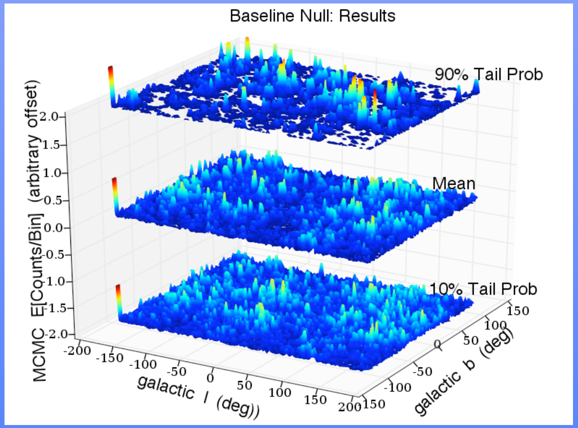
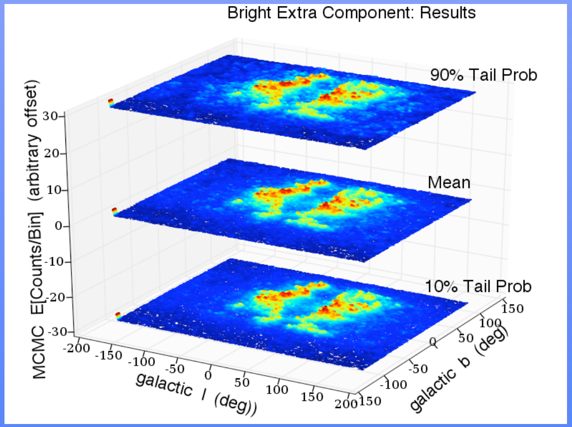
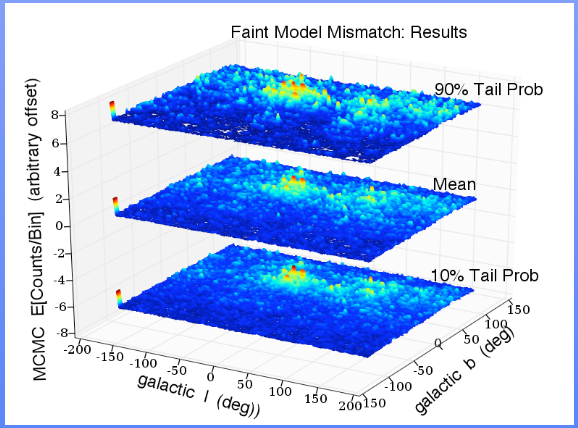
Quantifiying Doubt and Confidence in Image "Deconvolution"

Enhanced Imaging Multiscale Methods
for
Diffuse Emission and/or Model Fitting

A. Connors, D. van Dyk, J.Chiang, A. Roy, R. Izem, CHASC;
(D. Esch, M.Karovska)

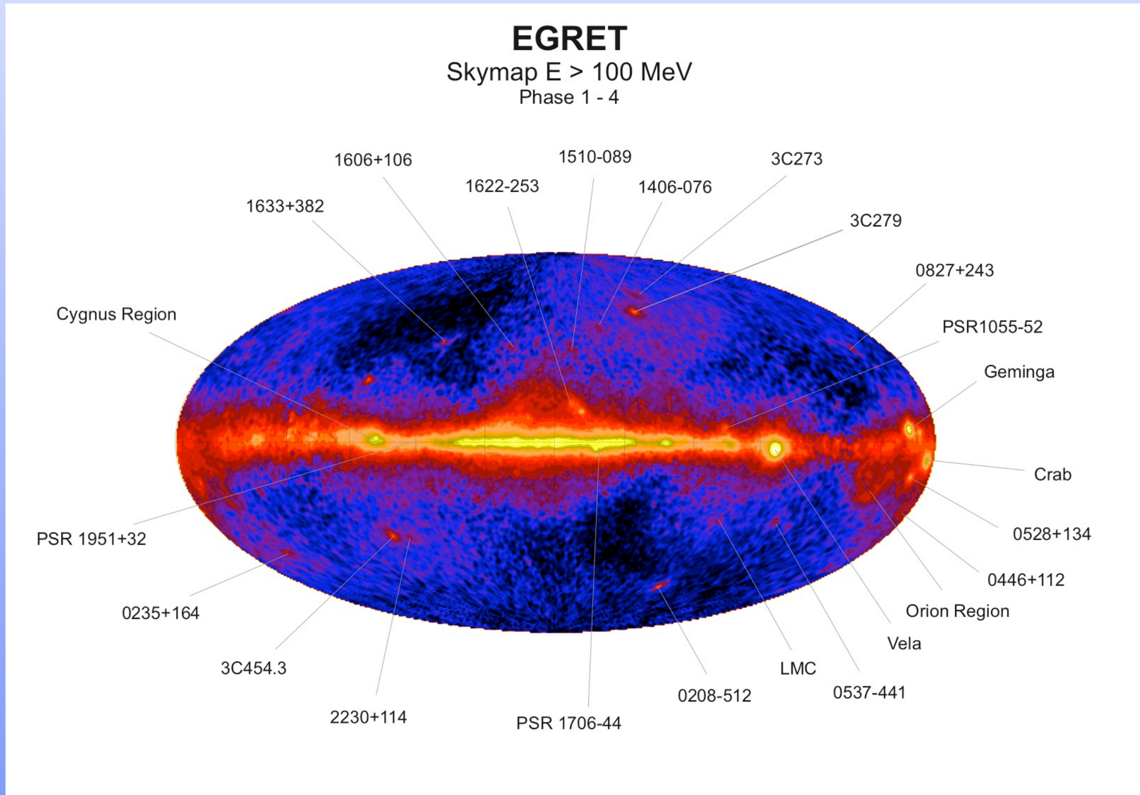




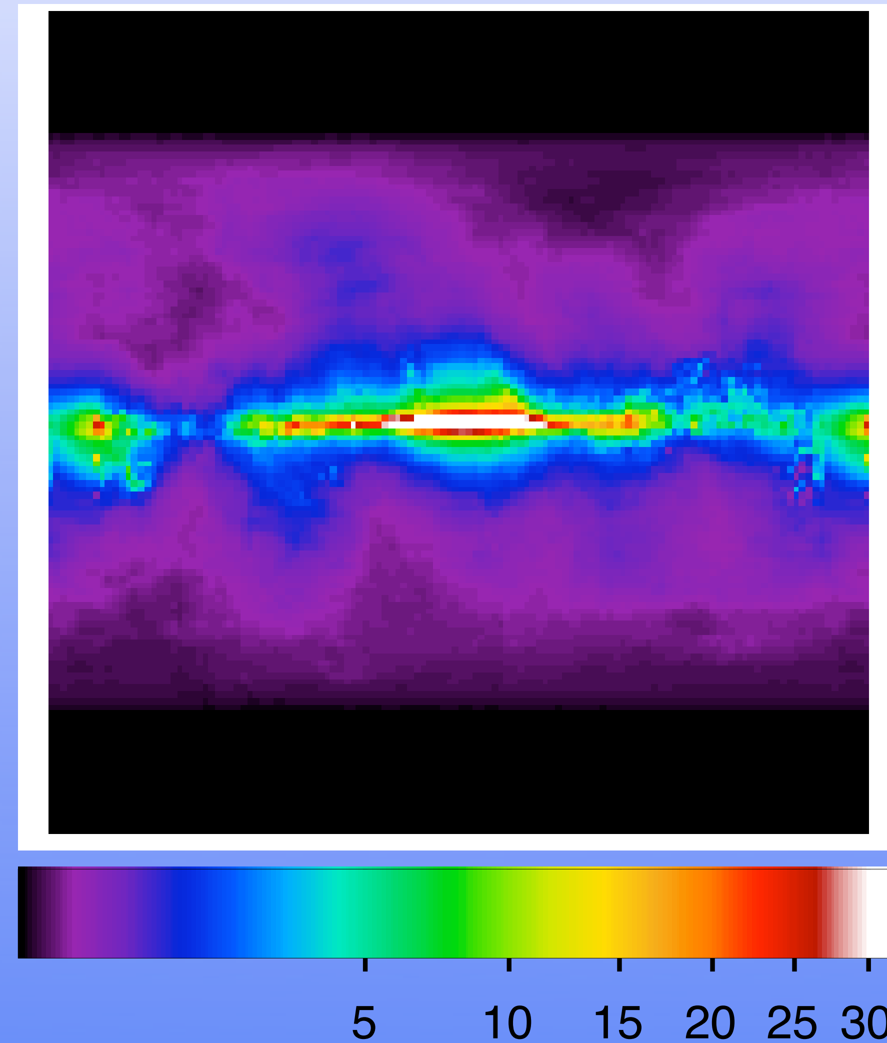


What's the Problem ?

True Sky:

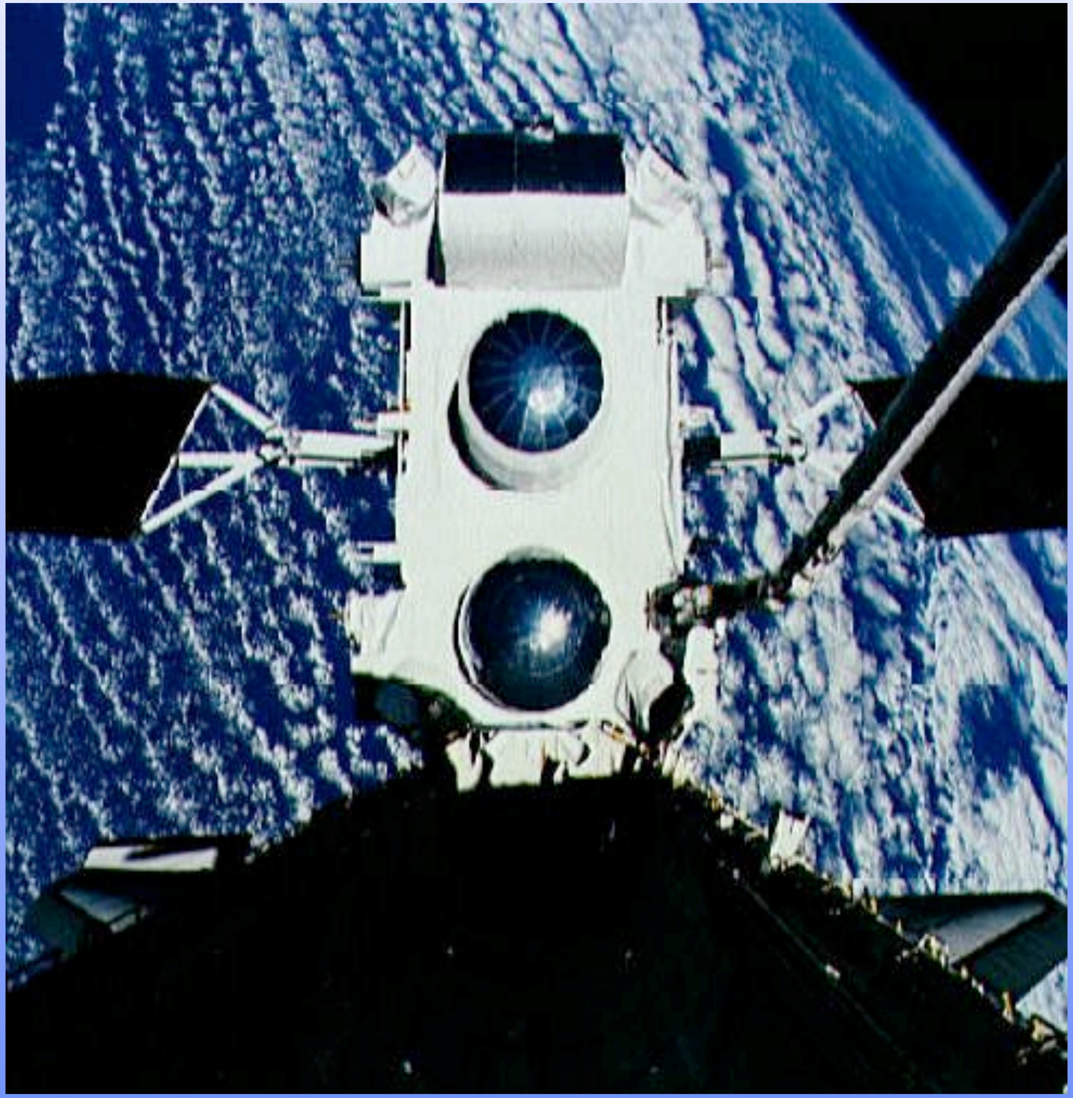


Model Sky:



