Highly repeatable 3D compressive full-azimuth towed-streamer time-lapse acquisition-a numerical feasibility study at scale

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Rajiv Kumar, Haneet Wason, Shashin Sharan

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"Highly repeatable 3D compressive full-azimuth towed-streamer time-lapse acquisition –- a numerical feasibility study at scale", *The Leading Edge*, vol. 36, p. 677-687, 2017

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.
Gilles Hennenfent and Felix J. Herrmann, "Simply denoise: wavefield reconstruction via jittered undersampling", Geophysics, vol. 73, p. V19-V28, 2008.
Felix J. Herrmann and Gilles Hennenfent, "Non-parametric seismic data recovery with curvelet frames", Geophysical Journal International, vol. 173, p. 233-248, 2008.

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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

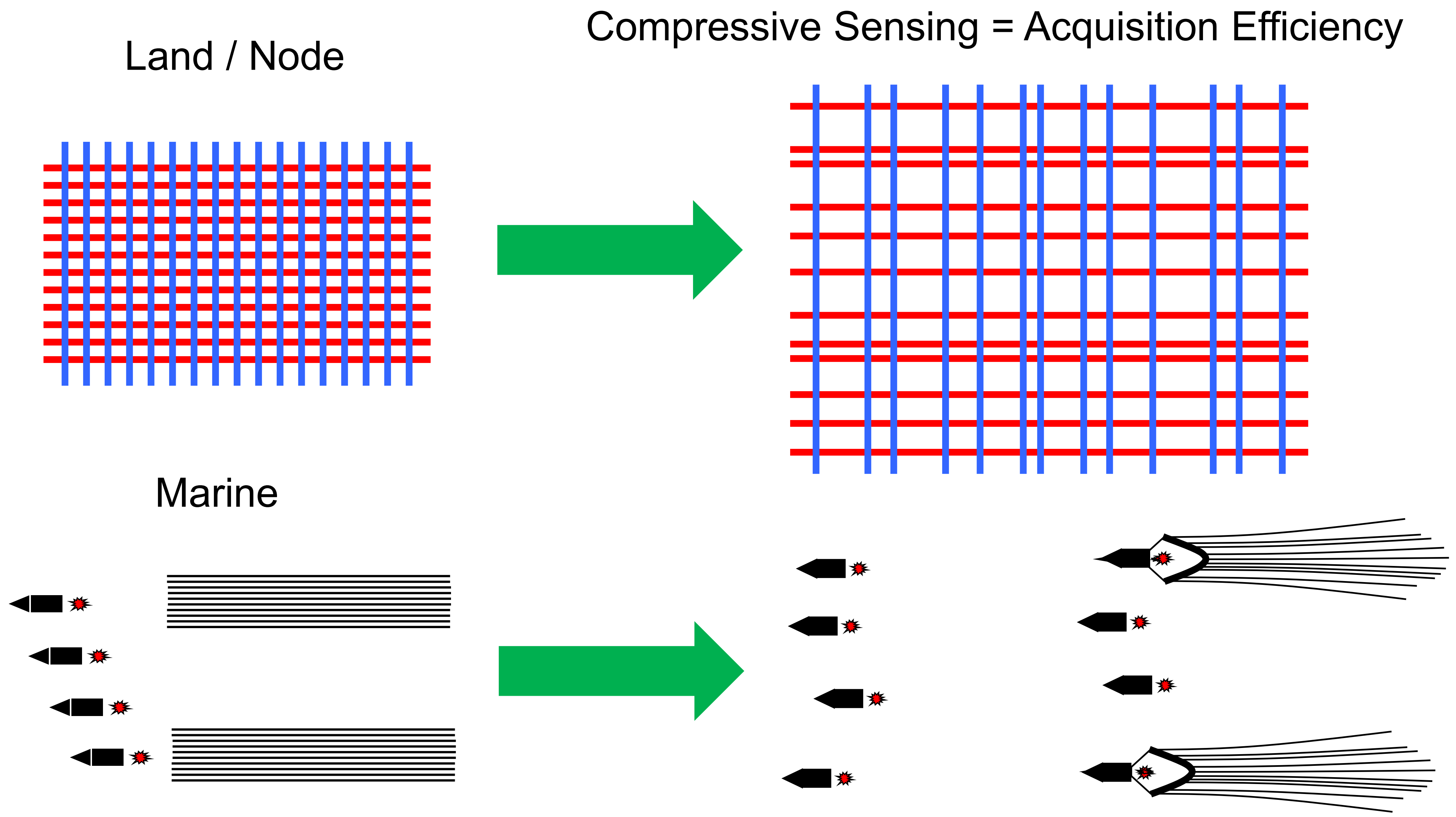
Mosher, C. C., Keskula, E., Kaplan, S. T., Keys, R. G., Li, C., Ata, E. Z., ... & Sood, S. (2012, November). **Compressive Seismic Imaging**. In *2012 SEG Annual Meeting*. Society of Exploration Geophysicists.

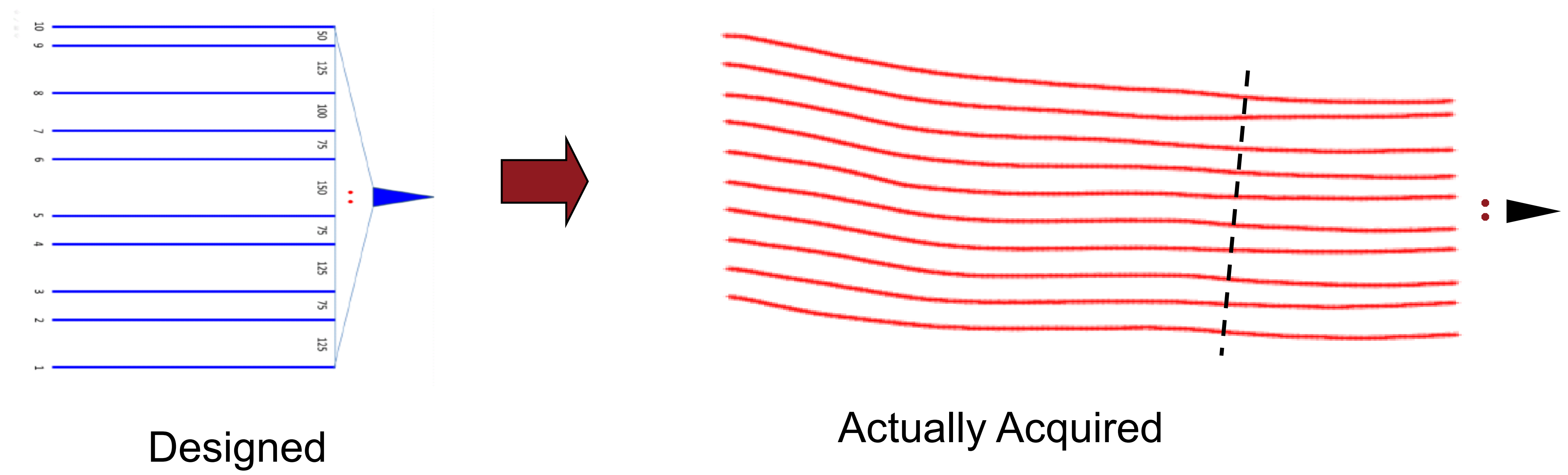
Randomized acquisition

examples from industry (ConocoPhilips)

Deliberate & natural randomness in acquisition

(thanks to Chuck Mosher)





Bottom line

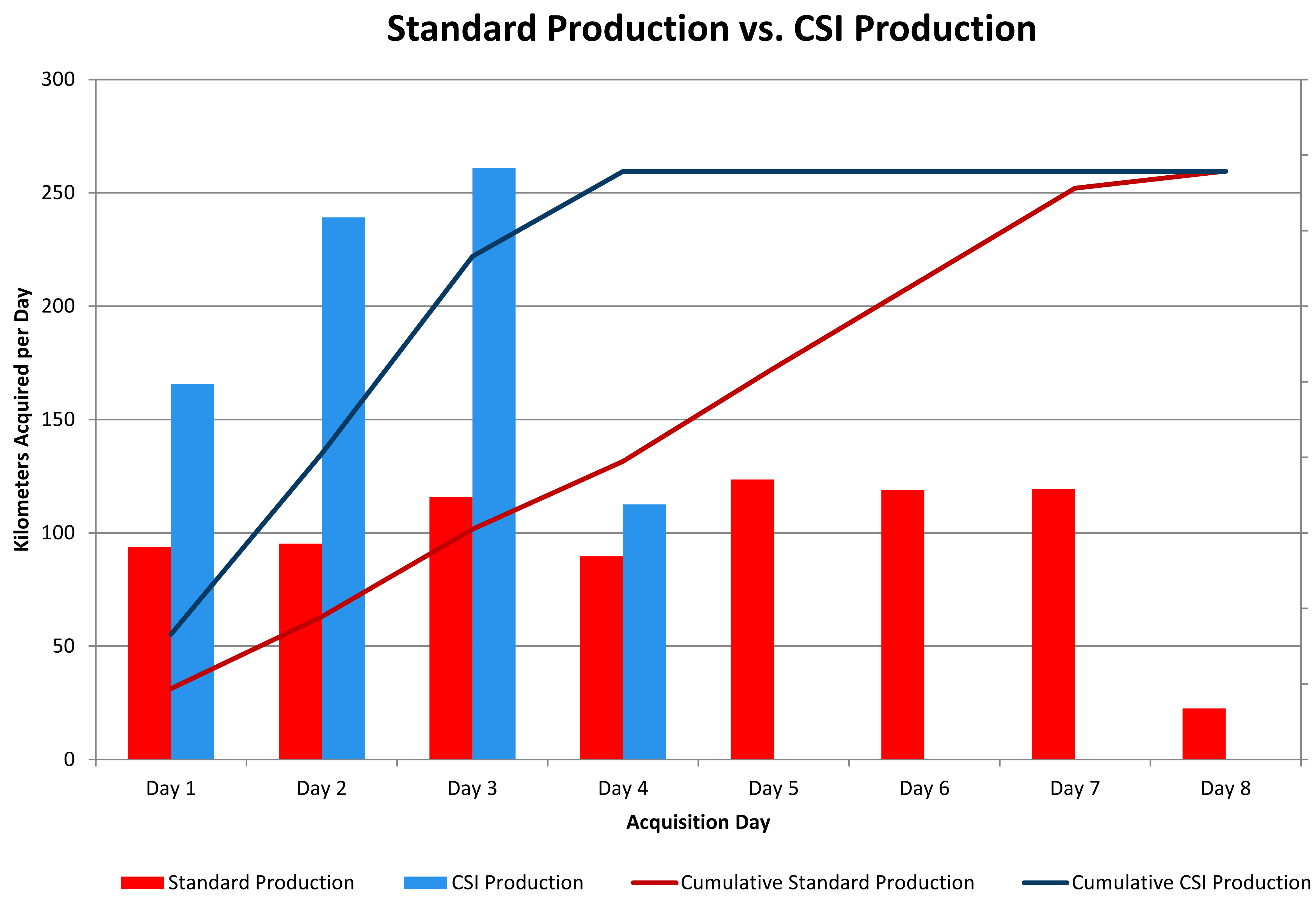
examples from industry (ConocoPhilips)

Randomized subsampling:

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

Output:

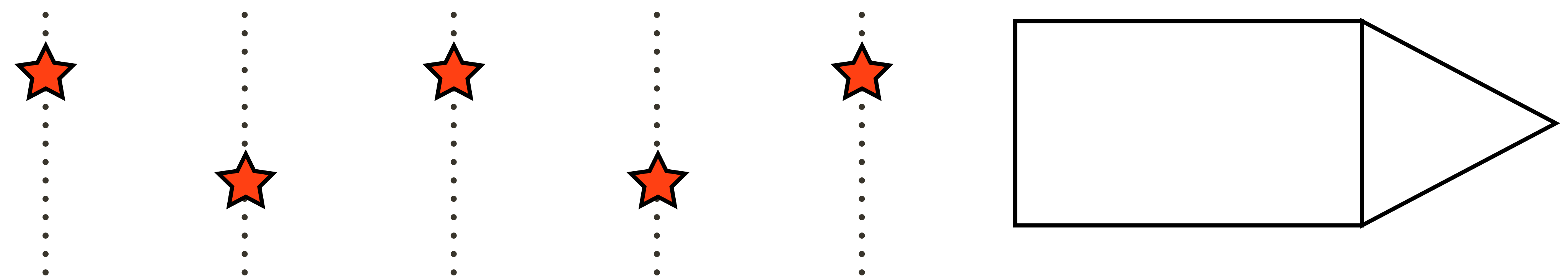
- improved quality artifact-free long-offset wide-azimuth data
- 5 X – 10 X cost & environmental impact reduction



Breaking structure

shot-time randomness

✗ **periodically** sampled spatial grid

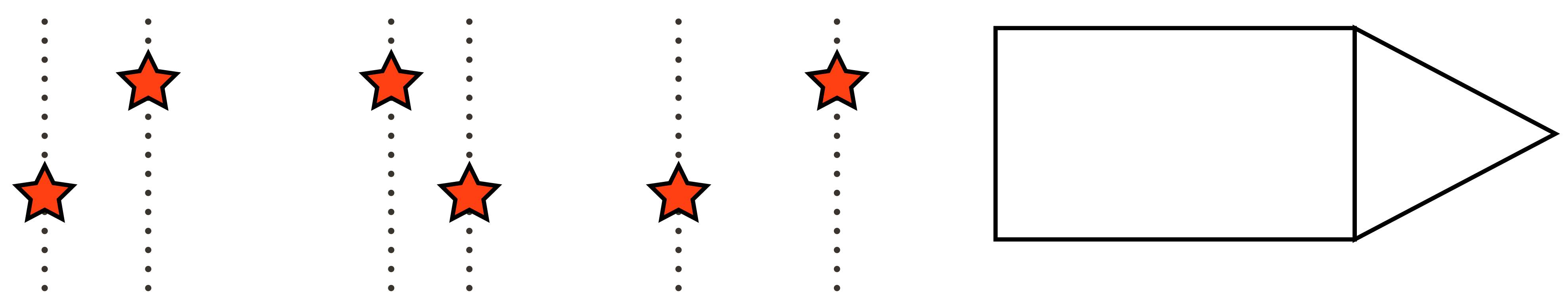


NONE

✓ **randomly** jittered sampled spatial grid

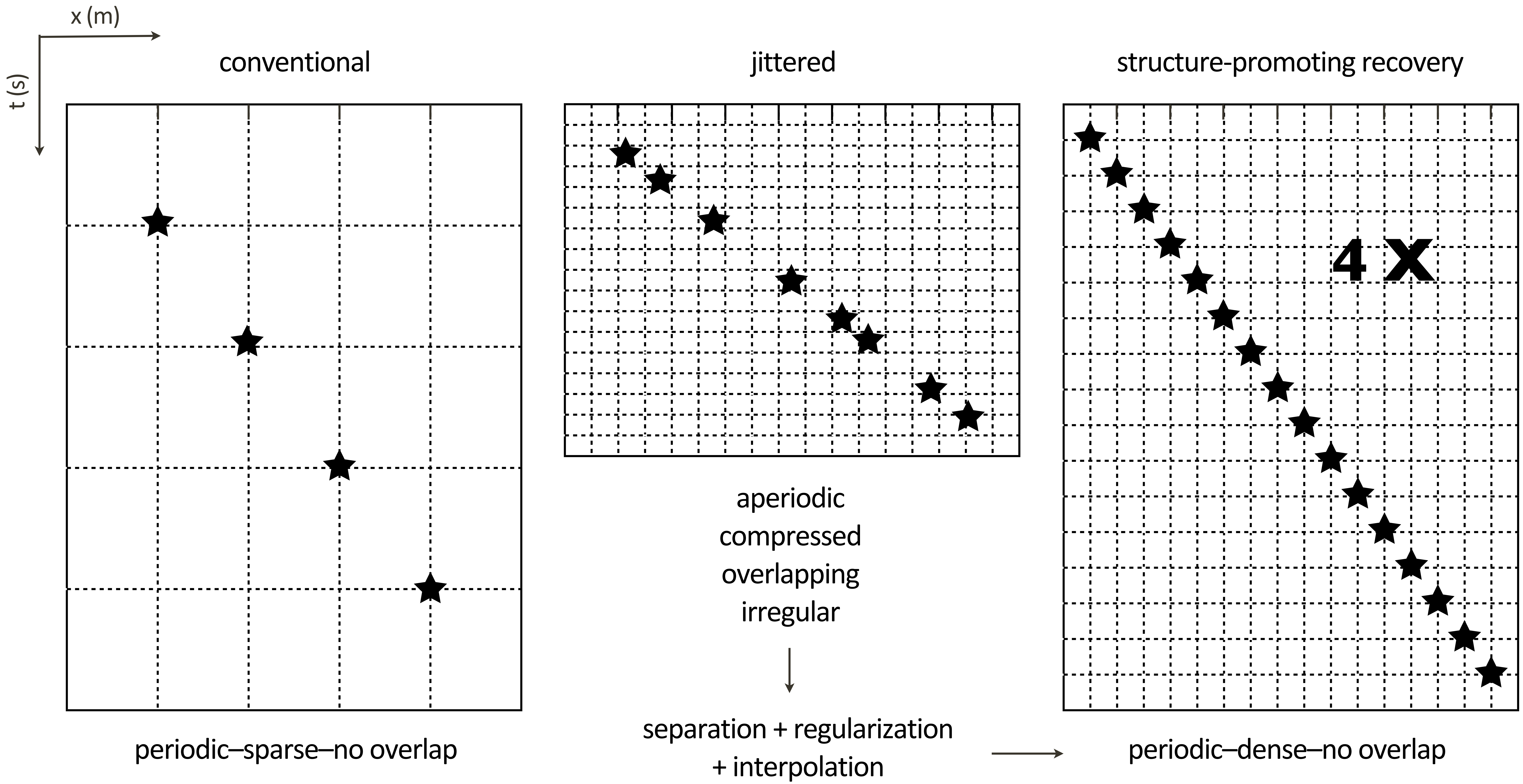
(time-jittered acquisition;
static acquisition geometry: OBC/OBN)

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



HIGH

Time-jittered OBC/OBN acquisition



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

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.
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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**

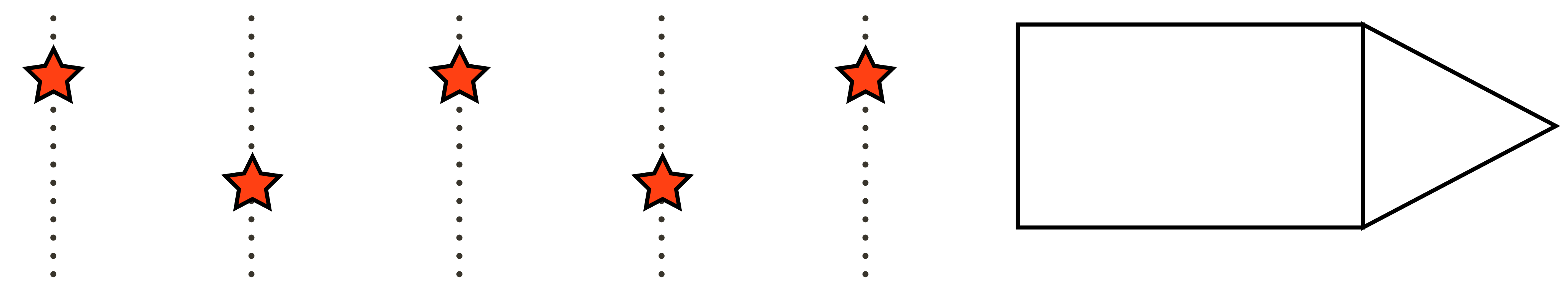
* source/receiver sampling grid

still want more economical .....

Breaking structure

shot-time randomness

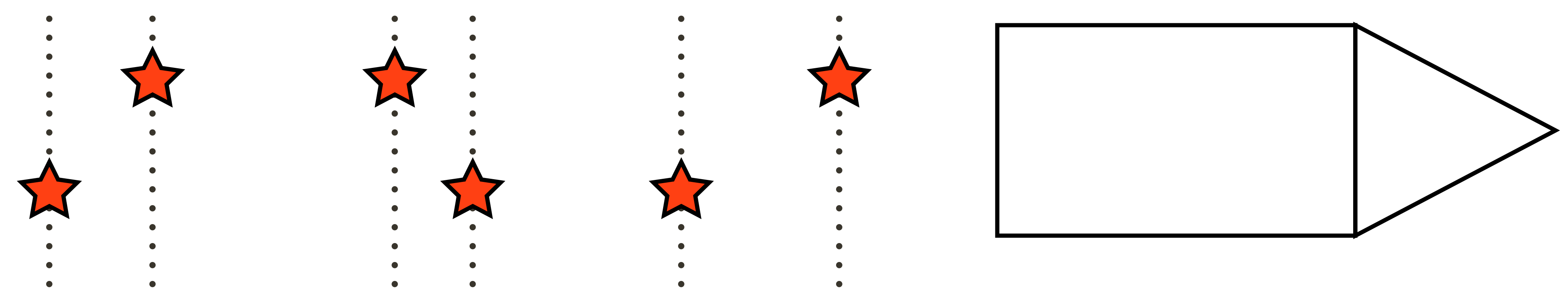
✗ **periodically** sampled spatial grid



NONE

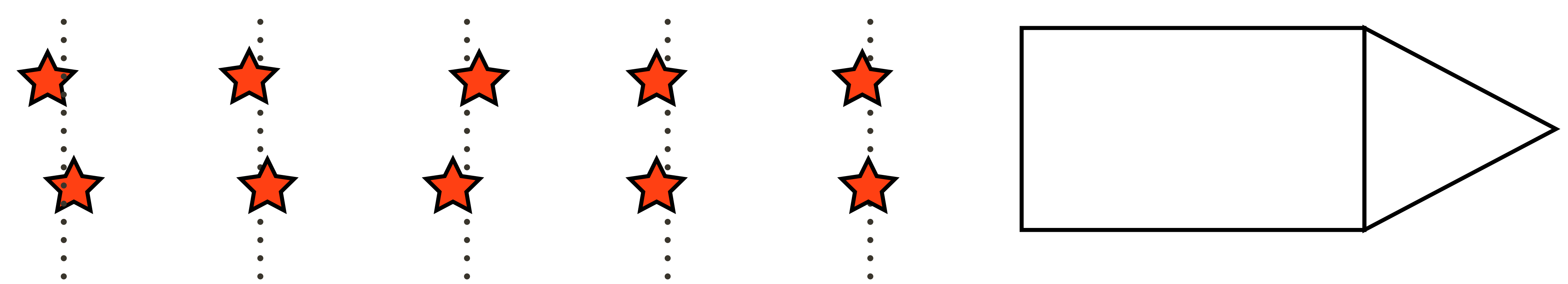
✓ **randomly** jittered sampled spatial grid
(time-jittered acquisition;
static acquisition geometry: OBC/OBN)

