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Recent ND developments and plans at UU

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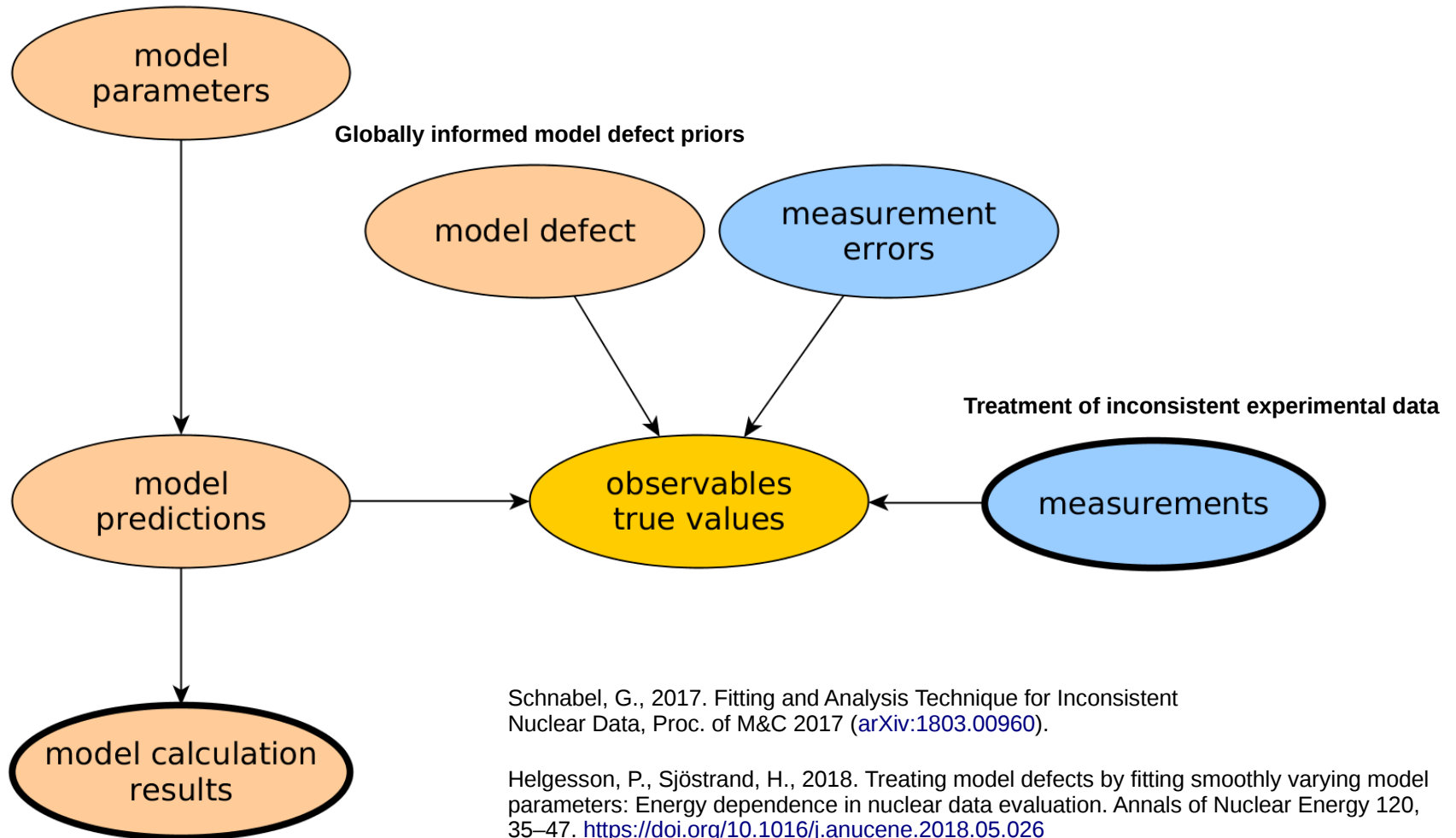


Parameters & Complexity



Outline

Energy-dependent model parameters

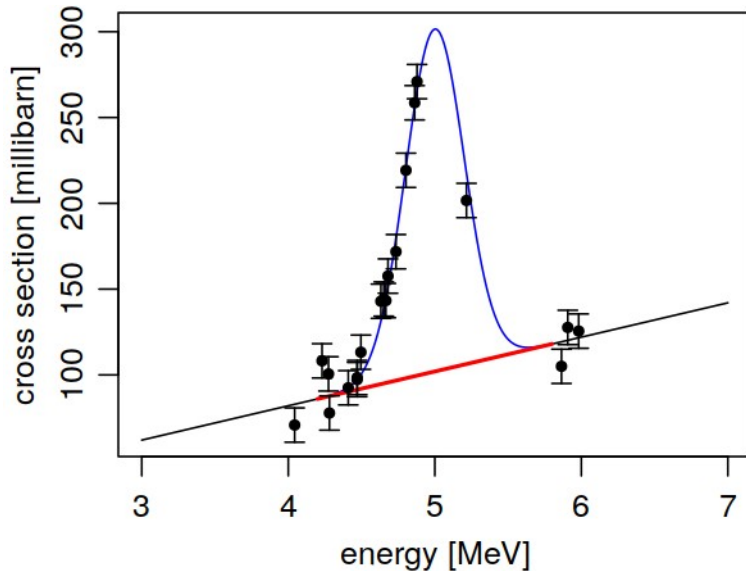


Schnabel, G., 2017. Fitting and Analysis Technique for Inconsistent Nuclear Data, Proc. of M&C 2017 ([arXiv:1803.00960](https://arxiv.org/abs/1803.00960)).

Helgesson, P., Sjöstrand, H., 2018. Treating model defects by fitting smoothly varying model parameters: Energy dependence in nuclear data evaluation. Annals of Nuclear Energy 120, 35–47. <https://doi.org/10.1016/j.anucene.2018.05.026>

Schnabel, G., Sjöstrand, H., Construction of model defect priors inspired by dynamic time warping, WONDER 2018

Motivation of GP regression



Background + Signal

$$f(E) = a_1 + a_2 E + a_3 \exp\left(-\frac{(\mu - E)^2}{2\sigma^2}\right)$$

More general

$$f(E) = \sum_{k=1}^{\infty} a_k \sin(2\pi c k E)$$

Prior / Regularization

$$a_k \sim \mathcal{N}(0, 1/k)$$

Model + Defect

$$f(E) = \mathcal{M}_{\vec{p}}(E) + \delta(E) = \mathcal{M}_{\vec{p}}(E) + \sum_{k=1}^{\infty} a_k \sin(2\pi c k E)$$

Gaussian process

- infinite series
- normal prior on coeffs

Covariance matrix

Covariance matrices can represent a variety of things such as normalization uncertainties, linear trends, splines, Fourier series, polynomial expansions, white noise, etc.



$$y(x) = kx + d, \quad k \sim \mathcal{N}(0, \delta_k^2), \quad d \sim \mathcal{N}(0, \delta_d^2)$$

Observations $(\vec{y}_{\text{exp}}, \vec{x}_{\text{exp}})$

$$\vec{p} = \begin{pmatrix} k \\ d \end{pmatrix} = AS^T (SAS^T + B)^{-1} \vec{y}_{\text{exp}}$$

$$\vec{y}_{\text{pred}} = S_{\text{pred}} \vec{p} = \begin{pmatrix} \vec{x}_{\text{pred}}, \vec{1} \end{pmatrix} \begin{pmatrix} k \\ d \end{pmatrix}$$

$$S_{\text{exp}} = \begin{pmatrix} \vec{x}_{\text{exp}}, \vec{1} \end{pmatrix}$$

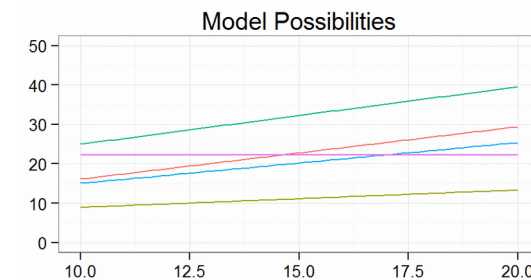
$$A = \begin{pmatrix} \delta_k^2 & 0 \\ 0 & \delta_d^2 \end{pmatrix}$$

$$B = \begin{pmatrix} \varepsilon_1^2 & 0 & 0 \\ 0 & \varepsilon_2^2 & 0 \\ 0 & 0 & \ddots \end{pmatrix}$$

$$\kappa(x_1, x_2) := \text{Cov}[y(x_1), y(x_2)] = \delta_k^2 x_1 x_2 + \delta_d^2$$

$$K_{\text{pred,exp}} = \kappa(\vec{x}_{\text{pred}}, \vec{x}_{\text{exp}}) \quad K_{\text{exp,exp}} = \kappa(\vec{x}_{\text{exp}}, \vec{x}_{\text{exp}})$$

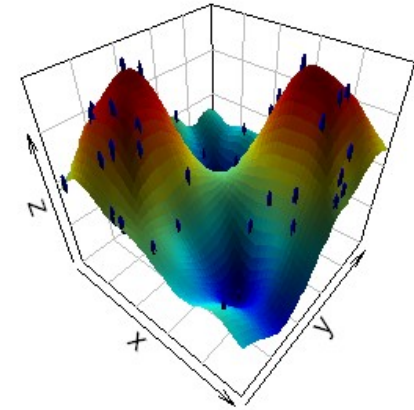
$$\vec{y}_{\text{pred}} = K_{\text{pred,exp}} K_{\text{exp,exp}}^{-1} \vec{y}_{\text{exp}}$$



Power of GP

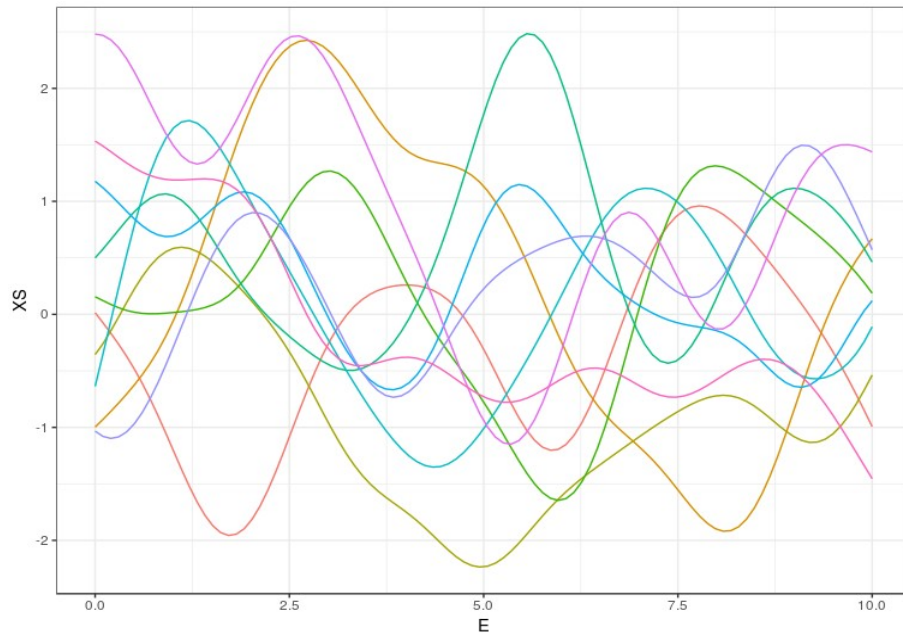
Powerful concept

Directly parametrize covariance matrix and work implicitly with an infinite number of parameters/basis functions!

