

Fast imaging with multiples by sparse inversion

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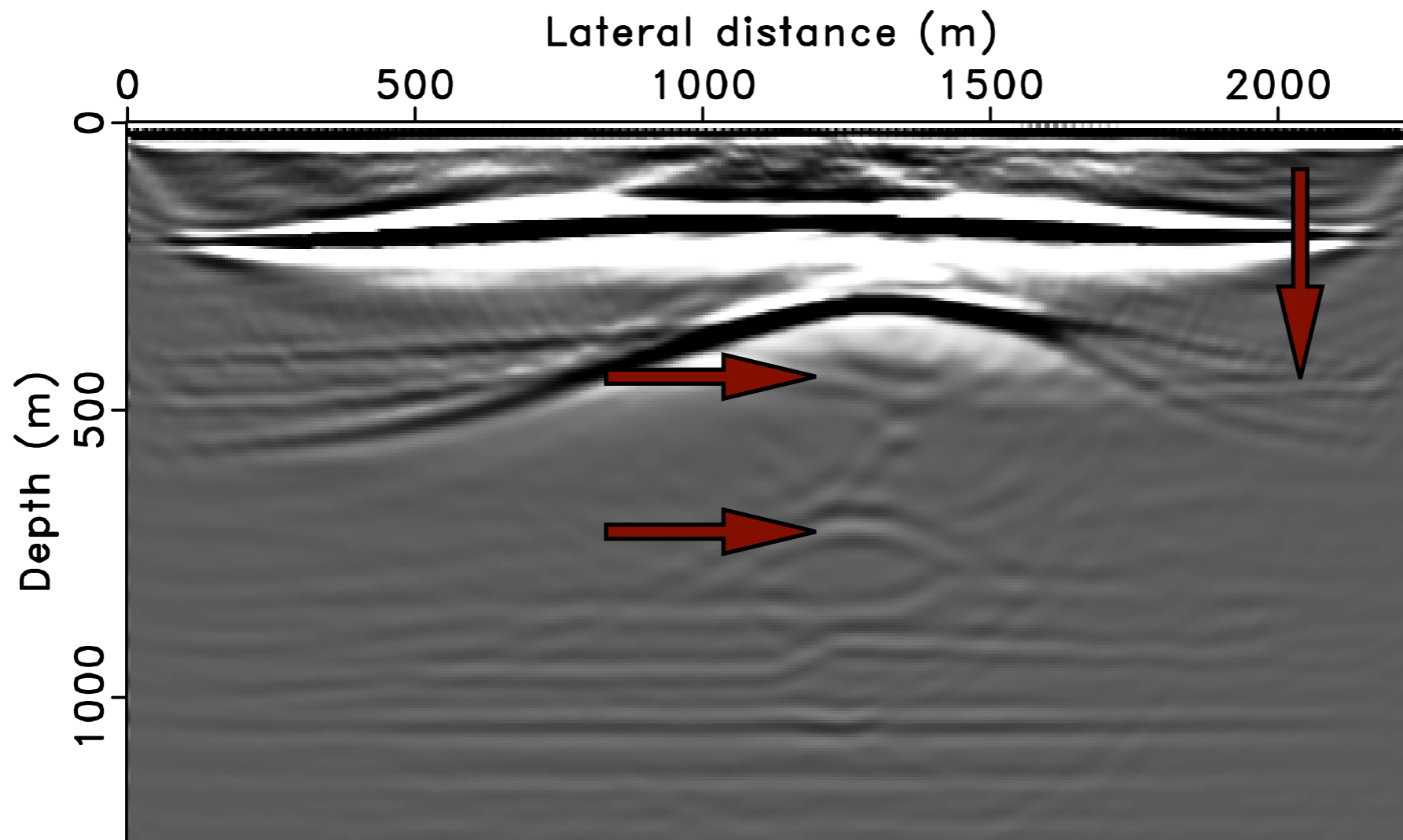
Motivation

- making use of primaries and multiples *simultaneously*
- avoiding imaging *artifacts* from multiples
- looking for a computationally *efficient* approach

Primaries & multiples: not “OR” but “AND”

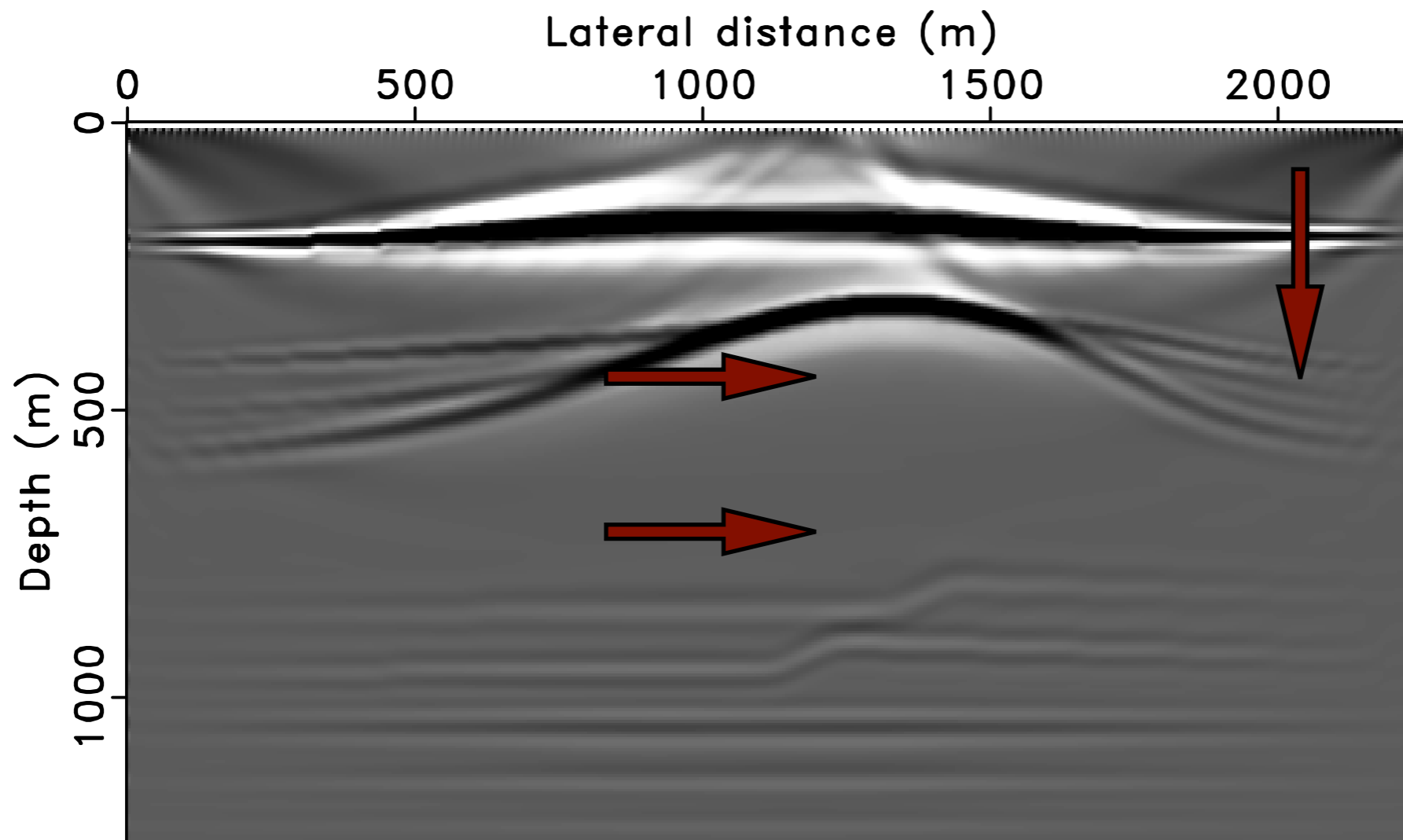
- primaries have a higher signal-to-noise ratio
- multiples provide extra illumination if correctly used
- skip the procedure of separating primaries/multiples

Artifacts from multiples



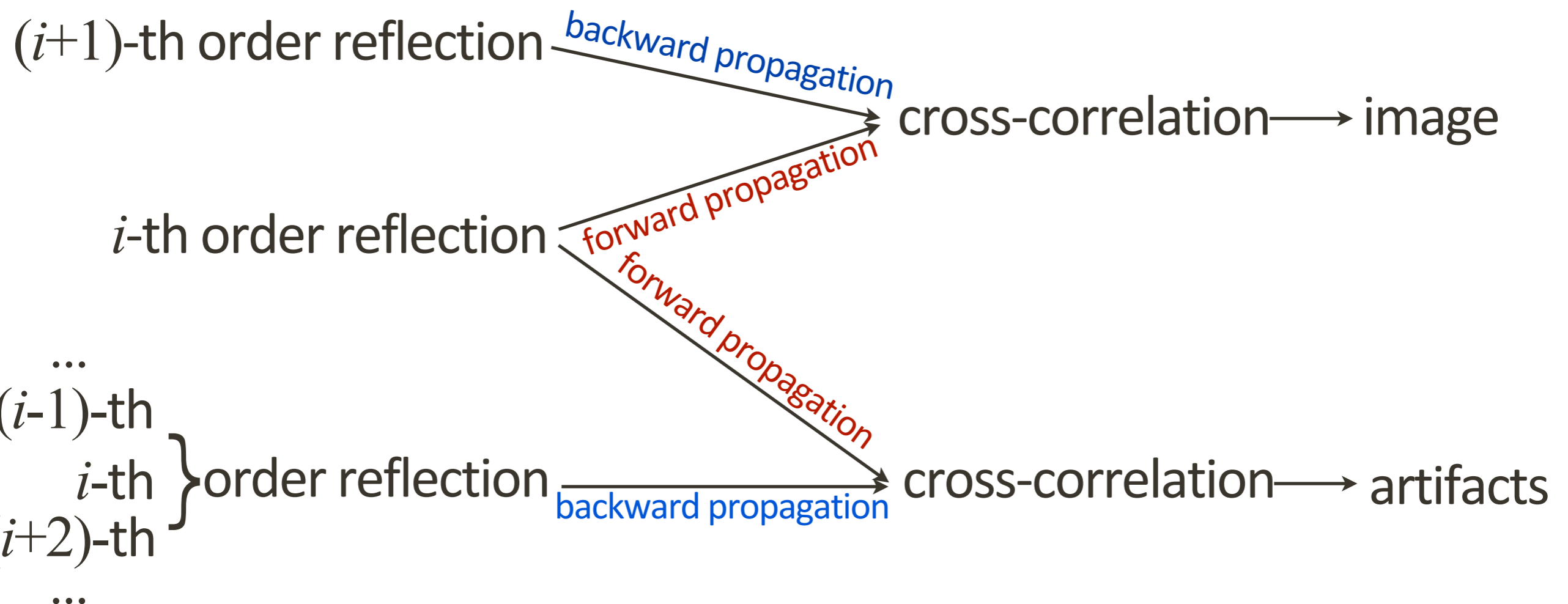
Reverse time migration of *multiples* using total data as “source”

Not there for primaries

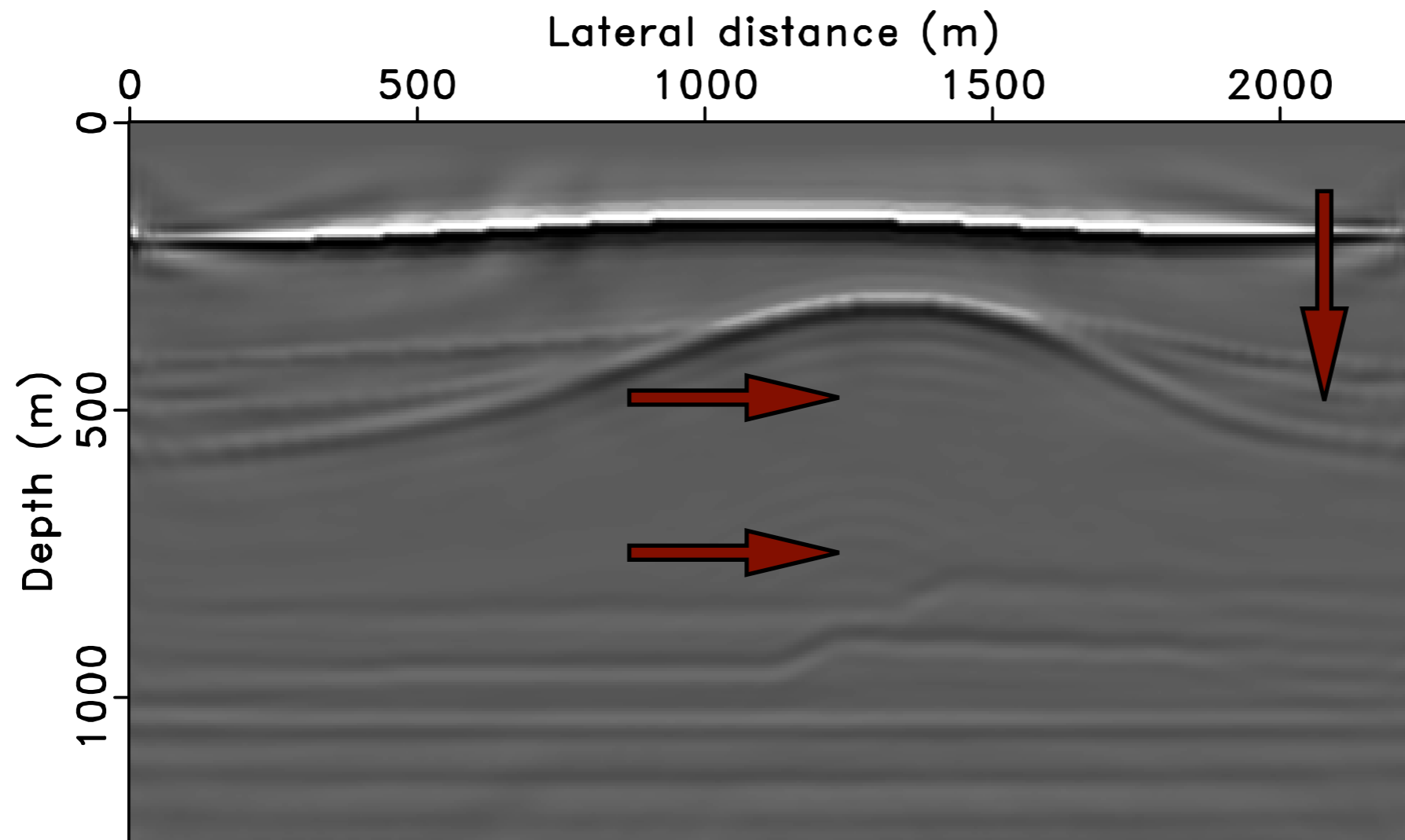


Reverse time migration of *primaries*

When a free-surface presents



Want to avoid them?



