

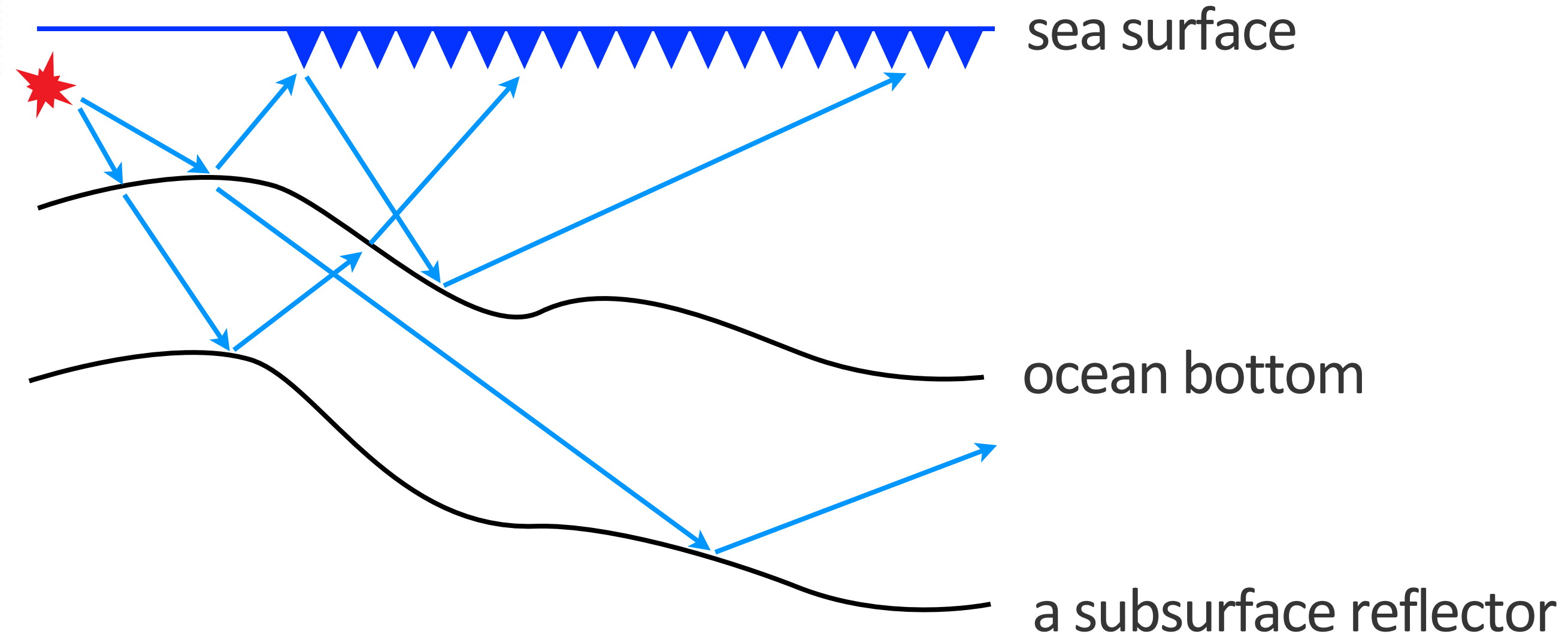
Fast imaging with surface-related multiples

Ning Tu supervised by Prof. Felix J. Herrmann

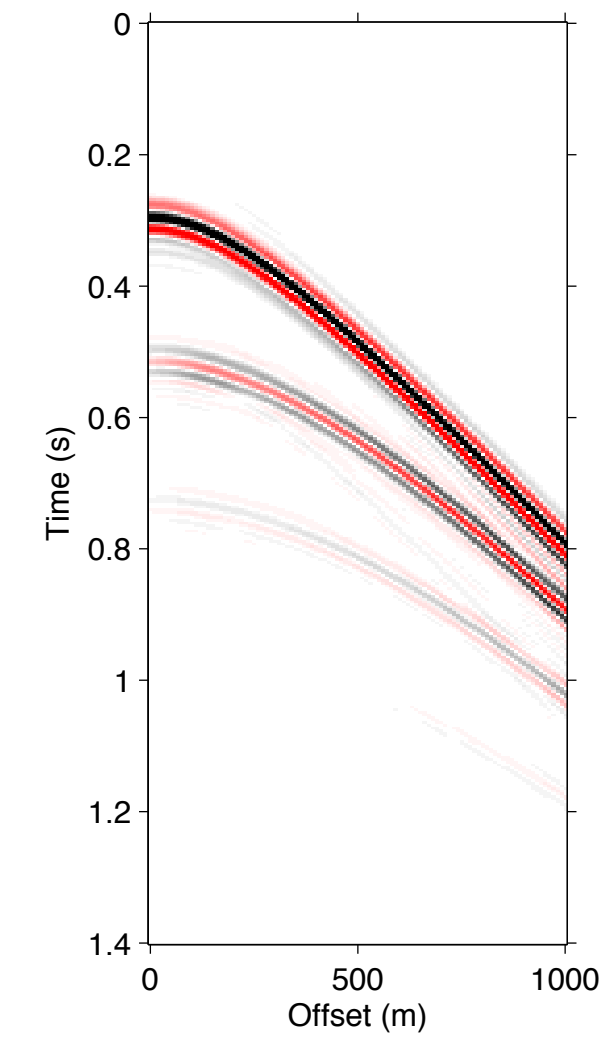


University of British Columbia

Seismic data acquisition and imaging

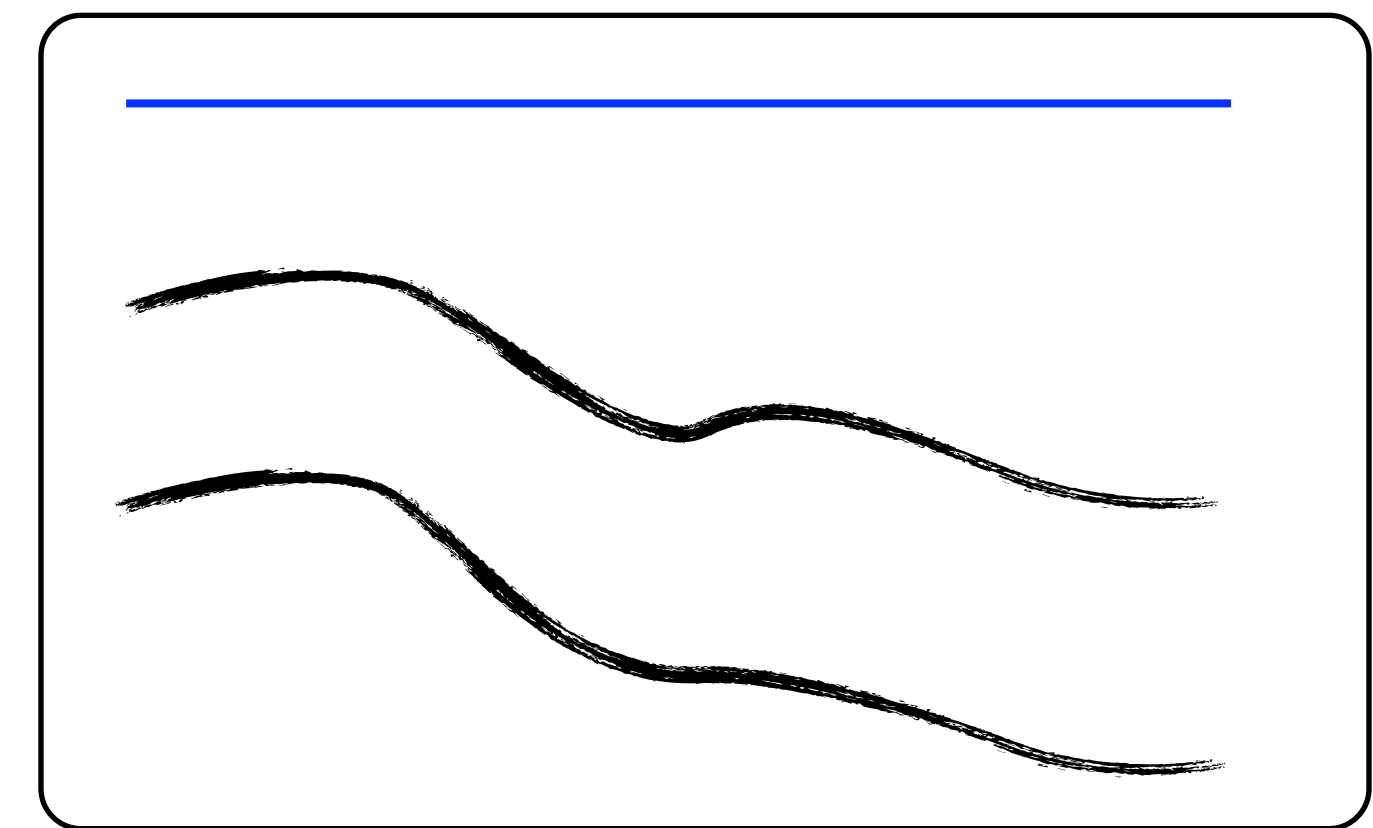


Earth model



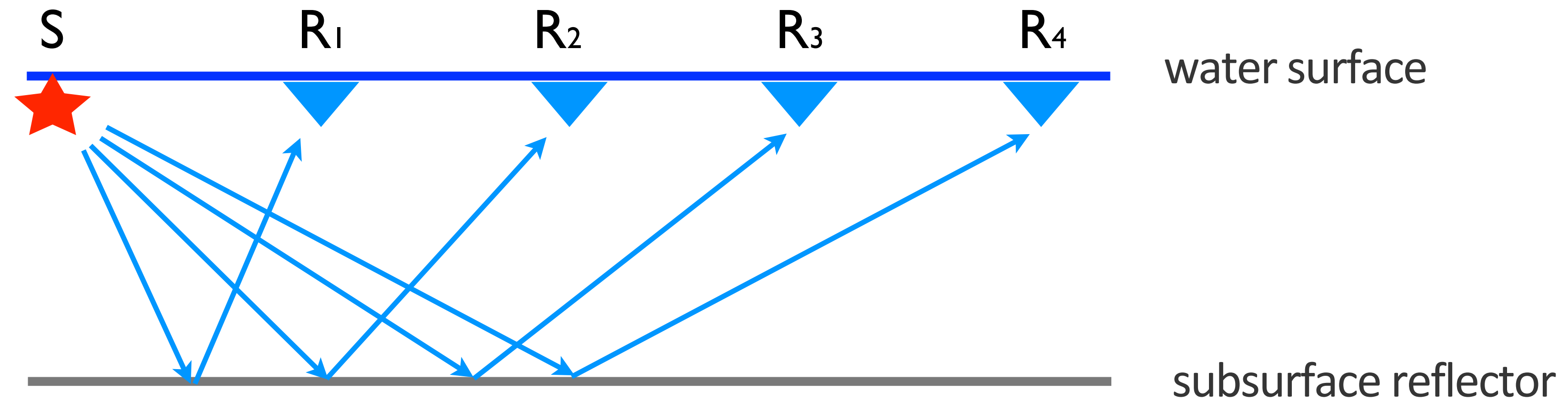
reflection
data

imaging



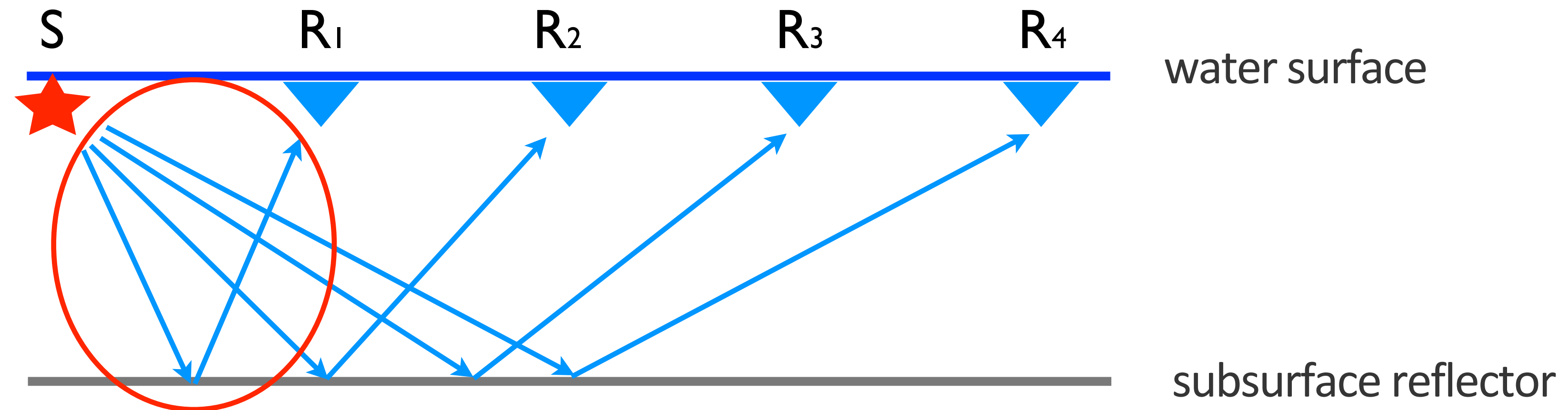
image

Surface-related multiples: the origin



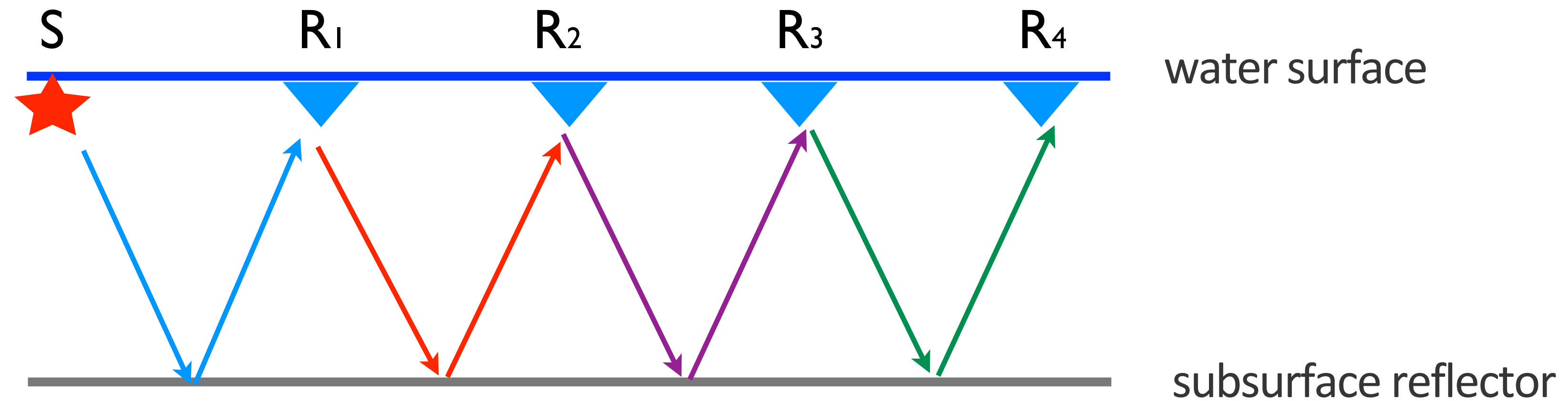
The *primary* reflections

Surface-related multiples: the origin



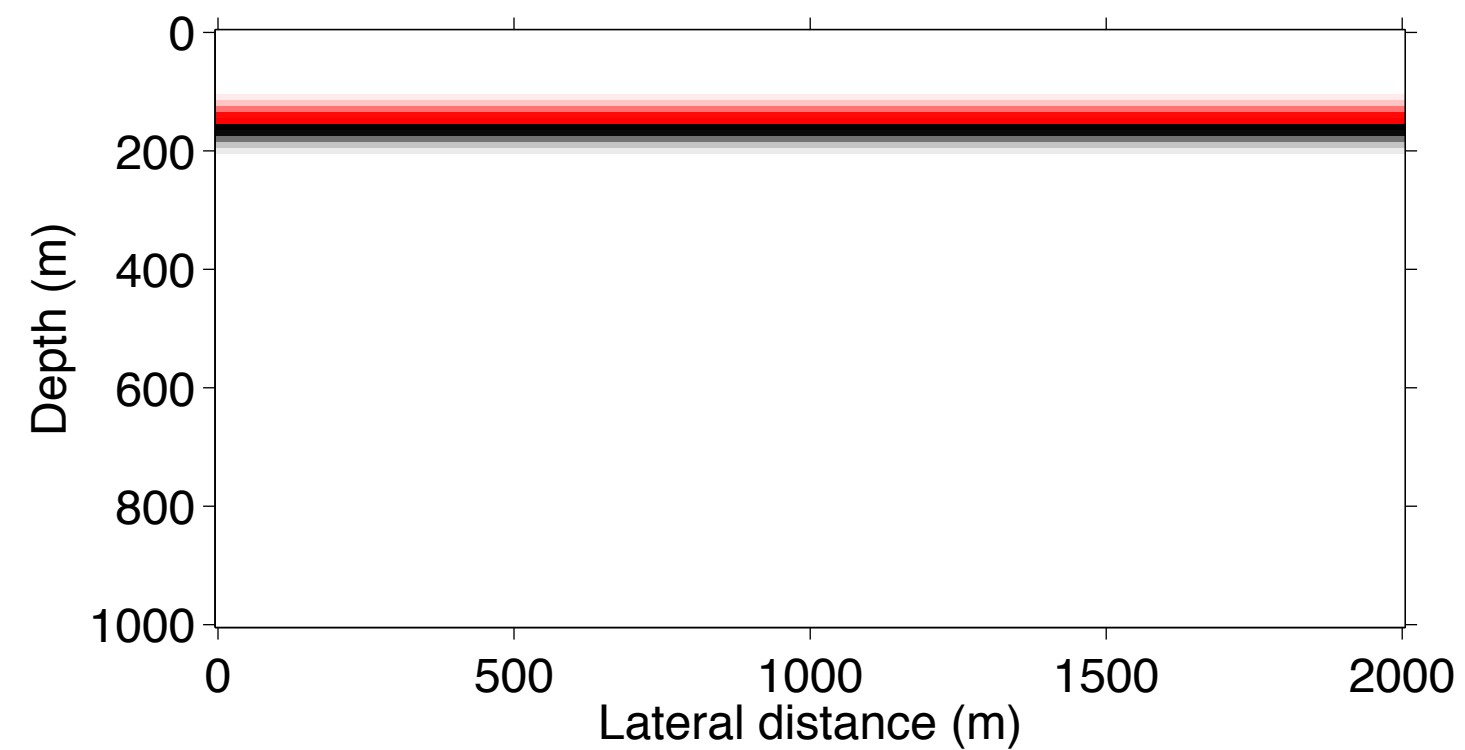
The *primary* reflections

Surface-related multiples: the origin

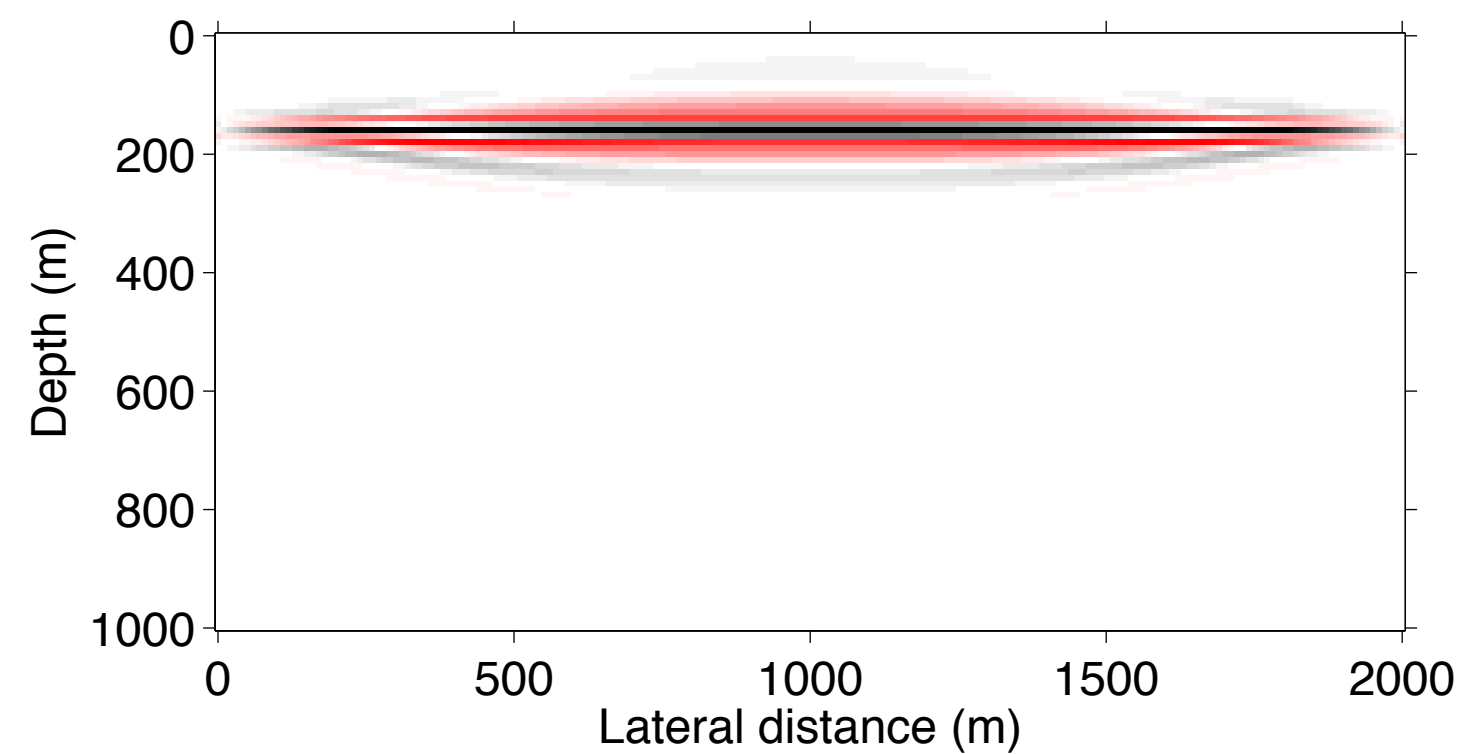


The **primary** + its 1st/2nd/3rd-order **surface-related multiples** reflections