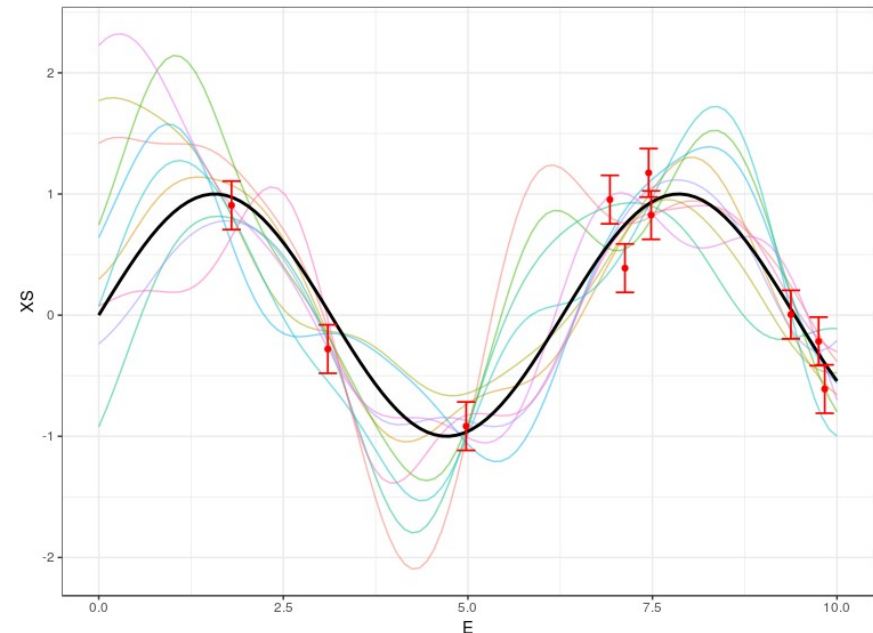


$$\kappa(\mathbf{x}_1, \mathbf{x}_2) = \delta^2 \exp\left(-\frac{(\mathbf{x}_1 - \mathbf{x}_2)^2}{2\lambda^2}\right)$$

Sample from prior ($\delta=\lambda=1$)

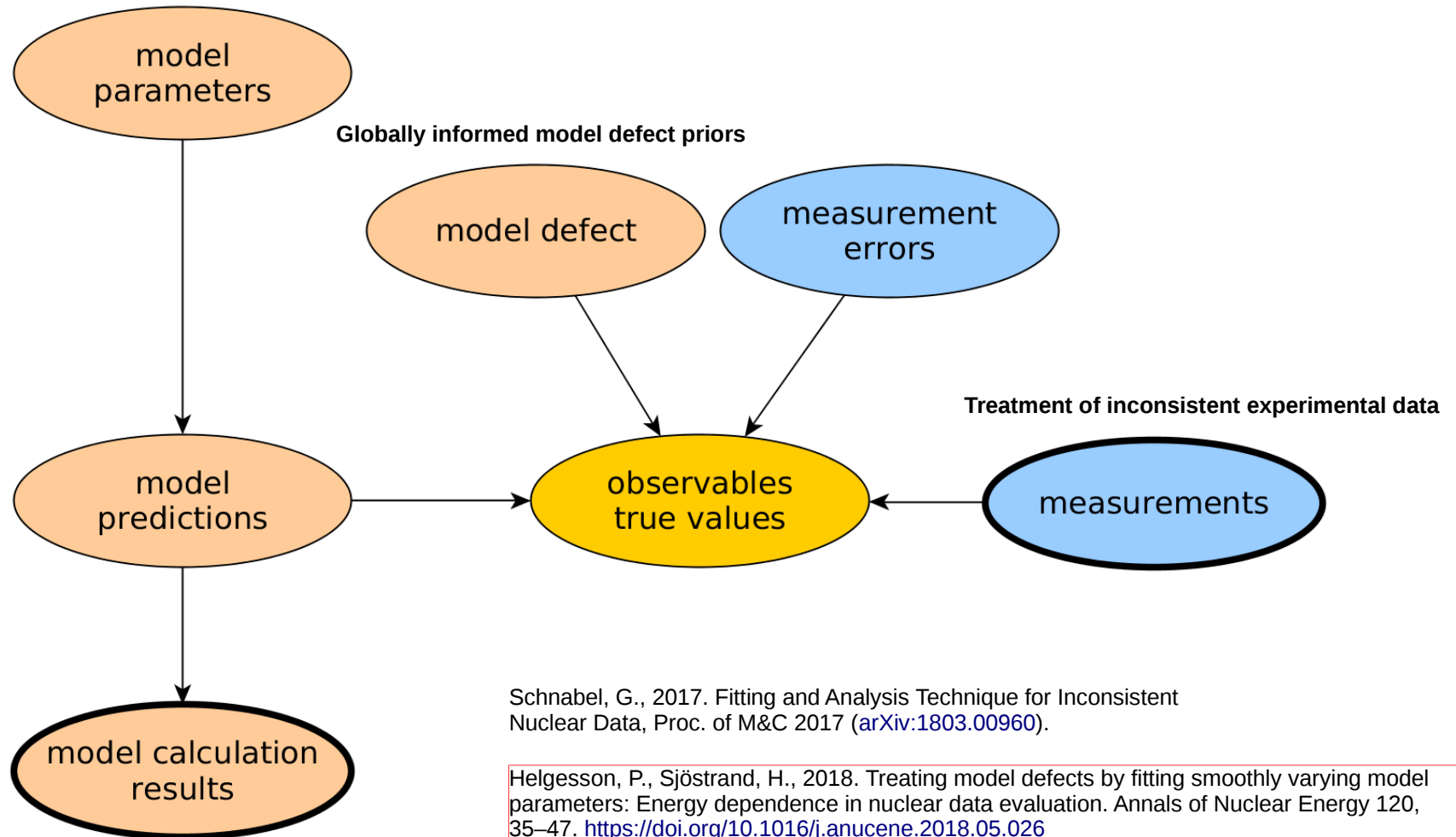


Sample from posterior



Energy-dependent parameters

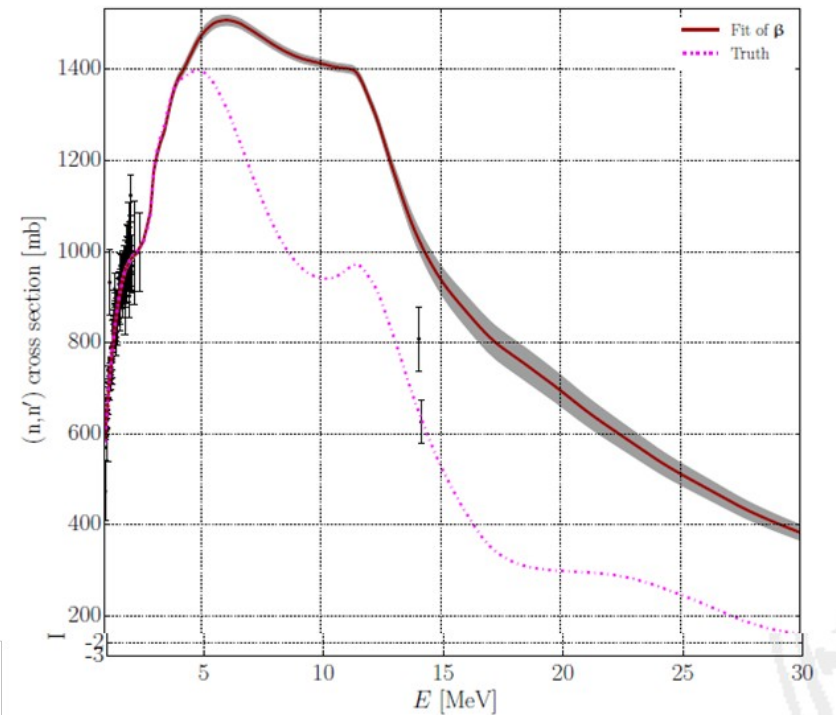
Energy-dependent model parameters



Schnabel, G., Sjöstrand, H., Construction of model defect priors inspired by dynamic time warping, WONDER 2018

Energy-dependent model parameters

- Some parameters energy dependent (e.g., optical potential)
- Use GPs to fine-tune energy dependence to get a better reproduction of data
- Better physics or vehicle to treat model defects



$$f(E) = \mathcal{M}(E | \vec{p}(E')) \longrightarrow \mathcal{M}(E | \vec{p}(E') + \vec{\delta}(E'))$$



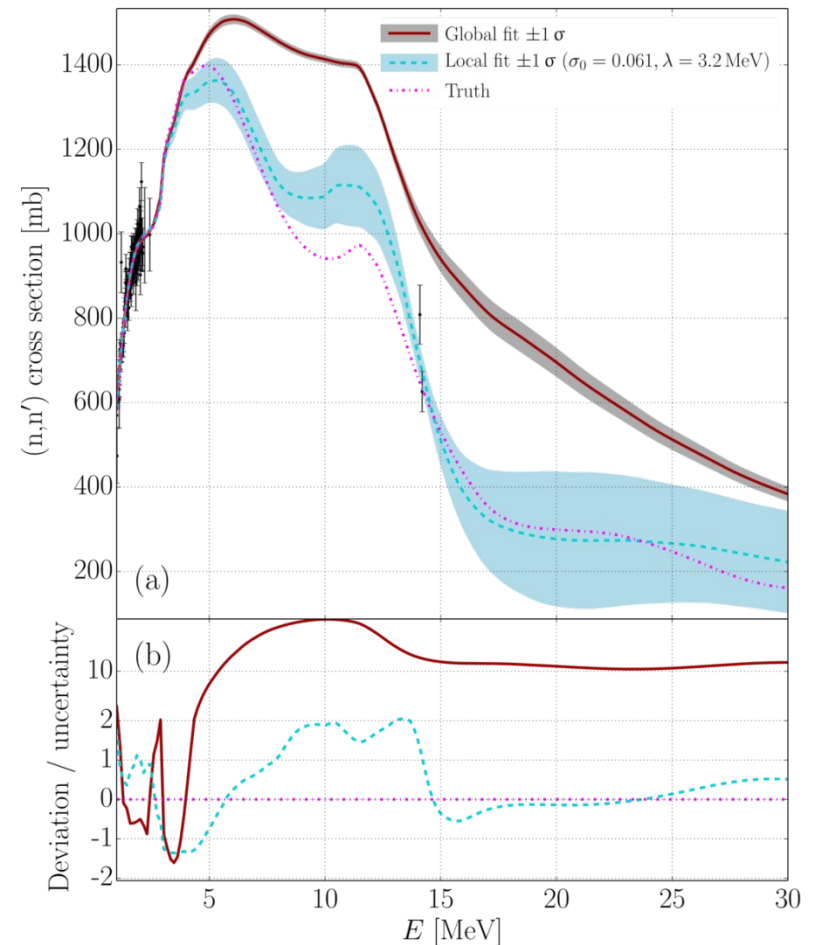
Gaussian process

$$k(E, E') = \delta^2 \exp\left(-\frac{1}{2} \frac{(E - E')^2}{\lambda^2}\right)$$

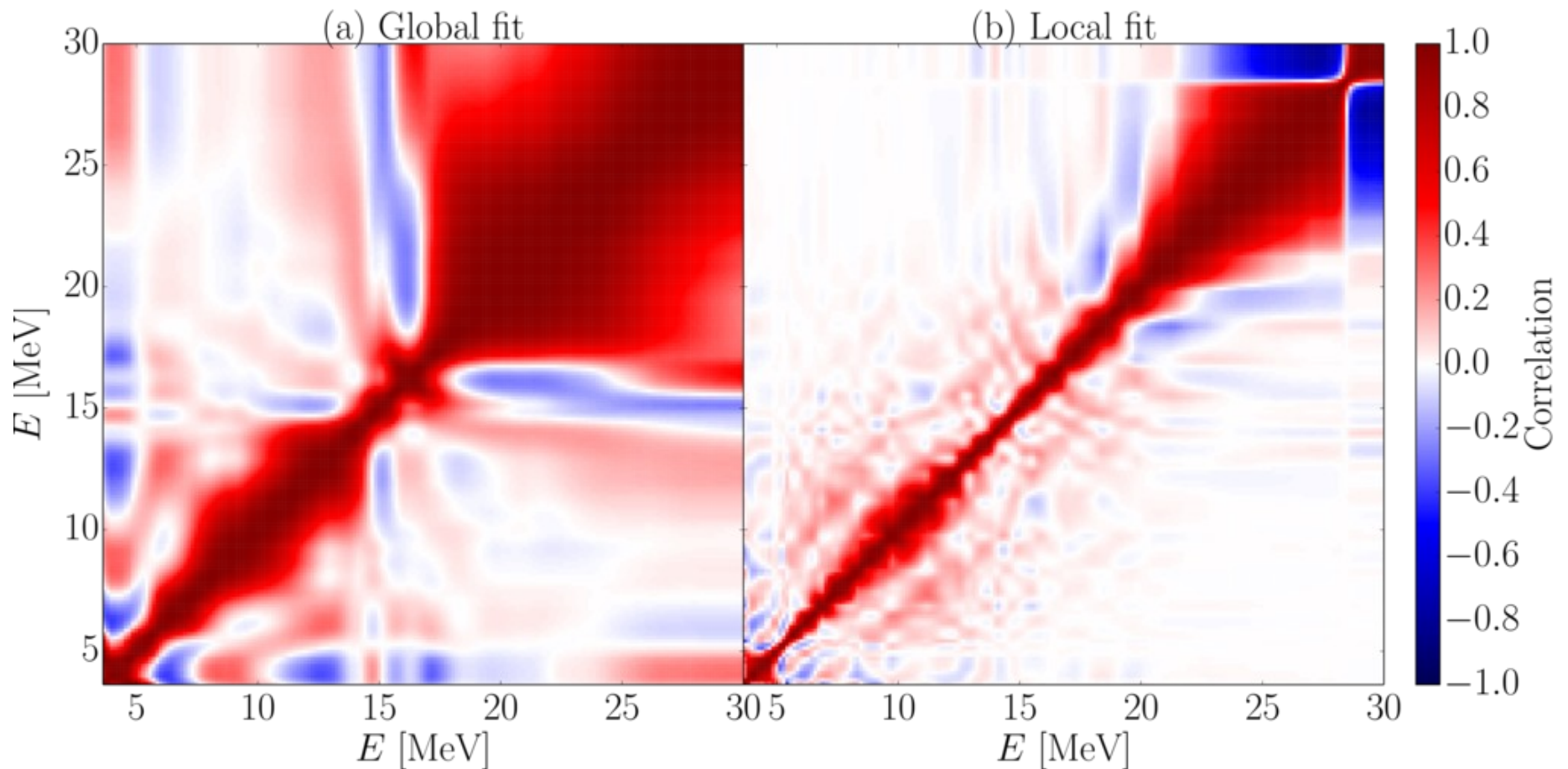
Synthetic data study

- Model: “Pseudo-TALYS” (^{56}Fe like data)
- Sampled truth:
- $f_{\text{true}}(x) = f(x, \boldsymbol{\beta})(1 + \xi(x))$
 - $\boldsymbol{\beta}$ and $\xi(x)$ sampled
 - ⇒ Varying model defect, $\xi(x)$
- Sampled experimental data

Found: Energy-dependent much more reasonable uncertainties.



