Next-Generation Solar Wind Modeling

Differentiable Framework & its Synergy with PUNCH

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SWx TREC

UCAR COMMUNITY PROGRAMS | CPAESS

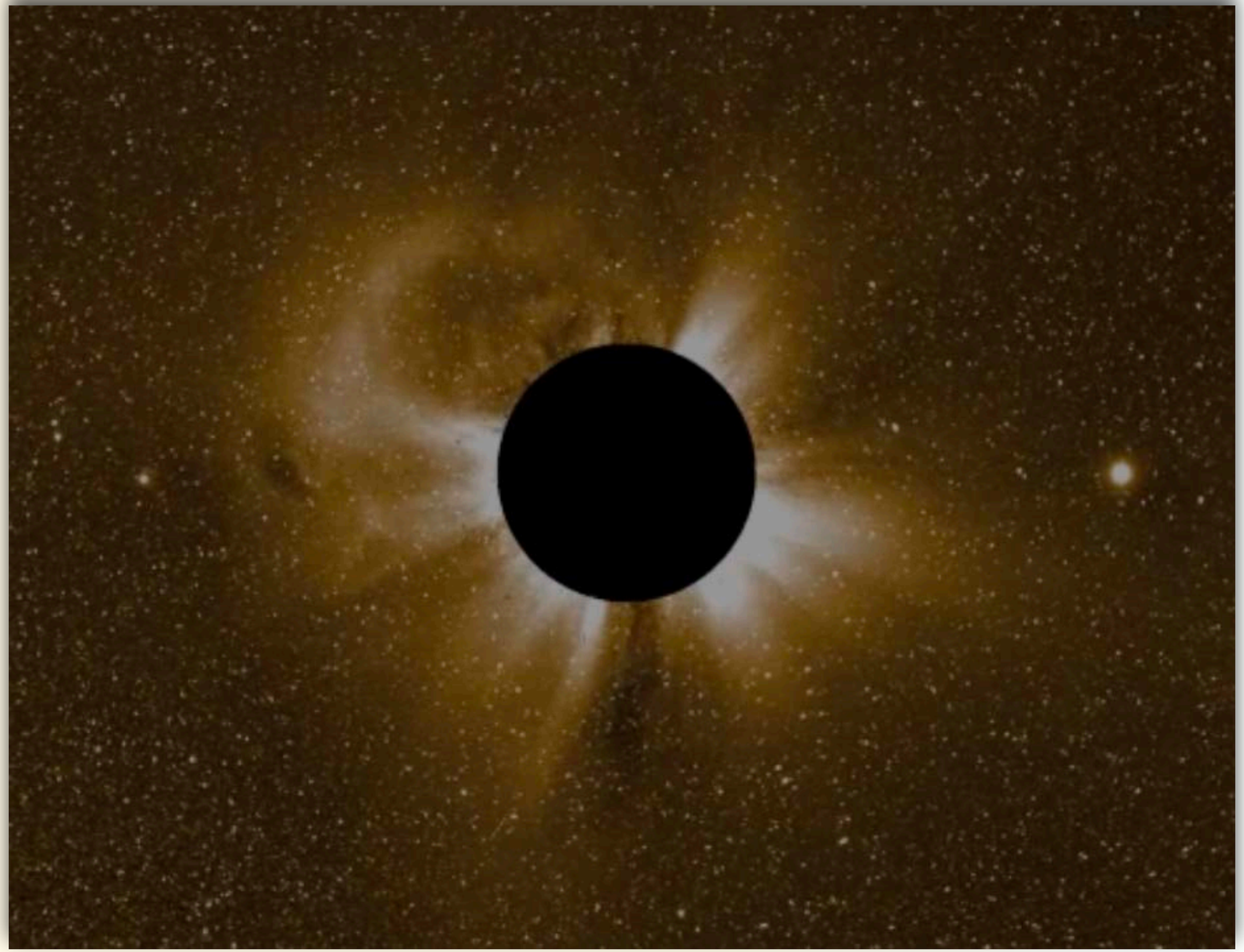
NASA | LWS LIVING WITH A STAR NASA

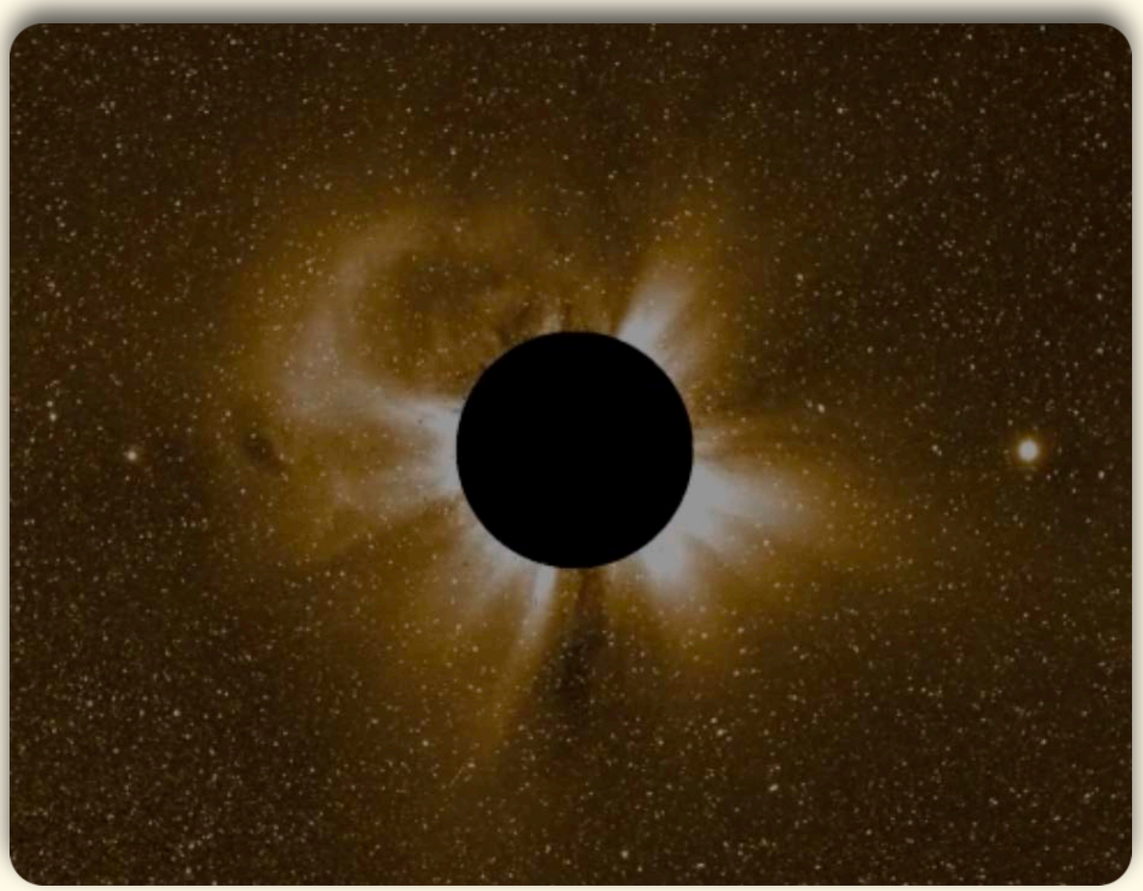
Enrico Camporeale

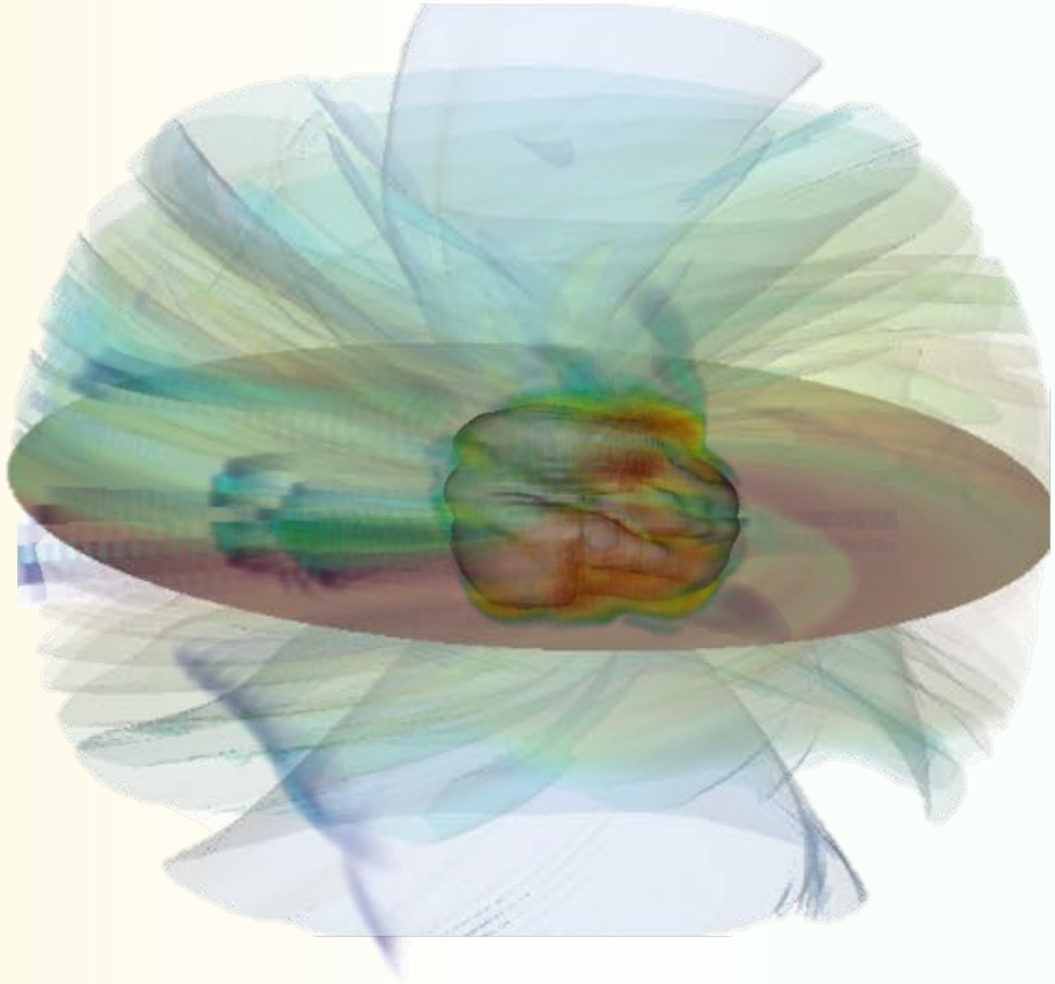
NSF | NCAR OPERATED BY UCAR Thomas Berger

