SuperBayeS

Roberto Ruiz de Austri
IFIC

In collaboration with:
R. Trotta, L. Roszkowski, M. Hobson, F. Feroz, J. Silk,
C. P. de los Heros, A. Casas, M. E. Cabrera, G. F. Bertone

Outline

- The problem: analysis pipeline for SUSY phenomenology
- The SuperBayeS package
- Parameter inference: present results and future prospects in the CMSSM

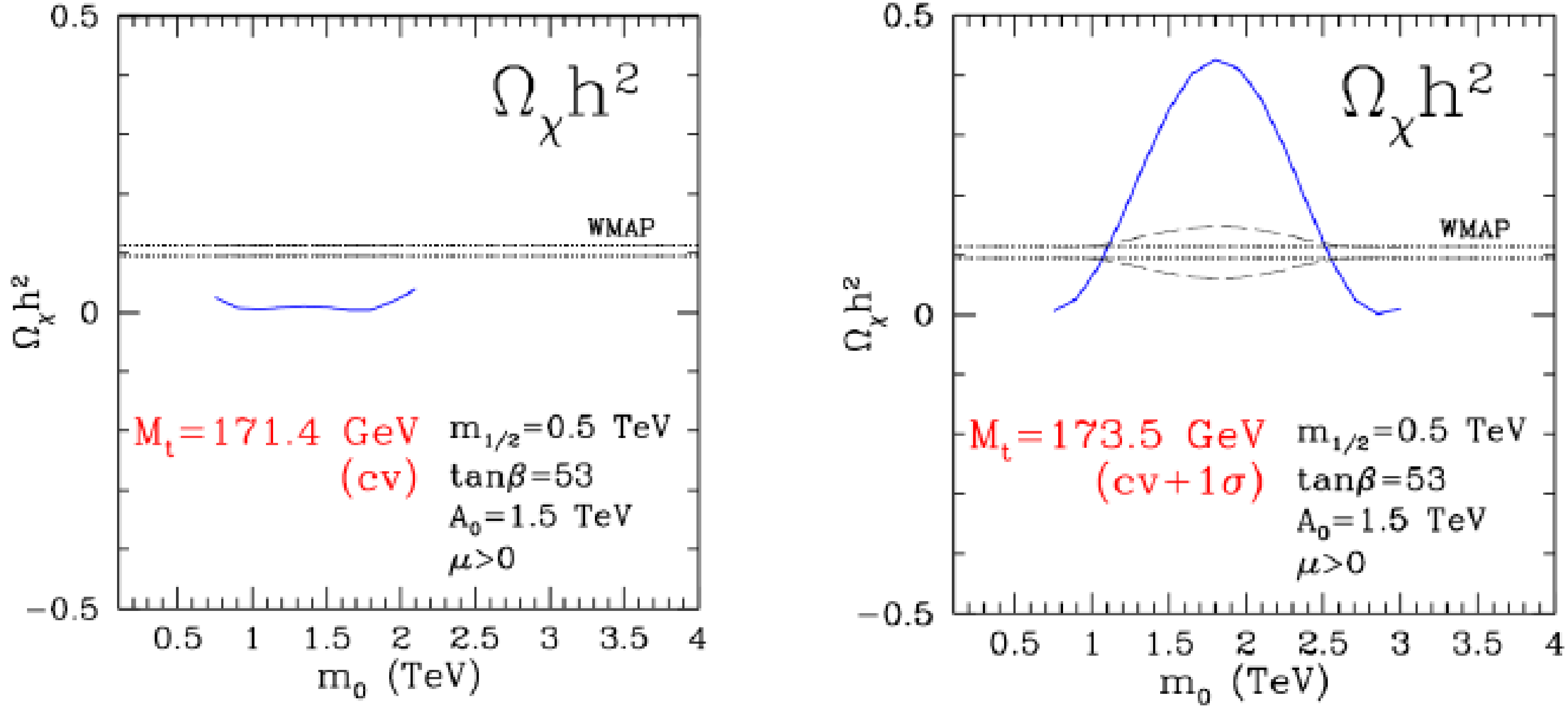
The model & data

- The general Minimal Supersymmetric Standard Model (MSSM): 105 free parameters!
- Need some simplifying assumption: i.e. the Constrained MSSM (CMSSM) reduces the free parameters to just 5 variables
- Present-day data: collider measurements of rare processes, CDM abundance (WMAP), sparticle masses lower limits, EW precision measurements. Soon, LHC sparticle spectrum measurements
- Astrophysical direct and indirect detection techniques might also be competitive: neutrino (IceCUBE), gamma-rays (Fermi), antimatter (PAMELA), direct detection (XENON, CDMS, Eureca, Zeplin)
- Goal: inference of the model parameters but it is difficult problem

Why is this a difficult problem?

- Inherently 8-dimensional: reducing the dimensionality over-simplifies the problem. Nuisance parameters (in particular mt) cannot be fixed!
- Likelihood discontinuous and multi-modal due to physicality conditions
- RGE connect input parameters to observables in highly non-linear fashion: only indirect (sometimes weak) constraints on the quantities of interest (-> prior volume effects are difficult to keep under control)
- Mild discrepancies between observables (in particular, g-2 and $b \rightarrow s\gamma$) tend to pull constraints in different directions

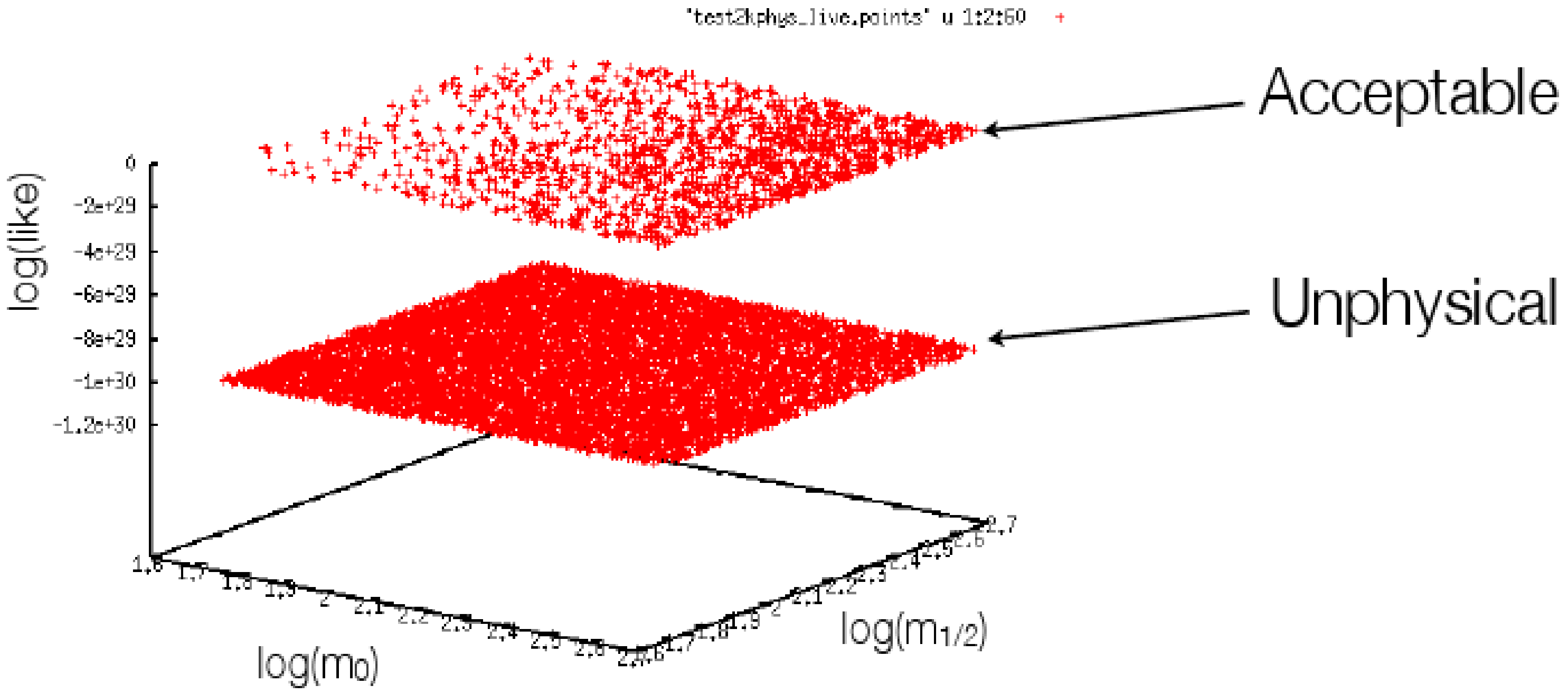
Impact of nuisance parameters



Roszkowki et al (2007)

The accessible “surface”

Scan from the prior with no likelihood except physicality constraints

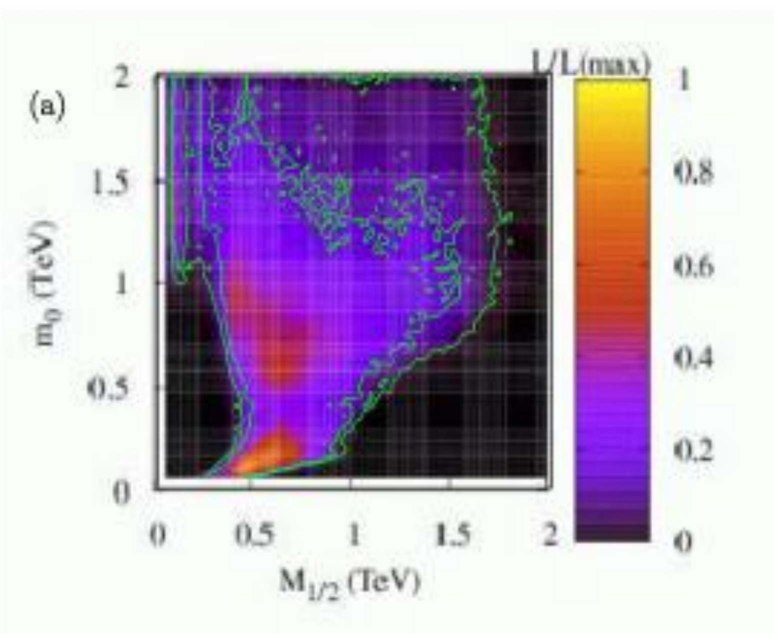


Courtesy F. Feroz & M. Bridges

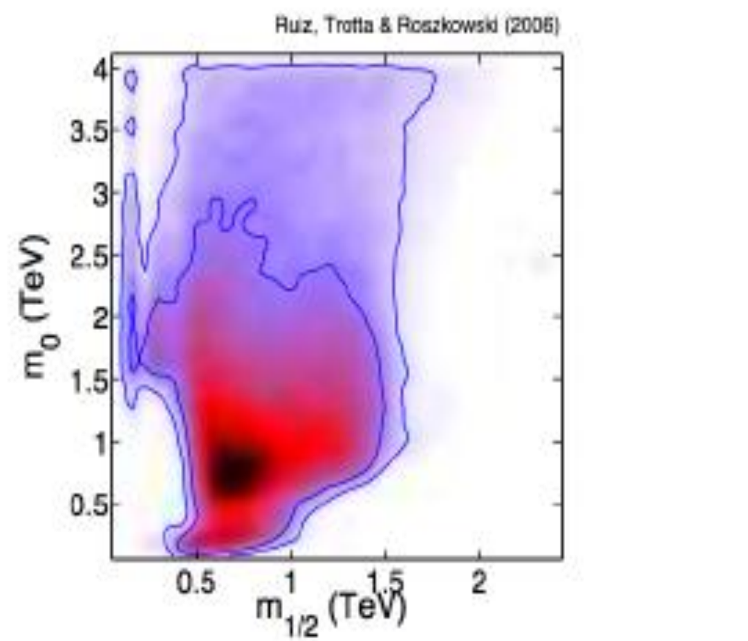
Bayesian parameter inference

The Bayesian approach

- Bayesian approach led by two groups (early work by Baltz & Gondolo, 2004):
- Ben Allanach (DAMPT) et al (Allanach & Lester, 2006 onwards, Cranmer, and others)
- RdA, Roszkowski & Roberto Trotta (2006 onwards)
  SuperBayeS public code (available from: superbayes.org)
  + Feroz & Hobson (MultiNest), + Silk (indirect detection), + de los Heros (IceCube), + Casas et al. (Naturalness) + Bertone et al. (pmssm)



Allanach & Lester (2006)



Ruiz de Austri, Roszkowski & RT (2006)

Bayes' theorem

posterior likelihood prior

$$P(H|d,I) = \frac{P(d|H,I)P(H|I)}{P(d|I)}$$

evidence

H: hypothesis

d: data

I: external information

- Prior: what we know about H (given information I) before seeing the data
- Likelihood: the probability of obtaining data d if hypothesis H is true
- Posterior: our state of knowledge about H after we have seen data d
- Evidence: normalization constant (independent of H), crucial for model comparison

...

- Ignoring the prior and identifying

$$p(\theta_i|\text{data}) \equiv p(\text{data}|\theta_i)$$

- implicitly amounts to

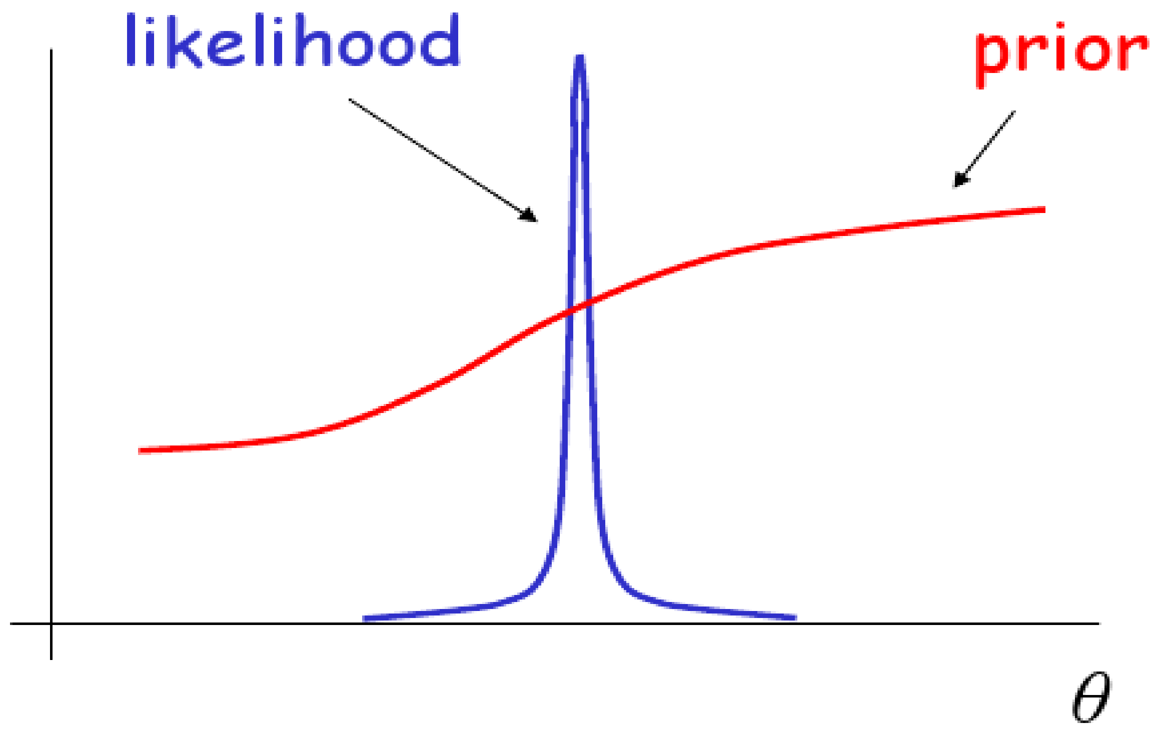
$$p(\theta_i) = \text{const.} \equiv \textit{“flat”}$$

- But e. g. $\theta_i \longrightarrow \theta_i^2$

$$\Rightarrow \textit{“flat”} \longrightarrow \textit{“non-flat”}$$

But

If data are good enough to select a small region of {θ} then the prior p(θ) becomes irrelevant



$$p(\theta_i|\mathrm{data}) \equiv p(\mathrm{data}|\theta_i)$$

Priors

- There is a vast literature on priors: Jeffreys', conjugate, non-informative, ignorance, reference, ...
- In simple problems, "good" priors are dictated by symmetry properties
- Flat: All values of θ equally probable

$$p(\theta) = \text{const.}$$

- Logarithmic: All magnitudes of θ equally probable

$$p(\ln\theta) = \text{const.}$$

$$p(\theta) \propto \frac{1}{\theta}$$

Key advantages

- Efficiency: computational effort scales ~ N rather than k^N as in grid-scanning methods. Orders of magnitude improvement over previously used techniques.

