Randomized subsampling in time-lapse surveys and recovery techniques

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Goal

Present a *viable* tool for processing time-lapse data

Obtain *excellent* time-lapse images

Recover *useful* time-lapse signals

Haneet Wason and Felix J. Herrmann, "**Time-jittered ocean bottom seismic acquisition**", in *SEG Technical Program Expanded Abstracts*, 2013, vol. 32, 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.

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Time-lapse seismic

Current acquisition paradigm:

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

New compressive sampling paradigm:

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

Sparsity promoting recovery

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

where

$\mathbf{A}$ sampling matrix

$\mathbf{b}$ observed data

CS in time-lapse

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

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

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

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

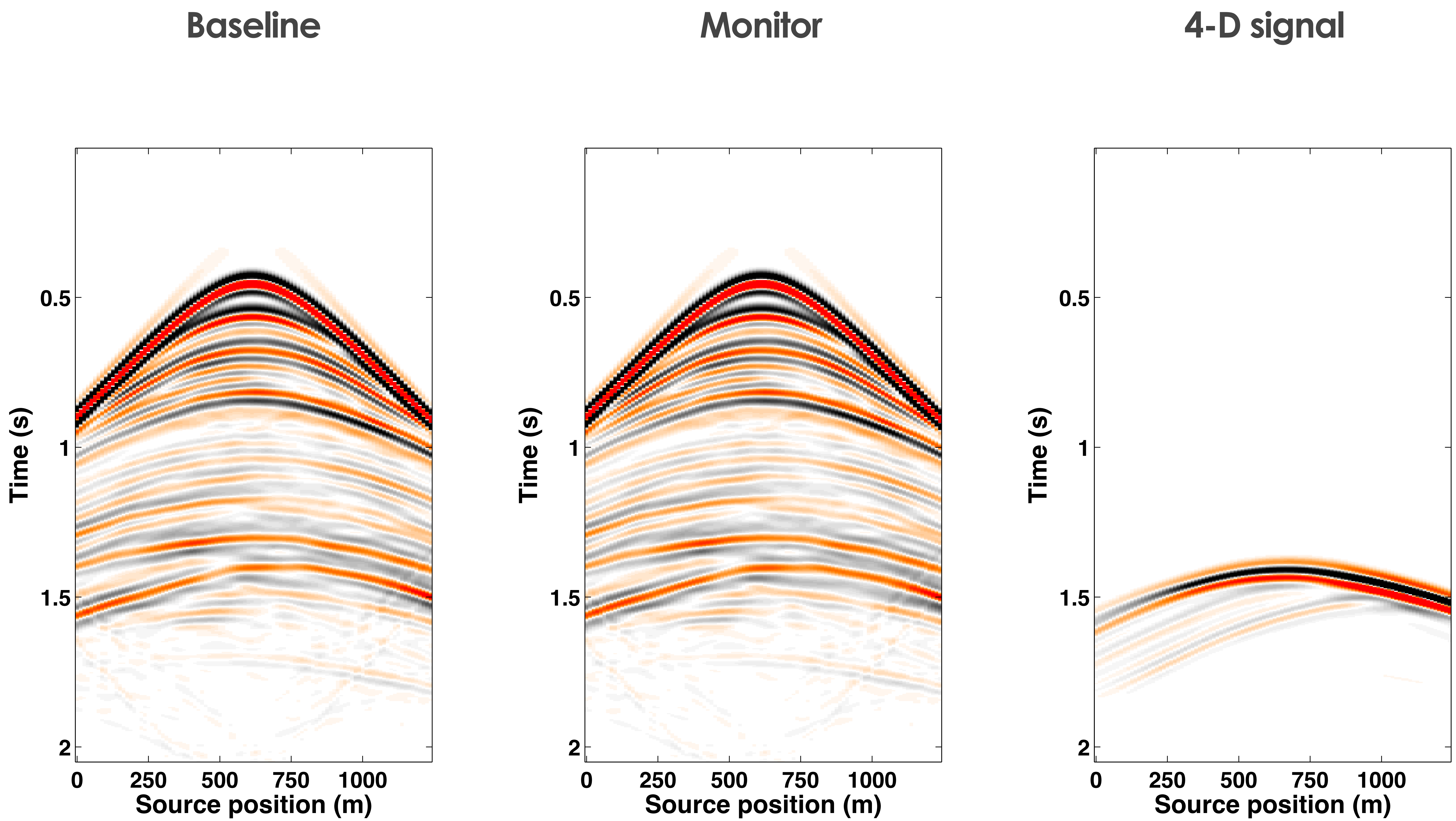
$$\text{what if } \mathbf{A}_1 \neq \mathbf{A}_2 \ ?$$

Question

Acquisition: *repeat* survey design or not ?

Processing: is there any significance?

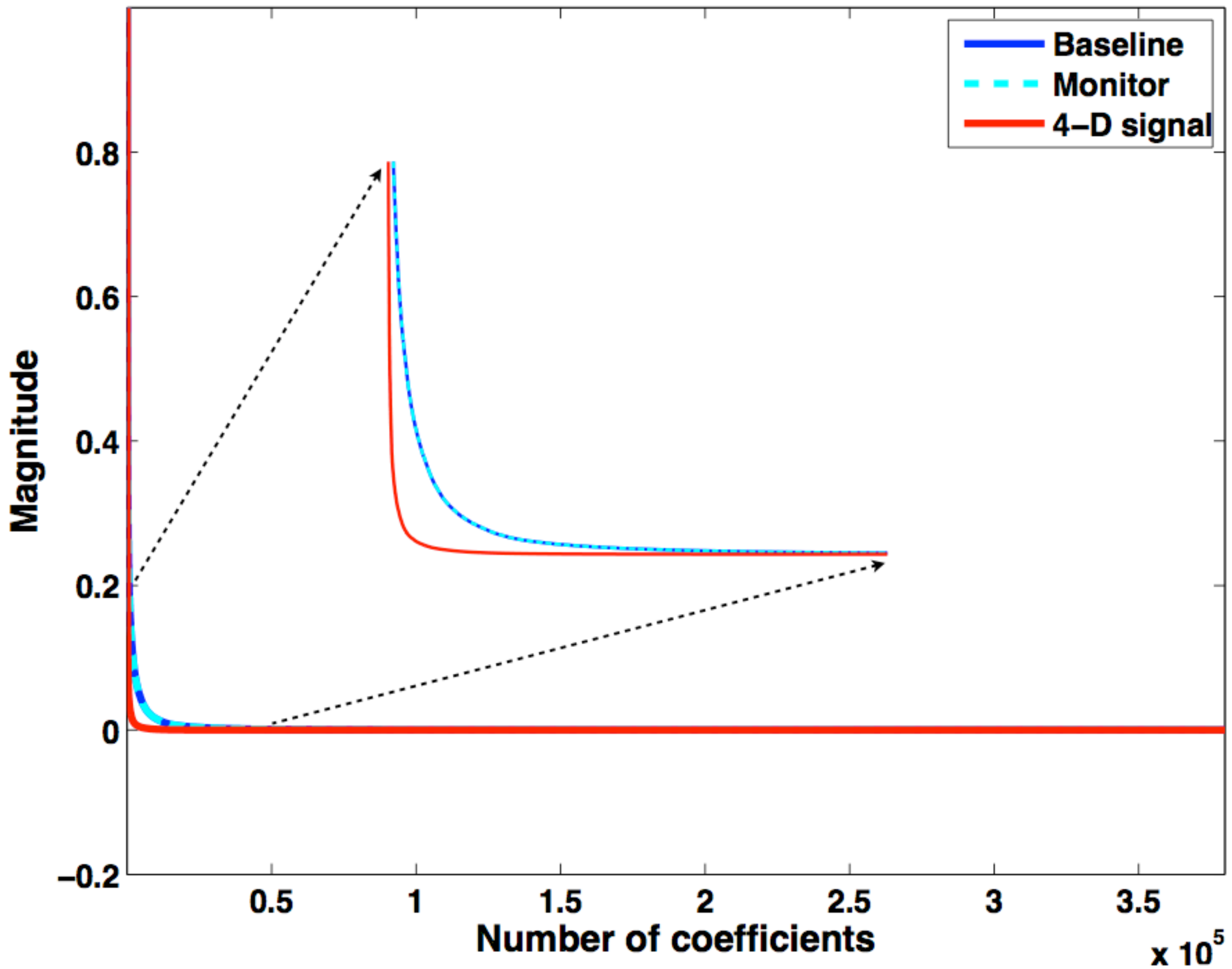
Simulated original data
– time-domain finite differences

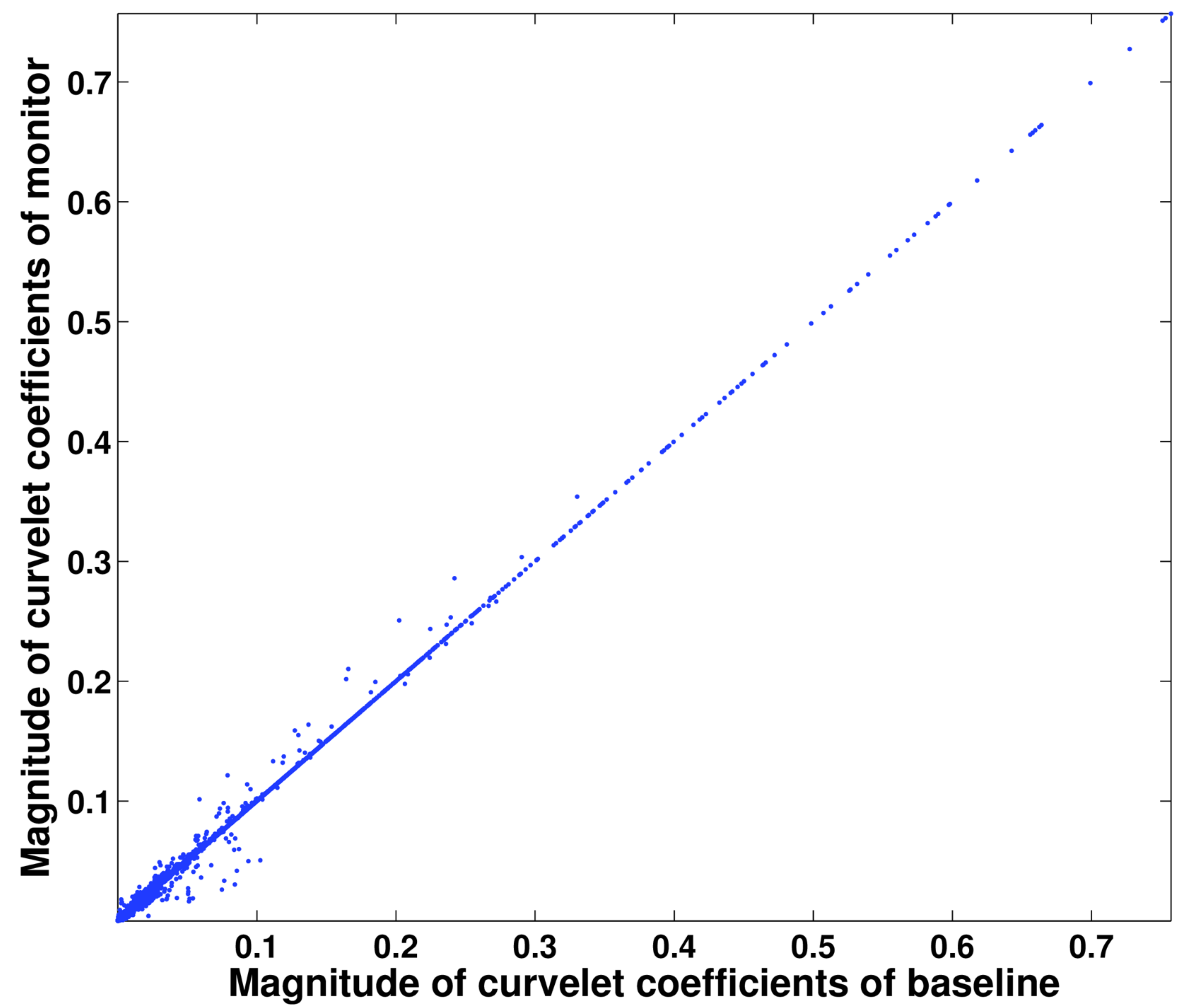


time samples: **512**
receivers: **100**
sources: **100**

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

Structure - curvelet representation





Observations

- Compressible
- Correlations in different vintages
- Time-lapse signal
  - sparse

Can we exploit the structure in time-lapse simultaneously ?

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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

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…

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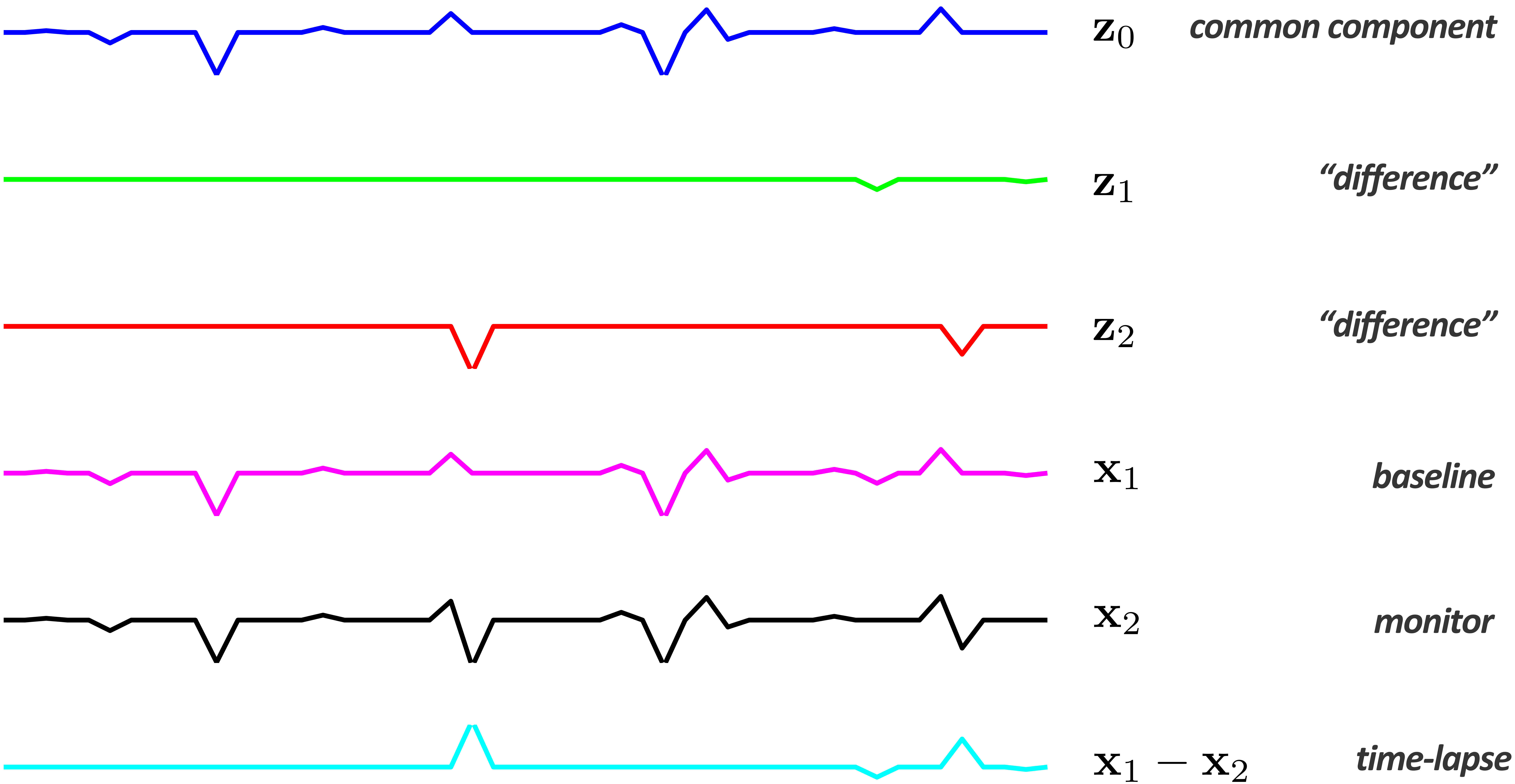
Interpretation of the model
– w/ & w/o repetition