UNIVERSITY OF MICHIGAN Zhenguang Huang

UNIVERSITY OF MICHIGAN Gabor Toth

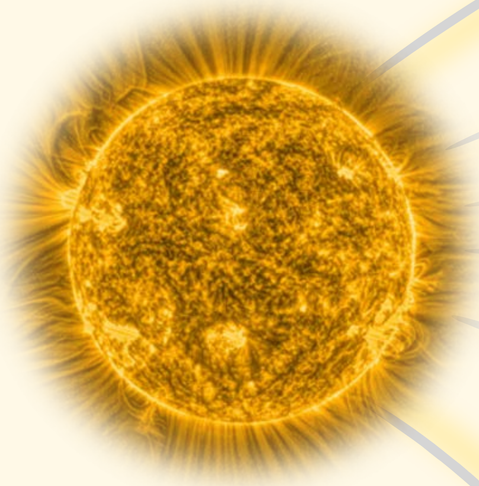






*from SWASTi simulation

Current Modeling Approaches



0.1 AU

1.0 AU

WSA
(semi-empirical)

MHD
(physics-based)

MHD
(physics-based)

Provides: **3D** magnetic field (**B**), velocity (**V**), pressure (P) & density (ρ)

Runtime: >200 CPU hours

- ENLIL
  Odstrcil et al., 2003
- AWSoM
  B. van der Holst et al 2014
- SWASTi
  Mayank et al., 2022

Analytical
(crude approximation)

Provides: **2D** speed (|**V**|) & |B| polarity

Runtime: few CPU minutes

- WSA kinematic
  Arge & *Pizzo 2000*
- HUX
  Riley & Lionello 2011
- HUXt
  Owens et al., 2020

Machine Learning
(data-based)

Provides: **1D** speed (|**V**|)

Runtime: few CPU seconds

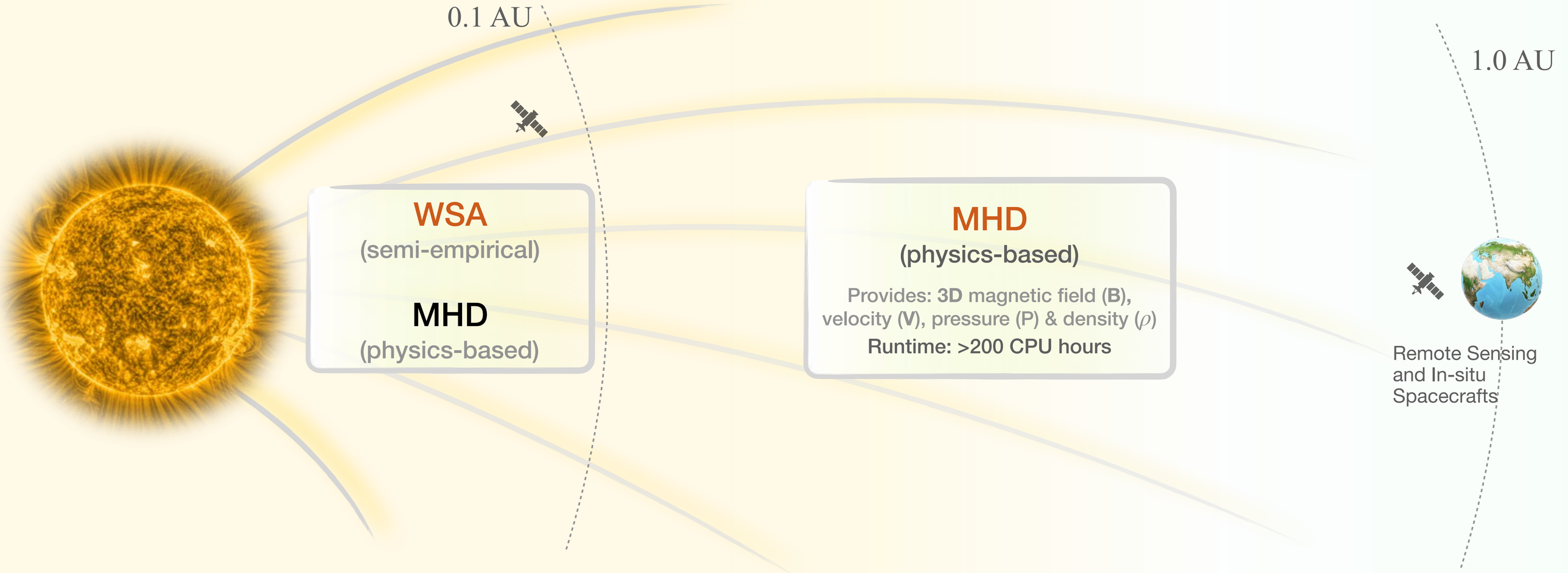
- *Yang et al., 2018*
- *Upendran et al, 2020*
- *Lin et al., 2024*
- *Cobos et al., 2025*

Remote Sensing and In-situ Spacecrafts

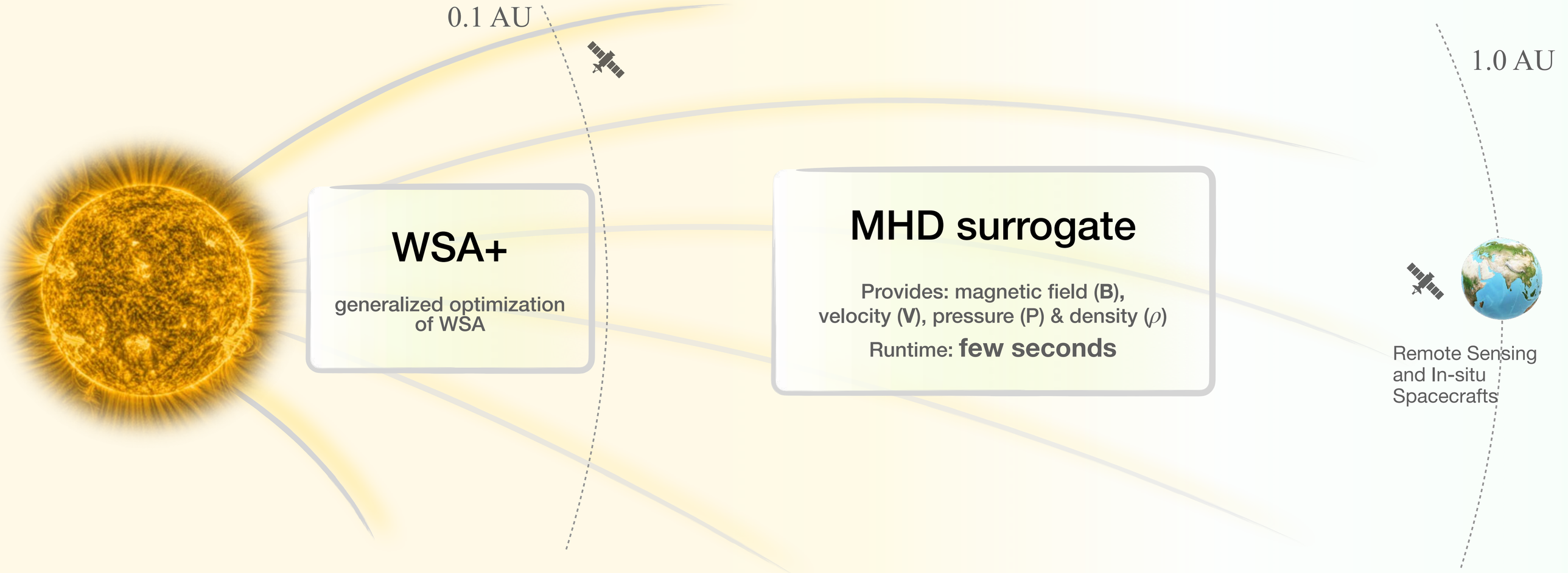
Solar Corona

Inner Heliosphere

Suitable Modeling Approach



Next-Generation Approach



WSA+

Neural enhancement of the Wang–Sheeley–Arge solar wind model

Smarter. More accurate. Ready to forecast.

