

Partnership jointly funded by FES and ASCR

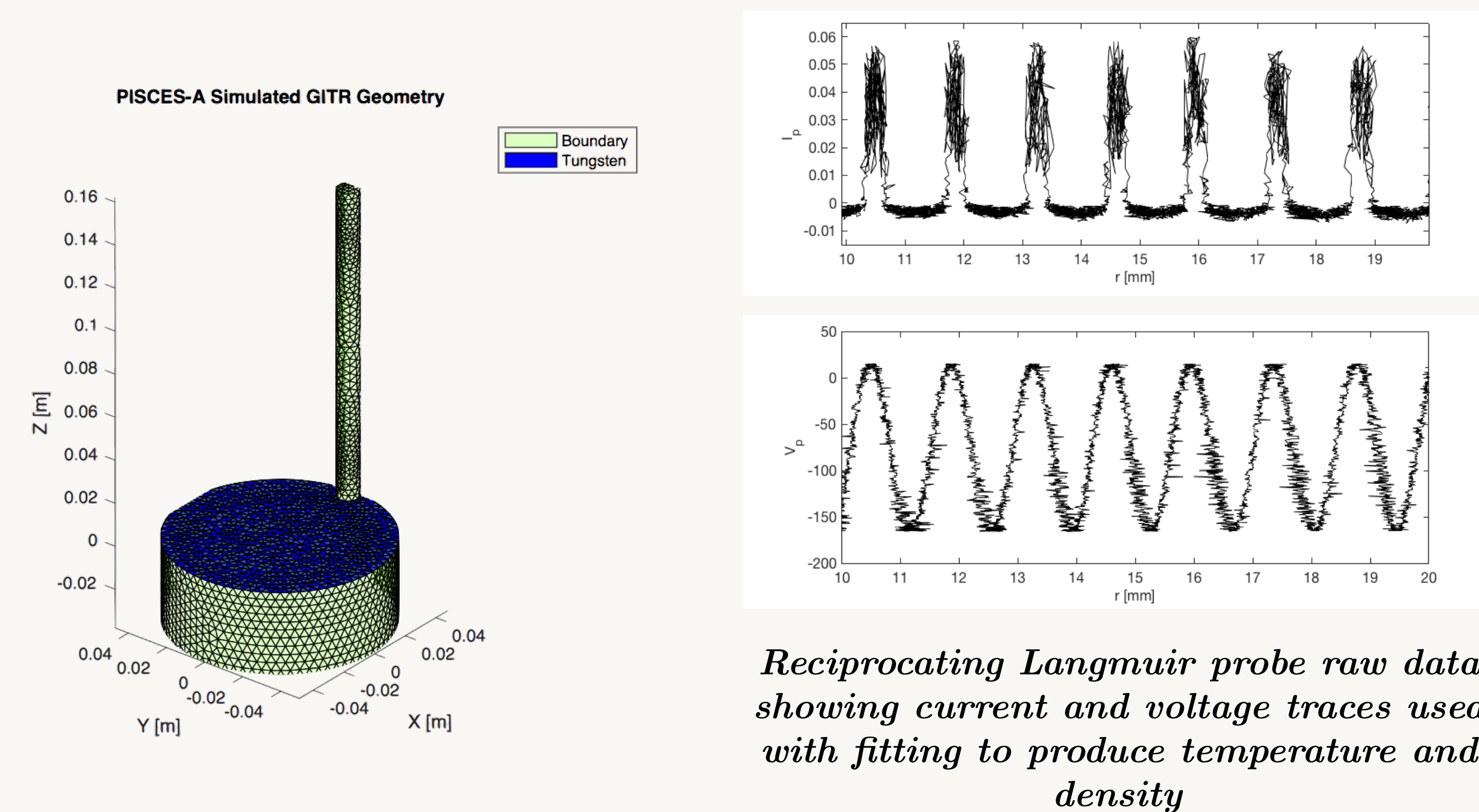
Plasma Surface Interactions 2:

Predicting the Performance and Impact of Dynamic Plasma Facing Component Surfaces

Develop and integrate high-performance simulation tools capable of predicting plasma facing component (PFC) operating lifetime and the impact of the evolving surface morphology of tungsten-based PFCs on plasma contamination, including the dynamic recycling of fuel species and tritium retention, in future magnetic fusion devices.

