

Update on LLNL cross section evaluation efforts

USNDP annual meeting 2025

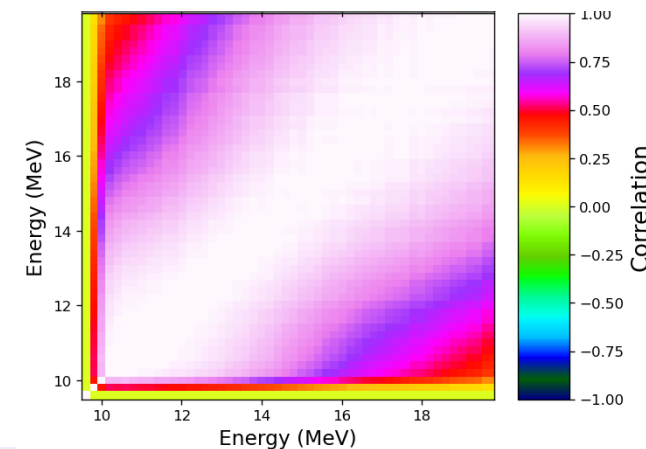
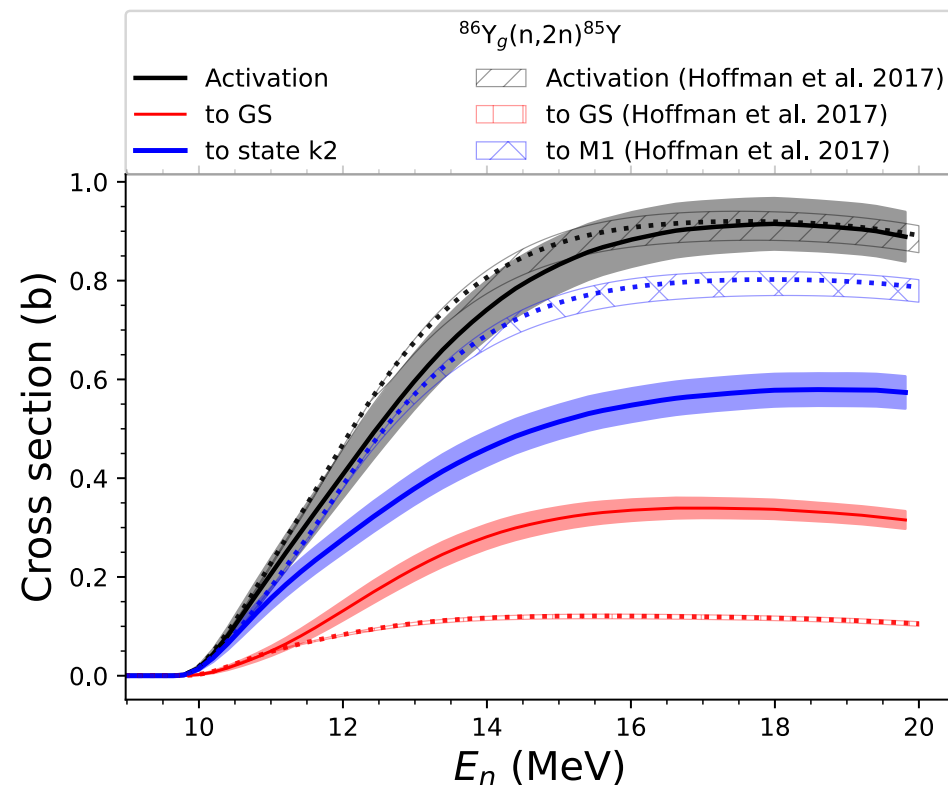
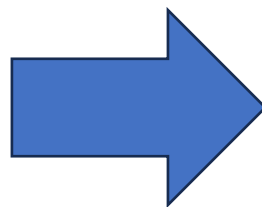
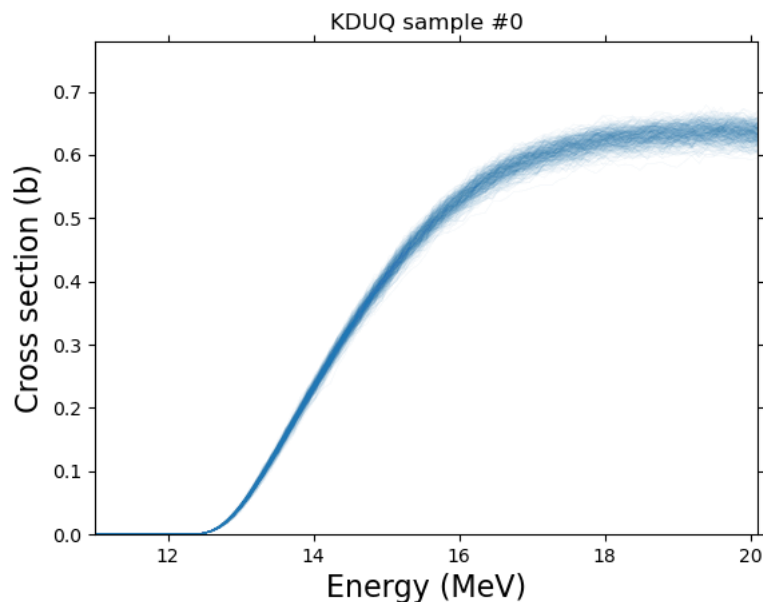
Outline

