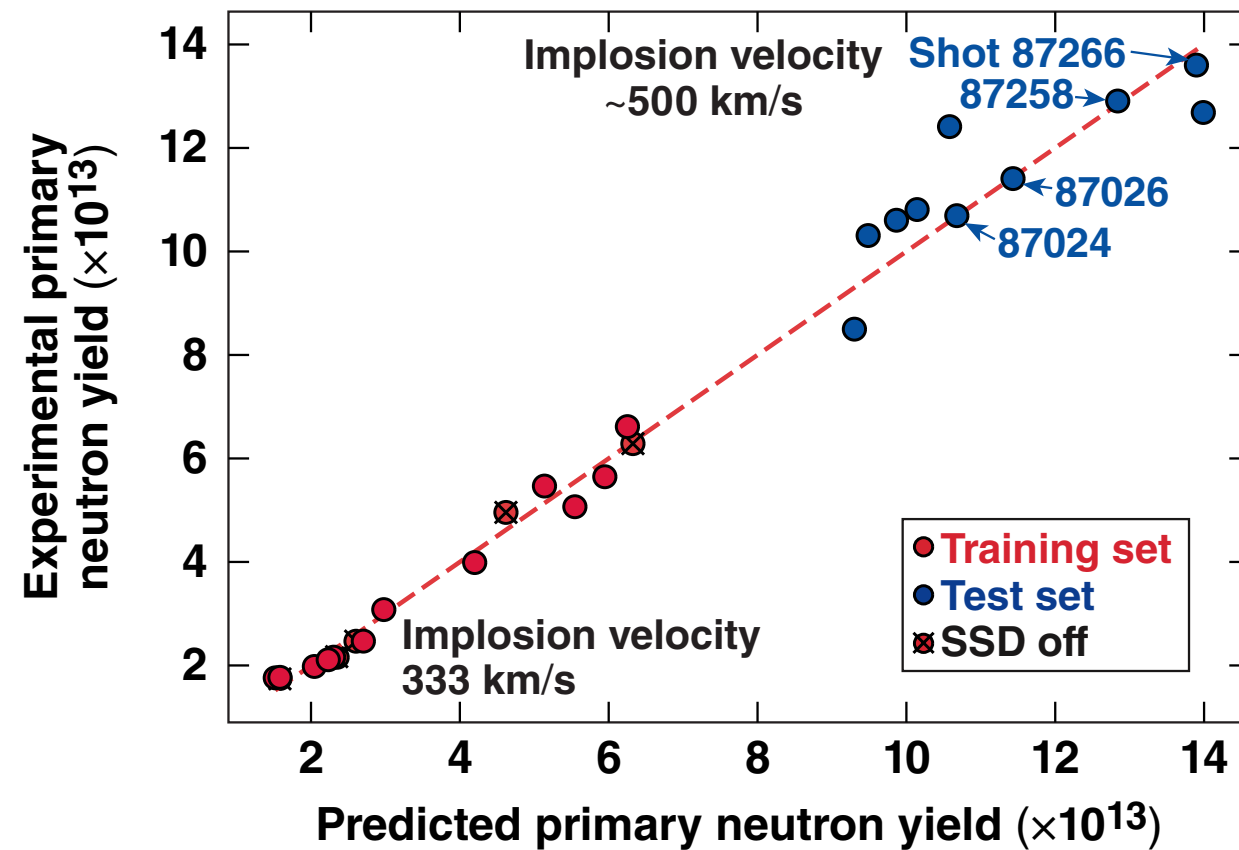


A Statistical Approach to Implosion Design on the OMEGA Laser

Prediction performance on the high-adiabat campaign ($\alpha \sim 5$ to 7)



$$\text{Yield}_{\text{pred}} \sim \frac{V_{\text{LILAC}}^{4.3} M_{\text{LILAC}}}{\delta_{\text{SSD}}^{0.3}}$$

V. Gopaldaswamy
University of Rochester
Laboratory for Laser Energetics

59th Annual Meeting of the
American Physical Society
Division of Plasma Physics
Milwaukee, WI
23–27 October 2017

Summary

A statistical model of OMEGA implosions has been developed to enable accurate preshot predictions and optimize implosion design



- A statistical approach is used to bridge the gap between experiments and simulations
- The statistical approach is tested on a simulation database
- Statistical predictions of yield are robust to modeling errors, while predictions of areal density are sensitive to errors in EOS*
- Predictive models are developed for the experimental neutron yield, ion temperature, and ρR by statistical mapping of the experimental database onto *LILAC* output variables

The statistical predictions enable the design of the highest primary yield cryo implosion on OMEGA ($Y = 1.34 \times 10^{14}$).