Surface-related multiples: the problem



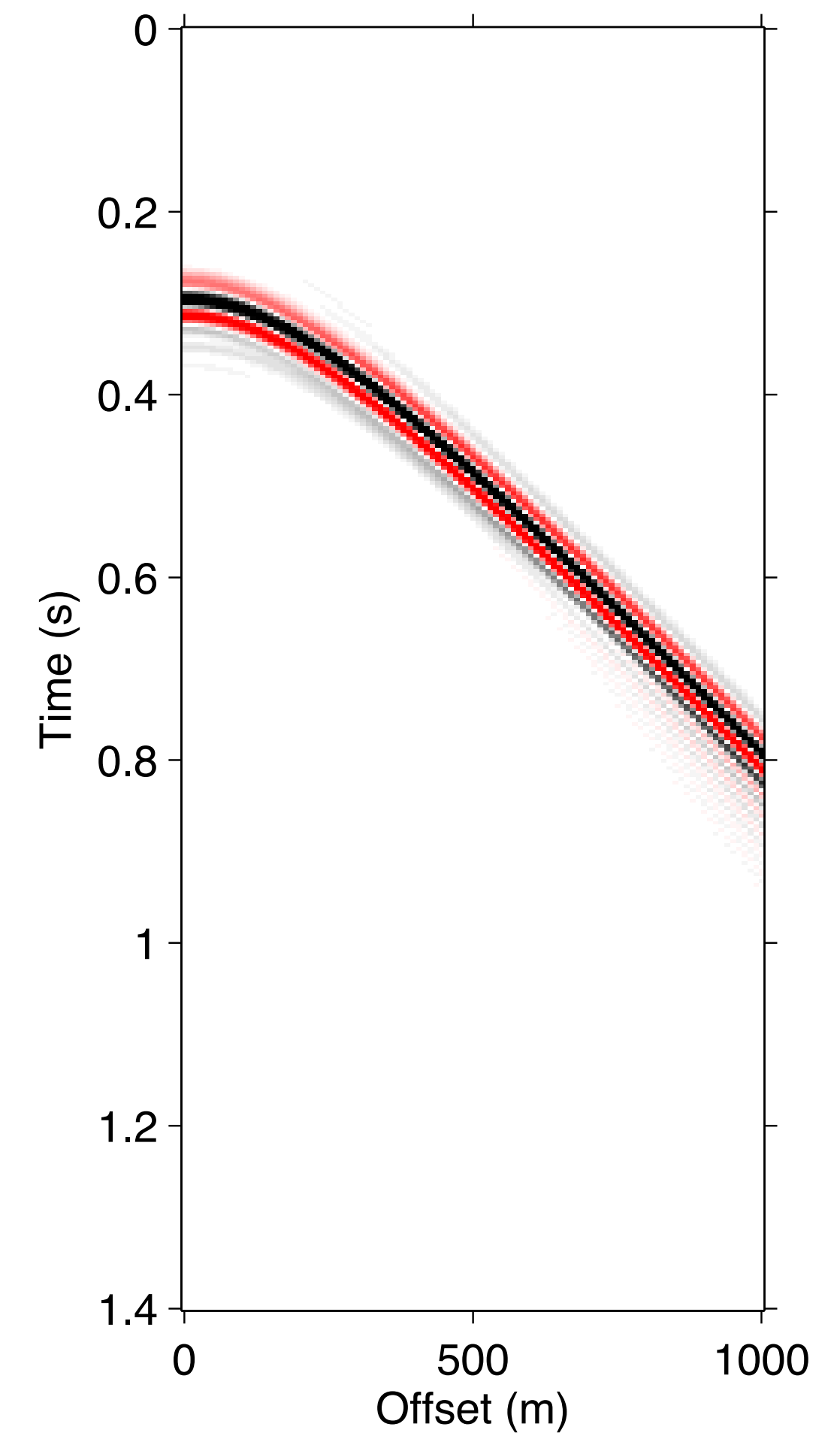
True model



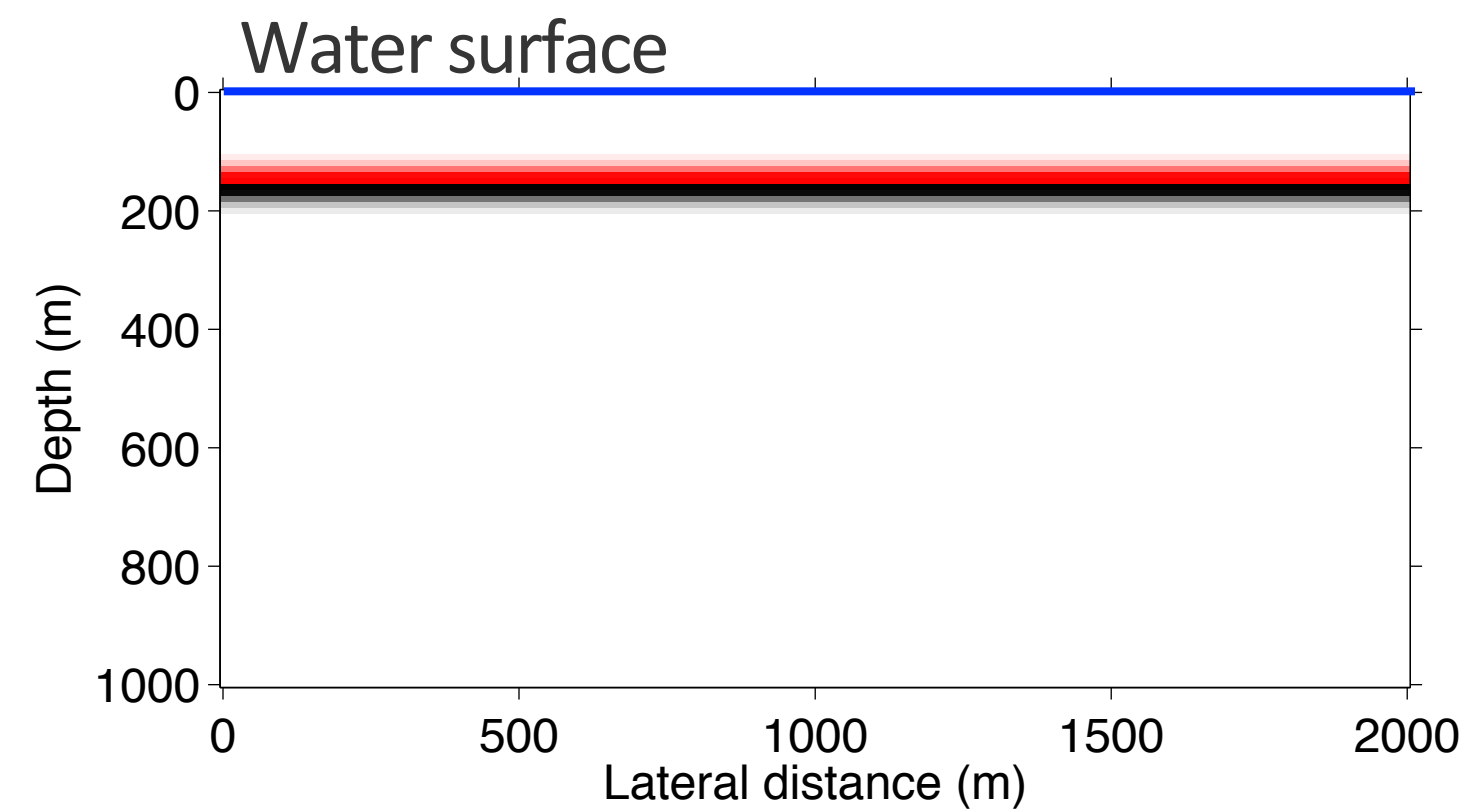
Image

“primary-only” data acquisition

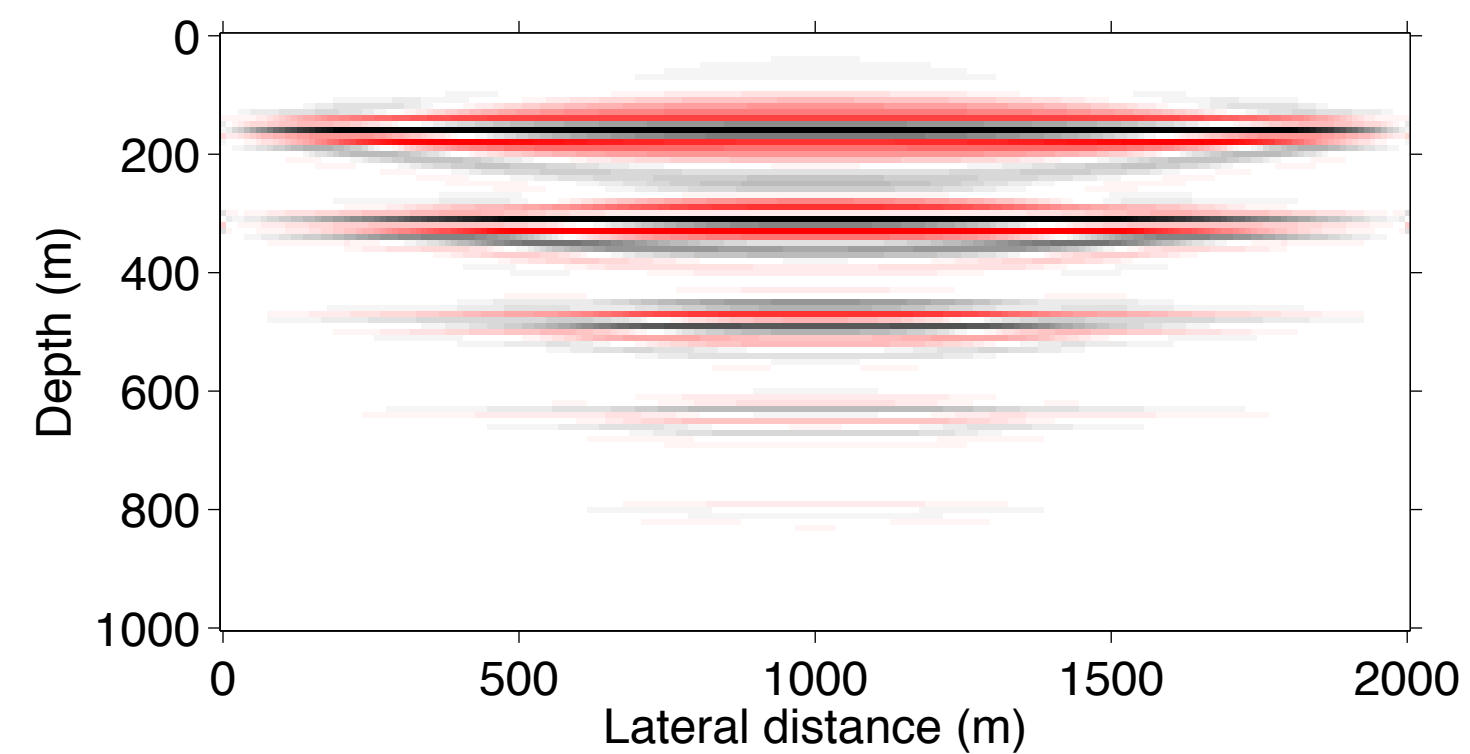
conventional imaging



Surface-related multiples: the problem



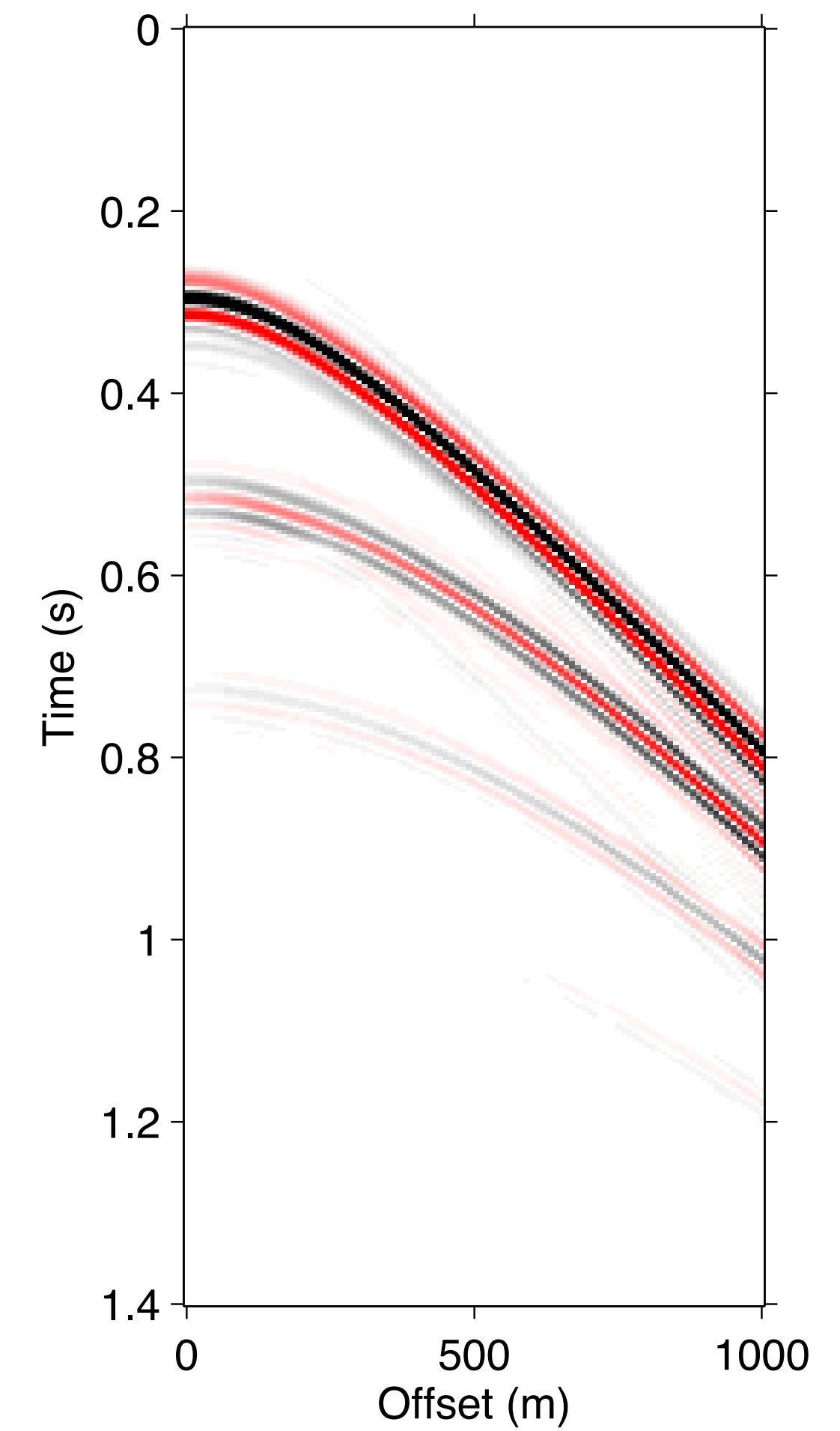
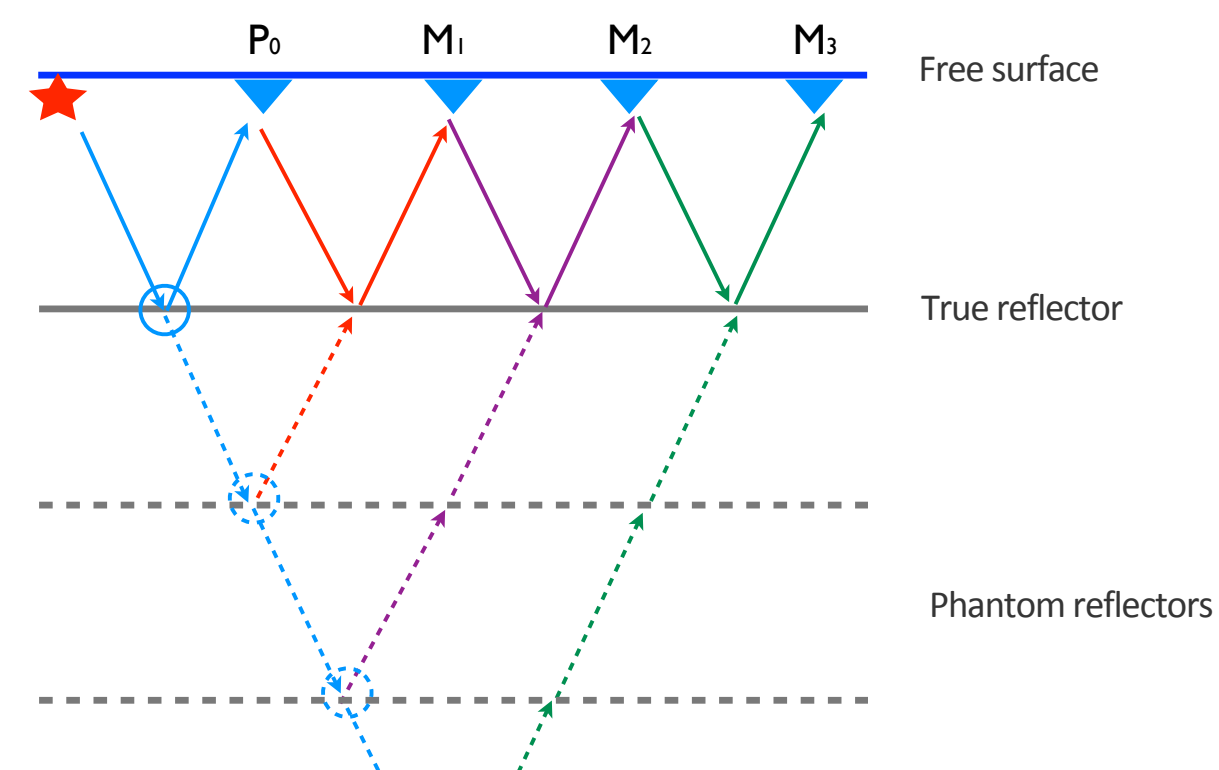
True model



Image

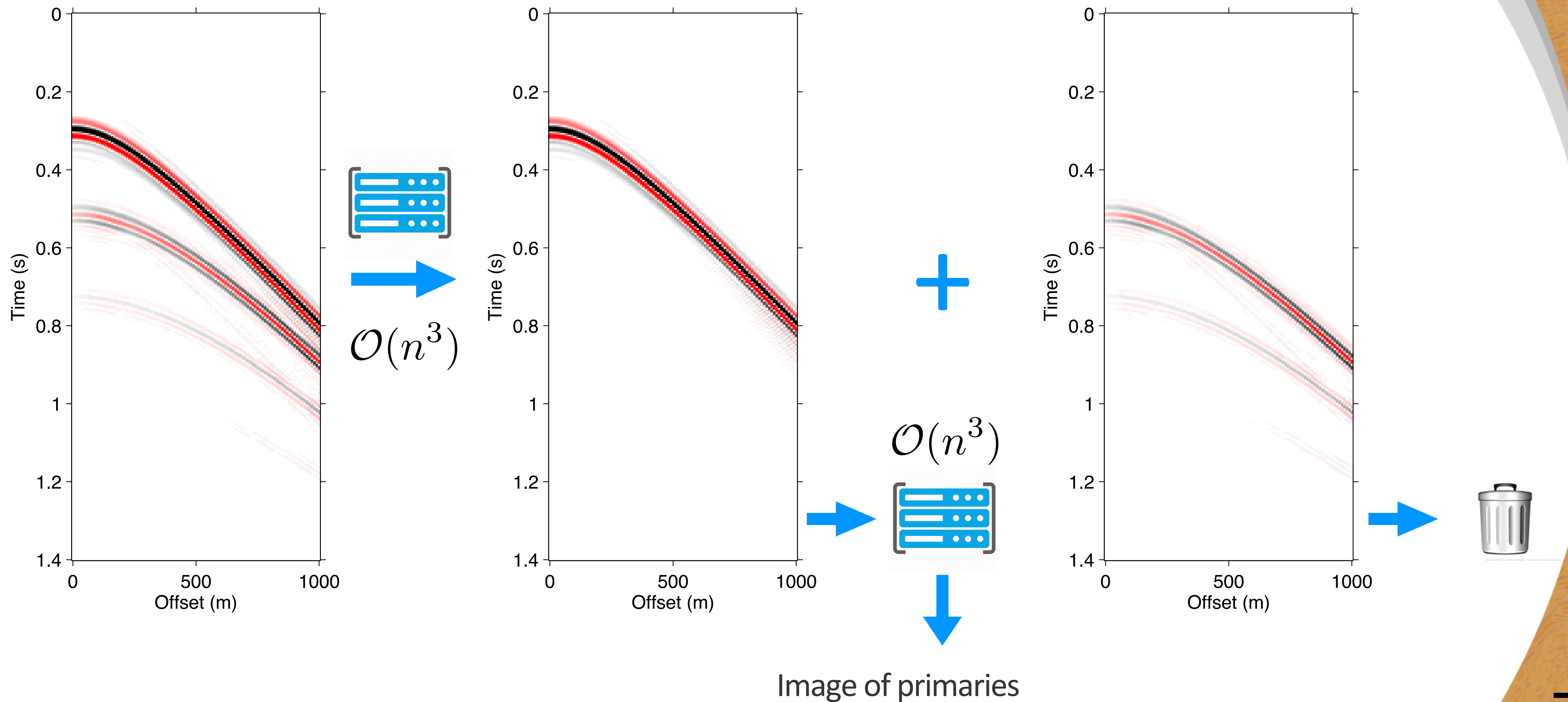
data acquisition *with multiples*

conventional imaging

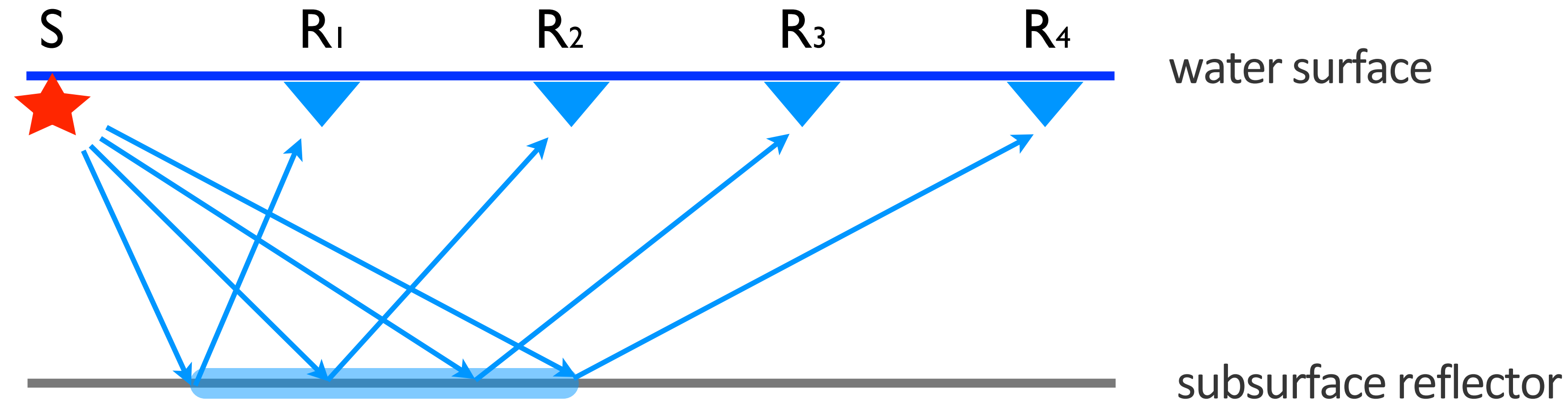


Existing data space solutions - demultiple

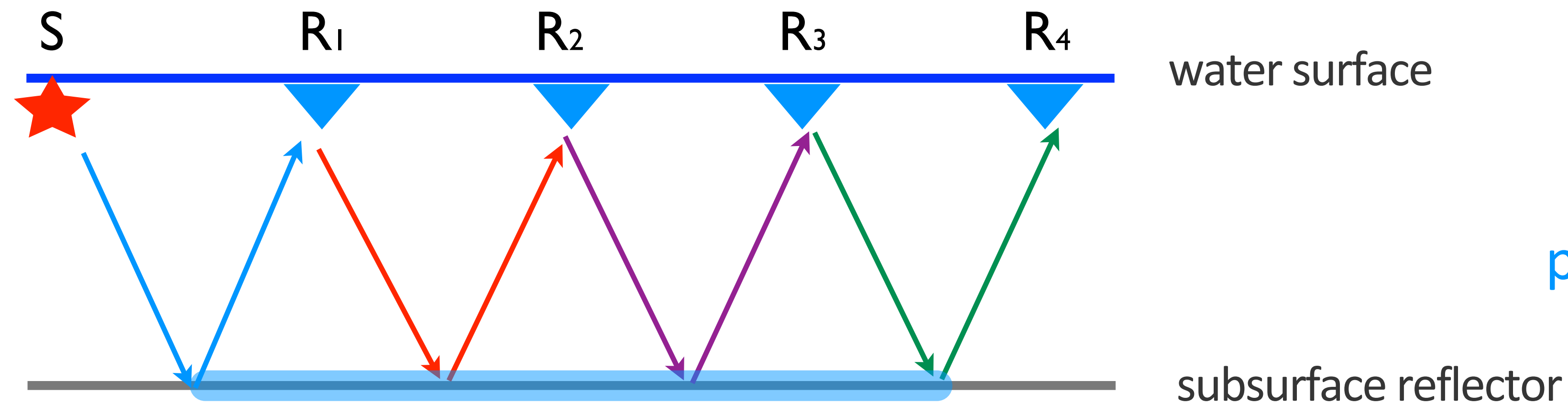
[Assumption: dense source/receiver sampling]



Model space solutions - imaging with multiples



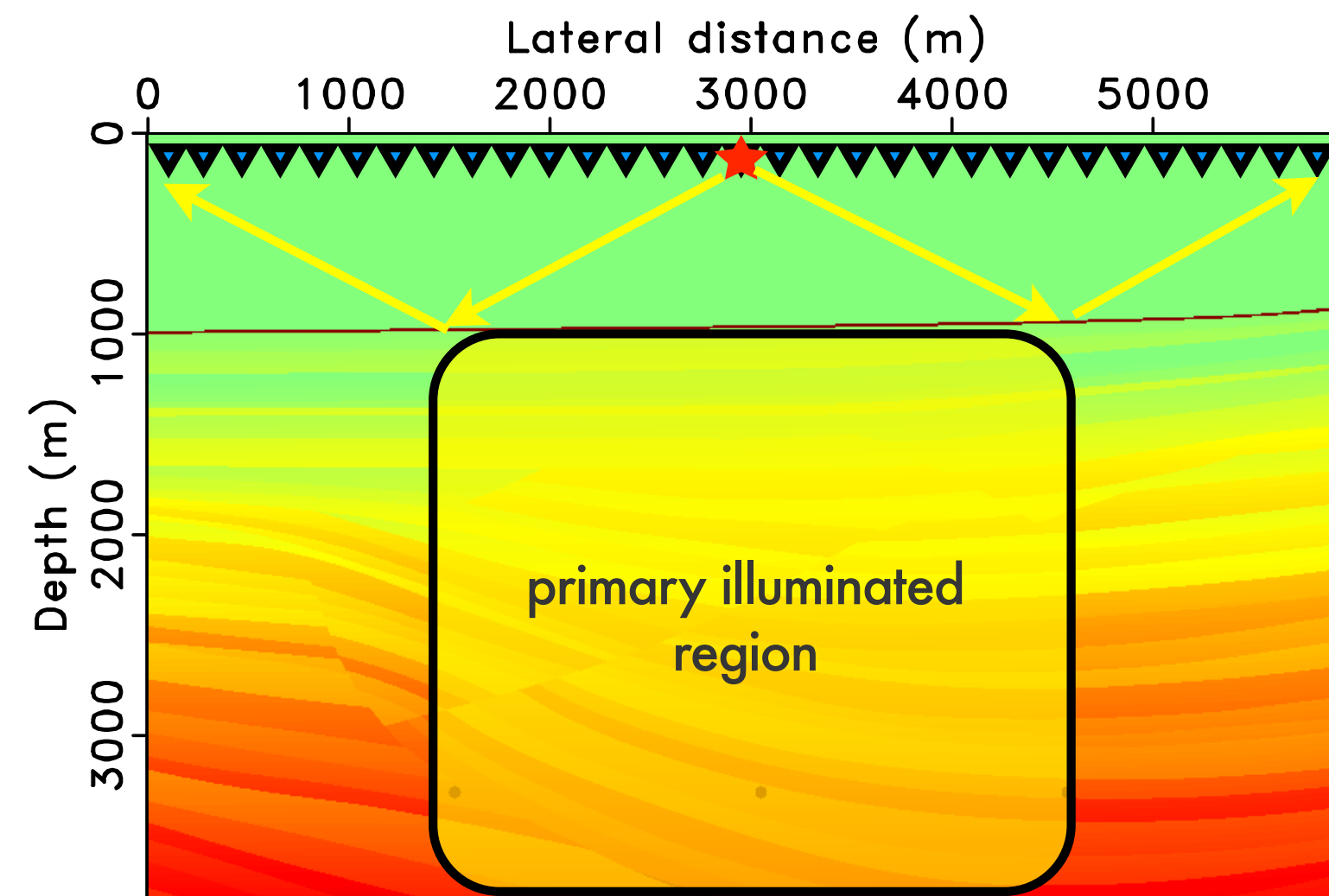
Illumination by
primaries



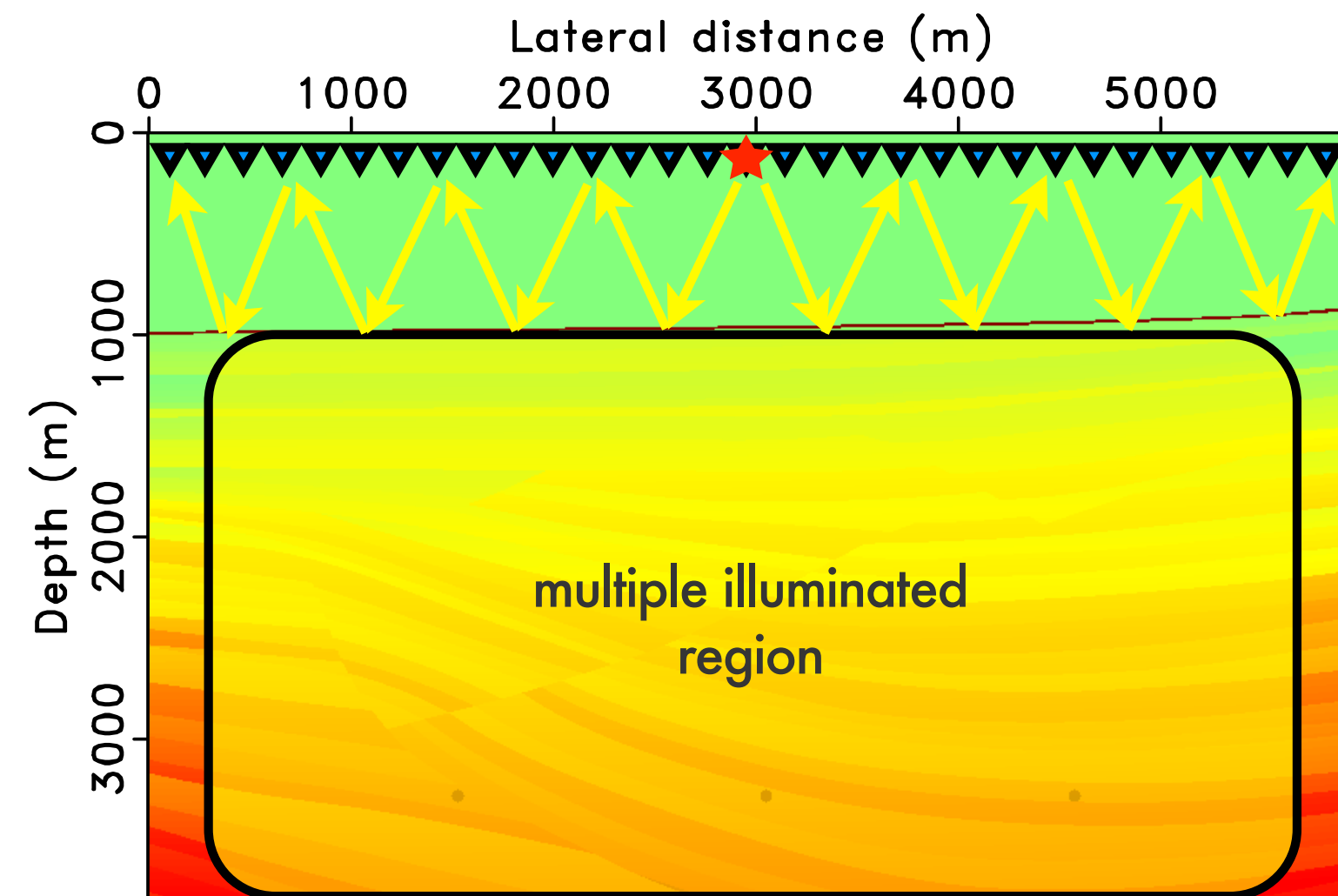
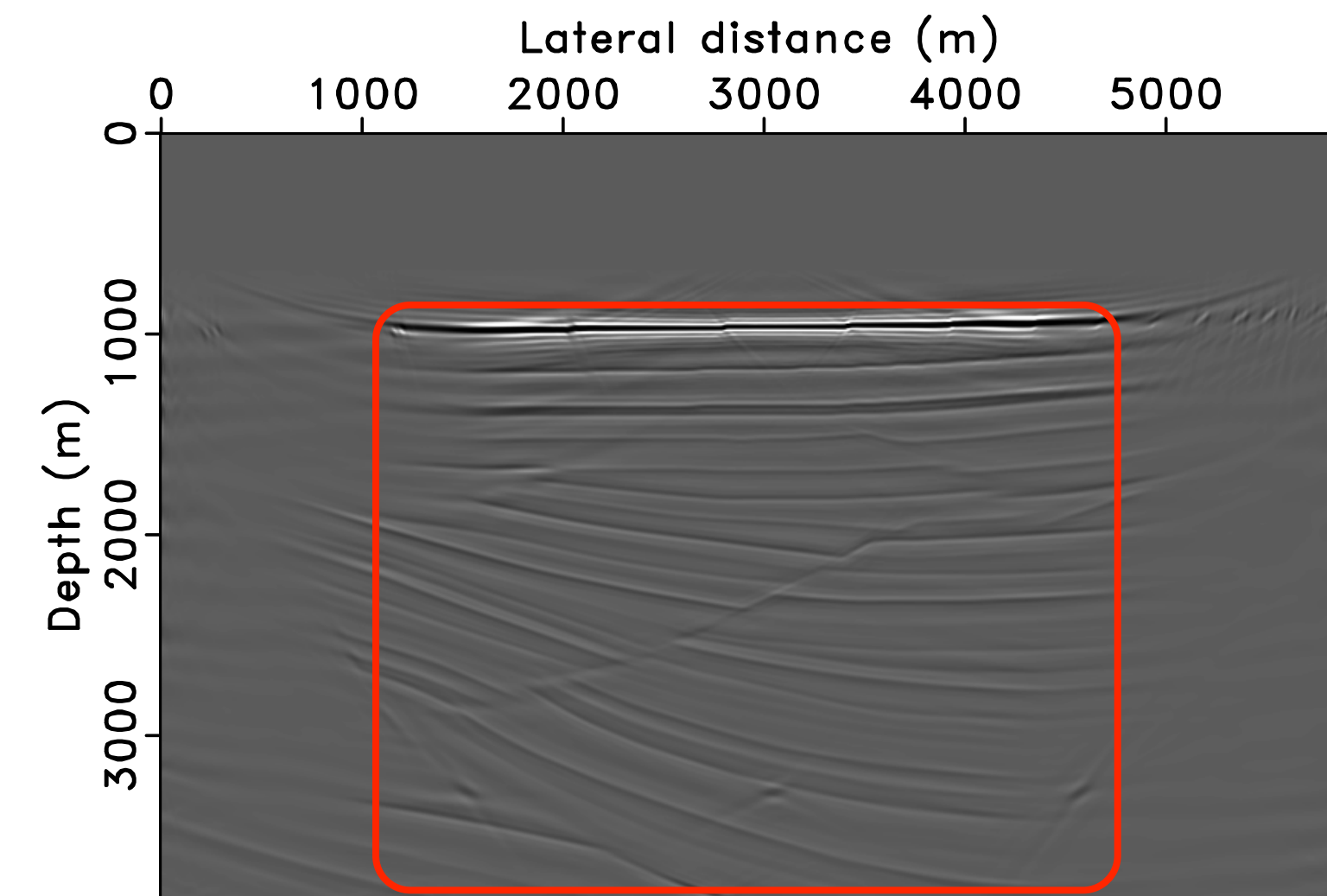
Illumination by
primaries+multiples

