



HiParT v1.0

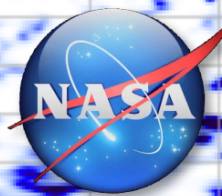
An Open Source High-Performance Flux Transport Model

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Predictive Science Inc.



- Surface flux transport models
- Open Source Flux Transport (OFT)
- High Performance Flux Transport (HipFT)
- Flow and diffusion models
- Data Assimilation
- Multiple Realizations
- Numerical Methods
- Code Implementation
- Examples
- Availability

- SFT treats the solar surface radial magnetic field as a scalar quantity subject to 2D surface flows and processes
- Used to **generate full-Sun maps**, constrain dynamo models, study surface dynamics, solar cycle prediction, etc.
- Many models exist:
ADAPT, LMSAL-ESFAM, AFT, etc.
- While some produce publicly available full-Sun maps, none are currently open-source or able to be run on-demand

- Part of the “*Improving Space Weather Predictions with Data-Driven Models of the Solar Atmosphere and Inner Heliosphere*” **SWQU** project
- Open source and extensible
- Three main components:



- OFTpy:** Acquire and prepare observational data
- ConFlow:** Generate supergranular convective flows
- HipFT:** Integrate the flux transport model





Implements advection, diffusion, data assimilation, and flux emergence over multiple realizations using high-accuracy numerical methods and CPU/GPU parallelism

$$\frac{\partial B_r}{\partial t} = -\nabla_s \cdot (B_r \mathbf{v}) + \nabla_s \cdot (\nu \nabla_s B_r) + S,$$

$$\nabla_s \cdot (B_r \mathbf{v}) = \frac{1}{R_\odot \sin \theta} \frac{\partial}{\partial \theta} (\sin \theta B_r v_\theta) + \frac{1}{R_\odot \sin \theta} \frac{\partial}{\partial \phi} (B_r v_\phi),$$

$$\nabla_s \cdot (\nu \nabla_s B_r) = \frac{1}{R_\odot^2 \sin \theta} \frac{\partial}{\partial \theta} \left(\nu(\theta, \phi, B_r) \sin \theta \frac{\partial B_r}{\partial \theta} \right) + \frac{1}{R_\odot^2 \sin^2 \theta} \frac{\partial}{\partial \phi} \left(\nu(\theta, \phi, B_r) \frac{\partial B_r}{\partial \phi} \right),$$

- Differential rotation

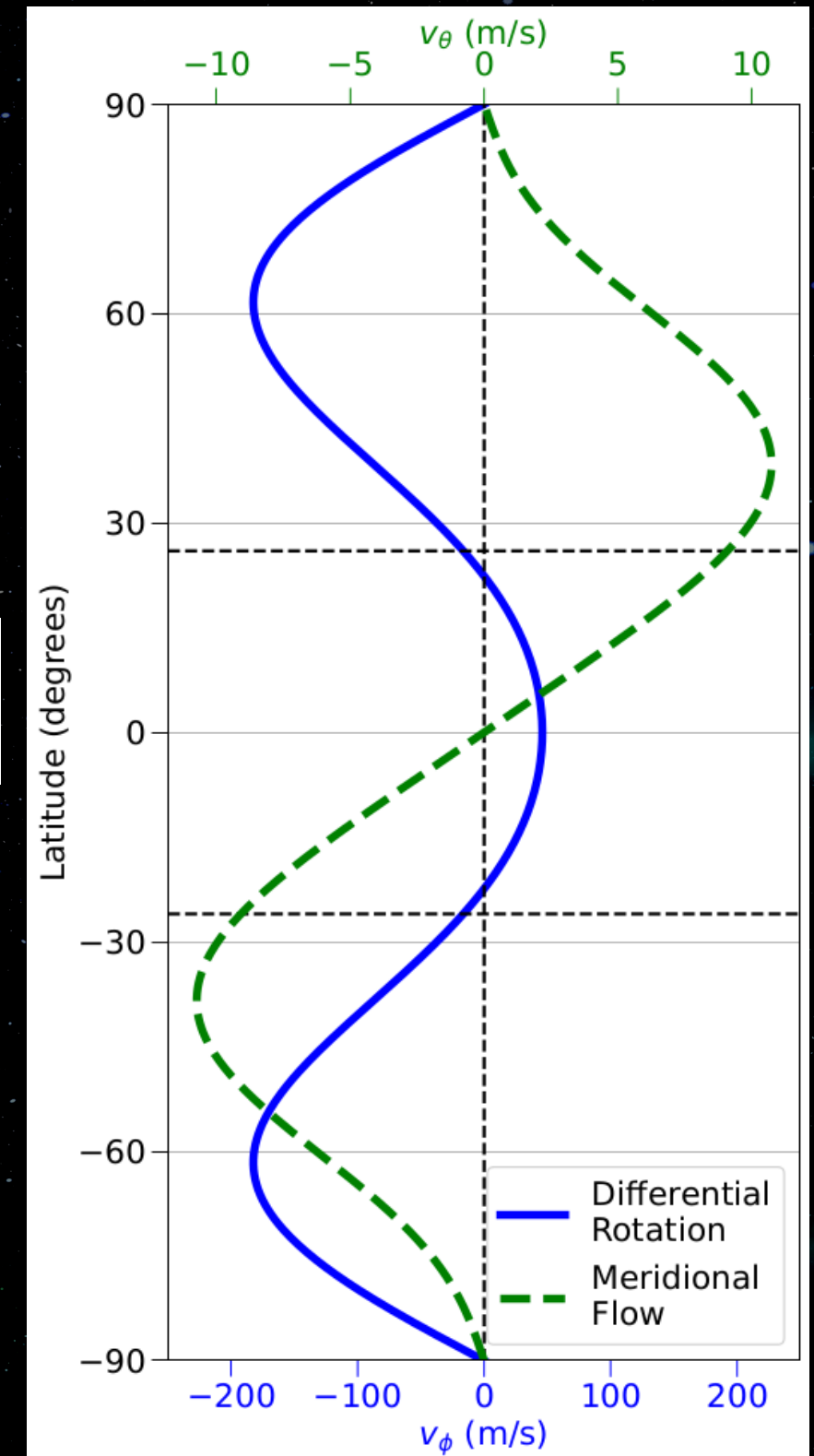
$$v_{\phi}(\theta) = [d_0 + d_2 \cos^2(\theta) + d_4 \cos^4(\theta)] \sin \theta,$$

- Meridional flows

$$v_{\theta}(\theta) = - [m_1 \cos \theta + m_3 \cos^3 \theta + m_5 \cos^5 \theta] \sin \theta,$$

