Released to public domain under Creative Commons license type BY (https://creativecommons.org/licenses/by/4.0). Copyright (c) 2018 SINBAD consortium - SLIM group @ The University of British Columbia.

A Unified 2D/3D Software Environment for Large Scale Time-Harmonic Full Waveform Inversion Curt Da Silva & Felix Herrmann



Tuesday, October 25, 2016



3D Full Waveform Inversion

Complicated process

- computationally intensive
- requires lots of memory, time
- large amount of programmer effort to get things *fast*
- often speed is the trade off for *correctness*



3D Full Waveform Inversion

Industry codebases, while fast

- are *inflexible* hard to integrate new changes
- are *incorrect* no 'true derivatives' of the underlying modelling code
- are poorly maintained a new hire will have no idea what's going on



3D Full Waveform Inversion

As a result

- codes are disconnected from mathematical underpinnings
- bugs are hard to diagnose
- to production-level codes

• difficult to incorporate new ideas from academia, research labs in



Software hierarchy manages complexity

- if a particular part of a program only has one function, people using/debugging it only have to think about that one function
- if software is easier to reason about -> it's easier to work with, easier to test

human brains have very limited working memory



Software hierarchy manages complexity

- we don't have to sacrifice performance
- hiding irrelevant details at each level
 - stuff

6

• lowest level operations implemented in C w/multithreading

• higher level functions don't have any idea about C/fortran/that gross



Anything that we do that isn't solving PDEs is essentially irrelevant, computation time-wise



Anything that we do that isn't solving PDEs is essentially irrelevant, computation time-wise

- advantageous for software design -> any overhead introduced is negligible compared to solving PDEs
 - if a single wavefield can be stored in RAM true for low frequency time harmonic FWI



PDEs are the computational bottleneck • design our software for maximum ease of use + "plug and play"

- components

• speedups made to solving PDEs propagate to whole framework



FWI Problem

$$\min_{m} \frac{1}{2N_s} \sum_{i=1}^{N_s} ||P_r H|$$

- m discrete model vector
- N_s number of shots
- P_r receiver restriction operator

 $H(m)u_i = q_i$ - monochromatic Helmholtz system for shot i d_i - measured data for shot

$(m)^{-1}q_i - d_i \|_2^2$



New way to organize FWI Software

opAbstractMatrix

Modeling matrix : multiplication/division



opAbstractMatrix

A SPOT operator

- linear operator class behaves like a matrix • knows how to multiply, divide itself • can handle matrix-free operations or form sparse matrix for 2D
- problems

Extensions

- Kaczmarz sweeps
- Jacobi iterations



opAbstractMatrix

Particular matrix-vector products specified at construction

discrete_helmholtz - constructs Helmholtz operator with particular parameters

- can swap between stencils
- construct multigrid preconditioner

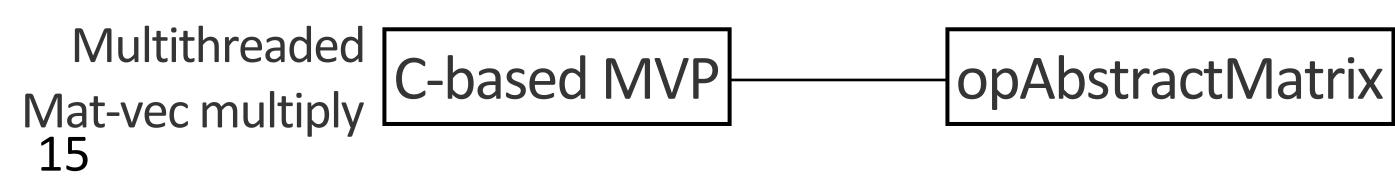


Excerpt from discrete_helmholtz

```
wn = param2wavenum(v pml,freq,model.unit);
switch scheme
  case PDEopts.HELM3D STD7
    Hmvp = FuncObj(@helm3d_7pt_mvp_mex,{vec(wn),vec(dt),vec(nt),npml,freq,[],[]});
    jacobi = FuncObj(@helm3d_7pt_jacobi_mex,{vec(wn),vec(dt),vec(nt),npml,freq,[],[],[],[]});
    kacz sweep = [];
  case PDEopts.HELM3D OPERTO27
    Hmvp = FuncObj(@helm3d_operto27_mvp, {wn,dt,nt,npml,[],n_threads,[],false});
    jacobi = [];
    kacz_sweep = FuncObj(@helm3d_operto27_kaczswp, {wn,dt,nt,npml,[],[],[],[],[]});
    if nargout >= 3
        [~,wn] = param2wavenum(v pml,freq,model.unit);
        dHmvp = FuncObj(@helm3d_operto27_mvp, {wn,dt,nt,npml,[],n_threads,[],true});
        [~,~,wn] = param2wavenum(v pml,freq,model.unit);
        ddHmvp = FuncObj(@helm3d_operto27_mvp,{wn,dt,nt,npml,[],n_threads,[],true});
    end
end
helm params = struct;
helm params.multiply = Hmvp;
helm params.jacobi = jacobi;
helm_params.kacz_sweep = kacz_sweep;
helm params.N = prod(nt);
helm params.iscomplex = true;
H = opAbstractMatrix(mat_mode,helm_params,opts.solve_opts);
```



New way to organize FWI Software



Modeling matrix : multiplication/division



C-based Matrix Vector Product

Implementation of 27-pt compact stencil [1]

Multi-threaded along the z-coordinate with openMP

Forward, adjoint modes

[1] Operto et. al. "3D finite-difference frequency-domain modeling of visco-acoustic wave propagation using a massively parallel direct solver: A feasibility study", Geophysics 2007



Helmholtz matrix

- In 2D, we can afford to use explicit sparse matrices + fast direct solvers
 - implementation of [1]

Explicit matrices VS implicit matrices is opaque to the user • interface remains the same

[1] Chen, et. al. "An Optimal 9-Point Finite Difference Scheme For The Helmholtz Equation With PML.", 2013



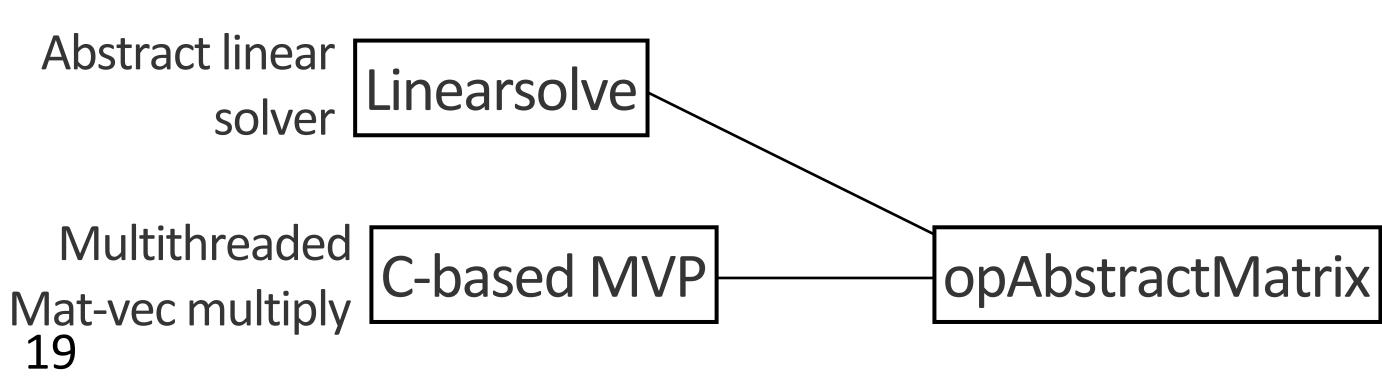
C-based Matrix Vector Product

Matlab Compiler

- write stencil-based code in Matlab -> C code with openMP multithreading
- nearly as fast as native C code, much easier to develop



New way to organize FWI Software



Modeling matrix : multiplication/division



Linearsolve

Abstract interface for "Solve Ax = b with a specified method" • encourages code reuse - smoothers for multigrid, preconditioner

- applications
- preconditioner

• calls the specified method (GMRES,CG, etc.) with the prescribed number of iterations, right hand side, initial guess, tolerance, and



LinSolveOpts

Object for storing

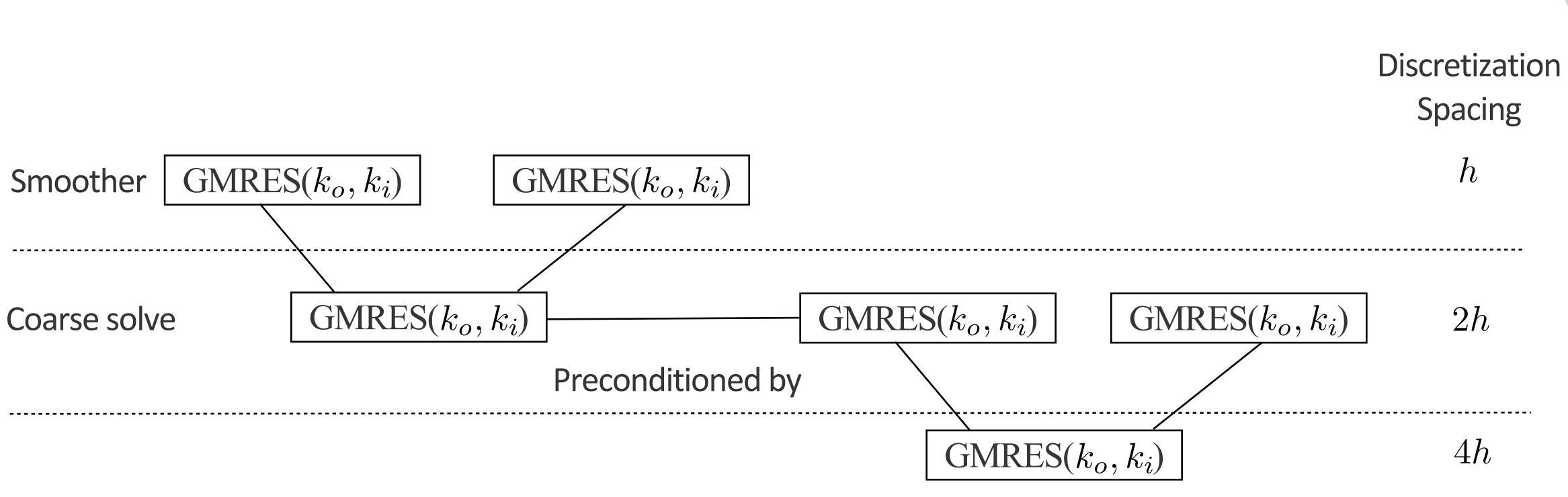
- linear solver method
- maximum outer iterations
- maximum inner iterations (for some solvers)
- tolerance
- preconditioner

As well as default options for these

- Solvers: CG, FGMRES, LU, etc.
- Preconditioners: ML-GMRES, Shifted Laplacian, etc.

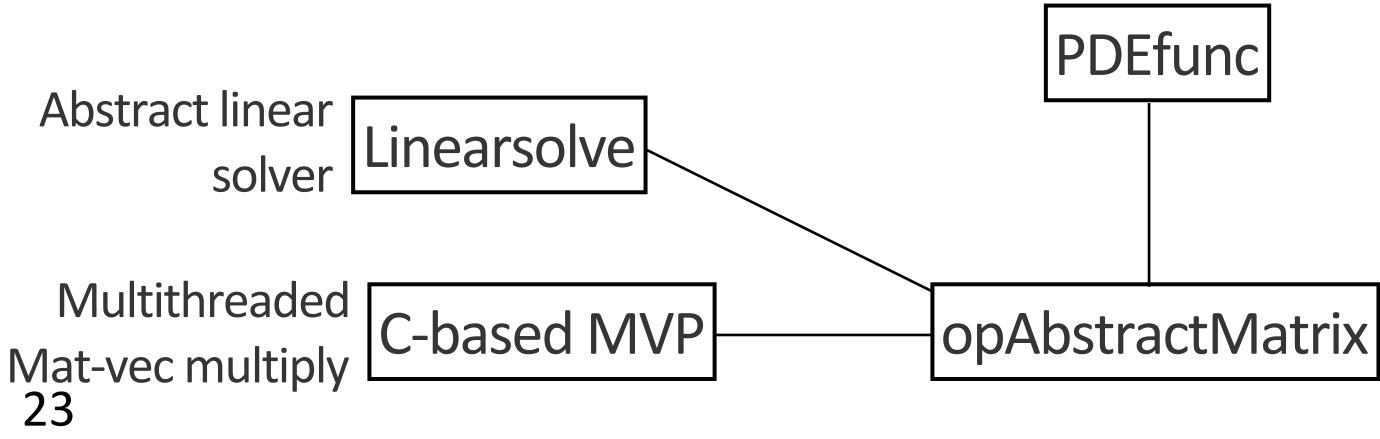


Multilevel-GMRES





New way to organize FWI Software



PDE-related quantities Serial version

Modeling matrix : multiplication/division



PDEfunc

Main workhorse function For each source index

- solve the Helmholtz equation don't care how
- use solution to compute objective + gradient, demigration/ the user requests

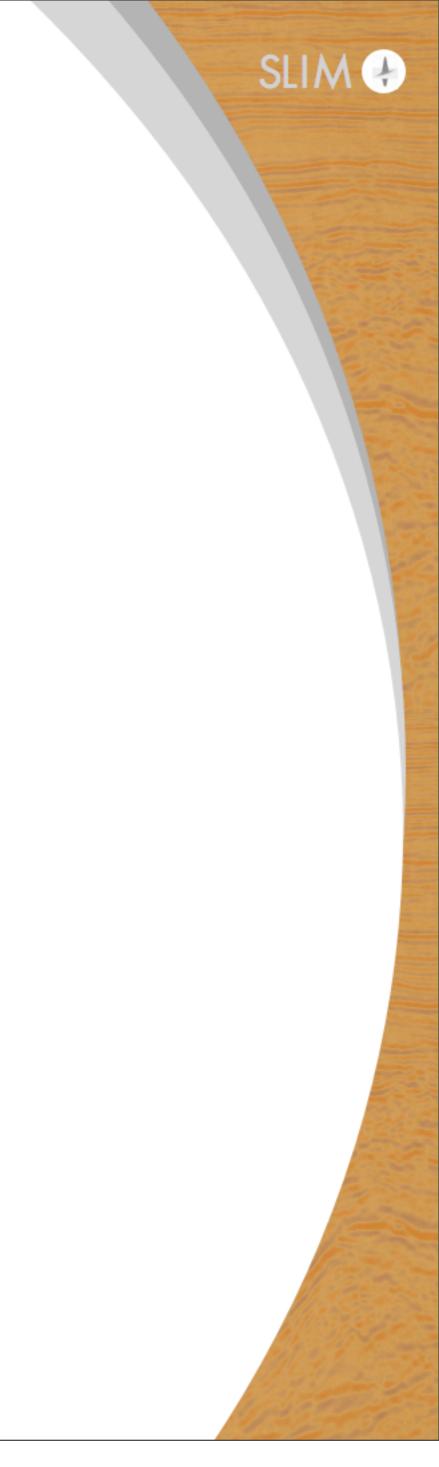
Serial code, implicitly multithreaded

migration, hessian/GN hessian matrix vector product - whatever



Excerpt from PDEfunc

```
Uk = Hk \setminus Qk_i;
switch func
   case OBJ
      [phi,dphi] = misfit(Pr*Uk,Dobs(:,data_idx),current_src_idx,freq_idx);
      f = f + phi;
      if nargout >= 2
        Vk = Hk' \setminus (-Pr'* dphi);
           g = g + sum(real(conj(Uk) .* (dH'*Vk)),2);
      end
    case FORW MODEL
      output(:,data idx) = Pr*Uk;
   case JACOB_FORW
      dUk = Hk \setminus (dHdm*(-Uk));
      output(:,data_idx) = Pr*dUk;
   case JACOB ADJ
      Vk = Hk' ( -Pr'* input(:, data idx) );
      output = output + sum(real(conj(Uk) .* (dH'*Vk)),2);
end
```



van Leeuwen and Herrmann, "Mitigating local minima in full-waveform inversion by expanding the search space, Geophysical Journal International (2013)

PDEfunc

Extensions to Wave-equation Reconstruction Inversion

Standard FWI

$$\min_{m} \frac{1}{2} \| P_r u(x) \|_{r^{-1}}$$
s.t. $H(m) u$

 $(m) - d||_2^2$ u(m) = q



van Leeuwen and Herrmann, "Mitigating local minima in full-waveform inversion by expanding the search space, Geophysical Journal International (2013)

PDEfunc

Extensions to Wave-equation Reconstruction Inversion

$$\min_{m} \frac{1}{2} \|P_{r}u(m) - d\|_{2}^{2} + \frac{\lambda}{2} \|H(m)u(m) - q\|_{2}^{2}$$
$$u(m) = \arg\min_{u} \left\| \begin{bmatrix} Pr\\\lambda H(m) \end{bmatrix} u - \begin{bmatrix} d\\\lambda q \end{bmatrix} \right\|_{2}$$



Song and Williamson, "Frequency-domain acoustic-wave modeling and inversion of crosshole data: Part I-2.5-D modeling method." Geophysics (1995)

PDEfunc

Extensions to 2.5D FWI • When the velocity is y-invariant v(x, y, z) = h(x, z)

• After a Fourier transform in y-, the Helmholtz equation reads as

 $(\partial_x^2 + \partial_z^2 + \omega^2 h(x, z) - k_y^2)u_{k_y}(x, z) = S(\omega)\delta(x - x_s)\delta(z - z_s)$



Song and Williamson, "Frequency-domain acoustic-wave modeling and inversion of crosshole data: Part I-2.5-D modeling method." Geophysics (1995)

PDEfunc

Extensions to 2.5D FWI • we can reconstruct the 3D wavefield u(x, y, z) as

$$u(x, y, z) = \frac{1}{\pi} \int_0^{k_{nyq}} \tilde{u}_{k_y}(x, z) \cos(k_y(y - y_s)) dk_y$$
$$= \sum_{j=1}^N w_j u_{k_y^j}(x, z)$$



Song and Williamson, "Frequency-domain acoustic-wave modeling and inversion of crosshole data: Part I-2.5-D modeling method." Geophysics (1995)

PDEfunc

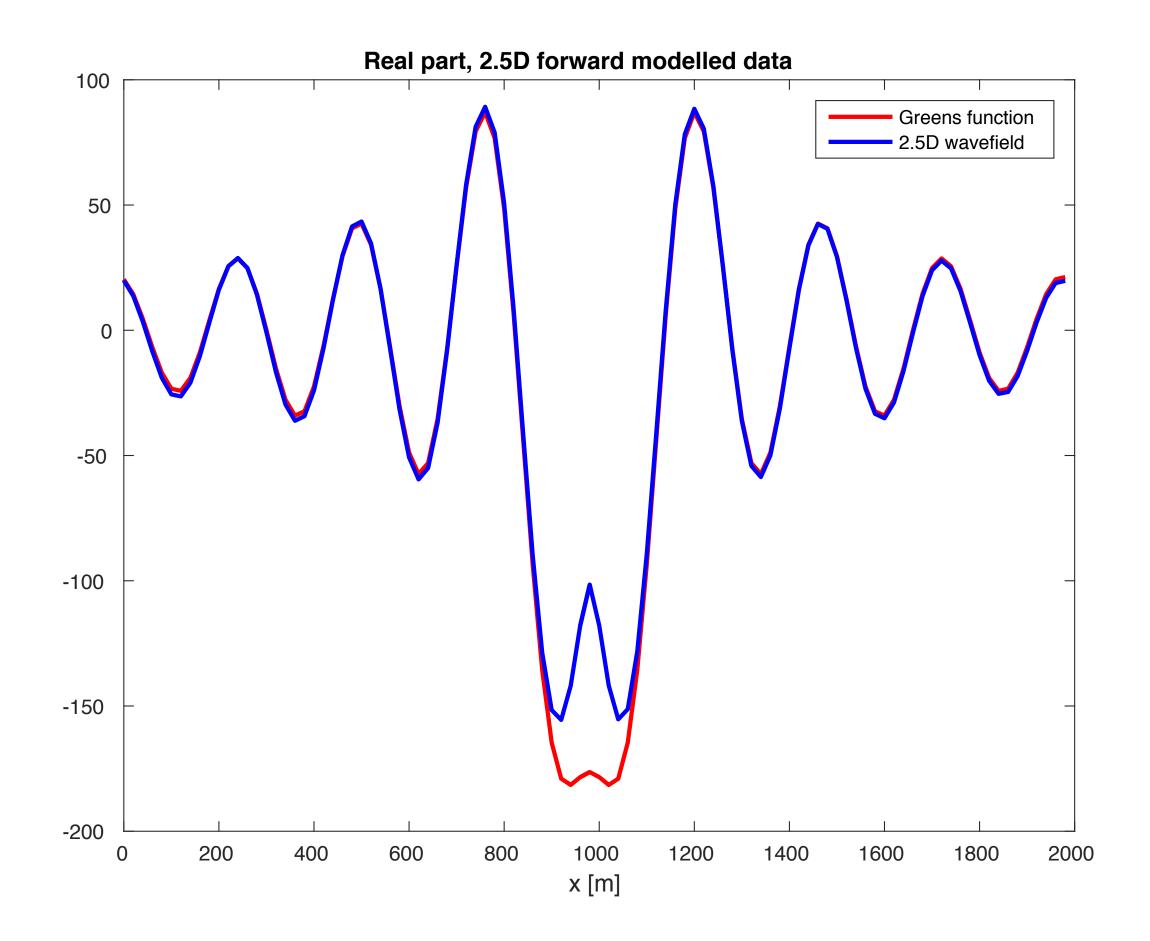
Extensions to 2.5D FWI

- weighted sum structure of the wavefield -> weighted sum structure for gradient, hessian, etc.
- correct 3D physics without full 3D costs

