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Forecasting the Solar Wind

with Sequential Monte Carlo Assimilation of Satellite Data

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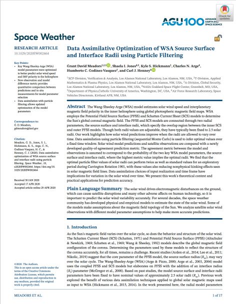
2021 March 11/5781 Adar 28 (JD 2459285)
Bar-Ilan University Astro Group

Introduction

‘Data Assimilative Optimization of WSA Source Surface and Interface Radii using Particle Filtering’, **GDM**,
S. Jones, K. Hickmann, C.N. Arge, H. Godinez-Vasquez, C. Henney
Space Weather 18 (2020) 5



Space Weather

RESEARCH ARTICLE
10.1029/2020SW002464

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

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Key Points:
- Key Wang-Sheeley-Arge (WSA) model parameters were optimized to better predict solar wind speed and IMF polarity in the heliosphere
- New observation and model difference metric provides quantitative comparison between predictions and in situ measurements for model parameter selection
- Data assimilation with particle filtering allows updated optimization of the model parameters

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Abstract The Wang-Sheeley-Arge (WSA) model estimates solar wind speed and interplanetary magnetic field polarity in the inner heliosphere using global photospheric magnetic field maps. WSA employs the Potential Field Source Surface (PFSS) and Schatten Current Sheet (SCS) models to determine the Sun's global coronal magnetic field. The PFSS and SCS models are connected through two radial parameters, the source surface and interface radii, which specify the overlap region between the inner SCS and outer PFSS models. Though both radii values are adjustable, they have typically been fixed to 2.5 solar radii. Our work highlights how solar wind predictions improve when the radii are allowed to vary over time. Data assimilation using particle filtering (sequential Monte Carlo) is used to infer optimal values over a fixed time window. Solar wind model predictions and satellite observations are compared with a newly developed quality-of-agreement prediction metric. The agreement metric between the model and observations is assumed to correspond to the probability of the two key WSA model parameters, the source surface and interface radii, where the highest metric value implies the optimal radii. We find that the optimal particle filter values of solar radii can perform twice as well as standard values for an exploratory period during Carrington Rotation 1901, with these values also reducing nonphysical kinking effects seen in solar magnetic field lines. Data assimilation choices of input realization and time frame have implications for variation in the solar wind over time. We present this work's theoretical context and practical applications for prediction accuracy.

Plain Language Summary The solar wind drives electromagnetic disturbances on the ground, which can cause satellite disruptions and many other adverse affects on human technology, so it is important to predict the solar wind variability accurately. For several decades, the space weather community has developed physical and empirical models to estimate the state of the solar wind. Some of the models make assumptions about the magnetic field topology of the Sun. We analyze satellite solar wind observations with different model parameter assumptions to help make more accurate predictions.

1. Introduction

As the Sun's magnetic field varies over the solar cycle, so does the behavior and structure of the solar wind. The Schatten Current Sheet (SCS) (Schatten, 1971) and Potential Field Source Surface (PFSS) (Altschuler & Newkirk, 1969; Schatten et al., 1969; Wang & Sheeley, 1992) models describe the global magnetic field configuration of the corona. Determining the parameters used by these models to reflect the structure of the corona accurately, for all times, remains a challenge. Recent studies (Arden et al., 2014; Lee et al., 2011; Nikolic, 2019) suggest that the core parameter of the PFSS model, the source surface radius (R_{ss}), may vary over the solar cycle. The Wang-Sheeley-Arge (WSA) (Arge & Pizzo, 2000; Arge et al., 2003, 2004) model uses the coupled PFSS and SCS models but elaborates on PFSS with the addition of an interface radius (R_i) parameter (McGregor et al., 2008). Based on past studies, the model source surface and interface radii parameters have been fixed to have nominal values of approximately 2.5 solar radii ($R_\odot$). Previous work explored the benefit of various data assimilation techniques applied to global solar magnetic maps used as input to WSA (Hickmann et al., 2015, 2016). In the work presented here, the radial model parameters

