

# Bayesian inference of tungsten transport coefficients from laser blow-off experiments in ASDEX Upgrade

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## INTRODUCTION AND MOTIVATION

1. Low-Z impurities (He, Ne, Ar, N,...) mostly dilute the main fuel ions
2. High-Z impurities (W) increase the radiative cooling of the plasma
  - a. High-Z ions accumulating on-axis can trigger a radiative collapse
  - b. Radiation of the W ions can deteriorate the fusion gain
3. To infer the transport coefficients  $D$  and  $V$ , we solve an ill-posed inverse problem by inverting the following forward model (Aurora [1,2]):

$$\frac{\partial n_{I,Z}}{\partial t} = -\frac{1}{r} \frac{\partial}{\partial r} (r \Gamma_{I,Z}) + S_{I,Z}$$

$$\Gamma_{I,Z} = -D \frac{\partial n_{I,Z}}{\partial r} + v n_{I,Z}$$

Diffusion coefficient  $D$   
Convective velocity  $V$

Impurity density  $n$

Synthetic diagnostics  $\epsilon_I = n_e n_I L_I(T_e, n_e)$

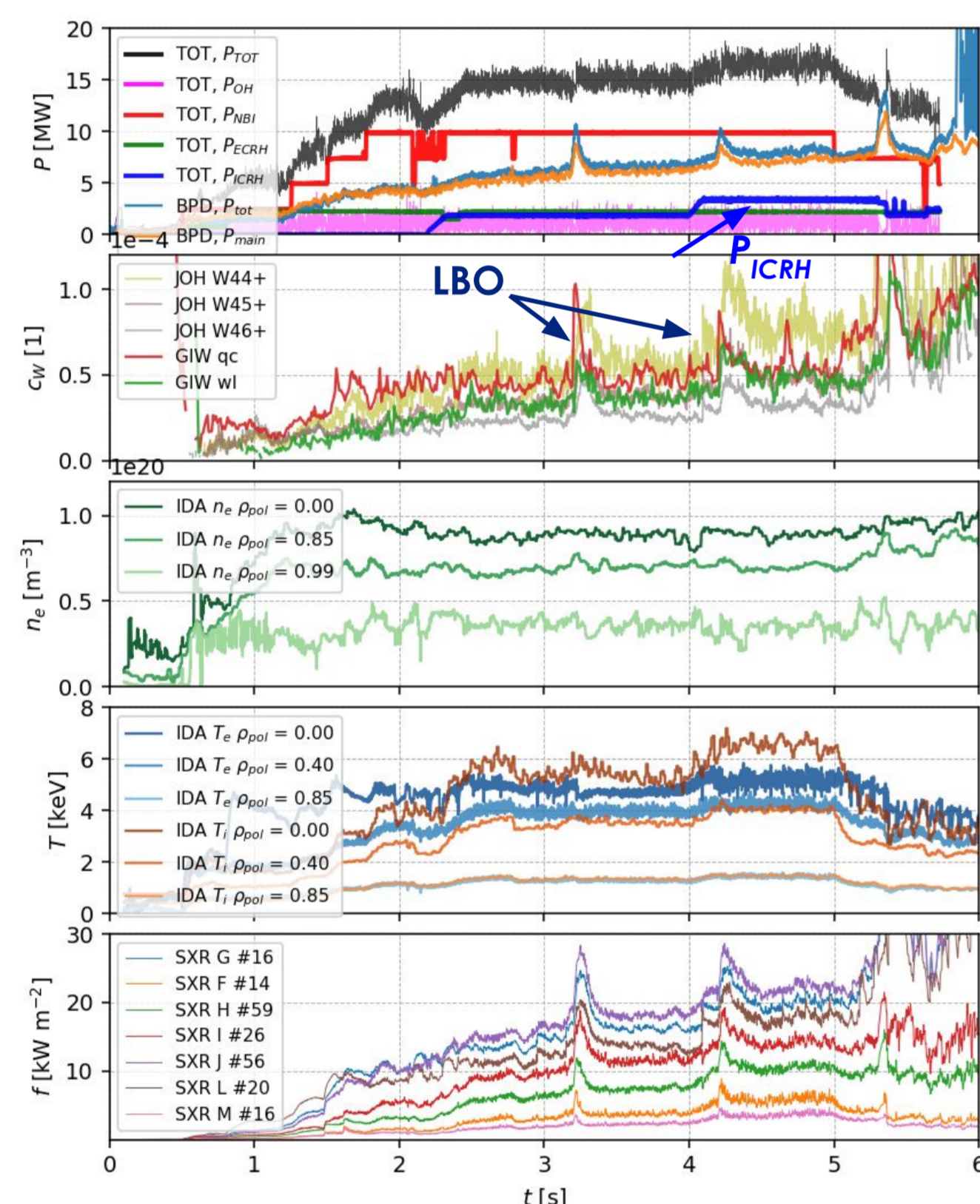
Forward model

Trace limit  $n_{I,Z} Z^2 \ll 1$

## EXPERIMENTAL DATA

Two successful LBOs in ASDEX Upgrade discharge #37614

1. at 3.15 s with  $P_{ICRH} = 1.8$  MW
2. at 4.15 s with  $P_{ICRH} = 3.3$  MW

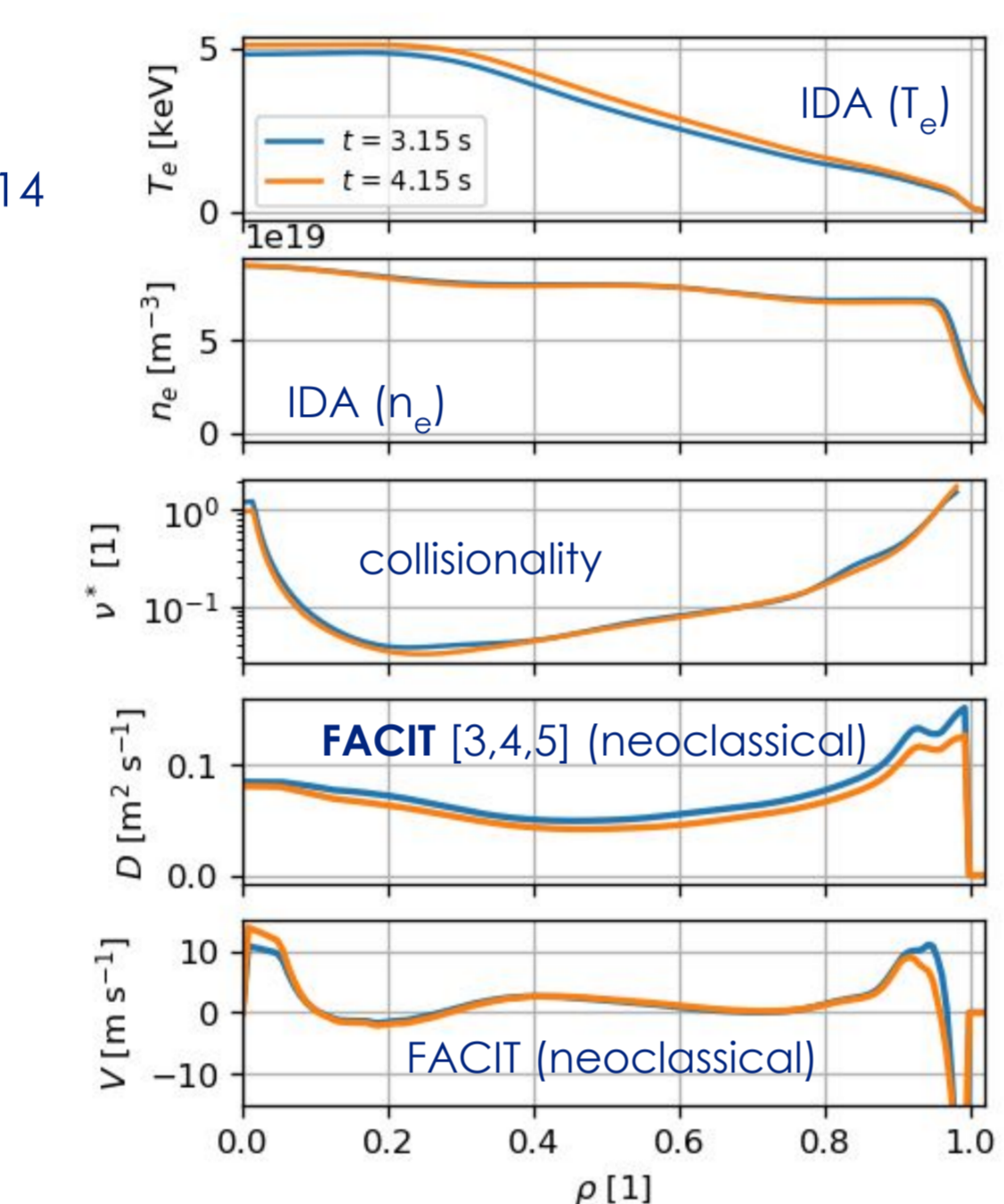
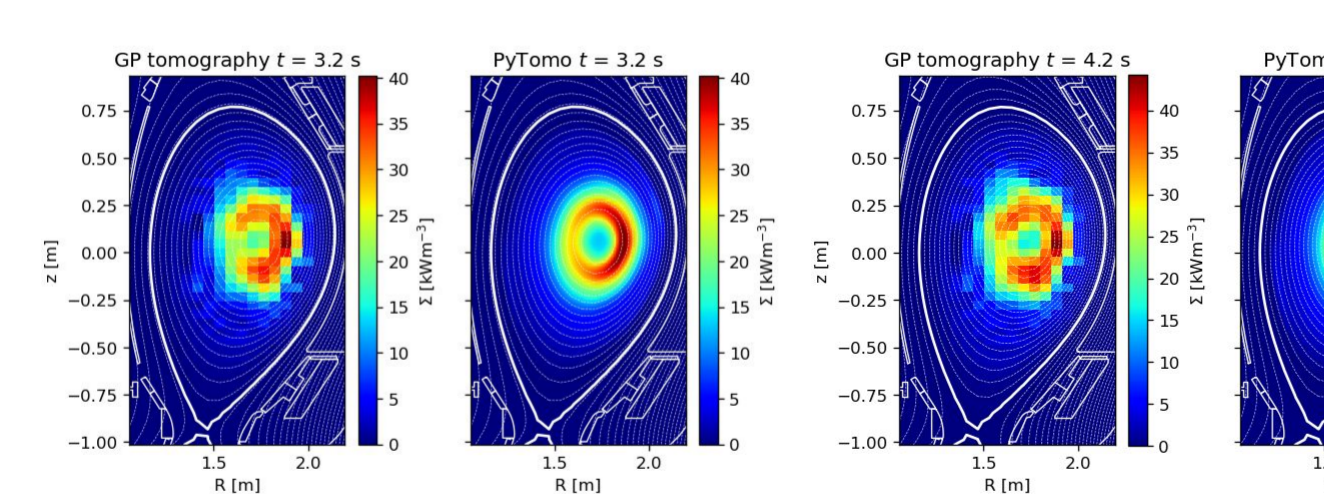