Comparison of correlations

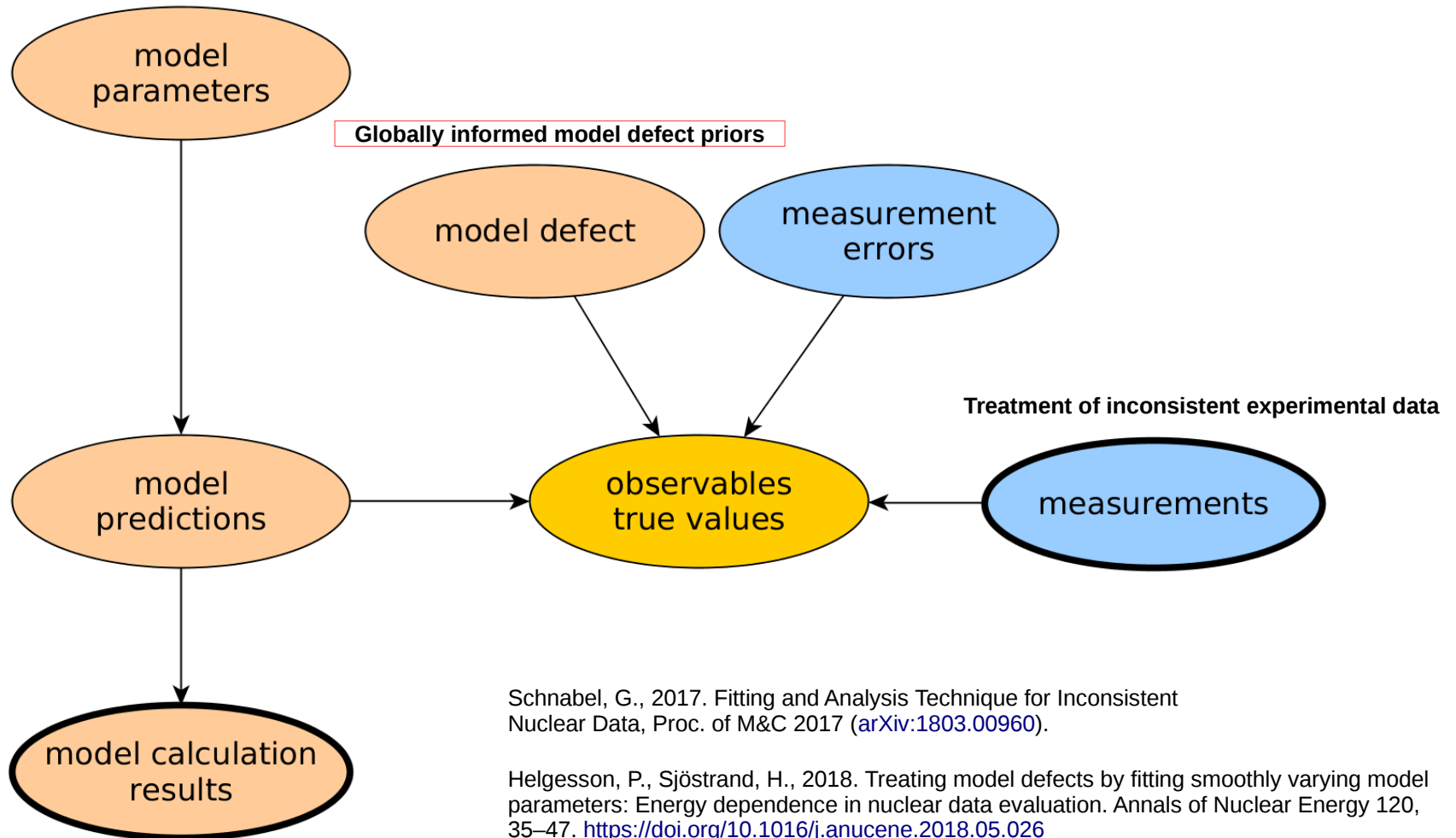


Global fit standard TALYS

Local fit energy-dependent parameters augmented with GPs

Globally informed defect priors

Energy-dependent model parameters



Schnabel, G., 2017. Fitting and Analysis Technique for Inconsistent Nuclear Data, Proc. of M&C 2017 ([arXiv:1803.00960](https://arxiv.org/abs/1803.00960)).

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Schnabel, G., Sjöstrand, H., Construction of model defect priors inspired by dynamic time warping, WONDER 2018

$$k(E, E') = \delta^2 \exp\left(-\frac{1}{2} \frac{(E - E')^2}{\lambda^2}\right)$$

Dynamic time warping GP

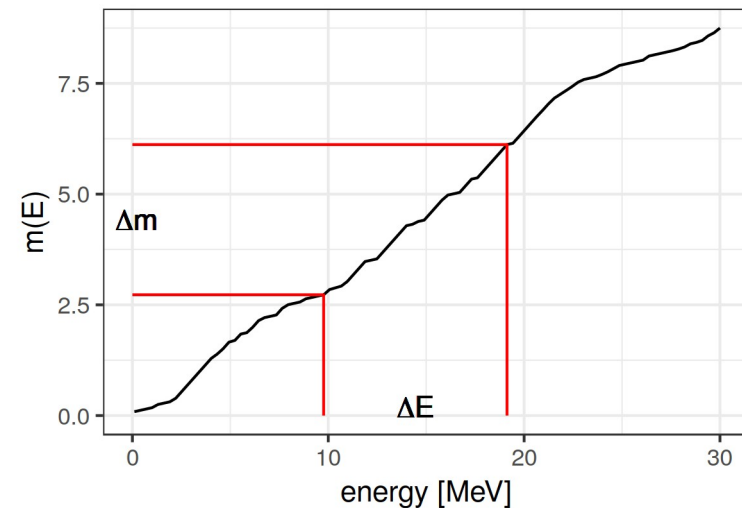
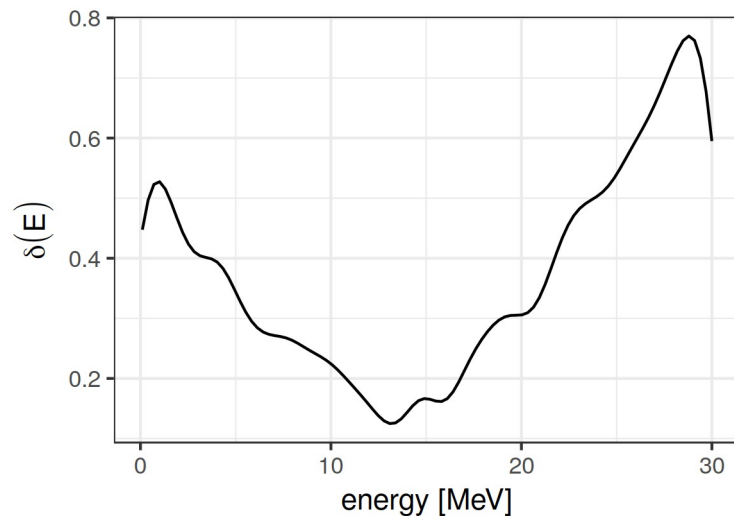
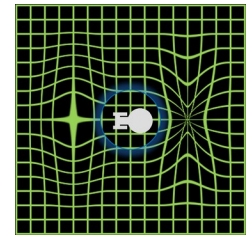
Happy! Got promoted to a function!



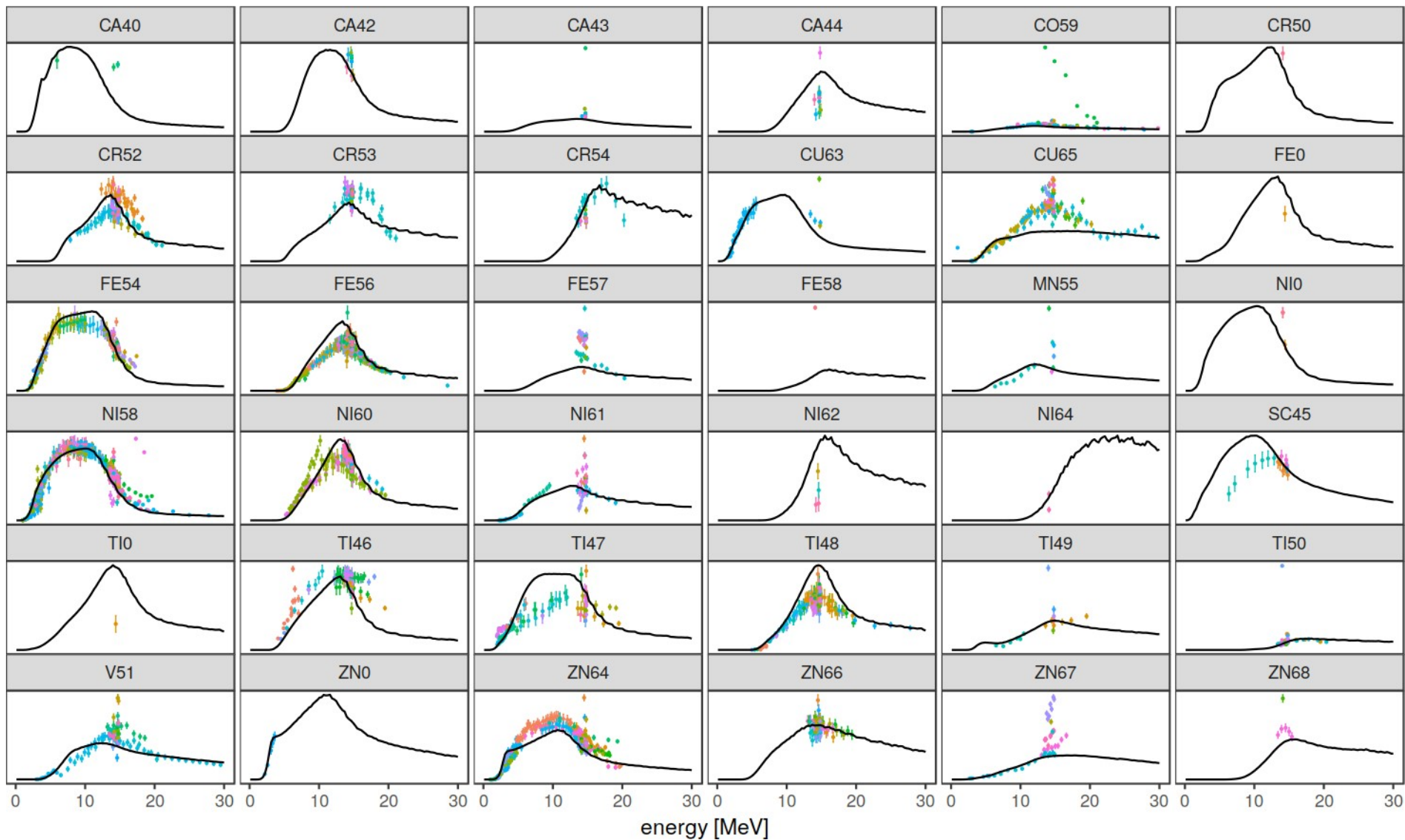
$$k(E, E') = \delta(E)\delta(E') \exp\left(-\frac{1}{2} \left(m(E) - m(E')\right)^2\right)$$

$$\delta(E) = \sum_{i=1}^{99} \left(\frac{E_{i+1} - E}{E_{i+1} - E_i} \mathbf{y}_i + \frac{E - E_i}{E_{i+1} - E_i} \mathbf{y}_{i+1} \right) \mathcal{I}_{(E_i \leq E < E_{i+1})}(E)$$

