geophysical electromagnetics imaging the subsurface from shallow to deep

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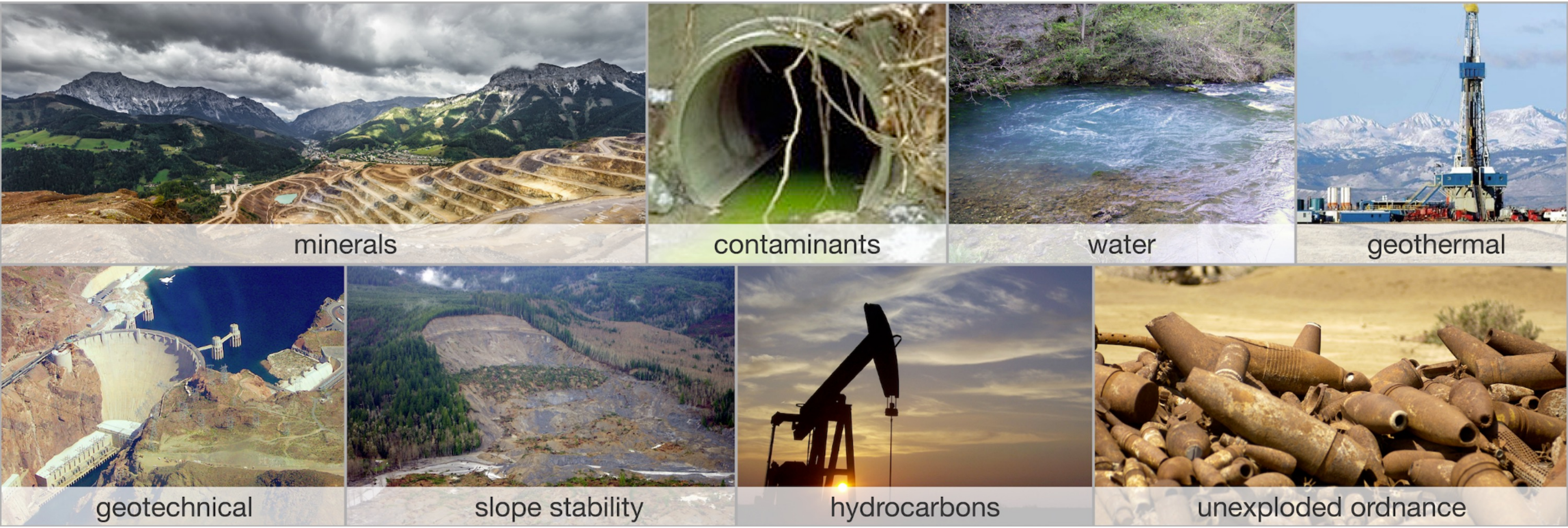
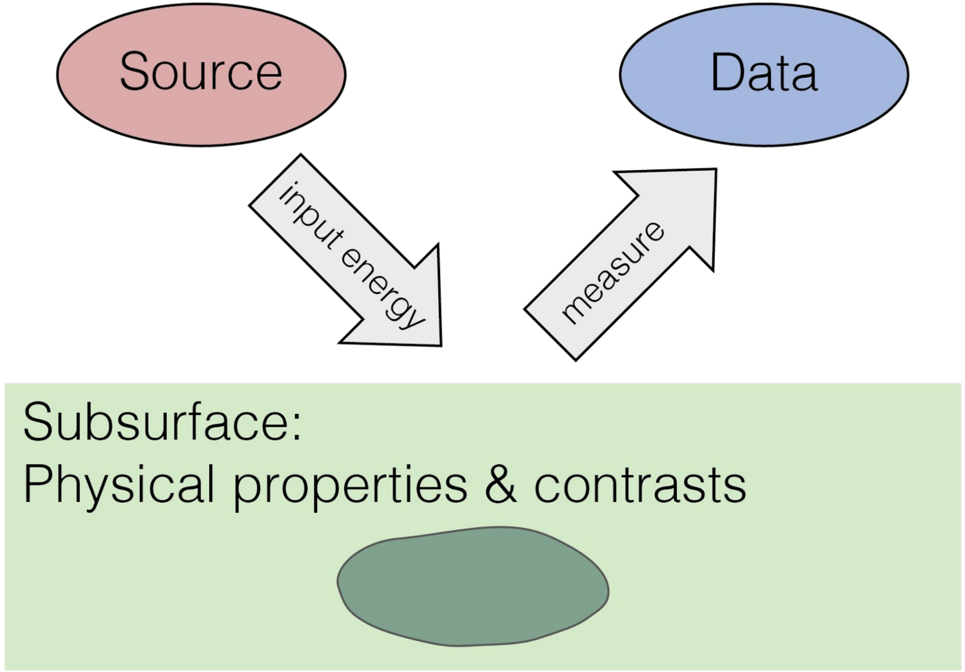
some important problems



have in common: need to (non-invasively) image the subsurface

geophysical experiments & physical properties



physical properties are intrinsic to a material (density, susceptibility, conductivity…)

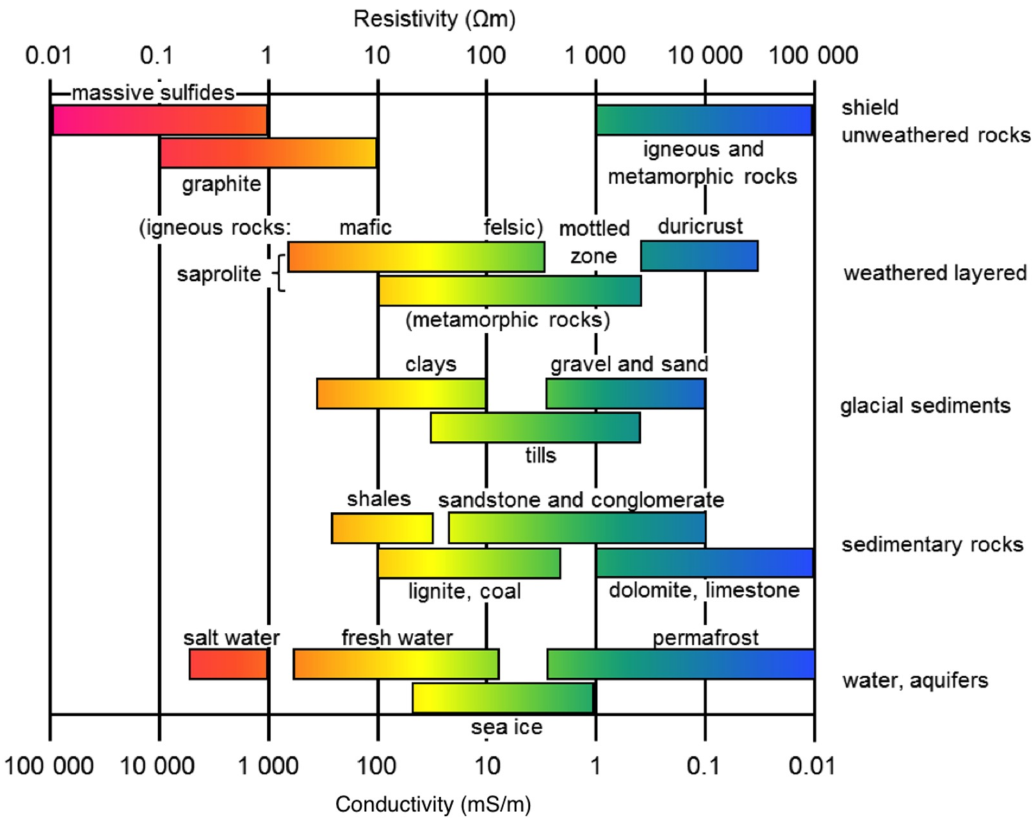
electrical conductivity / resistivity

A measure of how easily current passes through a material

- σ: conductivity [S/m]
- ρ: resistivity [Ωm]
- $\rho = 1/\sigma$

Depends on many factors

- Mineralogy
- Porosity
- Permeability
- Nature of pore fluid



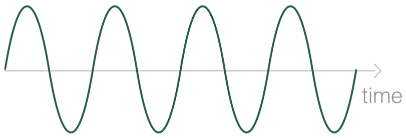
electromagnetic experiments

Sources:

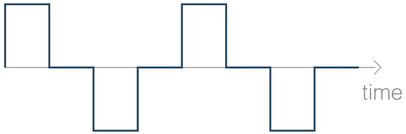
- grounded or inductive
- controlled or natural

Waveform

- harmonic (FDEM)



- transient (TDEM)

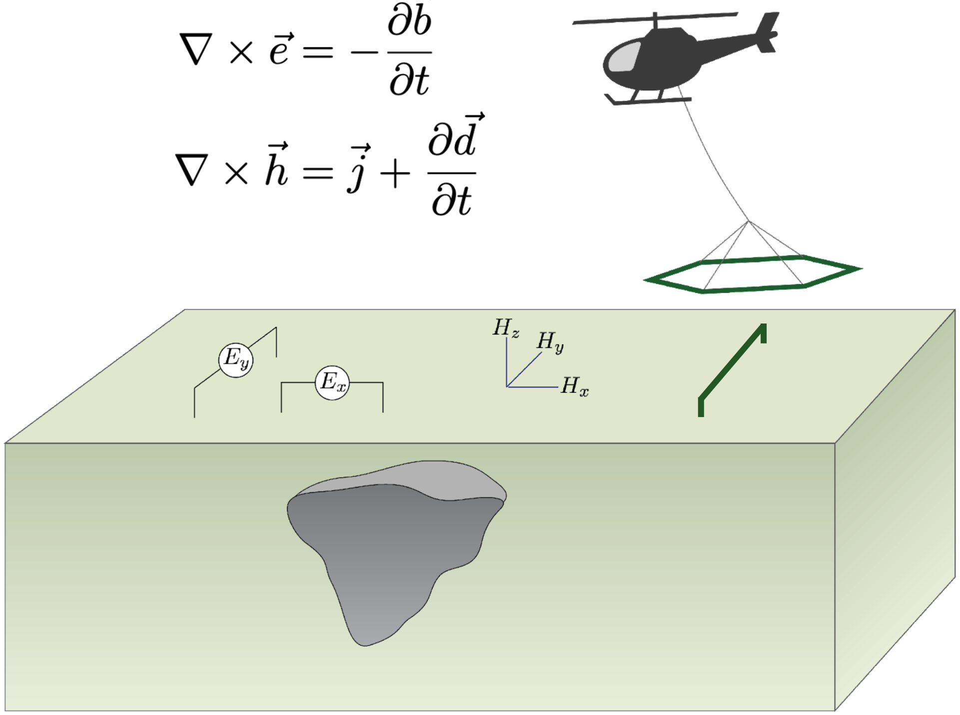


Survey location

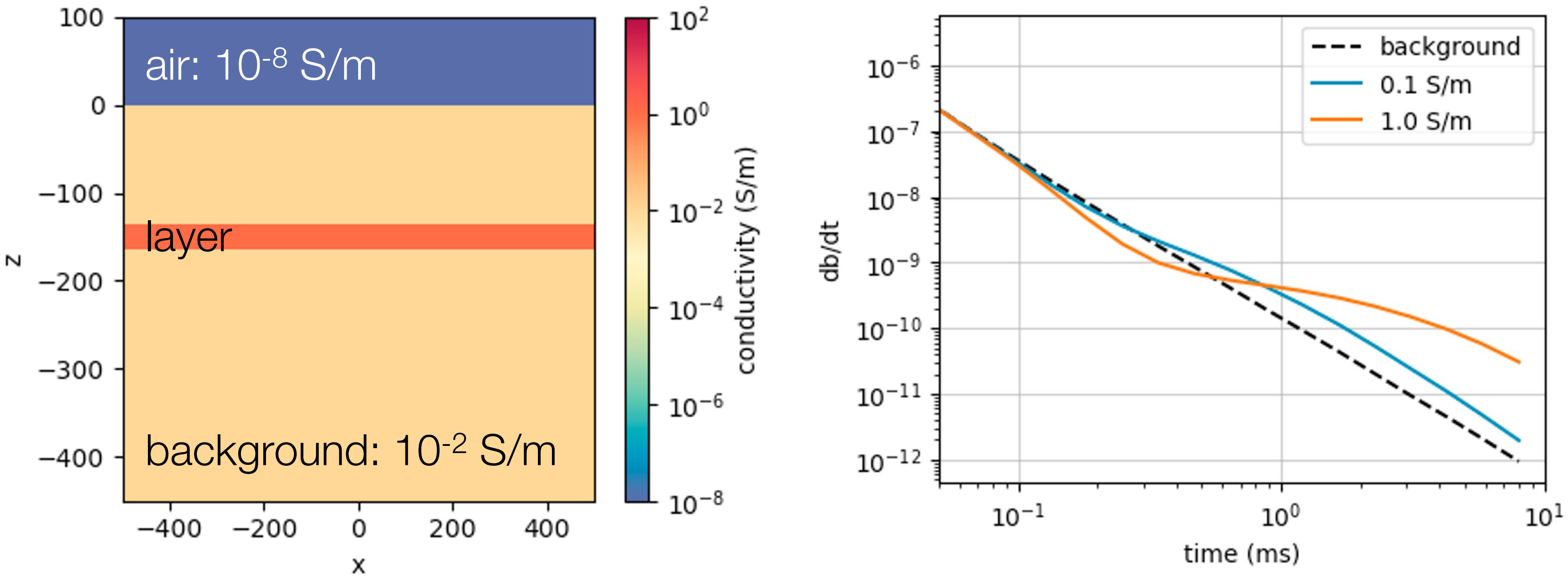
- airborne
- ground
- boreholes

$$\nabla \times \vec{e} = -\frac{\partial \vec{b}}{\partial t}$$

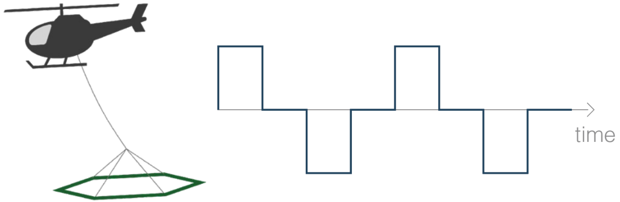
$$\nabla \times \vec{h} = \vec{j} + \frac{\partial \vec{d}}{\partial t}$$