Collaborators



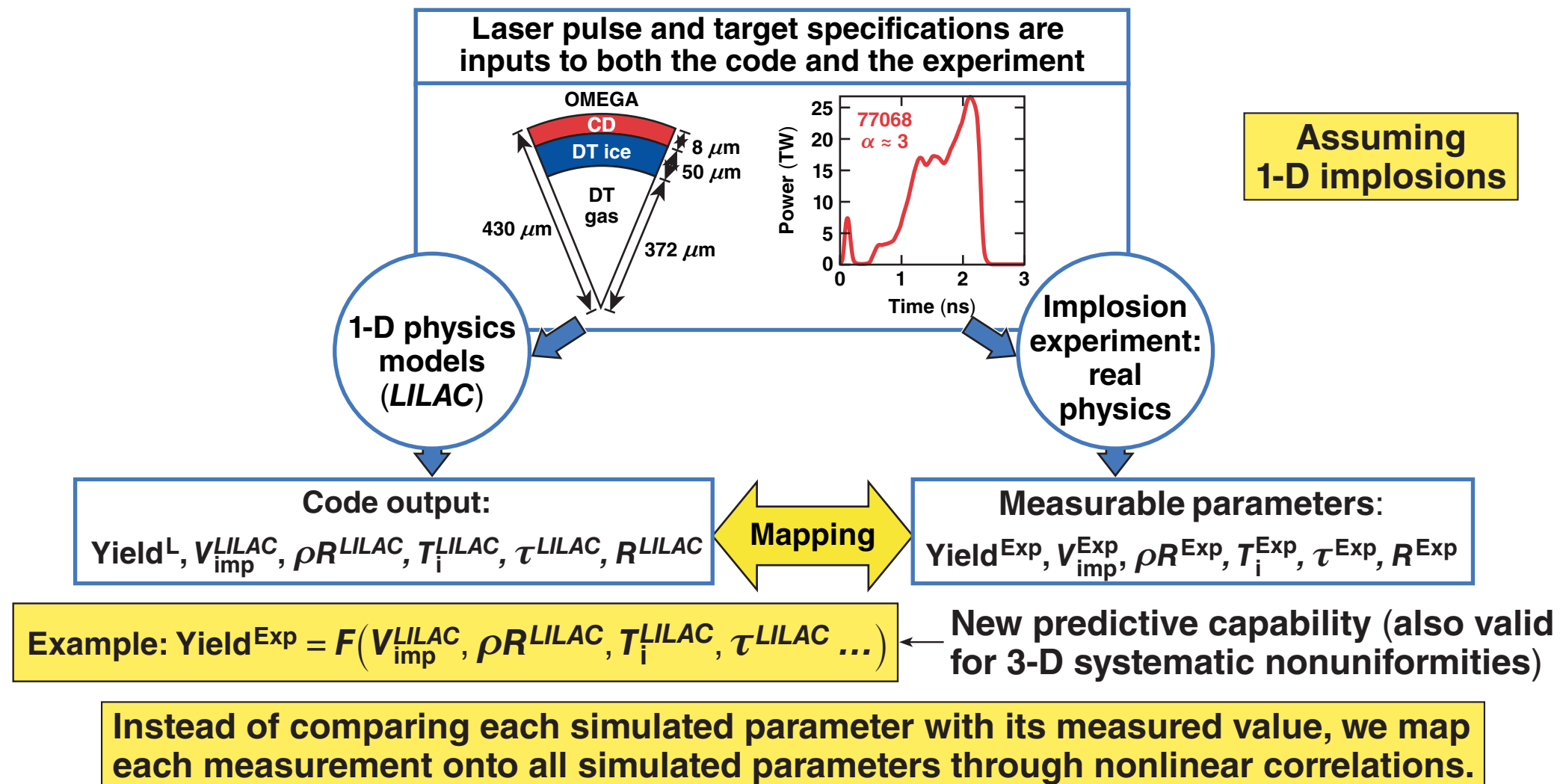
**R. Betti, J. P. Knauer, A. R. Christopherson, D. Patel, K. M. Woo,
W. Shang, A. Bose, K. S. Anderson, T. J. B. Collins, V. N. Goncharov,
P. B. Radha, V. Yu. Glebov, A. V. Maximov, C. Stoeckl, F. J. Marshall,
E. M. Campbell, and S. P. Regan**

**University of Rochester
Laboratory for Laser Energetics**

Statistical mapping of the experimental database onto *LILAC* output variables provides a predictive tool for 1-D or systematically perturbed implosions