1. Activation cross sections with uncertainties and covariance
2. AI/ML efforts
3. Finalizing Pu239 evaluation



Activation cross sections with uncertainties and covariances

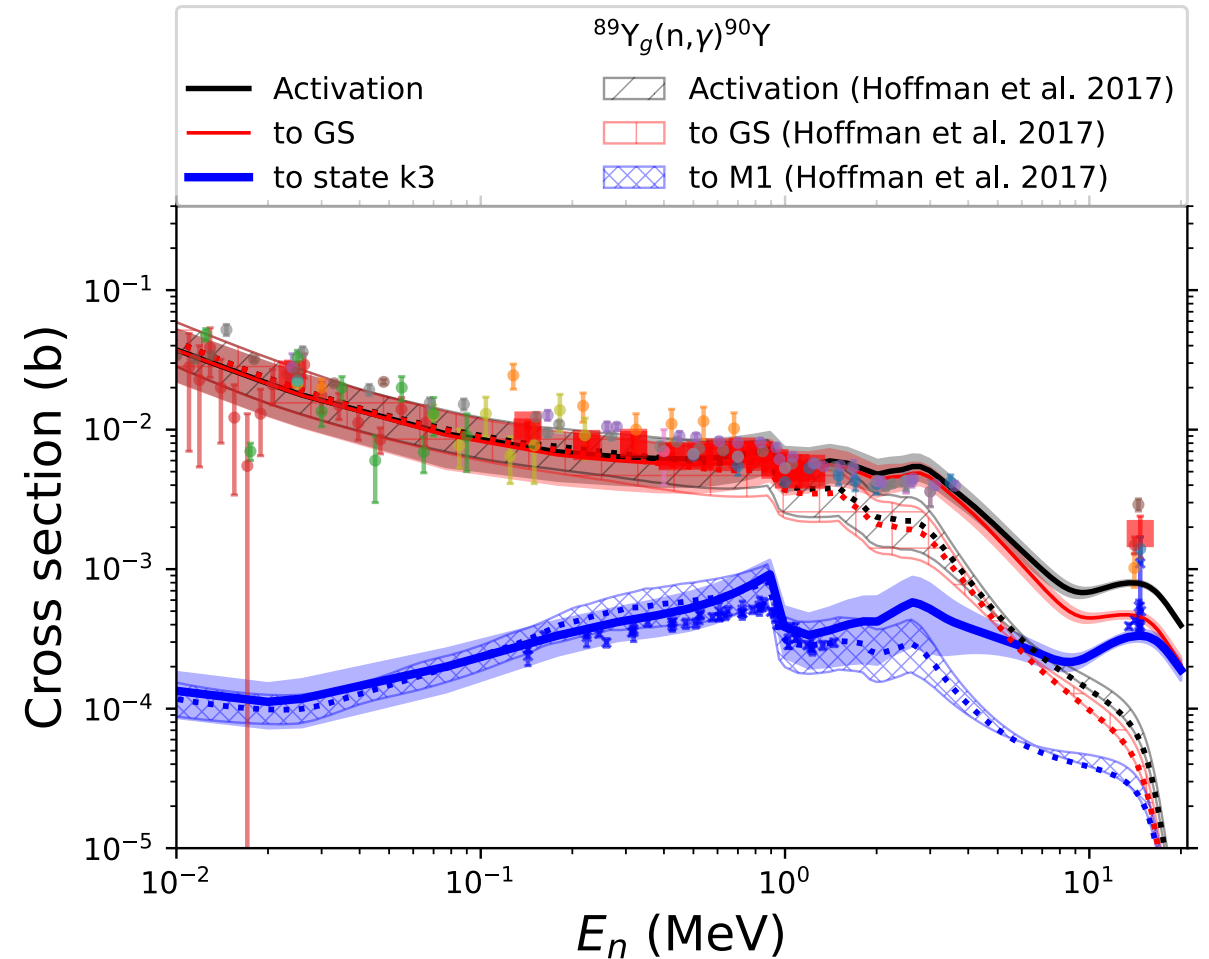
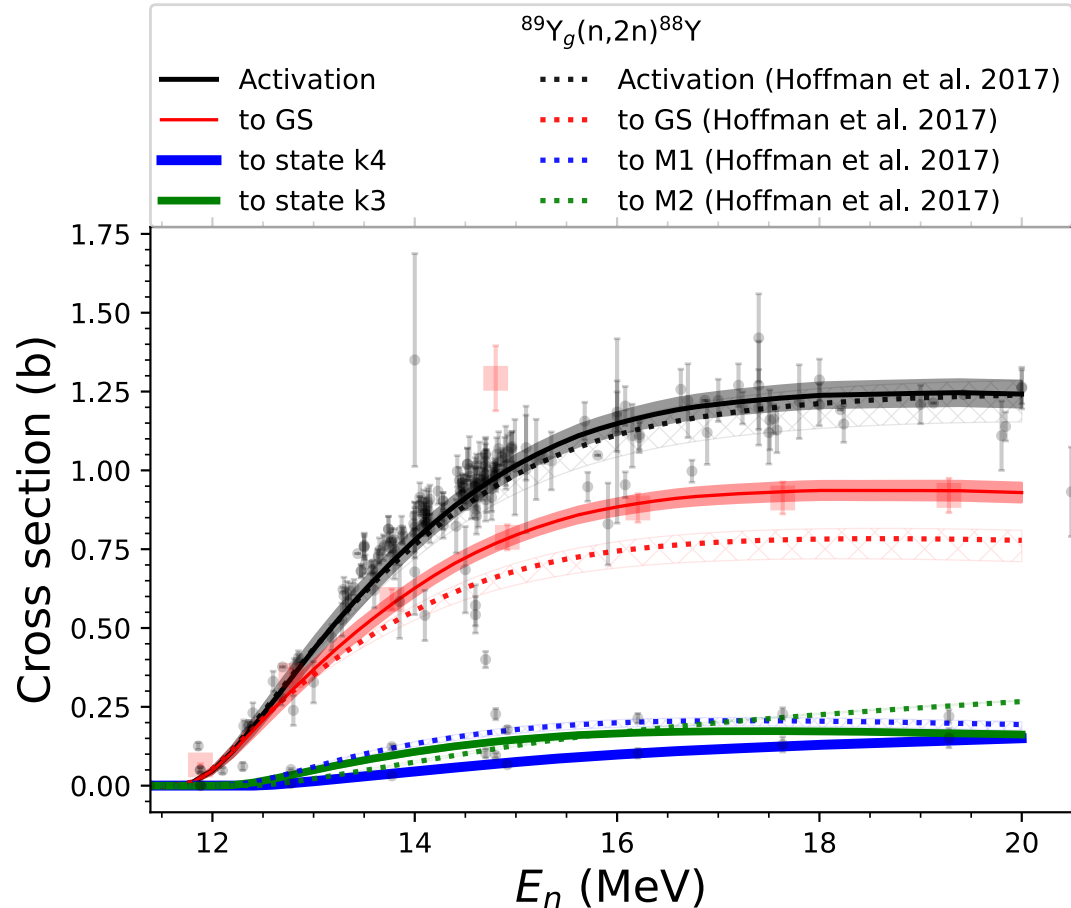
Forward-propagating parameter uncertainties



- Using uncertainty-quantified Koning-Delaroche OMP [Pruitt et al. 2023]
- Reaction model parameter systematics fit to data near stability
 - Uncertainties on $\langle \Gamma_\gamma \rangle_0$ and D_0 , i.e. gamma strength function and level density
- GNDS files with neutron-induced cross sections for $^{85-91}\text{Y}$, $^{86-90}\text{Zr}$

Validation by comparing to experimental data

No direct fit to the cross section data



- Validation for YAHFC reaction code
- Overall good performance with improvements over 2017 evaluation



AI/ML

Graph neural networks can predict unknown cross sections with remarkable accuracy



