SEG DENVER 2014

# Randomized sampling "*without repetition*" in time-lapse seismic surveys

Felix Oghenekohwo

SLIM
University of British Columbia

# Randomized sampling “*without repetition*” in time-lapse seismic surveys

Felix Oghenekohwo

**Team** : Rajiv Kumar, Haneet Wason, Ernie Esser, Felix Herrmann

SLIM
University of British Columbia

SEG DENVER 2014

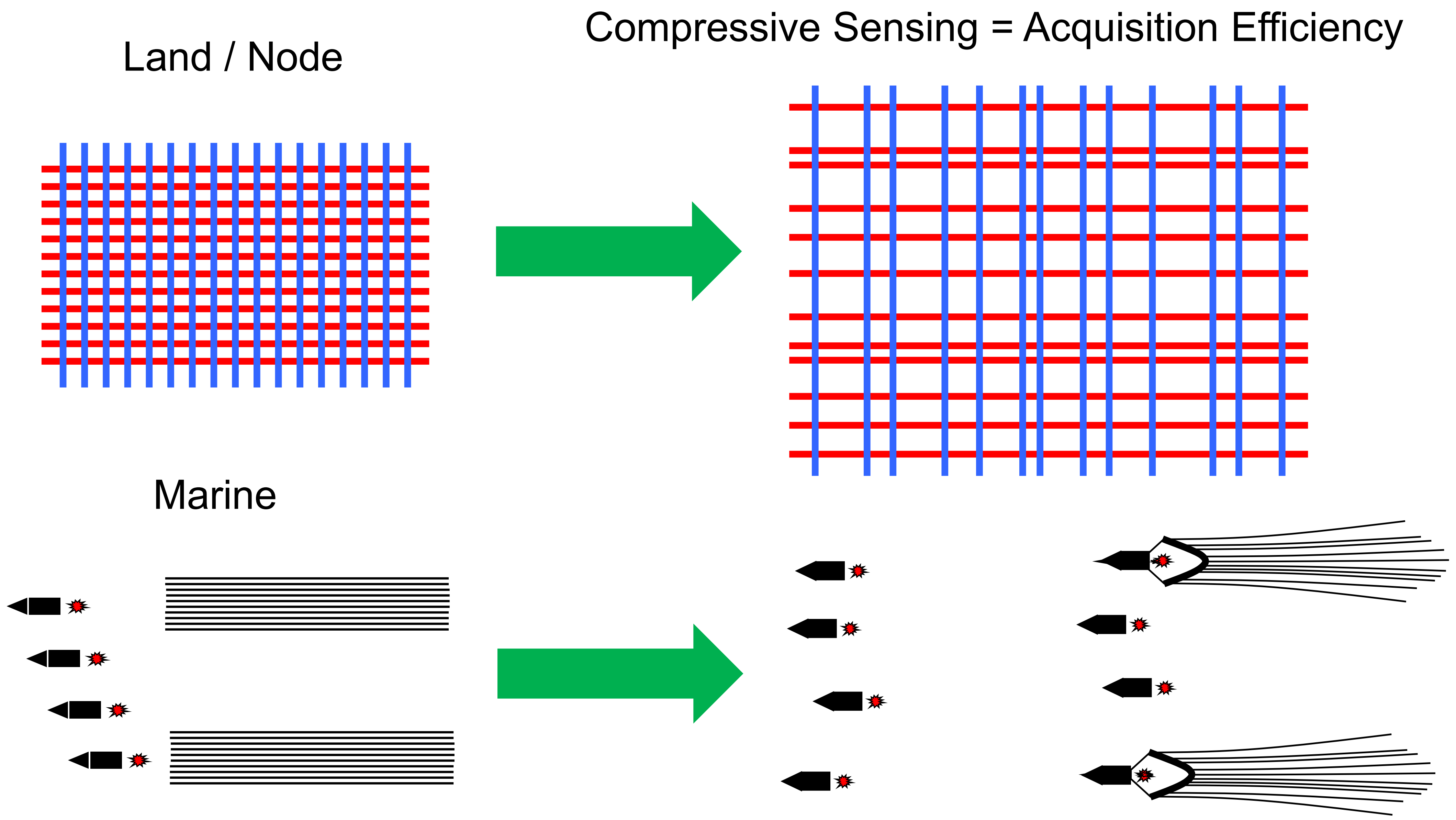
Mosher, C. C., Keskula, E., Kaplan, S. T., Keys, R. G., Li, C., Ata, E. Z., ... & Sood, S. (2012, November). Compressive Seismic Imaging. In *2012 SEG Annual Meeting*. Society of Exploration Geophysicists.

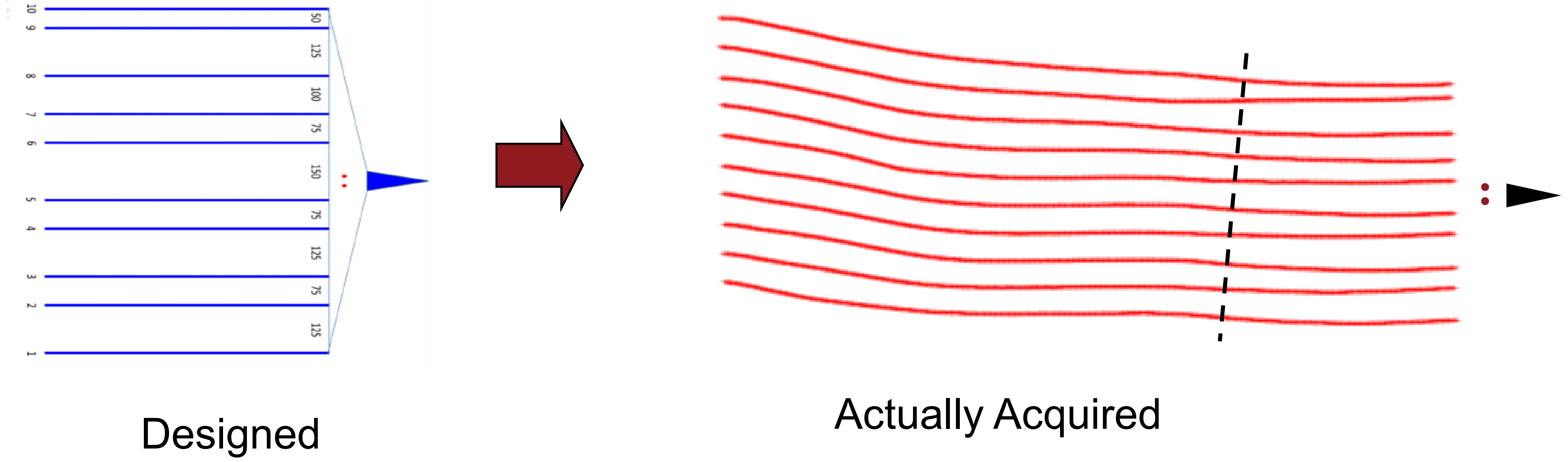
# *Randomized* undersampling

## – examples from industry (ConocoPhilips)

Deliberate & natural randomness in acquisition

(thanks to Chuck Mosher)



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.

SLIM

# 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*

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.

SLIM

# 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

# Framework

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

sampling matrix

observed subsampled measurements

**Sparsity-promoting recovery**

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

# Framework in 4-D

$$\mathbf{A}_1\mathbf{x}_1 = \mathbf{b}_1$$ ← subsampled baseline data

$$\mathbf{A}_2\mathbf{x}_2 = \mathbf{b}_2$$ ← subsampled monitor data

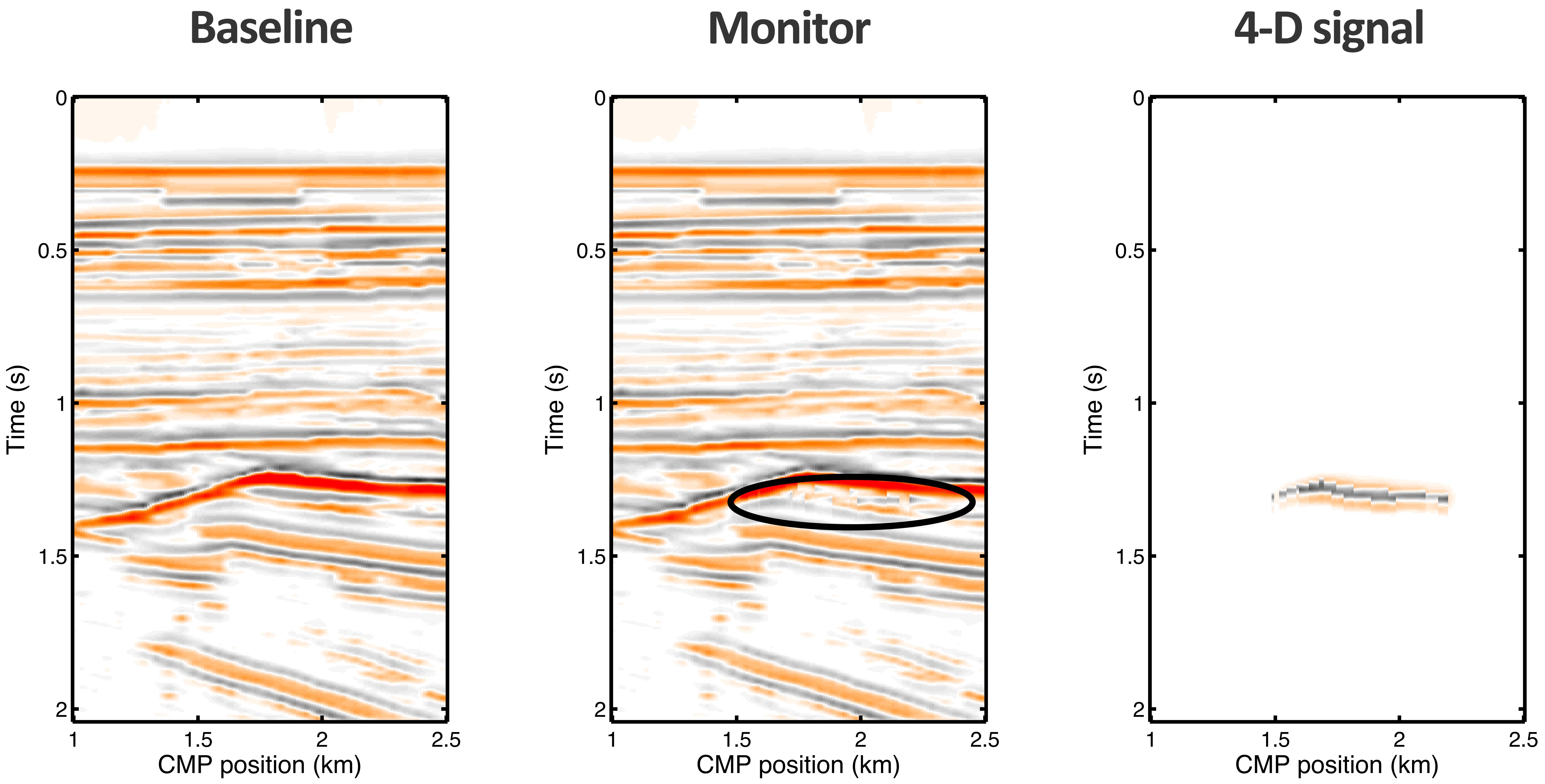
$$\text{should } \mathbf{A}_1 = \mathbf{A}_2 \text{ ?}$$

$$\text{what if } \mathbf{A}_1 \approx \mathbf{A}_2 \text{ ?}$$

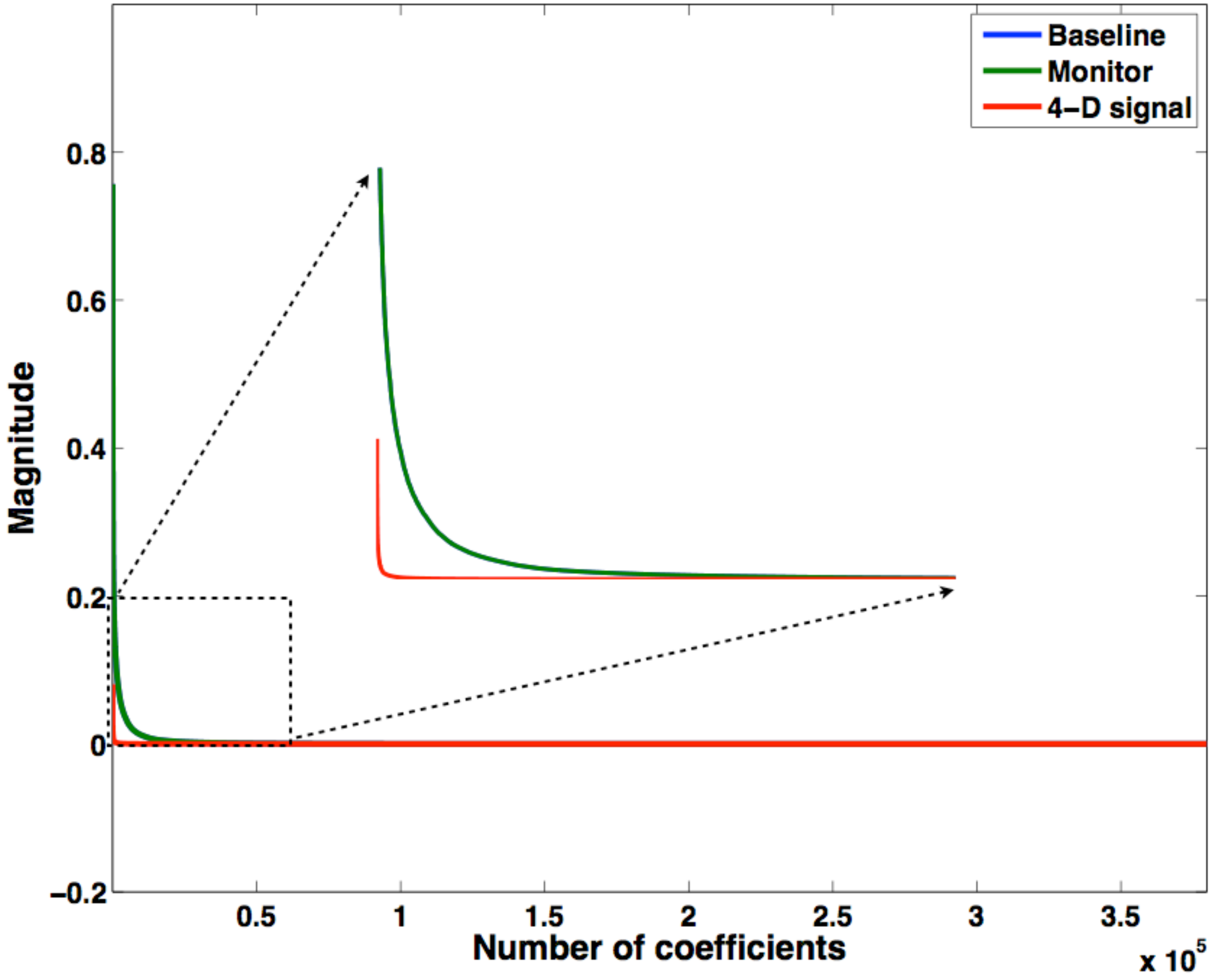
$$\text{what if } \mathbf{A}_1 \neq \mathbf{A}_2 \text{ ?}$$

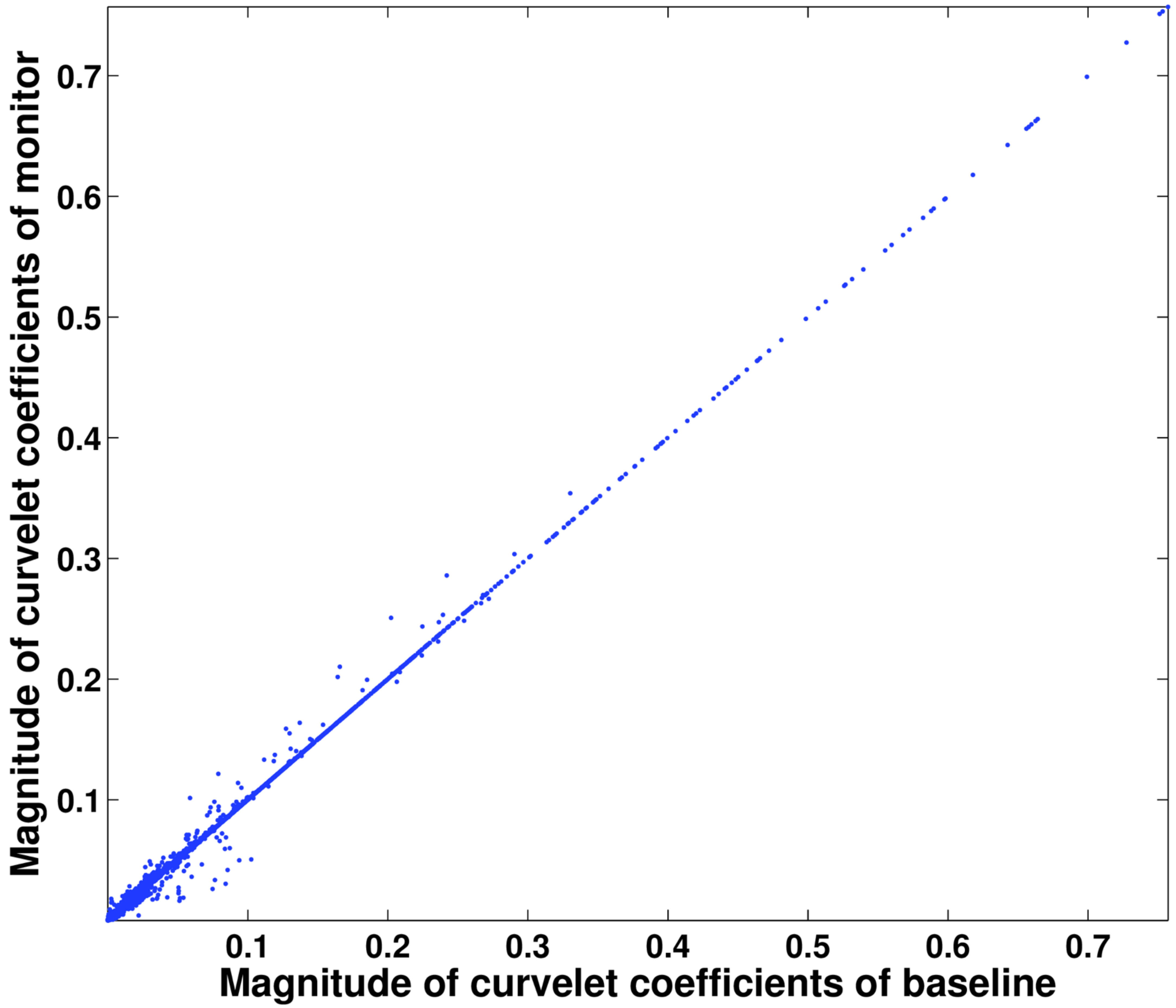
**Question** : To repeat survey design or not

# Idealized synthetic time-lapse data



# Structure - curvelet representation



# Observations

Time-lapse data has structure - significant correlations

*4-D signal has structure - increased sparsity*

Can we exploit the structure in the vintages and the difference simultaneously ?