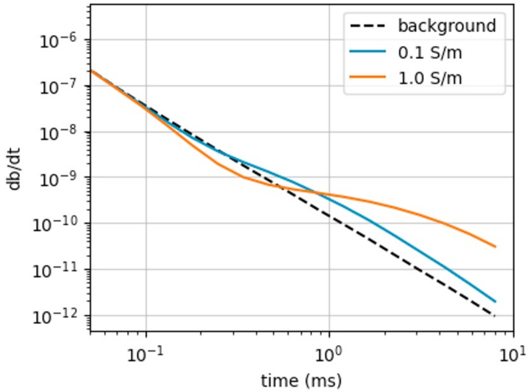


inductive sources: time-domain



inductive sources: time-domain

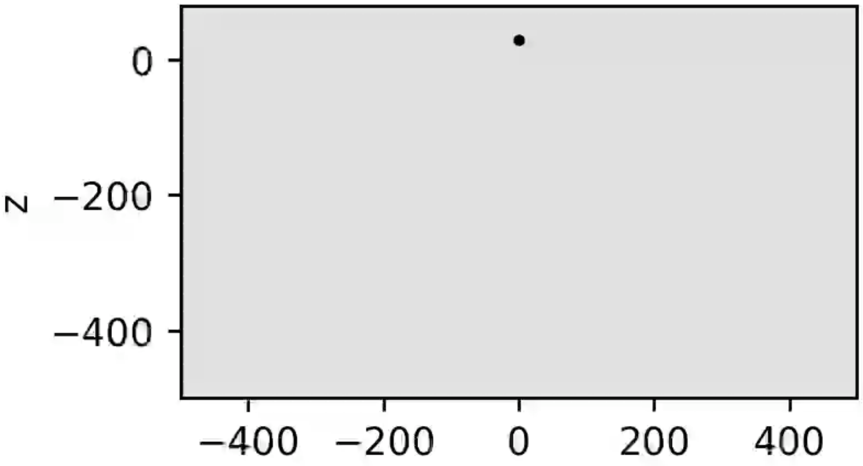


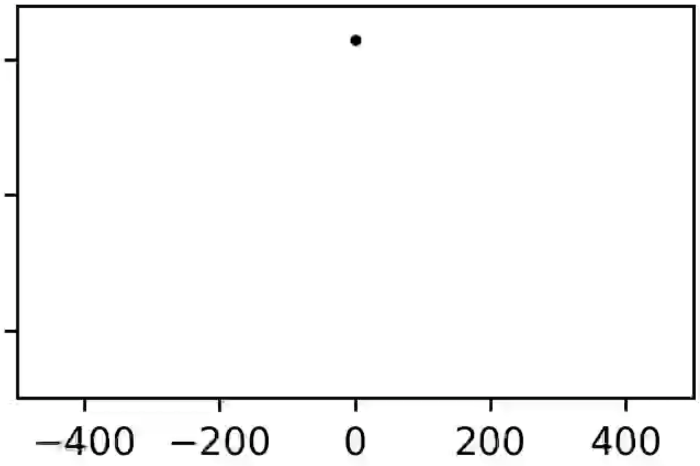


current density

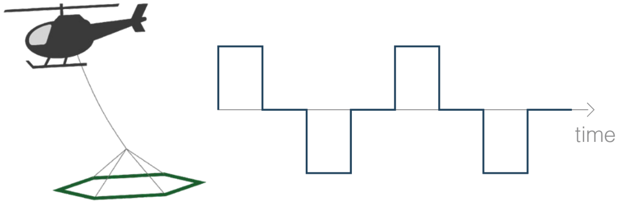
t=0.00 ms

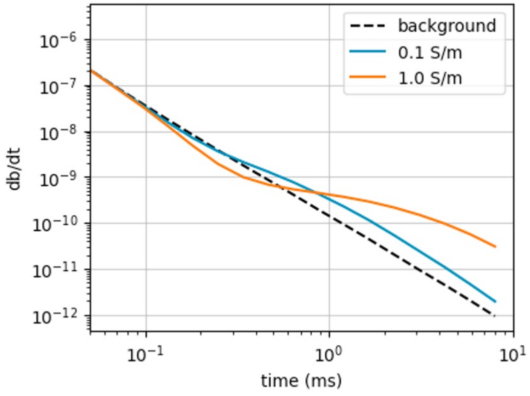
db/dt



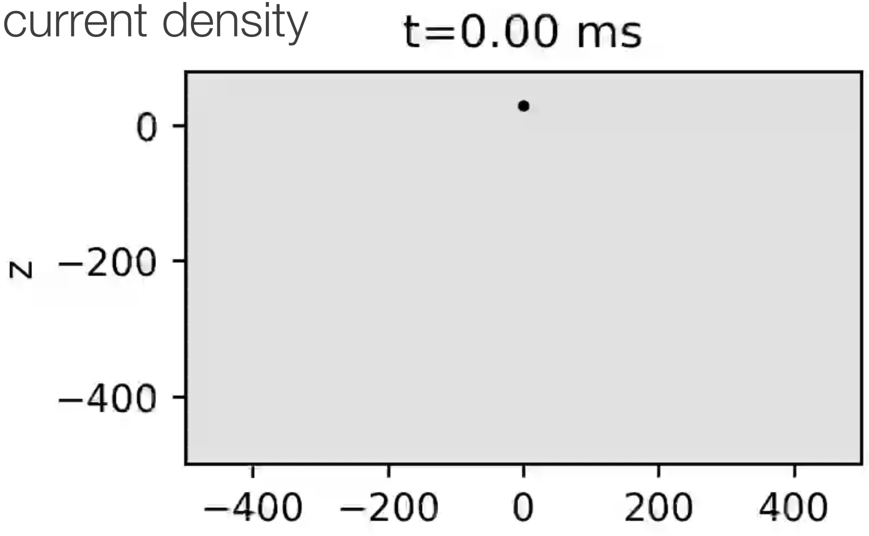


inductive sources: time-domain

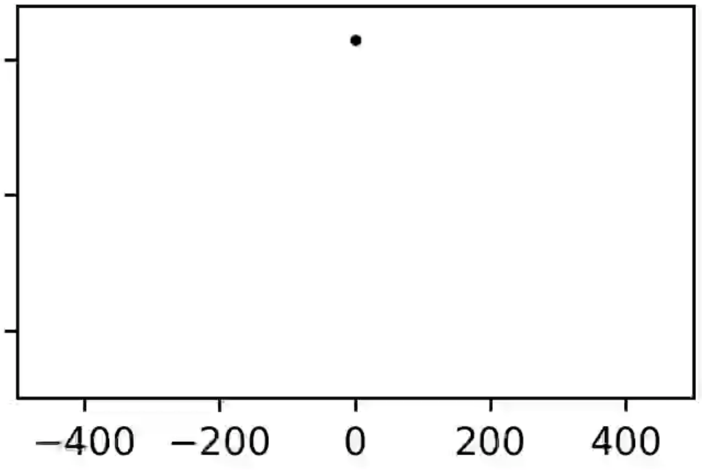




current density



db/dt



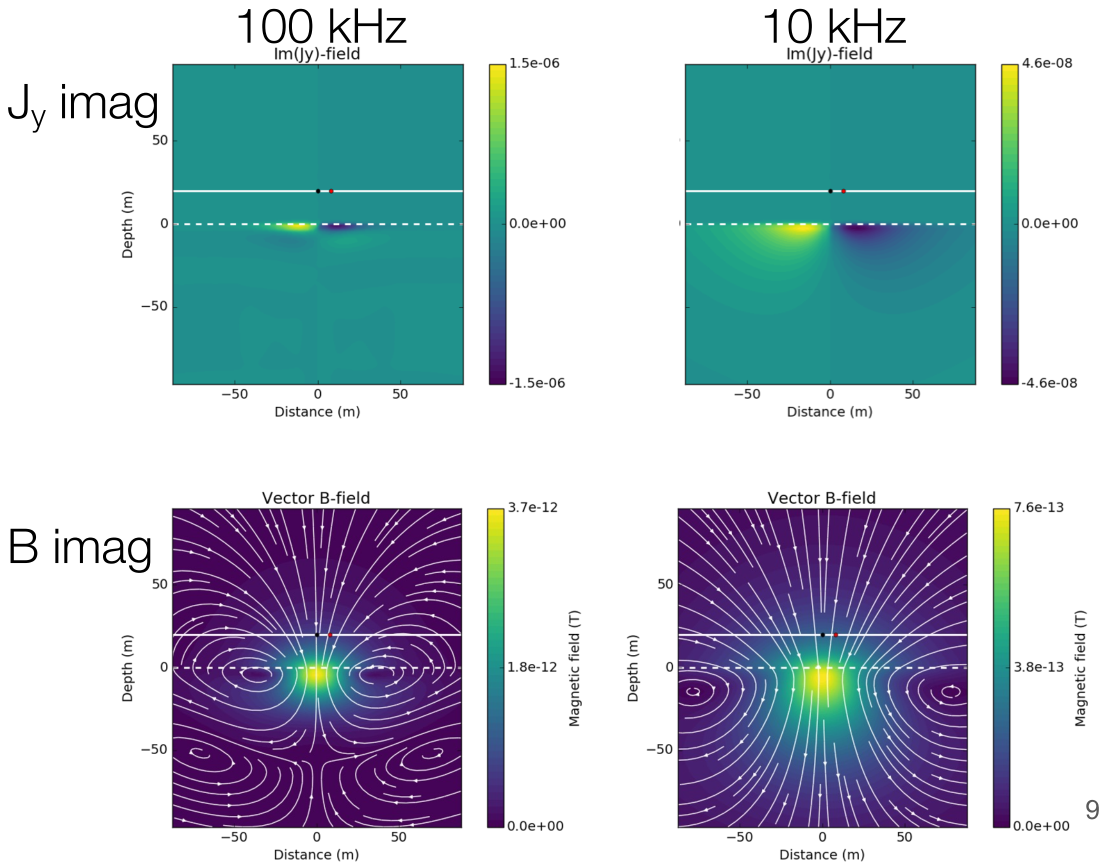
physics: frequency domain

high frequency ~ early times,
low frequency ~ later times

skin depth

$$\delta = 503\sqrt{\frac{\rho}{f}}$$

ρ : resistivity $[\Omega \mathrm{m}]$
f : frequency [Hz]

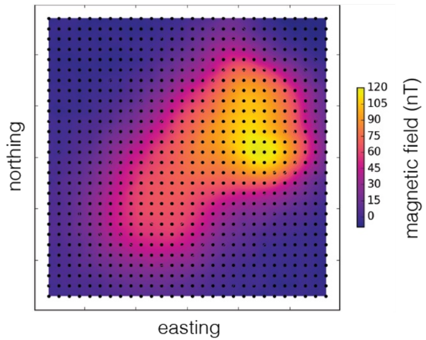


forward and inverse problems

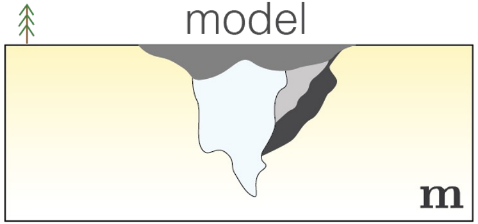
forward problem

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

data



physical property model



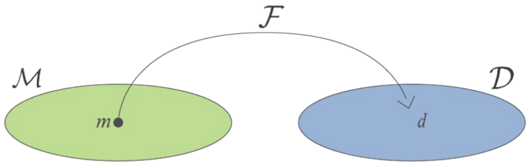
$$\tilde{\mathbf{m}} = \mathcal{F}^{-1}[\mathbf{d}]$$

inverse problem

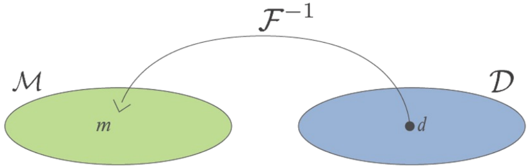
statement of the inverse problem

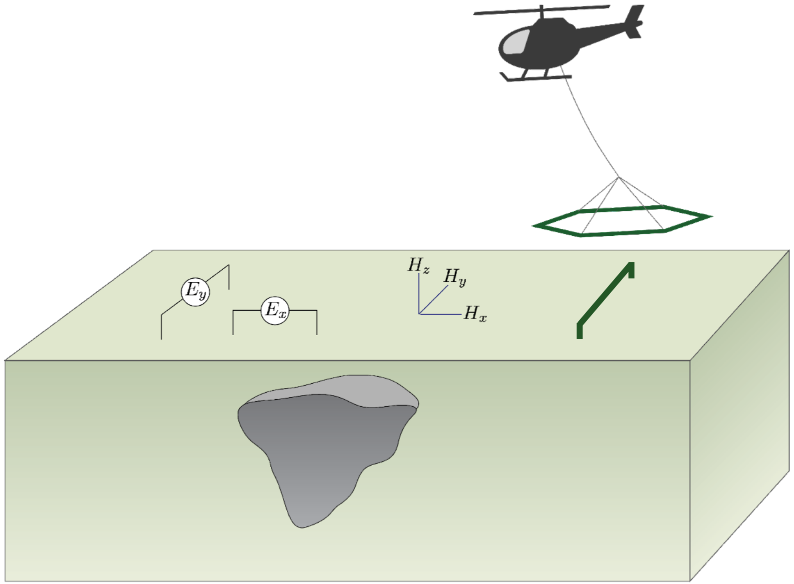
Given

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



Find the Earth model that gave rise to the data





statement of the inverse problem

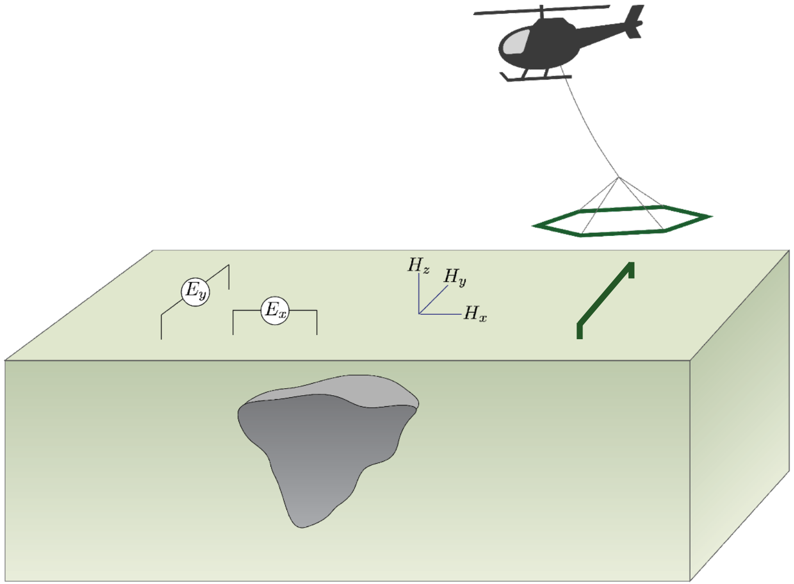
Given

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

Inverse problem: Find an Earth model that fits those data and a-priori information

$$\min_{\mathbf{m}} \phi(\mathbf{m}) = \phi_d(\mathbf{m}) + \beta\phi_m(\mathbf{m})$$

$$\text{s.t. } \phi_d \leq \phi_d^* \quad \mathbf{m}_L \leq \mathbf{m} \leq \mathbf{m}_U$$



simpeg

Simulation and parameter estimation in geophysics

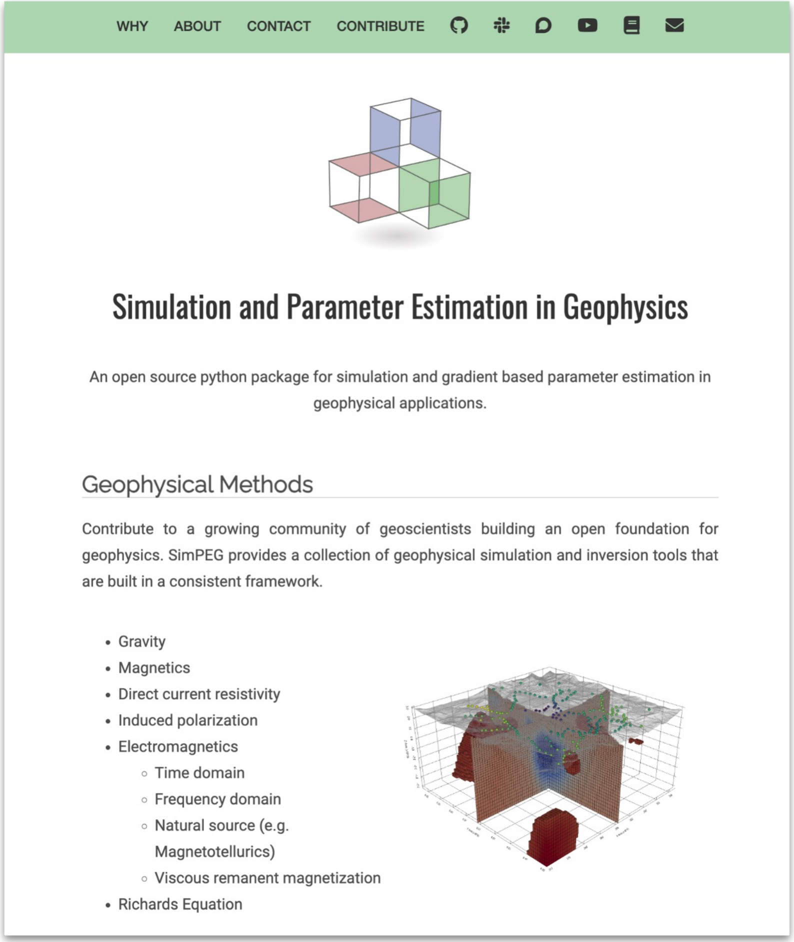
common framework for simulations & inversions

accelerate research: build upon others work

facilitate reproducibility of results

build & deploy in python

open-source



WHY ABOUT CONTACT CONTRIBUTE

Simulation and Parameter Estimation in Geophysics

An open source python package for simulation and gradient based parameter estimation in geophysical applications.

Geophysical Methods

Contribute to a growing community of geoscientists building an open foundation for geophysics. SimPEG provides a collection of geophysical simulation and inversion tools that are built in a consistent framework.

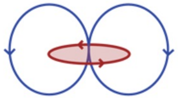
- Gravity
- Magnetics
- Direct current resistivity
- Induced polarization
- Electromagnetics
  - Time domain
  - Frequency domain
  - Natural source (e.g. Magnetotellurics)
  - Viscous remanent magnetization
- Richards Equation

https://simpeg.xyz

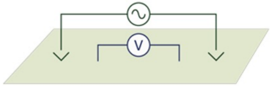
Multi-scale EM geophysical methods

Controlled-source EM

Inductive



Grounded



Natural source EM

Depth from the surface

meters

Tens of meters

Hundreds of meters

Kilometers

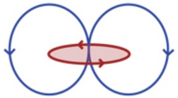
Tens of kilometers

Hundreds of kilometers

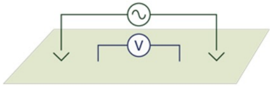
Multi-scale EM geophysical methods

Controlled-source EM

Inductive



Grounded



Natural source EM

Depth from the surface

meters

Tens of meters

Hundreds of meters

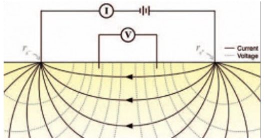
Kilometers

Tens of kilometers

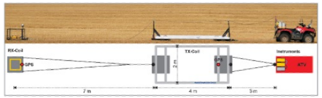
Hundreds of kilometers

Ground-based EM

ERT

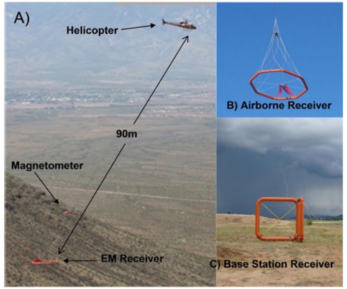


Towed-TEM

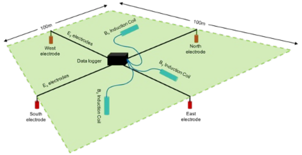


Airborne EM (AEM)

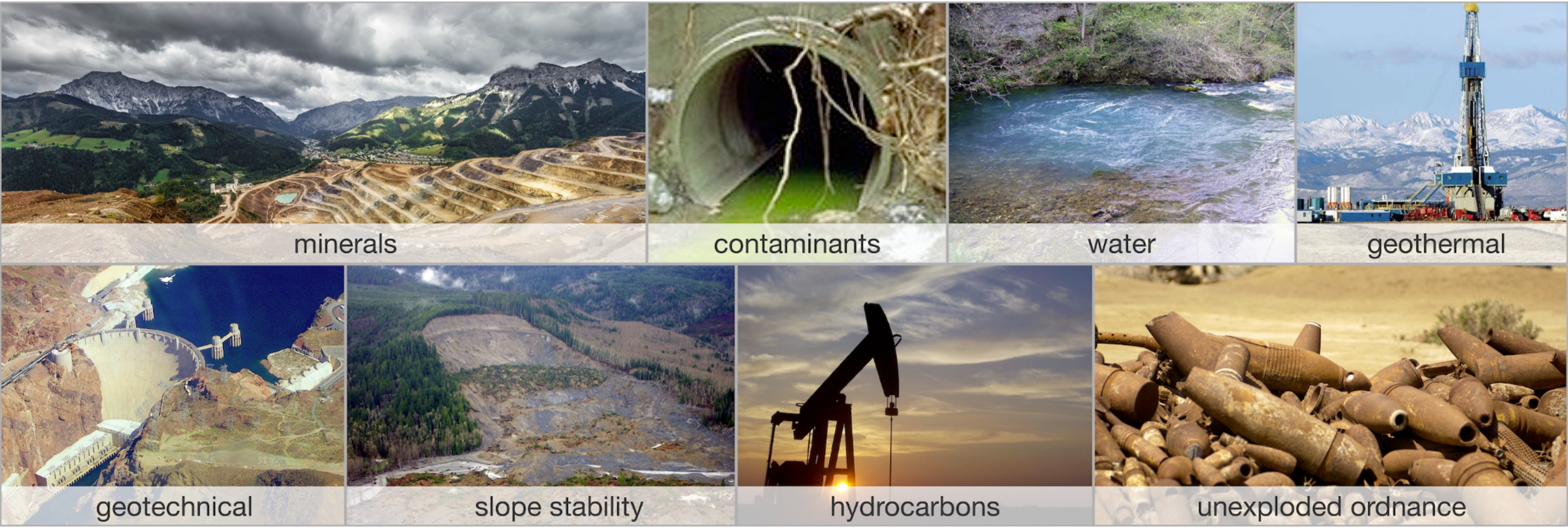
Z-axis Tipper EM (ZTEM)



Magnetotellurics (MT)

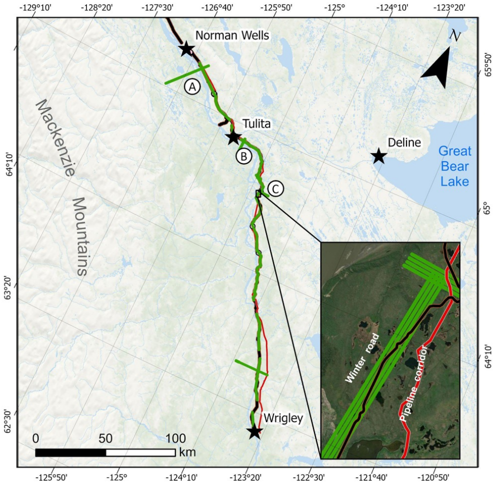


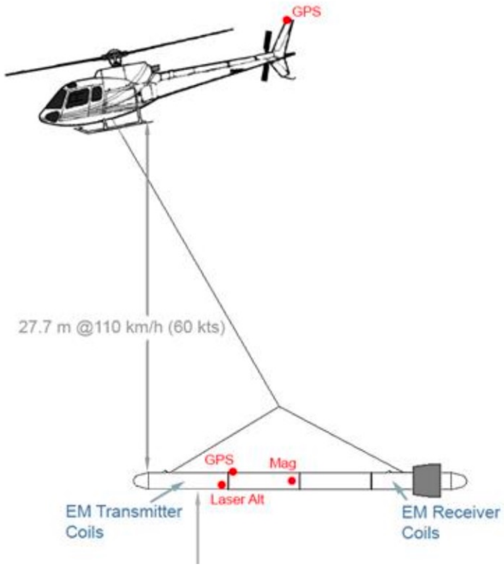
important problems: scales and surveys

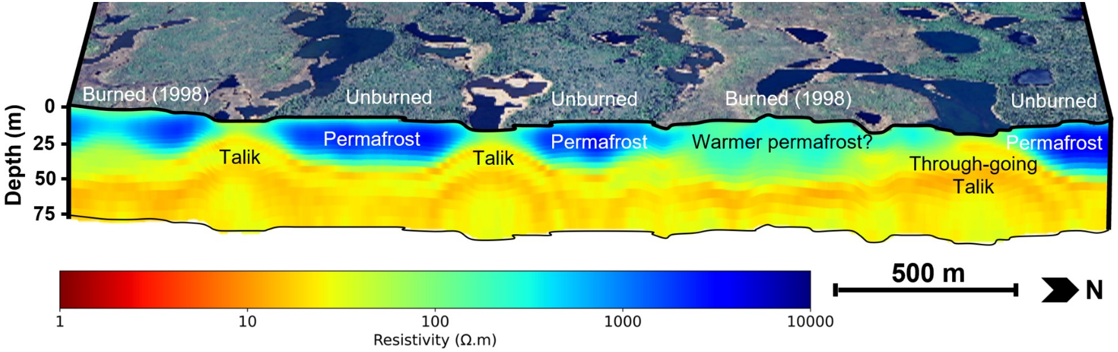


permafrost: near surface, large areas

Airborne : cover large areas
Frequency-domain EM system
(400Hz – 135k Hz)



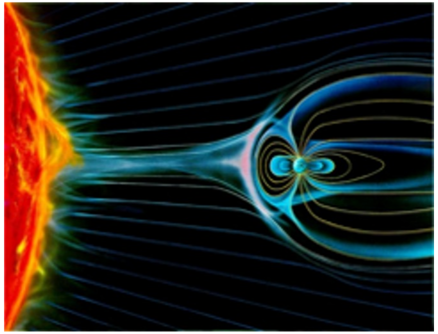


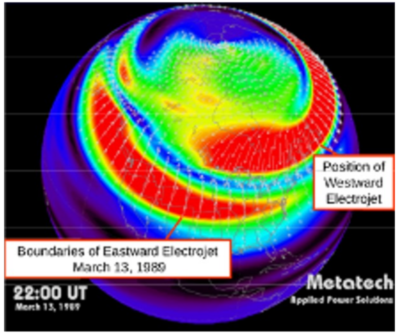


(Froese et al., 2024, Moshtaghian et al., 2024)

minerals, geothermal: large scales & seeing deep

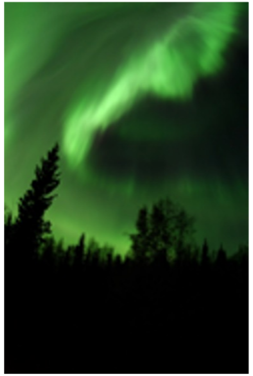
natural source: rely on lightning strikes, solar wind as our source (unknown strength)