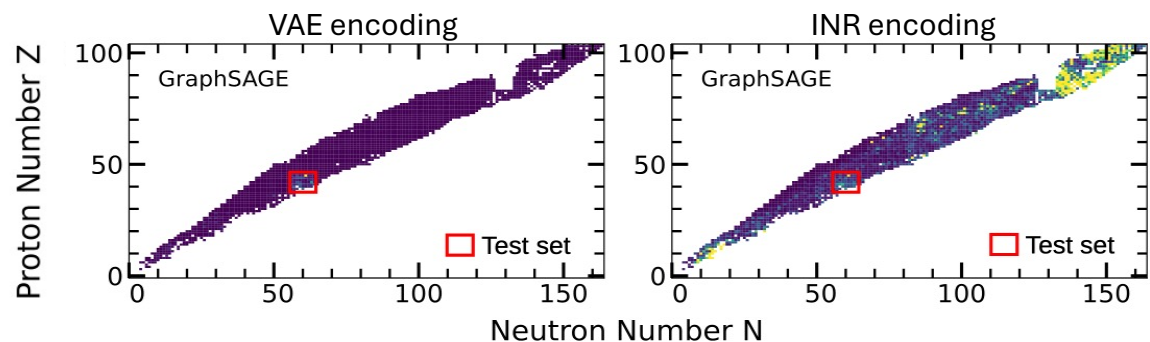
Hongjun Choi



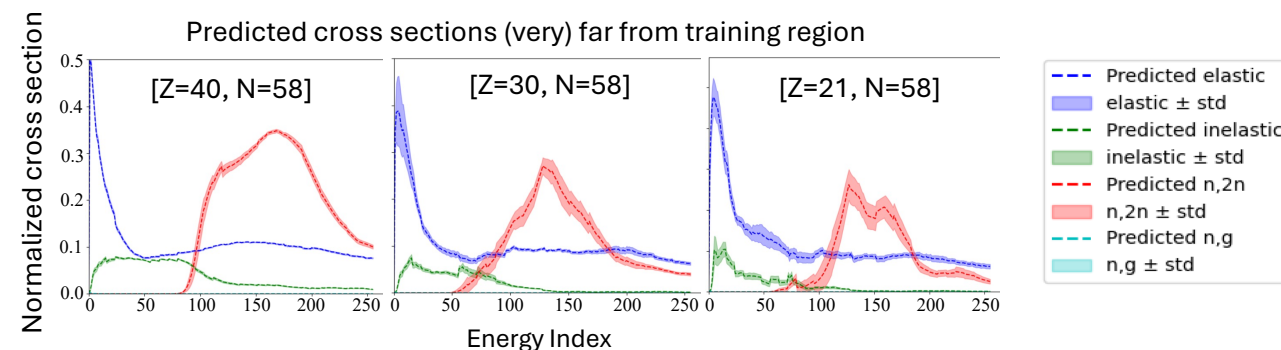
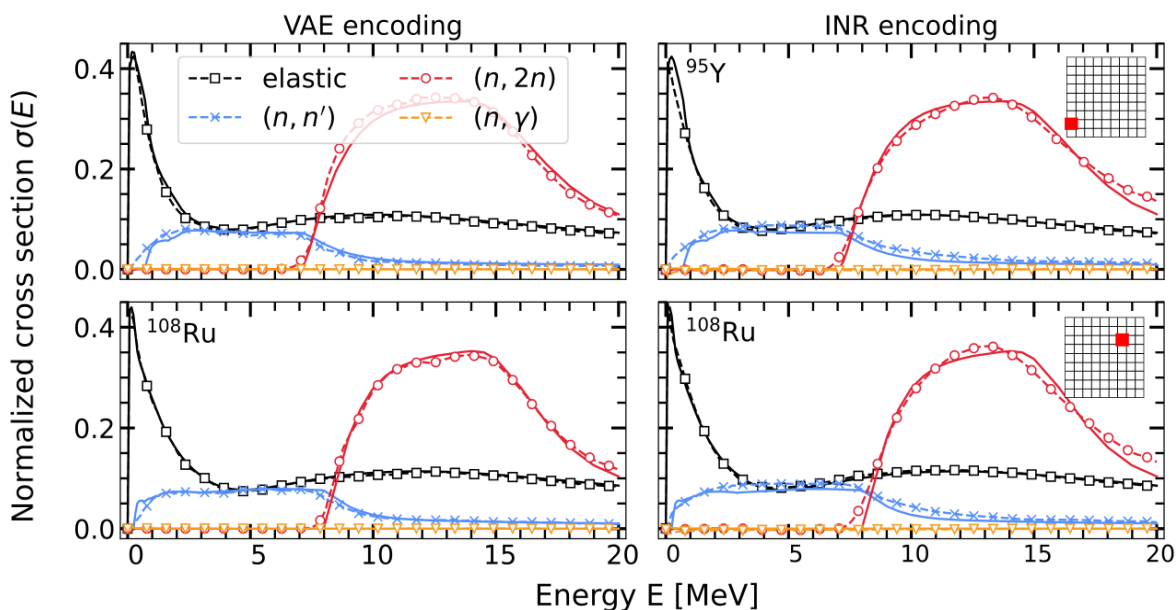
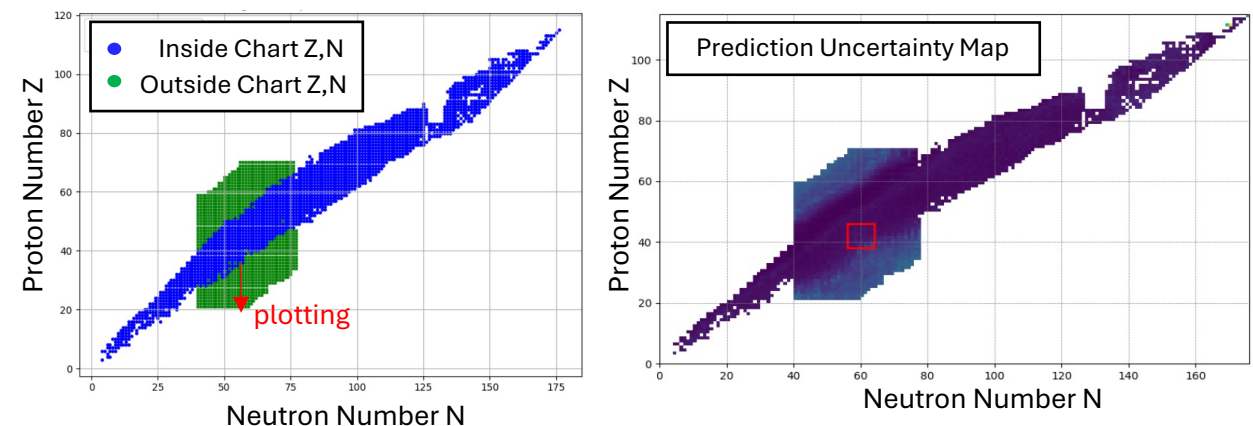
Sinjini Mitra



Shusen Liu



- Predicts extrapolated cross sections and estimates prediction uncertainty via Monte Carlo dropout.

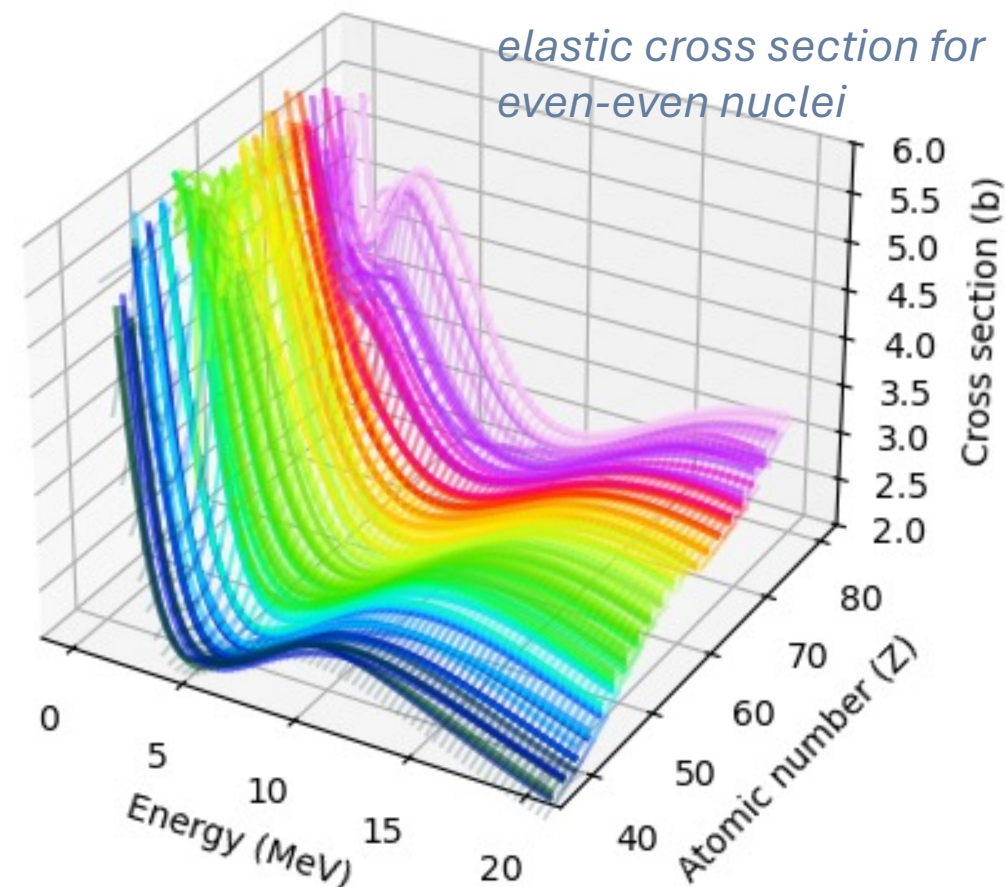


[Paper accepted in [Phys. Rev. C 112, Issue 4, id.044601](#)]

How to estimate uncertainties? How to propagate data or evaluated uncertainties?