Model space solutions - imaging with multiples

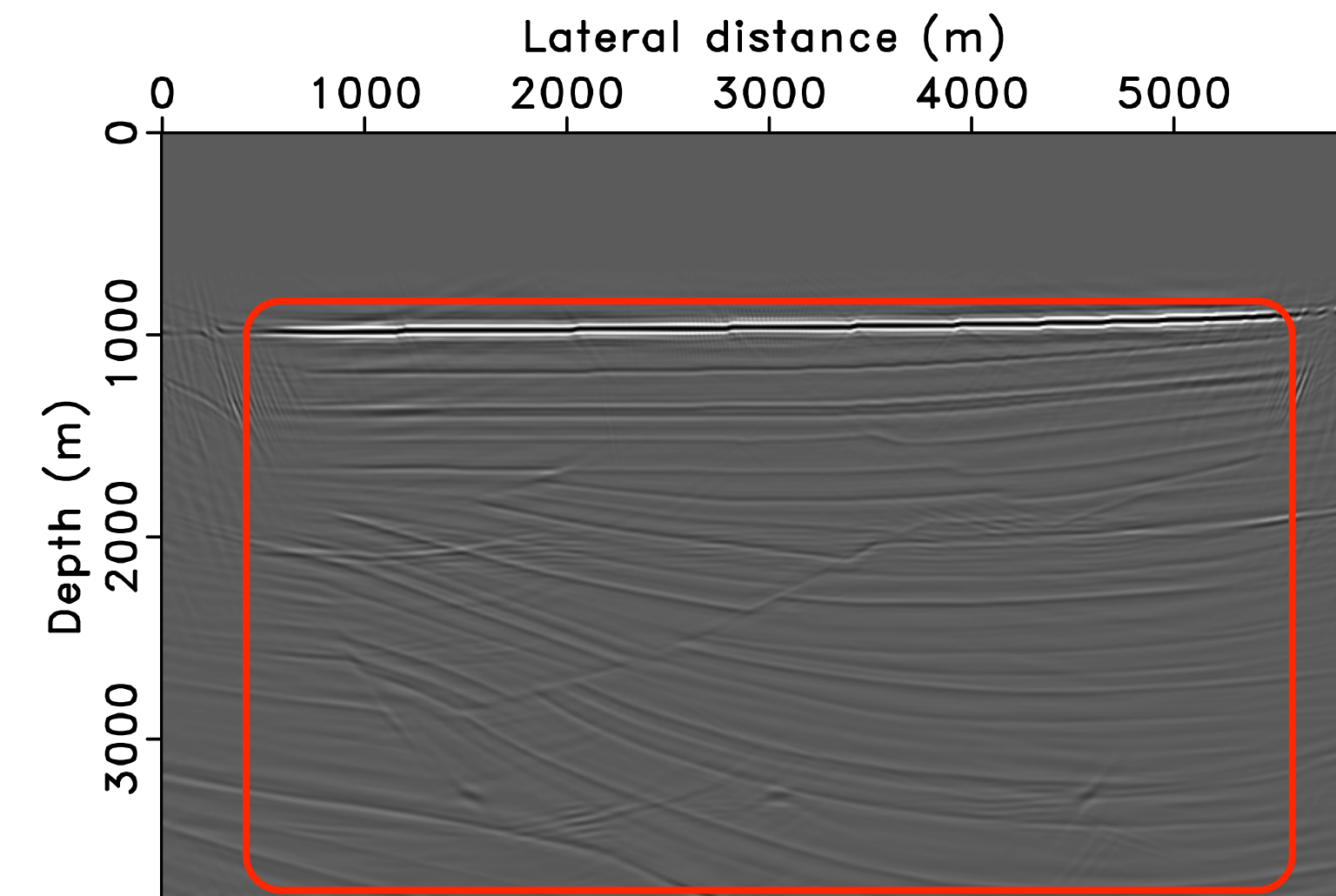
Chapter 6



Numerical
example

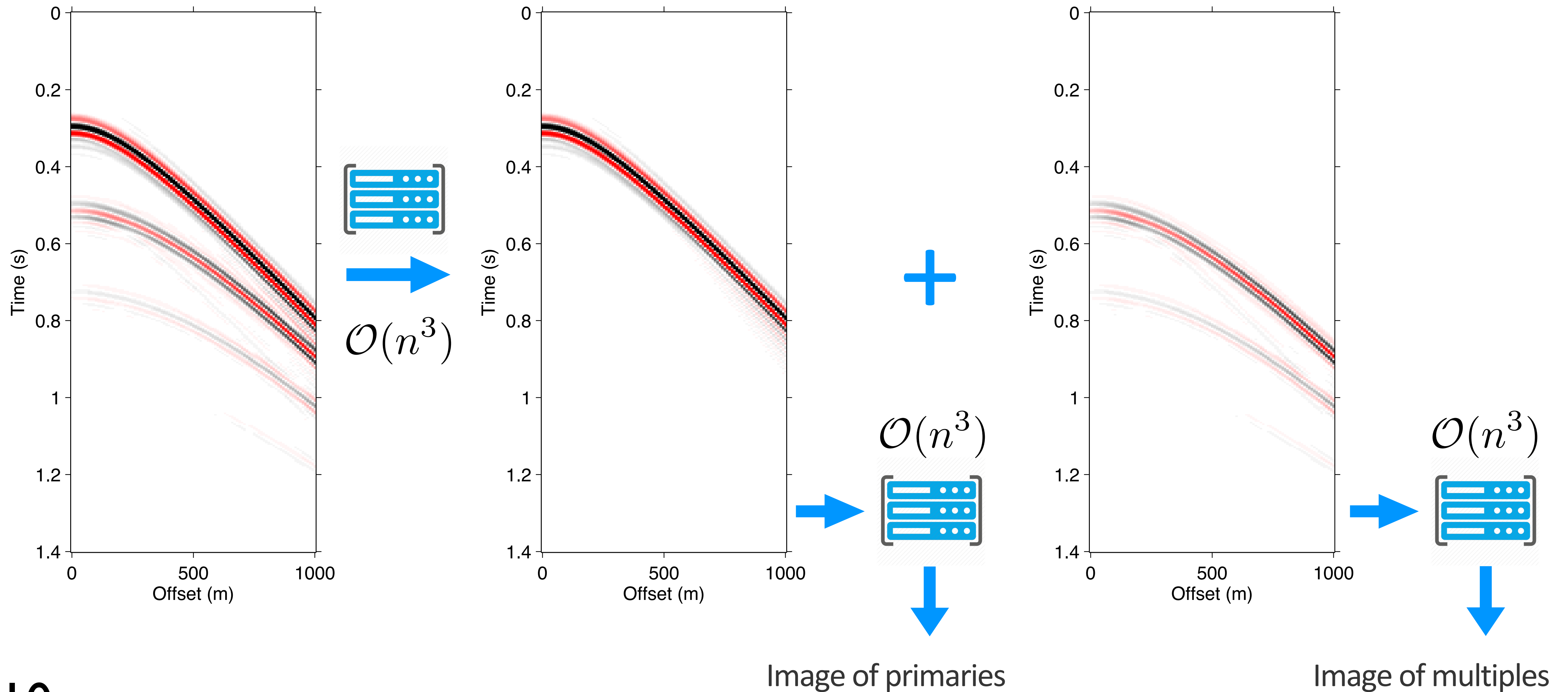


Numerical
example



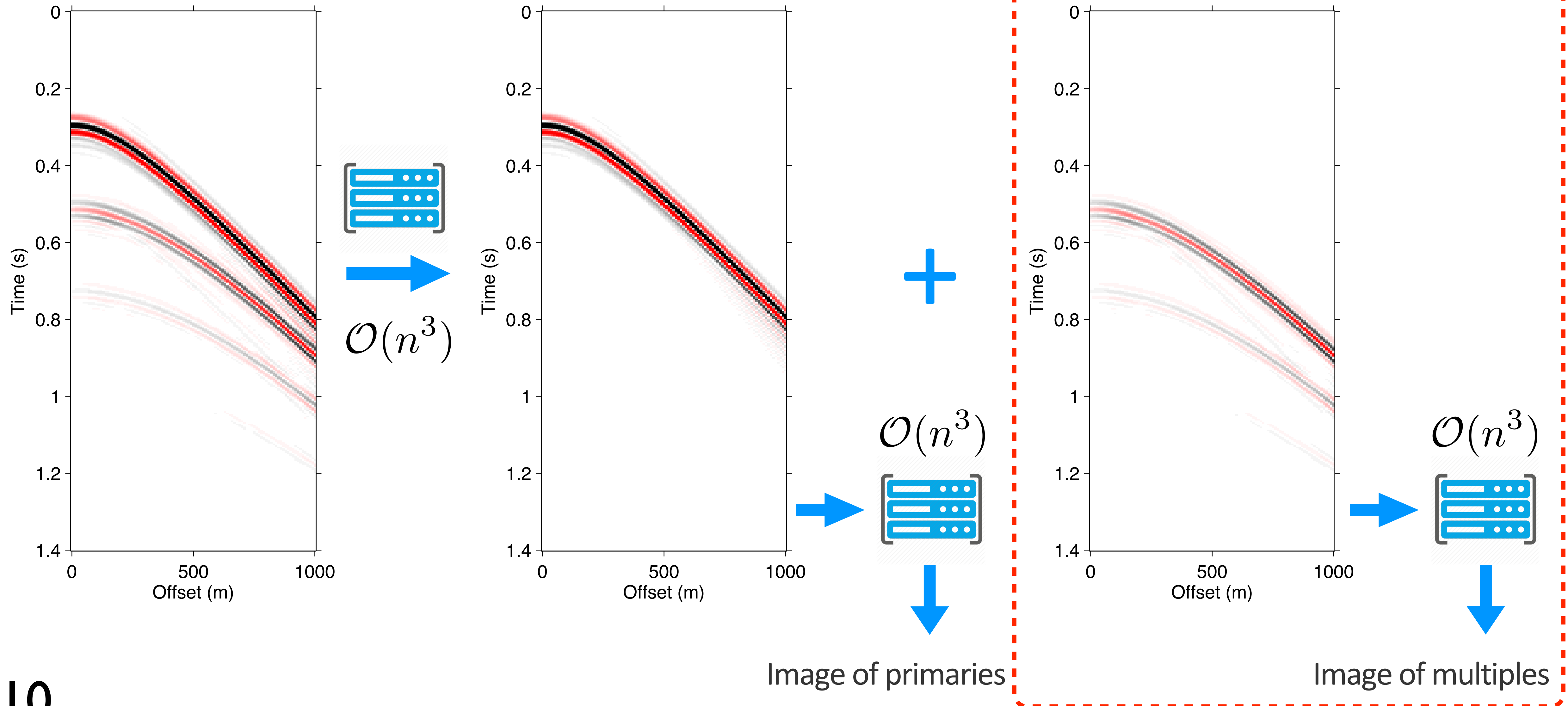
Model space solutions - the reality

[1] reliance on primary/multiple separation



Model space solutions - the reality

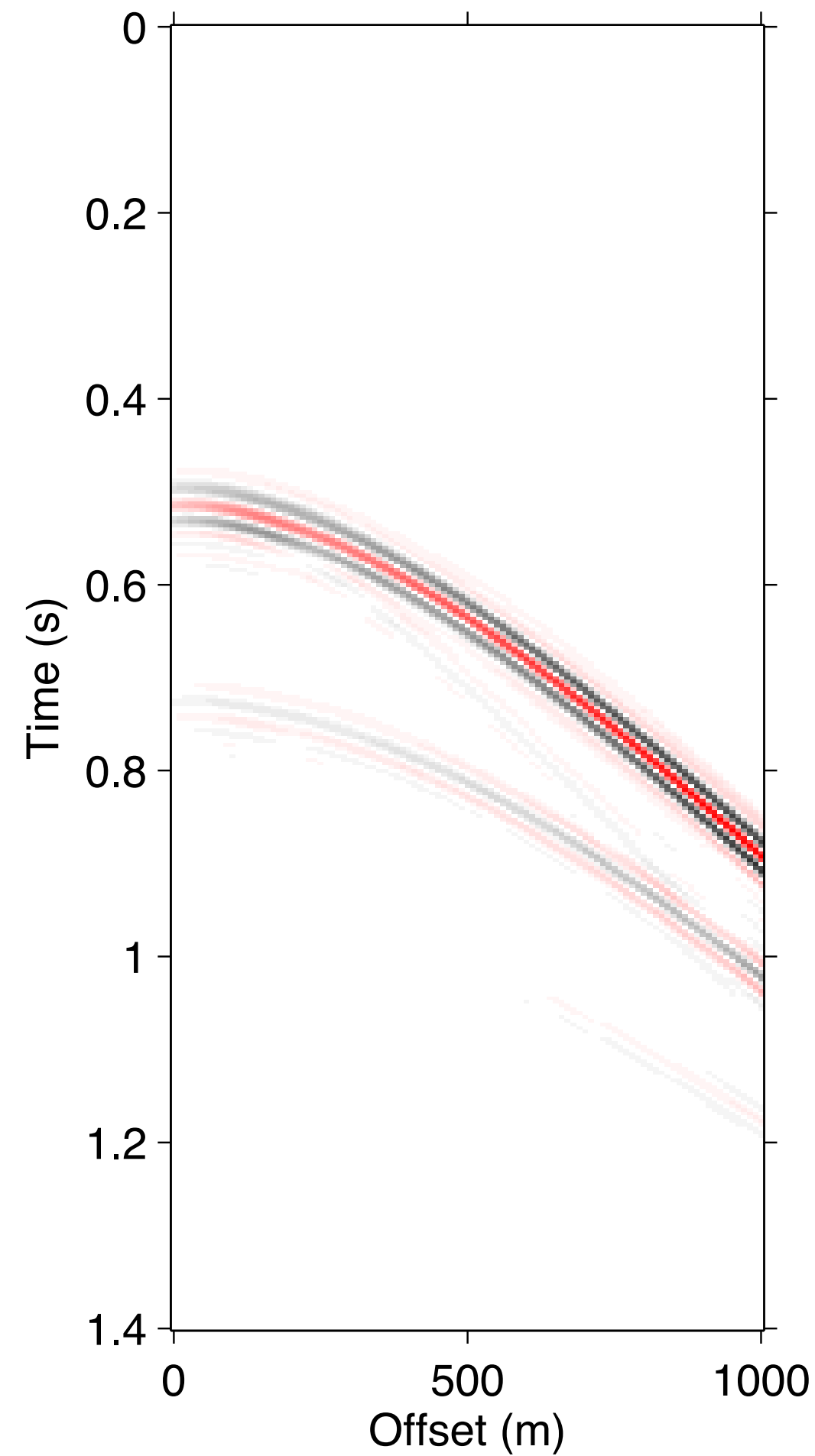
[1] reliance on primary/multiple separation



Model space solutions - the reality

[2] improper handling of multiples during imaging --- cross-correlation imaging

Chapter 2
Liu et al., 2011



Cross-correlation imaging by
injecting data as source

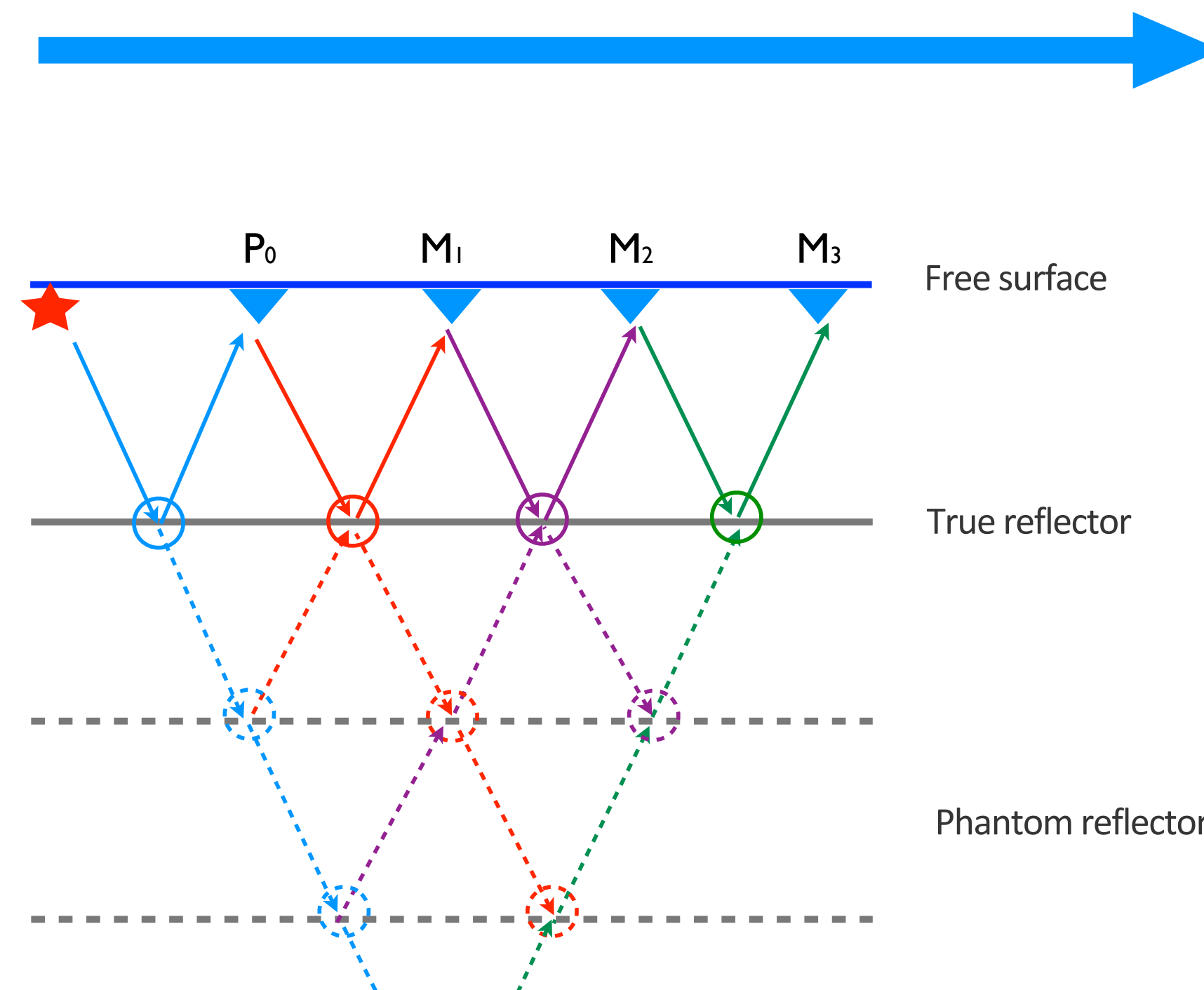
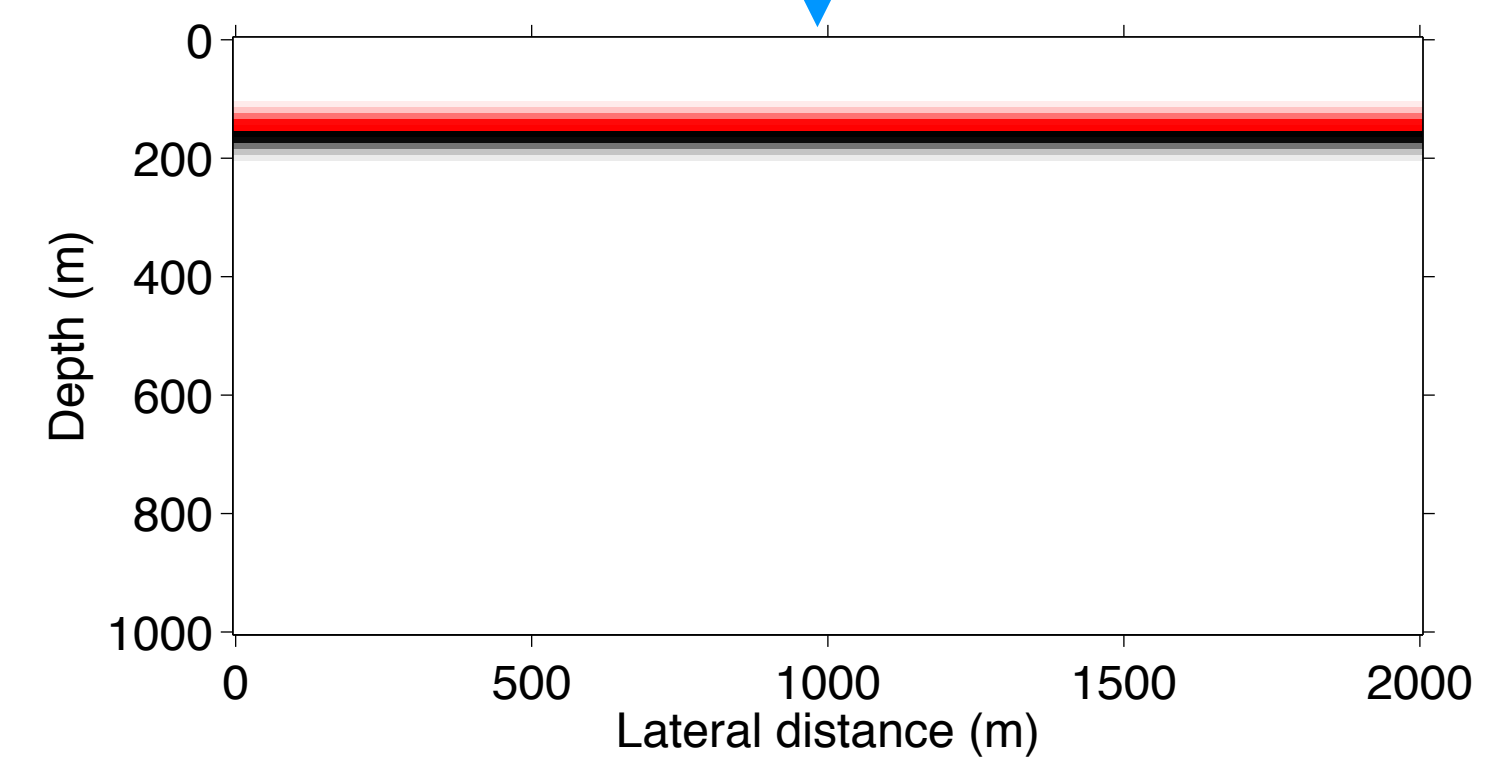
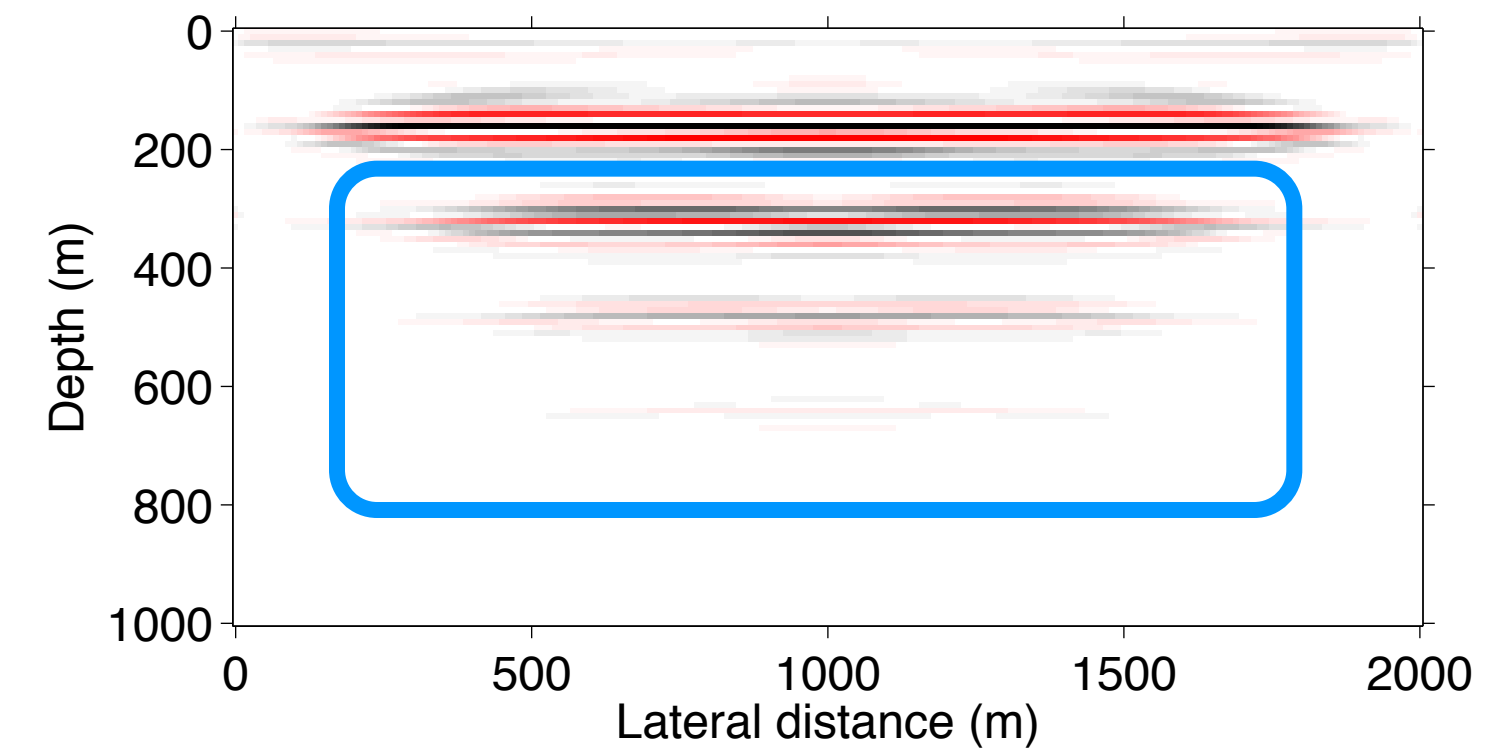


Image of multiples



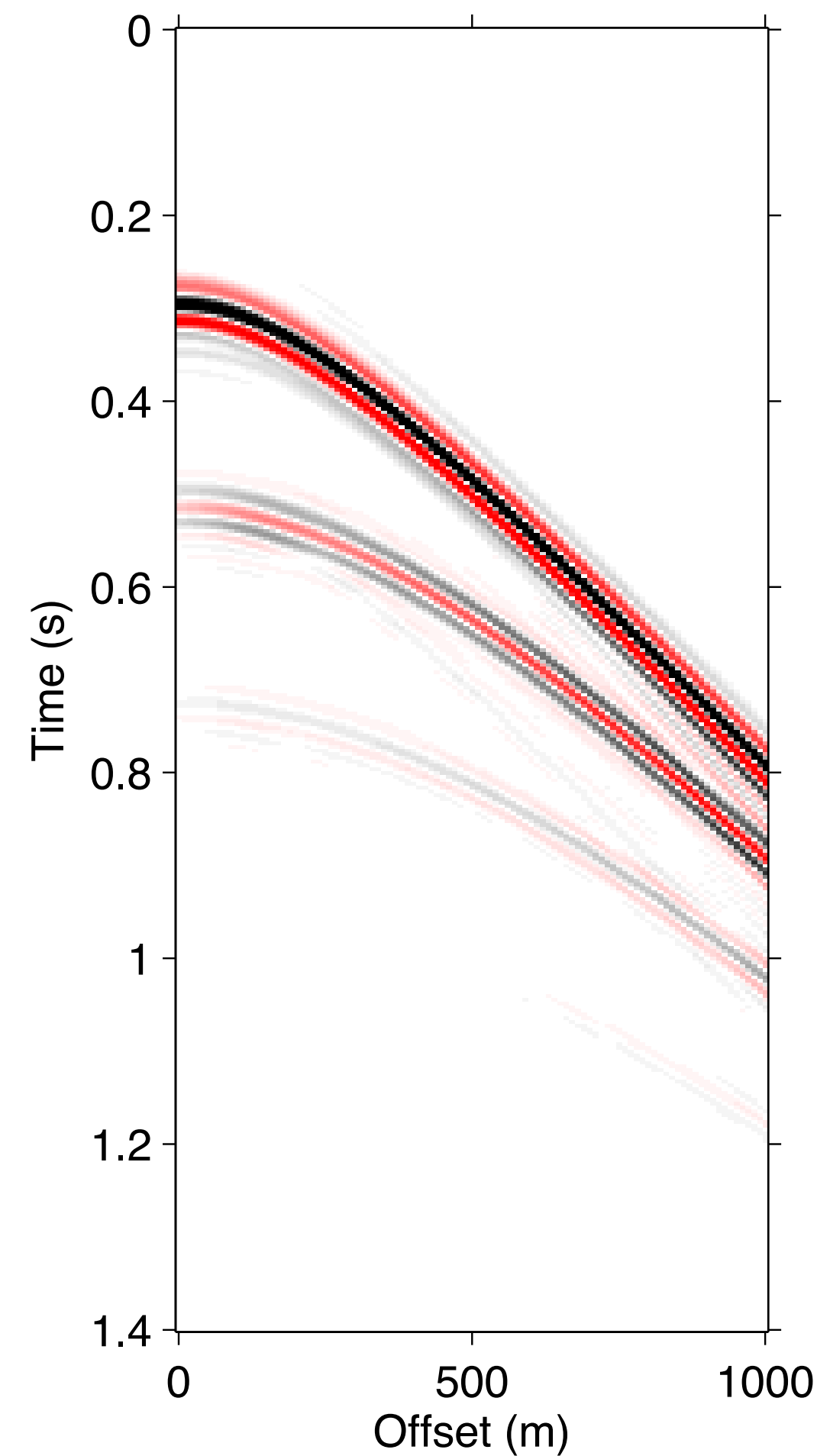
True model

Model space solutions - the reality

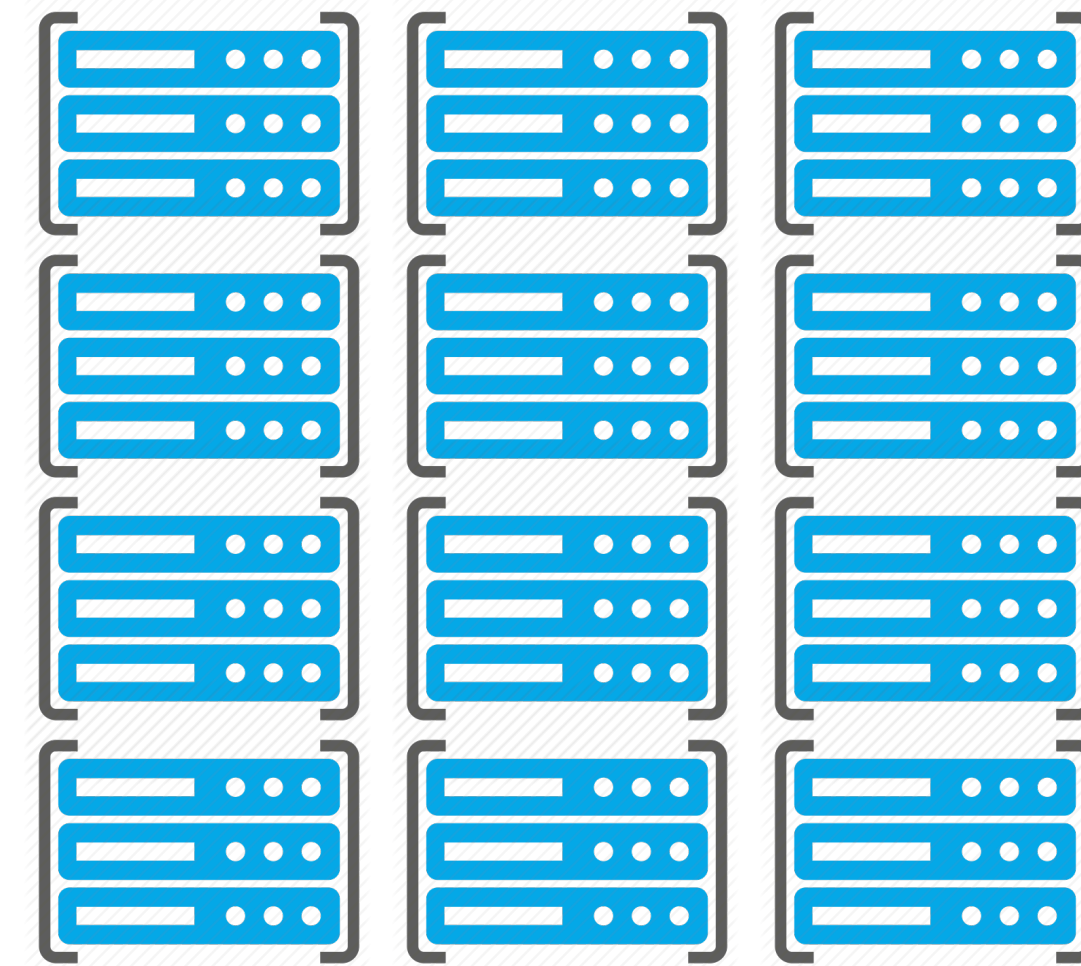
[3] expensive computation by iterative inversion