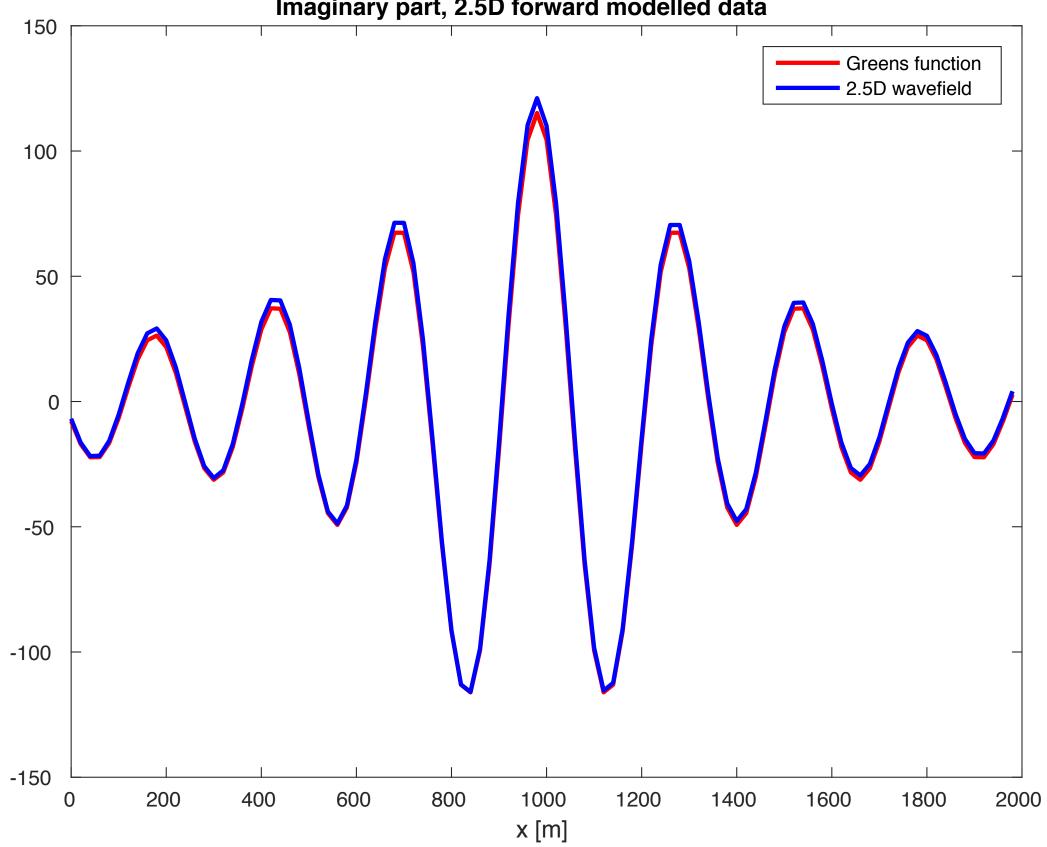




2.5D Modeling



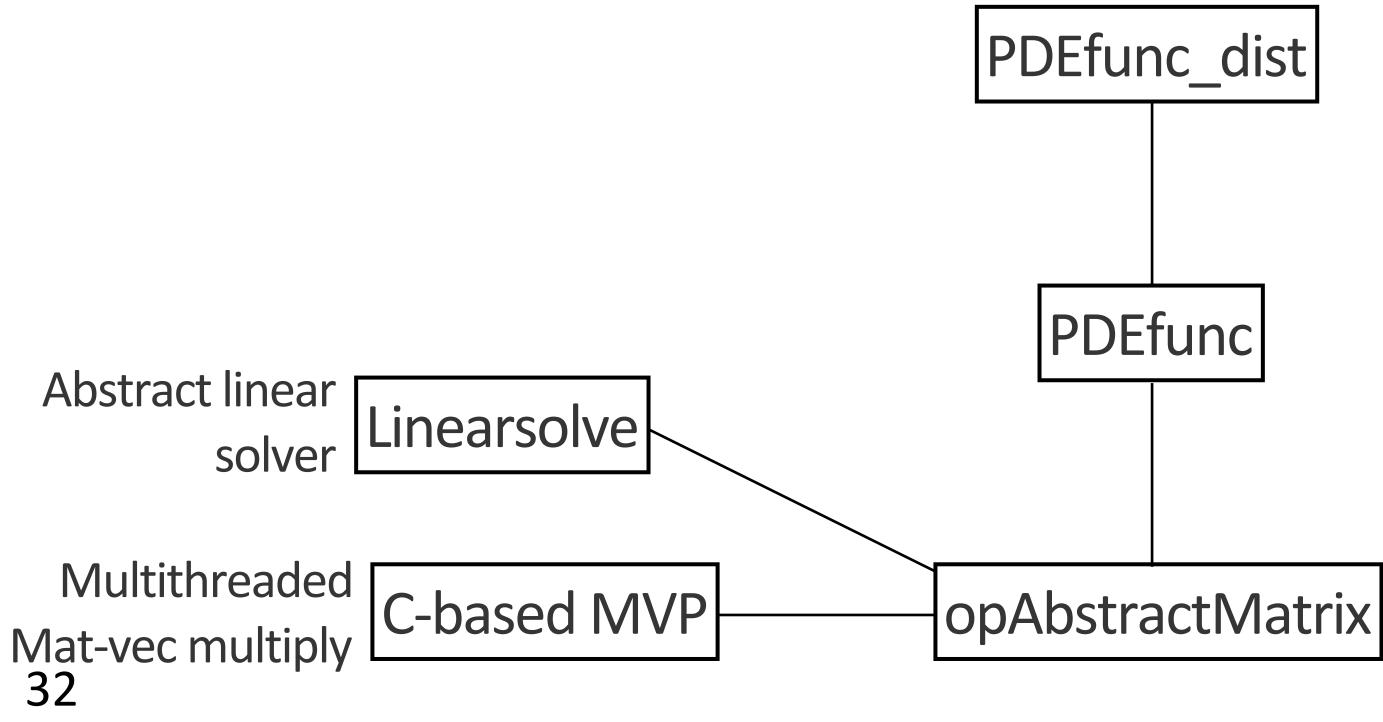
31



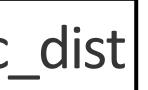
Imaginary part, 2.5D forward modelled data



New way to organize FWI Software







PDE-related quantities Parallel version

PDE-related quantities Serial version

Modeling matrix : multiplication/division



Separable objective function

$$f_I(m) = \frac{1}{2|I|} \sum_{i \in I} ||P_r|$$

$$= \frac{1}{2|I|} \sum_{i \in I} f_i(r)$$

The objective function is *separable* over shots/frequencies - distribute indices to parallel workers

Objective separable -> gradient, GN Hessian, Hessian are separable

PDEfunc_dist does no computation, just parallel distribution + summation - separate computation from parallelization - easiest component to 'swap out' with your own parallelization scheme

$\|H(m)^{-1}q_i - d_i\|_2^2$

m)

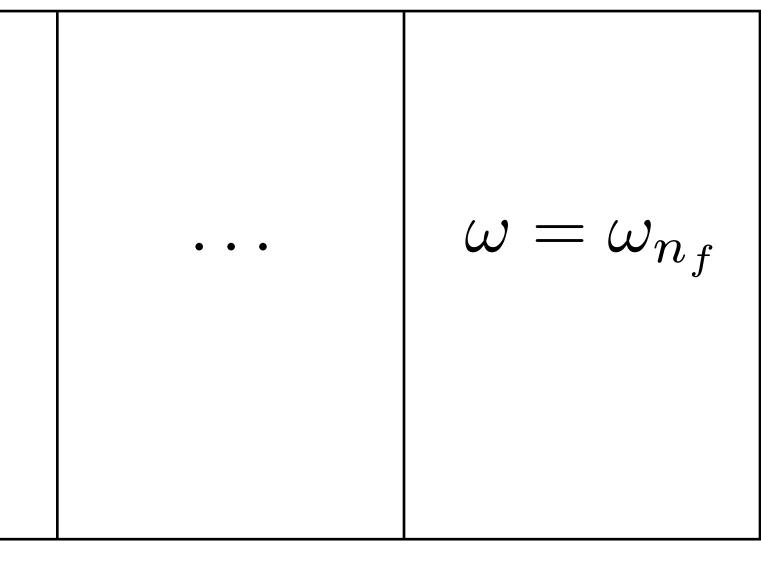


Data volume

$n_{\rm xrec} n_{\rm yrec}$

$\omega = \omega_1$	$\omega = \omega_2$

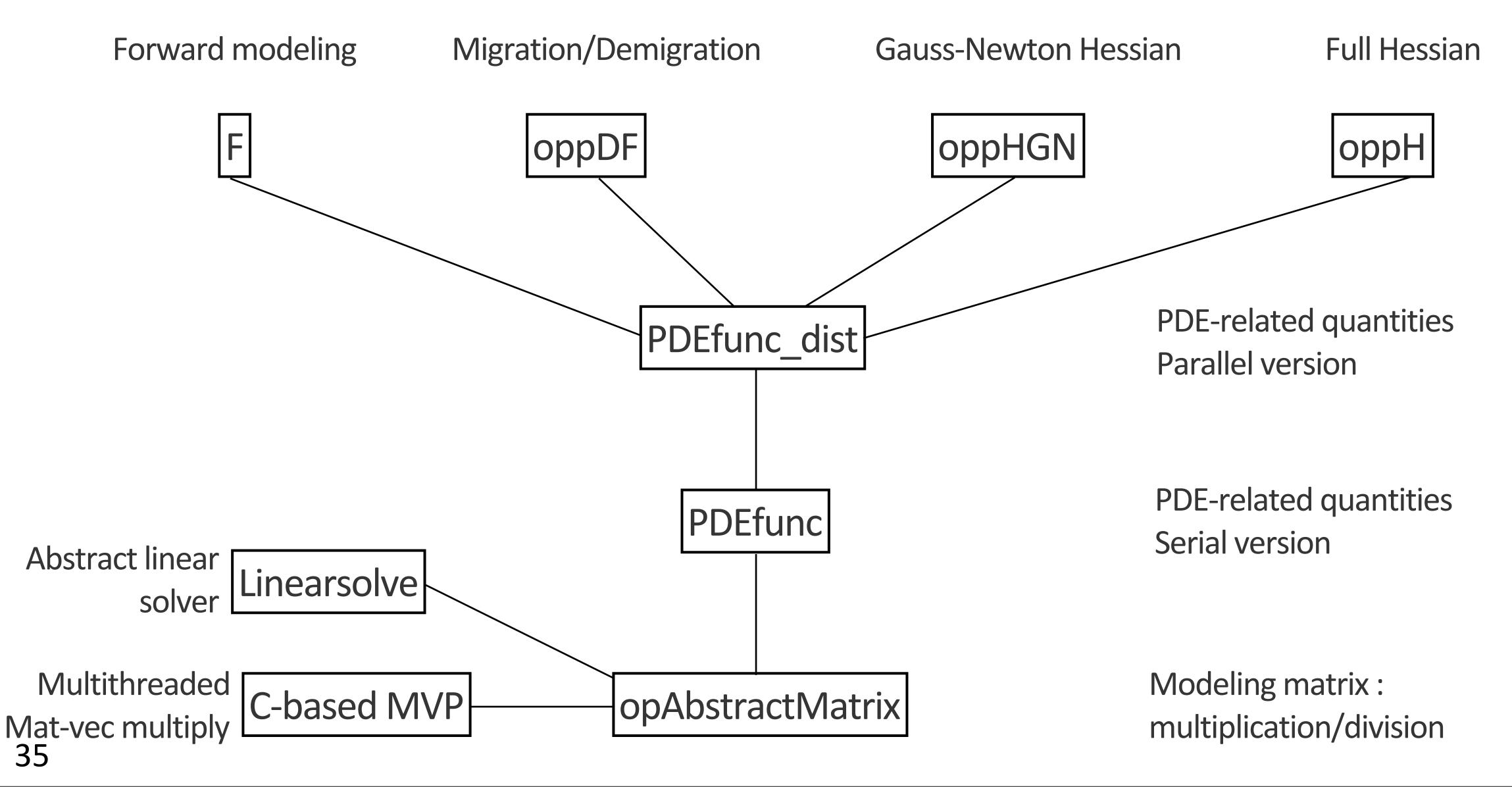
 $n_{\rm xsrc} n_{\rm ysrc} \ n_{\rm xsrc} n_{\rm ysrc}$



 $n_{\rm xsrc} n_{\rm ysrc}$



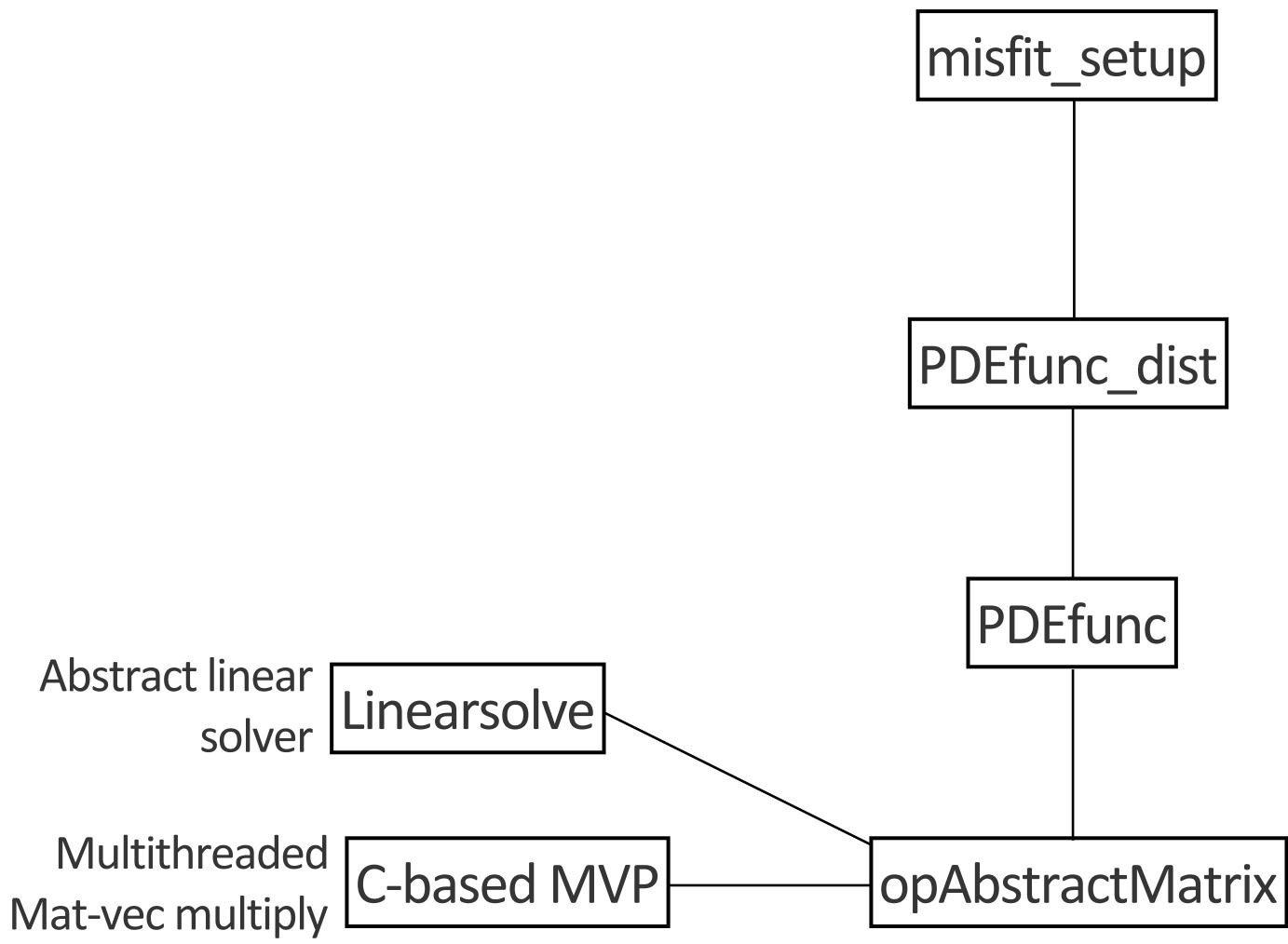
New way to organize FWI Software







New way to organize FWI Software







PDE-related quantities Parallel version

PDE-related quantities Serial version

Modeling matrix : multiplication/division



misfit_setup

Constructs function handle for objective

- velocity subsampling
- frequency slice distribution

Batch mode interface to the objective

use

Fancy wrapper around PDEfunc_dist

• stochastic inversion algorithm can specify which source indices to



PDEopts

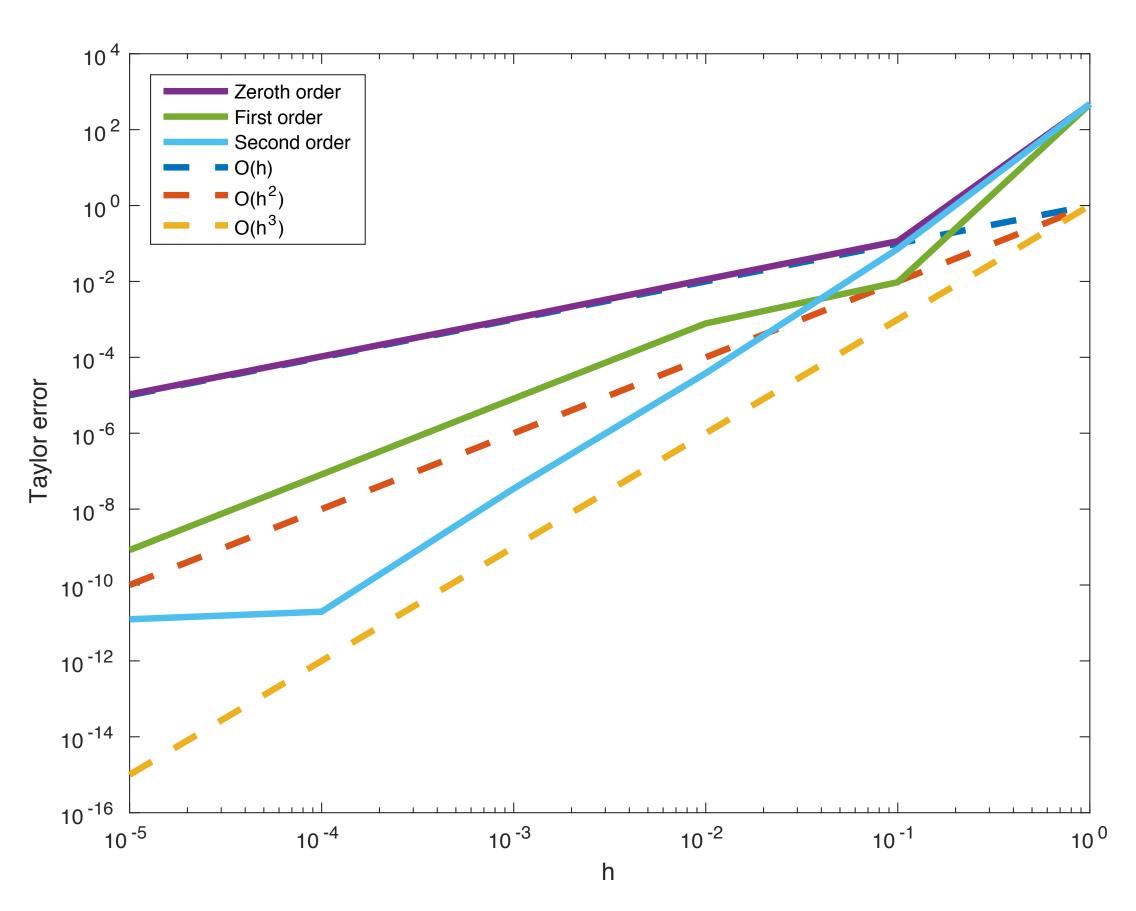
•

Options for specifying

- PDE stencil
- PML width/layout
- preconditioner
- source/receiver interpolation
- source estimation



Taylor error test $f(m + h\delta m) - f(m)$ $f(m + h\delta m) - f(m) - h\nabla f(m) - h\nabla f(m)^T \delta m - f(m) - h\nabla f(m) - h\nabla f(m)^T \delta m - f(m) - h\nabla f(m)^T \delta m - f(m) - h\nabla f(m) -$



$$= O(h)$$

$$7f(m)^T \delta m = O(h^2)$$

$$\frac{h^2}{2} \delta m^T \nabla^2 f(m) \delta m = O(h^3)$$



Adjoint Test

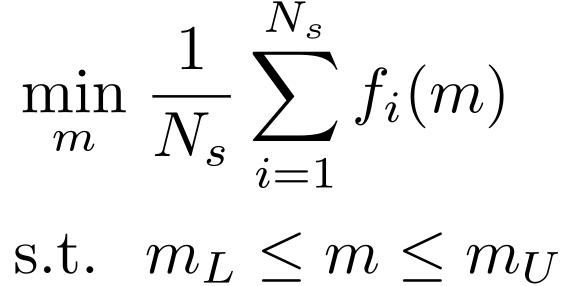
	$\langle Ax, y \rangle$	$\langle x, A^H y \rangle$	Relative Difference
Helmholtz system matrix	1.903020+ $2.087502i\cdot 10^{1}$	$1.903020+\ 2.087502i\cdot 10^1$	$1.51 \cdot 10^{-15}$
Jacobian	$-6.204229 \cdot 10^{-2}$	$-6.204229 \cdot 10^{-2}$	$6.8525 \cdot 10^{-10}$
Hessian	$-5.842717 \cdot 10^{-3}$	$-5.842717 \cdot 10^{-3}$	$7.9767 \cdot 10^{-11}$



Results



Algorithm



m - discrete model vector

$$f_i(m) = \frac{1}{2} \|P_r H(m)^{-1} q_i - d_i\|_2^2 - \frac{1}{2} \|P_r H(m)^{-1} q_i - \frac{1}{$$

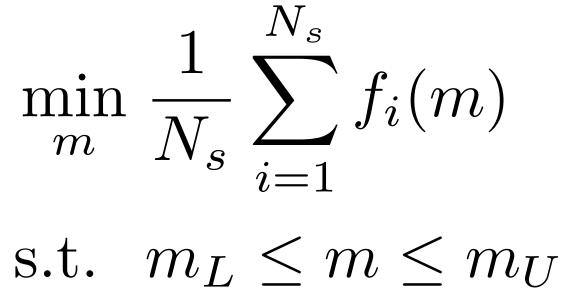
 P_r - receiver restriction operator $H(m)u_i = q_i$ - discrete Helmholtz system for shot i d_i - measured data for shot

 m_L, m_U - point-wise model bounds (water layer + constant min/max velocities)

per-shot misfit function







We have too many shots to process at once - Can process p shots at a time when we have p Matlab workers

Typically $N_s \gg p$



Schmidt, et. al., "Optimizing Costly Functions with Simple Constraints: A Limited-Memory Projected Quasi-Newton Algorithm", 2009 Algorithm 1

$$m_k = \arg \min_{m} \frac{1}{|I_k|} \sum_{i \in I_k} f_i(m)$$

s.t. $m_L \le m \le m_U$

gradient

Repeat for T iterations

Т

At the k th iteration, randomly draw a subset of sources $I_k \subset \{1, \ldots, N_s\}$ with $|I_k| = p$

Approximately solve the above problem with constrained LBFGS or spectral projected



Algorithm

Inner subproblem

- solved with $\frac{N_s}{p}$ function evaluations

We use three outer iterations • equivalent to three gradient steps with all the shots

• each subproblem is equivalent to one pass over the full data



3D FWI Example

Overthrust model

- 20 km x 20 km x 4.6 km 50 m spacing, 500m water layer
- 50 x 50 sources, 200m spacing 2500 shots
- 401 x 401 receivers, 50m spacing
- 3Hz 6Hz frequency range, single freq. inverted at a time