Motivation

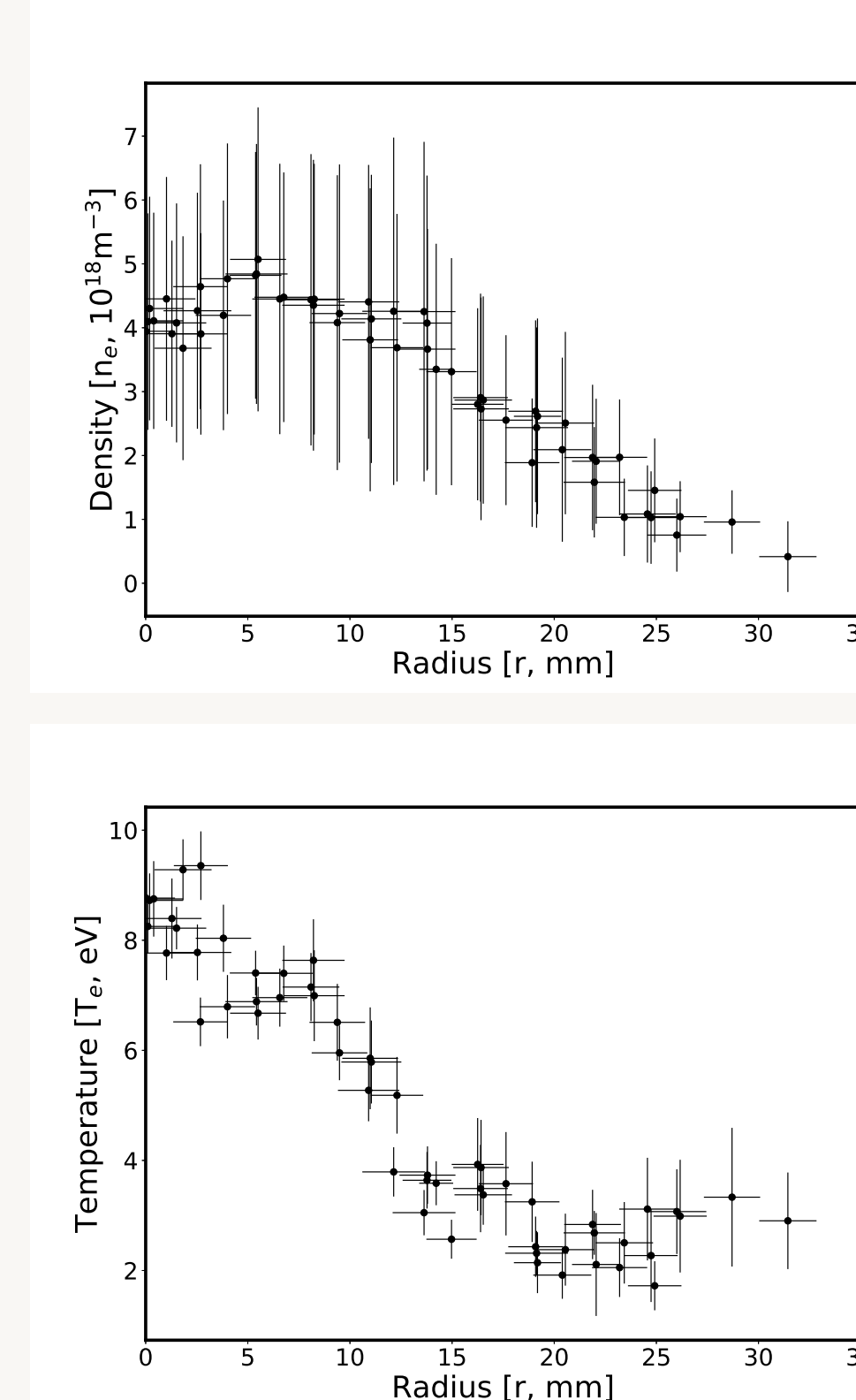
- Simulating PISCES-A linear device provides experimental benchmarking for impurity transport model and is a step towards modeling ITER tungsten components
- Comparison of impurity erosion, ionization, migration, and re-deposition model to experiment is essential before moving to more complicated cases
- Understanding sensitivity of impurity transport model to input parameters will enable quantification of uncertainty in net erosion, net deposition, and impurity density profiles
- Plasma profiles are measured by reciprocating probe 30cm upstream from the target and provide profiles for electron temperature, density, and ion flux



- FASTMath/UQ target: represent and propagate uncertain input profiles of density and temperature fields