Verschuur and Berkhout 2011

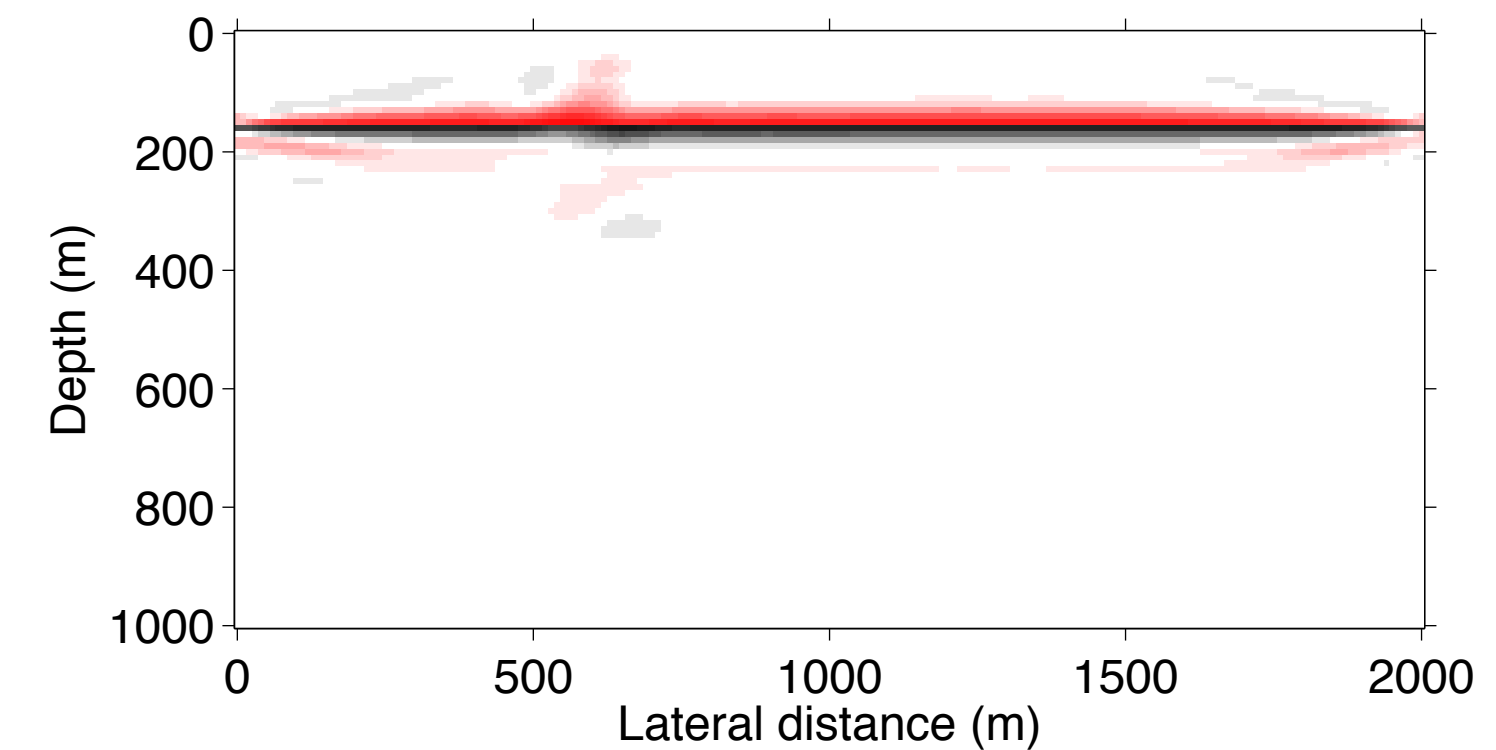
Wong et al. 2014



Iterative inversions w/
various **limitations**



$$\mathcal{O}(n^3 m), \quad m = \#iter$$

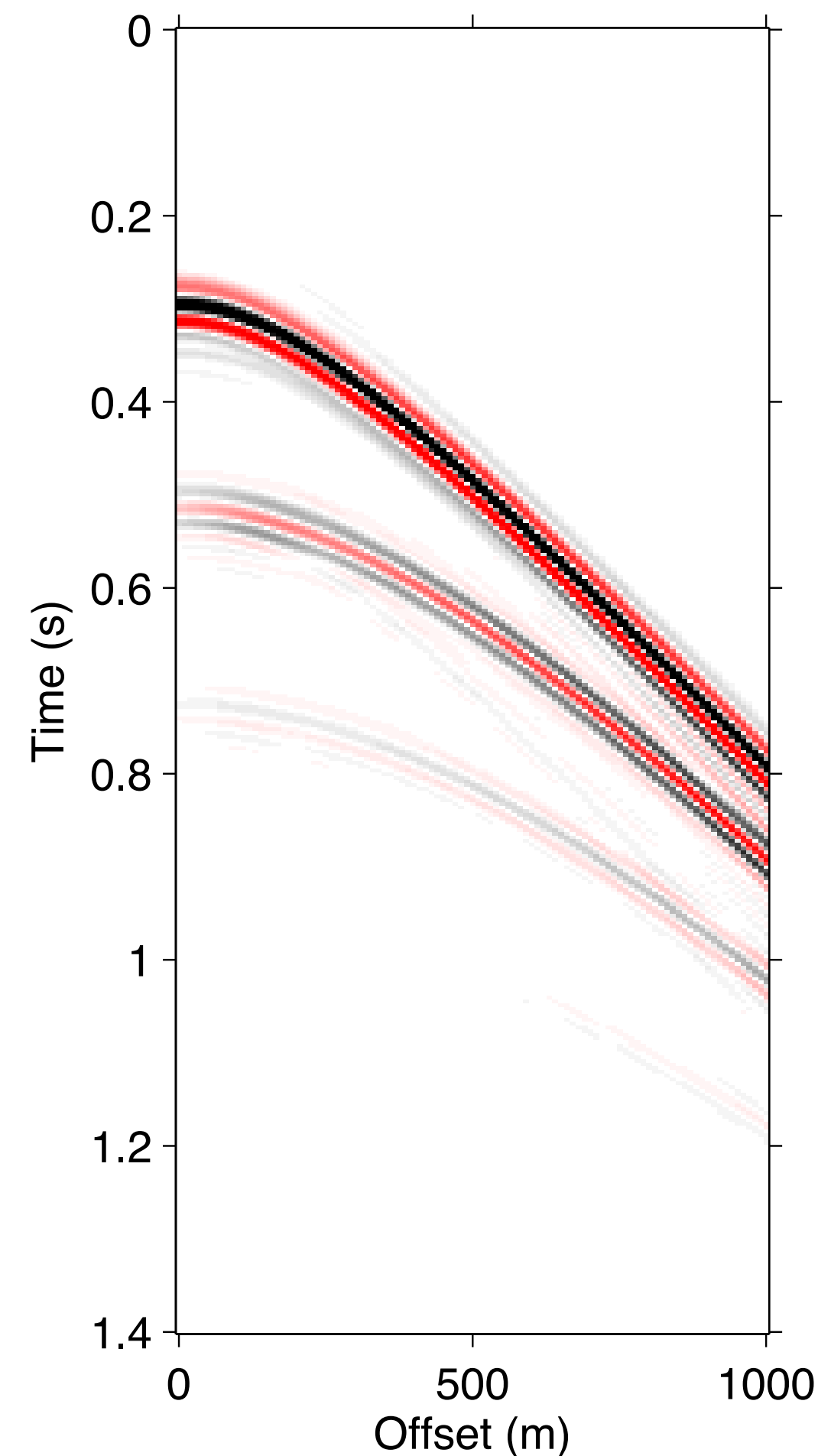


Model space solutions - the reality

[3] expensive computation by iterative inversion

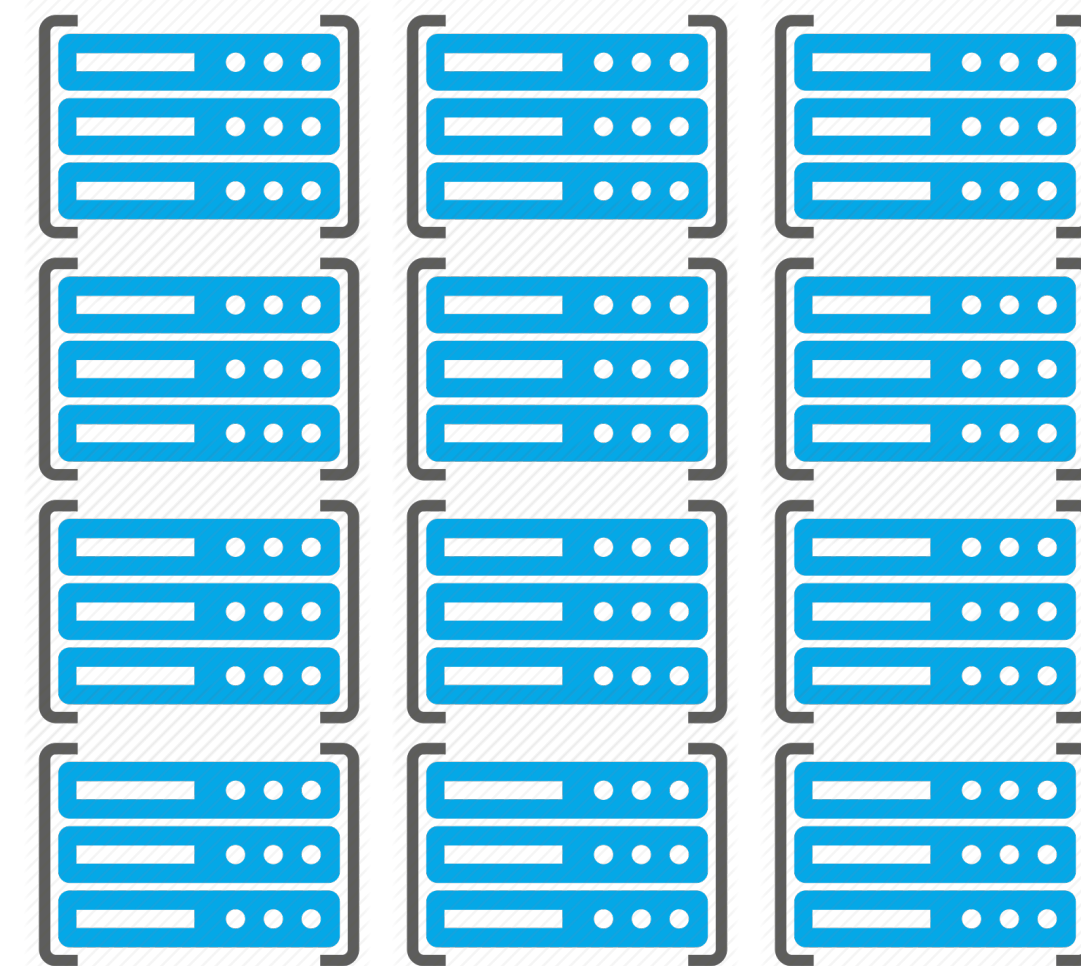
Verschuur and Berkhout 2011

Wong et al. 2014

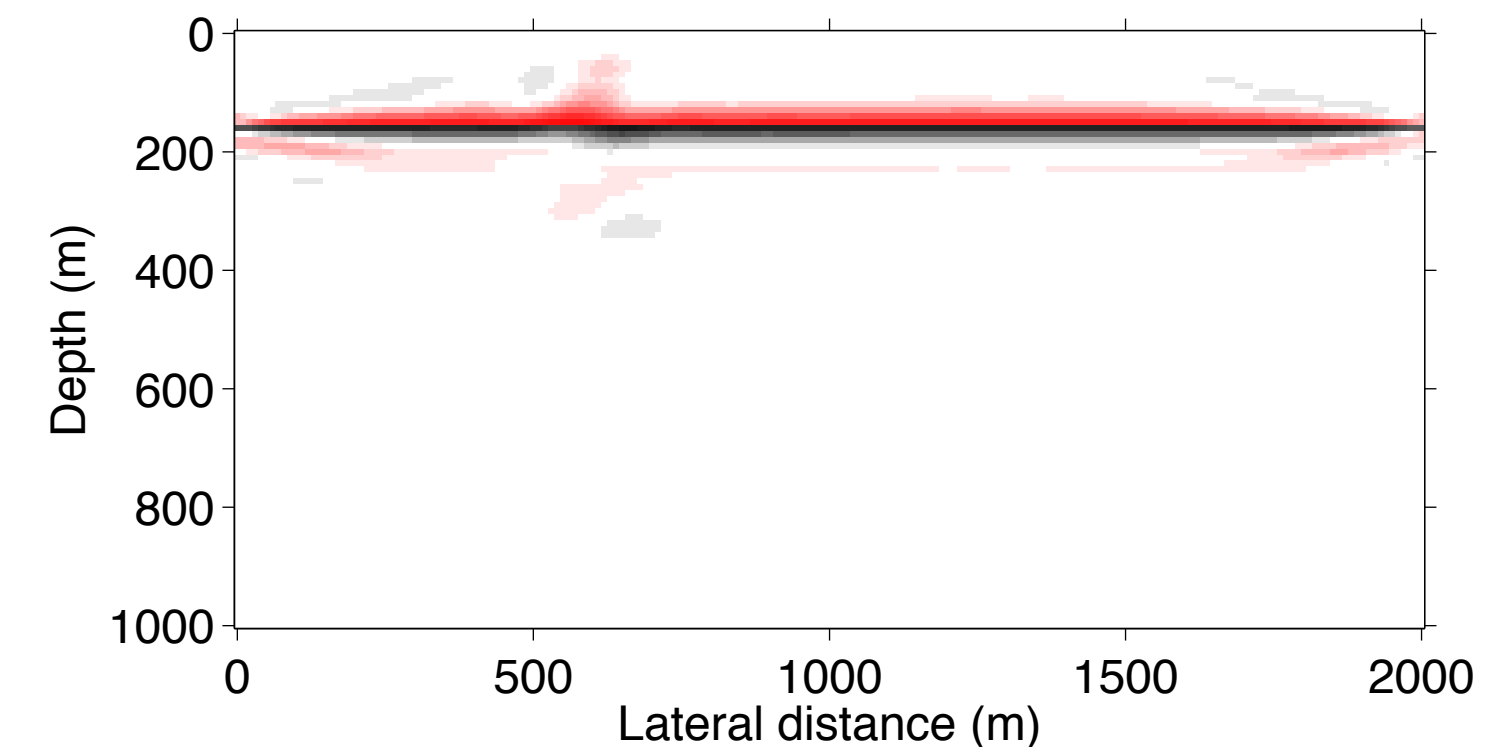


selected orders of multiples,
prior knowledge on the
source wavelet...

Iterative inversions w/
various **limitations**

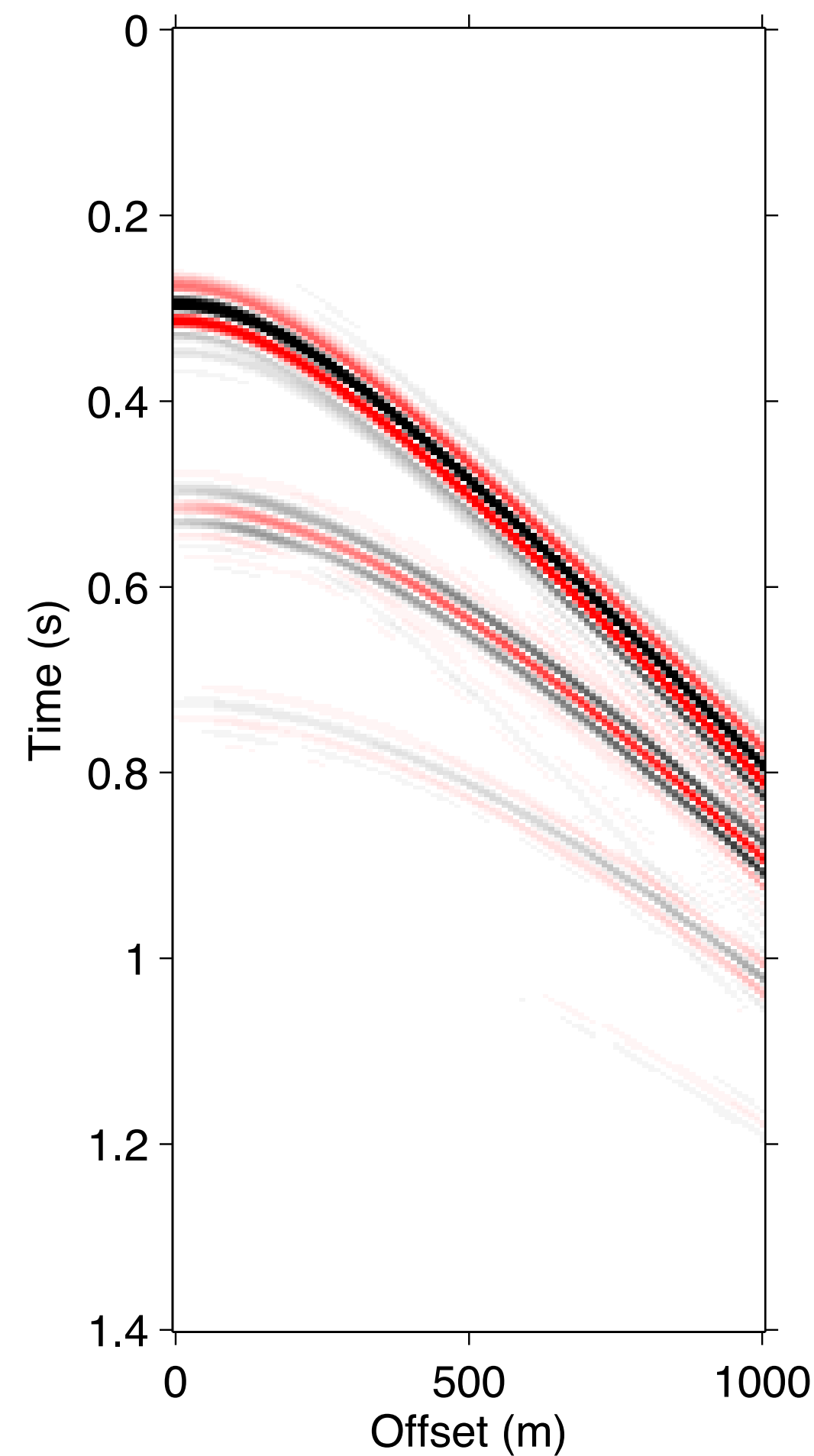


$$\mathcal{O}(n^3 m), \quad m = \#iter$$

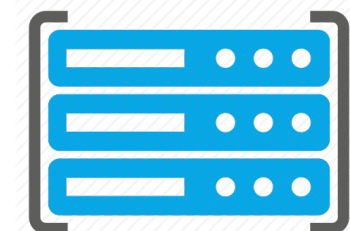
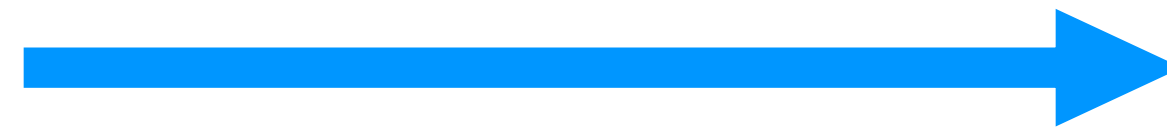


Objective & contribution of this work

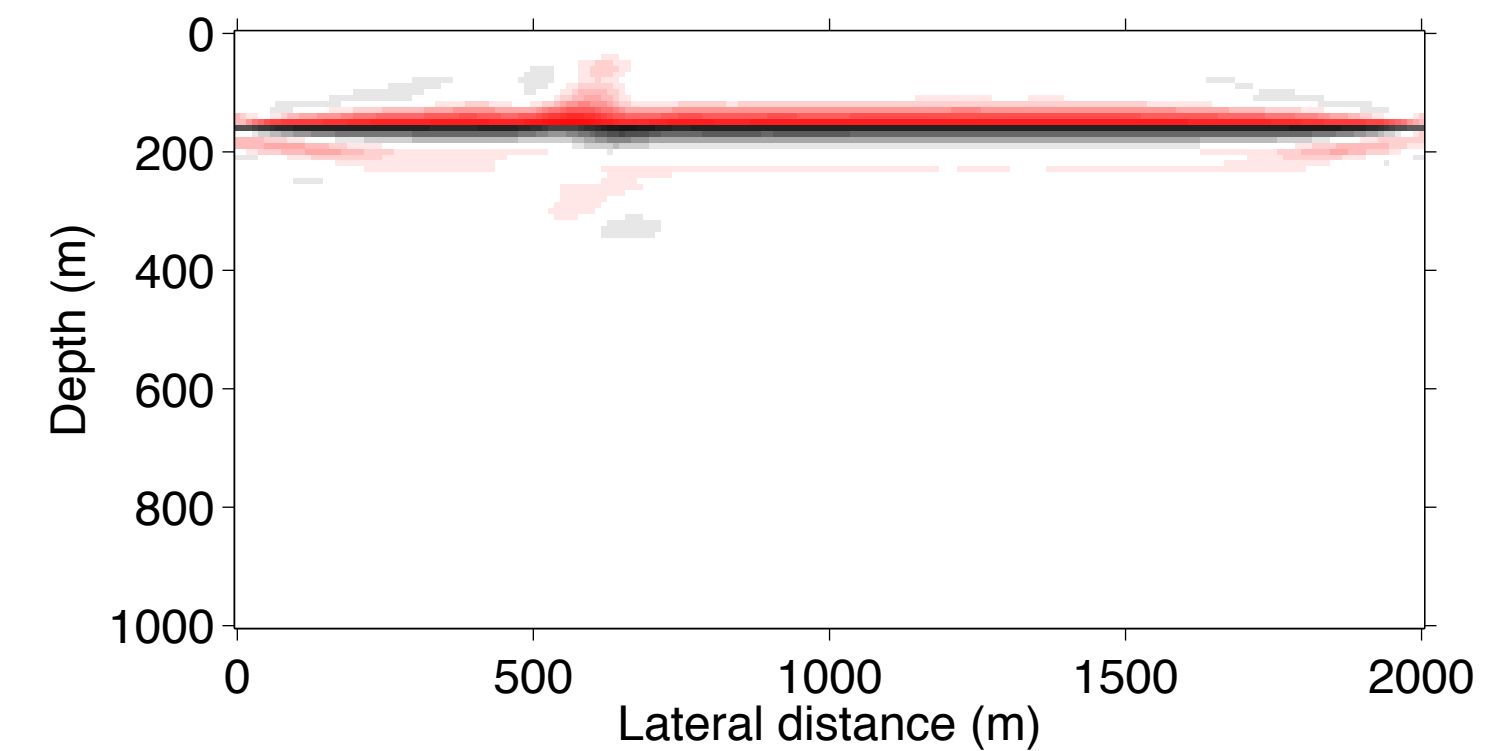
Assumption: dense receiver sampling, fixed receivers, knowledge of a background model



Ning Tu's PhD thesis



$$\mathcal{O}(n^3)$$



Method

Physics at the water surface

Verschuur et al., 1992

[The Surface-Related Multiple Elimination (SRME) relation]

$$\mathbf{P}_i = \mathbf{X}_i(\mathbf{S}_i + \mathbf{R}_i\mathbf{P}_i)$$

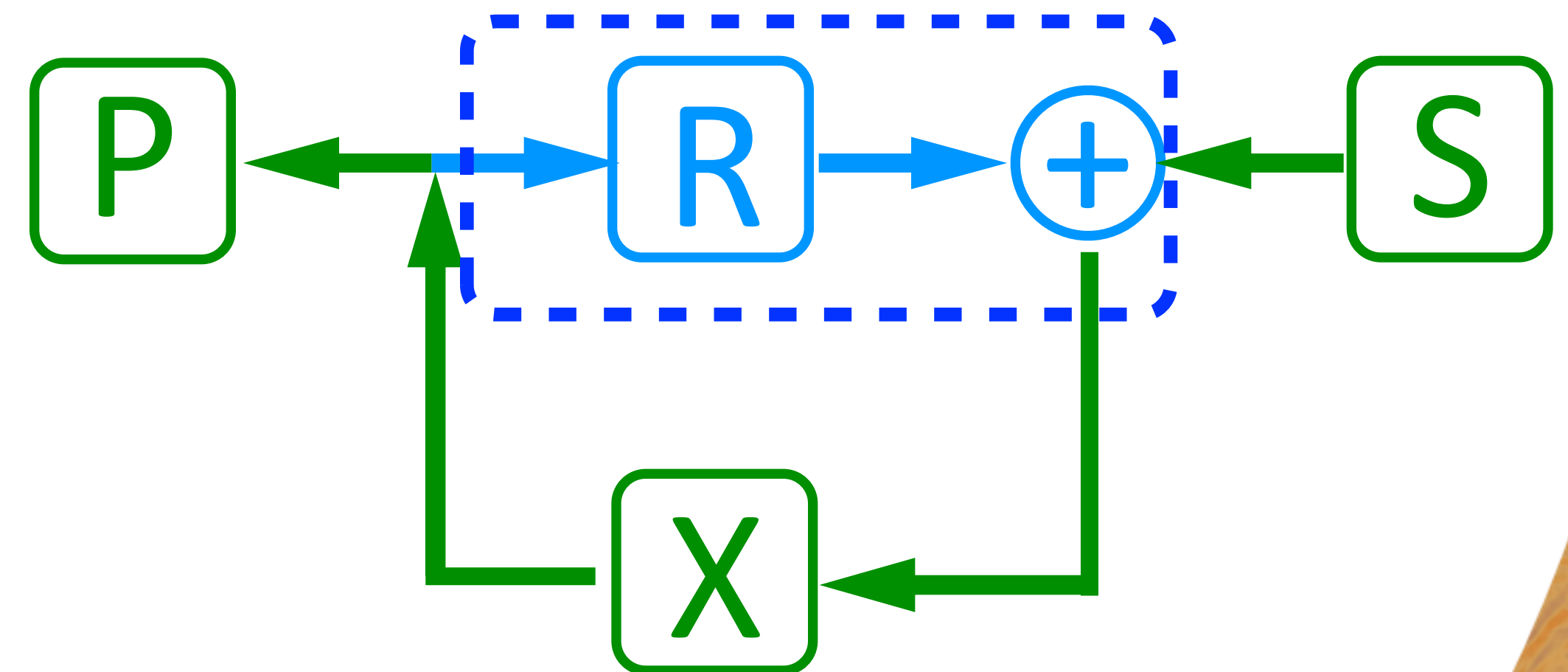
$\mathbf{P}$: pressure wavefield: primaries + multiples

$\mathbf{X}$: surface-free Green's function

$\mathbf{S}$: source wavefield $= w_i \mathbf{I}$

$\mathbf{R}$: surface reflectivity $\approx -\mathbf{I}$

i : frequency index $1 \cdots n_f$



Representation using linearized modelling

Linearized modelling of the surface-free Green's function:

$$\mathbf{X}_i \approx \nabla \mathcal{F}_i[\mathbf{m}_0, \delta \mathbf{m}](\mathbf{D}_s^* \mathbf{I})$$

$\nabla \mathcal{F}_i$: linearized modelling

$\mathbf{m}_0$: background model

$\delta \mathbf{m}$: model perturbations

$\mathbf{I}$: impulsive source array

$\mathbf{D}_s^*$: source injection operator

Eliminating dense matrix-matrix products

[SRME relation & wave-equation solver]

Combined with water-surface physics:

$$\begin{aligned}
 \mathbf{P}_i &\approx \overbrace{\nabla \mathcal{F}_i[\mathbf{m}_0, \delta \mathbf{m}] (\mathbf{D}_s^* \mathbf{I}) (\mathbf{S}_i - \mathbf{P}_i)}^{\mathbf{X}_i} \longrightarrow \text{Dense matrix products} \\
 &= \nabla \mathcal{F}_i[\mathbf{m}_0, \delta \mathbf{m}] (\mathbf{D}_s^* (\mathbf{S}_i - \mathbf{P}_i)) \longrightarrow \text{Wave-equation solves with} \\
 &\hspace{15em} \text{total downgoing data}
 \end{aligned}$$