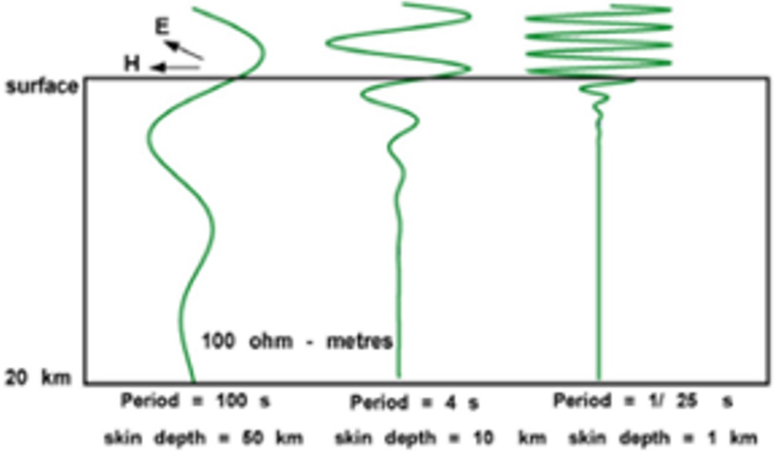
lightning

aurora



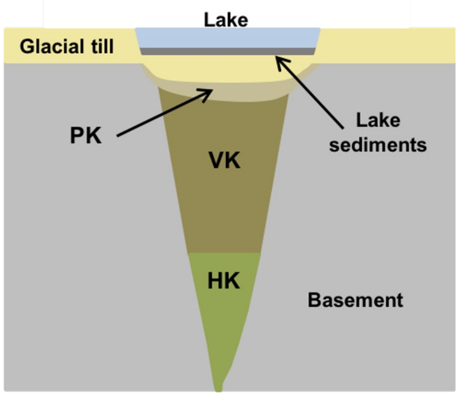
skin depth (m)

$$\delta = 503\sqrt{\frac{\rho}{f}} \qquad \begin{aligned} \rho &: \text{ resistivity } [\Omega\text{m}] \\ f &: \text{ frequency } [\text{Hz}] \end{aligned}$$

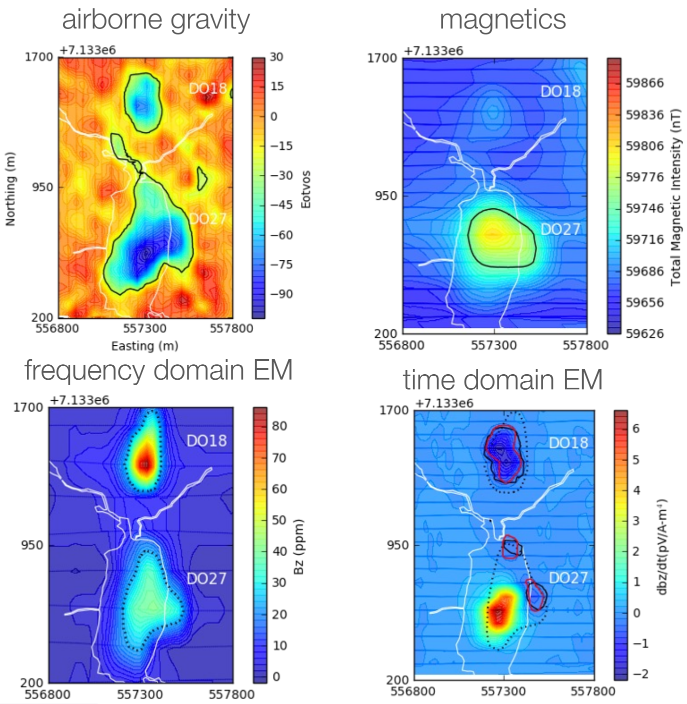


minerals: intermediate scale, multiple data types

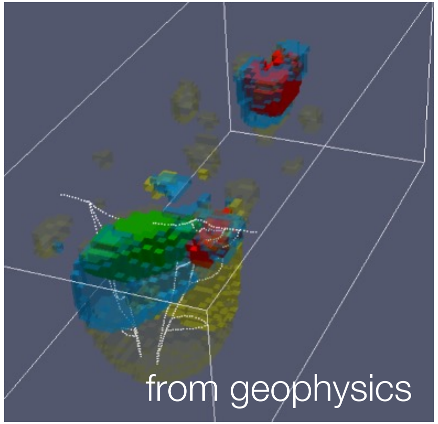
Diamond exploration: rock units identified using multiple physical properties

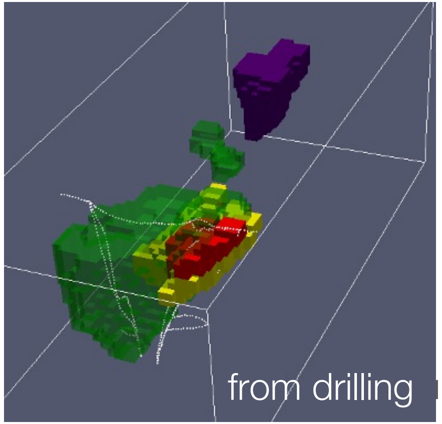


Rock type	Glacial till	Host rock	HK	VK	PK
Density	Moderate	Moderate	Low	Low	Low
Susceptibility	None	None	High	Low-moderate	Low-moderate
Conductivity	Moderate-high	Low	Low-moderate	Moderate-high	Moderate-high
Chargeability	Low	Low	?	?	?



Devriese *et al.* 2017,
Fournier *et al.* 2017,
Kang *et al.* 2017



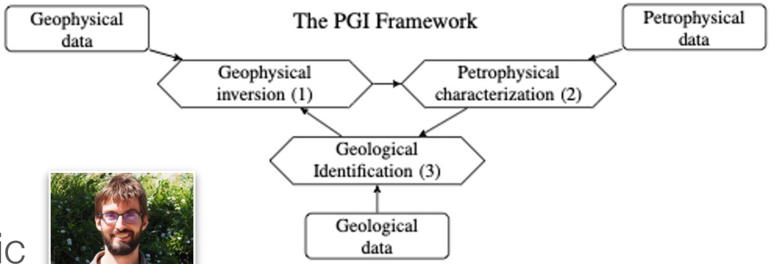


minerals: intermediate scale, multiple data types

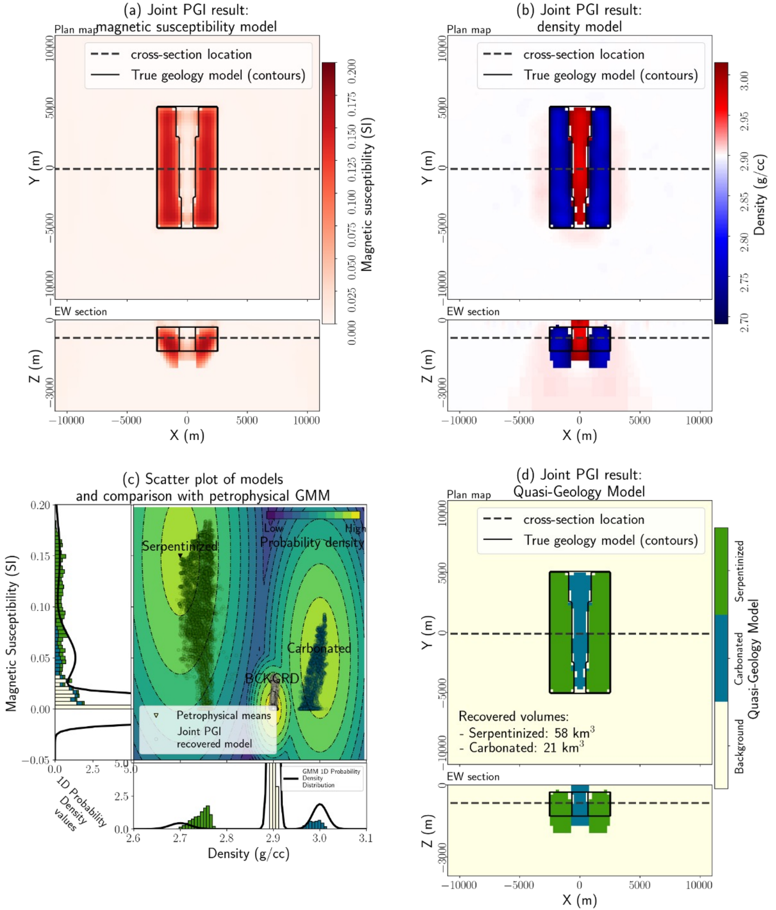
```
ϕ_data = ϕ_grav + ϕ_mag  # one earth?
```

Petrophysically and Geologically Guided Inversion

- brings in petrophysical information (GMM)
- builds a quasi-geology model
- important components in the inversion
  - multiple data misfits
  - including petrophysical information



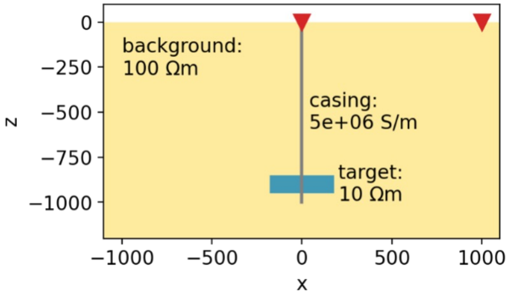
T. Astic

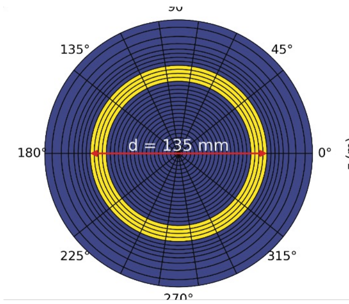


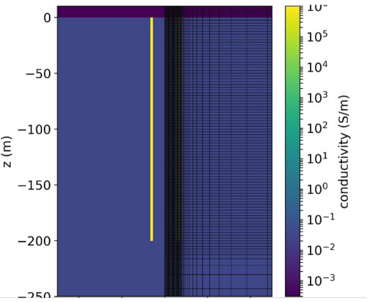
CO_2 sequestration, hydrocarbons: fine scales & large contrasts

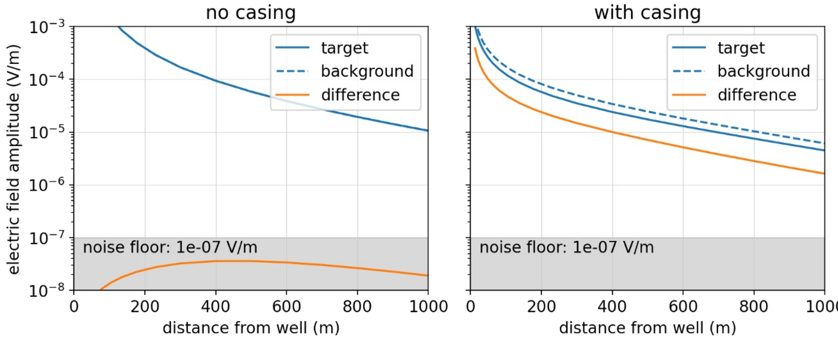
steel casings: highly conductive, magnetic

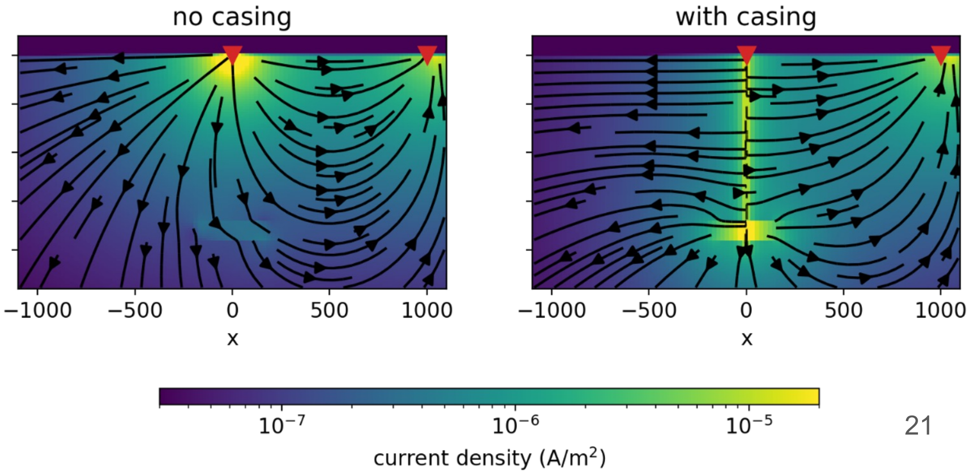
grounded sources: helpful for exciting & detecting deep targets











unexploded ordnance: small scales

near surface (or seafloor), need to detect & classify UXO vs clutter

This rocket warhead was found in September, 2008.
DEPARTMENT OF NATIONAL DEFENCE

?

A sign at the Goose Lake Range, on Okanagan Indian Band territory, warns of the presence of UXO. JEFF BASSETT/THE GLOBE AND MAIL

UXO

Not UXO

case studies

groundwater

CO_2 sequestration

unexploded ordnance

case studies

groundwater

CO_2 sequestration

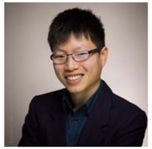
unexploded ordnance

groundwater in Myanmar

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 (Max)


Devin Cowan


Seogi Kang


Lindsey Heagy

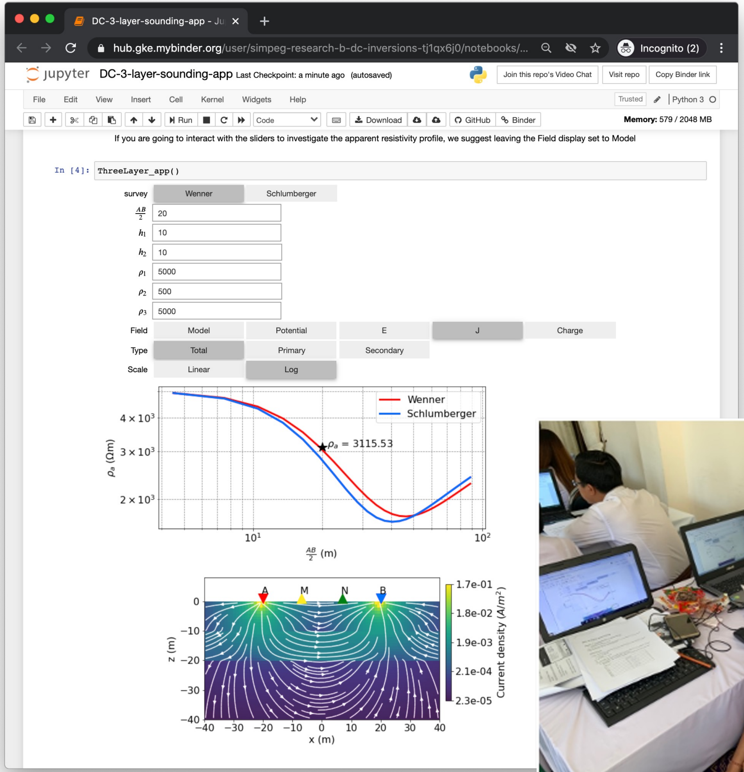
groundwater in Myanmar: important components

7 step framework for case studies

- Setup
- Physical properties
- Survey
- Data
- Processing
- Interpretation
- Synthesis

Open source software and resources

- Jupyter notebook “apps” for concepts and data processing



https://courses.geosci.xyz/gwb2020

groundwater in Myanmar

7 step framework

- **Setup**
- Physical properties
- Survey
- Data
- Processing
- Interpretation
- Synthesis

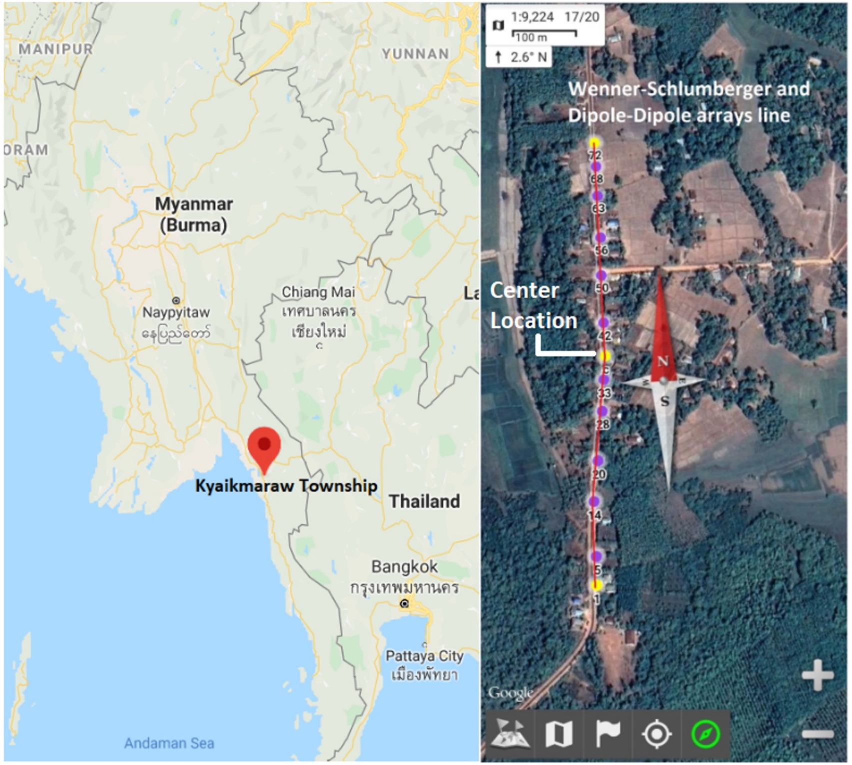
Phayar Ngoteto Village

In 2018: 1D inversion suggested aquifer at 30-50 m

- Well drilled to ~60 m: no significant water

In 2020 (before covid...):

- return and conduct a 2D survey

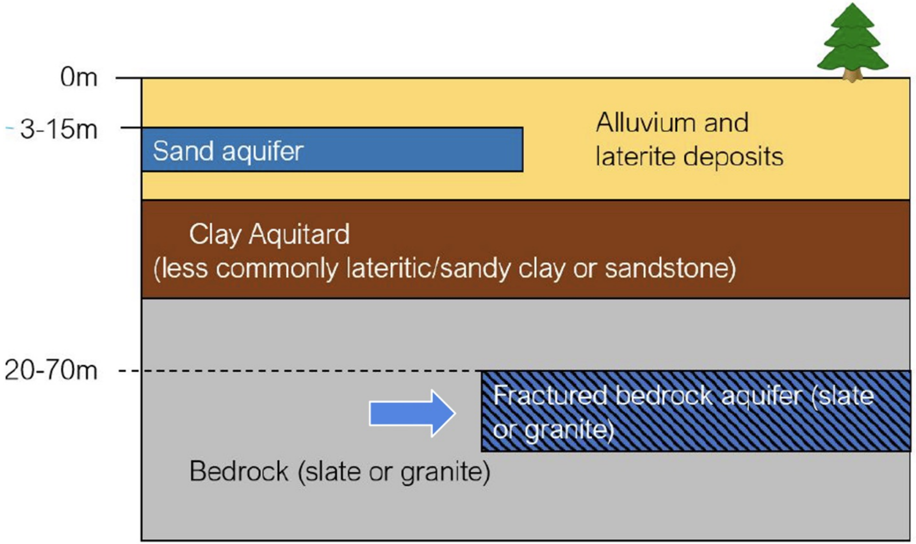


groundwater in Myanmar

7 step framework

- Setup
- **Physical properties**
- Survey
- Data
- Processing
- Interpretation
- Synthesis

Main diagnostic:
Water bearing region ~ 40-140 Ωm



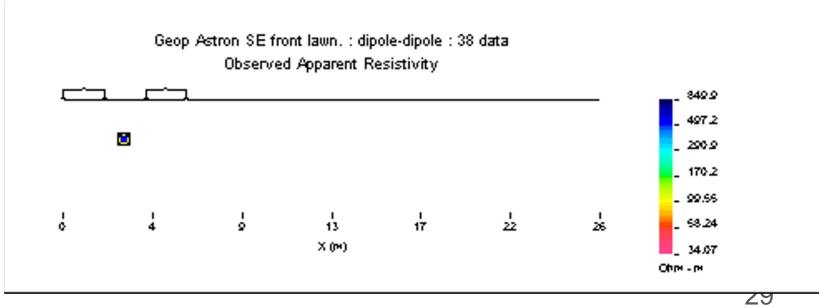
Hydrogeological Unit	**Resistivity (Ωm)**
Alluvium and laterite (dry)	200-800
Alluvium and laterite (saturated)	30
Sand aquifer	50-100
Clay aquitard	10-20
Bedrock (eg. granite)	500-1000
Fractured/Weathered bedrock (with fresh water)	40-400

groundwater in Myanmar

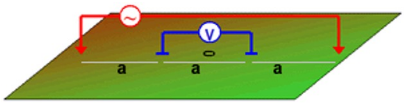
7 step framework

- Setup
- Physical properties
- **Survey**
- Data
- Processing
- Interpretation
- Synthesis

