Data assimilative optimization of Wang-Sheeley-Arge

source surface and interface radii using particle filtering

Grant David Meadors[1,2,3]
Shaela Jones[4],
Kyle Hickmann[1],
Charles Arge[4],
Humberto Godinez[2],
Carl Henney[5]
(LANL) [1]XCP-8, [2]T-5, [3]A-1,
[4]NASA GSFC, [5]AFRL/KAFB

Los Alamos NATIONAL LABORATORY EST. 1943

ASME Verification & Validation Symposium

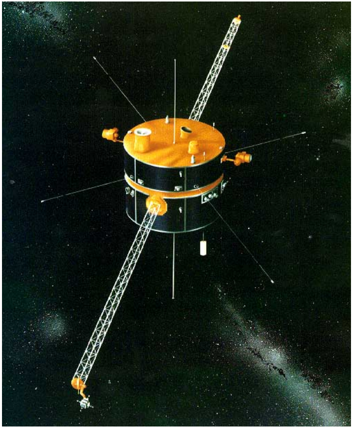
Space weather model adaptive validation

Definition

Data assimilation:
combining observation with theory to yield prediction

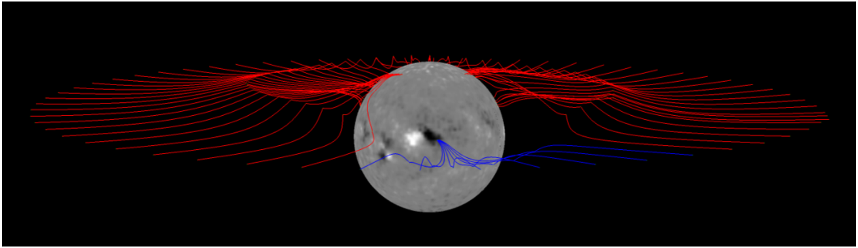
Outline

- Wang-Sheeley-Arge (WSA): a practical model for space weather predictions
- Validation: Assimilation and particle optimization of solar wind & polarity



WIND satellite
(Credit: NASA Goddard SFC)

Space weather: WSA as a simplified model



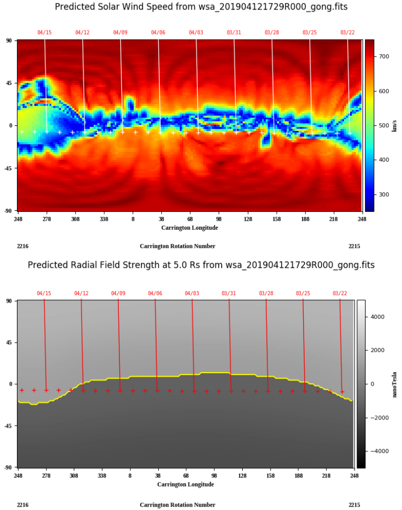
Solar magnetic field lines in Wang-Sheeley-Arge (WSA) model: red/blue = polarity. Kinked lines $\sim$ unphysical $\rightarrow$ must tune WSA

2 model parameters:

$$R_{ss} = \text{source surface radius} \approx 2.6\ R_\circ$$
$$R_i = \text{interface radius} \approx 2.3\ R_\circ$$

Validation: use satellite data to adaptively adjust/predict better

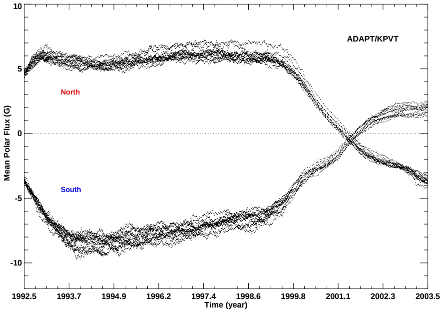
Space weather: predicting the sun



Solar wind & magnetic field polarity: WSA 2019 example prediction

Space weather: changing cycles

Space weather environment fluctuates
Prediction possible with models ∼ WSA



Input to WSA – 12 realizations of ADAPT global solar magnetograms (1992 to 2003) based on KPVT (Kitt Peak Vacuum Telescope) images

Space weather informed by inference

Verification: take NASA Fortran code as given
Validation: across time, must be studied

