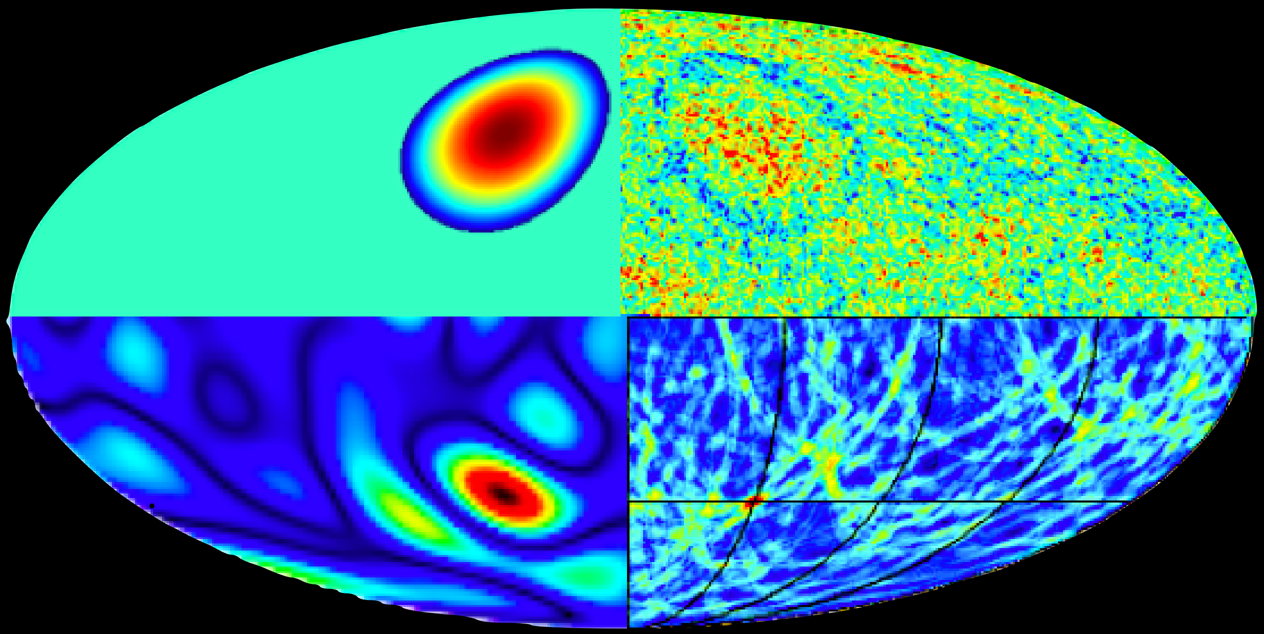
First observational tests of eternal inflation



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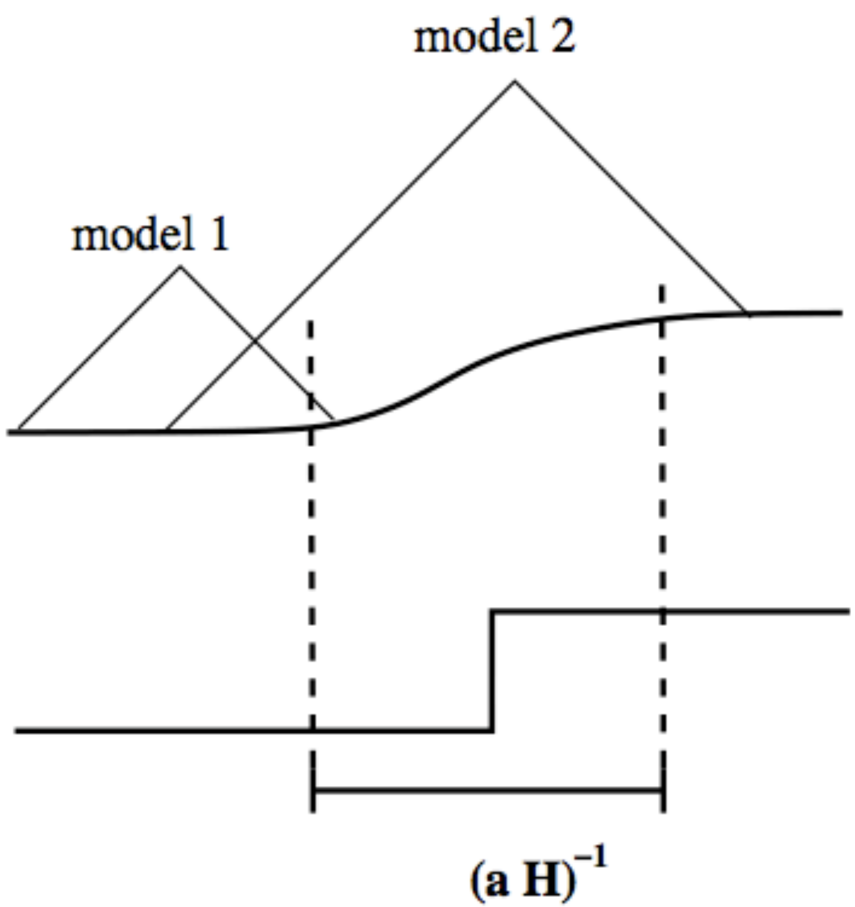
arxiv:1012.1995, 1012.3667

With: Stephen Feeney (UCL), Matt Johnson (Perimeter Institute), Daniel Mortlock (Imperial College London)

Bubble morphologies

- Analysis will target following generic features expected in a collision (from analytic arguments backed up by simulations of Chang, Kleban & Levi.)
  - Azimuthal symmetry
  - Causal boundary (?)
  - Long wavelength modulation inside the disk



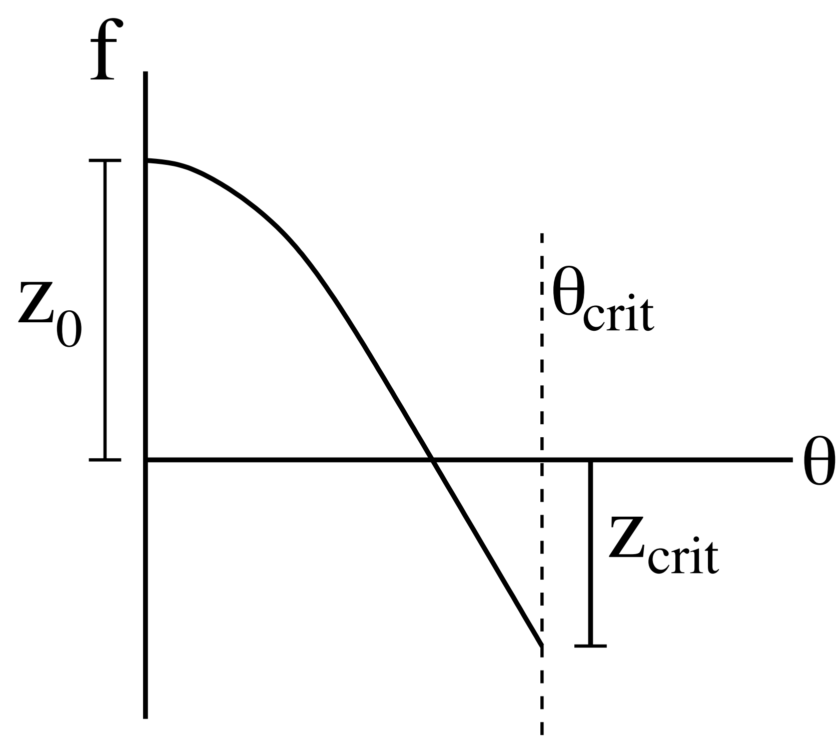
How a violent disturbance of the field at the collision is stretched and smoothed by inflation.

Bubble template

- Assume that the inflationary fluctuations are modulated by the collision (Chang et al 2009):

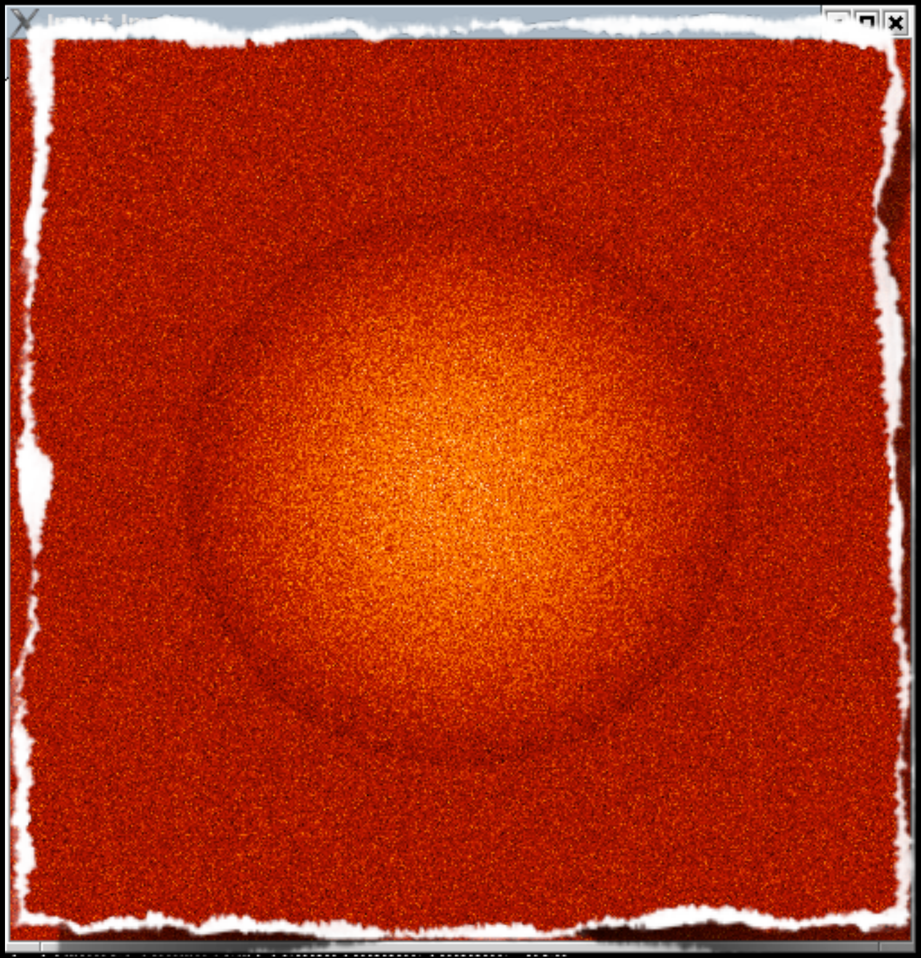
$$\frac{\delta T(\hat{\mathbf{n}})}{T_0} = (1 + f(\hat{\mathbf{n}}))(1 + \delta(\hat{\mathbf{n}})) - 1,$$

