Knowing our Sun:

data fusion for optimizing space weather forecasts

Grant David Meadors

Los Alamos National Laboratory

2020 November 18

LGBTQSTEMDay

Introduction

Data analysis
science of statistical analysis
across data types
including uncertainty

forward: cause $\rightarrow$ effect
inverse: effect $\rightarrow$ cause

Outline

- *Space weather:*
  model for predicting
  solar wind & polarity
- *Particle filtering:*
  optimization with Monte Carlo
- *Simulation & observation:*
  twin tests and real data
- *Back to Earth:*
  independent work in
  inertial confinement fusion
  (ICF)

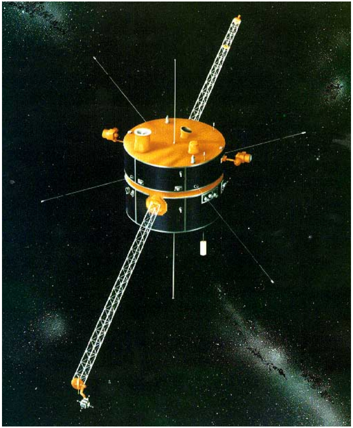
Space weather

Space weather model adaptive optimization

Published: Meadors, Jones, Hickmann *et al*
Space Weather 18 (2020) 5

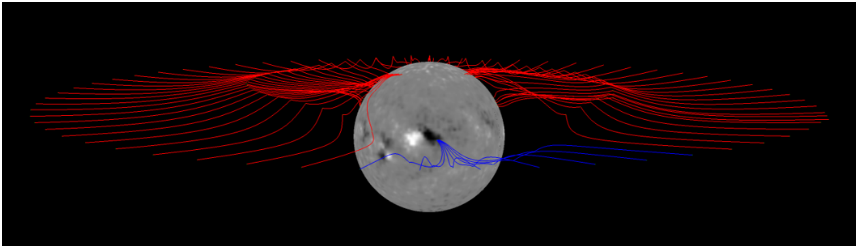
Definition
Data assimilation:
combining observation with theory to yield (better) prediction

- Wang-Sheeley-Arge (WSA): a practical `Fortran` model for space-weather prediction
- Space data science: particle filter/Monte Carlo – 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

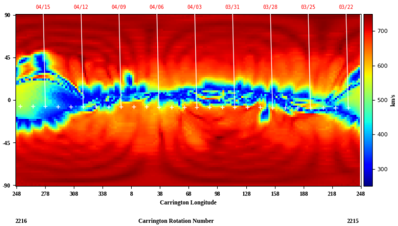
2 model parameters:

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

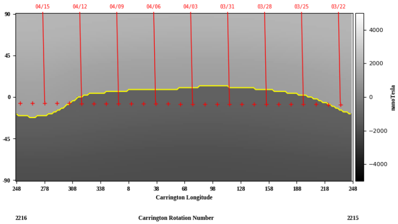
Optimization: use satellite data to adaptively adjust/predict better

Space weather: predicting the changing sun

Predicted Solar Wind Speed from wsa_201904121729R000_gong.fits



Predicted Radial Field Strength at 5.0 Rs from wsa_201904121729R000_gong.fits

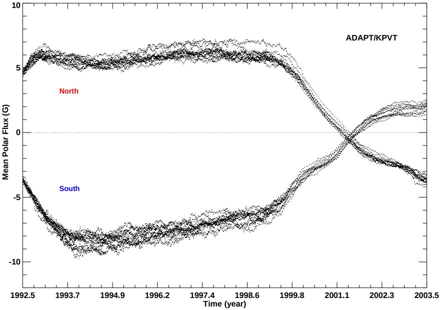


Solar wind (above), magnetic field polarity (below):