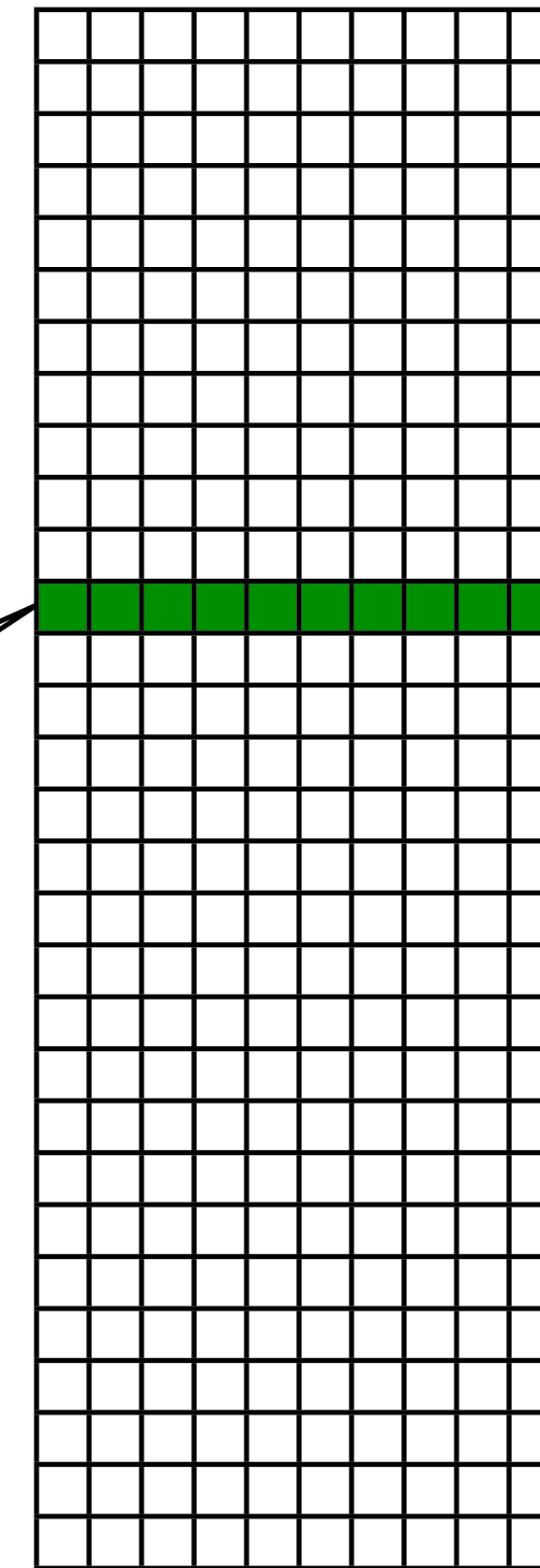
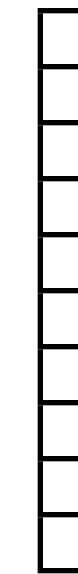
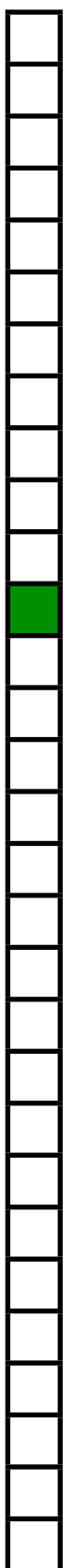
In canonical form of linear system of equations

[$\mathbf{Ax}=\mathbf{b}$ where $\mathbf{A}$ is a matrix, $\mathbf{x}$ and $\mathbf{b}$ are vectors]

$$\mathbf{p}_i = \text{vec}(\mathbf{P}_i)$$

$$\approx \nabla \mathbf{F}_i[\mathbf{m}_0; \mathbf{S}_i - \mathbf{P}_i] \delta \mathbf{m}$$

1 source experiment
1 frequency


 $\nabla \mathbf{F}$
 $*$

 $\delta \mathbf{m}$
 $=$

 $\mathbf{p}$

In canonical form of linear system of equations

[$\mathbf{Ax}=\mathbf{b}$ where $\mathbf{A}$ is a matrix, $\mathbf{x}$ and $\mathbf{b}$ are vectors]

$$\mathbf{p}_i = \text{vec}(\mathbf{P}_i)$$

$$\approx \nabla \mathbf{F}_i[\mathbf{m}_0; \mathbf{S}_i - \mathbf{P}_i] \delta \mathbf{m}$$

Example:

200 sources, 200 frequencies,

200 receivers, 500*500 model

(1) operator has 2×10^{12} entries

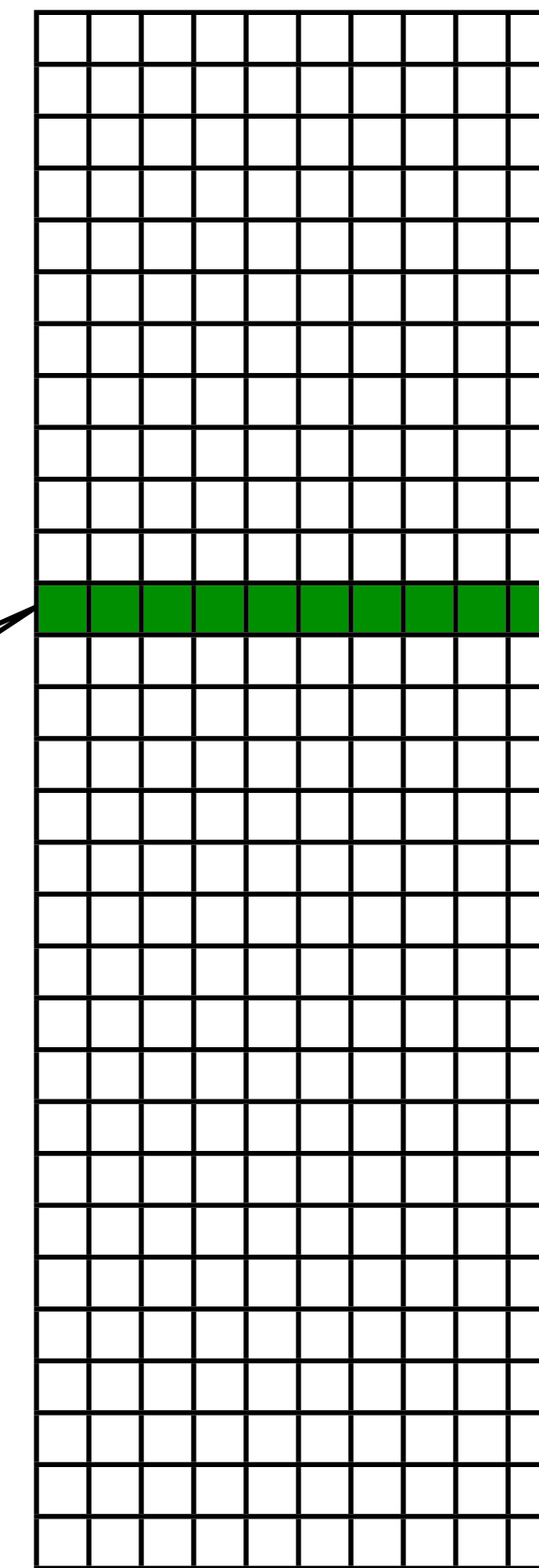
(2) conventional imaging involves

80,000 wave-equations solves

(3) iterative inversion w/ 50 iter.

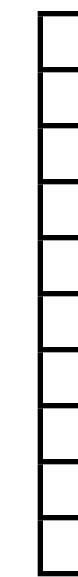
involves 8,000,000 wave-equation solves.

1 source experiment
1 frequency



$\nabla \mathbf{F}$

*



$\delta \mathbf{m}$

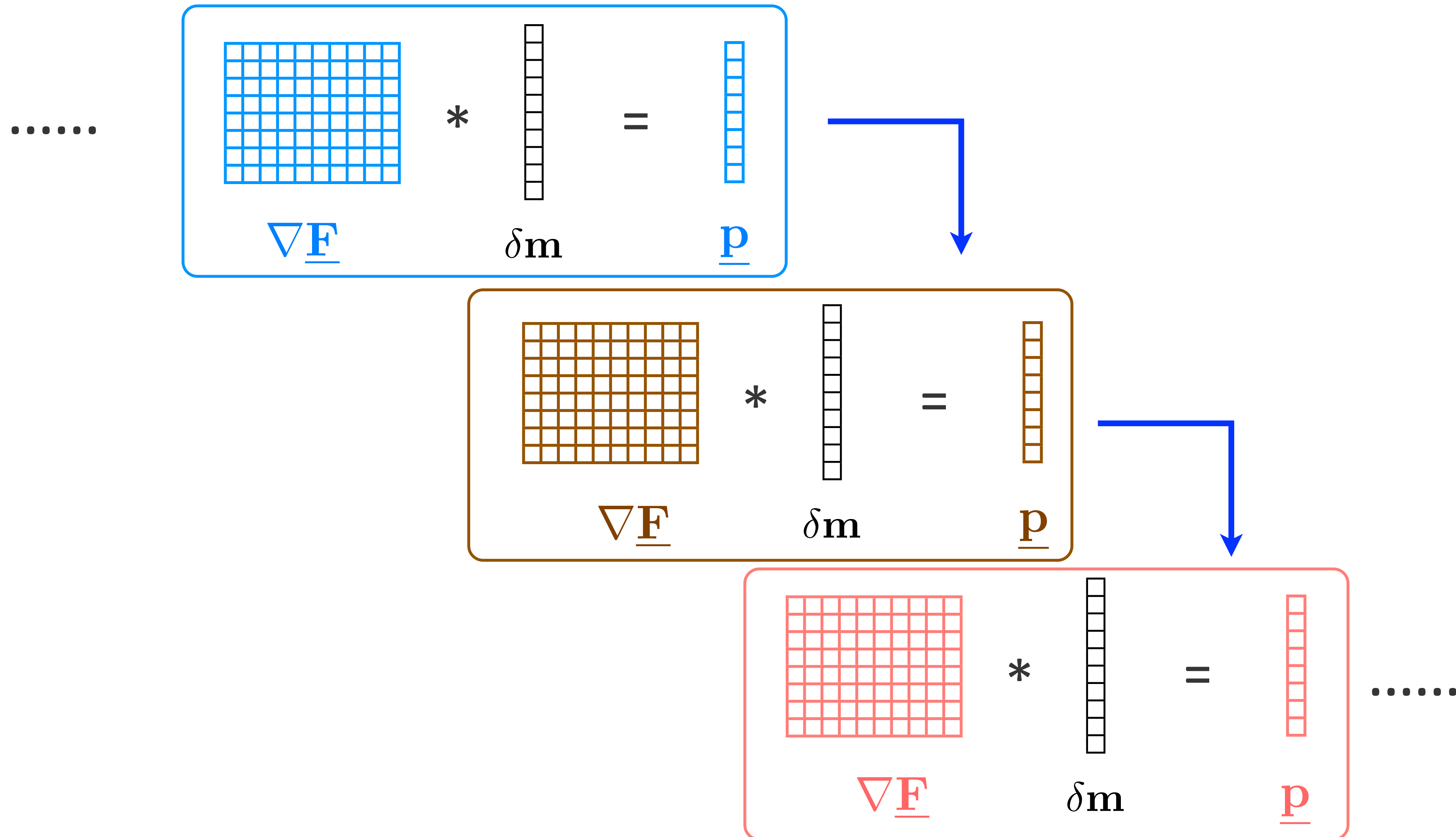
=



$\mathbf{p}$

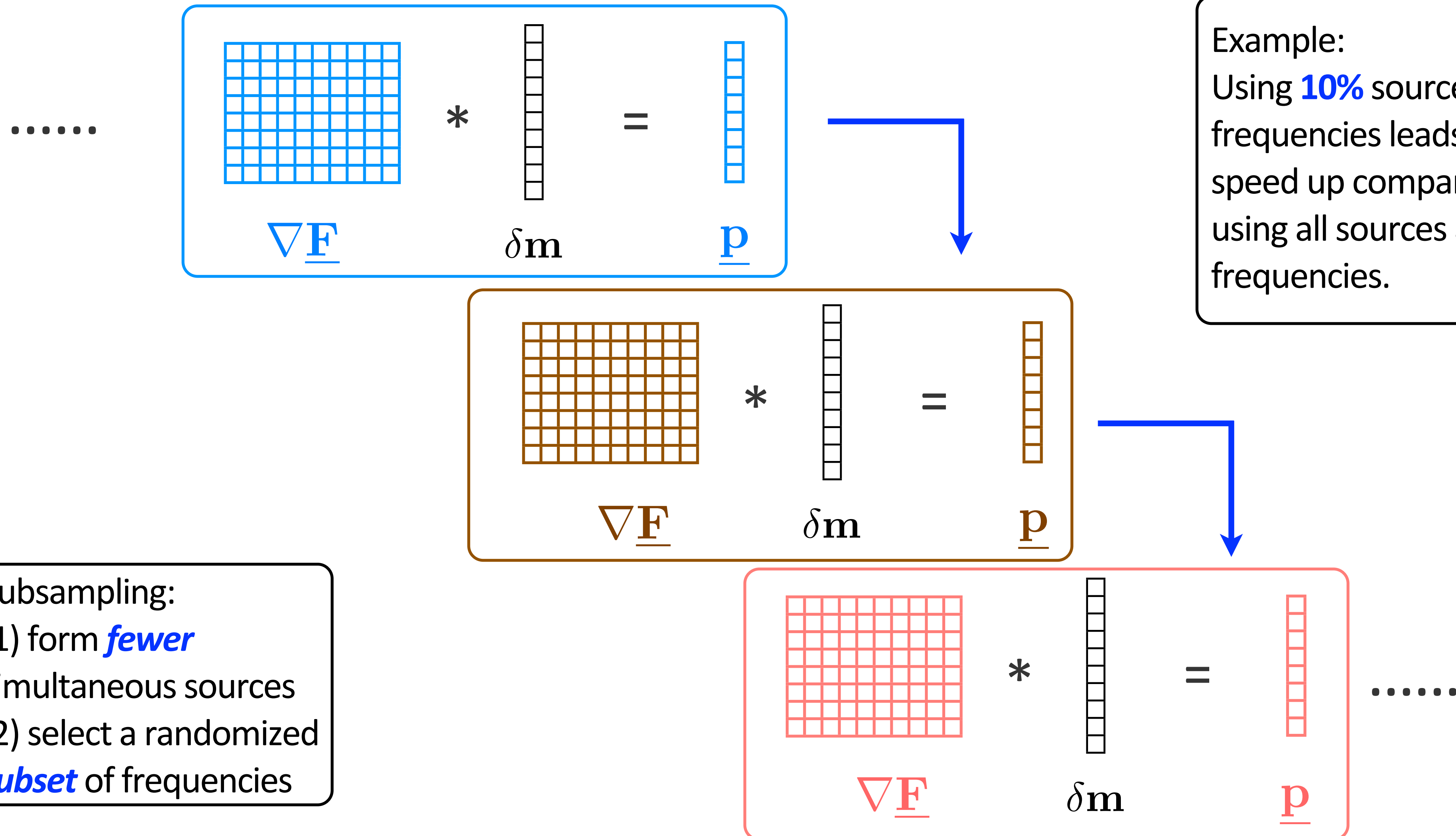
Dimensionality reduction w/ rerandomizaion

Chapter 2, 3



Dimensionality reduction w/ rerandomizaion

Chapter 2, 3



Example:

Using **10%** sources, **10%** frequencies leads to **100X** speed up compared with using all sources and frequencies.

Subsampling:

- (1) form ***fewer*** simultaneous sources
- (2) select a randomized ***subset*** of frequencies

Sparsity promoting imaging

van den Berg and Friedlander, 2008

Herrmann et al., 2008

Appendix A.1

Formulation of the l^{th} subproblem:

$$\underset{\mathbf{x}}{\operatorname{argmin}} \sum_{i \in \Omega_l} \|\underline{\mathbf{p}}_i - \nabla \mathbf{F}_i[\mathbf{m}_0, \underline{\mathbf{S}}_i - \underline{\mathbf{P}}_i] \underbrace{\mathbf{C}^* \mathbf{x}}_{\delta \mathbf{m}}\|_2^2$$

subject to $\|\mathbf{x}\|_1 \leq \tau_l$

Sparsity constraint τ_l is computed automatically using SPGL1.

$\mathbf{C}$: curvelet transform

$$\underline{\mathbf{S}}_i = \mathbf{S}_i \underline{\mathbf{E}}_l$$

$\underline{\cdot}$: wavefields with subsampled source experiments $\underline{\mathbf{P}}_i = \mathbf{P}_i \underline{\mathbf{E}}_l$

Ω : randomized frequency subset

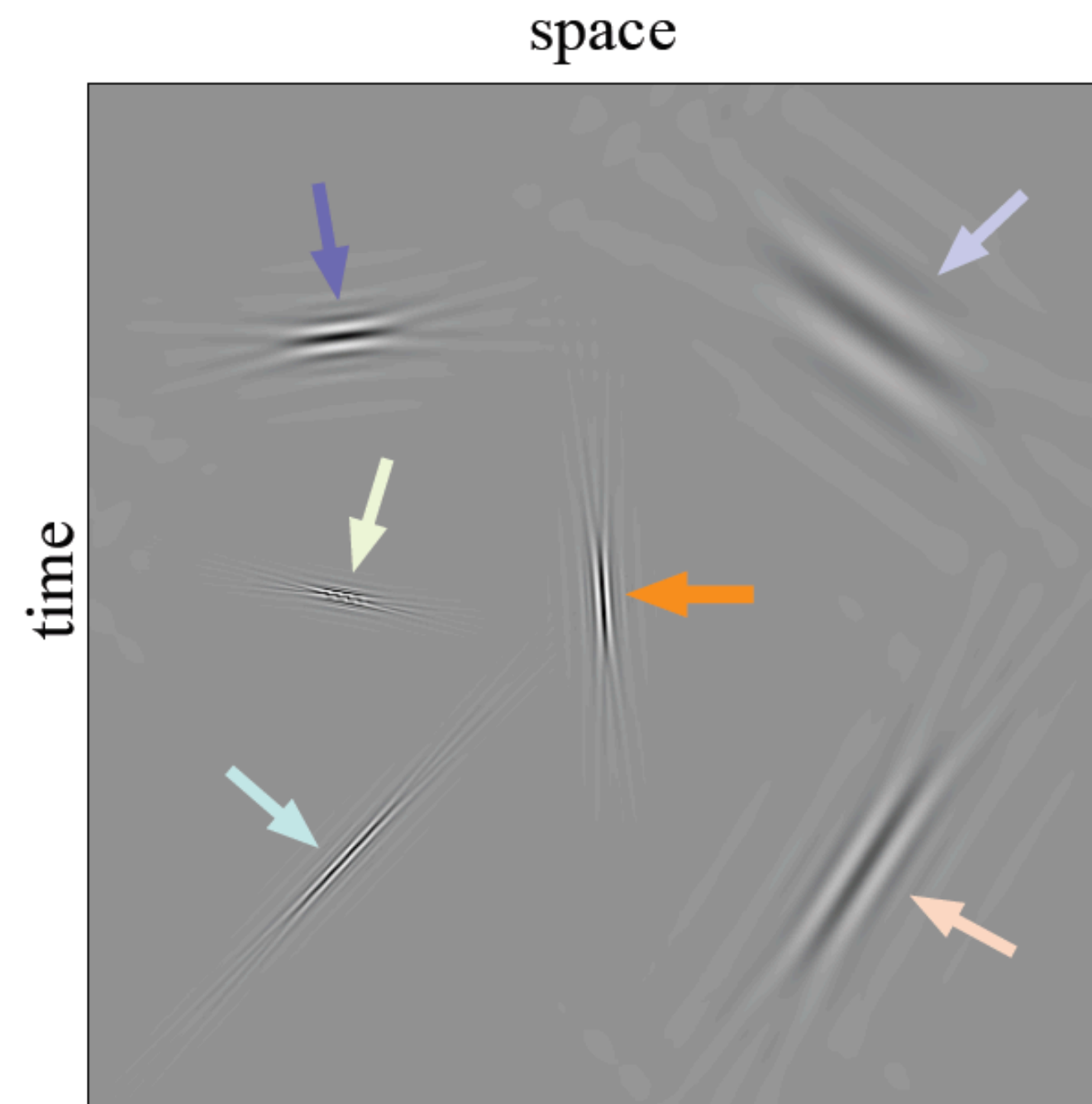
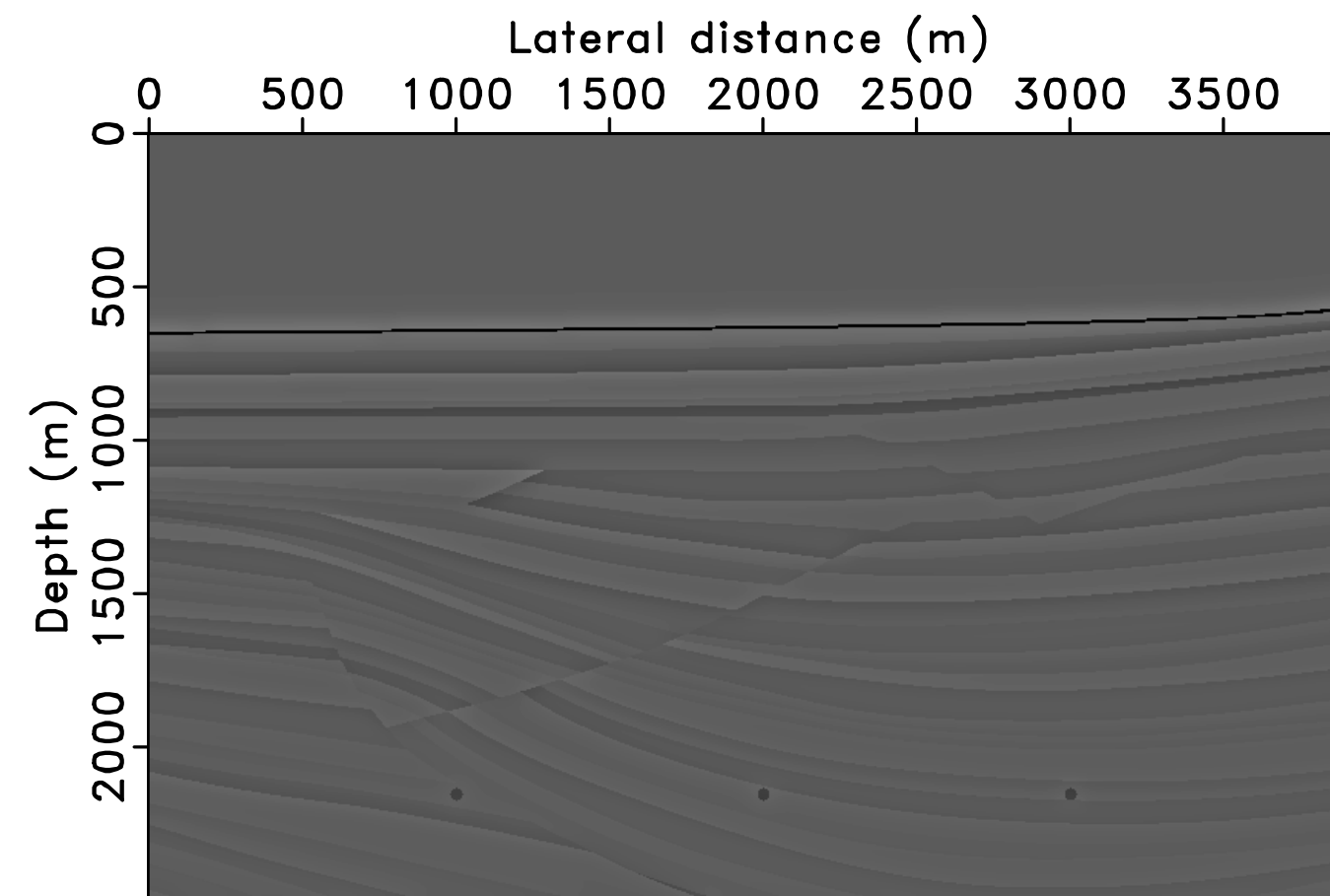
$\underline{\mathbf{E}}_l$: encoding operator

Curvelet domain sparsity

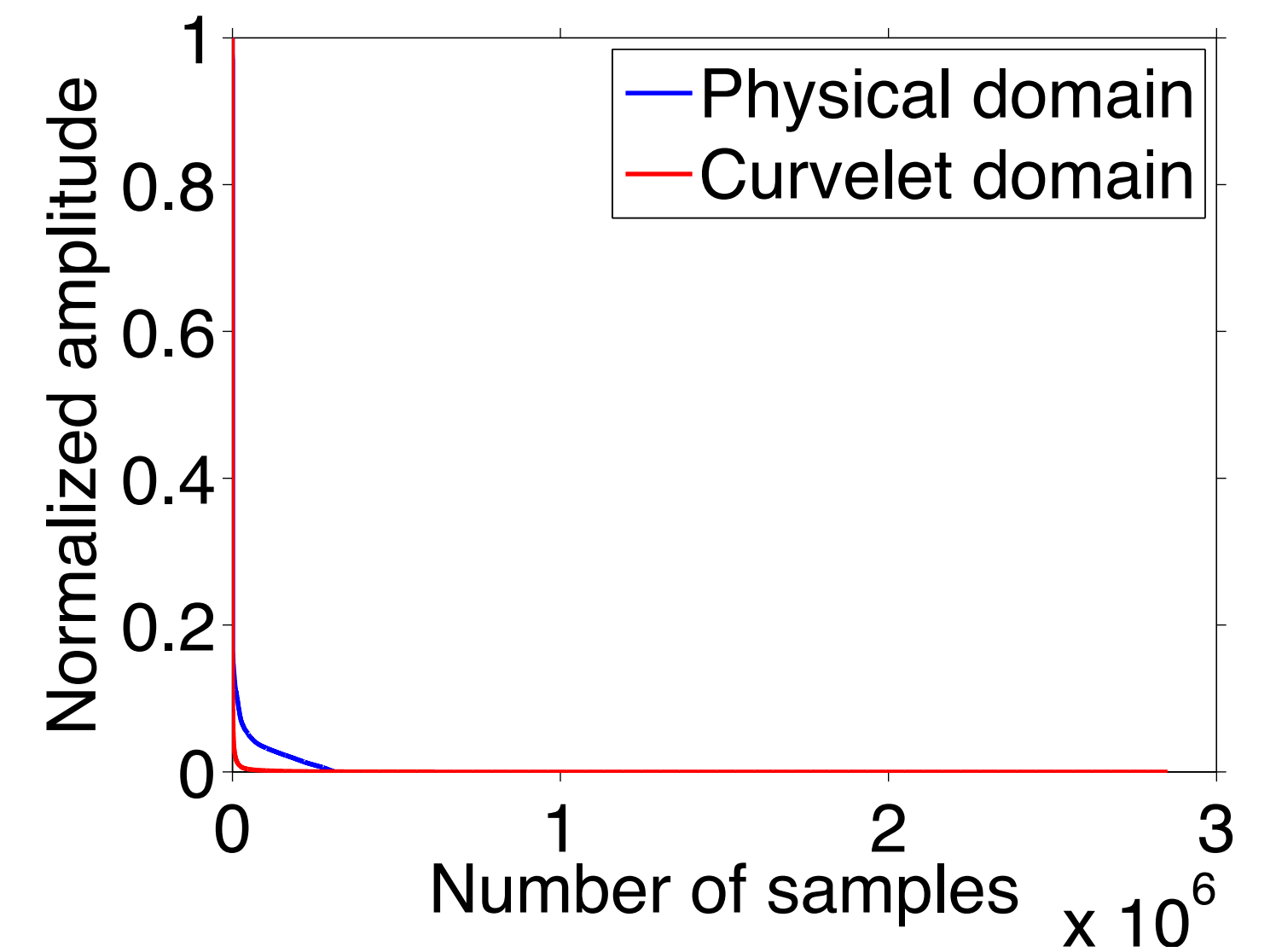
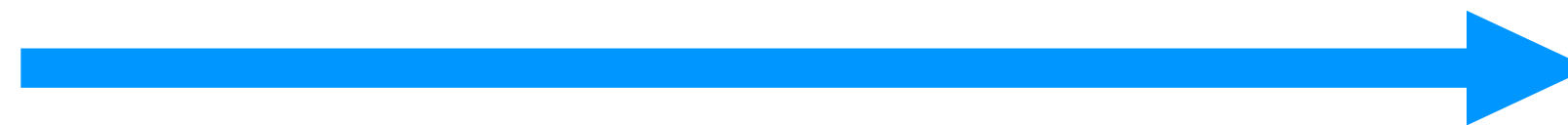
Candès and Donoho, 2004

Candès et al., 2006

Herrmann and Hennenfent, 2008



Curvelet "atoms"

