

# Fast imaging with multiples by sparse inversion

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# Motivation

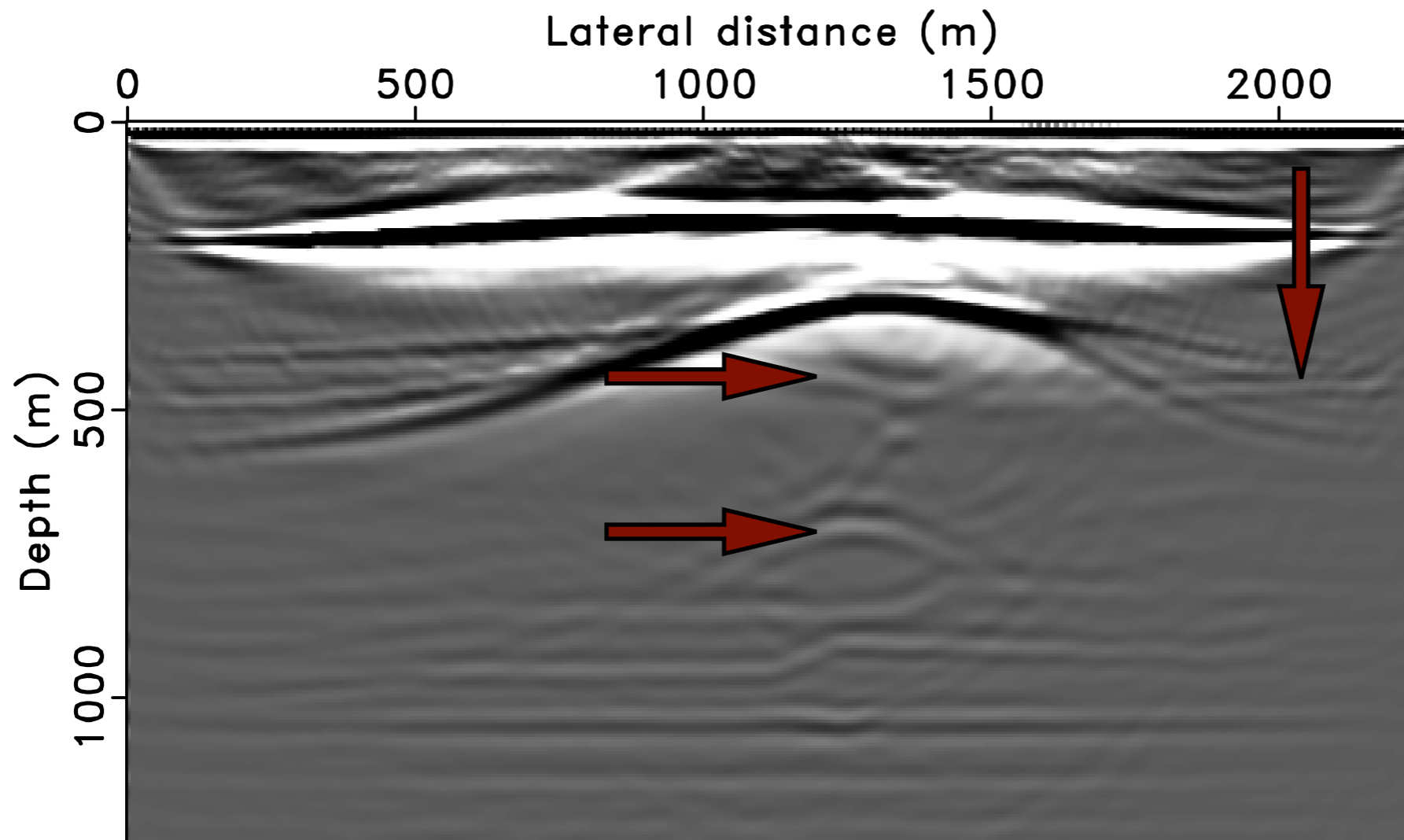
- making use of primaries and multiples *simultaneously*
- avoiding imaging *artifacts* from multiples
- looking for a computationally *efficient* approach

Tu and Herrmann, 2011; Verschuur and Berkhout, 2011; Lu et.al., 2011; Liu et.al., 2011

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

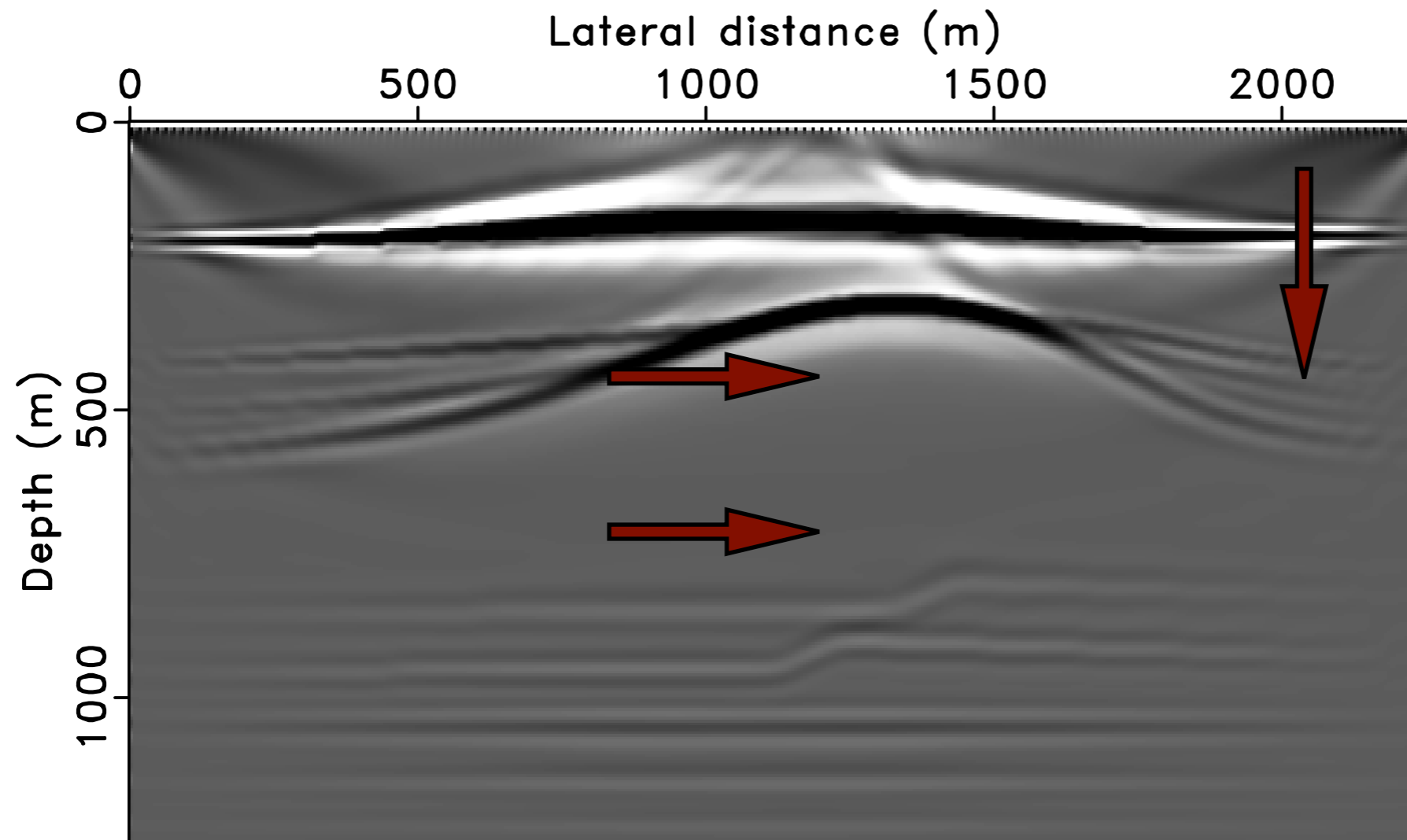
- primaries have a higher signal-to-noise ratio
- multiples provide extra illumination if correctly used

# Artifacts from multiples



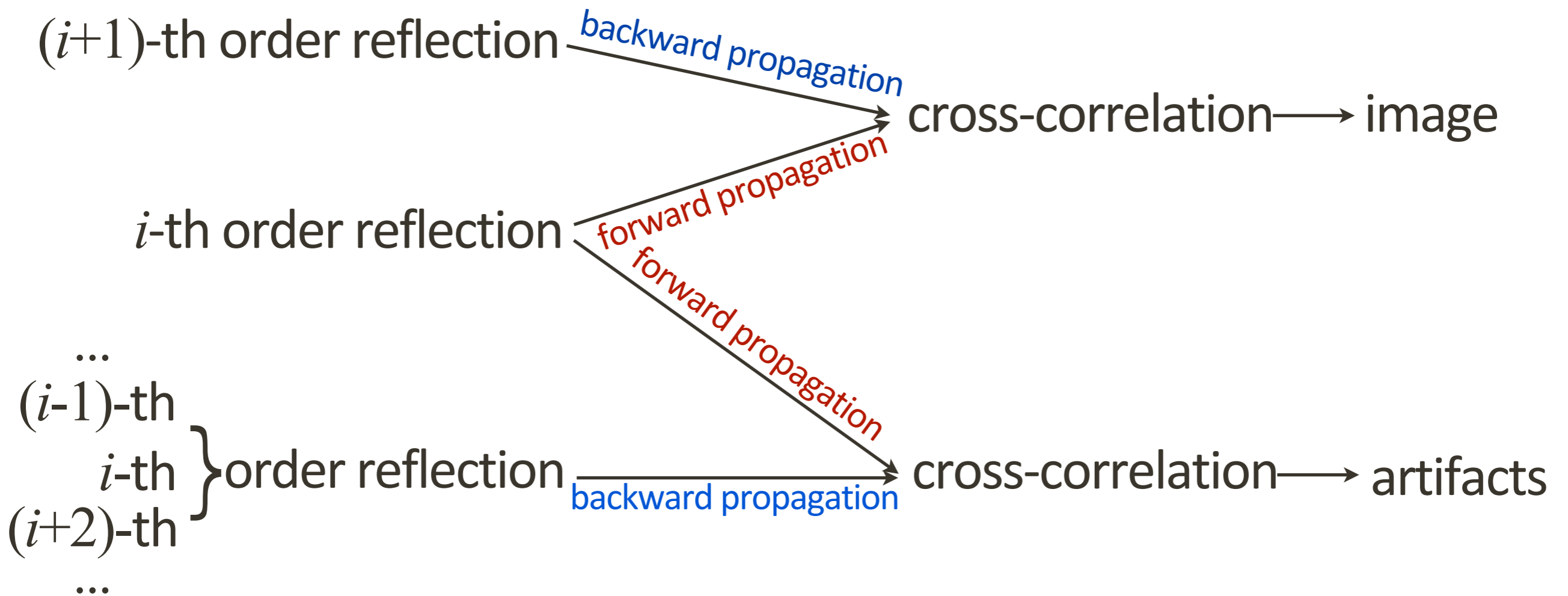
Reverse time migration of  *multiples*  using total data as “source”