Mayank et al. 2025
ApJ Lett., 994, L5

ENHANCED ACCURACY
Neural optimization of WSA parameters for best match to in-situ observations

DIFFERENTIABLE
End-to-end differentiable and physics-constrained pipeline

READY FOR OPERATIONS
Generalizes across solar conditions and enables real-time forecasting

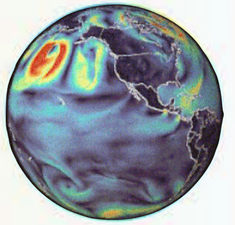
MAGNETOGRAM (Input)

Photospheric magnetic field observations

WSA+ (Neural Optimized)

Optimizes WSA parameters

SOLAR WIND SPEED MAP



Improved near-Sun solar wind speeds

- Higher correlation with in-situ data
- Lower errors across multiple metrics
- Robust across solar cycles

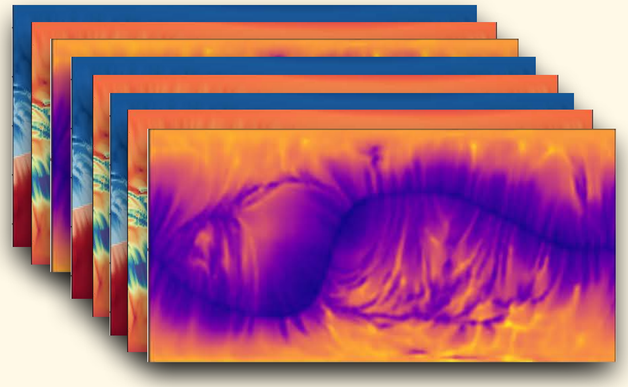
PROVEN & VALIDATED

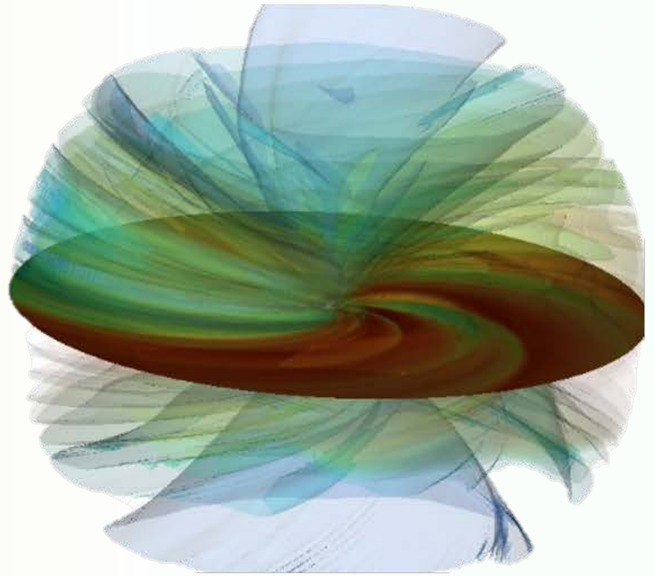
- Significant improvement over traditional WSA across multiple metrics
- ~40% average improvement
- Validated on multiple solar cycles and independent datasets

PIP INSTALL: WSAPLUS

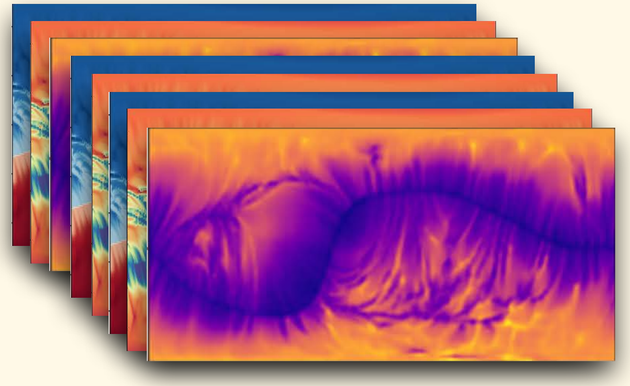
```
pip install wsaplus
```

MHD Surrogate Approach





MHD Surrogate Approach



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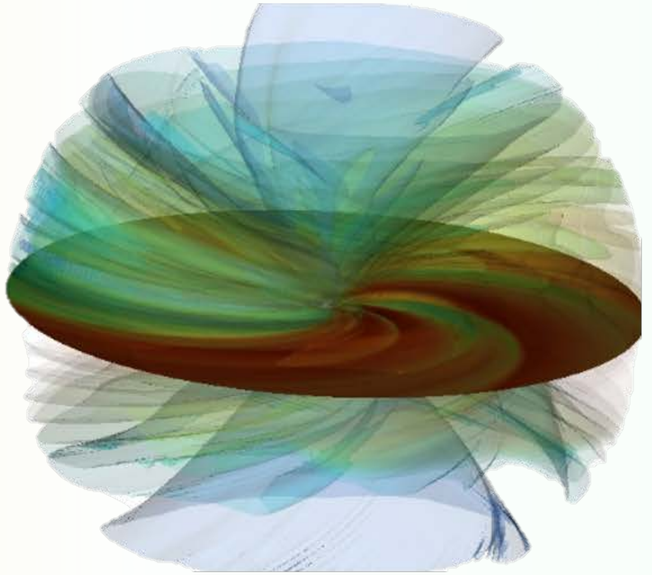


Architecture

- Spherical topology
- Multi-scale structures
- Radial propagation

Physics

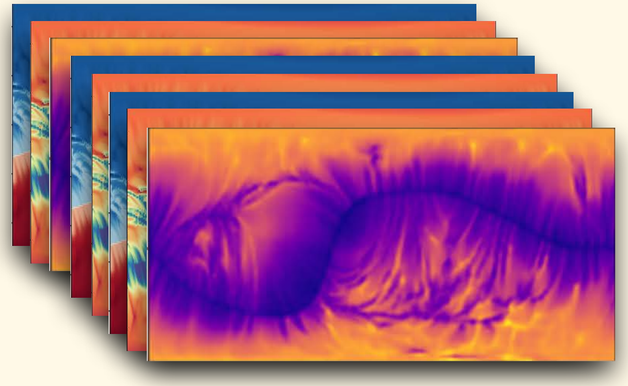
- PDE residuals
- Extra info of system

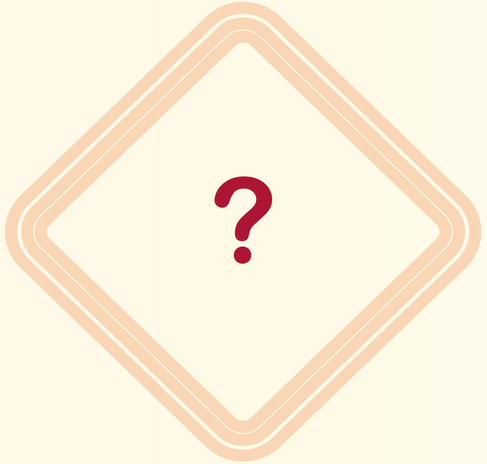
Target

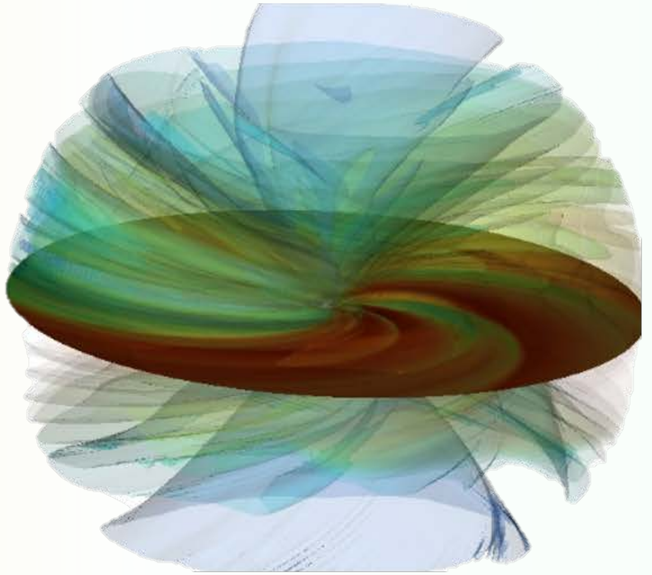
AwSOM simulations

- 20 $R_\odot$ — 250 $R_\odot$
- Rotating frame
- Res: 1 $R_\odot$ and 1 degree

MHD Surrogate Approach







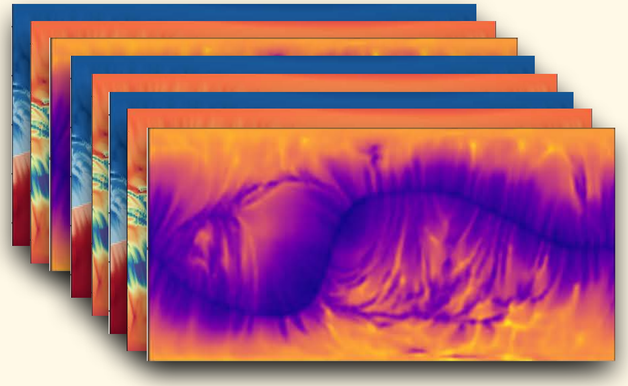
Neural Network

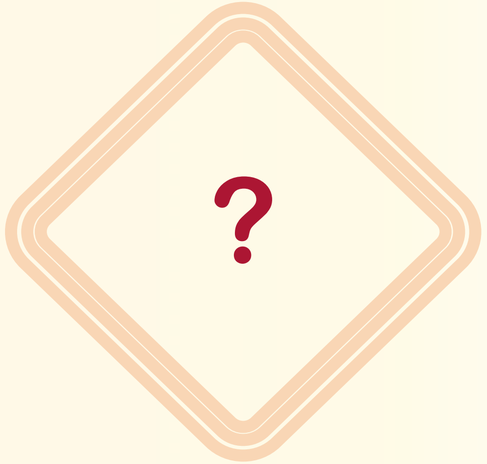
- Vector mapping
- Fixed Grid
- Classification & regression

