

Bayesian approach for centrality determination in MPD-FXT (Xe+W at $T = 2.5$ AGeV)

Idrisov Dim, Parfenov Peter, Fedor Guber

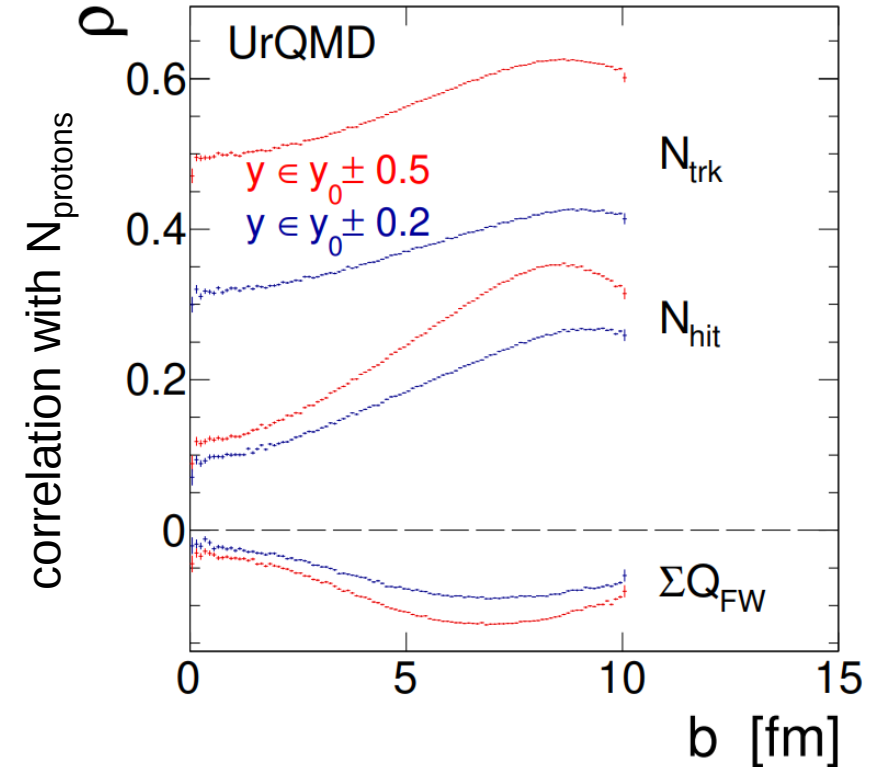
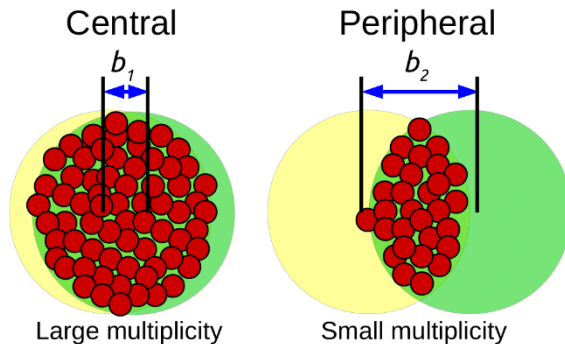
INR RAS, Moscow, Russia

08/04/25

Centrality

- Evolution of matter produced in heavy-ion collisions depend on its initial geometry
- Centrality procedure maps initial geometry parameters with measurable quantities (multiplicity or energy of the spectators)
- **This allows comparison of the future MPD results with the data from other experiments (STAR BES, NA49/NA61 scans) and theoretical models**

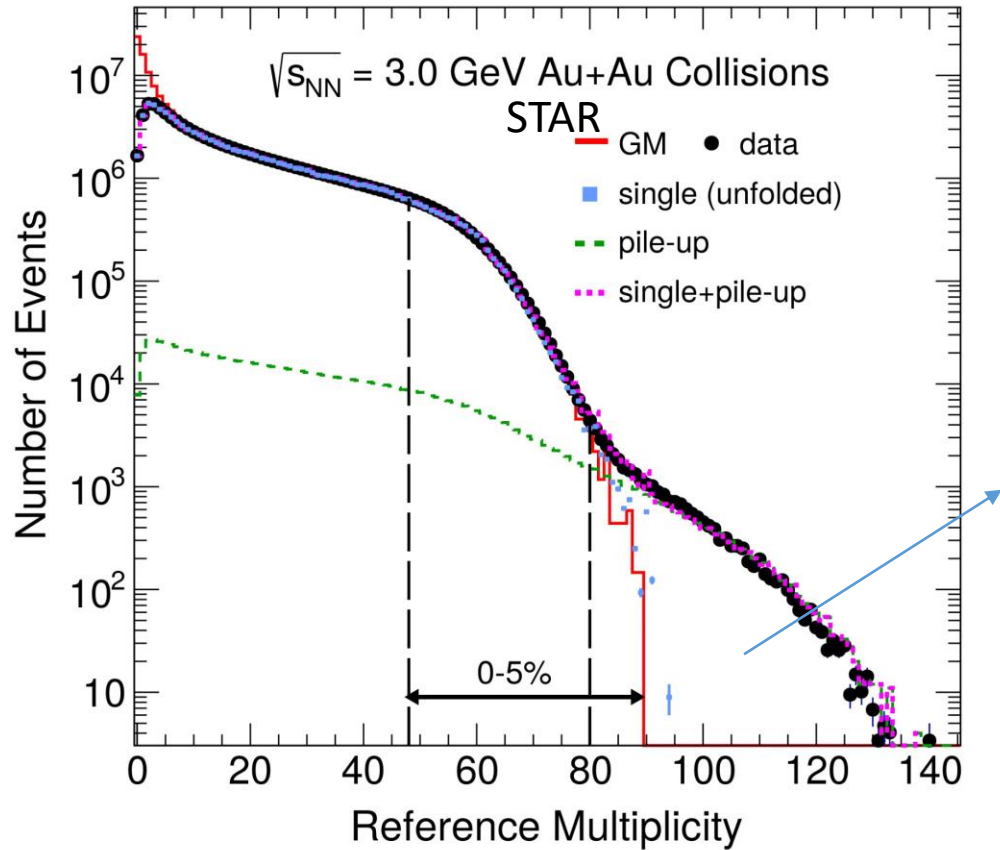
$$c(b) = \frac{\int_0^b \frac{d\sigma}{db'} db'}{\int_0^\infty \frac{d\sigma}{db'} db'} = \frac{1}{\sigma_{A-A}} \int_0^b \frac{d\sigma}{db'} db'$$



HADES; Phys.Rev.C 102 (2020) 2, 024914

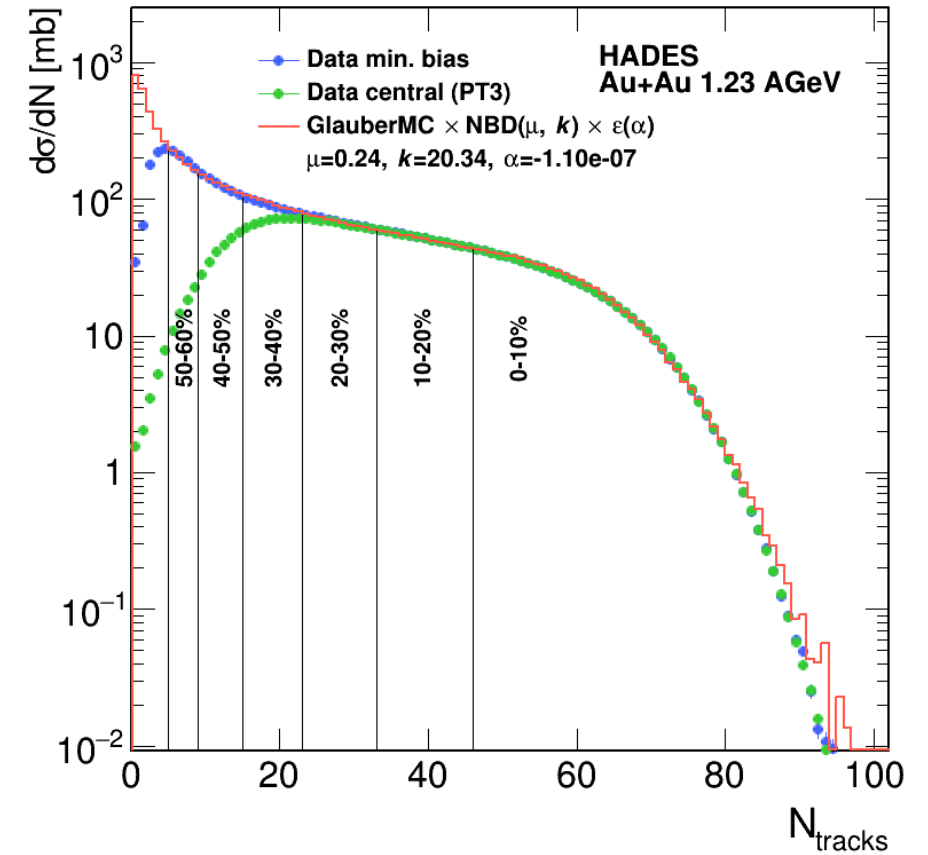
- A number of produced protons is stronger correlated with the number of produced particles (track & RPC+TOF hits) than with the total charge of spectator fragments (FW)
- to suppress self-correlation biases, it is necessary to use spectators fragments for centrality estimation

Centrality determination in the FIX-target experiments



Reference multiplicity distributions (black markers) in the kinematic acceptance within $-0.5 < y < 0$ and $0.4 < p_T < 2.0$ GeV/c, GM (red histogram), and single and pile-up contributions from unfolding.