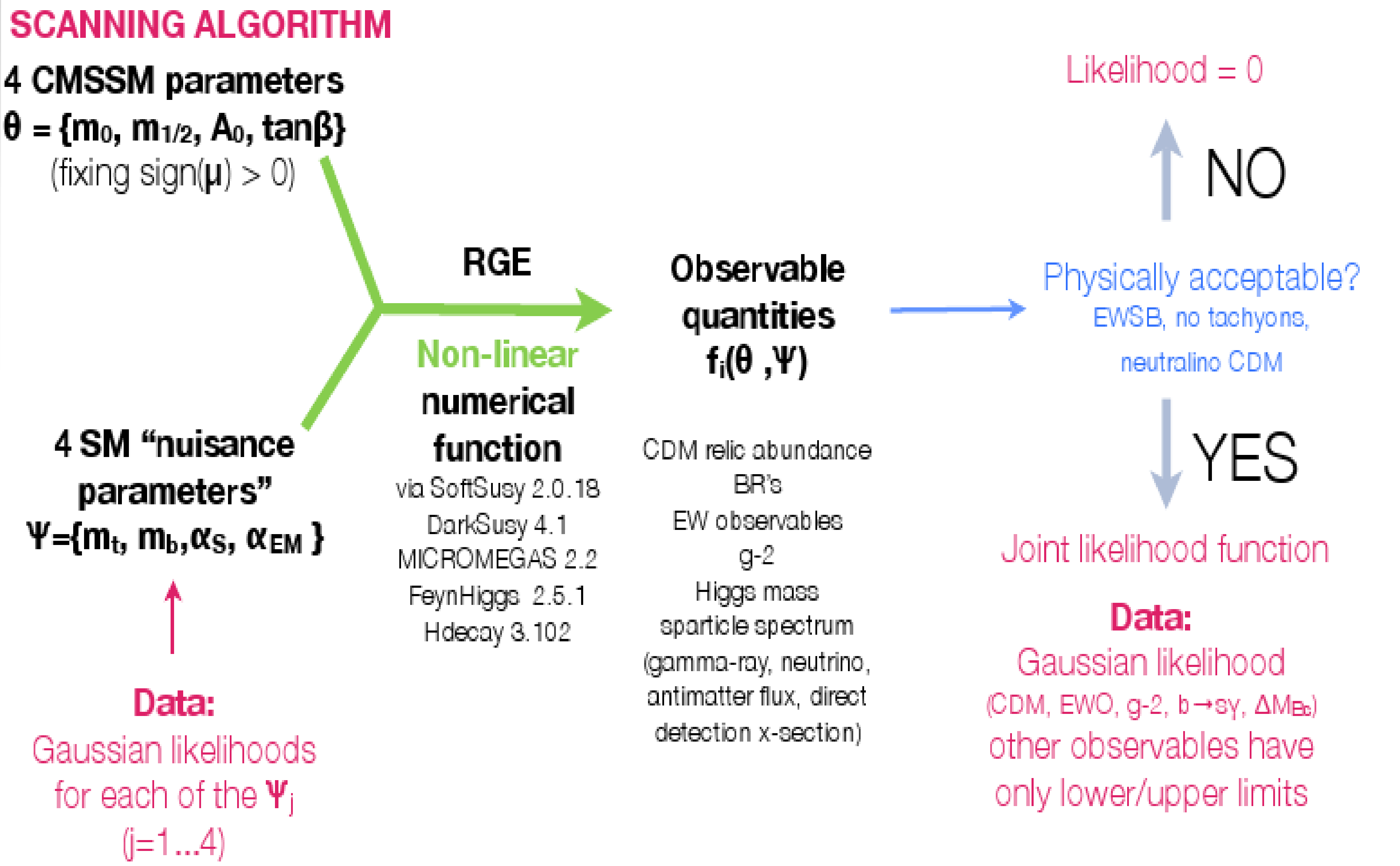
- Marginalisation: integration over hidden dimensions comes for free Suppose we have θ_i and are interested in $p(\theta_1|\mathrm{data})$

$$p(\theta_1|\mathrm{data}) = \int d\theta_2 \cdots d\theta_N \; p(\theta_i|\mathrm{data})$$

- Inclusion of nuisance parameters: simply include them in the scan and marginalise over them. Notice: nuisance parameters in this context must be well constrained using independent data.

- Derived quantities: probabilities distributions can be derived for any function of the input variables (crucial for DD/ID/LHC predictions).

Analysis pipeline



Posterior Samplers

- MCMC: A Markov Chain is a list of samples θ1, θ2, θ3,... whose density reflects the (unnormalized) value of the posterior
- Crucial property: a Markov Chain converges to a stationary distribution, i.e. one that does not change with time. In our case, the posterior
- Different algorithms: MH, Gibbs... all need a proposal distribution => difficult to find a good one in complex problems
- Nested: New technique for efficient evidence evaluation (and posterior samples) (Skilling 2004)
- MultiNest: Also an extremely efficient sampler for multi-modal likelihoods !
Feroz & Hobson (2007), RT et al (2008), Feroz et al (2008)

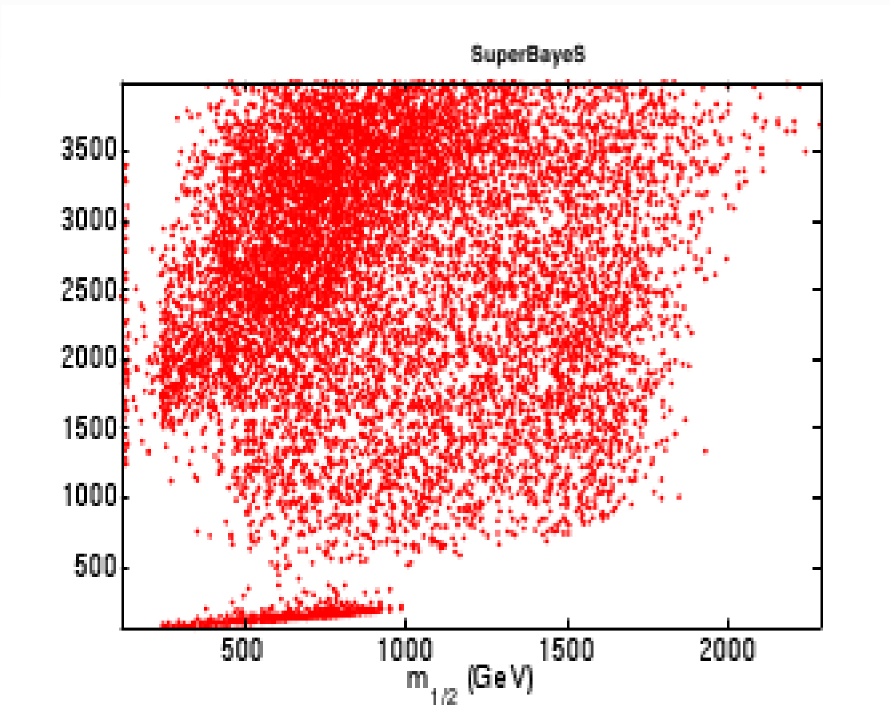
The SuperBayeS package (superbayes.org)

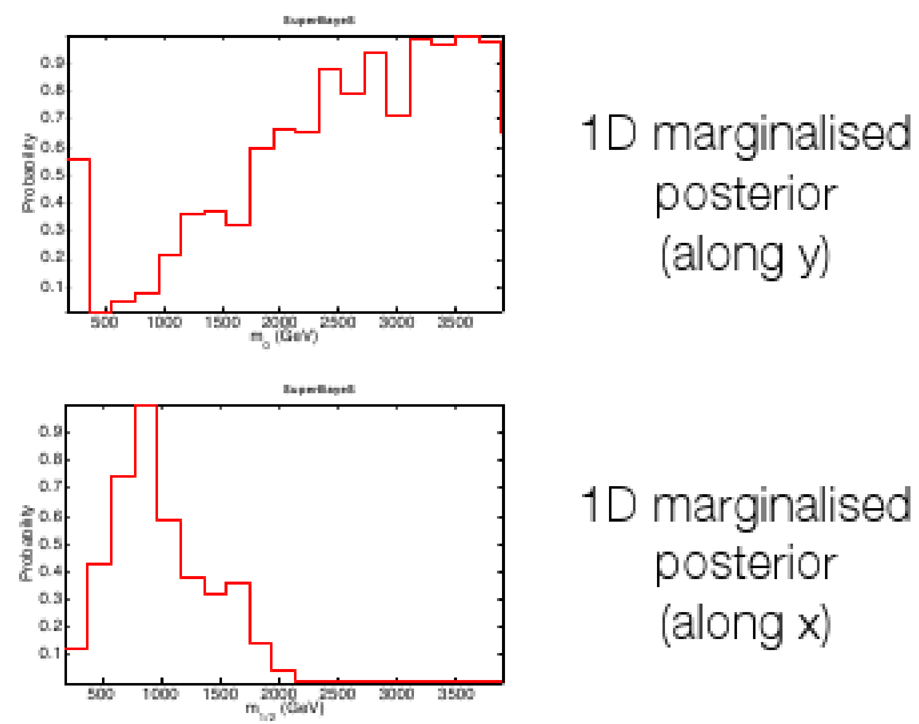
- Supersymmetry Parameters Extraction Routines for Bayesian Statistics
- Implements the CMSSM, but can be easily extended to the general MSSM
- Currently linked to SoftSusy 2.0.18, DarkSusy 4.1, MICROMEGAS 2.2, FeynHiggs 2.5.1, Hdecay 3.102. **New release (v 1.5)**
- Includes up-to-date constraints from all observables
- Bayesian MCMC, MULTI-MODAL NESTED SAMPLING or grid scan mode.
- MULTI-MODAL NESTED SAMPLING (Feroz & Hobson 2008), efficiency increased by a factor 200. **A full 8D scan now takes 3 days on a single CPU** (previously: 6 weeks on 10 CPUs)
- Fully parallelized, MPI-ready, user-friendly interface a la cosmomc (thanks Sarah Bridle & Antony Lewis),
- SuperEGO: SuperBayeS Enhanced Graphical Output as a MATLAB graphical user interface for statistical analysis and plotting

MCMC estimation

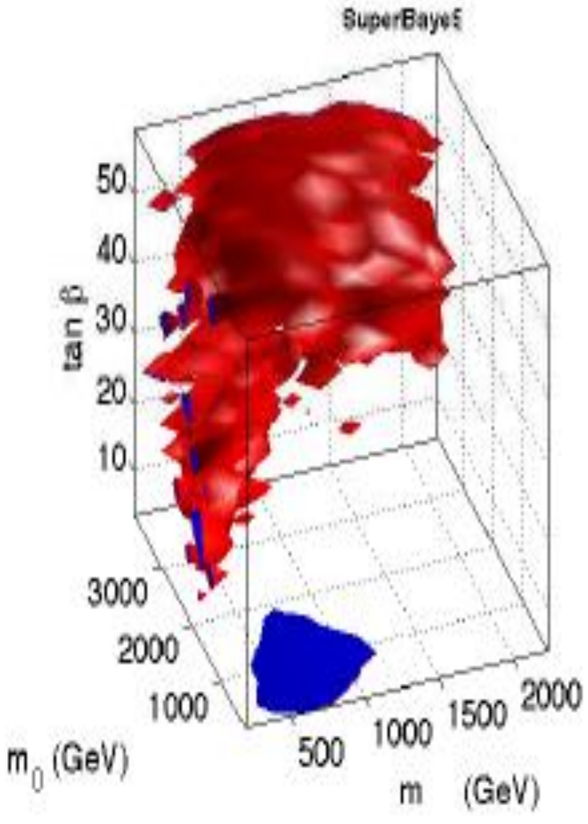
- Marginalisation becomes trivial: create bins along the dimension of interest and simply count samples falling within each bins ignoring all other coordinates
- Examples (from superbayes.org) :

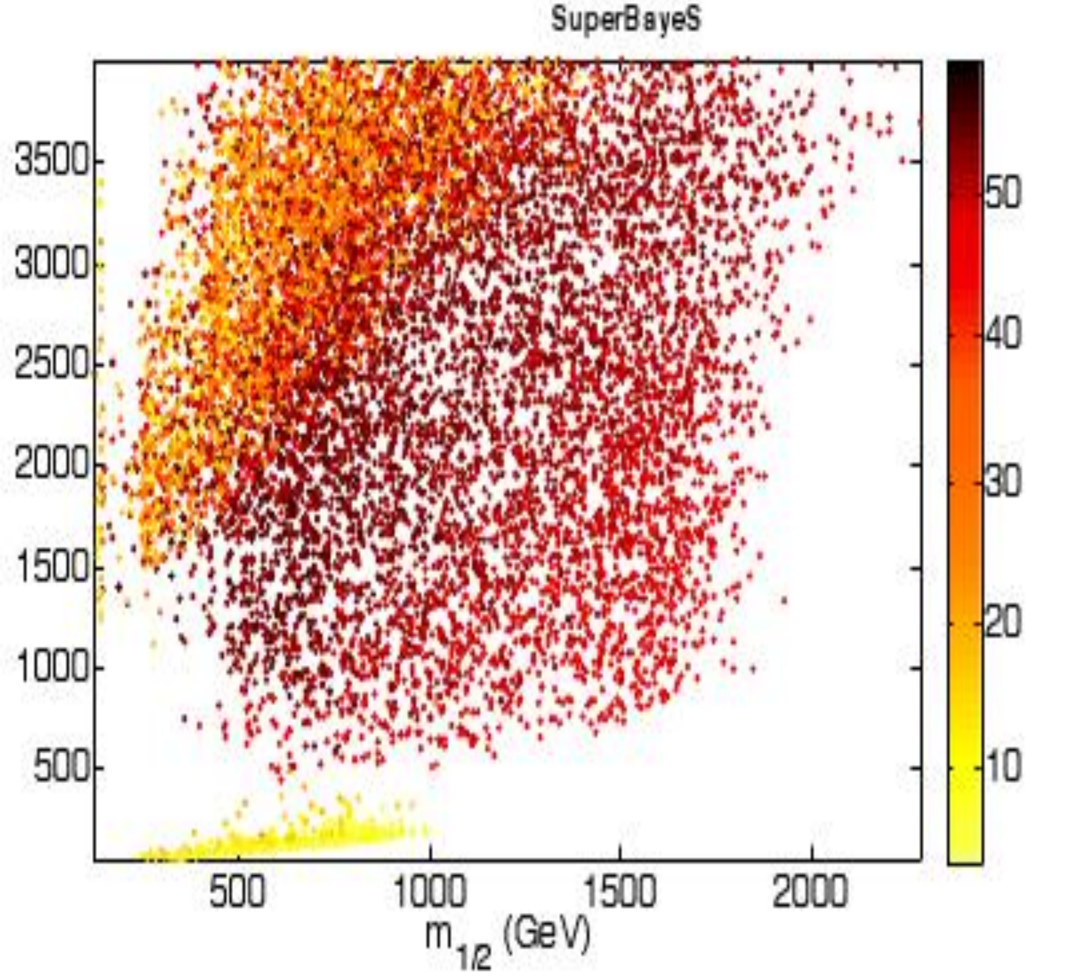
2D distribution of samples from joint posterior





SuperEGO


SuperBayeS
tan β
50
40
30
20
10
3000
2000
1000
m_0 (GeV)
500
1000
1500
2000
m (GeV)


SuperBayeS
3500
3000
2500
2000
1500
1000
500
500
1000
1500
2000
$m_{1/2}$ (GeV)
50
40
30
20
10

