Improving Space Weather Forecasts with Data-Driven Models of the Solar Atmosphere and Inner Heliosphere

N.V. Pogorelov,[1] C. N. Arge,[2] R. M. Caplan,[3] P. Colella,[4] J. A. Linker,[3] T. Singh,[1] B. Van Straalen,[4] L. M. Upton,[5] C. Downs,[3] C. Gebhart,[4] D.V. Hegde[1], S. Jones,[2] T. K. Kim,[1] A. Marble,[6] R. Attie,[2] S. Raza,[1] M. Stulajter,[3] J. Turtle[3]

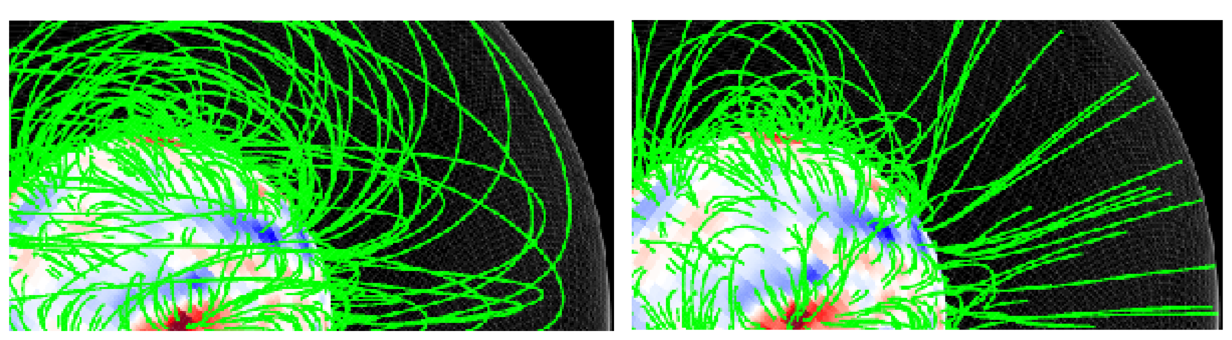
[1]University of Alabama in Huntsville, [2]Goddard Space Flight Center, [3]Predictive Science Inc., [4]Lawrence Berkeley National Laboratory, [5]Southwest Research Institute, [6]University of Colorado

Abstract

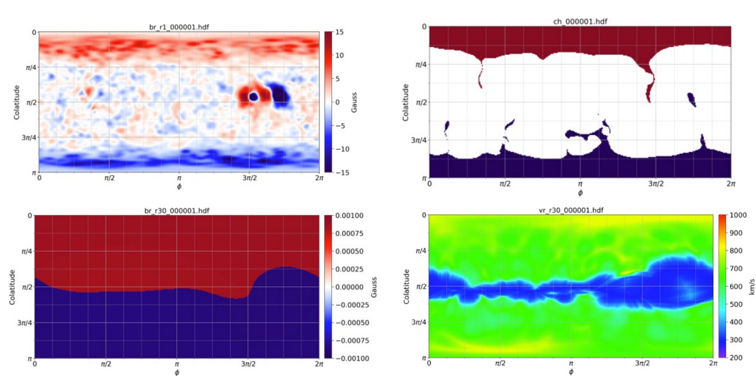
Space weather forecasts are lacking accuracy because they are based on the models describing the system of inter-related physical models, each of which has its own response to uncertainties in the boundary conditions. We address this issue systematically, by developing a new, open-source software to support data-driven, time-dependent models of the solar atmosphere and heliosphere suitable for near real-time predictions of the SW properties at Earth's orbit and in the interplanetary space.

1. A new Open surface Flux Transport (OFT) model which evolves information to the back side of the Sun and its poles and update the model flux with new observations using data assimilation methods.
2. A new potential field solver (POT3D) combined with the output from the traditional WSA model, and with remote coronal and in situ solar wind observations. WSA and the new potential field solver (PFSS and PFCS) are both be validated using the maps from the OFT.
3. A highly parallel, adaptive mesh refinement (AMR) code (HelioCubed) for the Reynolds-averaged, ideal MHD equations describing the solar wind flow in the region between R = 10−20 $R_\odot$ and 1–3 au. These equations will be accompanied by the equations describing the transport of turbulence. We have built on the Multi-Scale Fluid-Kinetic Simulation Suite (MS-FLUKSS) collaboratively developed at UAH using the Chombo AMR framework. The new version of our software is built on Chombo 4 and allow us to perform simulations with the fourth order of accuracy in time and space, and use cubed spheres to generate meshes around the Sun.
4. Machine learning is used to find a hypothetical member of the CME ensemble with the best predictive properties.