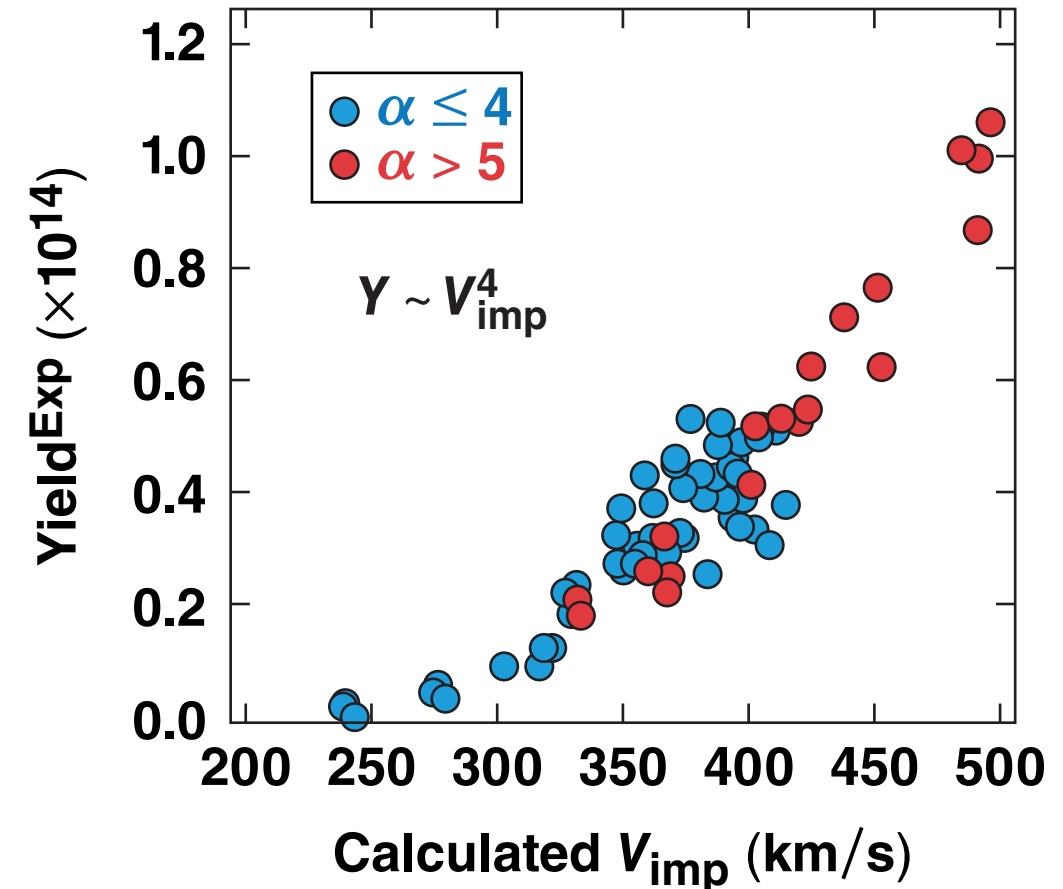


- Current hydrocodes are not accurate enough to predict experimental outcomes from first principles
- Use statistics to bridge the gap between simulation and experiment



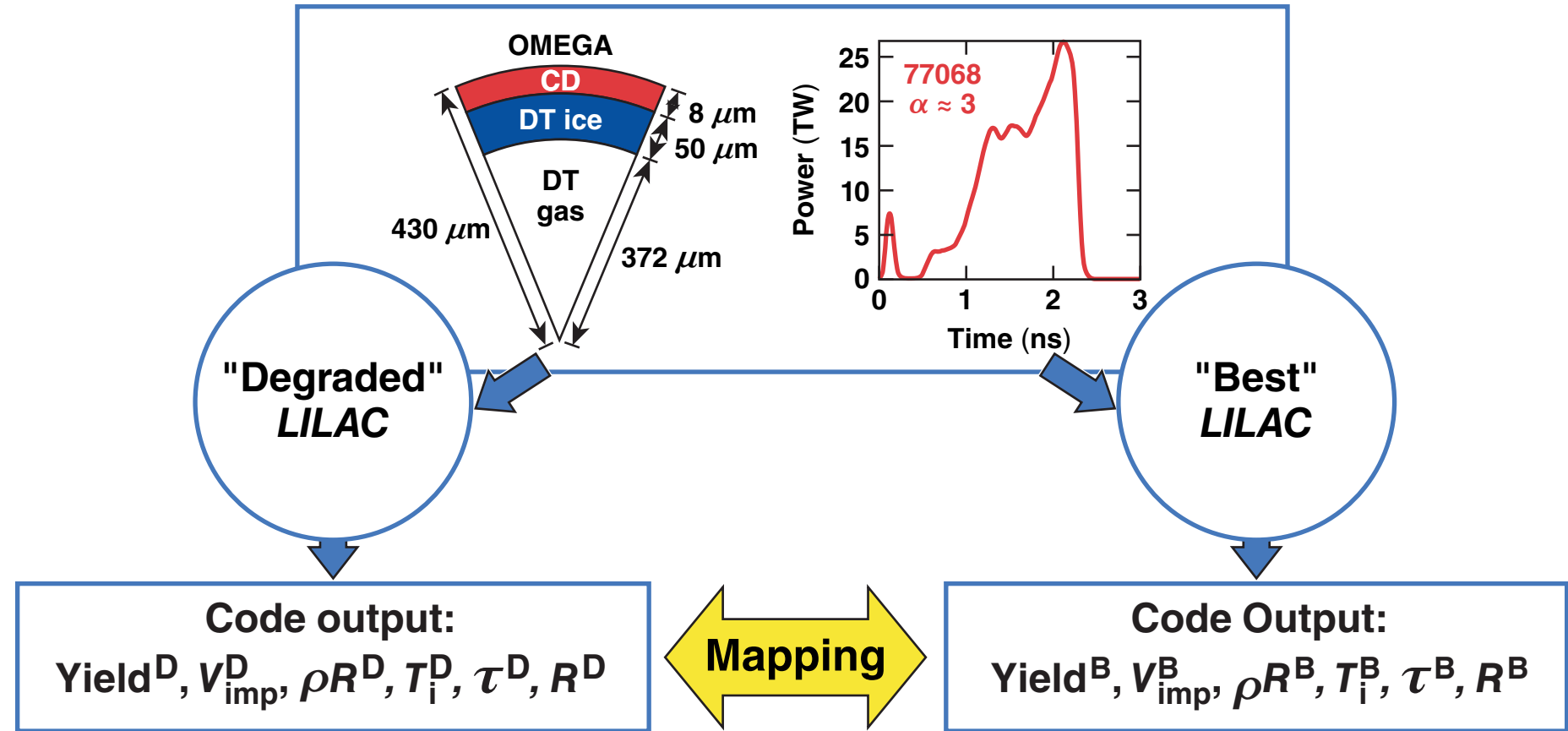
Predictive models from statistical mapping have been constructed in Python using simple regression analysis