Input data for inference: soft X-ray camera data processed using Gaussian process tomography [10]

1. Non-stationary Gibbs kernel
2. Hyperparameters inferred via MCMC sampling
3. Compared with AUG tomography (PyTomo)

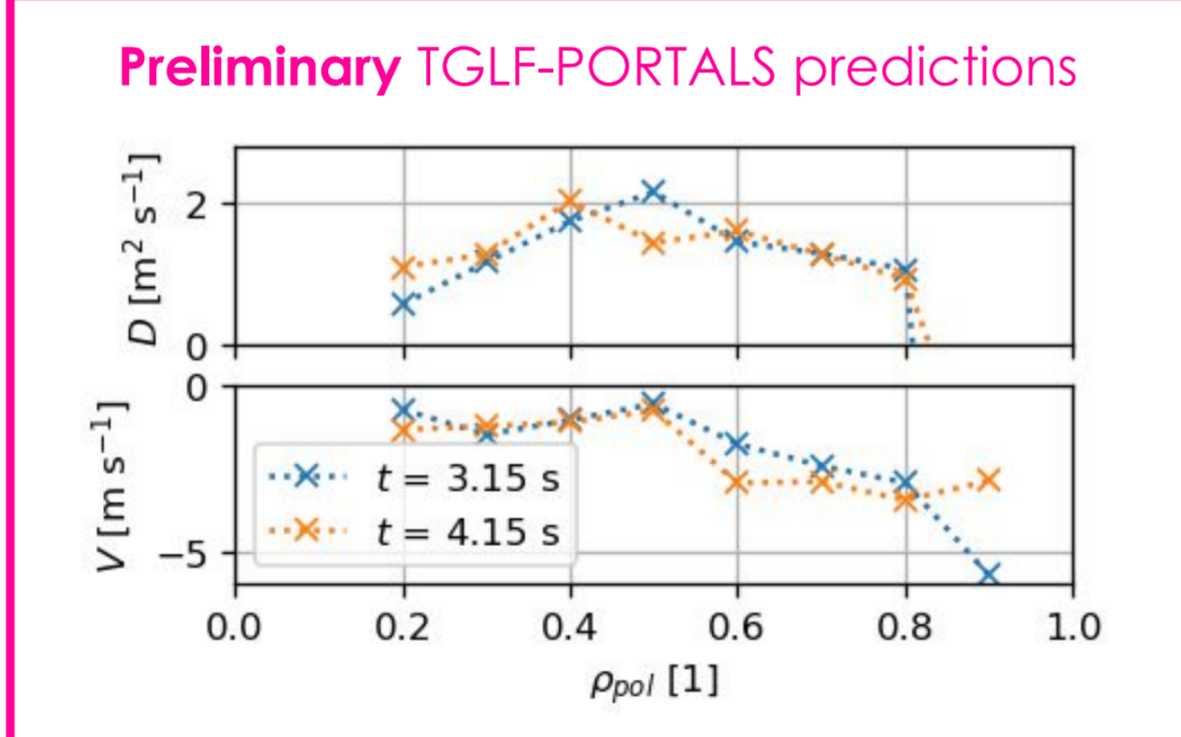
$$\hat{\mu}_{\text{post}} = \hat{\mu}_{\text{prior}} + (\Sigma_{\text{prior}}^{-1} + M^T \Sigma_d^{-1} M)^{-1} M^T \Sigma_d^{-1} (\hat{d} - M \hat{\mu}_{\text{prior}})$$

$$\Sigma_{\text{post}} = (\Sigma_{\text{prior}}^{-1} + M^T \Sigma_d^{-1} M)^{-1}$$



