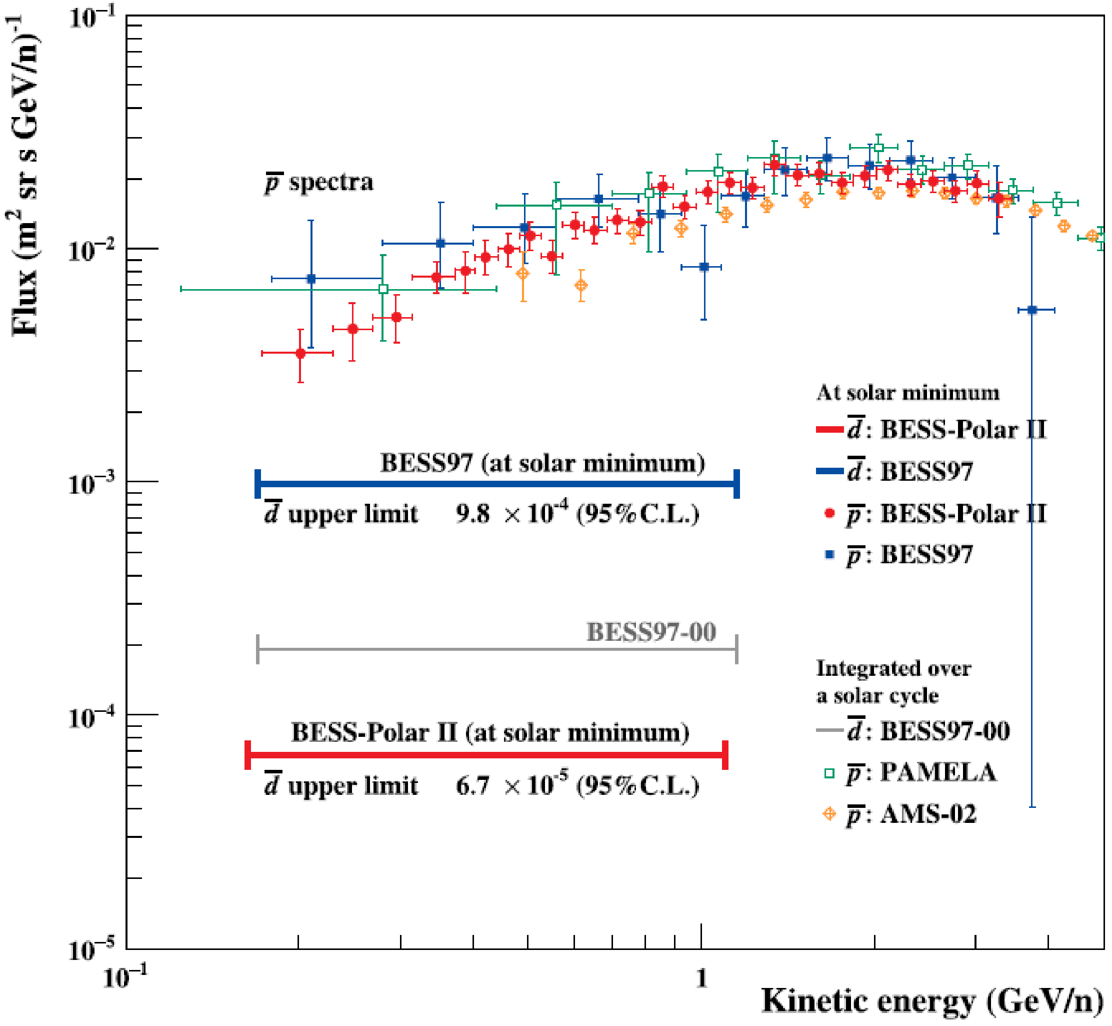
SEARCHING FOR ANTIDEUTERONS

STATUS OF THE DBAR ANALYSIS IN BOLOGNA

ANTIDEUTERONS IN COSMIC RAYS

Cosmic antideuterons are produced in collision between propagating primary cosmic rays and the interstellar medium. Detecting them and modeling their production in fundamental for the Dark Matter indirect search: secondary antideuterons are suppressed at low kinetic energies, while Dark Matter ones are not.

BESS Collaboration, PRL, 132, 131001 (2024)



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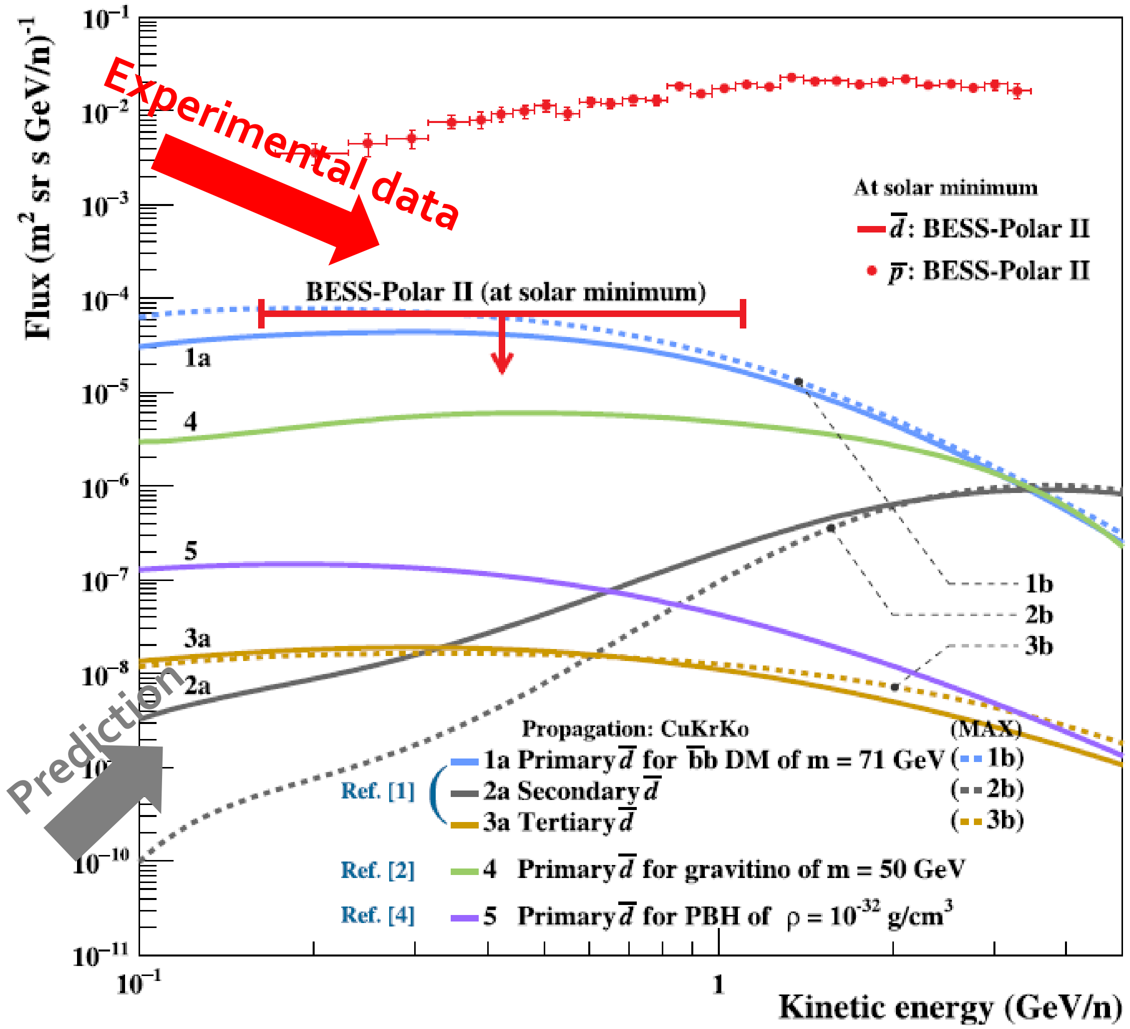
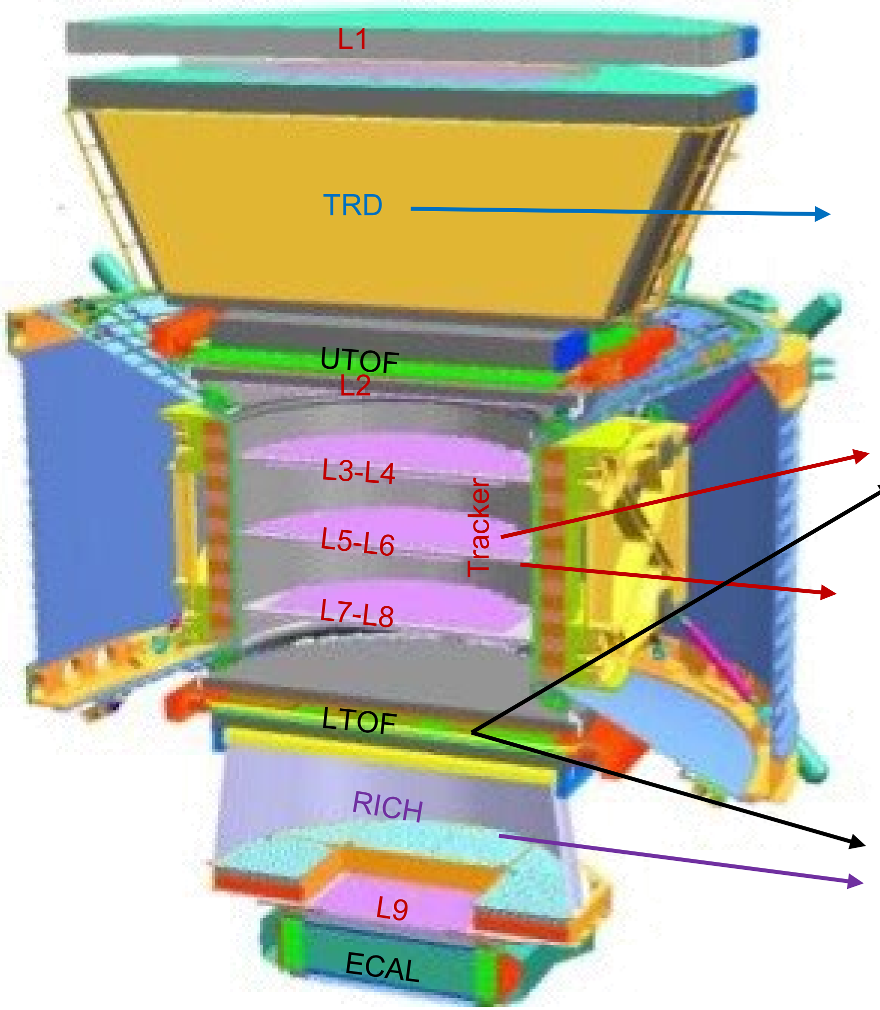


Search for heavy antideuterons in cosmic rays with the Alpha Magnetic Spectrometer



The **TRD** helps with the particle identification.

|Z| is reconstructed using both the **TOF** and the **Inner Tracker**.