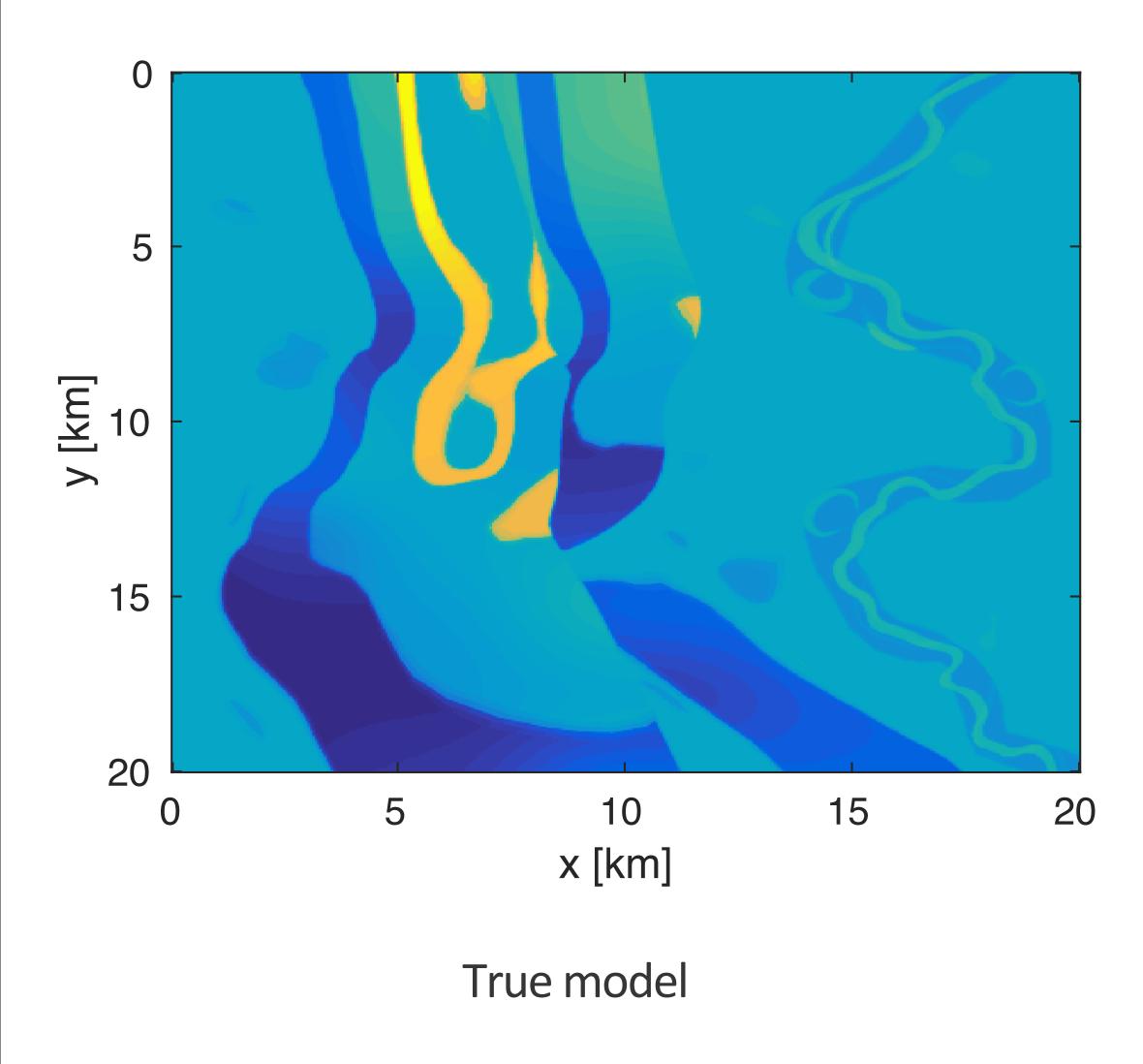
Computational Environment

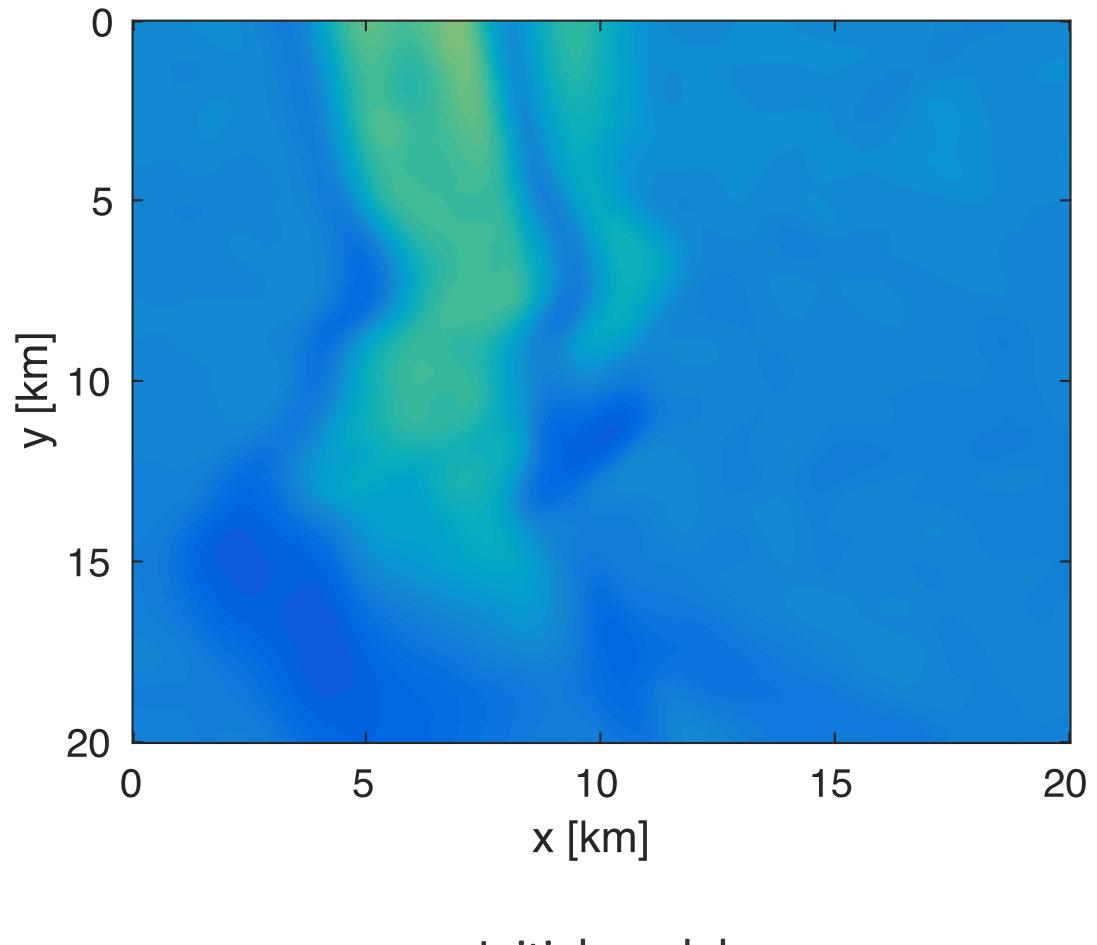
SENAI Yemoja cluster

- 100 nodes, 128 GB RAM each, 20-core processors
- threads full core utilization

• 400 Parallel Matlab workers (4 per node), Helmholtz MVP uses 5

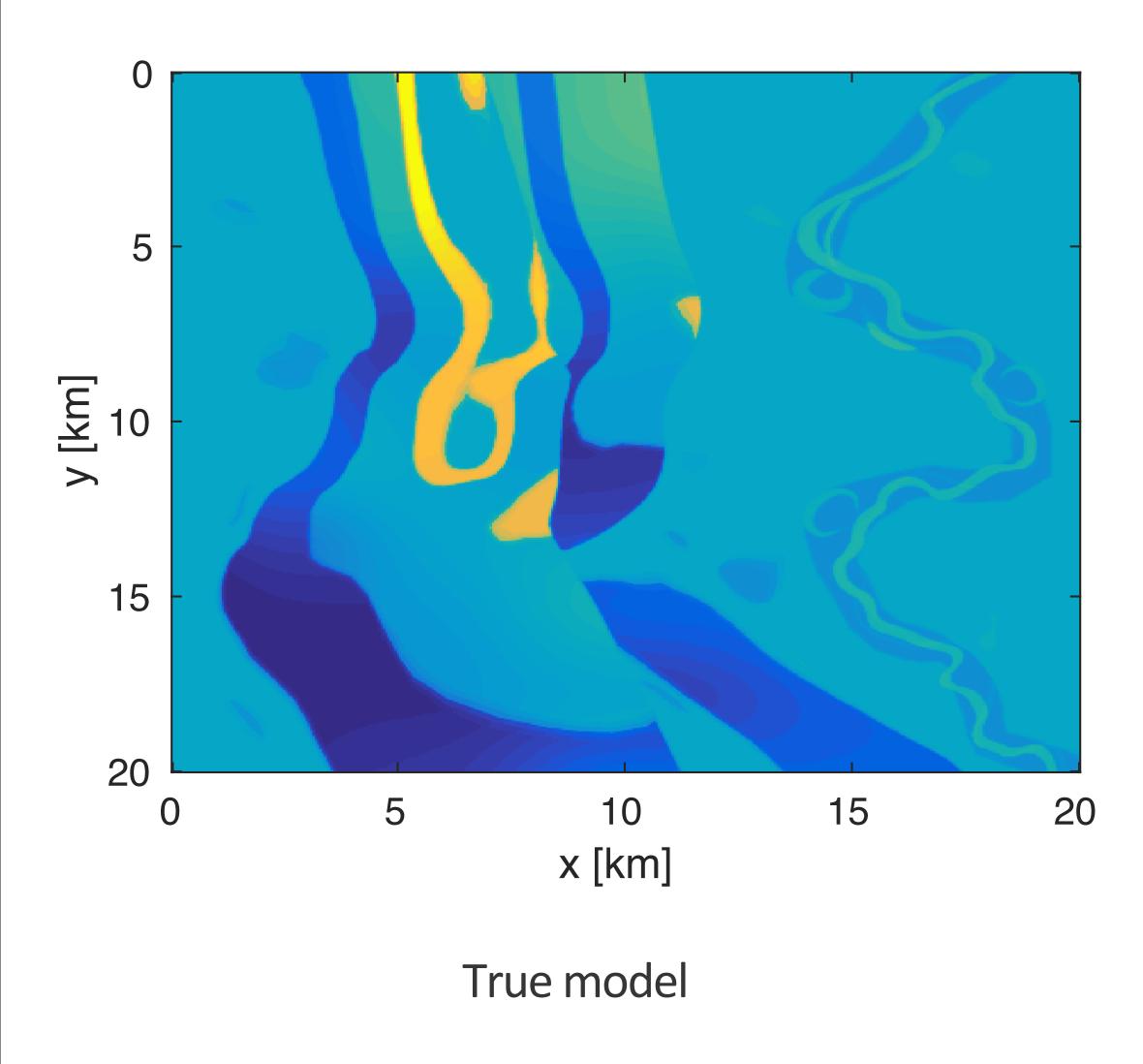


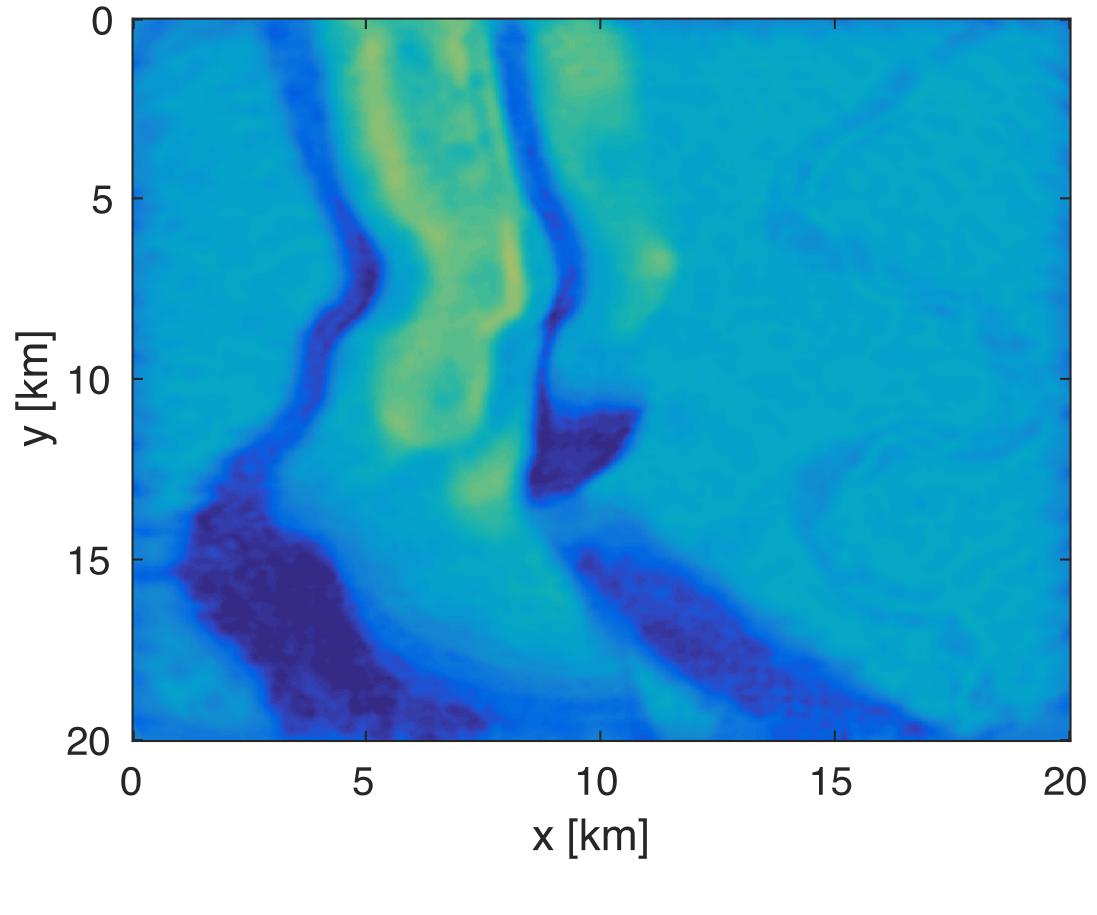




Initial model

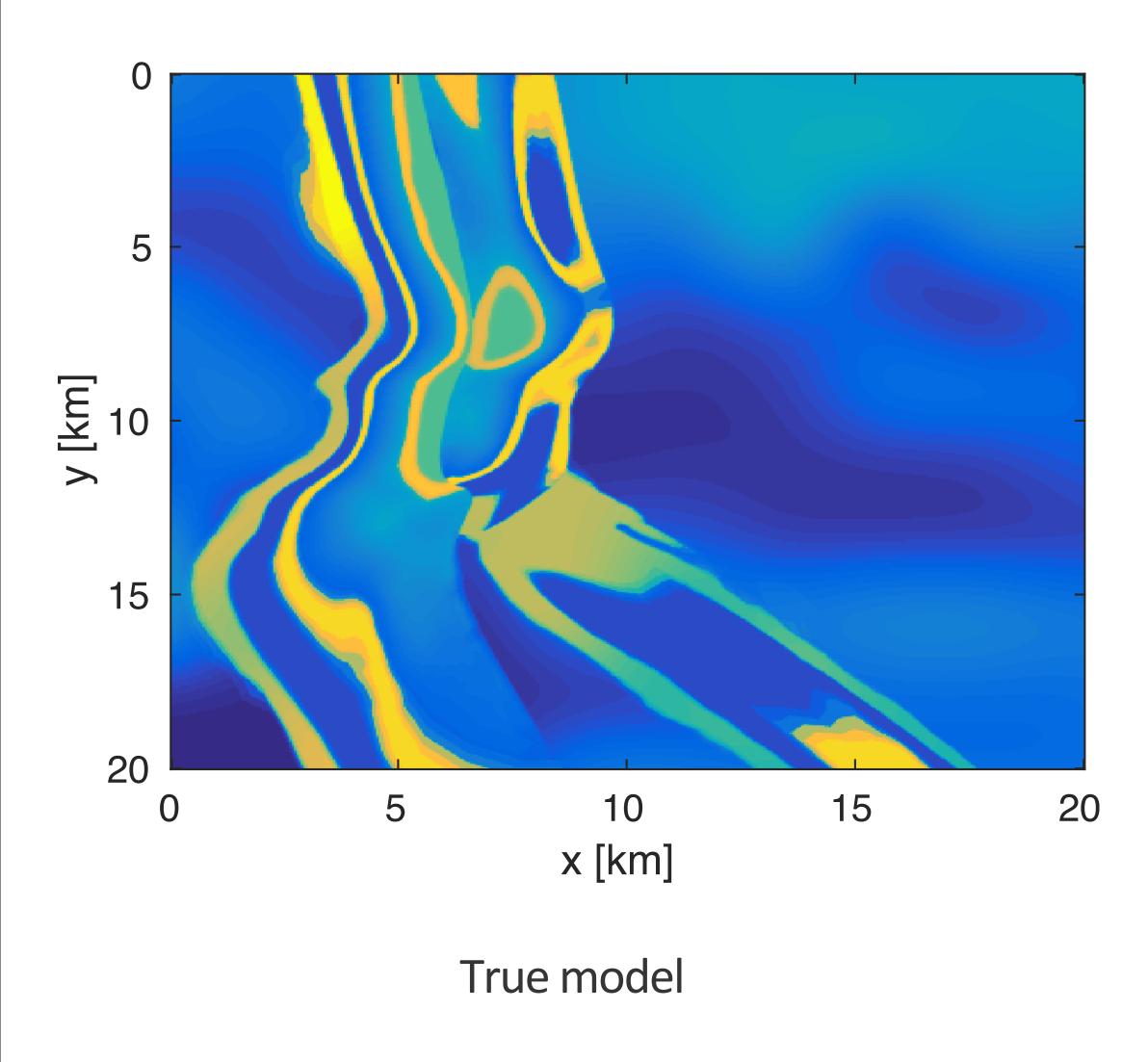