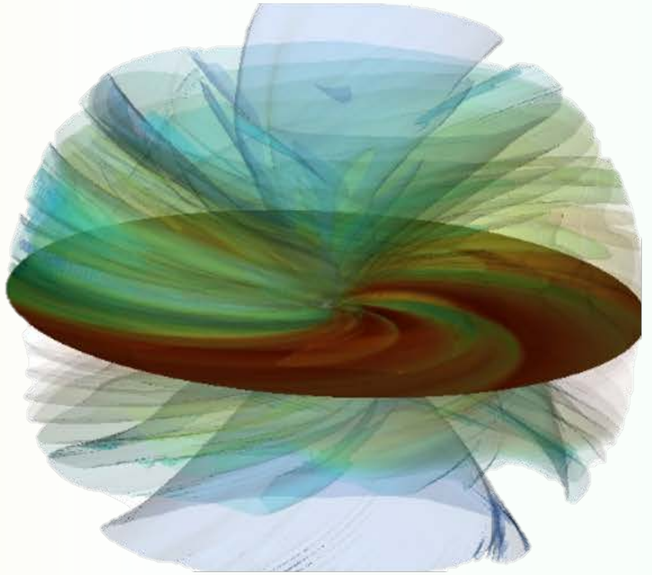
Neural Operator

- Function mapping
- Resolution Independent
- PDE surrogates

MHD Surrogate Approach







3D Fourier

- Fourier in r, θ, ϕ
- Not suitable for poles
- Requires higher computation

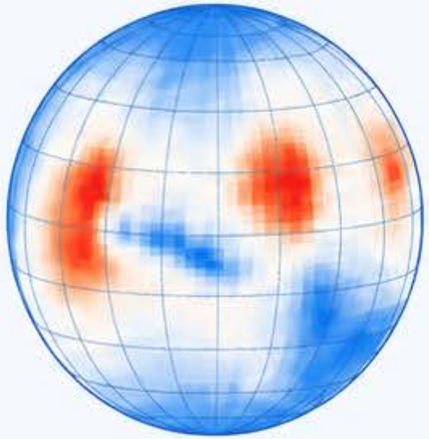
Spherical Harmonics

- Fourier in ϕ, Legendre in θ
- Suitable for spherical geometry
- Affordable computation budget

Flow of Model Architecture

1. Input

MHD state on sphere at r_i

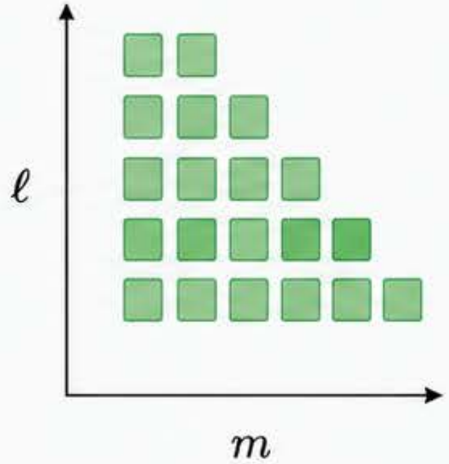


8 MHD variables

$(e.g.,\ \rho,\ v_r,\ v_\theta,\ v_\phi,$
$B_r,\ B_\theta,\ B_\phi,\ p)$

2. Spherical Harmonic Encoding

Transform to SH coefficients



3. Spherical Harmonics Operator (Surrogate)

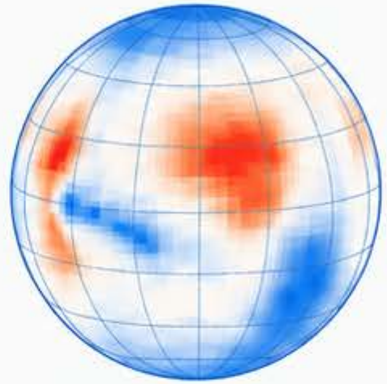
Input coeffs at r_i

Spectral mixing (ℓ–m coupling)