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



HIGH

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



LOW

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

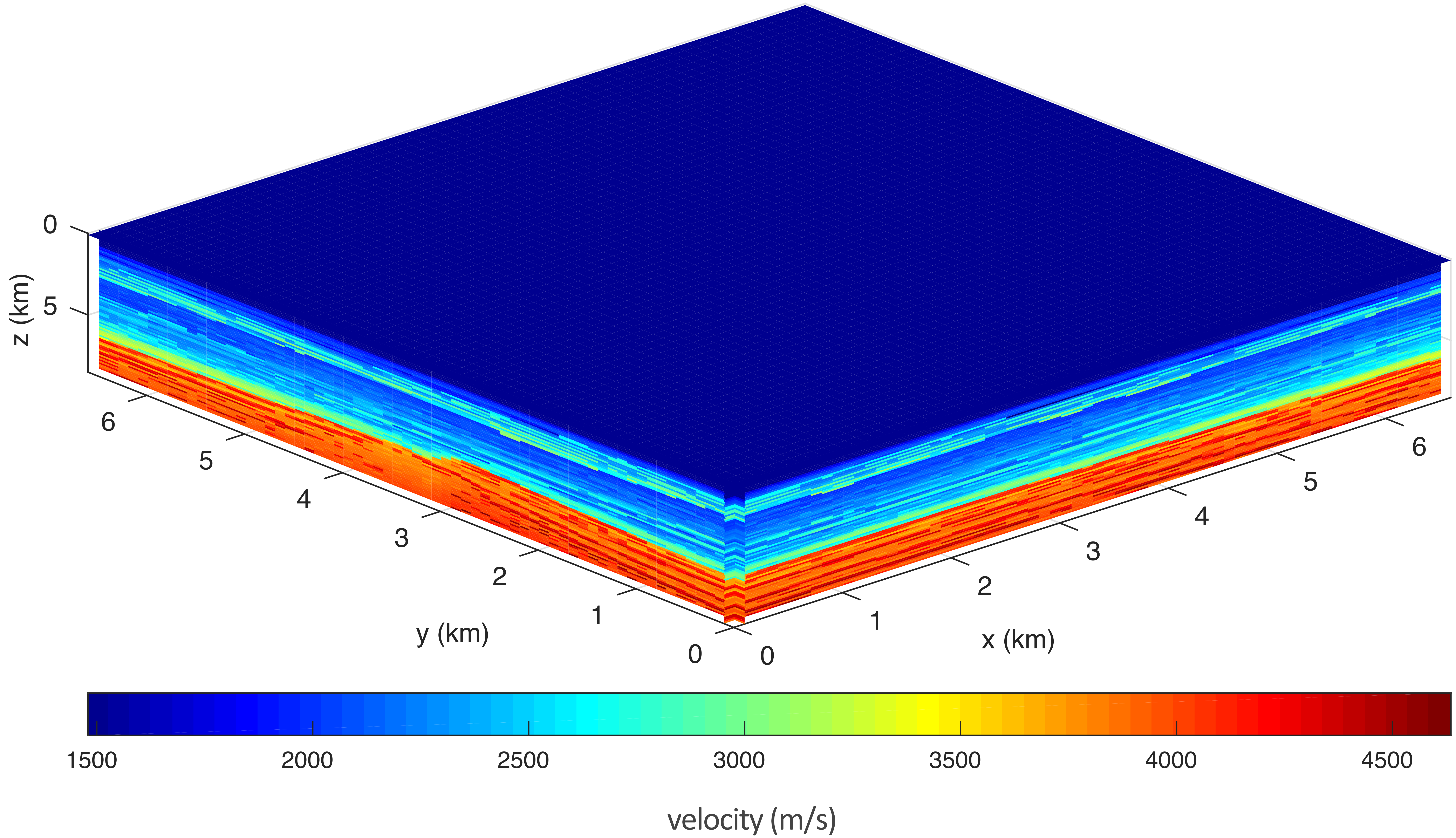
Maximum offset: 4 + 4 = 8 km

Number of streamers per source vessel: 12

Ricker wavelet with central frequency of 20 Hz

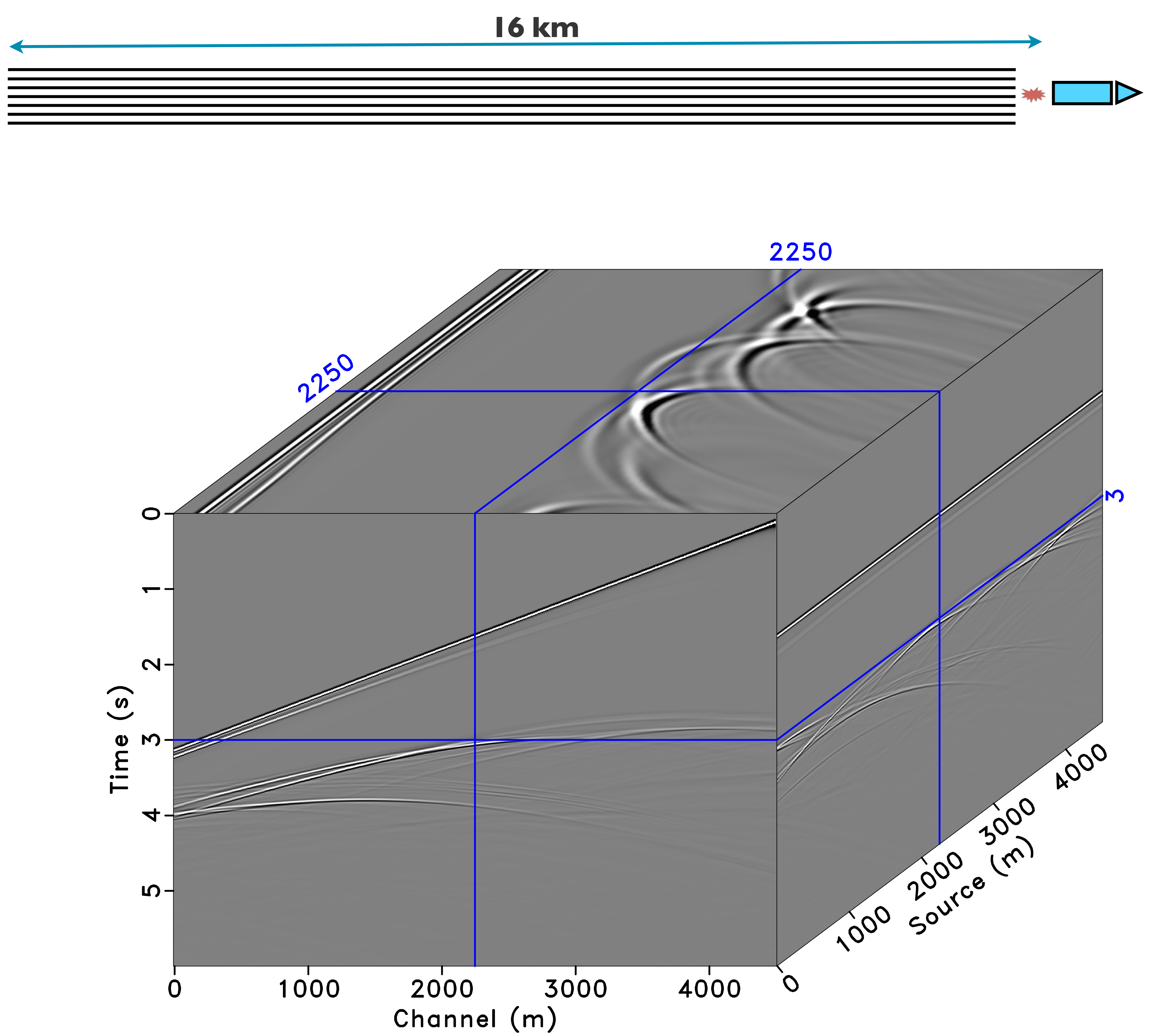
Effective sampling: 25-100 m in X & Y => 3 – 4 X cost reduction

3D baseline BG model

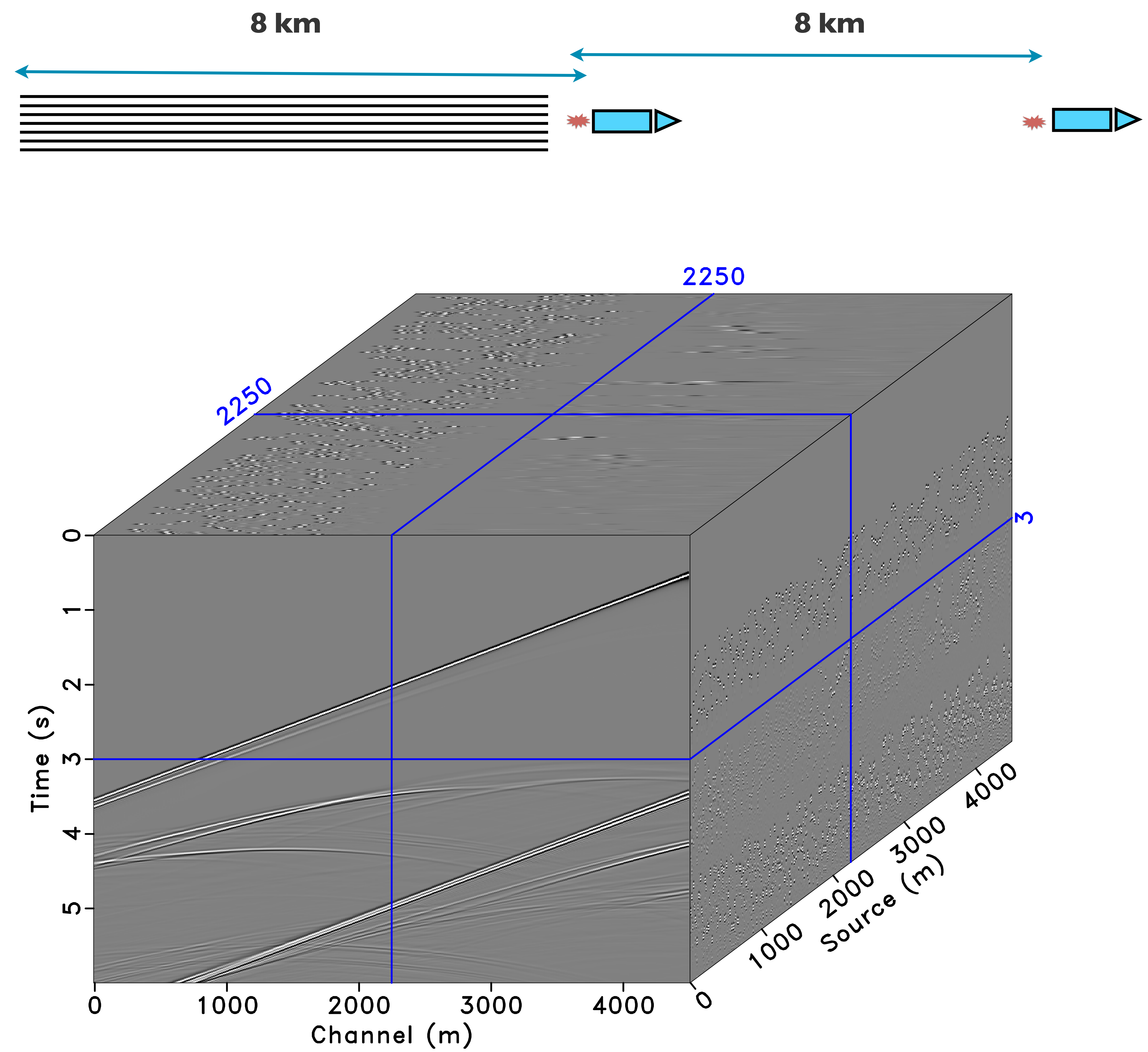


Low-cost marine acquisition

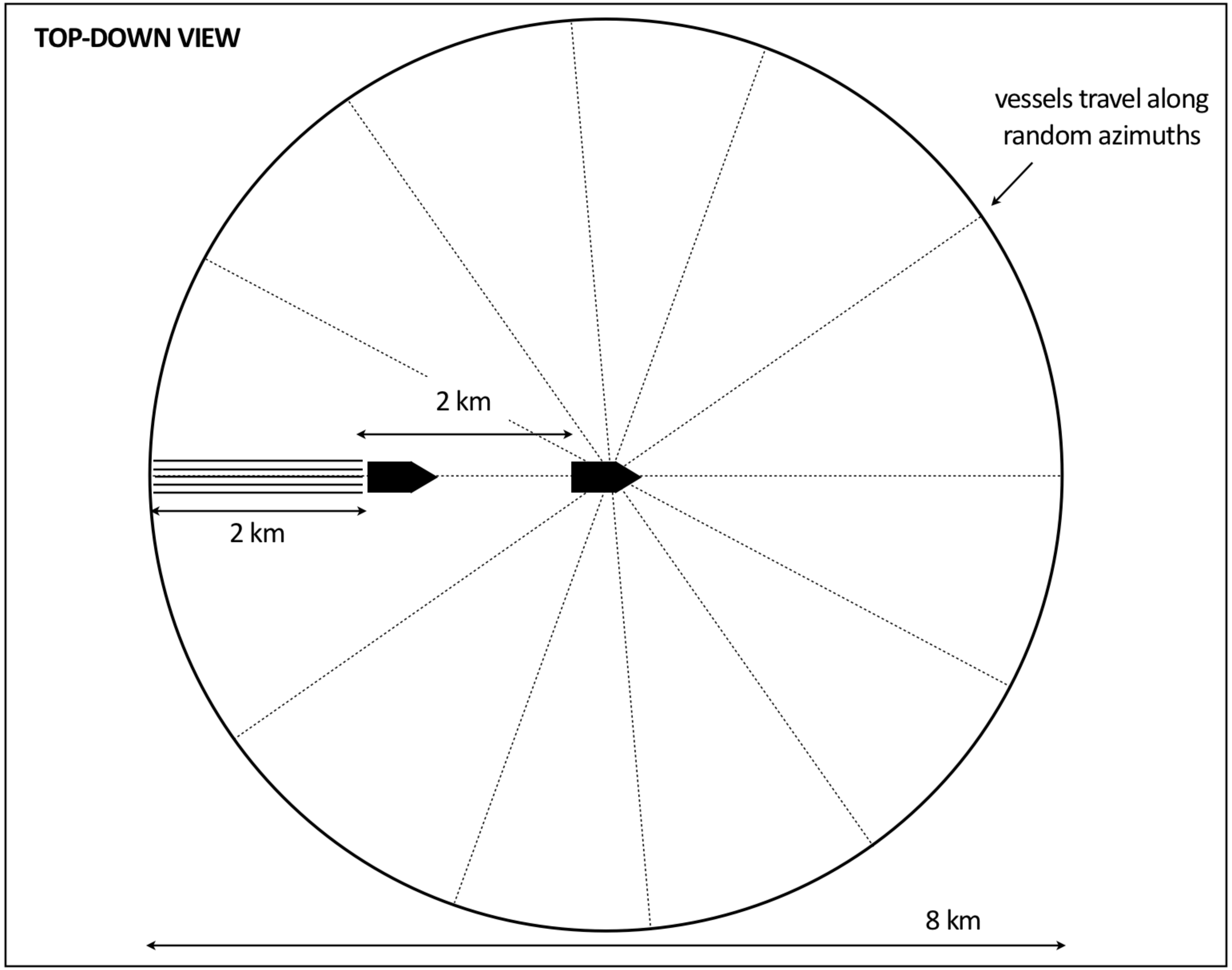
Conventional acquisition



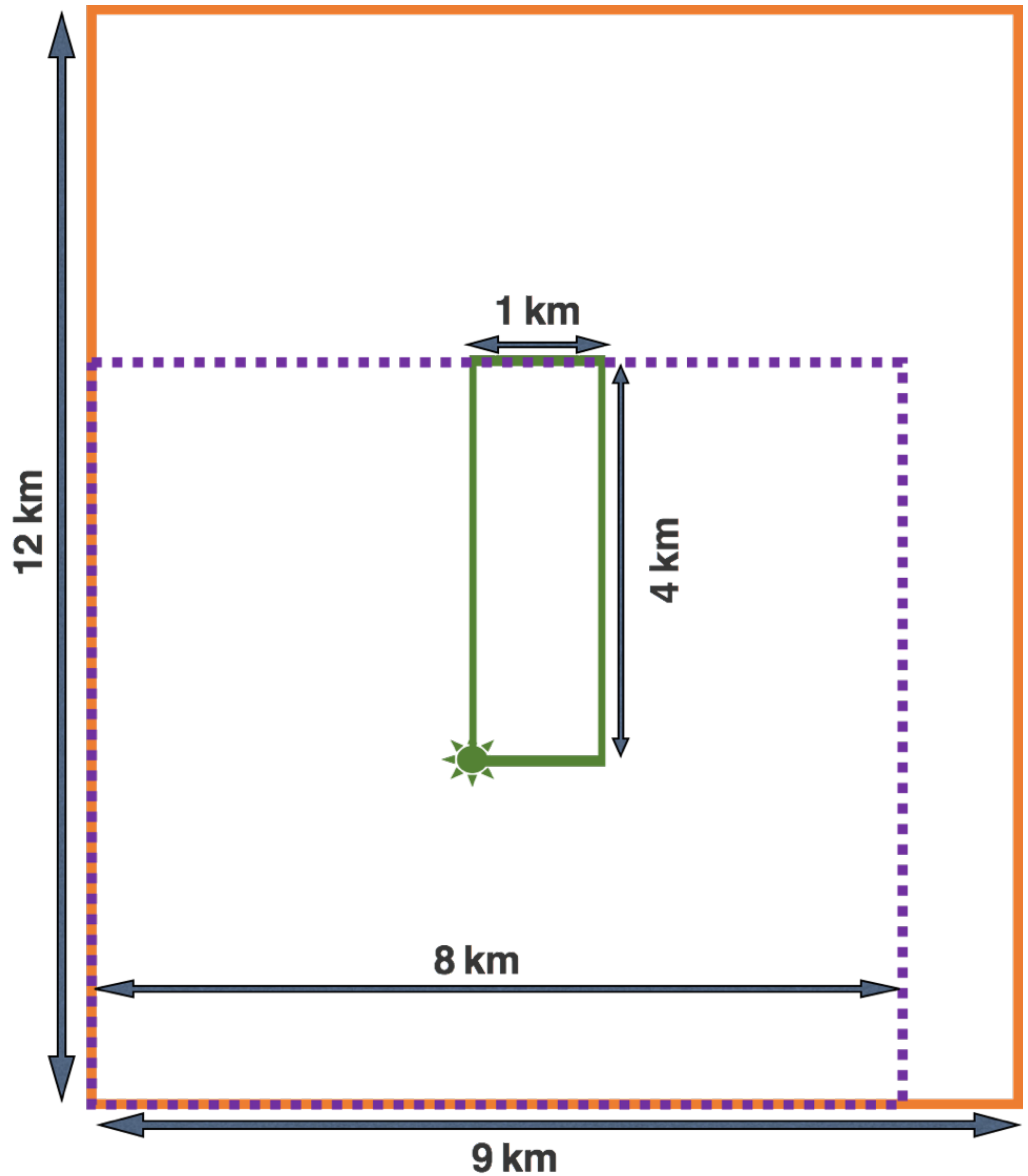
SLO acquisition



“Reduced“ multi-azimuth SLO acquisition

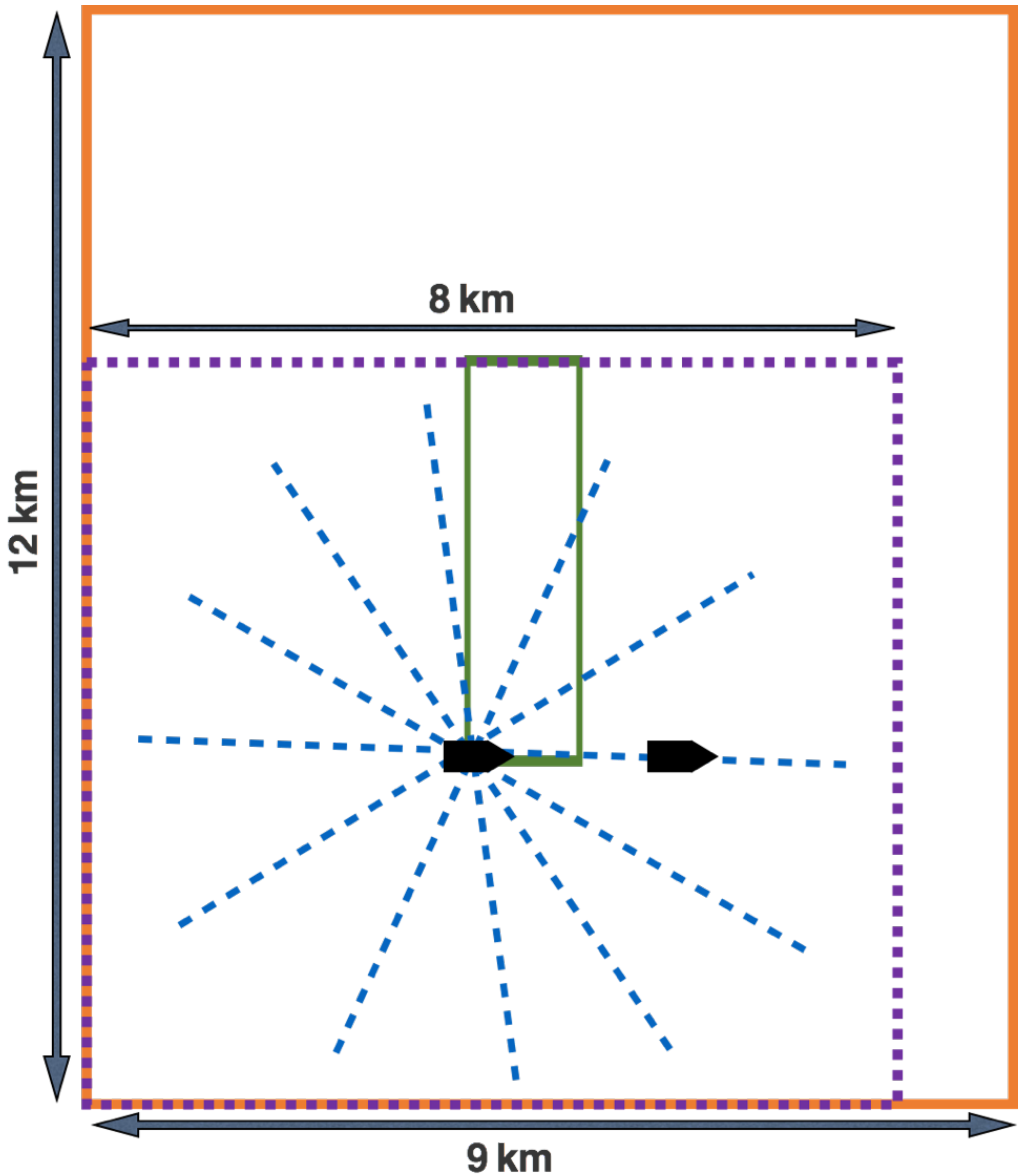


“Reduced“ multi-azimuth SLO acquisition



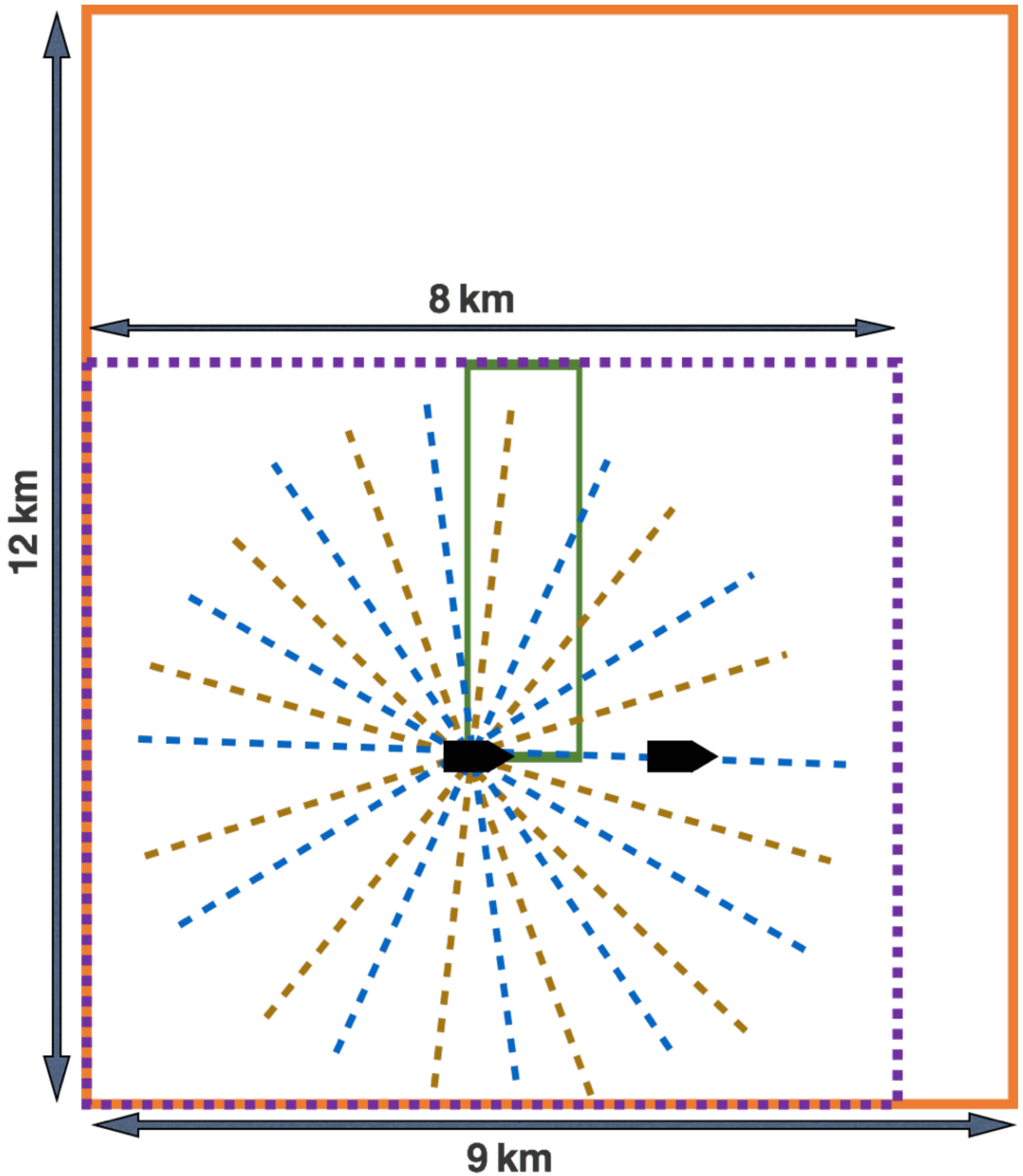
4 km streamer length (“reduced” acquisition)

