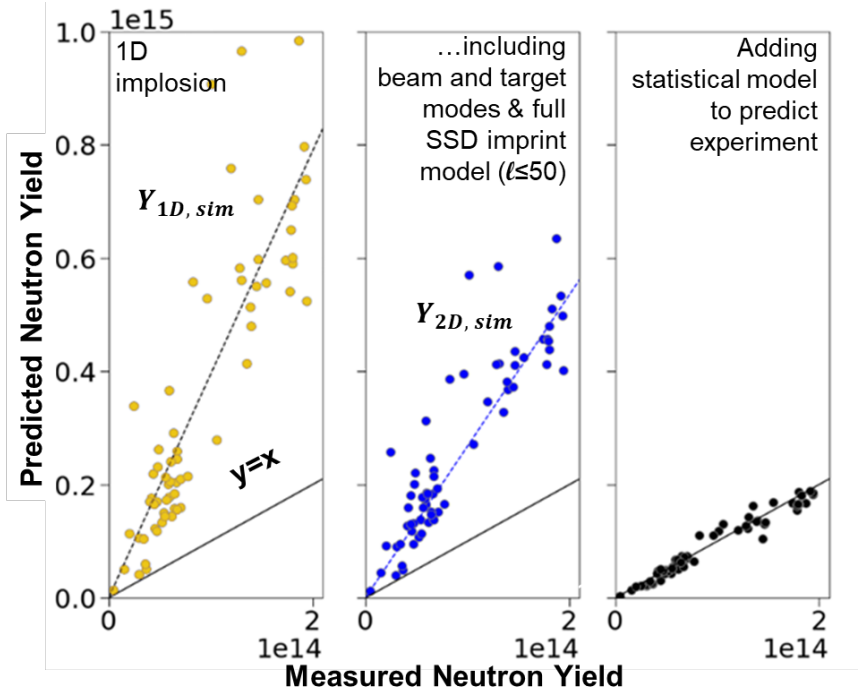
Understanding Cryogenic Target Modeling Gaps on OMEGA Using Statistics-Based Analysis with a 2-D DRACO Simulation Database



Duc Cao
University of Rochester
Laboratory for Laser Energetics

64st Annual Meeting of the
American Physical Society
Division of Plasma Physics
Spokane, WA
17–21 October 2022

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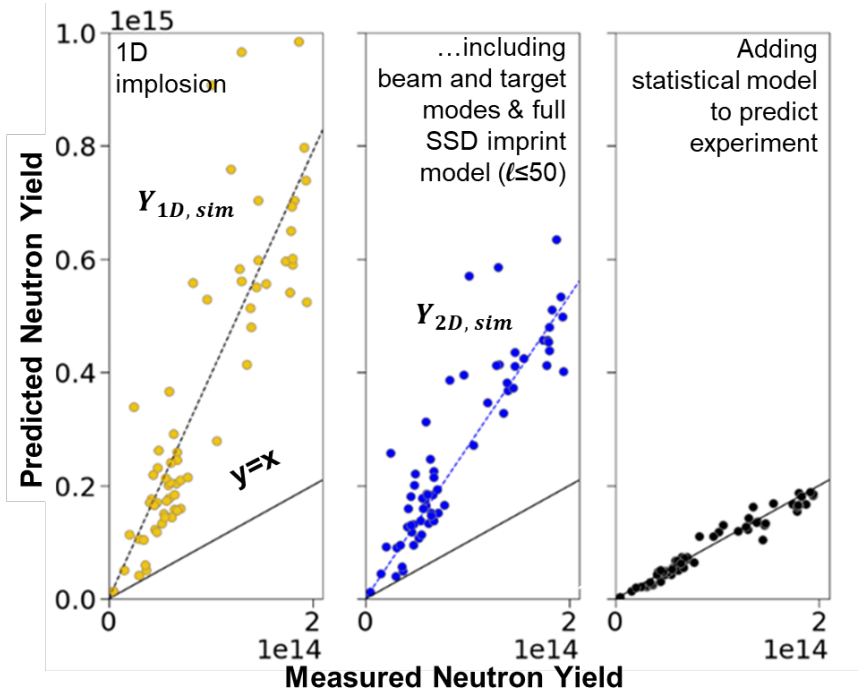

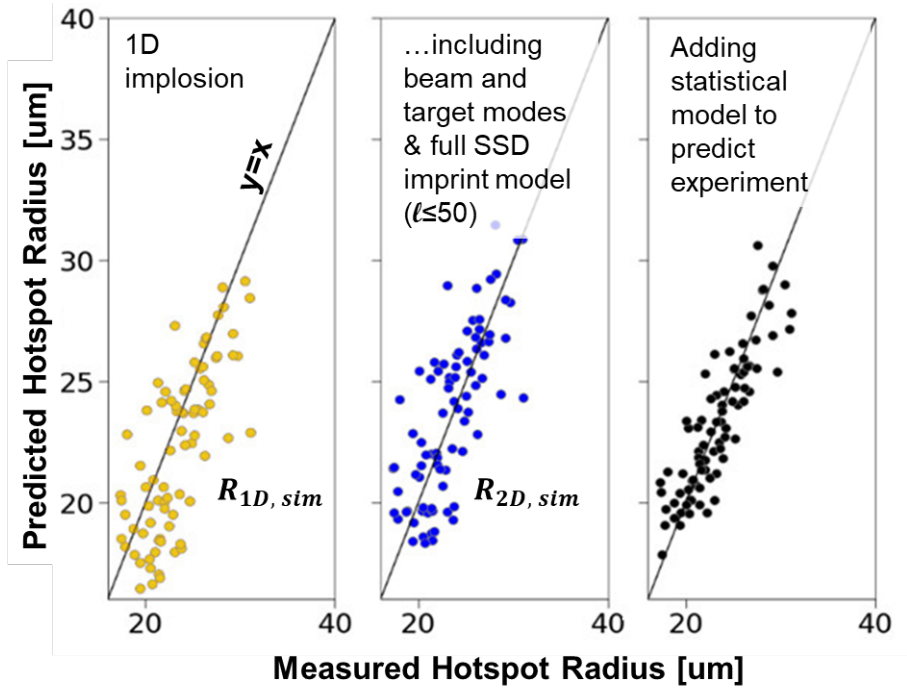

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Summary

Statistical modeling with multiple observables is being used to help guide code improvements