- **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



Signal length N = 50

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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

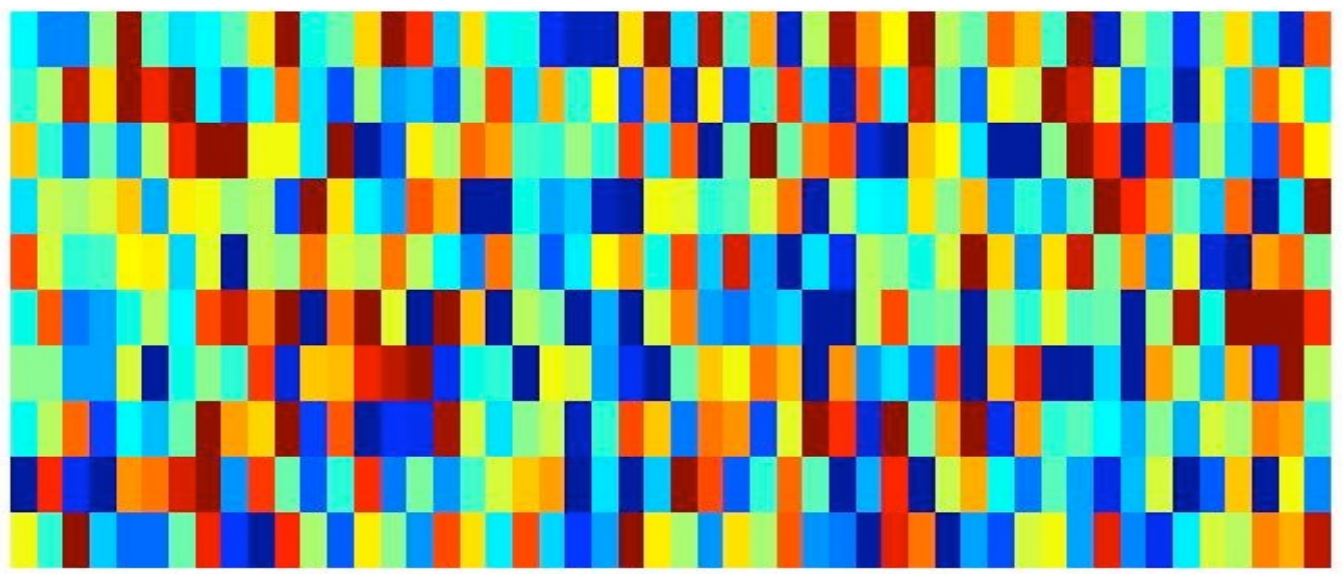
Stylized experiments

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

$\mathbf{A}_1$

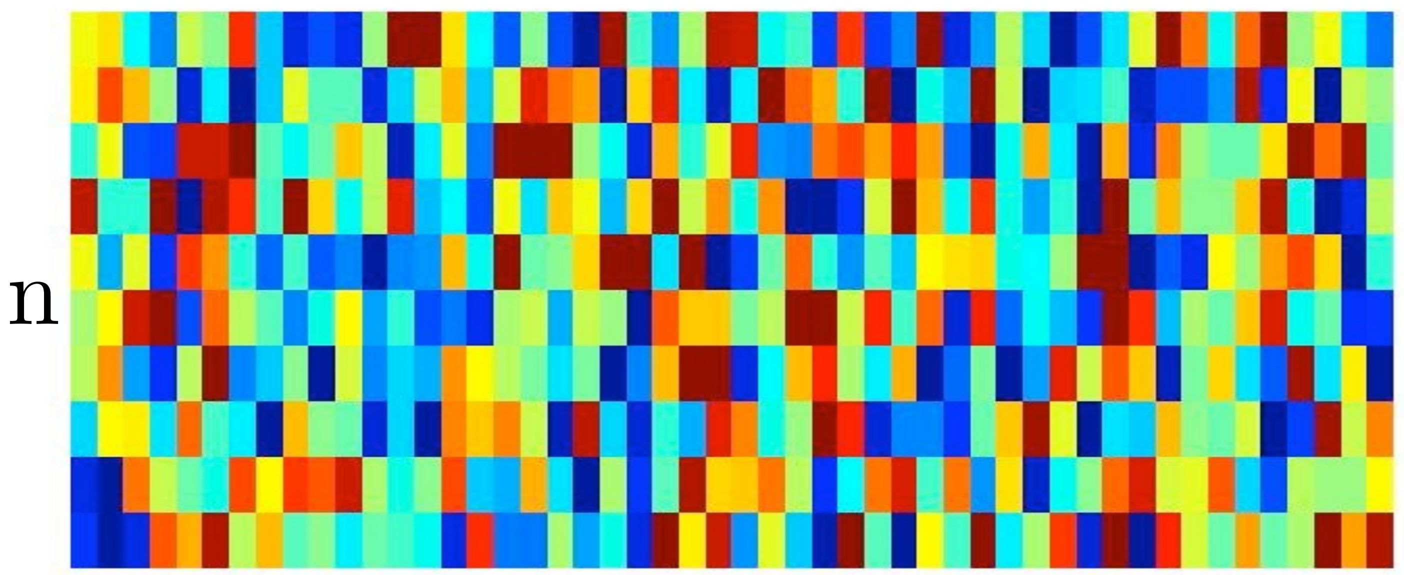
$n = 10$



n, N

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

$\mathbf{A}_2$



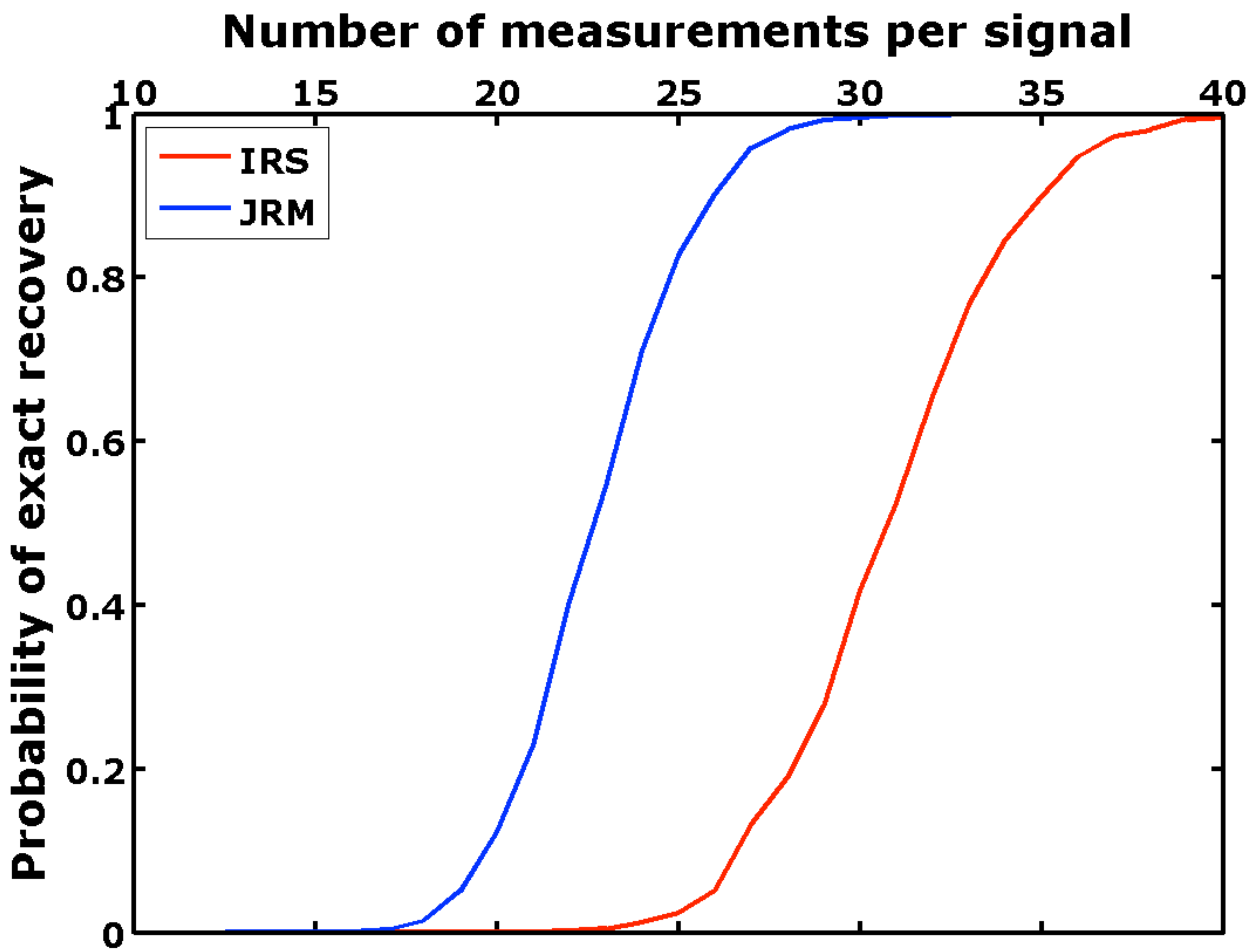
n, N

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

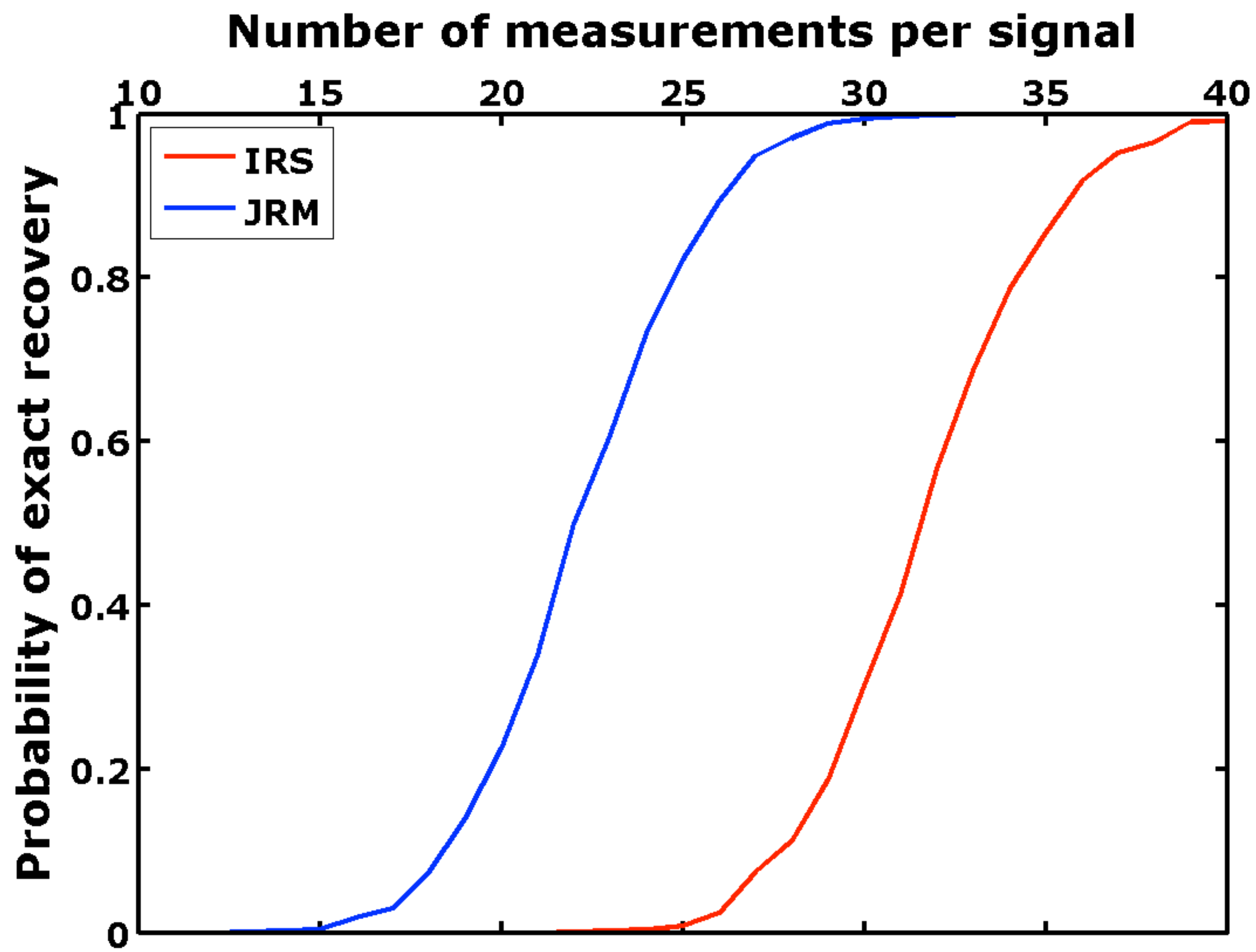
Run 2000 different experiments

Compute Probability of recovery

Results: *independent* versus *joint* recovery



Recovery of vintages



Recovery of difference

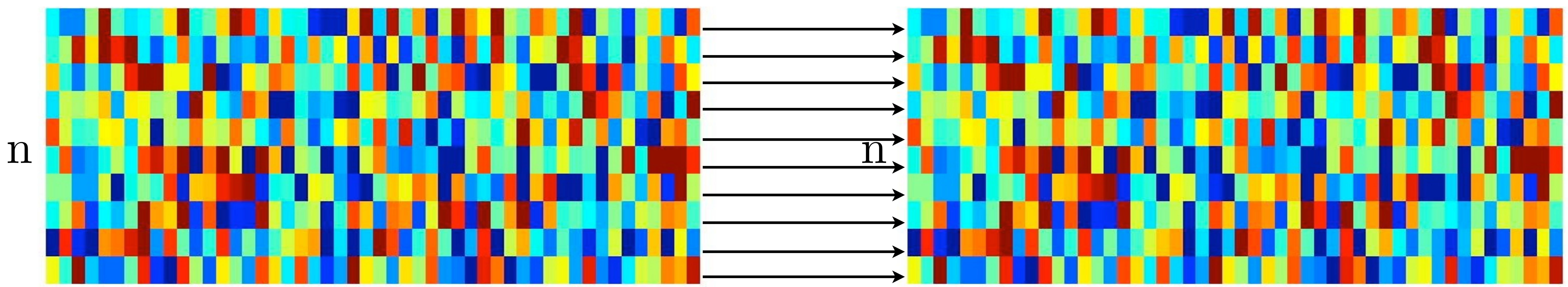
Observations

- Joint recovery (processing) is better than independent processing
- Improved recovery of vintages and difference
- Requires fewer samples (subsampled data)