Global CMSSM constraints

The CMSSM

Assuming Universal boundary conditions at M_{GUT}

- Gaugino masses

$$M_1 = M_2 = M_3 = m_{1/2}$$

- Scalar masses

$$m_{H_d}^2 = m_{H_u}^2 = M_L^2 = M_R^2 = M_Q^2 = M_D^2 = M_U^2 = m_0^2$$

- Trilinear couplings

$$A_u = A_d = A_l = A_0$$

- Higgs vev ratio

$$\tan\beta = v_u/v_d$$

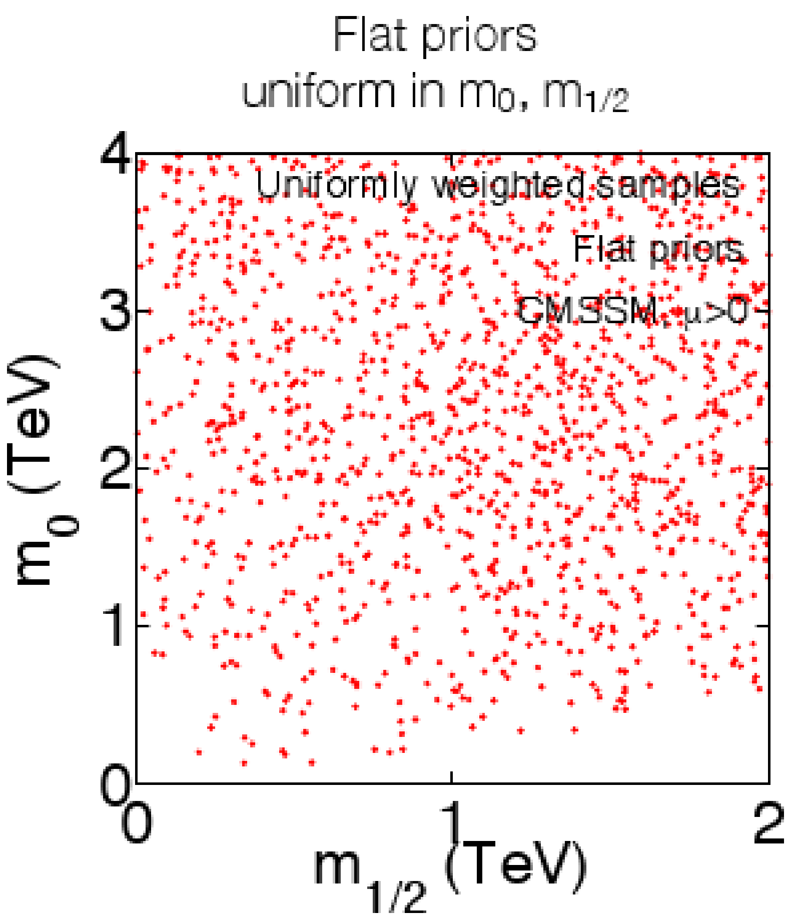
- μ^2 from EWSB

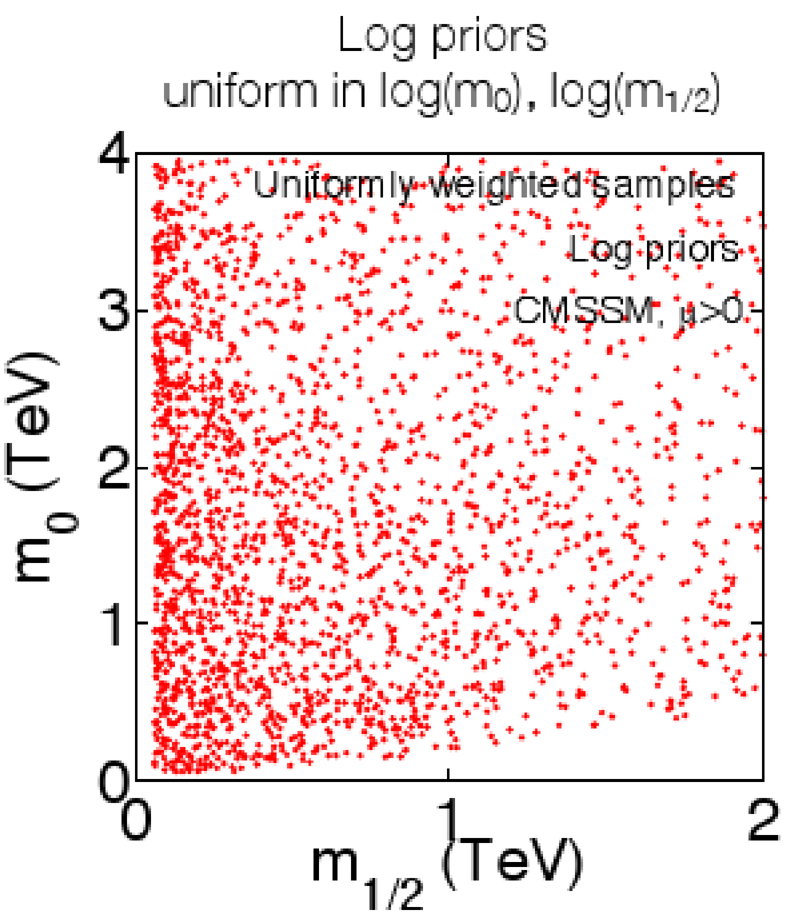
flat priors: CMSSM parameters
$50\ \text{GeV} < m_0 < 4\ \text{TeV}$
$50\ \text{GeV} < m_{1/2} < 4\ \text{TeV}$
$\lvert A_0 \rvert < 7\ \text{TeV}$
$2 < \tan\beta < 62$

Samples from priors only

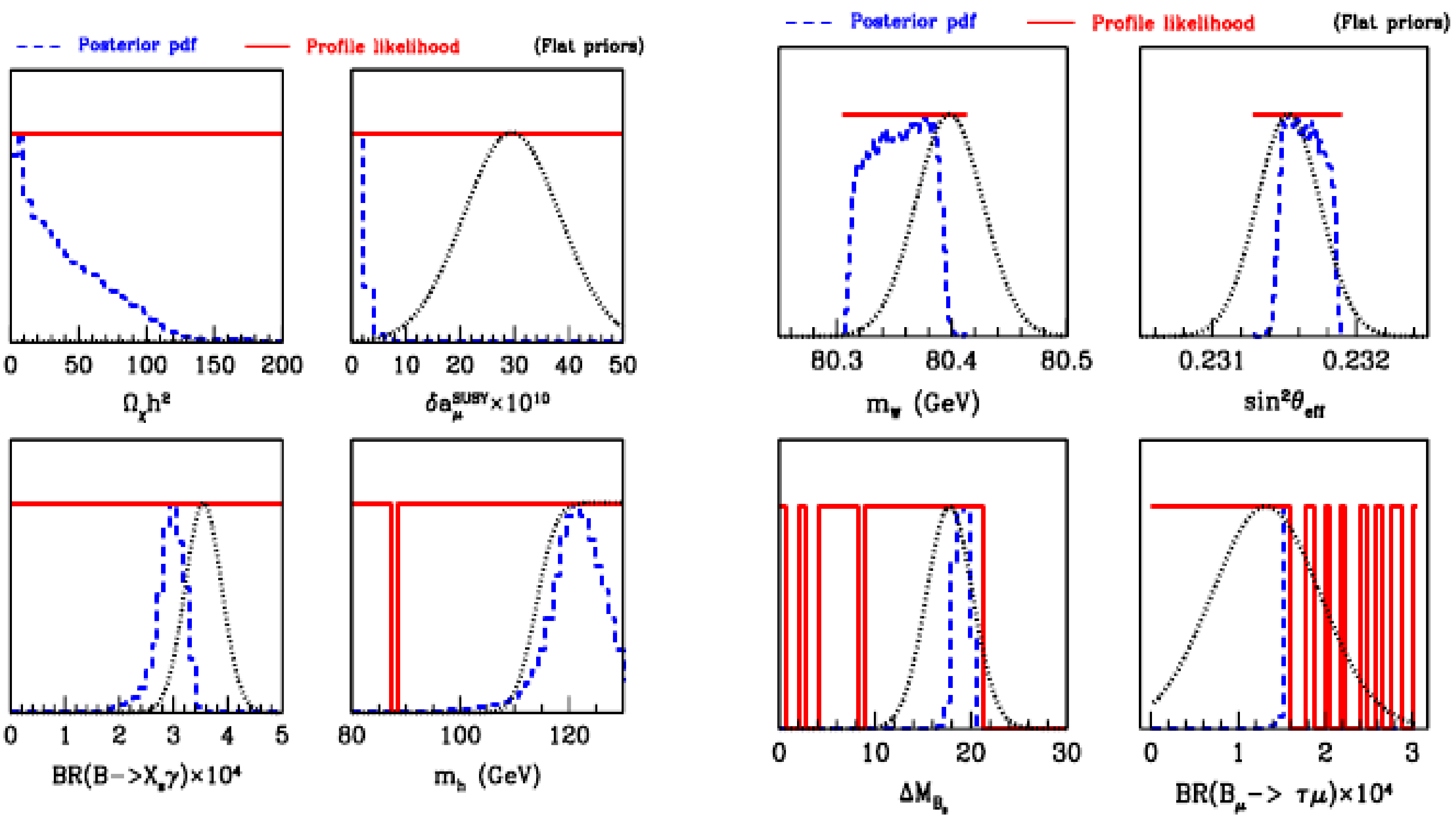
- No data in the likelihood, non-physical points discarged priors

$p(\mathcal{F}) = p(m) \left| \frac{\mathrm{d}m}{\mathrm{d}\mathcal{F}} \right|$ => flat prior on log means $p(m) \propto m^{-1}$





Priors distributions from observables



Priors are quite informative regardless the quantities being constrained !!!

Data included

Indirect observables

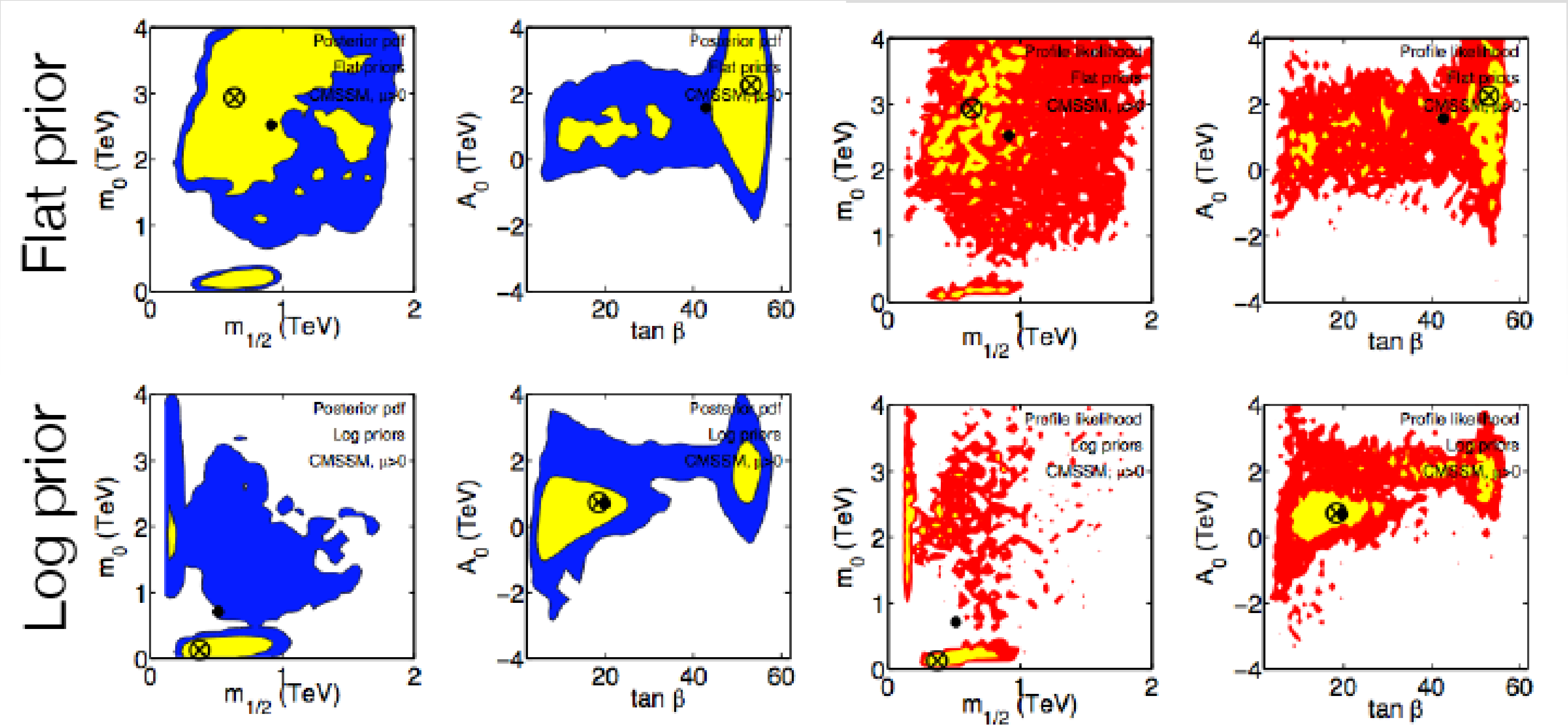
Observable	Mean value	Uncertainties		ref.
	μ	σ (exper.)	τ (theor.)	
M_W	80.398 GeV	25 MeV	15 MeV	[30]
$\sin^2\theta_{\rm eff}$	0.23153	16×10^{-5}	15×10^{-5}	[30]
$\delta a_\mu^{\rm SUSY}\times10^{10}$	29.5	8.8	1.0	[31]
$BR(\overline{B}\to X_s\gamma)\times10^4$	3.55	0.26	0.21	[32]
ΔM_{B_s}	17.77 ps^{-1}	0.12 ps^{-1}	2.4 ps^{-1}	[33]
$BR(\overline{B}_u\to\tau\nu)\times10^4$	1.32	0.49	0.38	[32]
$\Omega_\chi h^2$	0.1099	0.0062	$0.1\,\Omega_\chi h^2$	[34]
	Limit (95% CL)		τ (theor.)	ref.
$BR(\overline{B}_s\to\mu^+\mu^-)$	$< 5.8\times10^{-8}$		14%	[35]
m_h	$>$ 114.4 GeV (SM-like Higgs)		3 GeV	[36]
ζ_h^2	$f(m_h)$ (see text)		negligible	[36]
$m_{\tilde q}$	$>$ 375 GeV		5%	[25]
$m_{\tilde g}$	$>$ 289 GeV		5%	[25]
other sparticle masses	As in table 4 of ref. [6].			

SM parameters

SM (nuisance) parameter	Mean value μ	Uncertainty σ (exper.)	Ref.
M_t	172.6 GeV	1.4 GeV	[24]
$m_b(m_b)^{\overline{MS}}$	4.20 GeV	0.07 GeV	[25]
$\alpha_s(M_Z)^{\overline{MS}}$	0.1176	0.002	[25]
$1/\alpha_{\rm em}(M_Z)^{\overline{MS}}$	127.955	0.03	[26]

2D posterior vs profile likelihood

Posterior | Profile likelihood

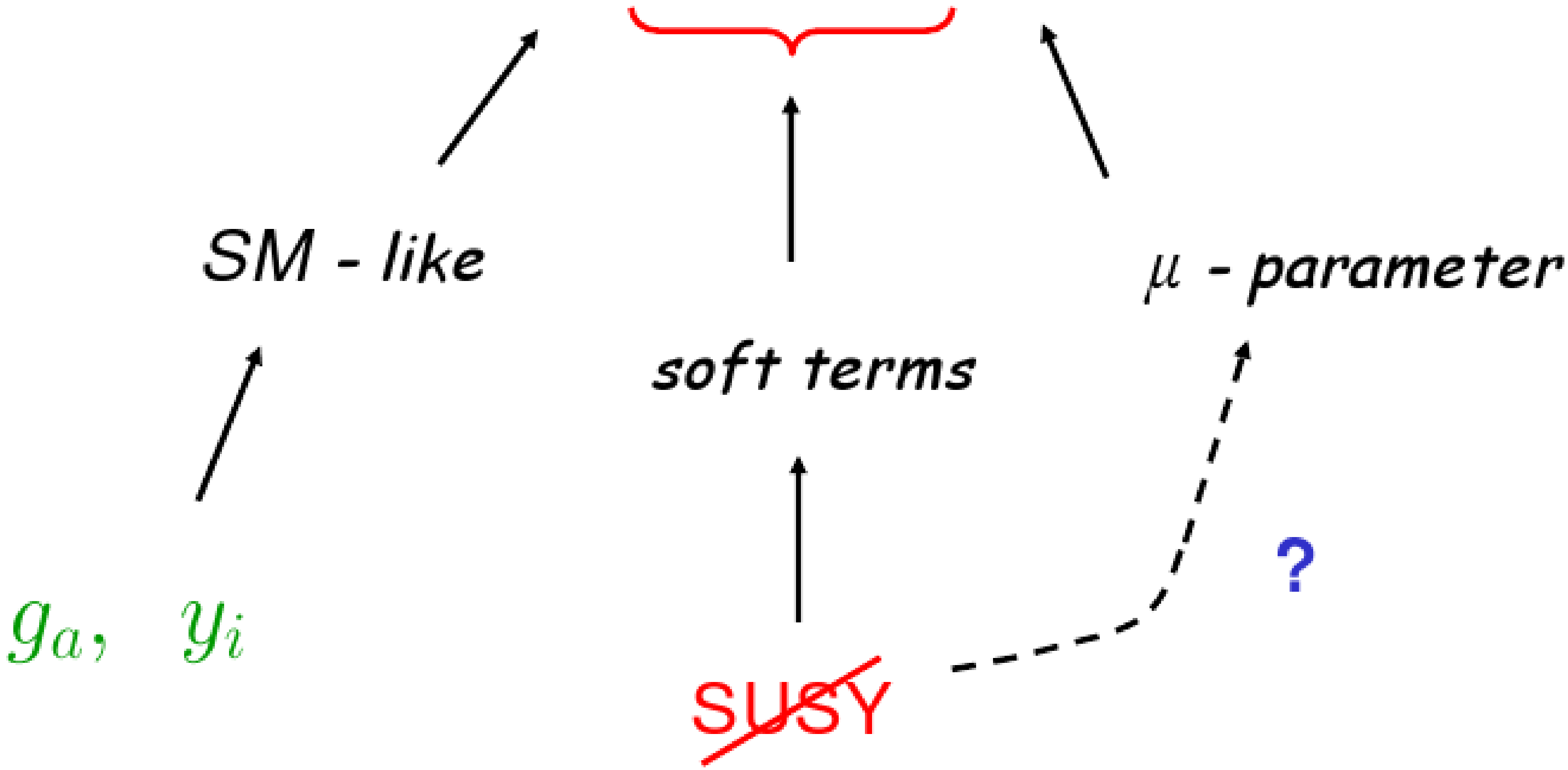


$$D_{KL} = \int d\theta P(\theta|d) \ln \frac{P(\theta|d)}{P(\theta)} = -\ln P(d) - \langle \chi^2/2 \rangle$$

Cosmology provides 80% for flat priors (95% for log priors) of the total constraining power on the CMSSM

Towards a more refine analysis

$$\{\theta_i\} \equiv \{s, \underbrace{m, M, A, B}, \mu\}$$



Universality at High Scale supported for FCNC constraints

Goal

- Scan the model

$$\{\theta_i\} = \{s, m, M, A, B, \mu\}$$

evaluating

$$p(\theta_i|\text{data}) \propto p(\text{data}|\theta_i)\ p(\theta_i)$$

Forecast map for LHC

Bayesian and Naturalness

- Recall an usual assumption

$$\underbrace{m, M, A, B, \mu}_{(\equiv M_{\rm soft})} \text{ should be } \lesssim \mathcal{O}(TeV)$$

- In order to get a

  Natural Electroweak symmetry Breaking
  (with no fine-tunings)

...

$$V(H_1, H_2) = m^2_{H_1}|H_1|^2 + m^2_{H_2}|H_2|^2 - 2B\mu H_1 H_2$$

$$+ \frac{1}{8}(g^2 + g'^2)\ (|H_1|^2 - |H_2|^2)^2$$

$$M_Z^2 = \frac{m^2_{H_1} - m^2_{H_2}\tan^2\beta}{\tan^2\beta - 1} - 2\mu^2$$

$$\sin 2\beta = \frac{2\mu}{B}\,(m^2_{H_1} + m^2_{H_2} + 2\mu^2_{\rm low})$$

Unnatural fine-tuning

unless $M_{\rm soft} \lesssim \mathcal{O}(\mathrm{TeV})$

...

