Julia Devito: A scalable research framework for seismic inversion

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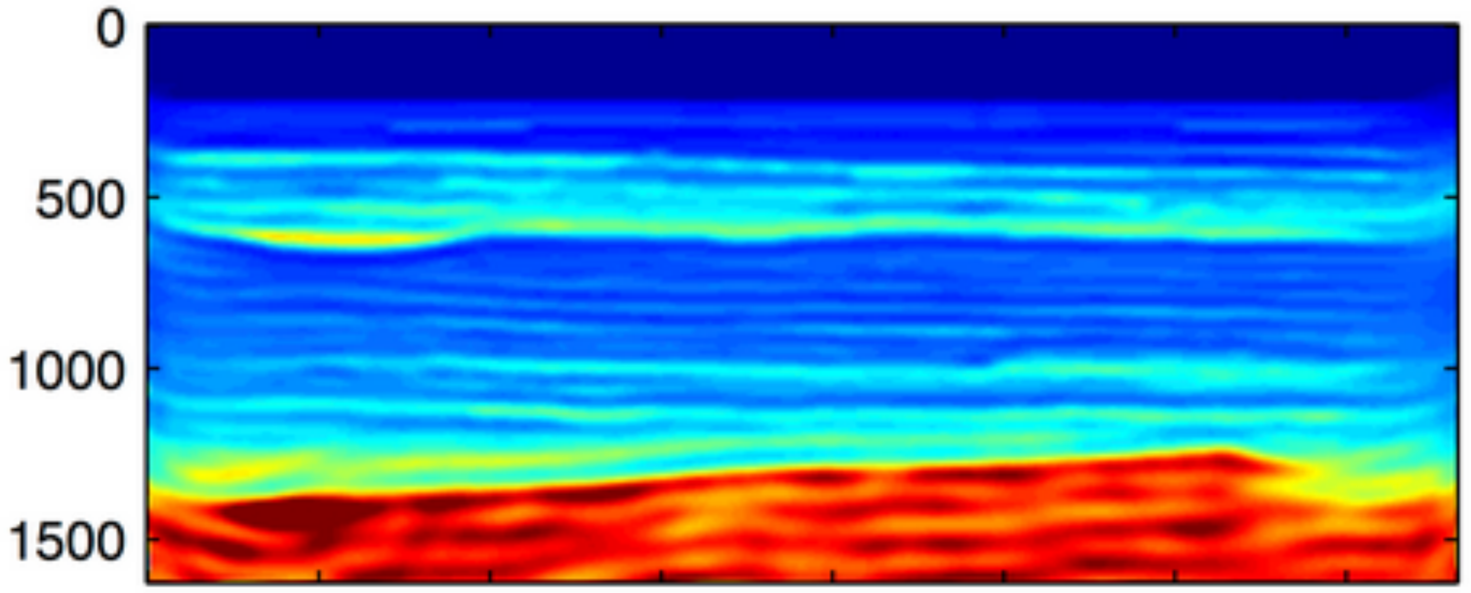
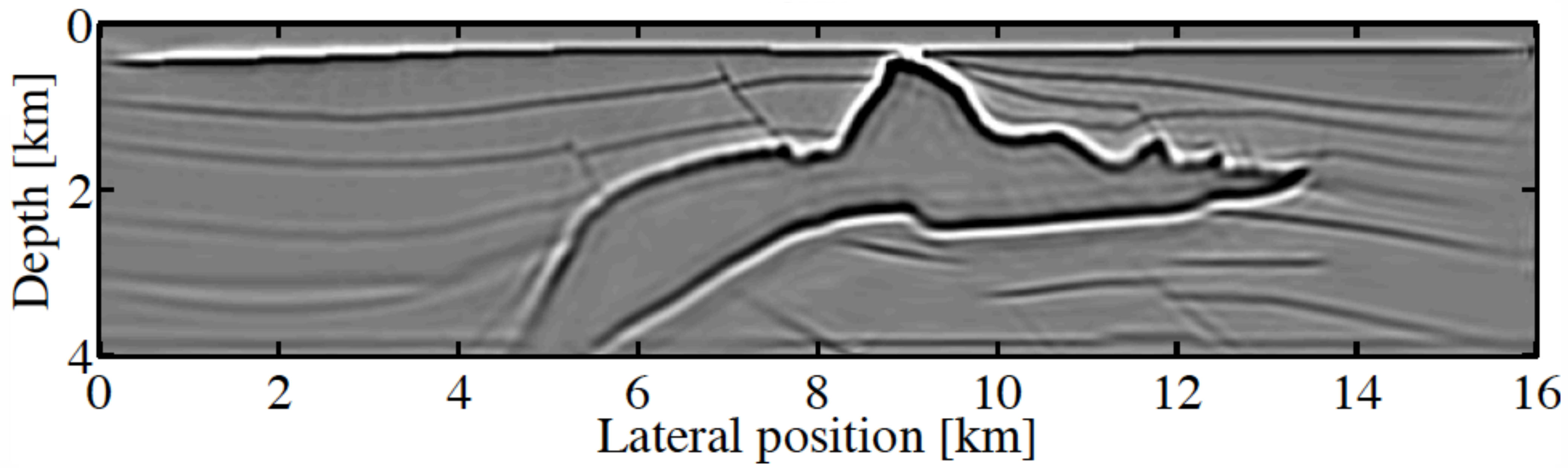
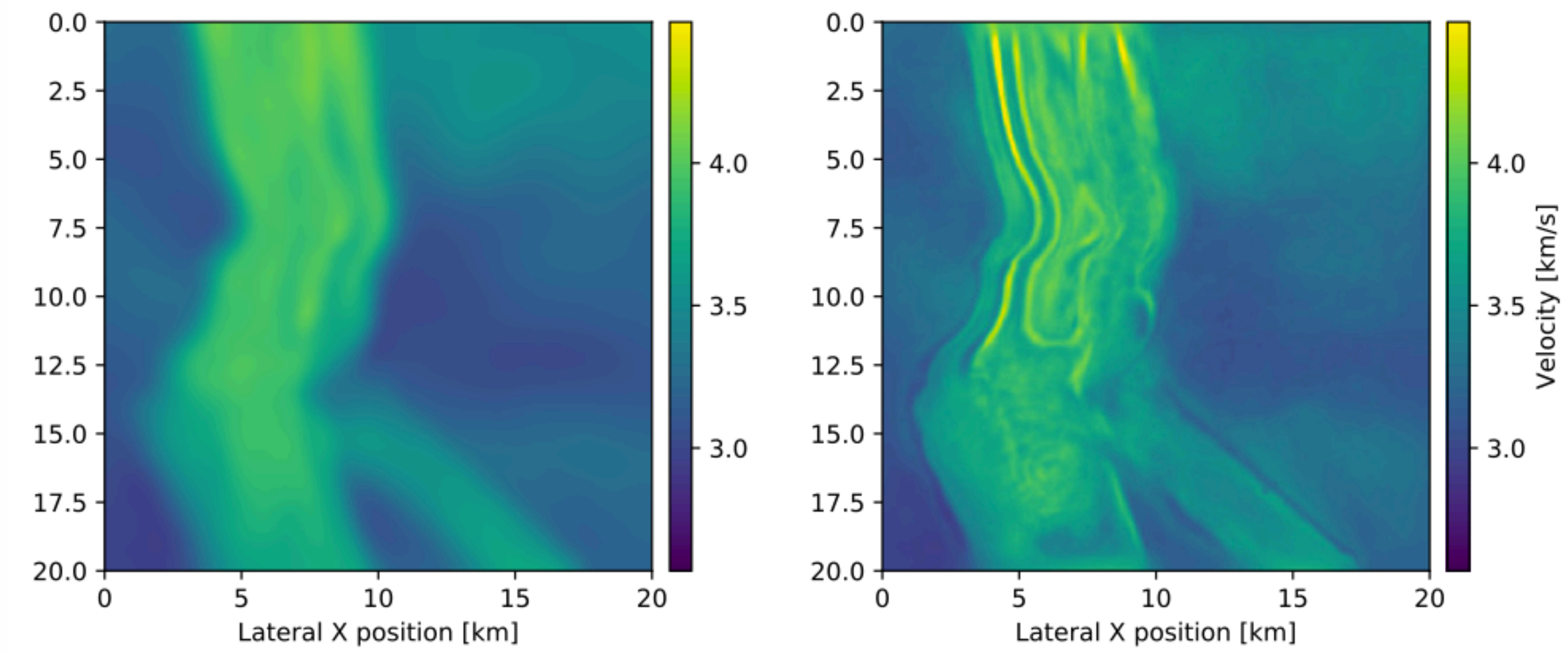
Research goals

SLIM

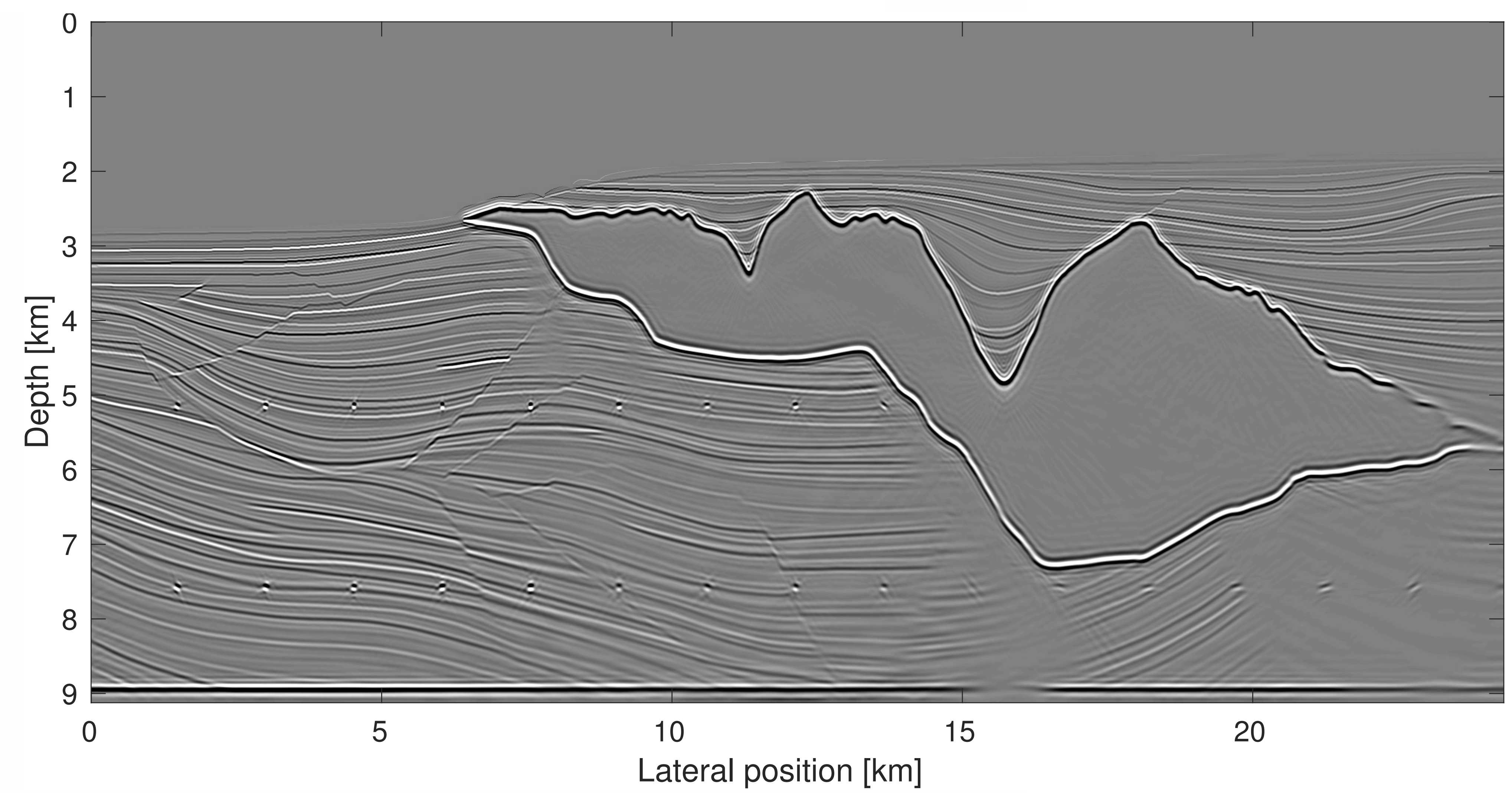
SLIM yesterday:



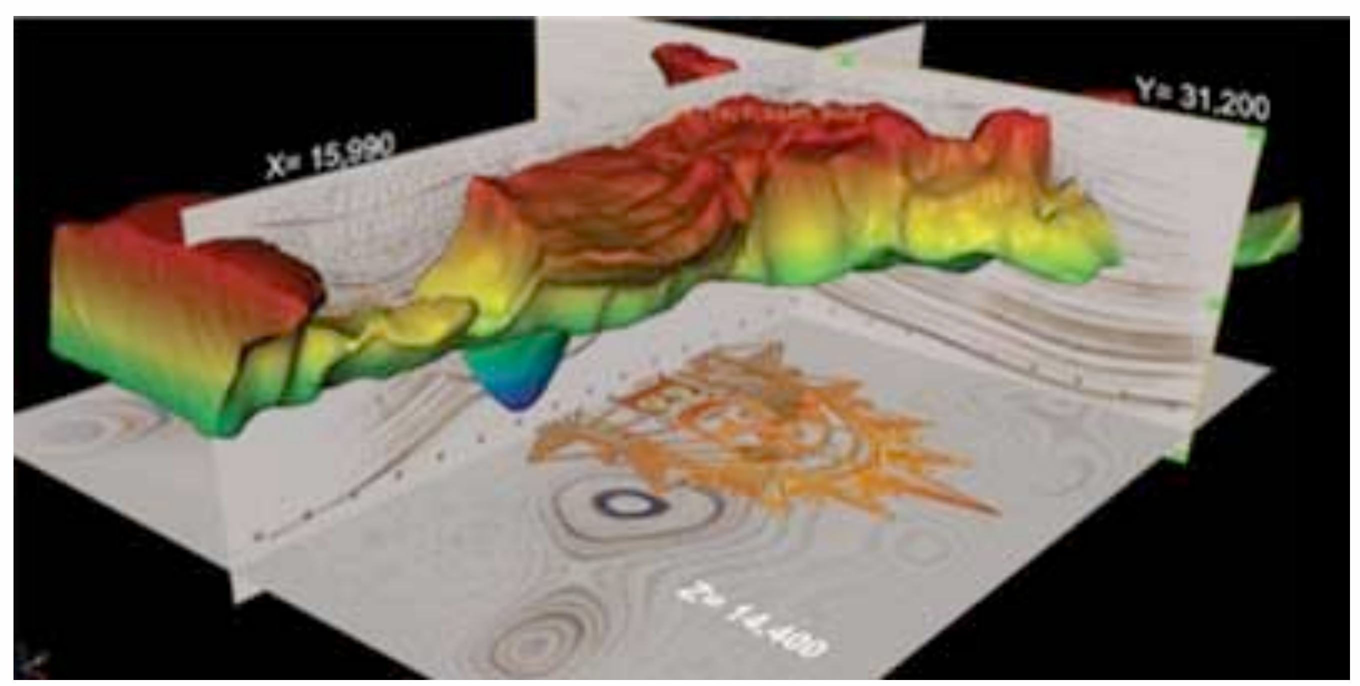




SLIM today:



SLIM tomorrow:



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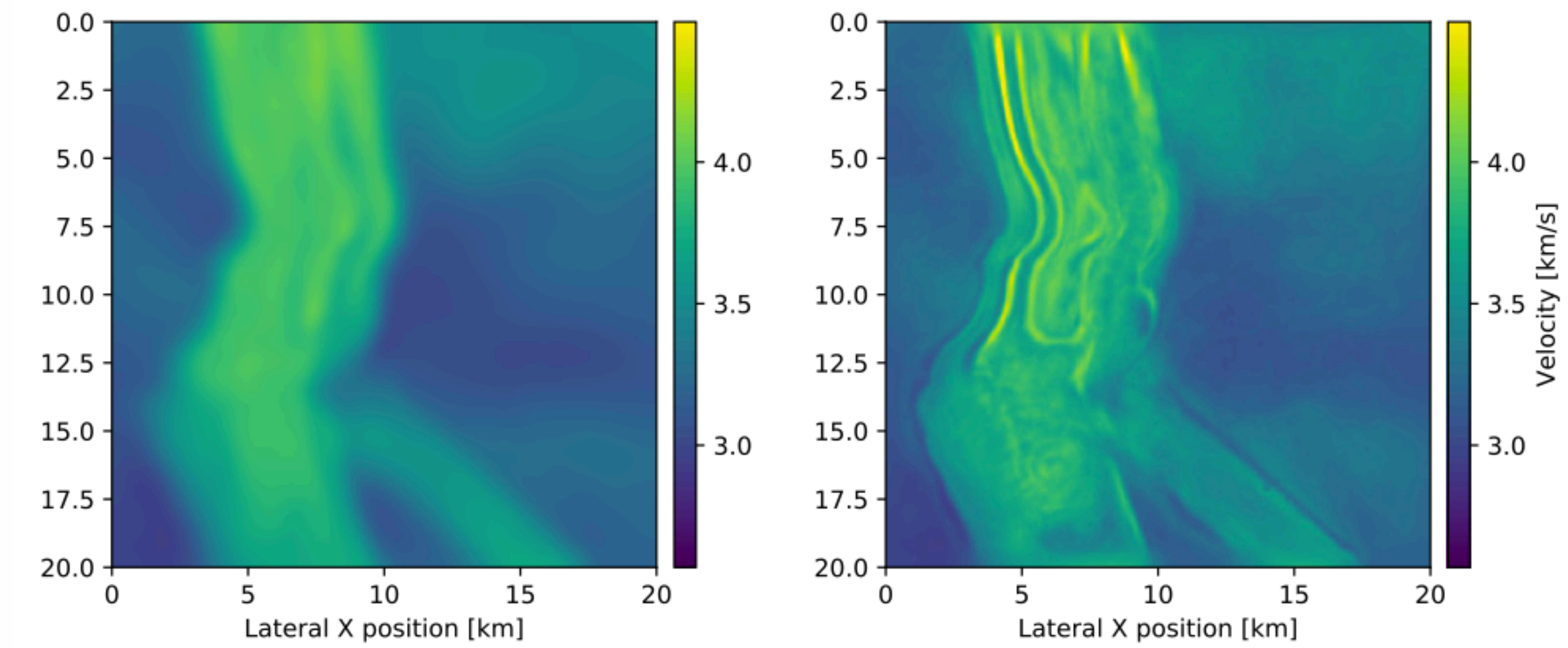
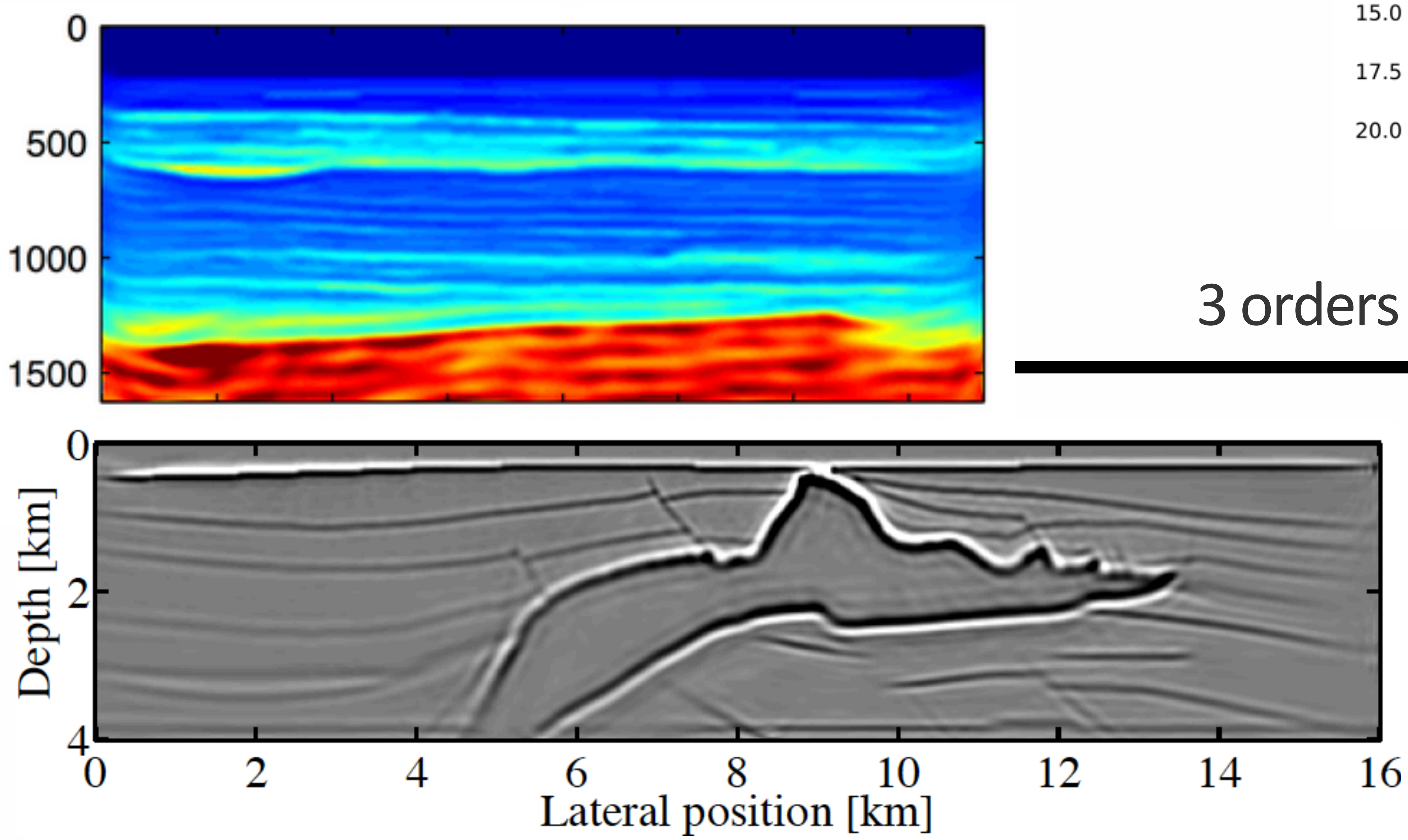
Research goals