- Velocity attenuation

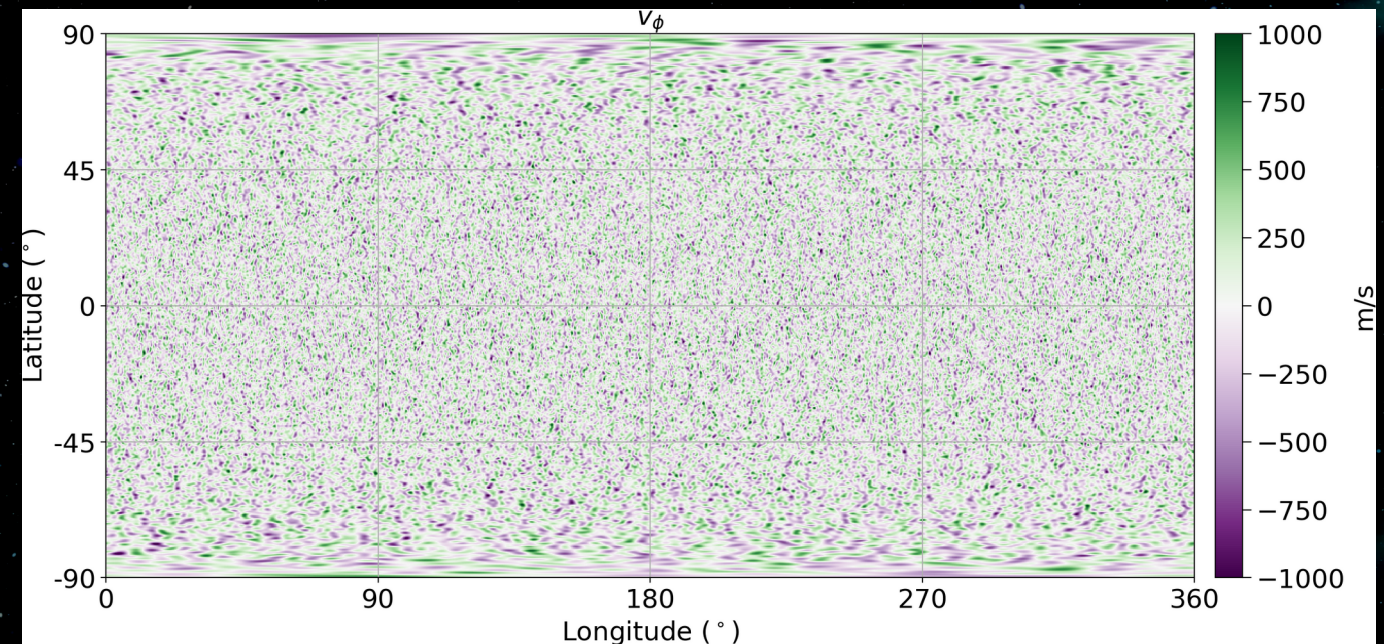
$$v_{\theta/\phi} \rightarrow v_{\theta/\phi} \left[1.0 - \tanh \left(\frac{|B_r|}{B_0} \right) \right],$$



- Diffusion in SFT models used as a proxy for the flux cancellation caused by granular and super-granular motions
- However, there are advantages to directly modeling these flows
- The default HipFT resolution of 1024x512 is high enough to resolve most of the super-granular scale sizes
- ConFlow generates a sequence of flow data encompassing random motions and super-granulation
- HipFT reads in the files and drives the FT with the flows
- Some diffusion is still necessary to represent flux cancellation at smaller scales



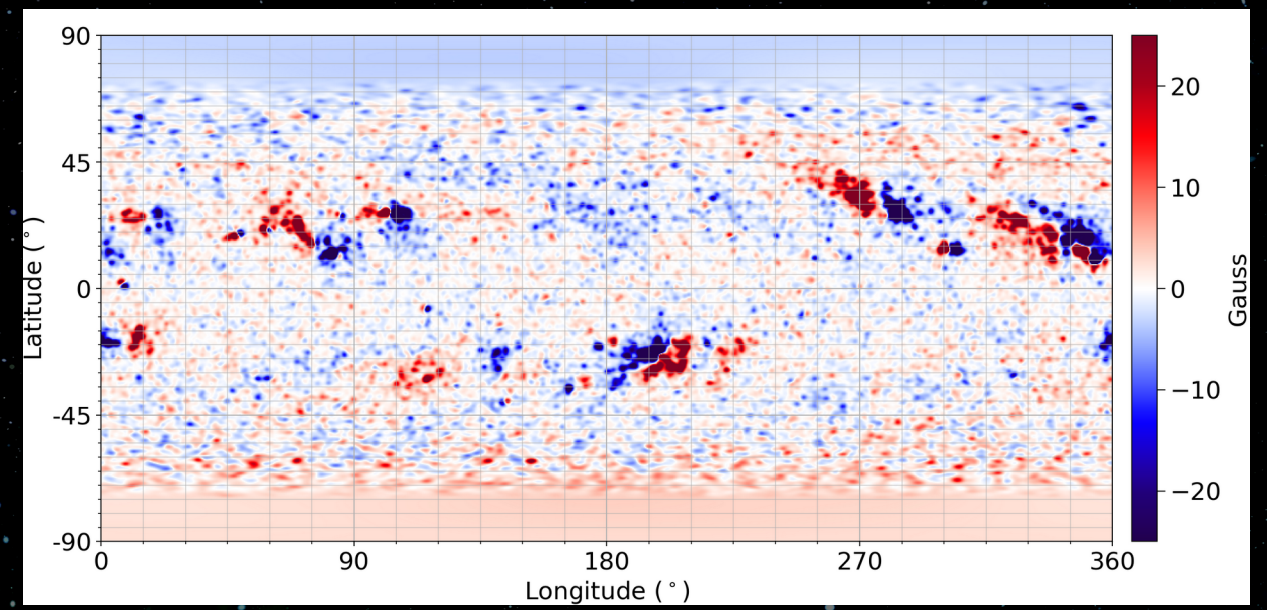
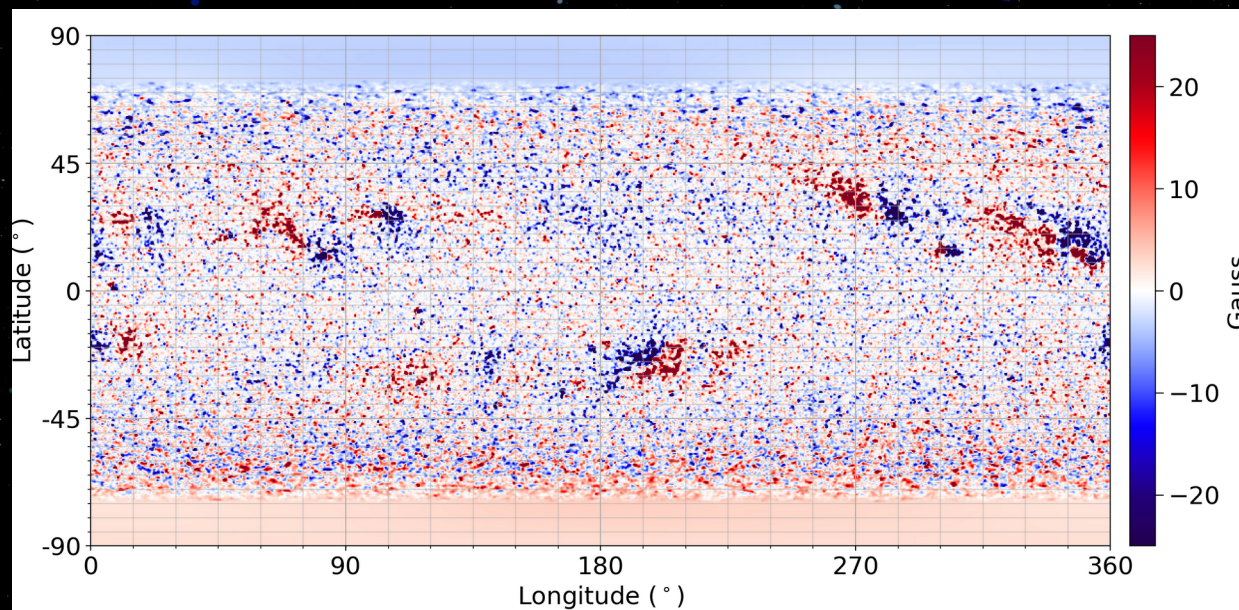
[Hathaway et. al. (2010,2015)]



- Diffusion coefficient can be constant, or a user-defined spatially varying file
- HipFT can be used as a magnetogram smoother, in which case one can select a grid-based diffusion coefficient