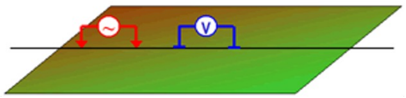
data plotted in pseudosections



Survey: 2D DC resistivity



Wenner-Schlumberger



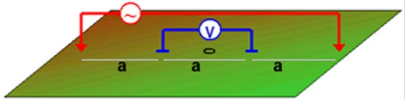
Dipole-Dipole

groundwater in Myanmar

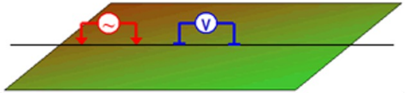
7 step framework

- Setup
- Physical properties
- Survey
- **Data**
- Processing
- Interpretation
- Synthesis

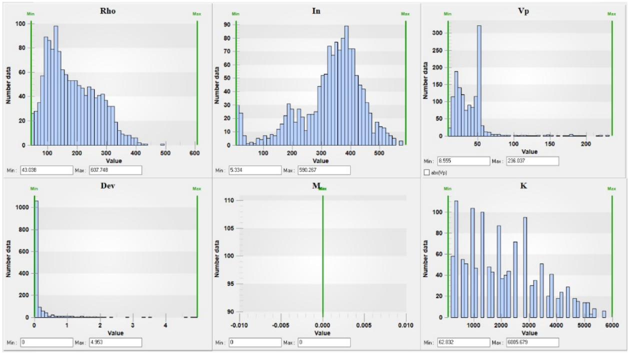
Survey: 2D DC resistivity

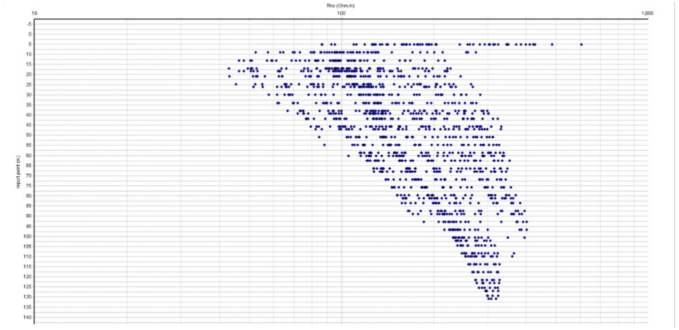


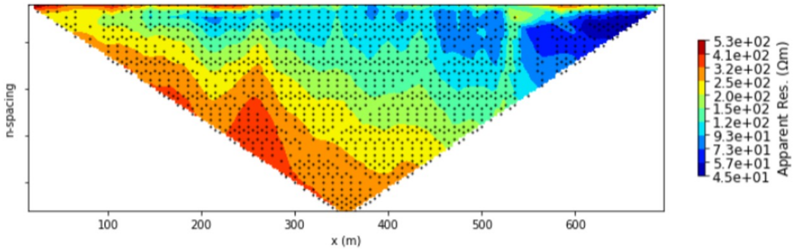
Wenner-Schlumberger



Dipole-Dipole







groundwater in Myanmar

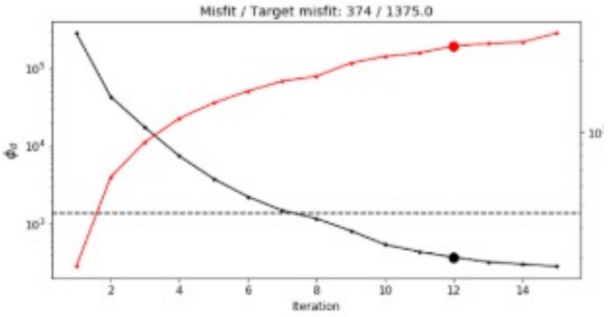
7 step framework

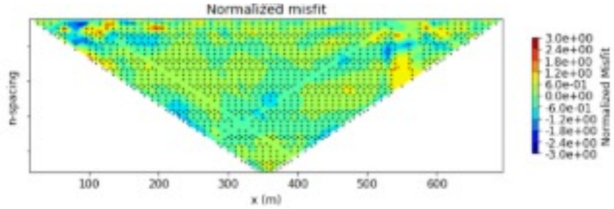
- Setup
- Physical properties
- Survey
- Data
- **Processing**
- Interpretation
- Synthesis

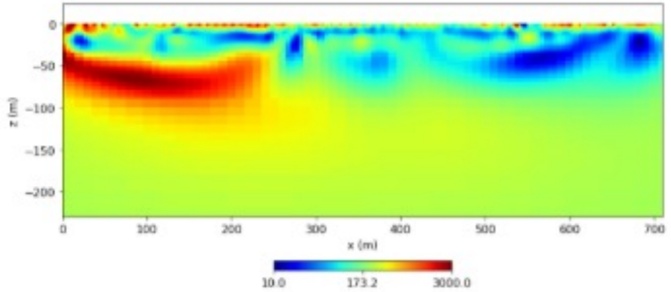
Inversion: estimate a model of the subsurface

$$\min_{\mathbf{m}} \phi(\mathbf{m}) = \phi_d(\mathbf{m}) + \beta\phi_m(\mathbf{m})$$

$$\text{s.t. } \phi_d \leq \phi_d^* \quad \mathbf{m}_L \leq \mathbf{m} \leq \mathbf{m}_U$$



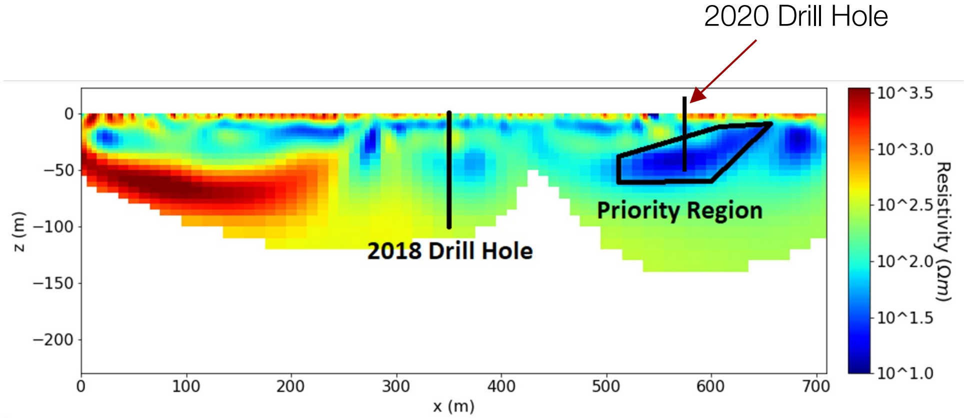




groundwater in Myanmar

7 step framework

- Setup
- Physical properties
- Survey
- Data
- Processing
- **Interpretation**
- Synthesis



groundwater in Myanmar

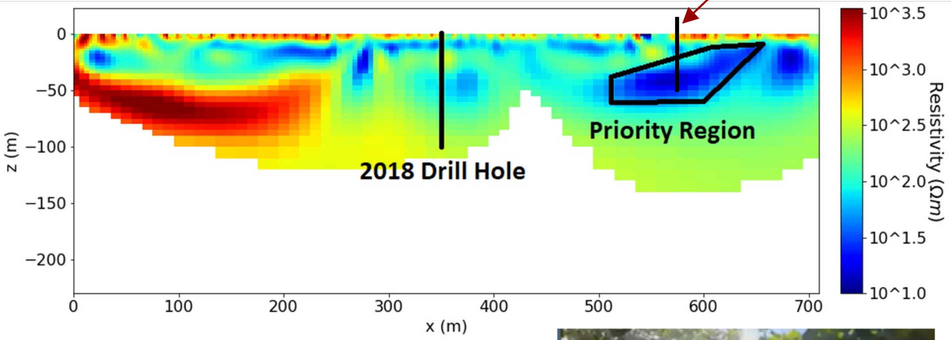
7 step framework

- Setup
- Physical properties
- Survey
- Data
- Processing
- Interpretation
- **Synthesis**

Field surveys at 23+ villages by engineers, geoscientists in Myanmar

Acquired data, interpreted, spotted drill holes using open source software

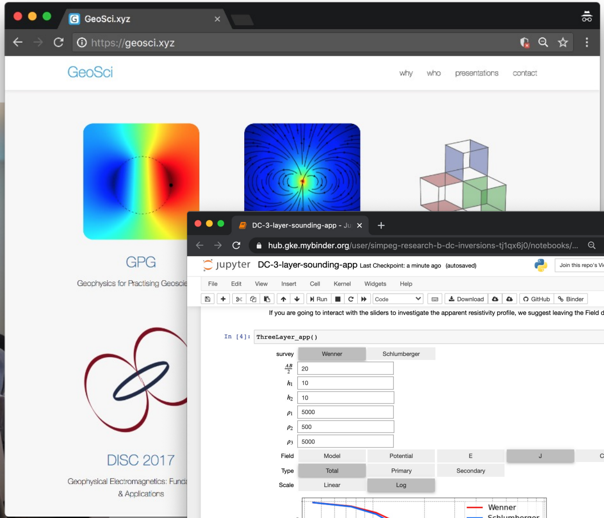
2020 Drill Hole

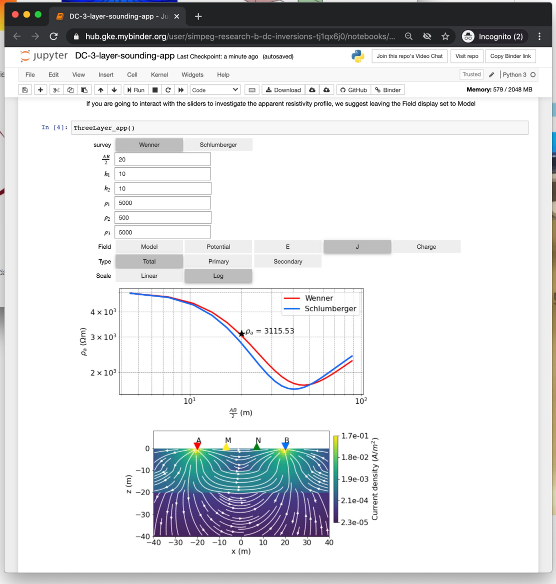


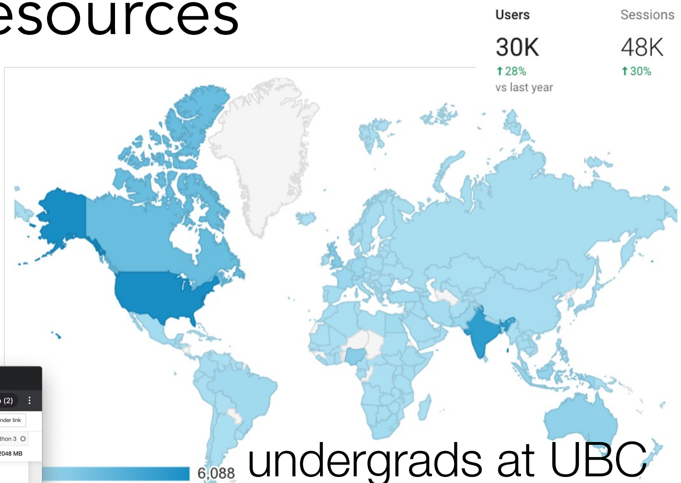
>1000 gph

GeoSci.xyz open educational resources

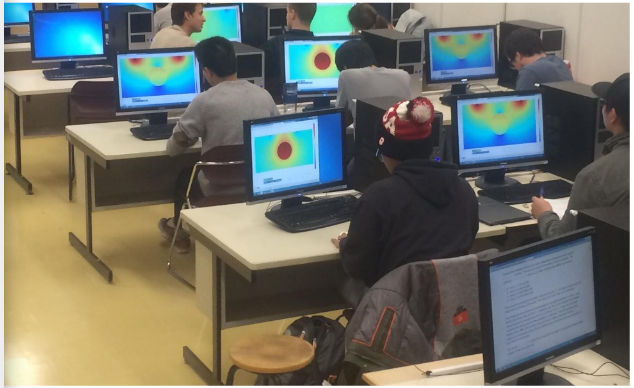
https://geosci.xyz







undergrads at UBC



electromagnetics course:
26 locations worldwide

case studies

groundwater

CO_2 sequestration

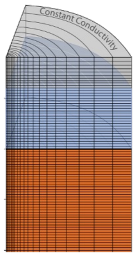
unexploded ordnance

an example: monitoring with steel cased wells

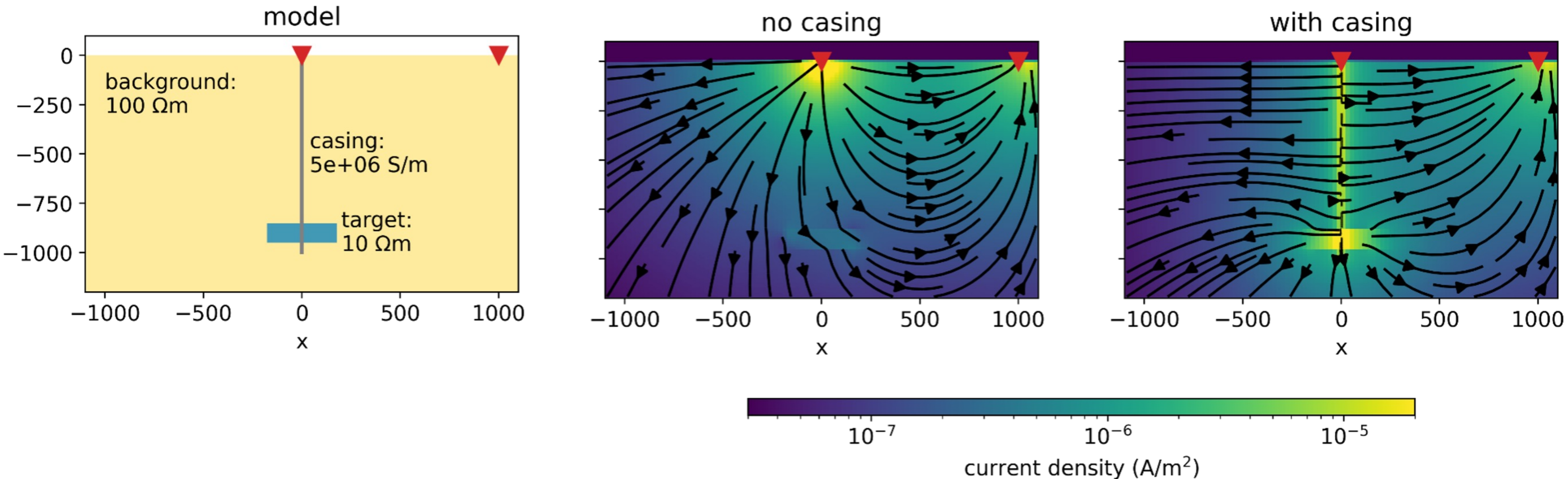
applications: CO_2, geothermal, wastewater injection, …

steel-casing: complicates numerical simulations (highly conductive, magnetic)

but… helpful for bringing current to depth



Cylindrical mesh



electromagnetics: basic equations (quasi-static)

	Time	Frequency
Faraday's Law	$\nabla \times \vec{e} = -\dfrac{\partial \vec{b}}{\partial t}$	$\nabla \times \vec{E} = -i\omega \vec{B}$
Ampere's Law	$\nabla \times \vec{h} = \vec{j} + \dfrac{\partial \vec{d}}{\partial t}$	$\nabla \times \vec{H} = \vec{J} + i\omega \vec{D}$
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

numerical simulations in SimPEG: frequency domain EM

Continuous equations

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

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

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

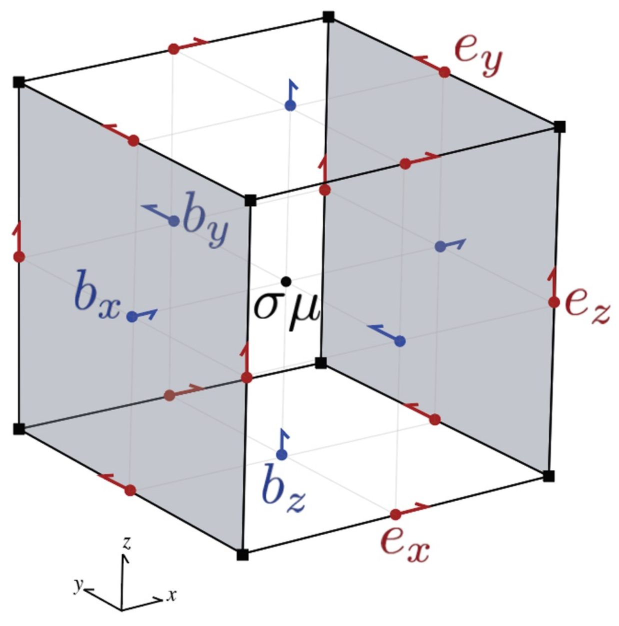
Finite volume discretization

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

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

Eliminate **b** to obtain a second-order system in **e**

$$\underbrace{\left(\mathbf{C}^\top\mathbf{M}^f_{\mu^{-1}}\mathbf{C} + i\omega\mathbf{M}^e_\sigma\right)}_{\mathbf{A}(\sigma,\omega)}\underbrace{\mathbf{e}}_{\mathbf{u}} = \underbrace{-i\omega\mathbf{M}^e\mathbf{j_s}}_{\mathbf{q}(\omega)}$$



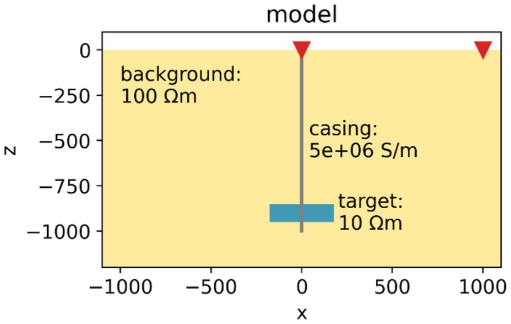
(Heagy et al., 2017)

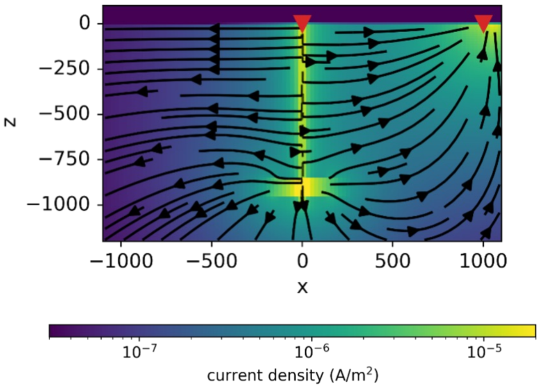
numerical simulations in SimPEG: frequency domain EM

$$\underbrace{(\mathbf{C}^\top \mathbf{M}^f_{\mu^{-1}} \mathbf{C} + i\omega \mathbf{M}^e_\sigma)}_{\mathbf{A}(\sigma,\omega)} \underbrace{\mathbf{e}}_{\mathbf{u}}$$

$$= \underbrace{-i\omega \mathbf{M}^e \mathbf{j_s}}_{\mathbf{q}(\omega)}$$

```
ω = 2 * pi * frequency

C = mesh.edge_curl
Mfμi = mesh.get_face_inner_product(1/mu_0)
Meσ = mesh.get_edge_inner_product(sigma)

A = C.T * Mfμi * C + i * ω * Meσ
Ainv = Solver(A)  # acts like A inverse

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

u = Ainv * q
```





numerical simulations in SimPEG: frequency domain EM

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

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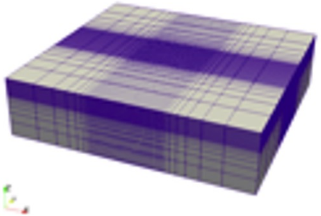
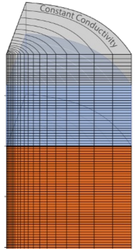
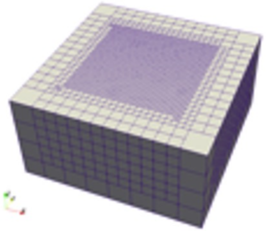


