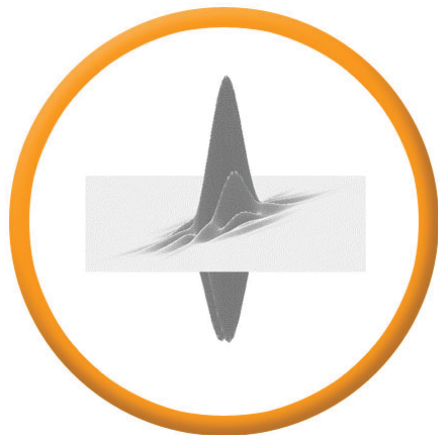


# Compressive sampling meets seismic imaging



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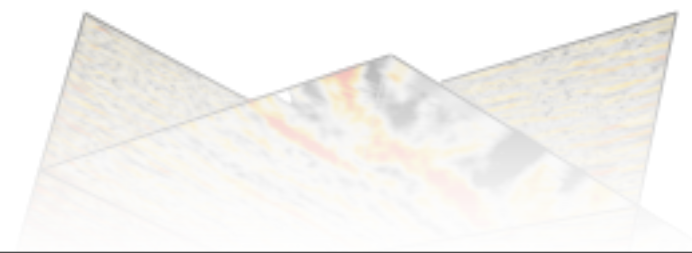
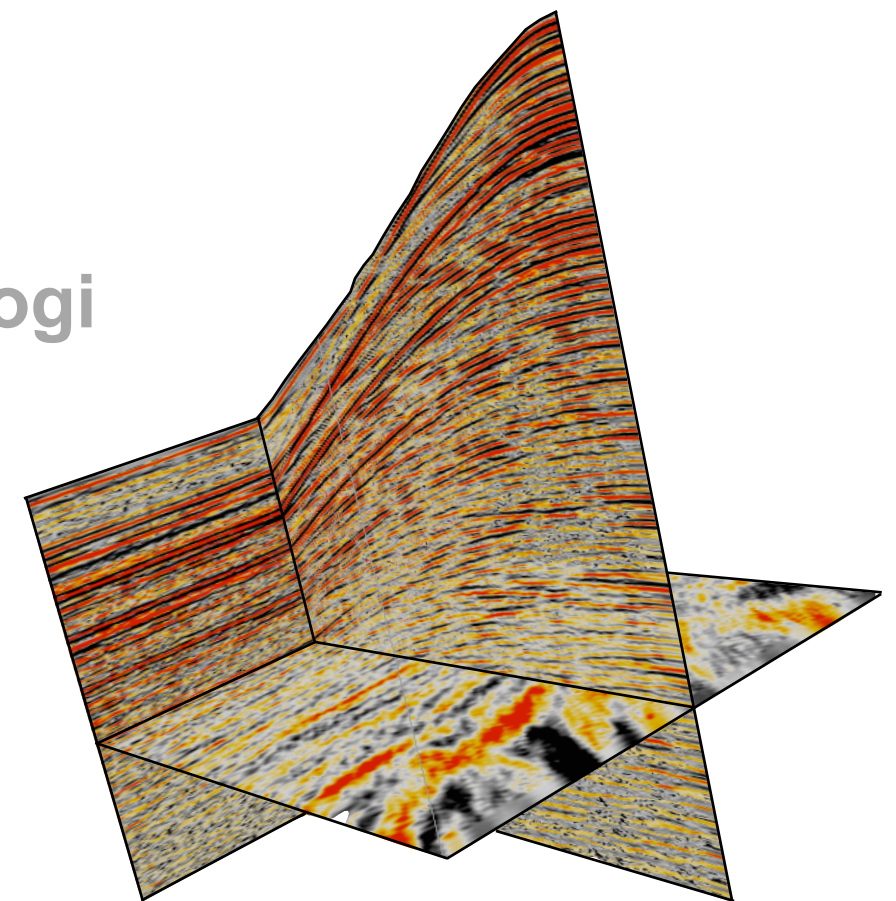
<http://slim.eos.ubc.ca>

joint work with Tim Lin and Yogi  
Erlangga

**Seismic Laboratory for Imaging & Modeling**

Department of Earth & Ocean Sciences

The University of British Columbia



SIAM Conference on Imaging Science  
San Diego, July 2008

# Motivation

---

## Seismic data processing, modeling & imaging

- firmly rooted in Nyquist's paradigm
  - sampling (e.g. of wavefields)
  - sampling of solutions (e.g. of PDEs)
- acquisition, modeling & inversion **costs** are proportional to the **size** of *data* and *model*

## New paradigm of *compressive sensing* (CS)

- Nyquist is too *pessimistic* for signals with *structure*
  - existence of some sparsifying transform (e.g. wavelets)
  - existence of some low-dimensional structure (smooth manifolds)
- allows for recovery from sample **rates  $\approx$  computational cost** *proportional* to the **complexity** of *data* and *model*

# Main ingredients

---

New **preconditioner** for the *Helmholtz* operator

[Erlanga & Nabben, '06-'08, Elangga, Lin, F.J.H., '08]

Current advent of **simultaneous & continuous** source acquisition and modeling

[Romero et. al., '00; Neelamani & C.E. Krohn, '08]

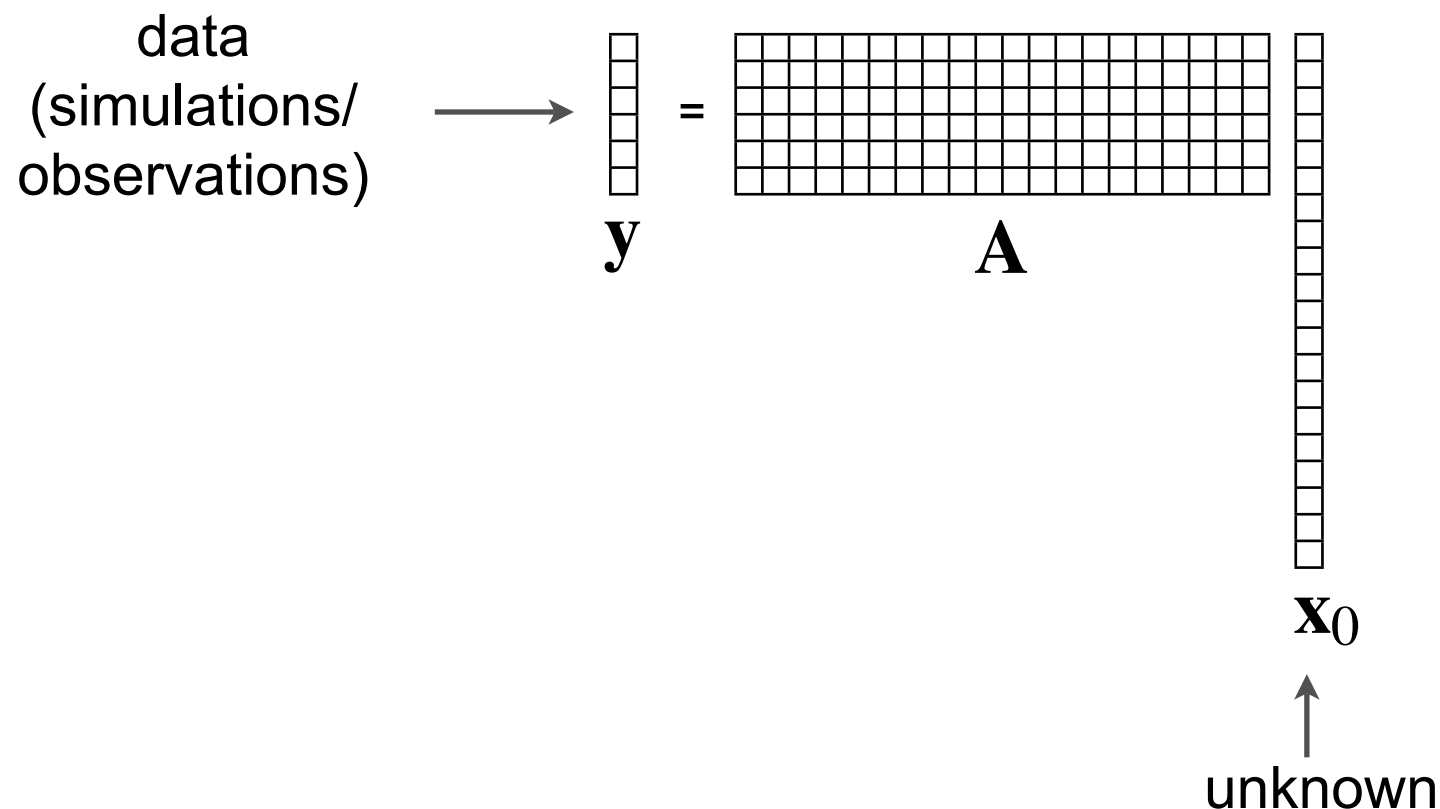
Sparsity-promoting **recovery** using results from **CS**

[Donoho, '06; Candes et al., '06; Candes and Tao, '06]

# CS

## problem statement

Consider the following (severely) underdetermined system of linear equations



Is it possible to recover  $\mathbf{x}_0$  accurately from  $\mathbf{y}$ ?



# CS

perfect recovery

$$\mathbf{y} = \mathbf{A} \mathbf{x}_0$$

## conditions:

- $\mathbf{A}$  obeys the *uniform uncertainty principle*
- $\mathbf{x}_0$  is *sufficiently sparse*

## procedure:

$$\underbrace{\min_{\mathbf{x}} \|\mathbf{x}\|_1}_{\text{sparsity}} \quad \text{s.t.} \quad \underbrace{\mathbf{A}\mathbf{x} = \mathbf{y}}_{\text{perfect reconstruction}}$$

## performance:

- *S*-sparse vectors recovered from roughly on the order of *S* measurements (to within constant and *log* factors)

# Adjoint state method

*Unconstrained* nonlinear LS problem

$$\min_{\mathbf{m} \in \mathcal{M}} \frac{1}{2} \|\mathbf{b} - \mathbf{F}[\mathbf{m}]\|_2^2$$

with

$$\mathbf{F}[\mathbf{m}] = \mathbf{D}\mathbf{A}^{-1}[\mathbf{m}]\mathbf{f}$$

and the ***gradient*** = - ***migrated image***,

$$[\nabla J(\mathbf{m})]_i = -\Re \left( \sum_{\omega} \sum_s \left\langle \left( \frac{\partial \mathbf{A}}{\partial \mathbf{m}} \mathbf{e}_i \right) \mathbf{u}_s, \mathbf{v}_s \right\rangle \right)$$

involves for each **monochromatic shot** the solution of

$$\mathbf{A}[\mathbf{m}]\mathbf{u} = \mathbf{f} \quad \text{and} \quad \mathbf{A}^H[\mathbf{m}]\mathbf{v} = \mathbf{r}$$

with

$$\mathbf{r} = \mathbf{D}^H(\mathbf{b} - \mathbf{F}[\mathbf{m}])$$

# Forward modeling

**Current paradigm:** *time-domain finite differences*

**Pro:** relatively simple, implicit and fast

**Con:**

- discretization criteria for numerical stability
- storage requirements for
  - model (domain decompositions)
  - imaging conditions (check pointing)

**New 'paradigm':** *implicit preconditioned Helmholtz solvers*

**Pro:**

- matrix free, favorable criteria for numerical stability
- embarrassing parallelization over angular frequency

**Con:**

- slow or no convergence of indirect Krylov methods

**Solution: preconditioner**

# Forward modeling

Discretize frequency-domain acoustic wave equation

$$\mathcal{H}u(\omega, x_s; x) := - \left( \nabla \cdot \nabla - \frac{\omega^2}{c(x)^2} \right) u(\omega, x_s; x) = b$$

Monochromatic linear system

$$\mathbf{A}_\omega[\mathbf{c}]\mathbf{u}^s = \mathbf{b}^s$$

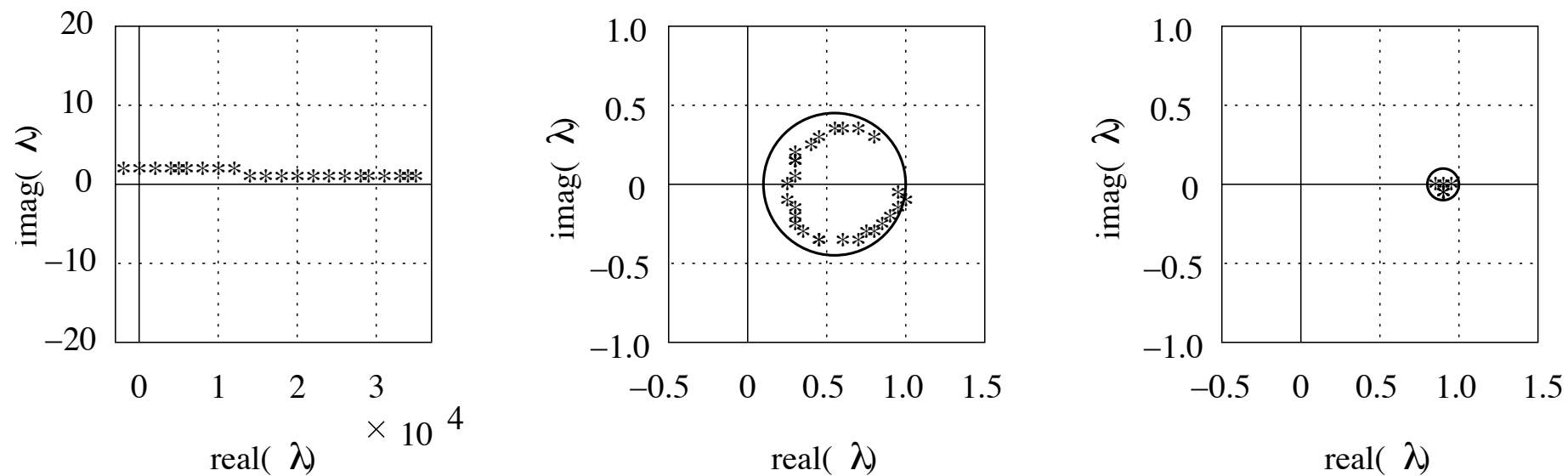
Preconditioned system

$$\mathbf{A}\mathbf{M}^{-1}\hat{\mathbf{u}} = \mathbf{b}, \quad \mathbf{u} = \mathbf{M}^{-1}\hat{\mathbf{u}},$$

derived from shifted Laplacian

$$\mathcal{M} := -\nabla \cdot \nabla - \frac{\omega^2}{c(x)^2} (1 - \beta i) \quad \text{with} \quad i = \sqrt{-1}, \beta > 0$$