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***

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

$\mathbf{z}_1$, $\mathbf{z}_2$ → ***differences***

$\mathbf{z}_0$ → ***common** component*

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

$\mathbf{b}_1$ → ***baseline***

$\mathbf{b}_2$ → ***monitor***

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*

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

*differences*

*common* component

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

*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

# Sparsity-promoting recovery

Joint recovery model (JRM)

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

Independent reconstruction

$$\tilde{\mathbf{x}}_i = \arg\min_{\mathbf{x}_i} \|\mathbf{x}_i\|_1 \quad \text{subject to} \quad \mathbf{A}_i\mathbf{x}_i = \mathbf{b}_i, \text{ for } i = 1, 2$$

# *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...

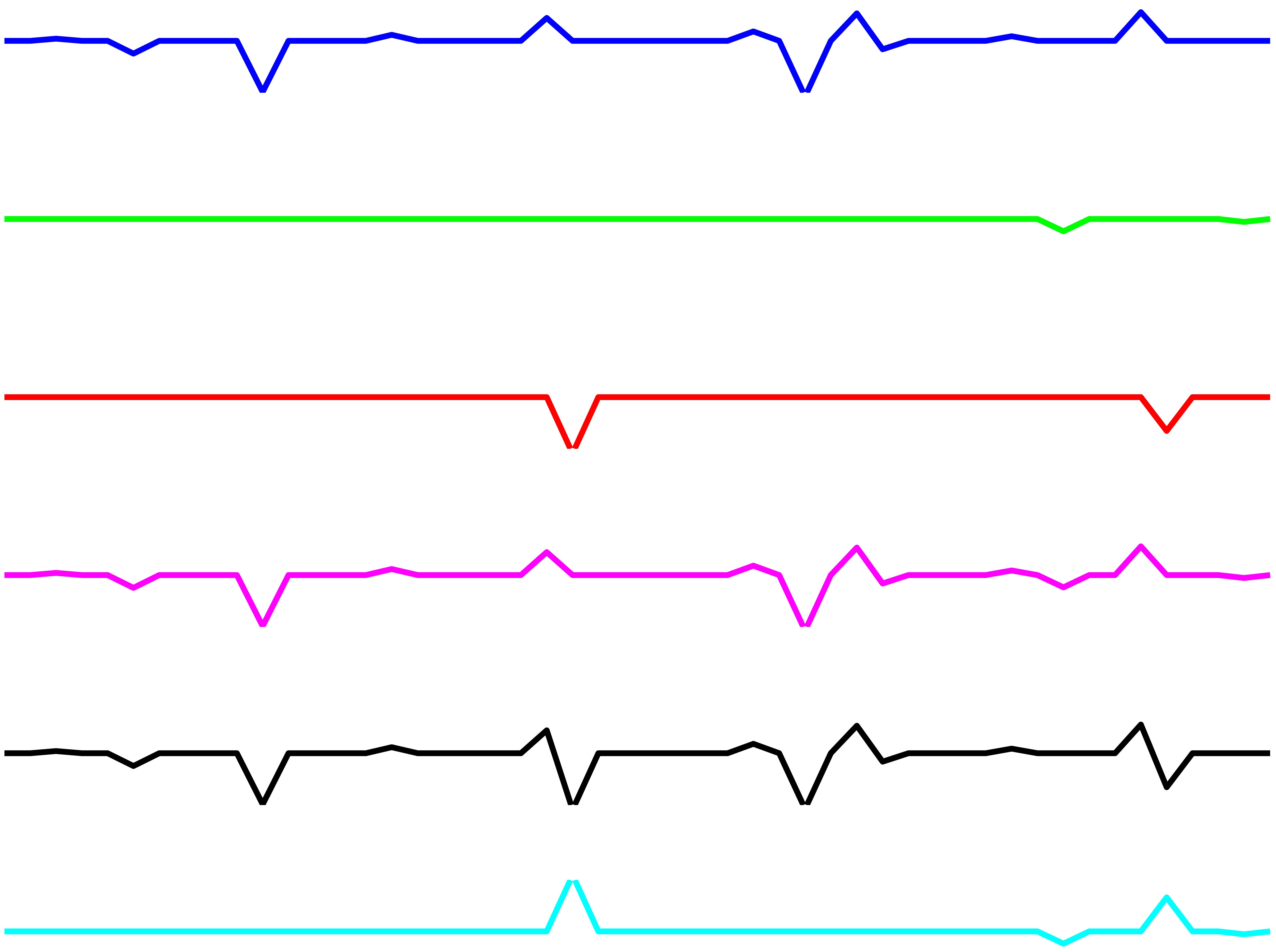
## *Interpretation of the model*
### – w/ & w/o repetition

- **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



$\mathbf{z}_0$ *common component*

$\mathbf{z}_1$ *"difference"*

$\mathbf{z}_2$ *"difference"*

$\mathbf{x}_1$ *baseline*

$\mathbf{x}_2$ *monitor*

$\mathbf{x}_1 - \mathbf{x}_2$ *time-lapse*

*Signal length N = 50*

## *Stylized* experiments

Conduct *many* CS experiments to compare

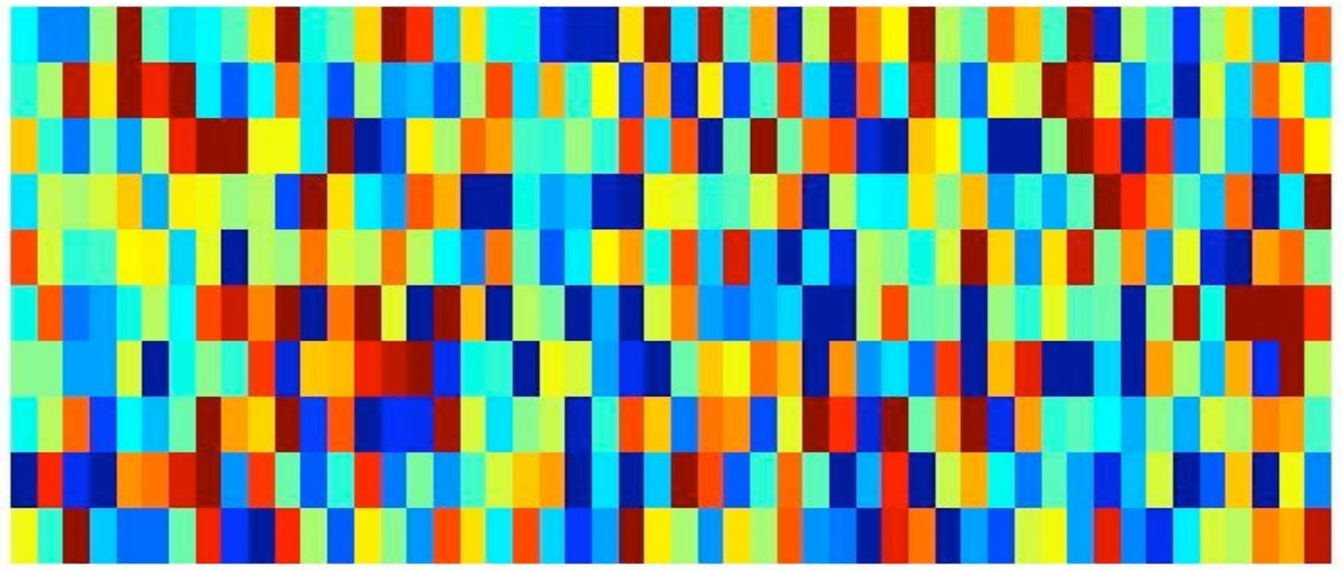
- *joint* vs *parallel* recovery of signals and the difference
- recovery with *completely* independent $\mathbf{A}_1,\ \mathbf{A}_2$
- *random* acquisition with different numbers of samples

# *Stylized* experiments

Conduct *many* CS experiments to compare

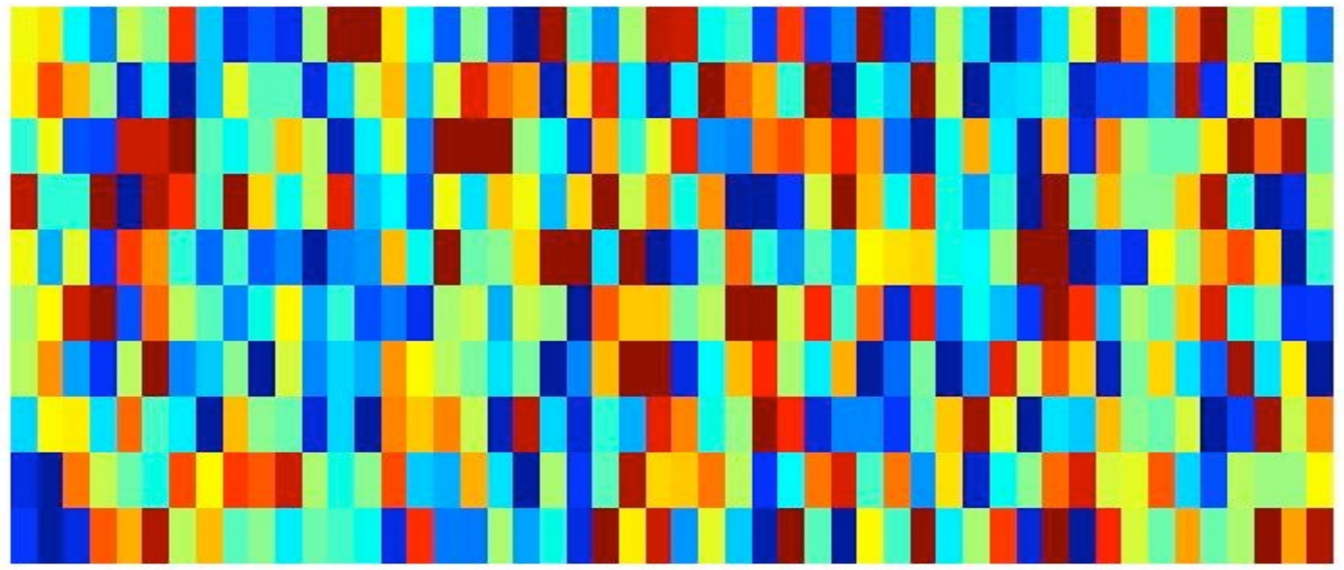
- *joint* vs *parallel* recovery of signals and the difference
- recovery with *completely* independent $\mathbf{A}_1,\ \mathbf{A}_2$
- *random* acquisition with different numbers of samples

$\mathbf{A}_1$



$\mathrm{n} = 10$

$\mathbf{A}_2$



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

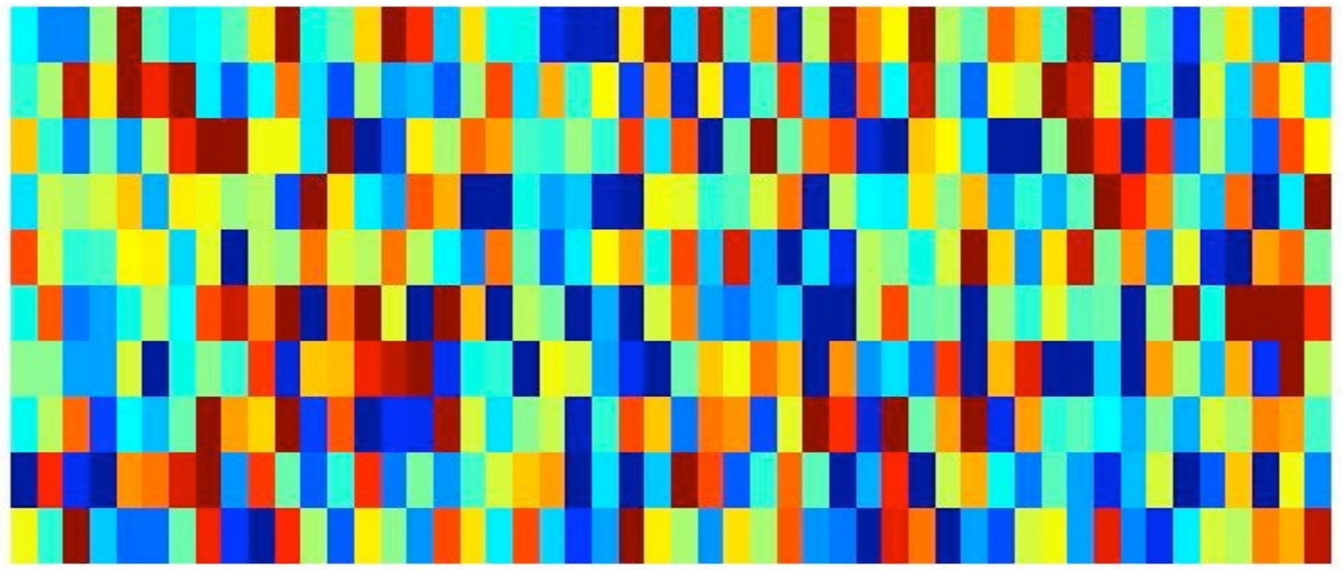
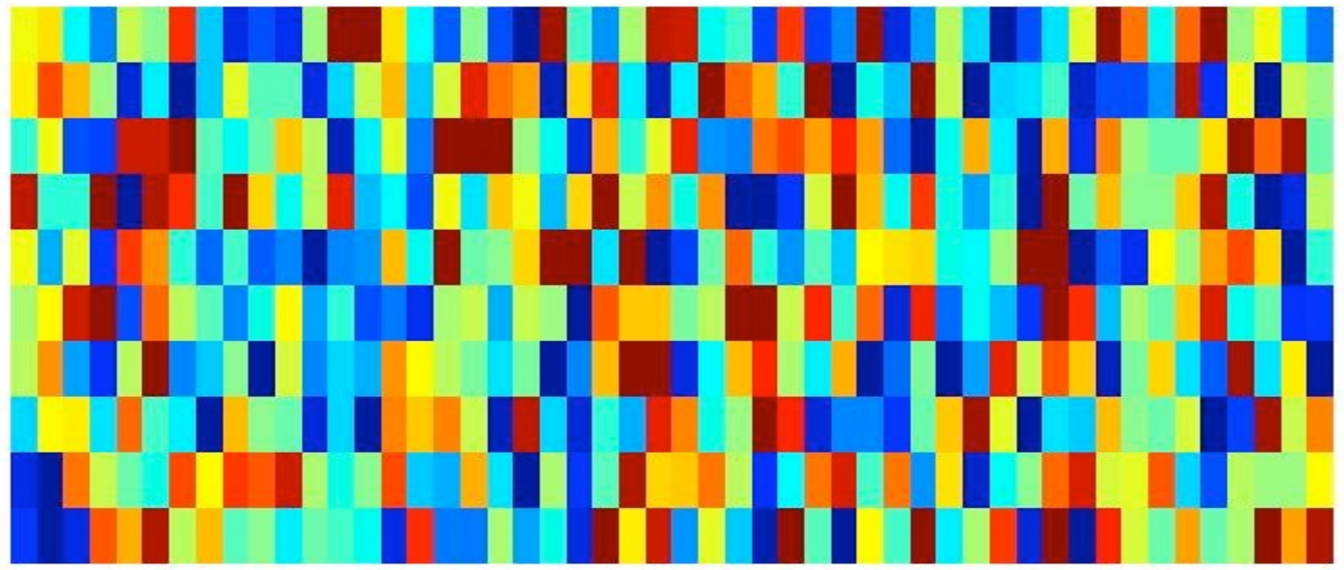
$\mathbf{b}_2 = \mathbf{A}_2\mathbf{x}_2$

# *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

$\mathbf{A}_1$ $\quad$ $\mathrm{n} = 10$ $\quad$ $\mathbf{A}_2$

n  n 

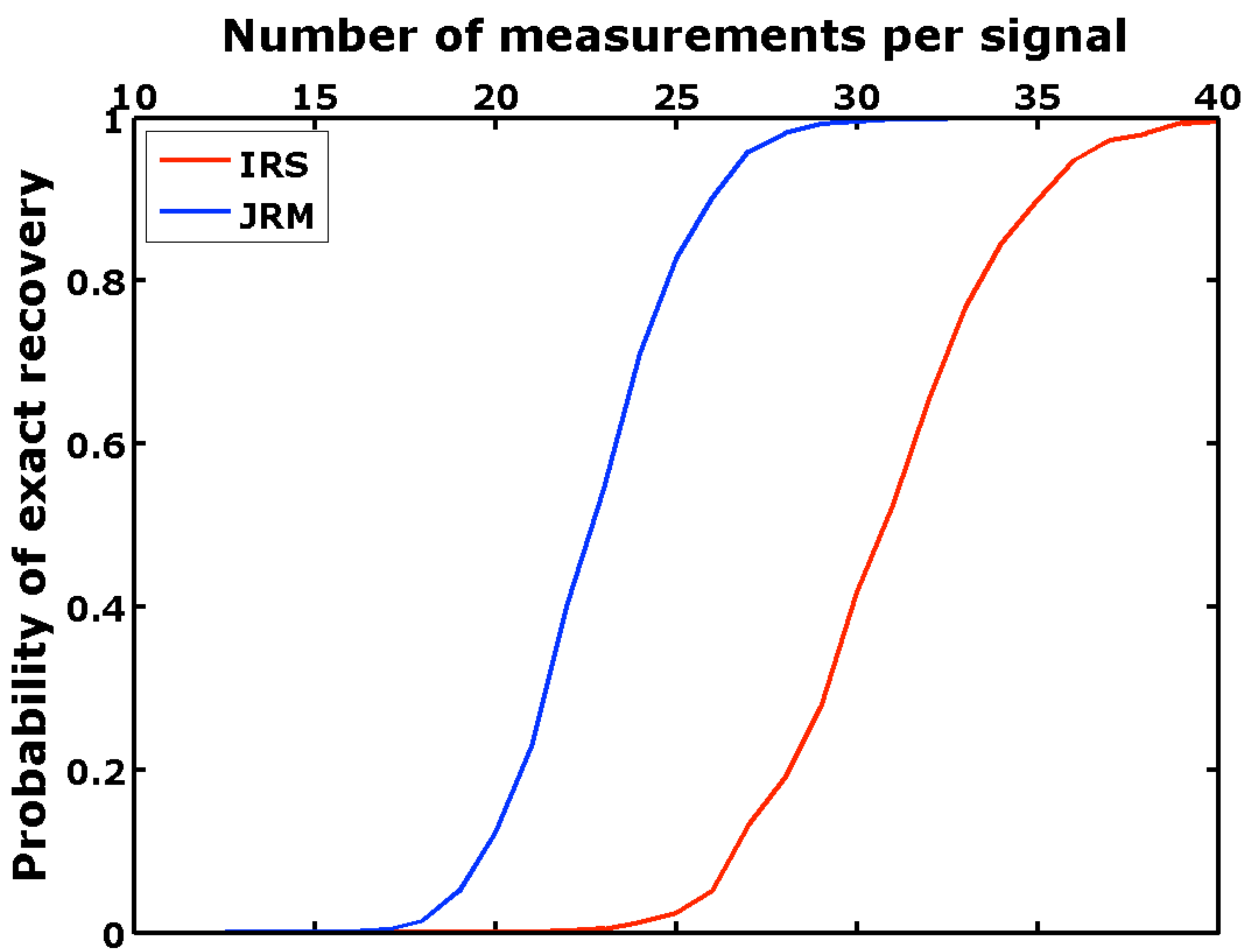
N $\quad$ N

$\mathbf{b}_1 = \mathbf{A}_1\mathbf{x}_1$ $\quad$ $\mathbf{b}_2 = \mathbf{A}_2\mathbf{x}_2$