- Since the collision is a pre-inflationary relic, a reasonable template is: $f(\hat{n}) = (c_0 + c_1 \cos\theta + \mathcal{O}(\cos^2\theta))\Theta(\theta_{\rm crit} - \theta)$



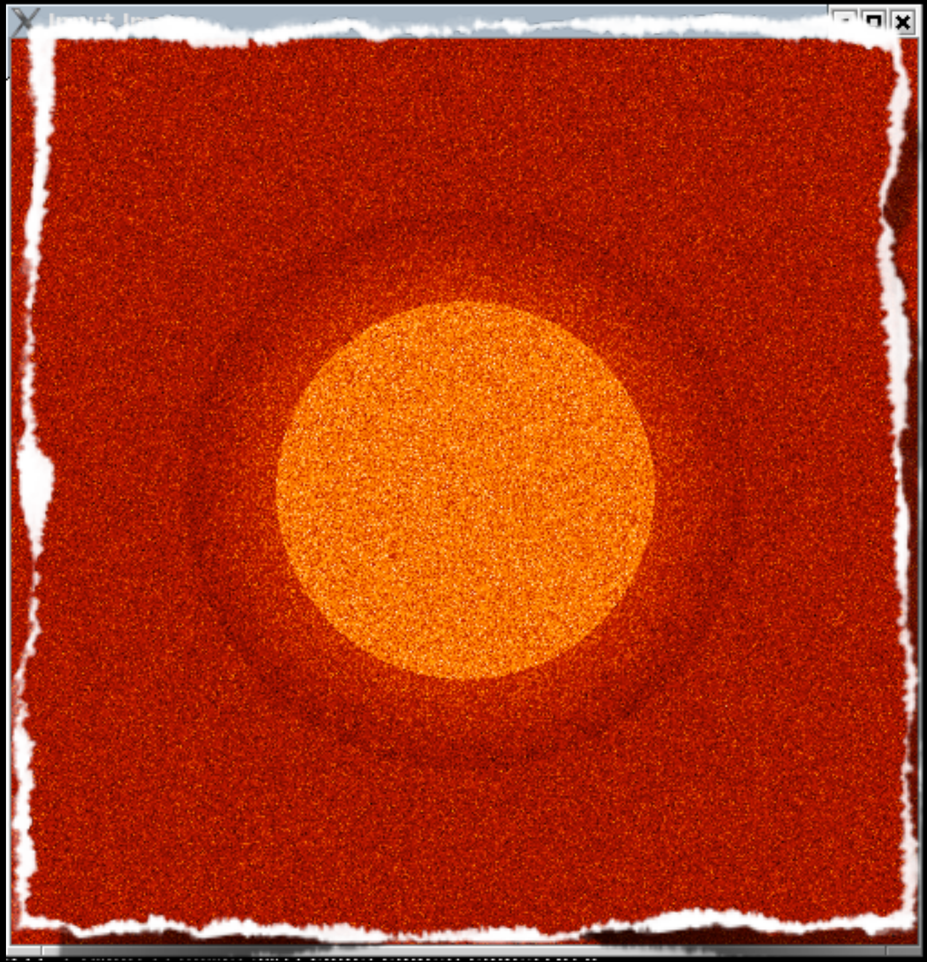
Bubble template

Model 1



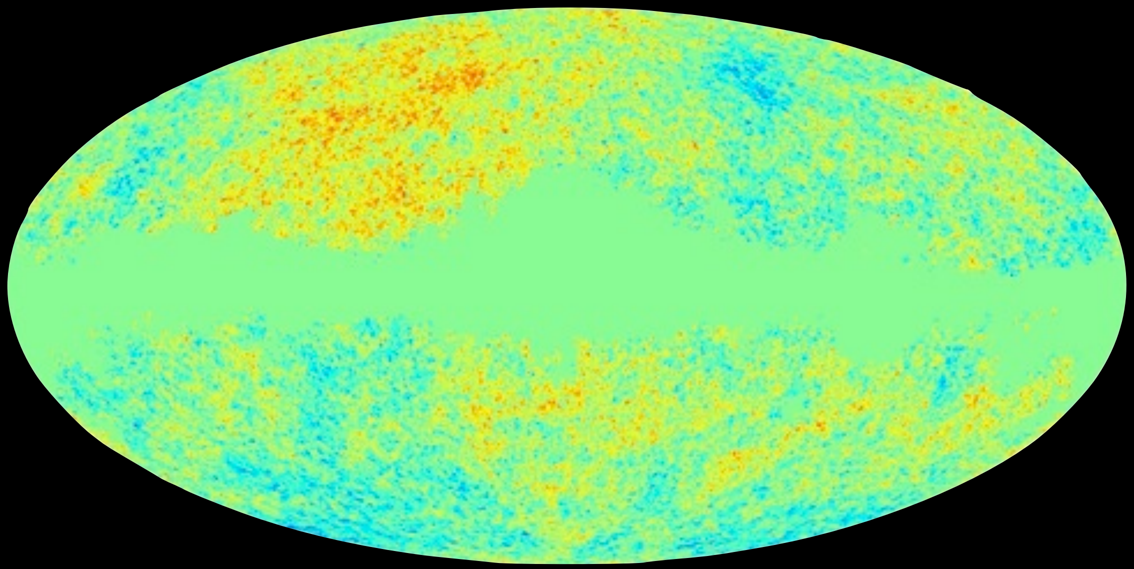
See small portion of
smoothed collision

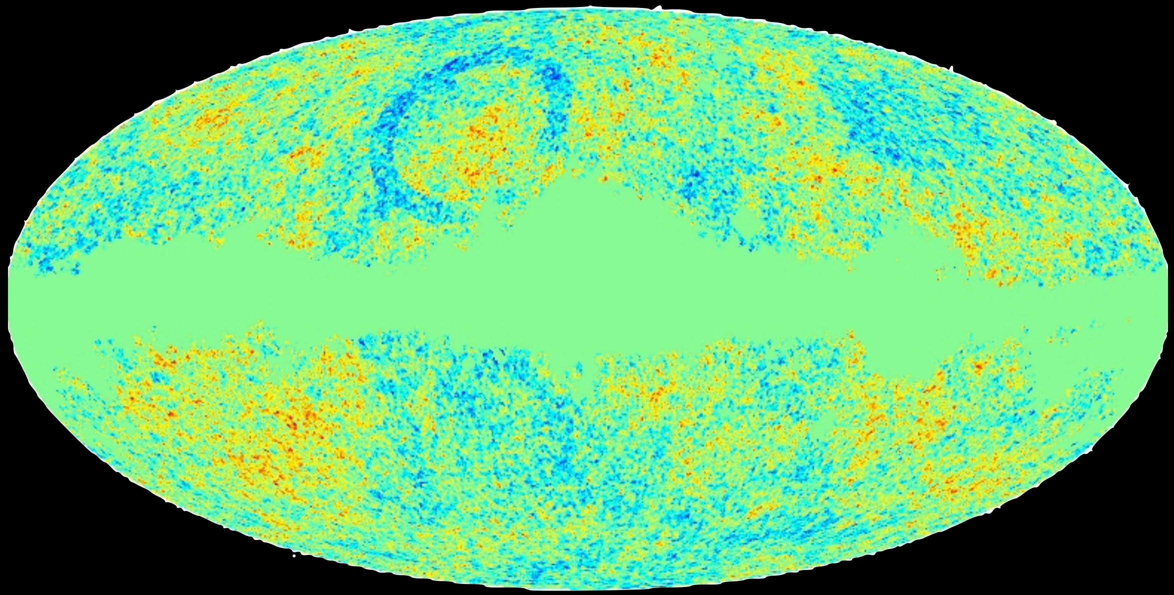
Model 2



See large portion of
smoothed collision

Exaggerated CMB examples





Data Analysis Pipeline: Motivation I

- CMB is a large dataset. Easy to find “weird” features.

- *A posteriori* statistics promote high *p*-values and wrong inferences.

a posteriori

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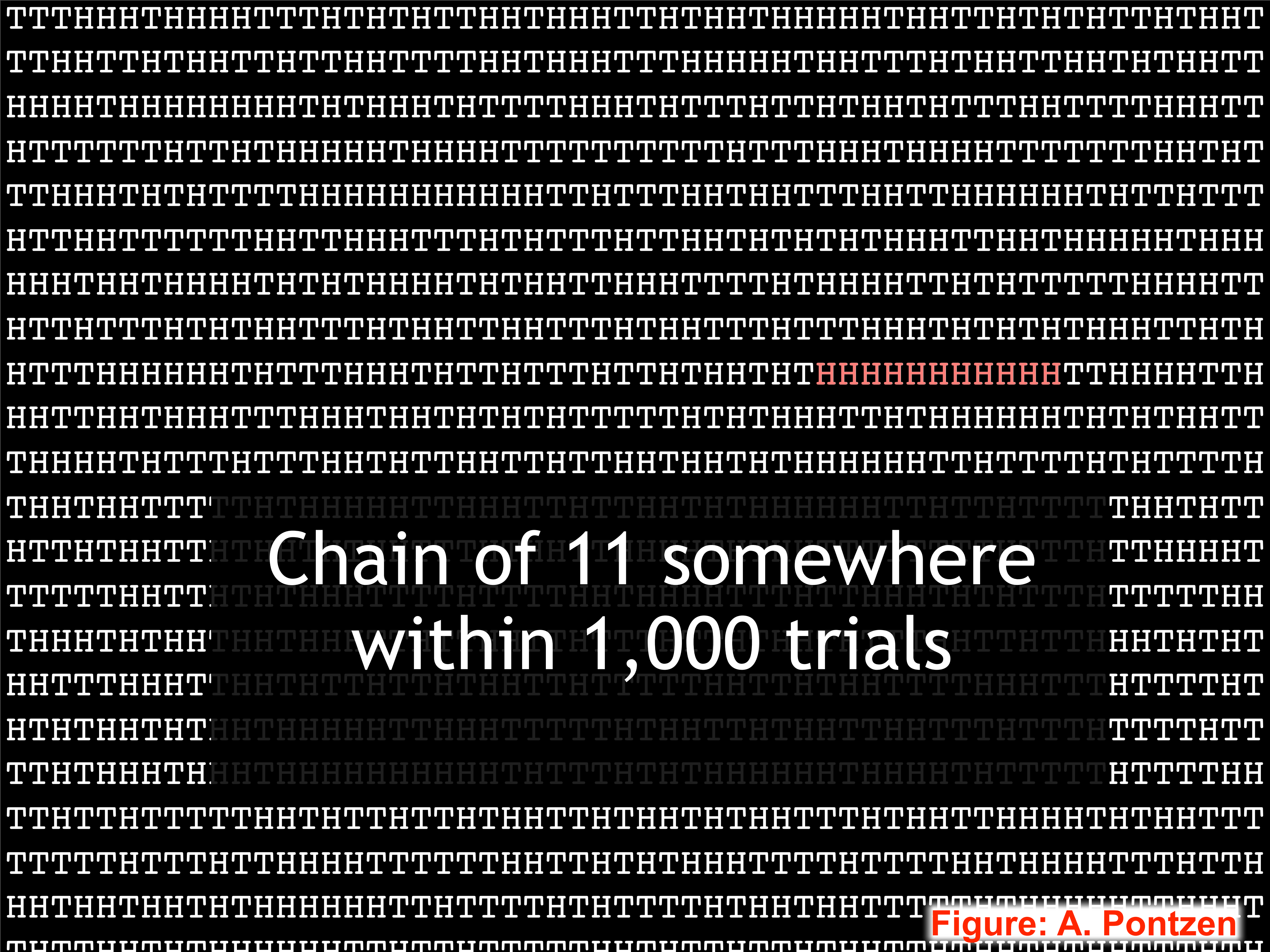
Figure: A. Pontzen