- We have developed the statistical modeling and visualization tool, pyCAT, to interrogate a database of experimental and simulation results
- We assume mapping is of the form $\hat{y} = a_0 \prod x_i^{a_i}$
- Overfitting is controlled by
 - choosing a limited quantity of physically relevant regression variables
 - cross validation
 - parameter hypothesis testing
 - choosing reasonable Bayesian prior for parameters



The validity of the statistical mapping is tested by deliberately choosing suboptimal models in *LILAC*

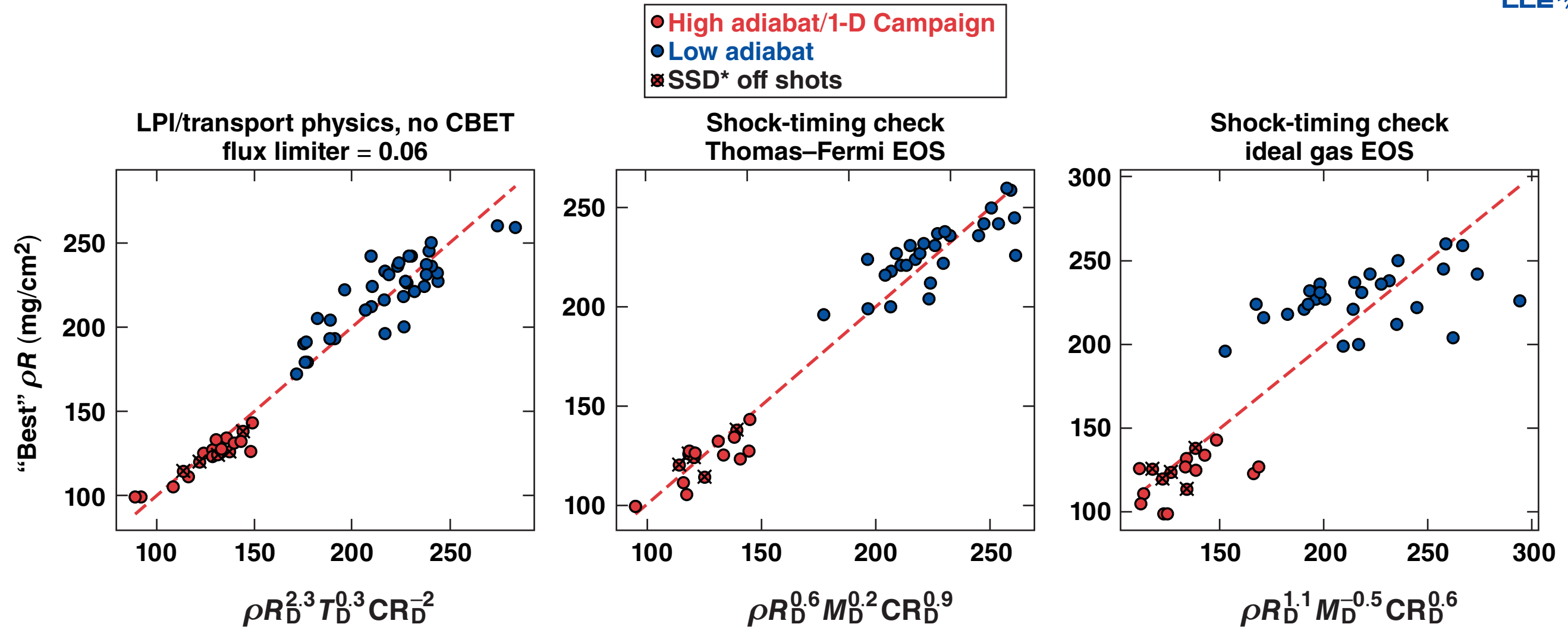
- “Best” *LILAC* includes: CBET,* nonlocal electron transport, FPEOS,** radiation transport
- “Degraded” *LILAC*
 - turn off radiation transport
 - change EOS to ideal gas/Thomas–Fermi (shock-timing physics)
 - turn off CBET and nonlocal thermal transport [laser–plasma interaction (LPI) and transport physics]



Can we use the “degraded” *LILAC* to predict the “best” *LILAC* using statistical mapping?

