

computational geophysics in a changing climate

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University of Tasmania | April 2022

UBC Vancouver is
located on the
traditional, ancestral,
and unceded territory
of the xʷməθkʷəy̓əm
people



climate crisis

solutions & mitigating impacts: opportunities for geophysics



critical minerals



geologic storage of CO₂



geotechnical
(e.g. permafrost)



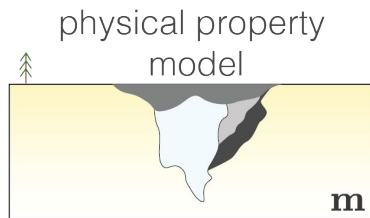
groundwater

research interests: computational geoscience

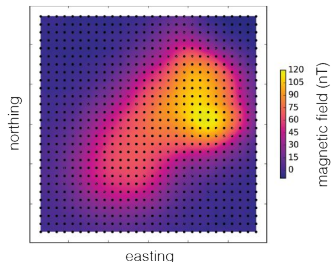
physics-driven, inverse problems

forward problem

$$\mathbf{d} = \mathcal{F}[\mathbf{m}]$$



data



$$\tilde{\mathbf{m}} = \mathcal{F}^{-1}[\mathbf{d}]$$

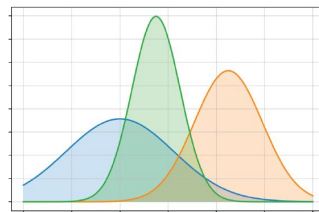
inverse problem

statistics, machine learning

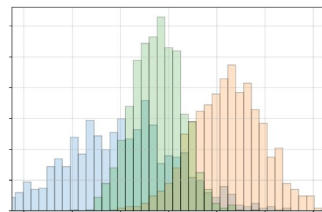
probability

$$\mathbf{X} \sim \mathcal{N}(0, 1)$$

statistical model



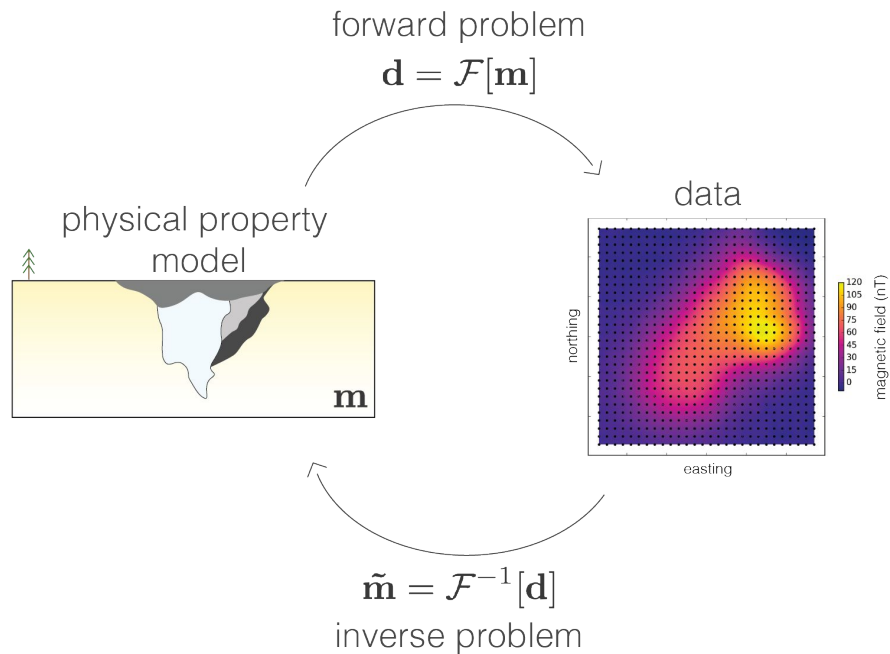
observations



$$\mathbf{X} \sim \mathcal{N}(\mu, \sigma)$$

statistics
(inverse probability)

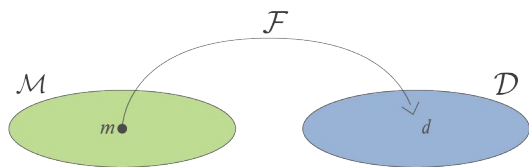
geophysical inversions



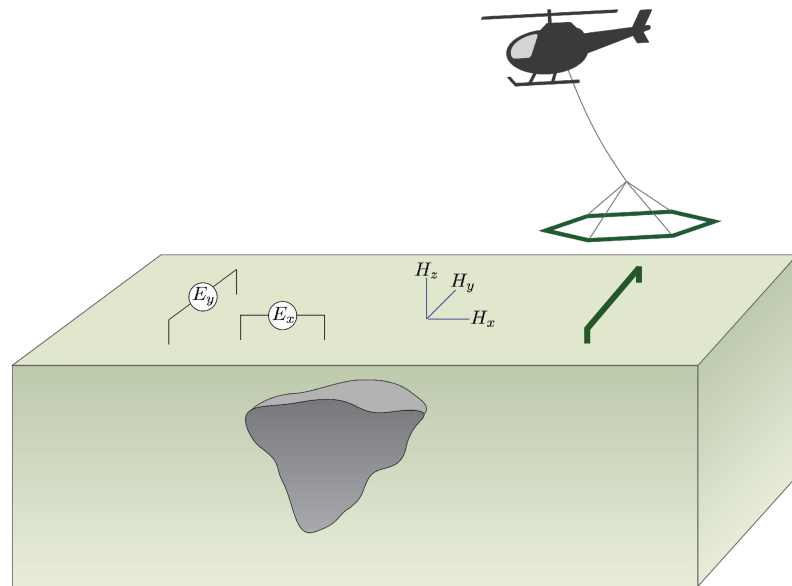
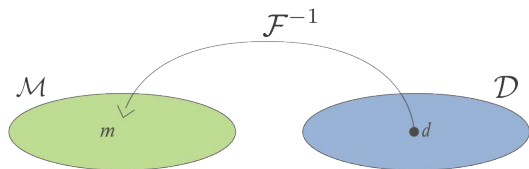
statement of the inverse problem

Given

- observations: d_j^{obs} , $j = 1, \dots, N$
- uncertainties: ϵ_j
- ability to forward model: $\mathcal{F}[m] = d$



Find the Earth model that gave rise to the data

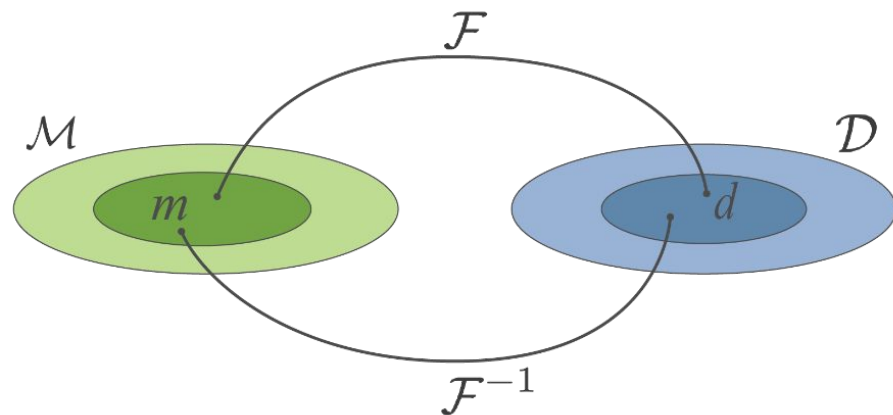


inverse problem

The inverse problem is ill-posed

- non-unique
- ill-conditioned

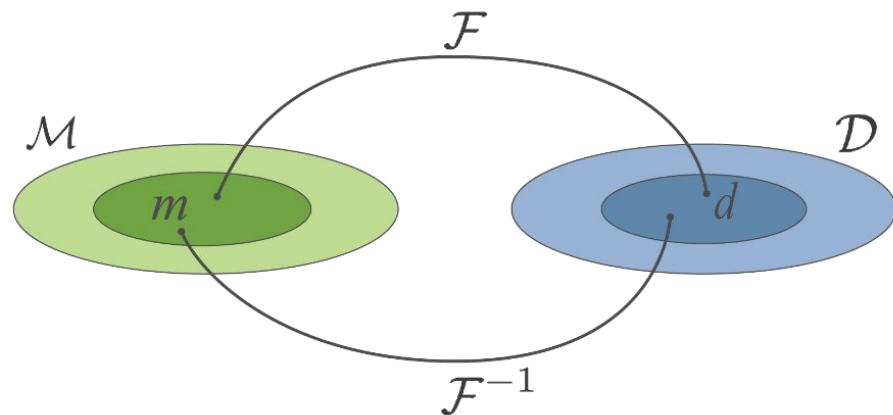
Any inversion approach must address these issues.



inverse problem

Prior information important to constrain the inversion

- geologic structures
- boreholes
- reference model
- bounds
- physical properties
- other geophysical data
- ...



need a framework for inverse problem

Tikhonov (deterministic)

Find a single “best” solution by solving optimization

$$\text{minimize} \quad \phi = \phi_d + \beta \phi_m$$

$$\text{subject to} \quad m_L < m < m_H$$

$$\left\{ \begin{array}{l} \phi_d: \text{data misfit} \\ \phi_m: \text{regularization} \\ \beta: \text{trade-off parameter} \\ m_L, m_H: \text{lower and upper bounds} \end{array} \right.$$

Bayesian (probabilistic)

Use Bayes' theorem

$$P(m|d^{obs}) \propto P(d^{obs}|m)P(m)$$

$$\left\{ \begin{array}{l} P(m): \text{prior information about } m \\ P(d^{obs}|m): \text{probability about the data errors (likelihood)} \\ P(m|d^{obs}): \text{posterior probability for the model} \end{array} \right.$$

Two approaches:

- (a) Characterize $P(m|d^{obs})$
- (b) Find a particular solution that maximizes $P(m|d^{obs})$
MAP: (maximum a posteriori) estimate