Chain of 11

$0.1\% = 1$ in 2^{10}

HHHHHHHHHHH

Figure: A. Pontzen


Chain of 11 somewhere
within 1,000 trials
Figure: A. Pontzen

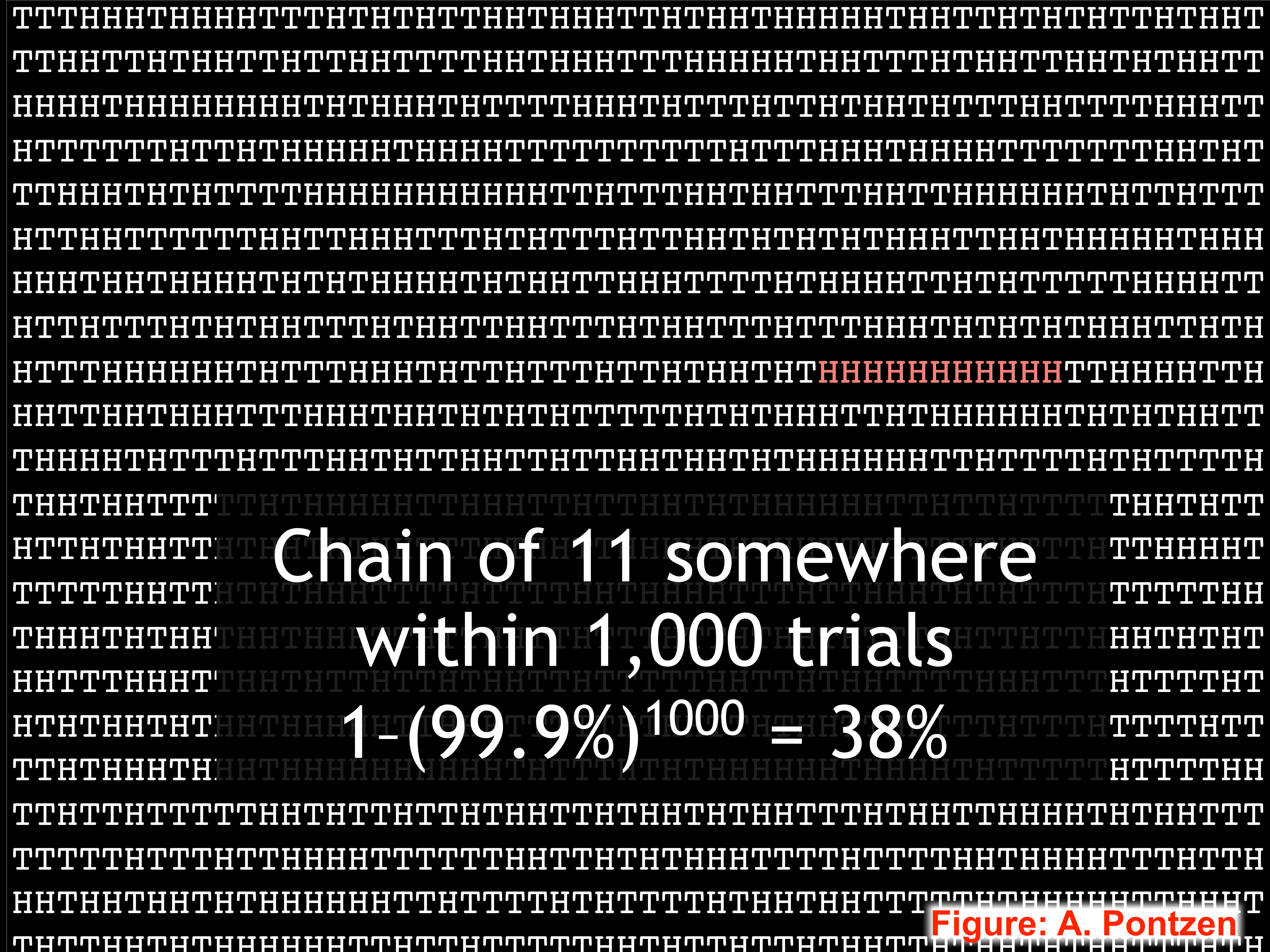


Figure: A. Pontzen

Data Analysis Pipeline: Motivation II

- Very important to perform blind analysis with no *a posteriori* selection effects!
  - Design pipeline with model and specific dataset in mind
  - Calibrate using instrument simulation: null test
  - Test sensitivity of pipeline to simulated dataset with signal
  - Pipeline “frozen” before looking at data

Data analysis pipeline

- Must reduce data volume: target model features
- Collision localized on the sky: don't want to go to harmonic space.
- Observables:
  - -azimuthal symmetry
  - -causal boundary (?)
  - -long-wavelength modulation inside a disk
- Pipeline:
  - wavelet analysis: pick out significant localized features
  - edge detection: sensitive to causal boundary
  - Bayesian model selection/parameter estimation: is collision model favoured over just CMB+noise?

needlet transform (a.k.a. blob detector)

- spherical needlets have nice localization properties in both real and harmonic space

- Use three types:

  -standard spherical needlets B=2.5
  -standard spherical needlets B=1.8
  -Mexican needlets with B=1.4

- “Bandwidth parameter” B chosen for physics reasons (sensitivity to bubble sizes of interest)

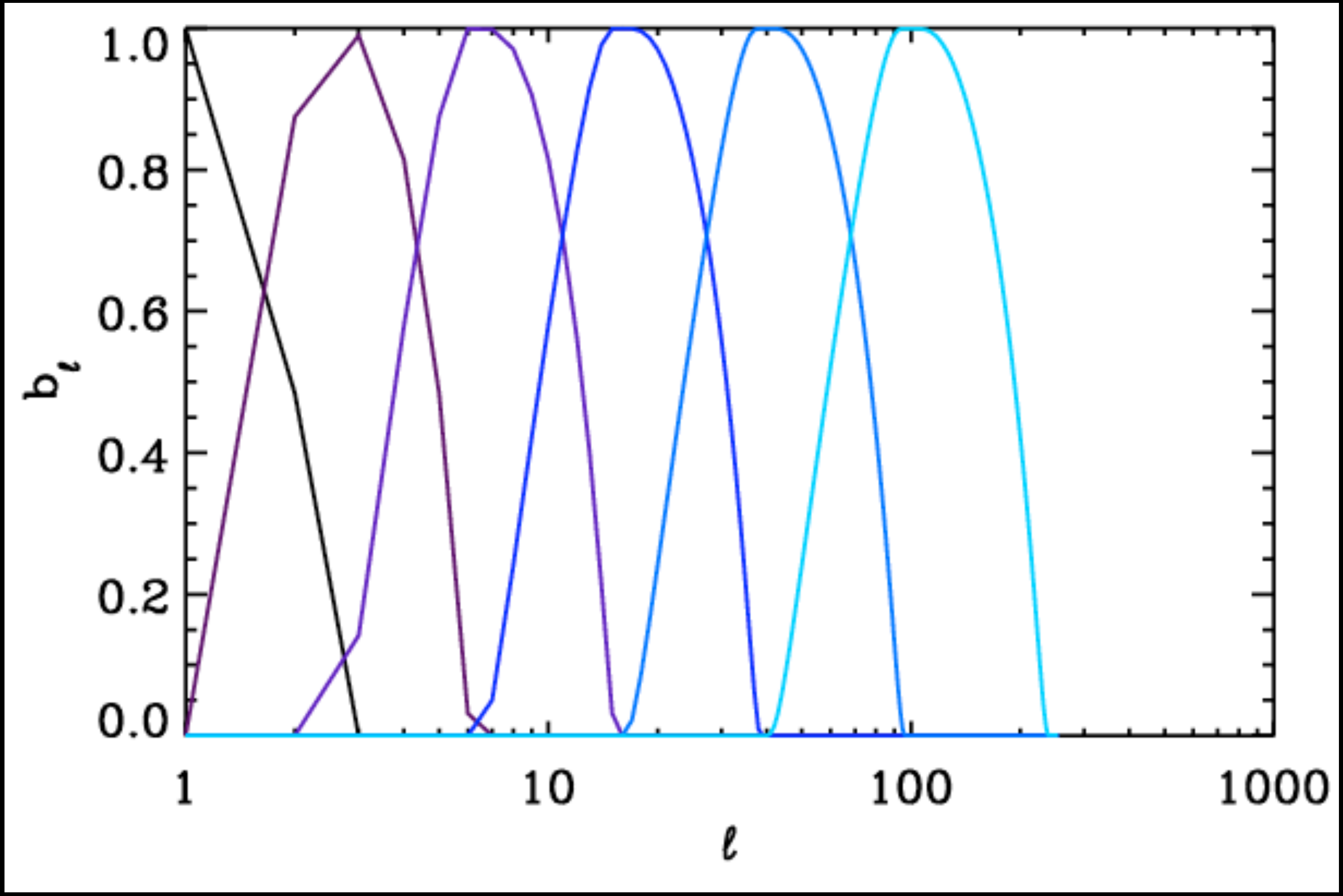
- Calibrate variance at each pixel for a given mask with 3000 cosmic variance sims (interested in features at large scales where WMAP is CV-limited)

needlet coefficient map

$$\beta_{jk} = \sqrt{\lambda_{jk}} \sum_{\ell} b\left(\frac{\ell}{B^j}\right) \sum_{m=-\ell}^{\ell} a_{\ell m} Y_{\ell m}(\hat{\gamma}_k)$$

