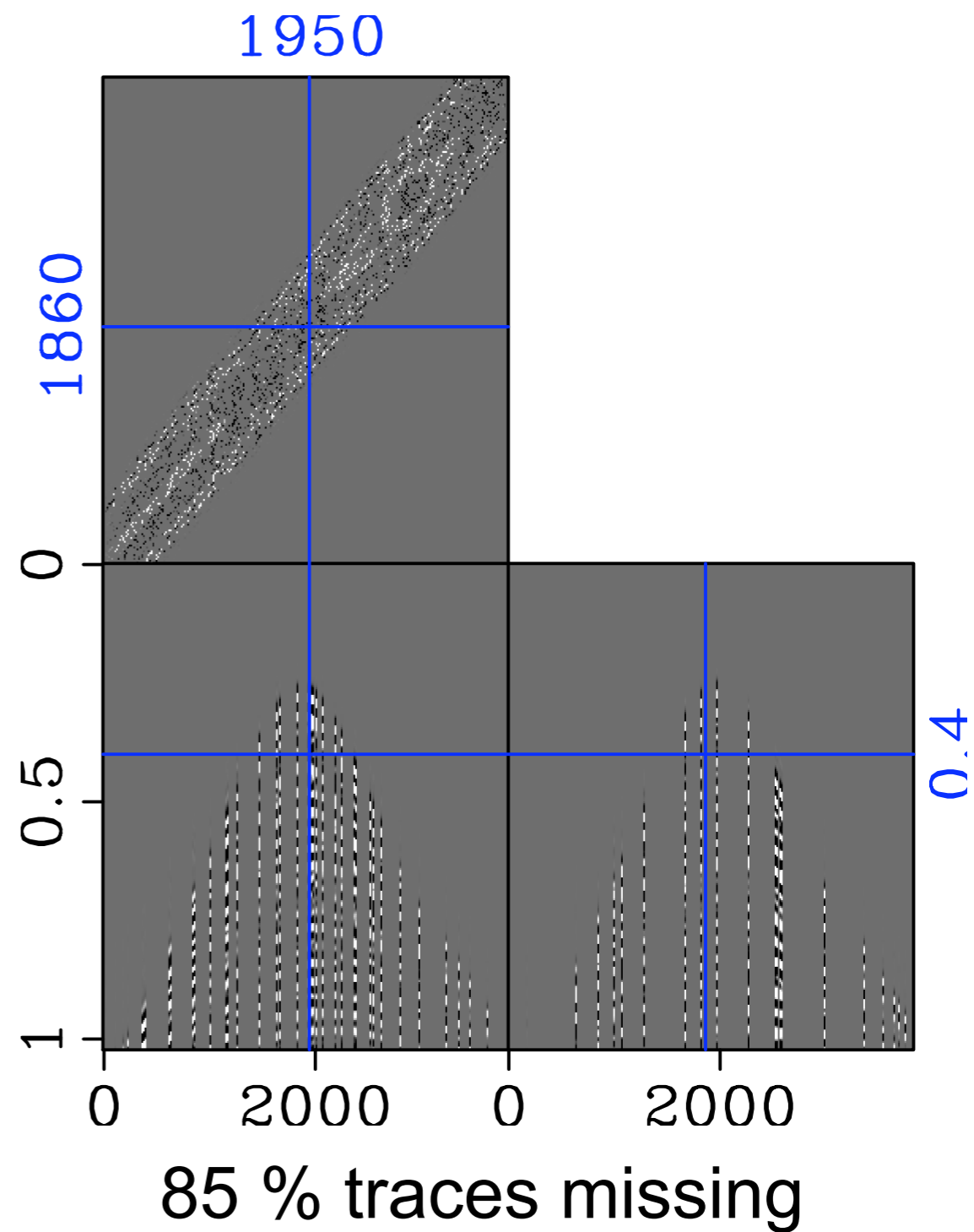
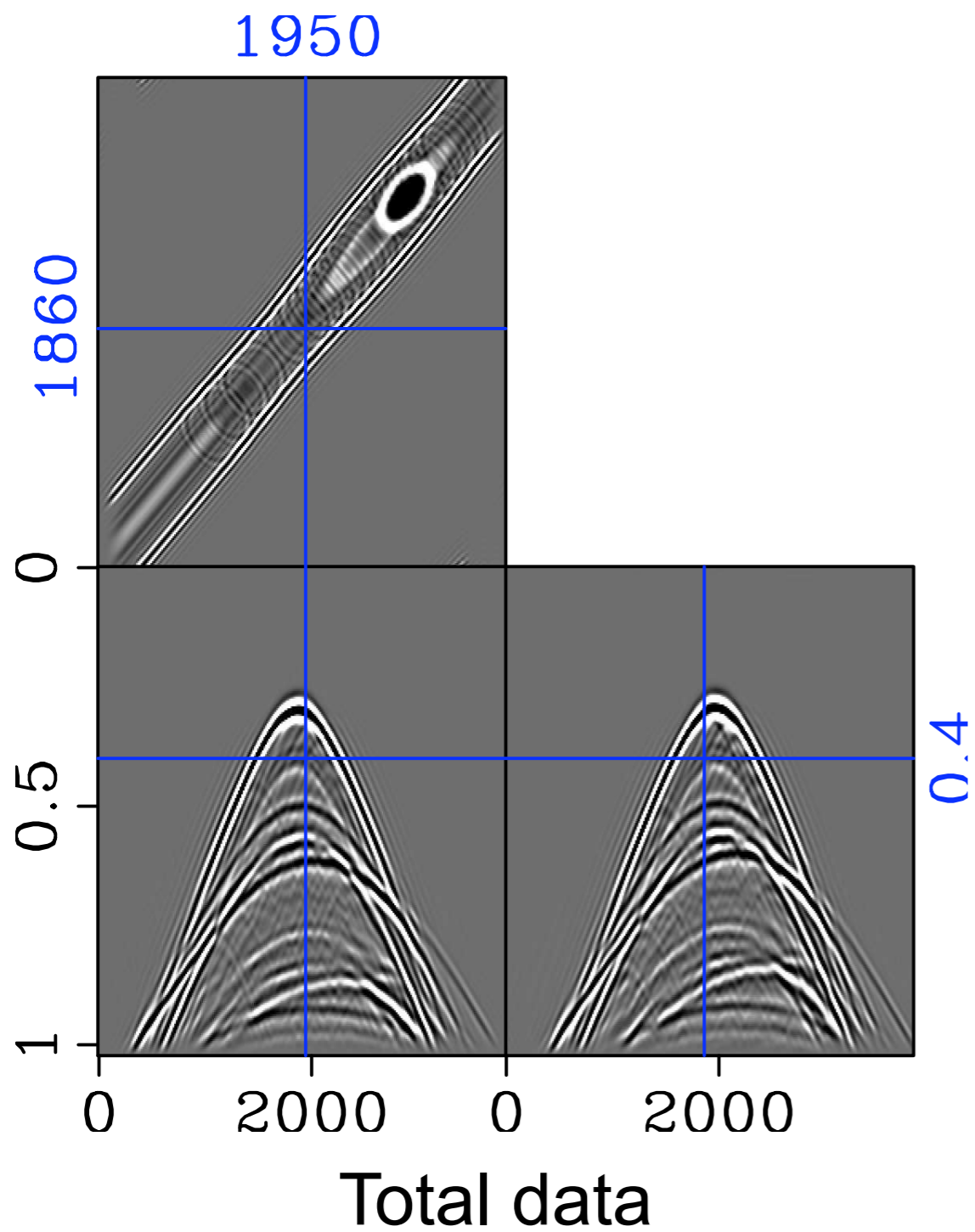


Multiple prediction from incomplete data with the focused curvelet transform

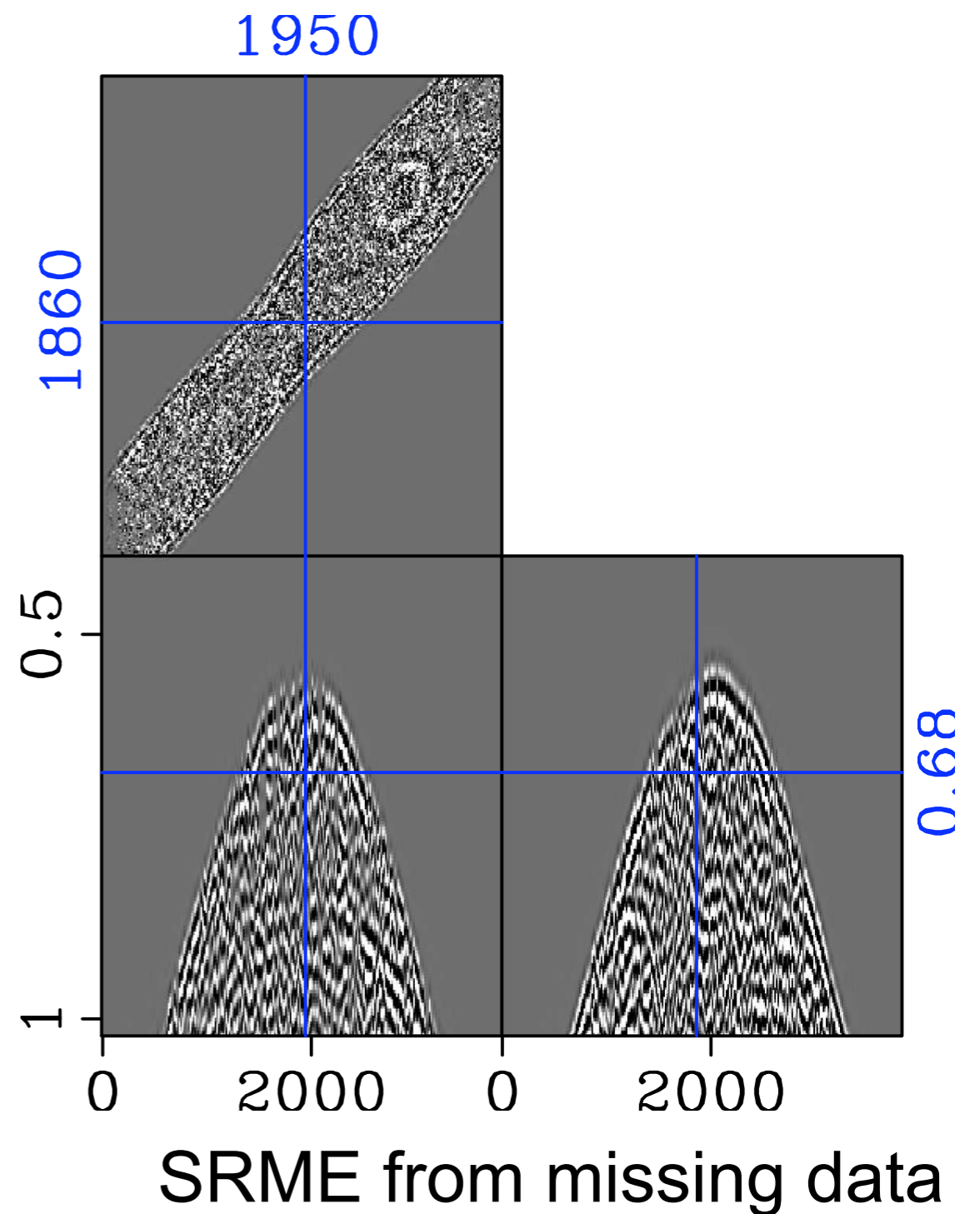
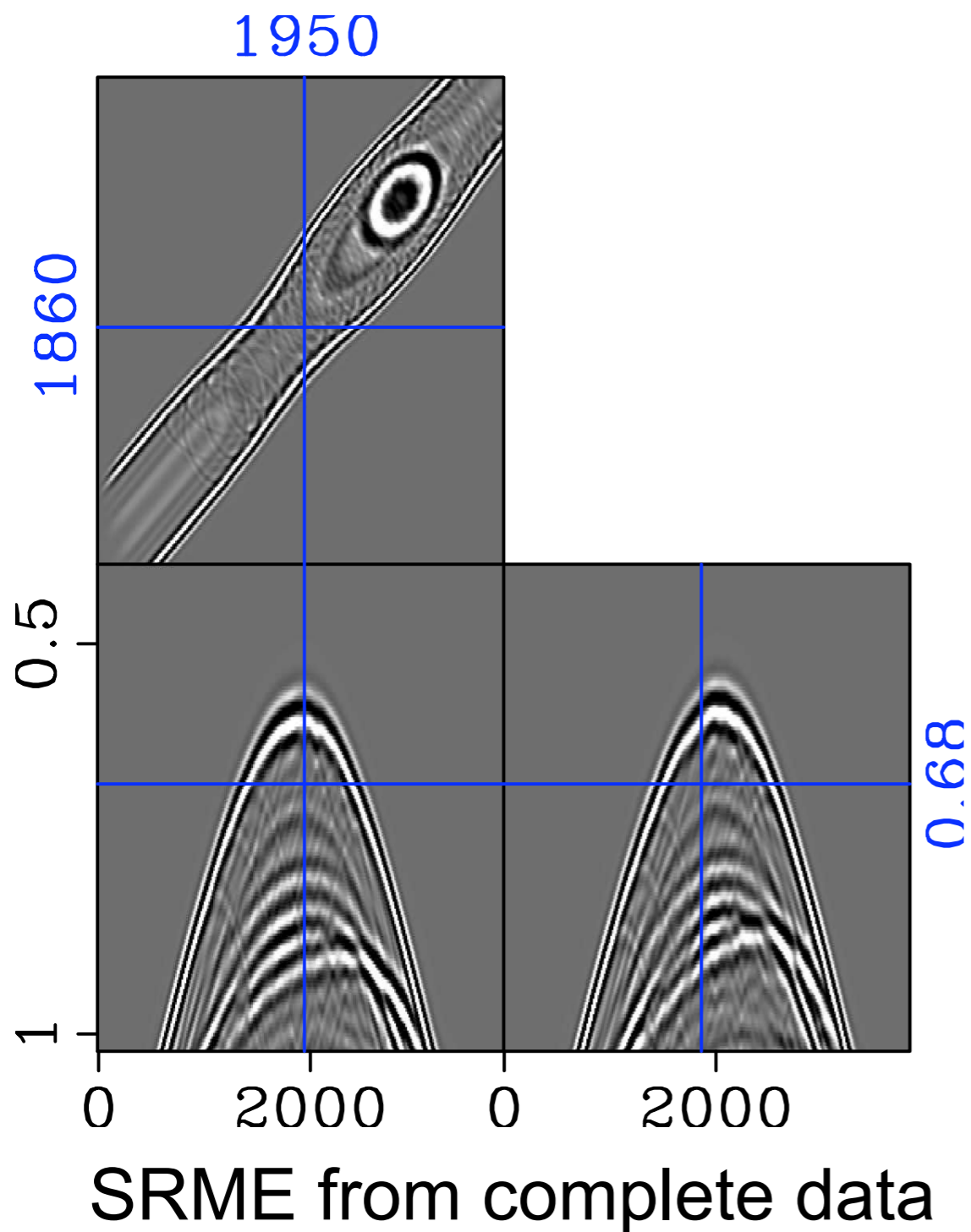
Felix J. Herrmann

joint work with Deli Wang and Gilles
Hennenfent.

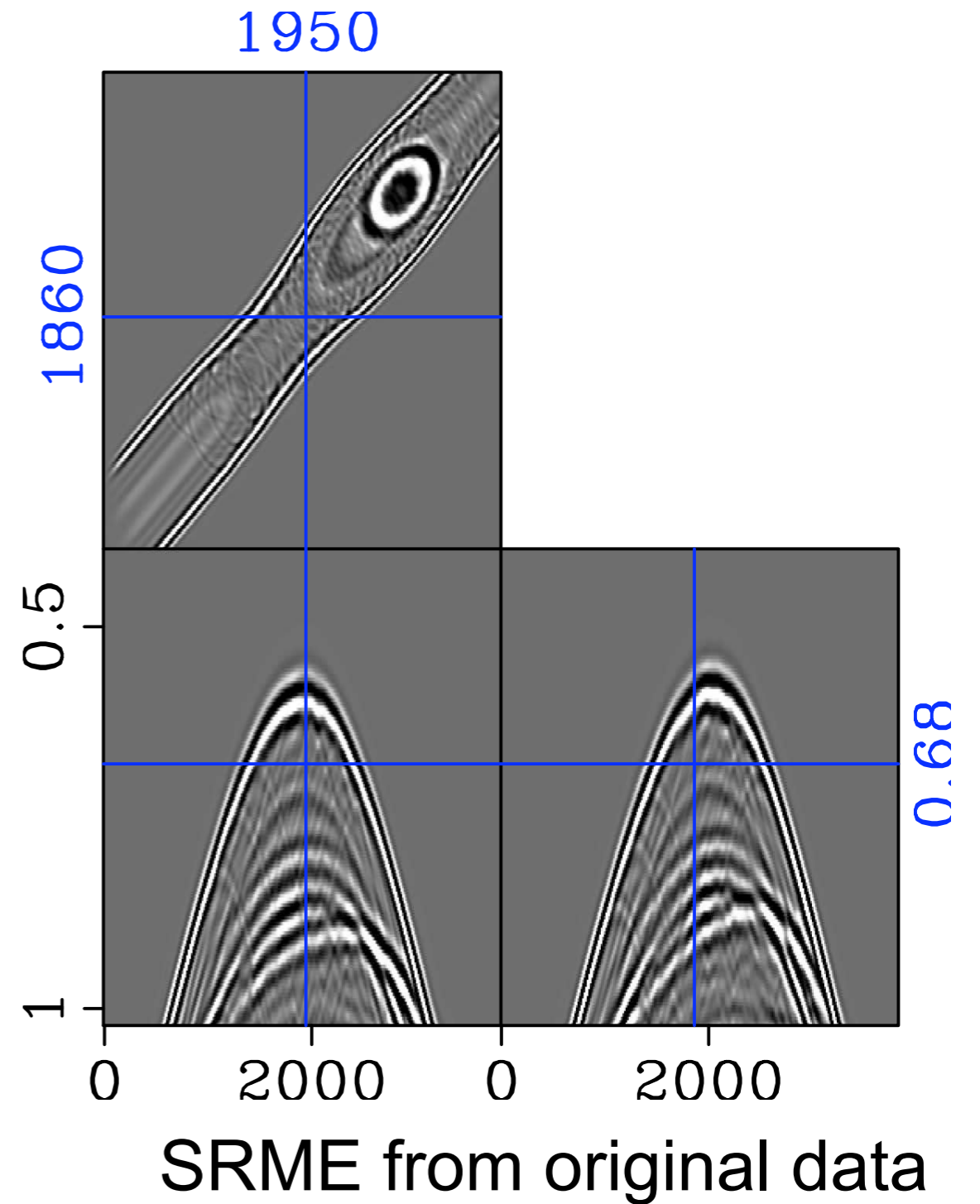
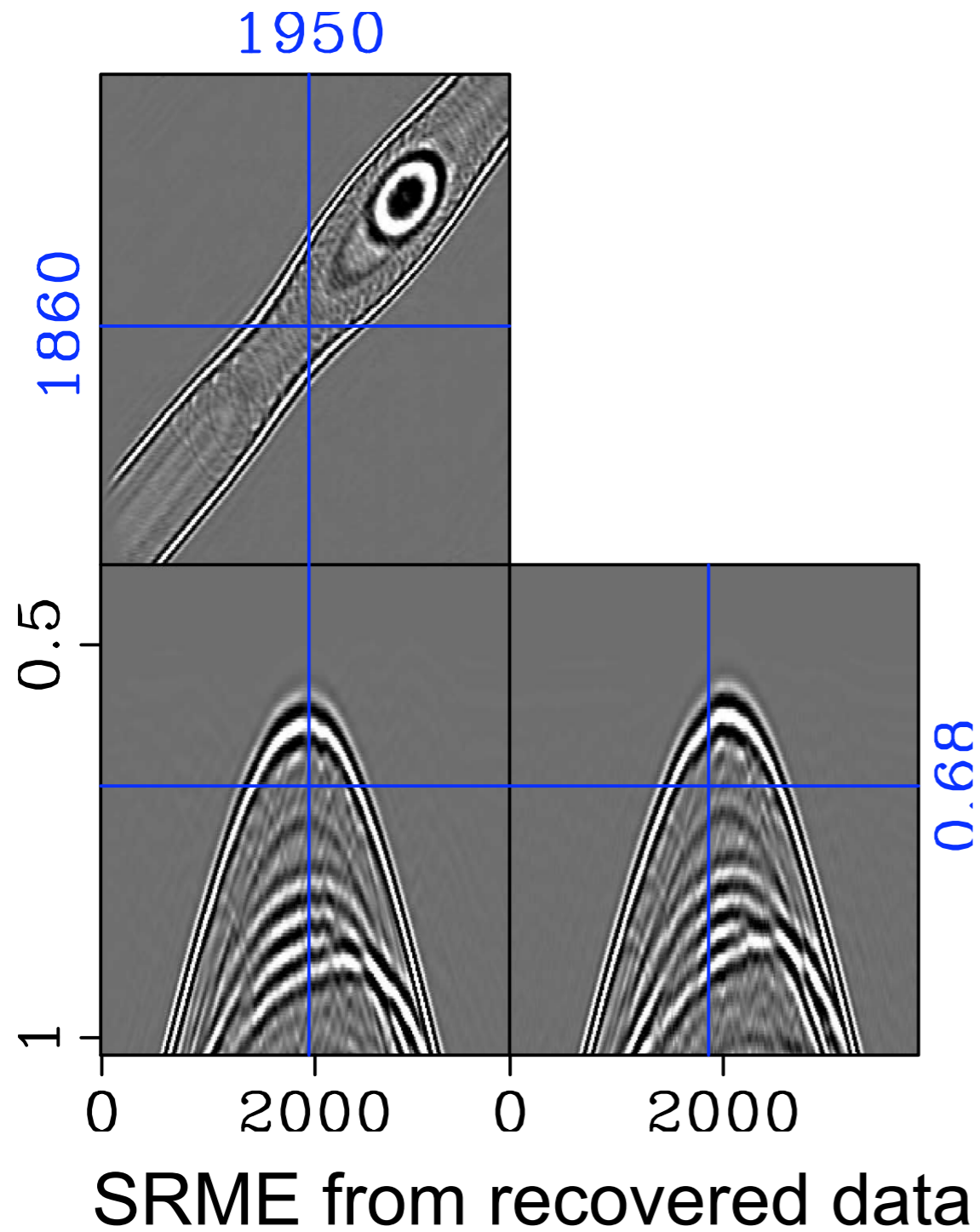
The problem



The problem cont'd



Our solution



Motivation

Data-driven (SRME) multiple prediction requires *fully* sampled data.

