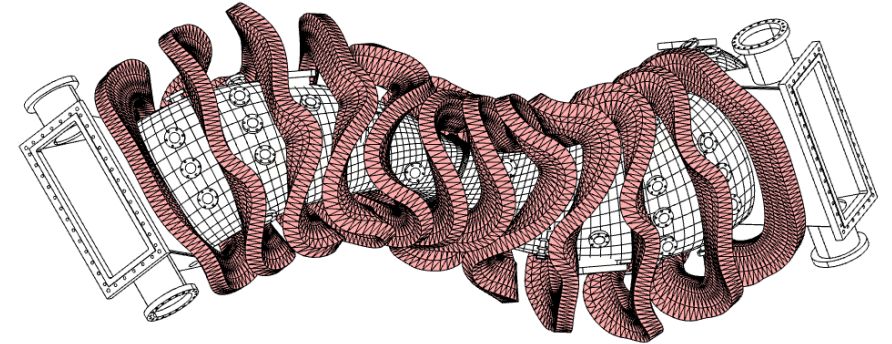




Use of Integrated Data Analysis to Maintain Diagnostic Calibrations in a Fusion Reactor



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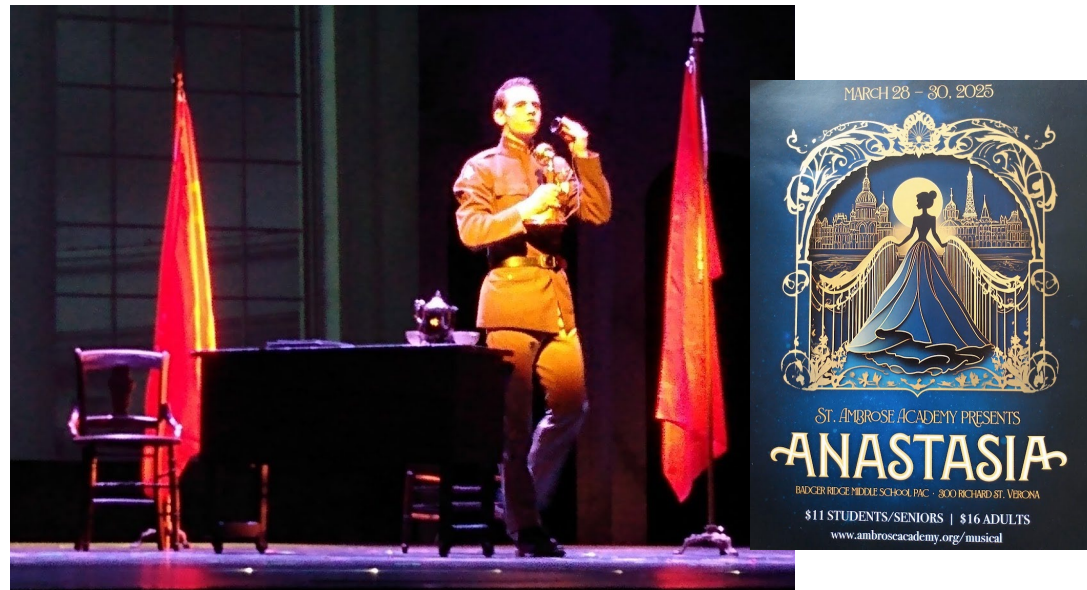
A little bit about myself:

My family enjoys camping and kayaking for recreation



We sing in a choir and my youngest son plays the pipe organ

My children perform in a high school musical, and I build the set





Maintaining diagnostic calibrations in a steady-state reactor is a challenge



- Diagnostics will require calibrations (e.g. spatial localization, absolute signal level) which can depend on varying conditions¹
 - Difficult to maintain absolute calibration of optical systems due to surface erosion, deposition, irradiation
 - Requires deployment of cleaning systems that also change surfaces
- Need for calibration is determined by consistency between multiple measurements
 - E.g. optical & millimeter wave measurements of temperature and density
- Real-time control systems can detect calibration drift through error-correction
 - Possibility of tracking when further calibrations are needed
- Proposal: develop diagnostic forward models that explicitly incorporate calibration information employ Bayesian inference methods

¹Vayakis, *J. Inst.* **19**, C04013 (2024)



