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Potential Fields Modeling to Support Machine Learning Applications in Maritime Environments

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Port of Gulfport, Gulfport MS

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The Roger F. Wicker Center for Ocean Enterprise is Located at the Port and is comprised of two buildings on Port property: The Marine Research Center (MRC), and the Roger F. Wicker Ocean Enterprise Facility (Wicker Building or OEF)

Motivation

Unmanned Underwater Vehicles (UUVs) equipped with magnetic sensors are crucial for detecting ferromagnetic objects underwater. Accurate modeling of the magnetic and gravitational field interactions in these environments ensures the effectiveness of detection operations.

- Numerical modeling potential fields in maritime settings is important
  - UXO
  - Archeological Items (e.g. shipwrecks)
  - Geological features
- Field experiments are complex
- Data collection areas are cluttered
- Calibrated simulations are ideal to generate quality training data to develop ATRs using AI/ML techniques
- Multiphysics modeling can be important (magnetic/gravity/acoustics)

UUV SideScan Testing in Shallow Harbor

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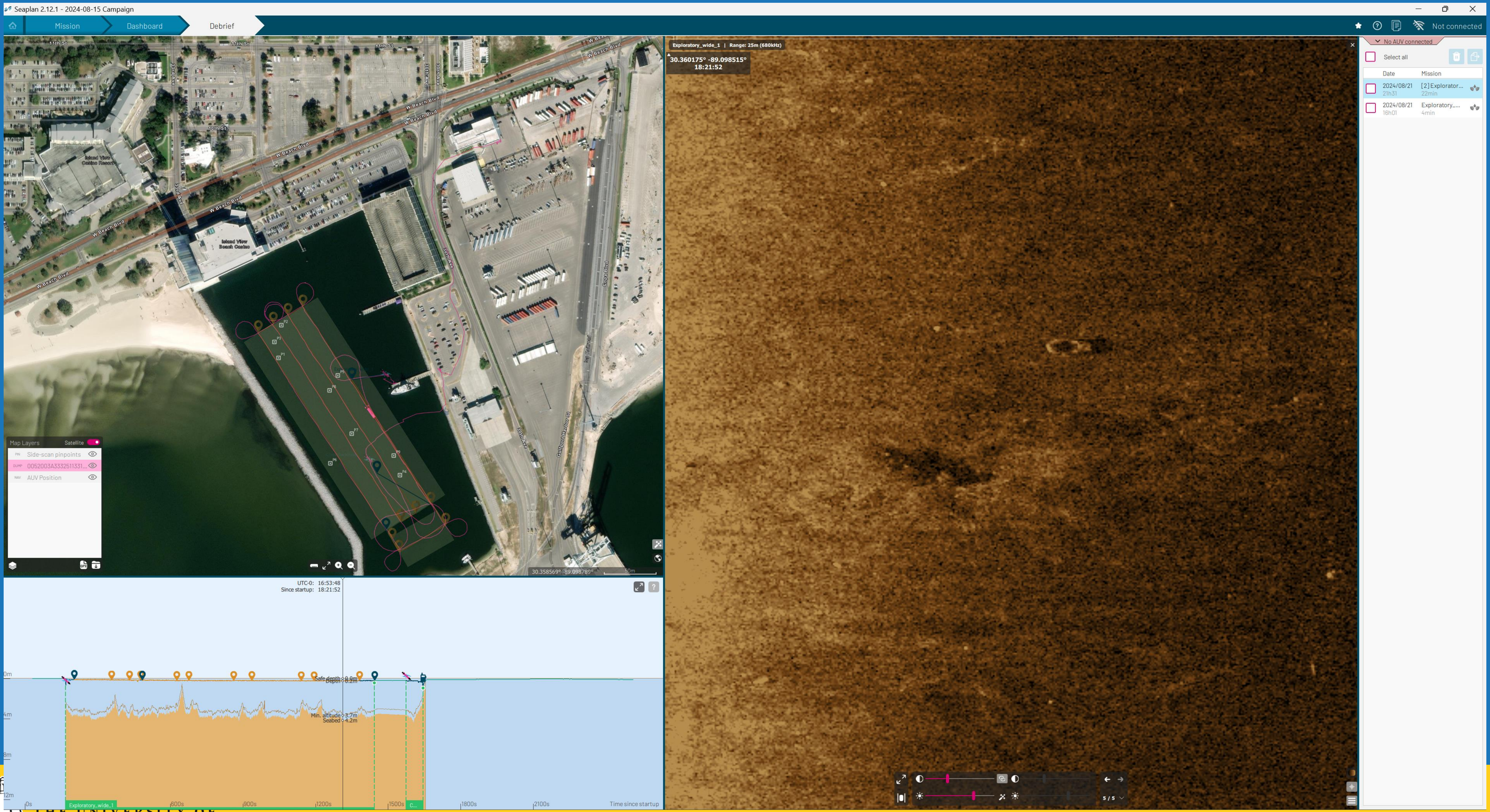

UUV SideScan Testing in Shallow Harbor

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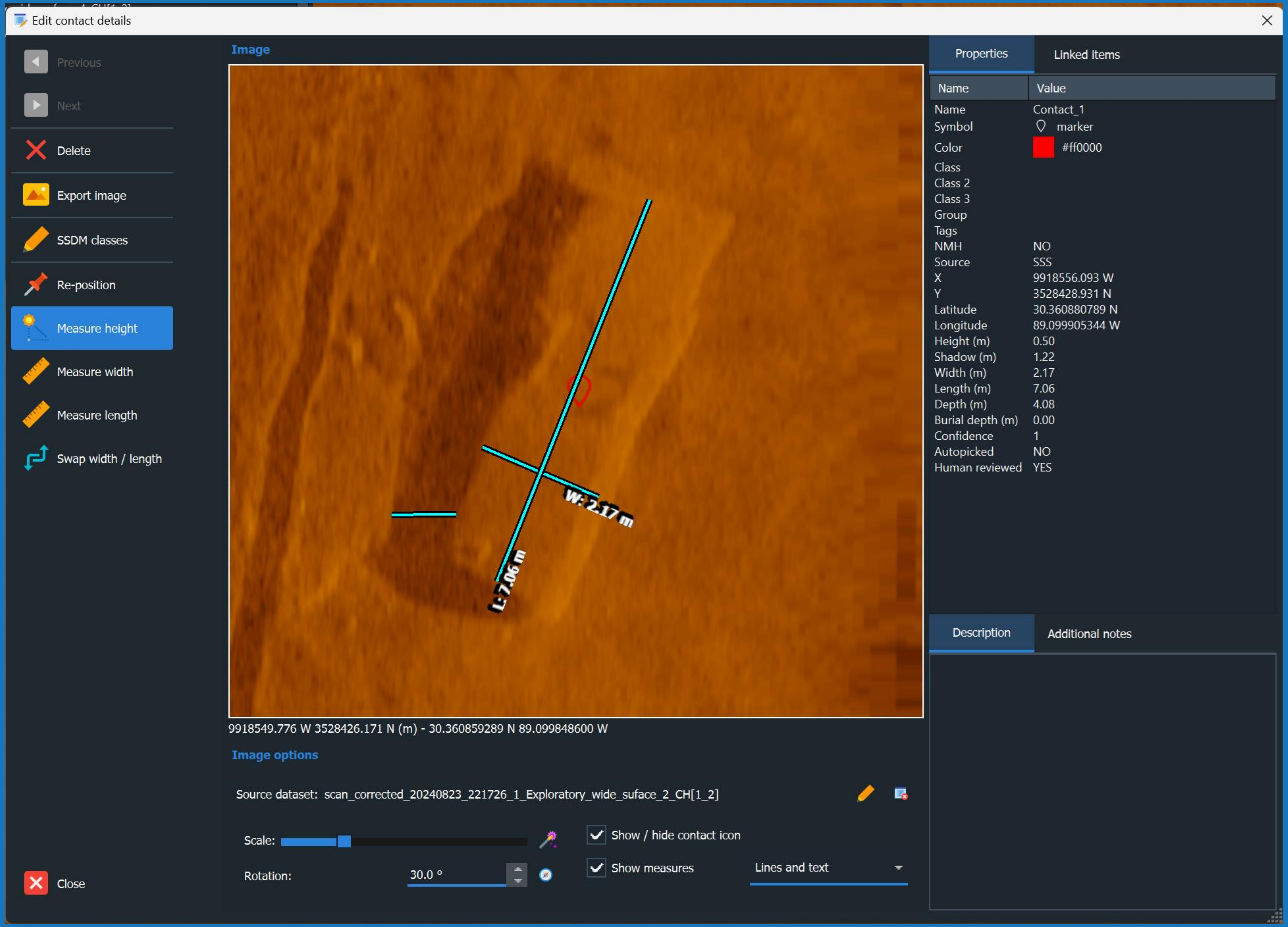

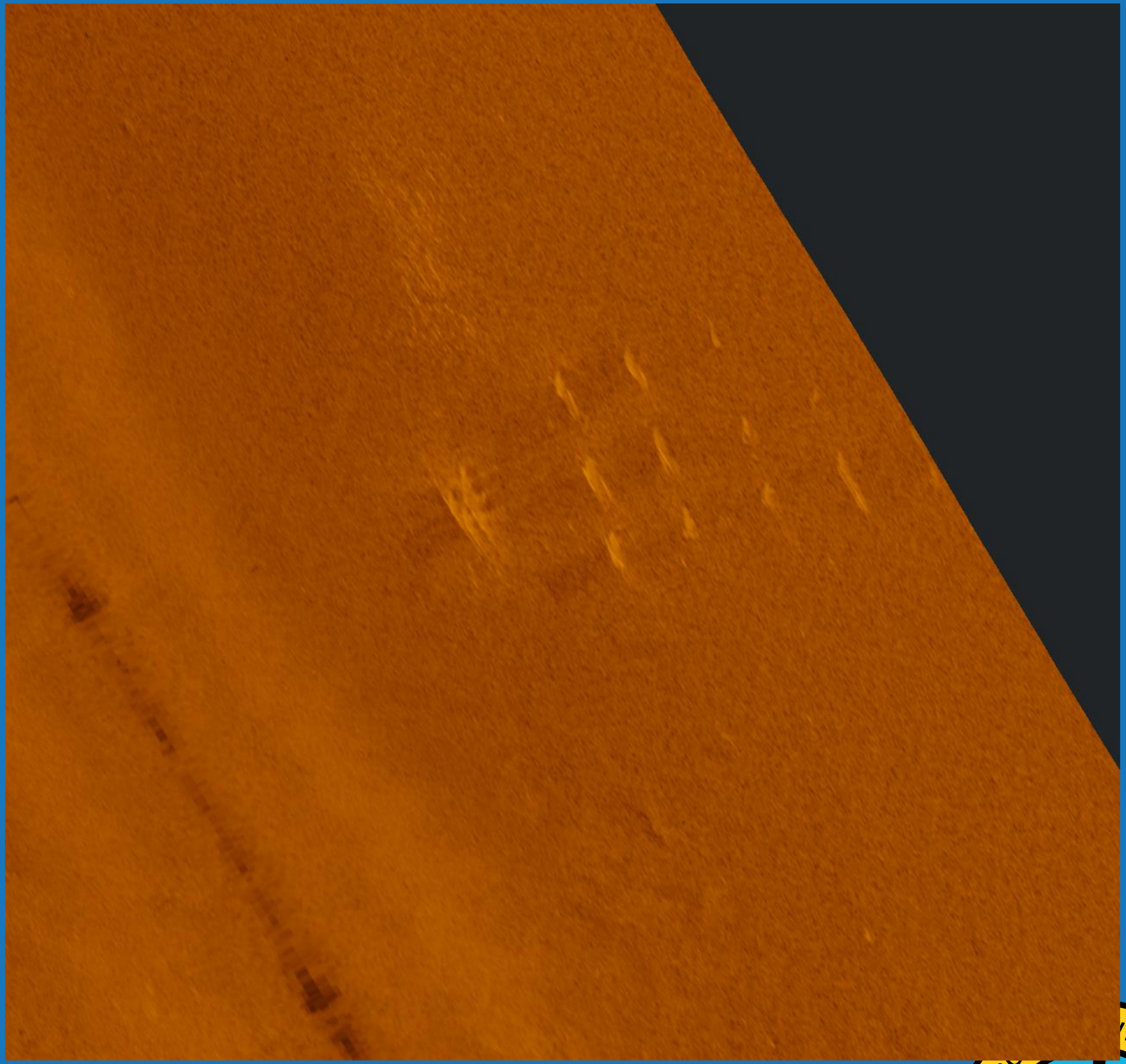

Background Theory

First Order Modeling: Earth's Magnetic Field Induces the Observed Anomaly

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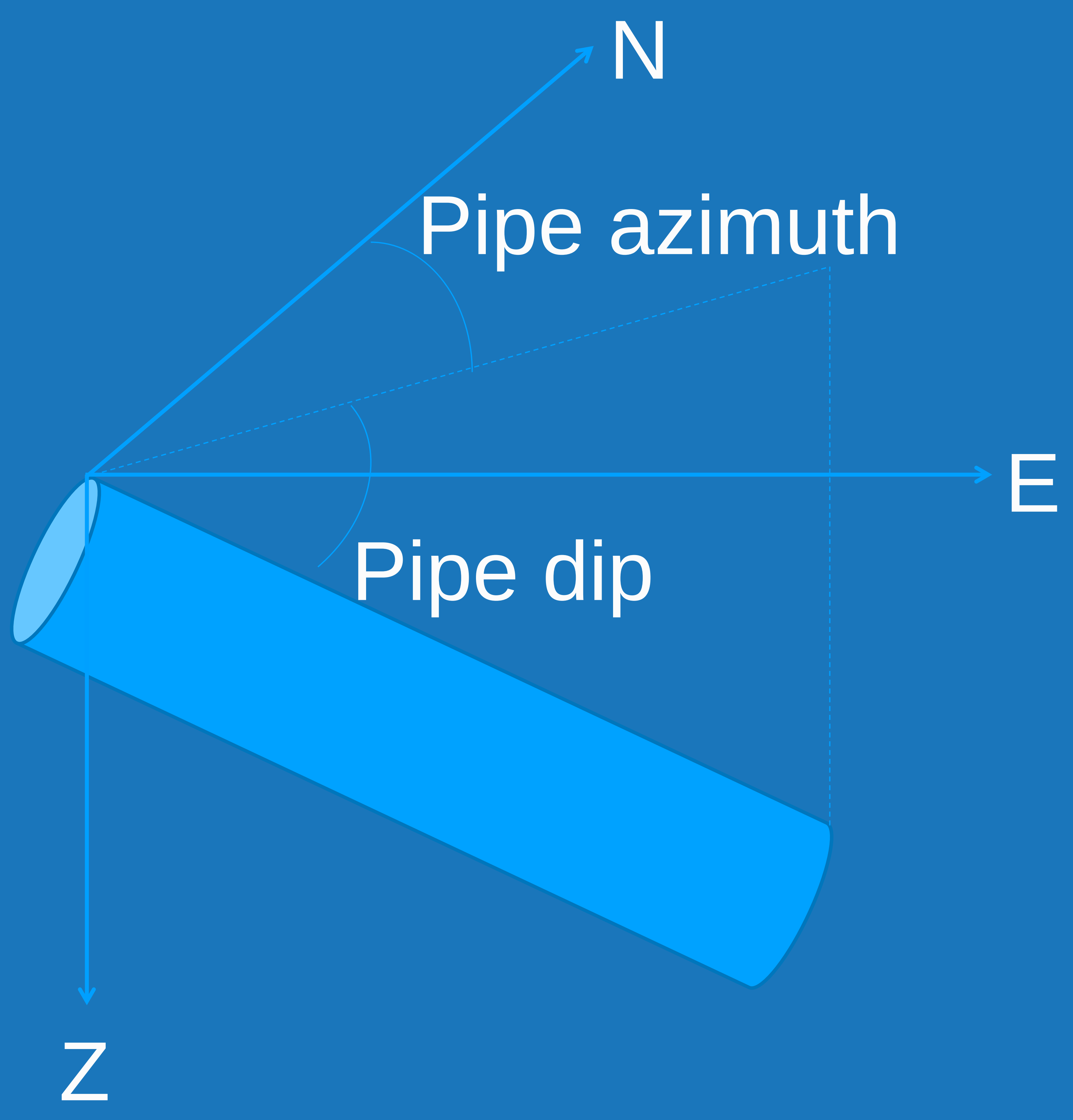
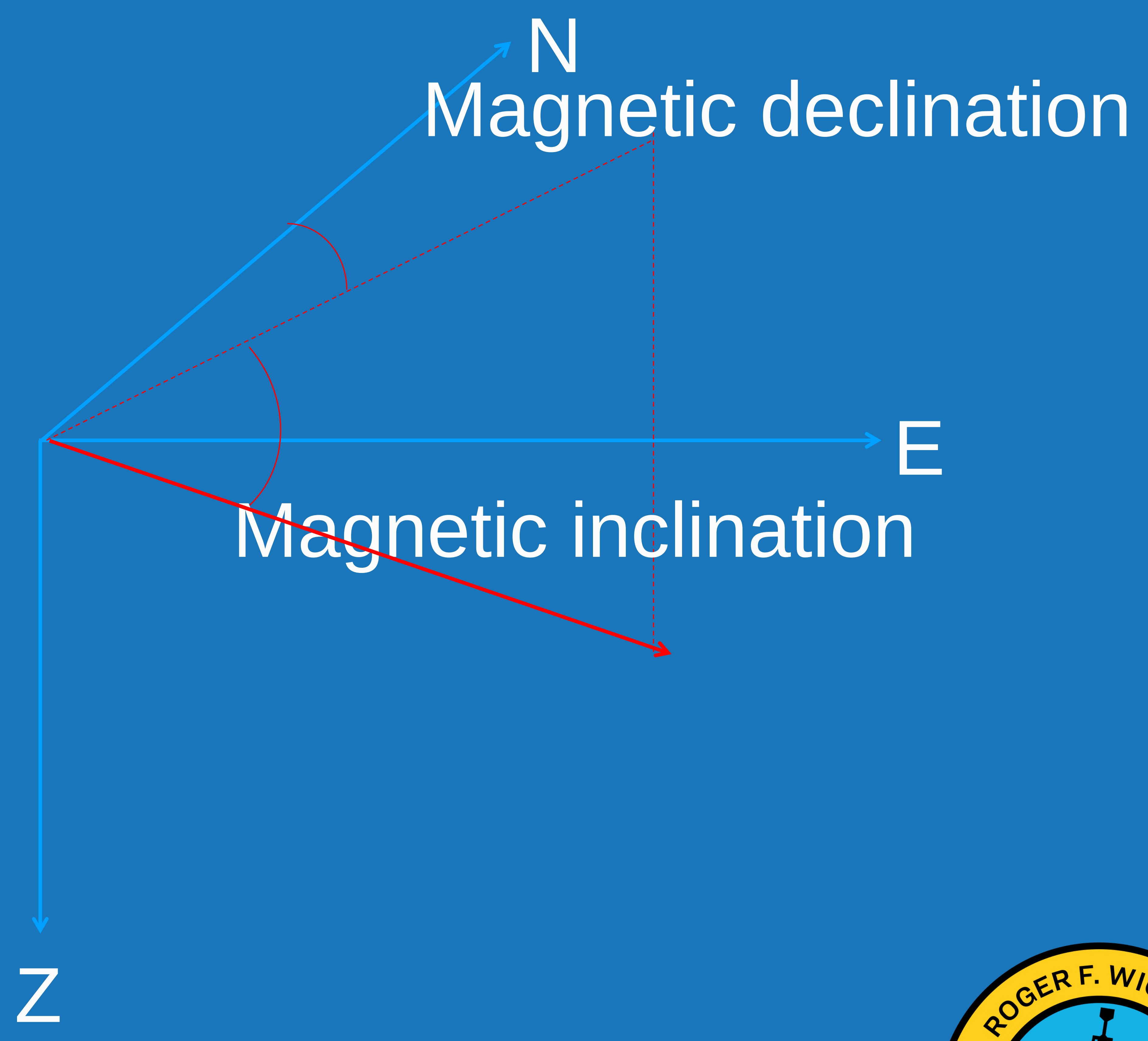
Angles needed to calculate the perpendicular and parallel components of B_0