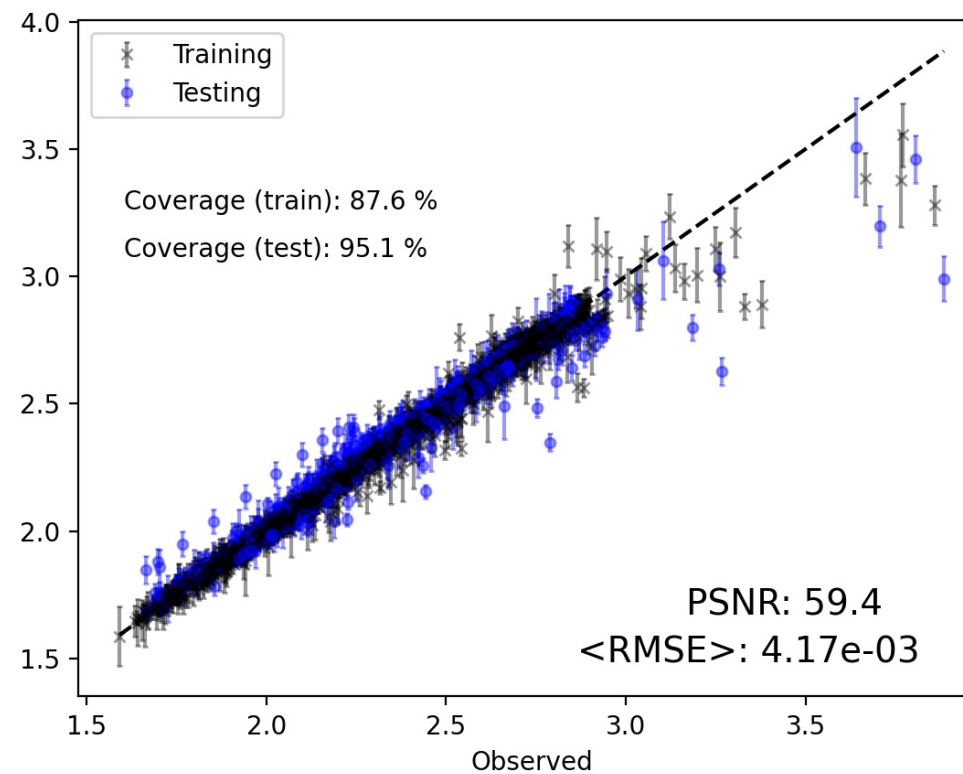
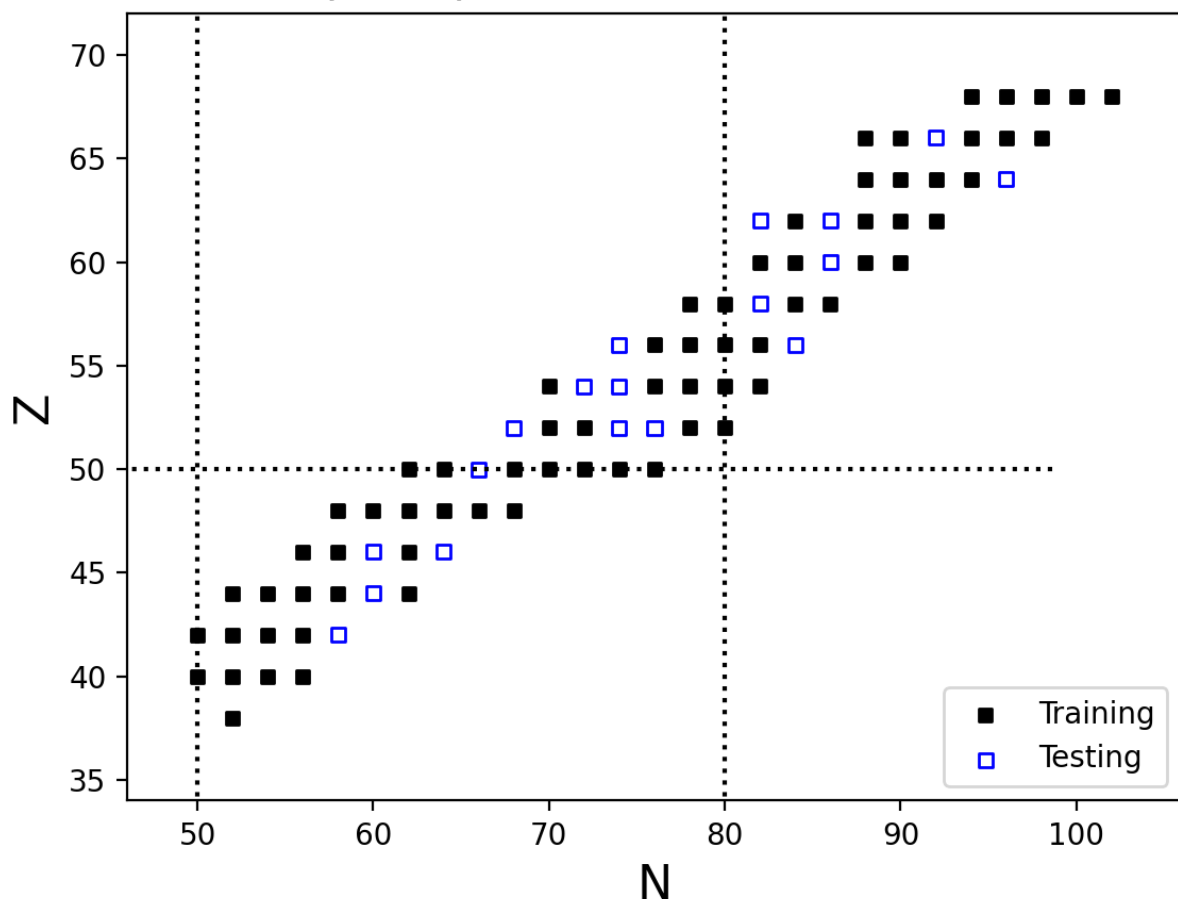
Gaussian process model for cross sections

- The elastic scattering cross section is generally smooth and a “bulk property” of nuclei
- Most naïve approach:
 - Describe $\sigma(N, Z, E)$ as 3->1 Gaussian process regression
 - Focus on even-even nuclei to increase smoothness (for now)
 - For simplicity we use TENDL as baseline dataset

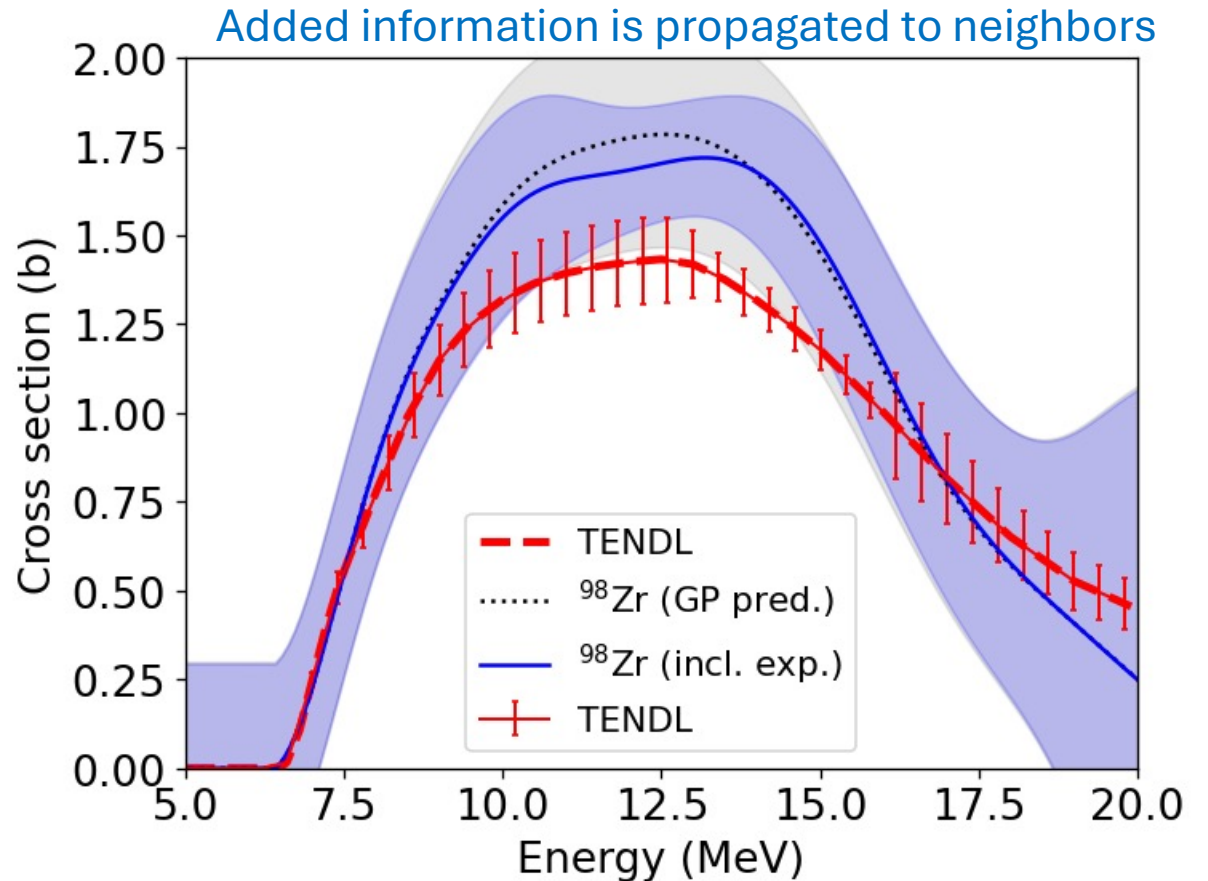
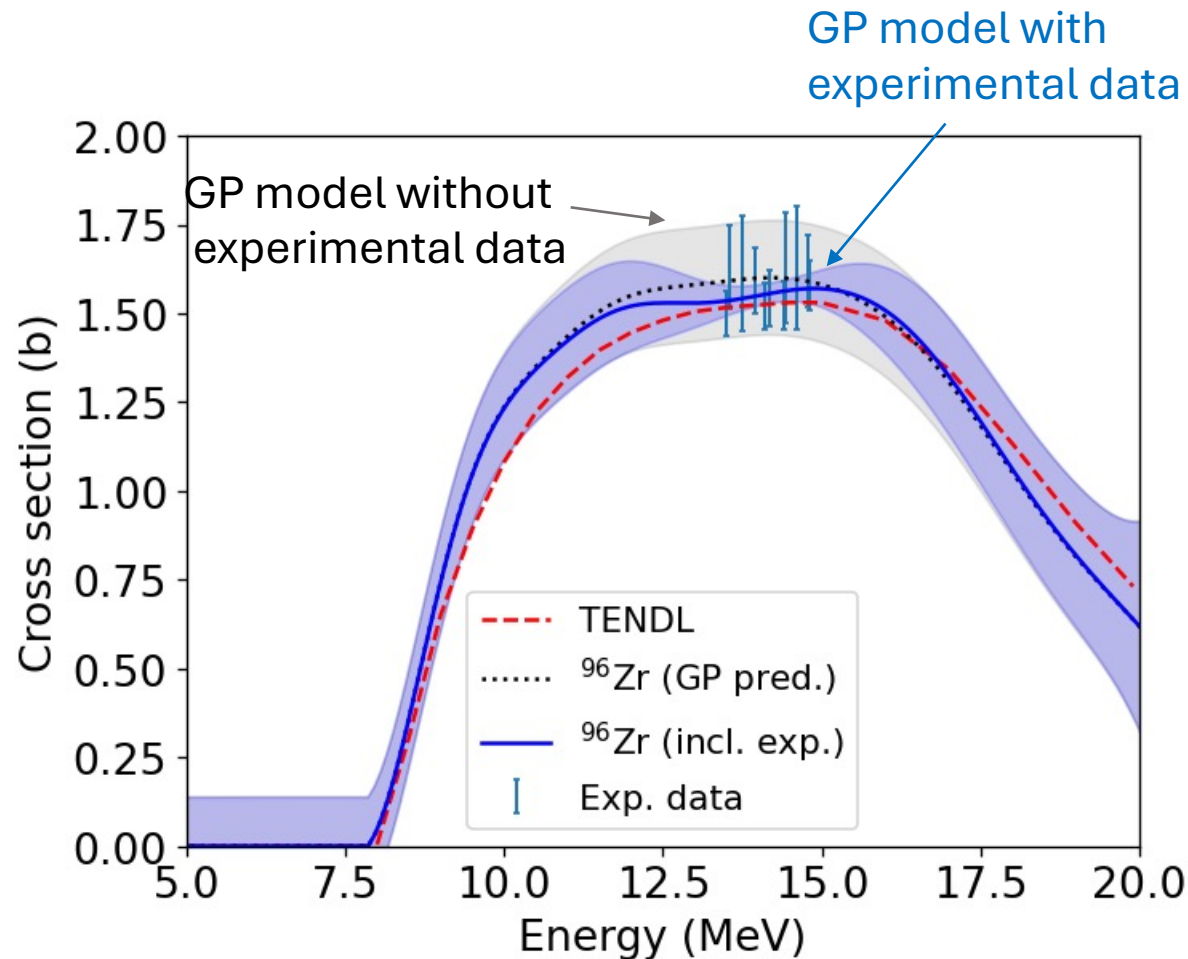