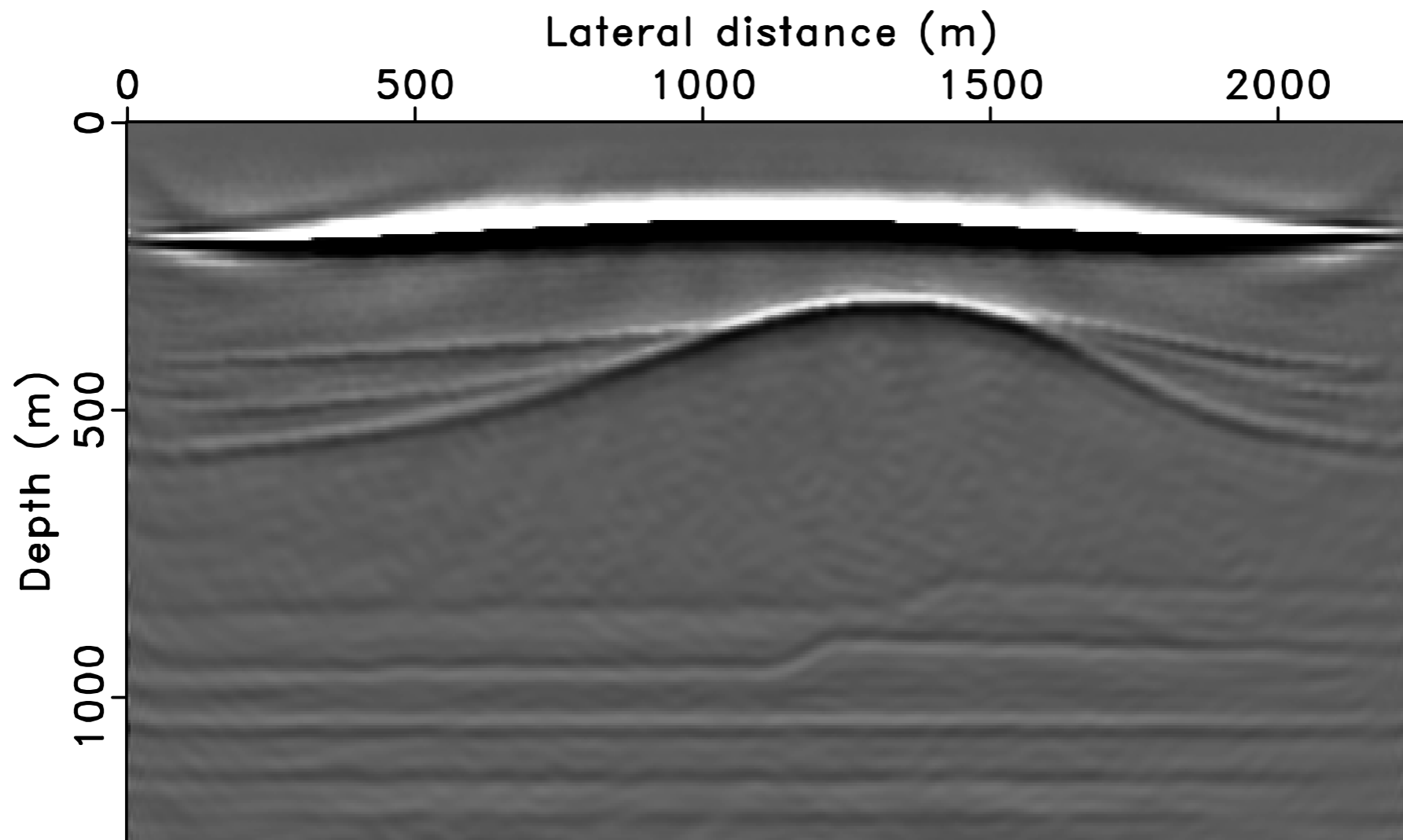
Imaging of *multiples* by *inversion*

Inversion? Sounds expensive...

- repeated evaluations of the Born scattering operator and its adjoint
- each evaluation requires solving $4 * (\text{\#source}) * (\text{\#frequencies})$ PDEs

Sneak peek of our result

[with a computational budget of a single RTM with all data]



Fast imaging of *total up-going wavefield* by sparse inversion
120X speed up compared with the previous result

Method

Incorporating the free surface

Total data and the surface-free Green's function can be related by the SRME formulation:

$$\mathbf{P}_{\omega_i} = \mathbf{G}_{\omega_i} (\mathbf{Q}_{\omega_i} + \mathbf{R}_{\omega_i} \mathbf{P}_{\omega_i})$$

P : total up-going wavefield

G : surface-free Green's function

Q : source wavelet

R : surface reflectivity

Expressed in model space

$$\begin{aligned}\mathbf{P}_{\omega_i} &= \text{vec}^{-1}(\mathbf{F}_{\omega_i}[\mathbf{m}, \mathbf{I}])(\mathbf{Q}_{\omega_i} + \mathbf{R}_{\omega_i}\mathbf{P}_{\omega_i}) \\ &= \mathbf{D}_r\mathbf{H}_{\omega_i}^{-1}[\mathbf{m}](\mathbf{D}_s^*\mathbf{I})(\mathbf{Q}_{\omega_i} + \mathbf{R}_{\omega_i}\mathbf{P}_{\omega_i}) \\ &= \mathbf{D}_r\mathbf{H}_{\omega_i}^{-1}[\mathbf{m}](\mathbf{D}_s^*(\mathbf{Q}_{\omega_i} + \mathbf{R}_{\omega_i}\mathbf{P}_{\omega_i})) \\ &\doteq \text{vec}^{-1}(\mathbf{F}_{\omega_i}[\mathbf{m}, \mathbf{Q}_{\omega_i} + \mathbf{R}_{\omega_i}\mathbf{P}_{\omega_i}])\end{aligned}$$

F : modelling operator

m : true velocity/density model

I : impulsive source array

D : detection operator at receiver/source locations

Linearization

$$\mathbf{p}_{\omega_i} = \nabla \mathbf{F}_{\omega_i} [\mathbf{m}_0, \mathbf{Q}_{\omega_i} + \mathbf{R}_{\omega_i} \mathbf{P}_{\omega_i}] \delta \mathbf{m}$$

$\nabla \mathbf{F}$: Born scattering operator

\mathbf{m}_0 : background model

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

\mathbf{P}_{ω_i} : vectorized wavefield

Stacking over frequencies

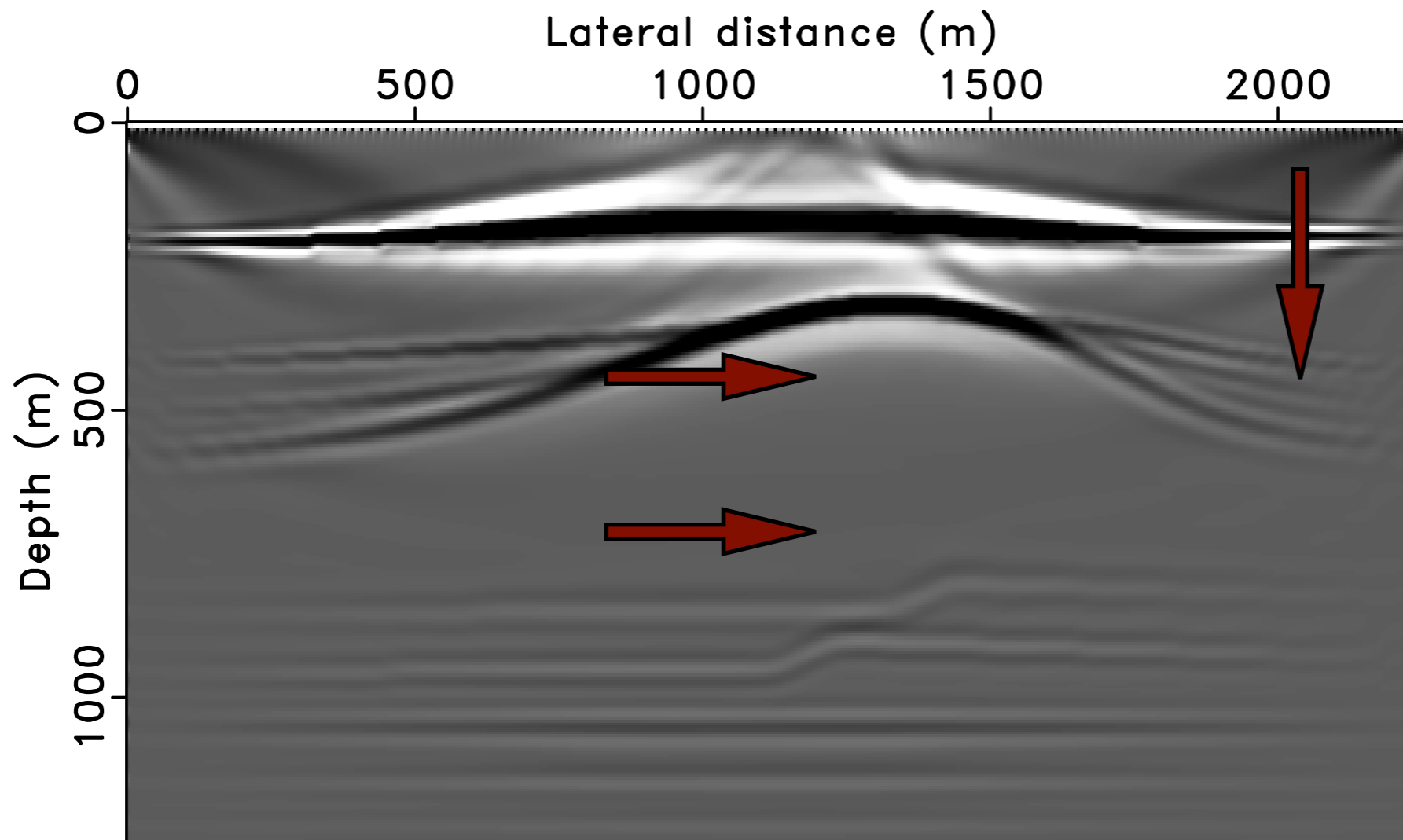
$$\mathbf{p} = \begin{bmatrix} \nabla \mathbf{F}_{\omega_1}(\mathbf{m}_0, \mathbf{Q}_{\omega_1} + \mathbf{R}_{\omega_1} \mathbf{P}_{\omega_1}) \\ \vdots \\ \nabla \mathbf{F}_{\omega_{nf}}(\mathbf{m}_0, \mathbf{Q}_{\omega_i} + \mathbf{R}_{\omega_i} \mathbf{P}_{\omega_i}) \end{bmatrix} \delta \mathbf{m}$$
$$\doteq \nabla \mathbf{F}[\mathbf{m}_0, \mathbf{Q} + \mathbf{R}\mathbf{P}] \delta \mathbf{m}$$



$$\delta \mathbf{m} = \nabla \mathbf{F}^\dagger[\mathbf{m}_0, \mathbf{Q} + \mathbf{R}\mathbf{P}] \mathbf{p}$$