Tensor

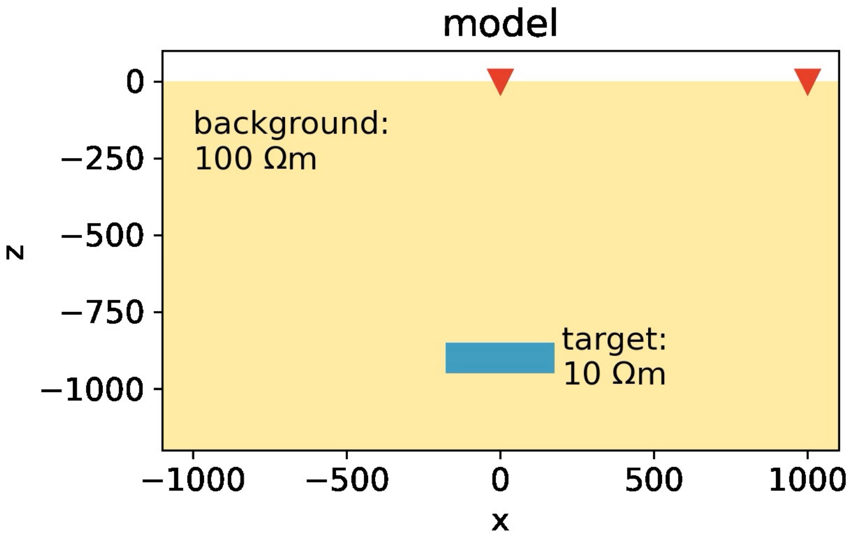


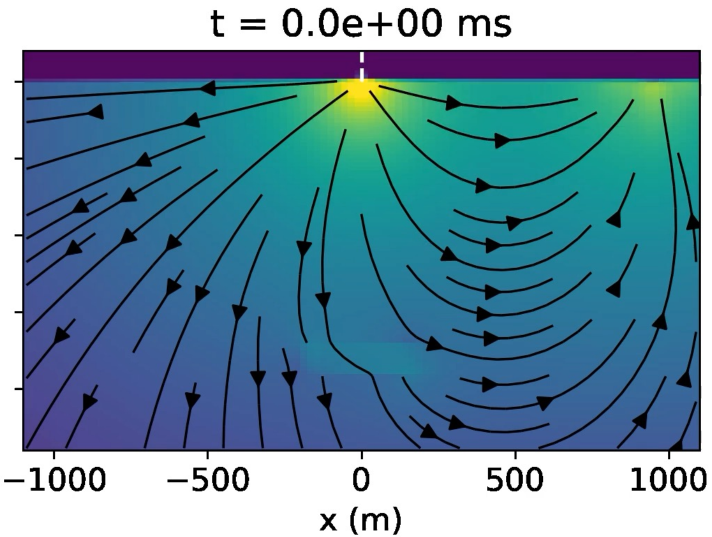
Cylindrical



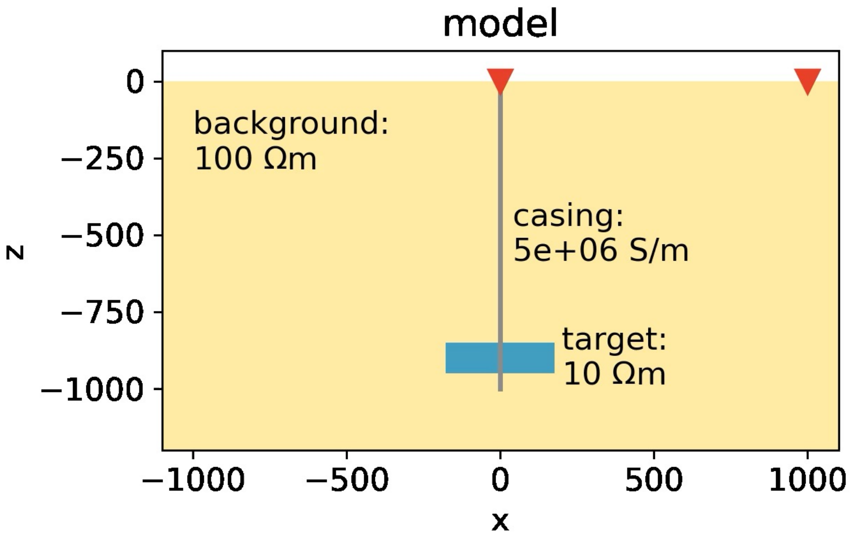
OcTree

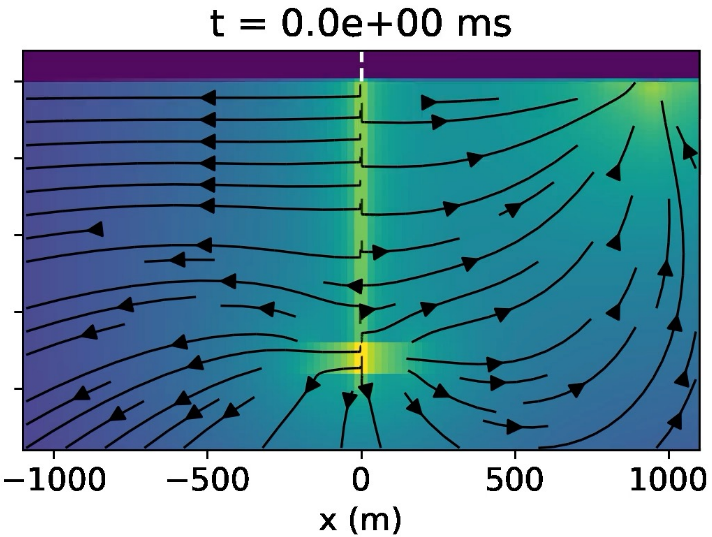
EM experiment: no casing

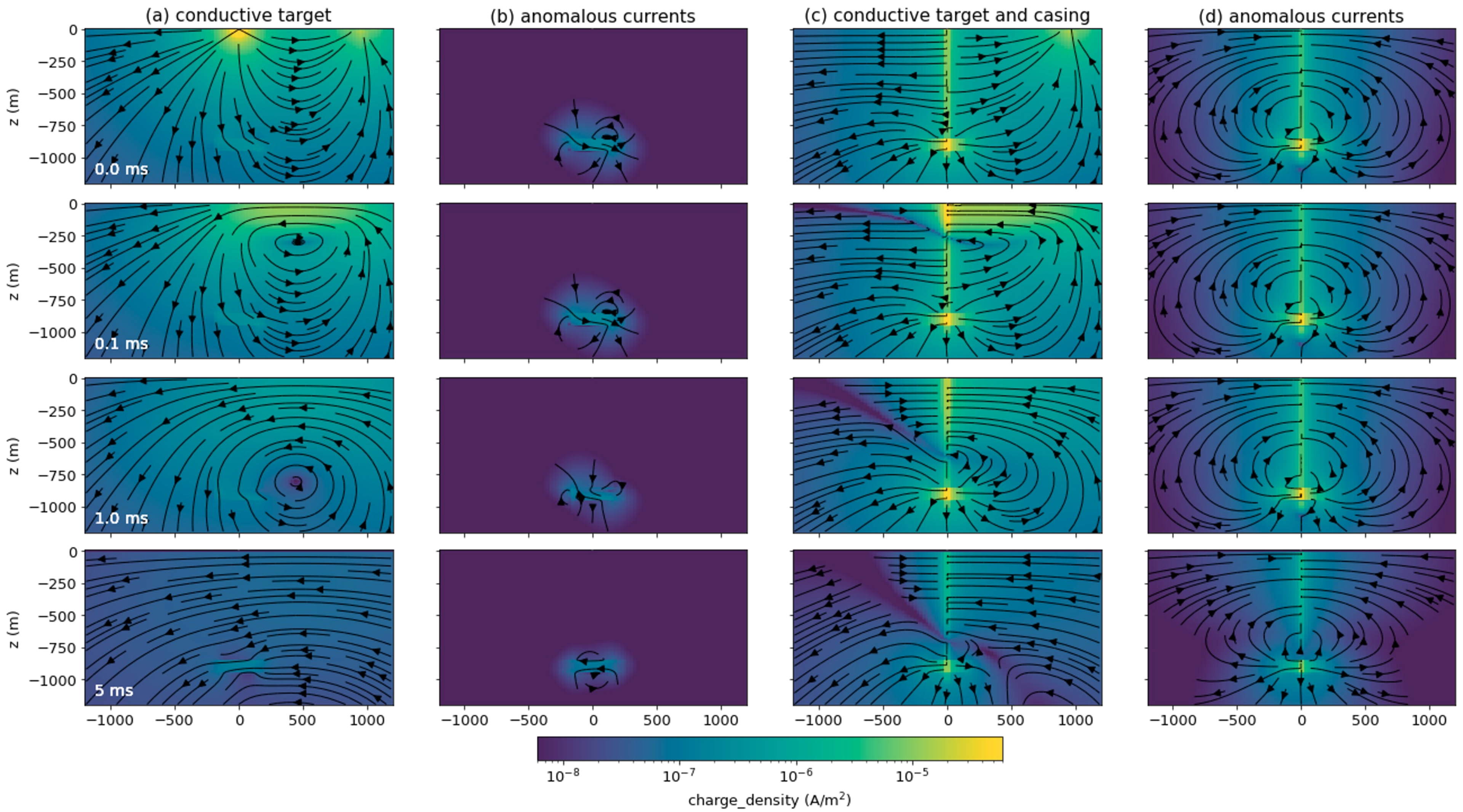




EM experiment with casing







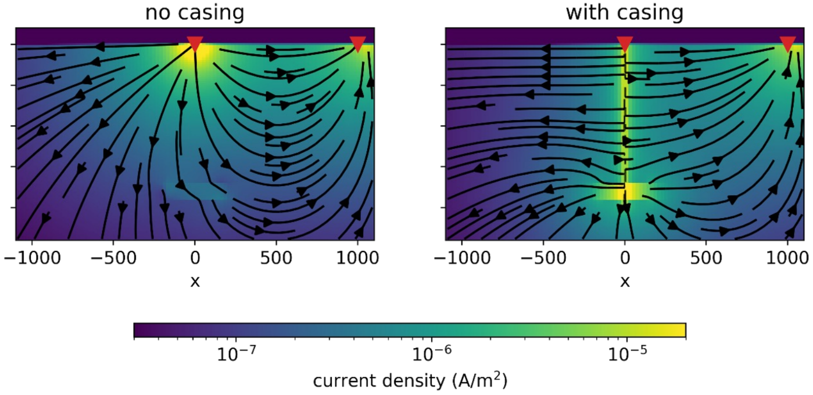
(a) conductive target
(b) anomalous currents
(c) conductive target and casing
(d) anomalous currents
z (m)
0.0 ms
0.1 ms
1.0 ms
5 ms
charge_density (A/m^2)

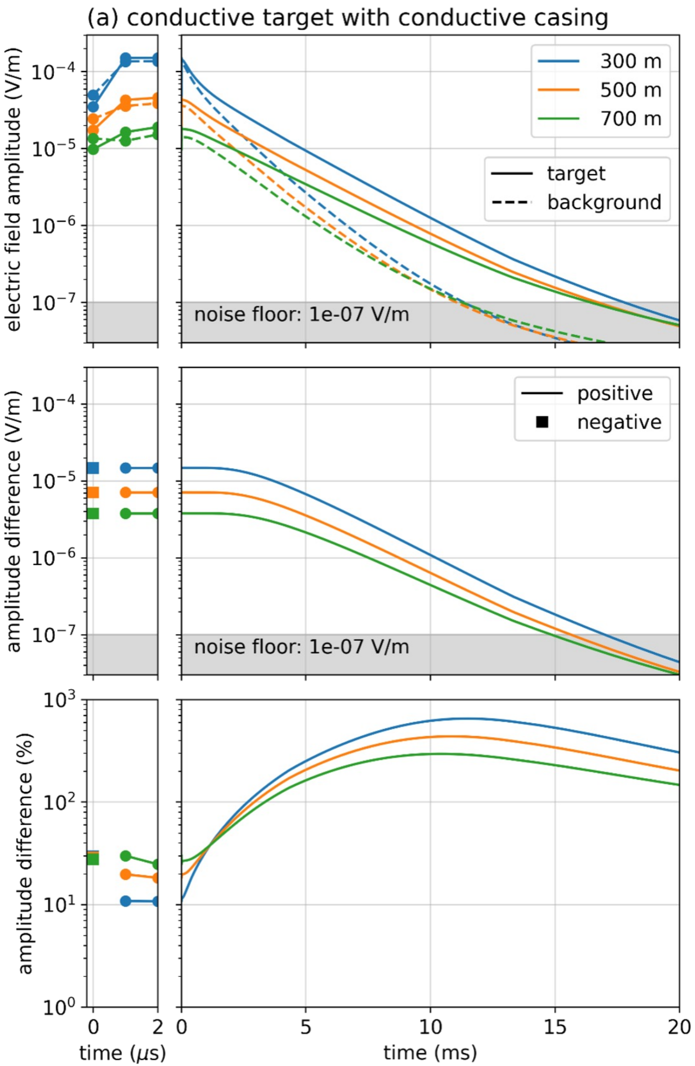
EM monitoring with casing

applications: CO_2, geothermal, wastewater injection, settings with infrastructure…

steel-casing: complicates numerical simulations (highly conductive, magnetic)

but… helpful for bringing current to depth





Heagy & Oldenburg (2022)

case studies

groundwater

CO_2 sequestration

unexploded ordnance

Unexploded ordnance (UXO): A global problem

Definition: a munition that was armed, fired and remains unexploded

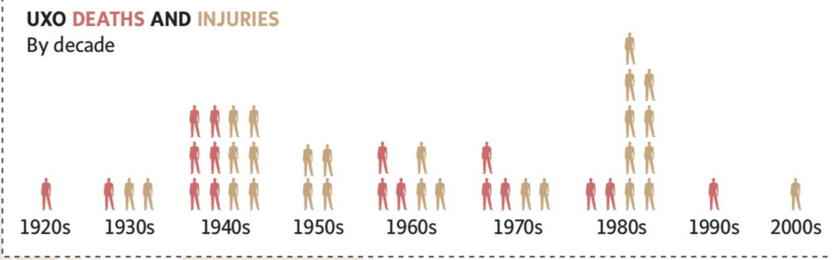
Sources:

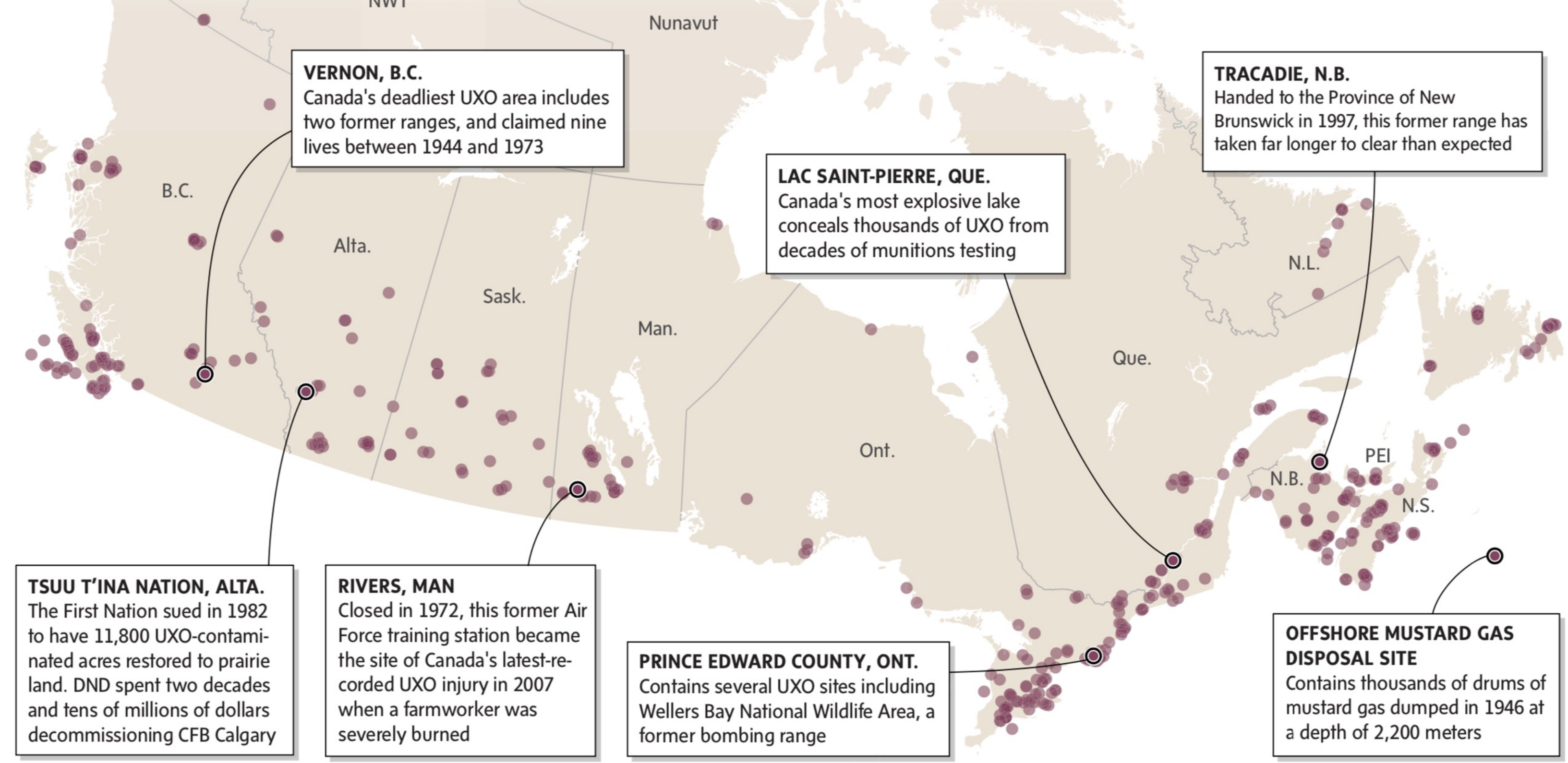
- Regions of military conflict
- Munitions and bombing ranges
- Avalanche control

Countries significantly impacted by UXO

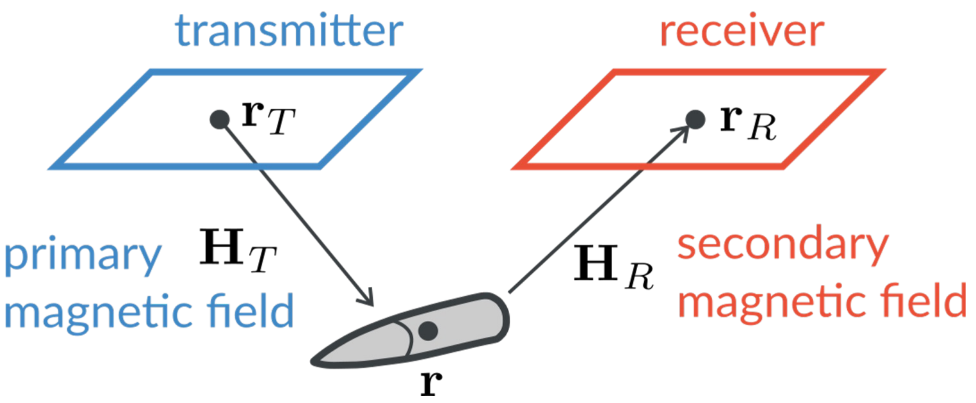
UXO SITES ACROSS CANADA

DND estimates 521 UXO sites across Canada may require clearance. A handful have proved particularly daunting and expensive–or in some instances, even fatal





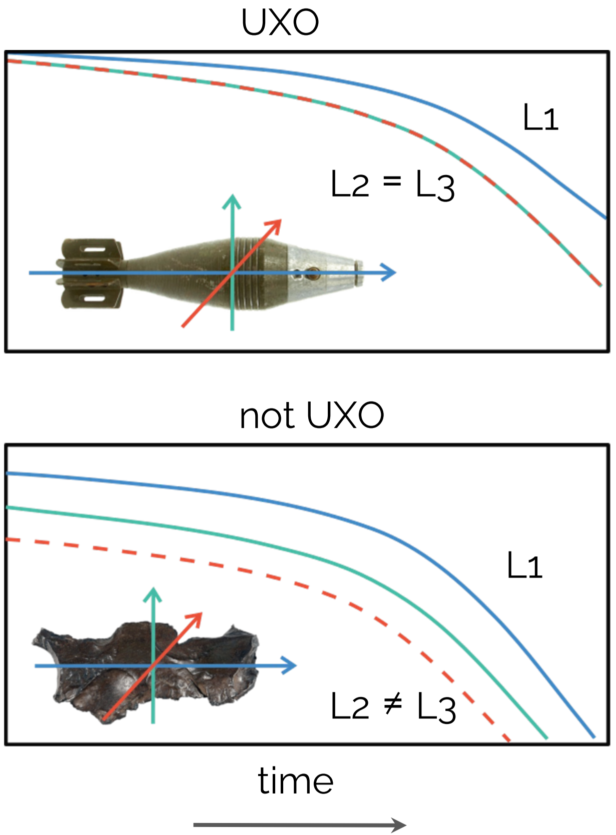
Time-domain EM response of a UXO



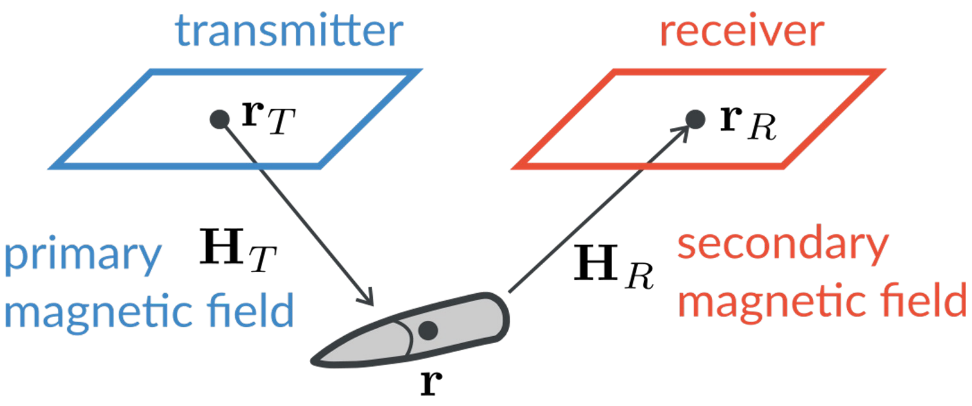
$$d(\mathbf{r}_R, t) = \mathbf{H}_R(\mathbf{r}, \mathbf{r}_R) \cdot \mathbf{P}(t) \cdot \mathbf{H}_T(\mathbf{r}, \mathbf{r}_T)$$