- Instead solving μ^2 in terms of M_Z and the other soft-terms, treat M_Z as another exp. Data
- Approximate the likelihood as

$$\mathcal{L} = N_Z \, e^{-\frac{1}{2}\left(\frac{M_Z - M_Z^{\rm exp}}{\sigma_Z}\right)^2} \mathcal{L}_{\rm rest}$$

$$\simeq \delta(M_Z - M_Z^{\rm exp}) \, \mathcal{L}_{\rm rest}$$

Likelihood associated to
the other observables

...

- Use M_Z to marginalize μ

$$p(s,m,M,A,B|\,\text{data}) \;=\; \int d\mu\, p(s,m,M,A,B,\mu|\text{data})$$
$$\simeq \;\; \mathcal{L}_{\text{rest}} \left[\frac{d\mu}{dM_Z}\right]_{\mu_Z} p(s,m,M,A,B,\mu_Z)$$

$$p(s,m,M,A,B|\,\text{data}) \;=\; 2\,\mathcal{L}_{\text{rest}}\,\frac{\mu_Z}{M_Z}\,\frac{1}{c_\mu}\,p(s,m,M,A,B,\mu_Z)$$

$$c_\mu \;=\; \frac{\partial\,\ln M_Z^2}{\partial\,\ln\theta_i}$$

(Ellis et al, Barbieri-Gudice measure of fine-tunning)

$c^{-1} \sim$ Probability of cancellation between the various contributions to get $M_Z \sim \mathcal{O}(90\text{GeV})$

At practical level

- Besides, we have done a similar analysis for the fermion masses

$$y_t \longrightarrow m_t$$

- And traded

$$B \longrightarrow \tan\beta$$

Putting all the pieces together

$$\{\mu, y_t, B\} \xrightarrow{J} \{M_Z, m_t, \tan\beta\}$$

$$p(m_t, m, M, A, \tan\beta|\text{data}) \;=\; \underbrace{J|_{\mu=\mu_Z}\, p(y_t, m, M, A, B, \mu_Z)}_{\boxed{p_{\text{eff}}(m_t, m, M, A, \tan\beta)}}\, \mathcal{L}_{\text{rest}}$$

$$p_{\text{eff}}(m_t, m, M, A, \tan\beta) \;\propto\; \underbrace{\left[\frac{E}{R_\mu^2}\right] \frac{y}{y_{\text{low}}} \frac{t^2-1}{t(1+t^2)} \frac{B_{\text{low}}}{\mu_Z}}_{J}\, p(m, M, A, B, \mu=\mu_Z)$$

model-independent part !

still undefined

It contains the fine-tuning penalization

It penalizes large tan β

Finally

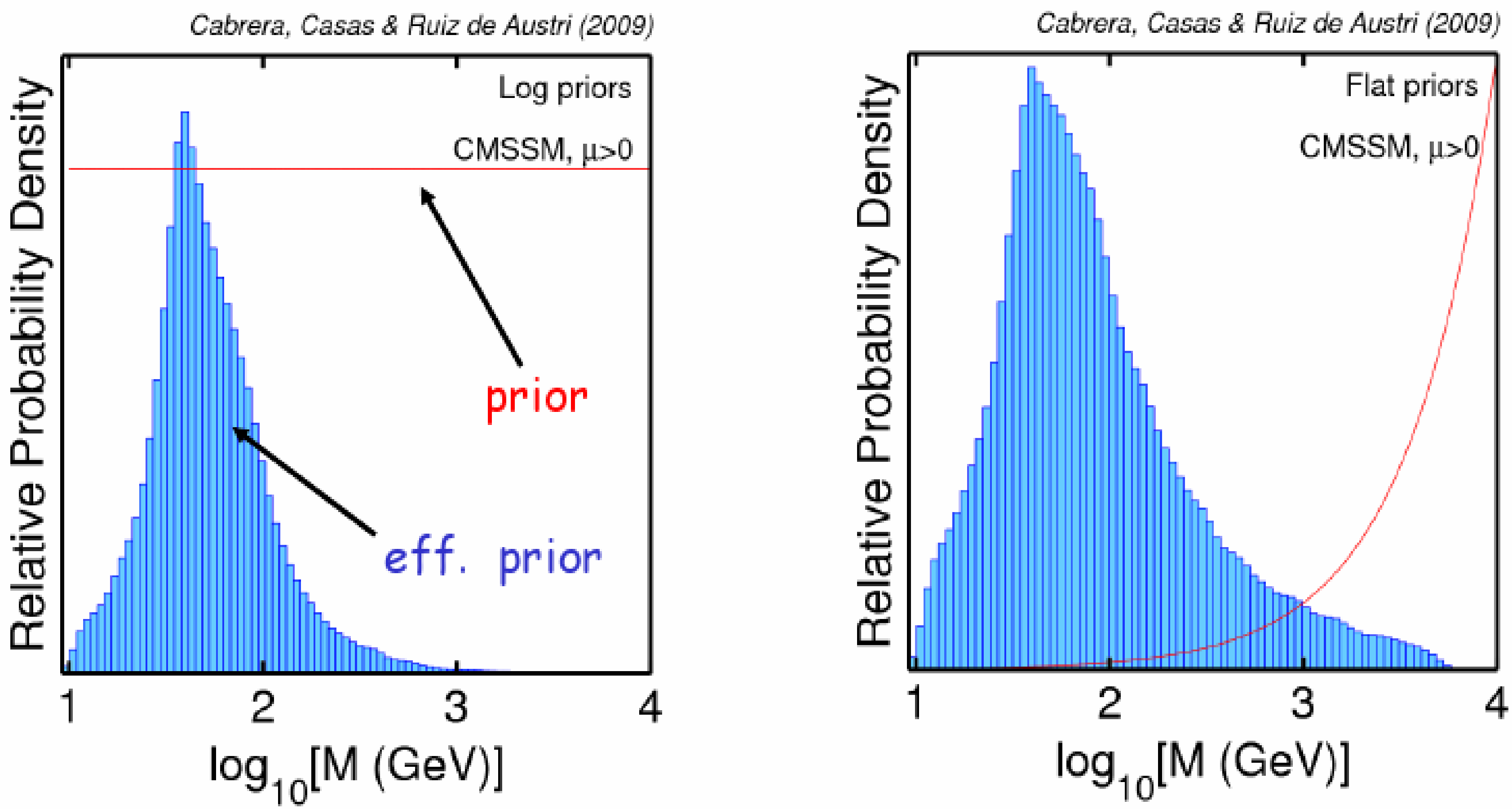
- For the prior

$$p(m, M, A, B, \mu)$$

we take the two basic possibilities:

flat

logarithmic



$M_Z^{\rm exp}$ brings SUSY to the LHC region

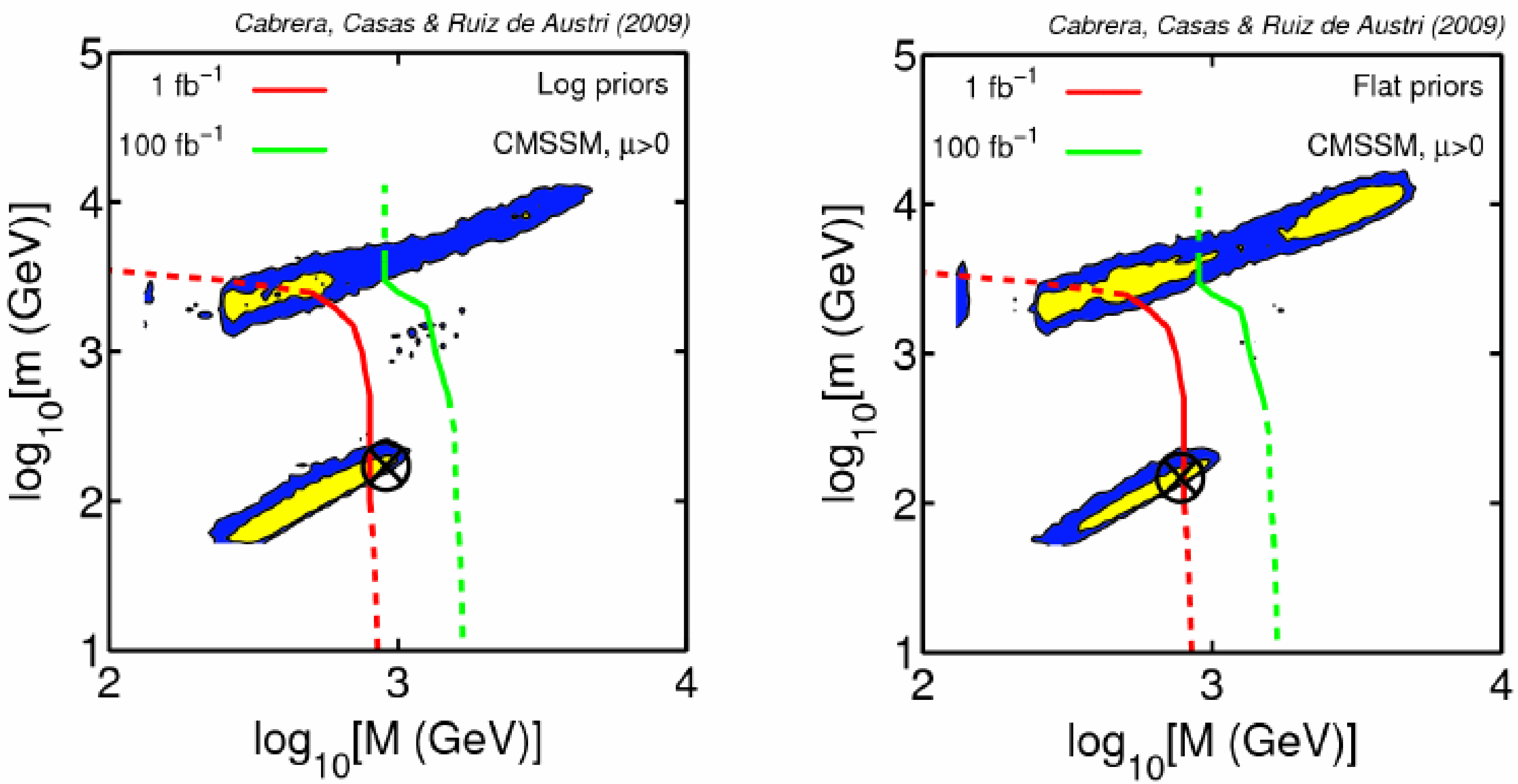
- We may vary $M_{\rm soft}$ up to M_X the results do not depend on the range choosen
- This suggests that large soft-masses are disfavoured

Data Included

Observable	Mean value μ	Uncertainties σ (exper.)	τ (theor.)
M_W	80.398 GeV	27 MeV	15 MeV
$\sin^2\theta_{\rm eff}$	0.23149	17×10^{-5}	15×10^{-5}
$\delta a_\mu^{\rm SUSY}\times10^{10}(e^+e^-)$	29.5	8.8	2.0
$\delta a_\mu^{\rm SUSY}\times10^{10}(\tau)$	14.0	8.4	2.0
ΔM_{B_s}	17.77 $\rm ps^{-1}$	0.12 $\rm ps^{-1}$	2.4 $\rm ps^{-1}$
$BR(\overline{B}\to X_s\gamma)\times10^4$	3.52	0.33	0.3
$\frac{BR(B_u\to\tau\nu)_{MSSM}}{BR(B_u\to\tau\nu)_{SM}}$	1.28	0.38	0
$\Delta_{0-}\times10^2$	3.6	2.65	0
$\frac{BR(B\to D\tau\nu)}{BR(B\to De\nu)}\times10^2$	41.6	12.8	3.5
R_{l23}	1.004	0.007	0
$BR(D_s\to\tau\nu)\times10^2$	5.7	0.4	0.2
$BR(D_s\to\mu\nu)\times10^3$	5.8	0.4	0.2
$\Omega_\chi h^2$	0.1099	0.0062	$0.1\,\Omega_\chi h^2$

	Limit (95% CL)	τ (theor.)
$BR(\overline{B}_s\to\mu^+\mu^-)$	$<5.8\times10^{-8}$	14%
m_h	>114.4 GeV (SM-like Higgs)	3 GeV
ζ_h^2	$f(m_h)$ (see text)	negligible
$m_{\tilde q}$	>375 GeV	5%
$m_{\tilde g}$	>289 GeV	5%
other sparticle masses	As in table 4 of ref. [?].	

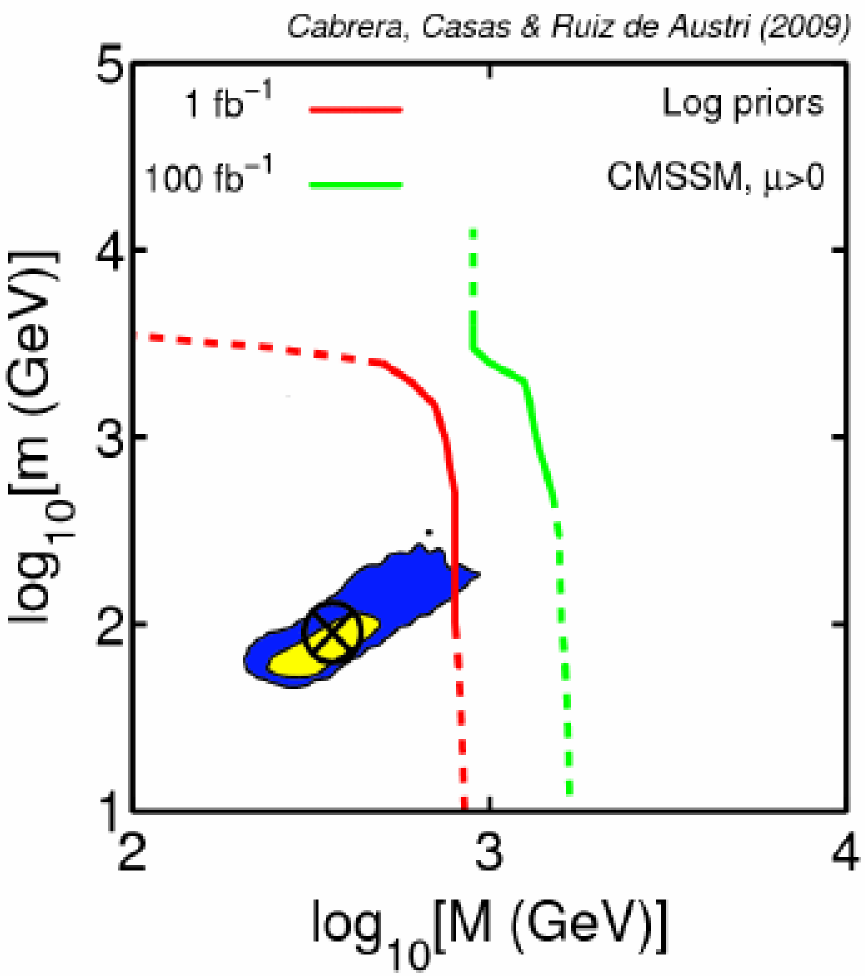
Adding Ω_{DM} [and not g-2]

