



# A Lightweight, Flexible, Multitask AI Pipeline for Geophysical Inversion

Innovations in Geophysics, Hydrogeology, and Biogeochemistry to Advance Subsurface Characterization and Monitoring Solutions

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Collaborators  
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PNNL is operated by Battelle for the U.S. Department of Energy





## Remediation challenge: locating and characterizing historical infrastructure

- Infrastructure locations are not always well-documented, particularly at legacy waste sites which include substantial anthropogenic infrastructure. We need fast, cost-effective methods to locate this infrastructure and support operations.

One example: Hanford

- The 2025 Hanford Lifecycle Scope, Schedule, and Cost Report lists the remediation of pipelines as a major objective in coming decades. In 2039-2041, pipeline remediation at Hanford is projected to cost approximately \$50M per year, about a quarter of all yearly costs.
- Site contains waste tanks and many miles of historical pipelines that are 50+ years old.



## Our goal: Real-time, AI-based inversion algorithms

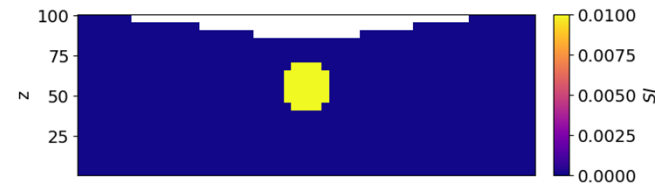
- We demonstrate an AI model for infrastructure detection on real-world surveys by corporate partner Exodigo.
- Work done through ARPA-E GOPHURRS project (Grid Overhaul with Proactive, High-Speed Undergrounding for Reliability, Resilience, and Security).
- Integrate geophysical methods with AI and edge computing for real-time inversion of near-surface anomalies, in support of electrical grid undergrounding.
- Our pipeline can be adjusted to novel scenarios with minimal changes.

## Geophysical methods at a glance

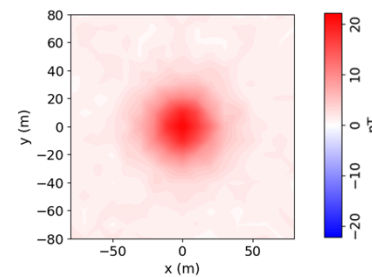
- Ground penetrating radar — Can investigate from meters to tens of meters deep. Contrasts in subsurface permittivity, conductivity, etc, reveal boundaries between objects/strata in the subsurface.
- Electromagnetic surveys — Various survey scales (centimeters to meters to kilometers). Electromagnetic induction excites currents in the ground and response reveals variations in permeability. Depth of investigation governed by frequency used.
- Magnetic surveys — Can be done at various scales (surface, airborne, etc). Earth's magnetic field induces a response in magnetically susceptible (e.g. metallic) objects in the subsurface.
- ...and many others (seismic, metal detector, induced polarization, resistivity, etc).

## Magnetic inversion (numerical approach)

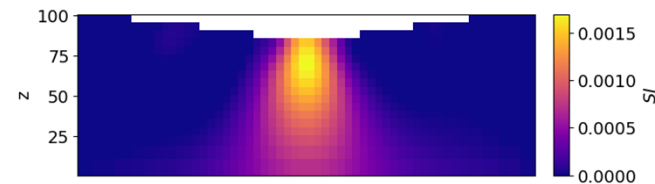
- Use numerical optimization and simulations to find a version of the subsurface that explains the surface observations
- No unique solution, expensive, slow, and sensitive to algorithm parameters



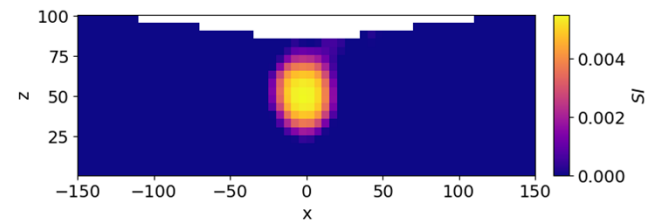
True subsurface  
(cross section in depth)



Observed surface anomaly  
(birds eye view)



Initial numerical  
inversion result



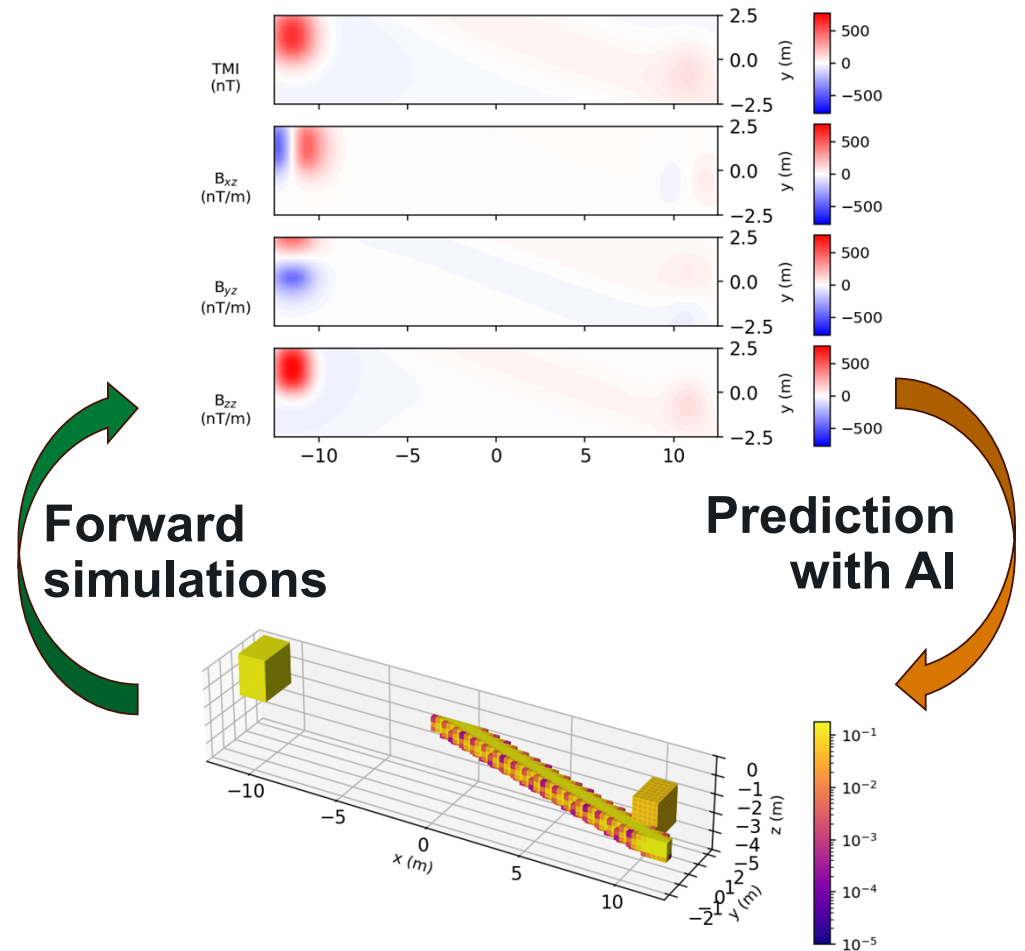
...after tweaking  
algorithm parameters