# Not there for primaries

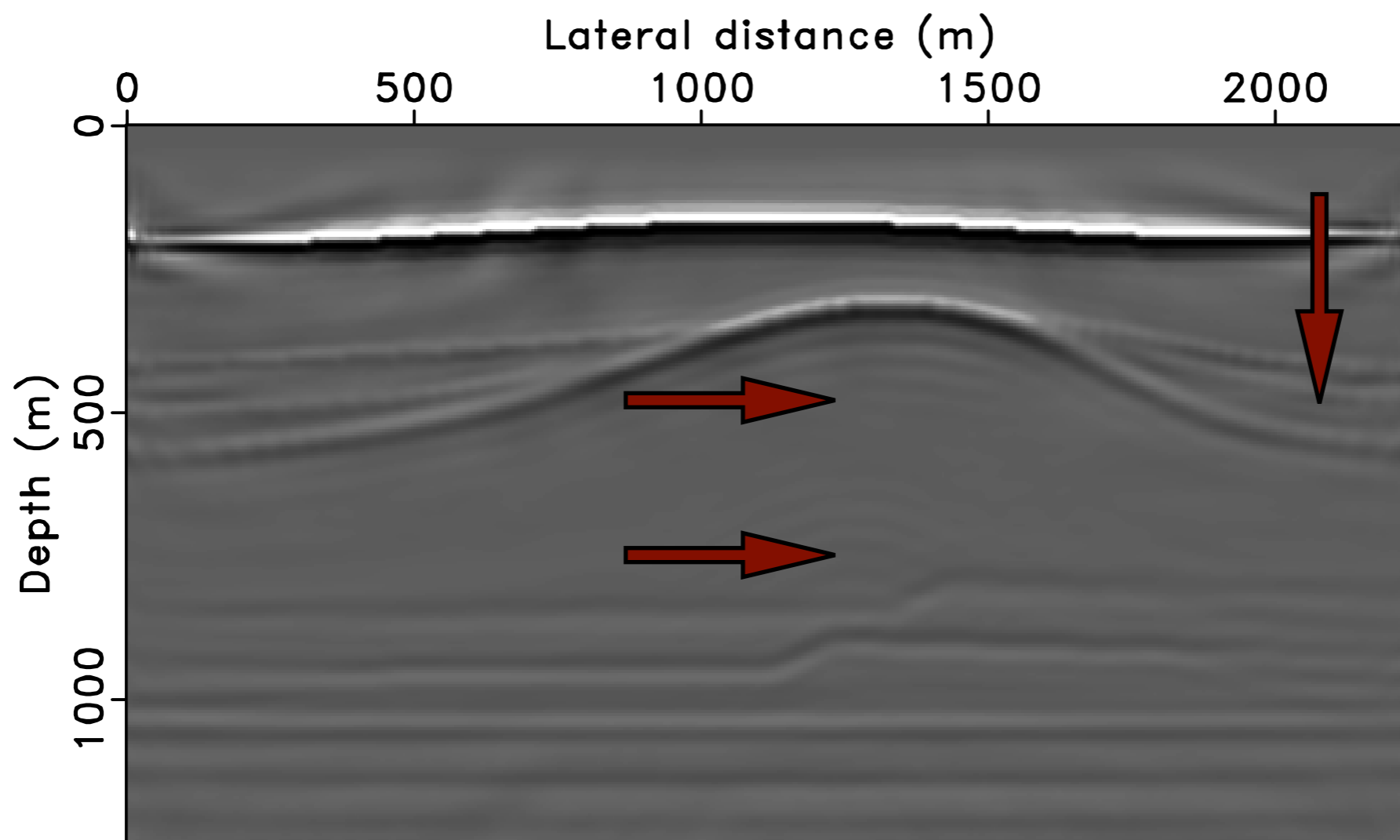


Reverse time migration of *primaries*

# When a free-surface presents



# Want to avoid them?



Imaging of multiples by *inversion*

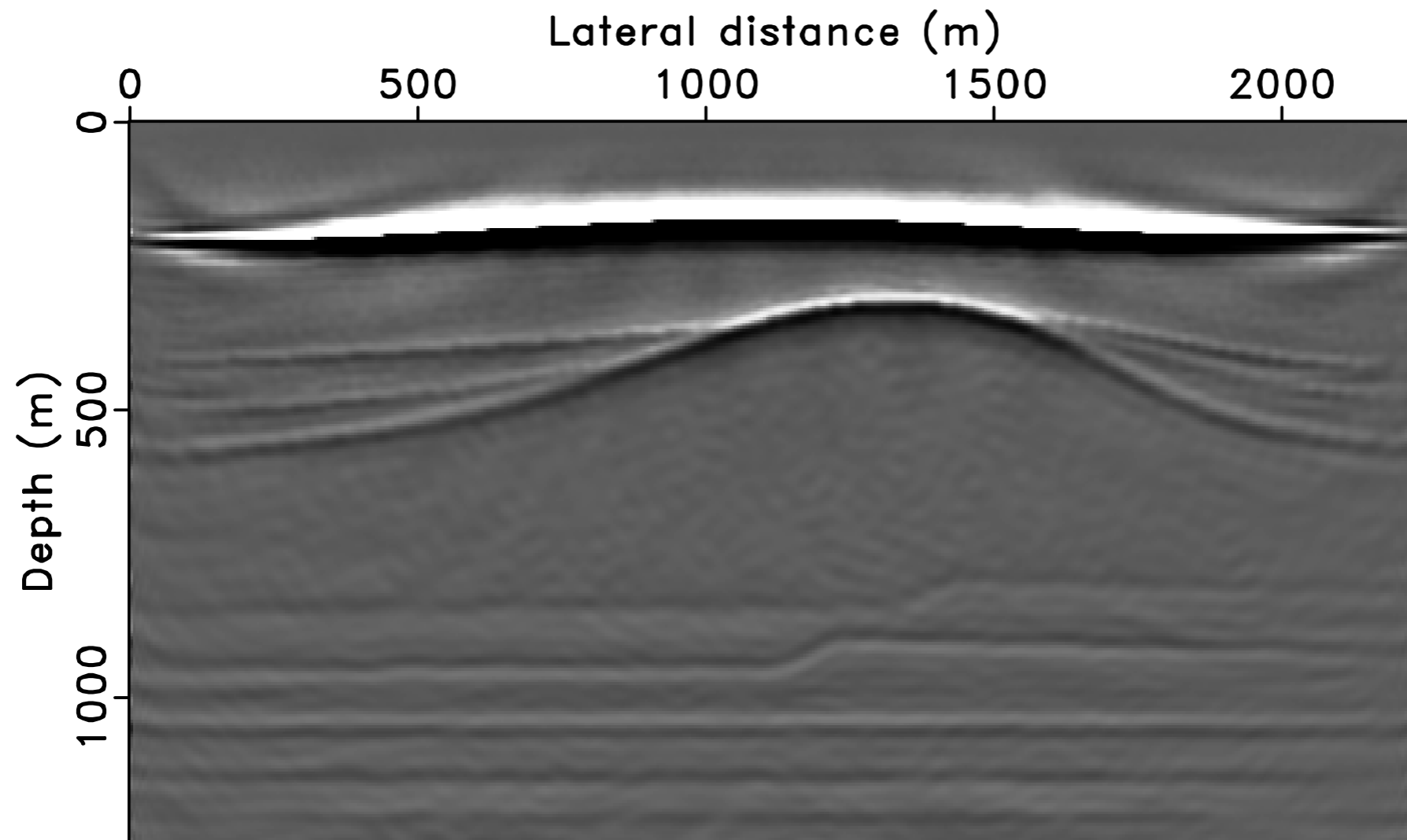
# Inversion? Sounds expensive...

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

# 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

$\mathbf{P}_{\omega_i}$ : vectorized wavefield

# Stacking over frequencies

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



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

# 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

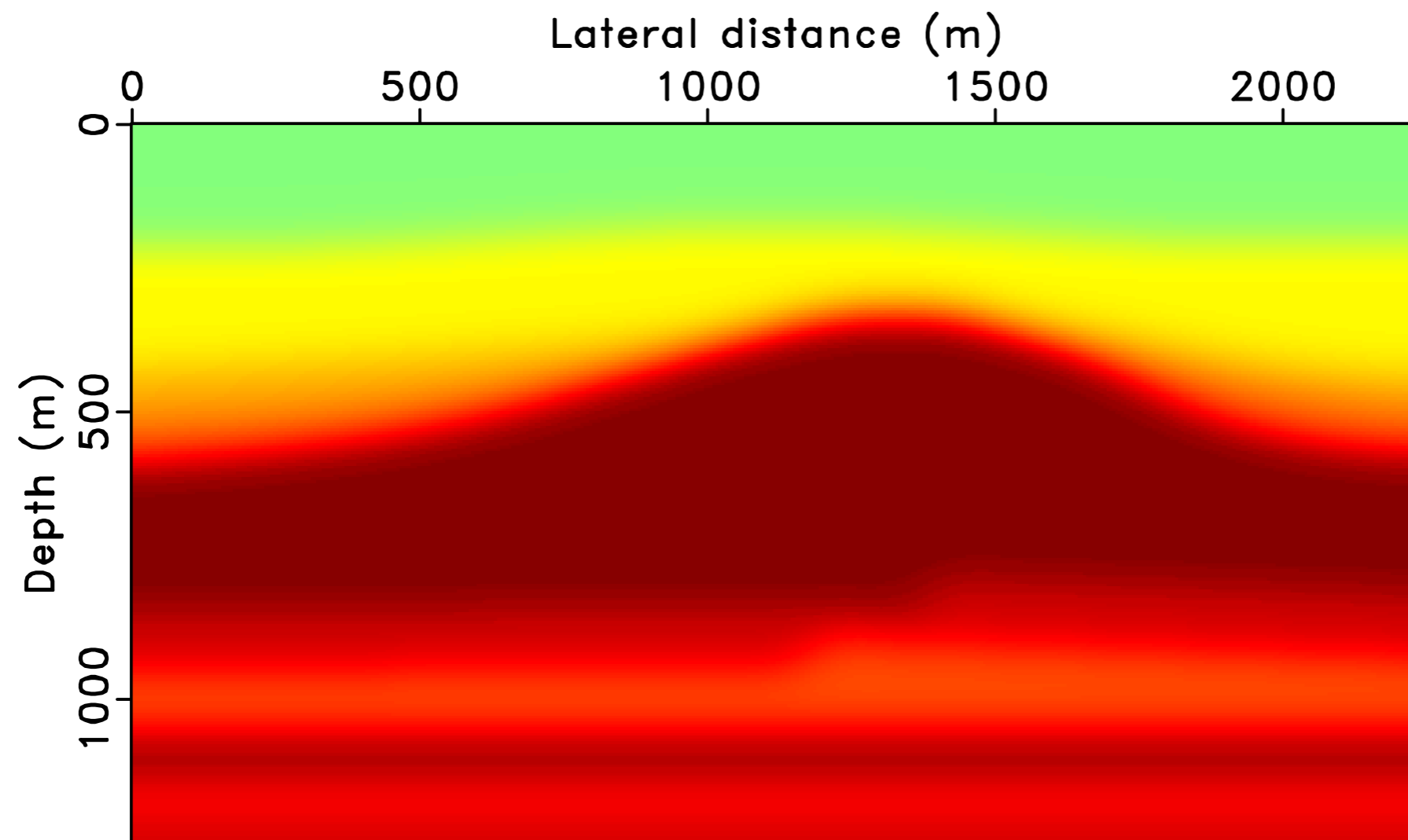
- model grid spacing: 5 meters
- using linearized data:

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

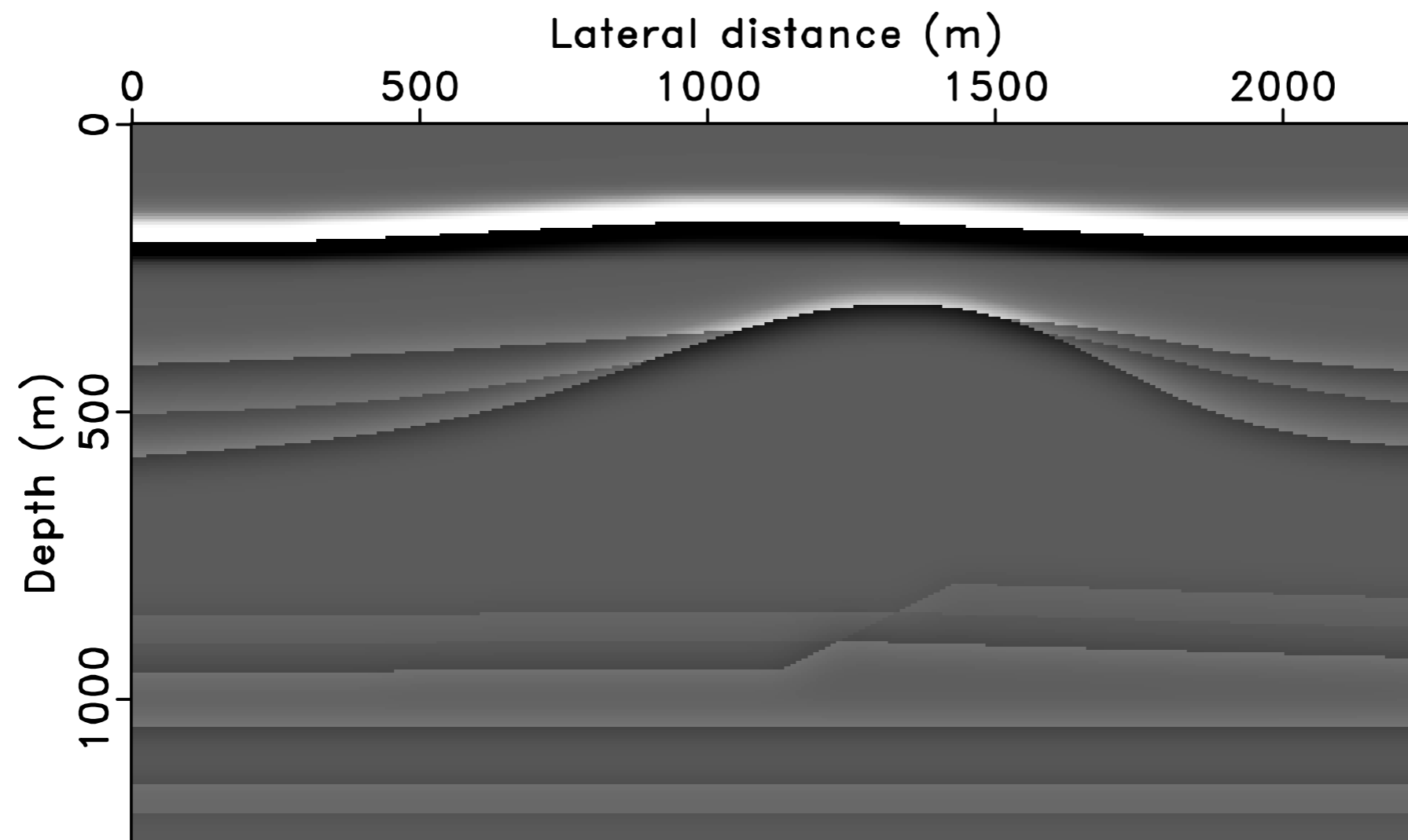
- 150 collocated sources/receivers
- 122 frequencies in 0-60Hz range



