Modeling Comic-Ray propagation for Lithium, Beryllium, and Boron

Master 2 - Internship defence

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Supervisor: David Maurin

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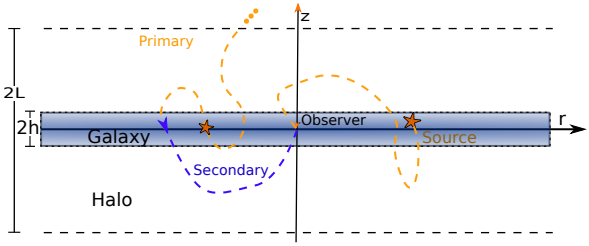
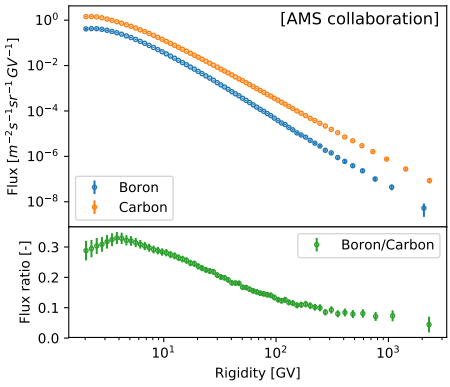
About Cosmic Rays



- Supernovae as primary particle sources ($q_i = q_0\, R^{-\alpha}$)
- Secondary particles through nucl. reactions with gas ($n\sigma_{ij}$)
- strong deflection by interstellar magnetic fields →diffusion ($K(R)$)



→Analyzing CR propagation with flux and flux ratio

Questions concerning Li, Be, & B data

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- **?** Same best-fit transport par. with different data (Li, Be, B)
- **?** Lower parameter uncertainties with data combinations
- **?** Simple vs. complex CR model (more parameters)

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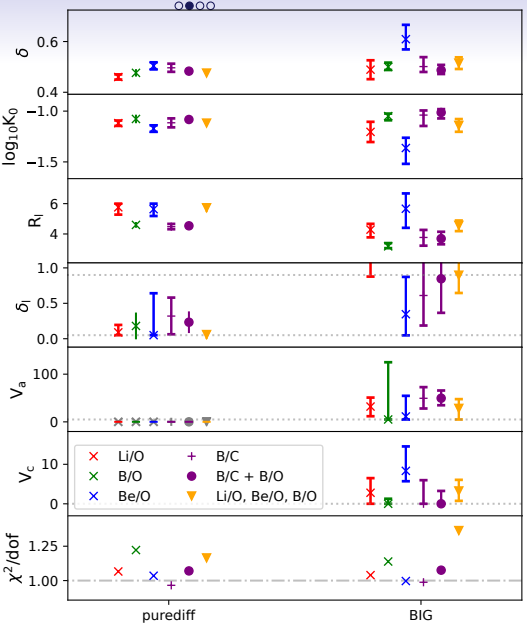
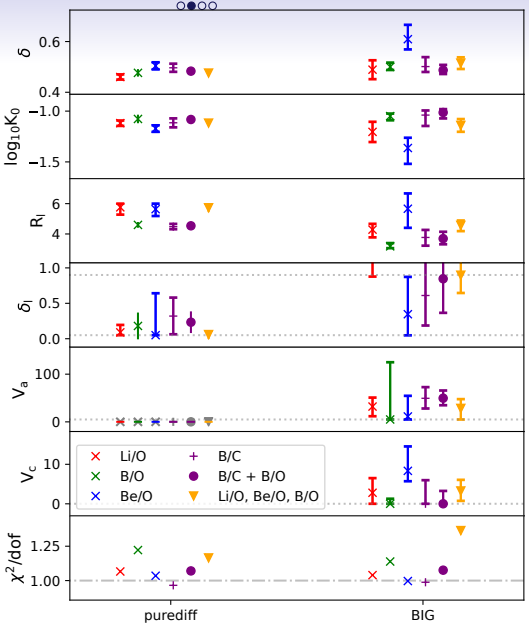
- **?** Simple vs. complex CR model (more parameters)