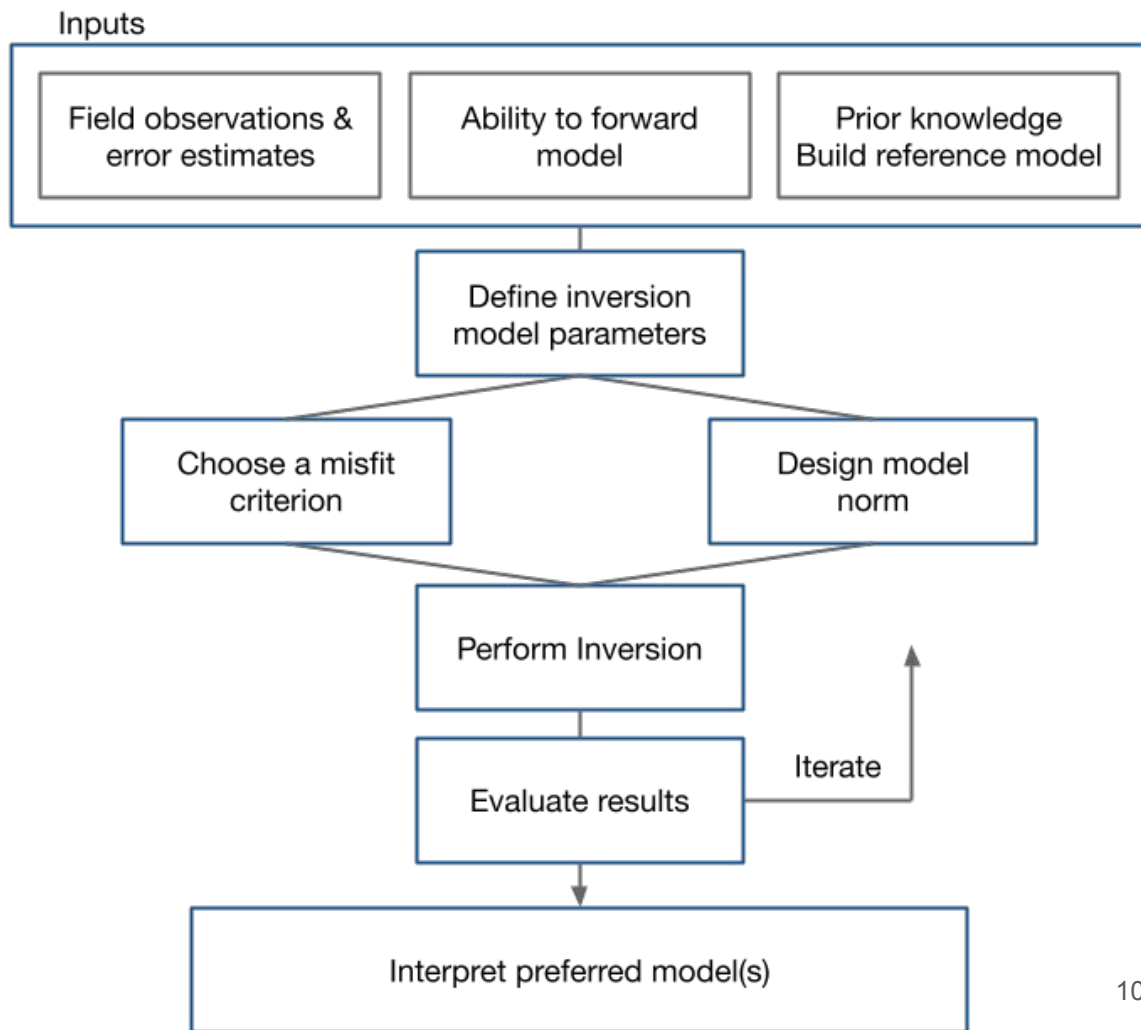
flow chart for the inverse problem

- many components
- iterative process to obtain solution
- each component requires evaluation, adjustment by user



Fundamentals of Inversion – D. Oldenburg
Capturing knowledge in code – L. Heagy

<http://www.mtnet.info/EMinars/EMinars.html>



choosing a software package

a sampling of open tools in EM

depends on needs / goals:

- production scale inversion
- methods oriented research
- education

influences priorities

- computational efficiency
- ease of use
- flexibility
- modularity
- license
- development style



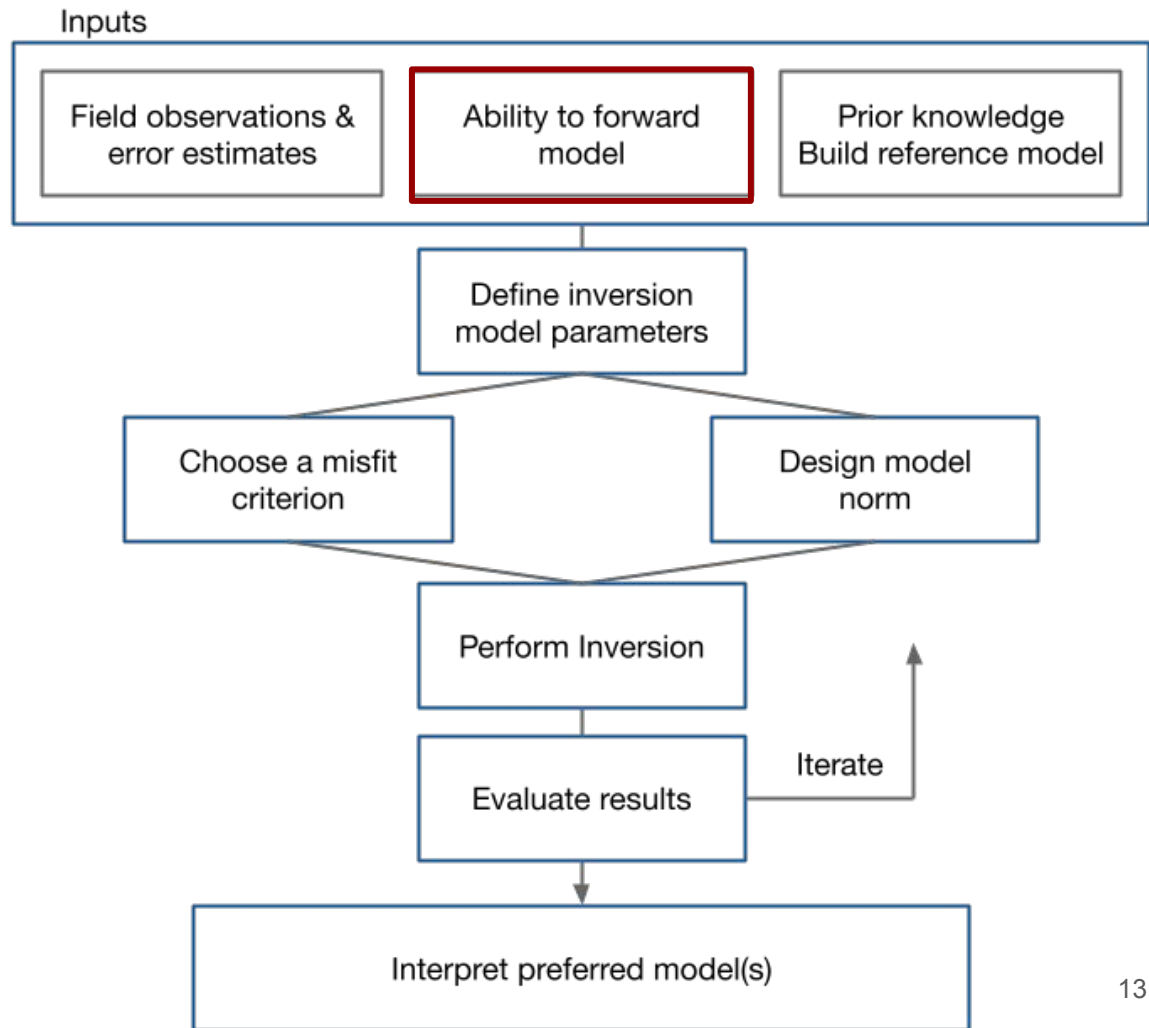
...

facilitate research in geophysics

prioritizes:

- **modularity:** building blocks, pieces available to manipulation
- **declarative code:** express intent, looks like the math
- **extensible:** integration of information
- **open community:** transparency, opportunities for collaboration

flow chart for the inverse problem



electromagnetics: basic equations (quasi-static)

	Time	Frequency
Faraday's Law	$\nabla \times \vec{e} = -\frac{\partial \vec{b}}{\partial t}$	$\nabla \times \vec{E} = -i\omega \vec{B}$
Ampere's Law	$\nabla \times \vec{h} = \vec{j} + \frac{\partial \vec{d}}{\partial t}$	$\nabla \times \vec{H} = \vec{J} + i\omega \vec{D}$
No Magnetic Monopoles	$\nabla \cdot \vec{b} = 0$	$\nabla \cdot \vec{B} = 0$
Constitutive Relationships (non-dispersive)	$\vec{j} = \sigma \vec{e}$ $\vec{b} = \mu \vec{h}$ $\vec{d} = \varepsilon \vec{e}$	$\vec{J} = \sigma \vec{E}$ $\vec{B} = \mu \vec{H}$ $\vec{D} = \varepsilon \vec{E}$

* Solve with sources and boundary conditions

electromagnetics: frequency domain

Continuous equations

$$\nabla \times \vec{E} + i\omega \vec{B} = 0$$

$$\nabla \times \mu^{-1} \vec{B} - \sigma \vec{E} = \vec{J}_s$$

$$\hat{n} \times \vec{B}|_{\partial\Omega} = 0$$

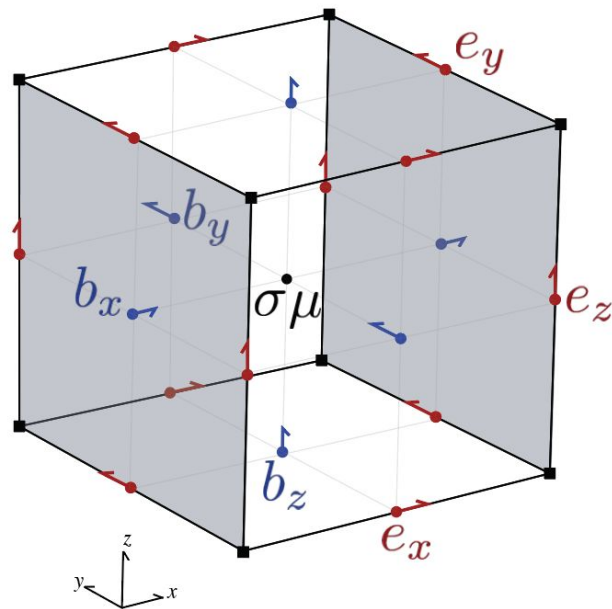
Finite volume discretization

$$\mathbf{C}\mathbf{e} + i\omega\mathbf{b} = 0$$

$$\mathbf{C}^\top \mathbf{M}_{\mu^{-1}}^f \mathbf{b} - \mathbf{M}_\sigma^e \mathbf{e} = \mathbf{M}^e \mathbf{j}_s$$