Image source: SimPEG

<https://simpeg.xyz/user-tutorials/inv-magnetics-induced-3d>

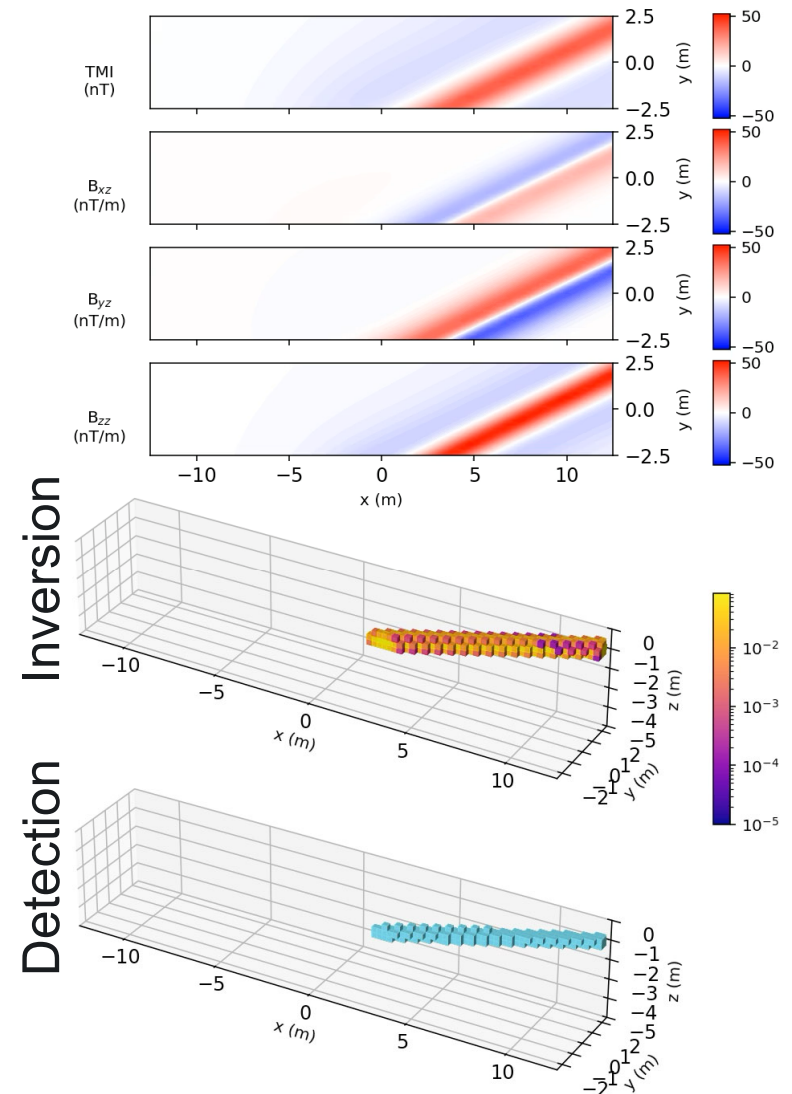
## Big picture: magnetic inversion with AI

- Create many data pairs (*subsurface, anomaly*) using forward simulations via open source SimPEG package
- Train a convolutional neural network (CNN) to predict the subsurface based on the anomaly