POT3D (Caplan et al., 2021) is a high performance Fortran MPI code that solves Laplace's equation using finite differences on a non-uniform spherical grid. It has been ported to GPUs using Fortran standard parallelism and OpenACC. It is available as part of the SPEChpc™2021 benchmark suites (https://www.spec.org/hpc2021) and is released as open-source via a GitHub repository at: https://www.github.com/predsci/pot3d

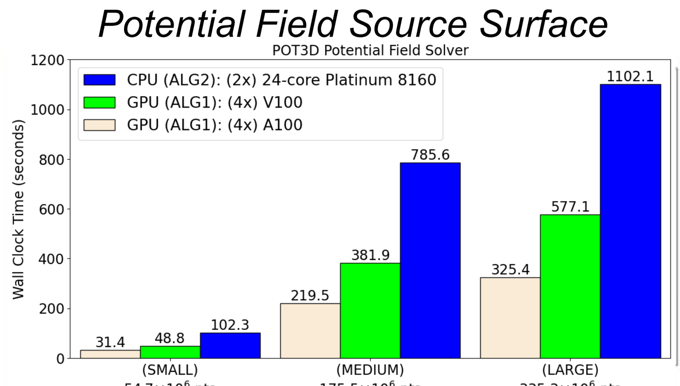


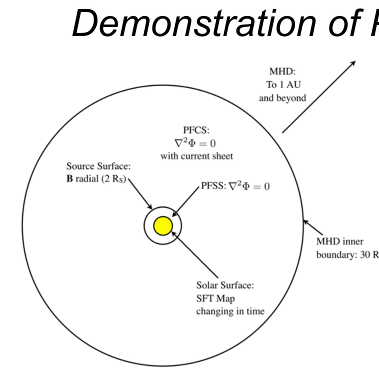
Potential field (closed wall) *Potential Field Source Surface*