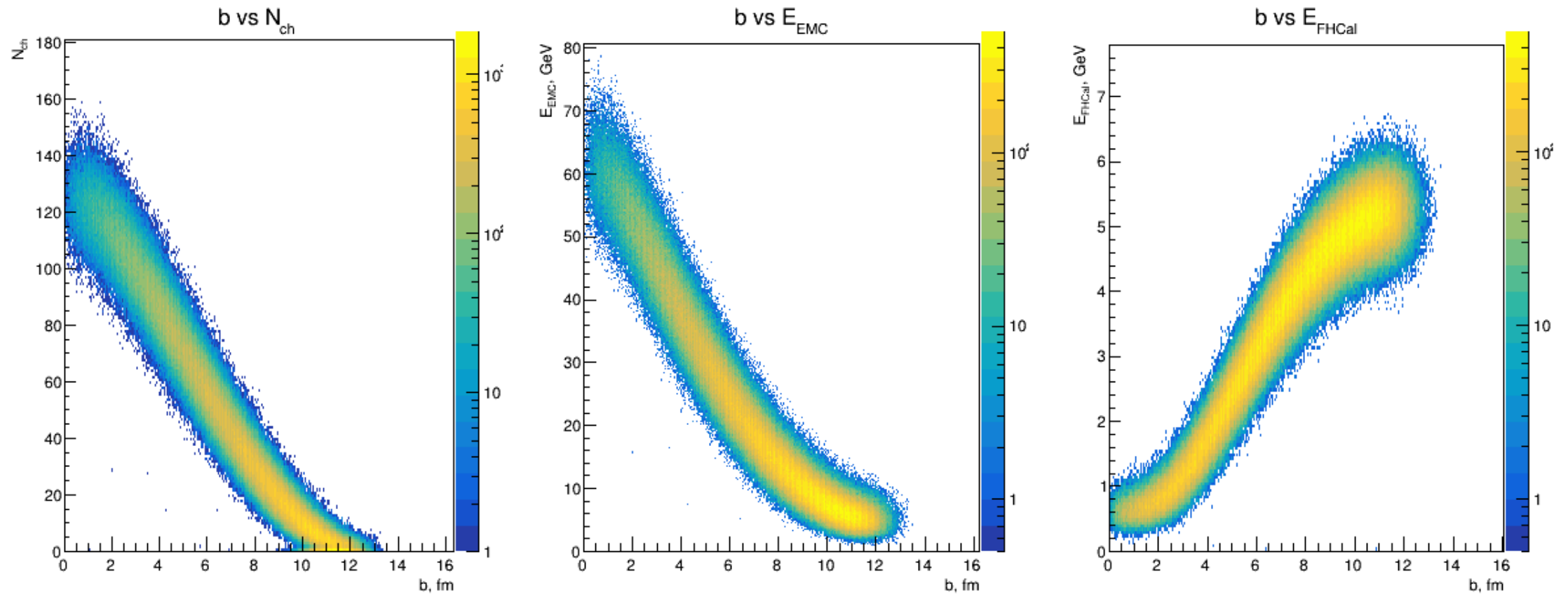
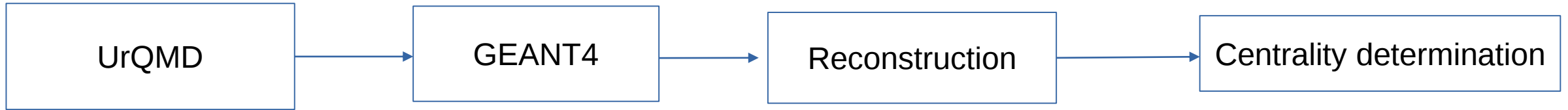
<https://arxiv.org/abs/2112.00240>



The cross section as a function of N_{tracks} for minimum bias (blue symbols) and central (PT3 trigger, green symbols) data in comparison with a fit using the Glauber MC model (red histogram).

<https://arxiv.org/abs/1712.07993>

Centrality determination in MPD



Relation between impact parameter and observables

The Bayesian inversion method (Γ -fit): multiplicity based

- The fluctuation kernel Gamma distr.:

$$P(M) = \int_0^1 P(M | c_b) dc_b$$

$$P(M | c_b) = \frac{1}{\Gamma(k(c_b))\theta^2} M^{k(c_b)-1} e^{-M/\theta}$$

$$c_b = \int_0^b P(b') db' \quad \text{– centrality based on impact parameter}$$

$$\theta = \frac{D(M)}{\langle M \rangle}, \quad k = \frac{\langle M \rangle}{\theta}$$

$\langle M \rangle, D(M)$ – average and variance of Multiplicity

$$\langle M \rangle = m_1 \cdot \langle M' \rangle$$

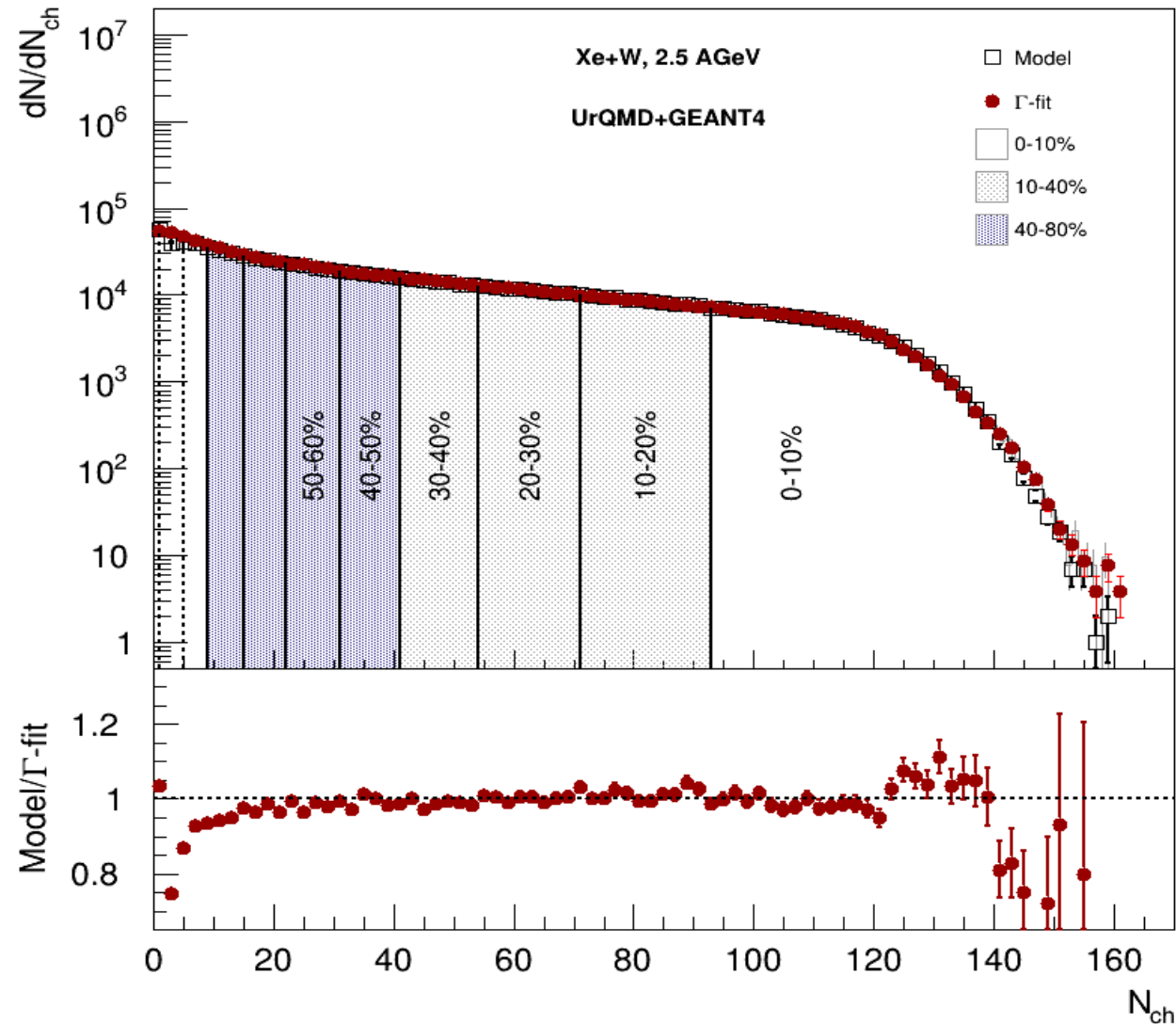
$$D(M) = m_1^2 \cdot D(M') + m_1 \cdot m_2 \langle M' \rangle$$

$\langle M'(c_b) \rangle$ – average value and var. of energy/mult.