Elastic scattering cross section

- Even-even nuclei only
- Random split between training and test cases
- Good performance on testing set
- Mostly interpolation



Combine with data



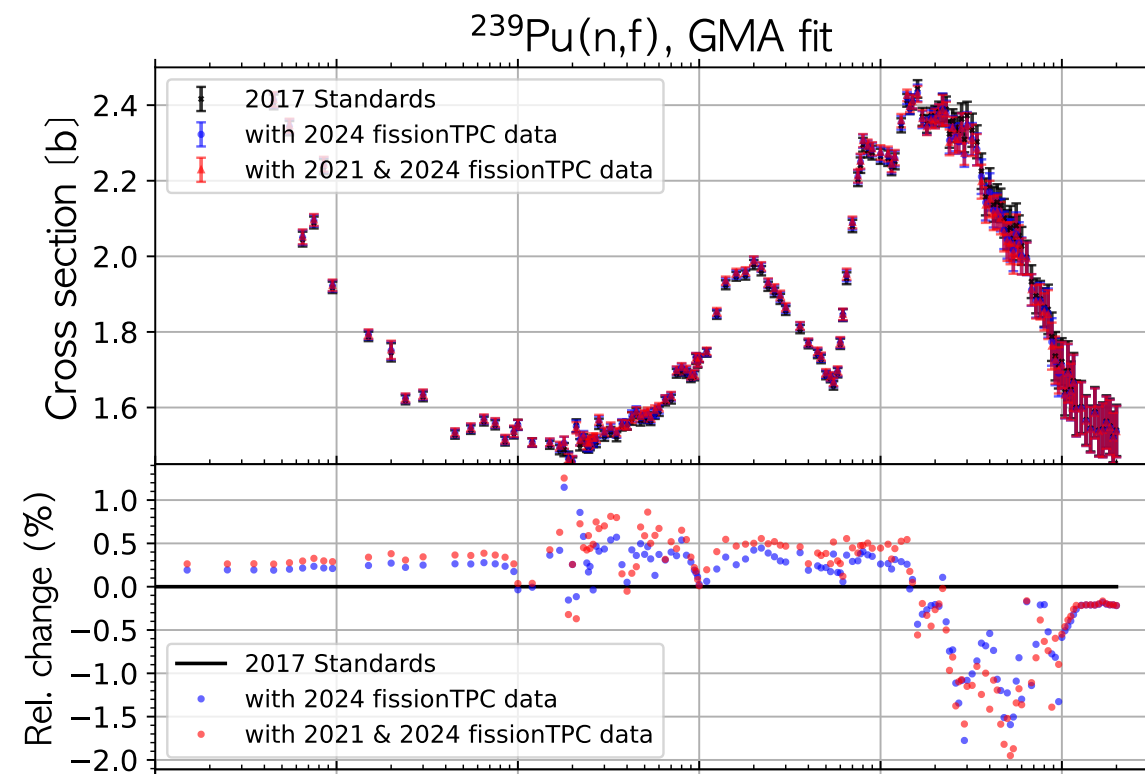
Adding new experimental data reduces the uncertainty of the prediction but still uses the knowledge of the model where no data is available



Finalizing ^{239}Pu evaluation

Summary of the LLNL $n+^{239}\text{Pu}$ evaluation (so far)