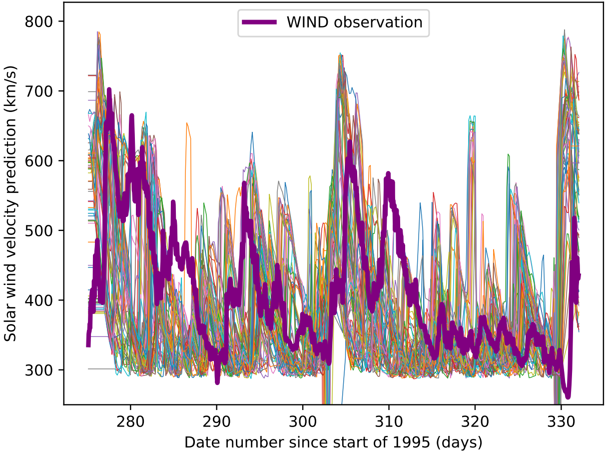
Reframe problem:

Solar magnetic field – a 2-D parameter space (shifting over time)
What determines shape? Goodness-of-fit H to satellite data[1],

$$H = \frac{\text{avg correct polarity}}{\text{avg solar wind velocity residual}}$$

[1] that is, compare WSA model predictions to satellite data (*e.g.*, WIND)

Space weather: implications for wind



Solar wind radial velocity (km·s^{-1}) at L1 (WIND: 1995-09-29/1995-11-24) for ensembles of varying (R_{ss}, R_i) – close fit $\propto \uparrow H$

Of performance metrics and particles

Likelihood and *probability* are inaccessible:
instrumental noise distribution not known

Performance metric H still calculable

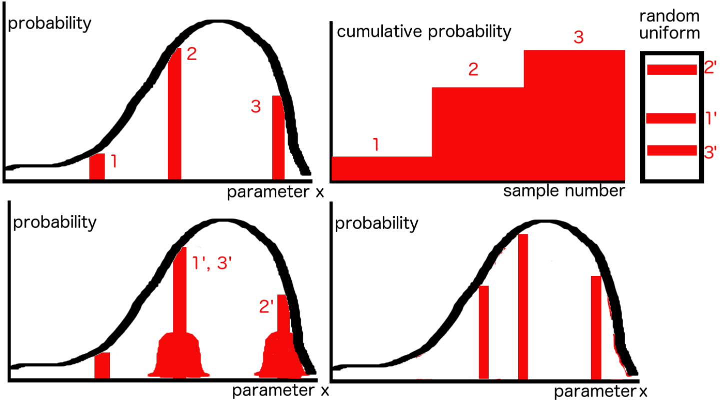
$\rightarrow$ How many H samples to tune (R_{ss}, R_i) optimally?

Grids work for big, stable spaces, but…

…WSA (R_{ss}, R_i) may vary – fast or slow
– metric behavior uncertain

Of performance metrics and particles

$\Longrightarrow$ ideal for particle filter (sequential Monte Carlo)
(like ensemble Kalman filter, applicable to terrestrial prediction)



(upper left) iteration 0: samples, (upper right): calculate total & resample
(lower left): perturbation kernel, (lower right) iteration 1: evaluate

Space weather: data assimilation

Past slides assume

- performance metric $\propto$ probability distribution
  not exact!
- constant distribution

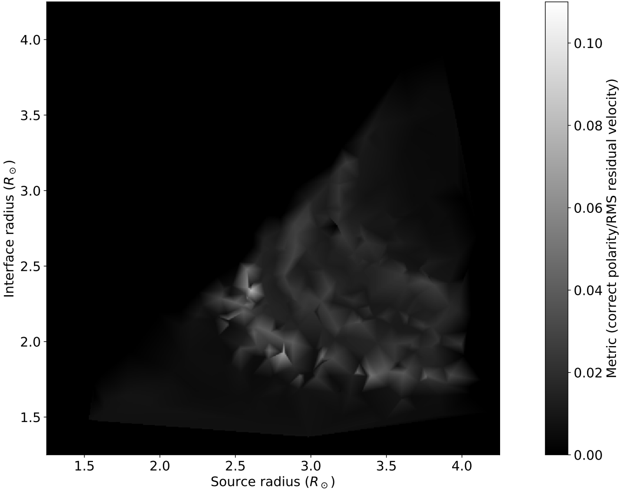
Data assimilation
take samples evaluated on time *window 0*
(optionally iterate)
$\rightarrow$ apply (re-)samples to next time *window 1*

requires slowly-evolving data $\implies$ sample density grows at peak

Validation process assures model performance with continual measurement, which iteratively tunes model

