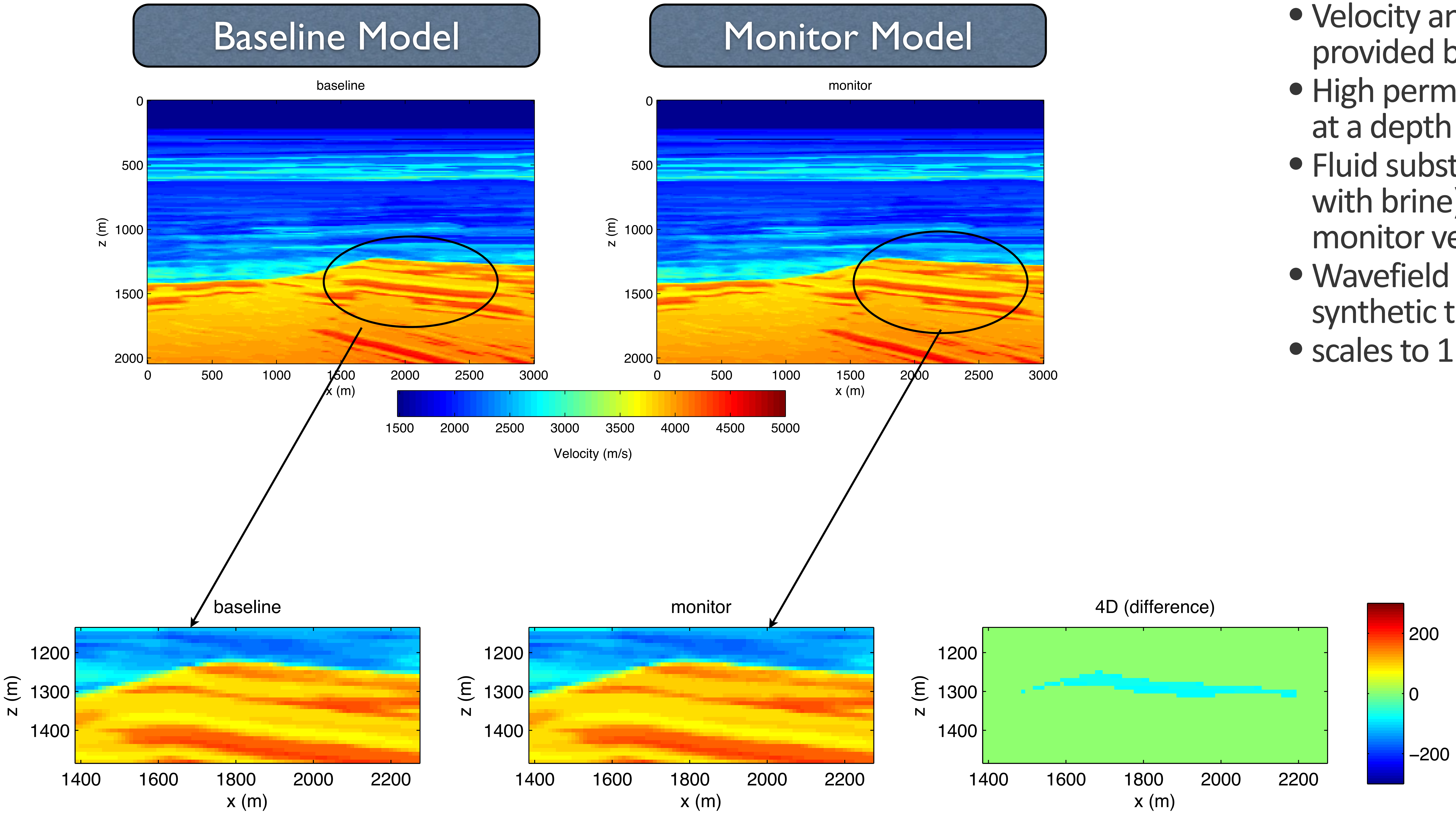
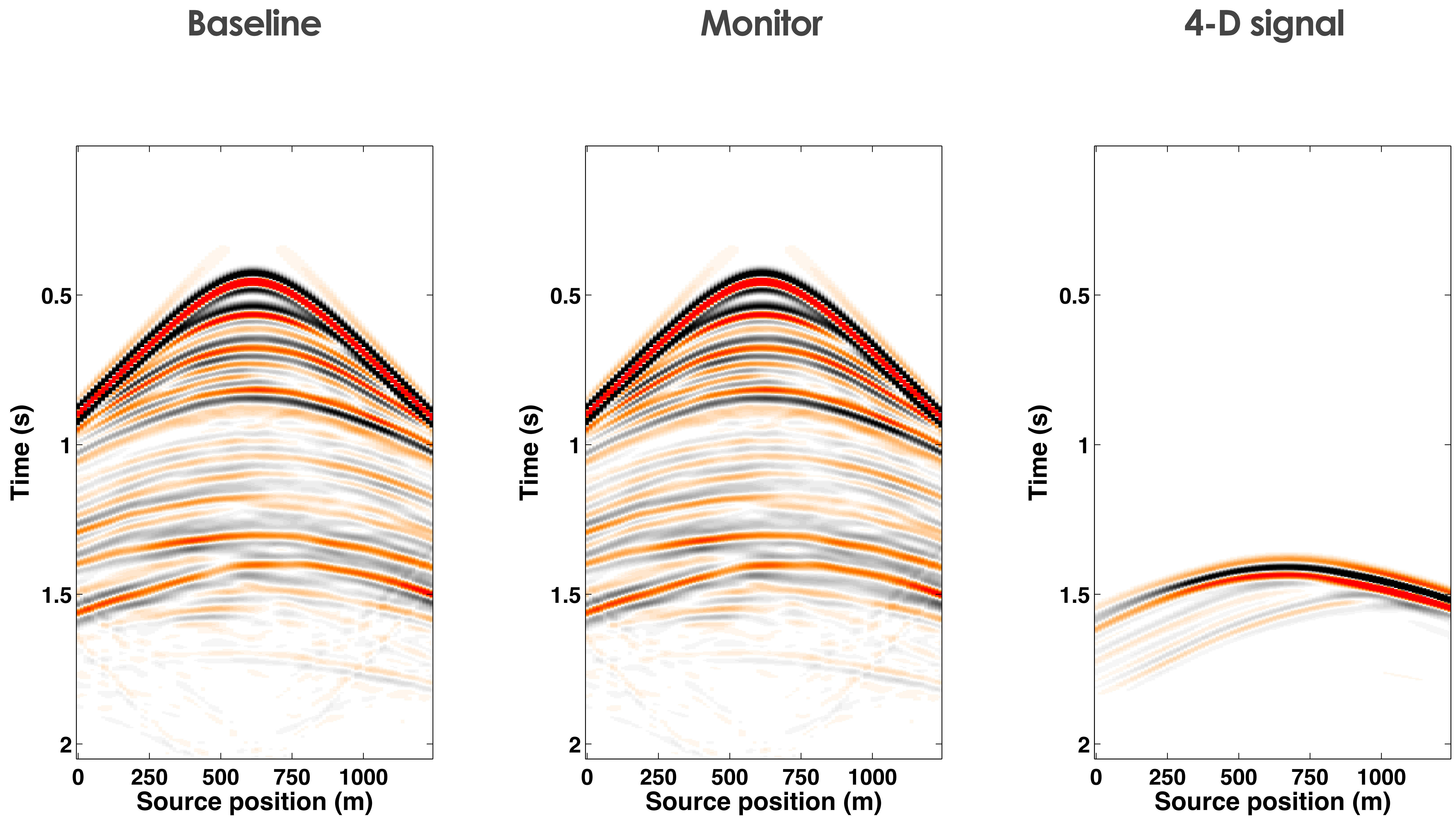
Method



- Velocity and density model provided by BG, 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

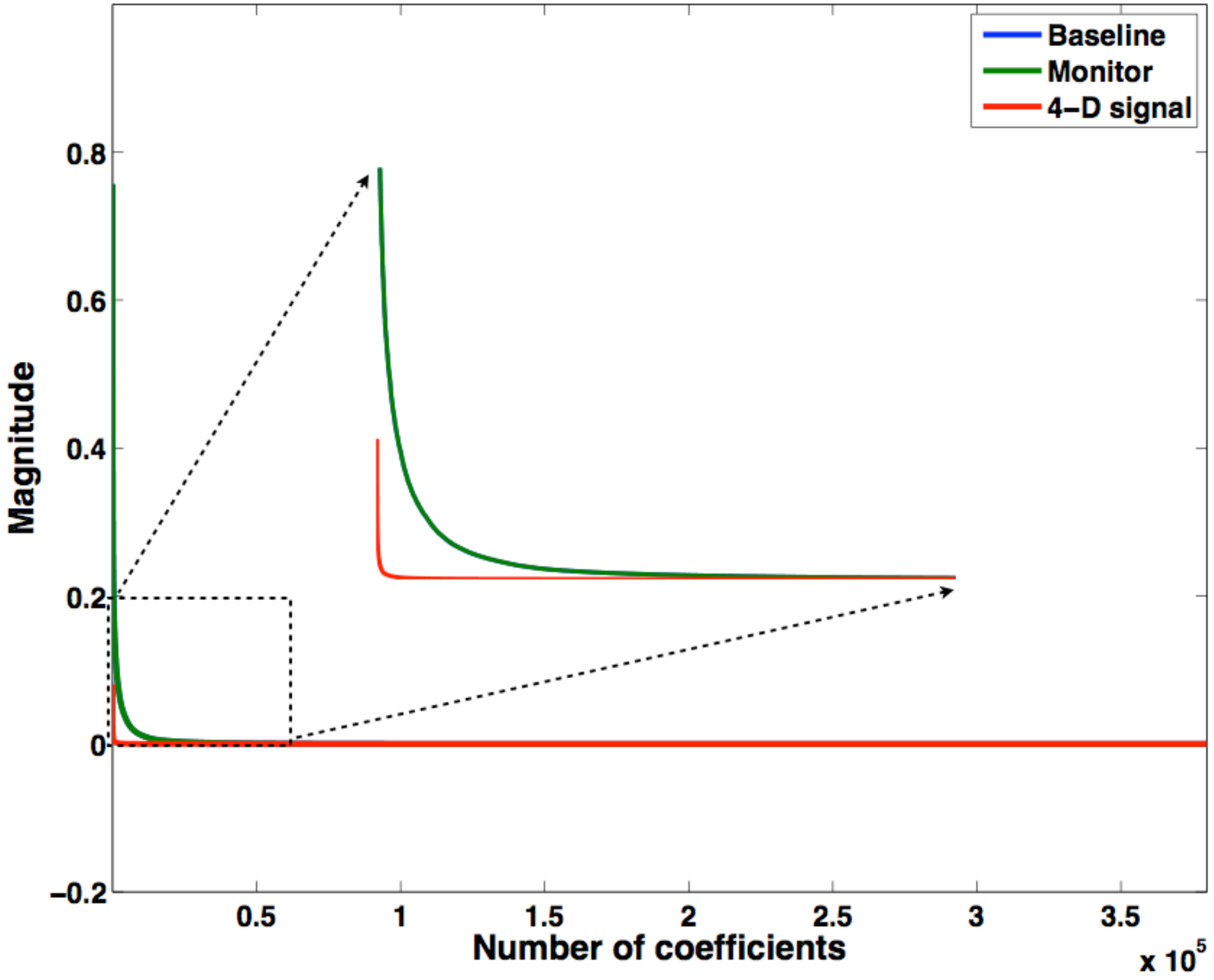
Simulated original data
– time-domain finite differences