With exact repetition

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

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

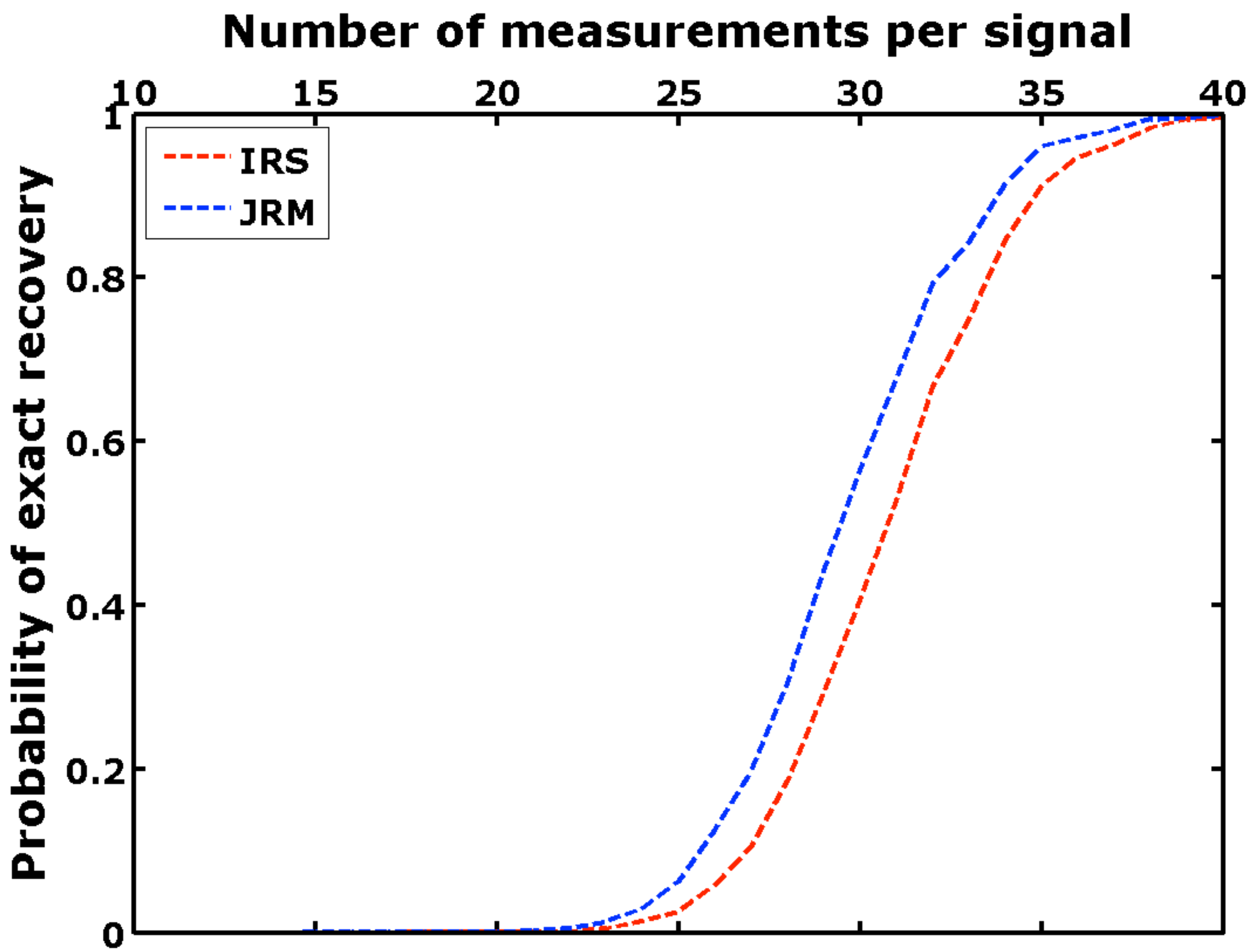


N $\quad$ N

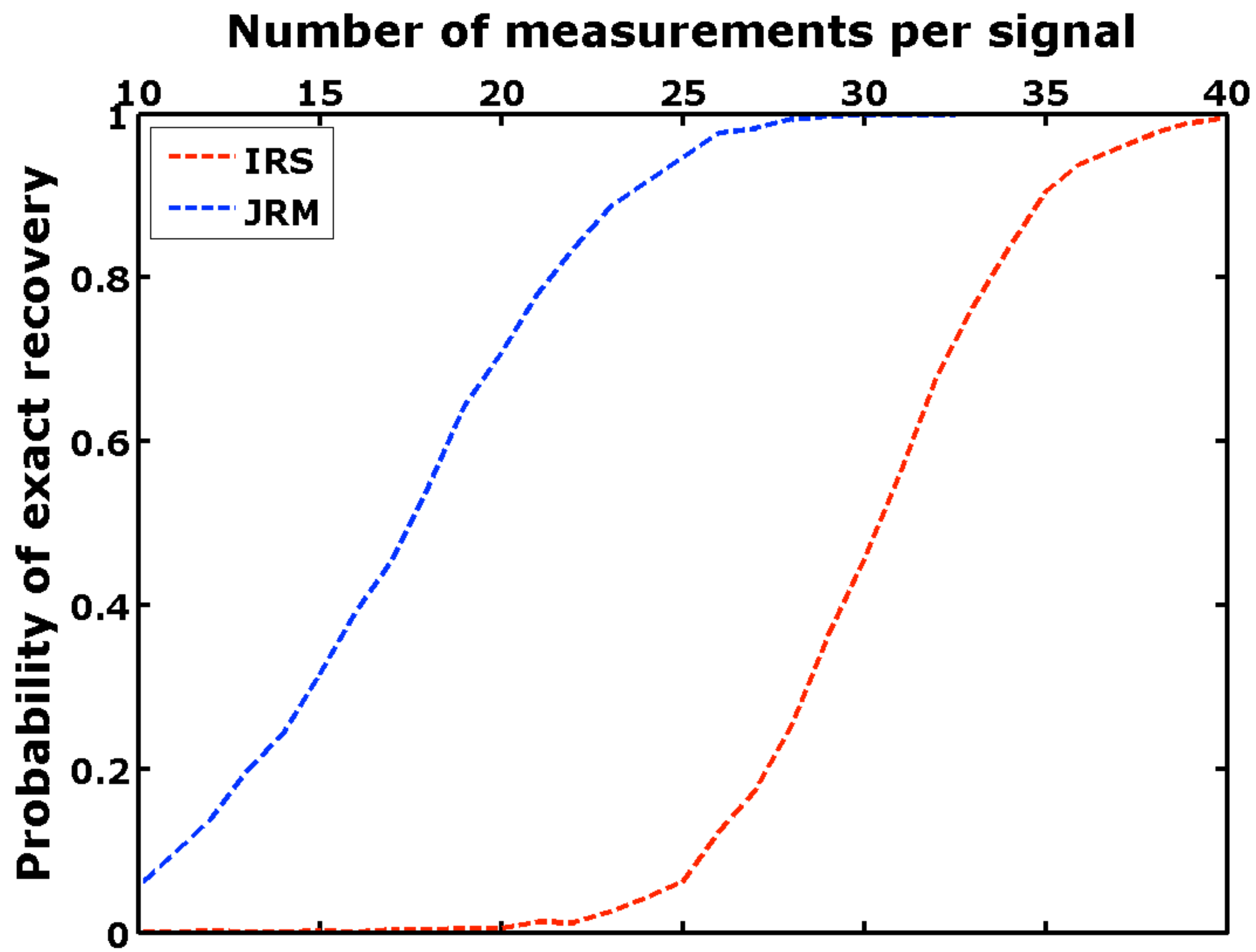
$\mathbf{b}_1 = \mathbf{A}_1\mathbf{x}_1$ $\quad$ $\mathbf{b}_2 = \mathbf{A}_2\mathbf{x}_2$