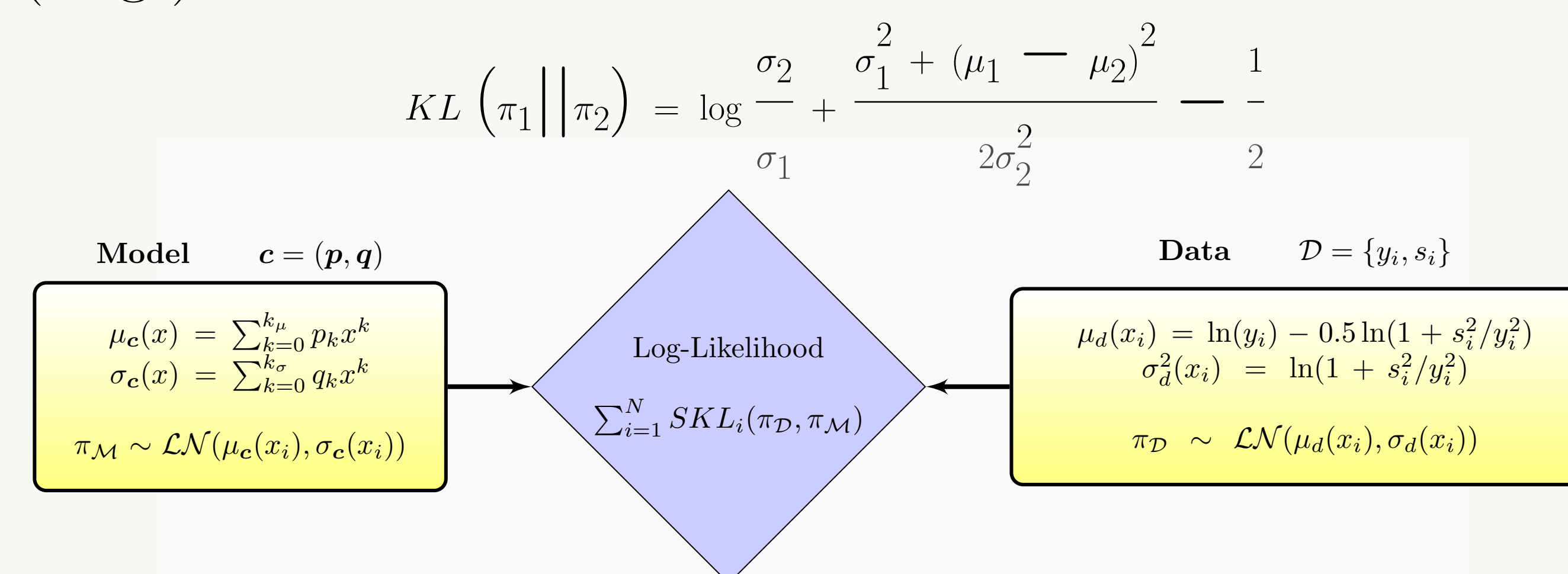
Bayesian Inference of Input Profiles

- Data on density and temperature
- Parameterize n_e and T_e profiles with uncertainty in order to propagate through impurity transport code, GTR
- Assume data is lognormal
- Assume the fit model is lognormal with polynomial log-mean $\mu(x)$ and log-stdev $\sigma(x)$
- Employ Bayesian inference with approximate likelihood set to symmetrized Kullback-Leibler (KL) divergence