# Forward modeling cont'd



## **Preconditioning** [Erlangga & Nabben, '06-'08]:

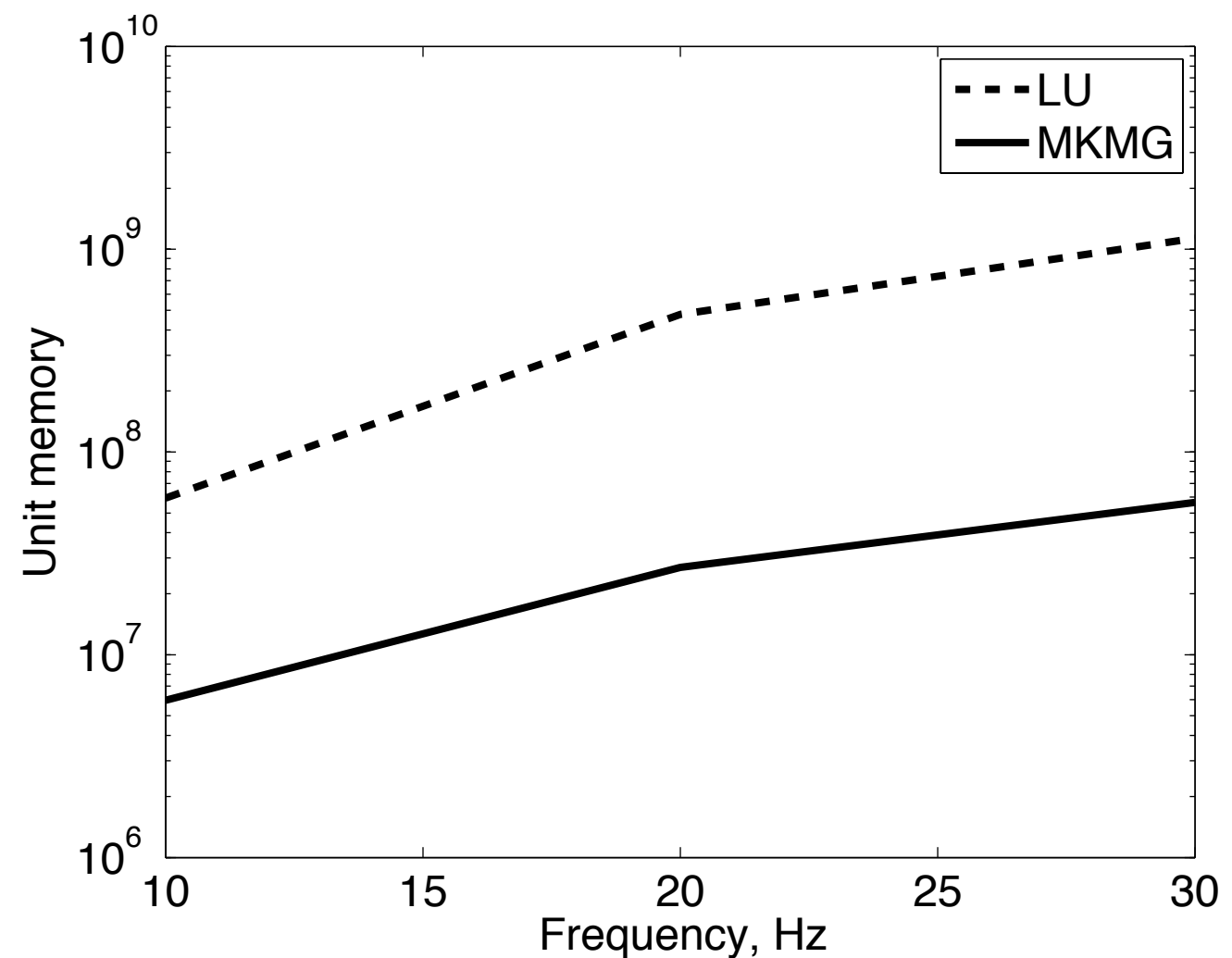
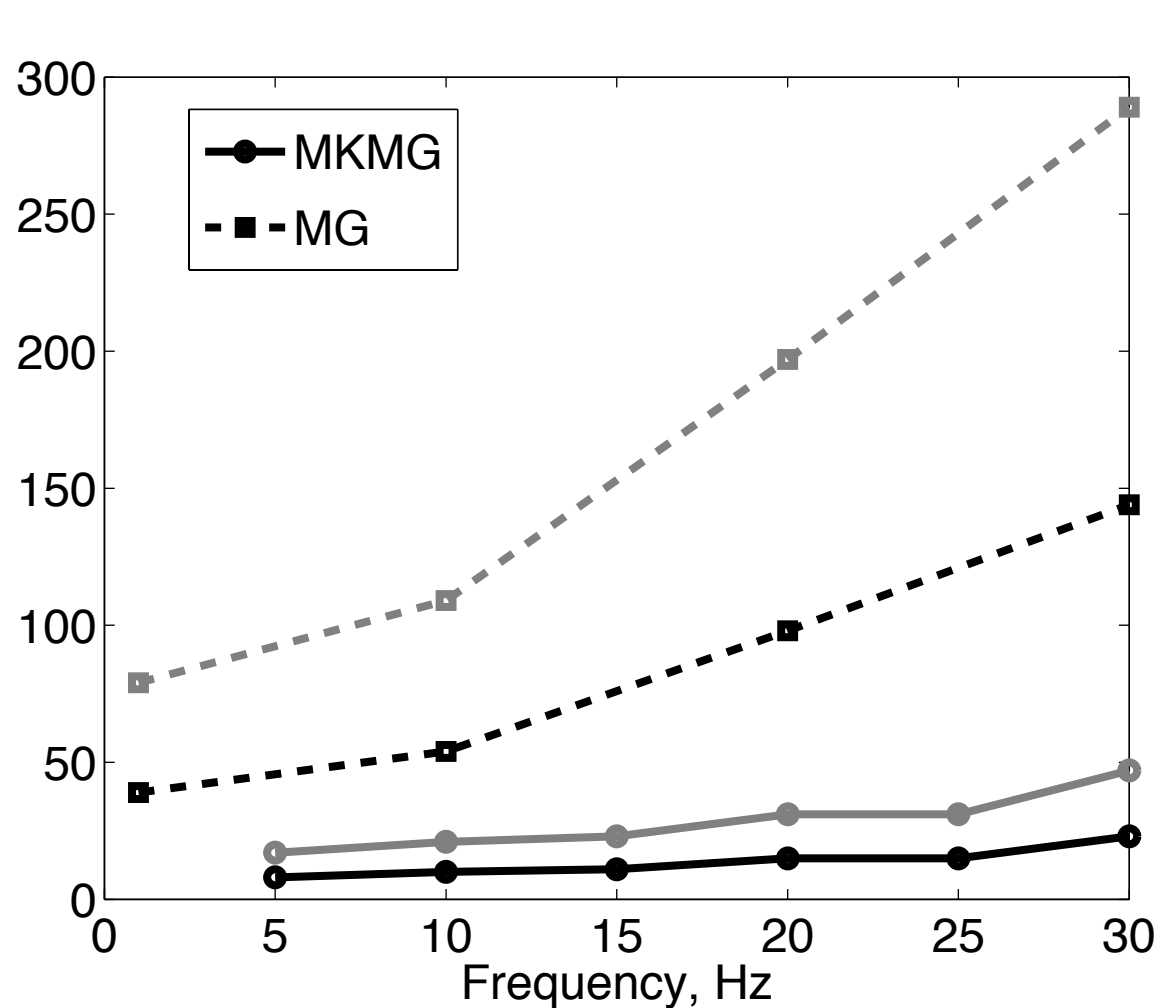
- moves eigenvalues to circle in complex plane
- is inverted using multigrid (no longer elliptic)

## **Additional multi-level Krylov projection:**

$$\mathbf{A}\mathbf{M}^{-1}\mathbf{Q}\hat{\mathbf{u}} = \mathbf{b}, \quad \mathbf{u} = \mathbf{M}^{-1}\mathbf{Q}\hat{\mathbf{u}},$$

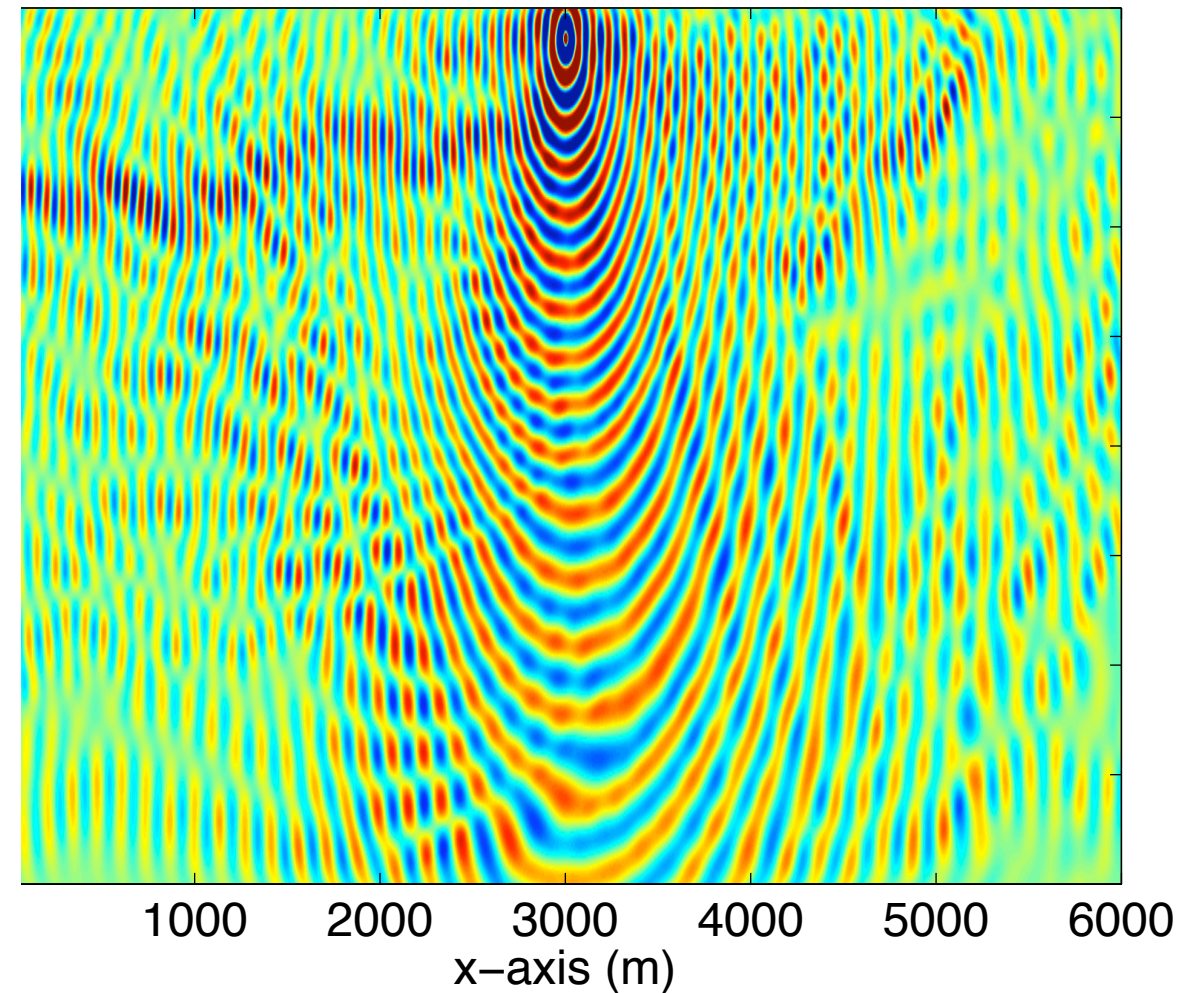
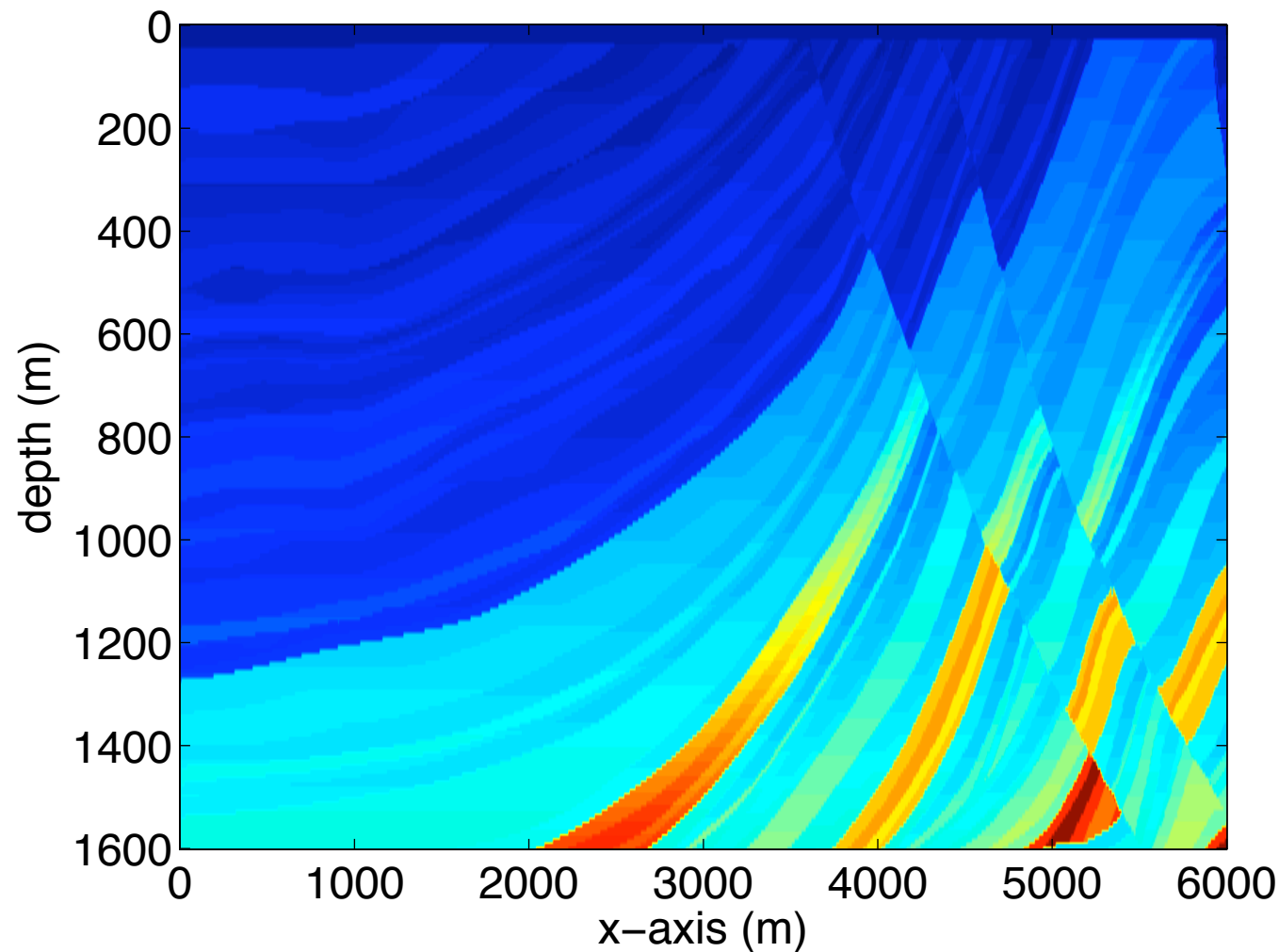
- moves eigenvalues to real axis near 1
- improves condition number