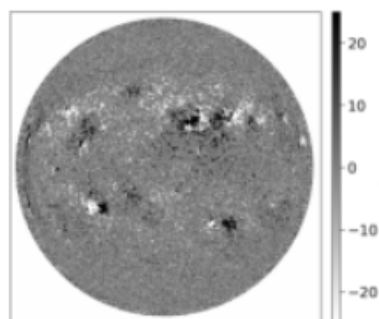
$$\nu(\theta, \phi)$$

$$\nu_g = \alpha_\nu [(\Delta\theta)^2 + (\Delta\phi \sin\theta)^2],$$

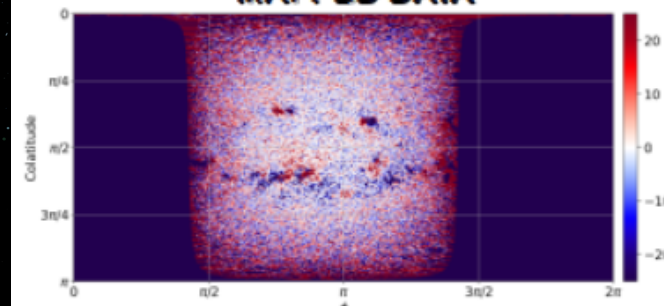


OFTpy

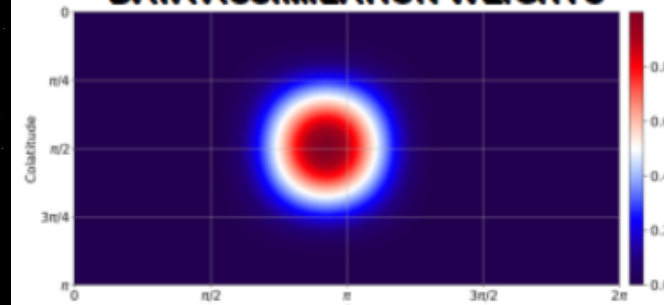
DISK LOS DATA



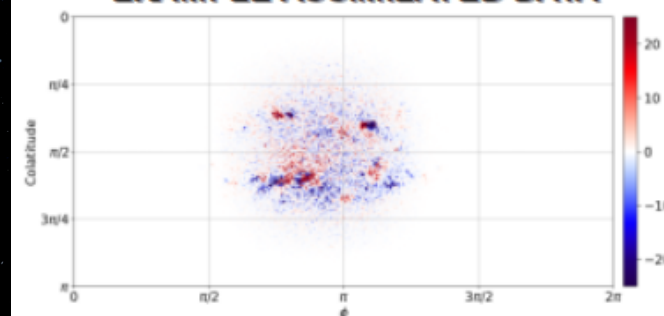
MAPPED DATA



DATA ASSIMILATION WEIGHTS



EXAMPLE ASSIMILATED DATA



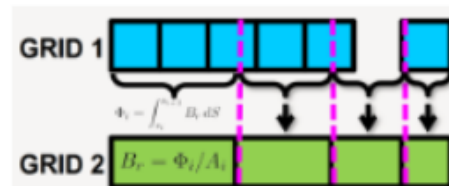
Acquire data (e.g. HMI M720s LOS through JSOC drms py package)

Convert line-of-sight field into radial field:

$$B_r = B_{\text{los}} / \mu$$

Map to Carrington frame with resolution **10240 x 5120** to avoid under-sampling

Reduce size with flux-preserving integral binning:



Set quality weights:

$$\mu = \cos \theta_d \in [0, 1]$$

θ_d is the center to limb angle

Use weights with power and cutoff parameters to assimilate data into HipFT:

$$F = \mu^{\alpha \mu} \quad \mu < \mu_{\text{lim}}$$

$$F = 0 \quad \text{o.w.}$$

$$D = \frac{1}{\Delta t} (F B_{r;d} - F B_r)$$

- Data assimilation uses the output data from OFTpy

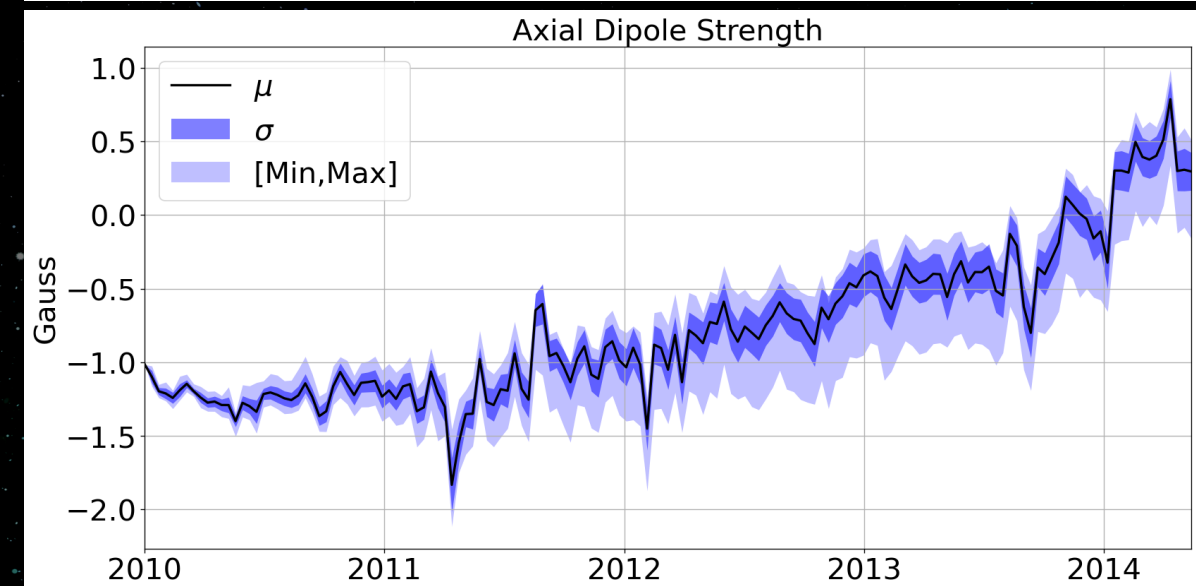
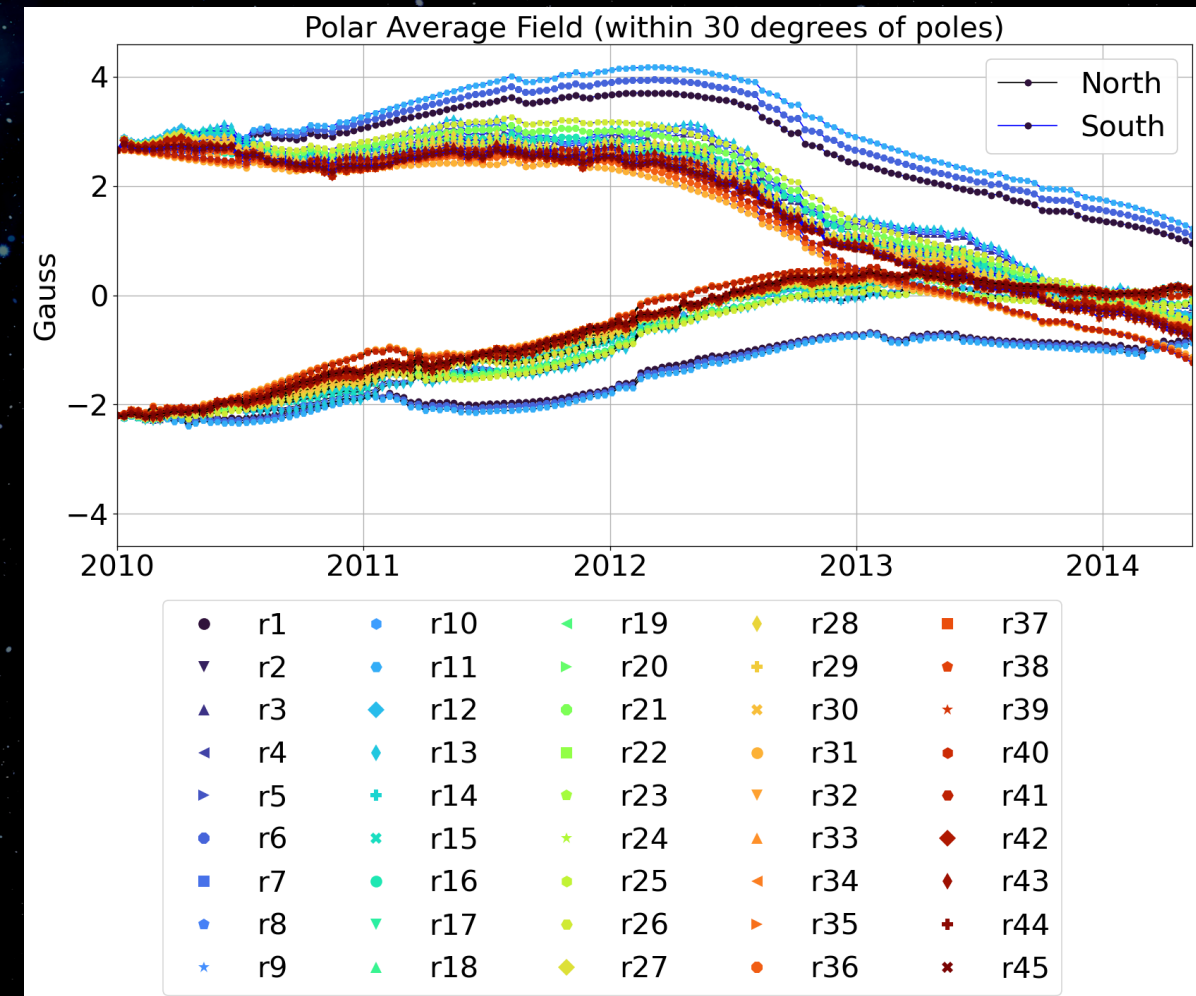
- A default weighting function is included in the data cube, applied as:

$$B_r \rightarrow F B_{r;d} + (1 - F) B_r,$$

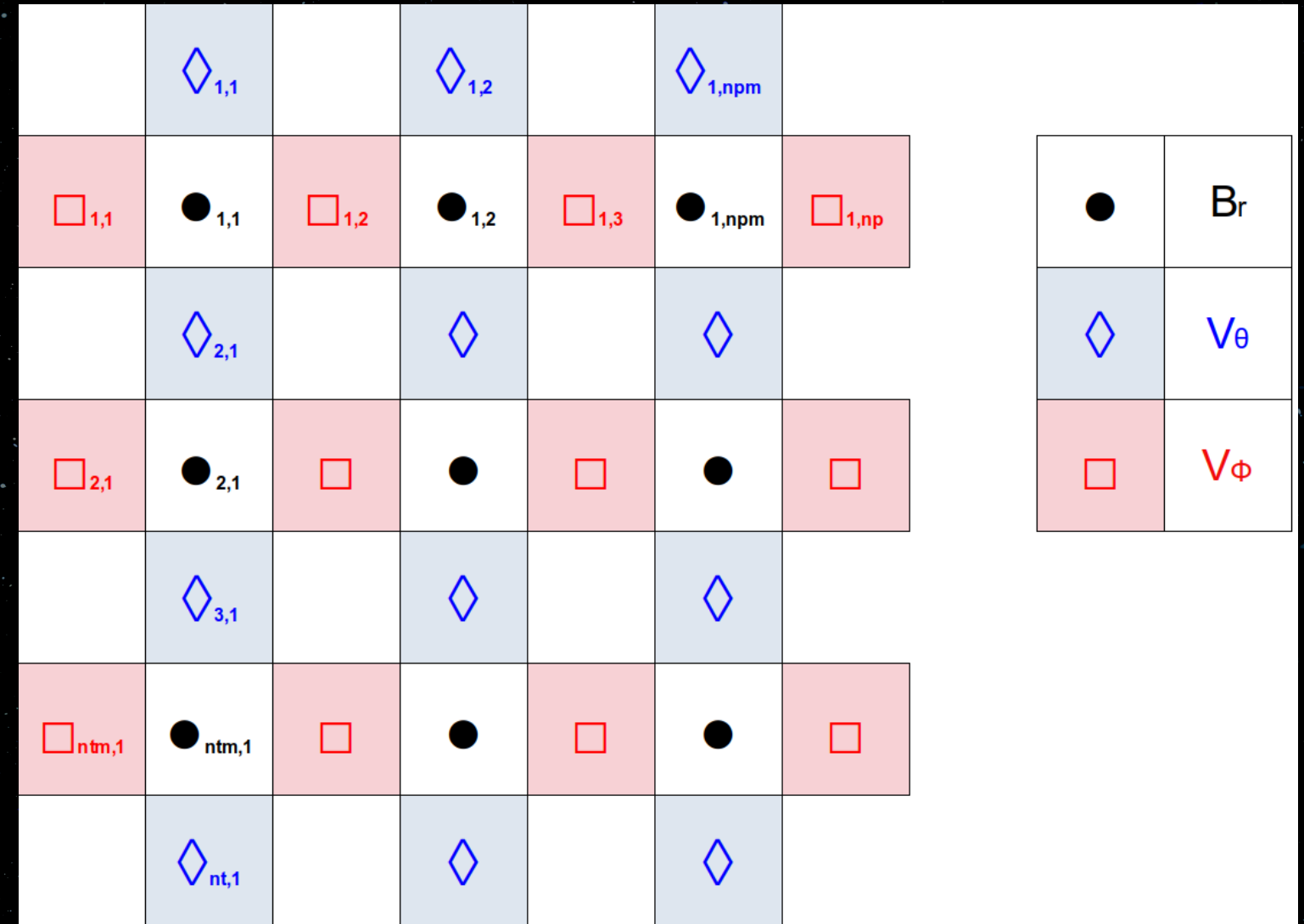
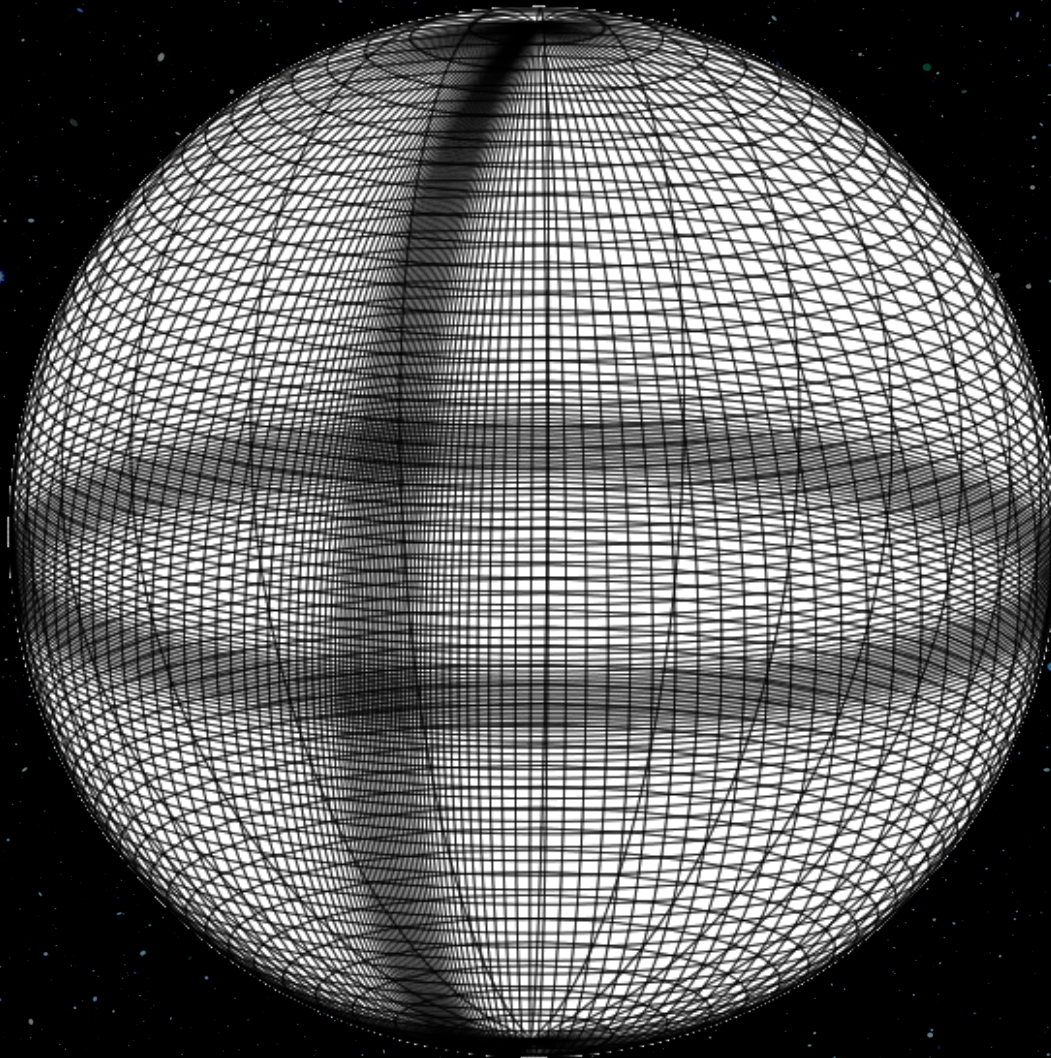
- The center-to-limb distance is also provided, which can be used to generate a user-defined custom weight profile:

$$F = \mu^{\alpha \mu} \quad \mu < \mu_{\text{lim}} \ \& \ |\theta_1| < \theta_{1,\text{lim}}, \quad F = 0 \ \text{o.w.},$$

- Can run multiple realizations simultaneously across many model parameters
- Current cross-realization parameters include diffusion rate, flow profile coefficients, flow attenuation levels, and data assimilation options
- Post processing python scripts are included to analyze results



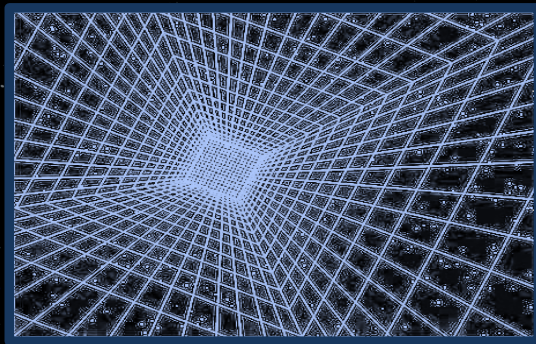
Non-uniform, logically-rectangular spherical surface staggered grid





ADVECTION: 3rd-order SSPRK(4,3)

DIFFUSION: 2nd-order Runge-Kutta-Gegenbauer Super Time-Stepping



ADVECTION: 3rd-order WENO3

DIFFUSION: 2nd-order Central Finite Difference

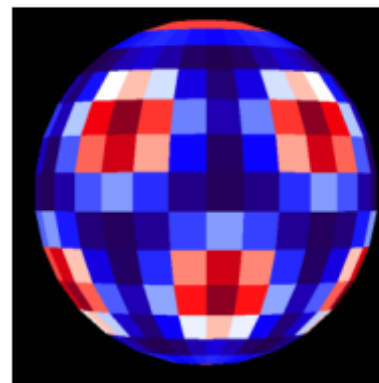
Validation:

$$v_\phi = \Omega \sin \theta$$

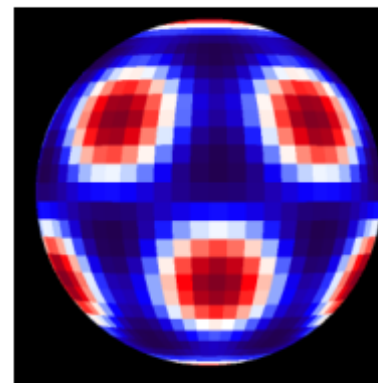
$$\Omega = 1.8076... \text{ km/s}$$

$$\nu = 500 \text{ km}^2/\text{s}$$

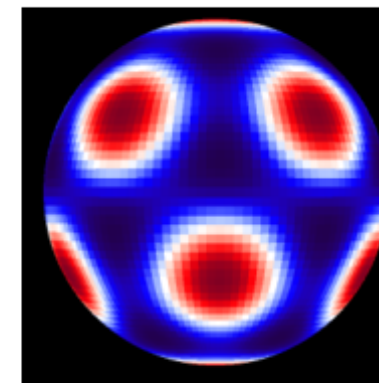
$$u(\theta, \phi, t) = 1000 e^{-42\nu t} \left(Y_6^0(\theta, \phi) + \sqrt{\frac{14}{11}} Y_6^5(\theta, \phi) \right)$$