- Statistical modeling has made successful predictions[1,2] while also revealing the dependencies of missing physics

- Statistical modeling with the DRACO-2D database[3-6] verifies improved yield predictions when known perturbations are added to codes

- When adding hypothesized perturbations, repeating the above exercise on multiple observables (e.g. yield, X-ray hotspot size) can help reveal which implementations are most physical

[1] A. Lees et al., Phys. Rev. Lett. 127, 105001 (2021),
[2] V. Gopalaswamy et al., Nature volume 565, pages 581–586 (2019).
[3] P. B. Radha et al., Physics of Plasmas 12, 056307 (2005)
[4] J. Marozas, Phys. Plasmas 25, 056314 (2018);
[5] D. Cao, Phys. Plasmas 22, 082308 (2015)
[6] With support from the ASCR Leadership Computing Challenge Program

Collaborators

R. C. Shah, C. A. Thomas, A. Lees, V. Gopalaswamy, R. Betti, D. Patel, W. Theobald,
J. P. Knauer, P. B. Radha, C. Stoeckl, S. P. Regan, W. Scullin,
T. J. B. Collins, and V. N. Goncharov

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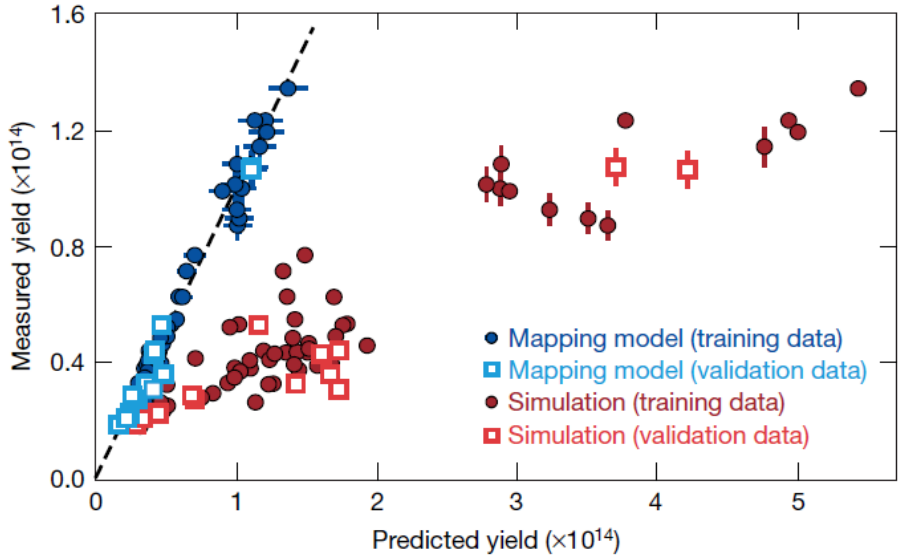
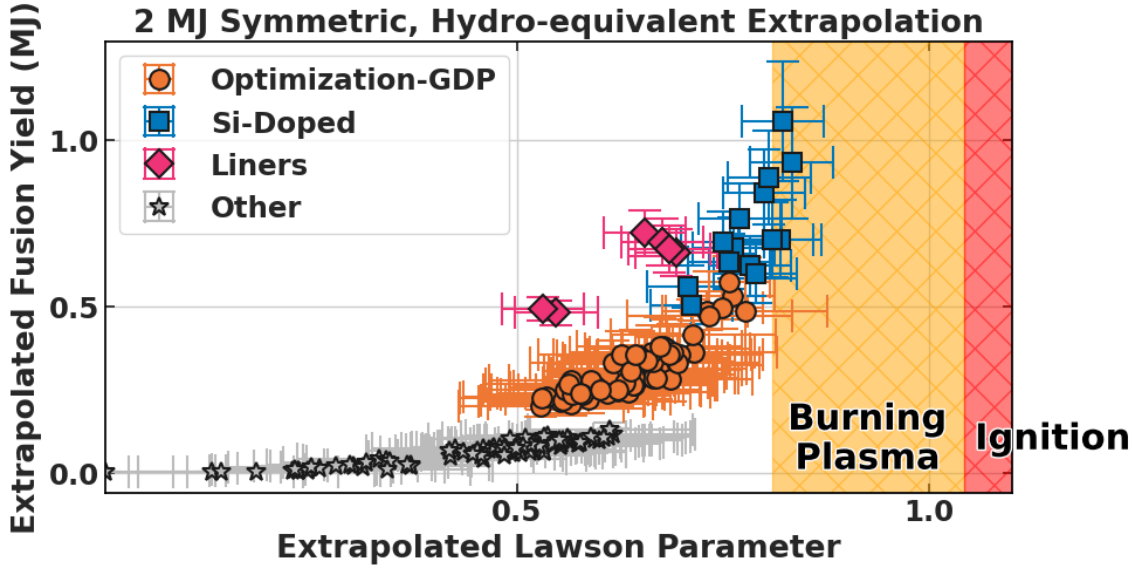
Motivation: Building on LLE's statistical modeling success, we want to also use it to improve codes

- **Statistical model efforts have done a great job at building predictive capability on OMEGA from imperfect 1D simulations[1-4]**





- **For codes, the statistical model could also be usable to guide improvements**

Improving code predictability is crucial for predicting performance at multi-MJ laser facilities

[1] V. Gopalaswamy et al., Nature volume 565, pages 581–586 (2019)
[2] A. Lees *et al.*, Phys. Rev. Lett. 127, 105001 (2021),
[3] V. Gopalaswamy, CO04:6 (this conference)
[4] C. Williams, NI02:4 (this conference)

Statistical modeling parameterizes observed modeling gaps reasonably well and can hint at the nature of what's missing (previously done for 1D[1,2])

$$\frac{Y_{\text{measured}}}{Y_{1-\text{D}}} \approx \text{YOC}_{\text{predicted}} = \text{YOC}_{R_b/R_t} \cdot \text{YOC}_{\text{hydro}} \cdot \text{YOC}_{\text{fuel age}} \cdot \text{YOC}_{\text{low-mode}}$$