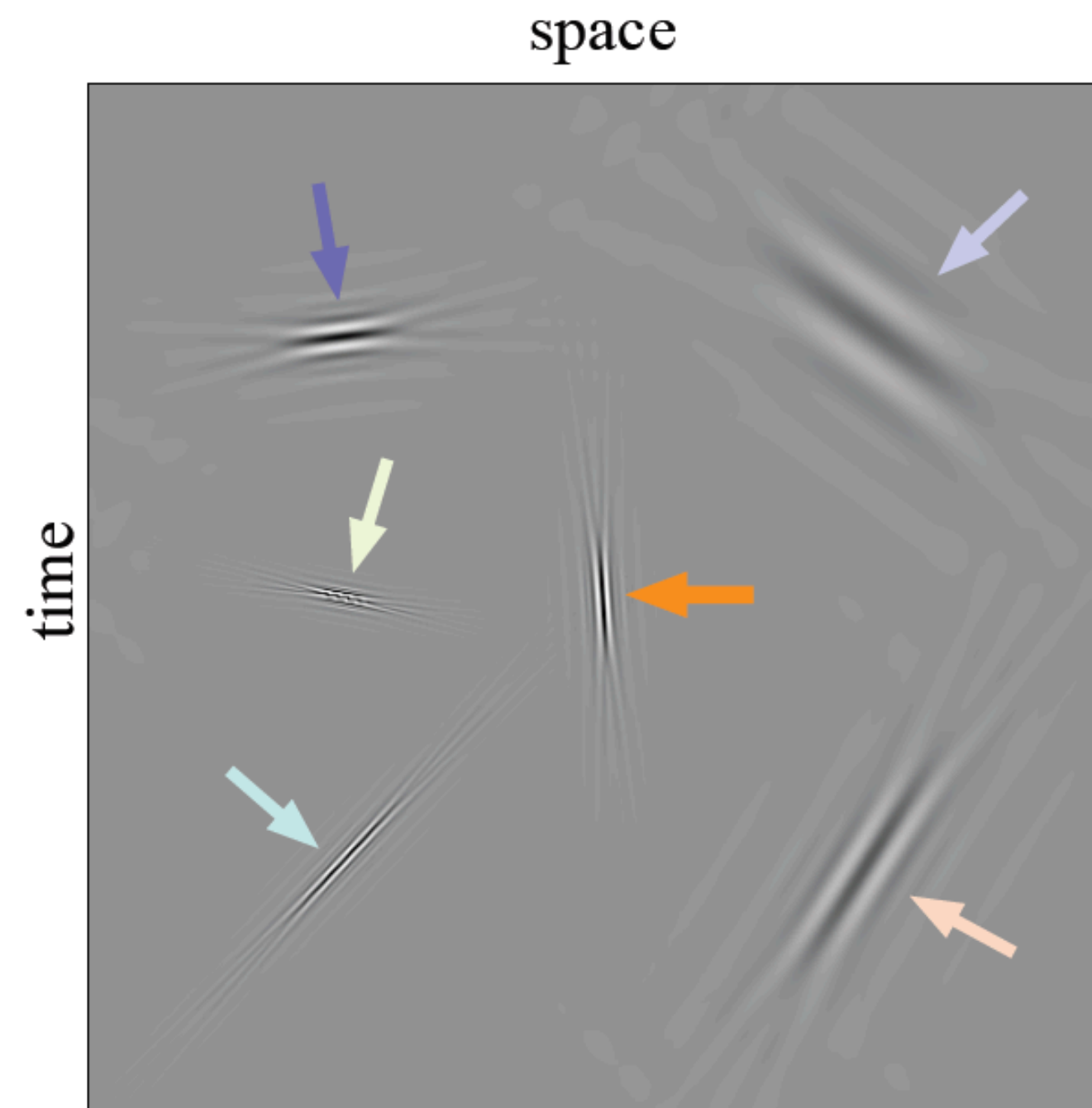
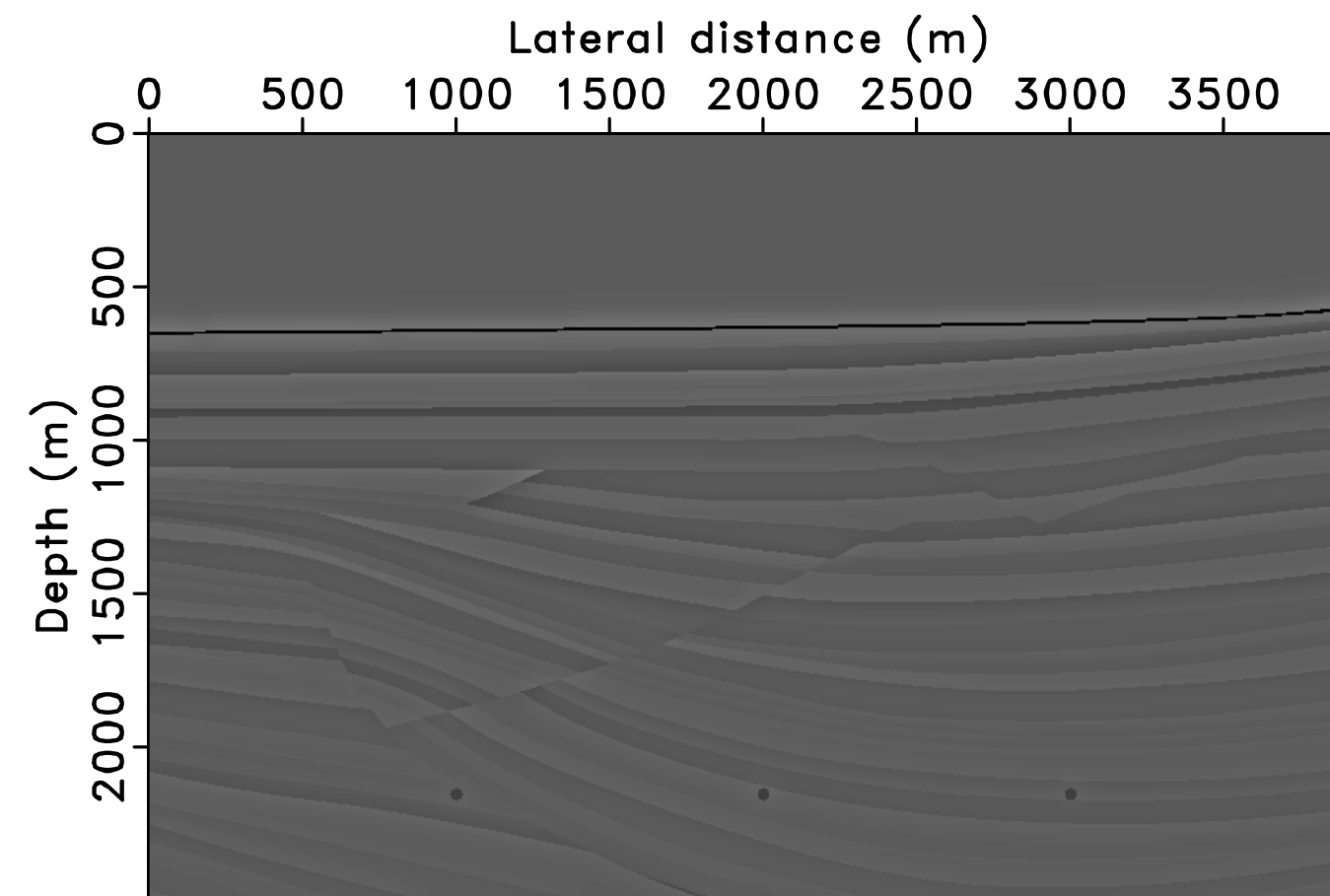


Curvelet domain sparsity

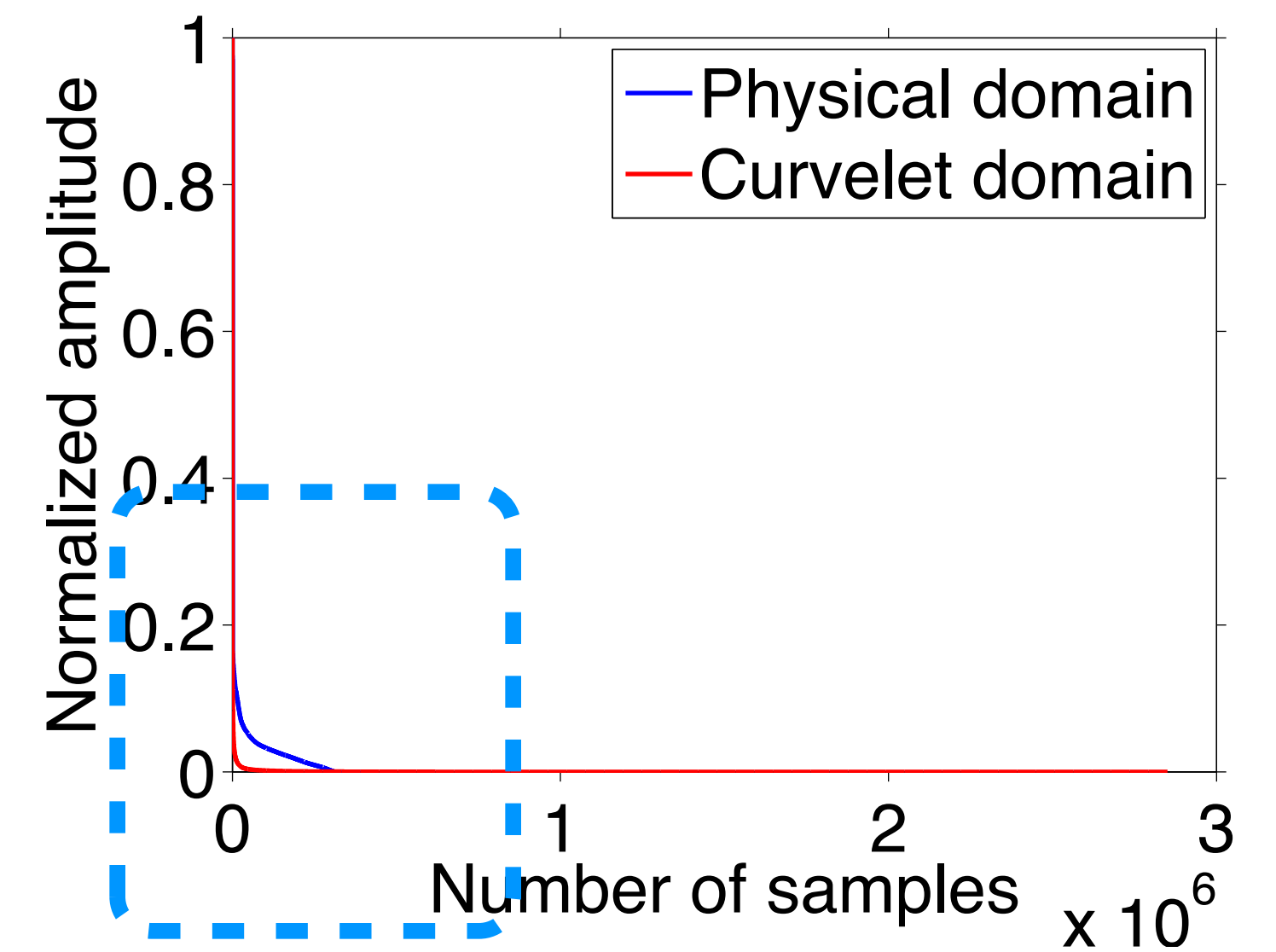
Candès and Donoho, 2004

Candès et al., 2006

Herrmann and Hennenfent, 2008



Curvelet "atoms"

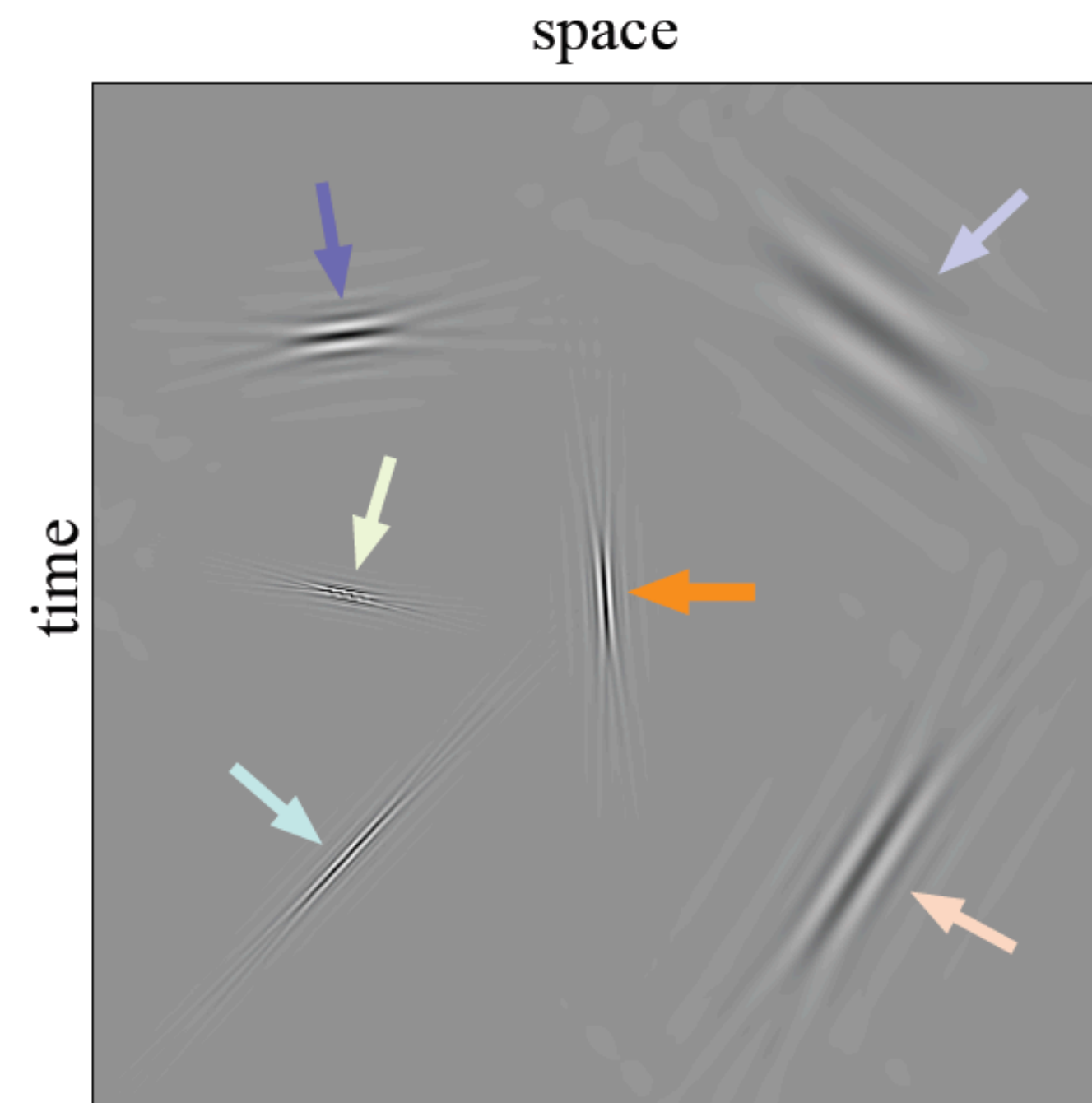
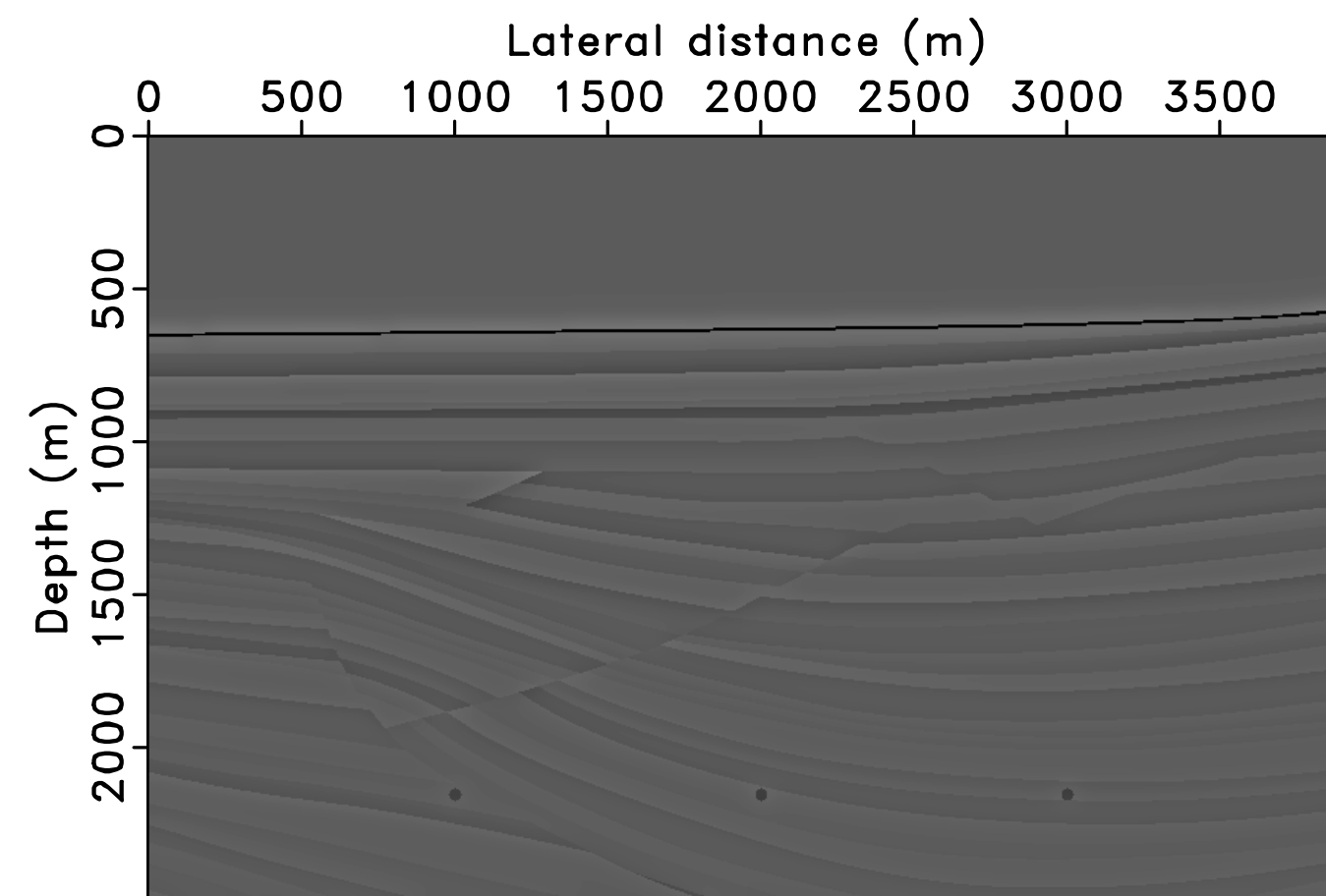


Curvelet domain sparsity

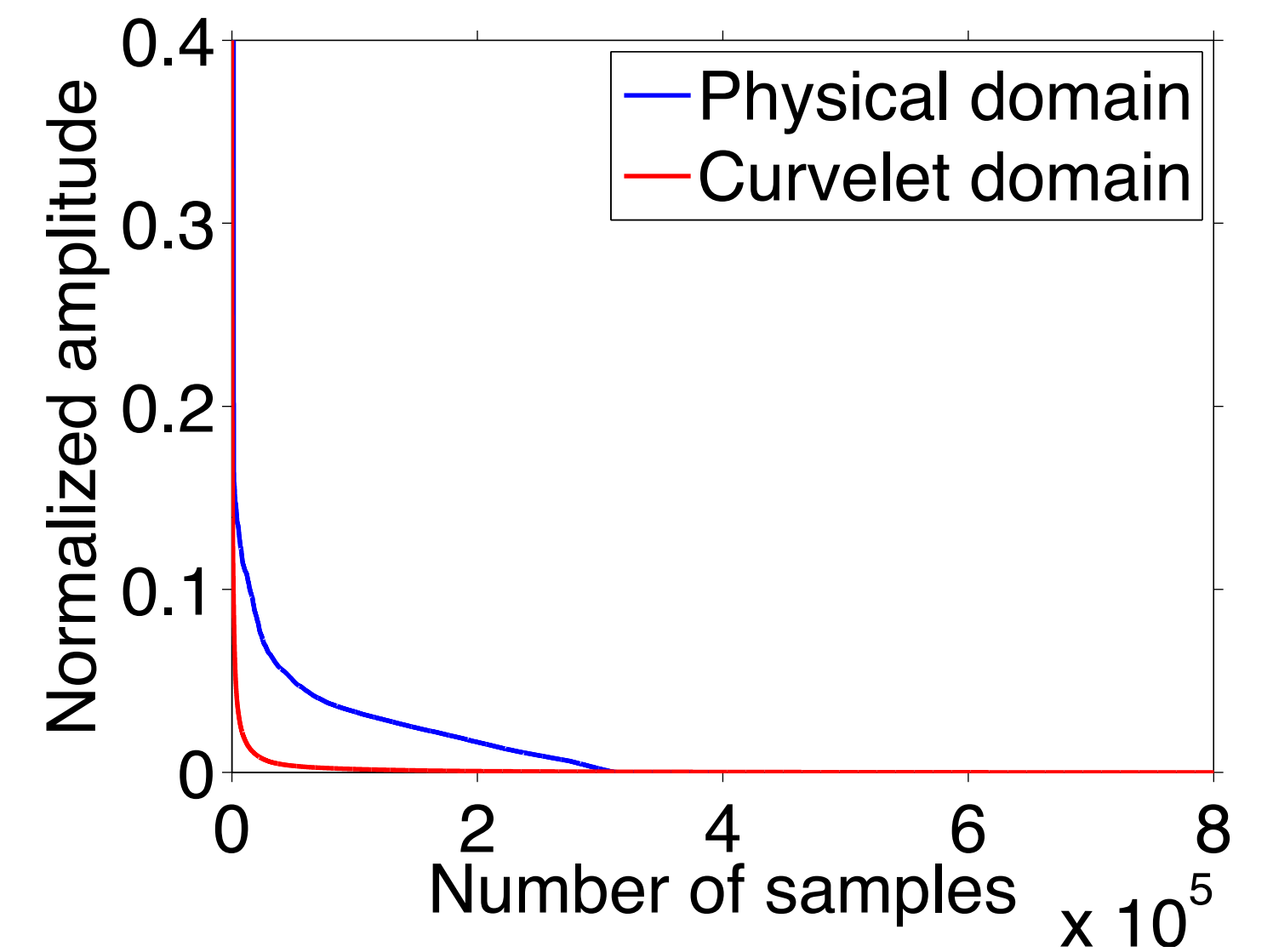
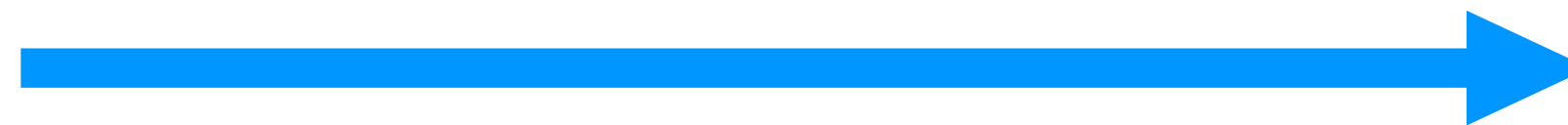
Candès and Donoho, 2004

Candès et al., 2006

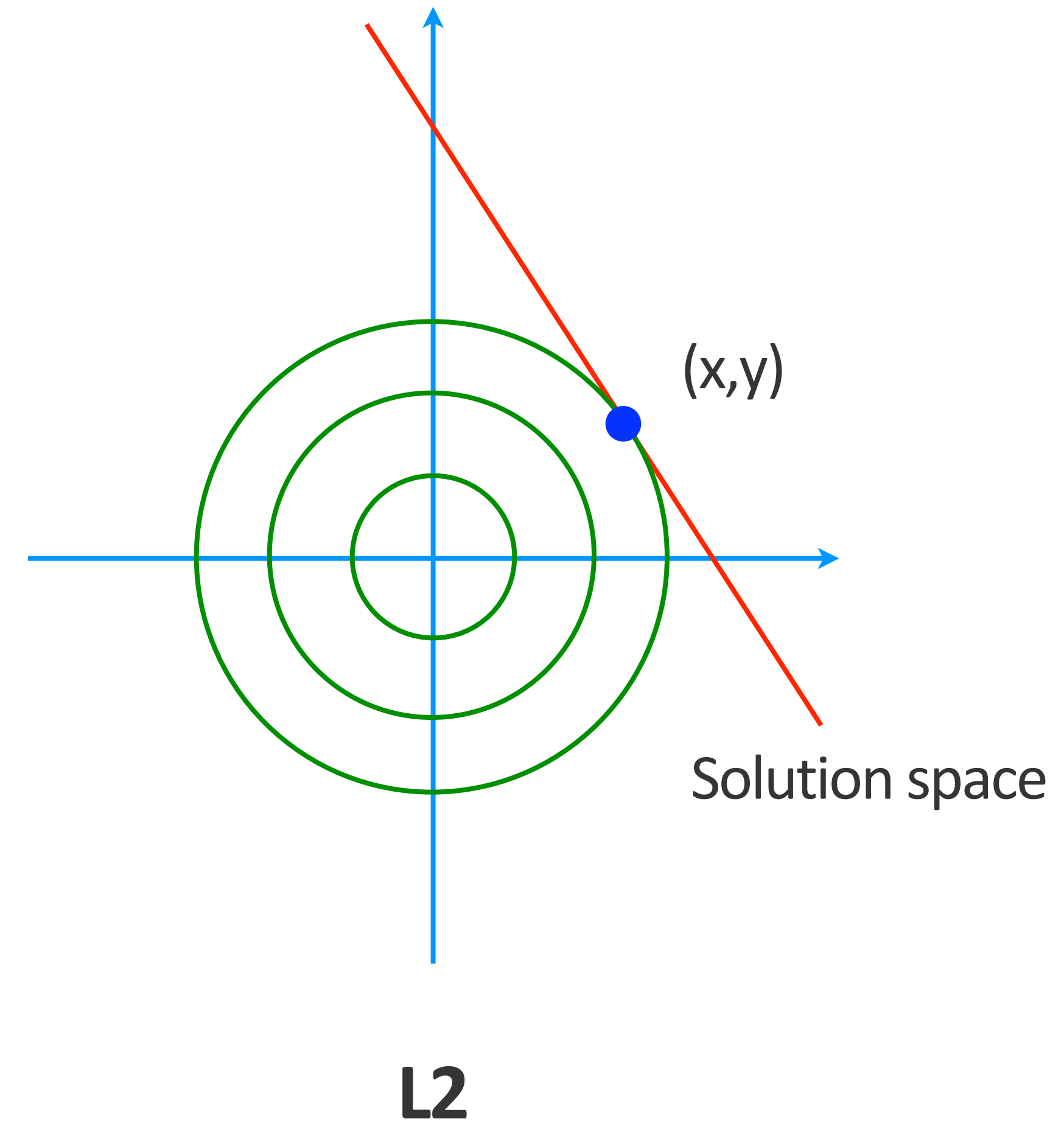
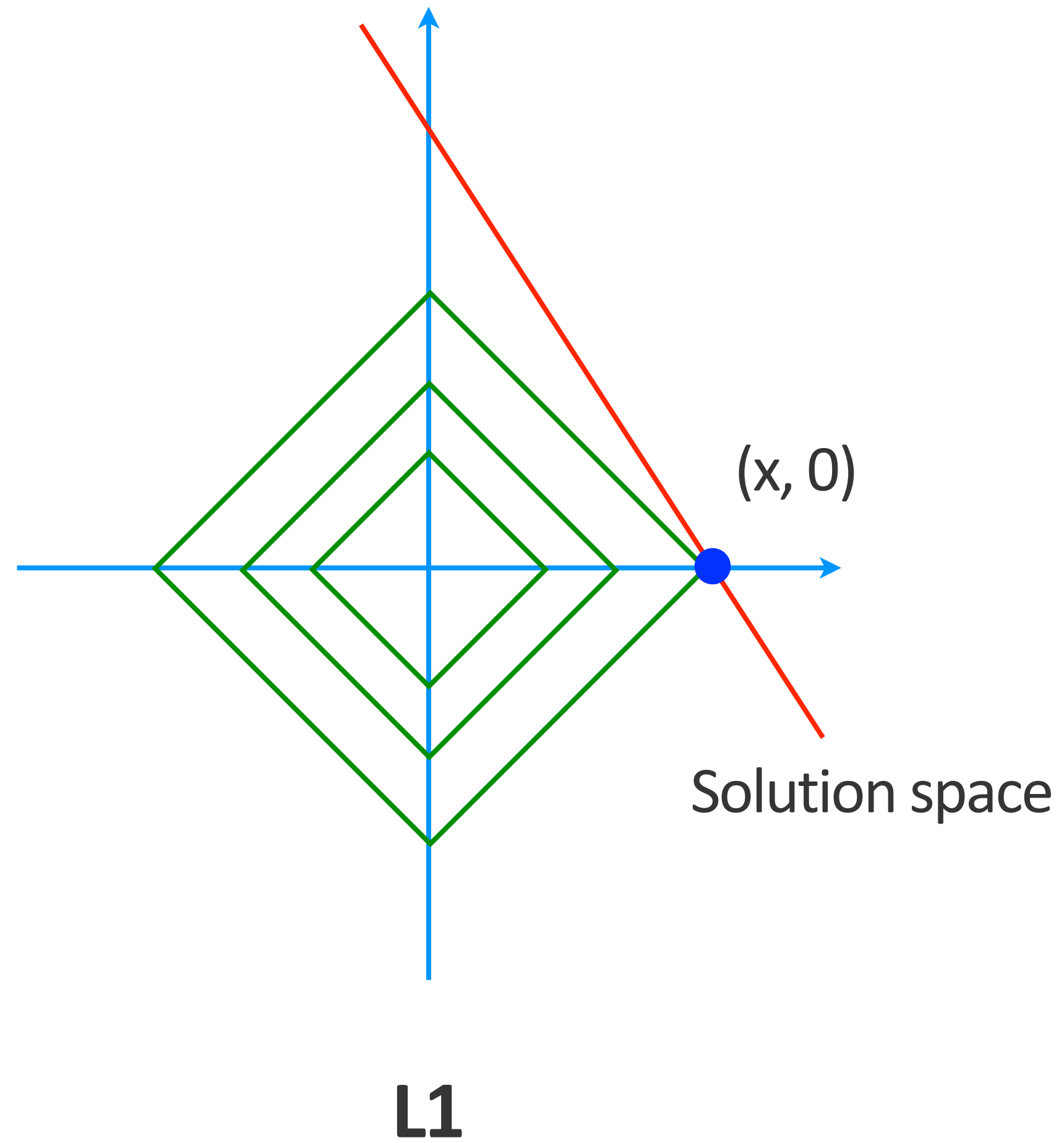
Herrmann and Hennenfent, 2008



Curvelet "atoms"



L1 vs L2 sparsity



Source estimation

- The joint inversion formulation requires the knowledge of the source wavelet:

$$\mathbf{S}_i = w_i \mathbf{I} \quad \longrightarrow \quad \underline{\mathbf{S}}_i = w_i \underline{\mathbf{E}}$$

- In each iteration, once $\mathbf{x}$ is updated, w_i is also updated:

$$\tilde{w}_i(\mathbf{x}) = \frac{\langle \underline{\mathbf{p}}_i - \nabla \mathbf{F}_i[\mathbf{m}_0, -\underline{\mathbf{P}}_i] \mathbf{C}^* \mathbf{x}, \nabla \mathbf{F}_i[\mathbf{m}_0, \underline{\mathbf{E}}] \mathbf{C}^* \mathbf{x} \rangle}{\langle \nabla \mathbf{F}_i[\mathbf{m}_0, \underline{\mathbf{E}}] \mathbf{C}^* \mathbf{x}, \nabla \mathbf{F}_i[\mathbf{m}_0, \underline{\mathbf{E}}] \mathbf{C}^* \mathbf{x} \rangle}$$