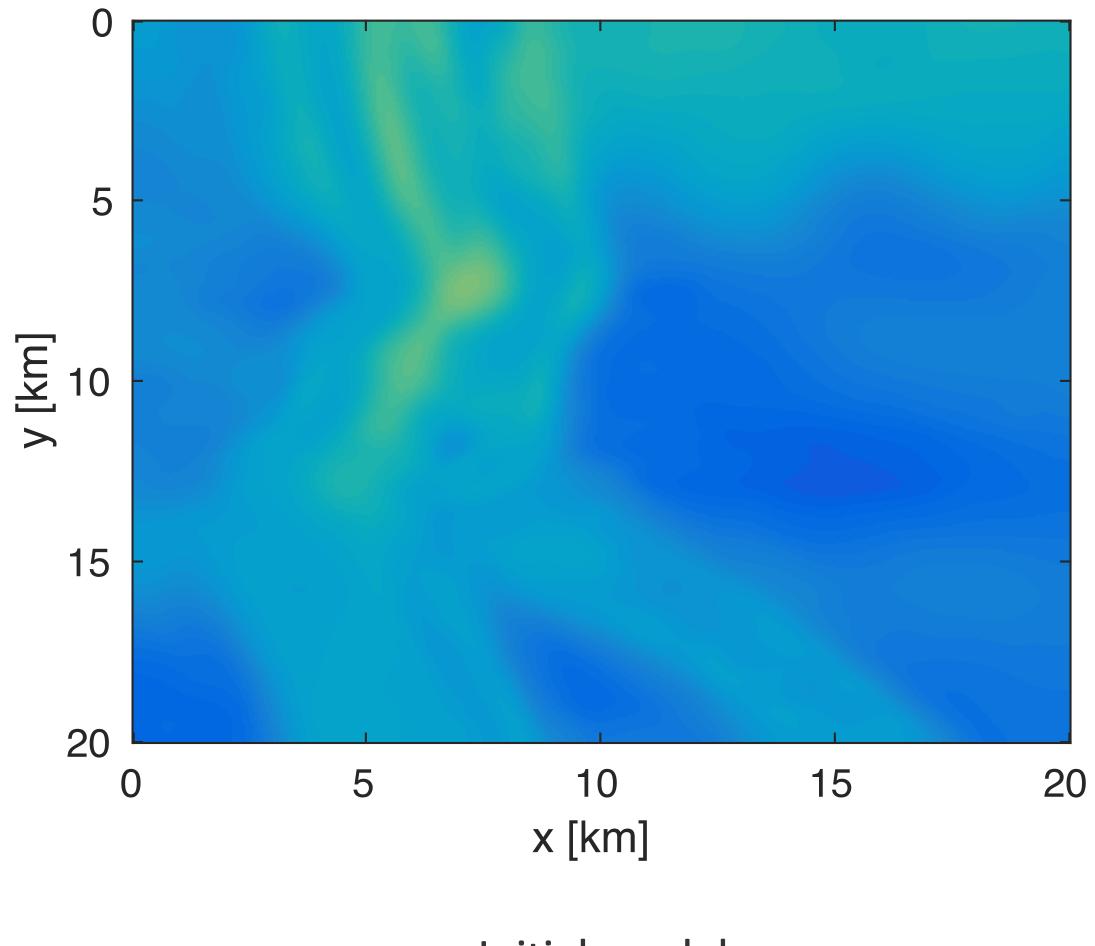




Stochastic LBFGS

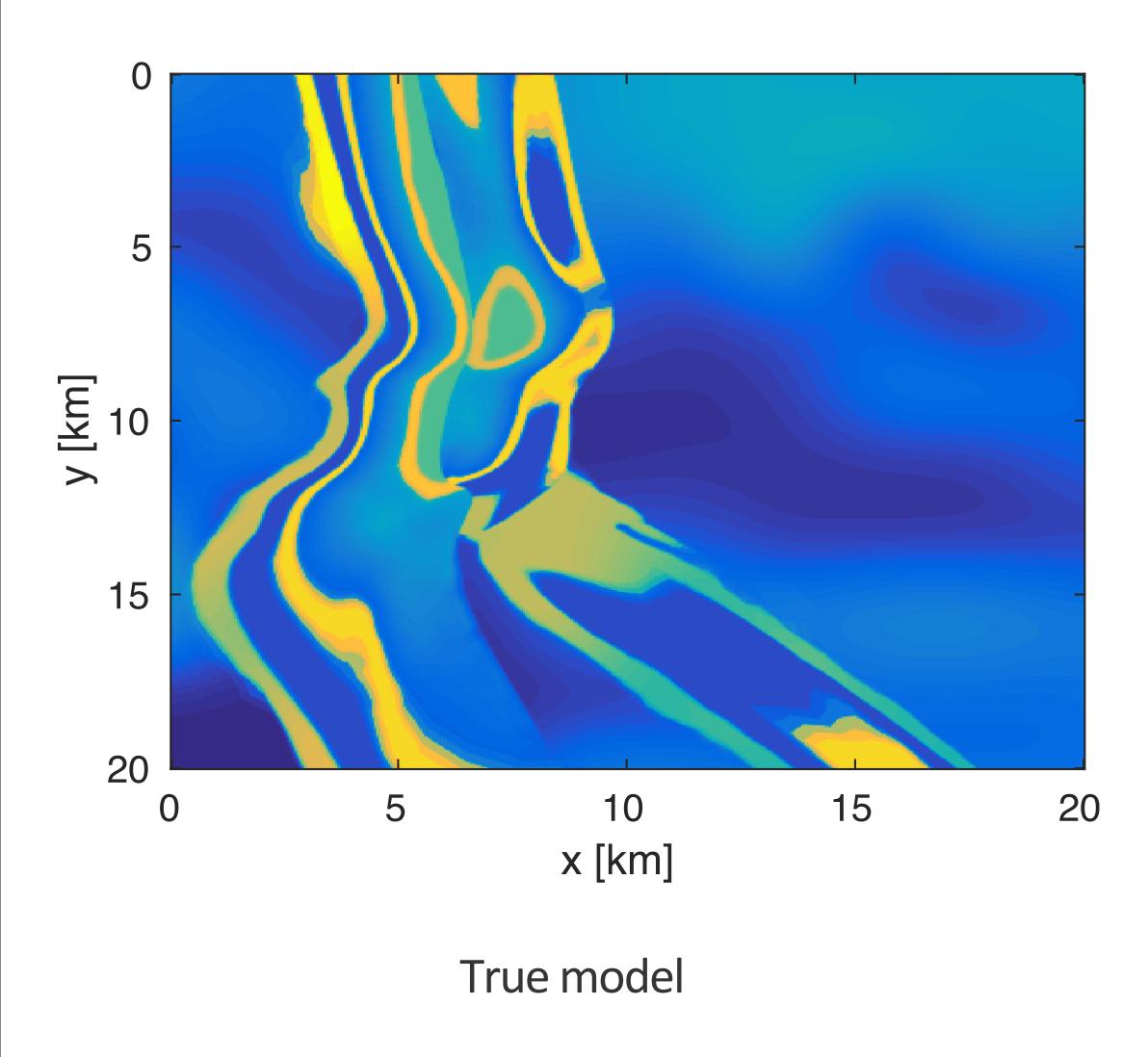


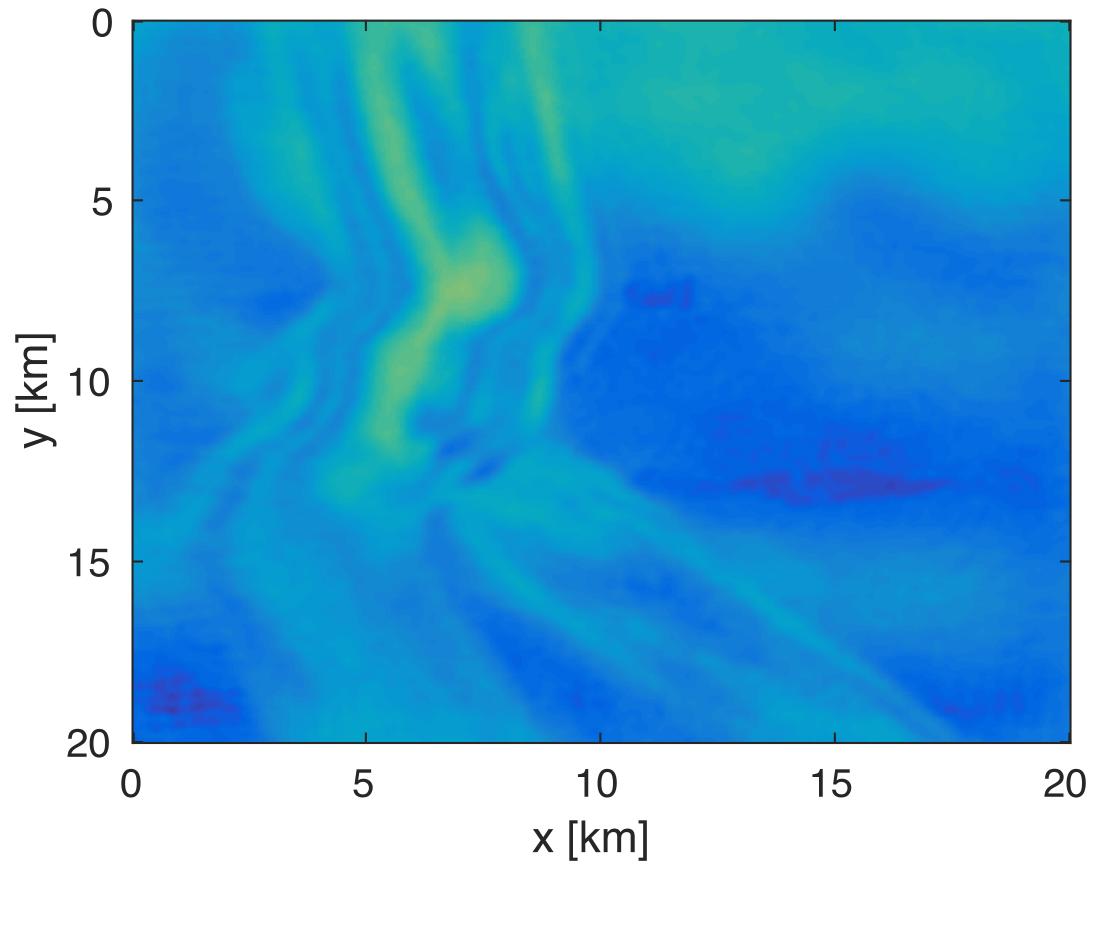




Initial model



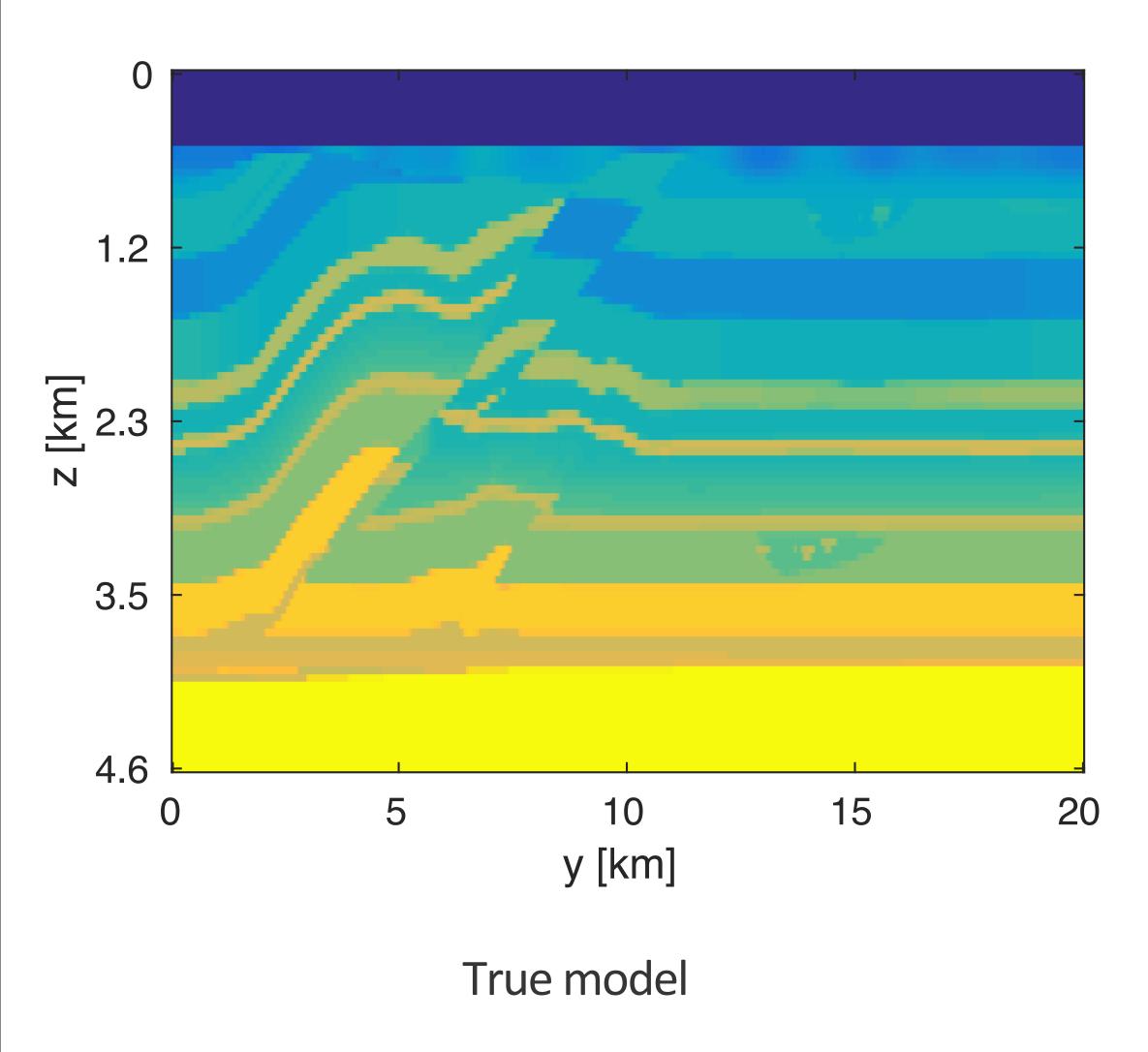


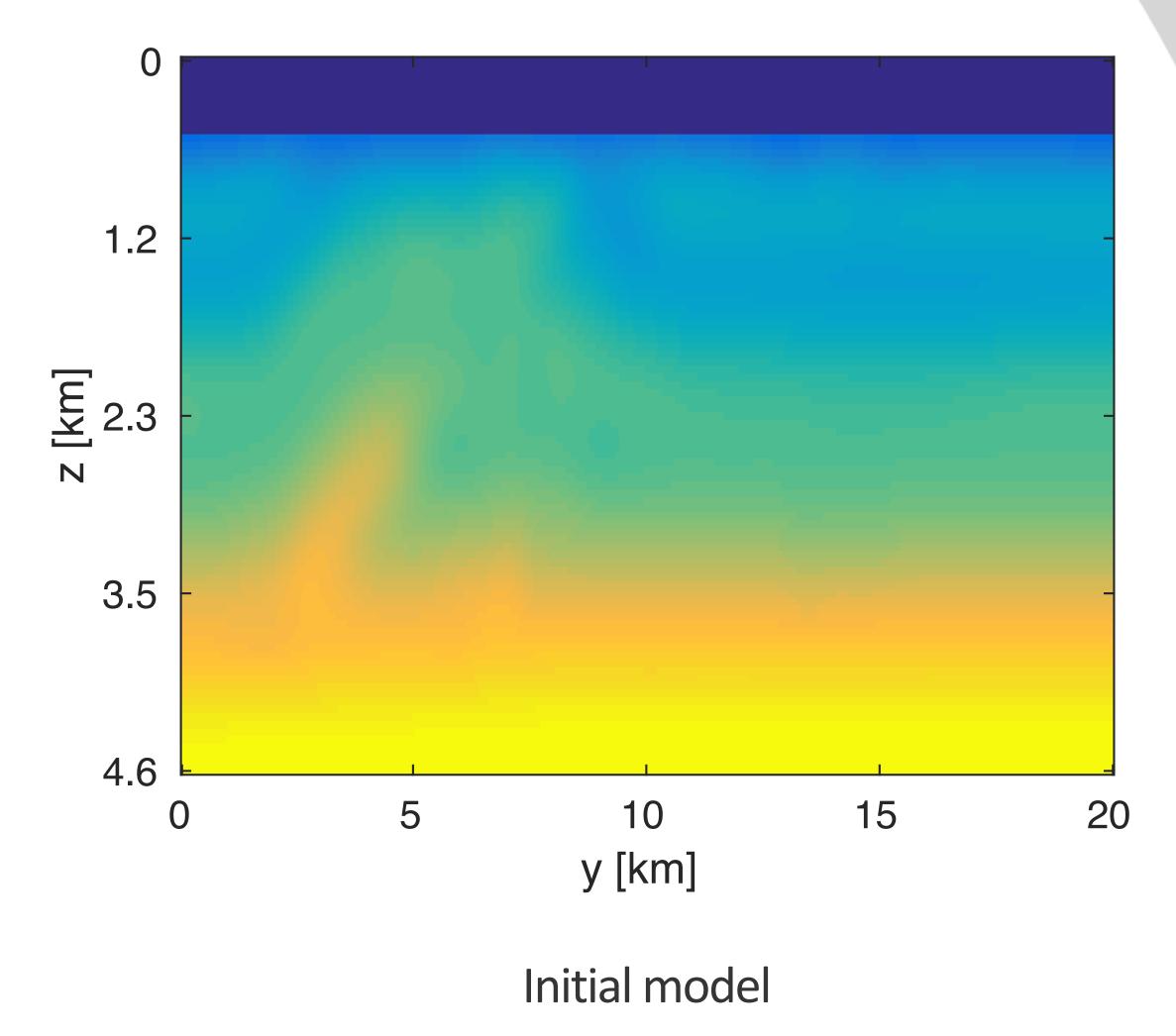


Stochastic LBFGS



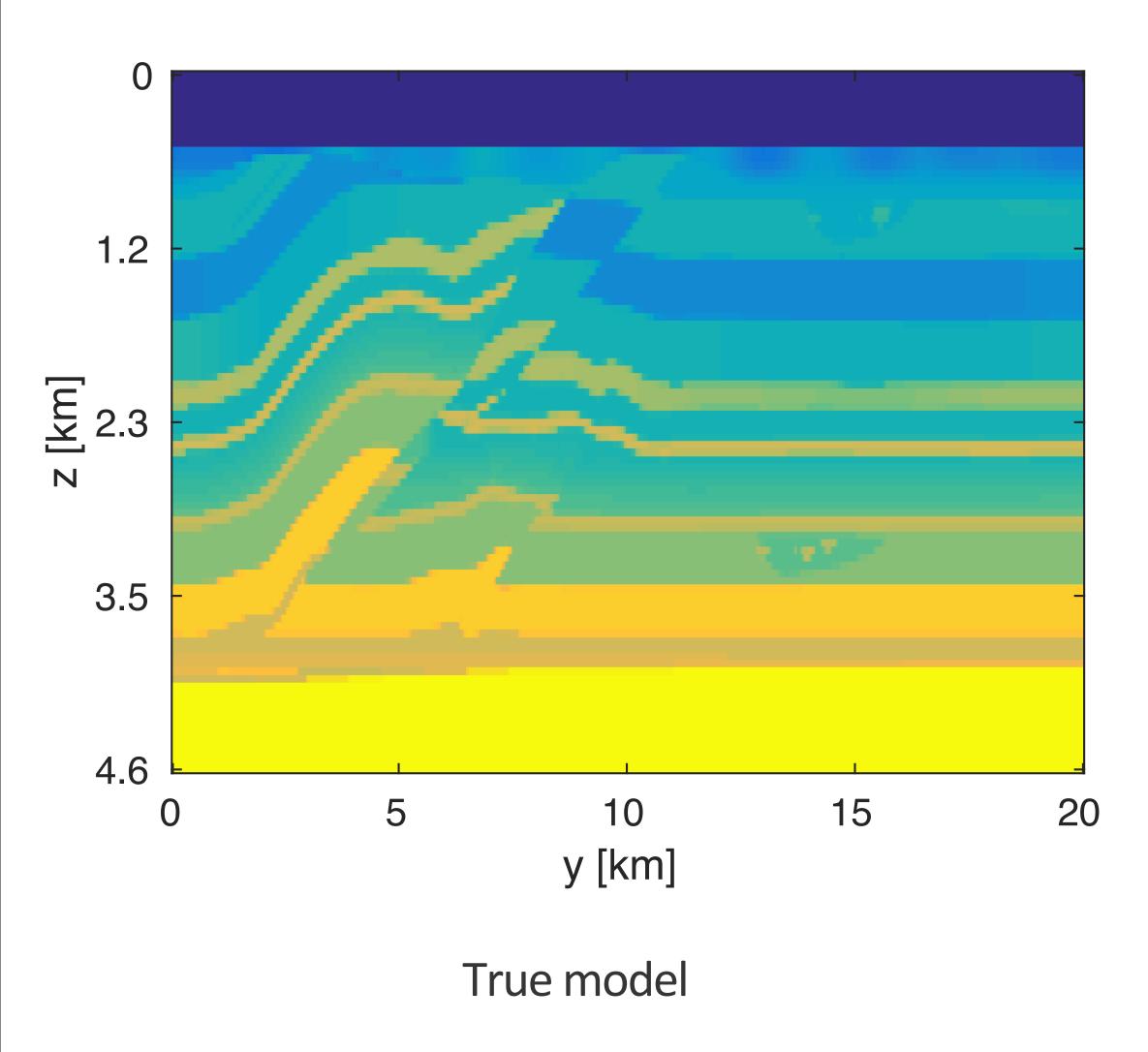
x=12.5km slice

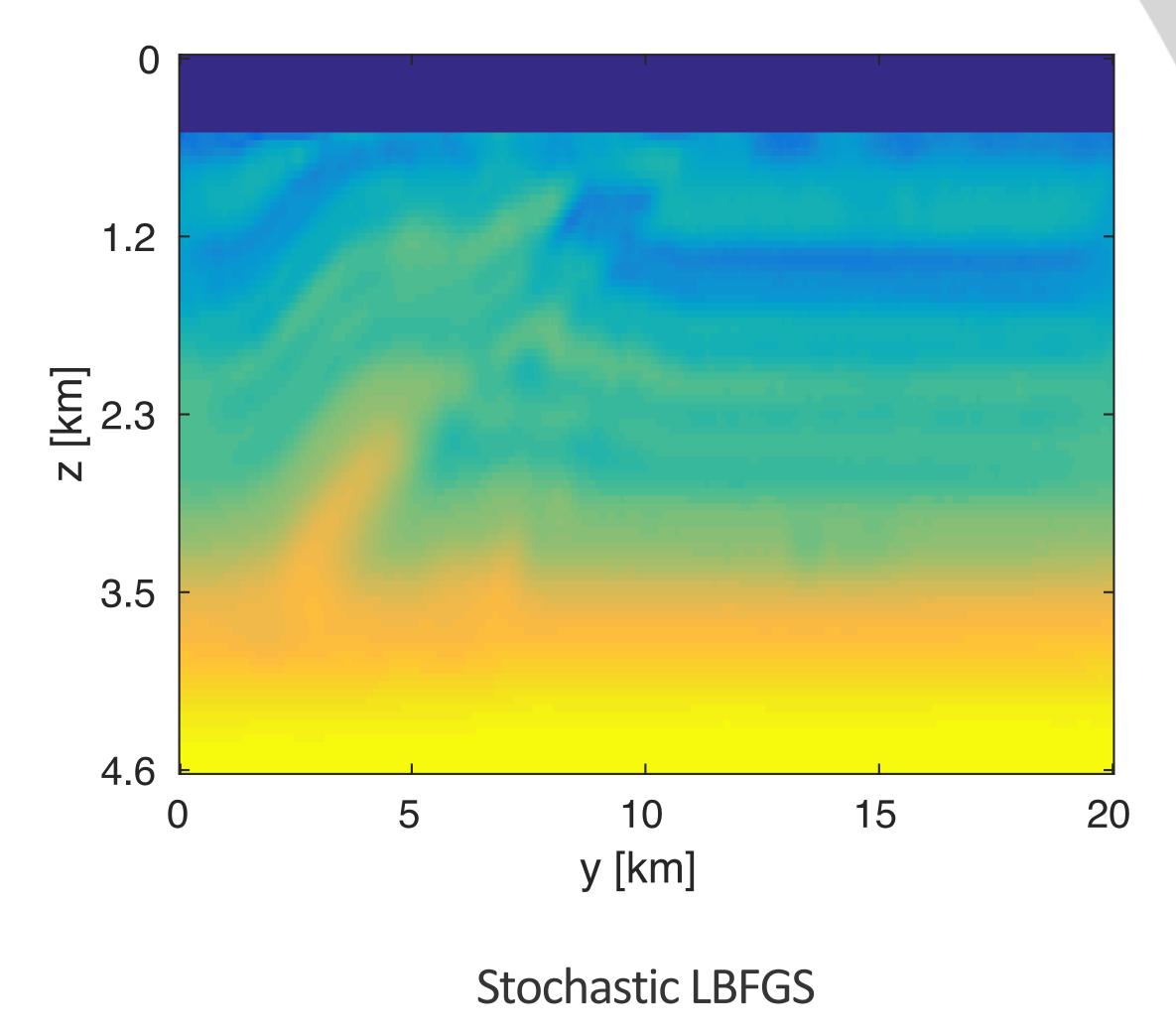






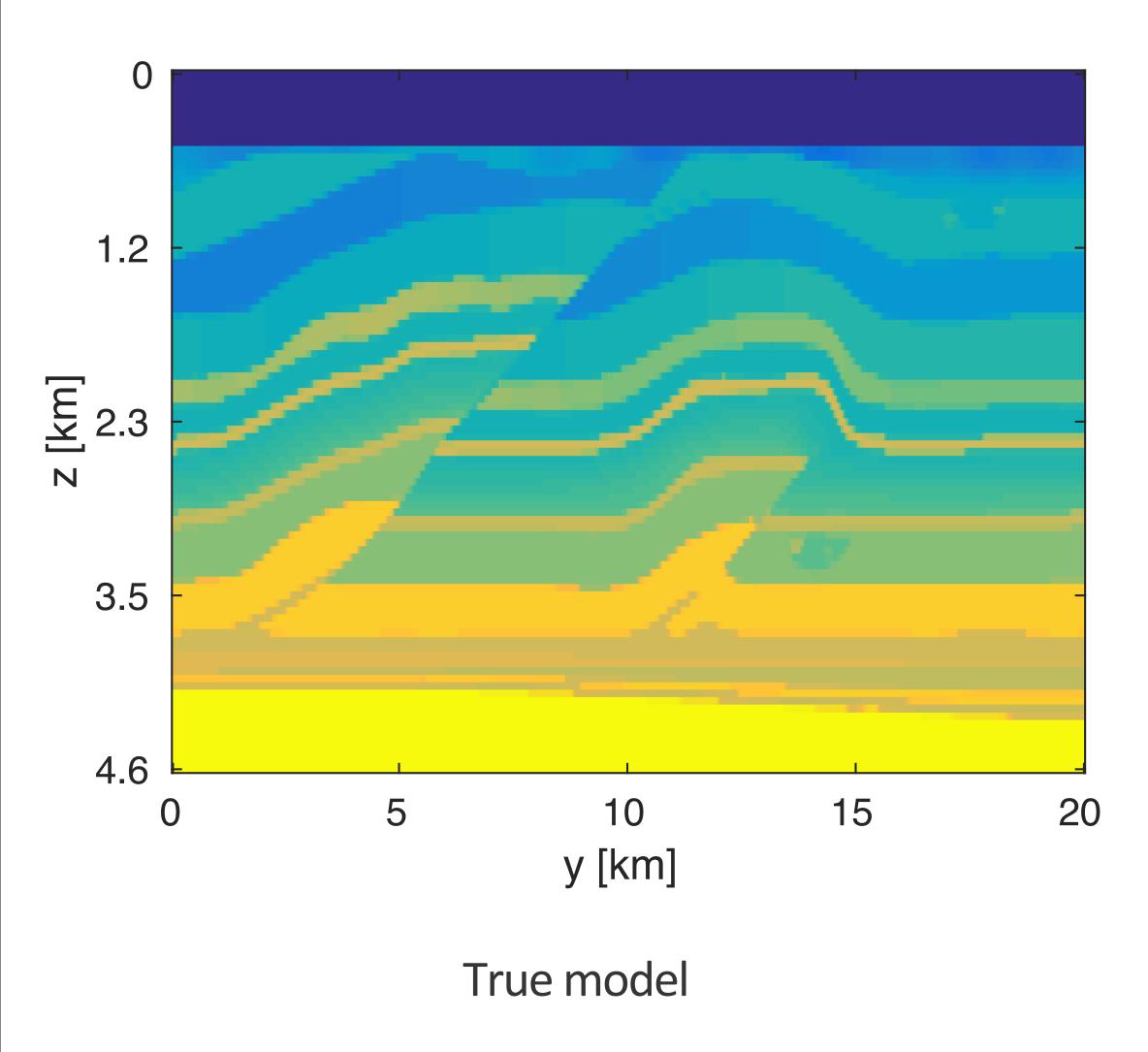
x=12.5km slice