# Forward modeling cont'd



- implicit solvers converge
- number of iterations flat in grid size & frequency
- opens perspective to large-scale parallel solver for 3-D models

# Forward modeling cont'd



Despite significant improvement by Helmholtz preconditioner

- redundancy  $\Leftrightarrow$  extreme large size seismic data volumes
- multiple frequencies & multiple right-hand sides
- expensive modeling, imaging & inversion costs

**Leverage new paradigm of CS ...**



# Relation to existing work

## **Simultaneous & continuous acquisition:**

- *Simultaneous Sourcing without Compromise* by R. Neelamani & C.E. Krohn, '08.

## **Simultaneous simulations & migration:**

- *Faster shot-record depth migrations using phase encoding* by Morton & Ober, '98.
- *Phase encoding of shot records in prestack migration* by Romero et. al., '00.

## **Imaging:**

- *How to choose a subset of frequencies in frequency-domain finite-difference migration* by Mulder & Plessix, '04.
- *Efficient waveform inversion and imaging: A strategy for selecting temporal frequencies* by Sirque and Pratt, '04.

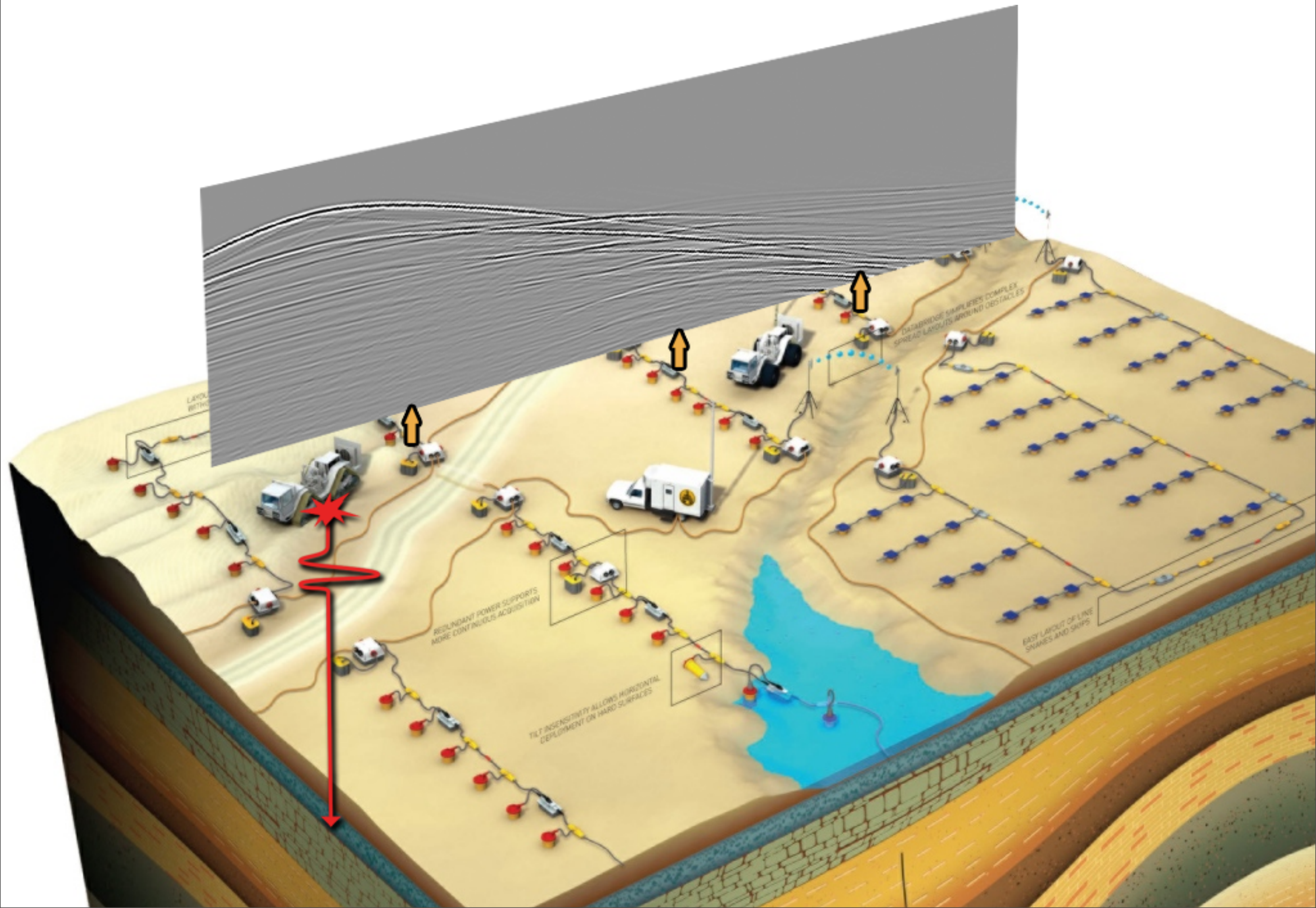
## **Wavefield extrapolation:**

- *Compressed wavefield extrapolation* by T. Lin and F.J.H, '07
- *Compressive wave computations* by L. Demanet in MS79



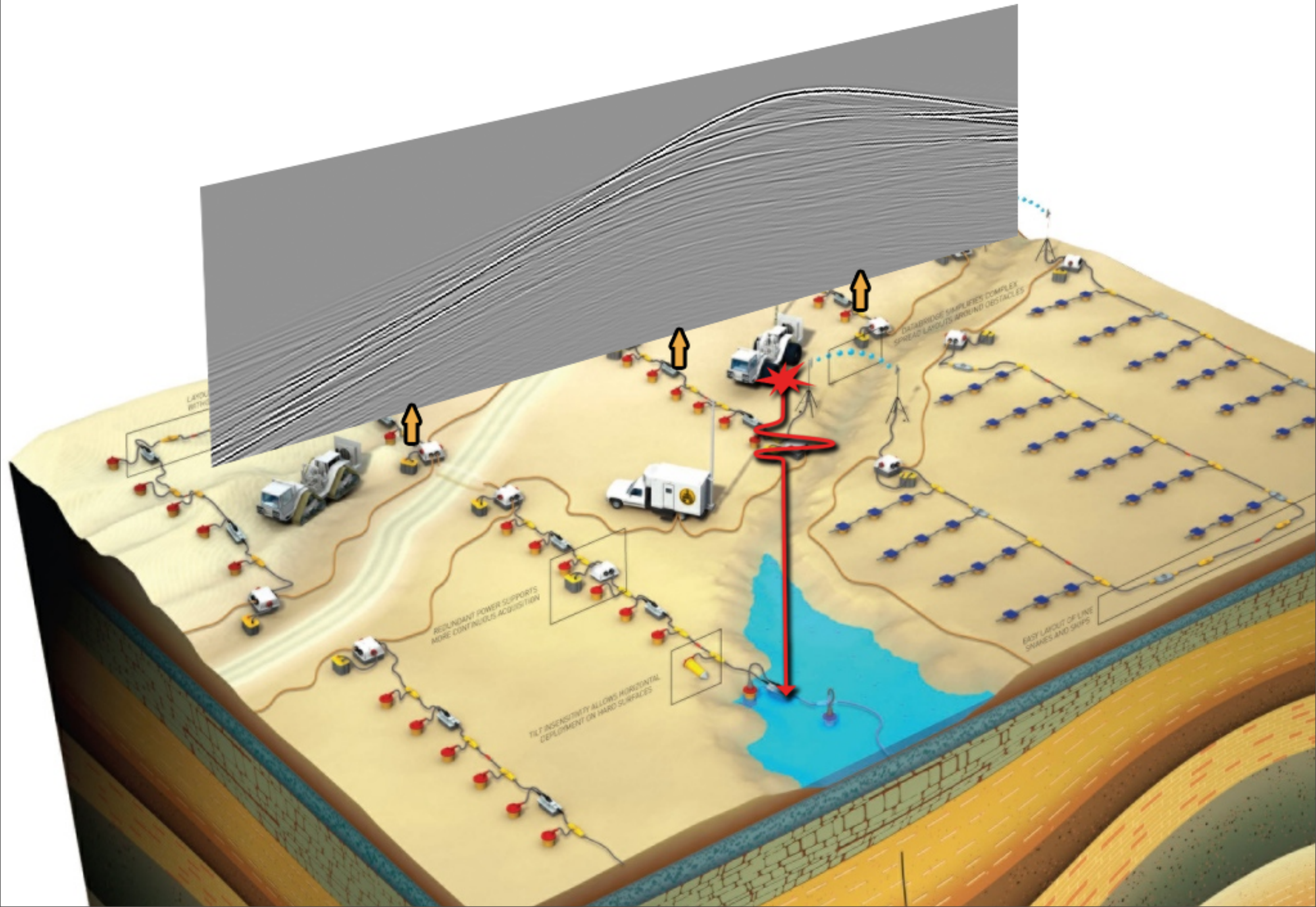


# Individual shots



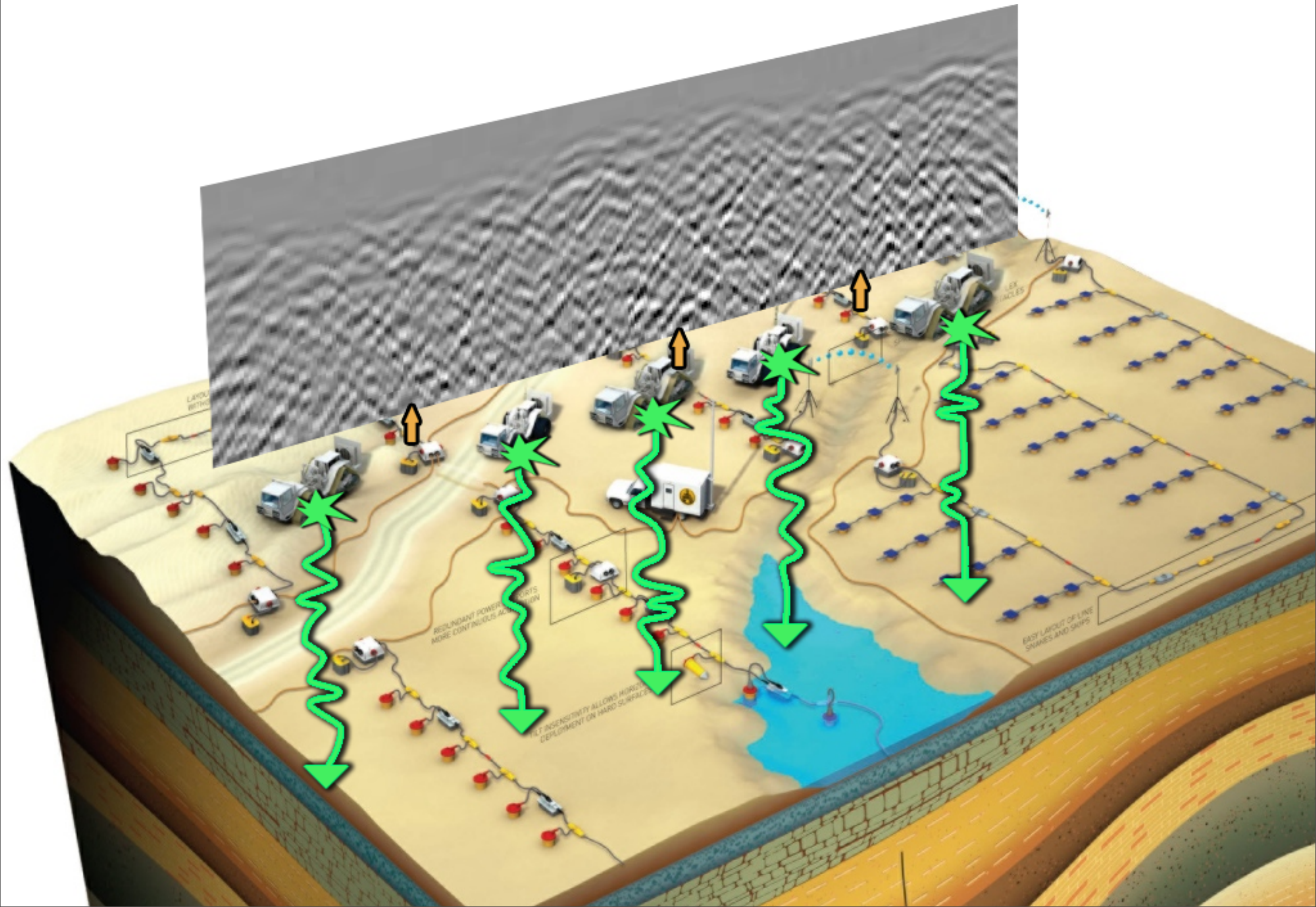


# Individual shots





# Simultaneous & continuous shots



# Simultaneous modeling & acquisition

## Current paradigm:

- ***separate*** single-source experiments in the field
- ***separate*** single-shot simulations in the computer
- **Con:** expensive