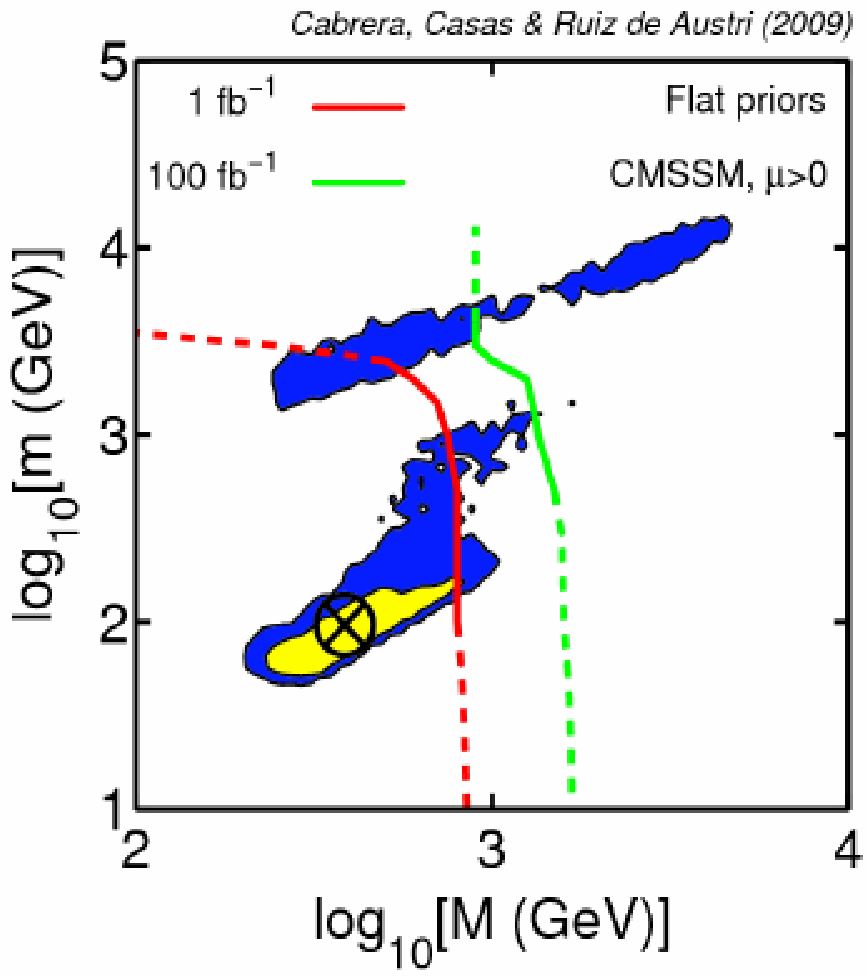


Events with more or equal to 2 jets [Baer et al 0907.1922]

(LHC contours at 14 TeV C.M)

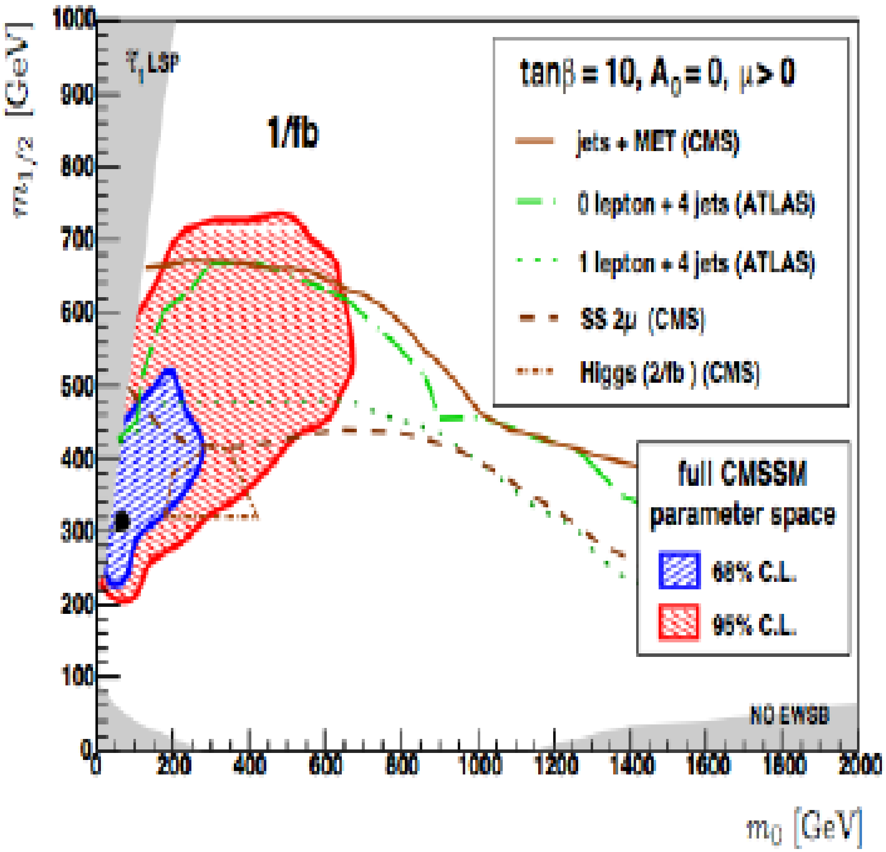
Adding all


Cabrera, Casas & Ruiz de Austri (2009)
1 fb^{-1}
100 fb^{-1}
Log priors
CMSSM, μ>0
log$_{10}$[m (GeV)]
log$_{10}$[M (GeV)]
1
2
3
4
5
2
3
4

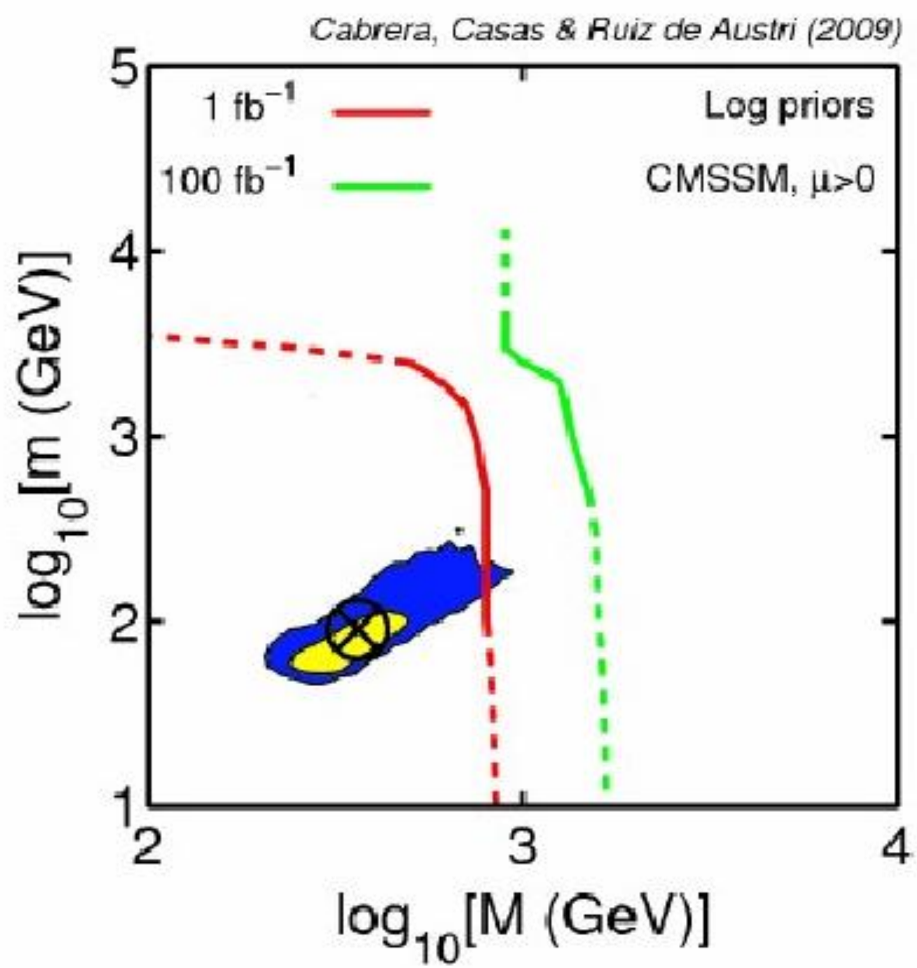

Cabrera, Casas & Ruiz de Austri (2009)
1 fb^{-1}
100 fb^{-1}
Flat priors
CMSSM, μ>0
log$_{10}$[m (GeV)]
log$_{10}$[M (GeV)]
1
2
3
4
5
2
3
4

Comparison with Likelihood based inference

Buchmueller et al. (2009)



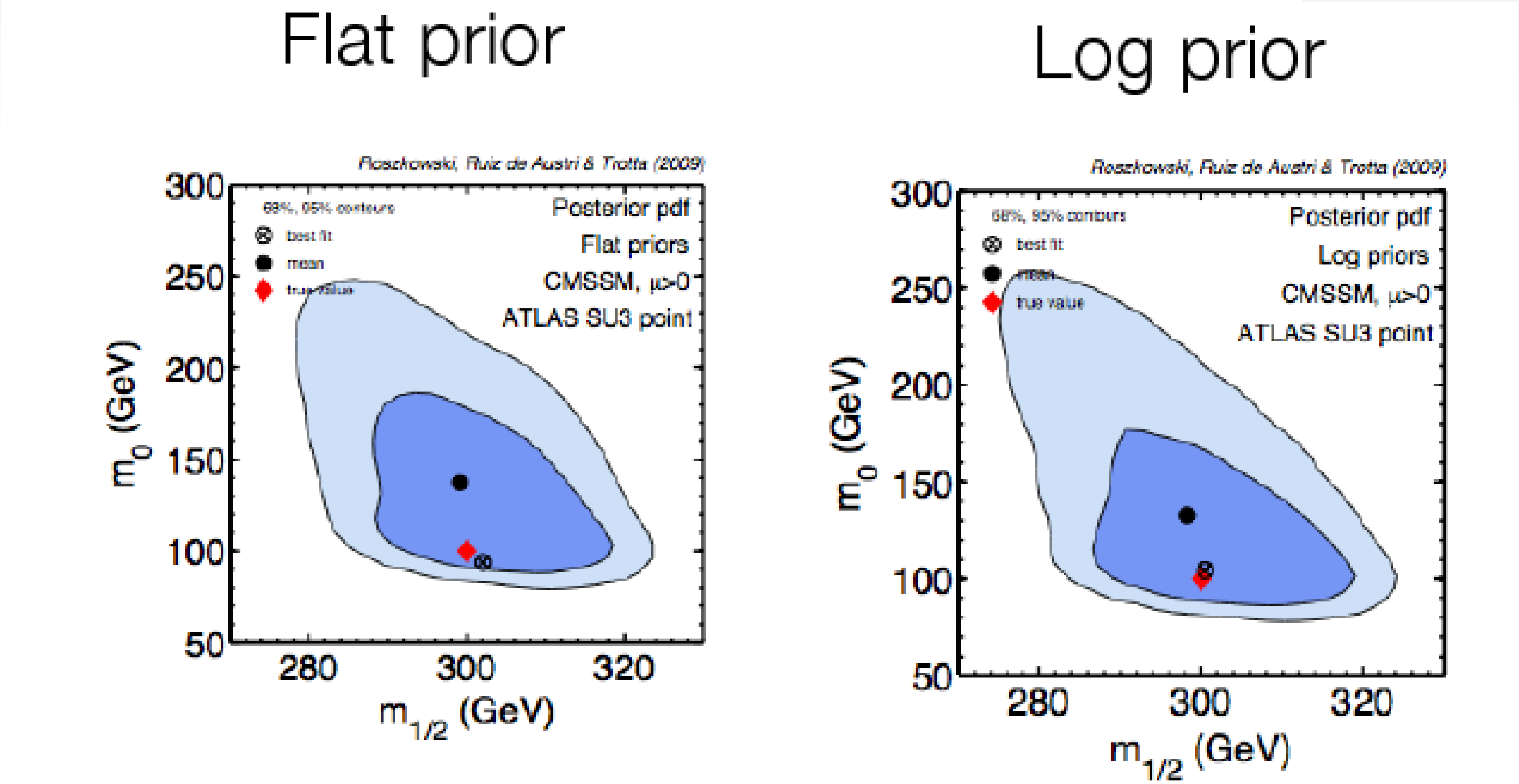
Cabrera et al. (2009)



ATLAS will solve the prior dependency

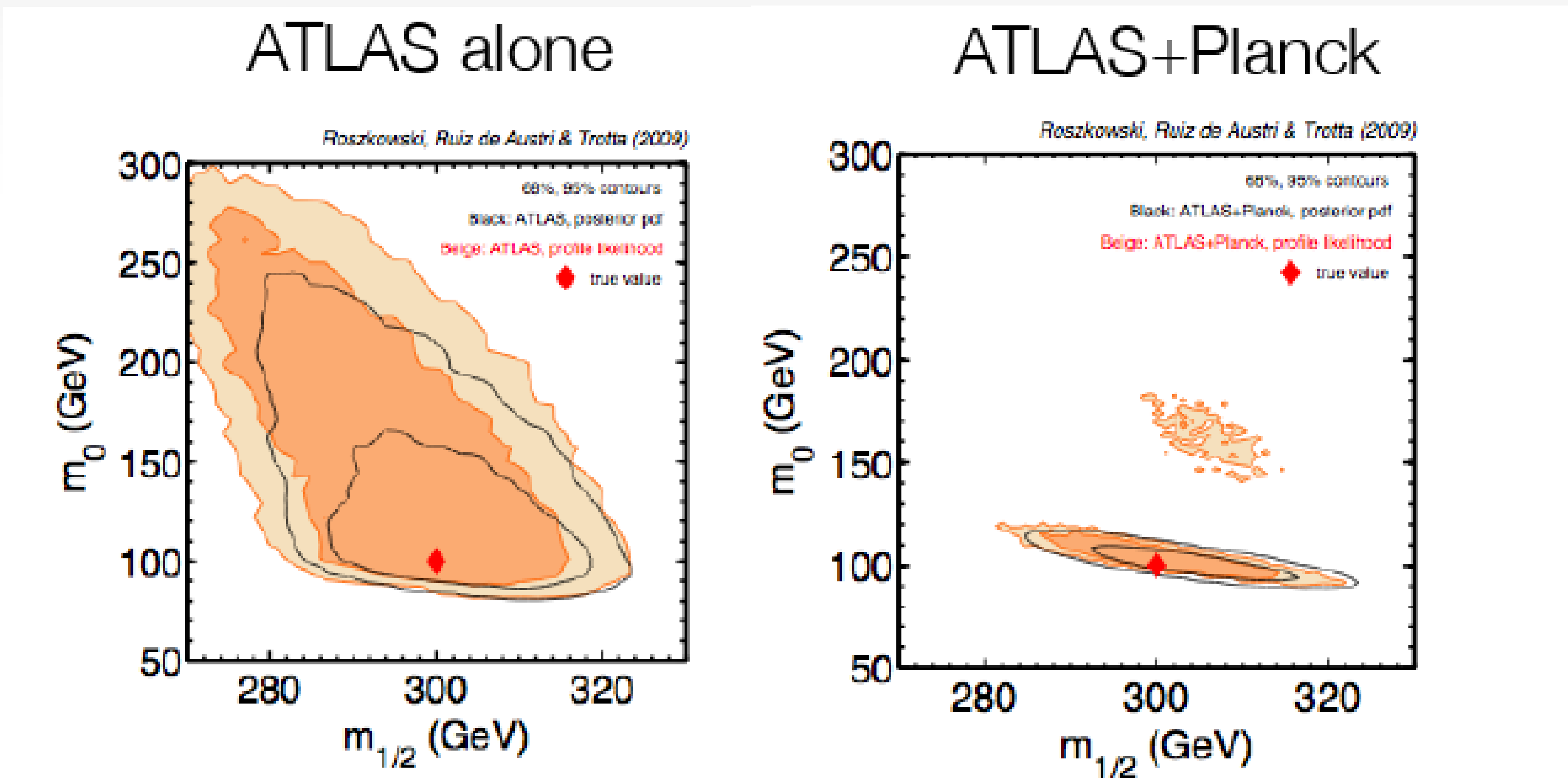
- Projected constraints from ATLAS, (dilepton and lepton+jets edges, 1 fb^-1 luminosity)

$$\theta = \{m_{\chi_1^0}, m_{\chi_2^0} - m_{\chi_1^0}, \tilde{m}_{\tilde{l}} - m_{\chi_1^0}, \tilde{m}_{\tilde{q}} - m_{\chi_1^0}\},$$