“Reduced“ multi-azimuth SLO acquisition



Sail lines for baseline survey

“Reduced“ multi-azimuth SLO acquisition

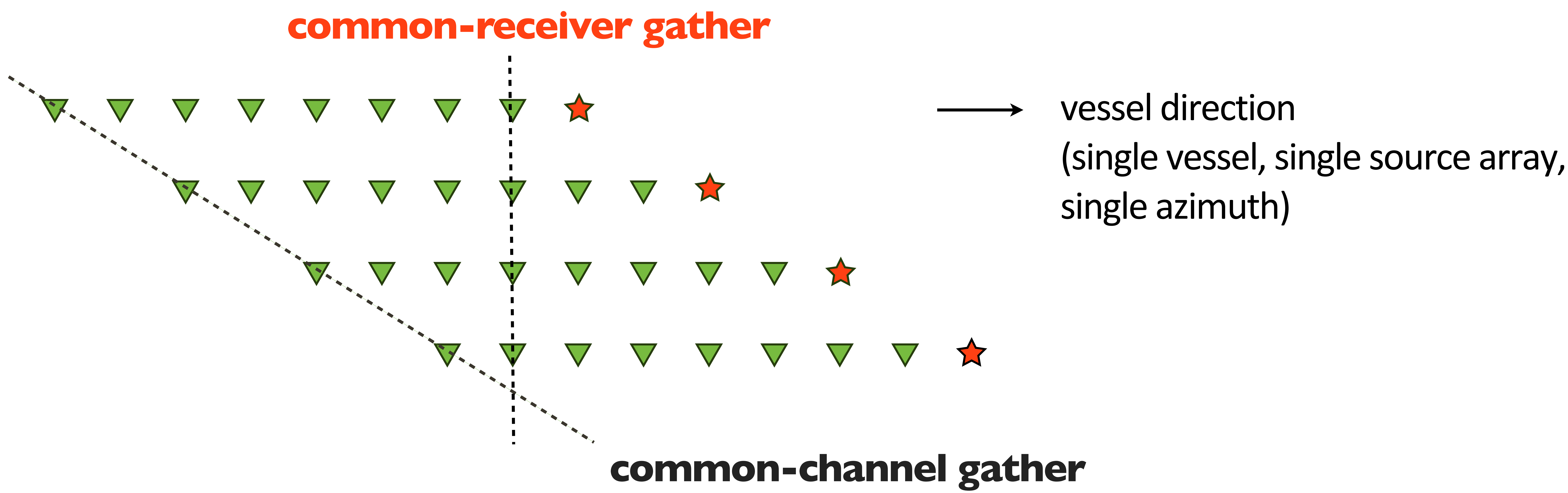


Sail lines for baseline survey

Sail lines for monitor survey

Data organization

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



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

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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.

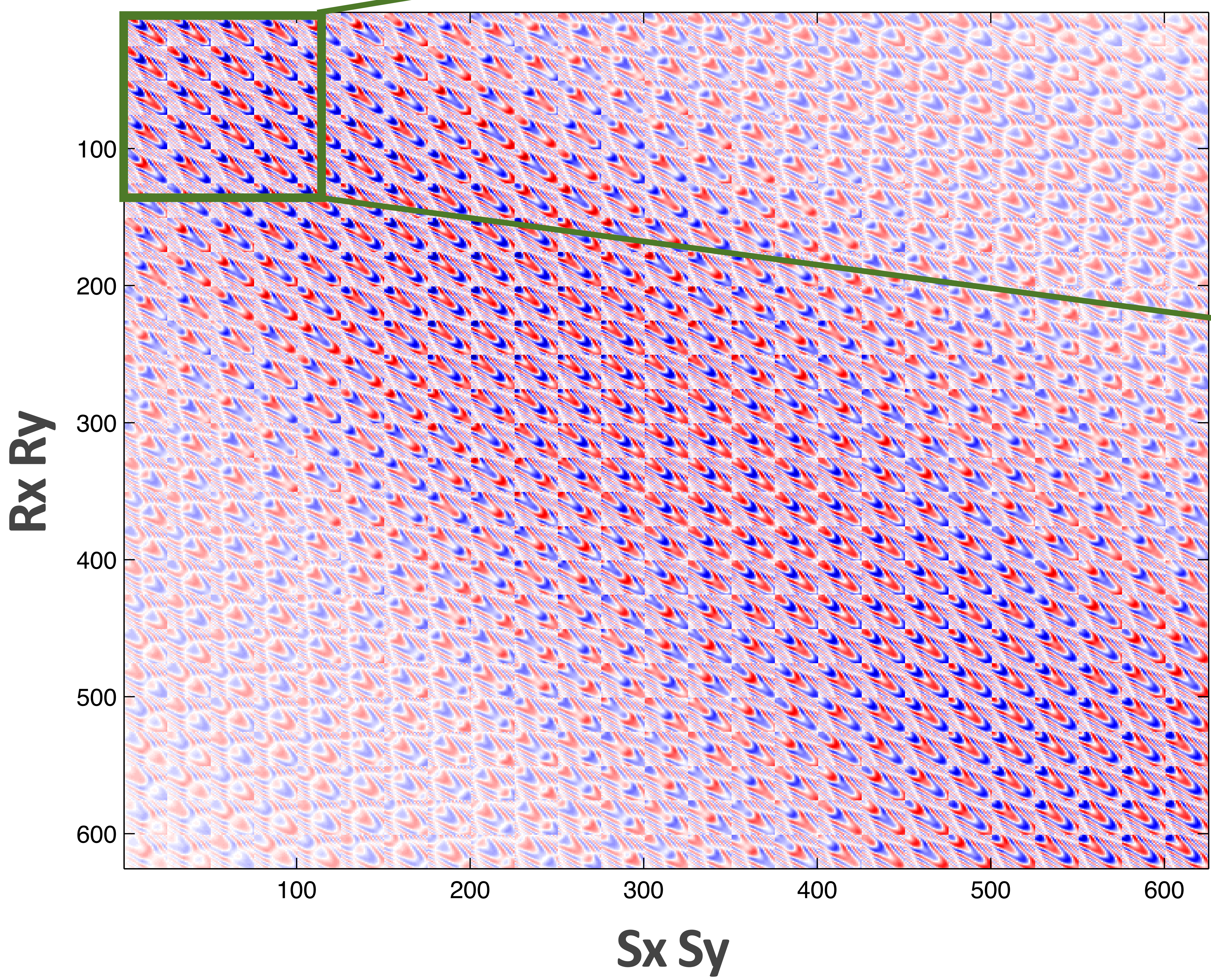
Low-rank structure

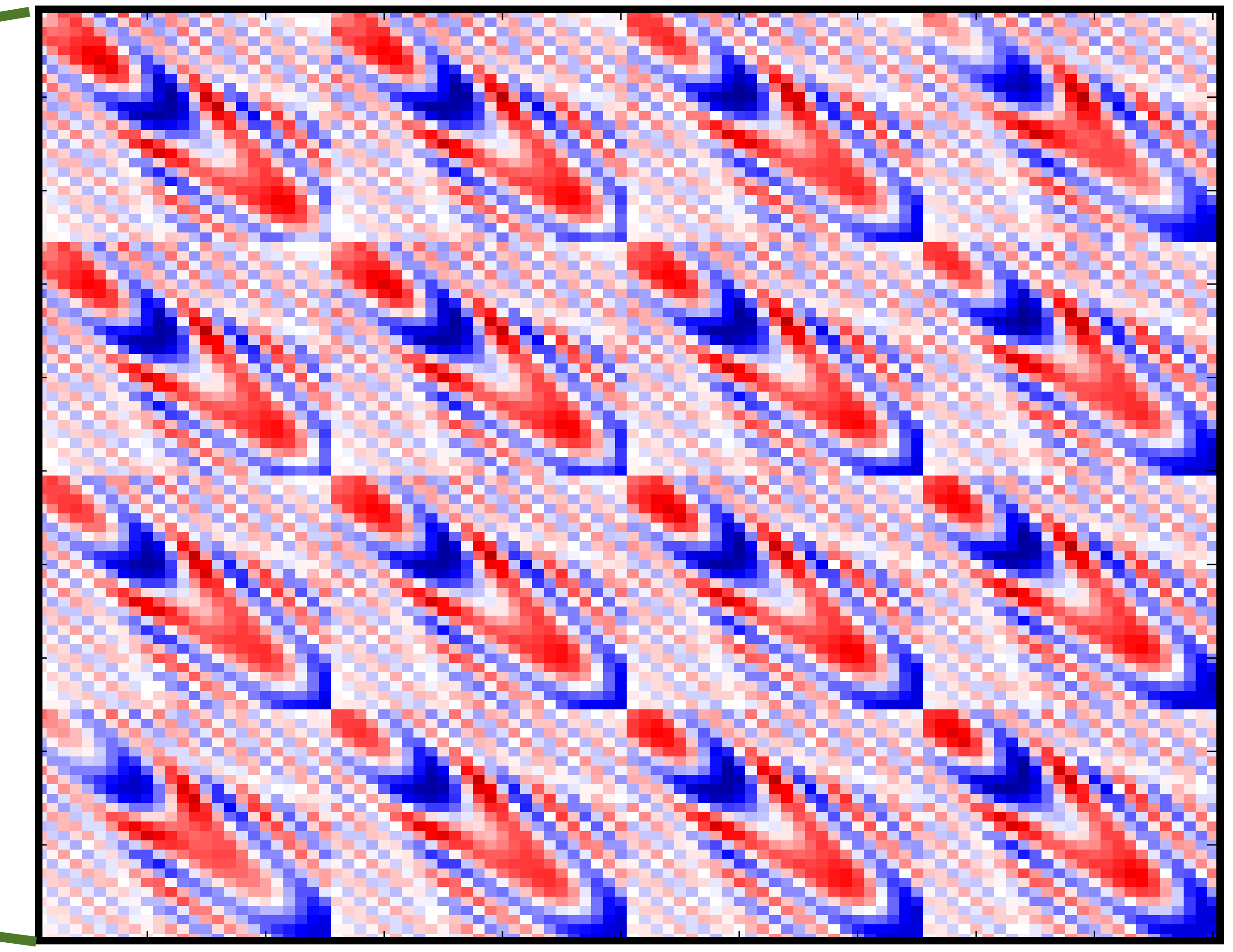
In which domain?