RTM of primaries

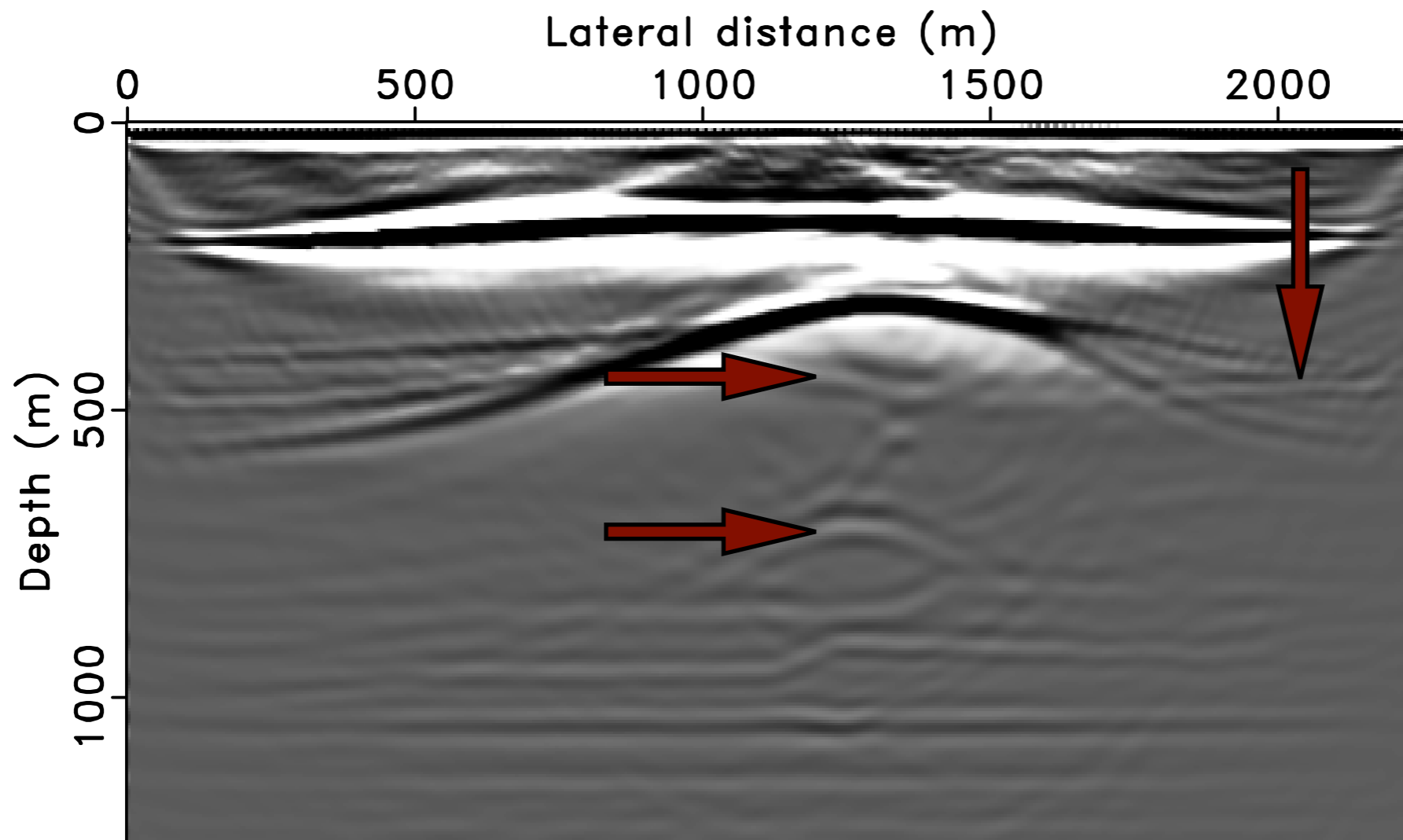
[replace inversion by adjoint]



Reverse time migration of *primaries* with all data
number of PDE solves: 36.6 thousand
vertical differentiation is applied

RTM of multiples

[replace inversion by adjoint]



Reverse time migration of *multiples* using total data as “source”
number of PDE solves: 36.6 thousand
vertical differentiation is applied

Sparse inversion

We use a sparsity-promotion formulation:

$$\delta \tilde{\mathbf{m}} = \mathbf{C}^H \underset{\delta \mathbf{x}}{\operatorname{argmin}} \|\delta \mathbf{x}\|_1$$

$$\text{subject to } \|\mathbf{p} - \nabla \mathbf{F}[\mathbf{m}_0, \mathbf{Q} + \mathbf{R}\mathbf{P}]\mathbf{C}^H \delta \mathbf{x}\|_2 \leq \sigma$$

\mathbf{C} : curvelet transform

solver: SPGL₁

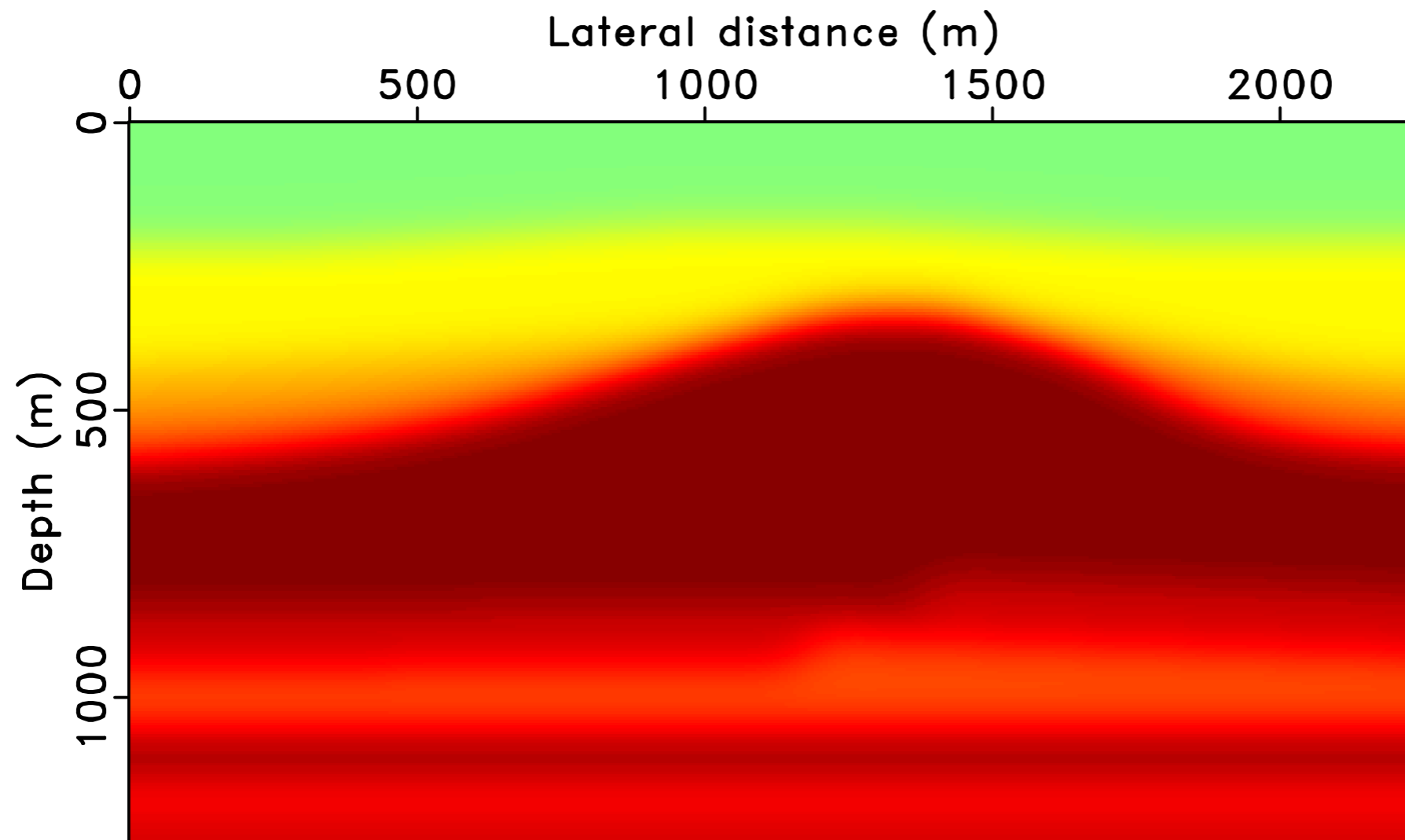
Demonstrative examples

- model grid spacing: 5 meters
- using linearized data:

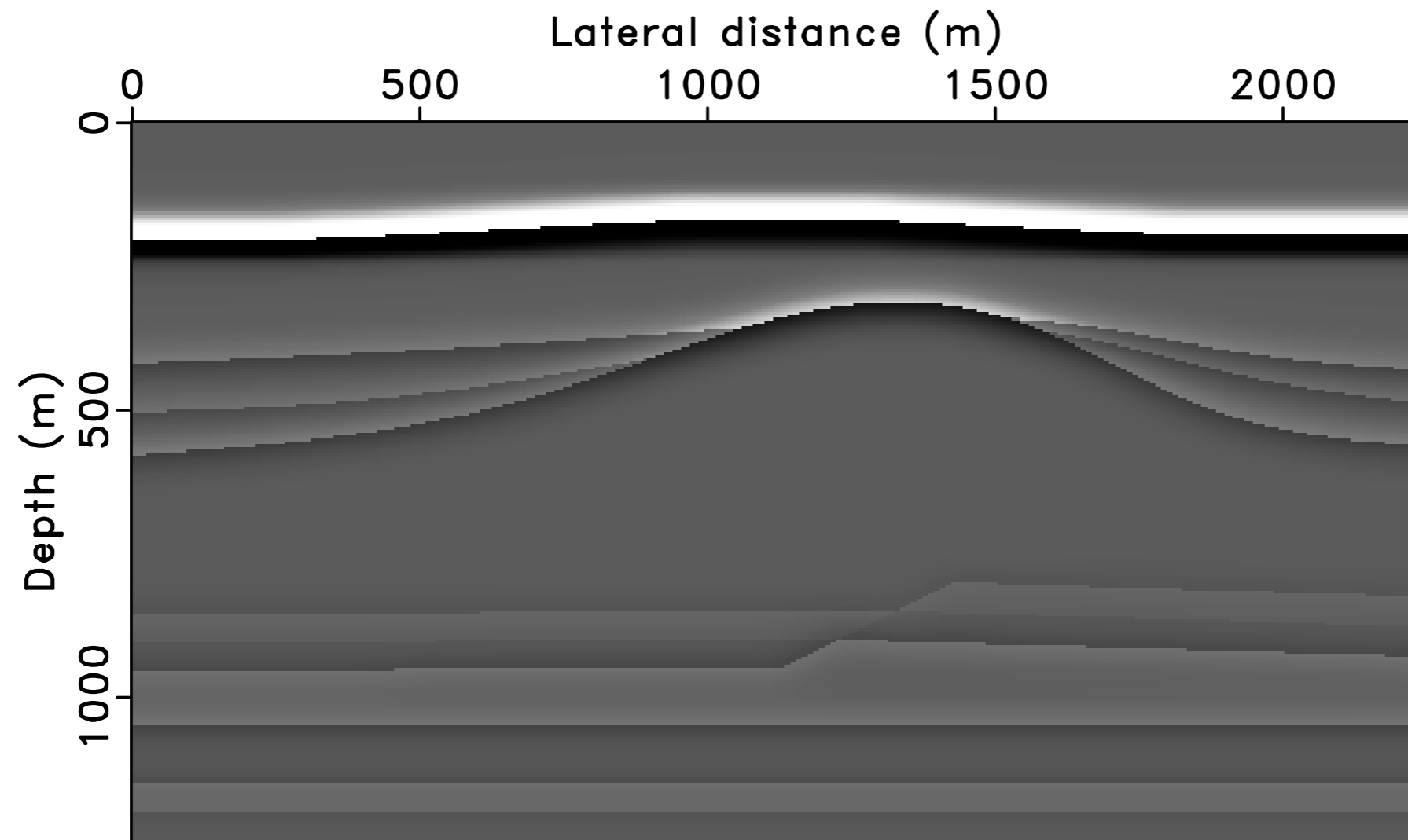
$$\nabla \mathbf{F}[\mathbf{m}_0, \mathbf{Q} + \mathbf{R}\mathbf{P}] \delta \mathbf{m}$$