Bayesian inference enables development of integrated data analysis frameworks



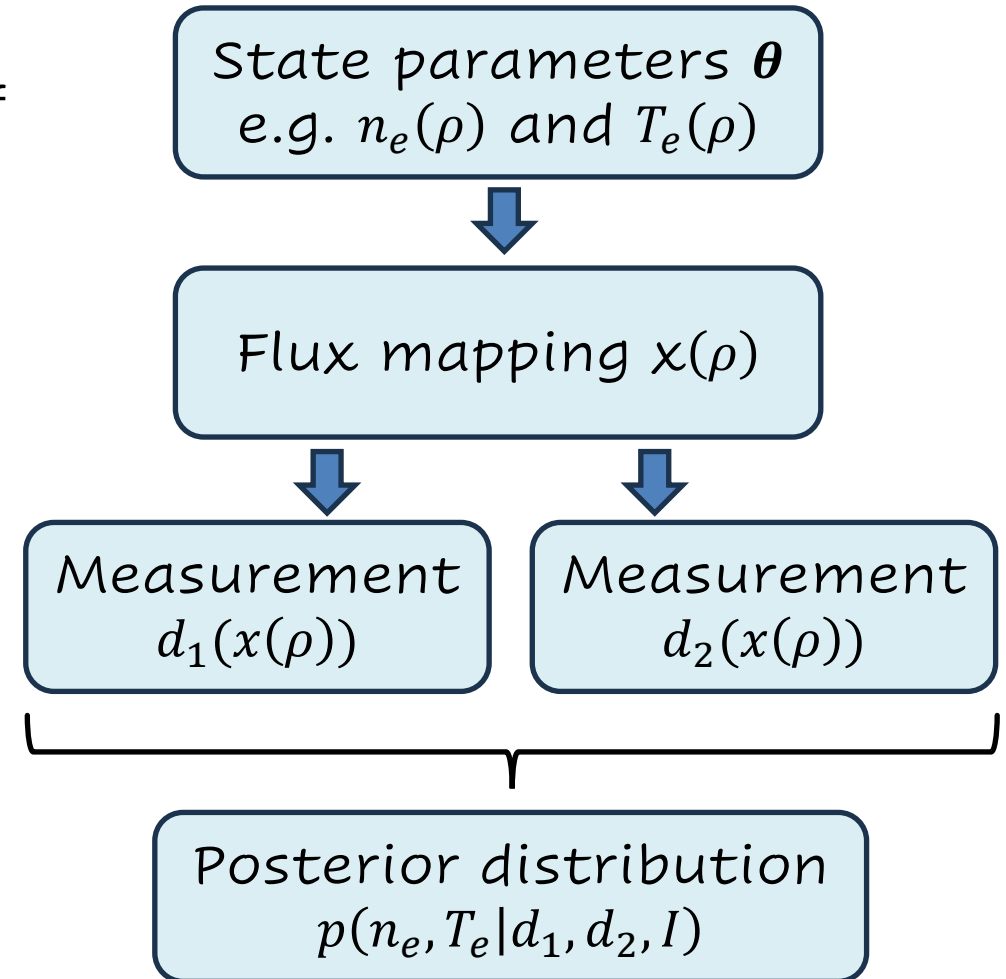
- Conditional probabilities quantify the probability of a plasma state parameter based on the likelihood of various measurements

$$p(\boldsymbol{\theta}|\mathbf{d}, I) = \frac{p(\mathbf{d}|\boldsymbol{\theta}, I) p(\boldsymbol{\theta}|I)}{p(\mathbf{d}|I)}$$

- Data from multiple diagnostics are independent so consistent inferences can be made by treating posterior of one measurement as the prior information of another measurement

$$p(\boldsymbol{\theta}|\mathbf{d}_1, \mathbf{d}_2, I) = \frac{p(\mathbf{d}_2|\boldsymbol{\theta}, I)}{p(\mathbf{d}_2|I)} p(\boldsymbol{\theta}|\mathbf{d}_1, I)$$

- Nuisance parameters (like misalignments) can be introduced to the model and accounted for by marginalization



