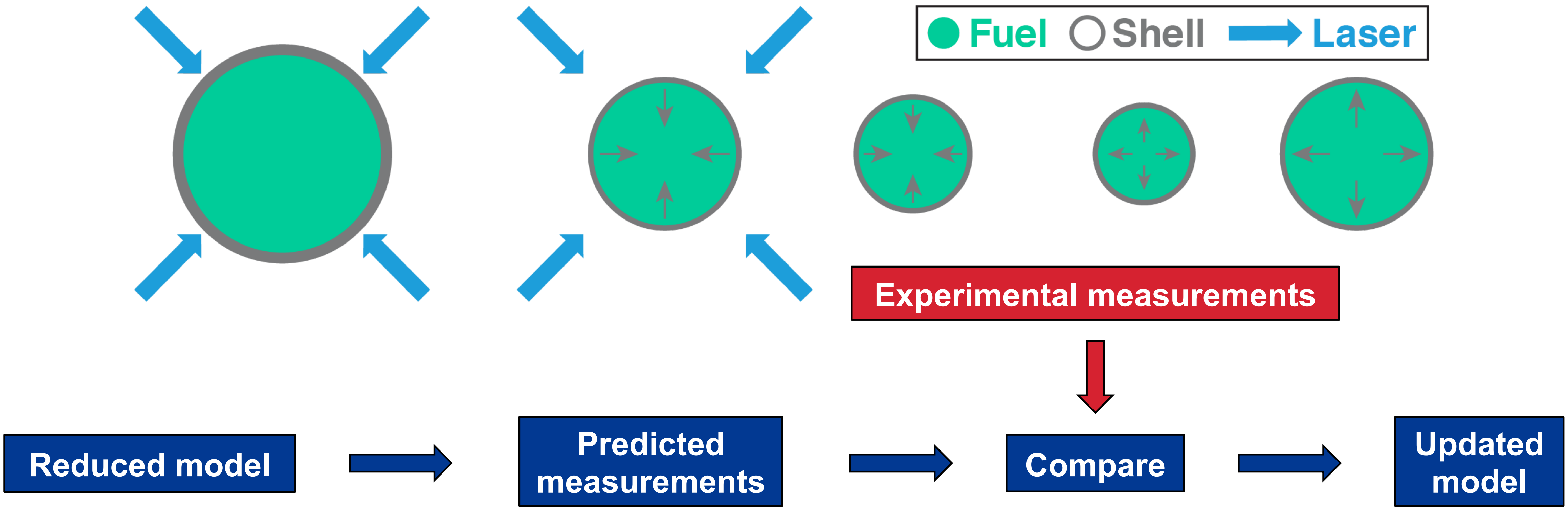
Bayesian Inference of Energy Transfer in Gigabar Convergent Experiments



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Bayesian inference is used to constrain the temporal evolution of energy in thin-shelled implosions from integrated measurements*

- Implosion experiments are able to access the most extreme thermodynamic states within laboratory settings, but characterizing those states is challenging

- Bayesian inference techniques, widely used in other areas of physics, bring together measurements and additional constraints, explicitly allowing for fully developed error quantification

- The time history of the energetics in an implosion experiment is extracted using the combination of a reduced physics model and Bayesian inference techniques

- This same methodology can be used to characterize a variety of convergent high-energy-density (HED) experiments to facilitate fundamental physics measurements

*J.J. Ruby et al. Phys. Rev. Let. (2020) (accepted)
*J.J. Ruby et al. Phys. Rev. E (2020) (accepted)

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Outline

- **Introduction**
- **Experimental setup and measurements**
- **Bayesian inference and model verification**
- **Results**
- **Extension to other systems**

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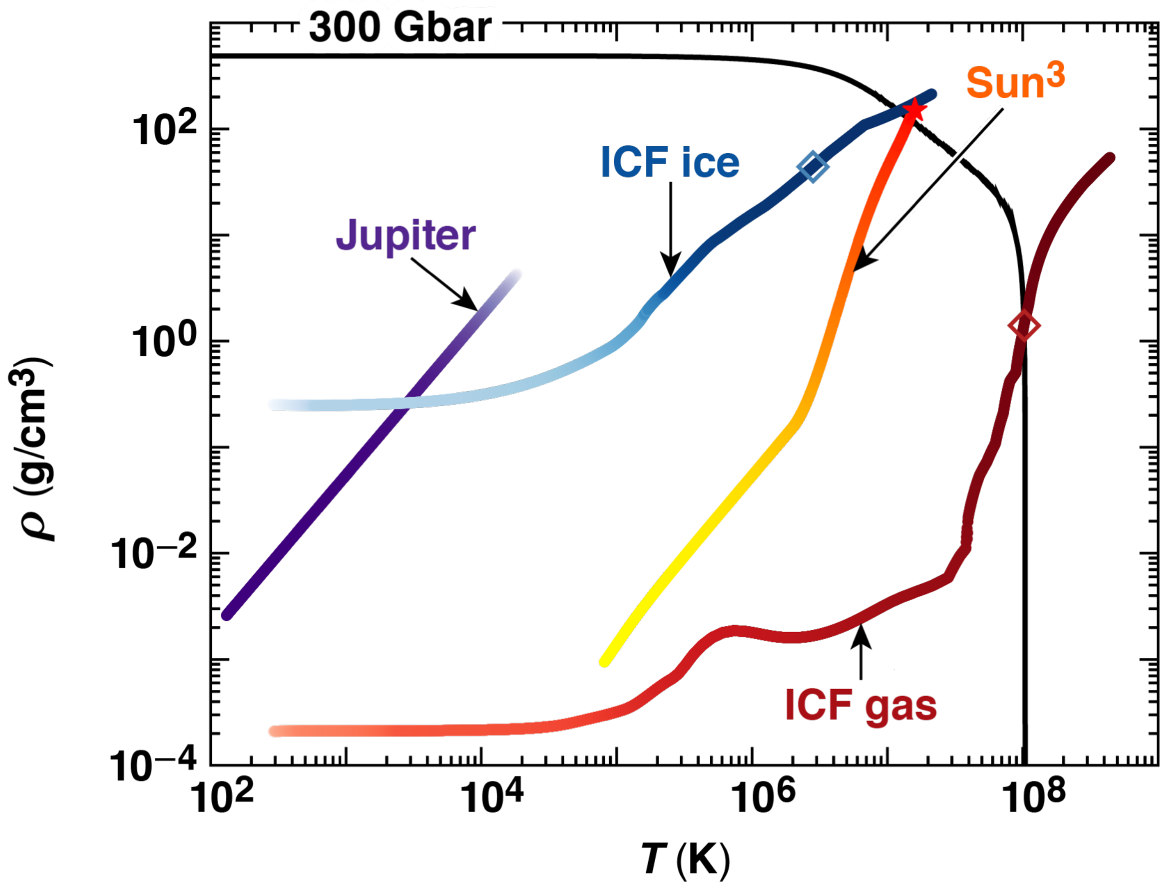
Motivation