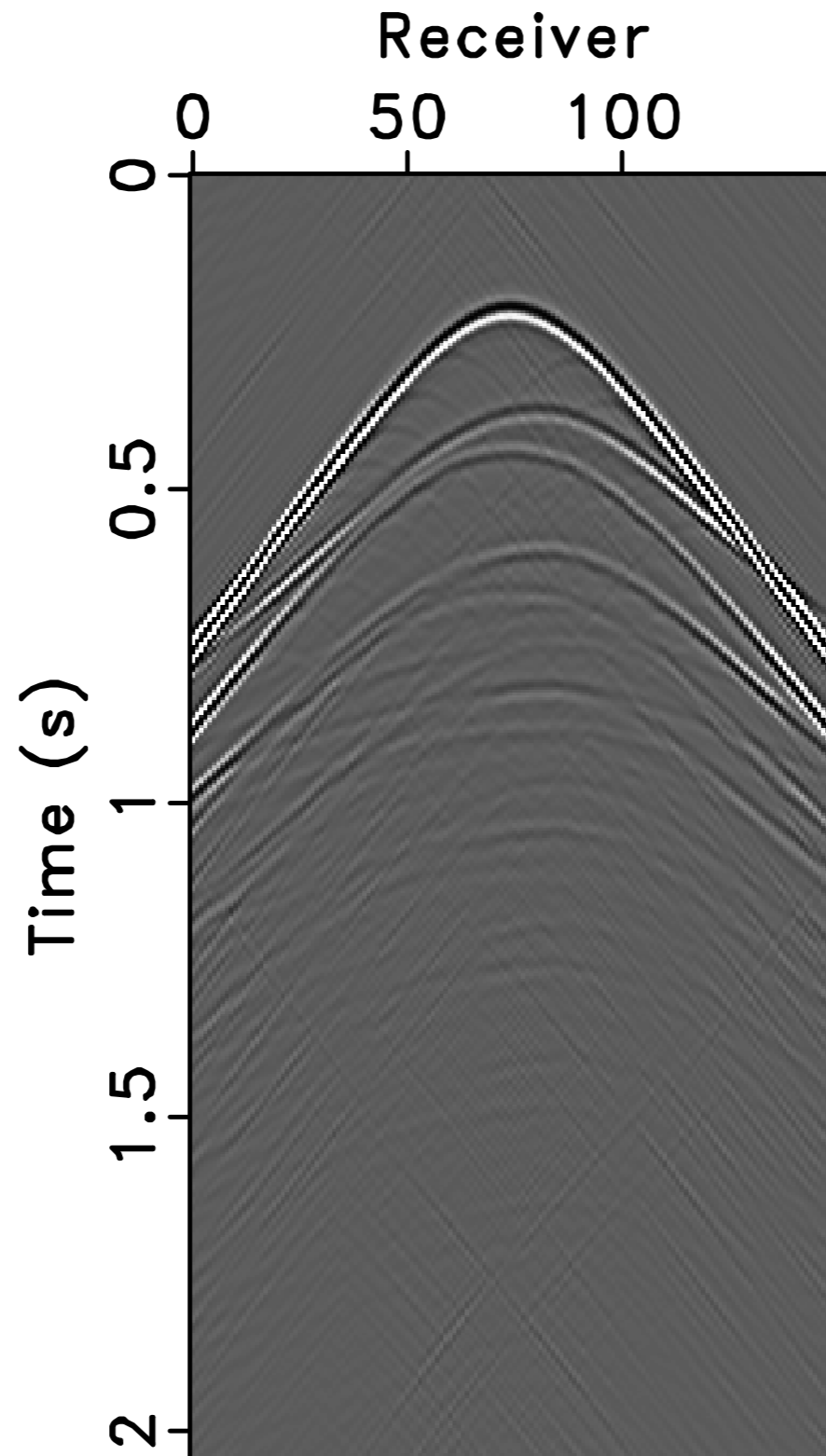
# Background model



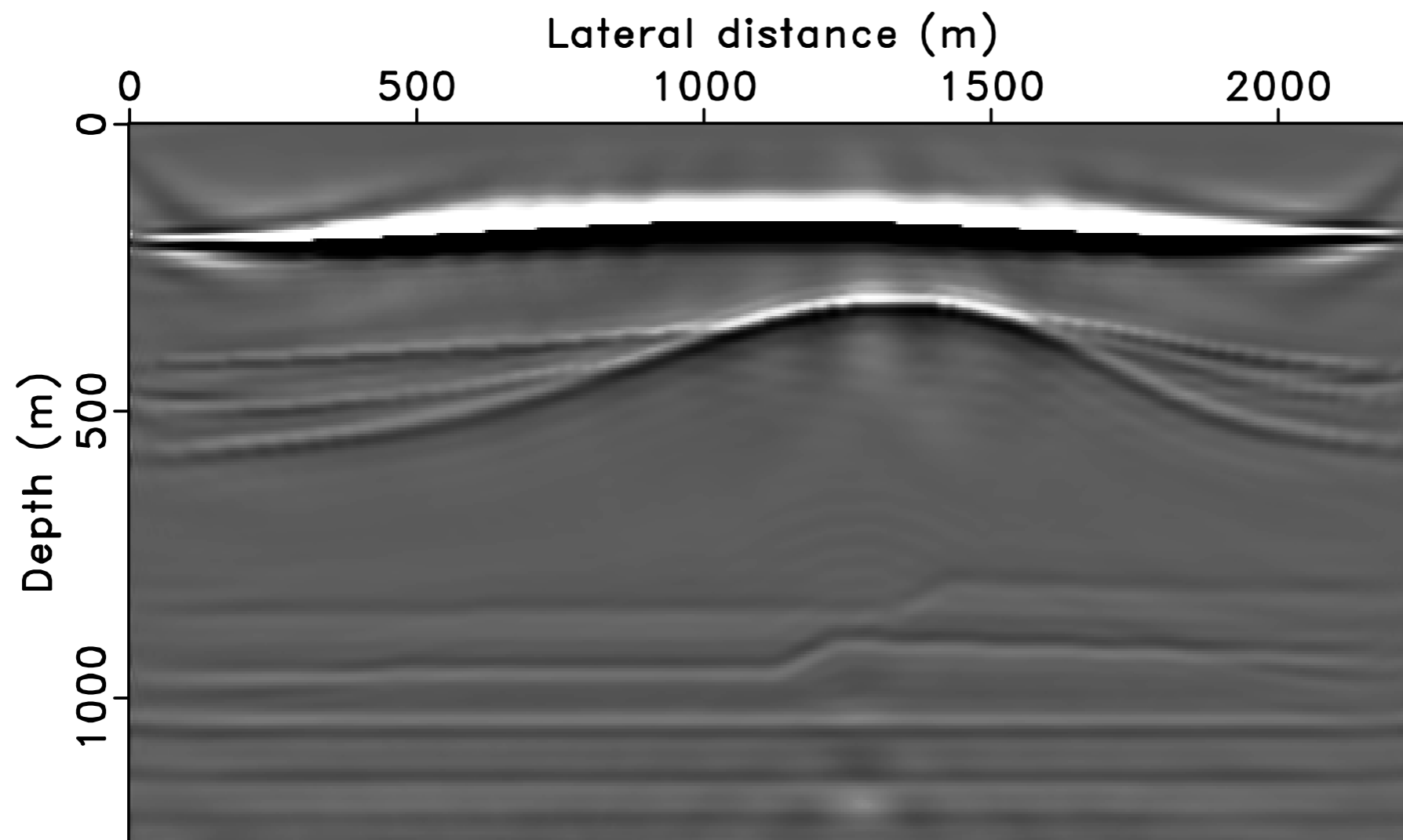
# True perturbation



# 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)

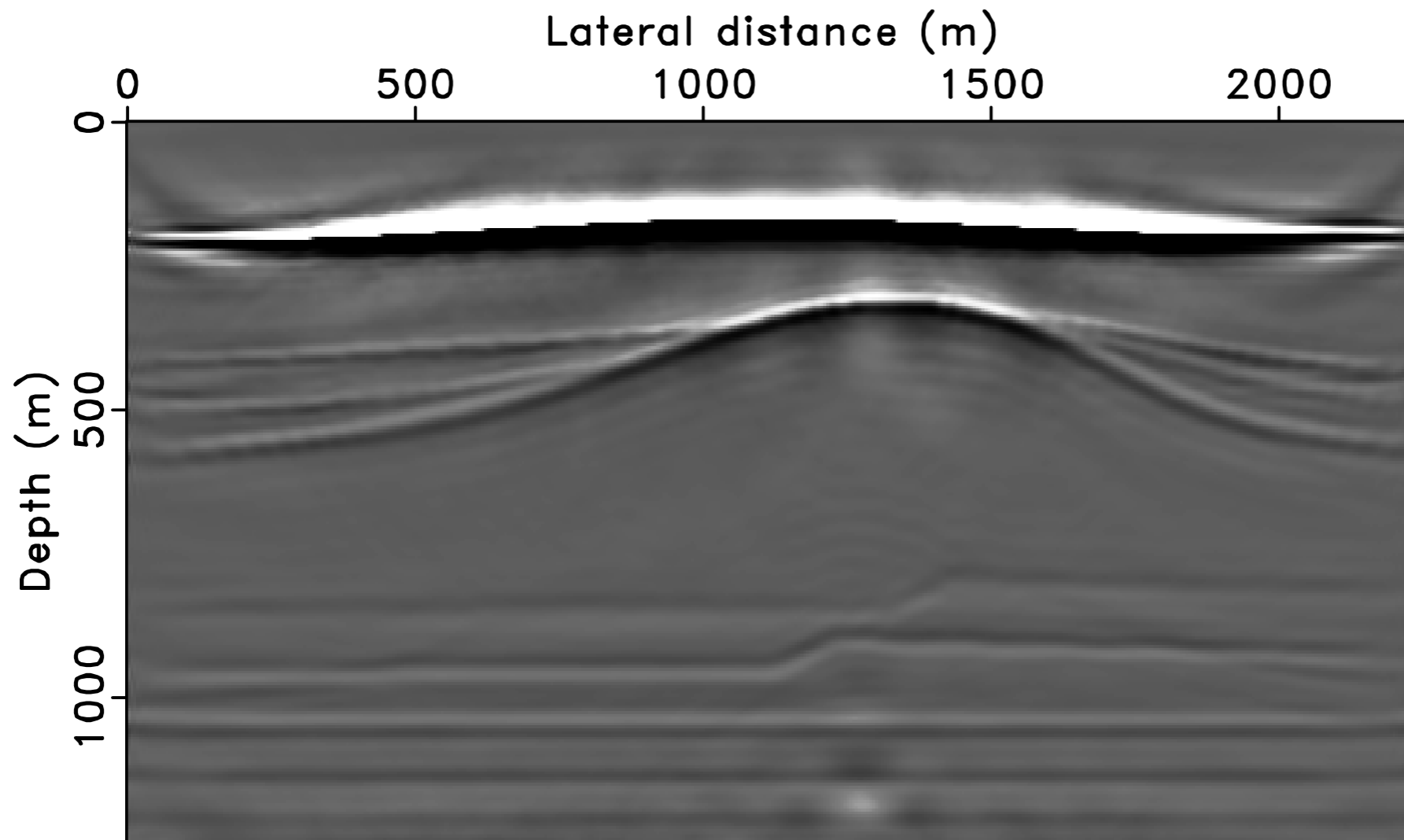
# Dimensionality reduction

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

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

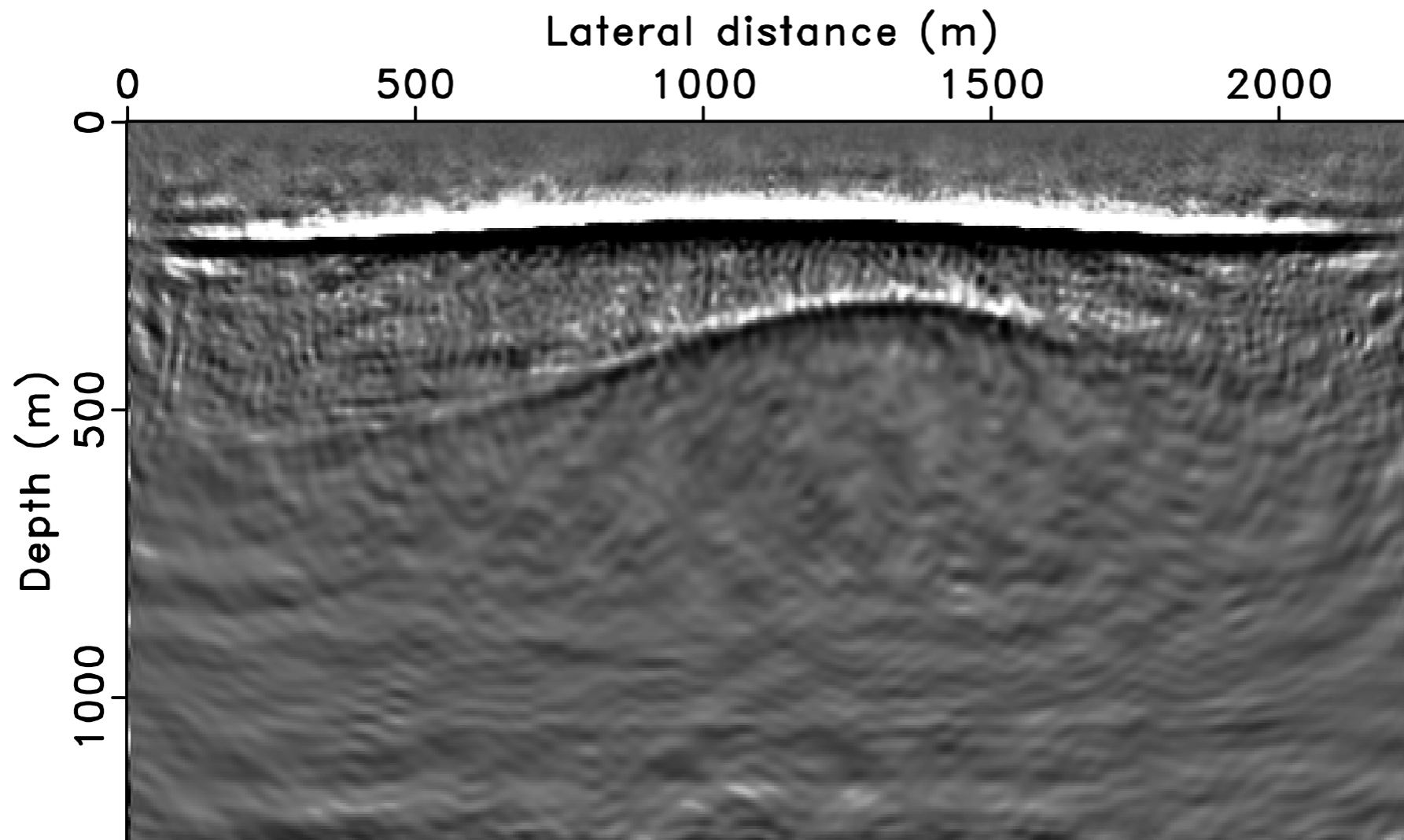
*source*: combine sources into a few simultaneous sources, using Gaussian distributed random weights  