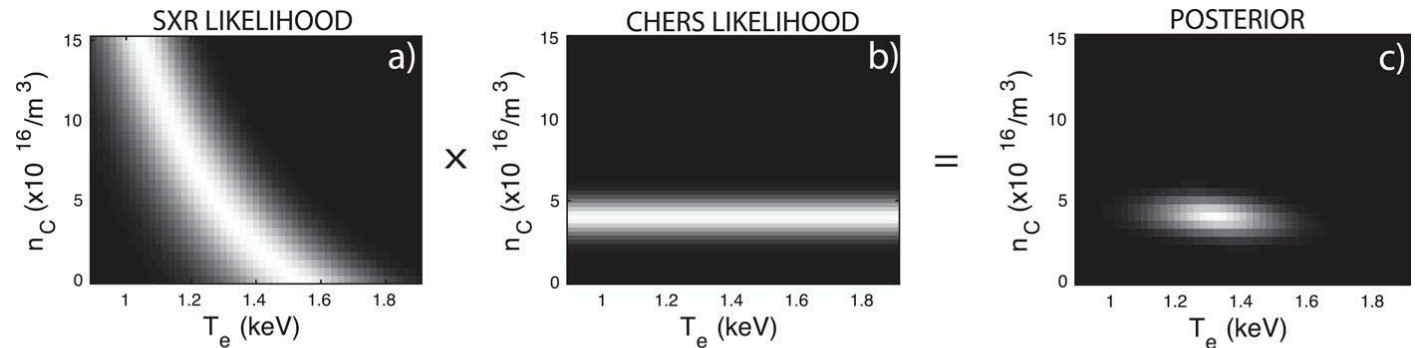


Example of Integrated Data Analysis: Determining Z_{eff}



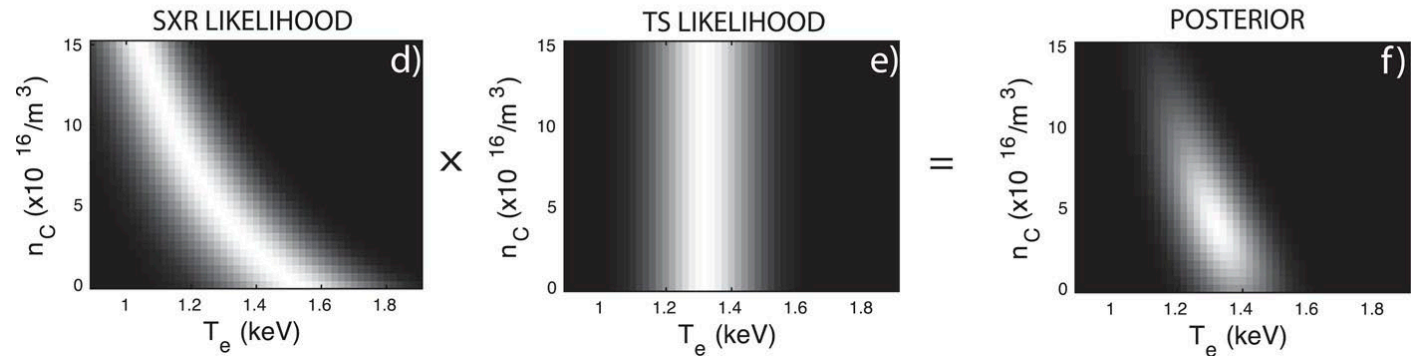
- Soft X-ray emission measurements are sensitive to electron temperature, density, and impurity density

$$p(\mathbf{d}_{SXR}|\boldsymbol{\theta}, I) = f_{SXR}(T_e, n_e, n_z, I)$$



- Thomson Scattering measurements are independent of impurity density

$$p(\mathbf{d}_{TS}|\boldsymbol{\theta}, I) = f_{TS}(T_e, n_e, I)$$



- Their joint likelihood reduces uncertainty in the inference of the impurity density³ yielding more precision in inferring Z_{eff}

³Reusch, et al., Rev. Sci. Instrum. 89, 10K103 (2018)