The Rigidity is reconstructed using the **Inner Tracker** and the magnet (and also the sign of Z).

The β is reconstructed using the **TOF** ($0.3 < \beta < 0.8$) and the **RICH** (**NaF** $0.75 < \beta < 0.99$ and **aerogel** $\beta > 0.96$) in three independent samples.

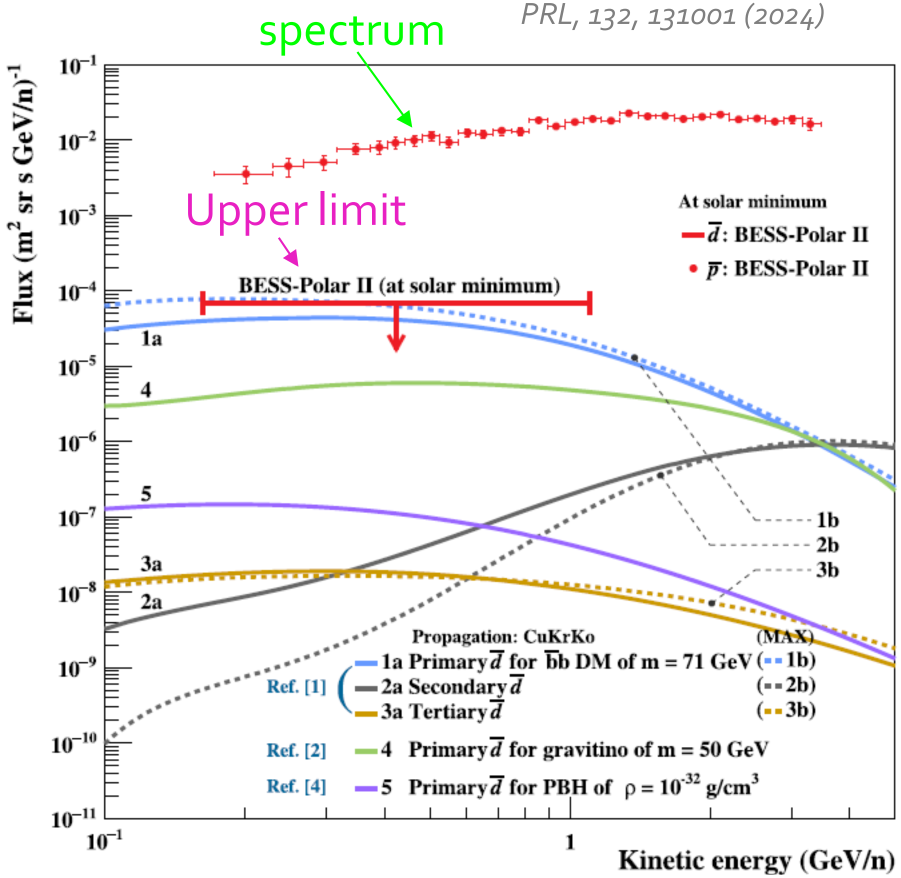
SEARCHING FOR ANTIDEUTERONS WITH AMS-02

BESS Collaboration
PRL, 132, 131001 (2024)

The quantity of a certain cosmic ray specie observed is calculated using the following flux formula :

$$\Phi(R_i) = \frac{N_i}{T_i \, A_i \, \Delta R_i}$$

N_i Number of counted signal events
ΔR_i Rigidity bin width
A_i acceptance
T_i Exposure time



This formula can be used to calculate a spectrum (such as antiprotons) or can be used to put an upper limit if nobody has been observed (such as antideuterons).

The rigidity bin width can be enlarged to obtain lower the limit, losing spectral information (such as *antideuterons*).

$$\Phi(R_i) = \frac{N_i}{T_i\ A_i\ \Delta R_i}$$

Find the number of good antideuterons is one of the most difficult thing of the analysis.

It means identify few events in more than ten billions. A tight standard selection has been applied to clean the sample from bad reconstructed events, but it's not enough. A more advanced selection is required (applying Machine Learning algorithms).

Standard selection

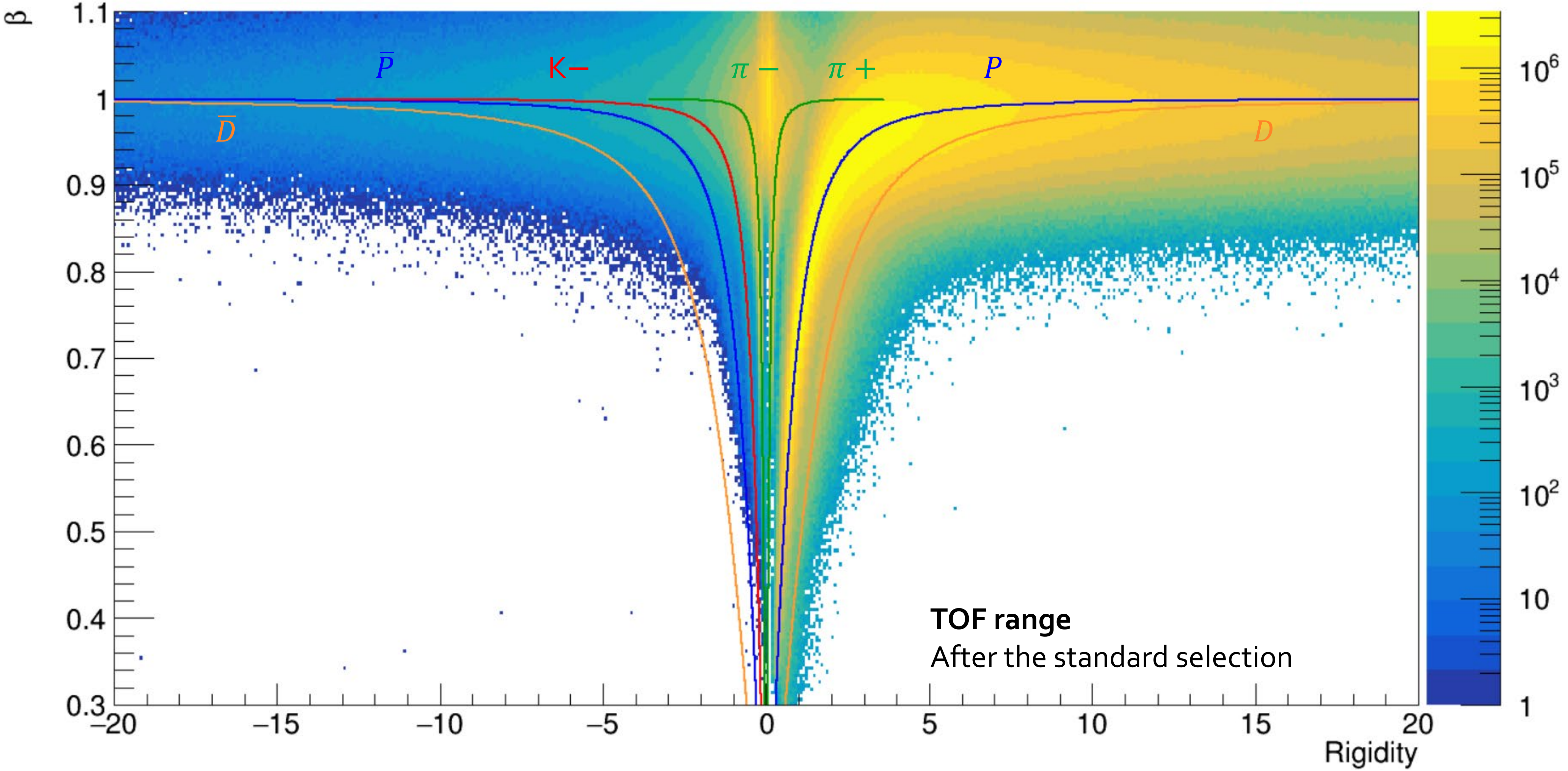
IsPhysicsTrigger
Fiducial Volume
RTI selection

TRD NHitsOnTrack > 10
TRD LikelihoodRatio e/p > 0.8
TRD LikelihoodRatio p/He < 0.3

TOF: NβClusters = 4
TOF: ChiSquareCoo < 4
TOF: TotalCluster(onTime+OffTime) < 2
TOF: $\left|\frac{Z_{utof}-Z_{ltof}}{Z_{utof}}\right| < 0.2$ (TOF sample only)

IT PatternY: L2 & (L3|L4) & (L5|L6) & (L7|L8)
IT Chisquare Y < 10
IT $\frac{\sigma_{Z(IT)}}{Z_{IT}} < 0.1$
IT NhitsY > 5
IT Nhits XY > 3

RICH: NHitsUsed > 2 (only NaF and agl samples)
RICH: RingGeomTest (only NaF and agl samples)
RICH: NPMTsRing > 2 (only NaF and agl samples)