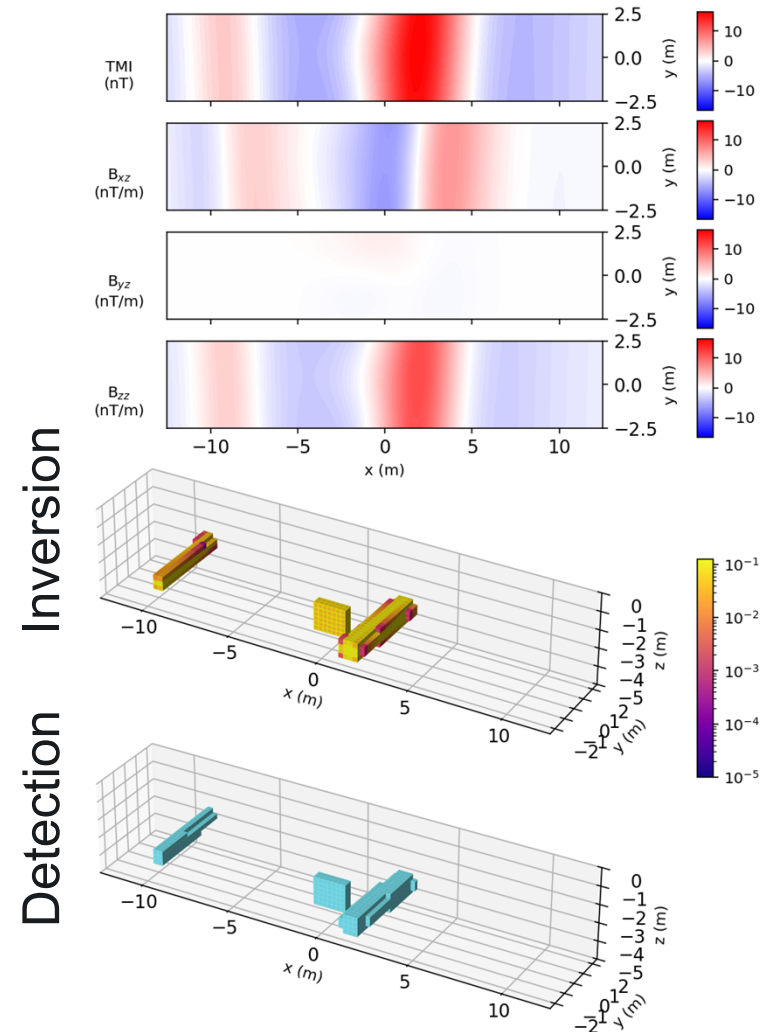
## Our training data

- **Subsurface:** 25m x 5m x 5m volume discretized into 40,000 cubes
- **Survey:** 25m x 5m grid of 3,125 receivers, capturing total magnetic field and vertical derivatives
- **160,000 data**, (~60GB) with randomly varying buried objects
- **Multitask approach:** simultaneous inversion and anomaly detection. To our knowledge, our work is the first to train a model for multitask prediction with magnetic data

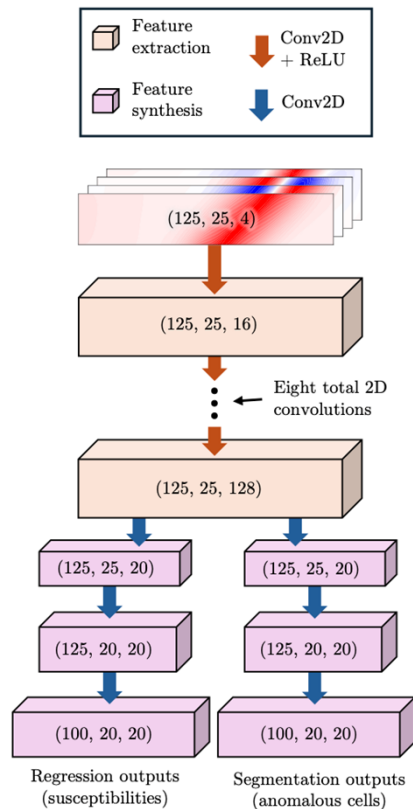


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## AI architecture — our model



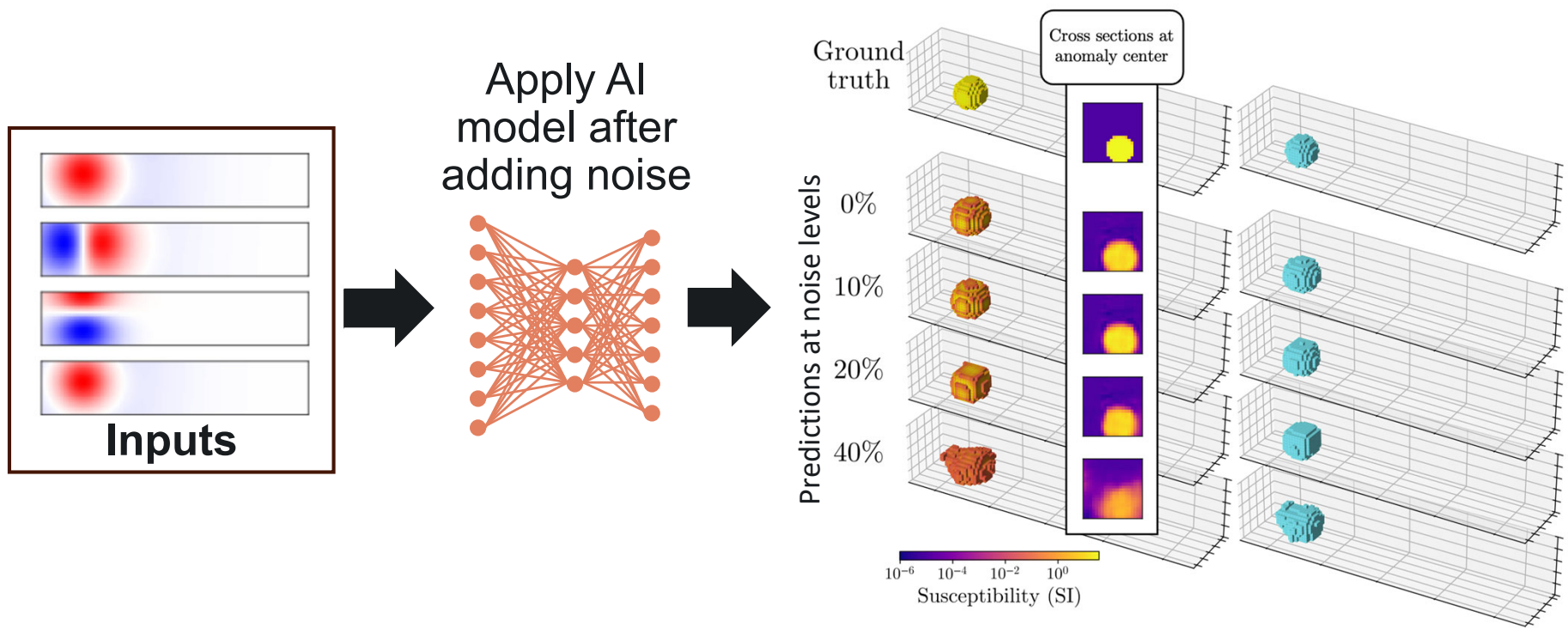
**Encoder:** Eight ordinary convolutional layers