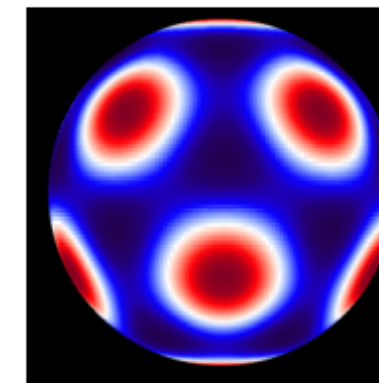
$\Delta\theta, \Delta\phi = \pi/16$



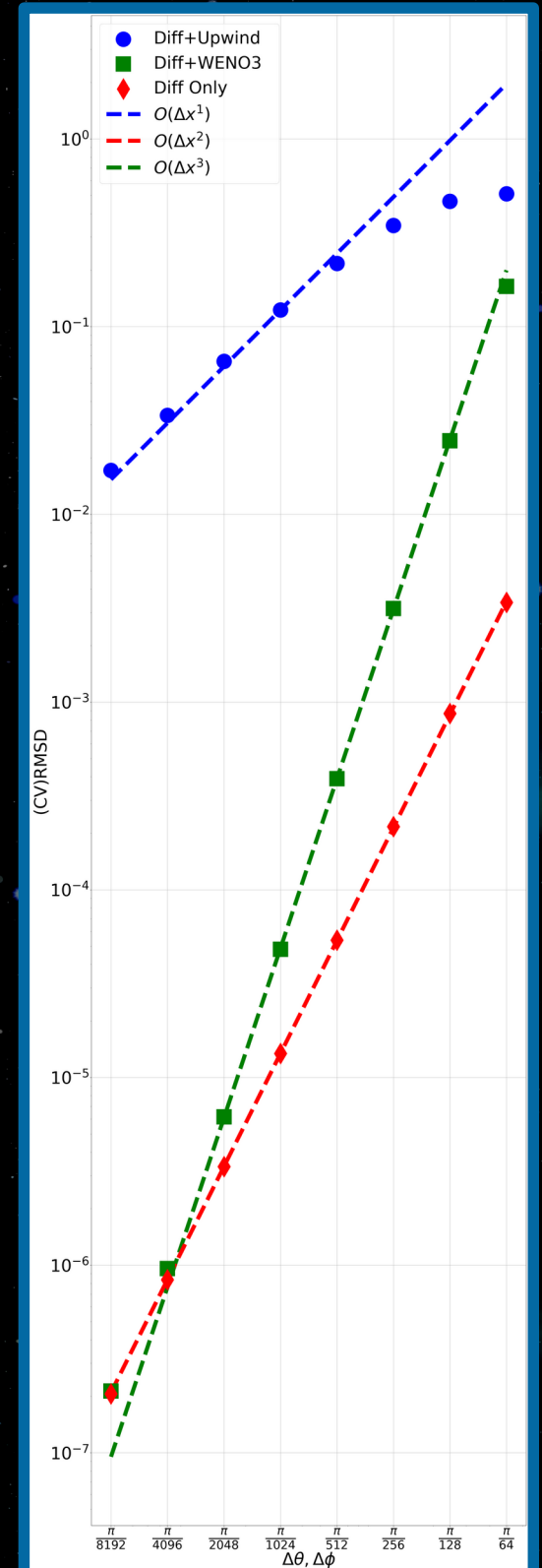
$\Delta\theta, \Delta\phi = \pi/32$



$\Delta\theta, \Delta\phi = \pi/64$



$\Delta\theta, \Delta\phi = \pi/128$



- Written in Fortran 2023
- Parallelized for multi-core CPU and GPUs with Fortran standard's `do concurrent` and OpenMP Target for CPU-GPU data movement

```
do concurrent (i=1:N, j=1:M)
  Computation
enddo
```

```
!$omp target enter data map(to:a)
!$omp target enter data map(alloc:b)
  Computation
!$omp target exit data map(from:a)
!$omp target exit data map(release:b)
```

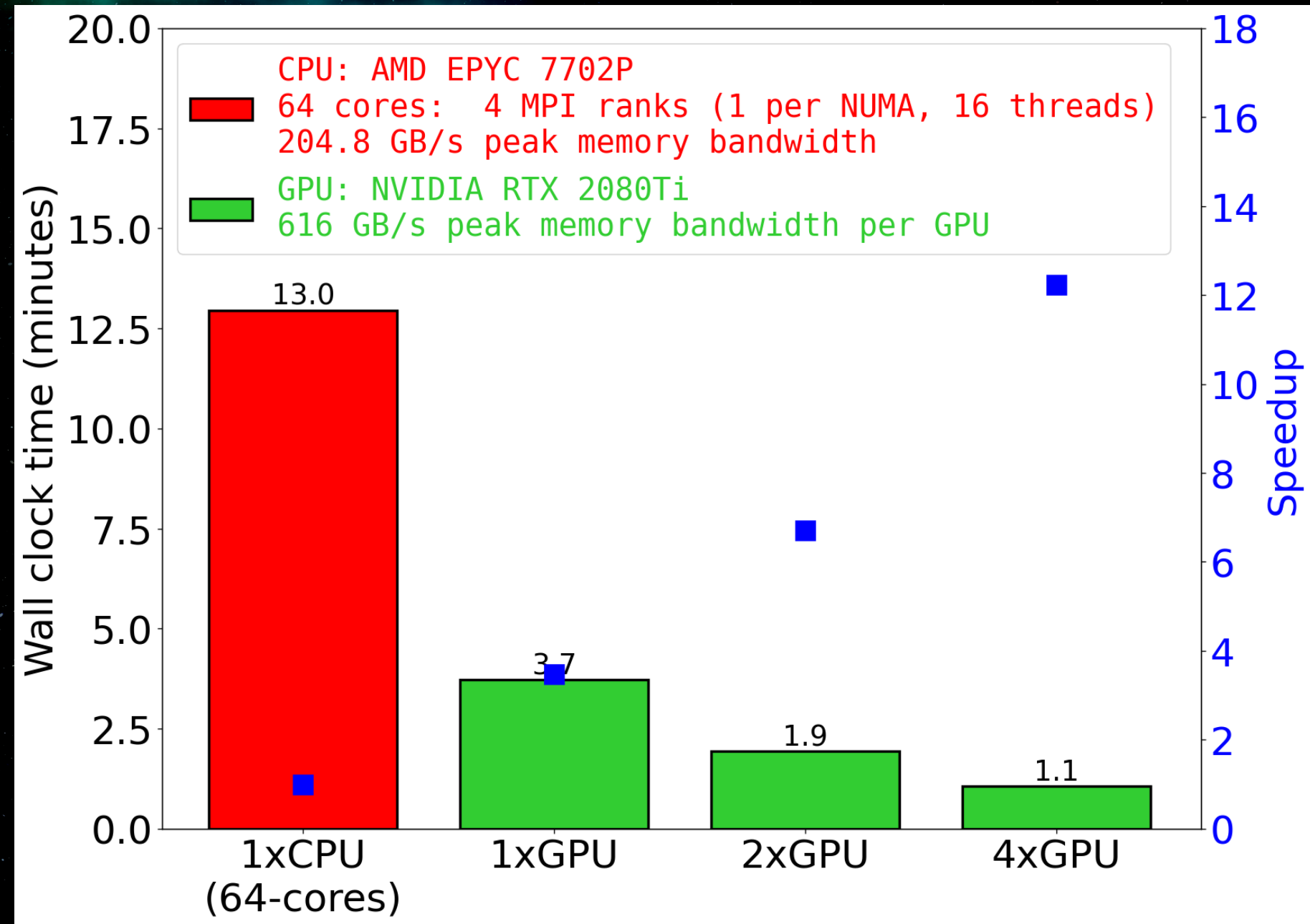
- Parallelized for multiple multi-CPU/GPU nodes across realizations with MPI