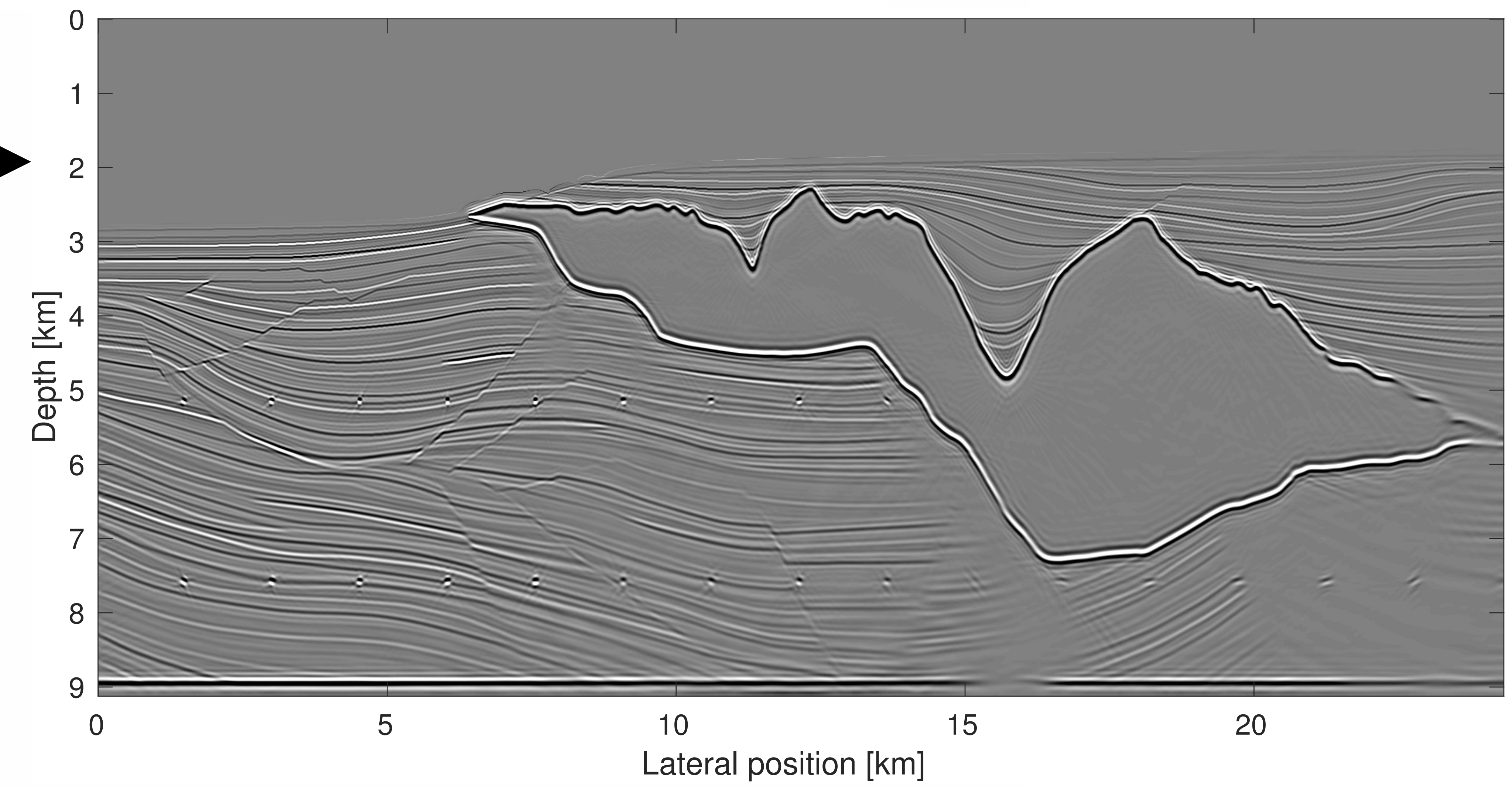


SLIM yesterday:

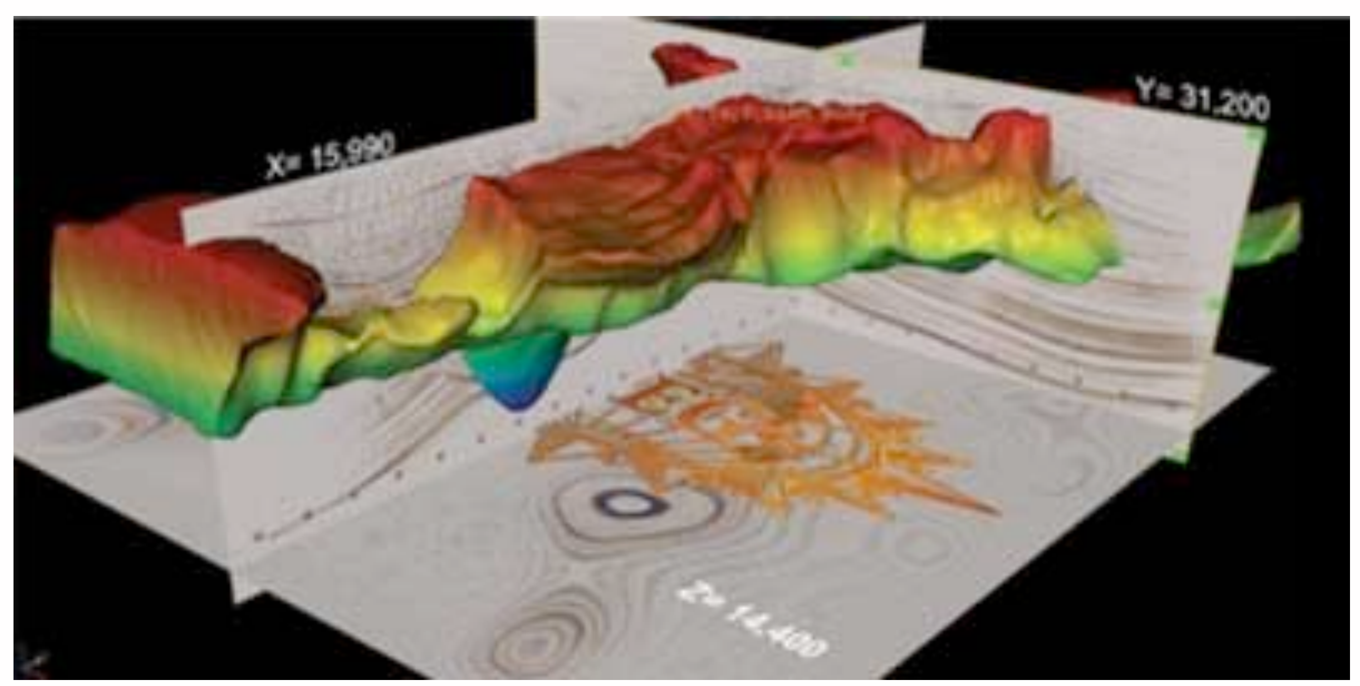


3 orders of magnitude

SLIM today:



SLIM tomorrow:



2 more to go

Motivation

Academic software frameworks:

- only for small 2D/3D problems (Madagascar, SeismicJulia) **or**
- unmaintainable low-level black-box spaghetti codes
- without detailed knowledge of code, hard to:
  - change a line search
  - keep history of gradients (e.g for SPG)
  - change parallelization
  - change the underlying physics, correct adjoints

But there is also iWave:

- well designed, abstractions
- high accuracy, testing framework, correct adjoints
- **but**: written in C/C++, not primarily designed for performance, not very intuitive to use

Motivation

Potential applications of software:

- linear least squares problems such as LS-RTM

$$\underset{\delta\mathbf{m}}{\text{minimize}} \quad \frac{1}{2}|| \ \nabla\mathcal{F}(\mathbf{m}_0, \mathbf{q}) \ \delta\mathbf{m} - \delta\mathbf{d}||_2^2$$

- non-linear optimization problems such as FWI

$$\underset{\mathbf{m}}{\text{minimize}} \quad \phi\Big(\ \mathcal{F}(\mathbf{m}, \mathbf{q}) - \mathbf{d}\Big), \text{where} \quad \phi(\mathbf{x}) = \frac{1}{2}||\mathbf{x}||_2^2$$

Maintain flexibility:

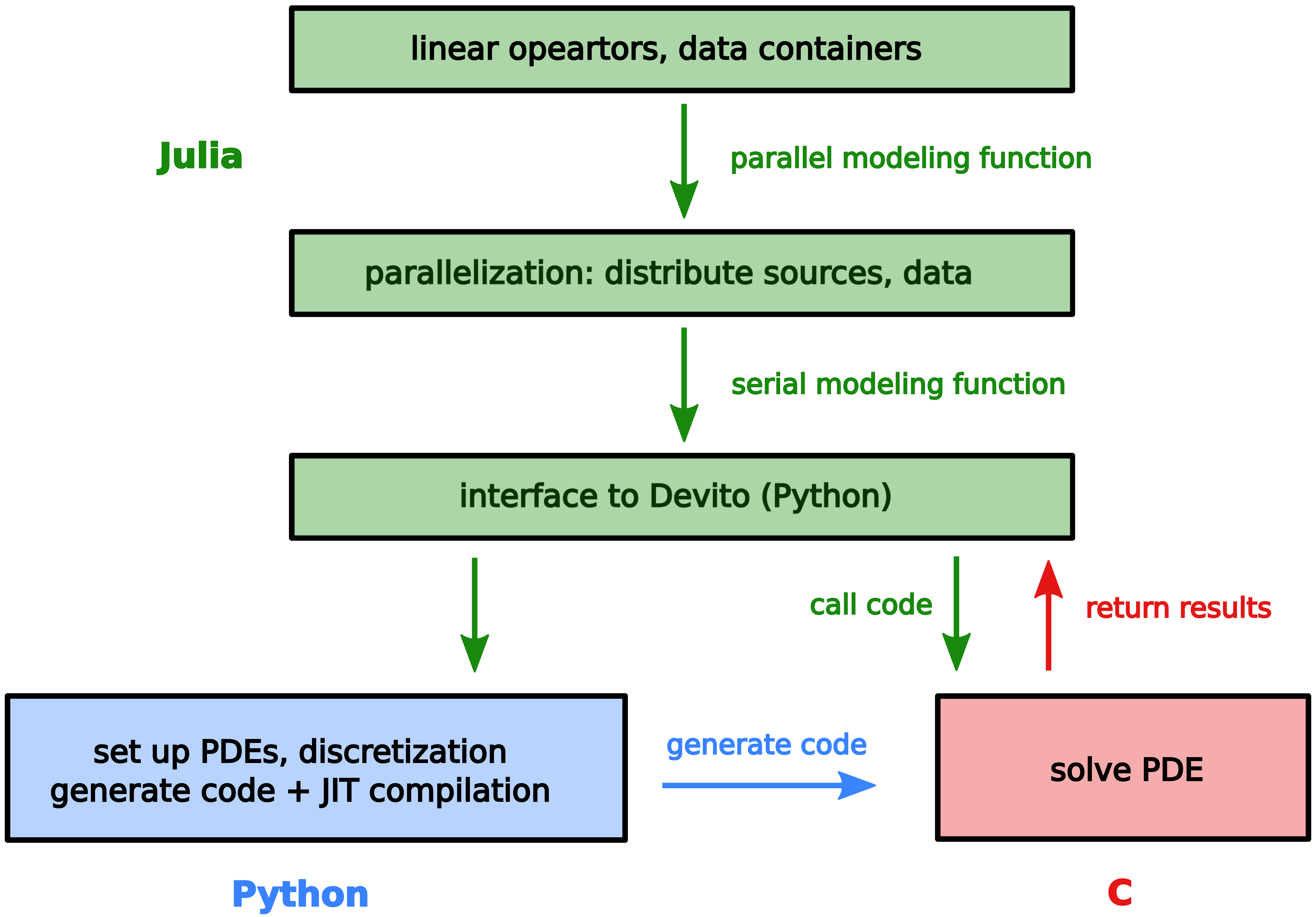
- change $\mathcal{F}(\mathbf{m}, \mathbf{q})$, the underlying wave equation solver
- change the formulation (different misfits $\phi(\mathbf{x})$, constraints, penalties)
- choose from large variety of optimization algorithms

Overview of Julia Devito

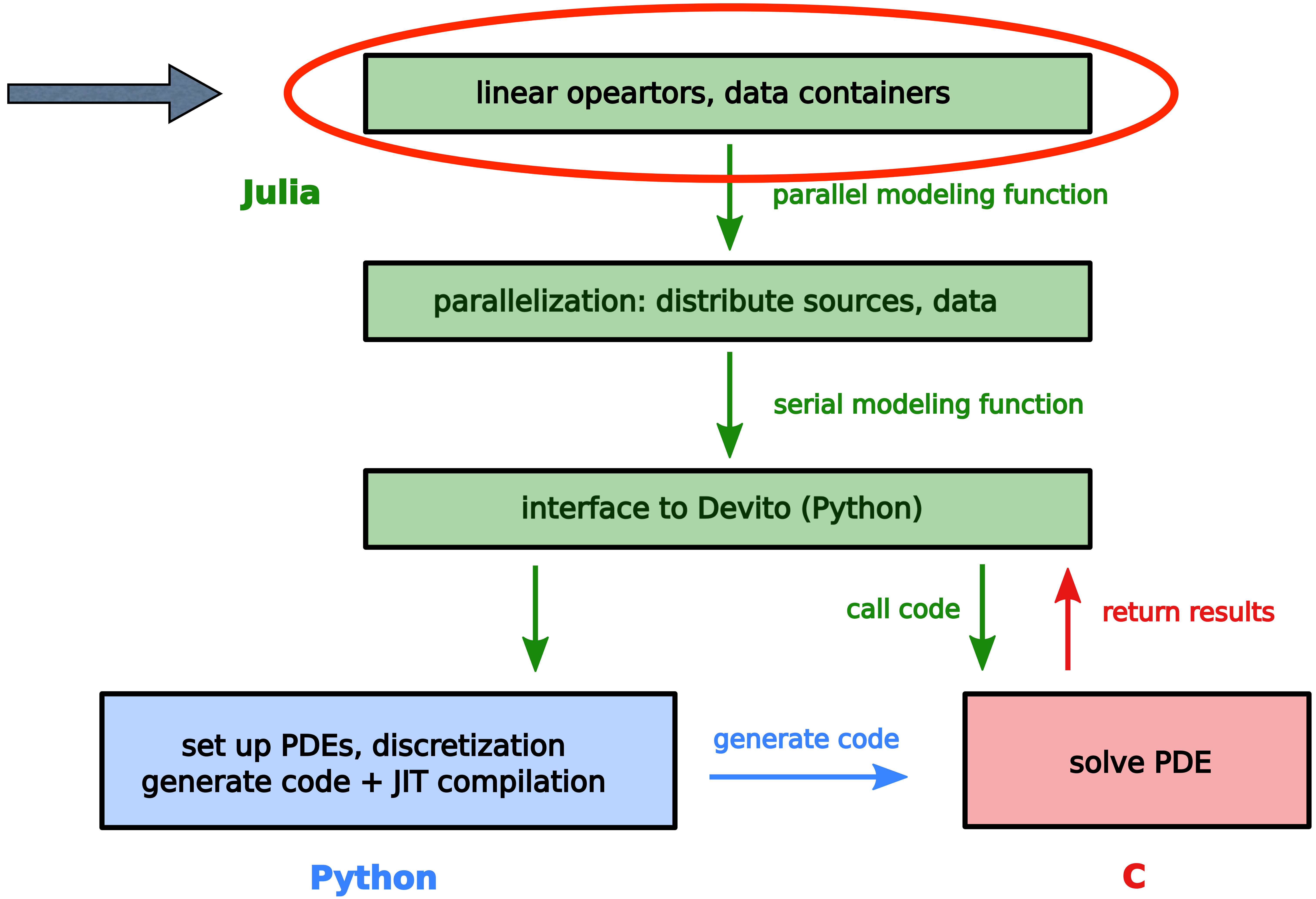
Julia Devito is a wave-equation based inversion framework:

- non proprietary Julia programming language (public license)
- uses Devito to express and solve underlying PDEs
- matrix-free linear operators and out-of-core SEG-Y data containers
- resilient parallelization
- unified 2D-3D environment
- can interact with variety of general-purpose optimization libraries
- **designed to push inversion to the next scale**
- **scalable but also flexible**

Overview of Julia Devito



Overview of Julia Devito



Linear operators and data containers

Linear algebra notation is intuitive for seismic operations:

- forward modeling/time reversal modeling

$$\mathbf{d} = \mathcal{P}_r \, \mathbf{F} \, \mathcal{P}_s^\top \mathbf{q}, \quad \widehat{\mathbf{q}} = \mathcal{P}_s \, \mathbf{F}^\top \, \mathcal{P}_r^\top \mathbf{d}$$

- demigration/migration

$$\delta \mathbf{d} = \mathbf{J} \, \delta \mathbf{m}, \quad \widehat{\delta \mathbf{m}} = \mathbf{J}^\top \delta \mathbf{d}$$

- FWI gradients, Gauss-Newton step, etc.

$$\mathbf{g} = \mathbf{J}^\top (\mathcal{P}_r \, \mathbf{F} \, \mathcal{P}_s^\top \mathbf{q} - \mathbf{d}_{obs})$$

$$\delta \mathbf{m} = (\mathbf{J}^\top \mathbf{J})^{-1} \mathbf{J}^\top \delta \mathbf{d}$$

Linear operators and data containers

Challenges of this approach for time-domain modeling/inversion:

- seismic data is multidimensional volume with meta data
- simply vectorizing the input data not an option
- data typically too big to fit in memory

$$\mathbf{d} = \mathcal{P}_r \, \mathbf{F} \, \mathcal{P}_s^\top \mathbf{q}$$

Linear operators and data containers

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$$\mathbf{d} = \mathcal{P}_r \, \mathbf{F} \, \mathcal{P}_s^\top \mathbf{q}$$

- cannot be formed explicitly
- need physical information (model, source/receiver locations)

Linear operators and data containers

Challenges of this approach for time-domain modeling/inversion:

- seismic data is multidimensional volume with meta data
- simply vectorizing the input data not an option
- data typically too big to fit in memory

$$\mathbf{d} = \mathcal{P}_r \, \mathbf{F} \, \mathcal{P}_s^\top \mathbf{q}$$

- cannot be kept in memory
- not a vector
- contains header information

- cannot be formed explicitly
- need physical information (model, source/receiver locations)

Linear operators and data containers

Abstract in-core and out-of-core data vectors:

- inspired by iWave, RVL and others (Symes, Padula)
- can be formed directly from single/multiple SEG-Y files
- parallel read/write chunks of data

(joint work with Keegan Lensink)

```
julia> container = segy_scan(pwd(), "overthrust_shots", ["GroupX","GroupY"]);
Scanning ... /home/slim/pwitte/overthrust_shots_41_60.segy
Scanning ... /home/slim/pwitte/overthrust_shots_21_40.segy
Scanning ... /home/slim/pwitte/overthrust_shots_61_80.segy
Scanning ... /home/slim/pwitte/overthrust_shots_1_20.segy
Scanning ... /home/slim/pwitte/overthrust_shots_81_97.segy

julia> d = joData(container)
(opesciSLIM.TimeModeling.joData{Float32}, "Julia seismic data container", 15029763, 1)

julia> size(d)
(15029763, 1)

julia> norm(d)
7371.35f0

julia> dot(d,d)
5.432854f7

julia> typeof(d.data[1])
SeisIO.SeisCon
```

(Instructional video at: https://www.youtube.com/watch?v=tx530QOPeZo)

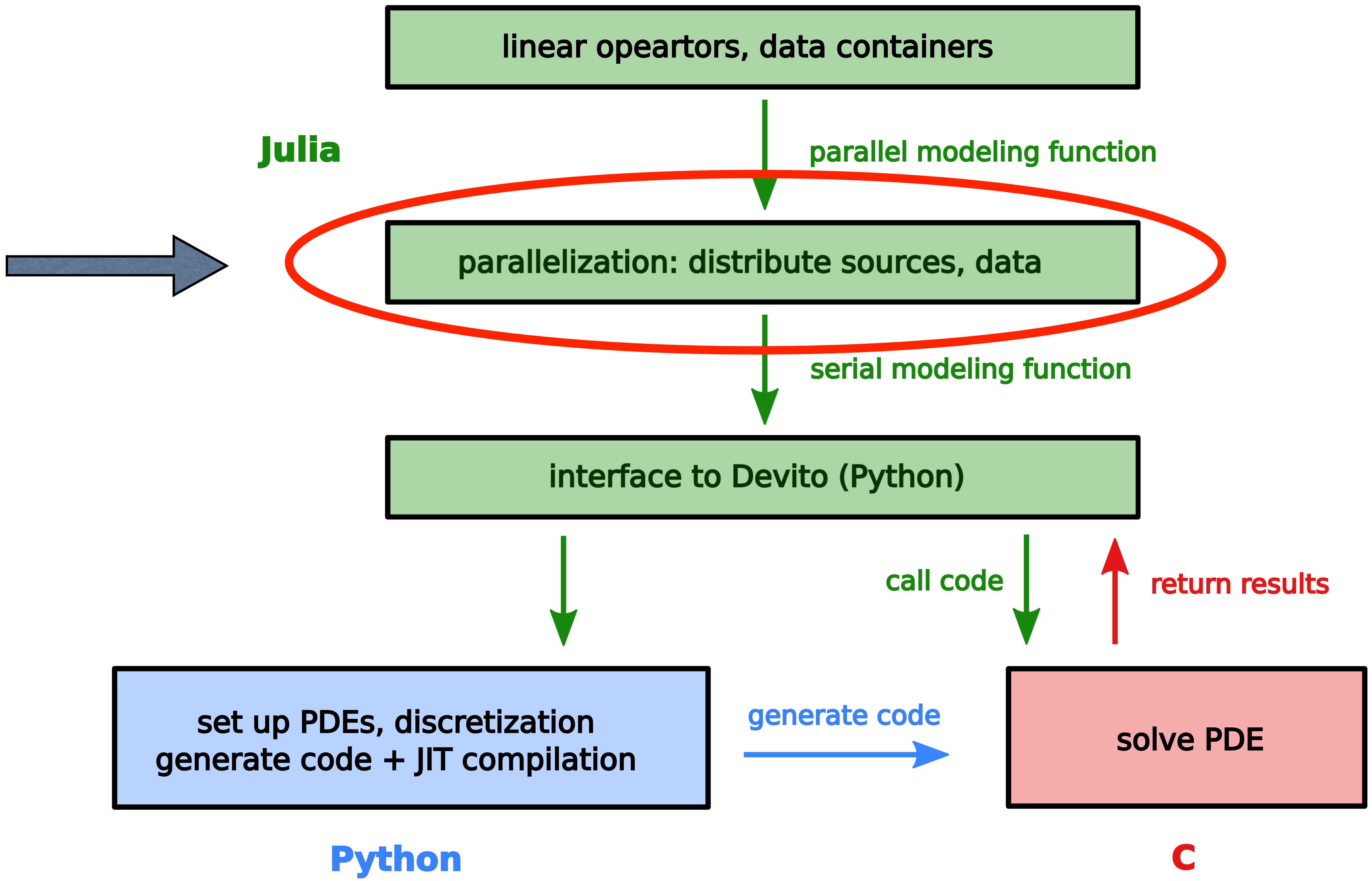
Linear operators and data containers

Matrix-free linear operators

- read necessary meta information from data objects
- use like explicit matrices

```
julia> F = joModeling(info,model0)
(opesciSLIM.TimeModeling.joModeling{Float32,Float32}, "forward wave equation", 27566740206, 27566740206)

julia> Pr = joProjection(info,d.geometry)
(opesciSLIM.TimeModeling.joProjection{Float32,Float32}, "restriction operator", 15029763, 27566740206)

julia> Ps = joProjection(info,q.geometry)
(opesciSLIM.TimeModeling.joProjection{Float32,Float32}, "restriction operator", 72847, 27566740206)

julia> d_pred = Pr*F*Ps'*q
```