Implosions access temperature and density conditions where many interesting physical phenomena occur

- The temperature and density conditions within implosions lead to interesting thermodynamic and atomic processes[1,2]
- Understanding these processes requires characterizing the physical states within implosions
- The energy and, ultimately, pressure are key ways to characterize the high-energy-density states



E29299

[1]S. X. Hu *et al.*, Nat. Commun. 11, 1989 (2020).
[2]E. R. Harrison, Proc. Phys. Soc. 84, 213 (1964).
[3]J. N. Bahcall, A. M. Serenelli, and S. Basu, Astrophys. J. 621, L85 (2005).
ICF: inertial confinement fusion

The detailed measurements made during implosion experiments contain much information but extracting information is difficult

- The ICF community has developed many techniques and diagnostics to make very detailed measurements of implosions
- These same measurements can be applied to less-complex implosions to constrain reduced physics models of the system
- Bayesian inference allows for physical parameter estimation with a robust uncertainty quantification

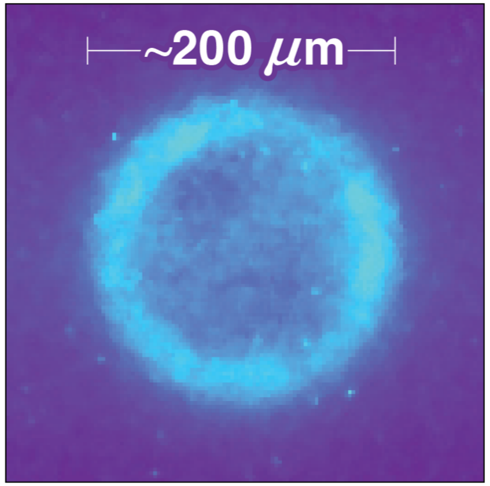
- Energy coupling
- Thermal Conductivity
- Equilibration Rate
- Radiation Transport

→

- Pressure
- Temperature
- Density
- Ionization

→

X-ray image of exploding shell



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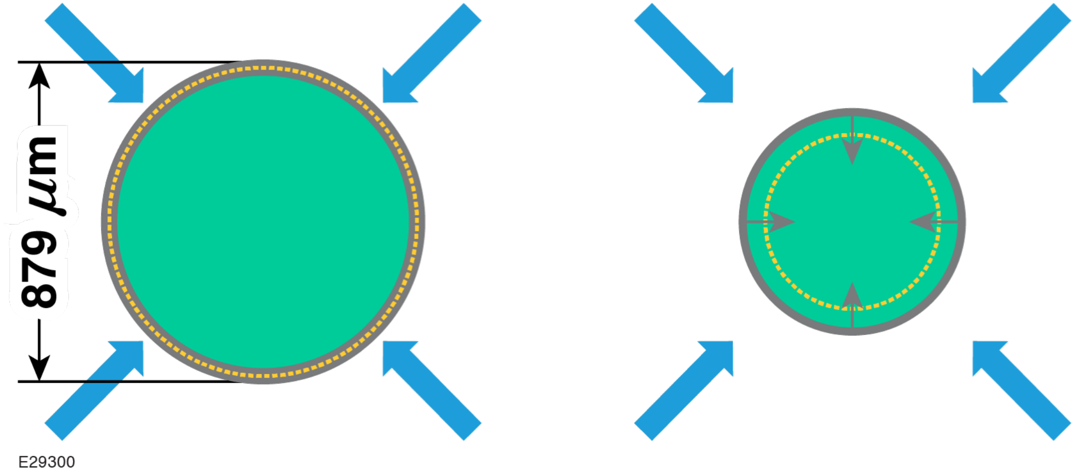
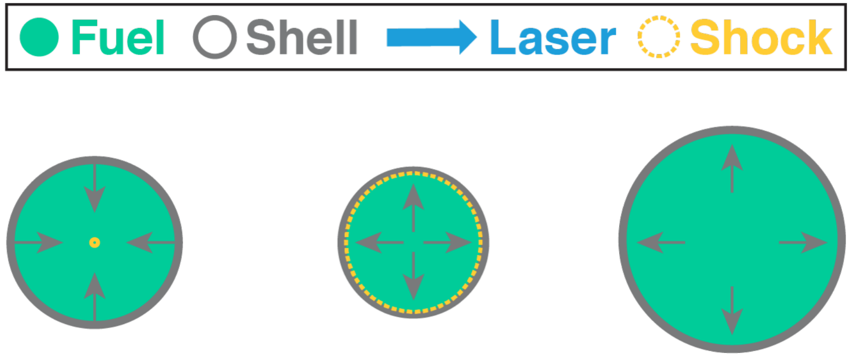
Thin-shelled "*exploding-pusher*" targets provide an established* implosion platform that is simpler than cryogenic implosions