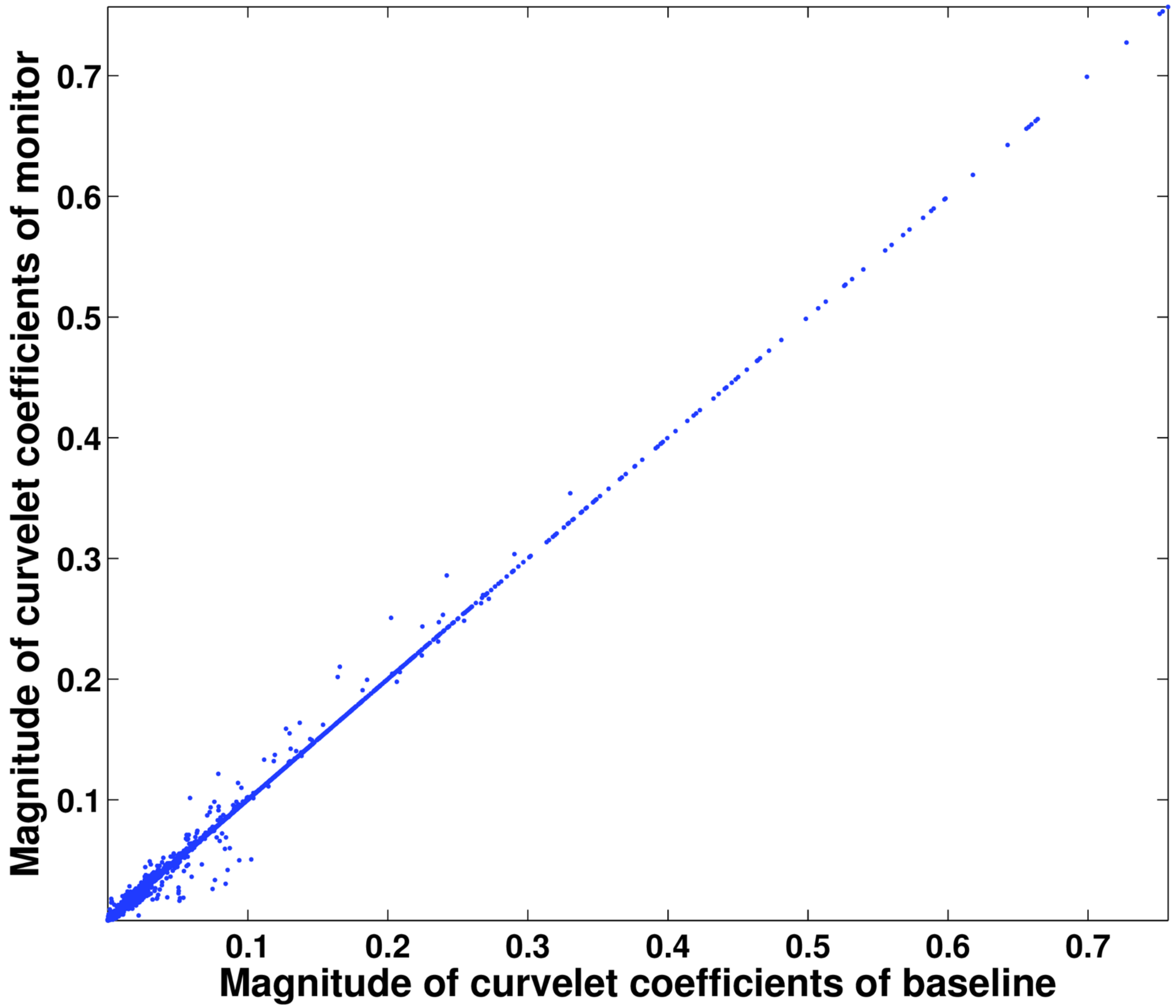


time samples: **512**
receivers: **100**
sources: **100**

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

Time-lapse data - curvelet representation





Observations

- *Time-lapse data are sparse/compressible in curvelet domain*
- *The difference (4-D signal) is much more sparse/compressible*
- *The data have significant correlations in the curvelet domain*

Questions

Can we use this property of time-lapse data in any way?

How does this information affect design of time-lapse surveys?

Does this say anything about repeating surveys?

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

$SPG\ell_1$

Van Den Berg, Ewout, and Michael P. Friedlander. "Probing the Pareto frontier for basis pursuit solutions."
SIAM Journal on Scientific Computing 31, no. 2 (2008): 890-912.

Sparsity-promoting recovery

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

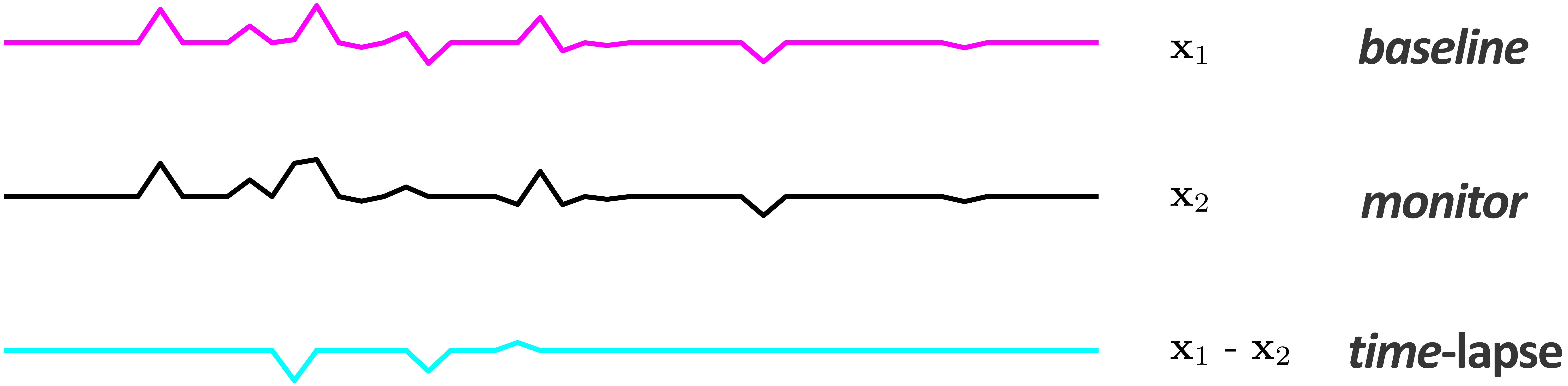
$\mathbf{A}$ *measurement operator/sampling matrix*

$\mathbf{b}$ *observed data*

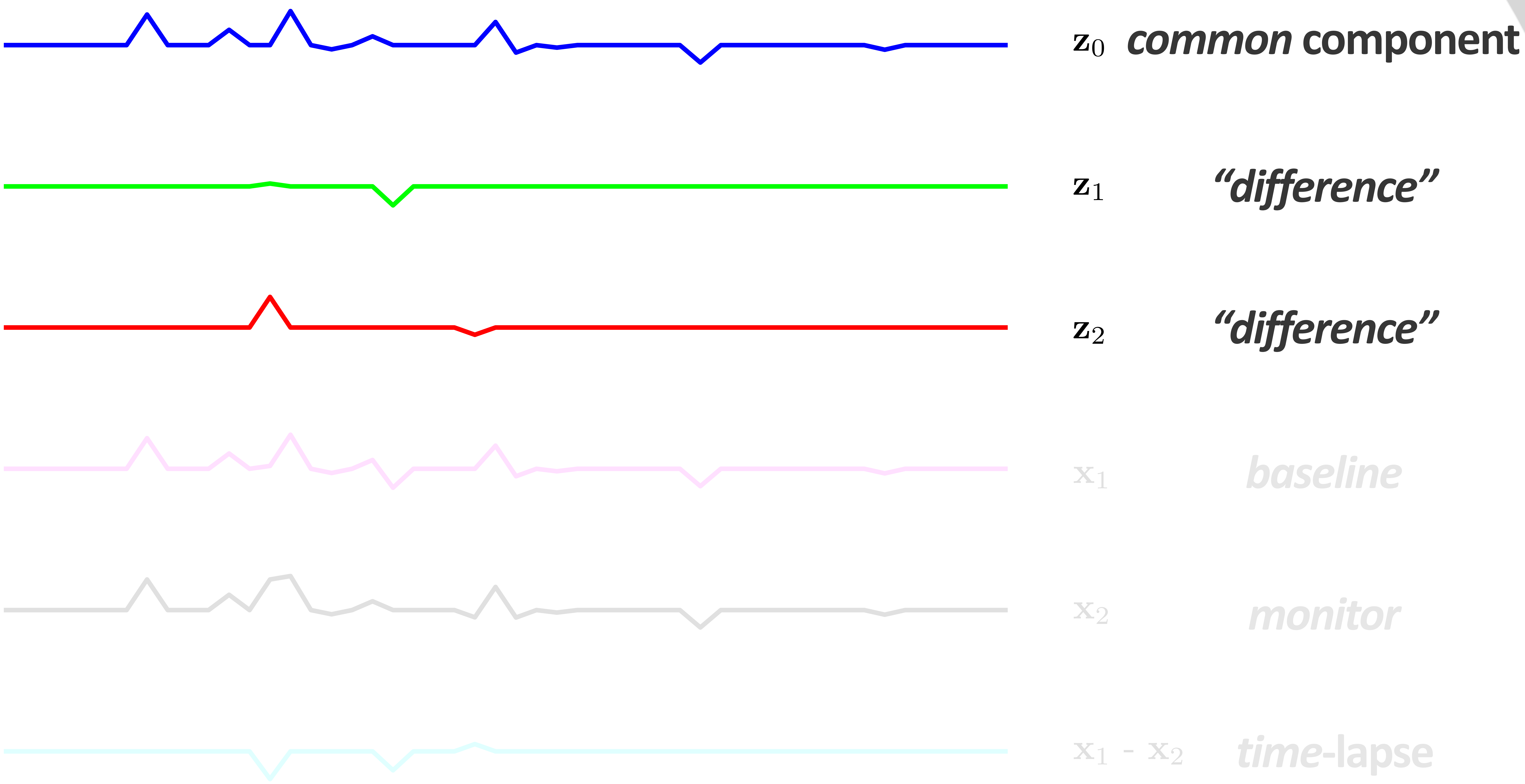
$\tilde{\mathbf{z}}$ *estimated representation of true data*

we use $SPG\ell_1$

Sparse baseline, monitor & time-lapse signals



Sparse Joint Recovery Model (JRM)