Eliminate \mathbf{b} to obtain a second-order system in \mathbf{e}

$$\underbrace{(\mathbf{C}^\top \mathbf{M}_{\mu^{-1}}^f \mathbf{C} + i\omega \mathbf{M}_\sigma^e)}_{\mathbf{A}(\sigma, \omega)} \underbrace{\mathbf{e}}_{\mathbf{u}} = \underbrace{-i\omega \mathbf{M}^e \mathbf{j}_s}_{\mathbf{q}(\omega)}$$



solving a FDEM problem

$$\underbrace{(C^T M_{\mu-1}^f C + i\omega M_{\sigma}^e)}_{A(\sigma, \omega)} \underbrace{\mathbf{e}}_{\mathbf{u}} = \underbrace{-i\omega M_{\sigma}^e \mathbf{j}_s}_{\mathbf{q}(\omega)}$$

```

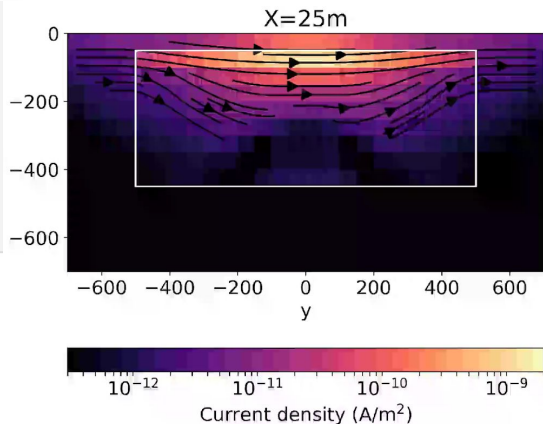
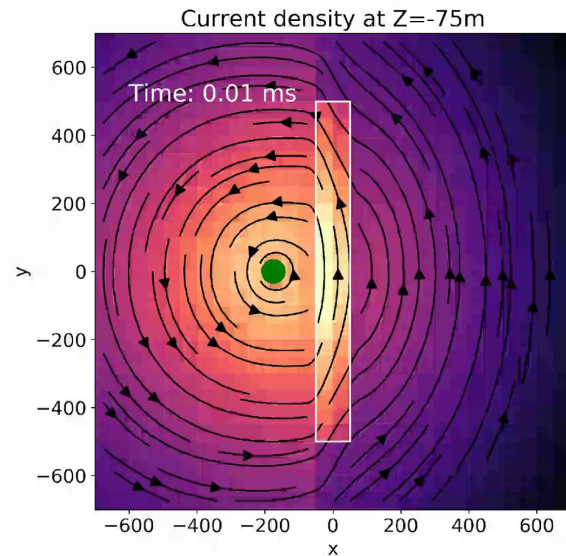
omega = 2 * pi * frequency

C = mesh.edge_curl
Mfmu = mesh.get_face_inner_product(1/mu_0)
Meos = mesh.get_edge_inner_product(sigma)

A = C.T * Mfmu * C + i * omega * Meos
Ainv = Solver(A) # acts like A inverse

Me = mesh.get_edge_inner_product()
q = -i * omega * Me * js

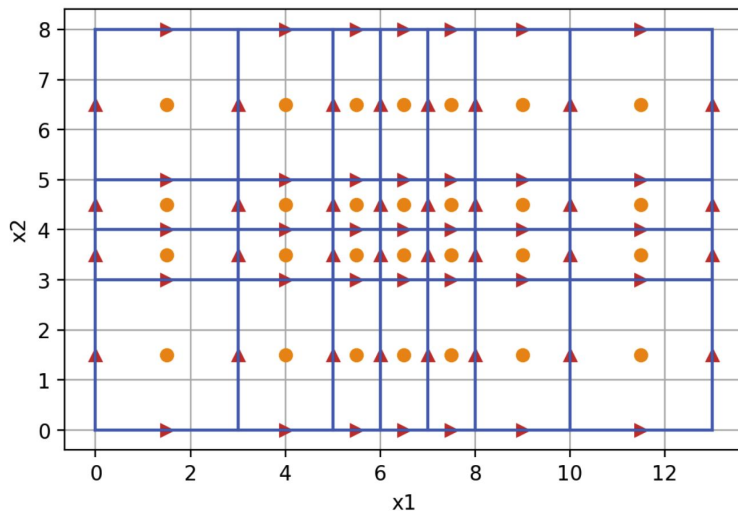
u = Ainv * q
    
```



create a mesh: the discretize package

```
import discretize
```

```
hx = [3, 2, 1, 1, 1, 2, 3]  
hy = [3, 1, 1, 3]  
mesh = discretize.TensorMesh([hx, hy])  
mesh.plot_grid(edges=True, centers=True);
```



Properties or Methods

dim, origin

n_cells, n_nodes, n_faces, n_edges

cell_volumes, face_areas, edge_lengths

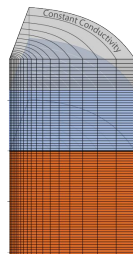
cell_centers, nodes, edges, faces

nodal_gradient, face_divergence, edge_curl

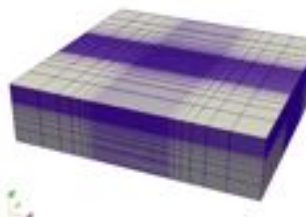
average_edge_to_cell, average_node_to_cell, ...

get_edge_inner_product()

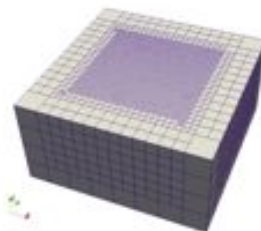
get_interpolation_matrix(location)



Cylindrical



Tensor



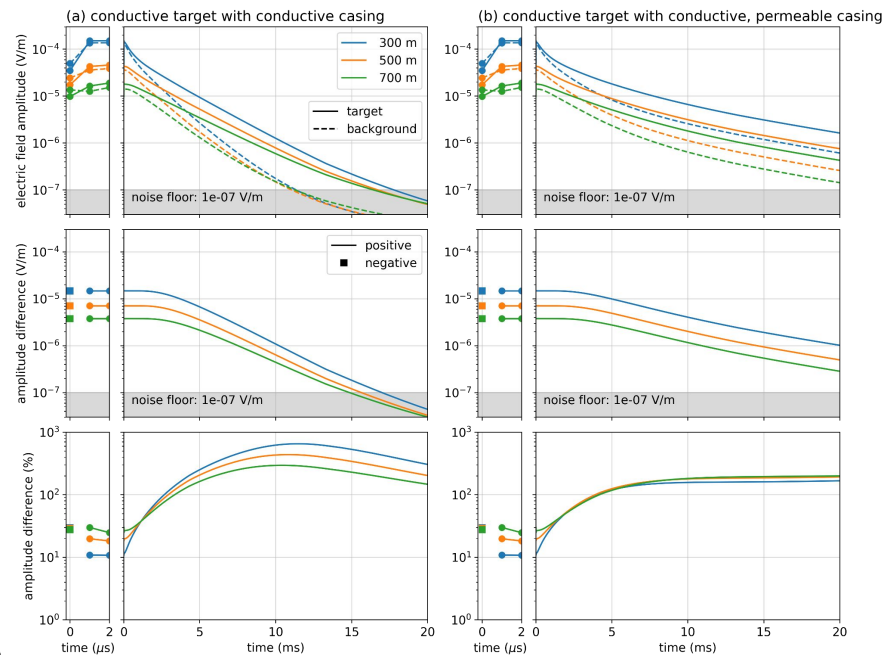
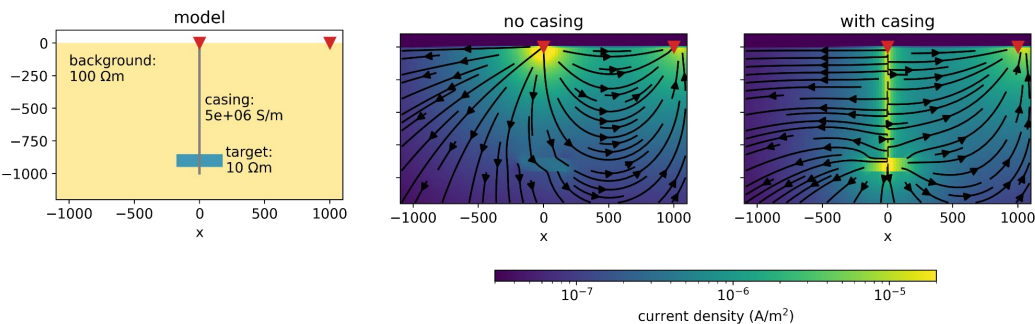
OcTree



J. Capriotti

an example: monitoring with steel-cased wells

- steel: highly conductive, also substantial magnetic permeability
- challenging geometry for numerical simulations
- but... advantageous for helping deliver current to depth



(Heagy & Oldenburg, 2022)

flow chart for the inverse problem

What do we need for inversion?