The Focal transform (Berkhout & Verschuur '06) allows for

- mapping of multiples => primaries
- incorporation of *prior* information in the recovery

Present a curvelet-based scheme for sparsity-promoting

- recovery of missing data
- prediction of primaries from multiples
- data inverse ...

The curvelet transform

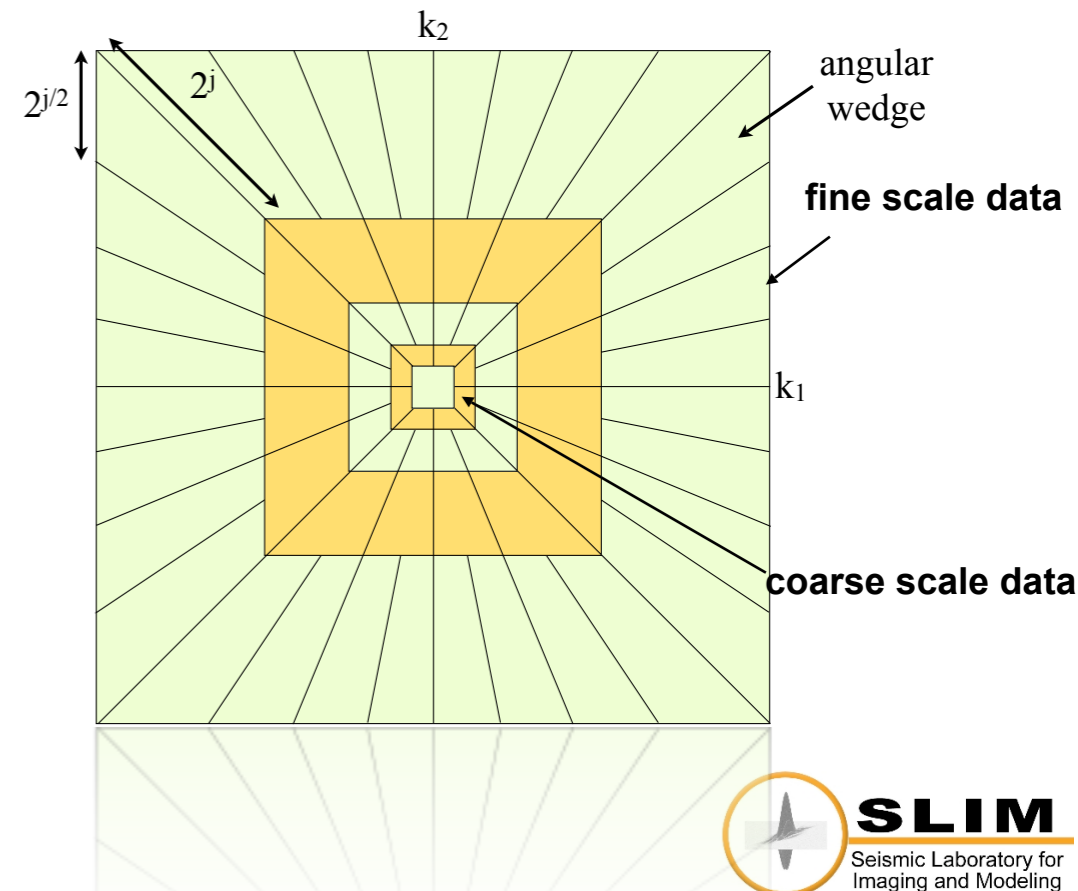


Representations for seismic data

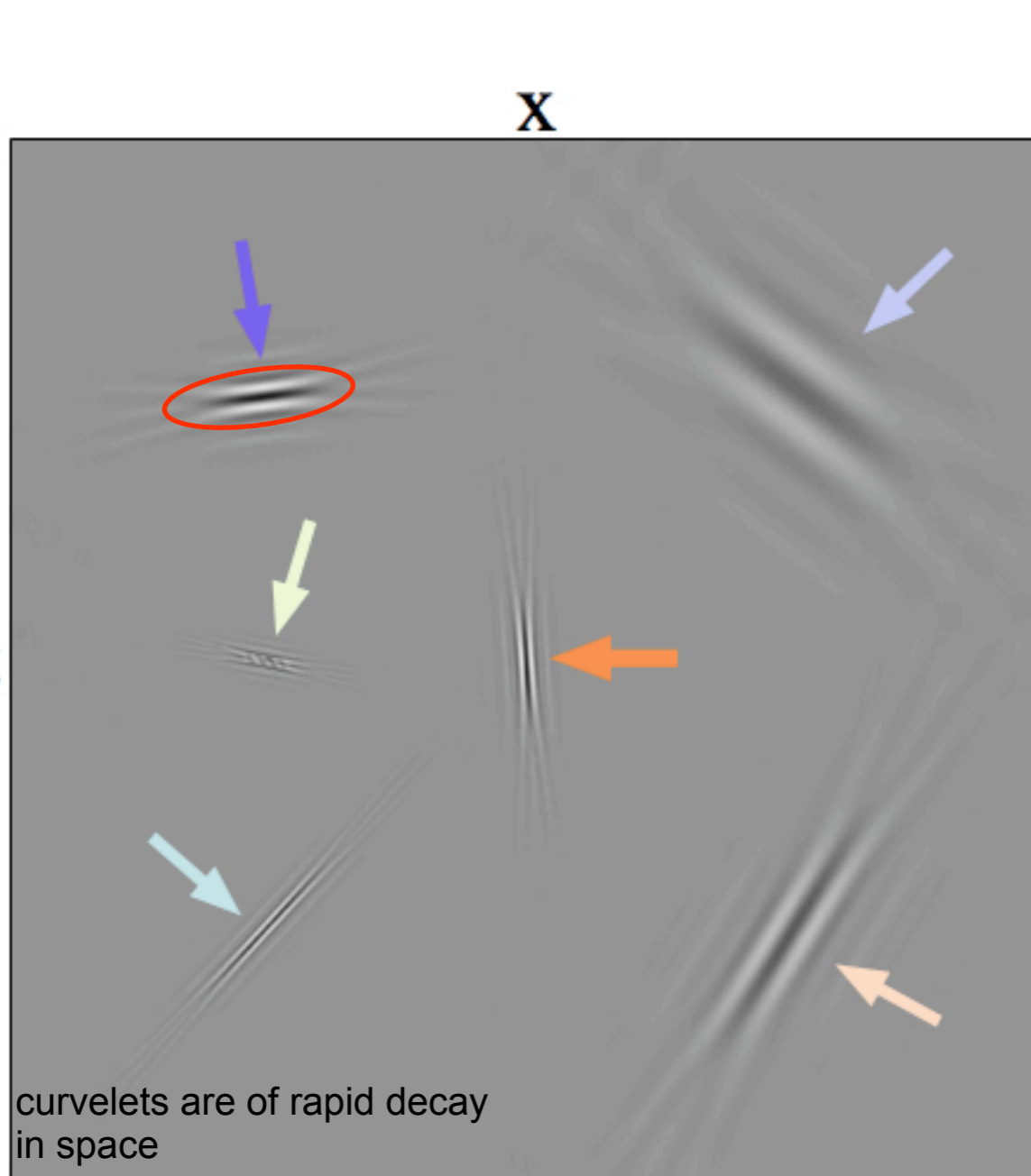
Transform	Underlying assumption
FK	plane waves
linear/parabolic Radon transform	linear/parabolic events
wavelet transform	point-like events (1D singularities)
curvelet transform	curve-like events (2D singularities)

Properties curvelet transform:

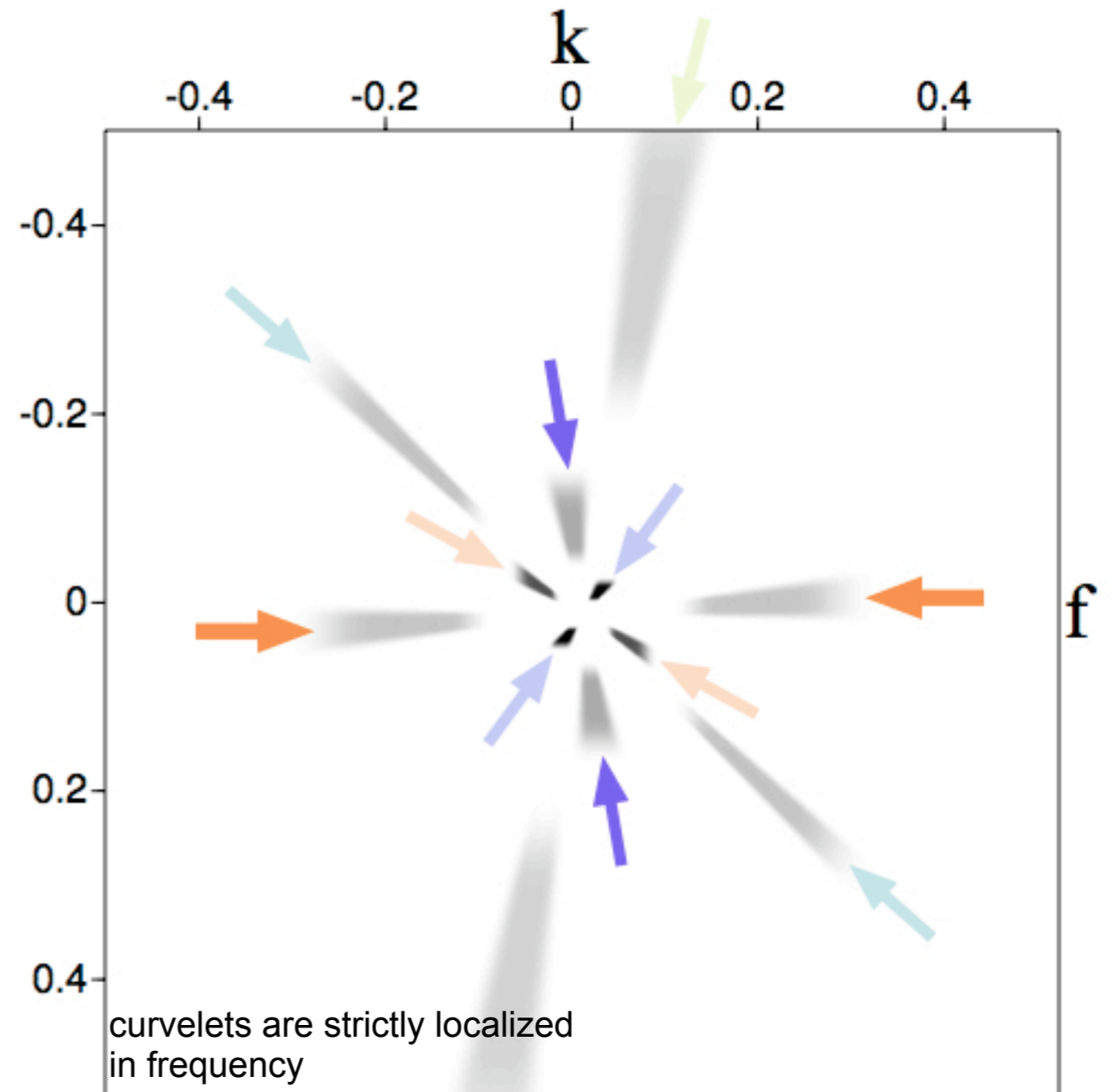
- **multiscale:** tiling of the FK domain into dyadic coronae
- **multi-directional:** coronae sub-partitioned into angular wedges, # of angle doubles every other scale
- **anisotropic:** parabolic scaling principle
- **Rapid decay space**
- **Strictly localized in Fourier**
- **Frame with moderate redundancy (8 X in 2-D and 24 X in 3-D)**



2-D curvelets



$x-t$

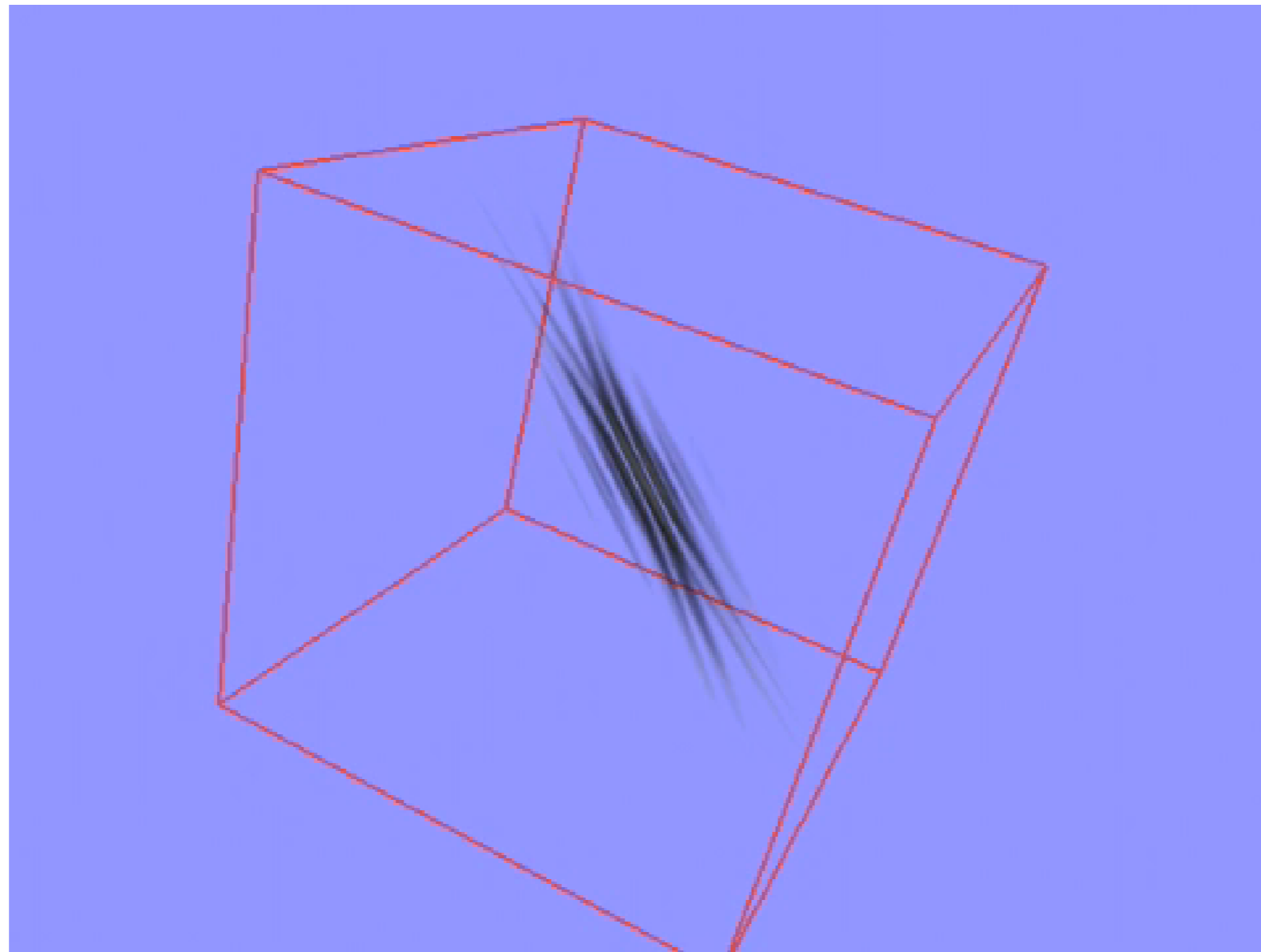


$f-k$

Oscillatory in one direction and smooth in the others!

Obey *parabolic* scaling relation $\text{length} \approx \text{width}^2$

3-D curvelets



Curvelets are oscillatory in one direction and smooth in the others.

Curvelet sparsity promotion



Sparsity-promoting program

Solve for \mathbf{x}_0



with

$$\mathbf{P}_\epsilon : \begin{cases} \tilde{\mathbf{x}} = \arg \min_{\mathbf{x}} \|\mathbf{x}\|_1 & \text{s.t.} \quad \|\mathbf{A}\mathbf{x} - \mathbf{y}\|_2 \leq \epsilon \\ \tilde{\mathbf{m}} = \mathbf{C}^T \tilde{\mathbf{x}} \end{cases}$$

*restricted compounded
curvelet representation
of ideal data*

- exploit **sparsity** in the curvelet domain as a **prior**.
- find the sparsest set of curvelet coefficients that match the data.
- invert an *underdetermined* system.

Focused wavefield reconstruction with curvelets



Focused recovery

Non-data-adaptive Curvelet Reconstruction with Sparsity-promoting Inversion (CRSI) derives from ***curvelet-sparsity*** of seismic data.

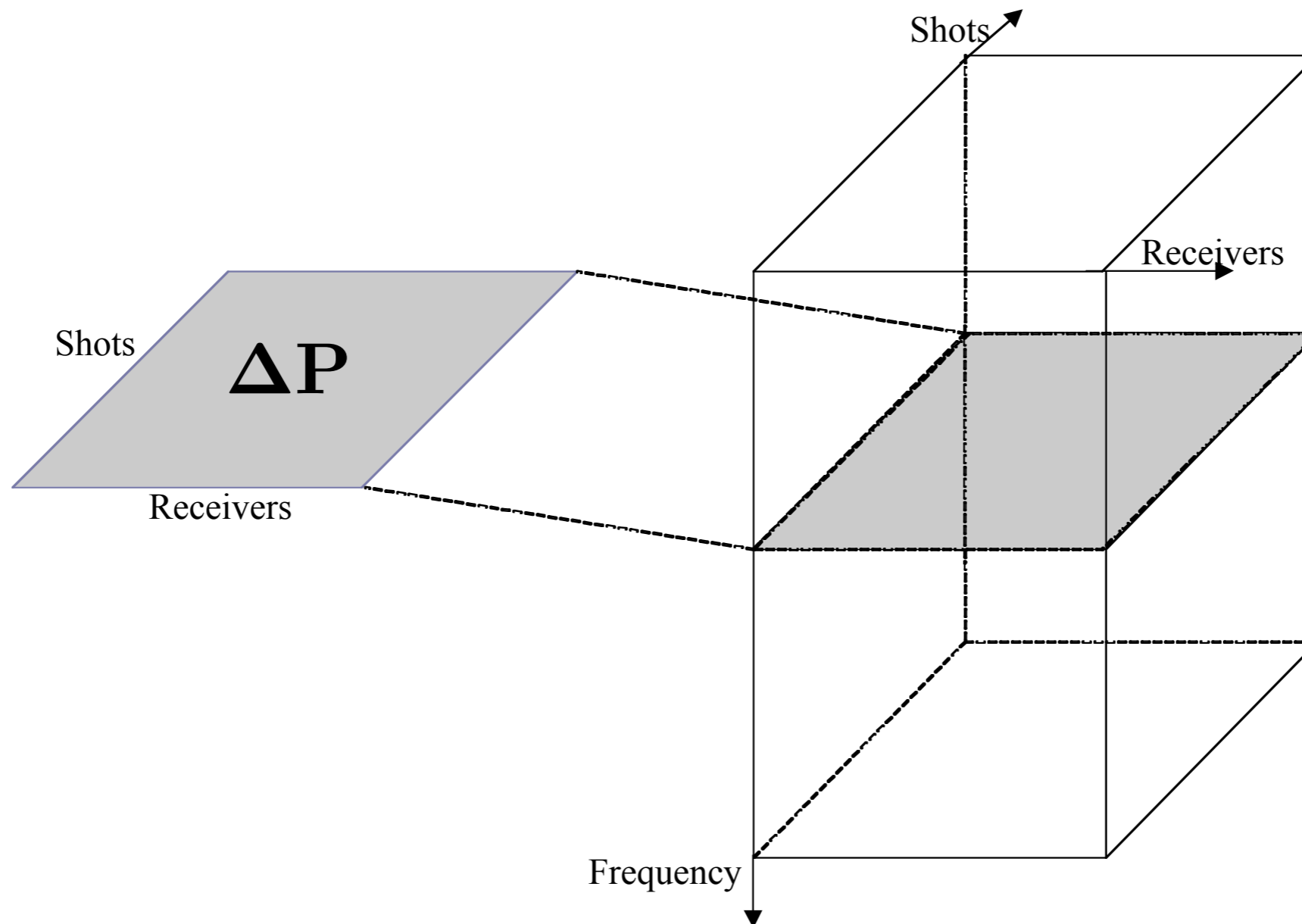
Berkhout and Verschuur's ***data-adaptive*** Focal transform derives from ***focusing*** of seismic data by the ***major*** primaries.