First Order Modeling: Earth's Magnetic Field Induces the Observed Anomaly

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- For assumed relative permeability 2, 5, 50, 100, 200, 500, corresponding susceptibility k would be 1, 4, 99, 199, and 499

- For the direction perpendicular to the pipe, the effective susceptibility is given below with N being the self-demag factor (*N=1*)

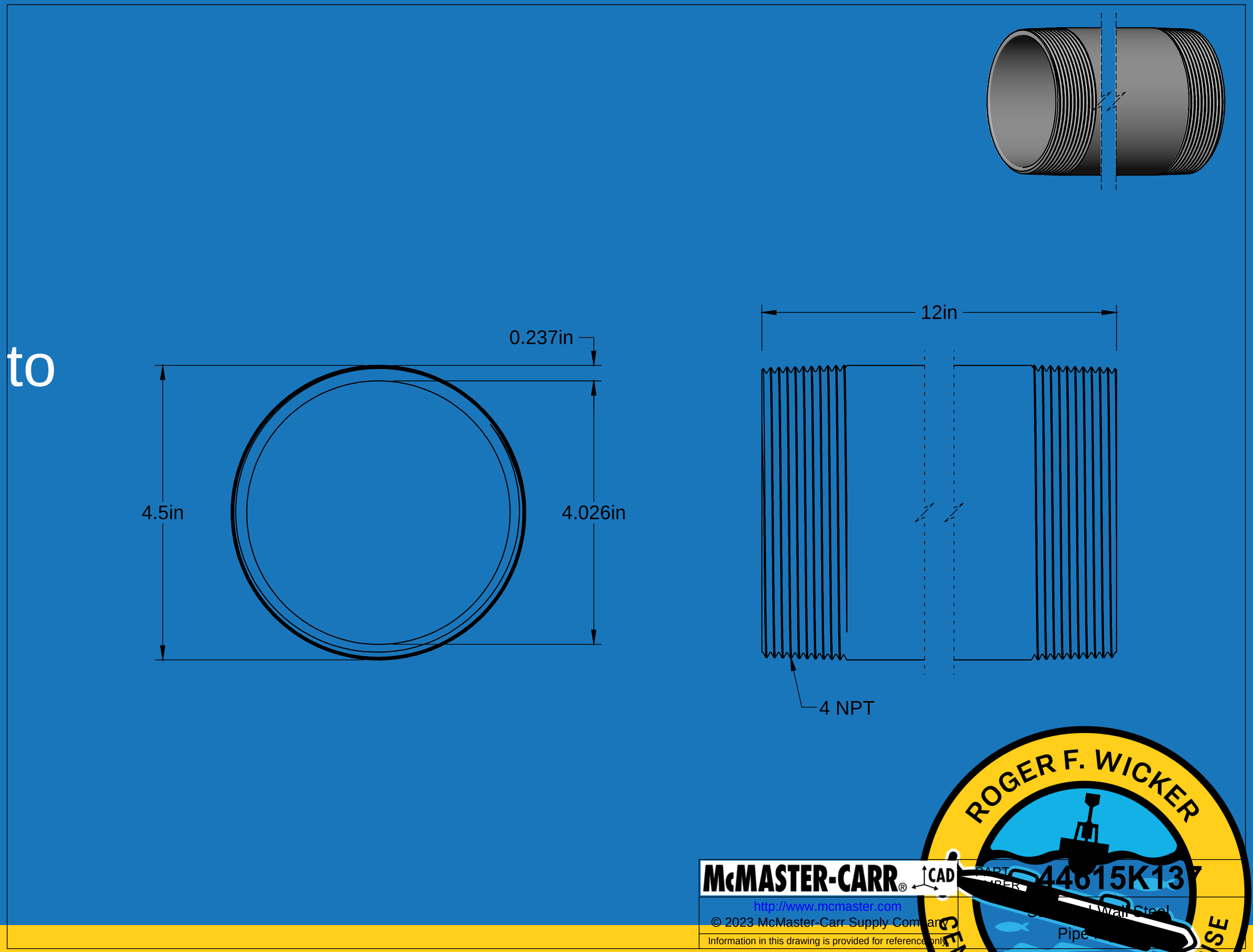
$$\kappa_e = \frac{\kappa}{1 + N\kappa}$$

- Along the pipe length, the self-demag factor is approximately 0

- For the first order modeling, we do the following:
  - Calculate the pipe volume, and equivalent spherical radius
  - Project the inducing field to two components: (1) perpendicular to the pipe and parallel to the pipe
  - Obtain the magnetization for both directions:

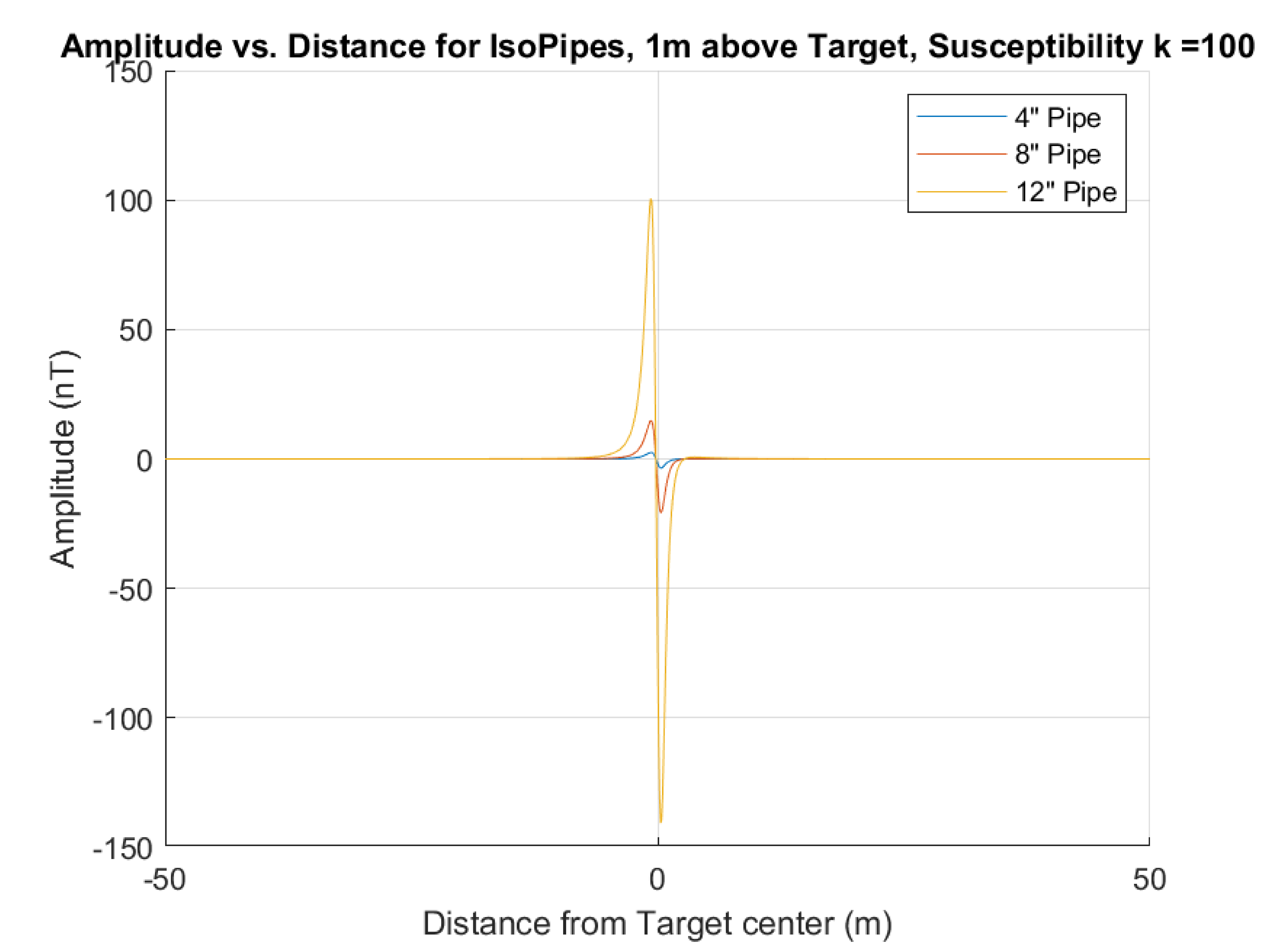
$$J^{\perp} = \kappa_e B_0^{\perp} / \mu_0 \qquad J^{||} = \kappa_e B_0^{||} / \mu_0$$

  - Calculate the responses by using a sphere with the above magnetization and equivalent volume of the pipe



Frist Order Modeling: Earth's Magnetic Field Induces the Observed Anomaly

- Assumptions: large stand-off distance (~5x target size)
- Approximations: dipole representation
- Inputs: calculated dipole moment
- Outputs: magnetic anomaly



Field Data

USV/UUV Platforms

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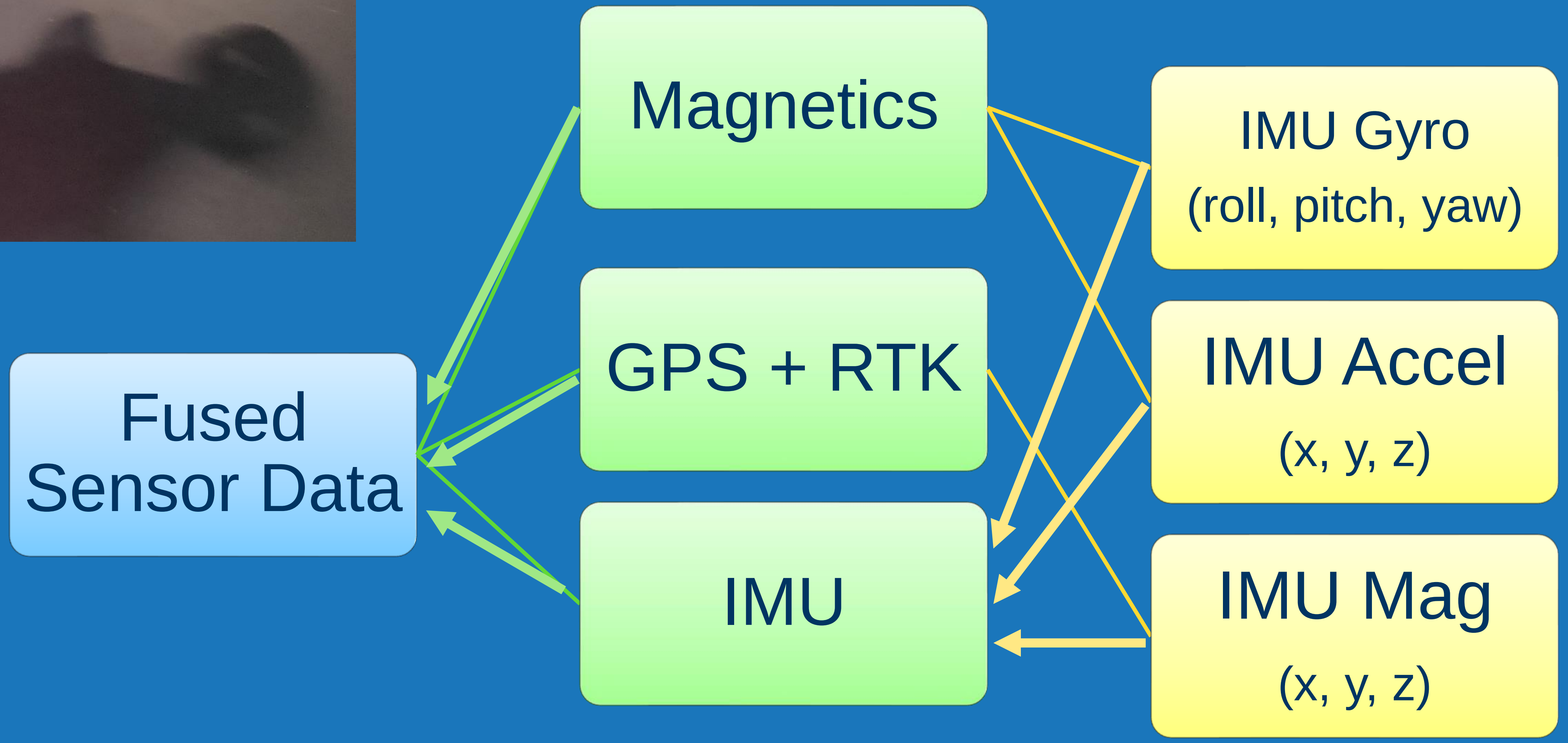

