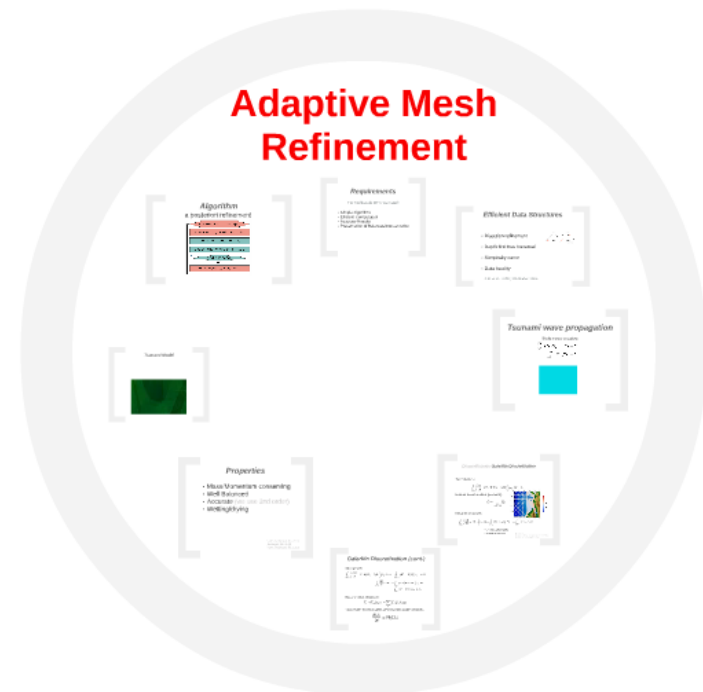
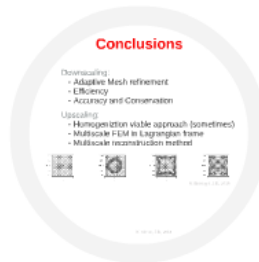
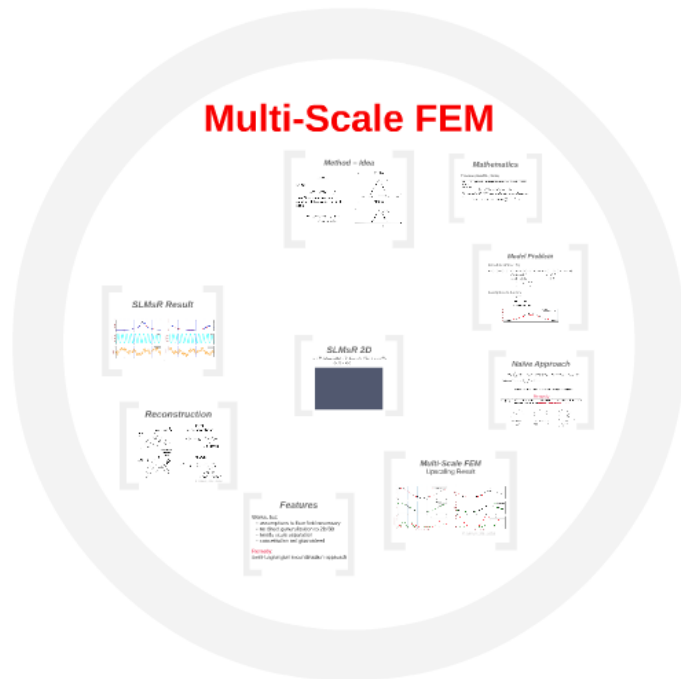
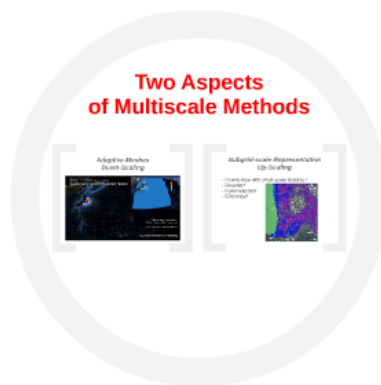
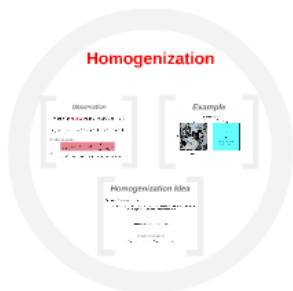
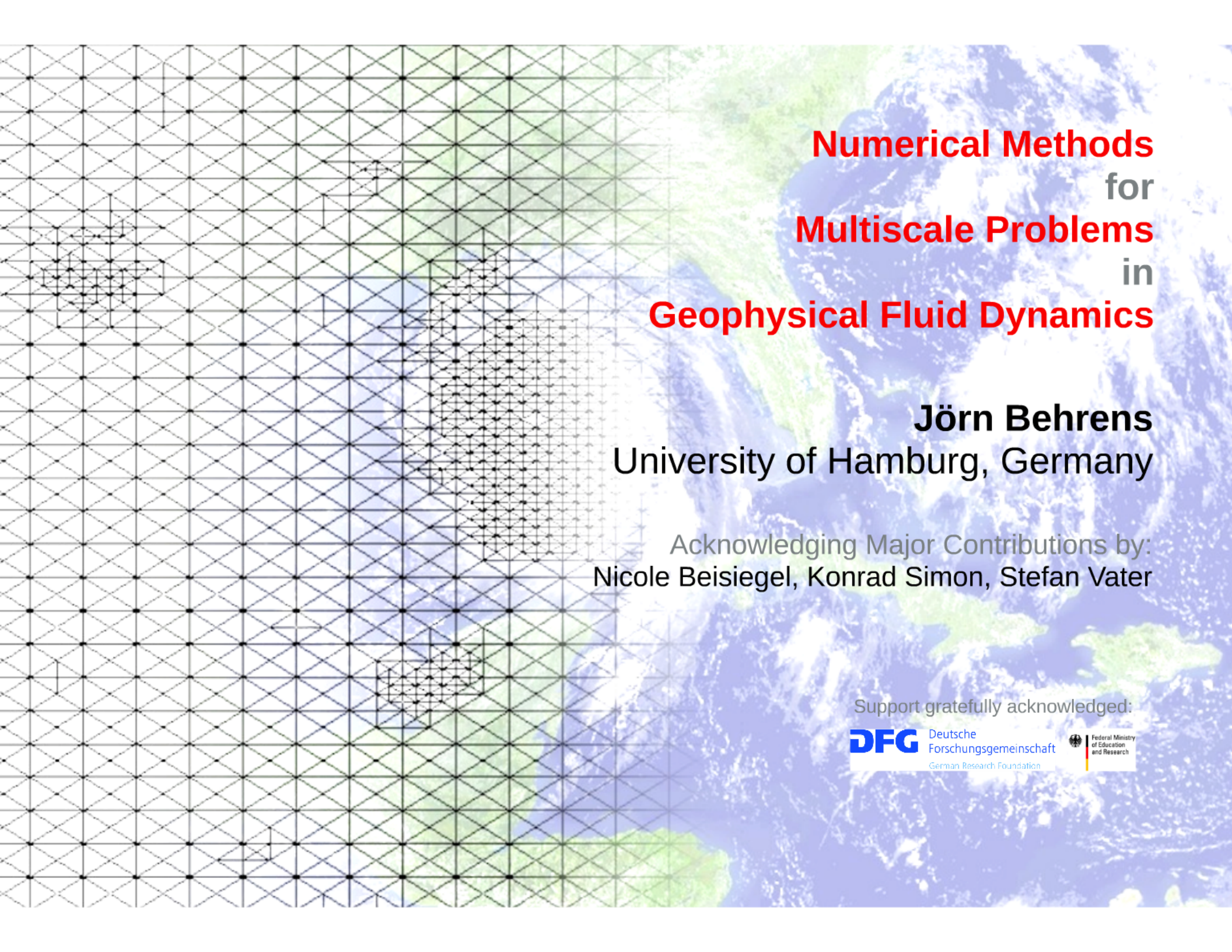






Numerical Methods for Multiscale Problems in Geophysical Fluid Dynamics

Jörn Behrens
University of Hamburg, Germany

Acknowledging Major Contributions by:
Nicole Beisiegel, Konrad Simon, Stefan Vater

Support gratefully acknowledged:



Motivation

Tsunami

$$\frac{\partial \mathbf{v}}{\partial t} + (\mathbf{v} \cdot \nabla) \mathbf{v} + g \nabla \eta = \mathbf{R}_b$$

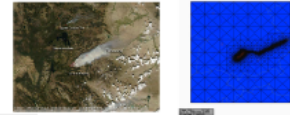
$$\frac{\partial \eta}{\partial t} + \nabla \cdot (H \mathbf{v}) = 0$$

$\mathbf{R}_b = \mathbf{R}_b^{(1)} + \mathbf{R}_b^{(2)} + \mathbf{R}_b^{(3)}$
 Terms:
 - Coriolis
 - Bottom friction
 - Bottom topography (nonlinear)



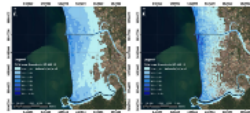
Pollutant Dispersion

Advection-Diffusion-Reaction Eq.
 $\frac{\partial p}{\partial t} + \nabla \cdot (\mathbf{v} p) - \nabla \cdot (\mu \nabla p) = \mathcal{R}$



Upscaling

- Resolving small scale
- Parameterization
- Neglecting small scale



The Problem of Scales

Tides

Ocean-wide range: $O(10^4 \text{ m}) \times O(10^4 \text{ m})$

Tsunami wave propagation

Deep-ocean wave length: $O(10^4 \text{ m})$

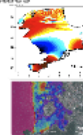
Near-shore wave behavior

Shoaling effect: $O(10^3 \text{ m})$

Inundation (parameterized - no buildings, etc.)

Inundation: $O(10^3 \text{ m}) \times O(10^3 \text{ m})$

On uniform grid: 10^{12} grid points



Multiple scales in plume dispersion

Total Area affected

Forest fire industrial single source: $O(10^4 \text{ m}^2)$

Local concentration extremes

Converging/diverging advection: $O(10^3 \text{ m}^2)$

Chemical reactions

Sedimentation, etc.: $O(10^{-1} \text{ m}^2)$

$O(10^{14})$ unknowns



Tsunami

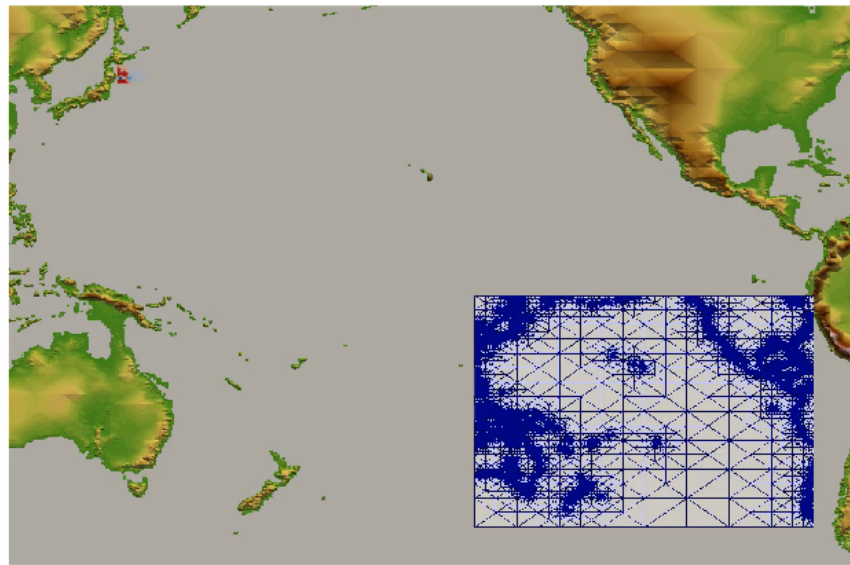
$$\frac{\partial \mathbf{v}}{\partial t} + (\mathbf{v} \cdot \nabla) \mathbf{v} + g \nabla \eta = R,$$

$$\frac{\partial \eta}{\partial t} + \nabla \cdot (H \mathbf{v}) = 0.$$

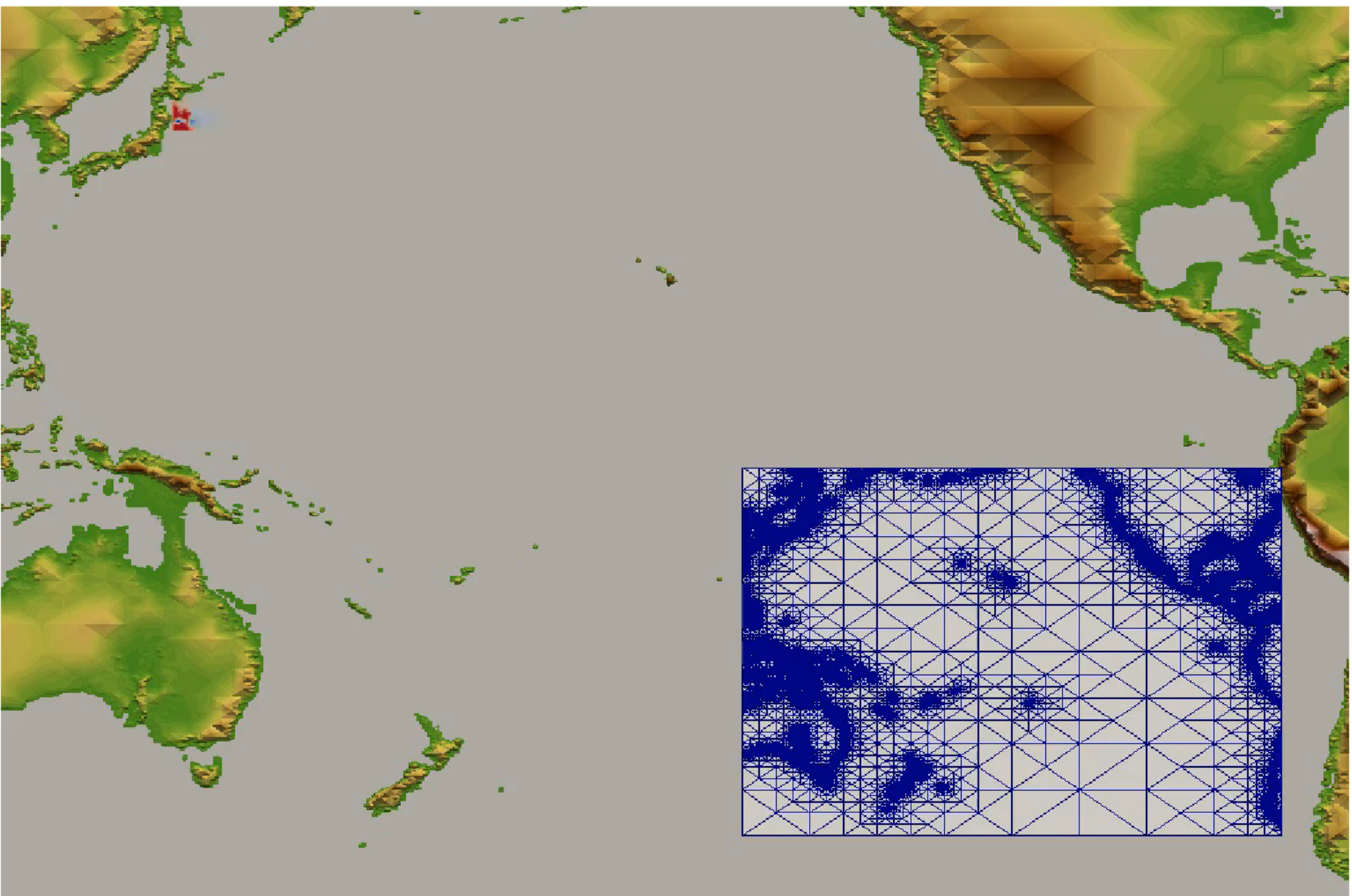
$$R = -f \mathbf{k} \times \mathbf{v} - r H^{-1} \mathbf{v} |\mathbf{v}| + H^{-1} \nabla (K_h H \nabla \mathbf{v})$$