Both approaches entail the ***inversion*** of a linear operator.

Combination of the two yields

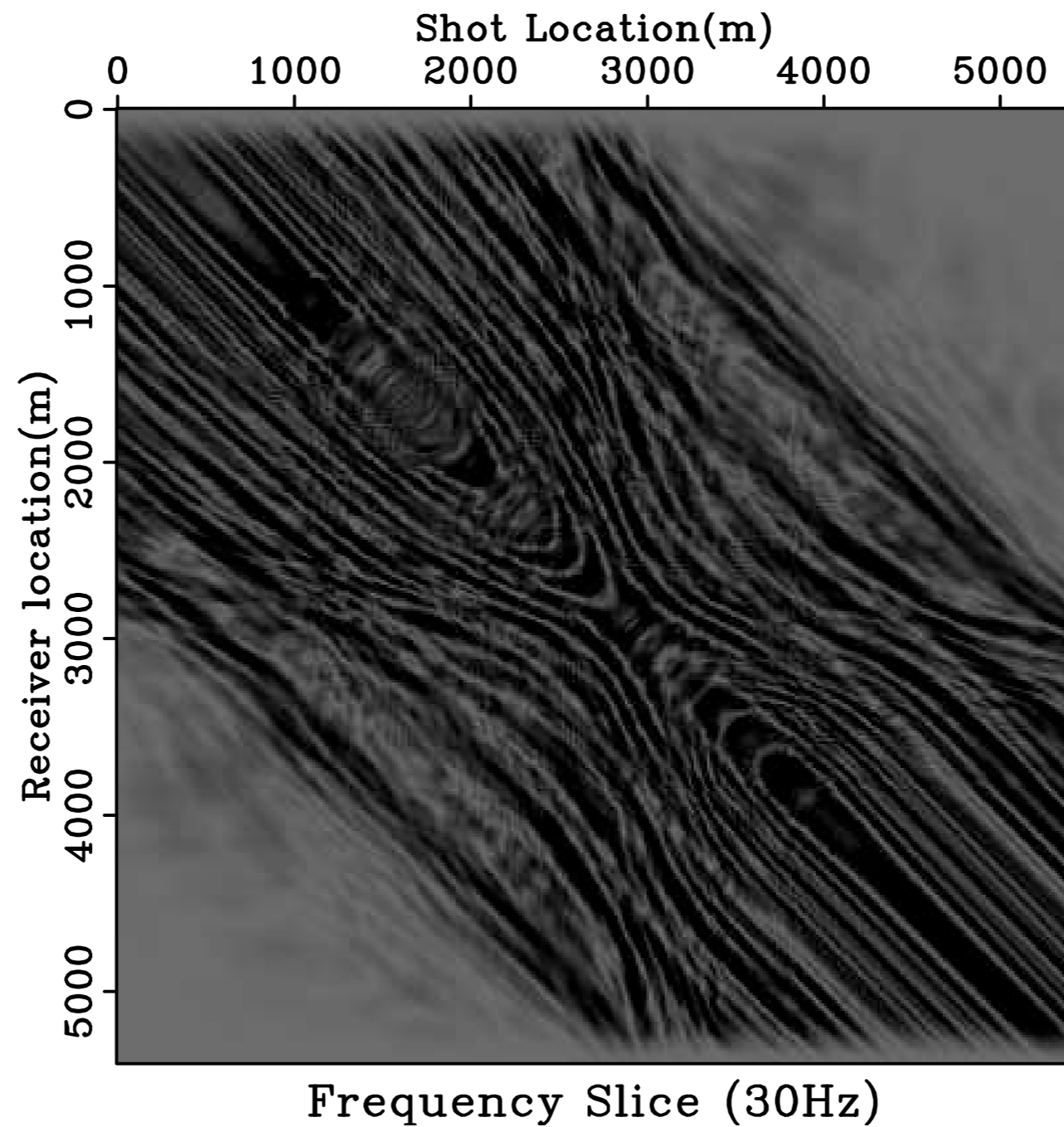
- *improved* focusing => more *sparsity*
- *curvelet sparsity* => better *focusing*

Primary operator



Frequency slice from data matrix with dominant primaries.

Primary operator



Primary operator

Primaries to first-order multiples:

$$\Delta \mathbf{p} \mapsto \mathbf{m}^1 = (\Delta \mathbf{P} \mathcal{A} *_{t,x} \Delta \mathbf{p})$$

First-order multiples into primaries:

$$\mathbf{m}^1 \mapsto \Delta \mathbf{p} \approx (\Delta \mathbf{P} \mathcal{A} \otimes_{t,x} \Delta \mathbf{p})$$

with the acquisition matrix

$$\mathcal{A} = \left(\mathcal{S}^\dagger \mathbf{R} \mathcal{D}^\dagger \right)$$

“inverting” for source and receiver wavelet wavelets geometry and surface reflectivity.

Curvelet-based Focal transform

Solve with 3-D curvelet transform

$$\mathbf{P}_\epsilon : \begin{cases} \tilde{\mathbf{x}} = \arg \min_{\mathbf{x}} \|\mathbf{x}\|_1 & \text{s.t.} \quad \|\mathbf{A}\mathbf{x} - \mathbf{y}\|_2 \leq \epsilon \\ \tilde{\mathbf{f}} = \mathbf{S}^T \tilde{\mathbf{x}} \end{cases}$$

with

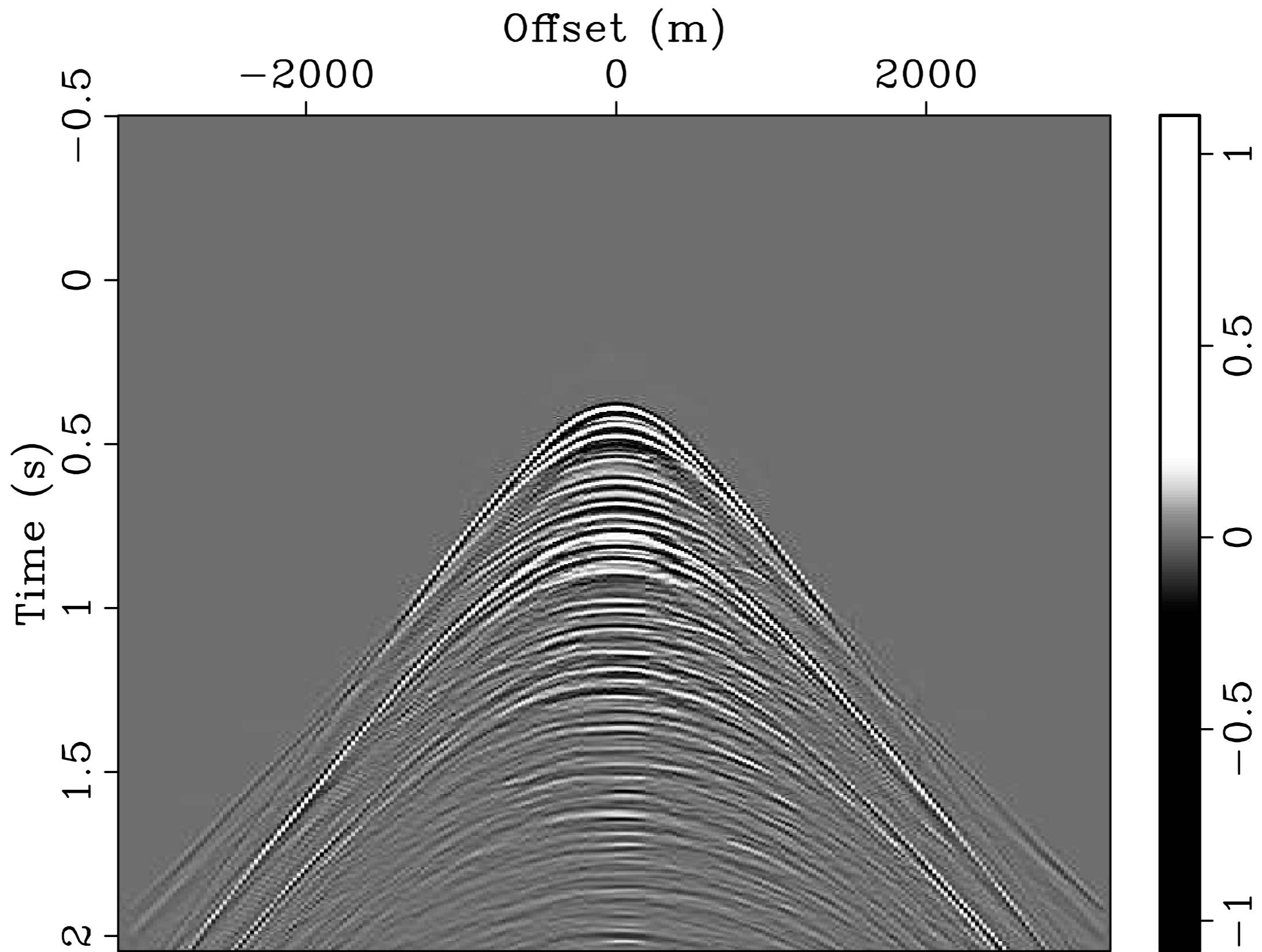
$$\mathbf{A} := \Delta \mathbf{P} \mathbf{C}^T \text{ and } \Delta \mathbf{P} := \mathbf{F}^H \text{block diag}\{\Delta \mathbf{p}\} \mathbf{F}$$

$$\mathbf{S} := \mathbf{C}$$

$$\mathbf{y} = \mathbf{p}$$

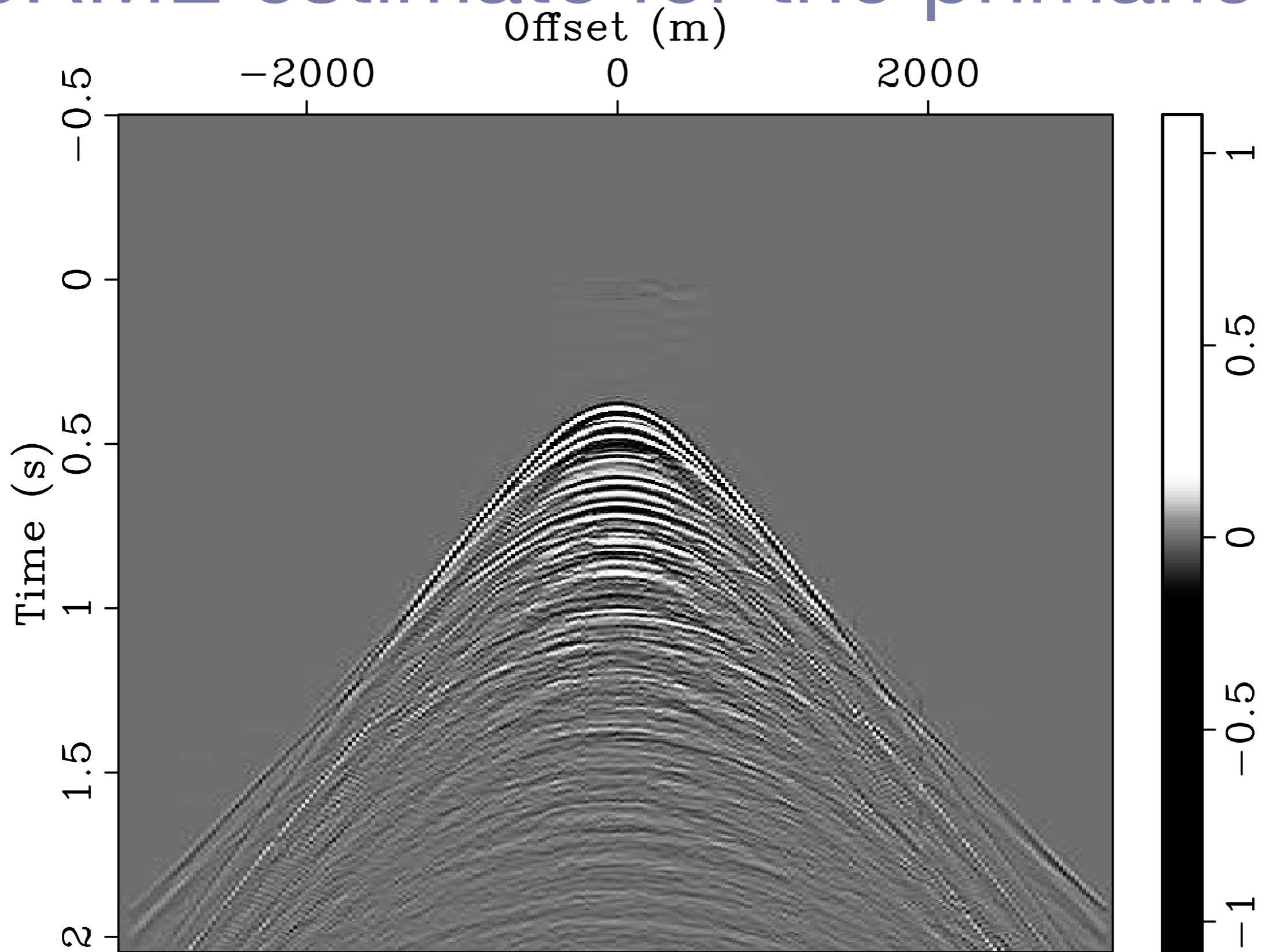
$$\mathbf{p} = \text{total data.}$$

Total data



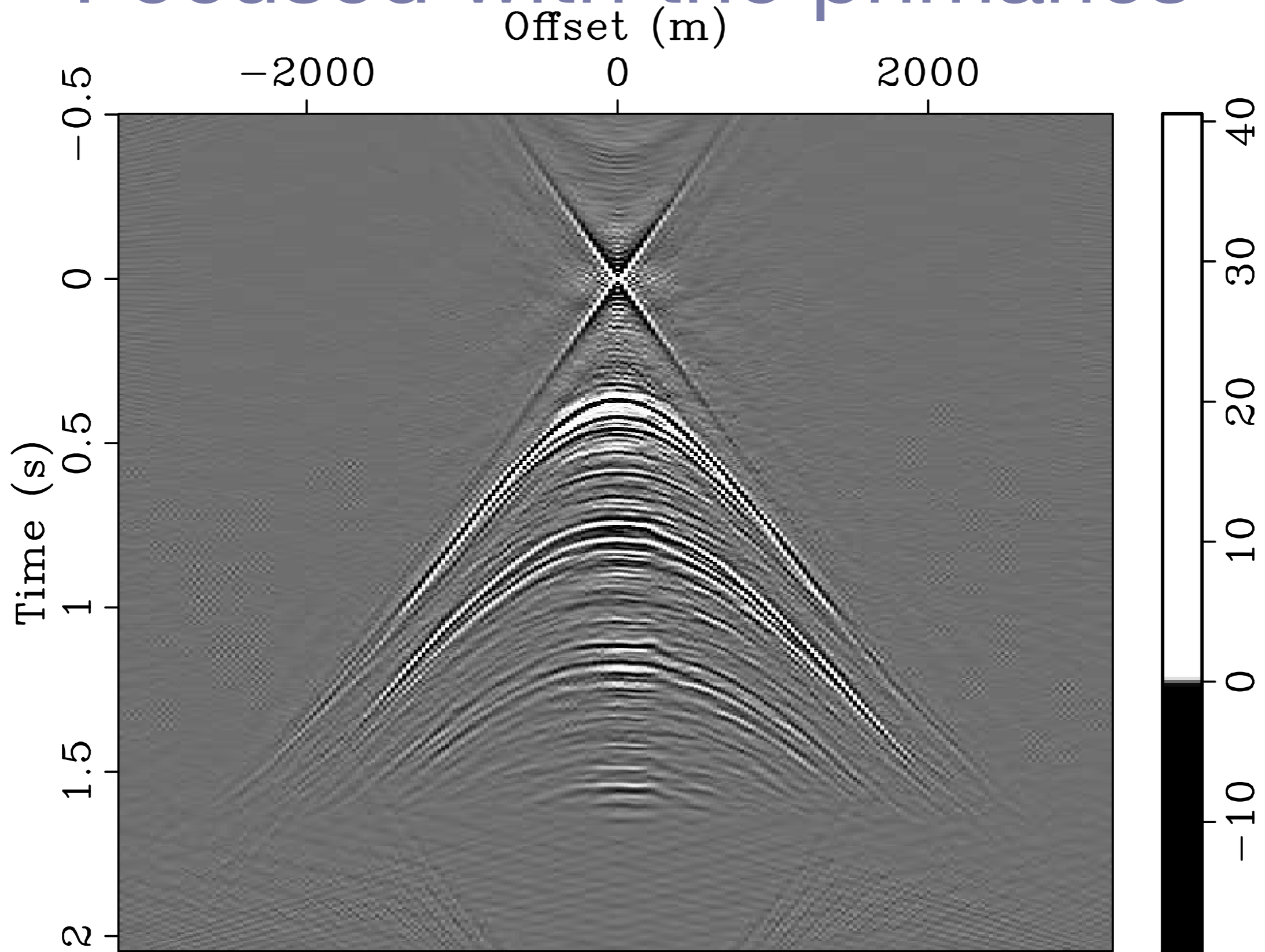
Original data

SRME estimate for the primaries

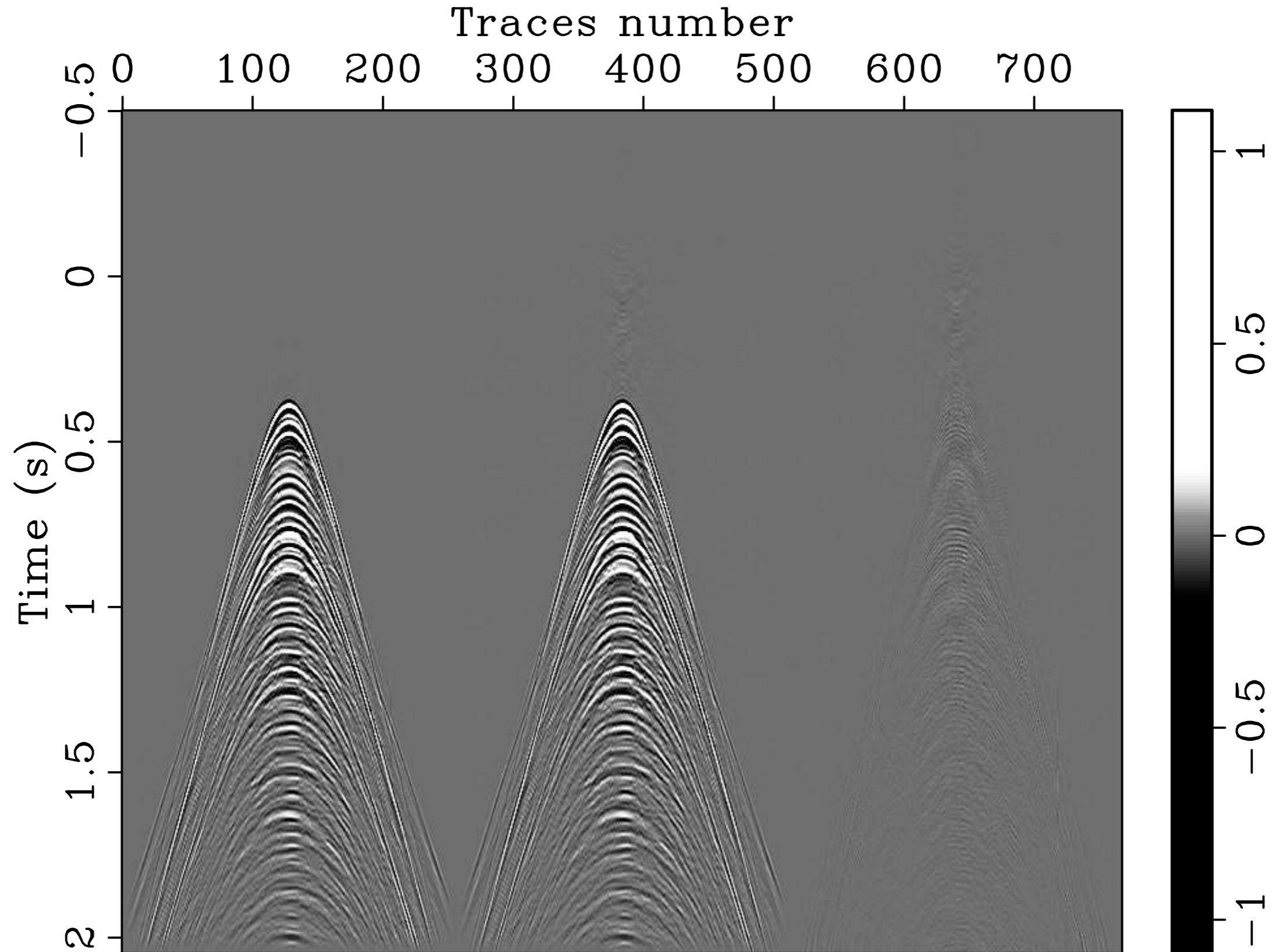


SRME primaries

Focused with the primaries



Difference



Recovery with focussing

Solve

$$\mathbf{P}_\epsilon : \begin{cases} \tilde{\mathbf{x}} = \arg \min_{\mathbf{x}} \|\mathbf{x}\|_1 & \text{s.t.} \quad \|\mathbf{A}\mathbf{x} - \mathbf{y}\|_2 \leq \epsilon \\ \tilde{\mathbf{f}} = \mathbf{S}^T \tilde{\mathbf{x}} \end{cases}$$