$D(M'(c_b))$ from the rec. model data

- can be approximated by polynomials and exponential polynomial

Multiplicity-based Γ -fit: MPD-FXT Xe+W



Good agreement with fit

Track selection:

- $N_{hit} > 10$
- $0.5 < \eta < 2$
- $2 > p_T > 0.2 \text{ GeV}/c$

The Bayesian inversion method (Γ-fit): 2D approach

- The fluctuation kernel for observables at fixed impact parameter can be describe by 2D Gamma distr.:

$$P(E, E_F | c_b) = G_{2D}(E, E_F, \langle E \rangle, \langle E_F \rangle, D(E), D(E_F), R)$$

$$c_b = \int_0^b P(b') db' \quad \text{– centrality based on impact parameter}$$

$\langle E \rangle, D(E)$ – average value and variance of energy in EMC

$\langle E_F \rangle, D(E_F)$ – average value and variance of energy in FHCaI

$R(E, E_F)$ – Pirson correlation coefficient

$$R(E, E_F) = \frac{\varepsilon_1^2 m_1^2}{\varepsilon_2 m_2} R(E', E_F')$$

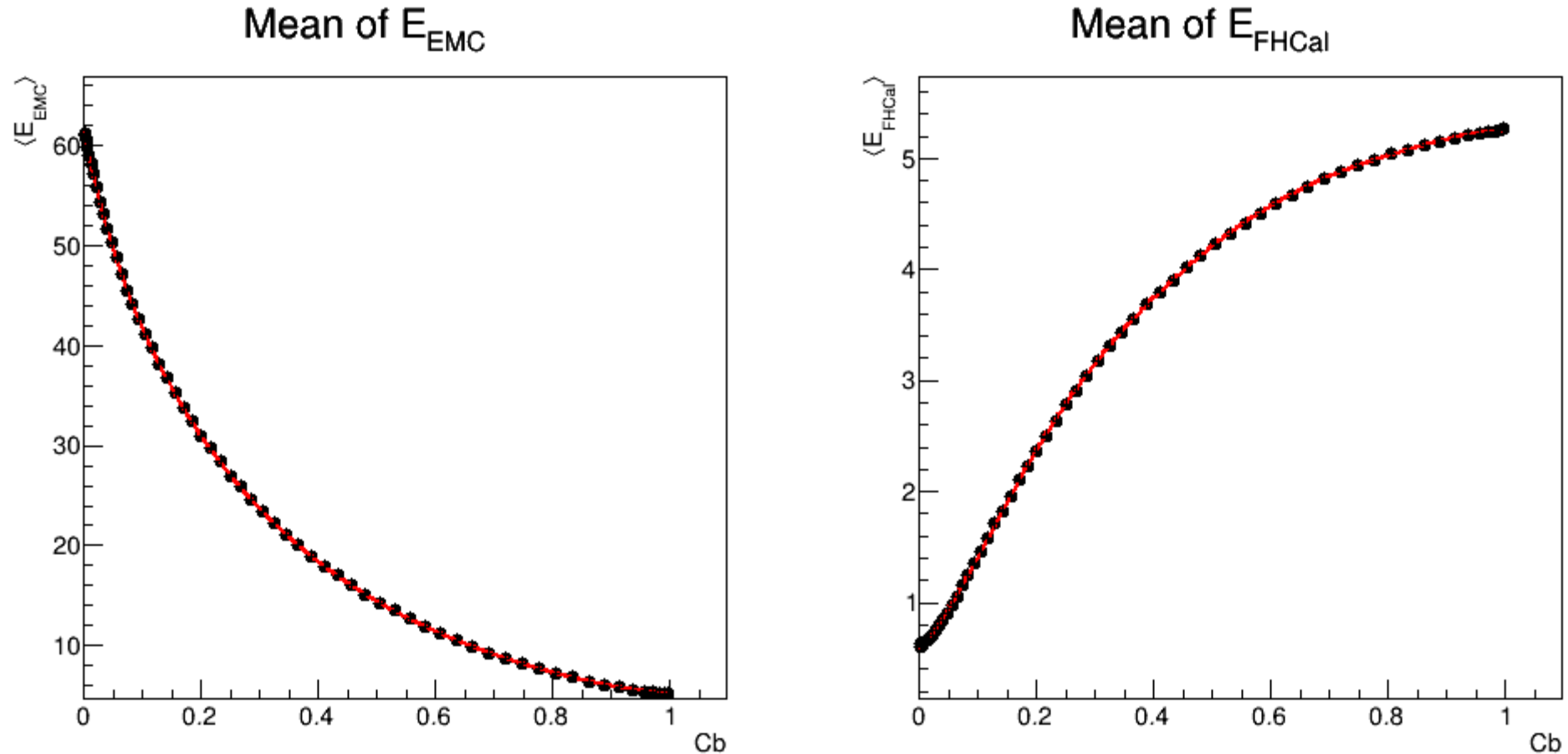
$\varepsilon_1, \varepsilon_2, m_1, m_2$
– fit parameters

$\langle E'(c_b) \rangle$ – average value and var. of
 $D(E'(c_b))$ energy[EMC/FHCaI] from the model

$$\begin{aligned} \langle E \rangle &= \varepsilon_1 \langle E'(c_b) \rangle, & D(E) &= \varepsilon_2 D(E'(c_b)) \\ \langle E_F \rangle &= m_1 \langle E_F'(c_b) \rangle, & D(E_F) &= m_2 D(E_F'(c_b)) \end{aligned}$$

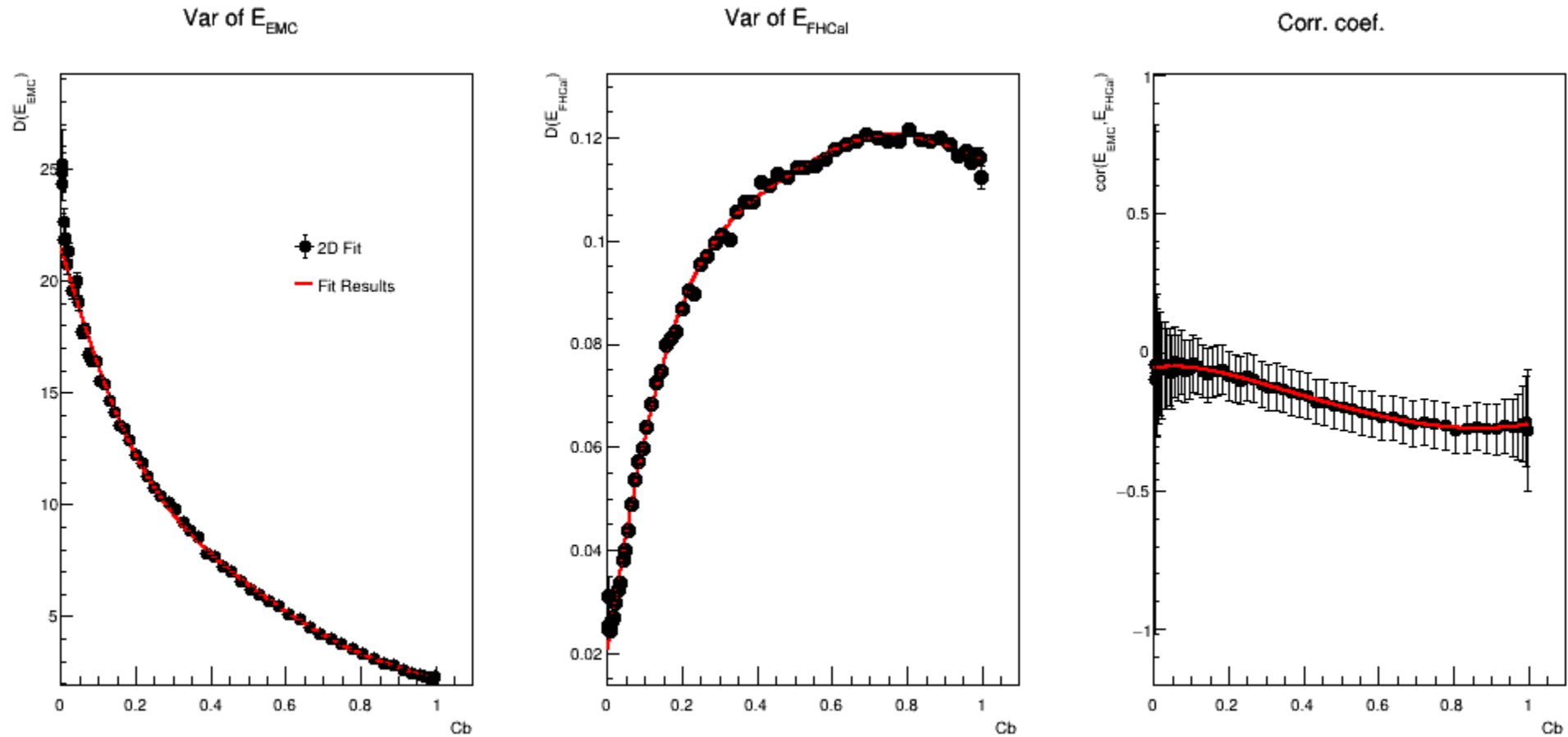
$\langle E'(c_b) \rangle, D(E'(c_b))$ - can be approximated by a polynomial or any other smooth function

Dependence of the average value of energy in EMC and FHCal on centrality



Mean values for E_{EMC} and E_{FHCal} from UrQMD and parametrization are in a good agreement over all c_b

Dependence of the variance of observables on centrality



Variance for E_{EMC} and E_{FHCal} from UrQMD and parametrization are in a good agreement over all c_b