Preliminary anomalous transport - TGLF [6,7] predictions

1. Performed within the MITIM-PORTALS [8,9]
2. SAT2 saturation rule used
3. Power-balance profiles not yet available  $\Rightarrow$  METIS profiles used temporarily



## MODEL

$$P(\theta | d_{\text{SXR}}, M) \propto P(d_{\text{SXR}} | \theta, M) P(\theta | M)$$

1. Gaussian process (GP) prior for  $D$  and  $V$  profiles with stationary RBF kernel on 5 non-uniformly spaced nodes
2. Infers GP hyperparameters and latent variables together in a single run
3. Prior mean defined via a hyperbolic tangent function to describe core/pedestal behavior
4. Nested sampling with a slice sampler (UltraNest [11,12])  $\Rightarrow$  wall-time  $\sim 72$  hours per run on 36 CPUs

Priors (18 parameters in total):

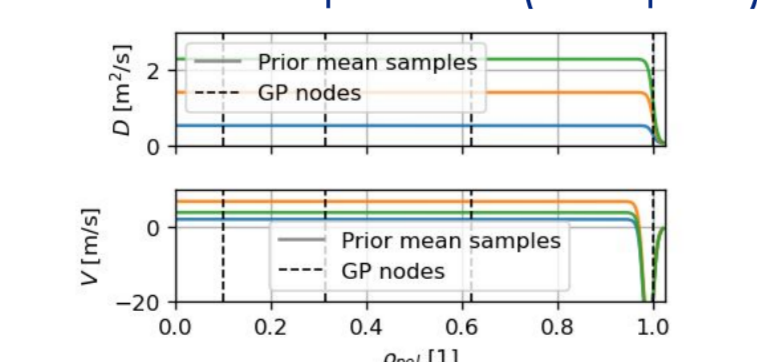
$$\ln(S_{\text{div}}) \sim \mathcal{N}(\mu, \sigma^2), \quad \ln(S_{\text{LBO}}) \sim \mathcal{N}(\mu, \sigma^2)$$

$$\ln(\theta) \sim \mathcal{N}(\mu, \sigma^2) \quad \text{for } \theta \in \{D_{\text{core}}, \ell_D, \sigma_D, \ell_V, \sigma_V\}$$

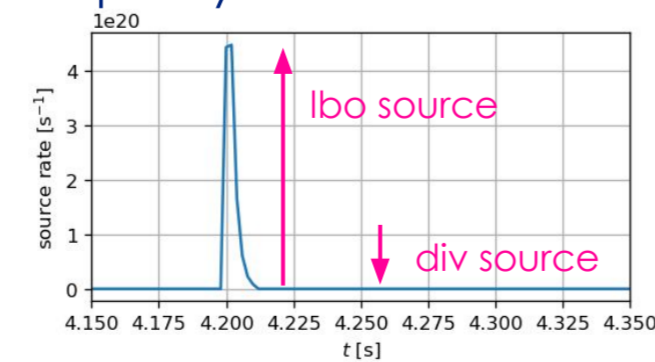
$$V_{\text{core}} \sim \mathcal{N}(\mu, \sigma^2)$$

$$\eta_{D,i}, \eta_{V,i} \sim \mathcal{N}(0, 1) \quad \text{for } i = 1, \dots, N_{\text{nodes}}$$

Prior mean profiles (samples)

