



Applications of Bayesian data analysis at W7-X stellarator



Maciej Krychowiak, S. Kwak, J. Svensson, S. Bannmann, F. Henke, D. Gradic, O. Ford, R. König, et al.

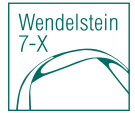


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- Basics of Bayesian data analysis
- Core: Inference of electron density profiles and particle sources from BES
 - Complexity
- Edge: Gaussian Process Tomography of carbon radiation in divertor plasma
 - Model (hyperparameters) optimization
- Wall: Ellipsometry to measure parameters of thin layer coating on first wall components
 - Bayesian diagnostic design

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Bayesian approach: constructing the posterior distribution

- Model evidence $P(D)$
 - Optimisation of model parameters (hyperparameters)

Example emission tomography

Posterior probability distribution

$$P(Z_{eff}) = \frac{P(D|Z_{eff}) \times P(Z_{eff})}{P(D)}$$

- Explore posterior distribution to find
 - Most probable solution
 - Uncertainties of inferred parameters
 - Correlations between parameters

Analysis in all three cases done in the Minerva Bayesian modeling framework

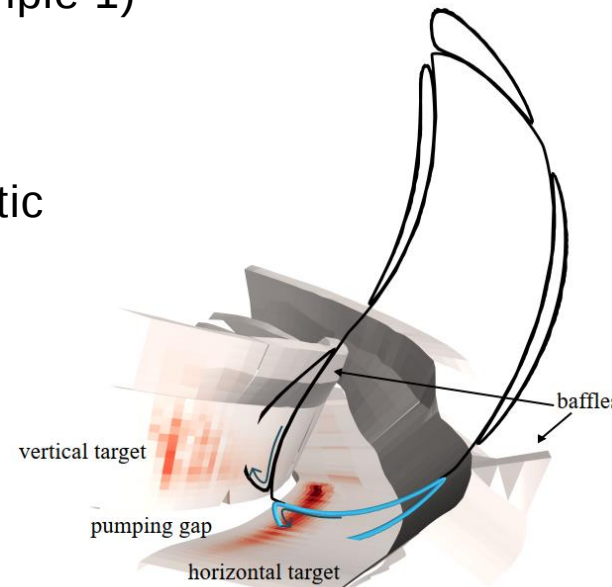
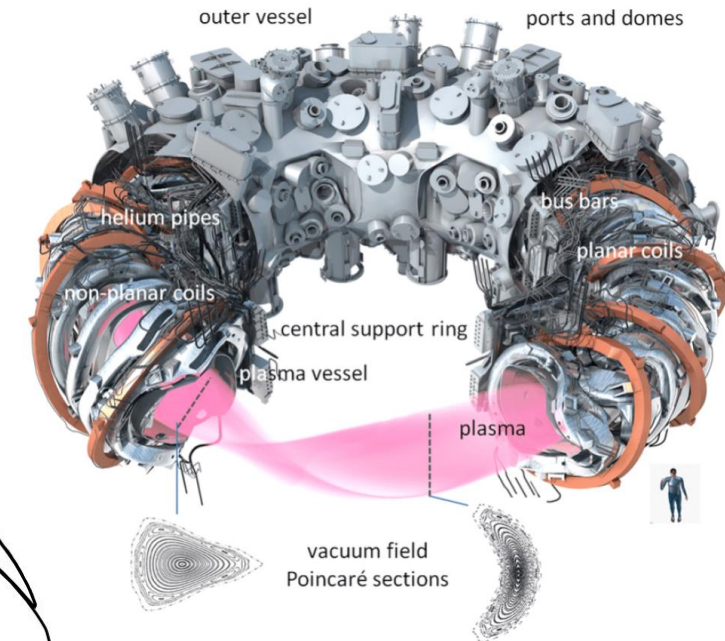
Seed eScience Research

W7-X: superconducting stellarator with island divertor

- Largest stellarator in the world ($R = 5$ m)
- Superconducting magnetic field coils
- Long pulse operation (30 min.)
- Intensive program on plasma wall interaction (example 3)
- Optimised to reduce neoclassical transport
- Turbulent transport the major player (example 1)

Island divertor

- Plasma-wall interaction defined by magnetic islands cutting divertor surface
- At 10 discrete divertor modules
- One of the goals: impurity retention
- Therefore tomographic reconstruction of impurity emission in divertor (example 2)



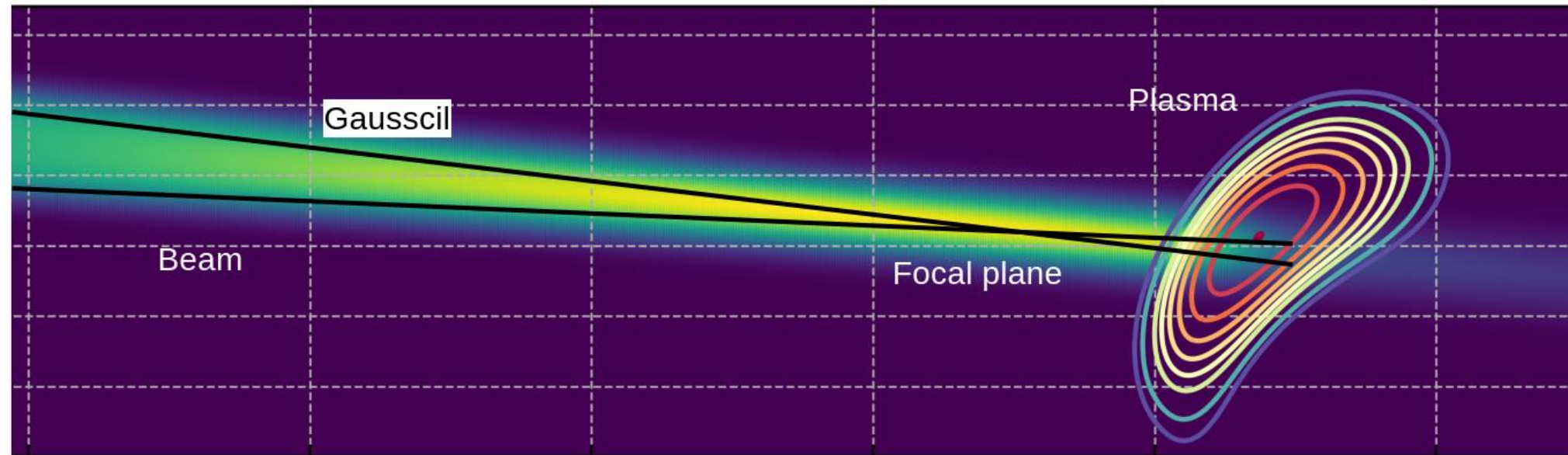
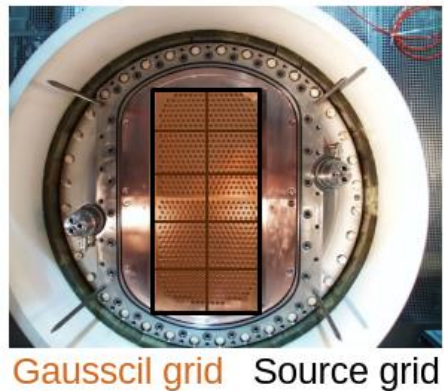
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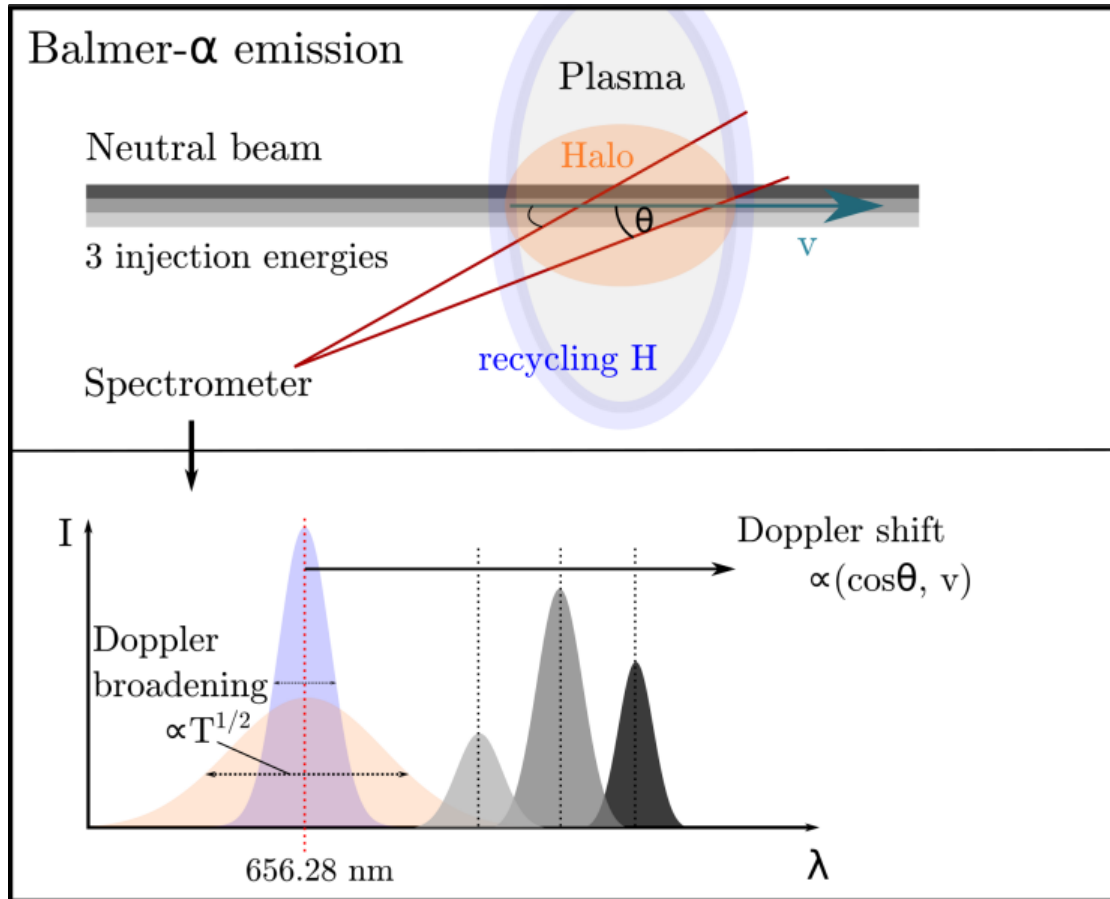
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Neutral Beam Injection for heating at W7-X