**Decoders:** Three convolutions to interpolate data to the correct shape while simultaneously synthesizing features

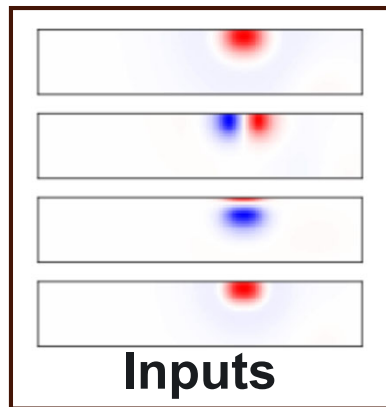
### Key specs:

- 968,000 parameters (< 4MB in memory)
- Performs inversion in a fraction of a second once trained
- Flexible to different input shapes — pipeline can be applied to different survey configurations, subsurface meshes, etc

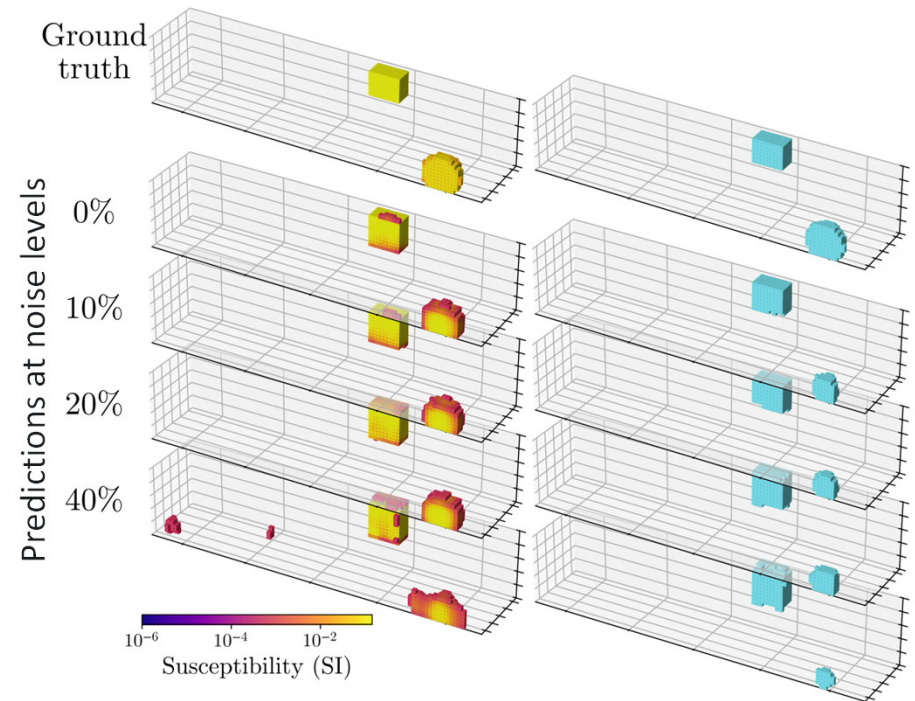
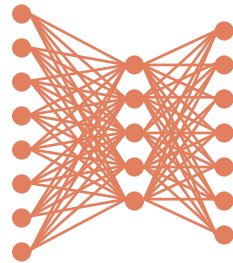
# Model performance — a qualitative look



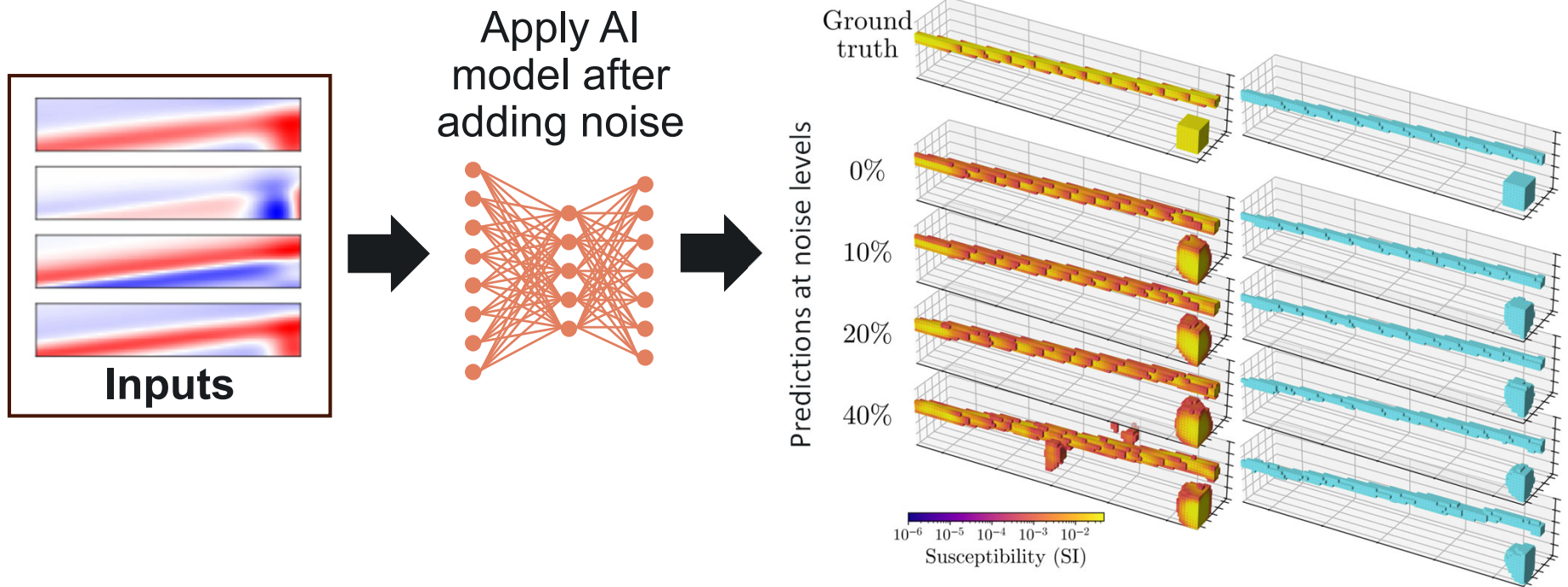
# Model performance — a qualitative look