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],

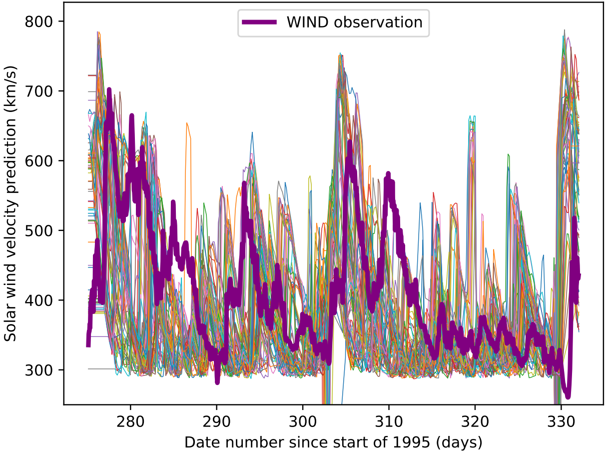
$$H = \frac{\text{avg correct polarity}}{\text{avg solar wind velocity residual}}$$

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·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

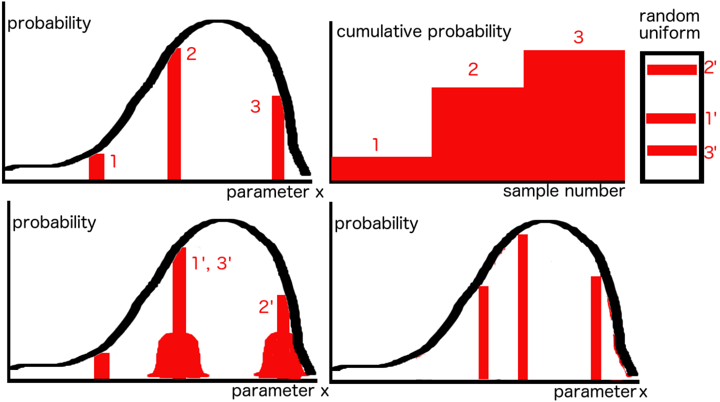
Data assimilation
take samples evaluated on time *window 0*
$\rightarrow$ apply (re-)samples to next time *window 1*

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)

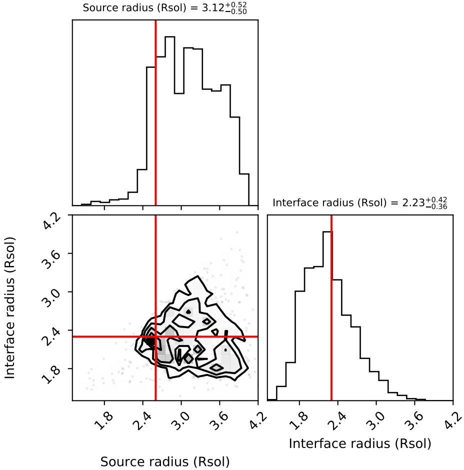


(upper left) iteration 0: samples, (upper right): calculate total & resample
(lower left): perturbation kernel, (lower right) iteration 1: evaluate

Space weather (simulation)

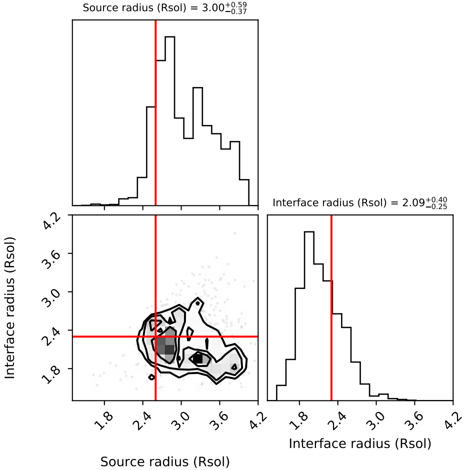
Simulation

Space weather (simulation): filter, window 0



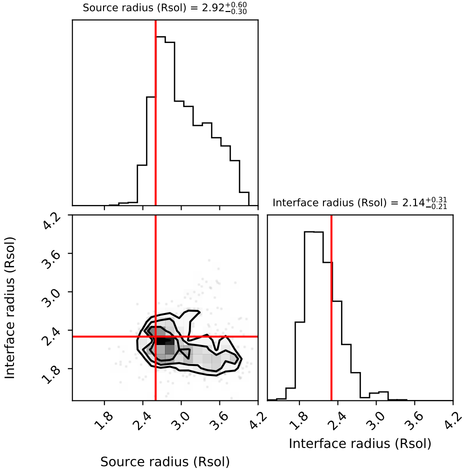
'Twin' experiment at $(R_{ss}, R_i) = (2.6, 2.3)$, 512 samples, 7 days
particle filter (true value marked by red crosshairs)