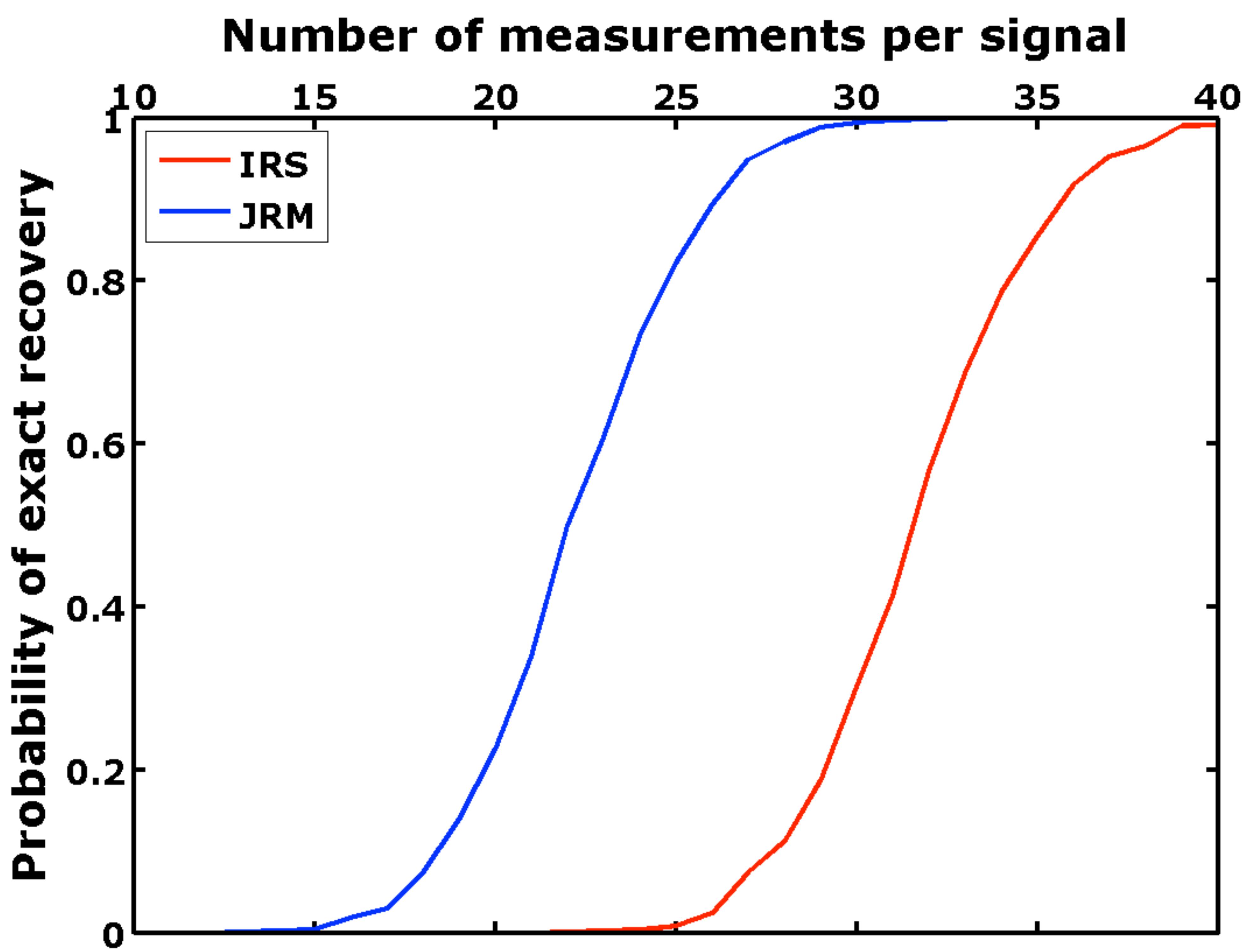
Run 2000 different experiments

Compute Probability of recovery

# Results: *independent* versus *joint* recovery




Recovery of vintages




Recovery of difference

# Observations

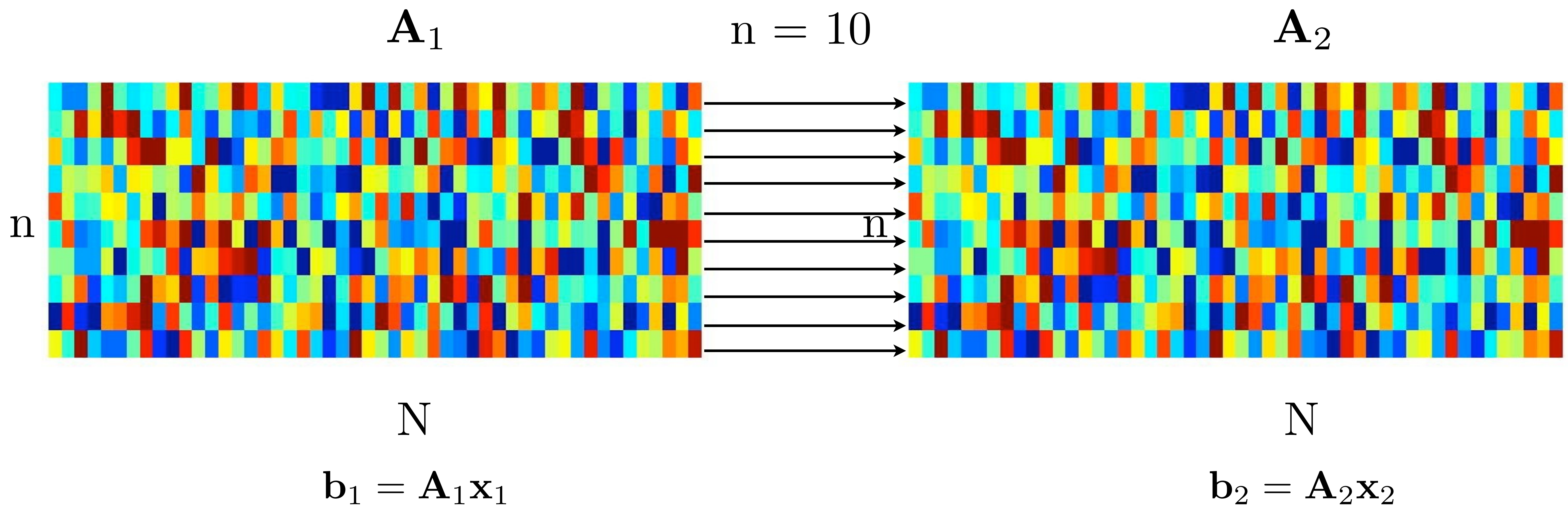
Joint recovery is better than independent