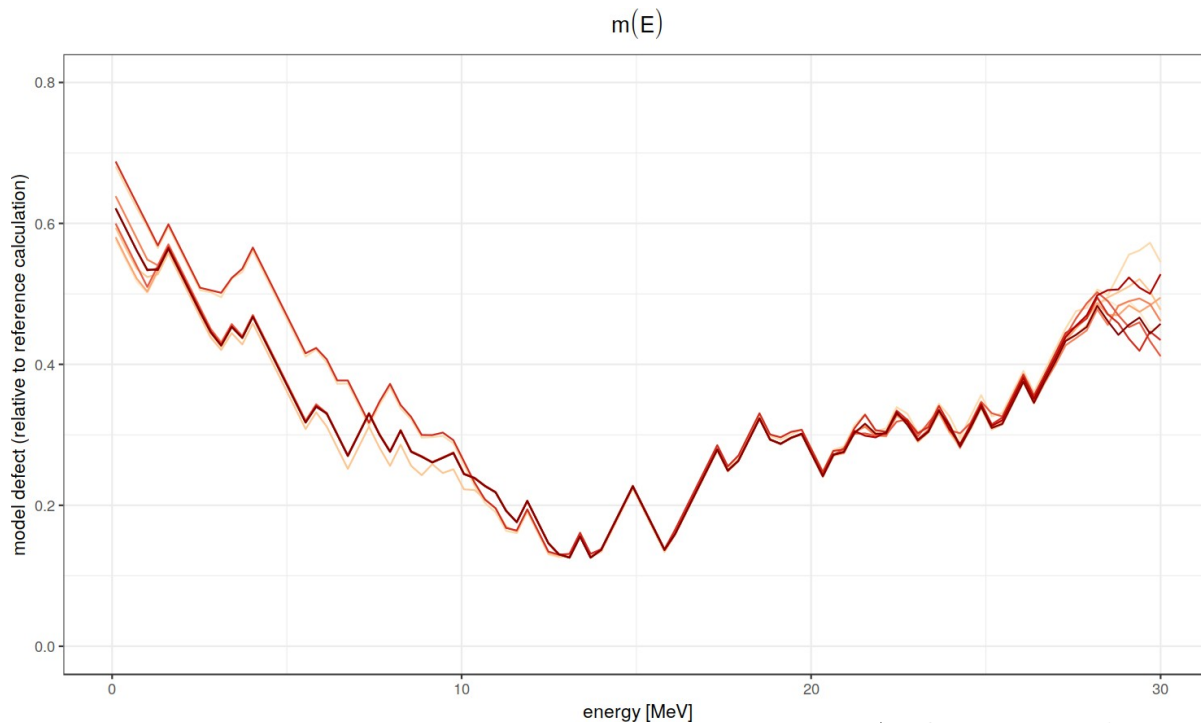
$$m(E) = \sum_{i=1}^{99} \left(\frac{E_{i+1} - E}{E_{i+1} - E_i} \mathbf{z}_i + \frac{E - E_i}{E_{i+1} - E_i} \mathbf{z}_{i+1} \right) \mathcal{I}_{(E_i \leq E < E_{i+1})}(E)$$



Global prior construction (n,p) reactions as examples

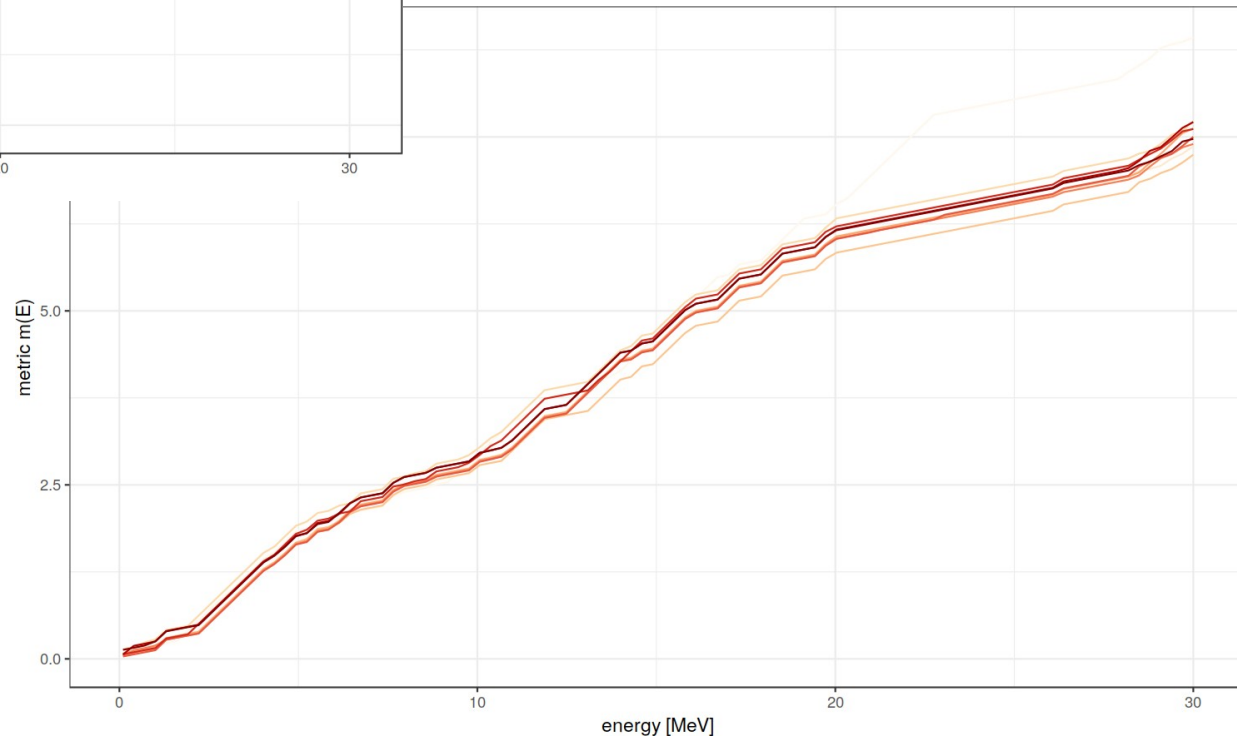


Resulting defect prior



[Link to animation \[MP4\]](#)

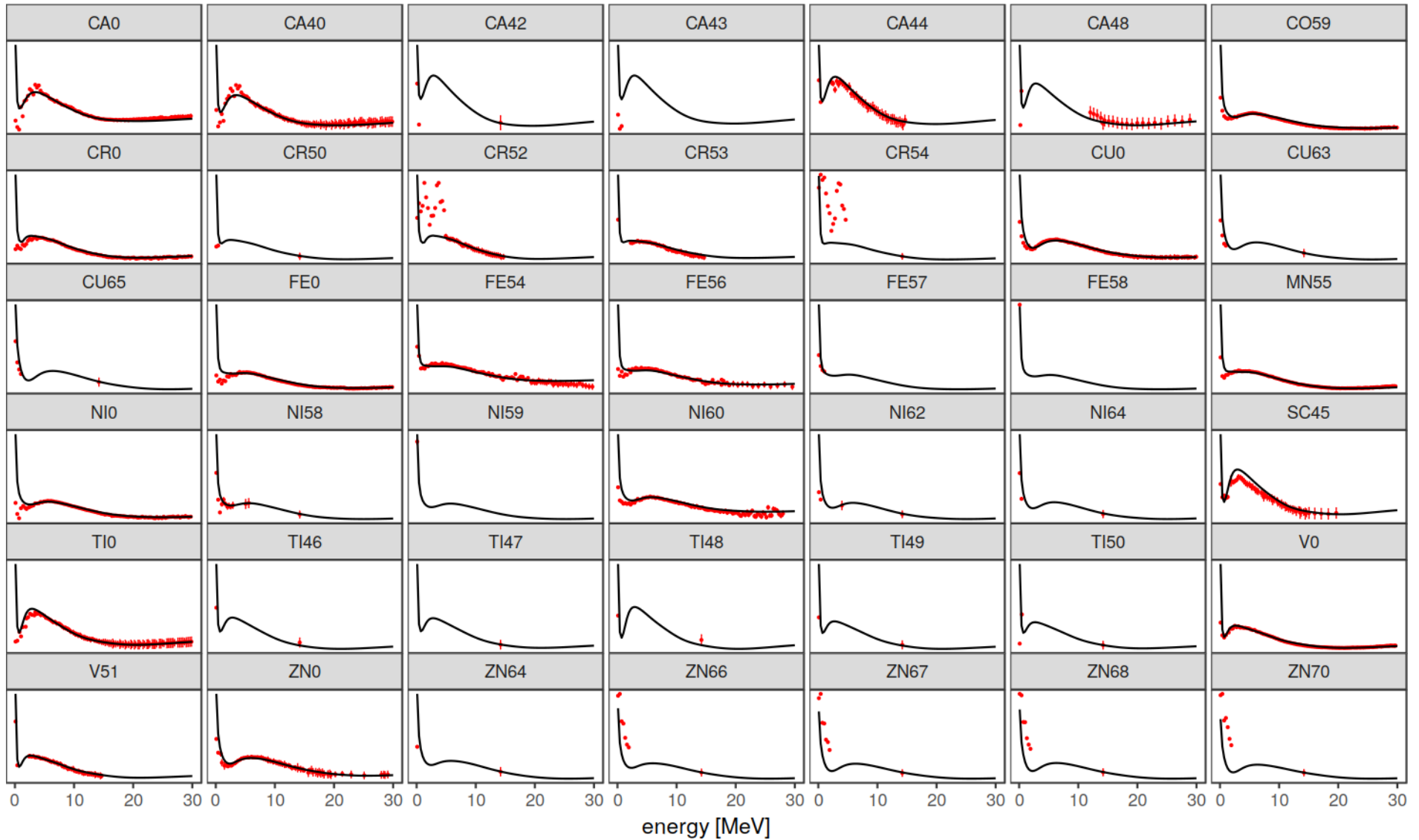
[Link to animation \[GIF\]](#)



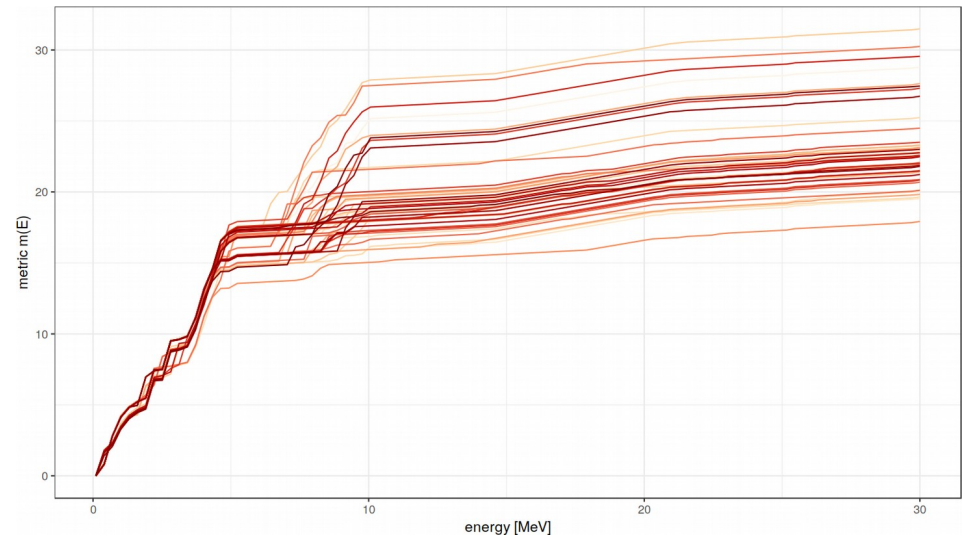
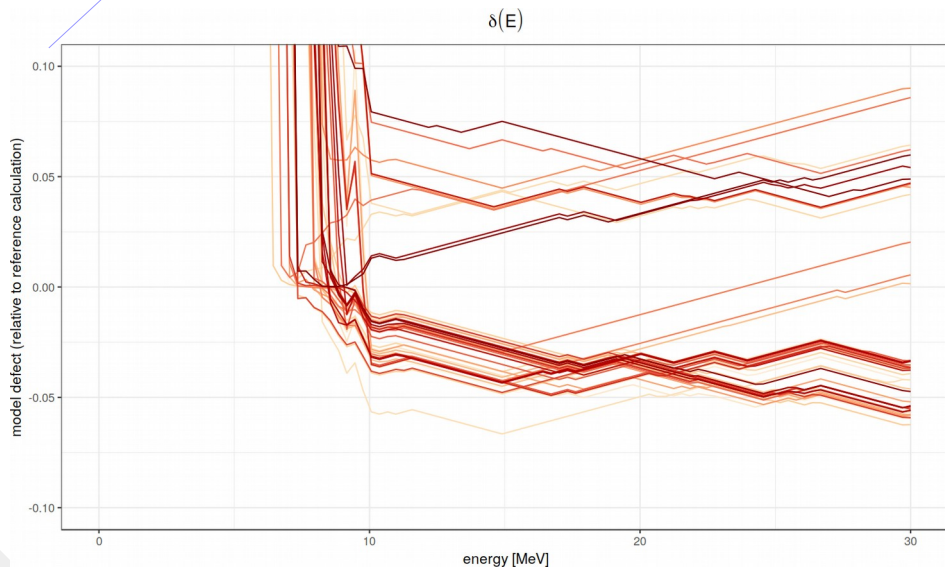
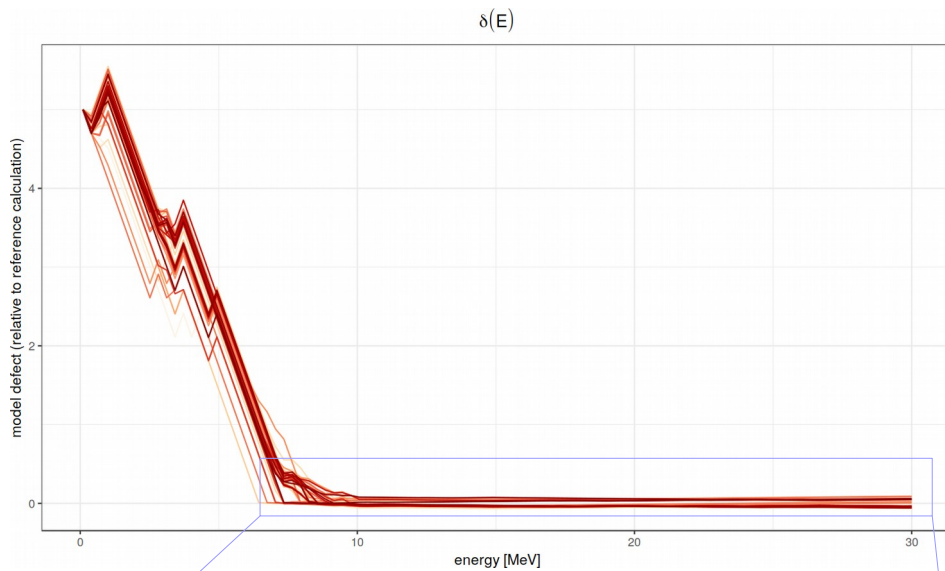
Remark

Reasonable constraints are important for a successful optimization (e.g., lower bound for length-scale, upper bound for maximal local difference of amplitude, etc.)