Overview of Julia Devito



Parallelization

Modeling multiple shots happens in parallel:

```
julia> d = Pr*F*Ps'*q
	From worker 2:	Nonlinear forward modeling (source no. 1)
	From worker 5:	Nonlinear forward modeling (source no. 4)
	From worker 3:	Nonlinear forward modeling (source no. 2)
	From worker 4:	Nonlinear forward modeling (source no. 3)
(opesciSLIM.TimeModeling.joData{Float32}, "Seismic data vector", 240480, 1)
```

Same for adjoint modeling:

```
julia> q̂ = Ps*F'*Pr'*d
	From worker 2:	Nonlinear adjoint modeling (source no. 2)
	From worker 3:	Nonlinear adjoint modeling (source no. 3)
	From worker 4:	Nonlinear adjoint modeling (source no. 1)
	From worker 5:	Nonlinear adjoint modeling (source no. 4)
(opesciSLIM.TimeModeling.joData{Float32}, "Seismic data vector", 2004, 1)
```

Parallelization

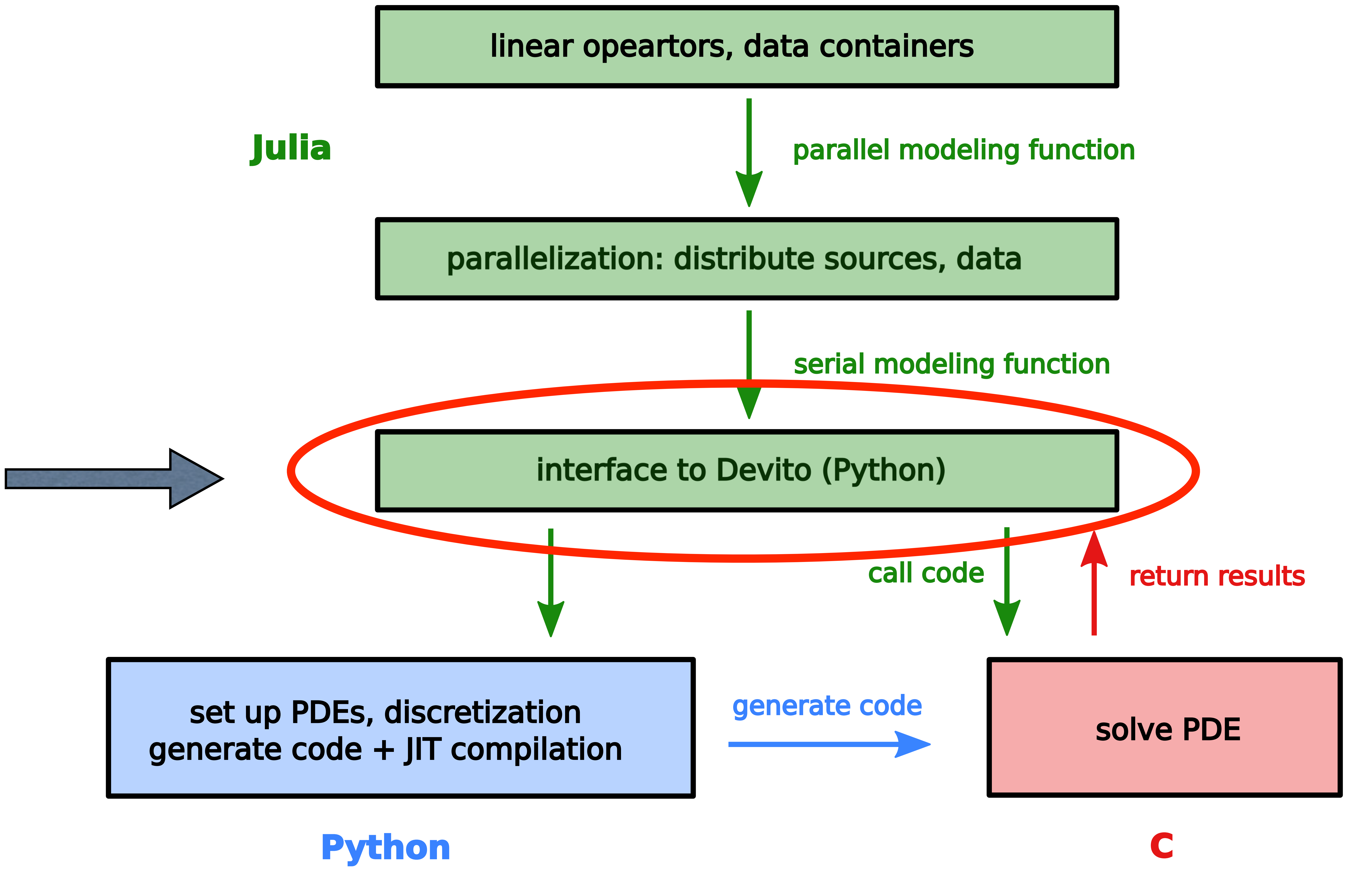
Parallelization in our framework:

- 2 levels of parallelization
- distribution of sources/shots (shared/distributed memory)
- parallelization over modeling domain via OpenMP (shared memory)
- in future Devito release: domain decomposition for distributed memory

Julia's parallel framework has built-in resilience:

- in case of worker/node failure, workload is redistributed to remaining processors
- program is not interrupted

Overview of Julia Devito



Interface to Devito

(joint work with Mathias Louboutin)

What is Devito?

- domain-specific language for Python
- symbolically set up variety of wave equations (acoustic, anisotropic)
- Devito compiler automatically generates optimized C code
- optimizes Flop count, loops, memory alignment, etc.
- details in the next talk by Mathias

Interfacing Devito from Julia:

- Julia allows direct Python and C function calls
- call Devito functions that generate optimized C code
- call generated C code directly from Julia (no data copies)

Numerical case studies

Full-waveform inversion:

- vanilla FWI w/ gradient descent and line search
- FWI with different misfit functions
- Interfacing optimization libraries for more advanced algorithms

Least-squares migration:

- parallel algorithms: LS-RTM w/ elastic average SGD
- strategies for large-scale migration: compressive LS-RTM
- imaging in the presence of salt

Example 1: FWI with a line search

Full-waveform inversion w/ least squares misfit:

$$\underset{\mathbf{m}}{\text{minimize}} \quad \frac{1}{2}\| \mathcal{F}(\mathbf{m},\mathbf{q}) - \mathbf{d}\|^2$$

Optimization:

- gradient given by $\mathbf{g} = \mathbf{J}^\top\big(\mathcal{F}(\mathbf{m},\mathbf{q}) - \mathbf{d}\big)$
- implement (stochastic) gradient descent w/ approximate line search
- bound constraints for velocity

Example 1: FWI with a line search

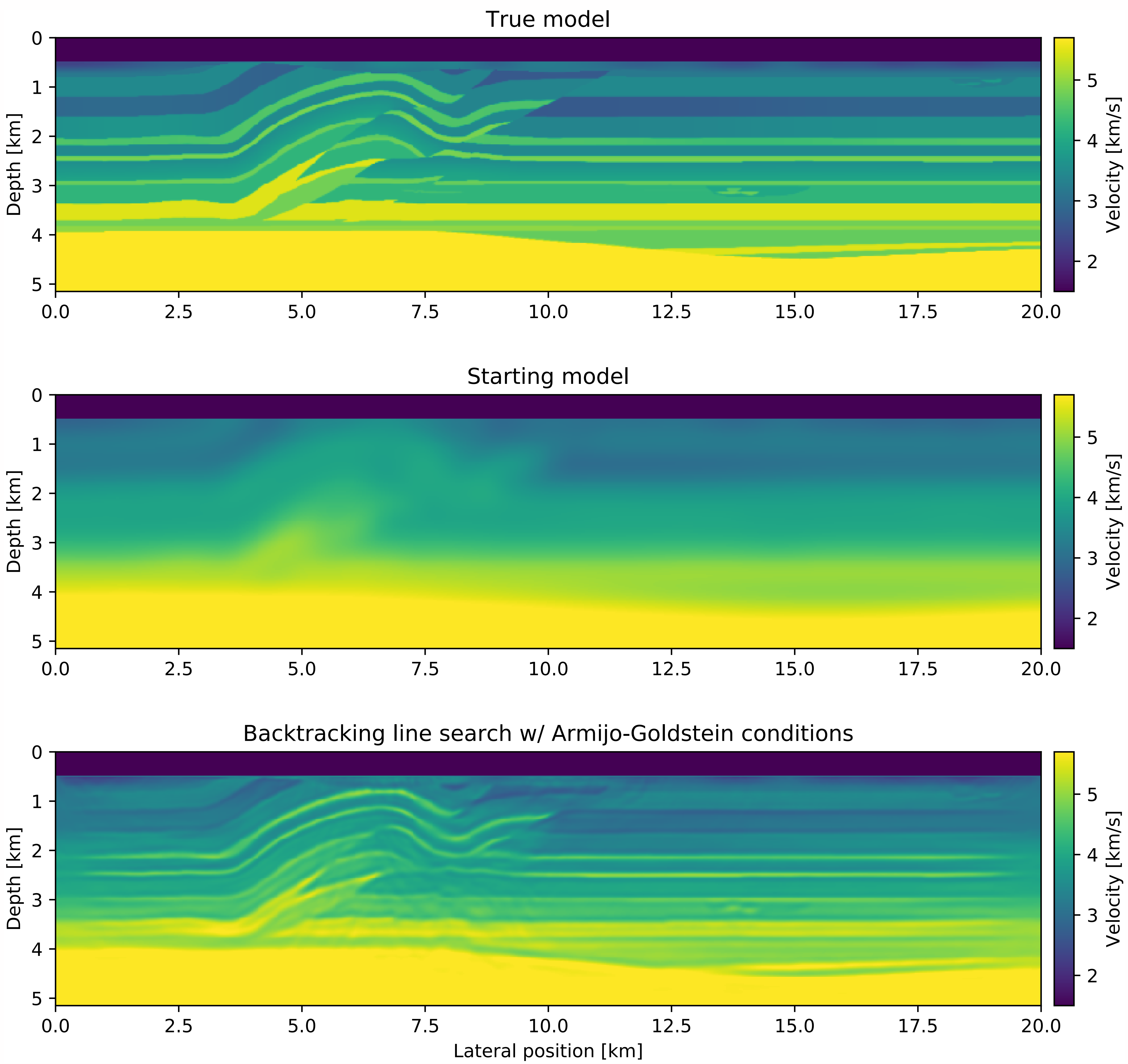
Runnable Julia code:

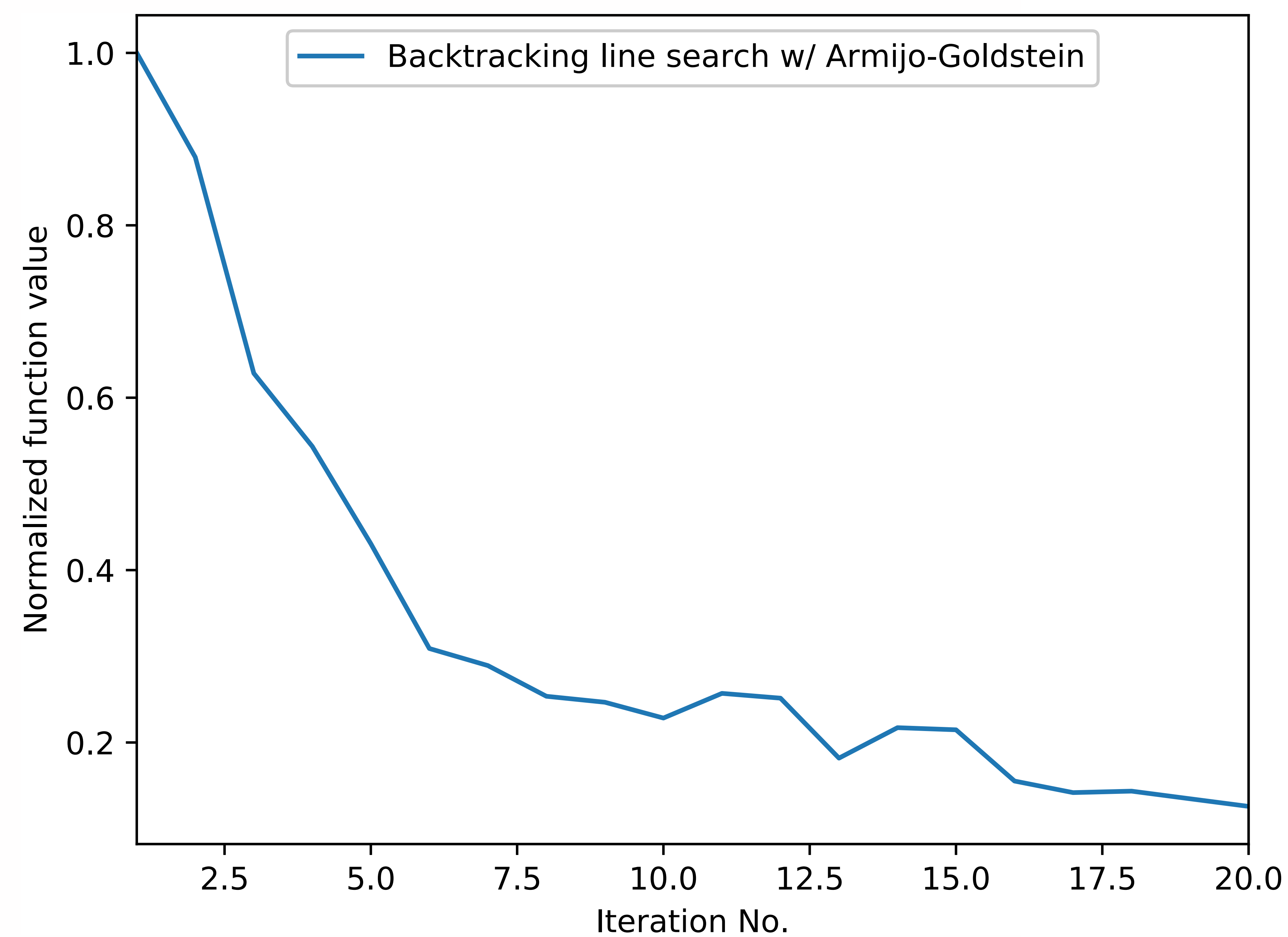
```
# Main loop
for j=1:maxiter

   # select current batch
   idx = randperm(dobs.nsrc)[1:batchsize]
   dsub = subsample(dobs,idx)
   qsub = subsample(q,idx)

   # get fwi objective function value and gradient
   f, g = fwi_objective(model0,qsub,dsub)

   # linesearch
   step = backtracking_linesearch(vec(model0.m), g; varargs...)

   # Update model and bound projection
   model0.m = proj(model0.m + step)

   # termination criteria
   if f <= fTerm || norm(g) <= gradTerm
      break
   end
end
```

alternatively:

- line search w/ (strong) Wolfe conditions
- Barzilai-Borwein step size
- constant step size
- etc.

Example 1: FWI with a line search





Example 2: FWI with different misfit functions

Previous example:

- objective function that returns function value and gradient for ℓ_2 -misfit

```
# get fwi objective function value and gradient
f, g = fwi_objective(model0,qsub,dsub)
```

Change to different misfit:

- if observed data has strong outliers: (pseudo-) Huber misfit

$$\phi(\mathbf{x}) = \epsilon^2 \sqrt{1 + (\mathbf{x}/\epsilon)^2} - 1$$

(Guitton and Symes, 2003; van Leeuwen et al., 2013)

- gradient given by

$$\nabla\phi(\mathbf{x}) = \frac{\mathbf{x}}{\sqrt{1 + (\mathbf{x}/\epsilon)^2}}$$

Example 2: FWI with different misfit functions

Objective function w/ ℓ_2-misfit

```
# FWI with least squares misfit function
function fwi_objective_l2(model::Model,q::joData,d::joData)

   # Set up operators
   nt = get_computational_nt(q.geometry,d.geometry,model)
   info = Info(prod(model.n),d.nsrc,nt)
   F = joModeling(info,model,q.geometry,d.geometry)
   J = joJacobian(F,q)

   # Data residual, function value and gradient
   r = F*q - d
   f = .5*norm(r,2)^2
   g = J'*r
   return f,g
end
```

Objective function w/ pseudo-Huber misfit:

```
# FWI with pseudo-huber misfit function
function fwi_objective_huber(model::Model,q::joData,d::joData)

   # Set up operators
   ...

   # Data residual, function value and gradient
   r = F*q - d
   f = eps^2*sqrt(1 + dot(r,r)/eps^2) - eps^2 # e.g. eps=1
   g = J'*r/sqrt(1 + dot(r,r)/eps^2)
   return f,g
end
```

→ change misfit independently from the rest of the code

Example 3: FWI using optimization libraries

What if we want to use more complicated algorithms?

- previous misfit functions can be passed to third-party optimization libraries
- access to large variety of optimization methods
- no need to implement everything from scratch

Tested for various libraries:

- Julia implementation of minConf (included in software release) (Schmidt et al., 2009)
- Bas' framework for constrained optimization w/ projections onto intersections of convex sets (Peters and Herrmann, 2017)
- NLopt.jl (native Fortran library) (Johnson et al., 2017)
- Optim.jl (native Julia library) (White et al., 2017)

Example 3: FWI using optimization libraries

Does this scale to 3D?

- case study w/ 3D Overthrust velocity model
- 801 x 801 x 207 grid points + PML (222 million unknowns)
- $\sim$10k shot records, 8 km max. offset, 3 seconds recording time (100 billion data points, over 1.2 TB of data)
- spectral-projected gradient algorithm from minConf library
- backtracking line search
- 15 iterations w/ 1080 shot records per iteration

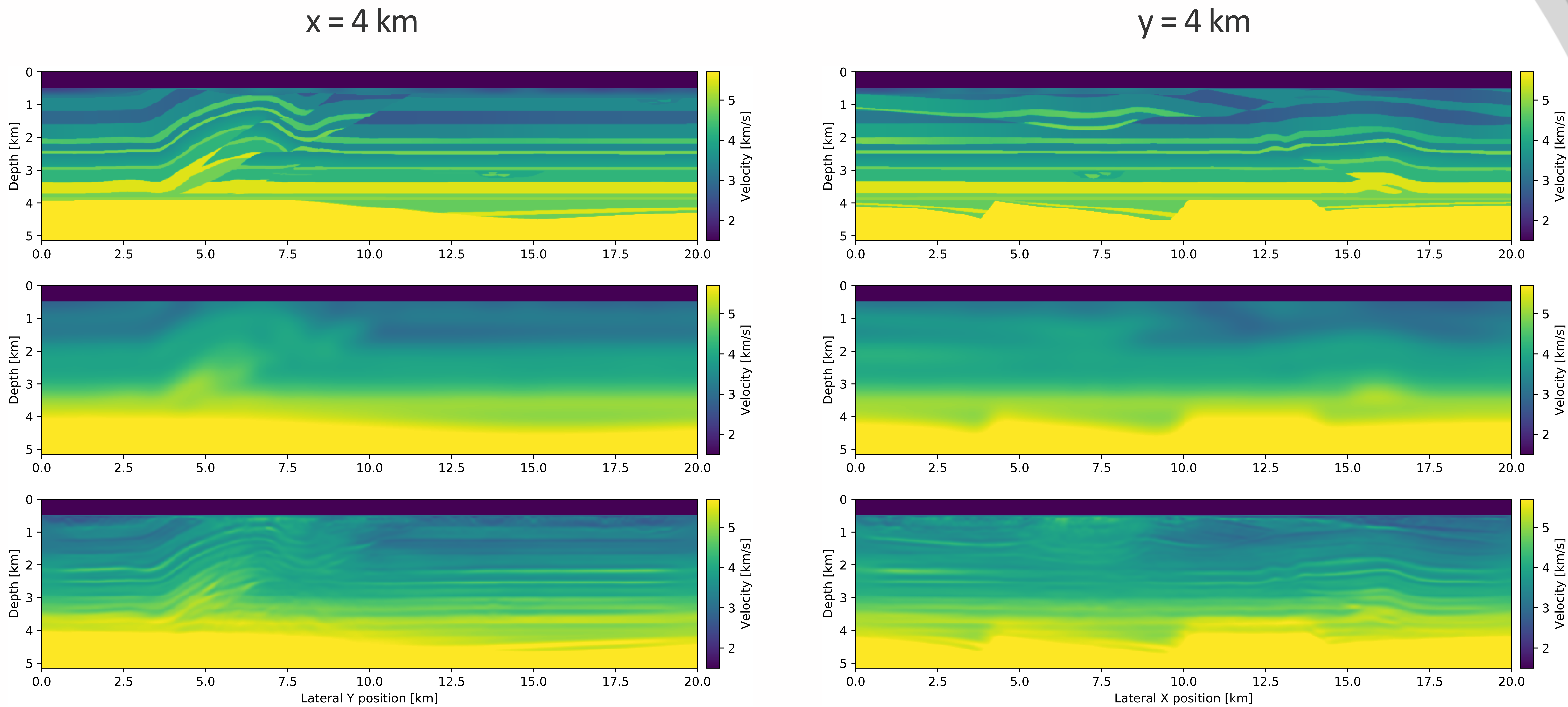
Example 3: FWI using optimization libraries

```
# Optimization parameters
fevals = 15
batchsize = 1080

# Objective function that is passed to library
function objective_function(x)

  # update model
  model0.m = reshape(x,model0.n);

  # select batch
  idx = randperm(dobs.nsrc)[1:batchsize]
  dsub = subsample(dobs,idx)
  qsub = subsample(q,idx)

  # fwi function value and gradient
  fval, grad = fwi_misfit(model0,qsub,dsub;options=opt)

  # reset gradient in water column to 0.
  grad = reshape(grad,model0.n)
  grad[:,:,1:21] = 0.f0

  return fval, vec(grad)
end

# Bound projection
Proj(x) = median([mmin x mmax],2)

# FWI with spectral projected gradient from minConf library
x,fval = minConf_SPG(objective_function,vec(model0.m),Proj,opt)
```