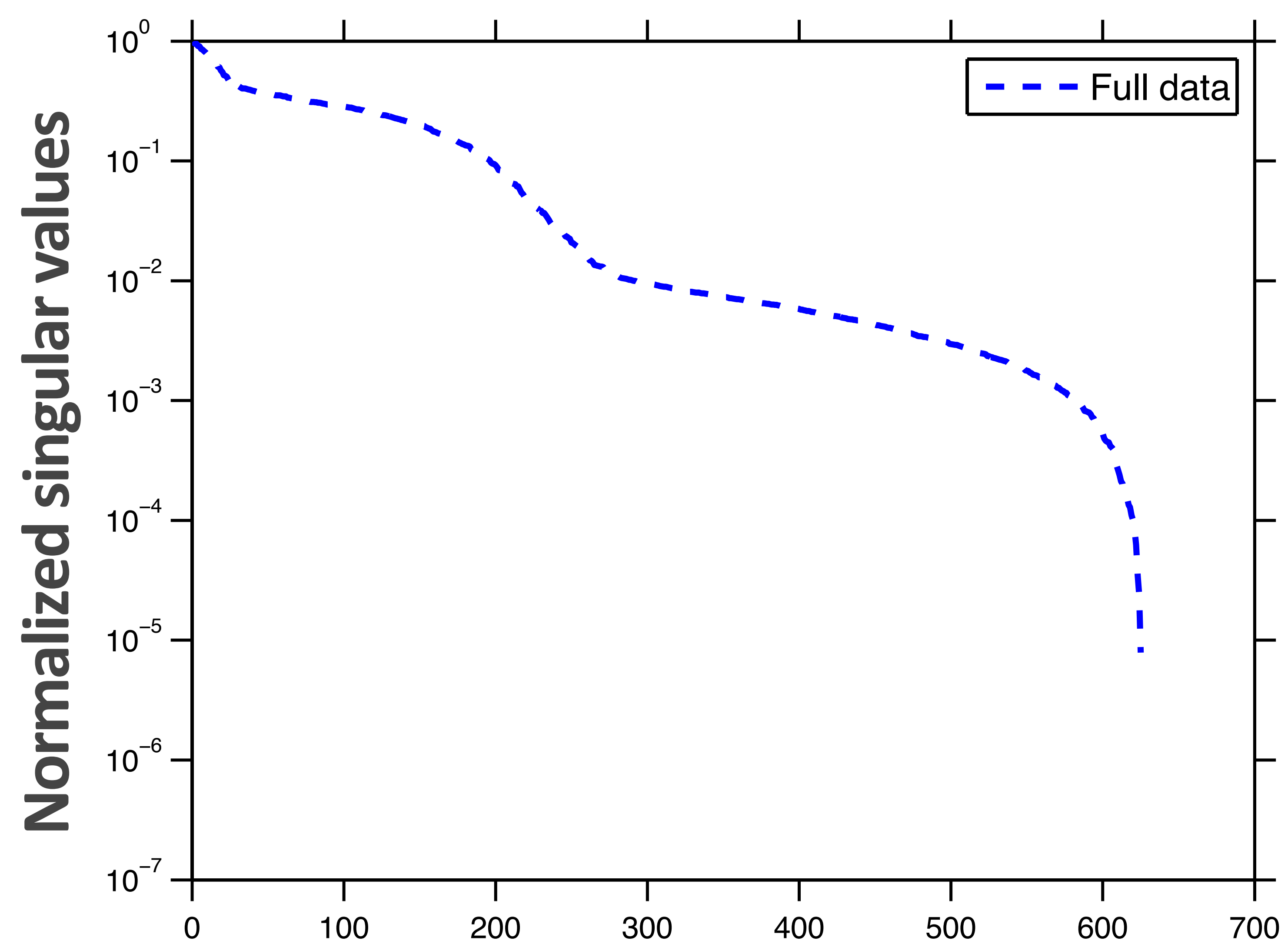
explore different matricizations

Low-rank structure

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



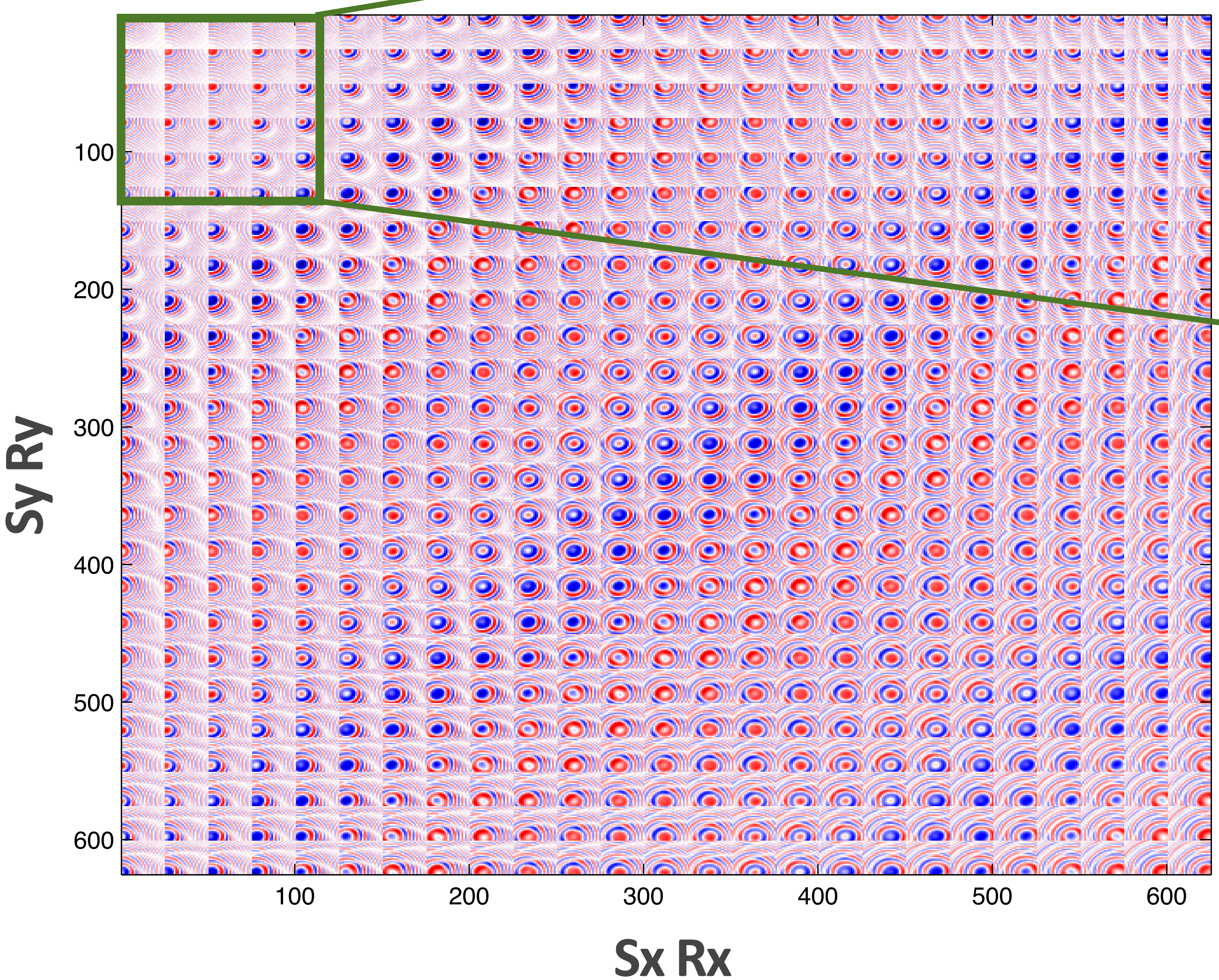


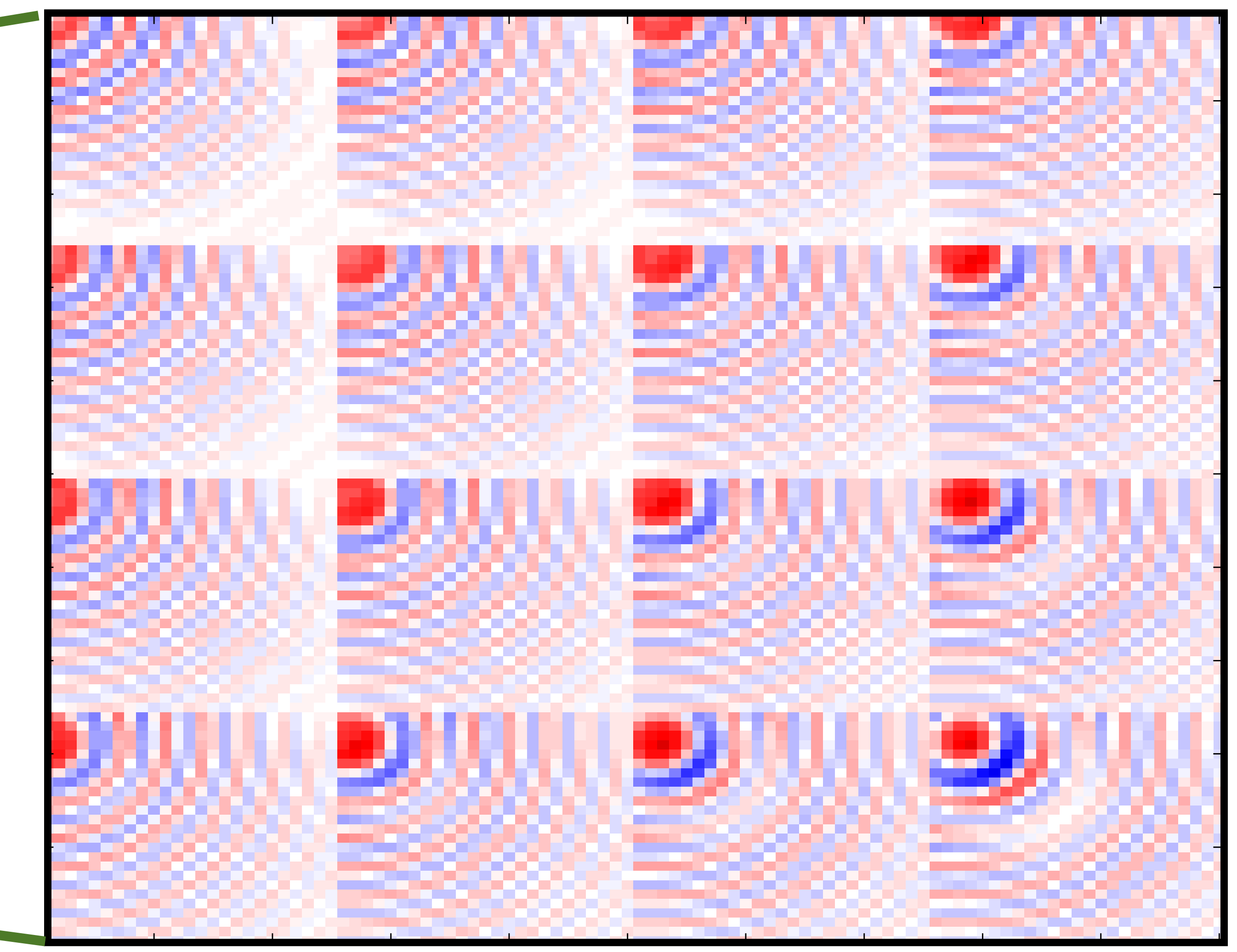


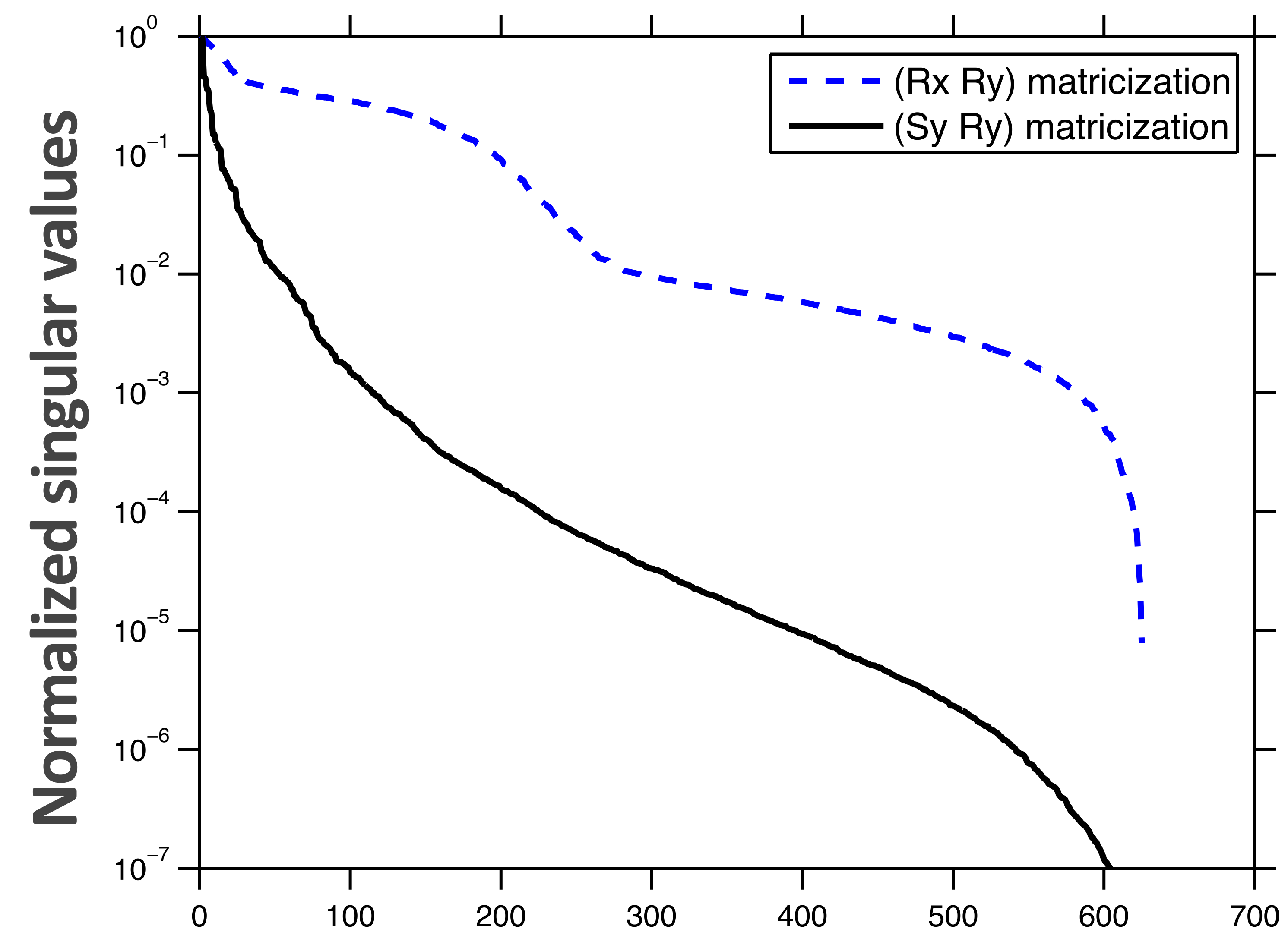
✗

Low-rank structure

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







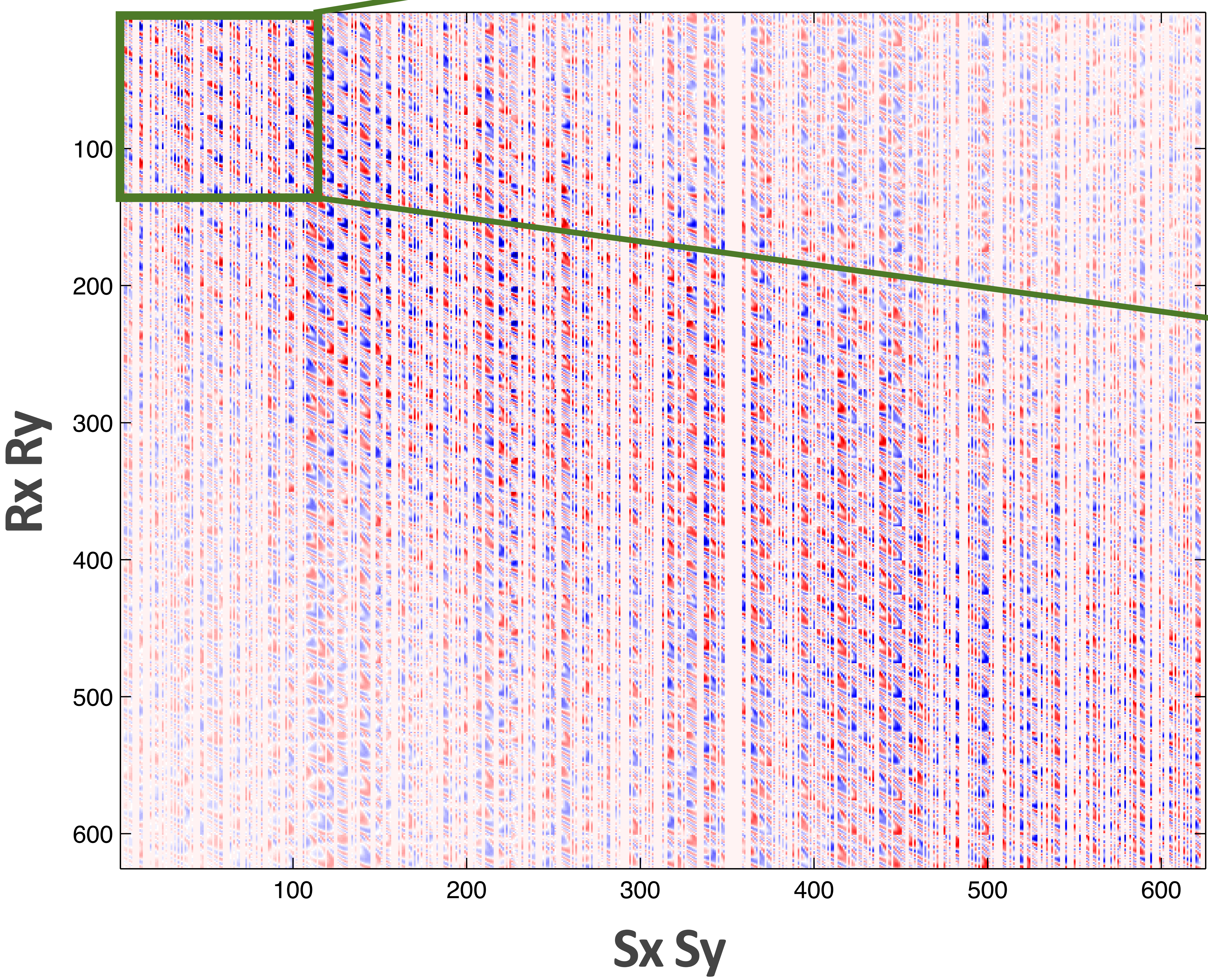
Sampling scheme

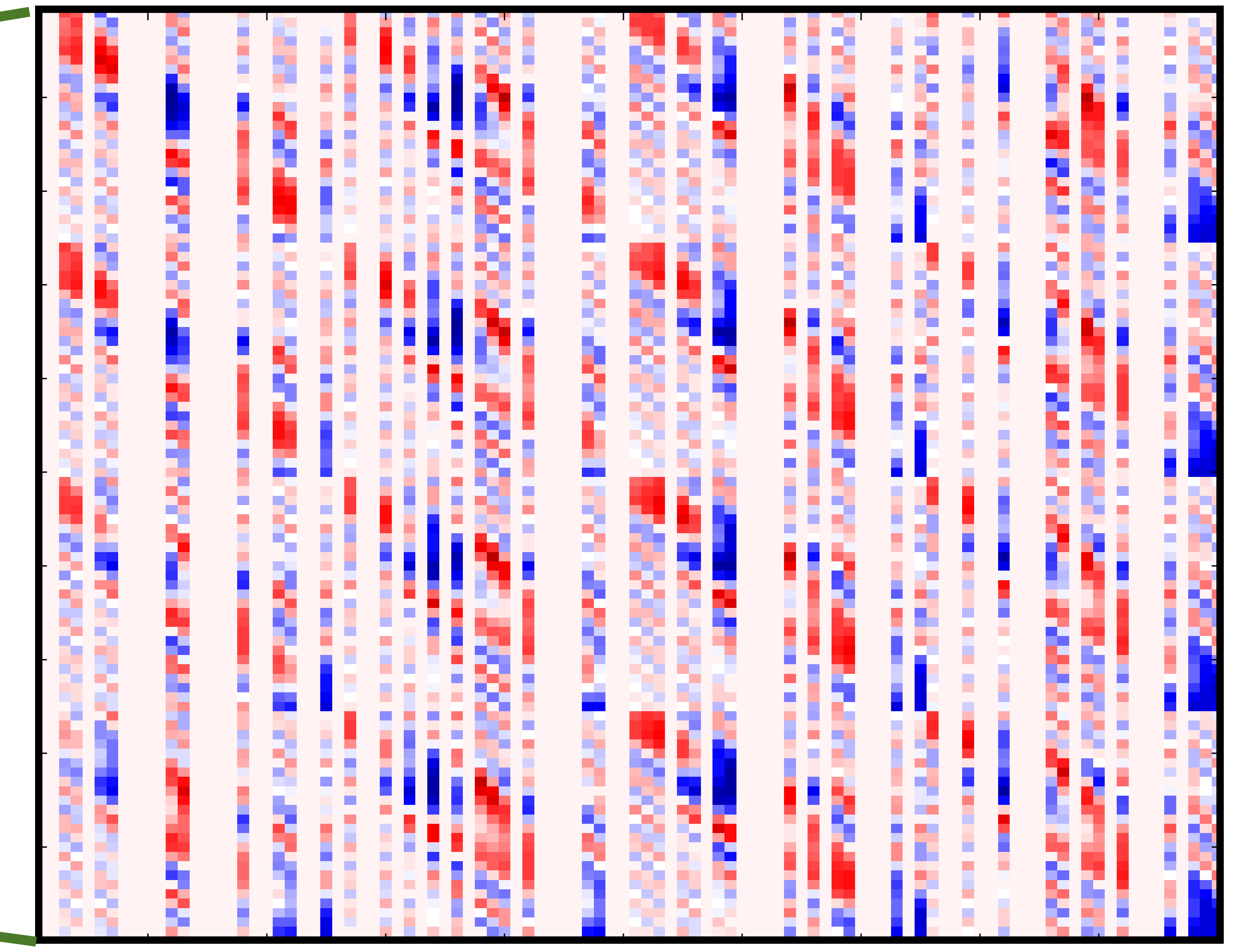
sample to *break* the structure

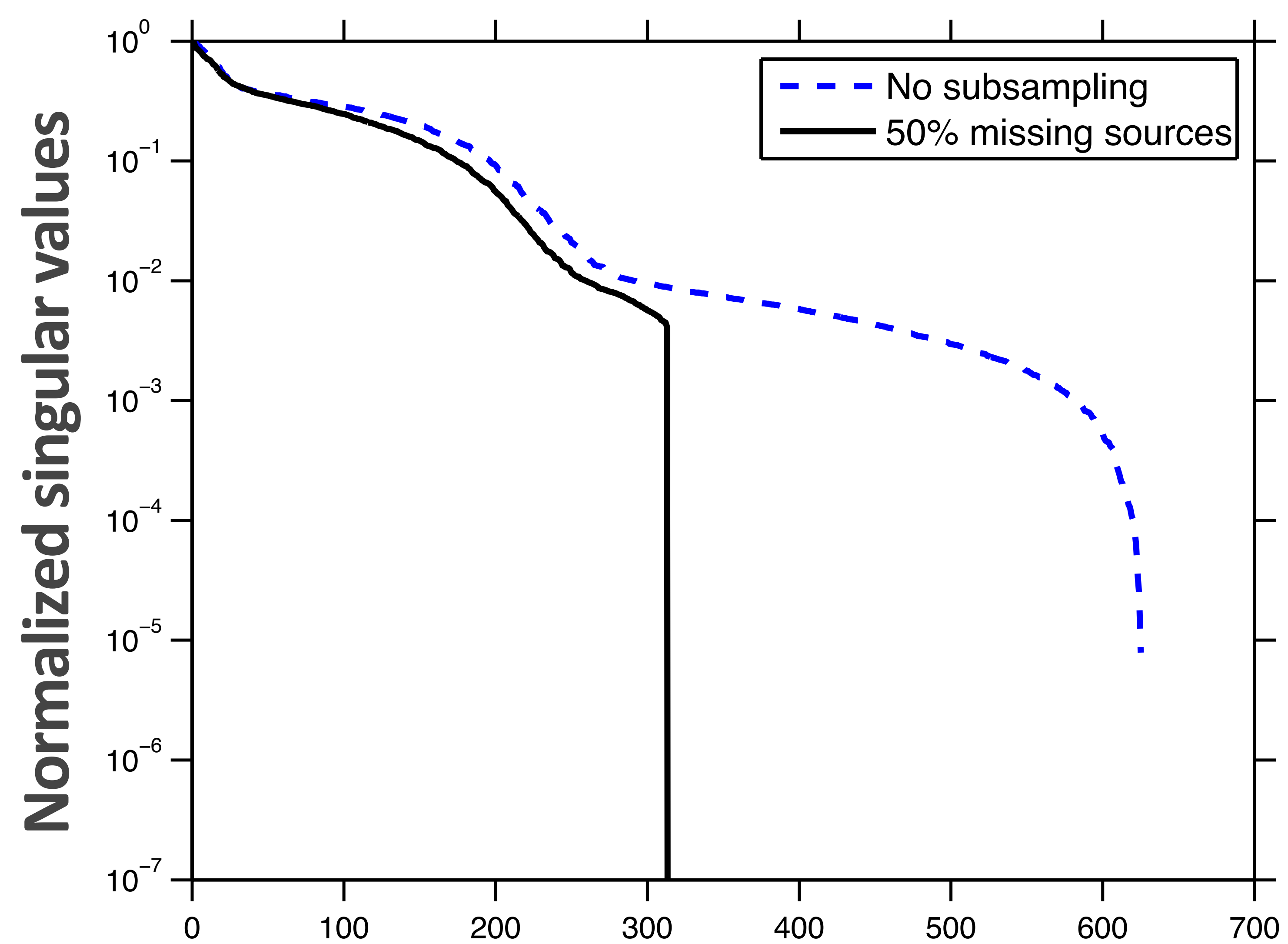
random missing entries break the structure

