Low-cost, randomized 3D towed-marine time-lapse seismic acquisition

Rajiv Kumar, Felix Oghenekohwo, Shashin Sharan, Haneet Wason*, and Felix J. Herrmann



SLIM
University of British Columbia

Motivation

How to minimize costs of time-lapse seismic w/o impacting repeatability?

Solution:

- sample w/ insights from Compressive Sensing to lower cost
- leverage information shared amongst vintages to improve data quality & repeatability w/o need to replicate surveys (e.g. w/ expensive OBC/OBN)

New paradigm:

- give up on dense & replicated acquisition
- sample coarsely at random
- works as long as we know where we were in the field

Compressive Sensing = design method to increase acquisition productivity

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.

Compressive sensing paradigm

Sample to break structure = renders interference into incoherent noise

- randomized acquisition (e.g., time-jittered, over/under, continuous recording etc.)
- destroys sparsity/low rank

Find representations that reveal structure = separate signal from "noise"

- transform-domain sparsity (e.g., Fourier, curvelets, etc.)
- low-rank revealing matrix or tensor representations

Recover by structure promotion = obtain artifact-free densely sampled data

- sparsity via one-norm minimization, or
- nuclear-norm minimization

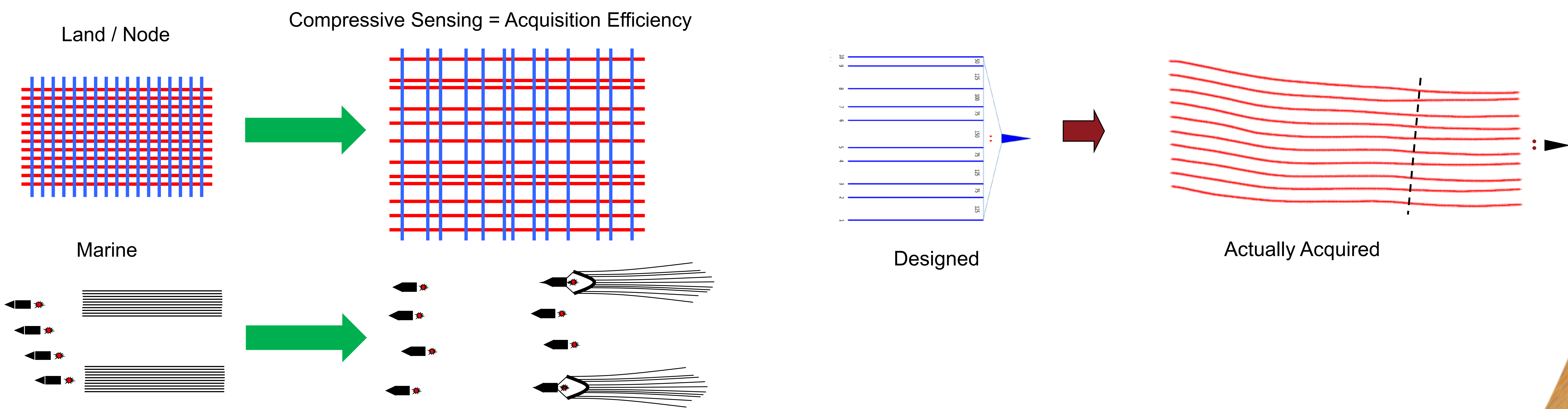
Mosher, C. C., Keskula, E., Kaplan, S. T., Keys, R. G., Li, C., Ata, E. Z., ... & Sood, S. (2012, November). **Compressive Seismic Imaging**. In *2012 SEG Annual Meeting*. Society of Exploration Geophysicists.

Randomized acquisition

examples from industry (ConocoPhilips)

Deliberate & natural randomness in acquisition

(thanks to Chuck Mosher)



Bottom line

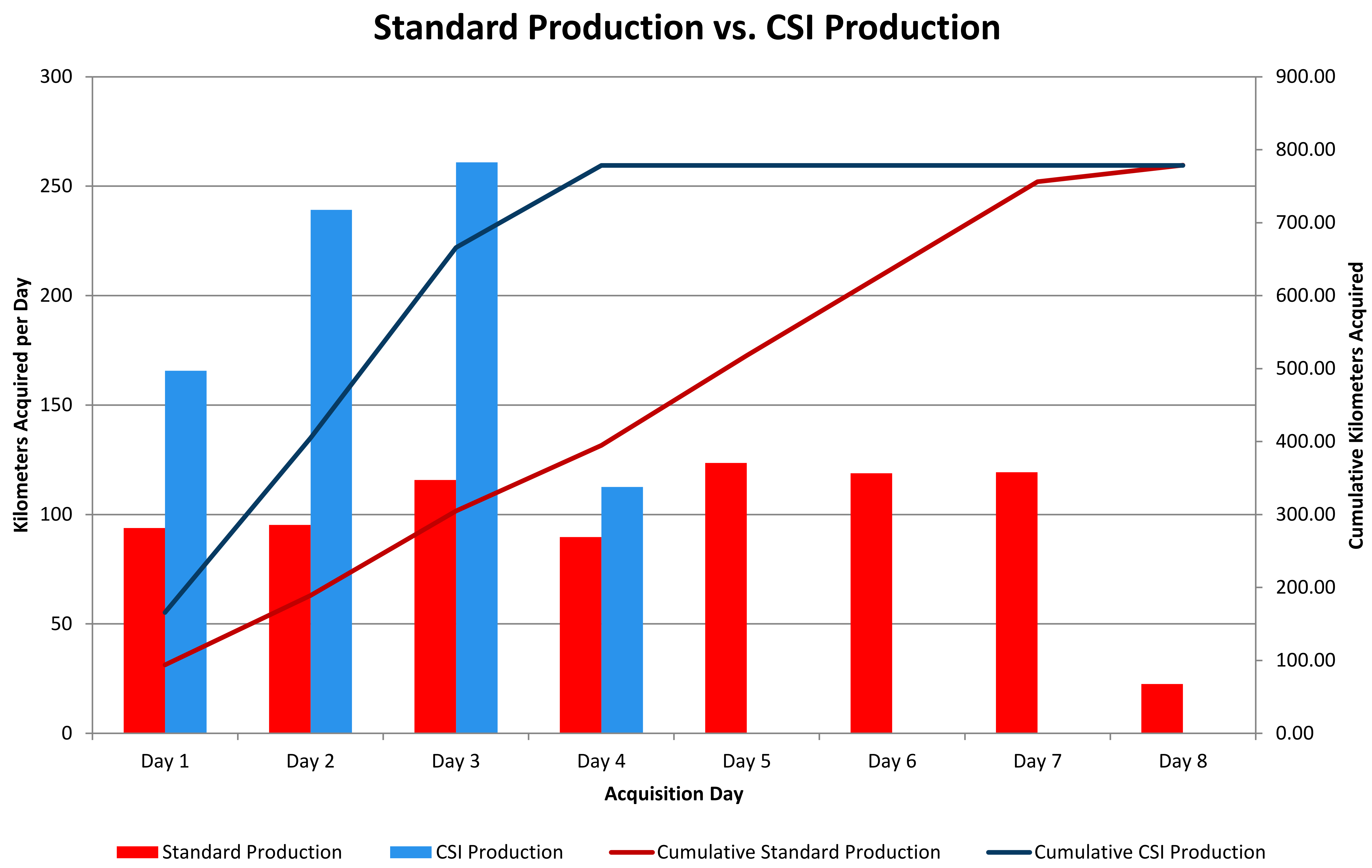
examples from industry (ConocoPhilips)

Randomized subsampling:

- exploits (natural) randomness & structure in seismic
- recovers dense data via structure-promoting inversion

Output:

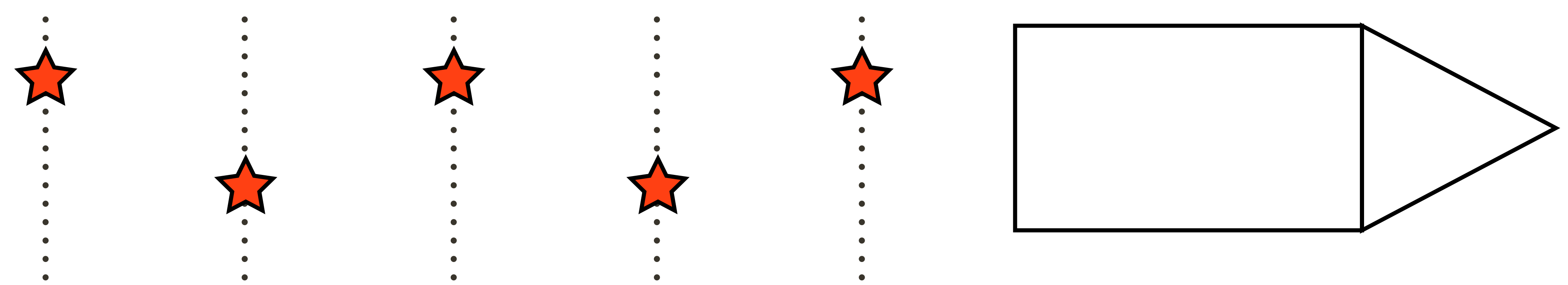
- improved quality artifact-free long-offset wide-azimuth data
- 5 X – 10 X cost & environmental impact reduction



Breaking structure

shot-time randomness

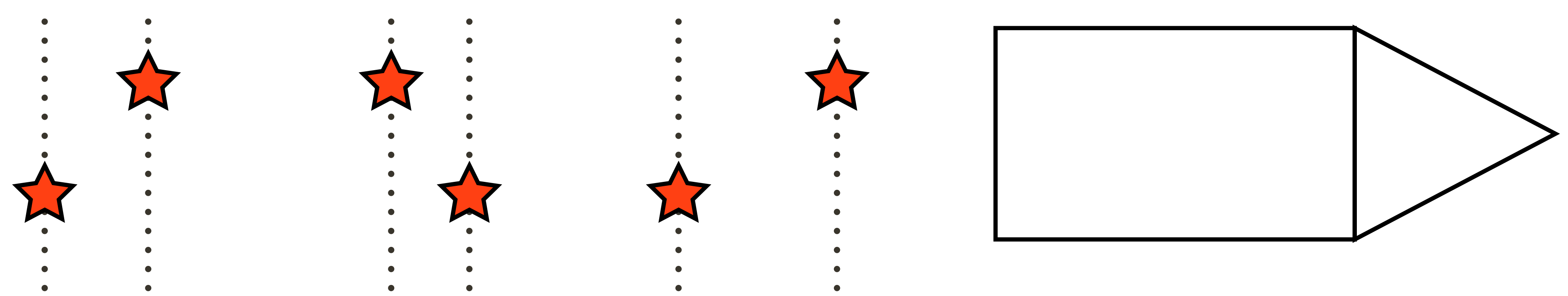
periodically sampled spatial grid



NONE

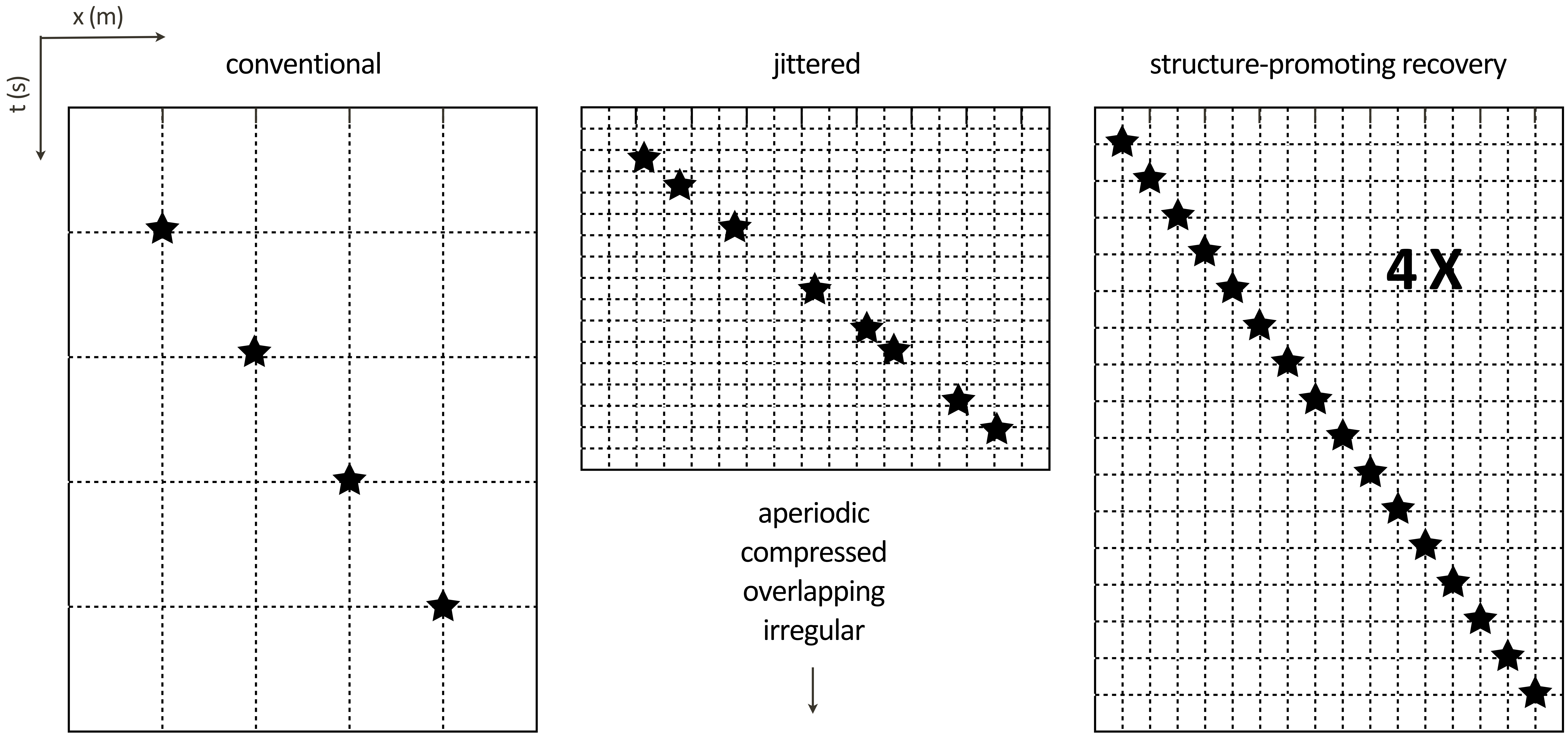
randomly jittered sampled spatial grid
(time-jittered acquisition;
static acquisition geometry: OBC/OBN)

[Wason and Herrmann, 2013]
[Mansour et al., 2012]



HIGH

Time-jittered OBC/OBN acquisition



periodic–sparse–no overlap | separation + regularization + interpolation → | periodic–dense–no overlap

source sampling : 25 m (flip-flop) | 25 m (flip-flop) jittered | 6.25 m

Felix Oghenekohwo, Haneet Wason, Ernie Esser, and Felix J. Herrmann, "**Cheap time lapse with distributed Compressive Sensing–-exploiting common information among the vintages**". 2016. To appear in GEOPHYSICS.
Haneet Wason, Felix Oghenekohwo, and Felix J. Herrmann, "**Cheap time lapse with distributed Compressive Sensing–-impact on repeatability**". 2016. To appear in GEOPHYSICS.

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Economical time-lapse acquisition (OBC/OBN)

Observed sampling grid* (m)	Recovered sampling grid* (m)	% Subsampling	Gain in sampling
25	12.5	50	**2X**
25	6.25	75	**4X**

* source/receiver sampling grid

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25	12.5	50	**2X**
25	6.25	75	**4X**

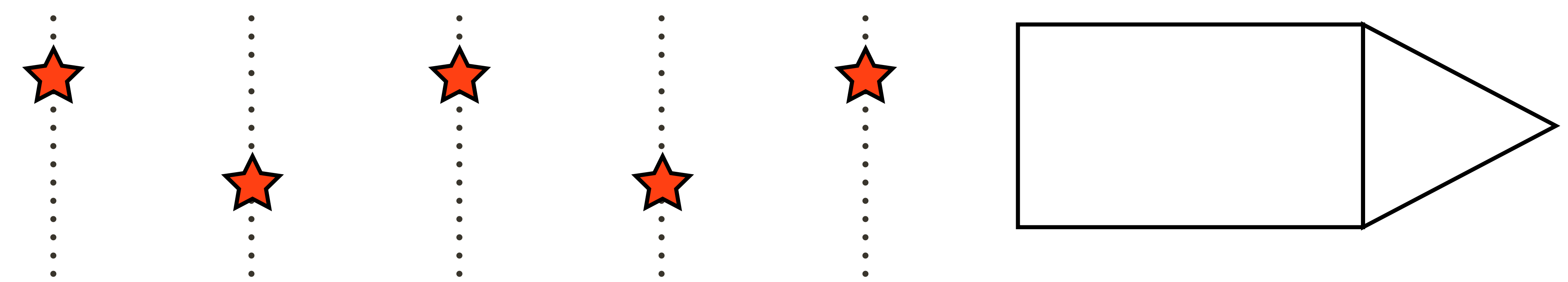
* source/receiver sampling grid

want more economical still .....

Breaking structure

shot-time randomness

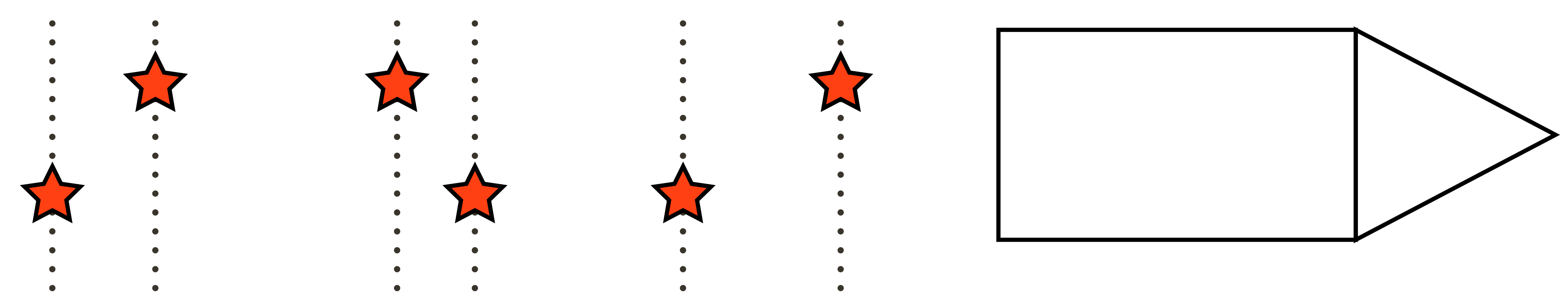
✗ **periodically** sampled spatial grid



NONE

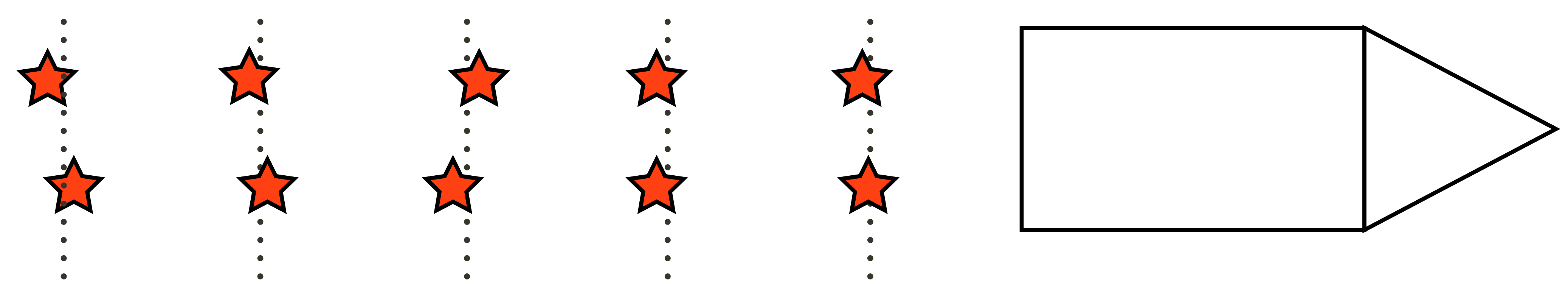
✓ **randomly** jittered sampled spatial grid
(time-jittered acquisition;
static acquisition geometry: OBC/OBN)

[Wason and Herrmann, 2013]
[Mansour et al., 2012]



HIGH

✓ **almost periodically** sampled spatial grid
(dynamic acquisition geometry:
towed arrays)



LOW

Source separation for simultaneous towed-streamer acquisition via compressed sensing

Haneet Wason*, Rajiv Kumar and Felix J. Herrmann

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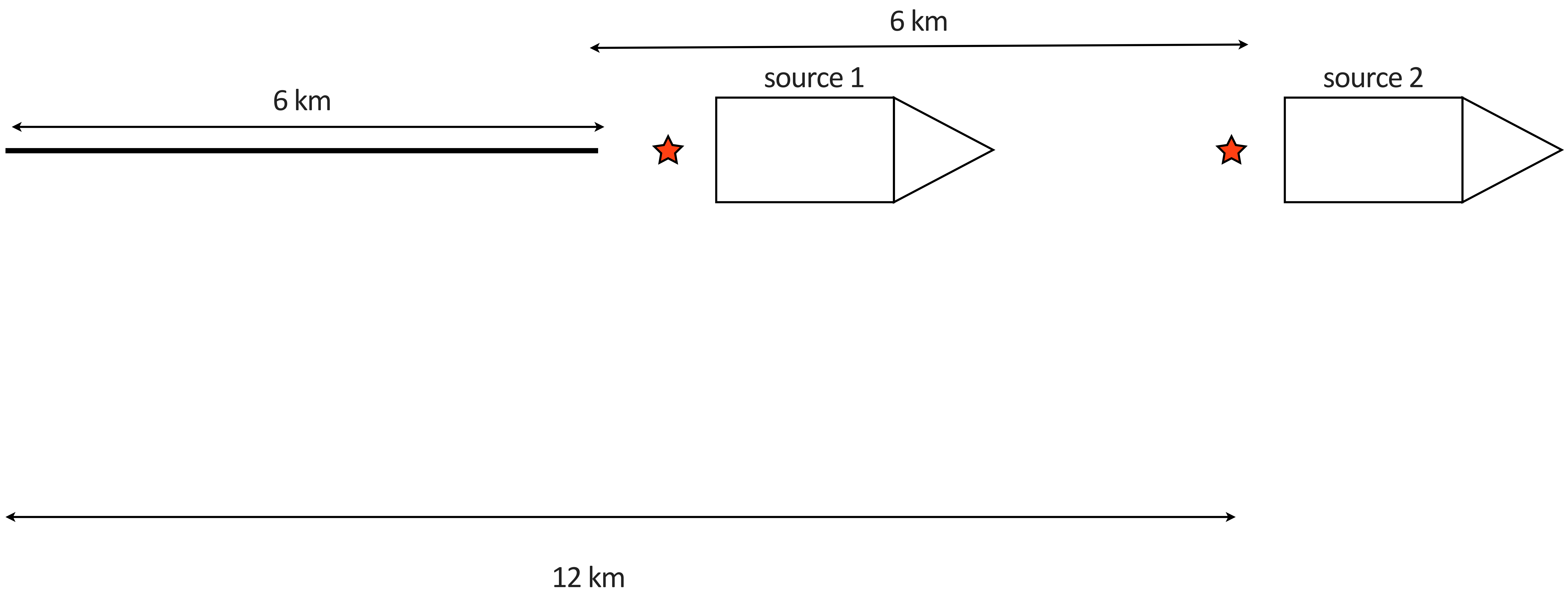
University of British Columbia

Rajiv Kumar, Haneet Wason and Felix J. Herrmann, "**Source Separation for simultaneous towed-streamer marine acquisition: a compressed sensing approach**", *Geophysics*, vol. 80, p. WD73-WD88, 2015

Goal: To double maximum offset w/ two source vessels

Simultaneous long-offset (SLO) acquisition

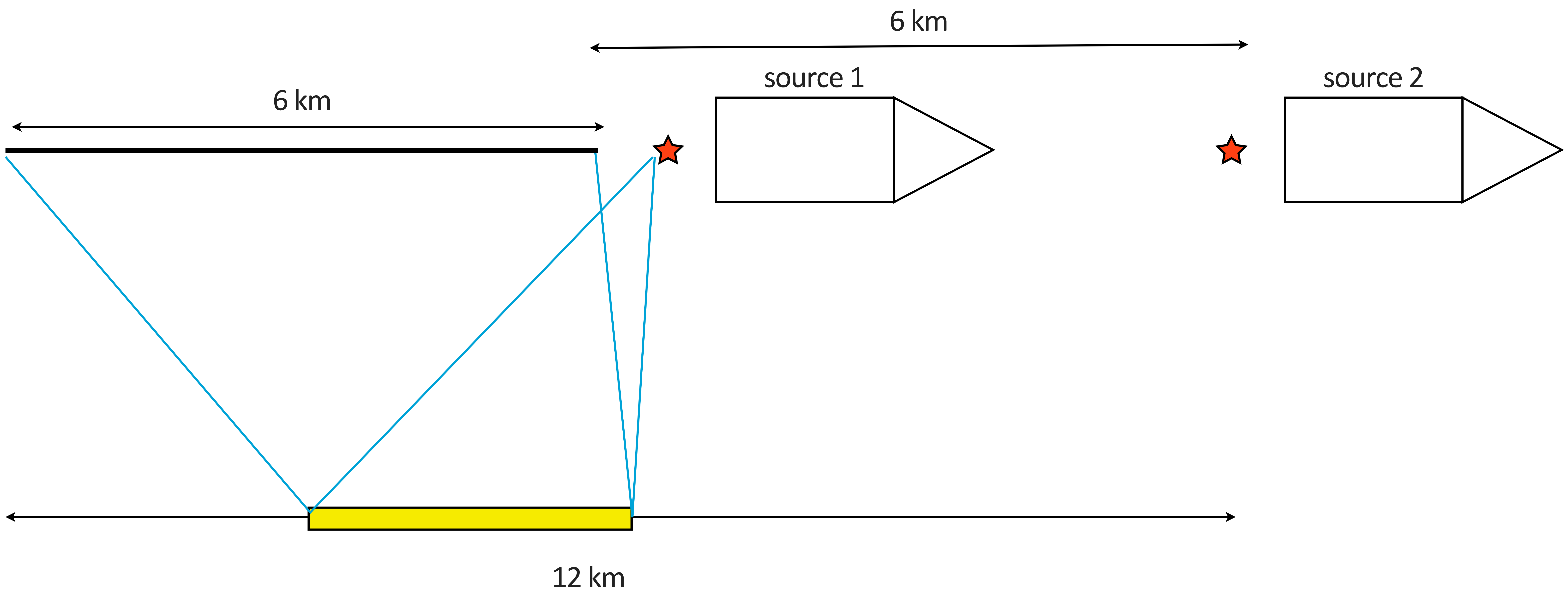
[adapted from Long et al., 2013]



A. S. Long et al., "**Simultaneous long offset (SLO) towed streamer seismic acquisition**", presented at the *75th EAGE Conference and Exhibition*, June 2013.