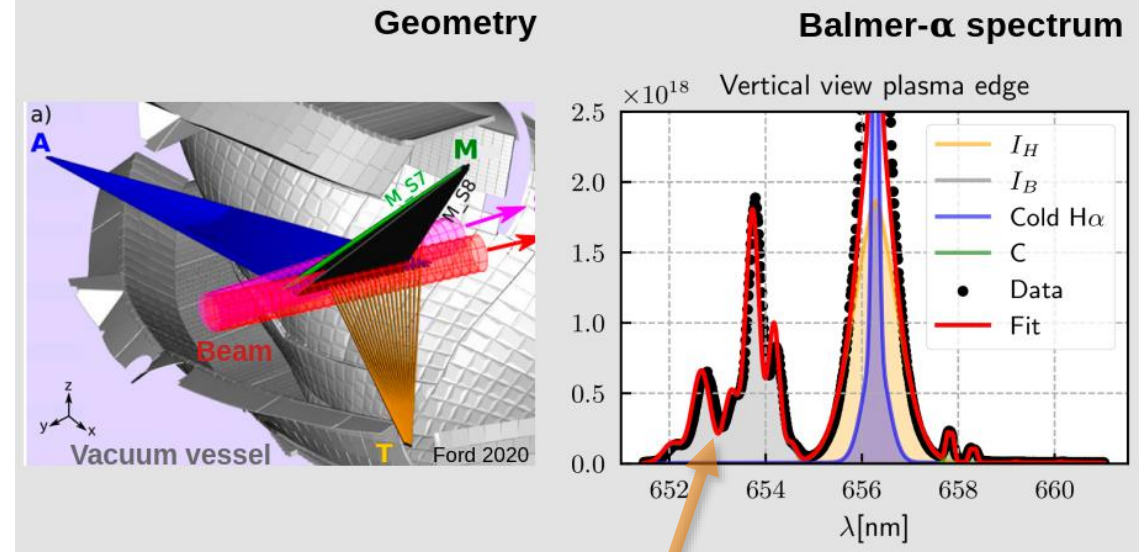
- 4 out of 8 planned beams commissioned so far
- Radial injection, 1.8 MW/source, 55 keV
- The source grid made up of pinholes → Several Gaussian beamlets used in the model



Spectral composition of beam emission



BES + CXRS spectroscopy system (W7-X)



Additional splitting due to MSE

- Up to 54 lines of sight from three different ports used
- Complex spectra fitted well

Model of beam particle emission

- Collisional-radiative model
 - Needed to model beam attenuation and emission
 - Track ground state + 5 excited states

$$\frac{d\Phi(u)}{du} = \frac{1}{v_b} \mathbf{T}_{CR} \Phi(u) \quad \text{Neutral flux}$$

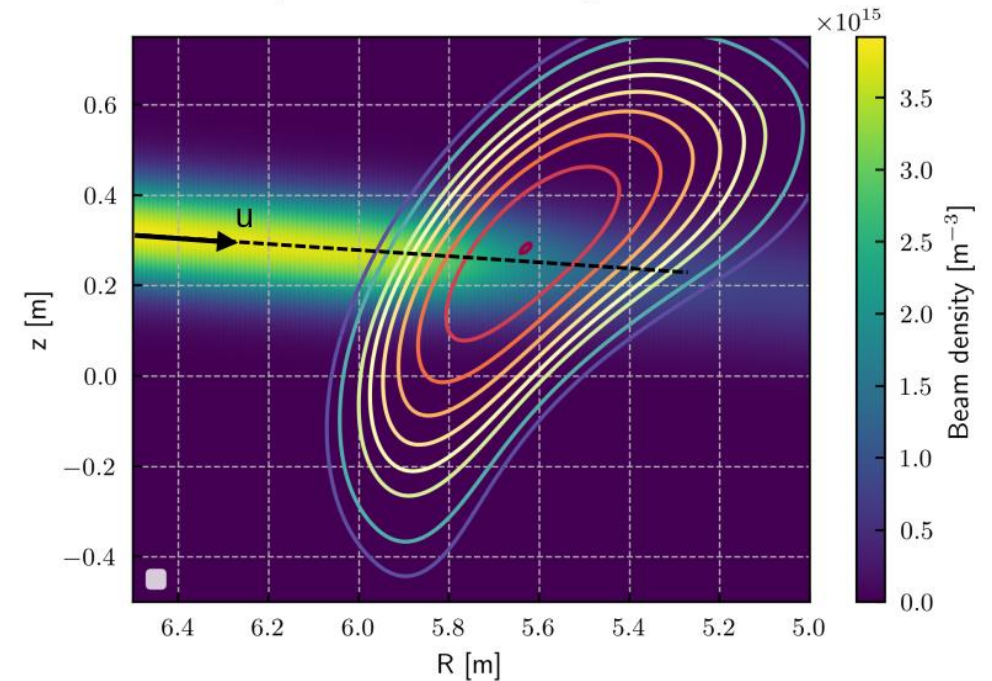
$$\mathbf{T}_{CR} = \mathbf{T}_{CR}(T_e, T_i, n_e) = \begin{bmatrix} -L_1 & A_{21} & A_{31} & \cdot & A_{k1} \\ E_{12} & -L_2 & A_{32} & \cdot & A_{k2} \\ E_{13} & E_{23} & -L_3 & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & A_{ki} \\ E_{1k} & E_{2k} & \cdot & E_{jk} & -L_k \end{bmatrix} \quad \text{ColRad matrix}$$

$$E_{ij} = n_e \langle \sigma_e^{(ij)} v \rangle + n_p \langle \sigma_p^{(ij)} v \rangle \quad \text{Excitation rate}$$

$$L_i = \Delta_i + \sum_{m=i+1}^k E_{im} + \sum_{m=1}^{i-1} A_{im} \quad \text{Total losses}$$

$$\Delta_i = n_e \langle \sigma_e^{(iI)} v \rangle + n_p (\langle \sigma_p^{(iI)} v \rangle + \sum_{j=1}^k \langle \sigma_{CX}^{(ij)} v \rangle) \quad \text{Ionization losses}$$

Computed beam density distribution



- Differential equations solved stepwise along each beamlet

Model of halo emission



- CX collisions of beam particles with background ions are source of the beam halo

Halo source term

$$S_{\text{DCX}}^{(i)} = n_p \sum_{j=1}^k n_{\text{B}}^{(j)} \langle \sigma_{\text{CX}}^{(ij)} v \rangle$$

Halo density

$$\mathbf{n}_{\text{Ha}} = (n_{\text{Ha}}^{(1)}, \dots, n_{\text{Ha}}^{(i)}, \dots, n_{\text{Ha}}^{(k)})$$

- Halo particles undergo several CX collisions
- Travel ballistically between them → **Diffusion ansatz**

Diffusion ansatz

$$D_{\text{CX}}^{(i)} = \frac{v_{\text{th}}^2}{2n_p \sum_{j=1}^{j_{\text{max}}} \langle \sigma_{\text{CX}}^{(i \rightarrow j)} v_r \rangle}$$

Assumptions

$$\begin{aligned} \partial_t \mathbf{n} &= 0 \\ \Delta_z, \Delta_\phi &\ll \Delta_r \end{aligned}$$

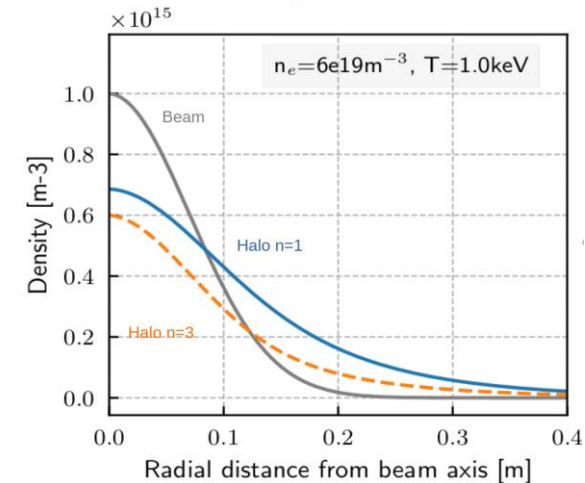
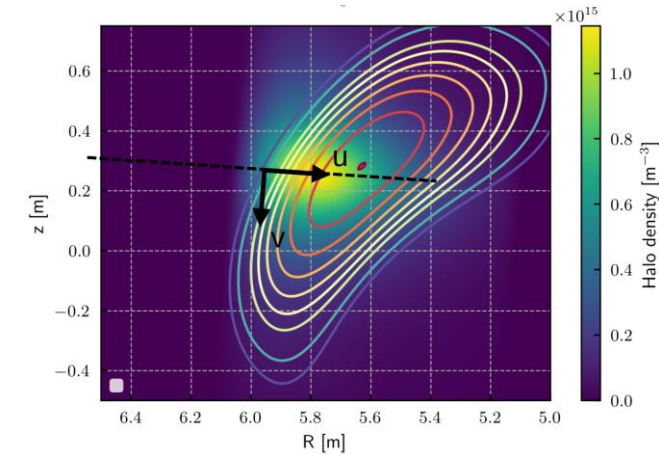
- 1D diffusion equation coupled to CR model

$$-\nabla_r (D_{\text{CX}}^{(i)} \nabla_r n_{\text{Ha}}^{(i)}) = \sum_{j=1}^k T_{\text{CR}}^{(ij)} n_{\text{Ha}}^{(j)} + S_{\text{DCX}}^{(i)} \quad \text{Diffusion equation of state } i$$

ColRad term couples diffusion eqs.!