Apply AI  
model after  
adding noise



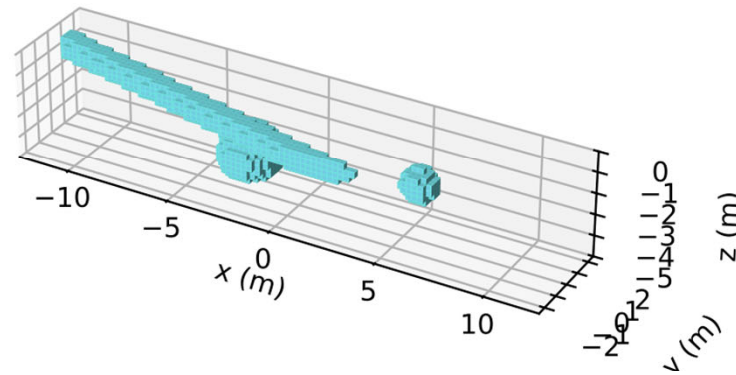
## Model performance — a qualitative look



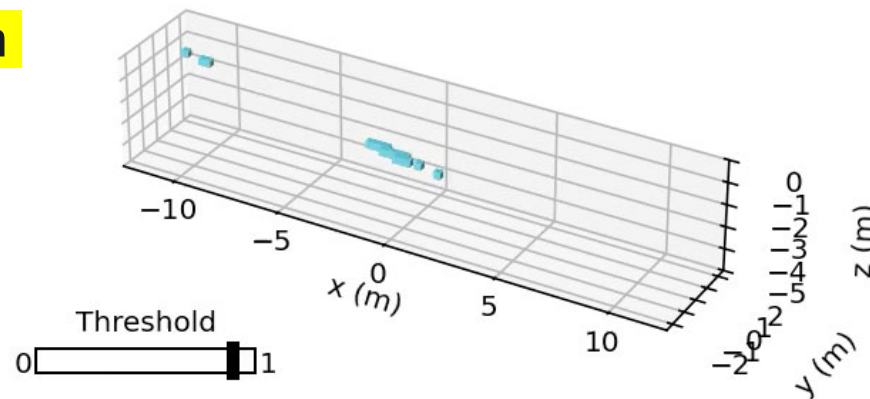
## Model performance — thresholding

Our model outputs probabilities for the segmentation mask

Can vary detection confidence threshold to support **robust decision making in the field**



**True anomaly mask**

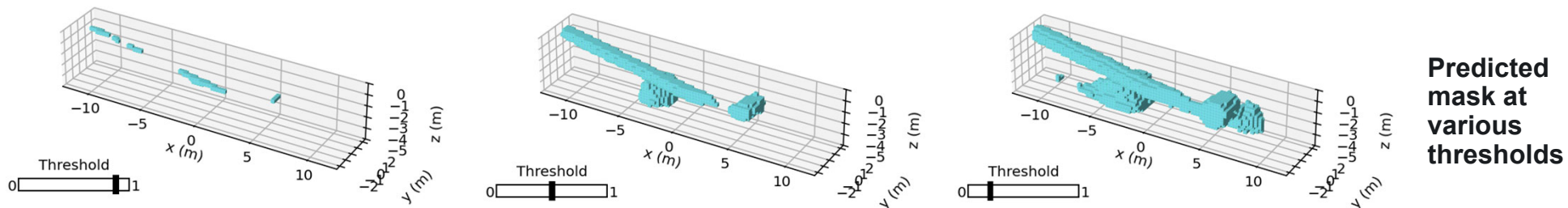
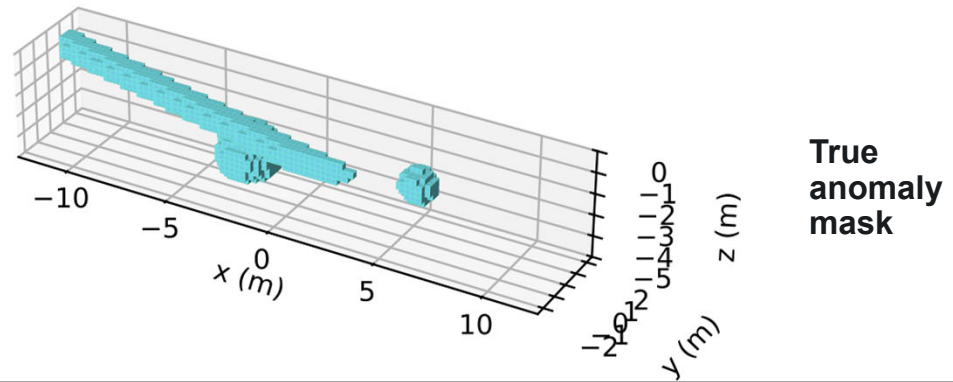