Global defect (n,tot)



Marlike maxim with (n,tot) data



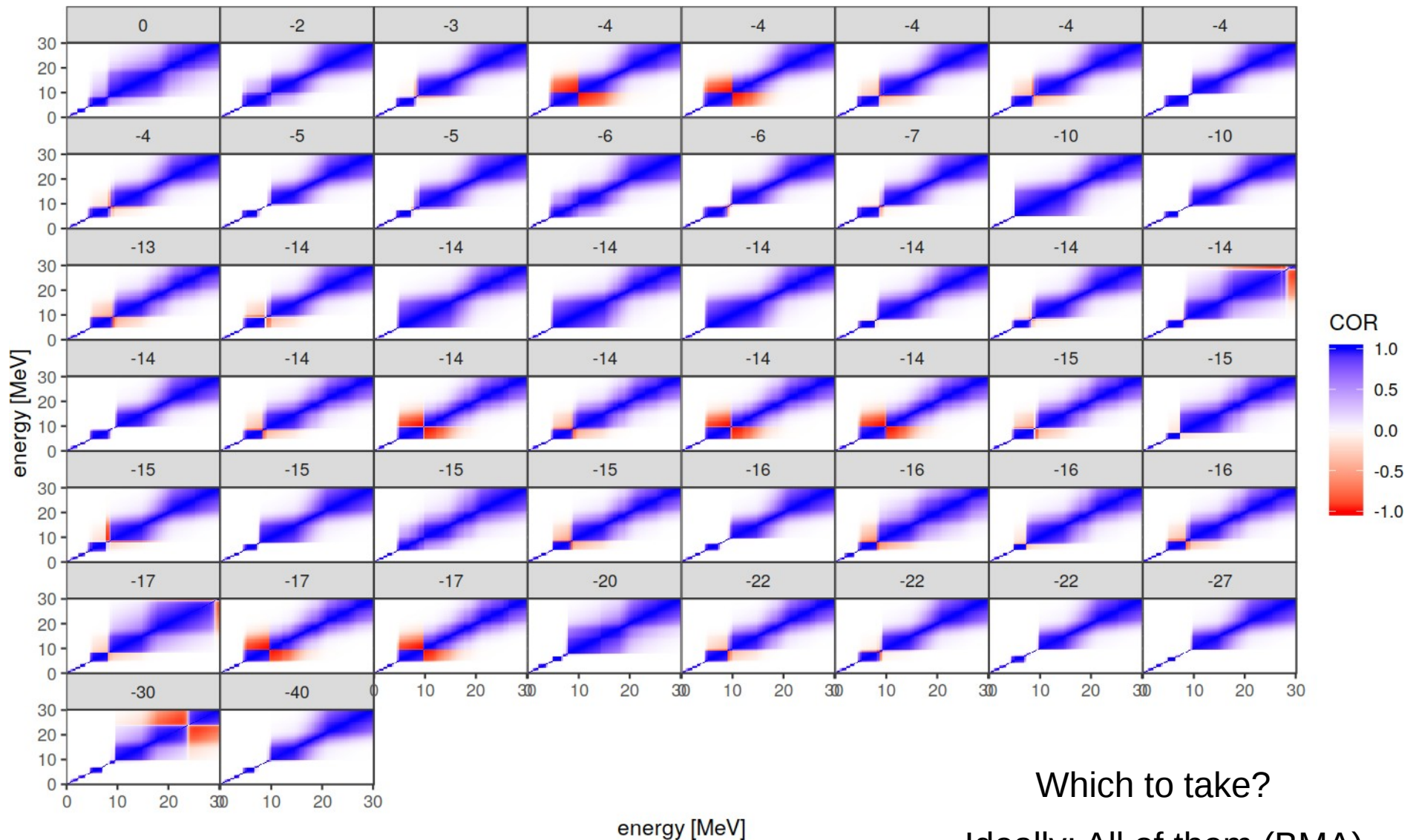
Remark

Optimization was guided by allowing more flexibility at lower than at higher energies.

[Link to animation \[GIF\]](#)

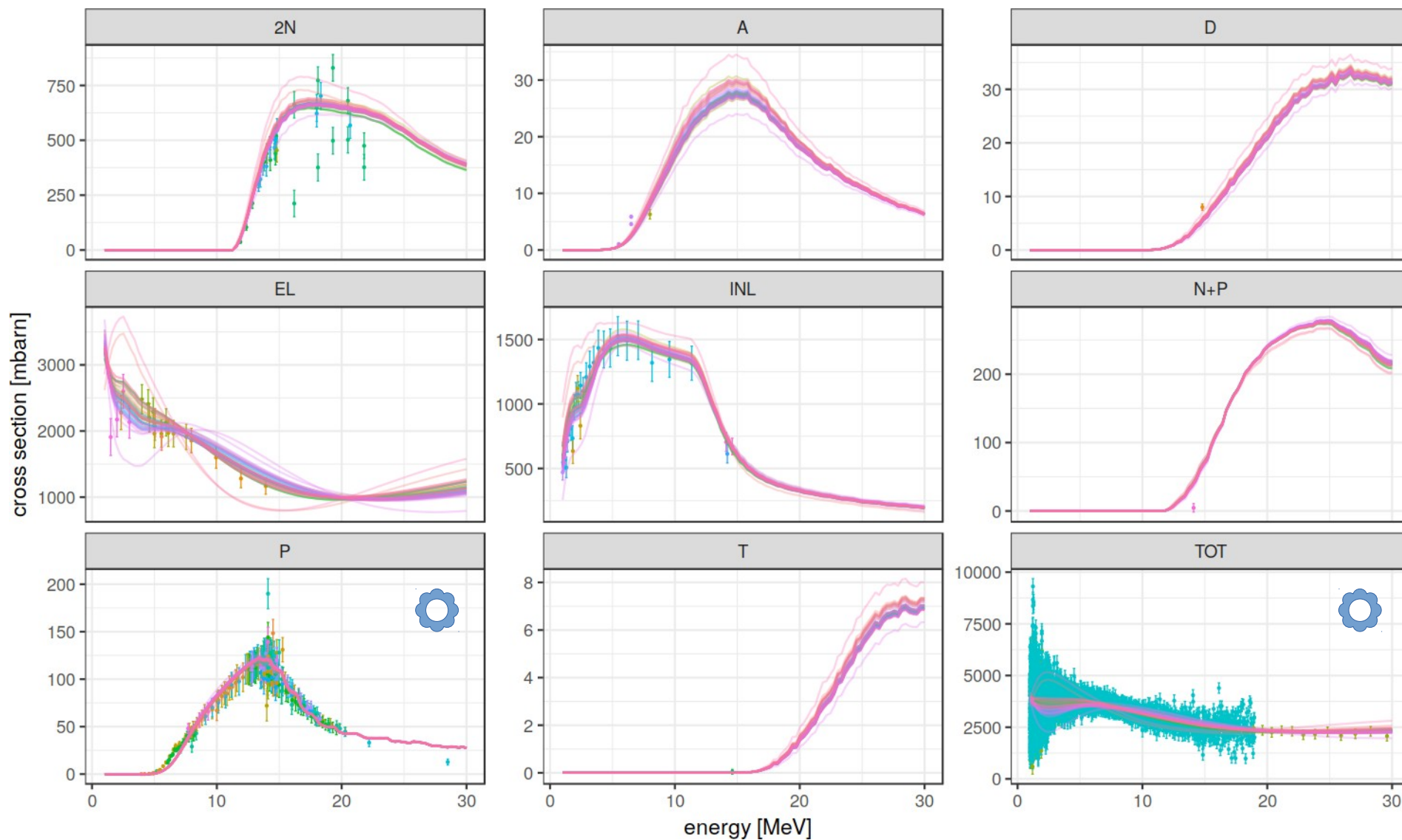
[Link to animation \[MP4\]](#)

Correlation matrices of defect (n,tot)



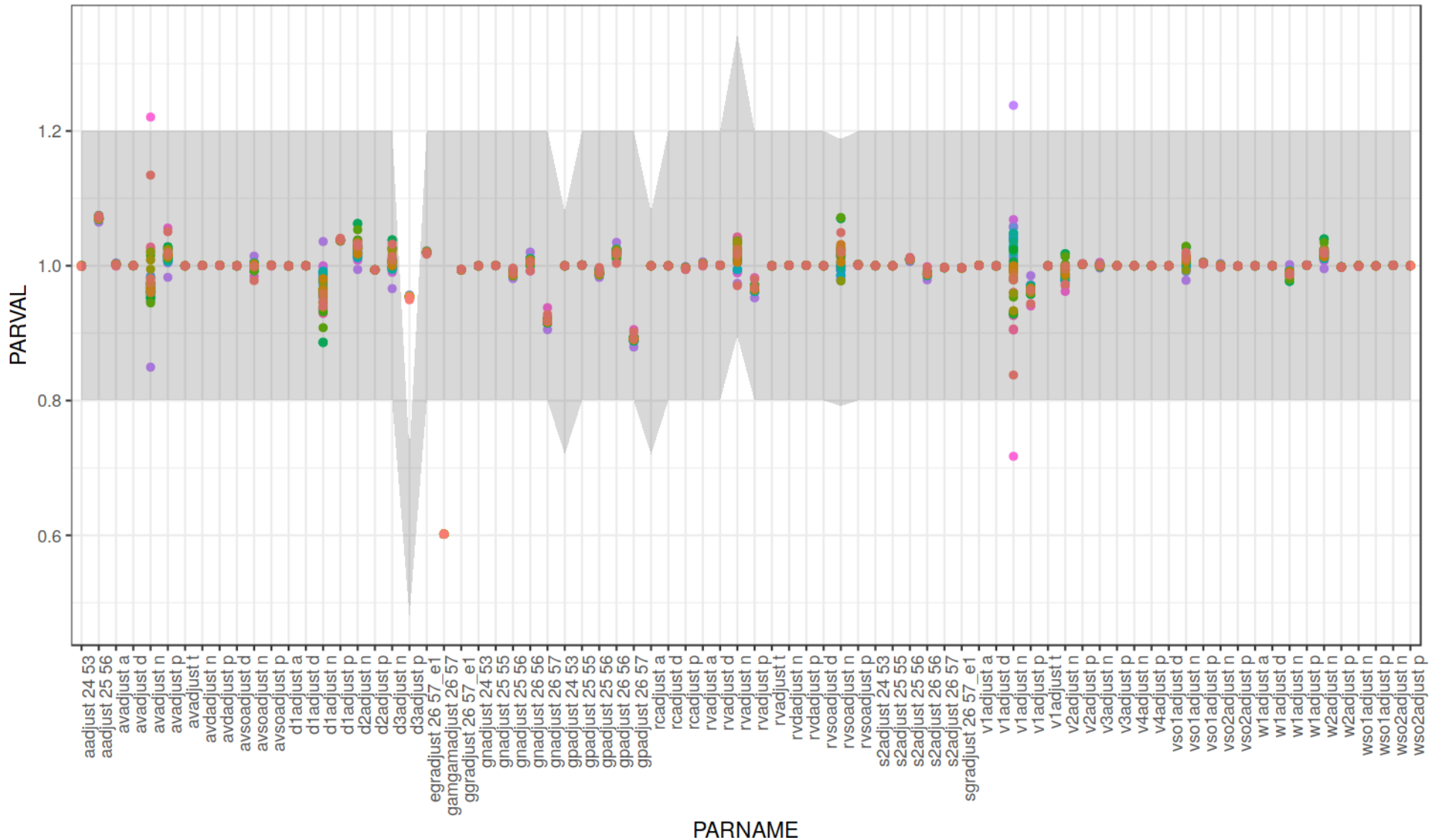
Poor man's BMA

[again ^{56}Fe update (n,p) and (n,tot)]