Sources: Point; Compact or Broad Diffuse (SNR, Clouds); Other (Dark Matter??)

Real Instrument:

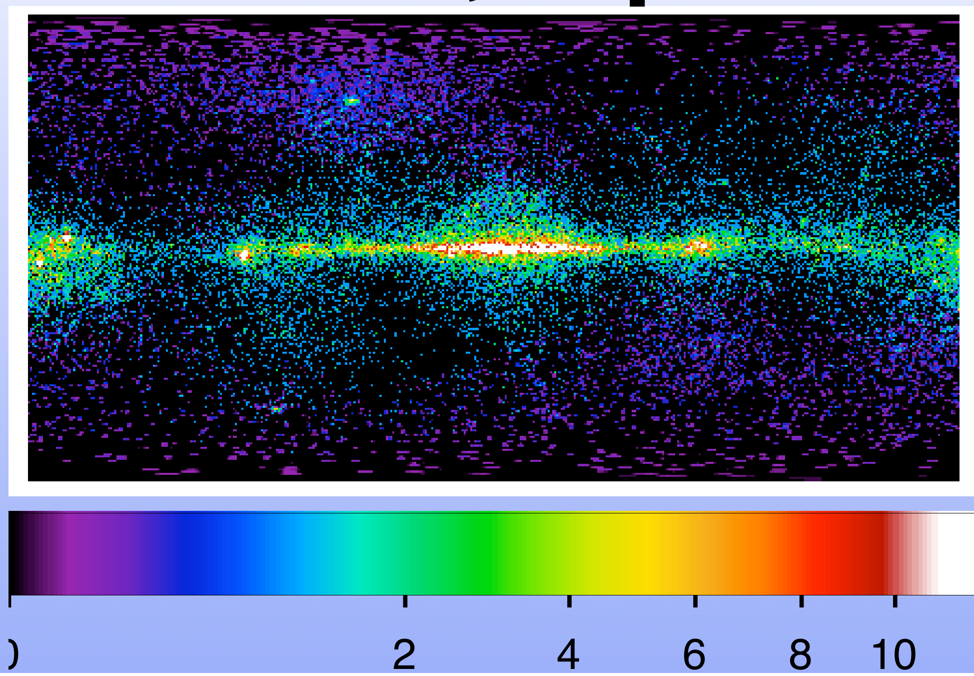


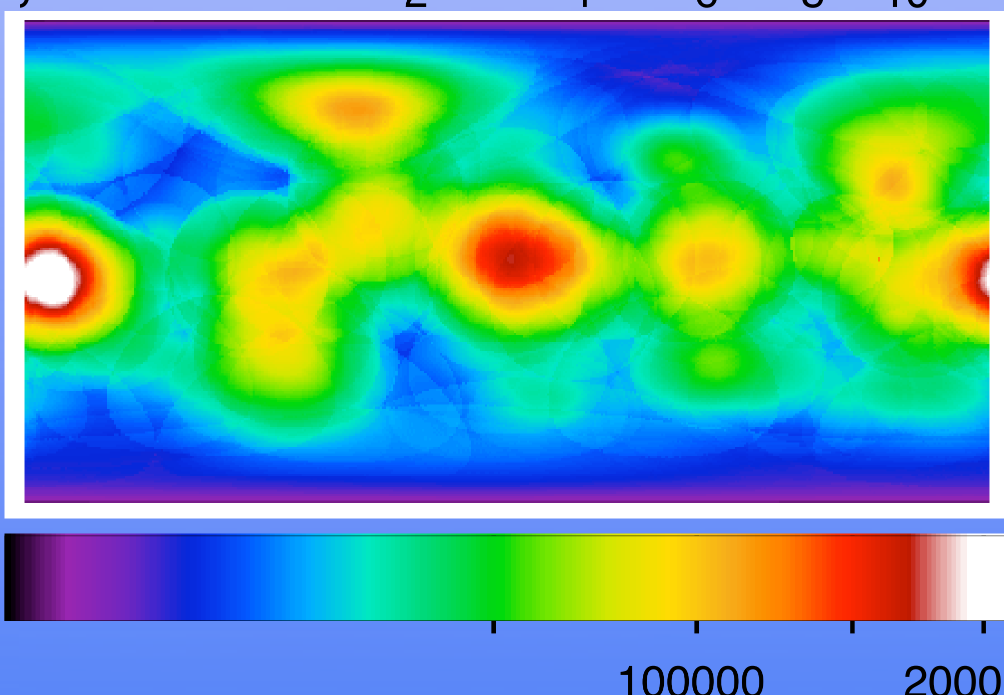
Model Instrument:

Instruments: Exposure; Effective Area (e.g. ARF) ; Spatial Response (e.g. PSF); Energy Response (e.g. RMF) ... (All with Calibration Uncertainties)

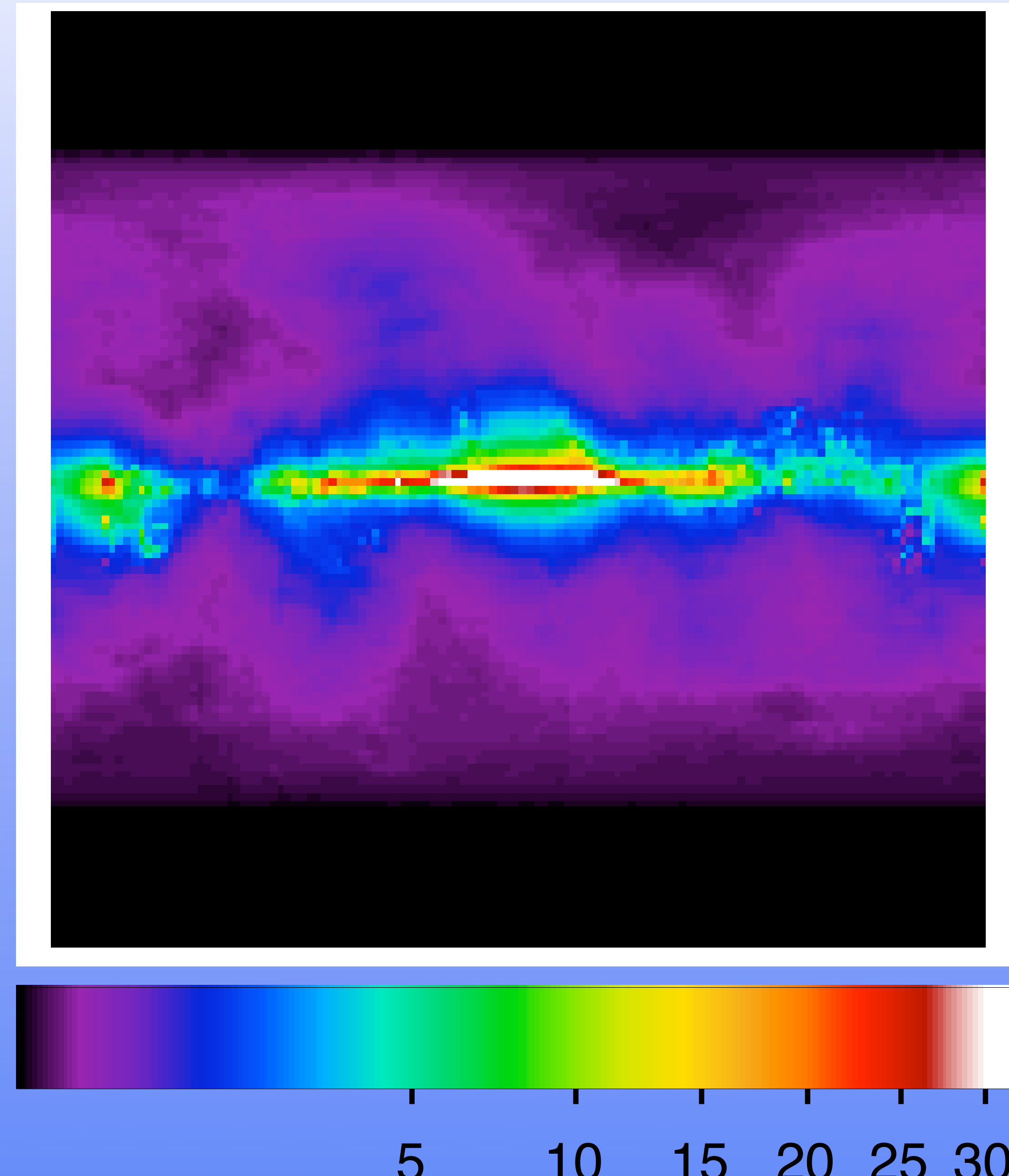
* **Data:** *Poisson, Other complications* **:**

Real Data, Exposure:





Model Expected Rate:



CGRO/EGRET Data from HEASARC;
Model from GALPROP collaboration

What's the Problem? Looks Easy!

1. *MODEL* the SKY
2. *MODEL* the INSTRUMENT RESPONSE
3. *MODEL* any BACKGROUND
4. *PREDICT* the EXPECTED RATE
5. *COMPARE* EXPECTED RATE to DATA:
   - Search through parameter-space
   - Using Likelihood framework
6. PROBLEMS:
   - "Unknown" (i.e. no physics model) components;
   - What's a "Good-Enough-Fit" (e.g. Poisson)?
   - Correlations among (say) neighboring pixels
   - Significance of unknown (maybe irregular) features?
   - Searching larger and larger parameter spaces

Our Solution - Plain but Tedious!