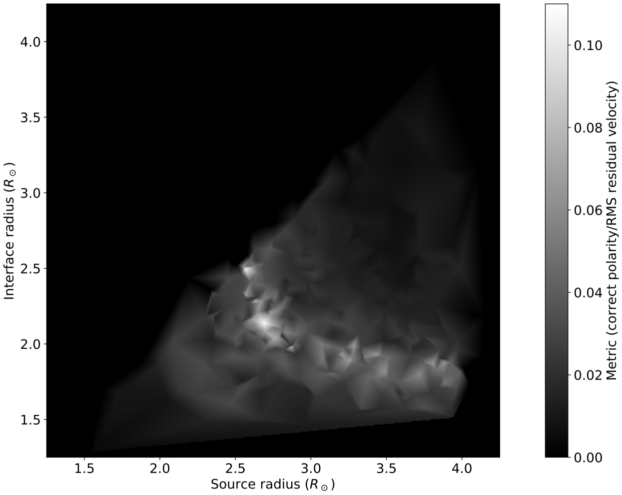
Simulation

Space weather (simulation): metric, window 0



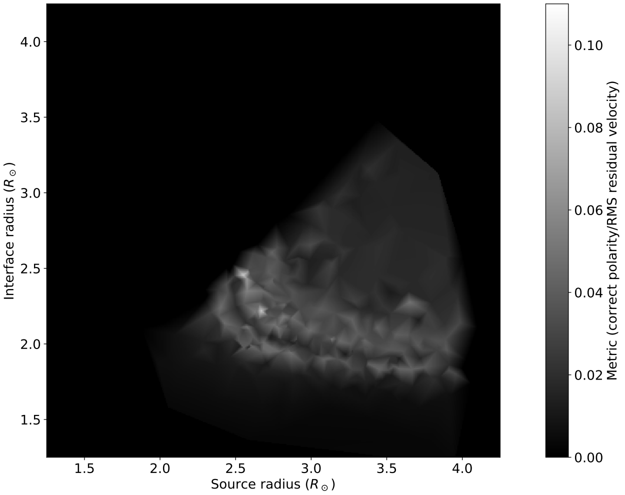
'Twin' experiment at $(R_{ss}, R_i) = (2.6, 2.3)$, 512 samples, 7 days, metric H

Space weather (simulation): metric, window 1



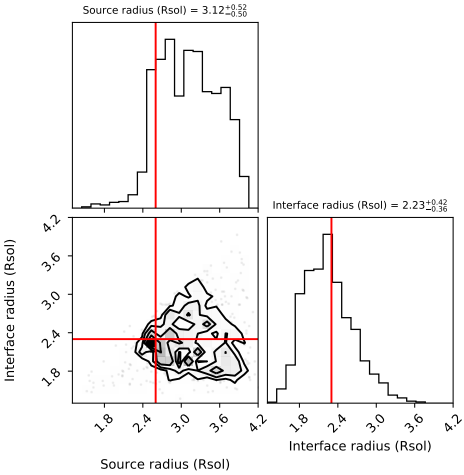
'Twin' experiment at $(R_{ss}, R_i) = (2.6, 2.3)$, 512 samples, 7 days, metric H

Space weather (simulation): metric, window 2



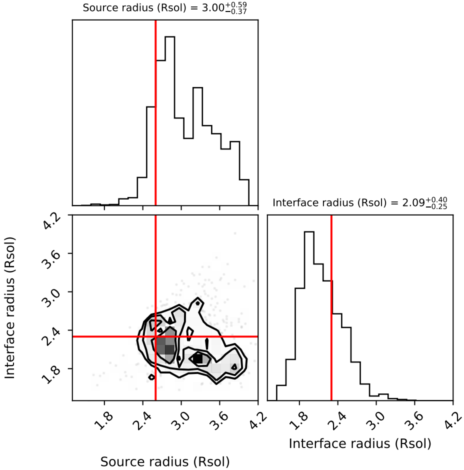
'Twin' experiment at $(R_{ss}, R_i) = (2.6, 2.3)$, 512 samples, 7 days, metric H