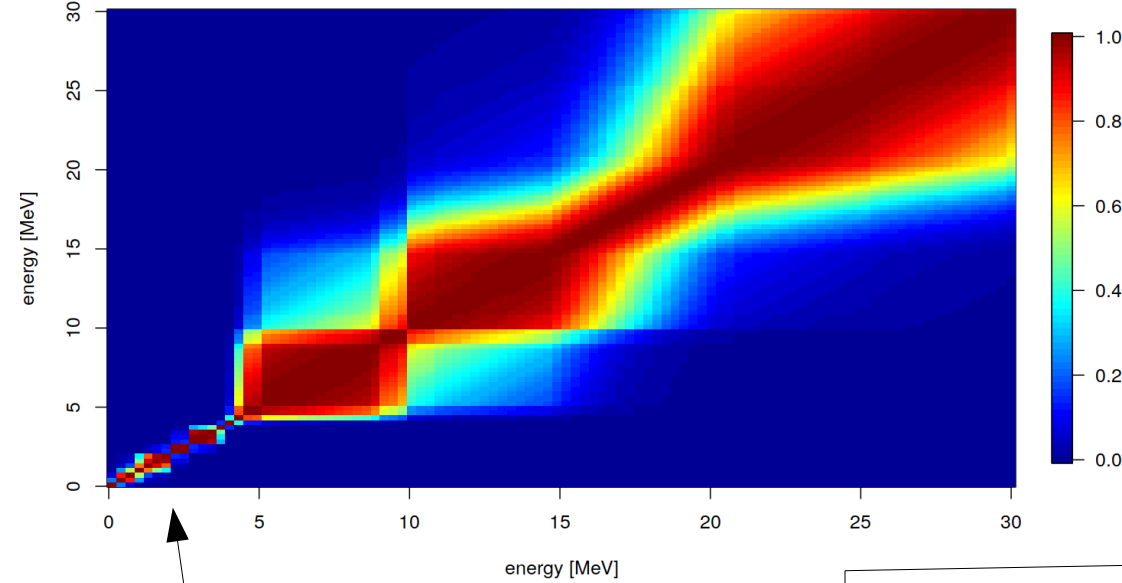
Poor man's BMA

[again ^{56}Fe update (n,p) and (n,tot)]



Correlation structure

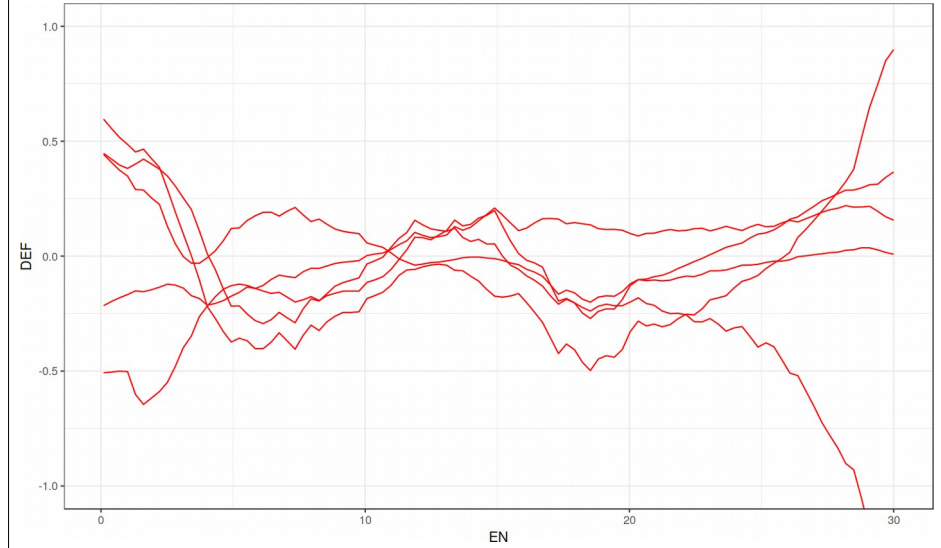
correlation of defect for (n,tot)



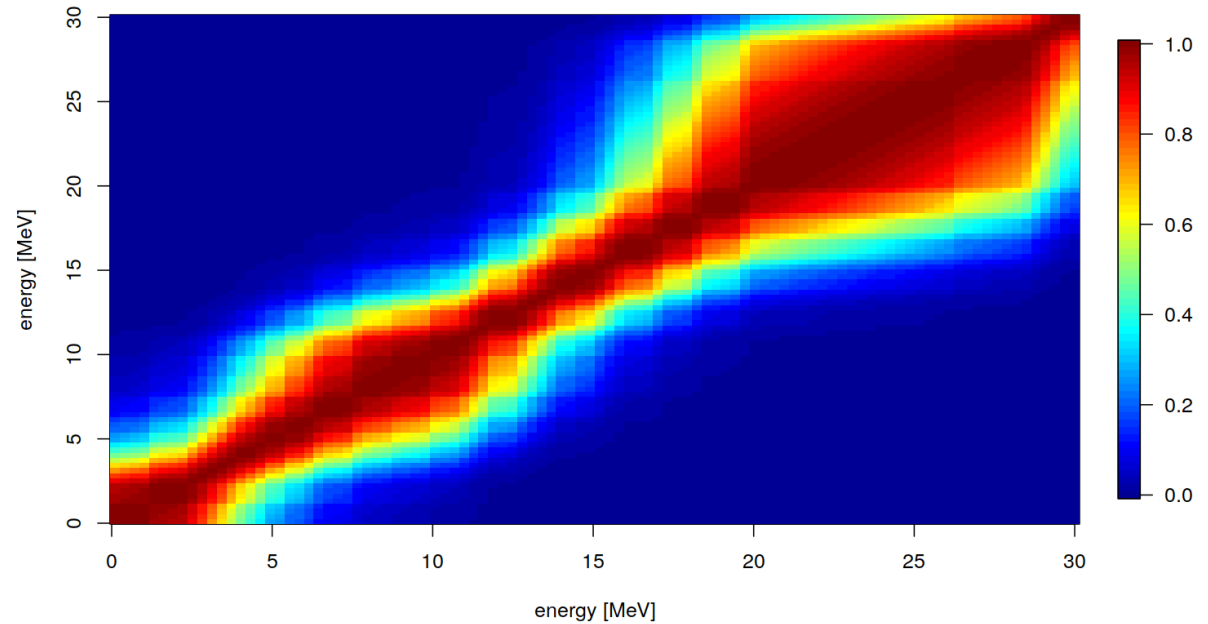
resonance region

[Link to animation \[GIF\]](#)

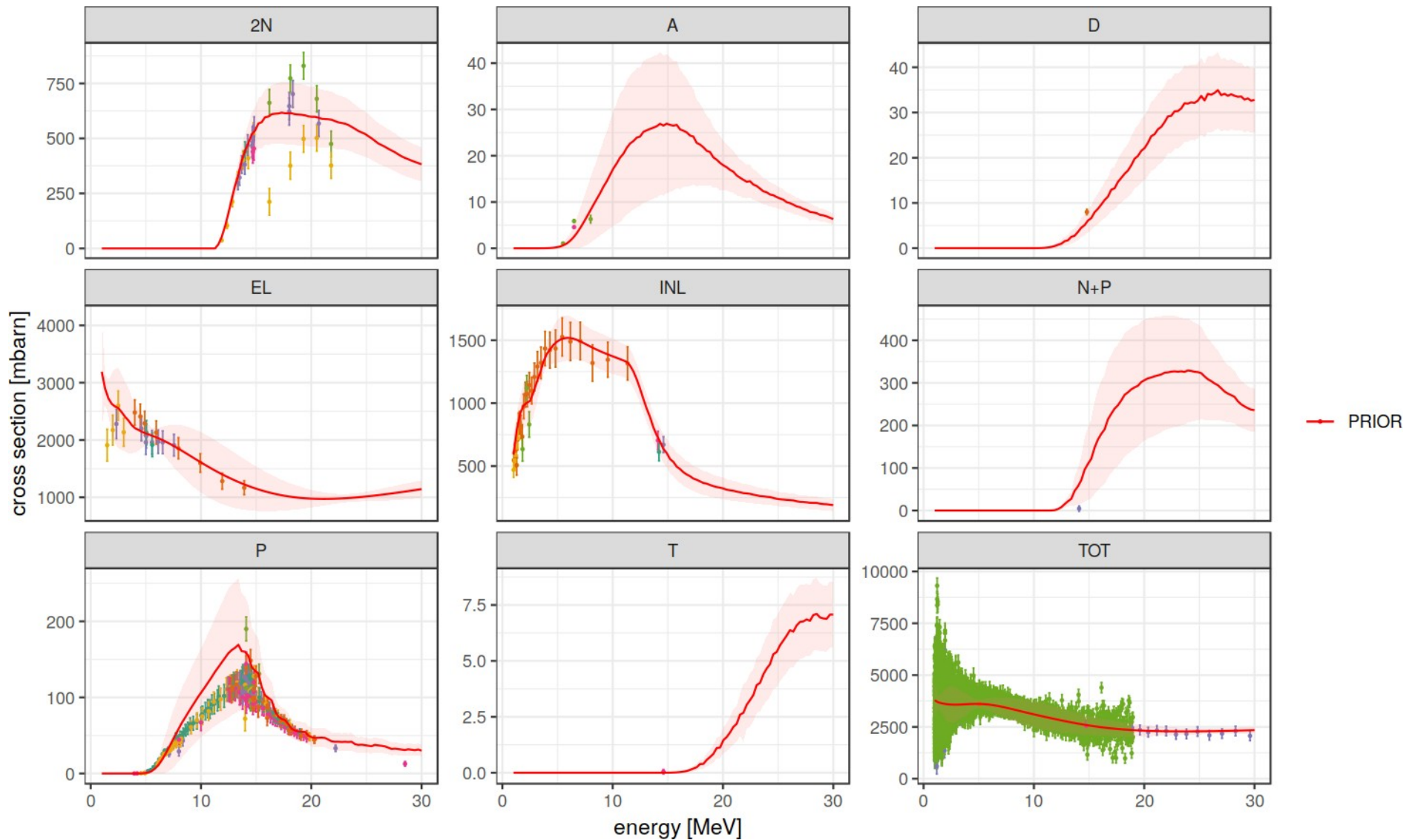
[Link to animation \[MP4\]](#)



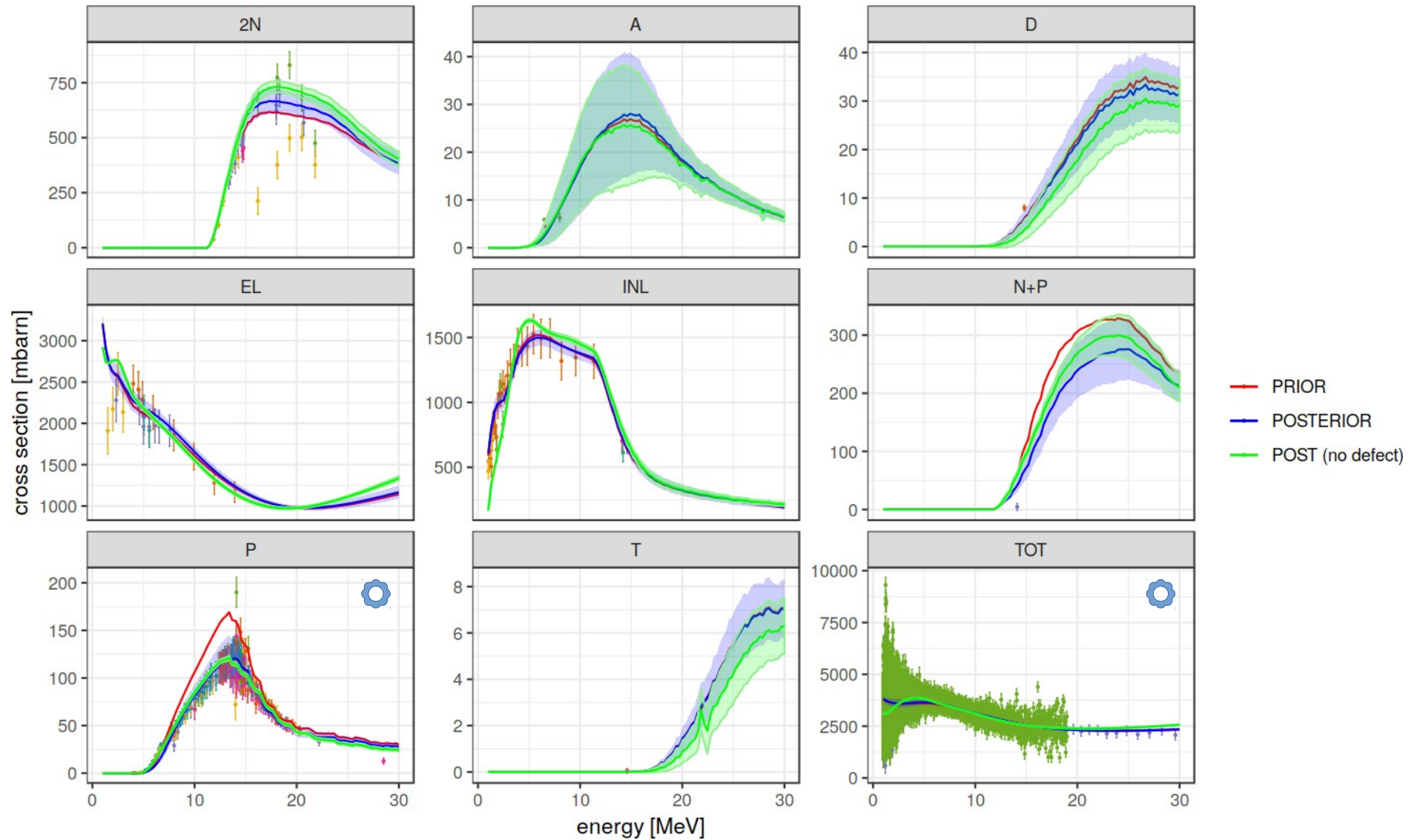
correlation of defect for (n,p)