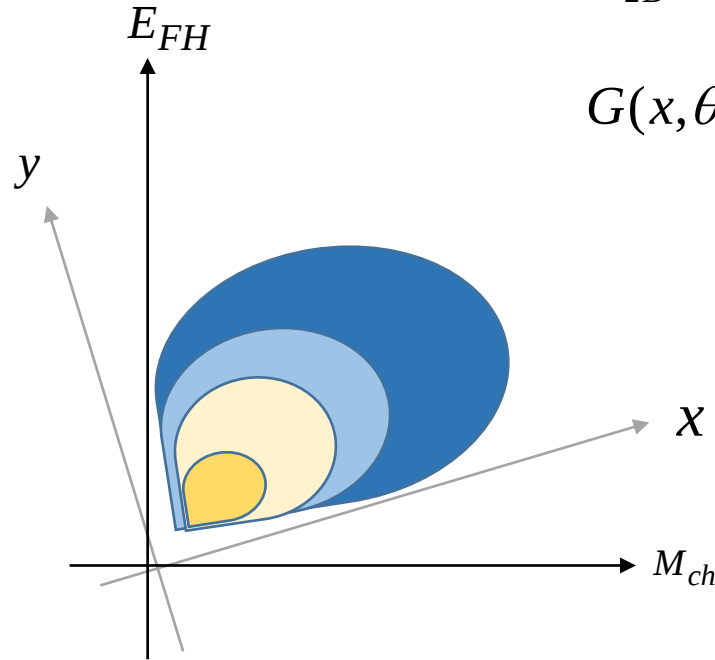
2D Gamma distribution

It is possible to find such a rotation angle of the system that $\text{cov}(x, y) = 0$

Then the two-dimensional distribution in the new coordinate system will be

$$G_{2D}(E, E_F, \langle E \rangle, \langle E_F \rangle, D(E), D(E_F), R) = G(x, \theta_x, k_x) \cdot G(y, \theta_y, k_y)$$

$$G(x, \theta_x, k_x) \cdot G(y, \theta_y, k_y) = \frac{(x)^{k_x(c_b)-1} e^{-x/\theta_x}}{\Gamma(k_x(c_b))\theta_x^2} \cdot \frac{(y)^{k_y(c_b)-1} e^{-y/\theta_y}}{\Gamma(k_y(c_b))\theta_y^2}$$



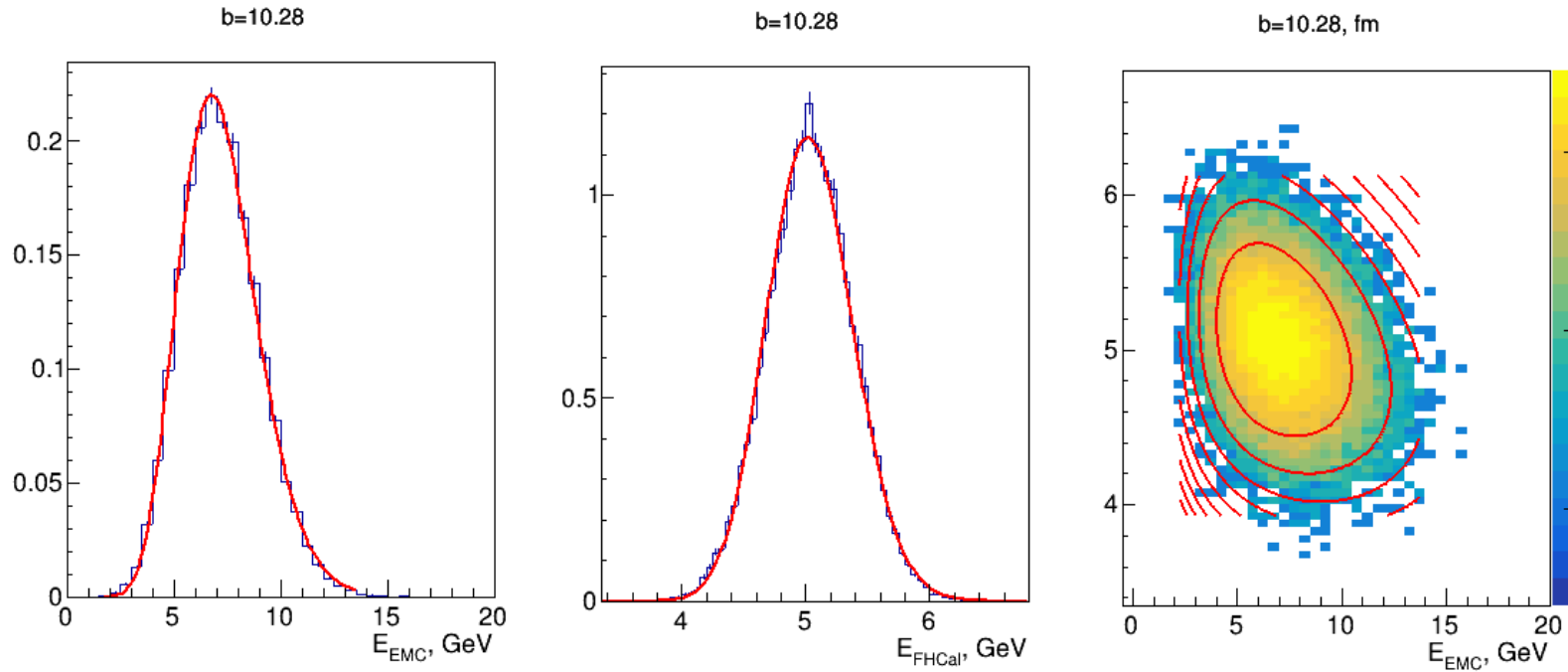
$$\theta_x = \frac{D(x)}{\langle x \rangle}, \quad k_x = \frac{\langle x \rangle^2}{D(x)}, \quad \theta_y = \frac{D(y)}{\langle y \rangle}, \quad k_y = \frac{\langle y \rangle^2}{D(y)}$$

$$\alpha = \arctan \left(\frac{2\sqrt{D(E)D(E_F)}R(E, E_F)}{D(E) - D(E_F)} \right)$$

mean value and variance in the new coordinate system

$$\begin{aligned} \langle x \rangle &= \cos(\alpha) \langle E \rangle + \sin(\alpha) \langle E_F \rangle & D(x) &= D(E) \cos(\alpha)^2 + R \sqrt{D(E)D(E_F)} \sin(2\alpha) + D(E_F) \sin(\alpha)^2 \\ \langle y \rangle &= -\sin(\alpha) \langle E \rangle + \cos(\alpha) \langle E_F \rangle & D(y) &= D(E) \sin(\alpha)^2 - R \sqrt{D(E)D(E_F)} \sin(2\alpha) + D(E_F) \cos(\alpha)^2 \end{aligned}$$

The fluctuation of observables at fixed impact parameter

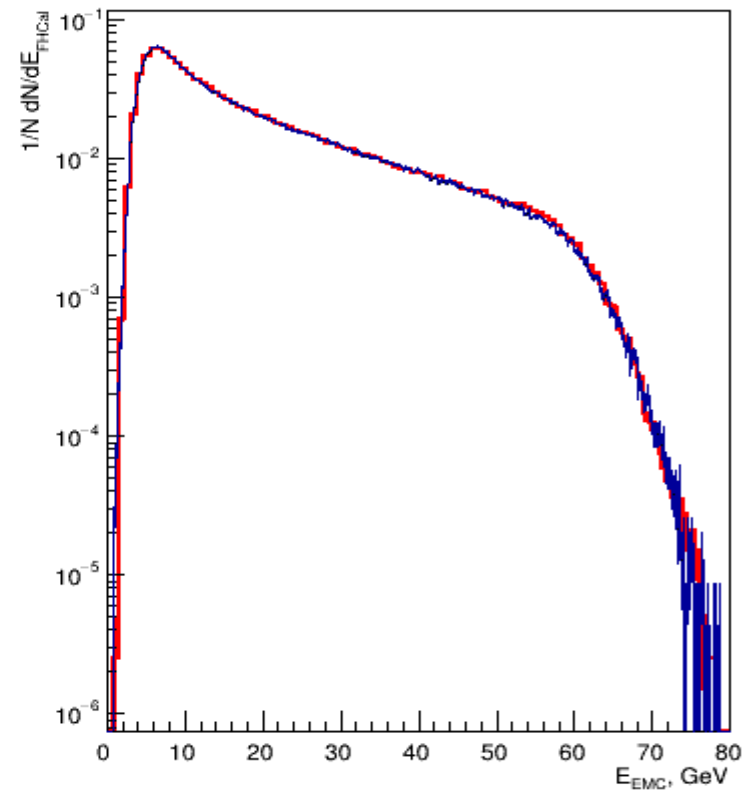
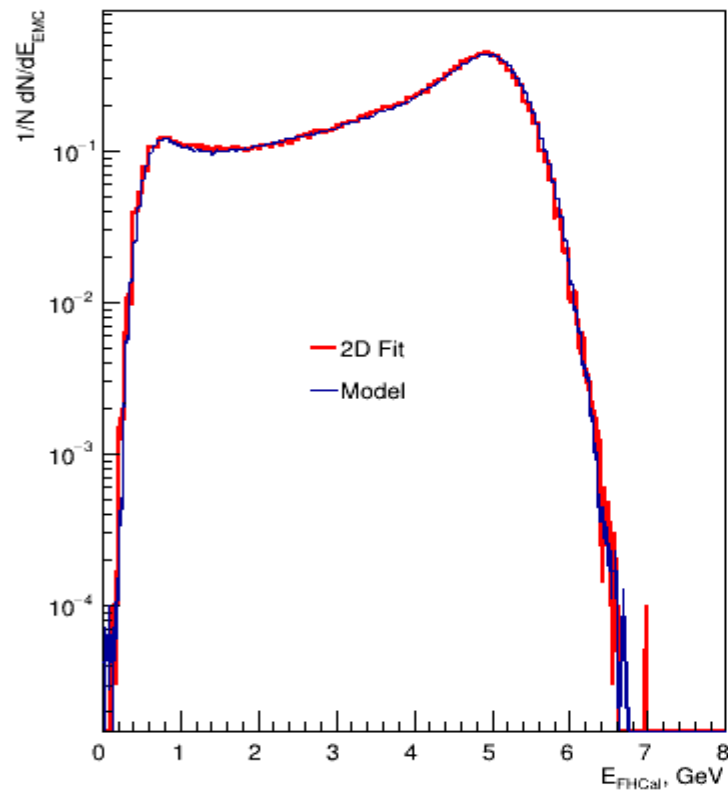
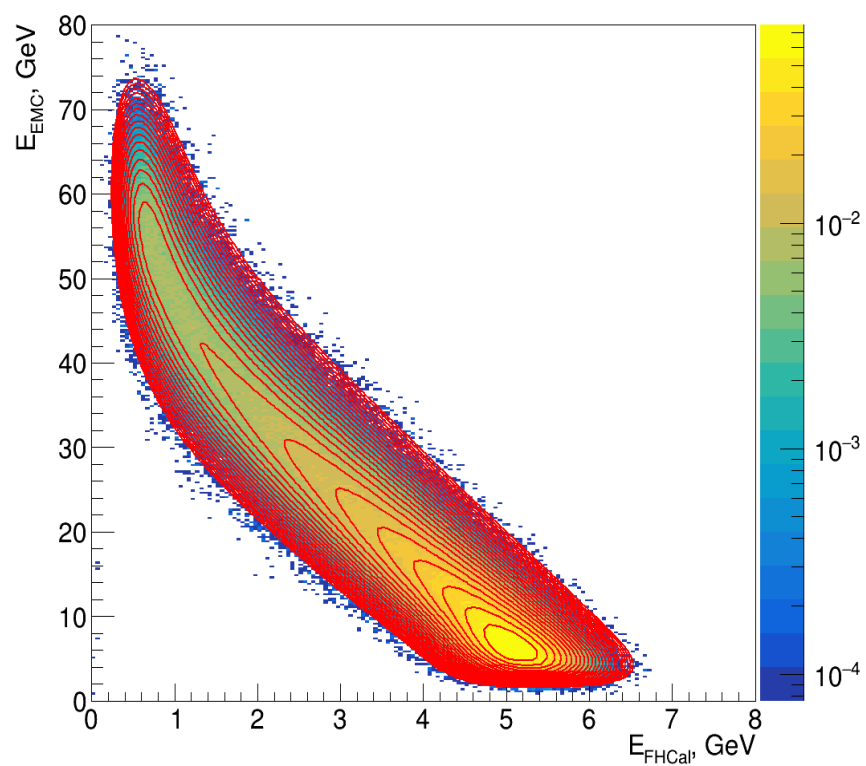


