Data Assimilative Optimization of WSA Source Surface and Interface Radii using Particle Filtering

Grant David Meadors[1,2], Shaela I. Jones[3,4], Kyle S. Hickmann[1], Charles N. Arge[3], Humberto C. Godinez-Vasquez[2], Carl J. Henney[5]

[1] Los Alamos National Laboratory, XCP-Division, Verification & Analysis, Los Alamos, NM, [2] Los Alamos National Laboratory, T-Division, Applied Mathematics & Plasma Physics, Los Alamos, NM, [3] NASA Goddard Space Flight Center, Greenbelt, MD, [4] Catholic University of America, Washington, DC, [5] Air Force Research Laboratory, Space Vehicles Directorate, Kirtland AFB, NM

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Abstract

- *Wang-Sheeley-Arge* (WSA): model estimates solar wind & polarity
- Potential Field Source Surface (PFSS) & Schatten Current Sheet (SCS) used to determine Sun's global coronal magnetic field
- 2 radial parameters: source surface & interface radii $\theta \equiv (R_{ss}, R_i)$
- **Idea**: optimize predictions by tuning – time-varying – radii

Introduction

- CR1901-2 (1995-09-29/1995-11-24) chosen, as difficult in past work

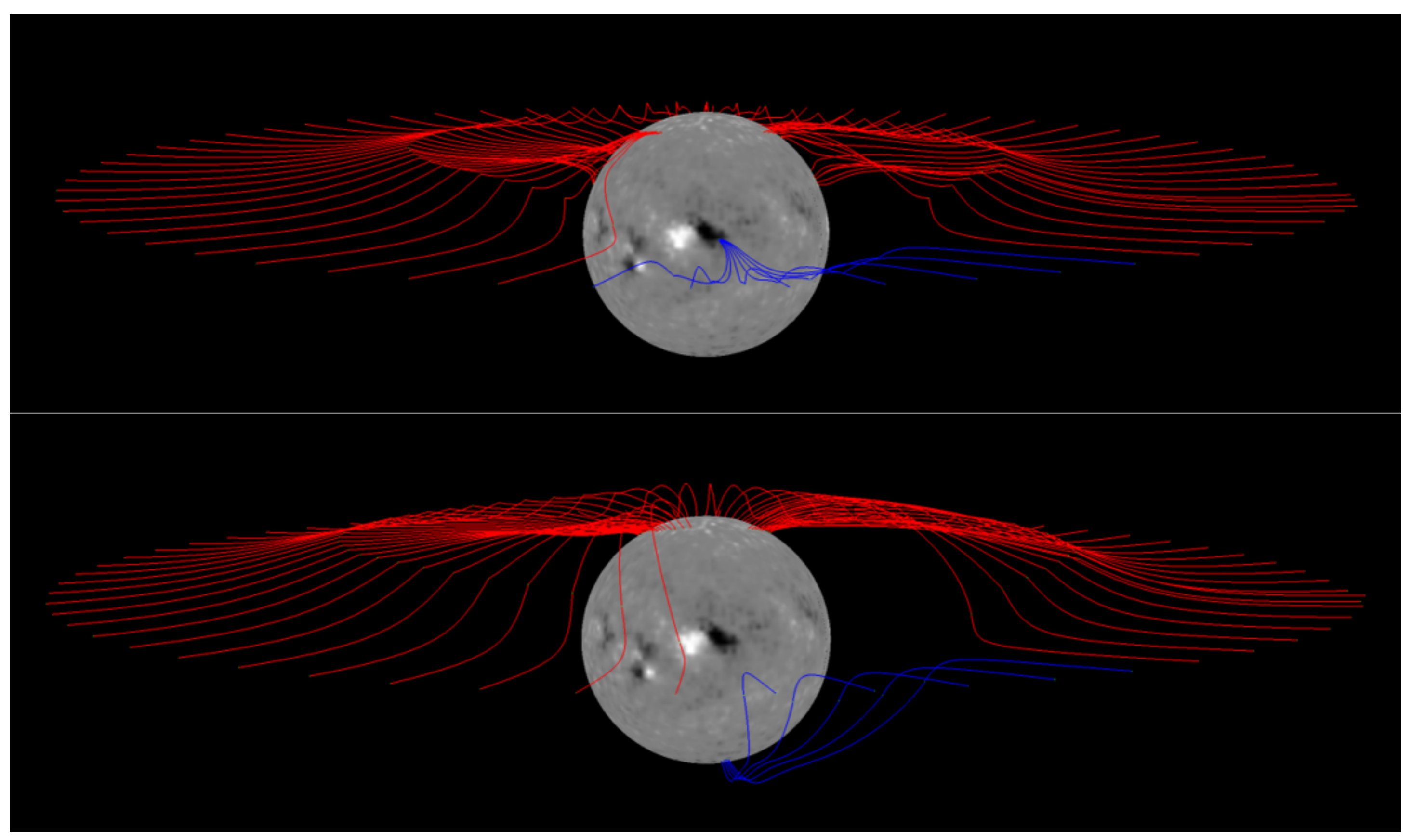

Figure: Magnetic field lines for different (R_{ss}, R_i): standard $(2.51, 2.49)$ (ABOVE) vs one optimum $(3.50, 2.51)$ (BELOW) as predicted by WSA model. Particle filtering minimizes error between model & data, which also helps smooth unphysical kinks.