REPEAT EXPERIMENT AS BEFORE

Results: *independent* versus *joint* recovery

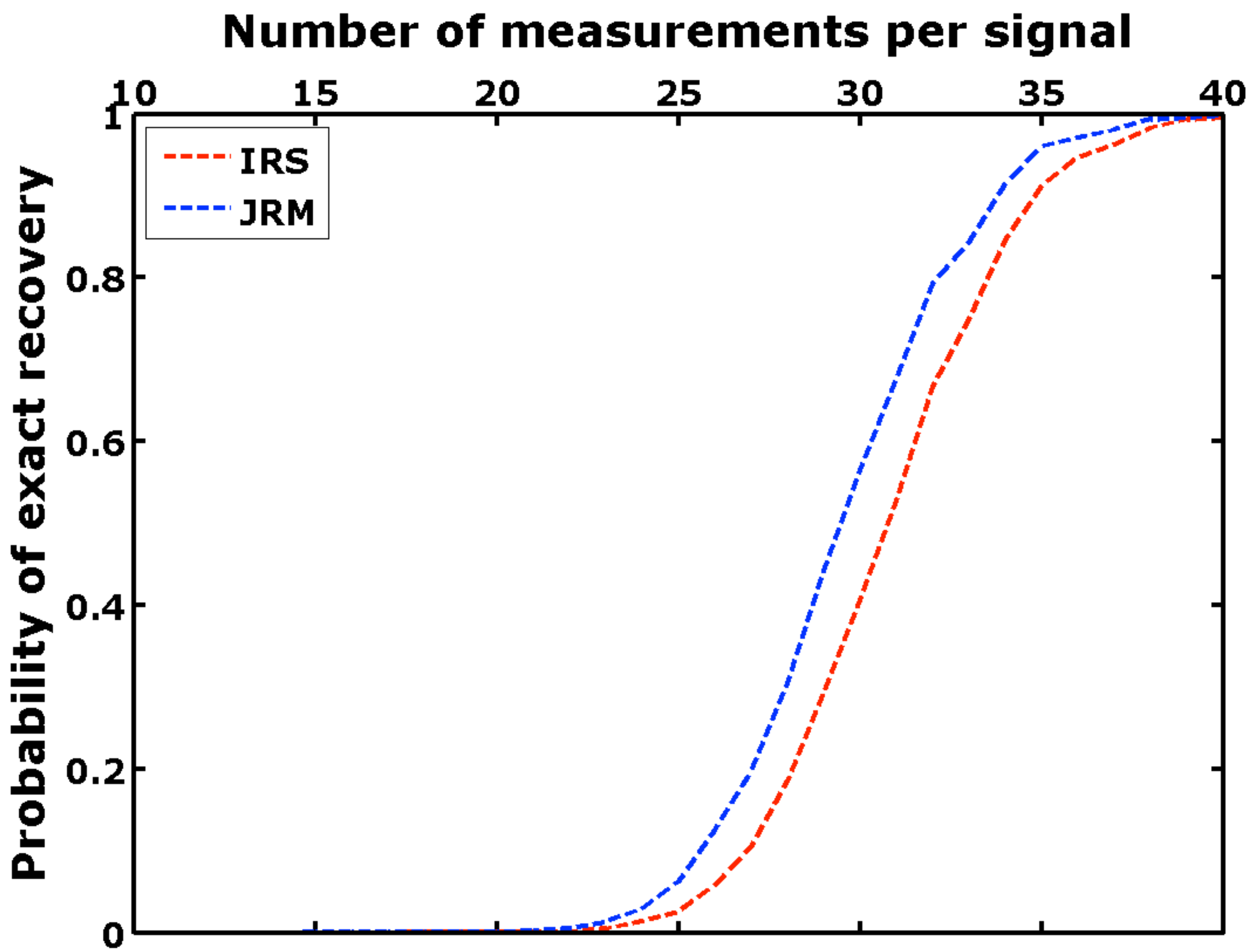


Recovery of vintages

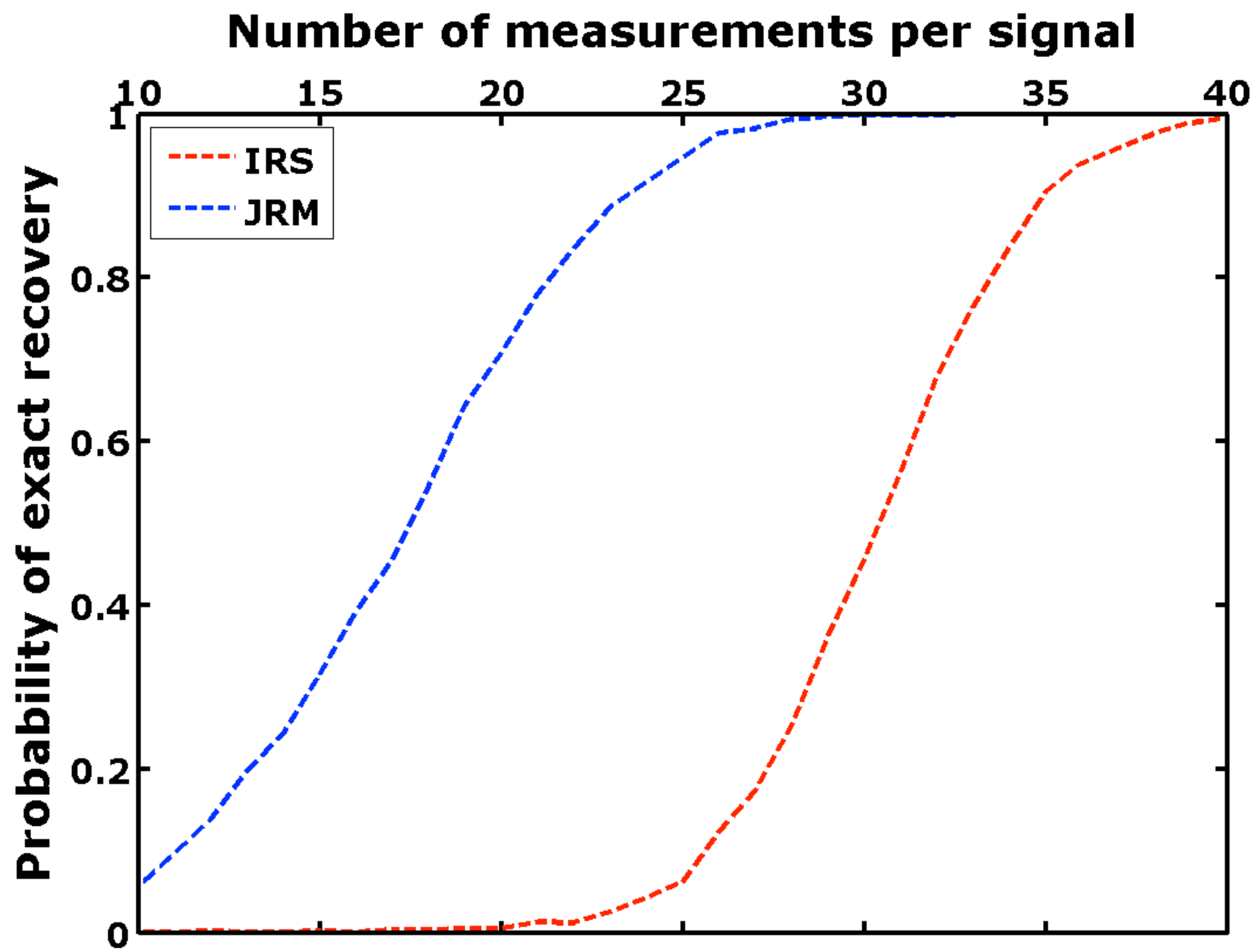


Recovery of difference

WITH Repetition

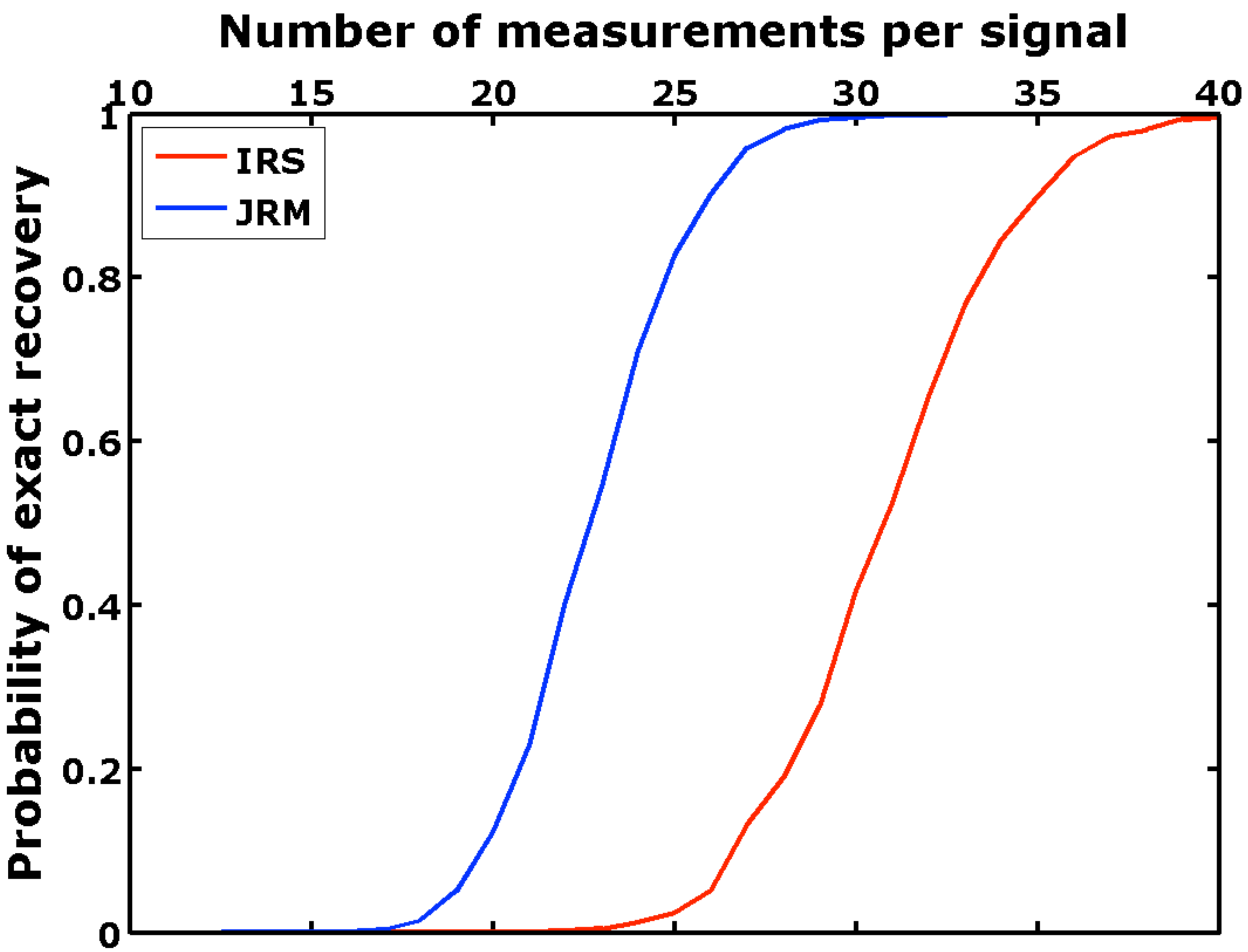


Recovery of vintages

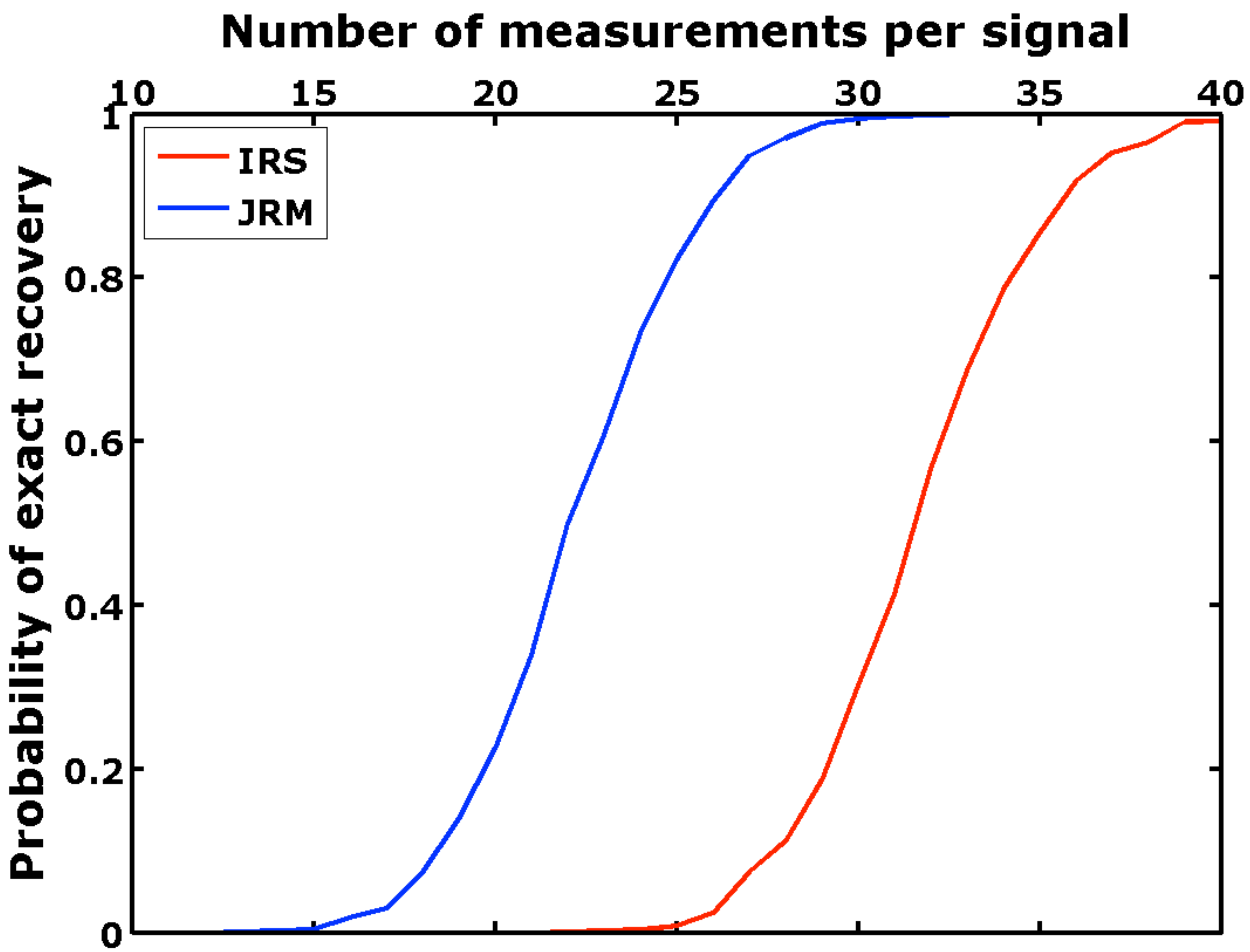


Recovery of difference

WITHOUT Repetition



Recovery of vintages



Recovery of difference

Summary

- Without repetition, recovery of vintages improves
  - recovery of difference not bad
- With “exact” repetition, recovery of difference is enhanced
  - difference is sparser than vintages
  - while vintage recovery is not as good
- Question : Is there a “sweet spot” where we can get the best of both?

Joint recovery is better than independent

Time-lapse in imaging

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Migration

Problem formulation

$$\tilde{\mathbf{x}} = \arg\min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{subject to} \quad \|\mathbf{A}\mathbf{x} - \mathbf{b}\|_2 \leq \sigma$$

where

Linearized Demigration operator

$$\mathbf{A} = \overbrace{\nabla \mathrm{F}[\mathbf{m}_0, q]}^{}\mathbf{C}^H$$

$$\mathbf{b} = \delta\mathbf{d}$$

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

Felix J. Herrmann and Xiang Li, "Efficient least-squares imaging with sparsity promotion and compressive sensing", *Geophysical Prospecting*, vol. 60, p. 696-712, 2012.

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Migration

Dimensionality reduction

$$\tilde{\mathbf{x}} = \arg\min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{subject to} \quad \|\underline{\mathbf{A}}\mathbf{x} - \underline{\mathbf{b}}\|_2 \leq \sigma_k$$

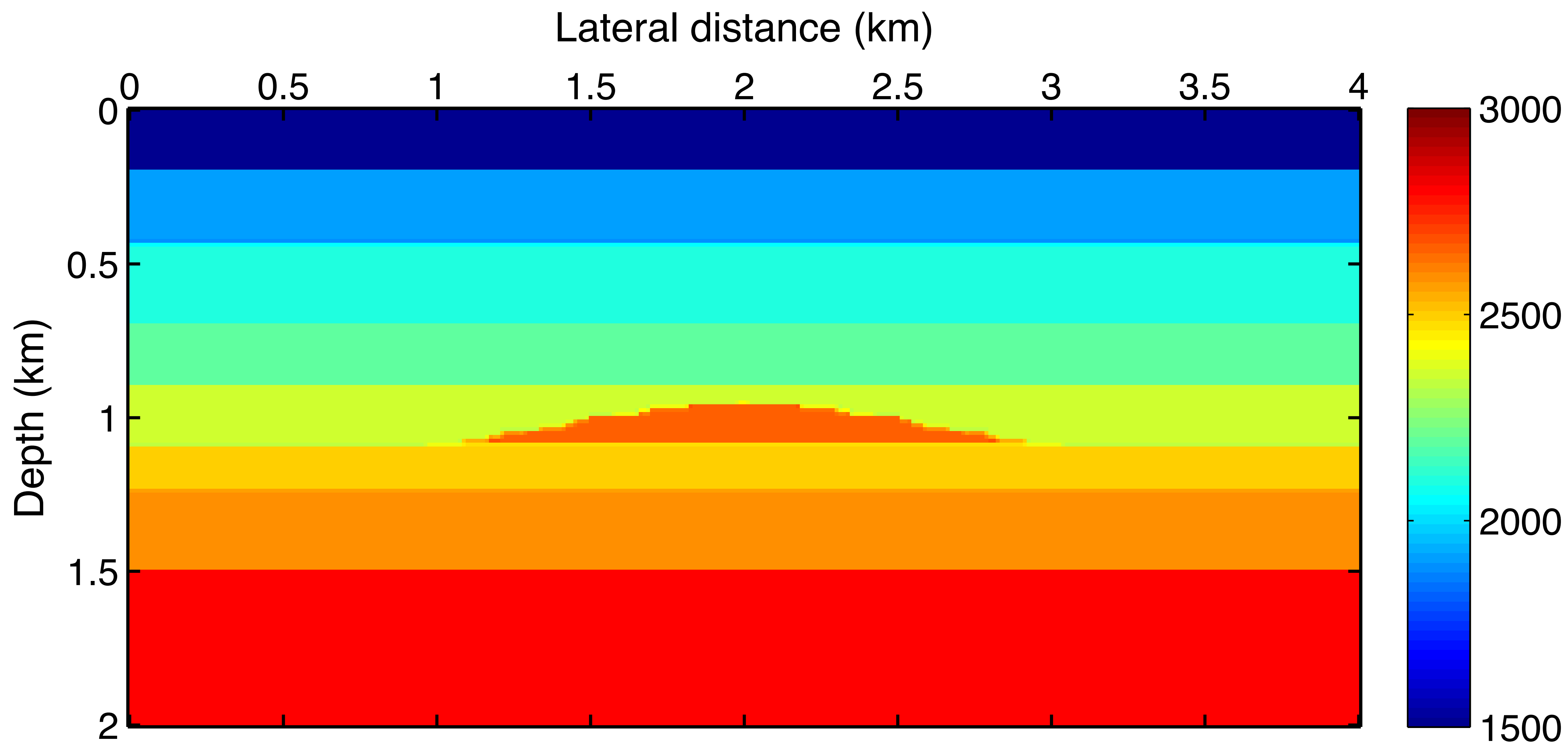
where

$$\underline{\mathbf{A}} = \mathrm{RM}\mathbf{A}$$

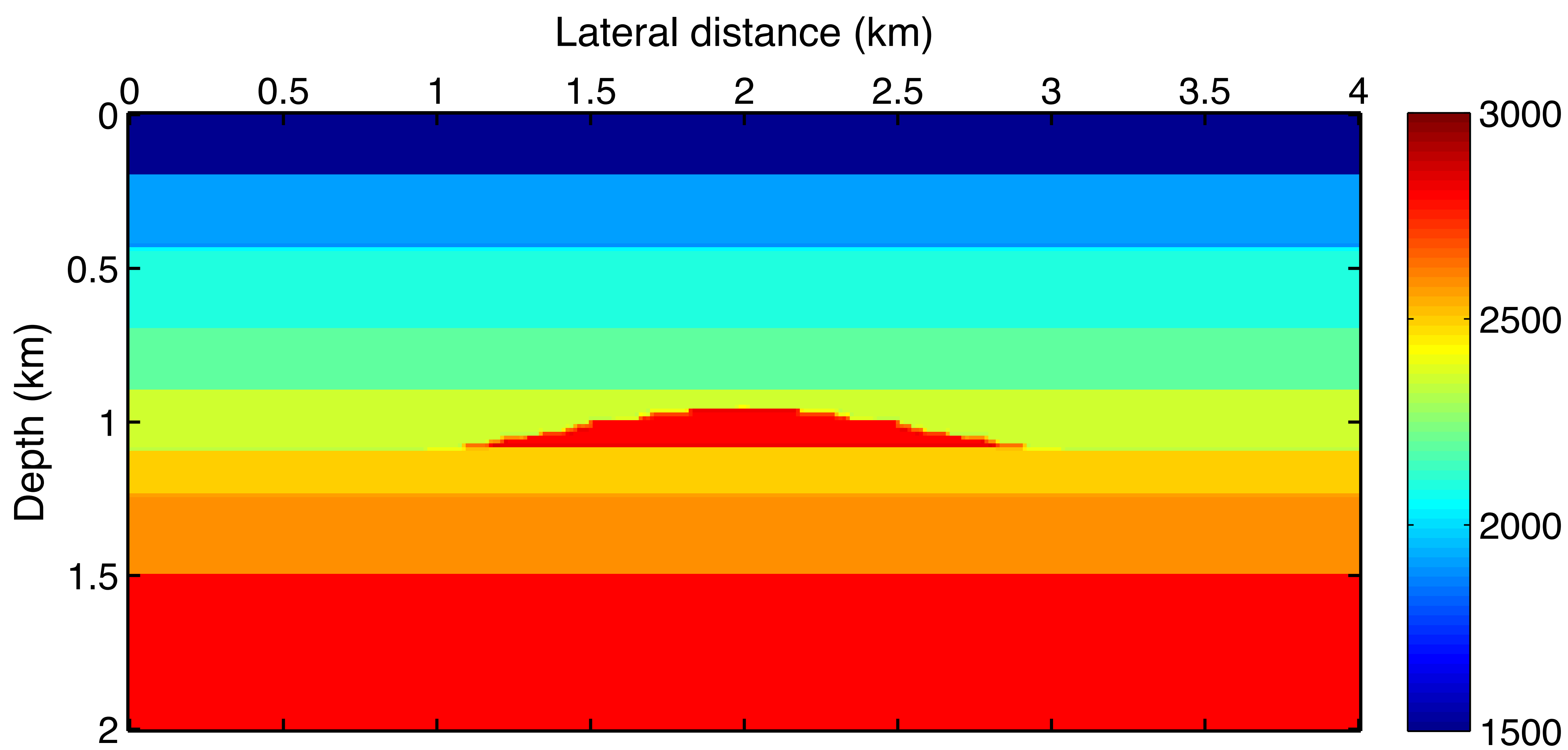
$$\underline{\mathbf{b}} = \mathrm{RM}\mathbf{b}$$