Simultaneous long-offset (SLO) acquisition

[adapted from Long et al., 2013]



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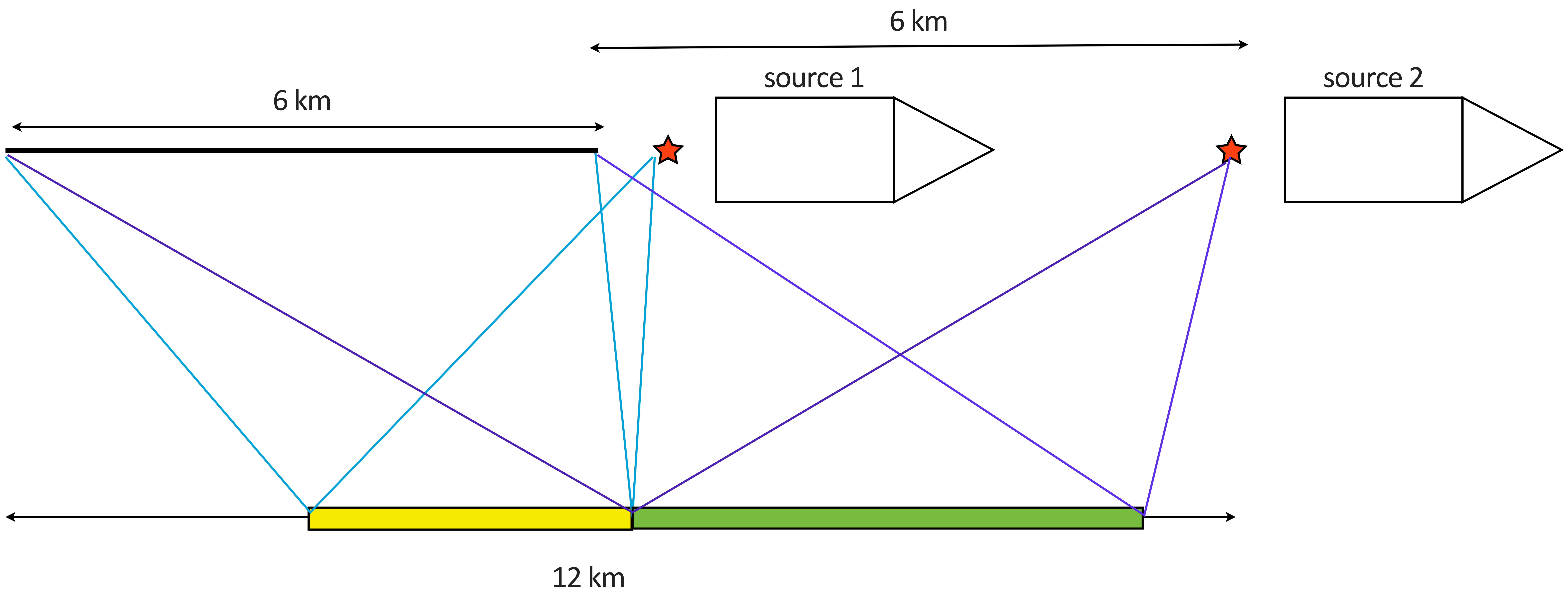
[adapted from Long et al., 2013]



A. S. Long et al., "**Simultaneous long offset (SLO) towed streamer seismic acquisition**", presented at the *75th EAGE Conference and Exhibition*, June 2013.

Sparsity-promoting minimization

[Candes et al., Donoho '06]

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

Nuclear-norm minimization

convex relaxation of rank-minimization

[Recht et al., '10]

$$\min_{\mathbf{X}} \quad \underbrace{||\mathbf{X}||_*}_{\text{sum of singular values of } \mathbf{X}} \quad \text{s.t.} \quad \|\mathcal{A}(\mathbf{X}) - \mathbf{b}\|_2 \leq \epsilon$$

$$\mathcal{A} := \begin{bmatrix} \mathbf{M}\mathbf{T_1}\mathbf{S^H} & \mathbf{M}\mathbf{T_2}\mathbf{S^H} \end{bmatrix}$$

$\mathbf{S^H}$ transform domain matrix

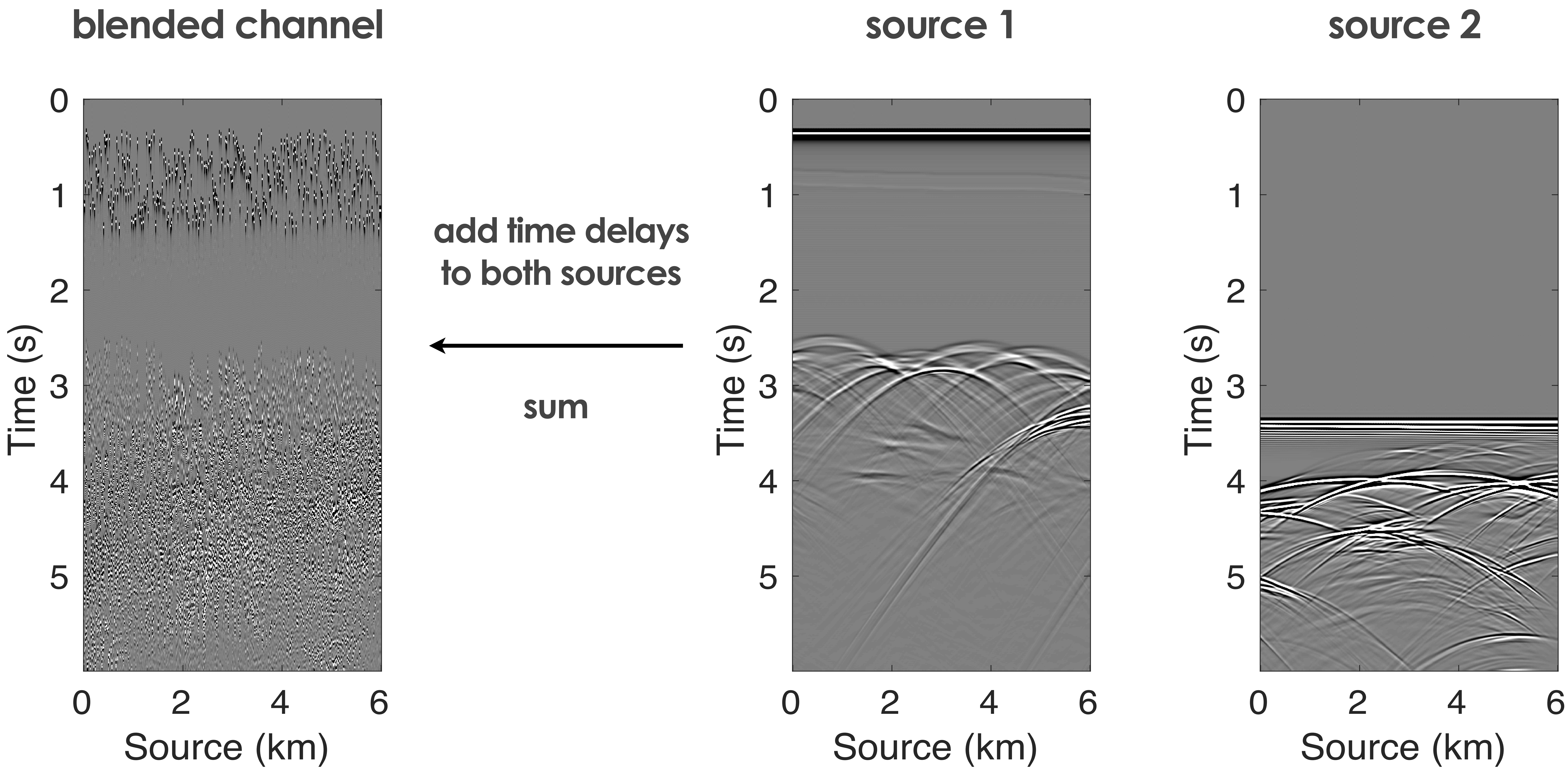
$\mathbf{T}$ time-delay matrices

$\mathbf{M}$ measurement matrix

[Kumar et al., '15]

Blended data – common channel/offset gather

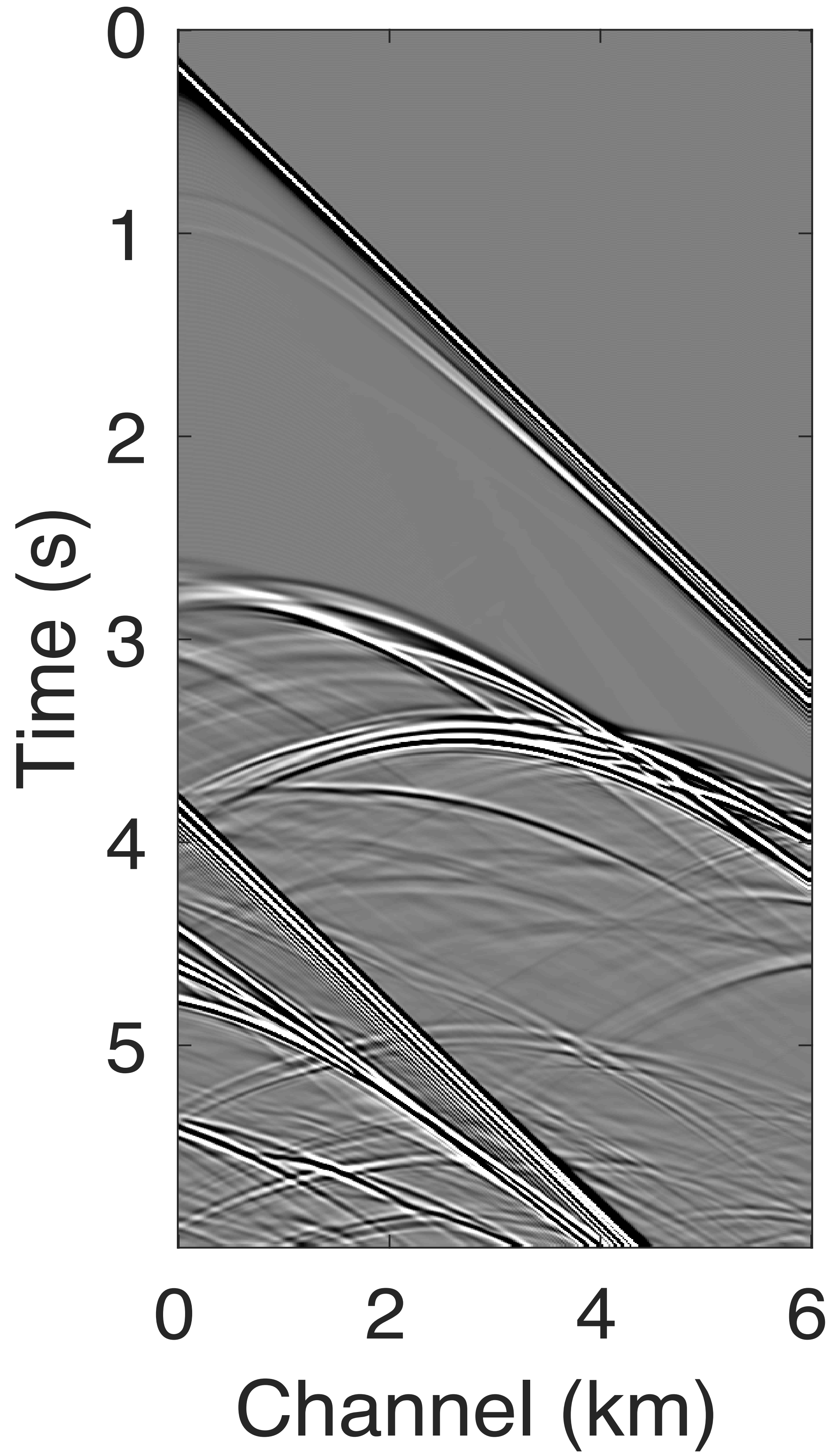
random time delays (< 1 sec) applied to both sources



Blended data – shot gather

random time delays (< 1 sec) applied to both sources

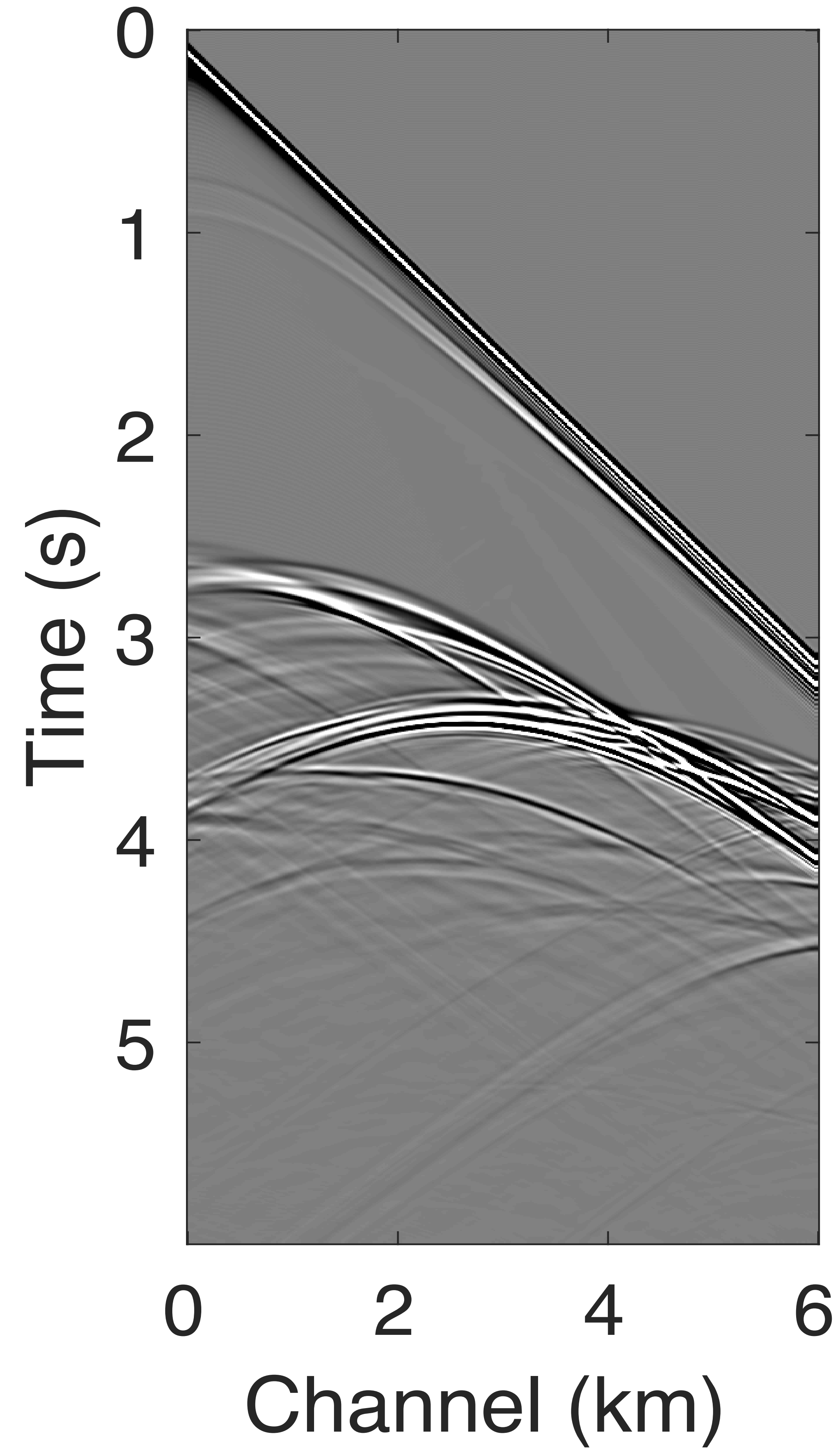
blended shot



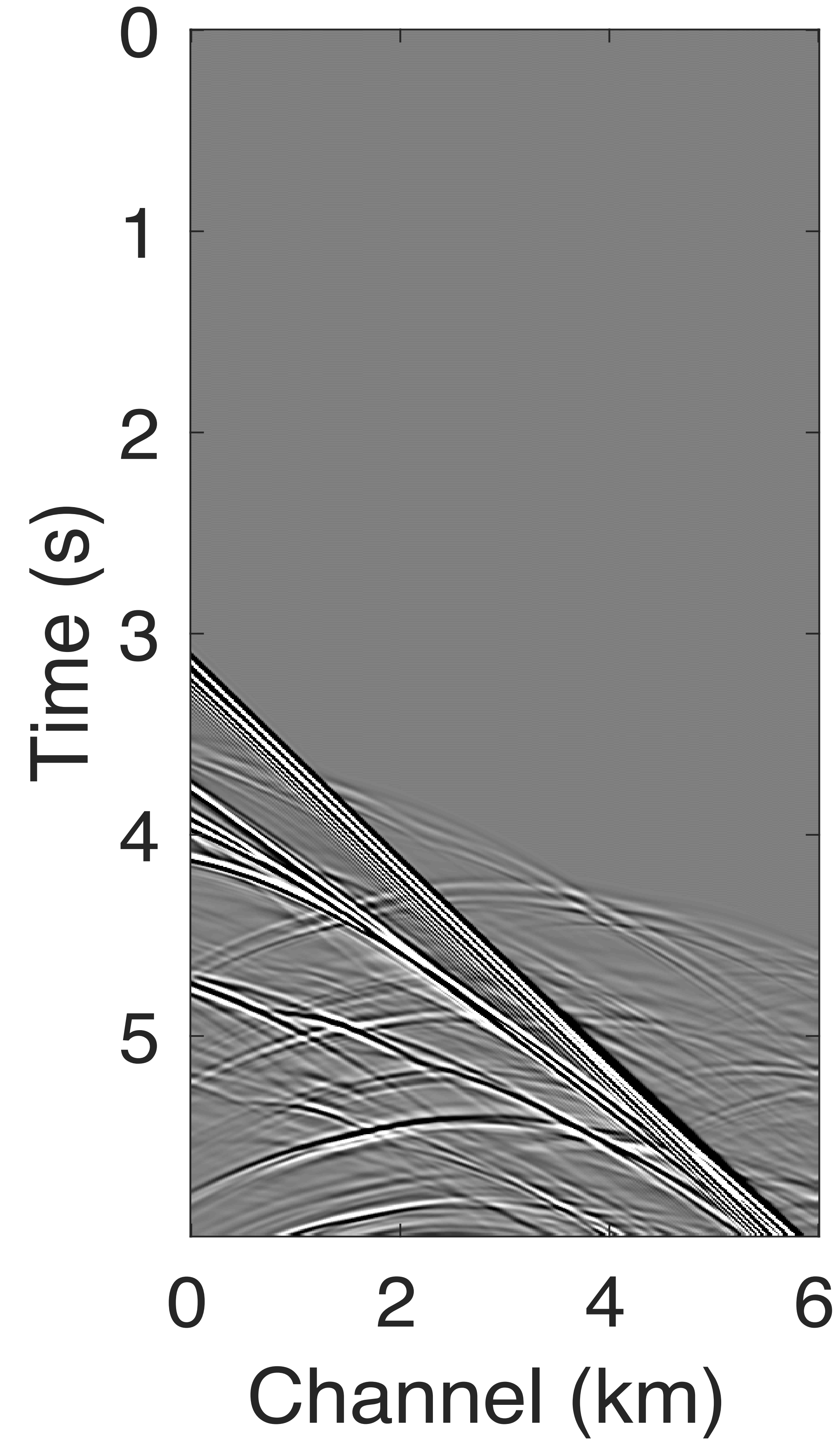
add time delays to both sources

sum

source 1

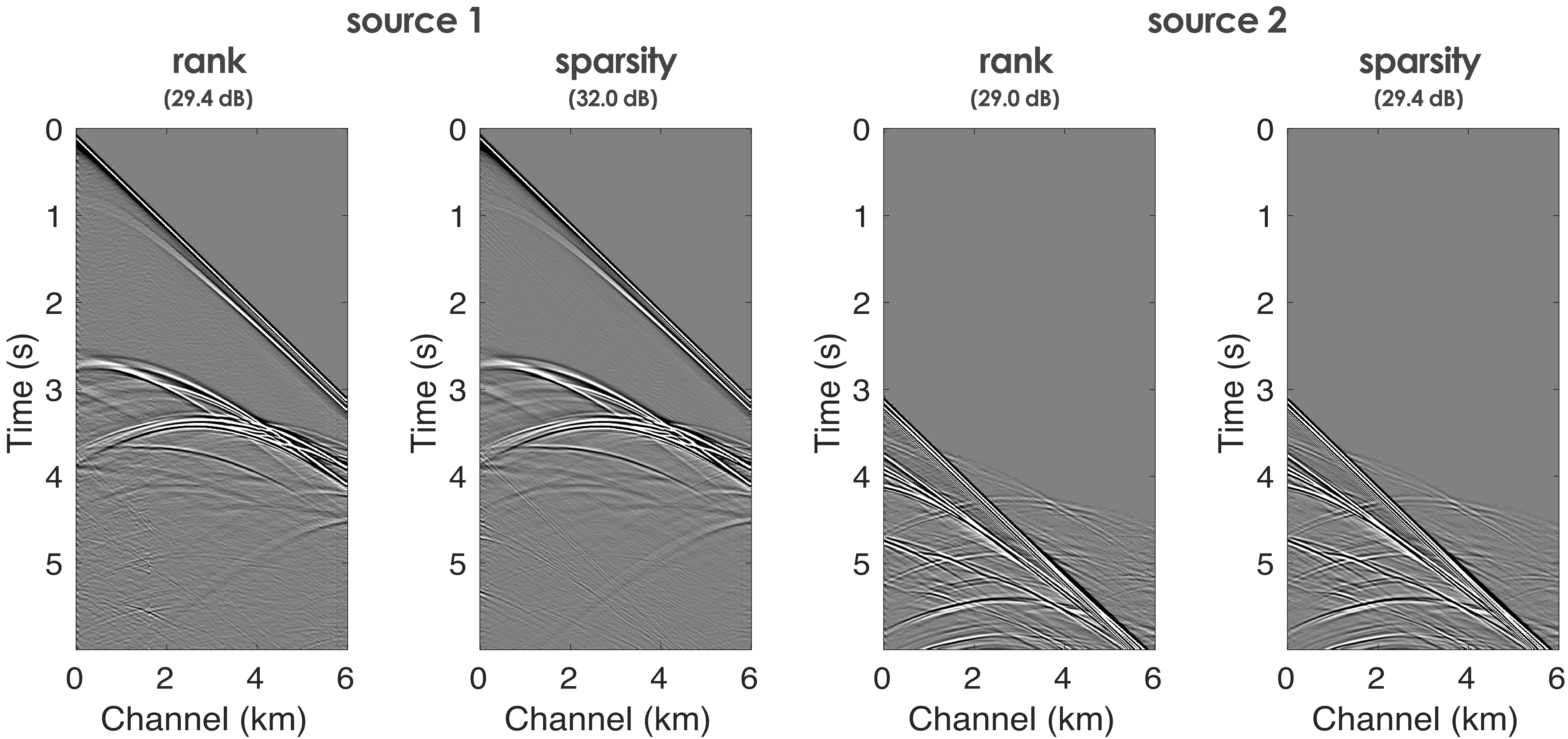


source 2



Source separation - rank vs. sparsity

serial computation time (all data) = 19 vs. 120 hours; memory usage = 6 vs. 12 GB