- **?** Fitting fluxes vs. ratios

$\rightarrow$ All config. studied with Minuit + Minos



Different flux ratio data

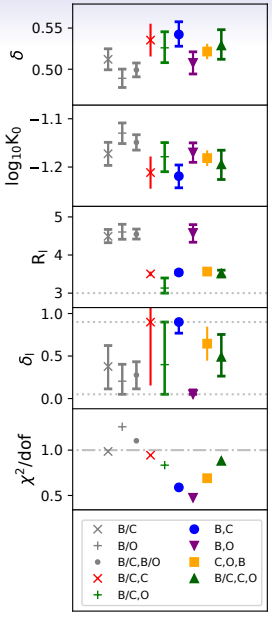


Different flux ratio data

→ Good agreement for some parameters (δ, K_0), difficulties with others (δ_l)

→ Combinations reduce uncertainties a bit

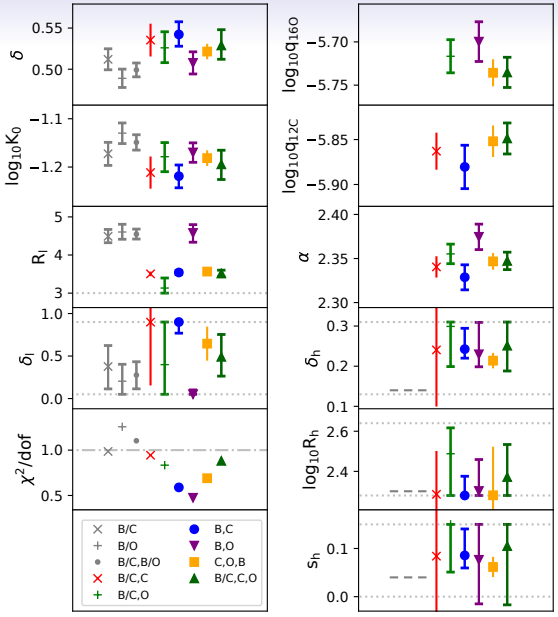
? Effect of ^{10}Be (radioactive → sensitive to Galactic geometry)



Fitting combinations of fluxes and flux ratios

→ Transport parameters are consistent

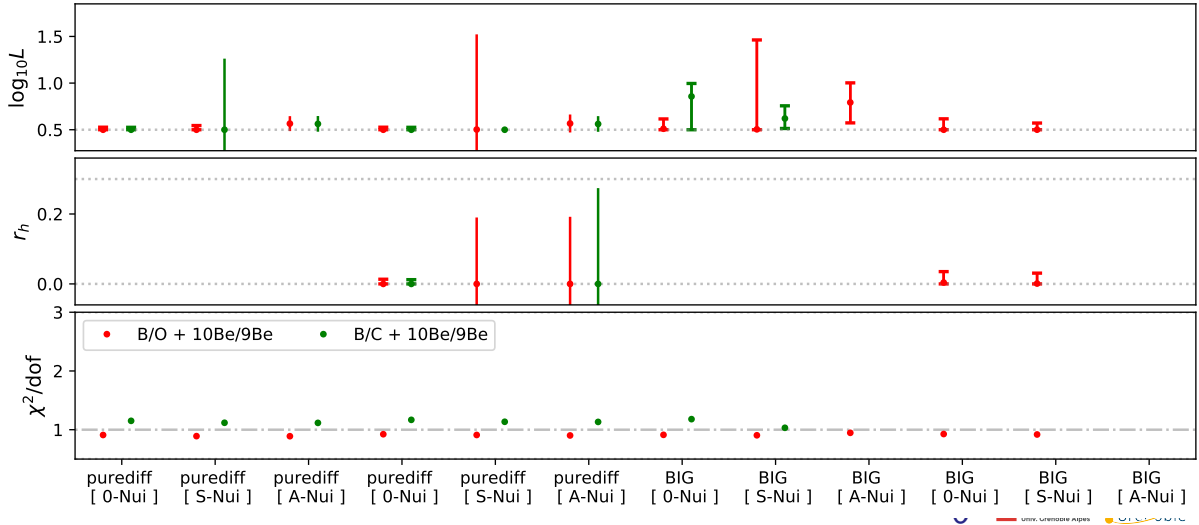
? Overfitting of fluxes? ($\chi^2 < 1$)



Fitting combinations of fluxes and flux ratios

- → Transport parameters are consistent
- **?** Overfitting of fluxes? ($\chi^2 < 1$)
- → Consistency in source parameters (q_i, α)