Best (R_{ss}, R_i) appear to vary in time, based on kinking, coronal holes. A metric $H =$ (fractional polarity)/(RMS residual $\mathbf{v}$), measures fit. Instead of fixed radii, can **optimize** fit by maximizing peak H over radii.

Particle filtering

Like Monte Carlo but **resample** $\propto$ metric H w/ N samples $\theta = (R_{ss}, R_i)$:

$$\mathrm{Prior}(\theta(R_{ss} > R_i)) = \mathrm{Uniform}(1.5R_{\odot}, 4.0R_{\odot}).$$

Data assimilation – apply resampling, with Gaussian perturbation kernel, to incoming ADAPT map data. Converge over iterations k:

$$q(j) \equiv \min_j \{j | c_j > U(0,1)\}, \text{ where } c_j = \sum_{i=0}^{j} H(\theta_i) / \sum_{m=0}^{N} H(\theta_m),$$

$$\theta_j^{k+1} = \theta_{q(j)}^{k} + \left(2\pi\sigma^2\right)^{-1} \exp\left(-\theta^2 / \left[2\sigma^2\right]\right).$$

Samples move toward high H (good fit), adapting as (R_{ss}, R_i) evolve.

Sensitivity & twin testing: simulation and inference

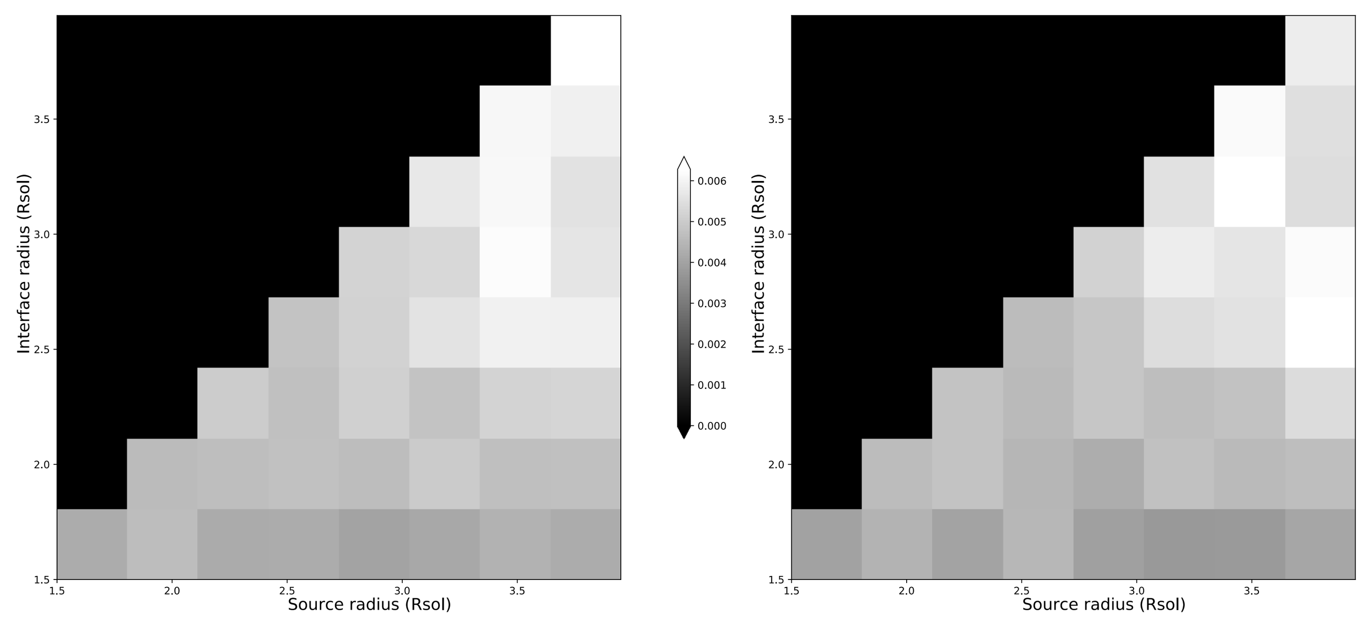

Figure: Heatmaps of H for 36 points on the R_i vs R_{ss} plane for 2 ADAPT synoptic maps. $H \uparrow$ (lighter) is more accurate. The upper, black, triangles are outside of physical bounds (R_i must be $< R_{ss}$). Particle filtering can refine H near *optima*.