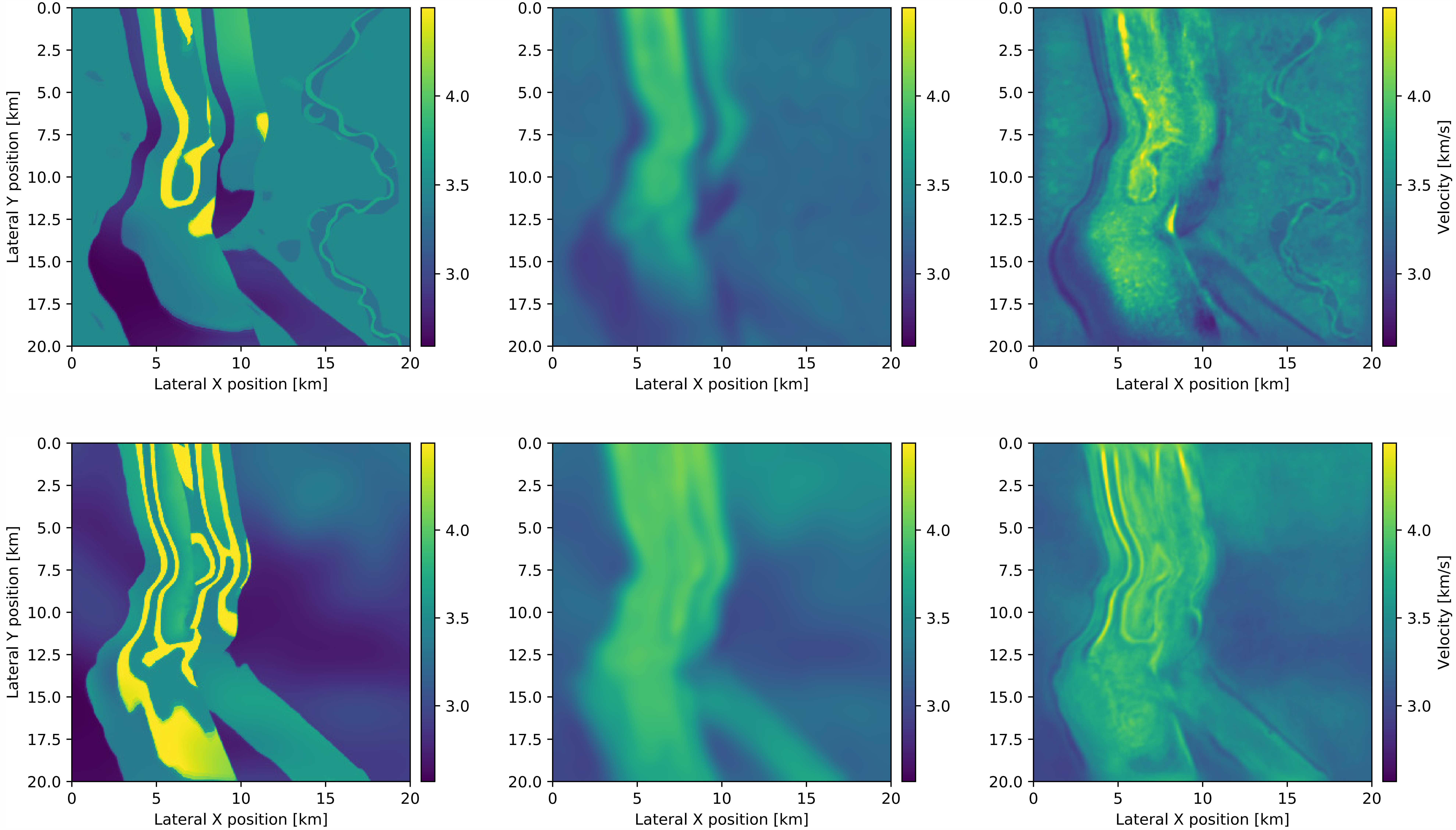
Set up 3D FWI in < 50 lines of code:

- possible to work w/ subset of shots
- still access to gradient (mute, scale etc.)
- change from SPG to L-BFGS by modifying 2 lines of code
- works with out-of-core data containers (handle arbitrary sized data sets)
- 4 minutes per gradient (1 node, 20 threads)

Example 3: FWI using optimization libraries



Example 3: FWI using optimization libraries



z = 400 m

z = 800 m

Example 4: Serial and parallel SGD

What about parallel algorithms?

- parallel version of stochastic gradient descent: elastic average SGD (Zhang et al., 2015)
- change from serial to parallel version in few lines of code

Case study for LS-RTM (but could be used for FWI as well):

$$\underset{\widehat{\delta \mathbf{m}}}{\text{minimize}} \quad \frac{1}{2} || \mathbf{M}_l^{-1} \mathbf{J} \mathbf{M}_r^{-1} \widehat{\delta \mathbf{m}} - \mathbf{M}_l^{-1} \delta \mathbf{d} ||_2^2$$

(e.g. Herrmann et al., 2008; Dai et al., 2012)

- $\mathbf{M}_l^{-1}, \mathbf{M}_r^{-1}$ are left- and right preconditioners (model-, data-topmute, scaling, etc.)

Example 4: LS-RTM w/ serial and parallel SGD

Algorithm 1 Preconditioned LS-RTM with SGD

for $j = 1$ to n **do**

$\mathbf{r}_j = \mathbf{M}_l^{-1}\mathbf{J}_{r(j)}\mathbf{M}_r^{-1}\mathbf{x}_j - \mathbf{M}_l^{-1}\delta\mathbf{d}_{r(j)}$

$\mathbf{g}_j = \mathbf{M}_r^{-\top}\mathbf{J}_{r(j)}^{\top}\mathbf{M}_l^{-\top}\mathbf{r}_j$

$t_j = \frac{\|\mathbf{r}_j\|^2}{\|\mathbf{g}_j\|^2}$

$\mathbf{x}_{j+1} = \mathbf{x}_j - t_j\mathbf{g}_j$

end for

```
# Stochastic gradient descent
batchsize = 10
niter = 32

for j=1:niter
   # Select batch
   idx = randperm(dD.nsrc)[1:batchsize]
   Jsub = subsample(J,idx)
   dsub = subsample(dD,idx)

   # Compute residual and gradient
   r = Ml*Jsub*Mr*x - Ml*dsub
   g = Mr'*Jsub'*Ml'*r

   # Step size and update variable
   t = norm(r)^2/norm(g)^2
   x -= t*g
end
```

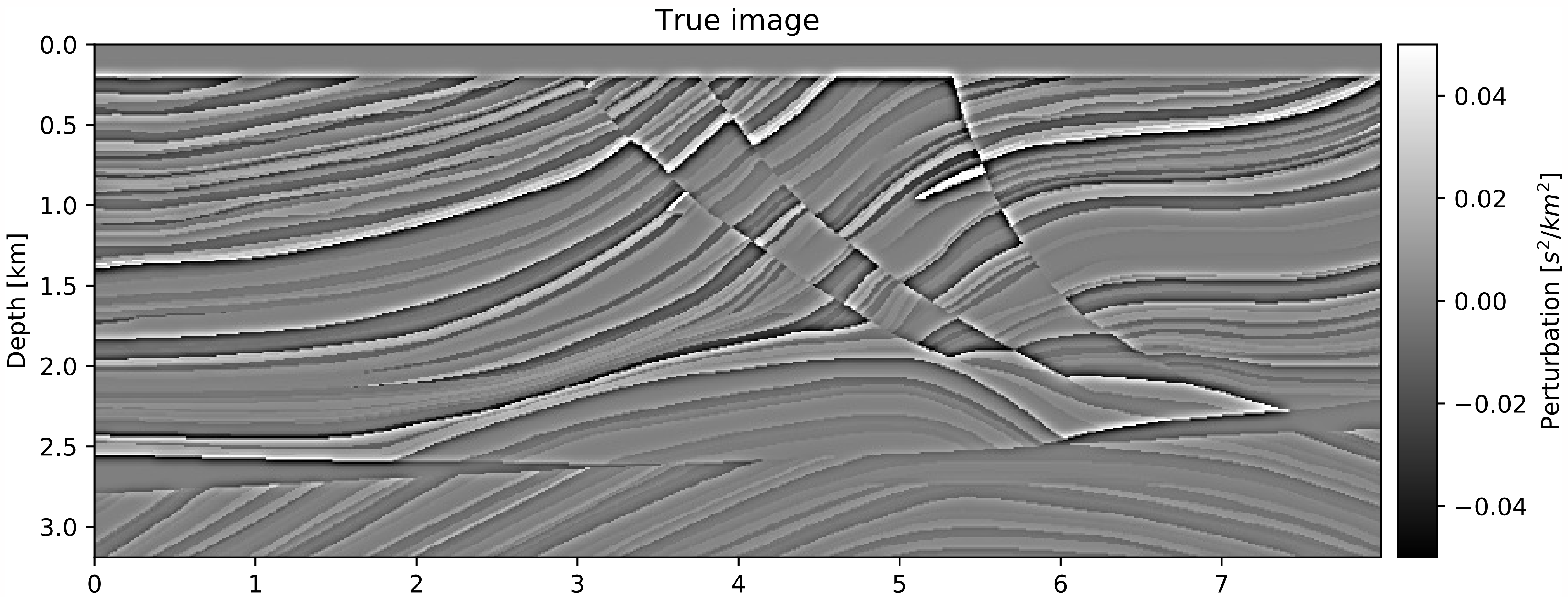
Example 4: LS-RTM w/ serial and parallel SGD

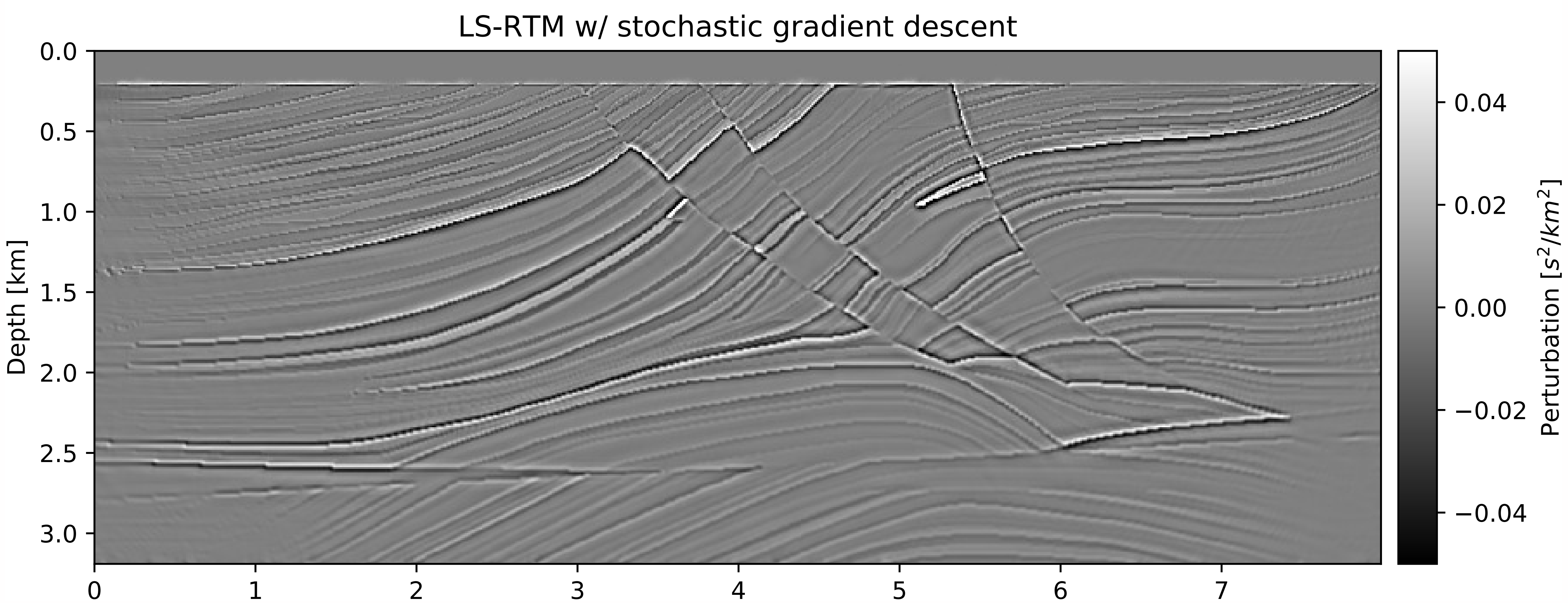
Algorithm 2 Preconditioned LS-RTM with elastic average SGD

for $j = 1$ to n **do**
  for $k = 1$ to p **do**
    $\mathbf{r}_j = \mathbf{M}_l^{-1}\mathbf{J}_{jk}\mathbf{M}_r^{-1}\mathbf{x}_j^k - \mathbf{M}_l^{-1}\delta\mathbf{d}_{jk}$
    $\mathbf{g}_j = \mathbf{M}_r^{-\top}\mathbf{J}_{jk}^{\top}\mathbf{M}_l^{-\top}\mathbf{r}_j$ and
    $\mathbf{x}_{j+1}^k = \mathbf{x}_j^k - \eta\mathbf{g}_j^k(\mathbf{x}_j^k) - \alpha(\mathbf{x}_j^k - \tilde{\mathbf{x}}_j)$
  end for
  $\tilde{\mathbf{x}}_{j+1} = (1-\beta)\tilde{\mathbf{x}}_j + \beta(\frac{1}{p}\sum_{i=1}^{p}\mathbf{x}_j^i)$
end for

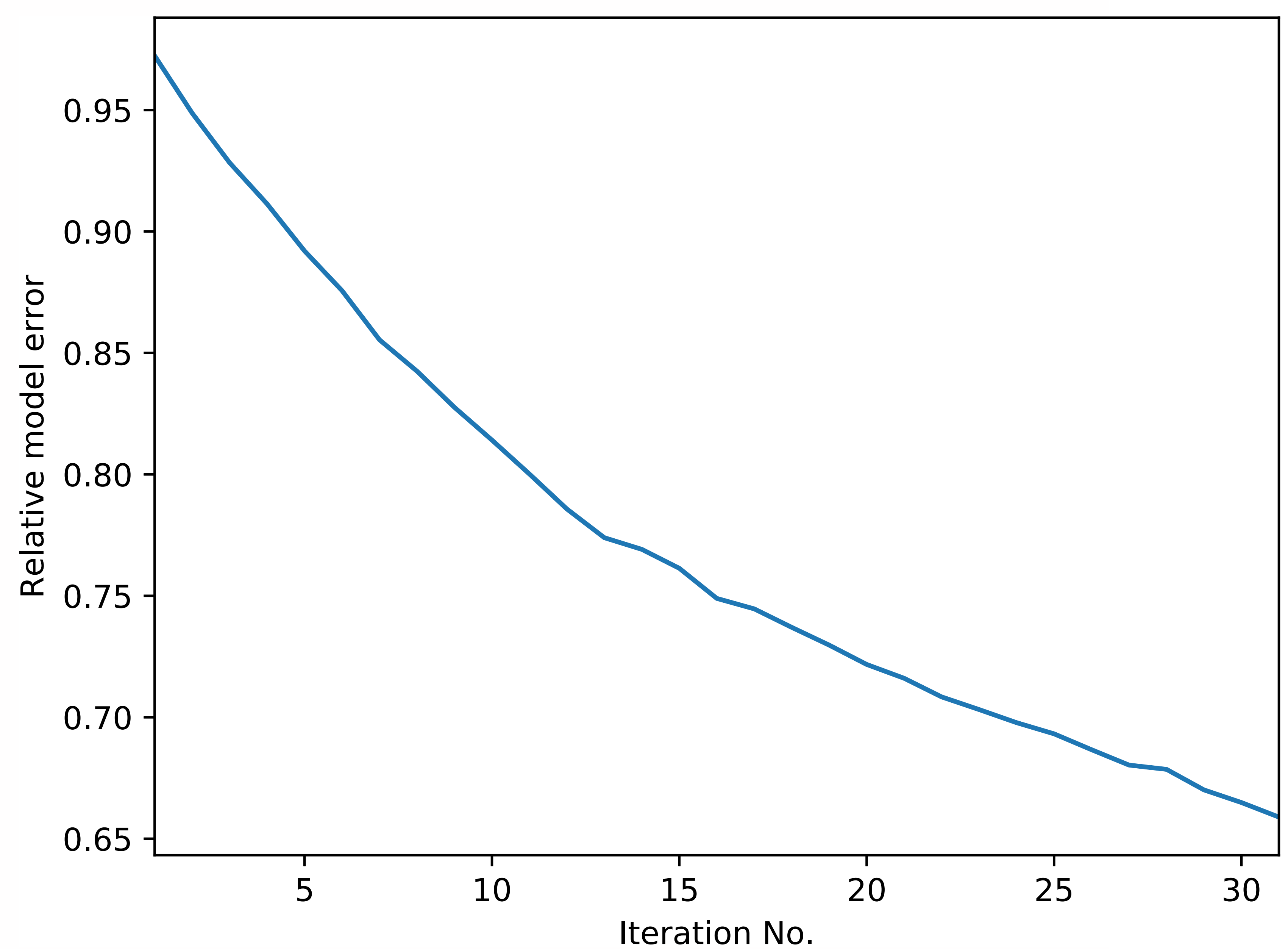
```
# Gradient function
@everywhere function update_x(Ml,J,Mr,x,d,eta,alpha,xav)
  r = Ml*J*Mr*x - Ml*d
  g = Mr'*J'*Ml'*r
  return x - eta*g - alpha*(x - xav)
end
update_x_par = remote(update_x) # Parallel function wrapper

for j=1:niter
  @sync begin
    for k=1:p

      # Select batch
      idx = randperm(dD.nsrc)[1:batchsize]
      Jsub = subsample(J,idx)
      dsub = subsample(dD,idx)

      # Calculate x update in parallel
      xnew[:,k] = update_x_par(Ml,Jsub,Mr,x[:,k],
                               dsub,eta,alpha,xav)
    end
  end

  # Update average variable
  xav = (1 - beta)*xav + beta*(1/p *sum(x,2))
  x = copy(xnew)
end
```

Example 4: LS-RTM w/ serial and parallel SGD





- marine streamer acquisition
- 320 shots
- 4 km maximum offset
- 32 iterations w/ 10 shots per iteration
- 1 pass through data



Example 5: Compressive inversion

Challenges of large-scale 3D inversion:

- save forward wavefields for gradient
- domain decomposition, checkpointing, boundary reconstruction
- on-the-fly DFT for frequency domain gradients (Sirgue et al., 2010)

Devito allows to easily implement:

- boundary reconstruction
- on-the-fly DFT
- domain decomposition + checkpointing require more effort (w.i.p.)