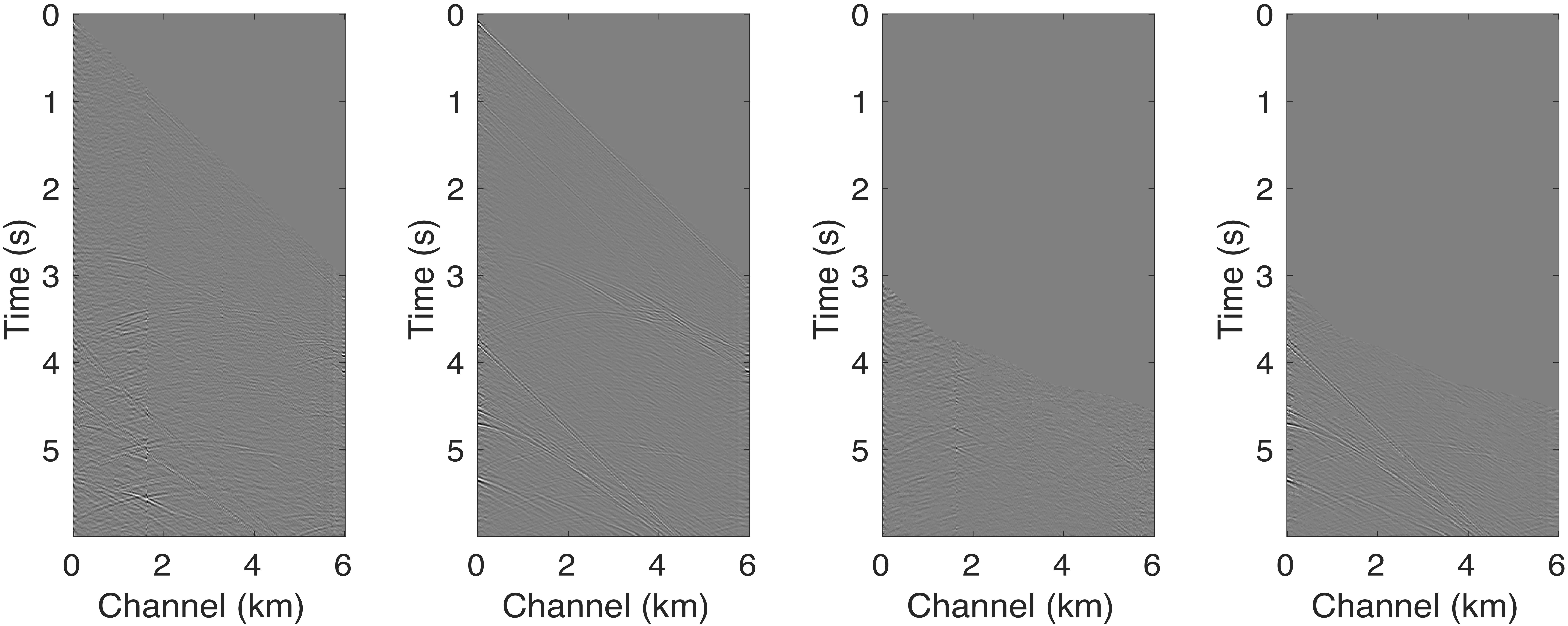
Residual

source 1

rank (29.4 dB) | **sparsity** (32.0 dB)

source 2

rank (29.0 dB) | **sparsity** (29.4 dB)



Source separation - rank vs. sparsity

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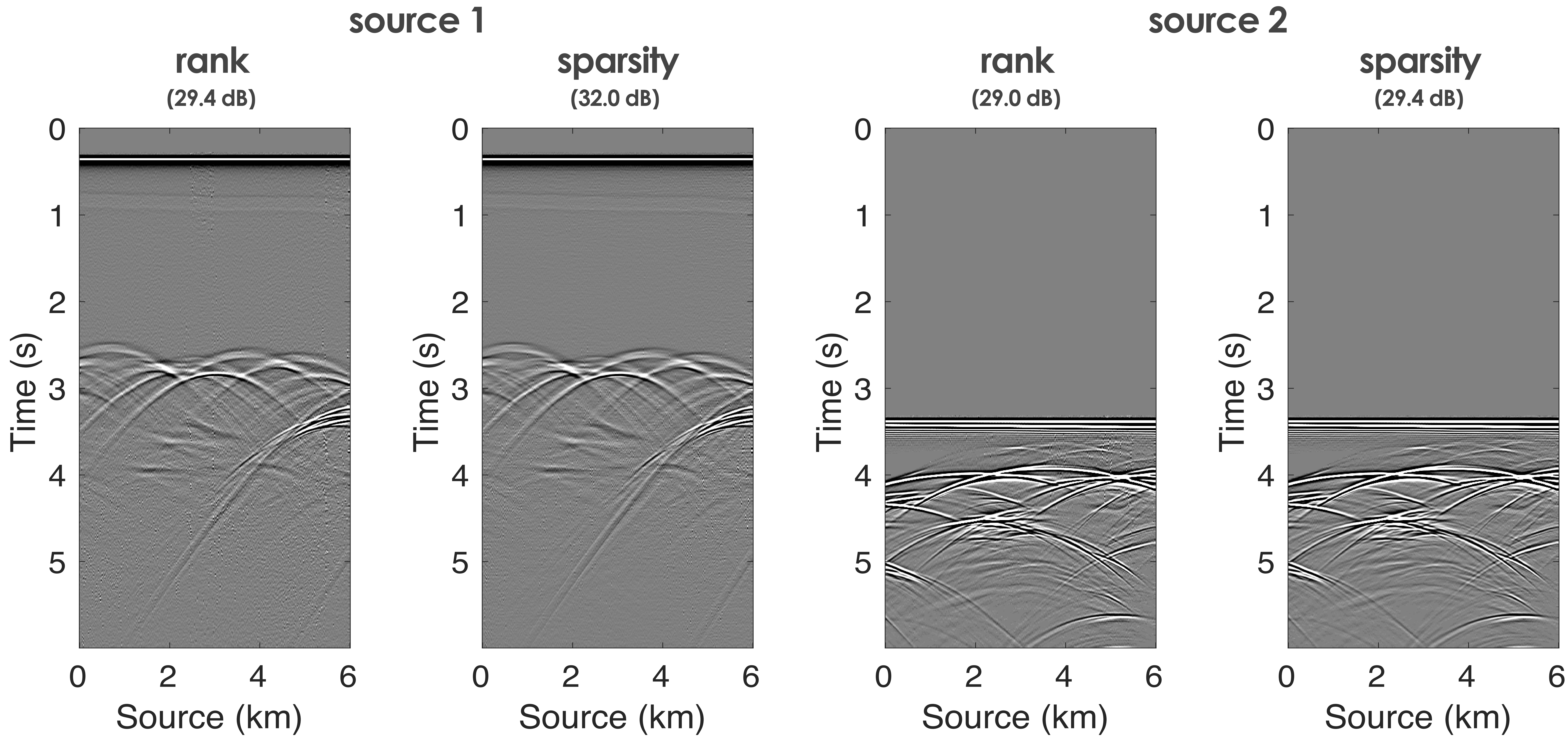

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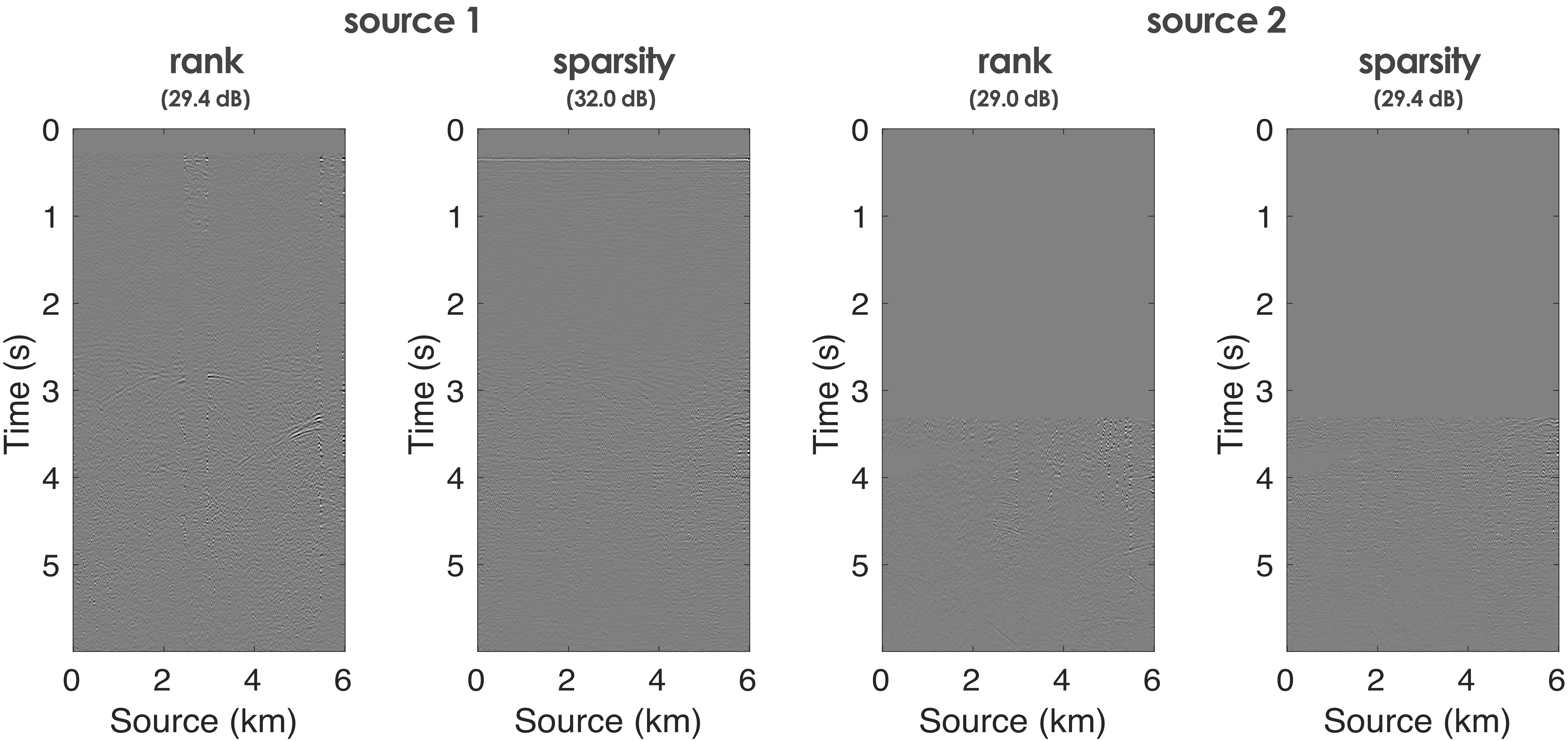
Residual


source 1
rank
(29.4 dB)
sparsity
(32.0 dB)
source 2
rank
(29.0 dB)
sparsity
(29.4 dB)
Time (s)
0
1
2
3
4
5
Source (km)
0
2
4
6

Low-cost, randomized 3D towed-marine time-lapse seismic acquisition - *preliminary results*

Rajiv Kumar, Felix Oghenekohwo, Shashin Sharan, Haneet Wason*, and Felix J. Herrmann

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University of British Columbia

Goals

Design of economic dense multi-azimuth long-offset 3D time-lapse marine acquisition w/ high degree of repeatability

- w/o replication of source locations
- w/o expensive OBN/OBC
- w/o precise adherence to planned sail lines

Use simulations to demonstrate the potential of cheap dynamic acquisition in 4D seismic for FWI

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Acquisition parameters

Underlying grid:

Source X, Source Y: 25 m

Receiver X, Receiver Y: 25 m

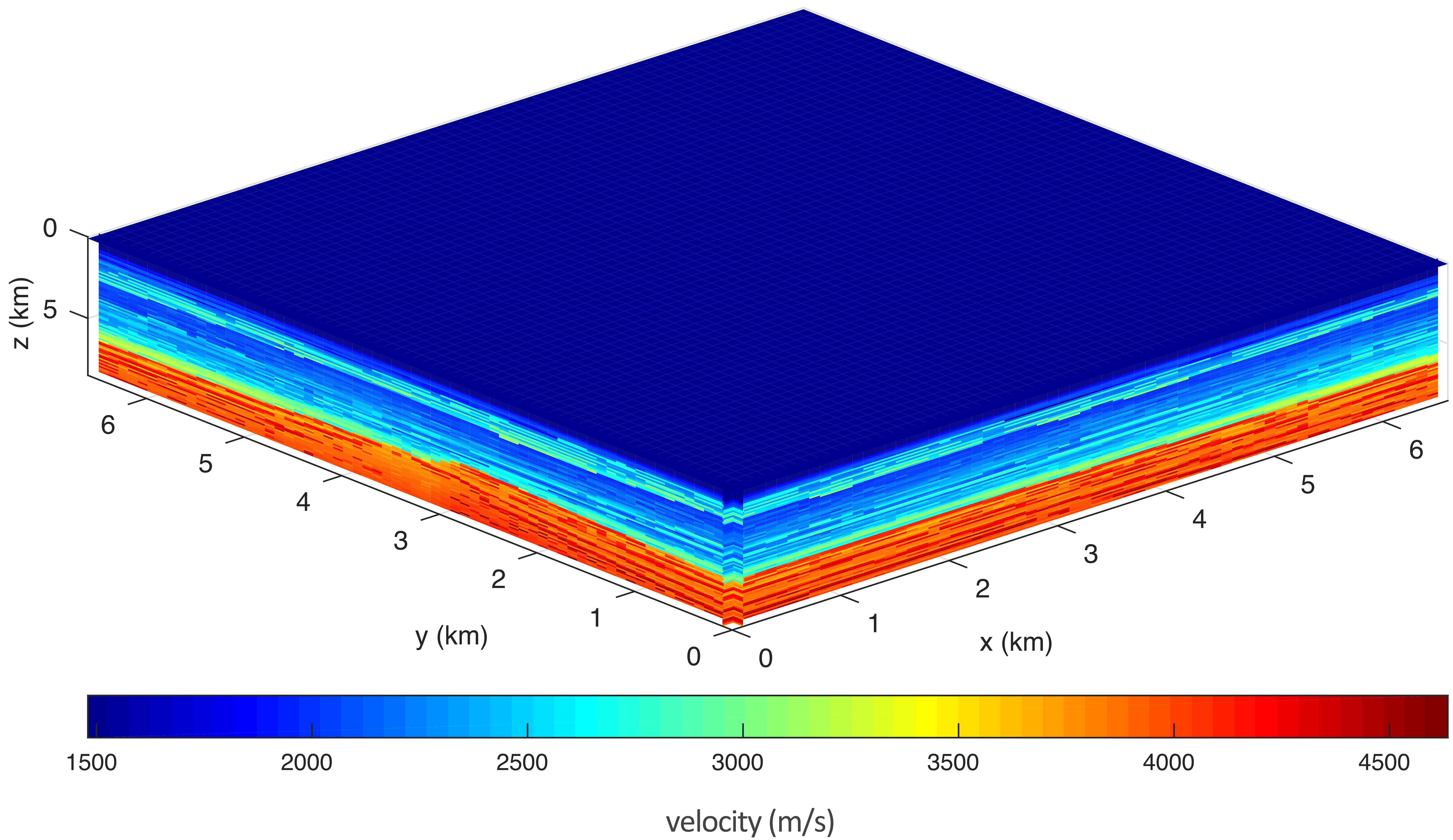
Maximum offset: 4 + 4 = 8 km

Number of streamers per source vessel: 12

Ricker wavelet with central frequency of 20 Hz

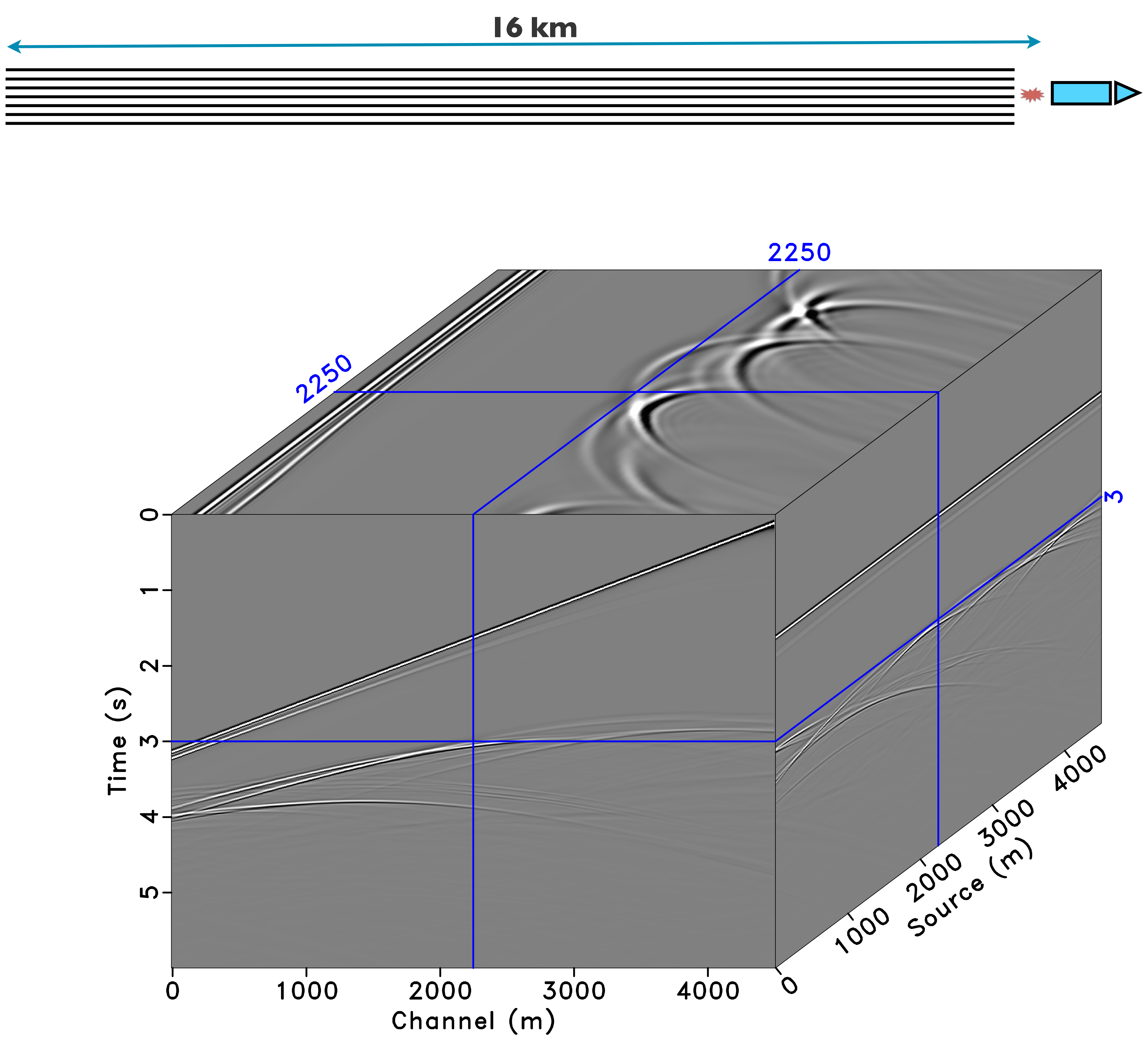
Effective sampling: 25-100 m in X & Y => 3 – 4 X cost reduction

3D baseline BG model

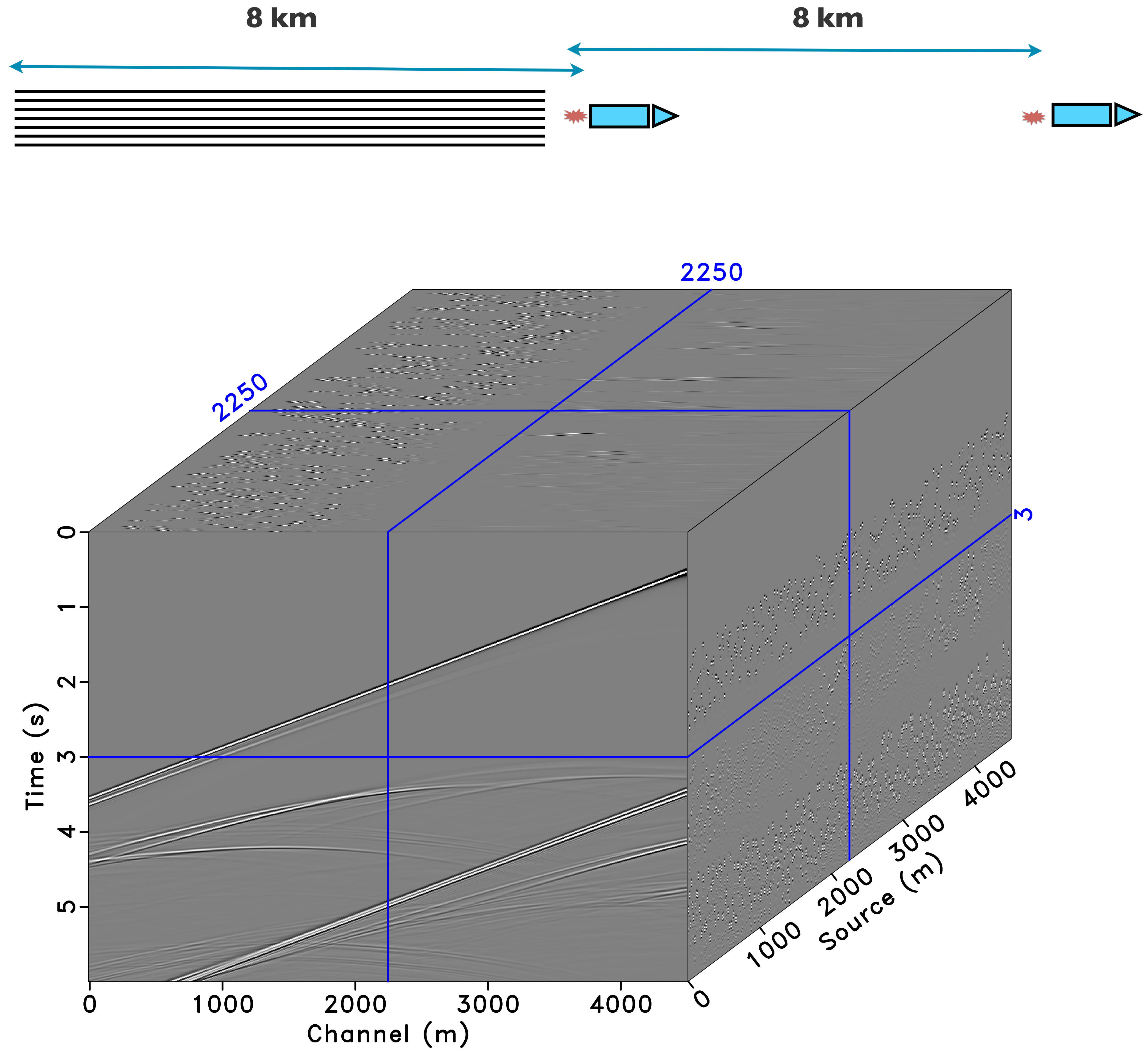


Low-cost marine acquisition

Conventional acquisition



SLO acquisition



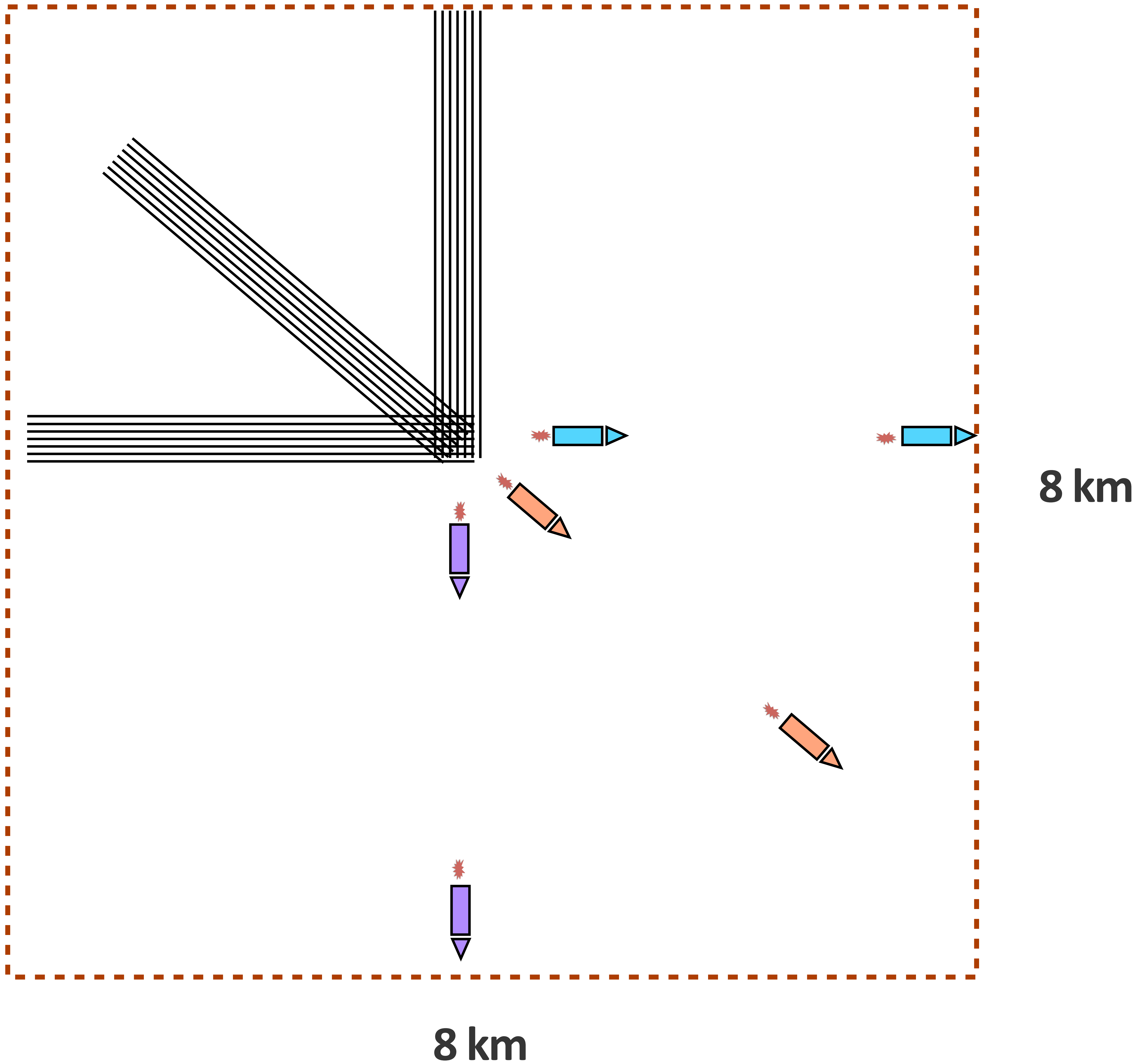
"Reduced" multi-azimuth SLO acquisition

acquisition domain

towed streamers

4 km streamer length
("reduced" acquisition)