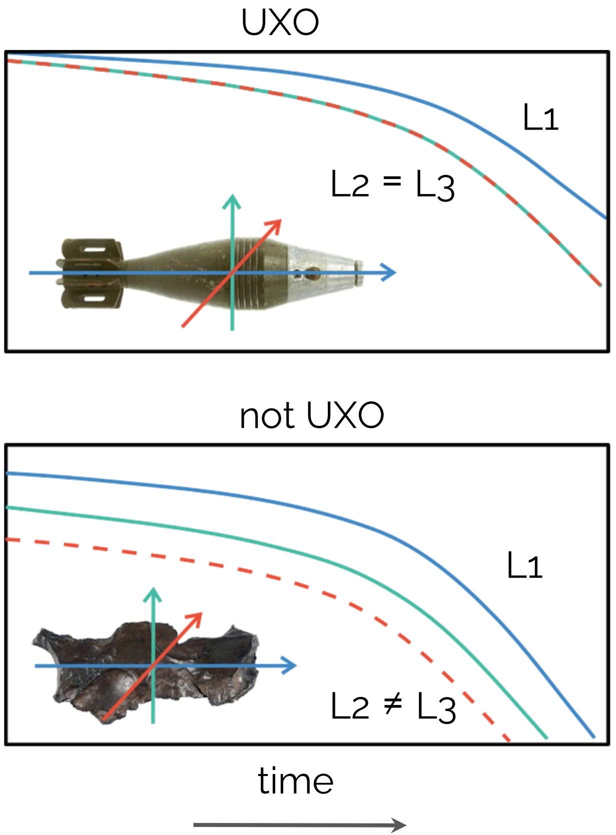
$$\mathbf{P}(t) = \mathbf{A}(\phi, \theta, \psi) \cdot \mathbf{L}(t) \cdot \mathbf{A}^\top(\phi, \theta, \psi)$$

$$\mathbf{L}(t) = \begin{pmatrix} L_1 & & \\ & L_2 & \\ & & L_3 \end{pmatrix}$$



Time-domain EM response of a UXO





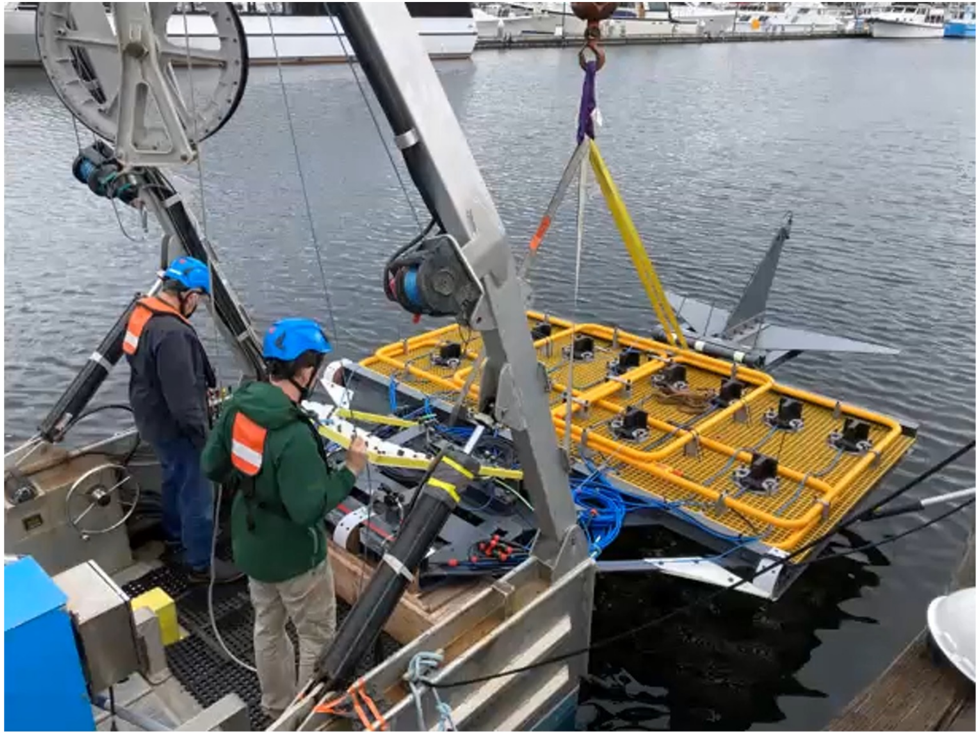
$$d(\mathbf{r}_R, t) = \mathbf{H}_R(\underbrace{\mathbf{r}}, \mathbf{r}_R) \cdot \mathbf{P}(t) \cdot \mathbf{H}_T(\mathbf{r}, \mathbf{r}_T)$$

$$\mathbf{P}(t) = \underbrace{\mathbf{A}(\phi, \theta, \psi)} \cdot \mathbf{L}(t) \cdot \mathbf{A}^\top(\phi, \theta, \psi)$$

$$\mathbf{L}(t) = \underbrace{\begin{pmatrix} L_1 & & \\ & L_2 & \\ & & L_3 \end{pmatrix}}$$

traditional approach: use inversion to get these and then classify by comparing **L**(t) with ordnance library

Survey and system



UltraTEMA-4 system:

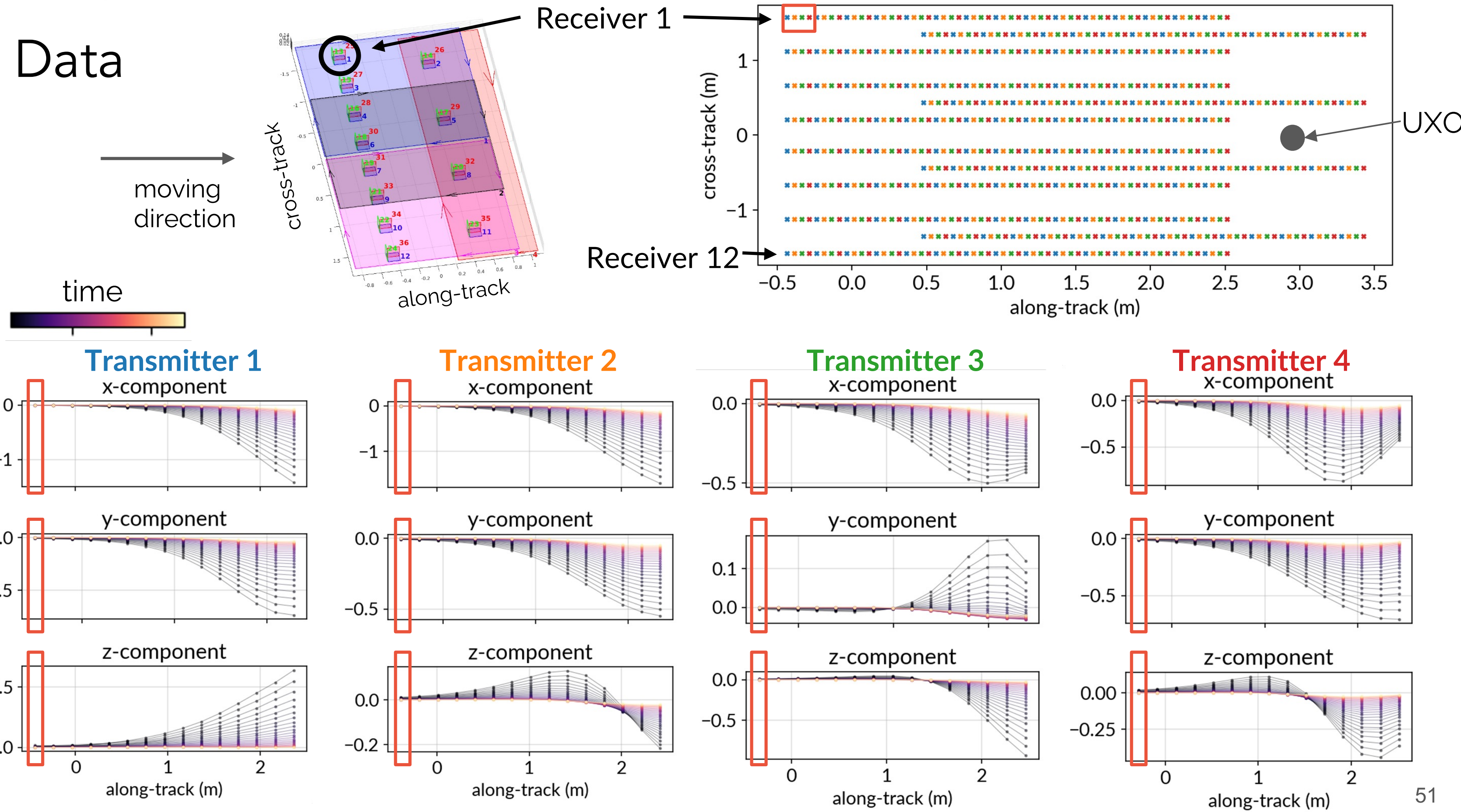
4 transmitters

12 receivers (3-component)

27 time channels

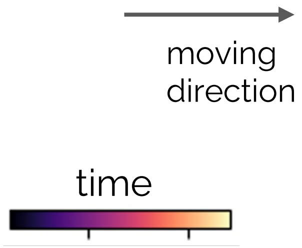
Height above seabed: ~1 m

Data

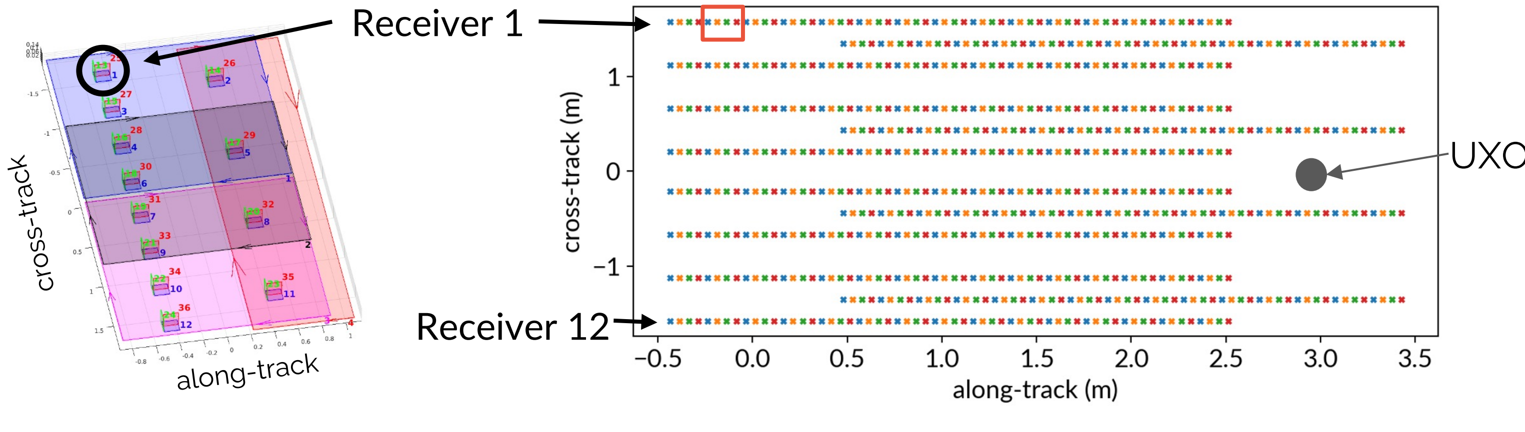


Receiver 1
Receiver 12
UXO
moving
direction
time
cross-track
along-track
cross-track (m)
along-track (m)
Transmitter 1
Transmitter 2
Transmitter 3
Transmitter 4
x-component
y-component
z-component
along-track (m)

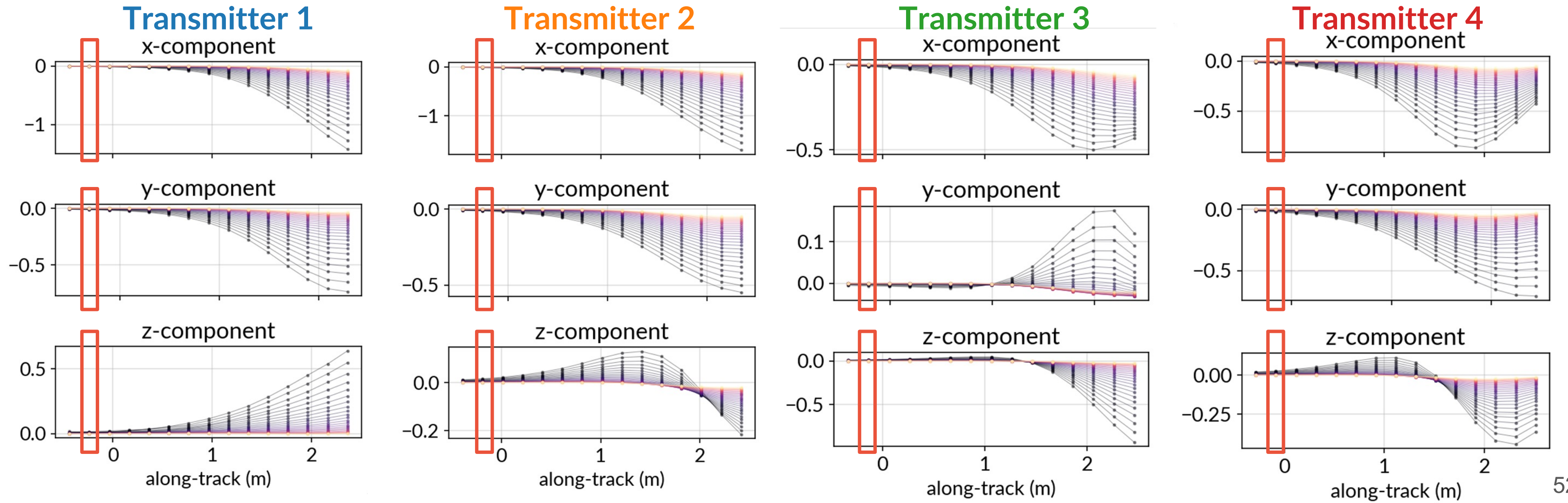
Data



moving
direction
time

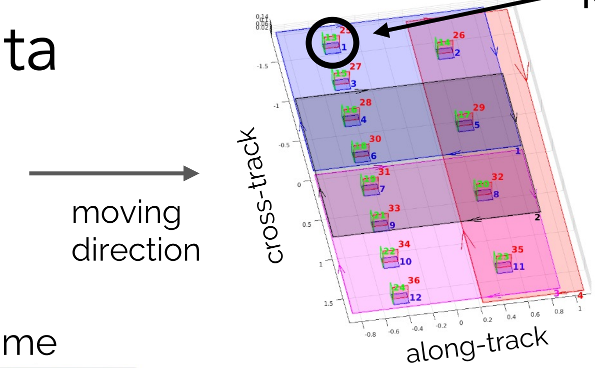


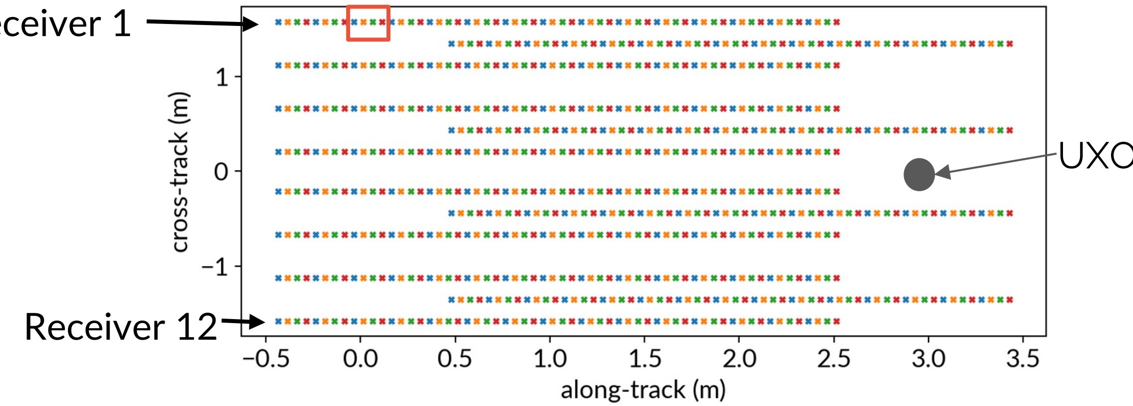
Receiver 1
Receiver 12
UXO
cross-track
along-track
cross-track (m)
along-track (m)

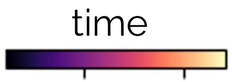


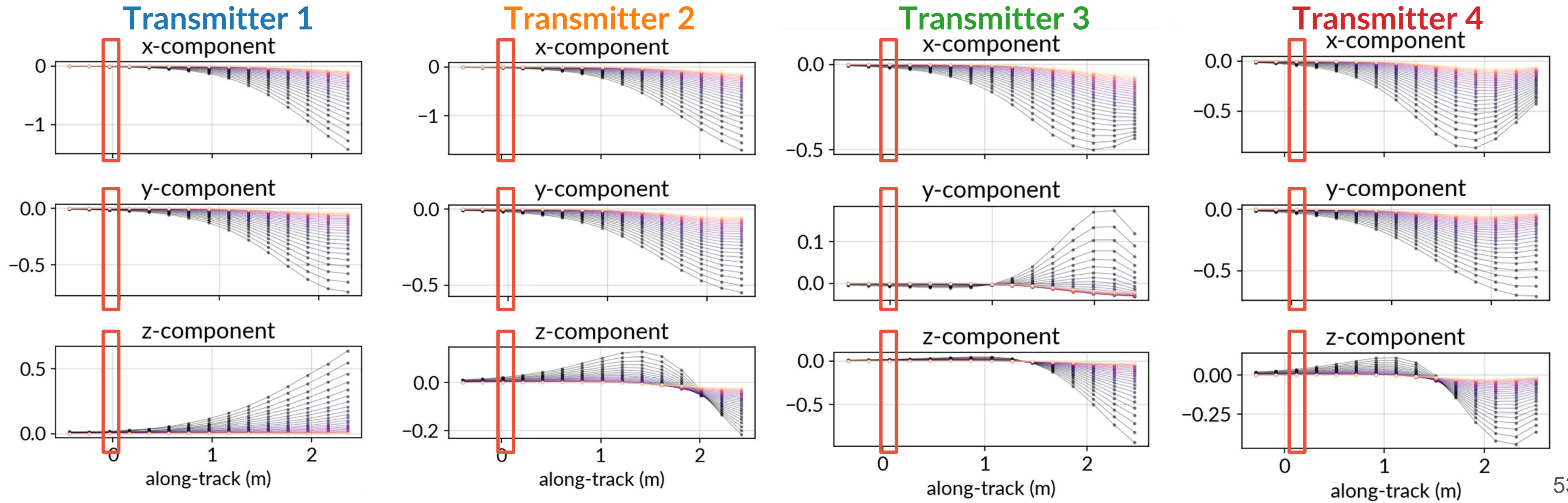
Transmitter 1
Transmitter 2
Transmitter 3
Transmitter 4
x-component
y-component
z-component
along-track (m)

Data

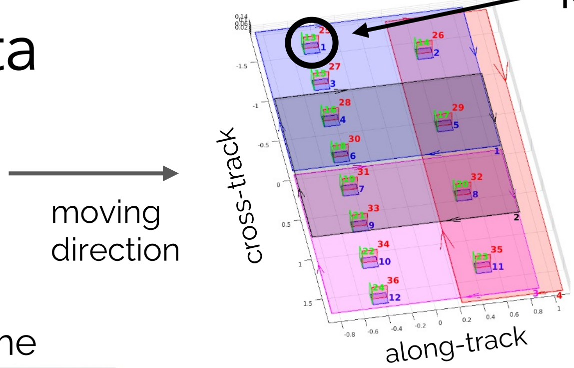

moving direction
cross-track
along-track

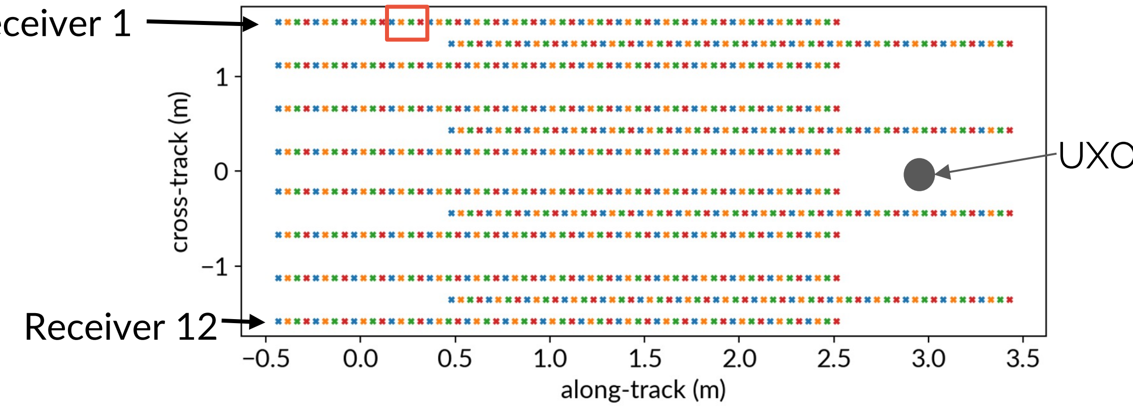

Receiver 1
Receiver 12
UXO
cross-track (m)
along-track (m)