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)

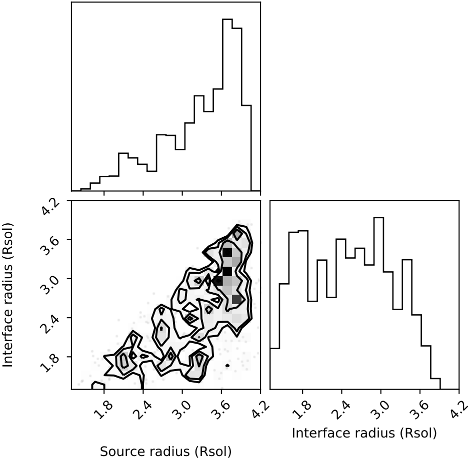
Space weather (simulation): filter, window 2



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

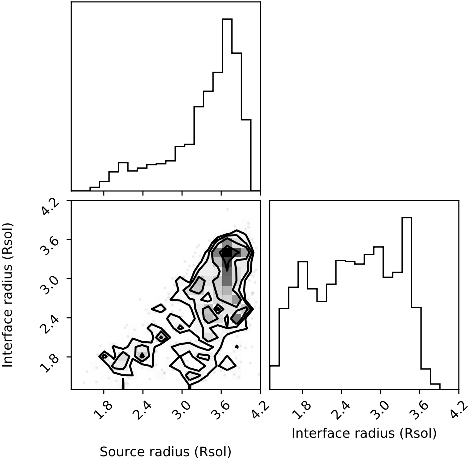
Real data

Space weather (real data): filter, window 0



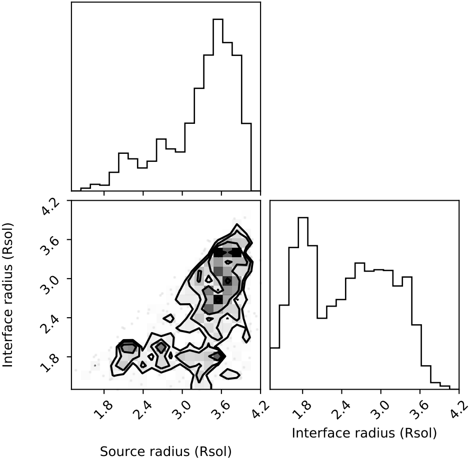
Carrington Rotation 1901/1902 real data (ADAPT map 5/WIND)
particle filter, 512 samples, 7-day windows (3-day advance predictions)

Space weather (real data): filter, window 1



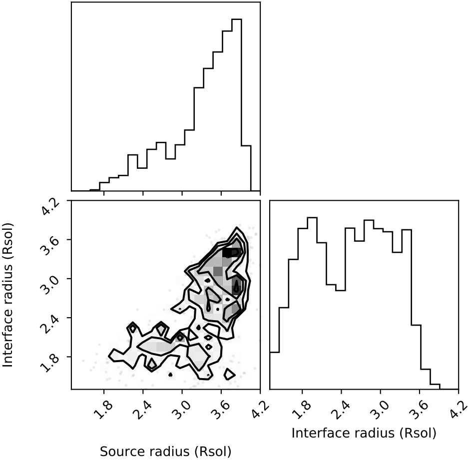
Carrington Rotation 1901/1902 real data (ADAPT map 5/WIND)
particle filter, 512 samples, 7-day windows (3-day advance predictions)

Space weather (real data): filter, window 2



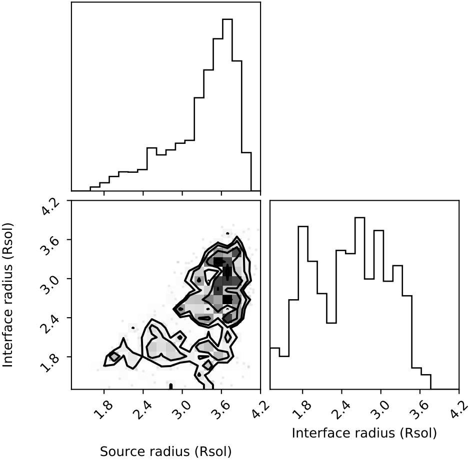
Carrington Rotation 1901/1902 real data (ADAPT map 5/WIND)
particle filter, 512 samples, 7-day windows (3-day advance predictions)