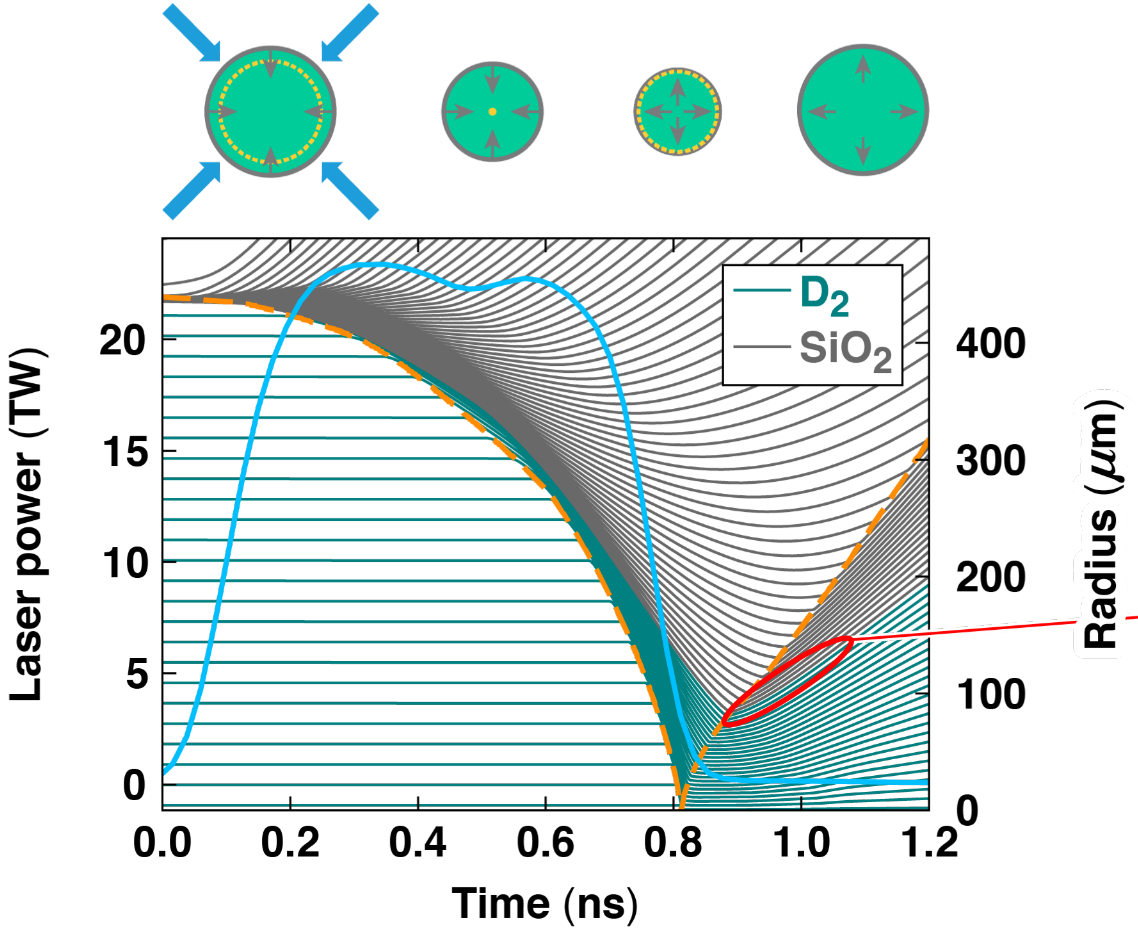
- Fuel = 18.9 atm D_2
- Shell = 3 μm SiO_2
- 600-ps square pulse
- 60-beam symmetric drive
- 14-kJ incident energy

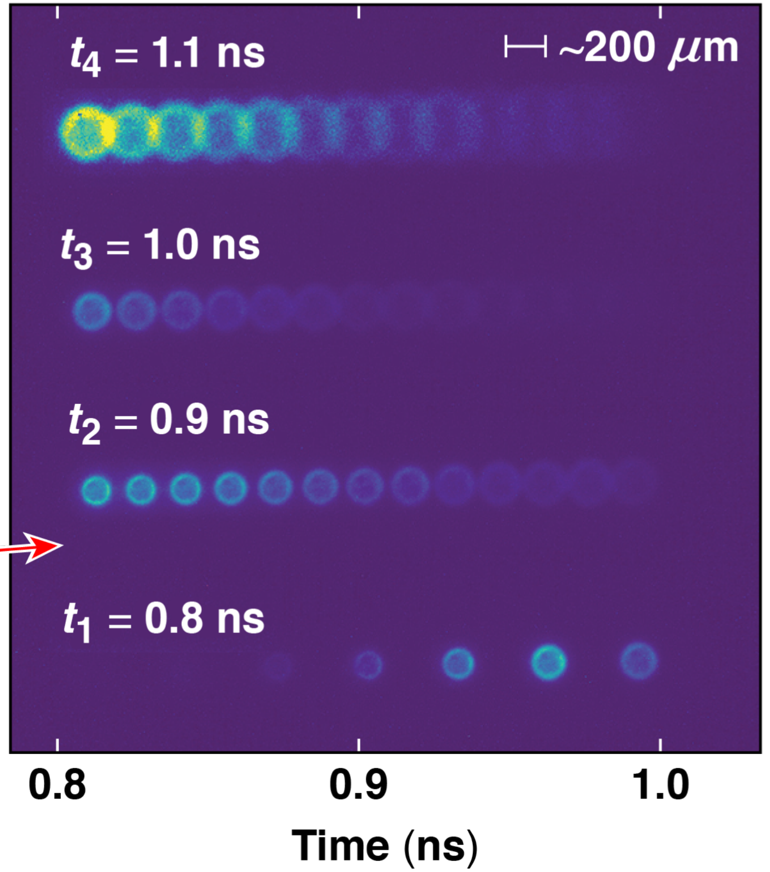
Exploding pushers are

- Low shell mass (low inertia)
- Shock dominated
- Low convergence
- One interface
- High stability

*B. Ahlborn, M. H. Key, and A. R. Bell, Phys. Fluids 25, 541 (1982).