TOF range

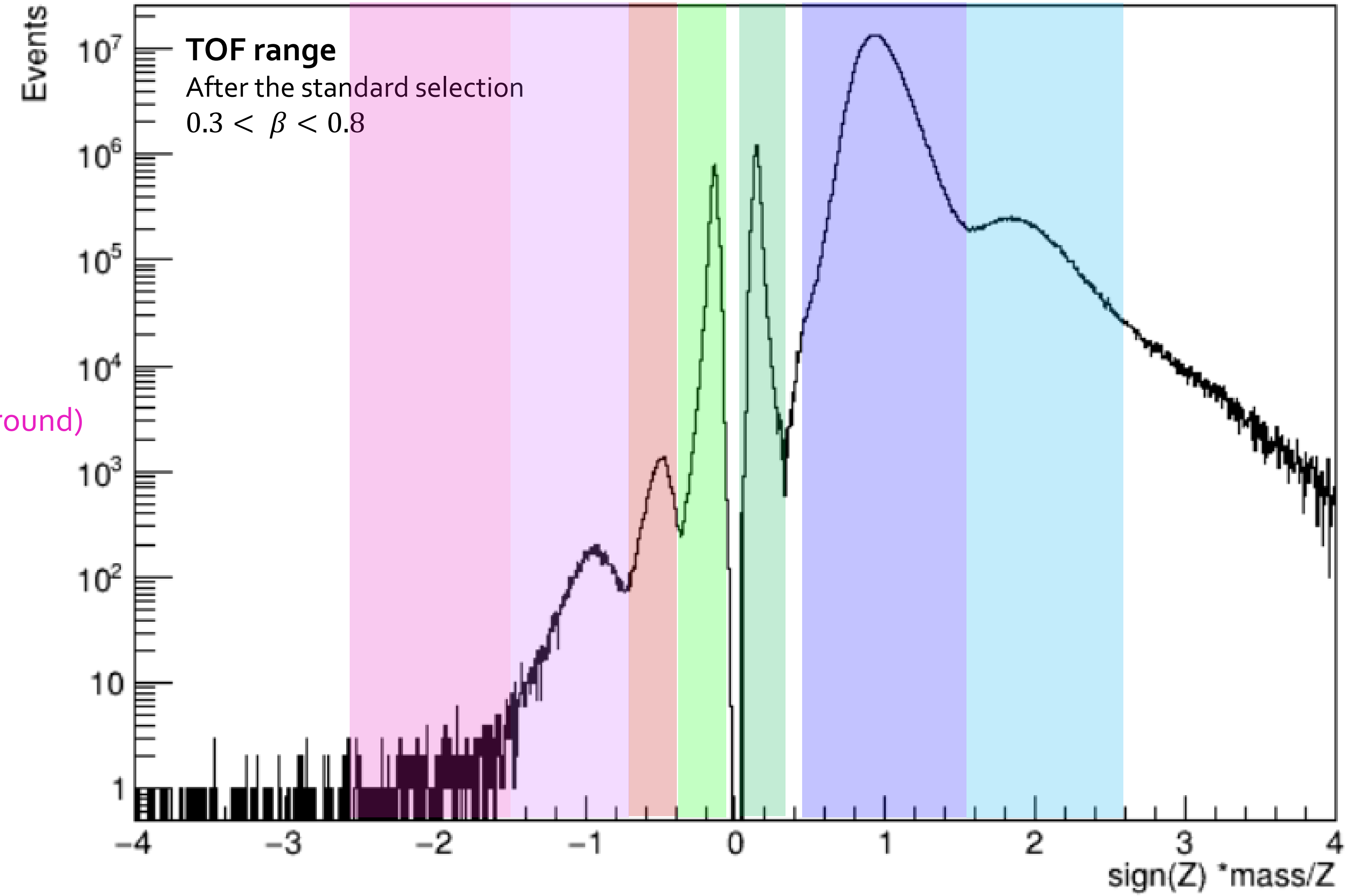
After the standard selection

SEARCHING FOR ANTIDEUTERONS WITH AMS-02: EVENT SELECTION

In **12.5 ys of data**, we have in the TOF range, with $0.3 < \beta < 0.8$:

861.5 millions of protons
32.4 millions of deuterons
12.2 millions of pi+
7.9 millions of pi-
42 265 K-
12446 antiprotons
270 antideuterons (probably background)

$$mass = \frac{ZR}{\gamma\beta}$$



We started to apply Machine Learning algorithms to try to further clean the TOF sample.

We did a first attempt using a **Deep Neural Network (DNN)**, based **on Inner Tracker (IT) variables**. We have trained the DNN using the **MC of protons**, starting with events in the **TOF samples**.

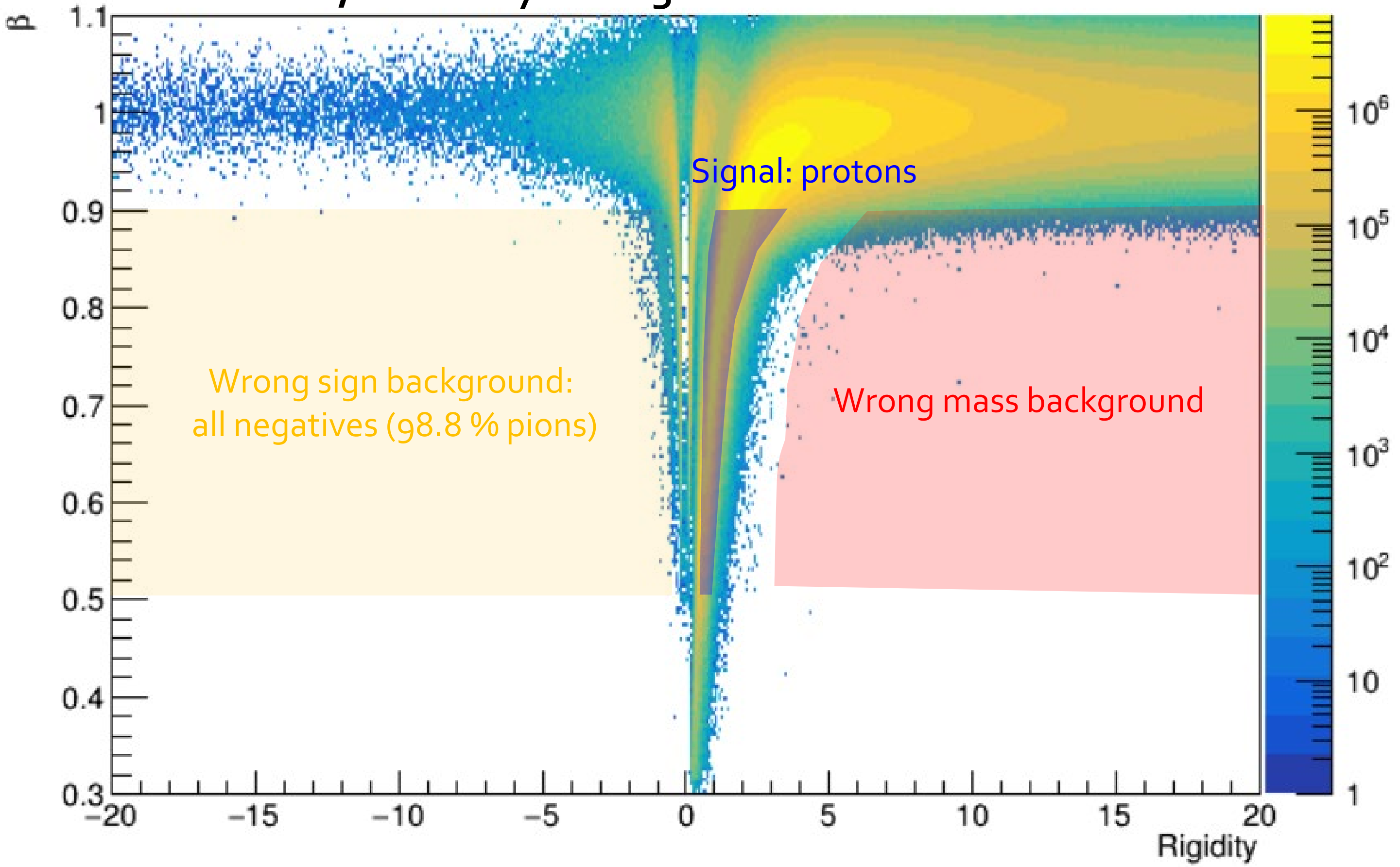
We have chosen the **protons as signal sample**.

We started considering two kind of backgrounds:

1. a **wrong charge background** composed by events with the wrong sign of the charge;
2. a **wrong mass background** composed by events where the mass in bad reconstructed (too high)

For statistical reasons, we enlarged the training samples to lie in the $0.5 < \beta < 0.9$ range

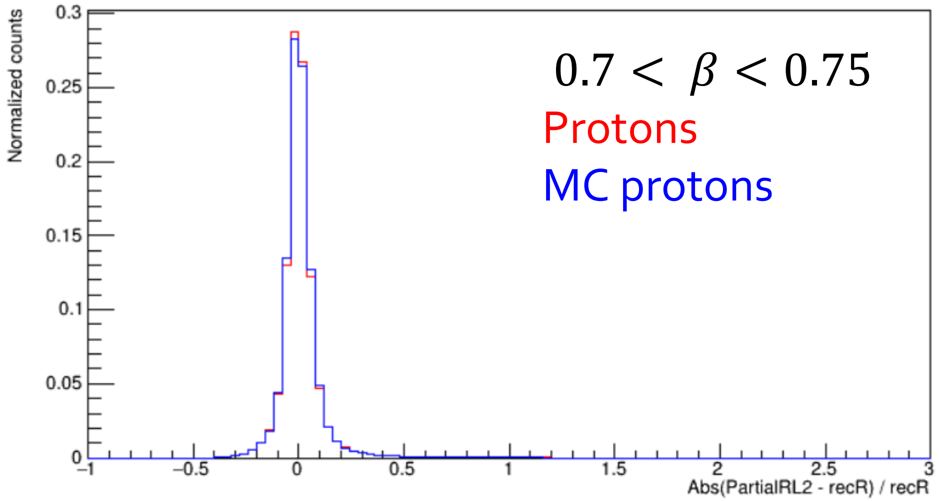
MC Protons, TOF analysis range:

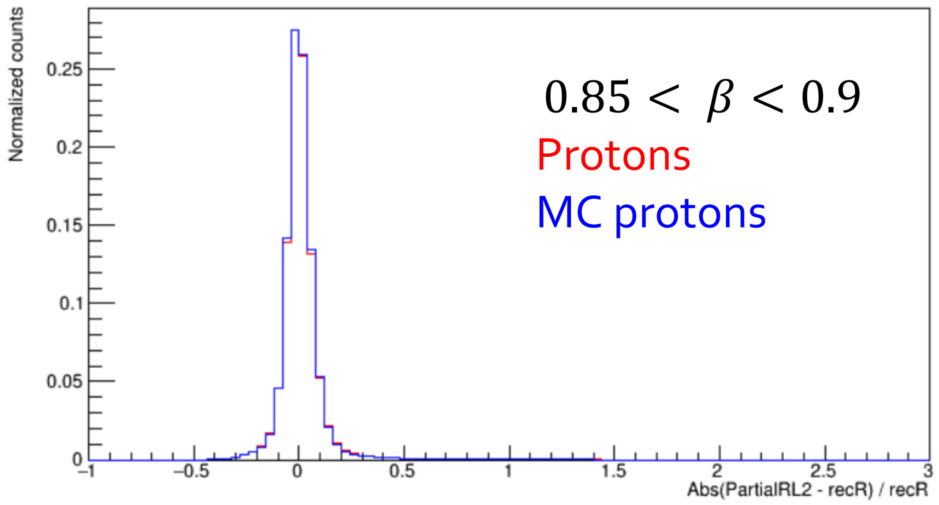


Choosing the IT variables

-> loose R dependence

-> agreement between data and MC

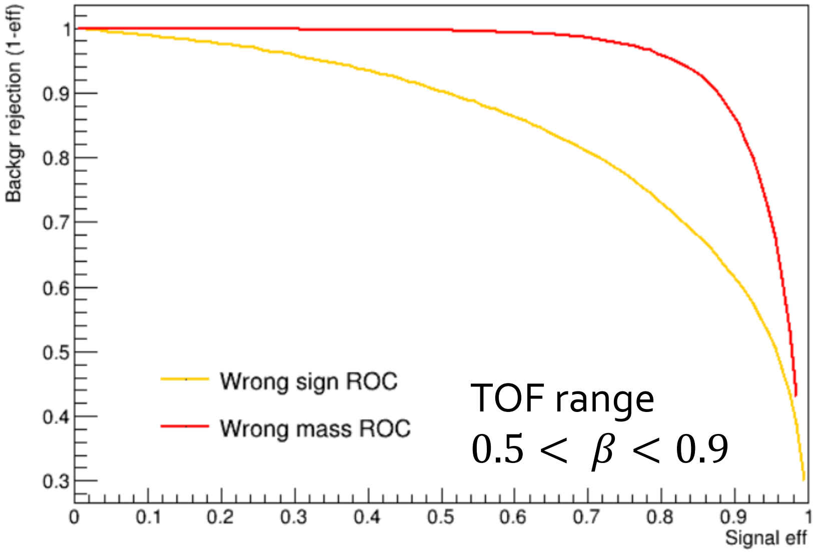




56 Variable used:

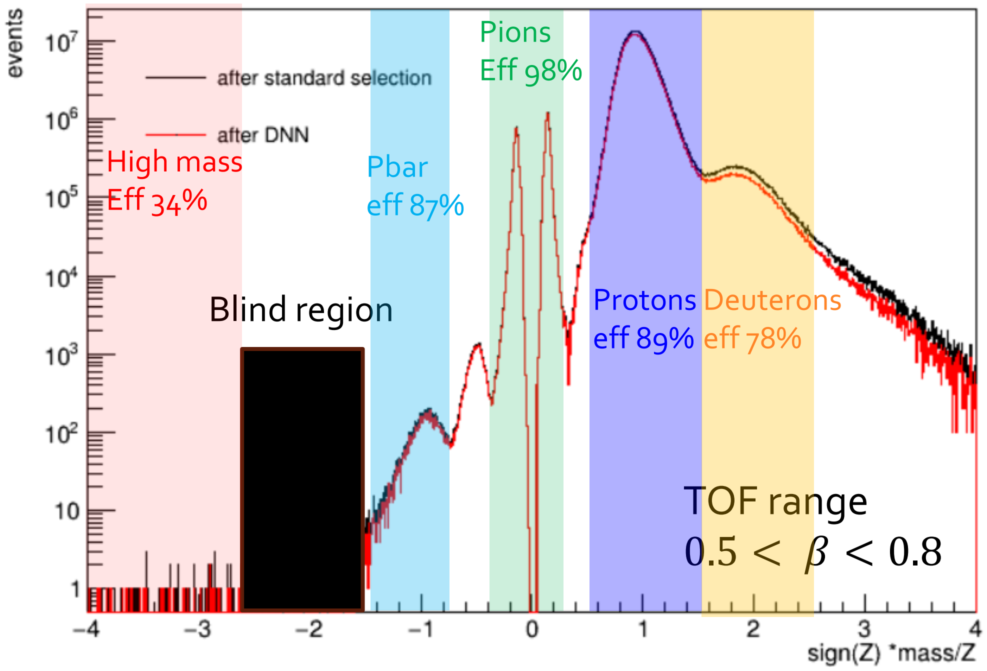
- N° 1 ChisquareX (IT) NO MS, GBL
- N°7 PartialR asymmetries (L2-L8)
- N°7 NCluster (IT), Side X, 1mm (L2-L8)
- N°7 NCluster (IT), Side X, 1cm from Track (L2-L8)
- N°7 NCluster (IT), Side X, 2cm from Track (L2-L8)
- N°7 NCluster (IT), Side Y, 1mm (L2-L8)
- N°7 NCluster (IT), Side Y, 1cm from Track (L2-L8)
- N°7 NCluster (IT), Side Y, 2cm from Track (L2-L8)
- NTotalCluster (IT), SideX, 1mm (sum on L2-L8)
- NTotalCluster (IT), SideX, 1cm (sum on L2-L8)
- NTotalCluster (IT), SideX, 2cm (sum on L2-L8)
- NTotalCluster (IT), SideY, 1mm (sum on L2-L8)
- NTotalCluster (IT), SideY, 1cm (sum on L2-L8)
- NTotalCluster (IT), SideY, 2cm (sum on L2-L8)

The DNNs performances have been evaluated using the ROC curve:

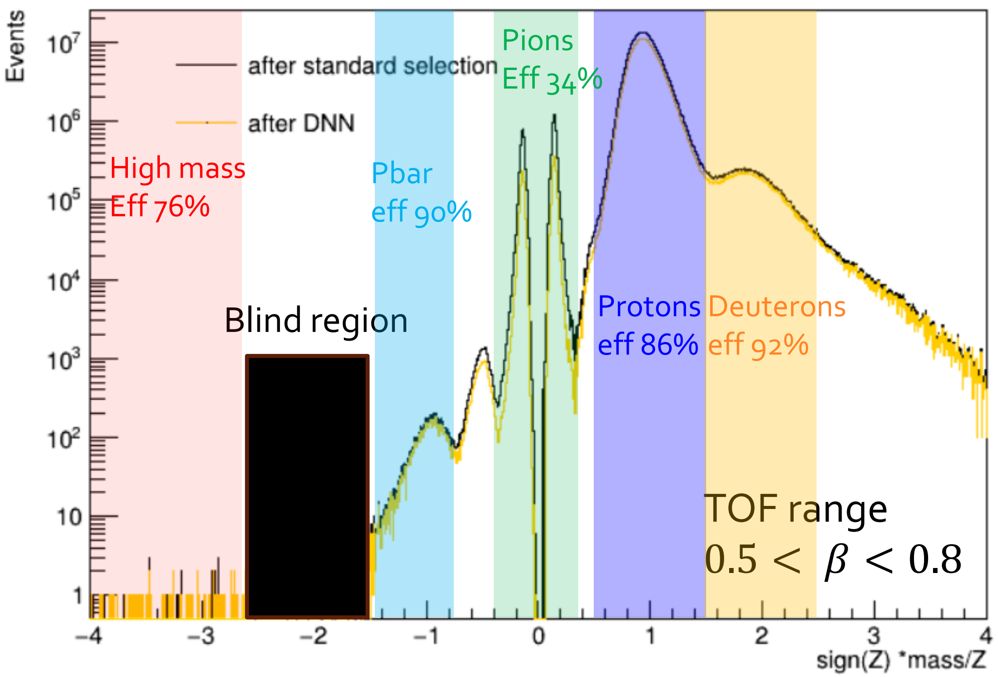


Adding L1 in the analysis -> ONGOING

DNN with wrong mass background



DNN with wrong charge background



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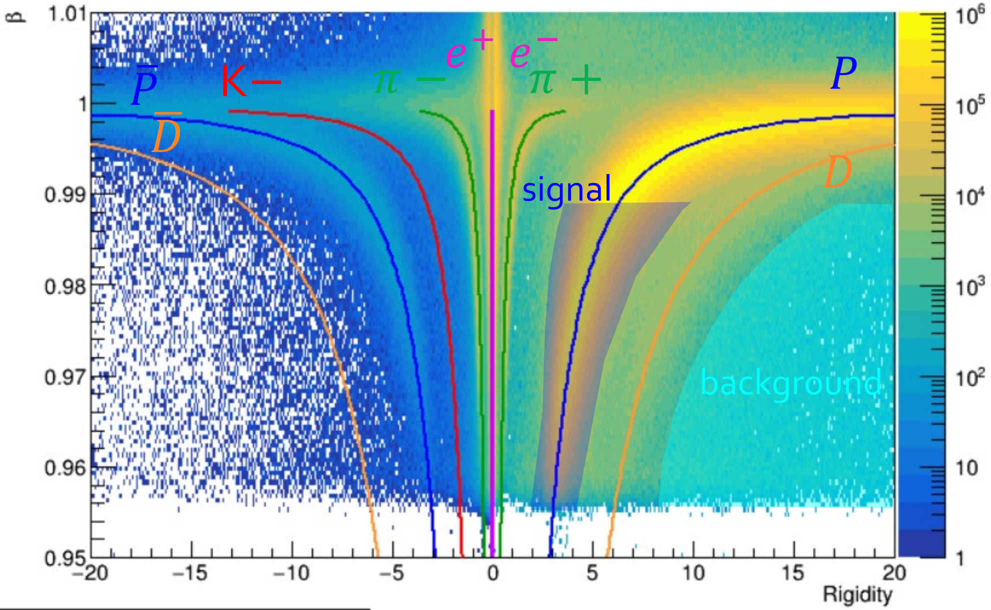
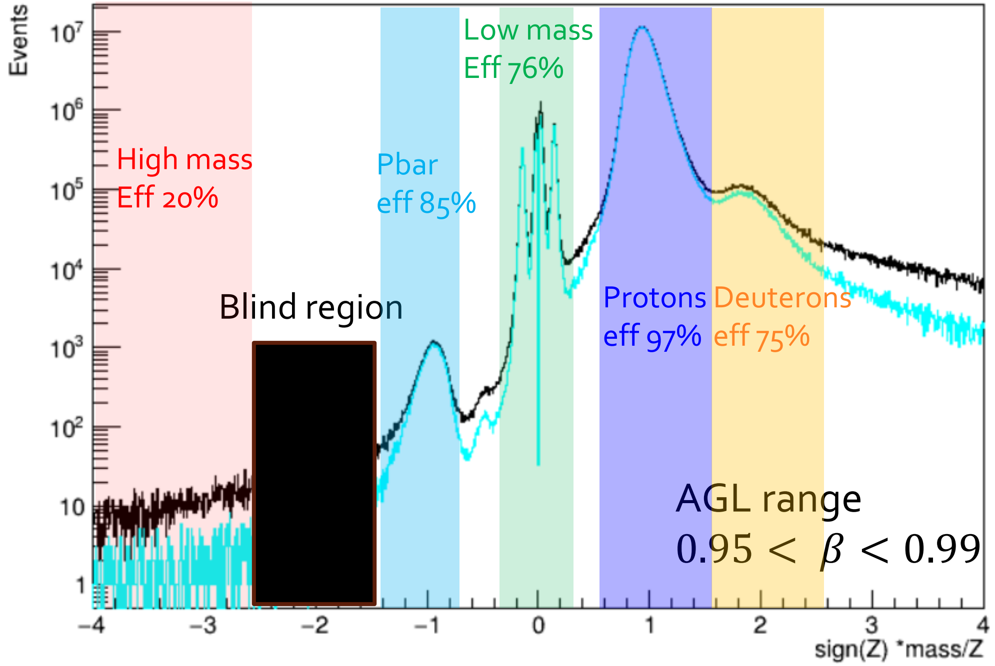
We have chosen the **wrong mass background** composed by events where the mass in bad reconstructed (too high)