Example 5: Compressive inversion

Implement inversion with on-the-fly DFT in Devito:

- sum wavefields in the forward time loop
- two extra lines of Python code

```
    # On-the-fly real-valued DFT
    eqn_f_r = [Eq(ufr, ufr + u*cos(2*np.pi*f*time*dt))]
    eqn_f_i = [Eq(ufi, ufi + u*sin(2*np.pi*f*time*dt))]
```

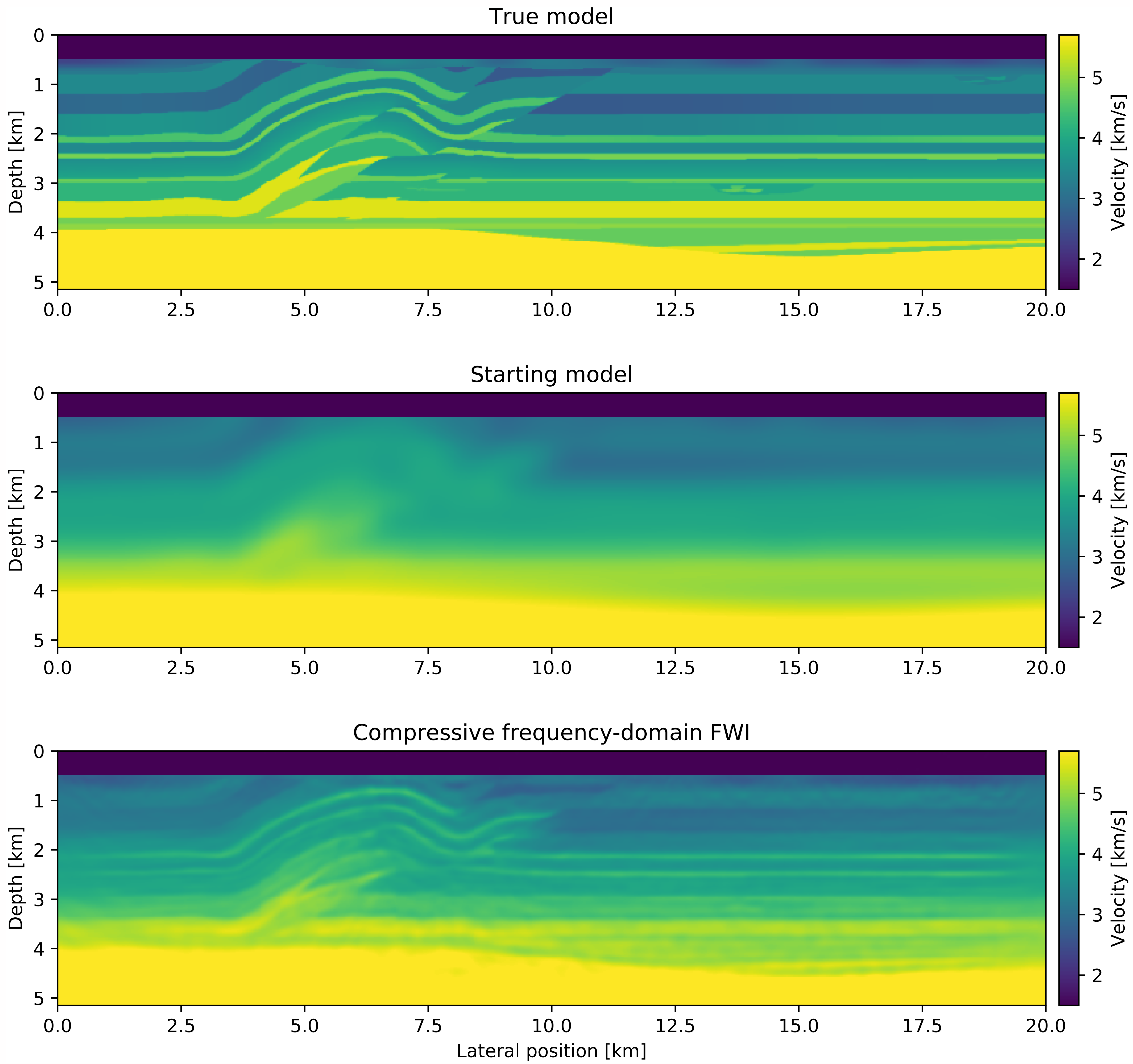
- similar change for gradients

Run FWI or LS-RTM **at any scale:**

- only save few frequency-domain wavefields
- integrates seamlessly into Julia framework
- applications: source encoded/simultaneous source FWI and LS-RTM

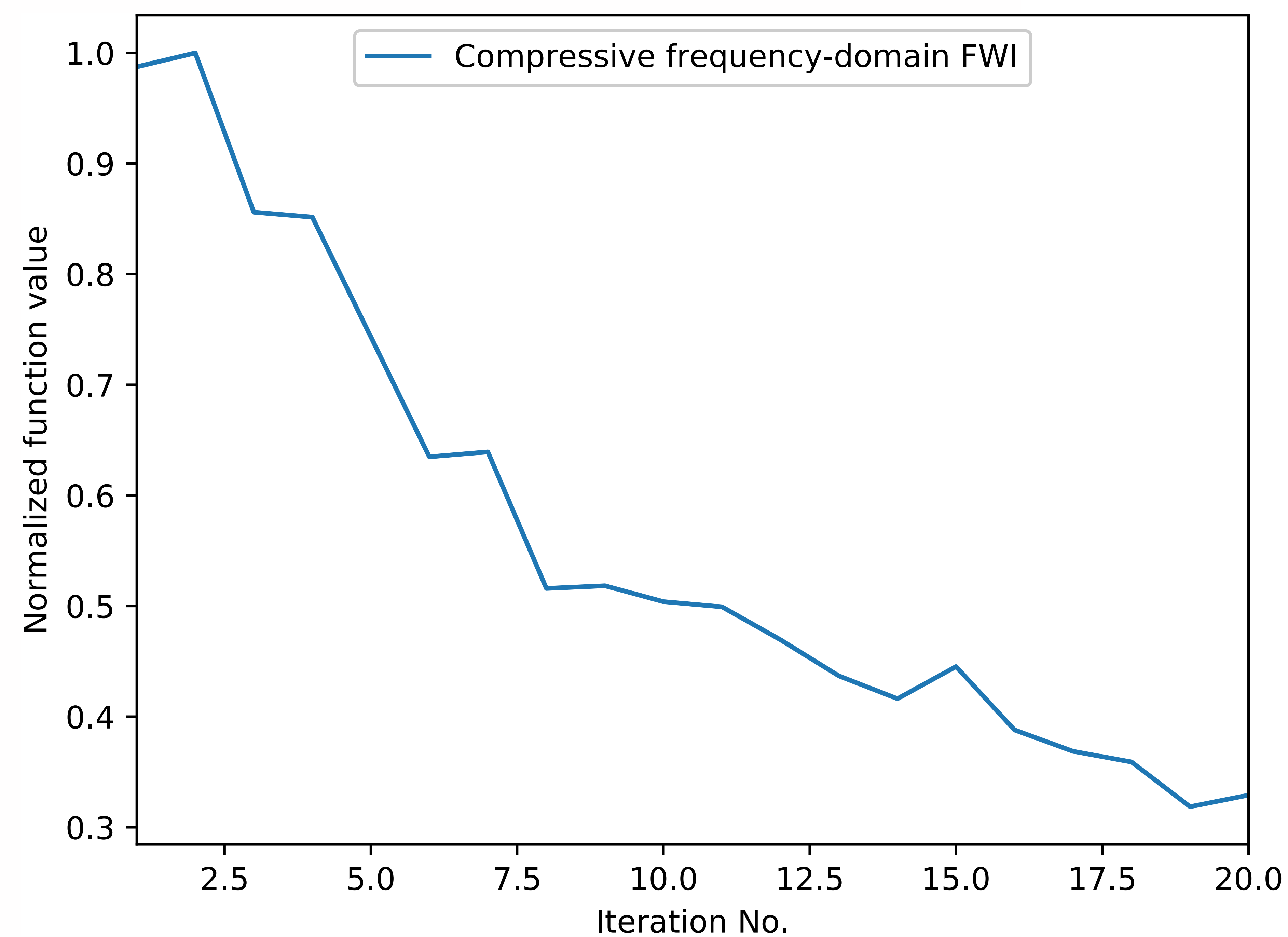
(e.g. Romero et al., 2000; Krebs et al., 2009; Herrmann et al., 2009; Dai et al., 2013)

Example 5a: Compressive FWI



FWI revisited:

- same data and script as before
- SGD w/ line search
- overlapping frequency bands from 3-15 Hz
- only save 5 wavefields in memory



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Example 5b: Compressive imaging

Imaging with frequency subsampling more challenging:

- subsampling creates noisy images
- want sharp image (broad frequency band) from few frequencies

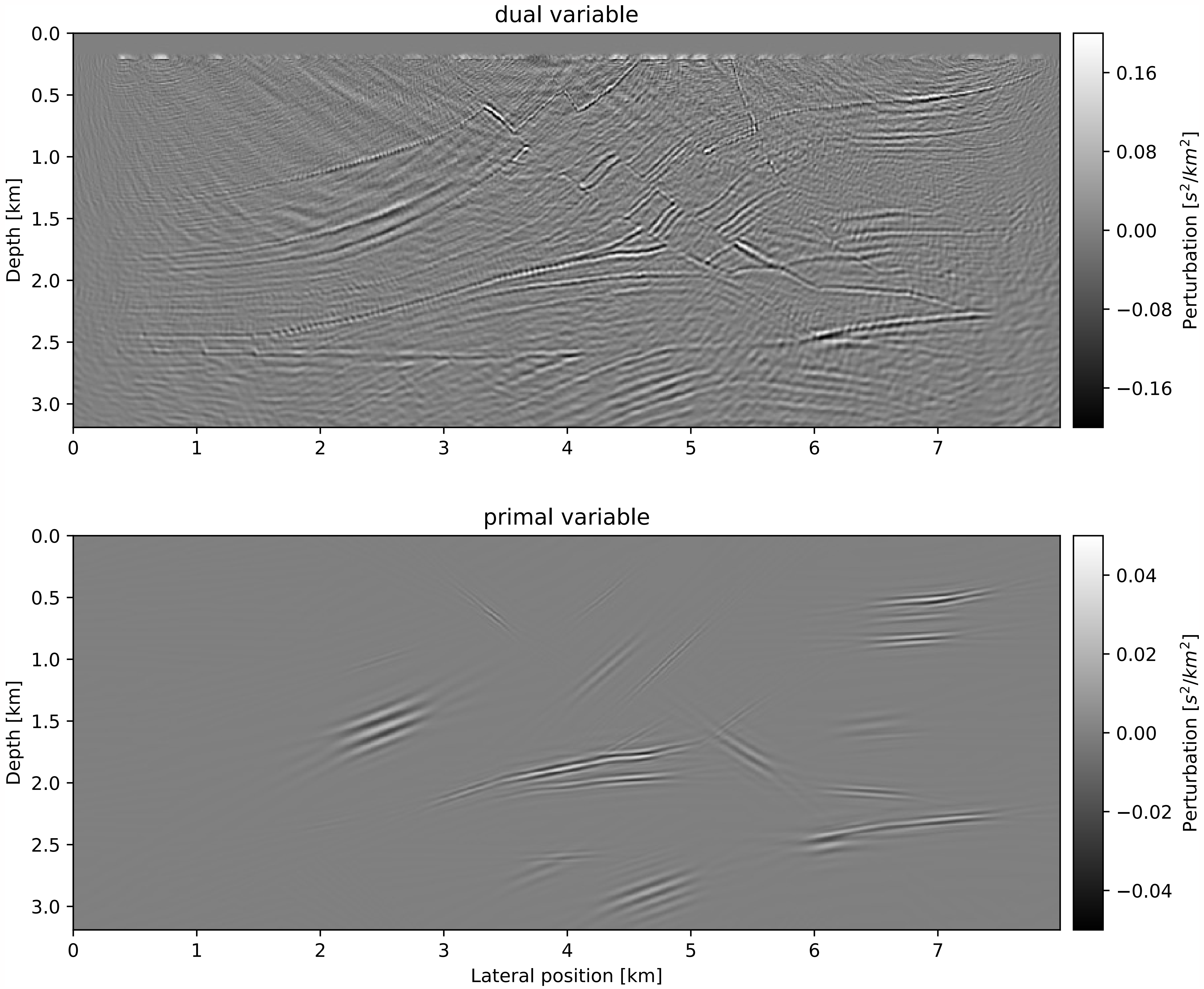
Sparsity-promoting "compressive" LS-RTM: (Herrmann and Li, 2012; Dai et al., 2013)

- frequency-domain imaging w/ time-domain modeling
- work with subsets of random shots and frequencies
- sparsity-promotion to address artifacts

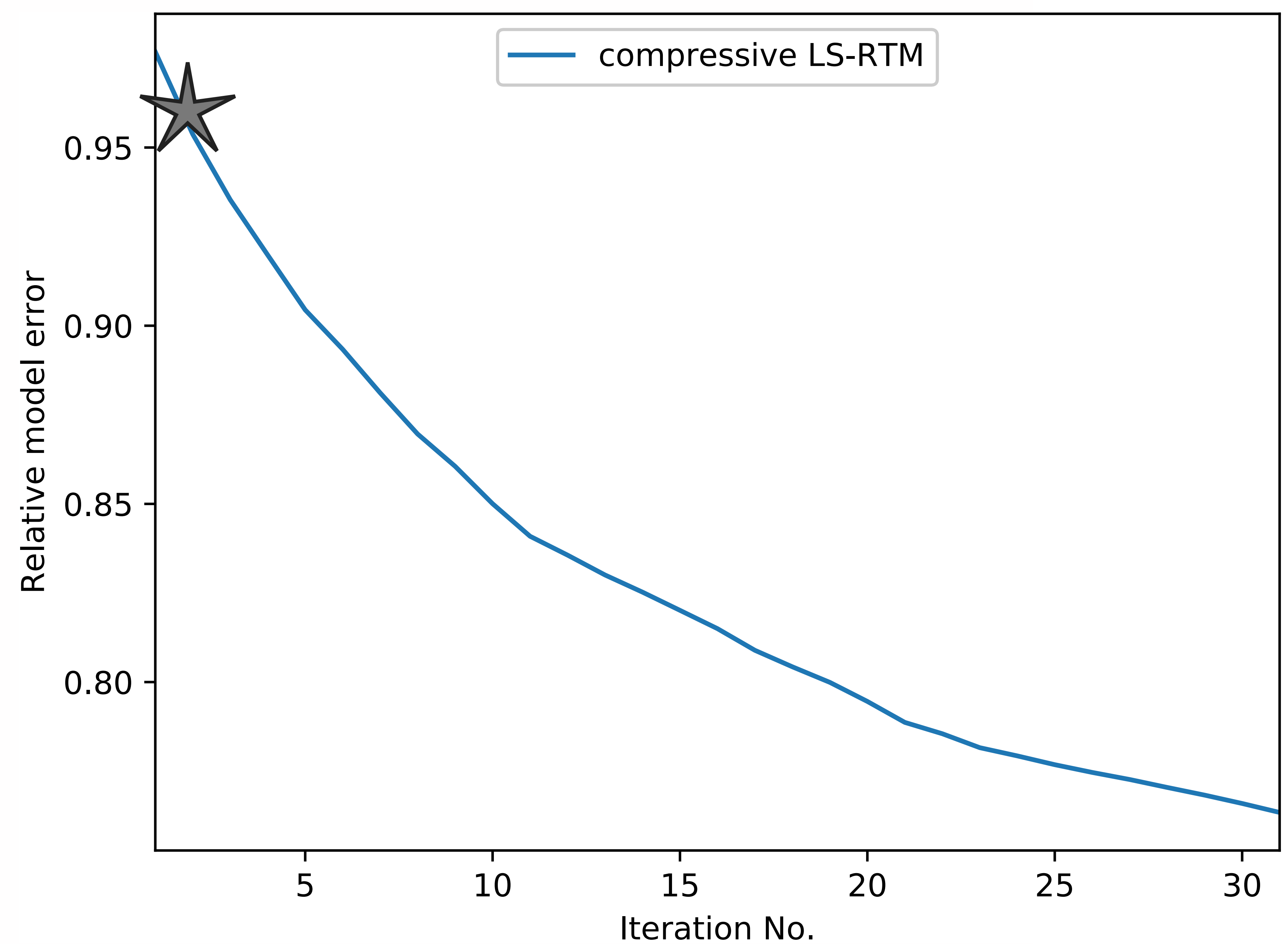
$$\begin{aligned}&\underset{\delta\mathbf{m}}{\text{minimize}} \quad \lambda\|\mathbf{C}\,\delta\mathbf{m}\|_1 + \frac{1}{2}\|\mathbf{C}\,\delta\mathbf{m}\|_2^2 \\ &\text{subject to: } \mathcal{F}\mathbf{J}\,\delta\mathbf{m} = \mathcal{F}\delta\mathbf{d}\end{aligned}$$