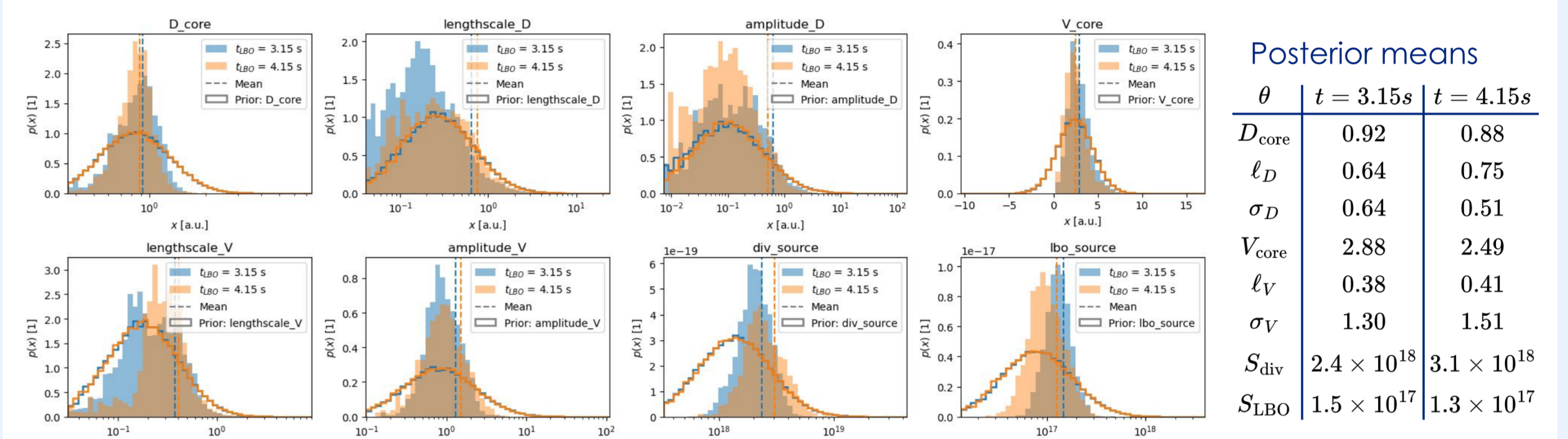


Impurity source function

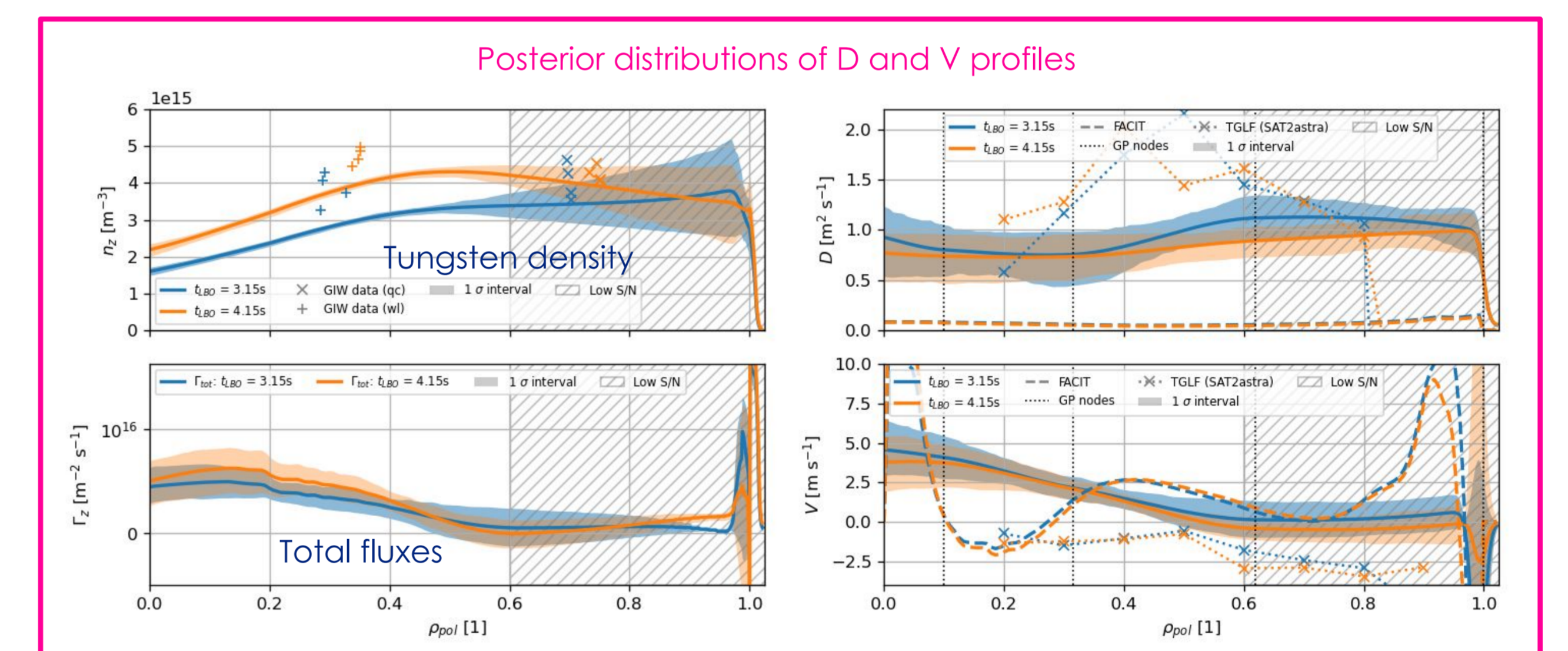
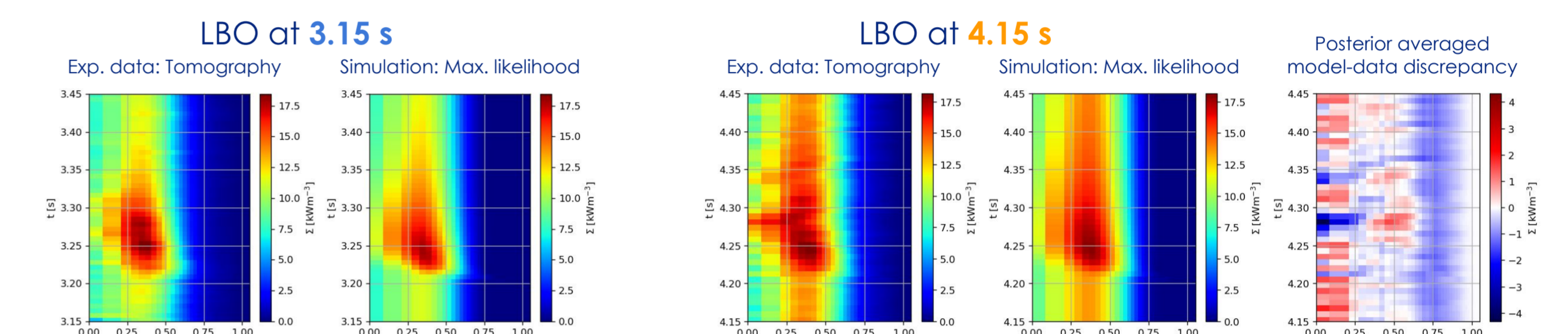