Improved recovery of the vintages and the difference

Requires fewer samples

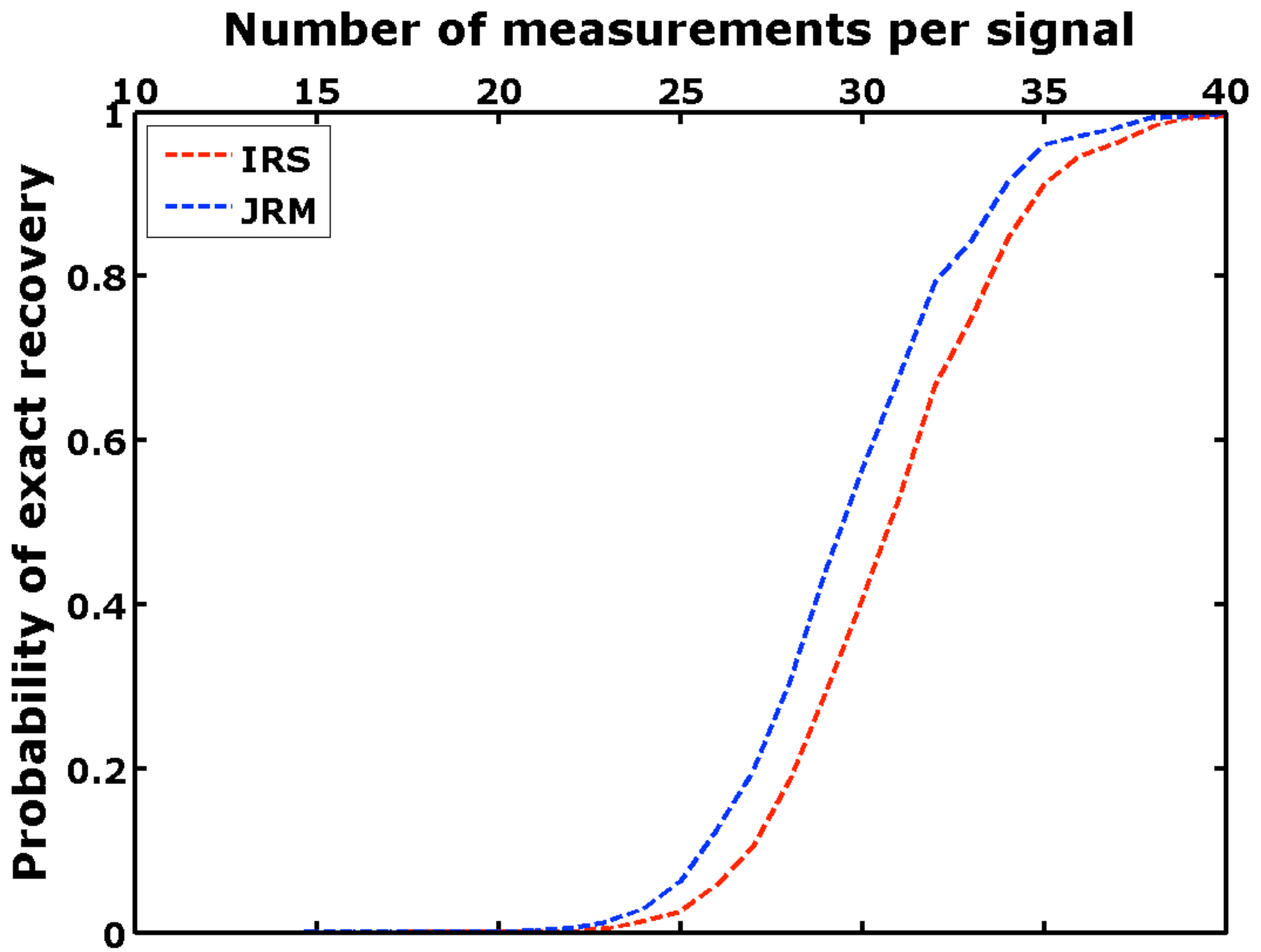
## With exact repetition

$$\mathbf{A}_1 = \mathbf{A}_2$$

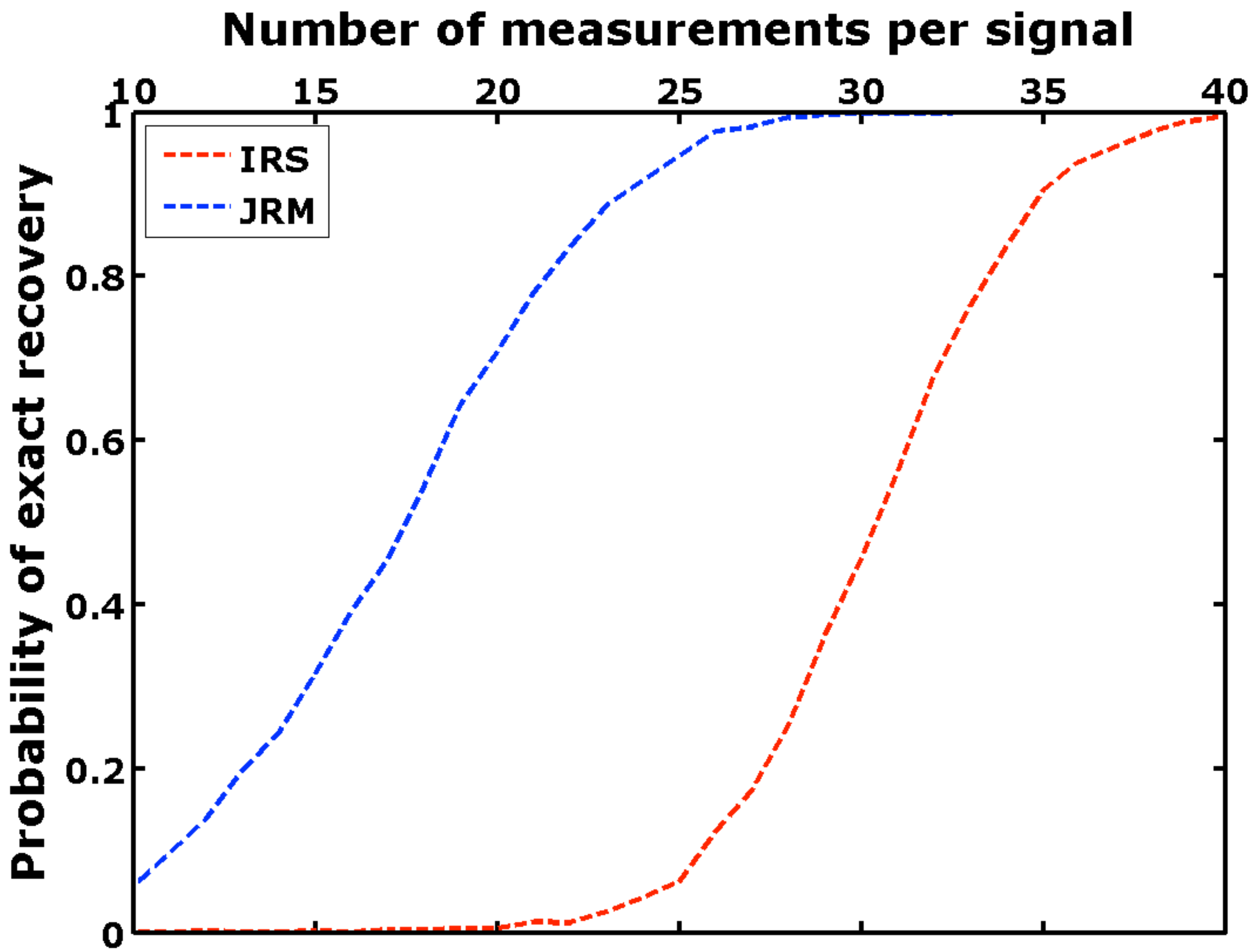



REPEAT EXPERIMENT AS BEFORE

# Results: *independent* versus *joint* recovery

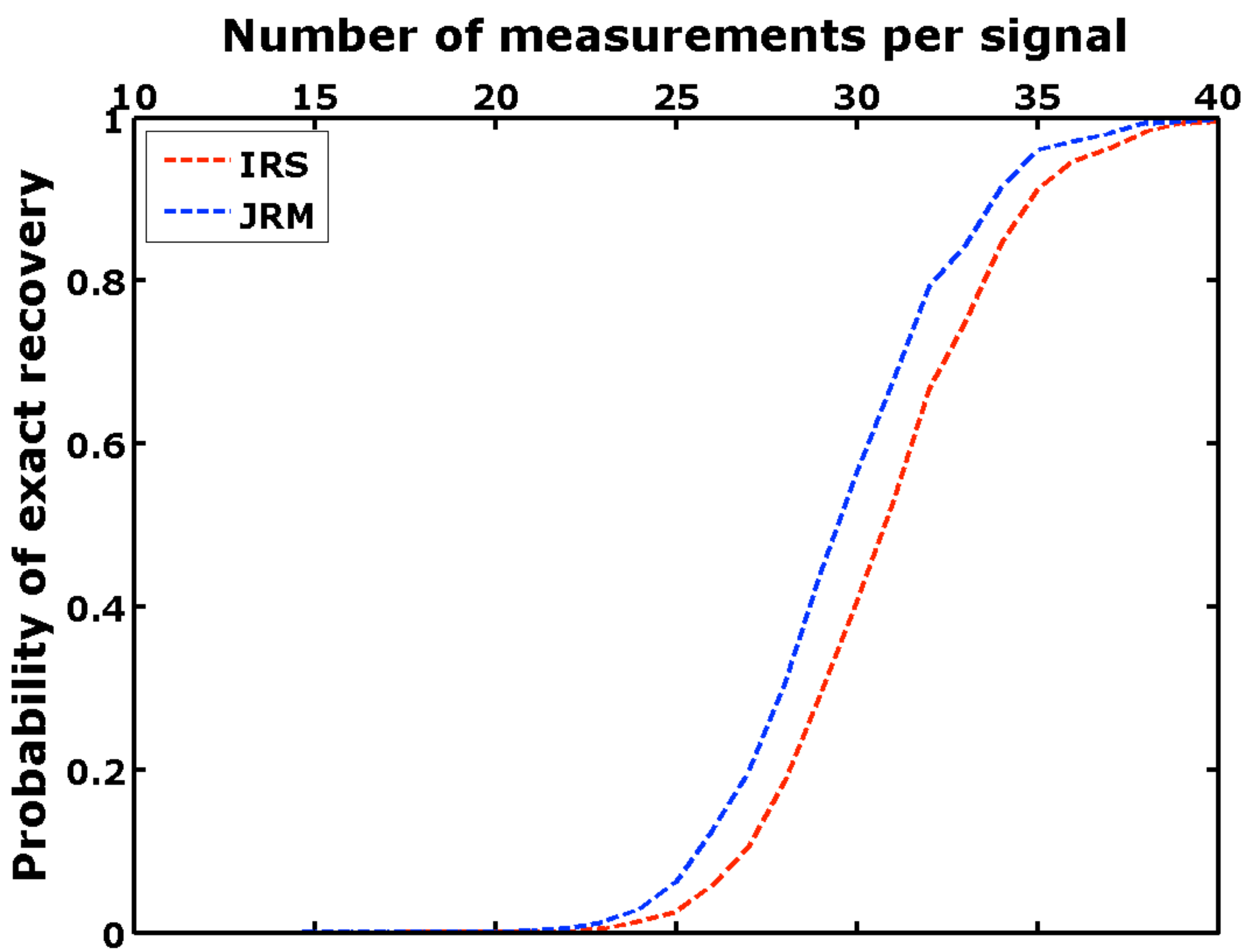



Recovery of vintages

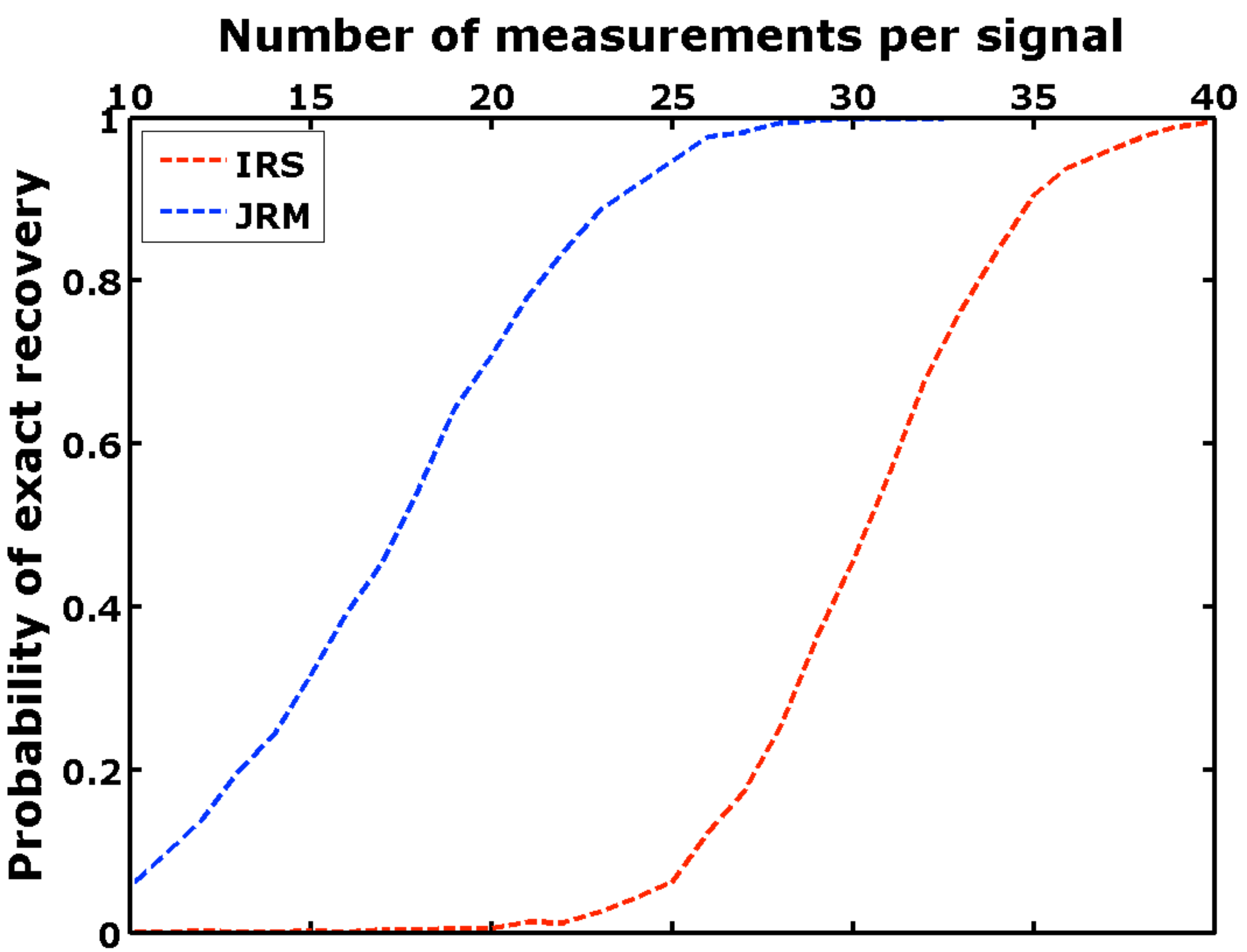



Recovery of difference

# *WITH* Repetition

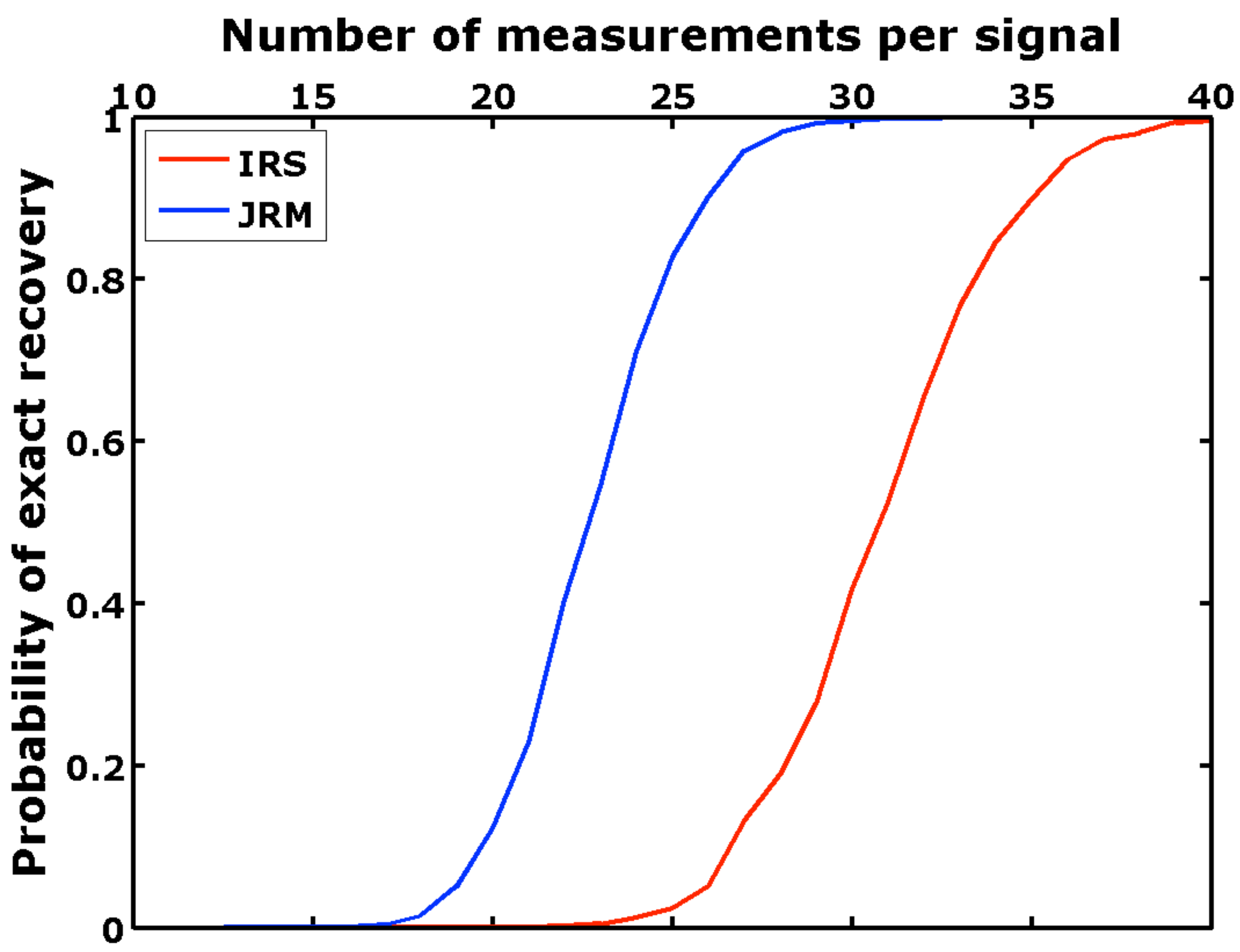



Recovery of vintages

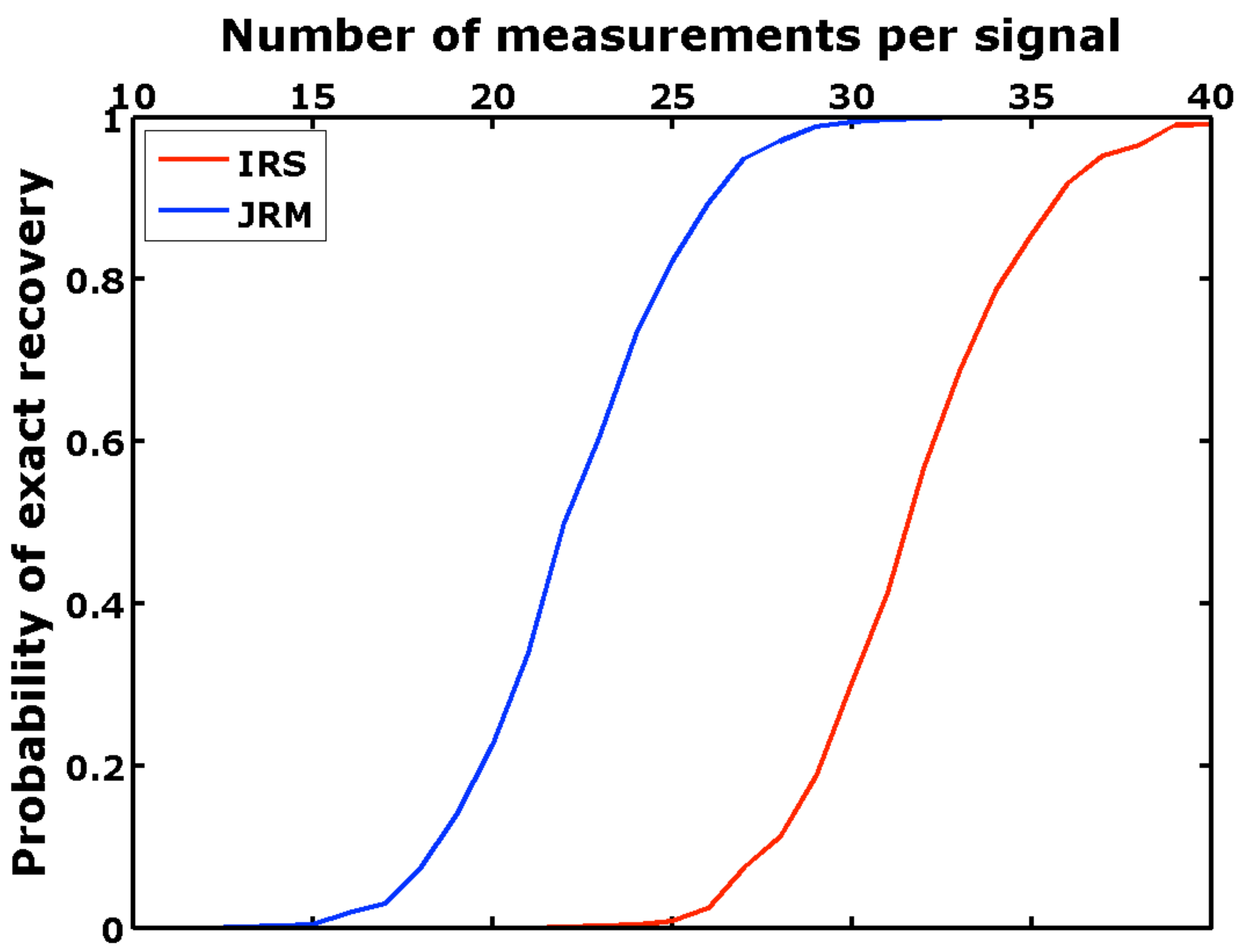



Recovery of difference

# ***WITHOUT*** Repetition




Recovery of vintages




Recovery of difference

## 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

# 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

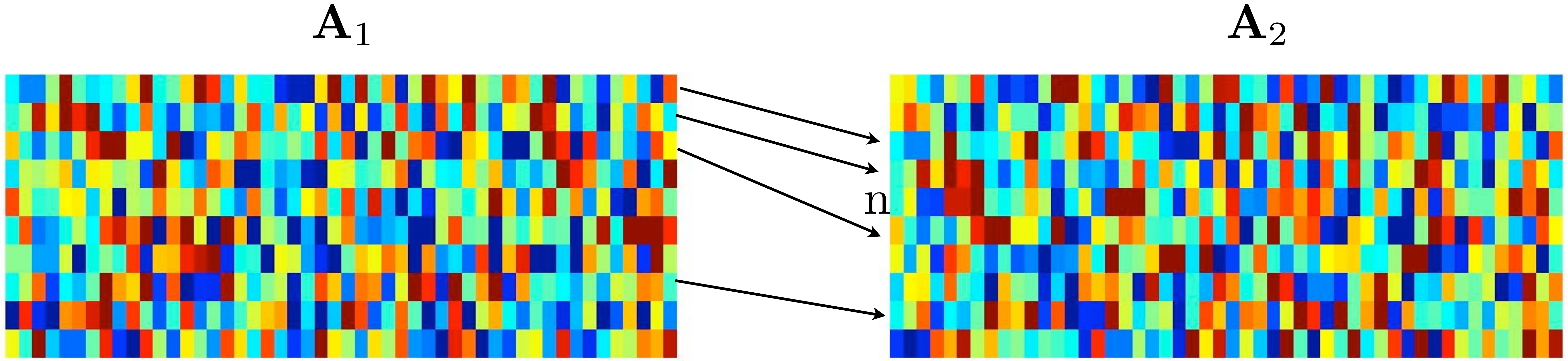
- ***Do the acquisitions really have to overlap?***

# 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

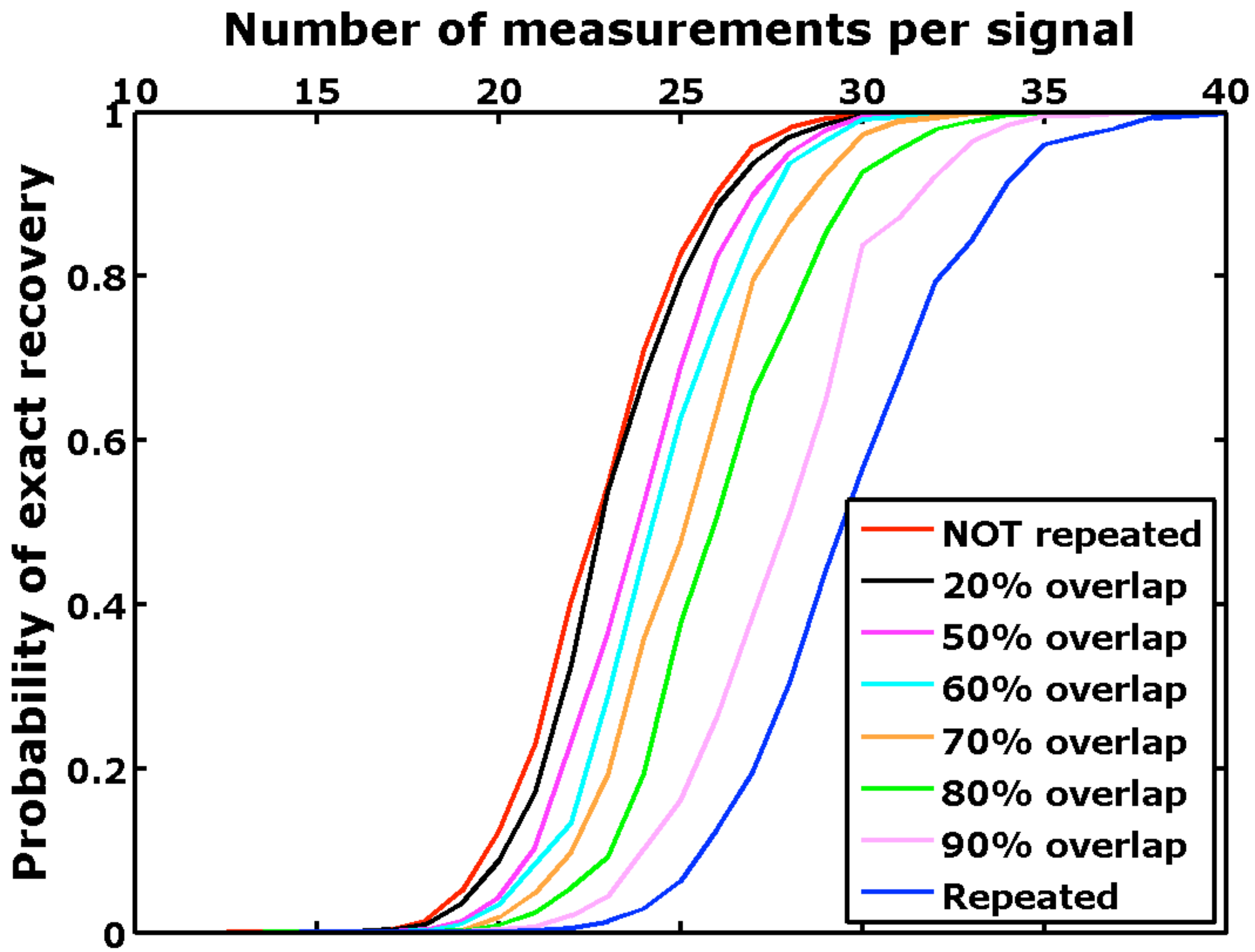
- ***Do the acquisitions really have to overlap?***

*Overlap*
40%

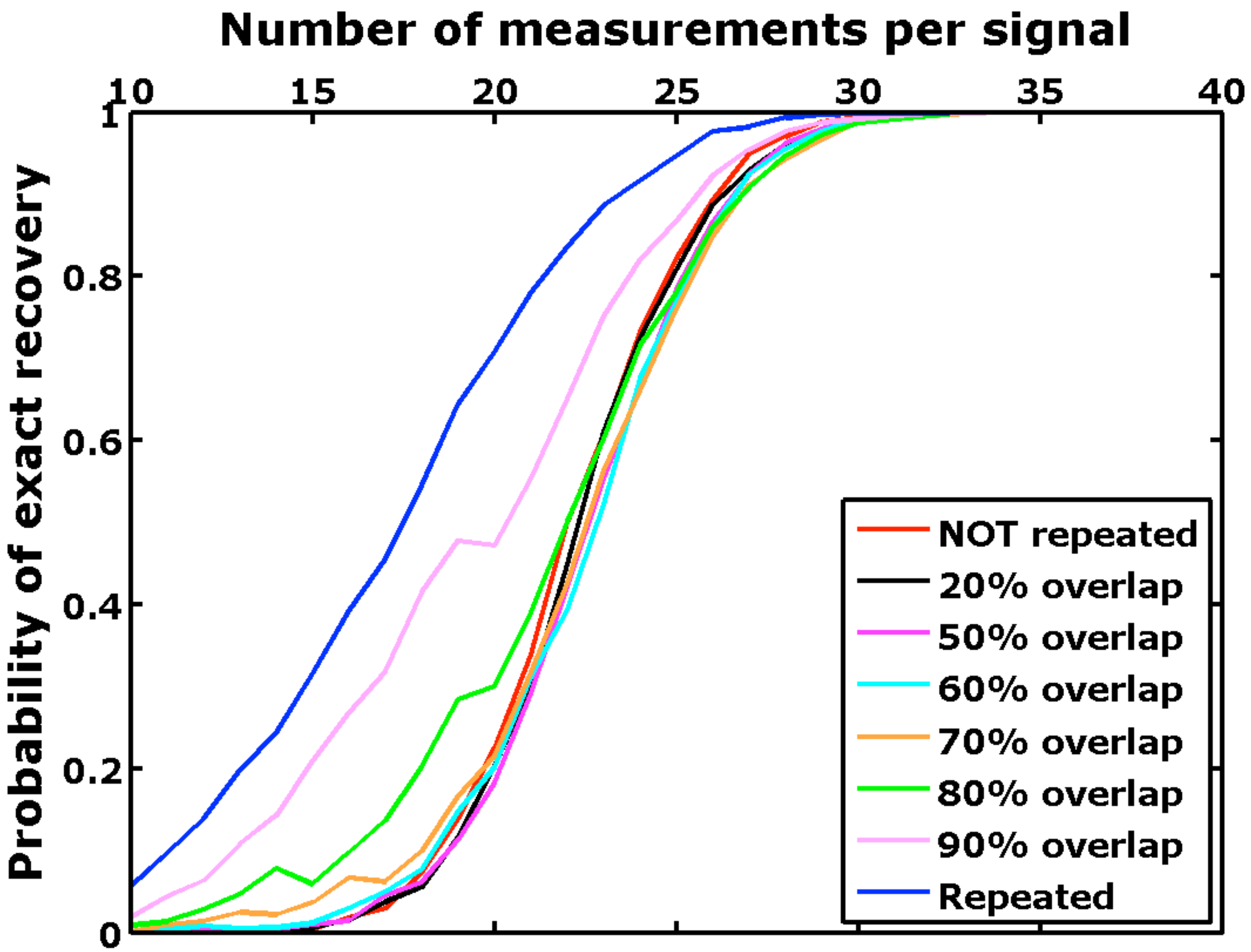



REPEAT EXPERIMENT AS BEFORE

# Results: *recovery and overlap dependency*




Recovery of vintages



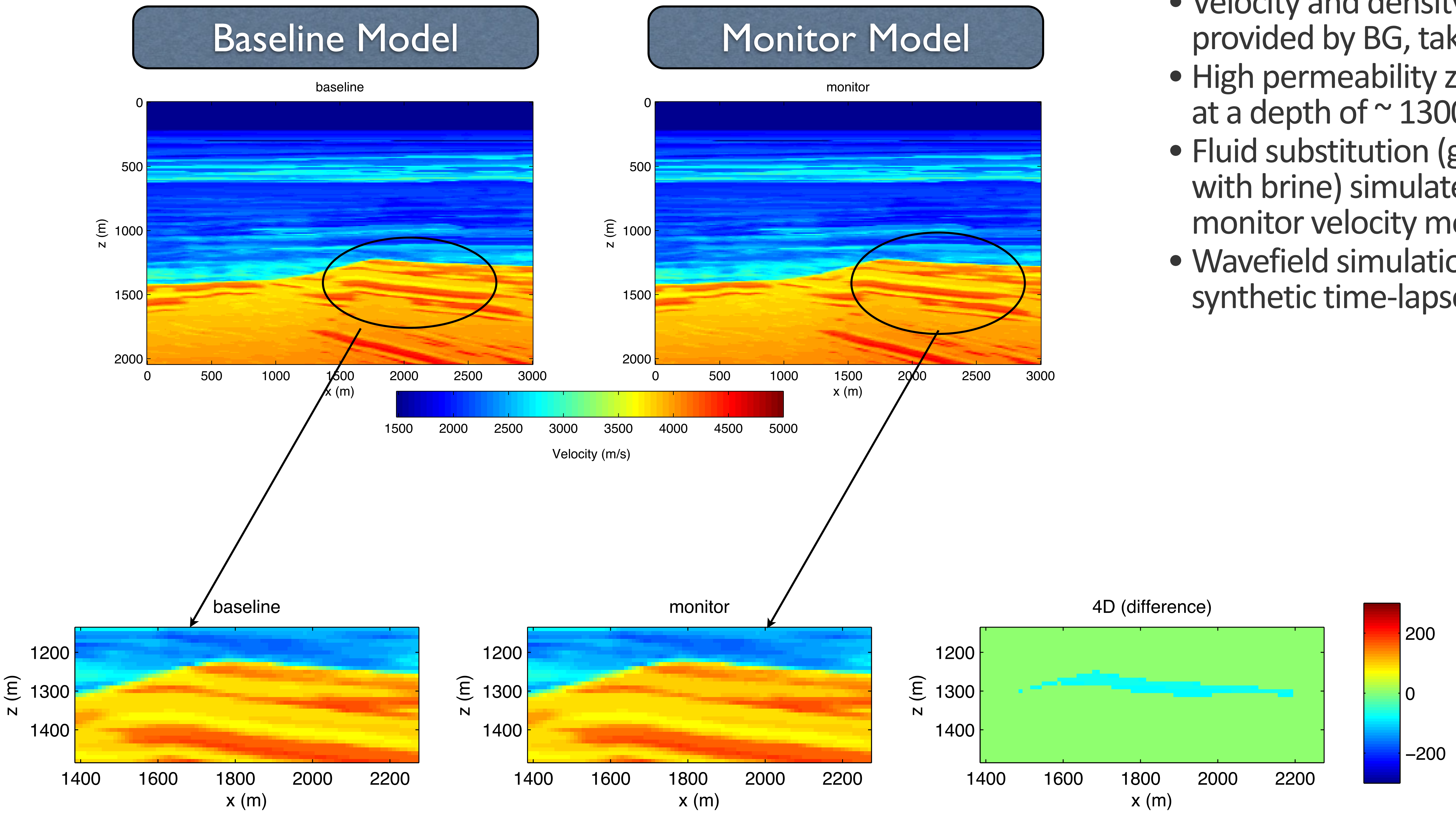

Recovery of difference

# Interpretation from the stylized example

- *Joint recovery model (JRM) is always superior to the independent or parallel method*
- *As the degree of overlap between the sampling increases, the recovery of the signals gets worse.*
- *Time-lapse signal recovery benefits from some overlap*