Attempting to fit L & r_h



Testing different χ^2 minimizers

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$\rightarrow$ Wrapper code to use the USINE (C++) χ^2 function in Python. (via PyBind11)

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→ Wrapper code to use the USINE (C++) χ^2 function in Python. (via PyBind11)

→ Retry the same tasks with different minimizers

trying out:

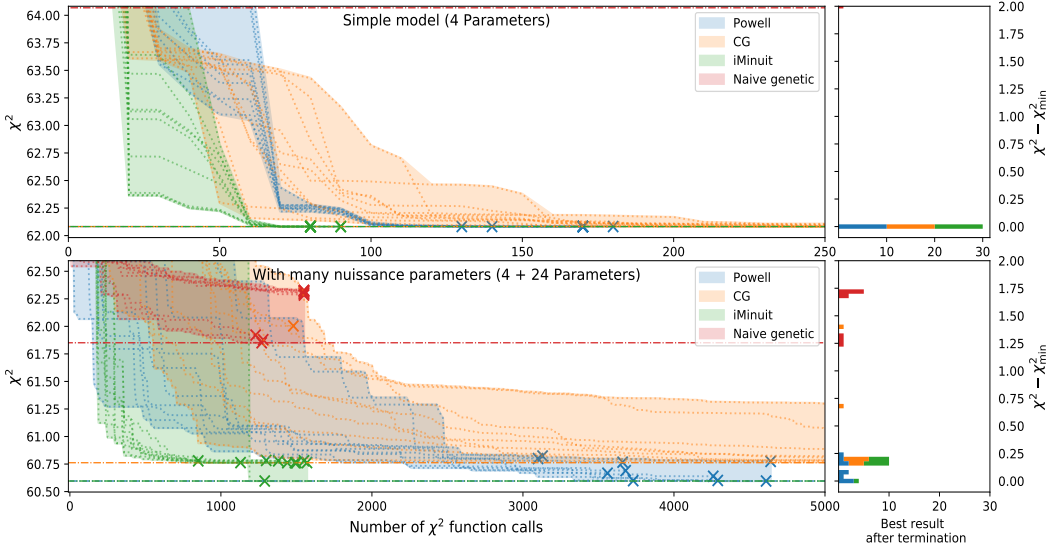
Minuit (Migrad) Default minimizer, Uses Gradients to find convex minimum.

Conjugate Gradient Sophisticated gradient descent

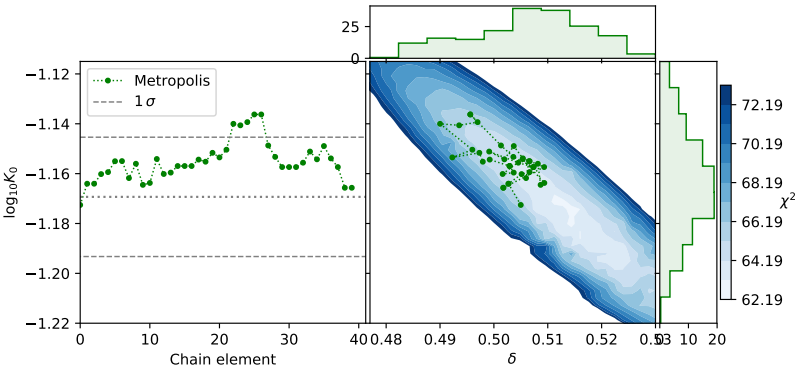
Powells method Line searches only

Simple Genetic Try and error. Random sample around previous best-fits.

Performance comparison



Motivation for MCMC



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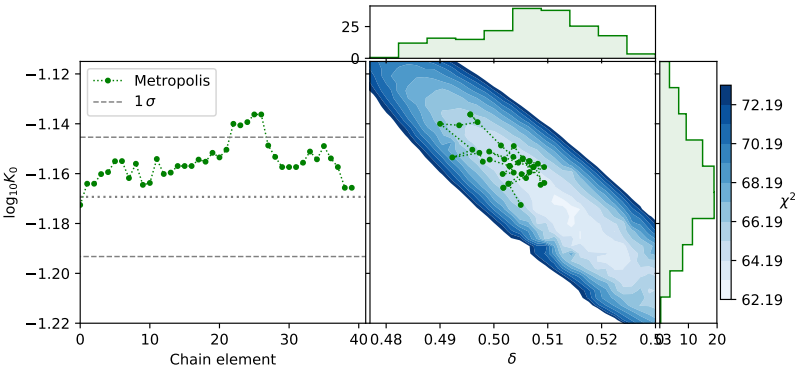