Stylized experiments

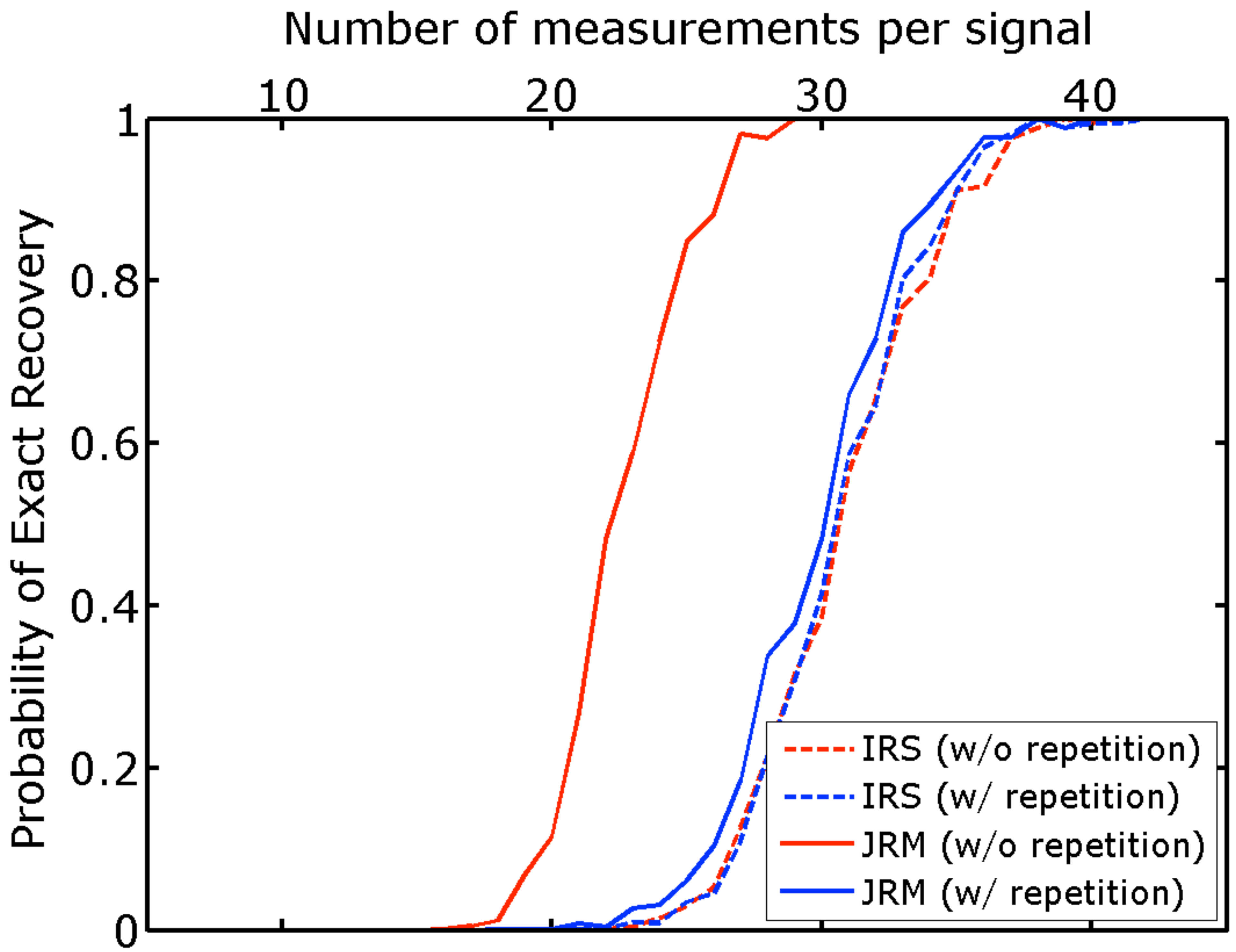
Conduct *many* CS experiments to compare