*frequency*: randomly choose a subset of frequencies

# 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

# Draw new subsampling operator

- SPGL<sub>1</sub> solves a series of subproblems:

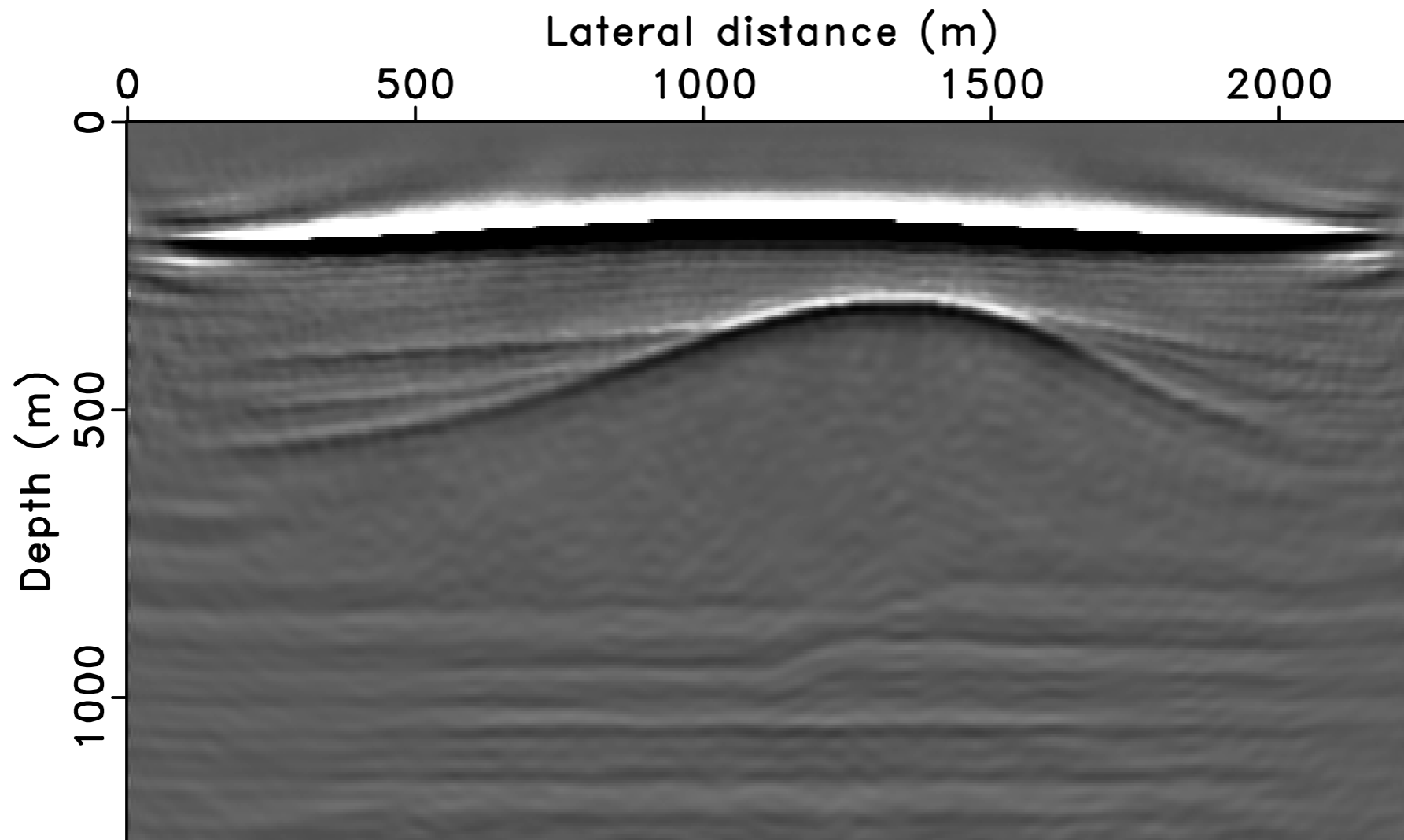
$$\operatorname{argmin}_{\delta \mathbf{x}} \|\underline{\mathbf{p}} - \nabla \mathbf{F}[\mathbf{m}_0, \underline{\mathbf{Q}} + \underline{\mathbf{R}}\mathbf{P}]\mathbf{C}^H \delta \mathbf{x}\|_2$$