→ Resulting chain resembles PDF $p(\theta) = \exp[-0.5\,\chi^2(\theta)]$

- Better understanding than only best-fit + errors

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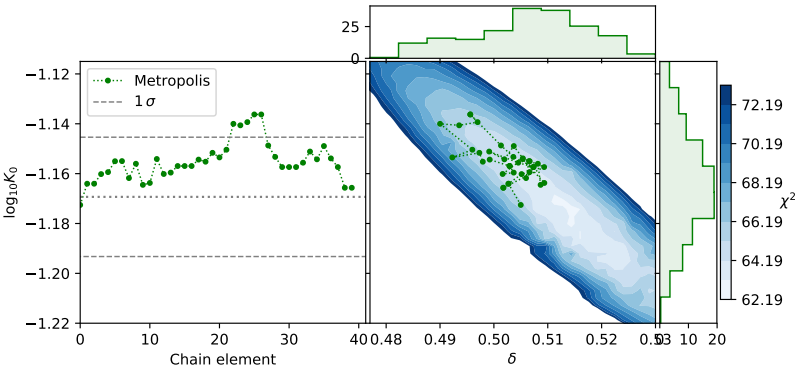

Mark. Chain sampling

1. Sample a random value θ_k
2. add to chain with prob. $\frac{P(\theta_k)}{P(\theta_{k-1})}$
3. repeat $k \rightarrow k+1$

$\rightarrow$ Resulting chain resembles PDF $p(\theta) = \exp[-0.5\,\chi^2(\theta)]$

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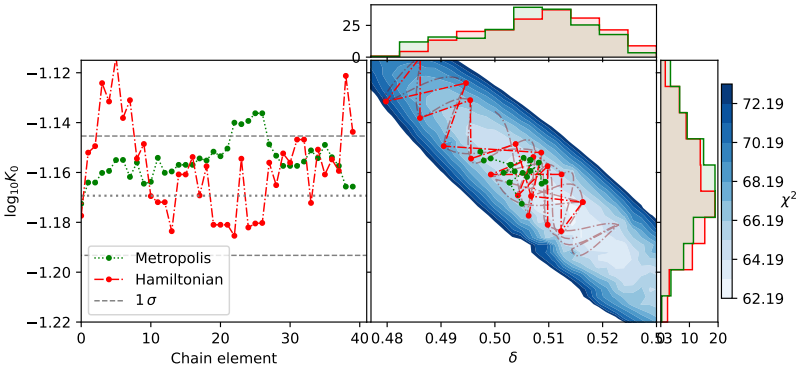
Metropolis vs Hamiltonian sampling



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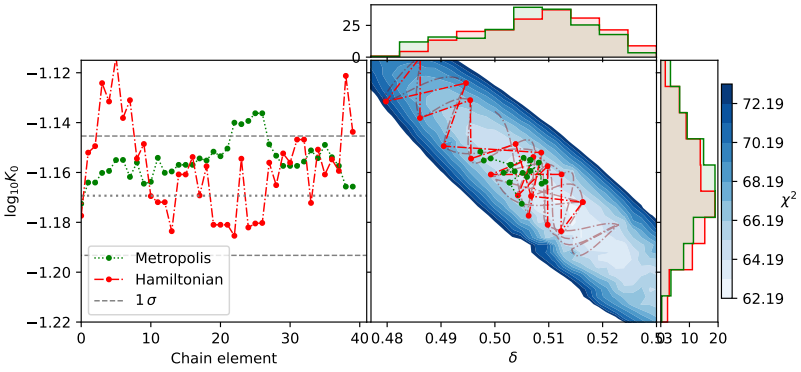
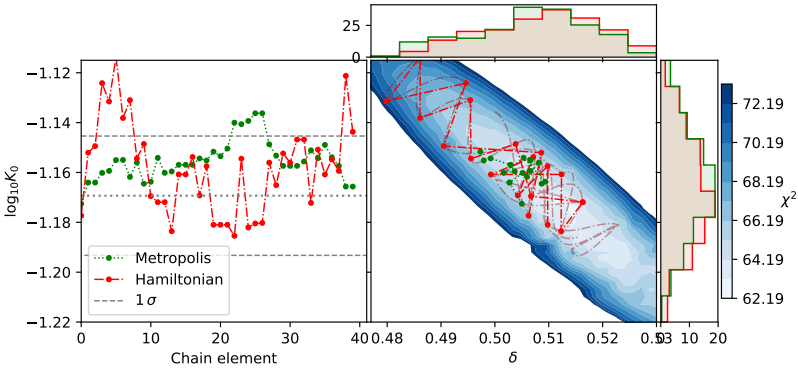