Determined from measured T_{ion} asymmetry

Beam Geom.

$$\sim \left(\frac{R_{\text{beam}}}{R_{\text{target}}}\right)^{3.0}$$

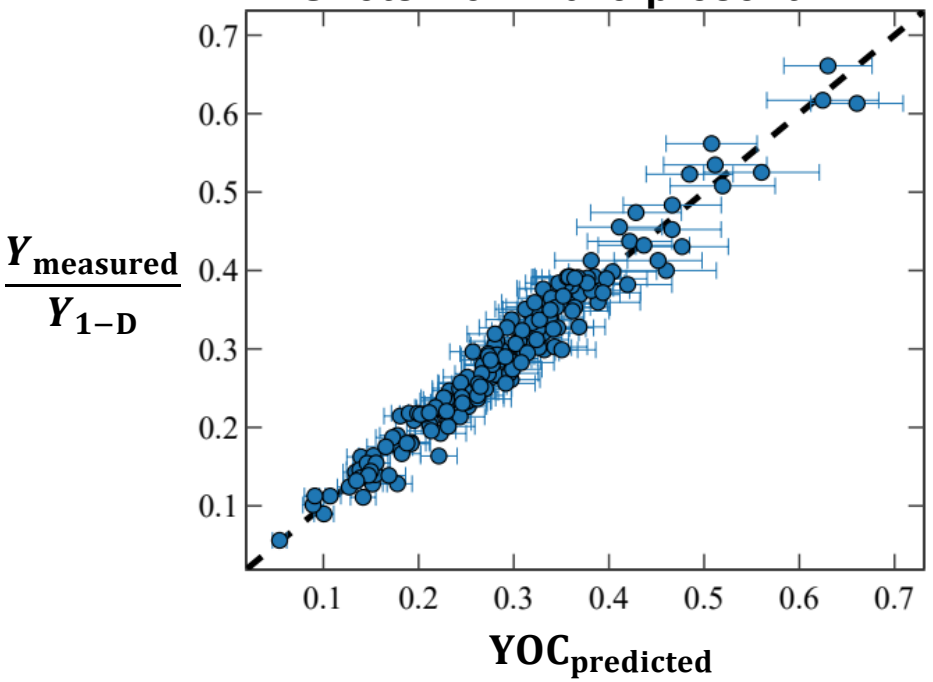
Hydro-instability effect

$$\sim \left(\frac{s_\alpha}{0.8}\right)^{\eta} \text{CR}^{-1.0} \left(\frac{R_{\text{target}}}{R_{\text{inner},0}}\right)^{-3.4}$$

$$s_\alpha = \frac{(\alpha/3)^{1.1}}{\text{IFAR}/20}, \qquad \eta = \begin{cases} 1.06 & s_\alpha < 0.8 \\ 0.45 & s_\alpha > 0.8 \end{cases}$$

These scalings should approach unity if the right missing physics is added

Shots from 2015-present



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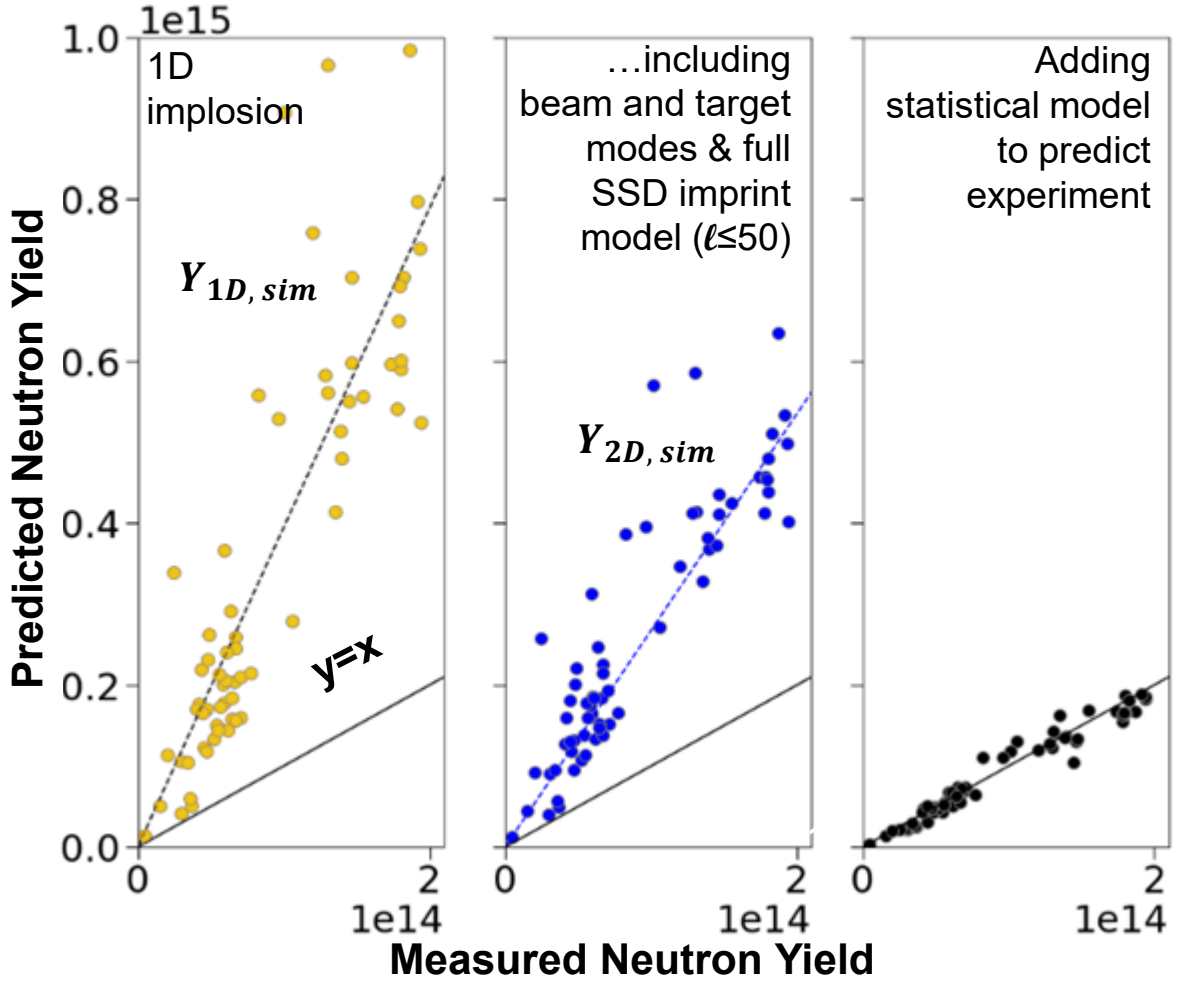
Known effects not captured in 1D codes were simulated in a DRACO 2D database to show their impact at reducing the modeling gap