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

- redraw subsampling operator for each new subproblem

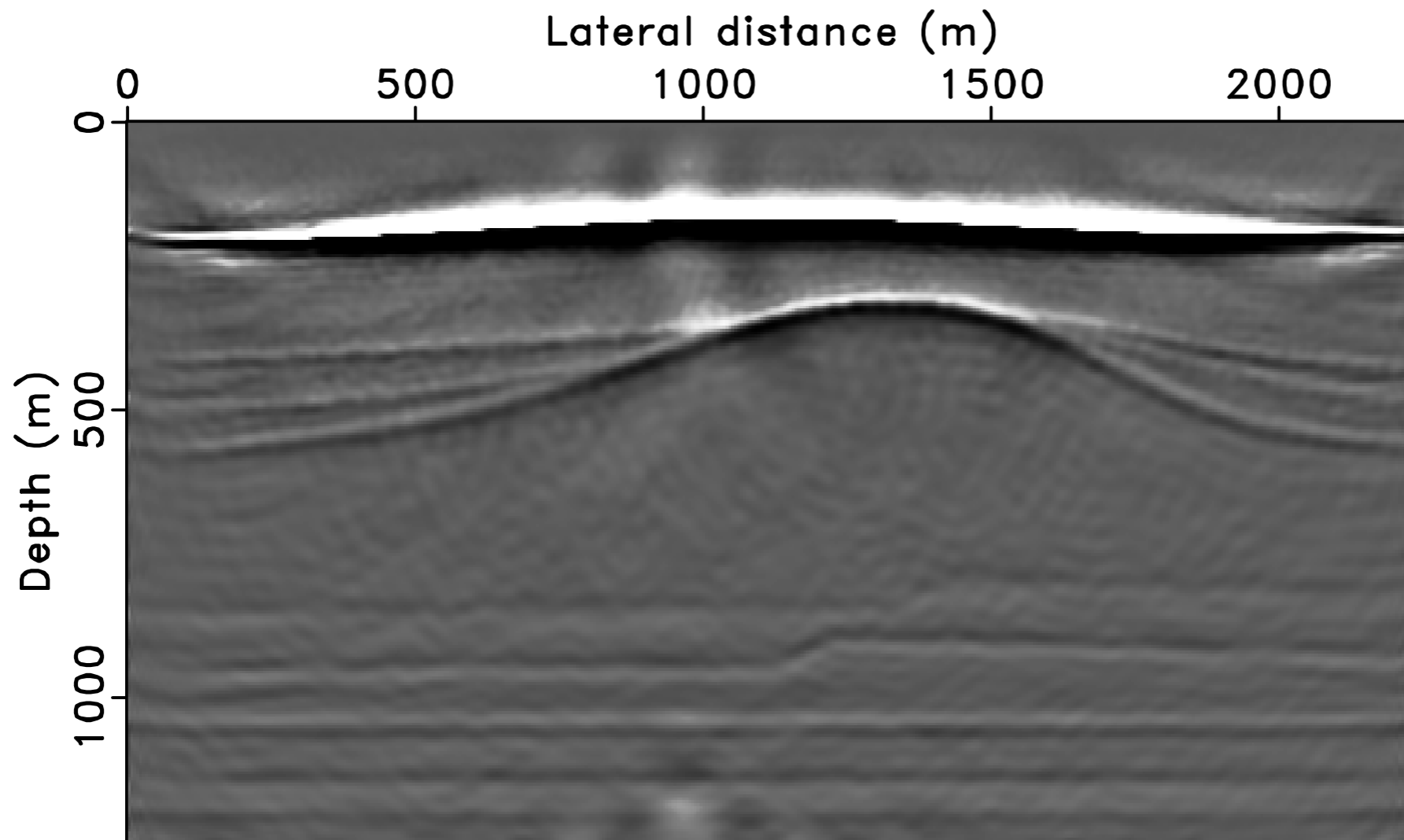


# Draw new sim. sources



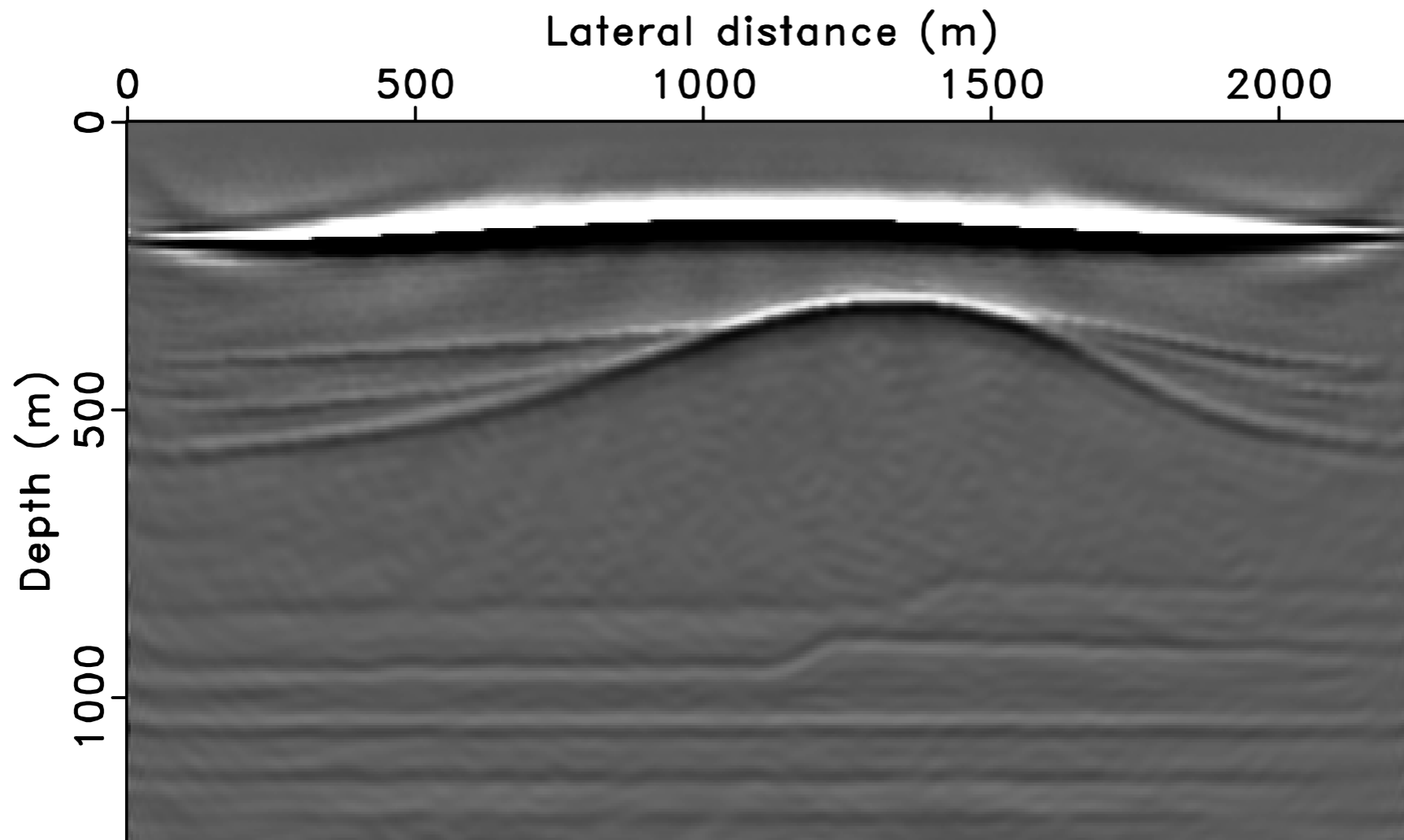
Inversion of the total up-going wavefield using 2 simultaneous sources and 15 frequencies  
number of PDE solves: 36.6 thousand (by calculation)

# Draw new frequencies



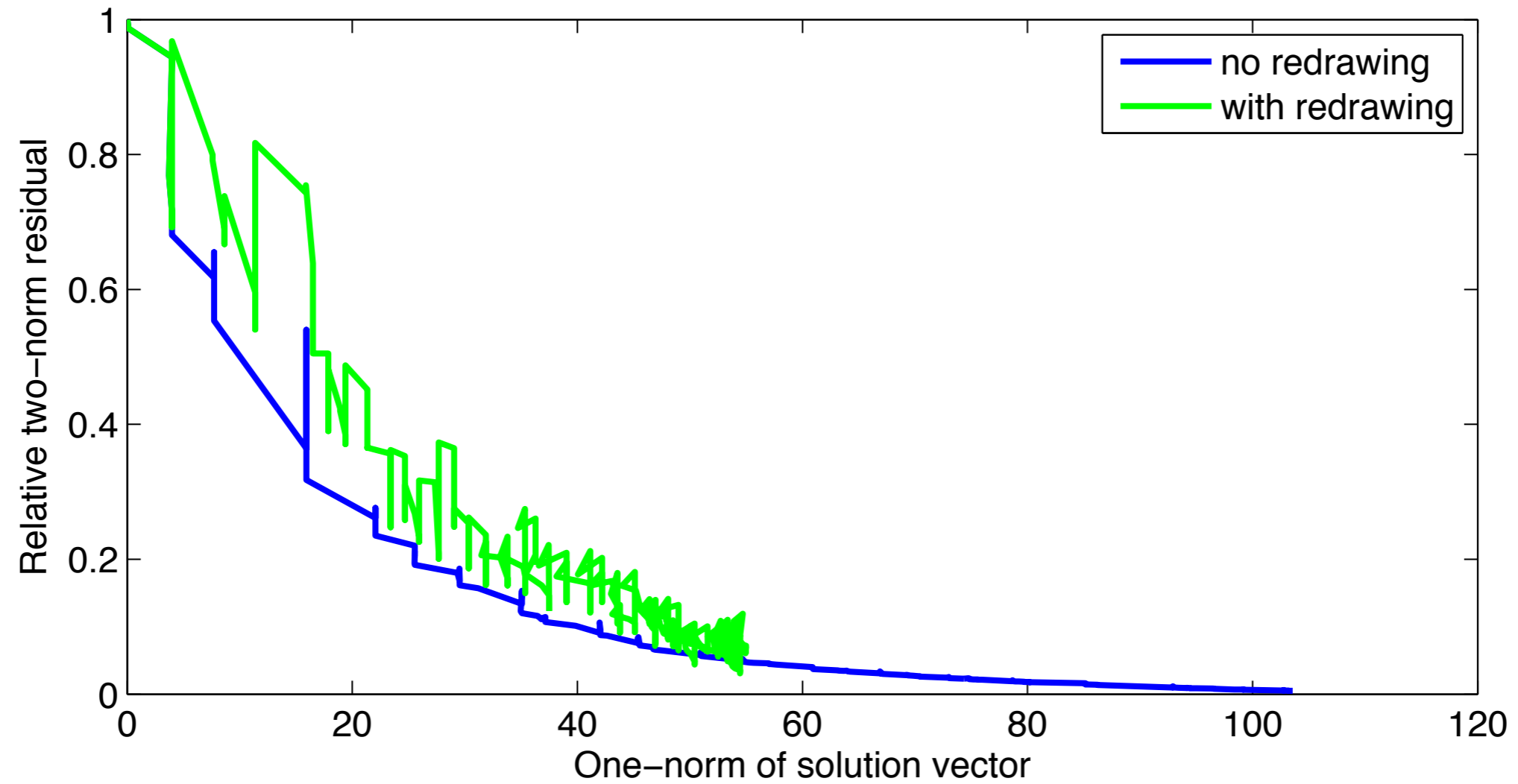
Inversion of the total up-going wavefield using 2 simultaneous sources and 15 frequencies  
number of PDE solves: 36.6 thousand (by calculation)

# Draw new sim. sources and frequencies

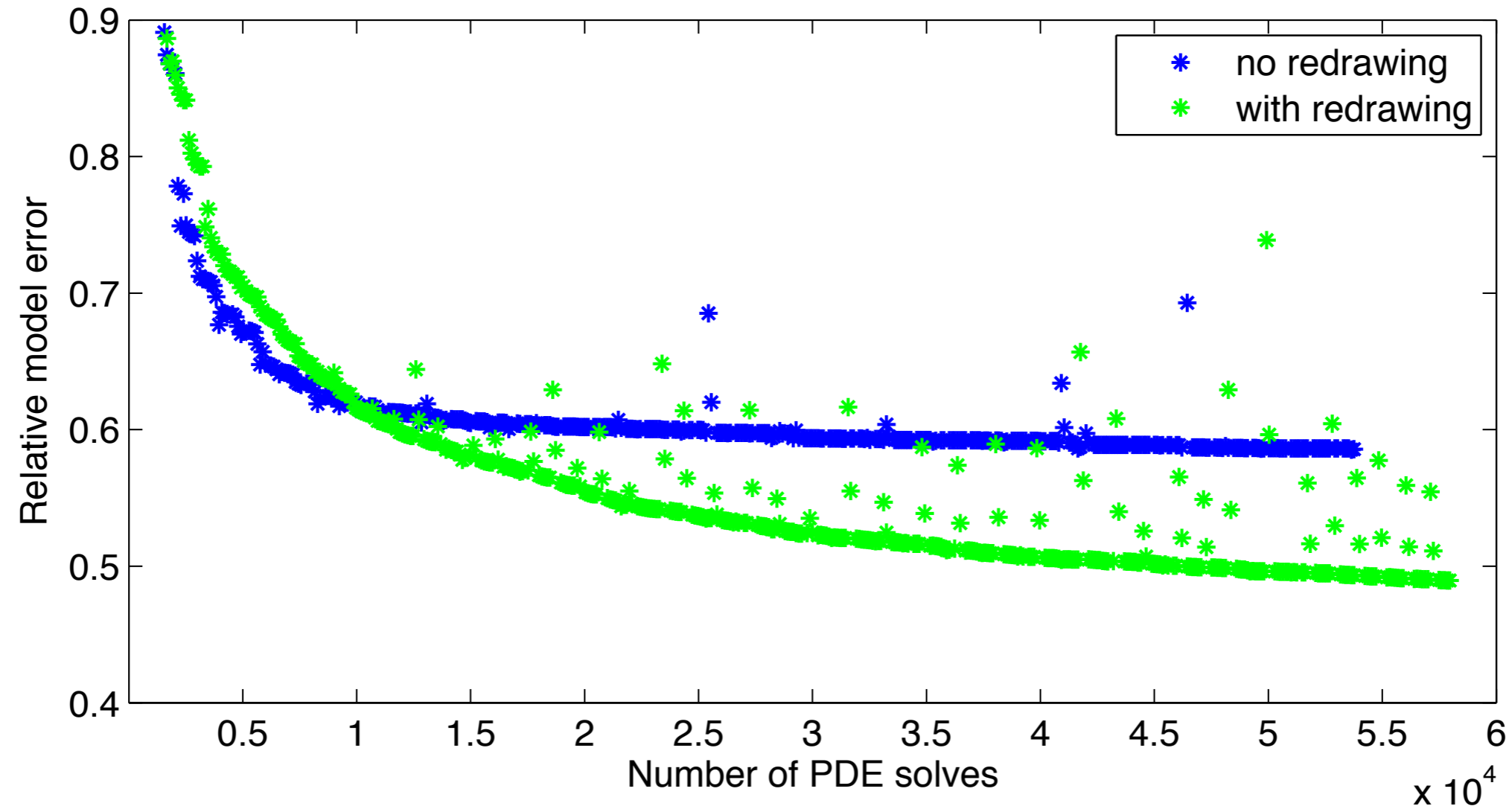


Inversion of the total up-going wavefield using 2 simultaneous sources and 15 frequencies  
number of PDE solves: 36.6 thousand (by calculation)