## New paradigm:

- ***simultaneous & continuous*** source experiments in the field
- ***simultaneous*** (continuous) simulations in the computer
- **continuous** simultaneous simulations are equivalent to **multiple** simultaneous experiments
- **Con:** *postprocessing necessary to separate into individual shots*

**Key observation: this is *really* CS ...**

# Forward modeling

multishot

$$\begin{bmatrix} \mathbf{A}_{\omega_1} & 0 & & \\ 0 & \mathbf{A}_{\omega_2} & \ddots & \\ & \ddots & \ddots & 0 \\ & & 0 & \mathbf{A}_{\omega_{n_f}} \end{bmatrix} \begin{bmatrix} \underbrace{\mathbf{u}_{\omega_1}}_{[\mathbf{u}_1 \ \mathbf{u}_2 \ \cdots \ \mathbf{u}_{n_s}]_{\omega_1}} \\ \vdots \\ \underbrace{[\mathbf{u}_1 \ \mathbf{u}_2 \ \cdots \ \mathbf{u}_{n_s}]_{\omega_{n_f}}}_{\mathbf{u}_{n_f}} \end{bmatrix} = \begin{bmatrix} \underbrace{\mathbf{B}_{\omega_1}}_{[\mathbf{b}_1 \ \mathbf{b}_2 \ \cdots \ \mathbf{b}_{n_s}]_{\omega_1}} \\ \vdots \\ \underbrace{[\mathbf{b}_1 \ \mathbf{b}_2 \ \cdots \ \mathbf{b}_{n_s}]_{\omega_{n_f}}}_{\mathbf{B}_{n_f}} \end{bmatrix}$$

Helmholtz equation solved for:

- individual angular frequencies, i.e.,

$$\omega_i = 2\pi i \cdot \Delta f, \ i = 1 \cdots n_f,$$

- $n_f$  number of frequencies
- $\Delta f$  the sample interval in frequency

- individual shots, i.e.,  $\mathbf{b}_i = \mathbf{e}_i$  for  $i = 1, \cdots, n_s$



# Forward modeling

## multishot

Rewrite into

$$\underbrace{\begin{bmatrix} \mathbf{A}_{\omega_1} & 0 & & \\ 0 & \mathbf{A}_{\omega_2} & \ddots & \\ & \ddots & \ddots & 0 \\ & & 0 & \mathbf{A}_{\omega_{n_f}} \end{bmatrix}}_{\mathbf{L}} \underbrace{\begin{bmatrix} \mathbf{U}_{\omega_1} \\ \vdots \\ \vdots \\ \mathbf{U}_{n_f} \end{bmatrix}}_{\mathbf{U}} = \underbrace{\begin{bmatrix} \mathbf{B}_{\omega_1} \\ \vdots \\ \vdots \\ \mathbf{B}_{n_f} \end{bmatrix}}_{\mathbf{B}}$$

or

$$\mathbf{LU} = \mathbf{B}.$$

Modeling involves the inversion of the matrix

$$\mathbf{L} \in \mathbb{C}^{n_d \times n_d} \text{ with } n_d = 2n_f n_s n_r$$

# Equivalence

Show equivalence between

- CS sampling of **full** solution for separate single-source (sweep) experiments
- Solution of **reduced** system after CS sampling the collective single-shot source wavefield => **simultaneous source experiments**

$$\left\{ \begin{array}{l} \mathbf{B} = \mathbf{D}^* \underbrace{\mathbf{S}}_{\text{single shots}} \\ \mathbf{L}\mathbf{U} = \mathbf{B} \\ \mathbf{y} = \mathbf{R}\mathbf{M}\mathbf{D}\mathbf{U} \end{array} \right. \iff \left\{ \begin{array}{l} \underline{\mathbf{B}} = \underline{\mathbf{D}}^* \underbrace{\mathbf{R}\mathbf{M}\mathbf{s}}_{\text{simul. shots}} \\ \underline{\mathbf{L}}\underline{\mathbf{U}} = \underline{\mathbf{B}} \\ \underline{\mathbf{y}} = \underline{\mathbf{D}}\underline{\mathbf{U}} \end{array} \right.$$

Show that  $\mathbf{y} = \underline{\mathbf{y}}$  for which it is sufficient to show that

$$\mathbf{R}_\Omega \underbrace{\mathbf{L}^{-1}\mathbf{B}}_{\text{full system}} \mathbf{R}_\Sigma^* = \underline{\underline{\mathbf{U}}} \iff \underline{\underline{\mathbf{U}}} = \overbrace{\left( \mathbf{R}_\omega \mathbf{L} \mathbf{R}_\Sigma^* \right)^{-1} \underline{\underline{\mathbf{B}}}}_{\text{reduced system}}$$

# Equivalence cont'd

## Fourier restriction:

$\mathbf{R}_\Omega : n'_f \times n_f$  block matrix,  $n'_f = \#\{\Omega\}, \Omega \subset \{\omega_i\}, i = 1, \dots, n_f, n_f \gg n'_f$

$$[\mathbf{R}_\Omega]_{J,I} = \begin{cases} \mathbf{I}_{n_x \times n_z}, & I \in \mathcal{I} \\ \mathbf{0}_{n_x \times n_z}, & I \notin \mathcal{I}, \end{cases}$$

with  $\mathcal{I}$  the index set of  $\Omega$ , and  $J = 1, \dots, n'_f$ .

Identity:  $\mathbf{R}_\Omega \mathbf{L} = \underline{\mathbf{L}} \mathbf{R}_\Omega$ , where

$$\underline{\mathbf{L}} = \text{diag}(\mathbf{A}_{\omega_I}), \quad I \in \mathcal{I}.$$

This implies:  $\mathbf{R}_\Omega \mathbf{L}^{-1} = \underline{\mathbf{L}}^{-1} \mathbf{R}_\Omega$ .

# Equivalence cont'd

## Shot restriction:

$\mathbf{R}_\Sigma : n'_s \times n_s$  rectangular matrix,  $n'_s = \#\{\mathcal{N}'_s\}$ ,  $\mathcal{N}'_s \subset \mathcal{N}_s$ , with  $\mathcal{N}_s$  the index set of  $\mathbf{b}_i$ .

$$[\mathbf{R}_\Sigma]_{j,i} = \begin{cases} 1, & i \in \mathcal{N}'_s, \\ 0, & i \notin \mathcal{N}'_s, \end{cases}$$

for  $j = 1, \dots, n'_s$  with  $n'_s \ll n_s$ .

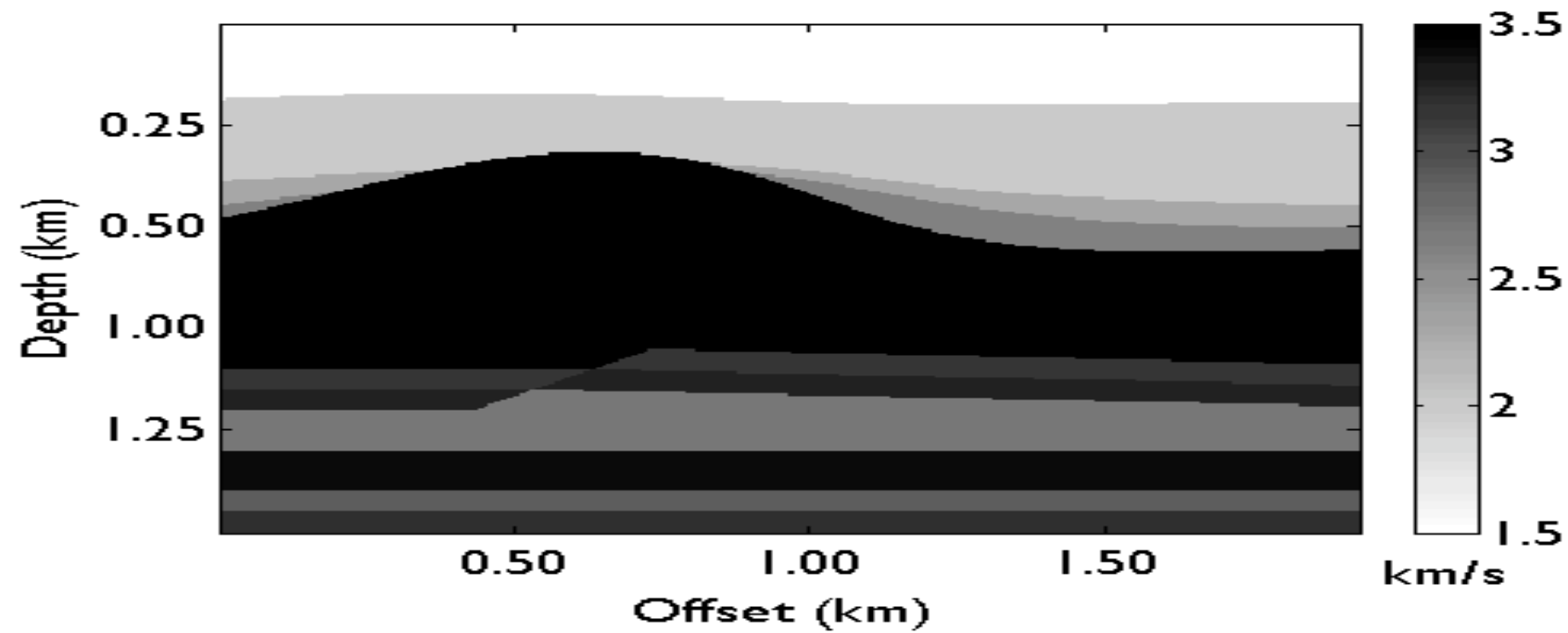
So we have,

$$\mathbf{R}_\Omega \mathbf{L}^{-1} = \underline{\mathbf{L}}^{-1} \mathbf{R}_\Omega \Rightarrow \underbrace{\mathbf{R}_\Omega \overbrace{\mathbf{L}^{-1} \mathbf{B} \mathbf{R}_\Sigma^*}^{\mathbf{U}}}_{\underline{\mathbf{U}}} = \underline{\mathbf{L}}^{-1} \underbrace{\mathbf{R}_\Omega \mathbf{B} \mathbf{R}_\Sigma^*}_{\underline{\mathbf{B}}} = \underline{\mathbf{U}}.$$

implying

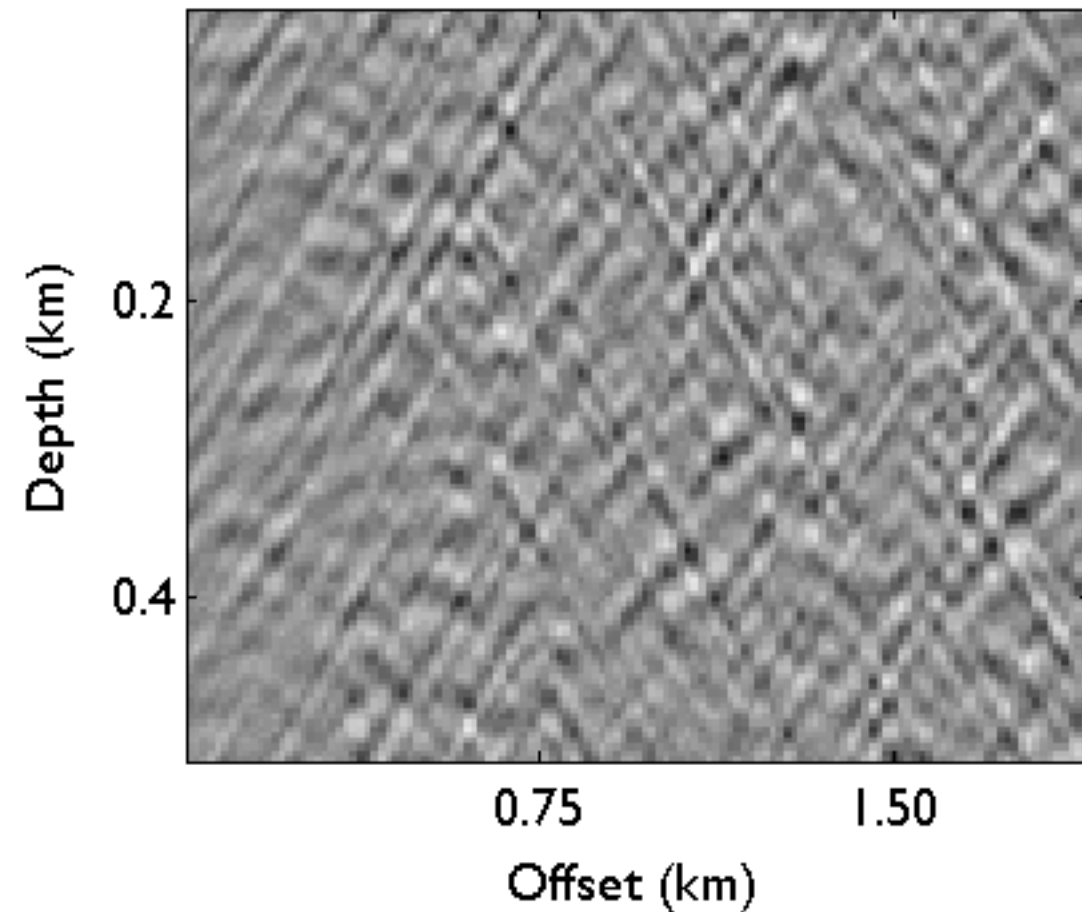
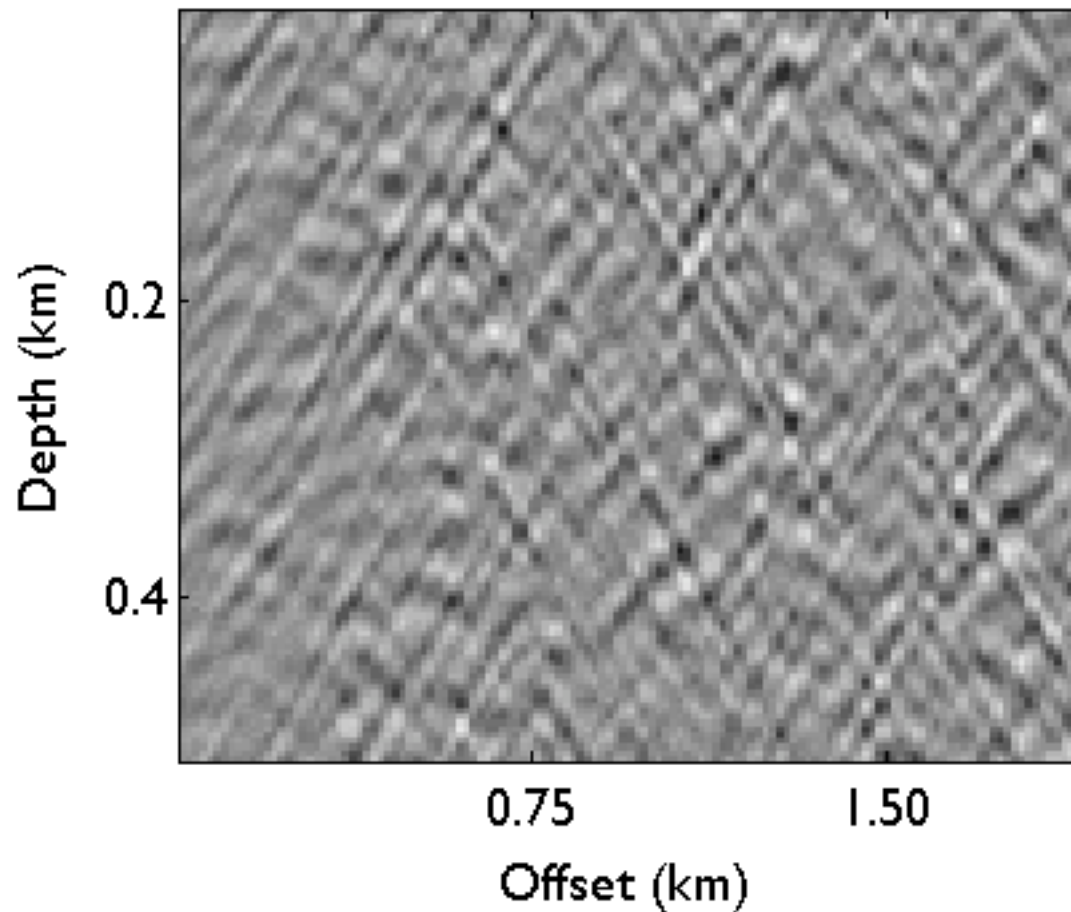
$$\mathbf{y} = \underline{\mathbf{y}}$$