*CBET: cross-beam energy transfer
 **FPEOS: first-principle equation of state

Statistical predictions of areal density require accurate enough EOS

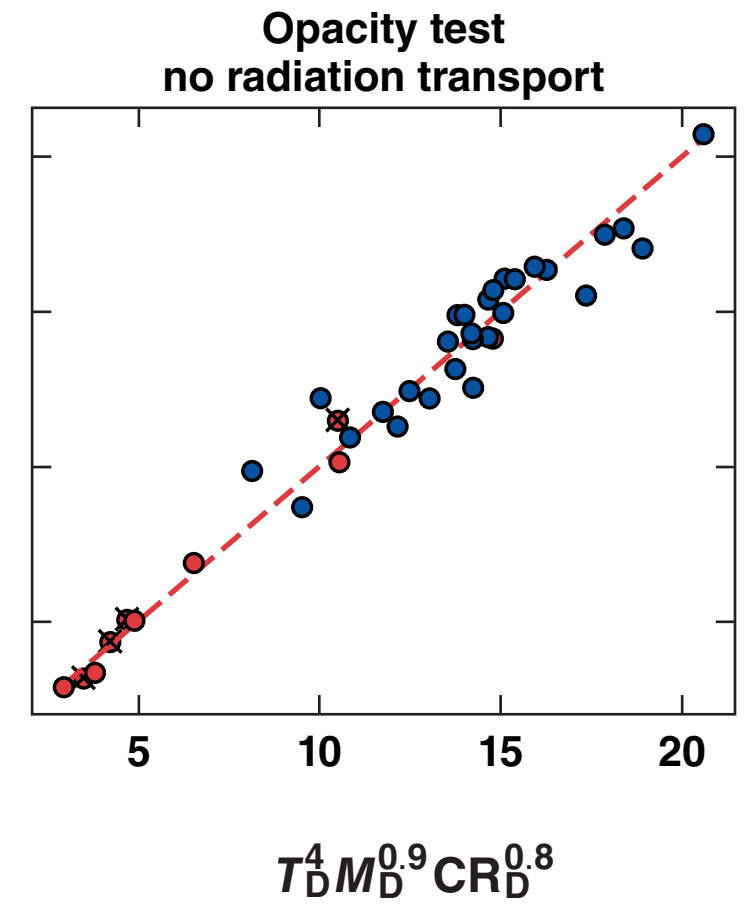
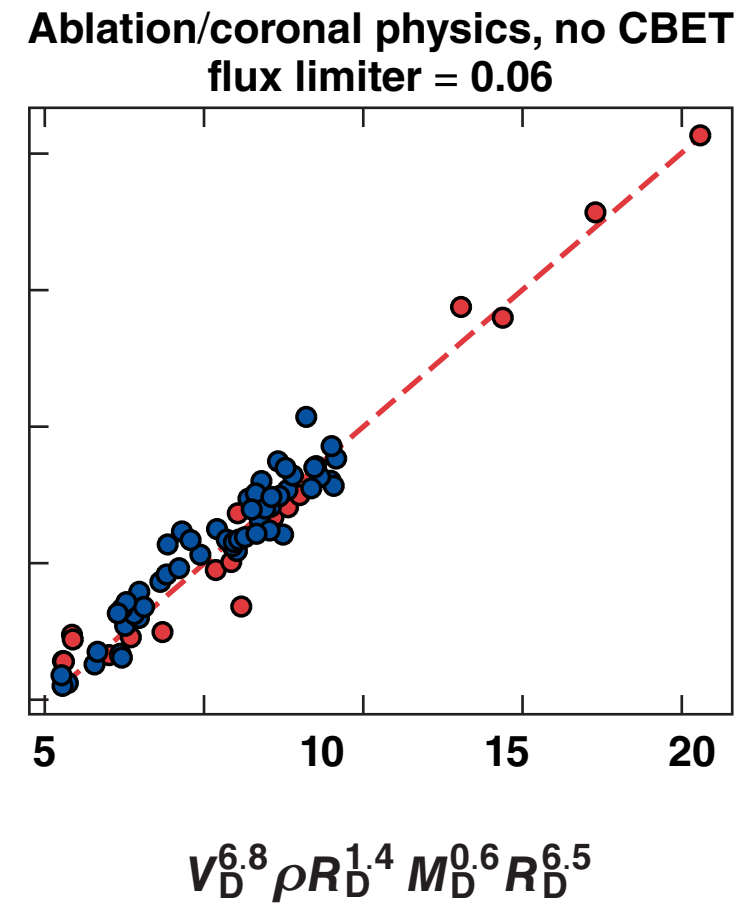
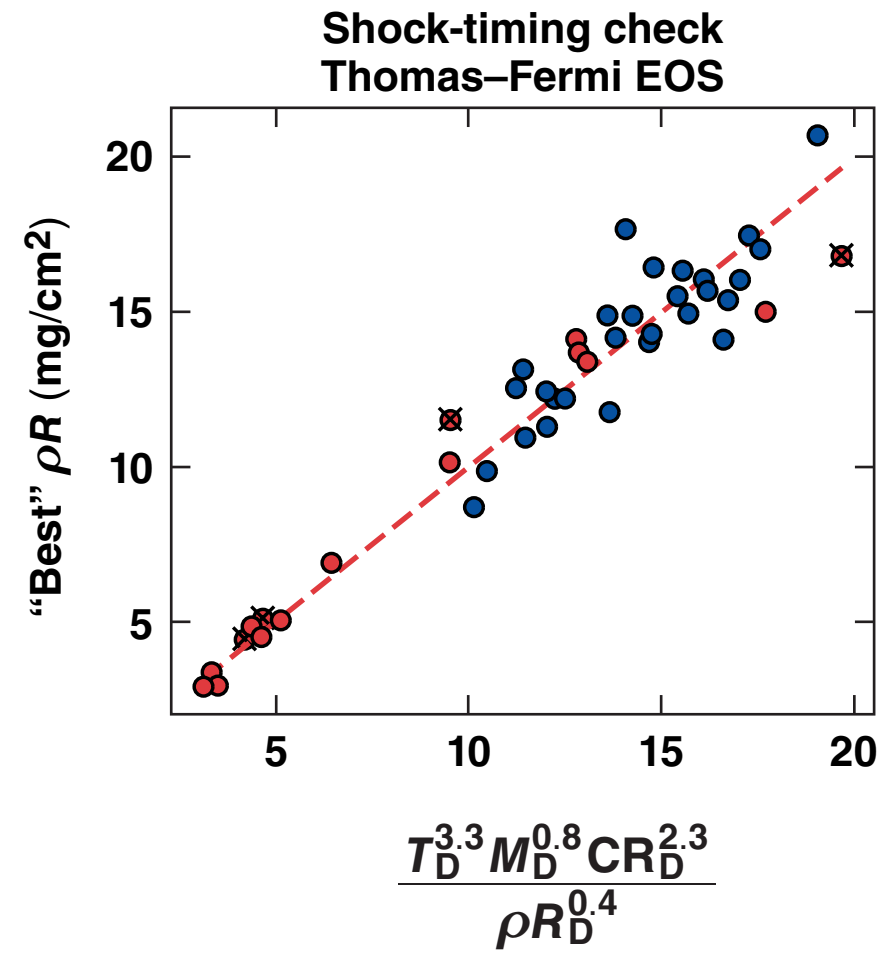