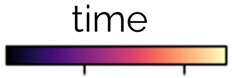

time

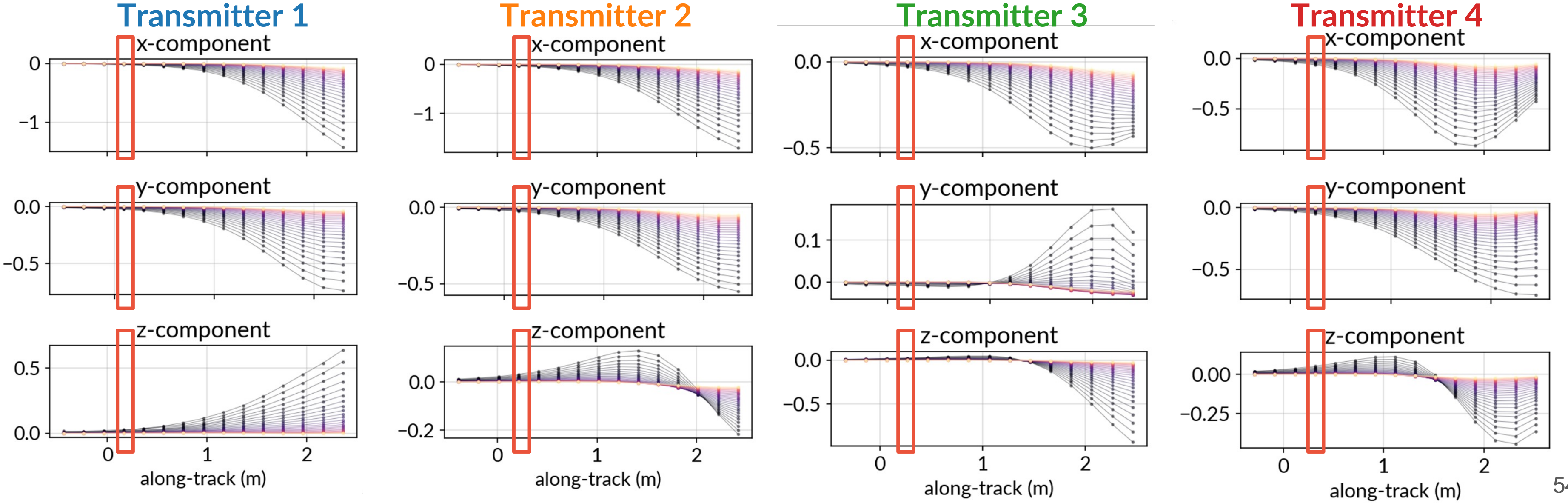

Transmitter 1
Transmitter 2
Transmitter 3
Transmitter 4
x-component
y-component
z-component
along-track (m)

Data


moving direction
cross-track
along-track


Receiver 1
Receiver 12
UXO
cross-track (m)
along-track (m)


time


Transmitter 1
Transmitter 2
Transmitter 3
Transmitter 4
x-component
y-component
z-component
along-track (m)

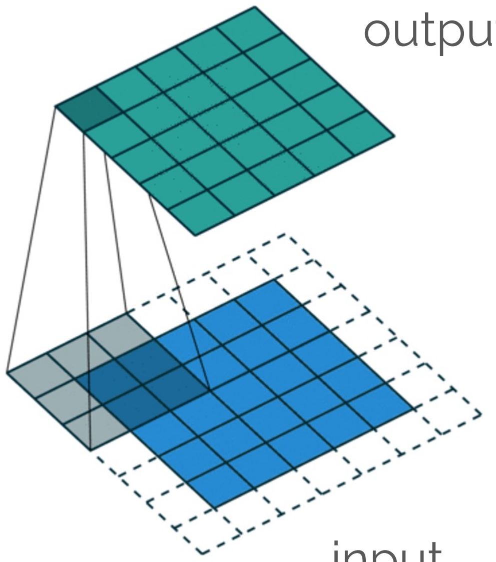
Can we classify directly from EM data?

Convolutional neural networks (CNNs)

- Convolutional filters look at spatial / temporal features in the data

Training EM data for UXO classification:

- Available library of ordnance objects with polarizations
- Fast geophysical simulations

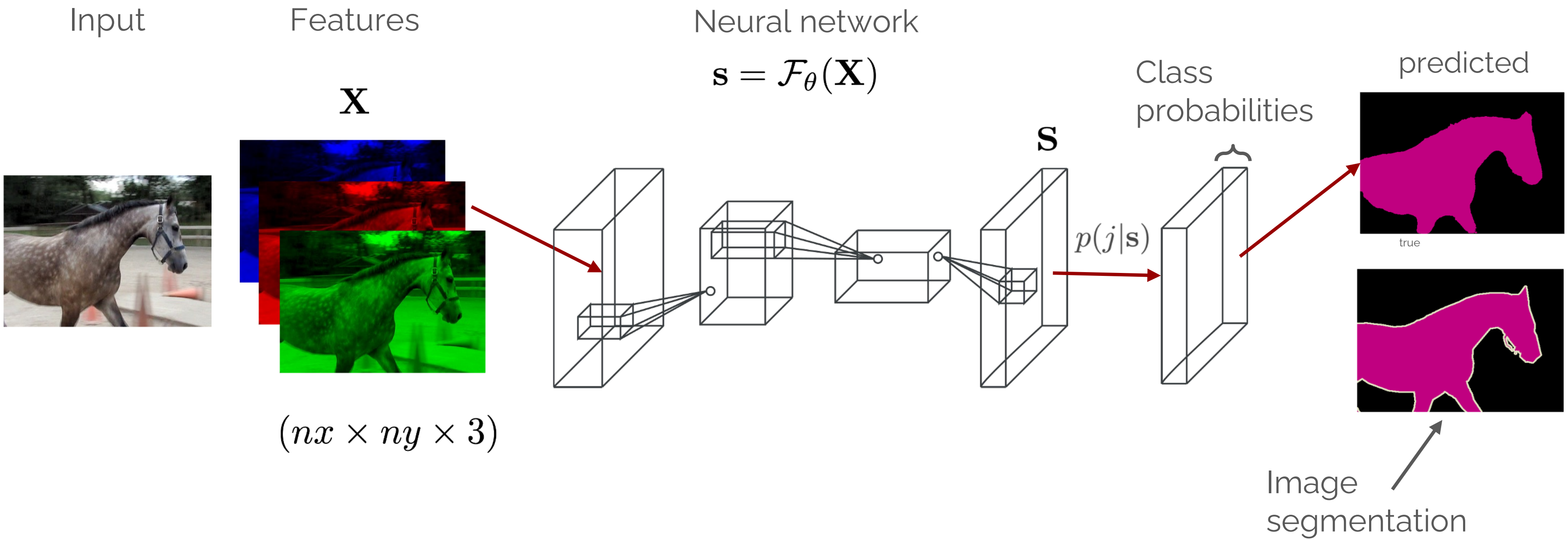


https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

Convolutional Neural Networks (CNNs)

Supervised classification problem

provided data with labels, construct a function (network) that outputs labels given input data

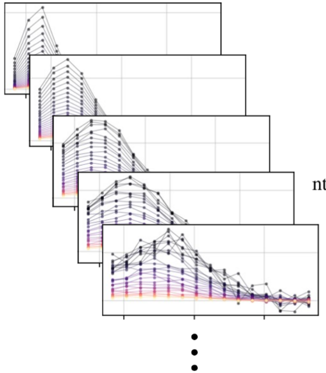


Convolutional Neural Networks (CNNs)

J. Lopez-Alvis

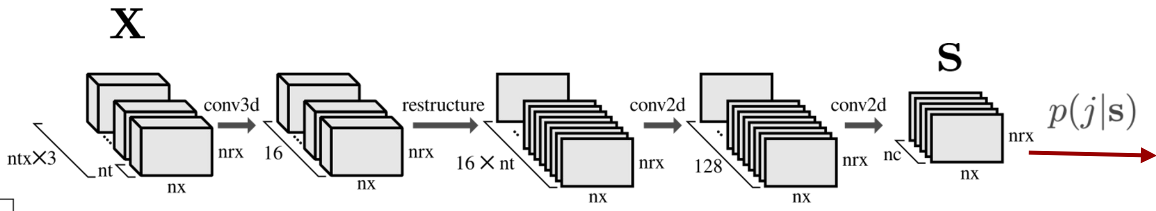
How do we translate these things to the UXO classification problem?

Input

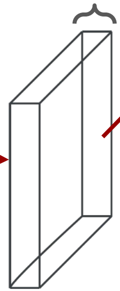


Features

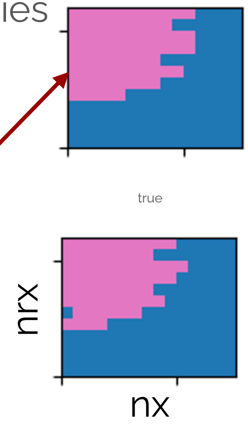
Neural network



Class probabilities



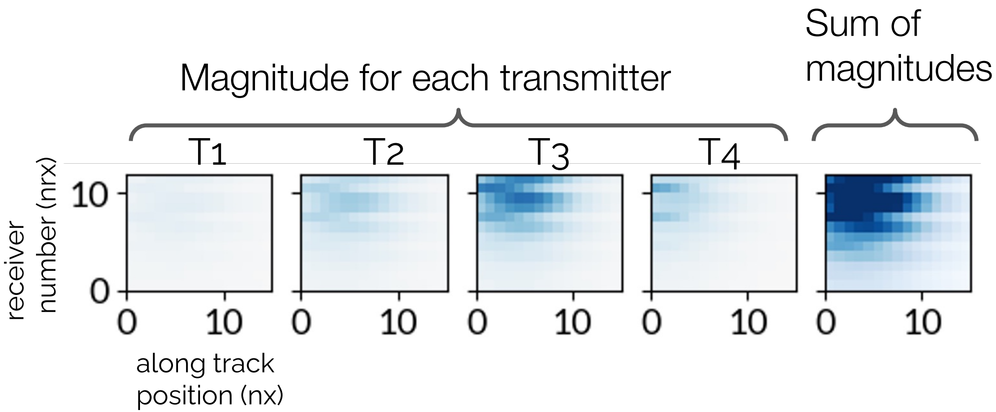
predicted

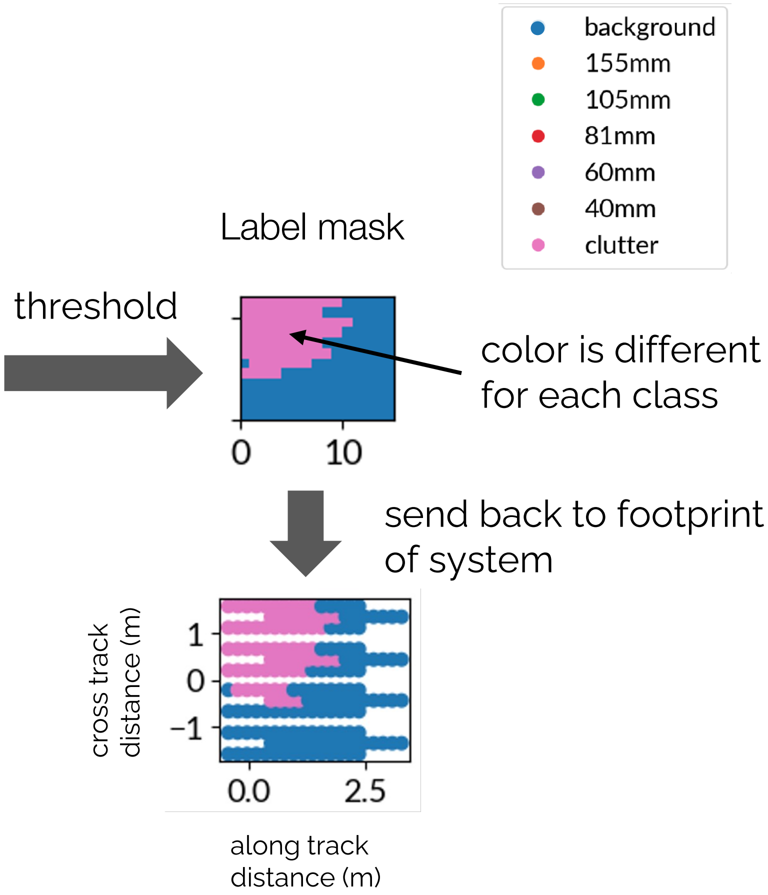


$$(nx \times nrx \times nt \times (ntx \times 3))$$

ntx = 4, number of transmitters
nrx = 12, number of receiver cubes
nt = 27, number of time channels
nx = 15, number of positions in spatial window (along track)
nc = 8, number of classes

Defining label masks

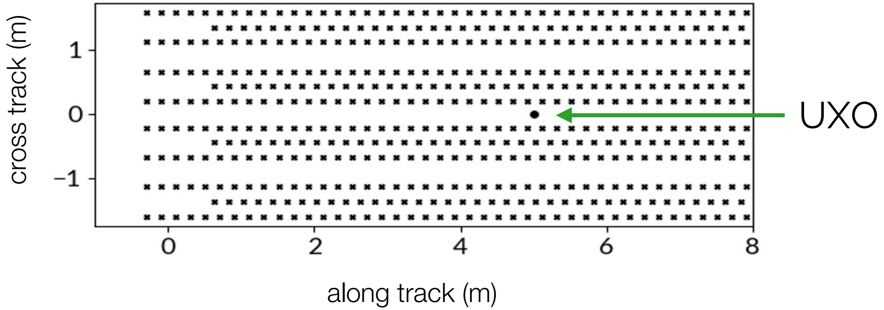




For time channel #5

Application to a line of data

Input features are created by using a sliding window:



Application to a line of data

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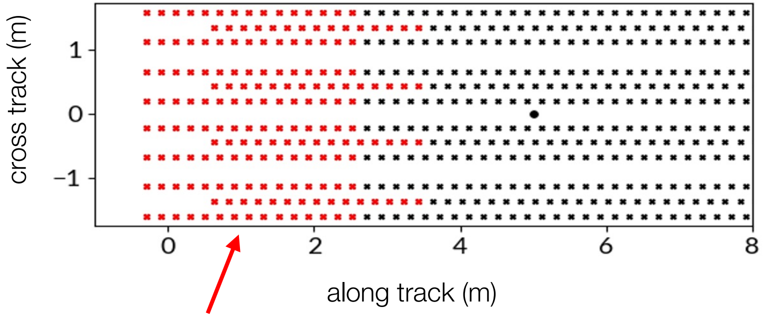
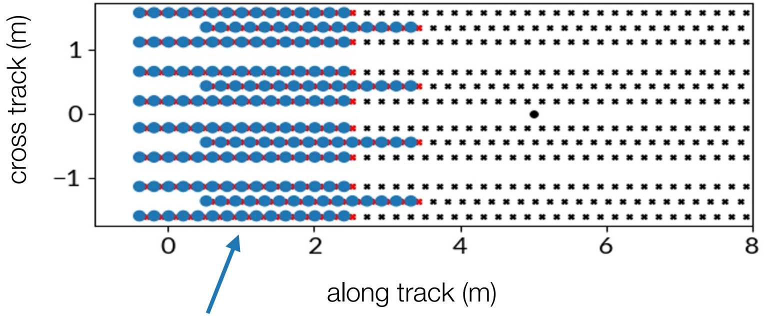


sliding window

Application to a line of data

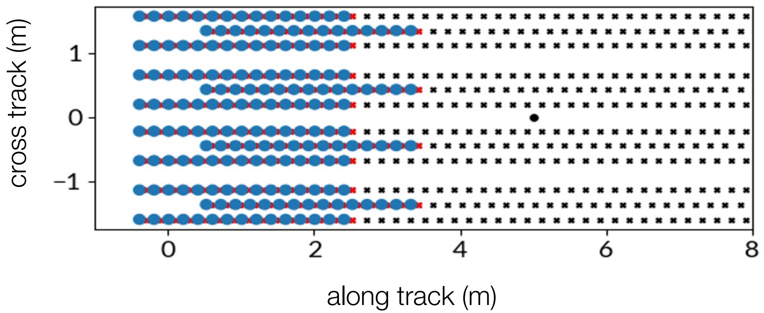
Input features are created by using a sliding window:



Neural network output (class)

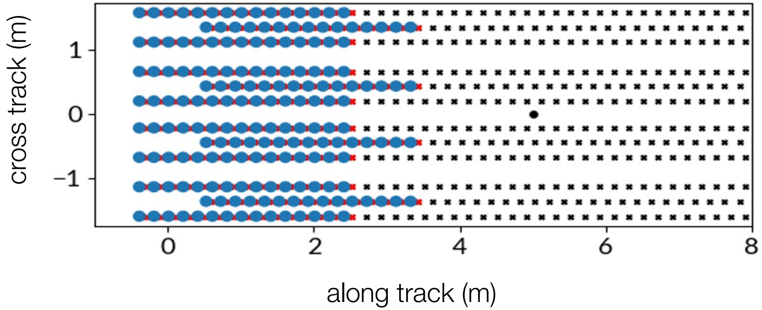
Application to a line of data

Input features are created by using a sliding window:

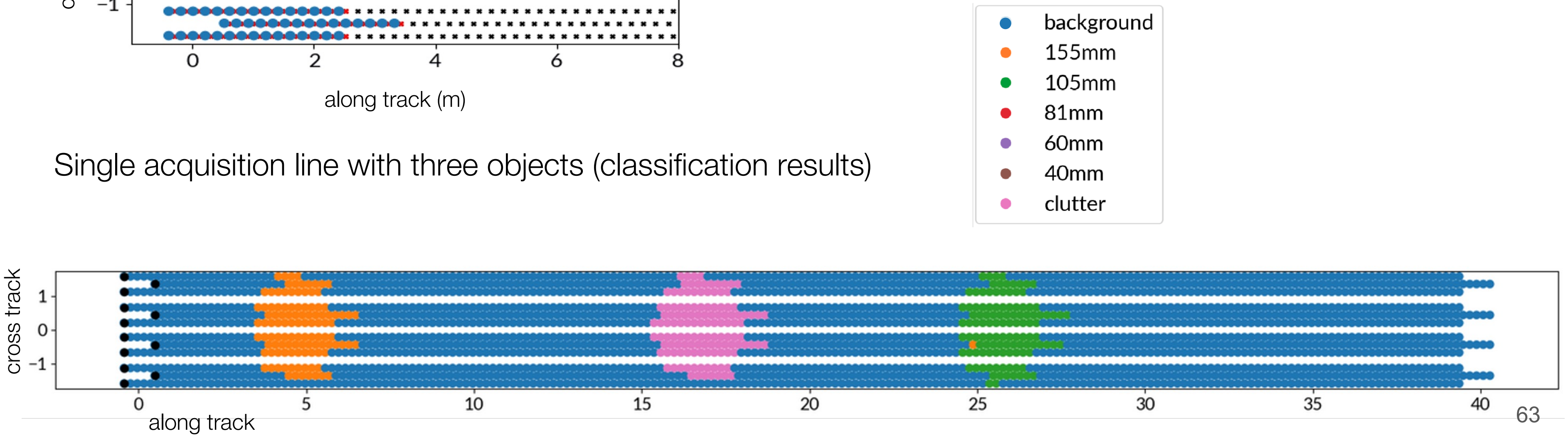


Application to a line of data

Input features are created by using a sliding window:



Single acquisition line with three objects (classification results)



Training dataset: dipole forward model

7 classes:

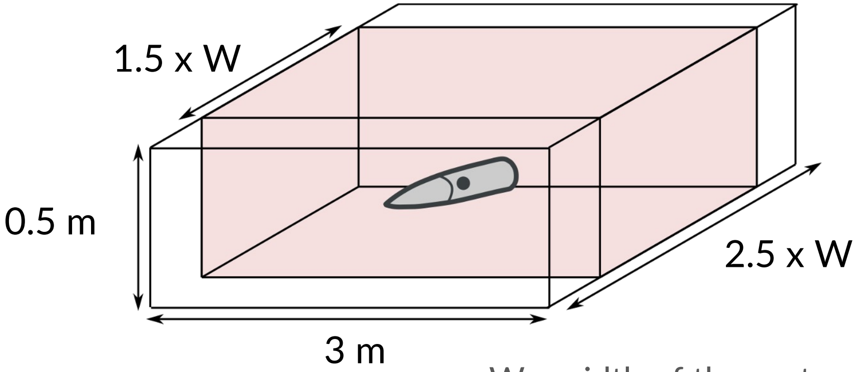
- background
- 155 mm
- 105 mm
- 81 mm
- 60 mm
- 40 mm
- clutter

# of realizations:

- Training (multi-class): 400,000
- Validation: 10,000

Randomly assign:

- Target class
- Location (x, y, z)
- Orientation (ϕ, θ, ψ)
- Noise level: approximate from background areas in the field data



W - width of the system

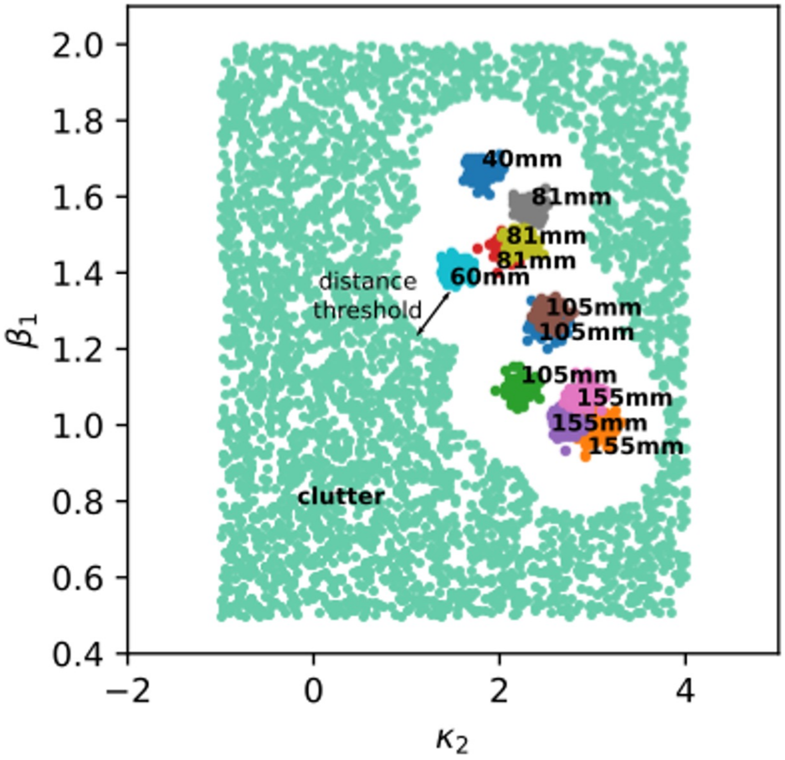
Clutter design

Physics-based parameterization of EM decay:

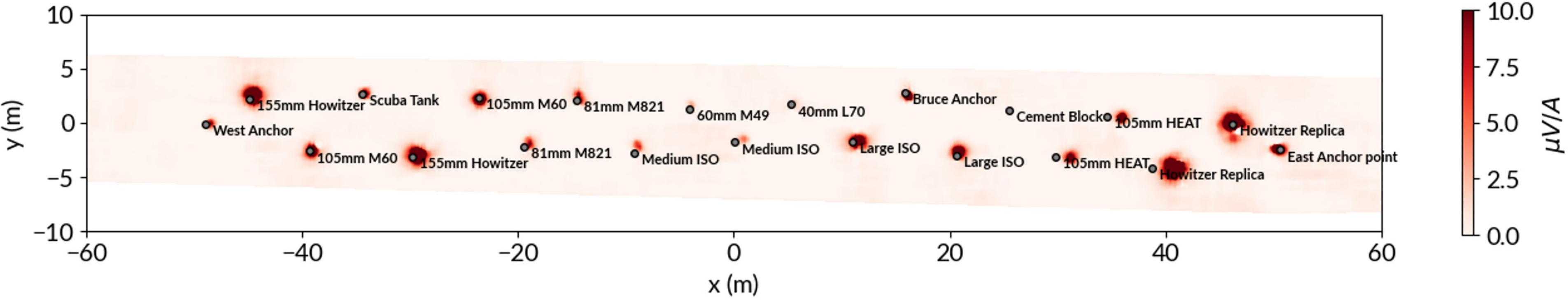
$$L(t) = kt^{-\beta}exp(-t/\gamma)$$

9 parameters in total:

1. Estimate values for UXOs in ordnance library
2. Define a distance threshold
3. Fill the remaining space with clutter objects

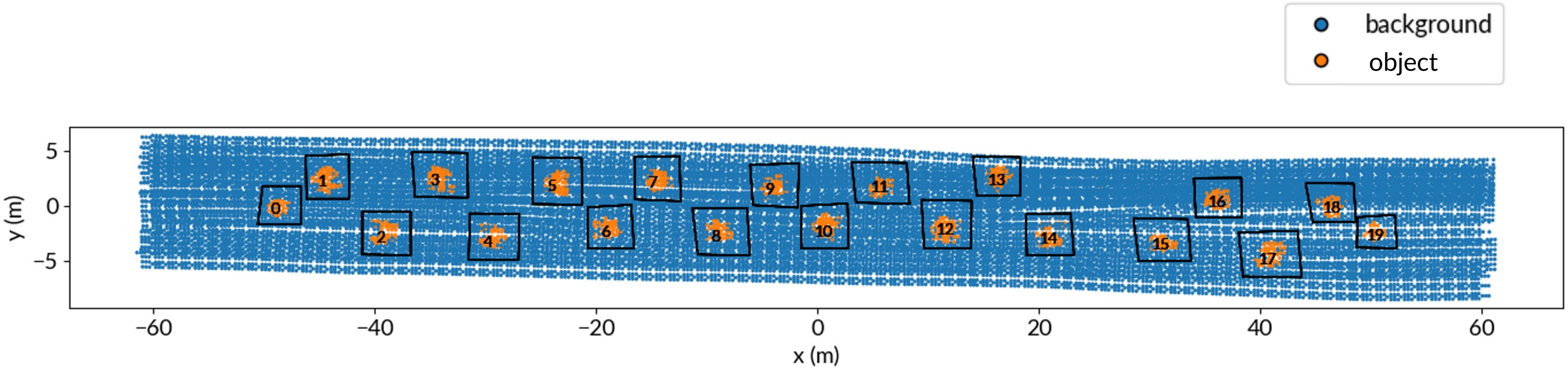


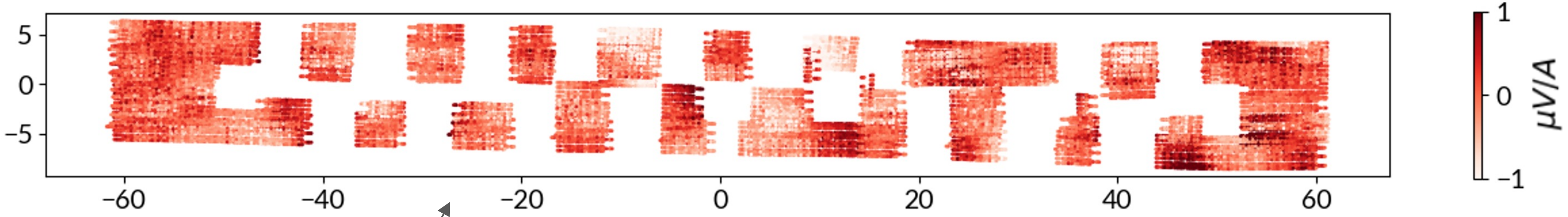
Field data - Sequim Bay test site (2022)



- 7 acquisition lines
- Current workflow requires seawater response removed
- Some ISOs present, we used only UXO objects to train (e.g. medium ISO ~ 81mm)

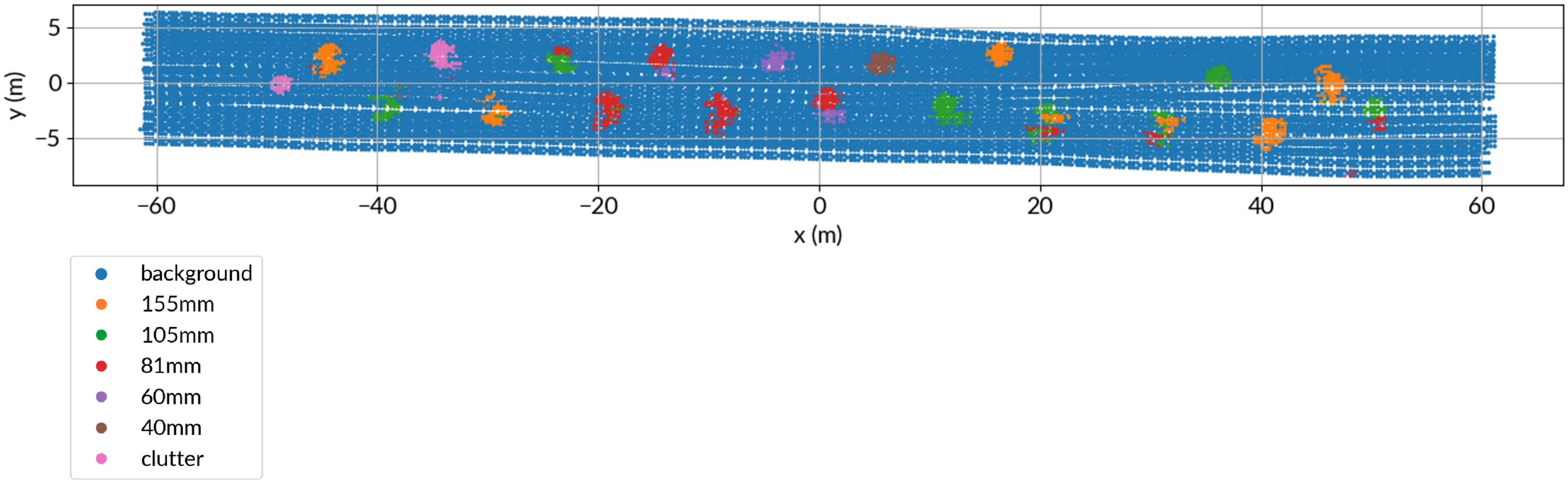
Get correlated noise using a binary classifier



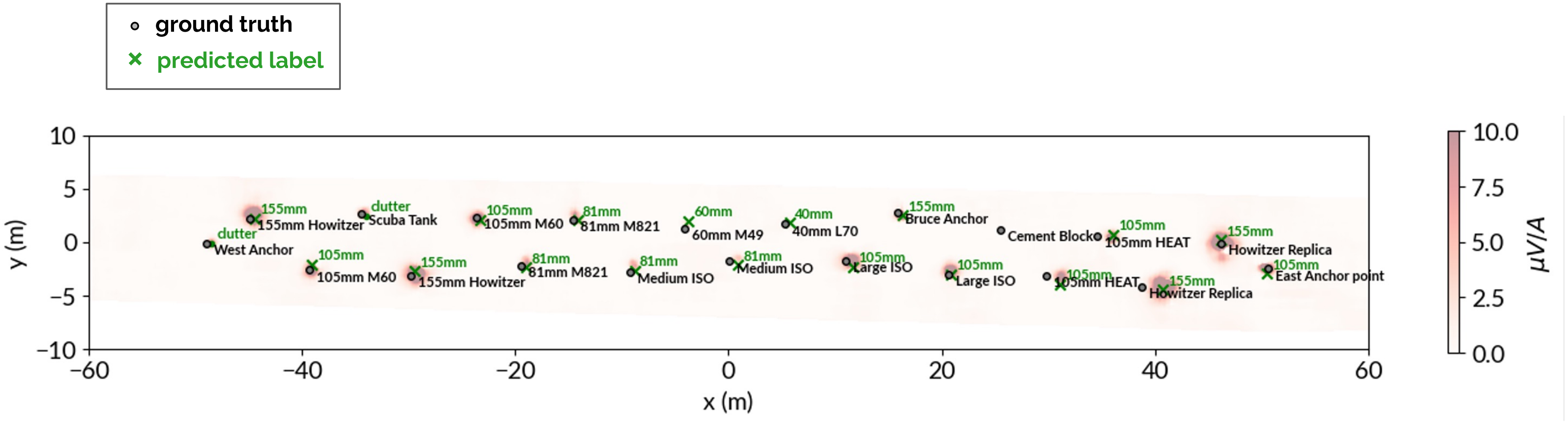


get spatially correlated noise from this subset of field data

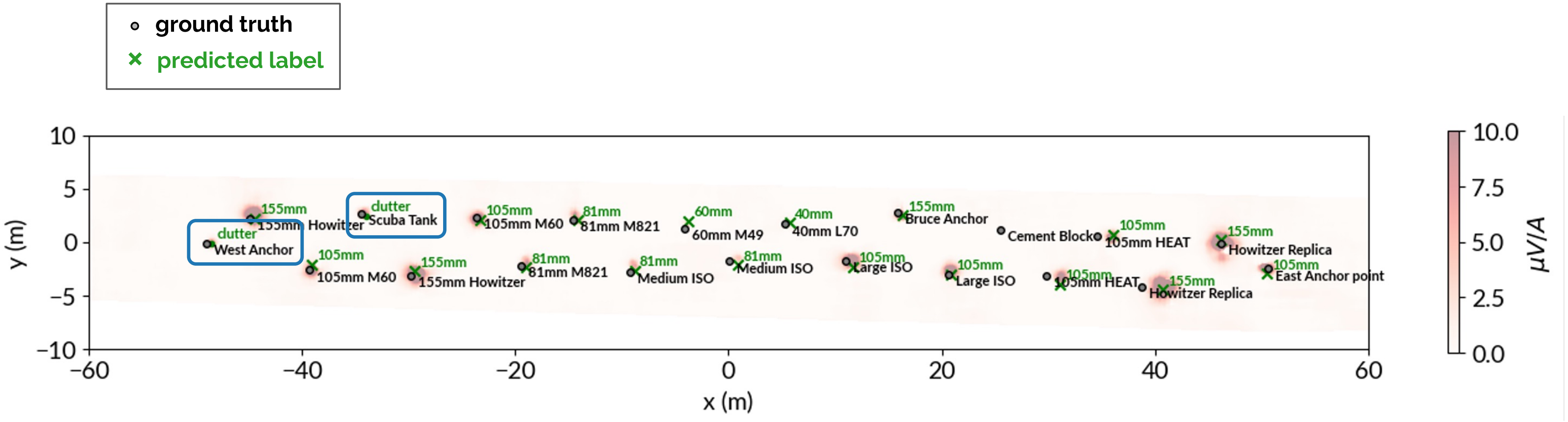
Classification map (output of CNN)



Predicted labels vs truth labels - field data

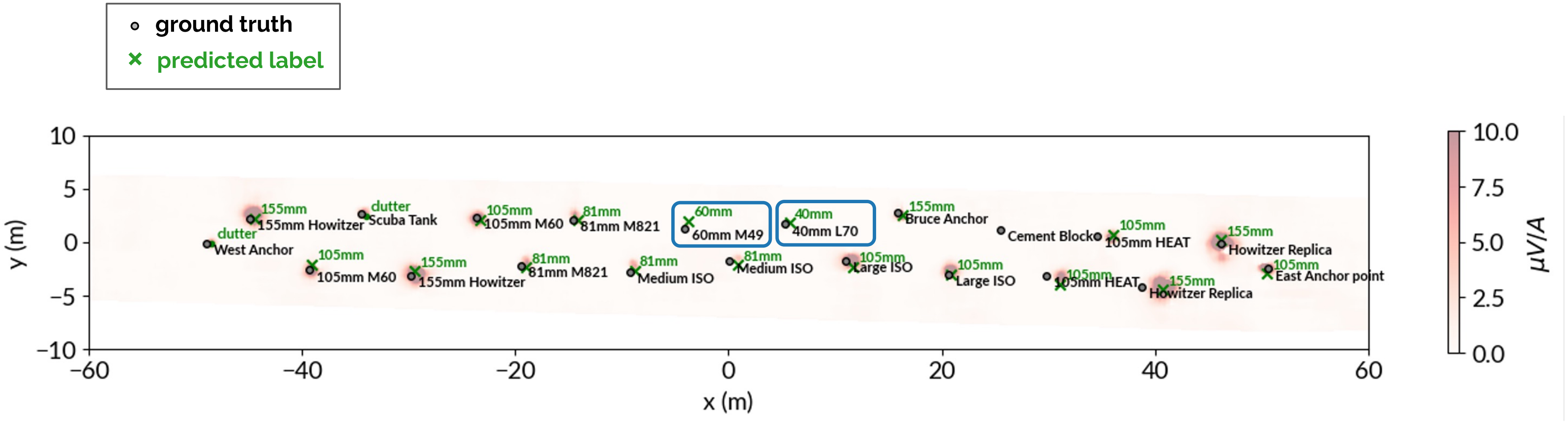


Predicted labels vs truth labels - field data



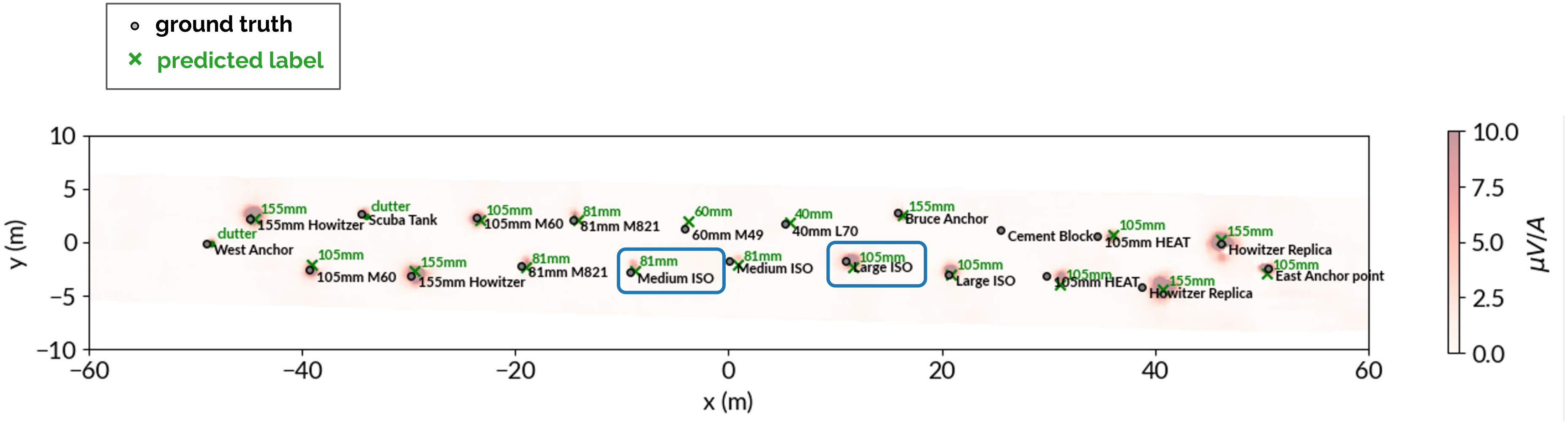
- Discriminated clutter

Predicted labels vs truth labels - field data



- Discriminated clutter
- Did not miss any UXO

Predicted labels vs truth labels - field data



- Discriminated clutter
- Did not miss any UXO
- Classified to closest object in training dataset

UXO classification

Key points:

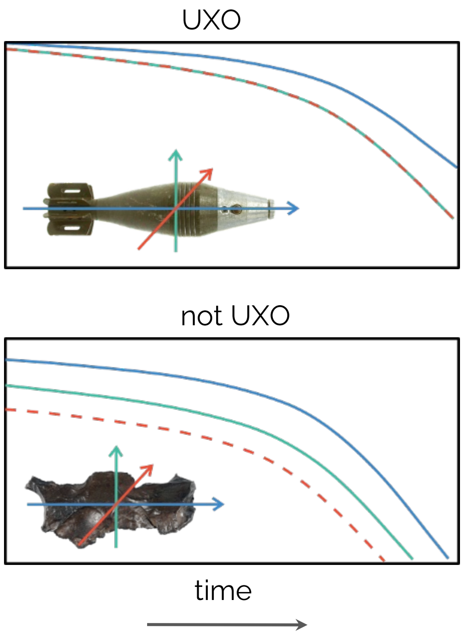
- image-segmentation architecture
- clutter design and correlated noise are important

Some limitations:

- not trained to handle multiple objects in the same window
- objects used to generate synthetic data should be close to the objects on the field

Future work:

- explore multi-target scenario
- combining with traditional approach



important problems

Electrical conductivity can be a diagnostic physical property in many settings

Electromagnetic methods can be useful across a wide range of scales

Numerical tools for simulation, inversion, machine learning enable understanding of physical responses, invaluable for interpretation of data

Thank you!

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