$$\text{minimize} \quad \phi = \phi_d + \beta \phi_m$$

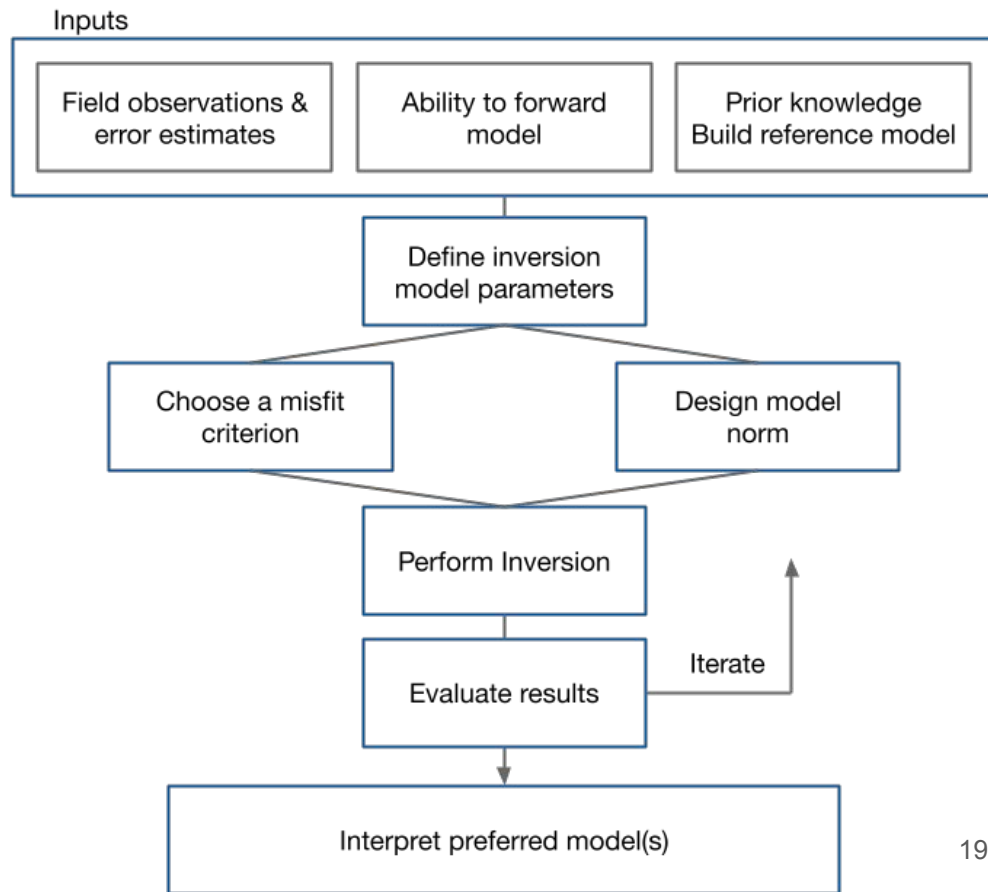
$$\text{subject to} \quad m_L < m < m_H$$

From the simulation

- adjoint sensitivity times a vector
- sensitivity times a vector

Inversion components:

- define a model norm
- perform optimization



sensitivities

For inverse problem, also need sensitivities (and adjoint)

$$\begin{aligned}\mathbf{J} &= \frac{\partial \mathbf{d}^{\text{pred}}}{\partial \mathbf{m}} \\ &= \frac{\partial \mathbf{P}(\mathbf{u}, \omega)}{\partial \mathbf{u}} \frac{\partial \mathbf{u}}{\partial \mathbf{m}}\end{aligned}$$

where the derivative of the fields (\mathbf{u}) is computed implicitly (requires a solve)

$$\frac{\partial \mathbf{A}(\sigma, \omega) \mathbf{u}^{\text{fixed}}}{\partial \mathbf{m}} + \mathbf{A}(\sigma, \omega) \frac{\partial \mathbf{u}}{\partial \mathbf{m}} = 0$$

\mathbf{J} is a large, dense matrix \rightarrow compute products with a vector if memory-limited

inversion as an optimization problem

$$\begin{aligned} \min_{\mathbf{m}} \phi(\mathbf{m}) &= \phi_d(\mathbf{m}) + \beta \phi_m(\mathbf{m}) \\ \text{s.t. } \phi_d &\leq \phi_d^* \quad \mathbf{m}_L \leq \mathbf{m} \leq \mathbf{m}_U \end{aligned}$$

data misfit

$$\phi_d = \|\mathbf{W}_d(\mathcal{F}(\mathbf{m}) - \mathbf{d}^{\text{obs}})\|^2$$

uncertainties captured in \mathbf{W}

$$\mathbf{W}_d = \text{diag}\left(\frac{1}{\epsilon}\right)$$

$$\epsilon_j = \%|d_j^{\text{obs}}| + \text{floor}$$

model norm

$$\phi_m = \underbrace{\alpha_s \int_V w_s (m - m_{\text{ref}})^2 dV}_{\text{smallness}} + \underbrace{\alpha_x \int_V w_x \frac{d(m - m_{\text{ref}})^2}{dx} dV}_{\text{smoothness}}$$

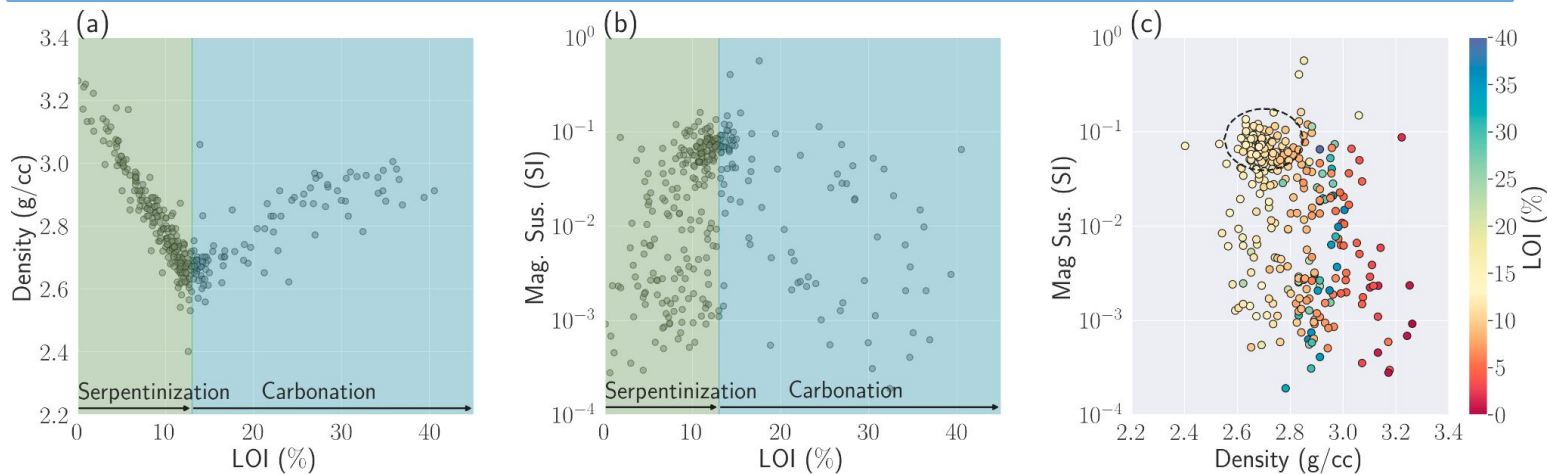
discretize

$$\phi_m = \alpha_s \|\mathbf{W}_s(\mathbf{m} - \mathbf{m}_{\text{ref}})\|^2 + \alpha_x \|\mathbf{W}_x(\mathbf{m} - \mathbf{m}_{\text{ref}})\|^2$$

an example: carbon mineralization

- ultramafic rocks rich in Ca, Mg can react with CO_2 to form carbonated minerals

R1: olivine \pm orthopyroxene + H_2O \rightarrow serpentine \pm brucite \pm magnetite	serpentinization
R2: olivine + brucite + CO_2 + H_2O \rightarrow serpentine + magnesite + H_2O R3: serpentine + CO_2 \rightarrow magnesite + talc + H_2O R4: talc + CO_2 \rightarrow magnesite + quartz + H_2O	carbonation

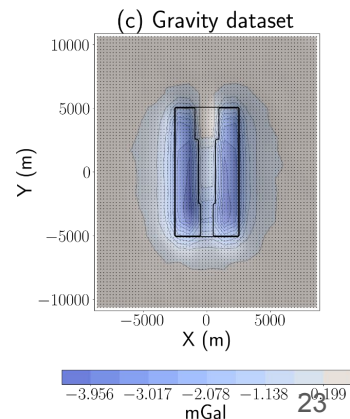
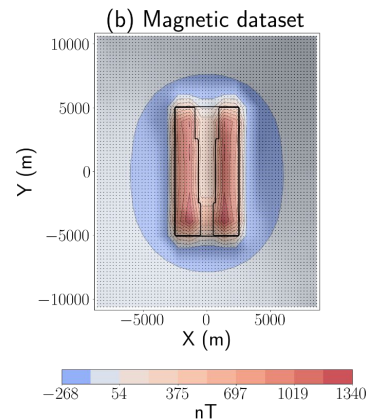
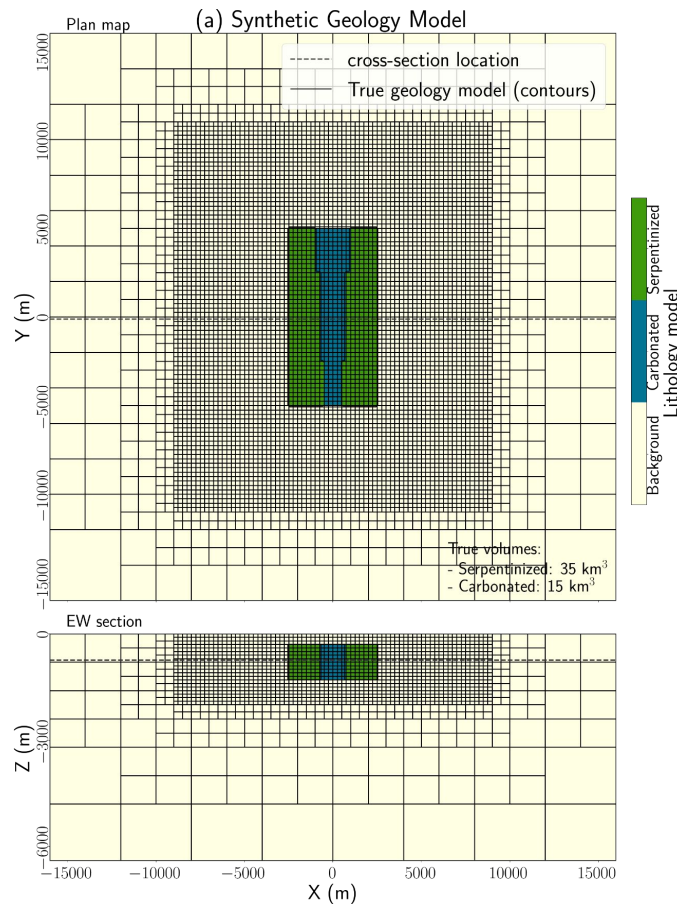


an example: carbon mineralization

- motivated by Decar in BC
- serpentinized region with central carbonated region
- physical properties