1. *We CRACKED the GOODNESS-OF-FIT, etc. (for Poisson, but method can work for any distribution).*
2. *We MODEL a MISMATCH (between data and expected rate; analogous to a residual) with a FLEXIBLE MODEL (like Multi-scale)*
3. *We FIT enhanced model (physics-model+flexible-model)*
   - *3.1 Using MCMC to explore the parmeter space;*
   - *3.2 Using MEAN as the "best estimate"*
   - *3.3 (Allows for calibration uncertainty - see H. Lee poster 41.15)*

Our Solution - Plain but Tedious, 2:

4. *We QUANTIFY the MISMATCH and get SIGNIFICANCE of UNKNOWN FEATURES by:*

4.1 ANALYZE the INTERESTING (usually, real) DATA

4.2 SIMULATING samples from the NULL (physics-model)

4.3 ANALYZE SIMULATIONS from NULL: I.E. in exactly the same way as for the INTERESTING DATA

4.4 NOW one has many MCMC SAMPLES of each.
Use a few key SUMMARIES like:
TOTAL COUNTS in flexible Multi-Scale component;
Norm, or SCALE FACTOR, of physics-based model

NOTE: Because of intrinsic correlations among pixels inherent in most multi-scale or flexible models, pixel-by-pixel significances won't work in a simple way.

Our Solution - Plain but Tedious, 3:

5. *COMPARE* EXPECTED RATE to DATA:

Search parameter-space; Using Likelihood framework

5.1 *We COMPARE the distributions of the SUMMARIES*

(e.g. Total MS Counts; scale factor)

for NULL and INTERESTING Data.

What is the probability of 'overlap' ?

THIS IS OUR GOODNESS-OF-FIT TEST.

5.2 We RANK these SUMMARY STATISTICS.

We take SLICES through the tails to get

(say) the +/-5% limits on flux and position.

THIS IS OUR FEATURE SIGNIFICANCE TEST.

5.3 PROBLEM: Currently takes a lot of time to do this nicely

(On the order of a day for a 128x128 sky image, on G4).

ASIDE: MULTI-SCALE FOR POISSON- called "Multiplicative Multiscale Innovation Models"

MMI Slides courtesy of
R.Willett, SAMSI 2006

Timmermann & Nowak, 1999
Kolaczyk, 1999

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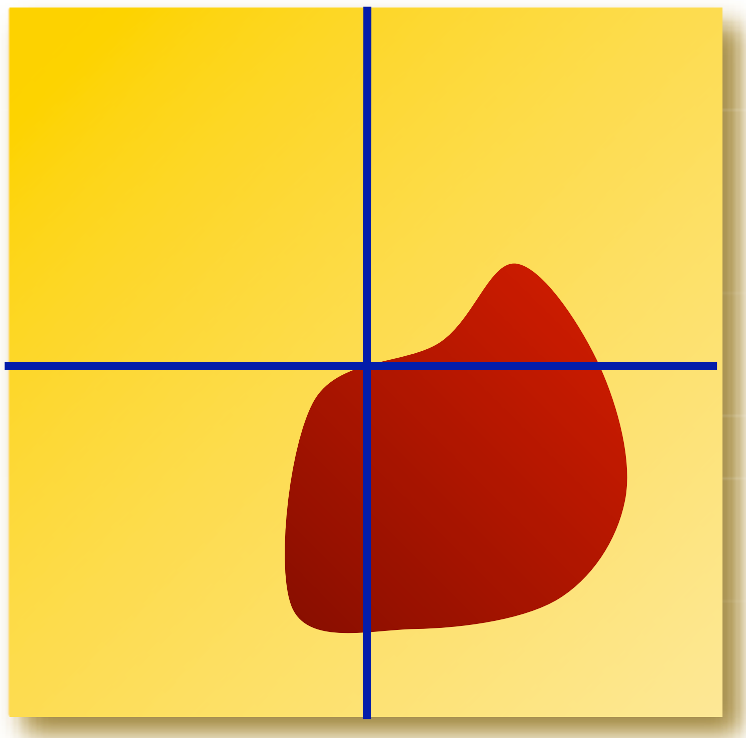

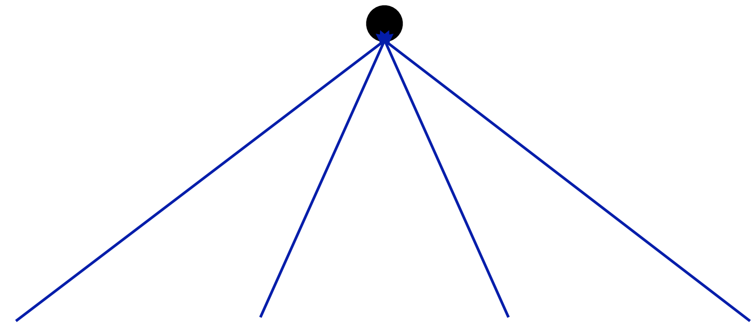

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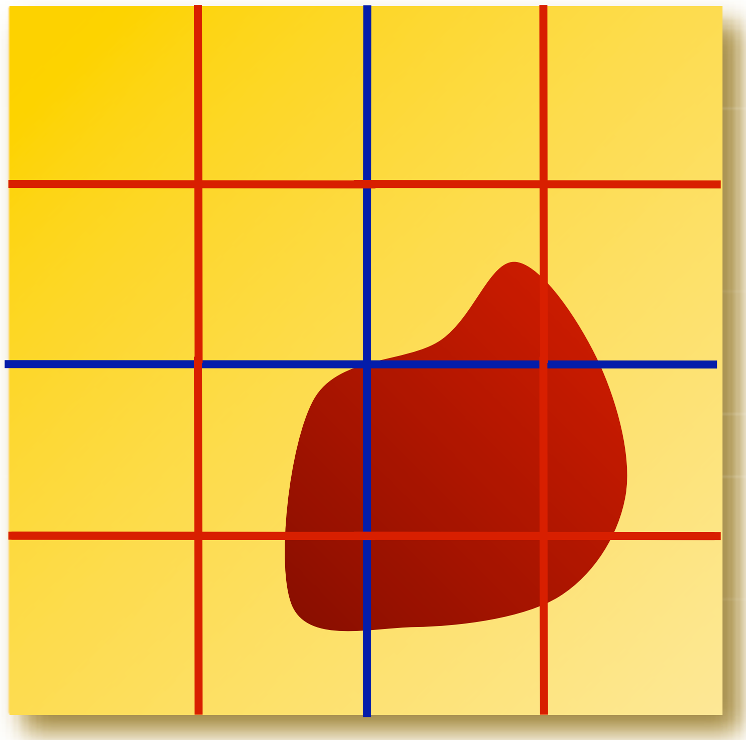

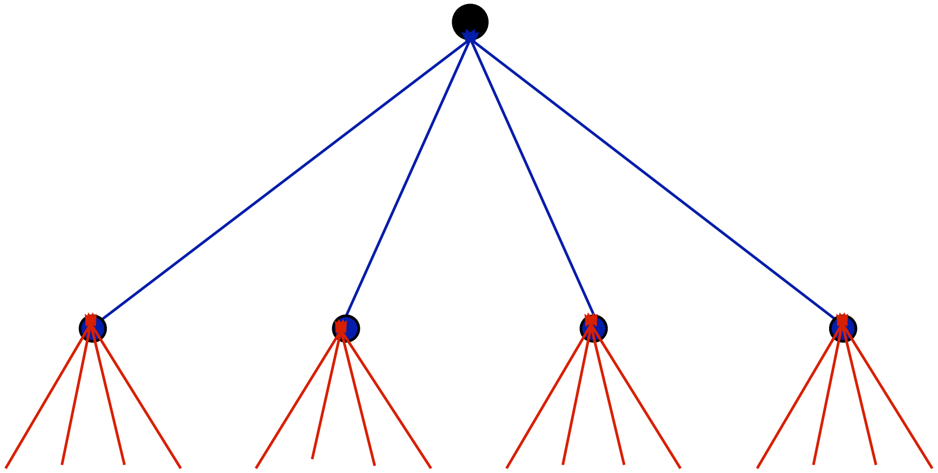

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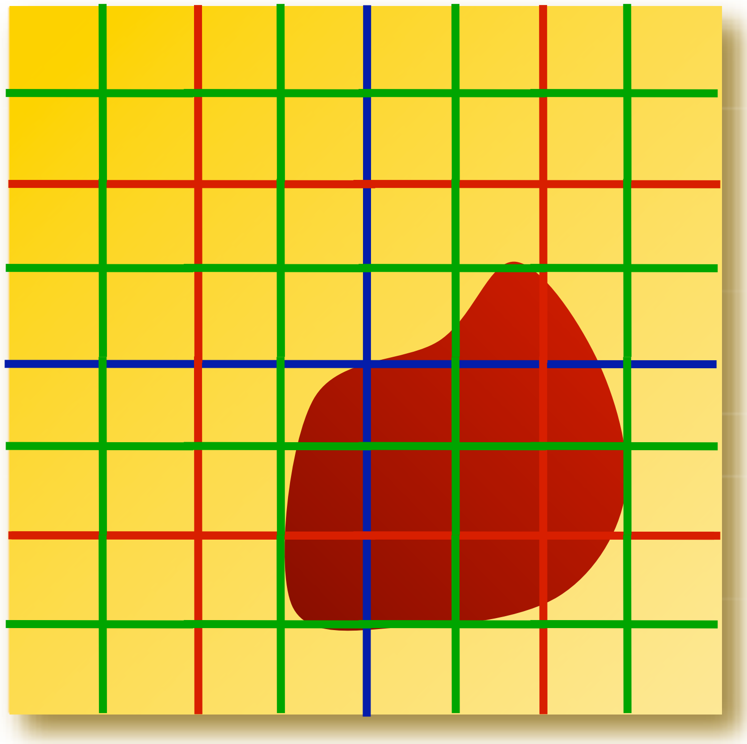