***DRACO* 2-D database includes 121 shots (440 simulations)**

$2 < \alpha < 10$

$11 < \mathrm{IFAR} < 53$

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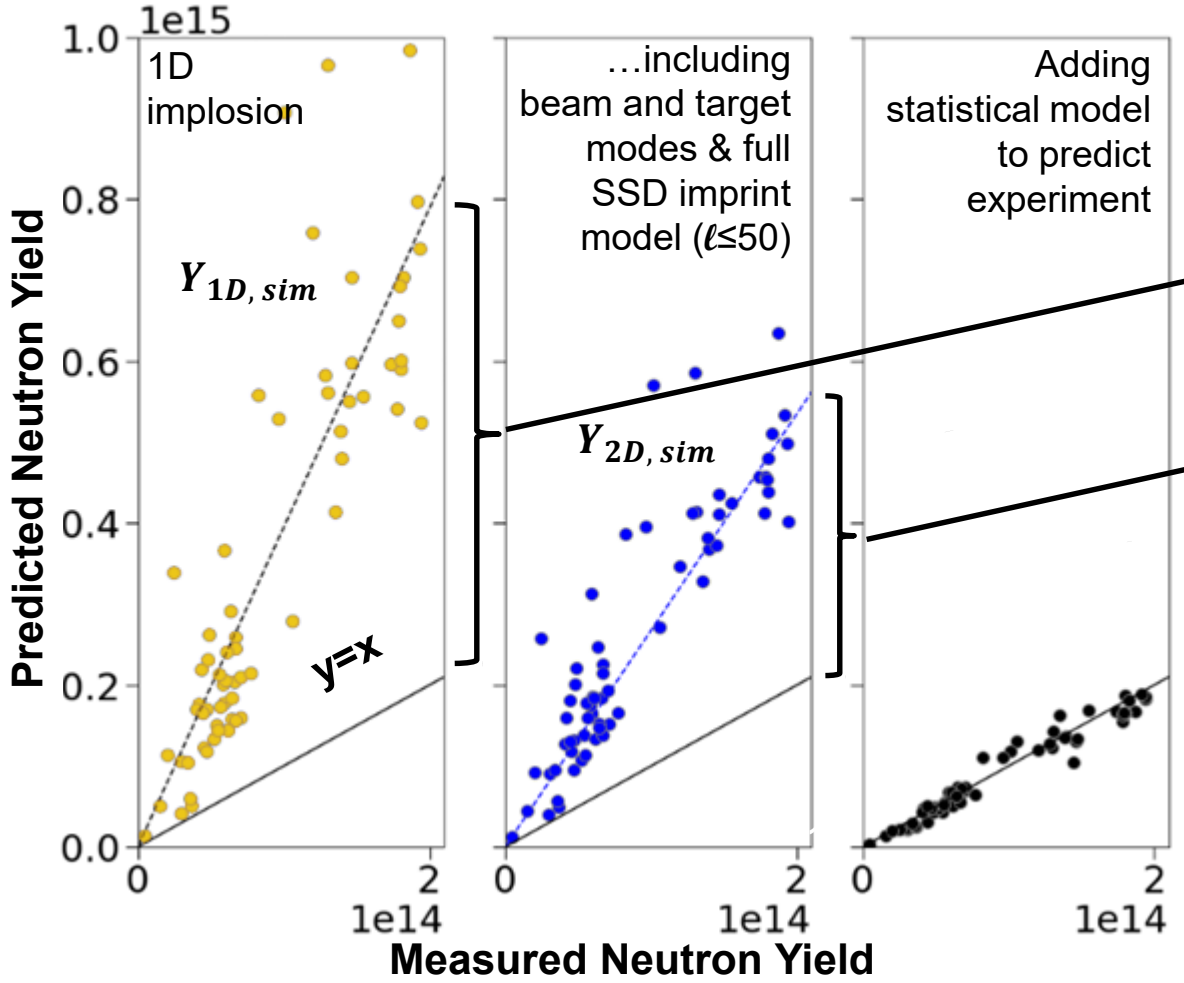

$$\frac{Y_{exp}}{Y_{sim}} = 1 \text{ (Desired)}$$

$$\frac{Y_{exp}}{Y_{1D,\,sim}} \sim \left(\frac{R_b}{R_t}\right)^{3.0} YOC_h\, YOC_{\ell=1}$$

$$\frac{Y_{exp}}{Y_{2D,\,sim}} \sim \left(\frac{R_b}{R_t}\right)^{1.2} YOC_h^{0.7} YOC_{\ell=1}$$