The distribution of observables at a fixed impact parameter is well described by the 2D gamma distribution

- Find probability of b for fixed range of observables using Bayes' theorem:

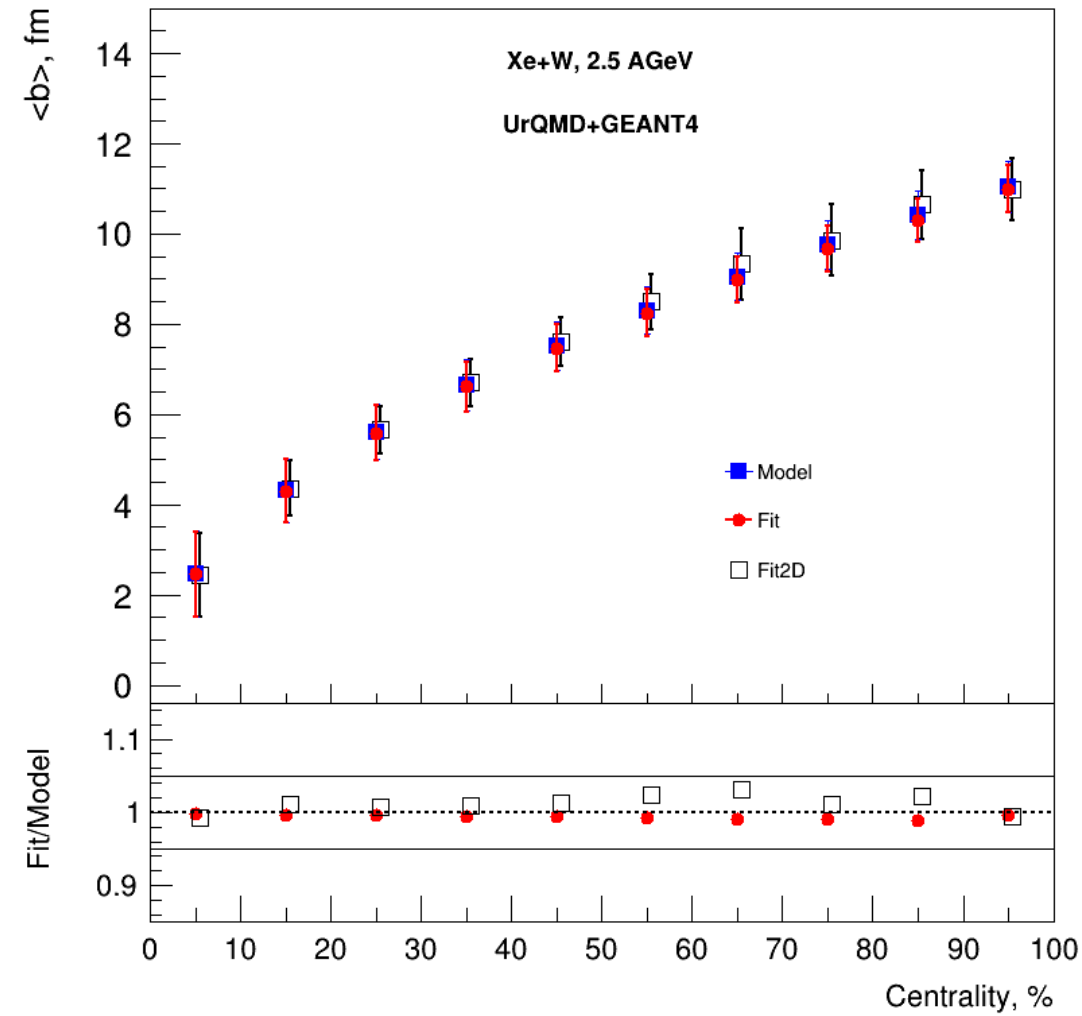
$$P(b | E_1 < E < E_2, E_F^1 < E_F < E_F^2) = P(b) \frac{\int_{E_1}^{E_2} \int_{M_1}^{M_2} P(E, E_F | c_b) dE_F dE}{\int_{E_1}^{E_2} \int_{E_F^1}^{E_F^2} \int_0^1 P(E, E_F | c_b) dE_F dE dc_b}$$

2D Bayesian approach: results



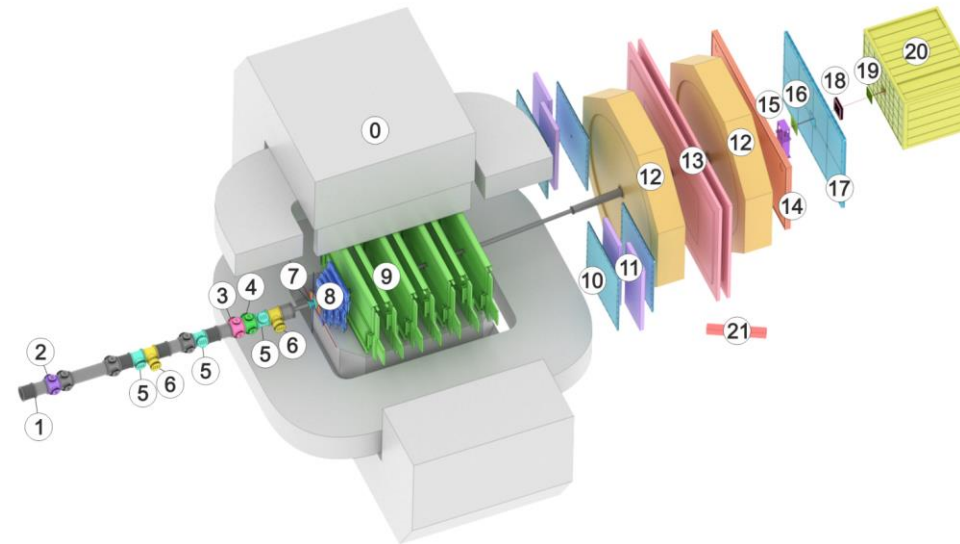
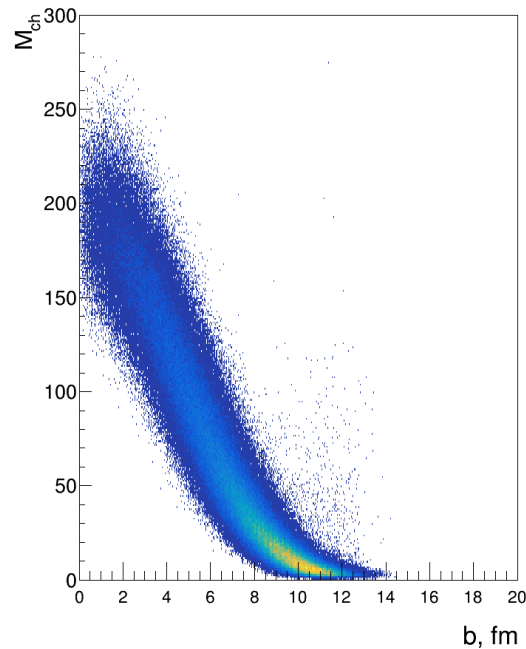
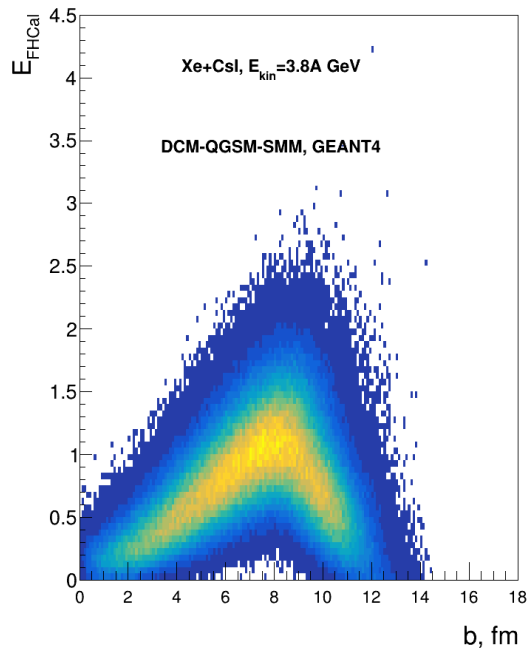
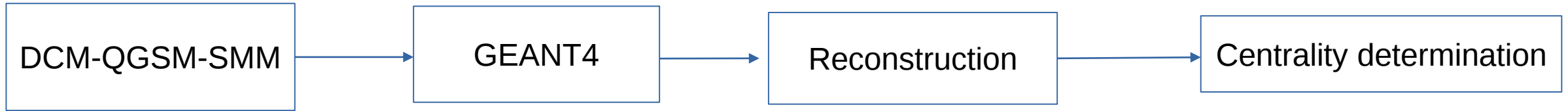
Good agreement between fit and data.