R_{ss} ($R_{\odot}$)	R_i ($R_{\odot}$)	H (km^{-1} s)
3.000001	2.900000	48.64546334
3.000010	2.900000	31.11168033
3.000100	2.900000	0.54772908
3.000000	2.900001	68.66813214
3.000000	2.900010	0.44581968
3.000000	2.900100	0.45486562

Table: Source *simulated* at $(R_{ss}, R_i) = (3.000, 2.900)$. Predictions used as observations for sensitivity analysis 7-day window time: 1995-10-05/1995-10-12.

'Twin testing' validates that the particle filter finds **optimal** radii. WSA, at an arbitrary point, makes a prediction set to *simulate* WIND satellite data. Then the particle filter is run, using the predictions in place of observations. The filter works if it can infer that point $\rightarrow$ it does.

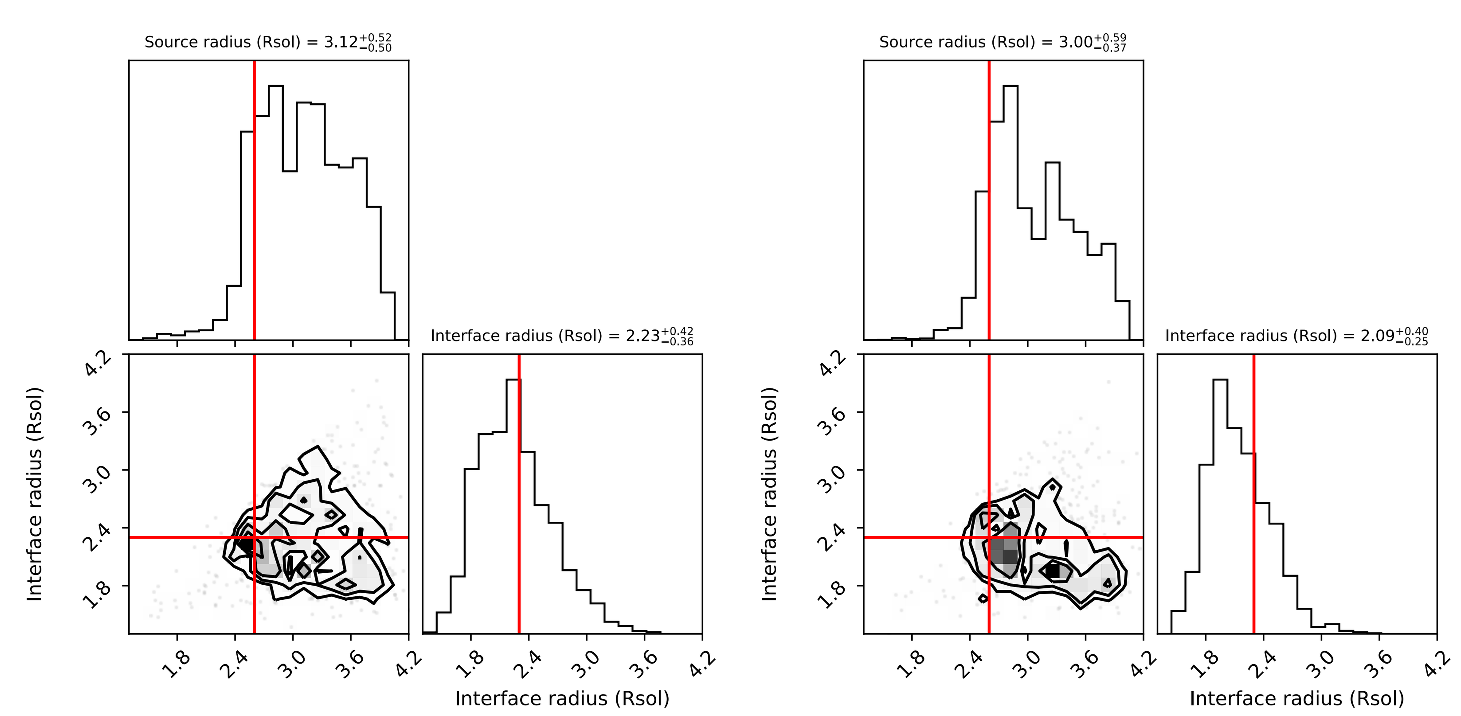

Figure: *Simulated* $(R_{ss}, R_i) = (2.6, 2.3)$ (red line). 512 samples, 7-day windows, ADAPT map 05 – 1st (LEFT) & 2nd (RIGHT) of CR 1901 simulated wind + polarities. Gray dots at sample points. 2D histogram (w/ 1D projections) show favored radii.