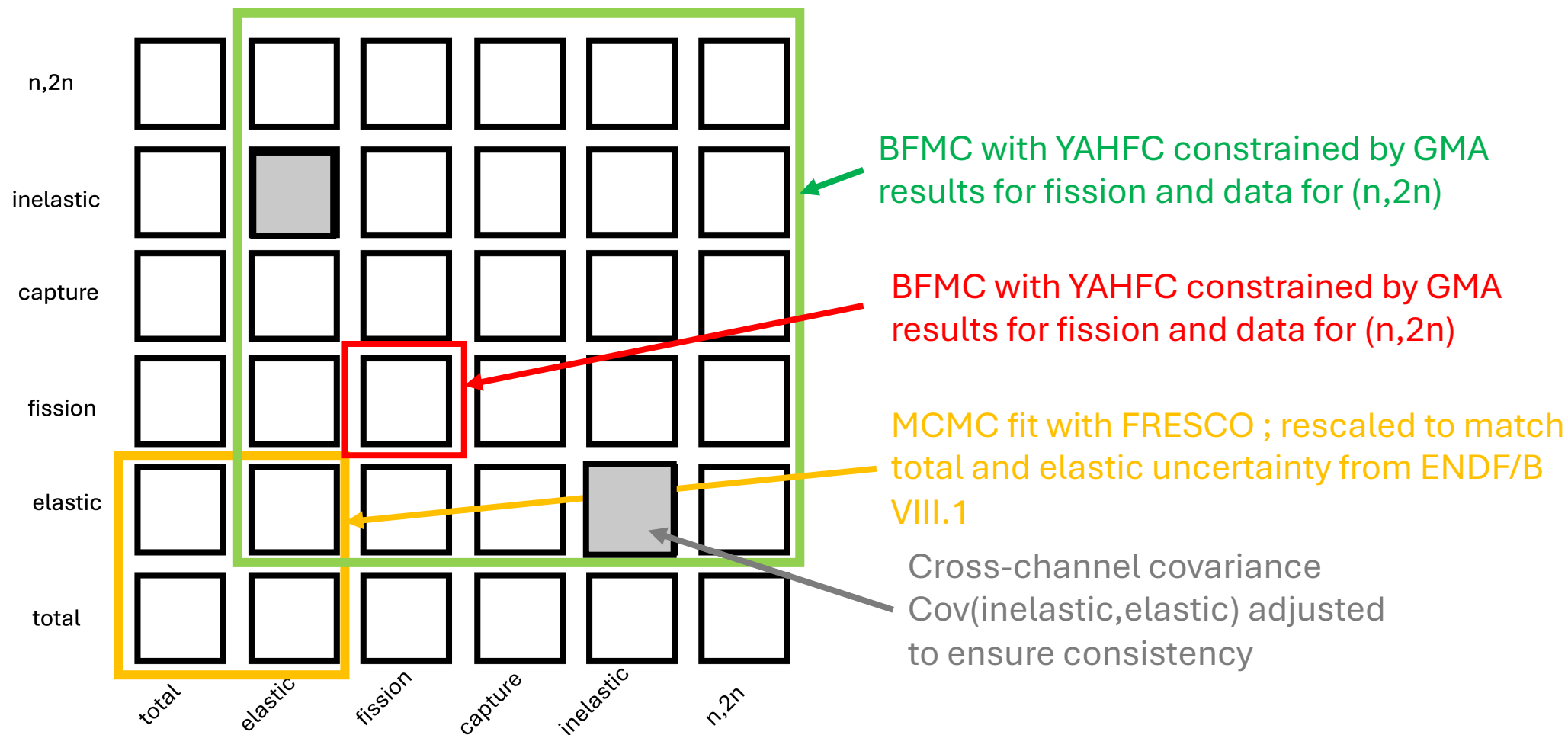
- Total cross section: Re-fit of OMP parameters to data using Soukhovitskiĭ (2016,2020) with FRESCO
- Fission: GMAP evaluation including fissionTPC datasets (generalized least squares fit across neutron standard cross sections)
- Other channels computed with LLNL's YAHFC reaction code with parameters optimized to (n,f) and (n,2n) data
- Cross sections below **30 keV** and fission product data are taken from ENDF/B VIII.1



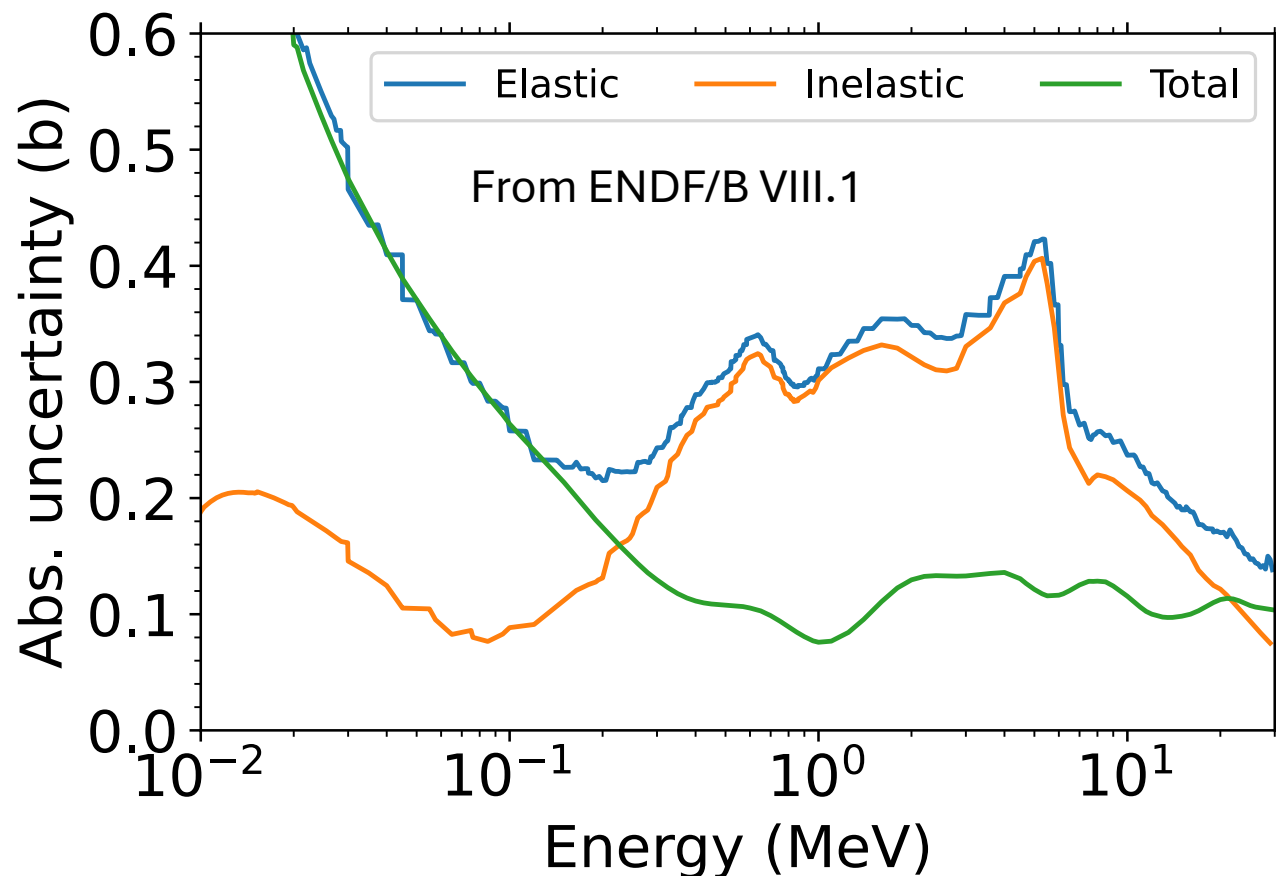
[c.f. presentation at Nuclear Data Week 2024]