Comparison centrality determination methods



There is agreement within 5%.

Centrality determination in BM@N

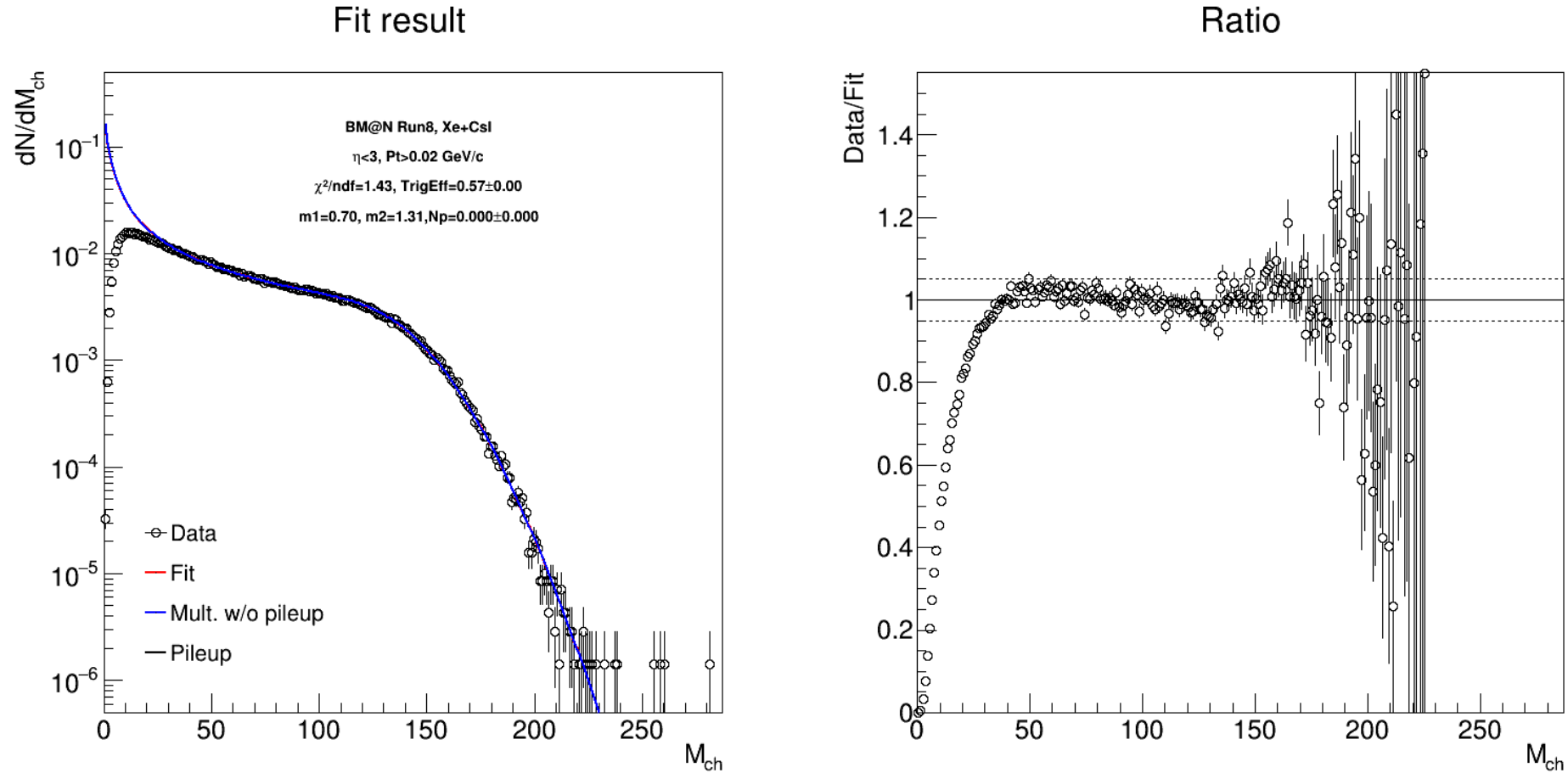


- 0 Magnet SP-41
- 1 Vacuum Beam Pipe
- 2-4 BC1, VC, BC2
- 5, 6 SiBT, SiProf
- 7 Triggers: BD + SiMD
- 8, 9 FSD, GEM
- 10 CSC 1x1 m²
- 11 TOF 400
- 12 DCH
- 13 TOF 700
- 14 ScWall
- 15 FD
- 16 Small GEM
- 17 CSC 2x1.5 m²
- 18 Beam Profilometer
- 19 FQH
- 20 FHCAL
- 21 HGN

Dependence of energy in FHCAL and track multiplicity on the impact parameter

BM@N setup overview

Multiplicity-based Γ -fit: BM@N Xe+CsI

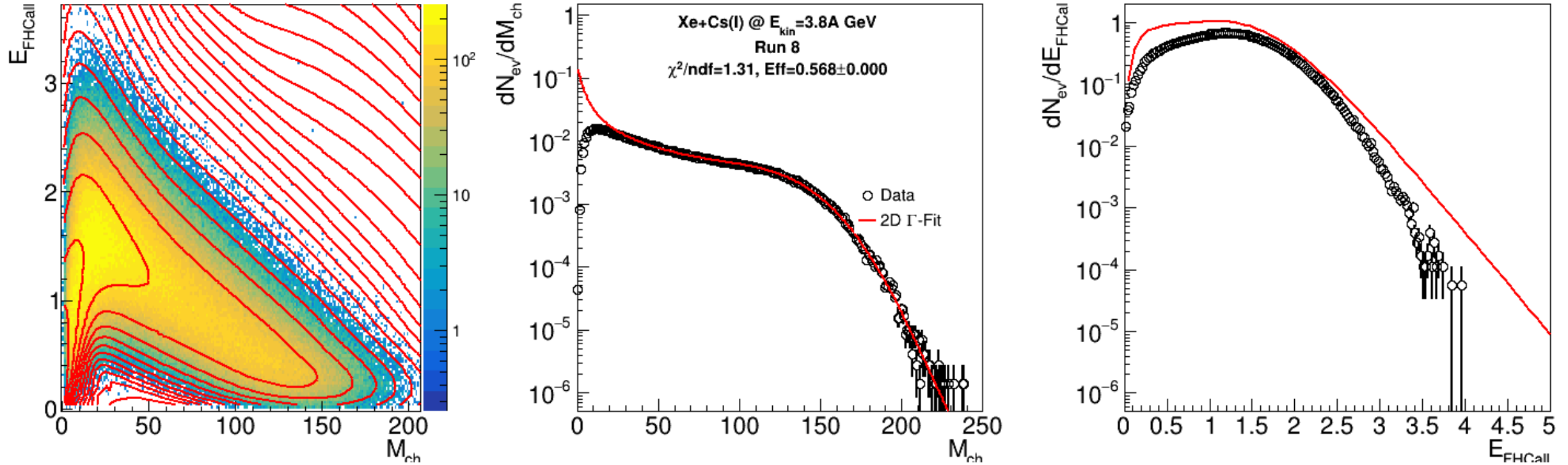


Vertex Cuts: CCT2 , $N_{\text{vtxTr}} > 1$, $|V_{x,y} - (0.3, 0.14)| < 1$ cm, $|V_z - 0.07| < 0.2$ cm