Low-rank structure

random missing sources, monochromatic slice, Sx-Sy matricization

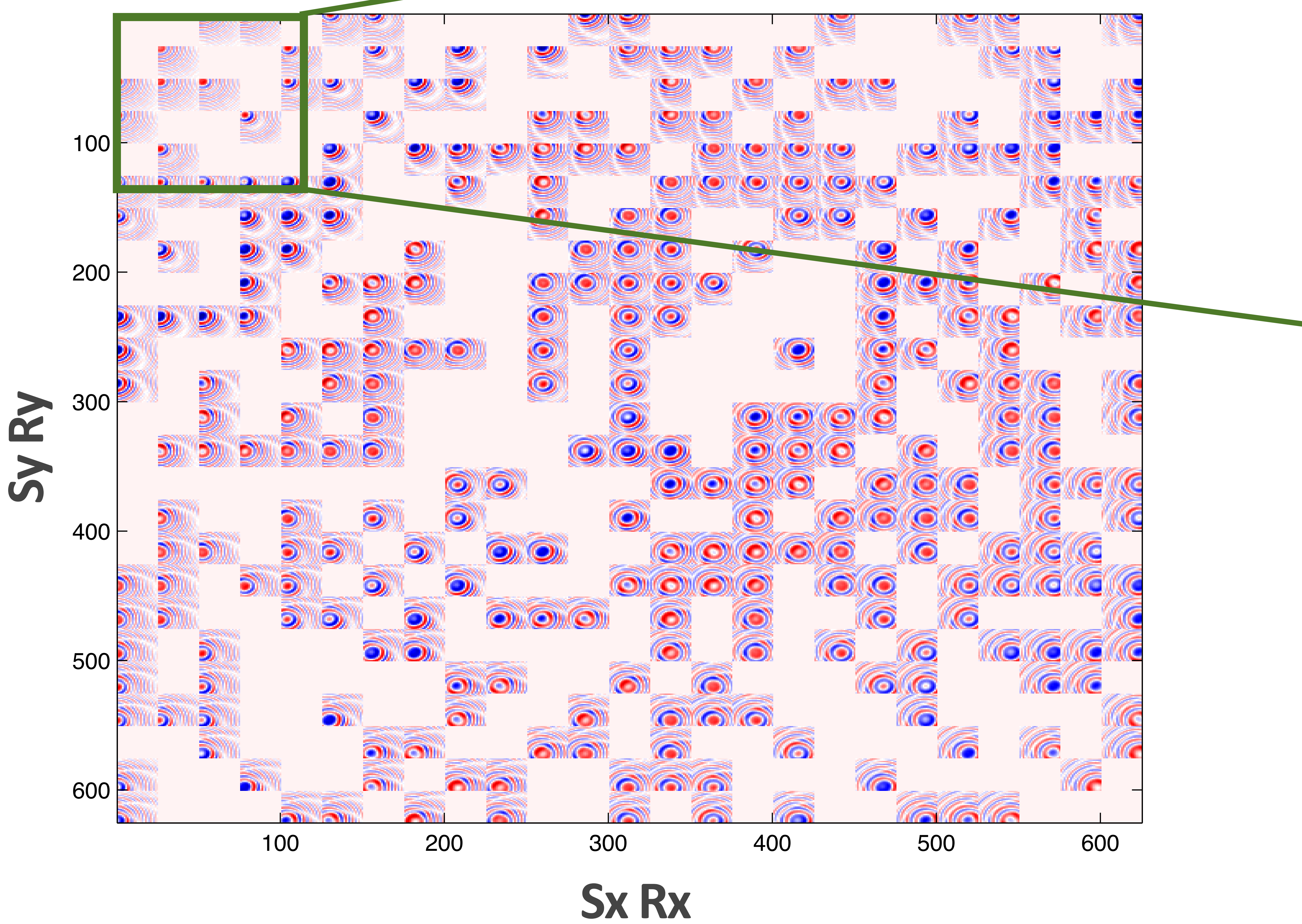


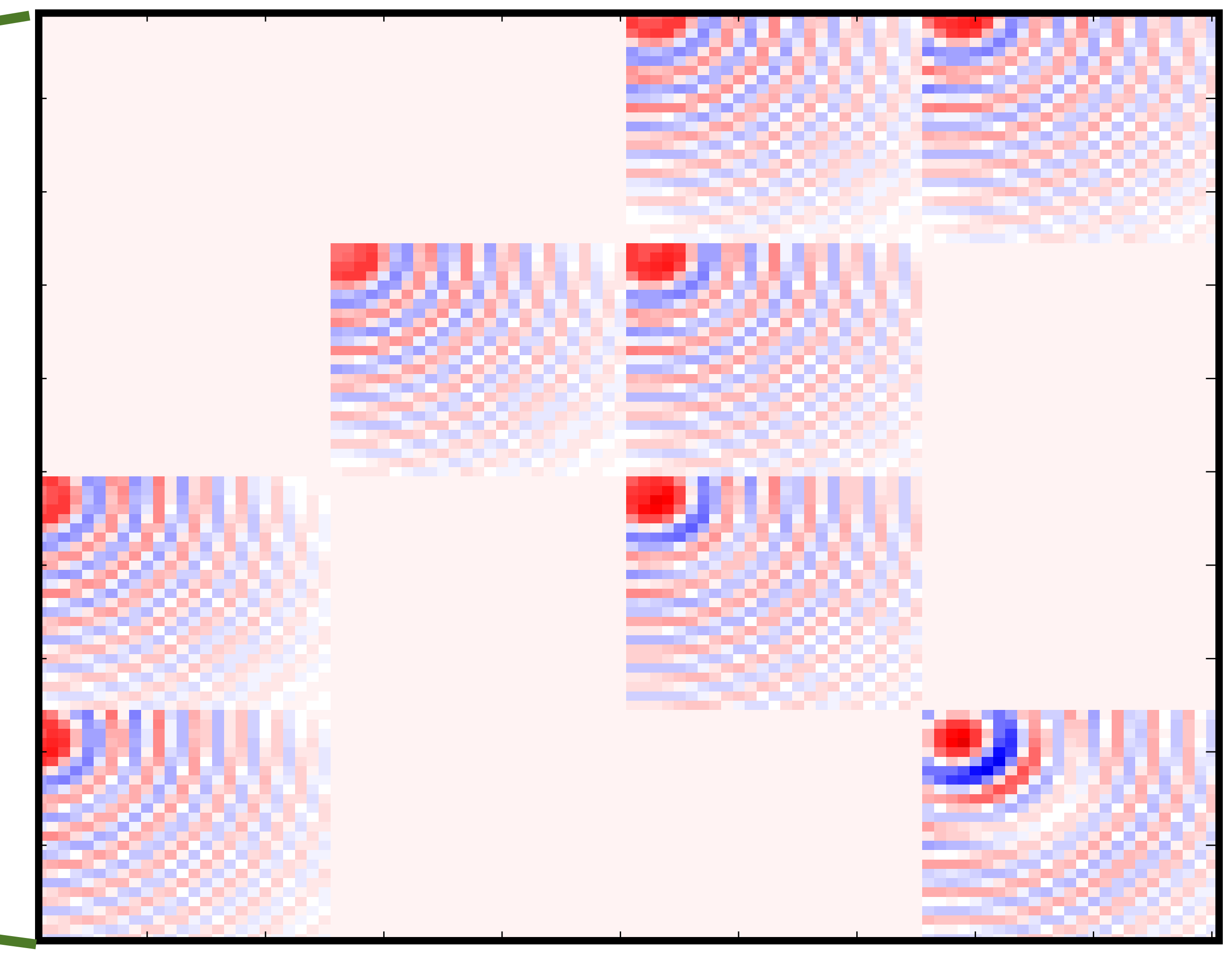


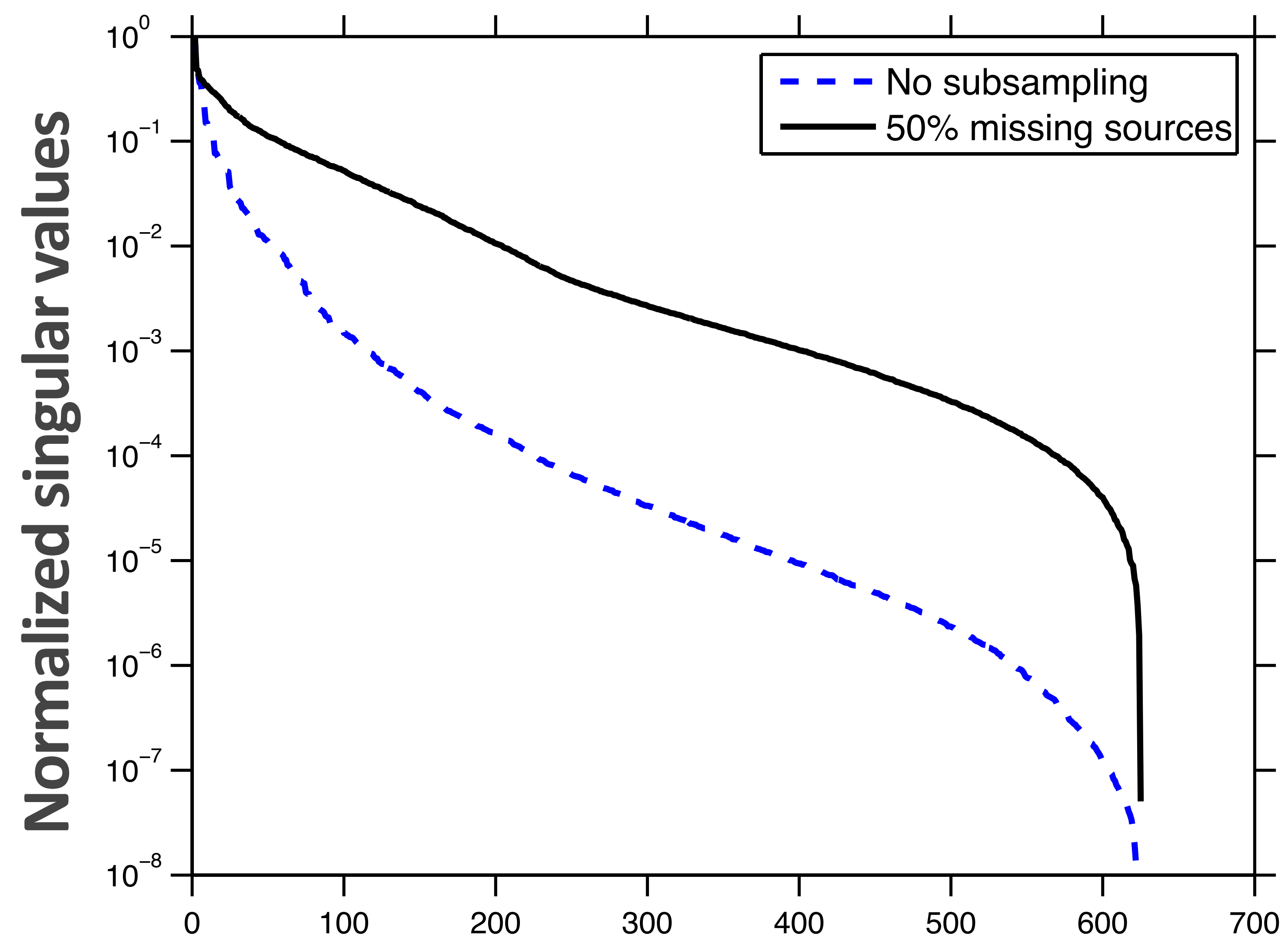


Low-rank structure

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







Data organization

(Sx, Sy) organization

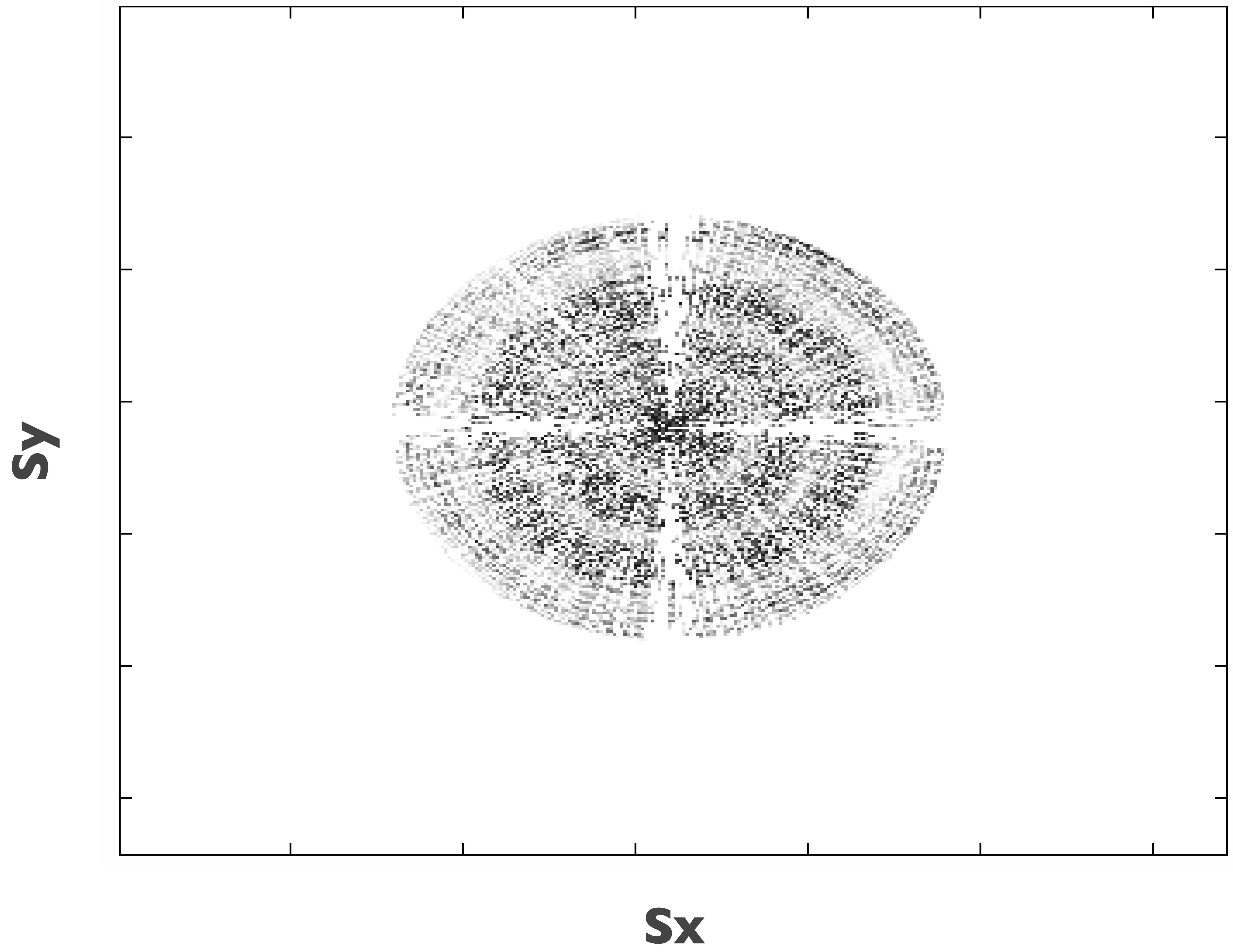
- high rank
- missing sources operator --- removes columns
- missing receivers operator --- removes rows
- **poor recovery** scenario

(Sx, Rx) organization

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

Observed data – 30%

monochromatic slice, common-receiver domain



Near 4 km offset
+
Outer 4 km offset

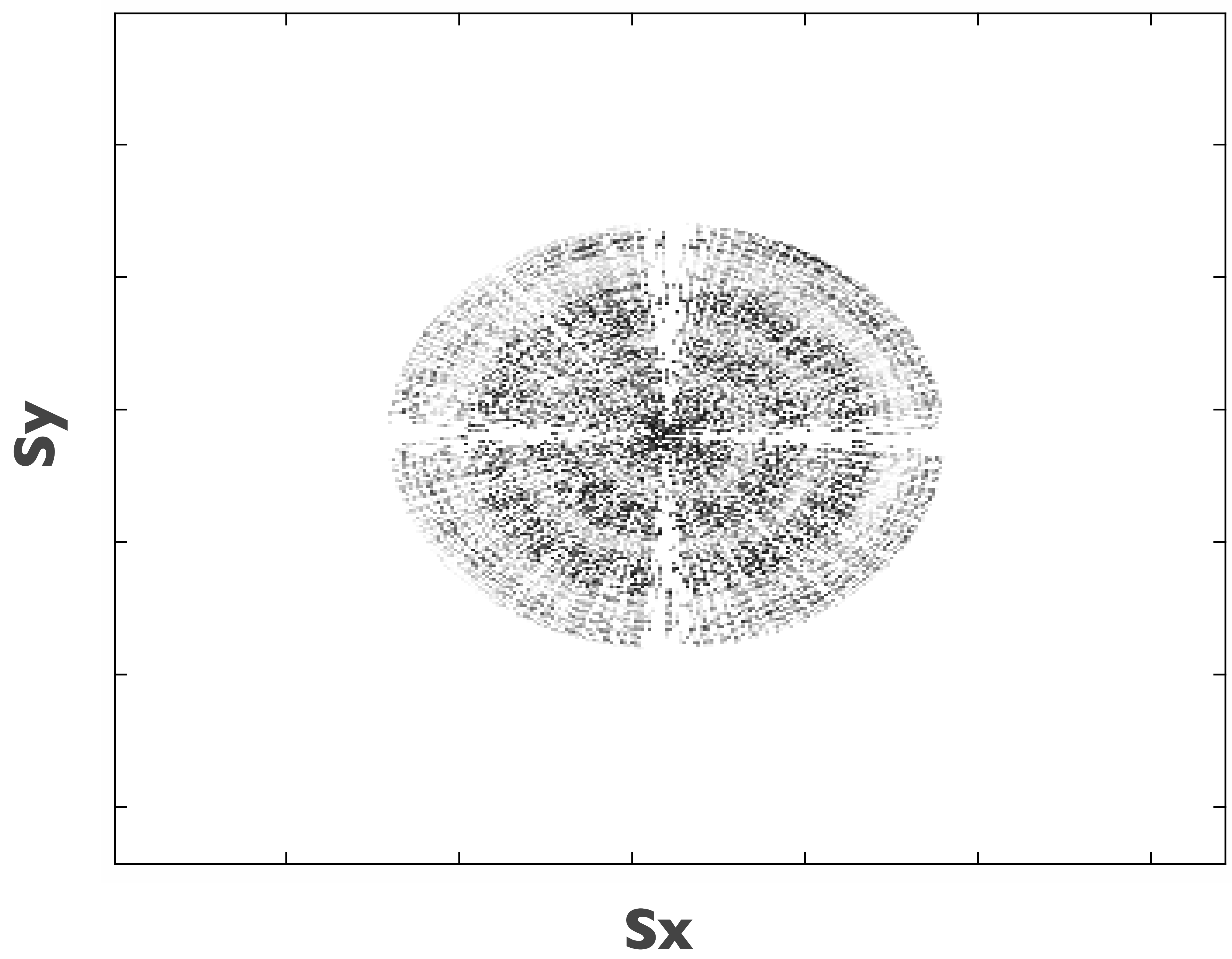
↓

blended & subsampled

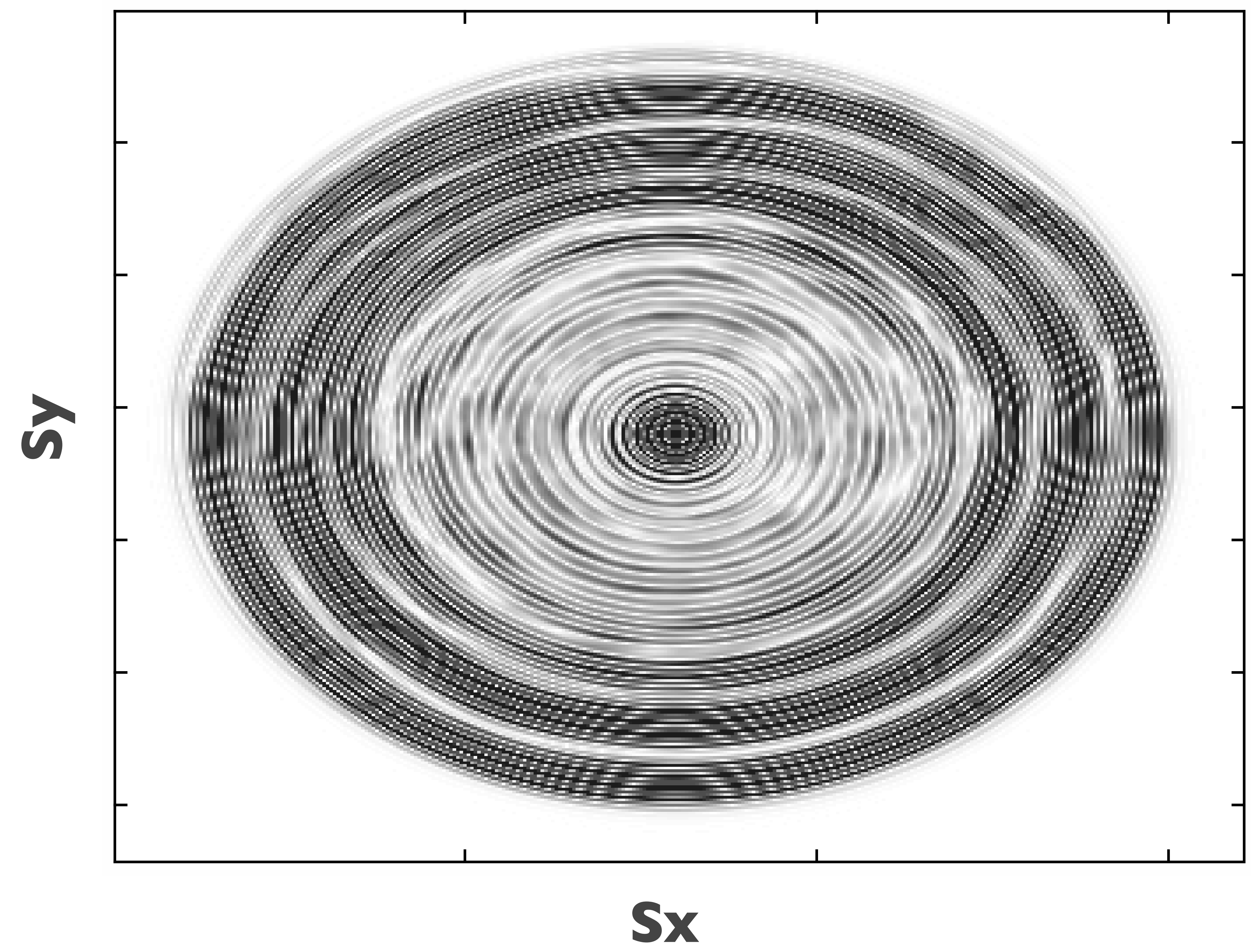
Recover full-azimuth data

one common-receiver gather

Multi-azimuth SLO data (observed)



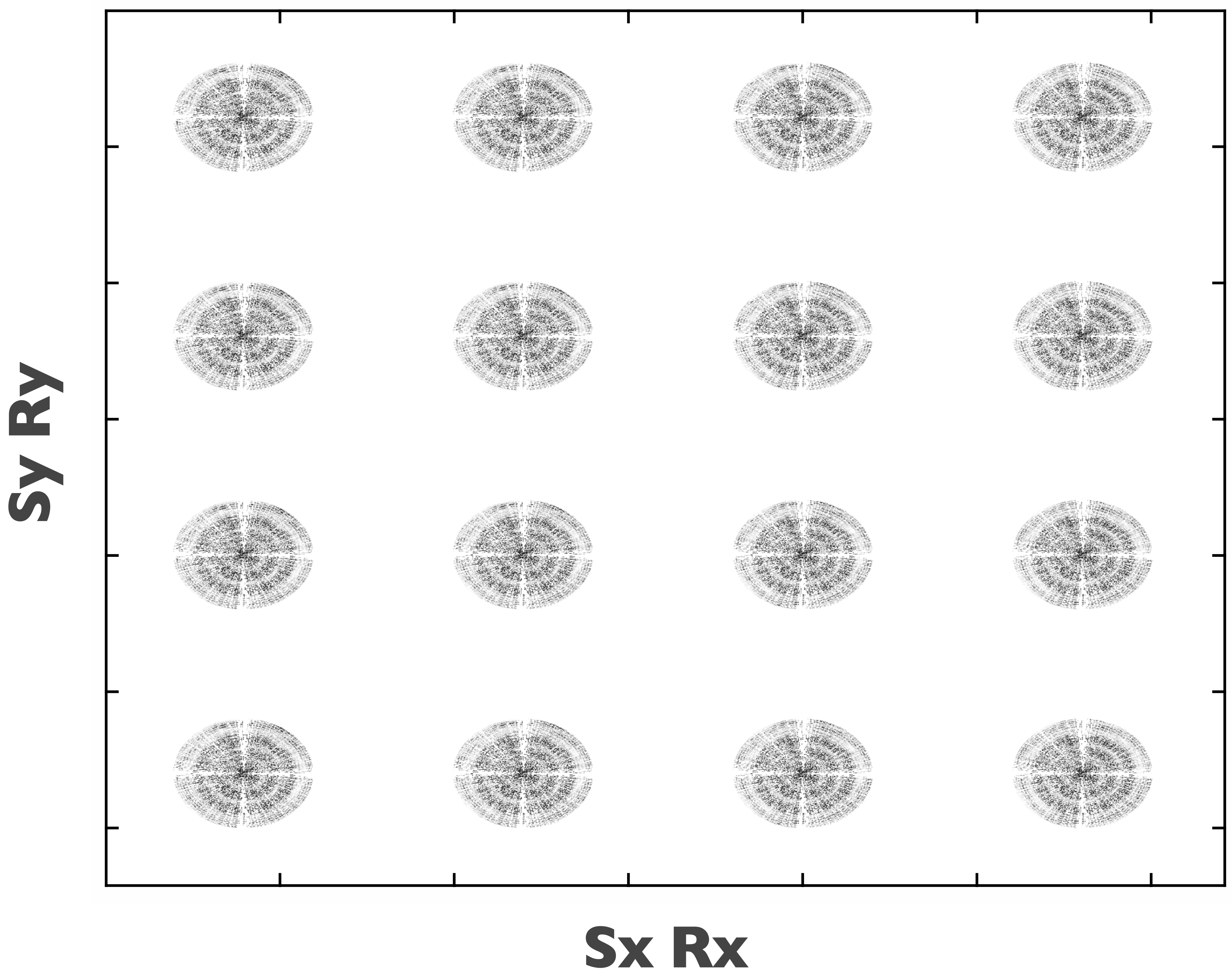
Full-azimuth data (deblended + interpolated)



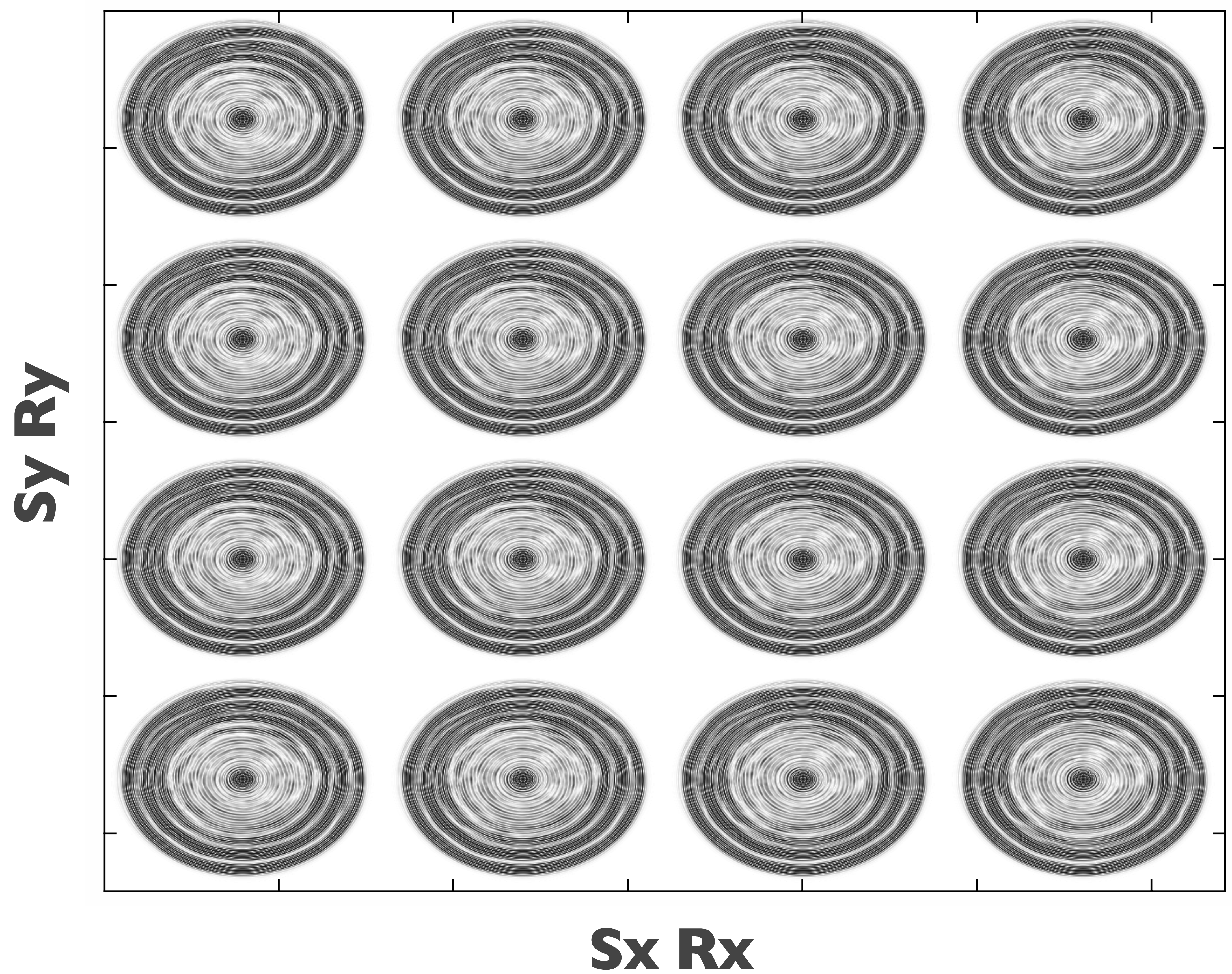
Recover full-azimuth data

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

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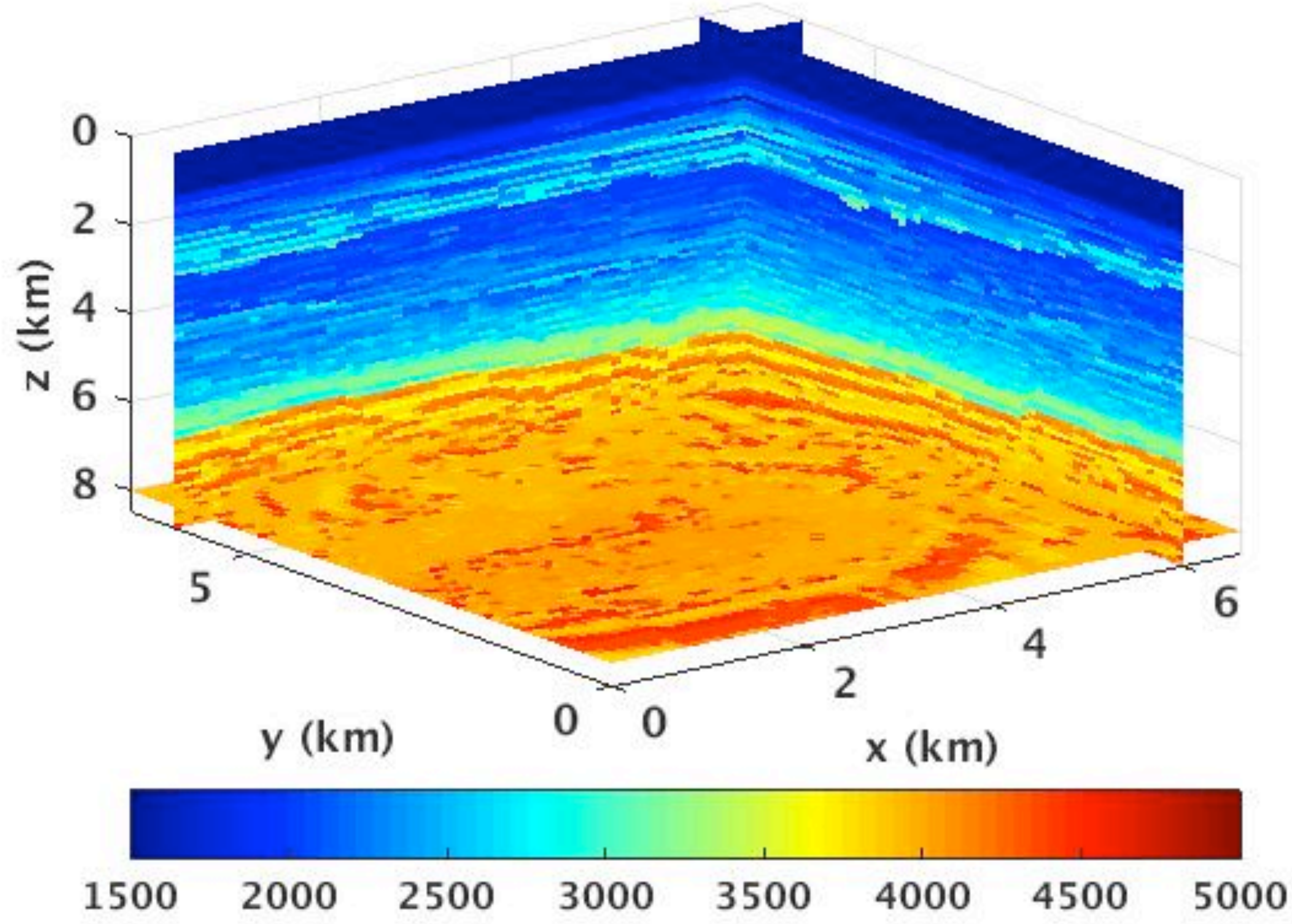
Haneet Wason, Felix Oghenekohwo, and Felix J. Herrmann, "**Cheap time lapse with distributed Compressive Sensing–-impact on repeatability**". 2016. To appear in GEOPHYSICS