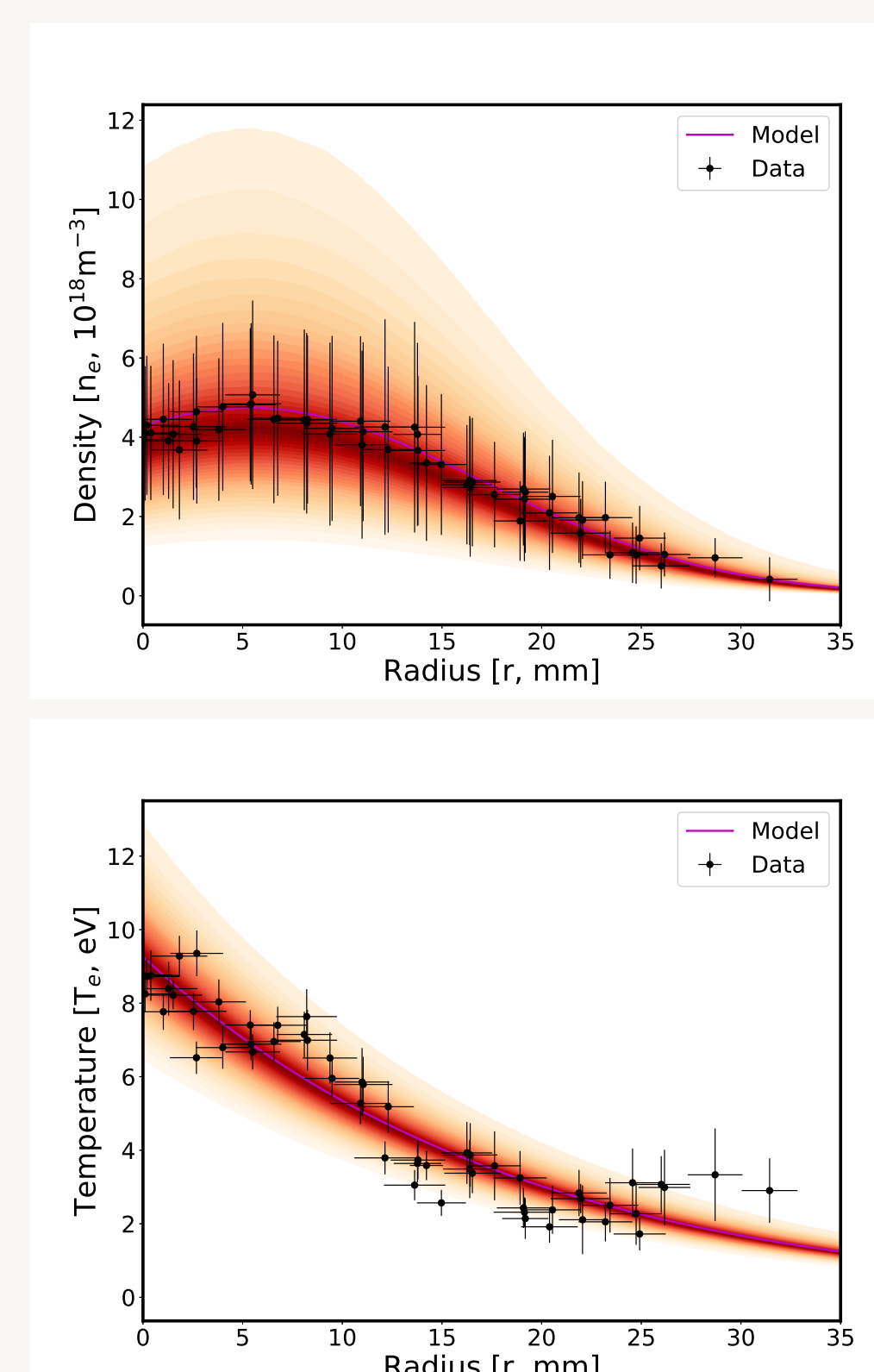


$$\log L_{\mathcal{D}}(\mathbf{c}) = -\sum_{i=1}^N [KL_i(\pi_{\mathcal{M}}||\pi_{\mathcal{D}}) + KL_i(\pi_{\mathcal{D}}||\pi_{\mathcal{M}})]$$