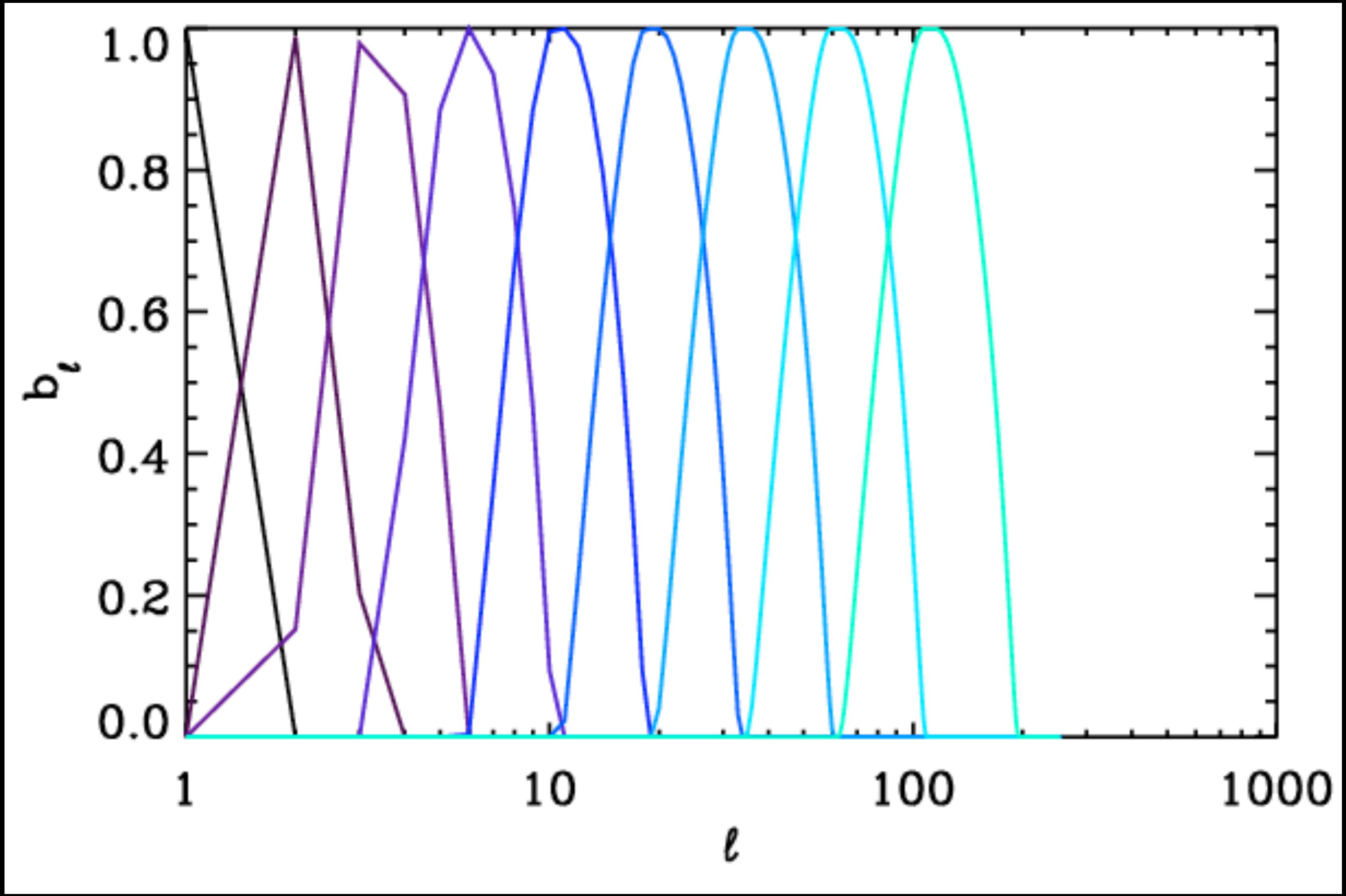
B = “bandwidth”
j = frequency
k = pixel

Standard needlets B=2.5



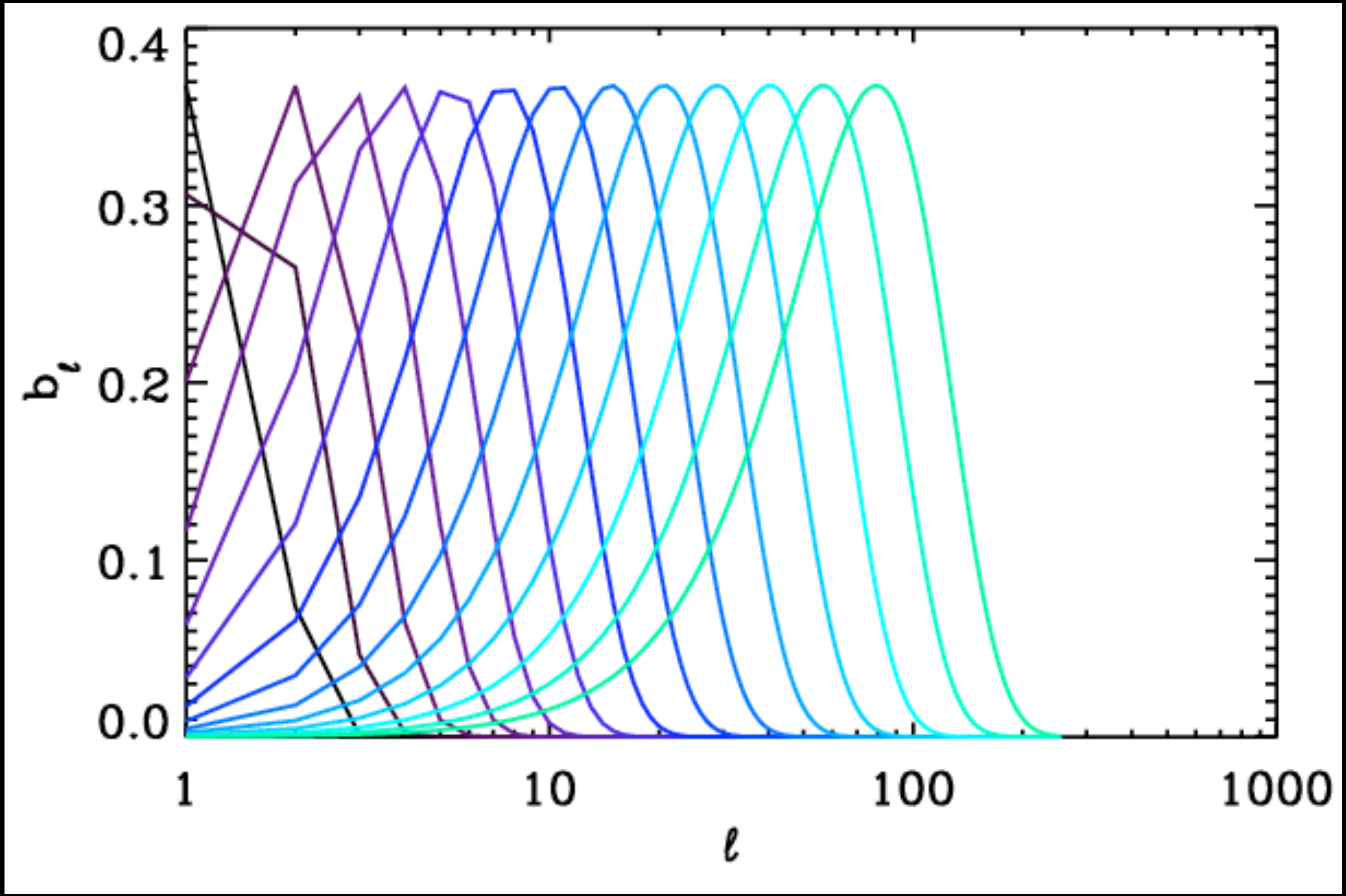
Marinucci et al. (arxiv: 0707.0844)

Standard needlets B=1.8



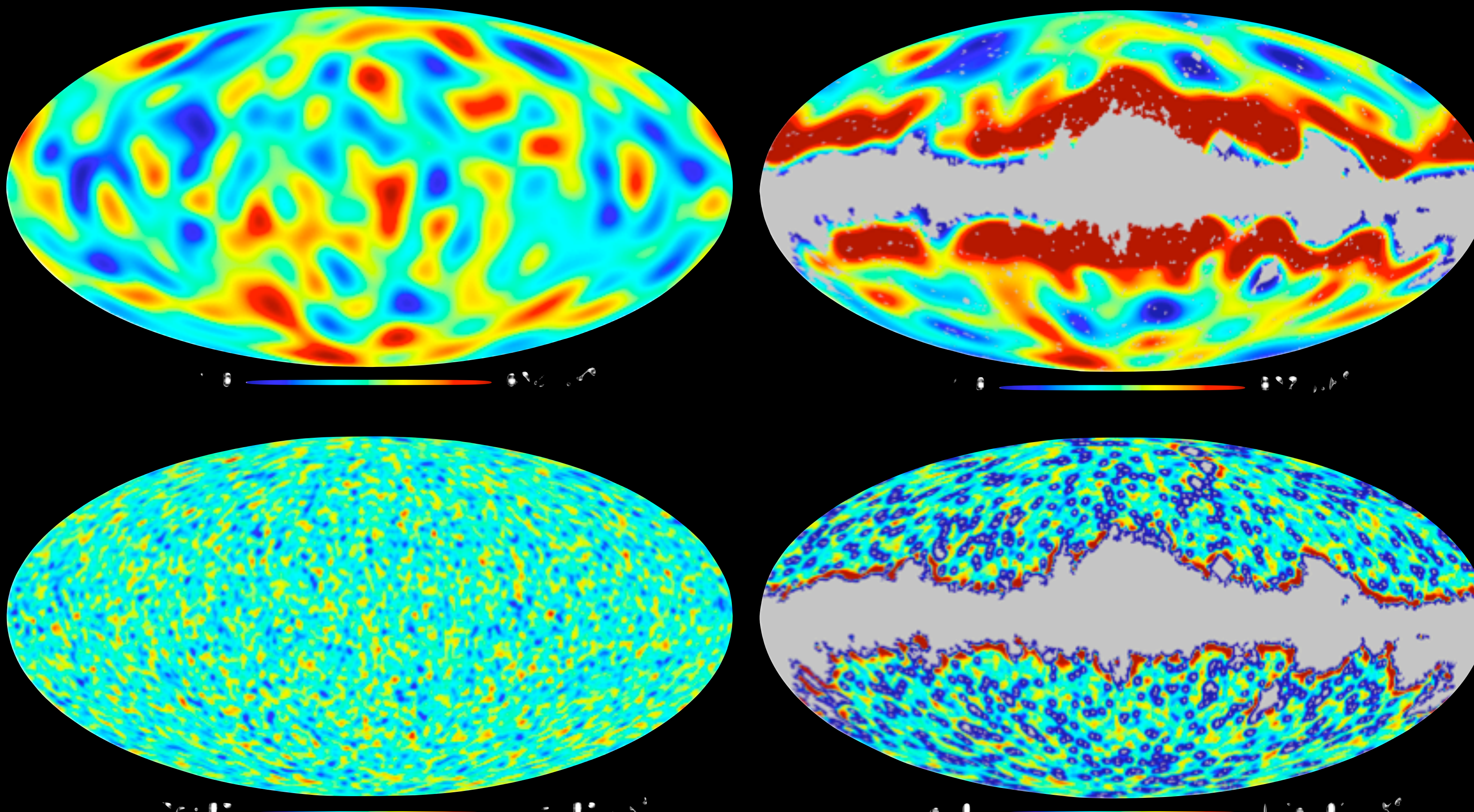
Marinucci et al. (arxiv: 0707.0844)