Output coeffs at r_{i+1}

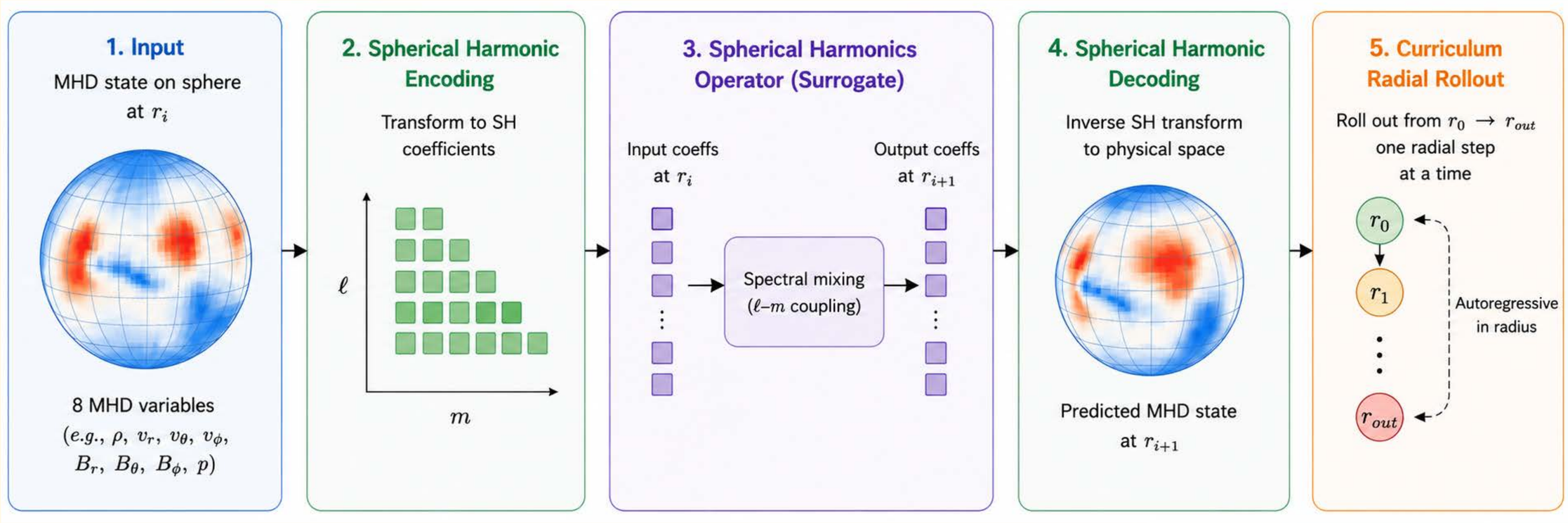
4. Spherical Harmonic Decoding

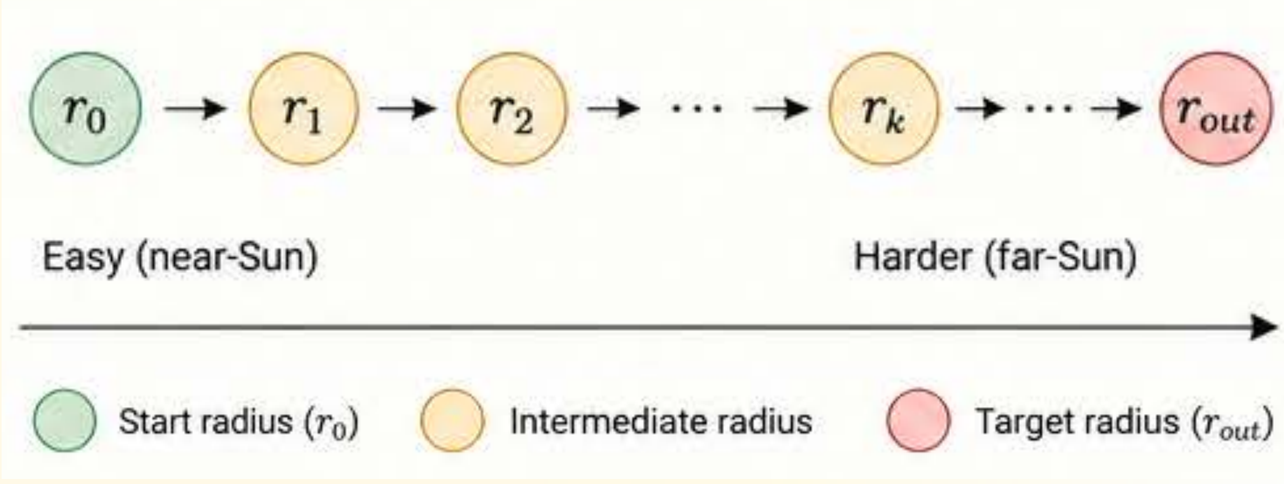
Inverse SH transform to physical space



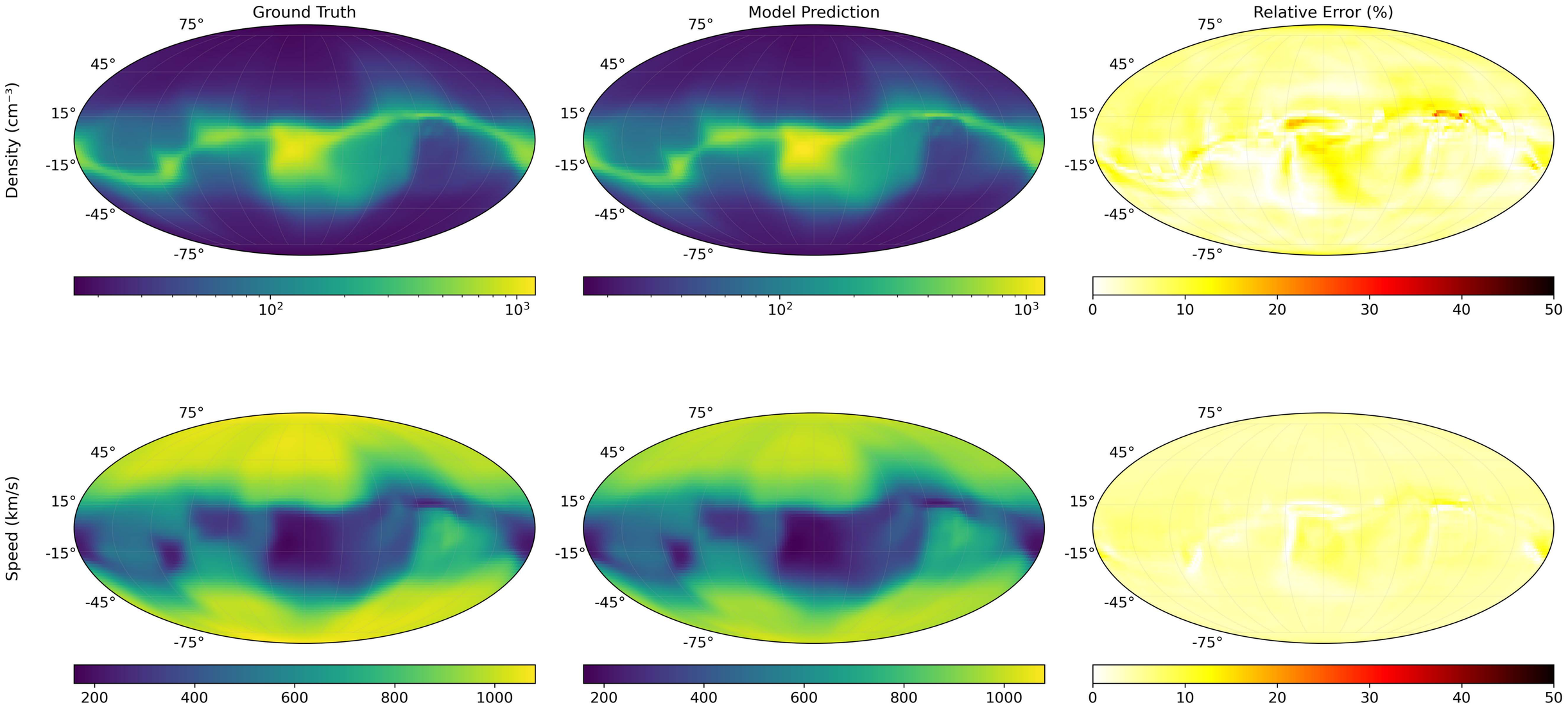
Predicted MHD state at r_{i+1}