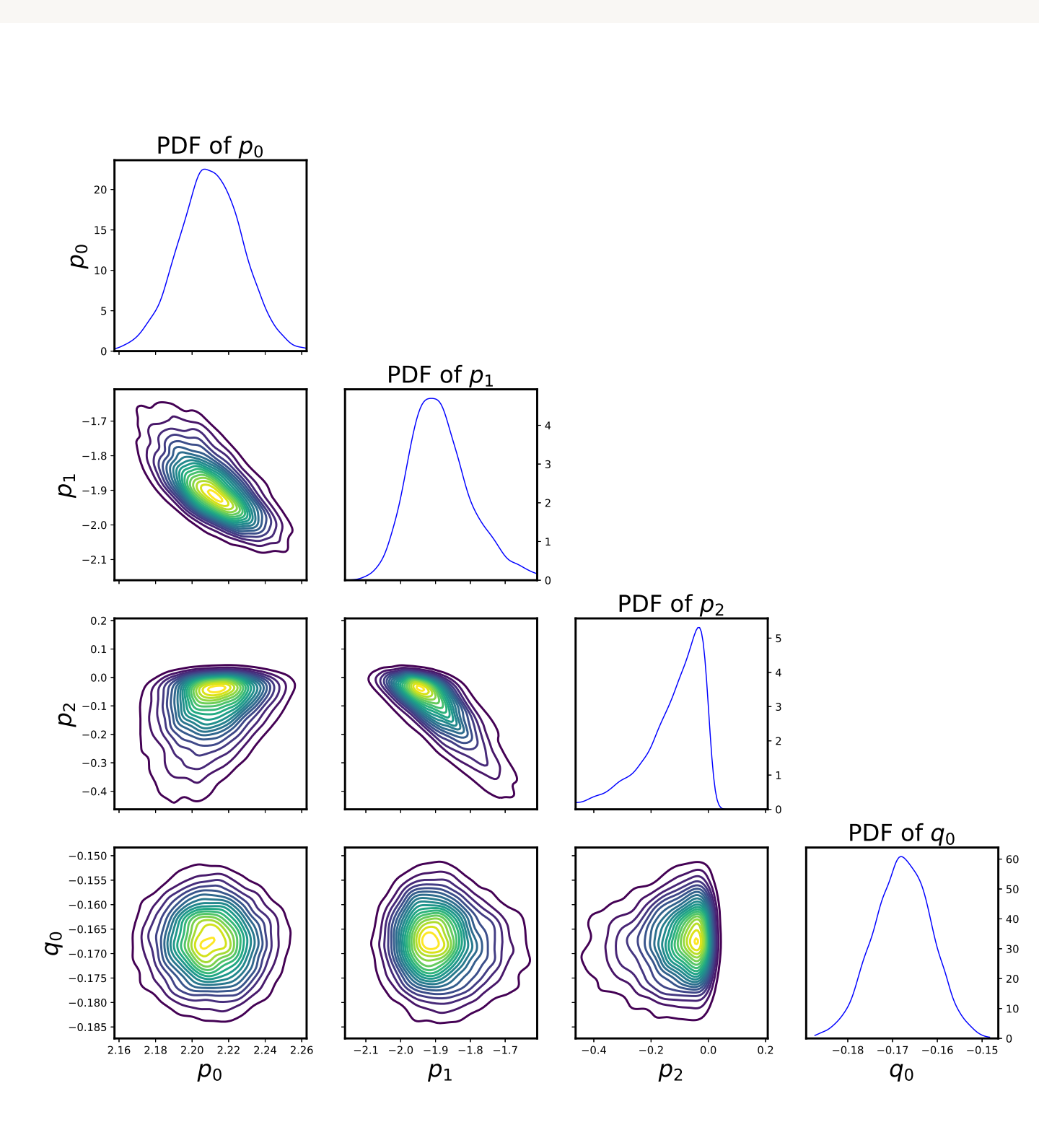
- (Log-)normal KL



Posterior predictive profiles