Metropolis

samples θ_k from normal distribution around θ_{k-1}.

Metropolis vs Hamiltonian sampling



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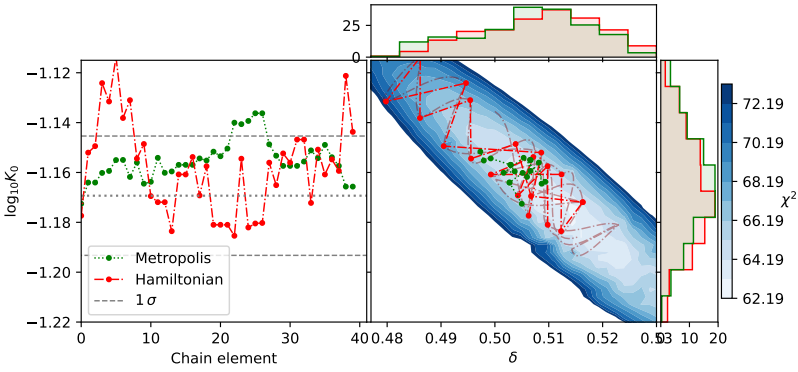
Metropolis vs Hamiltonian sampling



Both are expensive (number of χ^2 calls)
Minuit + Minos $\mathcal{O}(100)$, MCMC $\mathcal{O}(10\,000)$

Metropolis
samples θ_k from normal distribution around θ_{k-1}.

Hamiltonian
calculates movement from θ_{k-1} through χ^2 potential to θ_k with sub-steps.

Variable	Metropolis	Hamiltonian
δ	234.1	5.1
$\log_{10} K_0$	151.0	6.7
R_l	40.1	2.3
δ_l	237.4	3.7
Norm 12C+H	40.2	4.7
EAxisScale 12C+H	116.3	4.2
Norm 16O+H->6Li	48.0	3.6
SlopeLE 16O+H->6Li	14.9	2.0
Norm 7Be+H	37.5	3.5
EAxisScale 7Be+H	137.5	7.6
Norm 16O+H->7Be	65.2	6.8
SlopeLE 16O+H->7Be	15.1	2.1
Norm 11B+H	39.2	5.3
EAxisScale 11B+H	123.8	5.8
Norm 12C+H->11B	44.9	3.5
SlopeLE 12C+H->11B	12.4	1.0
Corellation	**237**	**8**
Calls per valid Element	237	$8 \cdot 14 \cdot 16 = 1792$

Auto-Corellation

(Pure-diffusion, 12 Nui.Pars., Li/O + Be/O + B/O)

The Markov Chain is trimmed down by the factor of the highest correlation.

MCMC: Critical settings/parameters

General

Chain length: what is statistical significant?

parallel Chains: - 10

Points of departure: Gaussian around Minuit results.