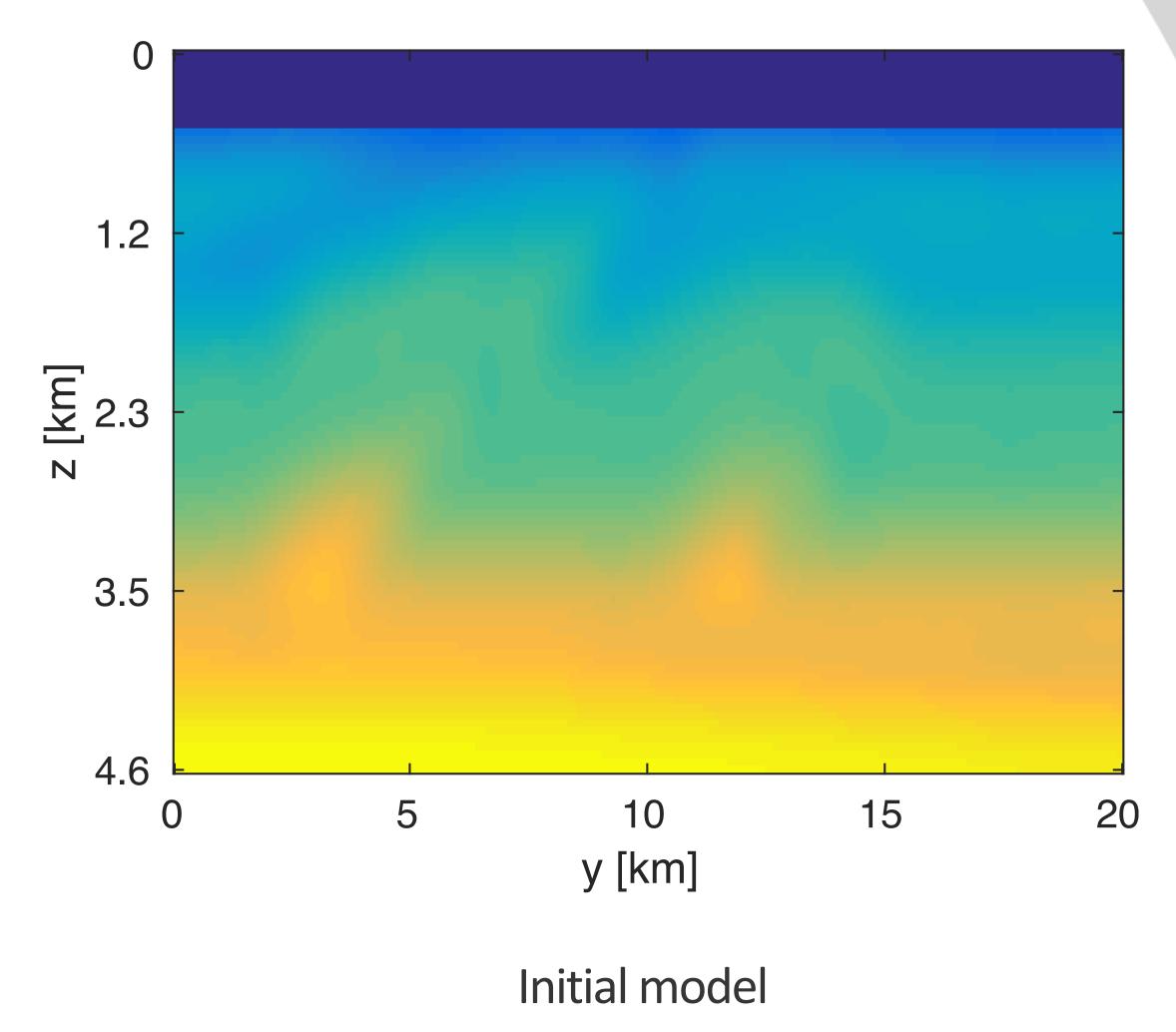






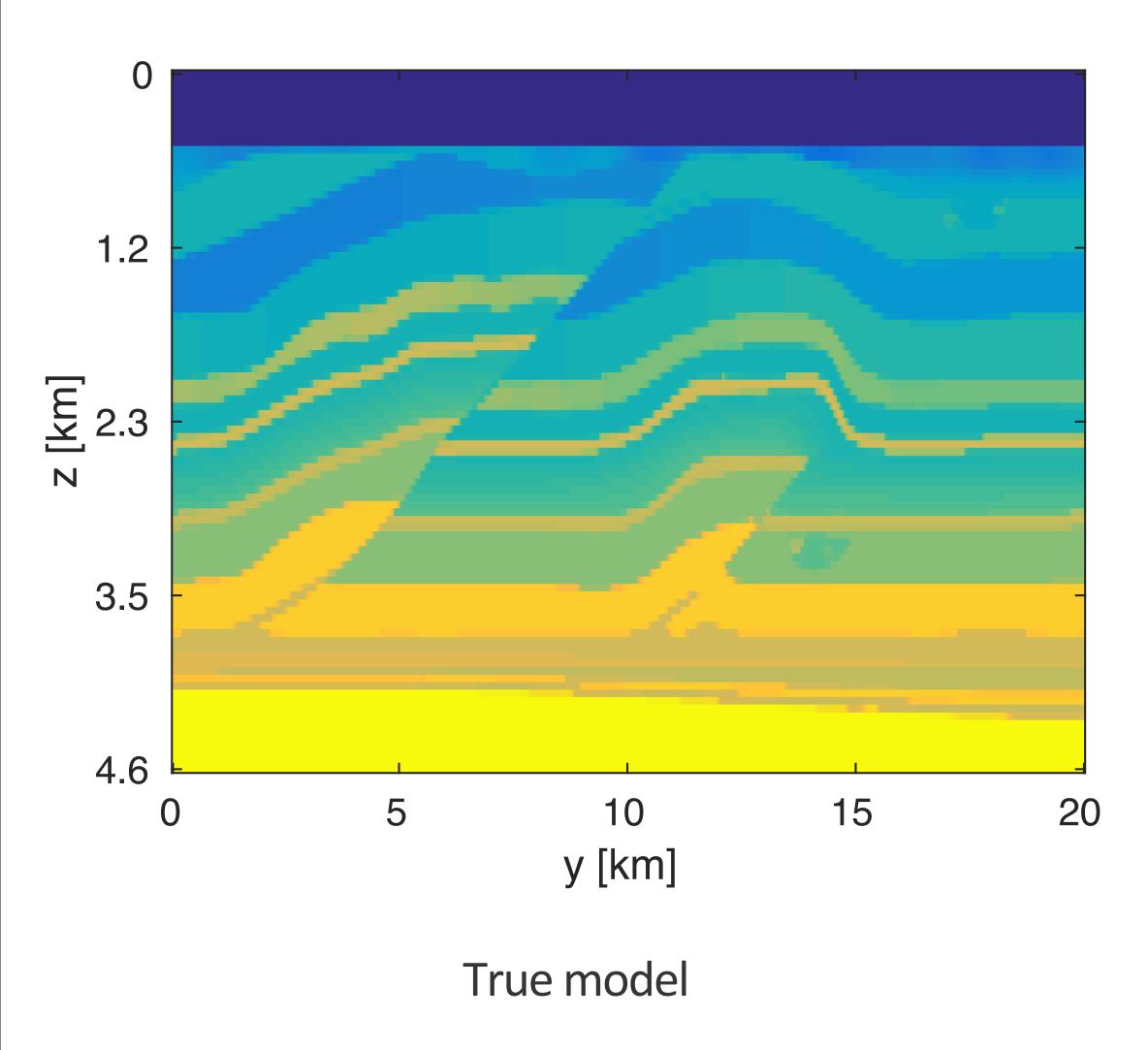
x=17.5km slice

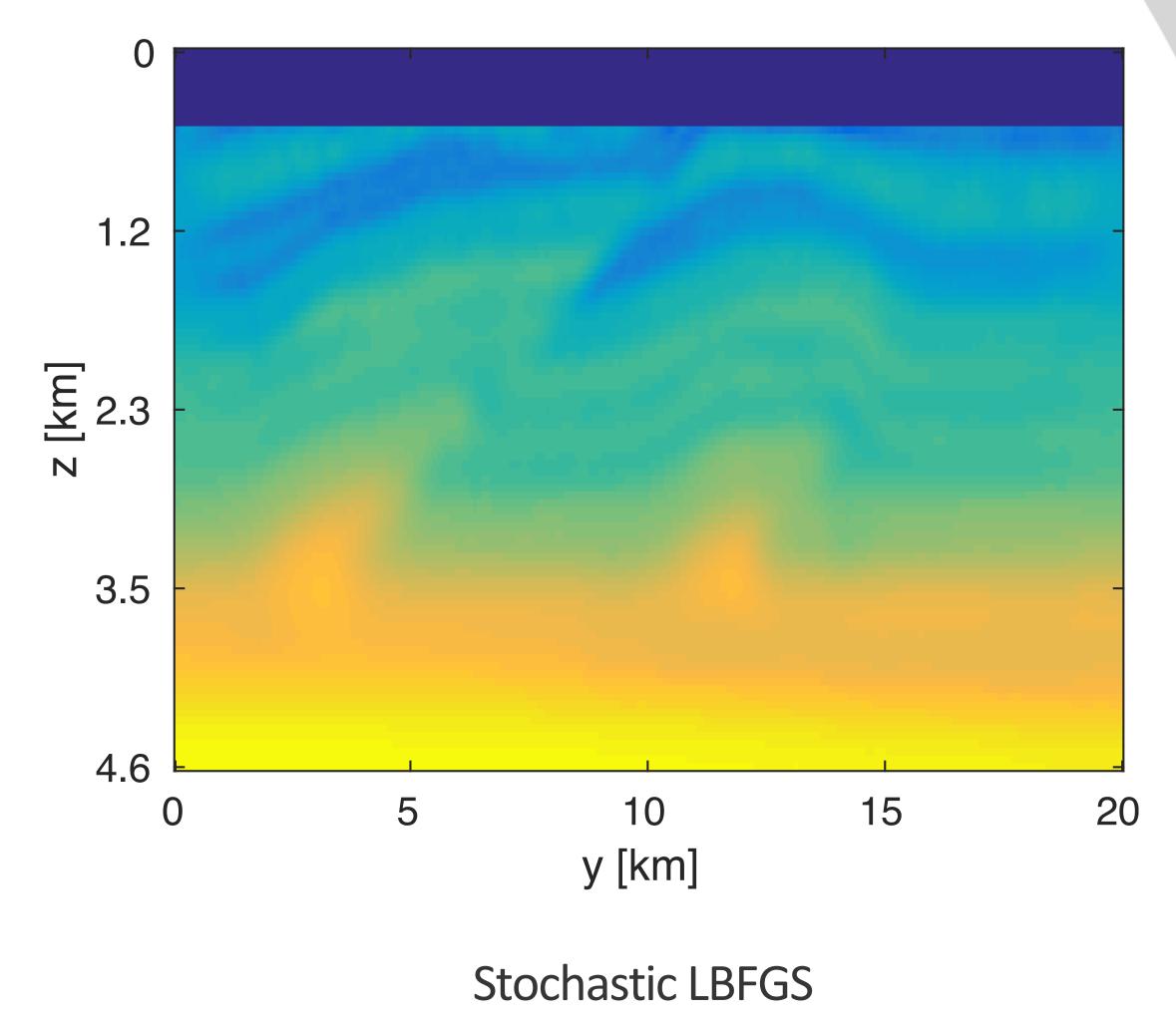






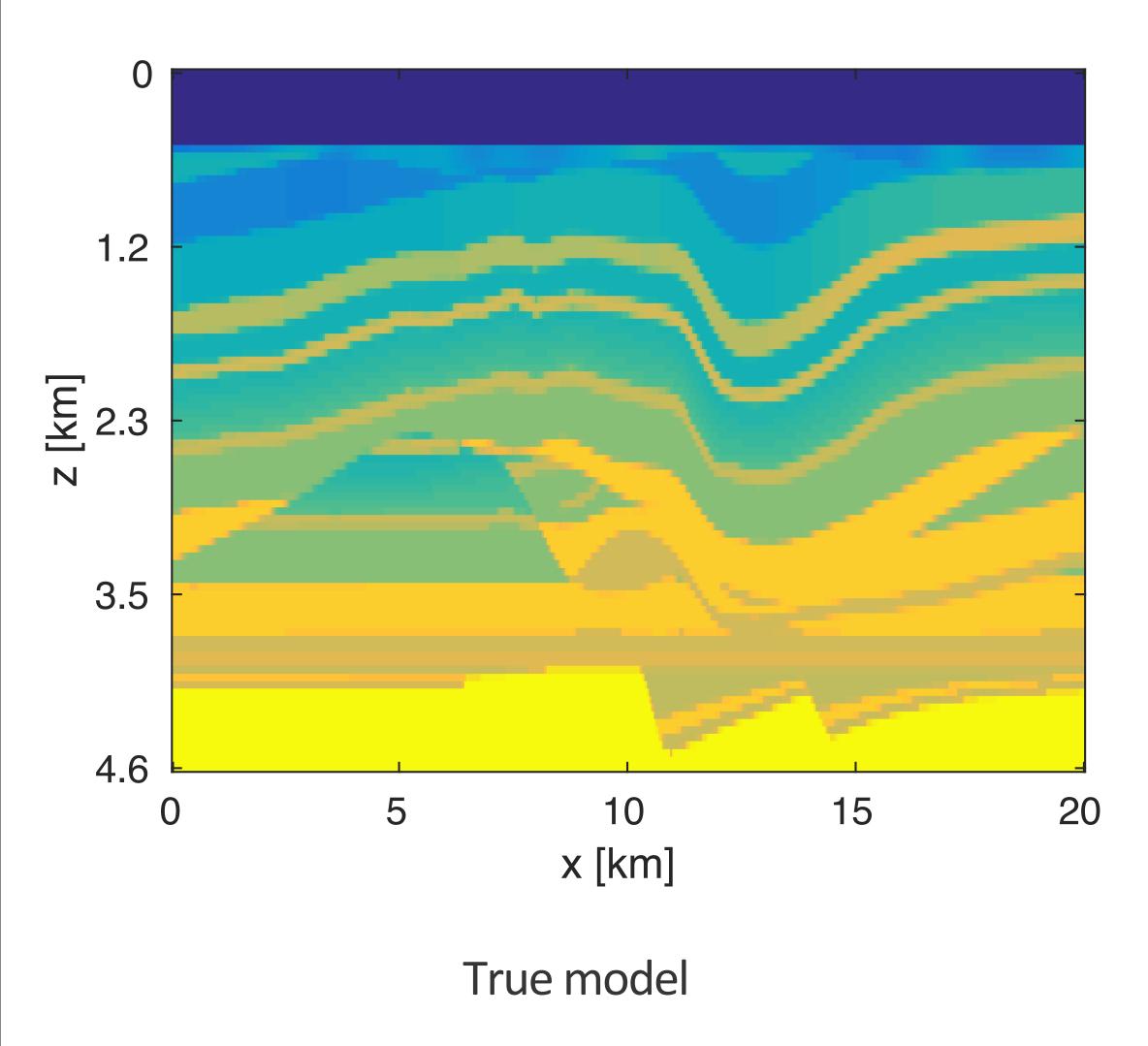
x=17.5km slice

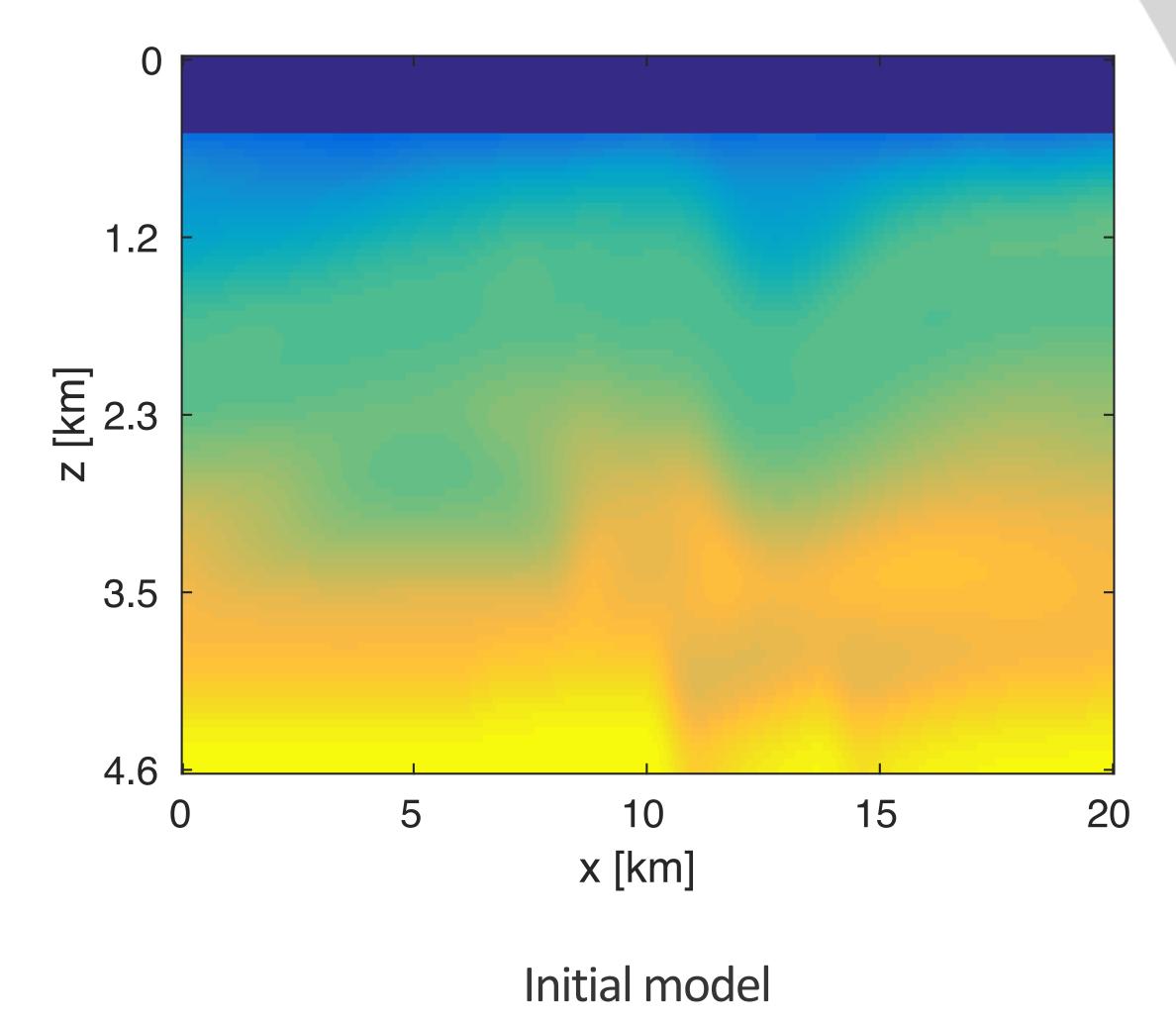






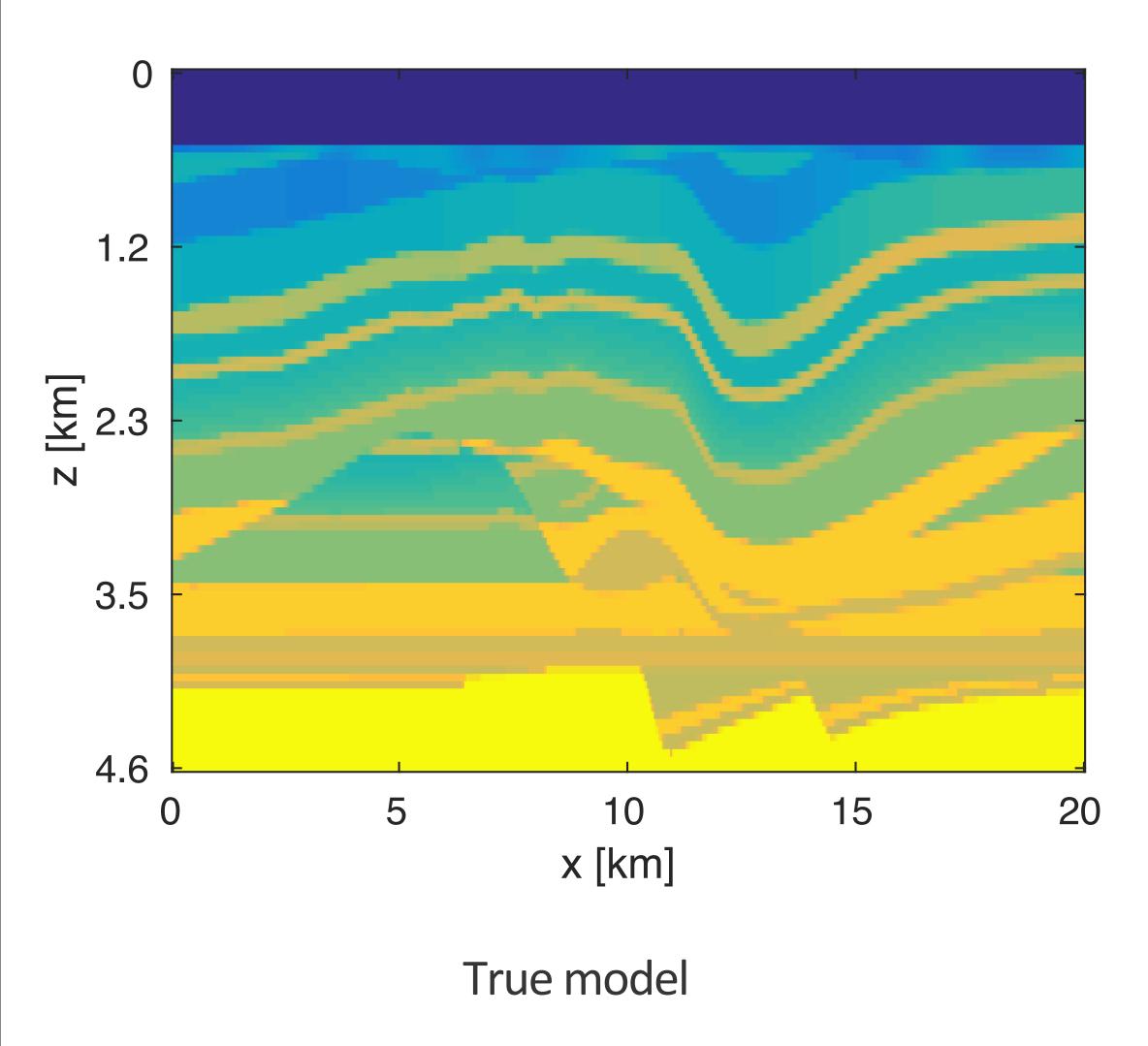


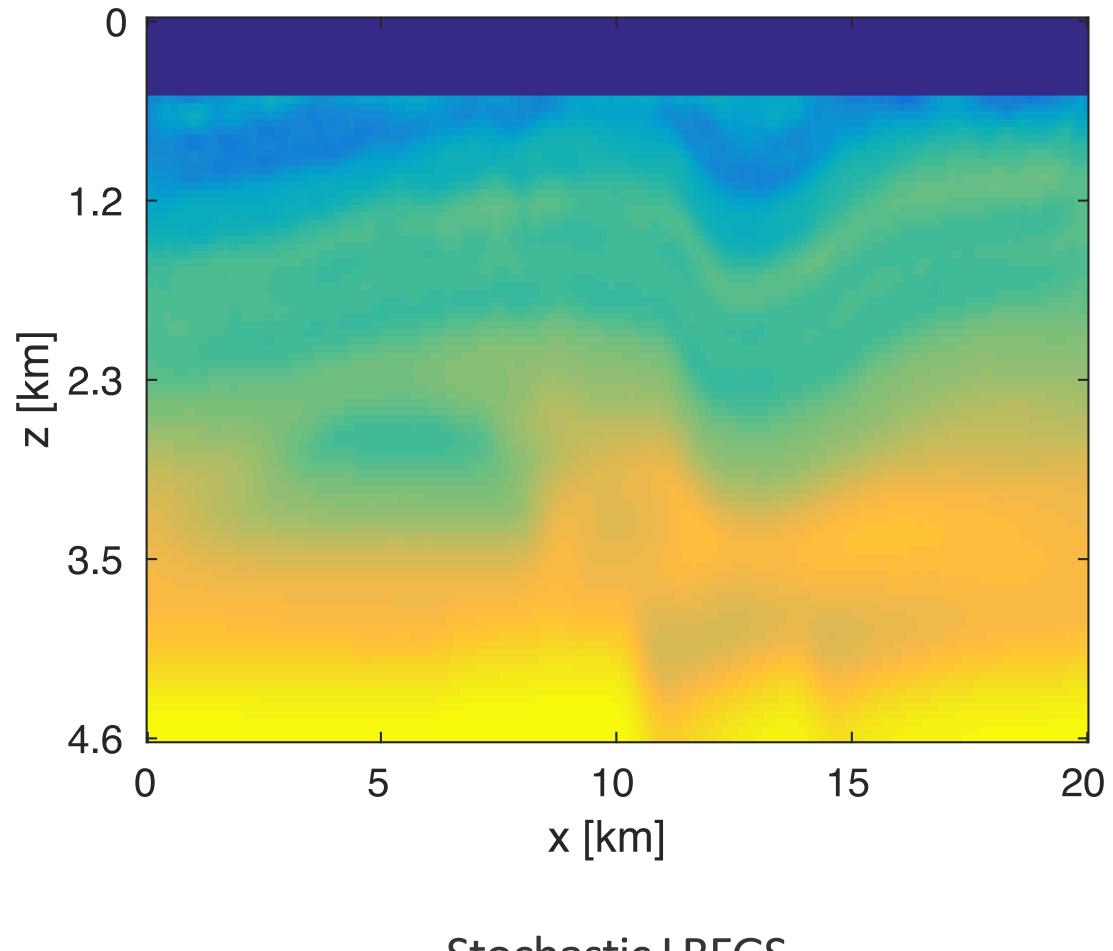








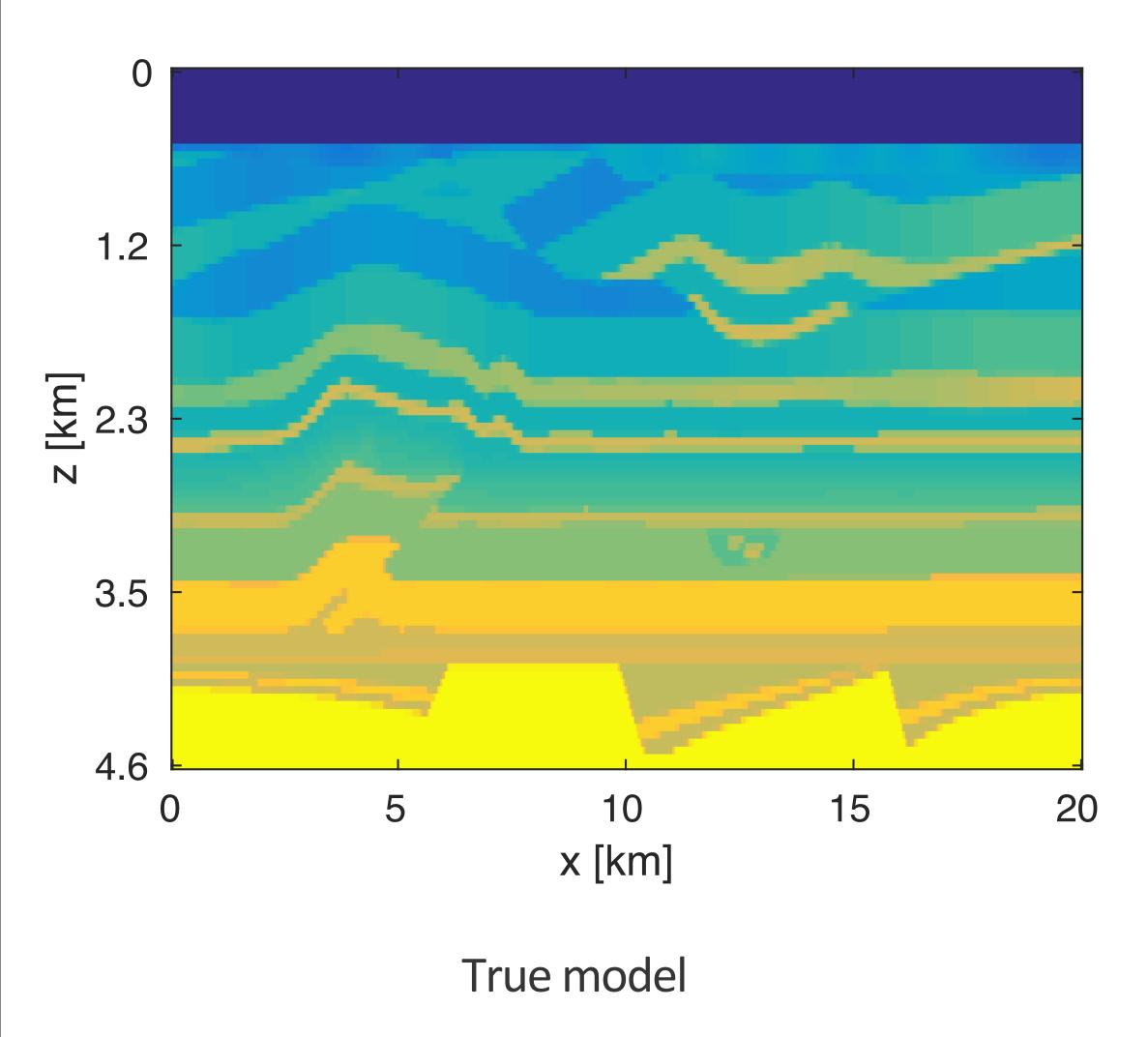




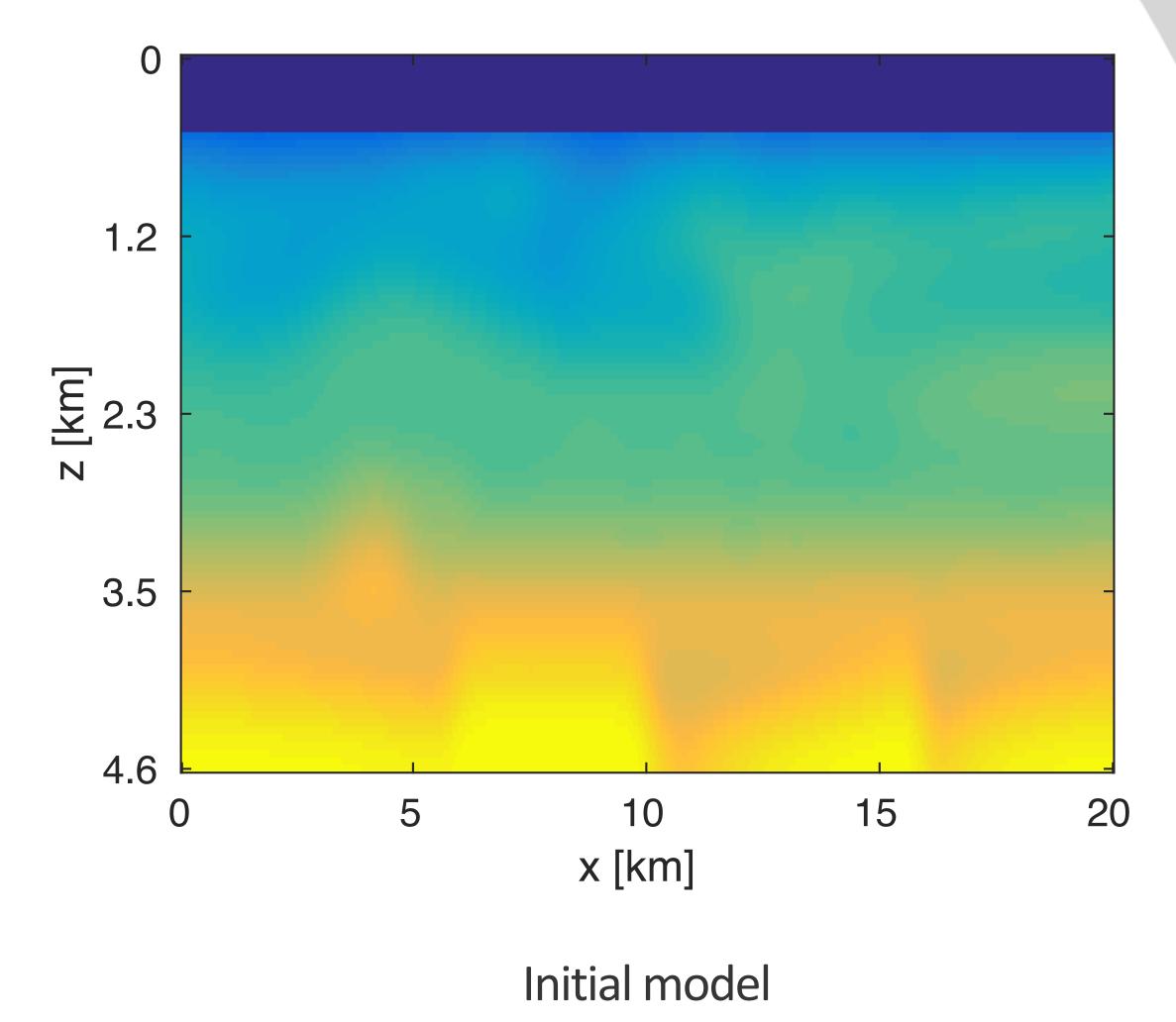
Stochastic LBFGS



y=10km slice