Example 5b: Compressive imaging

Iteration 2

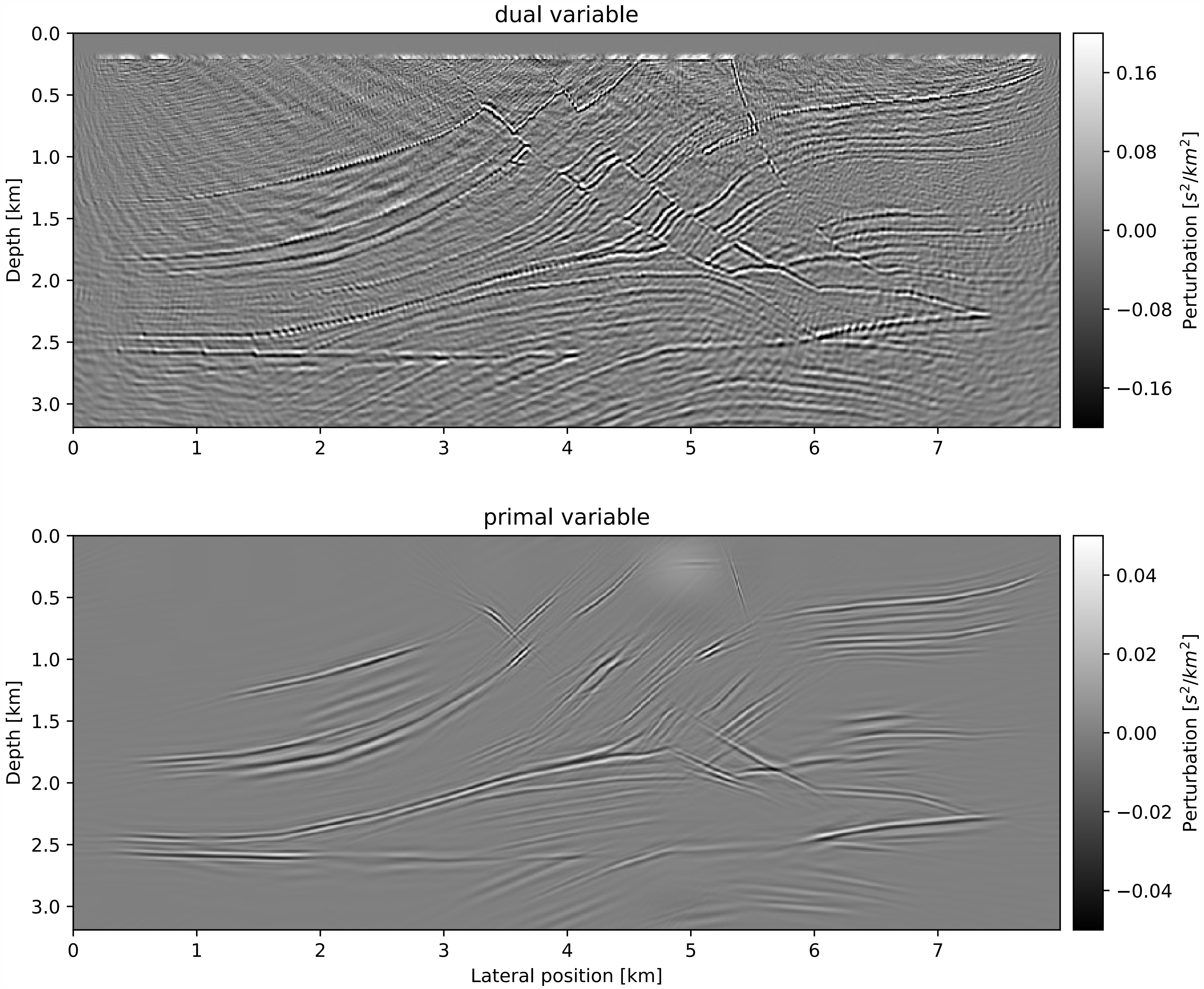


- per iteration: 20 randomly select shots w/ 10 random frequencies each

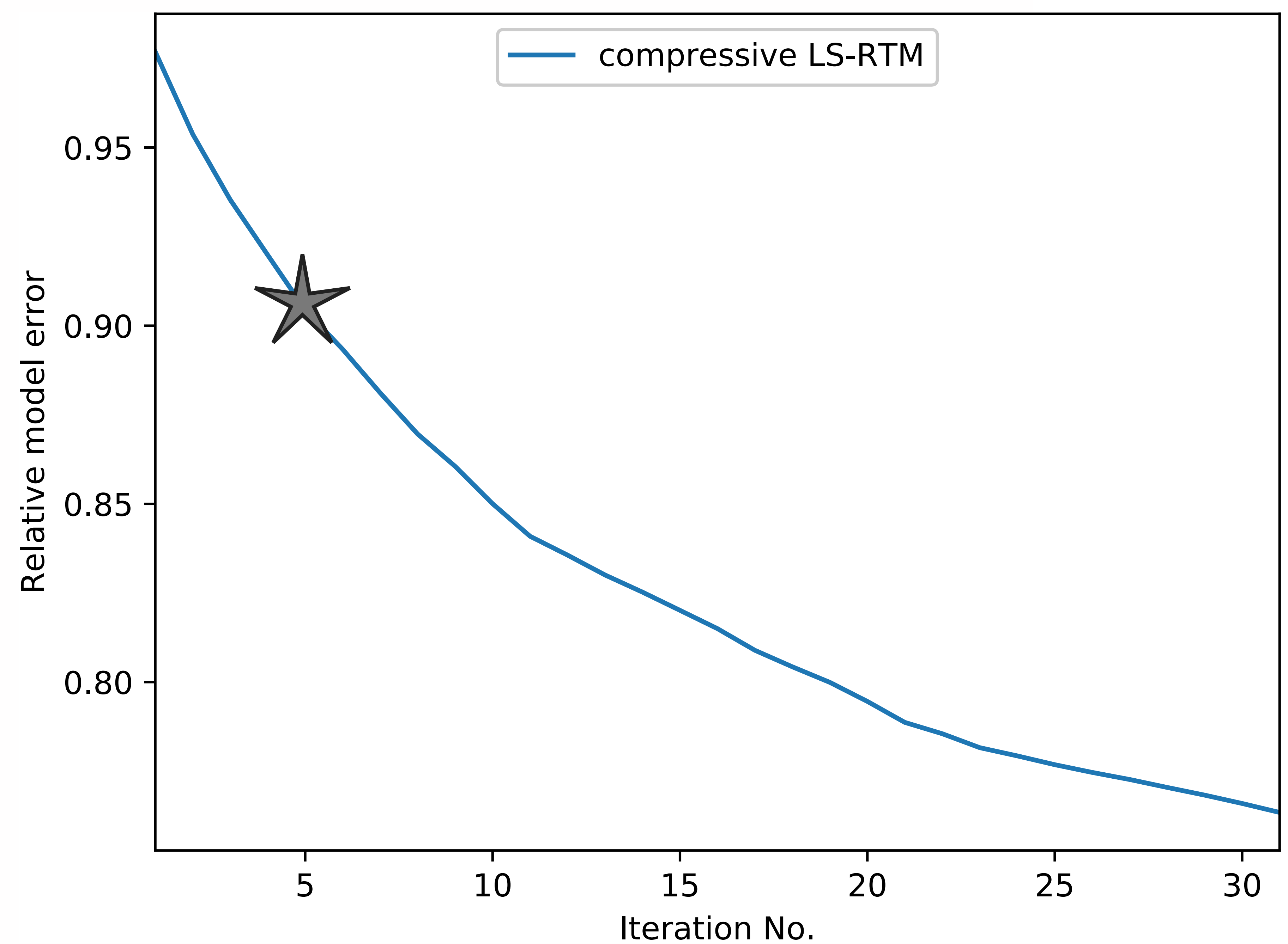


Example 5b: Compressive imaging

Iteration 5

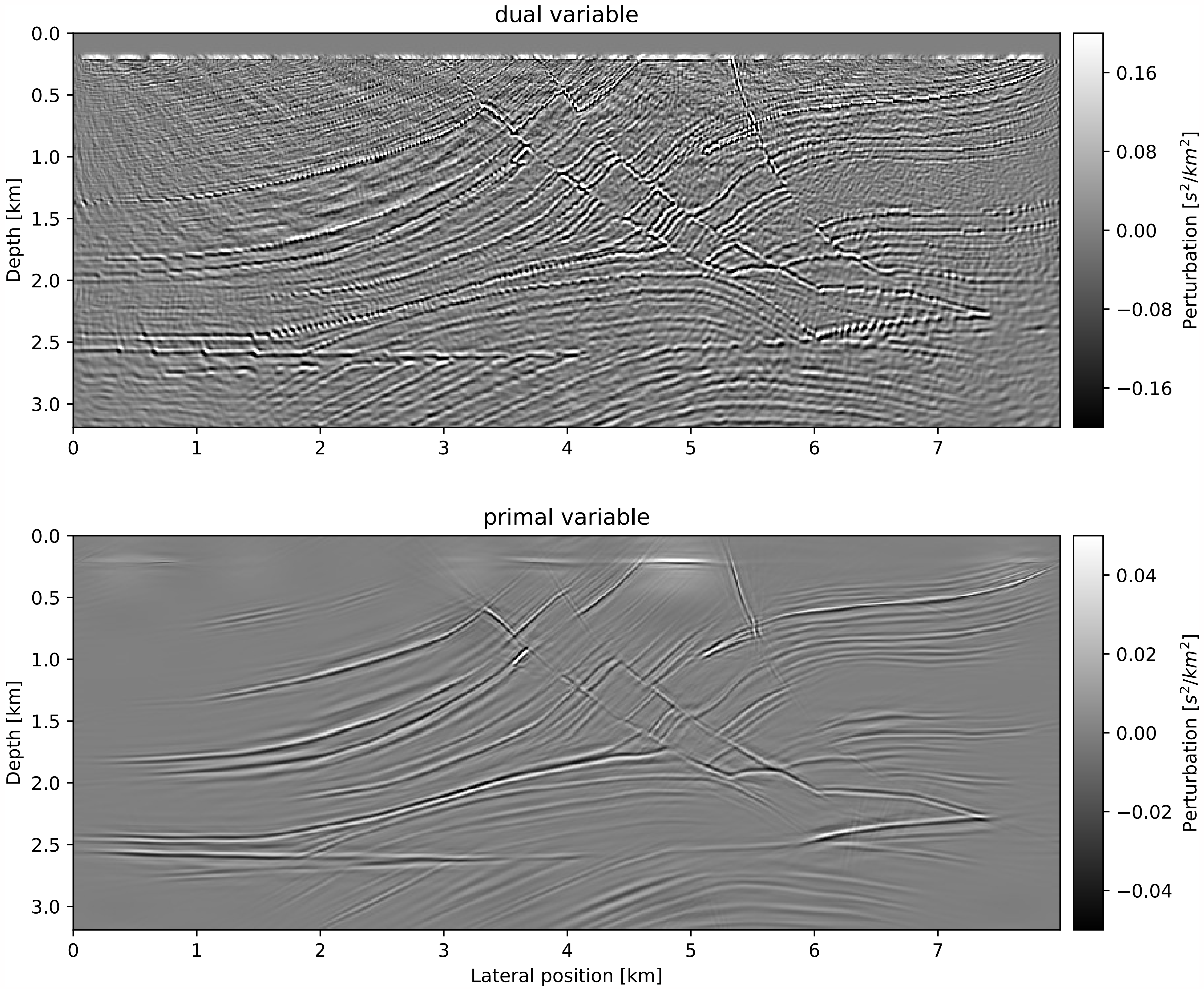


- per iteration: 20 randomly select shots w/ 10 random frequencies each

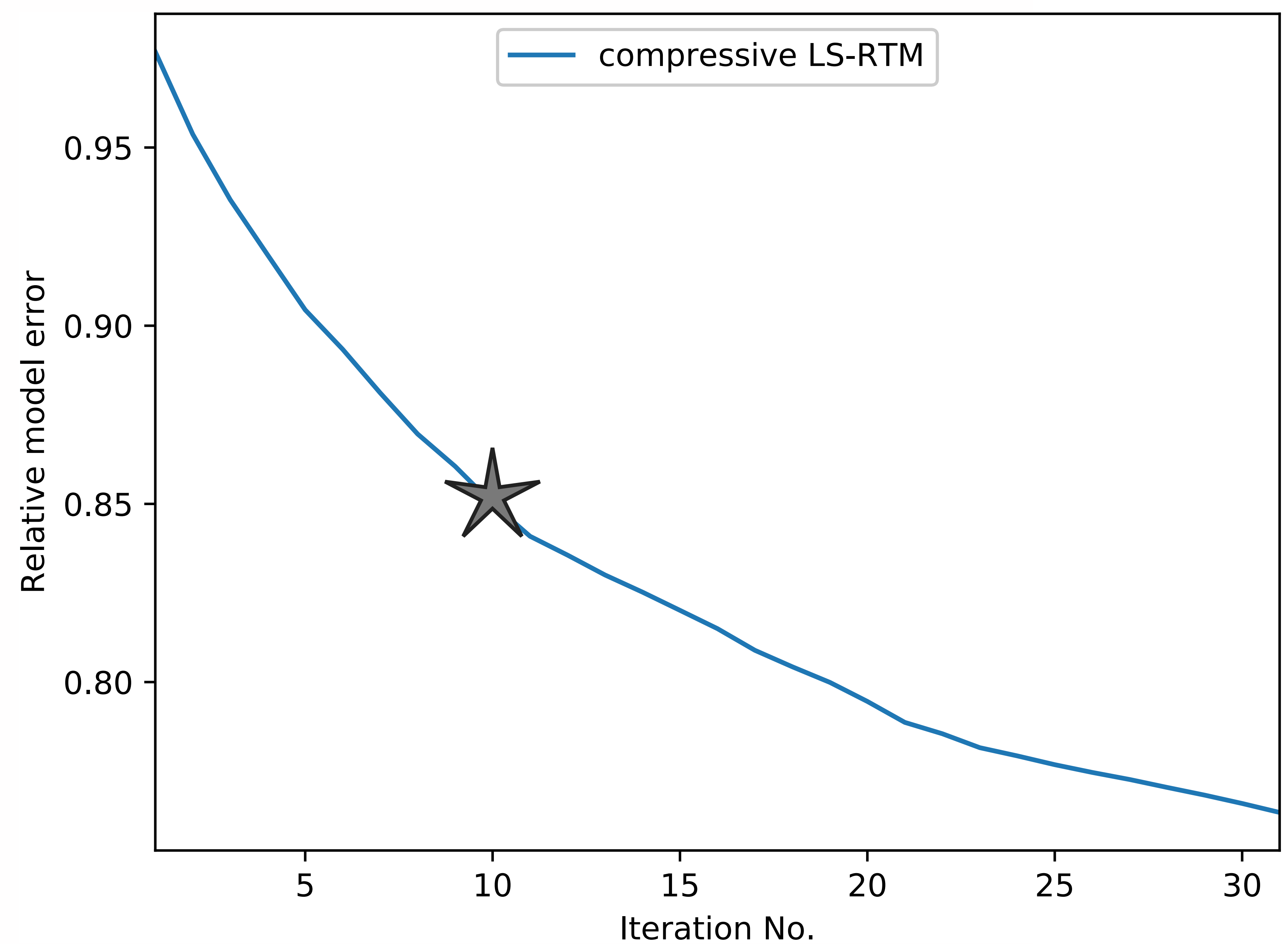


Example 5b: Compressive imaging

Iteration 10

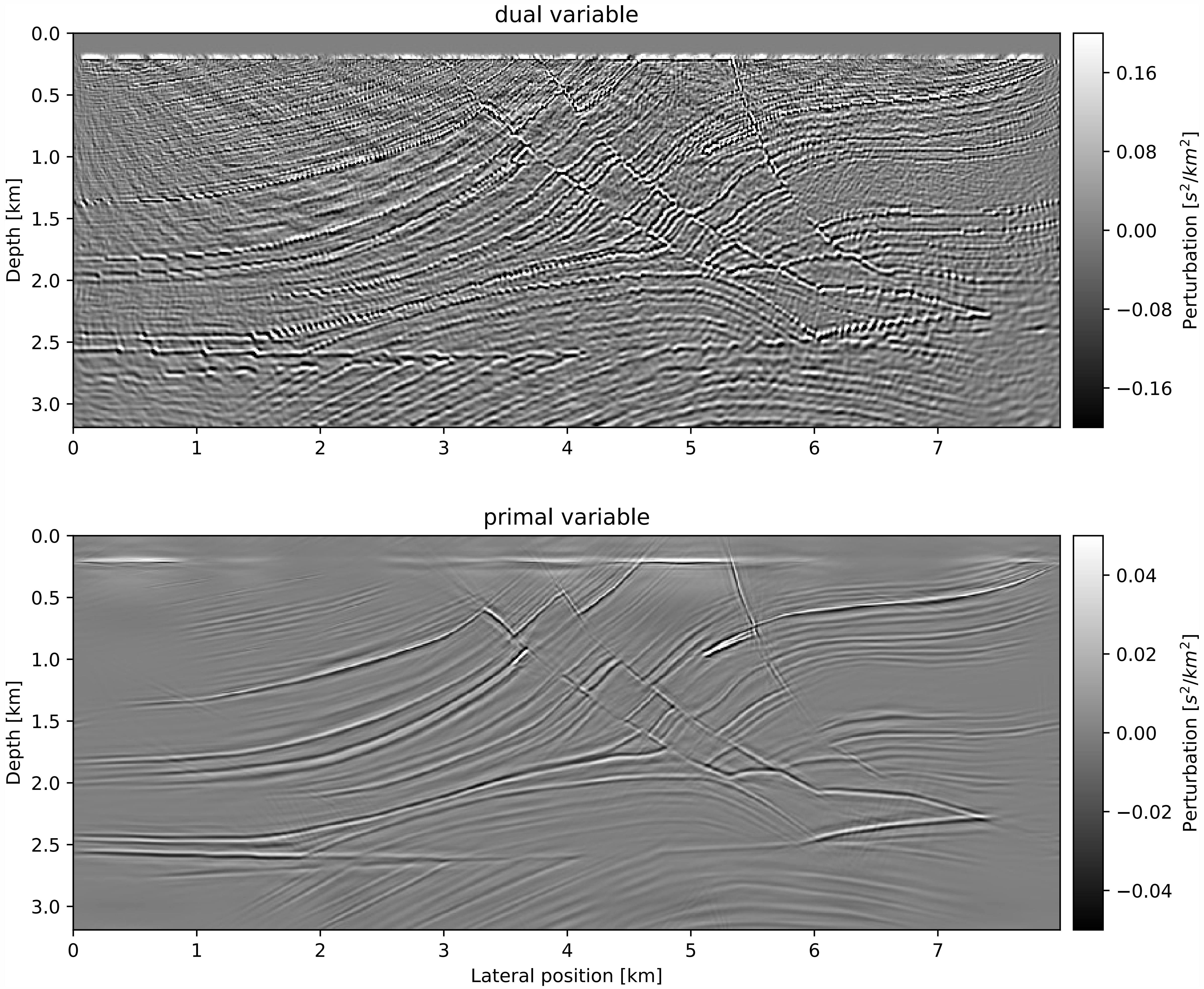


- per iteration: 20 randomly select shots w/ 10 random frequencies each

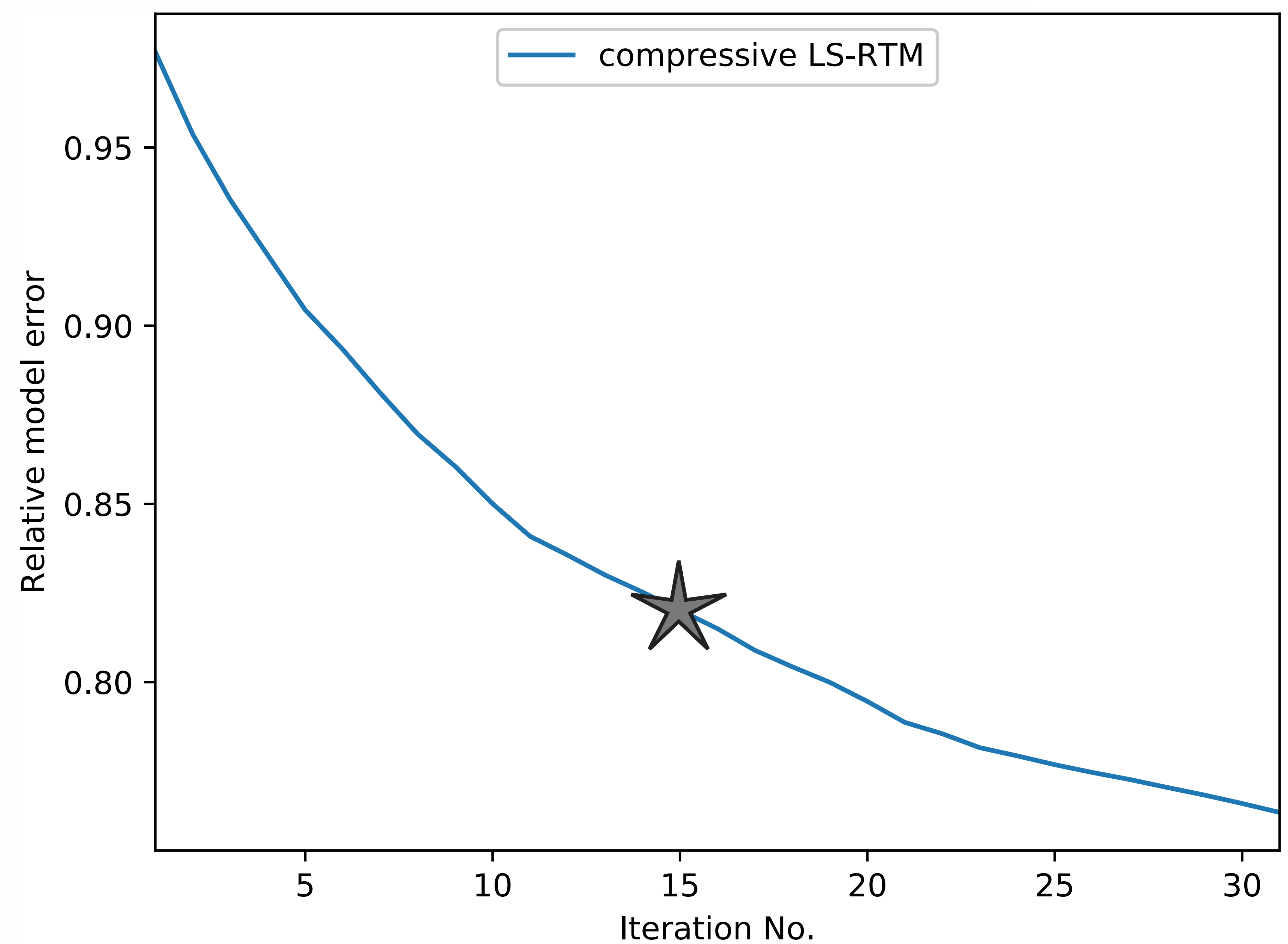


Example 5b: Compressive imaging

Iteration 15

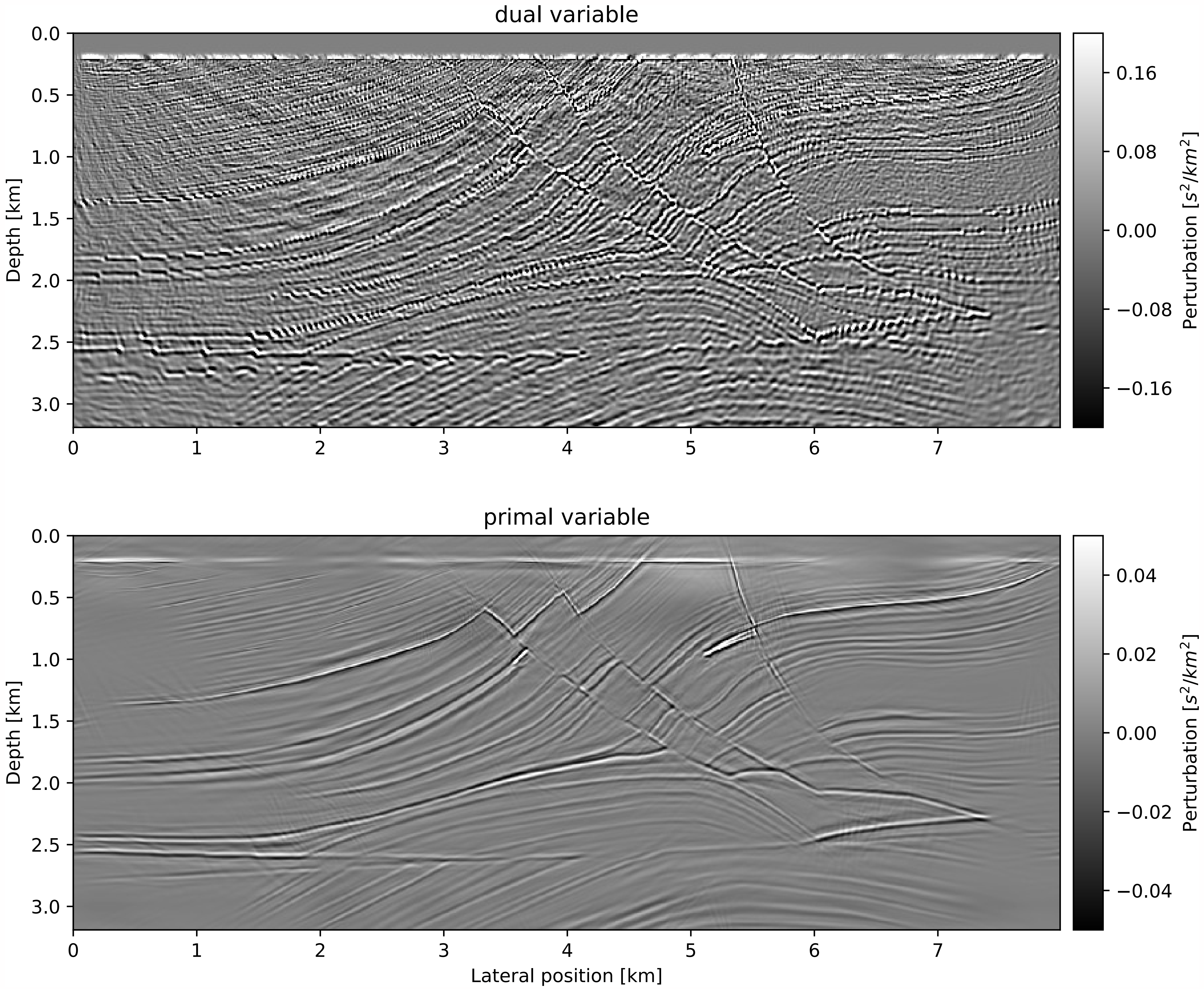


- per iteration: 20 randomly select shots w/ 10 random frequencies each

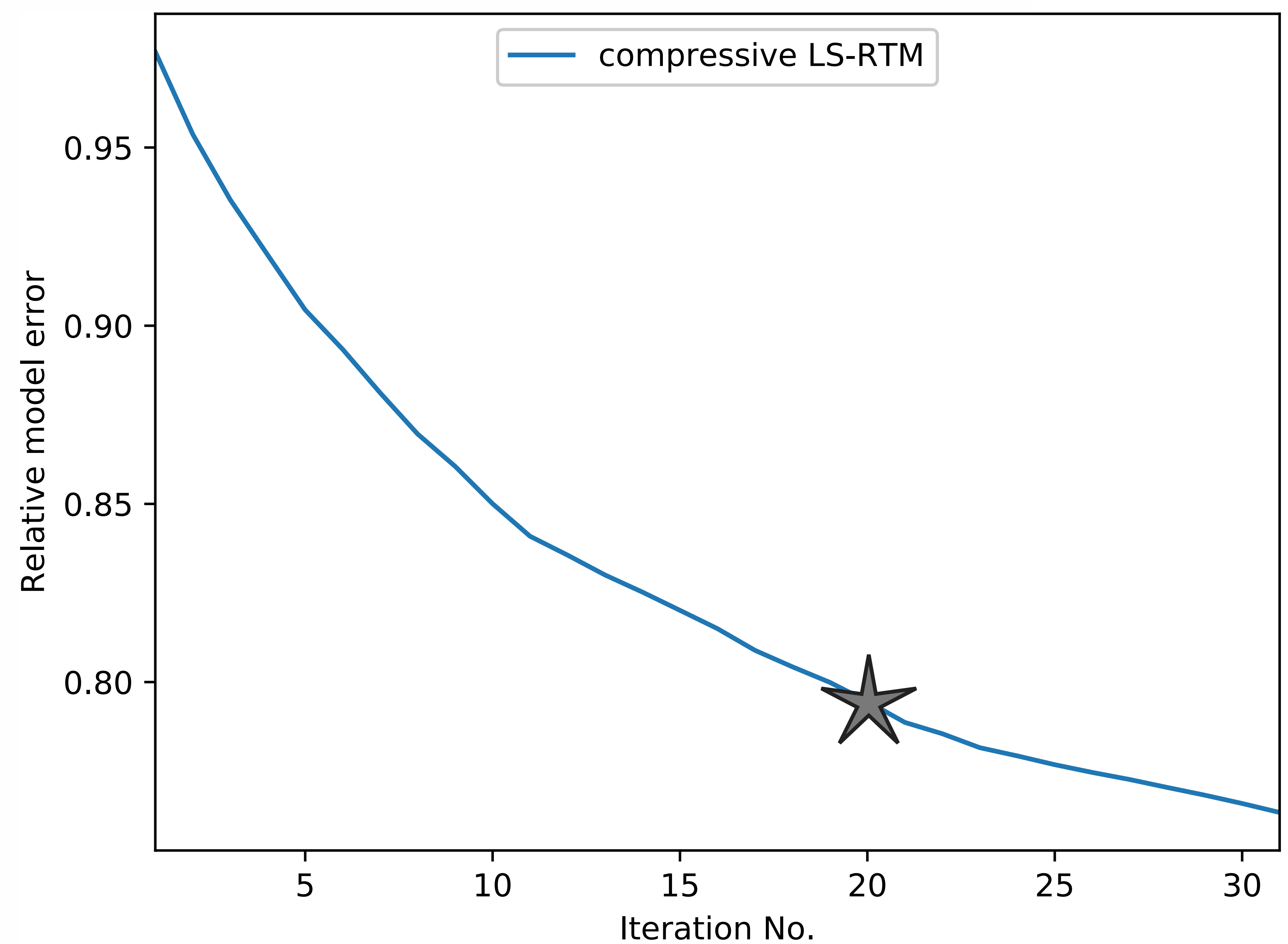


Example 5b: Compressive imaging

Iteration 20

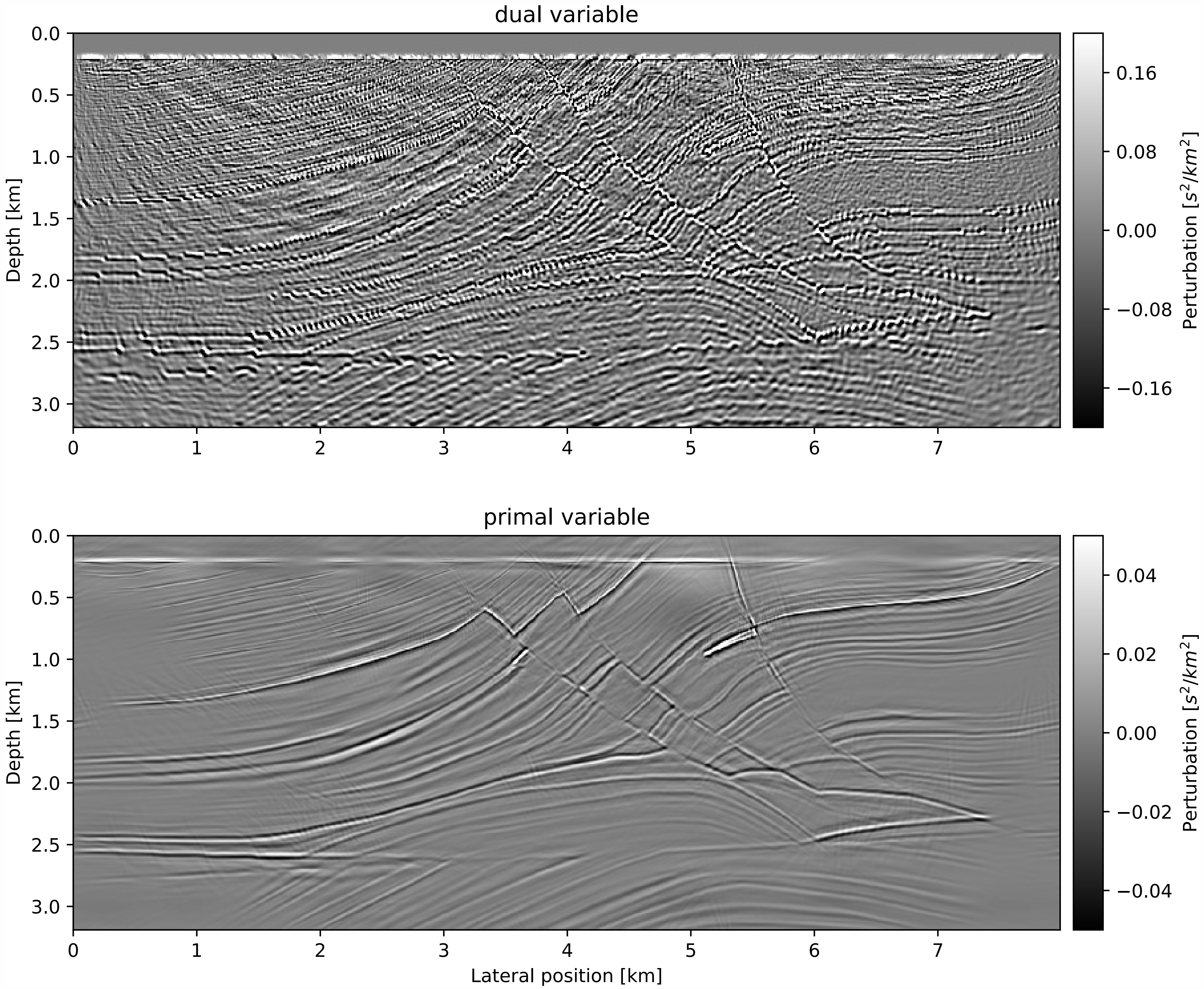


- per iteration: 20 randomly select shots w/ 10 random frequencies each

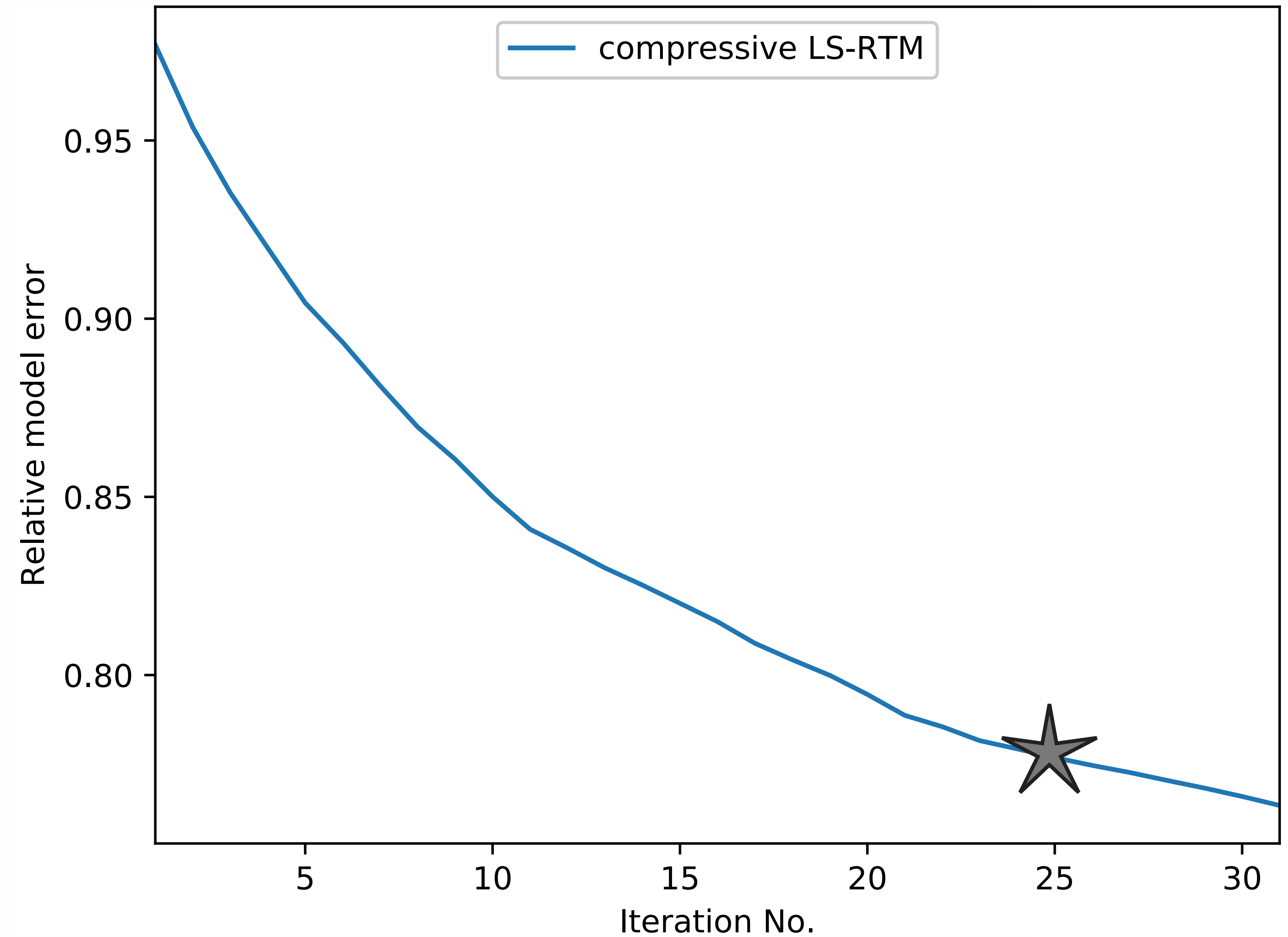


Example 5b: Compressive imaging

Iteration 25

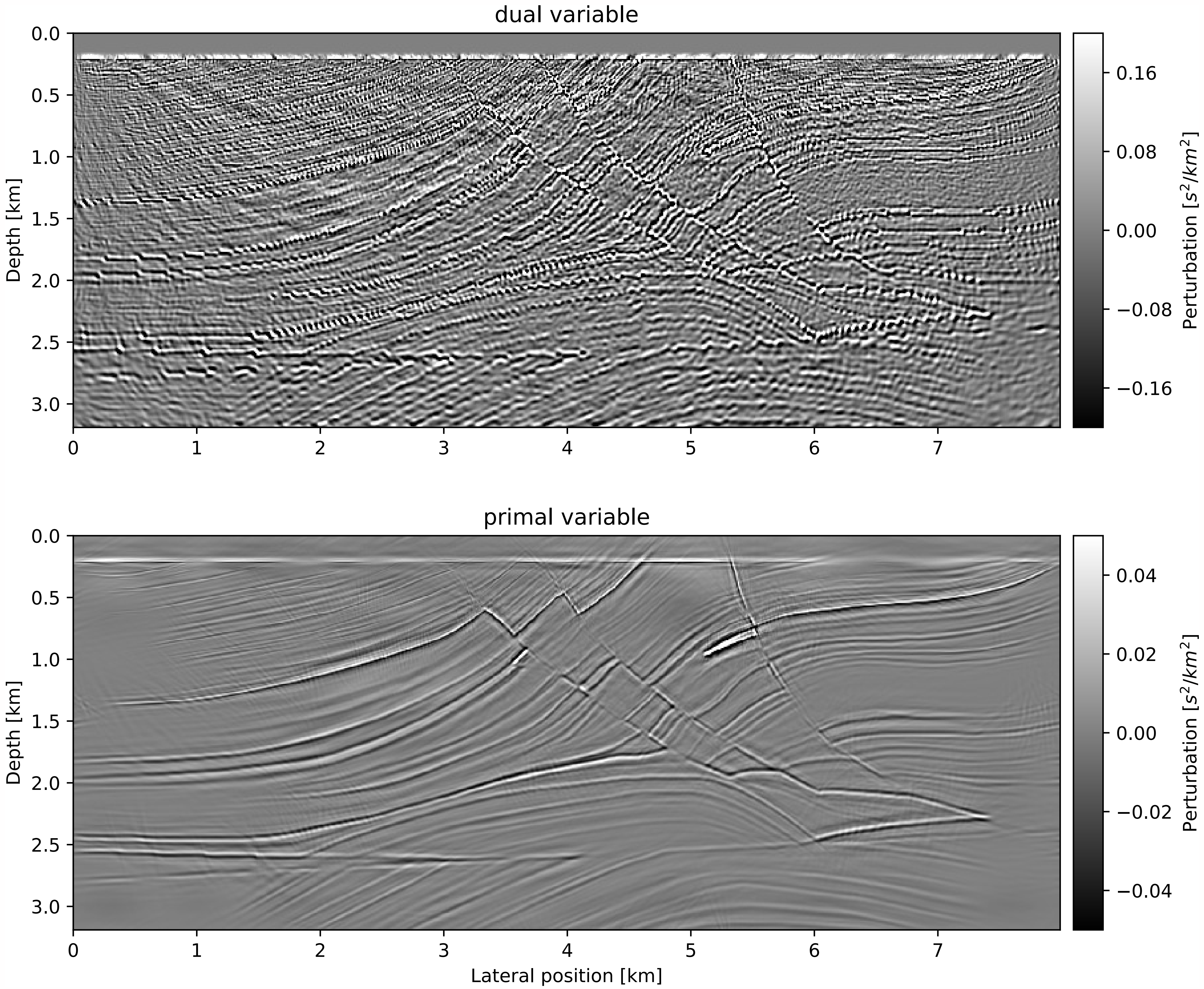


- per iteration: 20 randomly select shots w/ 10 random frequencies each

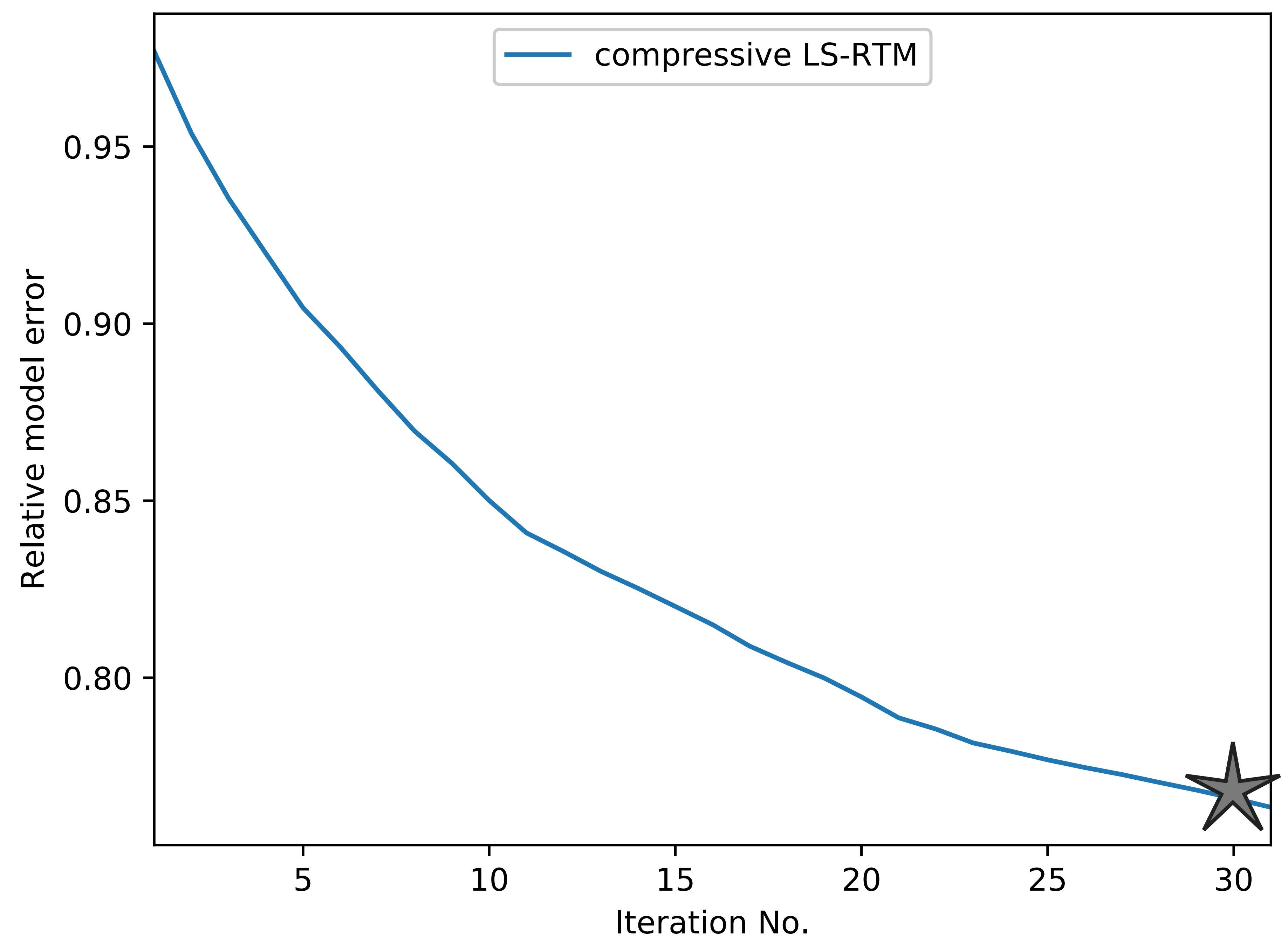


Example 5b: Compressive imaging

Iteration 30