Real data analysis on Carrington Rotation (CR) 1901

Particle filtering converges in real data, with greater uncertainty.

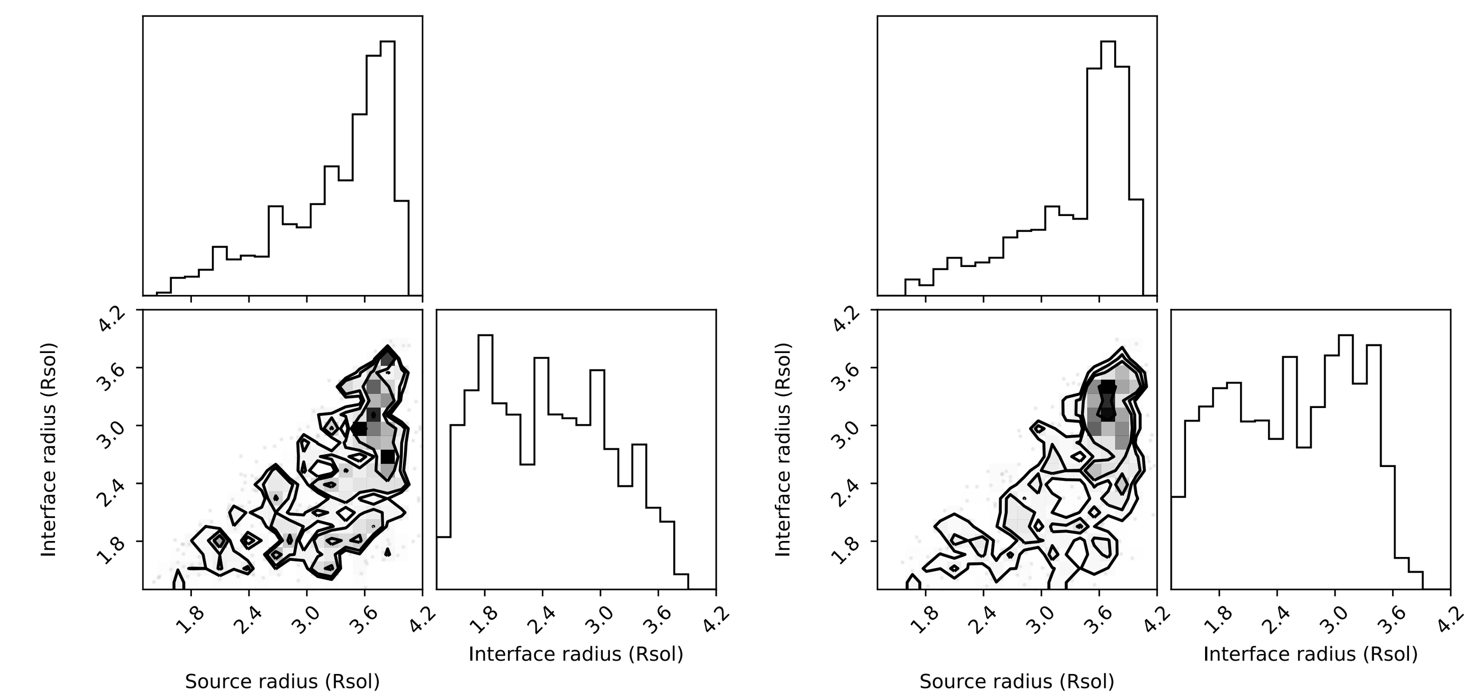

Figure: 512 samples, 7-day windows (start: 1995-09-29), ADAPT map 05 – 1st (LEFT) & 2nd (RIGHT) of CR 1901 real data. H metrics weight particle-filter resampling. Peak emerges at high source radius: $R_{ss} > 3.5R_{\odot}$ fit WIND data. Note: triangular-shaped prior distorts 1D projections, with effect smaller in later iterations.

Conclusions and future work

Demonstrated (for 2 Carrington Rotations): particle filtering can optimize and improve solar wind predictions. While this work is exploratory, it demonstrates how modern adaptive assimilation techniques are useful for space weather applications. Future ideas:

- More Carrington Rotations: show improvement across solar cycle
- ADAPT maps: another dimension to optimize
- Metrics? (1) field-line kinking (2) magnetic flux (3) more satellites

Acknowledgments

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