Space weather (real data): filter, window 3



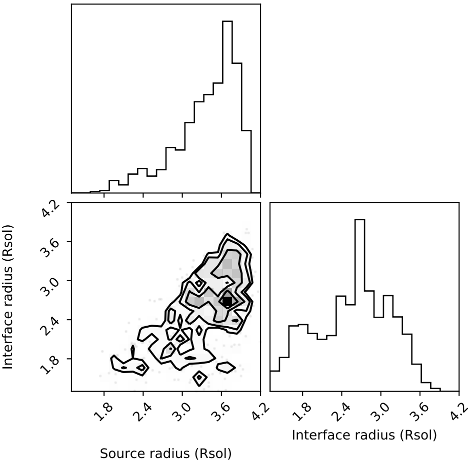
Carrington Rotation 1901/1902 real data (ADAPT map 5/WIND)
particle filter, 512 samples, 7-day windows (3-day advance predictions)

Space weather (real data): filter, window 4



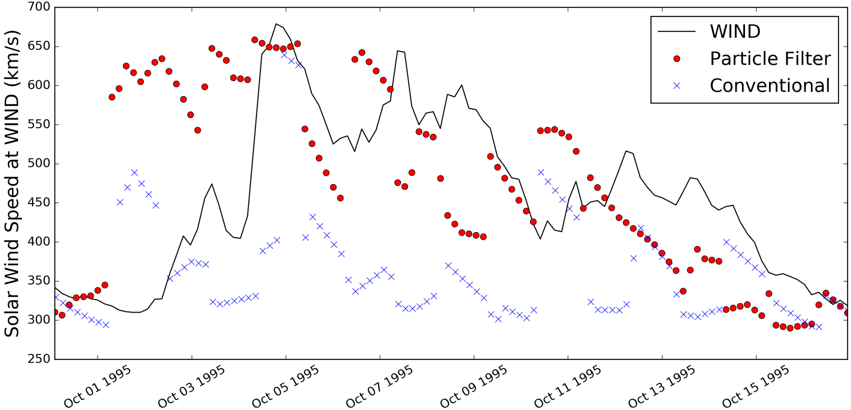
Carrington Rotation 1901/1902 real data (ADAPT map 5/WIND)
particle filter, 512 samples, 7-day windows (3-day advance predictions)

Space weather (real data): filter, window 5



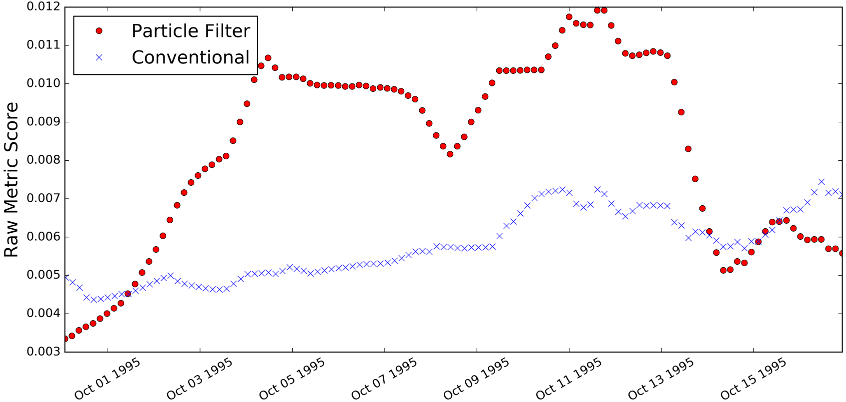
Carrington Rotation 1901/1902 real data (ADAPT map 5/WIND)
particle filter, 512 samples, 7-day windows (3-day advance predictions)

Analysis: comparison (solar wind)