The x-ray self-emission generated from the rebounding shock interacting with remaining shell material was measured*





E29301

*J.J. Ruby et al. Phys. Rev. Let. (2020) (accepted)
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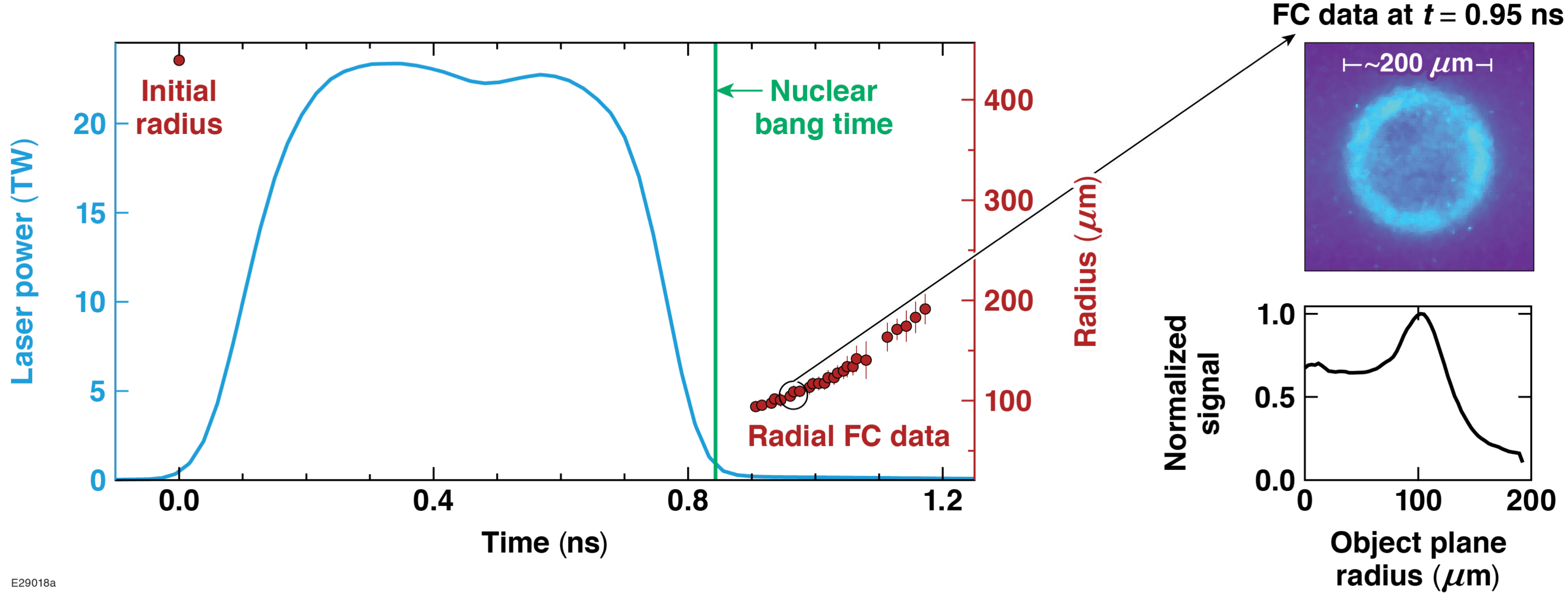
The radially averaged emission is used to track the position of the expanding shell as a function of time