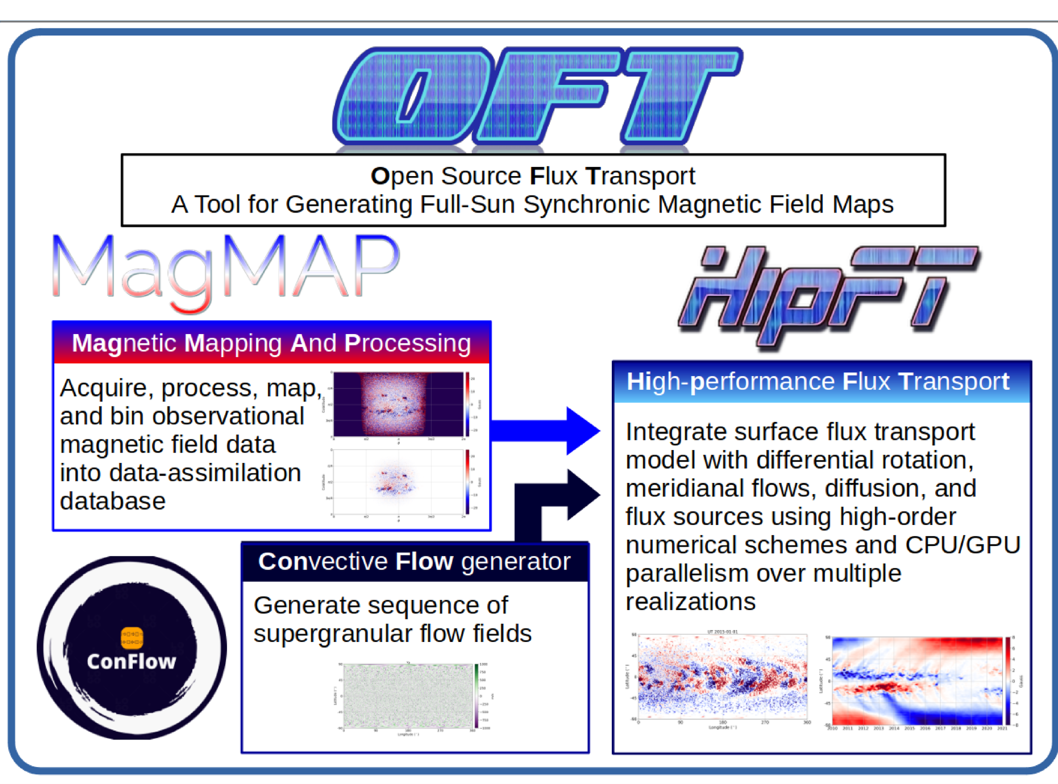
Demonstration of POT3D & WSA

Case	Resolution (r x theta x phi)	# cells	Theta-Phi Mesh
(i) Tiny	27x90x180	0.4x10⁶	uniform
(ii) Small	54x180x360	3.5x10⁶	uniform
(iii) Medium	135x450x900	55x10⁶	uniform
(iv) Large	207x900x1800	335x10⁶	uniform
(v) Custom	216x742x1095	175x10⁶	nonuniform

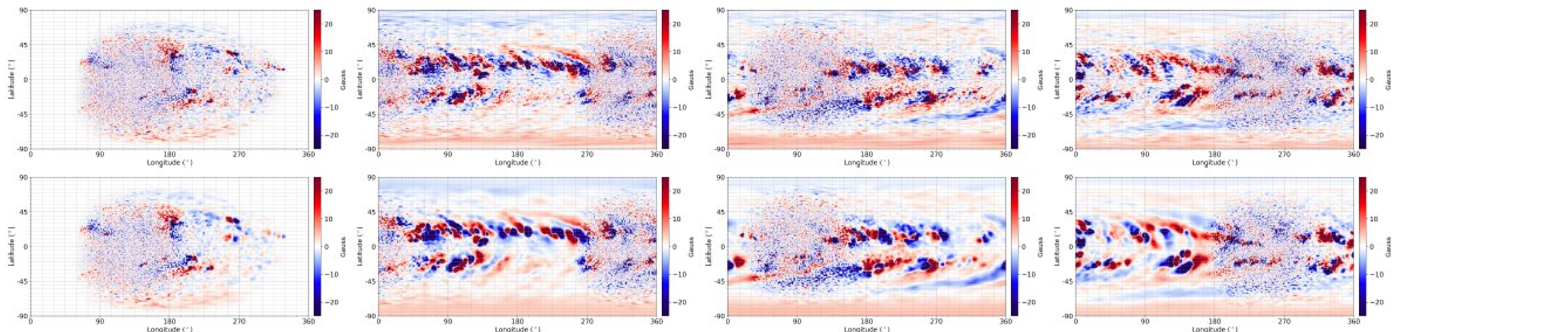




Simulation setup and the boundaries between the regions corresponding to different physical models.

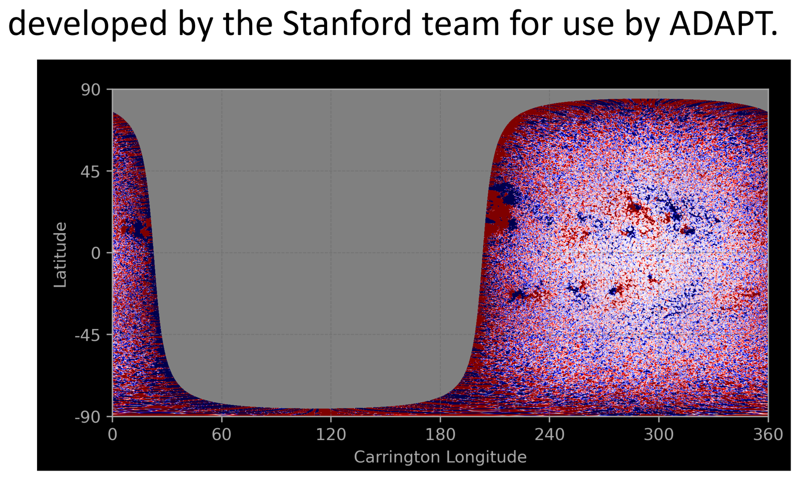


In addition to MagMAP and data assimilation modules, OFT involves a high-performance (implicit) and high-accuracy (2nd order of accuracy in space in time) FT module (HipFT). A key feature of HipFT that makes it high performance is the ability to run the code on GPU accelerators. HipFT models advection and diffusion of magnetic flux over the surface of the Sun. The AFT model is unique in that it explicitly models the turbulent surface flows produced by convection (Hathaway et al., 2010; Hathaway & Upton, 2021). We have added the ConFlow code to OFT to generate these flows for HipFT. These dramatically improves the quality and generation time of full-Sun maps. As an example, OFT performs a few tens of times faster than the AFT model. Snapshots of HipFT data simulation test. The top images are from the simulation with no diffusion, while the bottom are with a diffusion of 200 km²/s. The snapshots are shown at times 9.5, 349.5, 694.5, and 874.5 days.



