

FERMI-LAT
CONSTRAINTS ON
DIFFUSE DARK
MATTER ANNIHILATION
FROM THE GALACTIC
HALO

Brandon Anderson UC Santa Cruz anderson@physics.ucsc.edu

on behalf of the Fermi LAT collaboration

IDM 2010

OUTLINE

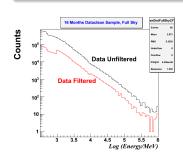
- 1. Dark Matter Signal
- 2. Diffuse Backgrounds
- 3. Profile Likelihood
- 4. Preliminary Results

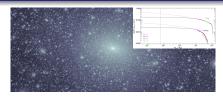
Instrument & Signal



Fermi Gammma-Ray Space Telescope

Using 16 months of Pass 6 'dataclean' (custom event class developed for the LAT EGB analysis) LAT data. Separate front and back conversions.





Galactic DM Halo

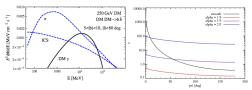
Source: WIMP annihilation and decay in the Milky Way host halo and galactic substructure.

Channel: $b\bar{b}$, $t\bar{t}$, $\tau^+\tau^-$, and $\mu^+\mu^-$.

Mass: 25 GeV increments (50 GeV for decay) from 25

GeV to 2 TeV.

Distribution: Einasto profile with extrapolated substructure content



Zaharijas et al., 2010 Stockholm University

BACKGROUND MODEL PARAMETER SPACE

GALPROP (Strong & Moskalenko 1998)

Cosmic-ray propagation code.

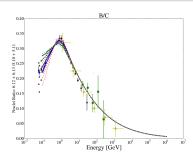
Pros: Physical model. Based on cosmic-ray measurements, instead of Fermi gamma-rays.

Cons: Considerable uncertainty in diffusion parameters. Fits the sky in a broad sense, but has large residuals on small scales.

Generate models to span this parameter space. Over 2k so far...

Parameter	Range
Diffusion Coefficient	$1 \times 10^{27} ightarrow 4 imes 10^{29}$
Halo Height	$oxed{1 o 11}$ kpc
Diffusion Index	0.33, 0.50
Alfven Velocity	$0 ightarrow 50 \; ext{km s}^{-1}$
Electron Injection Index	$1.8 \rightarrow 2.5$
Nucleon Injection Index (Low)	$1.7 \rightarrow 2.6$
Nucleon Injection Index (High)	2.26, 2.43
Source Distribution	Parameterized, SNR, Pulsars

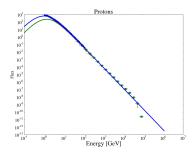
Cosmic Ray Fitting

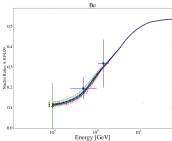


Reality Check

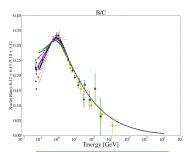
Version 54_z30FenpDT

For each diffusion setup, compare the CR at Earth's galactic radius (2-D Galprop) with local measurements.





Cosmic Ray Fitting

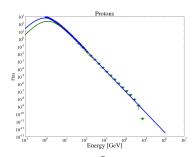


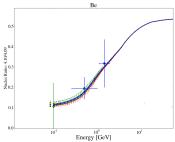
$$\chi^2$$
 Calculation
$$\chi^2 = \Sigma_j \Sigma_i^{Nj} \frac{(D_{ij} - T_{ij})^2}{\sigma_{ij}^2 + \Delta \phi_{ij}^2}$$

Solar Modulation Uncertainty

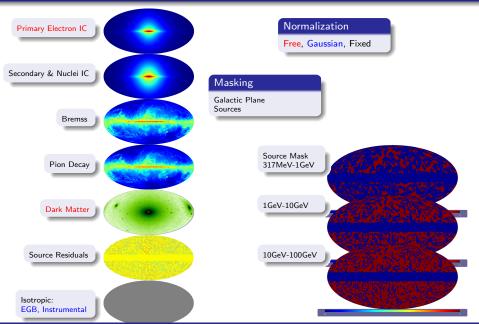
CR Data From:

HEAO-3, IMP, ATIC-2, CREAM, ACE, ISOMAX, AMS01, CAPRICE, & BESS

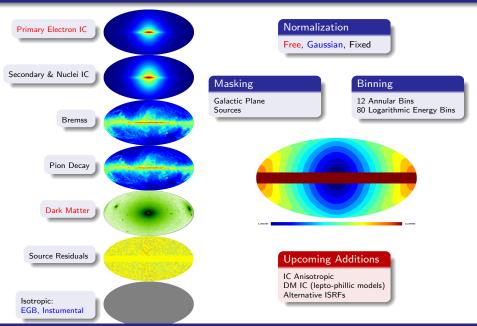




ASSEMBLING THE GAMMA-RAY SKY



ASSEMBLING THE GAMMA-RAY SKY



Profile Likelihood

In Principle

Scanning the DM normalization, we smoothly transition between background models.