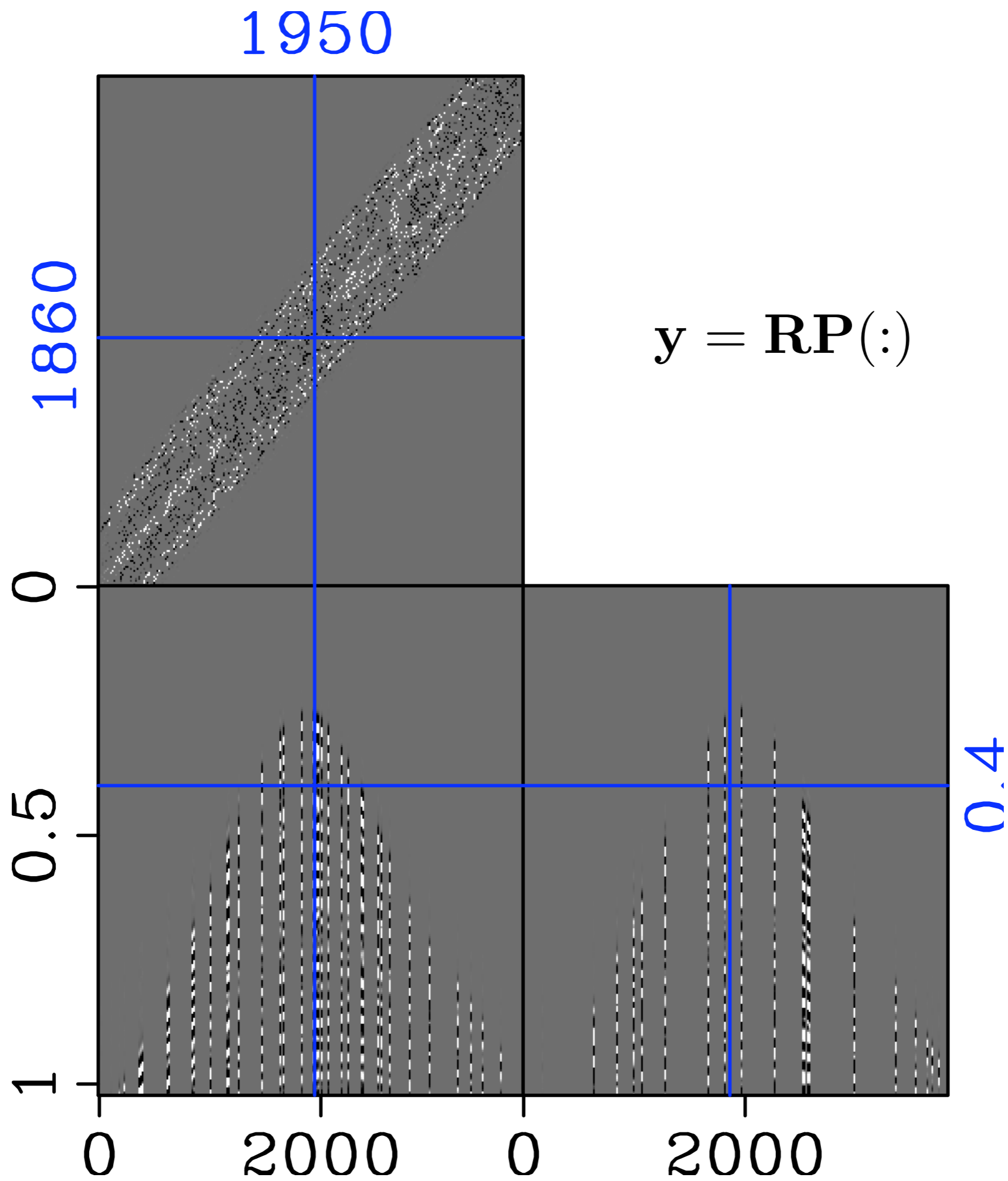
with

$$\mathbf{A} := \mathbf{R}\Delta\mathbf{P}\mathbf{C}^T$$

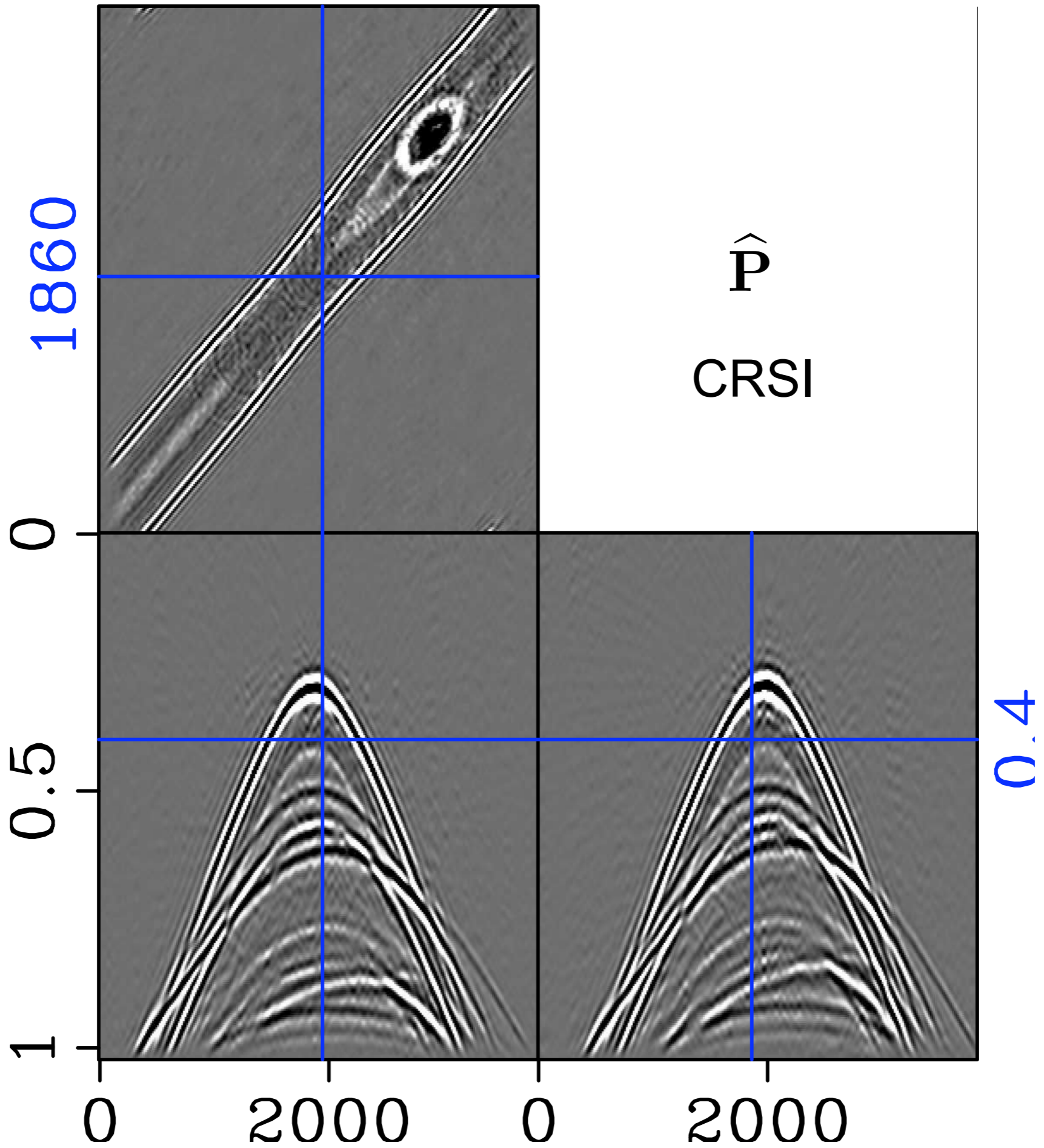
$$\mathbf{S}^T := \Delta\mathbf{P}\mathbf{C}^T$$