Data Acquisition and Processing: MagMAP

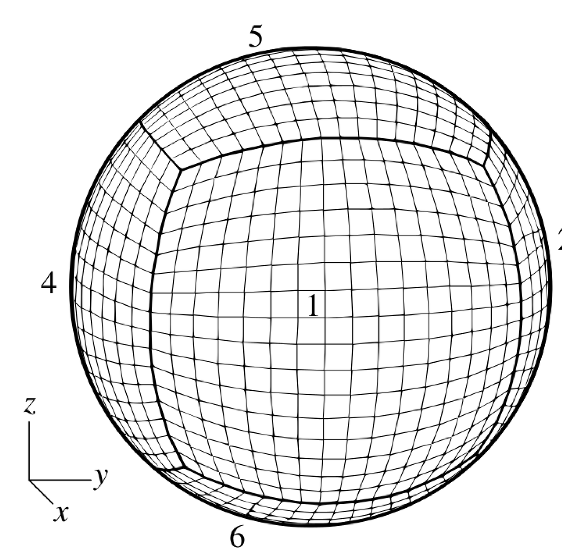
We have developed MagMAP, a python codebase that facilitates acquisition and processing of data products to a computation-ready format for HipFT. The current code supports full processing of JSOC HMI M720s line-of-sight (LOS) magnetograms to a radial-flux Carrington Rotation (CR) Map. This extensible software will also serve as a prototype/example for future users to incorporate magnetograms from alternative observatories. For data acquisition of HMI LOS magnetograms, OFTpy acts as a Python wrapper for product query and download from the Stanford JSOC). Figure at the bottom shows an example. We are presently comparing this mapping to a mapping product developed by the Stanford team for use by ADAPT.



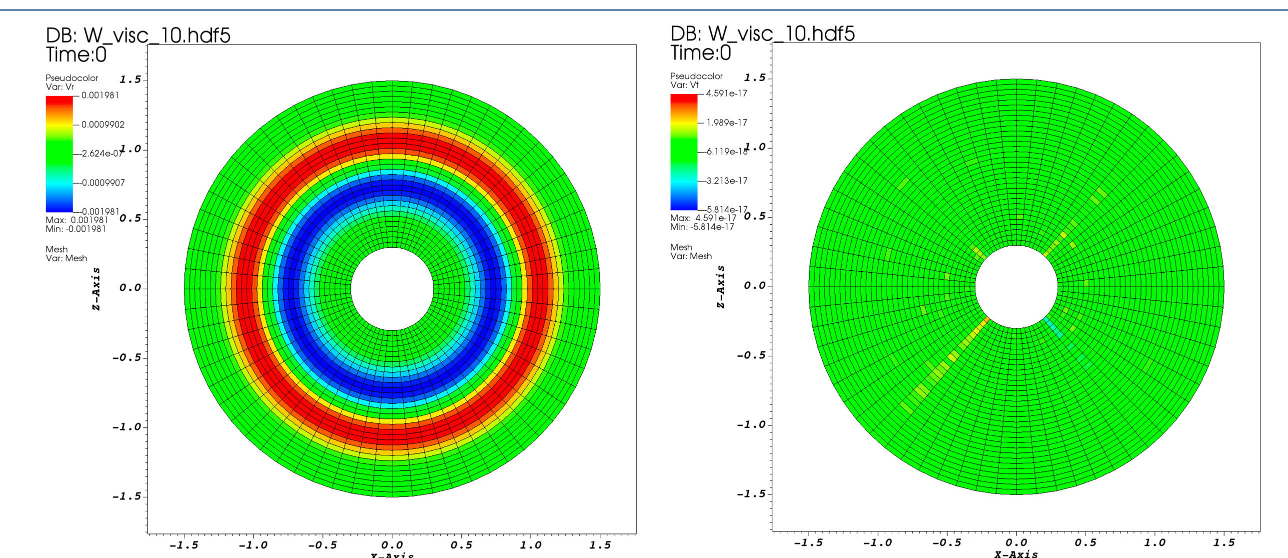
An HMI 720s magnetogram, observed on 2012/01/15 00:59:52, converted to radial flux and projected into Carrington Coordinates with MagMAP.