FC: framing camera

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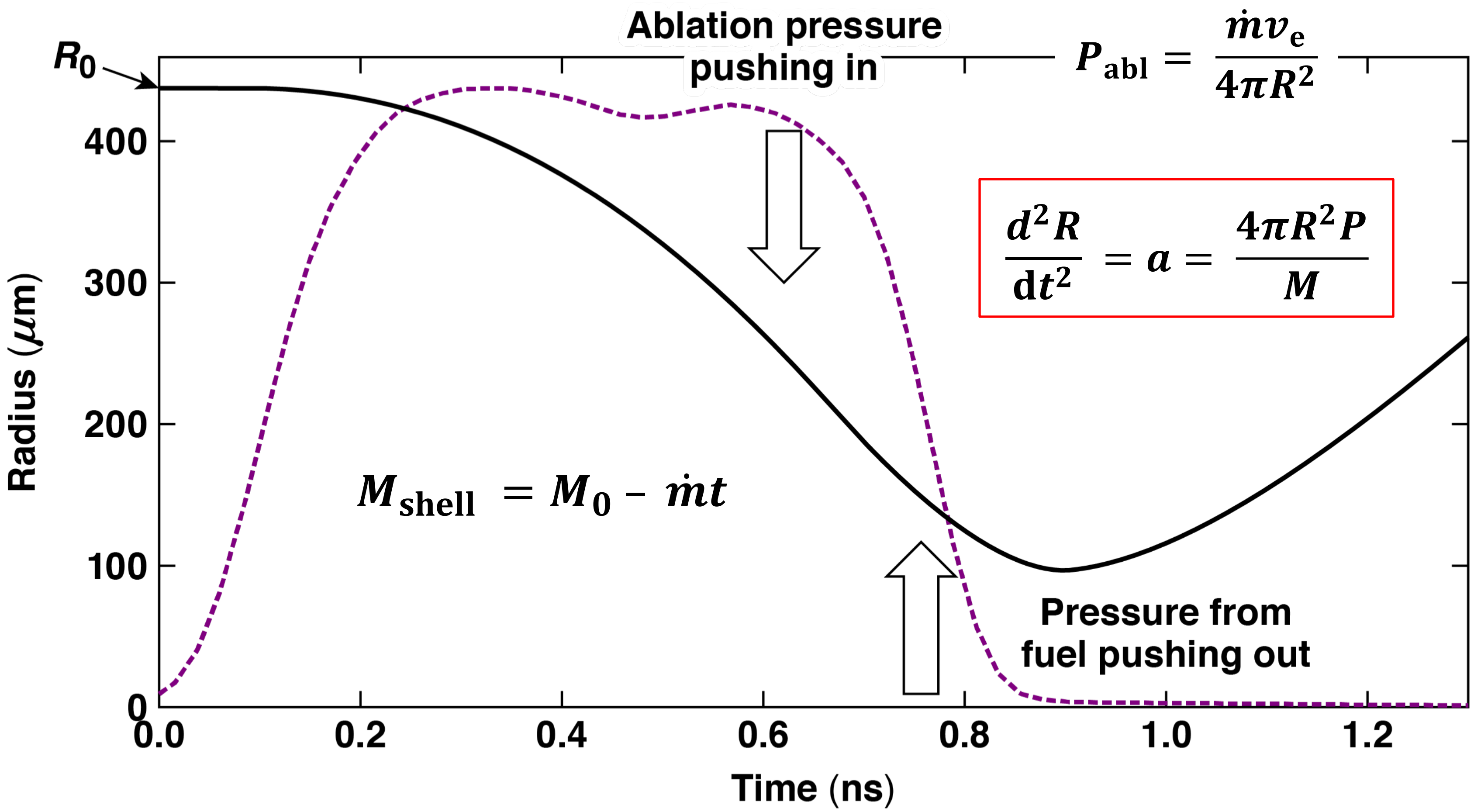
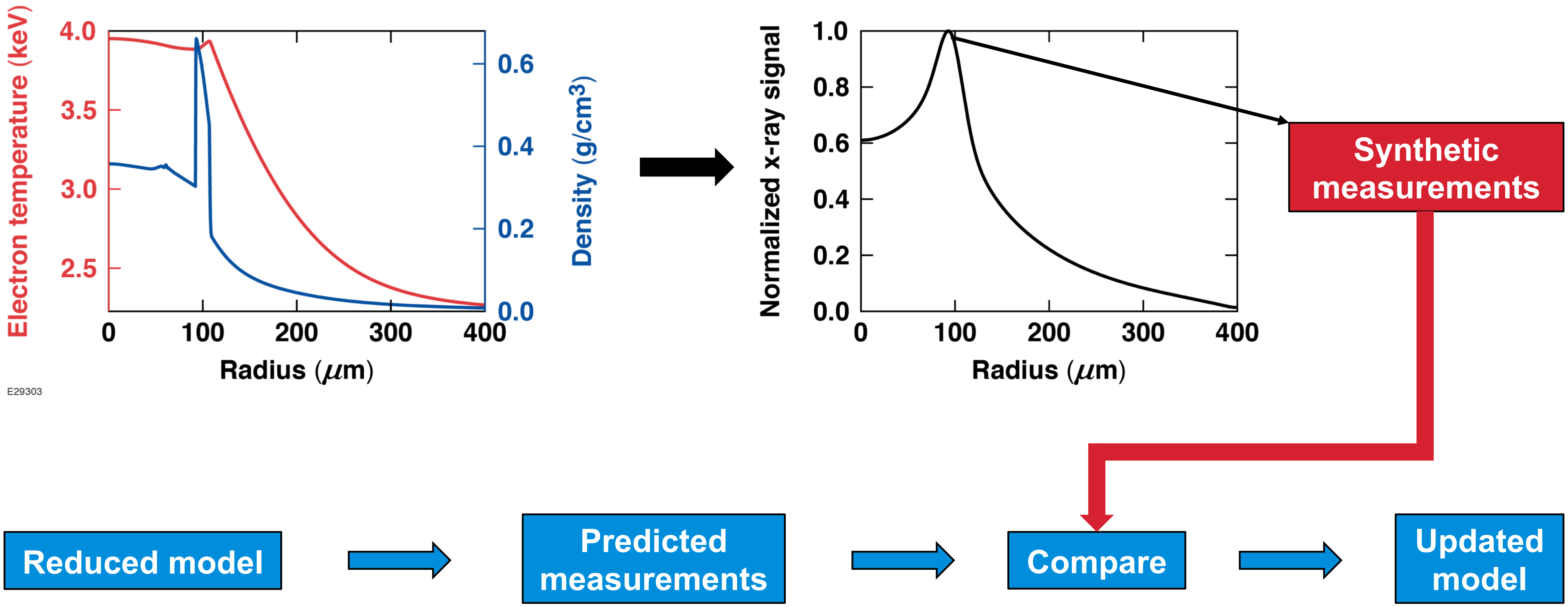
A mechanical model* of the shell is used to describe its trajectory