Adding L1 in the analysis -> ONGOING

DNN with wrong mass background



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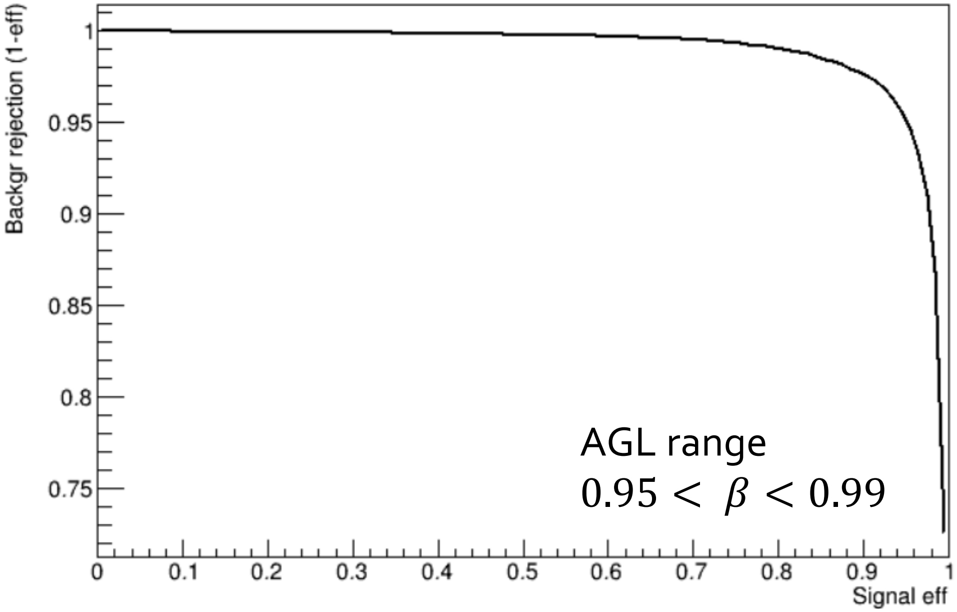


$$\Phi(R_i) = \frac{N_i}{T_i\, A_i\, \Delta R_i}$$

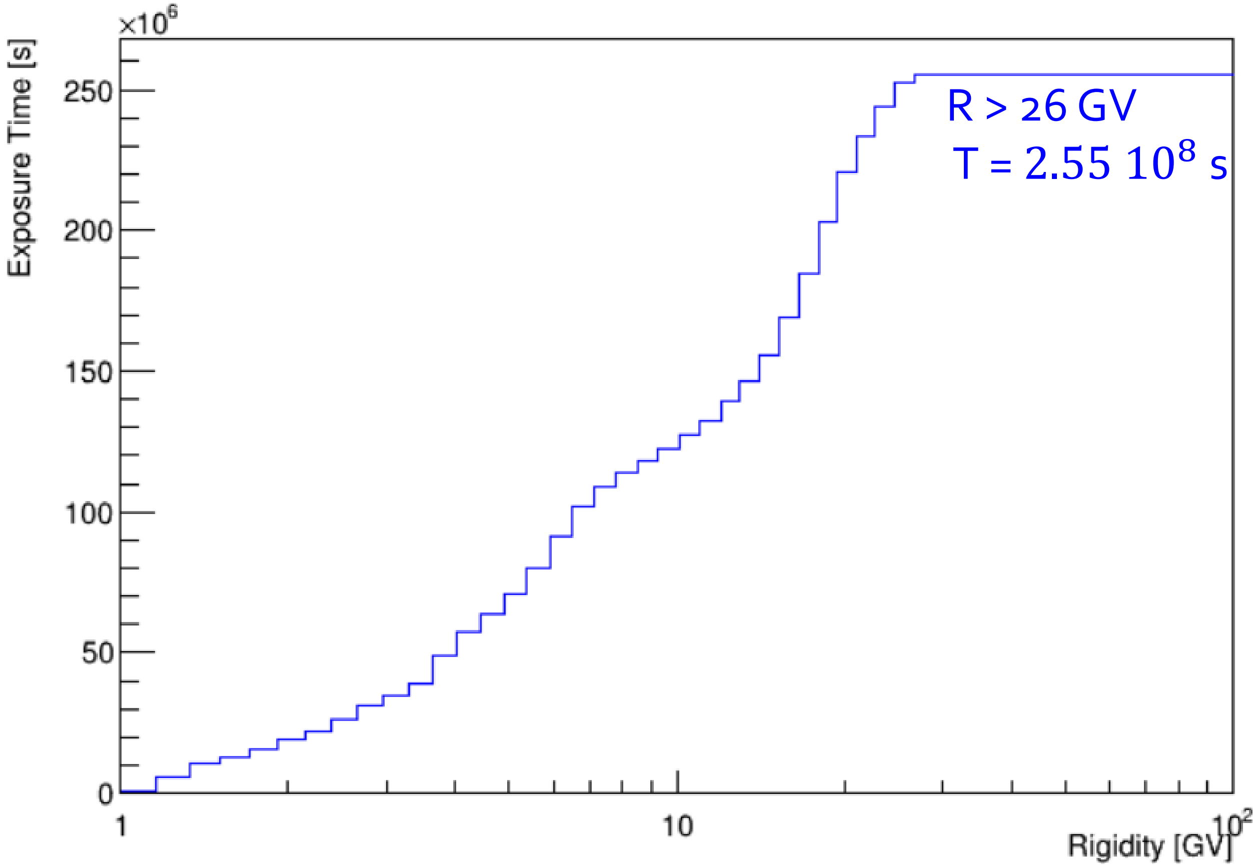
The exposure time has been calculated selecting al the seconds used in the analysis, according to a Real Time Information (RTI) selection.

Each second has been weighted using its livetime fraction.
The exposure time has been calculated using the Max IGRF cutoff, using 30° view.

RTI selection
Is not in SAA
Livetime Fraction > 0.5
AMS Zenit < 40°

12.5 years data:

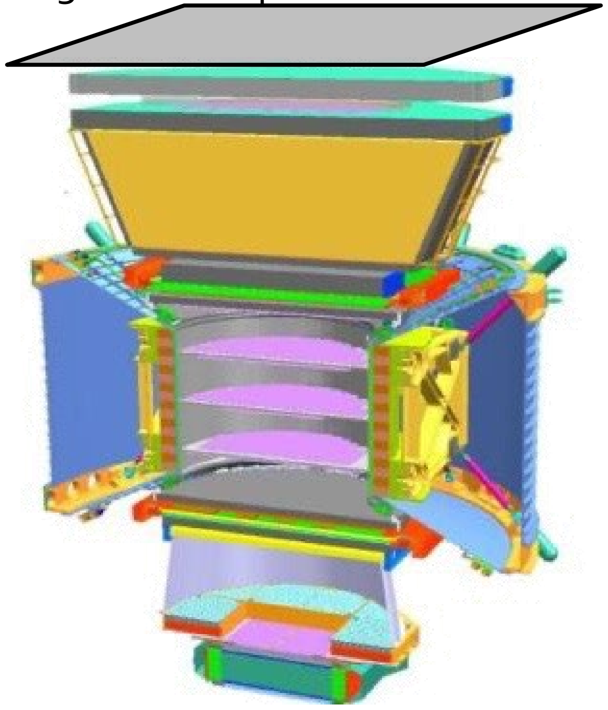
First event: May 2011
Last event: Nov 2023



$$\Phi(R_i) = \frac{N_i}{T_i\, A_i\, \Delta R_i}$$

The acceptance describes the ability of the detector to record particles.

MC generation plane: $l^2 = 3.9 \; x \; 3.9 \; m^2$



1: **Selection acceptance** of the detector: accounts for the selection used to detect particles

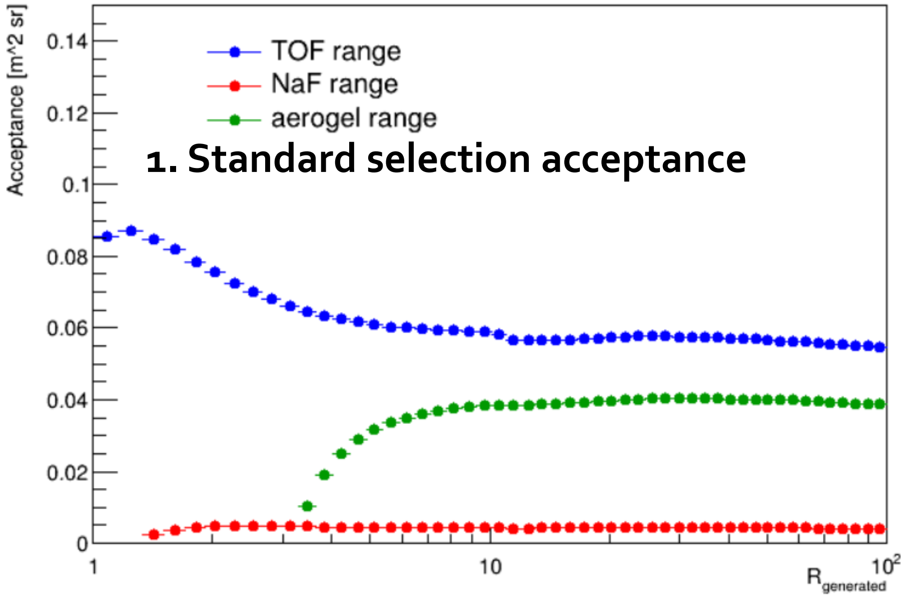
$$A_{sel} = \frac{N_{accepted}}{N_{generated}} \pi \, l^2 \longrightarrow$$

$N_{accepted}$ = events passing a certain selection in the MC

$N_{generated}$ = events generated in the MC

2: **Correpted acceptance** of the detector: accounts for the differences between data and MC.