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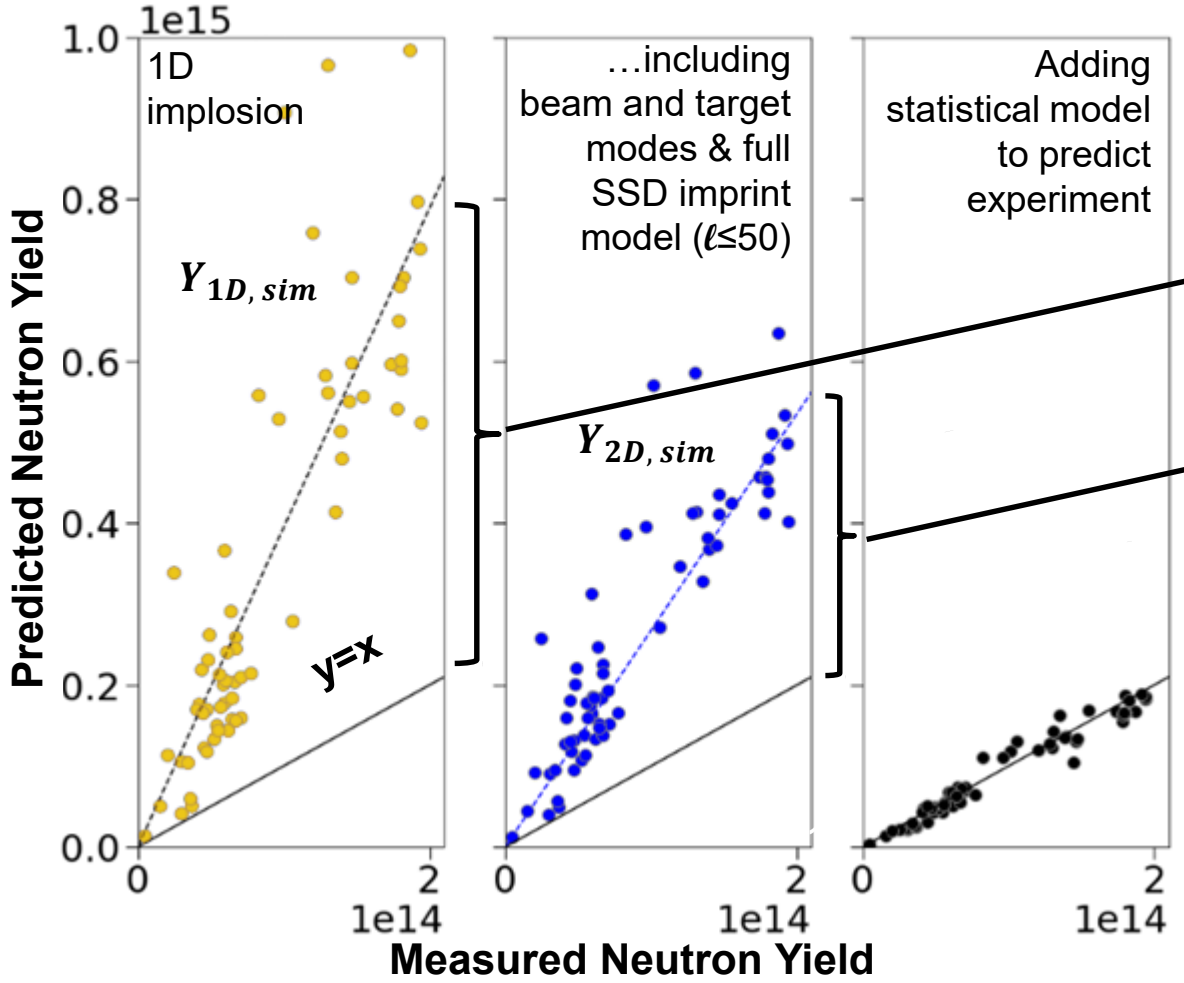

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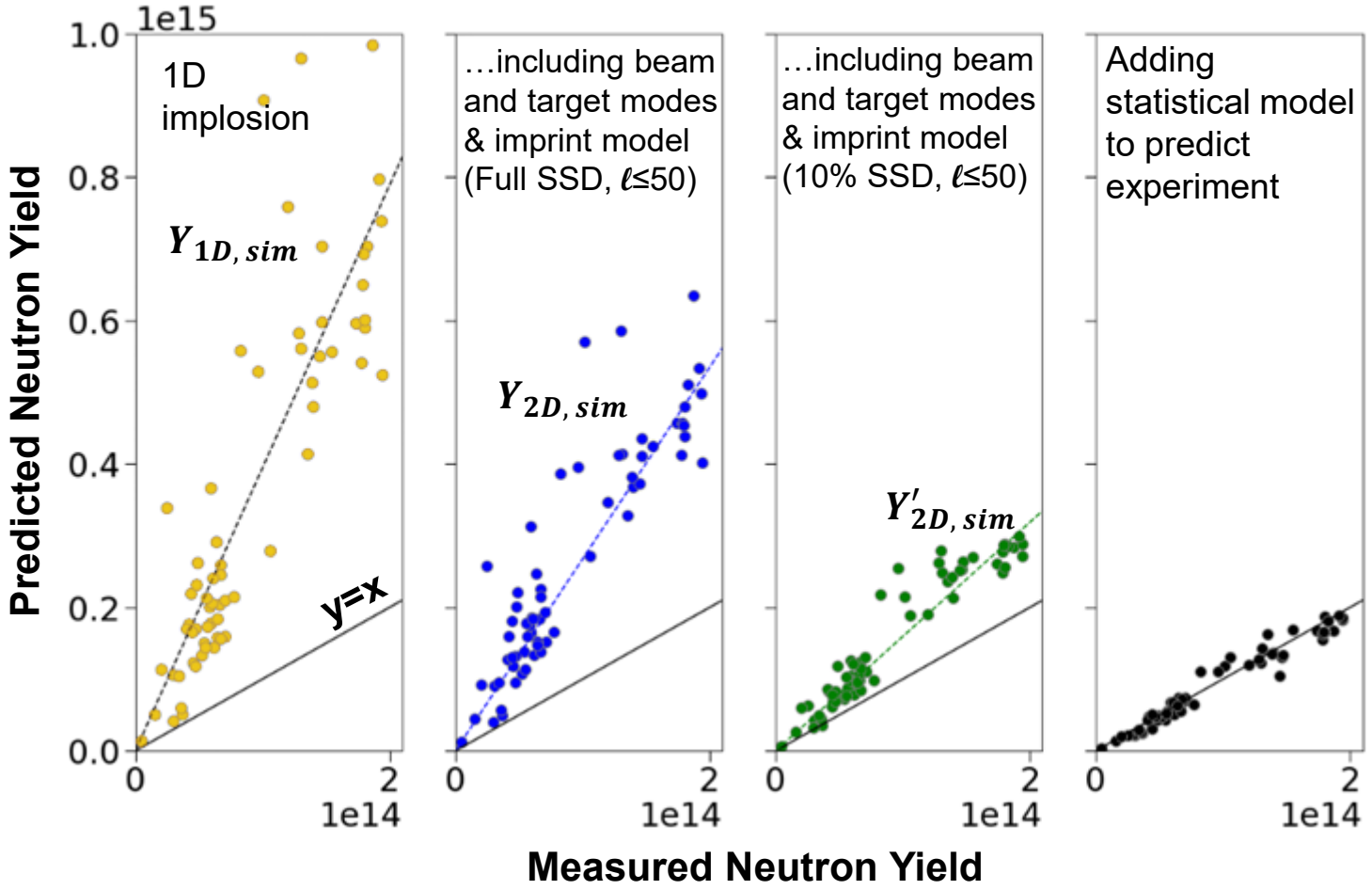
Missing physics related to beam-port geometry and hydro-instability factors still remains…