Where ρR_D , T_D , $C R_D$, and M_D are the areal densities, ion temperatures, inner convergence ratios, and stagnating masses of the degraded *LILAC* simulations.

*SSD: smoothing by spectral dispersion

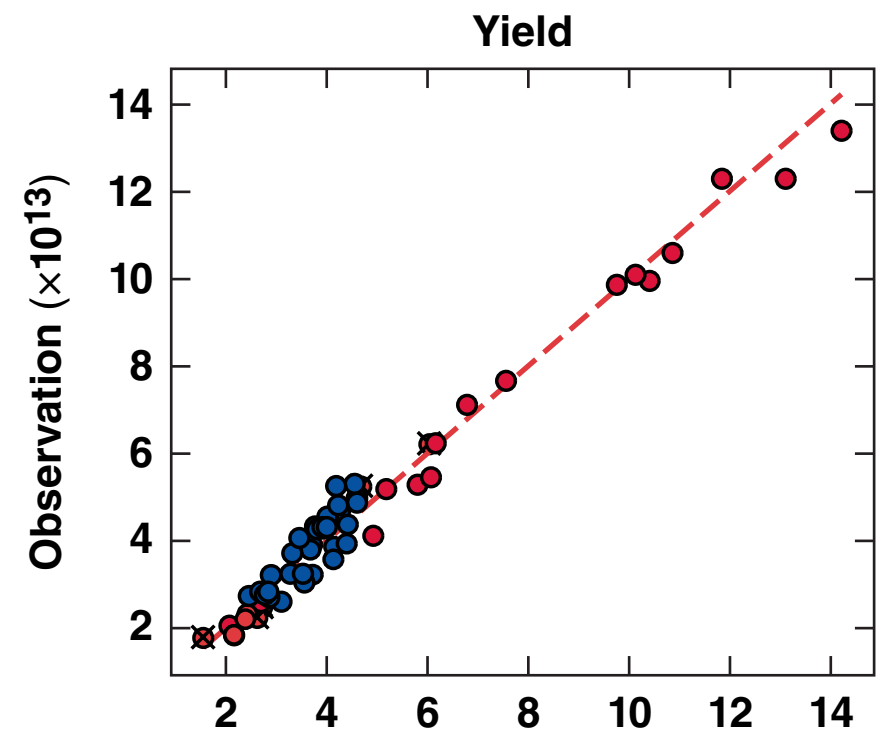
Predictions of the primary neutron yield are relatively robust to modeling errors

