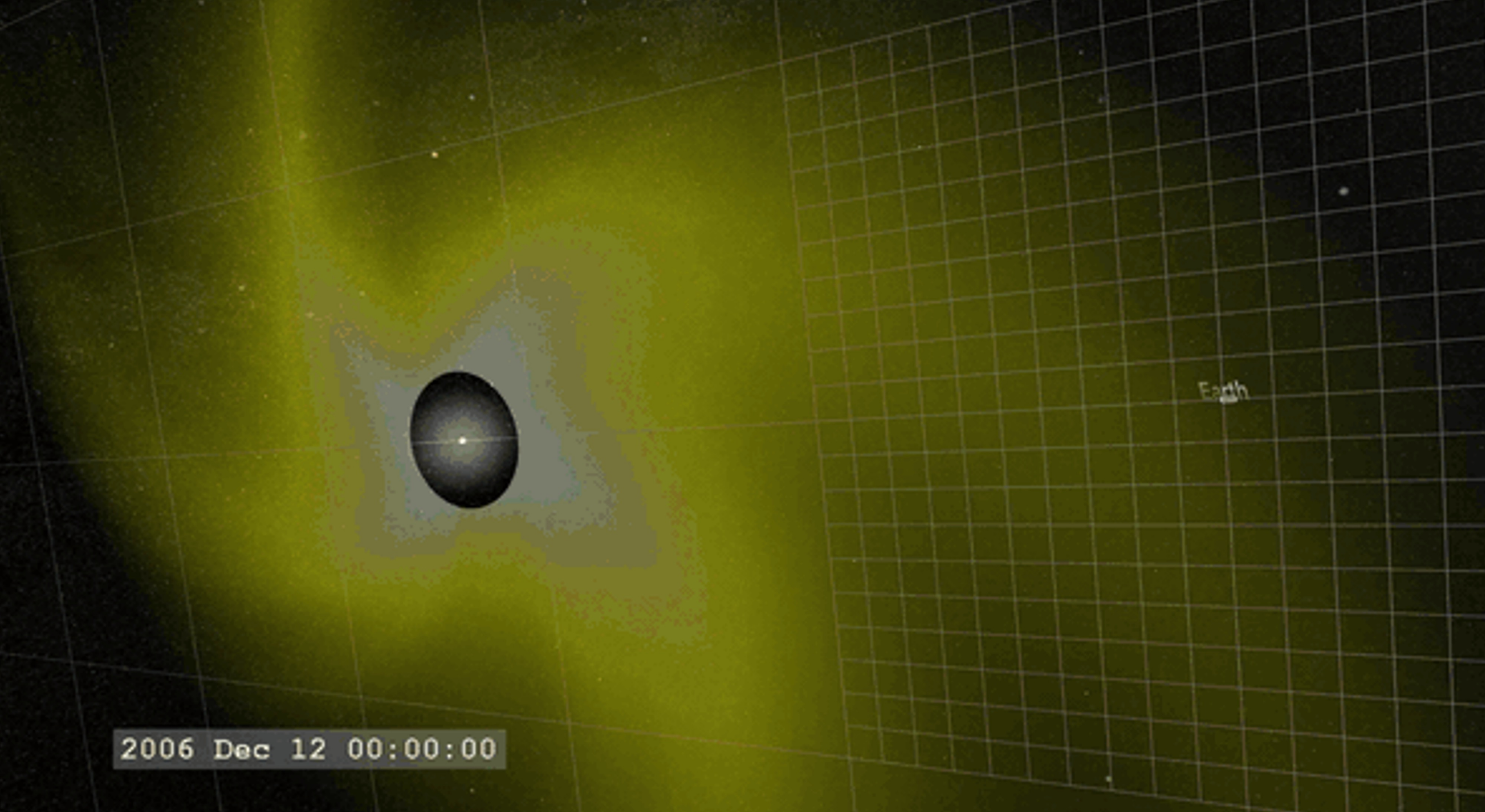