Metropolis

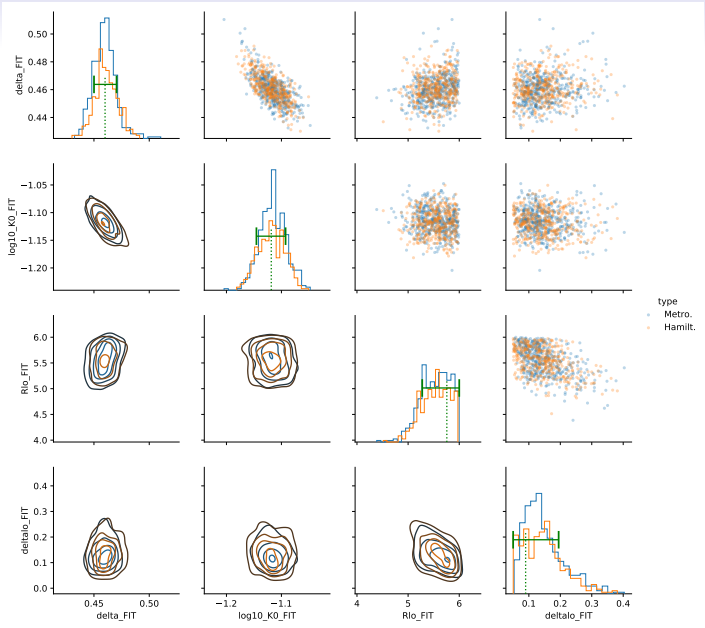
Covariance matrix: From USINE initialization file (diagonal). Updated during run with previous results.

Hamiltonian

Path length between to chain elements - $\mathcal{O}(\sigma)$

path substeps - $\mathcal{O}(10)$

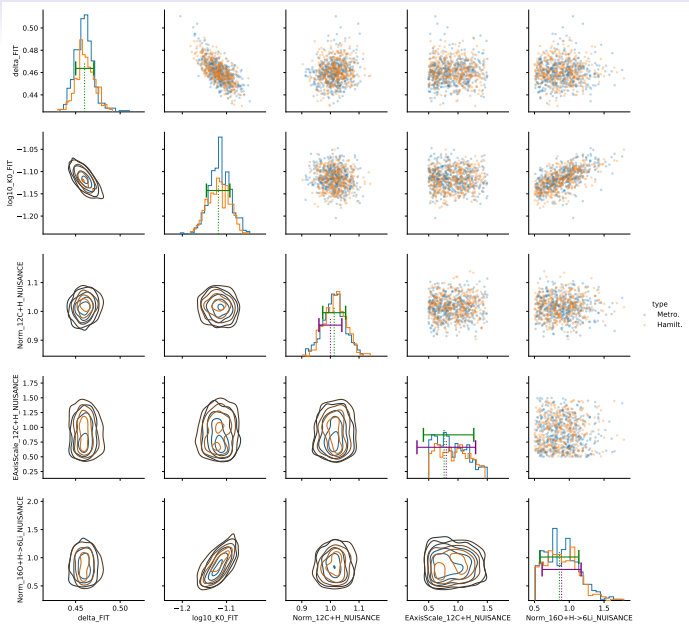
velocity scaling similar to Cov.Mat.



Li / O

(Pure-diffusion, 4 Nui.Pars.)

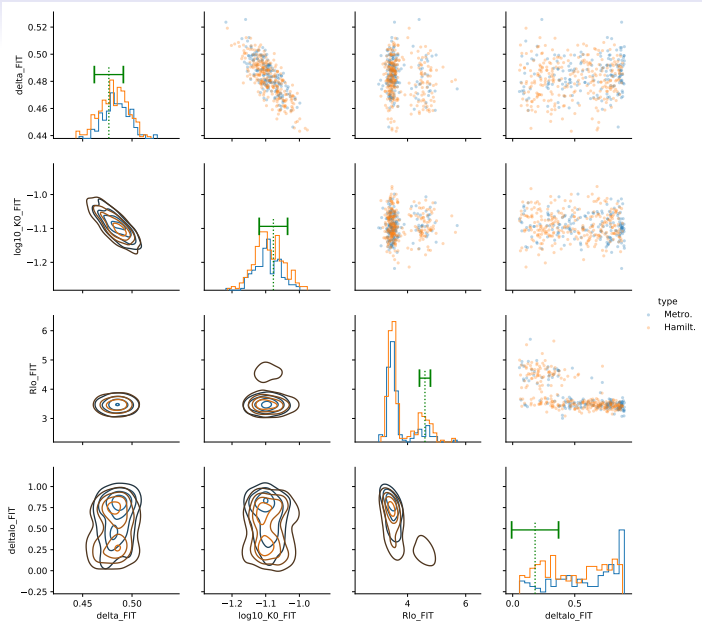
- In agreement with Minuit + Minos
- Both Methods working
- need for longer chains/more



Behavior of Nuisance Parameters (Li/O)

(Pure-diffusion, 4 Nui.Pars.)