Terms:

- Coriolis
- Bottom friction
- Viscosity (Smagorinsky approach)



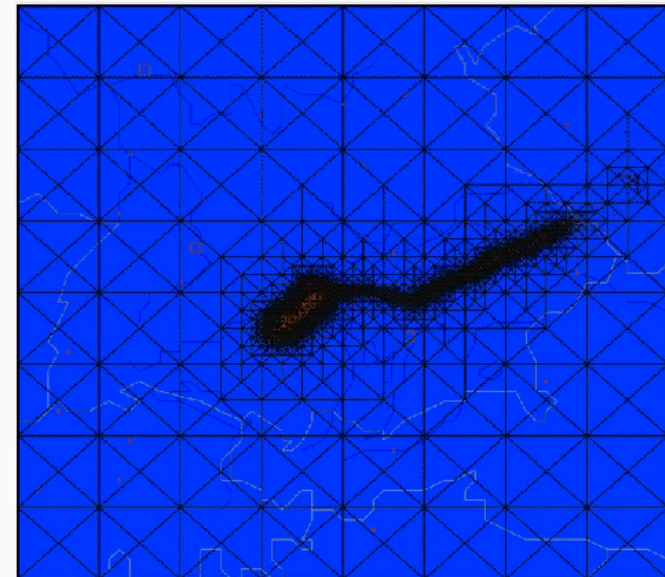
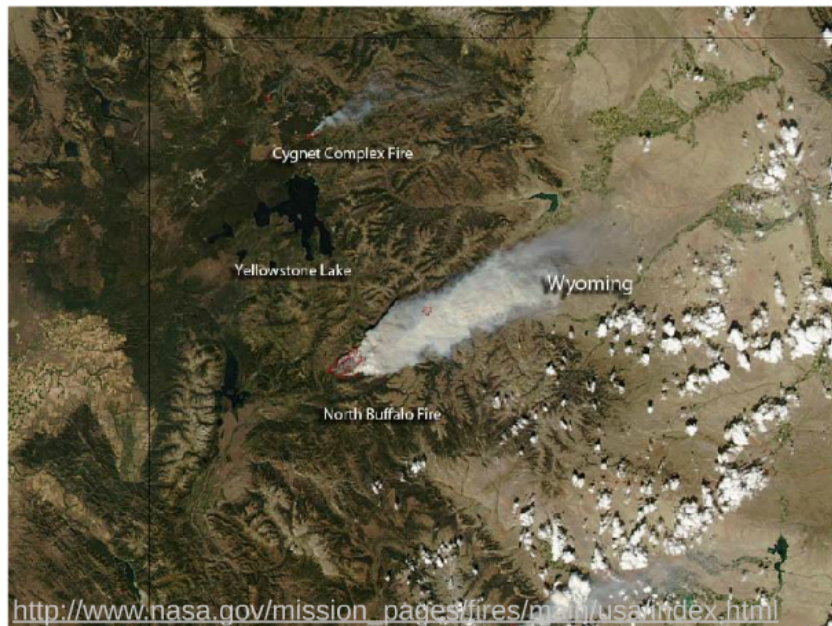
algorithmic approach,



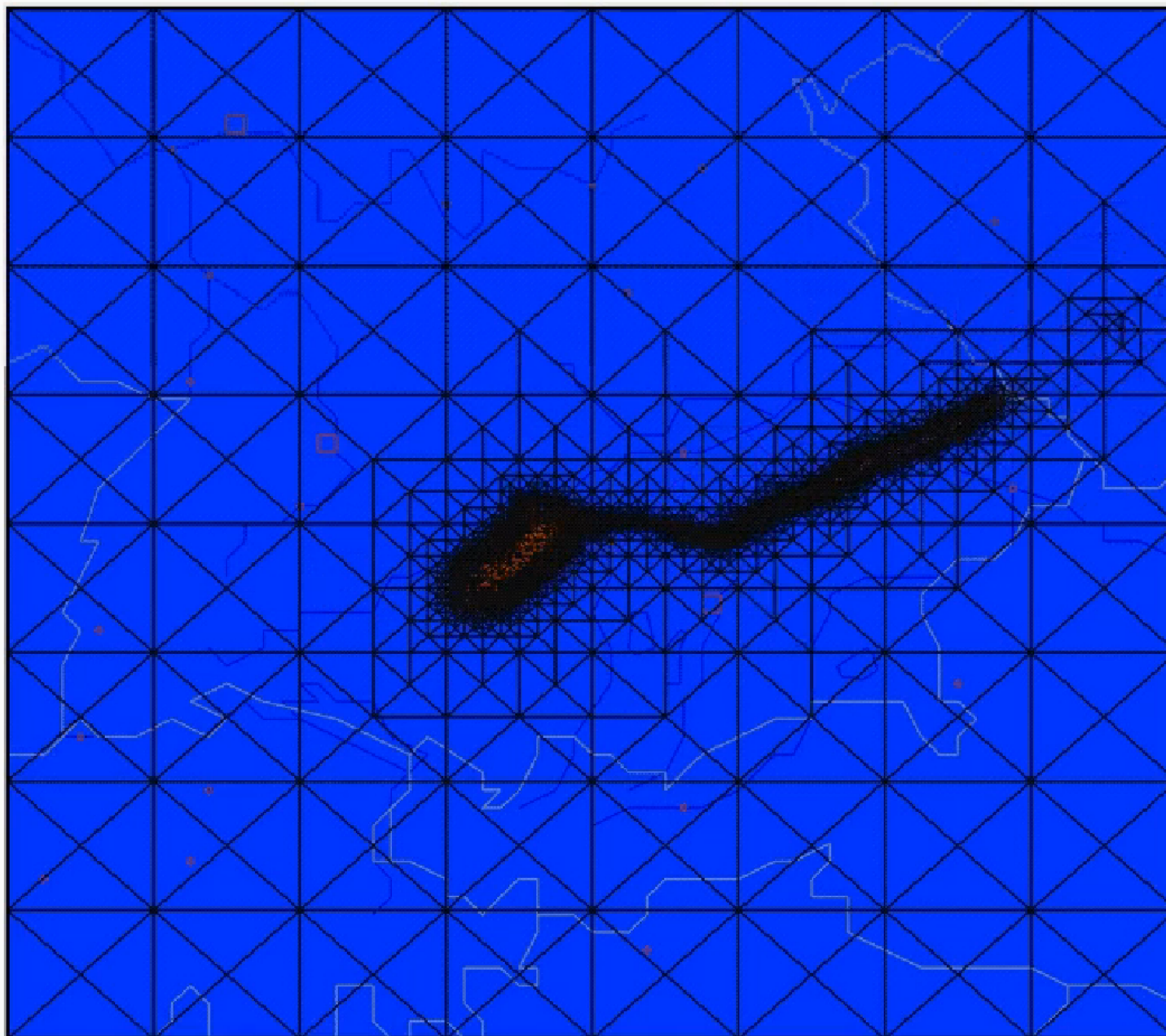
Pollutant Dispersion

Advection-Diffusion-Reaction Eq.

$$\frac{\partial \rho}{\partial t} + \nabla \cdot (\mathbf{v} \rho) + \nabla \cdot (\mu \nabla \rho) = 0$$



Time (h): 37.50
(c) J. Dehrens, 1999
Program: flash90



Time (h): 37.50
(c) J. Behrens 1999
Program: Flash90

Multiple scales in plume dispersion

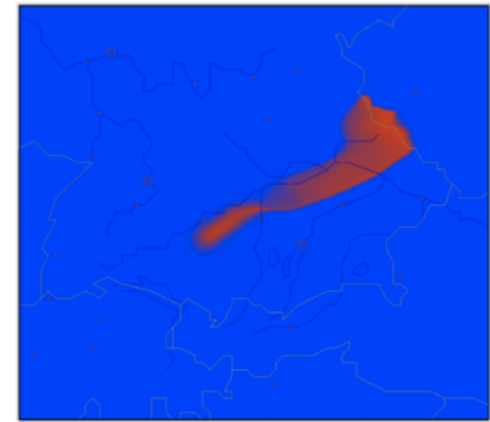
Total Area affected

Forest fire/ industrial single source: $\mathcal{O}(10^5 m^2)$



Local concentration extremes

Converging/diverging advection: $\mathcal{O}(10^2 m^2)$



Chemical reactions

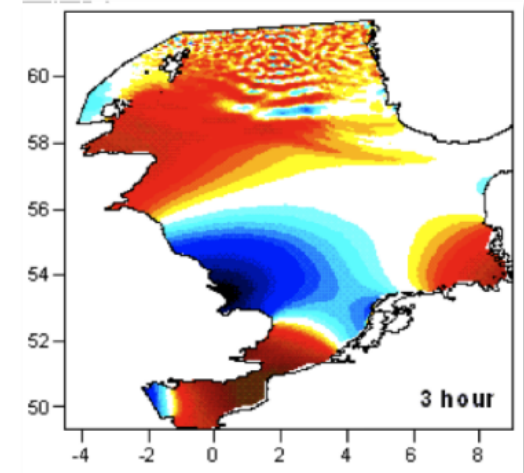
Sedimentation, etc.: $\mathcal{O}(10^{-1} m^2)$

$\mathcal{O}(10^{14})$ unknowns

The Problem of Scales

Tides

Ocean-wide range: $\mathcal{O}(10^7 m) \times \mathcal{O}(10^7 m)$

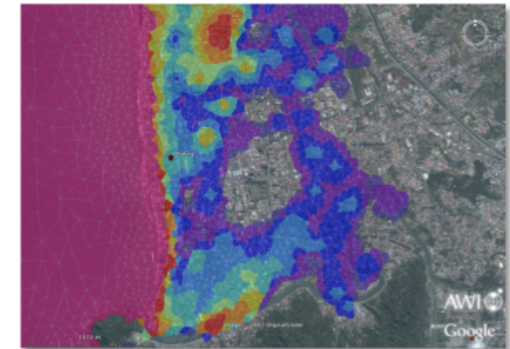


Tsunami wave propagation

Deep ocean wave length: $\mathcal{O}(10^5 m)$

Near-shore wave behavior

Shoaling effect: $\mathcal{O}(10^3 m)$



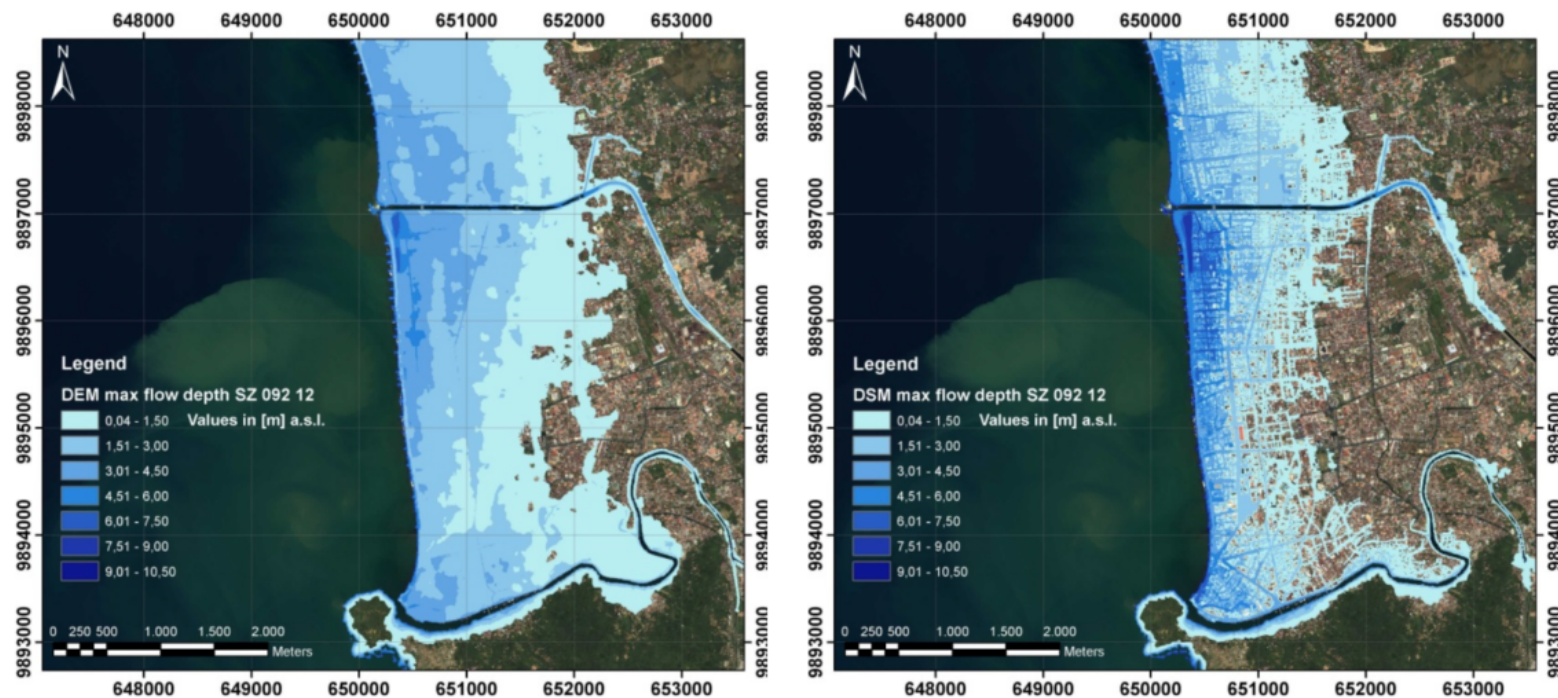
Inundation (parameterized - no buildings, etc.)