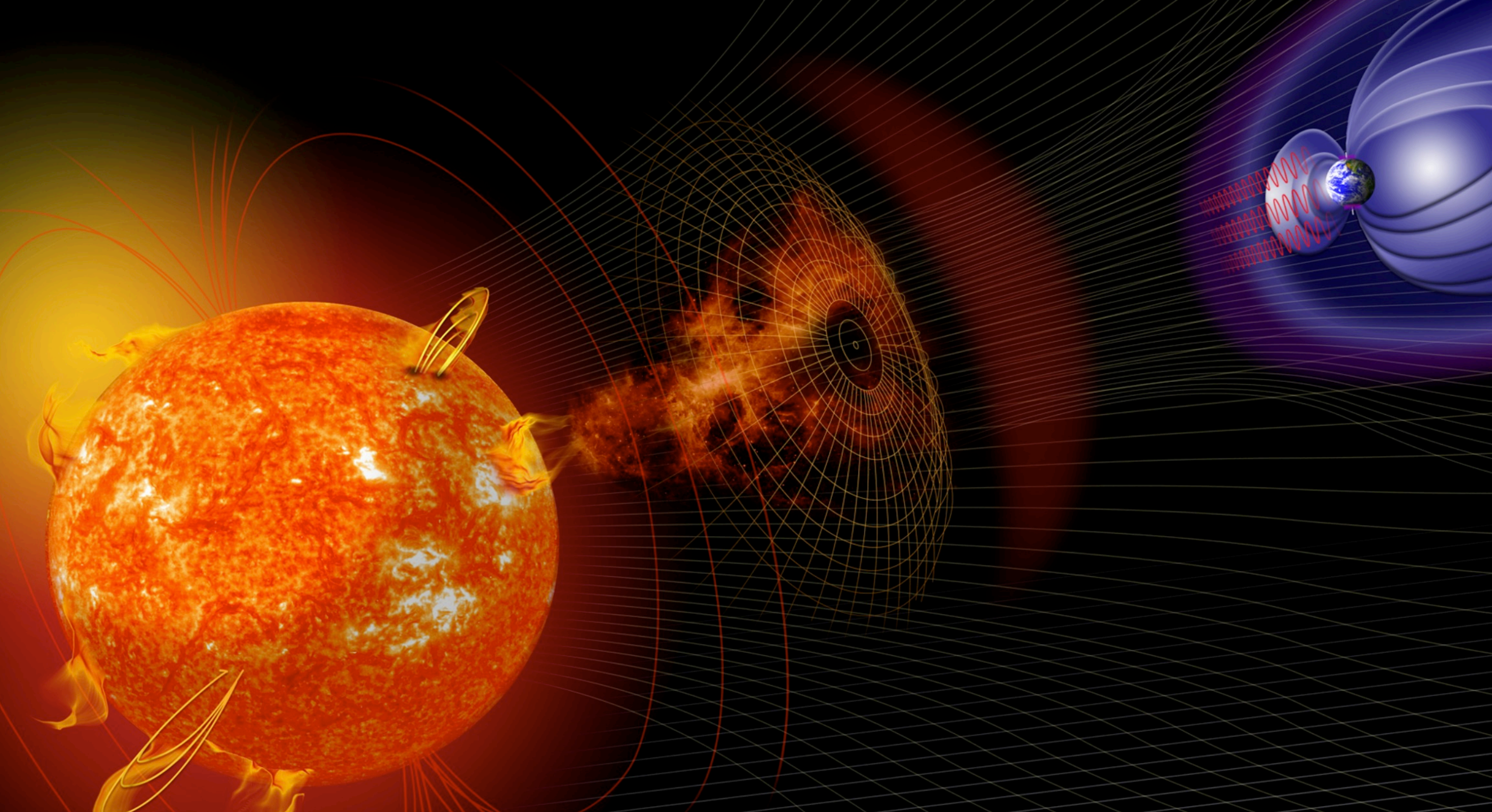