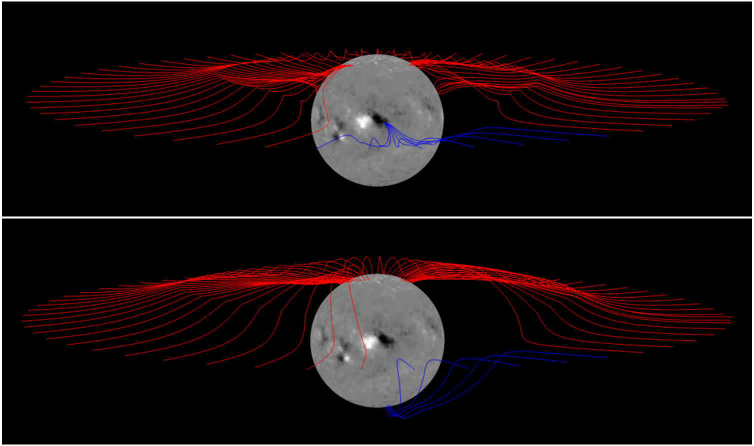
Solar wind radial velocity vs time for 2 weeks wrt WIND satellite data comparing standard $(R_{ss}, R_i) = (2.51, 2.49)$ to filter optimum $(3.9, 3.4)$

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 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 space weather

- (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

Now a preview of future work back on Earth...

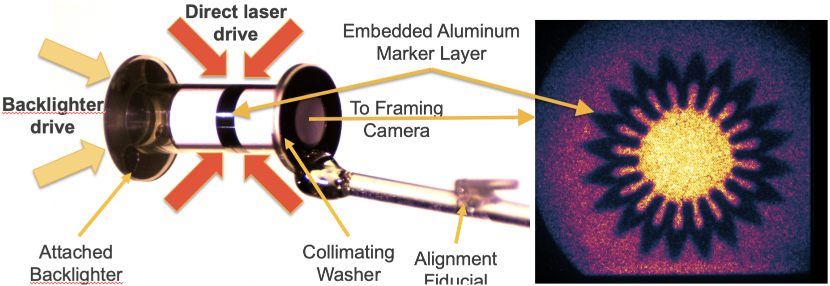
Inertial confinement fusion

Inertial confinement fusion (ICF)

In collaboration with
Brandon Wilson, Josh Sauppe, & Kyle Hickmann,
poster at the APS Division of Plasma Physics 2020:

- Laser-driven cylindrical implosions are used to study hydrodynamic instability growth, which aids in understanding the degradation mechanisms in inertial confinement fusion (ICF) implosions
- Convergent Rayleigh-Taylor instability (RTI) seeded by perturbations in experiments and simulations – intentional as well as tolerance variations
- *M* periodic perturbations in plane through cylinder axis
- **Goal:** min/max detectable perturbations
  $\rightarrow$ robustness, *uncertainty quantification*

Illustration of ICF capsules

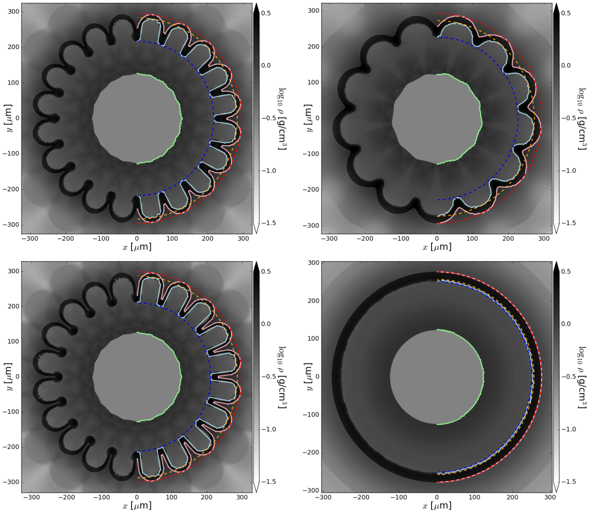


ICF modal decomposition

Angular-frequency spectra (FFT) of a *marker* gives amplitudes A for RTI modes m over n sampled angles w/ (inner) marker radius a, indexed by k (A_0 normed by $1/2$):