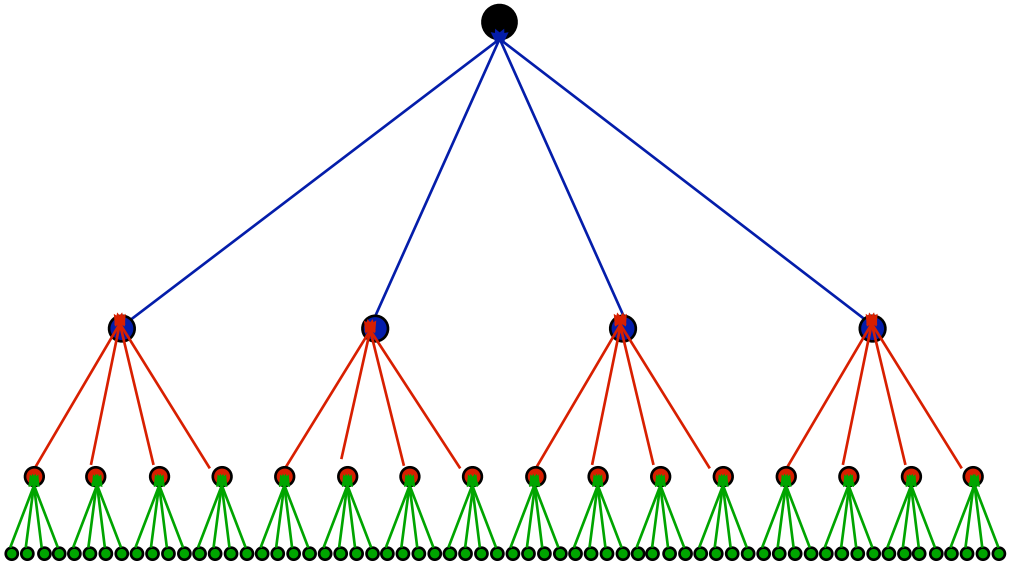

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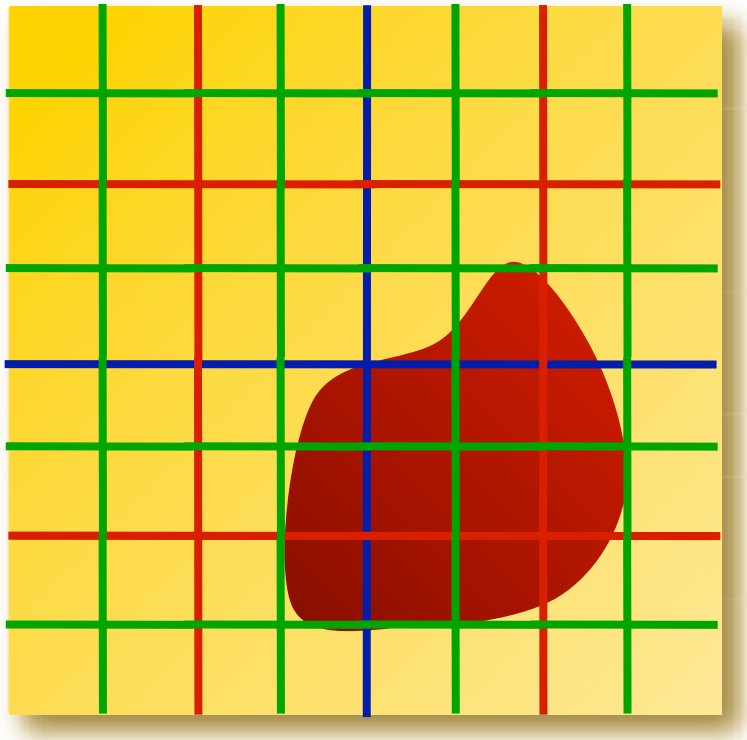
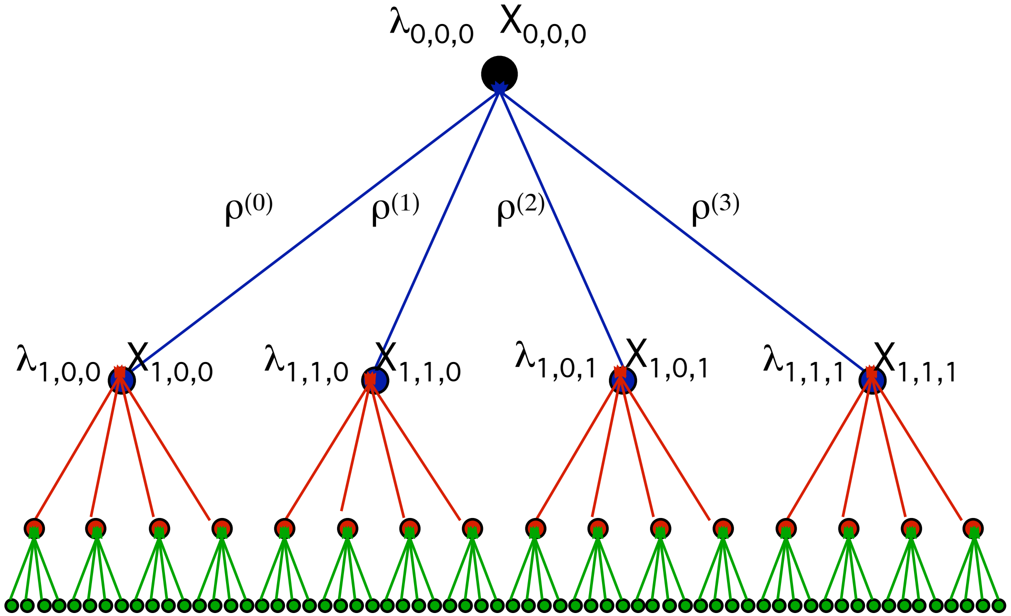




- Recursively subdivide image into squares
- Let $\{\rho\}$ denote the ratio between child and parent intensities
- Knowing $\{\rho\} \Leftrightarrow$ Knowing $\{\lambda\}$
- Estimate $\{\rho\}$ from empirical estimates based on counts in each partition square

MMI Slides courtesy of R.Willett, SAMSI 2006

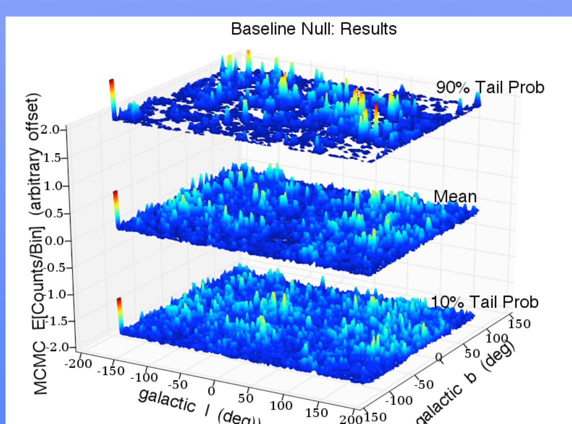
Timmermann & Nowak, 1999
Kolaczyk, 1999

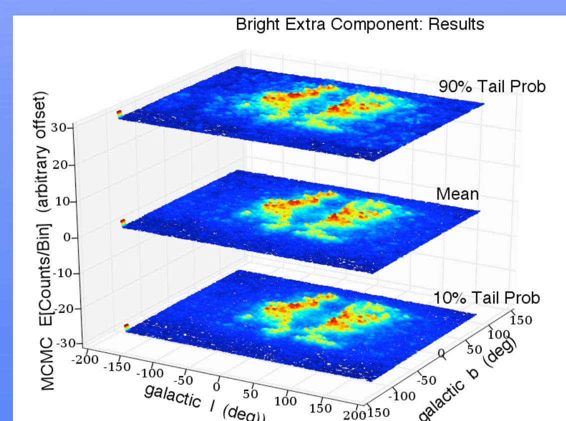
REMINDER OF TRICKS: (Using our MMI, Enhanced EMC2)

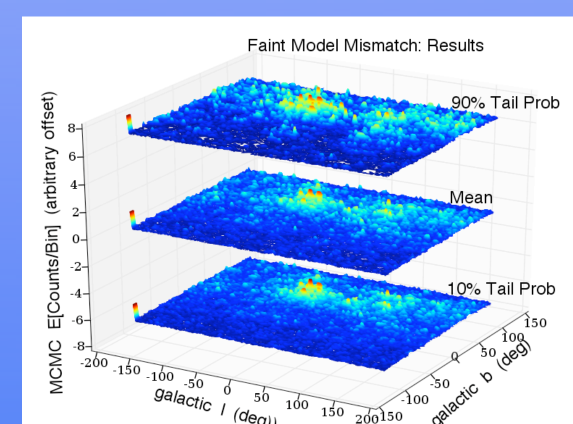
* Match Models to Physics: Multiply, Add; SO
  Quantify Difference: Multiscale + Scale-Factor*(Null)

* Get Uncertainties by Embedding in MCMC; SO
  Many Samples of Images

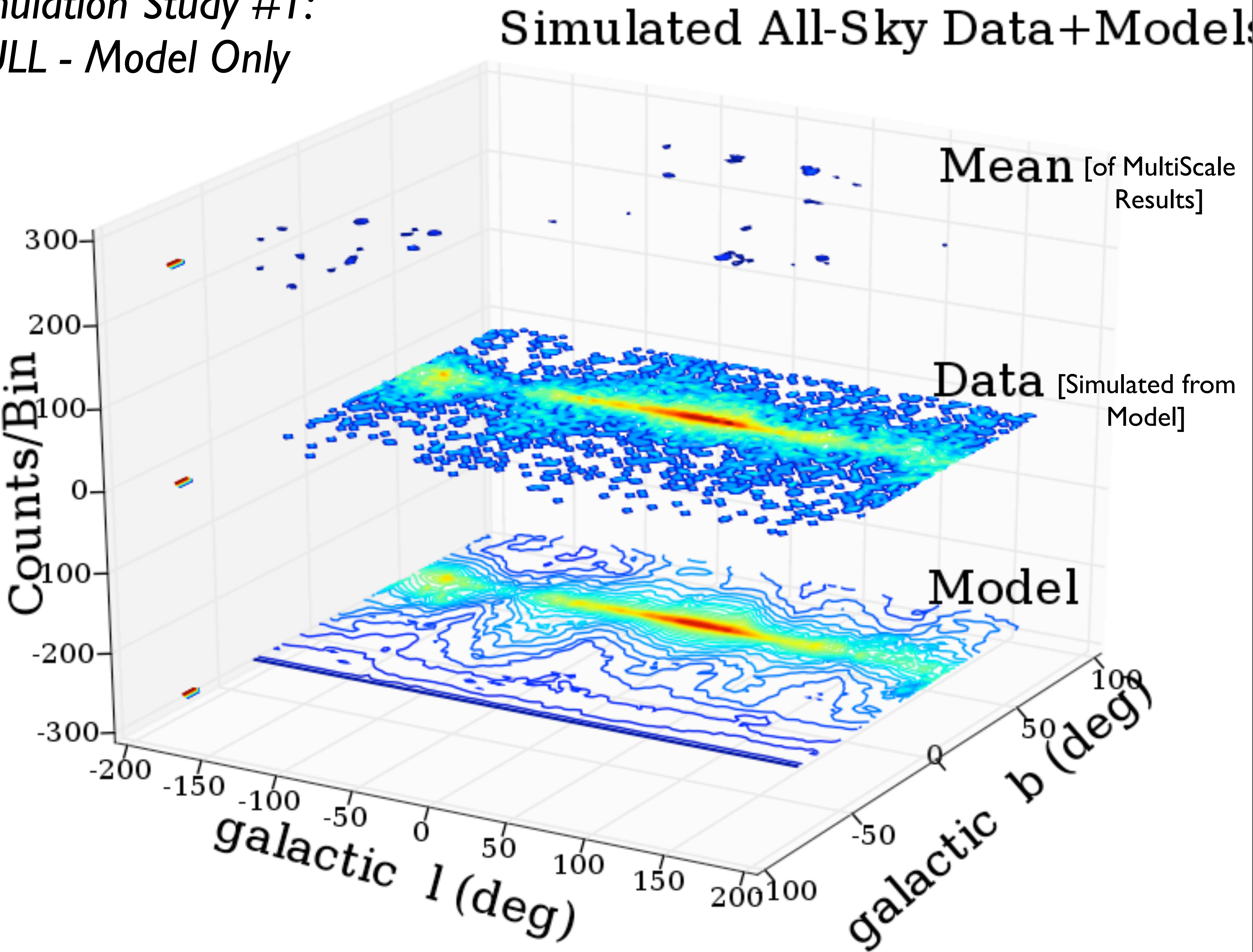
* Compare to Null Simulations: Low-Dim (2+) Summary