RM
RonnMurrayPhoto.com



https://svs.gsfc.n



Artist illustration of events on the sun changing the conditions in Near-Earth space. Credit NASA https://svs.gsfc.nasa.gov/3743

Global Geomagnetic Perturbation Forecasting using Deep Learning

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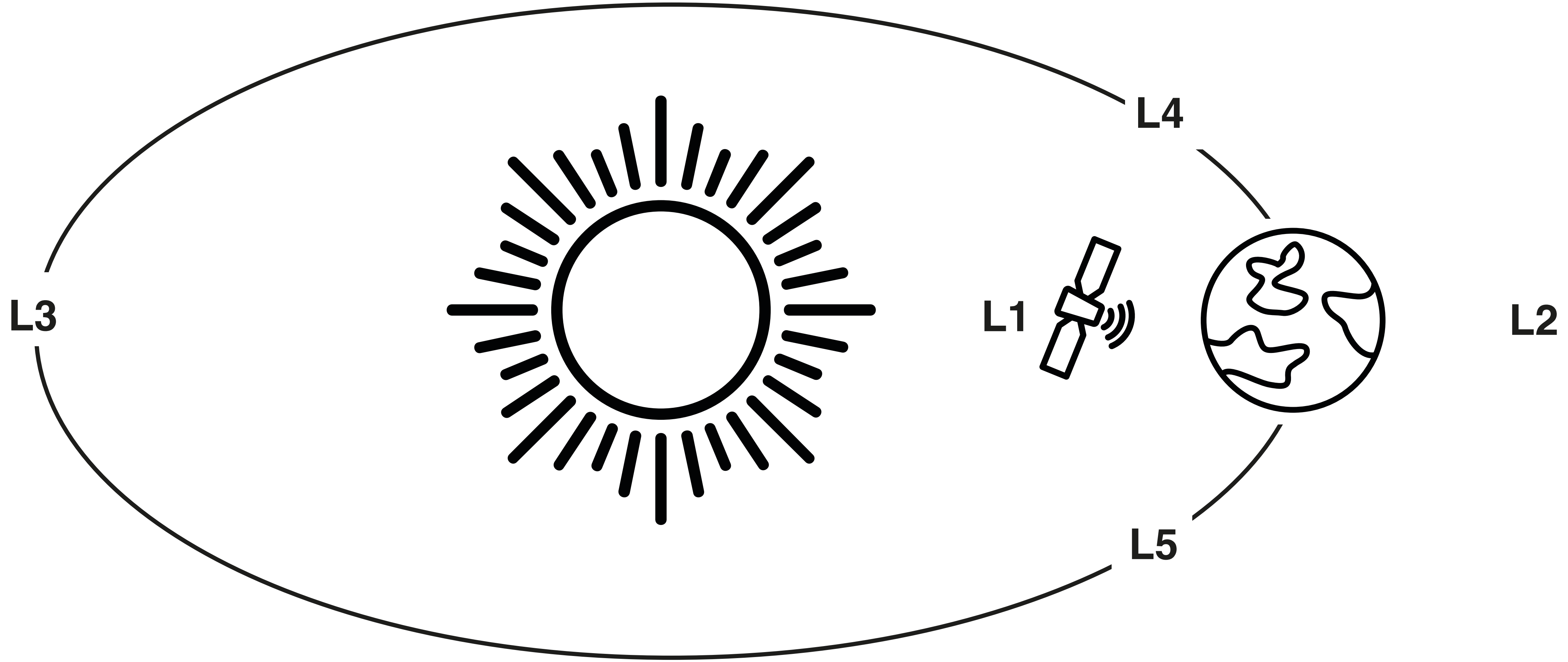
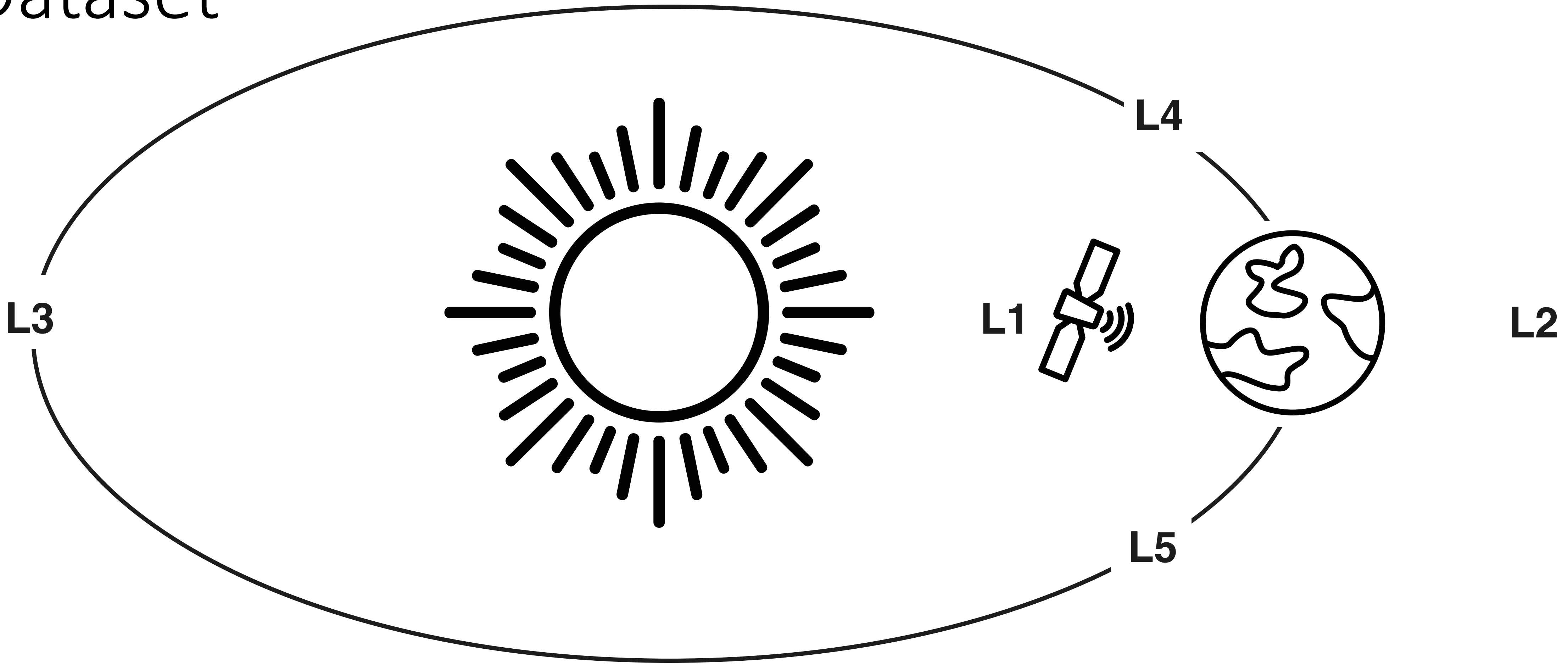