## Seismic example

# Time-jittered source in marine

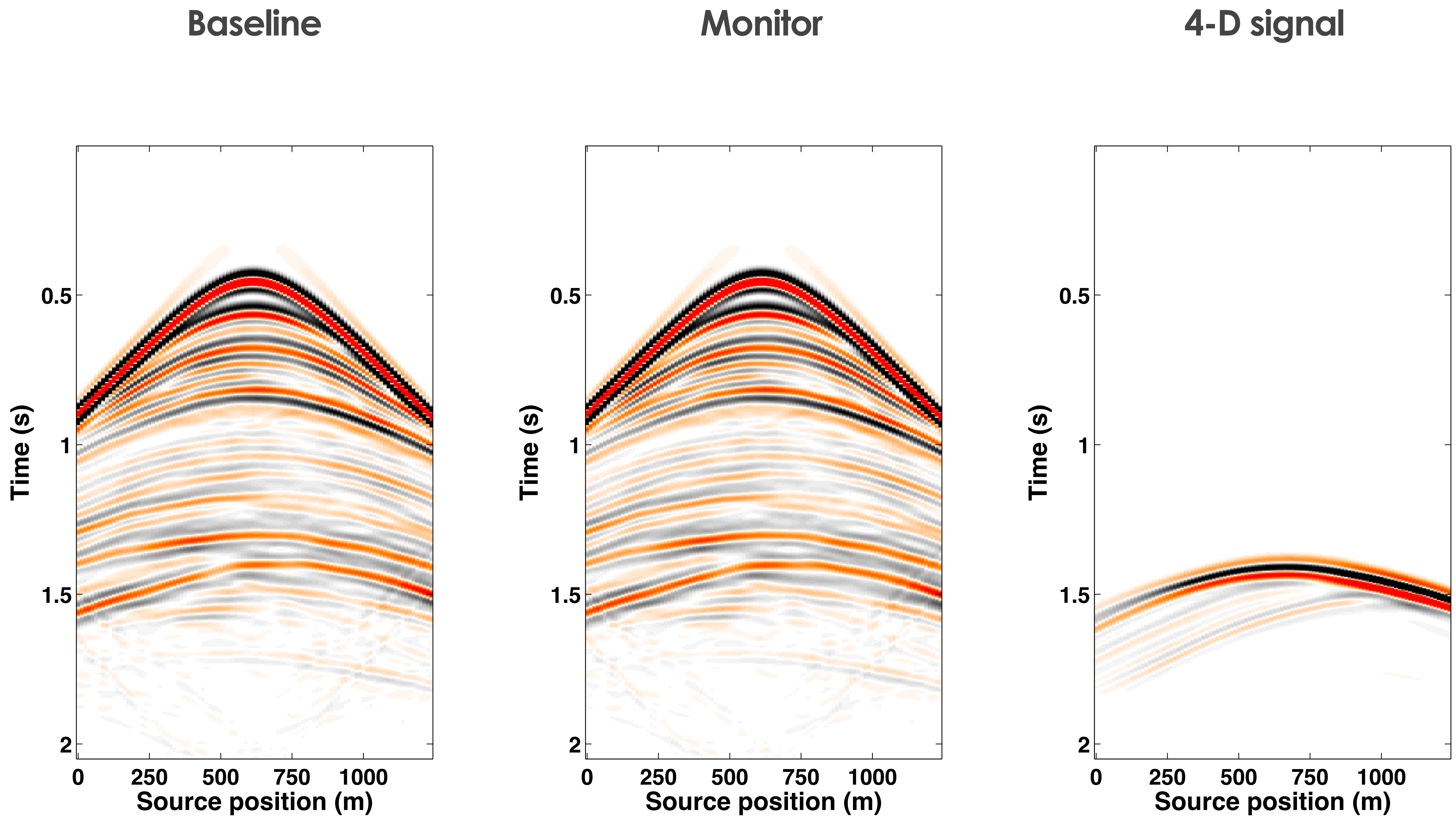



SLIM

# 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

# Simulated original data
## – time-domain finite differences

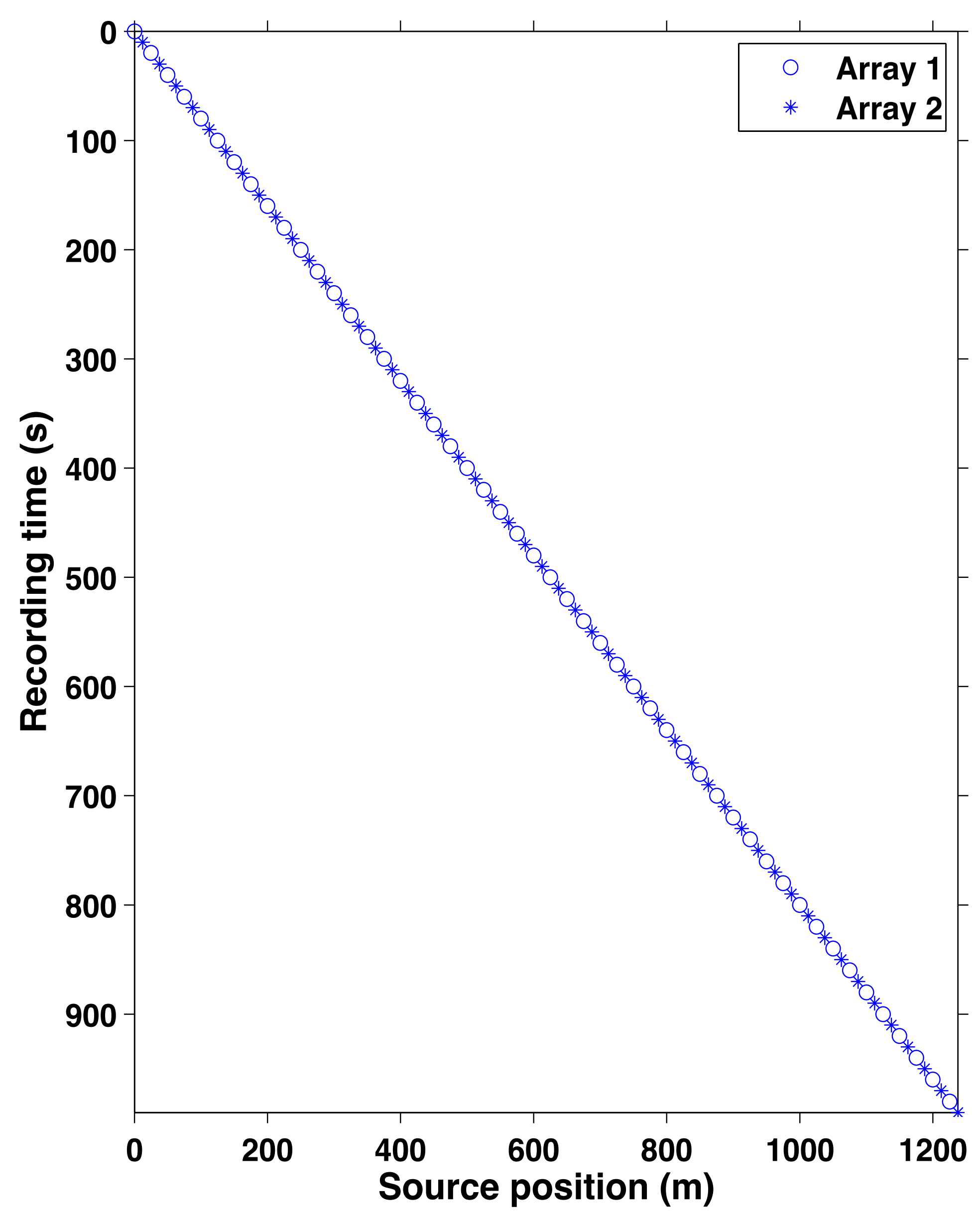



time samples: **512**
receivers: **100**
sources: **100**

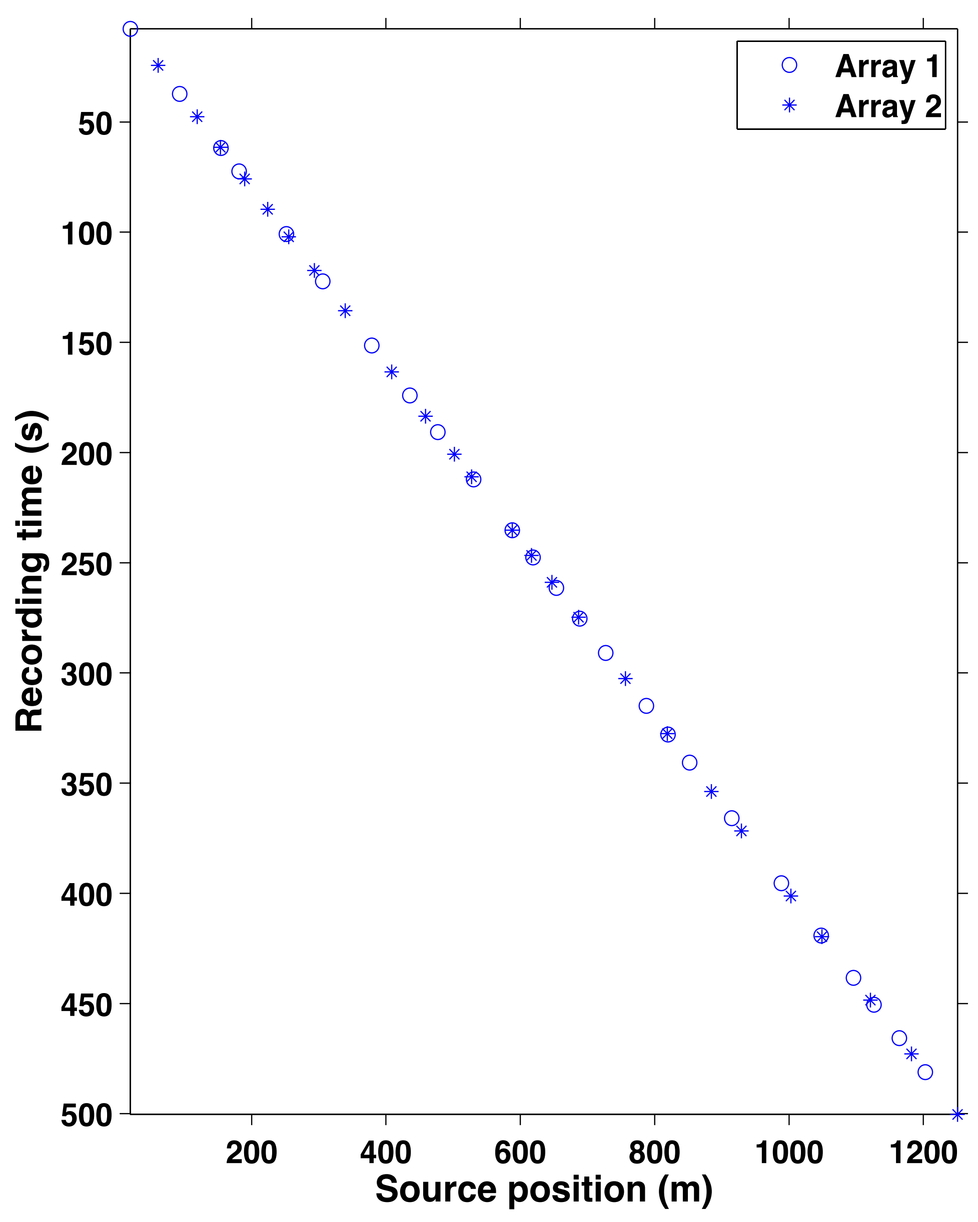
sampling
time: **4.0 ms**
receiver: **12.5 m**
source: **12.5 m**

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

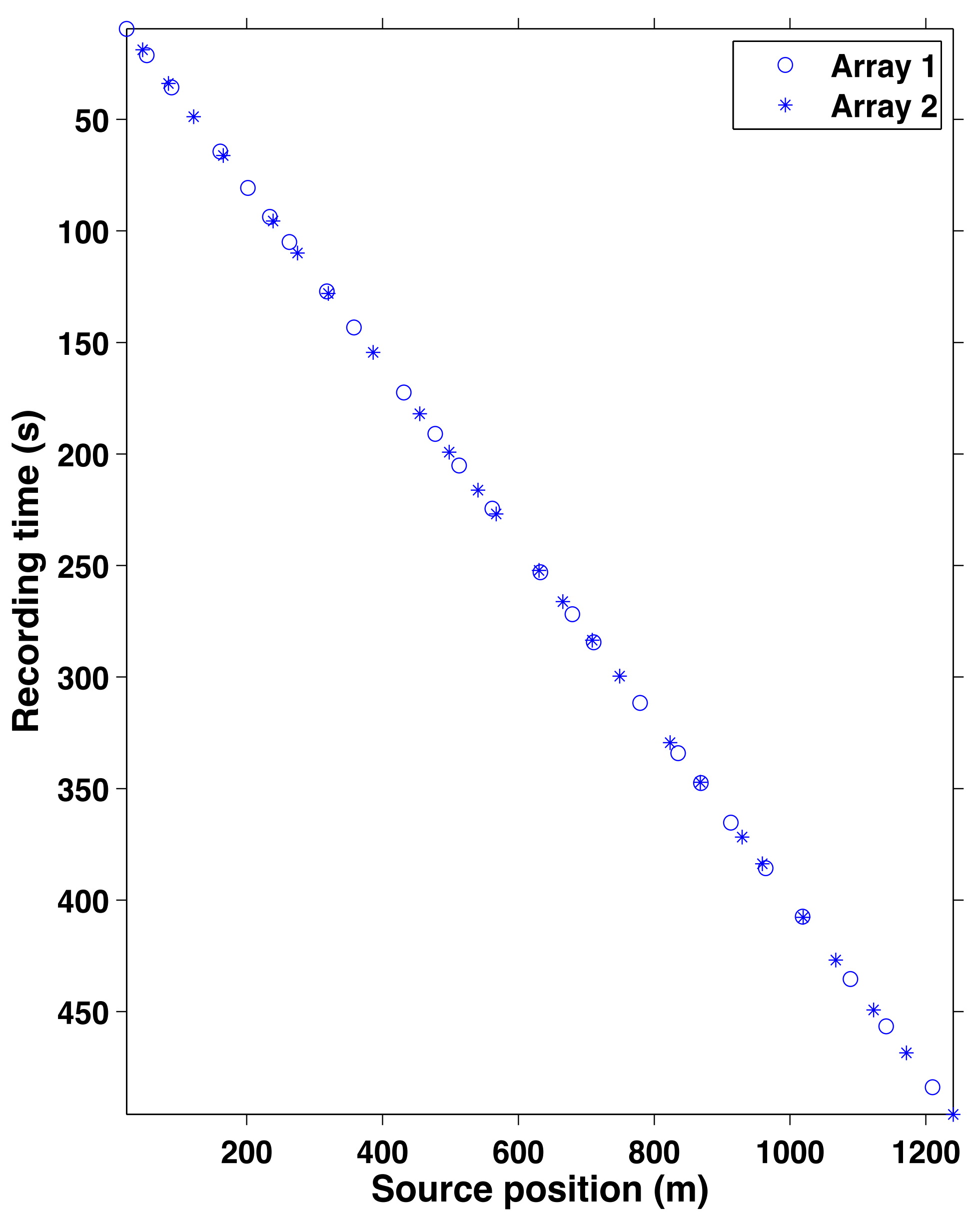
conventional




jittered acquisition 1
(for baseline)