Space weather (simulation): filter, window 0



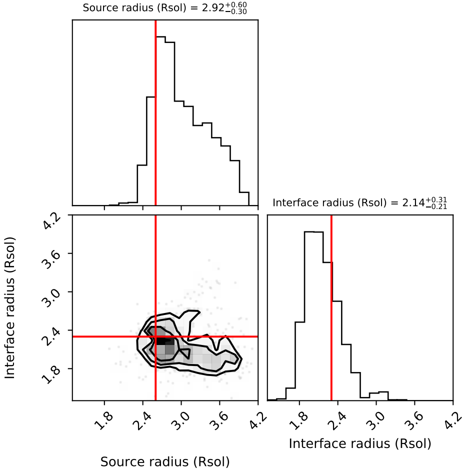
'Twin' experiment at $(R_{ss}, R_i) = (2.6, 2.3)$, 512 samples, 7 days
particle filter (true value marked by red crosshairs)

Space weather (simulation): filter, window 1



'Twin' experiment at $(R_{ss}, R_i) = (2.6, 2.3)$, 512 samples, 7 days
particle filter (true value marked by red crosshairs)

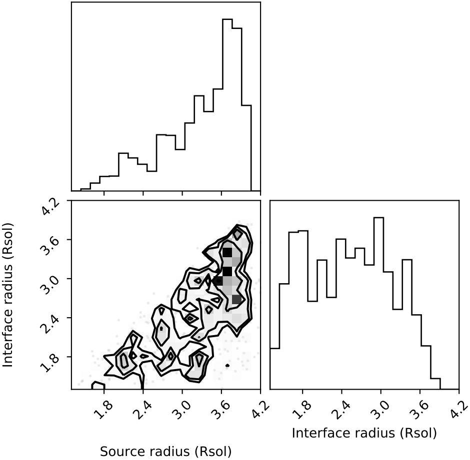
Space weather (simulation): filter, window 2



'Twin' experiment at $(R_{ss}, R_i) = (2.6, 2.3)$, 512 samples, 7 days
particle filter (true value marked by red crosshairs)

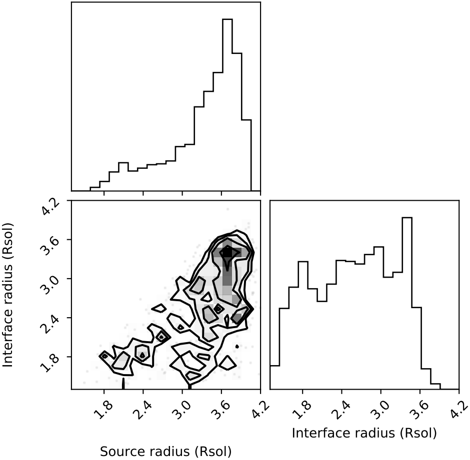
Real data

Space weather (real data): filter, window 0



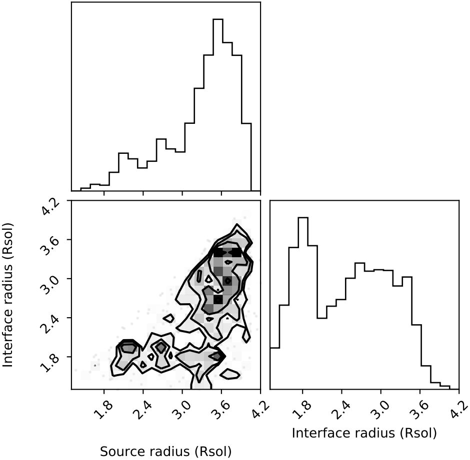
Carrington Rotation 1901/1902 real data (ADAPT map 5/WIND)
particle filter, 512 samples, 7-day windows (3-day advance predictions)