Inundation: $\mathcal{O}(10m) \times \mathcal{O}(10m)$

On uniform grid: 10^{12} grid points

Upscaling

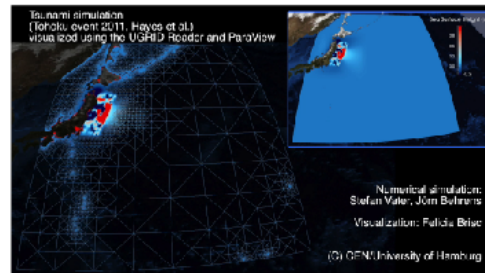
- Resolving small scale
- Parameterization
- Neglecting small scale



T. Schlurmann et al., Last Mile - Evacuation, 2010

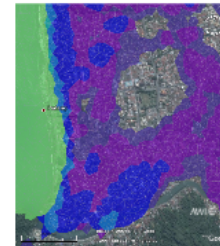
Two Aspects of Multiscale Methods

Adaptive Meshes Down-Scaling



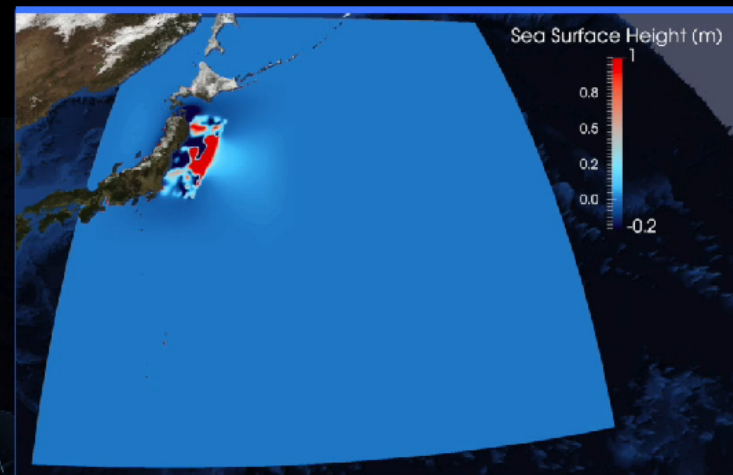
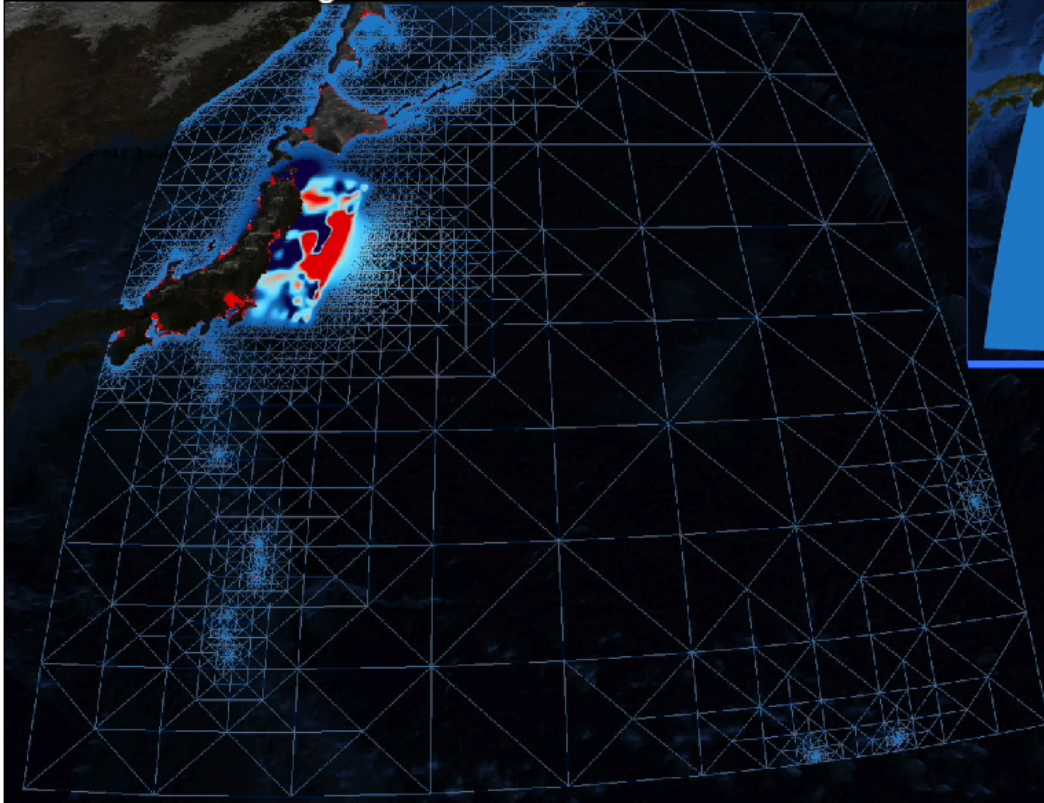
Subgrid-scale Representation Up-Scaling

- How to deal with small-scale features?
- Resolve?
- Parameterize?
- Efficiency?



Adaptive Meshes Down-Scaling

Tsunami simulation
(Tohoku event 2011, Hayes et al.)
visualized using the UGRID Reader and ParaView



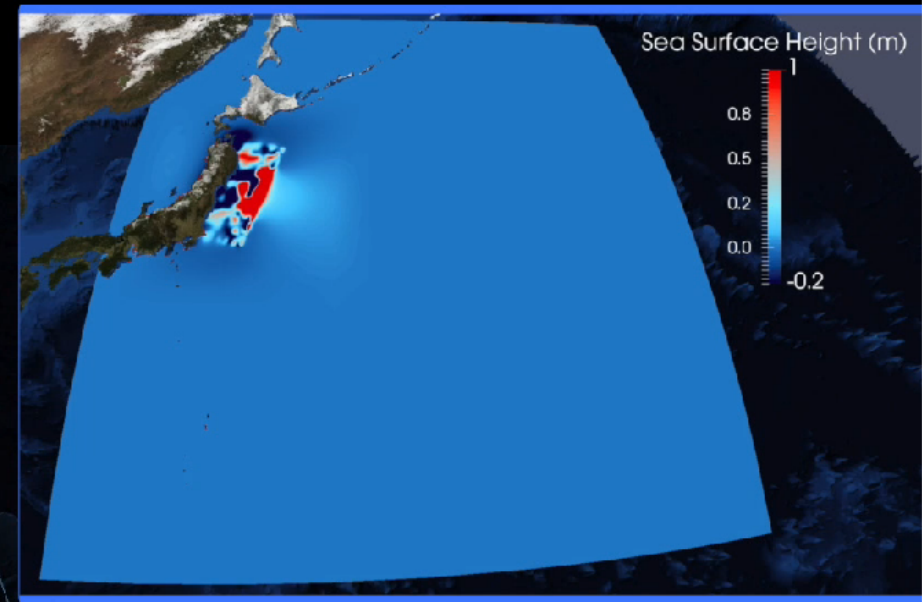
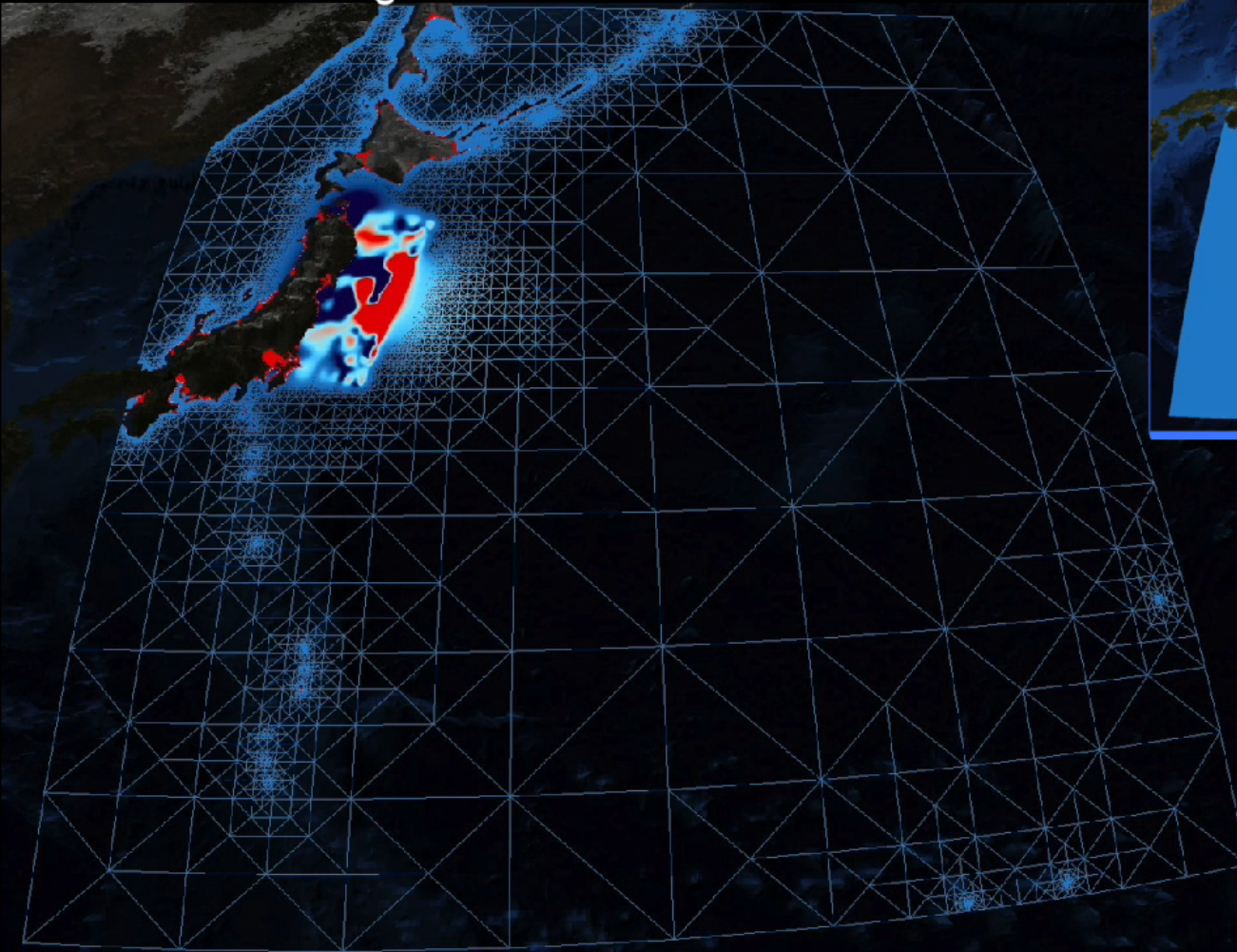
Numerical simulation:
Stefan Vater, Jörn Behrens

Visualization: Felicia Brisc

(C) CEN/University of Hamburg

Down-Scaling

Tsunami simulation
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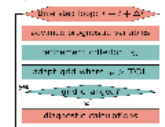
Subgrid-scale Representation Up-Scaling

- How to deal with small-scale features?
- Resolve?
- Parameterize?
- Efficiency?



Adaptive Mesh Refinement

Algorithm a posteriori refinement



Requirements

For multiscale GFD we need:

- Simple Algorithm
- Efficient Computation
- Accurate Results
- Preservation of Balances/Conservation



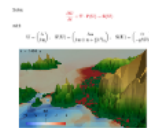
Efficient Data Structures

- Bisection refinement
- Depth first tree traversal
- Sierpinsky curve
- Data locality

J.B. et al., 2006; J.B./Bader, 2009



Tsunami Model

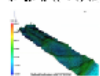


Tsunami wave propagation

Shallow water equations:

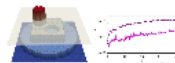
$$\frac{\partial \eta}{\partial t} + \nabla \cdot (\eta \mathbf{u}) = 0$$

$$\frac{\partial \mathbf{u}}{\partial t} + \nabla \cdot (\mathbf{u} \mathbf{u}) + \nabla \eta = 0$$



Properties

- Mass/Momentum conserving
- Well Balanced
- Accurate (we use 2nd order)
- Wetting/drying



Tsuna, Baskett, 2010
Baskett, 2010
Tsuna, Baskett, 2010

Discontinuous Galerkin Discretization

Test functions:

$$\int_{\Omega} \left(\frac{\partial \eta}{\partial t} + \nabla \cdot (\eta \mathbf{u}) - \eta \mathbf{u} \cdot \nabla \eta \right) \phi_i \, d\Omega = 0$$

Domain decomposition (element K):

$$\Omega = \bigcup_{K \in \mathcal{T}_h} K$$

Integration by parts:

$$\int_{\Omega} \left(\frac{\partial \eta}{\partial t} + \nabla \cdot (\eta \mathbf{u}) - \eta \mathbf{u} \cdot \nabla \eta \right) \phi_i \, d\Omega = \sum_{K \in \mathcal{T}_h} \int_K \left(\frac{\partial \eta}{\partial t} + \nabla \cdot (\eta \mathbf{u}) - \eta \mathbf{u} \cdot \nabla \eta \right) \phi_i \, d\Omega$$



if $\mathbf{u}$ is piecewise constant, we can write $\mathbf{u} = \mathbf{u}_K$

if $\mathbf{u}$ is piecewise linear, we can write $\mathbf{u} = \mathbf{u}_K$

if $\mathbf{u}$ is piecewise quadratic, we can write $\mathbf{u} = \mathbf{u}_K$

Galerkin Discretization (cont.)