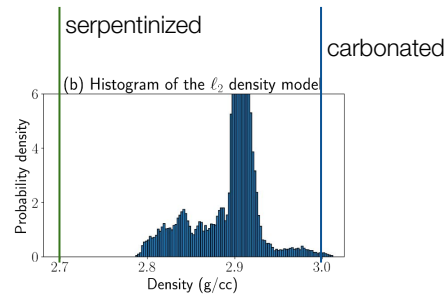
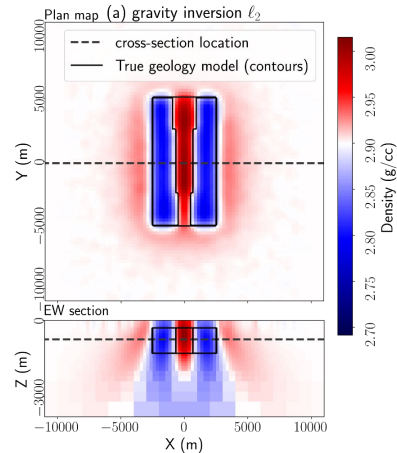
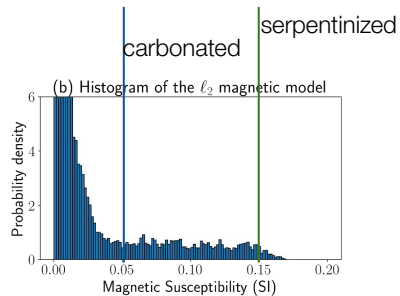
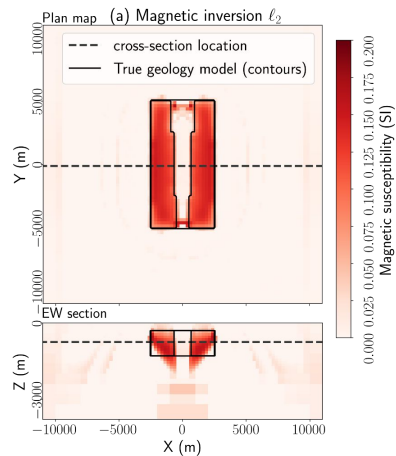
	mag susc (SI)	density (g/cc)	dens. contrast (g/cc)
background	0	2.9	0.0
serpentinized	0.15	2.7	-0.2
carbonated	0.05	3.0	0.1

- goals: delineate, estimate volumes

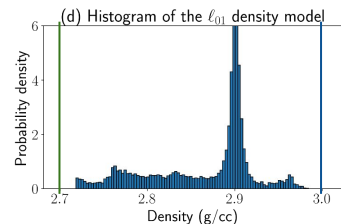
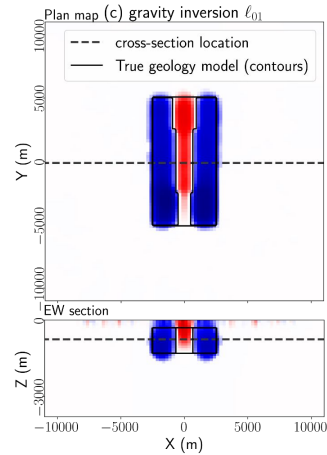
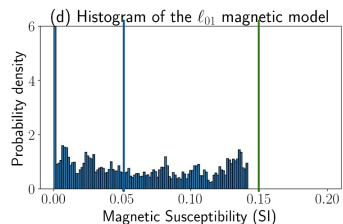
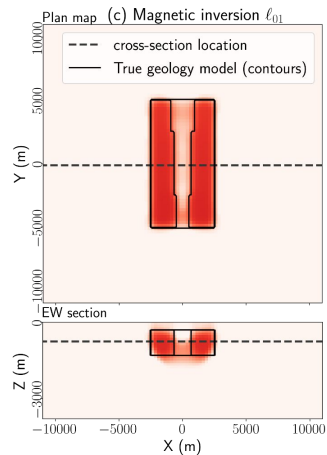


an example: carbon mineralization

ℓ_2



ℓ_{01}



inverse problem

Given data, estimate a physical property model

Pose as an optimization

$$\underset{m}{\text{minimize}} \phi(m) = \phi_d(m) + \beta \phi_m(m)$$

Model norm captures assumptions

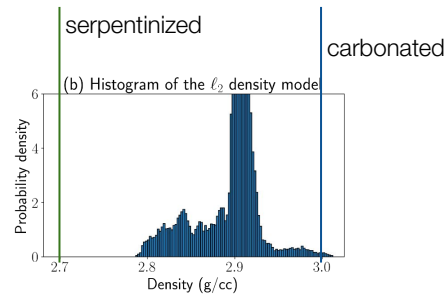
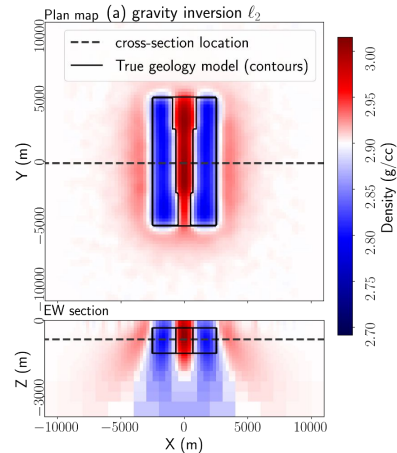
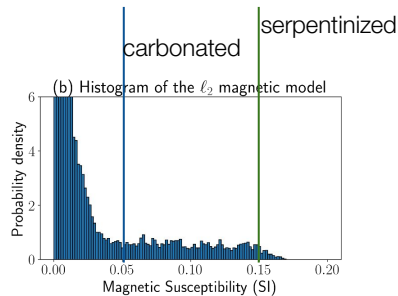
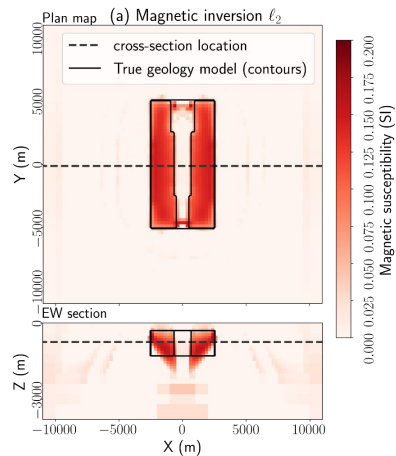
$$\phi_m(m) = \alpha_s \int |m - m_{\text{ref}}|^p dV + \alpha_x \int \left| \frac{dm}{dx} \right|^q dV + \alpha_y \int \left| \frac{dm}{dy} \right|^q dV + \alpha_z \int \left| \frac{dm}{dz} \right|^q dV$$

- ℓ_2 : $p, q = 2$: promotes smooth structures
- ℓ_{01} : $p, q < 2$: promotes sparse, compact structures

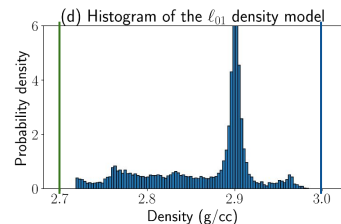
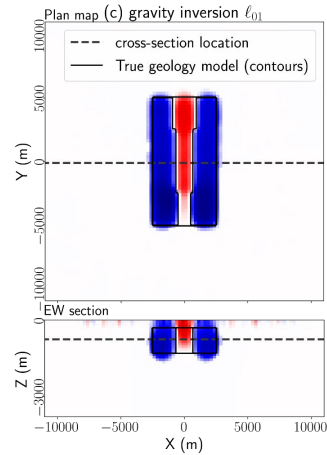
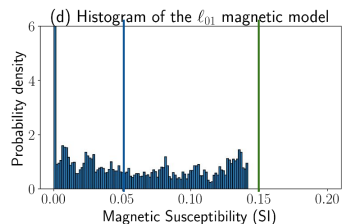
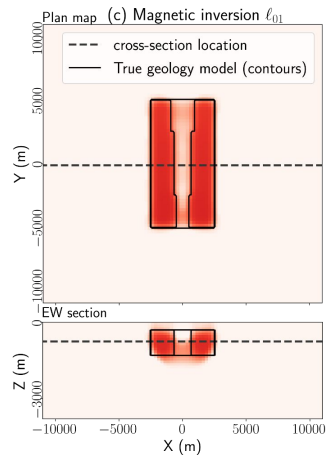


an example: carbon mineralization

ℓ_2

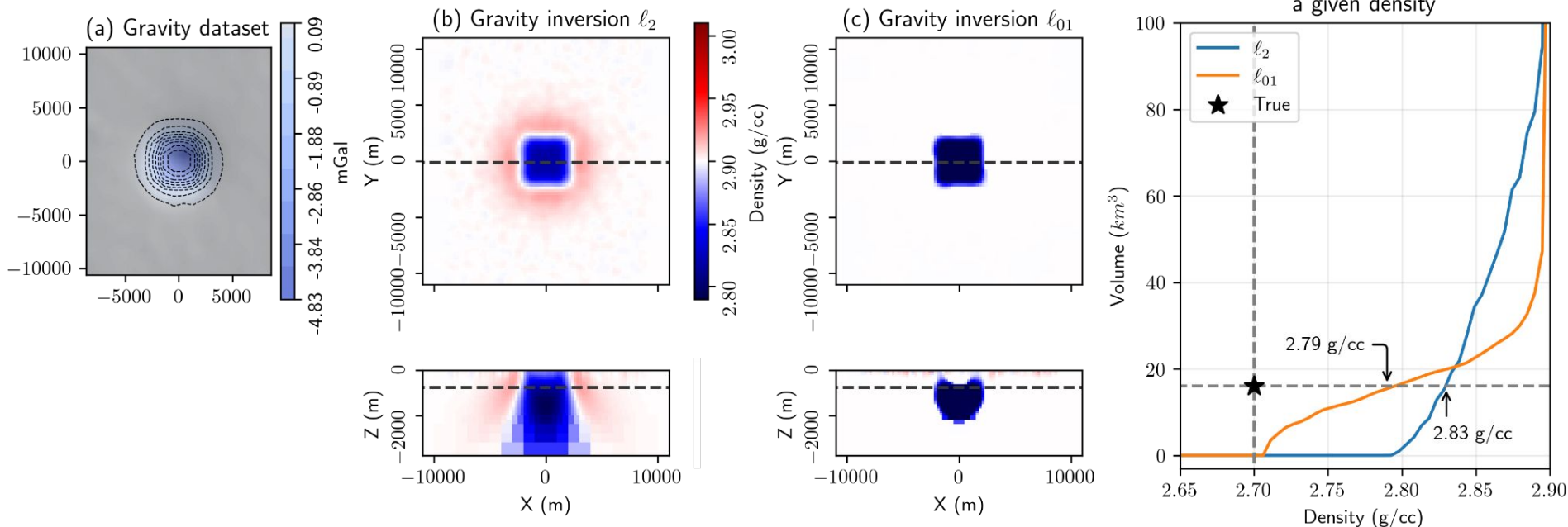


ℓ_{01}



how do we choose a threshold?