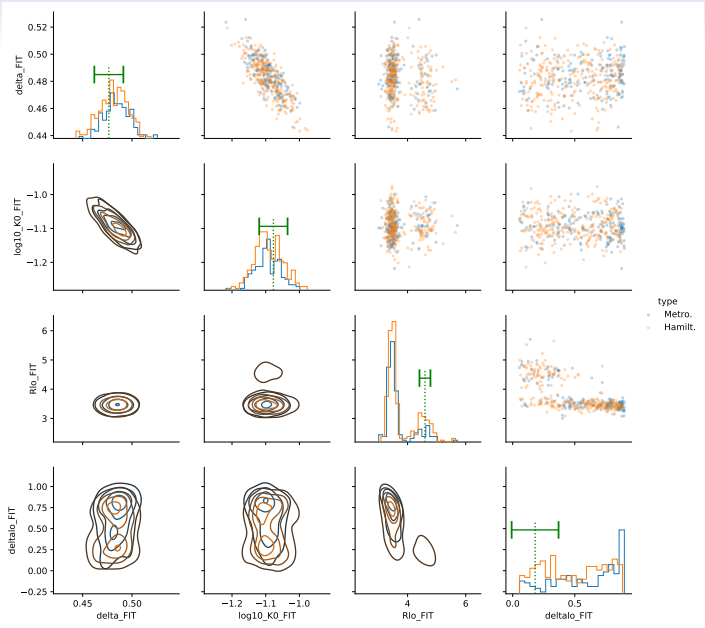
- Priors, Minos results



B / O

(Pure-diffusion, 4 Nui.Pars.)

- ? What is wrong with low-rigidity break?
- multiple local minima



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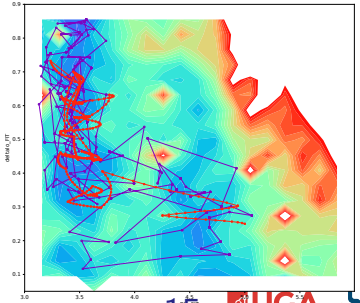

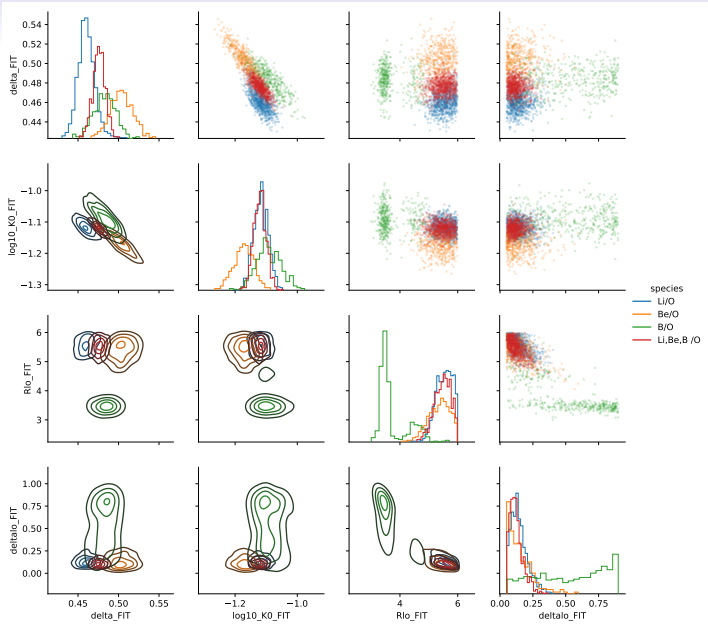

Li, Be, B, LiBeB

(Pure-diffusion,
(4,4,4,12) Nui.Pars.)

? B/O deviation

PyUsine

Interfacing Usine for Pythin with PyBind11

General usage

```
import PyProp as PP

PRP = PP.PyRunPropagation()
PRP.PySetLogFile("PRP_Usine.log")
PRP.PySetClass("init_file.par", 1, "Usine_OutDir")

Theta0 = [InitVal[0] for InitVal in PRP.PyGetInitVals()]

Chi2 = PRP.PyChi2(Theta0)
```

Summary and Outlook

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- Include diagnostics and evaluation routines into MCMC project.
- Study the Galactic geometry with radioactive ^{10}Be
- Combine data and techniques for source and transport parameter results. (Big, Slim, Quaint)

Ende