Strong form:

$$\int_{\Omega} \left(\frac{\partial \eta}{\partial t} + \nabla \cdot (\eta \mathbf{u}) - \eta \mathbf{u} \cdot \nabla \eta \right) \phi_i \, d\Omega = \int_{\Omega} \left(\mathbf{F} \cdot \nabla \eta - \eta \mathbf{u} \cdot \nabla \mathbf{F} \right) \phi_i \, d\Omega$$

$$\int_{\Omega} \frac{\partial \eta}{\partial t} \phi_i \, d\Omega = \int_{\Omega} \mathbf{F} \cdot \nabla \eta \phi_i \, d\Omega - \int_{\Omega} \eta \mathbf{u} \cdot \nabla \mathbf{F} \phi_i \, d\Omega$$

Weak form:

$$\mathbf{U} = \mathbf{U}_h(\mathbf{x}, t) = \sum_{i=1}^N \mathbf{U}_i(t) \phi_i(\mathbf{x})$$

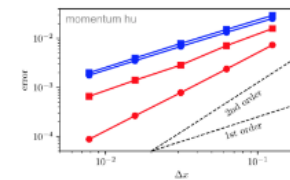
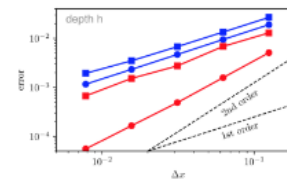
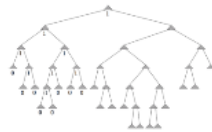
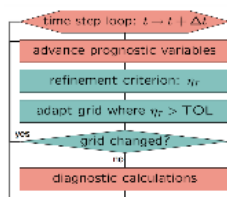
Mass matrix: discrete mass matrix: discrete update of GDFs:

$$\frac{\partial \mathbf{U}_h}{\partial t} = \mathbf{H}(\mathbf{U}_h)$$

Requirements

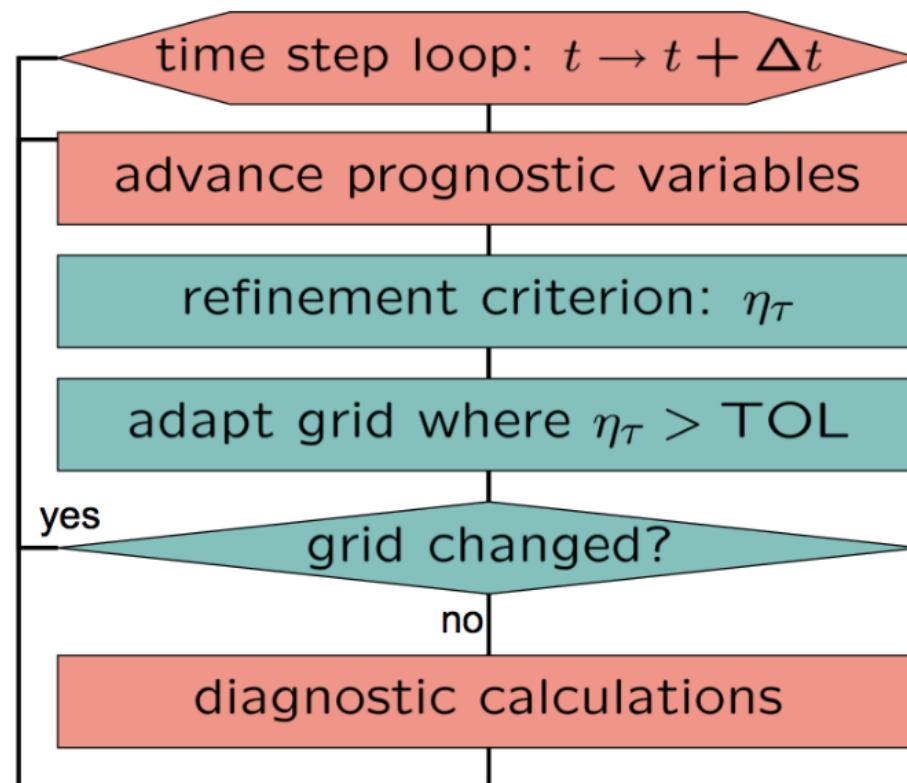
For multiscale GFD we need:

- Simple Algorithm
- Efficient Computation
- Accurate Results
- Preservation of Balances/Conservation



Algorithm

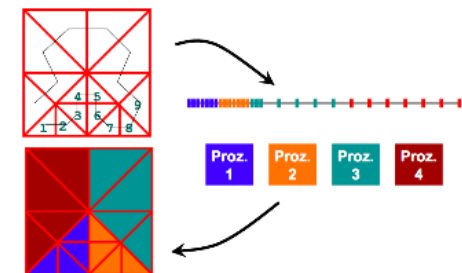
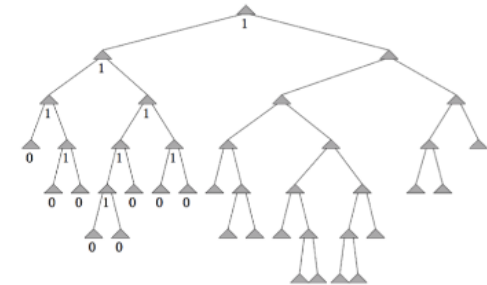
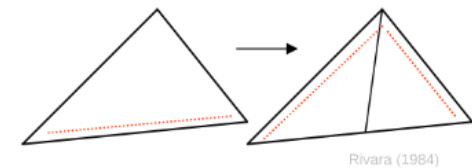
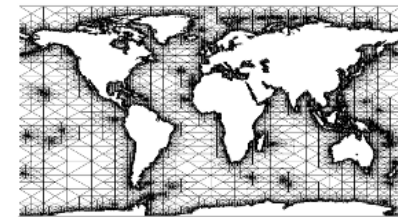
a posteriori refinement



Efficient Data Structures

- Bisection refinement
- Depth first tree traversal
- Sierpinsky curve
- Data locality

J.B. et al., 2005; J.B./Bader, 2009



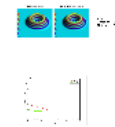
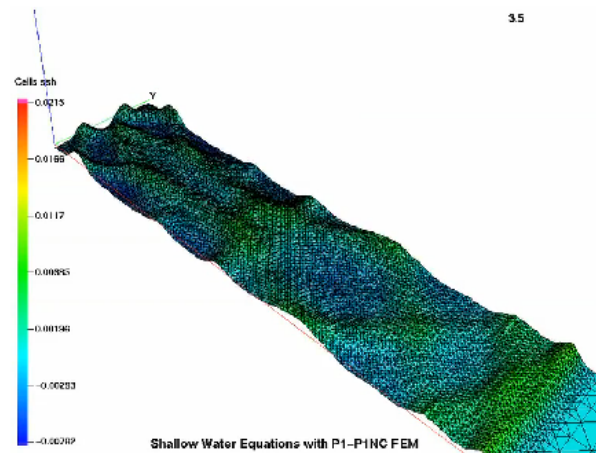
Tsunami wave propagation

Shallow water equations

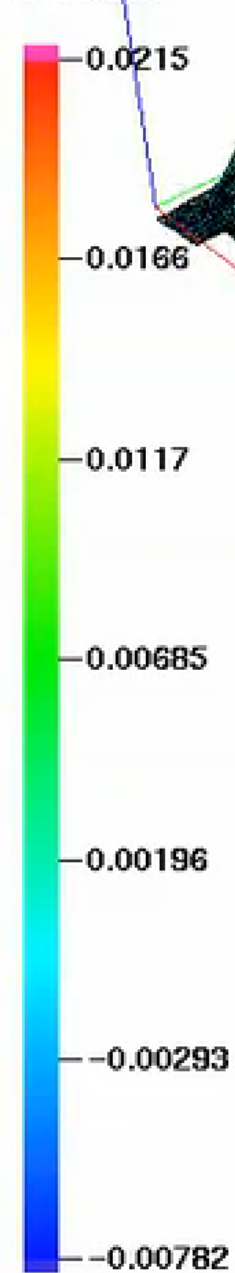
$$\frac{\partial \mathbf{v}}{\partial t} + (\mathbf{v} \cdot \nabla) \mathbf{v} + g \nabla \eta = R,$$

$$\frac{\partial \eta}{\partial t} + \nabla \cdot (H \mathbf{v}) = 0.$$

$$R = -f \mathbf{k} \times \mathbf{v} - r H^{-1} \mathbf{v} |\mathbf{v}| + H^{-1} \nabla (K_h H \nabla \mathbf{v})$$



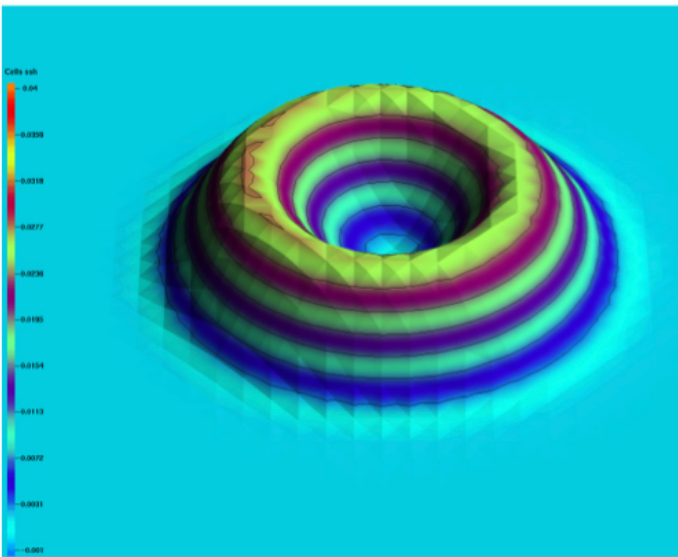
Cells ssh



Shallow Water Equations with P1-P1NC FEM

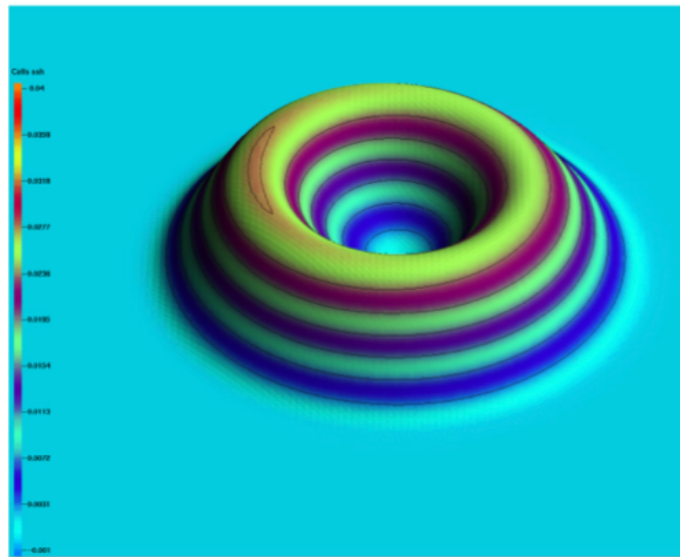
20480 cells uniform

0.2

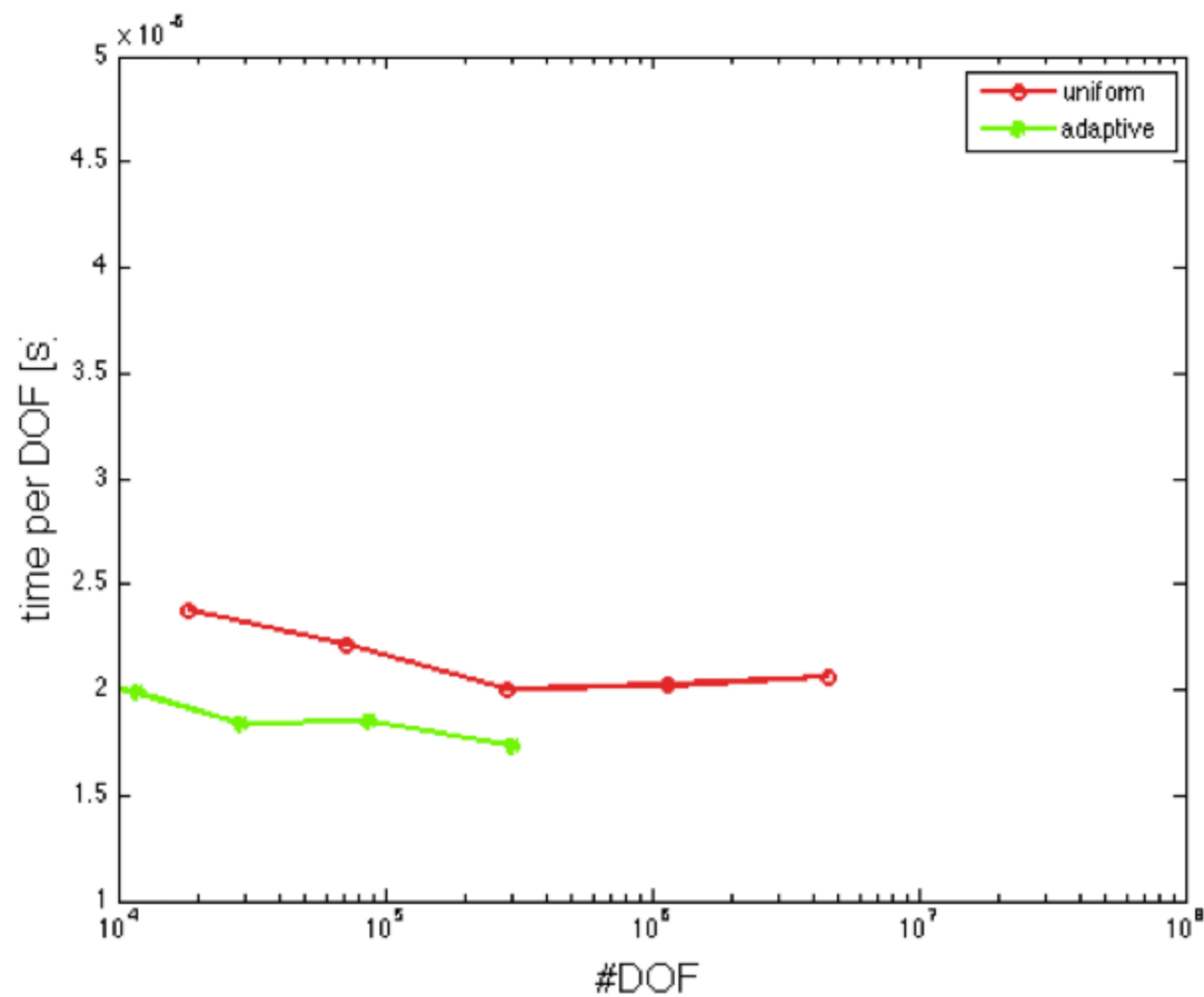


10576..24662 cells uniform

0.2



FEM:
Adaptive: 15.8 s
Uniform: 173 s



Discontinuous Galerkin Discretization

Test functions

$$\int_{\Omega} \left(\frac{\partial \mathbf{U}}{\partial t} + \nabla \cdot \mathbf{F}(\mathbf{U}) - S(\mathbf{U}) \right) \psi_j \, d\mathbf{x} = 0.$$