E29302

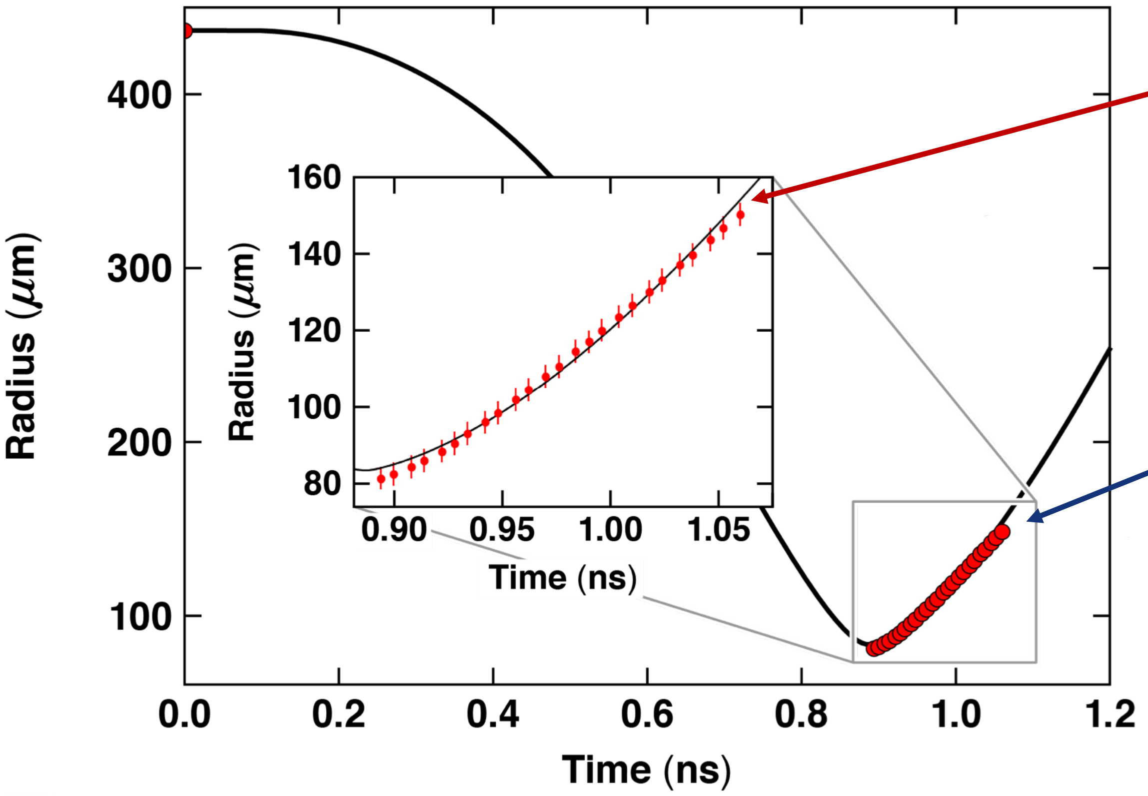
*J.J. Ruby et al. Phys. Rev. Let. (2020) (accepted)
*J.J. Ruby et al. Phys. Rev. E (2020) (accepted)

Synthetic data is generated using the 1-D hydrodynamics code *LILAC**



*J. Delettrez *et al.*, Phys. Rev. A 36, 3926 (1987).

Bayesian inference* is used to construct parameter probability distributions based on the synthetic data



E29304

Synthetic measurements — Errors comparable to typical experimental measurements

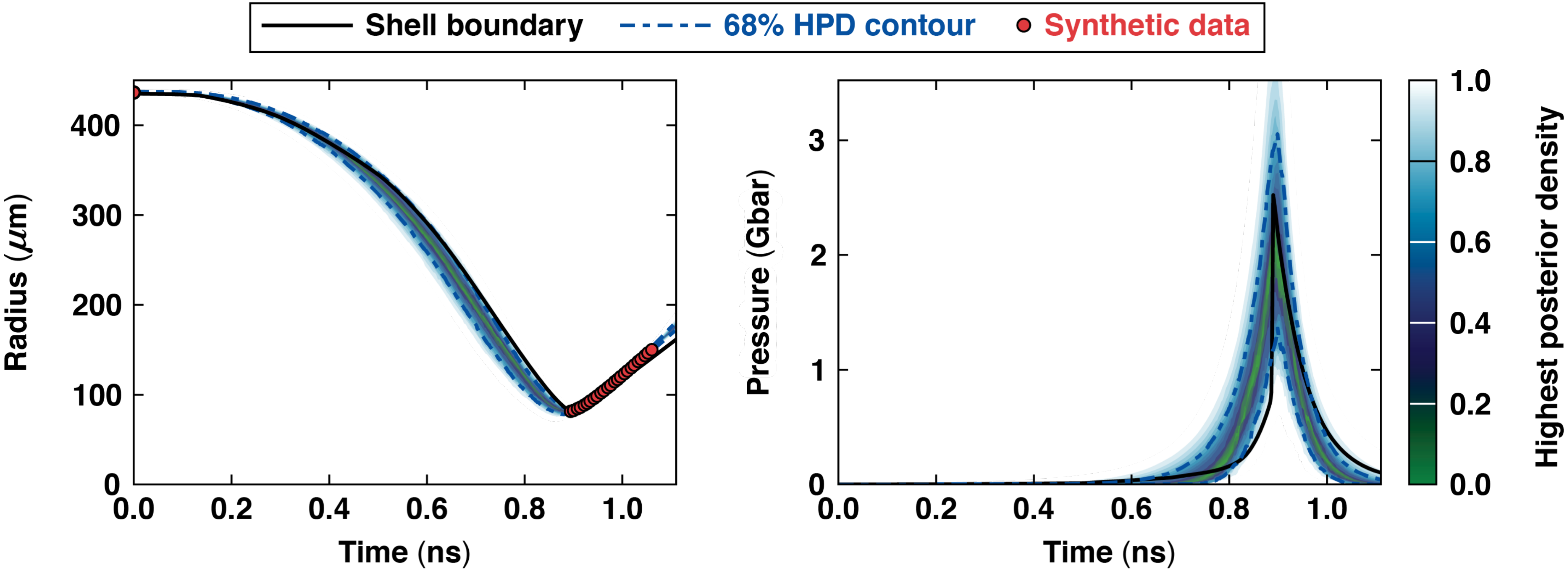
↓

Predicted measurements → **Compare**

Parameter probability distribution ∝ **Likelihood distribution** × **Parameter priors**

*D. S. Sivia and J. Skilling, *Data Analysis: A Bayesian Tutorial*, 2nd ed. (Oxford University Press, Oxford, 2006).