↑ As published

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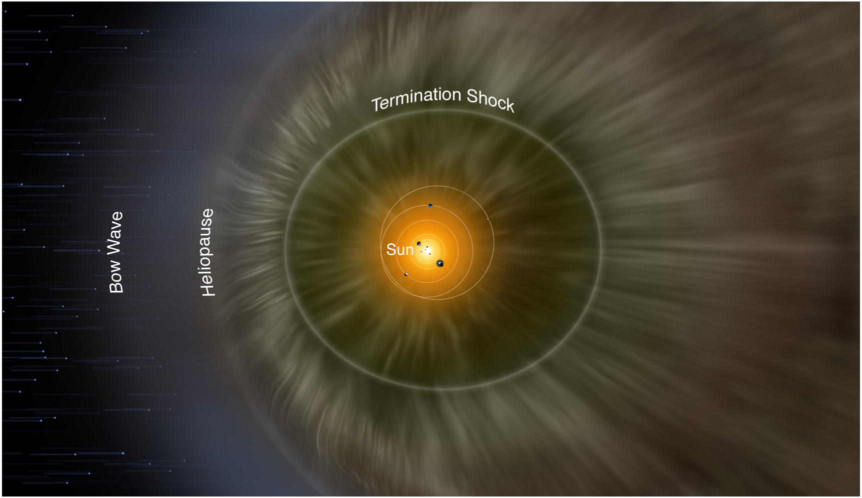
Acknowledgment of country

1st, **acknowledgment of country** practice learned in Australia:

I acknowledge the Tewa pueblo of Otowi as traditional owners of this land, from where I speak, and pay our respects to their elders, past, present, and future.

Zooming into our solar system



Solar wind and the heliosphere (Credit: NASA/IBEX)

Our star matters

We live near a G-type main-sequence star

Two central reasons to study the Sun:

1. We live here!
   the Sun is a dynamic object,
   sustaining and destroying life on/near Earth,
   including technological civilization
2. We can understand stellar phenomena *generally*
   better by close, high-resolution, multiple-perspective
   studies of our *particular* star

Stellar winds/magnetic fields important to many astro domains:
e.g., star formation and limits on growth
– **our own star may hold answers**

Our star matters

What questions pertain?

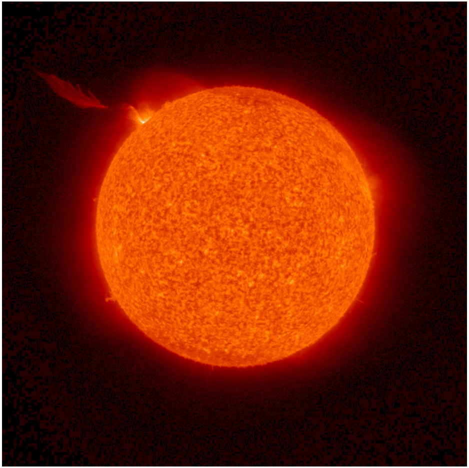
- Satellites & telescopes monitor the Sun,
  which rotates every $\sim$27 days (at equator),
- Models exist to predict solar winds,
  some days in advances,
  $\rightarrow$ magnetohydrodynamic (MHD) models, *and*
  $\rightarrow$ phenomenological models

MHD models $\propto$ *a priori* physics, computationally costly,
Phenomenological models approx. & derive simplified principles,
(talking about these today)

Goal: to take input observations (telescope/satellite data),
$\Longrightarrow$ predict/forecast solar environment in near-future