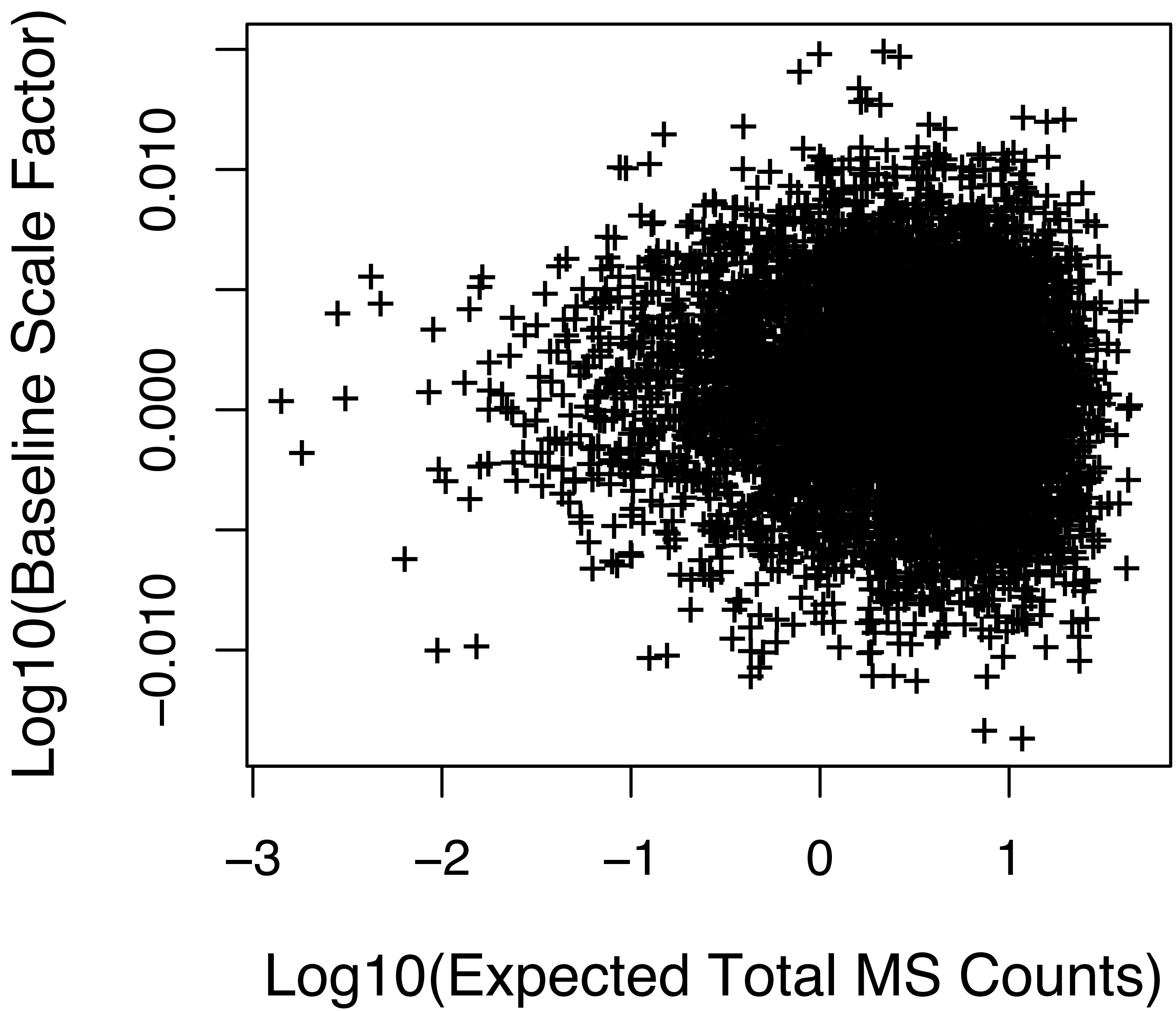


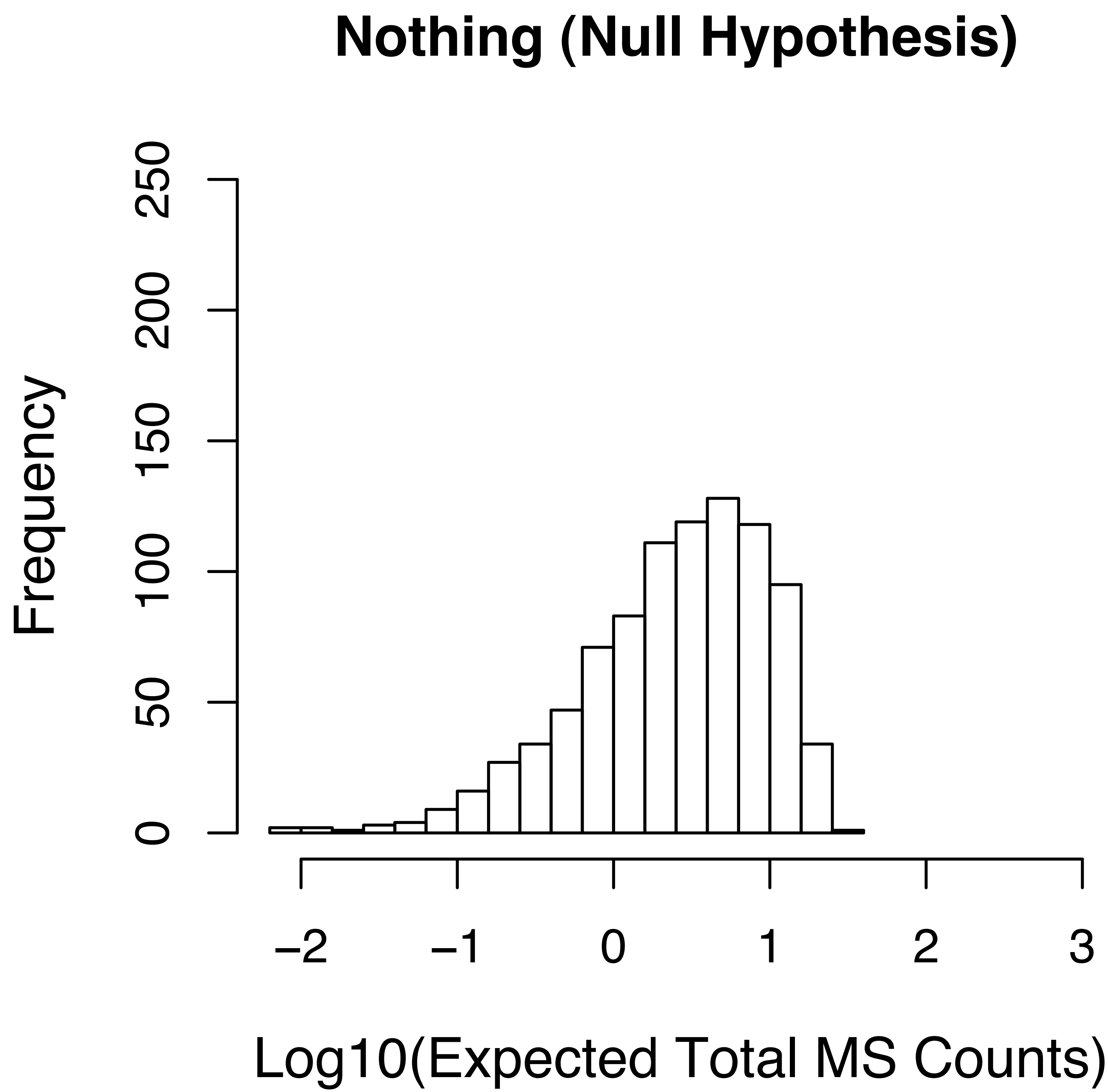


Simulation Study #1:
NULL - Model Only

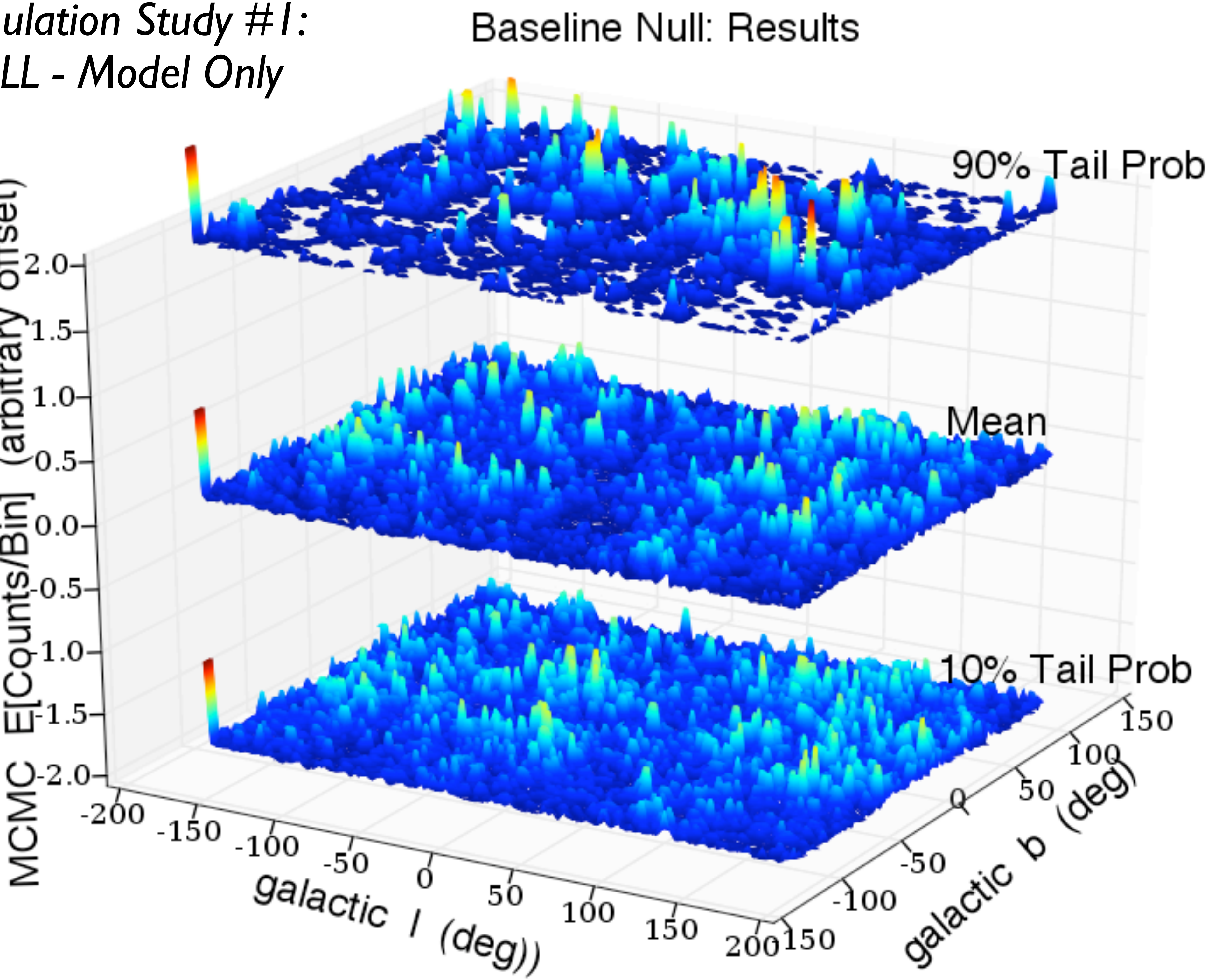


Nothing (Null Hypothesis