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

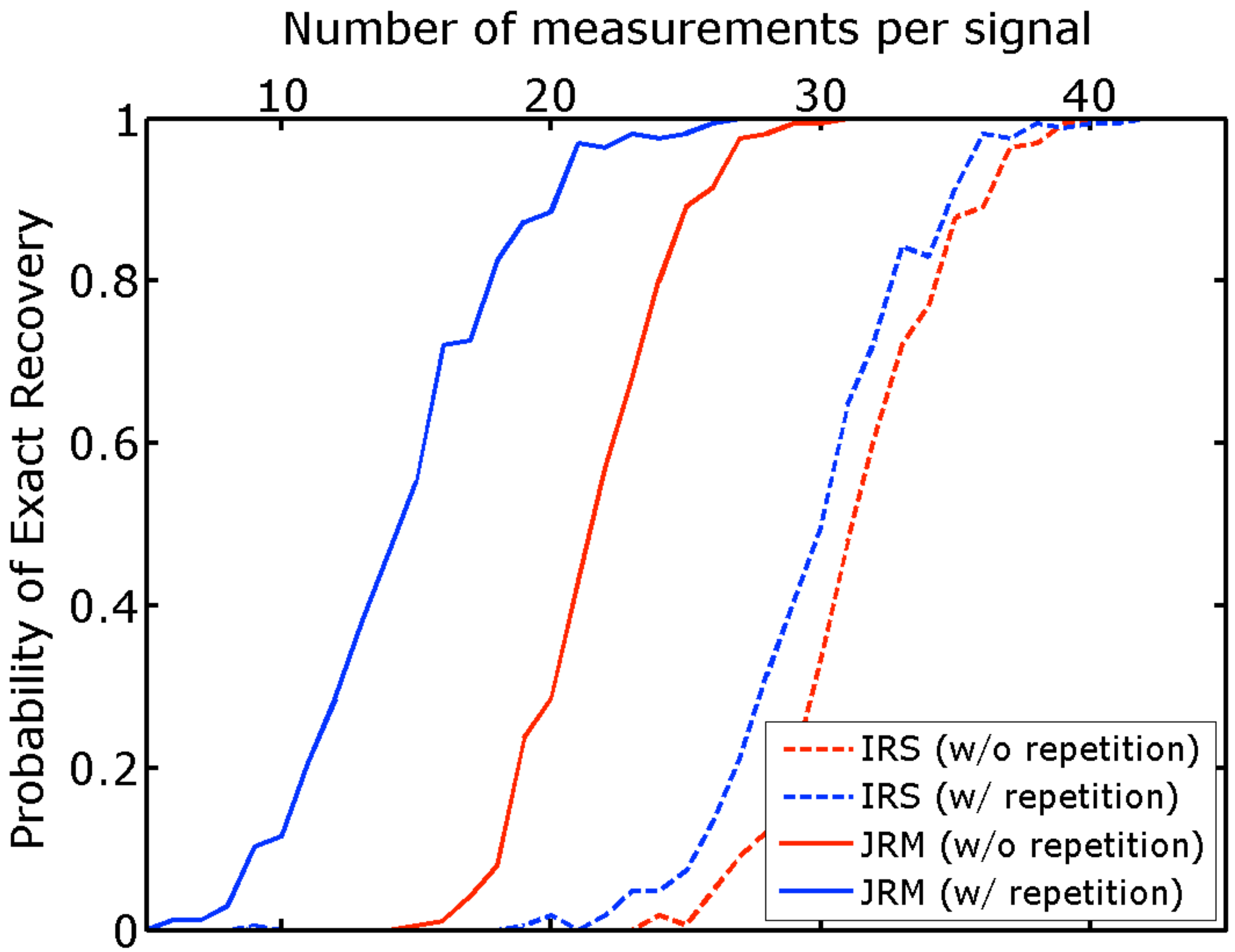
for *baseline* & *monitor* surveys that

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

Results : *independent* versus *joint* recovery

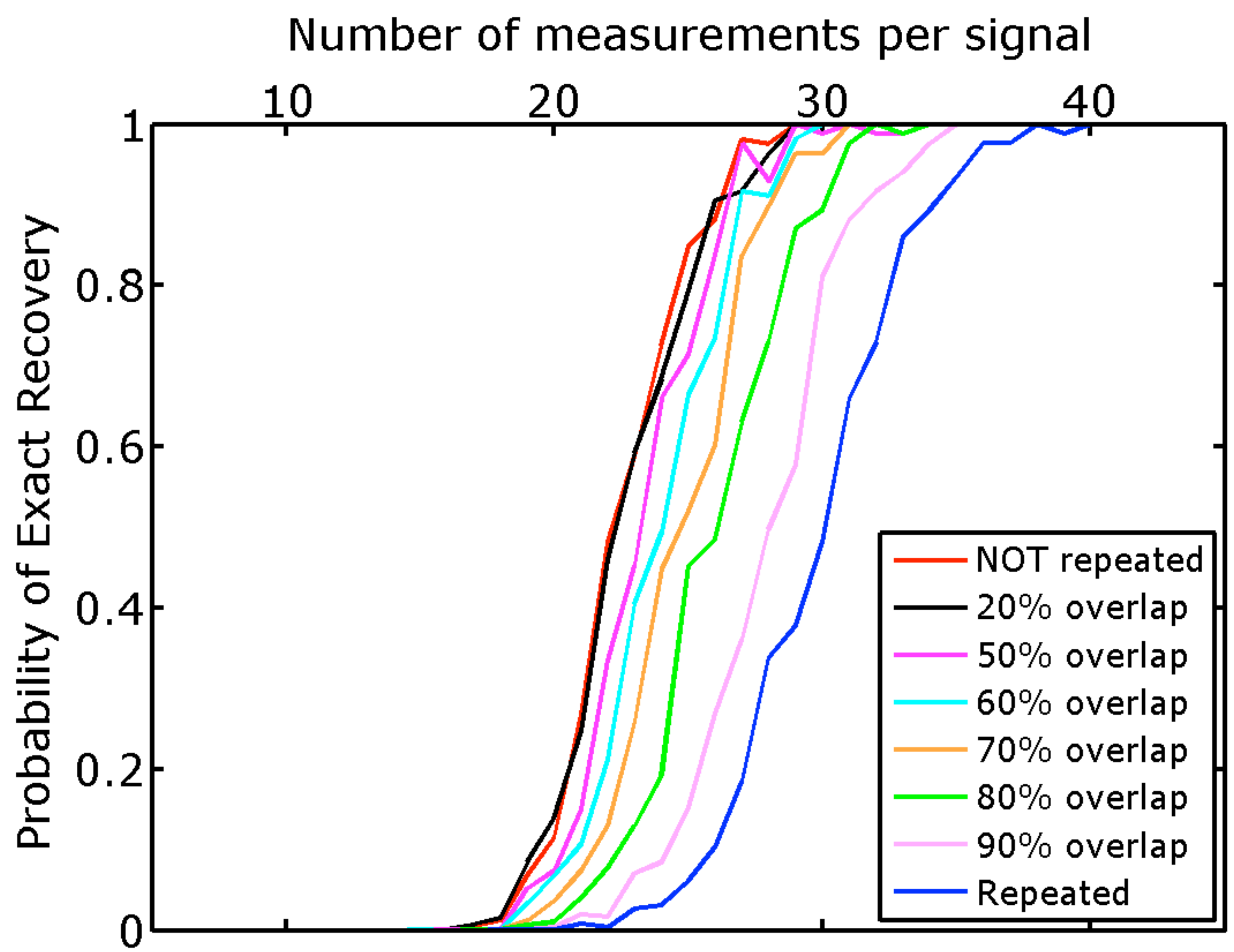


Recovery of the vintages

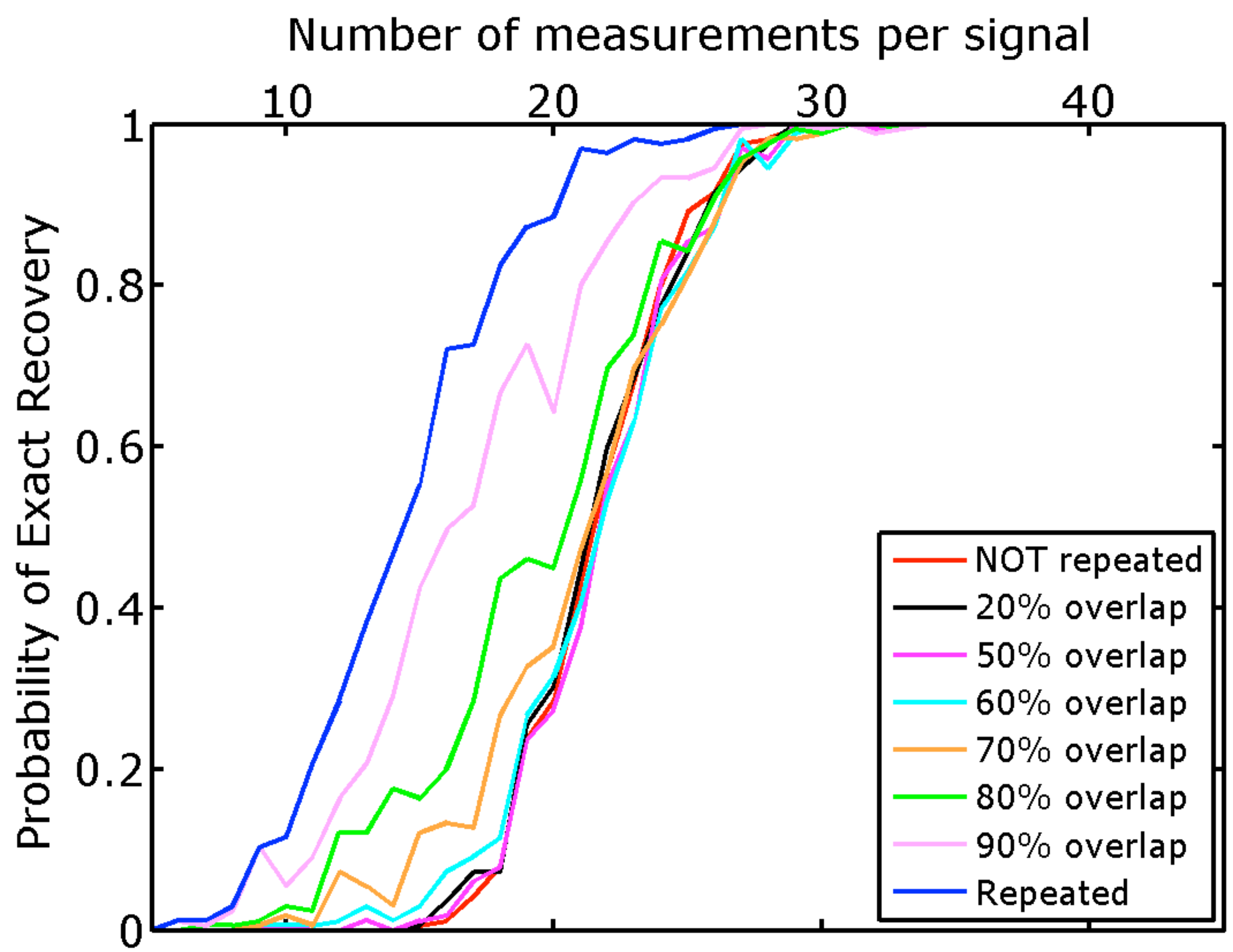


Recovery of the difference

Results : recovery and overlap dependency



Recovery of the vintages



Recovery of the difference

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...

Interpretation from the stylized example

The JRM gives better results than IRS

- *for the vintages*

As the degree of overlap between matrices ↑

- *the recovery of the signals gets worse.* ↓

Recovery of the difference is accurate for "exact" repetition (100% overlap)

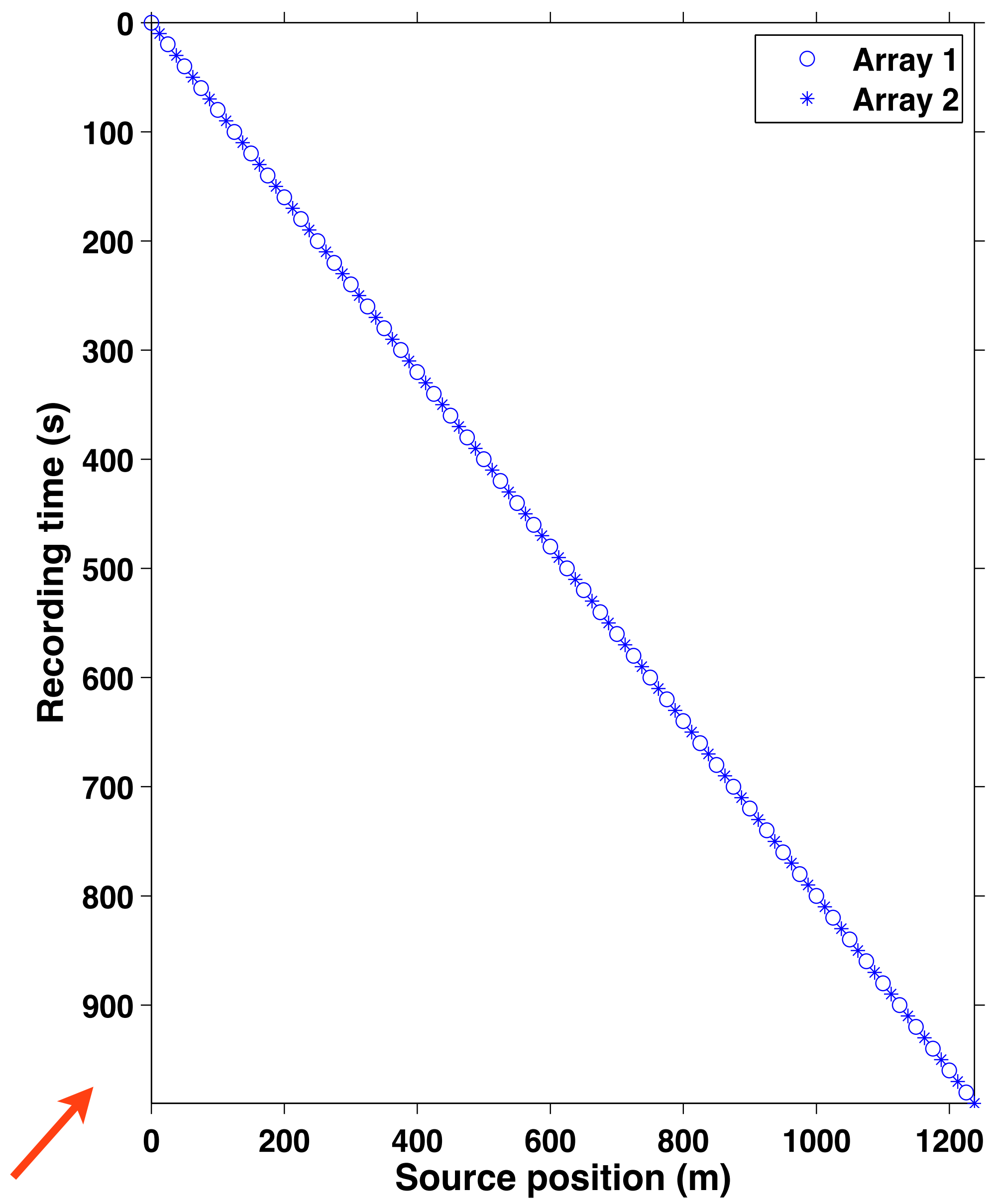
Time-jittered marine surveys

Haneet Wason

- *Symmetric measurements*
- *Assume fixed receiver array (e.g. OBCs or OBNs)*
- *Ignore noise*

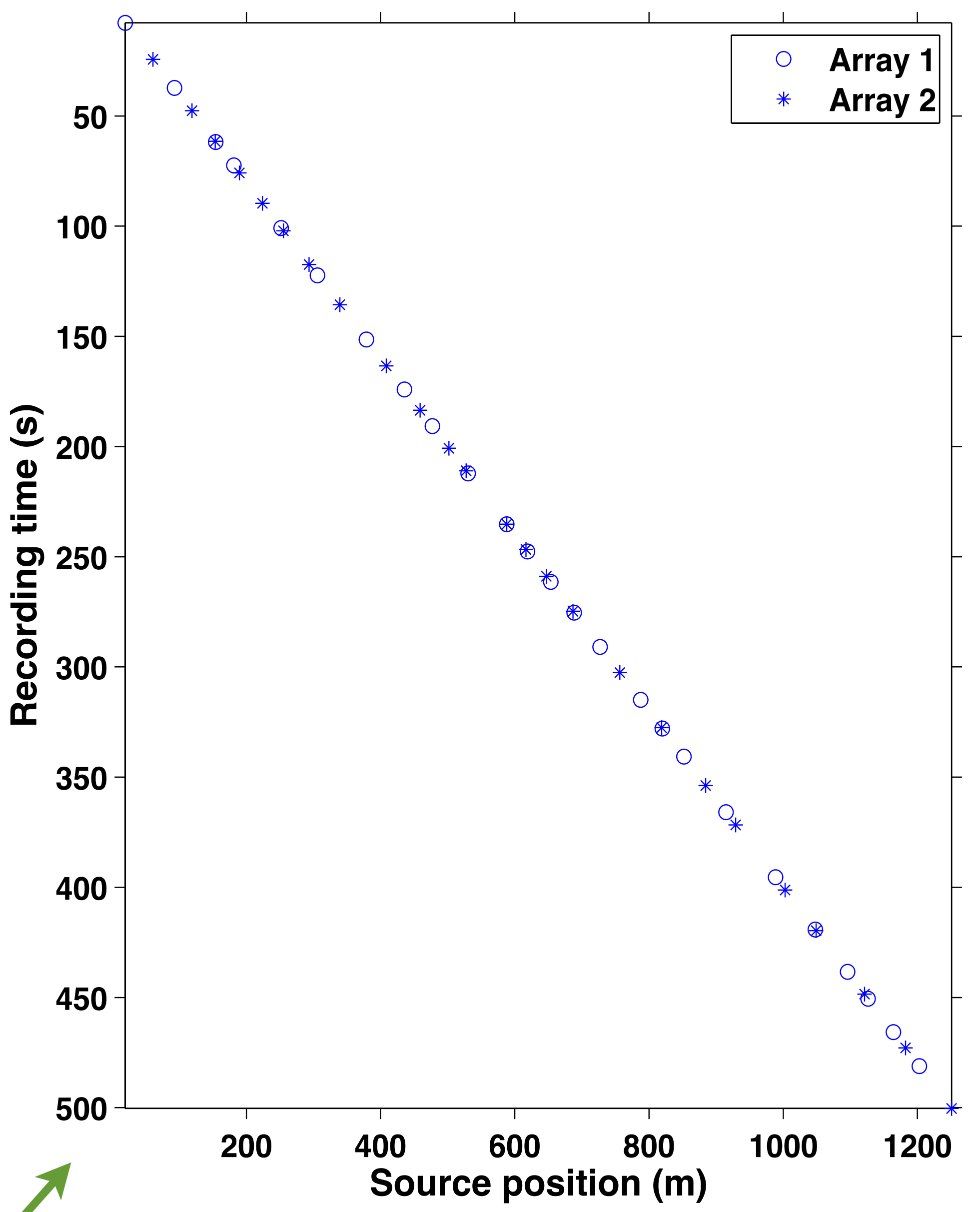
Conventional vs. *time-jittered* sources
– *under*sampling ratio = 2, 2 source arrays

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 x 10.0 = **1000.0 s**

jittered acquisition 1 (for baseline)