# Solution path

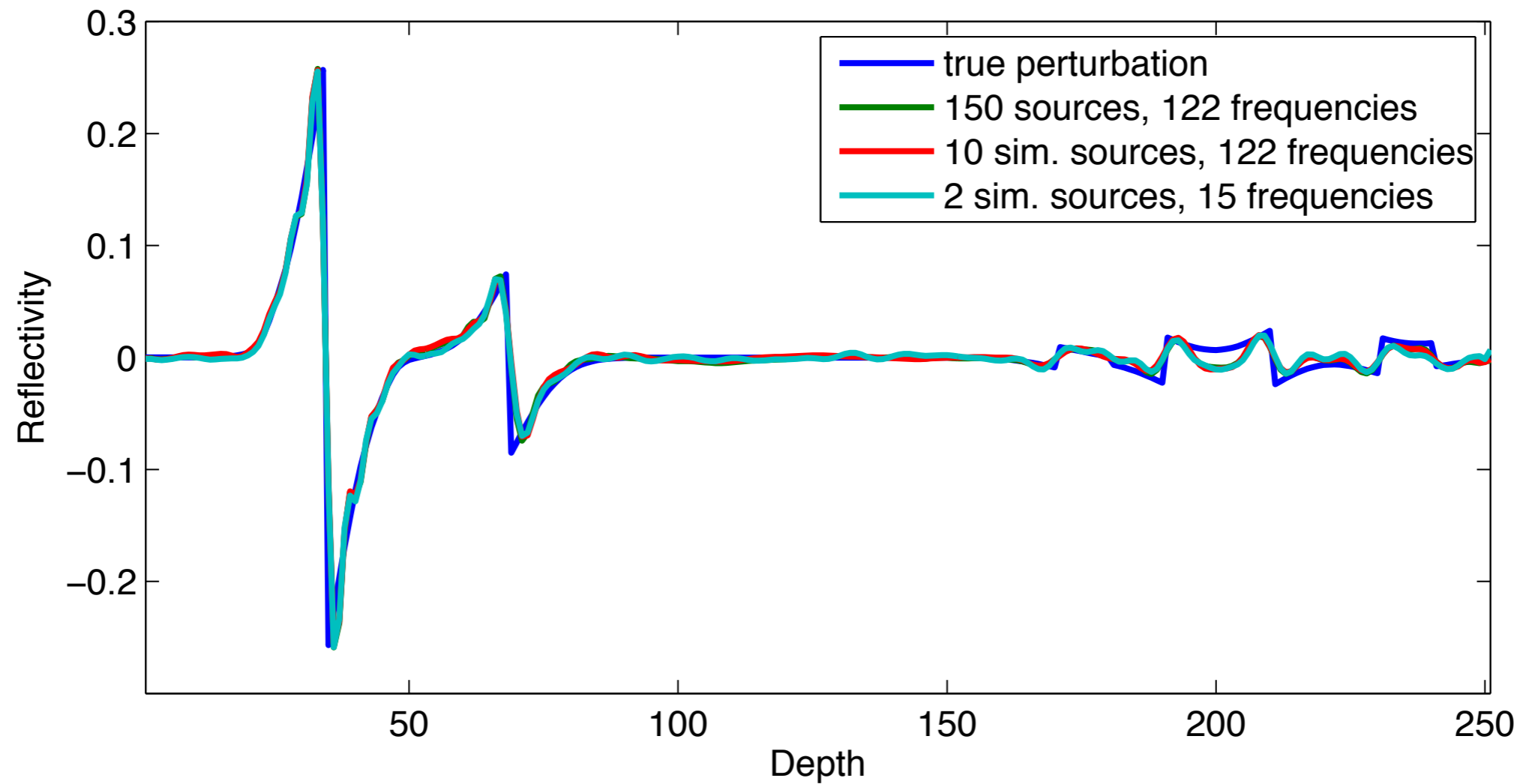


# Model error decrease



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

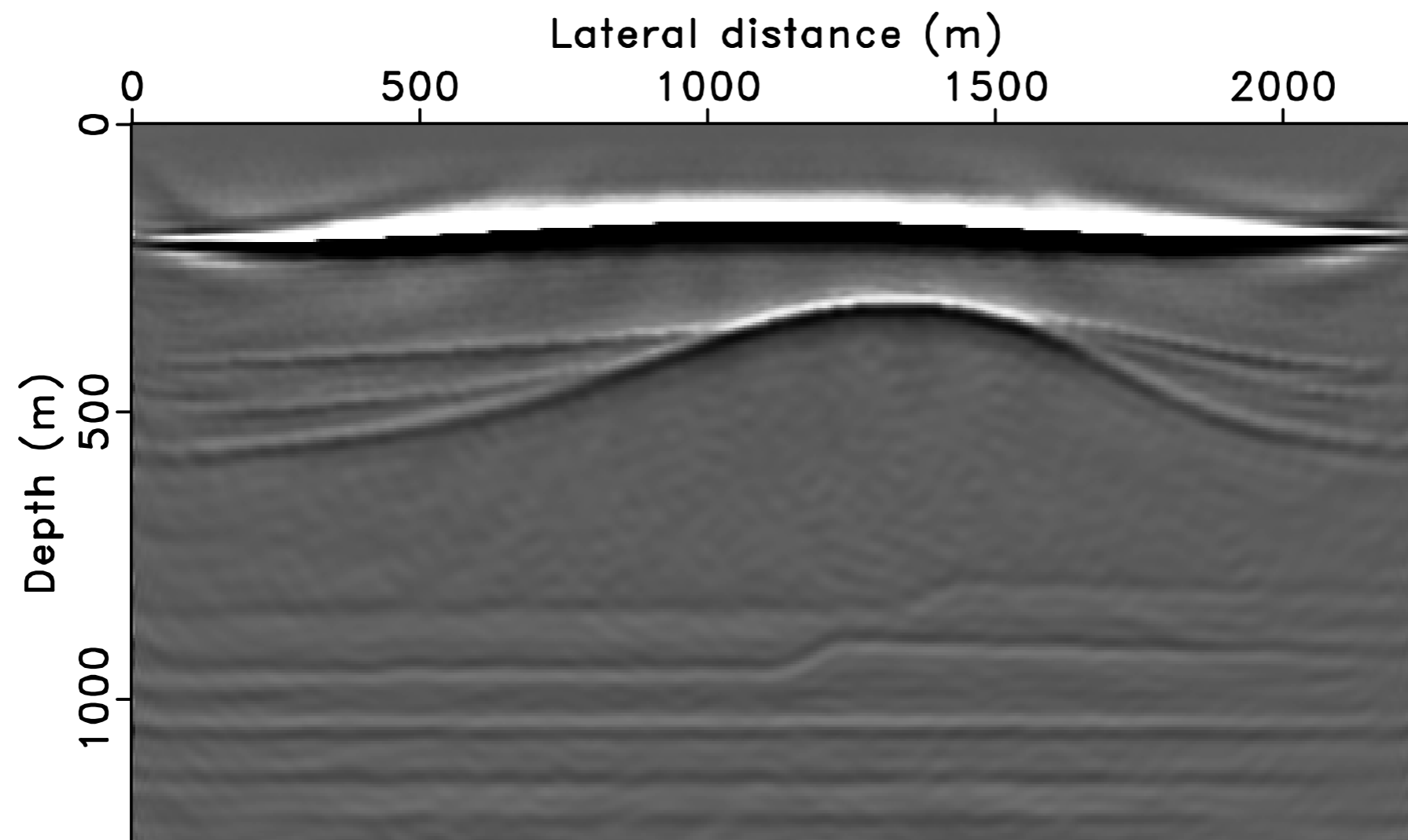
# Inversion results



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

# Comparison: batch size

[same budget of PDE solves]



Fast imaging of total data

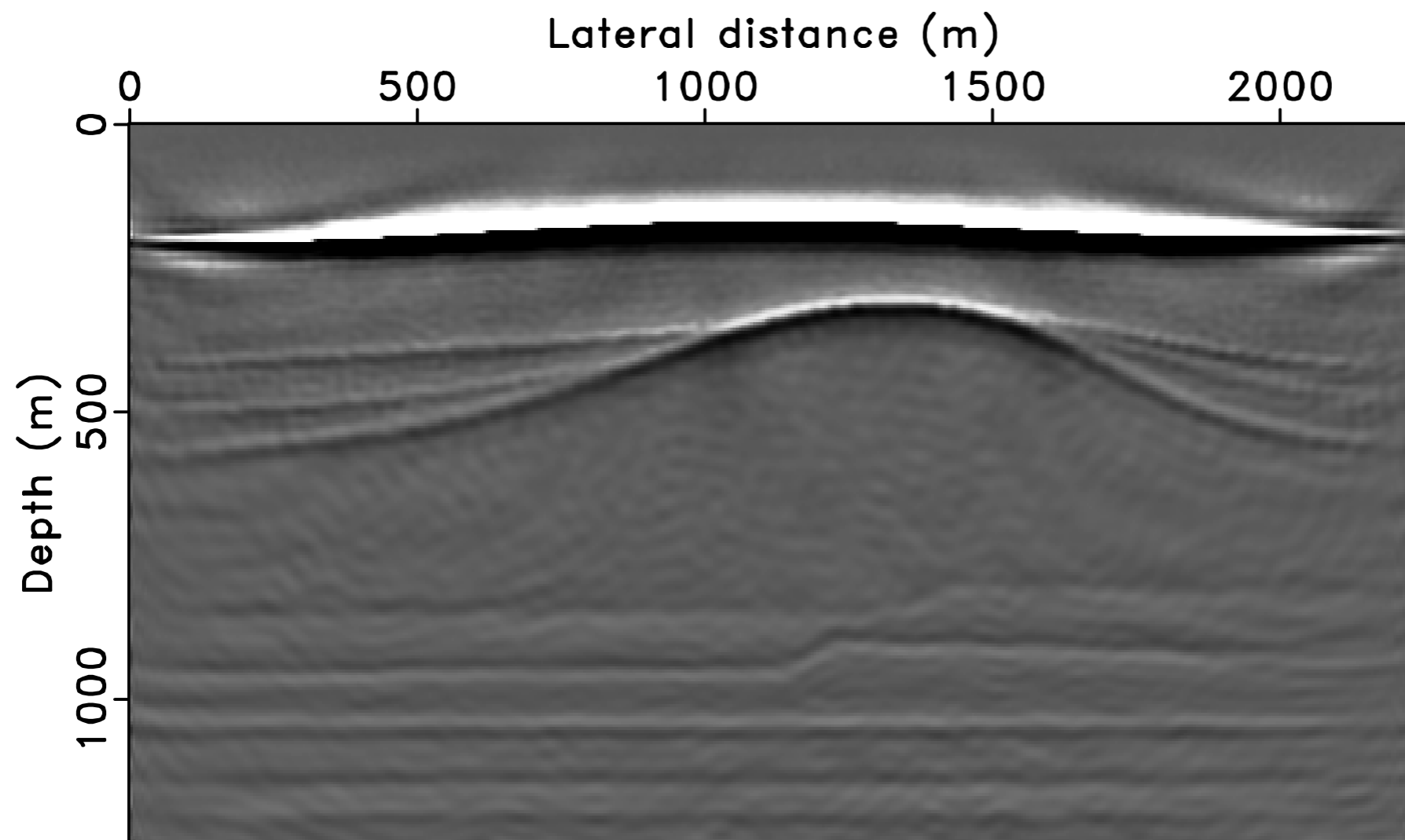
Batch size: 30 (2 simultaneous sources and 15 frequencies)

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)

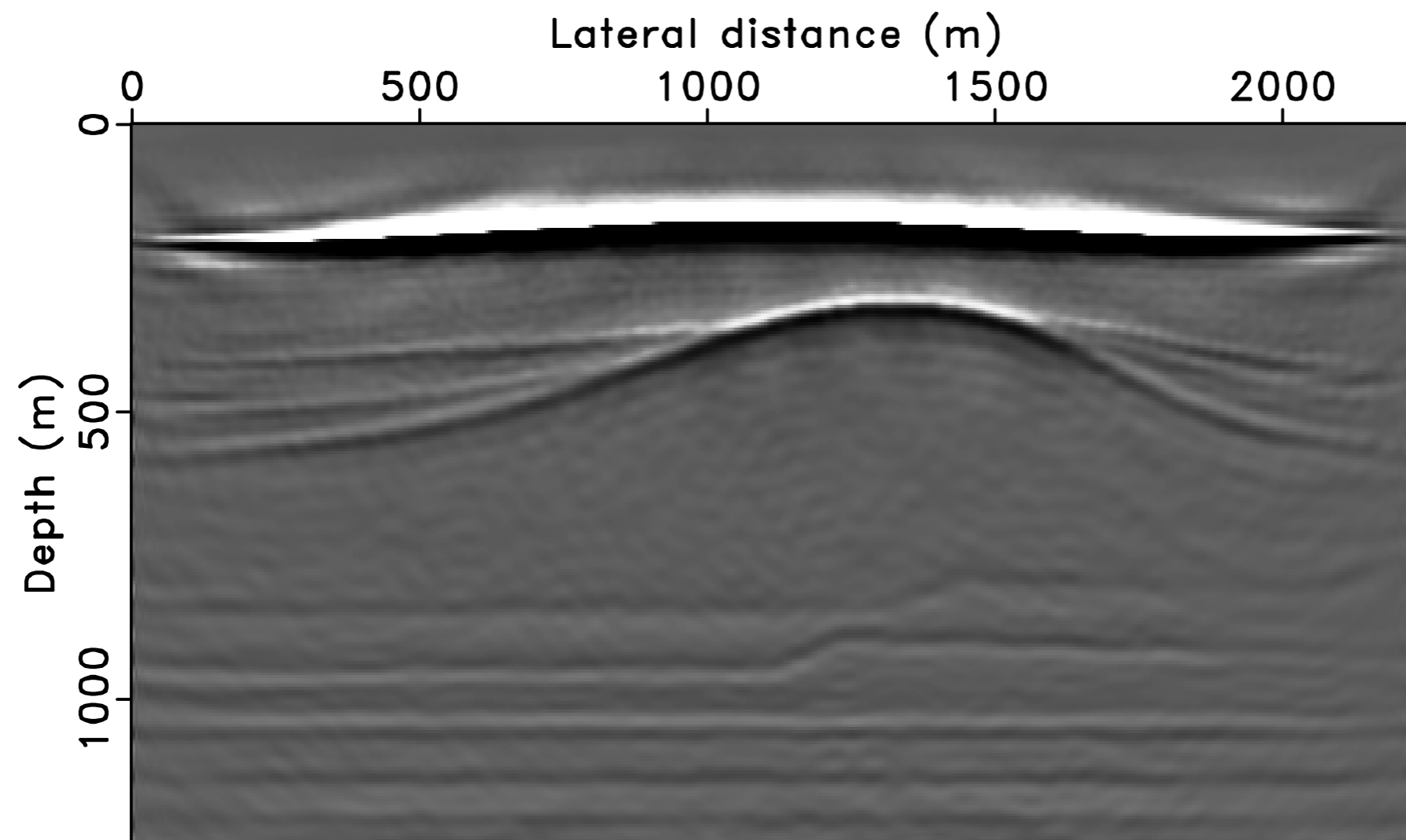
Iteration: 610

Number of PDE solves: 36.6 thousand (by calculation)