- 150 collocated sources/receivers
- 122 frequencies in 0-60Hz range

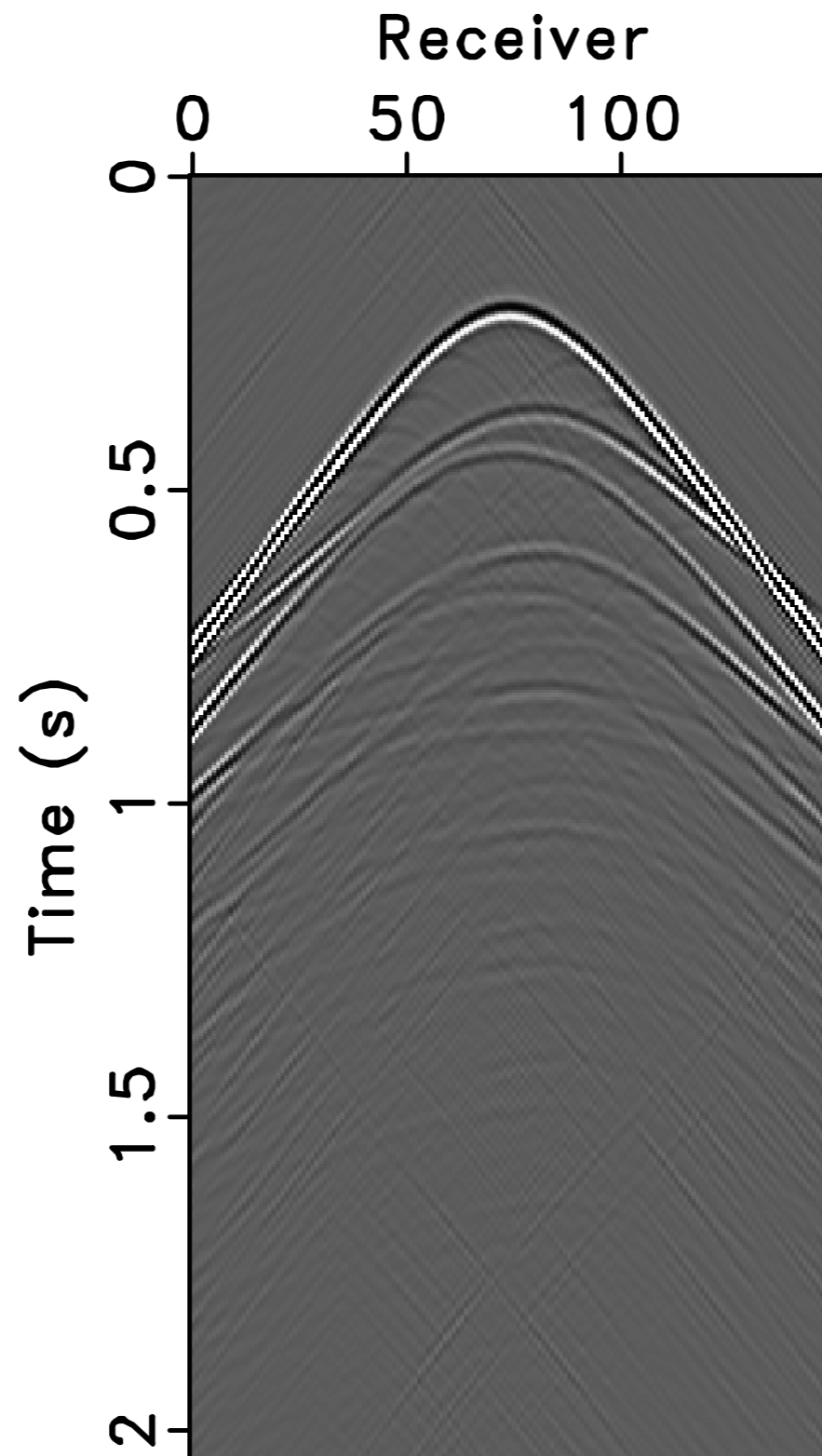
Background model



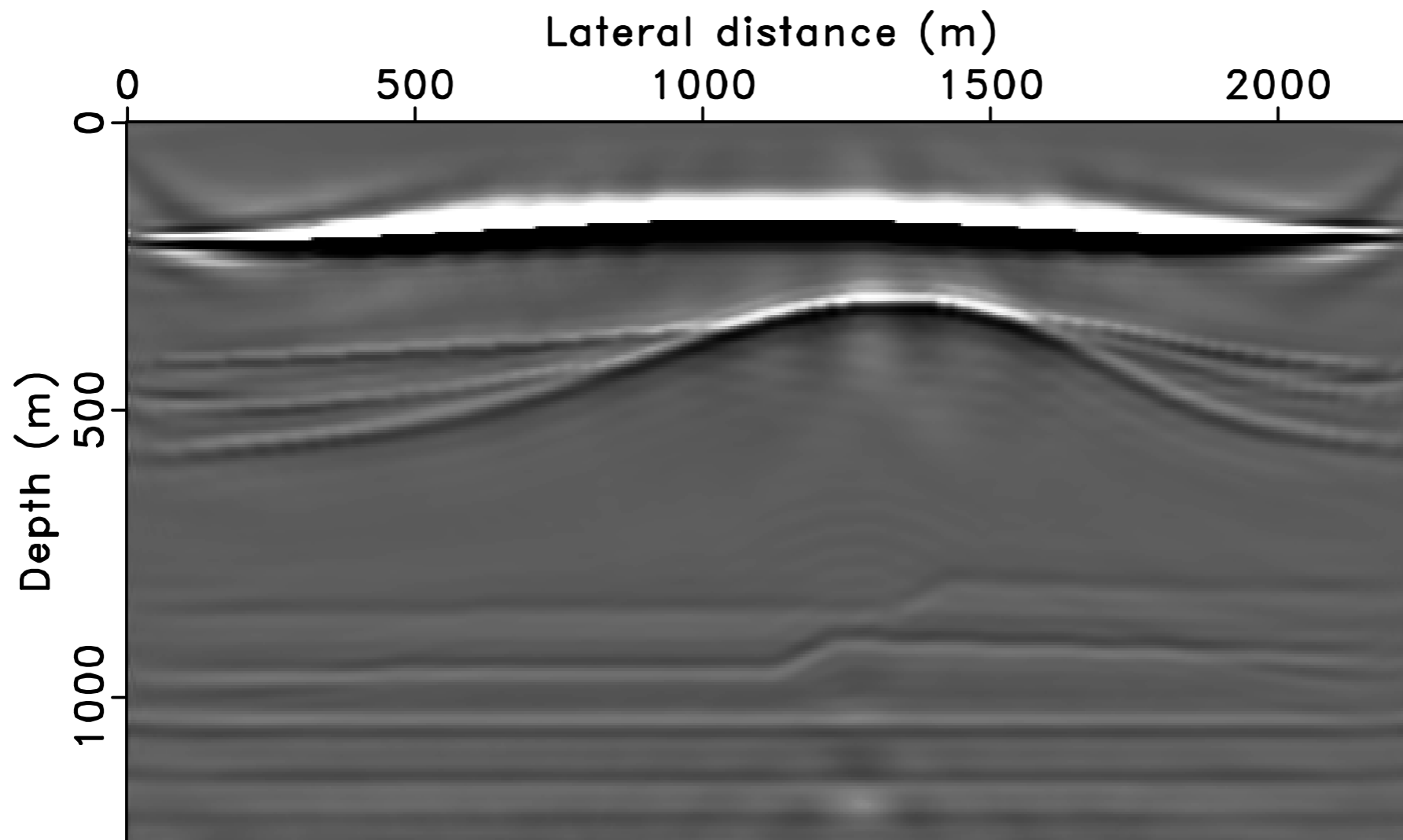
True perturbation



Linearized total data



Result



Inversion of the *total up-going wavefield* using all sequential sources and all frequencies
number of PDE solves: ~ 4.4 million (by calculation)

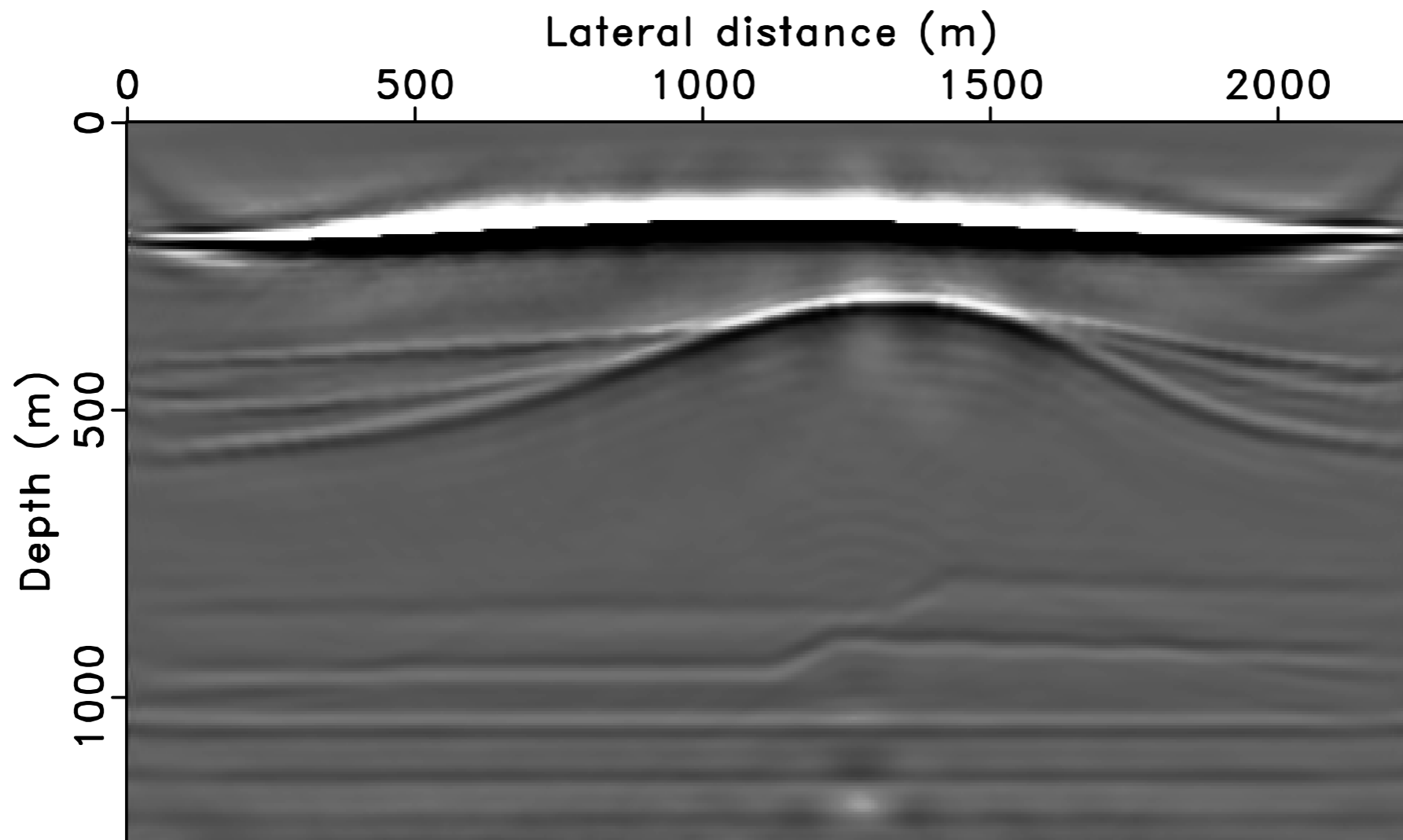
Dimensionality reduction

$$\delta \tilde{\mathbf{m}} = \mathbf{C}^H \underset{\delta \mathbf{x}}{\operatorname{argmin}} \|\delta \mathbf{x}\|_1$$

$$\text{subject to } \|\underline{\mathbf{p}} - \nabla \mathbf{F}[\mathbf{m}_0, \underline{\mathbf{Q}} + \underline{\mathbf{R}}\mathbf{P}]\mathbf{C}^H \delta \mathbf{x}\|_2 \leq \sigma$$

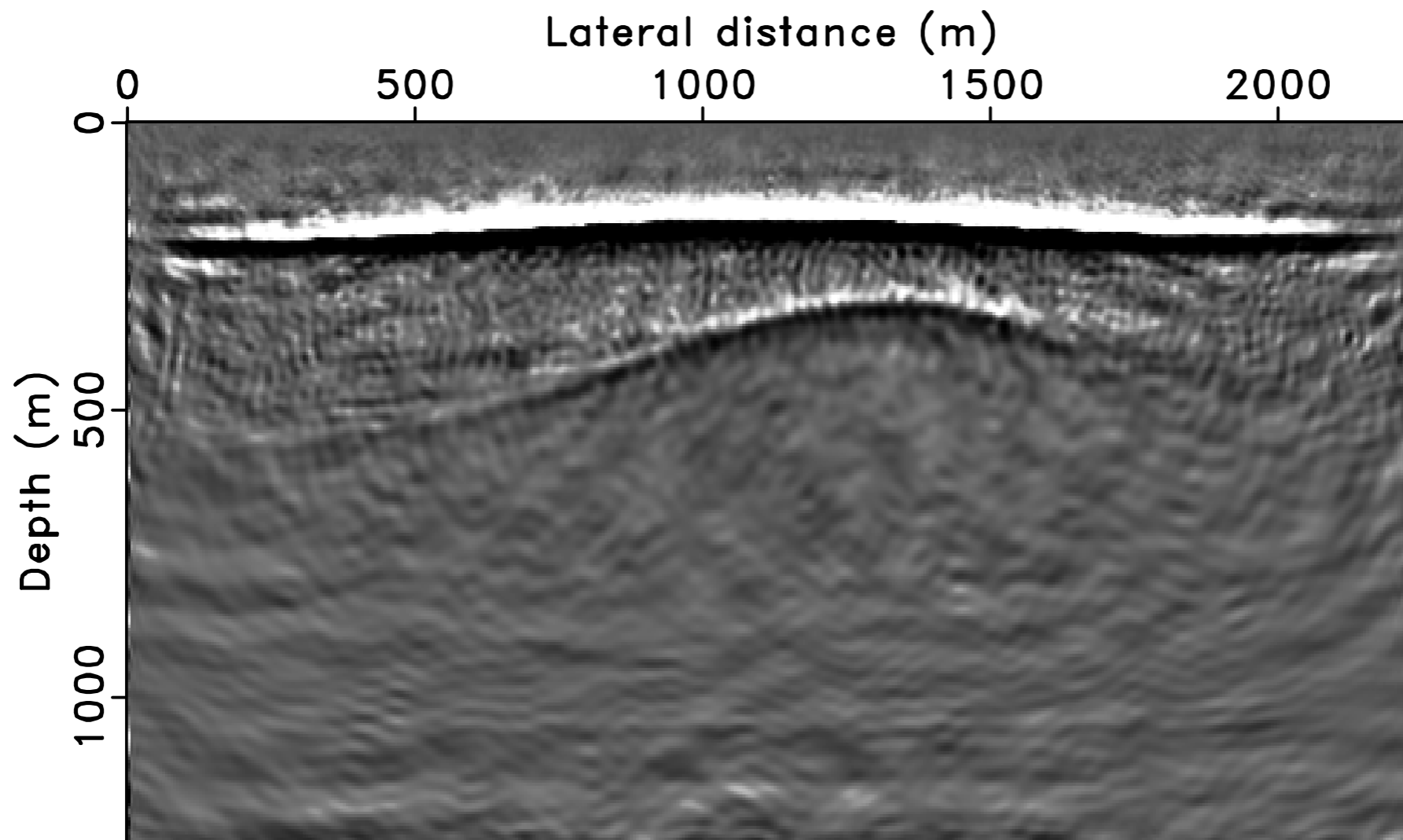
source: combine sources into a few simultaneous sources, using Gaussian distributed random weights
frequency: randomly choose a subset of frequencies

Result with 15x speed-up



Inversion of the total up-going wavefield using *10 simultaneous sources* and all frequencies
number of PDE solves: ~0.3 million