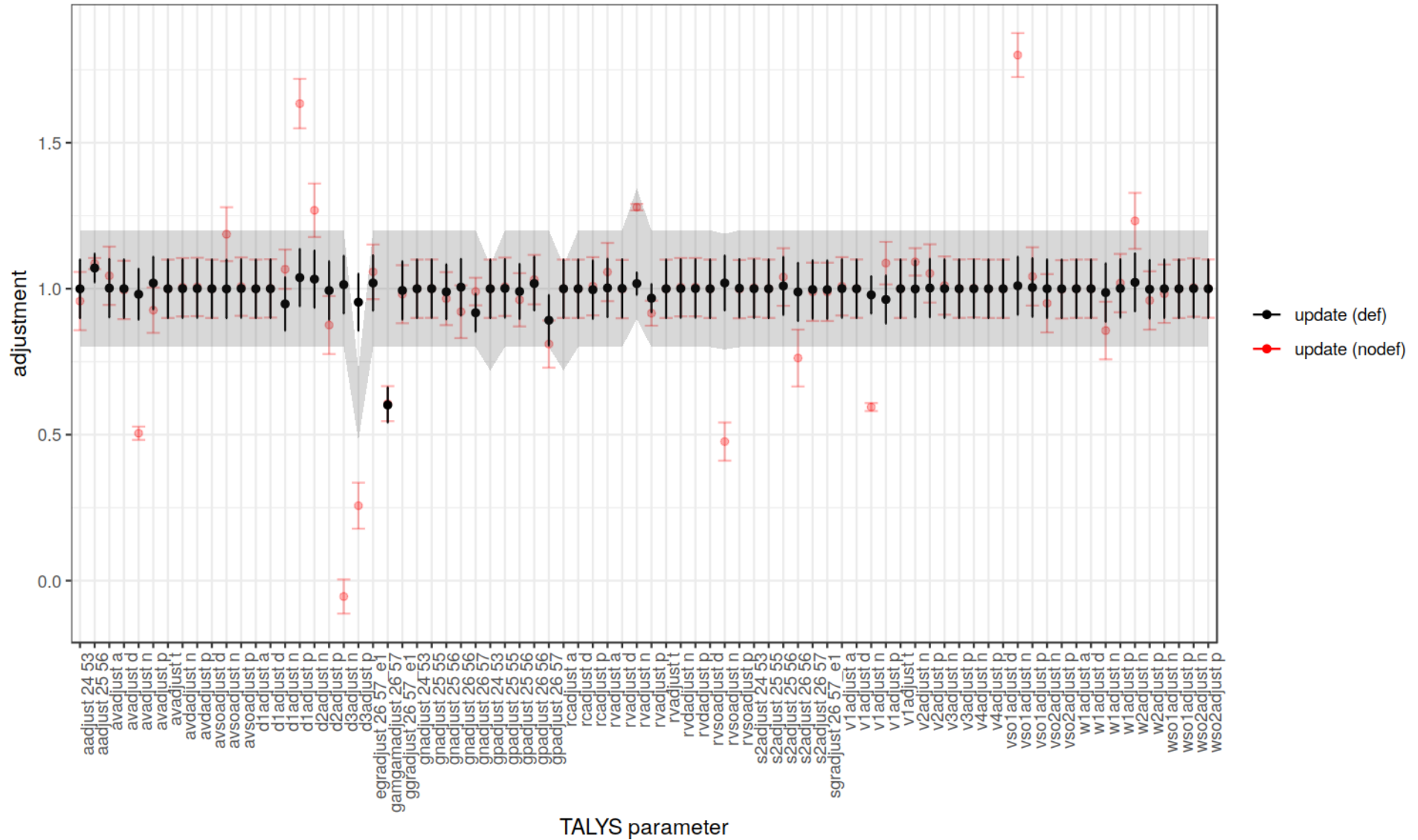
^{56}Fe differential cross sections (n, ...)



Comparison update (def/nodef)

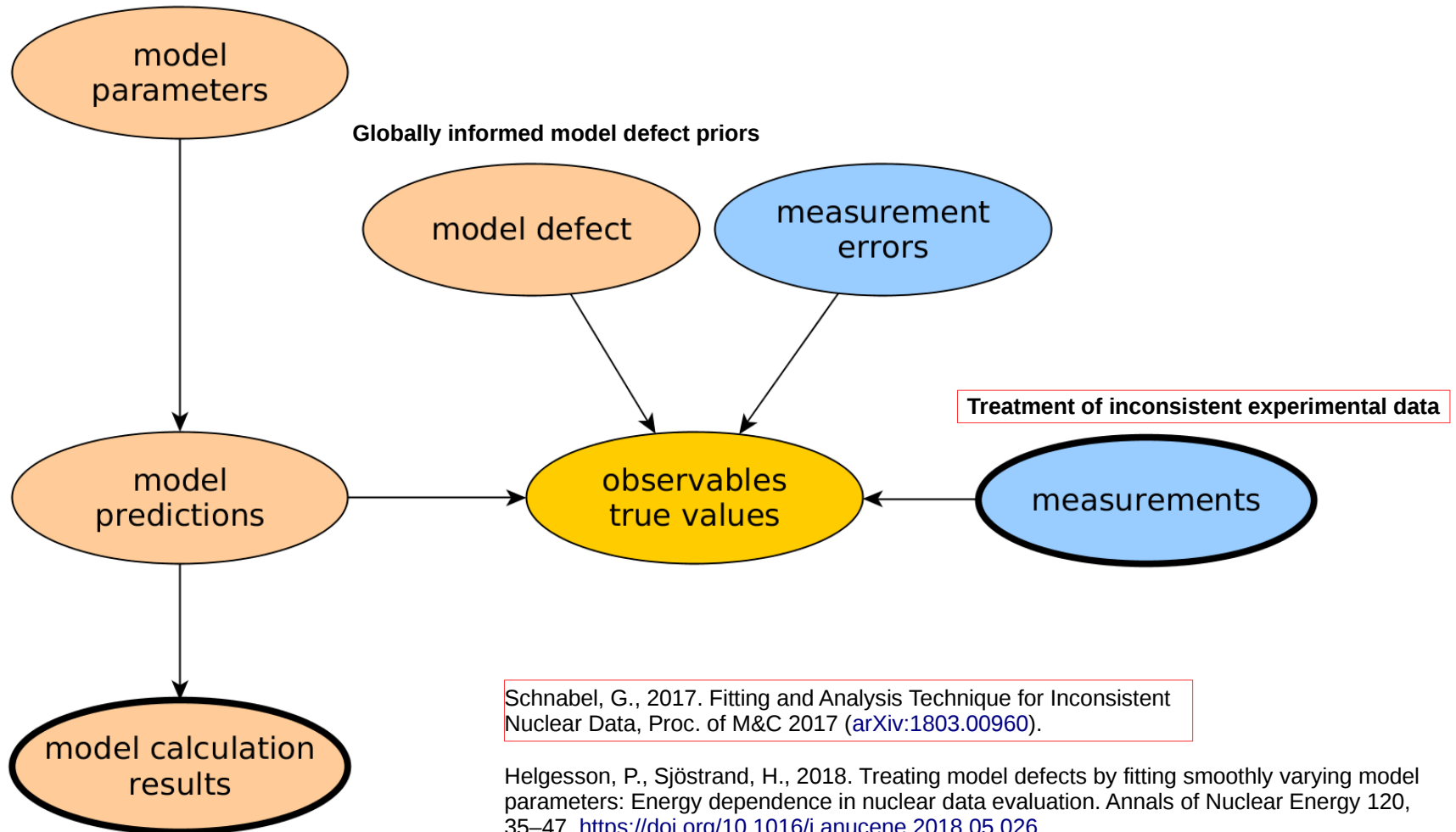


Consistent parameters



Treatment of inconsistent data

Energy-dependent model parameters



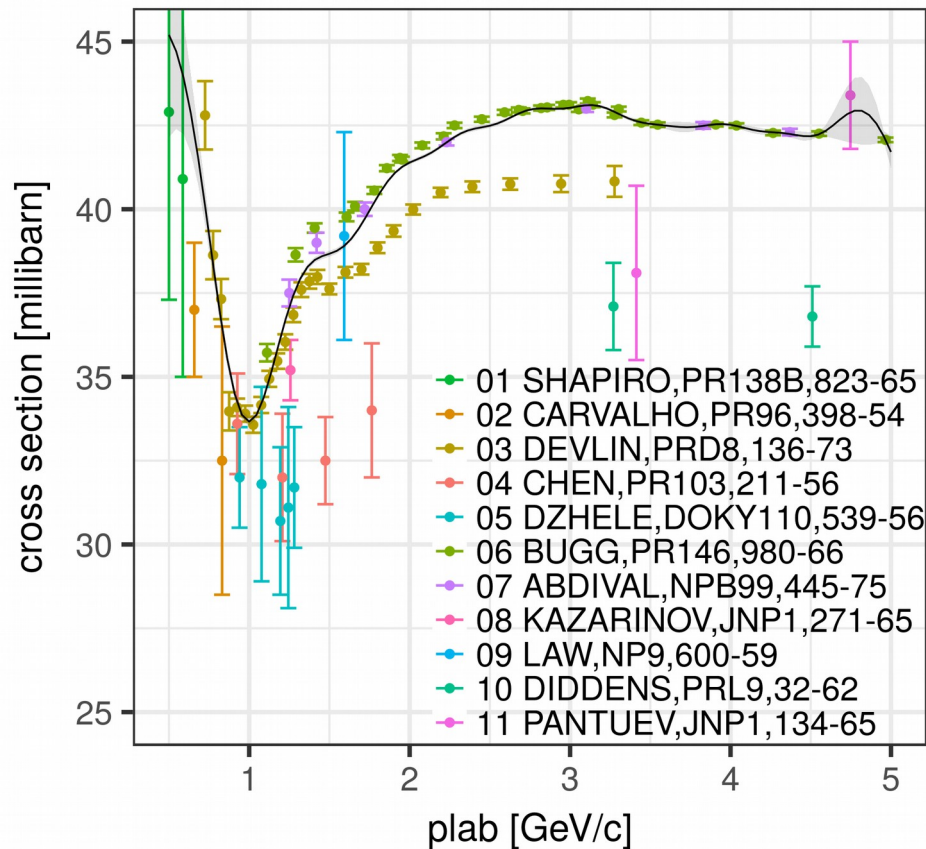
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Inconsistent data = trouble

Proton-Neutron total cross



Fit of

$$\sigma_{\text{fit}}(E) = \frac{\sum_{i=1}^M y_i \mathcal{N}(E | x_i, \lambda^2)}{\sum_{j=1}^M \mathcal{N}(E | x_j, \lambda^2)}$$

to the neutron-proton total cross section using just statistical uncertainties B_{stat}

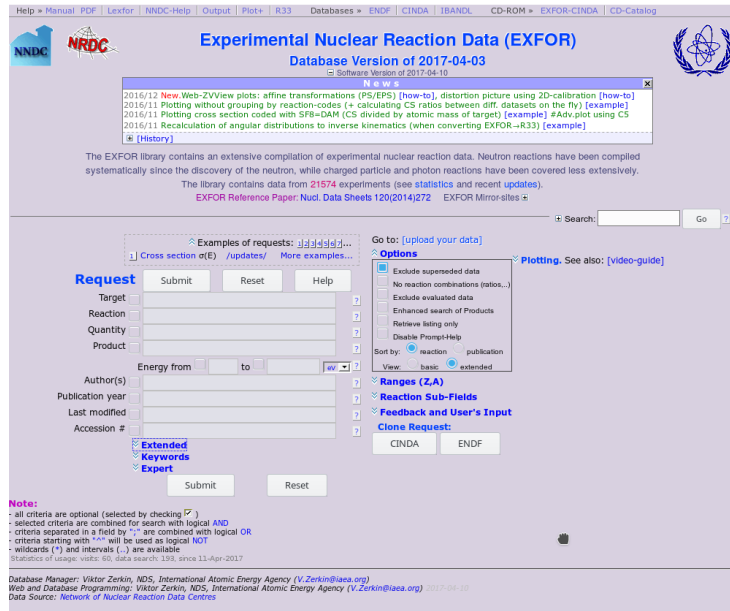
Problems

Final fit underestimates uncertainty

Associated $\chi^2/N \approx 16$ too large

Without visual inspection we do not know why

Large amount of data

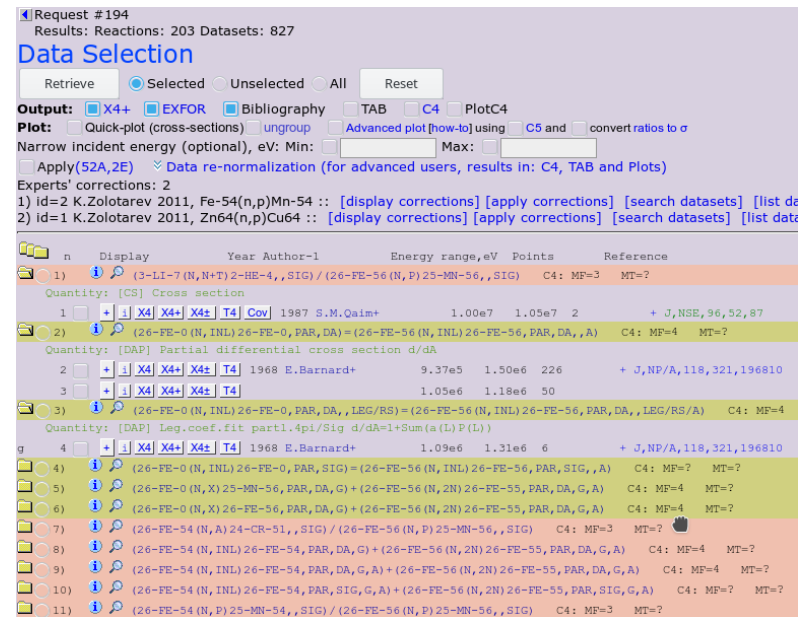


Database as of: 2017-04-

Number of ENTRY	21574	experimental works
Number of SUBENT	150976	data tables
Number of Datasets	167857	data tables of reactions
Number of Datapoints	14739297	total number of data points

Example: EXFOR Database

- Around **15 million data points**
- No covariance matrices for many measurements
- Direct fitting of models/functions not reasonable



Empirical Bayesian approach

$$\mathbf{B} = \begin{bmatrix} \mathbf{B}_1 & & \\ & \mathbf{B}_2 & \\ & & \ddots \end{bmatrix} \quad \vec{\sigma}_{\text{exp}} = \begin{pmatrix} \vec{\sigma}_{\text{exp},1} \\ \vec{\sigma}_{\text{exp},2} \\ \vdots \end{pmatrix}$$

Suggestion of a reasonable parametrization (*others are possible!*)

Additional normalization error (e.g. sample thickness, calibration, ...)