“Reduced“ multi-azimuth SLO acquisition



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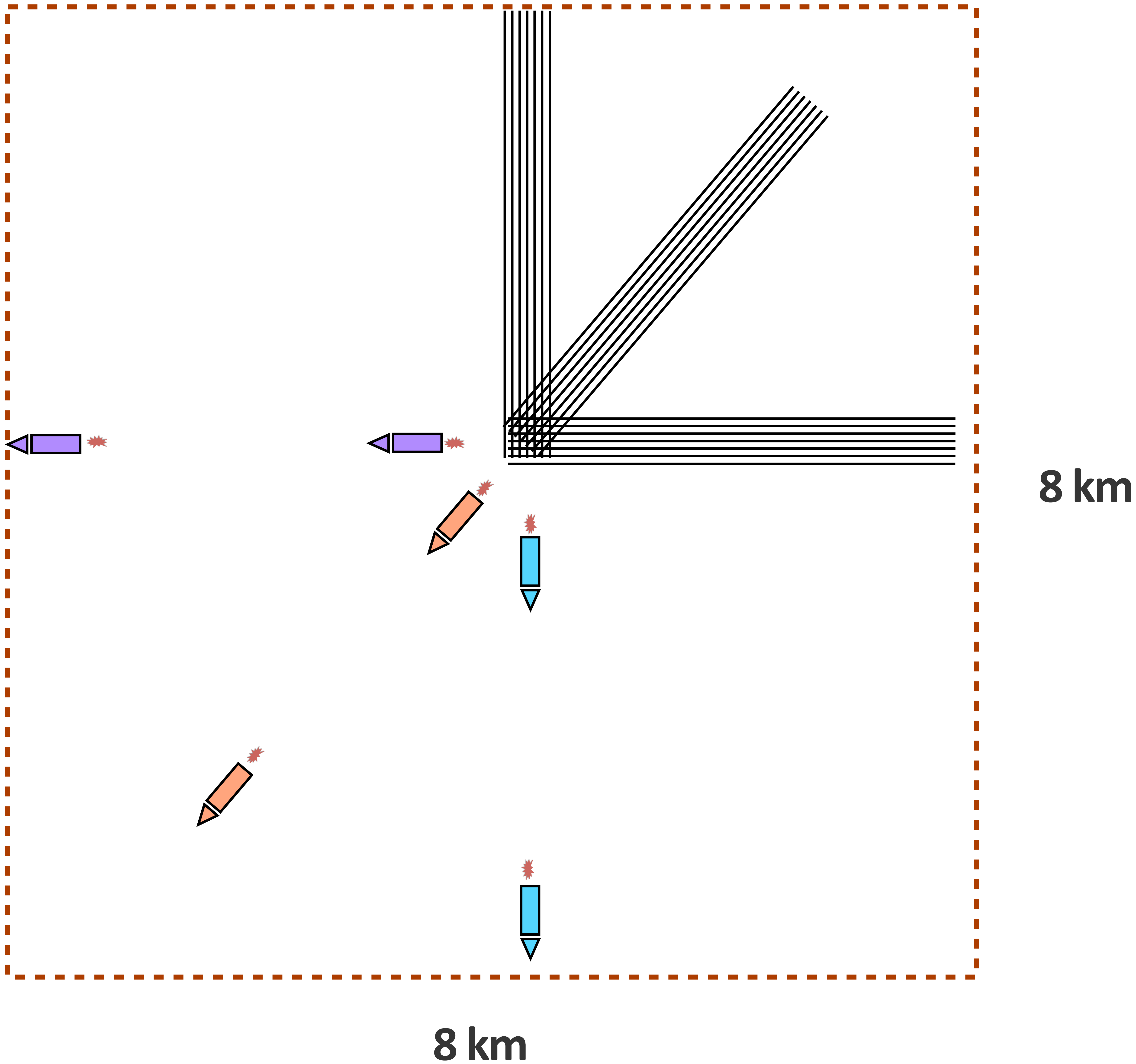

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“Reduced“ multi-azimuth SLO acquisition

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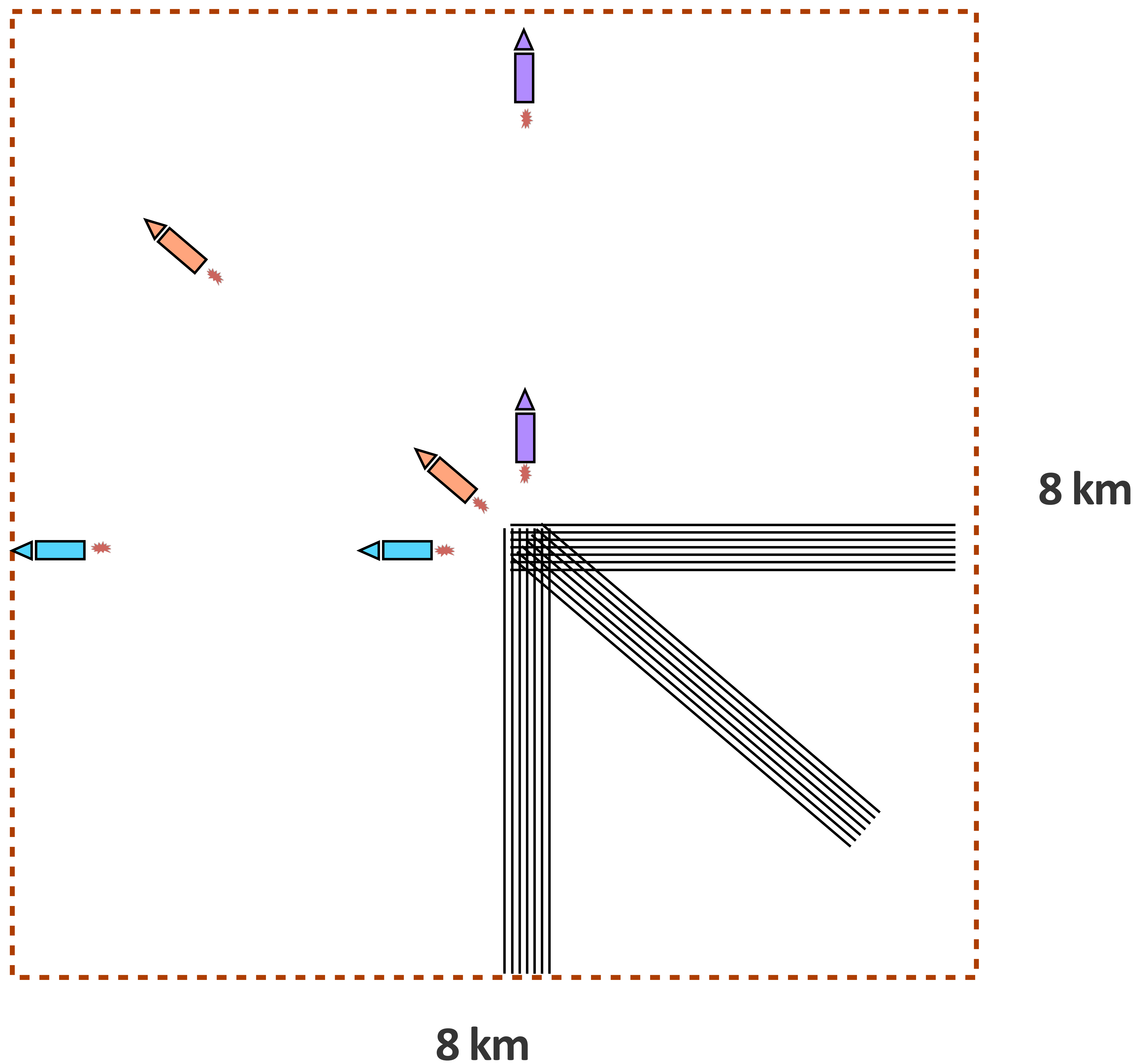

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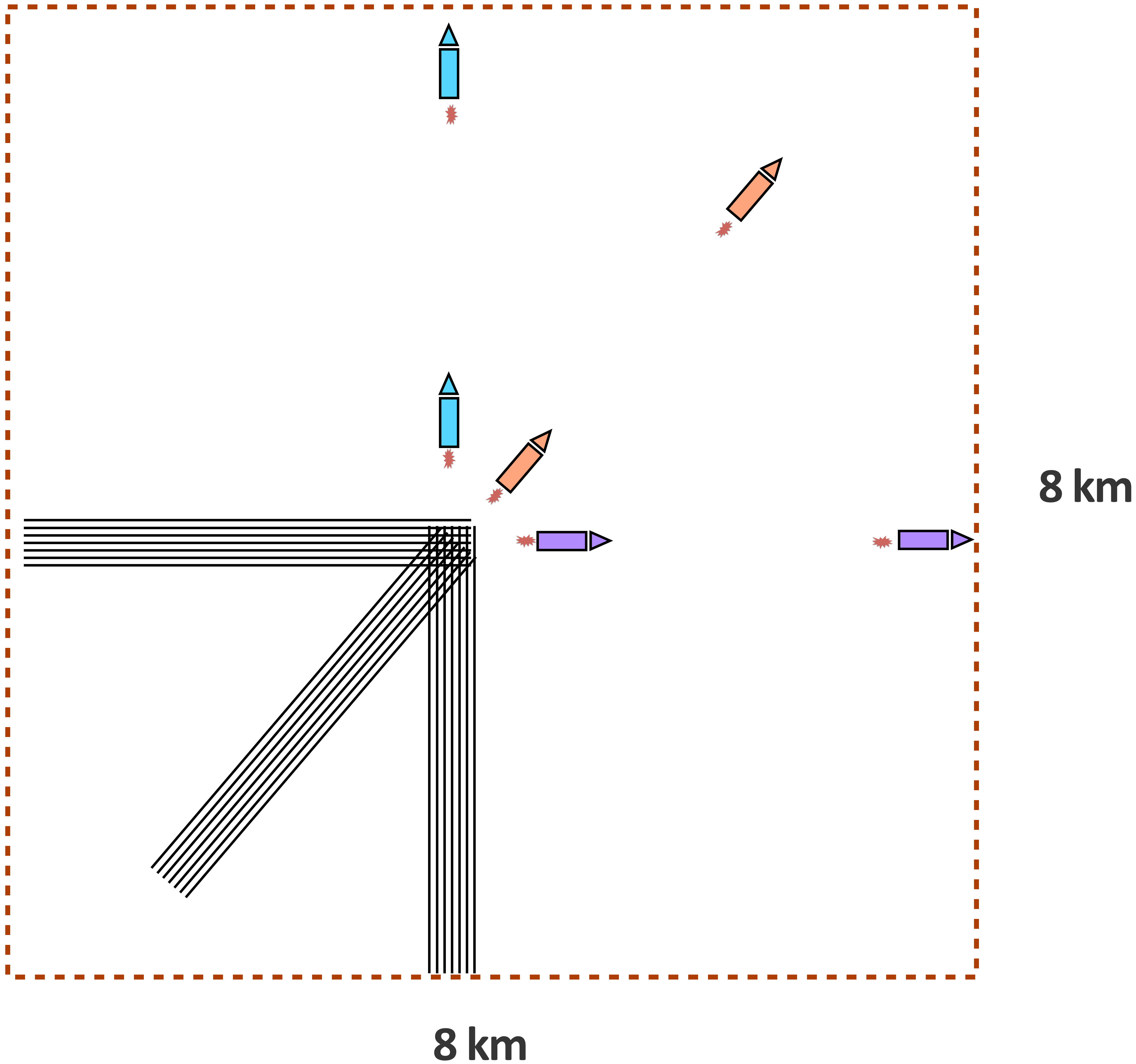

acquisition domain

towed streamers

4 km streamer length
(“reduced” acquisition)

“Reduced“ multi-azimuth SLO acquisition

acquisition domain

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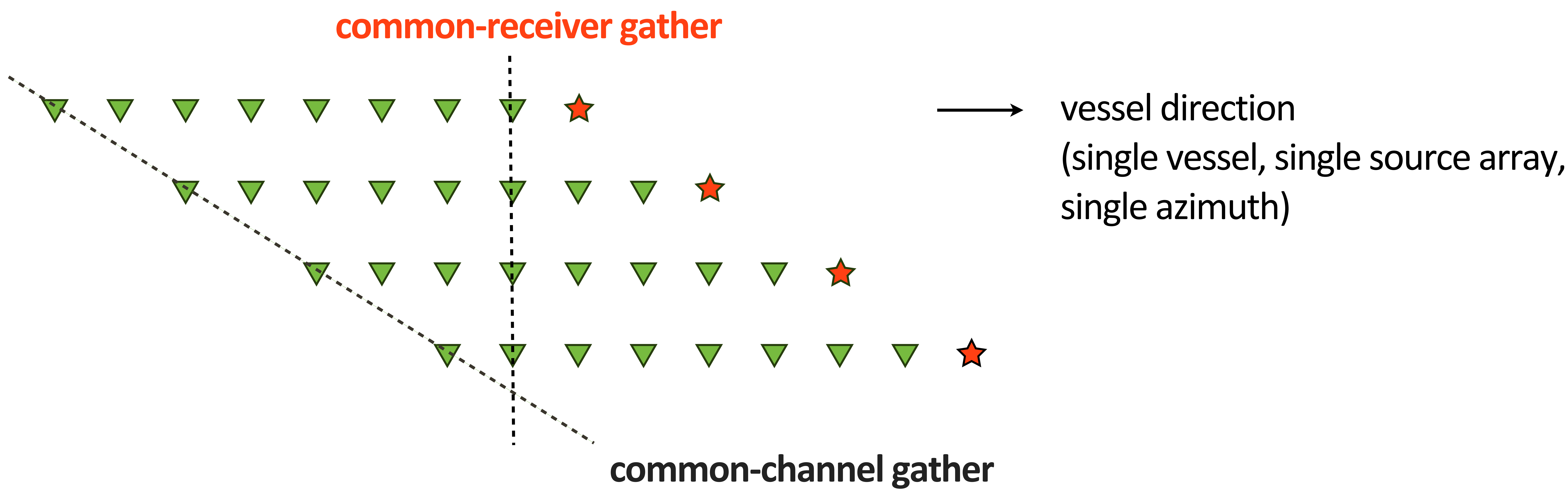
4 km streamer length
(“reduced” acquisition)

Data organization

- our preferred domain for data reconstruction is the common-receiver domain as shown below



[Candès and Plan, 2010, Oropeza and Sacchi, 2011]

Matrix completion

Successful reconstruction scheme

- exploit *structure*
  - *low-rank / fast decay* of singular values
- sampling
  - randomness *increases* rank in "transform domain"
- optimization
  - via *rank minimization (nuclear-norm minimization)*

Curt Da Silva, and Felix J. Herrmann, "**Optimization on the Hierarchical Tucker manifold - applications to tensor completion**", *Linear Algebra and its Applications,* vol. 481, p. 131-173, 2015.
Rajiv Kumar, Curt Da Silva, Okan Akalin, Aleksandr Y. Aravkin, Hassan Mansour, Ben Recht, and Felix J. Herrmann, "**Efficient matrix completion for seismic data reconstruction**", *Geophysics*, vol. 80, p. V97-V114, 2015.

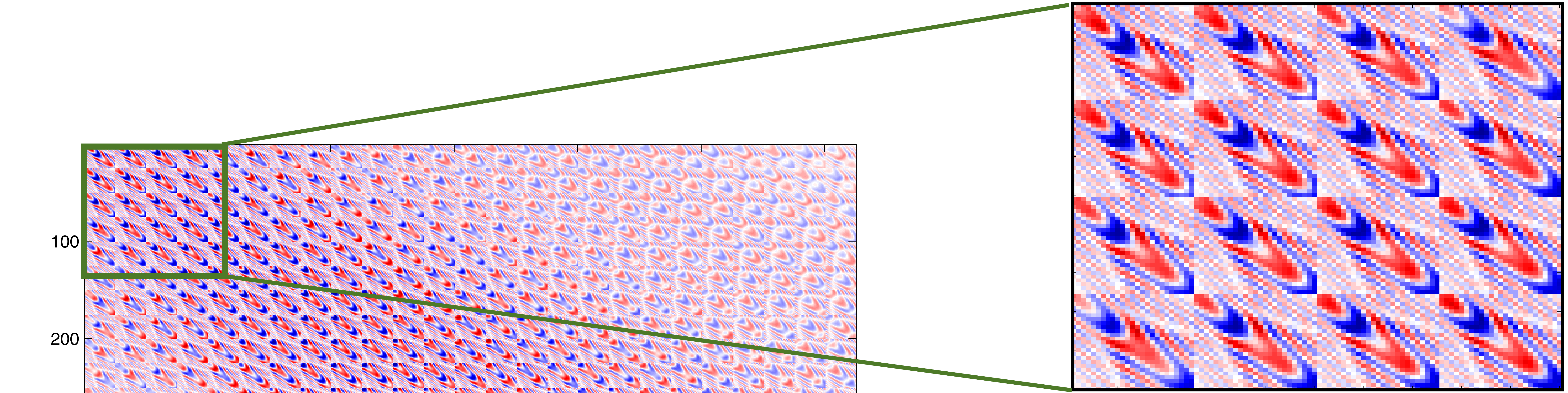
Low-rank structure

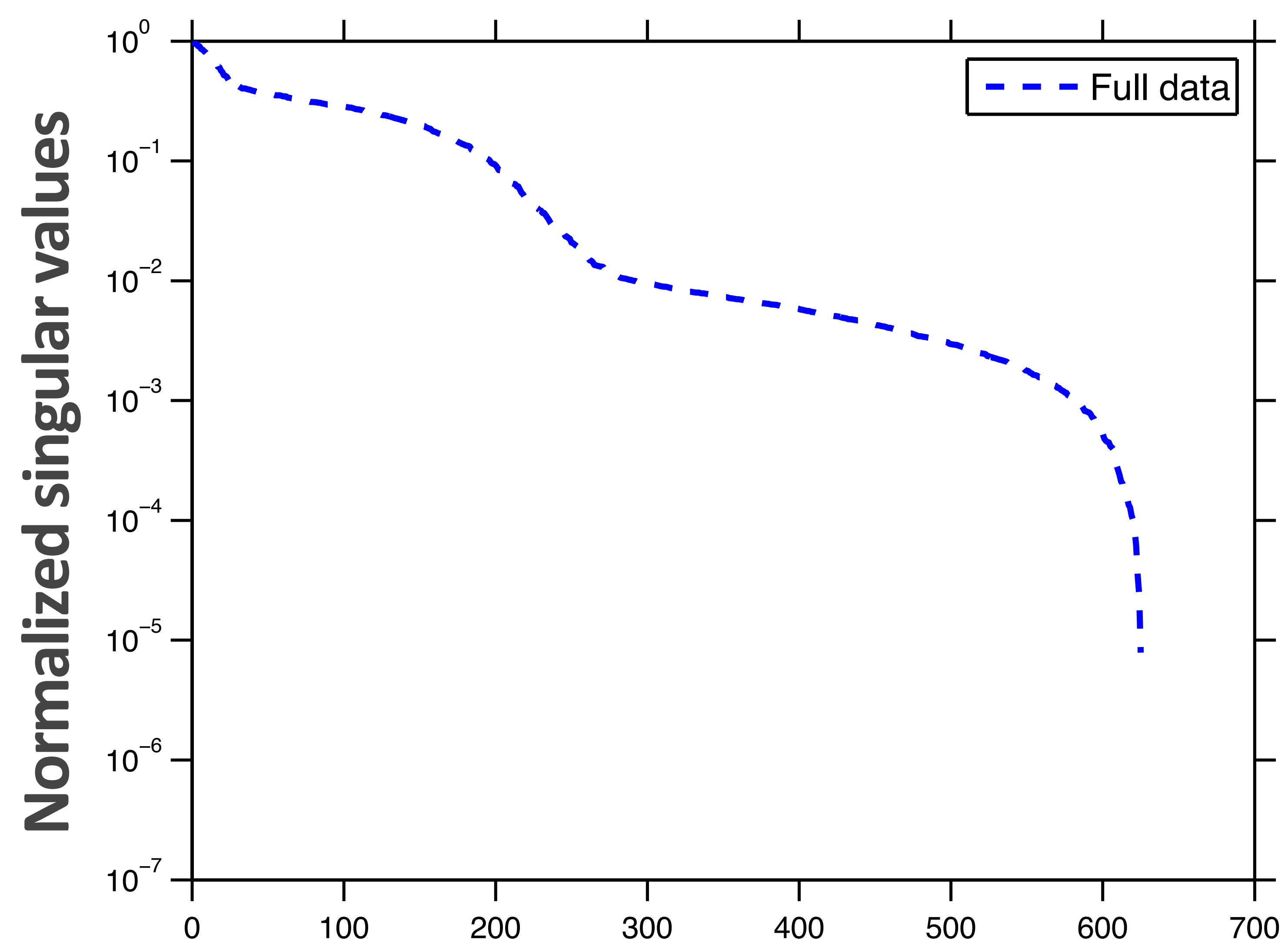
In which domain?

explore different matricizations

Low-rank structure

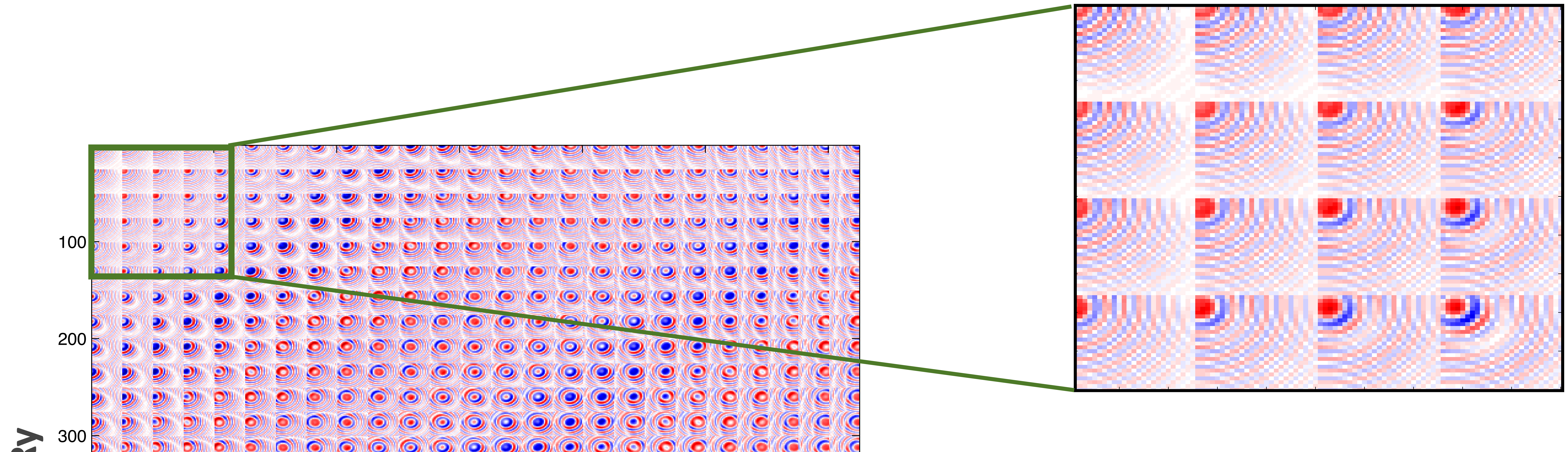
conventional 5D data, monochromatic slice, Sx-Sy matricization