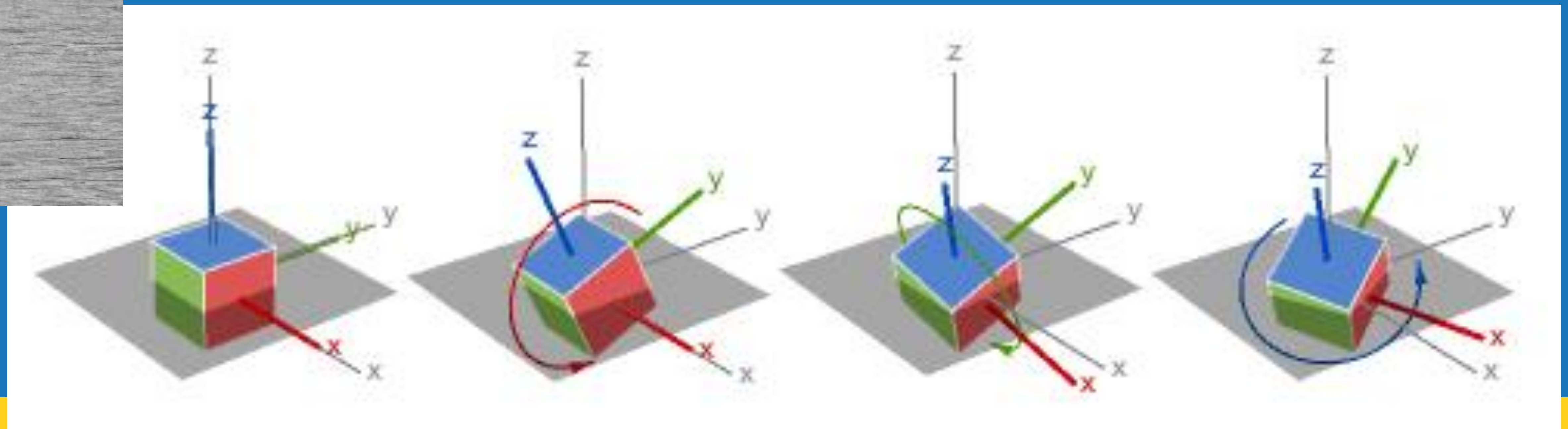

USV Orientation Correction

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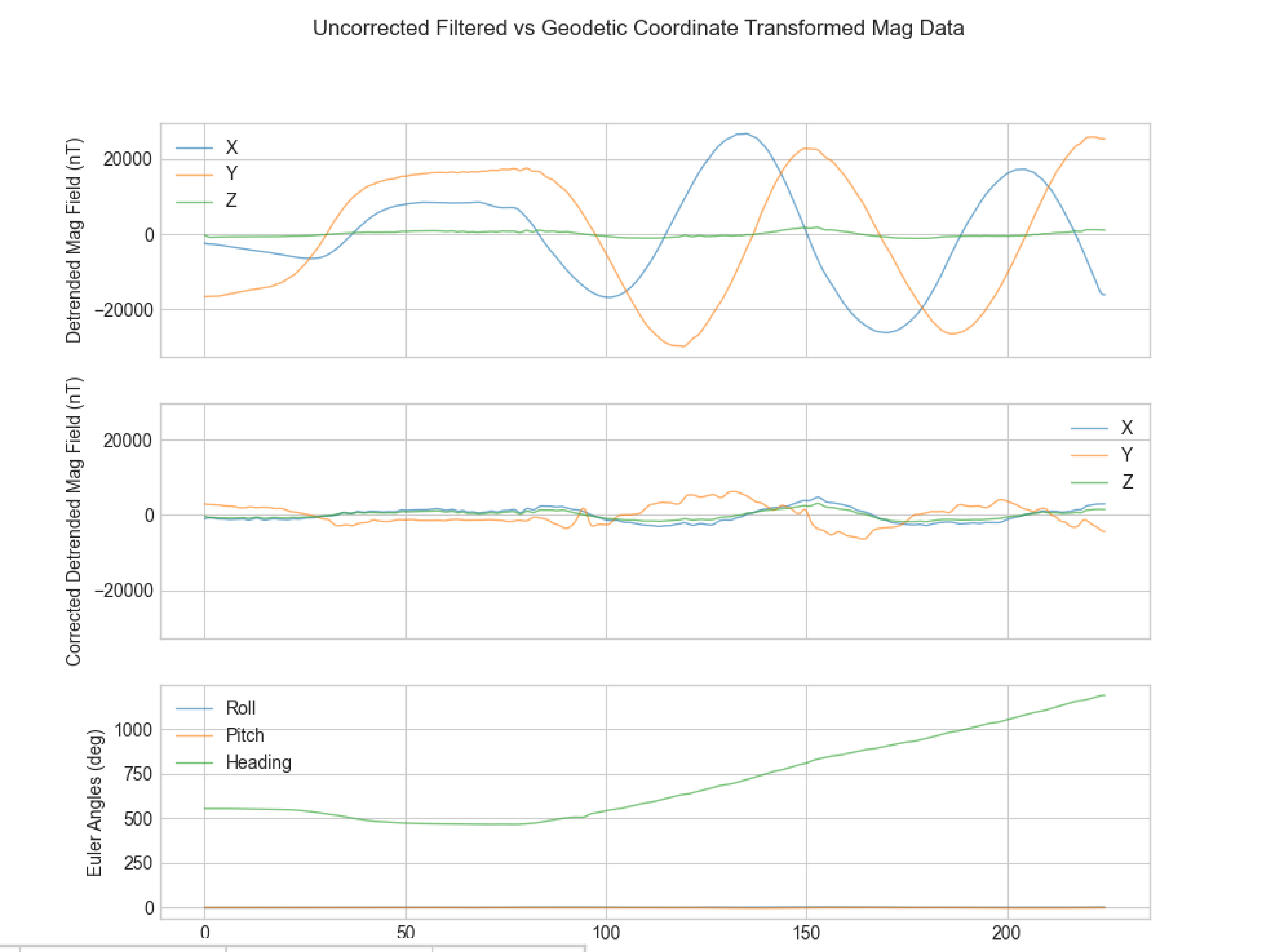
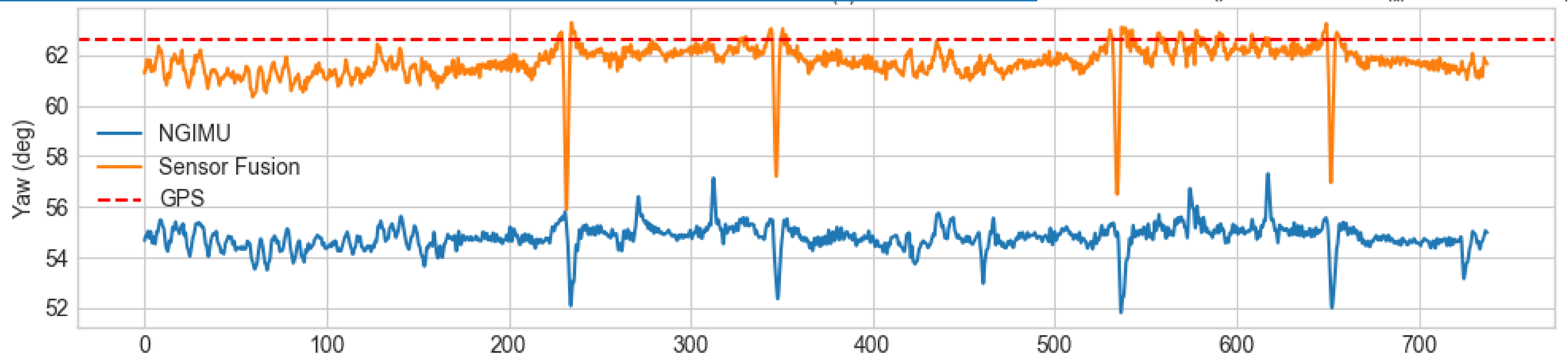
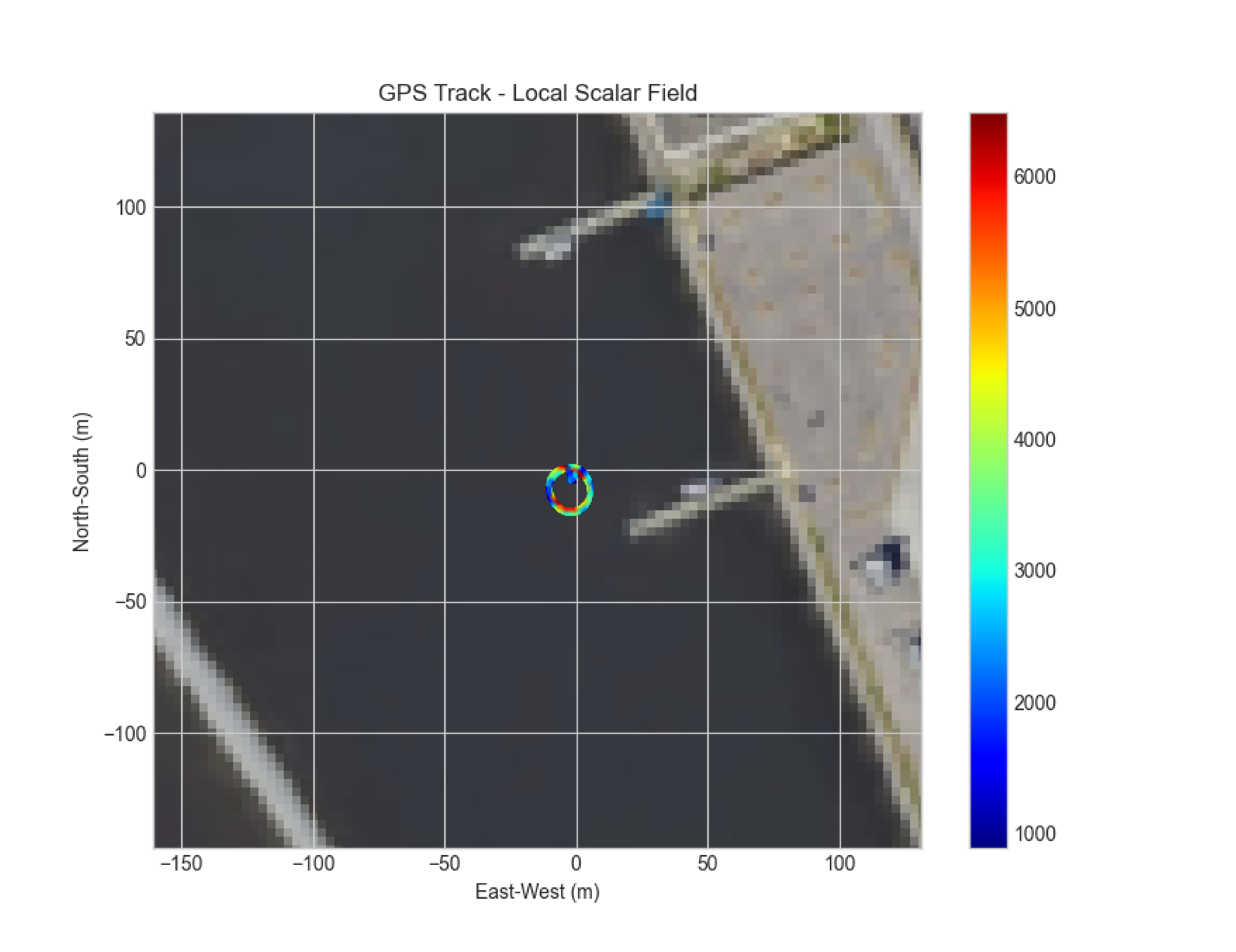
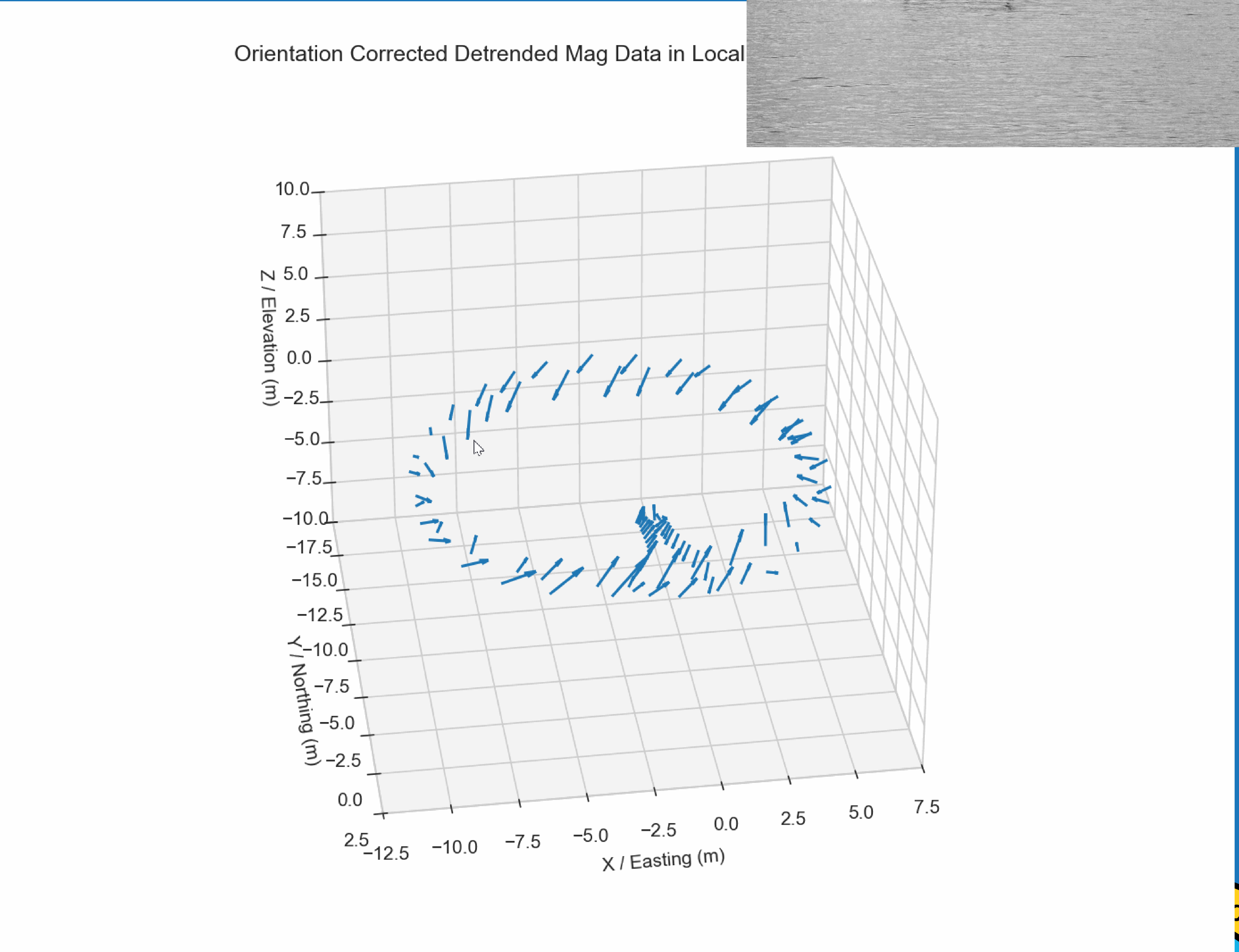
- The uncorrected data in the top subplot has dramatic changes due to the circular course of the vehicle in this test.
- After orientation correction, the second subplot shows a dramatically reduced variation in magnetic field due to the background environment. Note that onboard IMU data at a low sample rate was used for these corrections, and a higher quality source of orientation data would reduce these effects even further.
- This orientation corrected data is more suitable for analysis to detect small magnetic changes indicative of a target of interest.