We can try further, informed modeling changes to see what could reduce the modeling gap even further and improve code predictive capability

Example study: Reduced SSD bandwidth imprint model (mimics potentially uncaptured short-scale perturbations)



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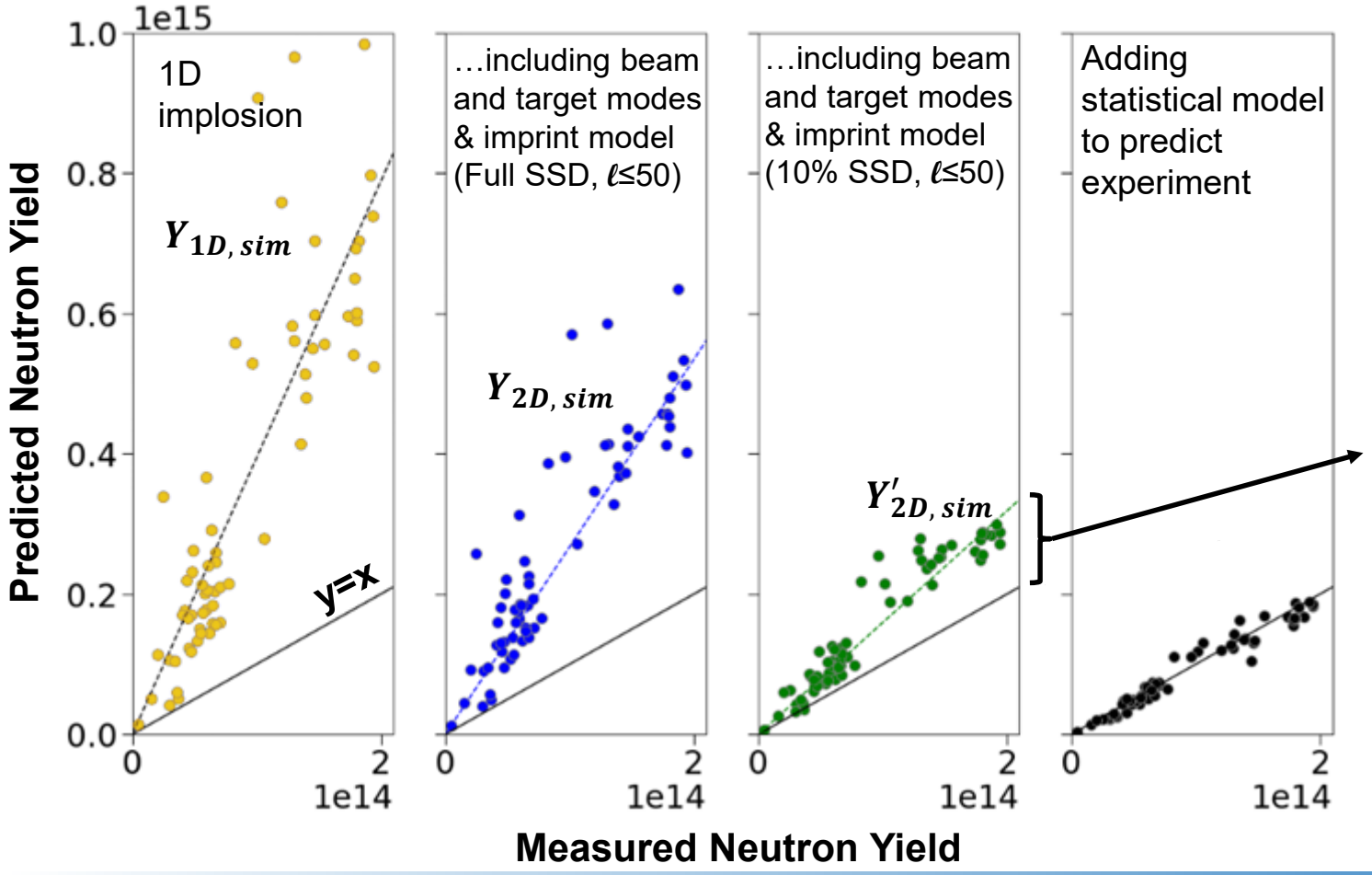

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$$\frac{Y_{exp}}{Y_{2D,\,sim}} \sim \left(\frac{R_b}{R_t}\right)^{1.2} YOC_h^{0.7} YOC_{\ell=1}$$