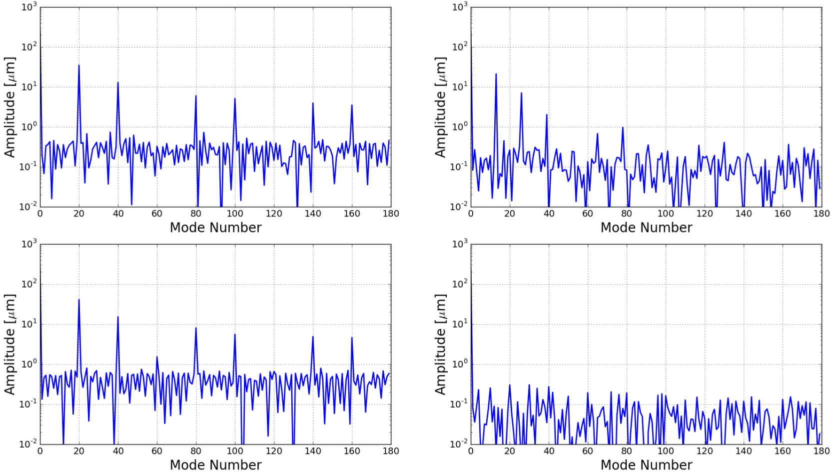
$$A_m \equiv \frac{2}{n} \sum_{k=0}^{n-1} a_k \exp\left[-2\pi \mathrm{i} \frac{mk}{n}\right]$$

ICF perturbation density profiles



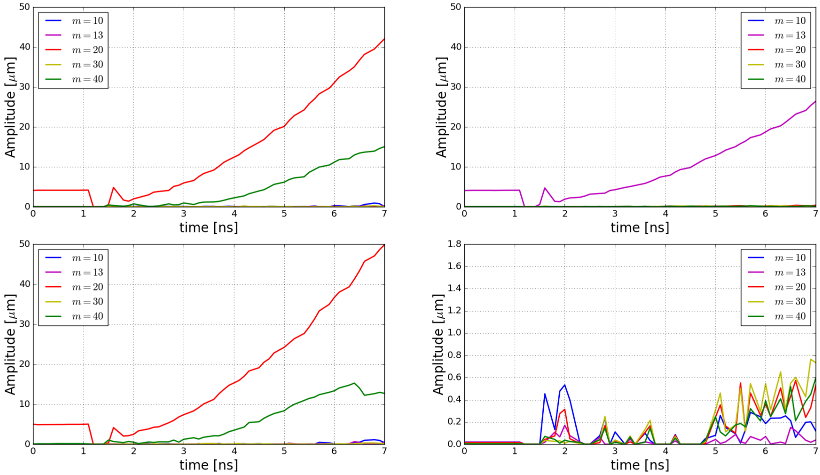
Density (g cm^{-3}) profiles in the (radius r, angle θ) plane at 5 nanoseconds (ns).

ICF modal spectra



Modal spectra (amplitude A_m in μm vs dimensionless mode number m), at 5 ns.

ICF modal evolution



(y-axis *scales vary*). A_m vs t (ns).

Summary of inertial confinement fusion

Spectral sensitivity is a **means** to understand simulation fidelity's limits.

Characterizing response to modes quantifies sensitivity to other effects, such as manufacturing tolerances, as spectra are the (orthonormal) *basis* for many other quantities of interest (QoIs).

This work uses `xRAGE` *and has been performed for the U.S. Department of Energy by Los Alamos National Laboratory.*

Conclusion

Acknowledgments
Thanks to Tania Regimbau, Samaya Nissanke, and Andrew Miller for inviting this LGBTQSTEMDay presentation to LIGO, Virgo, and KAGRA, and to my collaborators: Shaela Jones, Kyle Hickmann, Charles (Nick) Arge, Humberto Godinez-Vasquez, and Carl Henney.

This talk has been assigned Los Alamos Unlimited Release
LA-UR-20-29403

Questions: gdmeadors@lanl.gov

Happy LGBTQSTEMDay!

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).