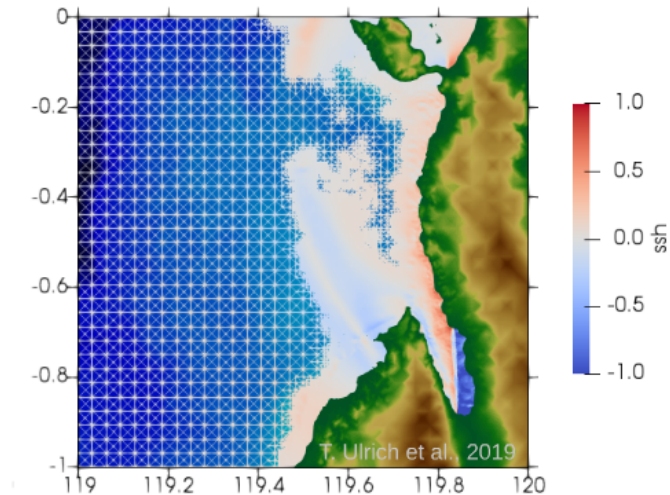
Domain decomposition (elements)

$$\Omega = \bigcup_{e=1:M} \Omega_e$$

Integration by parts

$$\int_{\Omega_e} \left(\frac{\partial \mathbf{U}}{\partial t} - S(\mathbf{U}) \right) \psi_j \, d\mathbf{x} - \int_{\Omega_e} \mathbf{F}(\mathbf{U}) \cdot \nabla \psi_j \, d\mathbf{x} = - \oint_{\partial \Omega_e} \mathbf{F}^* \psi_j \cdot \mathbf{n} \, dS.$$

- $\mathbf{F}^*$ a numerical flux function
- $\mathbf{n}$ outward normal vector



References:

Hesthaven (1998), Hesthaven&Warburton (2006),
Giraldo et al. (2002), Giraldo (2006).

Galerkin Discretization (cont.)

Strong Form

$$\int_{\Omega_e} \left(\frac{\partial \mathbf{U}}{\partial t} + \nabla \cdot \mathbf{F}(\mathbf{U}) - S(\mathbf{U}) \right) \psi_j \, d\mathbf{x} = - \oint_{\partial\Omega_e} (\mathbf{F}^* - \mathbf{F}(\mathbf{U})) \psi_j \cdot \mathbf{n} \, dS.$$

$$\begin{aligned} \int_{\Omega_e} \frac{\partial \mathbf{U}}{\partial t} \psi_j \, d\mathbf{x} &= - \int_{\Omega_e} (\nabla \cdot \mathbf{F}(\mathbf{U}) - S(\mathbf{U})) \psi_j \, d\mathbf{x} \\ &\quad - \oint_{\partial\Omega_e} (\mathbf{F}^* - \mathbf{F}(\mathbf{U})) \psi_j \cdot \mathbf{n} \, dS. \end{aligned}$$

Basis function expansion

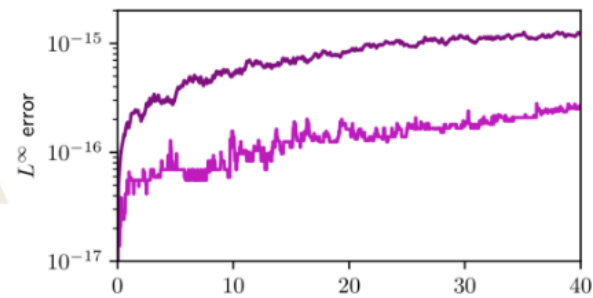
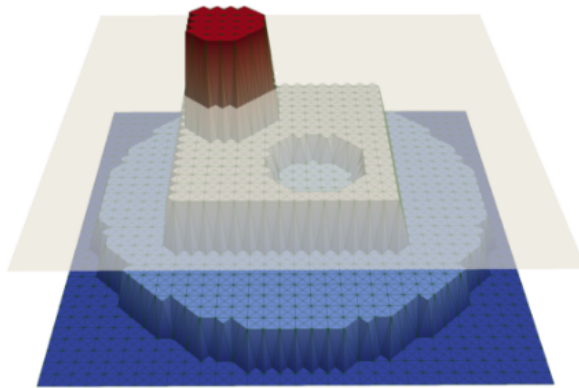
$$\mathbf{U} \approx \mathbf{U}_h(\mathbf{x}, t) = \sum_k \mathbf{U}_k(t) \psi_k(\mathbf{x})$$

Mass matrix inversion gives semi-discrete system of ODEs

$$\frac{\partial \mathbf{U}_h}{\partial t} = \mathbf{H}(\mathbf{U}_h)$$

Properties

- Mass/Momentum conserving
- Well Balanced
- Accurate (we use 2nd order)
- Wetting/drying



Vater, Beisiegel, JB, 2015;
Beisiegel, JB, 2015;
Vater, Beisiegel, JB, 2019.

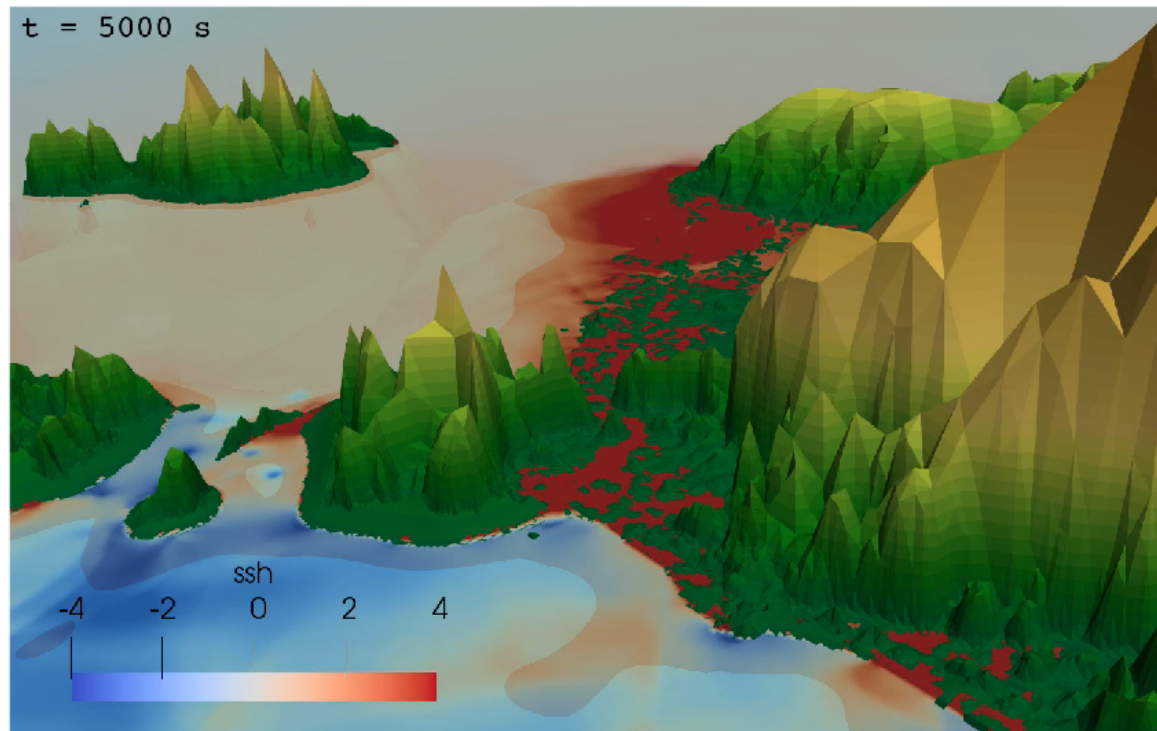
Tsunami Model

Solve

$$\frac{\partial \mathbf{U}}{\partial t} + \nabla \cdot \mathbf{F}(\mathbf{U}) = \mathbf{S}(\mathbf{U})$$

with

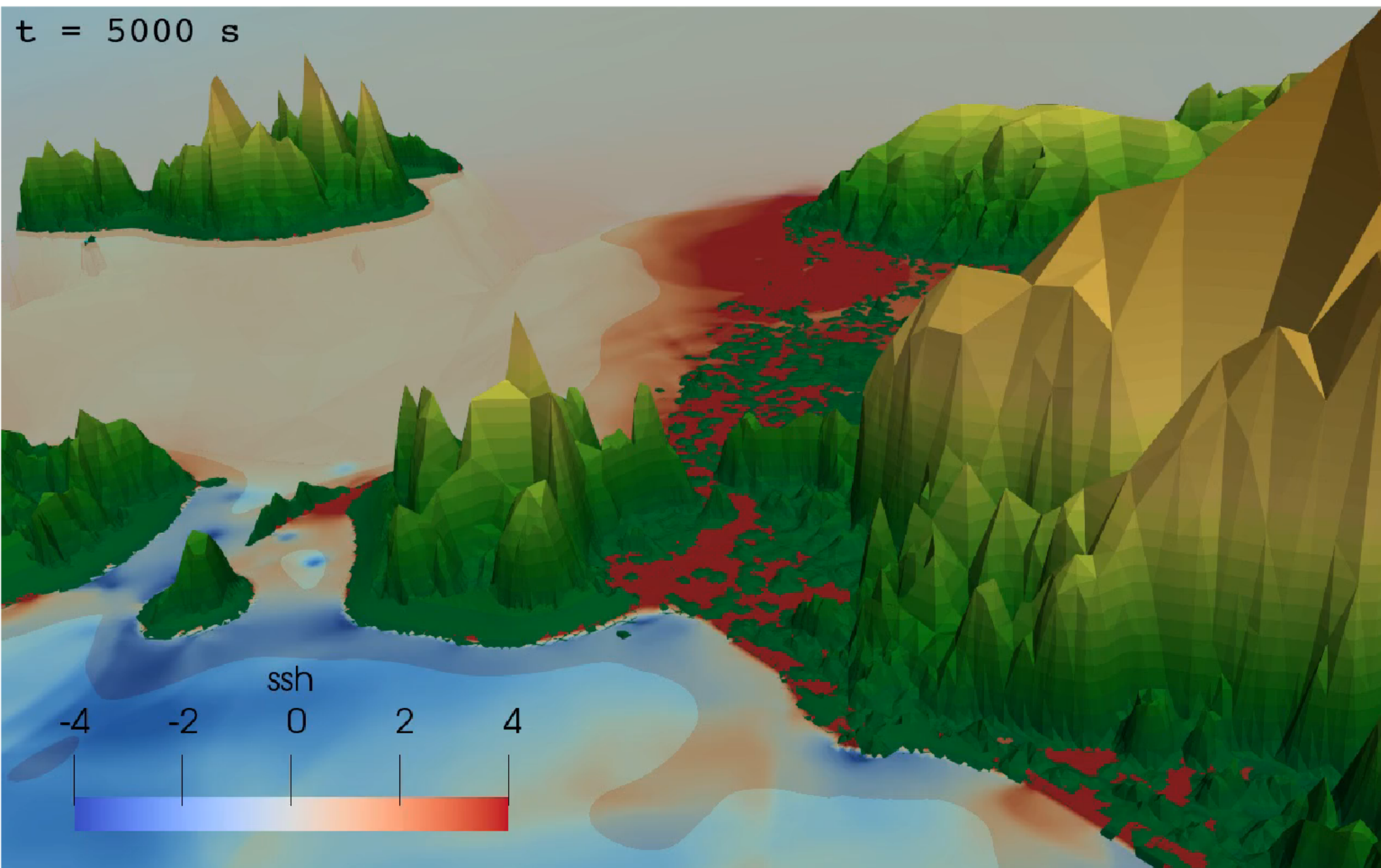
$$\mathbf{U} = \begin{pmatrix} h \\ h\mathbf{u} \end{pmatrix}, \quad \mathbf{F}(\mathbf{U}) = \begin{pmatrix} h\mathbf{u} \\ h\mathbf{u} \otimes \mathbf{u} + \frac{g}{2}h^2\mathbb{I}_2 \end{pmatrix}, \quad \mathbf{S}(\mathbf{U}) = \begin{pmatrix} 0 \\ -gh\nabla b \end{pmatrix}$$