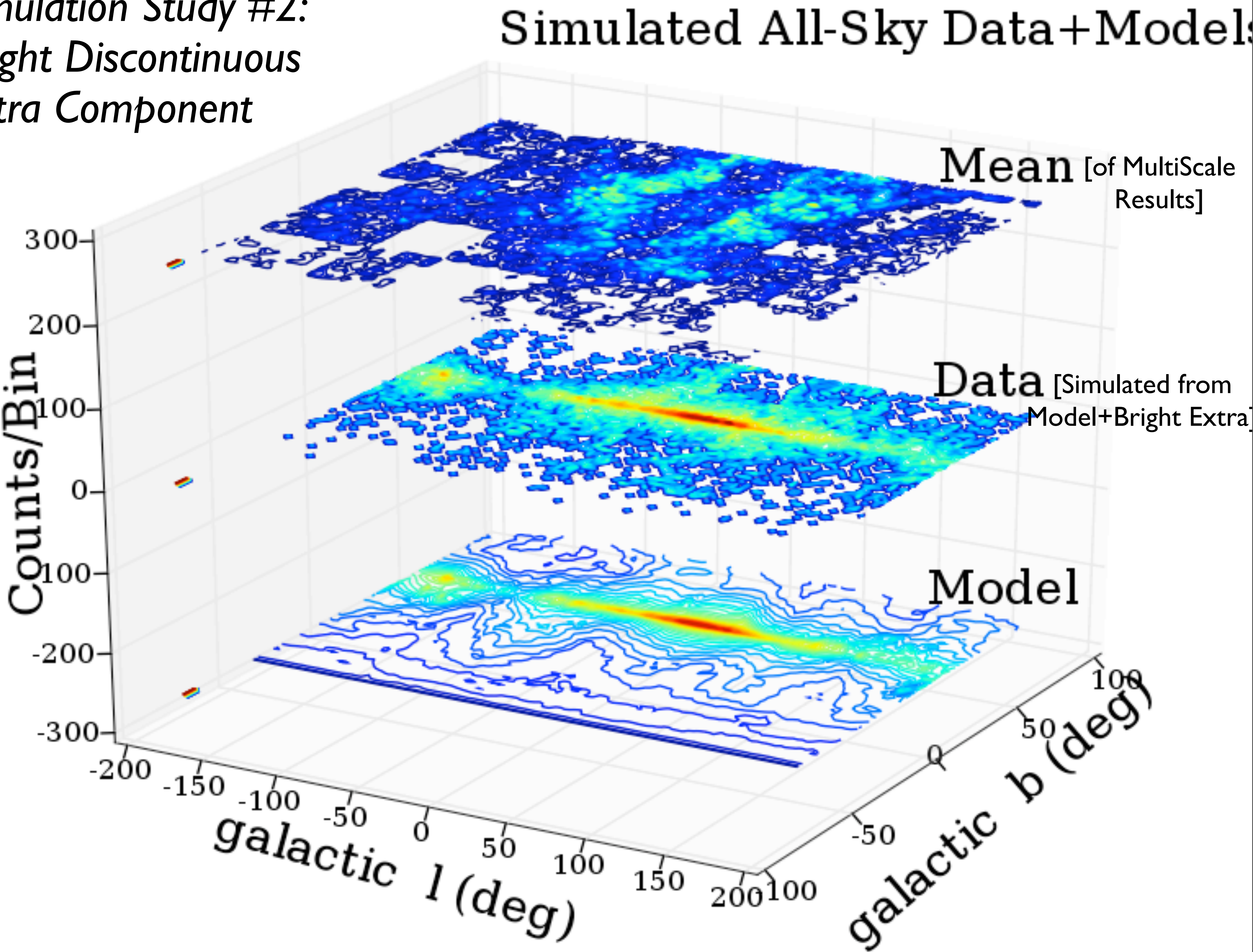


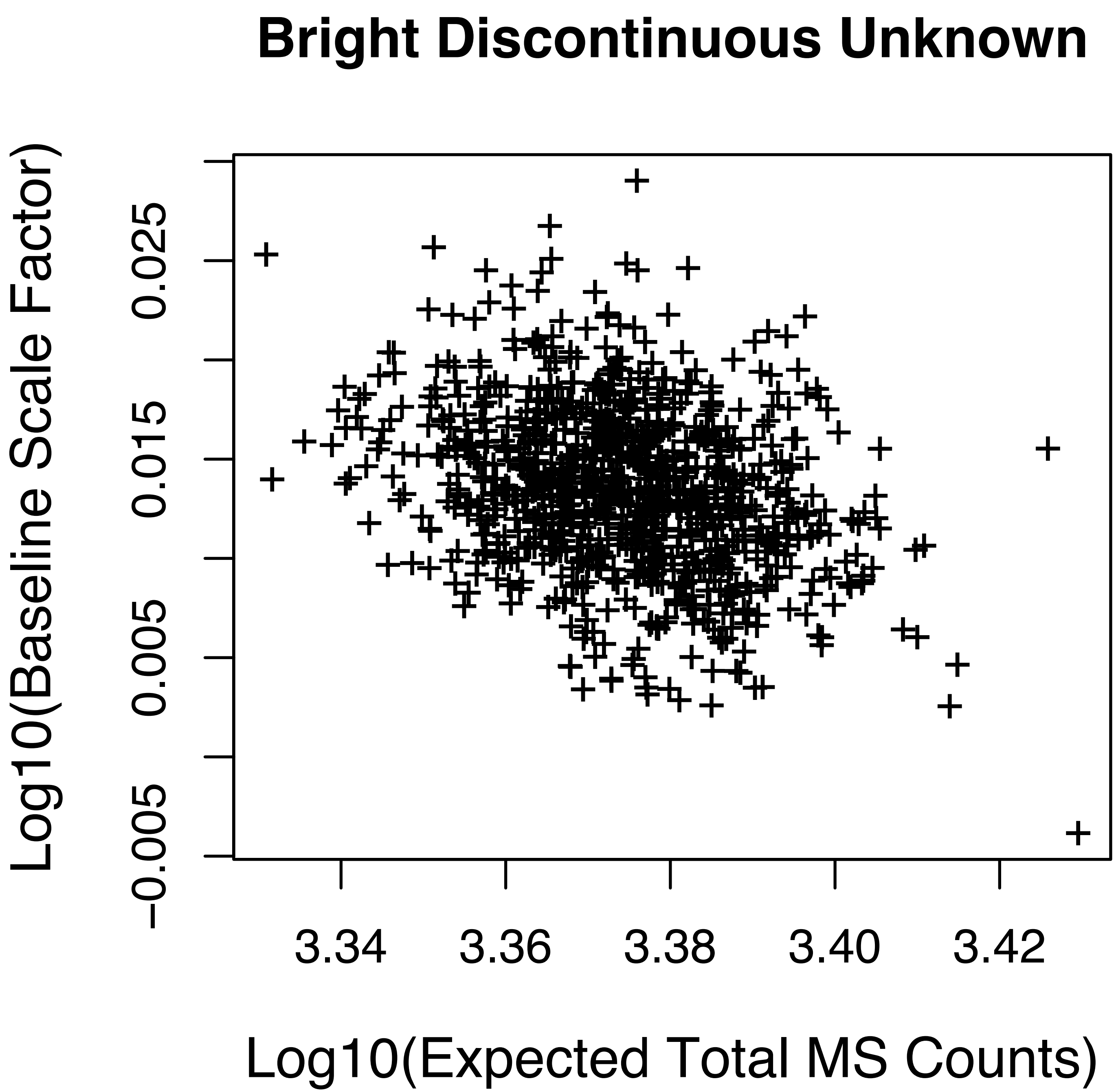

Nothing (Null Hypothesis)
Frequency
0
50
100
150
200
250
−2
−1
0
1
2
3
Log10(Expected Total MS Counts)