L4
L3
L1
L2
L5

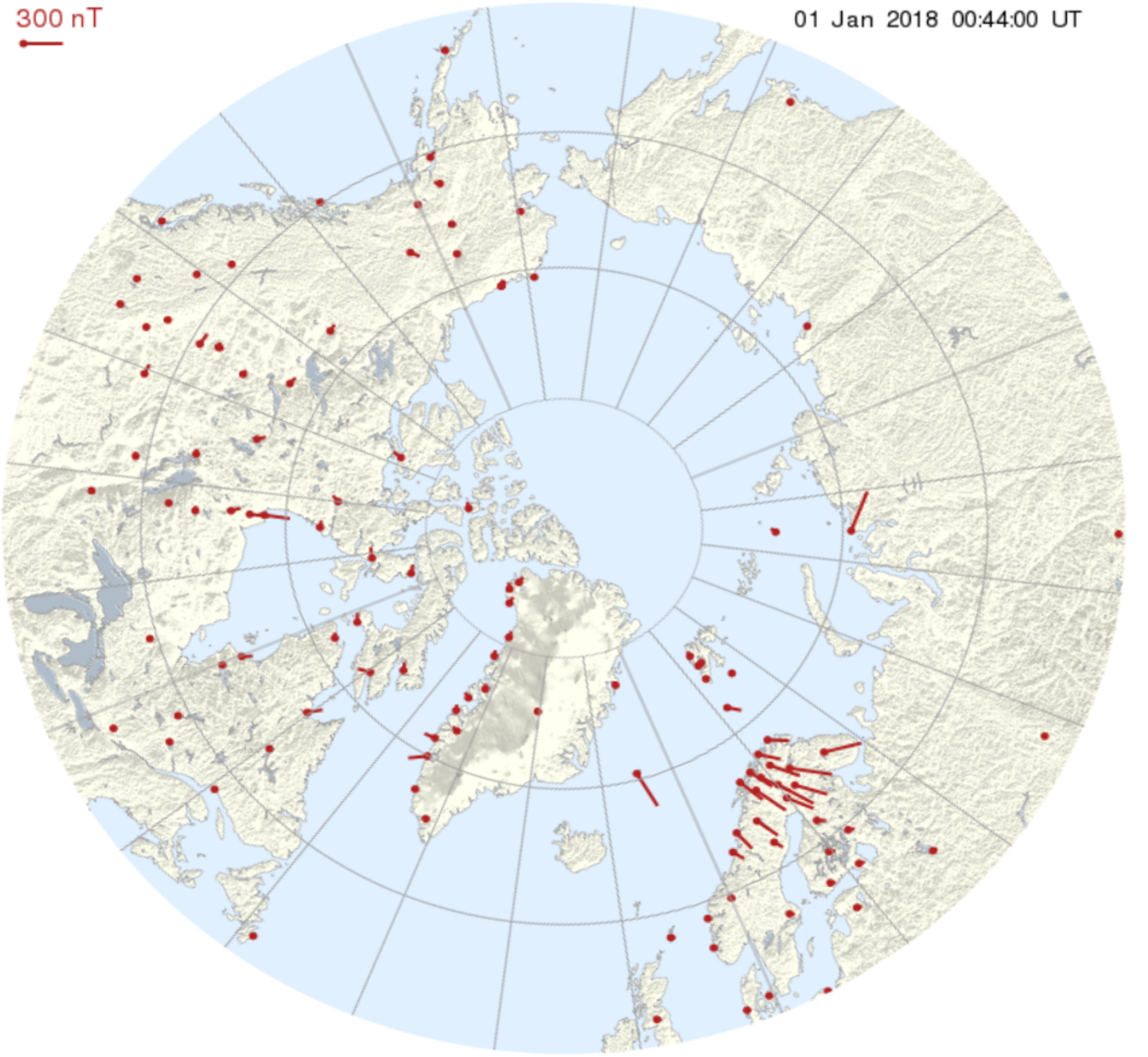
OMNI Dataset



OMNI Dataset

- IMF measurements at 1-minute cadence from NASA/GSFC OMNI dataset
- Features:
  - GSM coordinates (B_x, B_y, B_z), Solar wind Velocity, Dipole Axis, Solar wind proton Temperature, Clock angle, Solar radio flux at 10.7 cm