Example of Integrated Data Analysis: Neutral Beam Attenuation

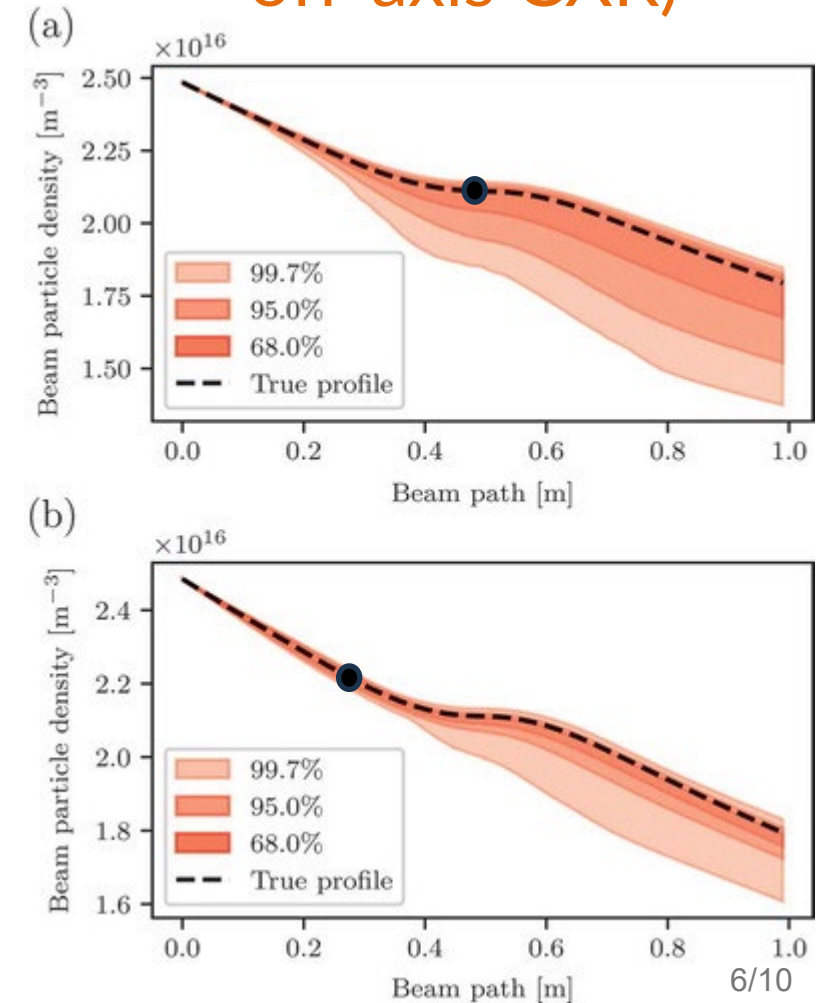
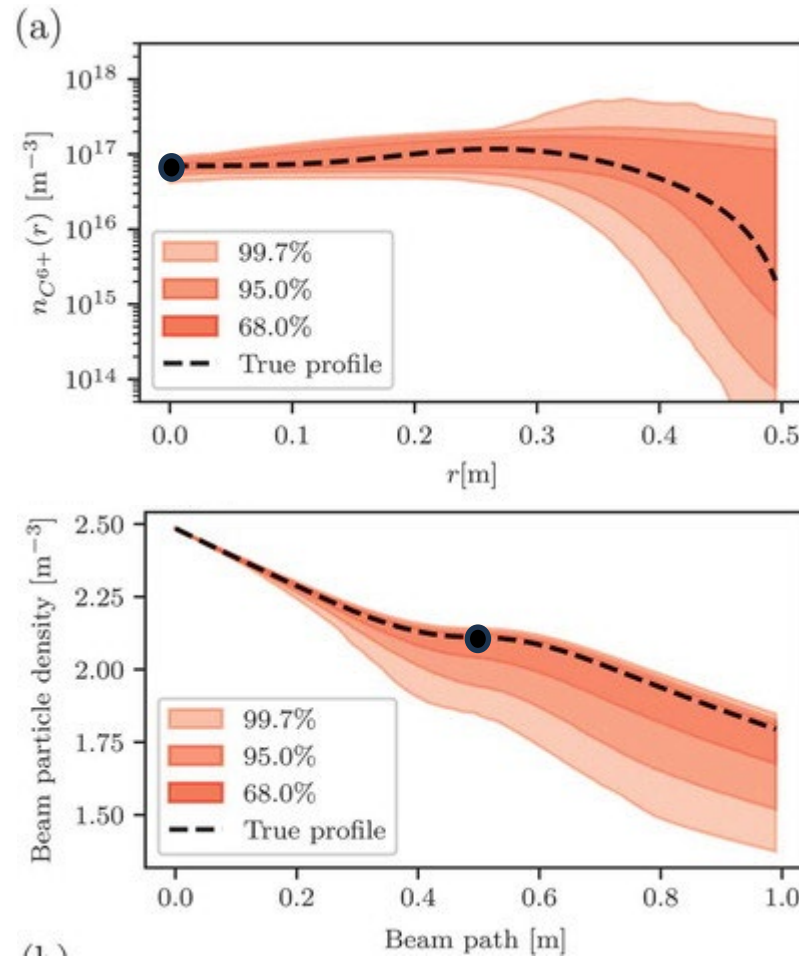
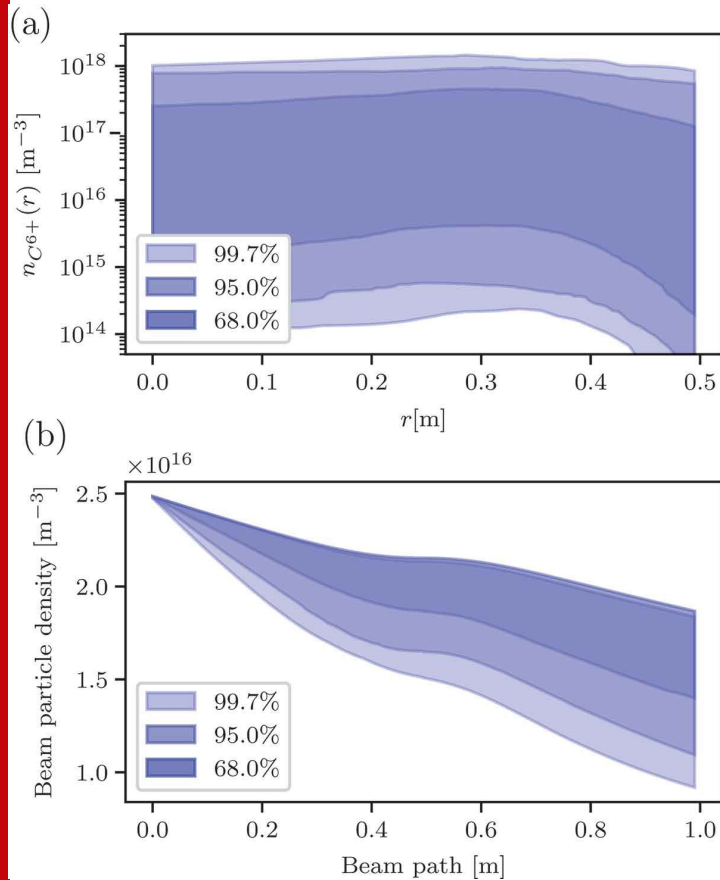