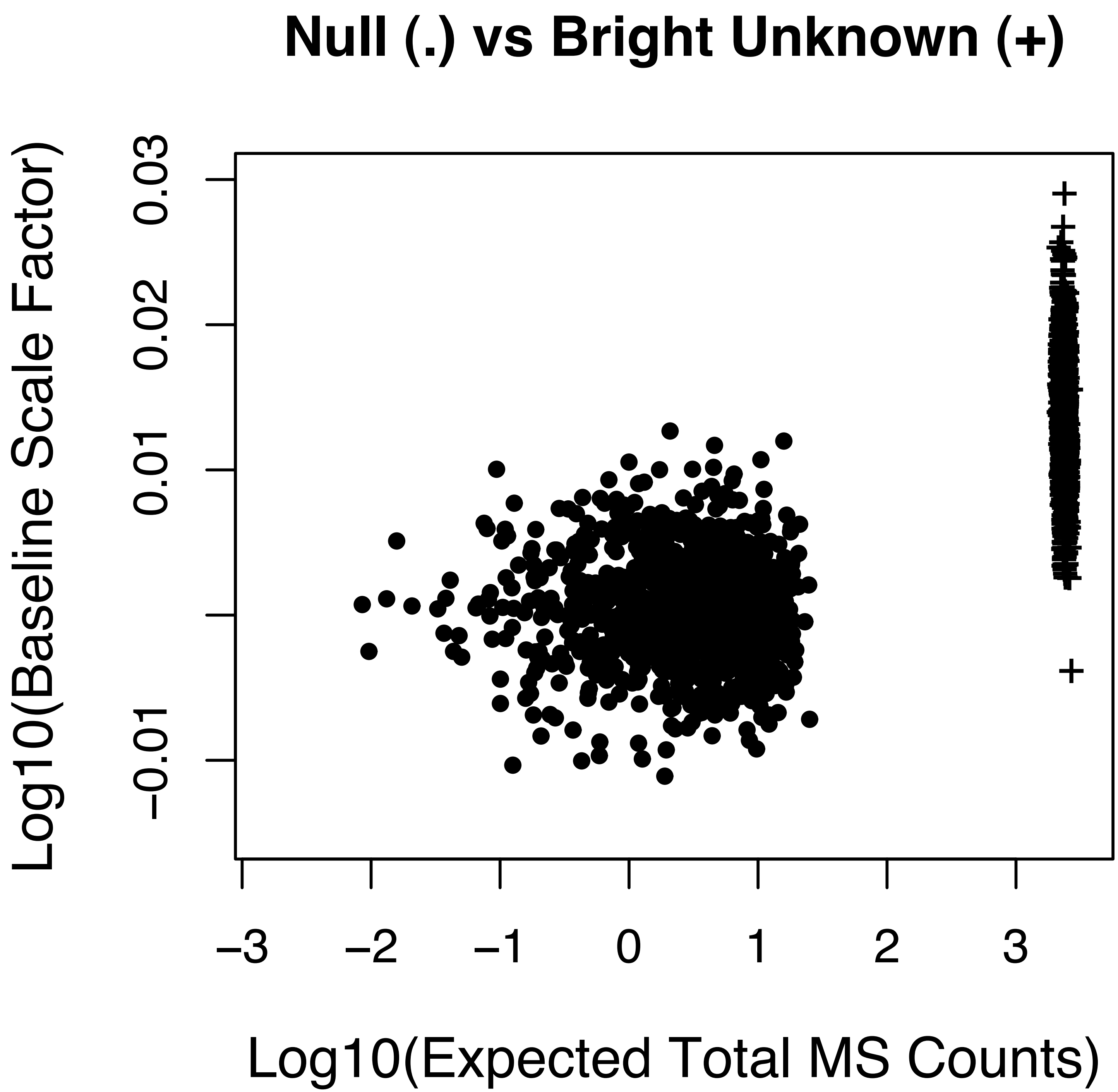
Simulation Study #1:
NULL - Model Only



Simulation Study #2: Bright Discontinuous Extra Component

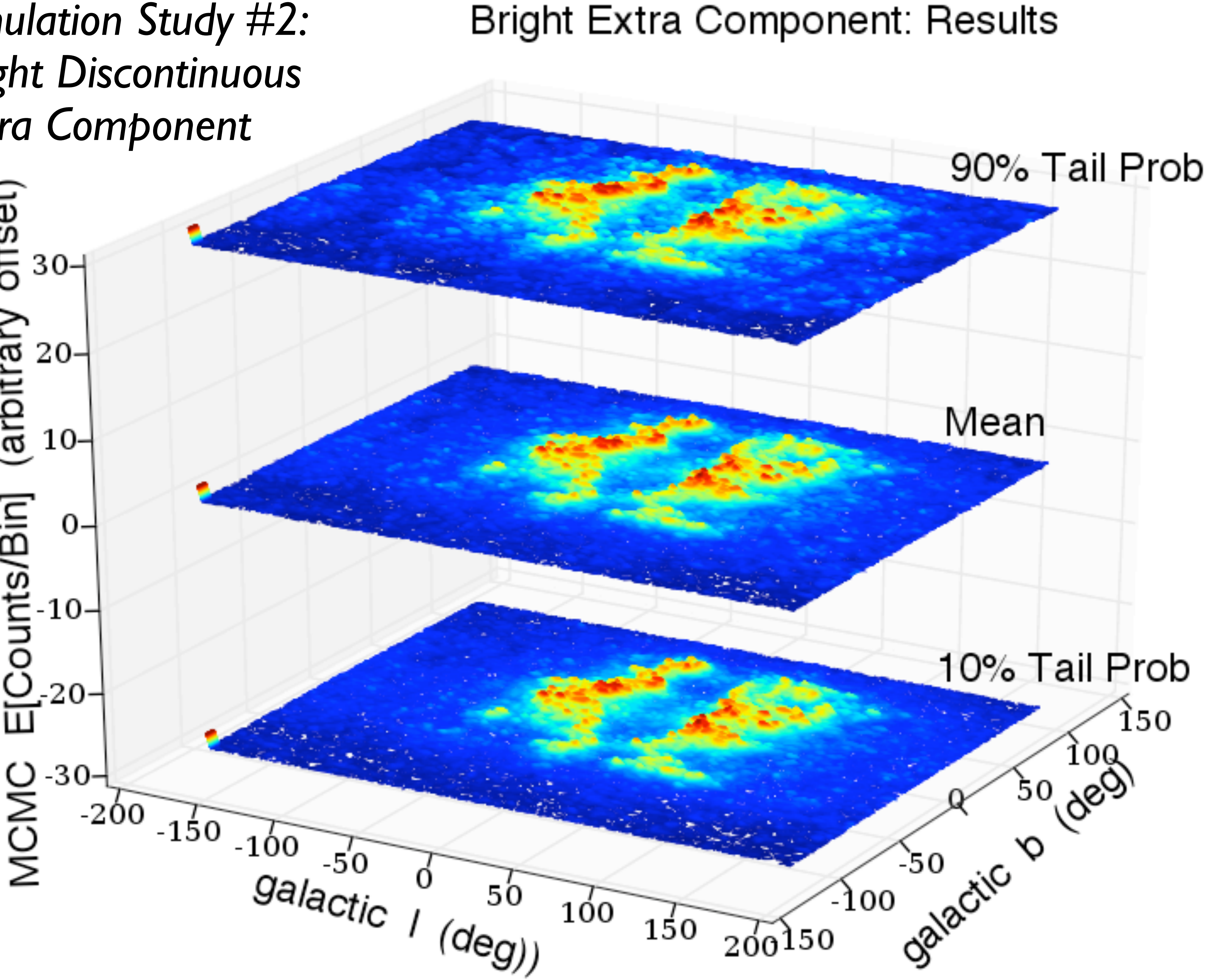



Bright Discontinuous Unknown
Log10(Baseline Scale Factor)
-0.005
0.005
0.015
0.025
3.34
3.36
3.38
3.40
3.42
Log10(Expected Total MS Counts)