SuperMAG Dataset



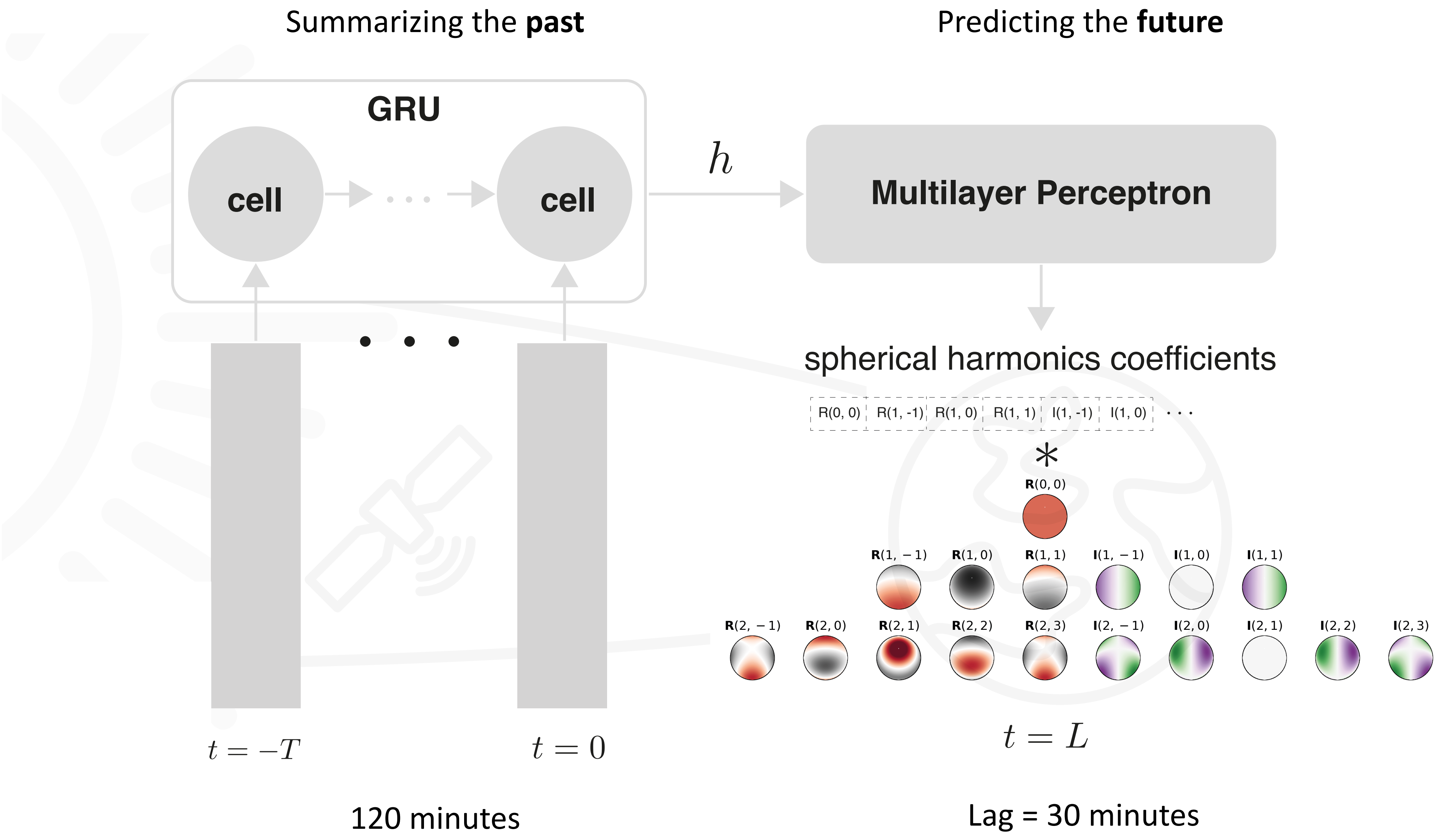
FRONTIER DEVELOPMENT LAB

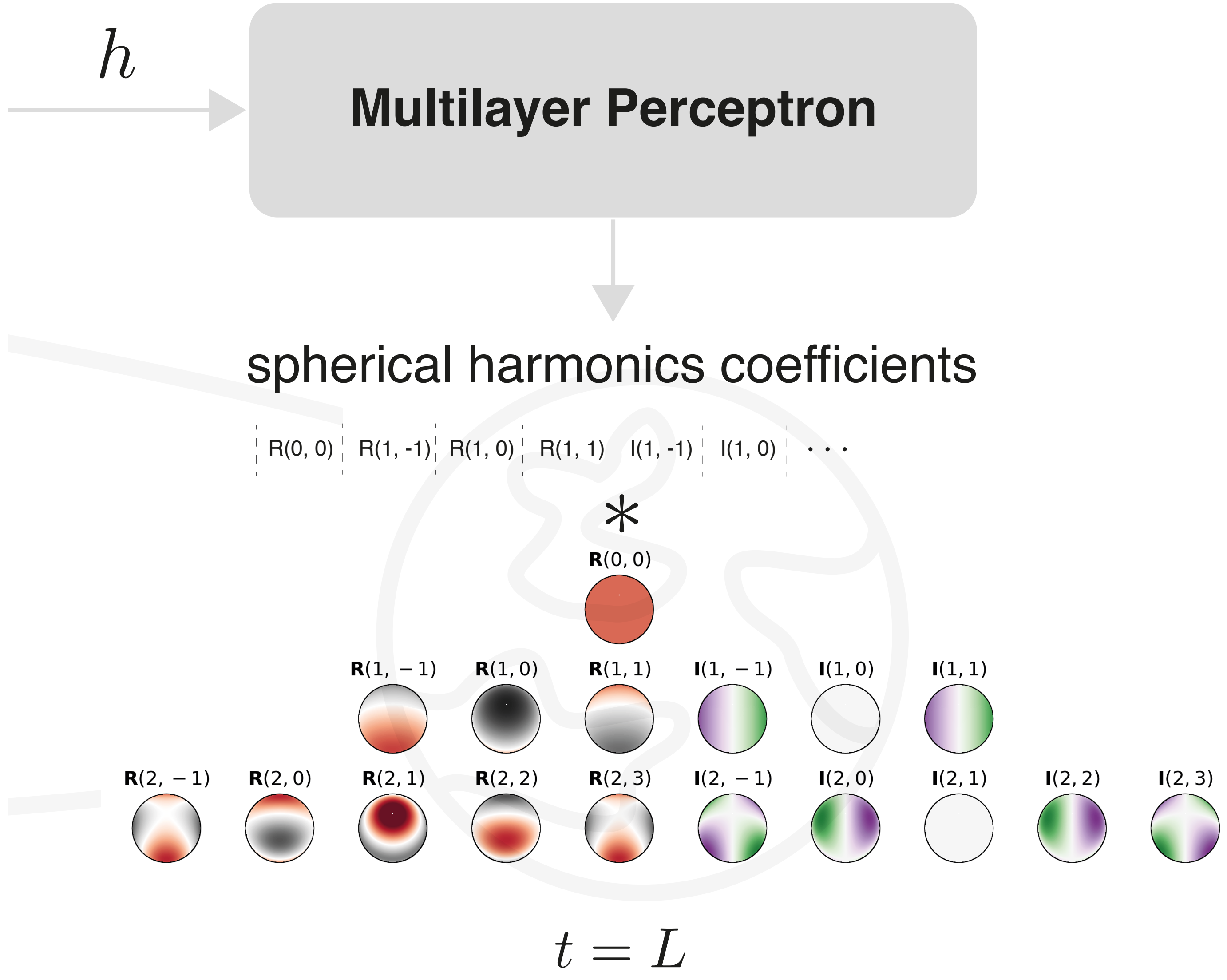
Few Details More

- Dates 2010-2019
- Standardized (based on 10k points)
- Train / Test / Val split based on 100 bins, randomly sampled (80/10/10)

THE MODEL

DAGGER **D**eep le**A**rninG **G**eomagnetic p**E**rtu**R**bation


Summarizing the **past**
Predicting the **future**
GRU
cell
cell
h
Multilayer Perceptron
spherical harmonics coefficients
R(0, 0)
R(1, -1)
R(1, 0)
R(1, 1)
I(1, -1)
I(1, 0)
$*$
R(1, −1)
R(1, 0)
R(1, 1)
I(1, −1)
I(1, 0)
I(1, 1)
R(2, −1)
R(2, 0)
R(2, 1)
R(2, 2)
R(2, 3)
I(2, −1)
I(2, 0)
I(2, 1)
I(2, 2)
I(2, 3)
$t = -T$
$t = 0$
$t = L$
120 minutes
Lag = 30 minutes



h
Multilayer Perceptron
spherical harmonics coefficients
R(0, 0)
R(1, -1)
R(1, 0)
R(1, 1)
I(1, -1)
I(1, 0)
. . .
*
R(0, 0)
R(1, − 1)
R(1, 0)
R(1, 1)
I(1, − 1)
I(1, 0)
I(1, 1)
R(2, − 1)
R(2, 0)
R(2, 1)
R(2, 2)
R(2, 3)
I(2, − 1)
I(2, 0)
I(2, 1)
I(2, 2)
I(2, 3)
t = L

Hyperparameters

Layer name	Size
GRU	8 units