S. Bannmann et al 2023 JINST 18 P10029

Computed halo density distribution



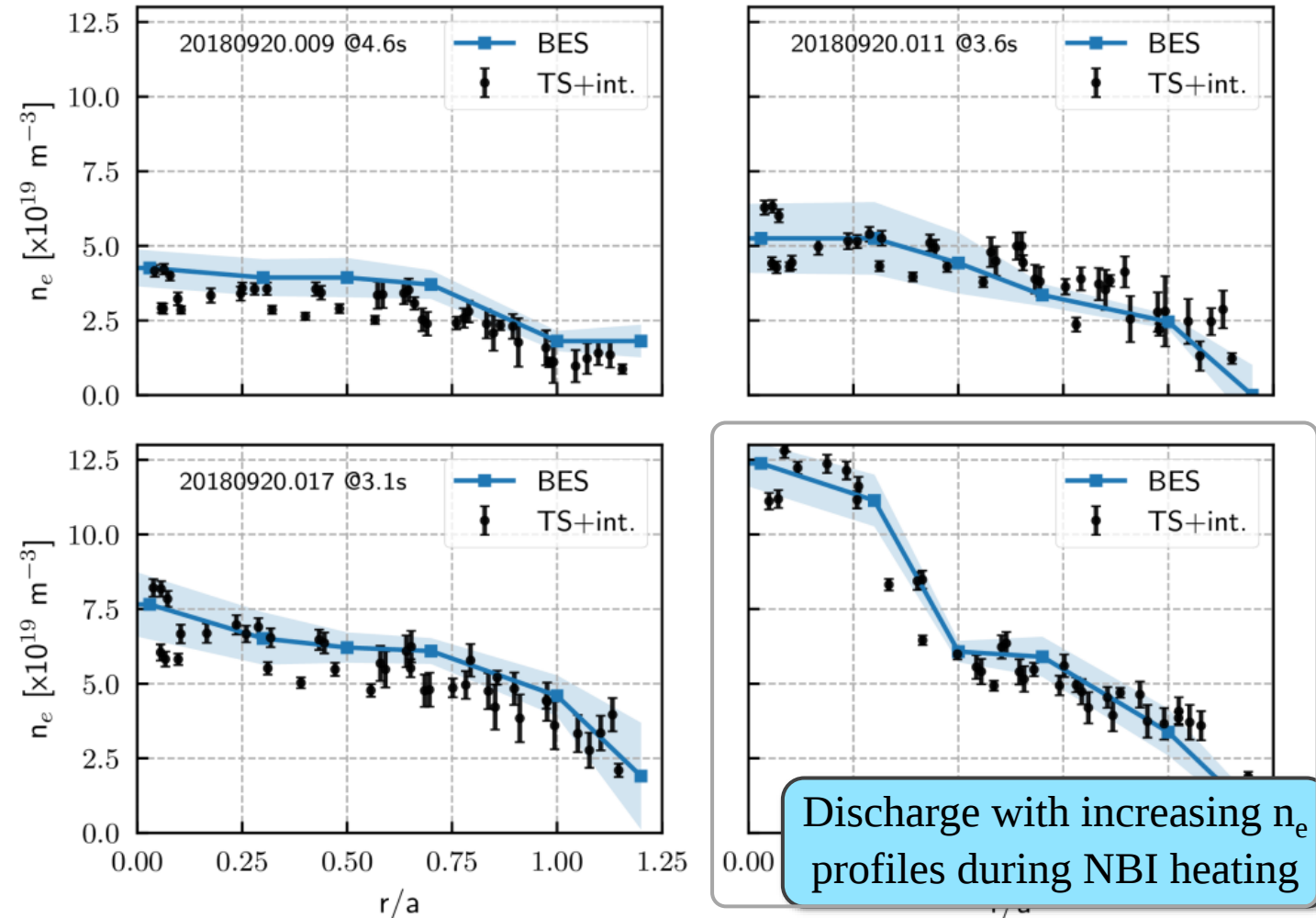
Highly complex model connecting n_e and T_i via various processes to measured H_α spectra

Beam emission spectroscopy – inference results

Bayesian MAP inference results

- Alignment of LOS – slightly adjusted
- Beam energy fractions and divergence – confirmed
- Vertical shift of the beam by ca. 5 cm
- Ion temperature profiles
- Electron density profiles →
- Very good agreement found between ne profiles from BES and Thomson scattering

Electron density profile inference



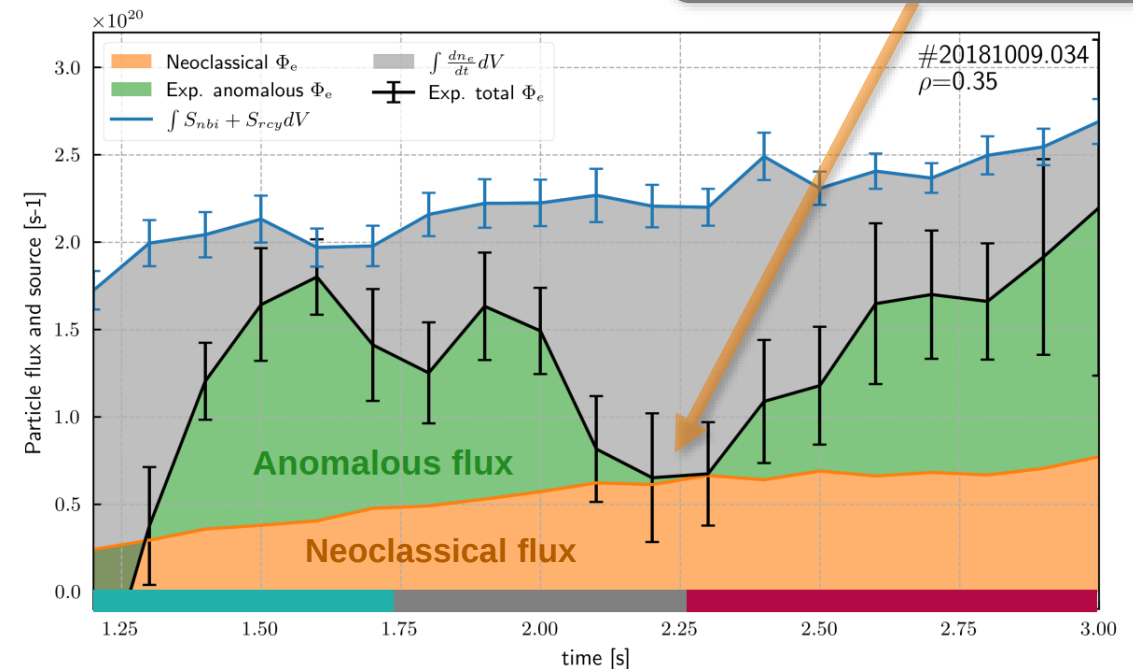
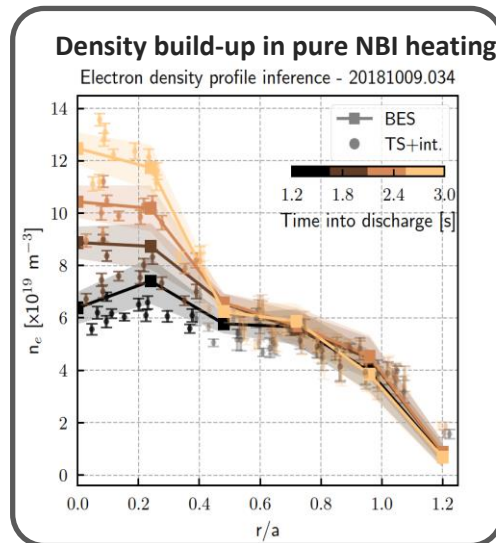
S Bannmann et al 2024 Plasma Phys. Control. Fusion **66** 065001

Beam emission spectroscopy – Experimental anomalous particle transport

- W7-X was optimised for low neoclassical particle transport
- Turbulence is a major player
- Expected reduction of turbulent transport in scenarios with peaked n_e profiles
- Experimental confirmation: from inferred n_e profiles and NBI and recycling sources

$$\Gamma(r) = \left(\frac{dV}{dr} \right)^{-1} \int_0^r (S_{\text{NBI}} + S_{\text{RCY}} - \partial_t n) \frac{dV}{dr'} dr'$$