Mexican needlets B=1.4



Scodeller et al. (arxiv: 1004.5576)

needlet variances



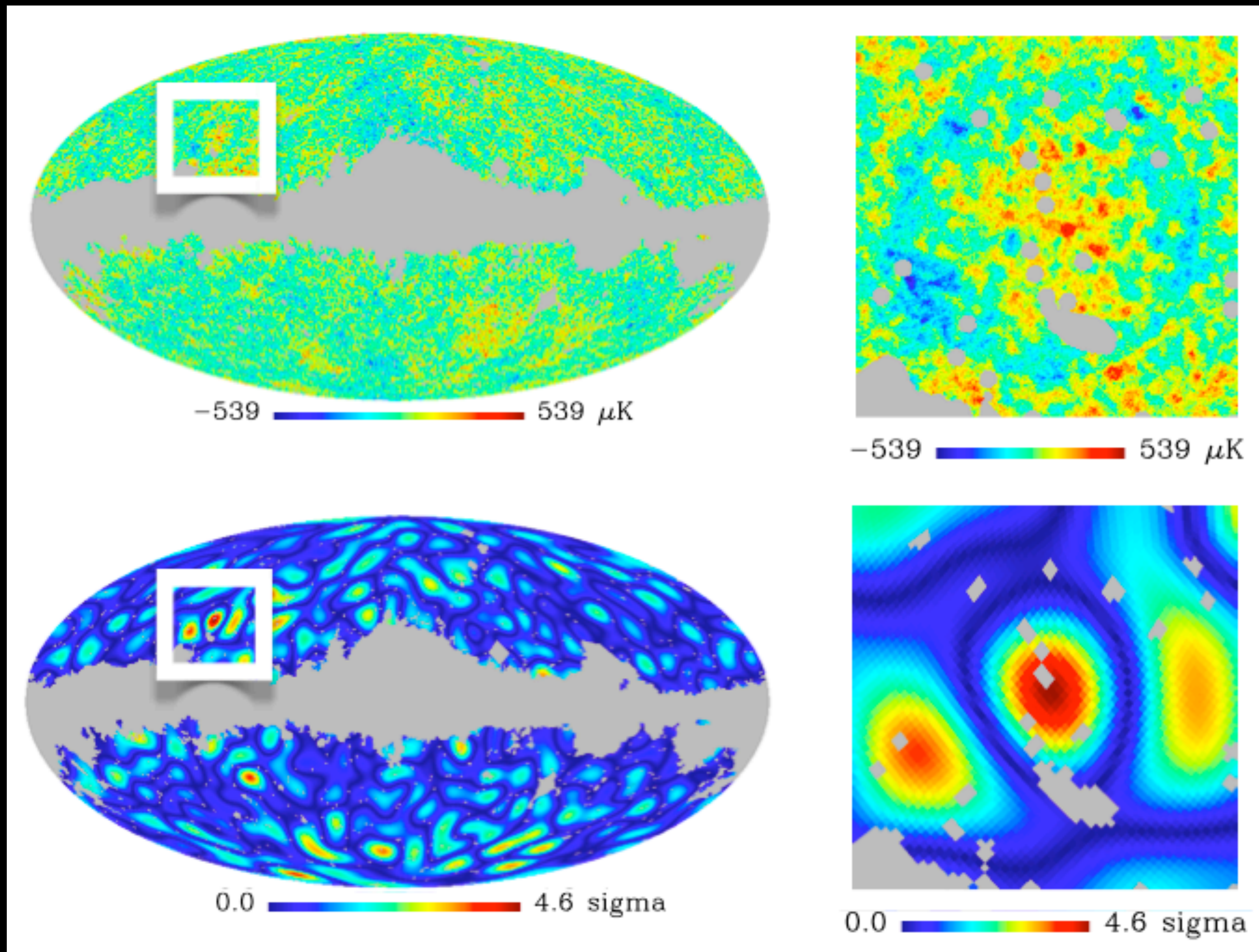
Top row: standard needlets B=2.5, j=2
Bottow row: Mexican needlets B=1.4, j=11

needlet significance statistic

$$S_{jk} = \frac{|\beta_{jk} - \langle \beta_{jk} \rangle_{\mathrm{gauss,cut}}|}{\sqrt{\langle \beta_{jk}^2 \rangle_{\mathrm{gauss,cut}}}}$$

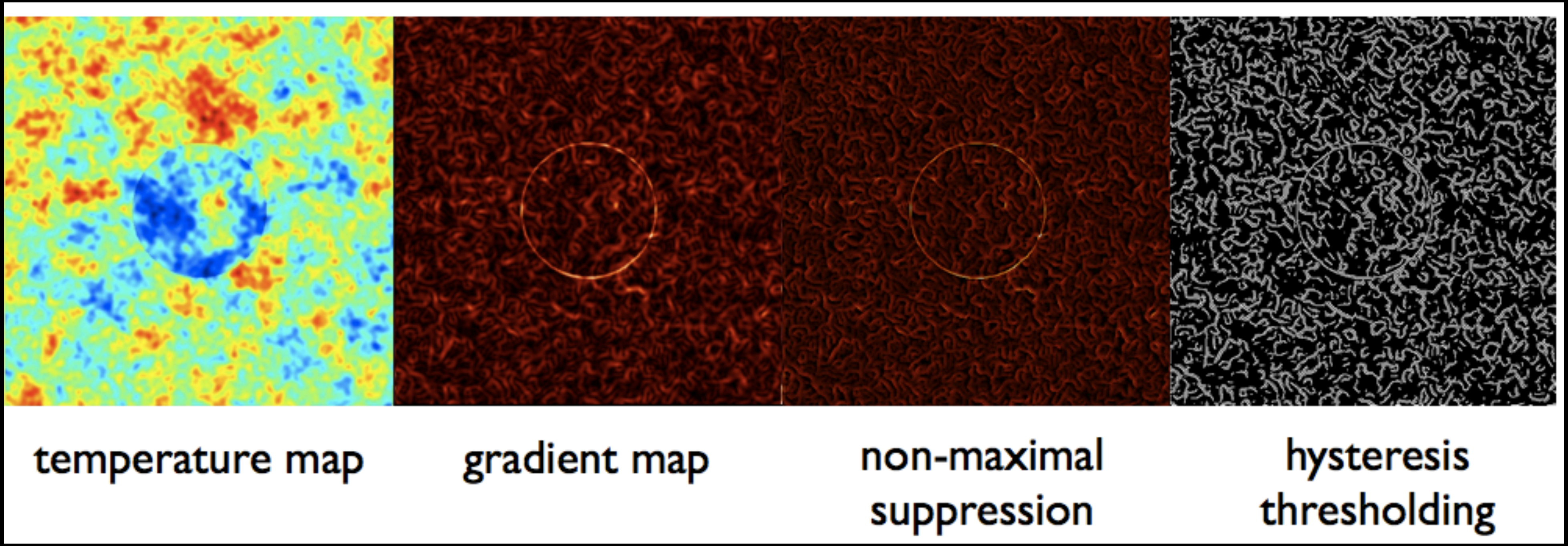
j = frequency
k = pixel

simulated needlet detection example



Edge detection algorithm

- Use Canny edge detection algorithm to search for circular edges allowed by model:
  - Generate image gradients
  - Thin into single-pixel proto-edges
  - Stitch together into “true” edges