Space weather (real data): filter, window 1



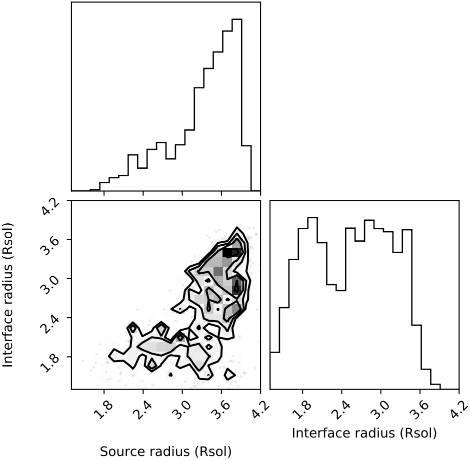
Carrington Rotation 1901/1902 real data (ADAPT map 5/WIND)
particle filter, 512 samples, 7-day windows (3-day advance predictions)

Space weather (real data): filter, window 2



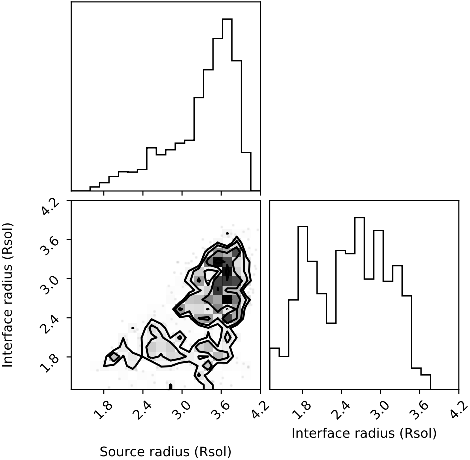
Carrington Rotation 1901/1902 real data (ADAPT map 5/WIND)
particle filter, 512 samples, 7-day windows (3-day advance predictions)

Space weather (real data): filter, window 3



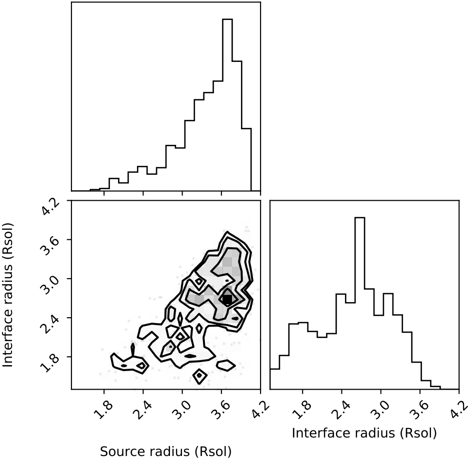
Carrington Rotation 1901/1902 real data (ADAPT map 5/WIND)
particle filter, 512 samples, 7-day windows (3-day advance predictions)

Space weather (real data): filter, window 4



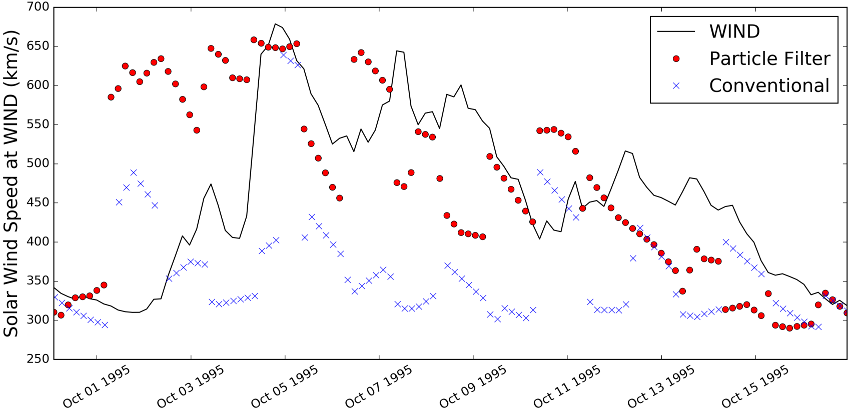
Carrington Rotation 1901/1902 real data (ADAPT map 5/WIND)
particle filter, 512 samples, 7-day windows (3-day advance predictions)