Particle source functions S [m⁻³s⁻¹] Change in density profile



S. Bannmann et al in Nucl. Fusion 64 106015

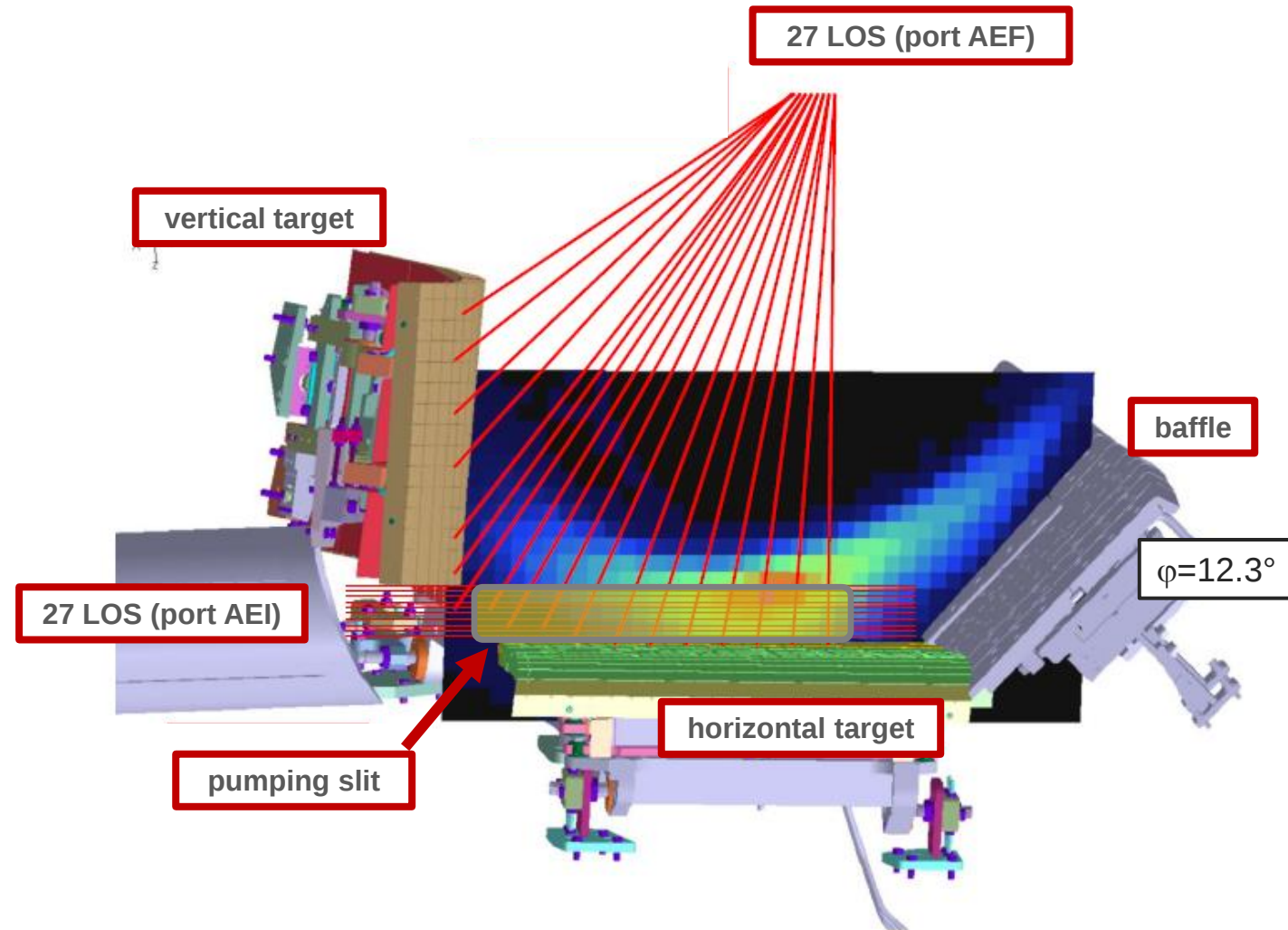
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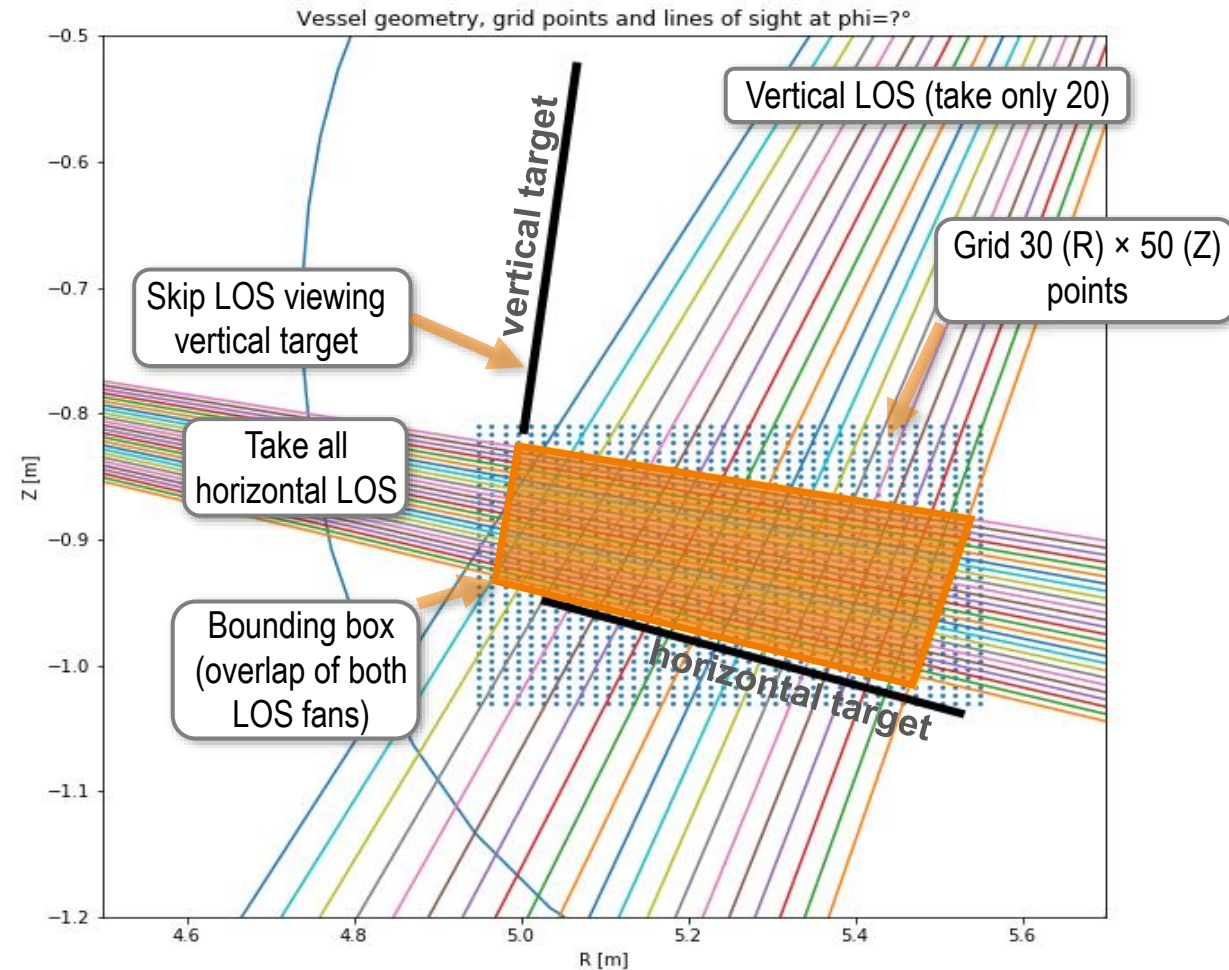
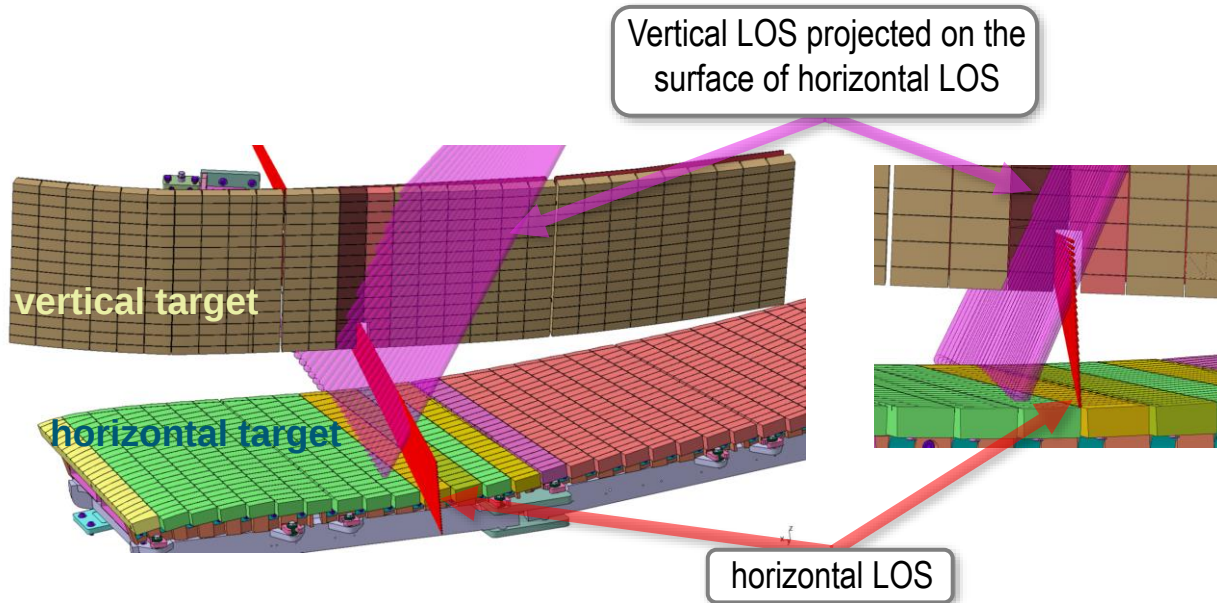
Divertor spectroscopy at W7-X

- 27 lines of sight in horizontal and vertical direction
- Same setup in one bottom (HM30) and one top (HM51) low iota divertor
- Light dispersed with several spectrometers with low, **middle** and high resolution attached
- Signals recorded with CCD cameras and IP160 spectrometers (f=160 mm) by Princeton Instruments



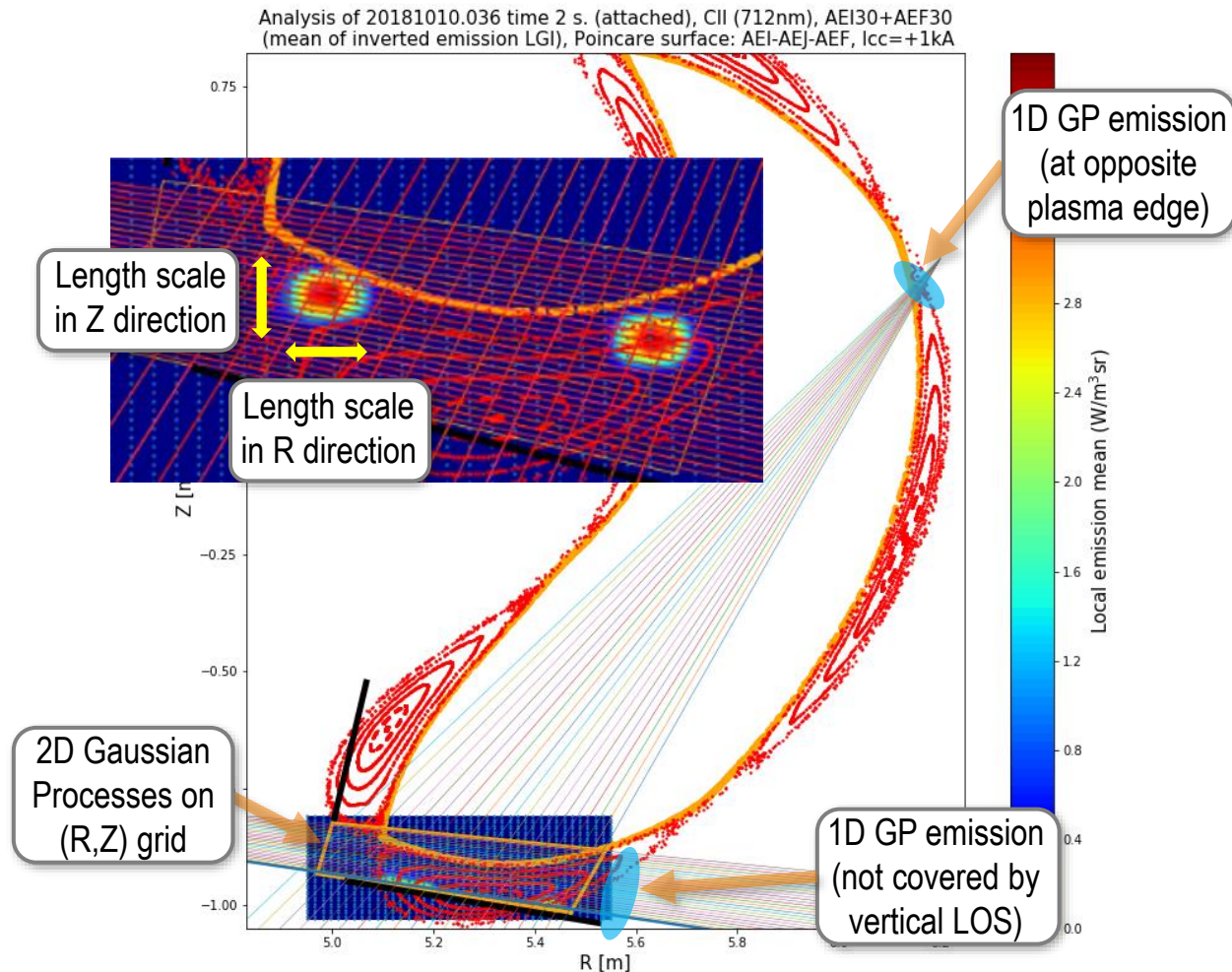
Geometry of the model

- Define a 2D grid of appr. 500 points where the horizontal and vertical LOS overlap
- Vertical and horizontal LOS fans tilted in toroidal direction
 - Project all LOS on one surface
 - Toroidal emission gradients are ignored