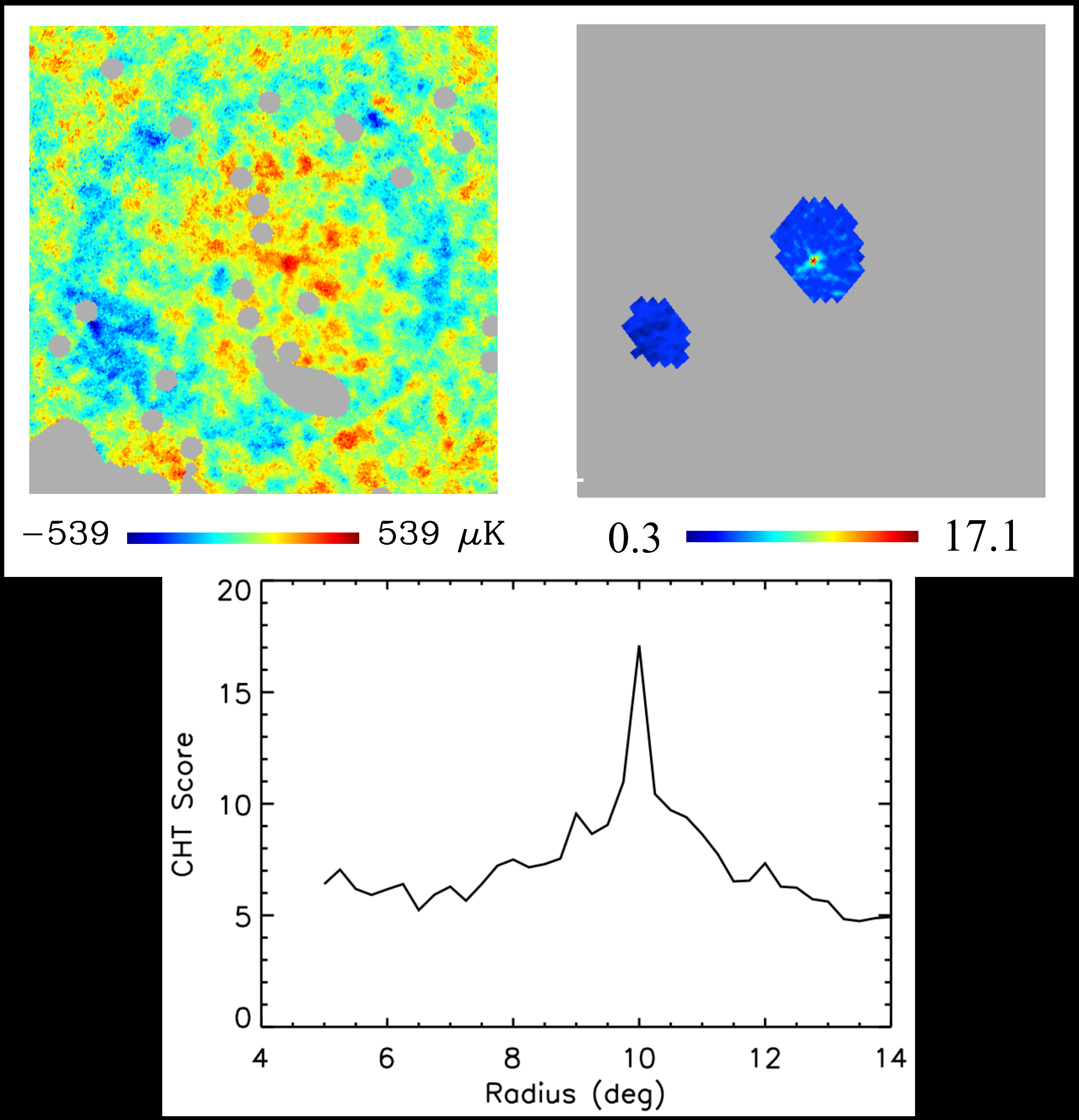


Circular Hough Transform

- Algorithm assumes each true edge pixel lies on the edge of a circle.
  - Scan true edge map accumulating most likely circle centres at a given radius.

Causal edge (if present) dramatically enhances observability!

simulated CHT detection example



P-values vs model selection

- Frequentist *p*-values quantify how discrepant a data statistic is under the “null hypothesis”
- Cannot be used to perform model selection!

$$p(A|B) \neq p(B|A)$$

100% 0.01%

A = I am a scientist

B = I am a CMB cosmologist

$$p(A|B) \neq p(B|A)$$

?? 0.01%

A = The standard model is basically correct

B = CMB anomalies

("some subset of the CMB data which we don't like the look of")

Reminder: parameter estimation vs model selection

posterior: probability of the model given the data

probability of the data given the model

prior probability

$$P(\theta|D) = \frac{P(D|\theta)P(\theta)}{\int P(D|\theta)P(\theta)\mathrm{d}\theta}$$

Evidence: normalizing factor

Evidence: model-averaged likelihood

Exact (pixel) likelihood includes CMB, spatially varying noise, Gaussian beam

Which model better describes the data?

$$\rho = \frac{p(M_b | D)}{p(M_0 | D)} = \frac{p(M_b)}{p(M_0)} \frac{Z_b}{Z_0}$$

evidence ratio

prior model probability ratio (assumed to be 1)

D = data highlighted by needlets
M_0 = CMB + instrument effects
M_b = bubble collision model

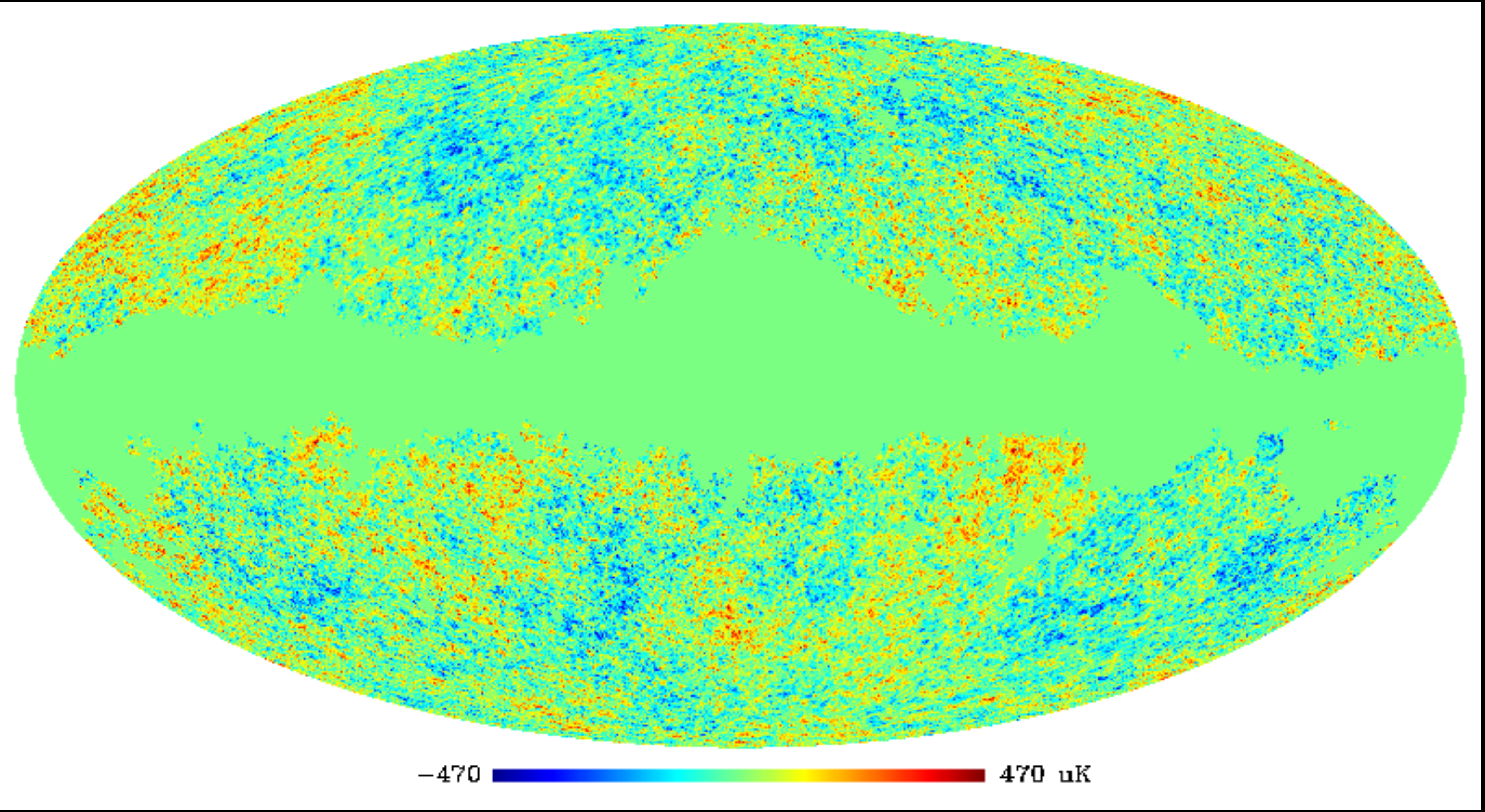
- Calculated using Multinest
- Computationally limited to < 11 deg patches (covmat inversion)
- model priors automatically set

Bayesian step examples

simulated model	$\ln \rho$
large central amplitude, strong edge	130
small central amplitude, strong edge	150
large central amplitude, weak edge	36
weak central amplitude, medium edge	5
small central amplitude, weak edge	3

Edge aids greatly in detection

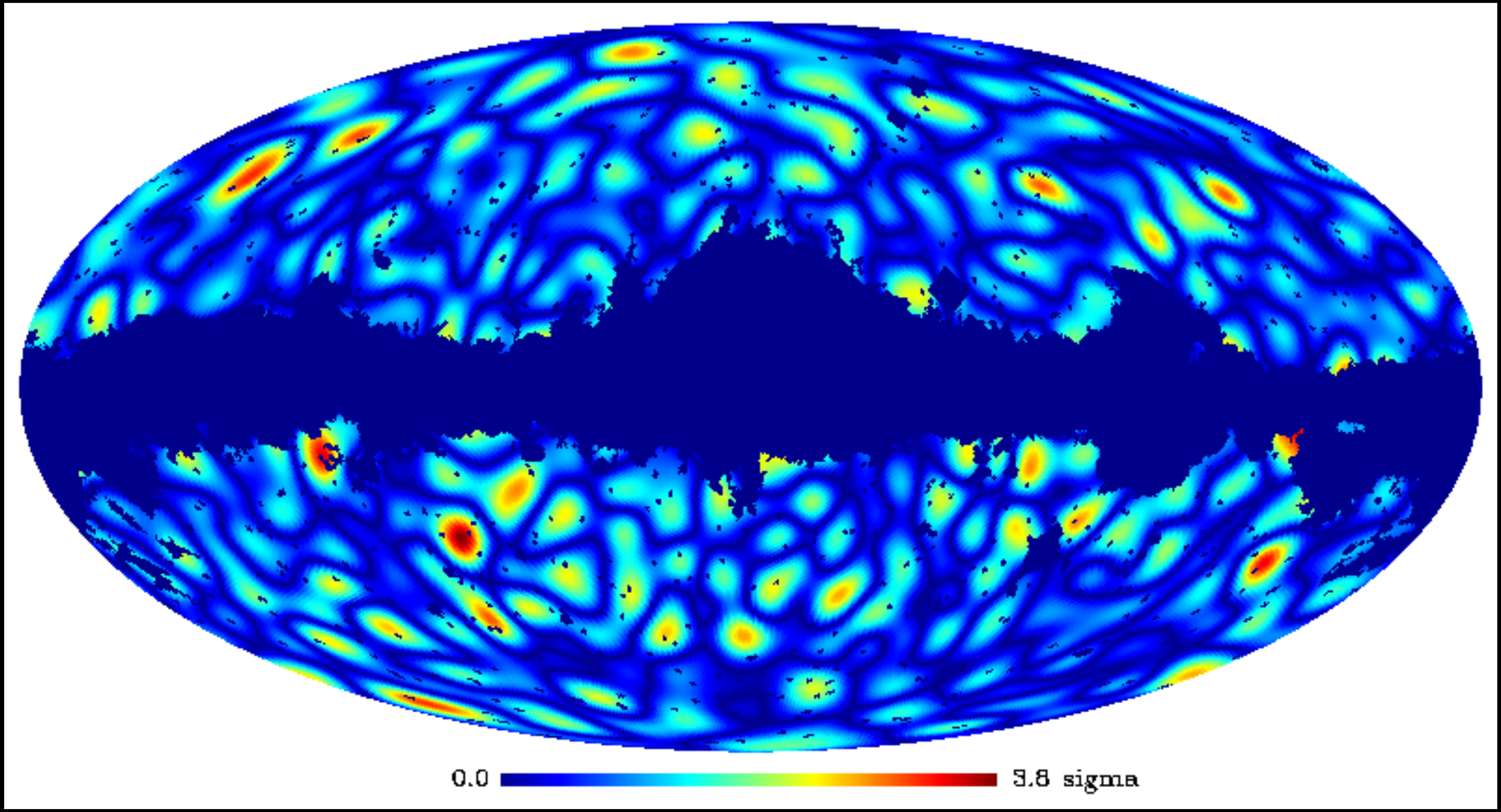
Systematics calibration simulation



WMAP7 W band end-to-end sim: starting from time stream, diffuse and point source foregrounds, realistic instrumental effects