Astro analytic methods (MC/Bayes) help us do better

Staring into the Sun



Solar flare in UV, 2020-05-29 (Credit: NASA/GEOS-16)

we do not predict flares but can study *how the wind moves*

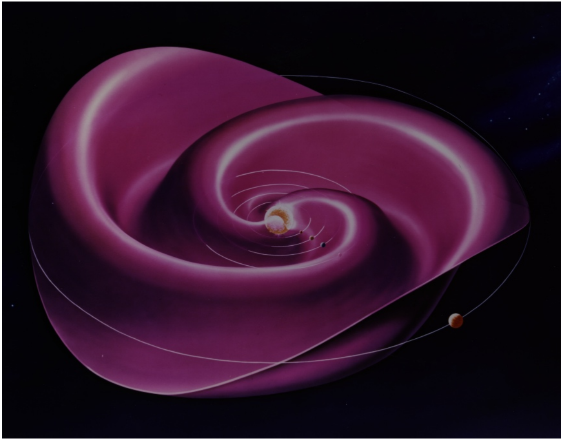
Lessons for deep-space astronomers

Avoid assumptions

In gravitational-wave astrophysics,
had assumed Gaussian noise models,
'simple' source-to-detector propogation,
& familiar systematics

In contrast,
heliophysics has complex source-to-detector propogation,
leaving less time to understand noise,
$\rightarrow$ especially combining heterogeneous data streams

The shape of the solar wind



Complex propgation: wind flows out at $\sim$400 km/s, rotating $\sim$27 days
Schatten Current Sheet (SCS) + Potential Field Source Surface (PFSS)
(Credit: Wilcox, Hoeksema, & Scherrer, Science 209, p. 603, 1980.)

The shape of the solar wind

All our vantage points
move through that complicated surface:

- Limited perspectives
- Particles move $\ll$ slower than light
- **but** light doesn't contain all info to determine forecast

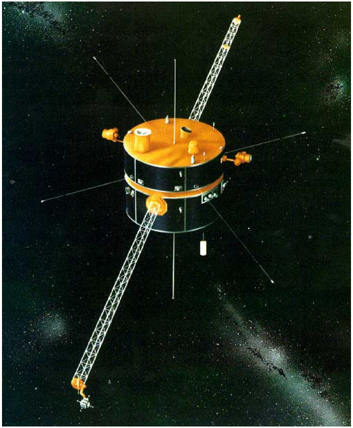
$\Longrightarrow$ However, we can observe over time
+ assimilate information into more complete model

Space weather models

Definition

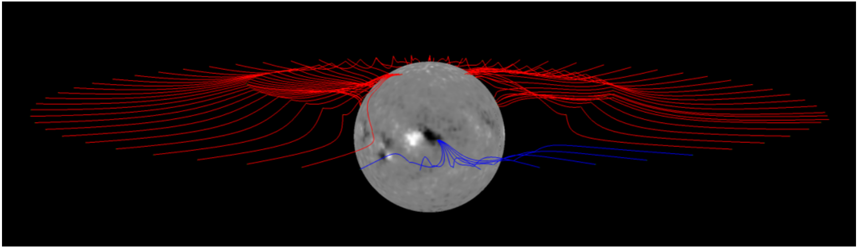
Data assimilation:
combining observation with theory to yield (better) prediction

- Wang-Sheeley-Arge (WSA): a practical `Fortran` model for space-weather prediction *(phenomenological, widely-used)*
- Space data science: particle filter/Monte Carlo – solar wind & polarity



WIND satellite at Lagrange Point L1
(Credit: NASA Goddard SFC)

Space weather: WSA as a simplified model



Solar magnetic field lines in Wang-Sheeley-Arge (WSA) model:
central image: magnetogram generated by another model, `ADAPT`
red/blue = polarity. Kinked lines $\sim$ unphysical $\rightarrow$ must tune WSA

2 model parameters: **optimize** w/ sat. data for adaptive $\uparrow$ prediction

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

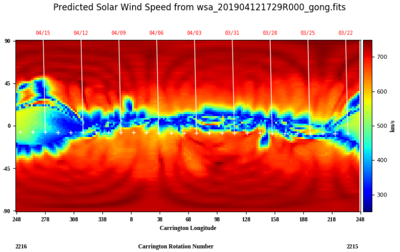
Space weather: WSA as a simplified model