Too much subsampling brings artifacts



Inversion of the total up-going wavefield using *2 simultaneous sources and 15 frequencies*

number of PDE solves: 36.6 thousand

If working alright, it will give us *120X speed-up*

Draw new subsampling operator

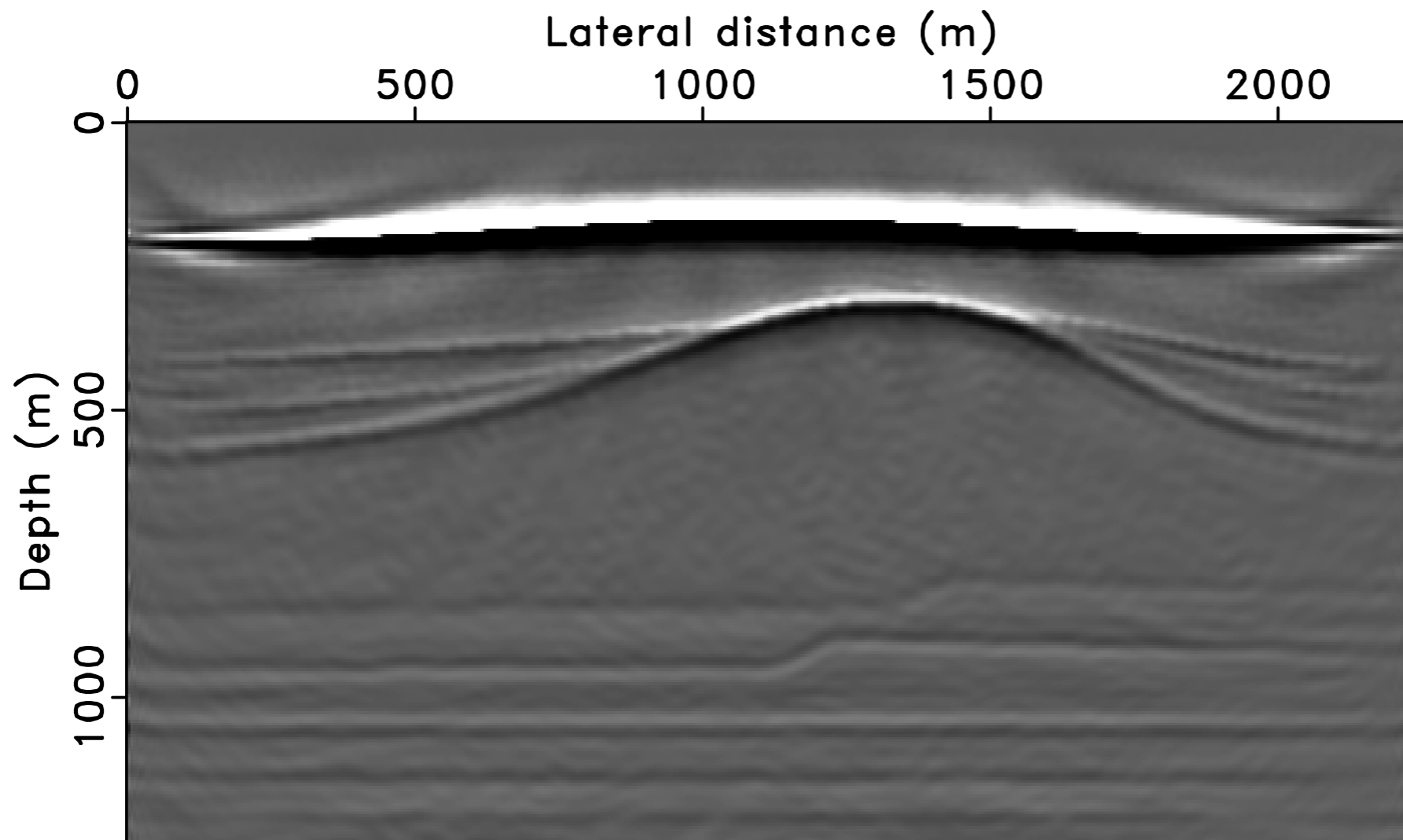
- SPGL₁ solves a series of subproblems:

$$\operatorname{argmin}_{\delta \mathbf{x}} \|\underline{\mathbf{p}} - \nabla \mathbf{F}[\mathbf{m}_0, \underline{\mathbf{Q}} + \underline{\mathbf{R}}\mathbf{P}] \mathbf{C}^H \delta \mathbf{x}\|_2$$

$$\text{subject to } \|\delta \mathbf{x}\|_1 \leq \tau$$

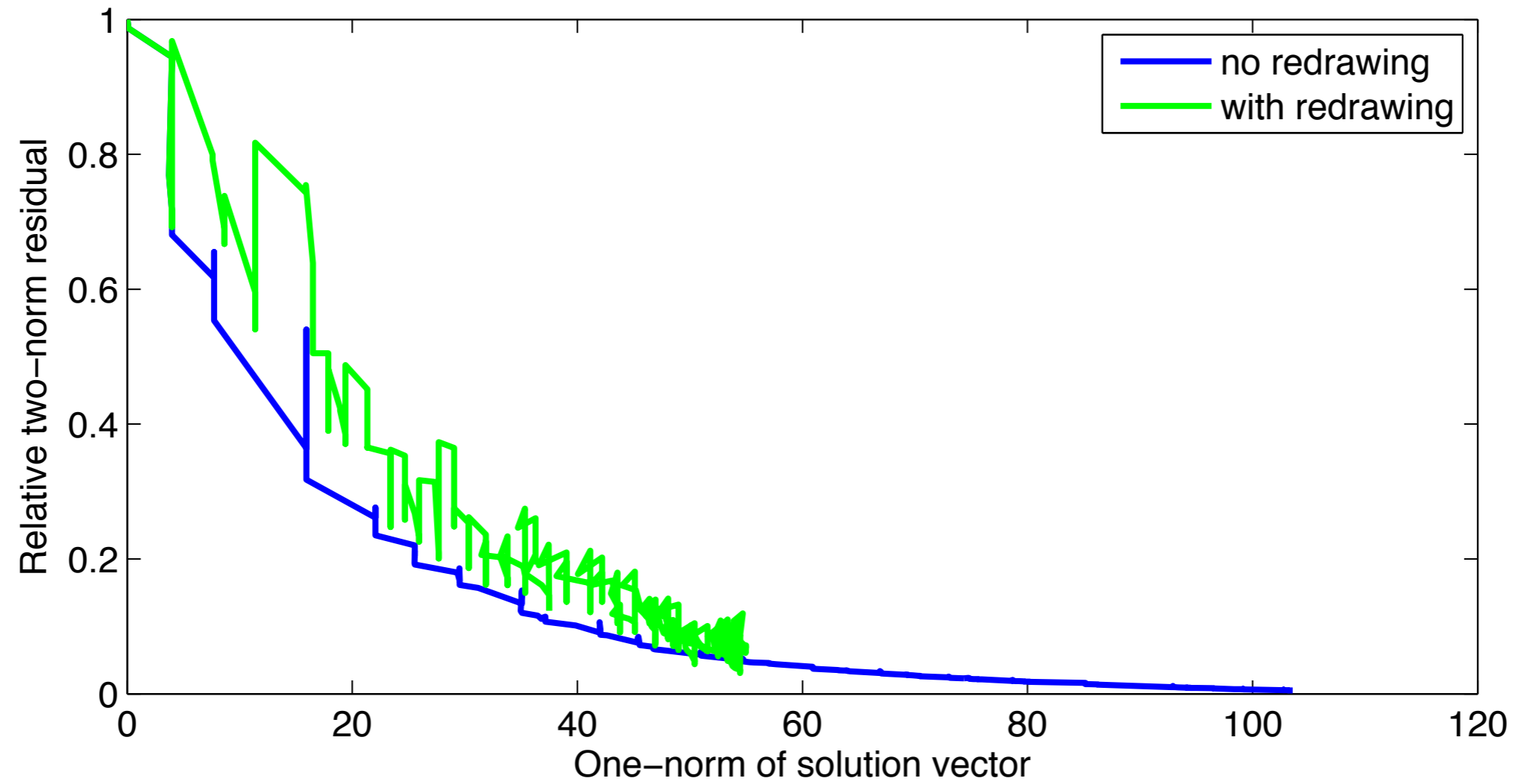
- redraw subsampling operator for each new subproblem

Draw new sim. sources and frequencies --*120X speed-up*

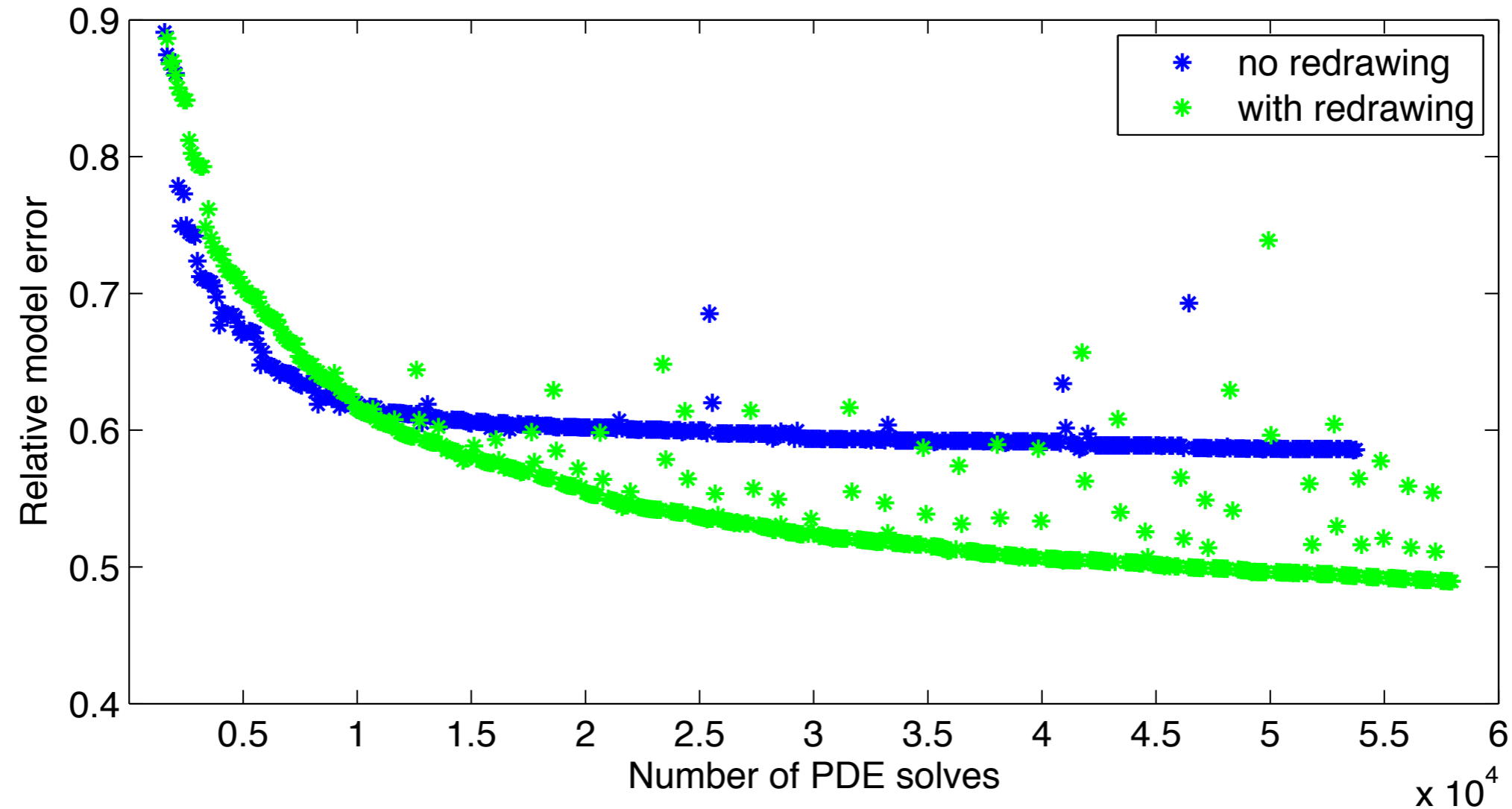


Inversion of the total up-going wavefield using 2 simultaneous sources and 15 frequencies
number of PDE solves: 36.6 thousand (by calculation)

Solution path

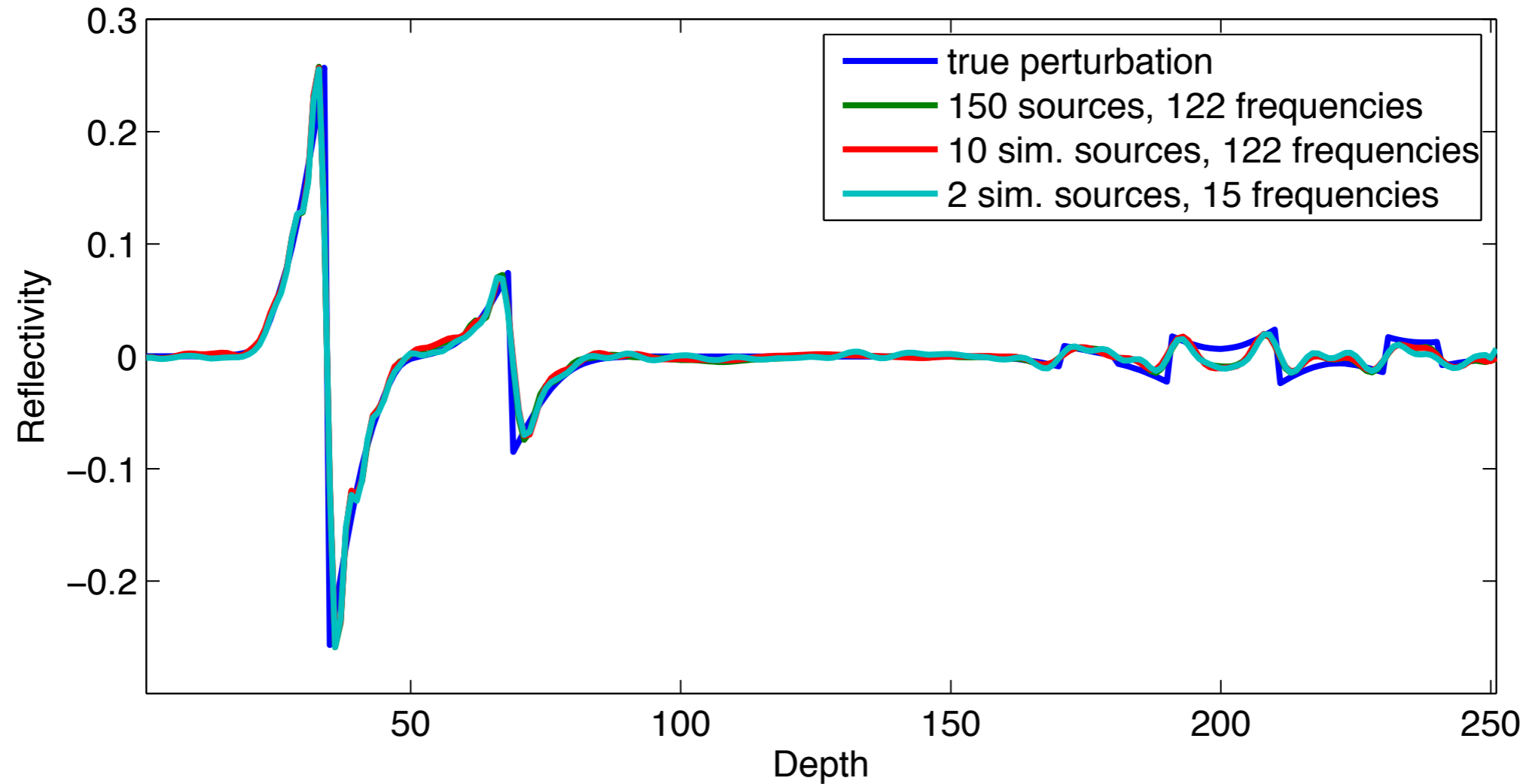


Model error decrease



Note: outliers are intermediate line-search results, not a concern; number of PDE solves in practice has ~50% overhead due to line search, etc.