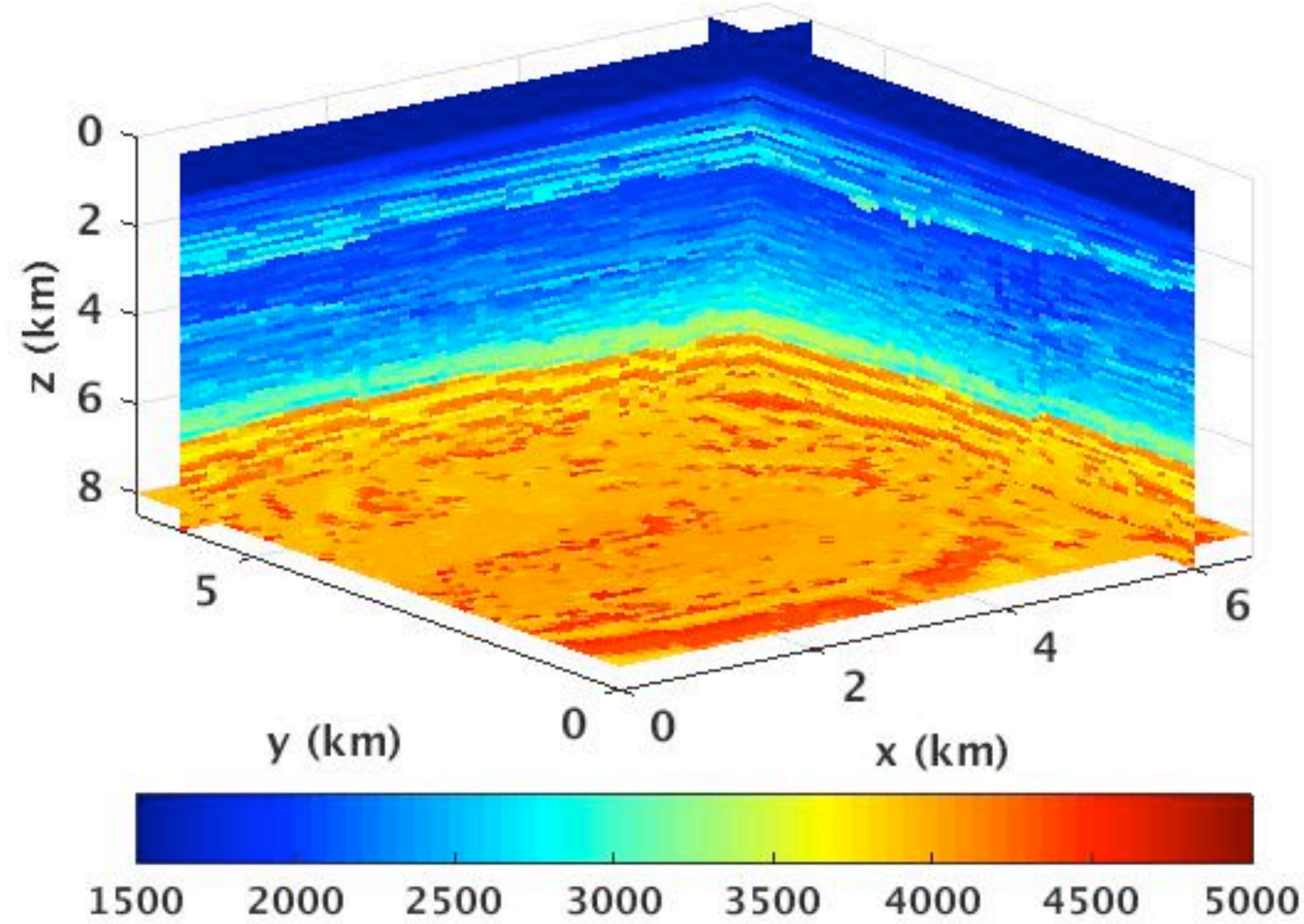
Extension to 3D time-lapse acquisition

3D baseline BG model



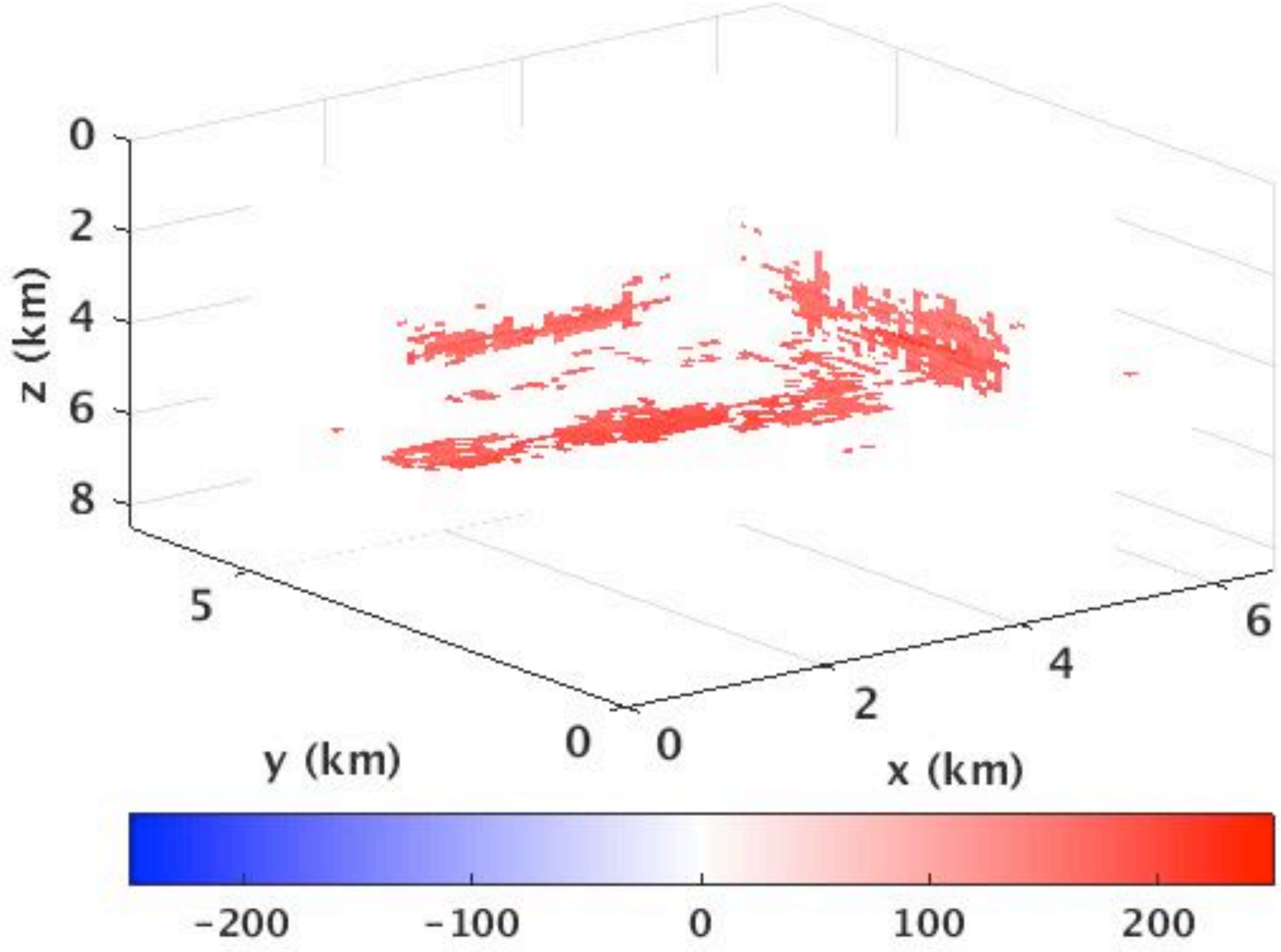
velocity (m/s)

3D baseline BG model



velocity (m/s)

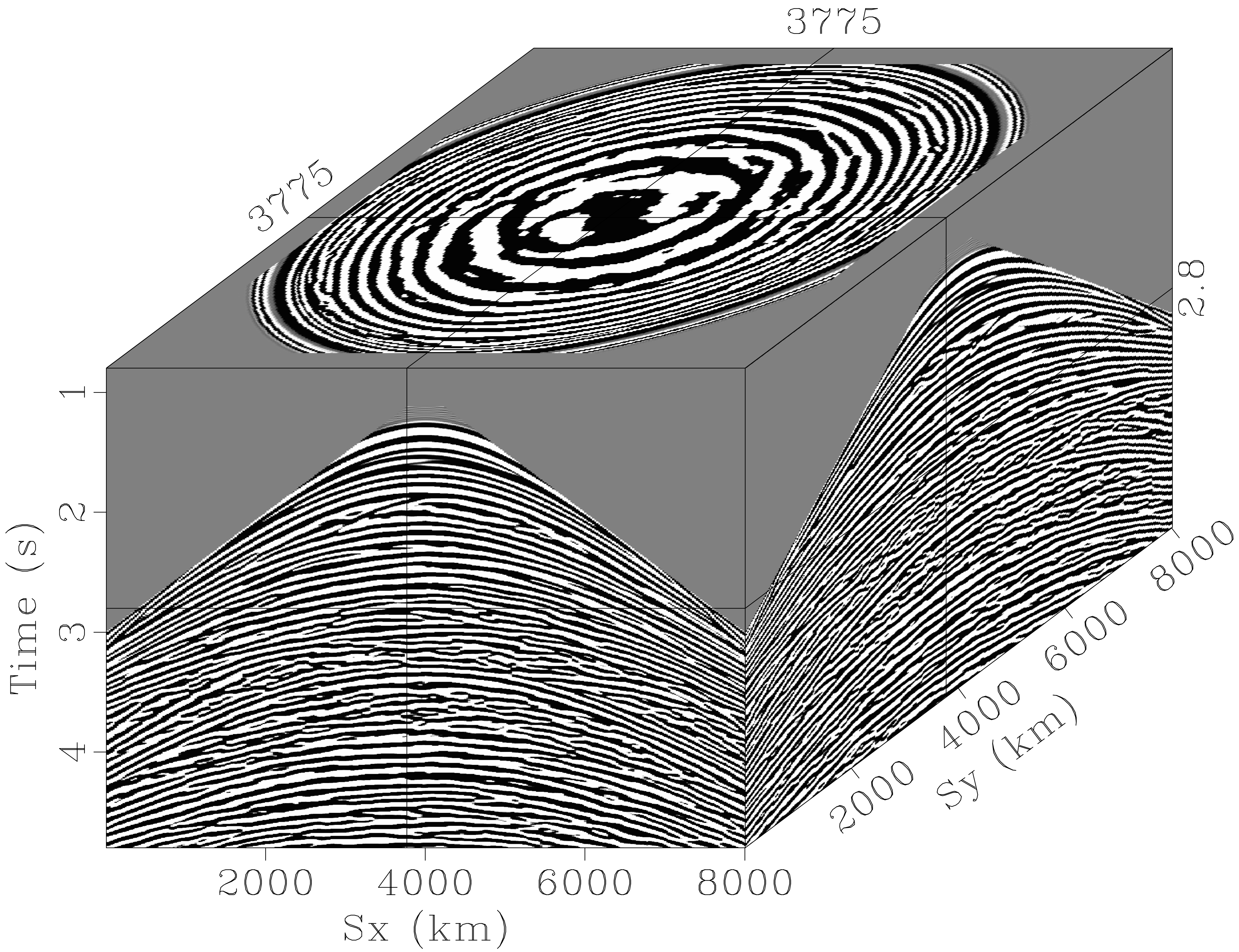
3D time-lapse BG model



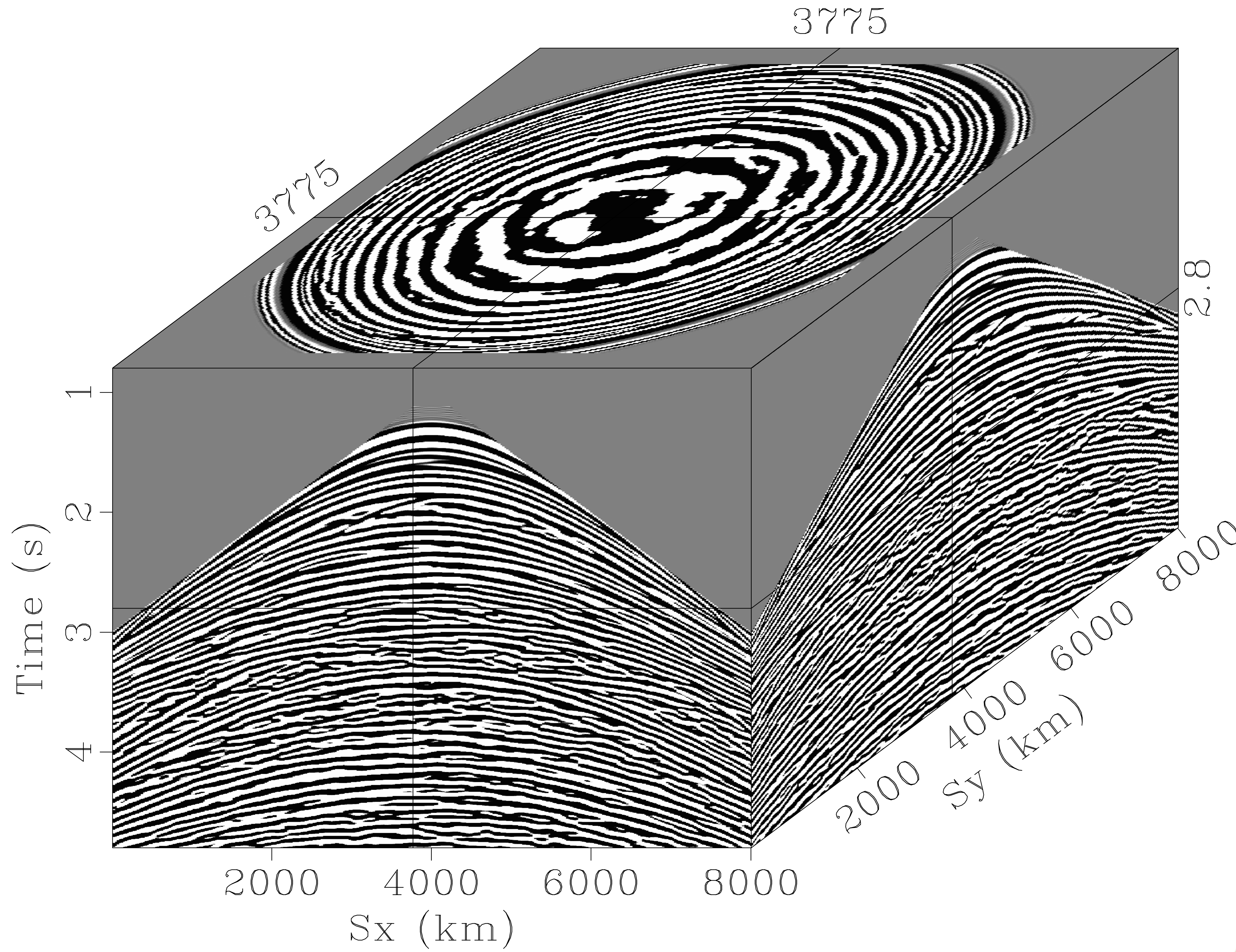
velocity (m/s)