## RESULTS

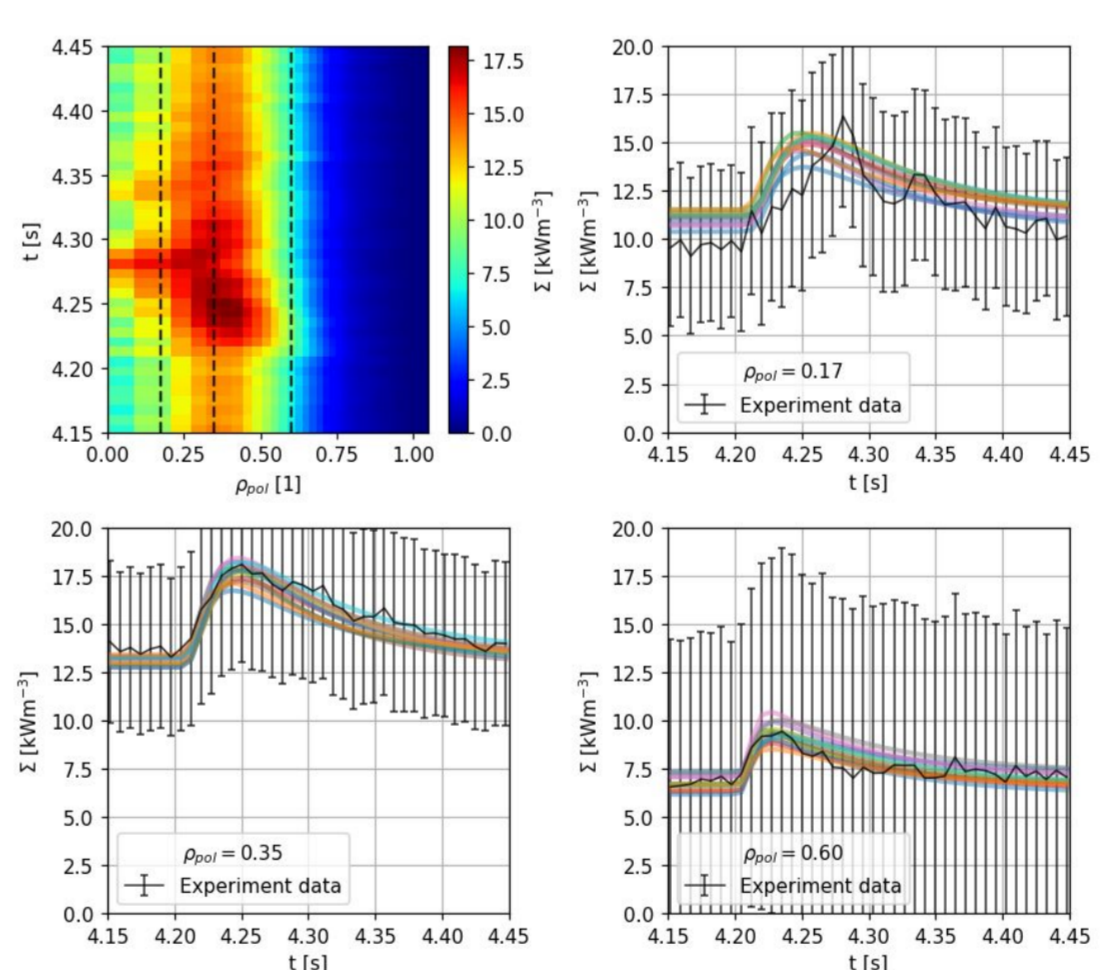
Marginal posterior distributions (histograms) for both LBOs (at 3.15 s and 4.15 s)