The parameter probability distributions are used to construct probabilities for unobserved quantities



E29019

HPD: highest posterior density

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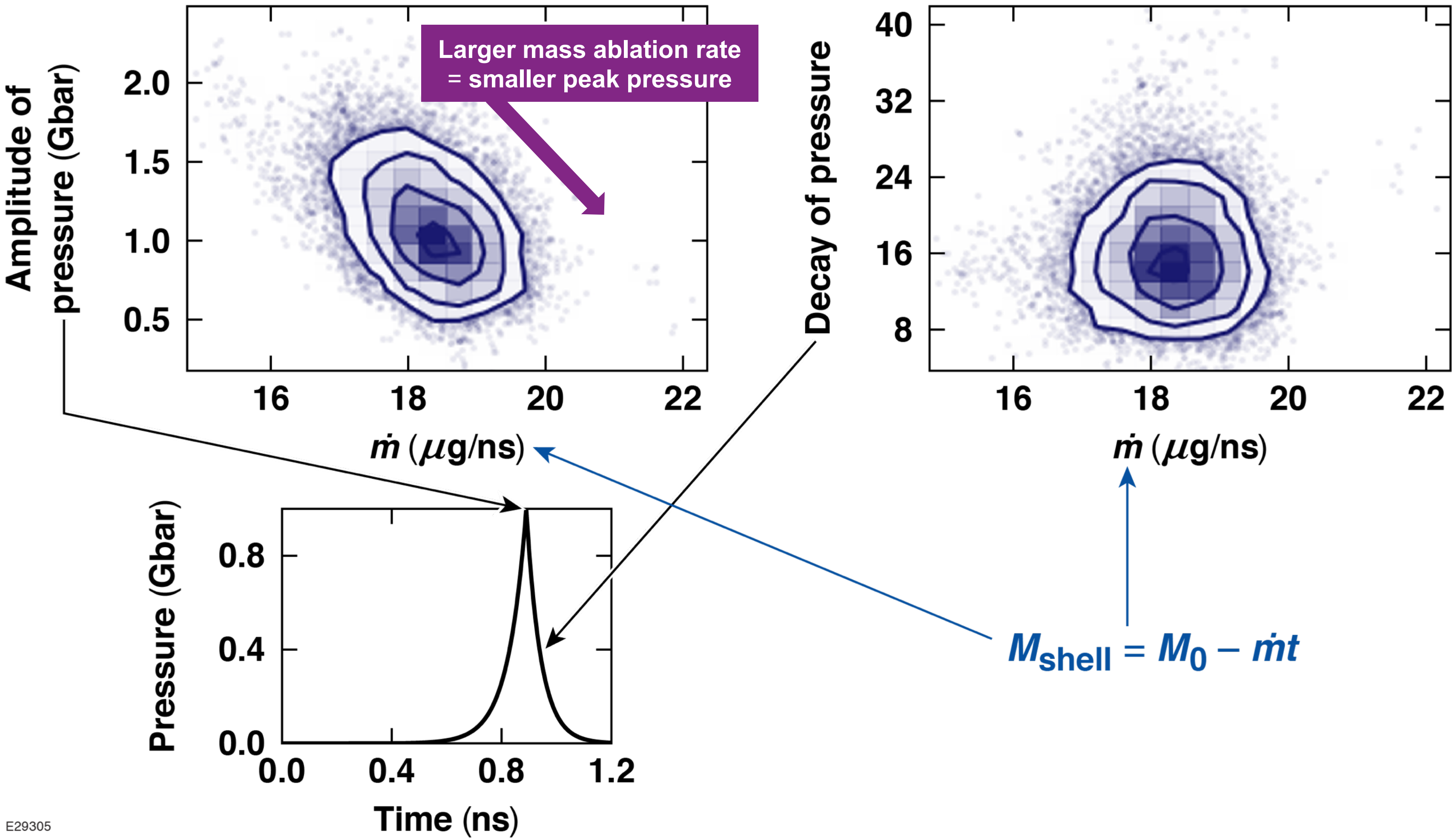
The parameter distributions resulting from the experimental data are single modal and some show correlations