# Comparison: batch size

[same budget of PDE solves]



Fast imaging of total data

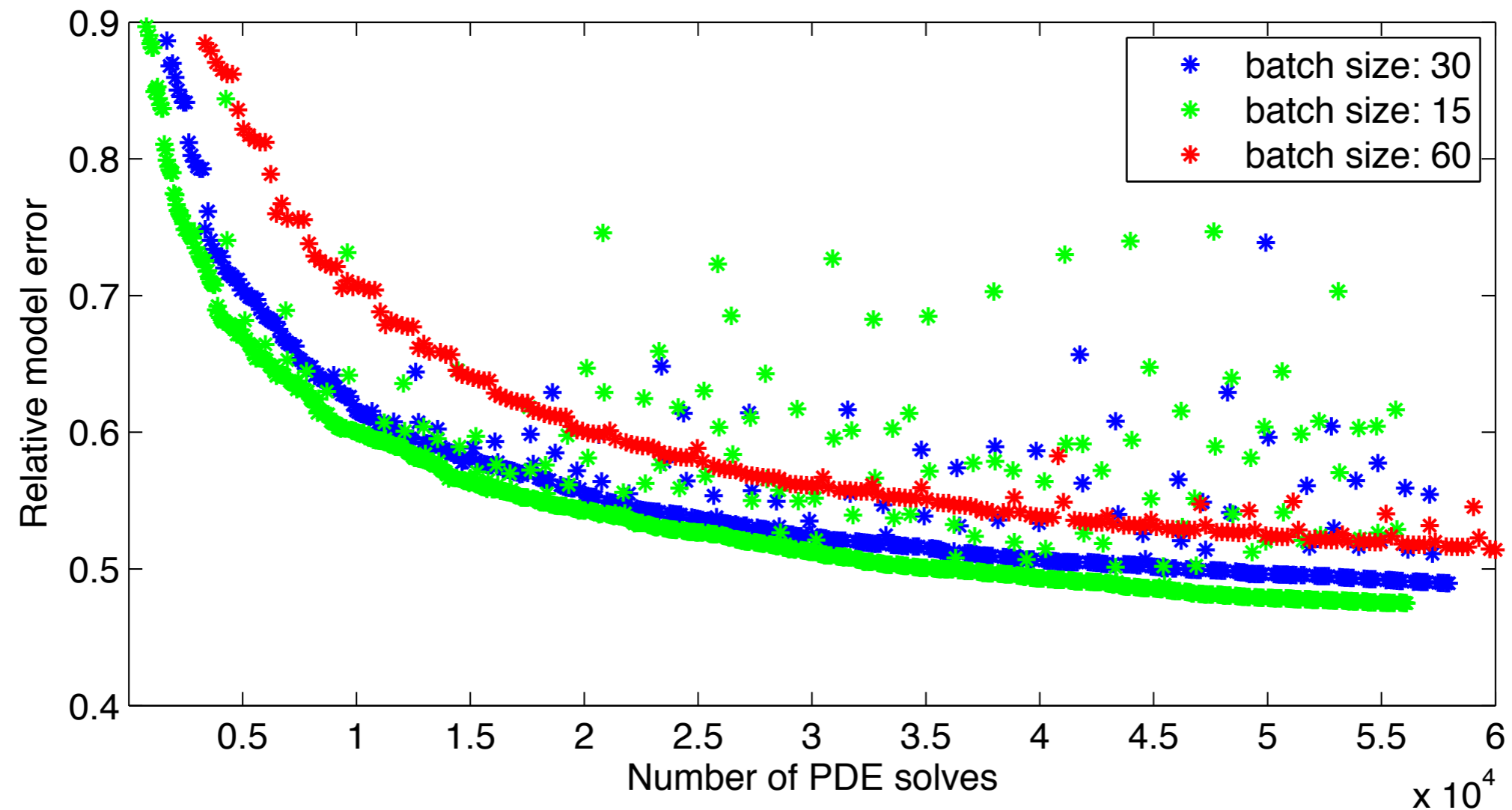
Batch size: 60 (4 simultaneous sources and 15 frequencies)

Iteration: 152

Number of PDE solves: 36.6 thousand (by calculation)

# Comparison: batch size

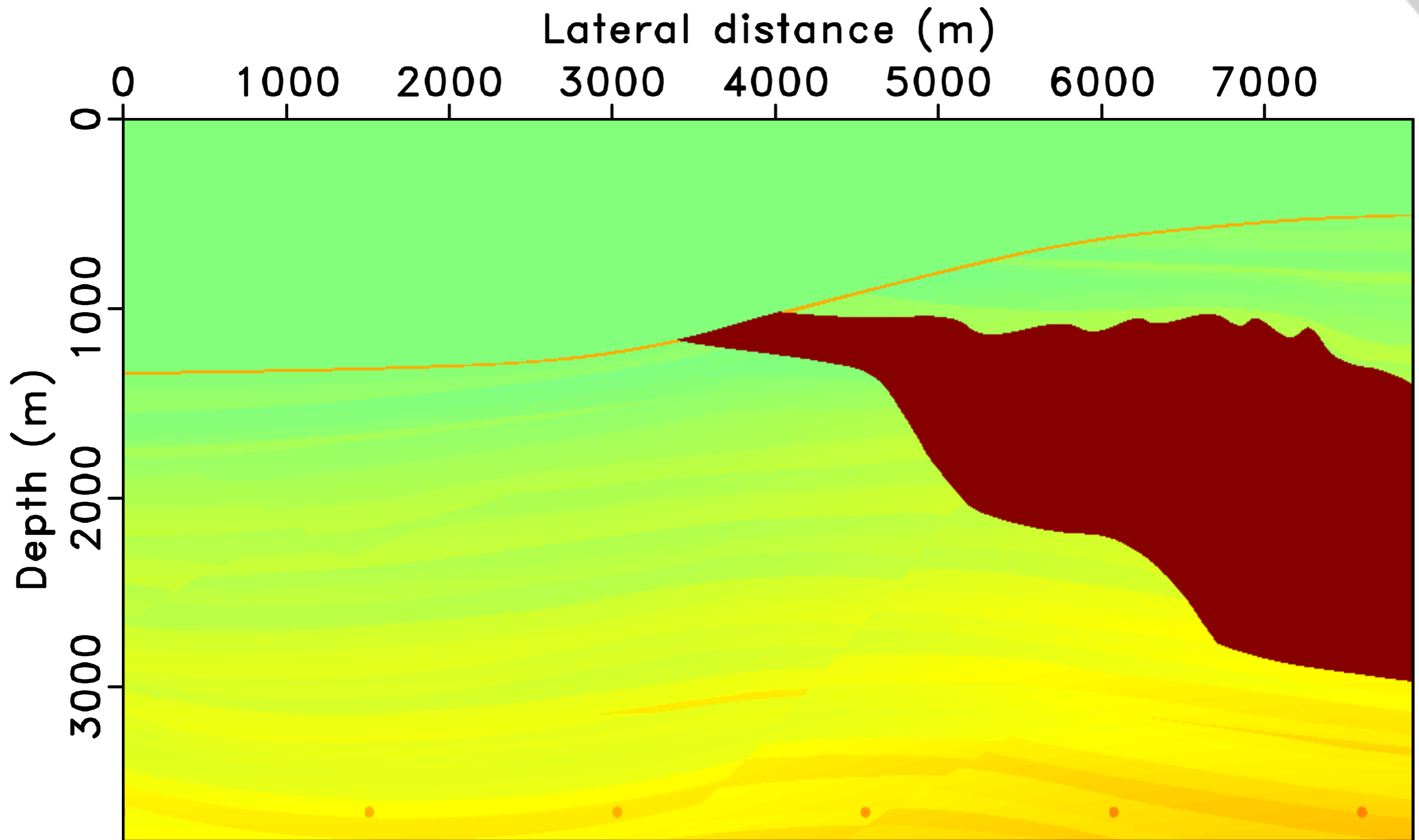
[same budget of PDE solves]



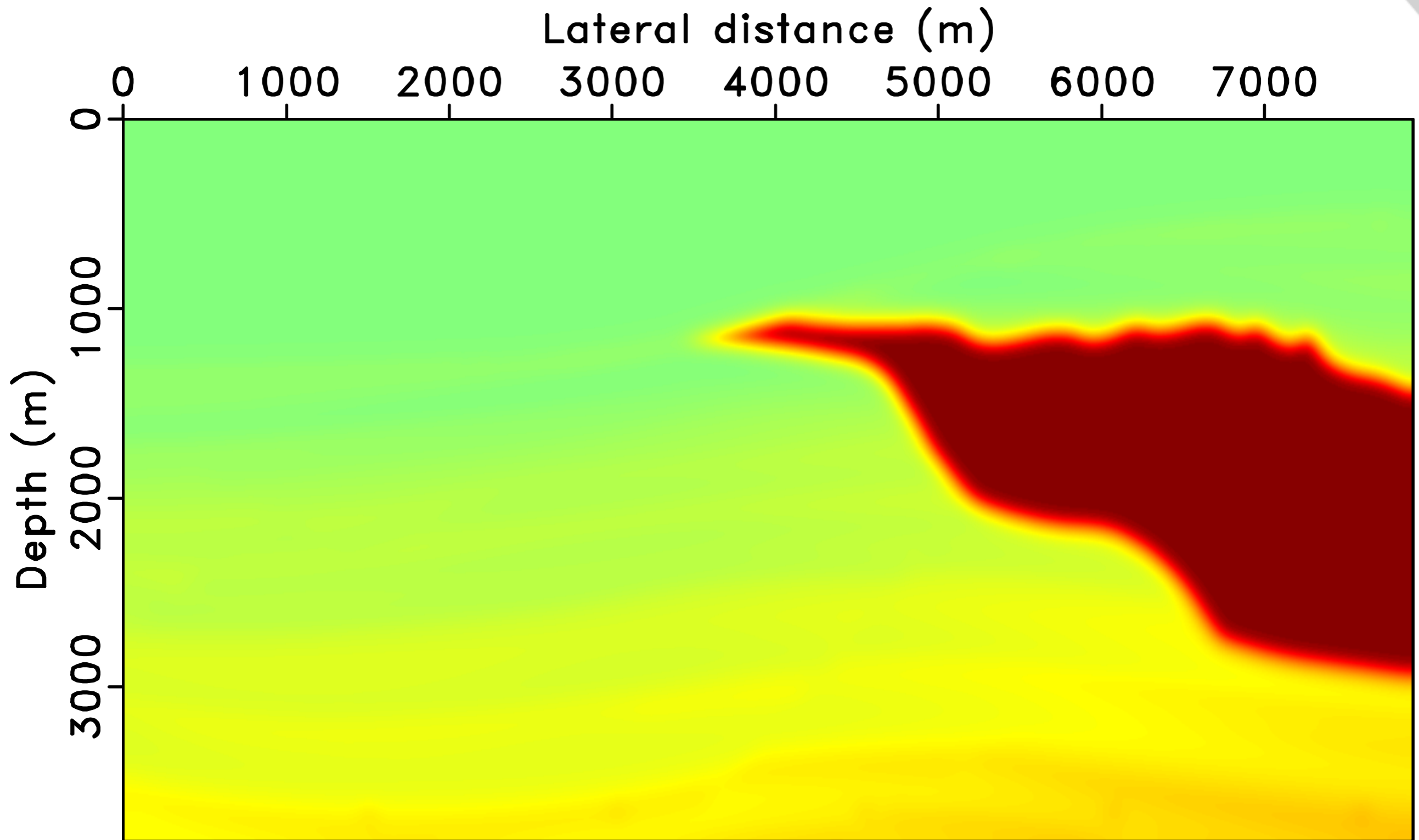
# The Sigsbee2B model (cropped)