$$\mathbf{y} = \mathbf{R}\mathbf{p}$$

$$\mathbf{R} = \text{picking operator.}$$

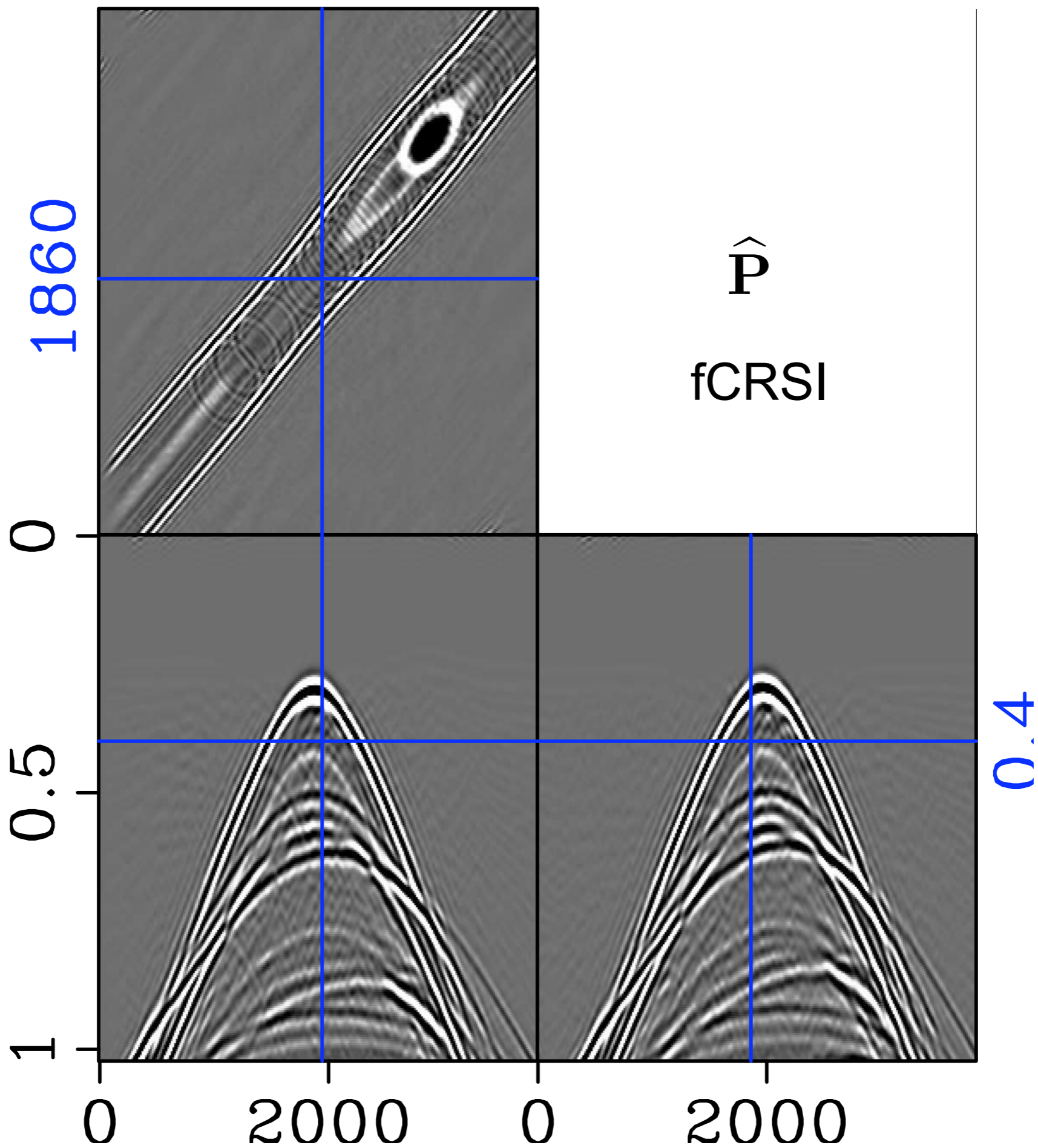


1950

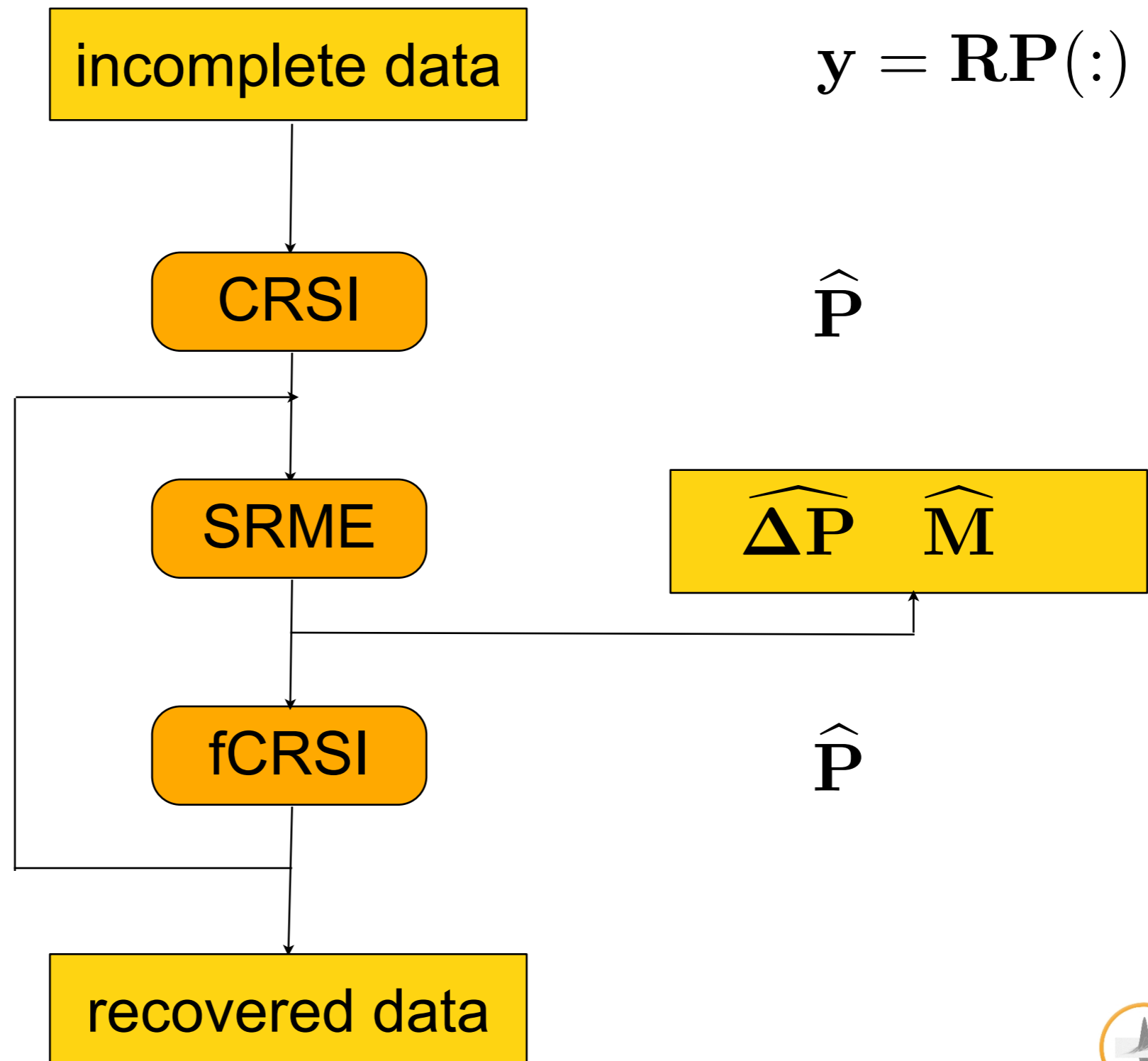


\hat{P}
CRSI

1950

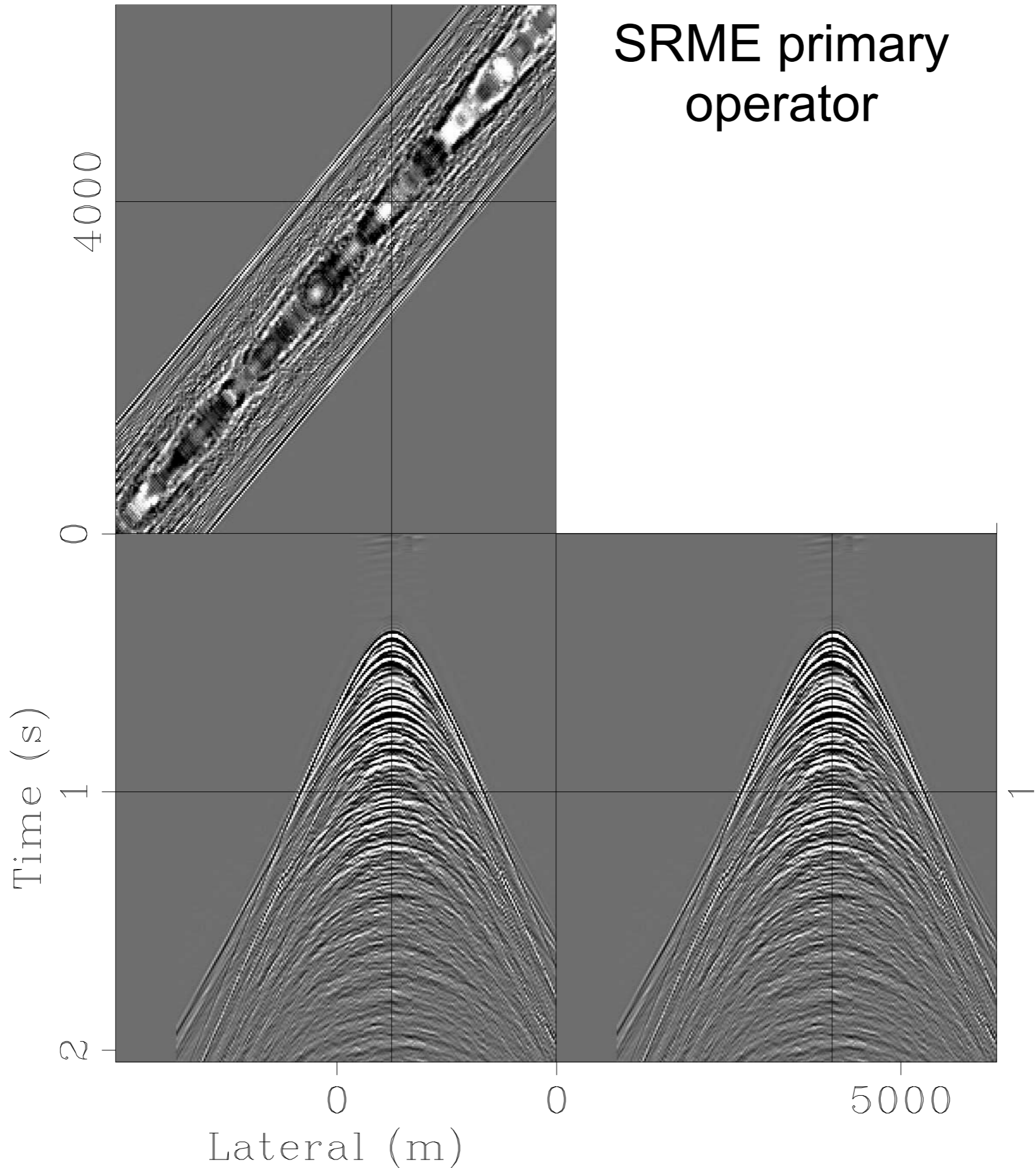


Multiple prediction with fCRSI



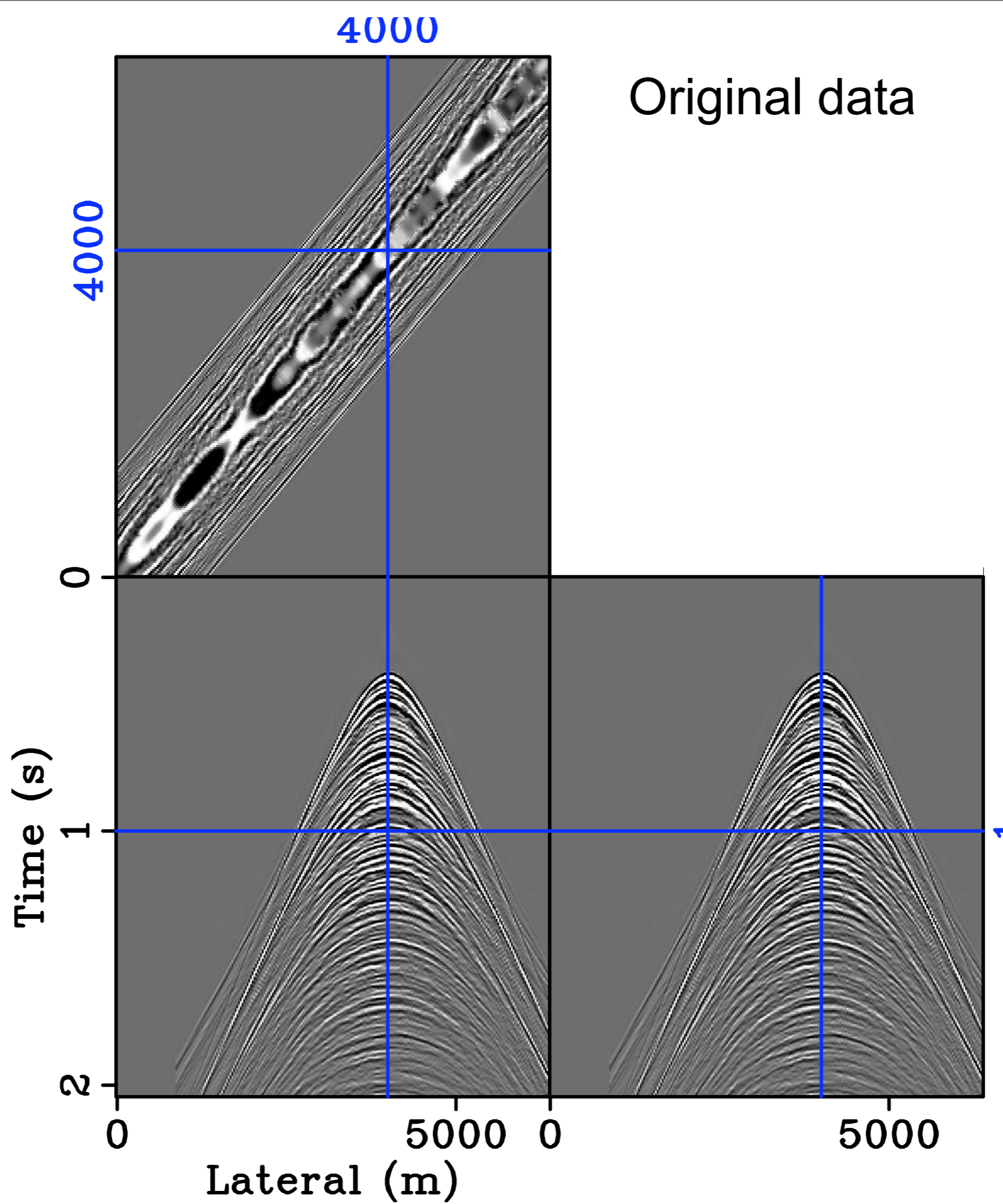
800

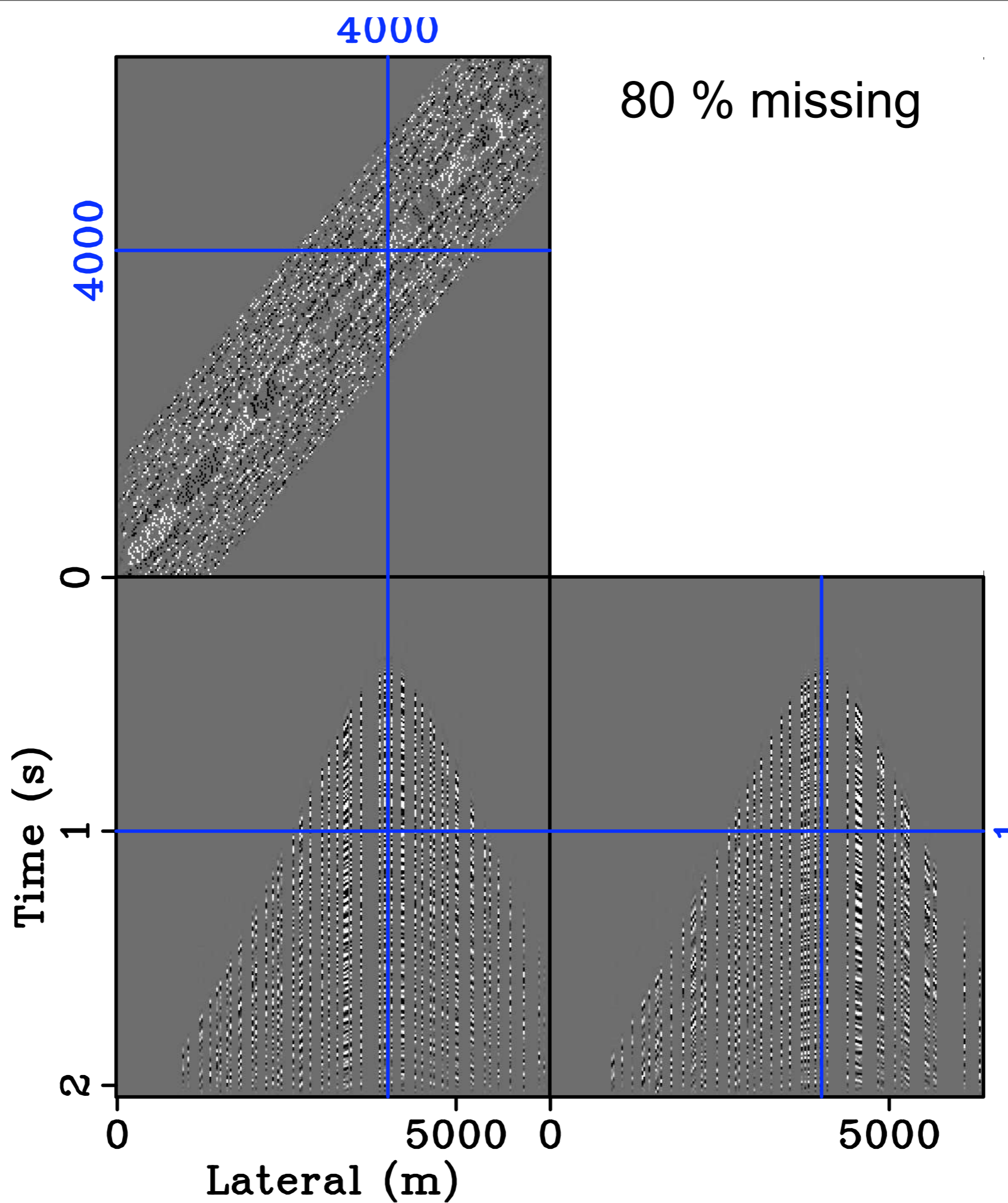
SRME primary operator

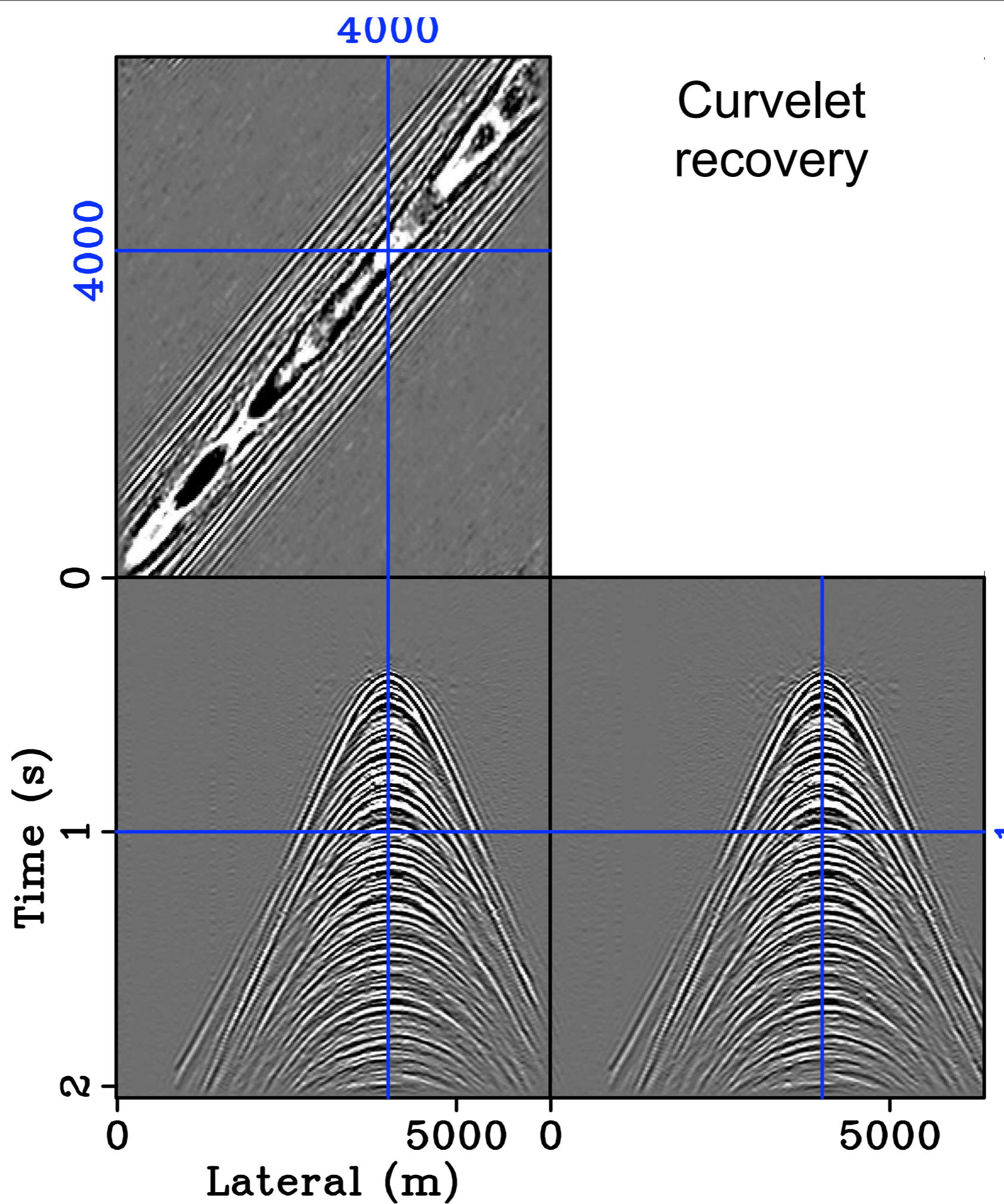


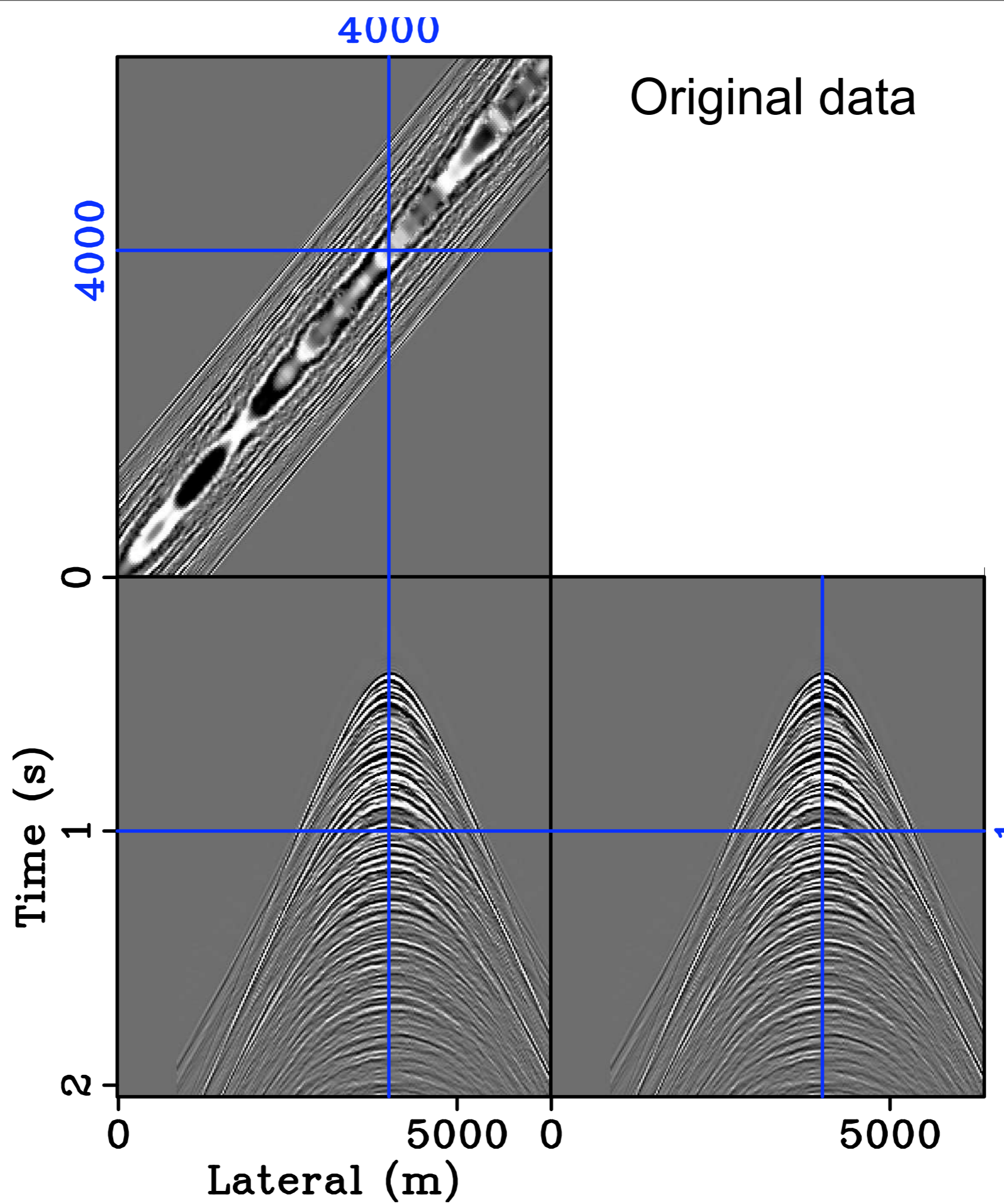
Wavefield reconstruction with fCRSI

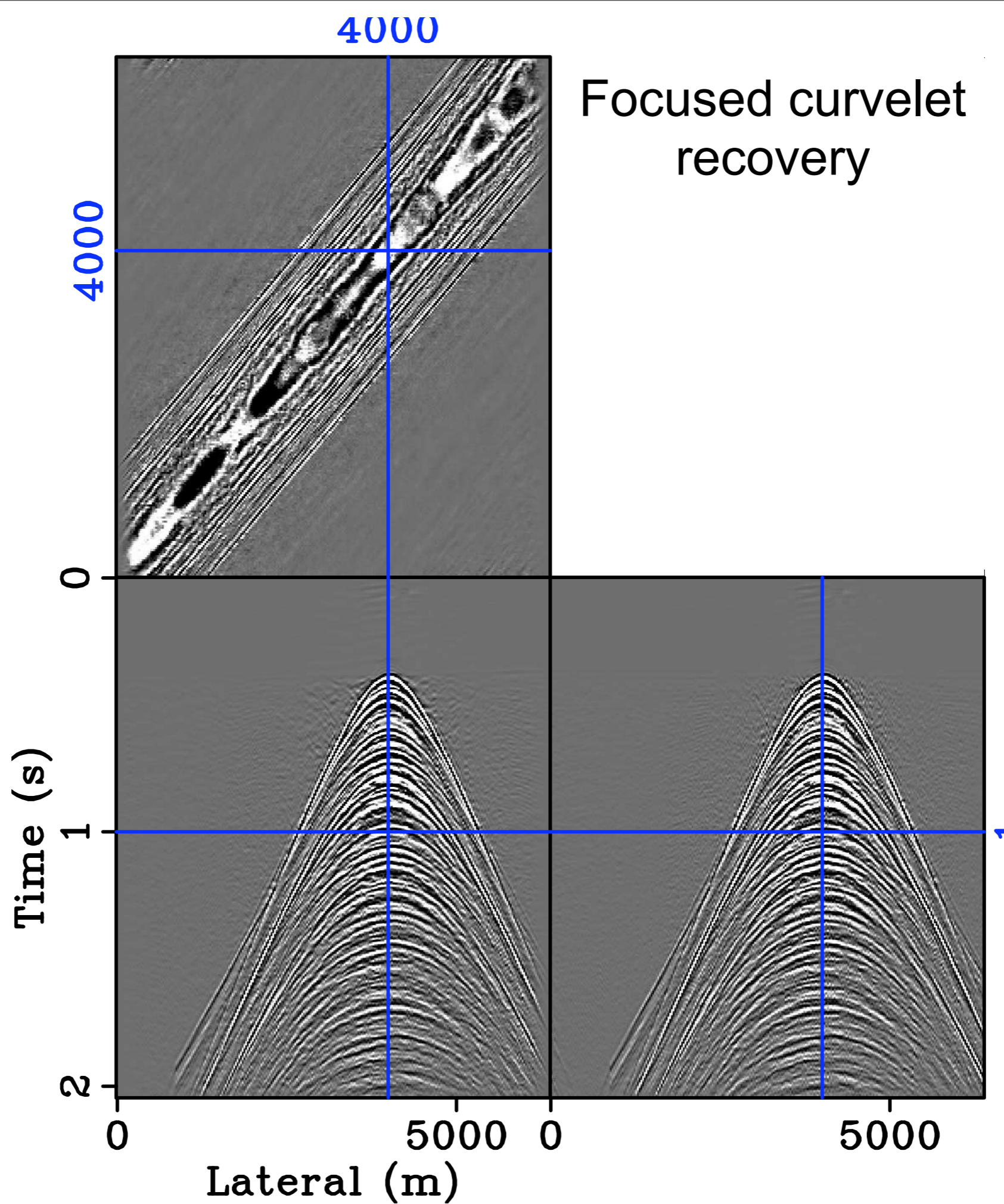


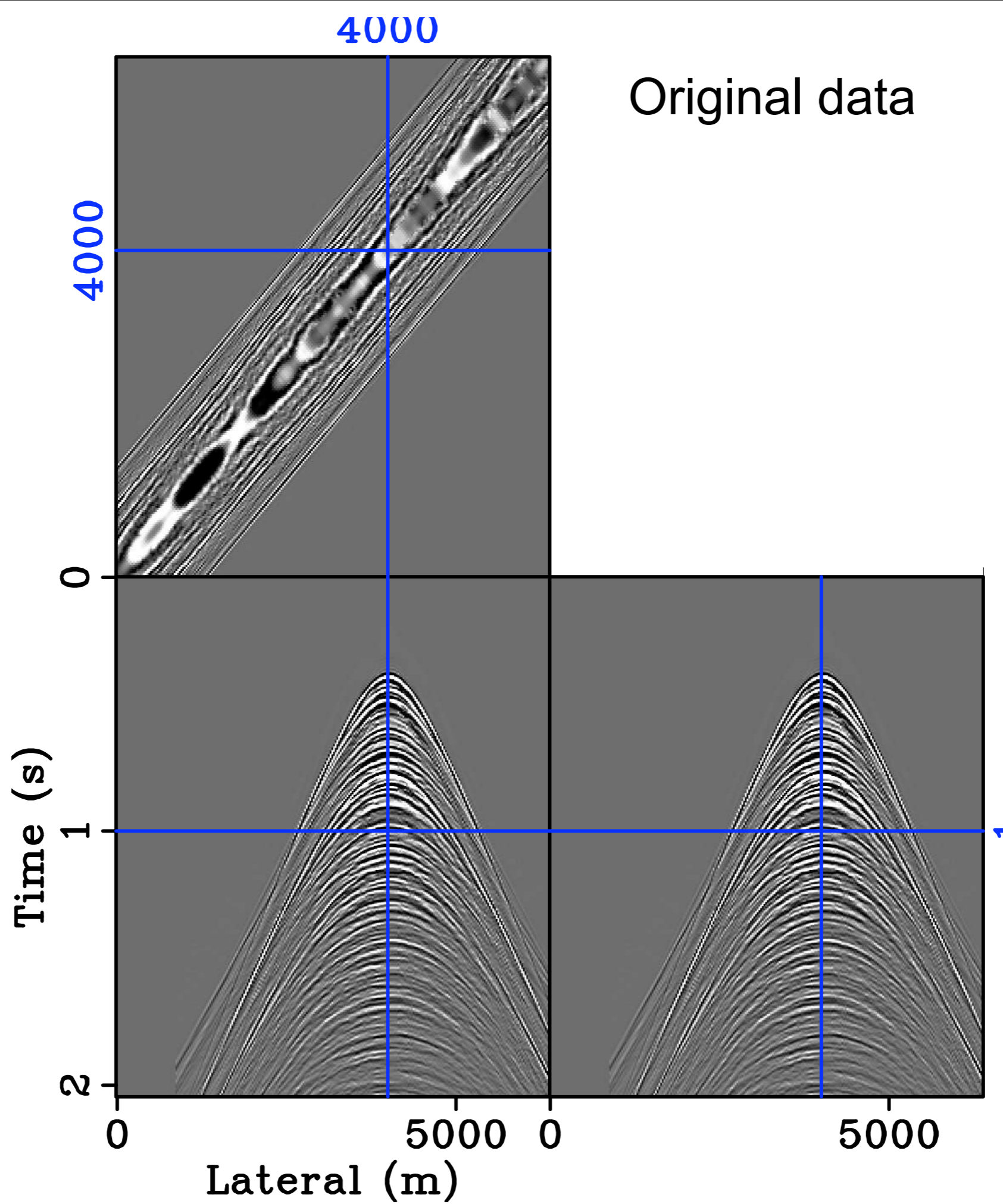




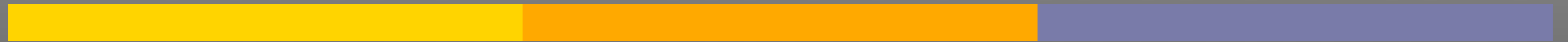