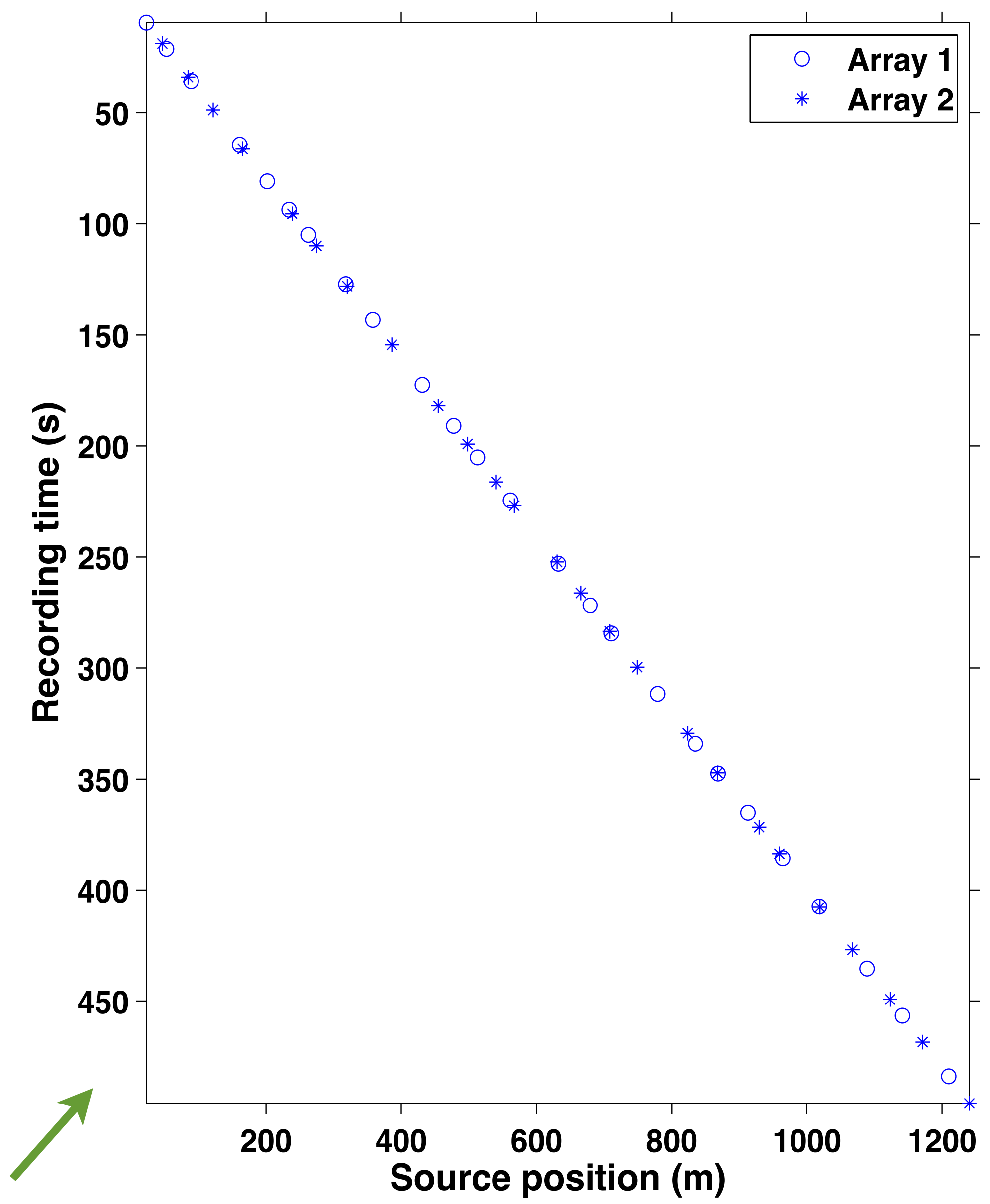
[BLENDING & UNDERSAMPLING]
spatial undersampling factor = 2

→

←

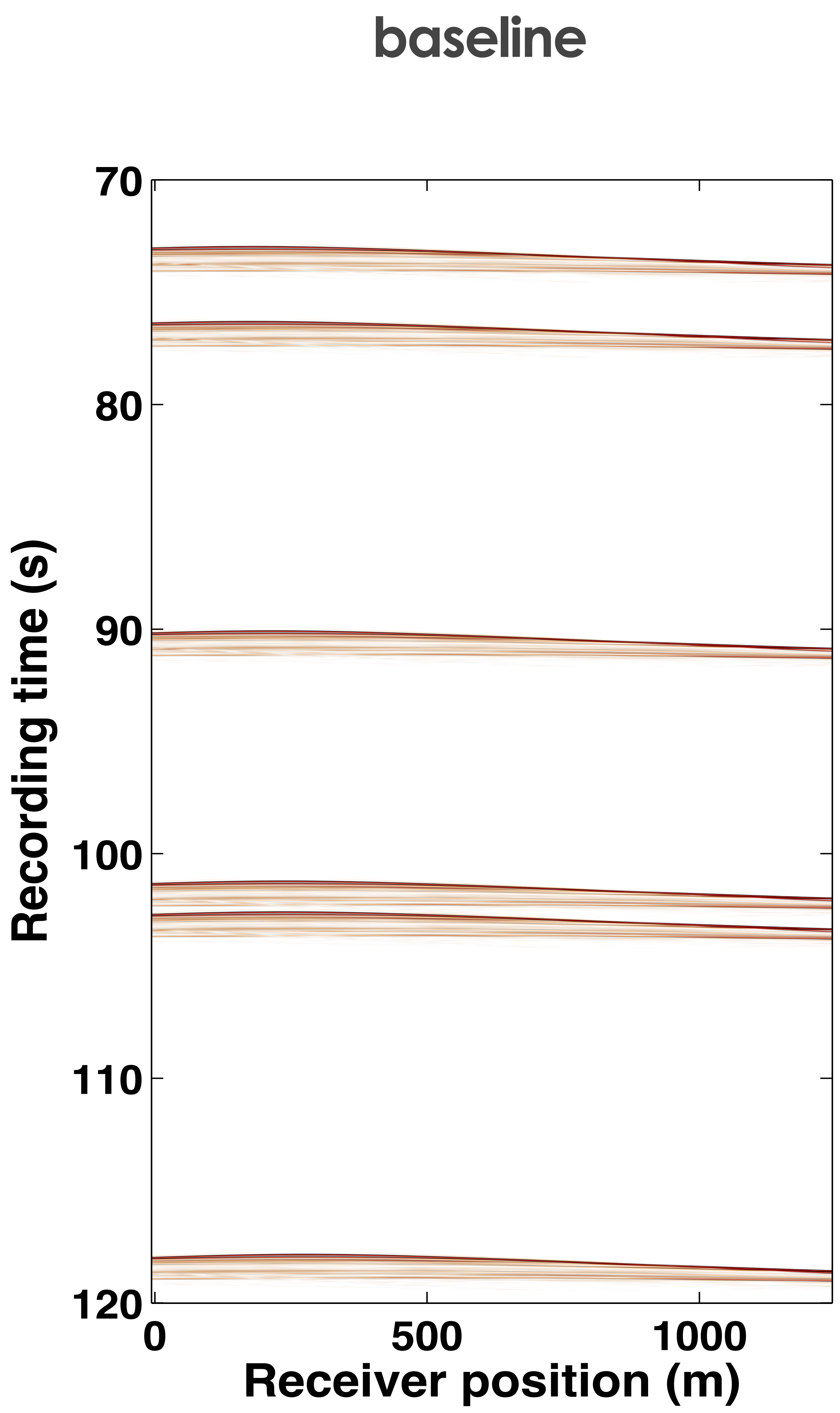
spatial sampling ***increase*** factor = 2
[DEBLENDING & INTERPOLATION]

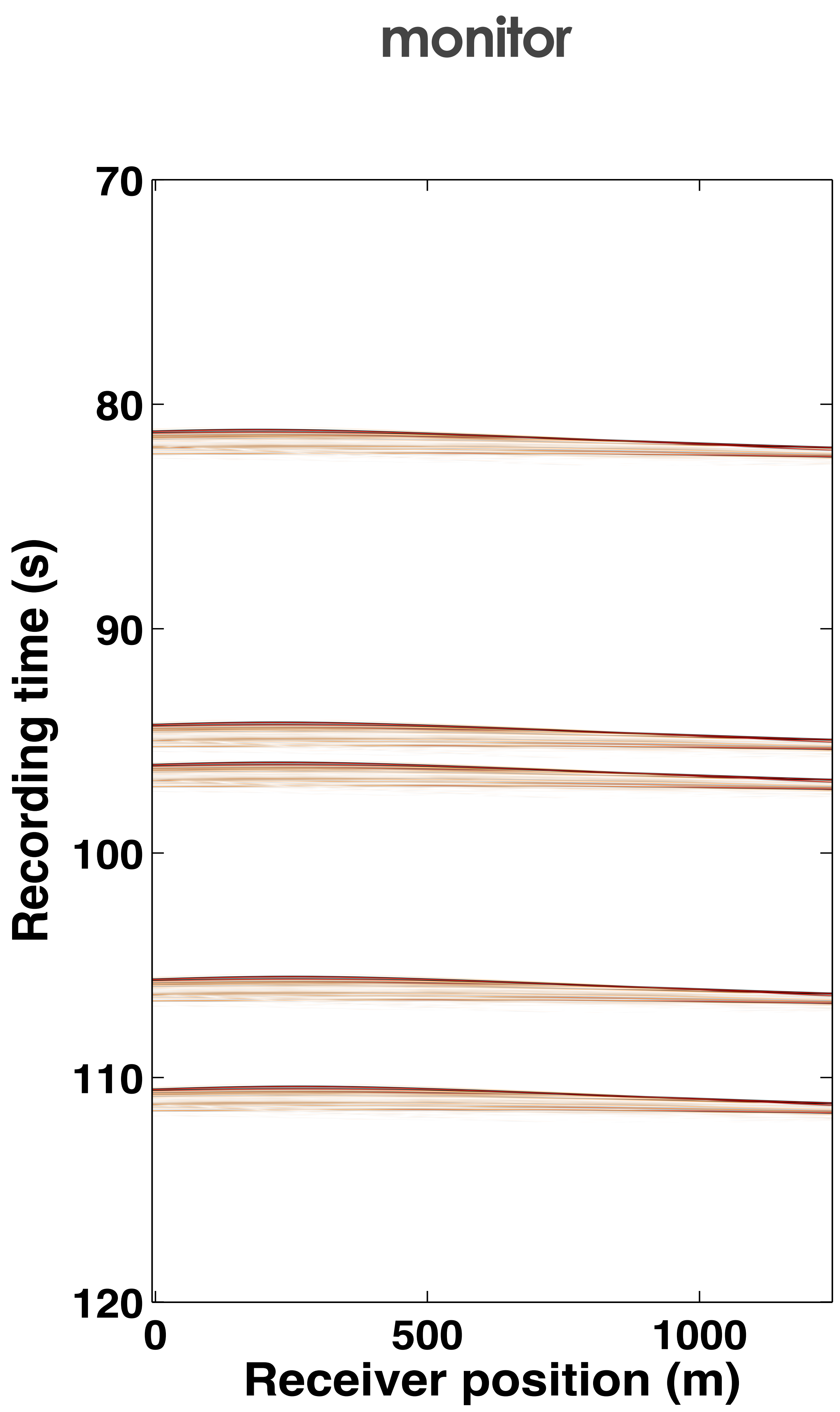
jittered acquisition 2 (for monitor)