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

True model

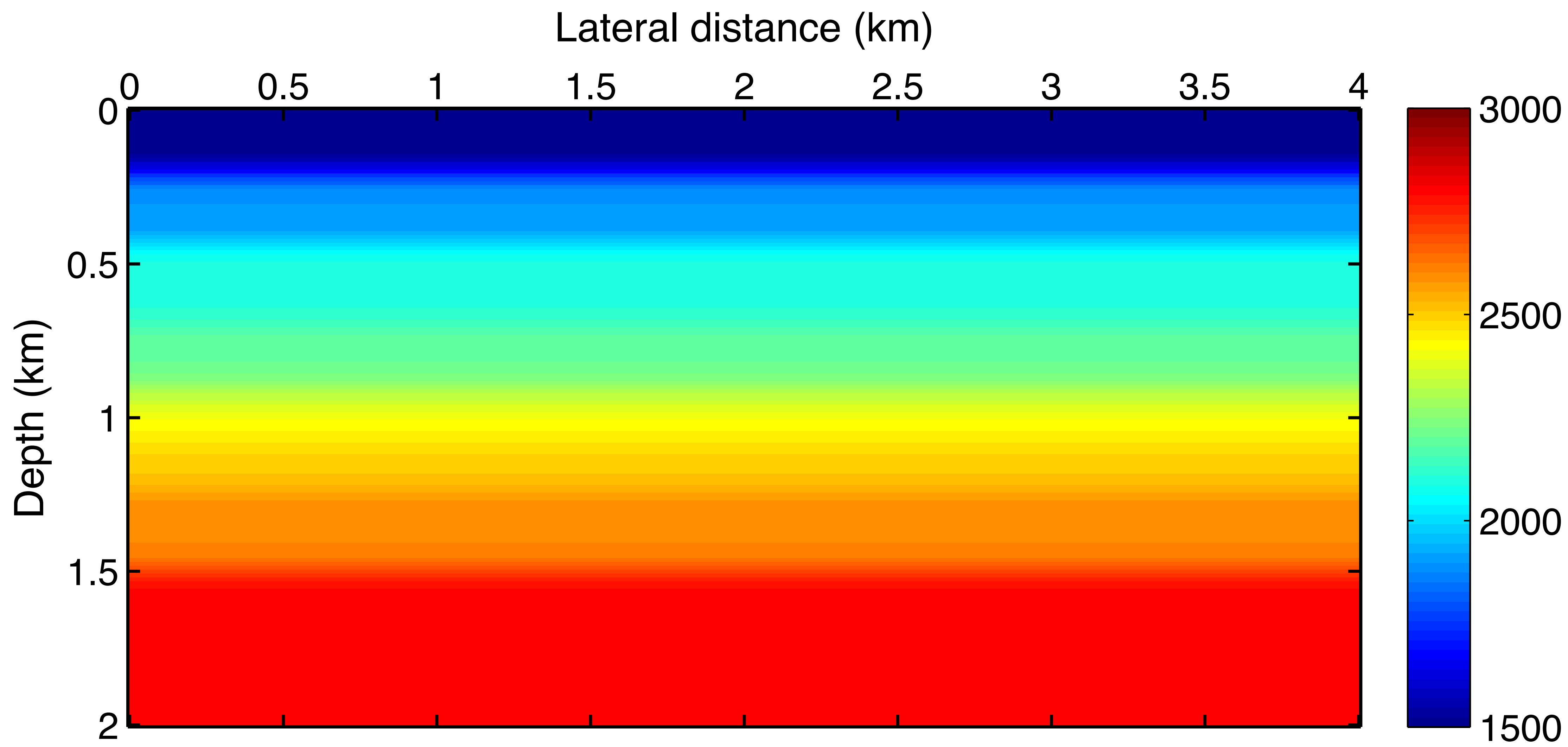


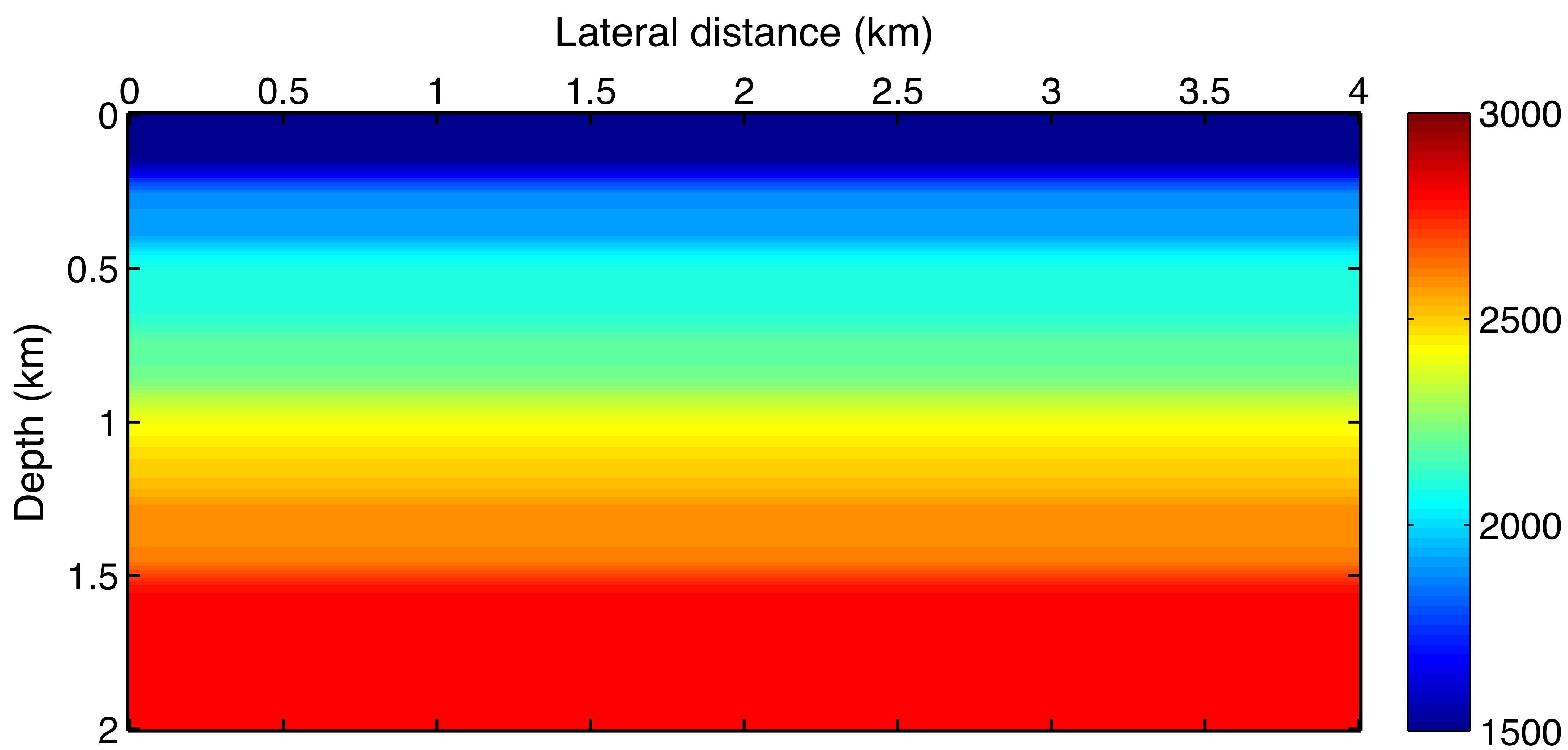
Baseline



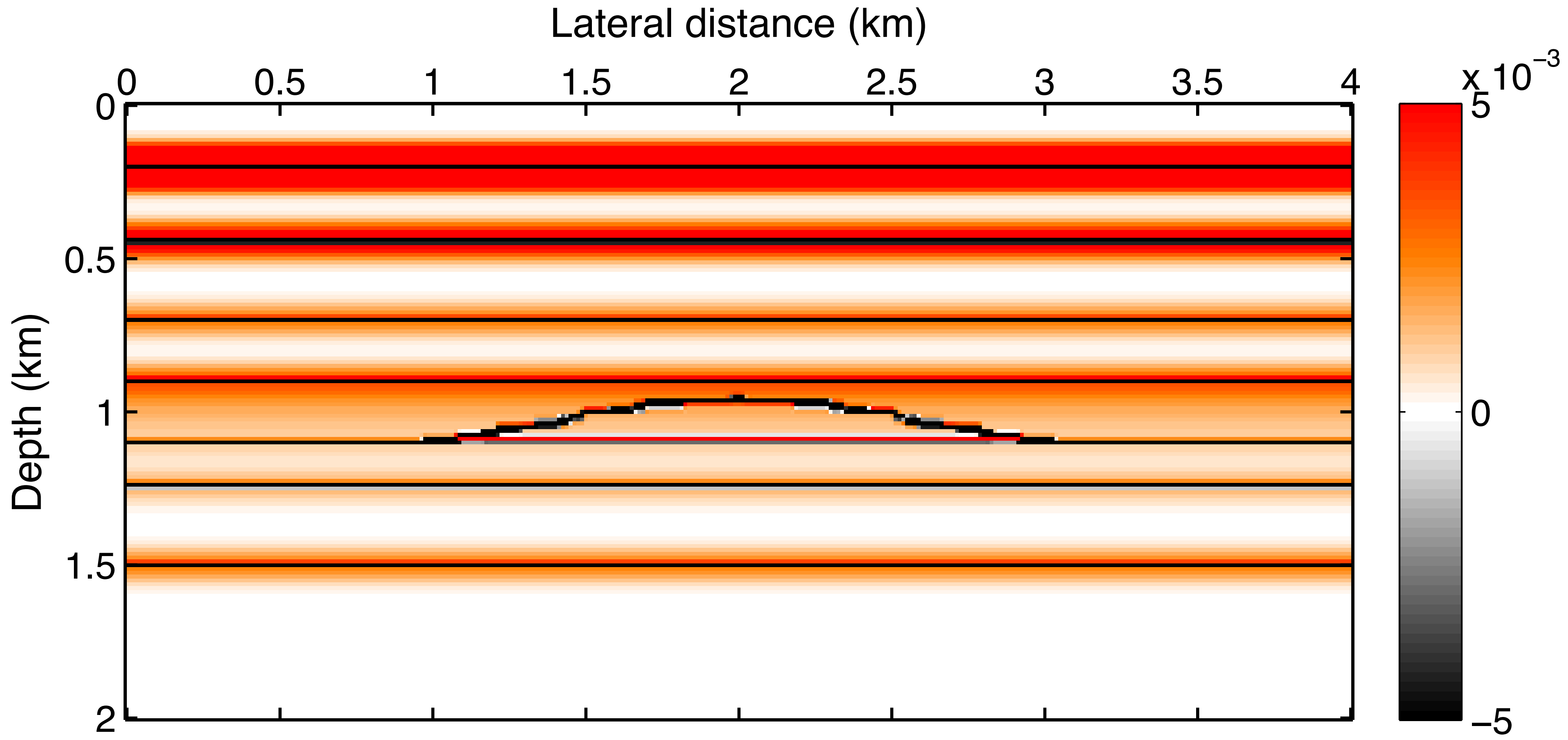
Monitor

Initial model

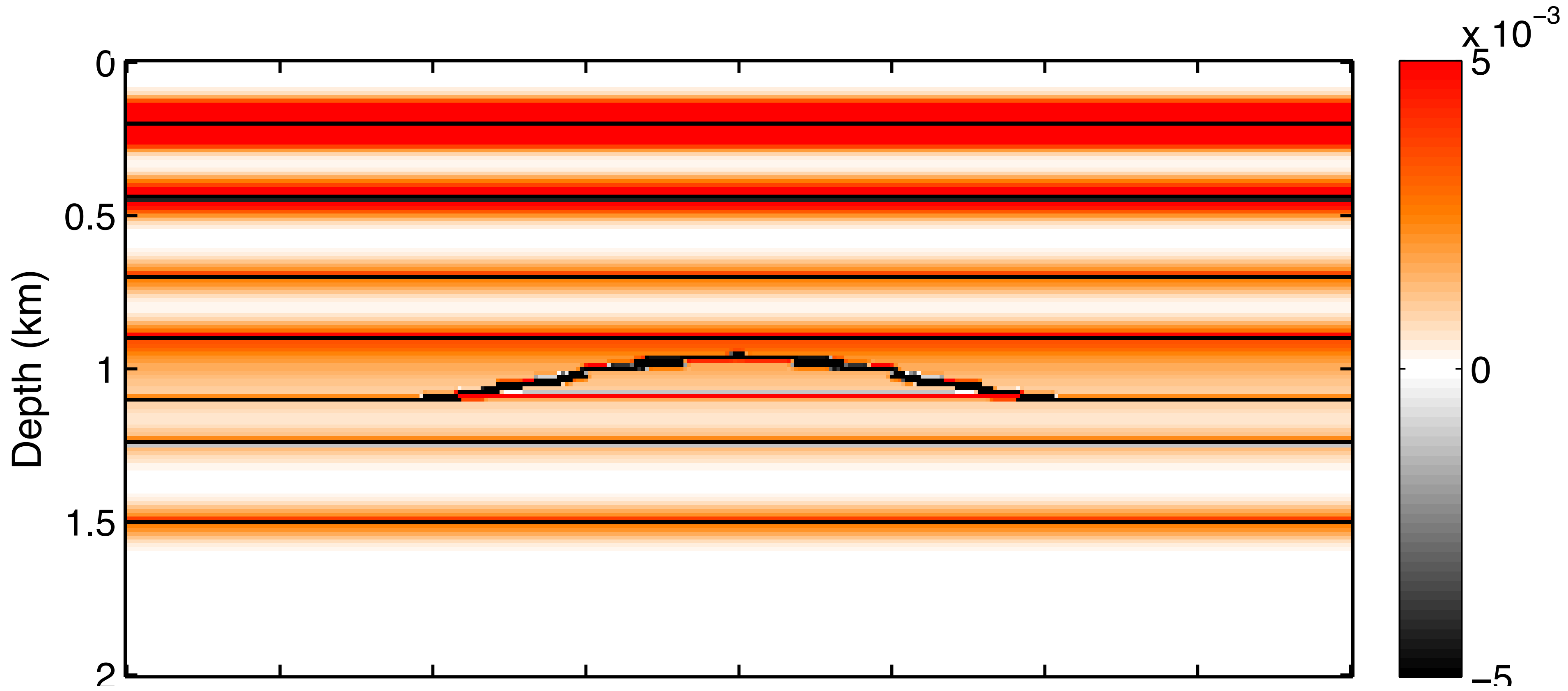




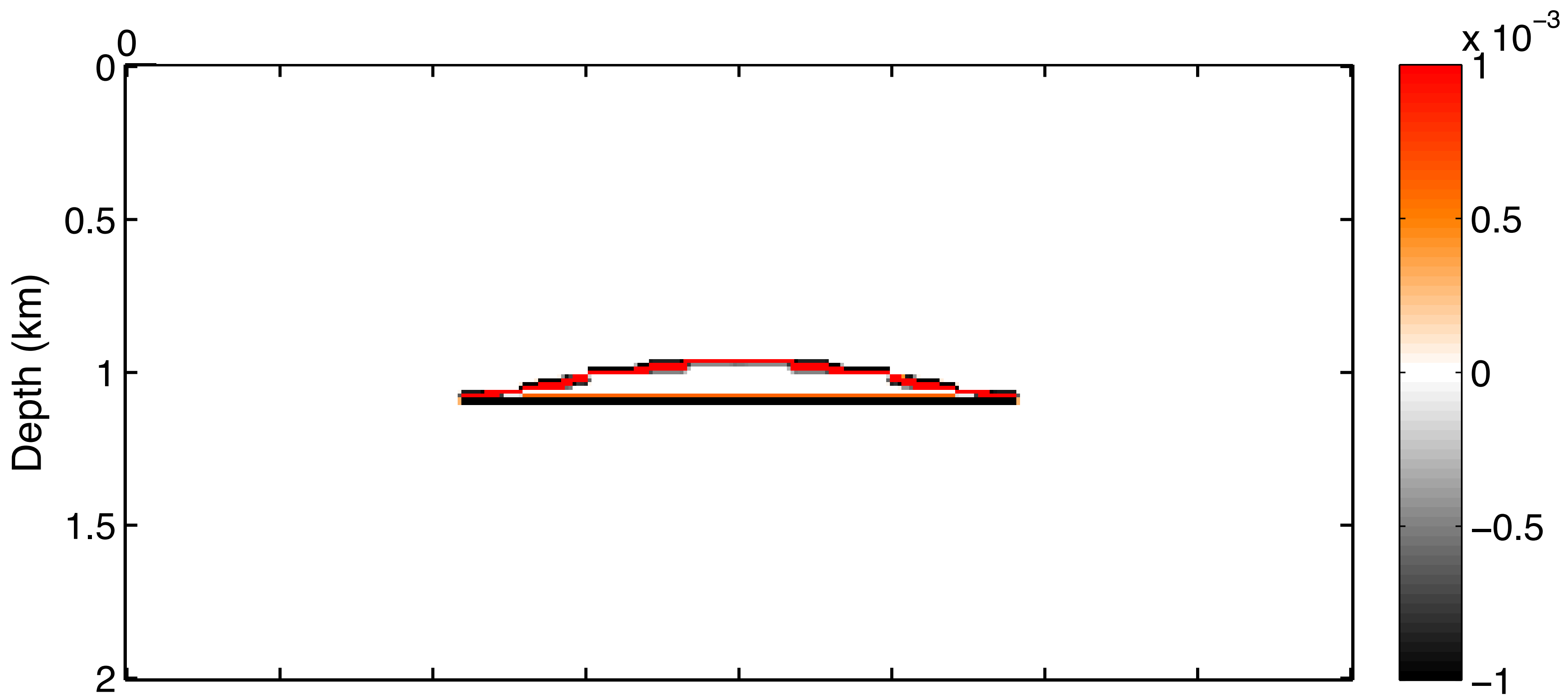
Perturbation



Baseline



Monitor



Difference

Migration

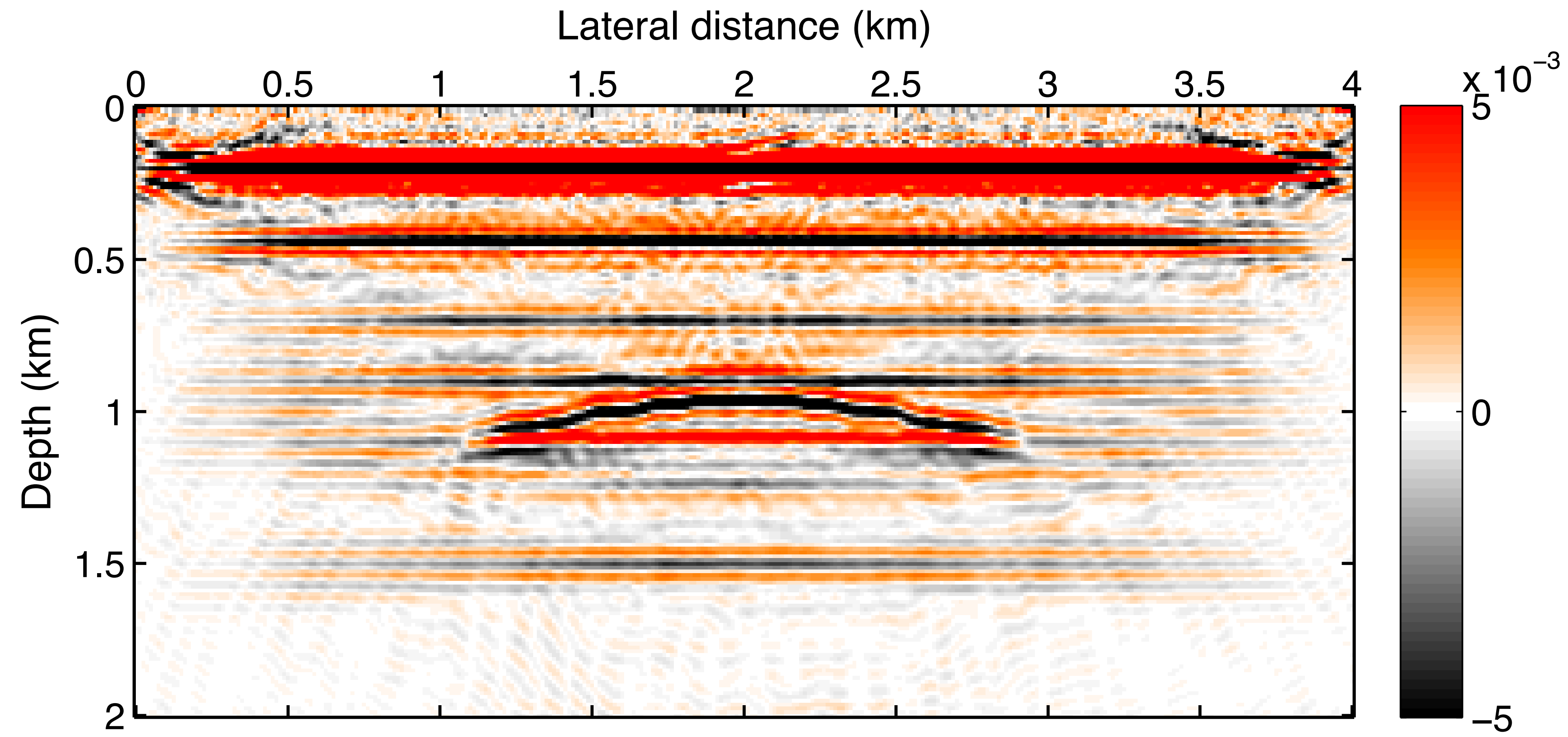