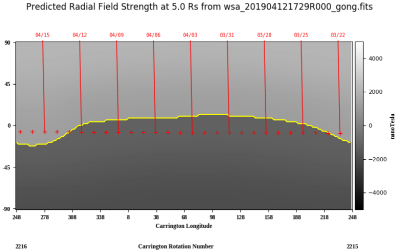
In other words

Hold all the other complicated physics fixed
only adjust the parameters that determine
where **B**-field straightens out

if they fit data better, move model that way
$\rightarrow$ Monte Carlo sampling, not deep physics

Space weather: predicting the changing sun



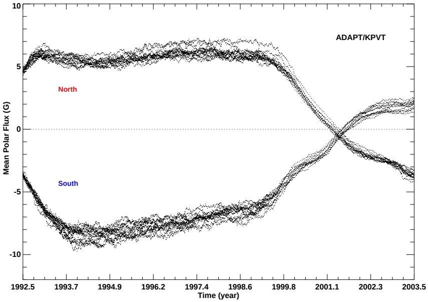


Solar wind (above), magnetic field polarity (below):

WSA 2019 example prediction

Space weather: changing cycles as input

Space weather environment fluctuates
Prediction possible with models $\sim$ 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

Wrap `Python` around operational NASA `Fortran` code

Reframe problem:

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

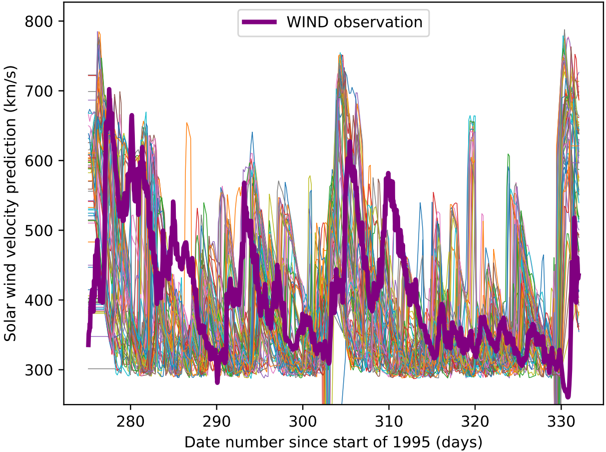
$$H = \frac{\text{avg correct polarity}}{\text{avg solar wind velocity residual}}$$

Likelihood & *probability* – inaccessible:
instrumental noise distribution unknown

Performance metric H is **calculable**

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

Space weather: implications for wind



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

Space weather: data assimilation

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

...WSA (R_{ss}, R_i) may vary – fast or slow
$\implies$ metric behavior uncertain

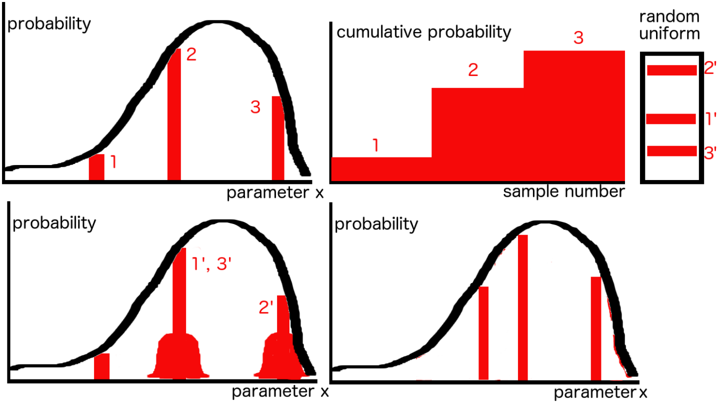
Data assimilation
take samples evaluated on time *window 0*
$\rightarrow$ apply (re-)samples to next time *window 1*

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

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

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

Of performance metrics and particles

Caution

shares similarities with inference/parameter estimation
but should not be naïvely interpreted as such
→ problem is lack of noise model,
so unsafe to interpret credible intervals