Up next: Add covariance data

Adding covariance data

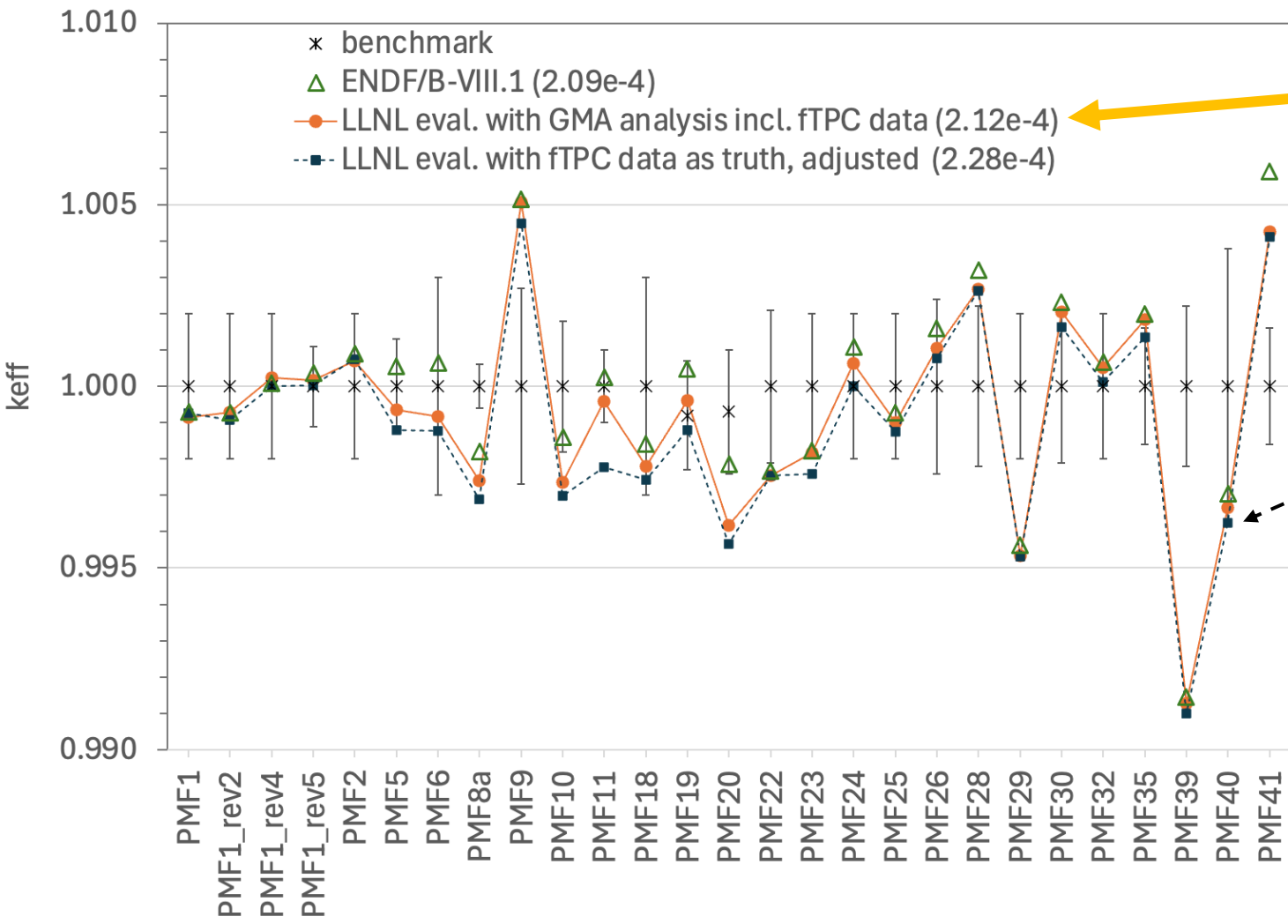


Covariances for ^{239}Pu



- Tight constraints on the total cross section enforce a strong correlation between the elastic scattering and inelastic cross sections between 300 keV and 20 MeV

Validation and Verification



- GMAP analysis of fissionTPC data: No adjustment needed
- Almost as good as ENDF/B VIII.1 across PMF benchmarks

- Taking the Pu239/U235 fission TPC data directly (no averaging with other measurements through GMA) **requires -1.4 % adjustment of $\bar{\nu}$** (which is outside of the uncertainties)

Conclusions

- Workflow and code development for large-scale HF reaction calculation, including uncertainty propagation
- AI/ML approaches for cross sections:
 - Neural networks
 - Gaussian processes
- Actinide evaluations:
 - n+Pu239 covariances with backward-forward Monte-Carlo
To do: Include OMP parameters in MC sampling to capture correlations between reaction channels and elastic scattering
 - Adjustment of n+²³⁹Pu to agree with fissionTPC Pu9/U5 data with more than $\bar{\nu}$?



Backup

Importance-sampling Backward-forward Monte-Carlo (iBFMC)



Development by
O.C. Gorton

Goal: approximate statistics of random variable x , such as the expected value: $E[x] = \int xp(x)dx$

- Direct Monte Carlo | $p(x)$ can be sampled:

- $E[x] = \int xp(x)dx \approx \frac{1}{N} \sum_i X_i$ where $X_i \sim p(x)$

Sampling from a uniform distribution often yields very few samples with non-zero weight

- BFMC | $p(X_i)$ can be computed:

- $E[x] \approx \frac{1}{N} \sum_i X_i w_i$ where $X_i \sim U(x_{min}, x_{max})$, $w_i = p(X_i) \rightarrow \bar{p}(X_i)$

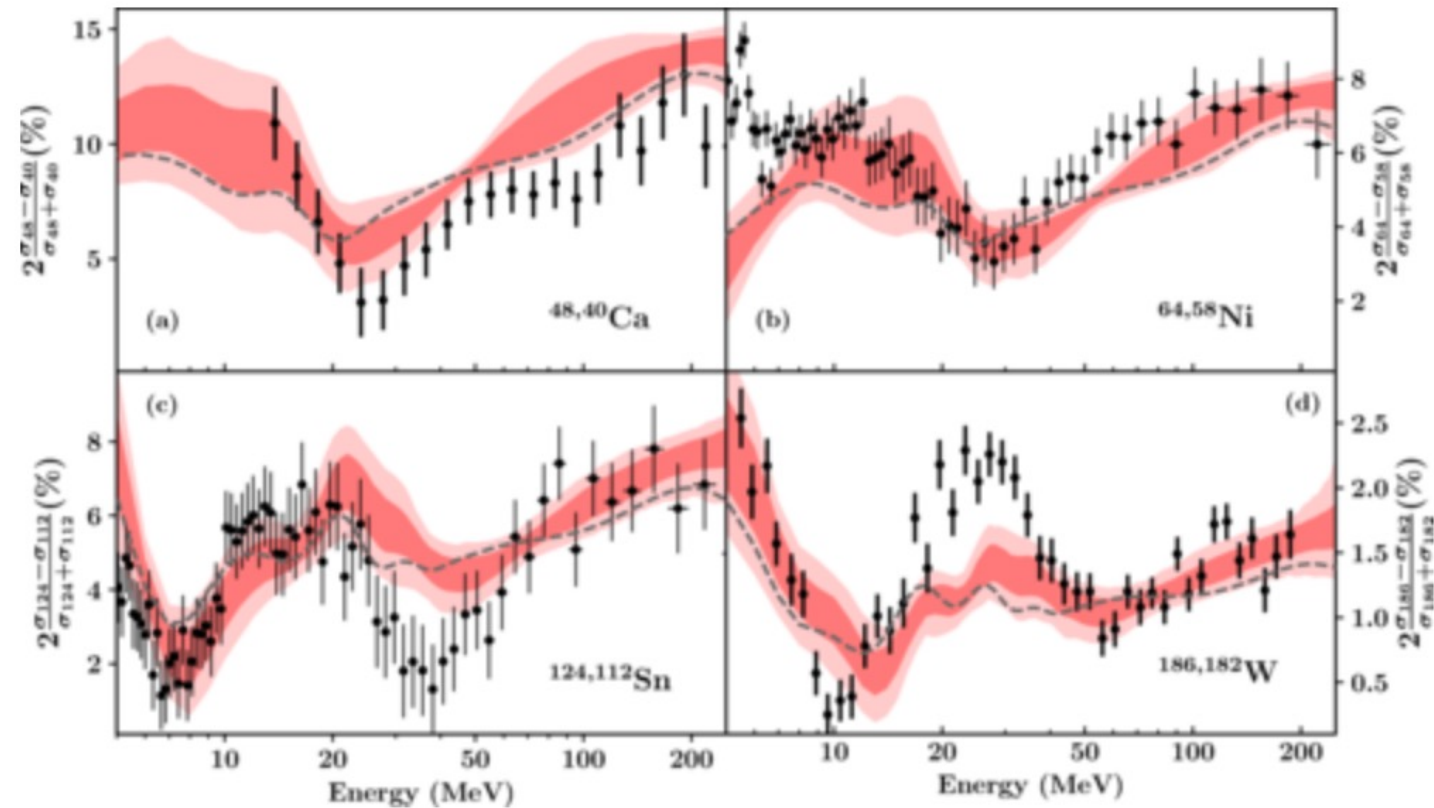
- Importance sampling BFMC | $p(x)$ can be sampled approximately:

- $E[x] \approx \frac{1}{N} \sum_i X_i \frac{w_i}{g_i}$ where $X_i \sim g(x)$, $w_i = p(X_i)$, $g_i = g(X_i)$