FC: MLP Layer 1	16
FC: MLP Layer 2	440*2 (real and imaginary parts)
Spherical harmonic layer (NOT trainable)	–

Hyperparameter	Value
OMNI time series length	120 min
Maximum number of modes	20
Learning rate	5×10^{-3}
L2 regularization coefficient	5×10^{-5}
Dropout probability	0.7
Batch size	8500
Optimizer	Adam, with default Pytorch parameters

BASELINES & RESULTS

Weimer Model (2013)

An empirical model of ground-level geomagnetic perturbations

$$\Delta B_X(\Lambda, \phi) = \sum_{l=0}^{31} \sum_{m=0}^{3<l} P_l^m(\cos\Lambda)\left(g_l^m cos\ m\phi \;+\; h_l^m sin\ m\phi\right)$$

$$\begin{gathered} g_l^m = c_0 + c_1 B_T + c_2 V_{SW} + c_3 t + c_4\sqrt{F_{10.7}} + \\ c_5 B_T \cos(\theta_c) + c_6 V_{SW}\cos(\theta_c) + c_7 t \cos(\theta_c) + c_8\sqrt{F_{10.7}}\cos(\theta_c) + \\ c_9 B_T \sin(\theta_c) + c_{10} V_{SW}\sin(\theta_c) + c_{11} t \sin(\theta_c) + c_{12}\sqrt{F_{10.7}}\sin(\theta_c) + \\ c_{13} B_T \cos(2\theta_c) + c_{14} V_{SW}\cos(2\theta_c) + c_{15} B_T \sin(2\theta_c) + c_{16} V_{SW}\sin(2\theta_c) \end{gathered}$$