**Predicted mask at changing threshold**

## Model performance — thresholding

Our model outputs probabilities for the segmentation mask

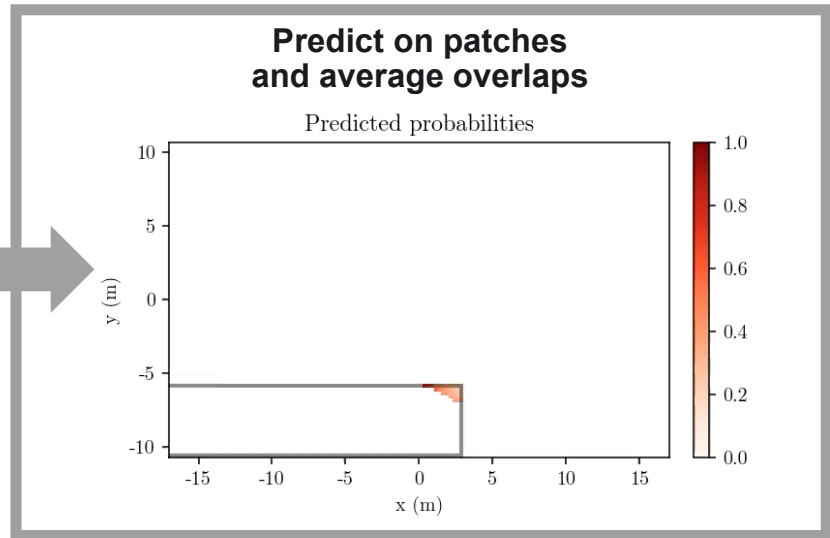
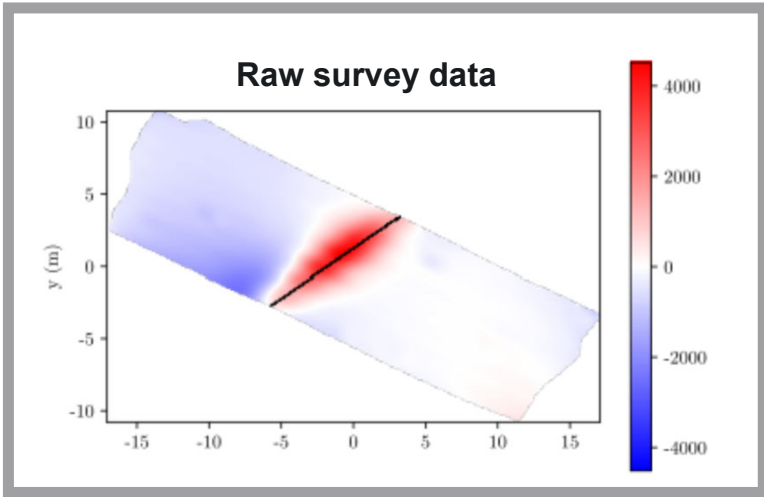
Can vary detection confidence threshold to support **robust decision making in the field**



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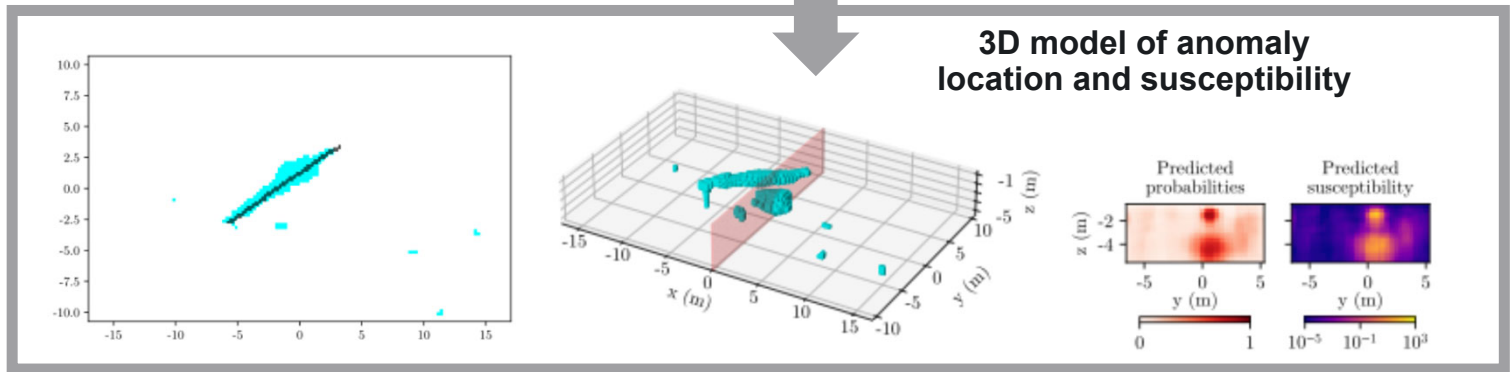
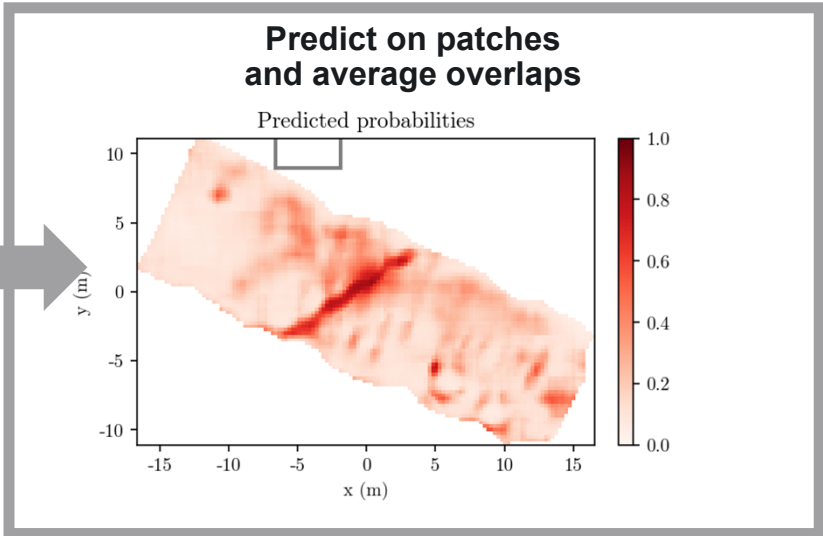
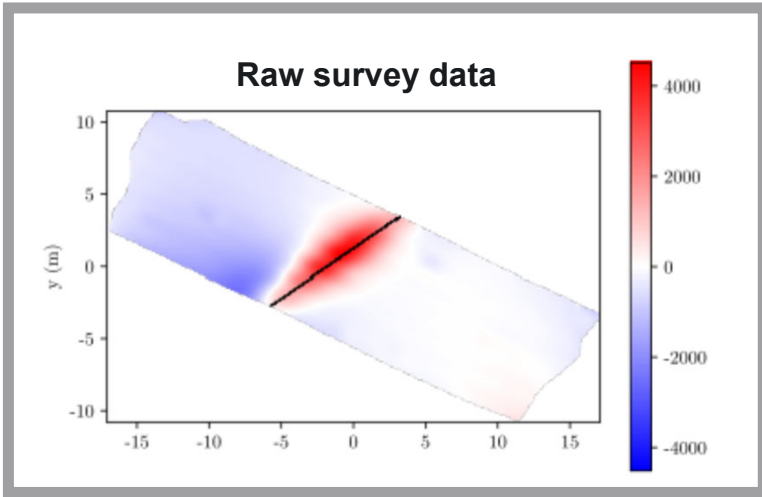
# Model performance — Exodigo field data