Modeling parameters

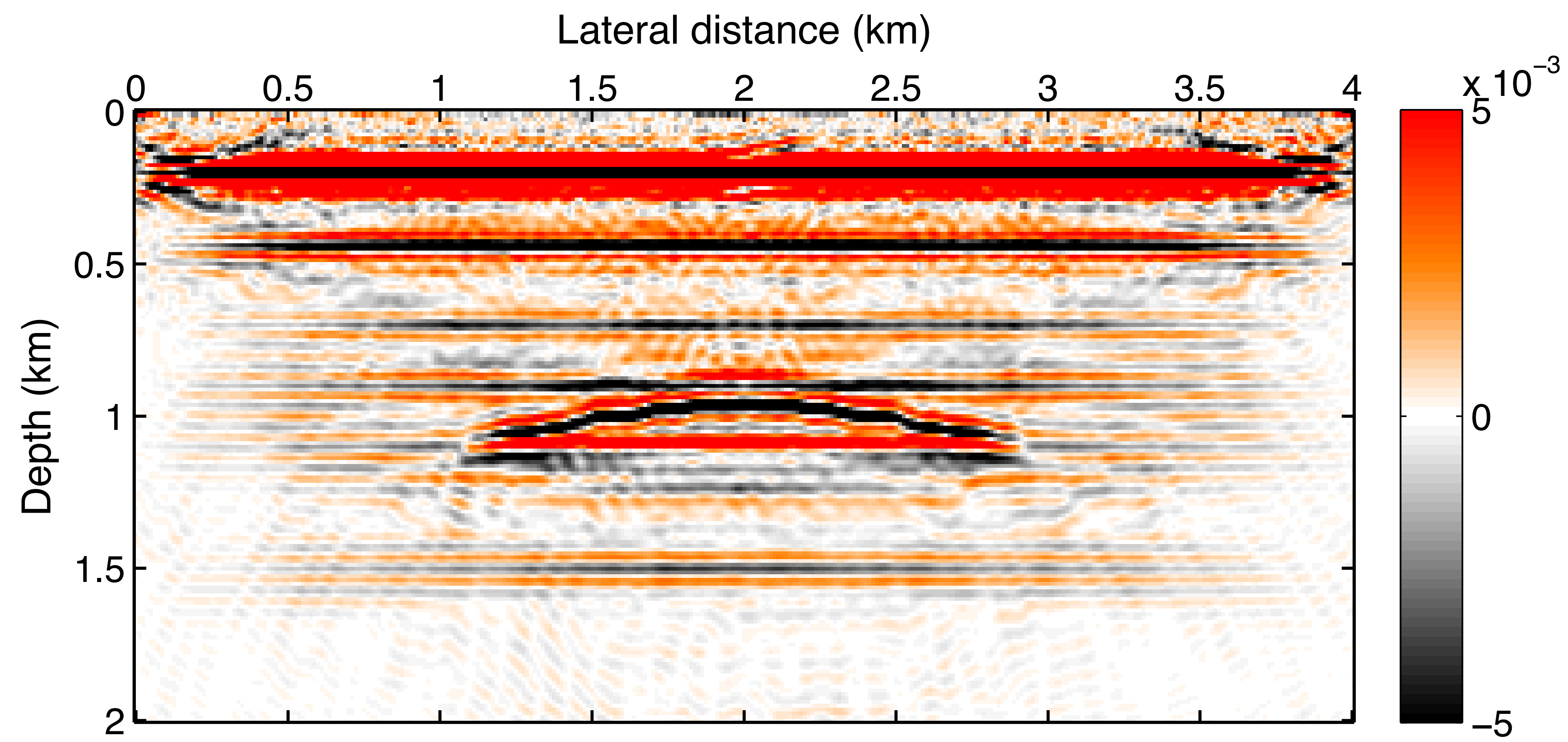
- 161 shots @ 25m interval
- 321 receivers @ 12.5m
- 16 frequencies from 17 to 25Hz
- Ricker wavelet @ 12.5Hz

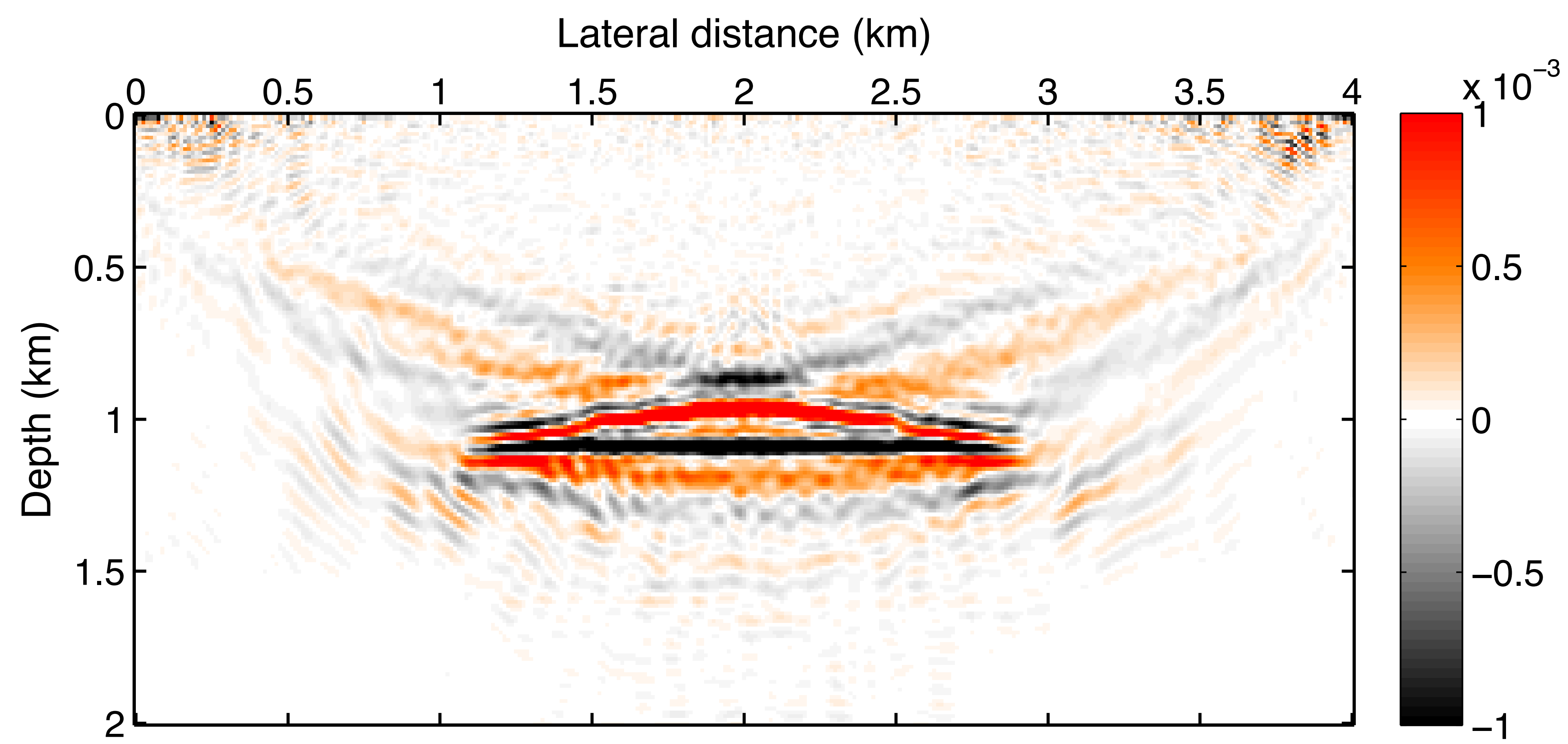
Imaging step

- Assume *good* background velocity model
- *Baseline* : use few simultaneous shots, with renewal
- *Monitor* : repeat similar encoding as baseline