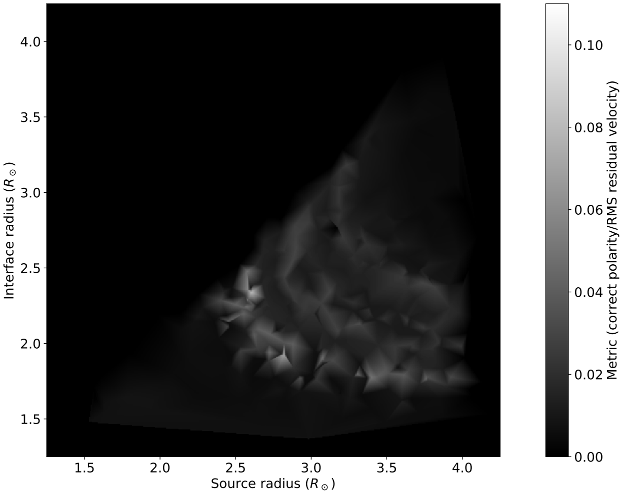
Space weather (simulation)

Simulation

Space weather (simulation)

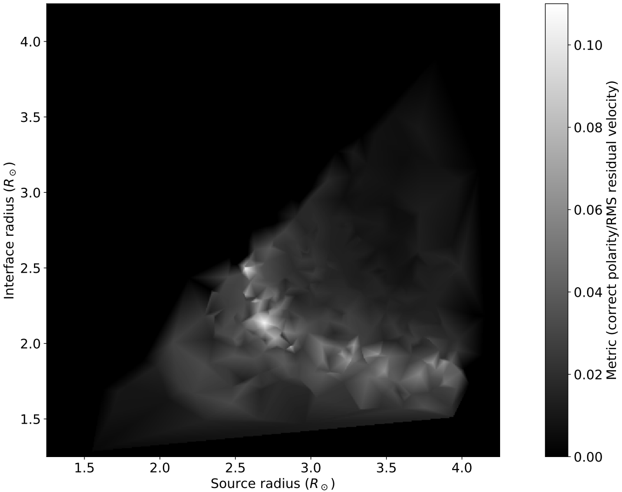
Remember, interface radius $R_i < $ source surface radius R_{ss} resulting in a triangular boundary to the parameter space

Space weather (simulation): metric, window 0



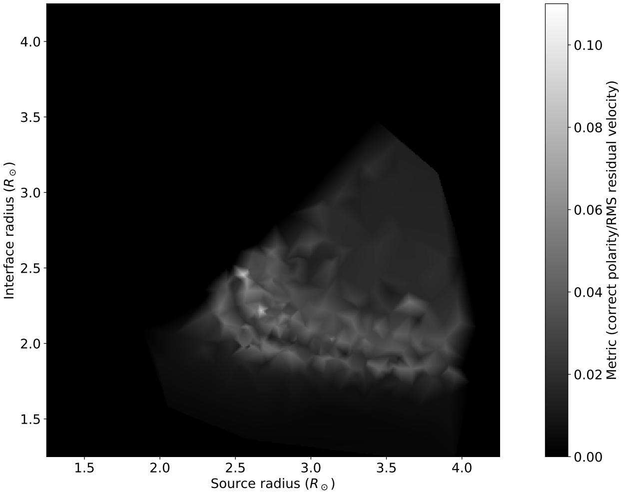
'Twin' experiment at $(R_{ss}, R_i) = (2.6, 2.3)$, 512 samples, 7 days, metric H

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)

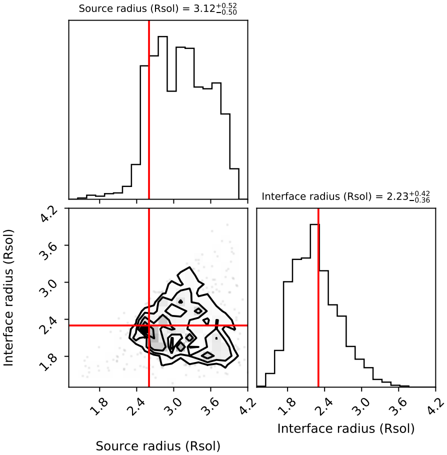
Degeneracy/correlation along band in R_{ss}