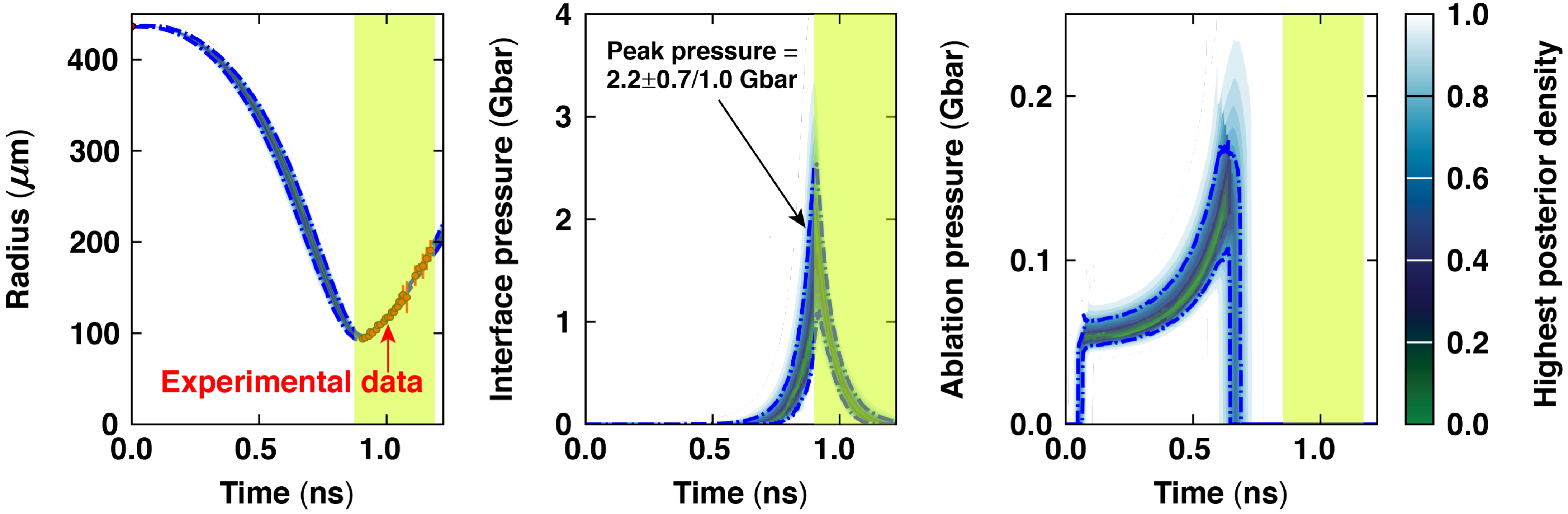


E29305

The measurements are able to constrain the trajectory and pressures at times before, during, and after the measurement

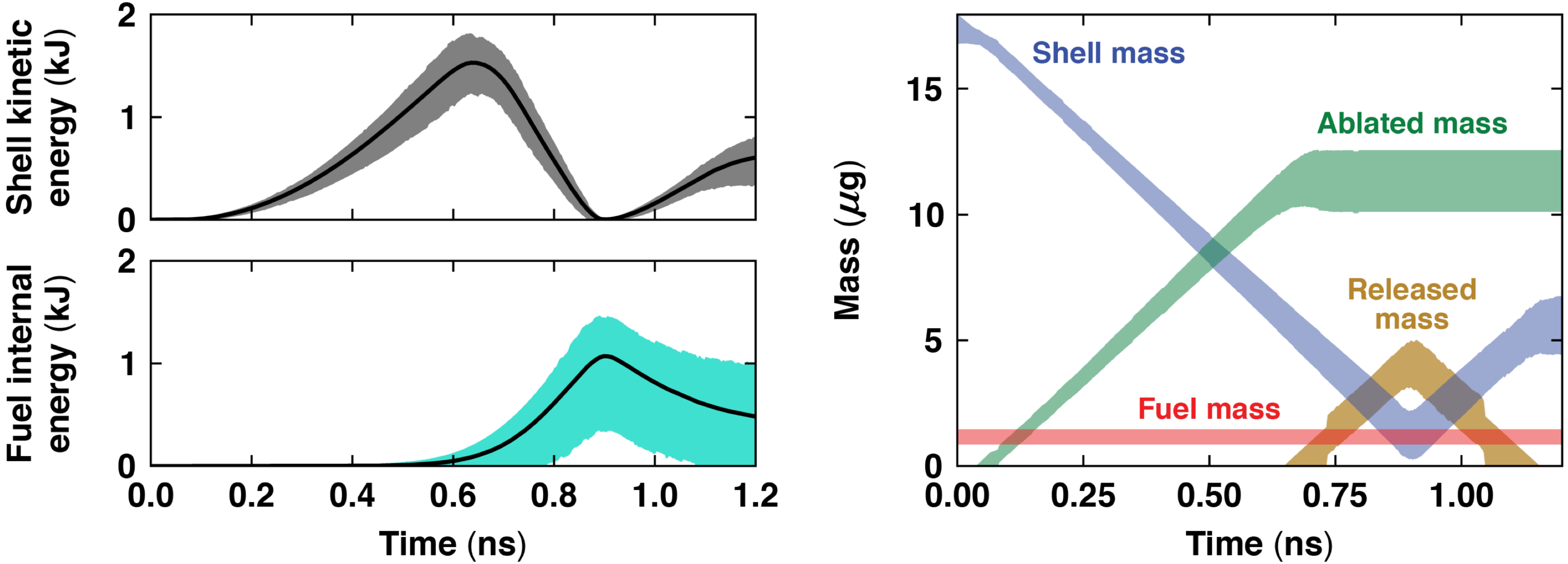
<5% error in radial measurements gives ~40% error in Pressure amplitude

Time of measurement



E29021

The distributions of energy and mass in time are also constrained, showing that the peak fuel internal energy is about 10% of the incident laser energy



E29198

Additional measurements, such as neutron yield, can be used to decrease error on energy measurements.

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Bayesian inference techniques can be used to extract information from a variety of experiments in HED science

- Previously difficult to analyze data sets can be self-consistently constrained
  - integrated measurements
  - correlated variables
- Physics intuition can be explicitly accounted for rather than appearing in implicit assumptions
- Different data sets can be brought together and used to constrain each other
  - joint analysis of all diagnostics from one experiment rather than separate pipelines
  - data from multiple experiments can be used in conjunction to constrain otherwise unconstrained models
- The information rich data will facilitate using more complex models

Mechanical → Thermodynamic → … → 1-D hydro → 2-D hydro → 3-D hydro

Using simulations, data analysis, and experimental design/execution in conjunction will allow accurate, self-consistent measurements of HED phenomena.

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Backup

Bayesian inference is used to estimate the parameters from the model based on the synthetic data

Set of model parameters

Likelihood function: probability of observing the data given certain parameters

Prior probability distributions for the parameters

Posterior probability density distribution

$$p(\vec{\theta}|D,M) = \frac{p(D|\vec{\theta},M)\,p(\vec{\theta}|\,M)}{p(D,M)}$$

Data

Model

Marginal likelihood or evidence

*D. S. Sivia and J. Skilling, *Data Analysis: A Bayesian Tutorial*, 2nd ed. (Oxford University Press, Oxford, 2006).