Ideal dense receiver gathers

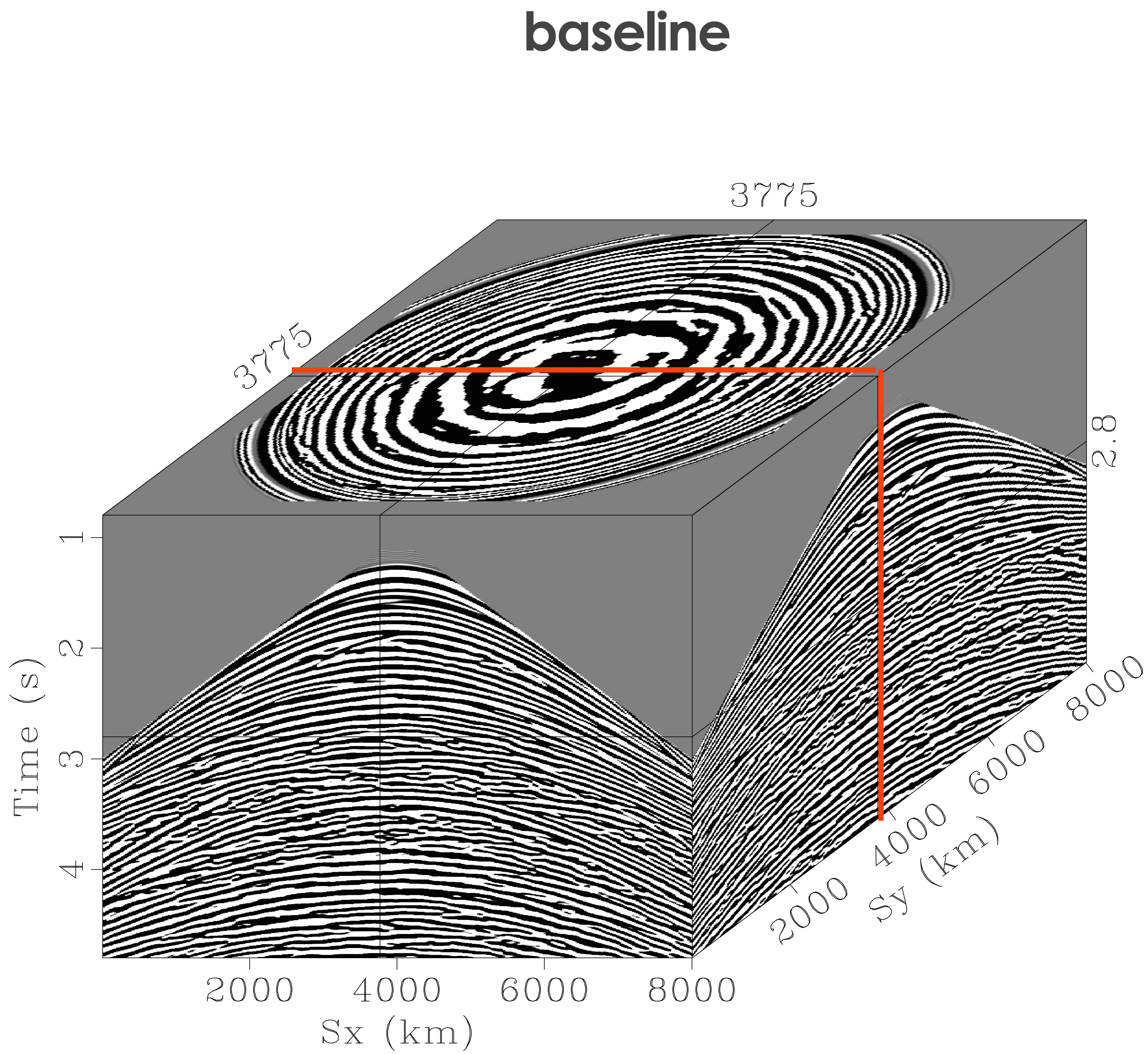
baseline

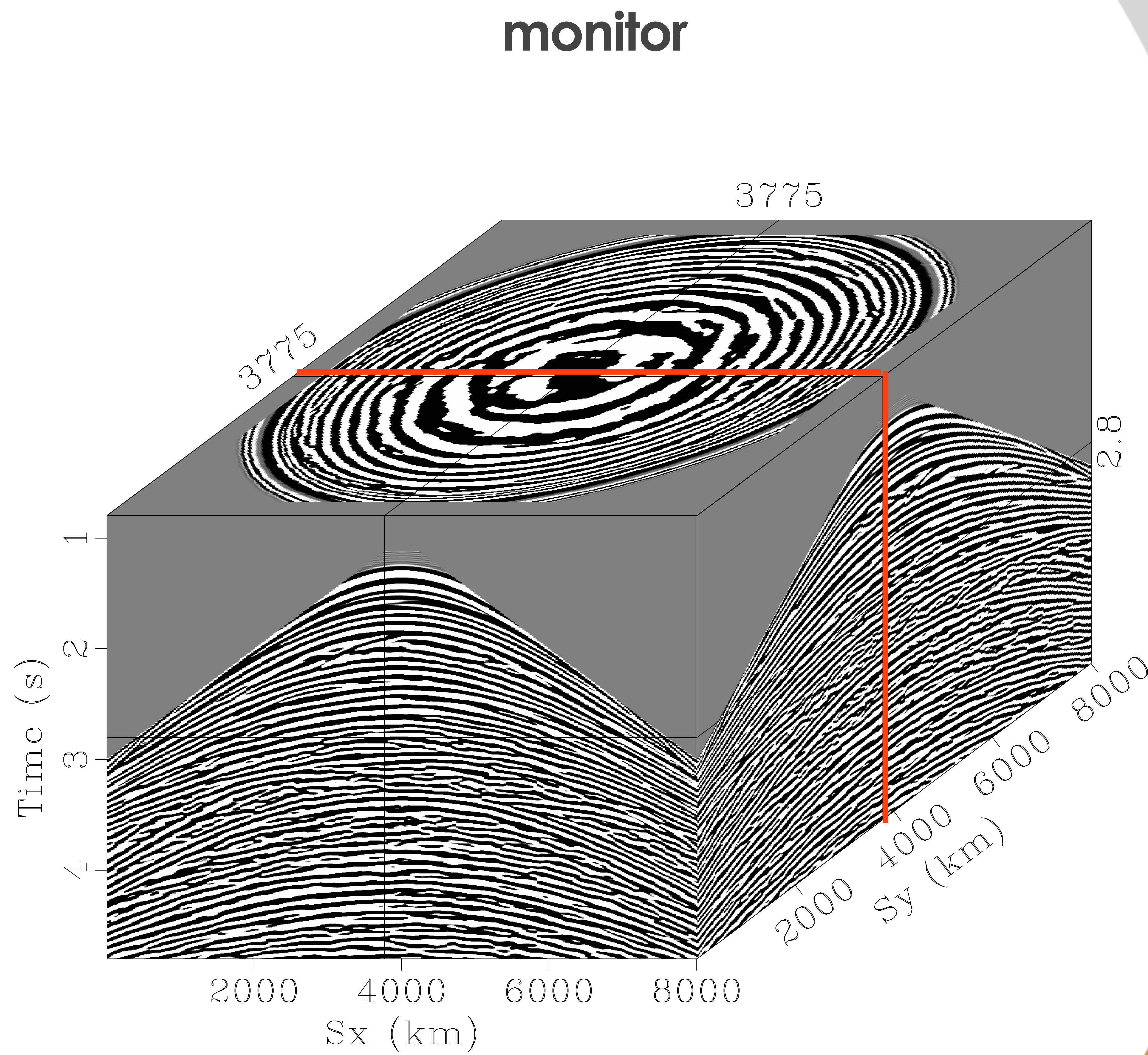


monitor

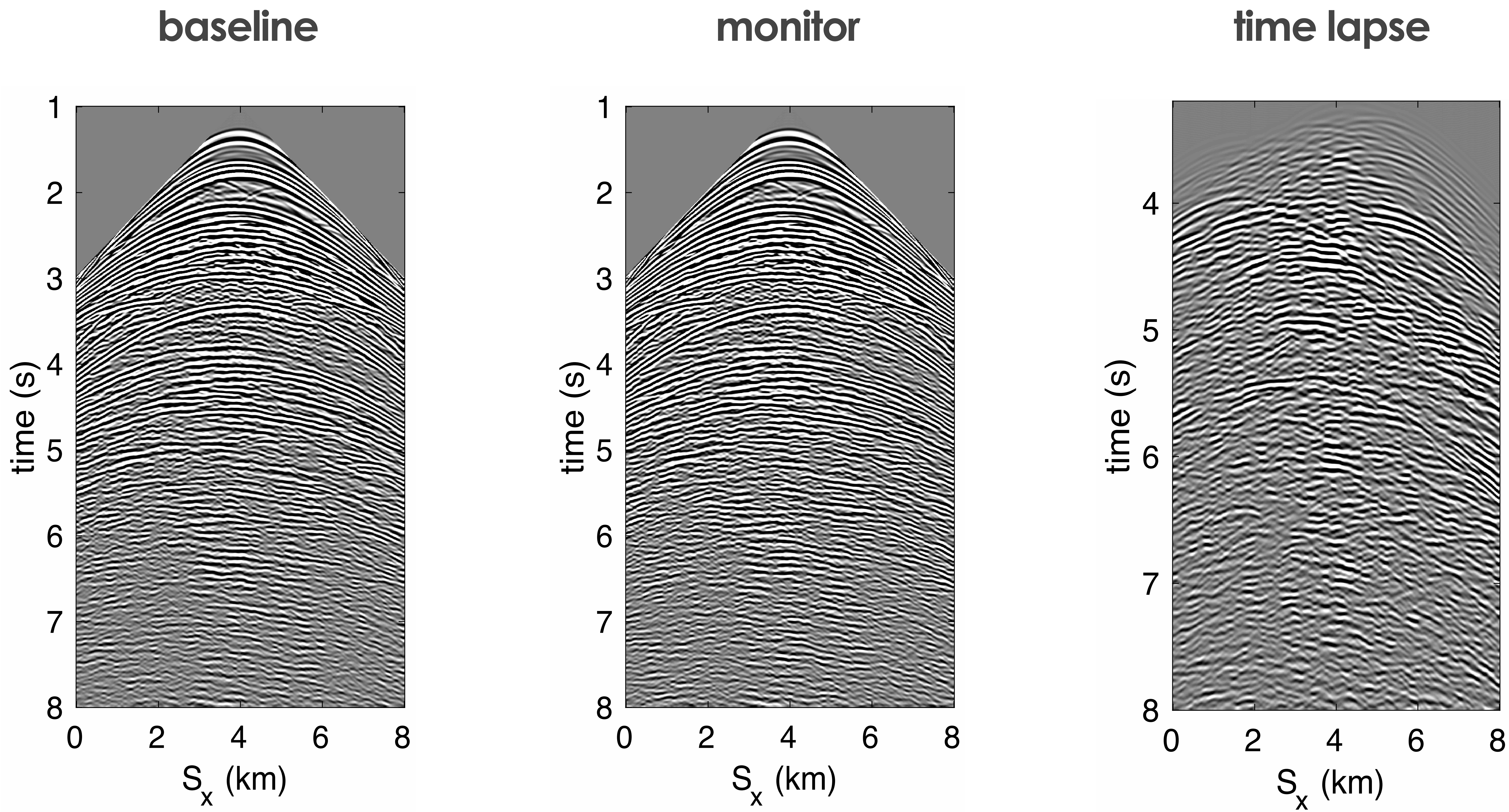


Ideal dense receiver gathers





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

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

baseline

monitor

Key idea:

- 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

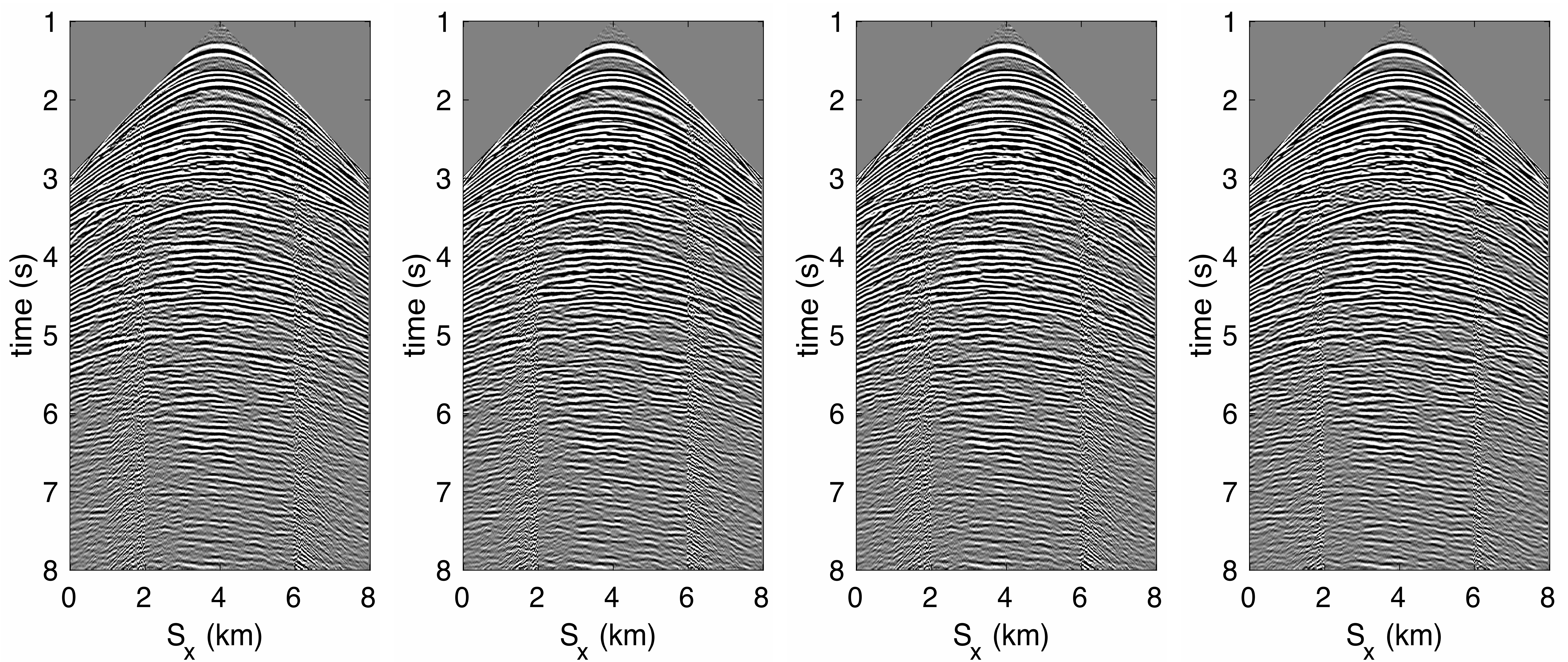
Baseline recovery

100% overlap

IRS (12.6 dB) | **JRM** (13.4 dB)

30% overlap

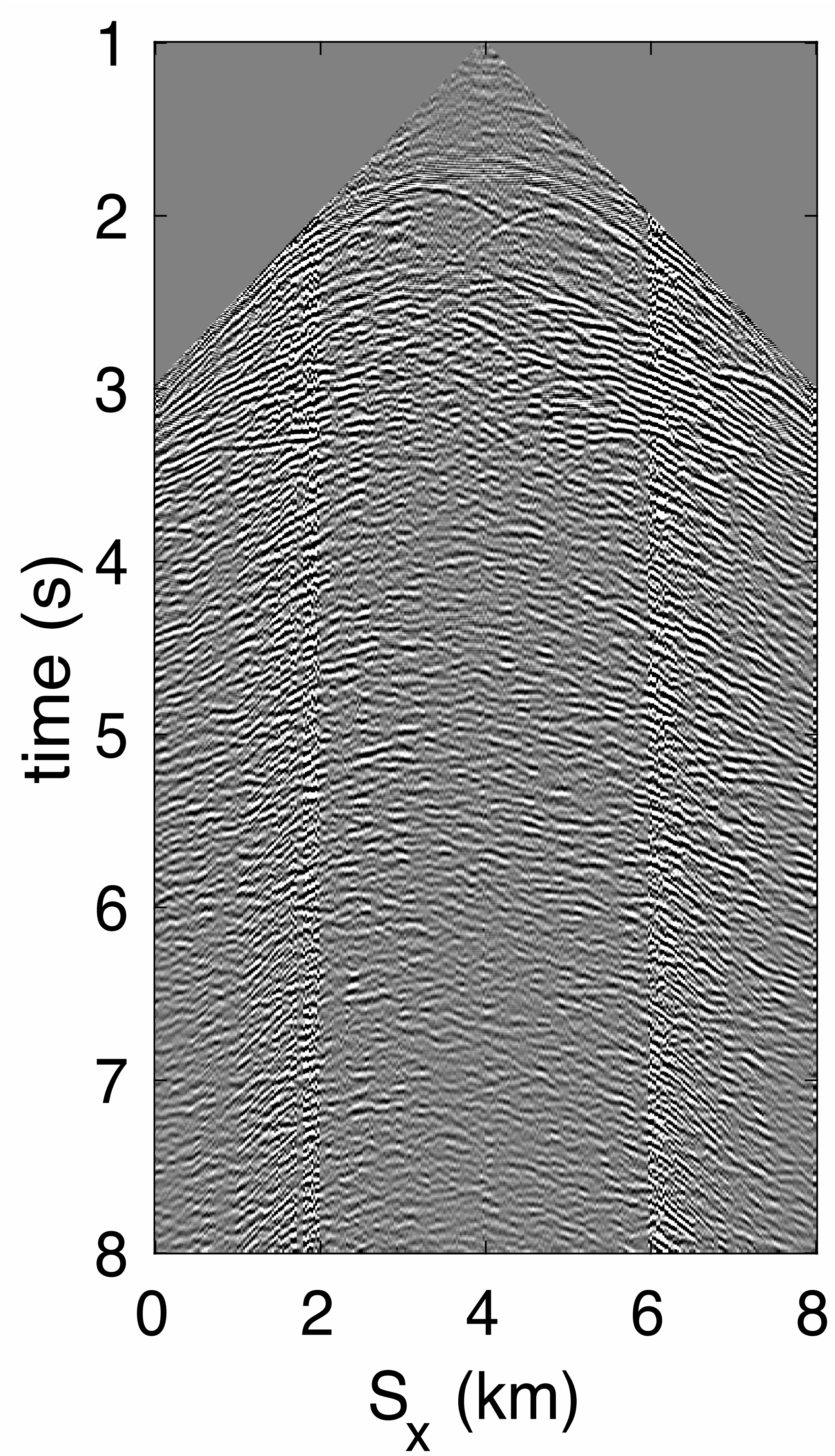
IRS (12.6 dB) | **JRM** (15.4 dB)



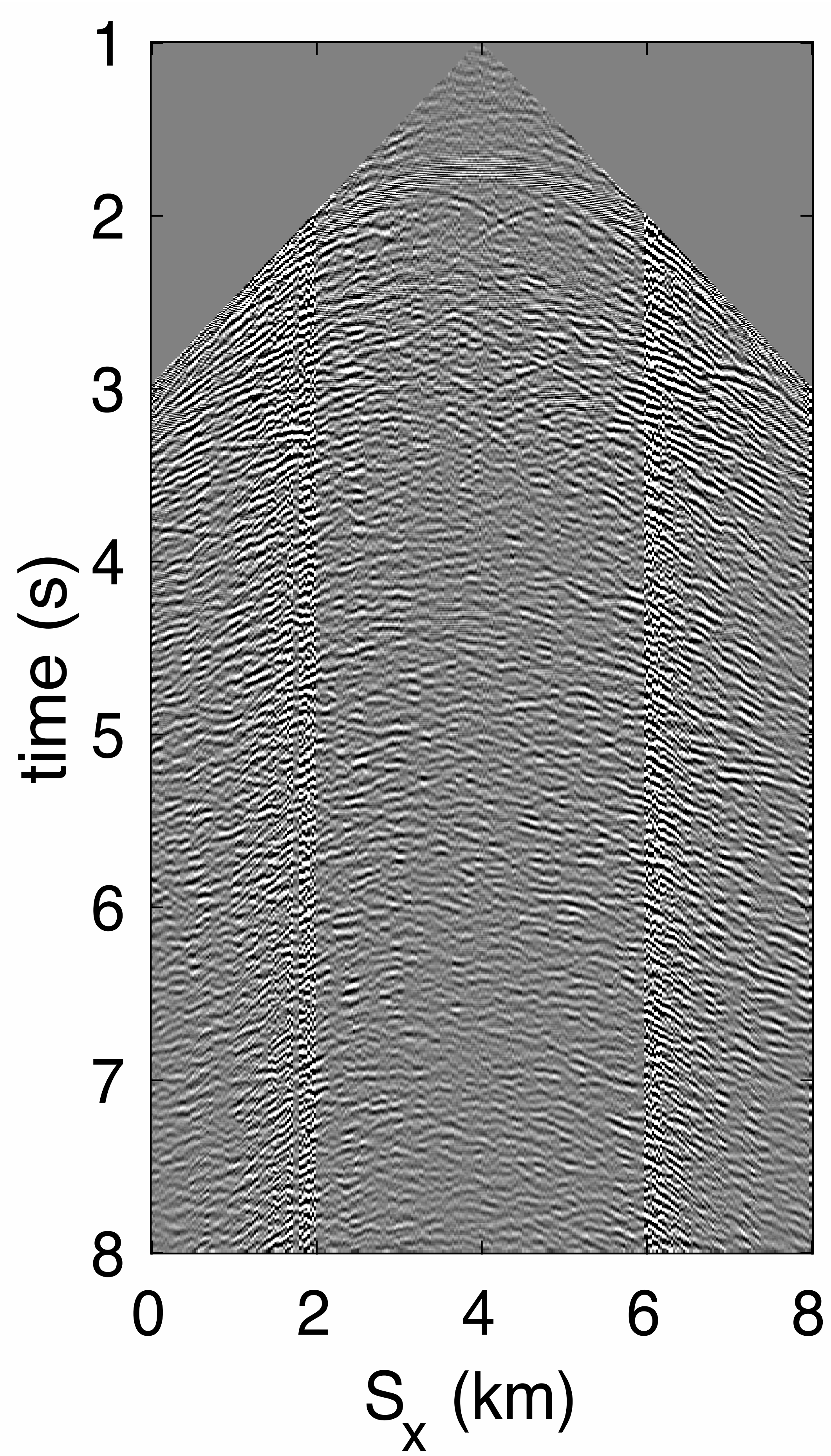
Residual

100% overlap

IRS
(12.6 dB)

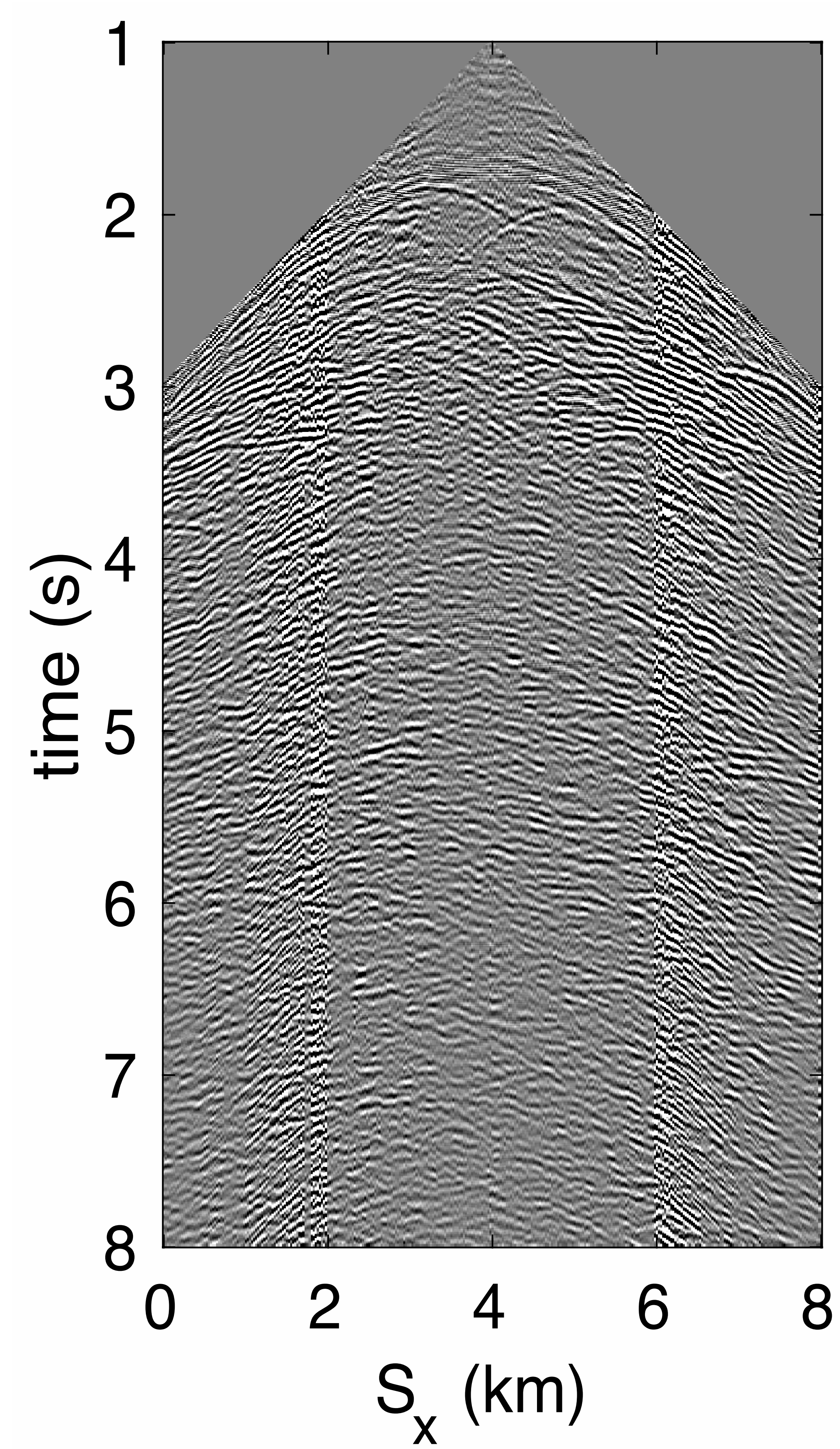


JRM
(13.4 dB)

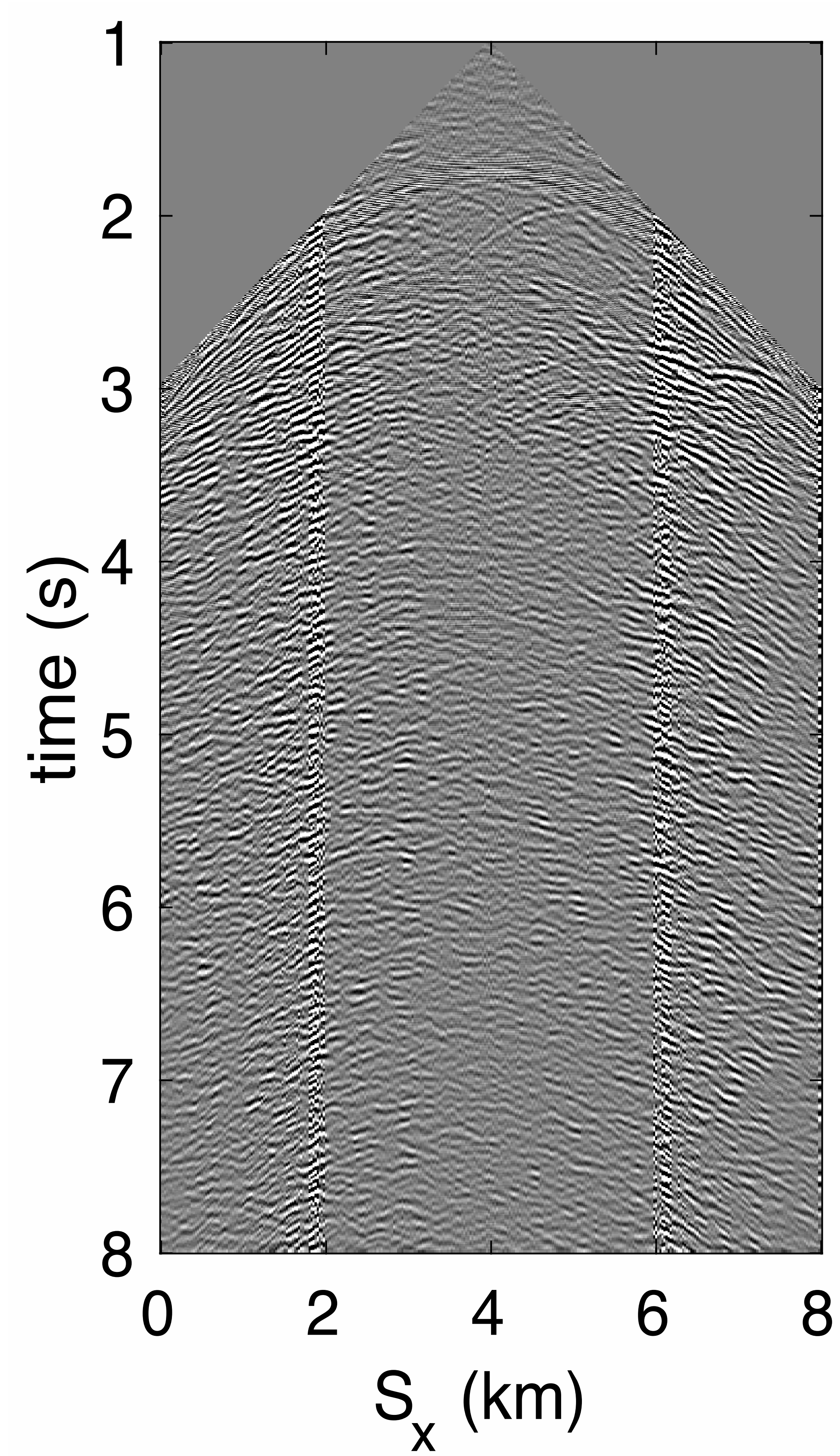


30% overlap

IRS
(12.6 dB)