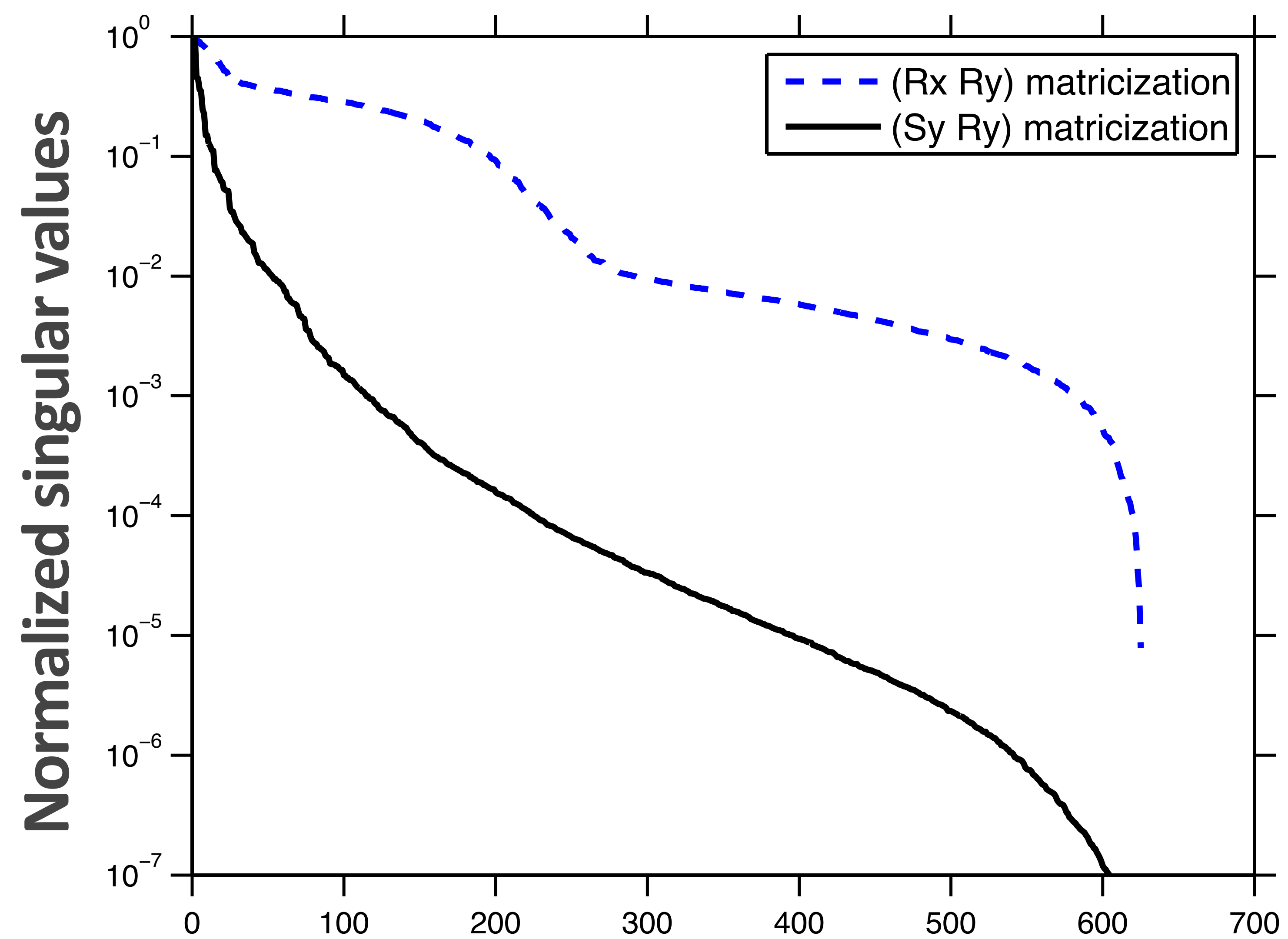




Low-rank structure

conventional 5D data, monochromatic slice, Sx-Rx matricization





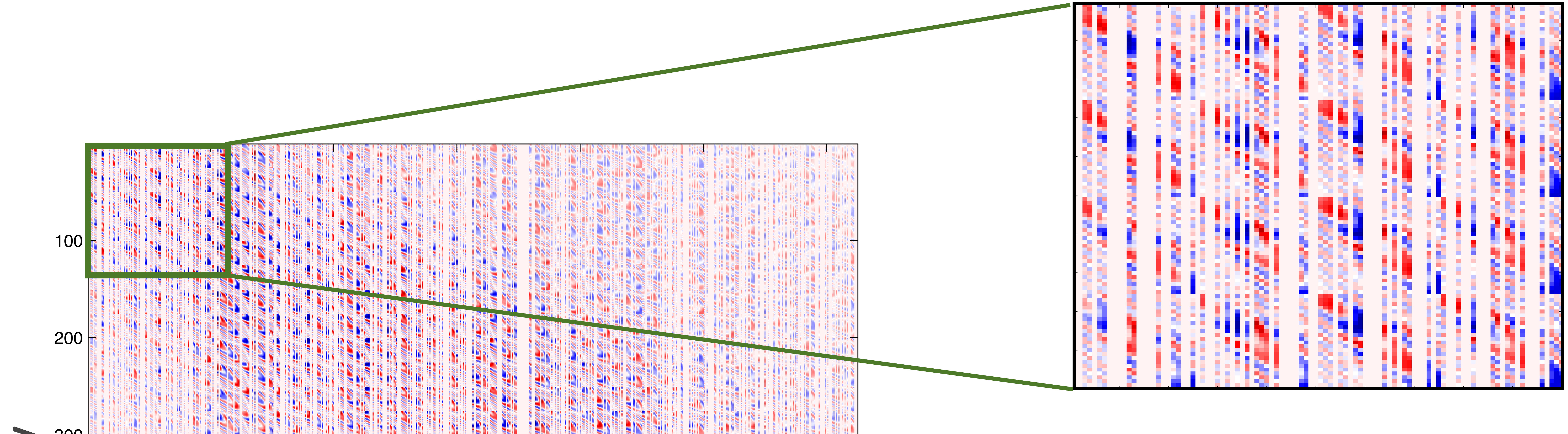
Sampling scheme

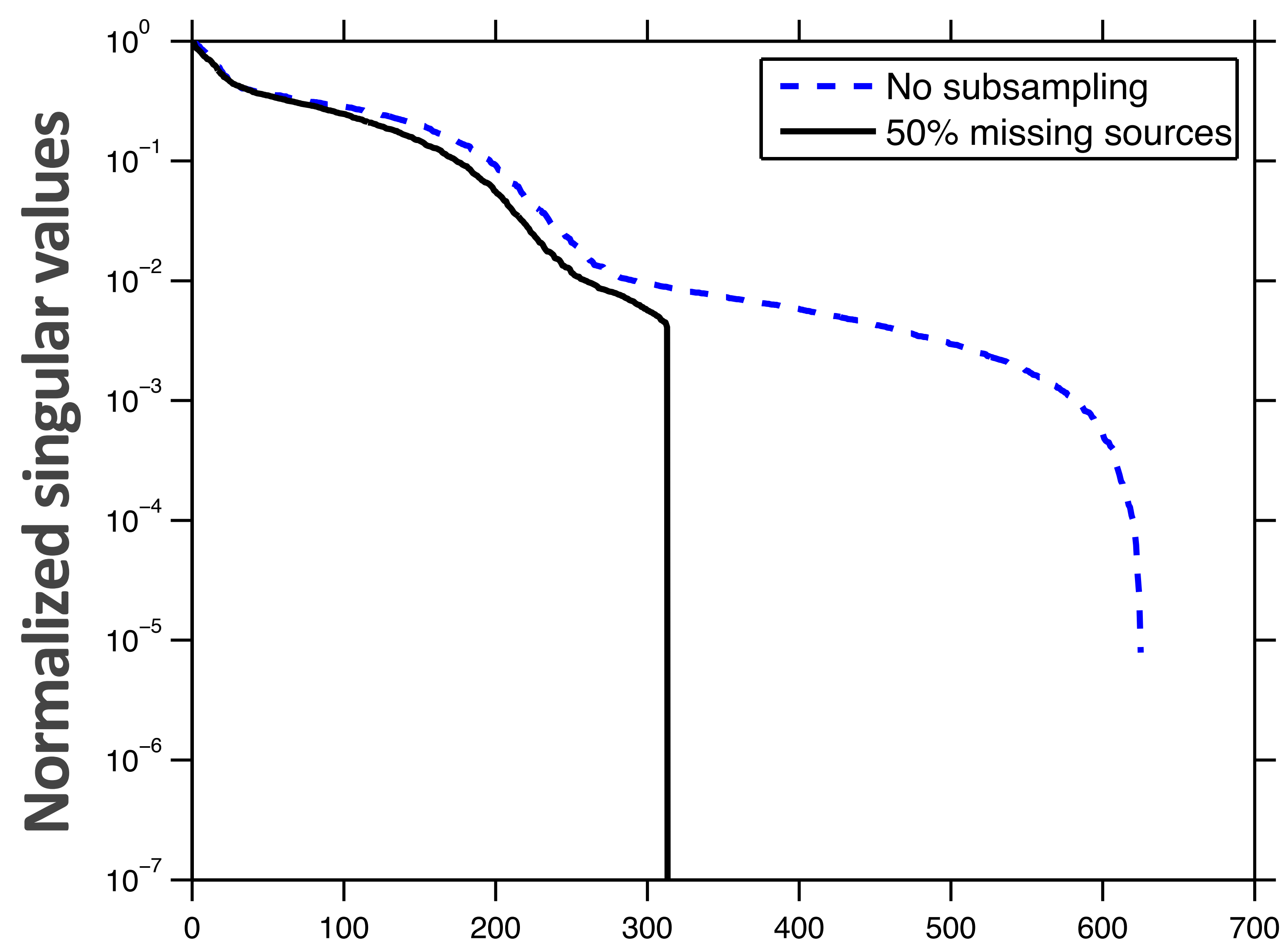
sample to *break* the structure

random missing entries break the structure

Low-rank structure

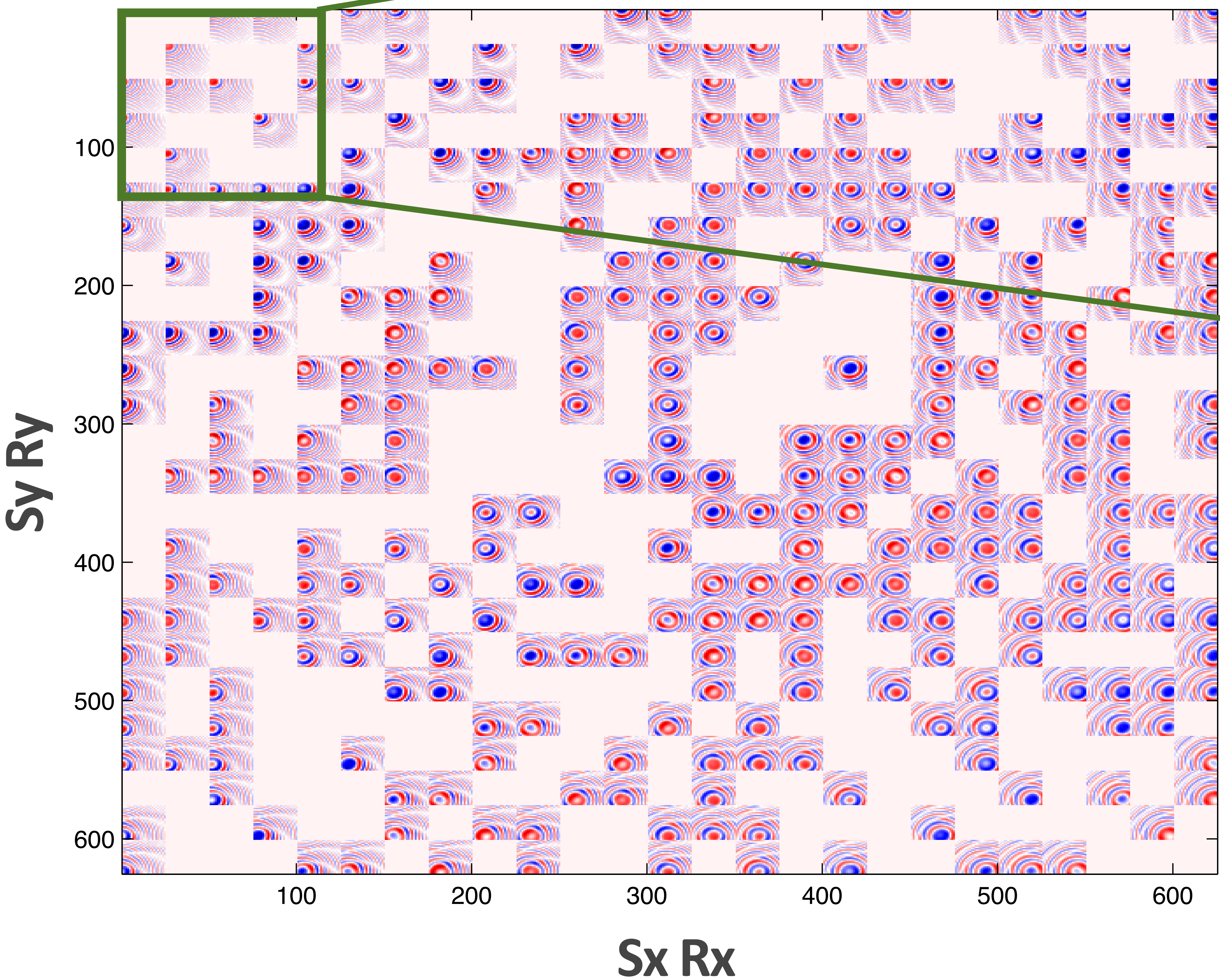
random missing sources, monochromatic slice, **Sx-Sy** matricization

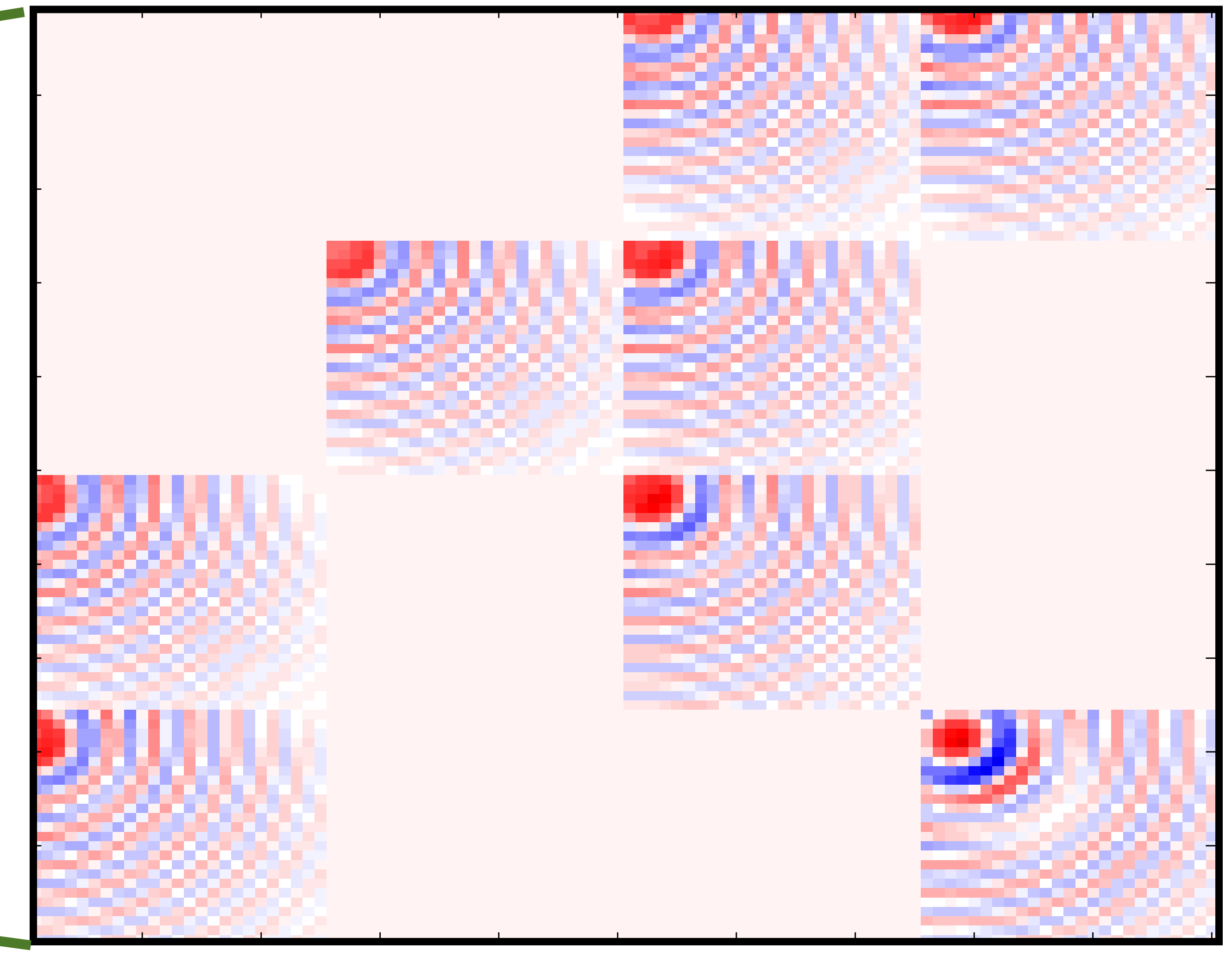


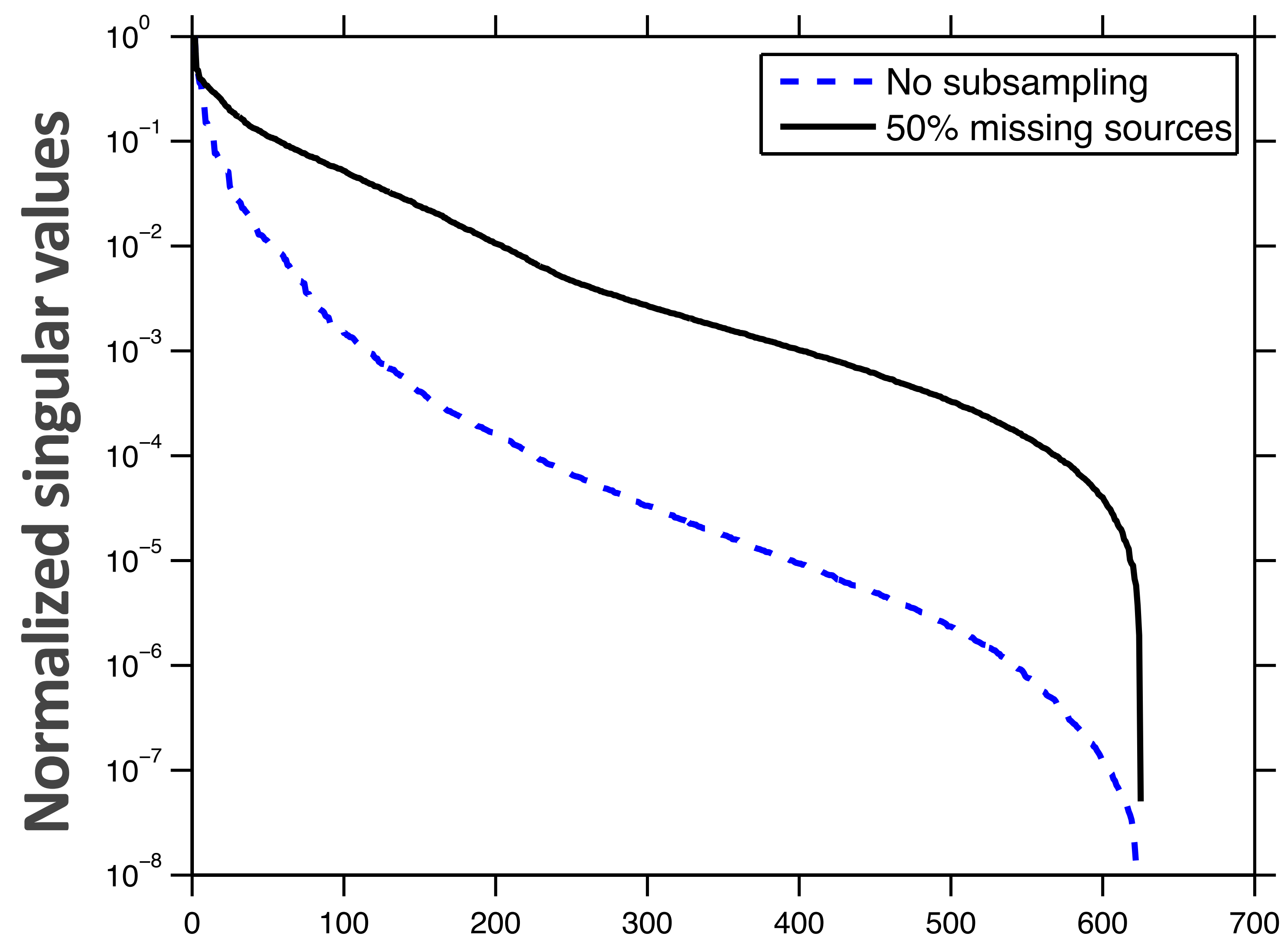


Low-rank structure

random missing sources, monochromatic slice, **Sx-Rx** matricization







Data organization

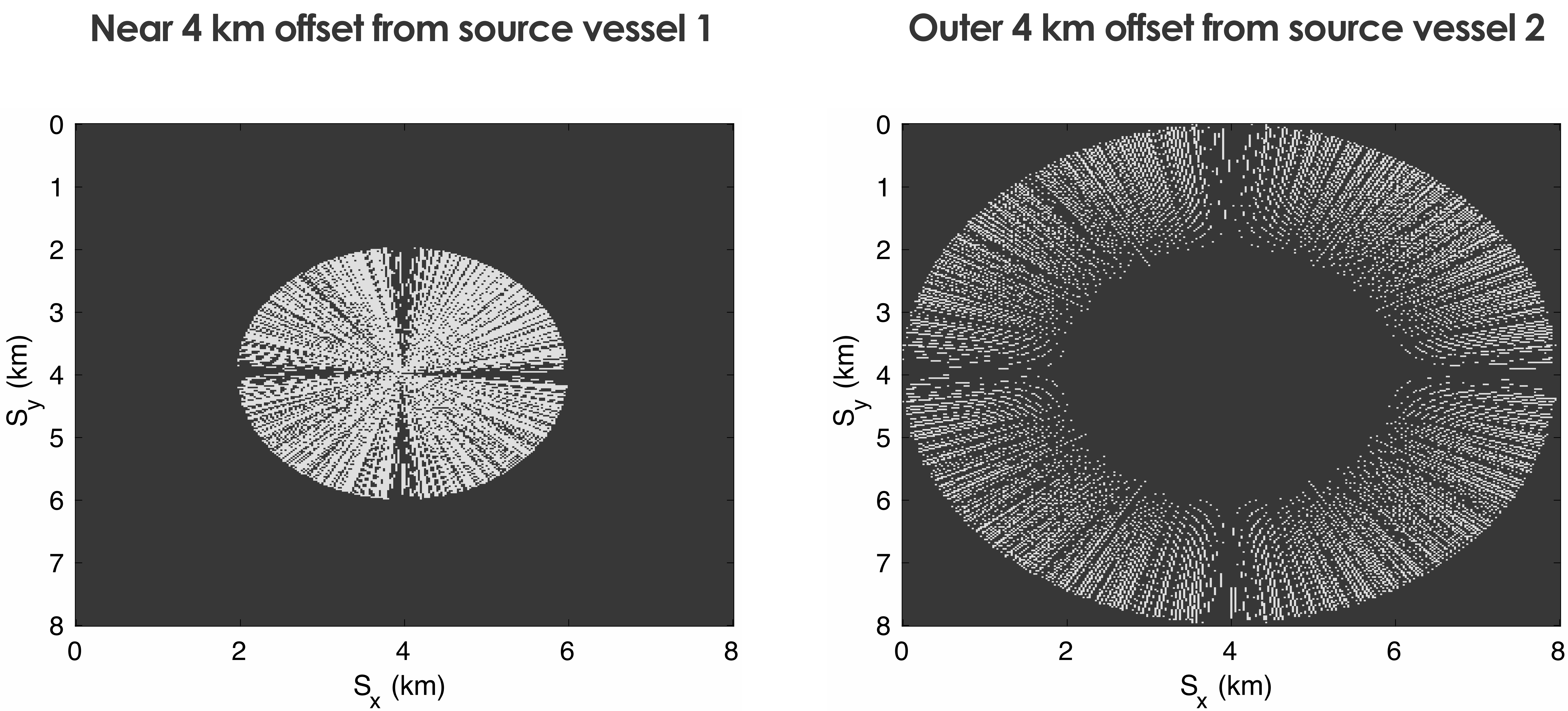
(Sx, Sy) organization

- high rank
- missing sources operator --- removes columns
- missing receivers operator --- removes rows
- **poor recovery** scenario