Removal of scaling ambiguity using multiples

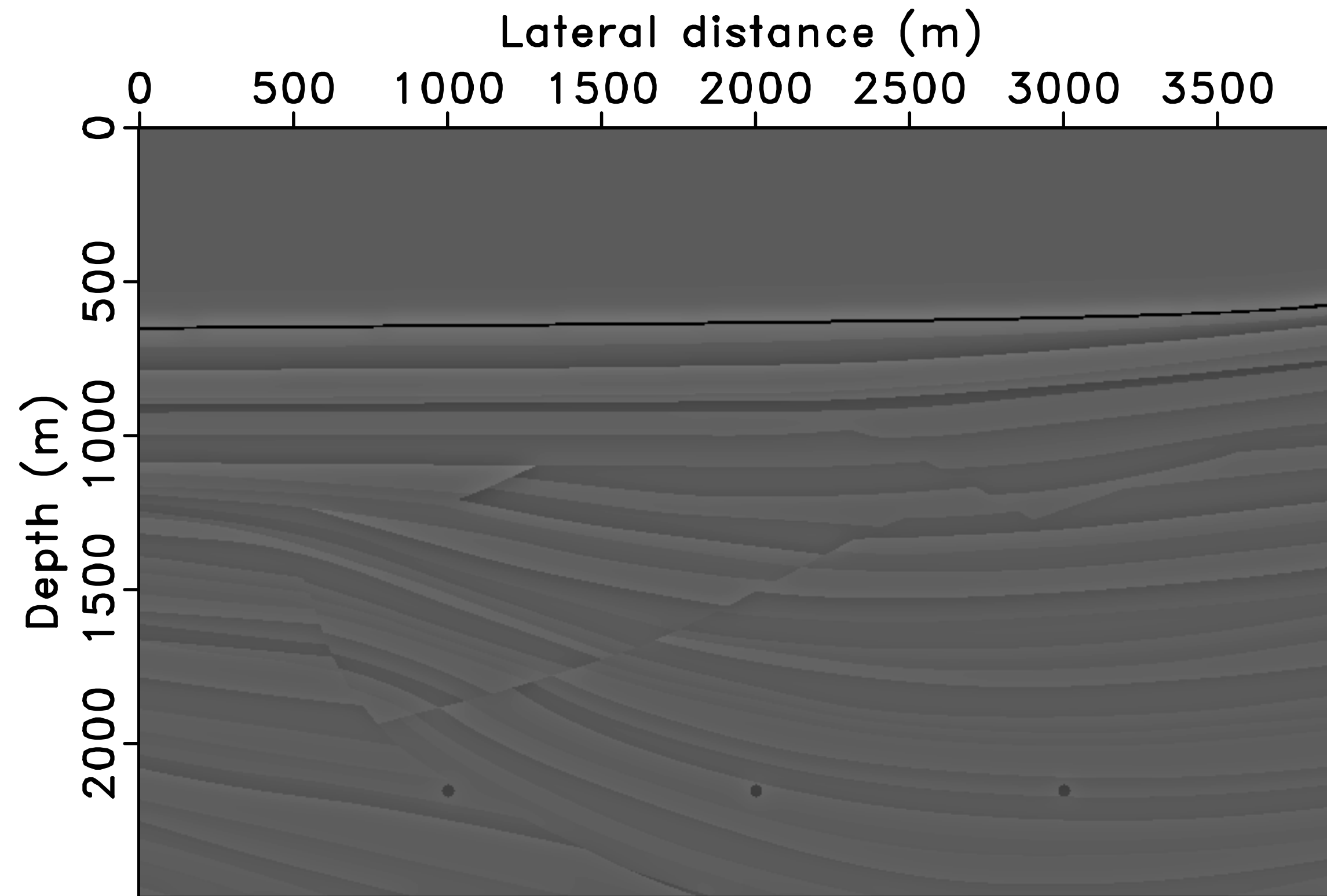
With *primary*-only data:

$$f(\mathbf{x}, \mathbf{w}) \doteq \sum_{i \in \Omega} \|\underline{\mathbf{p}}_i - \nabla \mathbf{F}_i[\mathbf{m}_0, w_i \underline{\mathbf{E}}] \mathbf{C}^* \mathbf{x}\|_2^2 \quad \longrightarrow \quad f(\mathbf{x}, \mathbf{w}) = f(\alpha \mathbf{x}, \frac{1}{\alpha} \mathbf{w})$$

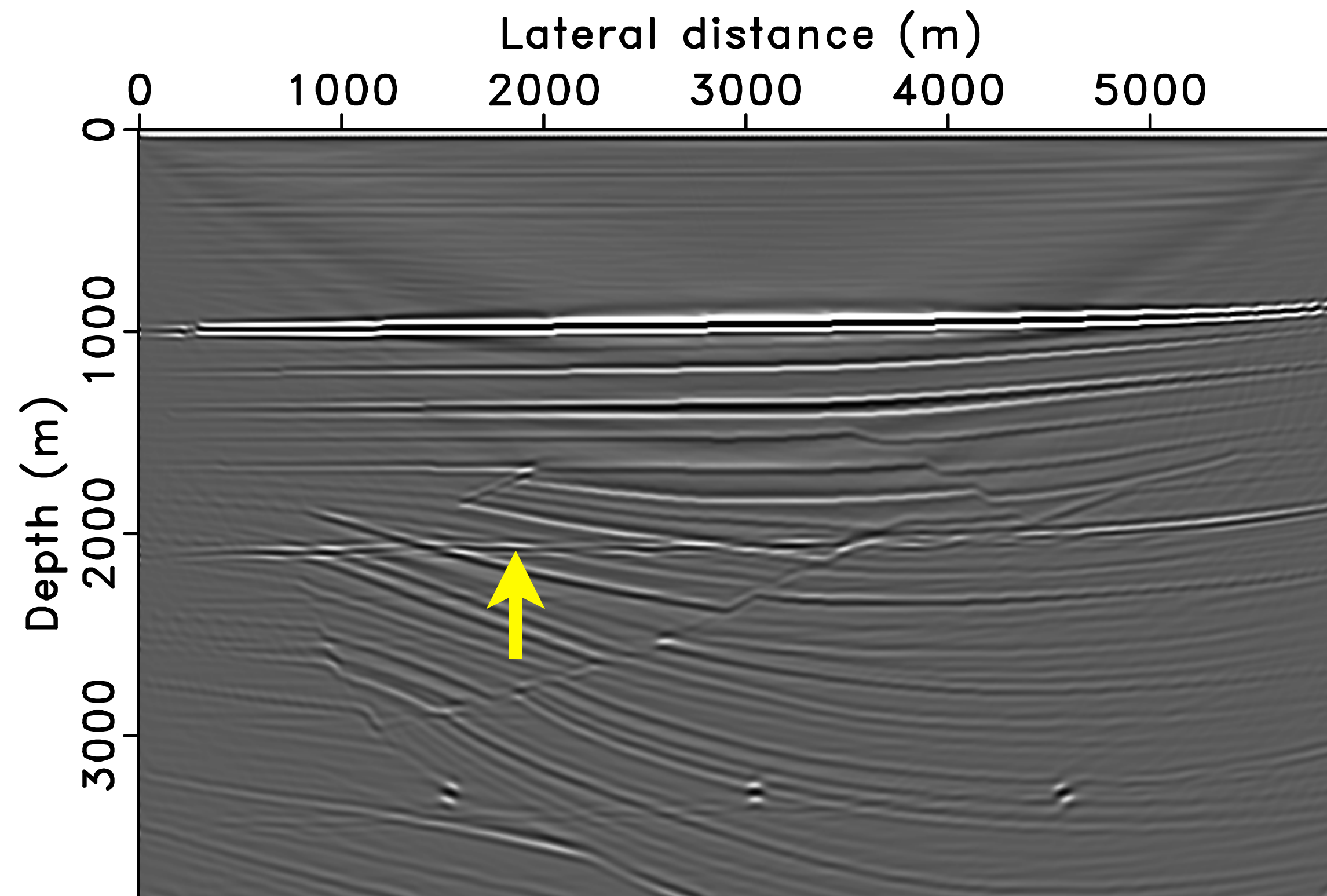
With *multiples*:

$$f(\mathbf{x}, \mathbf{w}) \doteq \sum_{i \in \Omega} \|\underline{\mathbf{p}}_i - \nabla \mathbf{F}_i[\mathbf{m}_0, w_i \underline{\mathbf{E}} - \underline{\mathbf{P}}_i] \mathbf{C}^* \mathbf{x}\|_2^2 \quad \longrightarrow \quad f(\mathbf{x}, \mathbf{w}) \neq f(\alpha \mathbf{x}, \frac{1}{\alpha} \mathbf{w})$$

Synthetic example

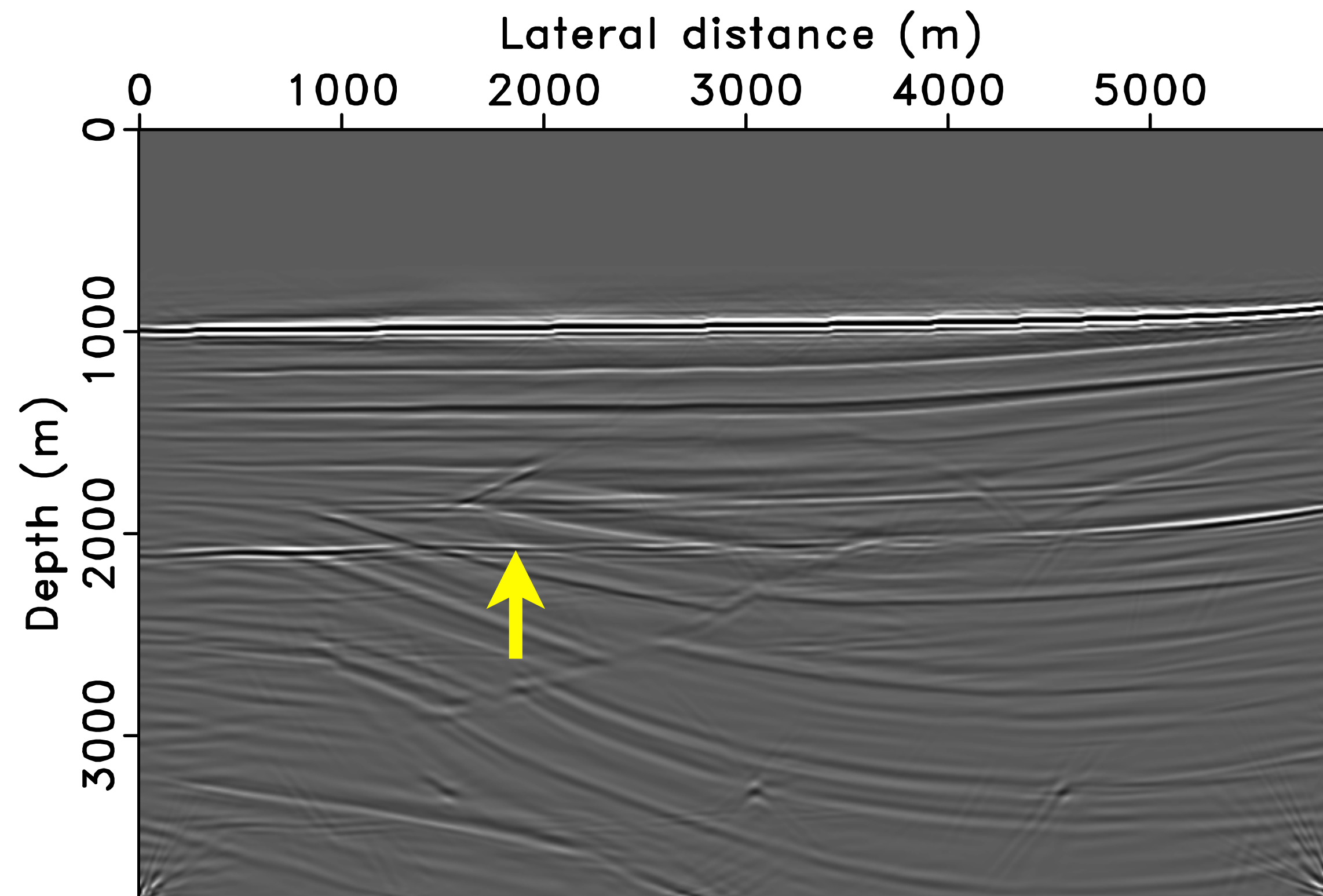


True perturbations



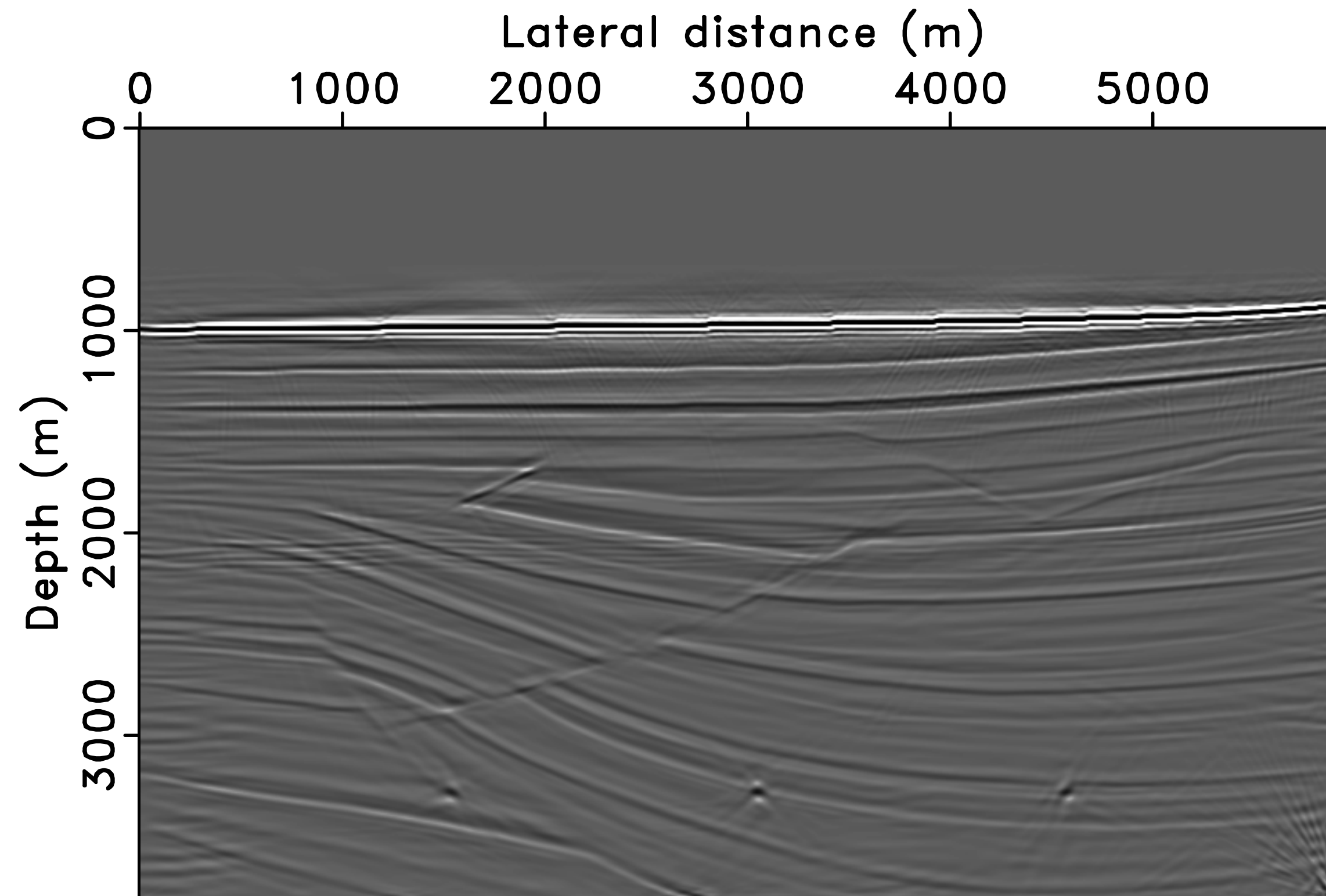
Cross-correlation image
w/ **total downgoing** data as areal source

simulation cost ~1 **conventional imaging** of all data



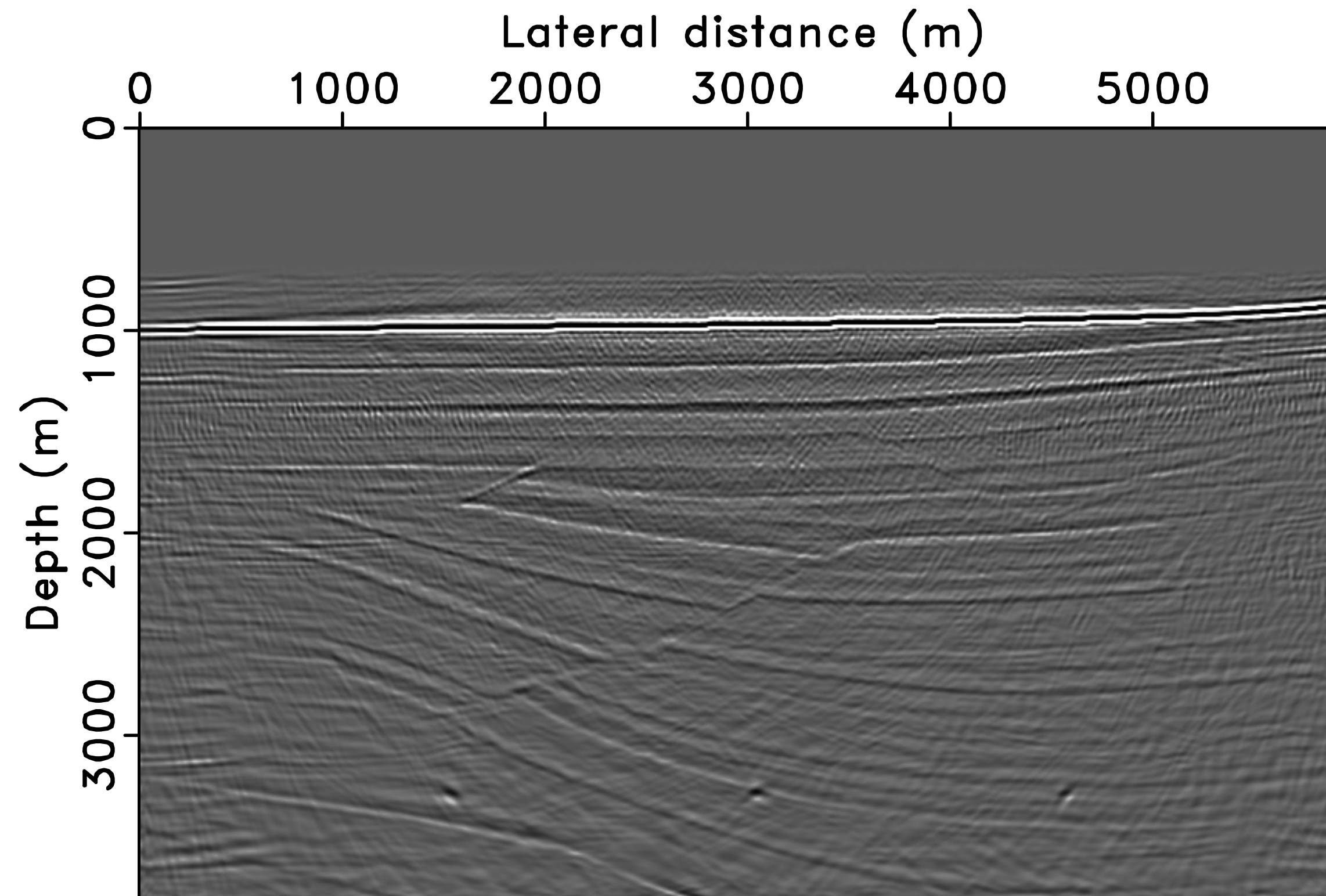
Fast inversion w/ sparsity promotion
w/o accounting for multiples

simulation cost ~1 **conventional imaging** of all data



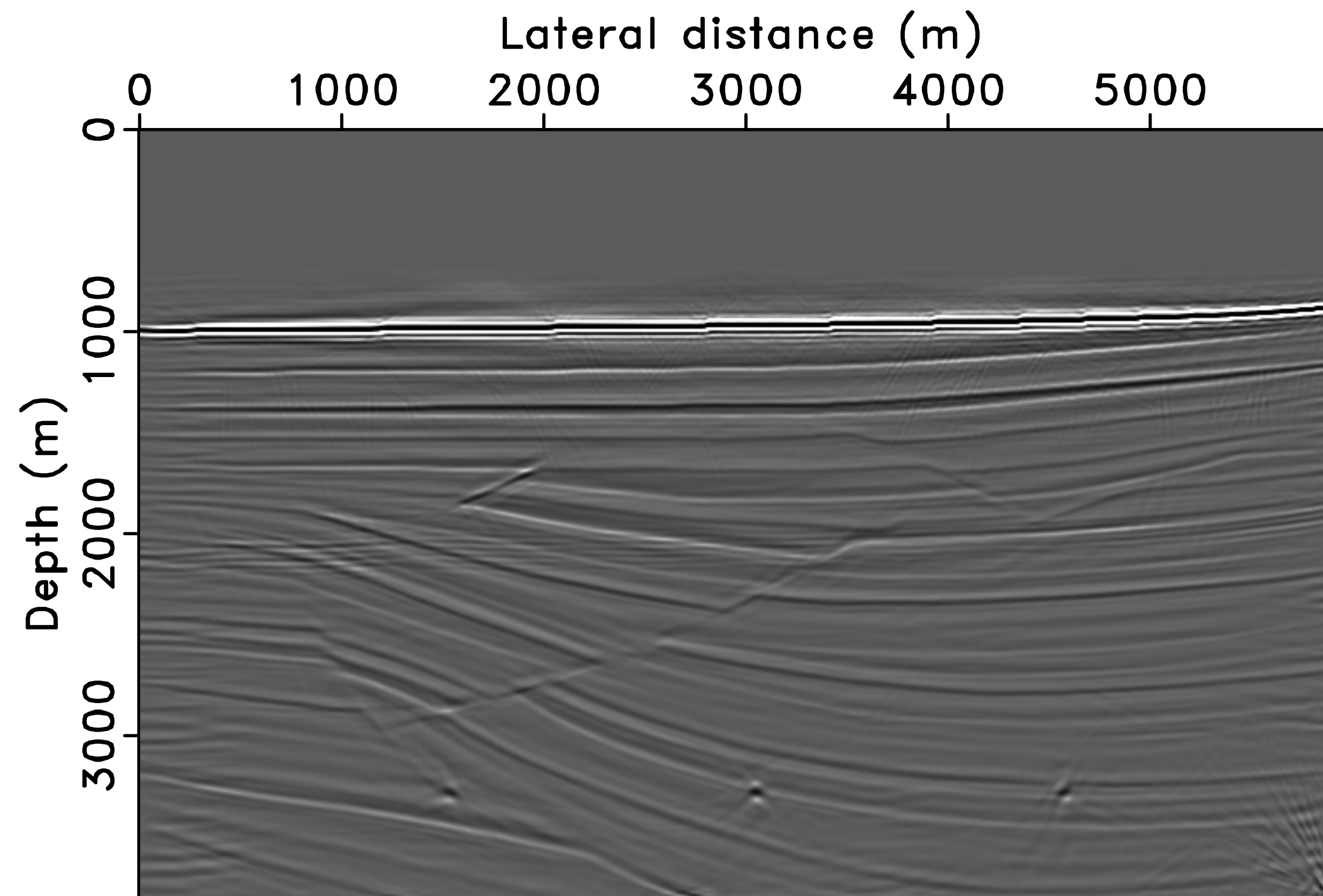
Fast inversion w/ sparsity promotion
w/ accounting for multiples

simulation cost ~1 **conventional imaging** of all data



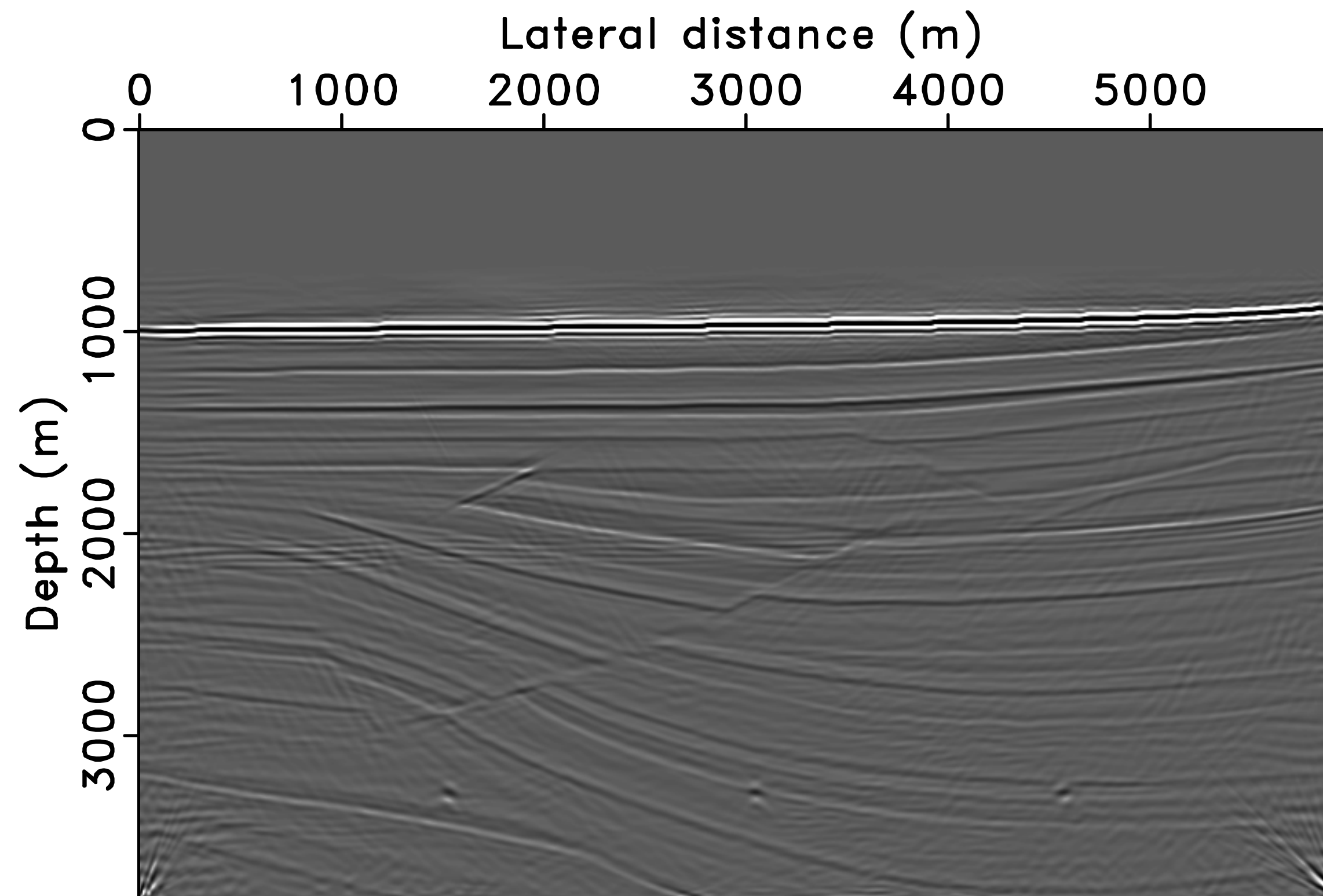
same as the previous image
except **without** rerandomization

simulation cost ~1 **conventional imaging** of all data



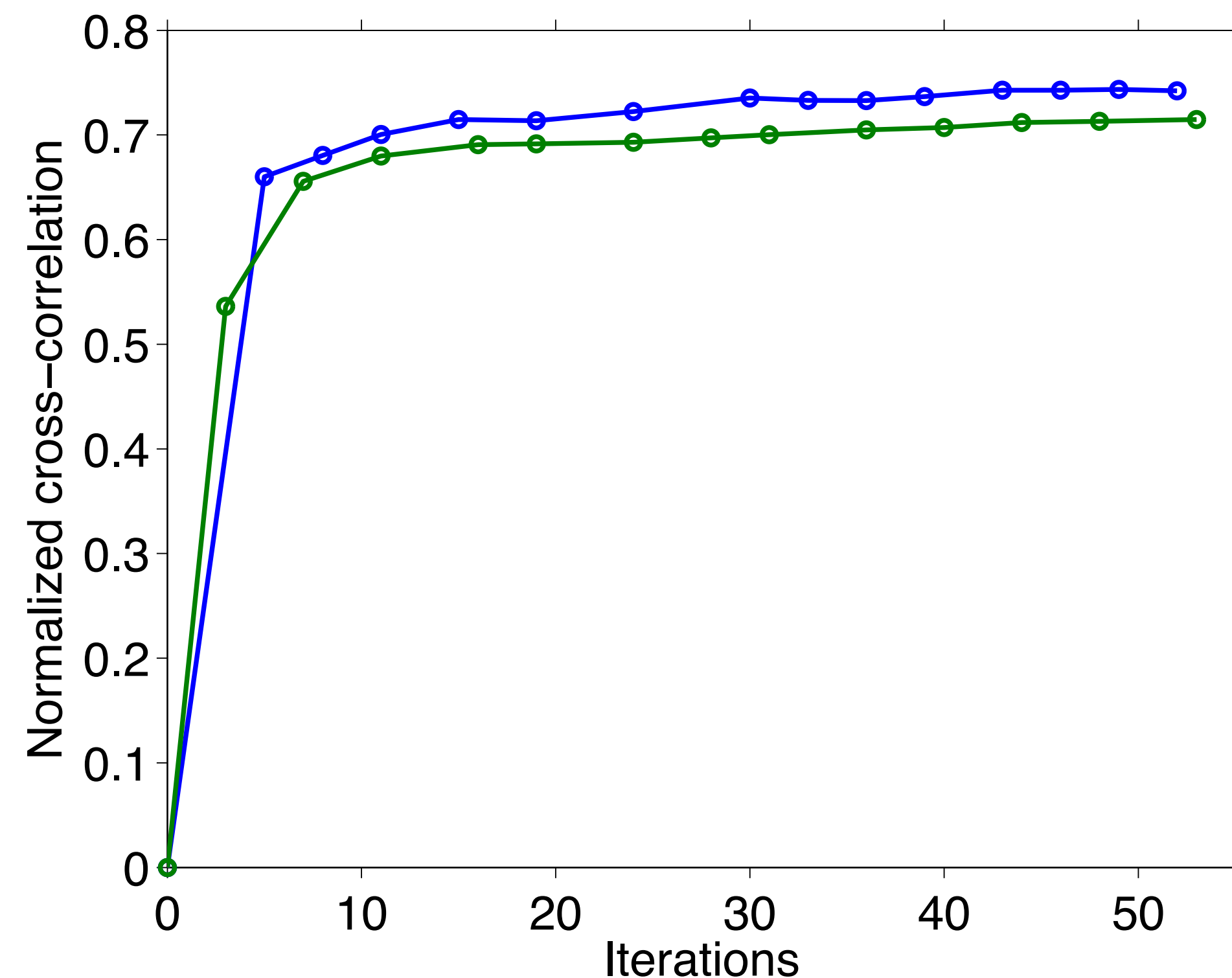
Fast inversion w/ sparsity promotion
w/ accounting for multiples

simulation cost ~**1.5 conventional imaging** of all data



Fast inversion w/ sparsity promotion
w/ accounting for multiples

Convergence analysis



Normalized cross-correlation:

$$\text{NCC}(\mathbf{v}_1, \mathbf{v}_2) = \frac{\langle \mathbf{v}_1, \mathbf{v}_2 \rangle}{\|\mathbf{v}_1\|_2 \|\mathbf{v}_2\|_2}$$

NCC between true model and inverted model:

blue: inversion w/ *true* source wavelet

green: inversion w/ source *estimation*

Conclusions

- Multiples, if properly used, *increase* subsurface illumination.
- Multiples can be properly imaged by iterative *inversion*.
- **Contributions** of this work:
 - ▶ The otherwise prohibitively expensive inversion w/ multiples can now be carried out *efficiently*.
 - ▶ Joint inversion of primaries and *all orders* of multiples is *feasible* via source estimation.