HipFT



In-house workstation:
 EPYC 7702P 64-core CPU
 Four RTX 2080Ti GPUs

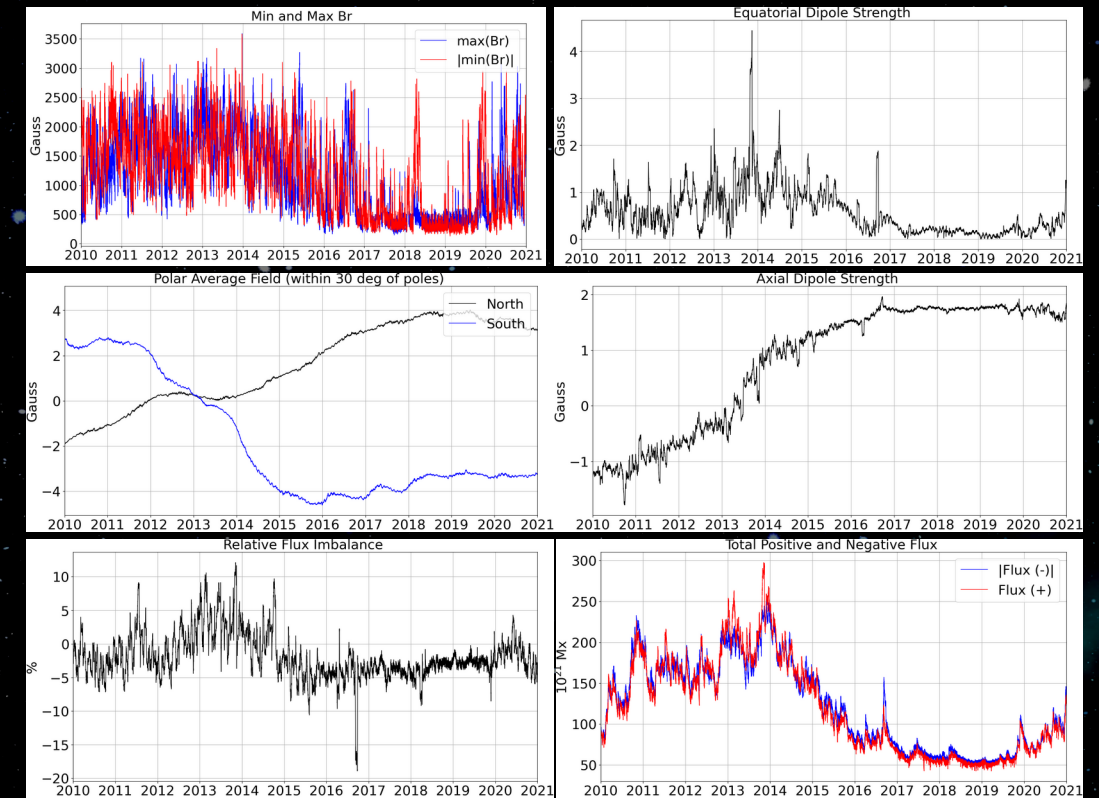
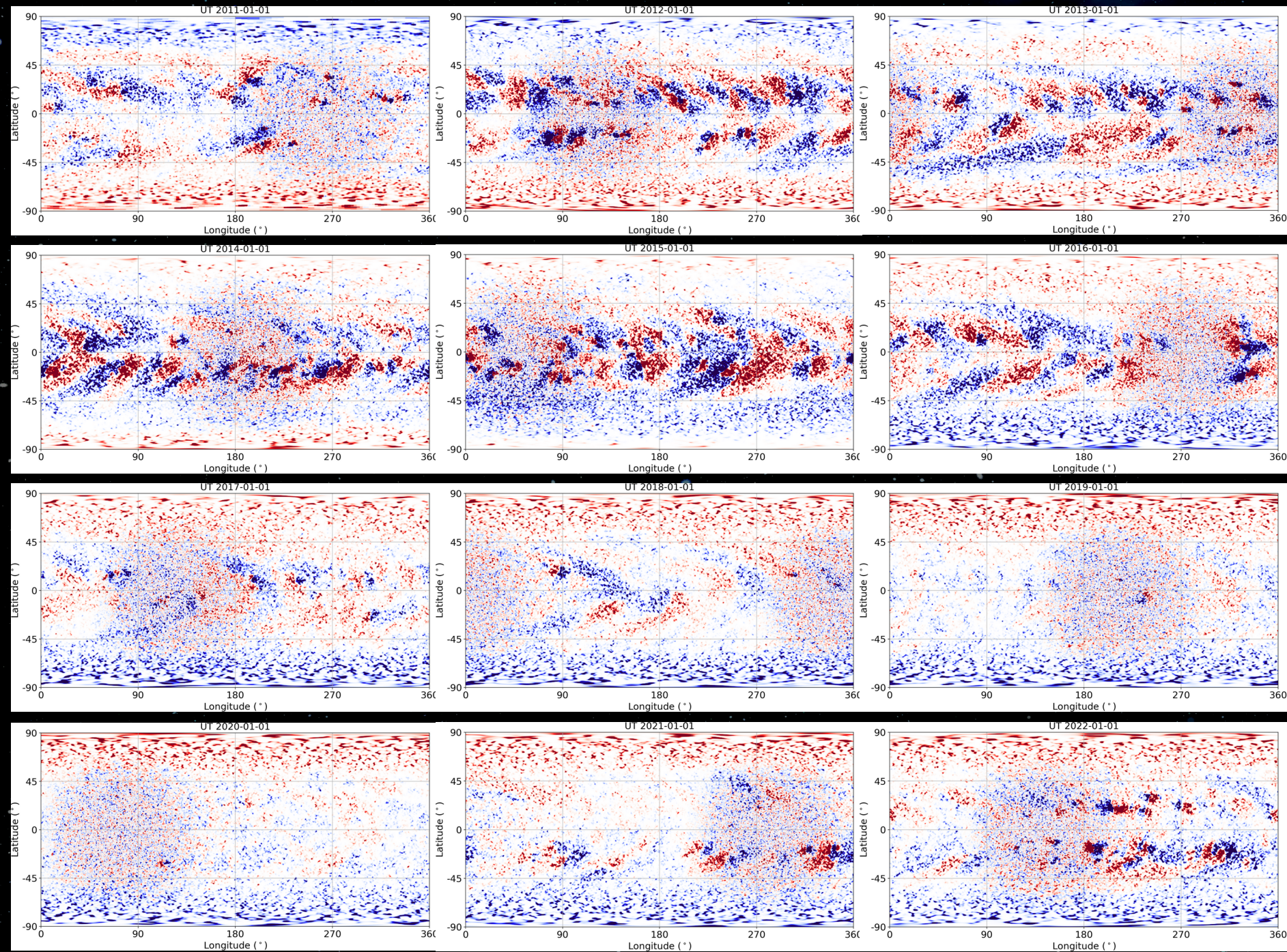


Test: 28-day run at 1024x512 with analytic flow models and diffusion. Eight realizations spanning various levels of diffusion and flow attenuation

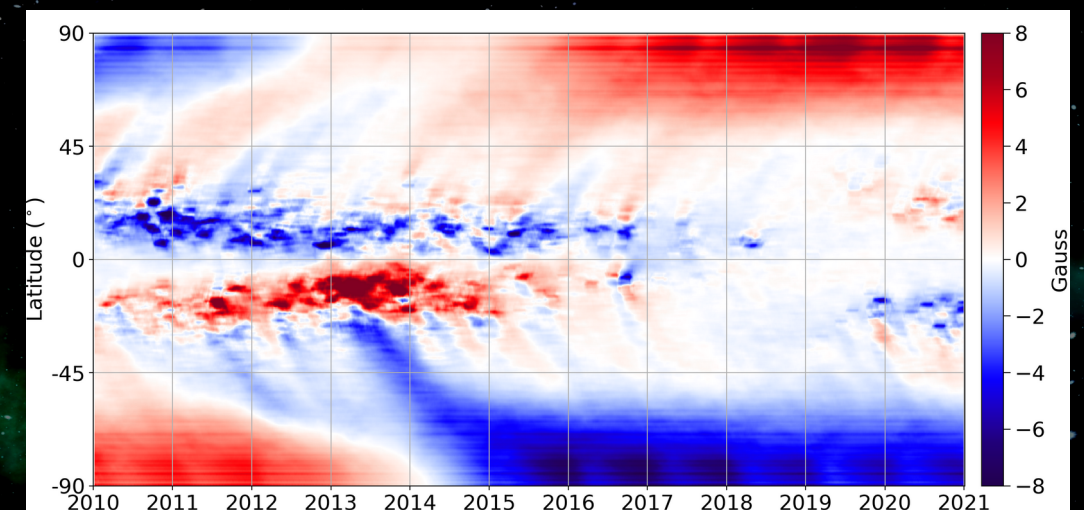
OFT Example Production Run

Initial map from AFT model, HMI data assimilation (1-hour cadence), ConFlow (1CR) and analytic flows with 500G attenuation, diffusion of $175 \text{ km}^2/\text{s}$

Runtime on an NVIDIA RTX 2080Ti GPU: 13:00:00



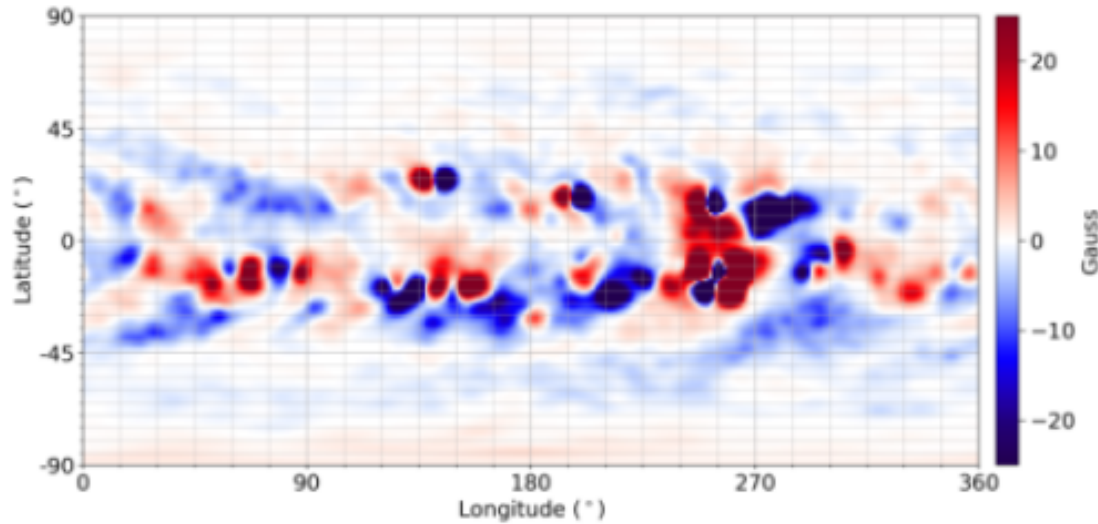
Butterfly Diagram (1CR average)