The Inner Heliospheric Model: HelioCubed

1. We use finite volume method to solve hyperbolic, Reynolds-averaged MHD equations in conservative form with 4th order of accuracy in space and time.
2. The average values of primitive variables are calculated on R and L side of the faces with the 4th order accuracy and a Riemann problem solver is used to find the 4th order accurate fluxes through these faces.
3. The 4th order accurate RK method is used to integrate the equations with time. Limiters specially designed for the 4th order accurate methods are used (McCorquodale et al 2011).
4. The MHD equations are solved using mapping functions that preserve exact radial solutions. Non-physical non-radial flows are damped using high order artificial linear viscosity.
5. Our approach solving this problem is based on the following ideas: a cubed-sphere representation of space, that has most of the same advantages as the widely-used spherical coordinate system, but does not have a polar singularity; a method-of-lines discretization of the evolution equations, with high-order accurate discretizations (fourth or fifth-order) in both space and time; and block-structured AMR.



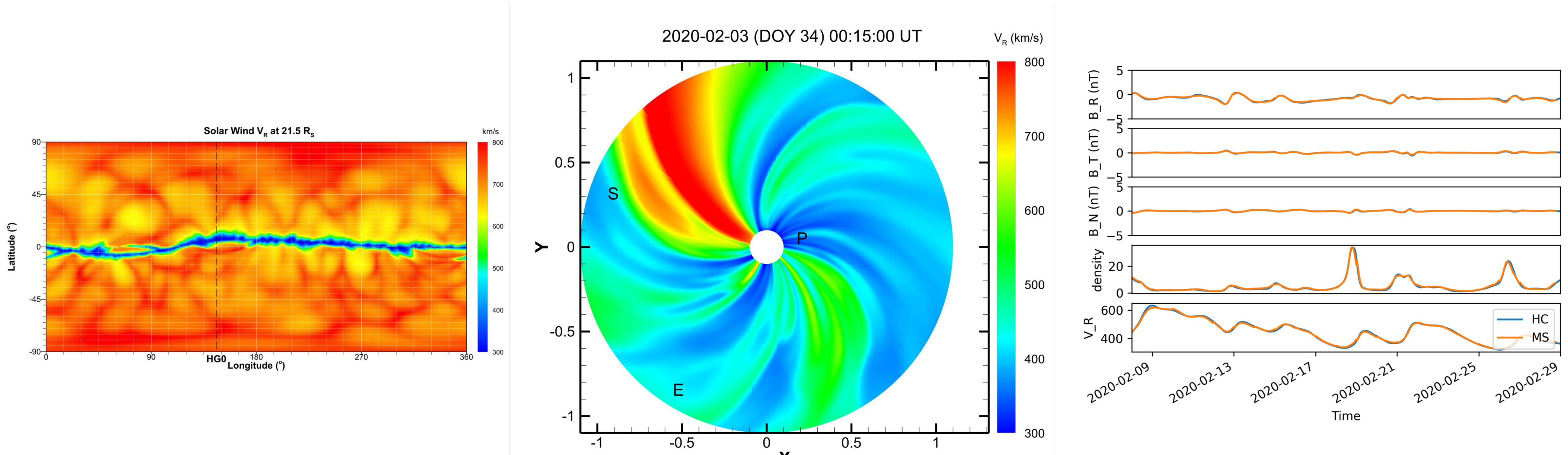
Mapped-multiblock gridding of the surface of a sphere



Preservation of the non radial flows for spherically symmetric initial conditions. Radial Velocity (left) and tangential velocity (right)

Convergence tests confirm that our simulation scheme using cubed sphere is 4th order accurate in both space and time.