# Experiment



$$\underline{y} = \mathbf{RMDU}$$

$$\underline{y} = \underline{\mathbf{D}}\underline{\mathbf{U}}$$



# CS

## **Current paradigm:** *Nyquist sampling*

### **Pro:**

- linear
- signal independent (aside from Nyquist frequency)

### **Con:**

- cost dependent on the Nyquist frequency and model size
- overly pessimistic for signals with *structure*

## **New paradigm:** *Compressive sensing*

### **Pro:**

- cost dependent on signal's *complexity*

### **Con:**

- solve a nonlinear recovery problem

**Can lead to reduced cost when recovery cost < reduced simulation costs ...**

# CS

$$\mathbf{P}_1 : \begin{cases} \mathbf{y} &= \mathbf{RMf} \\ \tilde{\mathbf{x}} &= \arg \min_{\mathbf{x}} \|\mathbf{x}\|_1 \quad \text{subject to} \quad \mathbf{Ax} = \mathbf{y} \\ \mathbf{A} &= \mathbf{RMS}^* \\ \tilde{\mathbf{f}} &= \mathbf{S}^* \tilde{\mathbf{x}} \end{cases}$$

CS provides conditions under which P1 recovers  $\mathbf{f}$ :

- selection of CS-matrix (Measurement & Restriction matrices)
- selection of sparsifying transform

Additional complications

- large-to-extremely large problem size
- projected gradient with root finding method (SPG $\ell_1$ , Friedlander & van den Berg, '07-'08)
- CS matrix has to lead to *physically **realizable*** source wavefield for modeling & acquisition



# CS

## Selection of the CS-matrix

- natural restriction in Fourier (**F**) with *importance* sampling in the temporal direction
- CS with Gaussian (**N**) matrix along shots => simultaneous sources
- assures *incoherence* with sparsifying transform

For each **simultaneous** shot, define different restrictions

$$\mathbf{RM} = \begin{bmatrix} \mathbf{R}_1^\Sigma \otimes \mathbf{R}_1^\Omega \\ \vdots \\ \mathbf{R}_{n_{s'}}^\Sigma \otimes \mathbf{R}_{n_{s'}}^\Omega \end{bmatrix} \otimes (\mathbf{N} \otimes \mathbf{F})$$

yielding the reduced simulated data

$$\mathbf{y} = \underline{\mathbf{y}} = \mathbf{RMd}, \mathbf{y} \in \mathbb{C}^{n'_d}$$

$$\text{with } n'_d = n'_f n'_s n_r \ll n_d = 2n_f n_s n_r$$

## Selection of the sparsifying transform:

- wavelet transform is known to compresses seismic data [Donoho '99]
- successfully applied in MRI (reconstructions from incomplete Fourier data)[Lustig et. al. '07]

Define

$$\mathbf{S} = \mathbf{W} \otimes \mathbf{W} \otimes \mathbf{W}$$

### Bottom line:

Computational gain of CS proportional to undersampling ratio

$$\frac{n'_d}{n_d} \text{ with } n'_d \approx 5 \times \#\{\mathcal{N}_\Omega \circ \mathcal{N}'_s\}$$

at the expense of solving a CS problem.

# Complexity analysis

Assume discretization size in each dimension is  $n$ , and

$$n_s = n_t = n_f = \mathcal{O}(n)$$

Time-domain finite differences:

- $\mathcal{O}(n^4)$  in 2-D
- large constants

Preconditioned Helmholtz (Riyanti '06):

- $\mathcal{O}(n^5) = n_f n_s n_{it} \mathcal{O}(n^2)$  with  $n_{it} = \mathcal{O}(n)$  asymptotically
- small constants

Multilevel-Krylov preconditioned (Erlangga and Nabben 08')

- $\mathcal{O}(n^4) = n_f n_s n_{it} \mathcal{O}(n^2)$  with  $n_{it} = \mathcal{O}(1)$
- small constants

# Complexity analysis cont'd

Cost sparsity promoting optimization problem dominated by matrix-vector products

- 3-D wavelets are  $\mathcal{O}(n^3)$
- Gaussian projection  $\mathcal{O}(n^3)$  per frequency
- **Cost**  $\mathcal{O}(n^4)$ , which does not lead to asymptotic improvement

Use fast transforms instead (e.g. Noiselets by Coifman '01)

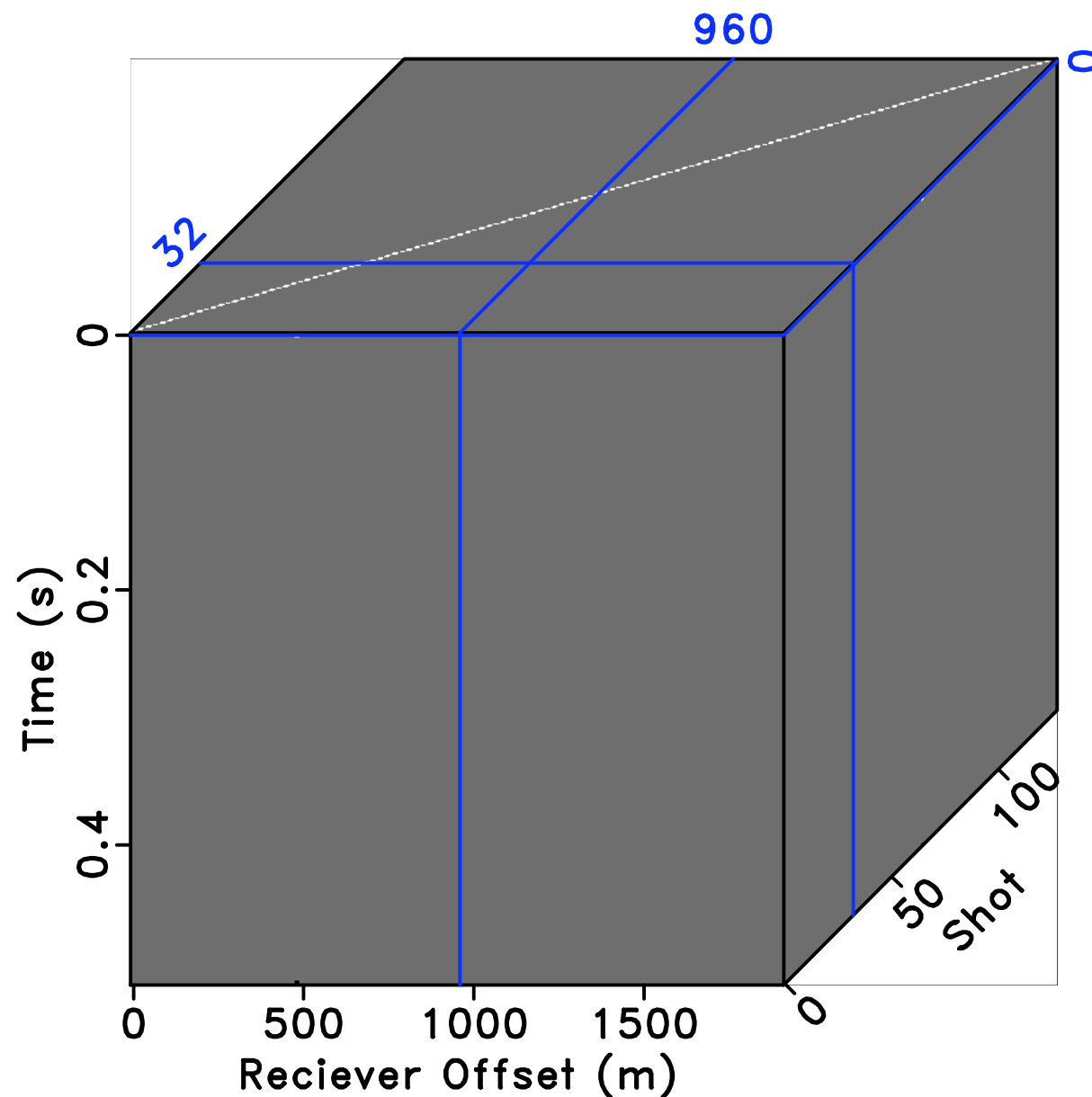
- fast projection in time & shot directions:  $\mathcal{O}(n \log n)$
- **Cost**  $\mathcal{O}(n^3 \log n)$  instead of  $\mathcal{O}(n^4)$

**Bottom line:** Computational cost for the  $\ell_1$ -solver is less ( $\mathcal{O}(n^3 \log n)$  vs.  $\mathcal{O}(n^4)$ ) than the cost for solving Helmholtz

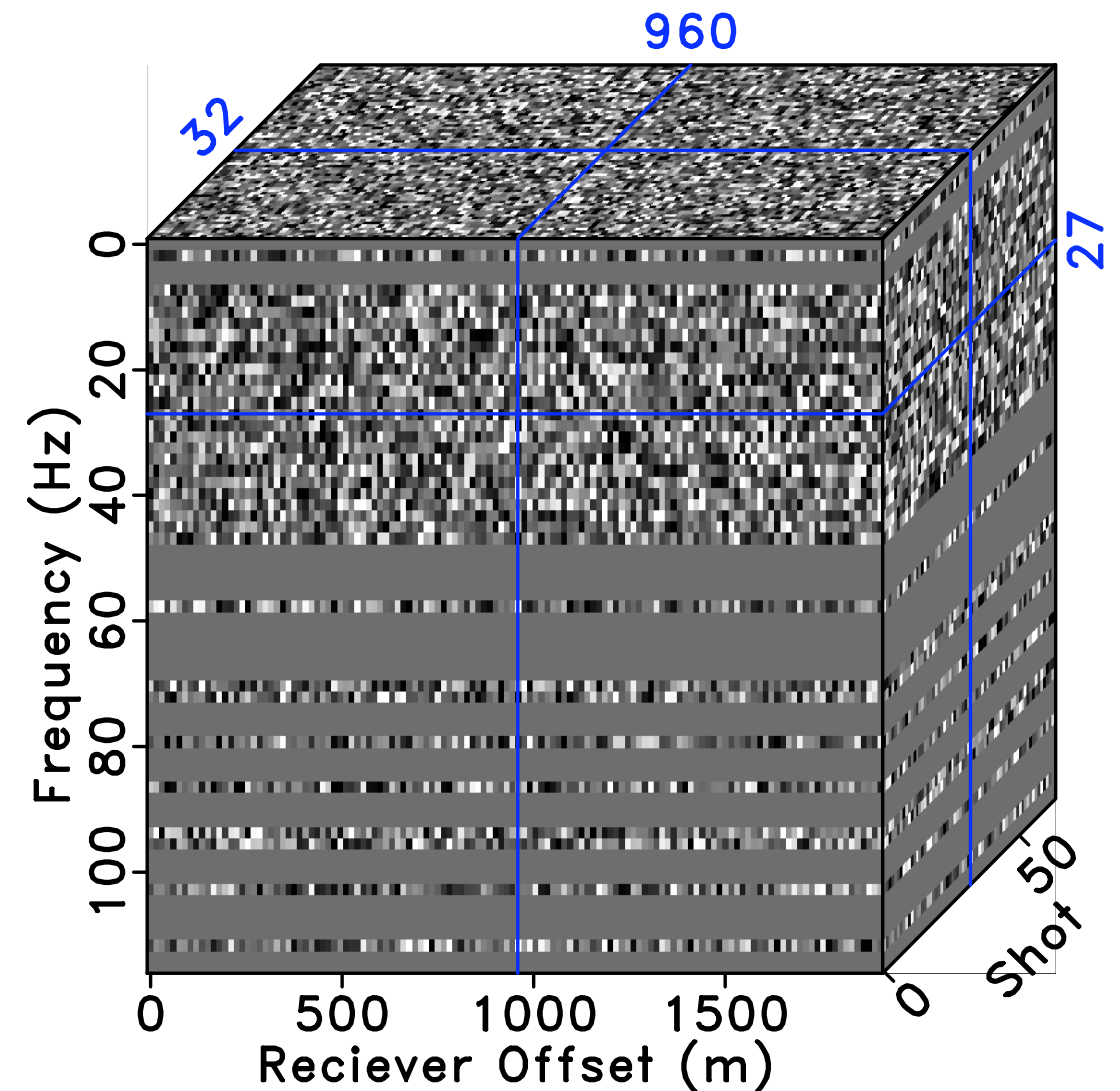
- smaller memory imprint
- smaller data volume requirement
- cost reduction dependent on complexity