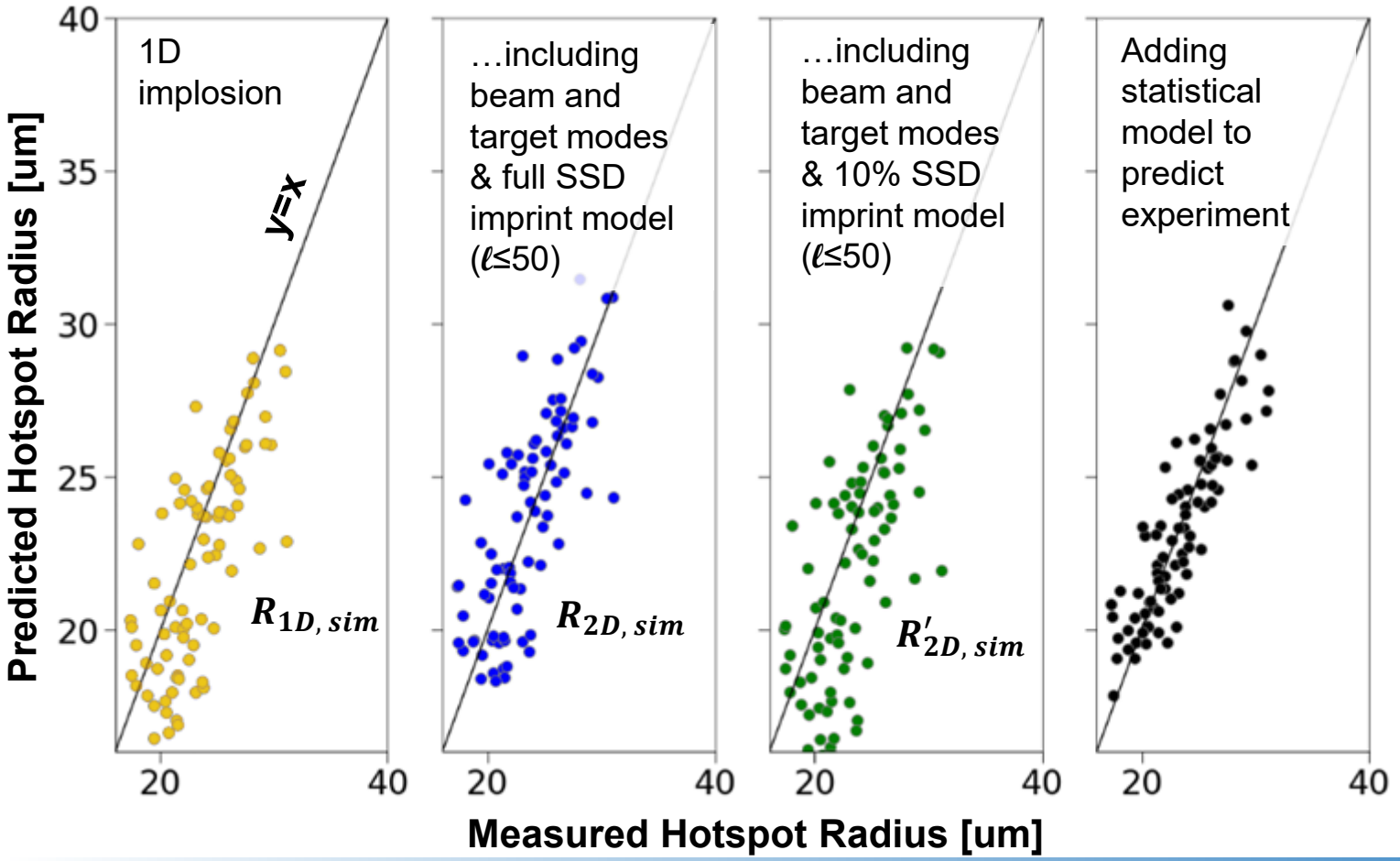
$$\frac{Y_{exp}}{Y'_{2D,\,sim}} \sim YOC_{\ell=1} \text{ (Approaching "Desired")}$$

Reduced SSD imprint model gives good yield predictability

Does it work for other observables?

We've recently added X-ray image analysis[1,2] to further constrain possible improvements to the code

Example study: Reduced SSD imprint model (mimics more short-scale perturbations that could be uncaptured)



[1] F. Marshall, Review of Scientific Instruments 68, 735 (1997)
[2] J. Macfarlene, High Energy Density Phys., Vol. 3, pp. 181-190 (2007)

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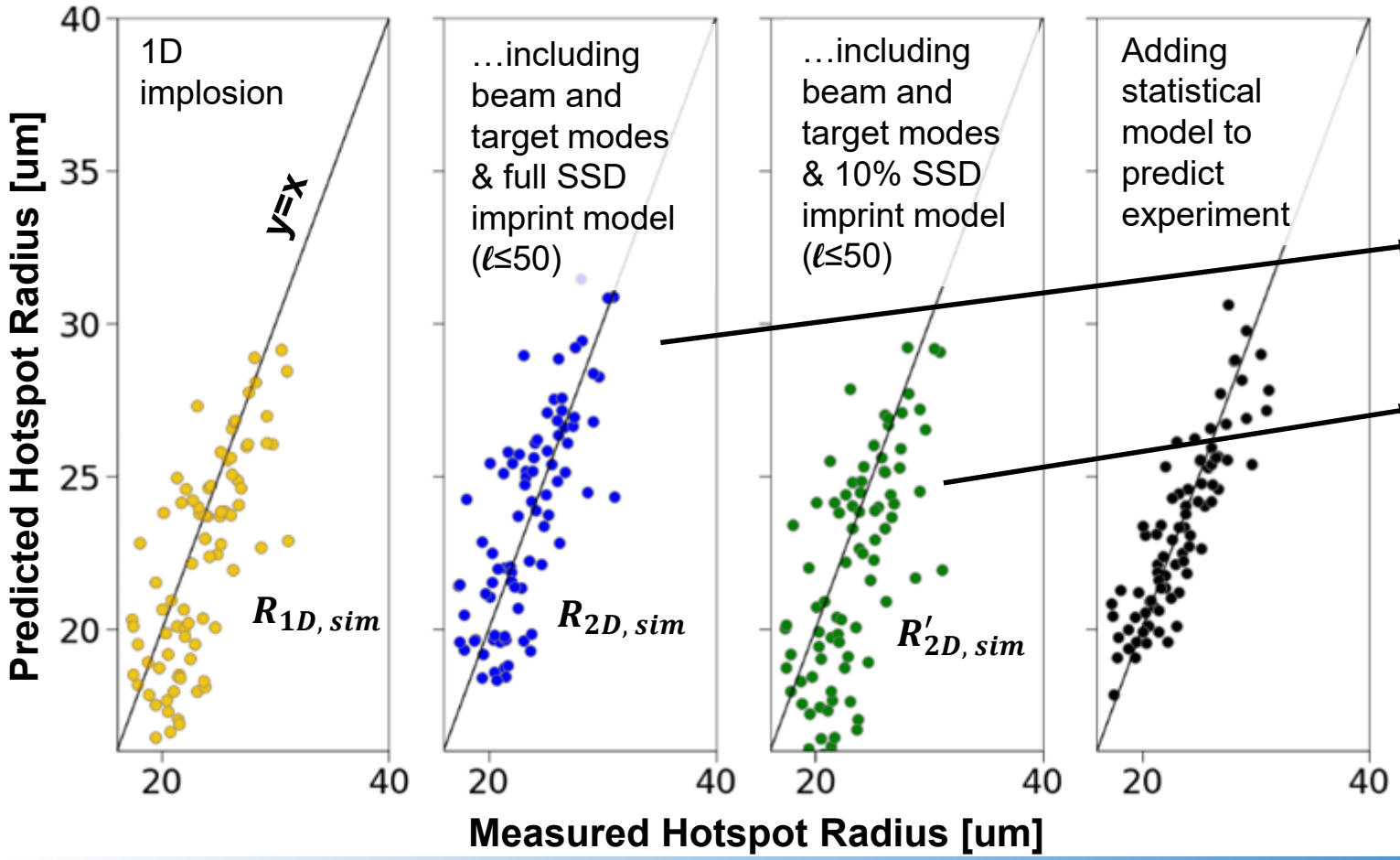