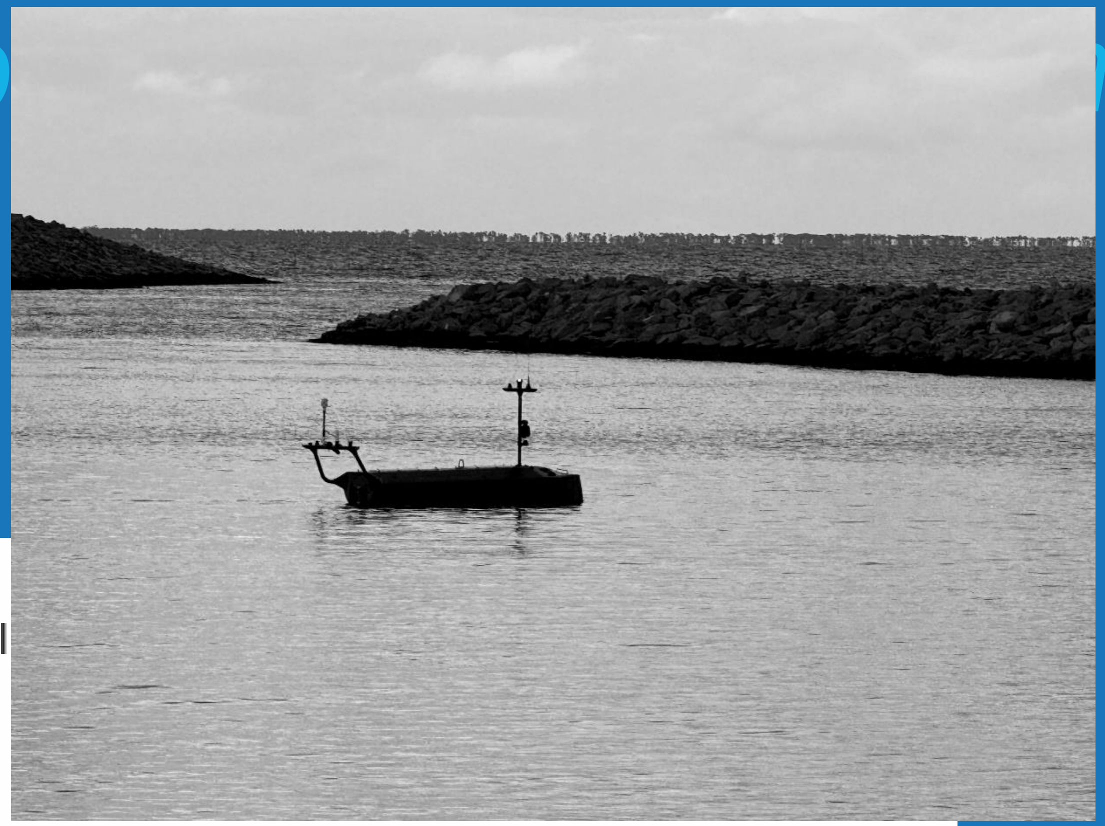




USV Shallow Harbor Data







Magnetic Testing

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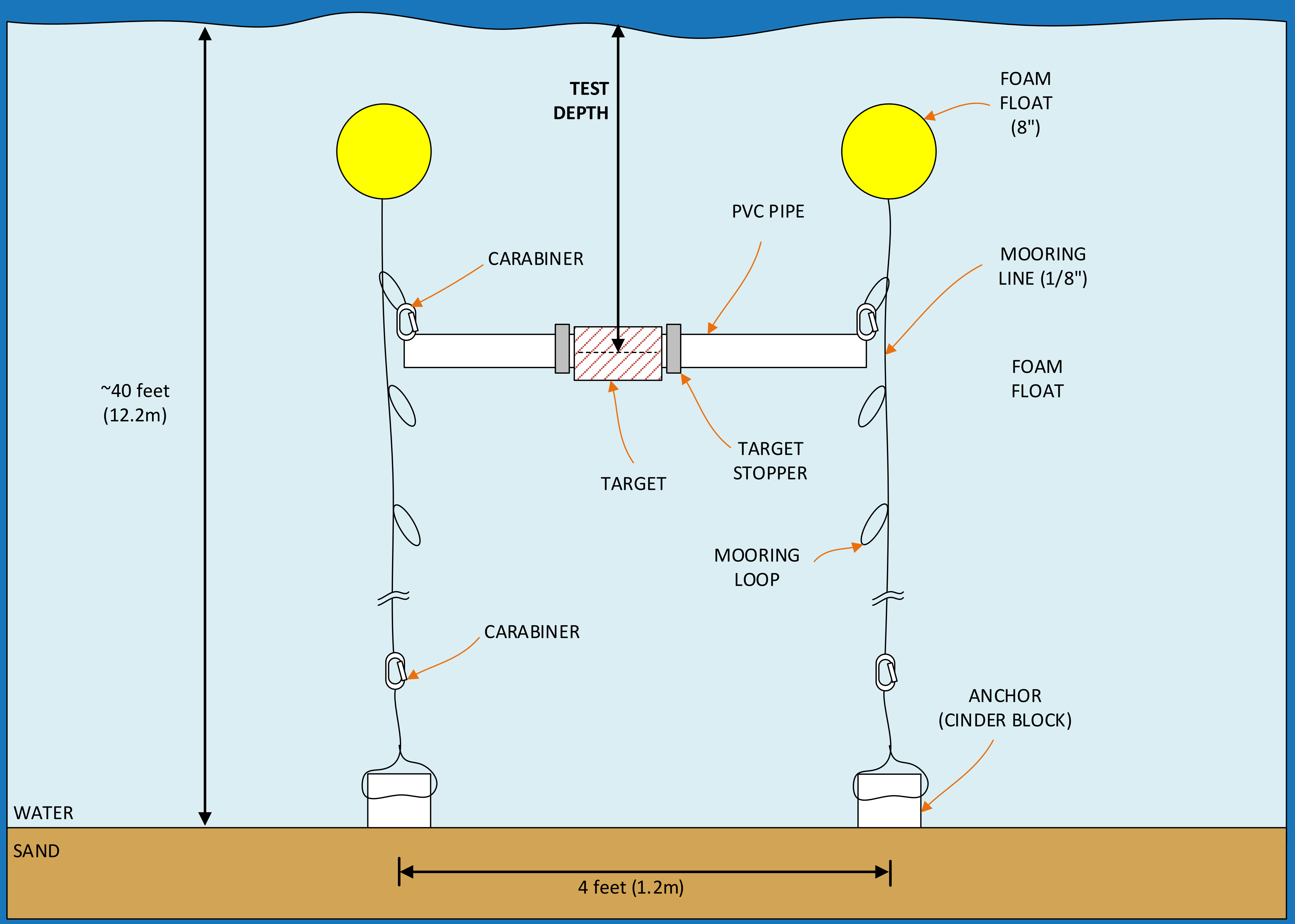
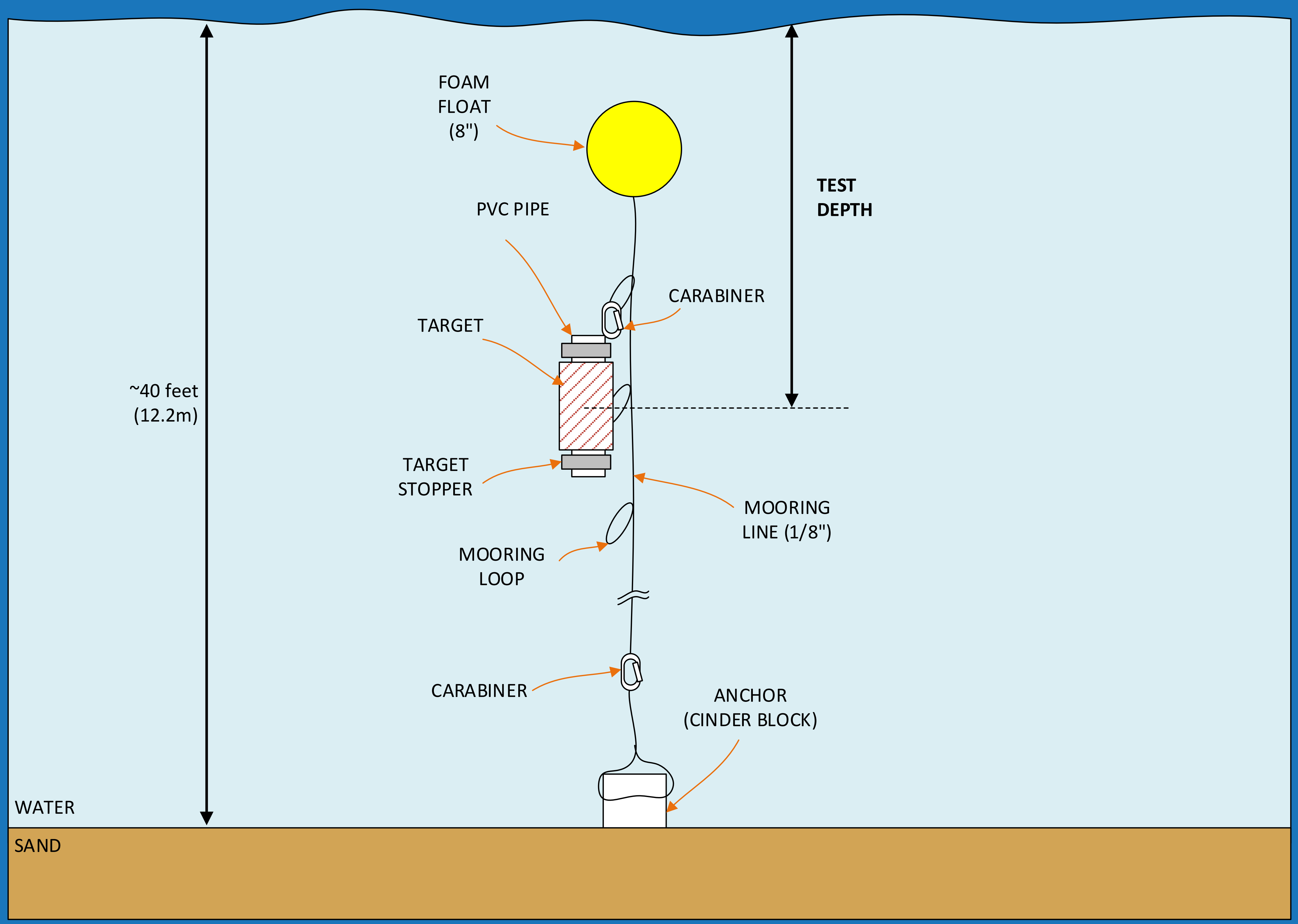


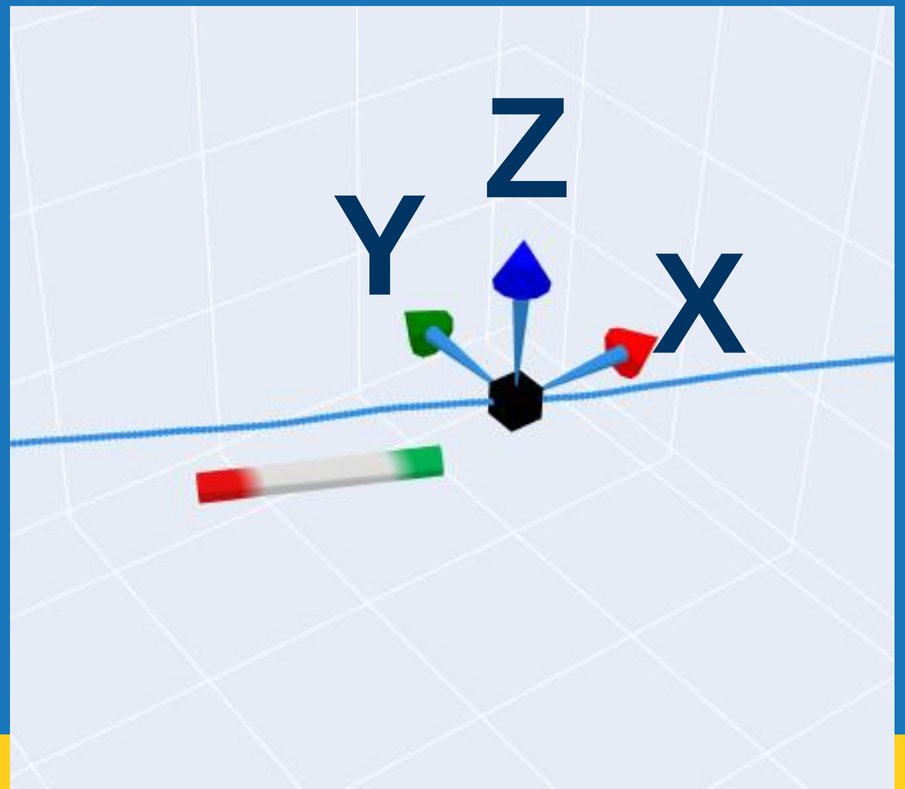
Pipe Parallel / Orthogonal

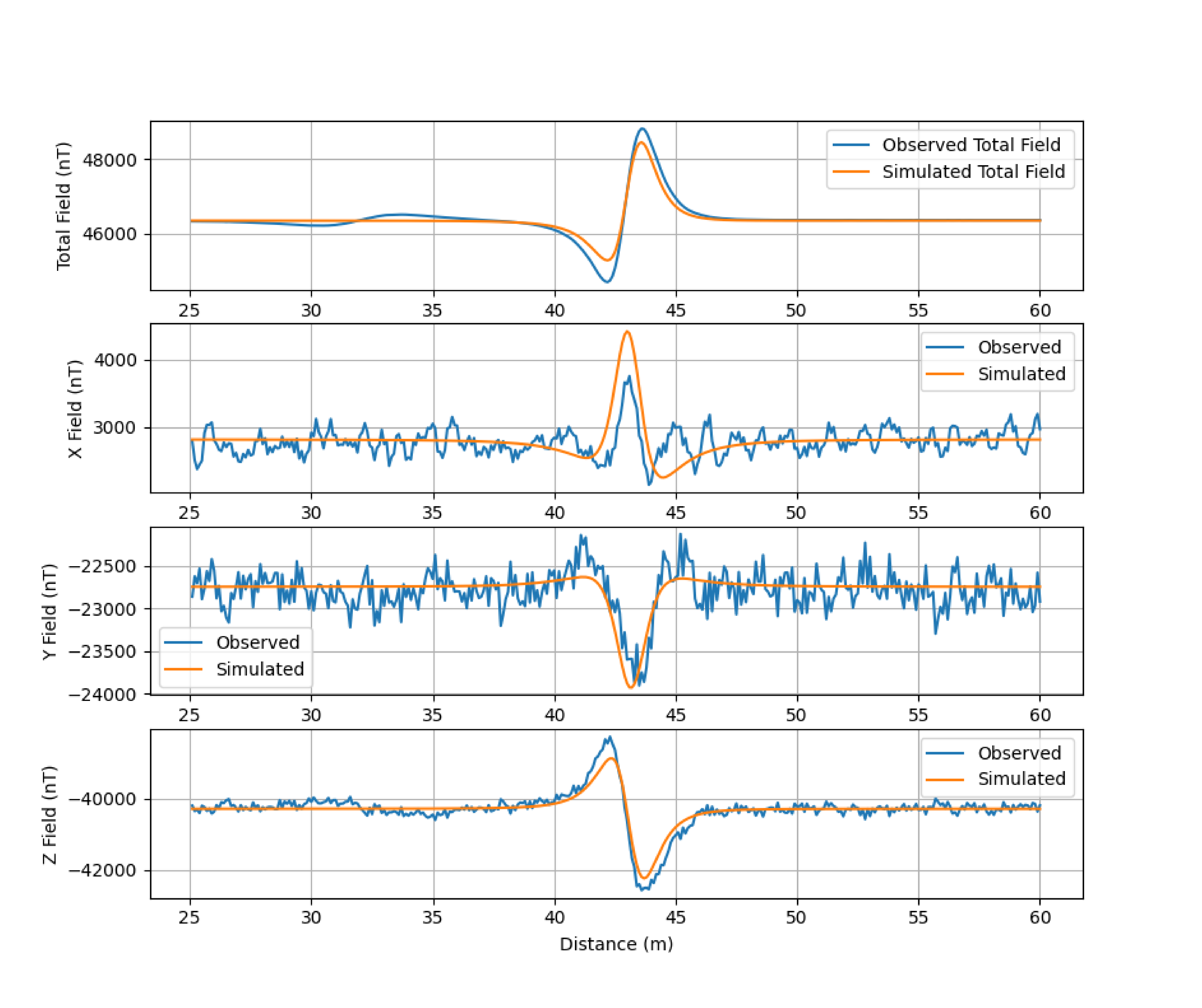


Pipe Vertical

USV: Cylindrical Magnet

- The plots at right show the observed vs simulation model results for an 8" long 1" diameter cylindrical magnet.The model uses the GPS path of the test platform, and target properties as input
- The sensor array travels along a West-Northwest direction (X is Easting, Y is Northing, Z is Vertical)
- The simulation matches the observed data within measurement accuracy for all four test passes for both the total field and vector components.