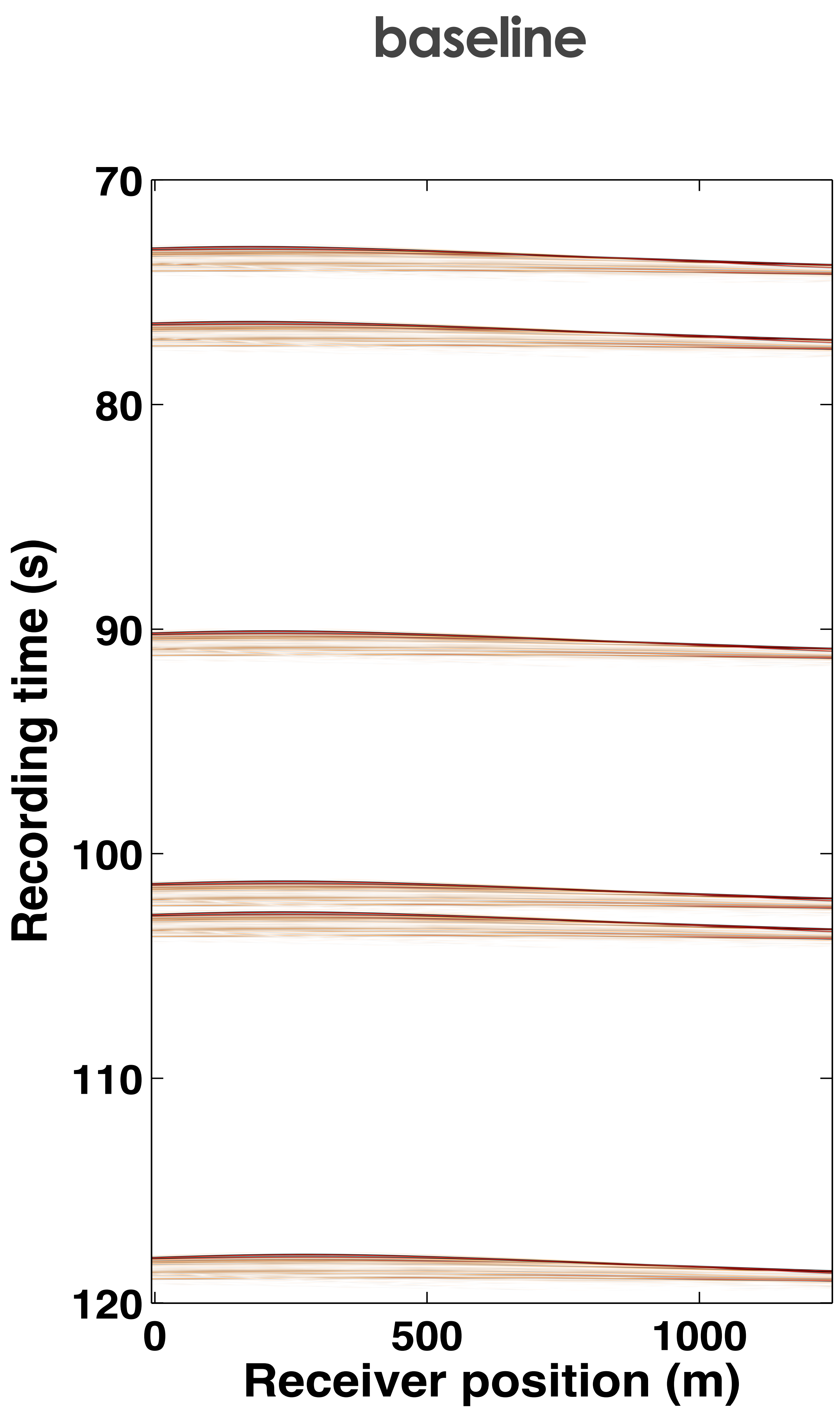

jittered acquisition 2
(for monitor)

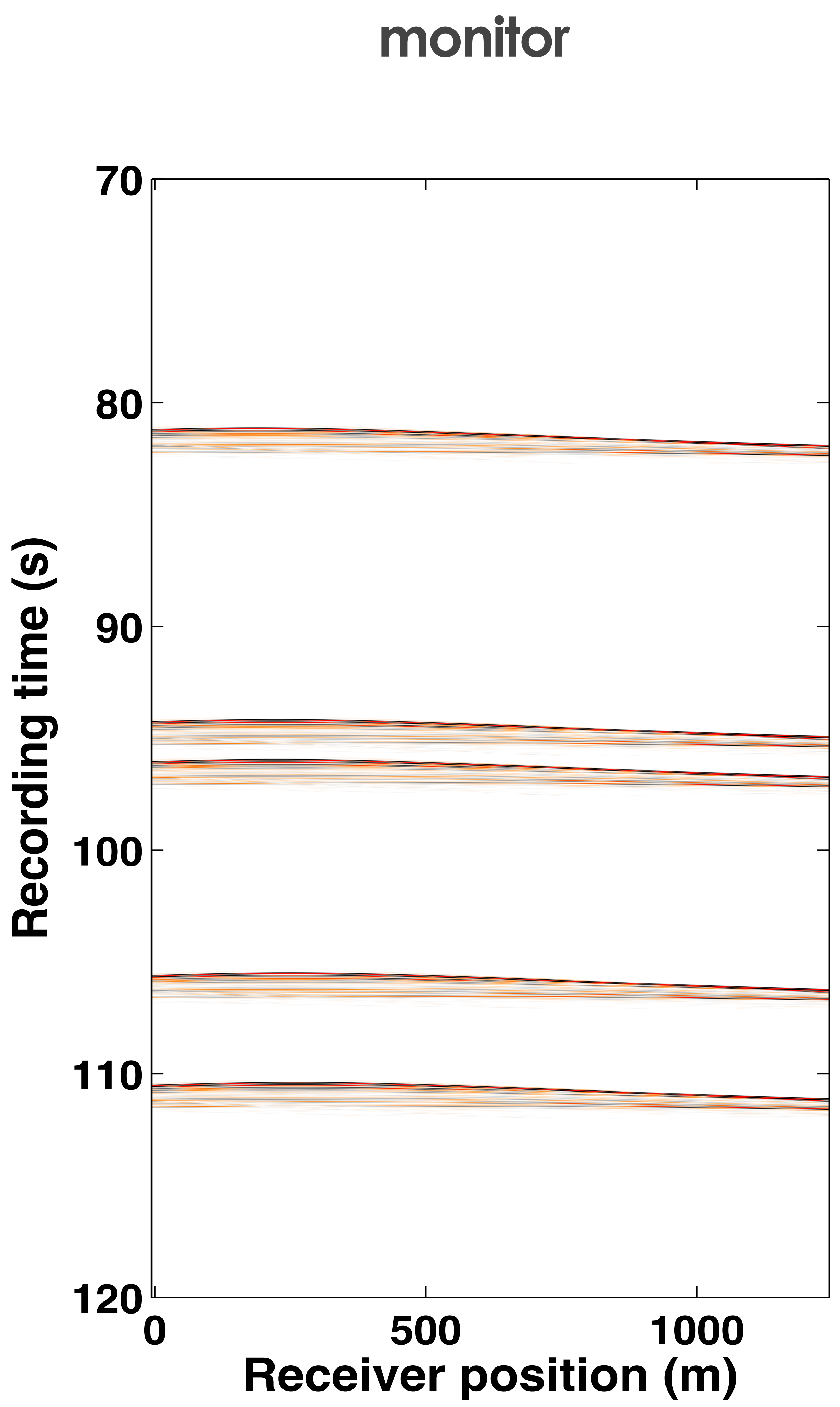



shorter acquisition time

geometry is not the same

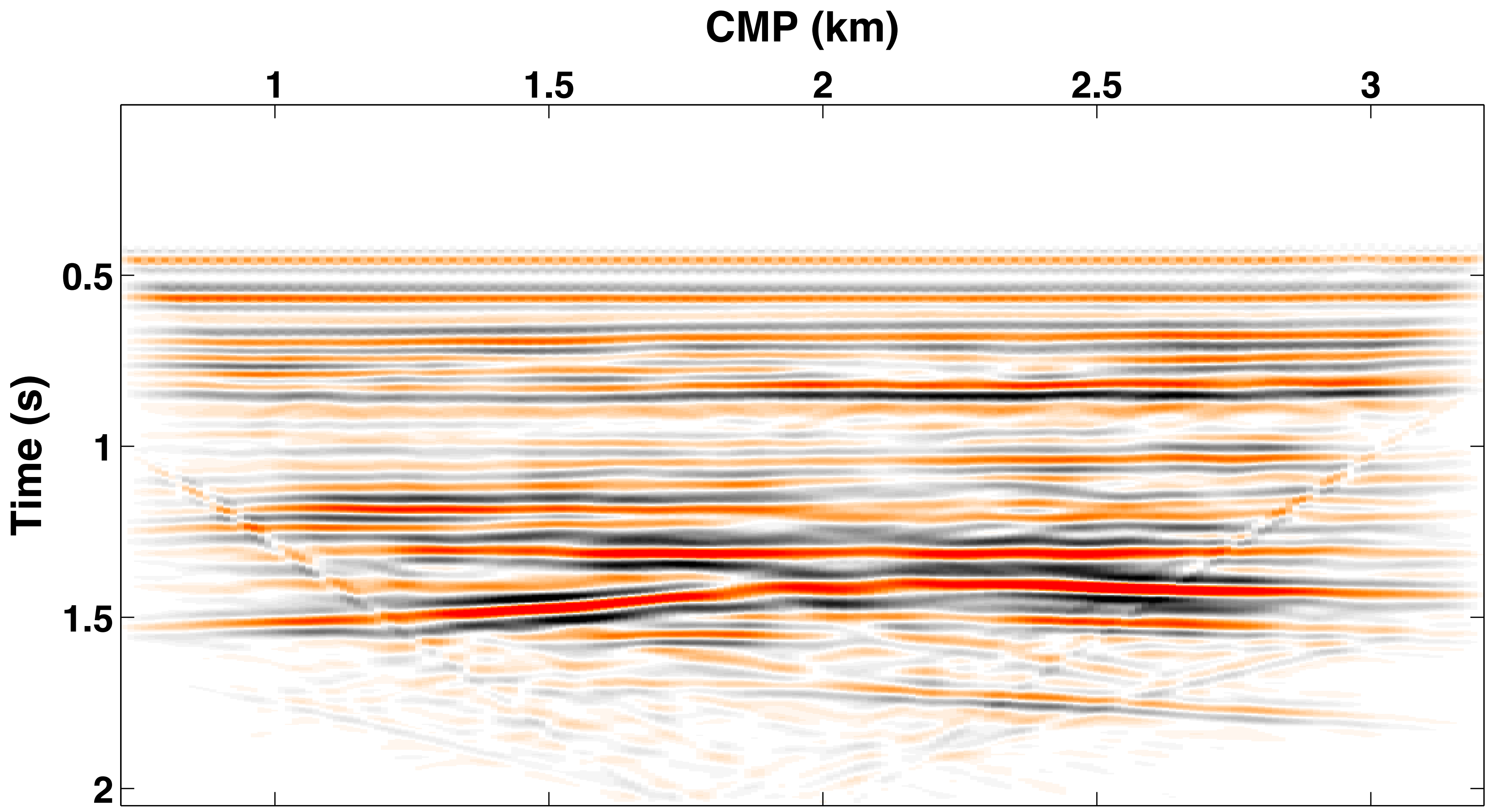
# Measurements
## – *undersampled* and *blended*