Nornberg, et al., *Fusion Sci. Tech.* 74, 144 (2018)

Posterior (on-axis CXR)

Posterior (on-axis vs. off-axis CXR)

Prior





Key approaches to getting the most from IDA



- Develop prior probability distributions based on uncertainties in physical model
 - Example: Establish bounds on diffusive particle transport for impurity transport modelling
 - Range from classical diffusion to Bohm diffusion
 - Example: Bounds on likely impurity density in a plasma for inferring neutral beam attenuation
 - Range from concentrations too low to affect radiative losses up to radiative collapse
- Data is data: treat data acquired from plasma and calibrations on equal basis
 - Example: Neutral beam emission analysis for Zeff measurement



Proposal: Develop an integrated model of plasma density and temperature measurements on HSX



- Develop forward models of interferometry, reflectometry, ECE, and Thomson Scattering
 - Differing dependencies help constrain state parameter inferences
 - Include nuisance parameters in model to account for changes to calibration values⁵

Examples:

$$p(\mathbf{d}_{TS}|\boldsymbol{\theta}, I) = f_{TS}(T_e, n_e) + \delta_{err}(\mathbf{x}_{align})$$

$$p(\mathbf{d}_{ECE}|\boldsymbol{\theta}, I) = f_{ECE}(T_e) + \delta_{err}(n_e, T_e, \Gamma_{reflect}, \mathbf{x}_{align})$$

- Treat calibration data on same level as data acquired from plasma discharges
- Take advantage of differences in measurement spatial localization, time resolution, and modelling uncertainties to reduce overall systematic uncertainty
- Determine whether loss of a diagnostic (like TS) can be compensated by treating it as a calibration measurement for the millimeter wave systems

⁵van Milligen, *Rev. Sci. Instrum.* **82**, 073503 (2011)