Curriculum Radial Rollout





Spherical Learning is Great



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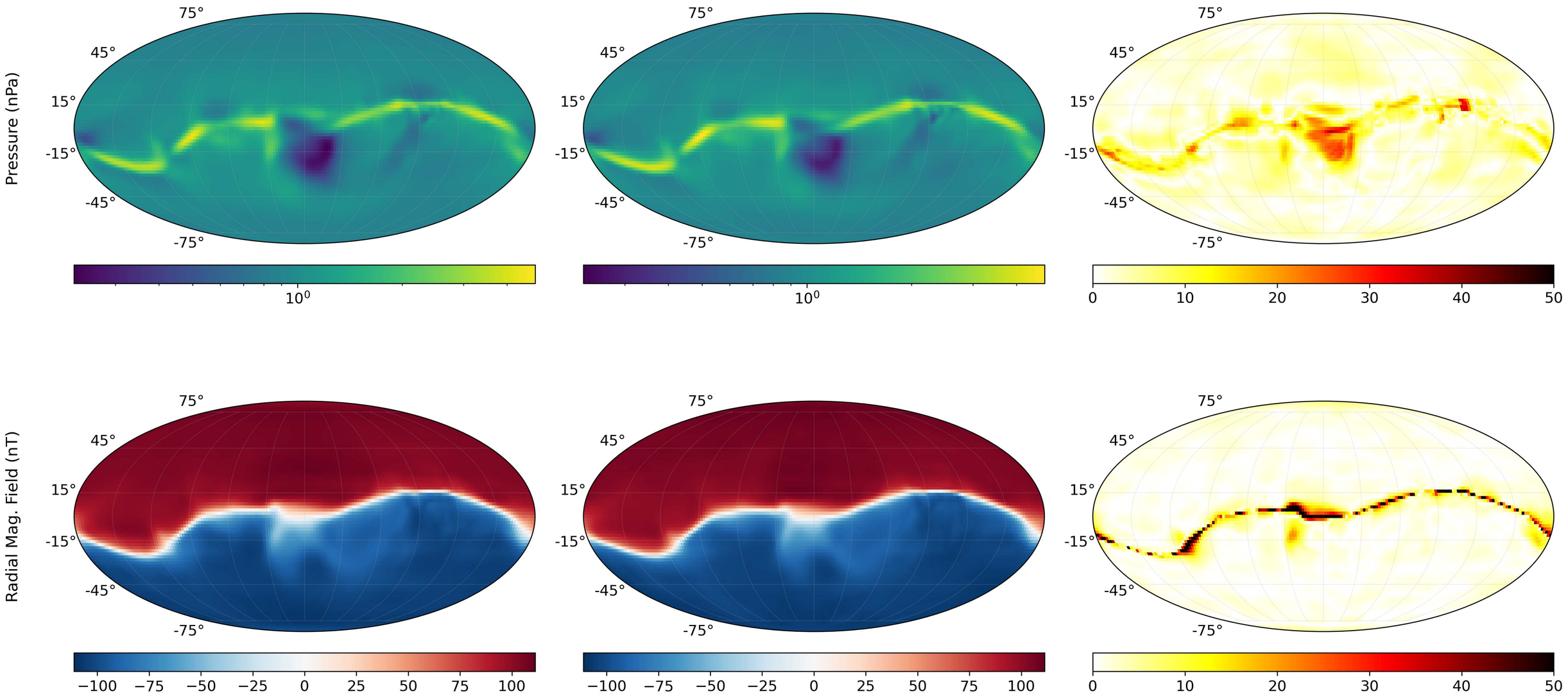
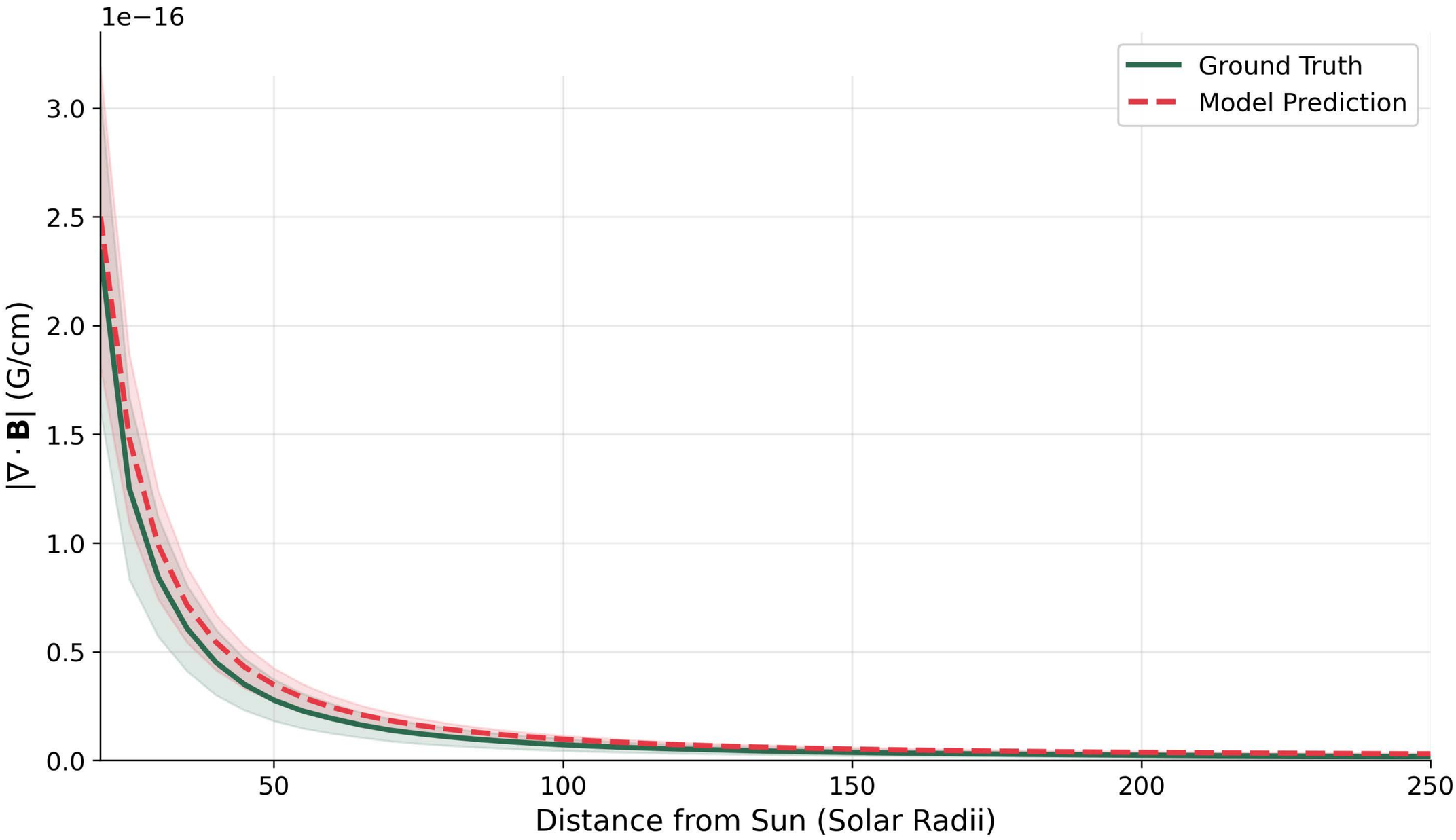
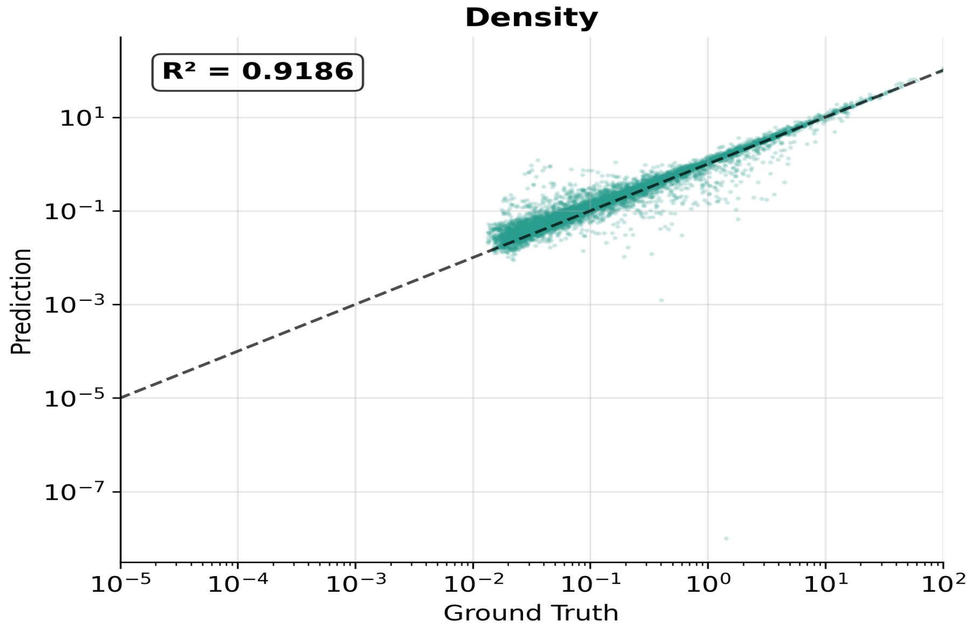
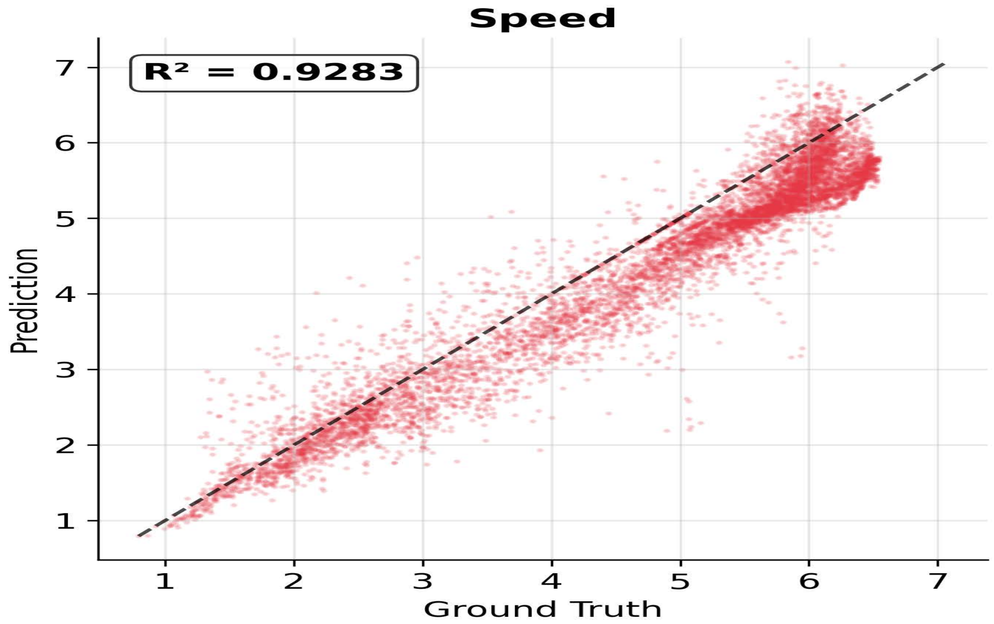