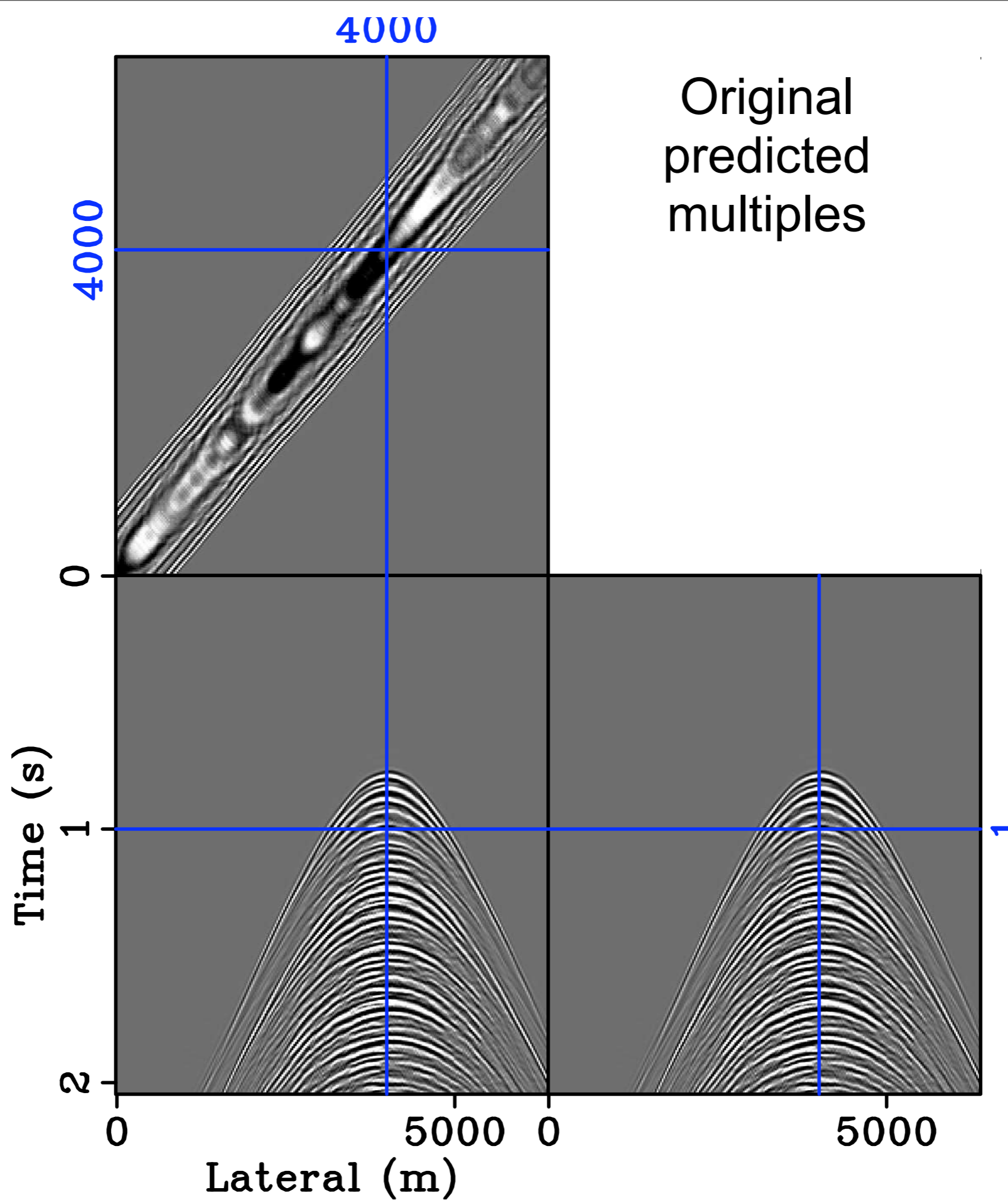


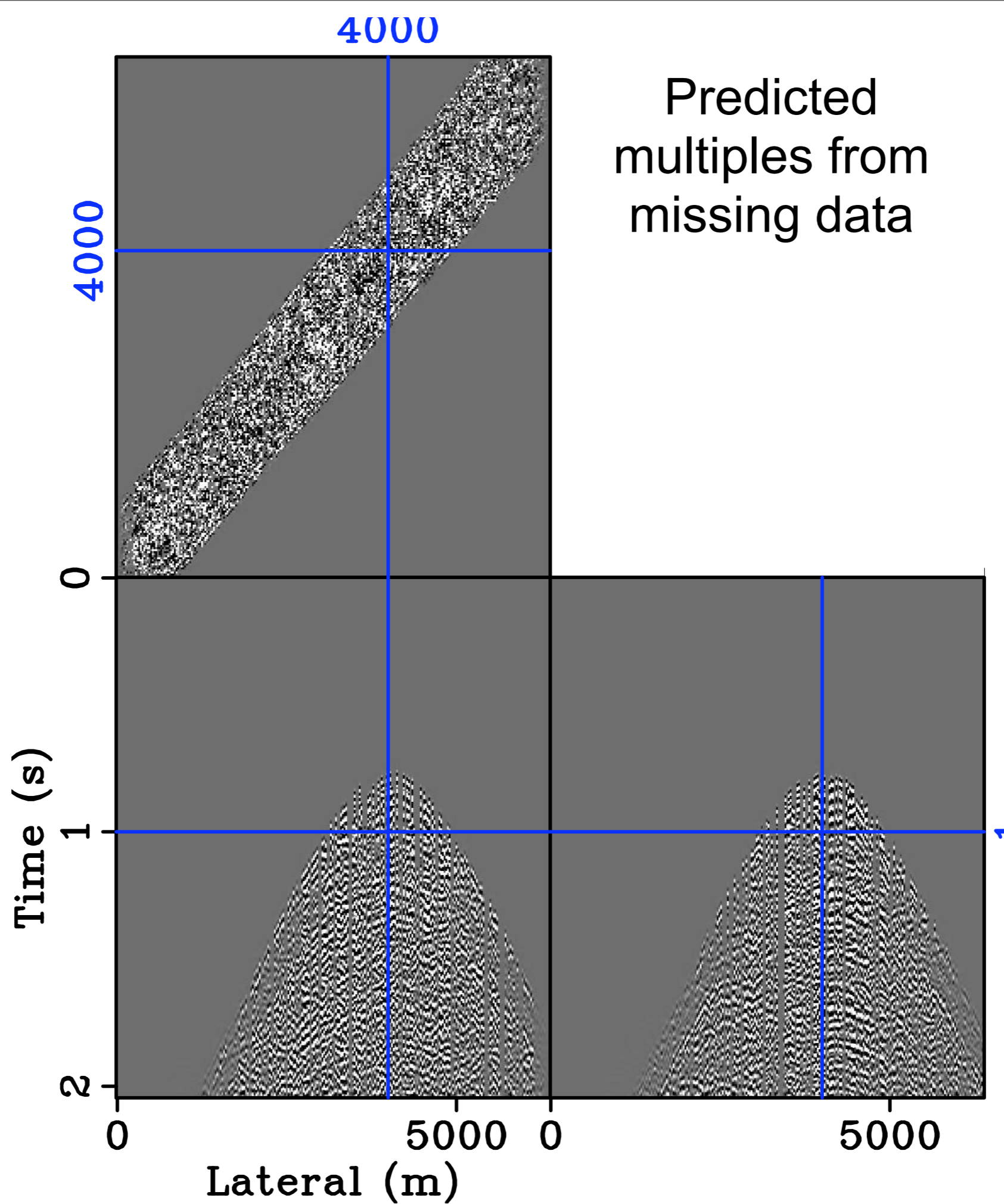


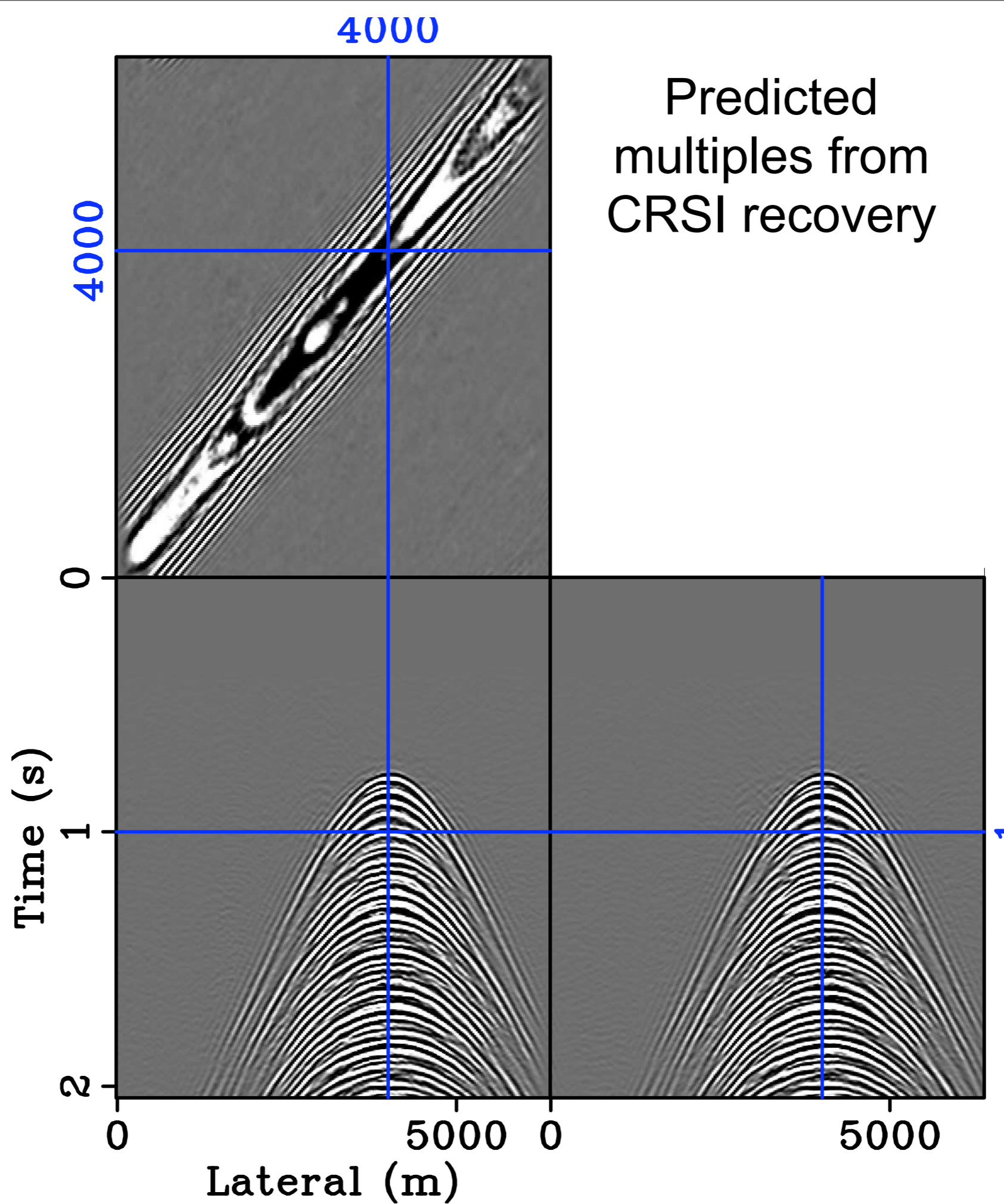


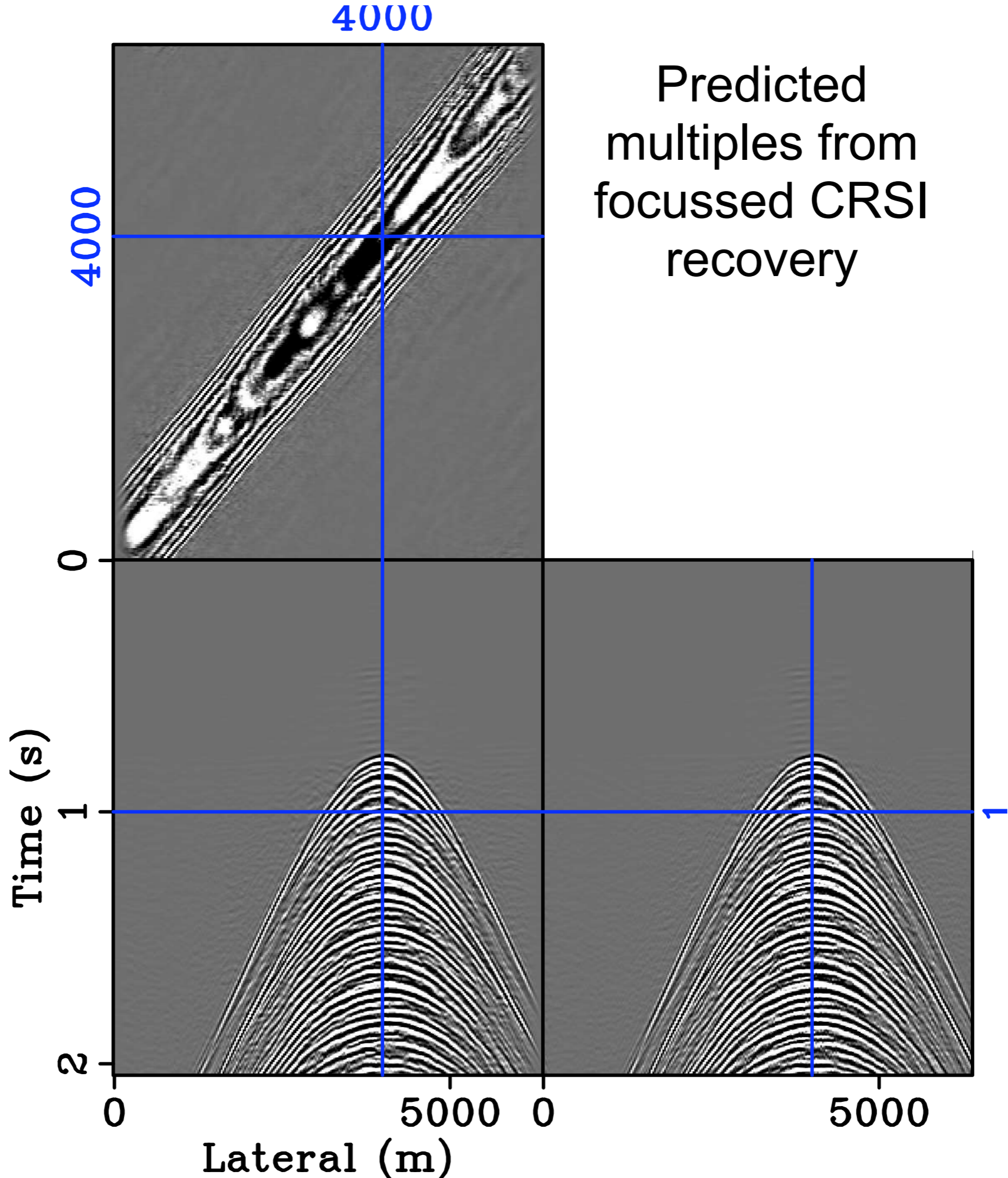
Multiple prediction

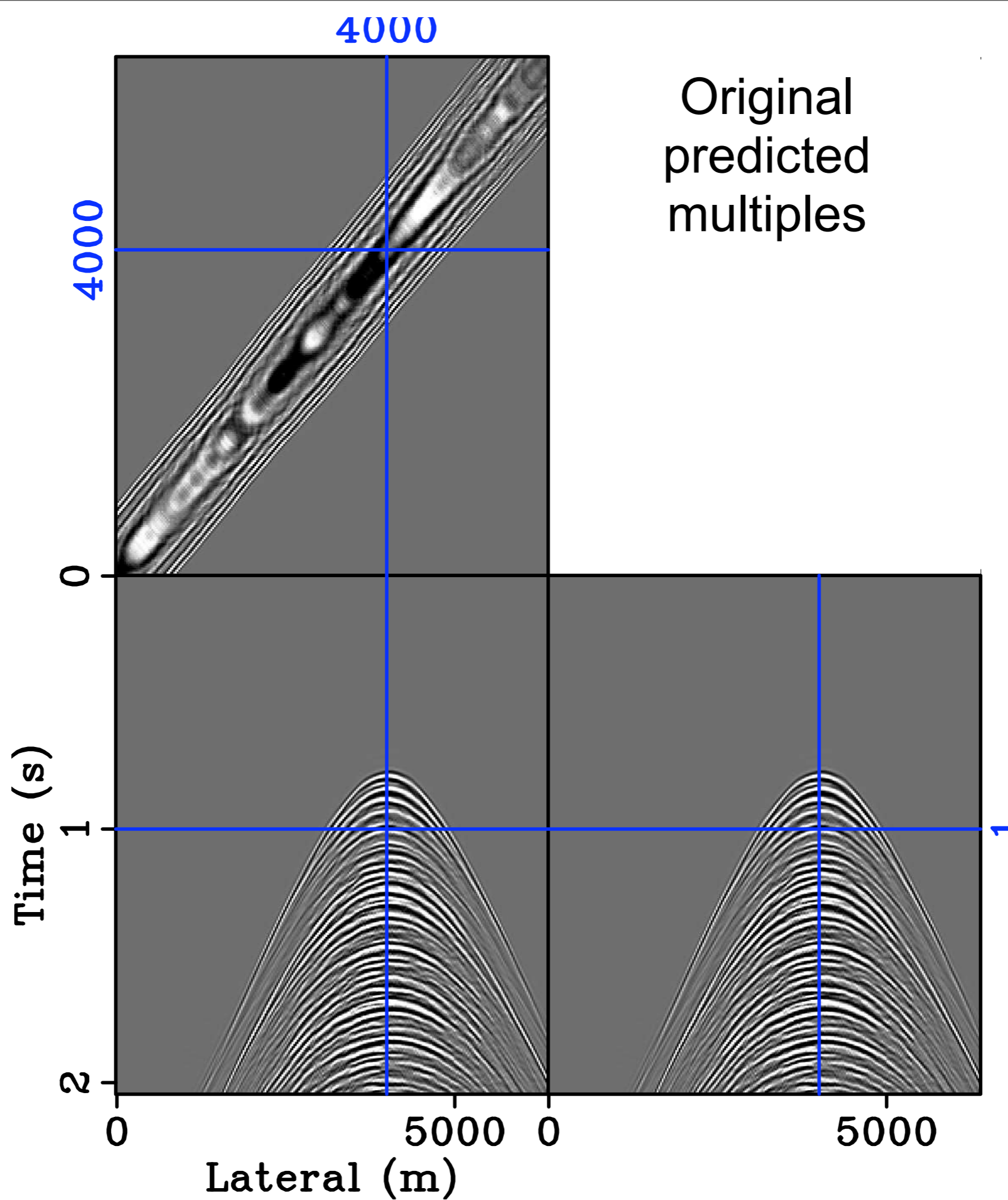




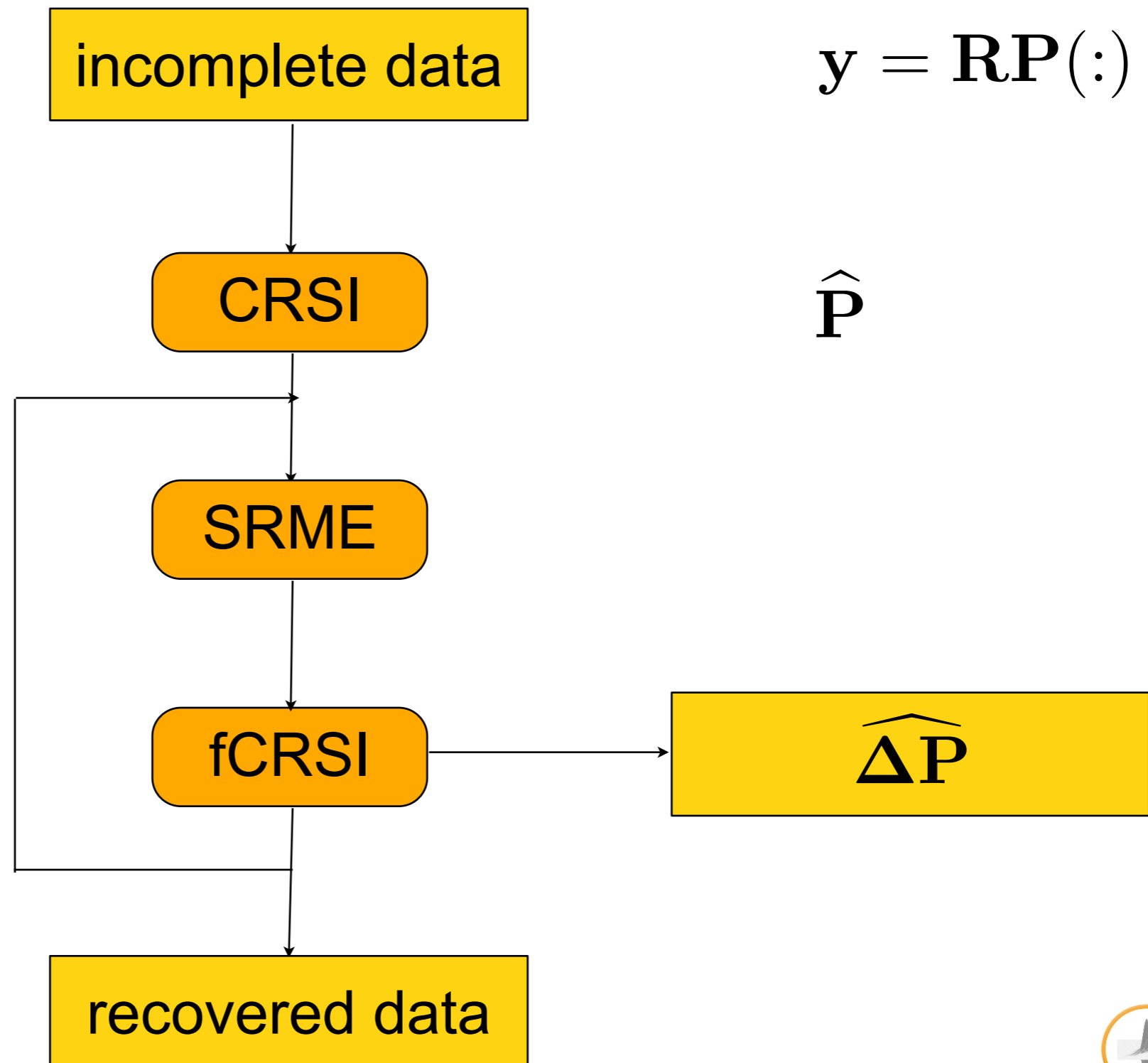








Primary prediction with fCRSI



Curvelet-based Focal transform

Solve

$$\mathbf{P}_\epsilon : \begin{cases} \tilde{\mathbf{x}} = \arg \min_{\mathbf{x}} \|\mathbf{x}\|_1 & \text{s.t.} \quad \|\mathbf{A}\mathbf{x} - \mathbf{y}\|_2 \leq \epsilon \\ \tilde{\mathbf{f}} = \mathbf{S}^T \tilde{\mathbf{x}} \end{cases}$$

with

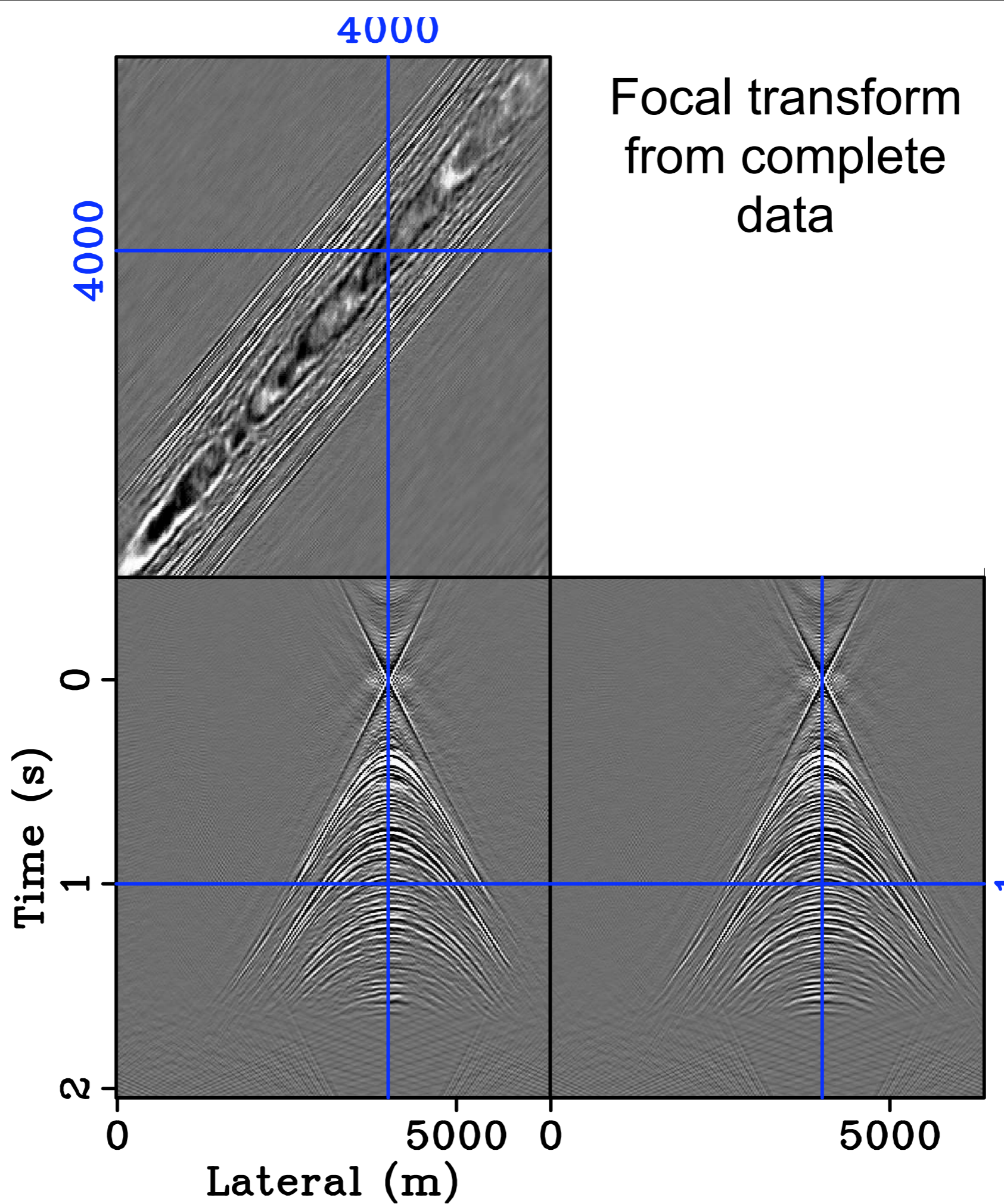