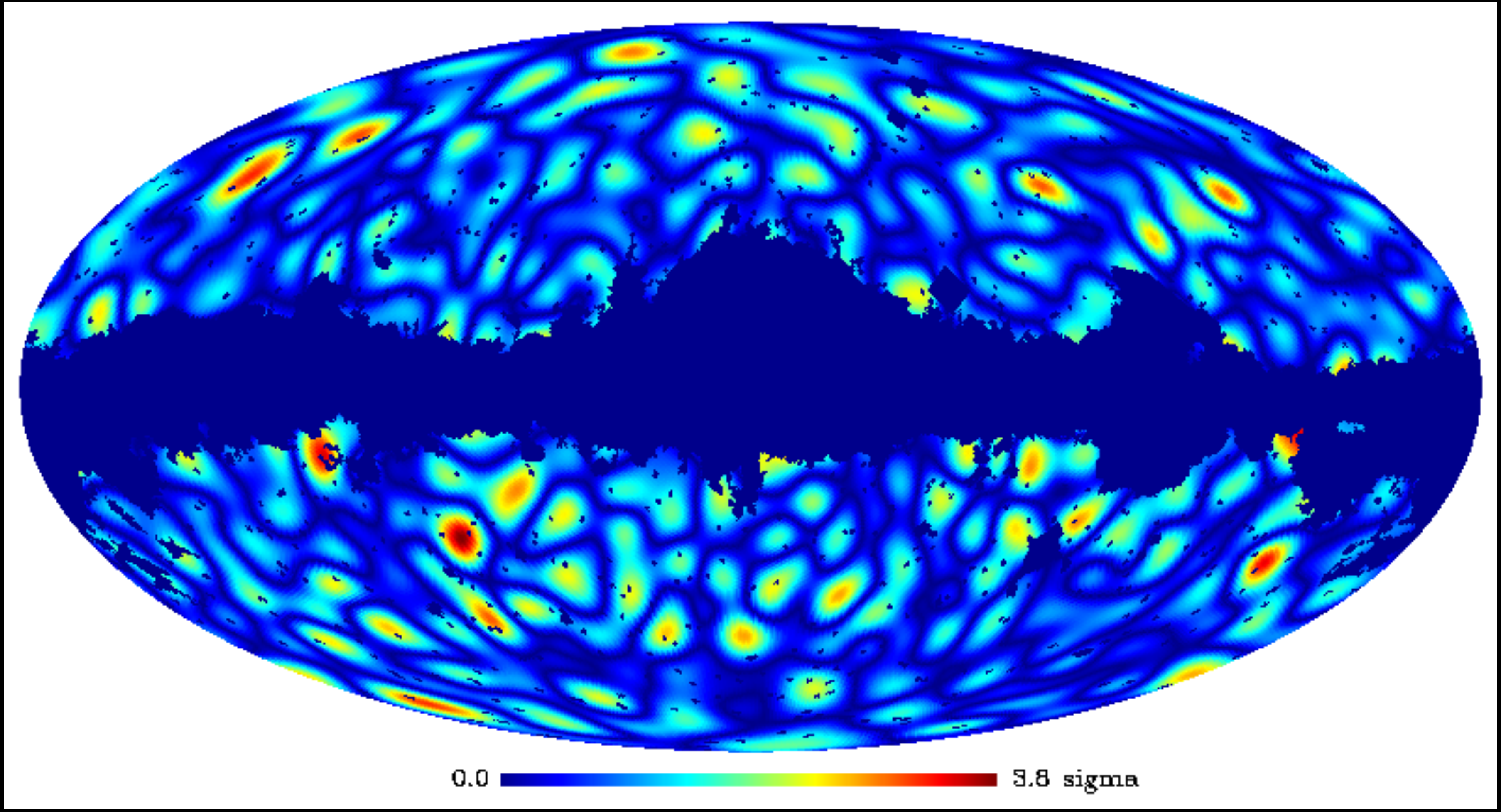
e2e simulation: needlet responses

WMAP7 W band sim example: std needlet 2.5 j=3



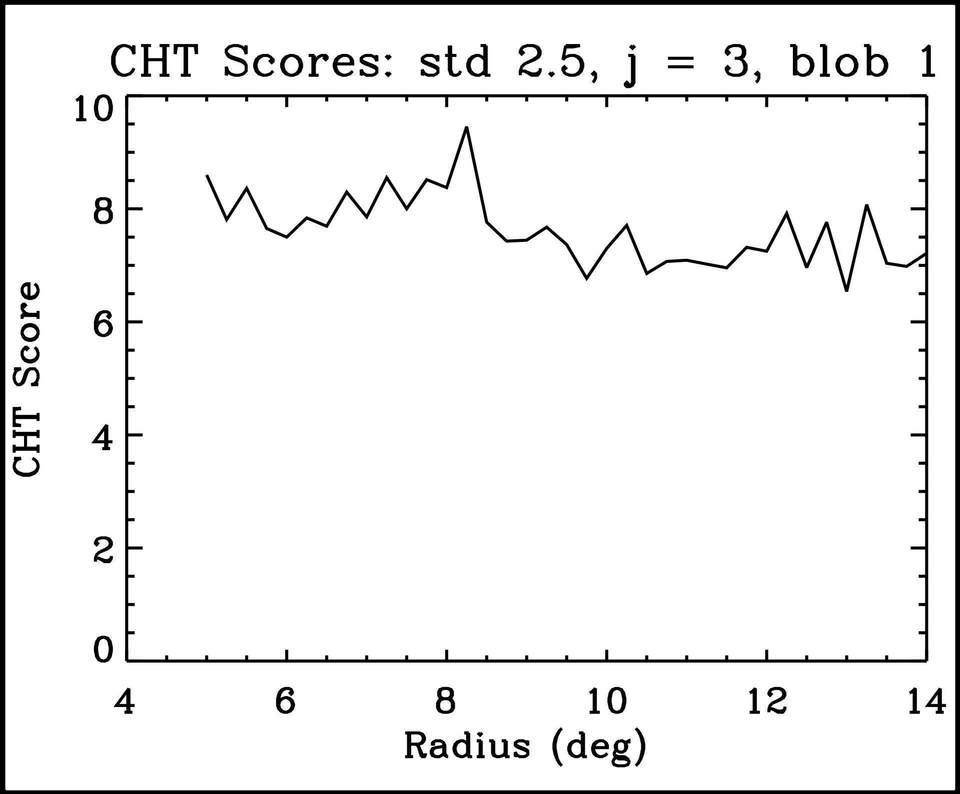
significances (sensitive to 5 - 14 degrees)

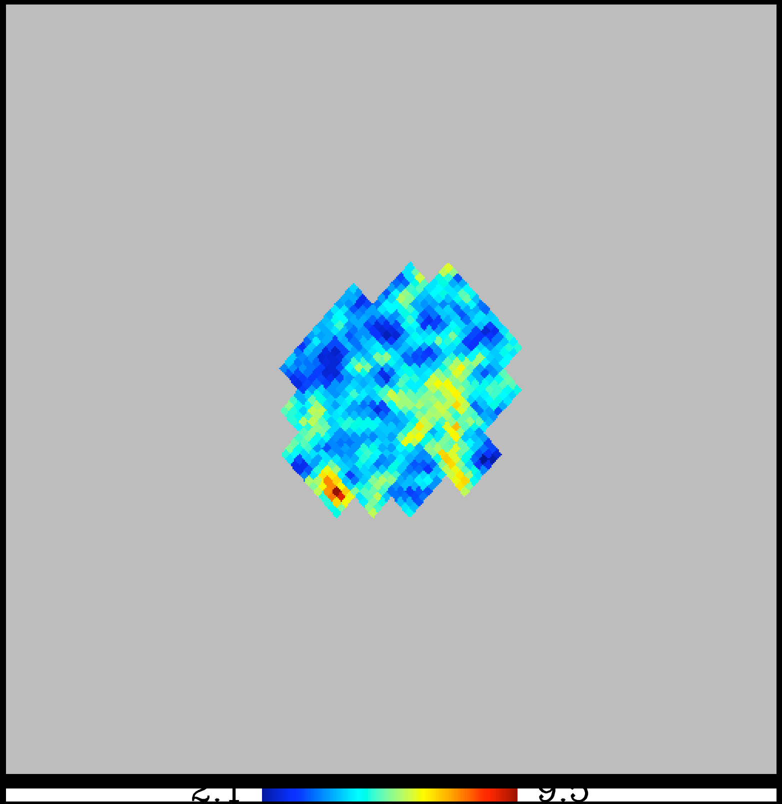
e2e simulation: needlet responses



Set thresholds such that 10 features pass: trying to discover rare, weak features, but later pipeline steps are computationally heavy