- initially unexpected, made sense to our solar physicists
- R_i affects physics more, so model more sensitive to it

Those plots used `imshow` to interpolate values
try plotting with `corner` to use weighted samples (gray dots) and their contours

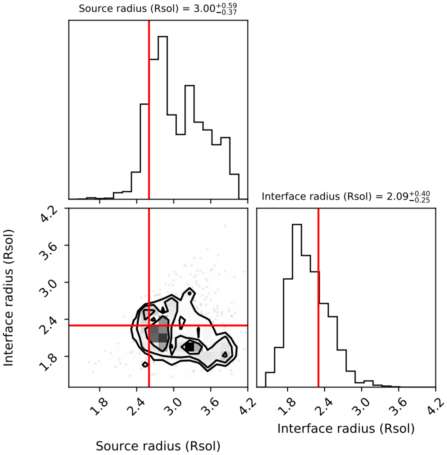
analogous $\sim$ likelihood samples (again, not strictly true)

Space weather (simulation): filter, window 0



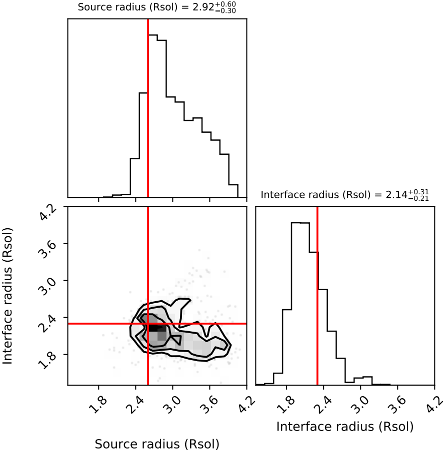
'Twin' experiment at $(R_{ss}, R_i) = (2.6, 2.3)$, 512 samples, 7 days
particle filter (true value marked by red crosshairs)

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)

Space weather (simulation)

Convergence!

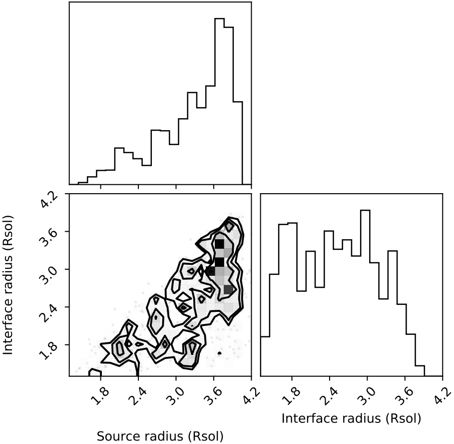
promising for particle filter

cautionary note:
triangular space induces biases in 1D marginalizations,
–math noted in paper, expectation value usually $\neq$ mode

Space weather (real data)

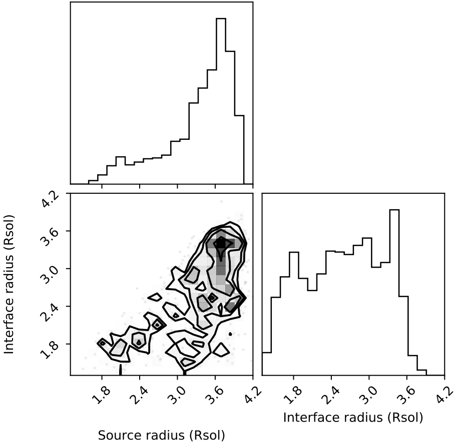
Real data

Space weather (real data): filter, window 0



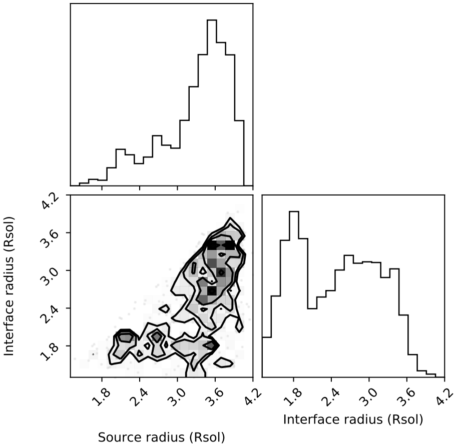
Carrington Rotation 1901/1902 real data (ADAPT map 5/WIND)
particle filter, 512 samples, 7-day windows (3-day advance predictions)