$$\sqrt{1-\epsilon^2}$$

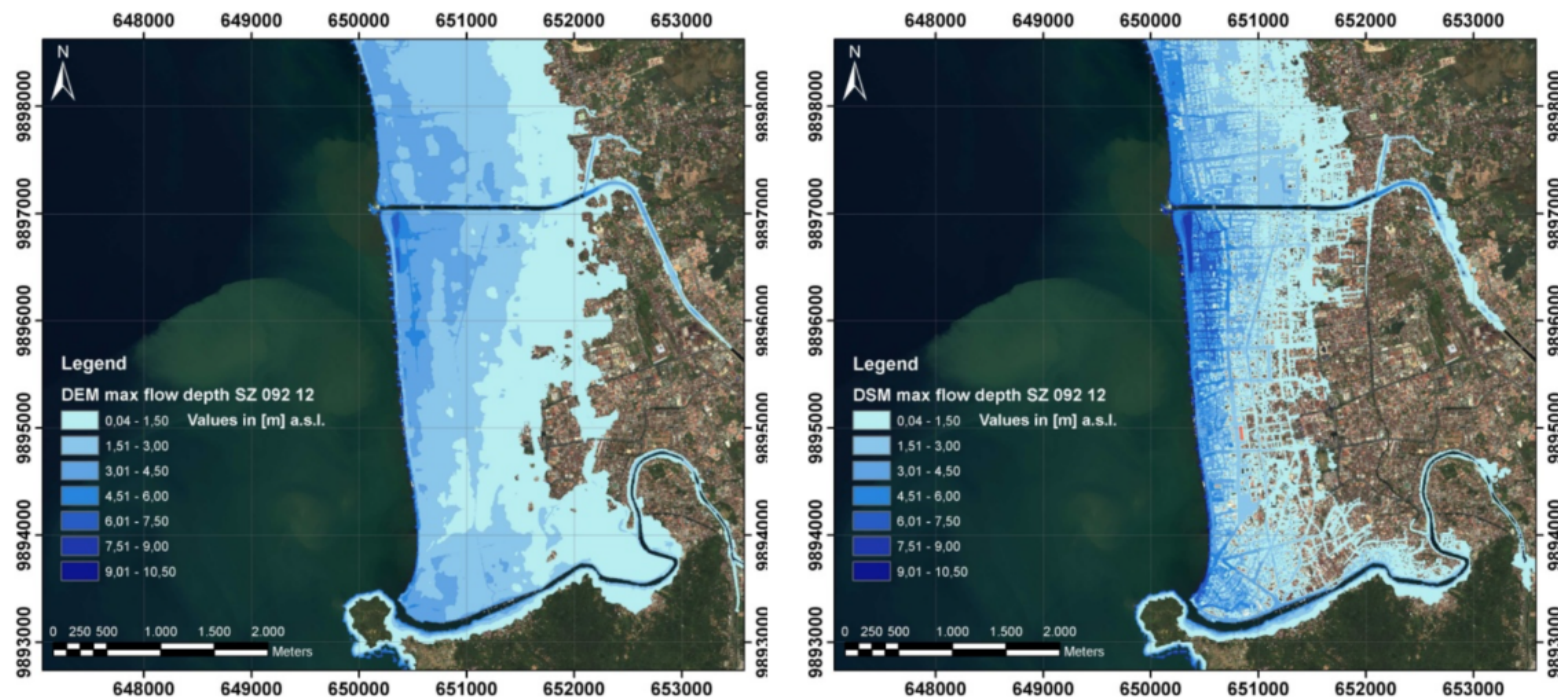
$$\sqrt{1-\epsilon^2} = 1 - \frac{\epsilon^2}{2} + \frac{\epsilon^4}{8} - \frac{\epsilon^6}{16} + \dots$$

$$\sqrt{1-\epsilon^2} \approx 1 - \frac{\epsilon^2}{2}$$



Upscaling

- Resolving small scale
- Parameterization
- Neglecting small scale



T. Schlurmann et al., Last Mile - Evacuation, 2010

Homogenization

Observation

What is the **effective** model of this PDE as $\varepsilon \rightarrow 0$?

$$\left(a\left(\frac{x}{\varepsilon}\right)u_x^\varepsilon\right)_x = f, \quad x \in I = [a, b], 0 < q \leq a \in L^\infty([0, 1])$$

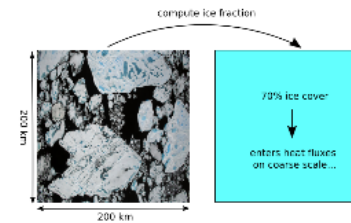
The effective model is

$$\frac{1}{m_H(a)}u_{xx}^* = f, \quad m_H(a) = \int_0^1 \frac{1}{a(y)} dy$$

not

$$m_A(a)u_{xx}^* = f, \quad m_A(a) = \int_0^1 a(y) dy \quad \text{in general } m_A(a) \geq \frac{1}{m_H(a)}$$

Example



Homogenization Idea

We have $F_\varepsilon(u_\varepsilon) = 0$ so maybe

Find F^* and u^* so that $u_\varepsilon \rightarrow u^*$ and $F_\varepsilon \rightarrow F^*$ (in some sense) in the limit of large range of scales, scale separation with

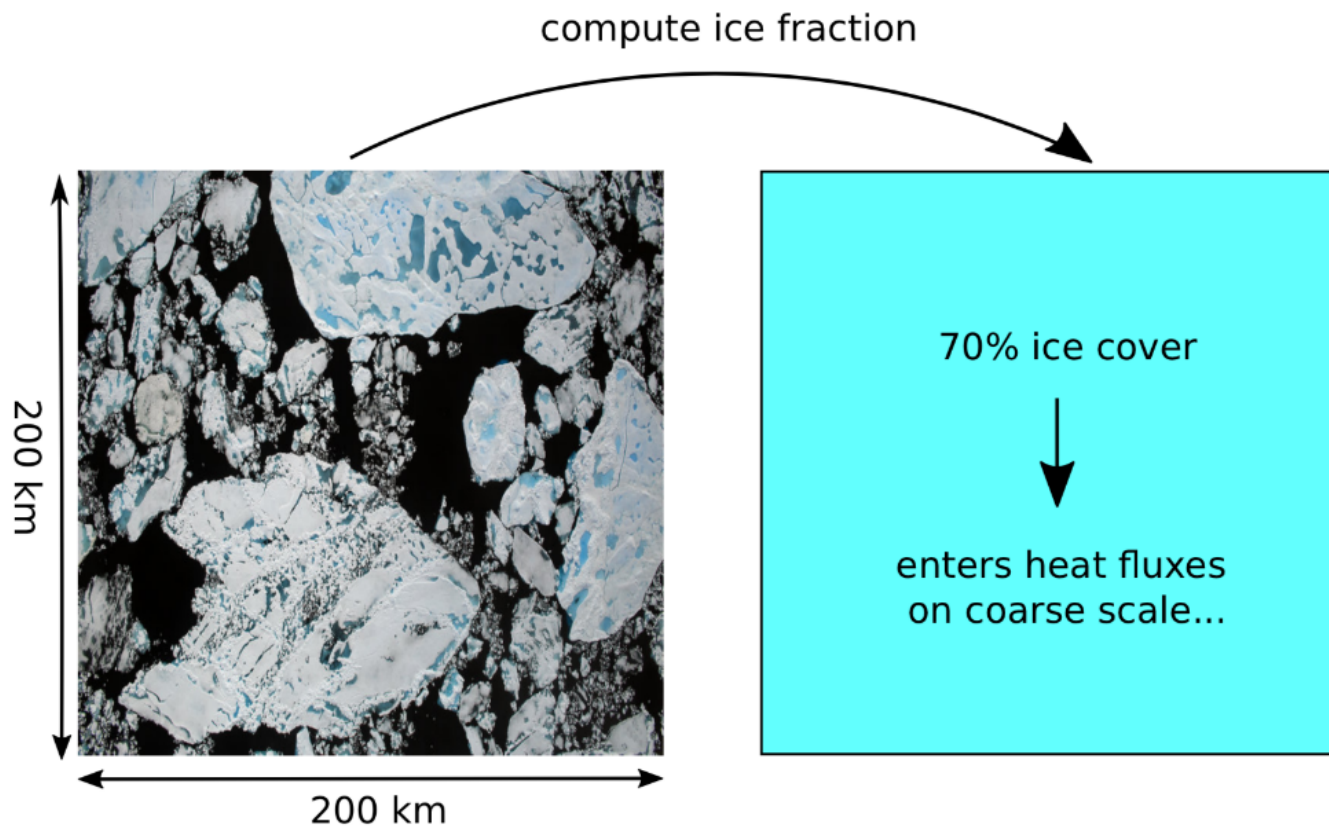
$$F^*(u^*) = 0.$$

This is called **effective model**.

Assume as our model

$$\left(a\left(\frac{x}{\varepsilon}\right)u_x^\varepsilon\right)_x = f, \quad x \in I = [a, b], 0 < q \leq a \in L^\infty([0, 1])$$

Example



Homogenization Idea

We have $F_\varepsilon(u_\varepsilon) = 0$ so maybe

Find F^* and u^* so that $u_\varepsilon \rightarrow u^*$ and $F_\varepsilon \rightarrow F^*$ (in some sense) in the limit of large range of scales, scale separation with

$$F^*(u^*) = 0 .$$

This is called **effective model**.

Assume as our model

$$\left(a \left(\frac{x}{\varepsilon} \right) u_x^\varepsilon \right)_x = f , \quad x \in I = [a, b] , 0 < q \leq a \in L^\infty([0, 1])$$

Observation

What is the **effective** model of this PDE as $\varepsilon \rightarrow 0$?

$$\left(a\left(\frac{x}{\varepsilon}\right) u_x^\varepsilon \right)_x = f, \quad x \in I = [a, b], \quad 0 < q \leq a \in L^\infty([0, 1])$$

The effective model is

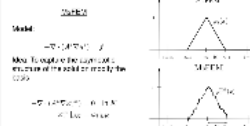
$$\frac{1}{m_H(a)} u_{xx}^* = f, \quad m_H(a) = \int_0^1 \frac{1}{a(y)} dy$$

not

$$m_A(a) u_{xx}^* = f, \quad m_A(a) = \int_0^1 a(y) dy \quad \text{In general } m_A(a) \geq \frac{1}{m_H(a)}!$$

Multi-Scale FEM

Method – Idea



Mathematics

Theorem (Hou/Wu, 1999)
 Let $\Omega \subset \mathbb{R}^d$ be a bounded domain and $\Gamma \subset \partial\Omega$ be a smooth subdomain.
 Let $\mathbf{u} \in H^1(\Omega)$ be the solution of the problem

$$-\Delta \mathbf{u} = \mathbf{f} \text{ in } \Omega, \quad \mathbf{u} = \mathbf{0} \text{ on } \Gamma$$

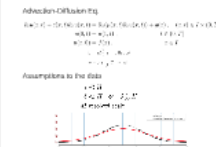
 Let $\mathbf{u}_\epsilon \in H^1(\Omega)$ be the solution of the problem

$$-\Delta \mathbf{u}_\epsilon = \mathbf{f} \text{ in } \Omega, \quad \mathbf{u}_\epsilon = \mathbf{0} \text{ on } \Gamma$$

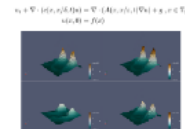
 Then

$$\|\mathbf{u} - \mathbf{u}_\epsilon\|_{H^1(\Omega)} \leq C \epsilon^{1/2} \|\mathbf{f}\|_{H^1(\Omega)}$$

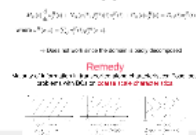
Model Problem



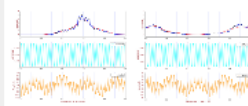
SLMsR 2D



Naïve Approach



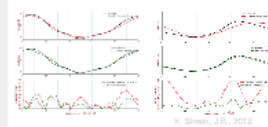
SLMsR Result



Reconstruction



Multi-Scale FEM Upscaling Result



Features

- Works, but:
- assumptions to flow field necessary
- no direct generalization to 2D/3D
- needs scale separation
- conservation not guaranteed

Remedy:
 semi-Lagrangian reconstruction approach

Method – Idea

MsFEM

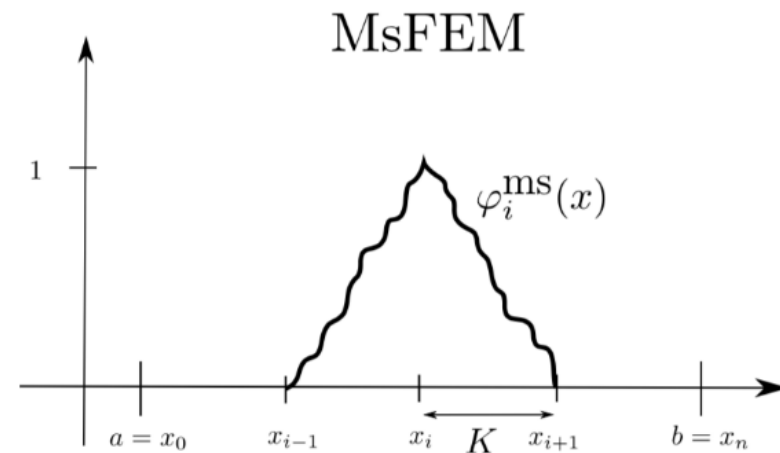
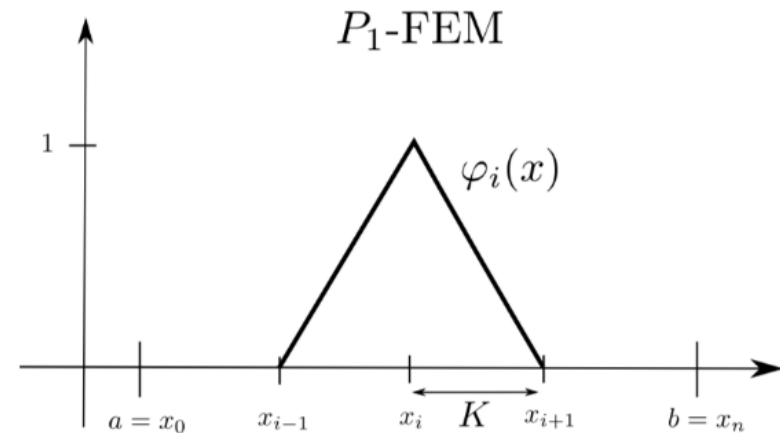
Model:

$$-\nabla \cdot (A^\varepsilon \nabla u^\varepsilon) = f$$

Idea: To capture the asymptotic structure of the solution modify the basis

$$-\nabla \cdot (A^\varepsilon \nabla \varphi_i^{\text{ms}}) = 0 \quad \text{in } K$$

$$\varphi_i^{\text{ms}}|_{\partial K} = \varphi_i|_{\partial K}$$



Mathematics

Theorem (Hou/Wu, 1999)

Let $u^\varepsilon \in H^2(\Omega)$ solve the model problem and $u^{\varepsilon,h} \in P^h$ be the MsFEM solution.