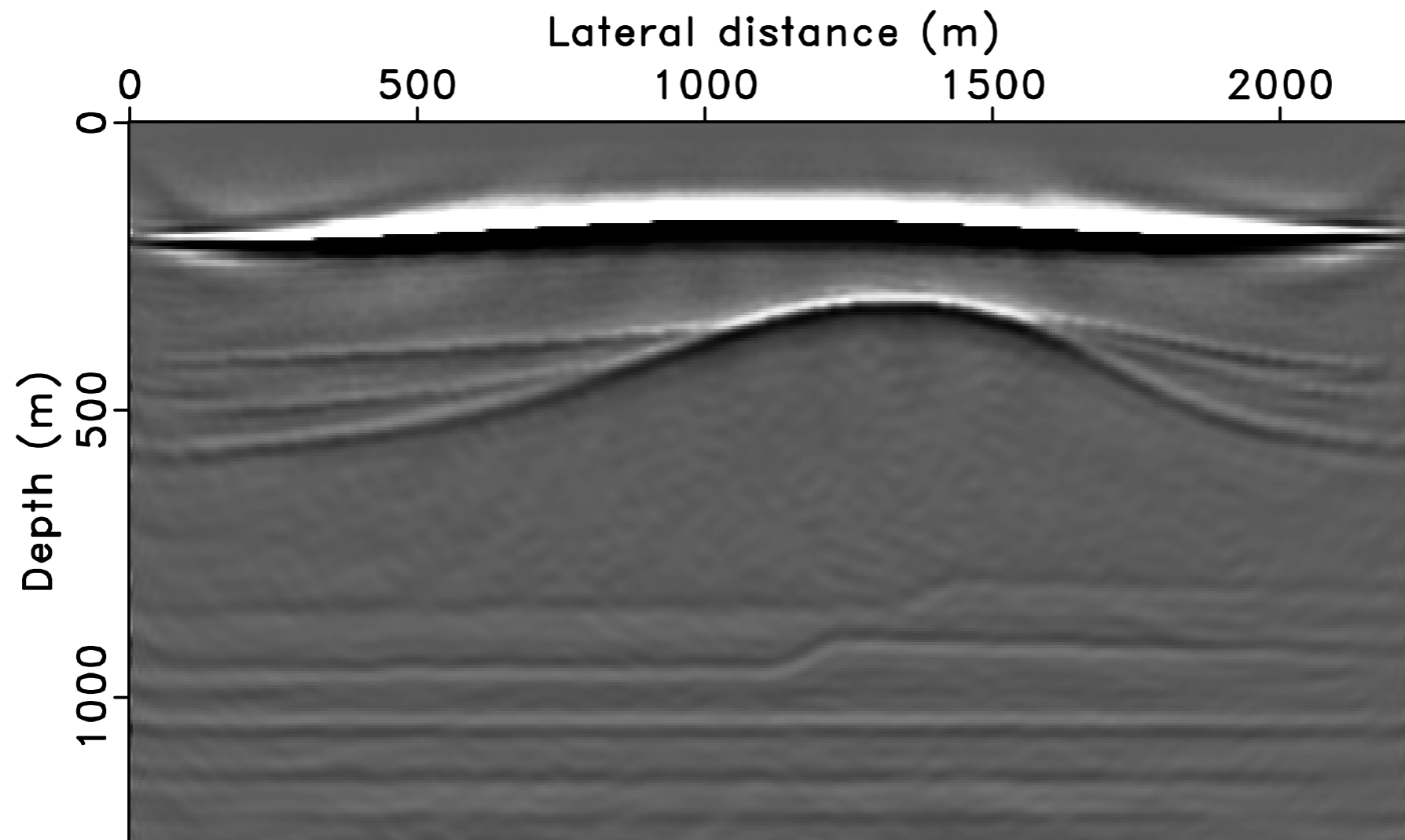
Inversion results



Trace to trace comparison: the 224th trace of model perturbation

Comparison: batch size

[same budget of PDE solves]



Fast imaging of total data

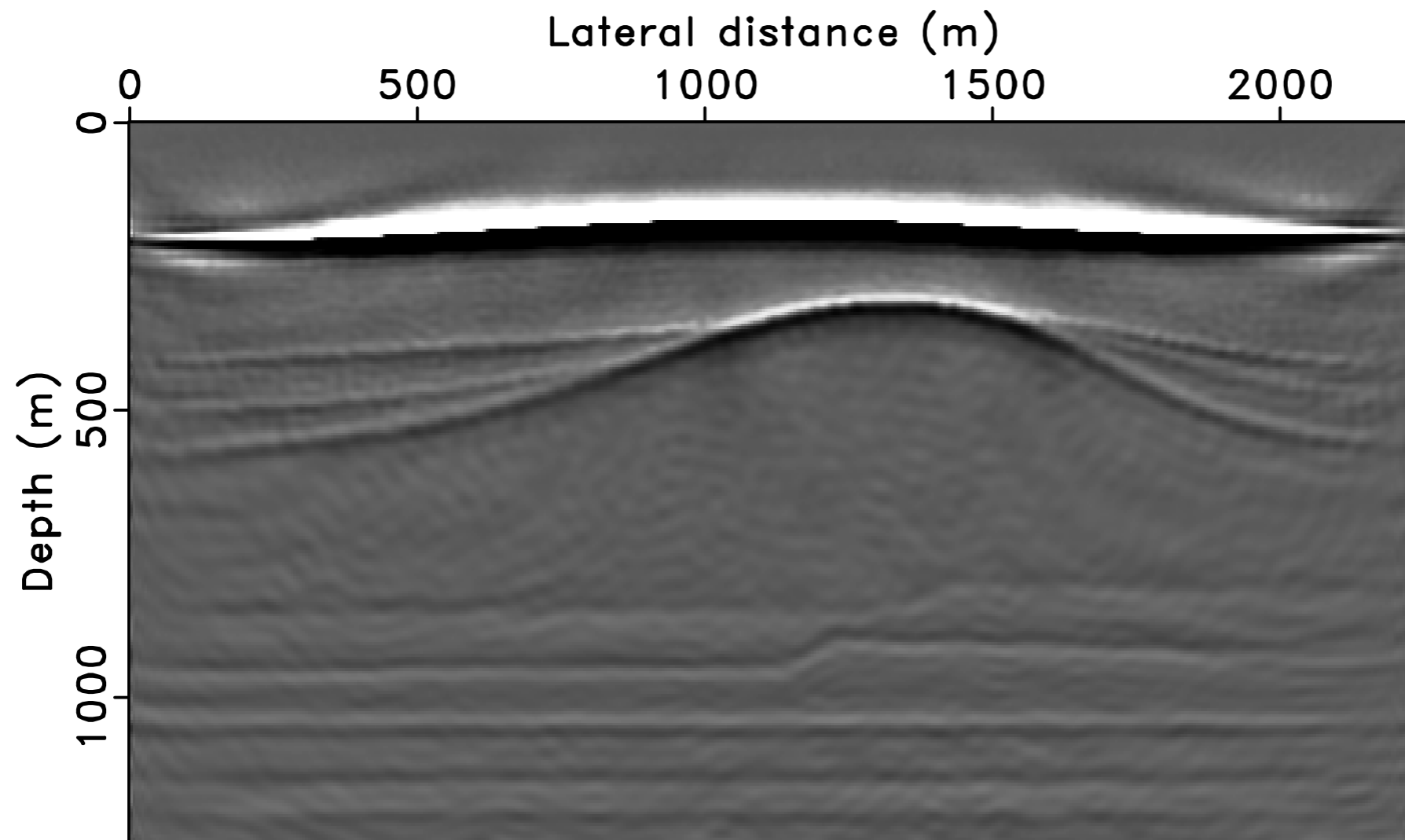
Batch size: 30 (2 simultaneous sources and 15 frequencies)

Iteration: 305

Number of PDE solves: 36.6 thousand (by calculation)

Comparison: batch size

[same budget of PDE solves]



Fast imaging of total data

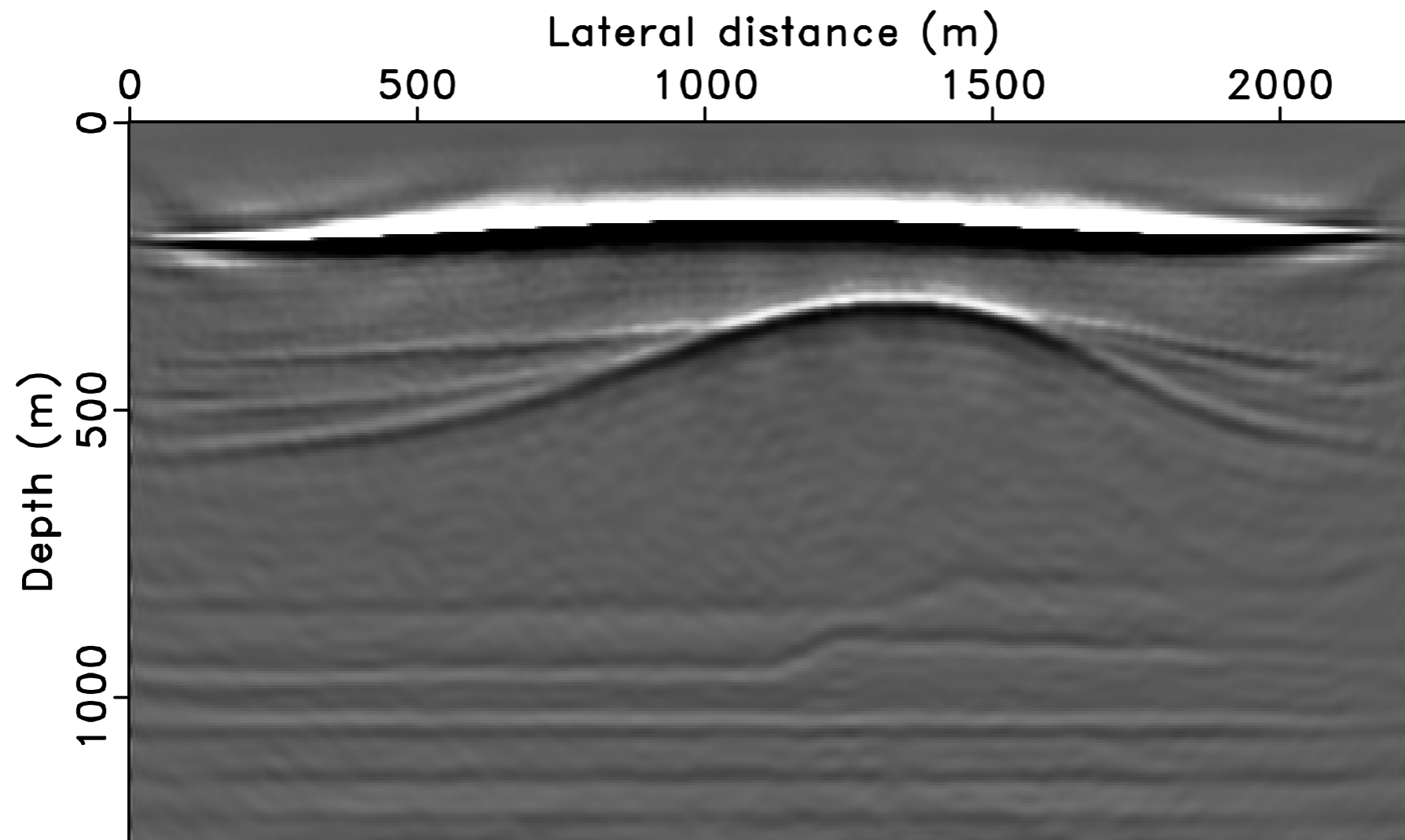
Batch size: 15 (1 simultaneous sources and 15 frequencies)

Iteration: 610

Number of PDE solves: 36.6 thousand (by calculation)

Comparison: batch size

[same budget of PDE solves]