- per iteration: 20 randomly select shots w/ 10 random frequencies each



Example 6: Imaging in the presence of salt

Imaging with salt models:

- backscattered energy from salt interfaces causes low-frequency artifacts
- Laplacian filtering, wavefield filtering, alternative imaging conditions

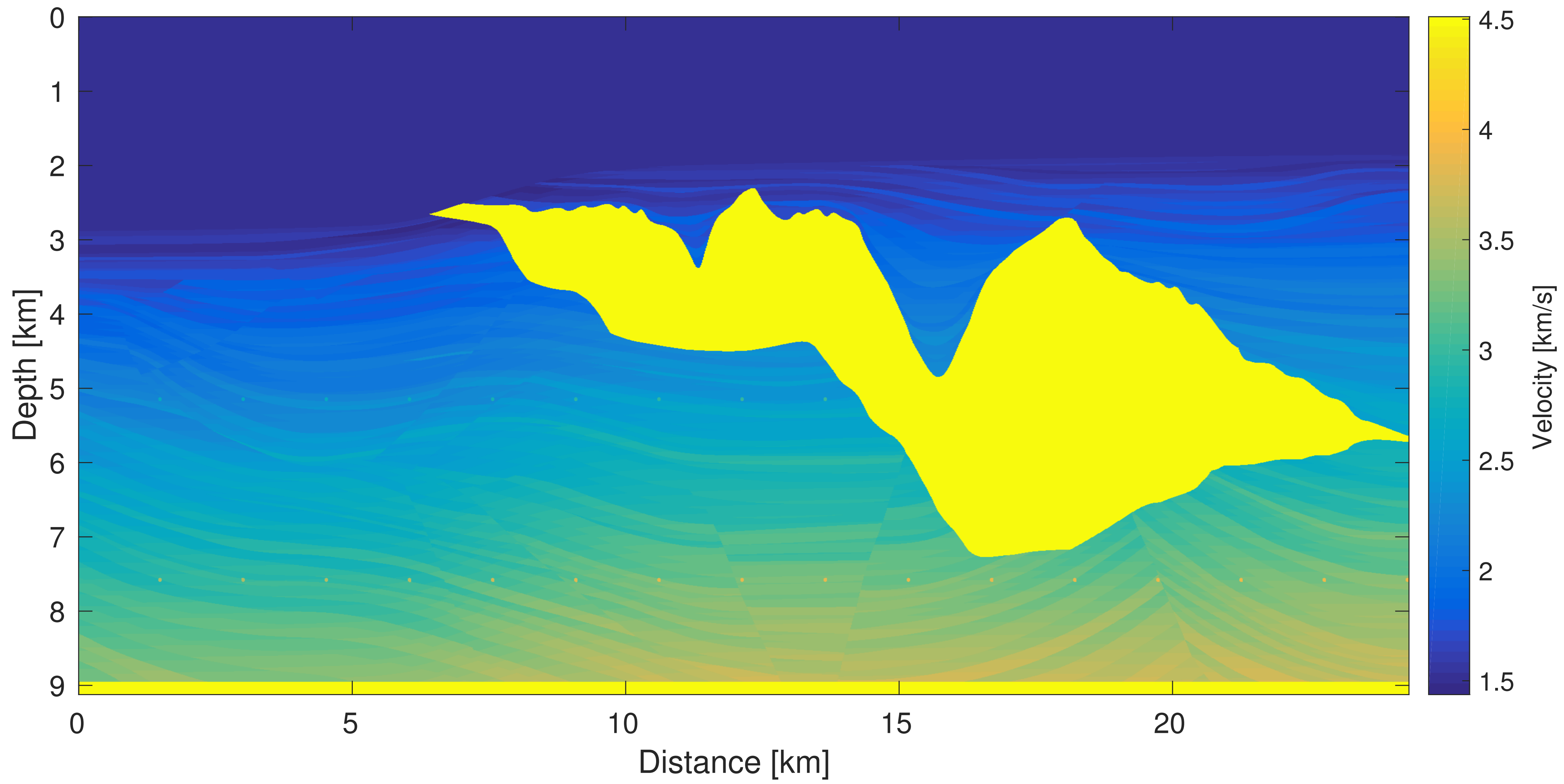
SPLS-RTM with linearized inverse scattering imaging condition:

- derive forward/adjoint pair of ISIC (Whitmore et al., 2012; Witte and Herrmann, 2017)

$$\widehat{\mathbf{J}}^\top \delta\mathbf{d} = \sum_t \left\{ \mathrm{diag}\Big(\ddot{\mathbf{u}}[t] \odot \mathbf{m}\Big)\Big(\mathbf{F}^\top \mathcal{P}_r^\top \delta\mathbf{d}\Big)[t] + \sum_{i=1}^{3} \mathrm{diag}\left(\frac{\partial \mathbf{u}[t]}{\partial \mathbf{x}_i}\right) \frac{\partial}{\partial \mathbf{x}_i} \left(\mathbf{F}^\top \mathcal{P}_r^\top \delta\mathbf{d}\right)[t] \right\}$$

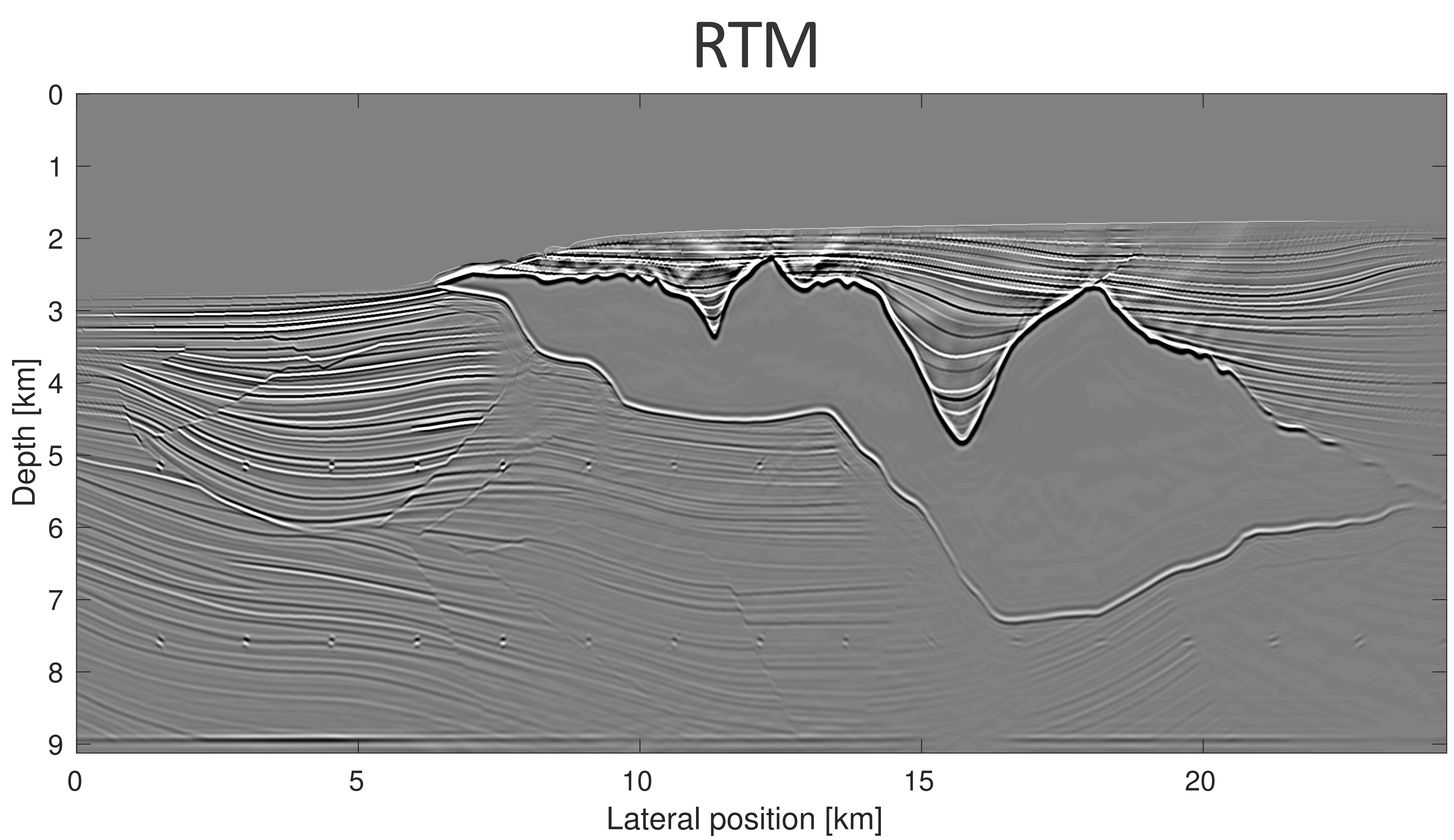
$$\widehat{\mathbf{J}} \delta\mathbf{m} = \left\{ \mathcal{P}_r \mathbf{F} \mathrm{diag}\Big(\ddot{\mathbf{u}}[t] \odot \mathbf{m}\Big) \delta\mathbf{m} + \mathcal{P}_r \sum_{i=1}^{3} \mathbf{F} \frac{\partial}{\partial \mathbf{x}_i} \mathrm{diag}\left(\frac{\partial \mathbf{u}[t]}{\partial \mathbf{x}_i}\right) \delta\mathbf{m} \right\}$$