(Sx, Rx) organization

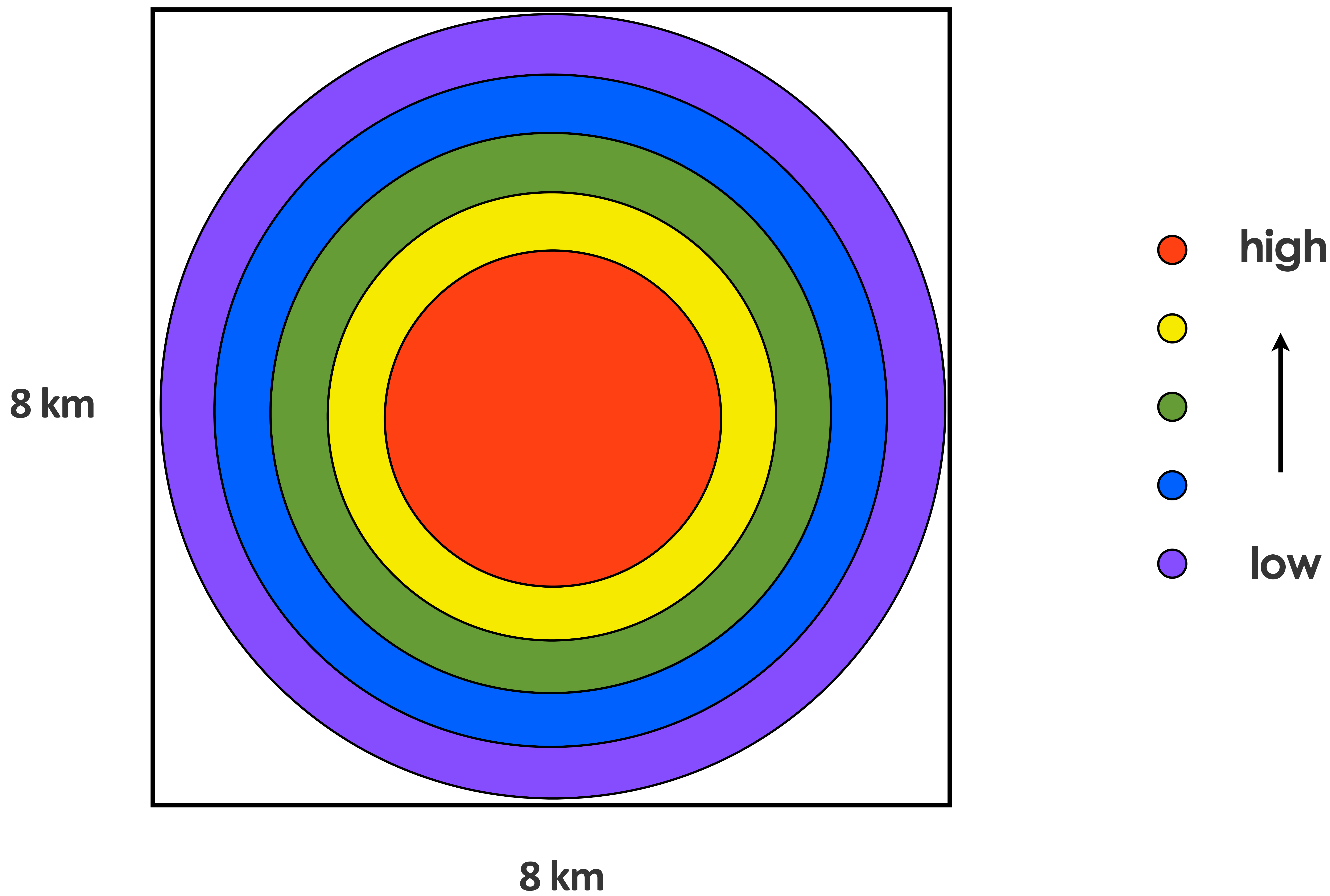
- low rank
- missing sources operator --- removes entries in each block
- missing receivers operator --- removes blocks
- closer to **ideal recovery** scenario

Acquisition mask – 30% acquired



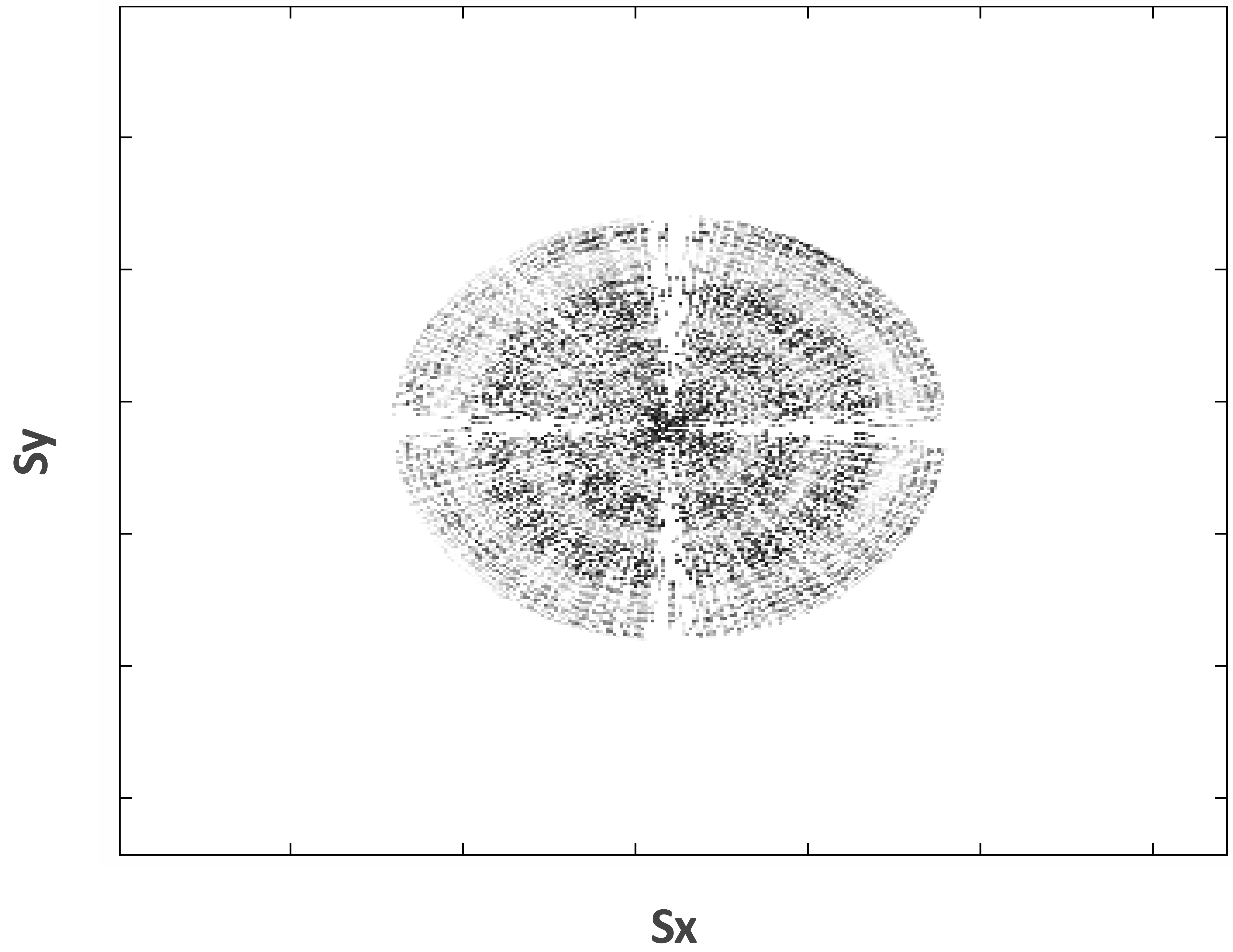
white: one; black: zero

Fold coverage



Observed data – 30%

monochromatic slice, common-receiver domain



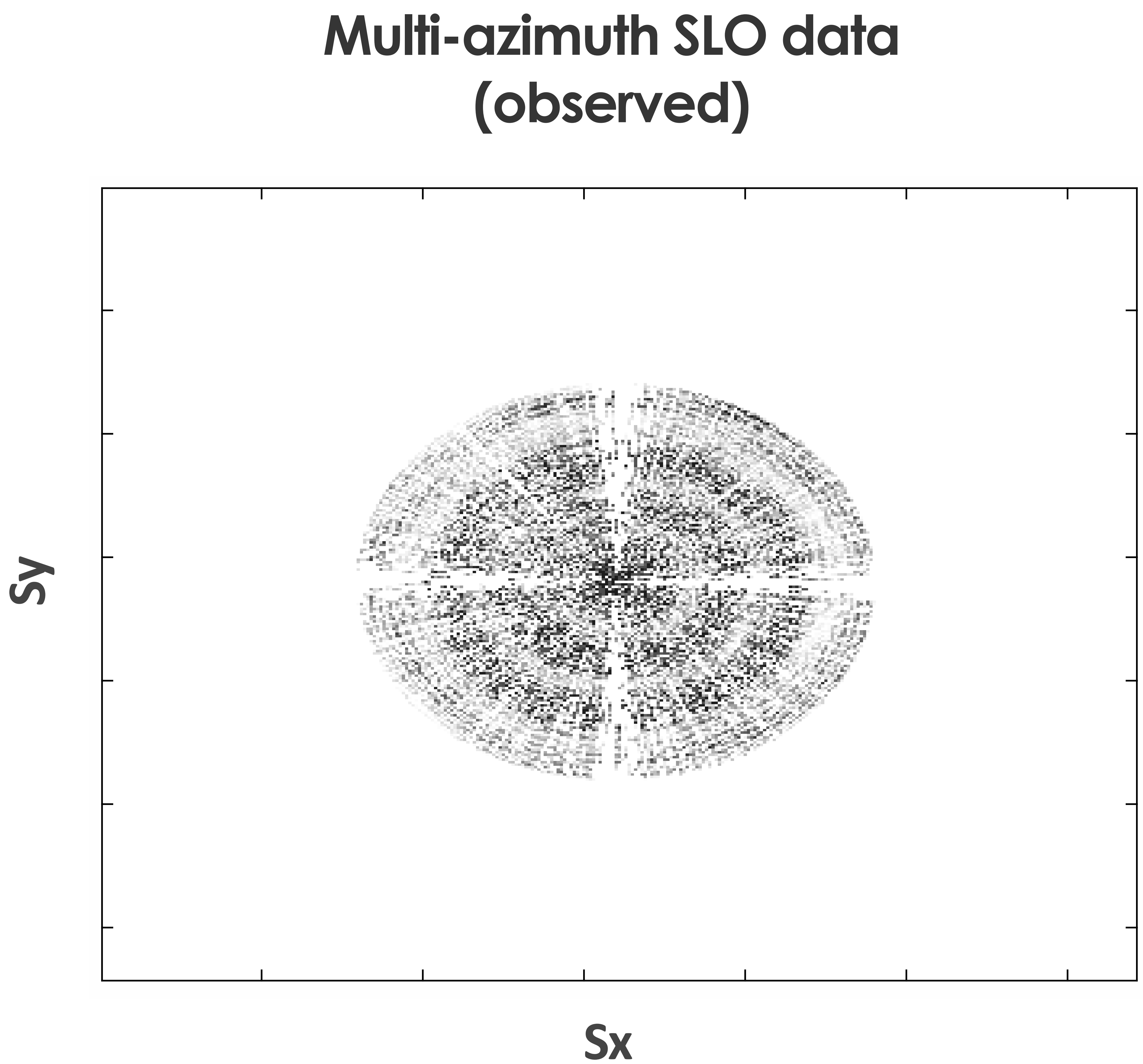
Near 4 km offset
+
Outer 4 km offset

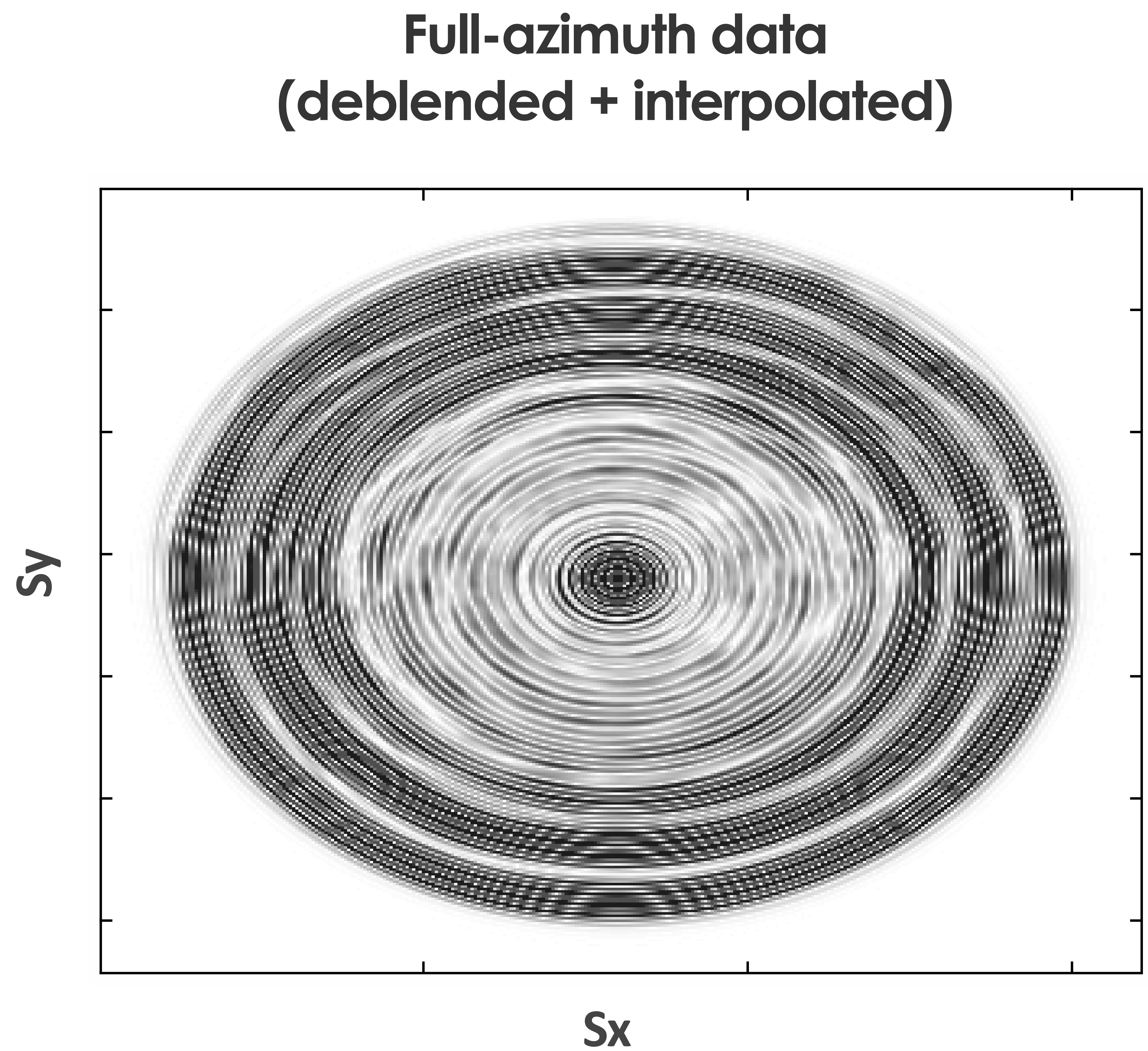
↓

blended & subsampled

Recover full-azimuth data

one common-receiver gather

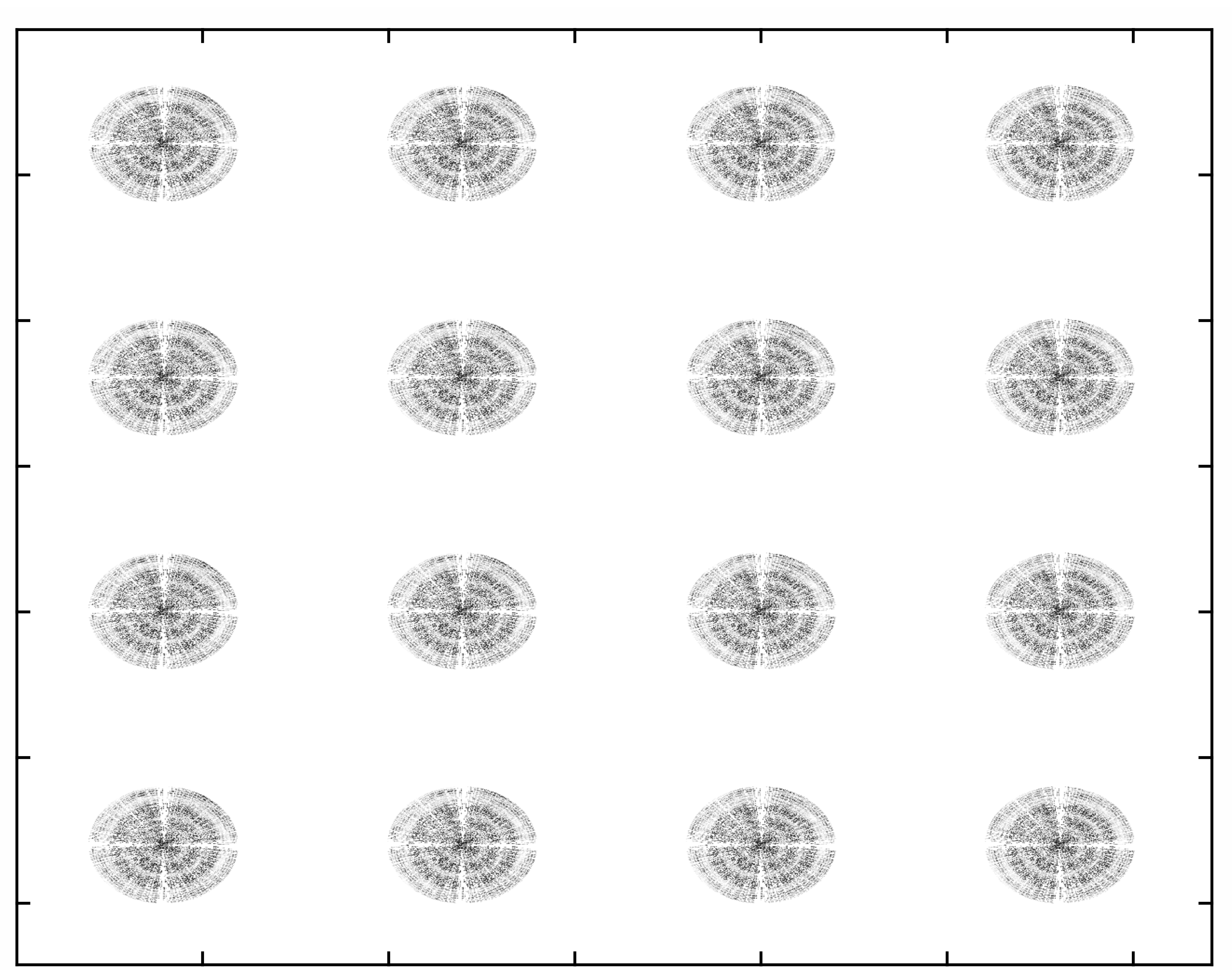




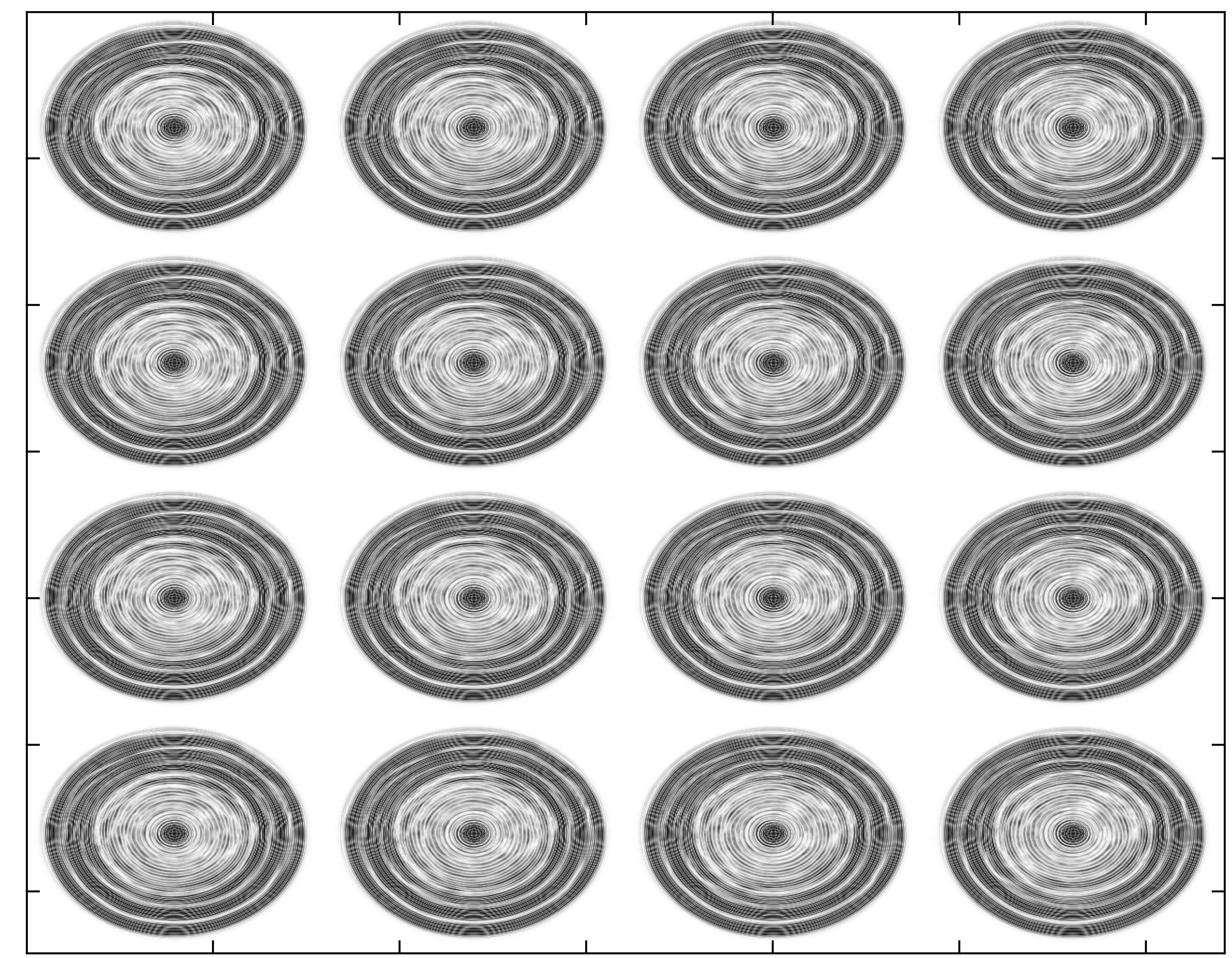
Recover full-azimuth data

multiple common-receiver gathers

Multi-azimuth SLO data (observed)



Full-azimuth data (deblended + interpolated)



Economical 3D time-lapse acquisition

Observed sampling grid* (m)	Recovered sampling grid* (m)	% Subsampling	Gain in sampling
25	25	70	**3X - 4X**
25	12.5	85	**6X - 8X**
25	6.25	93	**10X - 12X**