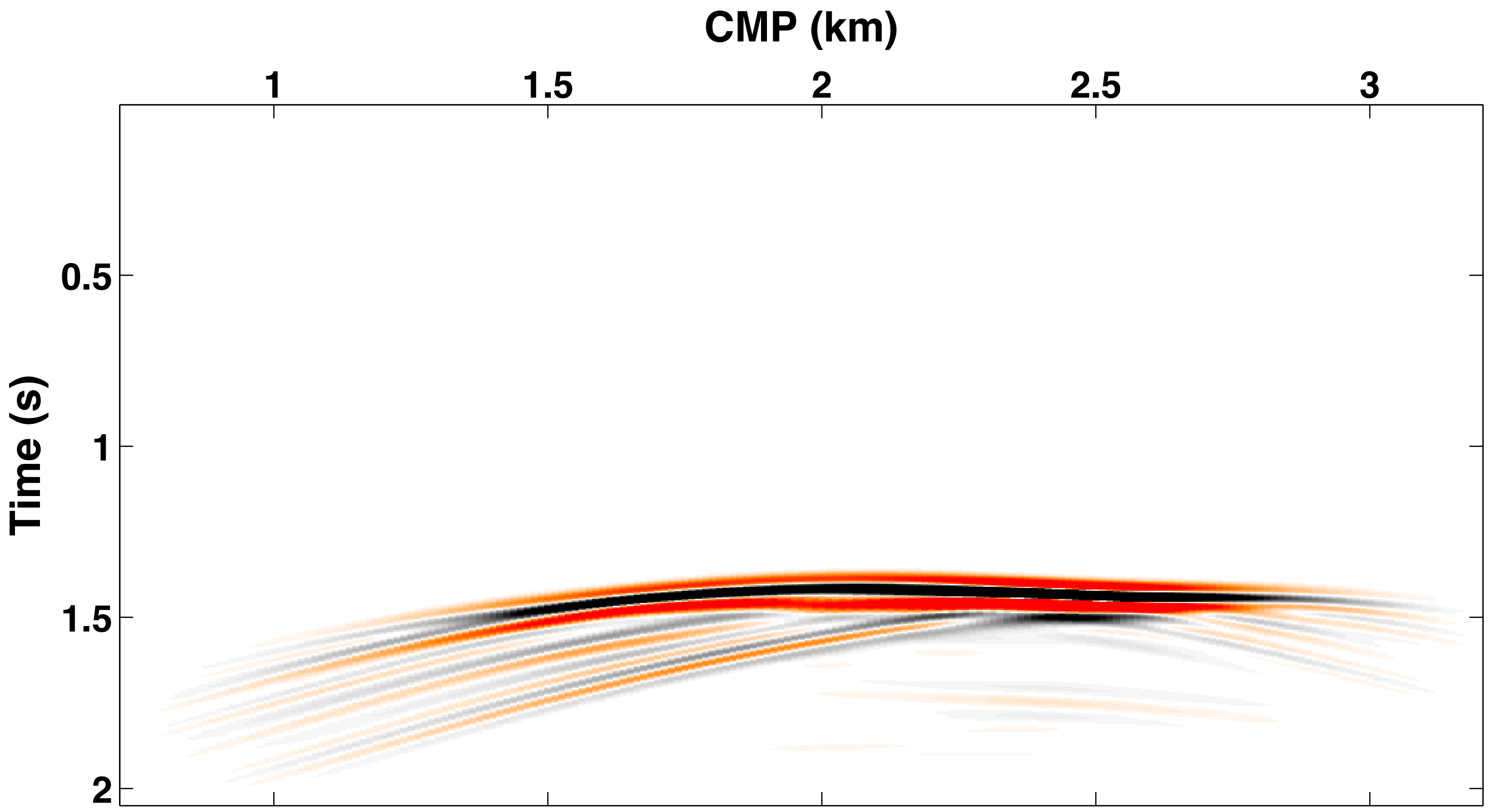



# *Stacked sections*

Original baseline

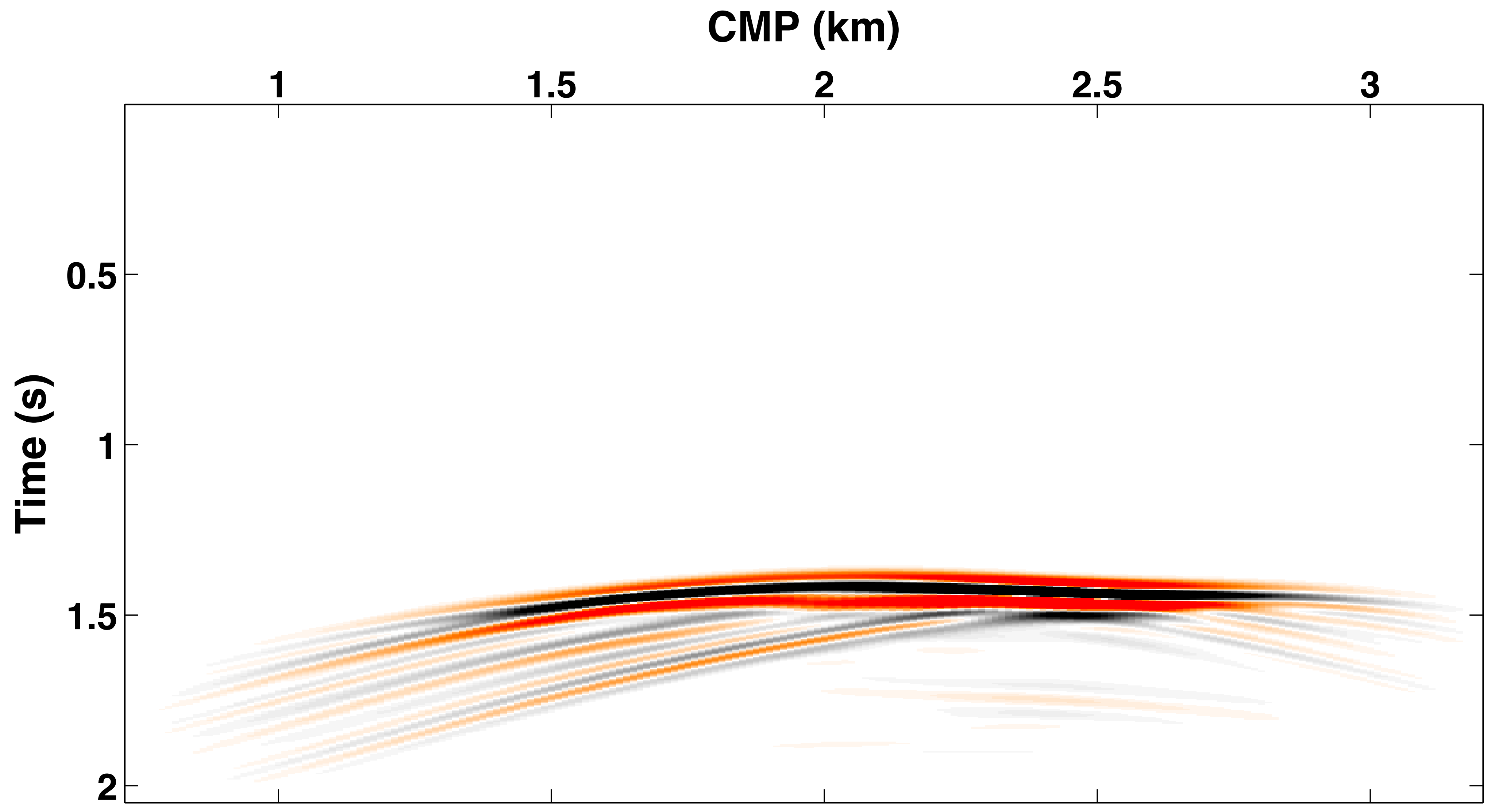



Original 4-D signal

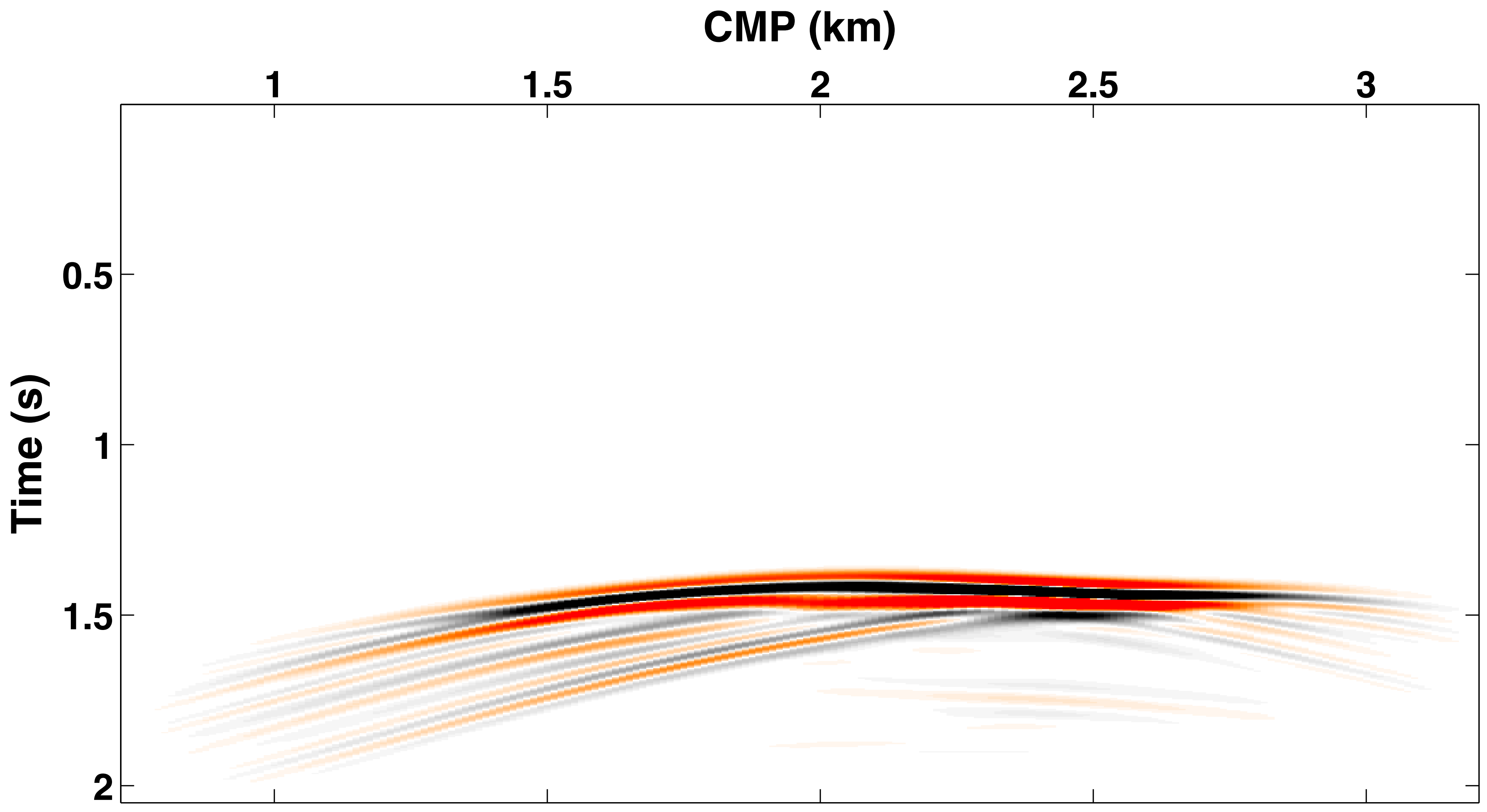


# Stacked sections

Original 4-D signal



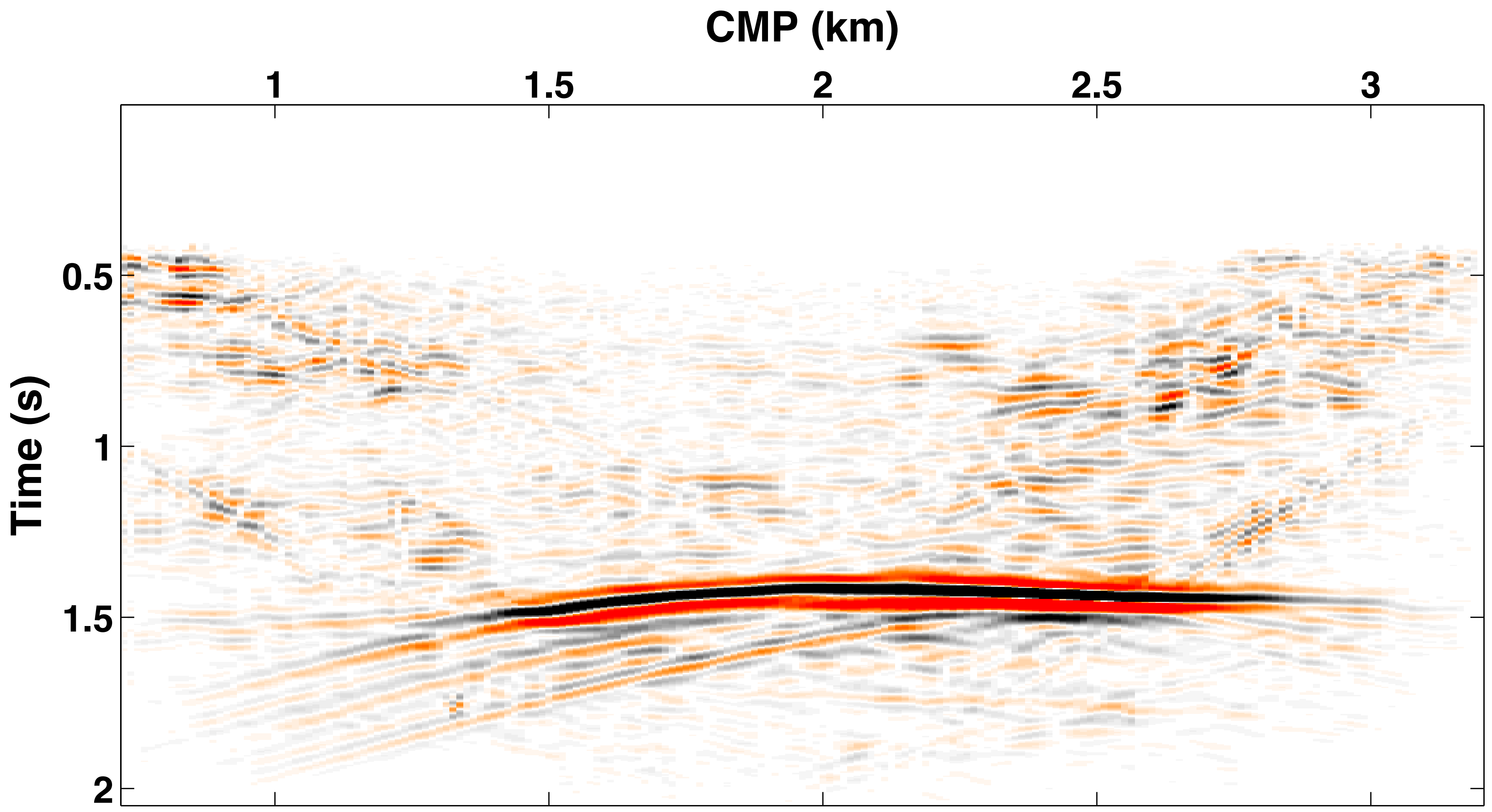

Original 4-D signal



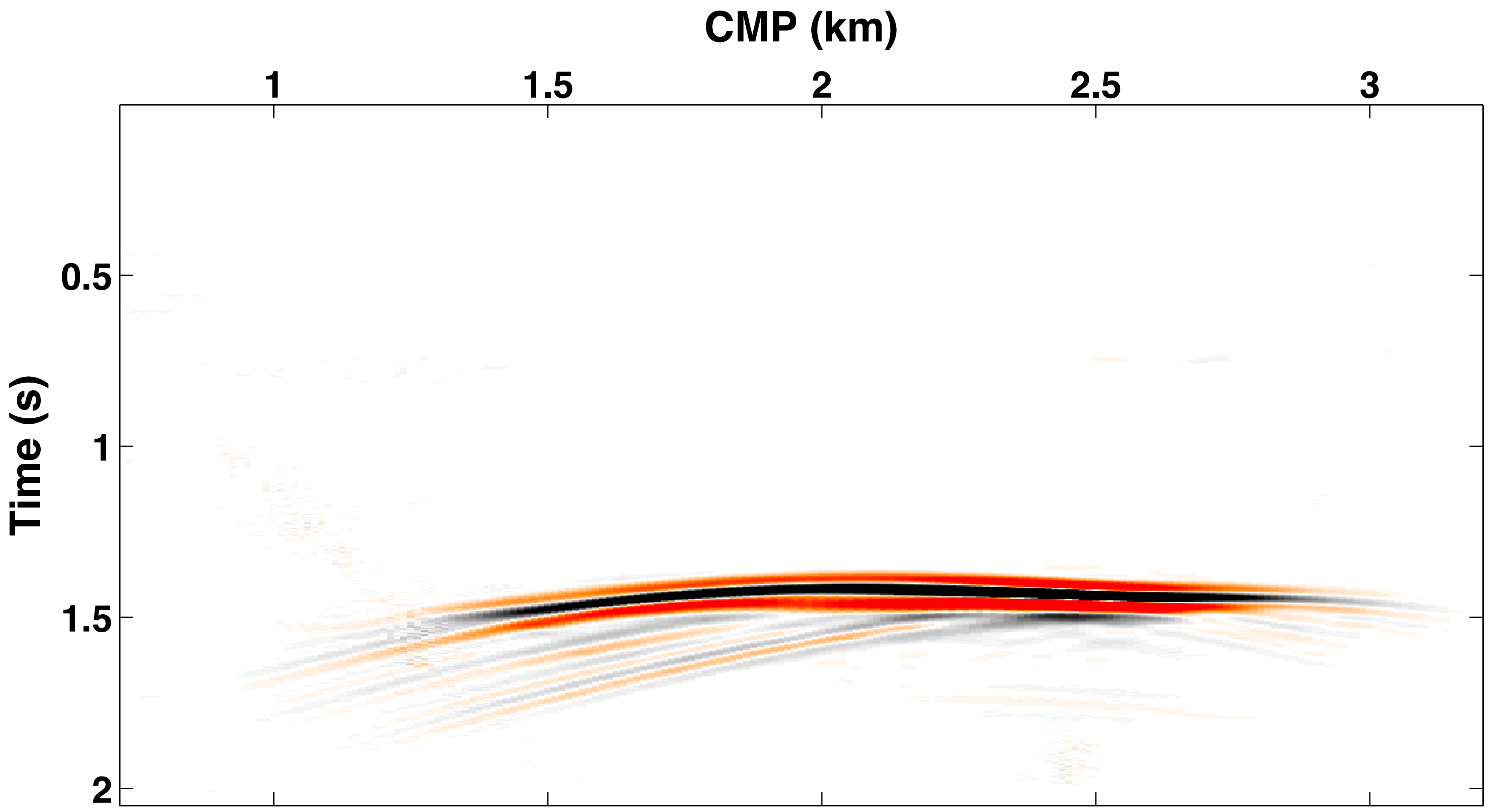
# *Stacked* sections

## – 50% overlap in *acquisition* matrices

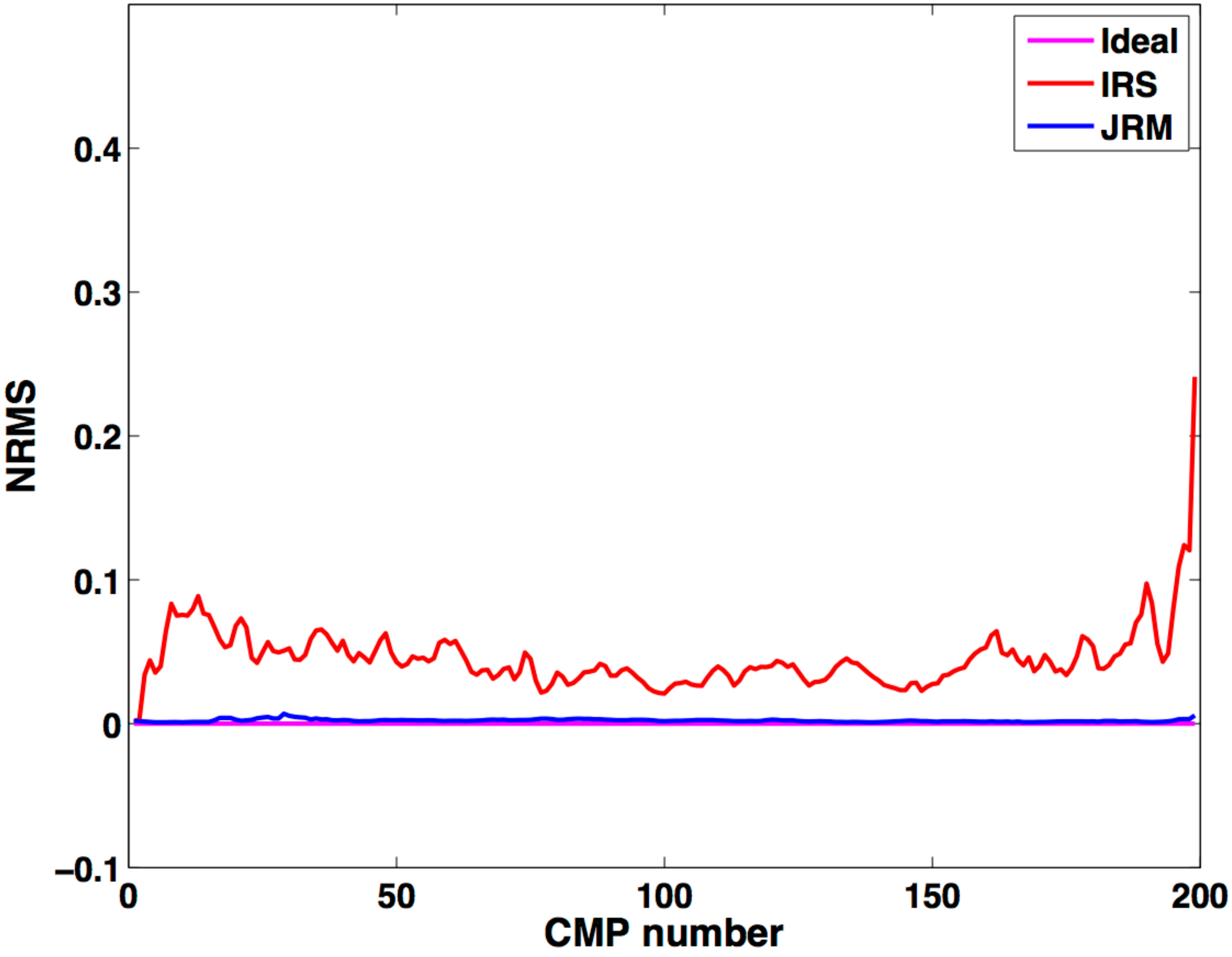
Parallel
(9.7 dB)




Joint
(18.2 dB)



# NRMS Plot



## Seismic example

# An extension to model space

# Example : Stacking

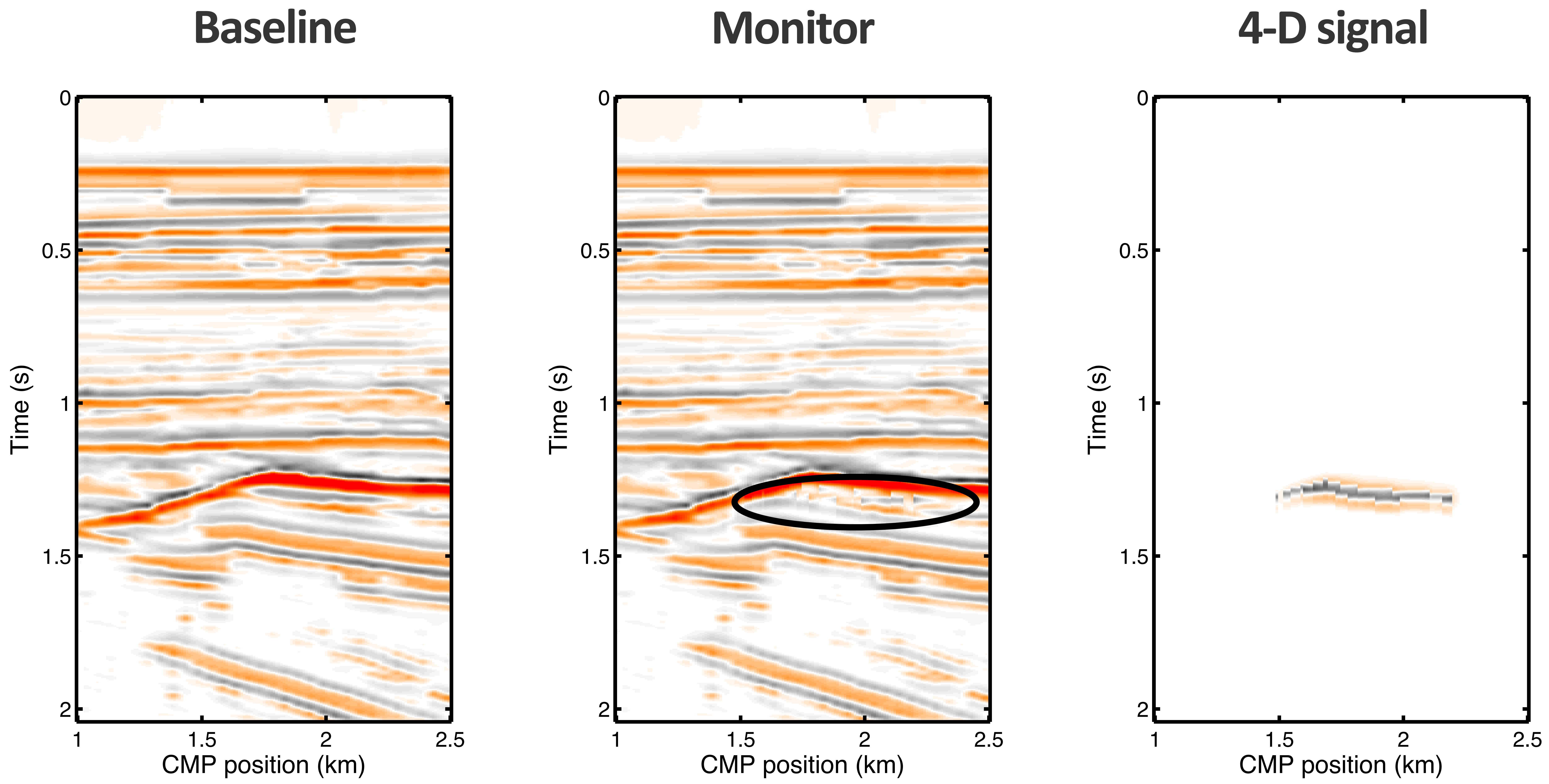
$$\mathbf{b} = \mathbf{M}^H \mathbf{N}^H \mathbf{S}^H \mathbf{C}^H \mathbf{x}$$

observed undersampled measurements → $$\mathbf{b} = \mathbf{A}\mathbf{x}$$

stacked section → $$\mathbf{m} = \mathbf{C}^H \mathbf{x}$$

| | |
|---|---|
| $\mathbf{M}$ | midpoint-offset |
| $\mathbf{N}$ | normal move-out |
| $\mathbf{S}$ | stacking |
| $\mathbf{C}$ | sparsifying operator |
| $H$ | adjoint |

# Idealized synthetic time-lapse data



# Method

- *Acquisition*
  - Subsampled baseline and monitor data, with independent and randomly missing shots
- *Processing*
  - Independent processing of the observed data (*Parallel*)
  - Joint processing  (*JRM*)

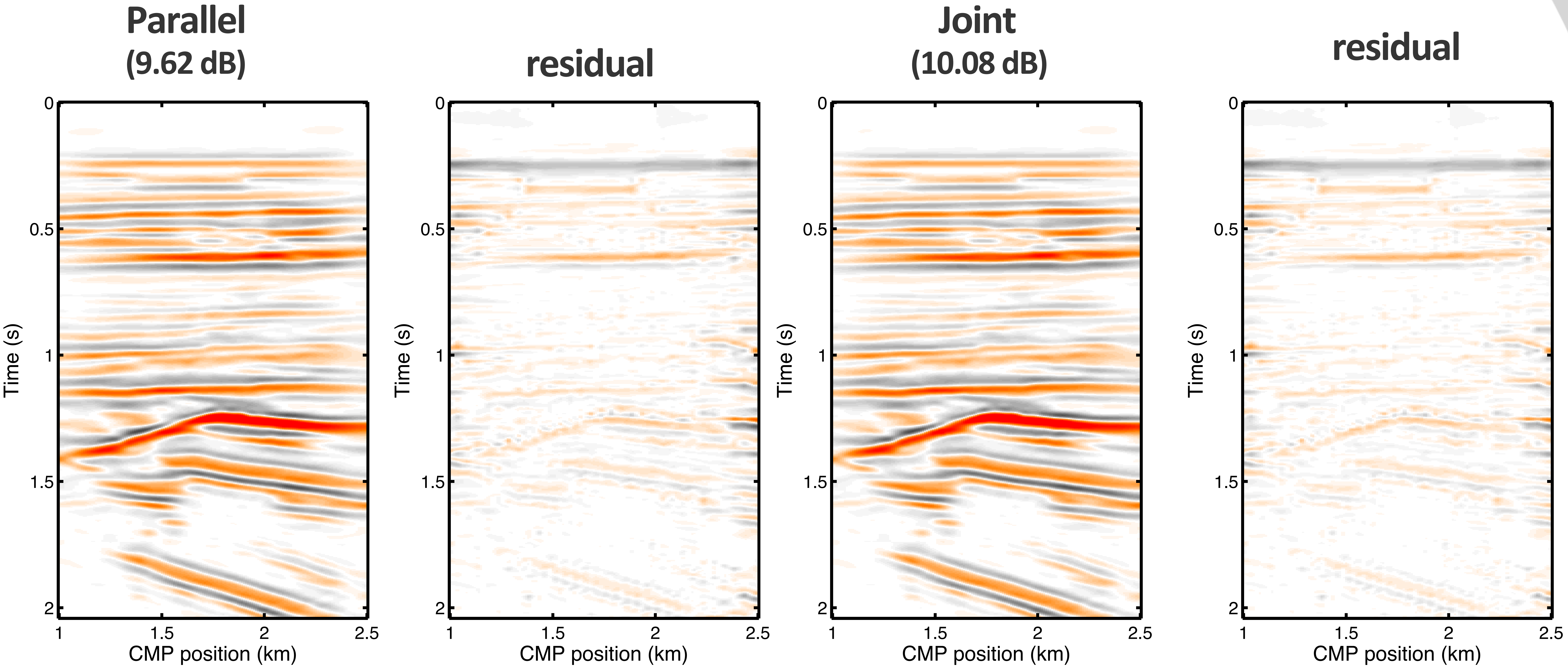
## Method

- *Acquisition*
  - Subsampled baseline and monitor data, with independent and randomly missing shots
- *Processing*
  - Independent processing of the observed data (*Parallel*)
  - Joint processing (*JRM*)