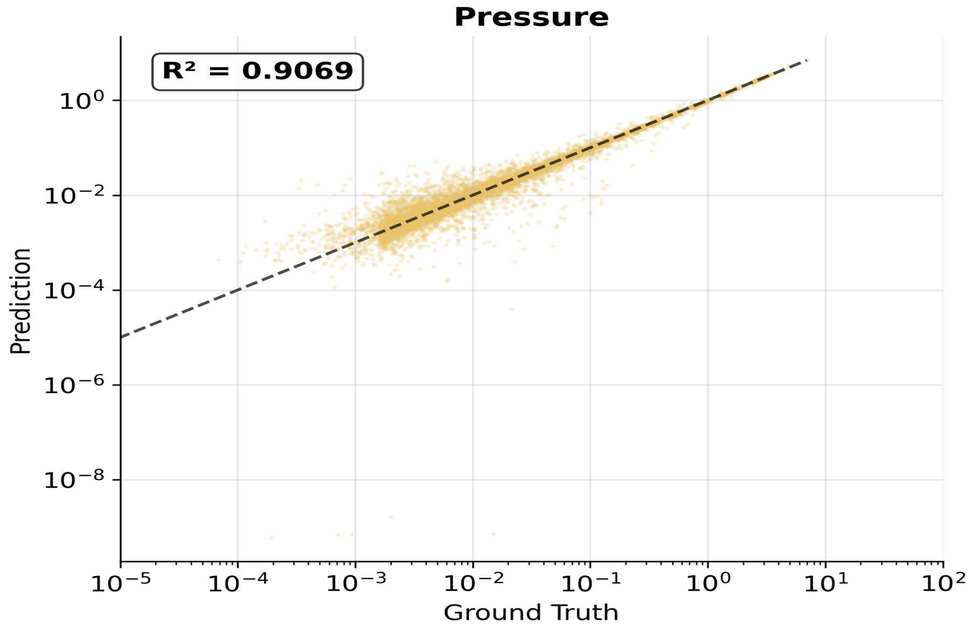
Divergence of B is Awesome

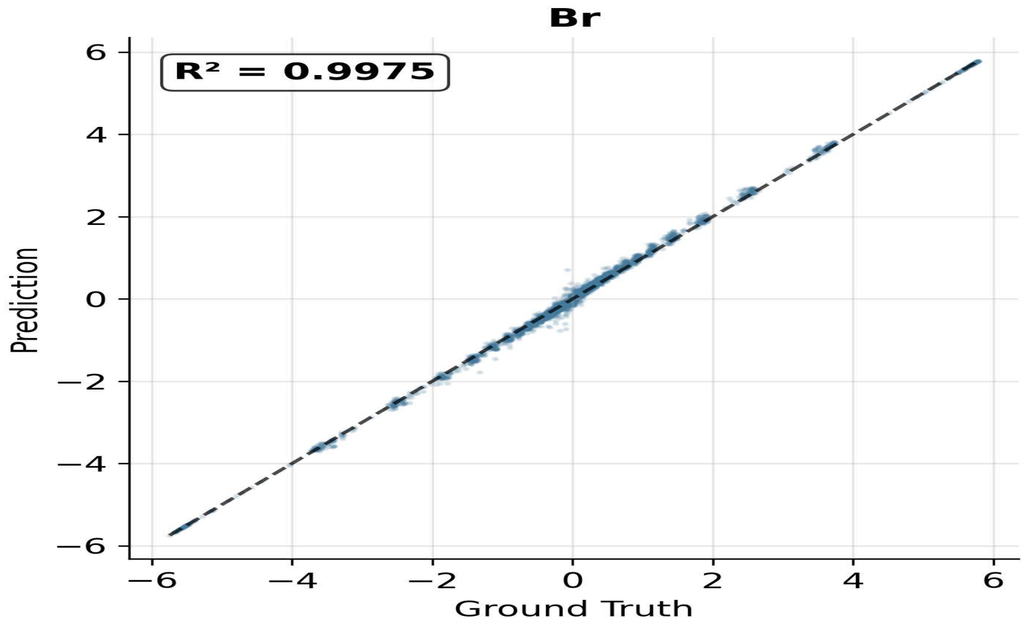


Far from Perfect

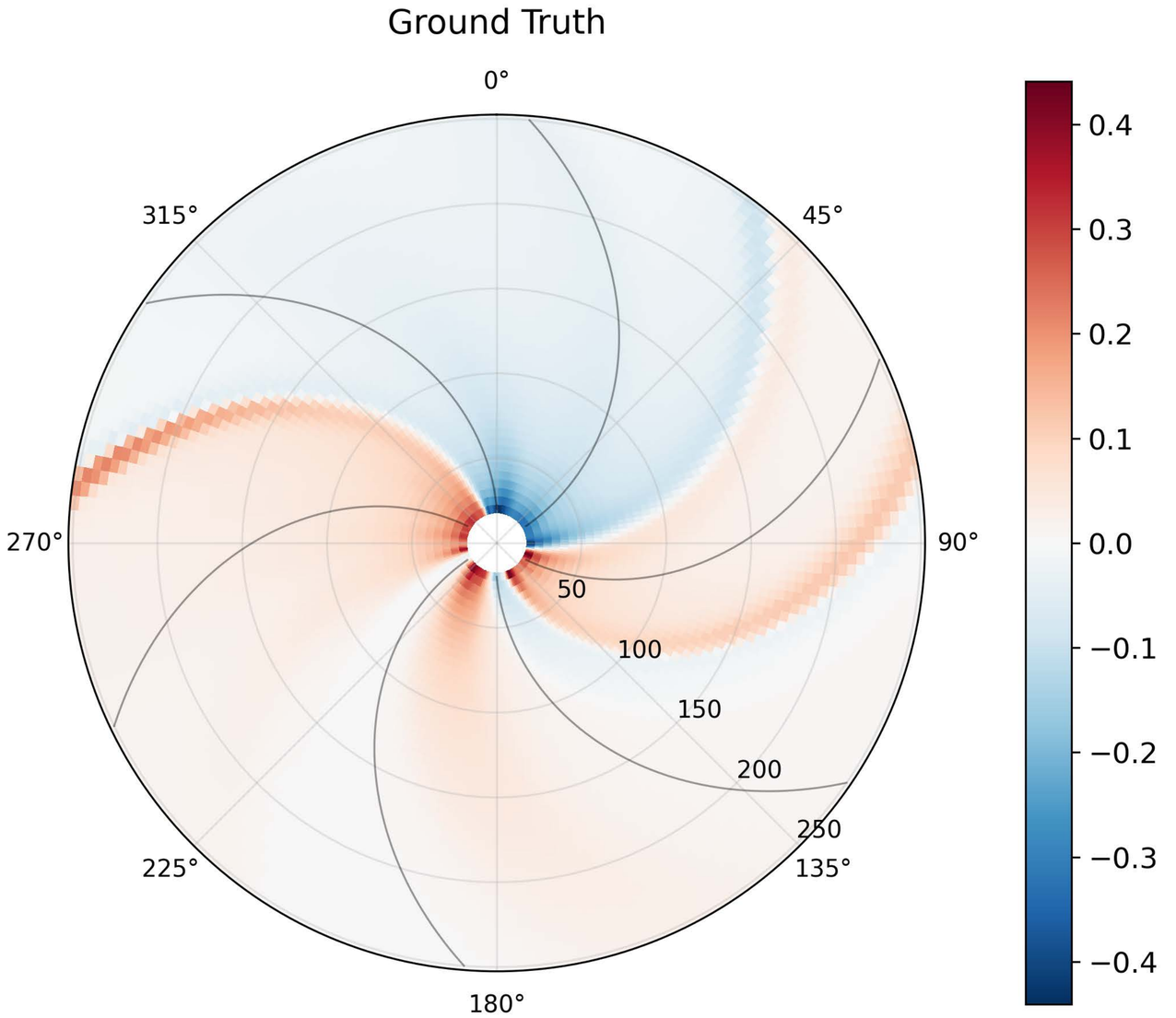


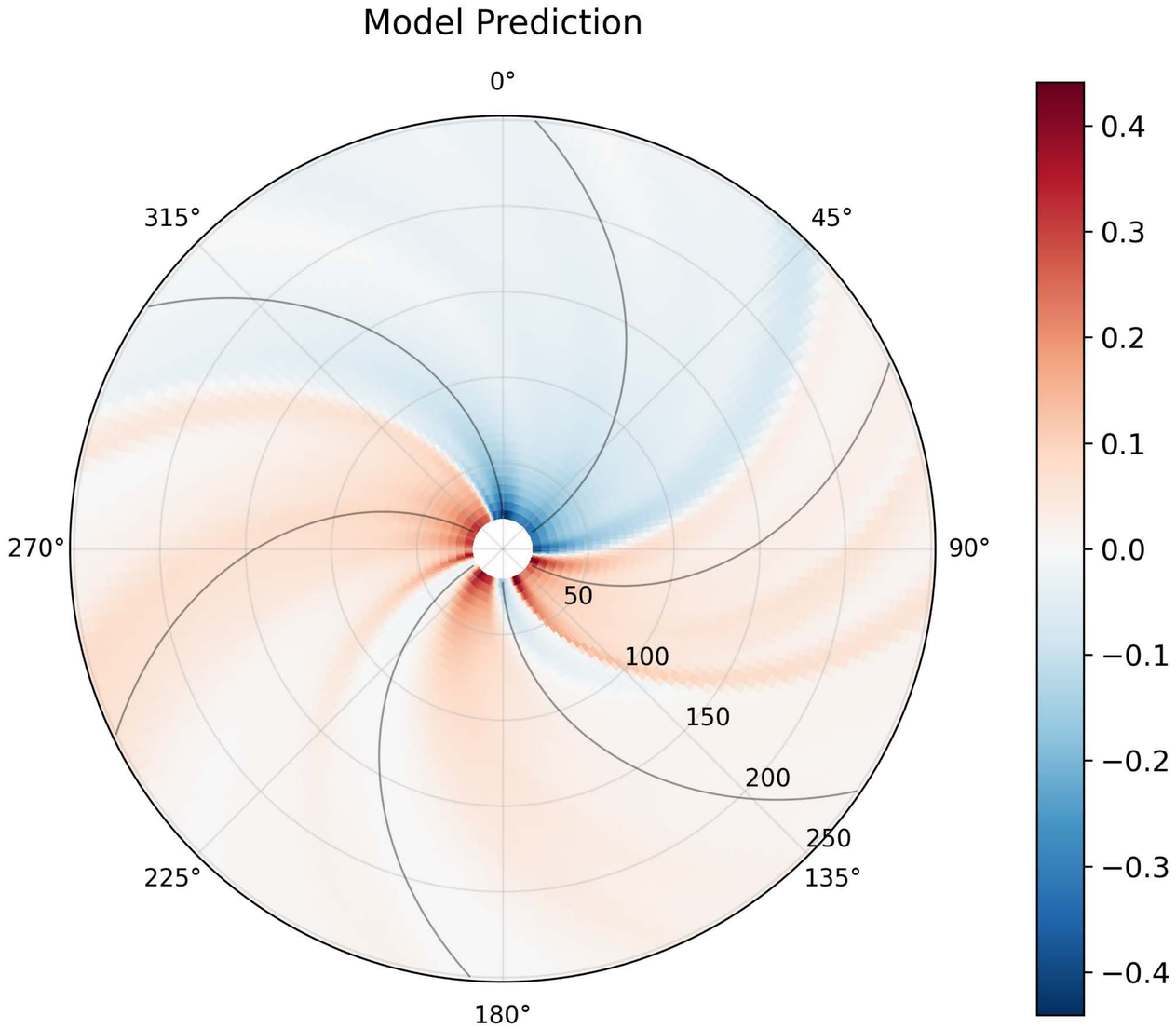






Challenges ...