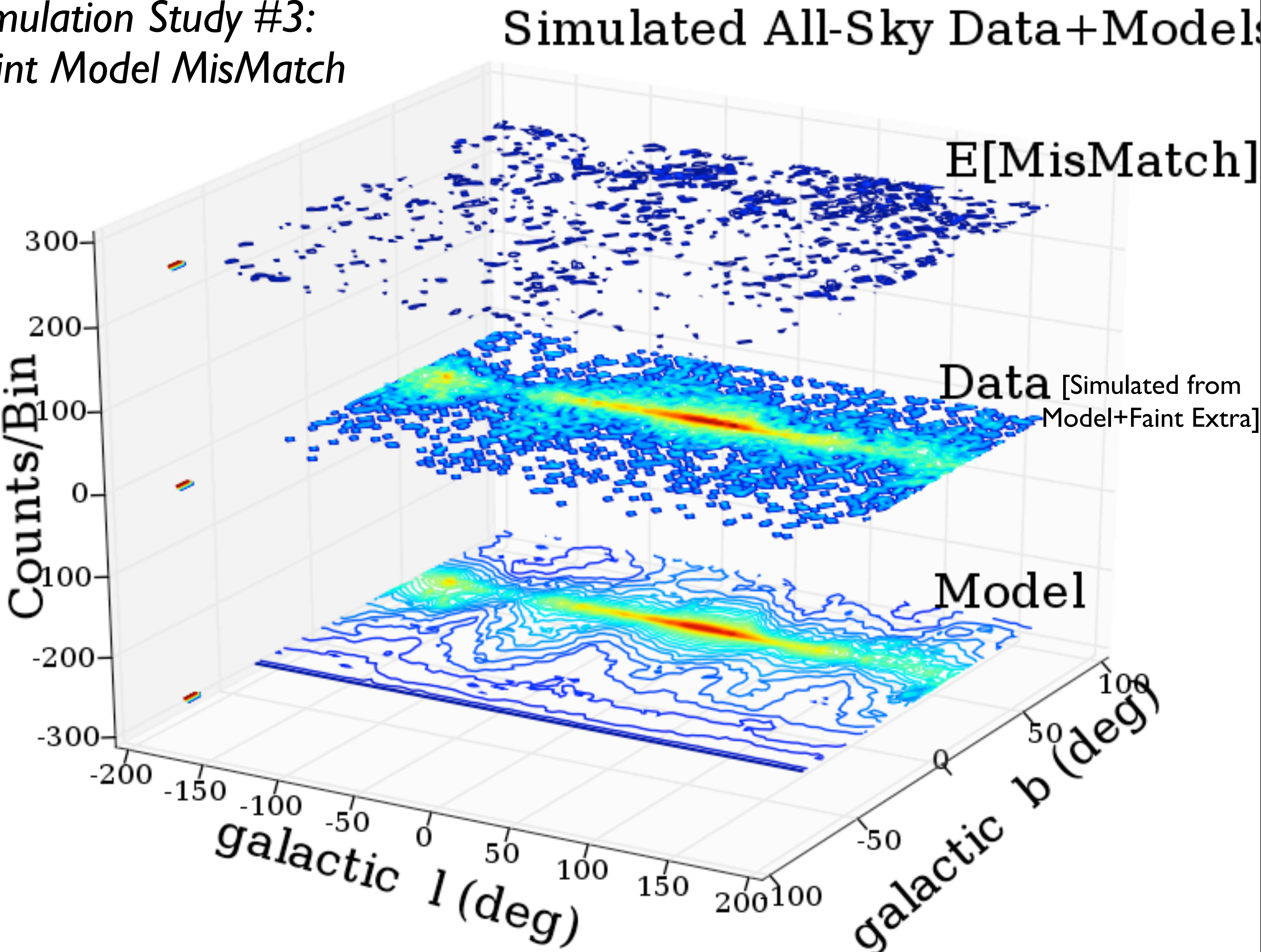


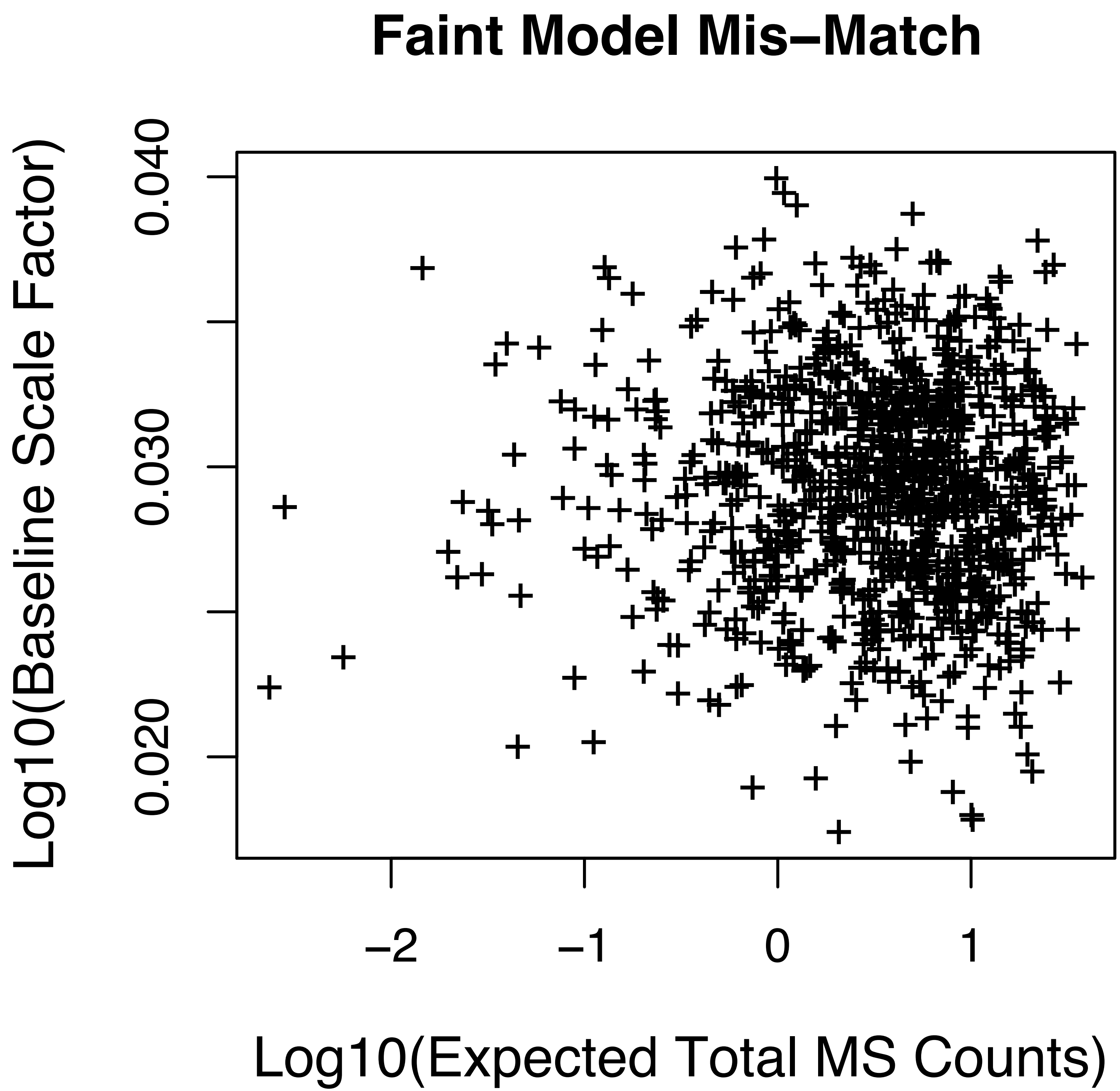
Null (.) vs Bright Unknown (+)
Log10(Baseline Scale Factor)
0.03
0.02
0.01
−0.01
−3
−2
−1
0
1
2
3
Log10(Expected Total MS Counts)

Simulation Study #2: Bright Discontinuous Extra Component

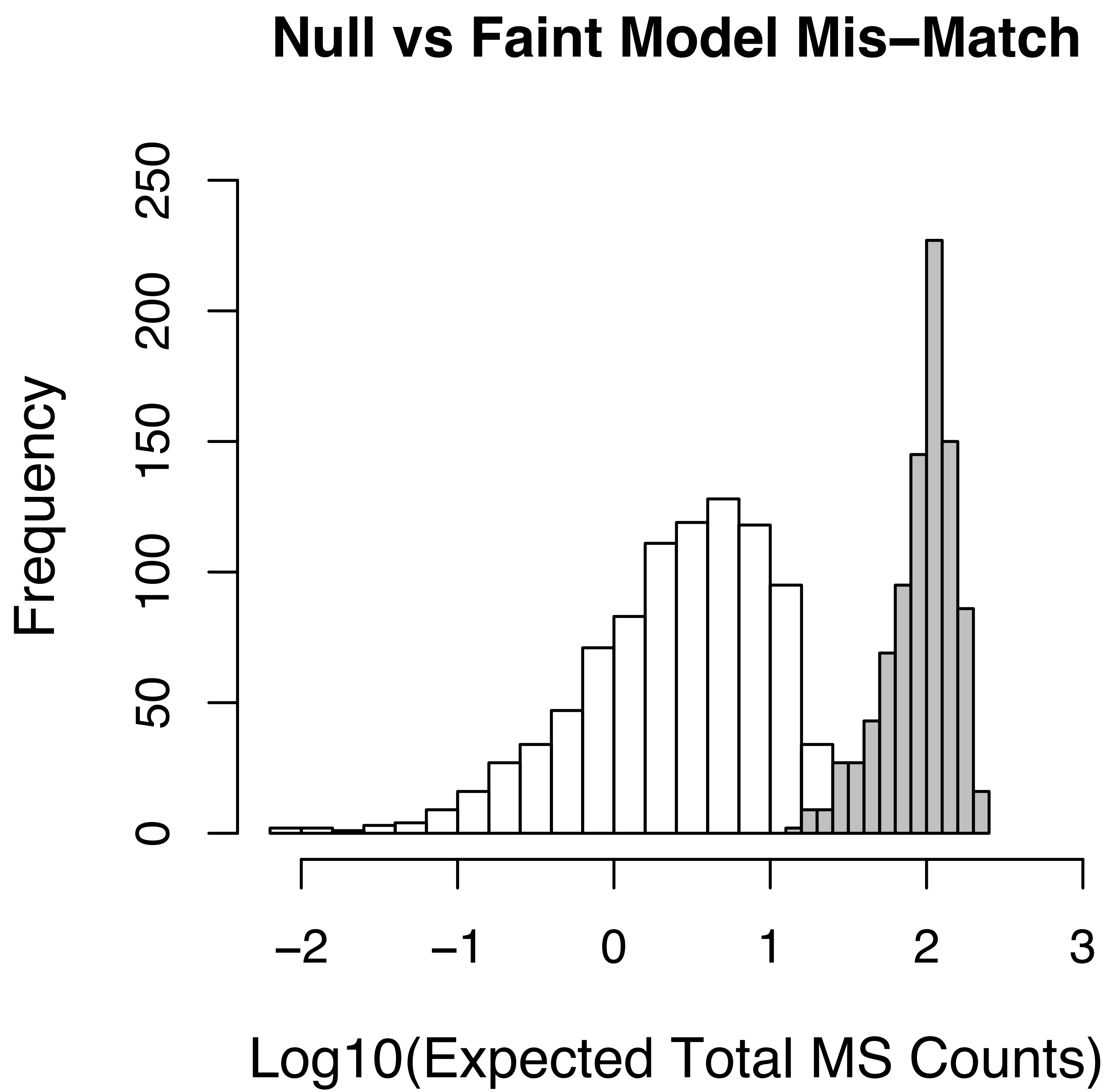


Simulation Study #3:
Faint Model MisMatch



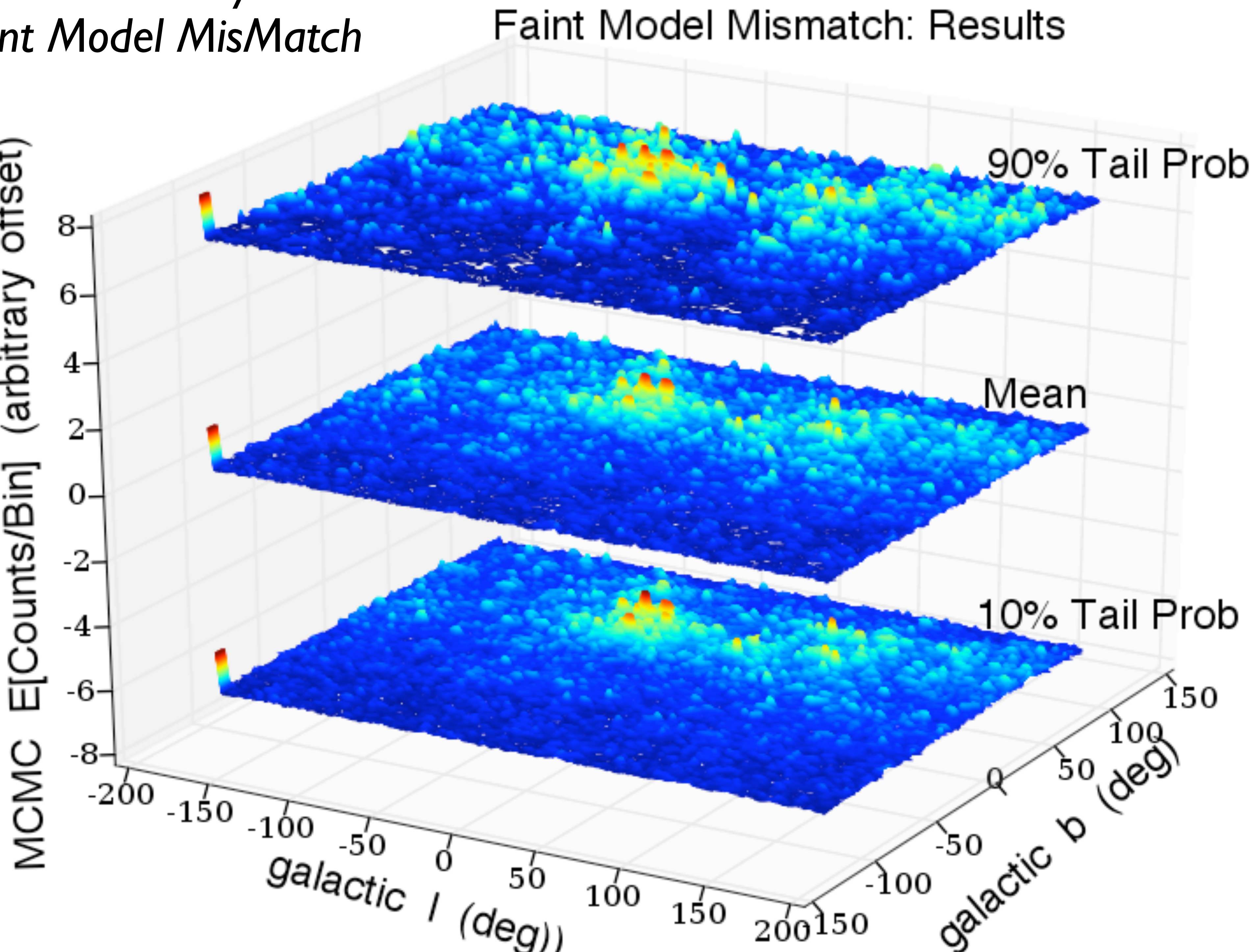


Faint Model Mis–Match
Log10(Baseline Scale Factor)
0.040
0.030
0.020
−2
−1
0
1
Log10(Expected Total MS Counts)



Null vs Faint Model Mis–Match
Frequency
0
50
100
150
200
250
−2
−1
0
1
2
3
Log10(Expected Total MS Counts)

Simulation Study #3:
Faint Model MisMatch



Special Thanks To:

NSF and SAMSI 2006 Special Topics in AstroStatistics

NASA and AISR Python Tools for AstroStatistics

CHASC: http://hea-www.harvard.edu/AstroStat/

Quick Reference: See *Statistical Challenges in Modern Astronomy IV, Proceedings, Connors and van Dyk, "How To Win With Non-Gaussian Data: Poisson Goodness-of-Fit"*.