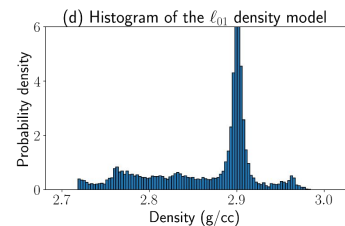
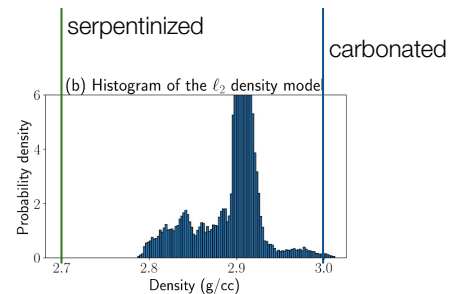
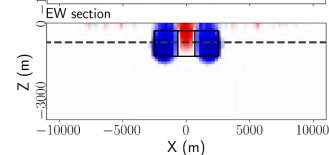
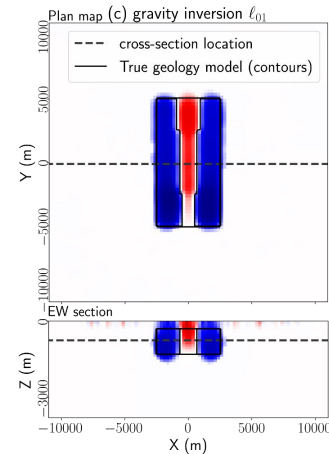
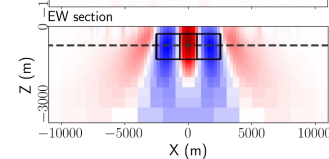
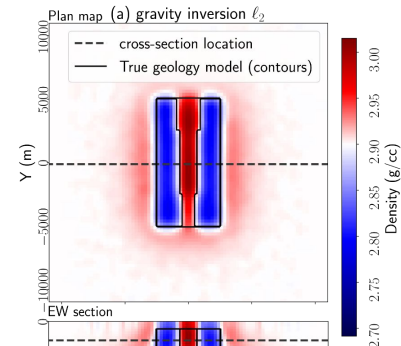
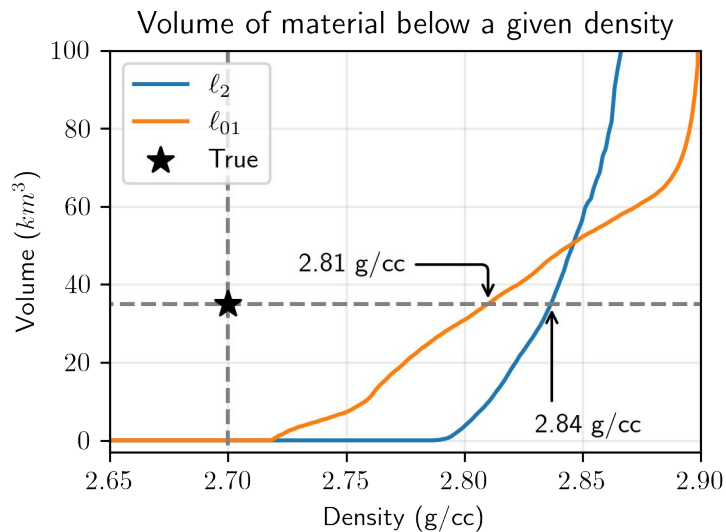
using: identical mesh, survey, inversion parameters, perform simulations and inversions with a representative block.



how do we choose a threshold?

Threshold from proxy: 2.83, 2.79 g/cc

- ℓ_2 : 27 km³
- ℓ_{01} : 27 km³

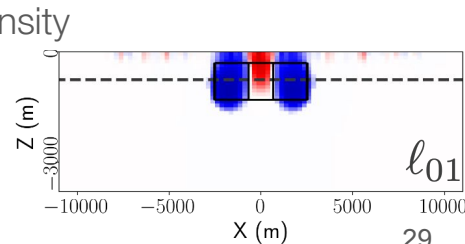
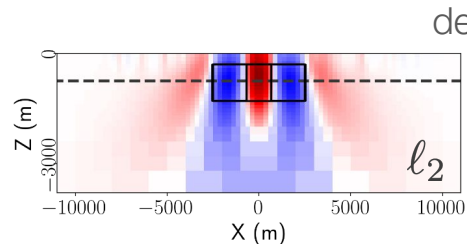
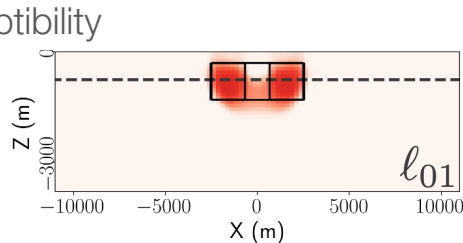
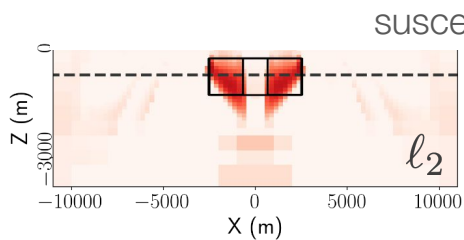


how do we choose a threshold?

- proxy model → tool for estimating an appropriate physical property threshold

Inversion	Threshold for correct volume	Threshold from proxy	Volume estimate with proxy threshold
ℓ_2 magnetics	0.08 SI	0.07 SI	40 km ³
ℓ_{01} magnetics	0.08 SI	0.07 SI	43 km ³
ℓ_2 gravity	2.84 g/cc	2.83 g/cc	27 km ³
ℓ_{01} gravity	2.81 g/cc	2.79 g/cc	27 km ³

- Also of interest:
 - delineating the top → ex-situ vs. in-situ
 - joint inversion → consistent model?

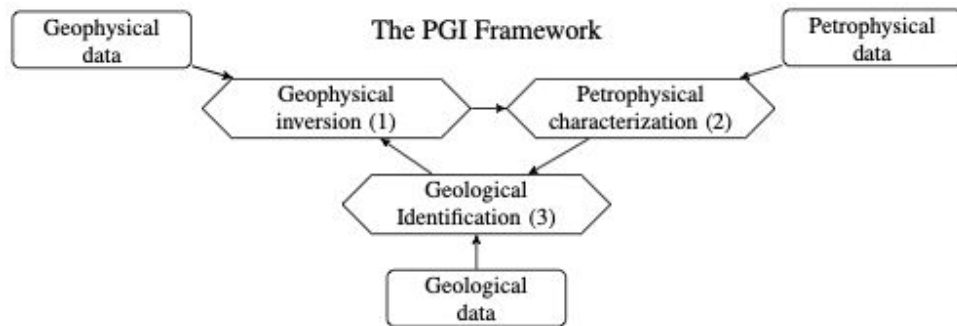


Petrophysically and Geologically Guided Inversion

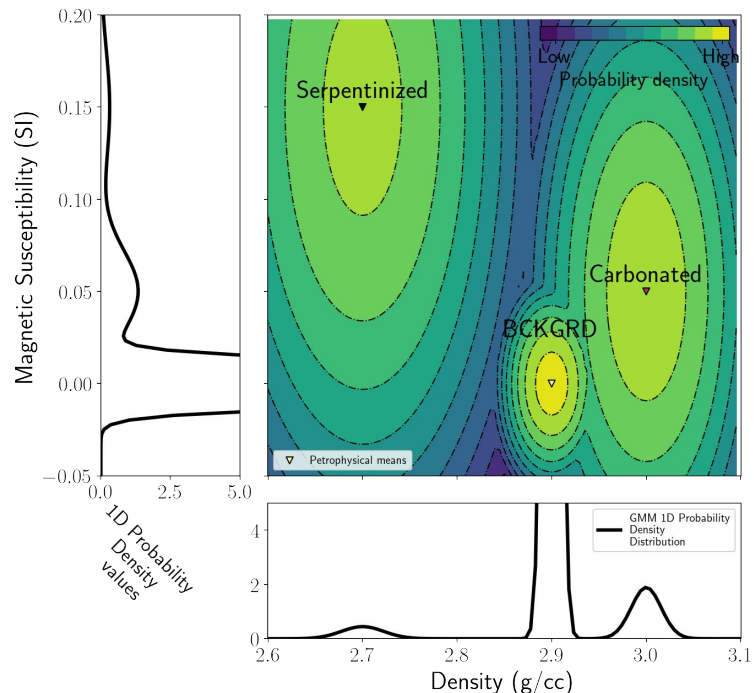
Gaussian mixture model (GMM)

Alternative approach to the inverse problem

- brings in petrophysical information (GMM)
- builds a quasi-geology model



- important components in the inversion
 - multiple data misfits
 - including petrophysical information