Compare *Parallel* versus *Joint*

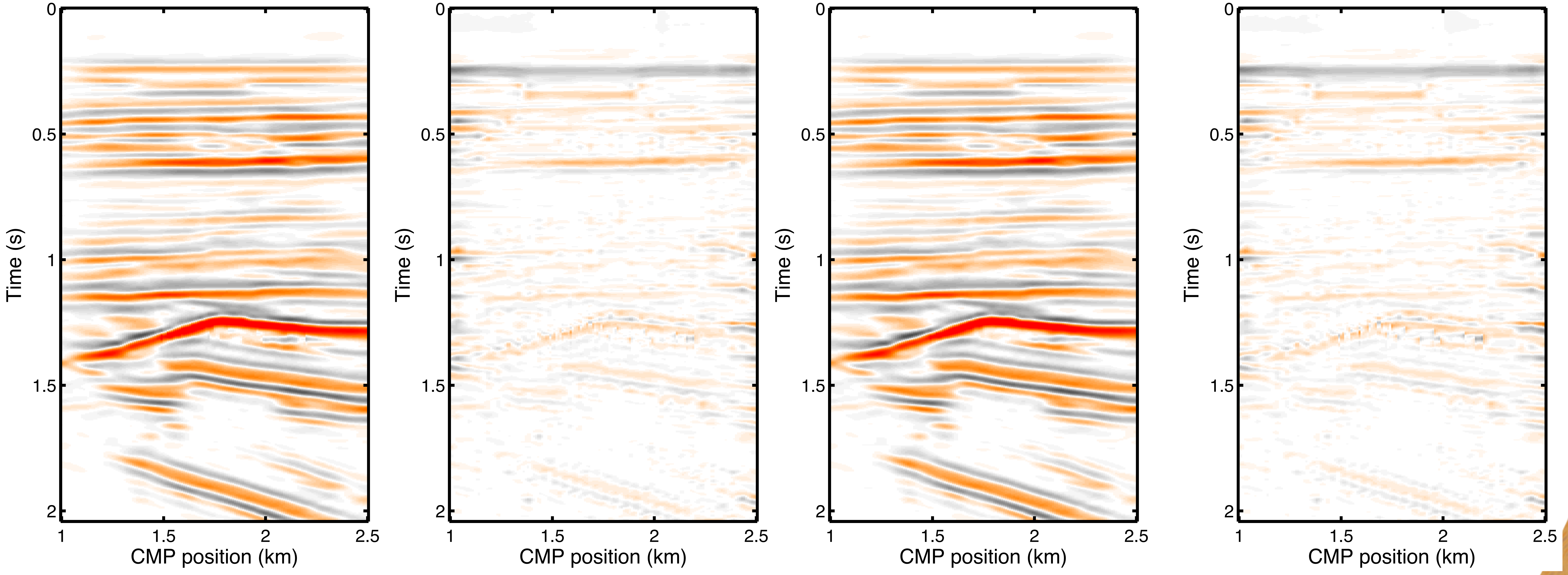
Repeat for a "*partial*" dependence in geometry

# Baseline recovery
## - 0% overlap in acquisition matrices

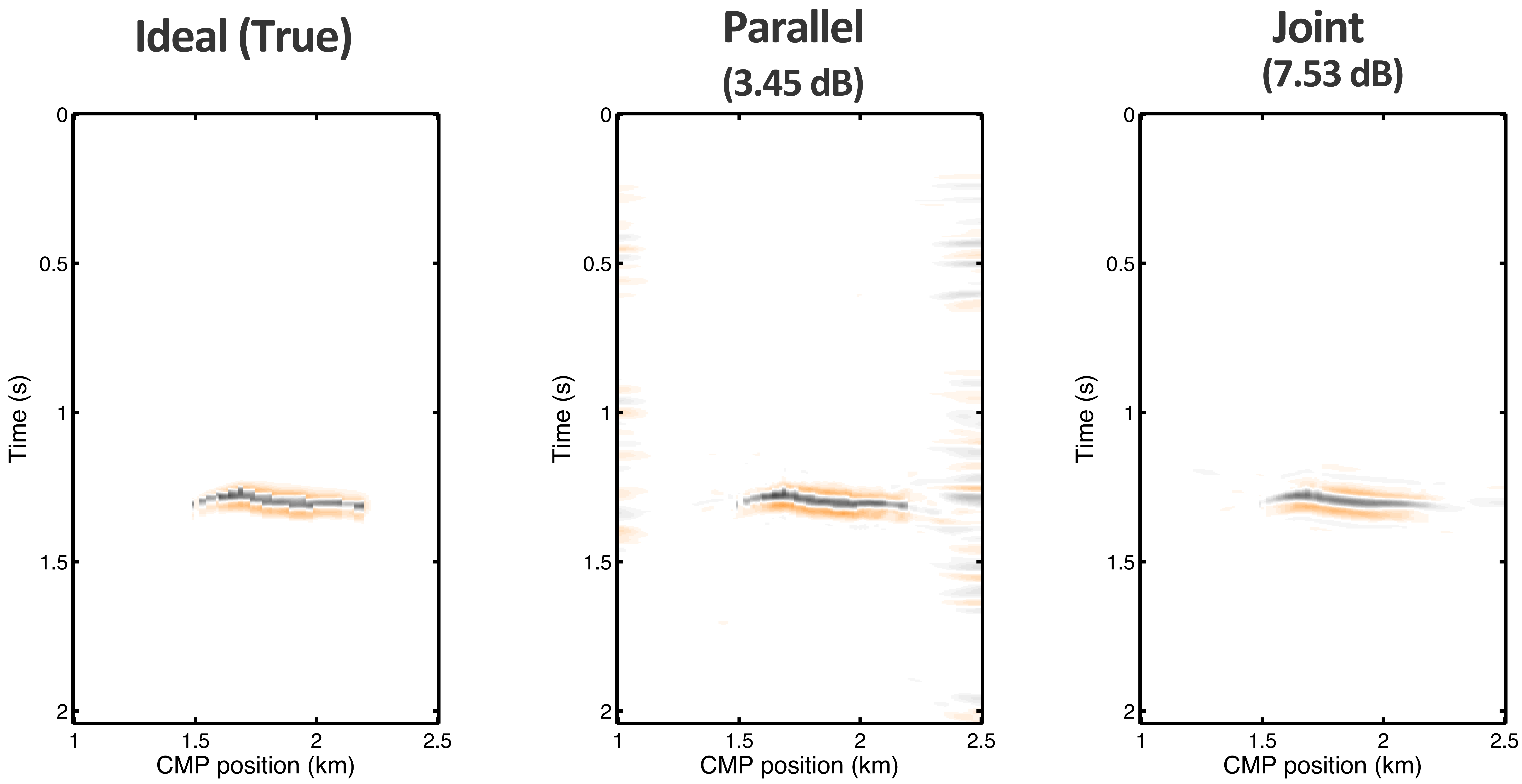


# Monitor recovery
## - 0% overlap in acquisition matrices

**Parallel (10.08 dB)** | **residual** | **Joint (10.02 dB)** | **residual**

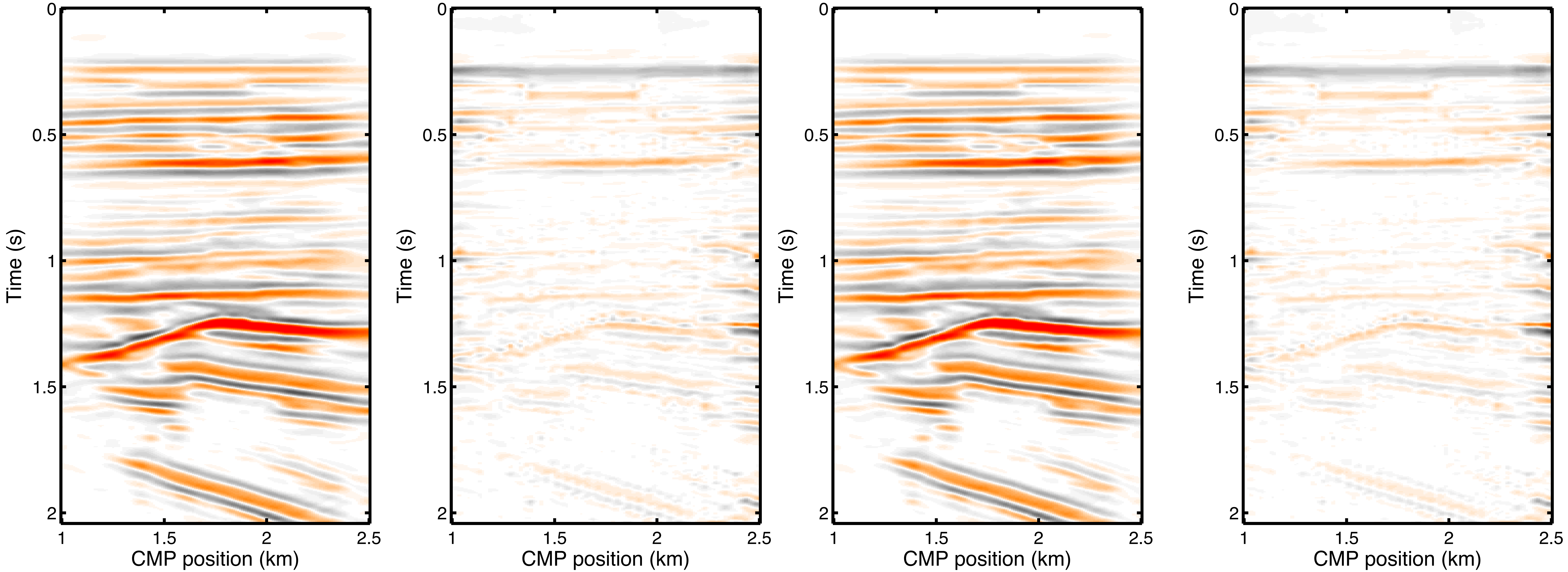


# 4-D recovery
## - 0% overlap in acquisition matrices

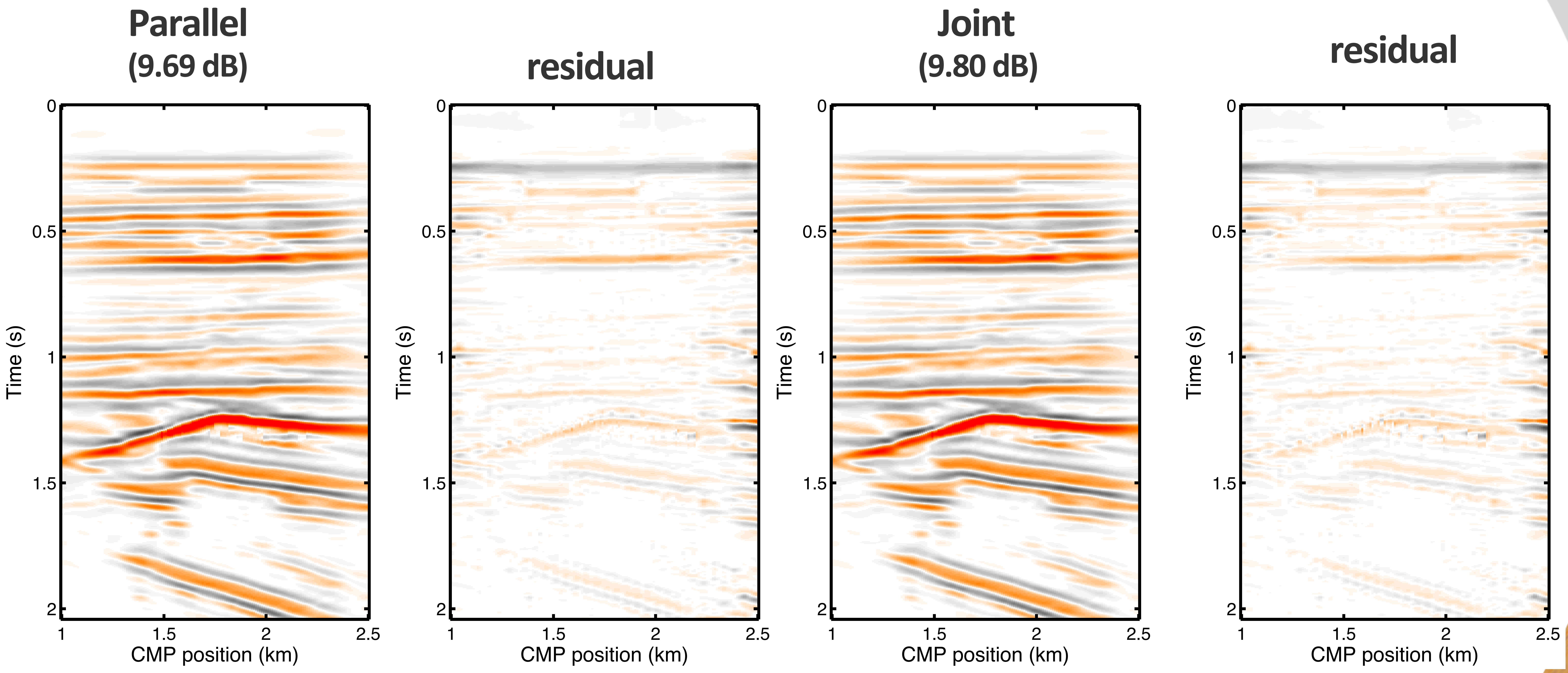


# Baseline recovery
## - 50% overlap in acquisition matrices

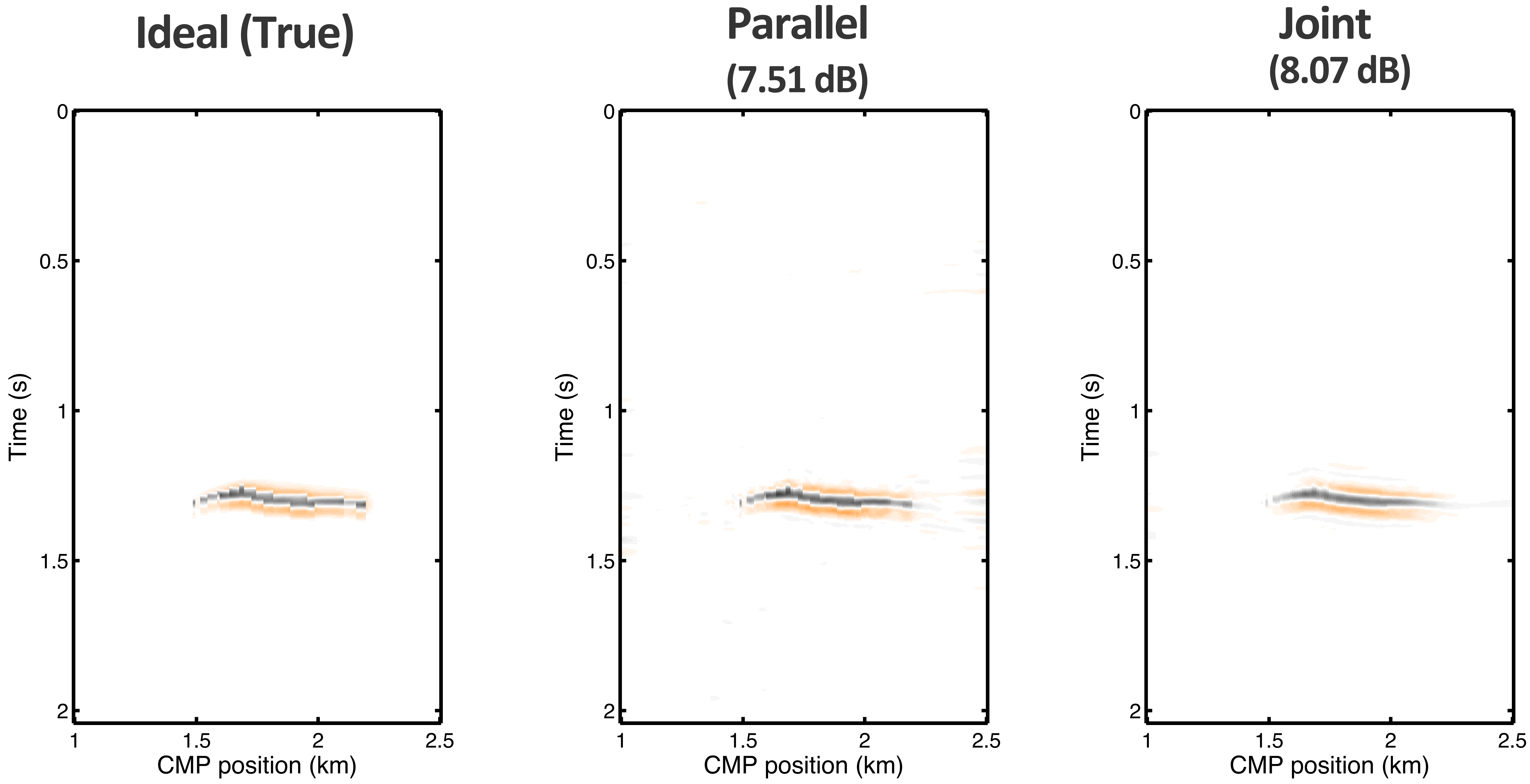
**Parallel (9.62 dB)** | **residual** | **Joint (9.79 dB)** | **residual**



# Monitor recovery
## - 50% overlap in acquisition matrices



# 4-D recovery
## - 50% overlap in acquisition matrices



# Conclusions

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

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

We can work with *subsampled* data, and recover densely sampled vintages **and** time-lapse differences.

Provided we understand the *physics* of our model, we can safely work with *subsampled* data from randomized sampling ideas.

**TAKE HOME**

Think randomized sampling in seismic surveys!! It **saves** cost!!!

# Acknowledgements

**Thank you for your attention!**

This work was in part financially supported by the Natural Sciences and Engineering Research Council of Canada Discovery Grant (22R81254) and the Collaborative Research and Development Grant DNOISE II (375142-08). This research was carried out as part of the SINBAD II project with support from the following organizations: BG Group, BGP, BP, CGG, Chevron, ConocoPhillips, ION, Petrobras, PGS, Statoil, Total SA, Sub Salt Solutions, WesternGeco, and Woodside.