$$\mathbf{A} := \Delta \mathbf{P} \mathbf{C}^T$$

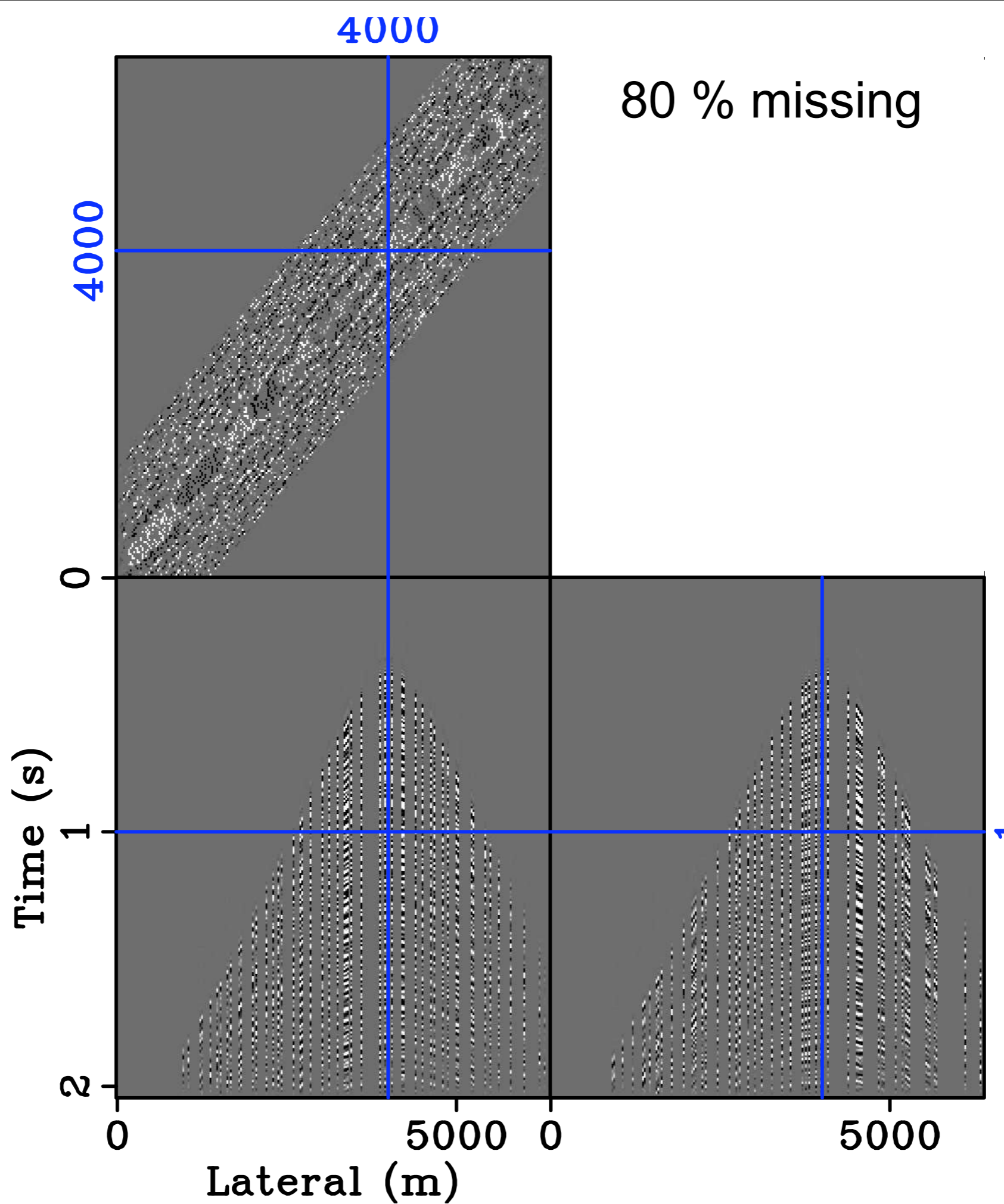
$$\mathbf{S} := \mathbf{C}$$

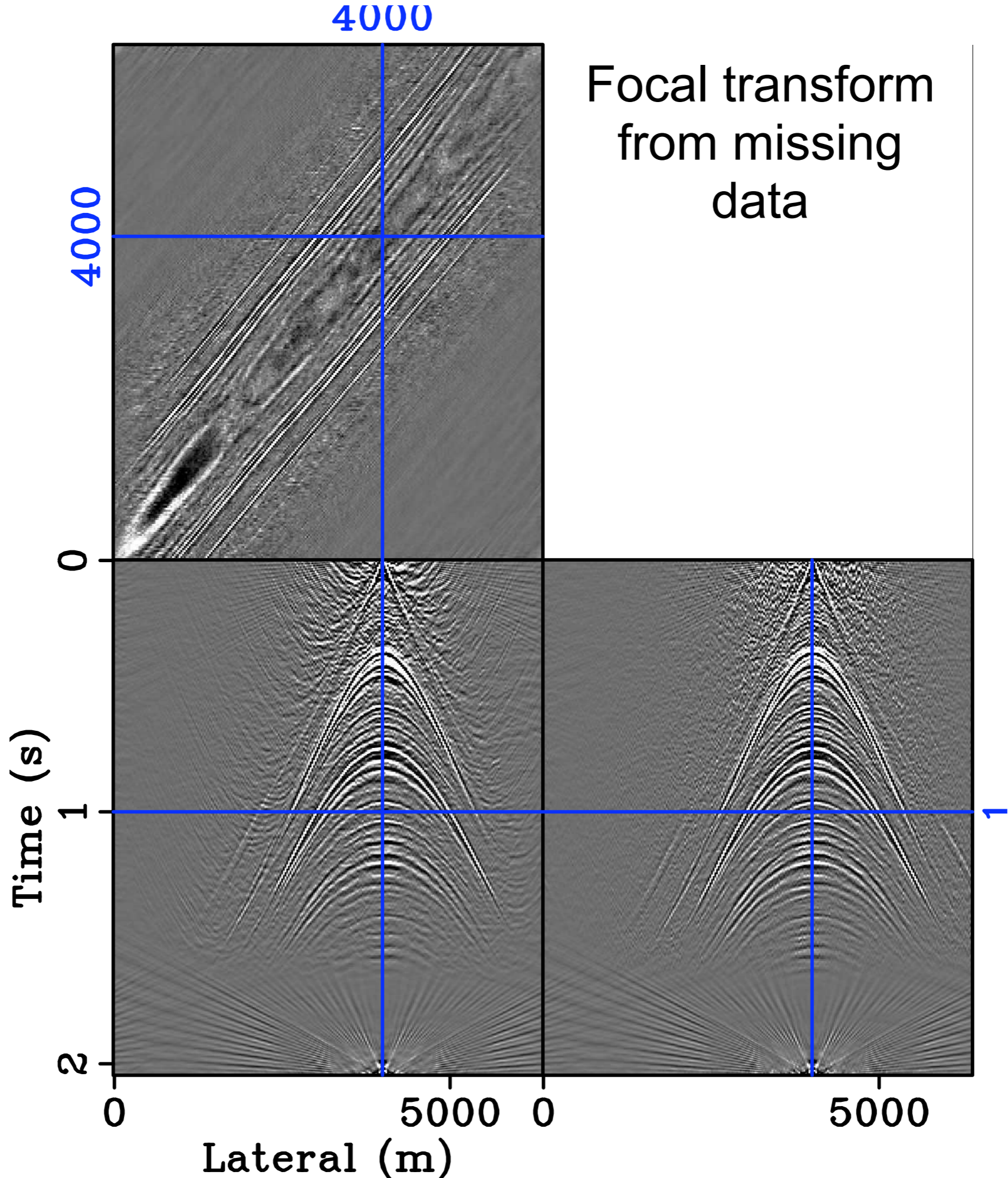
$$\mathbf{y} = \mathbf{P}(:,)$$

$$\mathbf{P} = \text{total data}$$

$$\tilde{\mathbf{f}} = \text{focused data.}$$







An encore ...
preliminary results for
the data inverse



Curvelet-based seismic data inverse

$$\mathbf{P}_\epsilon : \begin{cases} \tilde{\mathbf{x}} = \arg \min_{\mathbf{x}} \|\mathbf{x}\|_1 & \text{s.t.} \quad \|\mathbf{A}\mathbf{x} - \mathbf{y}\|_2 \leq \epsilon \\ \tilde{\mathbf{p}}^{-1} = \mathbf{S}^T \tilde{\mathbf{x}} \end{cases}$$