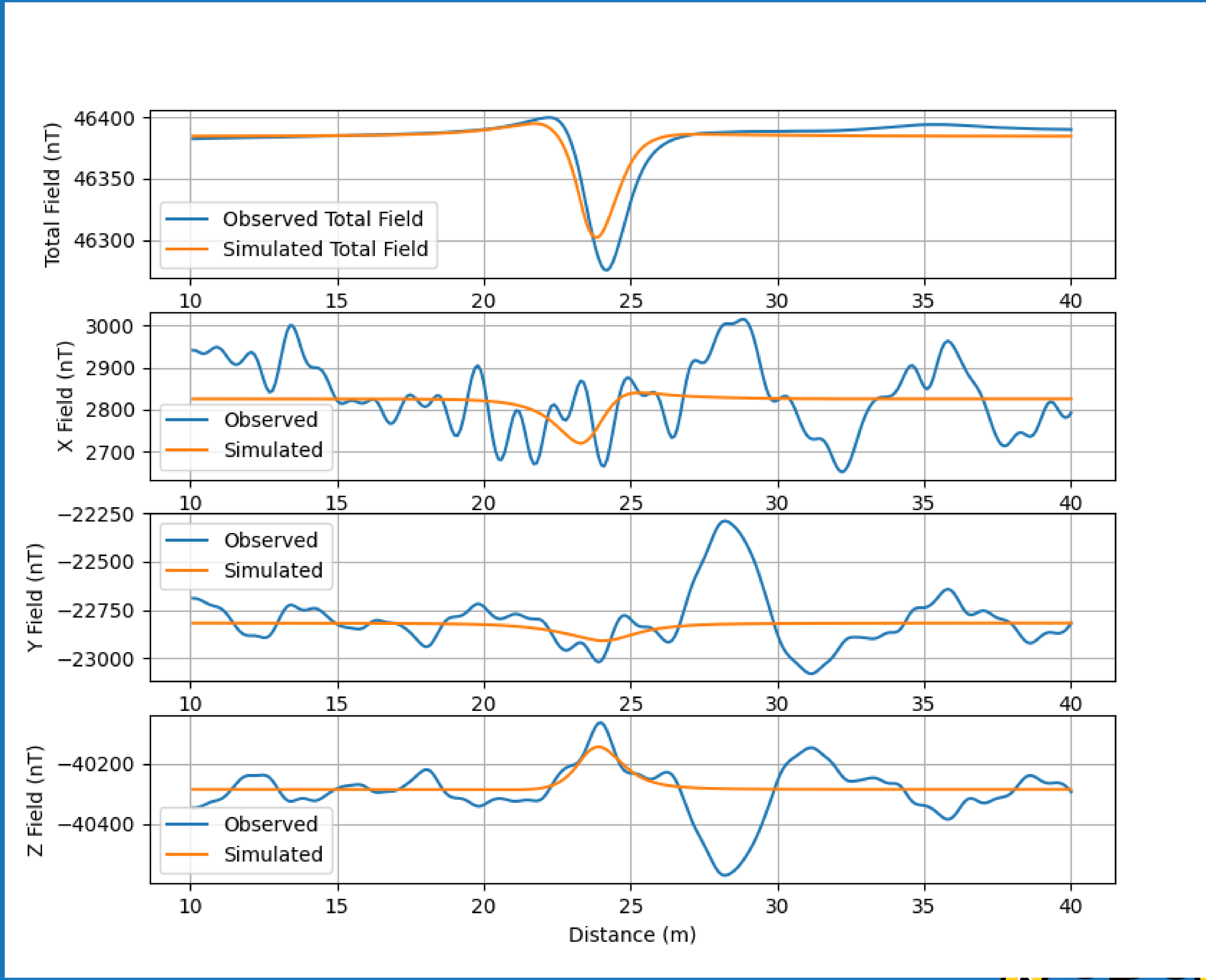


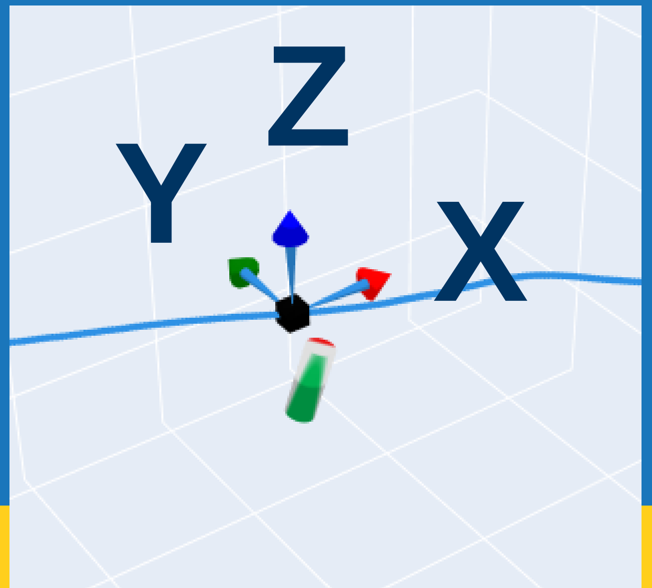


USV: 12" Vertical Pipe

- The plots at right show the observed vs simulation model results for a 12" long ~4.5" diameter steel pipe. The model uses the GPS path of the test platform, and target properties as input

- The simulation matches the observed data within measurement accuracy for all four test passes for both the total field and vector components. The background noise in this dataset is comparatively higher due to the lower amplitude of the pipe signature vs the magnet.





COMSOL Simulations

Parameters

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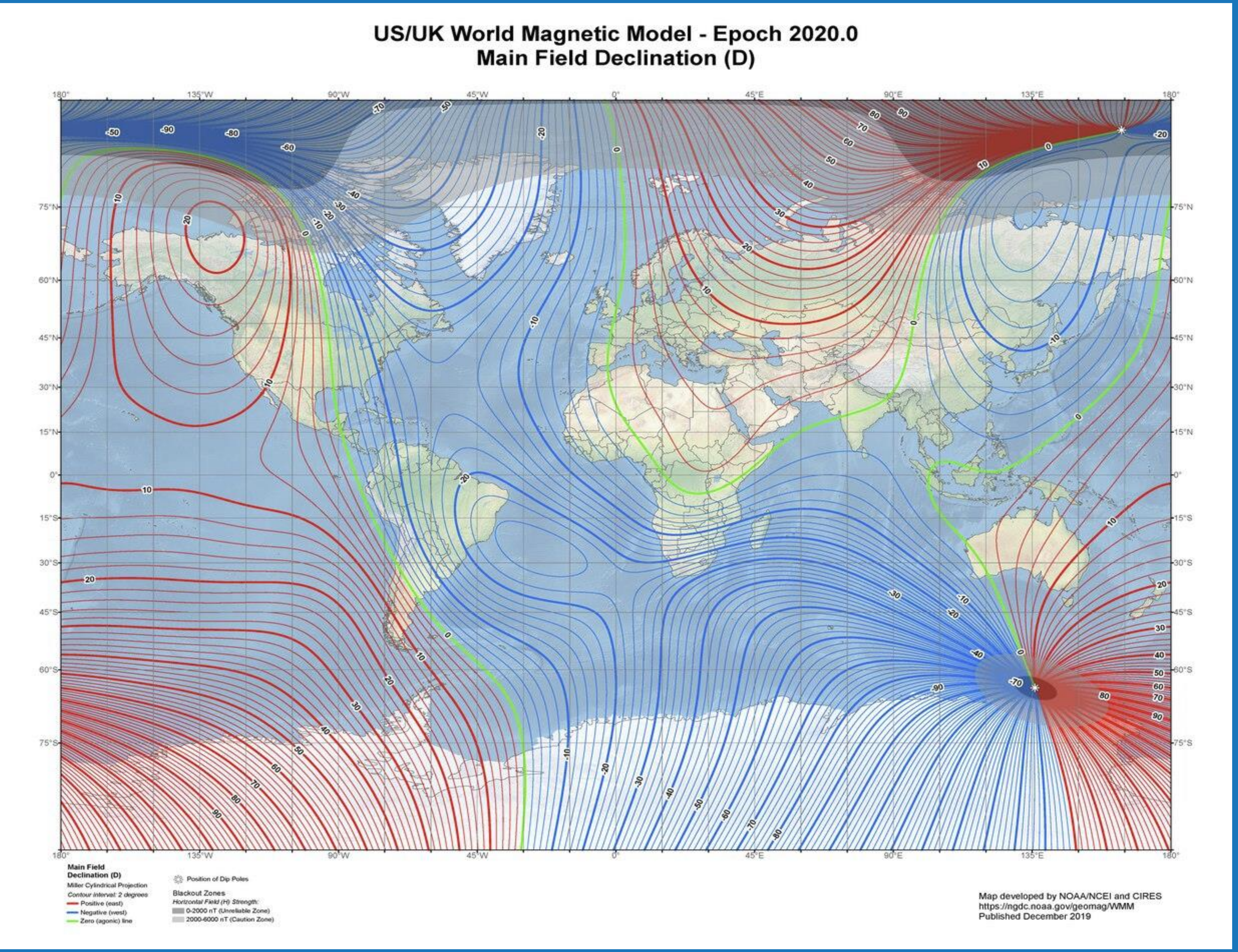
Name	Expression	Value	Description
mur_pipe	100	100	Relative permeability
H0	46353.6[nT]	4.6354E−5 T	Geomagnetic field
Incl	58.77291[deg]	1.0258 rad	Local inclination
Decl	-4.28[deg]	−0.0747 rad	Local declination
xx0	12[in]	0.3048 m	Length of pipe
xx	24[in]	0.6096 m	Length of pipe
xxx	36[in]	0.9144 m	Length of pipe
pir	4.026 [in]	0.10226 m	Inner radius of pipe
por	4.5[in]	0.1143 m	Outer radius of pipe

Variables

Variables

Name	Expression	Description
Gx	cos(Incl)*sin(Decl)	Geomagnetic field direction, x-component
Gy	cos(Incl)*cos(Decl)	Geomagnetic field direction, y-component
Gz	-sin(Incl)	Geomagnetic field direction, z-component

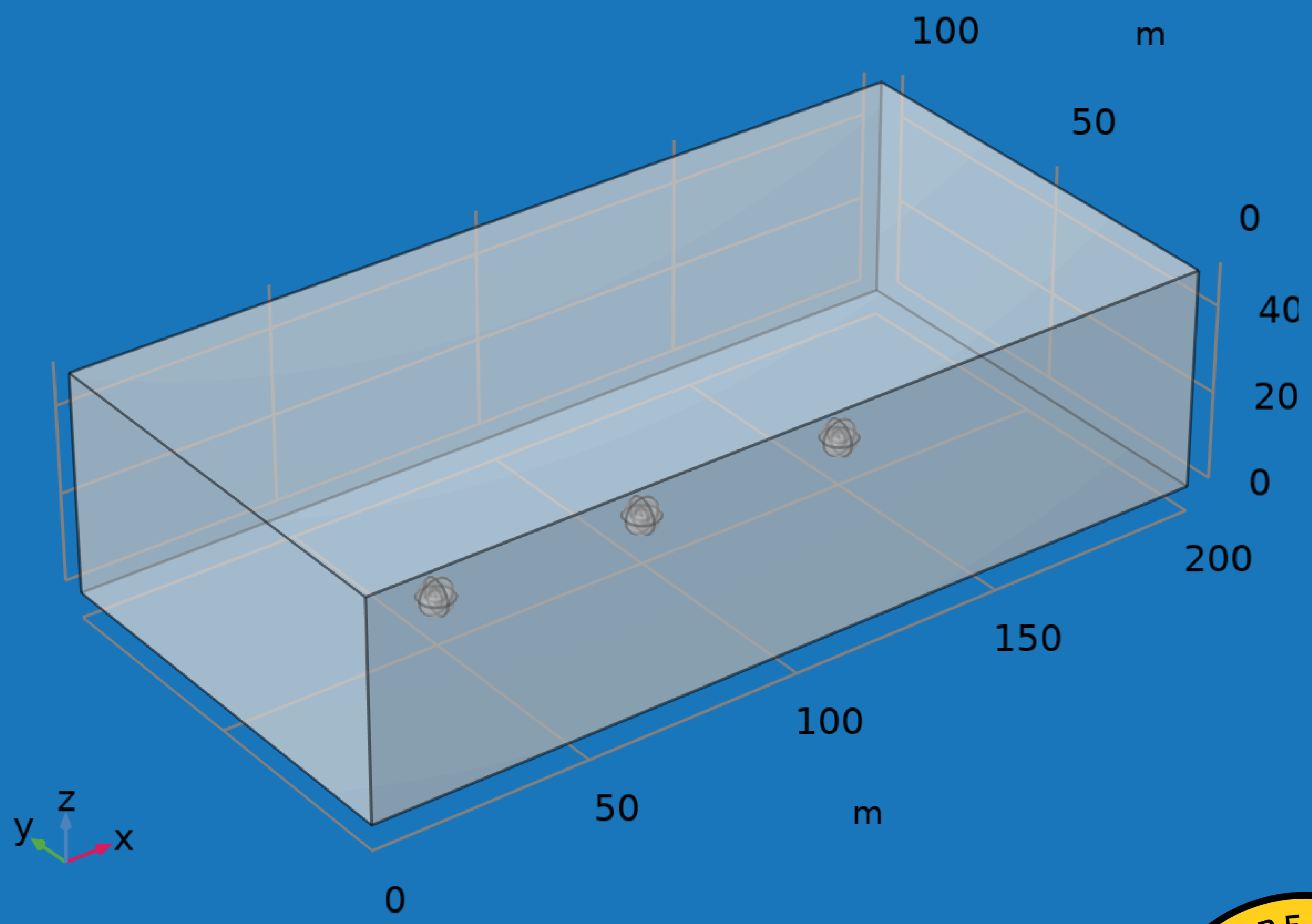


Component

Geometry

Geometry statistics

Description	Value
Space dimension	3
Number of domains	10
Number of boundaries	84
Number of edges	156
Number of vertices	92