* source sampling grid; can apply to receiver grid => increased economical gain

Economical 3D time-lapse acquisition

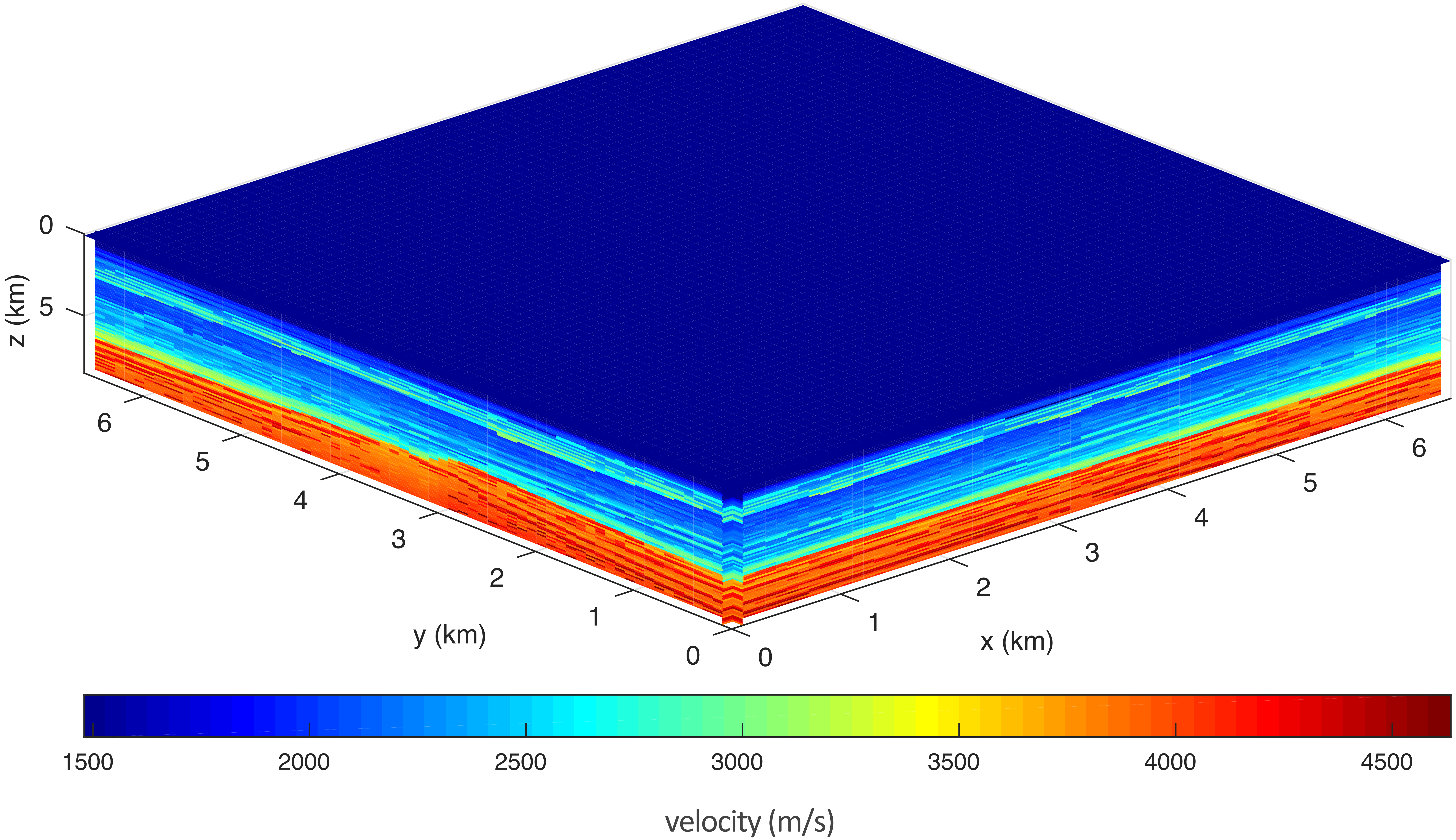
Observed sampling grid* (m)	Recovered sampling grid* (m)	% Subsampling	Gain in sampling
25	25	70	**3X - 4X**
25	12.5	85	**6X - 8X**
25	6.25	93	**10X - 12X**

* source sampling grid; can apply to receiver grid => increased economical gain

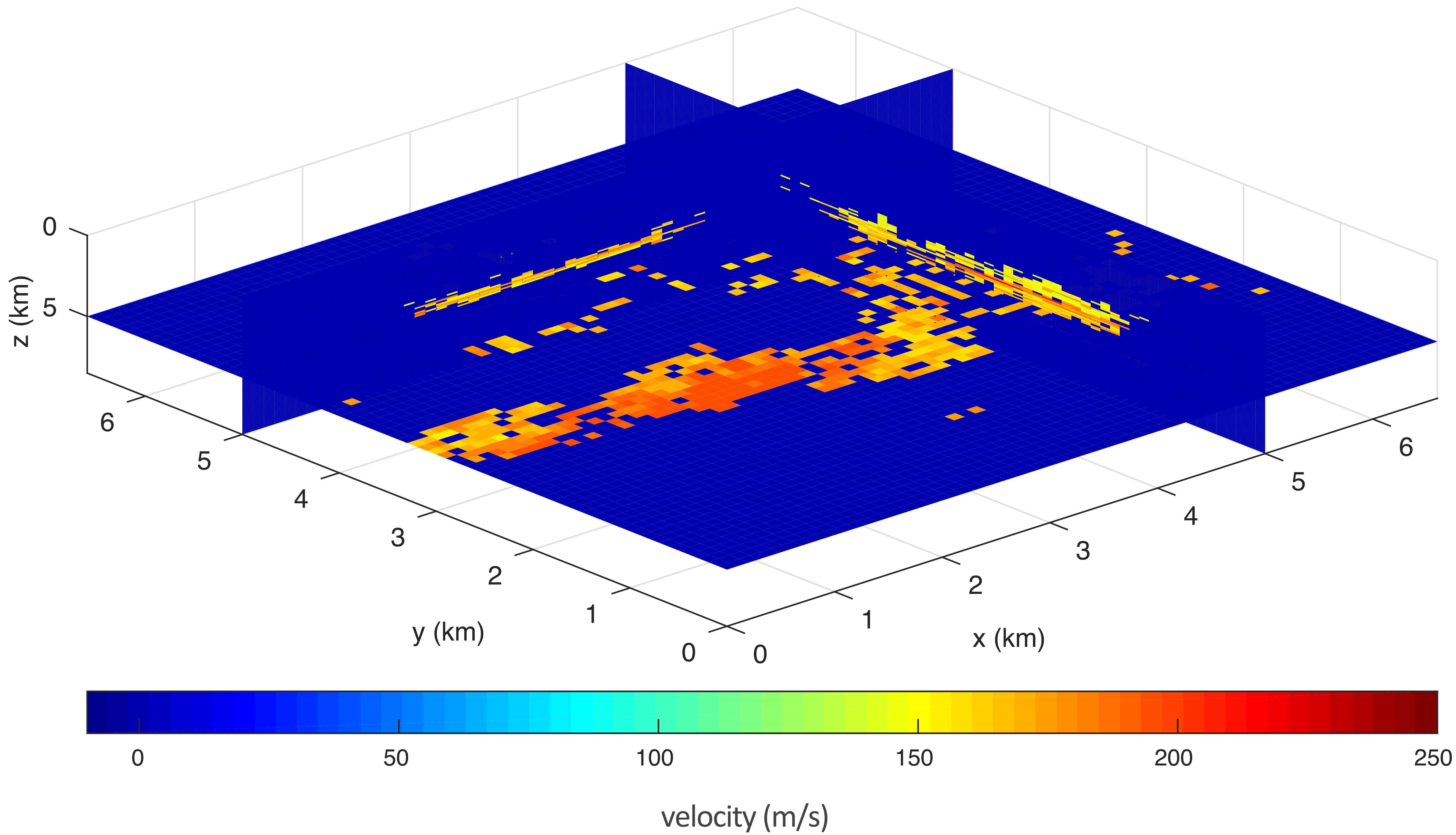
Felix Oghenekohwo, Haneet Wason, Ernie Esser, and Felix J. Herrmann, "**Low-cost time-lapse seismic with distributed Compressive Sensing–-exploiting common information amongst the vintages**". 2016. To appear in GEOPHYSICS
Haneet Wason, Felix Oghenekohwo, and Felix J. Herrmann, "**Cheap time lapse with distributed Compressive Sensing–-impact on repeatability**". 2016. To appear in GEOPHYSICS

Extension to 3D time-lapse acquisition

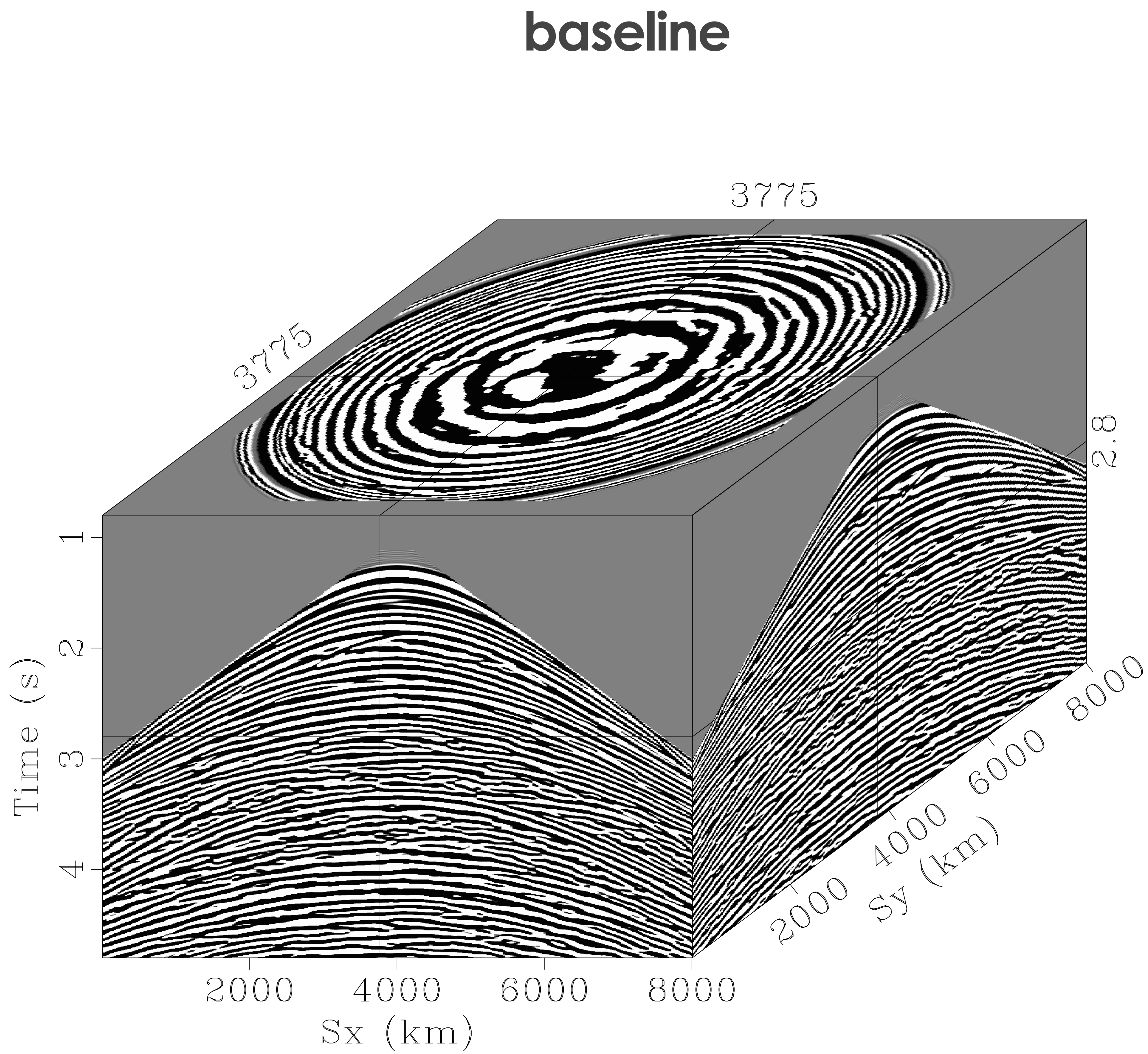
3D baseline BG model

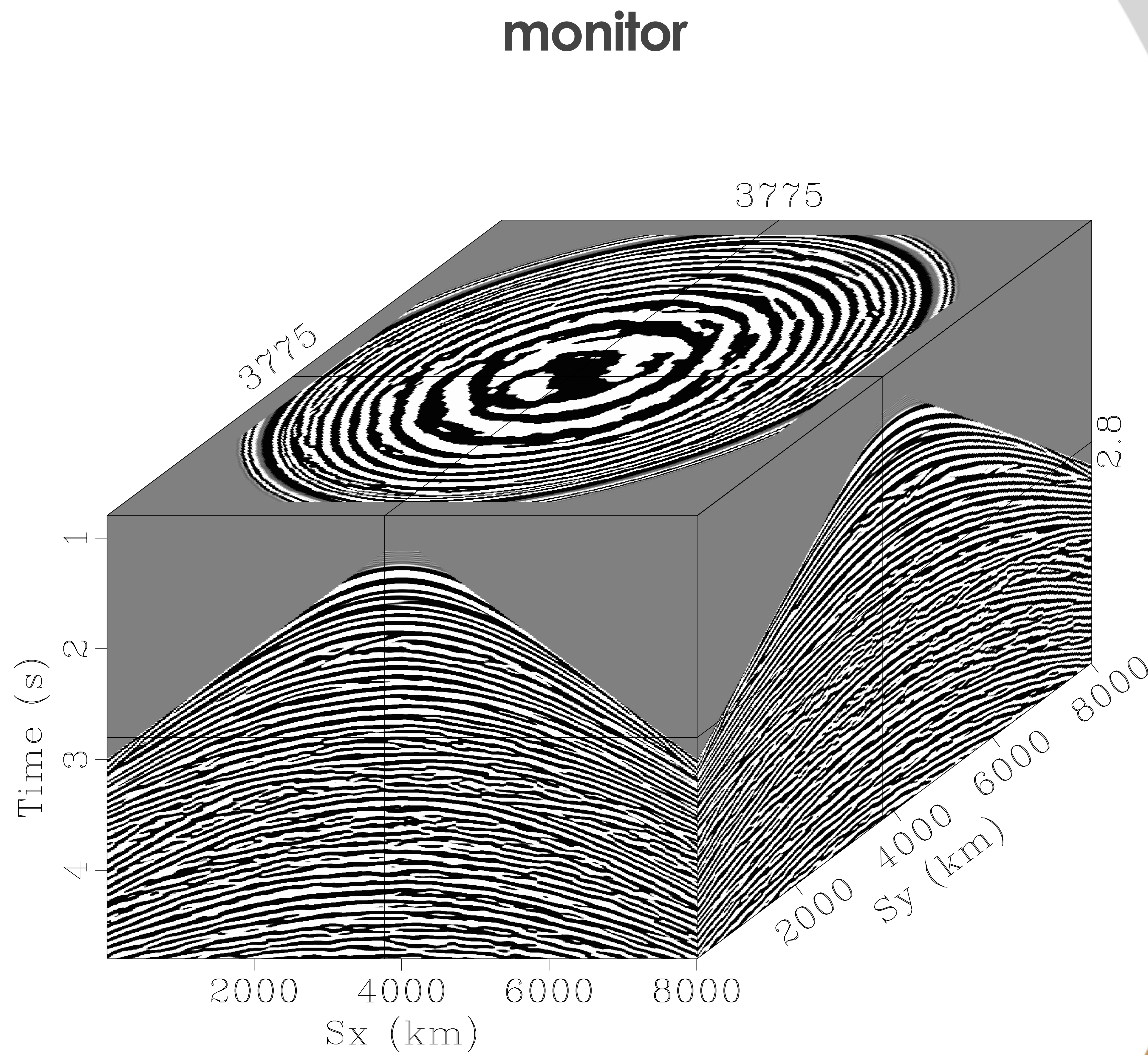


3D time-lapse BG model

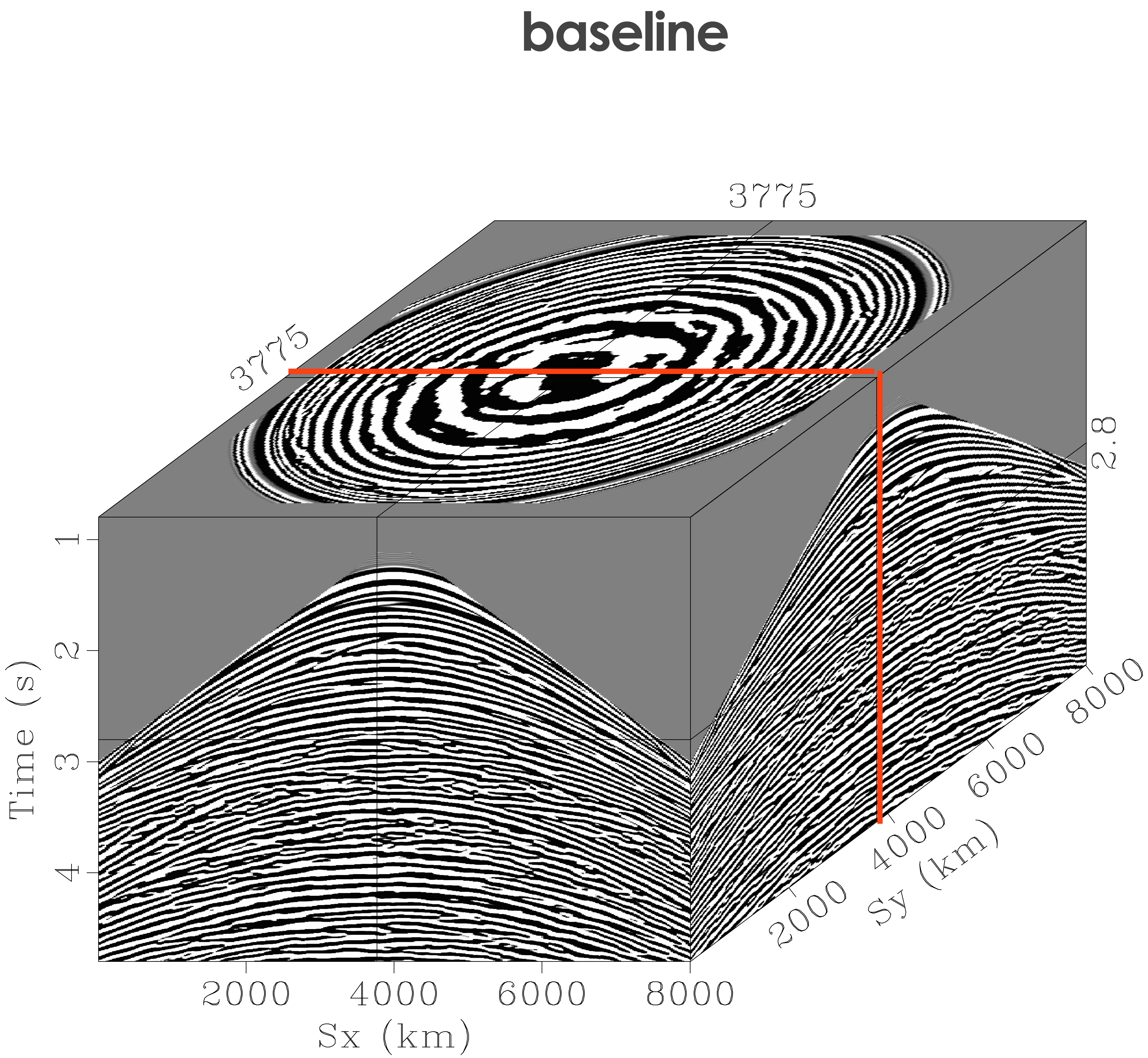


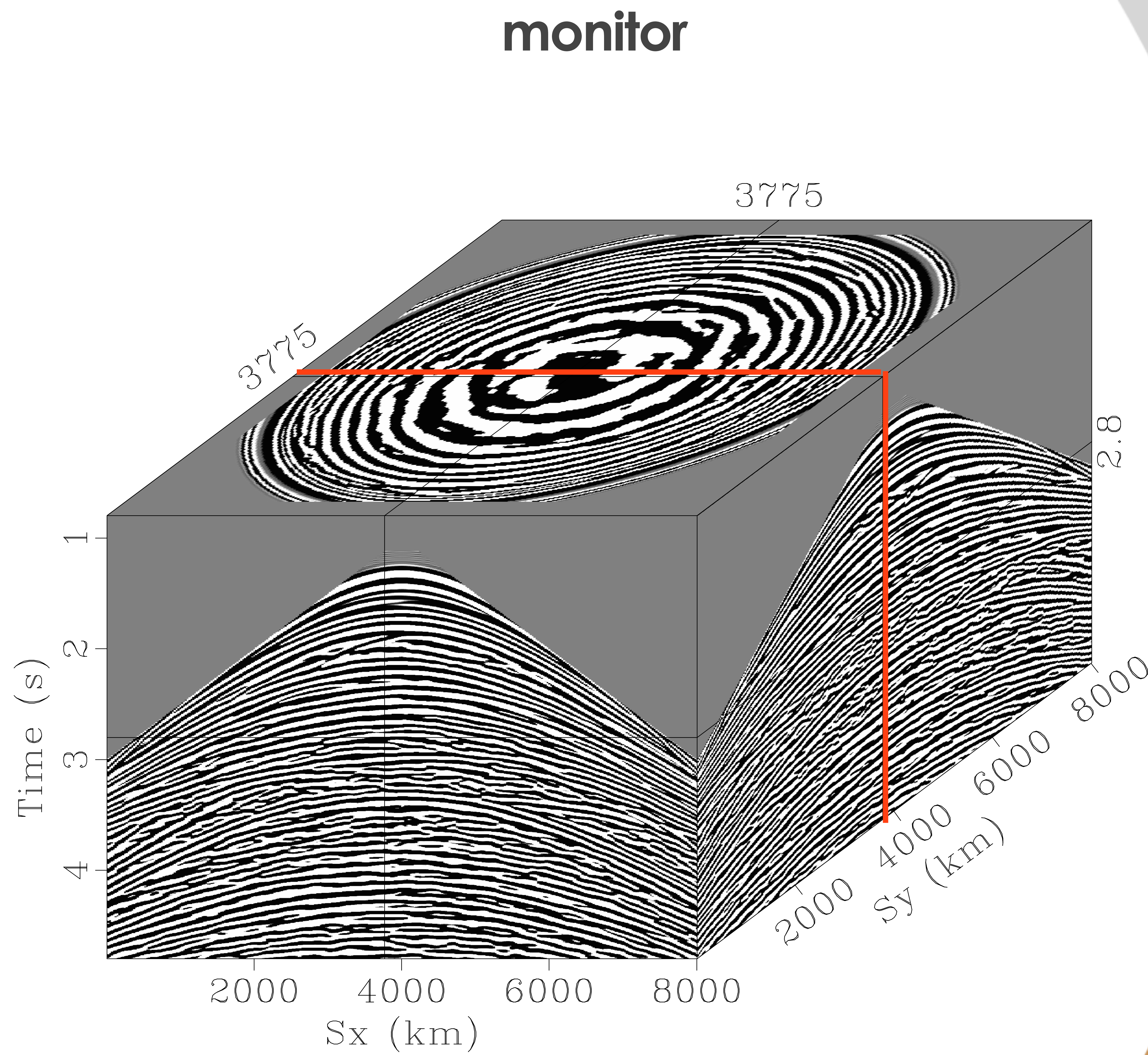
Ideal dense receiver gathers



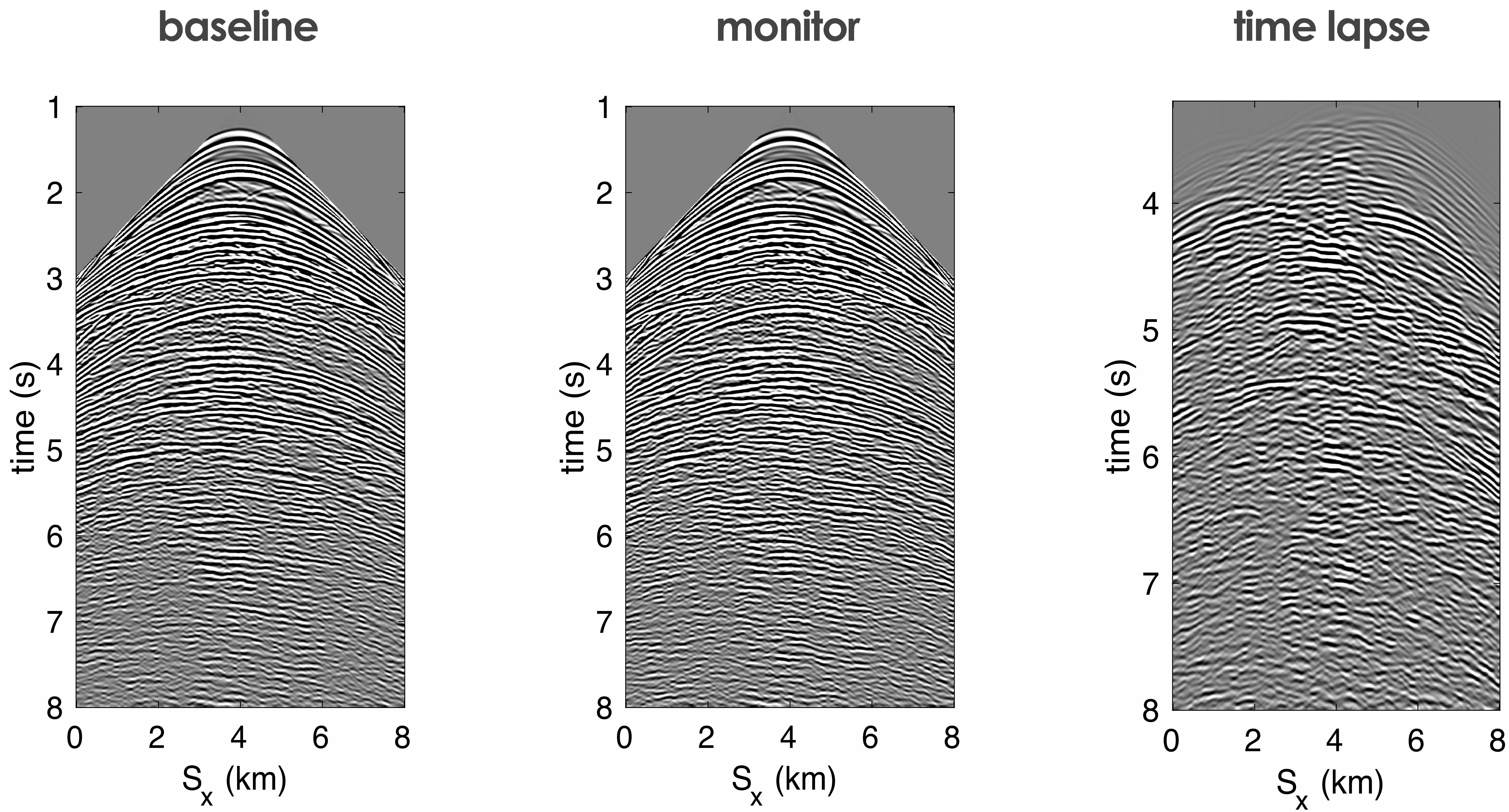


Ideal dense receiver gathers





Ideal dense receiver gathers & time lapse



JRM – Joint Recovery Model

vintages

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

differences

common **component**

forward model baseline

forward model monitor

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

baseline

monitor

Key idea:

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

Optimization information

Parallelized factorization framework over sources & receivers

Number of iterations: 400

Computational time: 3 hours per frequency slice

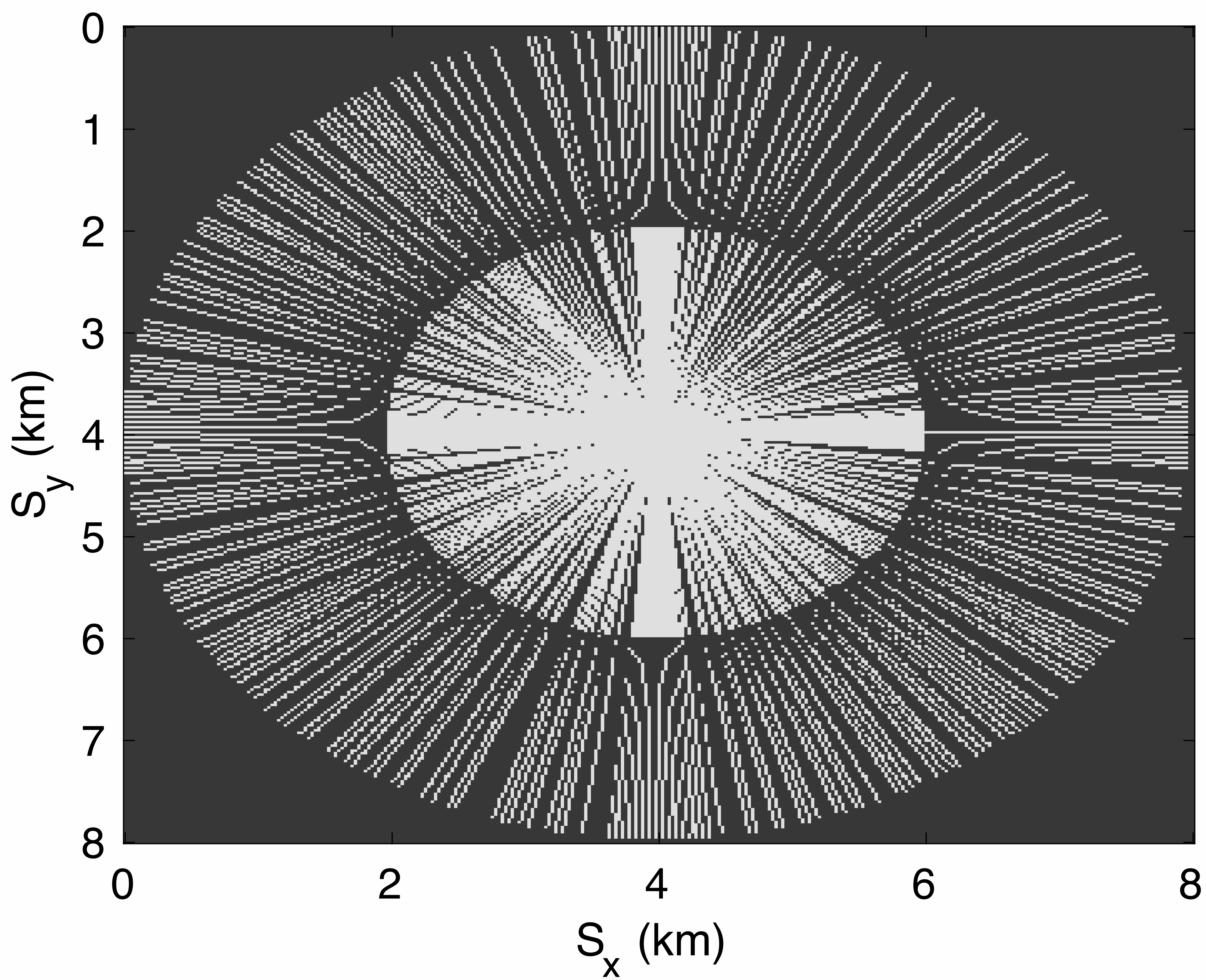
Separation & interpolation to 25 m grid

SENAI Yemoja cluster:

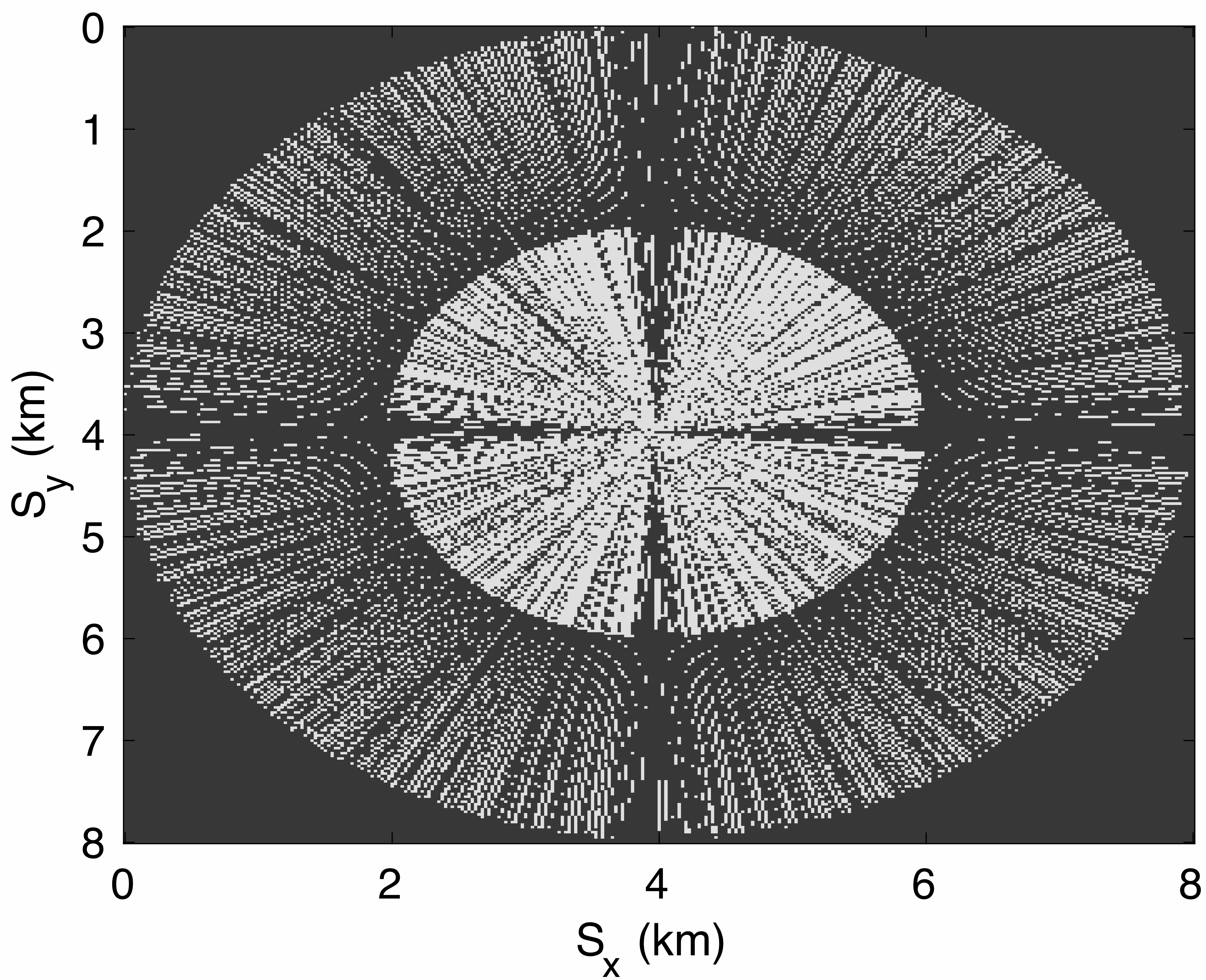
30 nodes w/ 128 GB RAM each, 20-core processors

300 Parallel MATLAB workers (10 per node), multithread, full core utilization

Random acquisition masks – 30% acquired



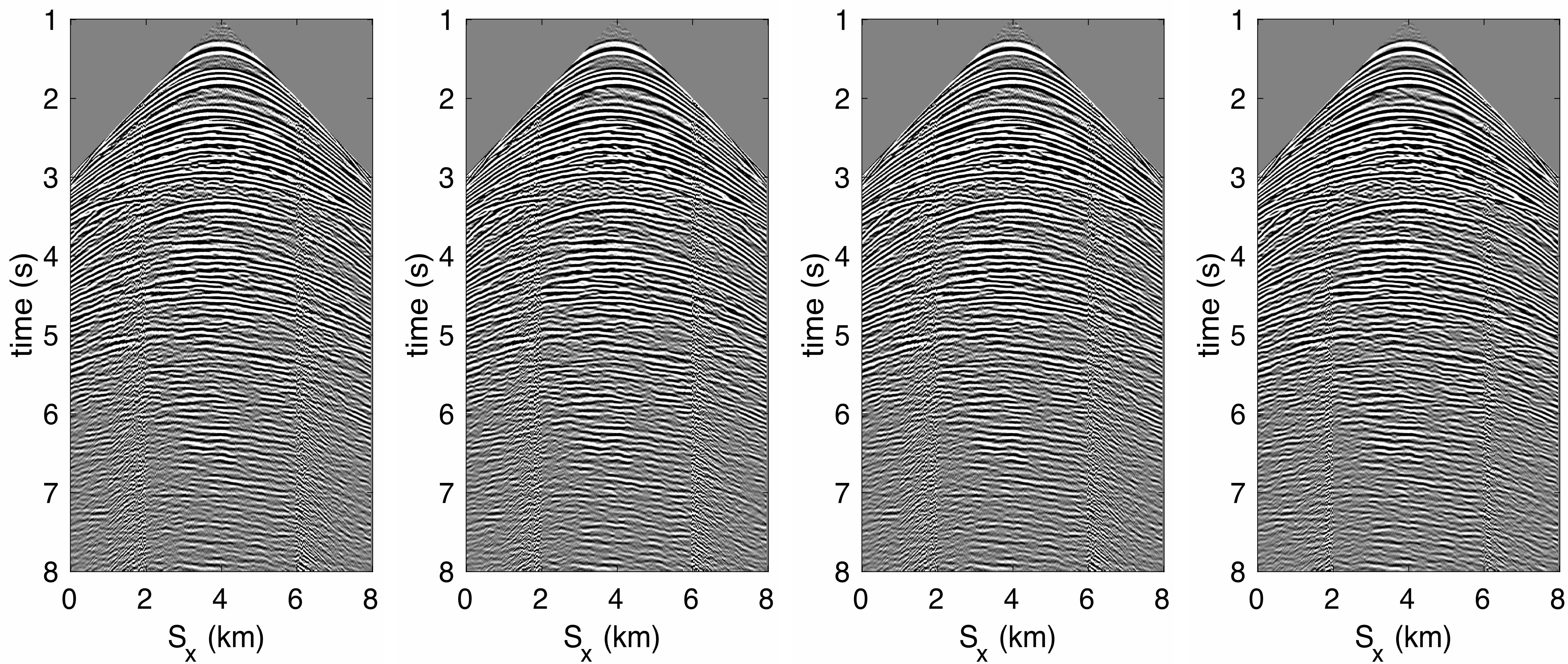
Random acquisition masks – 30% acquired



Baseline recovery

100% overlap | **30% overlap**

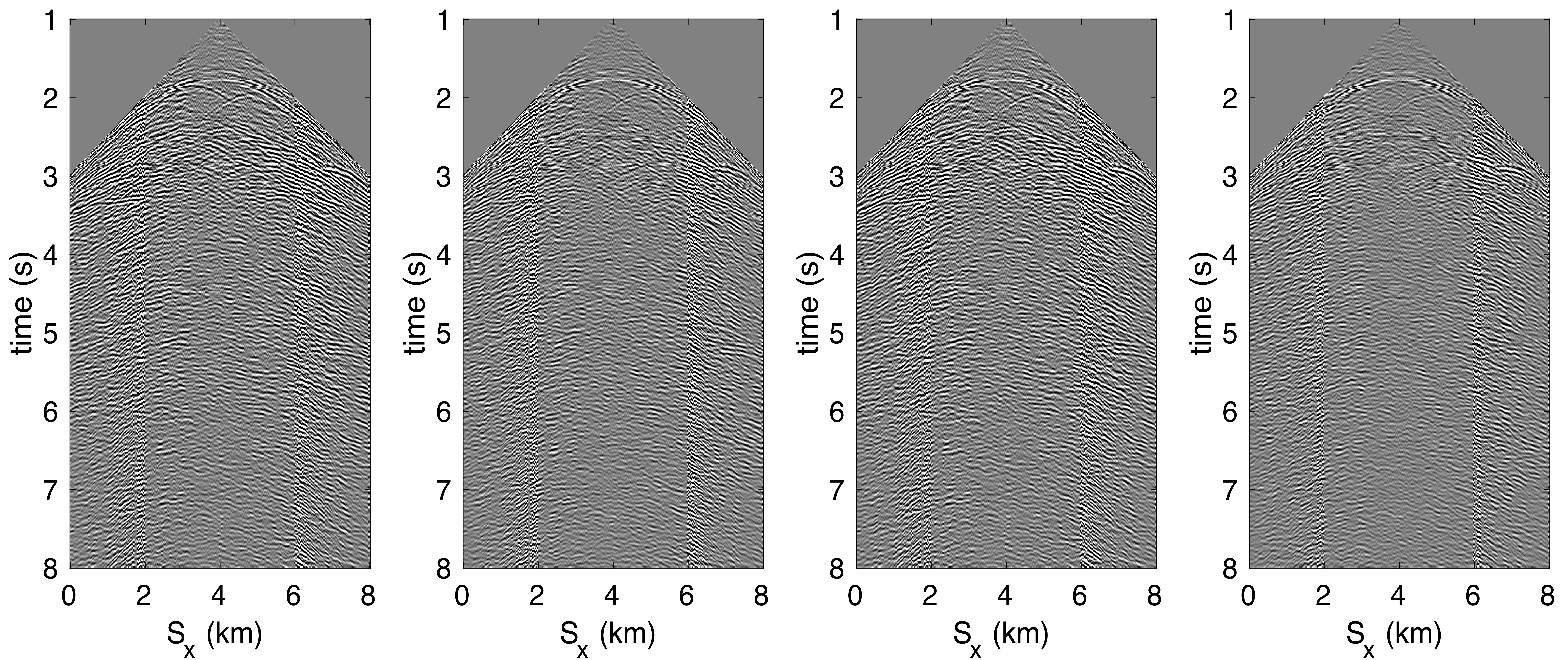
IRS (12.6 dB)	JRM (13.4 dB)	IRS (12.6 dB)	JRM (15.4 dB)



Residual

100% overlap | **30% overlap**

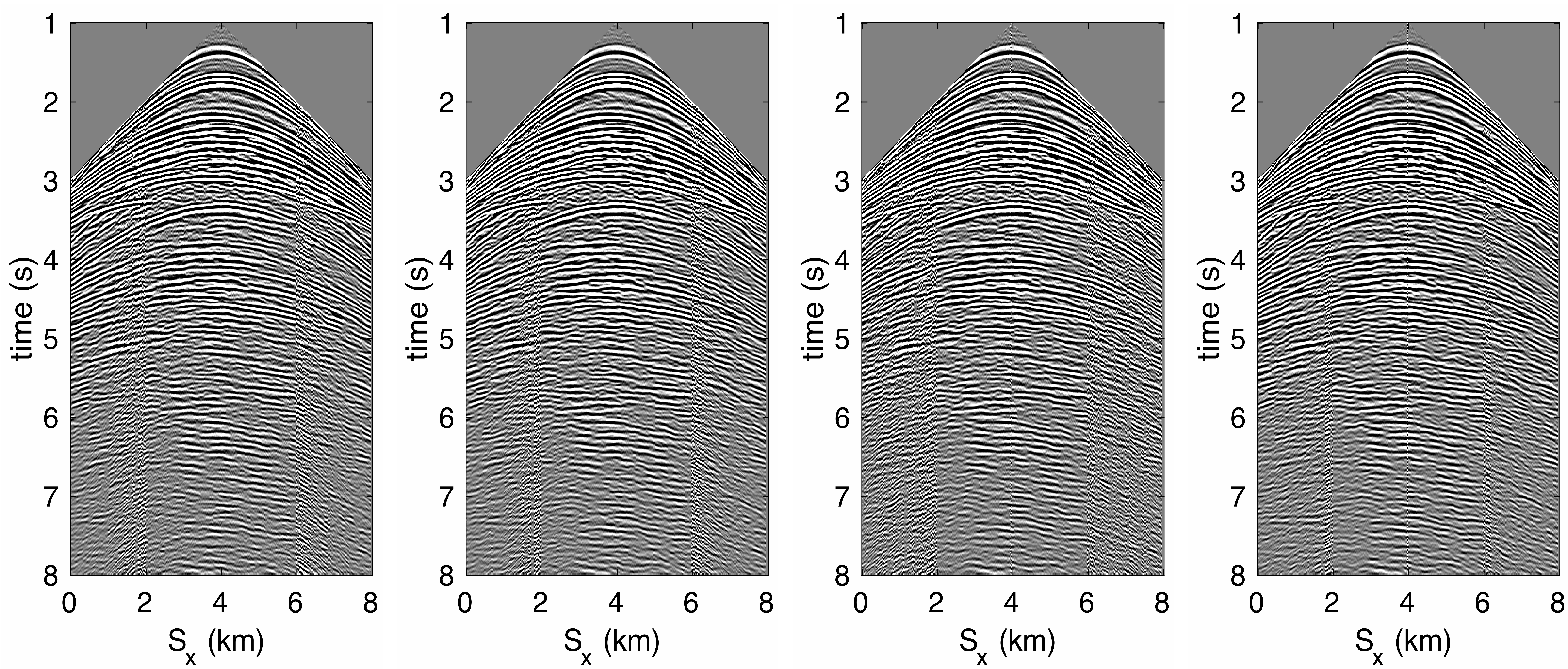
IRS (12.6 dB)	JRM (13.4 dB)	IRS (12.6 dB)	JRM (15.4 dB)



Monitor recovery

100% overlap | **30% overlap**

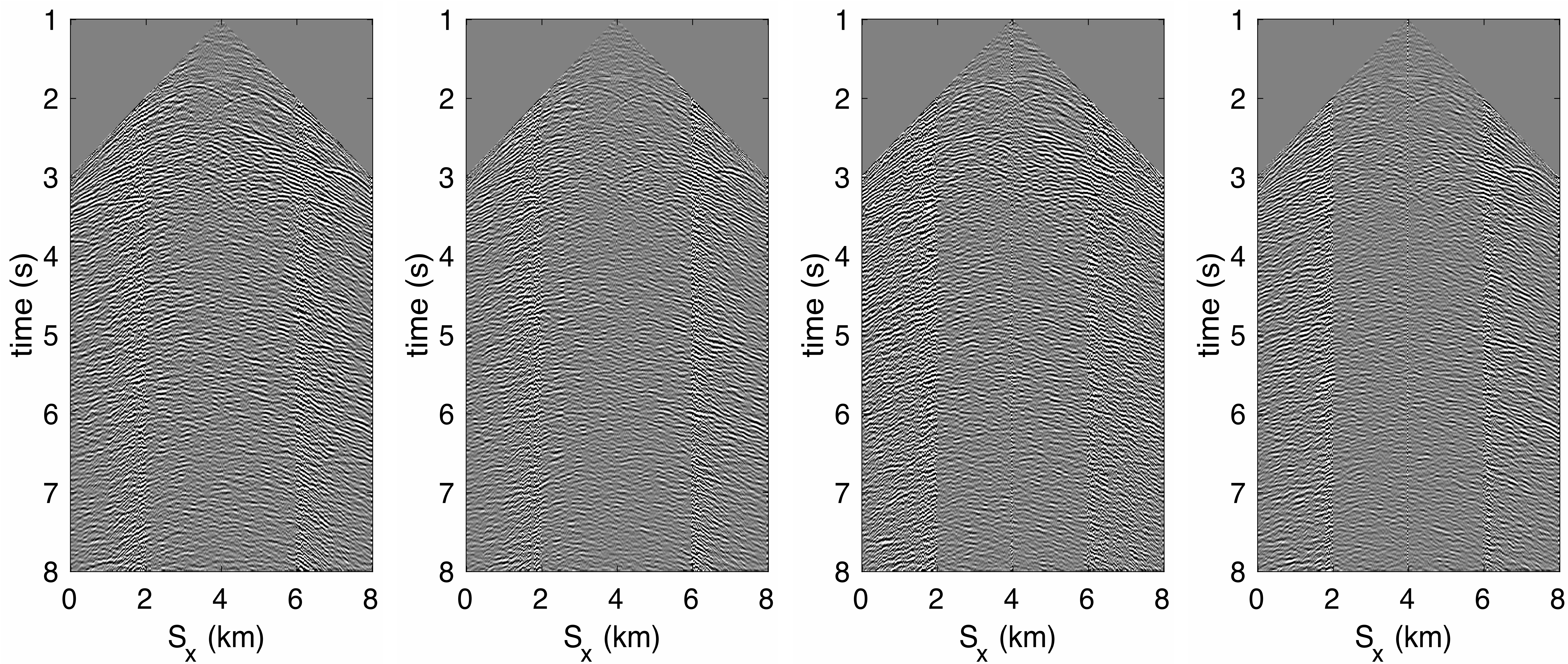
IRS (12.5 dB)	JRM (13.3 dB)	IRS (10.5 dB)	JRM (15.9 dB)



Residual

100% overlap | **30% overlap**

IRS	JRM	IRS	JRM
(12.5 dB)	(13.3 dB)	(10.5 dB)	(15.9 dB)



Take-away message

Size of final recovered data volume: 2.08 TB

- no need to save fully sampled seismic data volume

Save $\mathbf{L}$ and $\mathbf{R}$ factors

- compression rate: **98.5%**
- size of final compressed 5D seismic volume: ~ **31.2 GB**

Conclusions

Randomized sampling (joint) recovery leads to:

- economic acquisition for both static & dynamic acquisitions
- surveys w/ high degree of repeatability w/o replicating the surveys

Preliminary randomized 4D survey design:

- is feasible
- needs more randomness
- leads to at least cost reduction of 3 – 4 X

As long as we know where we were all acquisitions will benefit from embracing randomness in the field...

Future work

Run more experiments including extensions to off-the-grid acquisition design and processing

Test with realistic noise

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We would like to acknowledge Nick Moldoveanu from Schlumberger for useful discussions on 3D time-lapse acquisition and BG Group for providing the Compass 3D time-lapse model.

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SINBAD

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