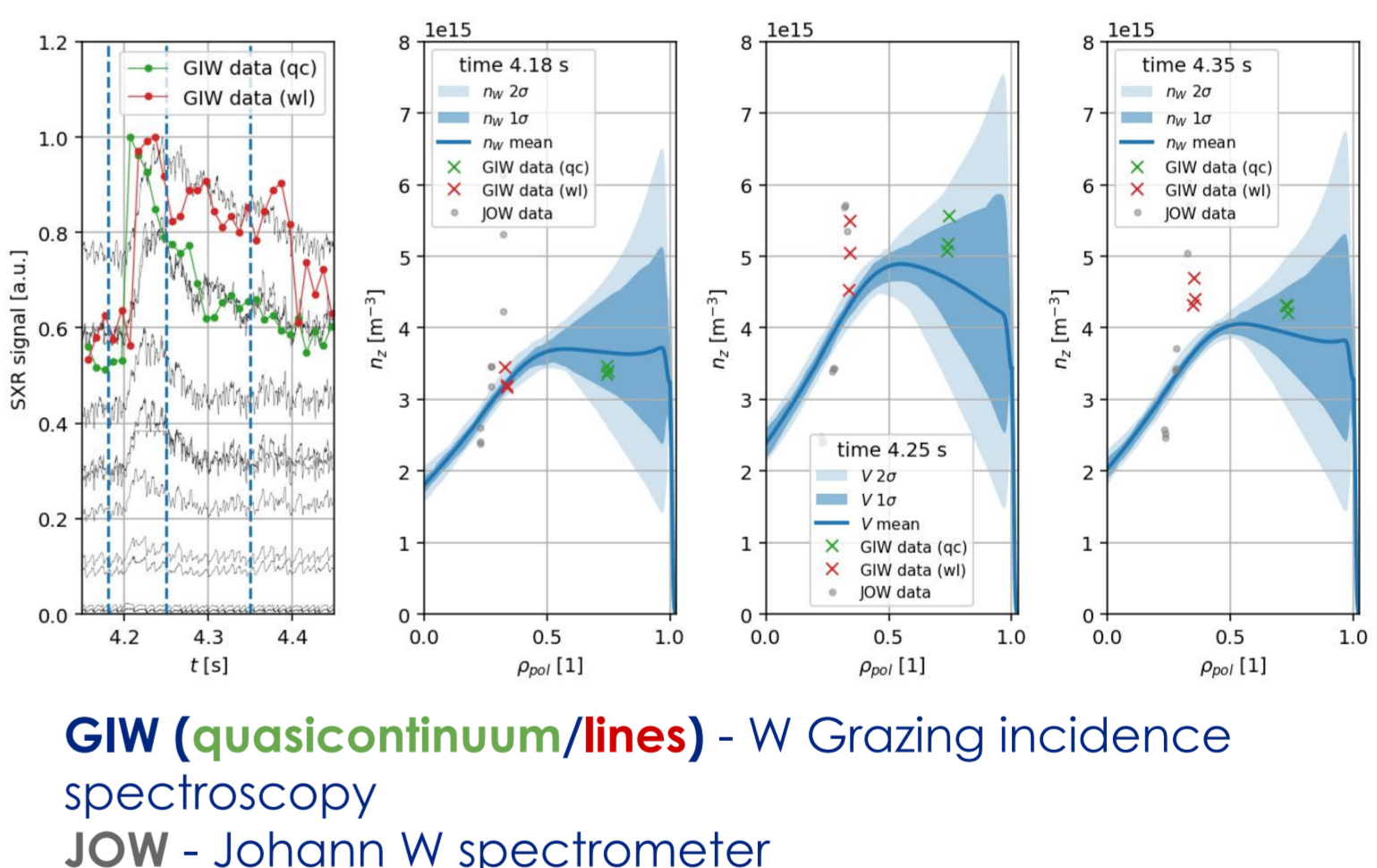
Good agreement between the synthetic data (evaluated at maximum likelihood) and the experimental data



Posterior predictive realizations vs. Experimental data (SXR GP tomography)