Neutron Transmission Coefficients



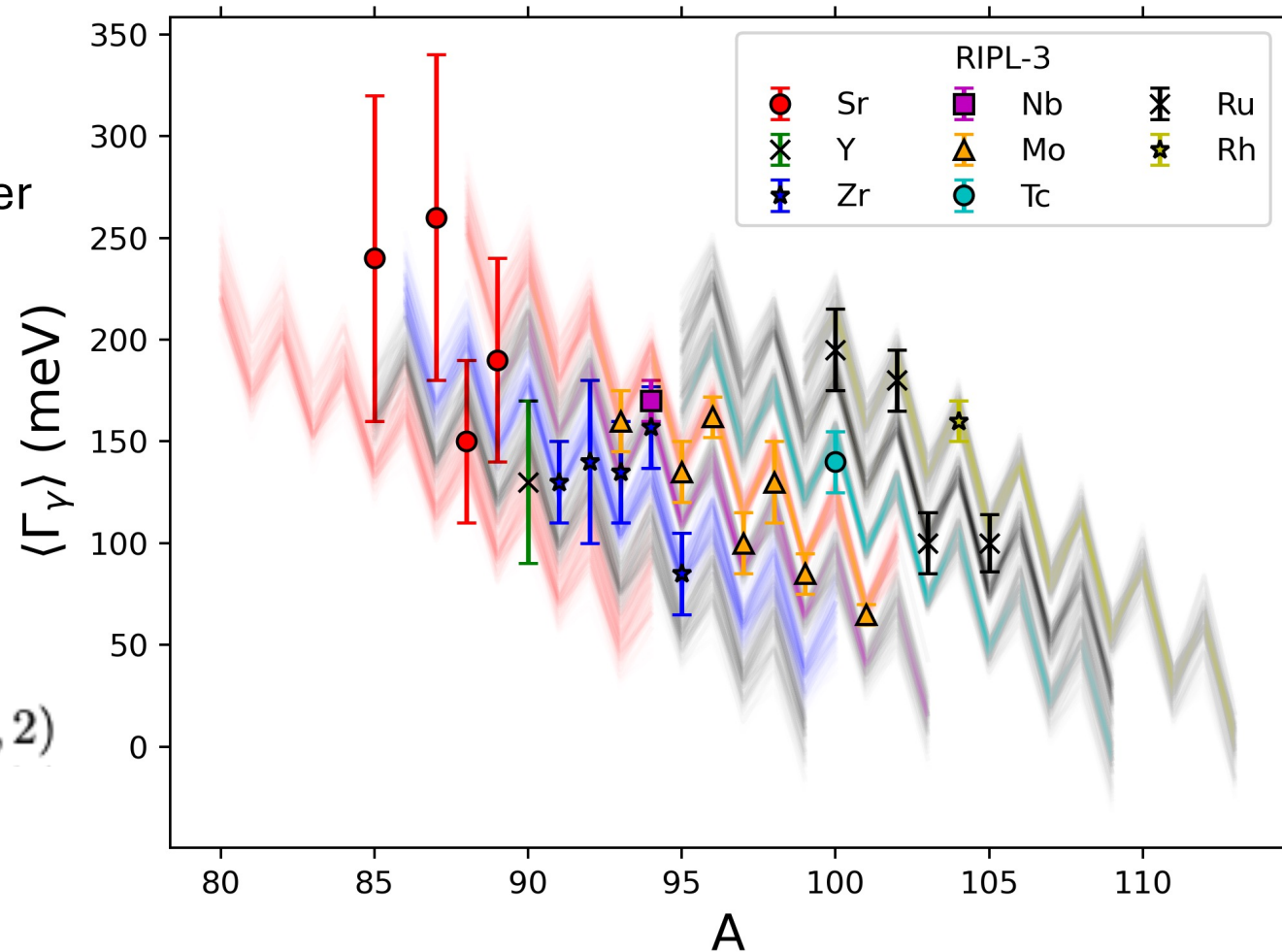
- Pruitt & Escher have re-evaluated the parameters of the Koning-Delaroche optical model
- Including MCMC UQ
- We consider a subset of 50 samples (out 400+) of pre-calculated neutron transmission coefficients



Gamma-ray Transmission Coefficients

- Average radiative width trends:
- $\langle \Gamma_\gamma \rangle_0$ increases with charge number (Z)
- $\langle \Gamma_\gamma \rangle_0$ generally decreases with mass number along an isotopic chain (N)
- $\langle \Gamma_\gamma \rangle_0$ shows an odd-even staggering in A, only observable for even-Z nuclei
- We choose to fit with an empirical form:

$$\langle \Gamma_\gamma \rangle_0(Z, A) = c_0 + c_1 A^2 + c_2 Z^2 + c_3 Z \bmod(A, 2)$$



Level Densities – shell corrections

- The fitted systematic is similar to hoffman:

$N \leq 50$

$$c_0 = -364 \pm 70$$

$$c_1 = 17.2 \pm 3.0$$

$$c_2 = -0.20 \pm 0.03$$

$N > 50$

$$c_0 = -202 \pm 12$$

$$c_1 = 6.67 \pm 0.43$$

$$c_2 = -0.053 \pm 0.004$$

- Uncertainties represent the 1σ quantile of the distributions that results from the MC fitting procedure. Close to normal distributions.

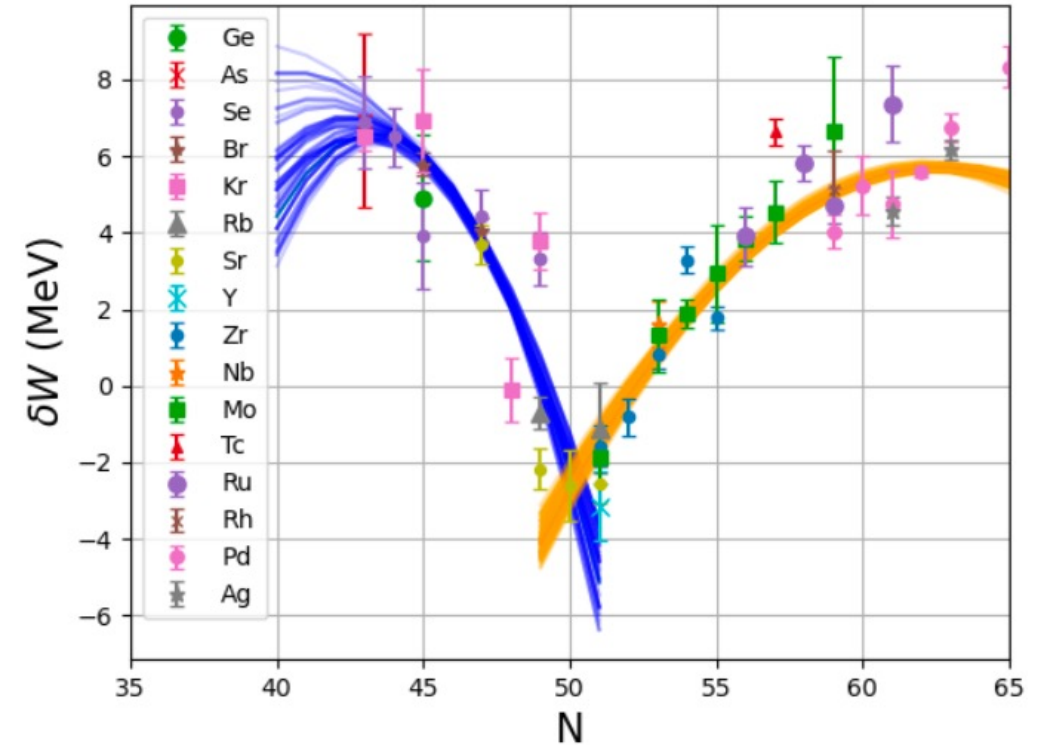
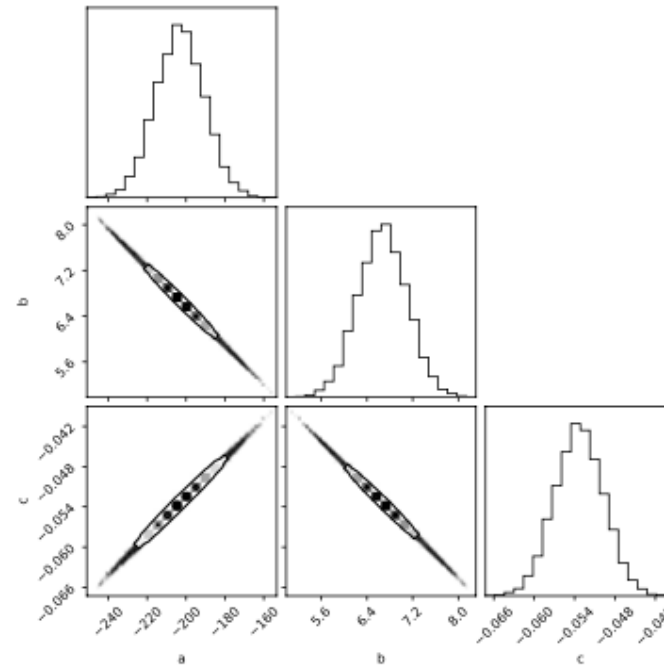


Figure 2: Results of the Monte-Carlo fitting procedure for the shell correction parameter δW .