Corrected acceptance $A_i = \frac{\varepsilon_{data}}{\varepsilon_{MC}} A_{sel} \longrightarrow \frac{\varepsilon_{data}}{\varepsilon_{MC}} = \prod_{i}^{subdetector} \frac{\varepsilon_{data,i}}{\varepsilon_{MC,i}}$



1. Standard selection acceptance

2. Standard selection Corrected acceptance

ONGOING

$$\Phi(R_i) = \frac{N_i}{T_i\, A_i\, \Delta R_i}$$

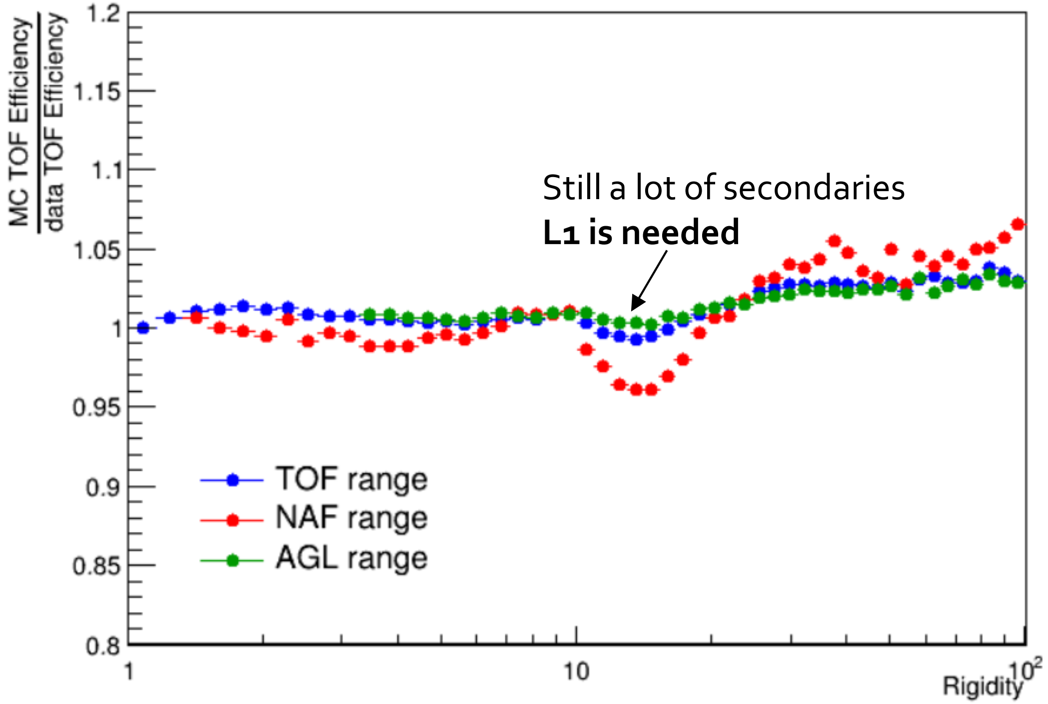
The acceptance is calculated using the MC. To calculate the acceptance "on the data" we need to correct the selection acceptance, using the efficiency ratio between data and MC.

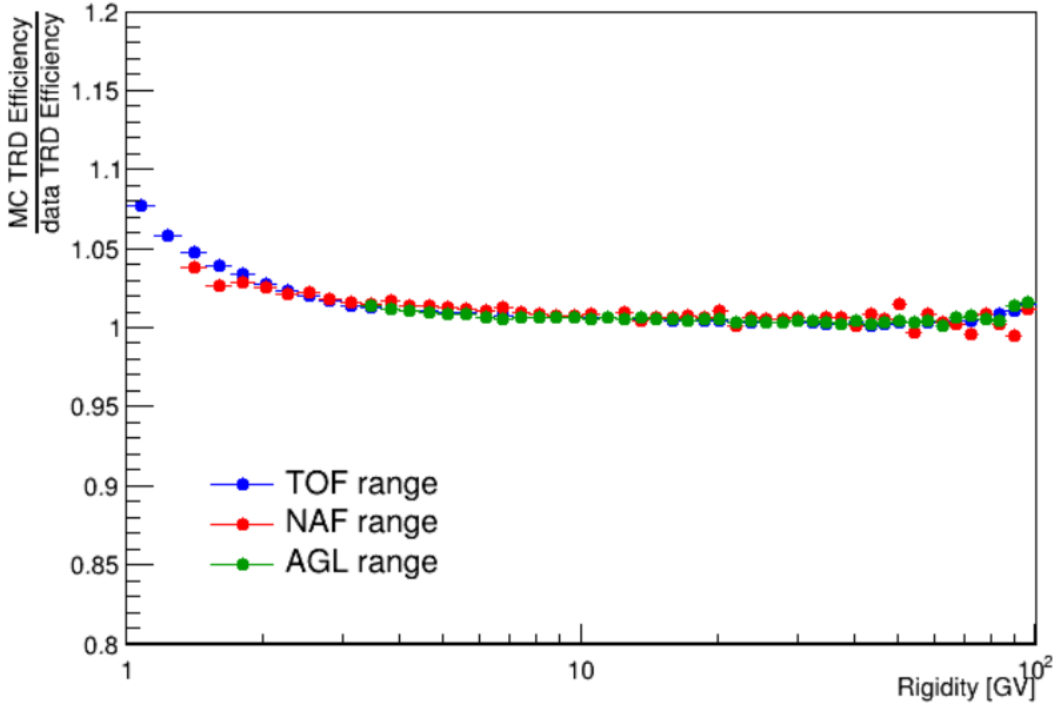
It accounts for the difference between data and MC, so when the MC is not perfectly simulating the detector response.

Data/MC correction in the efficiencies

Corrected acceptance $A_i = \frac{\varepsilon_{data}}{\varepsilon_{MC}} A_{sel} \longrightarrow \frac{\varepsilon_{data}}{\varepsilon_{MC}} = \prod_{i}^{subdetector} \frac{\varepsilon_{data,i}}{\varepsilon_{MC,i}}$

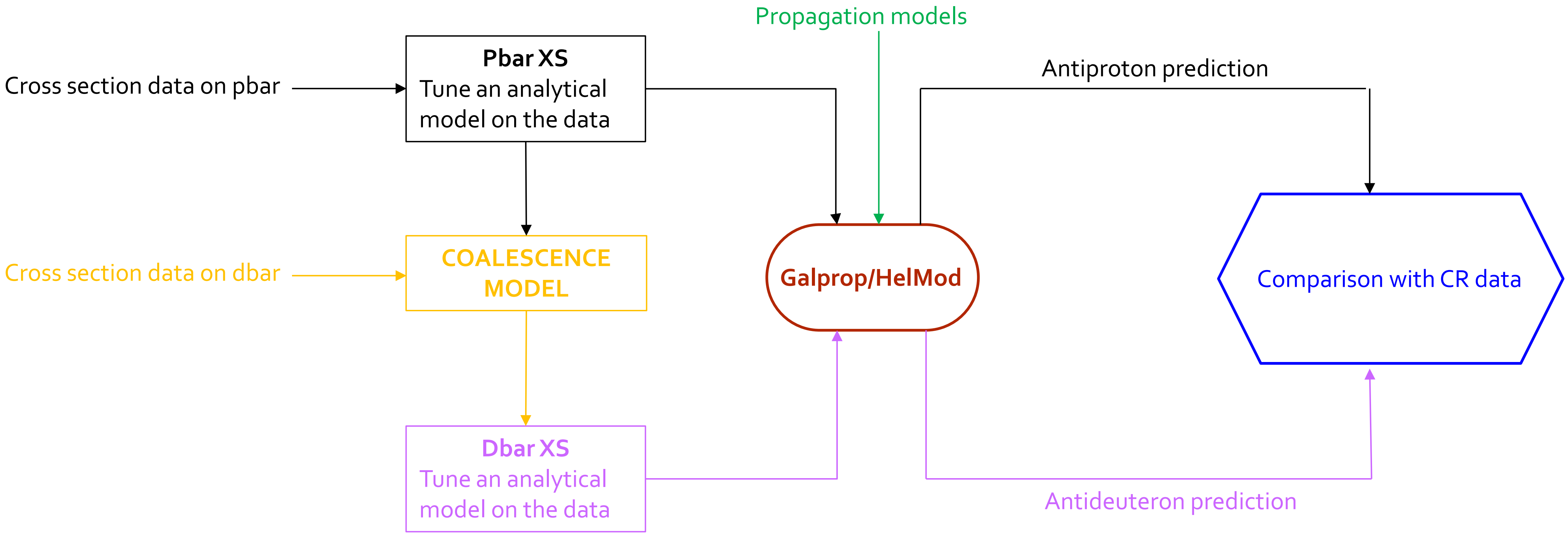
ONGOING





MODELING THE ANTIDEUTERONS PRODUCTION

Antideuterons are expected to be produced in collisions between primary CRs propagating through the galaxy, and the ISM.
To estimate this **secondary production**, we had decided to follow the path below:

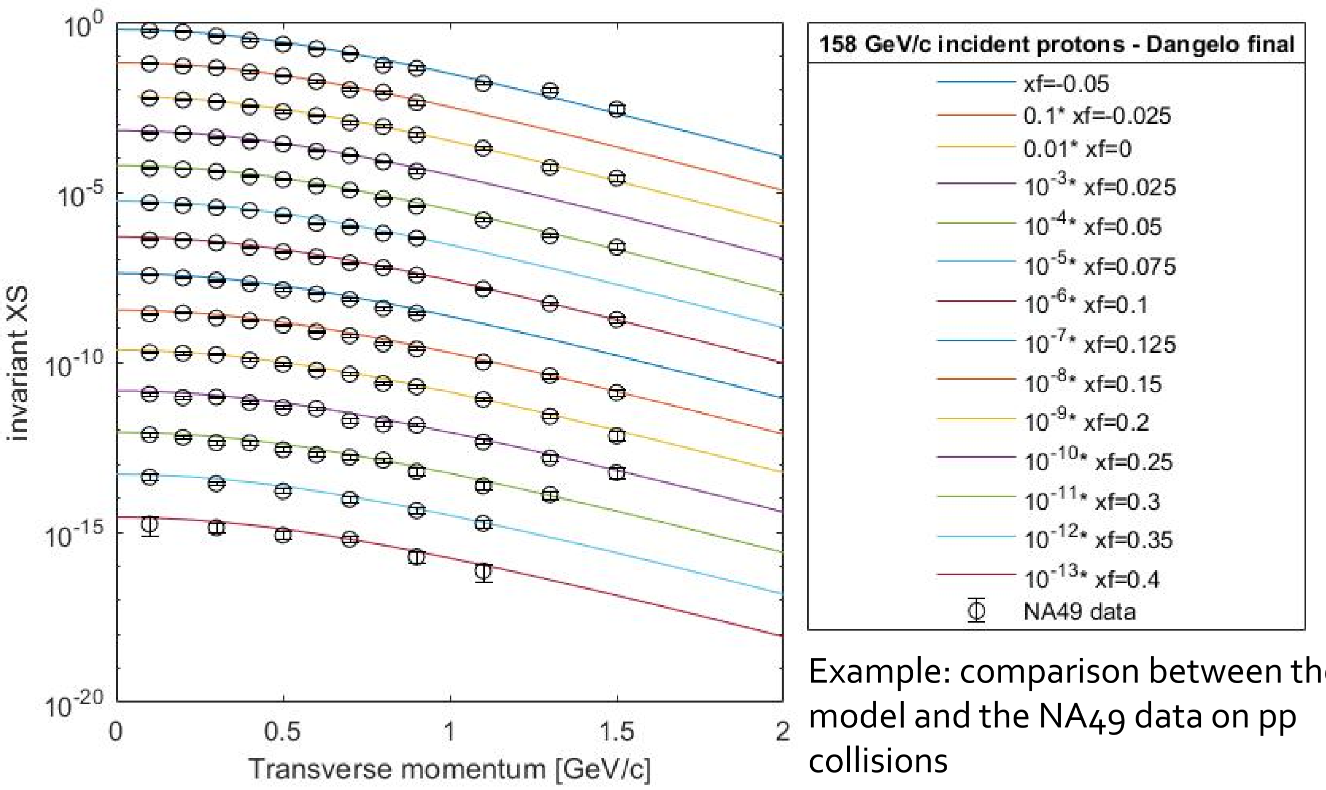


We have used the available data on pbar production cross section to fit an analytical model to calculated the pbar production in CRs.

Cross section data on pbar → **Pbar XS** Tune an analytical model on the data

Cross section data on dbar → COALESCENCE MODEL

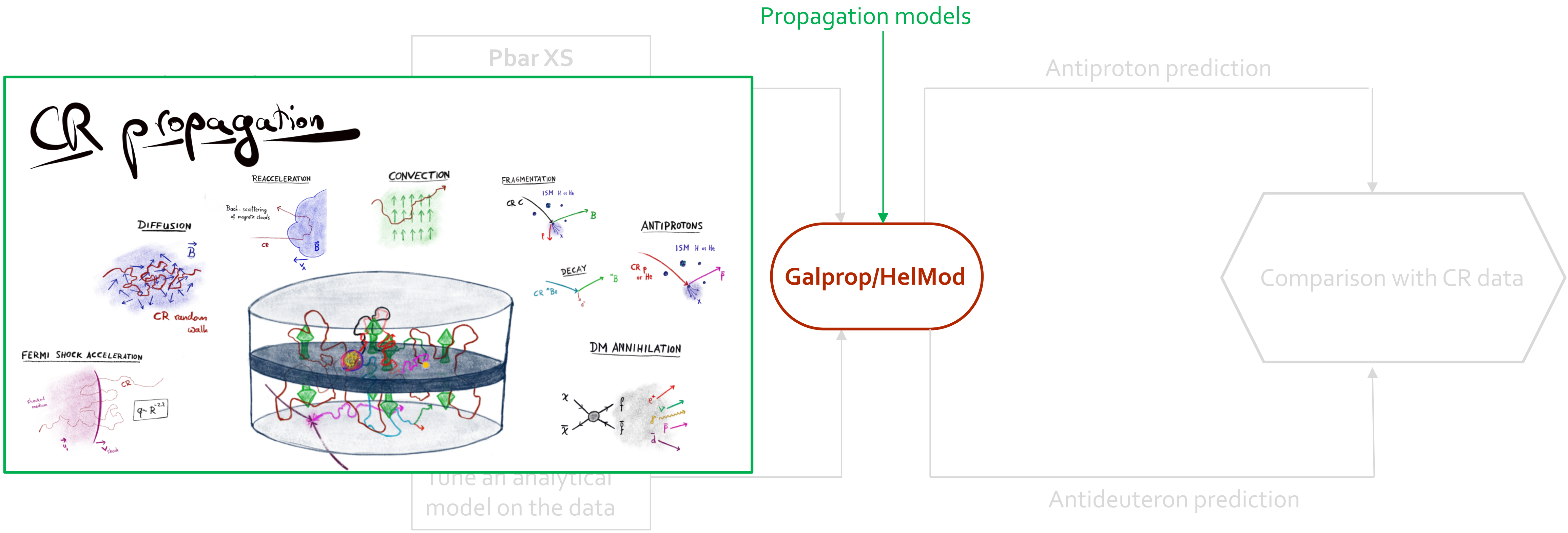
Dbar XS Tune an analytical model on the data



Example: comparison between the model and the NA49 data on pp collisions

MODELING THE ANTIDEUTERONS PRODUCTION

We used the propagation model described in *M. J. Boschini et al 2020 ApJS* ***250*** *27* and the framework Galprop/HelMod to predict the antiproton flux at the ISS.
The model can be used also to propagate the antideuterons in the Galaxy.



MODELING THE ANTIDEUTERONS PRODUCTION

We compared the predicted flux with the AMS data on the antiprotons *Phys. Rep.* ***894***, *1 (2021)*.