Then if $H < \varepsilon$

$$\|u^\varepsilon - u^{\varepsilon,h}\|_{H^1} \leq CH(\|u^\varepsilon\|_{H^2} + \|f\|_{L^2}) .$$

If $H > \varepsilon$ and $u^0 \in H^2 \cap W^{1,\infty}$ is the solution to the homogenized problem then

$$\|u^\varepsilon - u^{\varepsilon,h}\|_{H^1} \leq C(H + \varepsilon) \|f\|_{L^2} + C \left(\frac{\varepsilon}{H} \right)^{1/2} \|u^0\|_{W^{1,\infty}} .$$

Model Problem

Advection-Diffusion Eq.

$$\partial_t u(x, t) + c(x, t) \partial_x u(x, t) = \partial_x (\mu(x, t) \partial_x u(x, t)) + g(x), \quad (x, t) \in I \times (0, T]$$

$$u(0, t) = u(1, t), \quad t \in (0, T]$$

$$u(x, 0) = f(x), \quad x \in I$$

$$\mu = \mu\left(\frac{x}{\epsilon}, t\right) \quad \text{diffusion}$$

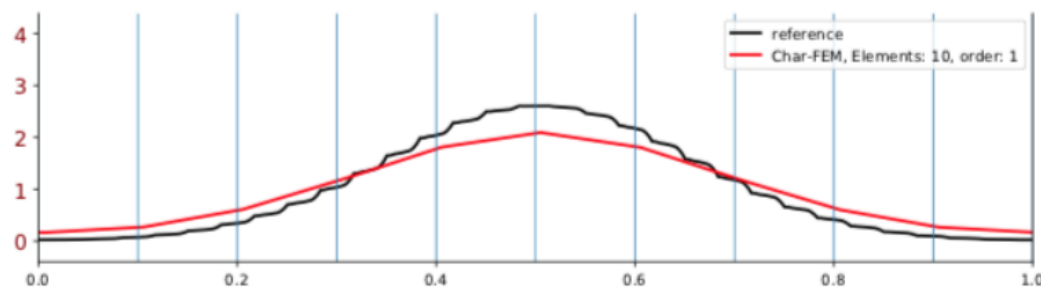
$$c = c\left(x, \frac{x}{\delta}, t\right) \quad \text{wind}$$

Assumptions to the data

$$\epsilon \ll H$$

$$\delta \ll H \quad \text{or} \quad \delta \gtrsim H$$

H resolved scale



Naïve Approach

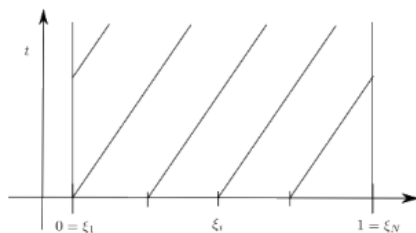
$$M_{ij}(t) \frac{d}{dt} u_j^H(t) + N_{ij}(\varphi_i^{\text{ms}}, \dot{\varphi}_j^{\text{ms}})(t) u_j^H(t) + C_{ij}(t) u_j^H(t) = D_{ij}(t) u_j^H(t)$$

where $u^H(x, t) = \sum_j u_j^H(t) \varphi_j^{\text{ms}}(x, t)$.

→ Does not work since the domain is badly decomposed

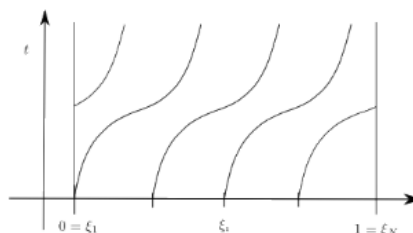
Remedy

Majority of information is transported along characteristics: Pose local problems with BCs on **coarse scale characteristics**.



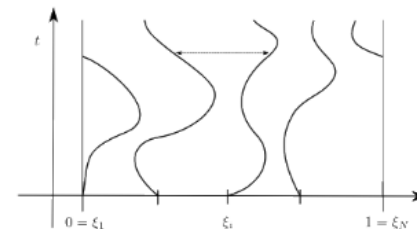
$$c(x, t) \equiv \text{const}$$

$$\begin{aligned} x(\xi, \tau) &= \xi + c\tau \\ t(\xi, \tau) &= \tau \end{aligned}$$



$$c = c(t) \text{ or } c = c(x, t)$$

$$\begin{aligned} x(\xi, \tau) &= \xi + \int_0^\tau \langle c \rangle(s) ds \\ t(\xi, \tau) &= \tau \end{aligned}$$

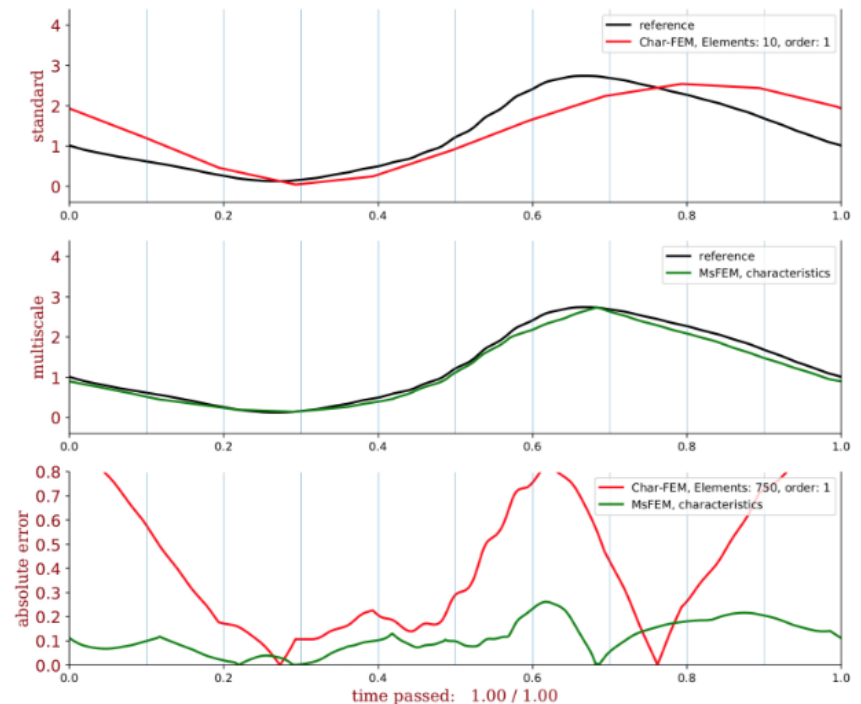
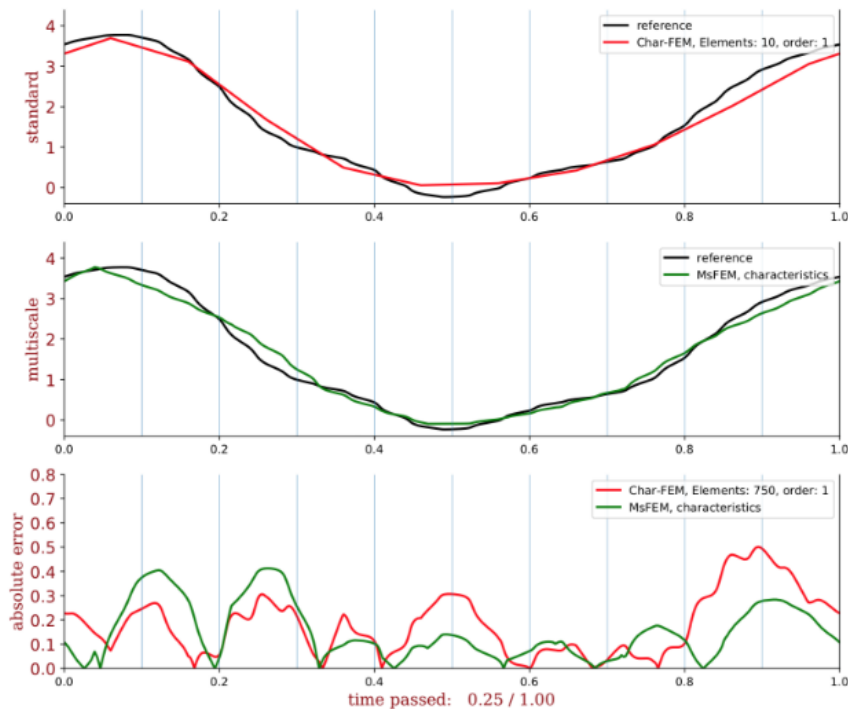


$$c = c(x, t)$$

$$\begin{aligned} \frac{d}{d\tau} x(\xi, \tau) &= c(x(\xi, \tau), \tau) \\ \frac{d}{d\tau} t(\xi, \tau) &= 1 \end{aligned}$$

Multi-Scale FEM

Upscaling Result



K. Simon, J.B., 2018

Features

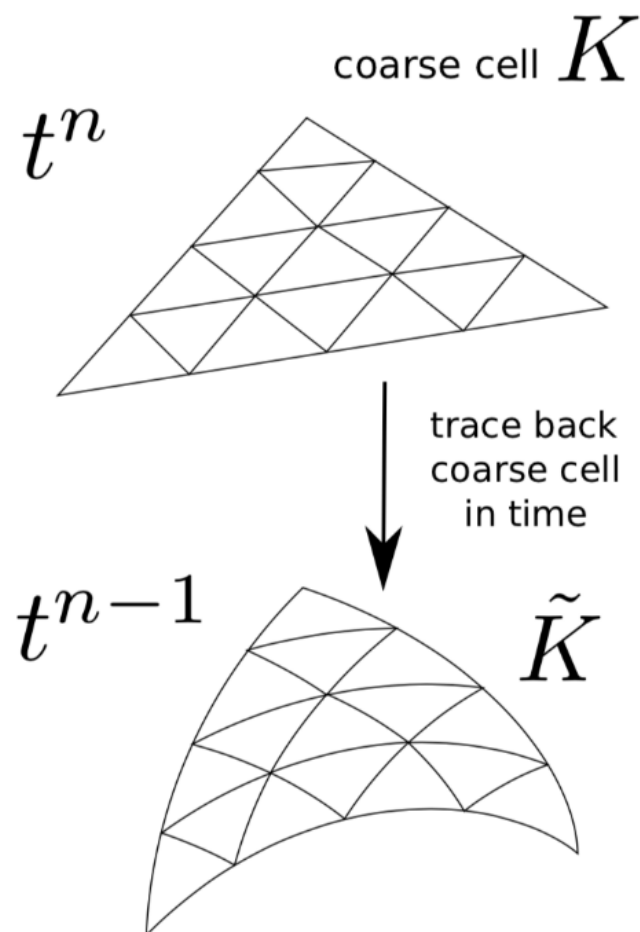
Works, but:

- assumptions to flow field necessary
- no direct generalization to 2D/3D
- needs scale separation
- conservation not guaranteed

Remedy:

semi-Lagrangian reconstruction approach

Reconstruction



local
representations:

$$u^n|_K = \sum_j u_{j,K}^n \varphi_{j,K}^n$$

↑
unknown

known
↓

$$u^{n-1}|_{\tilde{K}} = \sum_j u_{j,\tilde{K}}^{n-1} \varphi_{j,\tilde{K}}^{n-1}$$

↑
can be
reconstructed

1D Example

$$u_t + [c(x, x/\delta, t)u]_x = (\mu(x, x/\varepsilon, t)u_x)_x \quad x \in (0, 1)$$

$$u(0, t) = u(1, t)$$

$$u(x, 0) = f(x)$$

$$c(x, t) = \frac{1}{2} + \frac{1}{8}(\cos(8\pi x) + \cos(62\pi x) + \cos(150\pi x))$$

$$\mu(x, t) = \cos(10\pi t)(0.01 + 0.009 \cos(86\pi x))$$

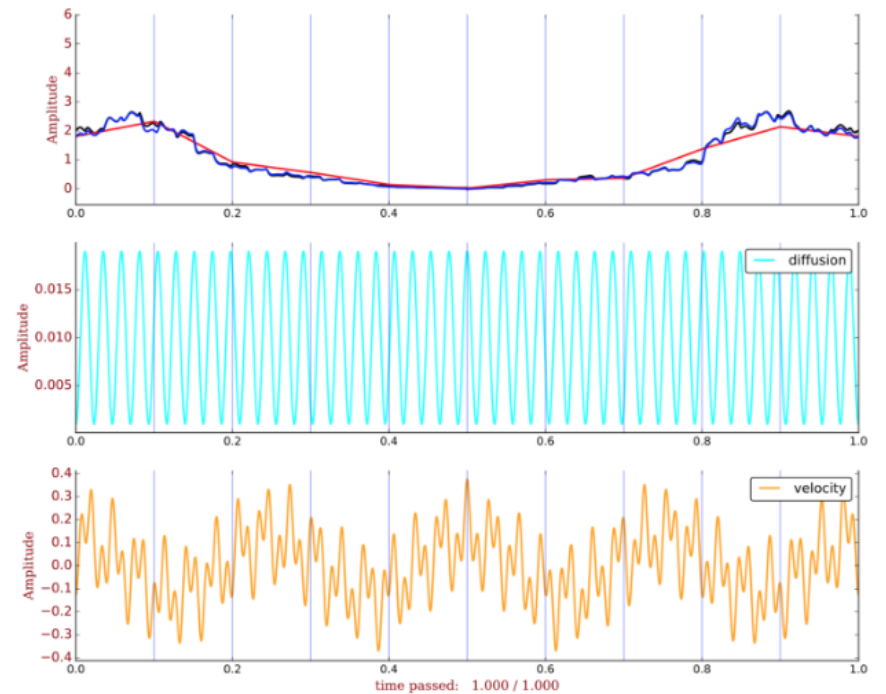
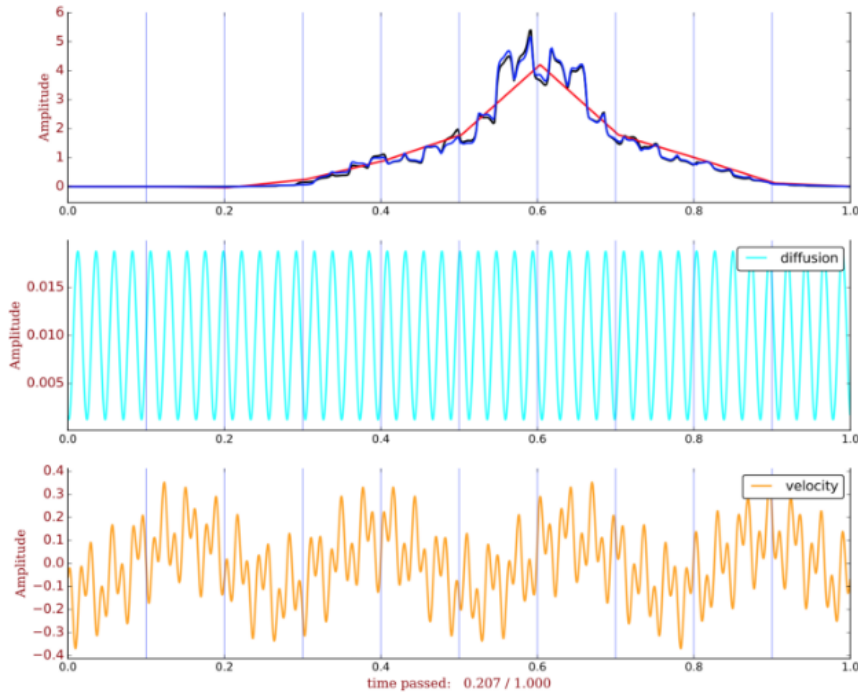
$$n_{\text{coarse}} = 10$$