- High adiabat/1-D Campaign
- Low adiabat
- ⊗ SSD off shots

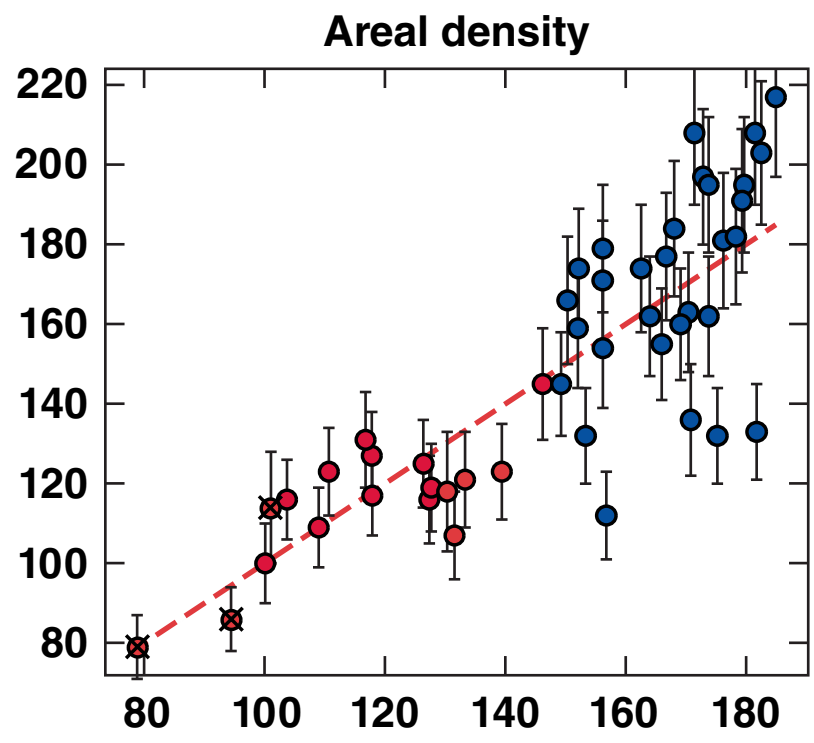


Predictive models are developed for the experimental primary neutron yield, ion temperature, and ρR , using only *LILAC* quantities

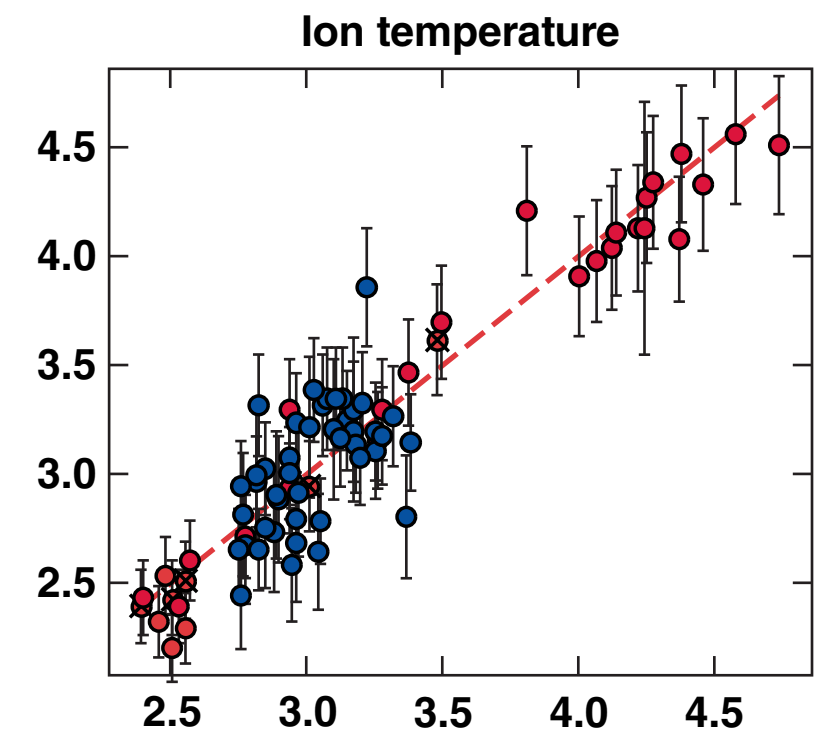
- High adiabat/1-D Campaign
- Low adiabat
- ⊗ SSD off shots



$$Y_{\text{exp}} \propto \frac{V_{\text{LILAC}}^{3.8} \rho R_{\text{LILAC}}^{0.2} M_{\text{LILAC}}^{0.45} E_L^{0.7}}{\delta_{\text{SSD}}^{0.3}}$$