With 5 simultaneous shots







Joint
10 iterations

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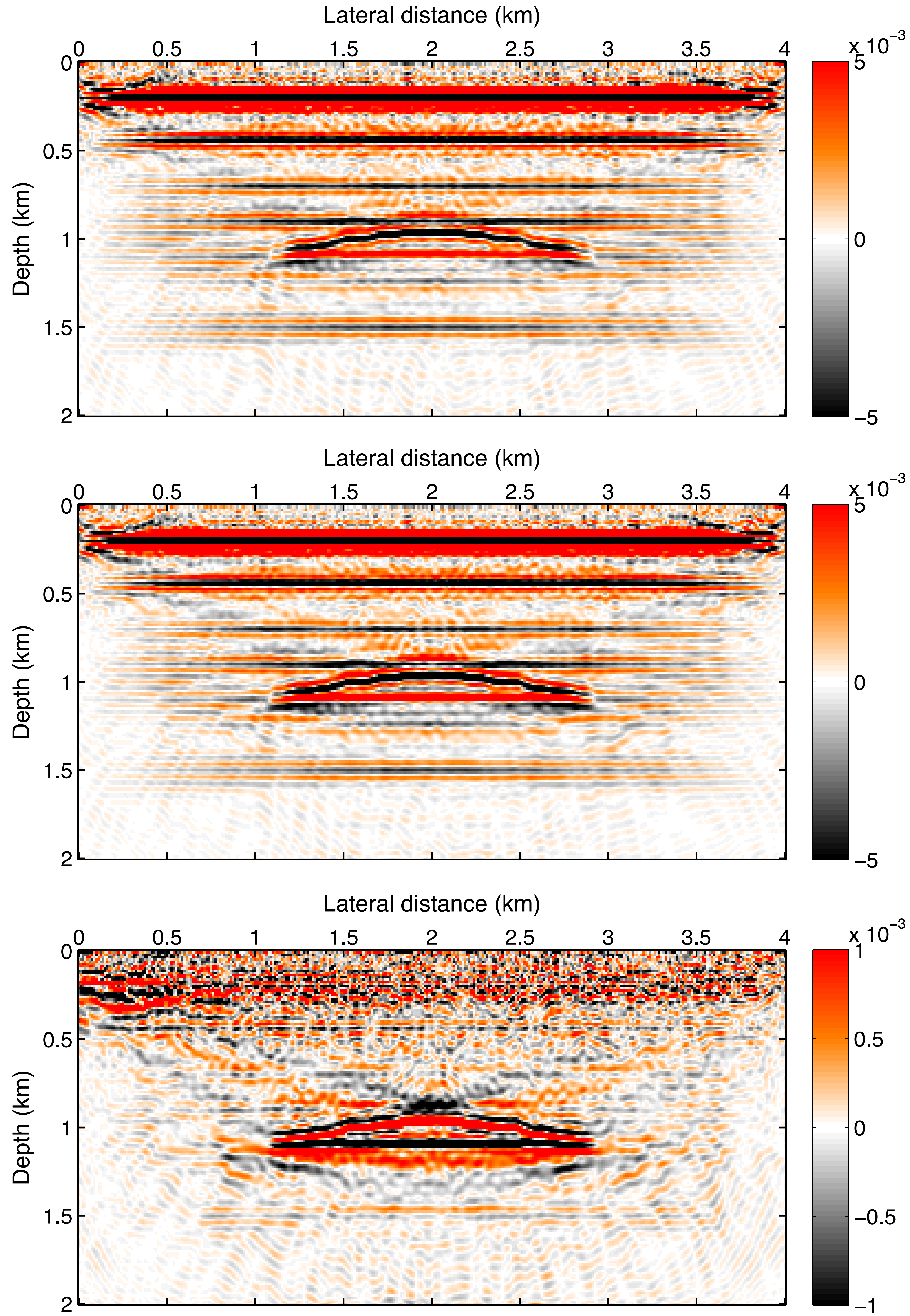
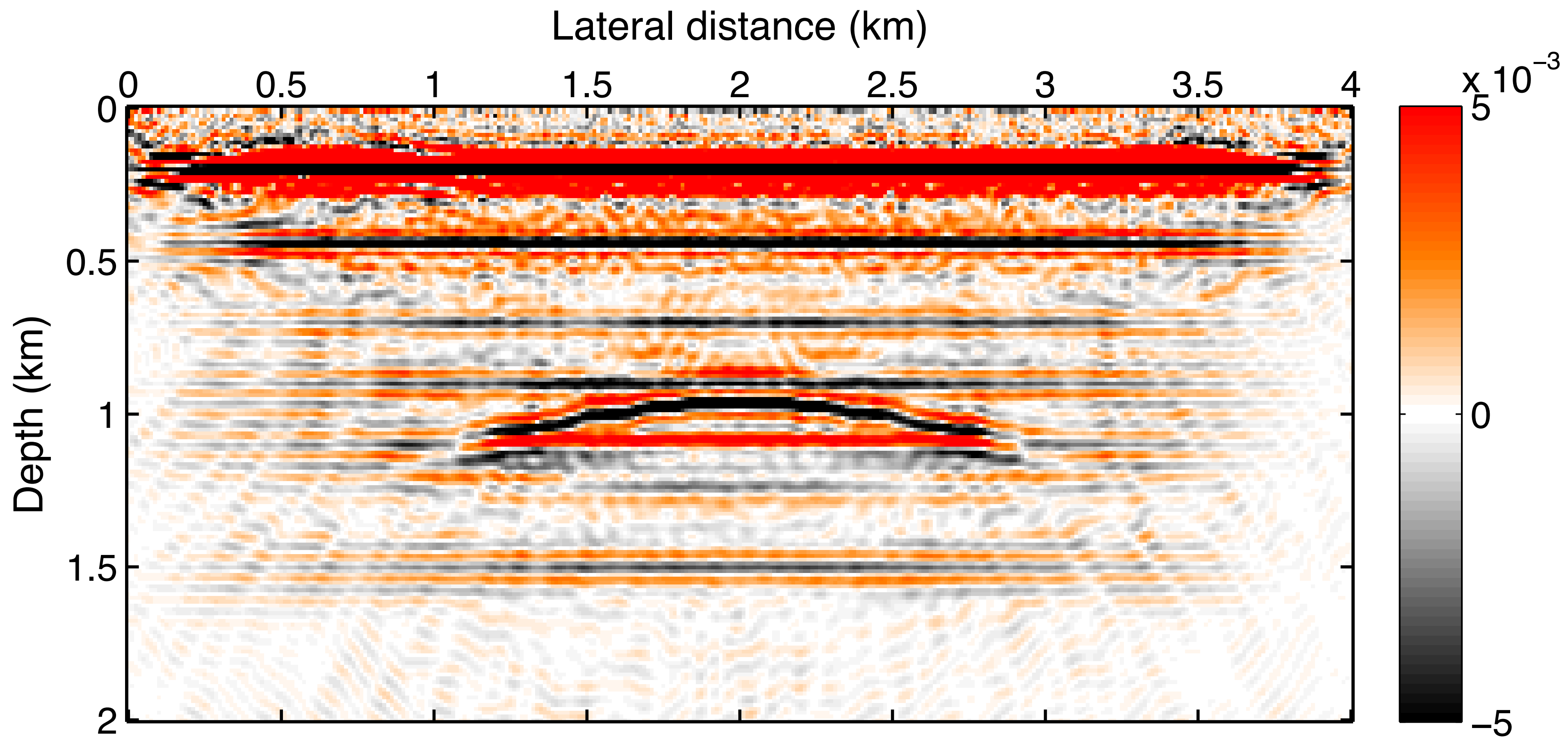
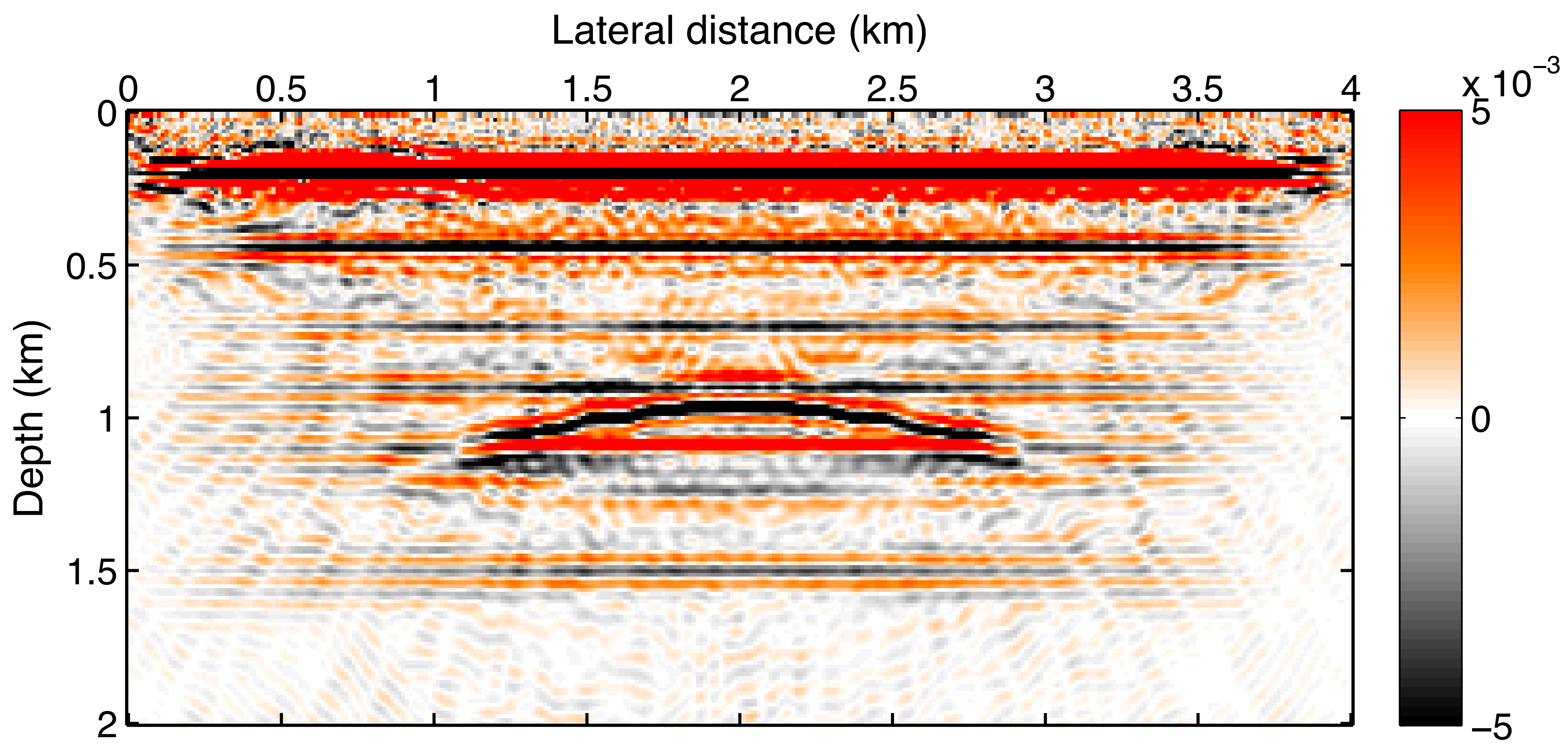
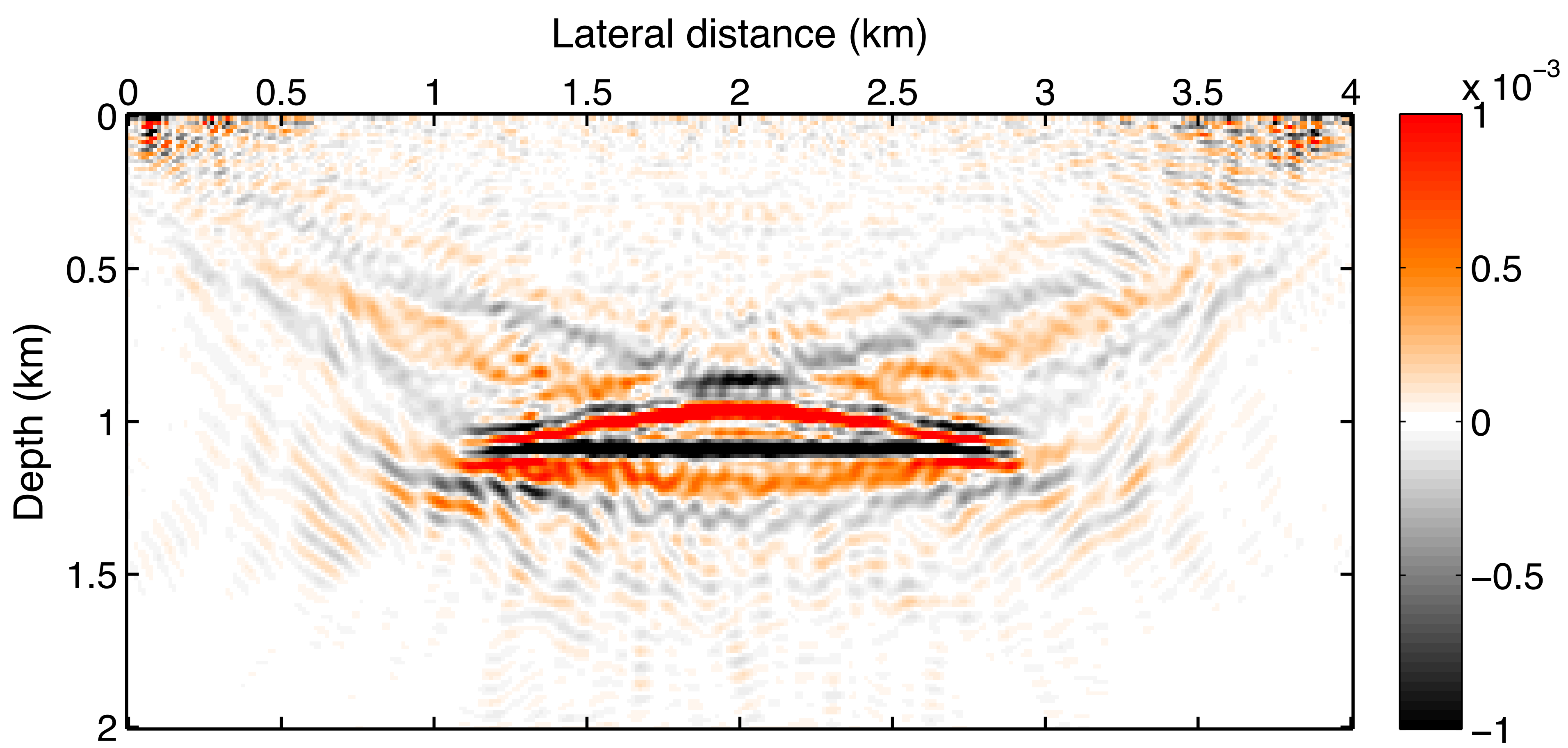