# Source wavefields

separated source



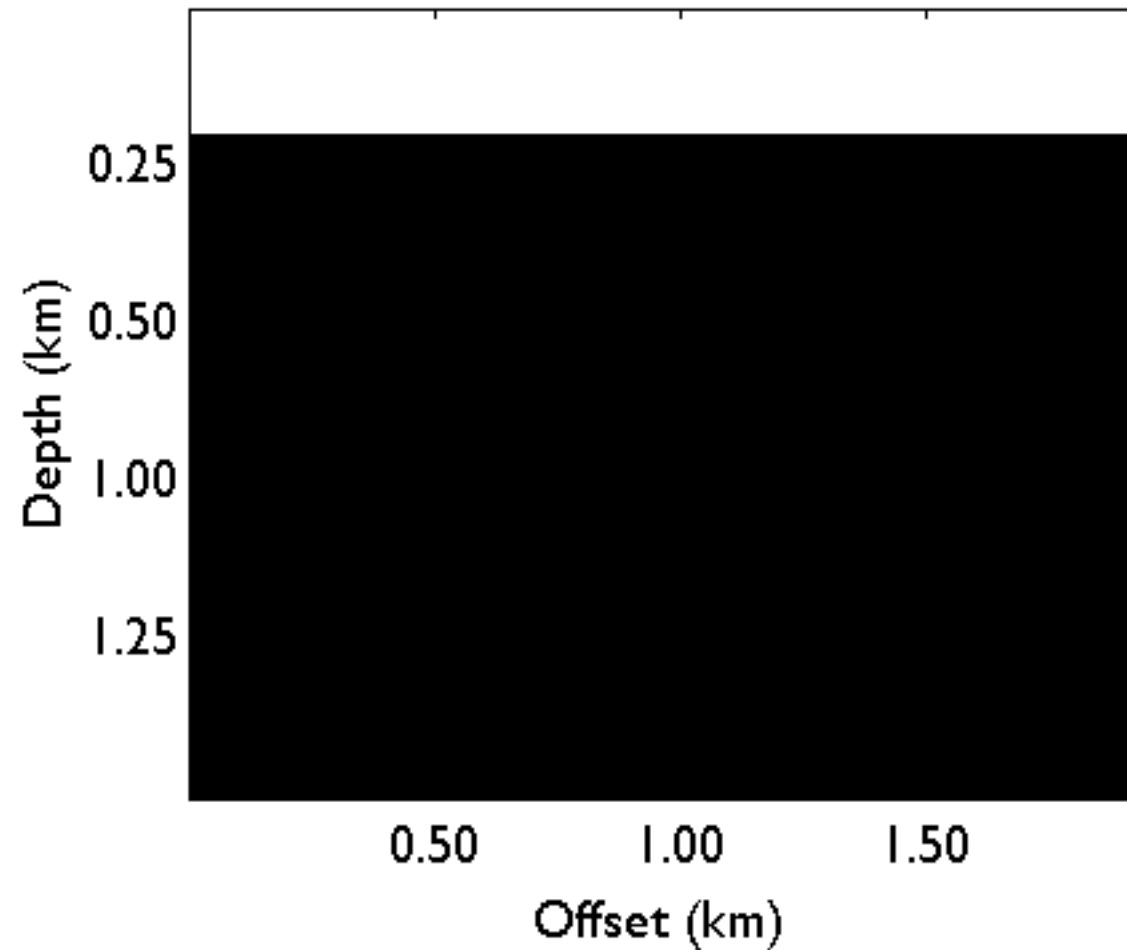
compressed source



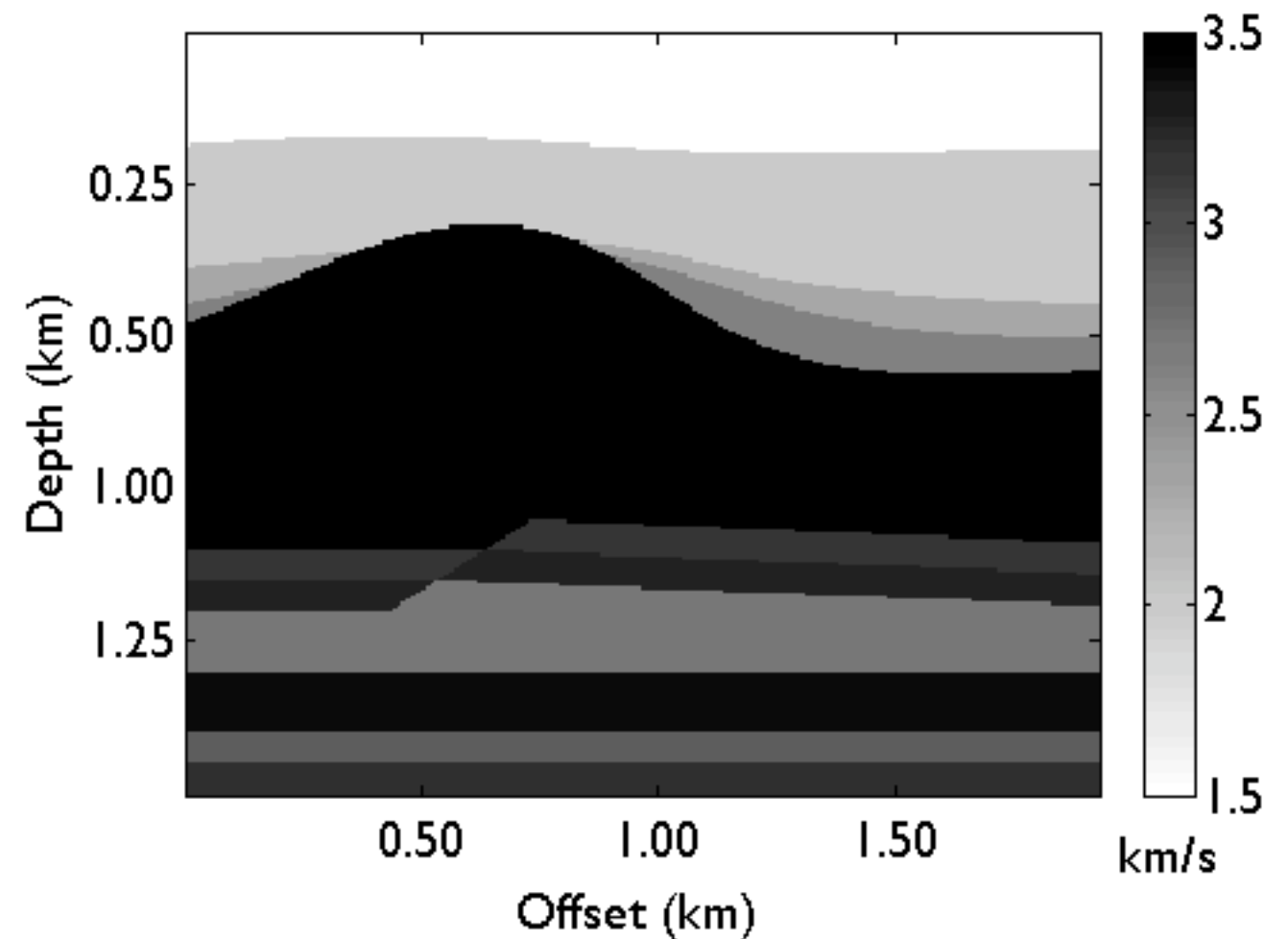
Freq sample 50%  
Shot sample 50%  
total sample 25%