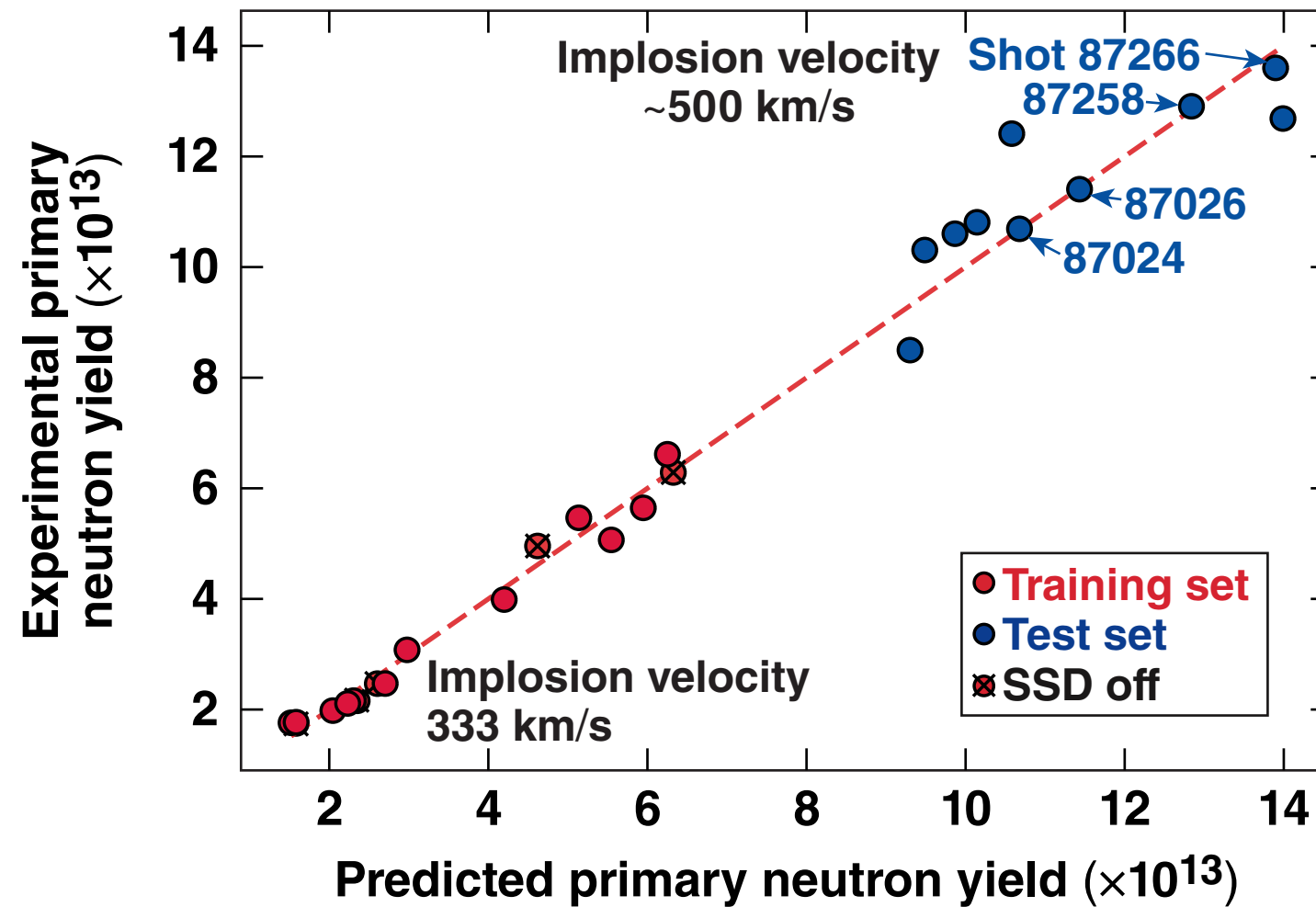
$$\rho R_{\text{exp}} \propto \frac{1}{V_{\text{LILAC}}^{0.95} R_{\text{LILAC}}^{0.85} \delta_{\text{SSD}}^{0.4}}$$



$$T_{\text{exp}} = 0.85 T_{\text{LILAC}}$$

The statistical model was used to design the highest-yield implosions on OMEGA

Prediction performance on the high-adiabat campaign ($\alpha \sim 5$ to 7)



$$\text{Yield}_{\text{pred}} \sim \frac{V_{\text{LILAC}}^{4.3} M_{\text{LILAC}}}{\delta_{\text{SSD}}^{0.3}}$$

Summary/Conclusions

A statistical model of OMEGA implosions has been developed to enable accurate preshot predictions and optimize implosion design



- A statistical approach is used to bridge the gap between experiments and simulations
- The statistical approach is tested on a simulation database
- Statistical predictions of yield are robust to modeling errors, while predictions of areal density are sensitive to errors in EOS*
- Predictive models are developed for the experimental neutron yield, ion temperature, and ρR by statistical mapping of the experimental database onto *LILAC* output variables

The statistical predictions enable the design of the highest primary yield cryo implosion on OMEGA ($Y = 1.34 \times 10^{14}$).

The dependence of the experimental yield on 1-D parameters will persist if the 3-D effects are dominated by systematic nonuniformities

- $Y_{\text{exp}} = Y_{1\text{-D}} \text{ (1-D parameters) YOC}^* \text{ (distortion)}$
- A_0 = initial nonuniformities (target and/or laser)
- f (1-D) = amplifications of distortion caused by implosion (RT,** RM,† BP‡)
- $\text{YOC} = \text{YOC} [\tilde{A}_0^{\text{systematic}} f_s \text{ (1-D)} + \tilde{A}_0^{\text{random}} f_r \text{ (1-D)}]$
- If systematic nonuniformities are dominant: $\tilde{A}_0^{\text{systematic}} \gg \tilde{A}_0^{\text{random}}$
- $Y_{\text{exp}} = Y_{1\text{-D}} \text{ (1-D parameters) YOC} [\tilde{A}_0^{\text{systematic}} f_s \text{ (1-D parameters)}]$
- If $\tilde{A}_0^{\text{systematic}} = \text{constant}$, the yield depends only on 1-D parameters even in distorted implosions

$$Y_{\text{exp}} = Y_{1\text{-D}} \text{ (1-D parameters)}$$

For 1-D implosions or 3-D with dominant systematic nonuniformities

*YOC: yield over clean
** RT: Rayleigh–Taylor
† RM: Richtmyer–Meshkov
‡ BP: Bell–Plesset