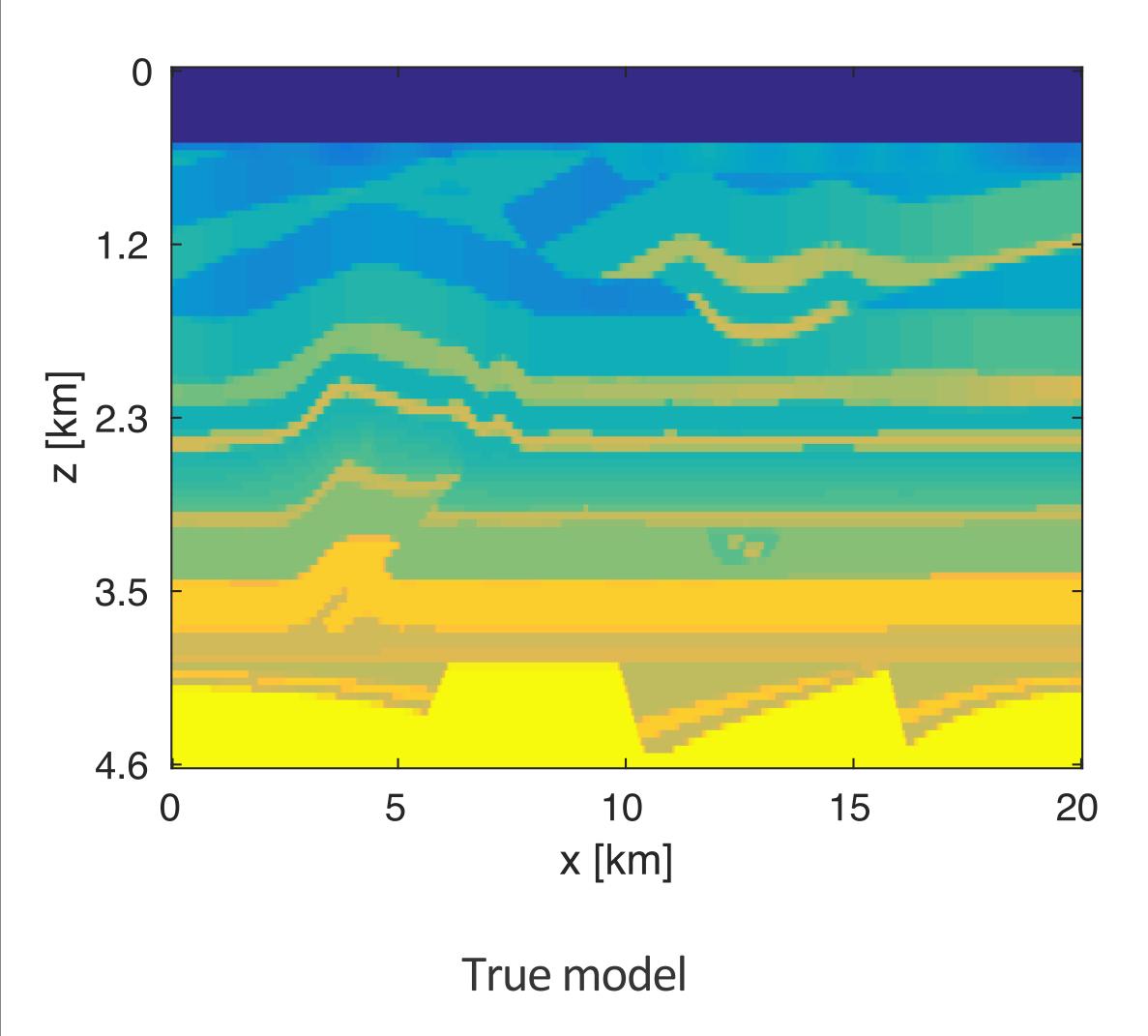


58

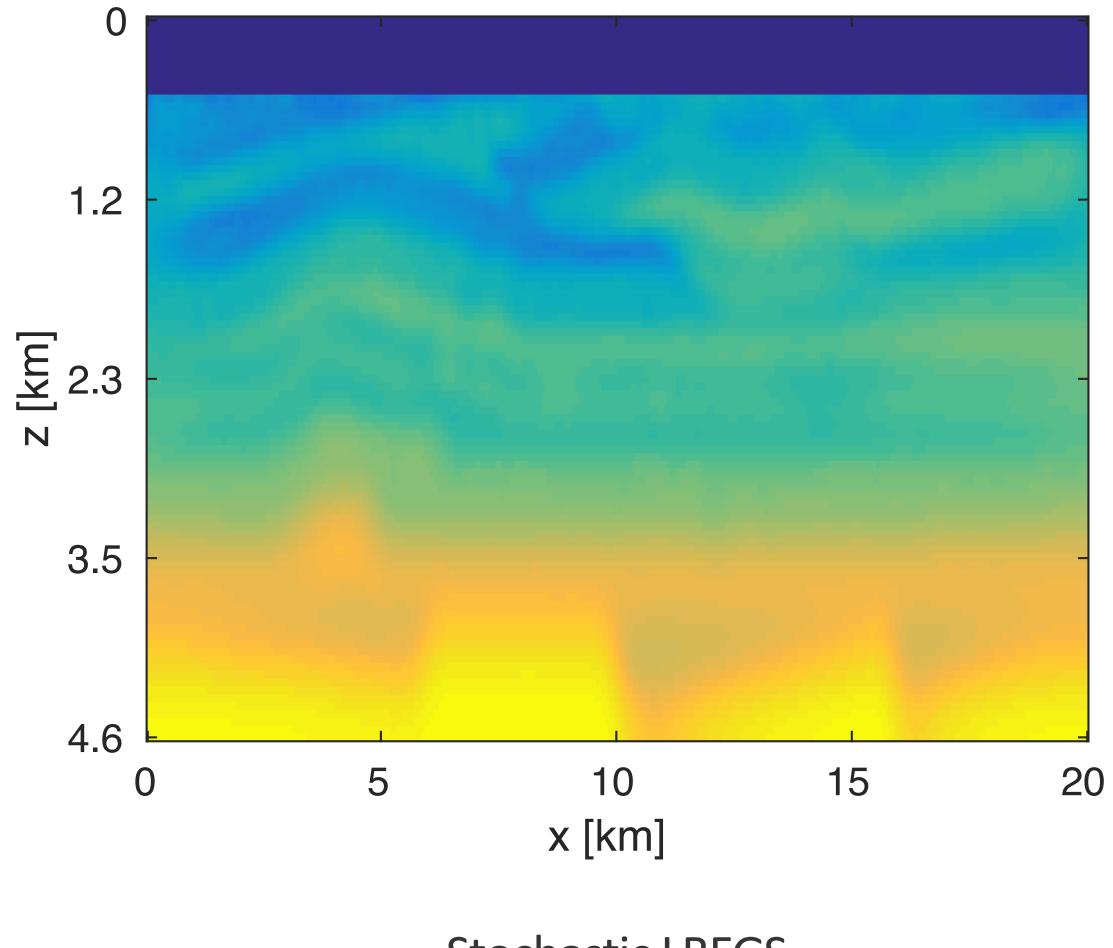




y=10km slice



59



Stochastic LBFGS



3D Overthrust Model

Same model as before, no water layer (SEG abstract results)

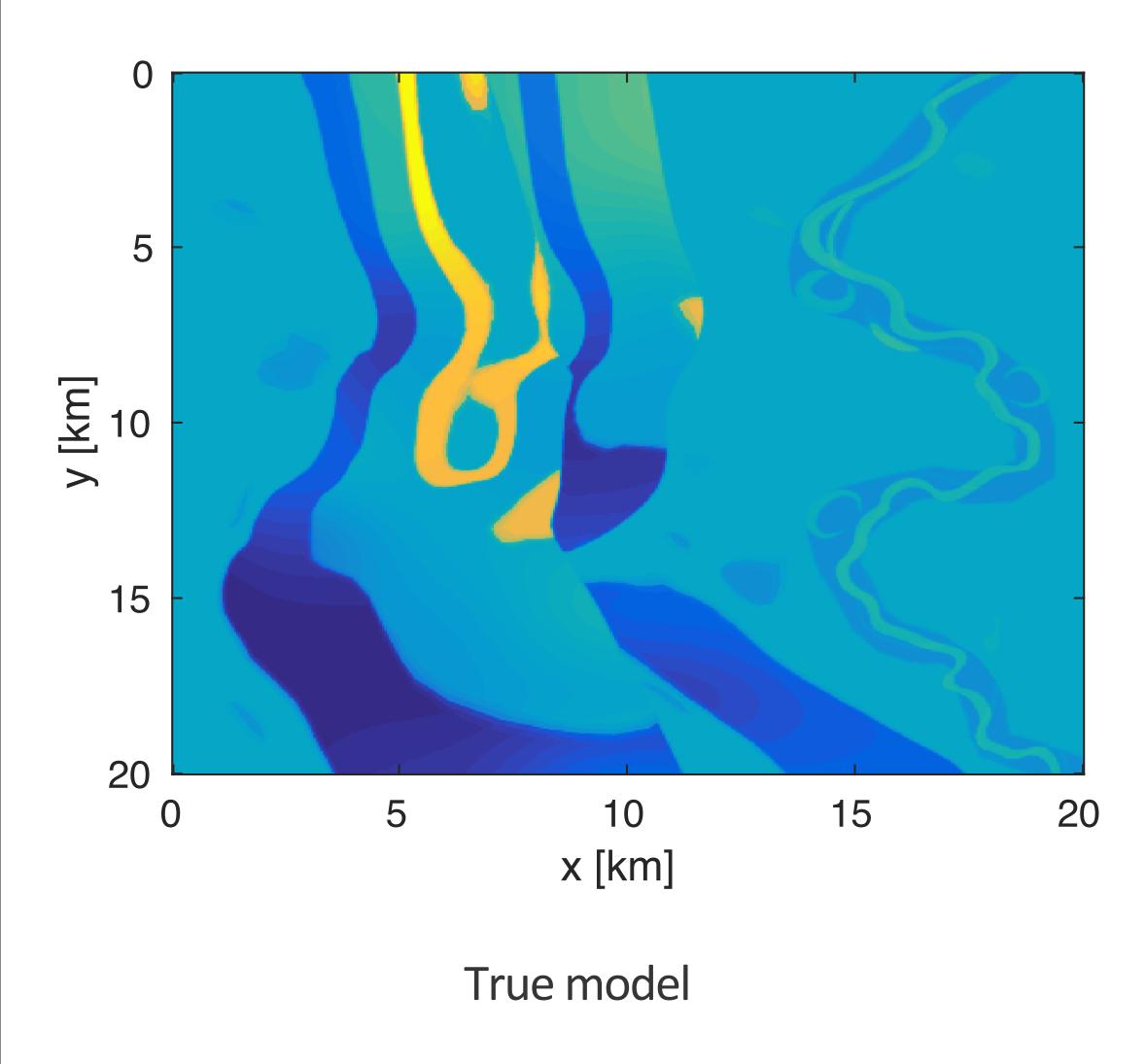
3Hz - 8Hz, inverted one frequency at a time

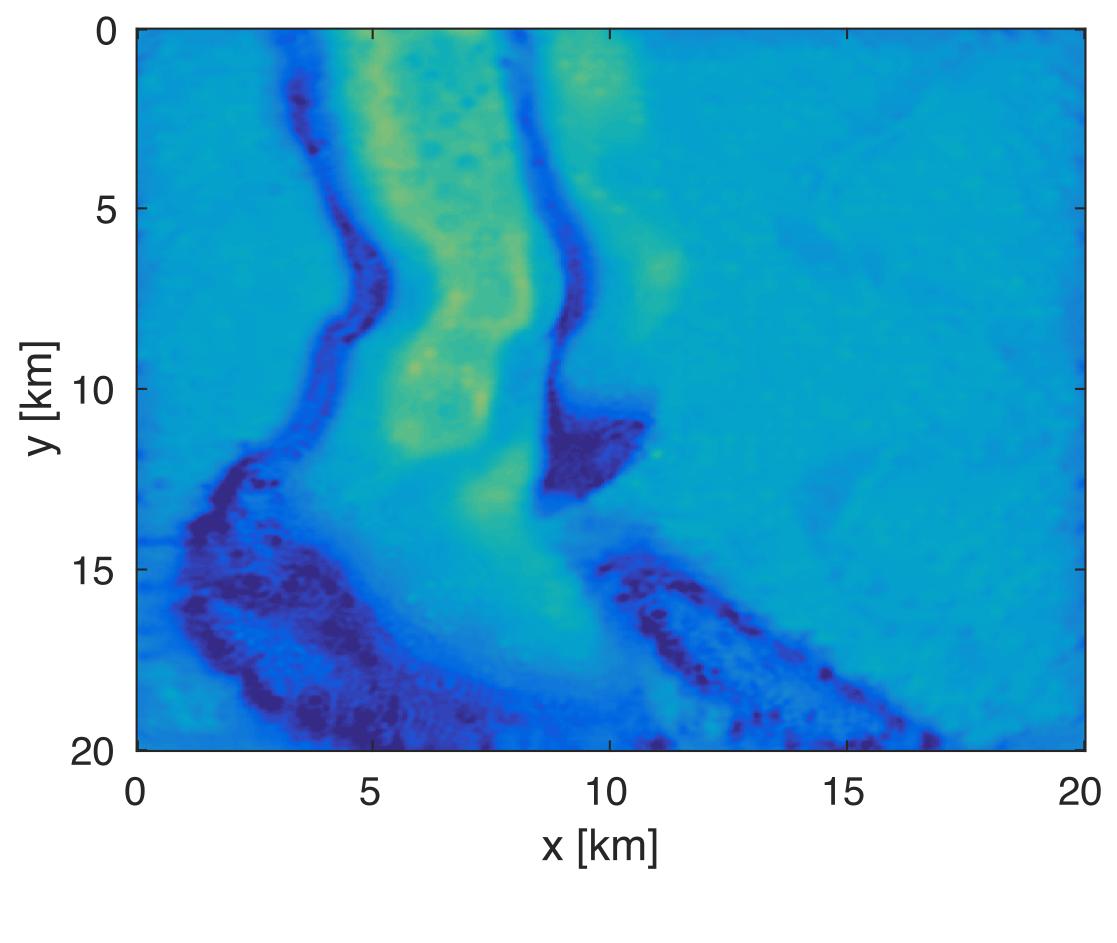
Compare the stochastic approach to the full-data approach (equivalent # of PDEs solved)