T. Astic

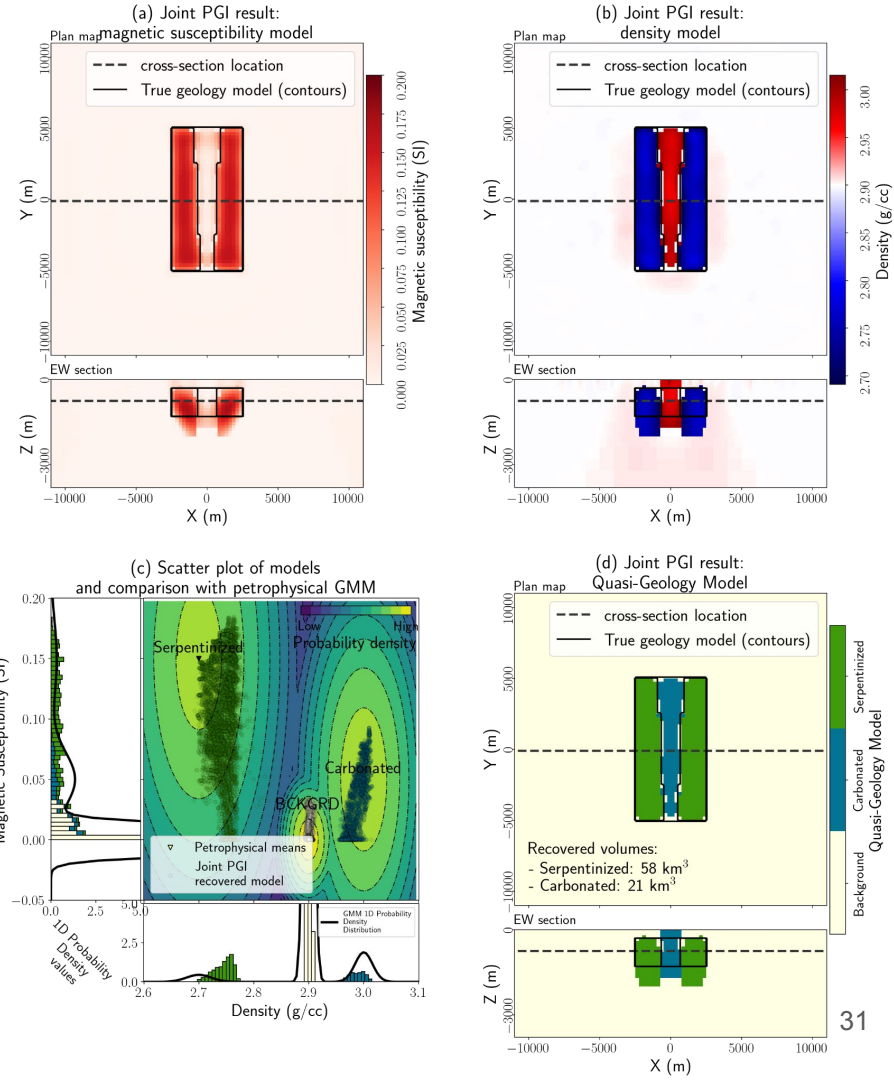


Joint PGI

- Inversion fits both geophysical data sets and petrophysical data

$$\phi_{\text{data}} = \phi_{\text{grav}} + \phi_{\text{mag}} \quad \# \text{ one earth?}$$

- Weighting strategies to balance contributions (Astic et al, 2021)
- One quasi geology model consistent with both data sets
- Good estimate to top of serpentized rock volume



geophysics and multidisciplinary problems



critical minerals



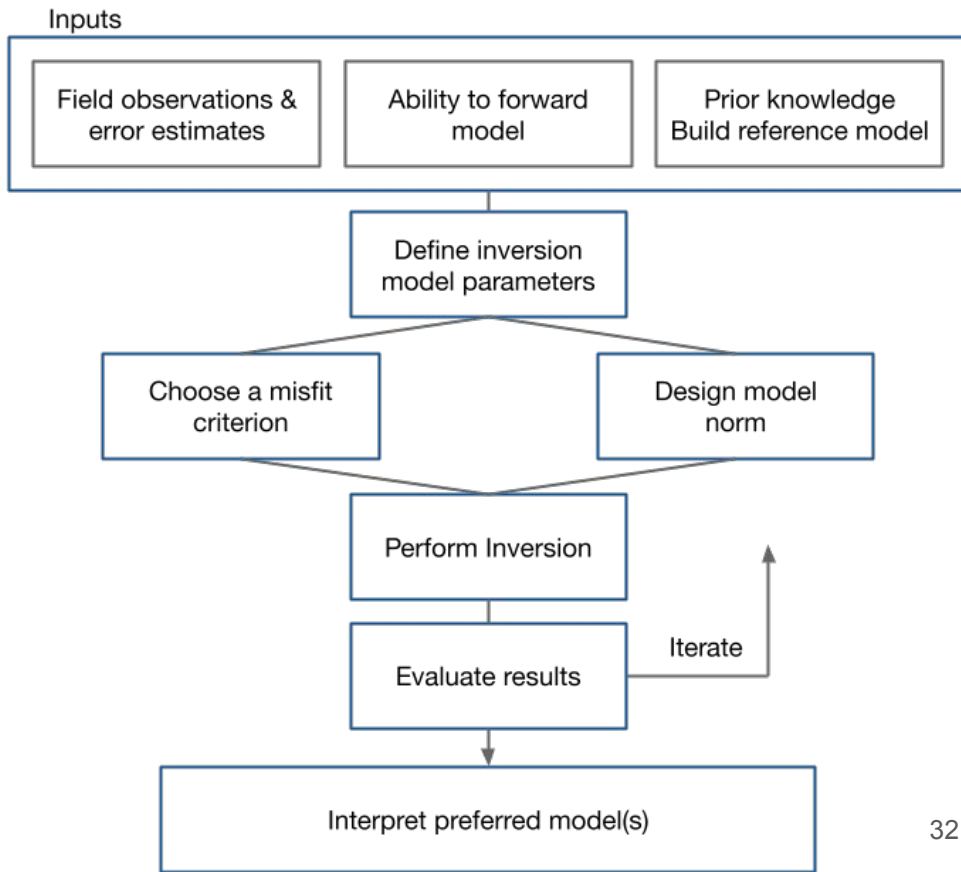
geologic storage of
 CO_2



geotechnical
(e.g. permafrost)

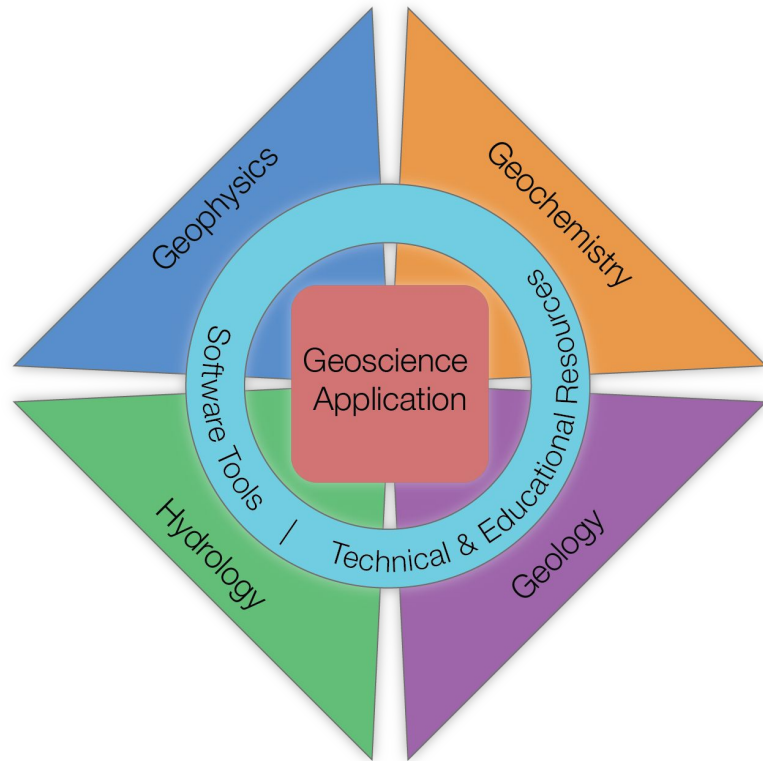


groundwater



geophysics and multidisciplinary problems

- geophysics one piece
- need for
 - Technical advances: machine learning + inversion for combining data
 - Collaboration: between disciplines
- role of open science, educational resources

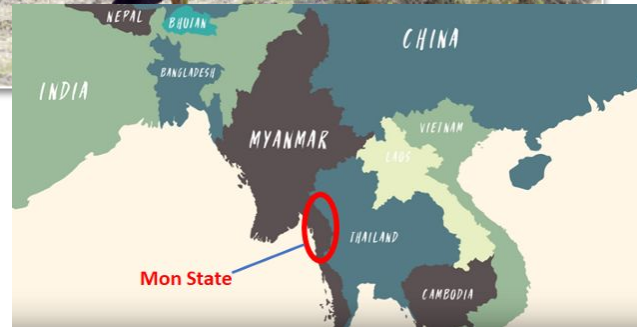


research + education: an example in humanitarian geophysics

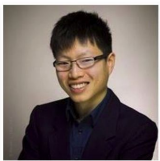


Improving Water Security in Mon state, Myanmar via Geophysical Capacity Building

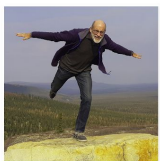
- Bring geophysical equipment to Mon state Myanmar
- Train local stakeholders
- Provide open-source software & educational resources



Doug
Oldenburg



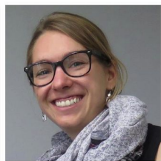
Kevin
Fan



Michael
Maxwell



Devin
Cowan



Lindsey
Heagy



Seogi
Kang



Joe
Capriotti

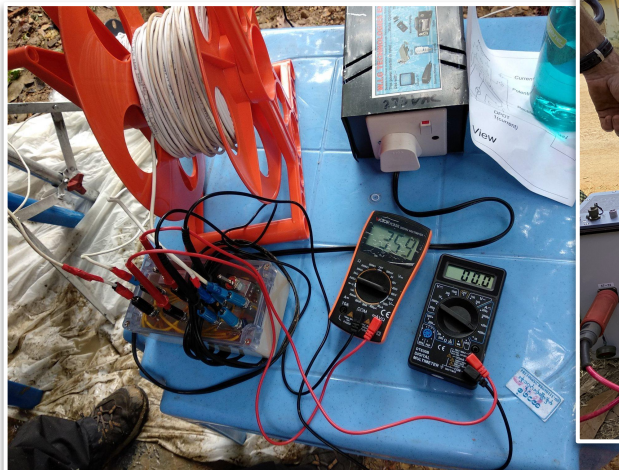
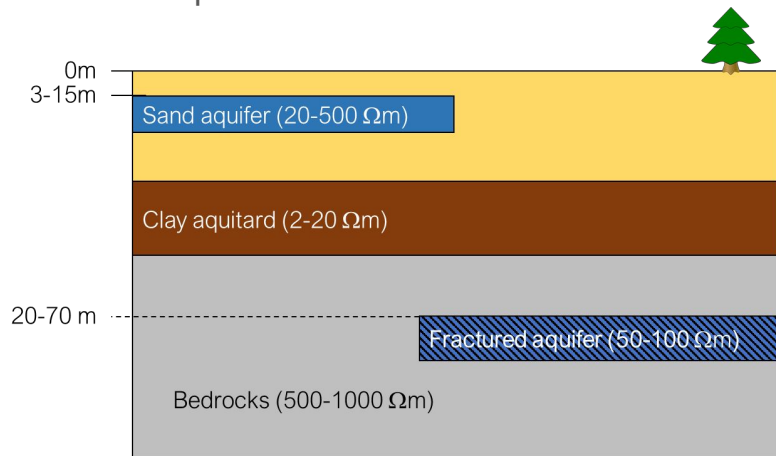


research + education: an example in humanitarian geophysics



Capabilities needed by local stakeholders:

- Understand the hydrogeologic problem and relationship to electrical resistivity
- Design field surveys
- Collect and process data
- Interpret those data



research + education: an example in humanitarian geophysics



Project stages

- Course instruction: fundamentals of DC resistivity & inversion
- Field surveying and processing
- Post-project sustainability

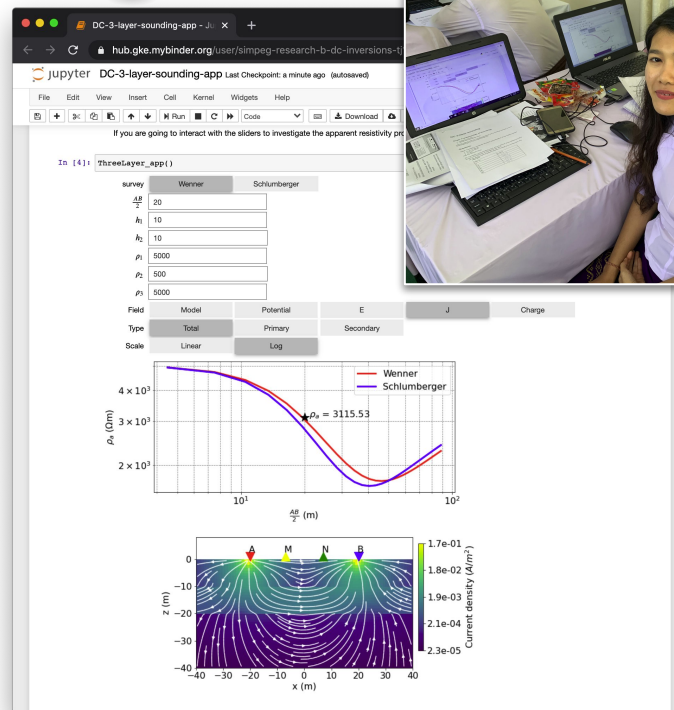


research + education: an example in humanitarian geophysics



Project resources

- Website for slides, videos and data
- Jupyter notebooks for teaching, working with data
- SimPEG software for processing
- Case History documents for collaboration and reproducibility
- Social media for collaboration



research + education: an example in humanitarian geophysics



5 wells (>1000 gph)

Benefits of using & developing open source resources

- No licensing or time-out concerns on software
- Easily design fit-for-purpose interactive tools for learning
- Readily update software, documentation based on user needs
- Encourage collaborative, reproducible practices



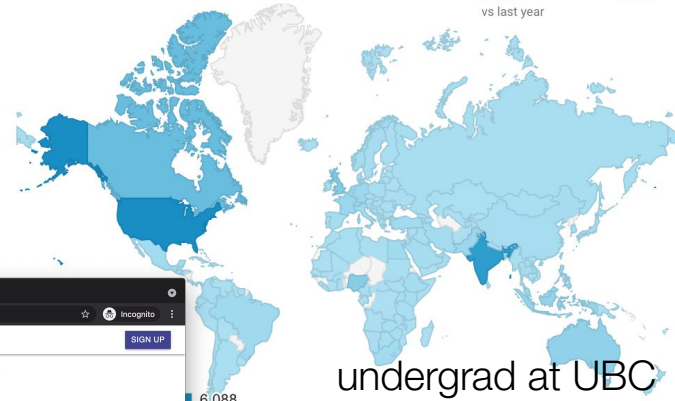


open educational resources

<https://geosci.xyz>

Users
30K
↑ 28%
vs last year

Sessions
48K
↑ 30%



undergrad at UBC



electromagnetics course:
26 locations worldwide

GeoSci

why who presentations contact

GPG
Geophysics for Practising Geoscientists

DISC 2017
Geophysical Electromagnetics: Fundamentals & Applications

Linear Tikhonov Inversion | Curvenote

curvenote

geosci / inversion-module / linear-tikhonov-inversion - v21

Linear Tikhonov Inversion

AUTHOR: Douglas Oldenburg
DATE: Jan 18, 2021

In this chapter we present the basic elements for how an inverse problem can be formulated and solved using optimization theory. The quantity to be minimized is a weighted sum of misfit and regularization terms with their relative importance controlled by an adjustable Tikhonov parameter.

The inverse problem has many elements and a solution is best achieved by adhering to the workflow shown below. Throughout this chapter we investigate each of these steps and illustrate the concepts with a simple linear problem. Jupyter notebooks are provided so that the concepts can be explored and all figures can be reproduced. The formative material for this chapter is extracted from the tutorial paper by Oldenburg and Li (Oldenburg & Li, 2005).

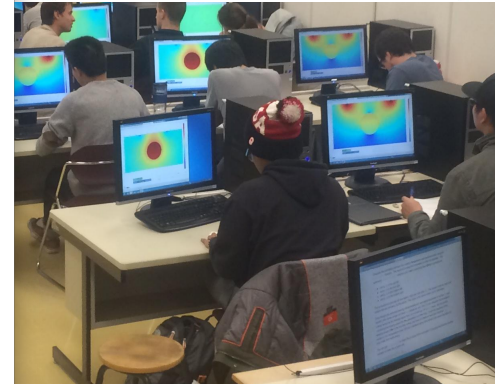
Inputs

- Field observations & error estimates
- Ability to forward model
- Prior knowledge (Build reference model)

Define inversion model parameters

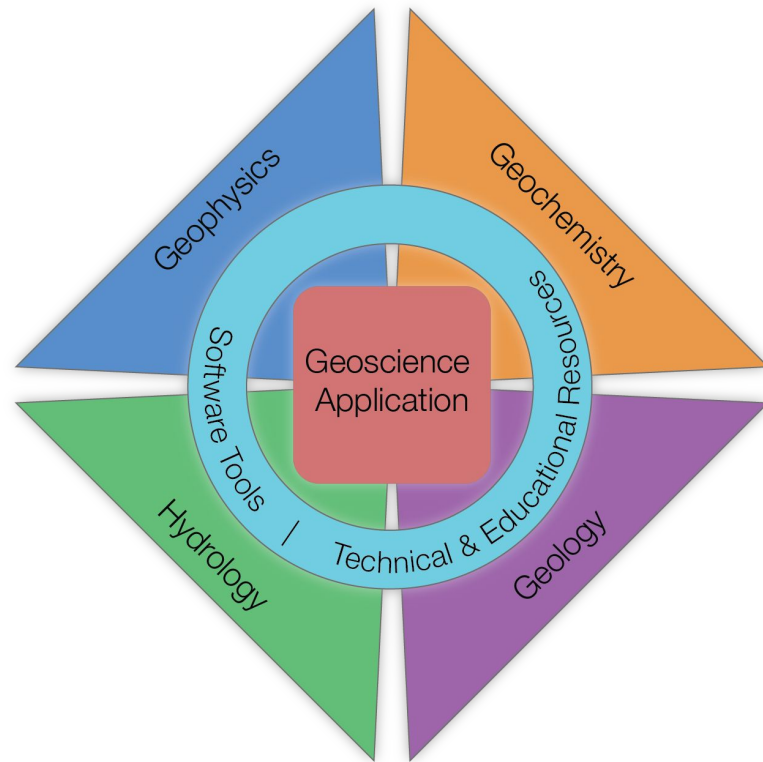
Choose a priori model

Form model



opportunities for open science

- **accelerate science:** collaboration & leveraging expertise, experience of others
- **broader impact:** enable others to build upon your work



thank you!



Tobias Stål



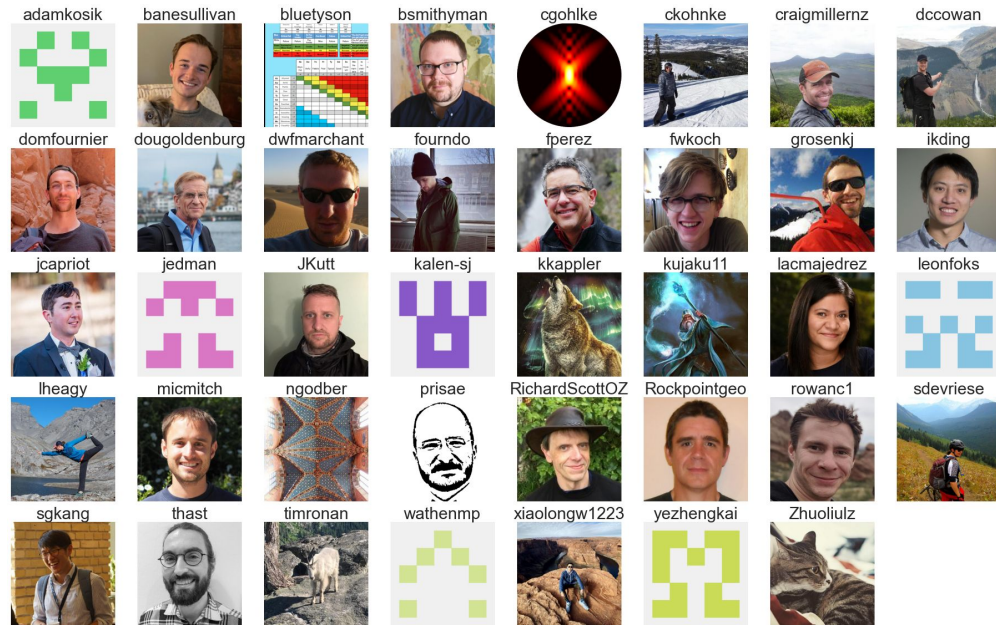
Contact



lheagy@eoas.ubc.ca



@lindsey_jh



<https://simpeg.xyz>