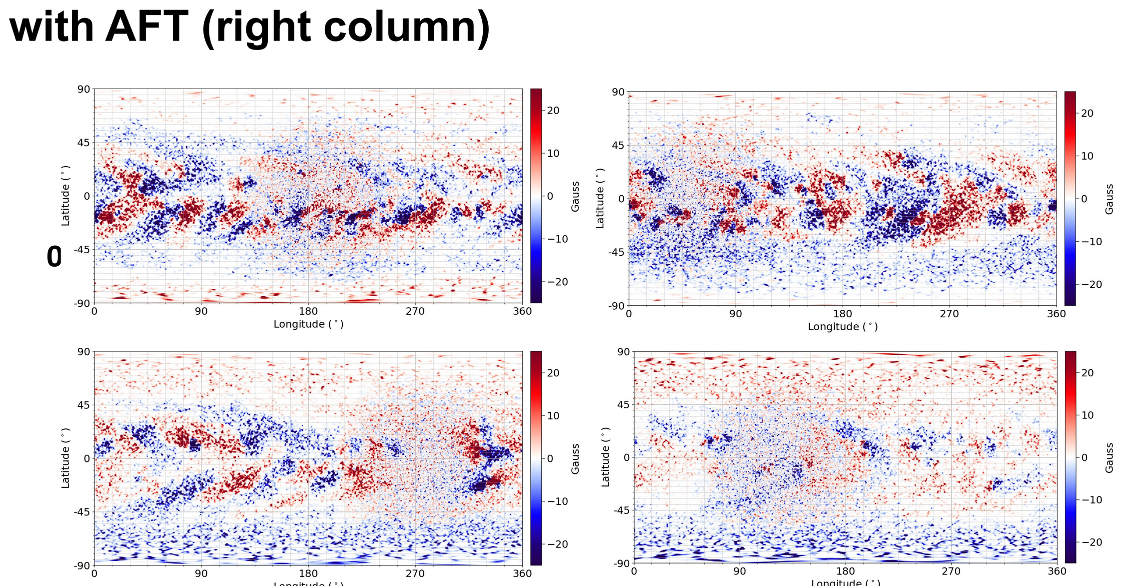
Simulation Parameters	32x16x16 Resolution, 10 iterations, dt timestep	64x32x32 Resolution, 20 iterations, dt/2 timestep	Order of Convergence: log(E1/E2)/ log(2)
L_∞ w.r.t. the finest resolution simulation	5.27258e-06	3.61363e-07	3.87

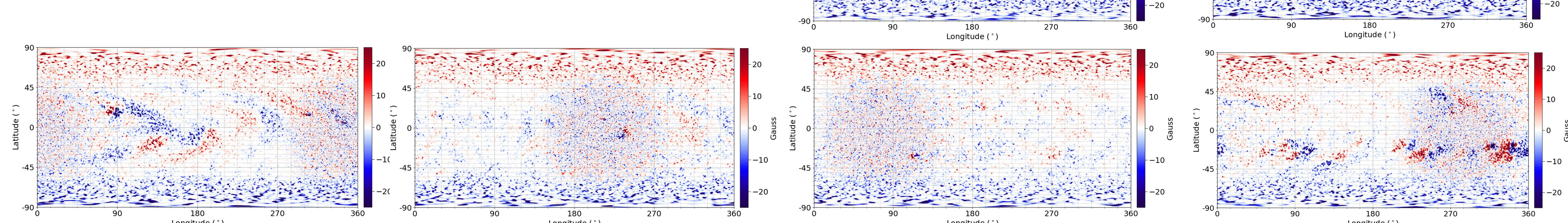


A simulation in the IH using OFT-POT3D-WSA-HelioCubed. Left panel: the initial speed distributions at the inner boundary at 21.5 Rs. (middle panel) the equatorial cut of the SW. The projected positions of Earth, Parker Solar Probe, and Stereo A are indicated with letters E, P. and S, respectively. and (right panel): validation of HelioCubed simulations with MS-FLUKSS.

Comparison of OFT (left column) with AFT (right column)

- 11-year run, 2011 to 2022 (only 2014 to 2021 shown)
- Convective flows from Conflow
- 1 hr data assimilation of HMI magnetograms
- 13 hour run time for OFT (NVIDIA GPU)
- 5 days, 12 hours for AFT
- HipFT has been extended to compute ensembles with MPI
- It can be run with very low diffusion – we are testing the implications





SWQU and ML aspects: (1) it was shown directly that the errors in CME arrival are due to subjective uncertainties in the CME property identification; (2) machine learning makes it possible to create an ideal, hypothetical ensemble with the CME arrival error decreasing at least twice, even if only STEREO_A data are available for training the ML algorithms.

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