Emission model using Gaussian Processes

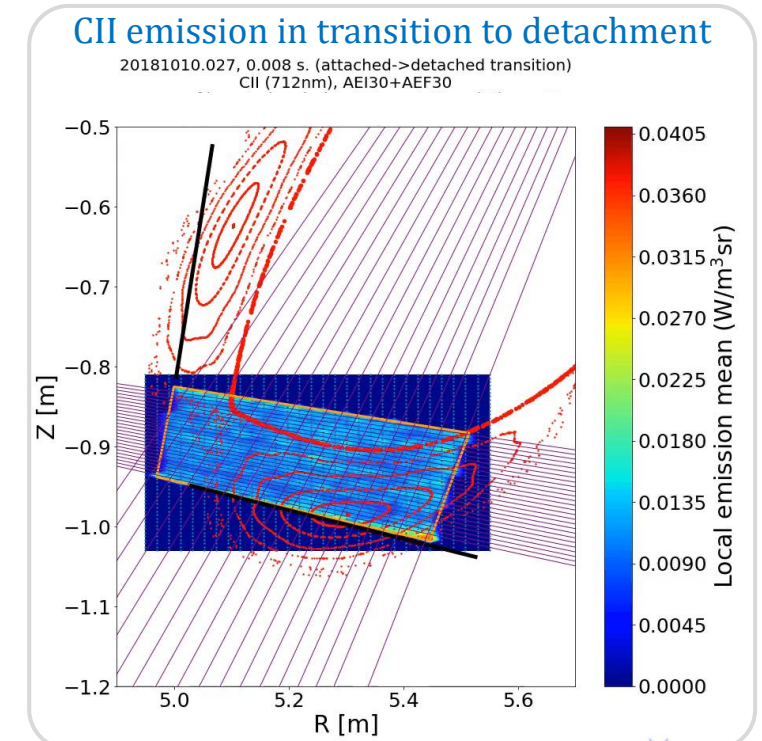
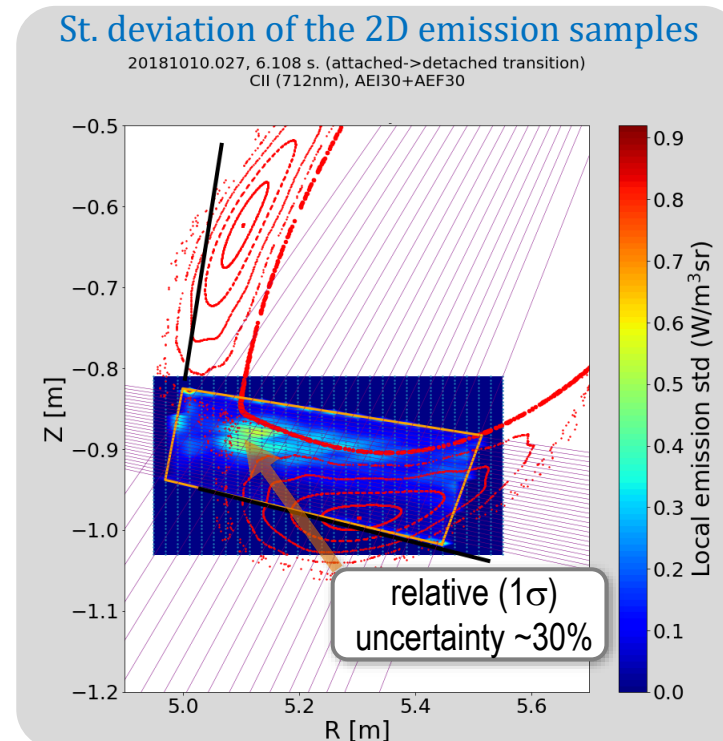
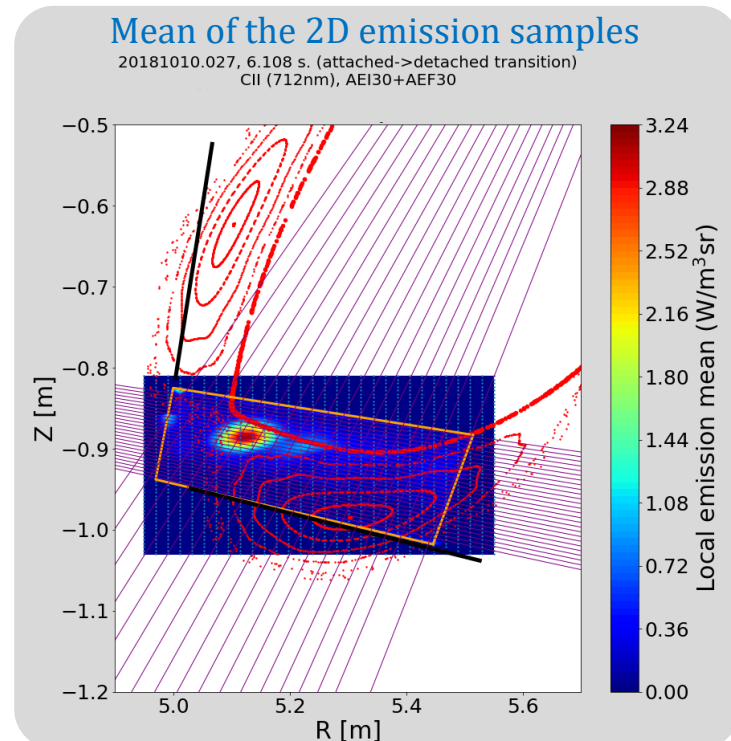
- 2D emission in divertor plasma modeled with non-parametric Gaussian Processes
- The only model (hyper)parameters
 - Correlation length scale in R and in Z direction
- The length scales are pre-optimised using the Bayesian Occam's razor principle
 - Reasonable optimum length scales obtained (Z: ~1 cm, R: ~5 cm)
- Two 1D emission zones added (not covered by 2D emission)
 - At horizontal target
 - At vertical port (AEF30)
- Additional assumptions on both emissions based on 3D plasma simulations could be added (e.g. shape of emission blob)



ill-posed tomographic problem with “incomplete” data set and uncertain outcome

Inferred local emissions with uncertainties

- Assumed emission models are linear
 - Analytic solution possible (even when using Gaussian Processes for emission models)
- Truncation the emission to positive values necessary to avoid negative emissions
- Applied method
 - Linear Gaussian Inversion
 - With sampling from the truncated multivariate normal distribution of the emission
 - Inversion time ~1 min./time slice