Step 1

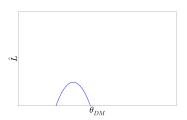
For each GALPROP model, maximize \hat{L} w.r.t. linear parameters, $\vec{\alpha}$, for each value of θ_{DM} (Flux Normalization).

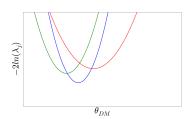
$$\hat{L}_{j}(\theta_{DM}) = \prod_{i} P_{ij}(n_{i}; \vec{\alpha}_{max}, \theta_{DM})$$

Step 2

Construct a test statistic for each diffuse model (different colors) using the best overall Likelihood and the CR fit probability.

$$\lambda_{j}(\theta_{DM}) = \frac{P_{j}^{CR} \hat{L}_{j}(\theta_{DM})}{(P_{i}^{CR} \hat{L}_{j})_{best}}$$





Profile Likelihood

In Principle

Scanning the DM normalization, we smoothly transition between background models.

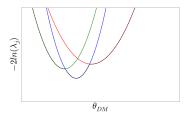
Step 3

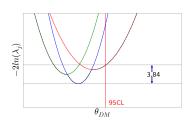
The profile likelihood is the curve that follows the minimum of all GALPROP models.

$$T_{chi^2}(\theta_{DM}) = -2ln\lambda_{j_{max}}(\theta_{DM})$$

Step 4

Since $\mathcal{T}_{chi^2}(\theta_{DM})$ behaves as a χ^2 with one d.o.f., we set the 95% confidence upper limit to where the profile likelihood rises by 3.84 above the absolute minimum.

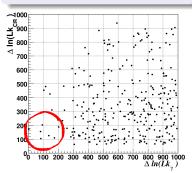




Profile Likelihood

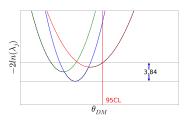
In Practice

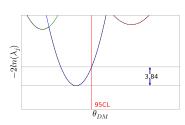
Sparse sampling means our limits all still come from a single model. $% \begin{center} \end{center} \begin{center} \begin{cen$



Sparse Sampling

Including χ^2 from the CR data in the Likelihood makes it difficult (naively sampling) to populate the region that satisfies both CR and gamma rays. This important region is currently dominated by a couple of models.





CLASSIFICATION TREE REFINEMENT

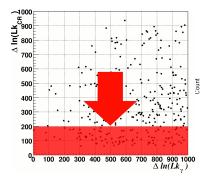
Intelligent Sampling

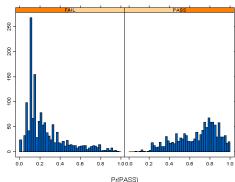
After some preliminary exploration, we can do better than blind sampling.

A classification tree 'learns' the complex relationship between a many parameter system and a conditional output - in our case, a χ^2 fit to CR data.

Predicting the CR- χ^2 before running GALPROP saves an immense amount of CPU-time, allowing us to focus on only the models which have some chance of affecting our limit.

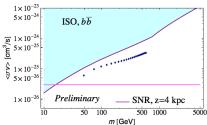






PRELIMINARY LIMITS

Zaharijas et al. 2010



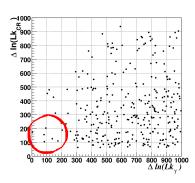
Note: Dots ightarrow 95% CL (this analysis, w/ DM subst.) Line ightarrow 3 σ

Remedies

Classification Tree.
 Small Variations around best fit.

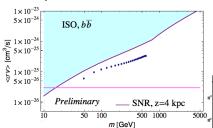
Caveats

Incomplete sampling of parameter space near best fit.



PRELIMINARY LIMITS

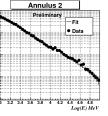


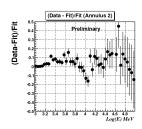


Note: Dots ightarrow 95% CL (this analysis, w/ DM subst.) $Line
ightarrow 3\sigma$

Caveats

- Incomplete sampling of parameter space near best fit.
- 2. Poor Residuals

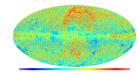




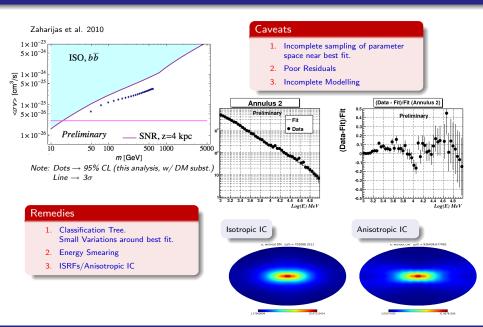
Remedies

- Classification Tree. Small Variations around best fit.
- 2. Energy Smearing

T. Porter, TeVPA 2010



PRELIMINARY LIMITS



SUMMARY & OUTLOOK

There is no significant detection of DM given the statistical errors and the systematic uncertainties in modeling the diffuse background.

Making progress on a thorough treatment of the physical background uncertainties.

Still need better model population around the best fit.

Sizeable residuals persist even in our best models. Working on several ideas to reduce them.

Working with another Fermi-LAT group at Stockholm University, who are performing a parallel analysis that uses a multi-component float fit based on a single conservative galactic diffuse model.