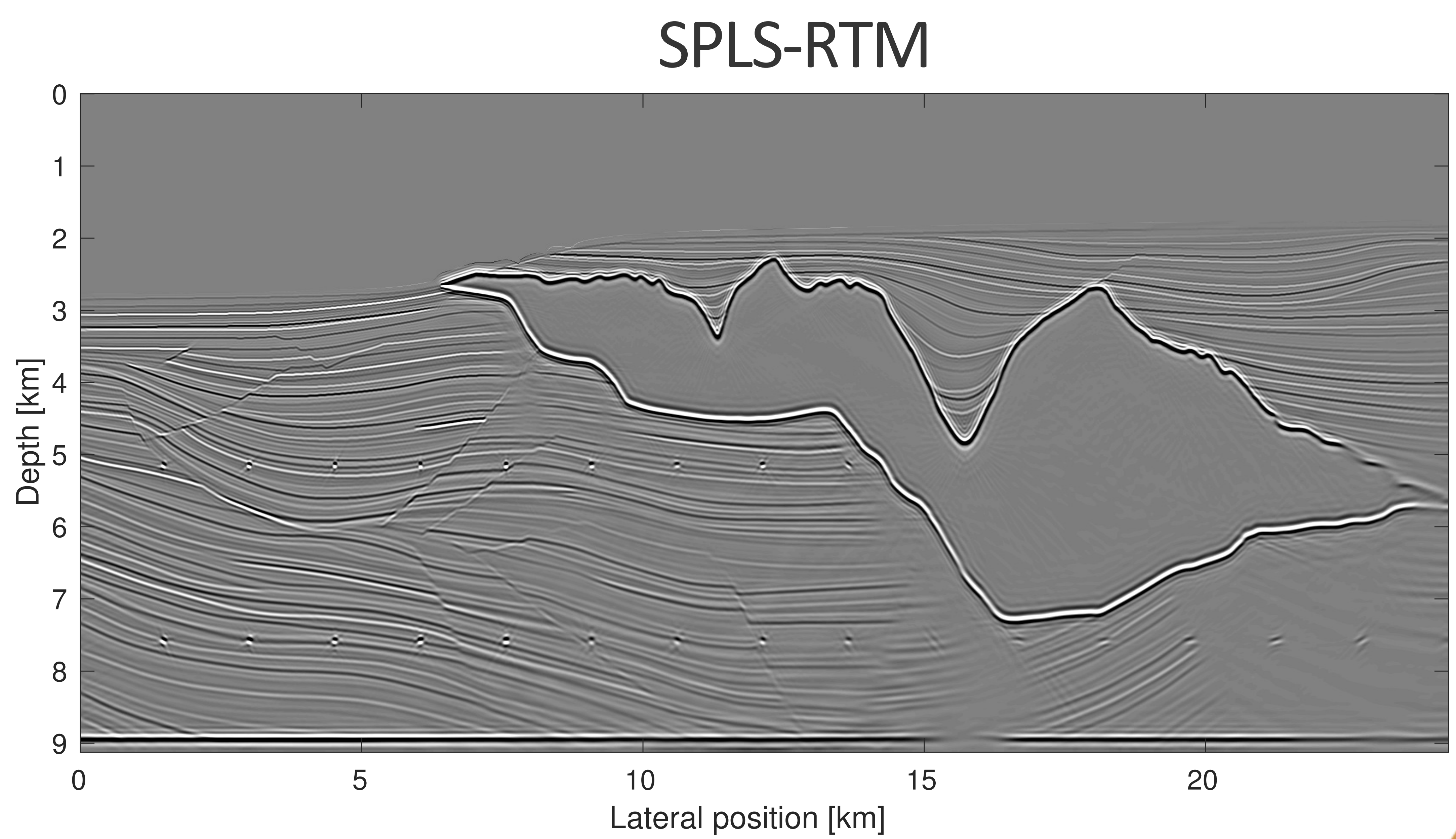
Example 6: Imaging in the presence of salt



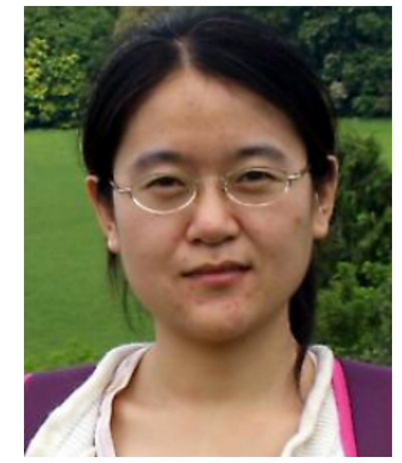
(joint work with Mengmeng Yang)

- sparsity-promoting LS-RTM
- linearized inverse scattering imaging condition
- 960 shots, 10 seconds recording
- 15 Hz peak frequency
- estimate source wavelet



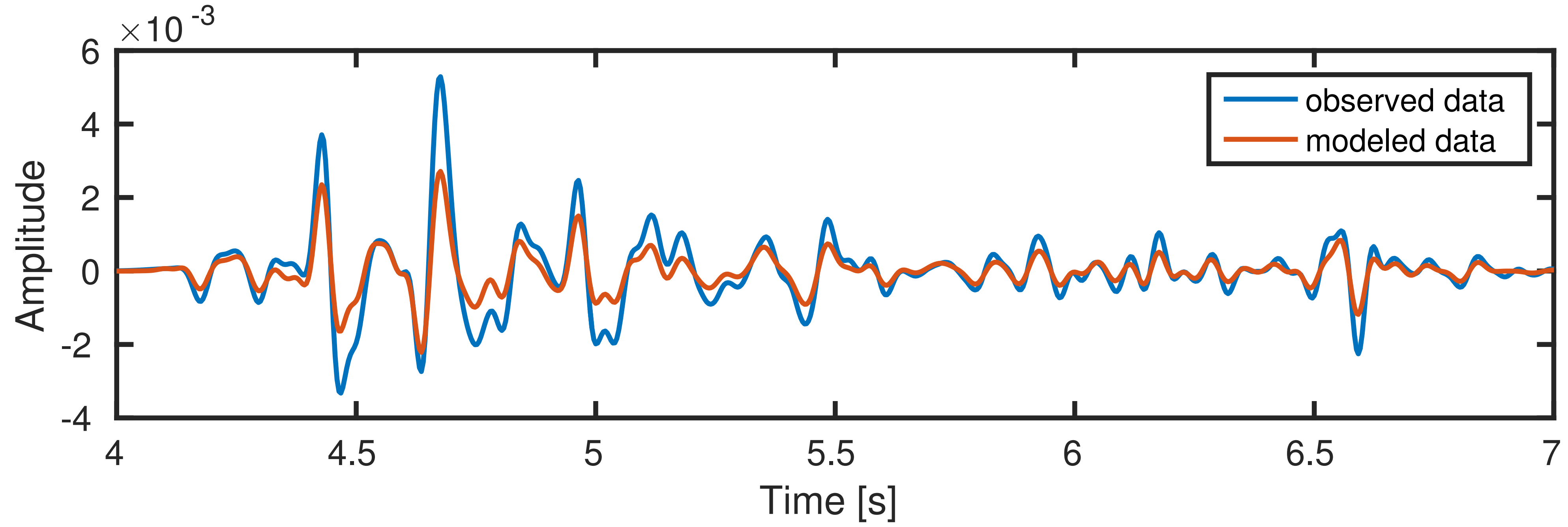


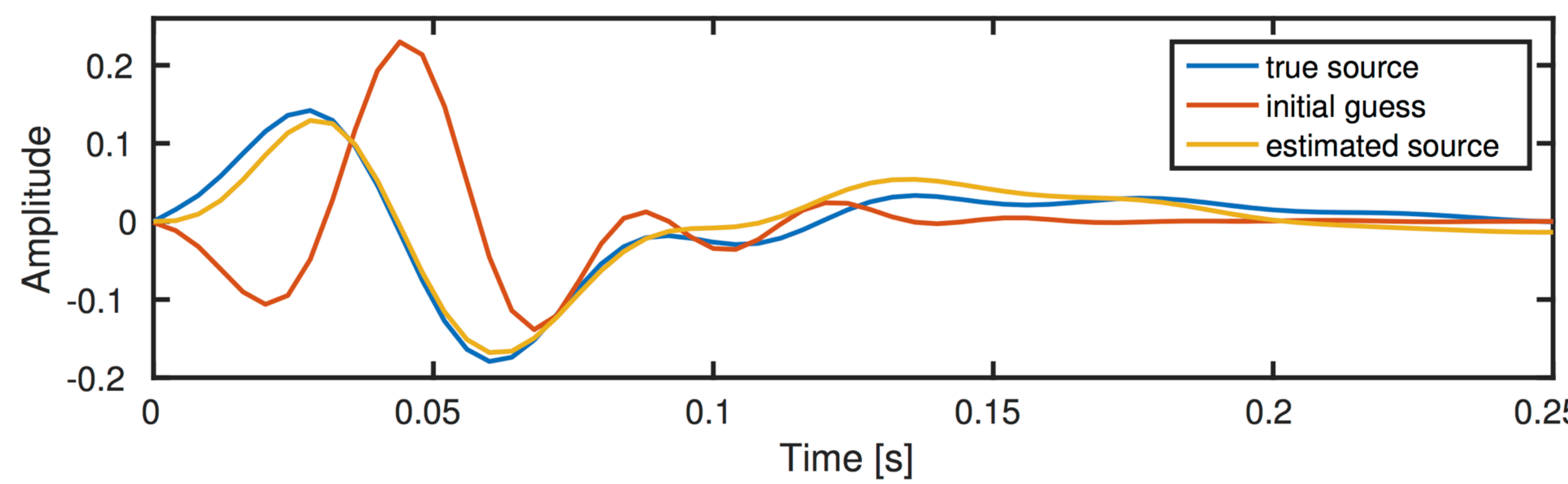
Example 6: Imaging in the presence of salt

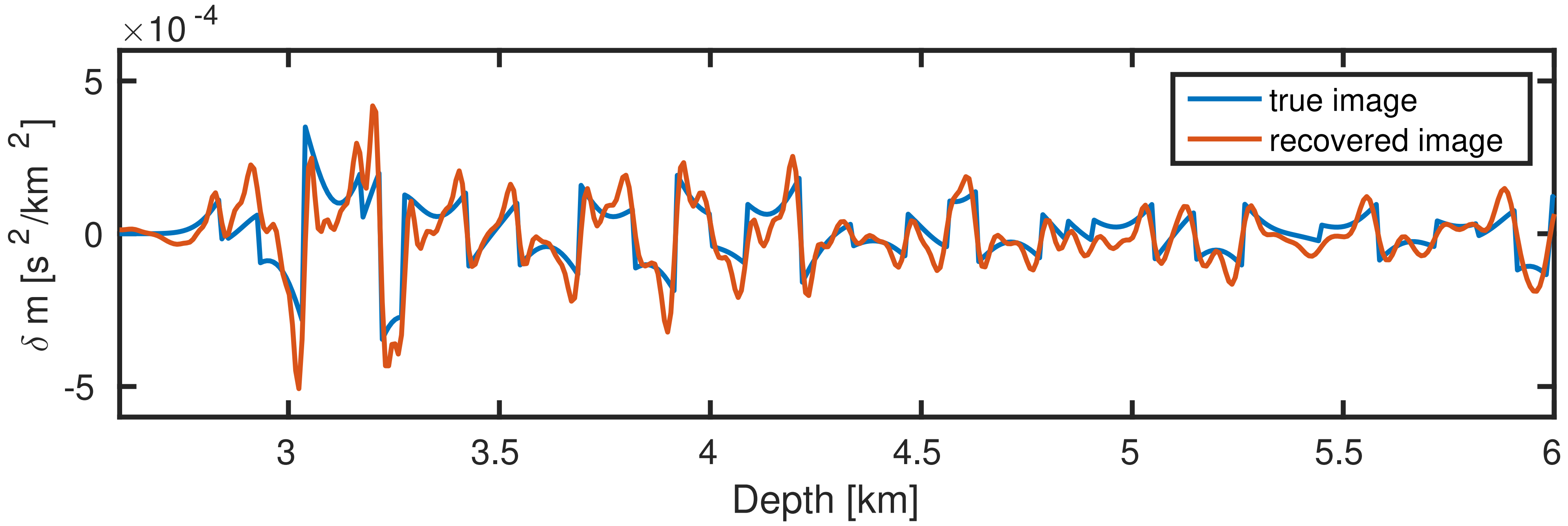


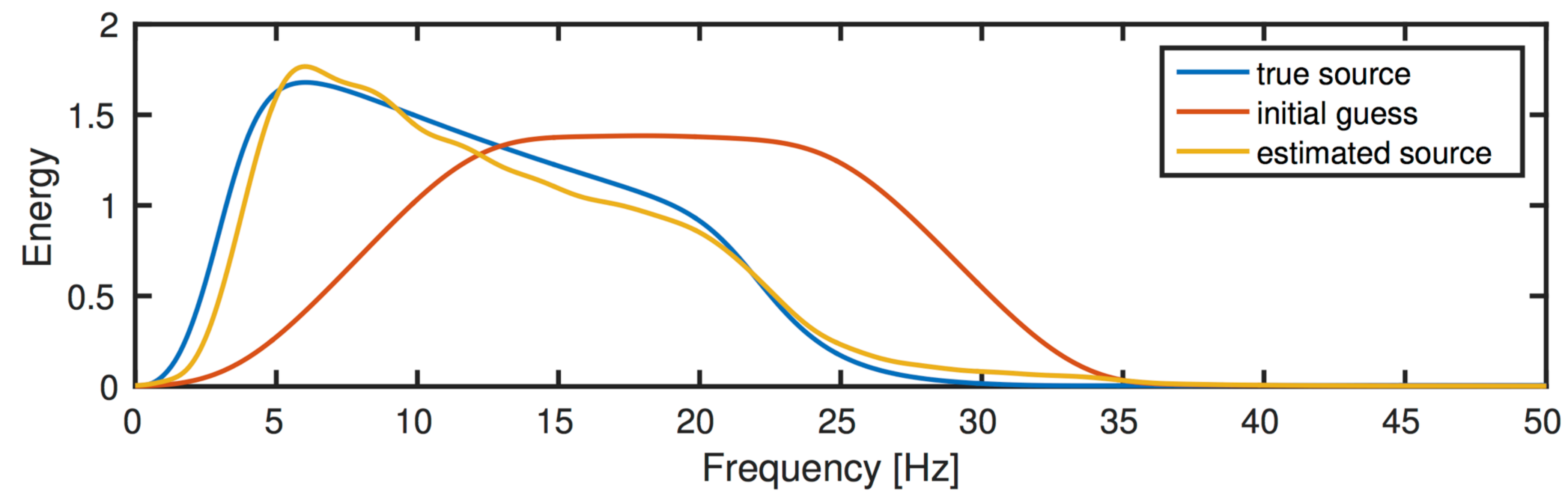
(joint work with Mengmeng Yang)

- sparsity-promoting LS-RTM
- linearized Bregman w/ 18 iterations
- 960 shots, 10 seconds recording
- 100 shots per iteration, 2 data passes
- estimate source wavelet on the fly









Summary

Julia framework for seismic modeling and inversion

- modular software structure
- matrix-free linear operators and out-of-core SEG-Y data containers
- implement variety of inverse problems in few lines of code
- efficient and fast PDE solves through Devito
- parallelization w/ resilience to hardware failures
- interface optimization libraries
- all ingredients for LS-RTM: correct adjoints, artifact-free salt imaging
- **scales to large-scale 3D problems**

The road ahead

Map Julia Devito to the cloud:

- provider independent (AWS, Google, Microsoft Azure or possibly others)
- utilize full range of cloud services (auto-scaling, elastic cache, etc.)
- scale algorithms to **ANY** number of workers

Possible future workflows:

- data sets stored in cloud (already some SEG datasets available)
- bring algorithms to the cloud and to the data
- anyone can buy cloud time and run certain algorithms on a data set
- no need to buy and maintain expensive HPC clusters

Reproducible examples

Examples from this talk can be found in the software release:

- FWI with a line search

  https://github.com/SINBADconsortium/SLIM-release-jlapps/blob/master/WaveformInversion/TimeDomain/2DFWI/scripts/fwi_overthrust_2D_linesearch.jl

- 2D and 3D FWI with spectral-projected gradient descent

  https://github.com/SINBADconsortium/SLIM-release-jlapps/blob/master/WaveformInversion/TimeDomain/2DFWI/scripts/fwi_overthrust_2D.jl

  https://github.com/SINBADconsortium/SLIM-release-jlapps/blob/master/WaveformInversion/TimeDomain/3DFWI/scripts/fwi_overthrust_3D.jl

- Preconditioned LS-RTM w/ SGD

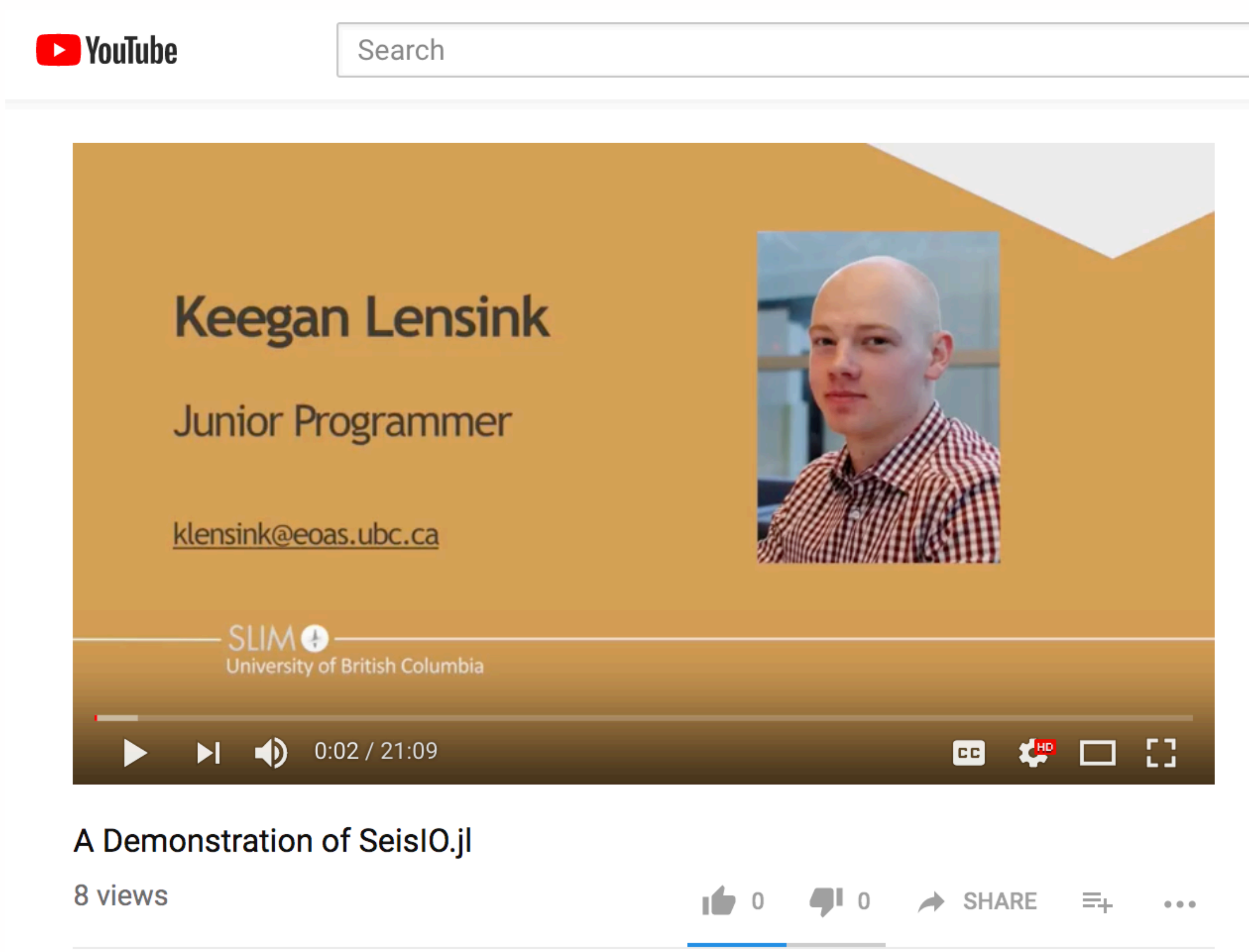
  https://github.com/SINBADconsortium/SLIM-release-jlapps/blob/master/Imaging/TimeDomain/2DLSRTM/scripts/lsrtm_marmousi.jl

- more to come!

Tutorial for data IO with SeisIO.jl

Demonstration and tutorial on Youtube:

- read and write SEG-Y in Julia (chunking, read/write blocks, create look-up tables)
- parallel scanning and reading of arbitrary size data sets



https://www.youtube.com/watch?v=tx530QOPeZo

- SeisIO.jl on git: https://github.com/slimgroup/SeisIO.jl

Acknowledgements

This research was carried out as part of the SINBAD project with the support of the member organizations of the SINBAD Consortium.

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