Possible uses of IDA within Data Assimilation systems



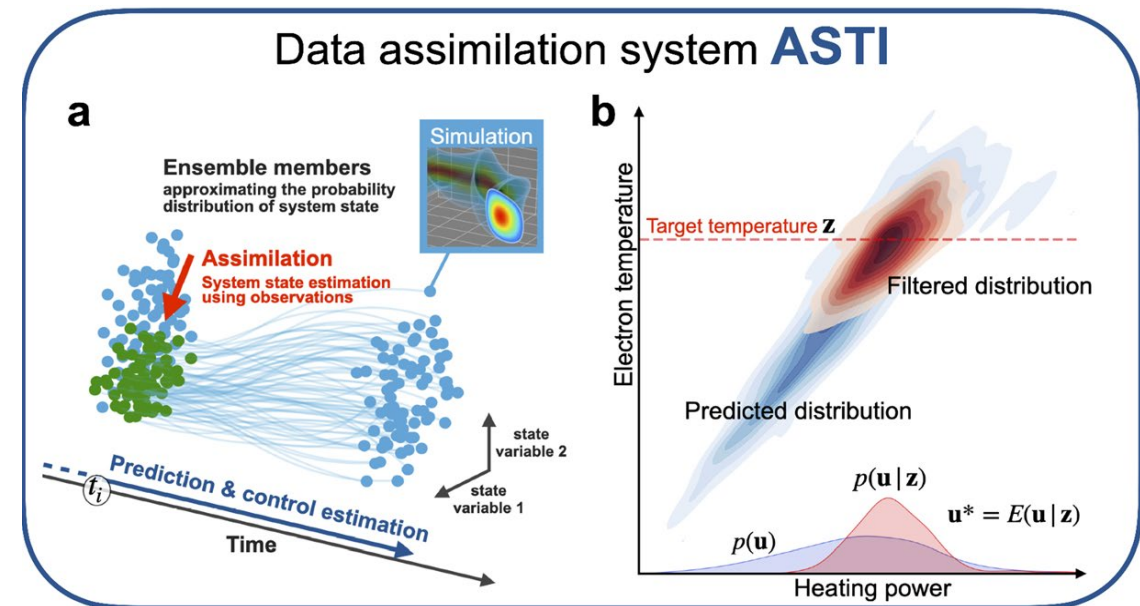
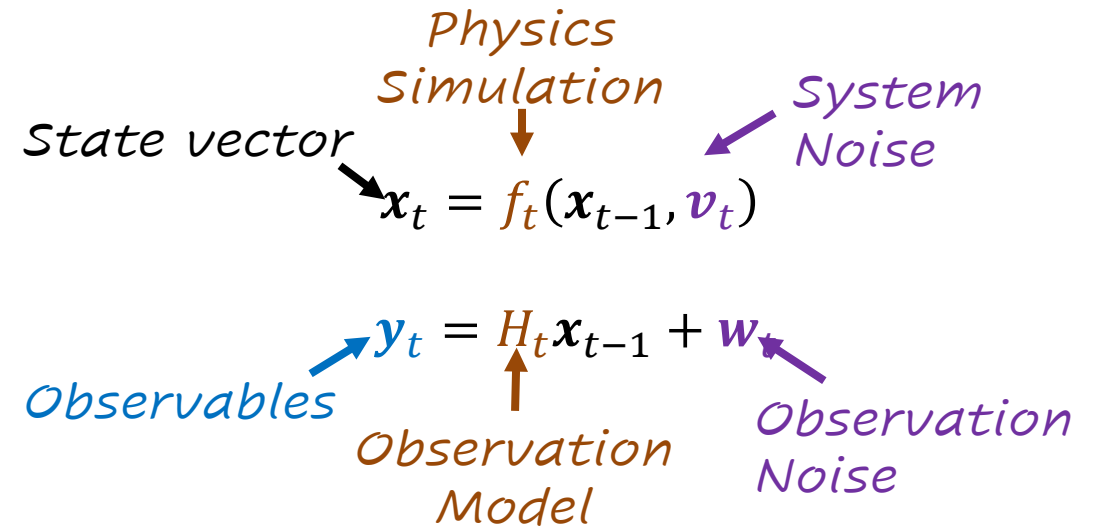
Can diagnostic calibration drift be accounted in real-time data assimilation controllers^{6,7} like ASTI?

Data assimilation entails employing physics-based simulations to create an evolving state vector correlated with the observations

- Can we model calibration drift as an increasing observation noise?
- Can the controller supply information to the diagnostic forward models on likely calibration shifts?
- Can the controller determine when calibration is necessary?

⁶Morishita, et al., *Sci Rep* **14**, 137 (2024)

⁷Morishita, et al., *Comp. Phys. Comm.* **274**, 108287 (2022)





Summary and discussion



- Maintaining diagnostic calibrations in steady-state reactors is a challenge
- Real-time controllers must be aware of calibration drift
- IDA techniques could be employed to track calibration drift to:
 - Determine when a maintenance shutdown is required
 - Identify which calibrations would be sufficient to restart