- 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

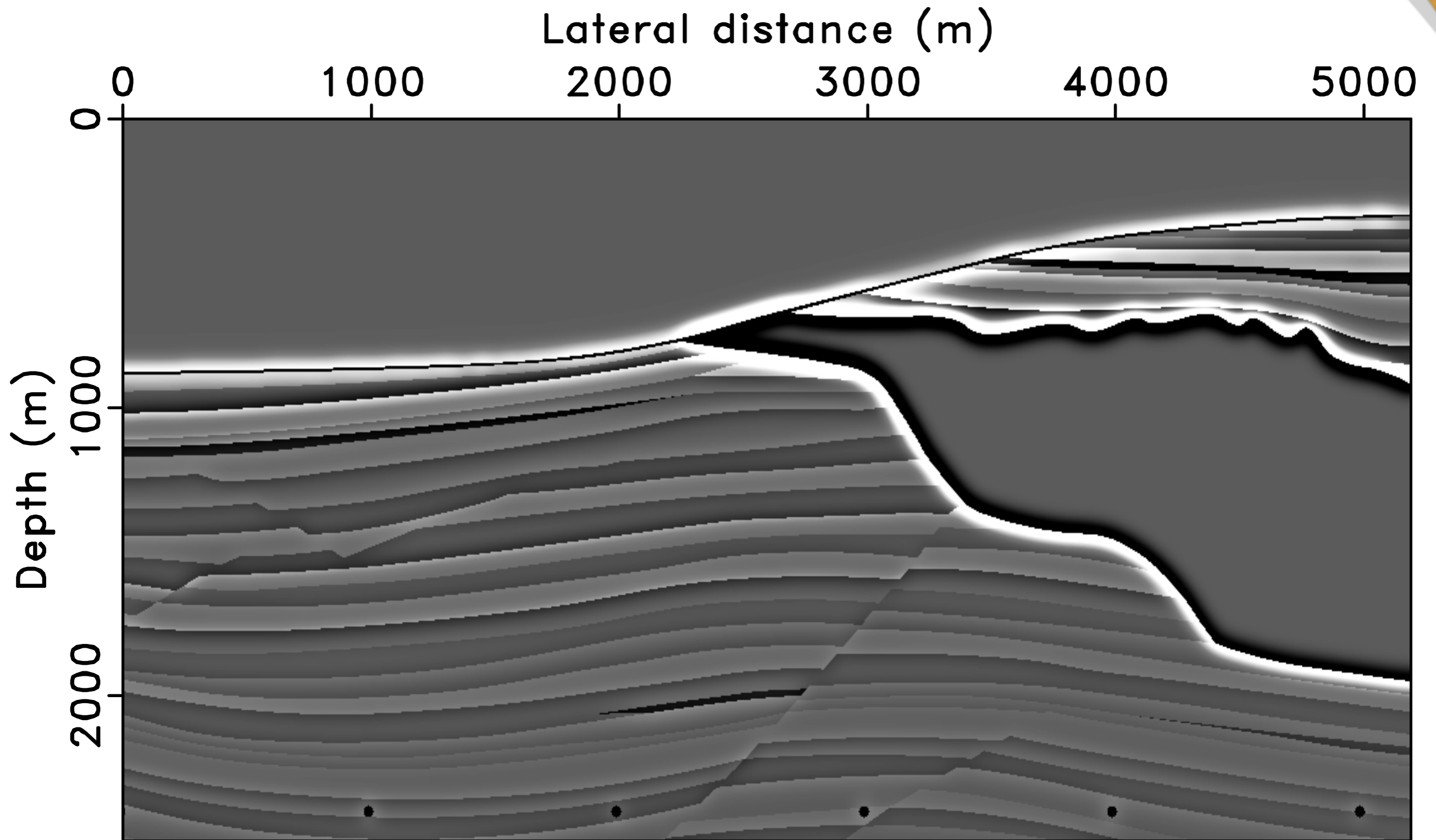
# The Sigsbee2B model



# Background model

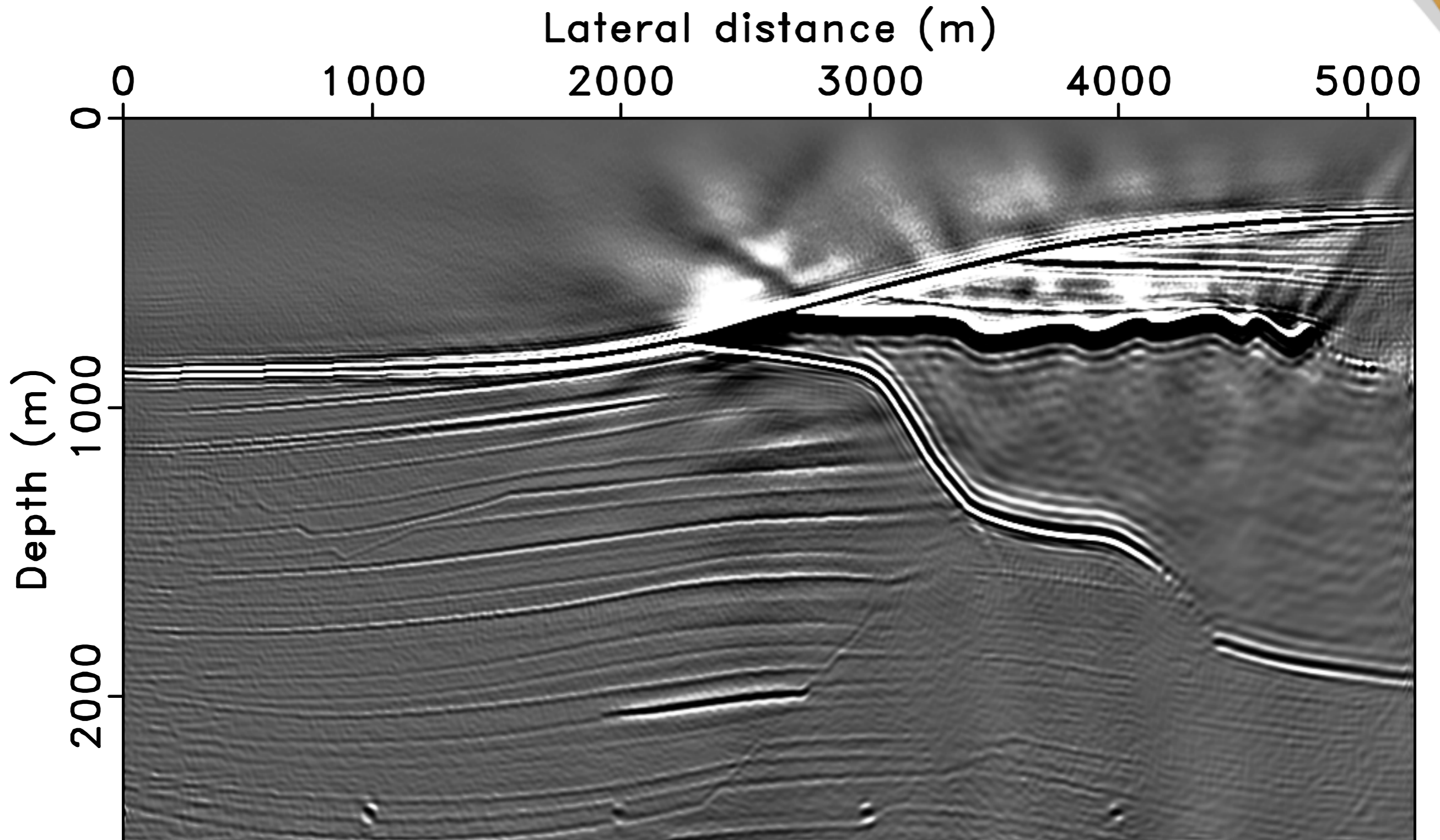


# True perturbation



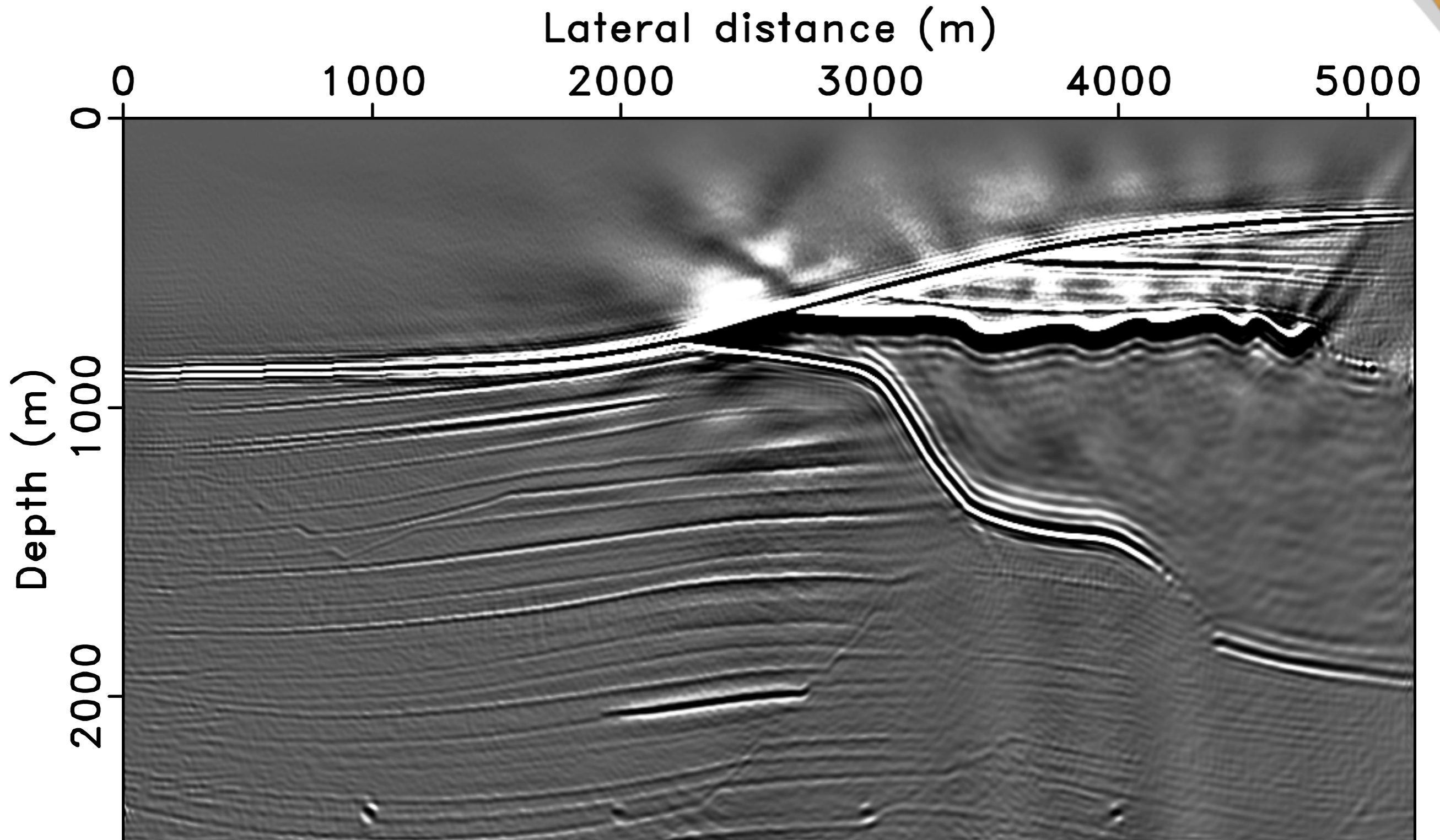
# Fast inversion of primaries

[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]





# 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

# Acknowledgements **NSERC CRSNG**

Thanks for your attention!

**SINBAD**



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