$$\frac{R_{exp}}{R_{2D,\,sim}} = 1 \text{ (Desired)}$$

$$\frac{R_{exp}}{R_{2D,\,sim}} \sim \left(\frac{R_b}{R_t}\right)^{0.1} YOC_h^{-0.2} YOC_{\ell=1}^{-0.2}$$

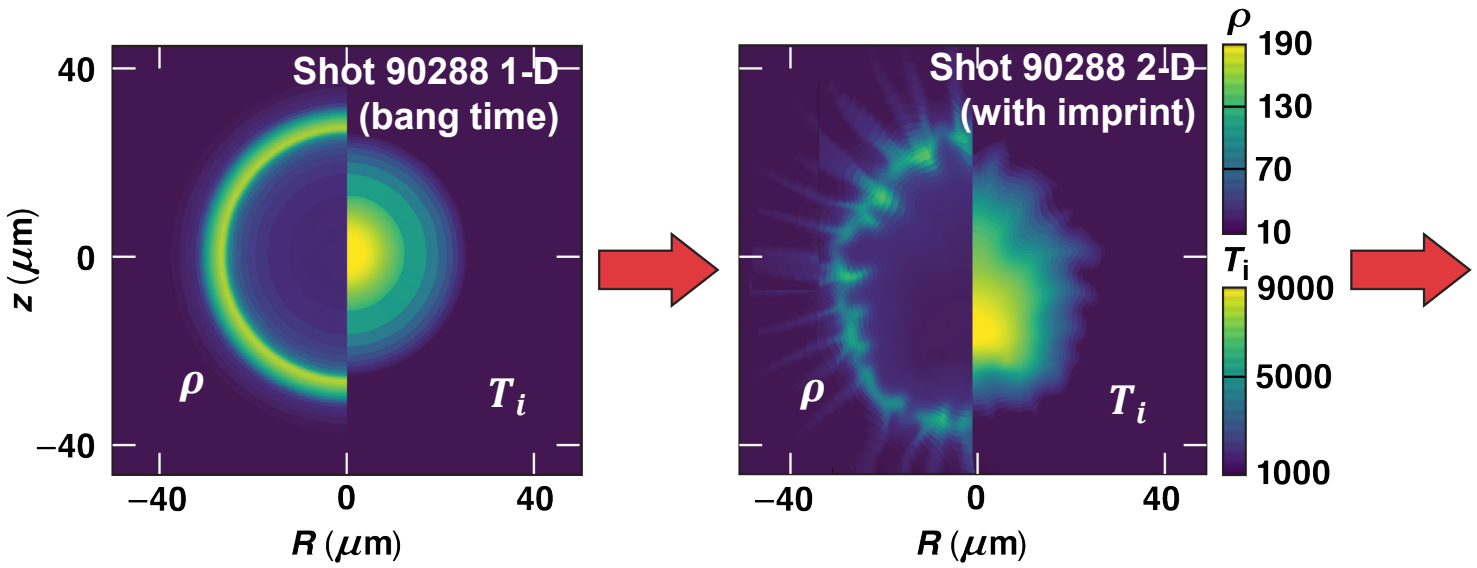
$$\frac{R_{exp}}{R'_{2D,\,sim}} \sim \left(\frac{R_b}{R_t}\right)^{0.4} YOC_h^{-0.3} YOC_{\ell=1}^{-0.3}$$

(Deviating from "Desired")

Reduced SSD imprint model does not improve X-ray image predictability

[1] F. Marshall, Review of Scientific Instruments 68, 735 (1997)
[2] J. Macfarlene, High Energy Density Phys., Vol. 3, pp. 181-190 (2007)

We are studying the effects of other perturbations that could improve code predictions



Some perturbations to examine:

- Stalk[1]
- 2D vs. 3D
- Laser-plasma interactions (TPD)
- Defects[2]
- etc.

More synthetic diagnostics and observables to include in analysis:

- SRTE[3] (T_{ele}, X-ray image)
- KODI[4] (X-ray imaging)
- TRXI[5] (X-ray imaging)
- nTOFs[6] (ρR, T_{ion})

Rerun database subset with new physics → Obtain new statistical scaling on all observables → If residual scaling closes across all, prediction power improved!

This effort can help justify focused experiments that confirm impacts of specific perturbations

[1] K. Anderson, UO04:11 (this conference)
[2] T. Collins, UO05:1 (this conference)
[3] R. Shah, Phys. Rev. E 106, L013201
[4] H. G. Rinderknecht, RSI 93, 093507 (2022)
[5] W. Theobald, RSI 89, 10G117 (2018)
[6] C. Forrest, RSI 83, 10D919 (2012)

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