Space weather (real data): filter, window 1



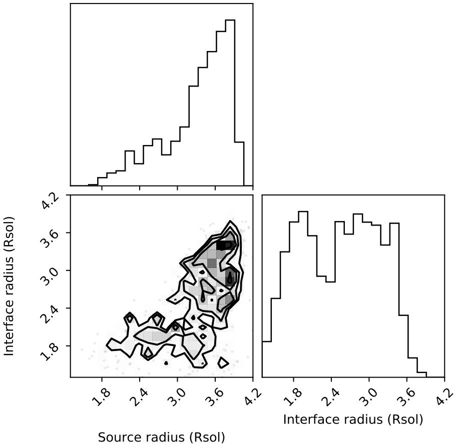
Carrington Rotation 1901/1902 real data (ADAPT map 5/WIND)
particle filter, 512 samples, 7-day windows (3-day advance predictions)

Space weather (real data): filter, window 2



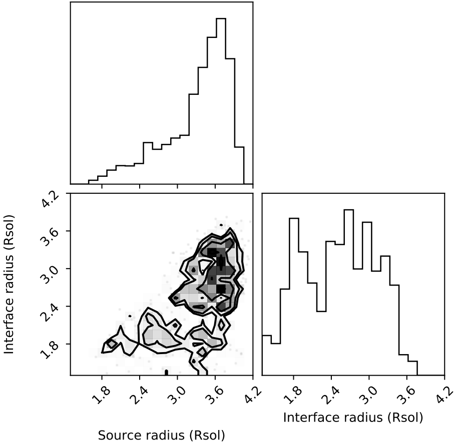
Carrington Rotation 1901/1902 real data (ADAPT map 5/WIND)
particle filter, 512 samples, 7-day windows (3-day advance predictions)

Space weather (real data): filter, window 3



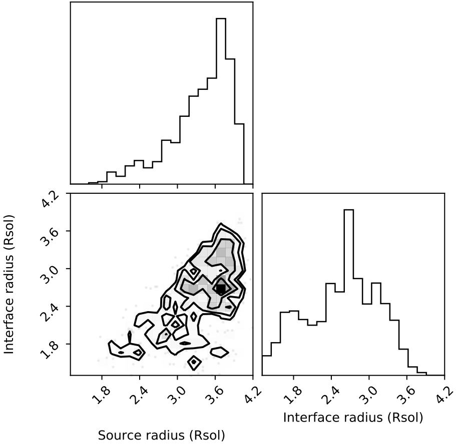
Carrington Rotation 1901/1902 real data (ADAPT map 5/WIND)
particle filter, 512 samples, 7-day windows (3-day advance predictions)

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)

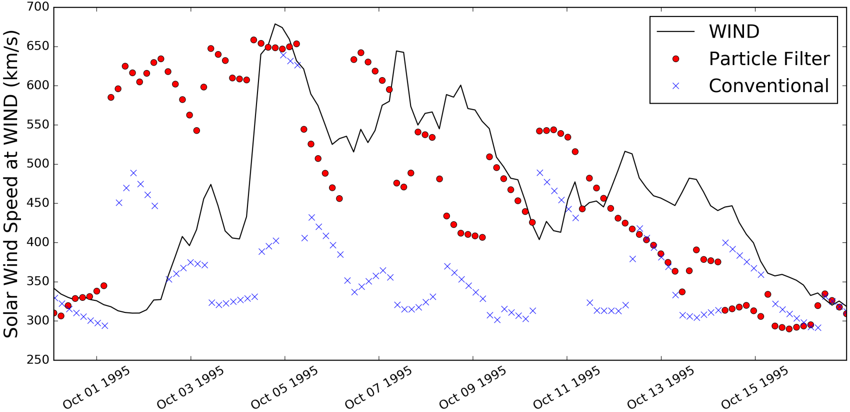
Space weather (real data)