***"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 ≈ 1000.0 s/2 = **500.0 s**

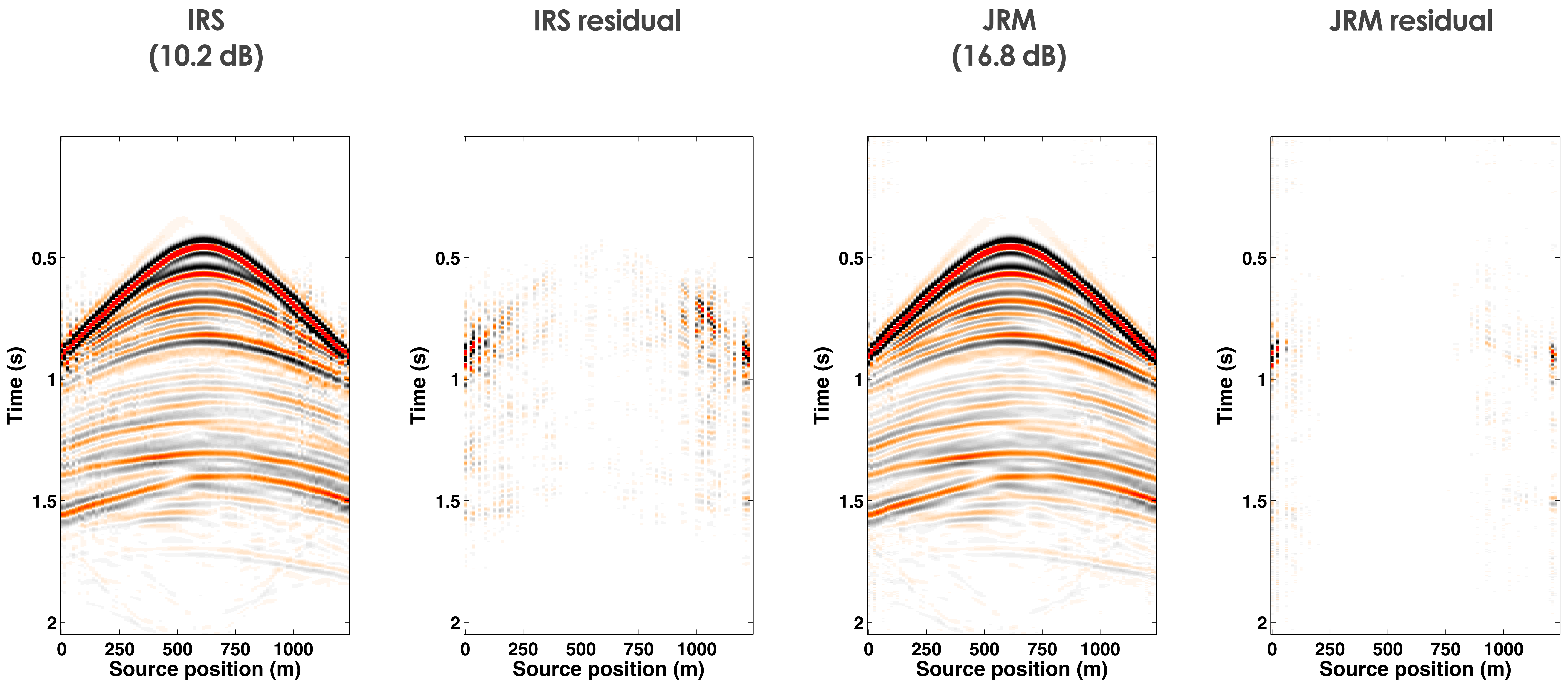
Measurements
– *undersampled* and *blended*