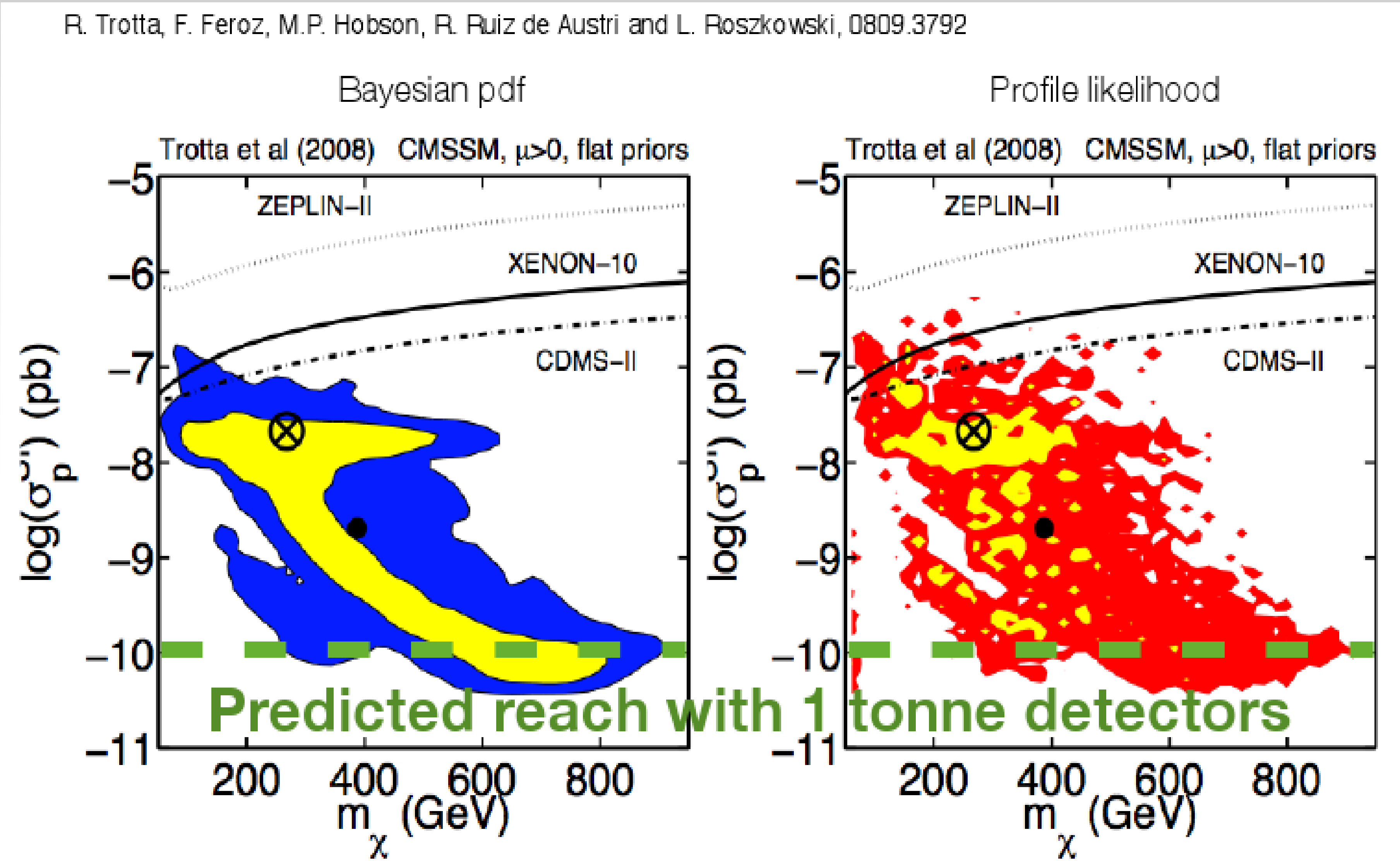
Residual dependency on the statistics

- Marginal posterior and profile likelihood will remain somewhat discrepant using ATLAS alone. Much better agreement from ATLAS+Planck CDM determination.



Direct and indirect detection prospects

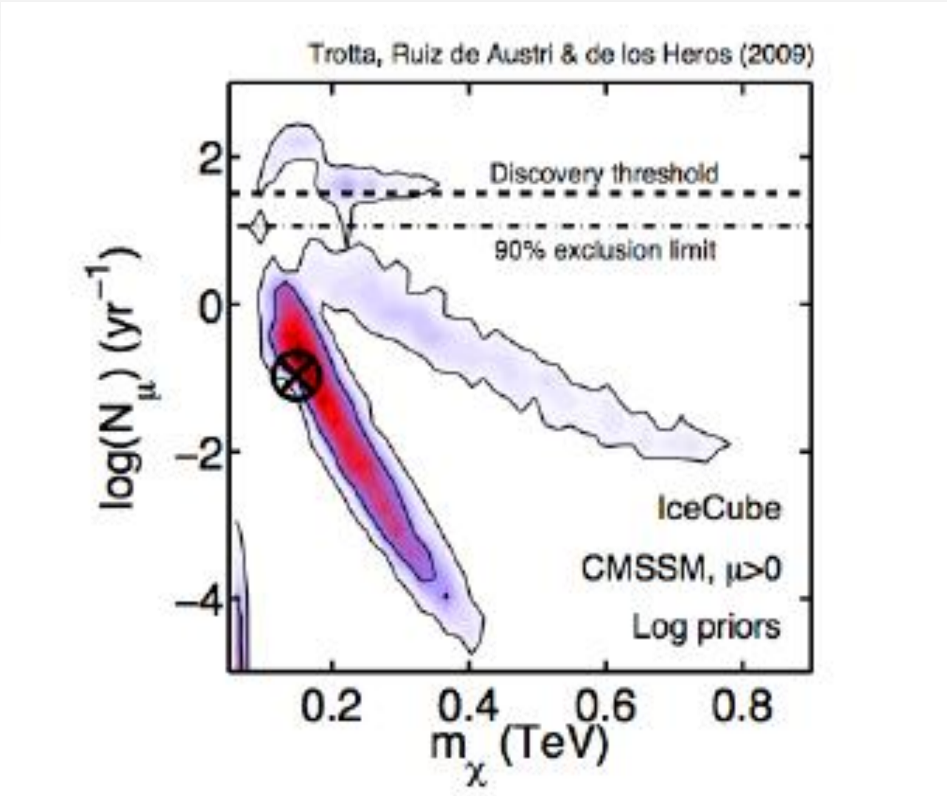
Direct detection prospects

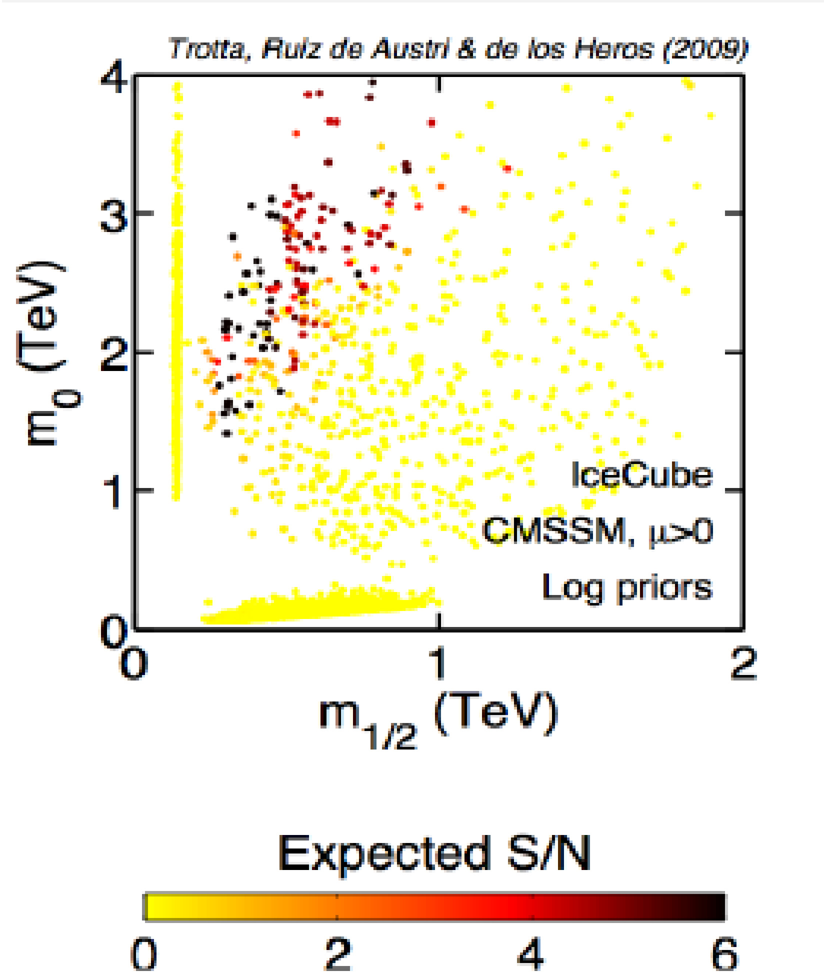


Direct detection experiments will probe most of the favoured region of the CMSSM

Neutrinos from WIMP annihilations in the Sun

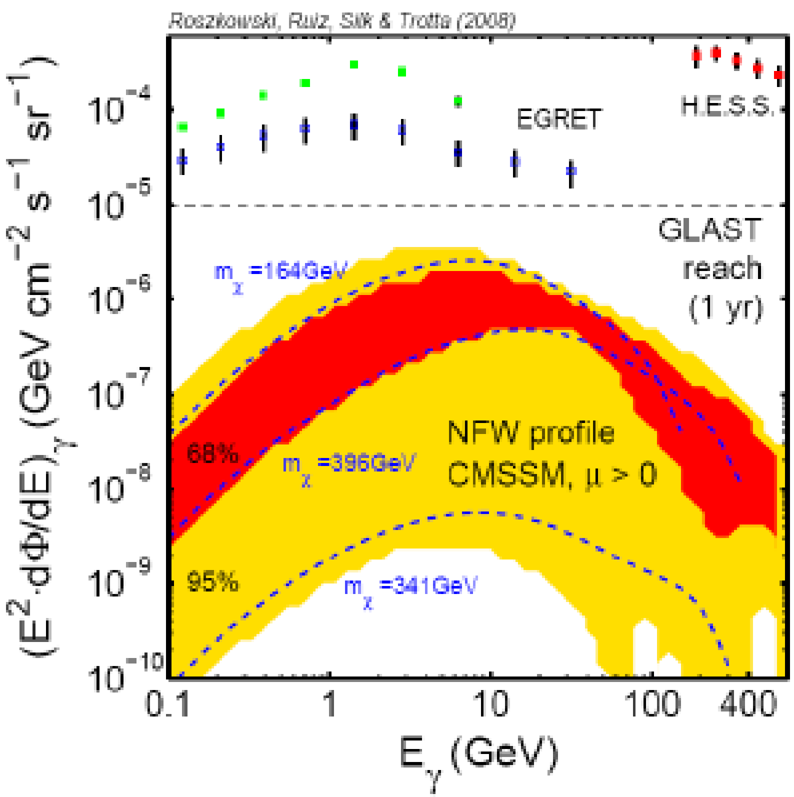
- In the context of the CMSSM, the final configuration of IceCube (with 80 strings) has between 2% and 12% probability of achieving a 5-sigma detection





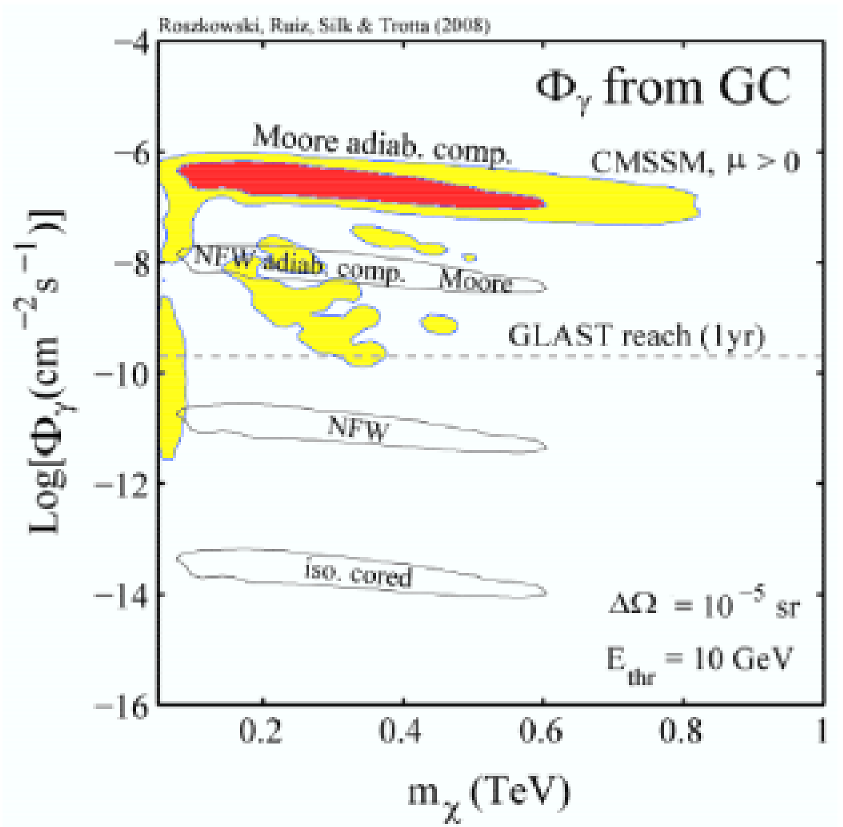
Predictions for Fermi in the CMSSM

Predicted gamma-ray spectrum probability distribution from the galactic center at Fermi resolution

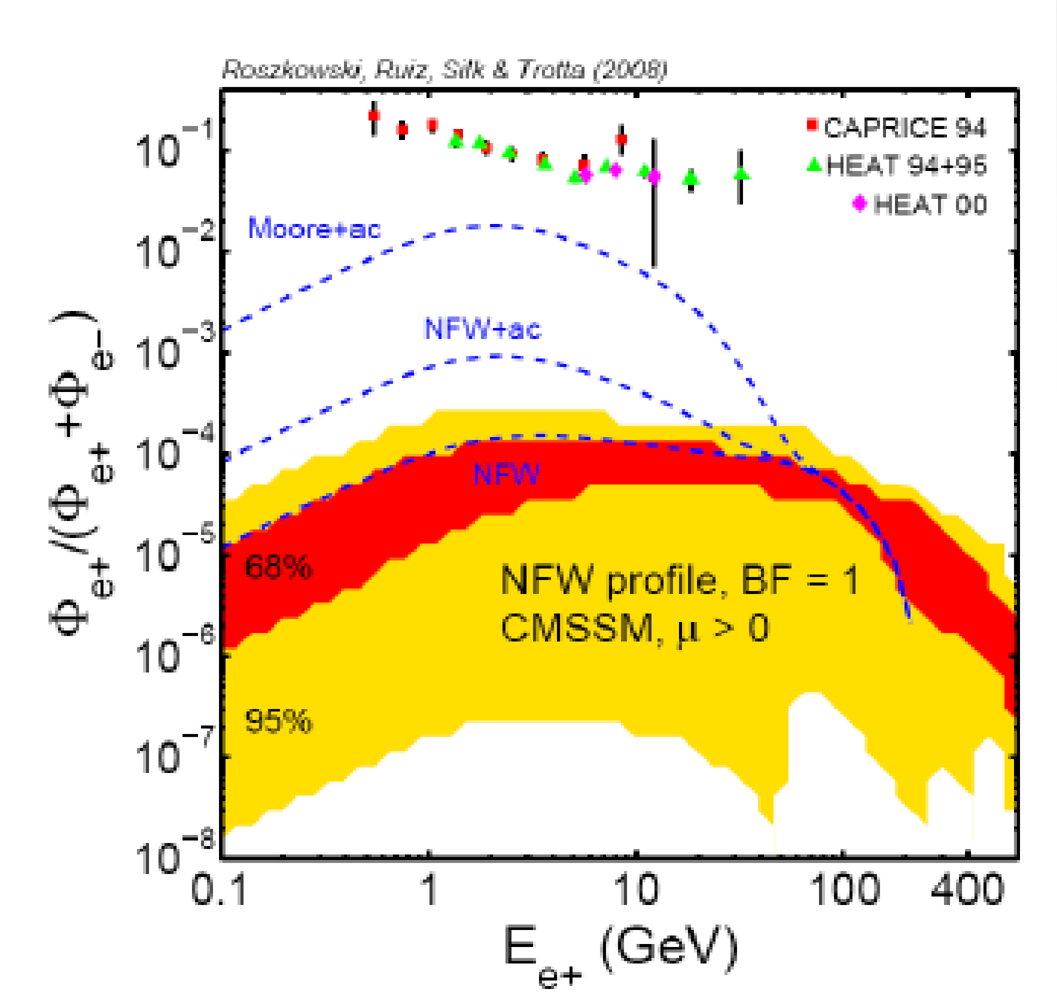


Roszkowski, Ruiz, Silk & RT (2008)

Predicted gamma-ray flux above 10 GeV at Fermi resolution



Predictions for the positrons spectrum



Conclusions

- SUSY phenomenology provides a timely and challenging problem for parameter inference and model selection. A considerably harder problem than cosmological parameter extraction!
- Bayesian advantages: higher efficiency, inclusion of nuisance parameters, predictions for derived quantities, model comparison
- CMSSM only a case study: Bayesian analysis naturally penalizes fine-tunings. The exp. value of MZ brings the relevant parameter space to the low-energy region (~ accesible to LHC). The results are quite stable under changes of the initial prior (logarithmic or flat) or in the ranges of the parameters
- Currently, even the CMSSM is somewhat underconstrained: ATLAS+Planck will take us to "statistics nirvana"
- CMSSM neutralino dark matter: direct detection possible by the end of the decade.

Bayesians address the question everyone is interested in by using assumptions no-one believes, while Frequentists use impeccable logic to deal with an issue of no interest to anyone" (L. Lyons)

THANKS !!!