Propagation models

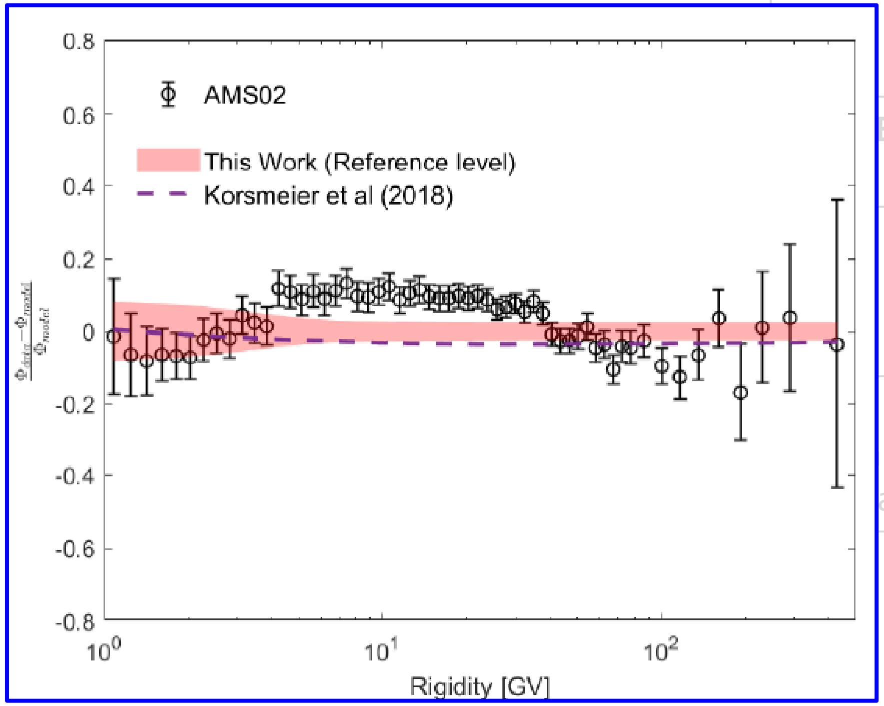
Cross section data on pbar

Pbar XS
Tune an analytical model on the data

Antiproton prediction

Galprop/HelMod

Comparison with CR data



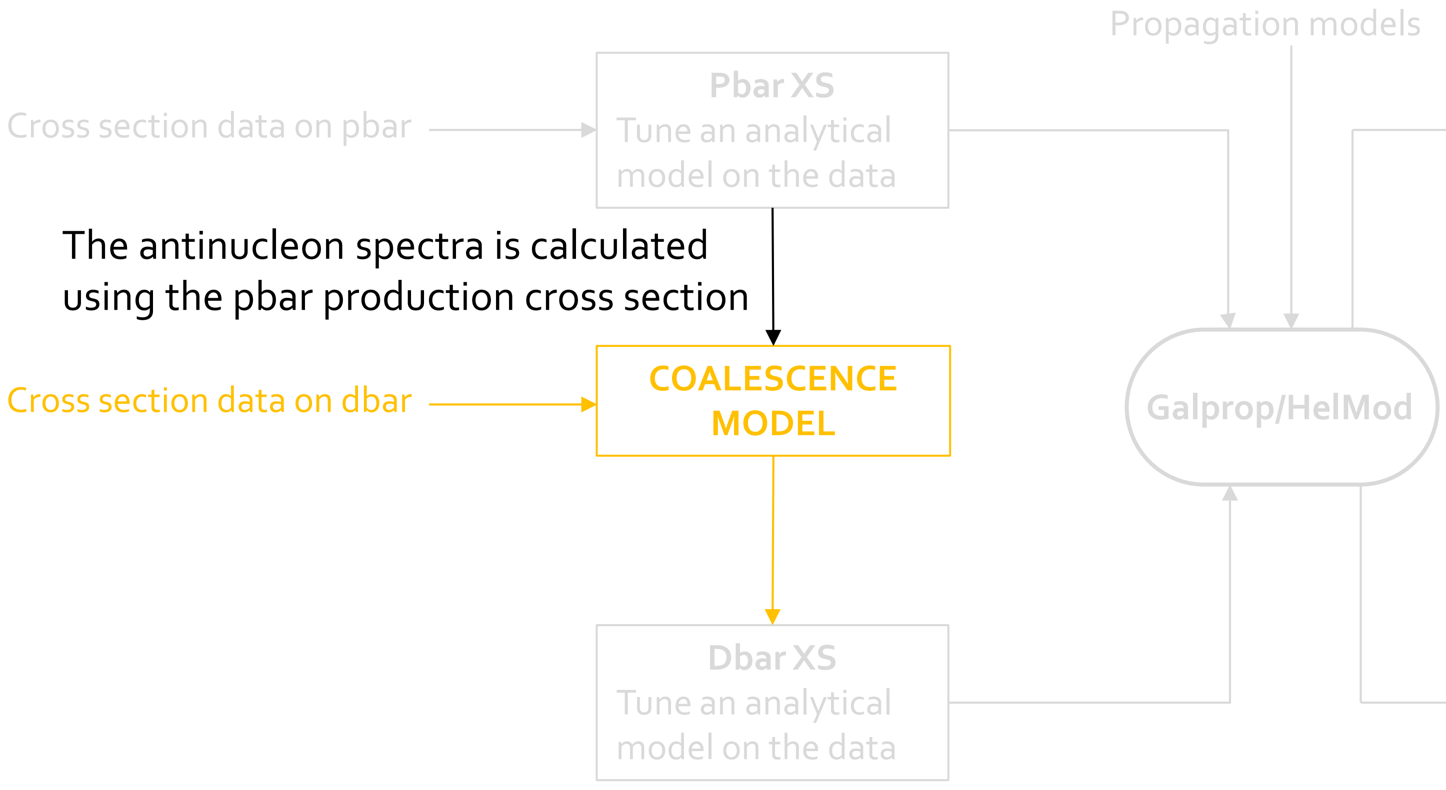
Antideuteron prediction

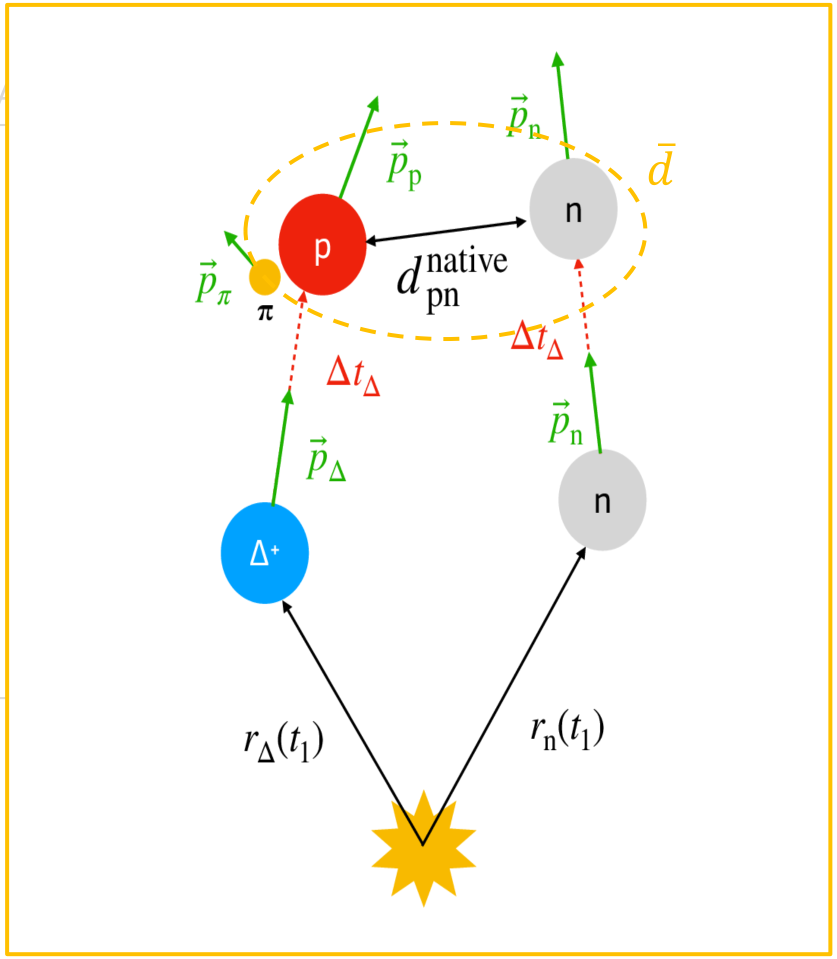
D'Angelo, Masi, Oliva - IL NUOVO CIMENTO 47 C (2024) 302

MODELING THE ANTIDEUTERONS PRODUCTION

If two antinucleons are produced near enough in coordinate and momentum space, they can merge and form an antideuterons.

The parameters of the coalescence model are tuned on dbar data.

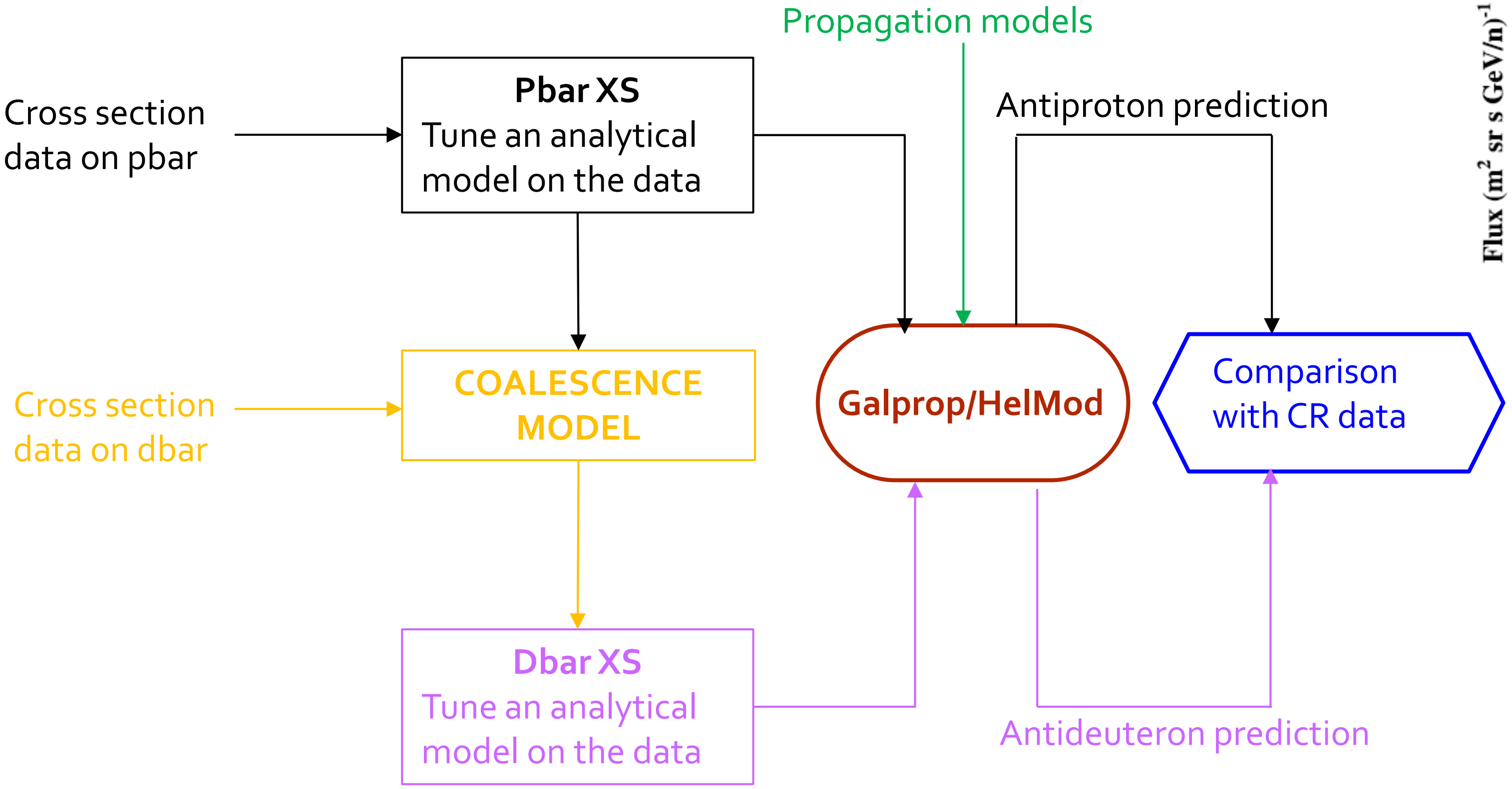




COMING SOON

MODELING THE ANTIDEUTERONS PRODUCTION

The whole picture allows us to predict the secondary dbar production and compare with the experimental bound we will calculate with AMS (adding to the plot on the right the AMS data and our antideuteron prediction).



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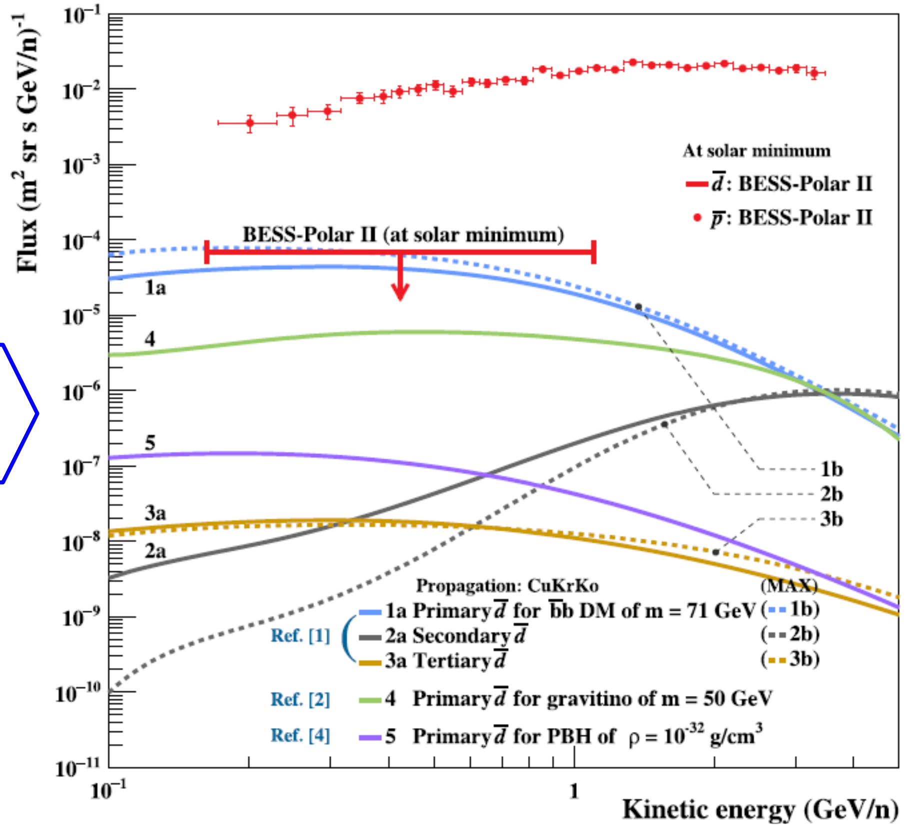

COMING SOON

SUMMARY

- Antideuterons search in on-going, using Machine Learning algorithm to suppress the background.
- Training classificators using MC events is very difficult: we don't have enough statistics when creating the background samples.
- Using the IT alone is difficult to clean further the samples. Furthermore, using ML algorithms based on the TRD variables can improve our analysis.
- L1 is needed in the analysis.
- We have started to cleaning the agl range using DNNs.
- Efficiencies correction calculations in ongoing.
- We have an analytical model to predict the antiproton secondary production in cosmic collision. It's the starting point to predict the antideuterons using a coalescence model.