Posterior PDFs of polynomial coefficients

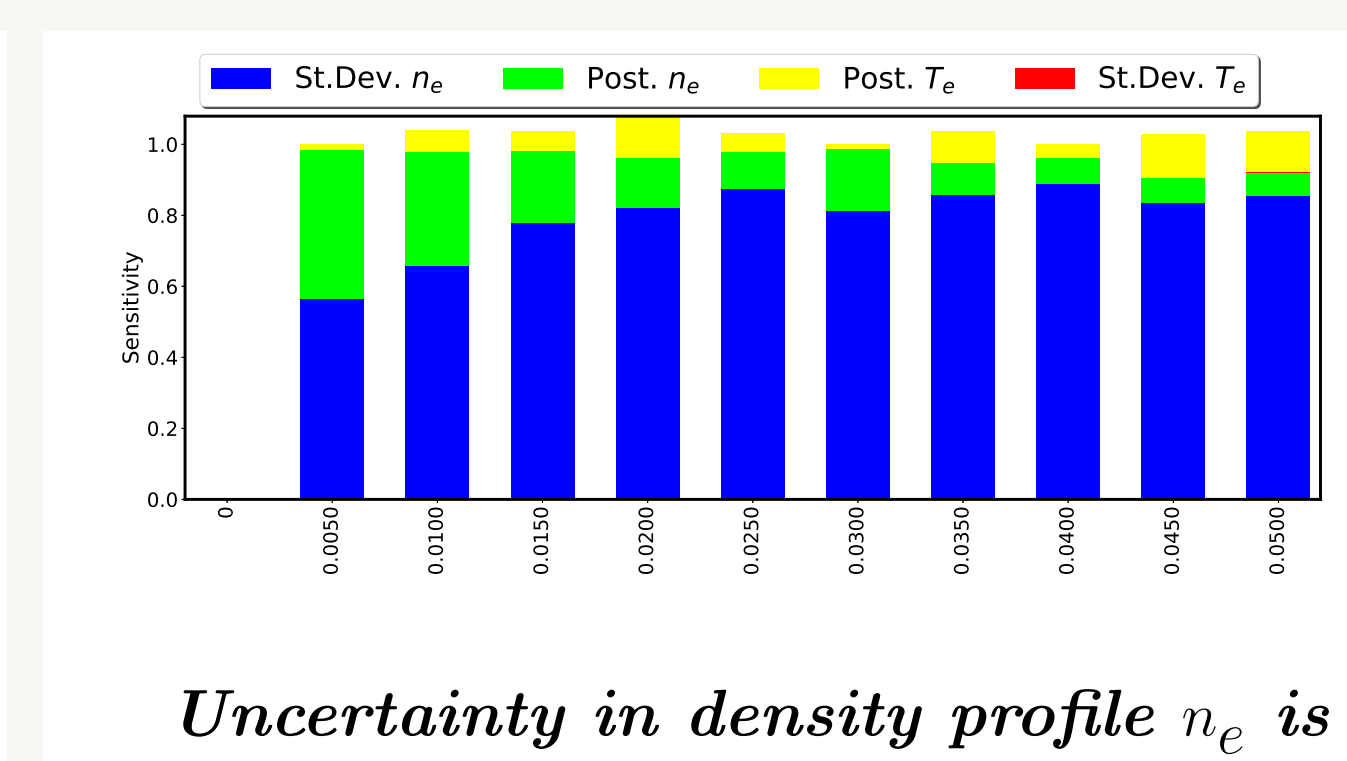
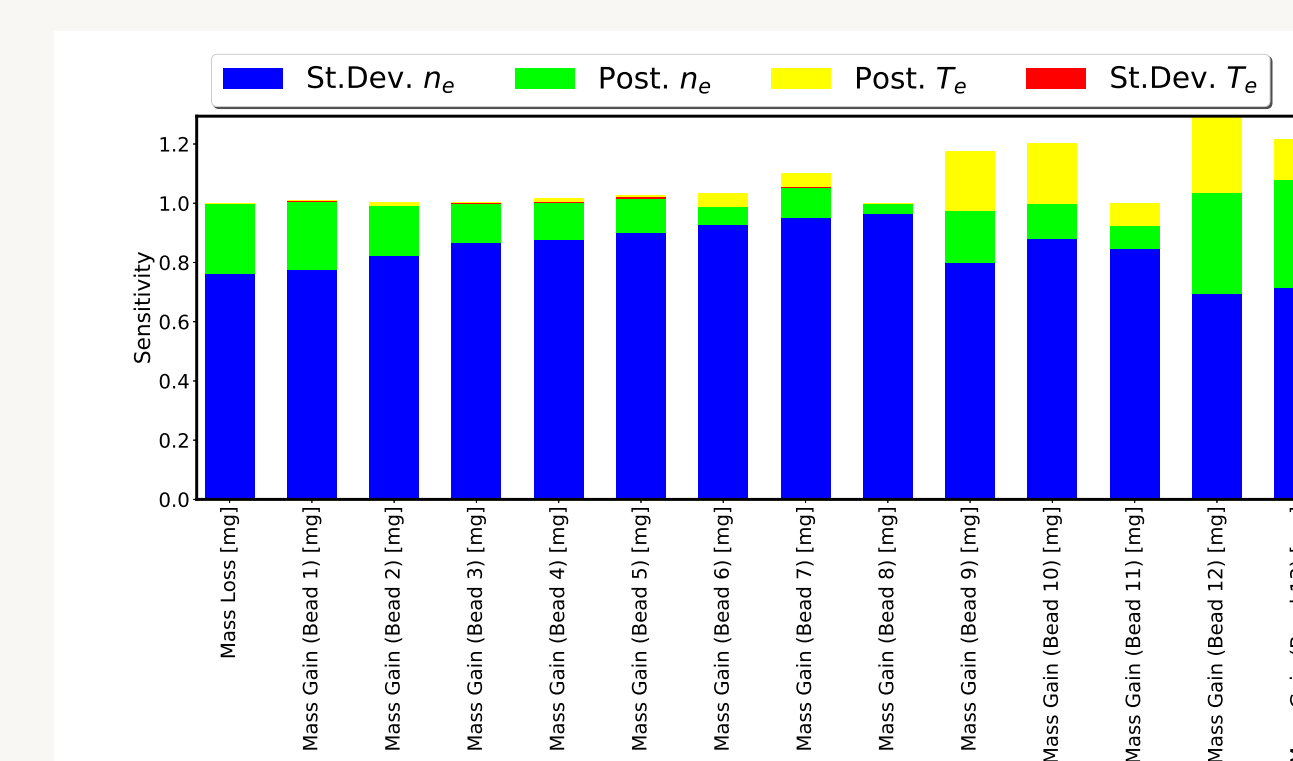