z=500m slice

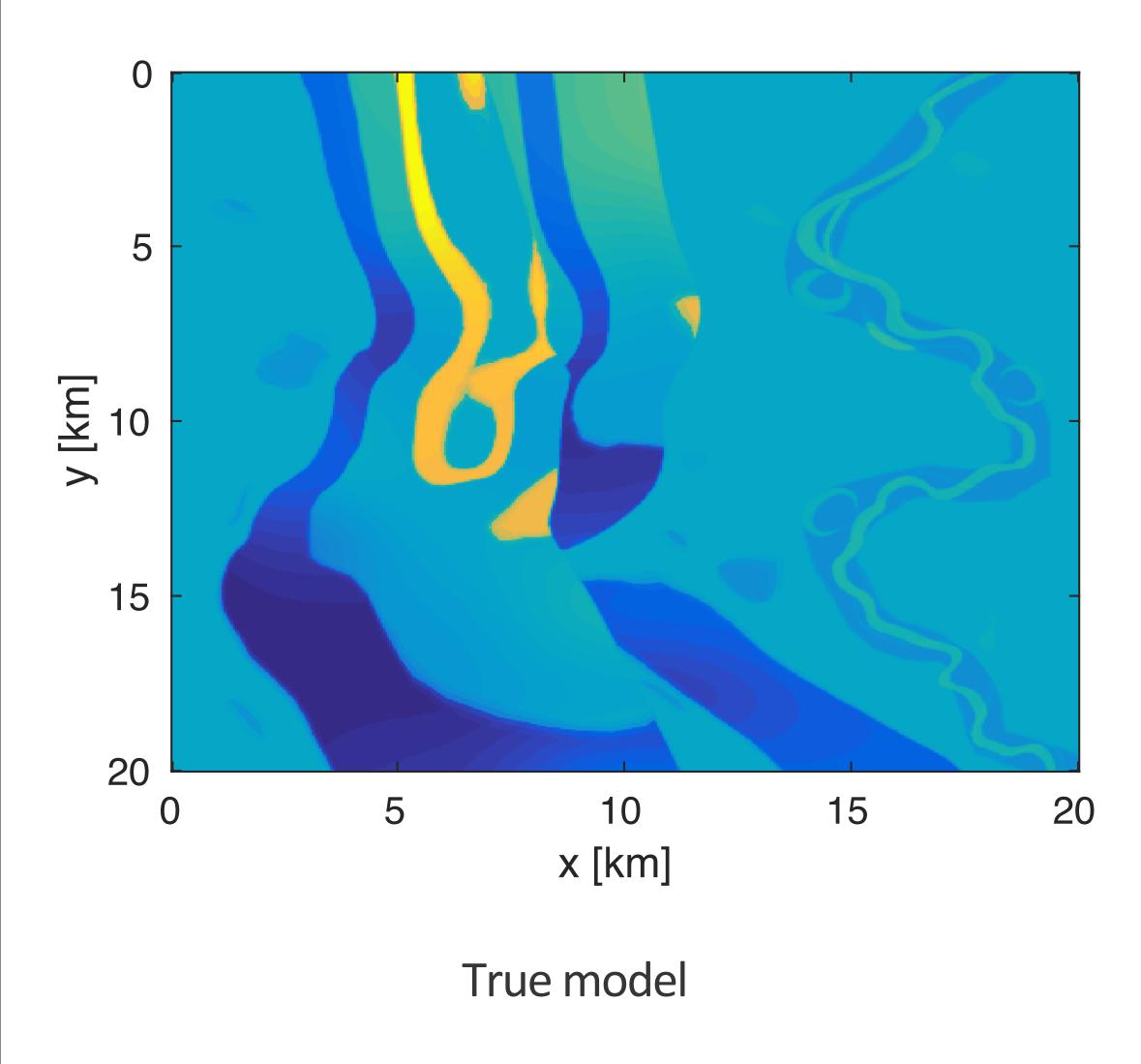


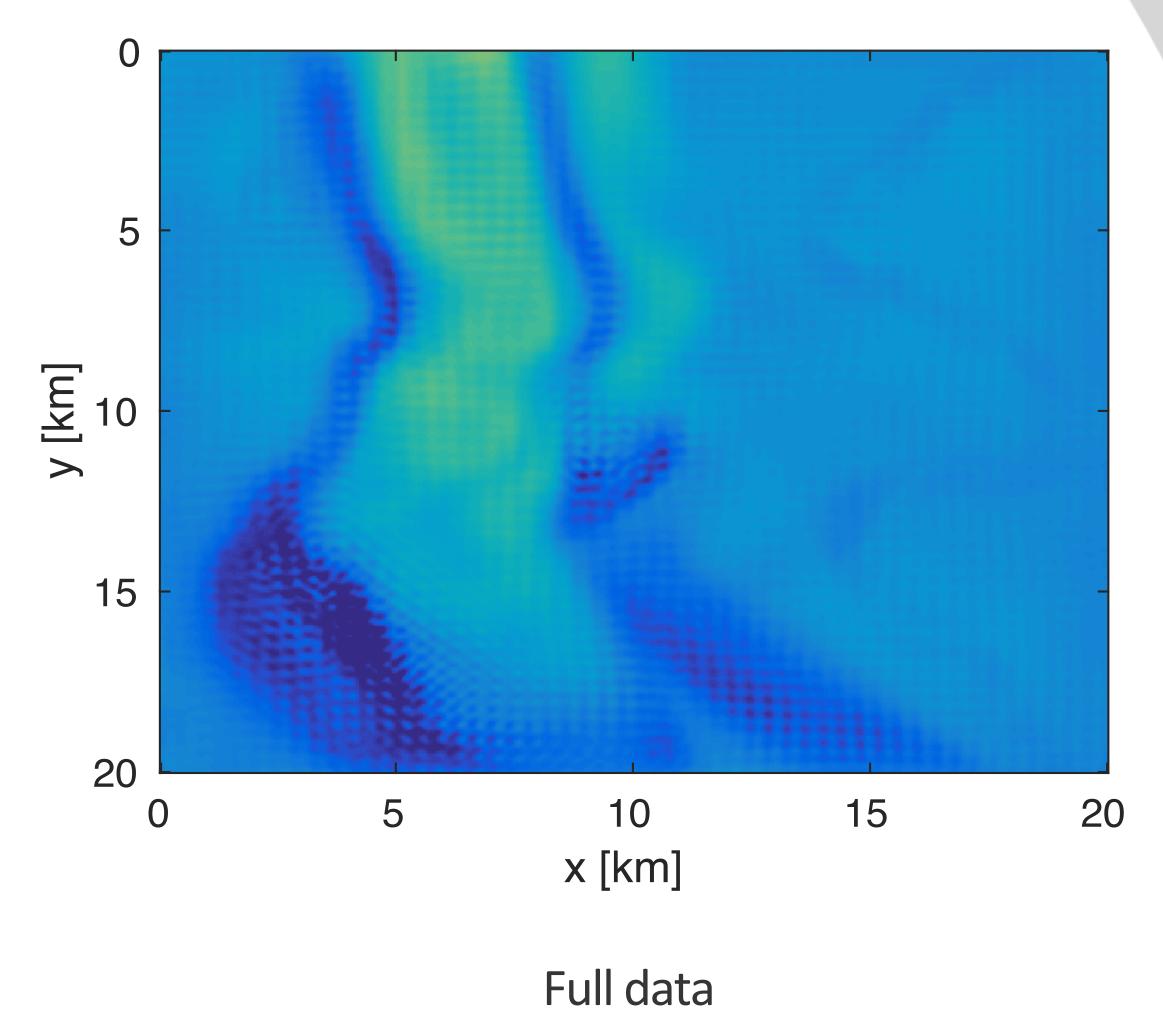


Stochastic LBFGS

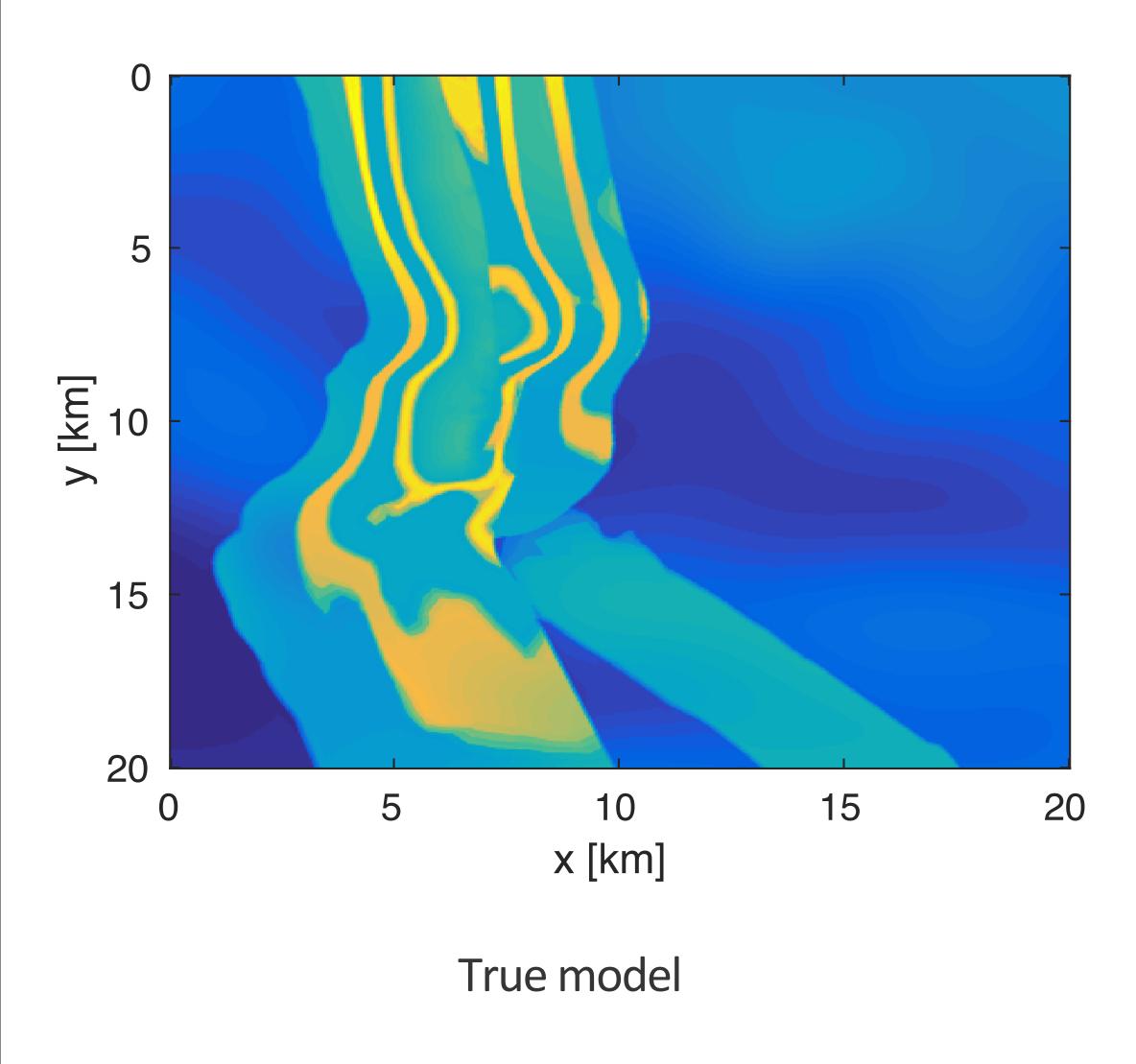


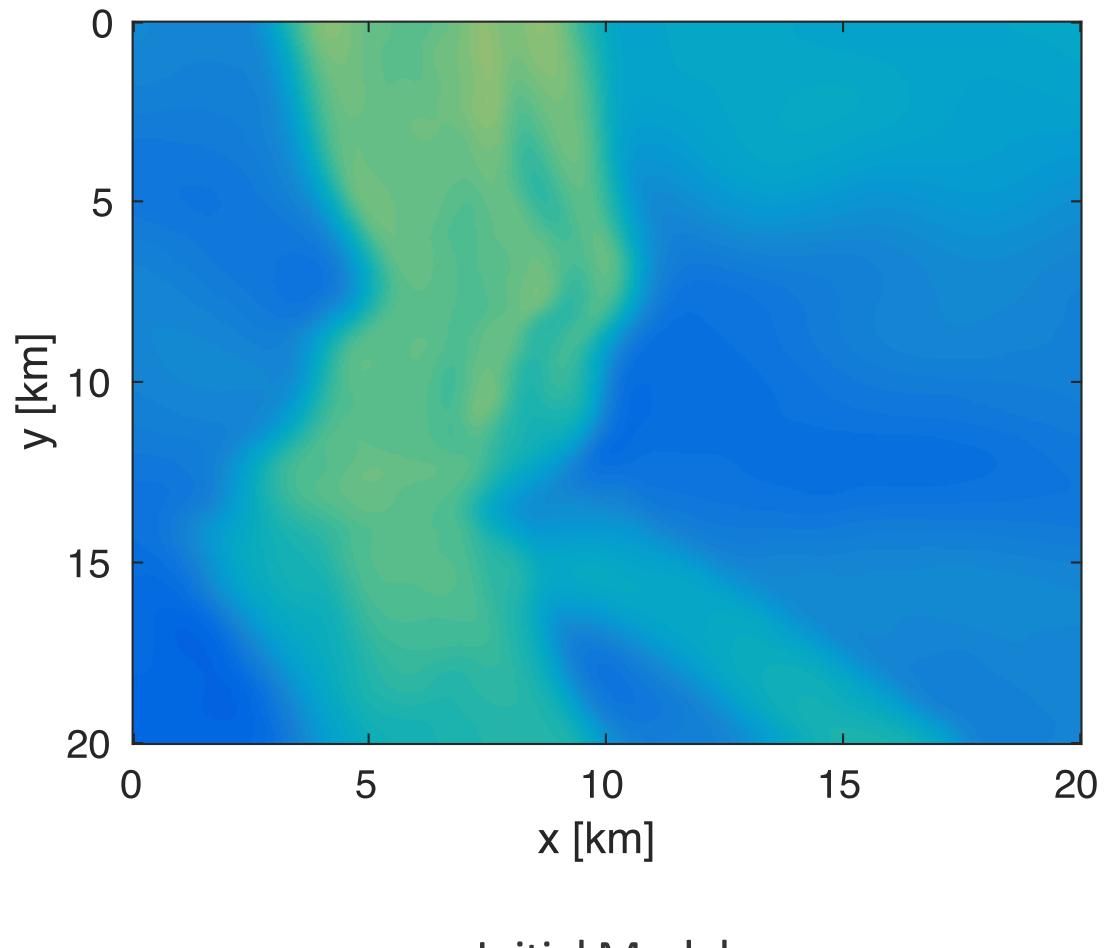
z=500m slice



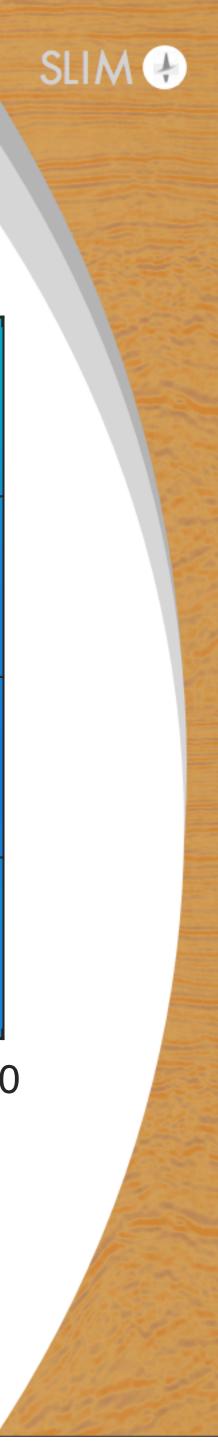


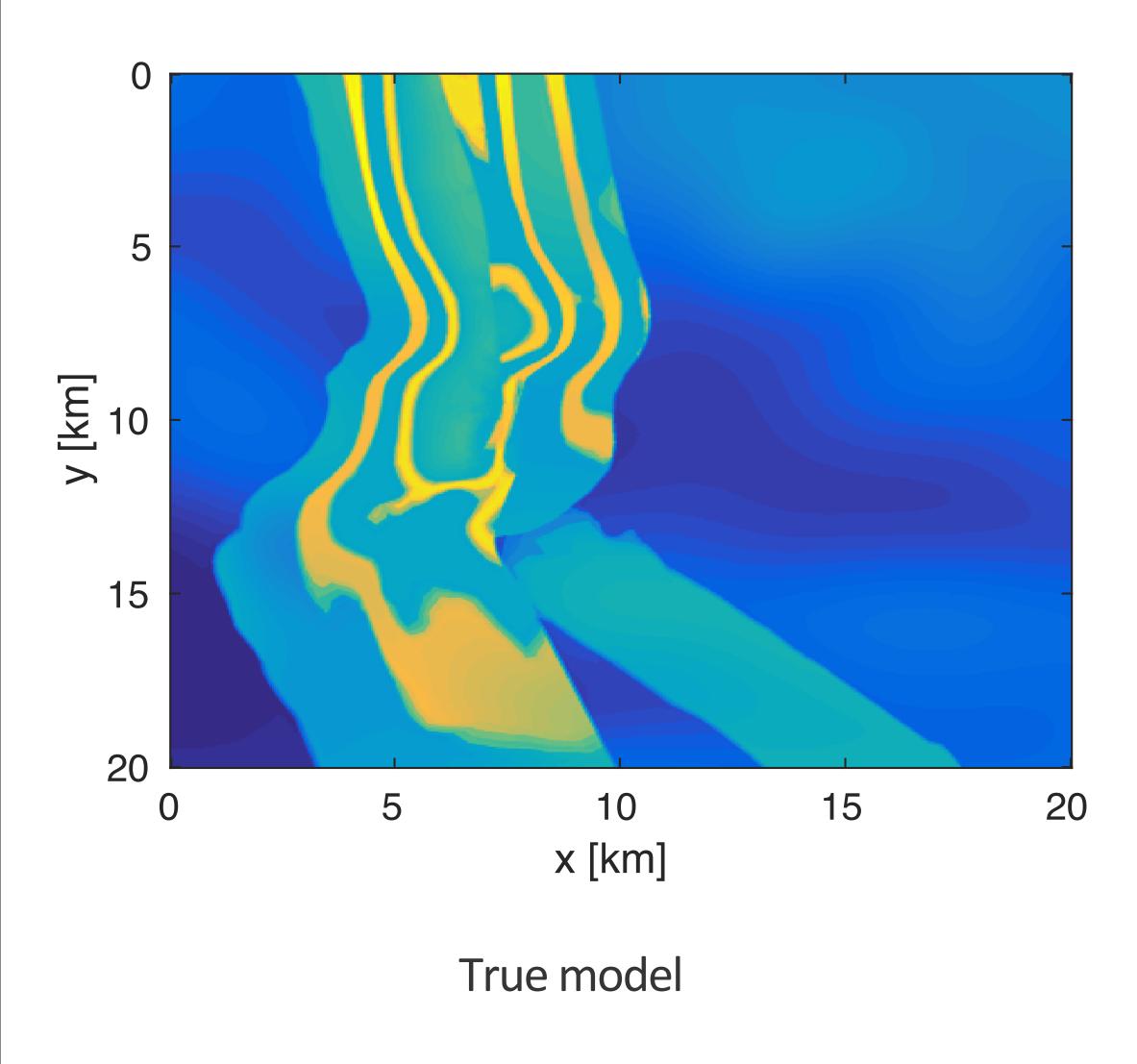


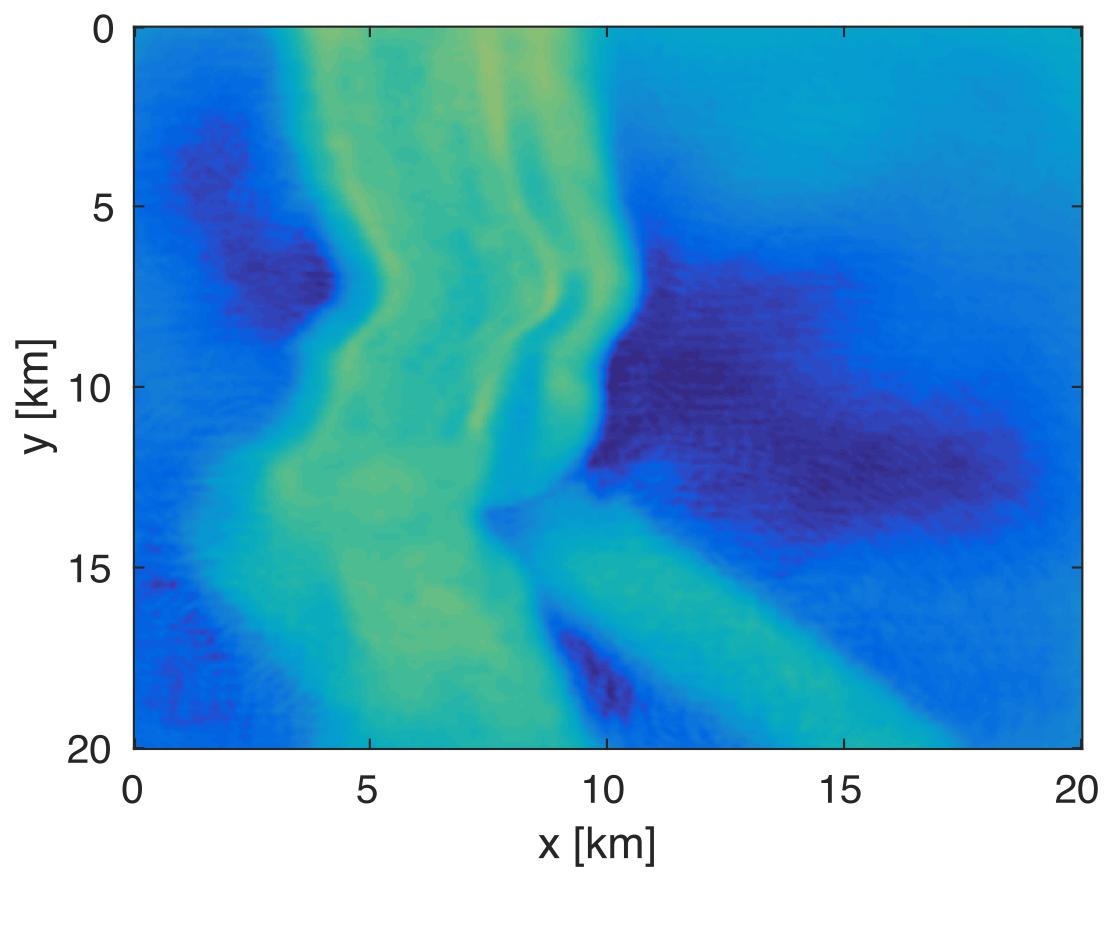




Initial Model

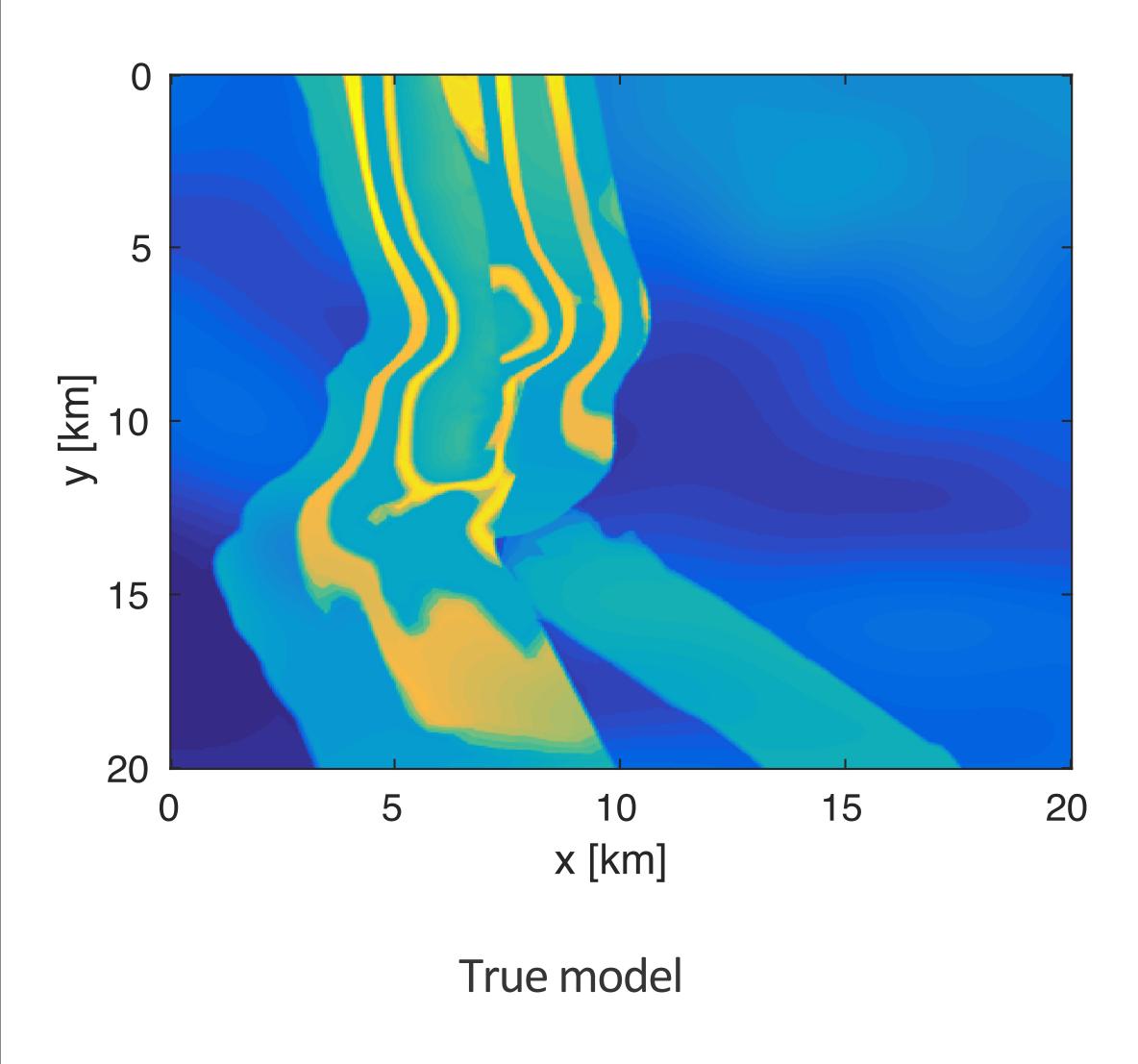


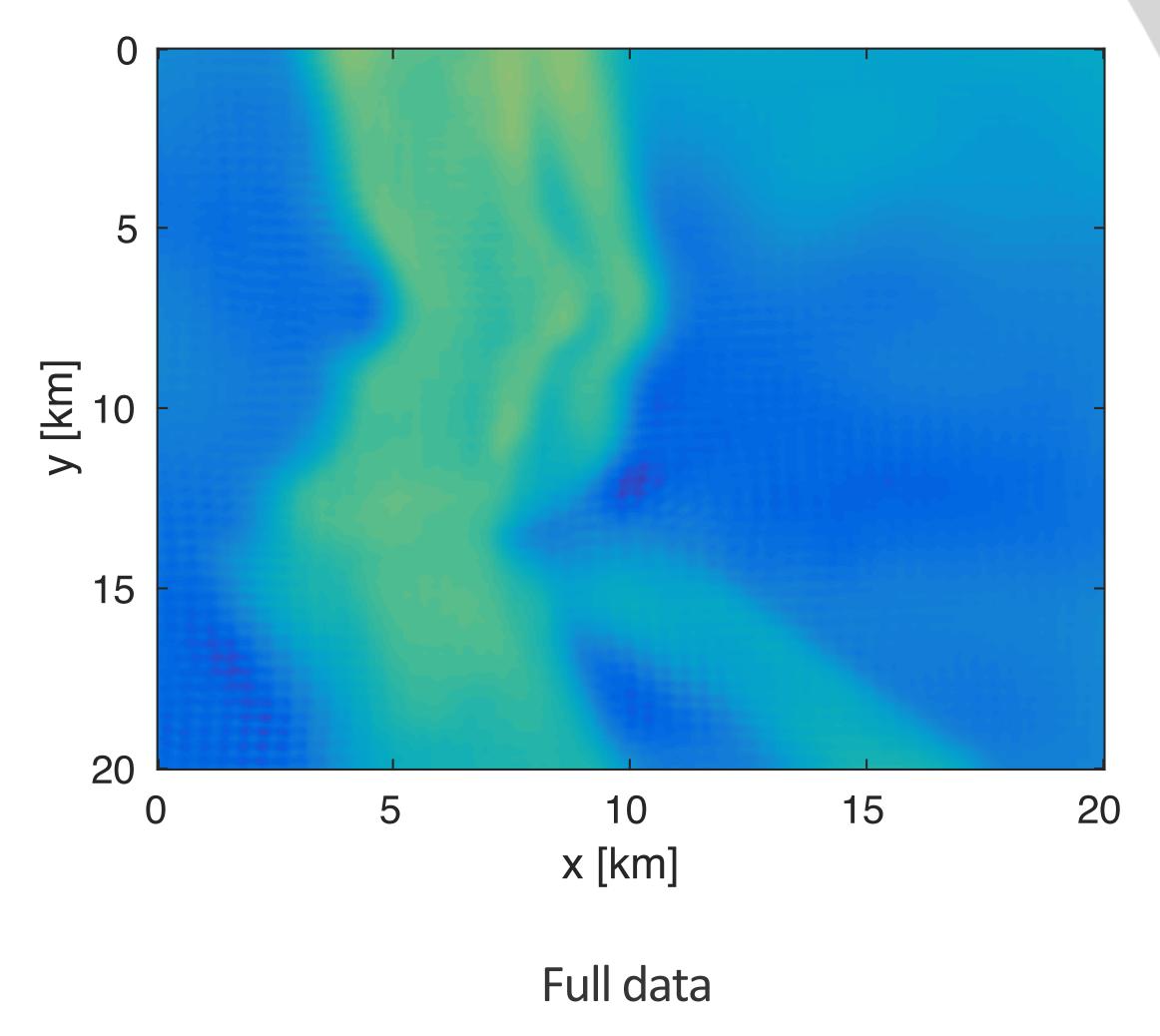




Stochastic LBFGS

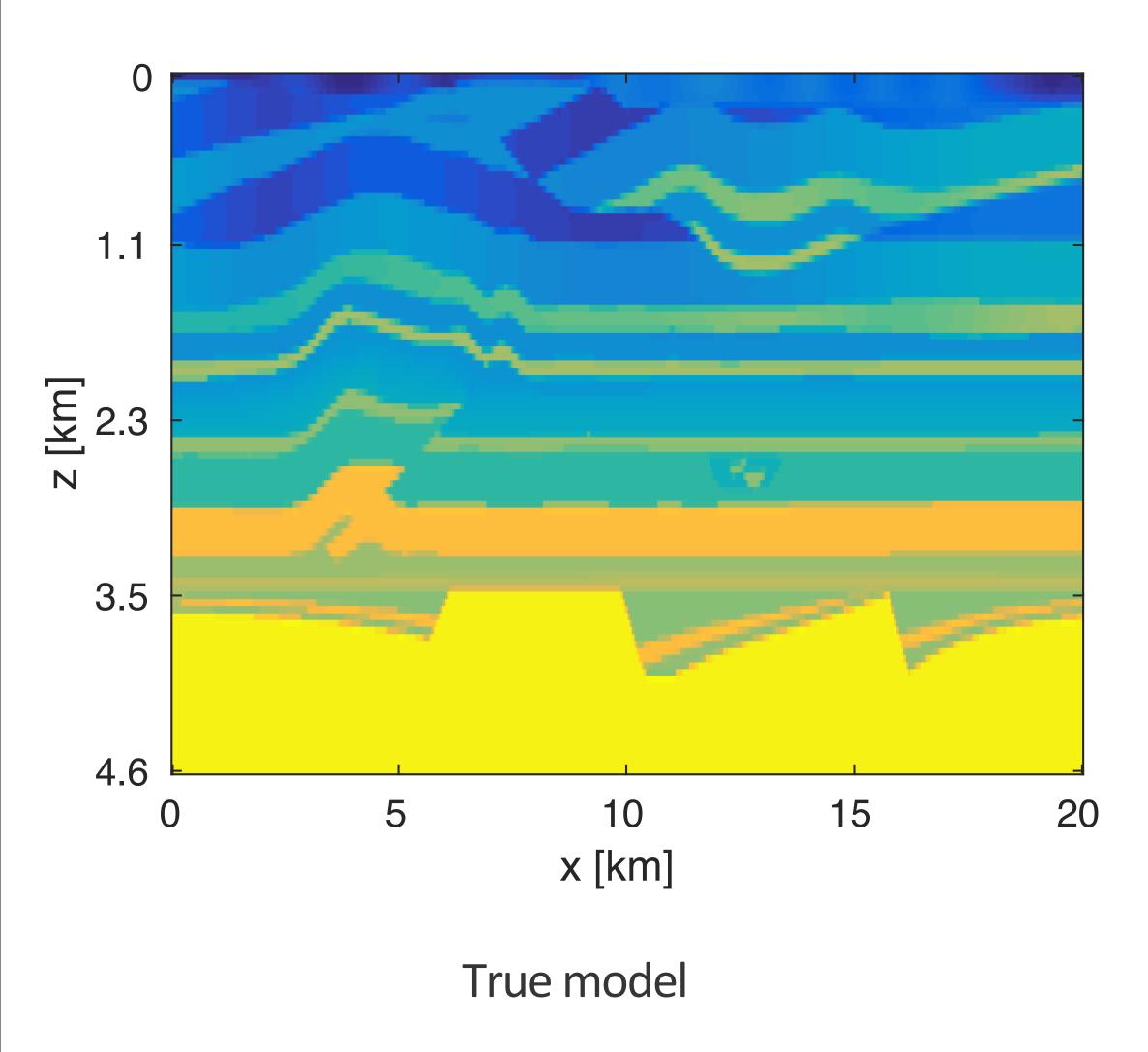


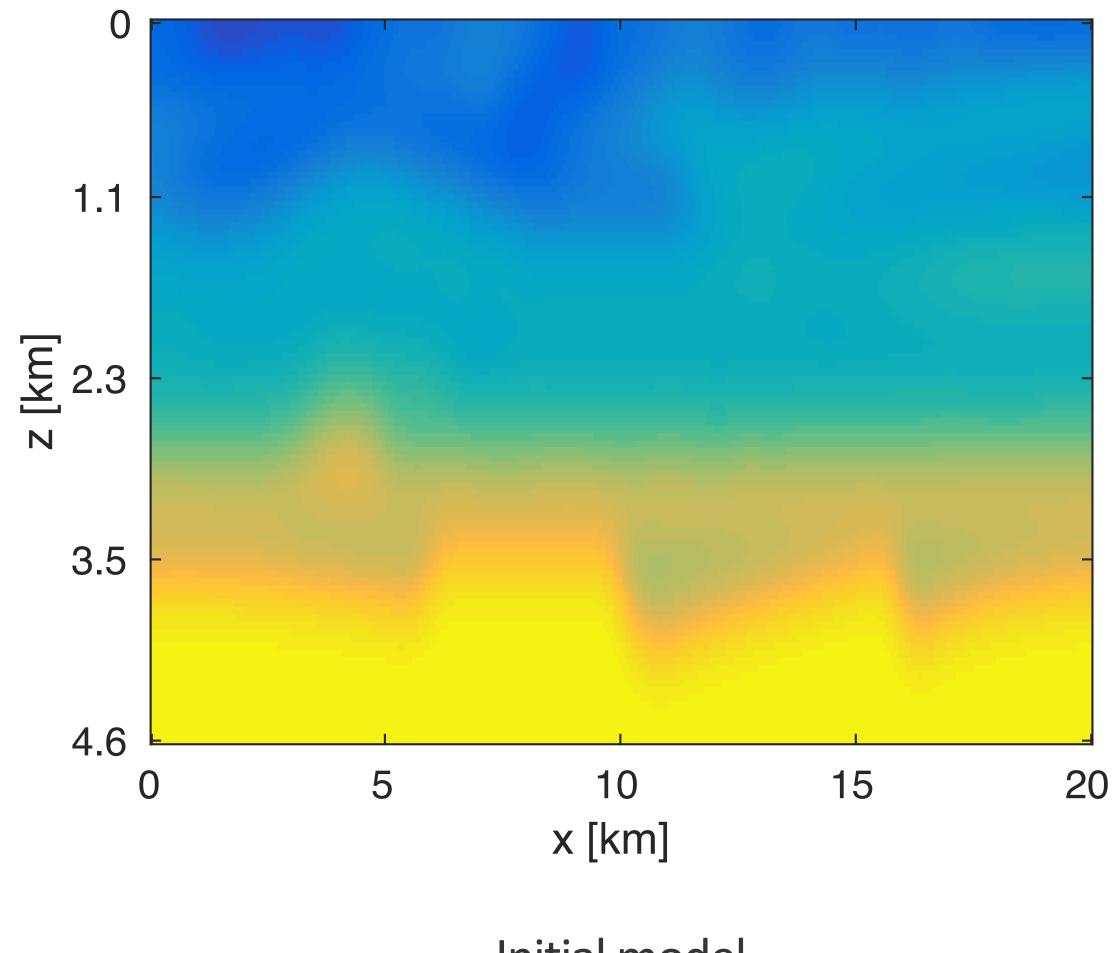






y=10000m slice

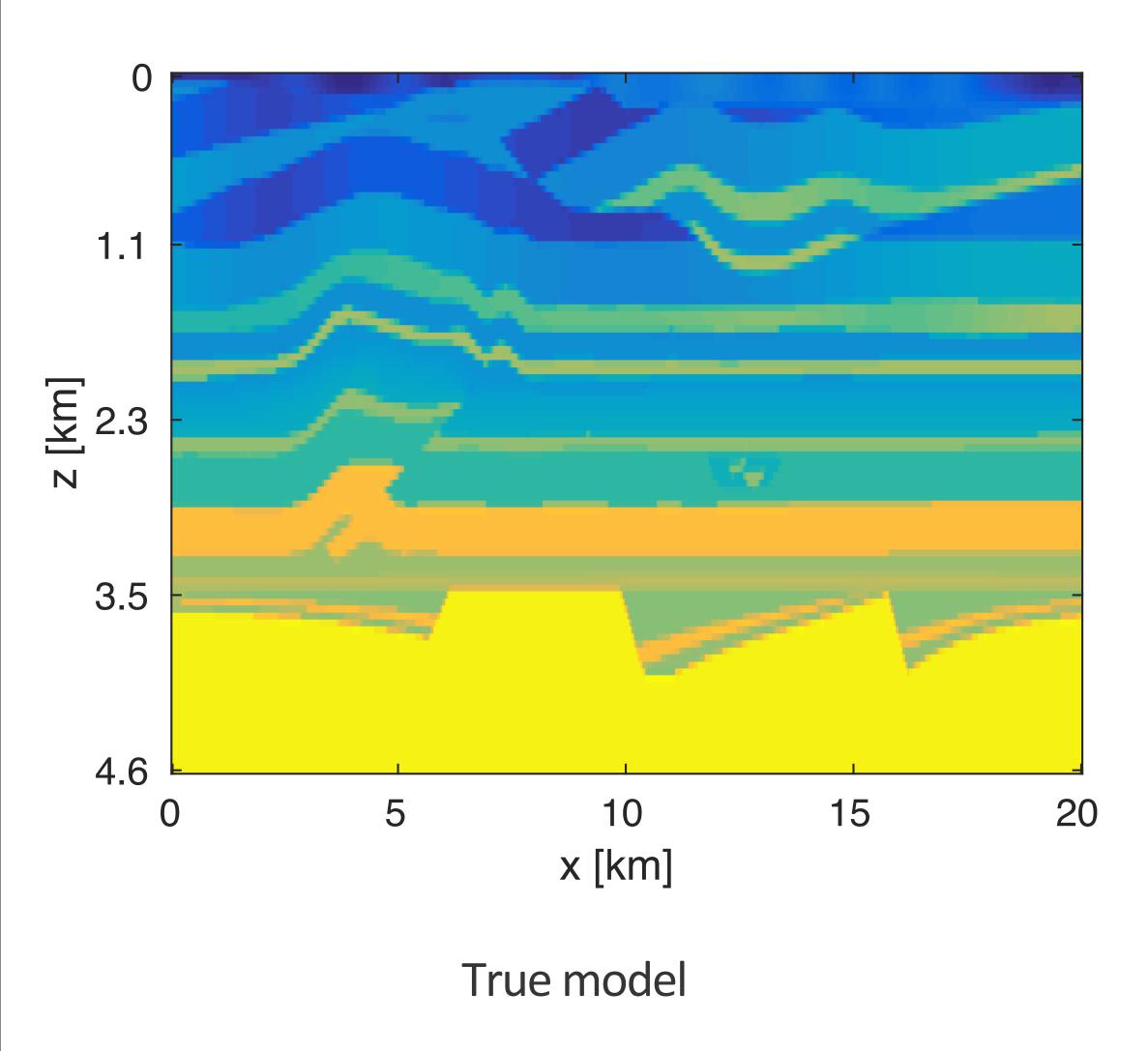


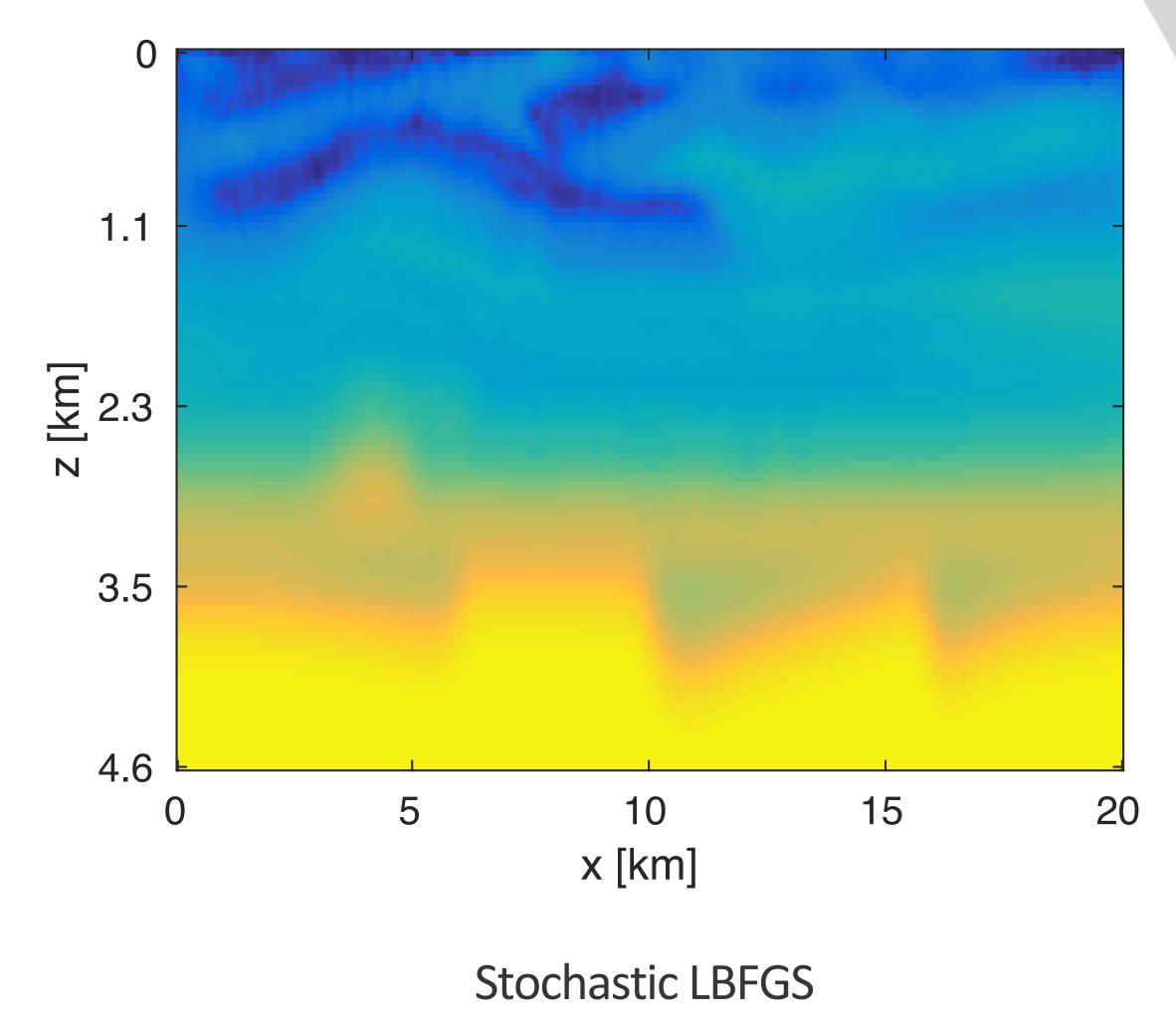


Initial model



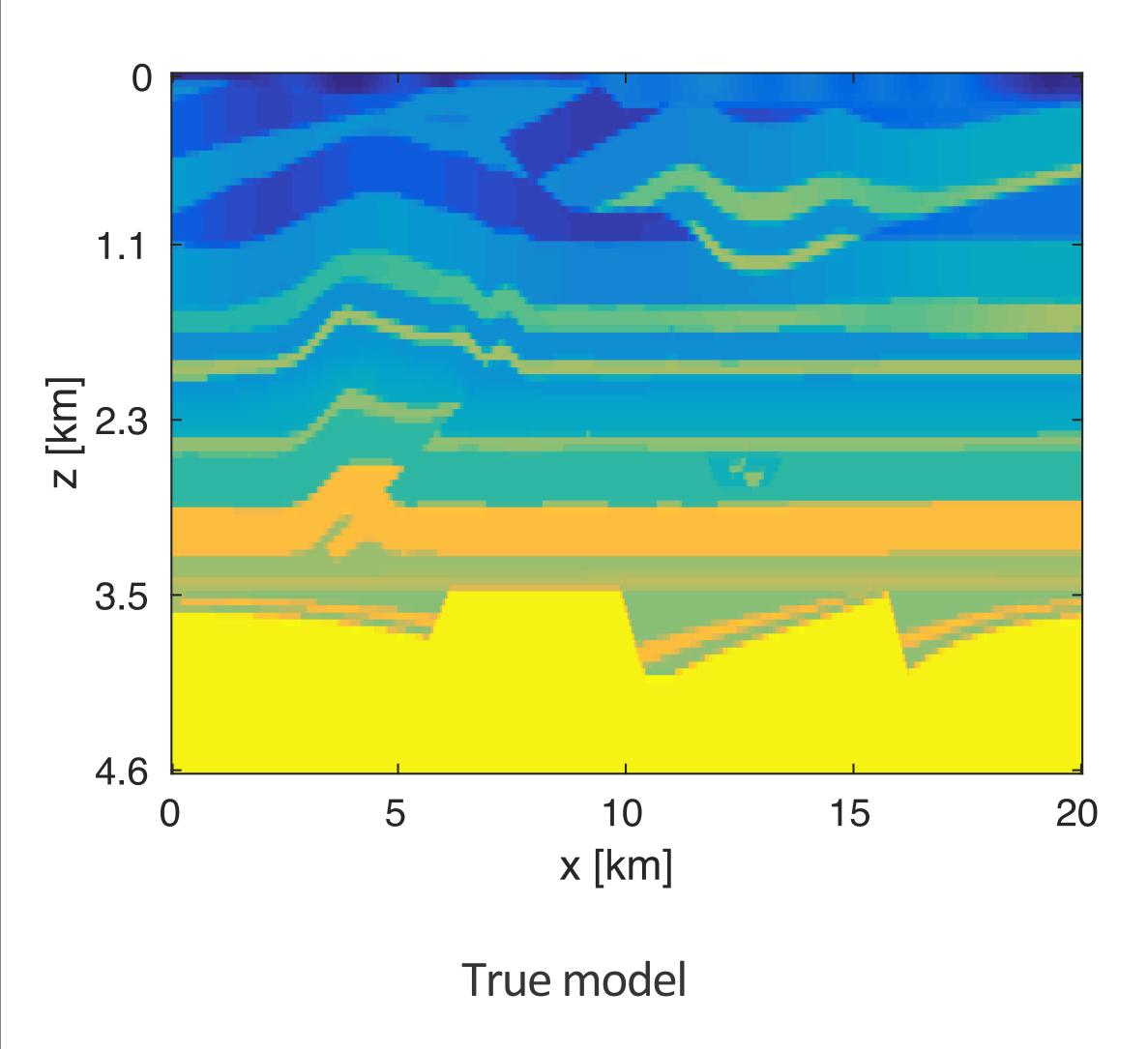
y=10000m slice

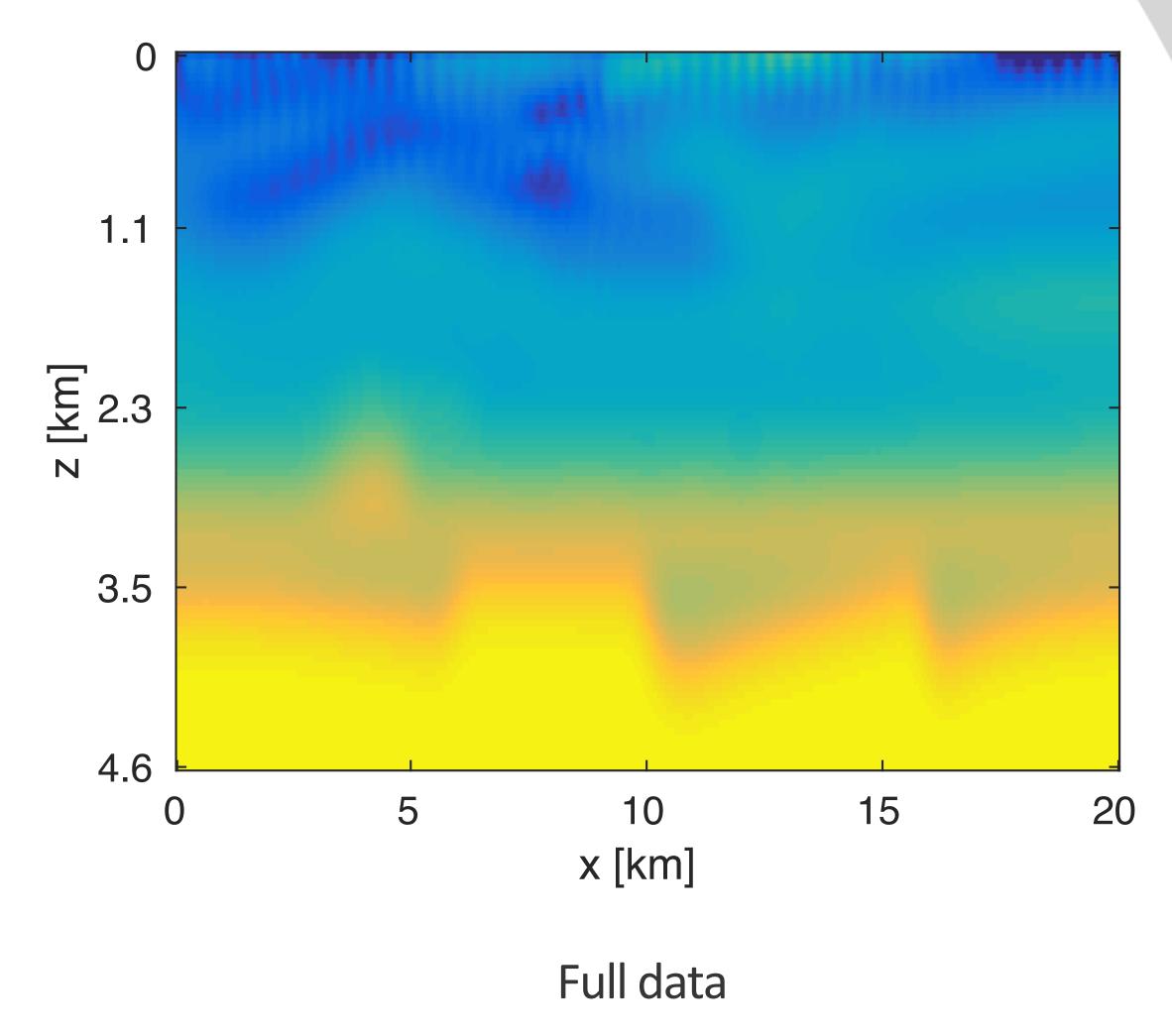






y=10000m slice







Summary

Performance and correctness don't have to be mutually exclusive • Design software in a modular, hierarchical way yields benefits of

both

Modularity -> flexibility