Encouraging

To converge and possibly ‘track’
a *changing* (?) value of (R_{ss}, R_i) over time
by assimilating satellite data

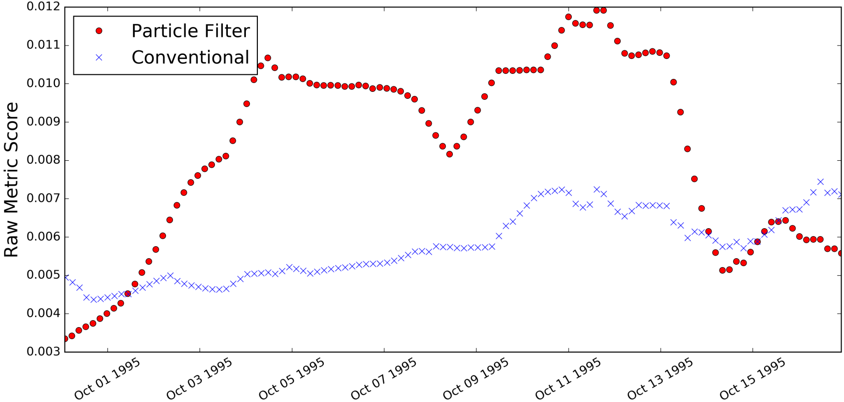
$\implies$ ability to adaptively forecast
a solar environment that
is known to be changing continually
(*e.g.,* 11-year solar cycle)

Analysis: 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 $(3.9, 3.4)$

Analysis: 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 $(3.9, 3.4)$

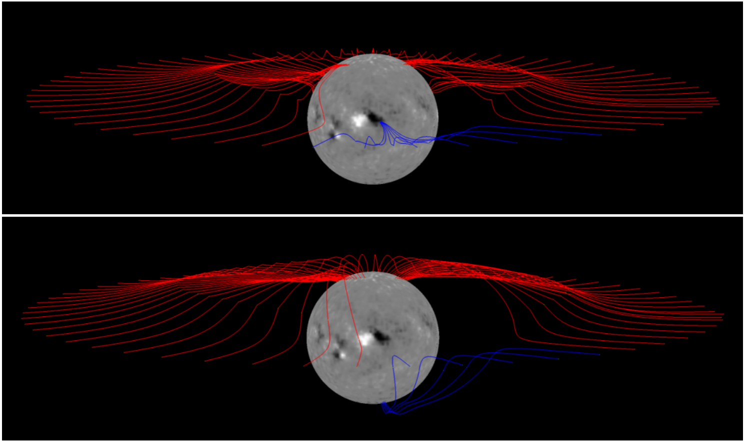
Solar magnetic fields: a validity check

Improving the metric was the direct goal
success was not guaranteed,. . .
(particle filter might not converge or show any gains)

. . . but can we show any other physical significance?

Yes: another improvement happens,
even *without* direct access to ‘knob-tuning’

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 of NASA Space Weather optimization

- (given base of NASA code, encapsulate in `Python`),
- Optimization: satellite observations,
  combined with particle filtering,
  can *tune* corona $\rightarrow$ solar wind models,
  & **optimize** parameters
  $\implies \uparrow$ sensitivity
- Widely-used WSA space weather model
  now *adapts & evolves* in time,
  $\rightarrow$ operationalization being studied by NOAA

Summary & Conclusion

Thank you for your attention – *shabbat shalom* tomorrow!

- SPACE WEATHER forecasting helps us predict our nearest star
- THE SUN stimulates many questions, despite its proximity
- ASTROPHYSICS methods improve solar physics, and solar physics can inform astrophysics

Acknowledgments
Thanks to Professor Ofek Birnholtz for inviting this seminar hosted by the Bar-Ilan University astro group, and Kyle Hickmann & Humberto Godinez as project PIs. This work is assigned LA-UR-21-xxxxx.
Questions: gdmeadors@lanl.gov

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