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# Model performance — Exodigo field data

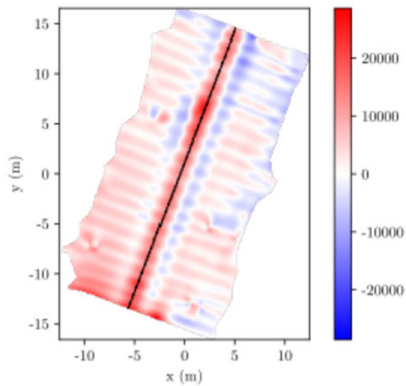




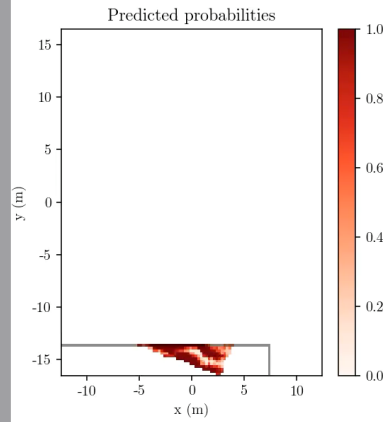
# Model performance — Exodigo field data



**Raw survey data**

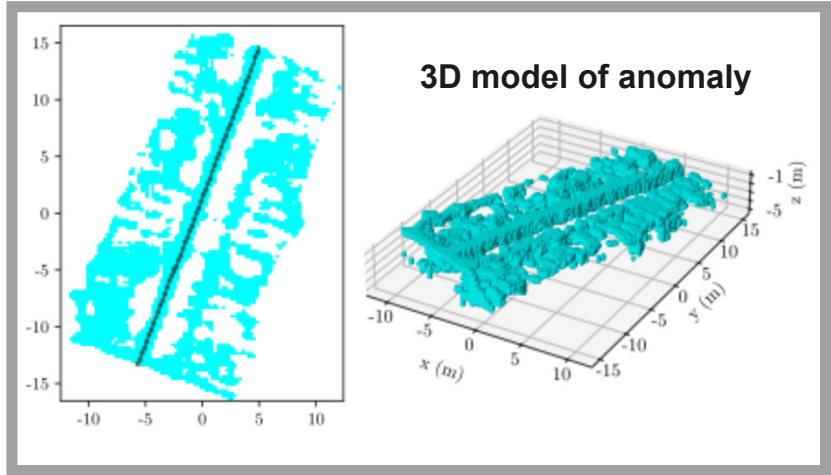
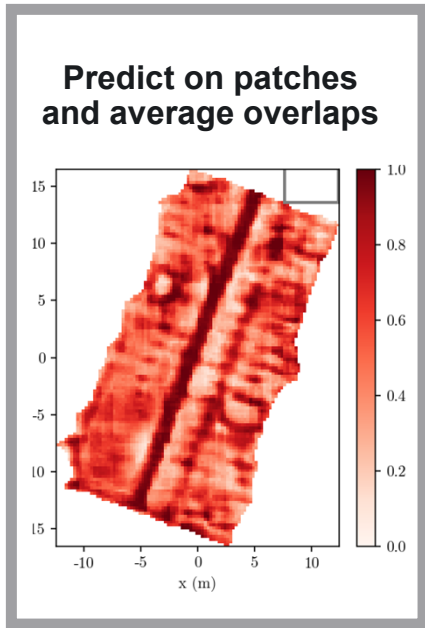
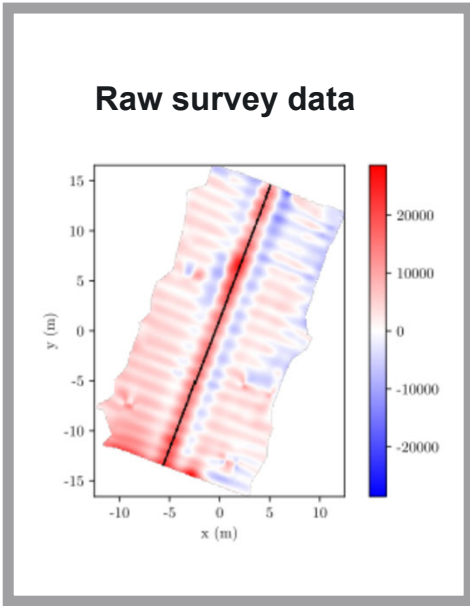