Good agreement with data

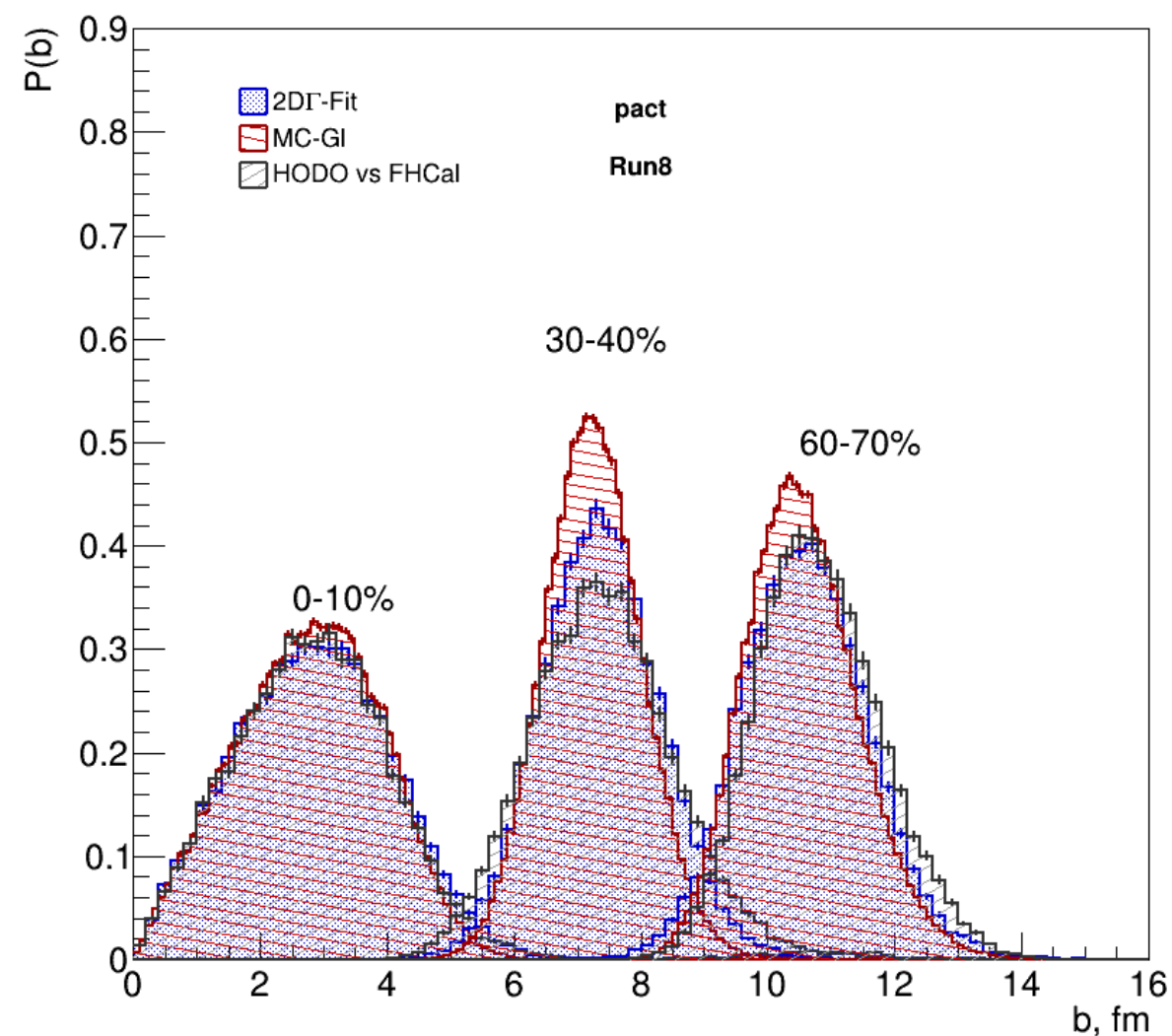
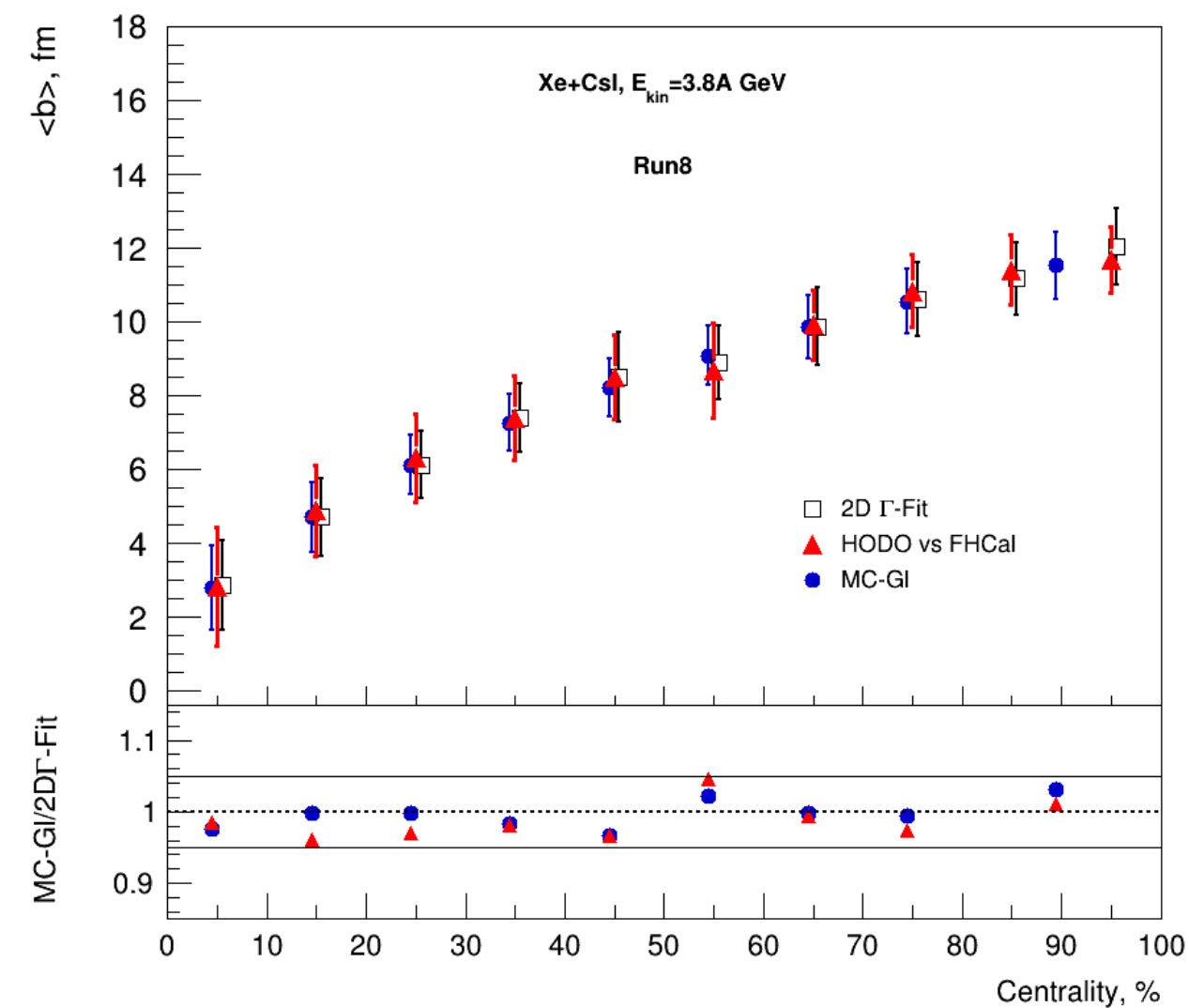
Track selection: $N_{\text{hit}} > 4$, $\eta < 3$, $P_t > 0.05$ GeV/c

2D Bayesian approach: BM@N Xe+CsI



The fit function qualitatively reproduces the multiplicity-energy correlation from FHCaI