Independent
10 iterations

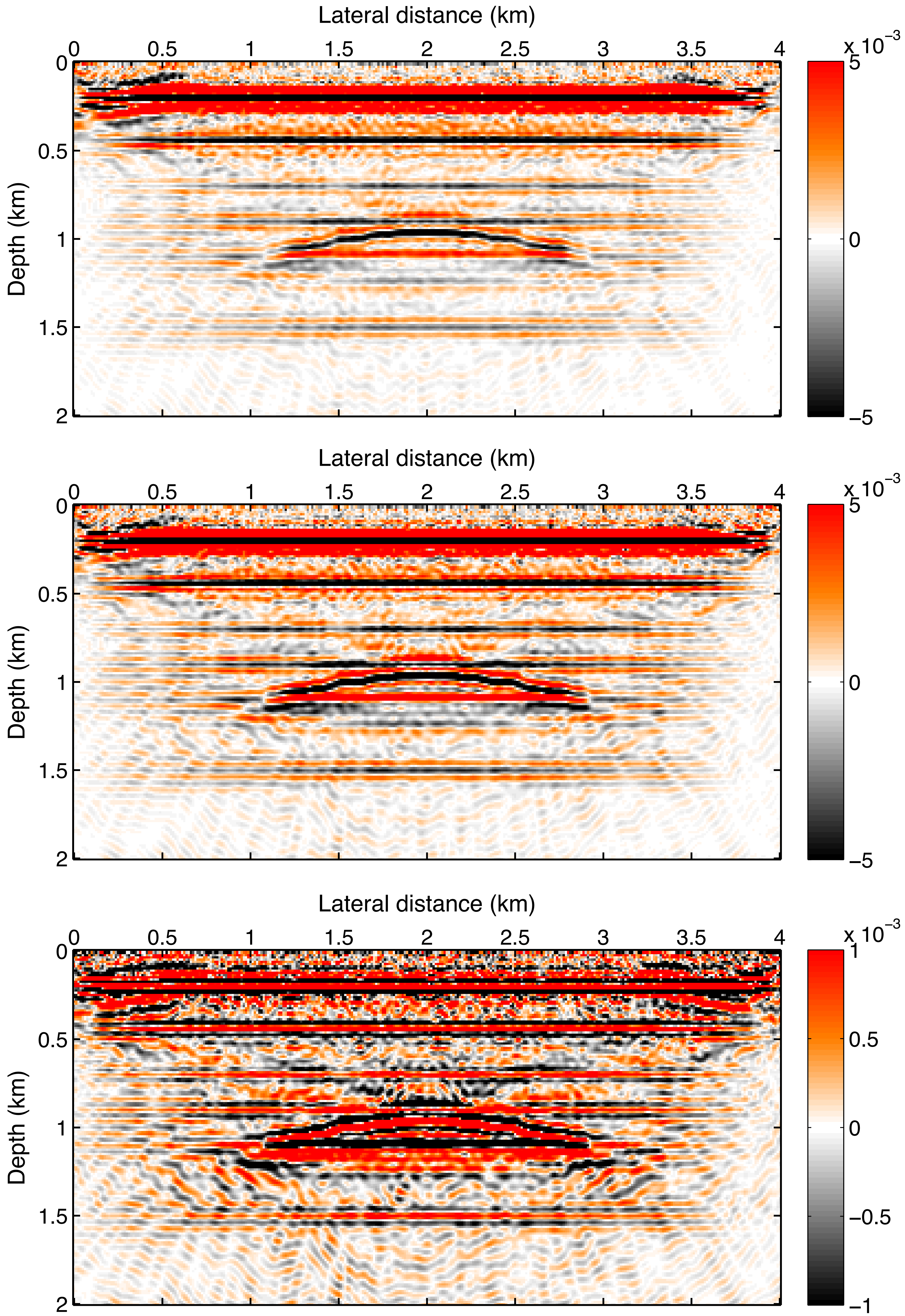
With 3 simultaneous shots







Joint
10 iterations



Independent

10 iterations

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 reconstruct, process and interpret time-lapse vintages accurately.

TAKE HOME

Our joint recovery framework allows us to extend our ideas to time-lapse data acquisition and processing.

Future work

Asymmetric acquisition

Multiple surveys

Uncertainty quantification

Extension to nonlinear FWI

See Tuesday's talk "*Use what's in common: time-lapse FWI with distributed Compressive Sensing*"

Time-lapse FWI

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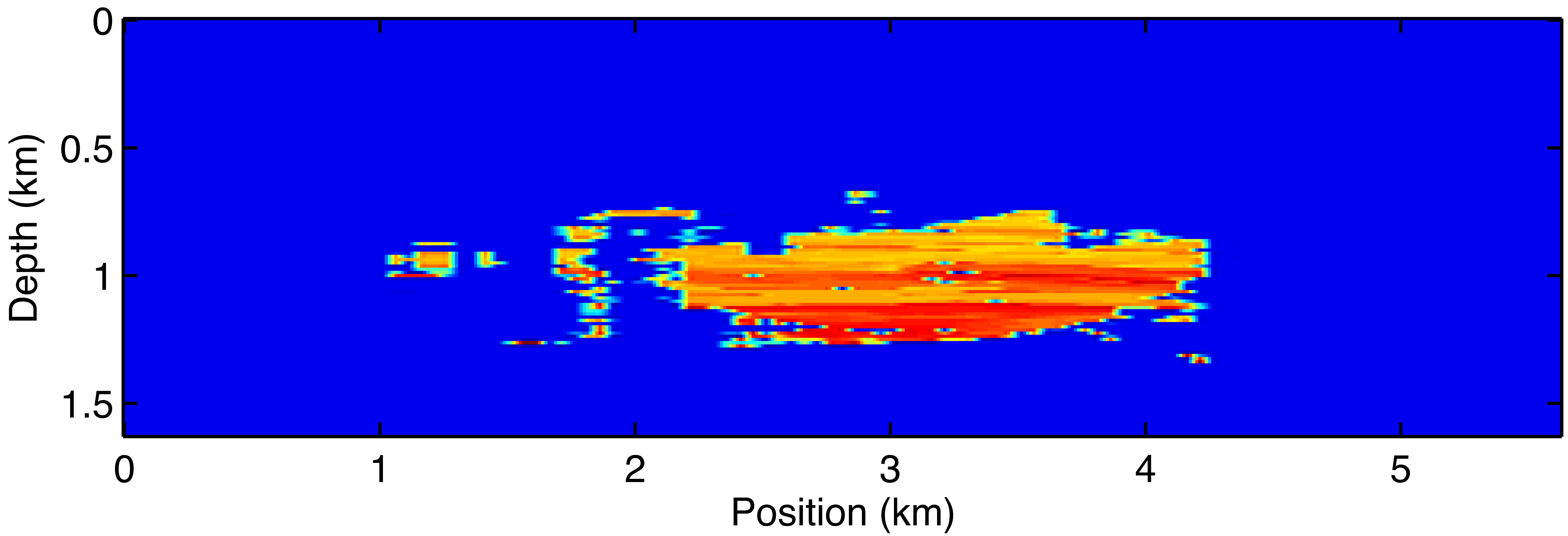
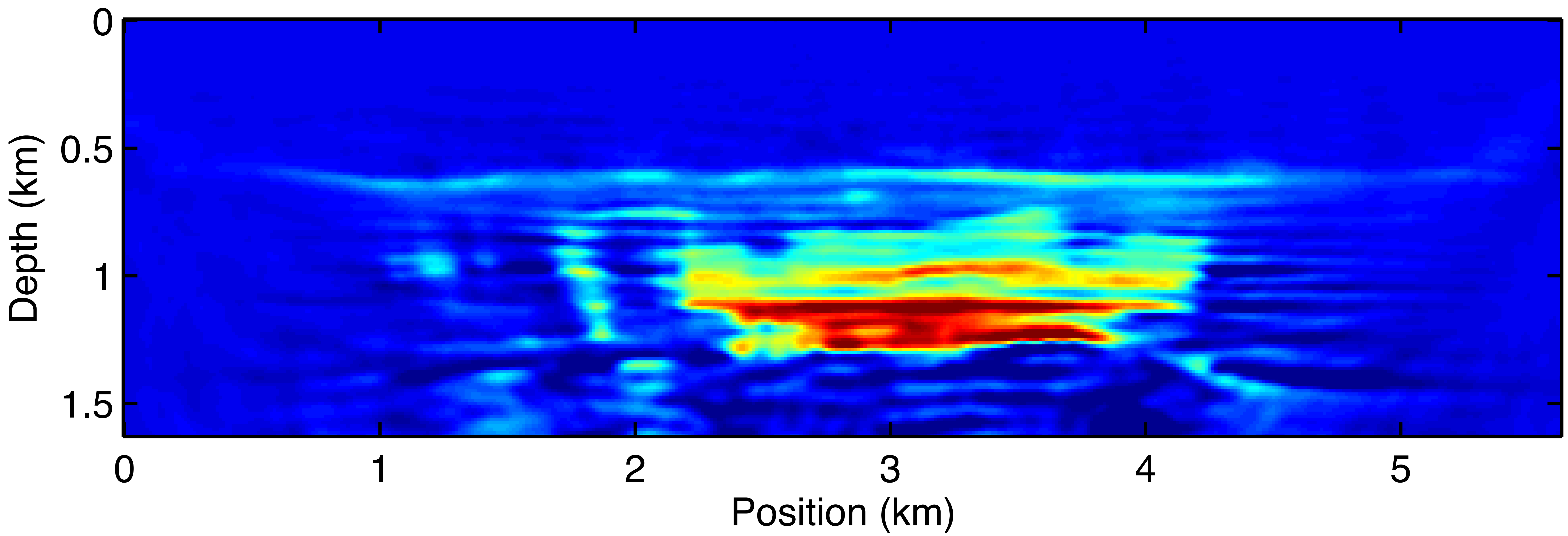
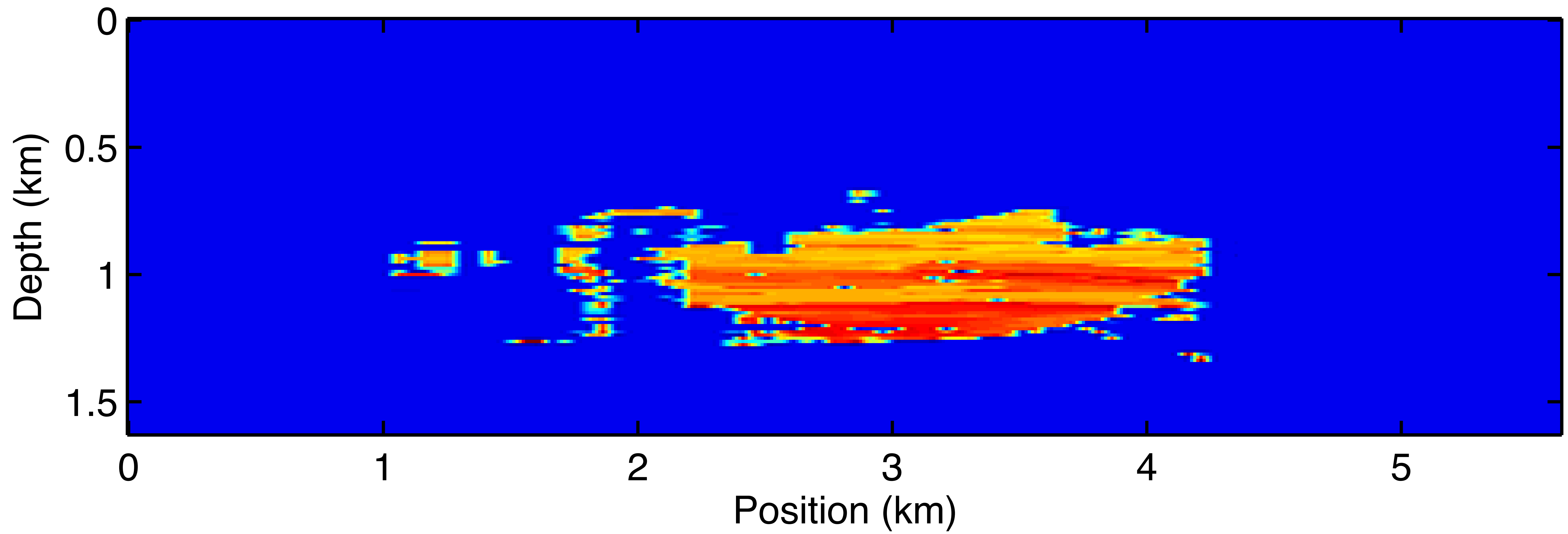


True difference

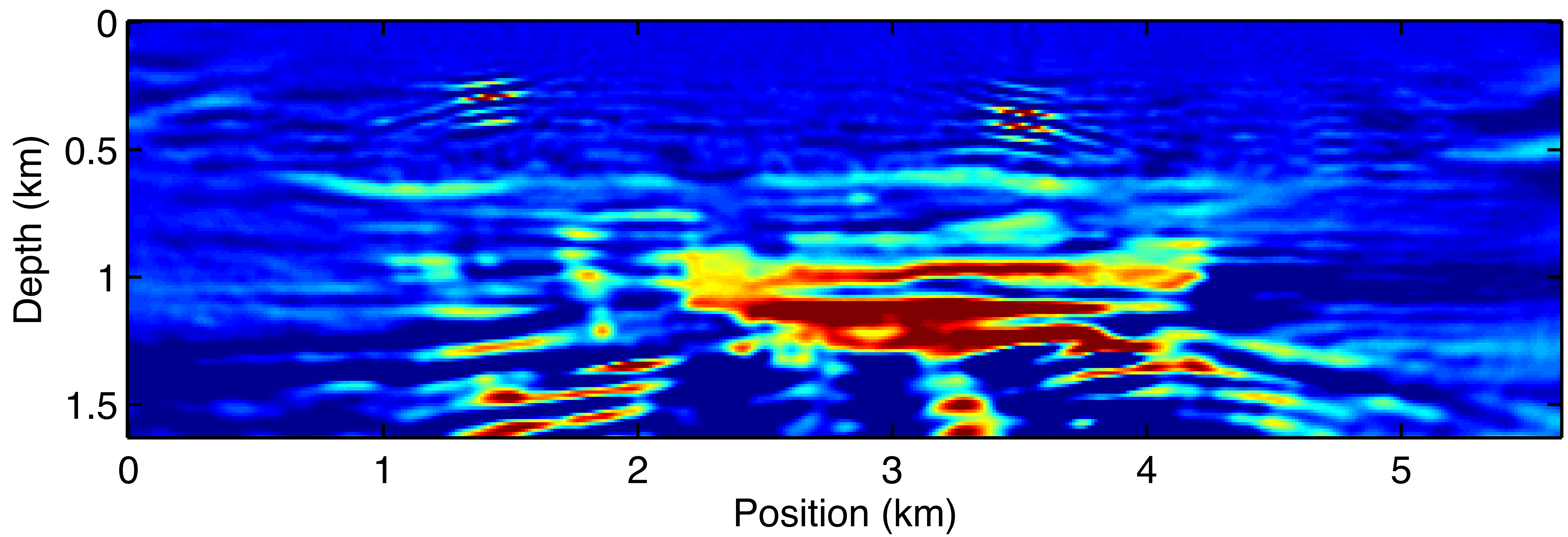


Joint Inversion

Time-lapse FWI



True difference



Independent Inversion

References

Submitted to Geophysics

https://www.slim.eos.ubc.ca/content/Compressive-4D—economic-time-lapse-seismic-randomized-subsampling-and-joint-recovery

Software

https://www.slim.eos.ubc.ca/SoftwareDemos/applications/Acquisition/TimeLapseJRM/

Conference

https://www.slim.eos.ubc.ca/content/randomization-and-repeatability-time-lapse-marine-acquisition

https://www.slim.eos.ubc.ca/content/randomized-sampling-without-repetition-time-lapse-surveys

https://www.slim.eos.ubc.ca/content/time-lapse-seismic-without-repetition-reaping-benefits-randomized-sampling-and-joint-recover

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Acknowledgements

Thank you for your attention!

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NSERC CRSNG

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