Fast imaging of total data

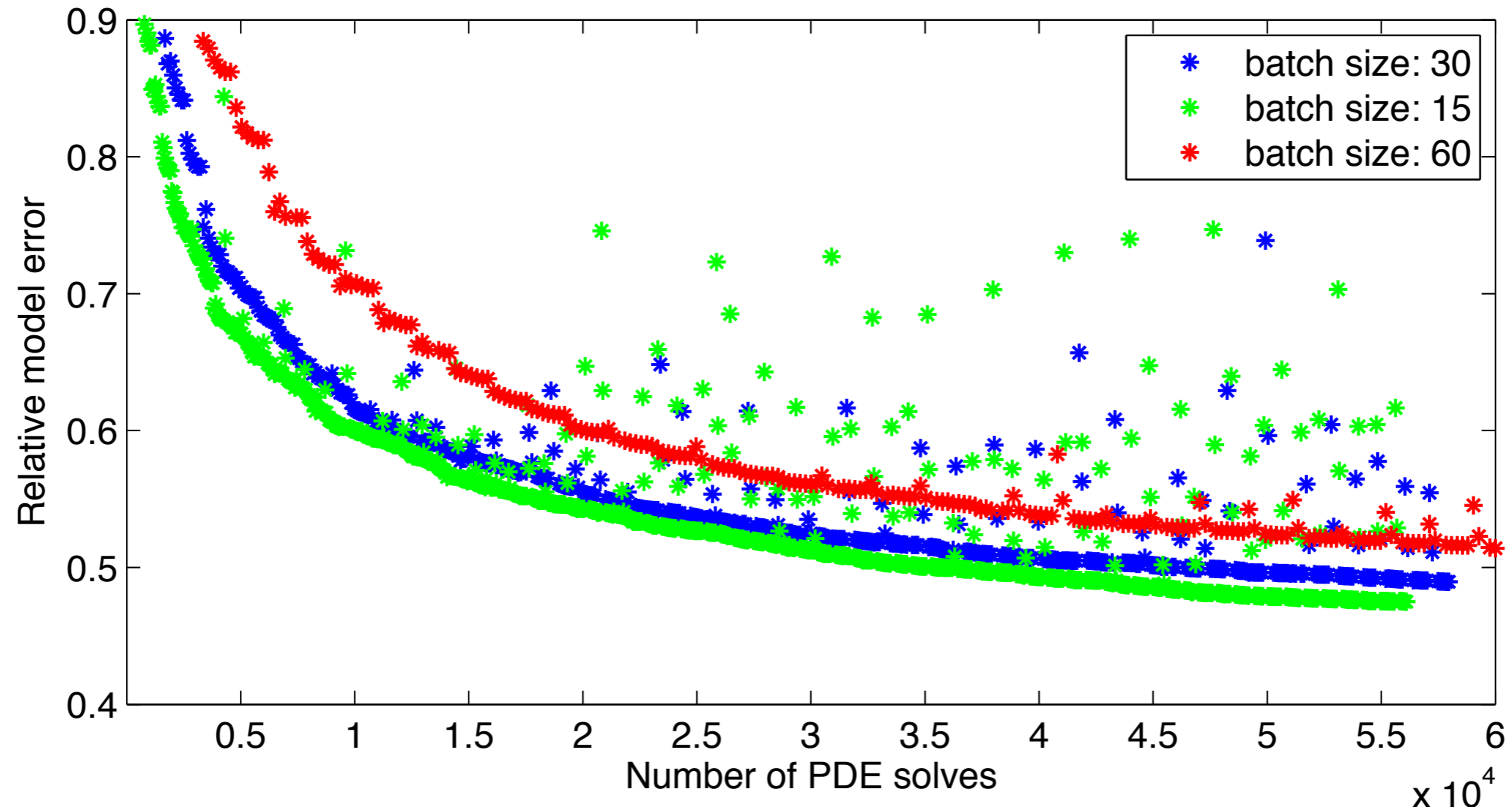
Batch size: 60 (4 simultaneous sources and 15 frequencies)

Iteration: 152

Number of PDE solves: 36.6 thousand (by calculation)

Comparison: batch size

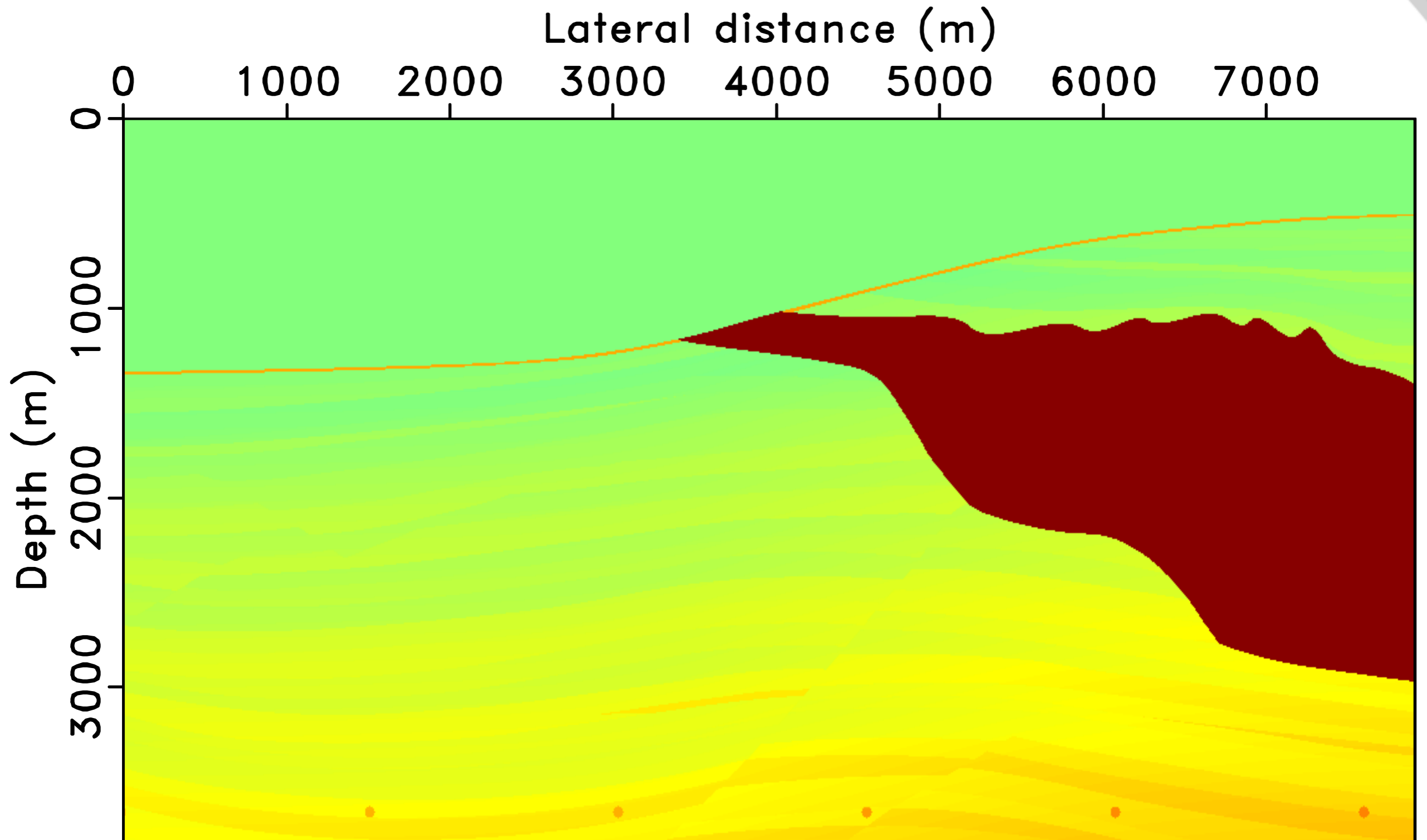
[same budget of PDE solves]



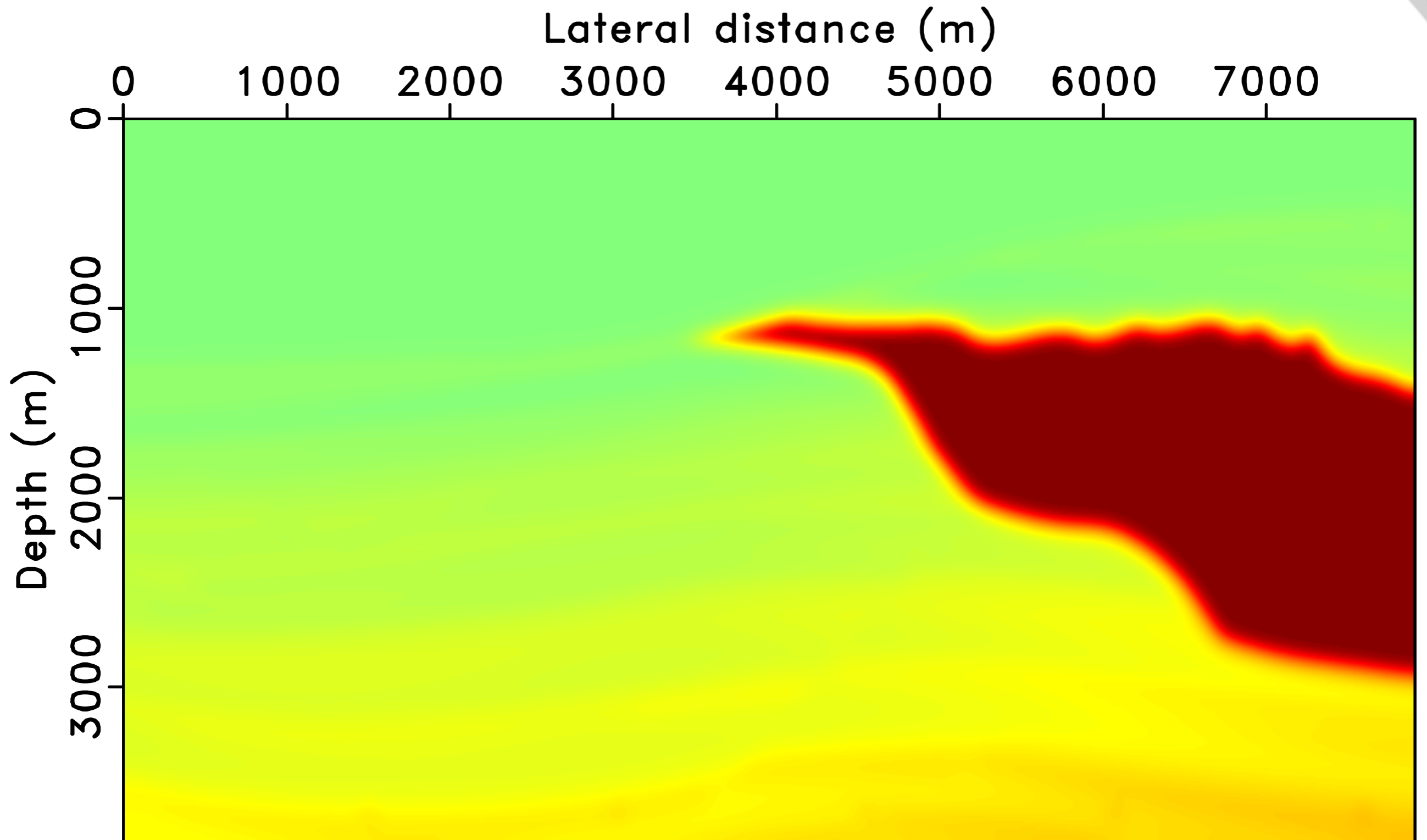
The Sigsbee2B model (cropped)

- model grid spacing: 7.62m
- using linearized data
- 174 sequential sources
- 278 frequencies in 0-34Hz range
- using 8 simultaneous sources and 15 frequencies with redrawing