Geometry 1

Materials

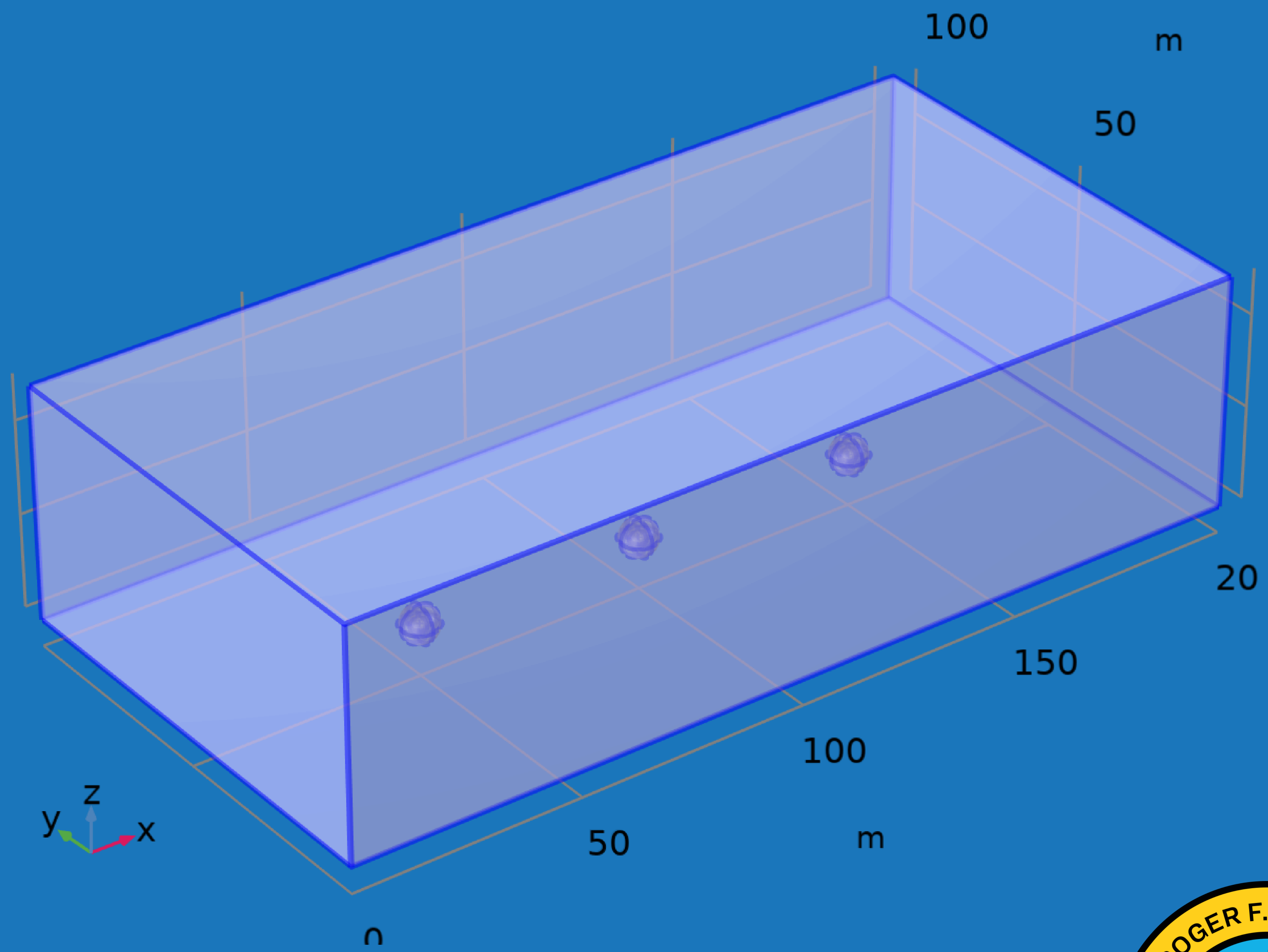
Background Material

Material parameters

Name	Value	Unit	Property group
Relative permeability	1	1	Basic

Basic

Description	Value
Relative permeability	1



Background Material

Pipe

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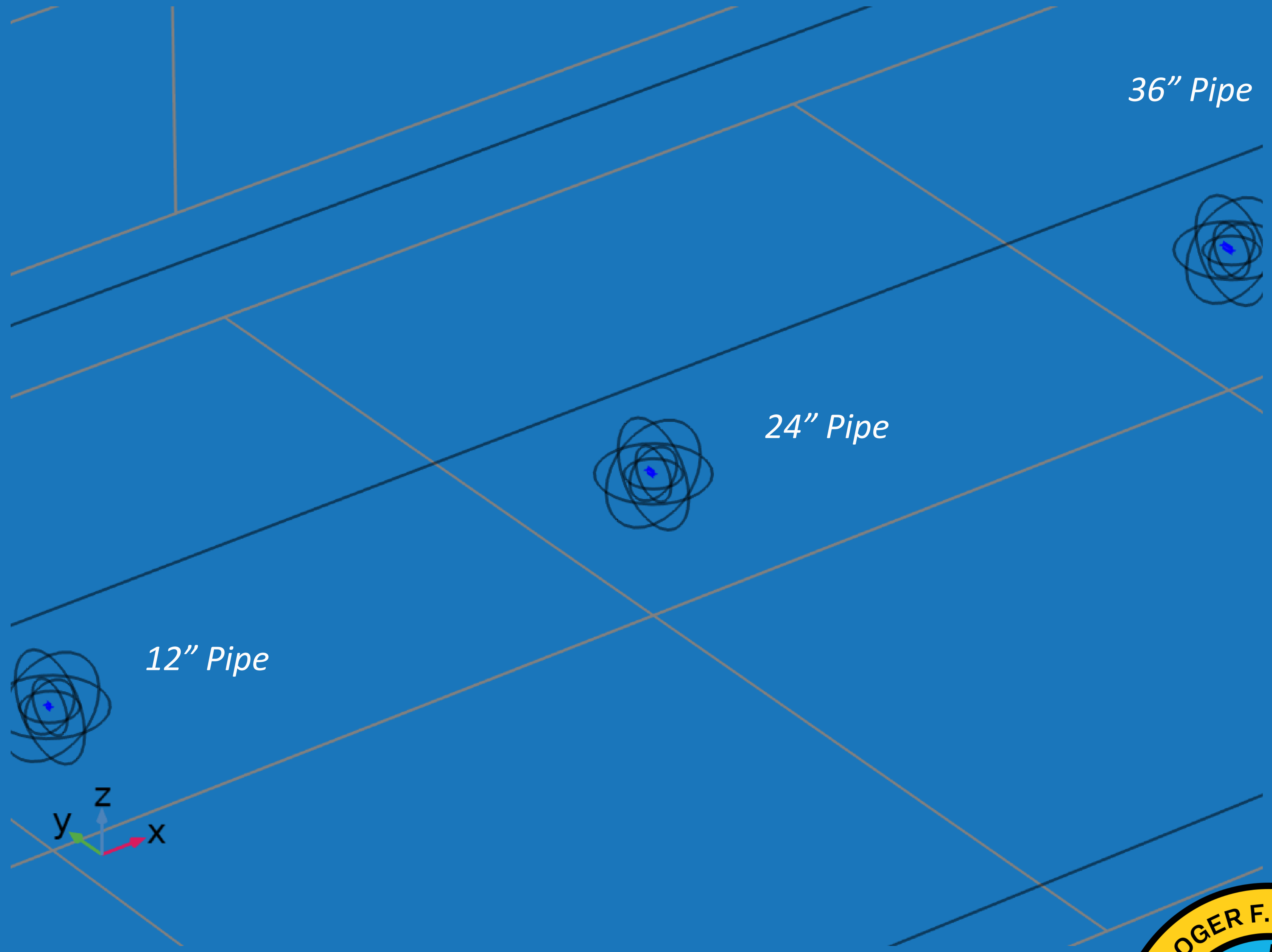
Material parameters

Name	Value	Unit	Property group
Relative permeability	mur_pipe	1	Basic

Basic

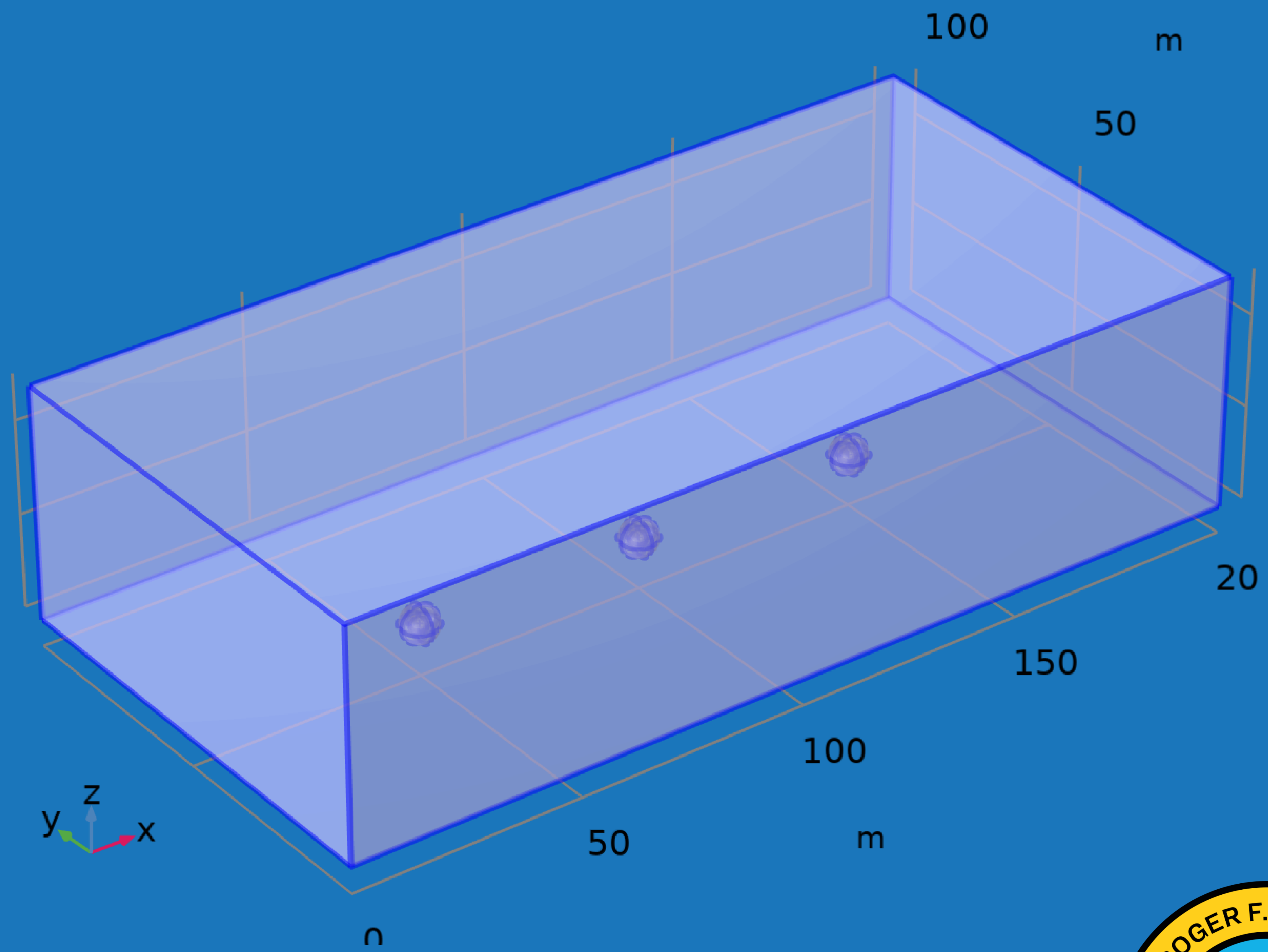
Description	Value
Relative permeability	mur_pipe



Magnetic Fields, No Currents

Settings

Description	Value	Unit
Solve for	Reduced field	
Background magnetic field, x-component	H0*Gx/mu0_const	A/m
Background magnetic field, y-component	H0*Gy/mu0_const	A/m
Background magnetic field, z-component	H0*Gz/mu0_const	A/m

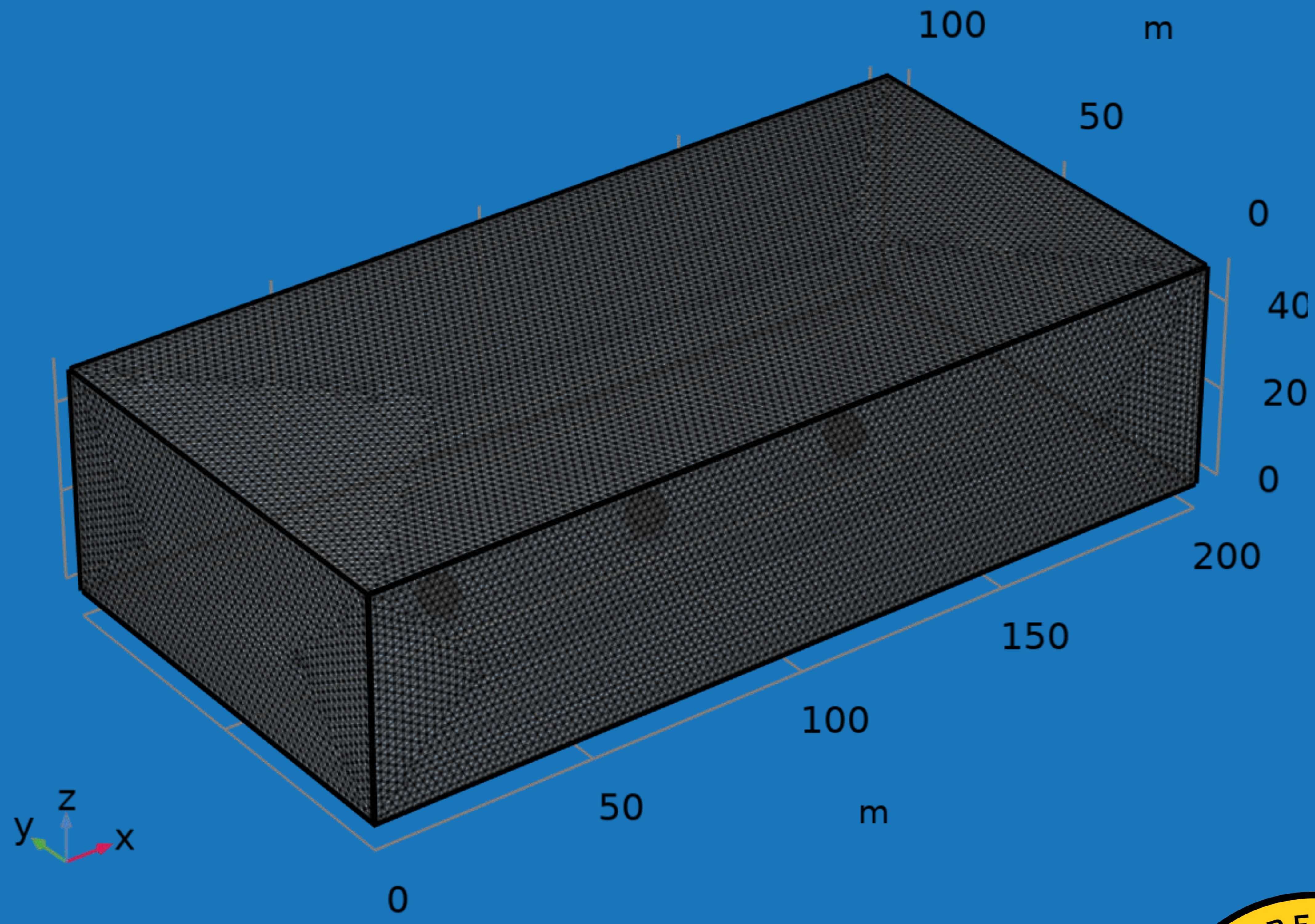


Magnetic Fields, No Currents

Mesh 1

Mesh statistics

Description	**Value**
Status	Complete mesh
Mesh vertices	396865
Tetrahedra	2328593
Triangles	50614
Edge elements	1868
Vertex elements	92
Number of elements	2328593



Mesh

Study

Computation information

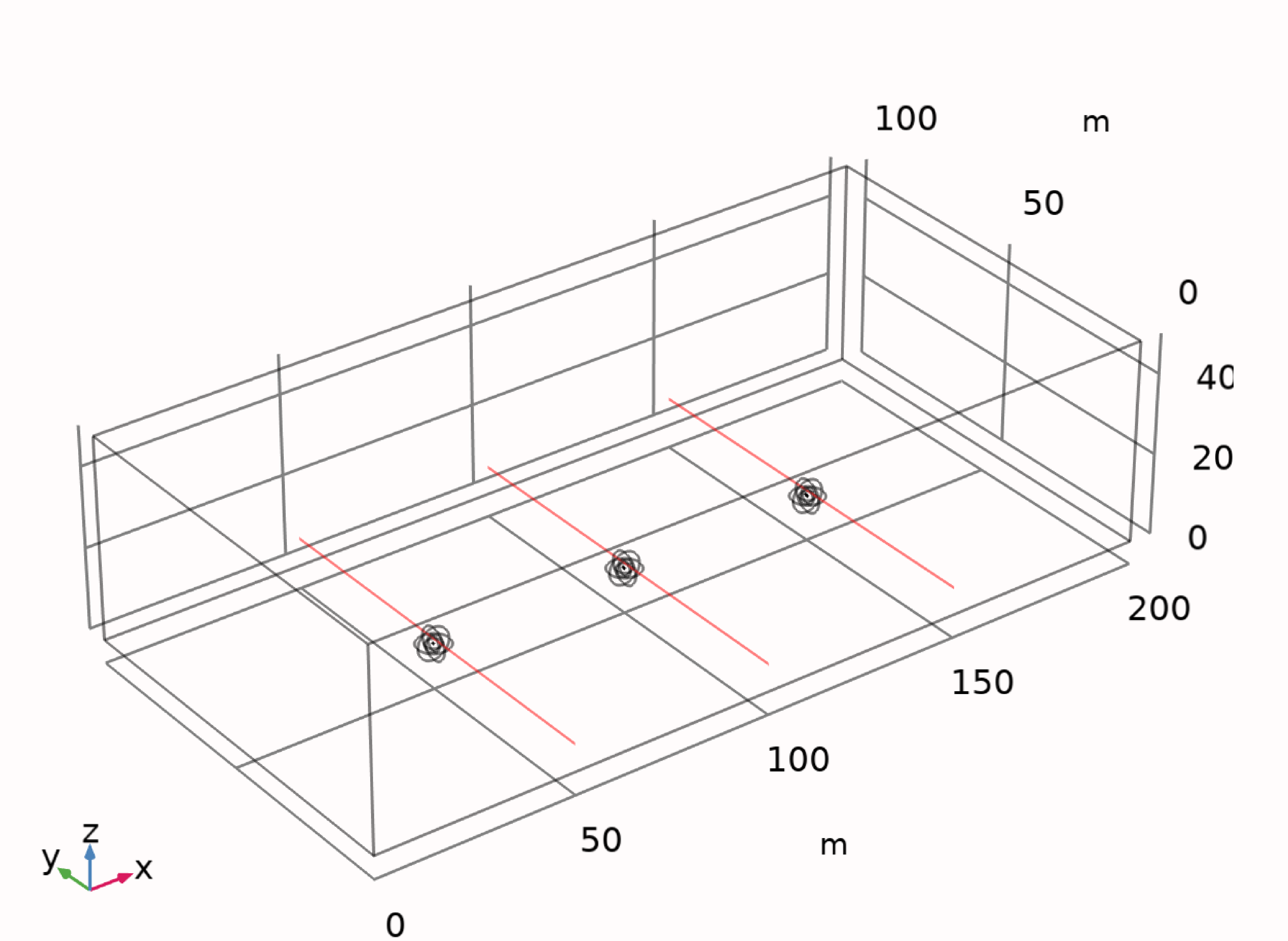
Computation time 2 min 37 s

Model Simulations

Cut Line Parallel to UUV: 1m Above

Line data

Description	**Value**
Line entry method	Two points
Points	{{50, 0, 6.8}, {50, 100, 6.8}}
Bounded by points	Off
Additional parallel lines	On
Distances	{50, 100}
Orthogonal vector	{1, 0, 0}