Space weather (real data): filter, window 5



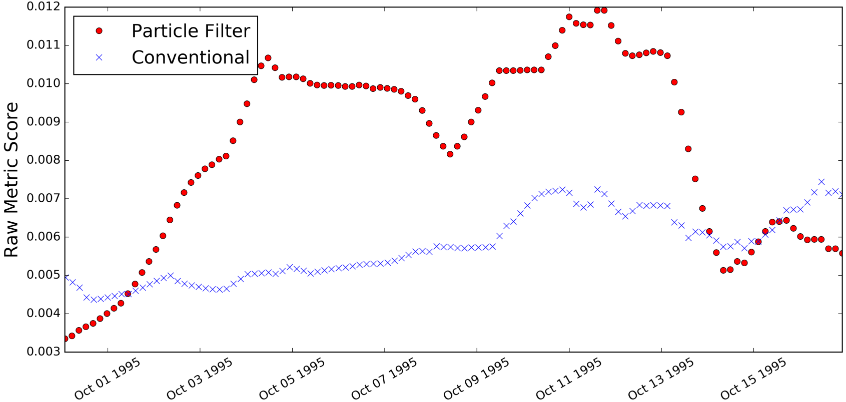
Carrington Rotation 1901/1902 real data (ADAPT map 5/WIND)
particle filter, 512 samples, 7-day windows (3-day advance predictions)

Validation: comparison (solar wind)



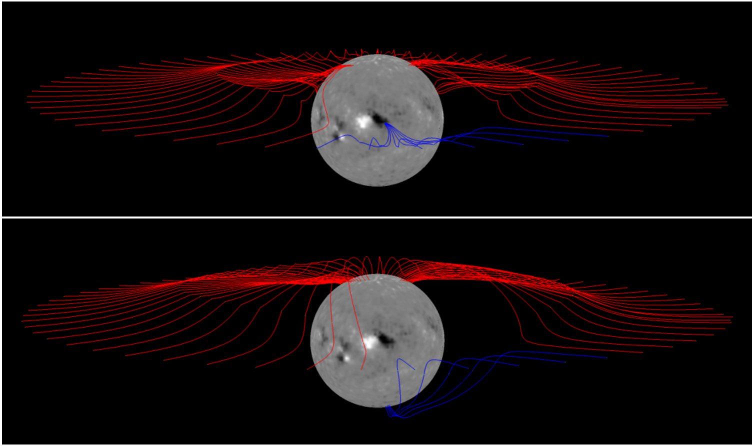
Solar wind radial velocity vs time for 2 weeks wrt WIND satellite data comparing standard $(R_{ss}, R_i) = (2.51, 2.49)$ to filter optimum $(3.9, 3.4)$

Validation: comparison (performance metric)



Metric H (higher $=$ better) vs time for 2 weeks wrt WIND satellite data comparing standard $(R_{ss}, R_i) = (2.51, 2.49)$ to filter optimum $(3.9, 3.4)$

Solar magnetic fields with better model results



Solar magnetic field lines traced at standard values (TOP) and at possible particle-filter optimum, $(R_{ss}, R_i) = (3.50, 2.51)$ (BOTTOM): smoothness $\implies$ greater physical self-consistency (+ accuracy)

Summary

- Verification: taking NASA WSA model as given,
- Validation: satellite observations,
  combined with particle filtering,
  can *tune* corona $\rightarrow$ solar wind models,
  & optimize parameters
  $\Longrightarrow \uparrow$ sensitivity
- Widely-used space weather model
  now *adapts & evolves* in time

Acknowledgments

Thanks to Kyle Hickmann, Humberto Godinez, Sara del Valle and Brandon Wilson for mentorship, to ASME for hosting this talk, and research sponsors at NASA. Slides LA-UR-20-23563, narration LA-UR-20-23634, questions: gdmeadors@lanl.gov.

Bibliography

References

- Y.-M. Wang and N. Sheeley Jr, Astrophys J **392**, 310 (1992).
- A. Doucet, S. Godsill, and C. Andrieu, Statistics and computing **10**, 197 (2000).
- C. Arge and V. Pizzo, J Geophys Res Space Physics **105**, 10465 (2000).
- D. Foreman-Mackey, The Journal of Open Source Software **24** (2016), URL `http://dx.doi.org/10.5281/zenodo.45906`.
- S. McGregor, W. Hughes, C. Arge, and M. Owens, J Geophys Res Space Physics **113** (2008).
- K. Hickmann, H. Godinez, C. Henney, and C. Arge, Solar Physics **290**, 1105 (2015).