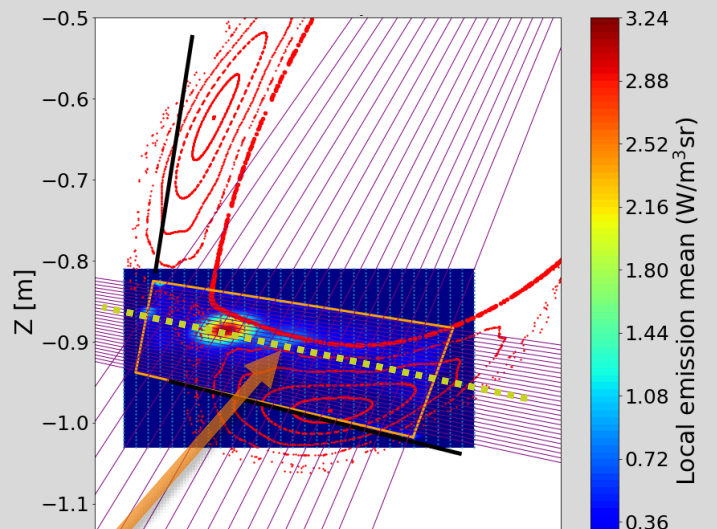


Inferred local emissions with uncertainties

Local emission along LOS

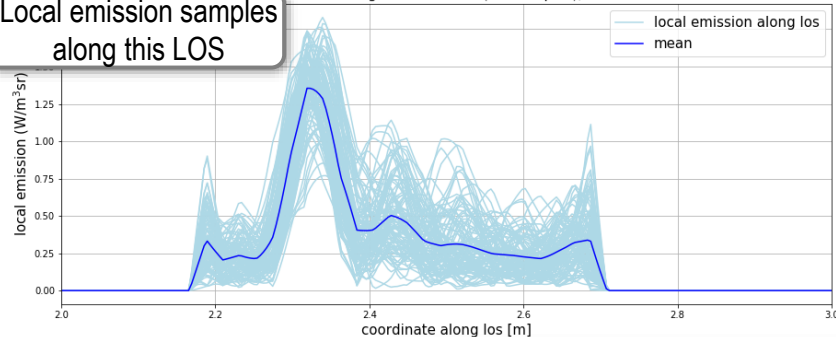
Mean of the 2D emission samples

20181010.027, 6.108 s. (attached->detached transition)
CII (712nm), AEI30+AEF30

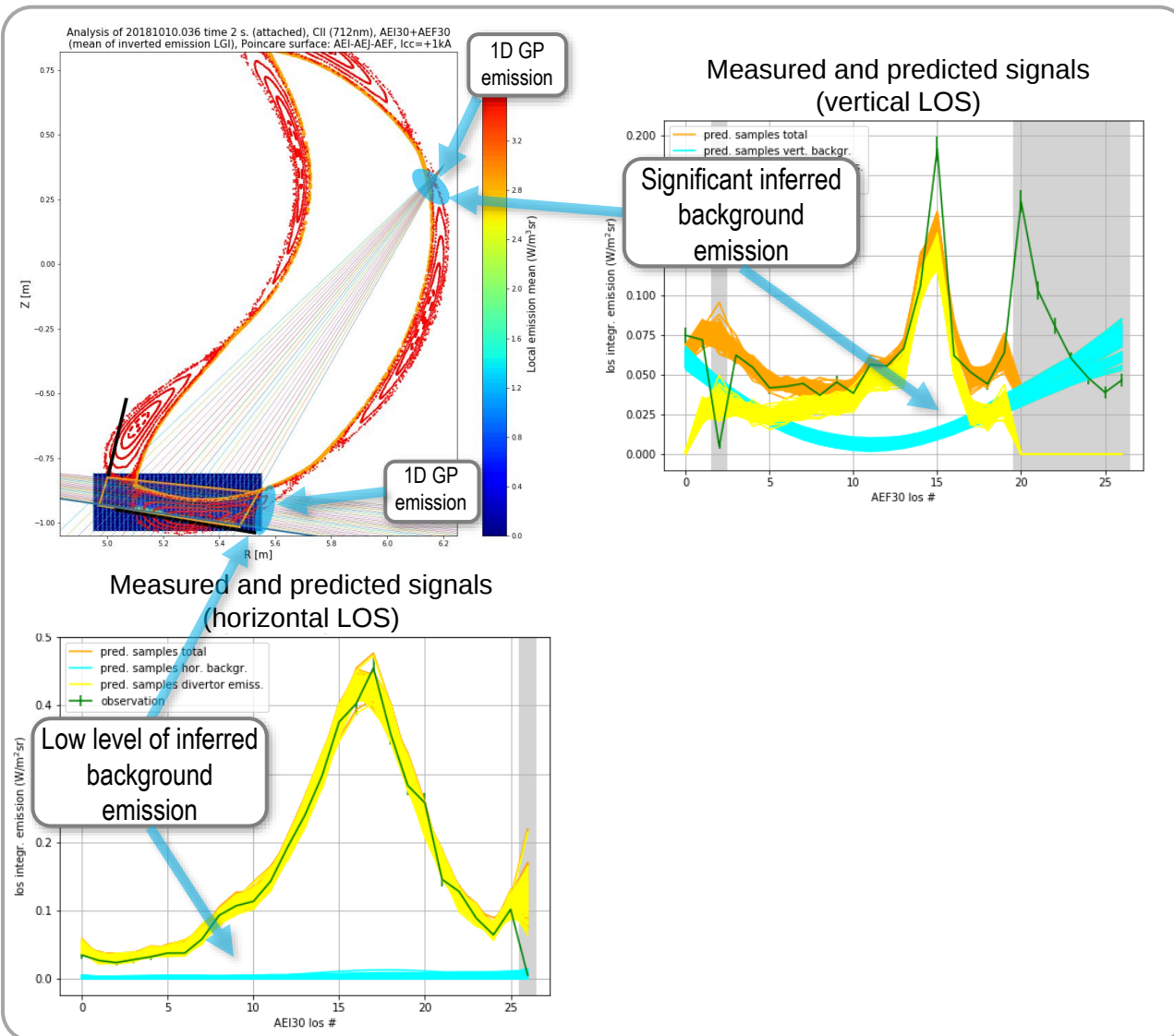


Analysis of 20181010.027 time 6.108 s. (attached->detached transition), CII (712nm), AEI30+AEF30
emission along AEI30 los #21 (LGI samples), 6.108 sec.

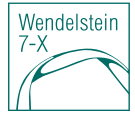
Local emission samples
along this LOS



Samples of local 2D emission in divertor
→ Use for further analysis (including error
propagation)



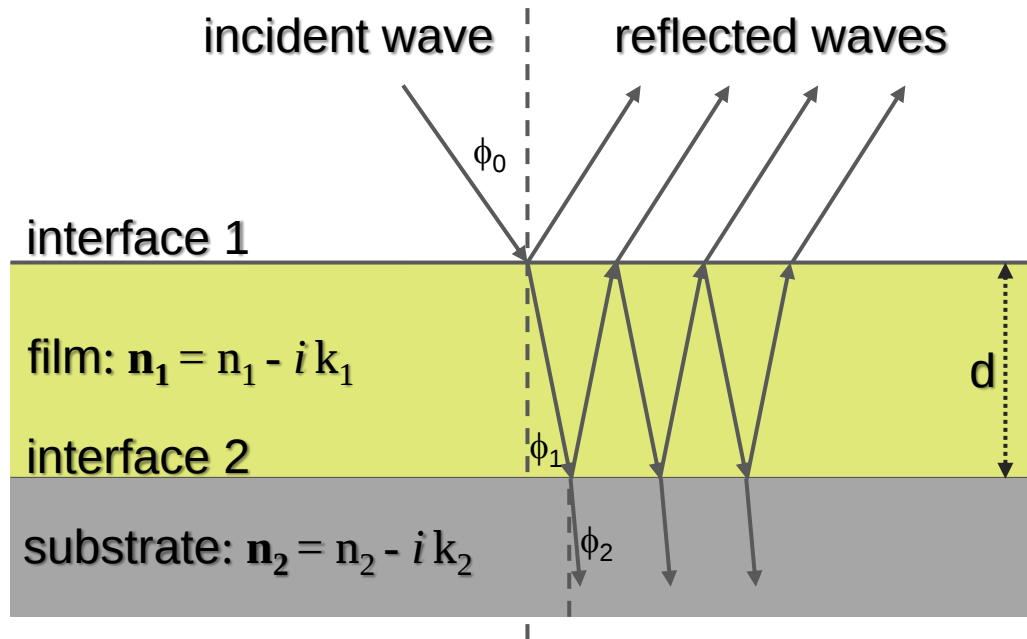
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Principles of ellipsometry

- Electromagnetic wave reflected at an interface
- Multiple reflections at a thin layer → Interference patterns in reflected spectra



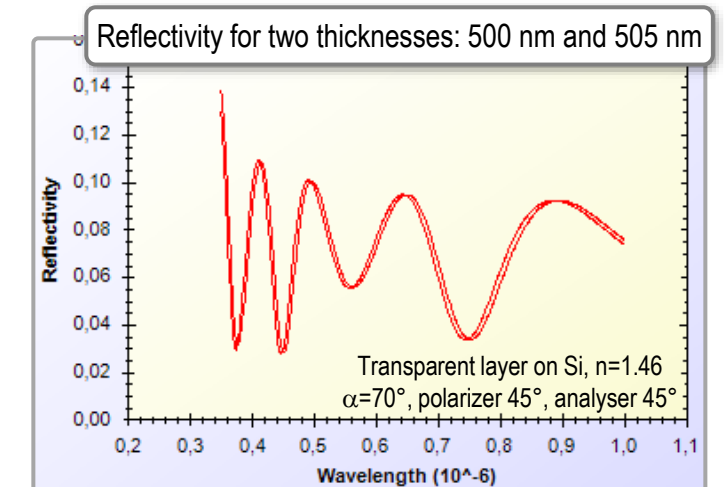
Fresnel equations

$$r^{\parallel} = \frac{n_0 \cos \phi_1 - n_1 \cos \phi_0}{n_0 \cos \phi_1 + n_1 \cos \phi_0}$$

$$r^{\perp} = \frac{n_0 \cos \phi_0 - n_1 \cos \phi_1}{n_0 \cos \phi_0 + n_1 \cos \phi_1}$$

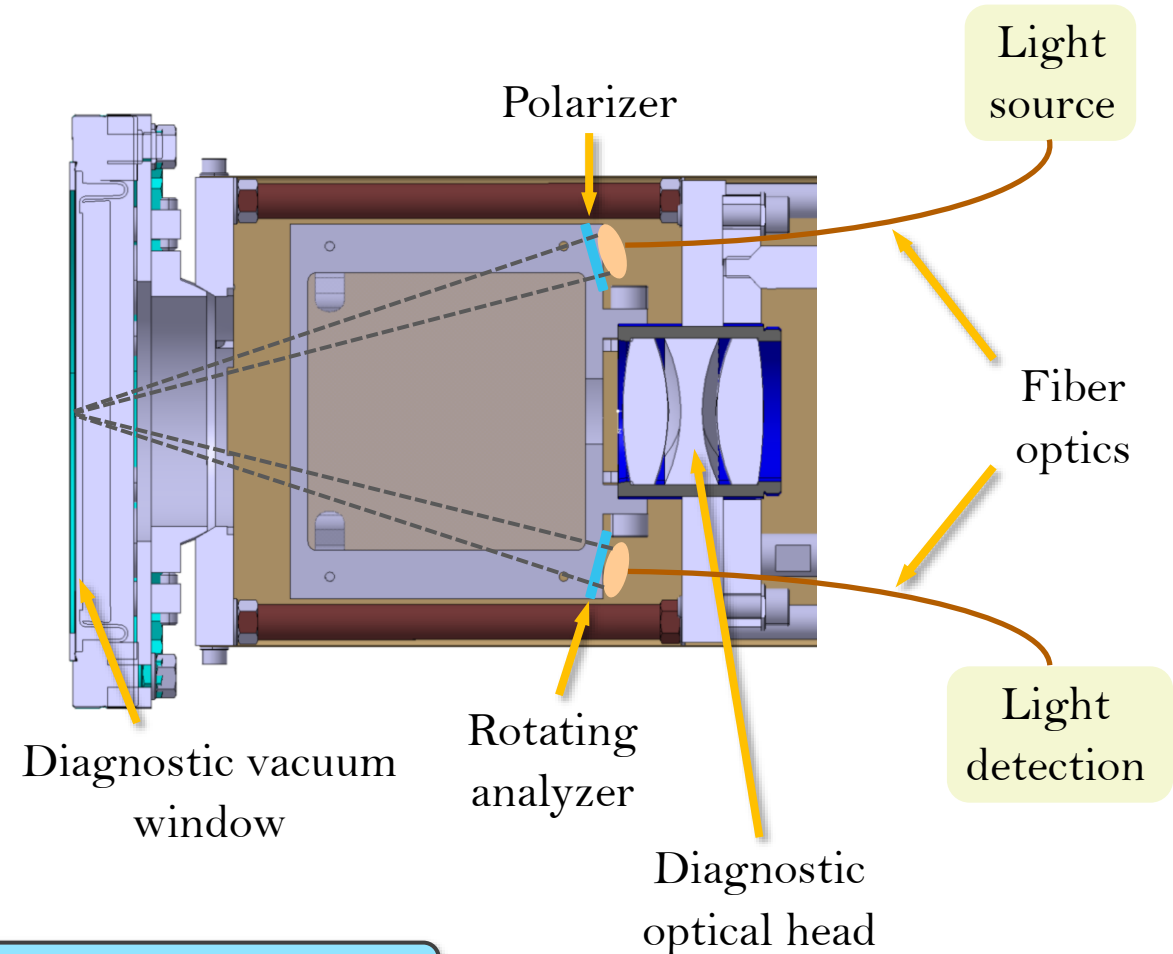
Total reflection at thin single layer

$$r = \frac{r_1 + r_2 e^{-i \frac{4\pi}{\lambda} n_1 d_1}}{1 + r_1 r_2 e^{-i \frac{4\pi}{\lambda} n_1 d_1}}$$