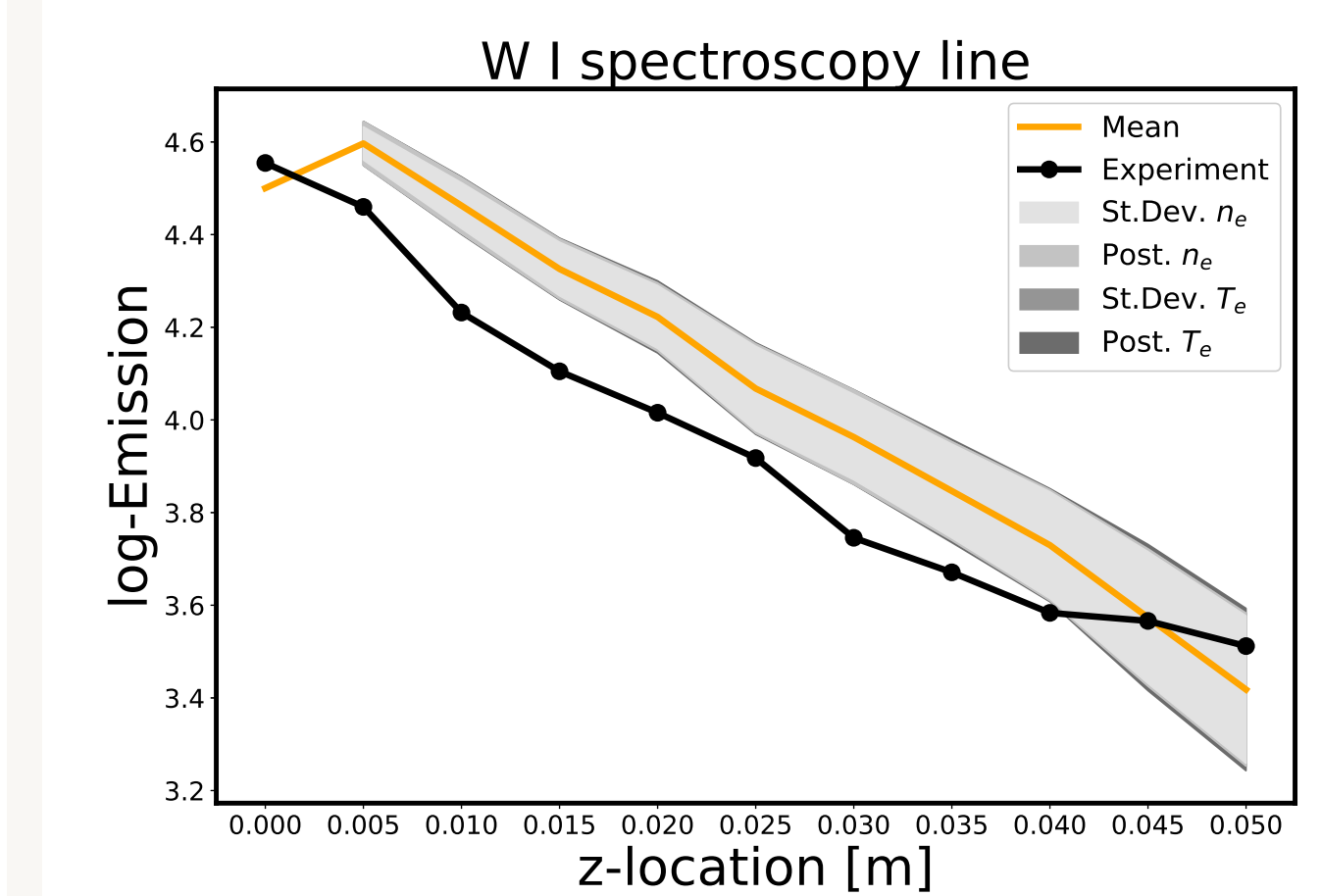
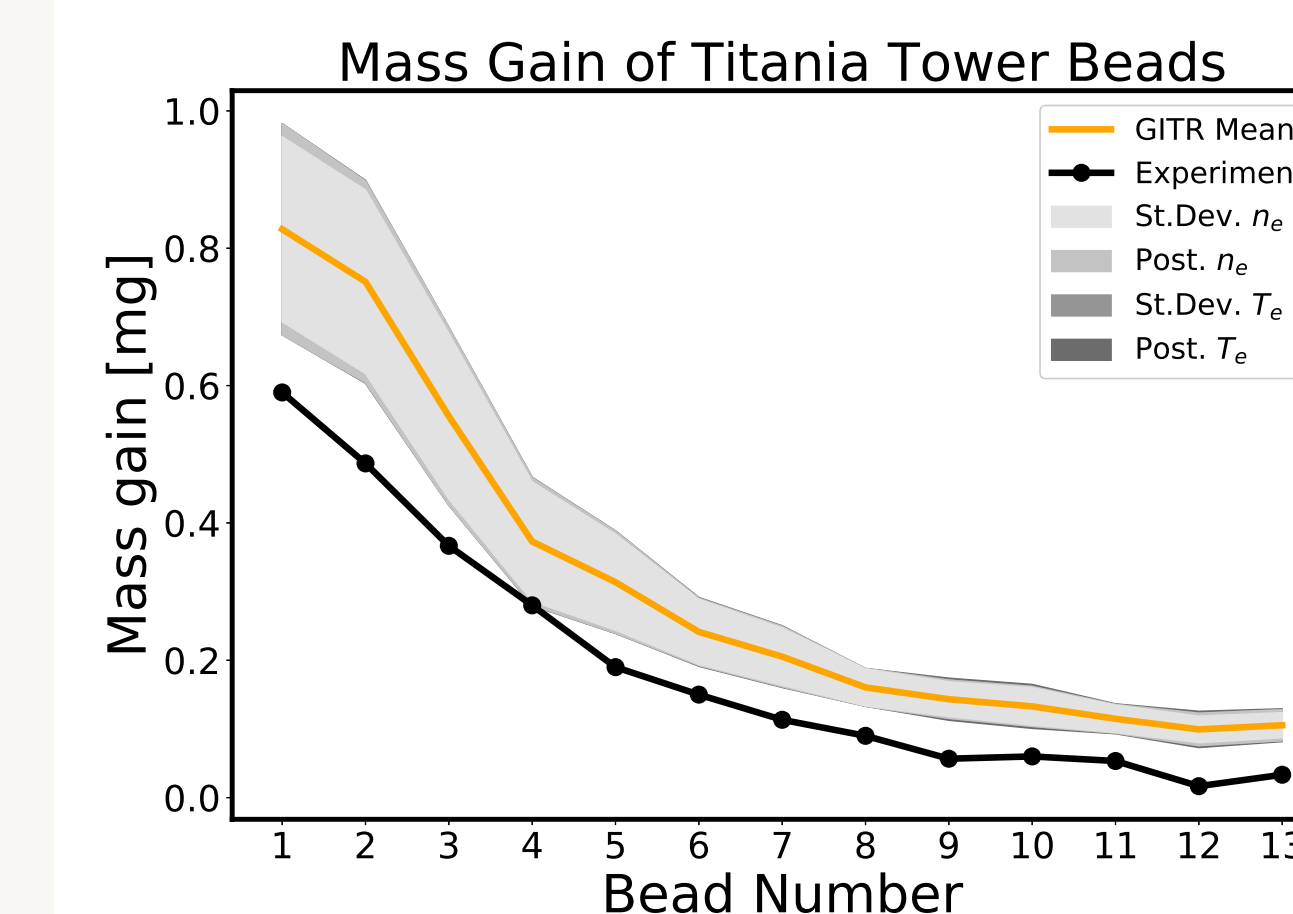