Comparison with MC-Glauber fit : BM@N



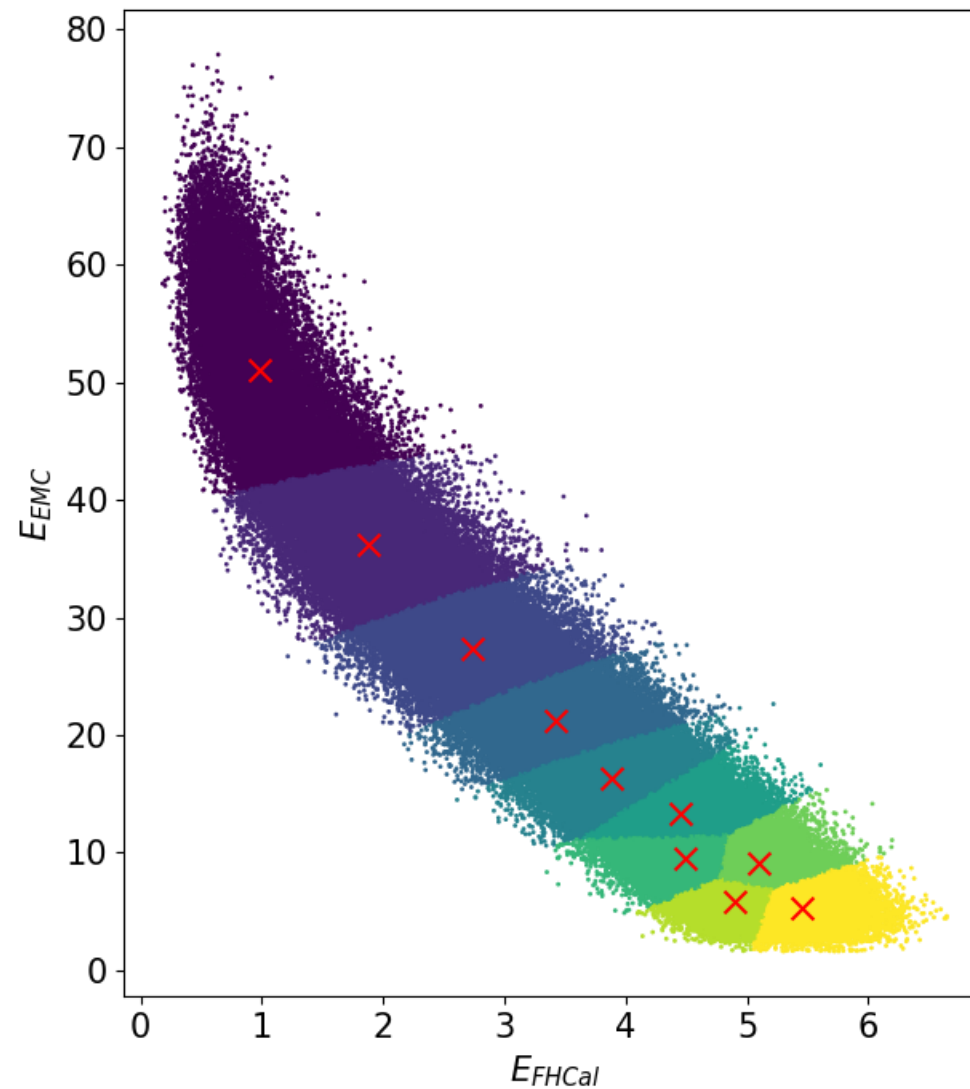
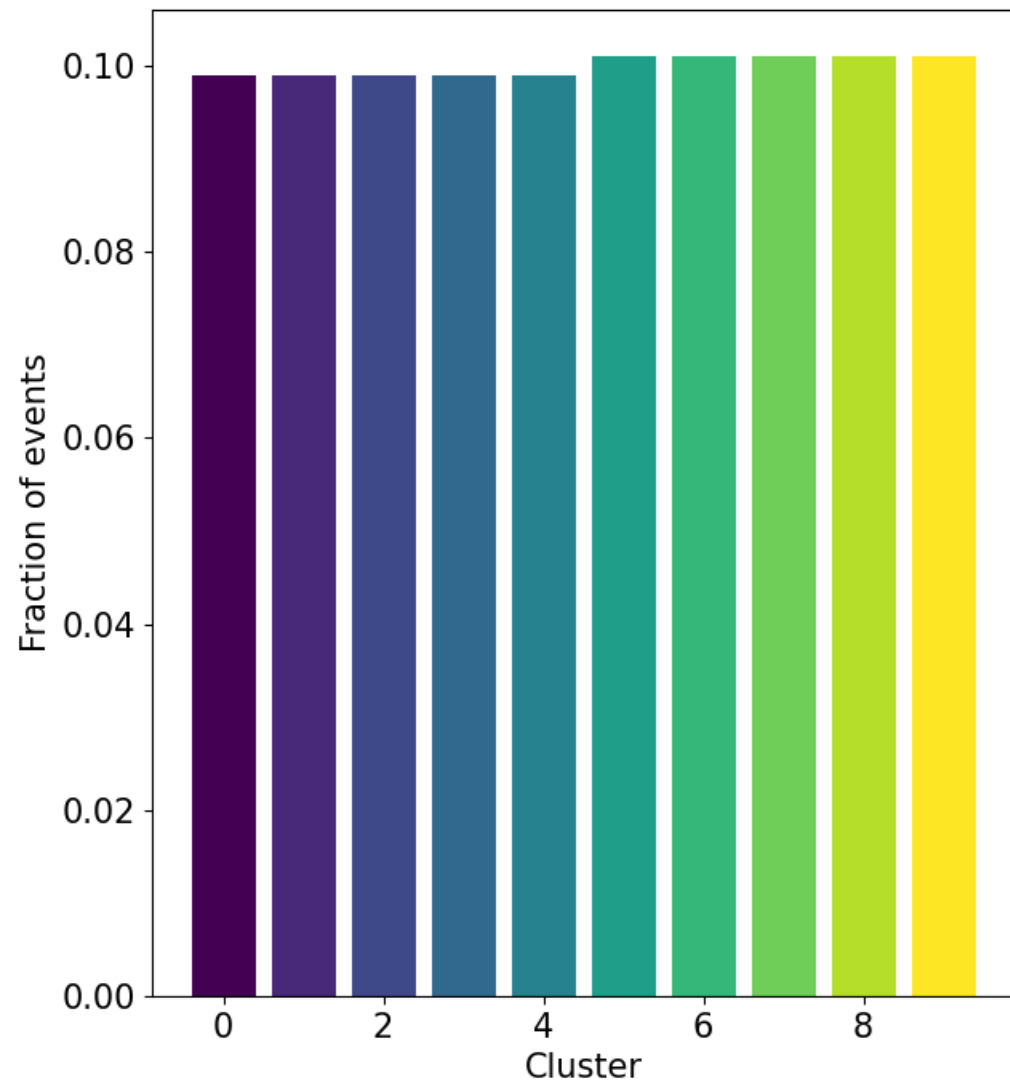
There is agreement within 5%.

Summary and outlook

- The Bayesian inversion method reproduce observables for fixed-target mode at MPD:
 - Multiplicity-based and 2D approaches using E_{EMC} and E_{FHCa} show consistent results with model data
- The proposed method was applied to the data from BM@N experiment:
 - Multiplicity-based and 2D approaches using Q^2_{Hodo} and E_{FHCa} describe experimental data reasonably well
- To do:
 - Systematic study of different models with and without realistic fragmentation
 - Study of the spectator contribution in the centrality determination based on multiplicity

Thank you for your attention!

Centrality classes

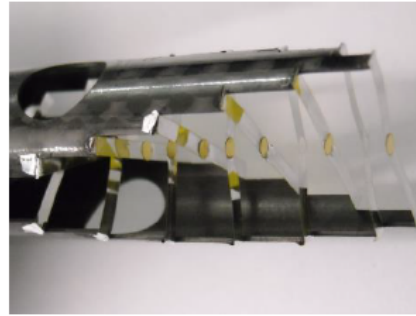


Centrality classes were obtained using the k-means algorithm

Event cleaning in HADES

Segmented gold target:

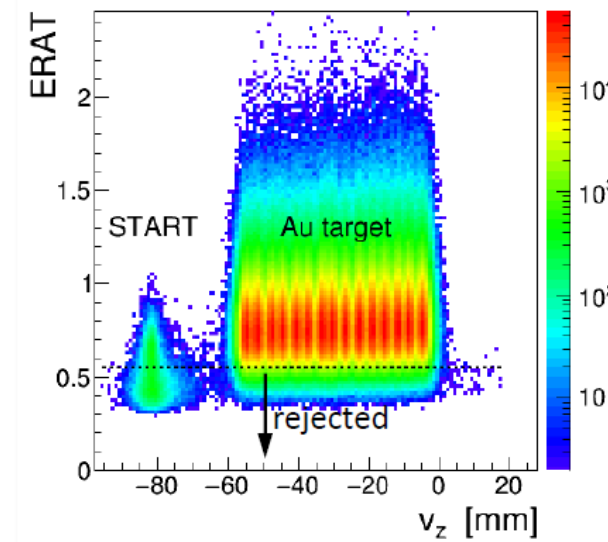
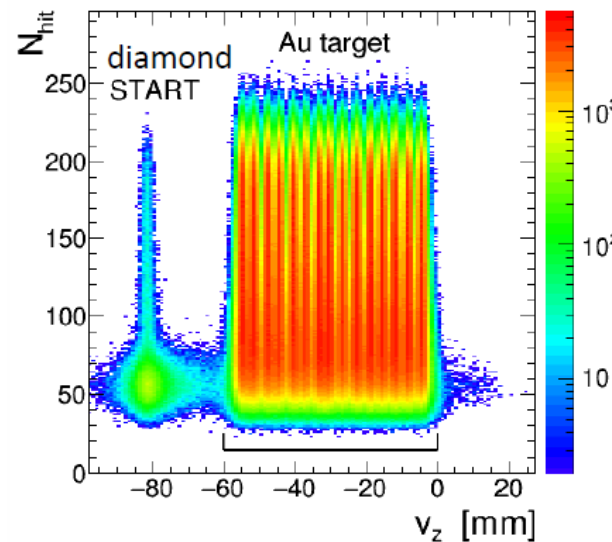
- ^{197}Au material
- 15 discs of $\varnothing = 2.2$ mm mounted on kapton strips
- $\Delta z = 3.6$ mm
- 2.0% interaction prob.



Kindler et al.,
NIM A 655 (2011) 95

Remove Au+C bkgd on the kapton
with a cut on $ERAT = \sum E_t / \sum E_l$

Event vertex cut on target region



beam direction

Reconstruction of b

- Normalized multiplicity distribution $P(N_{ch})$

$$P(N_{ch}) = \int_0^1 P(N_{ch}|c_b)dc_b$$

- Find probability of b for fixed range of N_{ch} using Bayes' theorem:

$$P(b|n_1 < N_{ch} < n_2) = P(b) \frac{\int_{n_1}^{n_2} P(N_{ch}|b)dN_{ch}}{\int_{n_1}^{n_2} P(N_{ch})dN_{ch}}$$

- The Bayesian inversion method consists of 2 steps:**

- Fit normalized multiplicity distribution with $P(N_{ch})$
- Construct $P(b|N_{ch})$ using Bayes' theorem with parameters from the fit