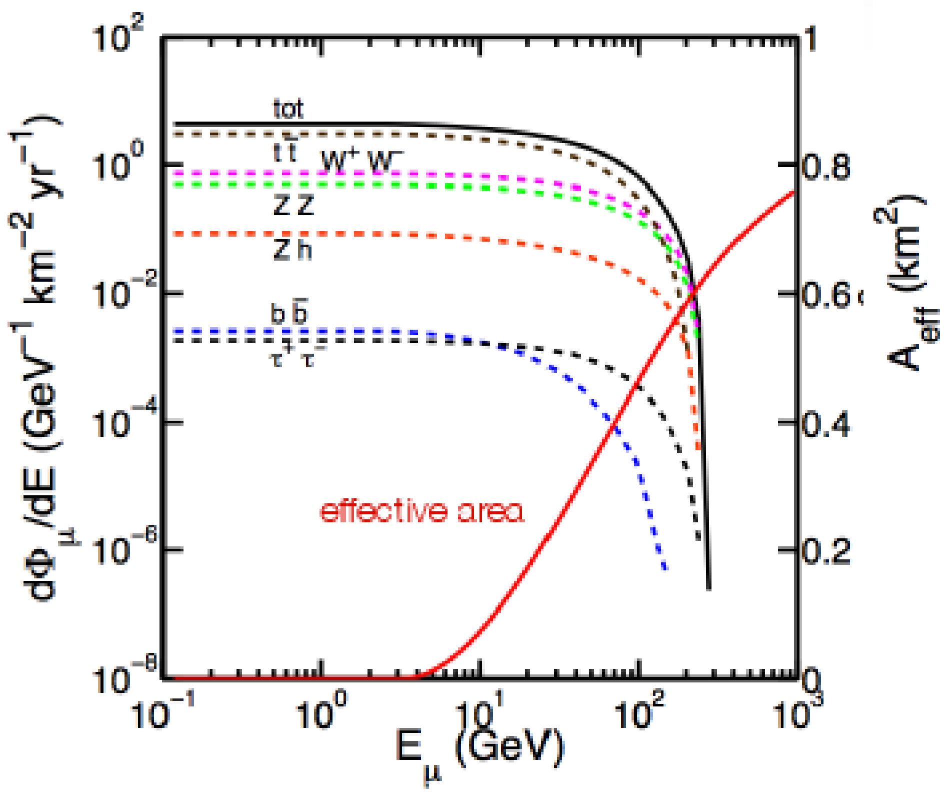
Backups

Bias from assuming the wrong final state

Muon events rate = $N_\mu = \int_{E_\mu^{\rm th}}^{+\infty} dE_\mu A_\mu^{\rm eff}(E_\mu) \frac{d\Phi_\mu}{dE_\mu}$

effective area

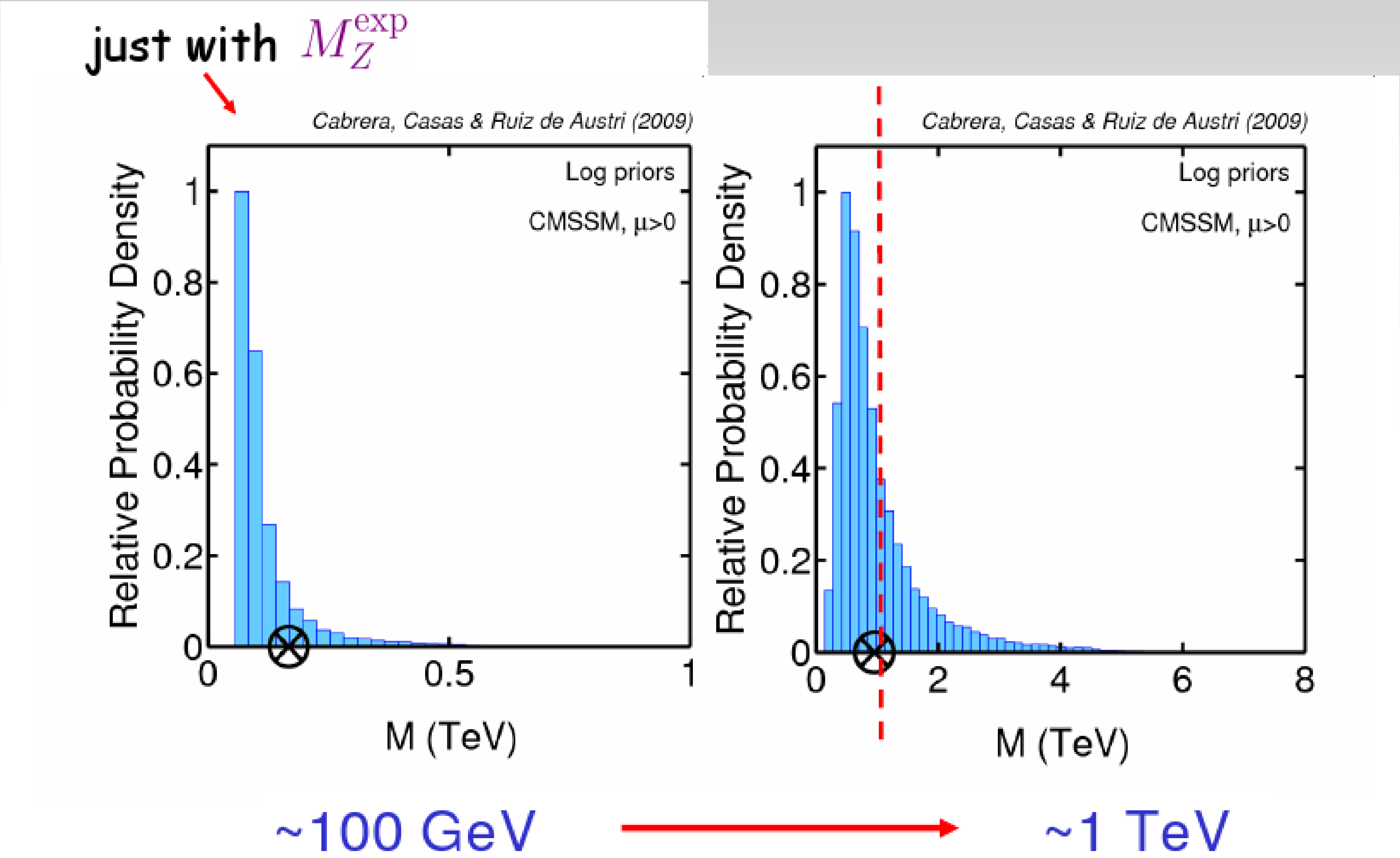
total spectrum - sum over final states



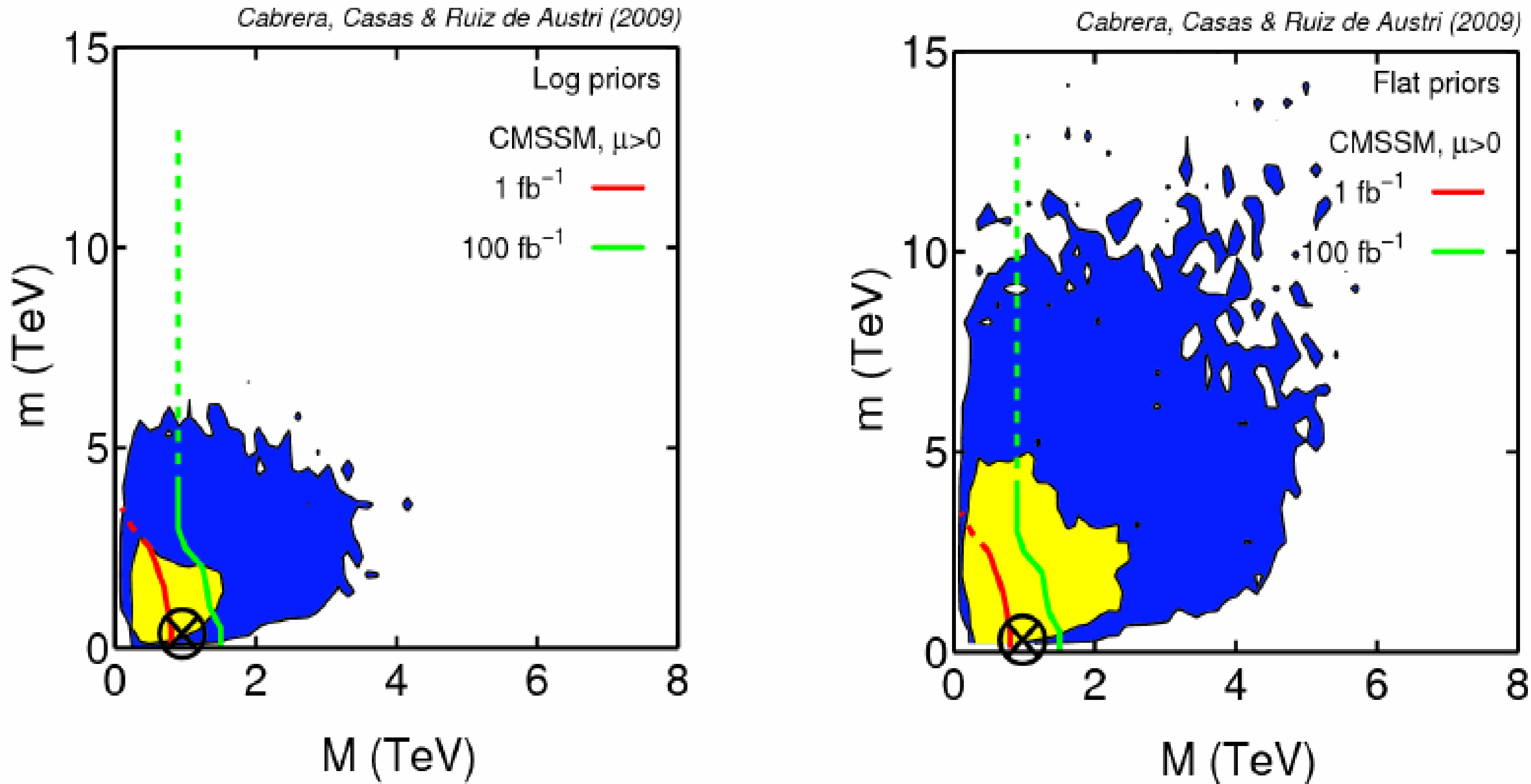
Total events = 34 1/yr

BR's for dominant channels		
$\mathrm{BR}(\chi\chi \to b\bar{b})$	2.1×10^{-3}	
$\mathrm{BR}(\chi\chi \to t\bar{t})$	0.717	
$\mathrm{BR}(\chi\chi \to W^+W^-)$	0.162	
$\mathrm{BR}(\chi\chi \to ZZ)$	0.094	
Muon events fraction for IceCube		Events/yr assuming only 1 channel
$N_{b\bar{b}}/N_\mu$	5×10^{-5}	0.8
$N_{t\bar{t}}/N_\mu$	0.46	
$N_{W^+W^-}/N_\mu$	0.30	64
N_{ZZ}/N_μ	0.21	

EW and B-phys. and limits on particle masses

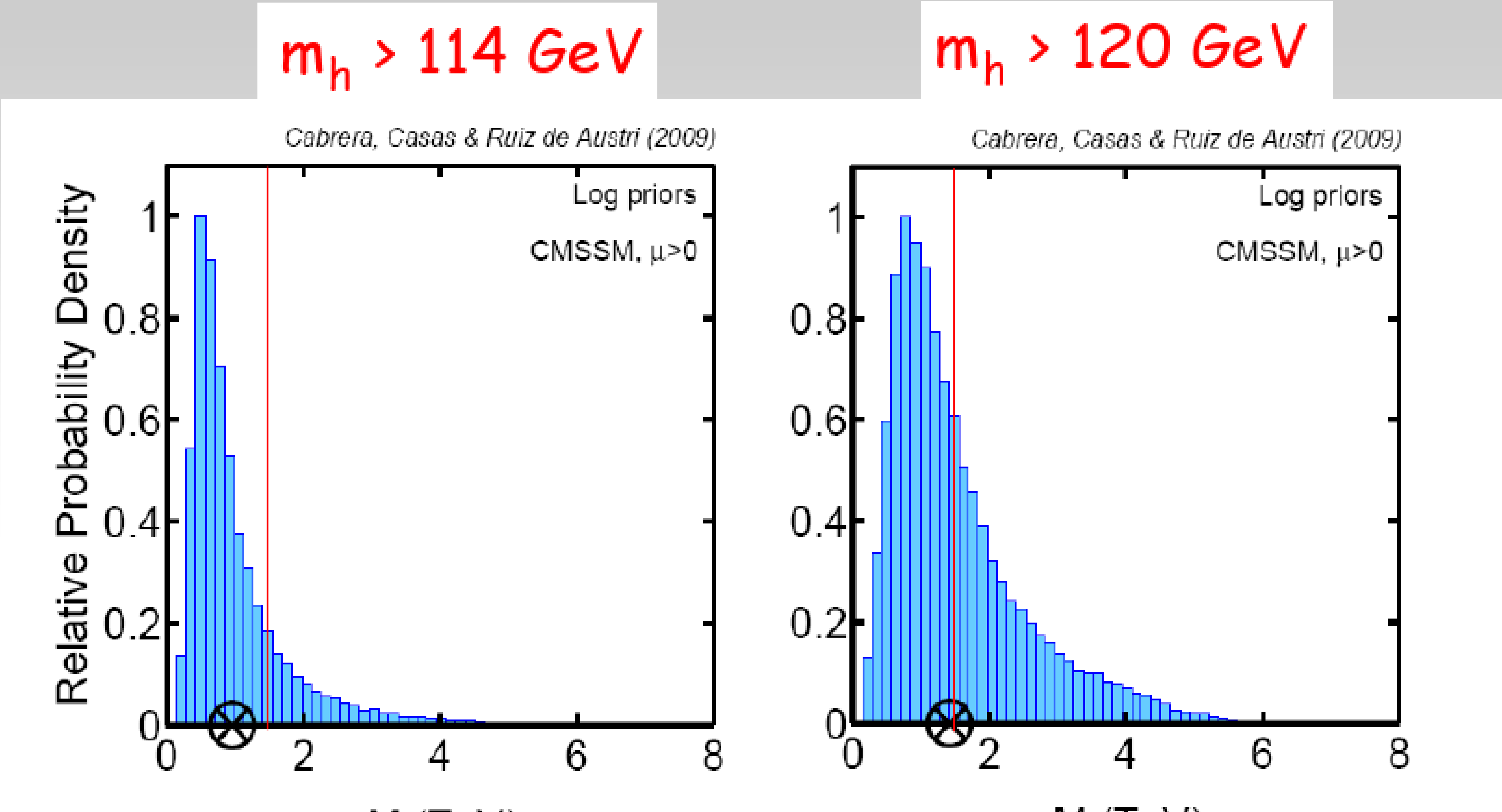


2D



Events with more or equal to 2 jets [Baer et al 0907.1922]

(LHC contours at 14 TeV C.M.)