Ground Truth
0°
45°
90°
135°
180°
225°
270°
315°
50
100
150
200
250
0.4
0.3
0.2
0.1
0.0
−0.1
−0.2
−0.3
−0.4


Model Prediction
0°
45°
90°
135°
180°
225°
270°
315°
50
100
150
200
250
0.4
0.3
0.2
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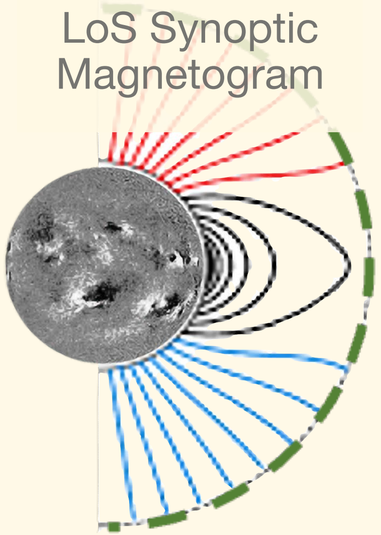
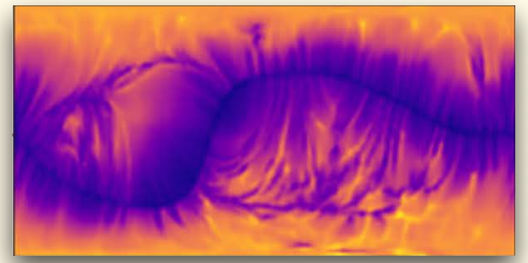
PUNCH informed Global Solar Wind

LoS Synoptic Magnetogram



WSA+ solar wind speed at 0.1 AU



MHD surrogate model

INPUT

2D plasma boundary condition at 0.1 AU

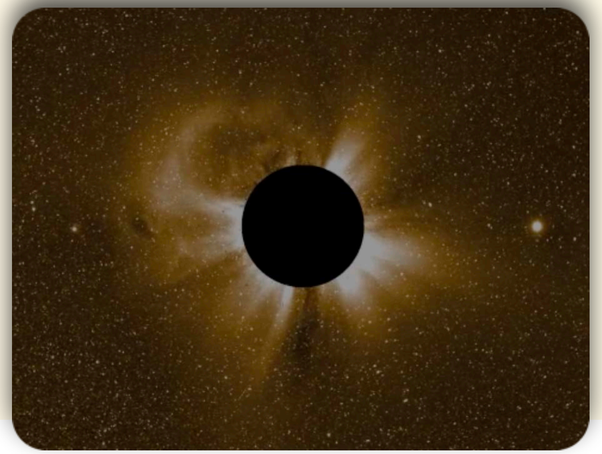
SW NO

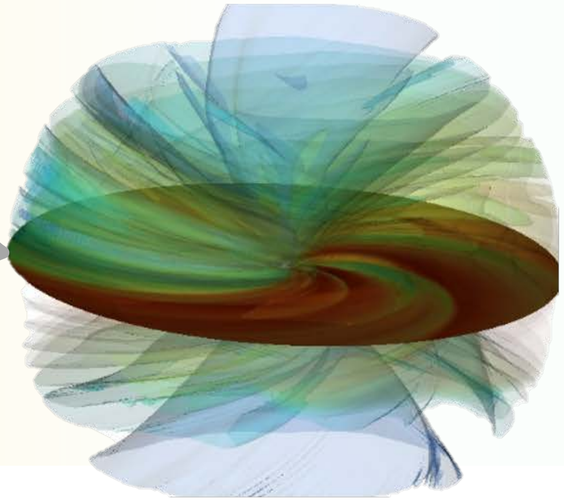
OUTPUT

3D plasma simulation from 0.1 to 2.0 AU

PDE Loss

Data Loss

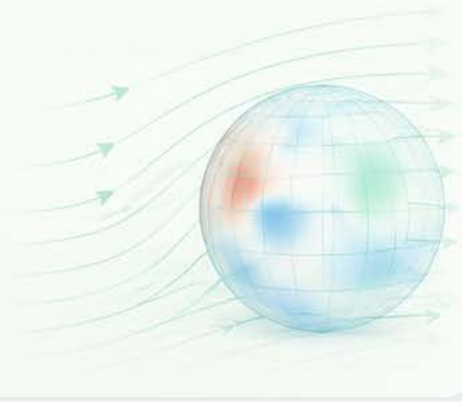




Take Away …

Orders of Magnitude Faster:

- from ~100 CPU hrs to mere few seconds on one GPU
- capable of real-time operational forecasting



SO WHAT ?

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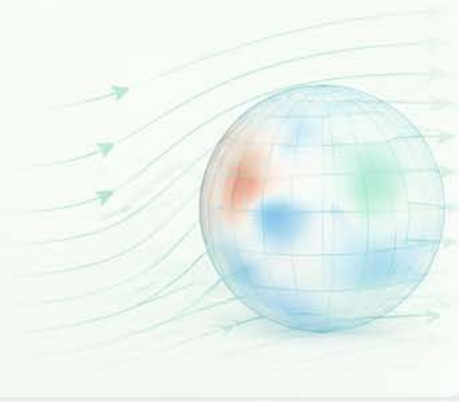
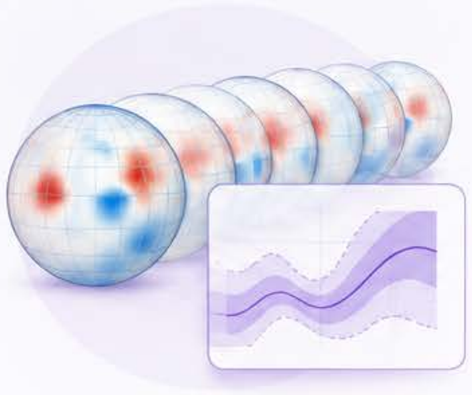
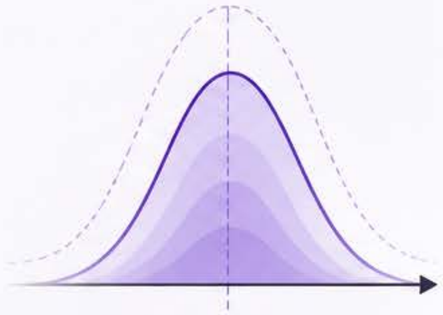




Uncertainty Quantification:

- large ensembles to generate confidence bounds
- capable of incorporating other approaches (e.g., Bayesian, HNN, CF)



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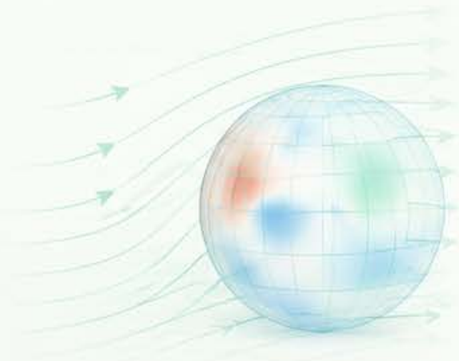

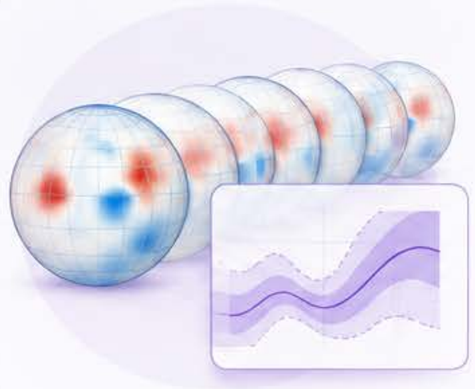

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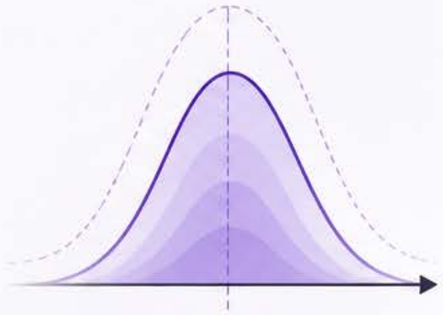
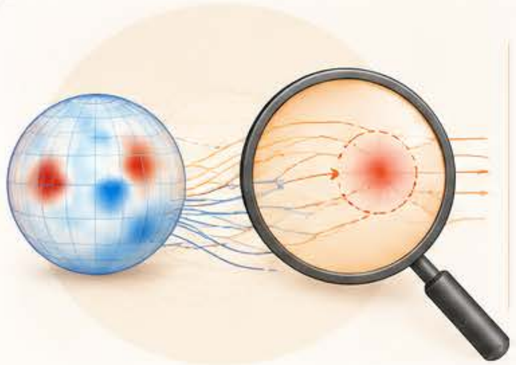
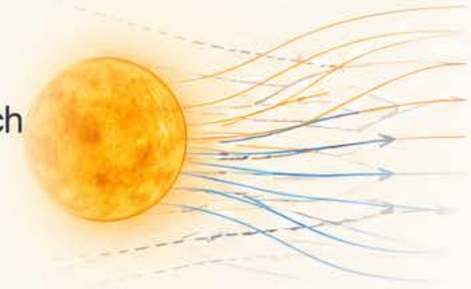




A Differentiable Diagnostic Lens:

- source discovery of model and observation mismatch
- *reverse-engineer* to correct near Sun solar wind conditions



Thank You!