**Predict on patches and average overlaps**





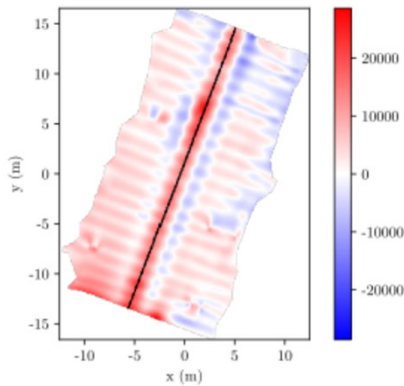
# Model performance — Exodigo field data



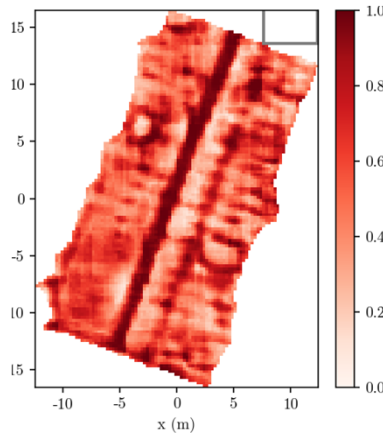
# Model performance — Exodigo field data



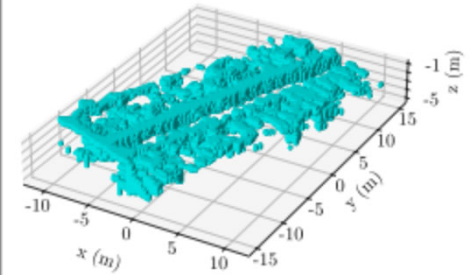
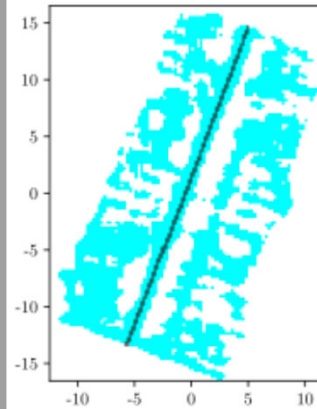
Raw survey data



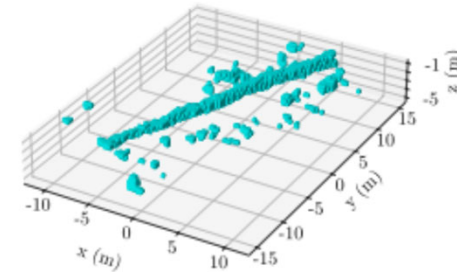
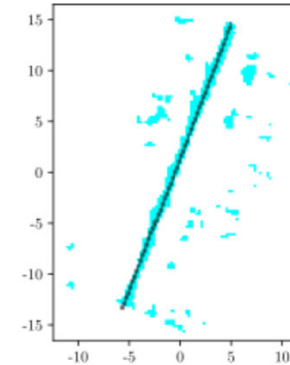
Predict on patches and average overlaps



3D model of anomaly



Adjust threshold to isolate anomaly





**Disclaimer:** The Advanced Research Project Agency-Energy (ARPA-E) within the U.S. Department of Energy supported this work under grant no. FWP 3047-1514. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States Government or any agency thereof.



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*Data Scientist & Computational Geophysicist*



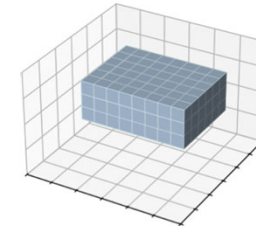
**Fred Day-Lewis**  
*Lab Fellow, Chief Geophysicist*

## Bonus: precision, recall, and fuzzy versions

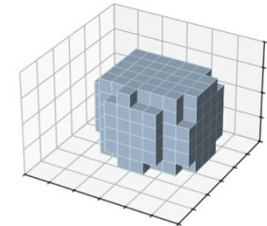
**Precision** describes how accurate the predicted anomaly is.

**Recall** describes how much of the true anomaly we correctly recover.

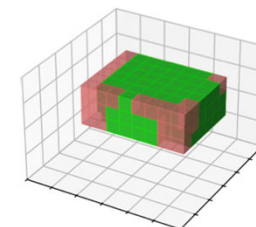
**Fuzzy** versions of these metrics allow one voxel of tolerance in the computations, i.e. 0.25m tolerance in the predictions.



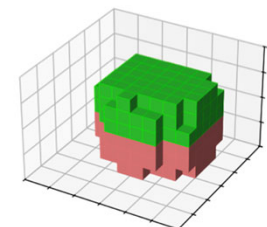
True anomaly



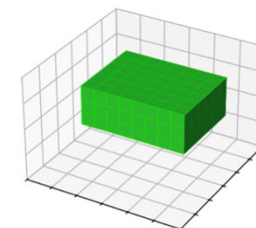
Predicted anomaly



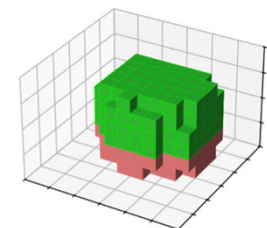
True positives: 117  
False negatives: 27  
Recall:  $117/144 = 81.2\%$



True positives: 117  
False positives: 119  
Precision:  $117/236 = 49.6\%$



True near predicted: 144  
True far away: 0  
Fuzzy recall:  
 $144/144 = 100\%$



Predicted near true: 159  
Predicted far away: 77  
Fuzzy precision:  
 $159/236 = 67.4\%$



# Bonus: forward response on Exodigo predictions