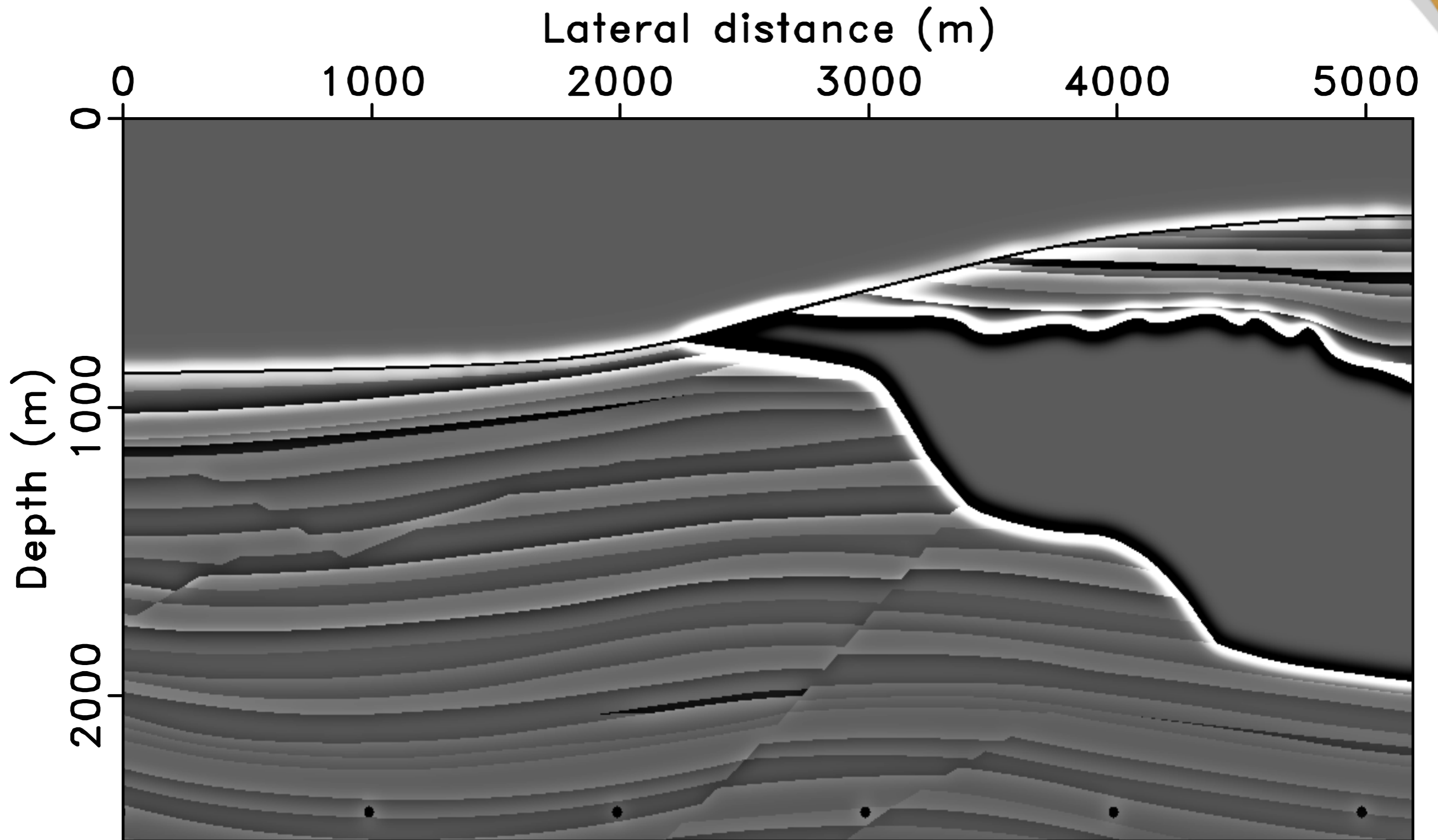
The Sigsbee2B model



Background model

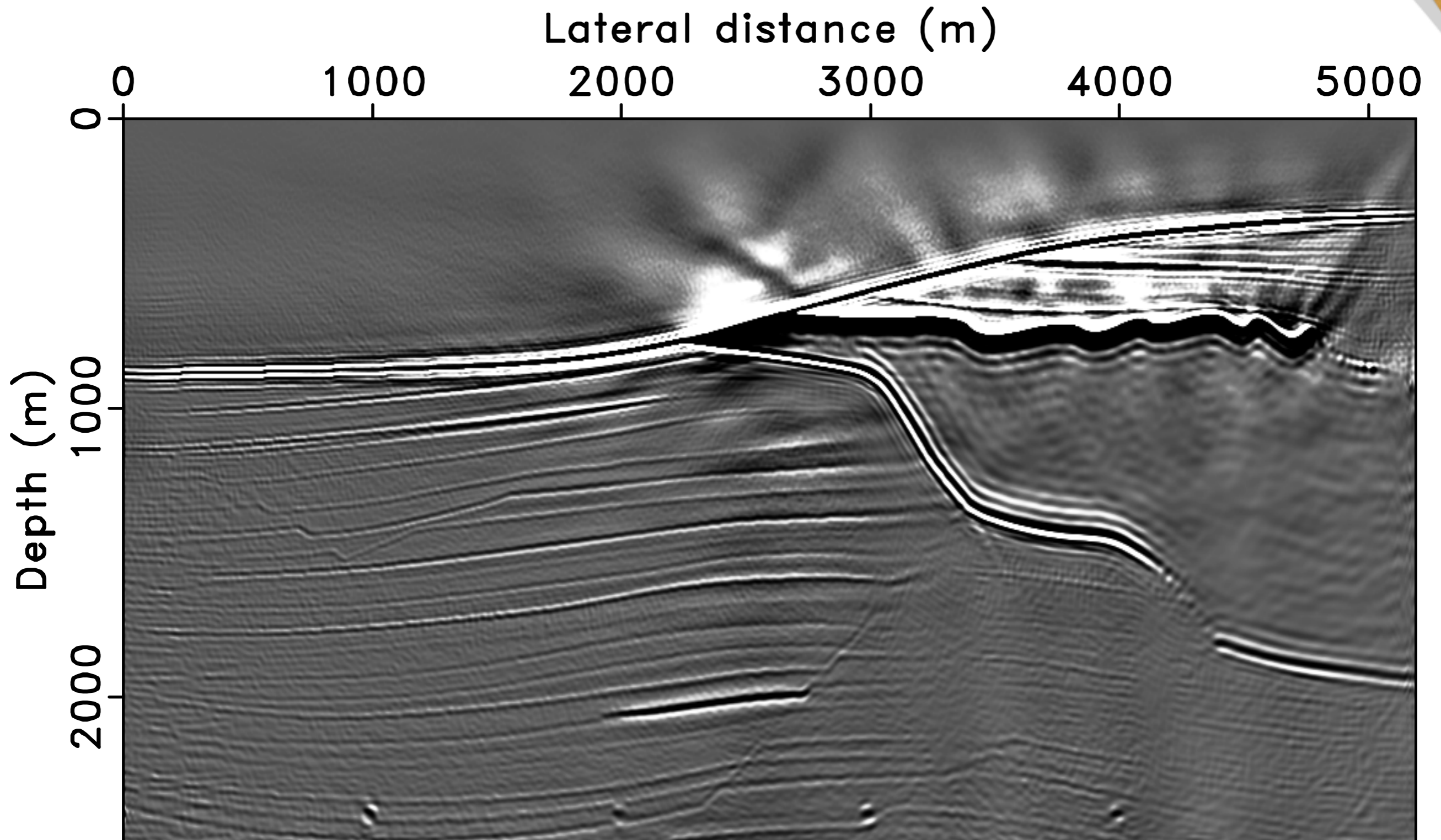


True perturbation



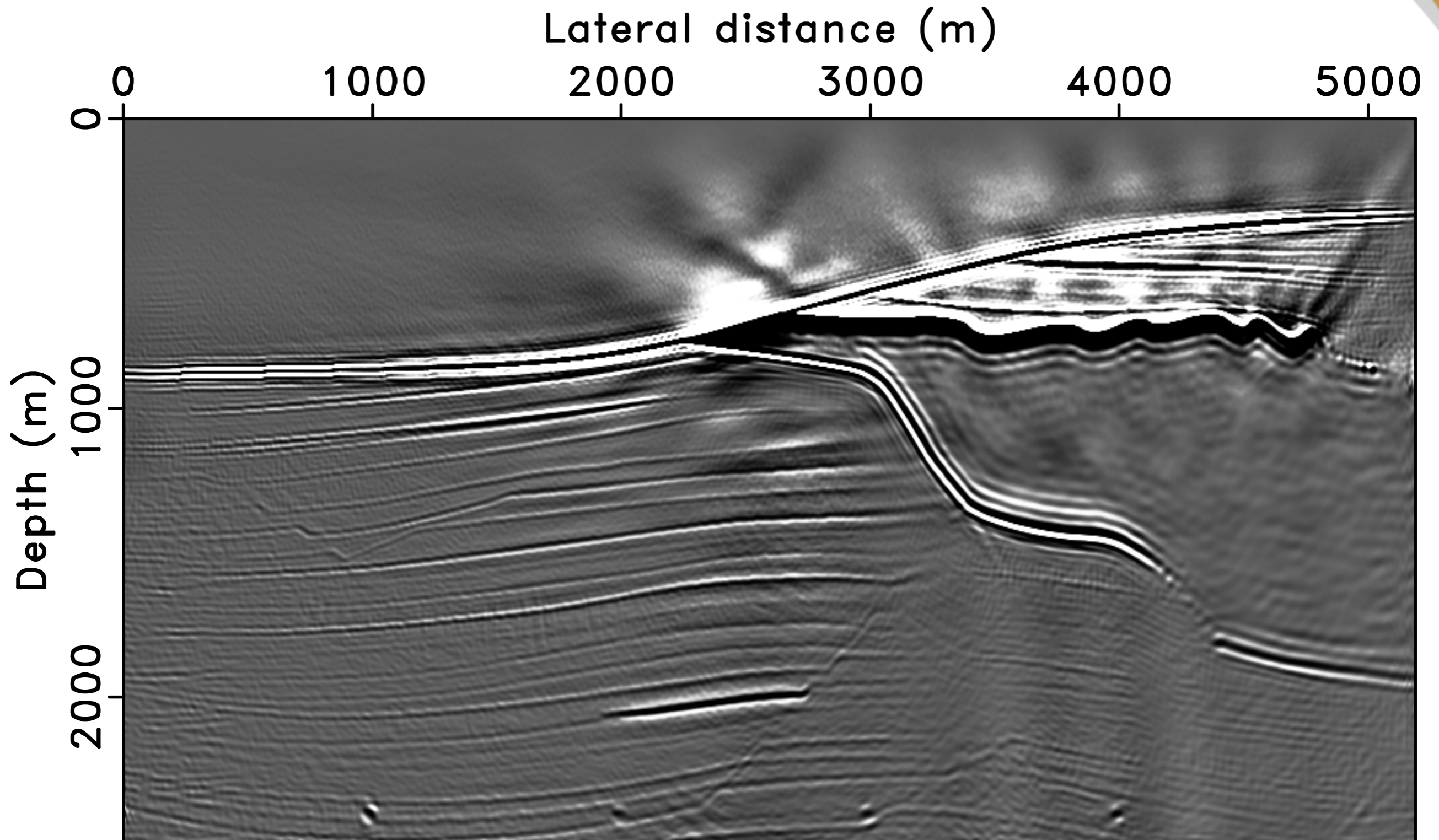
Fast inversion of primaries

[with a computational budget of a single RTM with all data]

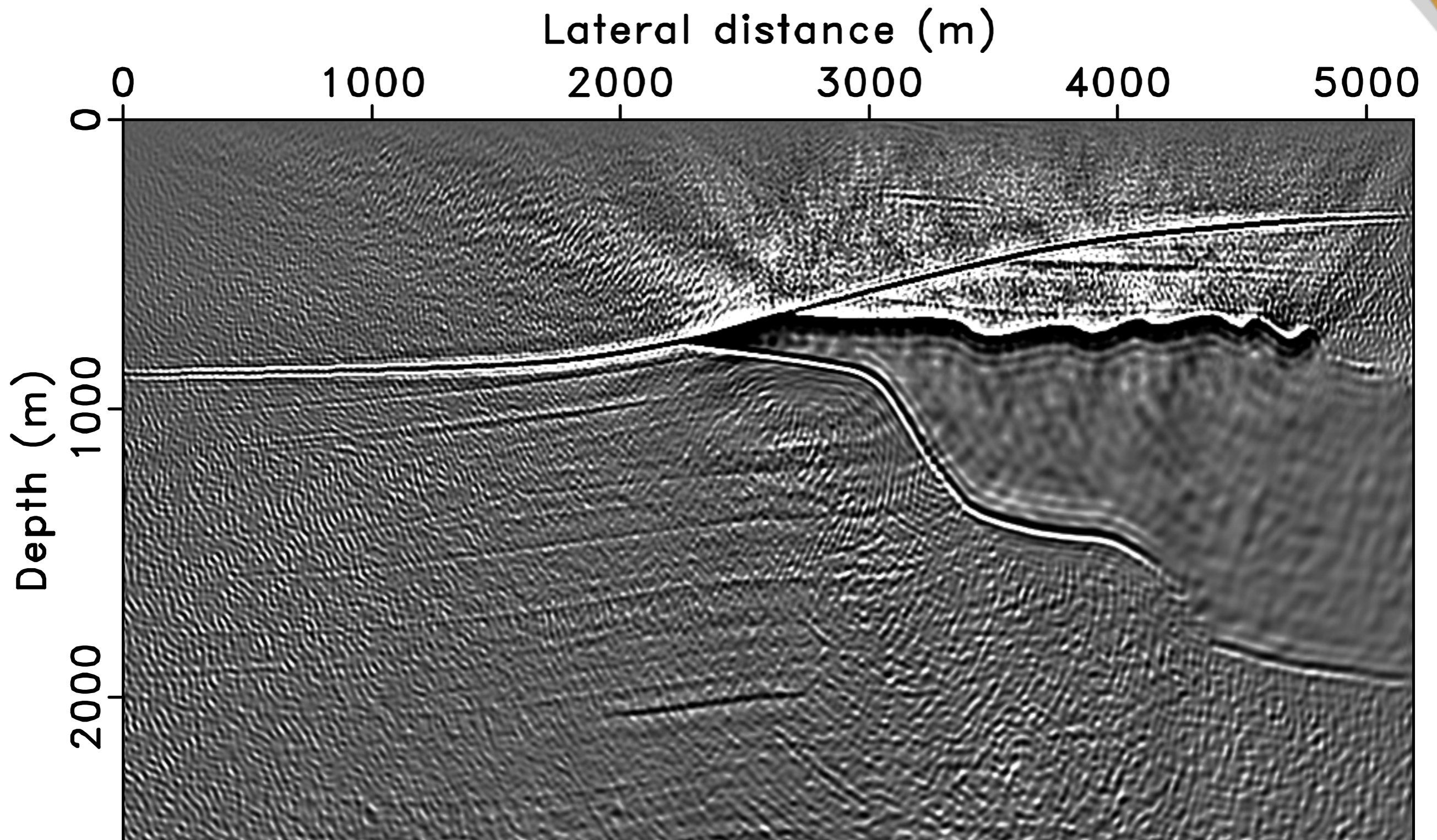


Fast inversion of total data

[with a computational budget of a single RTM with all data]



Ignore the multiples



Conclusions

- An formulation is derived to image the total data based on the SRME formulation.
- Non-causal cross correlations when imaging multiples can be avoided by inversion.
- We greatly speed up the inversion by subsampling and redrawing.

Future work

- take source/receiver ghosts into consideration
- accurate estimation of source wavelet

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Thanks for your attention!

SINBAD



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