Dataset: Cut Line Parallel to UUV: 1m Above

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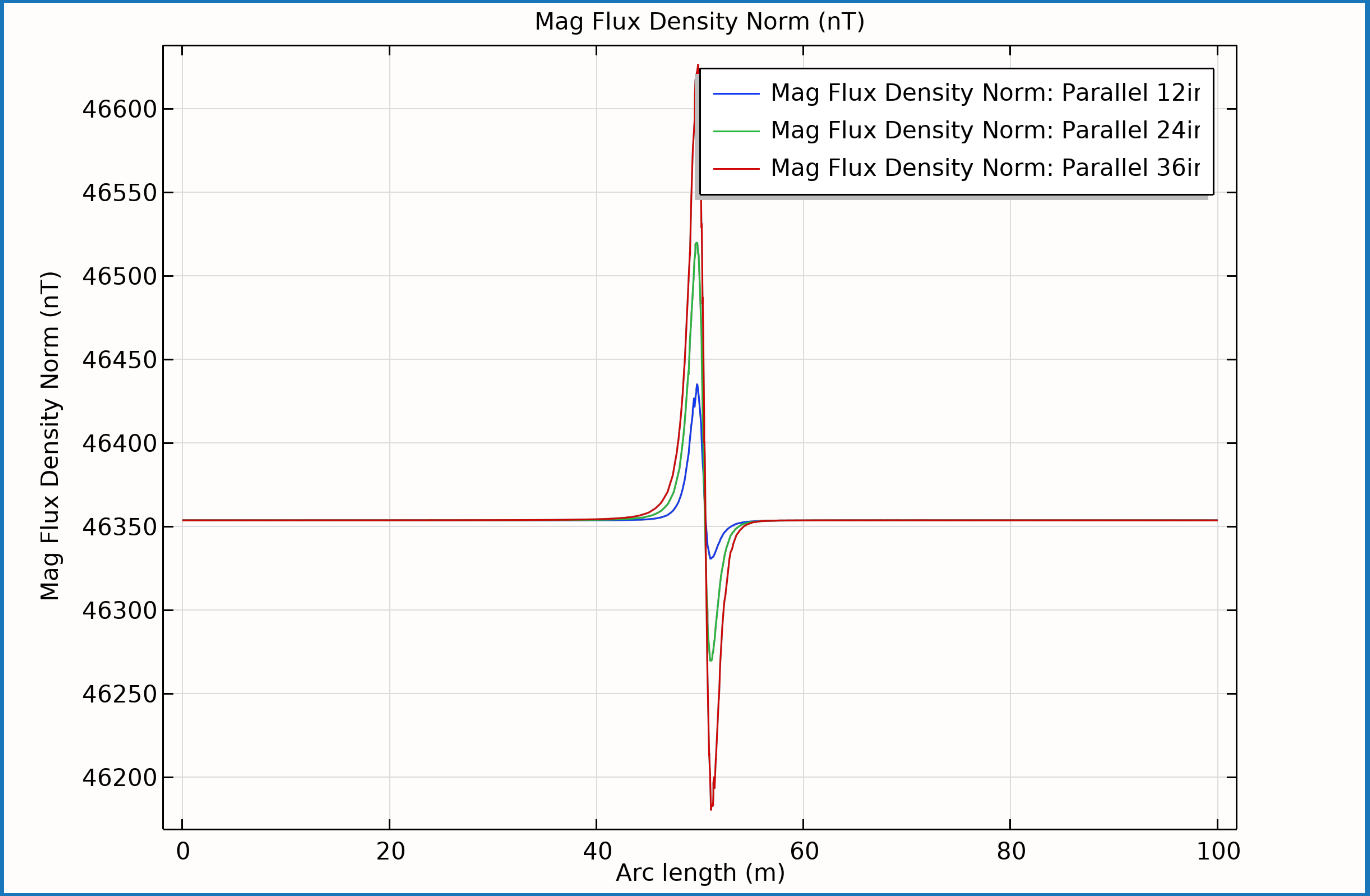
1m Above UUV Parallel to Path: B



Mag Flux Density Norm (nT)

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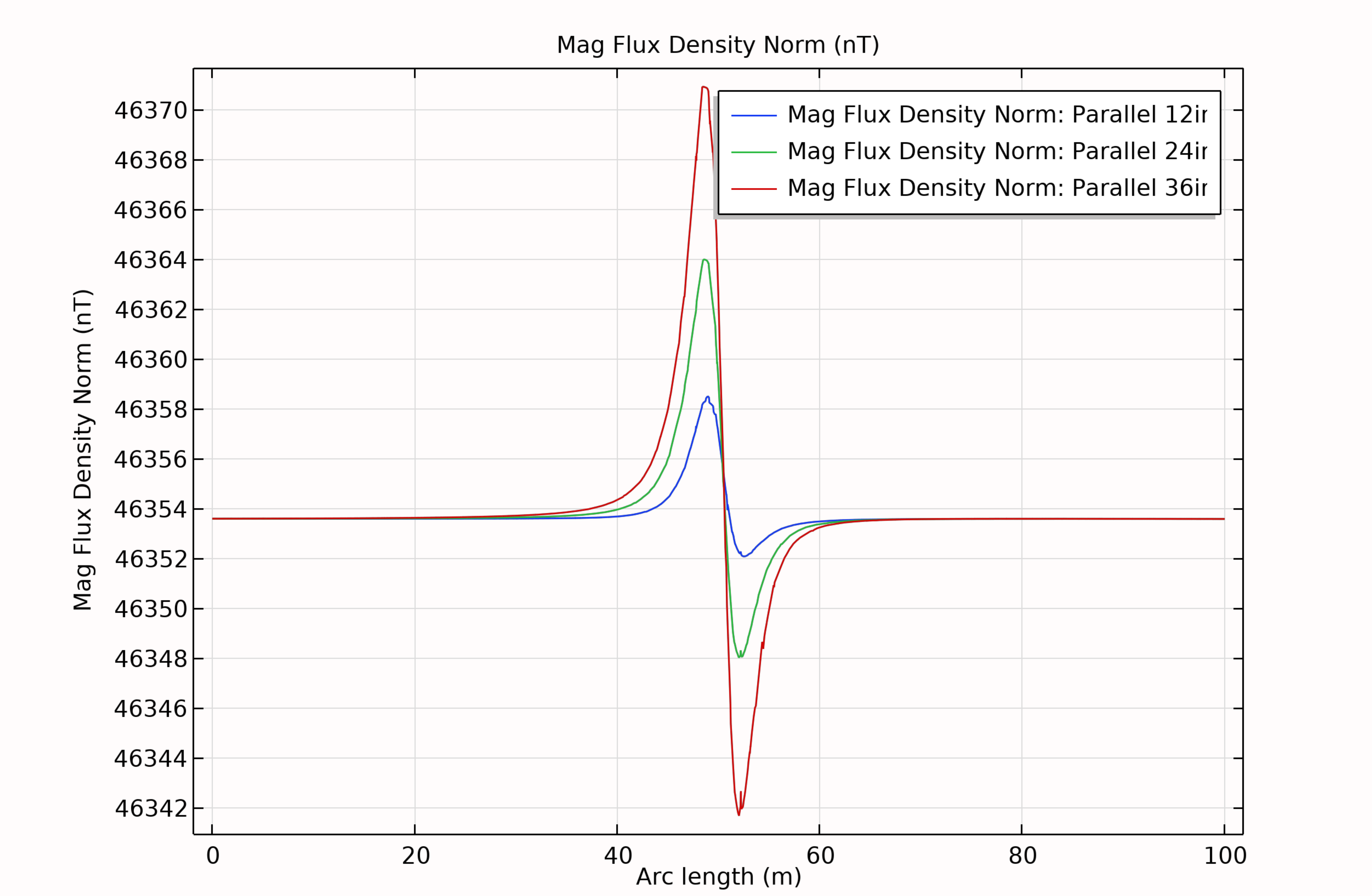
3m Above UUV Parallel to Path: B



Mag Flux Density Norm (nT)

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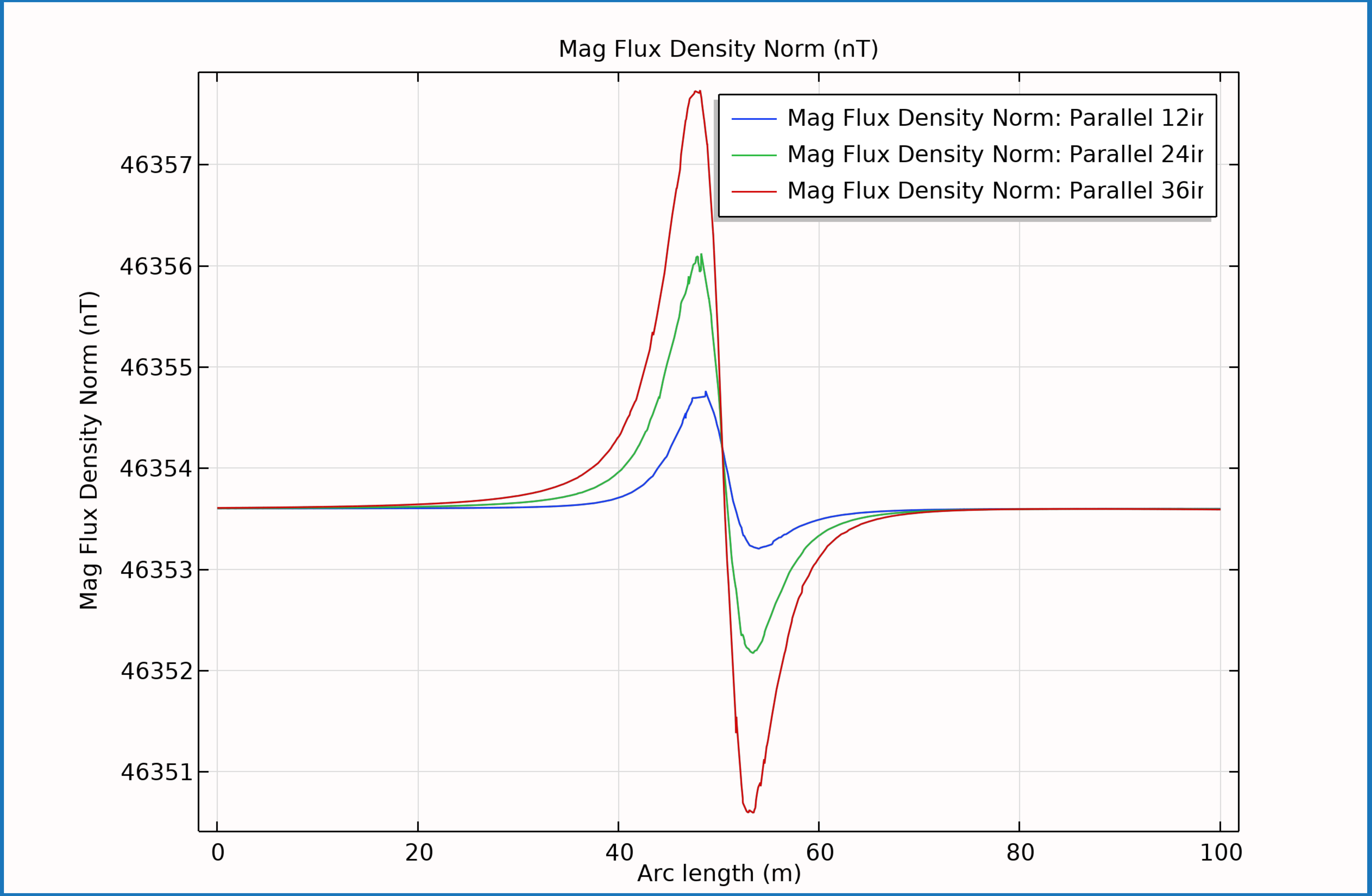
5m Above UUV Parallel to Path: B



Mag Flux Density Norm (nT)

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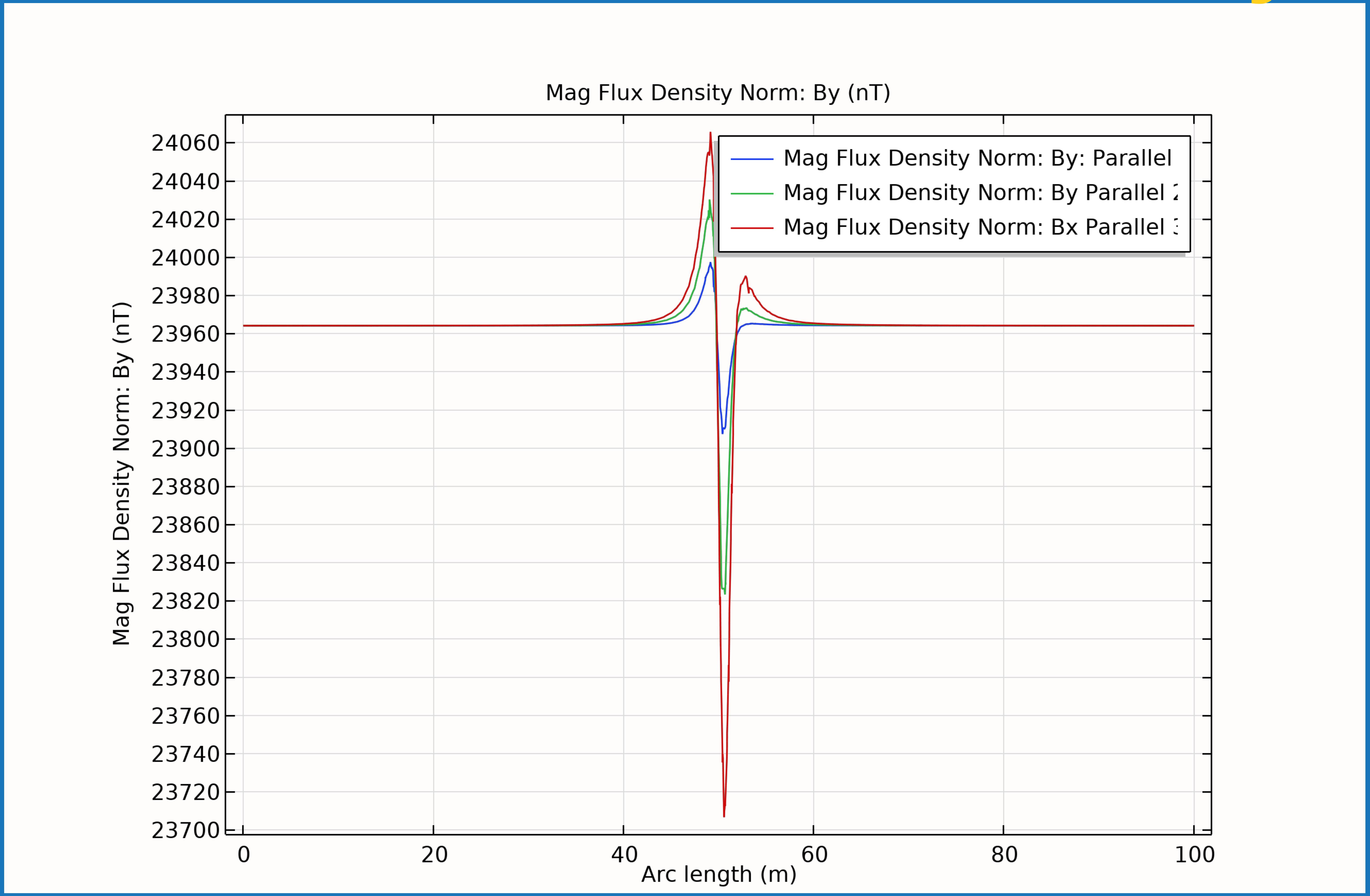
1m Above UUV Parallel to Path: By



Mag Flux Density Norm: By (nT)