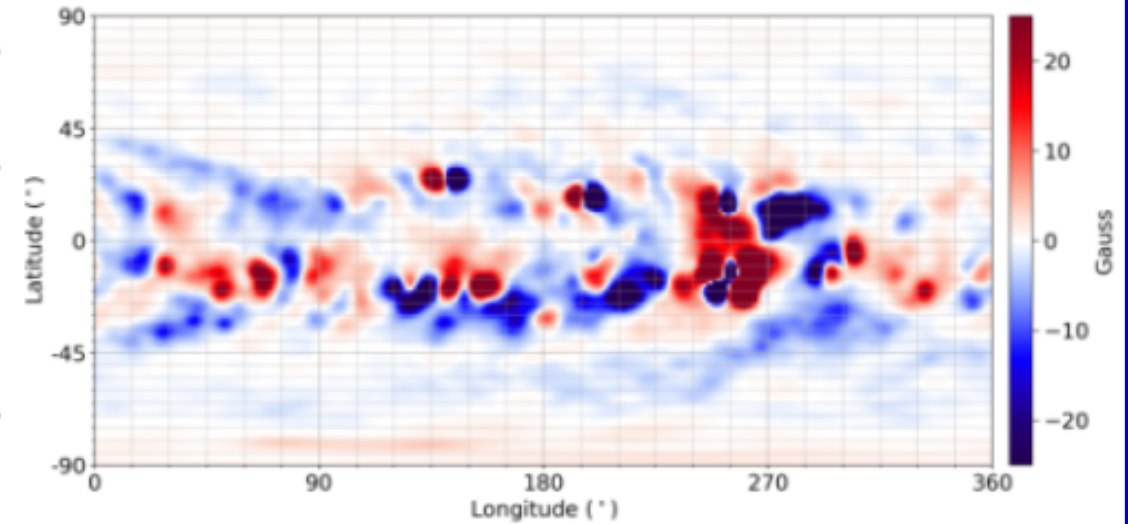
- Maps from FT models are processed by interpolating to 300x150 resolution, flux balancing, and smoothing
- Note some models apply scaling factors to the HMI data

OFT

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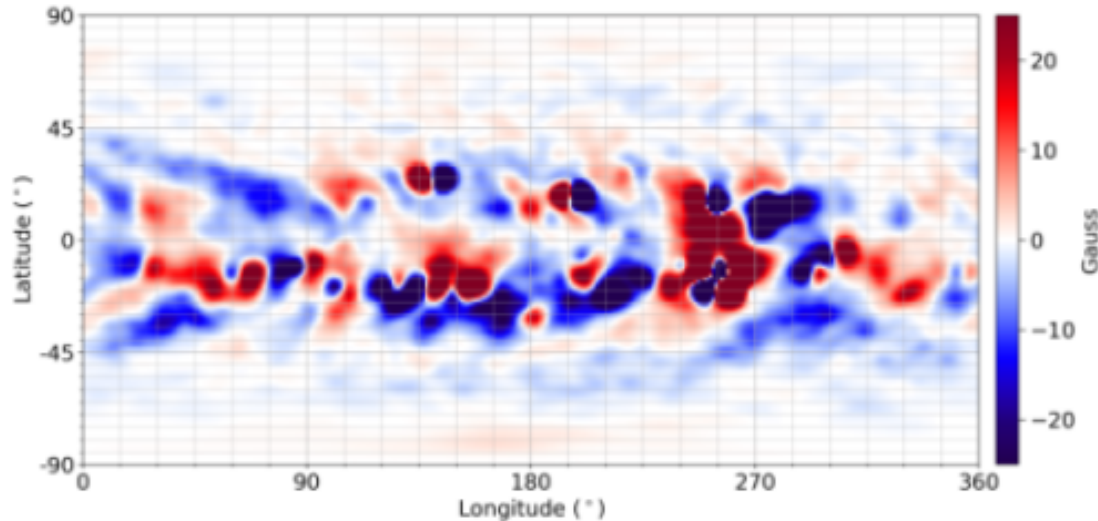


2014-06-15 08:00:00



AFT
Upton et. al. (2014)

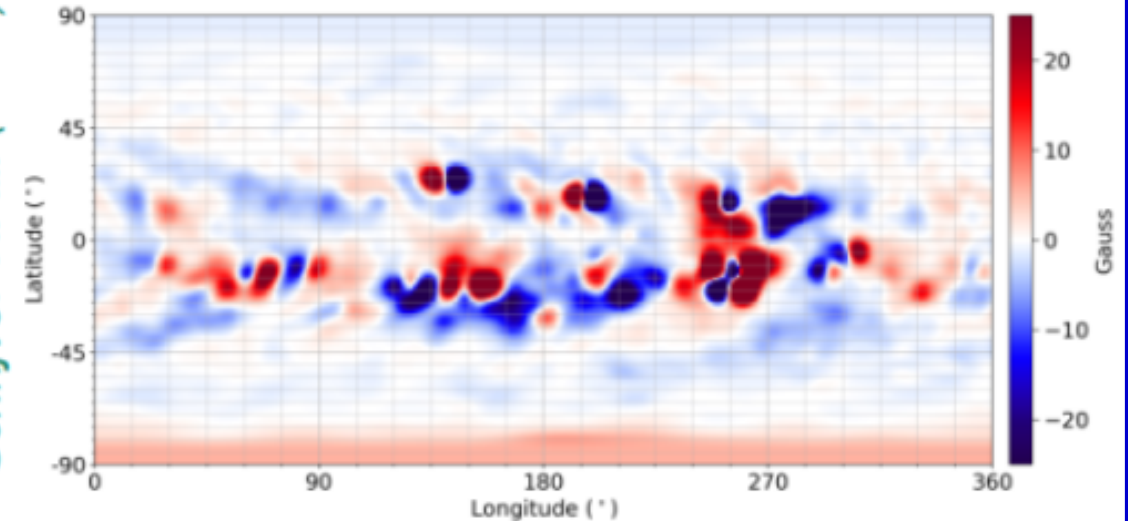
2014-06-15 20:00:00



ADAPT
Hickmann et. al. (2015)

LMSAL-ESFAM
Schrijver et. al. (2003)

2014-06-15 12:05:07



**Download Free
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**github.com/
predsci/hipft**

```
> git clone https://github.com/predsci/HipFT.git
```

```
> cd HipFT
```

```
> cp build_examples/build_<CLOSEST>.sh build_local.sh
```

Edit build_local.sh to reflect local system/compiler

```
> ./build_local.sh
```

```
> cd testsuite; ./run_test_suite.sh
```

Data set for production level example run:

<https://zenodo.org/records/10271121>



Full description of OFT (and HipFT) will be given in a series of papers (in preparation)

More features being added to HipFT:

- Random flux emergence, source terms
- Quality of life updates + processing