Uncertainty Propagation via PC

- Parameterize posterior PDF of polynomial coefficients with Polynomial Chaos (PC) expansion $\mathbf{c} = \mathbf{c}(\xi)$
- Augment $\xi = (\xi_1, \dots, \xi_K)$ with the input profiles stochasticity ξ_{K+1} to get $\tilde{\xi} = (\xi, \xi_{K+1})$
- Propagate input profiles...
$$f(x; \tilde{\xi}) = \exp(\mu_{\mathbf{c}(\tilde{\xi})}(x) + \sigma_{\mathbf{c}(\tilde{\xi})}(x)\xi_{K+1})$$
- ... through any model G (GTR in this case)

$$G(f(x; \tilde{\xi})) = g(\tilde{\xi}) = \sum_{j=0}^J g_j \Psi_j(\tilde{\xi})$$

GTR Prediction and Uncertainty Attribution



Uncertainty in density profile n_e is the main contributor to output variance

Summary

- Formal UQ for representing uncertain input profiles
- Uncertainty propagation through GTR, the impurity migration module of an integrated simulation for plasma surface interactions
- UQ Toolkit has been employed for both Bayesian inference and PC representations (www.sandia.gov/uqtoolkit)
- Next, augment the input profiles with the rest of the uncertain inputs, deal with the high-dimensionality