Ellipsometry ideas for W7-X: vacuum window monitor

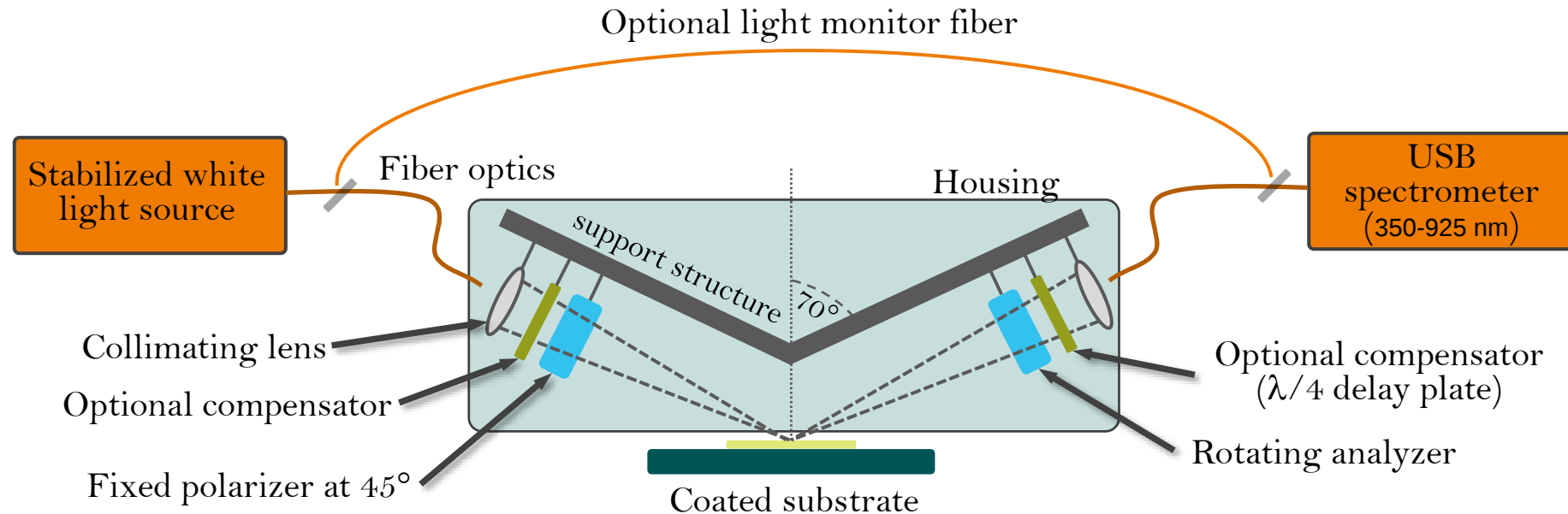
- During design phase of W7-X diagnostics
 - W7-X is a long-pulse machine (30 min.)
 - Coating of diagnostic windows expected
 - Attempt for in-situ monitoring of coatings
 - Self-made hardware setup
 - Compatible with considerable space restrictions
- “As simple as possible” ellipsometer
 - Detecting reflected intensities, relative (not absolute) phase delay
- Compensate simple hardware design by
 - Broad spectral range
 - Advanced data analysis to maximise the inference outcome



- W7-X behaves in a friendly manner towards vacuum windows
- The coating monitor was never built

Ellipsometry ideas for W7-X: thin layers at first wall components

- W7-X strongly involved in plasma wall interaction studies
- Hand-held ellipsometer for measurements of coating parameters in plasma vessel
- Various types of wall materials (steel, graphite, CFC, tungsten), roughness, shapes

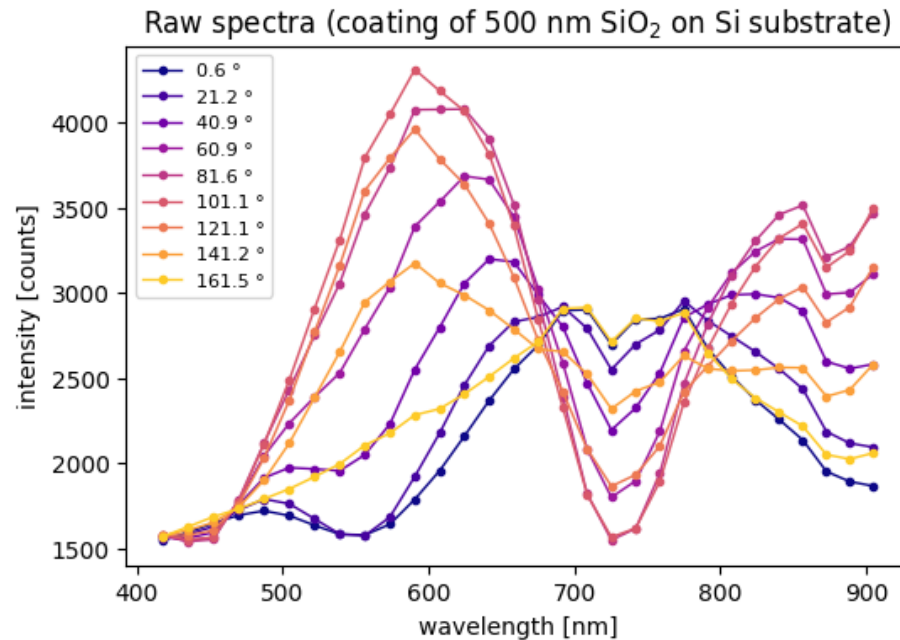


- Design is ready, device in manufacturing
- Planned to be used during actual opening phase (till Jan. 2026)

M. Krychowiak, Rev Sci Instrum. 2024 95(11)

Definition of spectral measurement set

- Full spectrum reflected at the layer
 - For different analyser angles (0-180°, e.g. in 20° steps) to sample the ellipticity of the polarised light
- Spectrum/intensity of incident light (at uncoated reference surface)
- Dark current



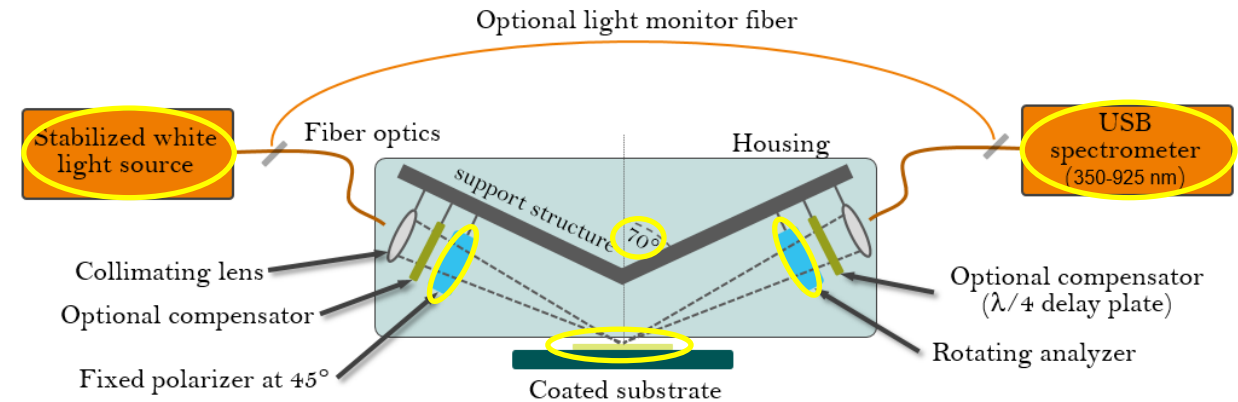
- Take only data points every ~15 nm
 - Speeds up the Bayesian analysis without loss of information
 - Number of data points can be optimised
- Raw spectra look very different for selected angles
 - Number and values of analyser angles can be optimised
- Wavelength range, exposure time, ...

Apply the Bayesian diagnostic design using test and synthetic measurements to optimize

- The choice of hardware (light source, spectrometer, polarizer, ...)
- Definition of the data set to be acquired
- Mechanical tolerances (reflected spectra sensitive to geometry)

Bayesian model of the ellipsometer

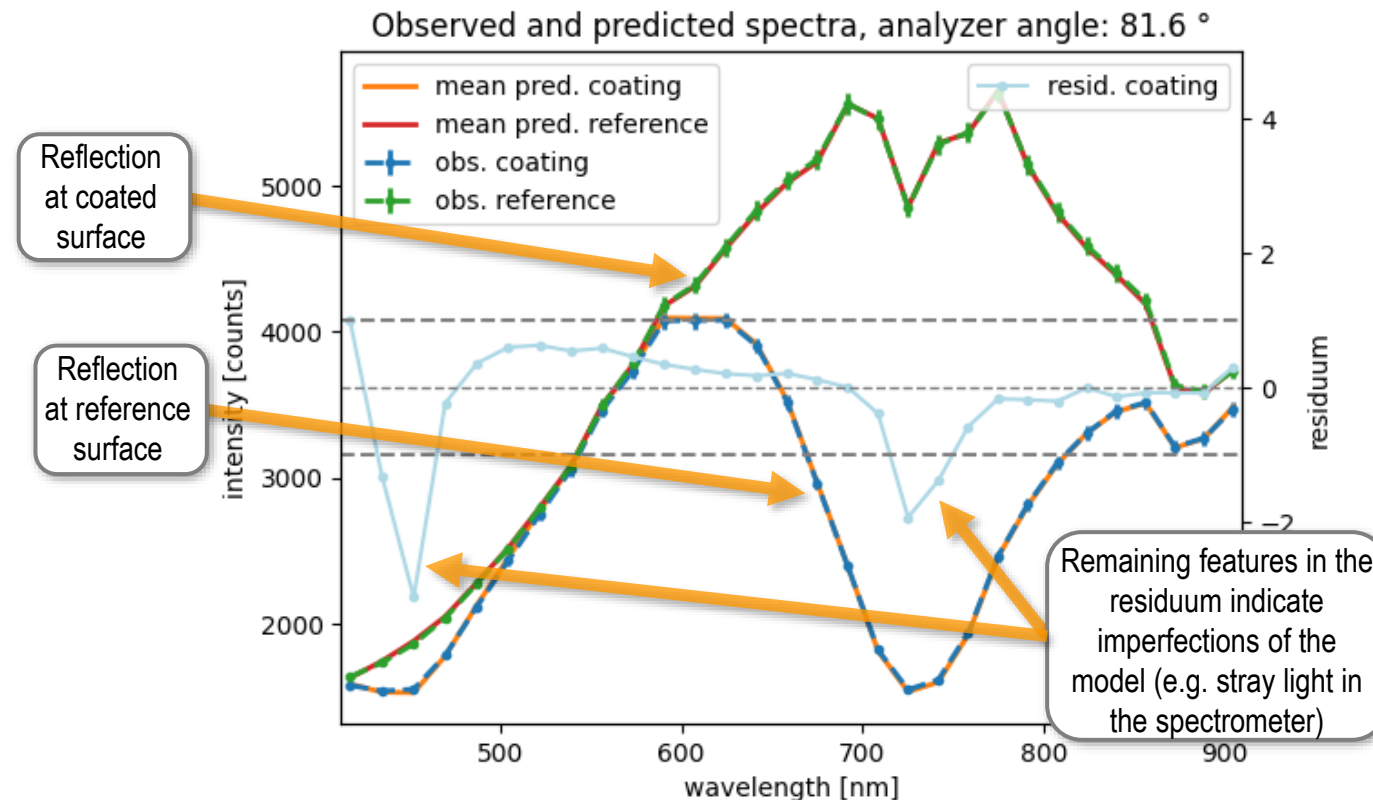
- Forward model for reflection of
 - Linearly polarised (p,s) light
 - At a single thin layer
 - Sampling the ellipticity of the reflected wave with the rotating analyser
- Free model parameters
 - Layer thickness, refractive index $n(\lambda)$ for some investigations
 - Geometric parameters: incident angle, polariser rotation angle, analyser rotation angles
 - Spectral shape of incident light (can change for longer measurements)
 - Linearity correction factors of the detector
- Non-linear model, apply MCMC to explore the posterior distribution