Posterior predictive distribution vs. Independent spectroscopy data

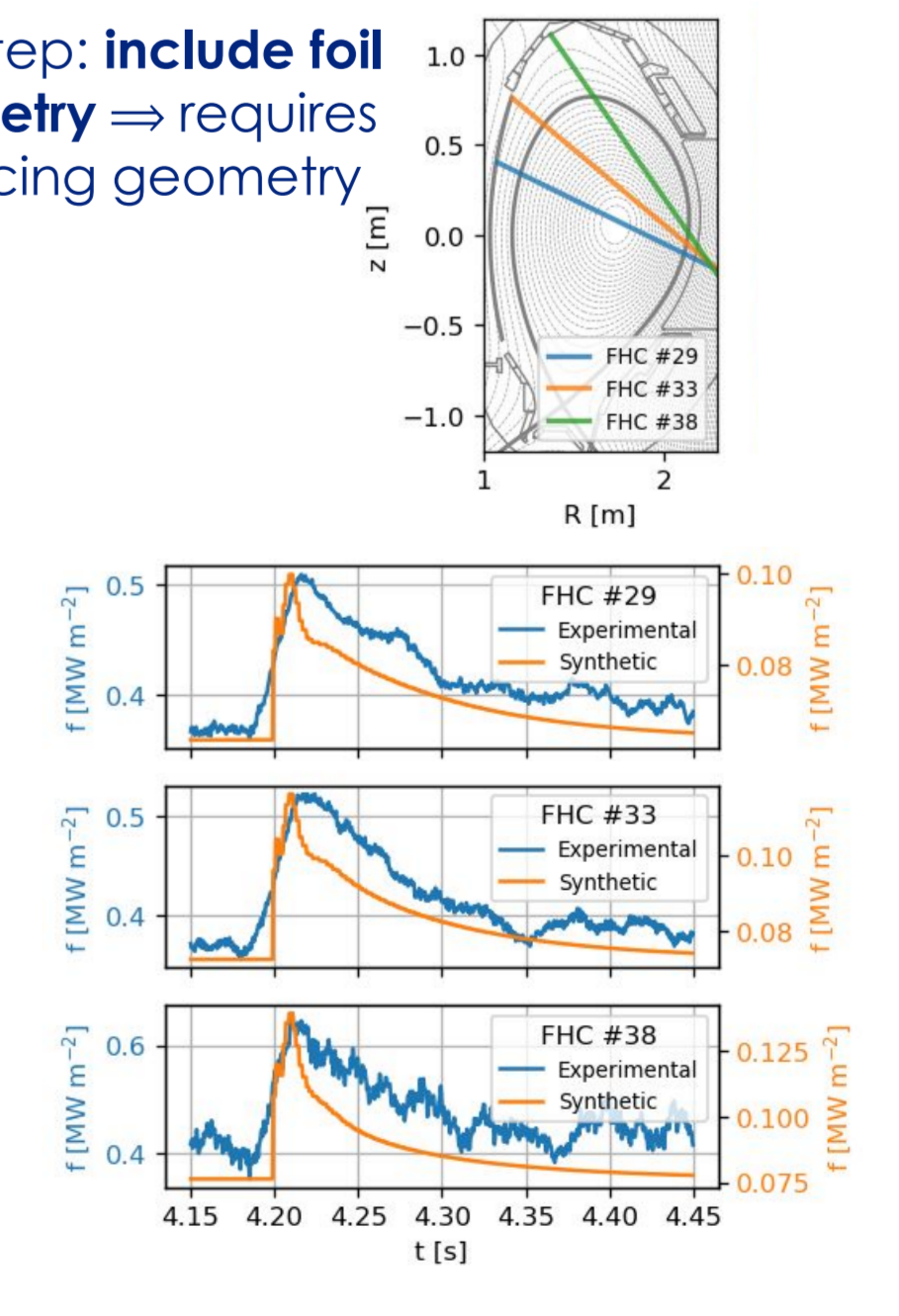


GIW (quasicontinuum/lines) - W Grazing incidence spectroscopy  
JOW - Johann W spectrometer

## CONCLUSION AND FUTURE PLANS

1. Developed a tool to infer  $D$  and  $V$  profiles from LBO experiments
2. Best performance with GP prior
3. Hyperparameters inferred for subsequent use
4. Good agreement between Aurora simulations and SXR tomography
5. The model remains weakly constrained at the plasma edge  $\Rightarrow$  additional edge diagnostics
6. No significant difference observed between experiments in #37614  $\Rightarrow$  different shots/experiments
7. TGLF results need to be derived from power balance, work in progress on the integrated modelling

Next step: include foil bolometry  $\Rightarrow$  requires raytracing geometry matrix



This work has been carried out within the framework of the EUROfusion Consortium, funded by the European Union via the Euratom Research and Training Programme (Grant Agreement No 101019720 - EUROfusion). Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Commission. Neither the European Union nor the European Commission can be held responsible for them. This work was supported by the Ministry of Education, Youth and Sports of the Czech Republic through the e-INFRA CZ (ID:90254).

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