# Velocity models

simple model

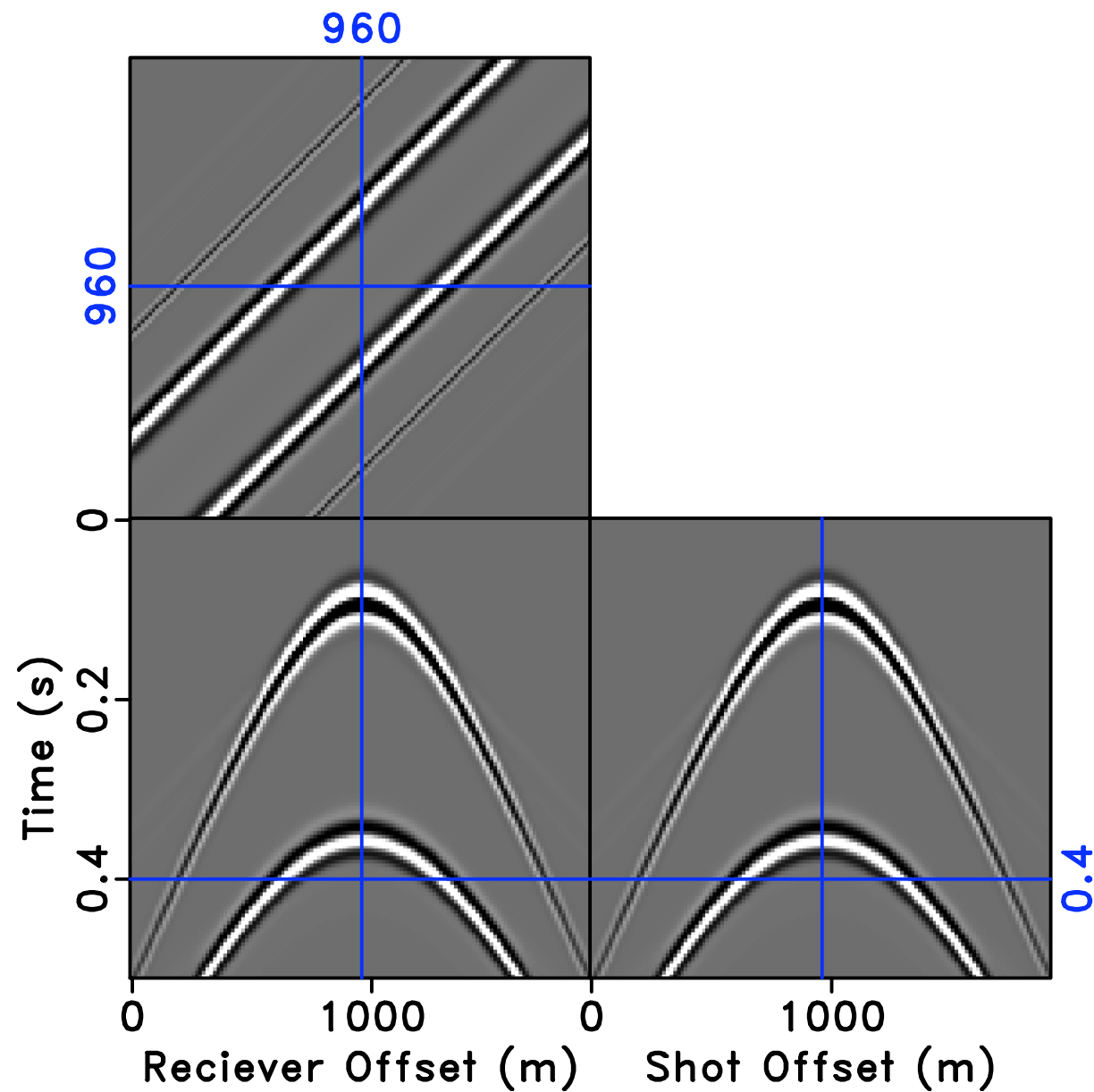


complex model

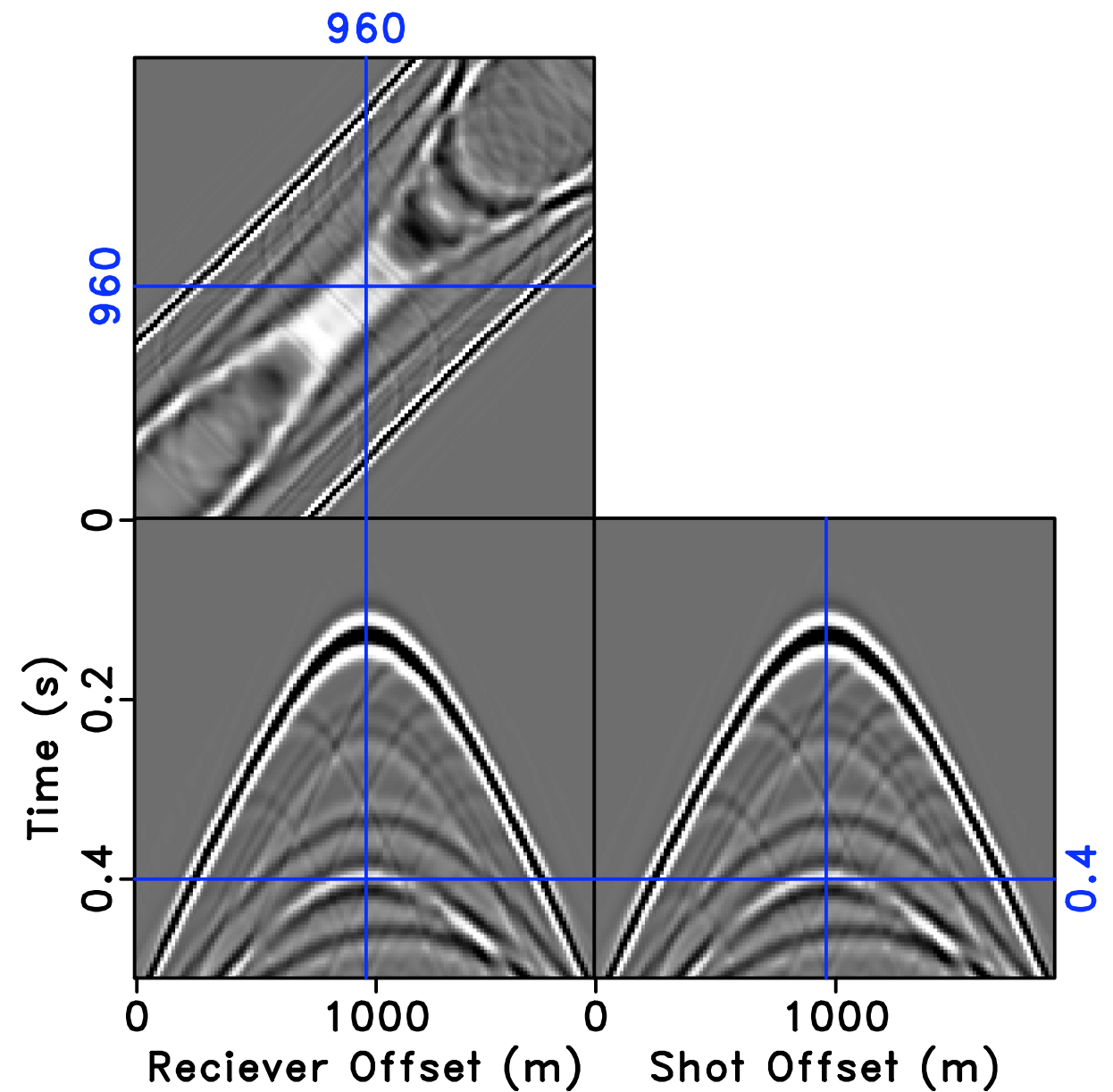


# Green's functions

simple model



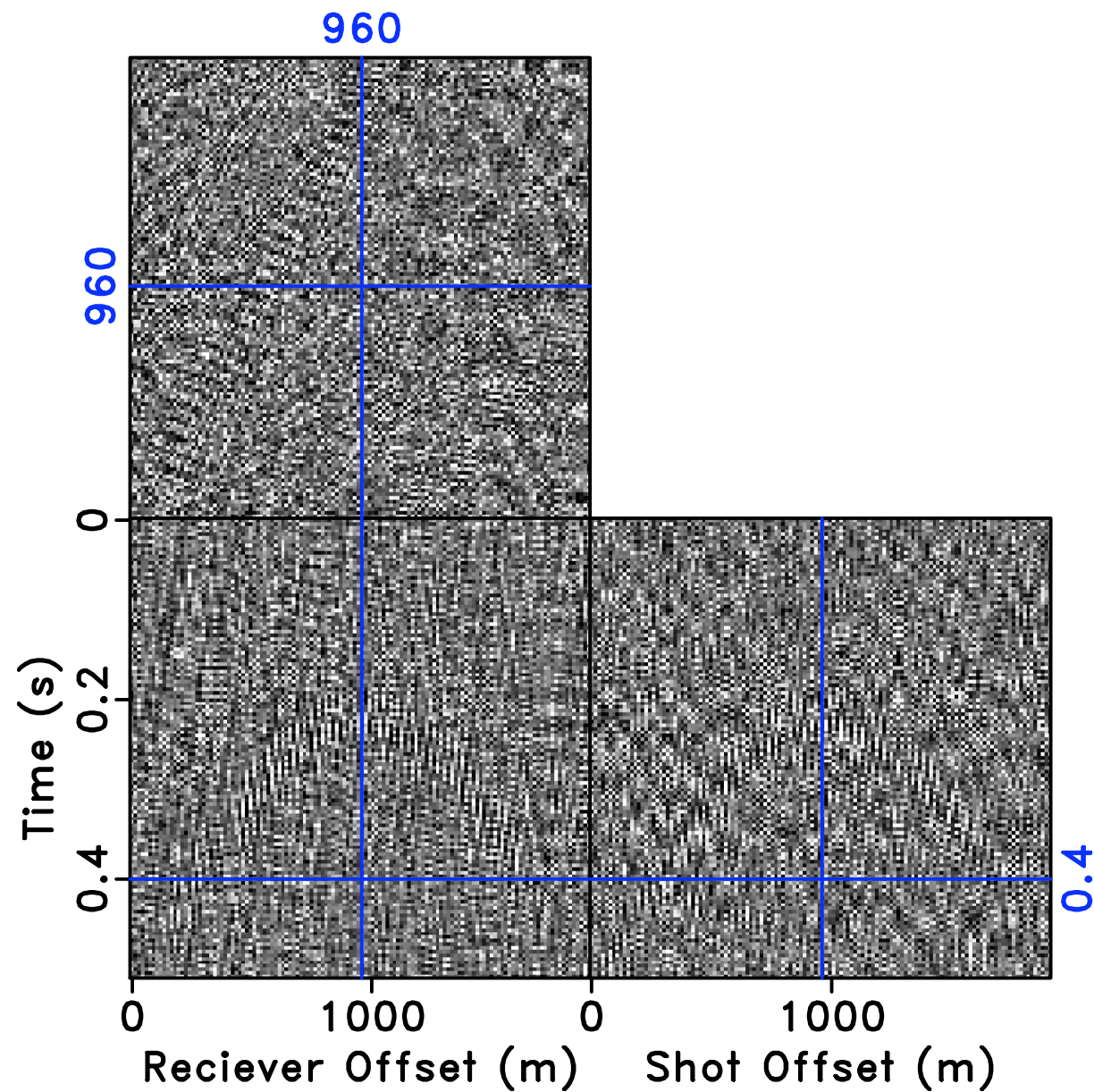
complex model



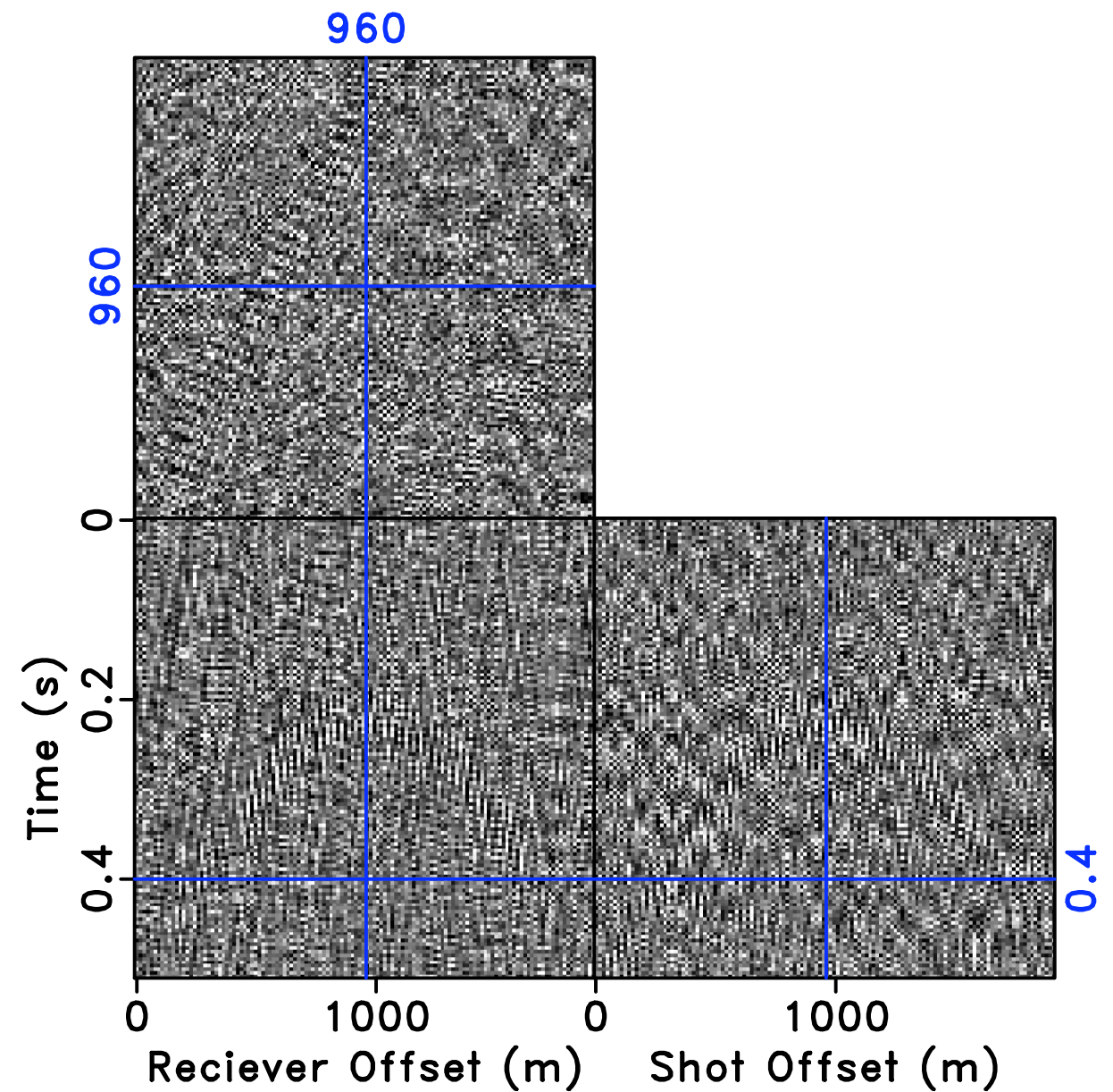


# Matched filter

simple model

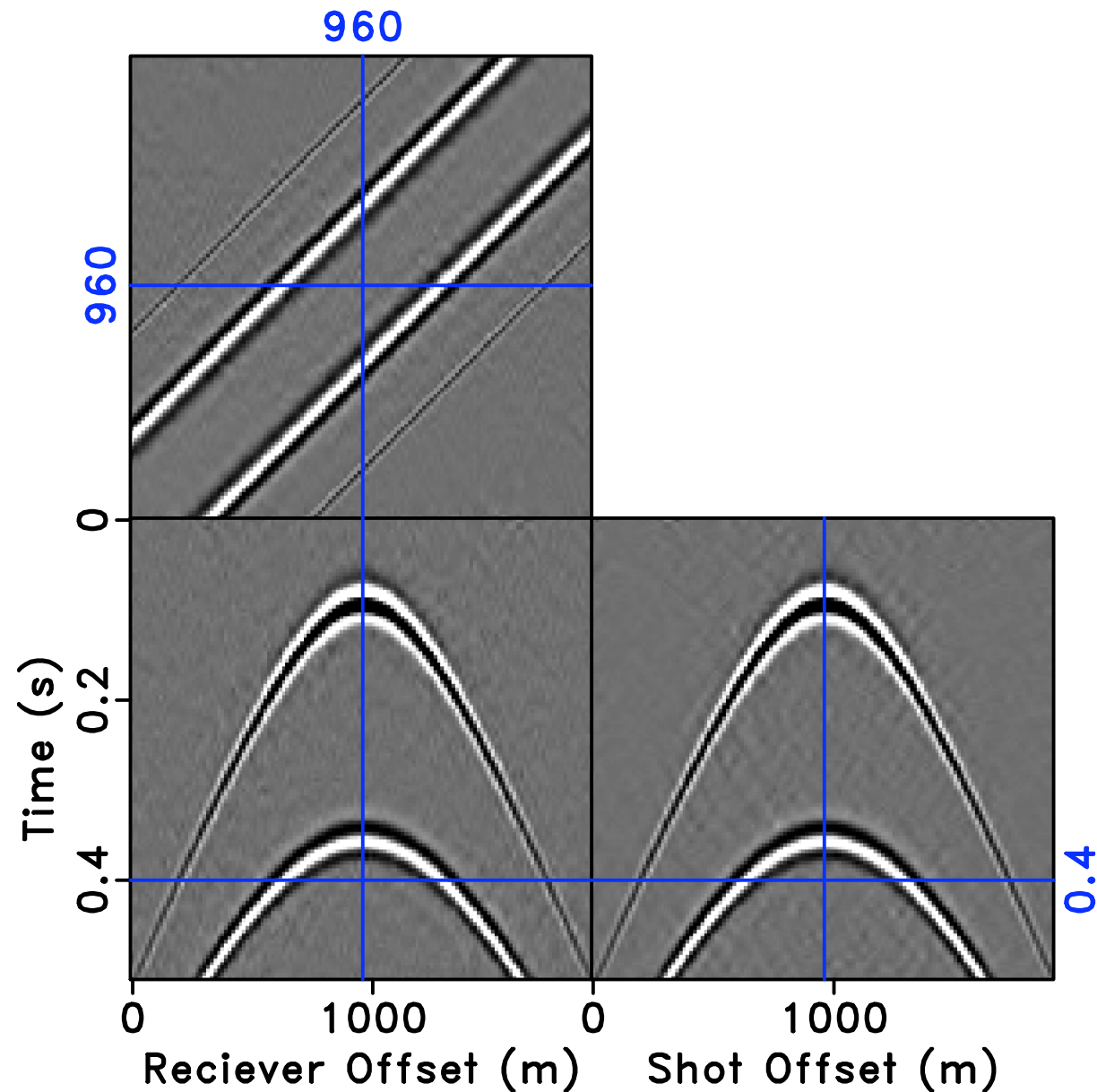


complex model



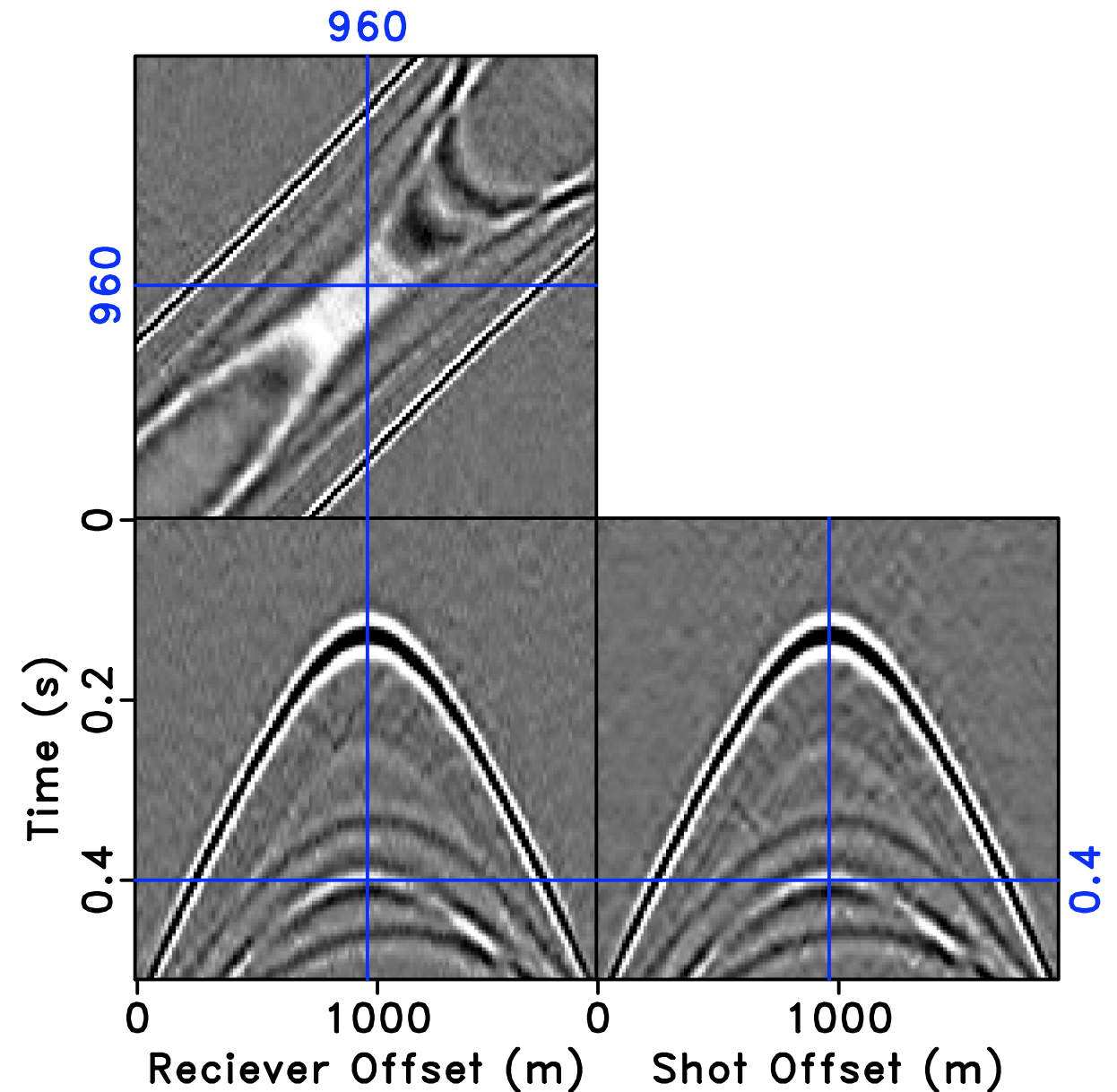
# Recovered data

simple model



16.9dB

complex model

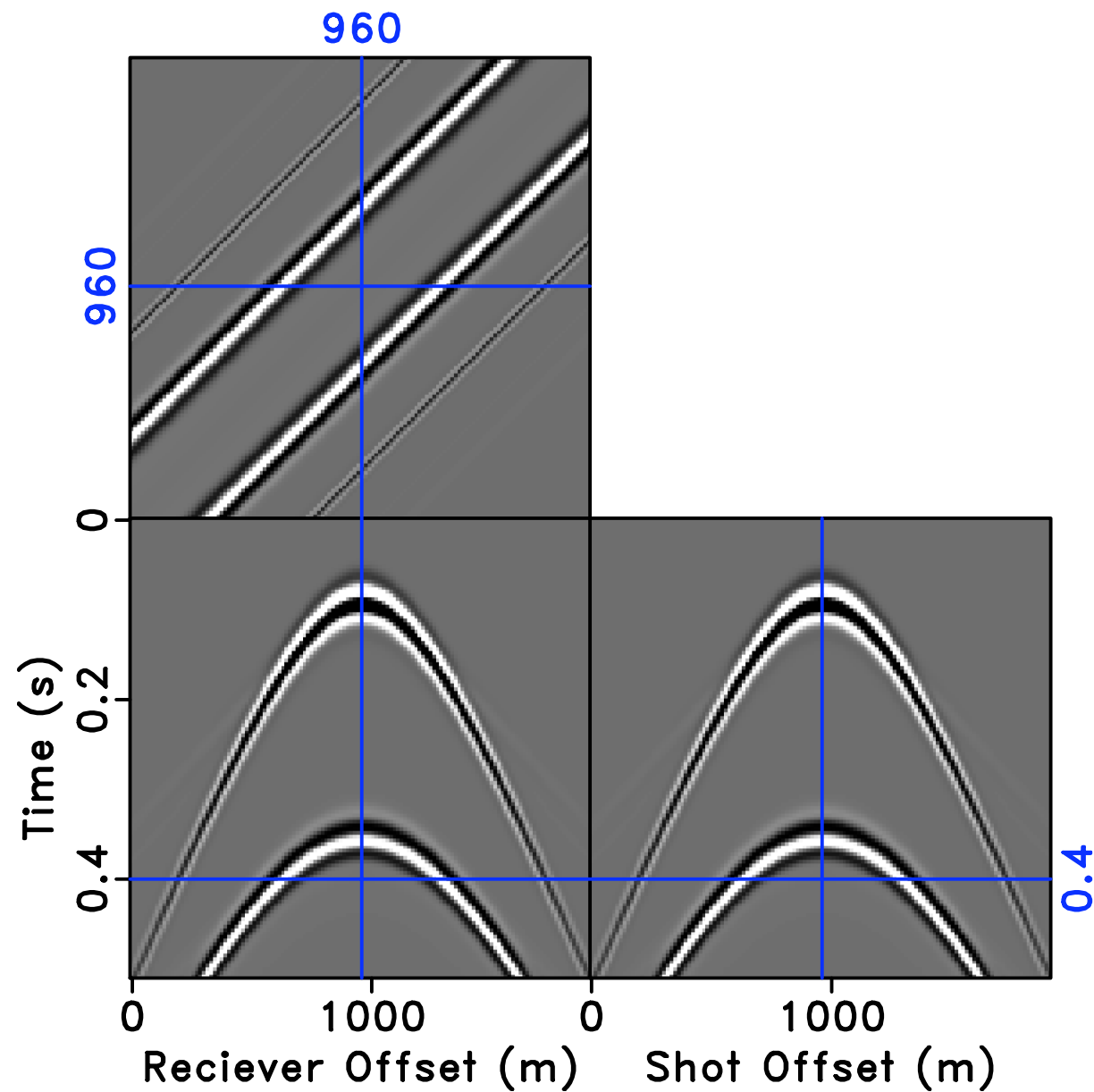


14.3dB

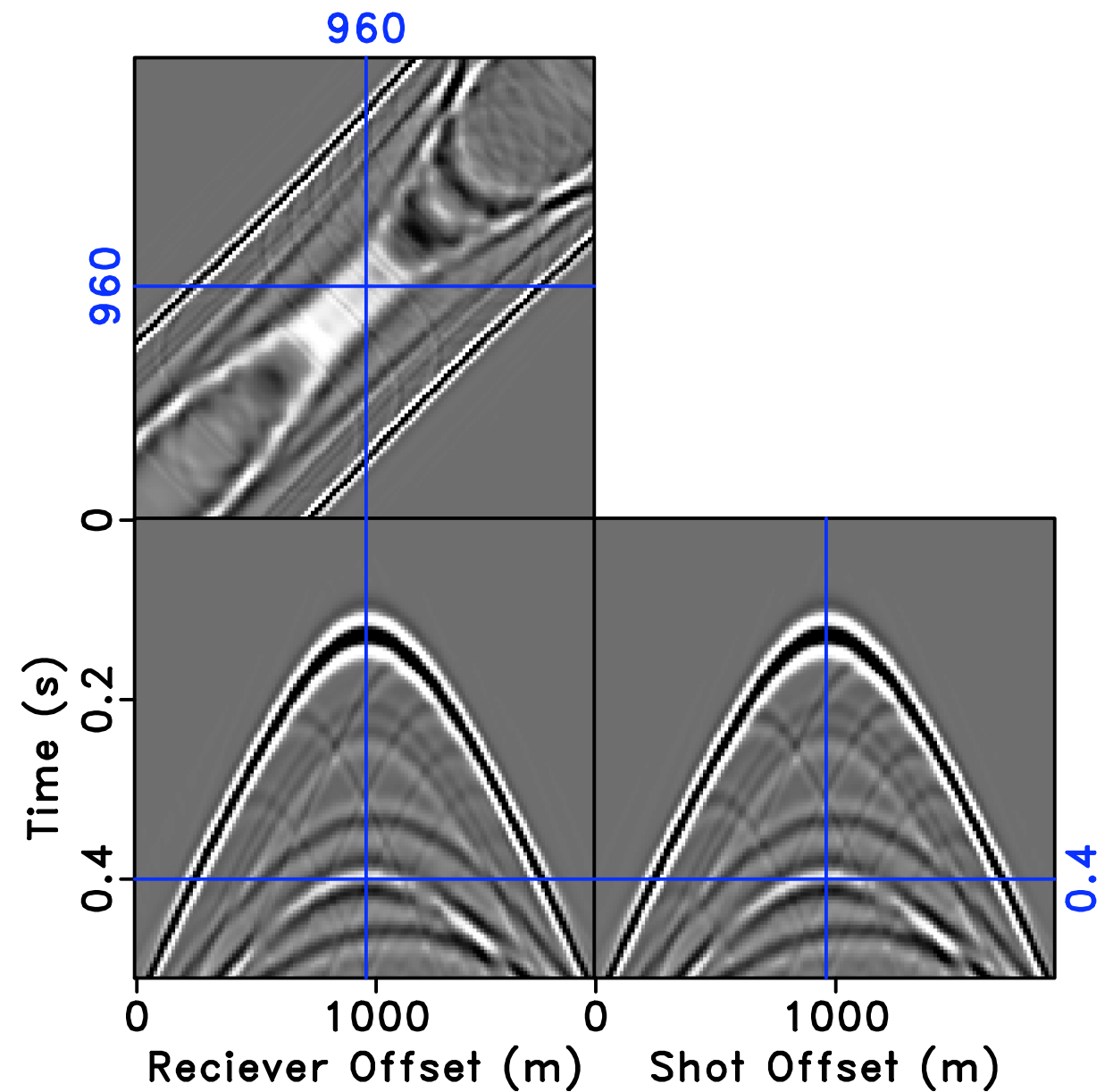
BP Solution ~3000 SPGL1 iteration

# Green's functions

simple model



complex model



# Sample ratio SNR (dB)

problem size  $2^{21}$

Total computed data fraction

# Frequencies / # Shots		0.25	0.15	0.07
	2	9.3	7.0	4.3
	1	13.7	9.2	3.7
	0.5	11.6	7.4	3.4

$$\text{SNR} = -20 \log \frac{\|\mathbf{d} - \tilde{\mathbf{d}}\|_2}{\|\mathbf{d}\|_2}$$

# Discussion & extensions

Compressive samplings are ***cumulative***

- **more** simultaneous experiments **improve** recovery
- equivalent to longer simultaneous & continuous acquisition and allow for **design** of beneficial insonifying **waveforms**.

Add sparsity-promoting prior to PDE constrained optimization problem:

$$\min_{\underline{\mathbf{U}} \in \underline{\mathcal{U}}, \mathbf{x} \in \mathcal{X}} \frac{1}{2} \|\mathbf{y} - \underline{\mathbf{D}}\underline{\mathbf{U}}\|_2^2 + \lambda \|\mathbf{x}\|_1 \quad \text{subject to} \quad \underline{\mathbf{L}}[\mathbf{S}^H \mathbf{x}] \underline{\mathbf{U}} = \underline{\mathbf{B}}$$