$$n_{\text{fine}} = 60$$

$$T_{\text{max}} = 1$$

$$\delta t = 1/1000$$

SLMsR Result



1D Example

$$u = \begin{pmatrix} \cos(x) \sin(4t) \\ \sin(x) \sin(4t) \end{pmatrix}, \quad (x, y, z) \in [0, \pi] \times [0, \pi] \times [0, \pi]$$

$$\Rightarrow \mathbf{u} = \begin{pmatrix} \cos(x) \\ \sin(x) \end{pmatrix} \sin(4t)$$

$$\Rightarrow \mathbf{u}_t = 4 \sin(x) \cos(x) \cos(4t)$$

$$\Rightarrow \mathbf{u}_{tt} = -16 \sin(x) \cos(x) \sin(4t) = -16 \sin(2x) \sin(4t)$$

$$\Rightarrow \mathbf{u}_{tt} = -16 \sin(2x) \sin(4t) = -16 \sin(2x) \sin(2 \cdot 2t)$$

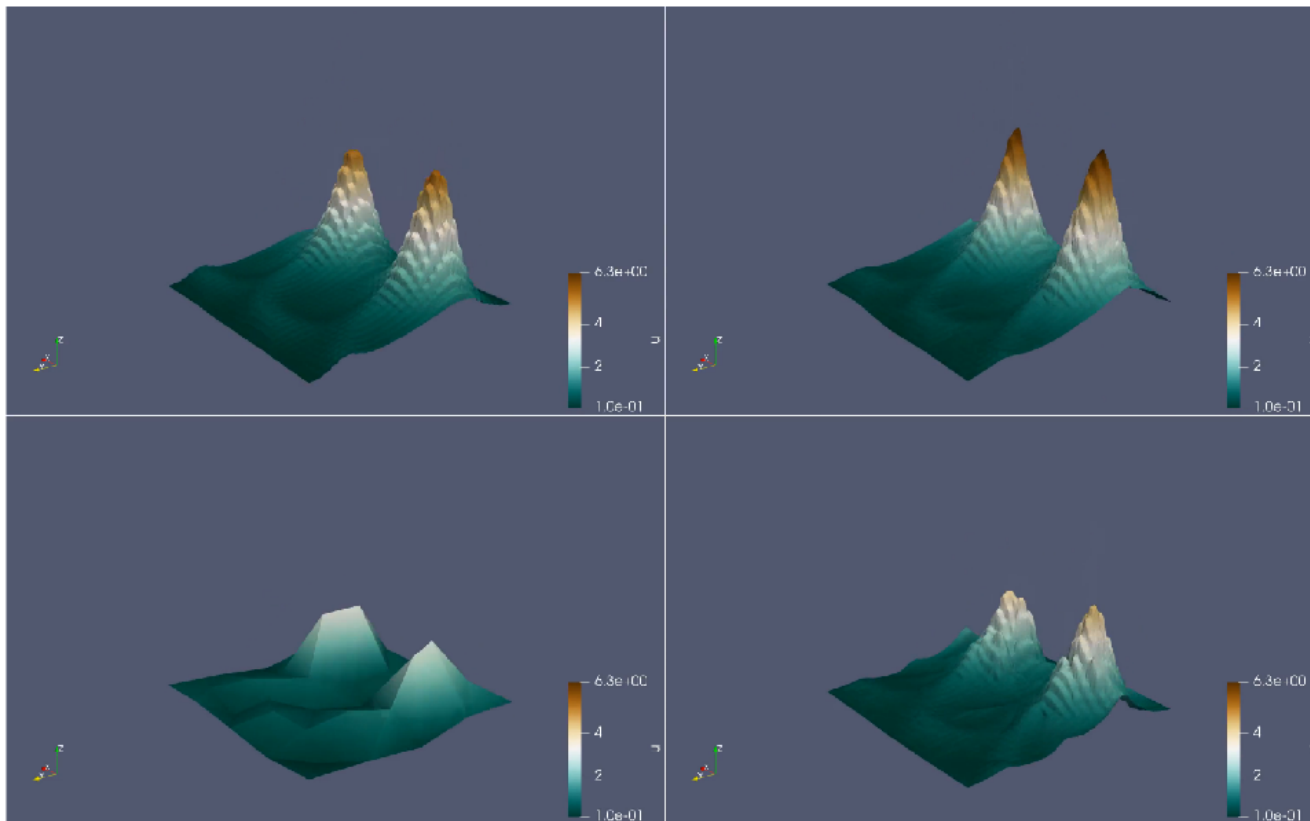
$$\Rightarrow \mathbf{u}_{tt} = -16 \sin(2x) \sin(2 \cdot 2t)$$

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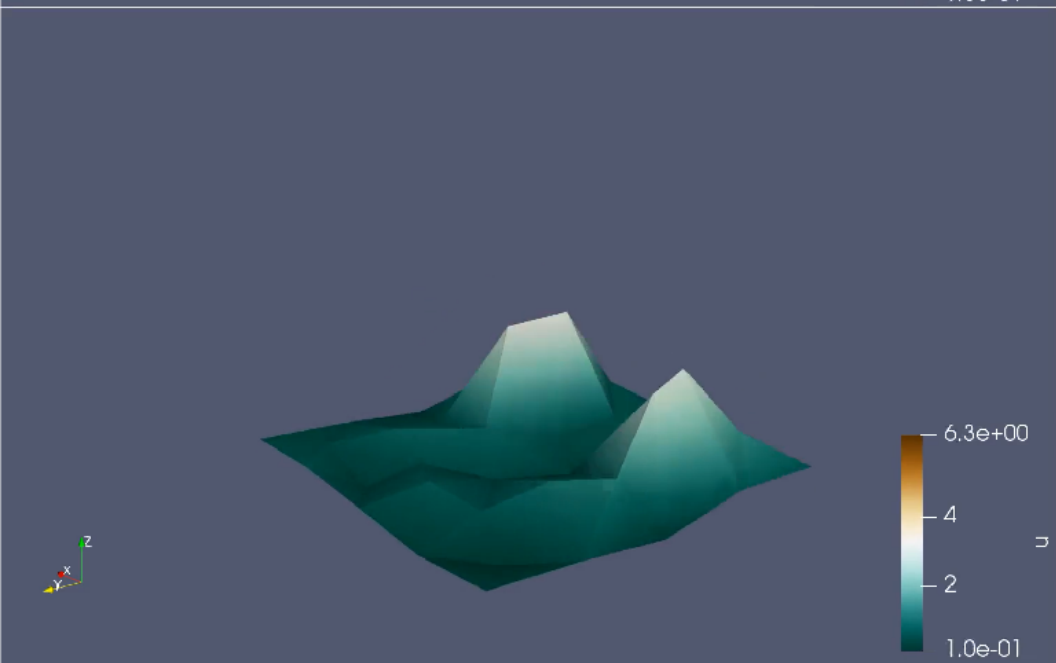
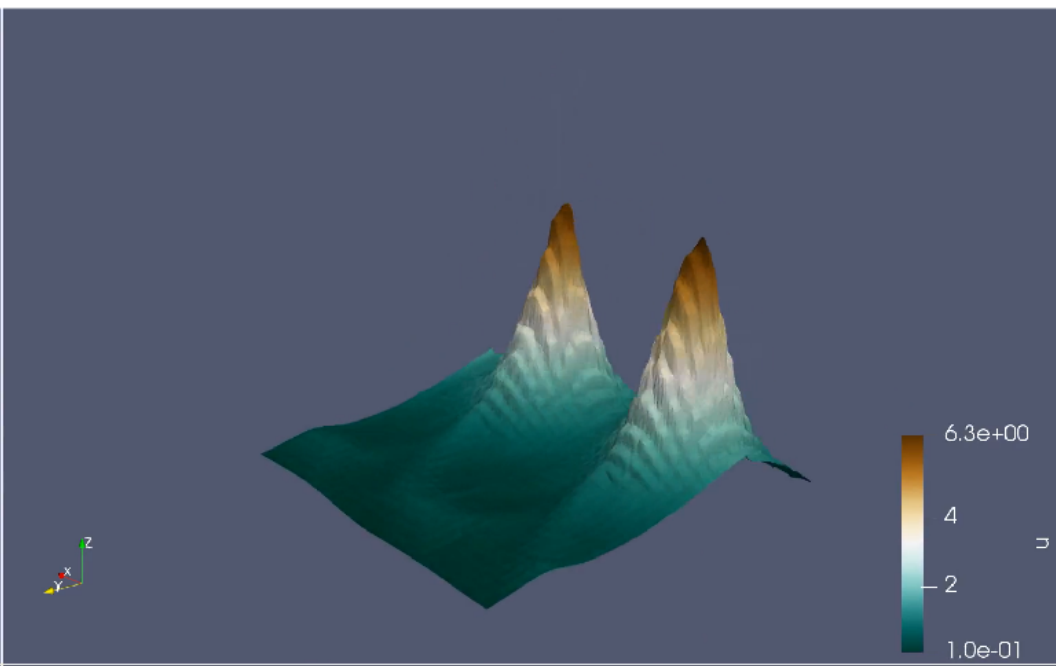
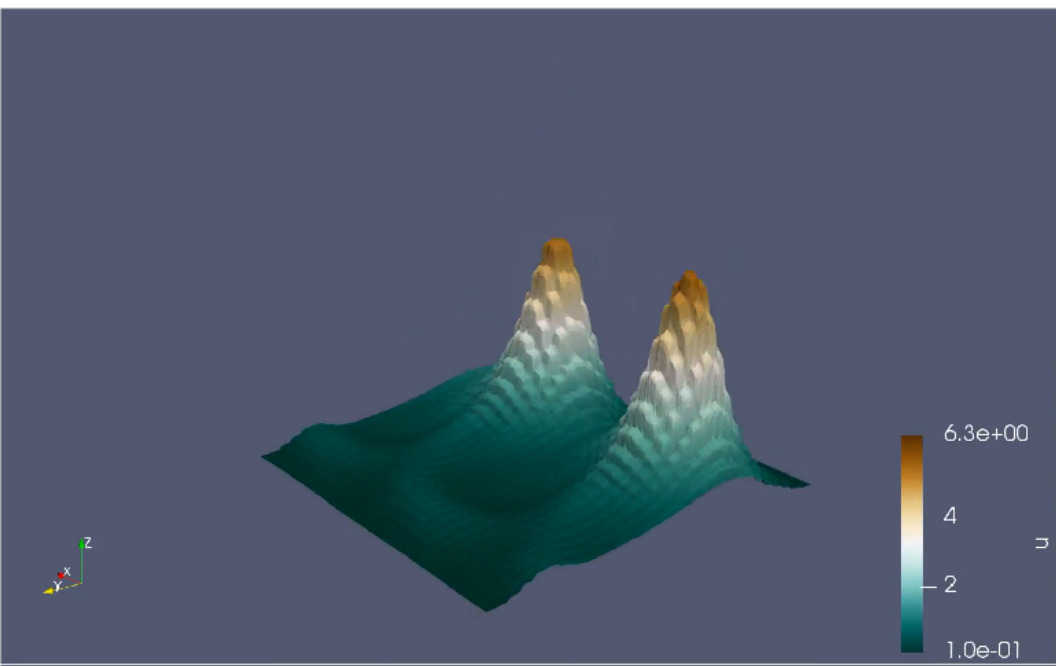
$$\Rightarrow \mathbf{u}_{tt} = -16 \sin(2x) \sin(2 \cdot 2t)$$

SLMsR 2D

$$u_t + \nabla \cdot (c(x, x/\delta, t)u) = \nabla \cdot (A(x, x/\varepsilon, t)\nabla u) + g, x \in \mathbb{T}_2$$
$$u(x, 0) = f(x)$$



$$u(x, 0) = f(x)$$



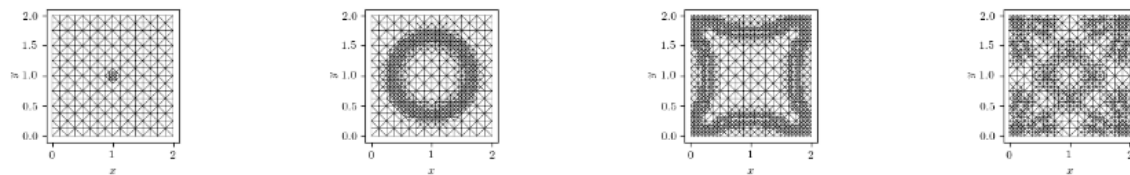
Conclusions

Downscaling:

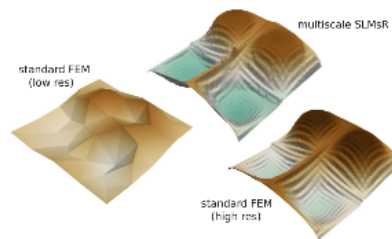
- Adaptive Mesh refinement
- Efficiency
- Accuracy and Conservation

Upscaling:

- Homogenization viable approach (sometimes)
- Multiscale FEM in Lagrangian frame
- Multiscale reconstruction method



N. Beisiegel, J.B., 2019



K. Simon, J.B., 2019