If the MSSM is true and we wish to detect it at the LHC, let us hope that the Higgs mass is close to the present exp. limit

Experimental Constraints

We have considered 3 groups of exp. Constraints

E.W. and B-physics observabes, and limits on particle masses

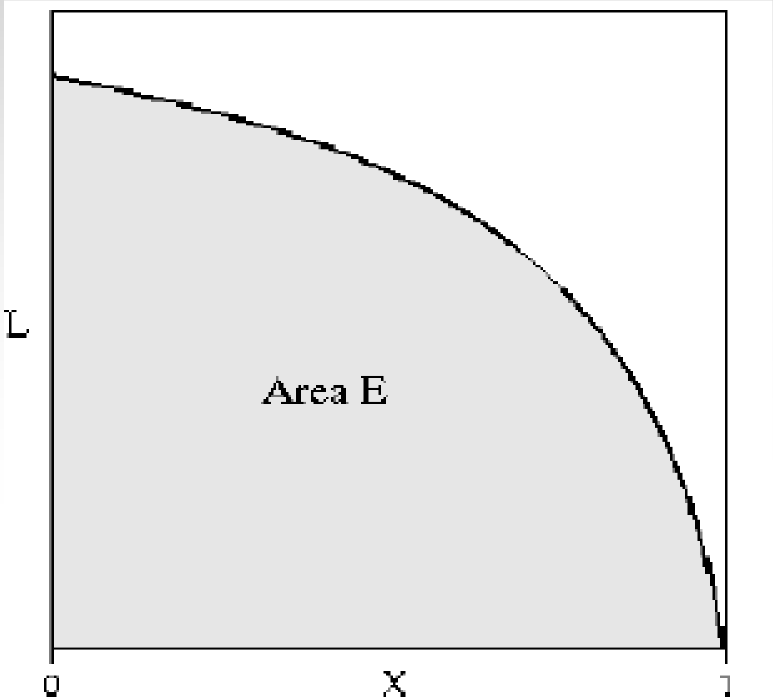
Constraints from $(g\text{-}2)_{\mu}$

Constraints from Dark Matter abundance

Nested

- New technique for efficient evidence evaluation (and posterior samples) (Skilling 2004)
- Define $X(\lambda) = \int_{L(\boldsymbol{\theta})>\lambda} \pi(\boldsymbol{\theta})\, d\boldsymbol{\theta}$
- Write inverse $L(X)$, i.e. $L(X(\lambda)) = \lambda$
- Evidence becomes one-dimensional integral

$$E = \int L(\boldsymbol{\theta})\pi(\boldsymbol{\theta})\, d\boldsymbol{\theta} = \int_0^1 L(X)\, dX$$

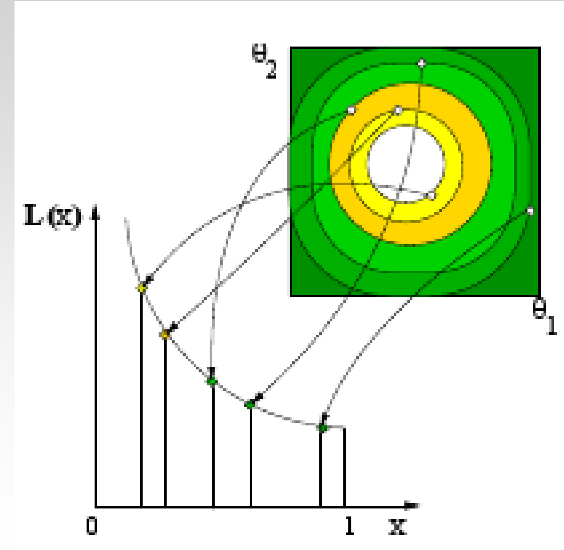


- Suppose can evaluate $L_j = L(X_j)$ where

$$0 < X_m < \cdots < X_2 < X_1 < 1$$

- ⇒ estimate E by any numerical method: $E = \sum_{j=1}^{m} L_j w_j$
- $w_j = \frac{1}{2}(X_{j-1} - X_{j+1})$ for trapezium r
- Posterior as a by product

- 1. Set i = 0; initially $X_0 = 1, E = 0$
- 2. Sample N points $\{\boldsymbol{\theta}_j\}$ randomly from $\pi(\boldsymbol{\theta})$ and calculate their likelihoods
- 3. Set i → i + 1
- 4. Find point with lowest likelihood value (L_i)
- 5. Remaining prior volume $X_i = t_i X_{i-1}$ where $\Pr(t_i|N) = N t_i^{N-1}$;
- 6. Incren $E \rightarrow E + L_i w_i$
- 7. Remove lowest point from active set
- 8. Replace with new point sampled from $\pi(\boldsymbol{\theta})$ within hard-edged region $L(\boldsymbol{\theta}) > L_i$
- 9. If $L_{\max} X_i < \alpha E$ (where some tolerance) $\Rightarrow E \rightarrow E + X_i \sum_{j=1}^{N} L(\boldsymbol{\theta}_j)/N$ stop; else goto 3



★ If nuisance parameter ⟷ high-quality exp. data

one-to-one

Then, the parameter is easily eliminated (without leaving any footprint)

E.g. g, g', g_3

(their prior is irrelevant)

★ This is not the case fo the Yukawa couplings, y_i, in the MSSM

E.g. $m_t = \frac{1}{\sqrt{2}} y_t v_2 = \frac{1}{\sqrt{2}} y_t v \sin\beta$

Derived quantity

Two different points in the MSSM-par. space will have in general different y_t. Thus the relative probability depends upon $p(y_t)$.

(something ignored in previous literature)

★ Thus the marginalization of y_i leaves a footprint in the pdf

Likelihood ~ $\delta(m_t - m_t^{\rm exp})\ \delta(m_b - m_b^{\rm exp})$ ....

Take $m_t = \frac{1}{\sqrt{2}} y_t^{\rm low} v s_\beta, \quad m_b = \frac{1}{\sqrt{2}} y_b^{\rm low} v c_\beta, \ \cdots$

(with $y_i^{\rm low} = R_i y_i$)

$$\int [dy_t\ dy_b \cdots]\ p(y, m, M, A, B|\ {\rm data}) \ \sim\ p(y) \left|\frac{dy_t}{dm_t}\right| \left|\frac{dy_b}{dm_b}\right| \cdots \ = \ p(y)\ s_\beta^{-1}\ c_\beta^{-1}\ \cdots$$

Normally people just take $\boldsymbol{y_i}$ “as needed” to reproduce m_i and forget about.

This equivales to take

$$p(y_i) \propto \frac{1}{y_i} \qquad \text{(log prior)}$$

reasonable.... $\quad y_e \sim 10^{-6}, \quad y_t \sim 1$

In order to write a sensible prior for $\{m, M, A, B, \mu\}$ one has to consider the dynamical origin of these parameters: $\cancel{\text{SUSY}}$

They typically go like $\sim \dfrac{F}{\Lambda} \equiv M_S$

A particular soft term, say ***A***, receives several $\mathcal{O}\left(\dfrac{F}{\Lambda}\right)$ contributions (dep. on the details of $\cancel{\text{SUSY}}$)

So, it is reasonable to expect

$$
\begin{aligned}
-qM_S \leq & \; B \; \leq qM_S \\
-qM_S \leq & \; A \; \leq qM_S \\
0 \leq & \; m \; \leq qM_S \\
0 \leq & \; M \; \leq qM_S \\
0 \leq & \; \mu \; \leq qM_S
\end{aligned}
$$

$q = \mathcal{O}(1)$

with *"flat"* probability

$$p(A) = \frac{1}{2M_S}, \qquad \text{etc.}$$

Recall: M_S is the scale of $\cancel{\text{SUSY}}$ in the observable

. sector

In principle M_S can have any value, say

$$M_S^0 \leq M_S \leq M_X \,, \qquad\qquad M_S^0 \sim 10 \text{ GeV}$$

with

flat: $p(M_S) \;=\; N_{M_S}$ or log: $p(M_S) \;=\; N_{M_S}\dfrac{1}{M_S}$

probability density

Log. prior:

$$p(m, M, A, B, \mu) \;=\; \int_{\max\{m,M,|A|,|B|,\mu,M_S^0\}}^{M_X} \;\; p(m, M, \mu, A, B)\, p(M_S)\, dM_S$$

$$\propto \;\; \frac{1}{[\max\{m, M, |A|, |B|, \mu, M_S^0\}]^5}$$

(neglecting $\frac{1}{M_X^5}$ terms)

For a particular parameter, say *M*:

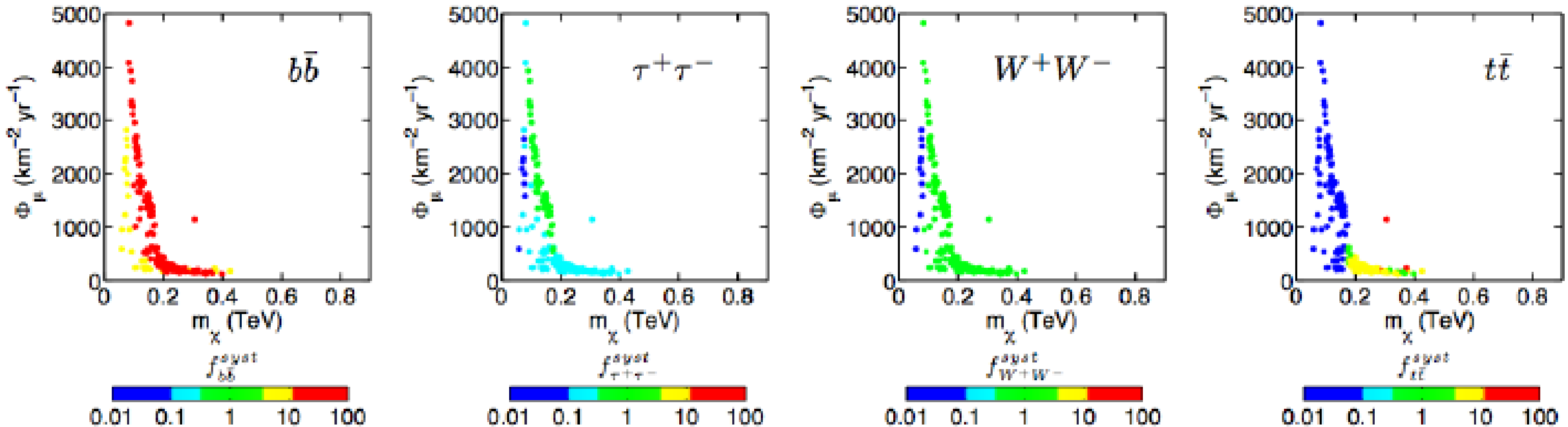
$$\mathcal{P}(M) \propto \frac{1}{\max\{M, M_S^0\}}$$

Bias from assuming the wrong final state

- In general, the systematic error from assuming only 1 dominating channel is given by

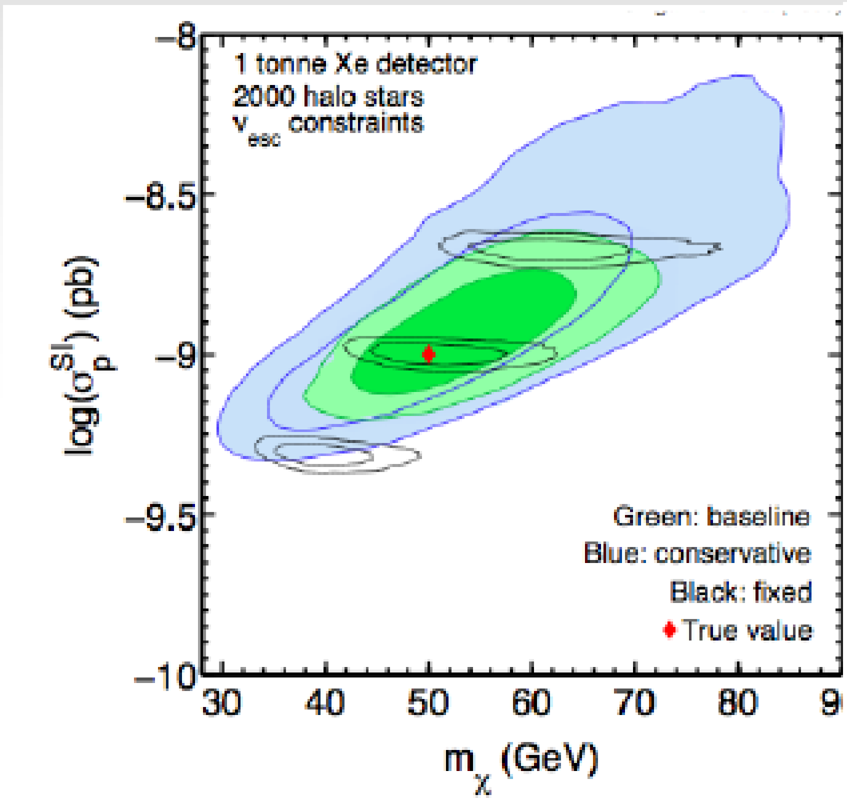
$$f_i^{\rm syst} = \frac{{\rm BR}(\chi\chi \to i)}{N_i/N_\mu}$$

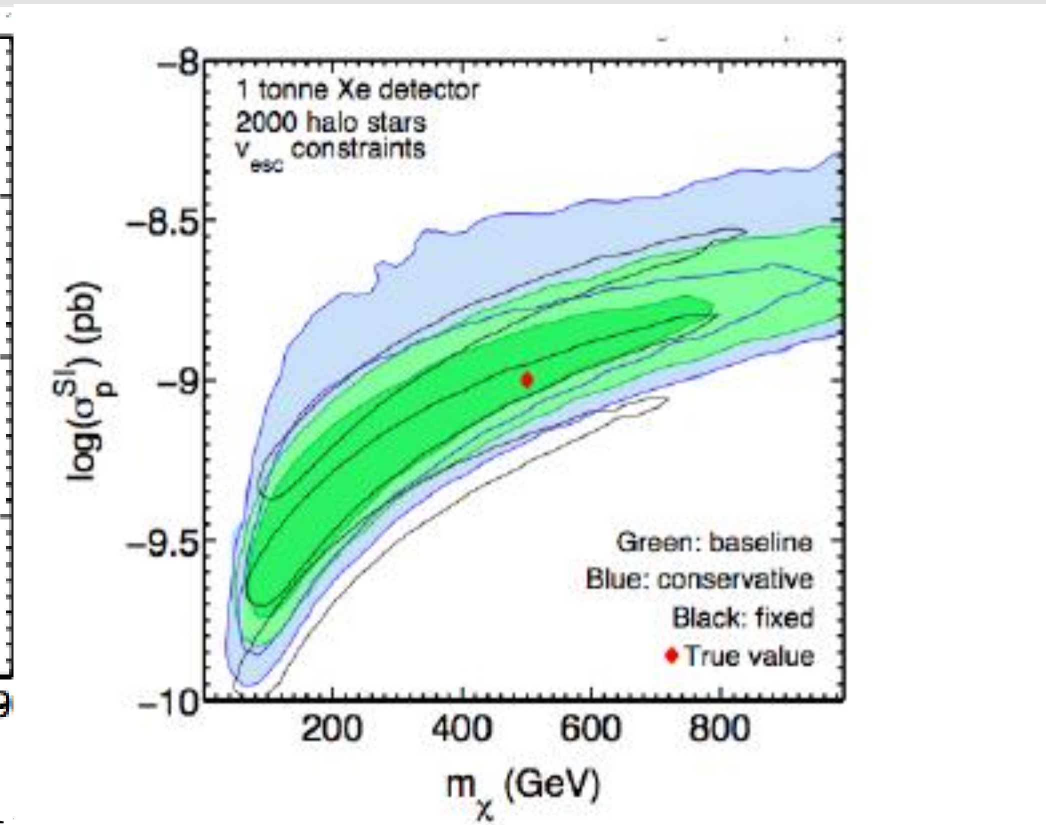
Systematic bias from assuming single-channel domination (IceCube)



Trotta, Ruiz de Austri & de los Heros (0906.0366)

The importance of modeling the MW





- 2) can lead to a 15 sigma bias in the reconstructed σ

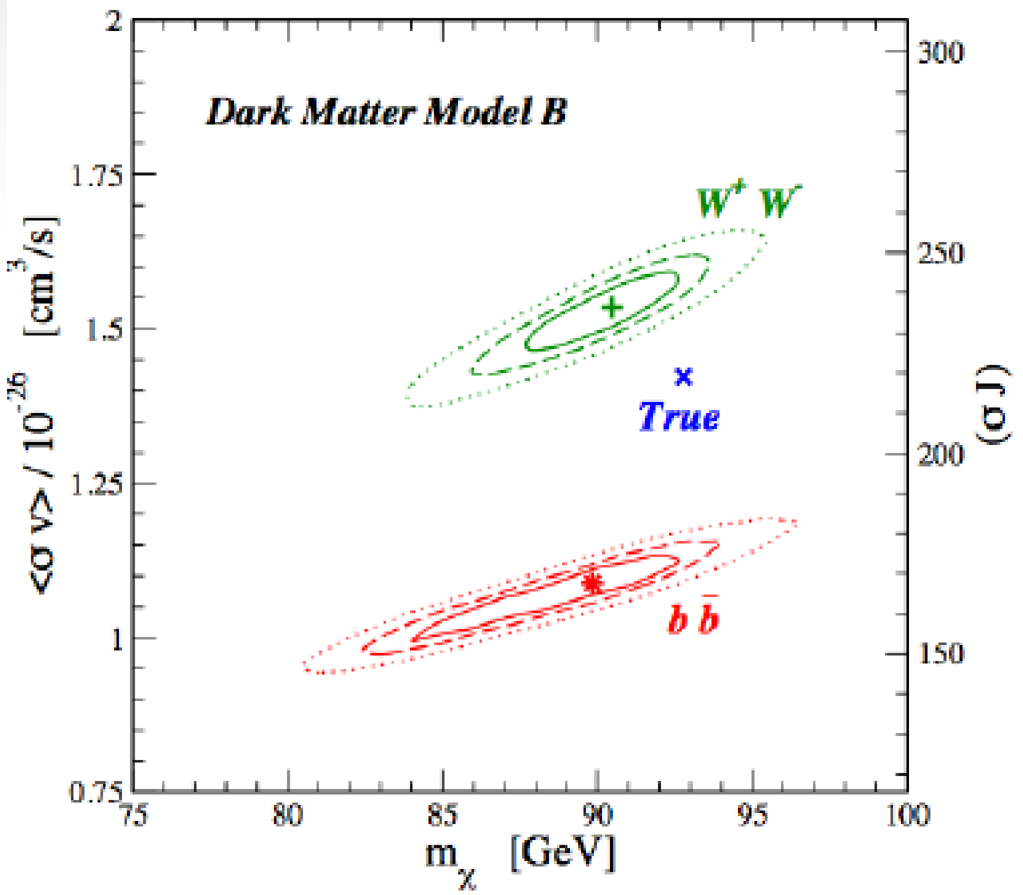
On going

- Neural Networks: computation reduced from 3 days to a few minutes
- Other SUSY scenarios and UED
- Analysis of Fermi data as external members of the DM group: DMBayes
- Cosmic rays determination in collaboration with Galprop team
- IceCube DM group collaboration
- Zeplin collaboration

Model independent reconstruction

$$\frac{d\Phi_\gamma}{dE_\gamma} \propto \sum_i \frac{\langle \sigma_i v \rangle}{m_\chi^2} \frac{dN_\gamma^i}{dE_\gamma} \int \rho_\chi^2 dl$$

- Assuming the wrong final state can lead to severe bias in the reconstructed WIMP properties
- Branching ratios must be estimated simultaneously!



Jeltema & Profumo (2009)