with $\mathbf{A} := \mathbf{P}\mathbf{C}^T$

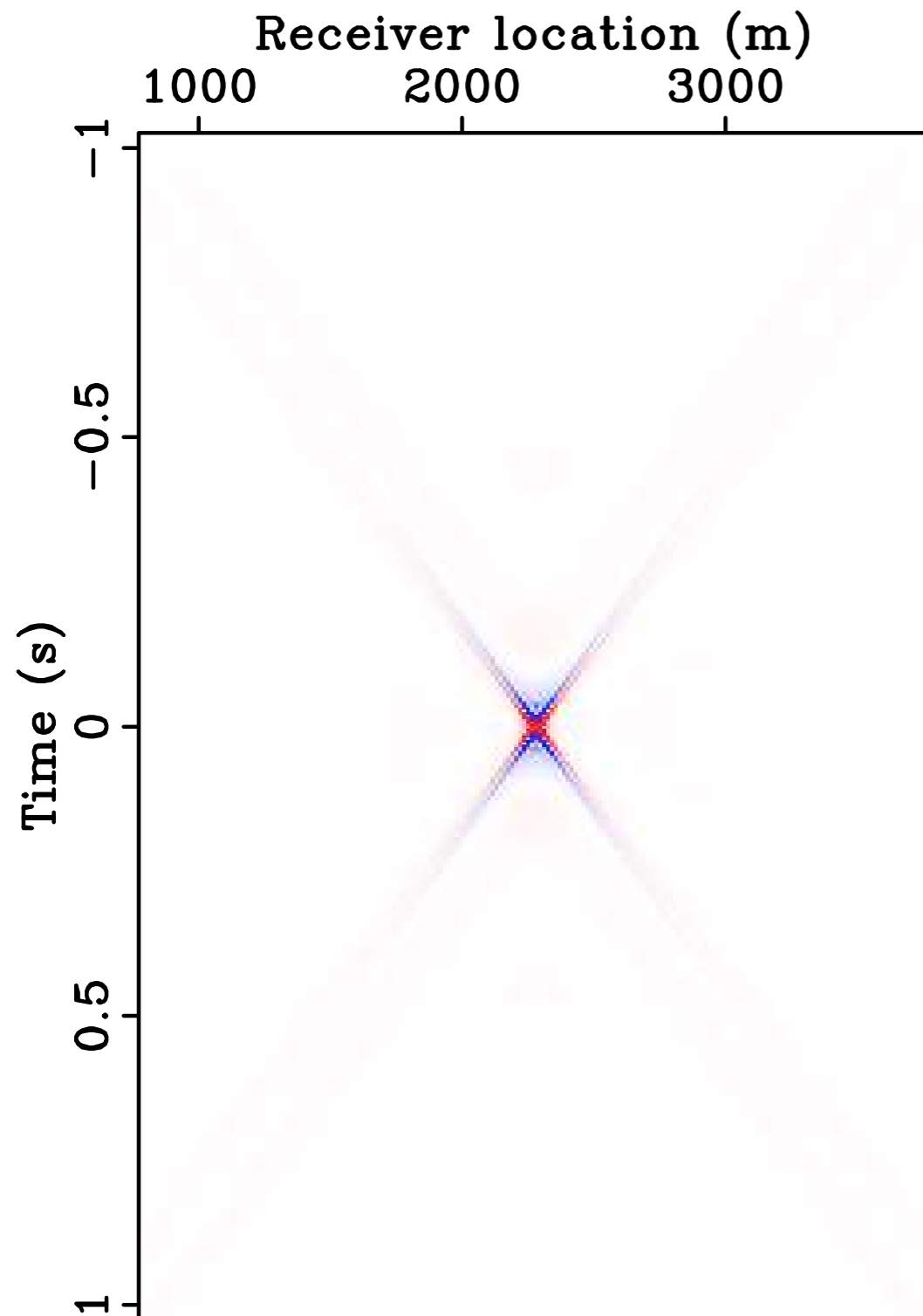
$$\mathbf{S}^T := \mathbf{C}^T$$

$$\mathbf{y} = \hat{\mathbf{I}}$$

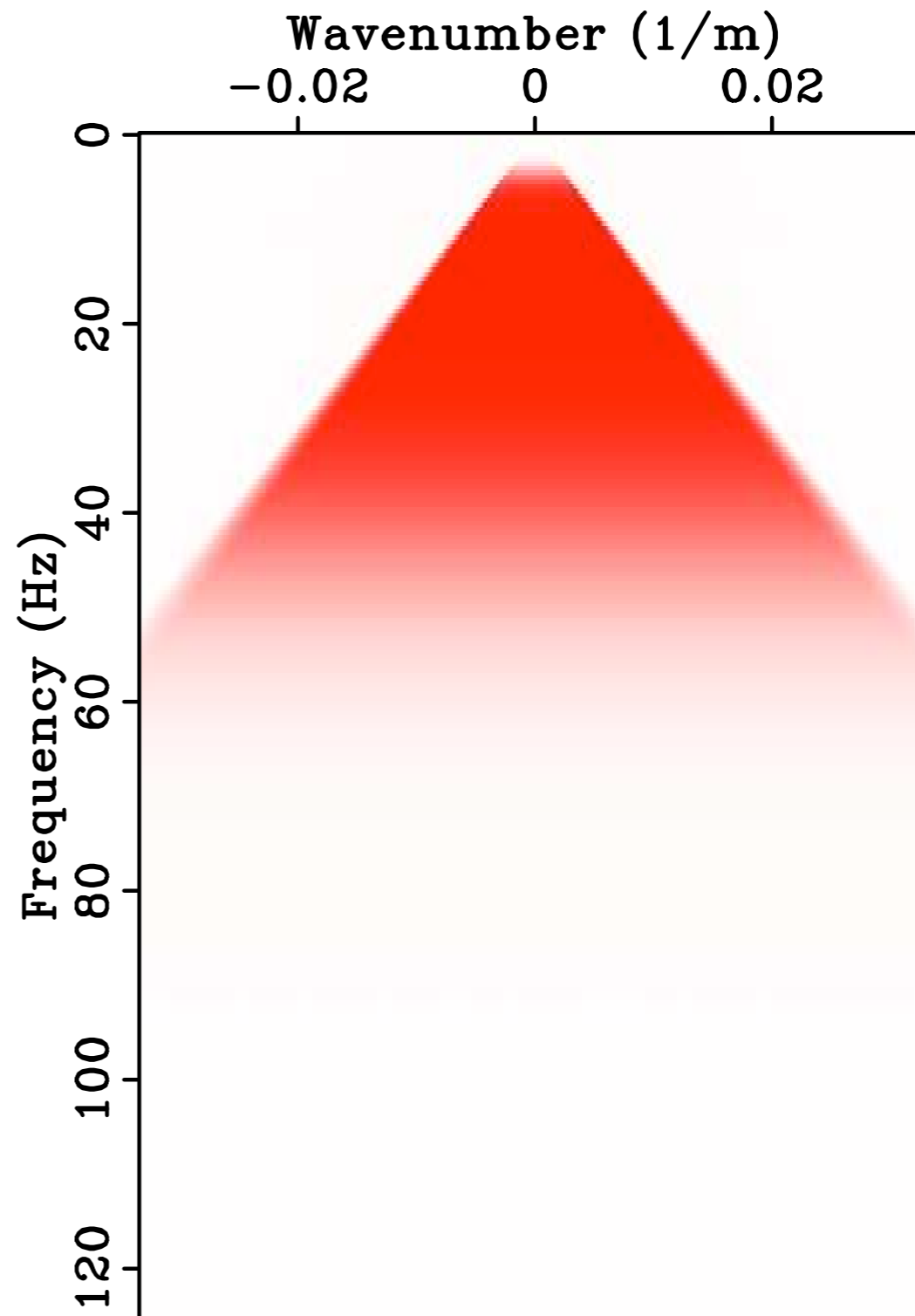
\mathbf{p} is the data to be inverted

Curvelet-sparsity regularized *data inverse* computed for the
whole data volume

Curvelet-based seismic data inverse

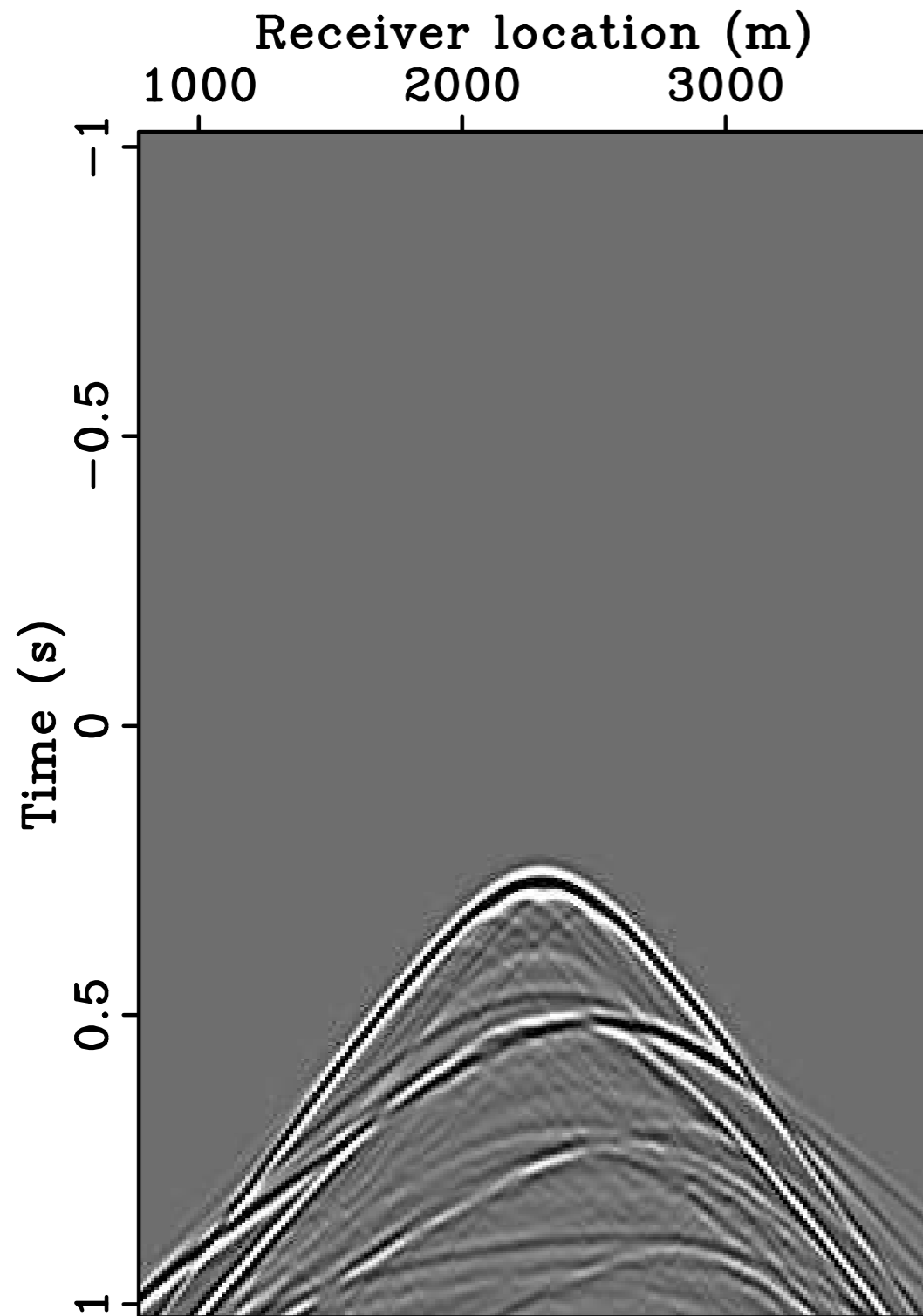


Band limit spike

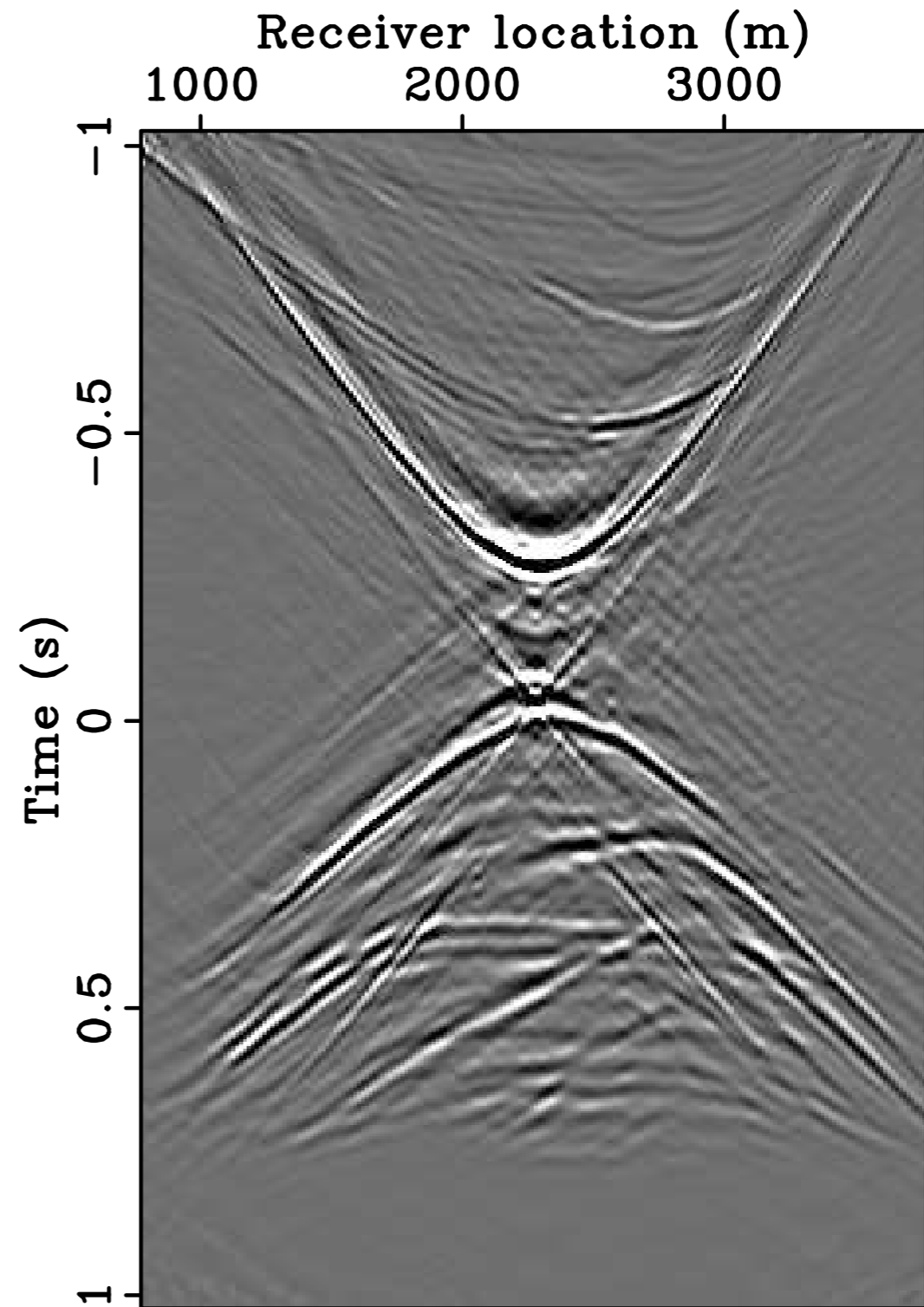


Band limit spike(FK)

Curvelet-based seismic data inverse

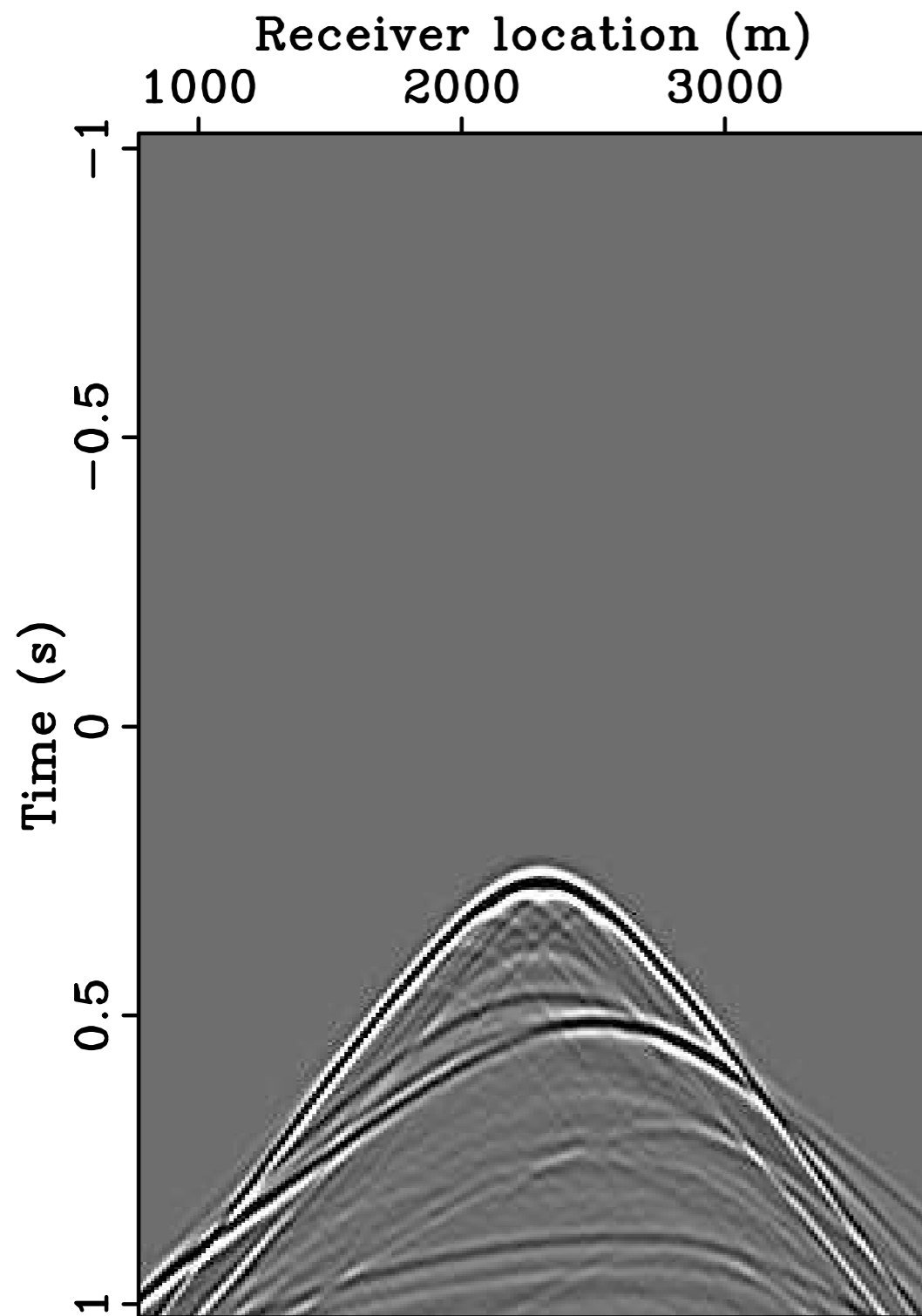


Data

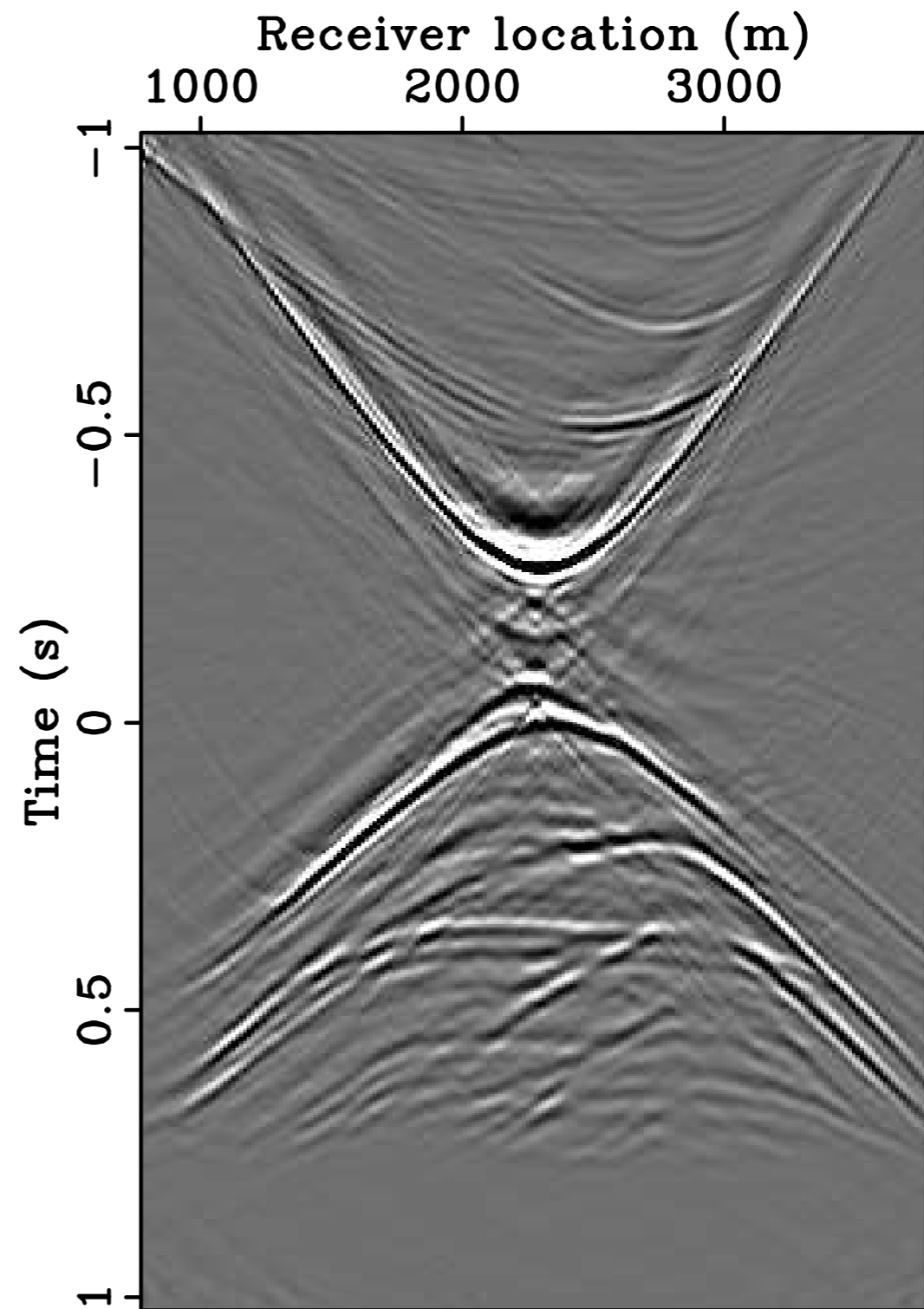


Data inverse

Curvelet-based seismic data inverse



Primaries



Primaries inverse

Conclusions

CRSI

- recovers data by curvelet sparsity promotion
- uses *sparsity* as a *prior*

Focused CRSI

- incorporates additional *prior* information
- strips interaction with the surface \Leftrightarrow more *sparsity*
- improves the recovery and hence predicted multiples
- precursor of migration-based CRSI

Results of curvelet-based computation of the data inverse are encouraging.

Acknowledgments

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Dr. Verschuur for his synthetic data and the estimates for the primaries.

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These results were created with Madagascar developed by Dr. Fomel.

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