*Unconstrained* optimization problem:

$$\min_{\mathbf{x} \in \mathcal{X}} \frac{1}{2} \|\mathbf{y} - \underline{\mathbf{F}}[\mathbf{x}]\|_2^2 + \lambda \|\mathbf{x}\|_1 \quad \text{with} \quad \underline{\mathbf{F}}[\mathbf{x}] = \underline{\mathbf{D}}\underline{\mathbf{L}}^{-1}[\mathbf{S}^H \mathbf{x}] \underline{\mathbf{B}}$$

Requires extension of projected gradient  $\ell_1$ -solver to nonlinear forward map ...

# Conclusions

Confluence of Compressive sensing, Simultaneous acquisition/modeling, and Helmholtz preconditioners leads to a formulation where cost to compute/acquire Green's functions are

- no longer dependent on the problem **size** but on the **complexity** (=sparsity) of the wavefield
- computed/acquired with a **gain** in speed *proportional* to the **compression** rate of the wavefield & behavior CS matrix
- obtained with an **overhead** for the recovery problem that becomes *negligible* for **large** problem sizes.

Extends to other forward modeling operators.

Room for analyses.

Interesting

- link with simultaneous acquisition and source design
- outlook towards complexity-driven solutions to inversion problems.



# Acknowledgments

E. van den Berg and M. P. Friedlander for *SPGL1*  
([www.cs.ubc.ca/labs/scl/spgl1](http://www.cs.ubc.ca/labs/scl/spgl1)) & *Sparco* ([www.cs.ubc.ca/labs/scl/sparco](http://www.cs.ubc.ca/labs/scl/sparco))

Sergey Fomel for Madagascar ([rsf.sf.net](http://rsf.sf.net))

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## Thank you!