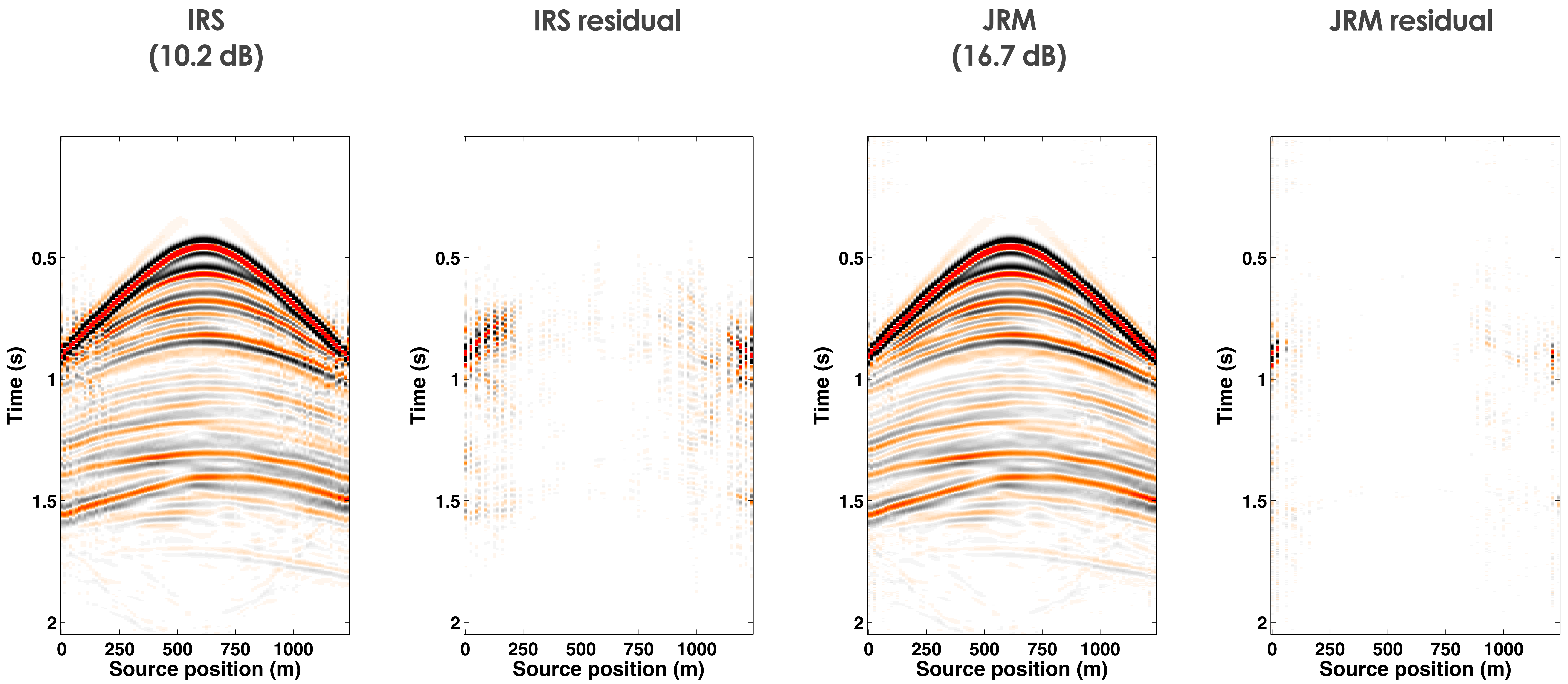
Baseline recovery

– 20% overlap in *acquisition* matrices



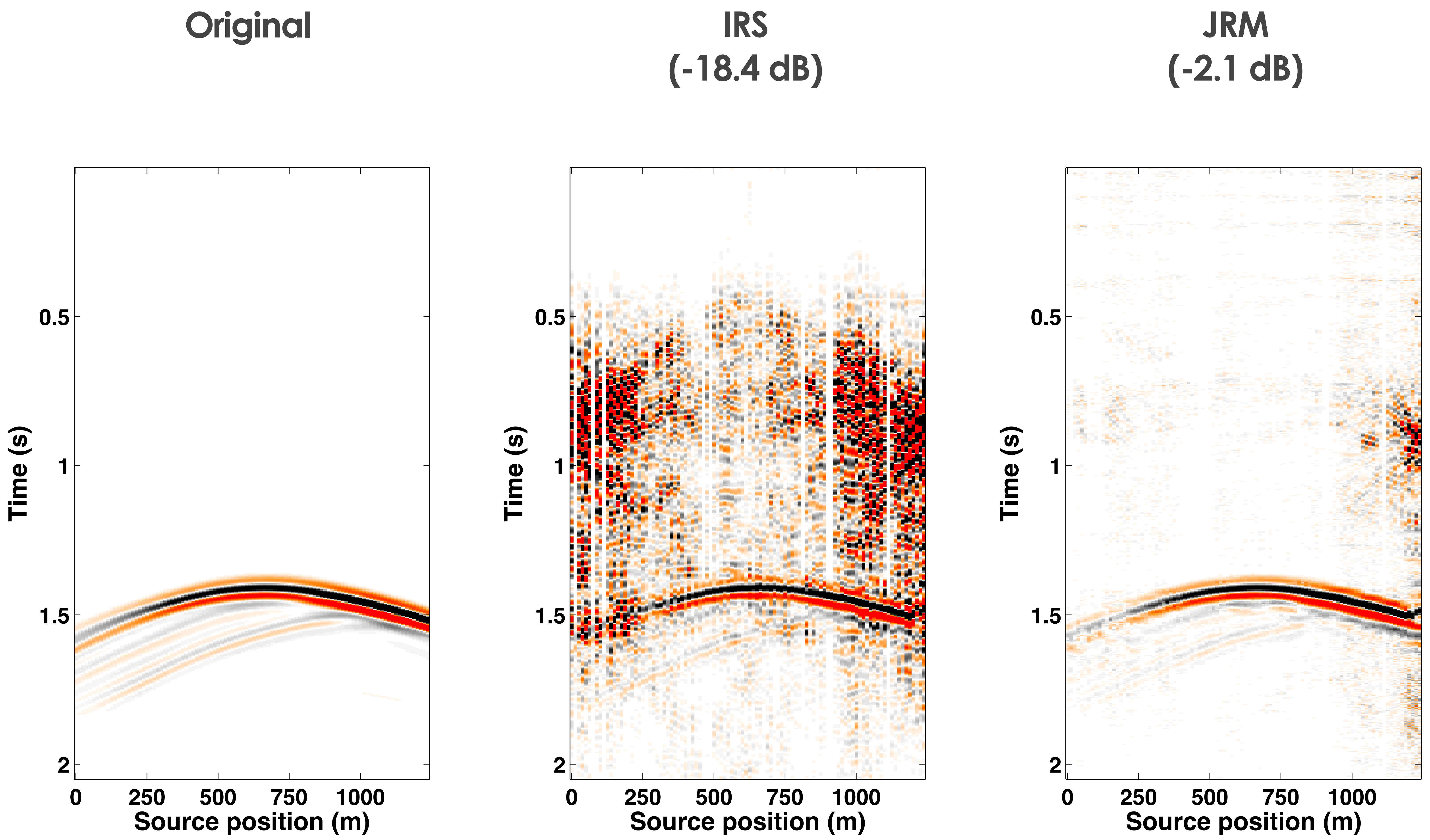
Monitor recovery

– 20% overlap in *acquisition* matrices



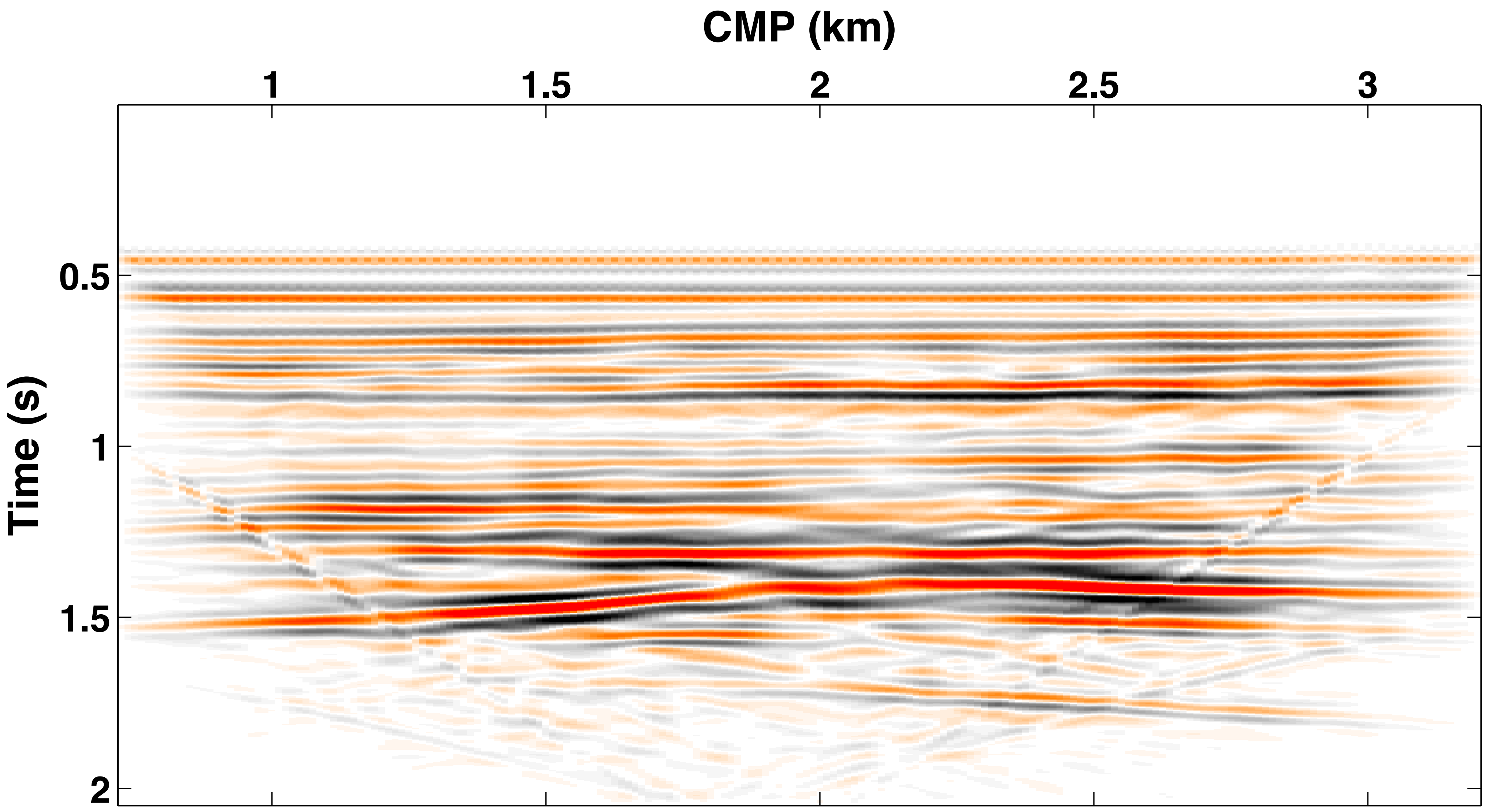
4-D recovery

– 20% overlap in *acquisition* matrices

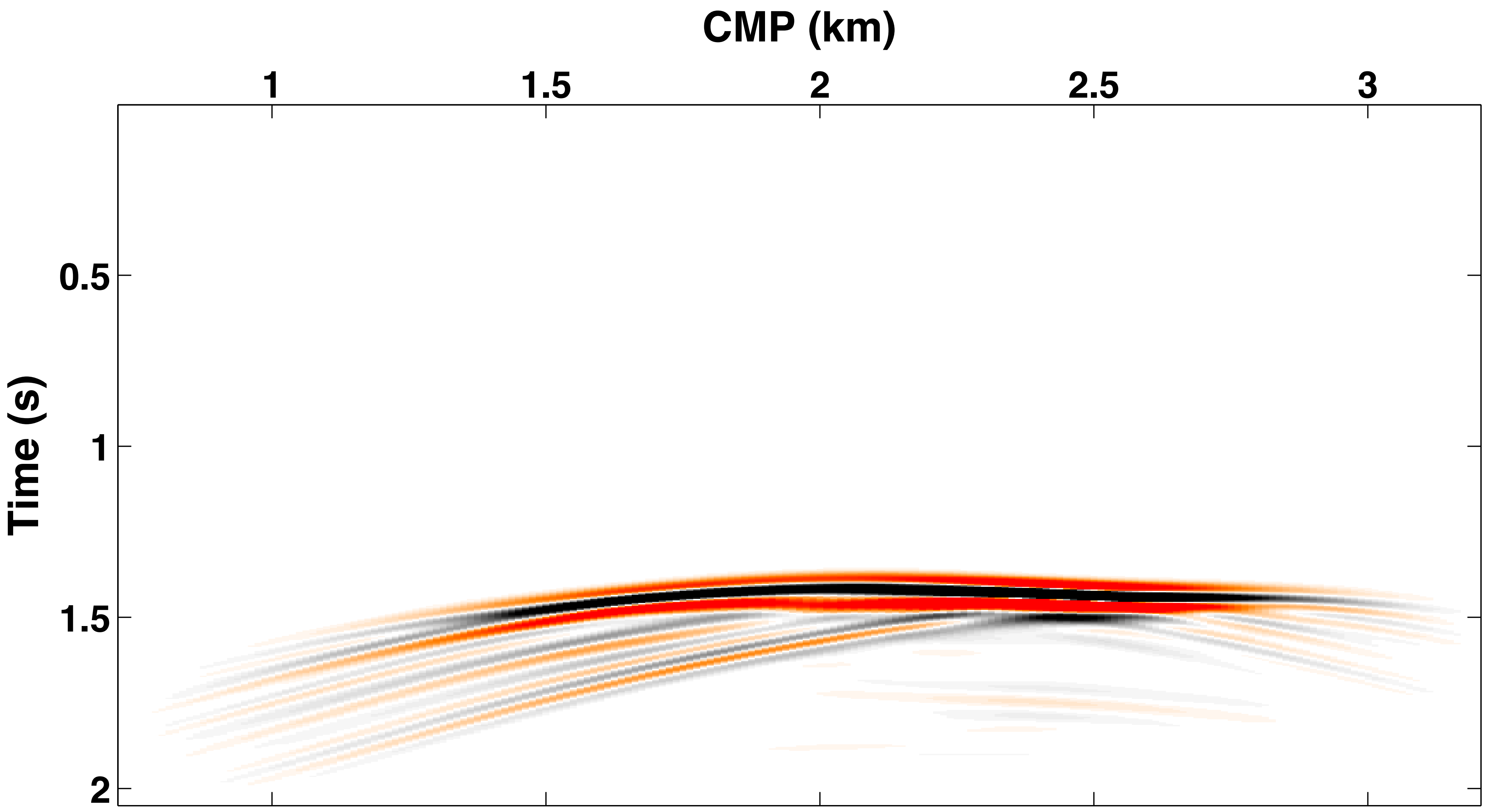


Stacked sections

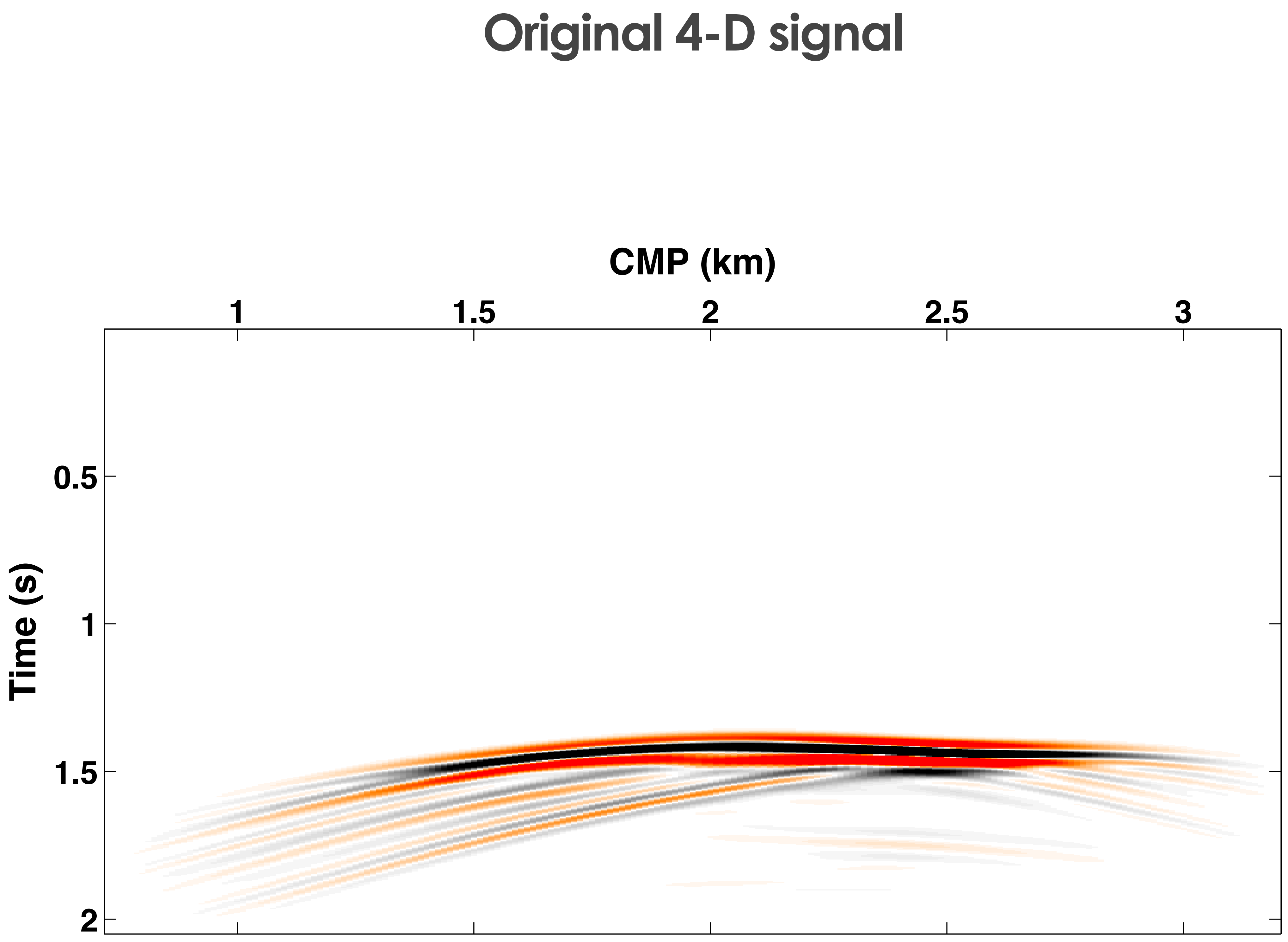
Original baseline

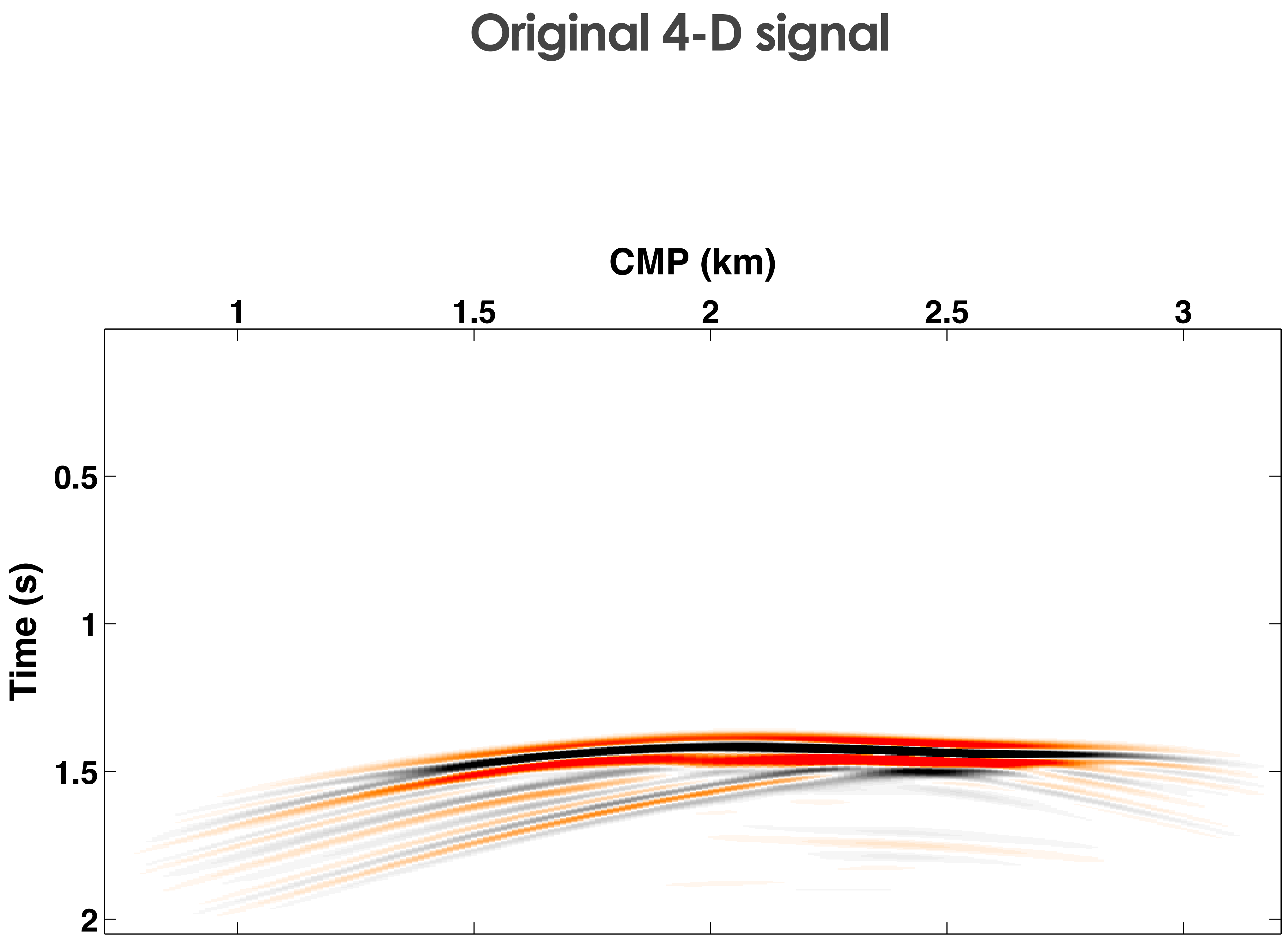


Original 4-D signal



Stacked sections

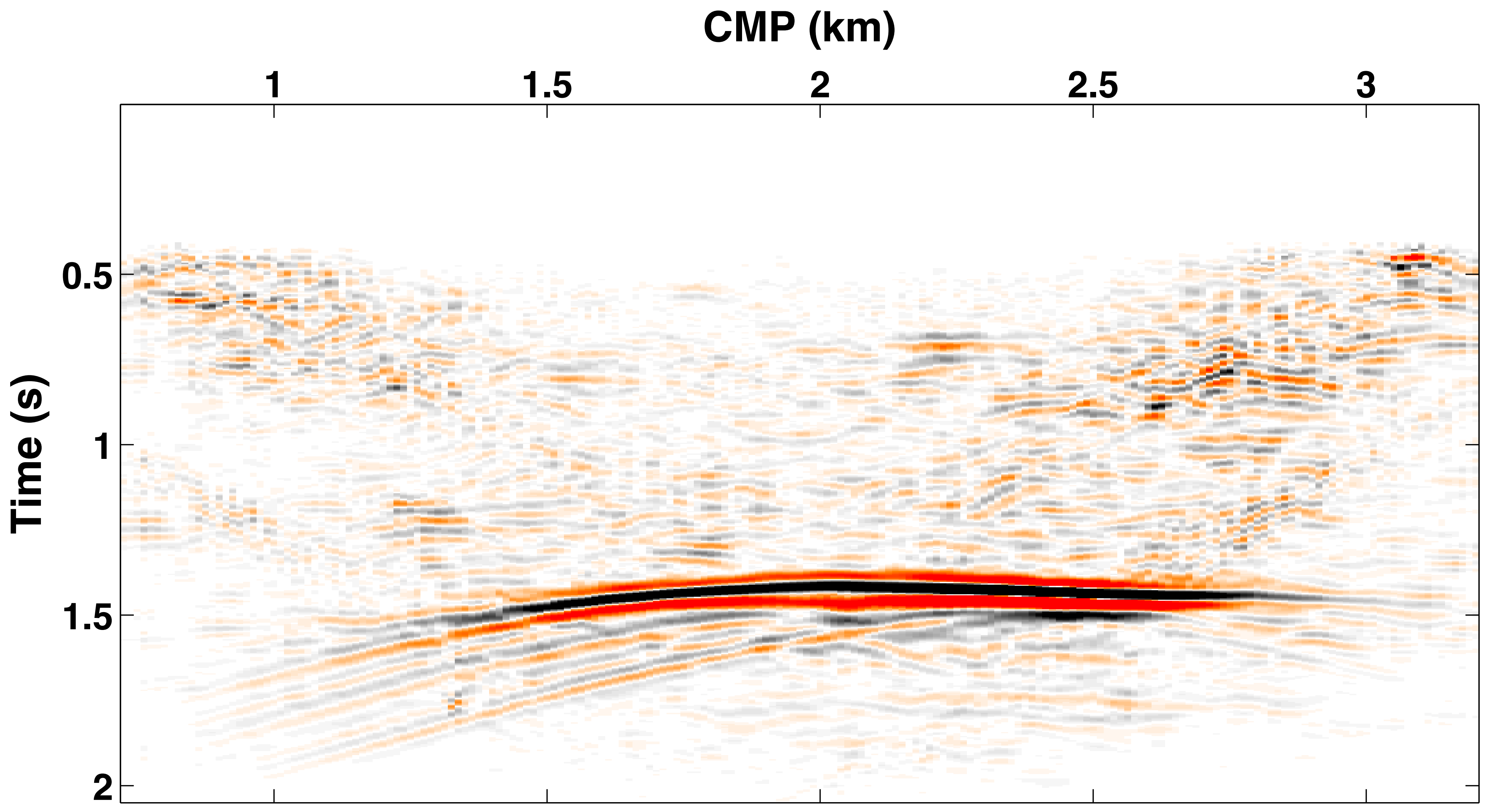




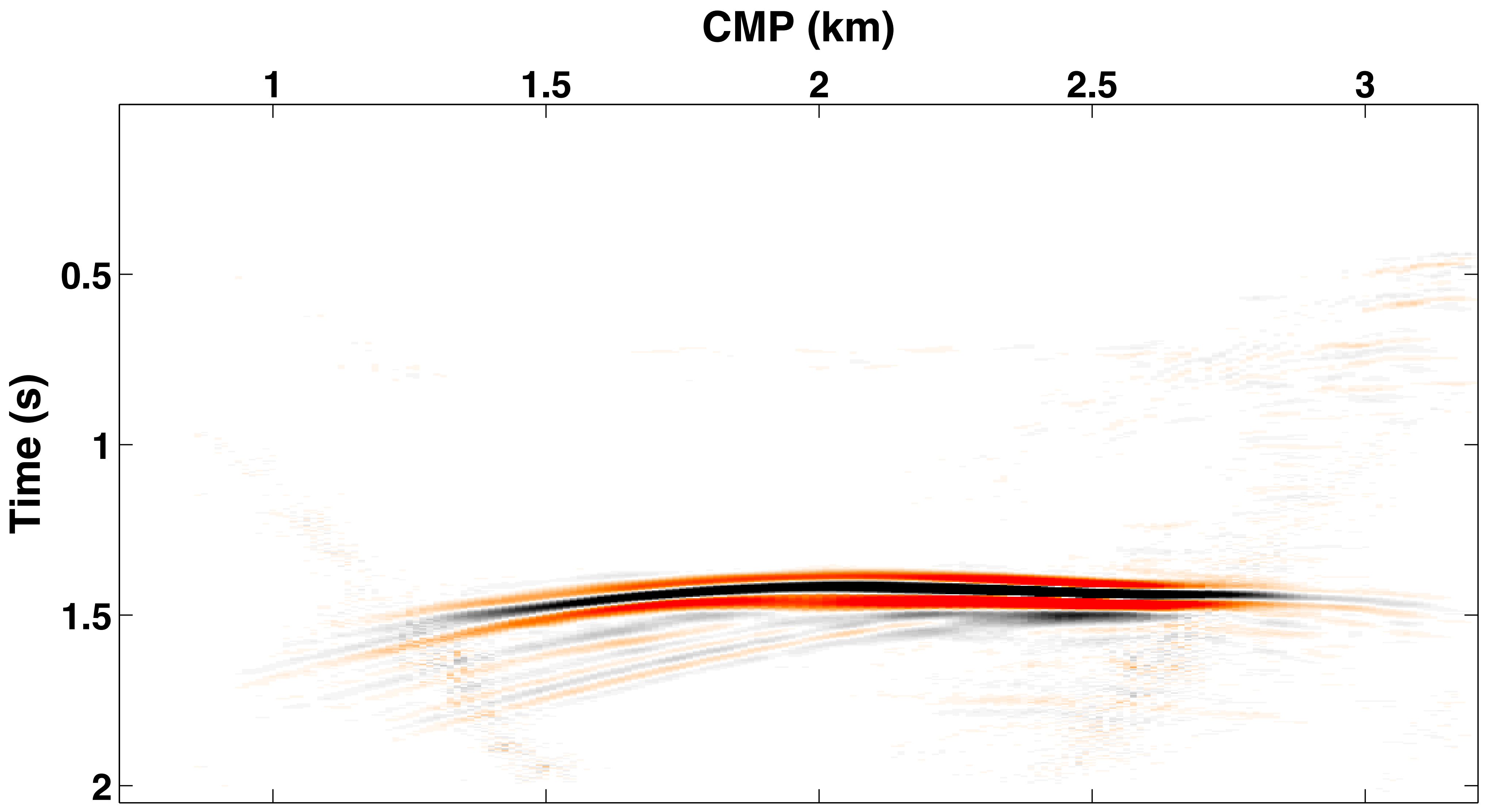
Stacked sections

– 20% overlap in *acquisition* matrices

IRS
(10.2 dB)



JRM
(14.7 dB)



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General remarks

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

From stylized examples, sufficient sampling without high degree of repetition can help recover the vintages and differences with high probability

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

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 provided there is sufficient measurements*

Acknowledgements

Thank you for your attention !

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

SINBAD

NSERC CRSNG

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