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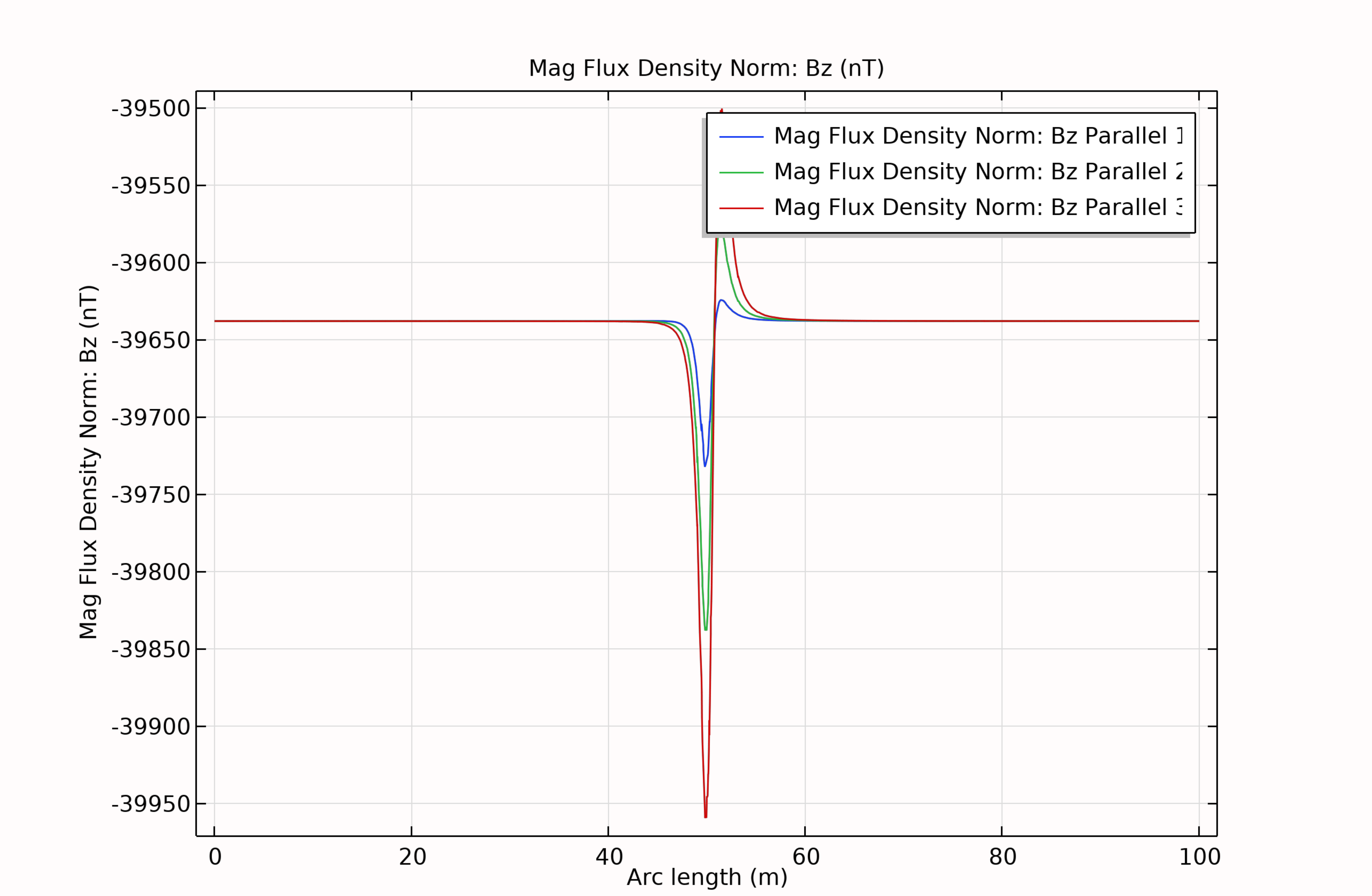
1m Above UUV Parallel to Path: Bz



Mag Flux Density Norm: Bz (nT)

ML Overview

- Purpose: Use simulated magnetic sensor data to predict anomaly signatures
- Approach: Four machine learning models for confirming findings
- Results: Labeled simulated vs predicted sensor measurements

Machine Learning (ML) Background

- An algorithm that "learns" from repetitive tasks
- Based on models with several thousand parameters
- Parameters are estimated using optimization
- Models need large amounts of data to converge
- Many models tend to be "black-box", not explainable inner-workings

ML Modeling

- Regression: ML model based on multiple regression
- Boosting: ML model based on tree ensembles
- DNN (Deep Neural Network): ML model based on neuron layers (relies on present state only)
- LSTM (Long Short-Term Memory): ML model based on present and past (remembered) states

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ML Approach

General regression model:

$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + e$, where

y is the dependent variable, β_0 is the intercept, β are coefficients, X are the predictors, and e is the independent and identically distributed error term.

- Regression
  - Trained as above for DNN:
    - Training data was simulated from a modeled 12-inch isopipe (100 permeability)
    - Testing data was simulated from a modeled 24-inch isopipe (100 permeability)
    - Used to predict the total field (magnetic flux density norm) measurements that a sensor would see in the field

ML Approach

- Boosting
  - Dichotomized sensor readings to above and below mean absolute value
  - Used target permeability, aspect ratio, and UUV speed as predictors
  - Used grid-search to find best values for tree number and maximum depth

ML Approach

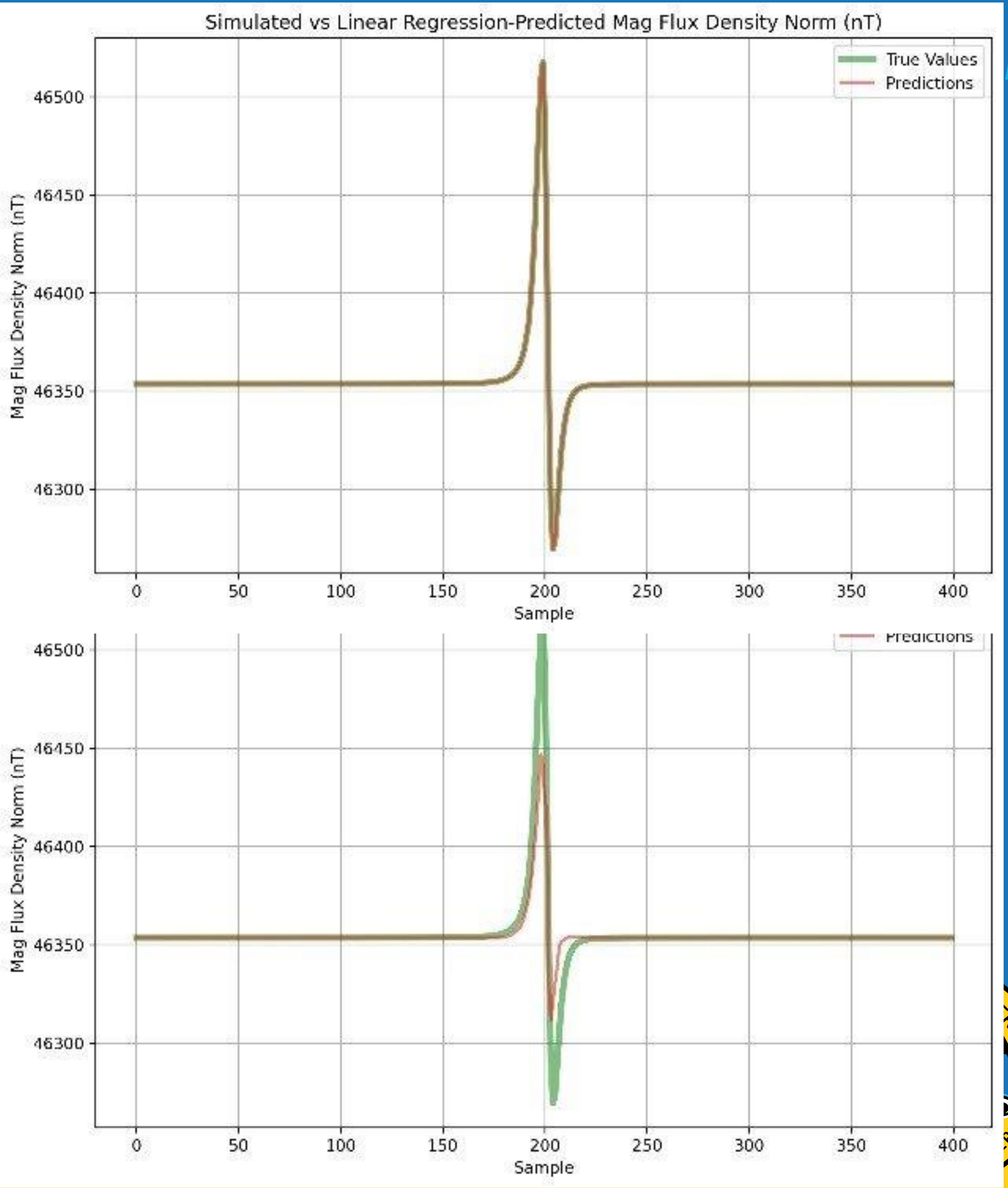
- DNN
  - Trained on the simulated vector components of the B field.
    - Training data was simulated from a modeled 12-inch isopipe (100 permeability)
    - Testing data was simulated from a modeled 24-inch isopipe (100 permeability)
    - Used to predict the total field (magnetic flux density norm) measurements that a sensor would see in the field

ML Approach

- Long Short-Term Memory (LSTM)
  - Trained on the simulated vector components of the B field.
  - Ran model for total-, x-, y-, and z-fields
  - Used a sequence of 10 past data points to predict current point
  - Iterated over entire data set

ML Results

- Regression
  - Best fit (top figure)
  - R-squared 0.98
- DNN
  - Good fit, may need to increase data size (bottom figure)



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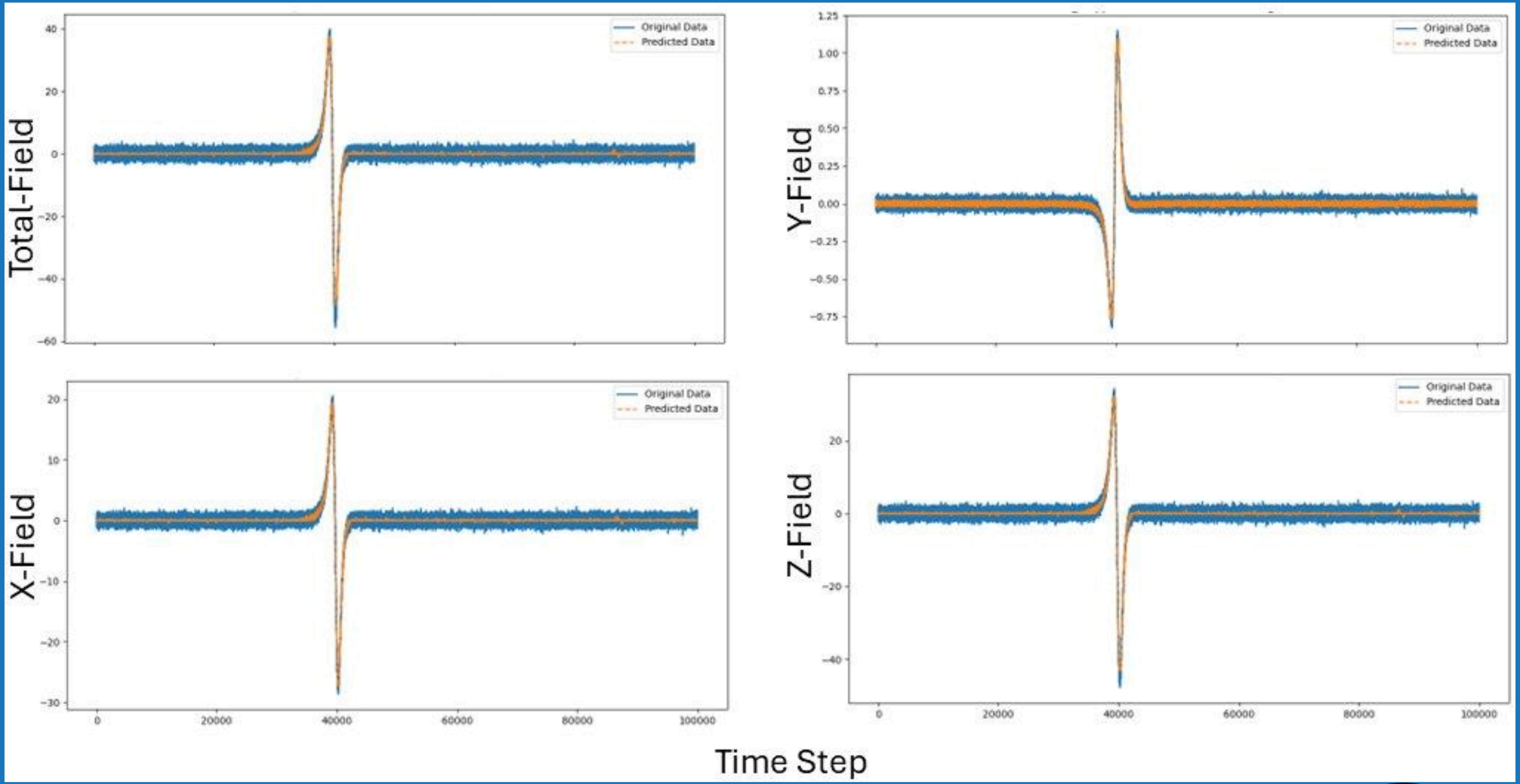
ML Results

- LSTM
  - Good fit (figure to the right)
- Boosting feature importance (%)
  - Target permeability (0.44)
  - Target aspect ratio (0.30)
  - UUV speed (0.26)



Conclusions & Way Ahead

- Simulations in data-scarce situations are essential
- Relatively simple ML models are able to reproduce simple target signatures for a variety of magnetic properties and geometries
- Once a base model is validated is straightforward to generate more data for certain ML approaches
- Next steps:
  - Add Acoustics/Gravity Physics
  - Deploy Apps internally for ML training using COMSOL Server
  - Perform Uncertainty Quantification/Optimization

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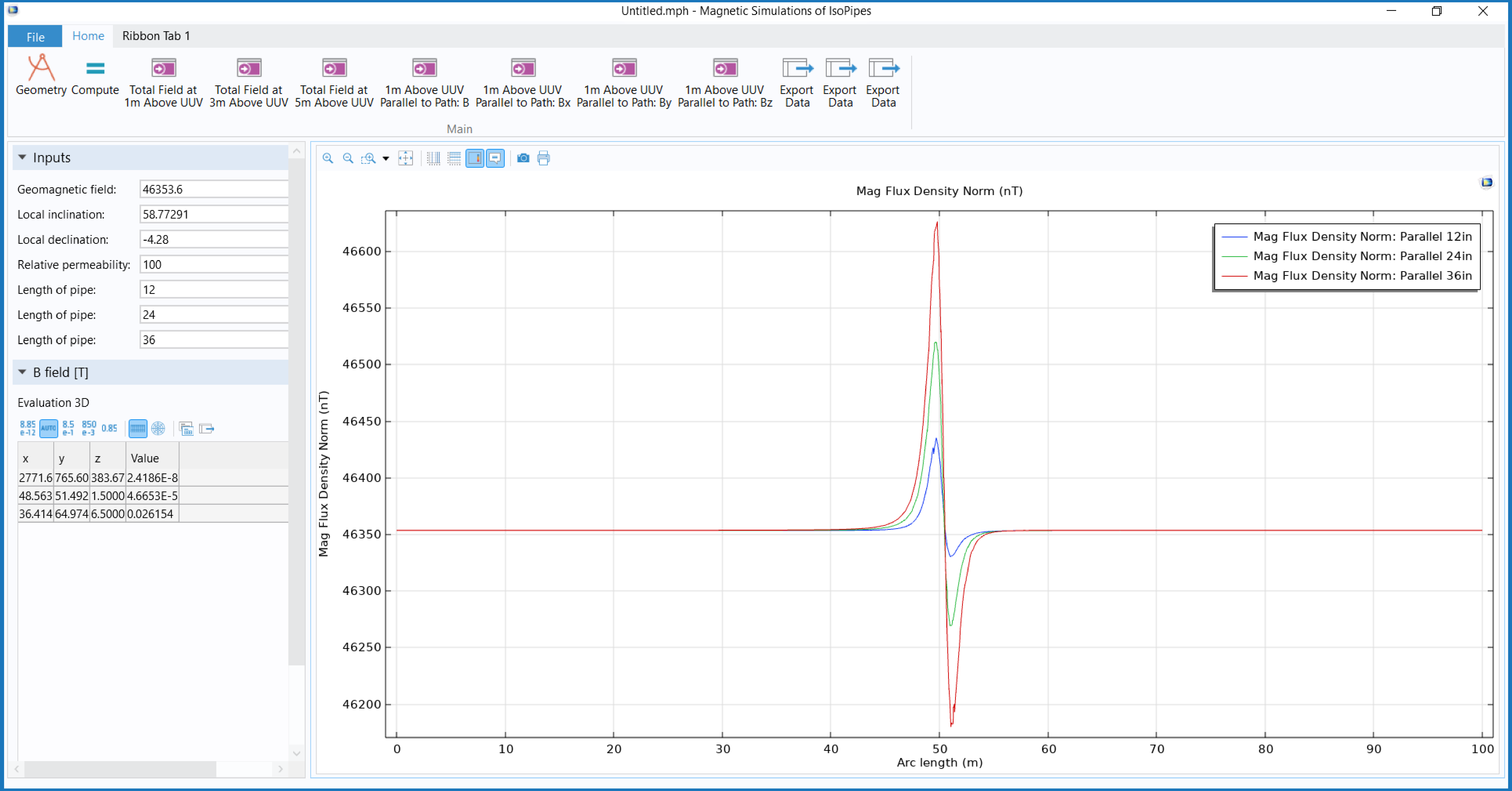
Simple COMSOL APP



Questions?

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