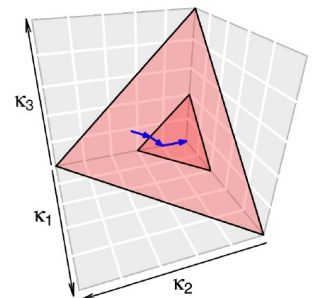
$$\tilde{\mathbf{B}}_i = \mathbf{B}_i + \kappa_i^2 \vec{\sigma}_{\text{exp},i} \vec{\sigma}_{\text{exp},i}^T$$

$$\pi_1(\vec{p}_{\text{true}}, \vec{\kappa} \mid \vec{\sigma}_{\text{exp}}, \vec{p}_0, \mathbf{A}_0) \propto \ell(\vec{\sigma}_{\text{exp}} \mid \vec{p}_{\text{true}}, \tilde{\mathbf{B}}(\vec{\kappa})) \times \pi_0(\vec{p}_{\text{true}} \mid \vec{p}_0, \mathbf{A}_0)$$

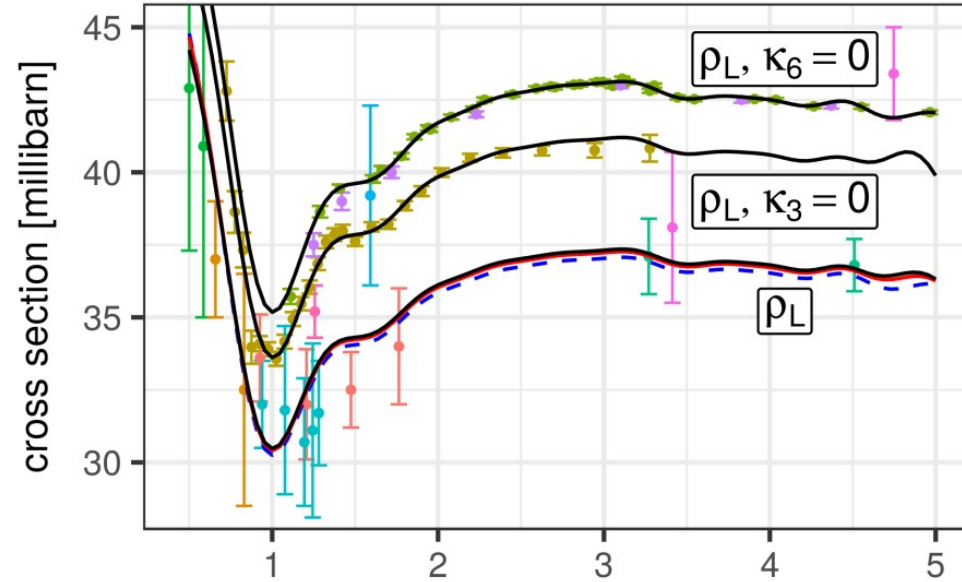
Criteria for choice of prior

- Simple parametrization
- “Uninformative”
- Favor sparse solutions

$\times \pi_0(\vec{\kappa})$



Schematic application



$$\tilde{\mathbf{B}}_i = \mathbf{B}_i + \kappa_i^2 \vec{\sigma}_{\text{exp},i} \vec{\sigma}_{\text{exp},i}^T \quad \text{plab [GeV/c]}$$

	δ	ℓ	κ_1	κ_2	κ_3	κ_4	κ_5	κ_6	κ_7	κ_8	κ_9	κ_{10}	κ_{11}	χ^2/N
GLS	—	—	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	16.13
ρ_U	—	—	.00	.04	.10	.00	.00	.14	.13	.06	.10	.00	.13	0.73
ρ_N	.11	—	.00	.03	.07	.00	.00	.10	.09	.04	.05	.00	.09	0.79
ρ_L	.13	1.0×10^0	.00	.00	.07	.00	.00	.09	.09	.03	.00	.00	.08	0.82
ρ_L	.13	1.8×10^{-3}	.00	.09	[.00]	.07	.07	.03	.03	.01	.00	.07	.00	0.98
ρ_L	.13	1.2×10^{-5}	.00	.12	.03	.10	.10	[.00]	.00	.06	.00	.10	.00	1.07
ρ_L	.17	—	.00	.00	.07	.00	.00	.10	.09	.04	.00	.00	.09	0.81

TABLE I. Posterior maxima κ based on the prior distributions specified in eqs. (50) to (52). For the pdfs ρ_N and ρ_L , results based on different values of δ are presented. Square brackets denote that the respective κ_i was fixed at zero. The index i refers to the experiment data set, see fig. 2. The value χ^2/N is the result of eq. (19) divided by the number of data points. Relative likelihoods ℓ are stated for the case ρ_L with $\delta = 0.13$.

Recent: Integral adjustment

- We add an extra uncertainty to each experiment.

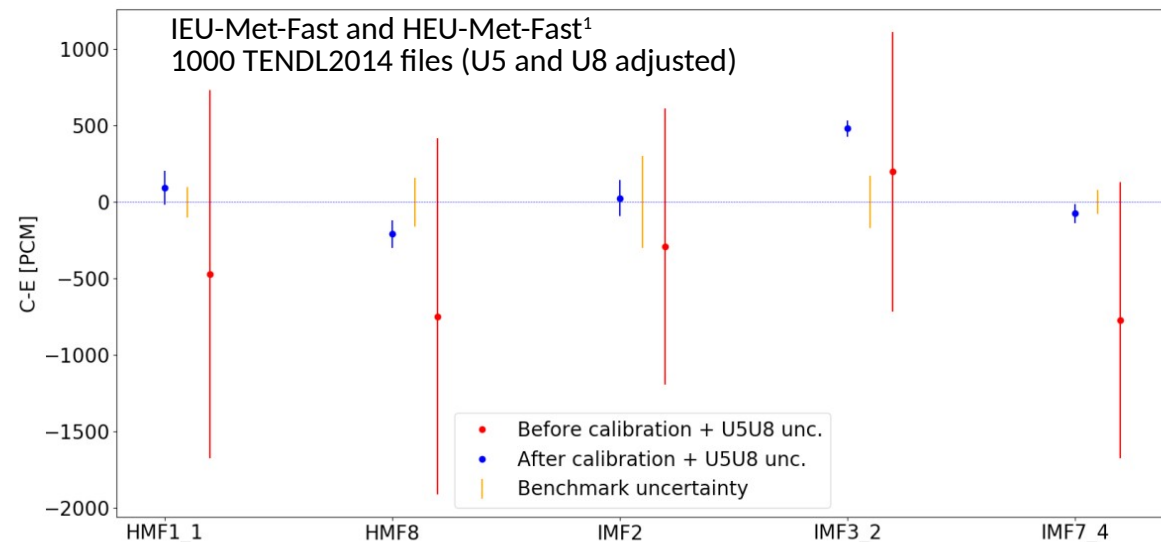
$$\sigma_{B,J}^2 = \sigma_E^2 + \sigma_{stat}^2 + \sigma_{defects}^2 + \sigma_{other}^2 + \sum_{\substack{\text{overall } p \\ \text{where } p \neq J}} \sigma_{ND,p}^2$$

$$\sigma_{B,l,J}^2 = \sigma_E^2 + \sigma_{stat}^2 + \sigma_{extra,l}^2 + \sigma_{extra,common}^2$$

- σ_{extra} found by maximizing L:

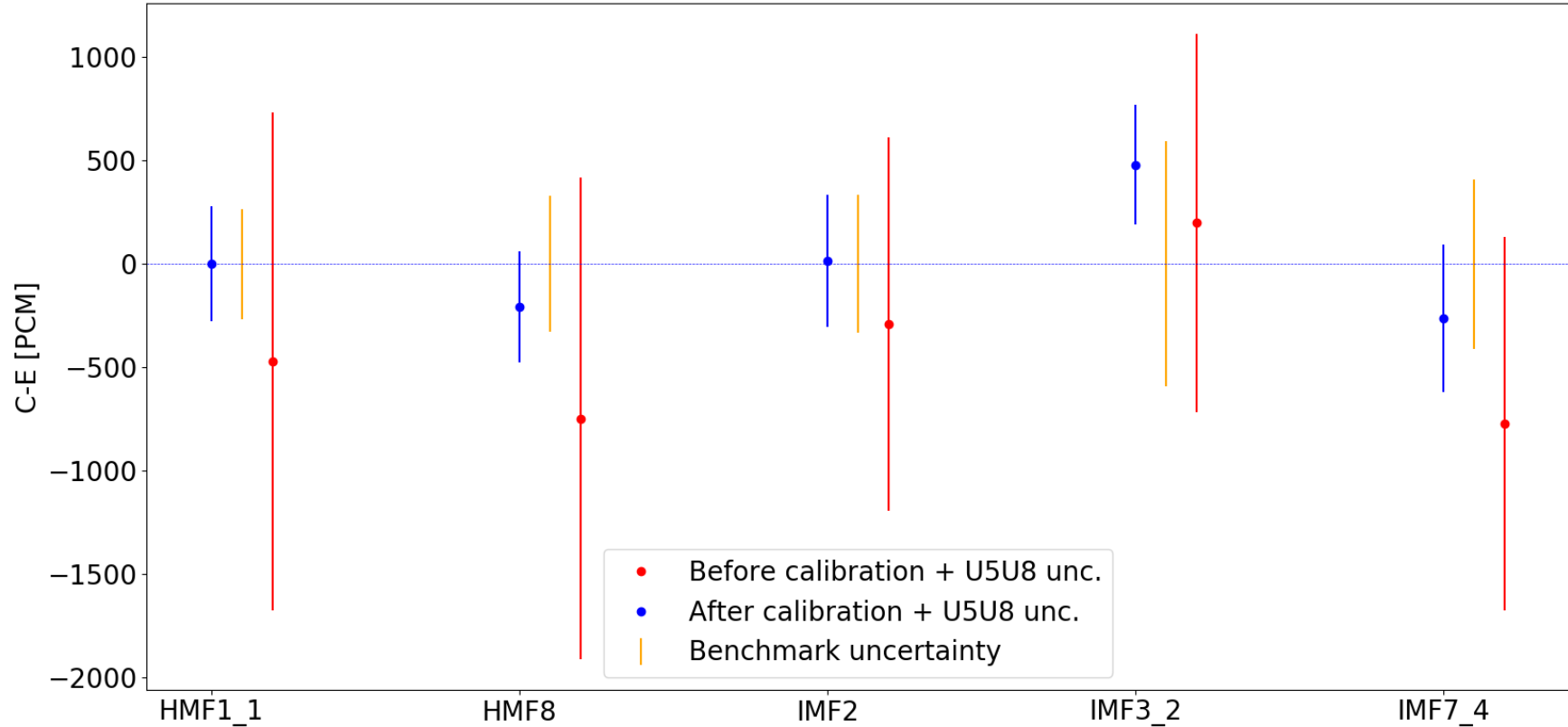
$$L = \frac{1}{\sqrt{(2\pi)^N |\text{COV}_{\text{stat,exp,extra}}|}} \sum_i e\left(\frac{-x_i^2}{2}\right)$$

Sjöstrand, H., Schnabel, G., Helgesson P., Monte Carlo integral adjustment of nuclear data libraries – experimental covariances and inconsistent data, WONDER 2018



¹Courtesy of Steven Van Der Marck

Some results



Benchmark uncertainties [PCM]	HMF1_1	HMF8	IMF2	IMF3_2	IMF7_4	Fully correlated
No ML: Reported uncertainties	100	160	300	170	80	0
Updated uncertainties	153	204	300	580	390	0
With correlation	267	329	333	591	409	257

Outlook

- Perform an evaluation of ^{56}Fe with GPs on parameter side¹
- Interface recent methodological developments with TALYS/TENDL
- Continue development of methodology for integral adjustment

1) UU contribution to Eurofusion2018

[VR contribution to PPPT nuclear data development: Evaluation of neutron cross section data in the fast energy range](#)