 Very easy to swap out modules (PDE discretizations, preconditioners) without changing code



Summary

Modularity -> Easier to test • Easier to test -> easier to get right

We can design code that is *demonstrably* correct • Reduce scope of potential problems in FWI



Summary

Right abstractions for FWI ->

- ease of use
- computationally efficient
- flexible
- easy to extend, understand, optimize
- can prototype algorithms in 2D, run immediately in 3D

optimize 2D, run immediately in 3D



Acknowledgements

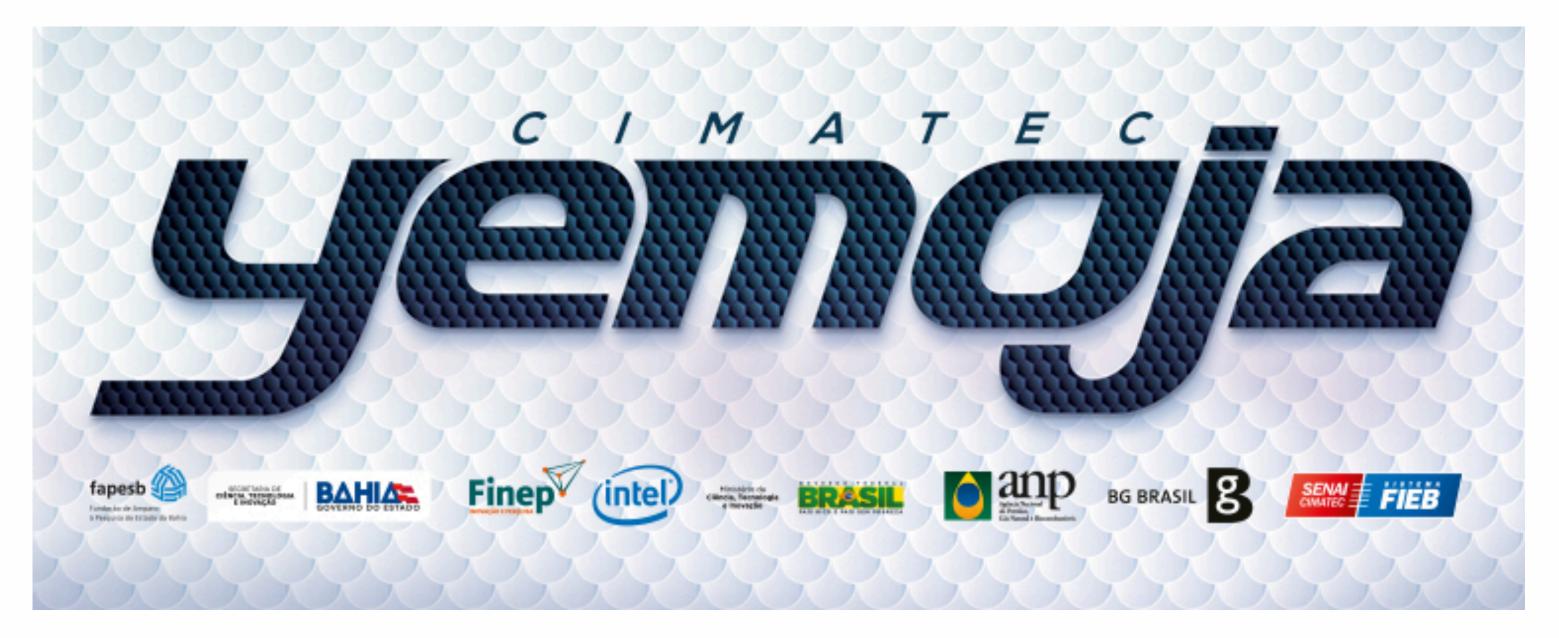
support of the member organizations of the SINBAD Consortium.

This research was carried out as part of the SINBAD project with the





Acknowledgements



The authors wish to acknowledge the SENAI CIMATEC Supercomputing Center for Industrial Innovation, with support from BG Brasil, Shell, and the Brazilian Authority for Oil, Gas and Biofuels (ANP), for the provision and operation of computational facilities and the commitment to invest in Research & Development.



Thank you for your attention