Ellipsometer model validation using test measurements

- Test measurements done using a lab setup
- A coating standard used with known parameters (492.4 nm of SiO_2 on Si substrate)
- Very good fits found for both spectra (also for all other analyser angles)

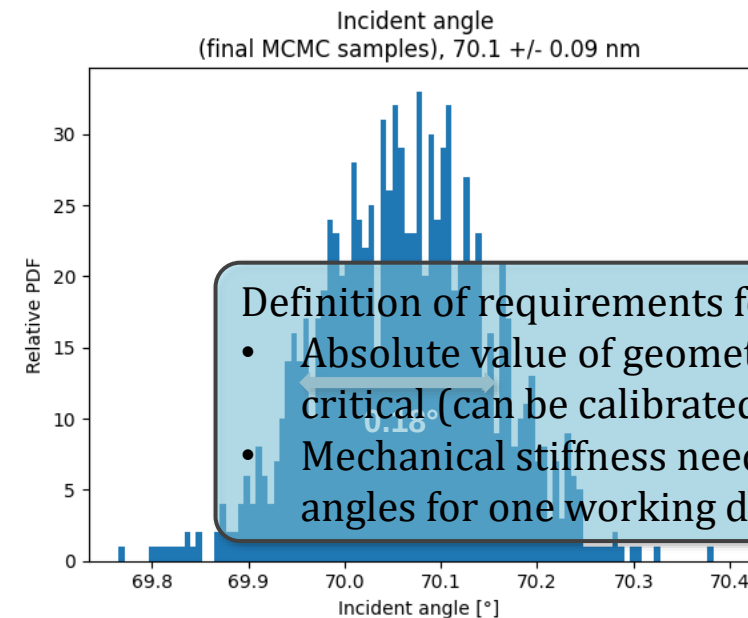
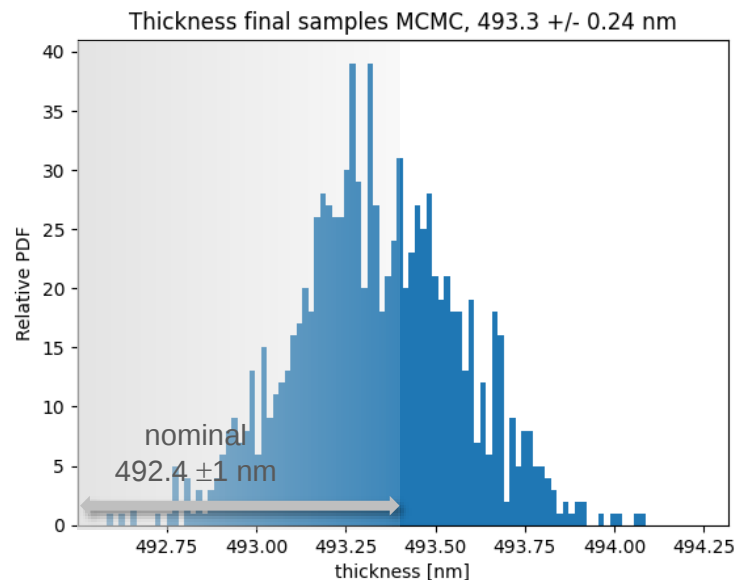
Coating standards (SiO_2 on Si)



Inference of test measurements: calibration of geometric parameters

- Inference done for a set of measurements at different analyser angles (in 20° steps)
- The relative final error: 0.5×10^{-3}
- The nominal layer thickness reproduced very well
- Small shift of central wavelength likely due to imperfections of the model

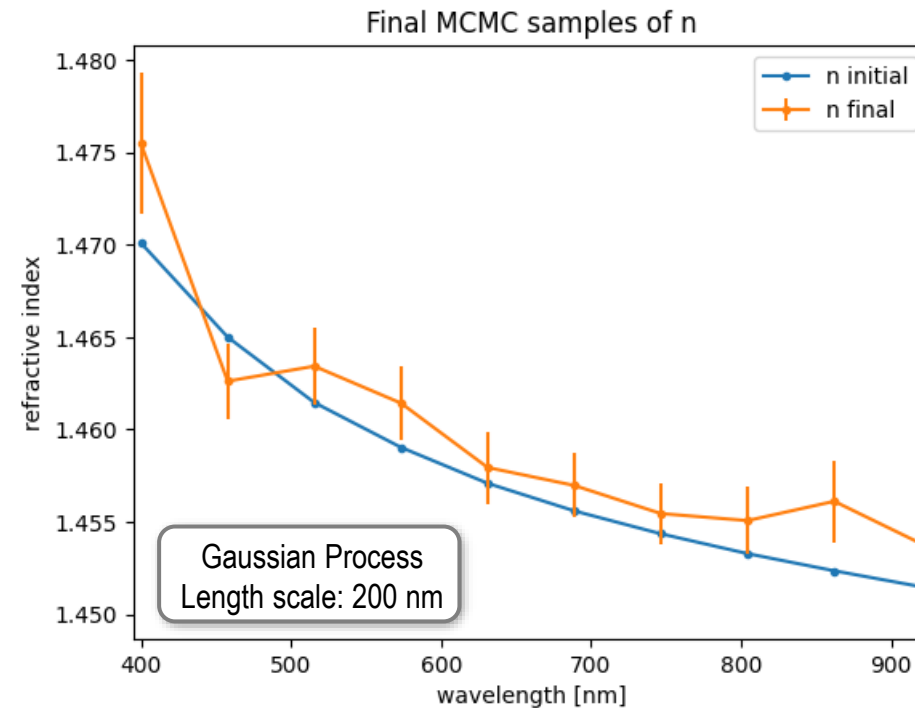
- Prior for incident angle: normal distribution, $70^\circ \pm 3^\circ$
- Final result: $70.1^\circ \pm 0.09^\circ$
- Similar accuracies (of $\sim \pm 0.15^\circ$) obtained **for all geometric parameters**
 - Ellipsometry is sensitive to geometric parameters
 - All angles can be precisely calibrated using the coating standard



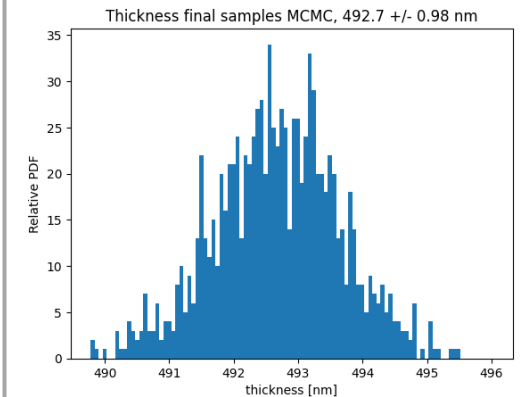
- Definition of requirements for mechanical design
- Absolute value of geometric parameters not critical (can be calibrated)
 - Mechanical stiffness needs to ensure constant angles for one working day within e.g. $\pm 0.1^\circ$

Inference of test measurements: fitting refractive index

- In last example refractive index $n(\lambda)$ was assumed as known
- Fit $n(\lambda)$ assuming geometric parameters: nominal values well reproduced
→ Potential of the method to derive even $n(\lambda)$ at least in some cases



Uncertainty of thickness increased
from ± 0.25 nm to ± 1 nm
still reasonably small



Bayesian diagnostic design with synthetic data

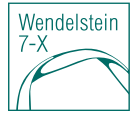
- In order to cover larger parameter space the diagnostic design can be done using synthetic (noisy) data

Change of the model	Layer thickness uncertainty
Assume lowest expected uncertainty of geometric parameters: $\pm 0.1^\circ$	very low (use of perfect model) ± 0.05 nm
Add refractive index $n = f(\lambda)$ to free parameters	considerably increased: ± 0.8 nm (n : ± 0.001)
Increase 5x (up to $\pm 0.5^\circ$) the uncertainty of: - incident angle - polarizer angle - all 9 analyzer angles	further increased: ca. ± 1.1 nm

Counter measures to reduce thickness uncertainty	
Doubled number of data points (every 7 nm)	± 1.05 nm
Extended wavelength range 350-1200 nm	± 1.08 nm
Doubled number of analyzer angles (10° steps)	considerably reduced: ± 0.50 nm

- Bayesian diagnostic design using synthetic data has a large potential to optimise hardware selection, define mechanical tolerances etc.
- Needs further analysis with other substrate materials (graphite, ...), not transparent layers, multi-layers, ...

Summary



- Three examples of Bayesian data analysis at W7-X discussed
- *Complexity*: Inference of n_e profiles and particle sources from BES
 - Experimental confirmation of reduced turbulent particle transport in plasmas with density gradients
- *Model (hyperparameters) optimisation*: Gaussian Process Tomography of carbon radiation in divertor plasma
 - Ill-posed problem with “incomplete” measurements
 - Pre-optimisation of emission correlation length scales was used
 - Reasonable behaviour of carbon emission in transition to detachment
 - Significant differences in emission position in comparison to EMC3-EIRENE modelling
- *Bayesian diagnostic design*: Ellipsometry to measure parameters of thin coatings at first wall components
 - Bayesian inference of test and synthetic data helped to define hardware components (light source, spectrometer) and mechanical tolerances
 - A hand-held ellipsometer in manufacturing for measurements in the plasma vessel this year

Thank you for your attention



View into the plasma vessel of W7-X
Courtesy. C. Biedermann, G. Wurden