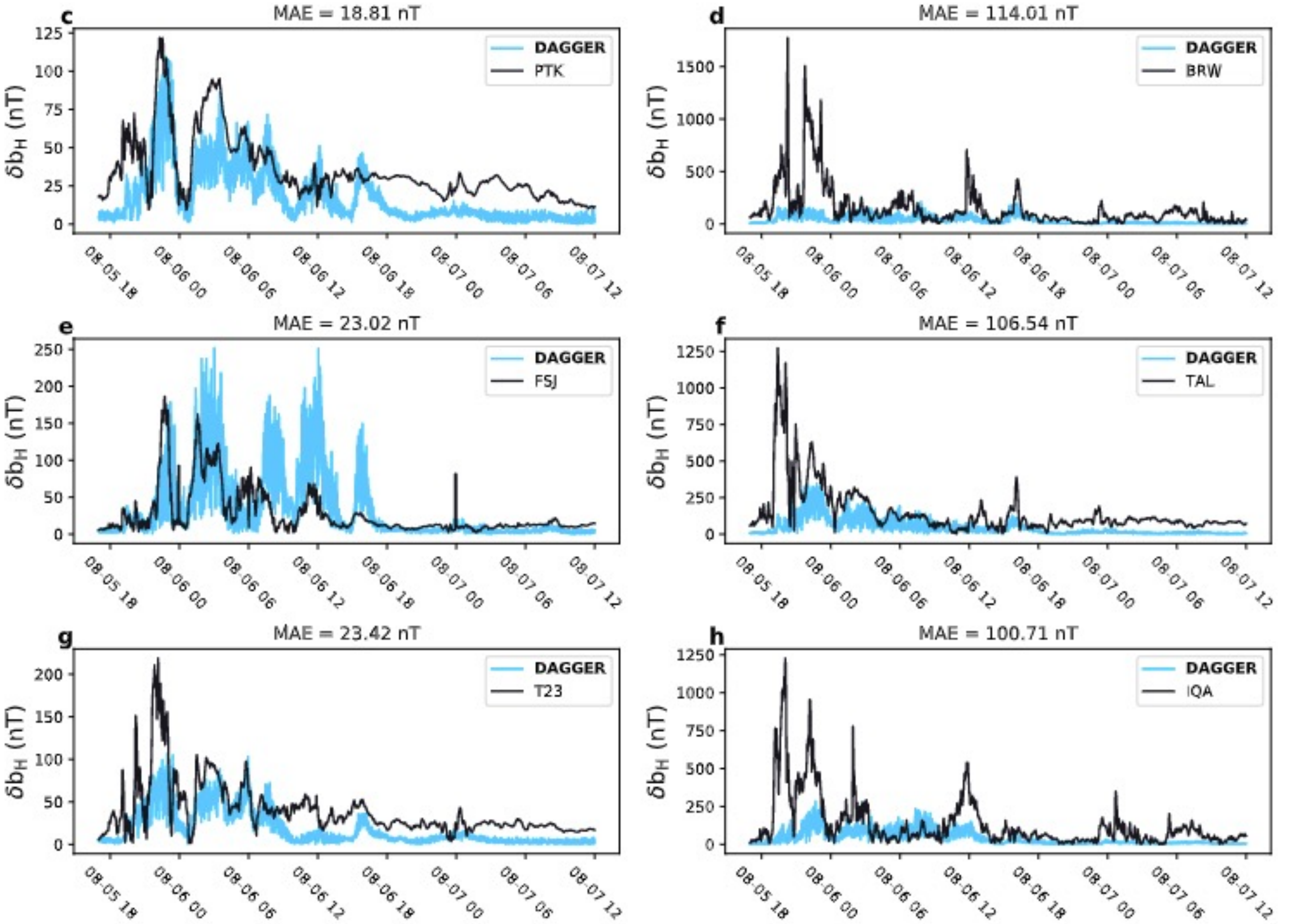
Benchmark Data

- 5 August 2011 storm
- 17 March 2015 storm

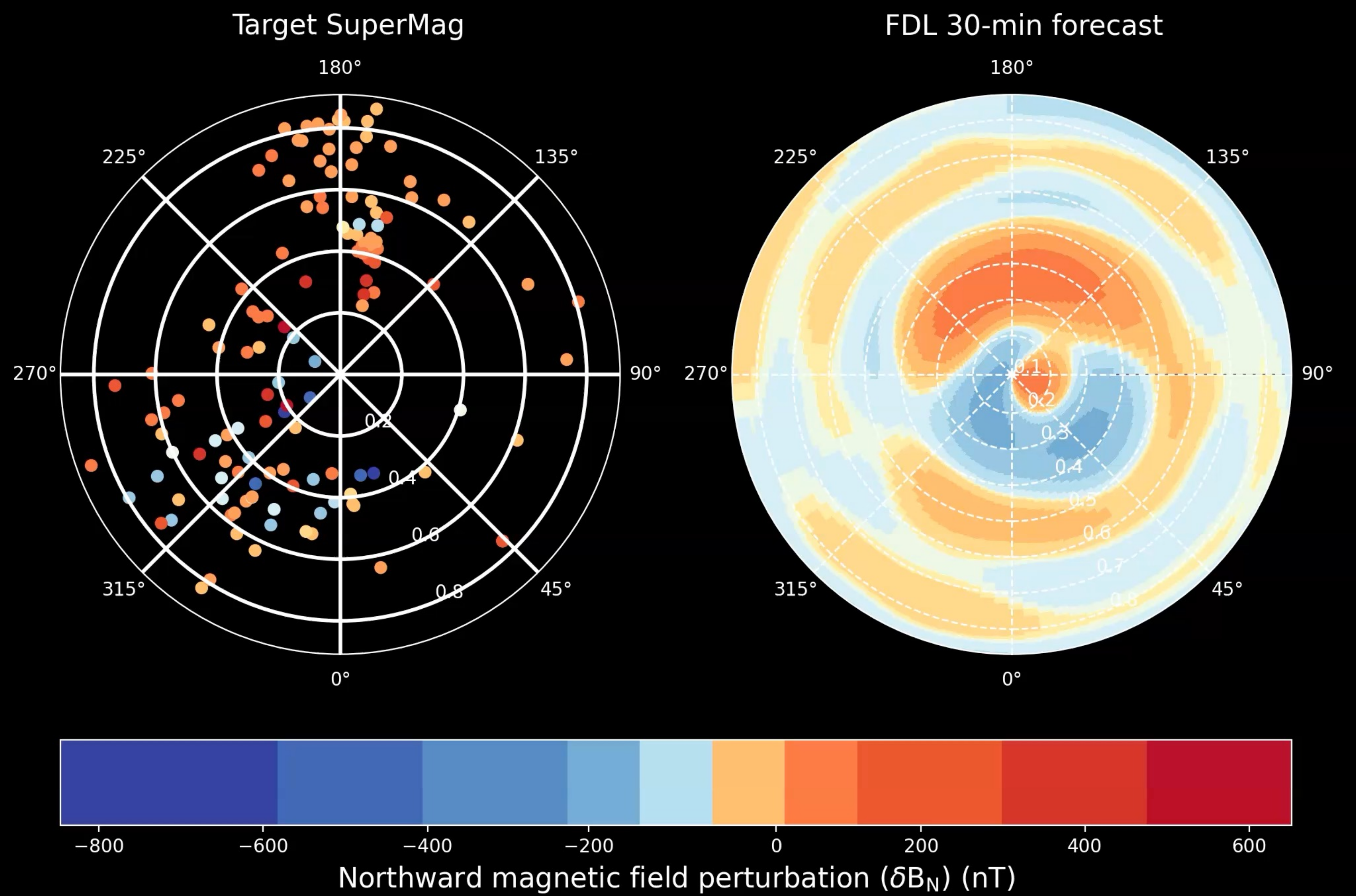
Quantitative Results

Storm	Metric	**DAGGER**		**W2013**		Persistence	
		δb_e	δb_n	δb_e	δb_n	δb_e	δb_n
2011	MAE	34.99	53.20	67.41	76.74	30.87	43.52
	RMSE	72.86	100.46	127.54	140.93	73.53	97.41
2015	MAE	61.44	104.7	104.69	121.48	47.17	67.4
	RMSE	102.45	**175.37**	179.97	195.52	87.78	128.90

Top performing stations



Worst performing stations


Target SuperMag
FDL 30-min forecast
180°
225°
135°
270°
90°
315°
45°
0°
0.2
0.4
0.6
0.8
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
−800
−600
−400
−200
0
200
400
600
Northward magnetic field perturbation (δB_N) (nT)

NEXT STEPS

Next Steps

- **Different Architectures:** Transformers (for OMNI data summarization) and Graph Neural Networks for modeling the spherical signal (SuperMAG prediction)
- **Data Fusion:** Fuse past SuperMAG with OMNI data for GIC forecasting

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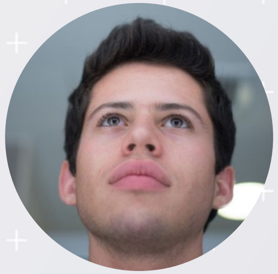

Yarin Gal

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Thank you

Code: https://github.com/ptigas/geoeffectivenet

Colab: https://colab.research.google.com/github/spaceml-org/helionb-geoeff/blob/main/notebooks/01_geoeff_2020/storm_forecast.ipynb

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