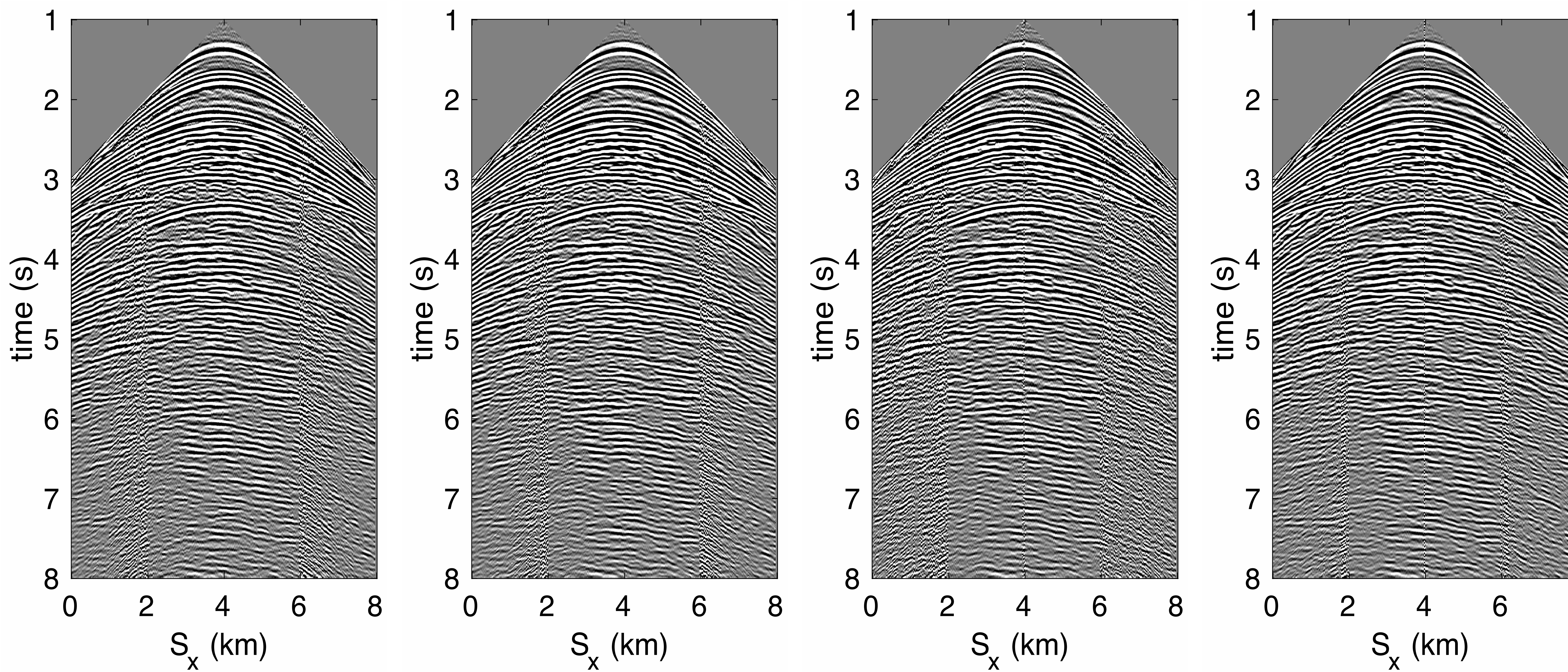


JRM
(15.4 dB)



Monitor recovery

100% overlap		30% overlap	
IRS (12.5 dB)	JRM (13.3 dB)	IRS (10.5 dB)	JRM (15.9 dB)



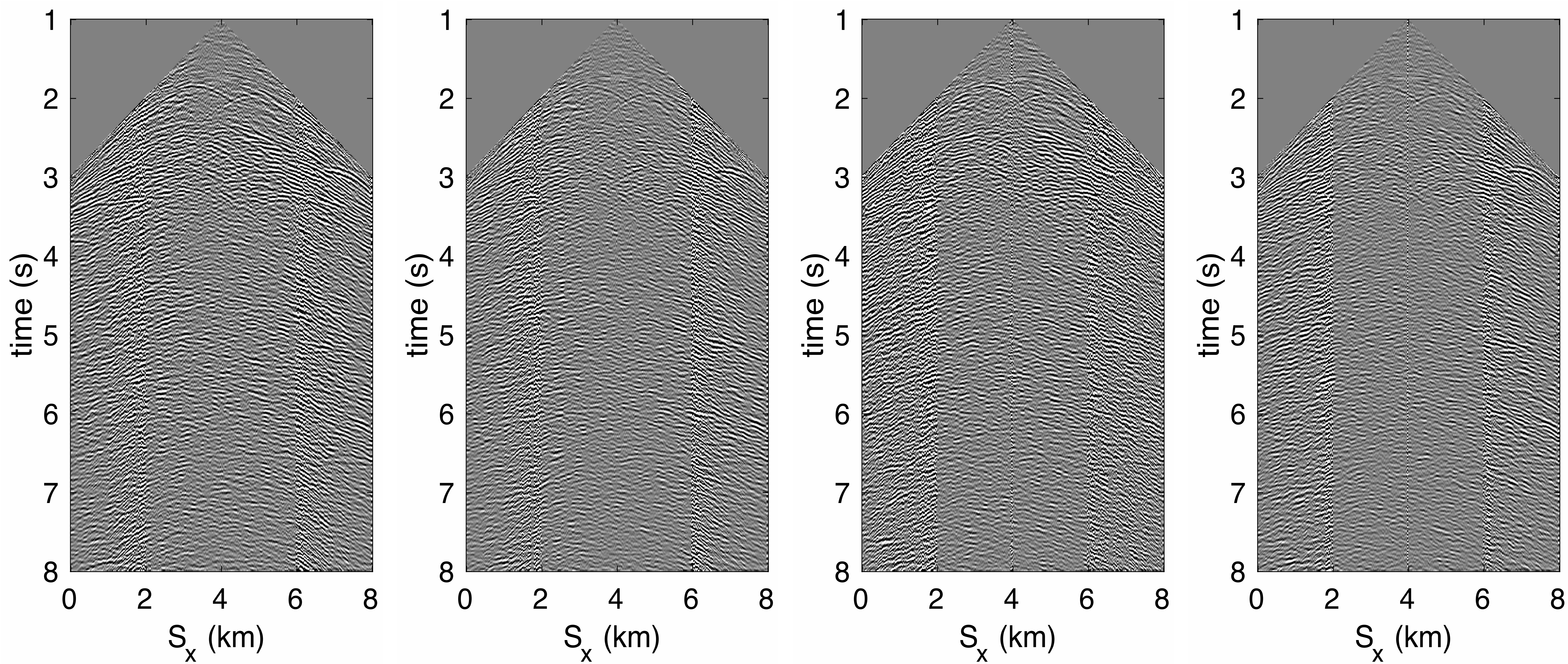
Residual

100% overlap

IRS (12.5 dB) | **JRM** (13.3 dB)

30% overlap

IRS (10.5 dB) | **JRM** (15.9 dB)



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Take-away message

Size of final recovered data volume: 800 GB

- no need to save fully sampled seismic data volume

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

- compression rate: **98.5%**
- size of final compressed 5D seismic volume: ~ **12 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

Highly repeatable time-lapse seismic with distributed Compressive Sensing--mitigating effects of calibration errors

Felix Oghenekohwo

SLIM
University of British Columbia

Felix Oghenekohwo and Felix J. Herrmann, "**Highly repeatable time-lapse seismic with distributed Compressive Sensing--mitigating effects of calibration errors**", *The Leading Edge*, vol. 36, p. 688-694, 2017.

1 Rajiv Kumar, Haneet Wason, Shashin Sharan, and Felix J. Herrmann, "**Highly repeatable 3D compressive full-azimuth towed-streamer time-lapse acquisition –- a numerical feasibility study at scale**", *The Leading Edge*, vol. 36, p. 677-687, 2017.
2 Felix Oghenekohwo and Felix J. Herrmann, "**Highly repeatable time-lapse seismic with distributed Compressive Sensing–-mitigating effects of calibration errors**", *The Leading Edge*, vol. 36, p. 688-694, 2017.
3 **Haneet Wason, Felix Oghenekohwo, and Felix J. Herrmann, "Low-cost time-lapse seismic with distributed compressive sensing–-Part 2: impact on repeatability", Geophysics, vol. 82, p. P15-P30, 2017.**
4 **Felix Oghenekohwo, Haneet Wason, Ernie Esser, and Felix J. Herrmann, "Low-cost time-lapse seismic with distributed compressive sensing–-Part 1: exploiting common information among the vintages", Geophysics, vol. 82, p. P1-P13, 2017.**

Observations

Randomized acquisition:

- independent surveys bring extra information
- "exactly" repeated surveys do not add new information
- for independent surveys, independent processing leads to poor recovery quality of vintages & time-lapse difference
- w/ joint recovery, we observe improvements in recovery quality of the vintages for independent surveys

*Our joint recovery model exploits the shared information in time-lapse data, improving the **repeatability** of the vintages.*

"Exact" replicability of the surveys seems essential for good recovery of the time-lapse signal...

What is the impact of calibration errors?

$$(\mathbf{A}_p \neq \mathbf{A}_t)$$

postplot
acquisition

true field
acquisition

SLIM

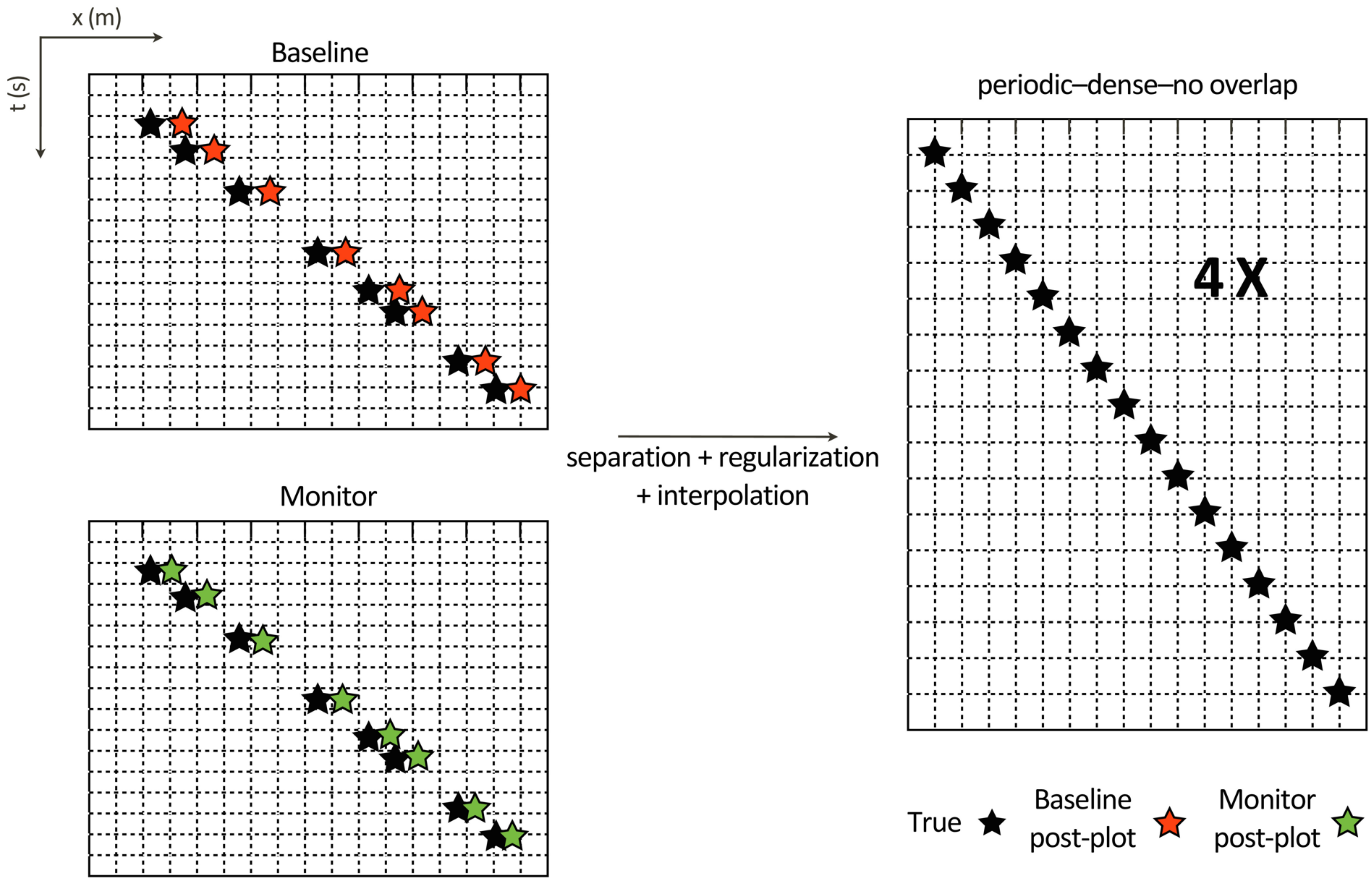
Goal

Evaluate the impact of deviations between true & recorded post-plot on time-lapse repeatability & quality of the vintages

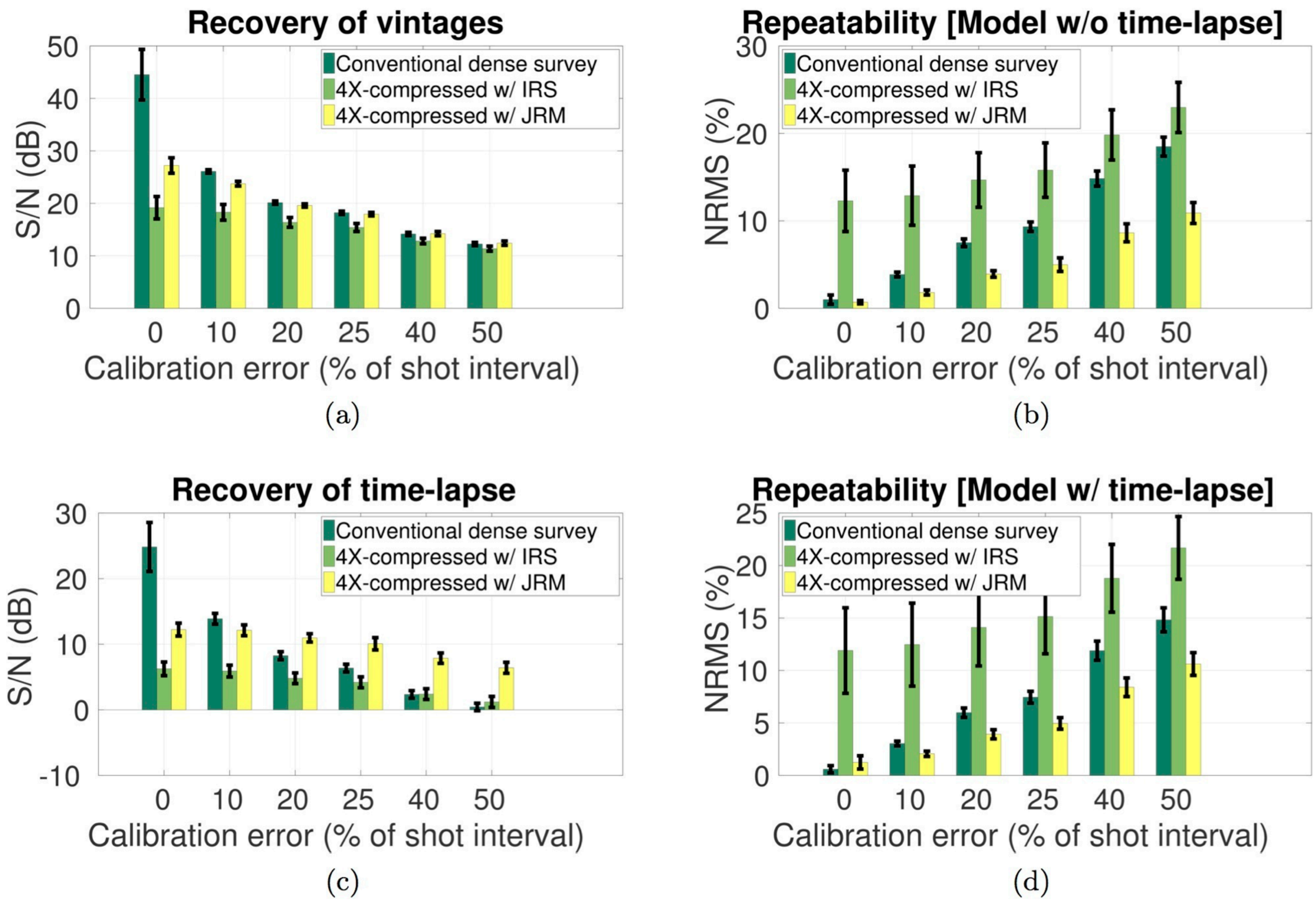
- w/ our low-cost marine acquisition (e.g. time-jittered sources in marine)
- w/o survey replication in the shot locations
- w/ our **joint recovery model**
- compared to conventional (non-replicated) dense surveys

In the idealized setting where nothing changes in the earth but acquisition & unknown calibration errors differ.

4-D time-jittered marine acquisition



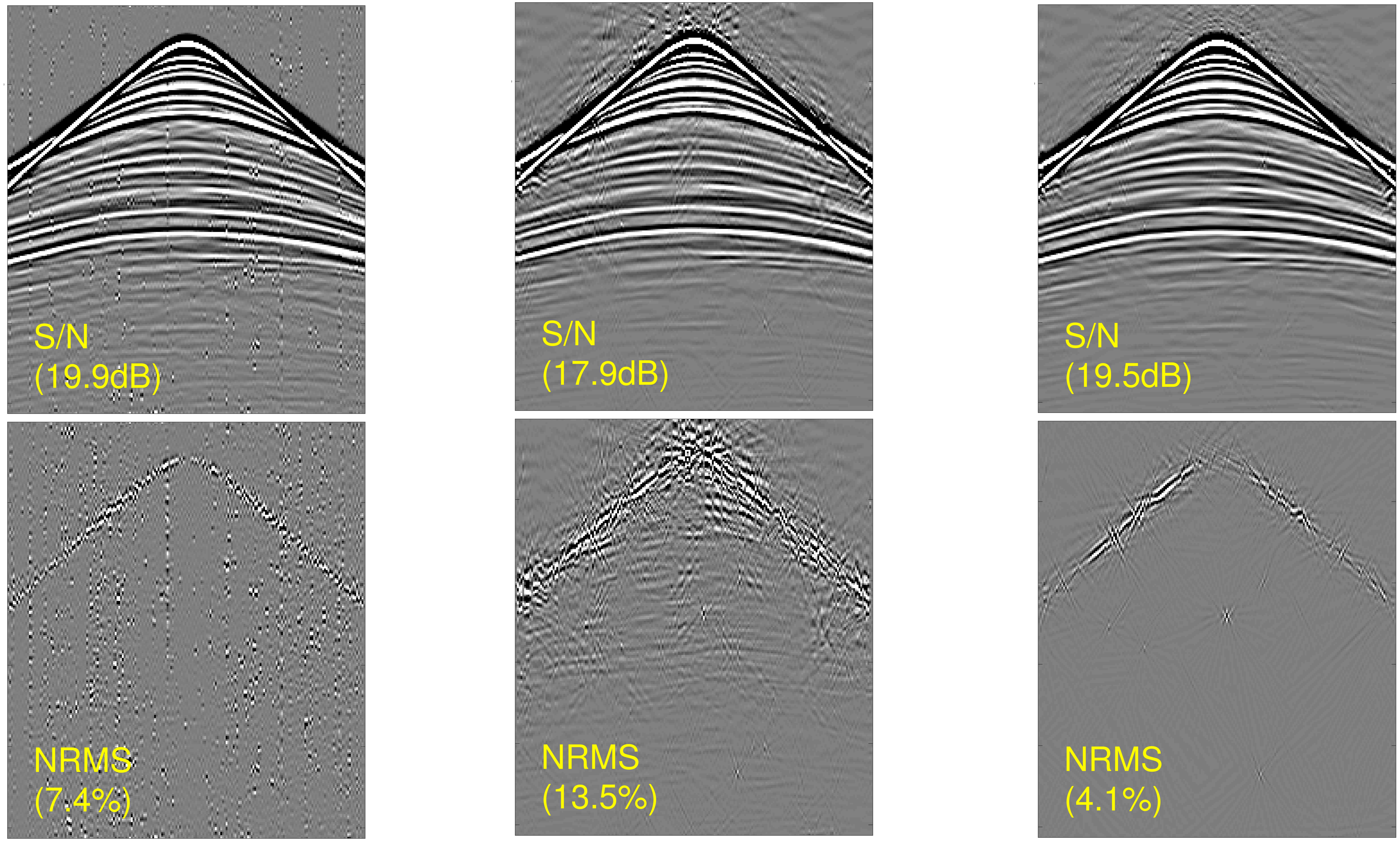
Recovery & repeatability



Recovery
- w/ up to 20% error (~ 2.5m) in shot position

Recovery of 2nd survey

Difference between pairs (1st & 2nd survey)



Conventional dense survey (after regularization)

Low-cost w/ Independent recovery (IRS)

Low-cost w/ Joint recovery model (JRM)

Summary

- High-cost densely sampled surveys give best quality & repeatability in the absence of calibration errors
- Quality of dense surveys decay rapidly in presence of small errors
- Independently recovering the CS-based surveys leads to the worst recovery quality & repeatability
- Low-cost randomized surveys show modest decay in quality & repeatability when recovered with the joint recovery model

Recovery with the JRM is stable with respect to calibration errors.

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