Future work and further extension

Simplified implementation of sparse inversion

Future work and further extension

Simplified implementation of sparse inversion

```
r = b_sub - A_sub*x;  
g = A_sub'*r;  
rnorm = norm(r,2);  
gnorm = norm(g,2);  
steplength = (rnorm/gnorm)^2;  
z = z+steplength*g;  
x = sign(z).*max(0,abs(z)-lambda);
```

LBP

Future work and further extension

Simplified implementation of sparse inversion

```

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```

LBP

SPGL1

```

function [x,r,g,info] = spgl1( A, b, tau, sigma, x, options )

m = length(b);

%-----
% Check arguments.
%-----
if ~exist('options','var'), options = []; end
if ~exist('x','var'), x = []; end
if ~exist('sigma','var'), sigma = []; end
if ~exist('tau','var'), tau = []; end

if nargin < 2 || isempty(b) || isempty(A)
    error('At least two arguments are required');
elseif isempty(tau) && isempty(sigma)
    tau = 0;
    sigma = 0;
    singleTau = false;
elseif isempty(sigma) % && ~isempty(tau) <-- implied
    singleTau = true;
else
    if isempty(tau)
        tau = 0;
    end
    singleTau = false;
end

%-----
% Grab input options and set defaults where needed.
%-----
defaultopts = spgSetParams(...
    'fid' , 1 , ... % File ID for output
    'verbosity' , 2 , ... % Verbosity level
    'iterations' , 10*m , ... % Max number of iterations
    'nPrevVals' , 3 , ... % Number previous func values for linesearch
    'bpTol' , 1e-06 , ... % Tolerance for basis pursuit solution
    'optTol' , 1e-04 , ... % Optimality tolerance
    'decTol' , 1e-04 , ... % Req'd rel. change in primal obj. for Newton
    'stepMin' , 1e-16 , ... % Minimum spectral step
    'stepMax' , 1e+05 , ... % Maximum spectral step
    'rootMethod' , 2 , ... % Root finding method: 2=quad,1=linear (not used).
    'activeSetIt' , Inf , ... % Exit with EXIT_ACTIVE_SET if nnz same for # its.
    'subspaceMin' , 0 , ... % Use subspace minimization
    'iscomplex' , NaN , ... % Flag set to indicate complex problem
    'maxMatvec' , Inf , ... % Maximum matrix-vector multiplies allowed
    'weights' , 1 , ... % Weights W in ||Wx||_1
    'Kaczmarz' , 0 , ... % Toggles whether Kaczmarz mode is on (experimental)
    'KaczScale' , 1 , ... % Scaling factor for Tau when using Kaczmarz-type submatrices
    'quitPareto' , 0 , ... % Exits when pareto curve is reached
    'minPareto' , 3 , ... % If quitPareto is on, the minimum number of iterations before checking for quitPareto conditions
    'lineSrchIt' , 1 , ... % Maximum number of line search iterations for spgLineCurvy, originally 10 ...
    'feasSrchIt' , 10000 , ... % Maximum number of feasible direction line search iterations, originally 10 ...
    'ignorePErr' , 0 , ... % Ignores projections error by issuing a warning instead of an error ...
    'project' , @NormL1_project , ...
    'primal_norm' , @NormL1_primal , ...
    'dual_norm' , @NormL1_dual , ...
    );
options = spgSetParams(defaultopts, options);

fid = options.fid;
logLevel = options.verbosity;
maxIts = options.iterations;
nPrevVals = options.nPrevVals;
bpTol = options.bpTol;
optTol = options.optTol;
decTol = options.decTol;
stepMin = options.stepMin;
stepMax = options.stepMax;
activeSetIt = options.activeSetIt;
subspaceMin = options.subspaceMin;
maxMatvec = max(3,options.maxMatvec);
weights = options.weights;
quitPareto = options.quitPareto;
minPareto = options.minPareto;
Kaczmarz = options.Kaczmarz;
lineSrchIt = options.lineSrchIt;
feasSrchIt = options.feasSrchIt;
ignorePErr = options.ignorePErr;

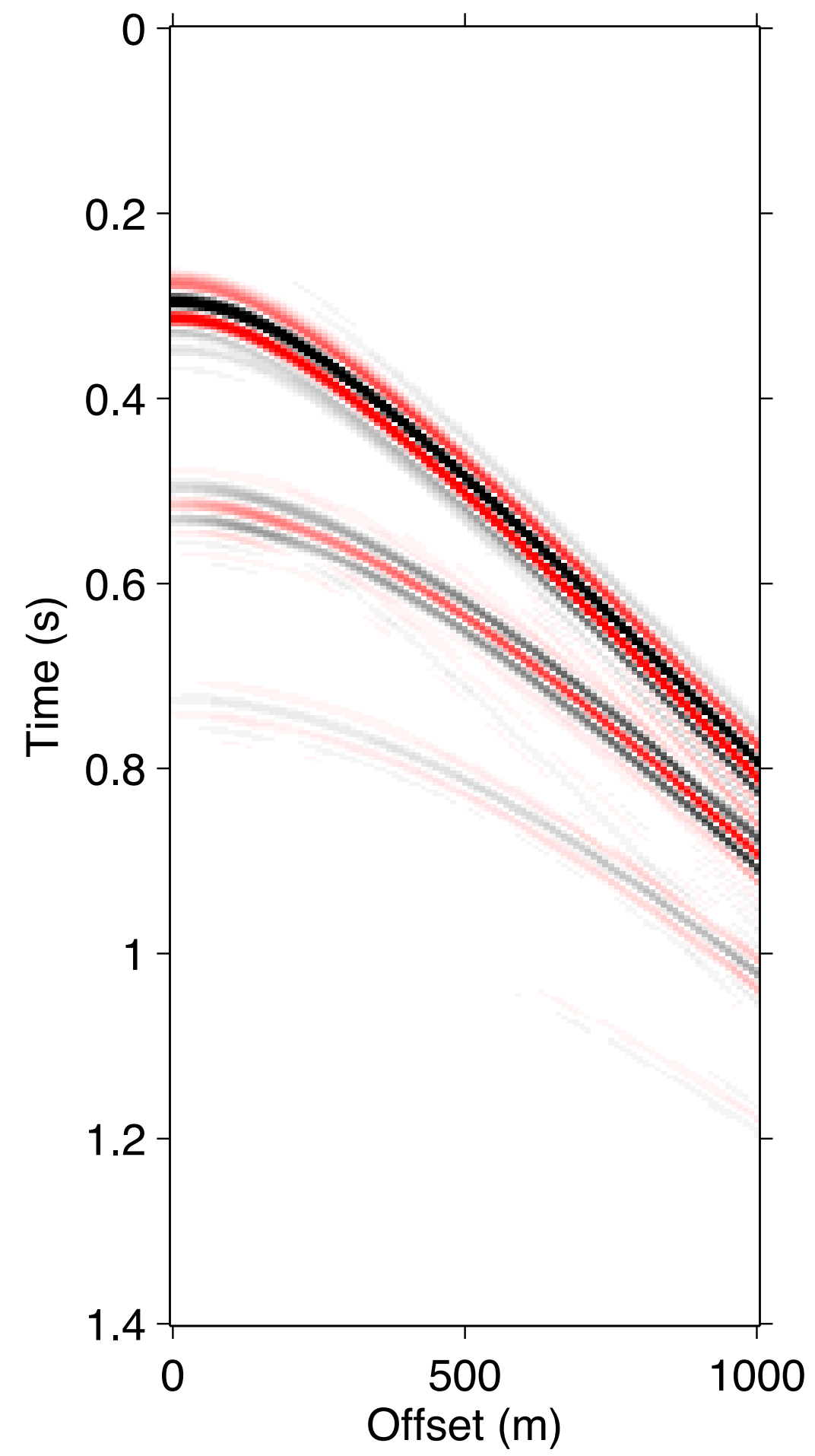
% maxLineErrors TEMPORARILY DISABLED to prevent very large scaling issue to throw off algorithm
maxLineErrors = Inf; % Maximum number of line-search failures.
pivTol = 1e-12; % Threshold for significant Newton step.

%-----
% Initialize local variables.
%-----
iter = 0; itnTotLSQR = 0; % Total SPGL1 and LSQR iterations.
nProdA = 0; nProdAt = 0;
lastFv = -inf(nPrevVals,1); % Last m function values.
nLineTot = 0; % Total no. of linesearch steps.
printTau = false;
nNewton = 0;
bNorm = norm(b,2);
stat = false;
timeProject = 0;
timeMatProd = 0;
nnzIter = 0; % No. of its with fixed pattern.
nnzIdx = []; % Active-set indicator.
subspace = false; % Flag if did subspace min in current itn.
stepG = 1; % Step length for projected gradient.
testUpdateTau = 0; % Previous step did not update tau

% Determine initial x, vector length n, and see if problem is complex

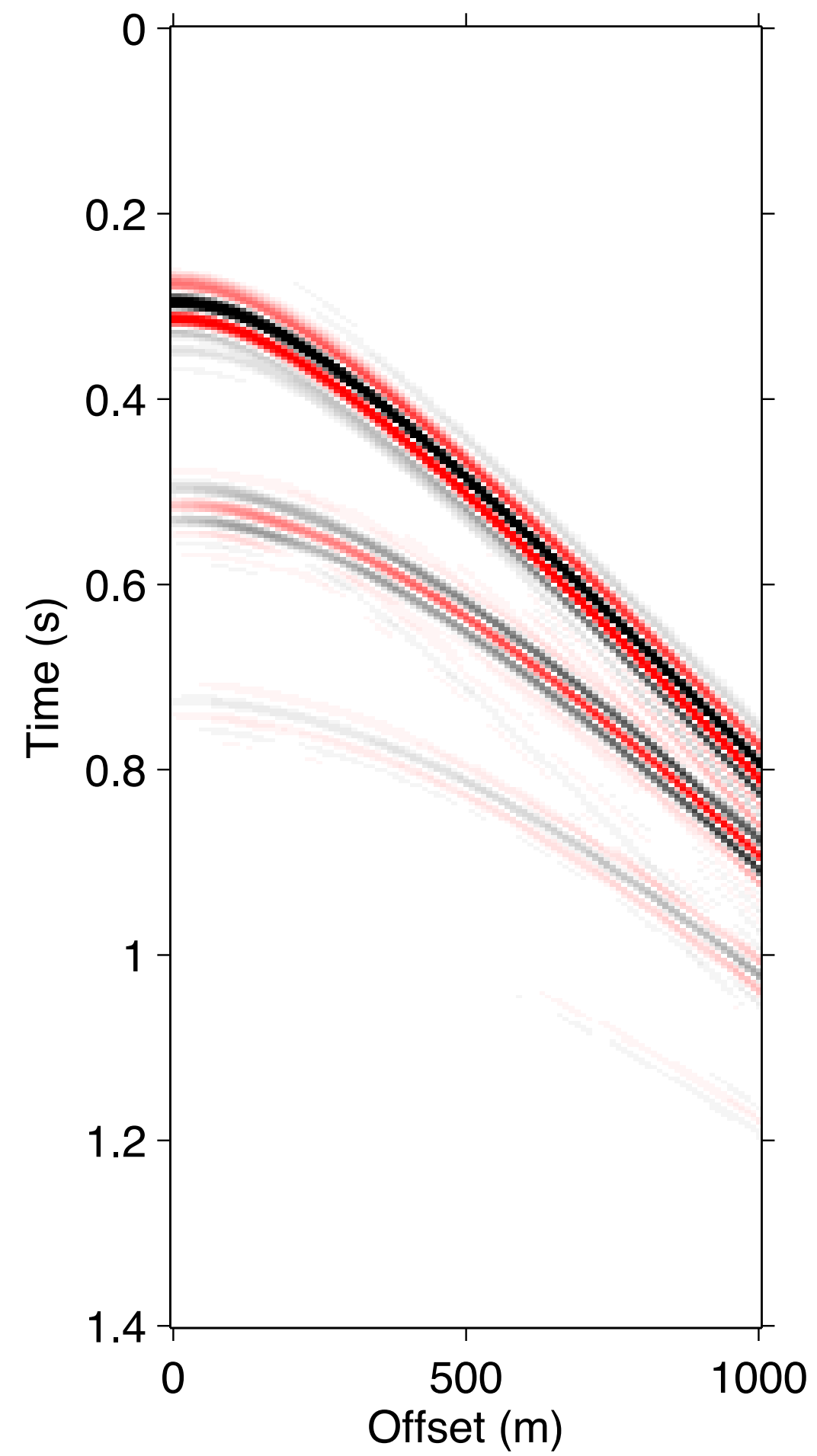
```


Future work and further extension

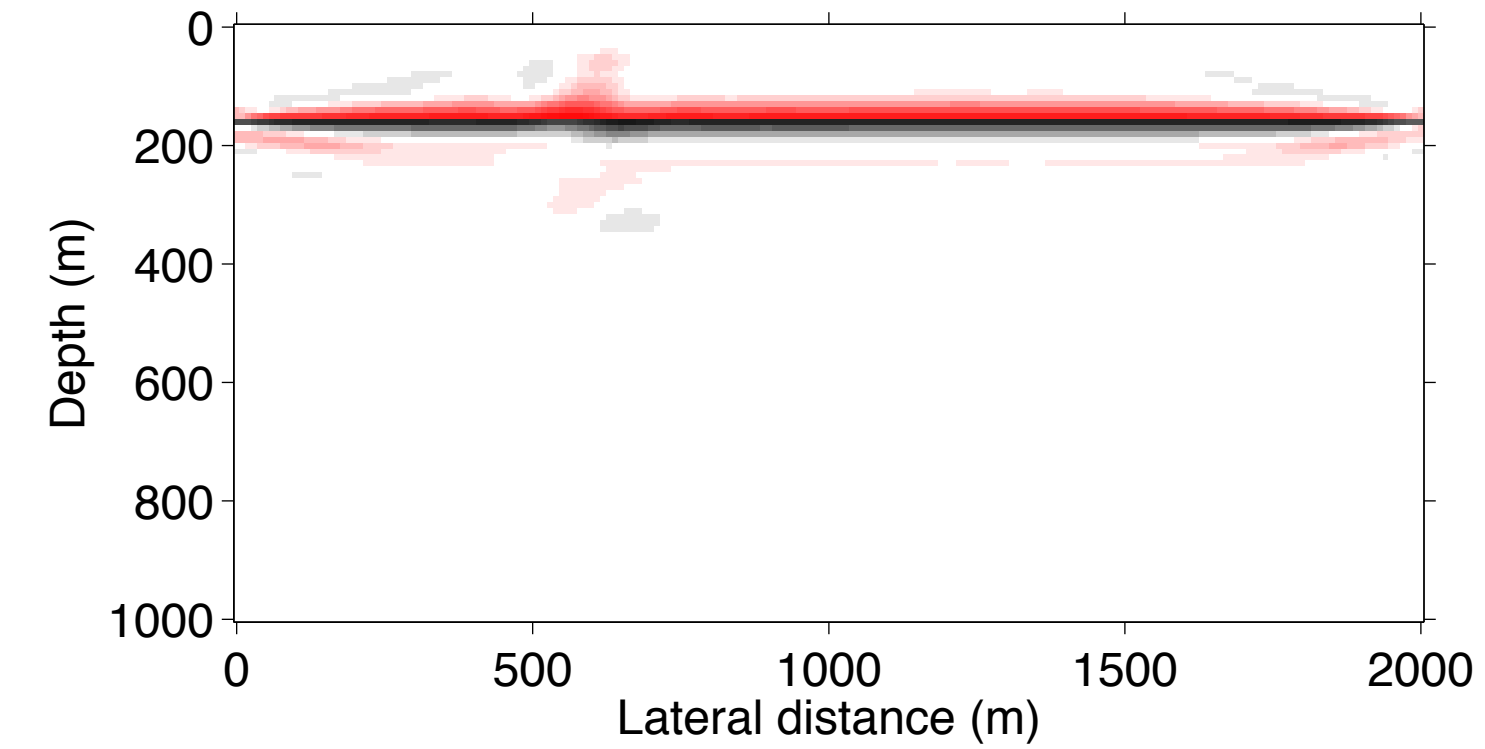


Future work and further extension

Chapter 8

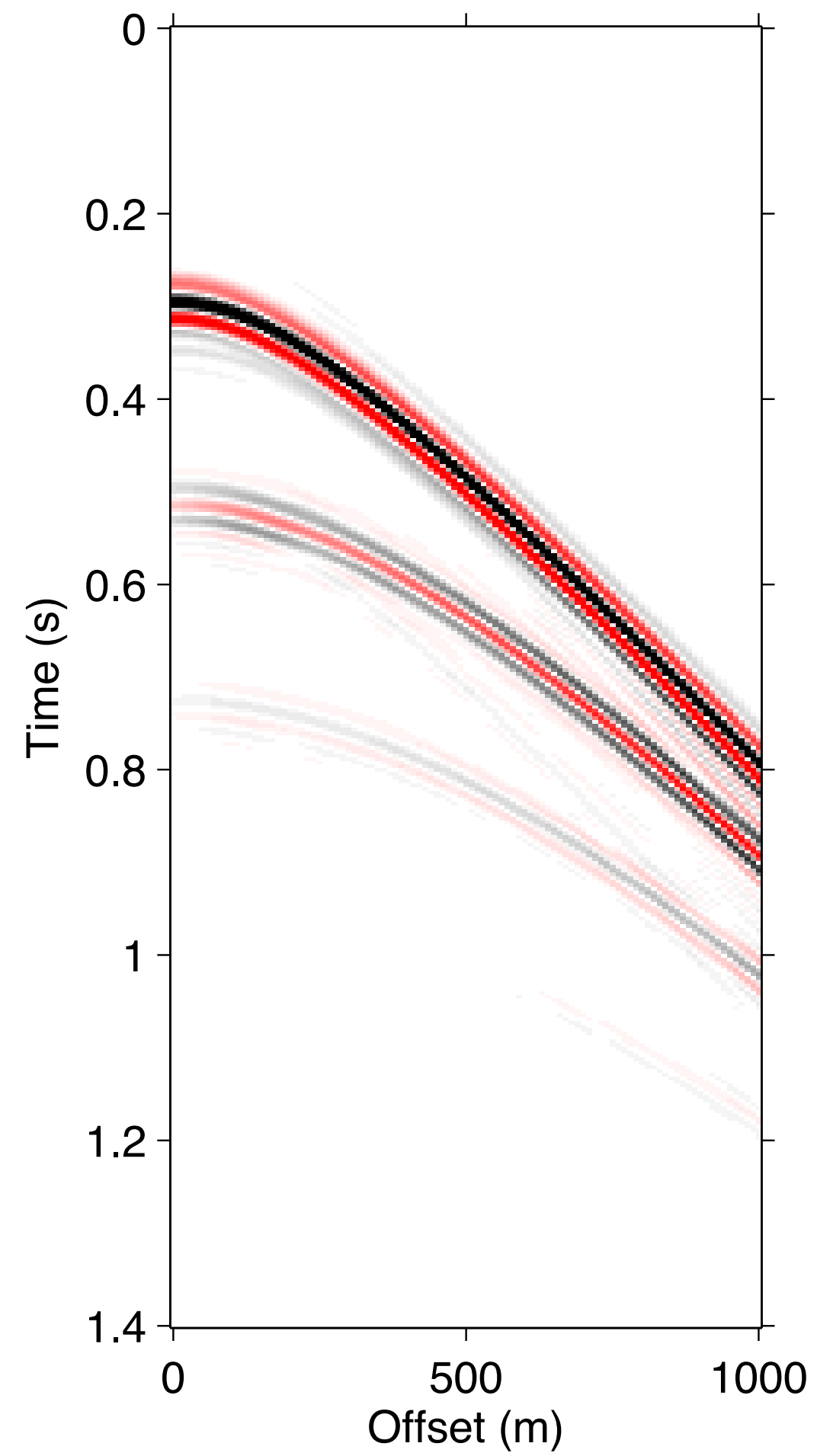


Imaging

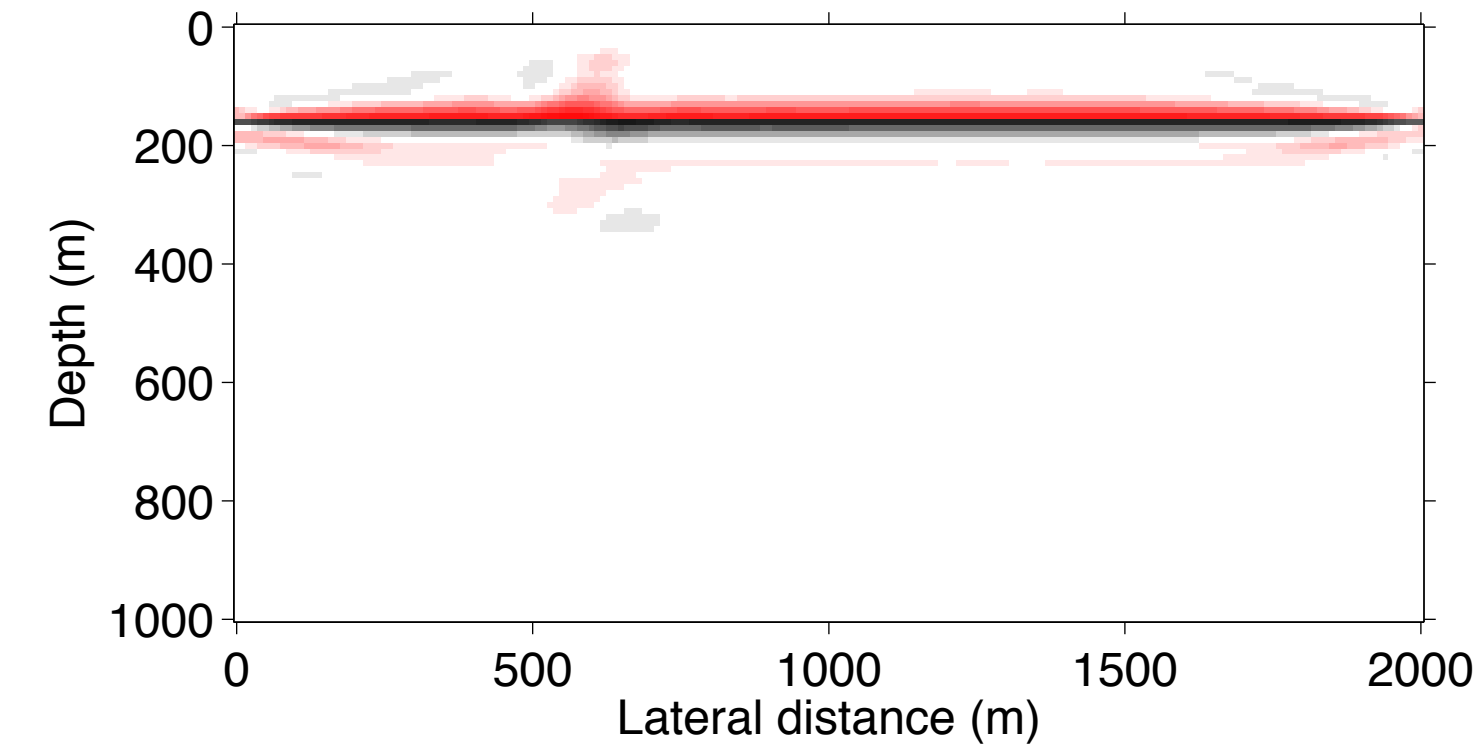


Future work and further extension

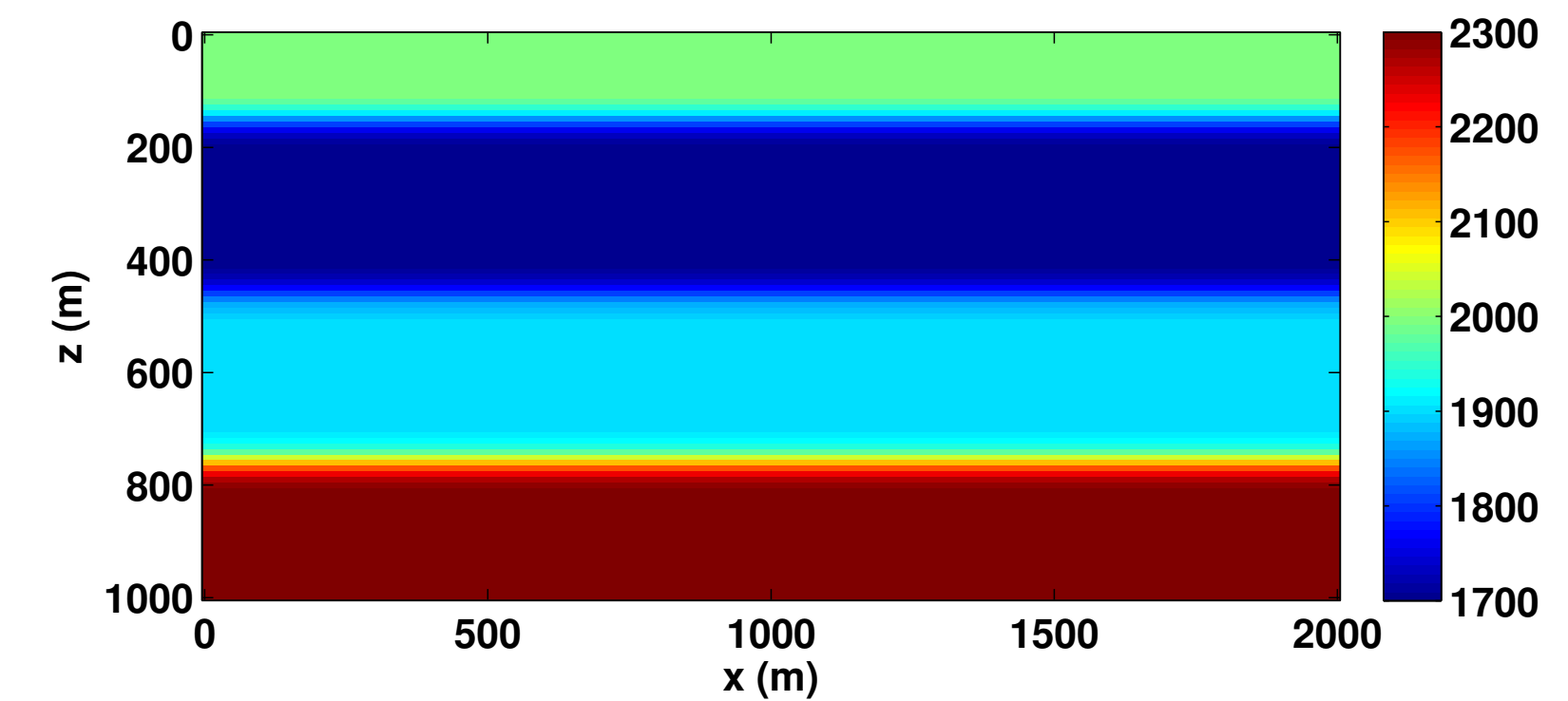
Chapter 8



Imaging



Velocity
model
building



Supervisory committee:

Felix J. Herrmann
Eldad Haber
Michael Bostock

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Family and friends**Exam committee:**

Valerie LeMay
Phil Austin
Tim Salcudean
Biondo Biondi

Thank you!
Questions?

SLIM group members:

Henryk Modzelewski
Miranda Joyce
Manjit & Harry Dosanjh
Ian Hanlon
Xiang Li
Tim Lin
Tristan van Leeuwen
Sasha Aravkin
Joost van der Neut
Rajiv Kumar
Haneet Wason
Lina Miao
Art Petrenko
Zhilong Fang
Bas Peters
Curt Da Silva
Navid Ghadermarzy
Felix Oghenekohwo
.....