e2e simulation: CHT responses





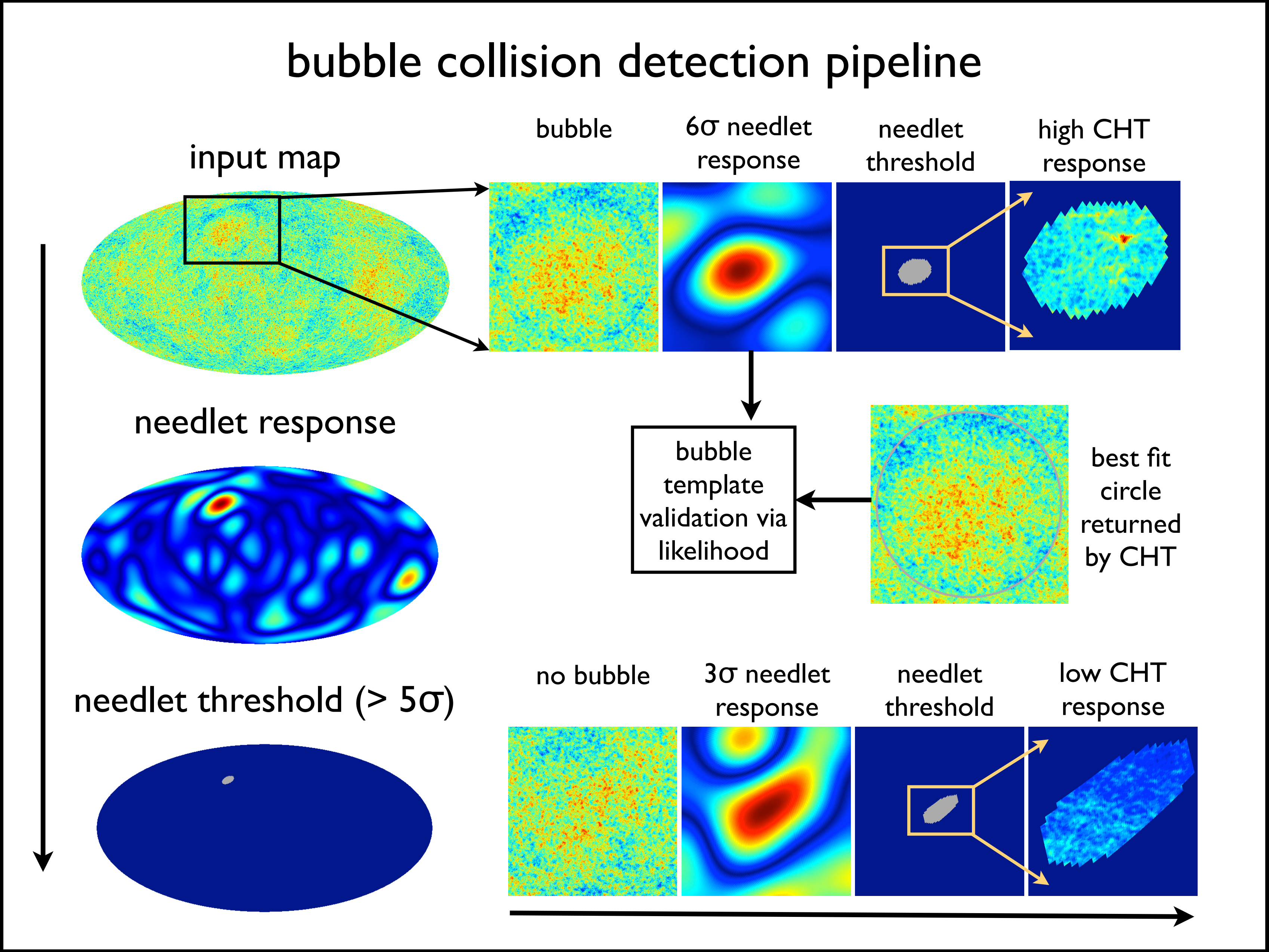
- "peakiest" CHT response found in e2e sim is small: no false detections
- confirms strong CHT peak is a "smoking gun"

e2e simulation: Bayesian analysis

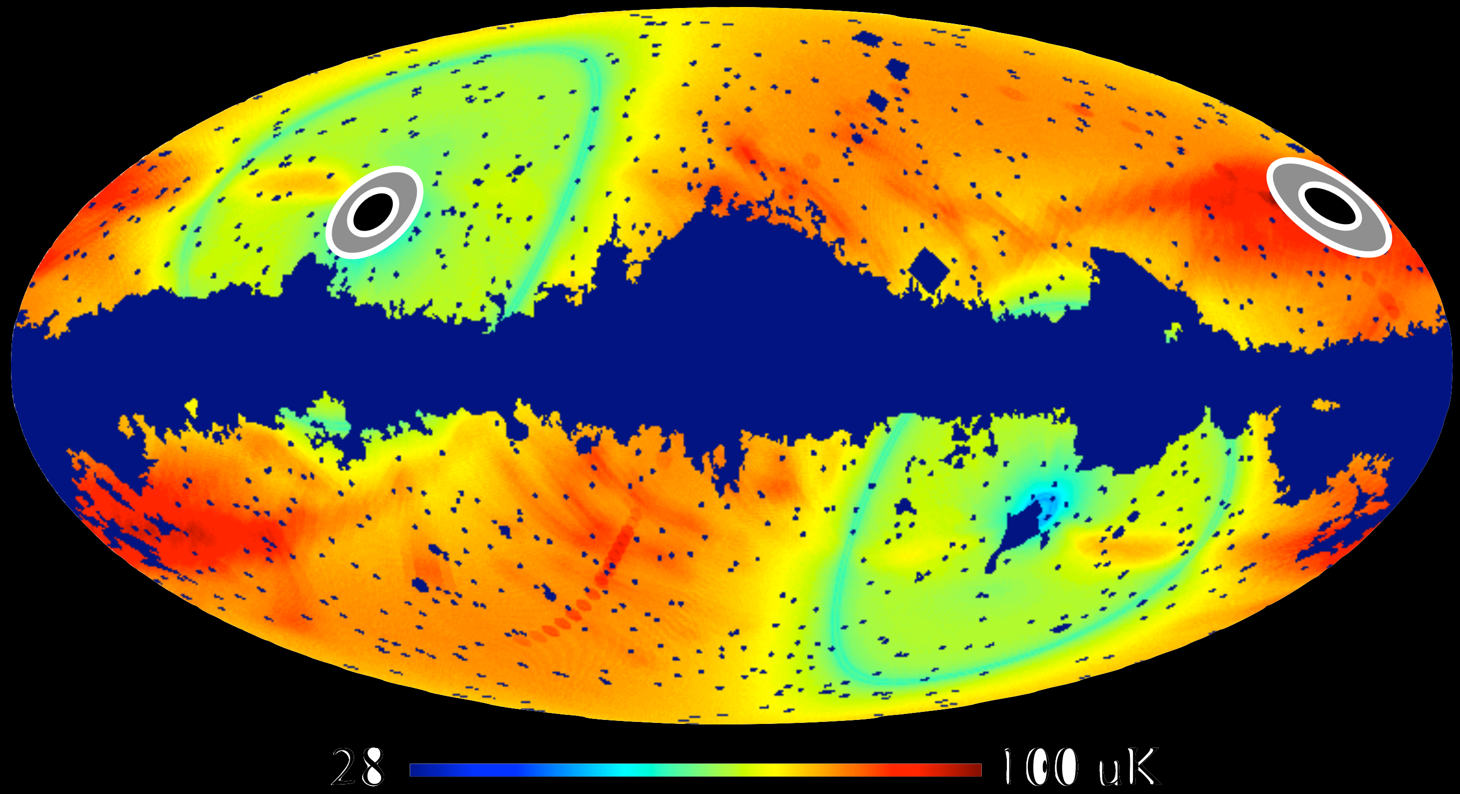
- Most “false detections” with size > 3 degrees passing the needlet threshold have very small evidence.

- For conclusive detection, require significantly exceeding threshold set by largest evidence for a “false detection” at these angular scales.

pipeline summary

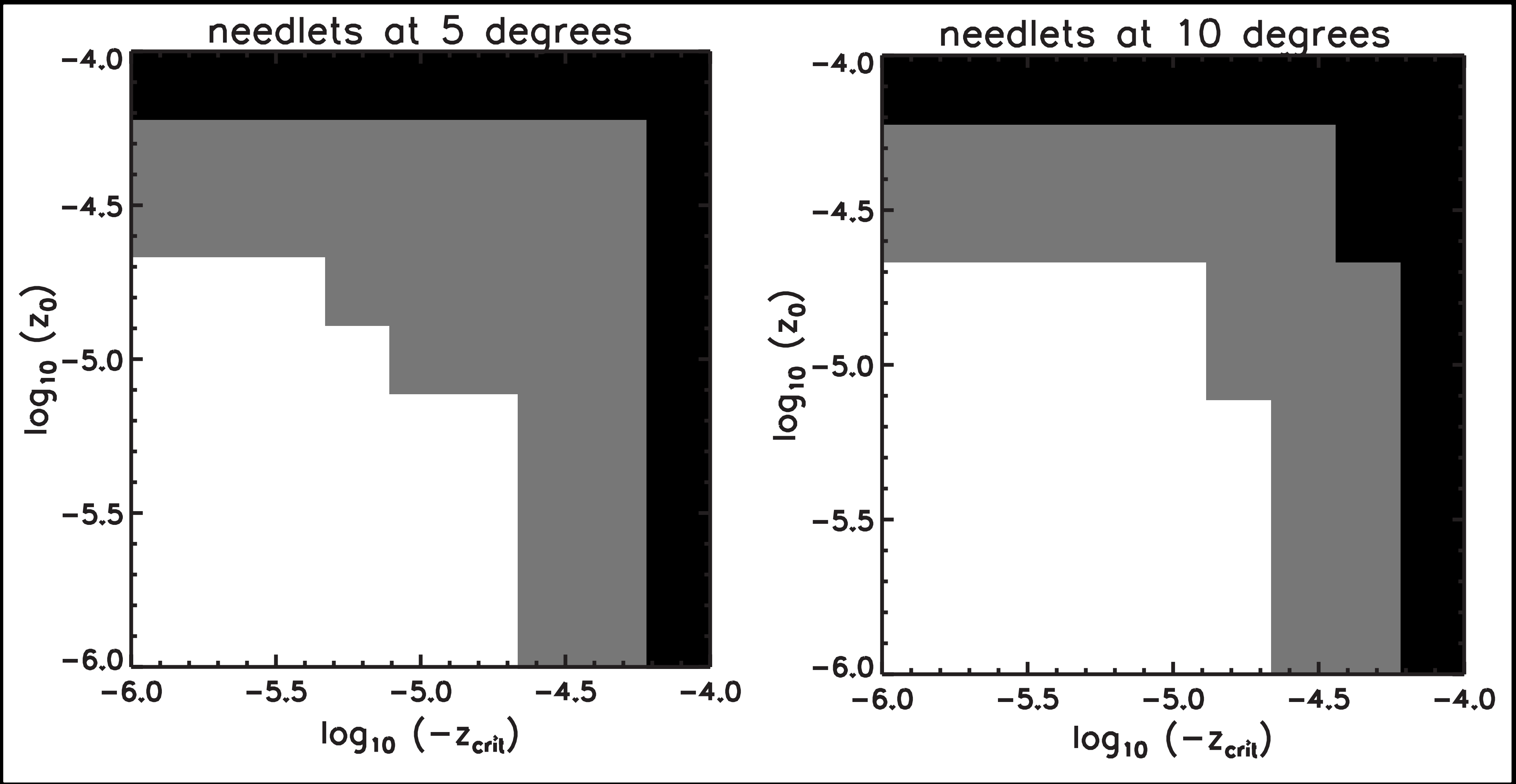


Sensitivity simulations



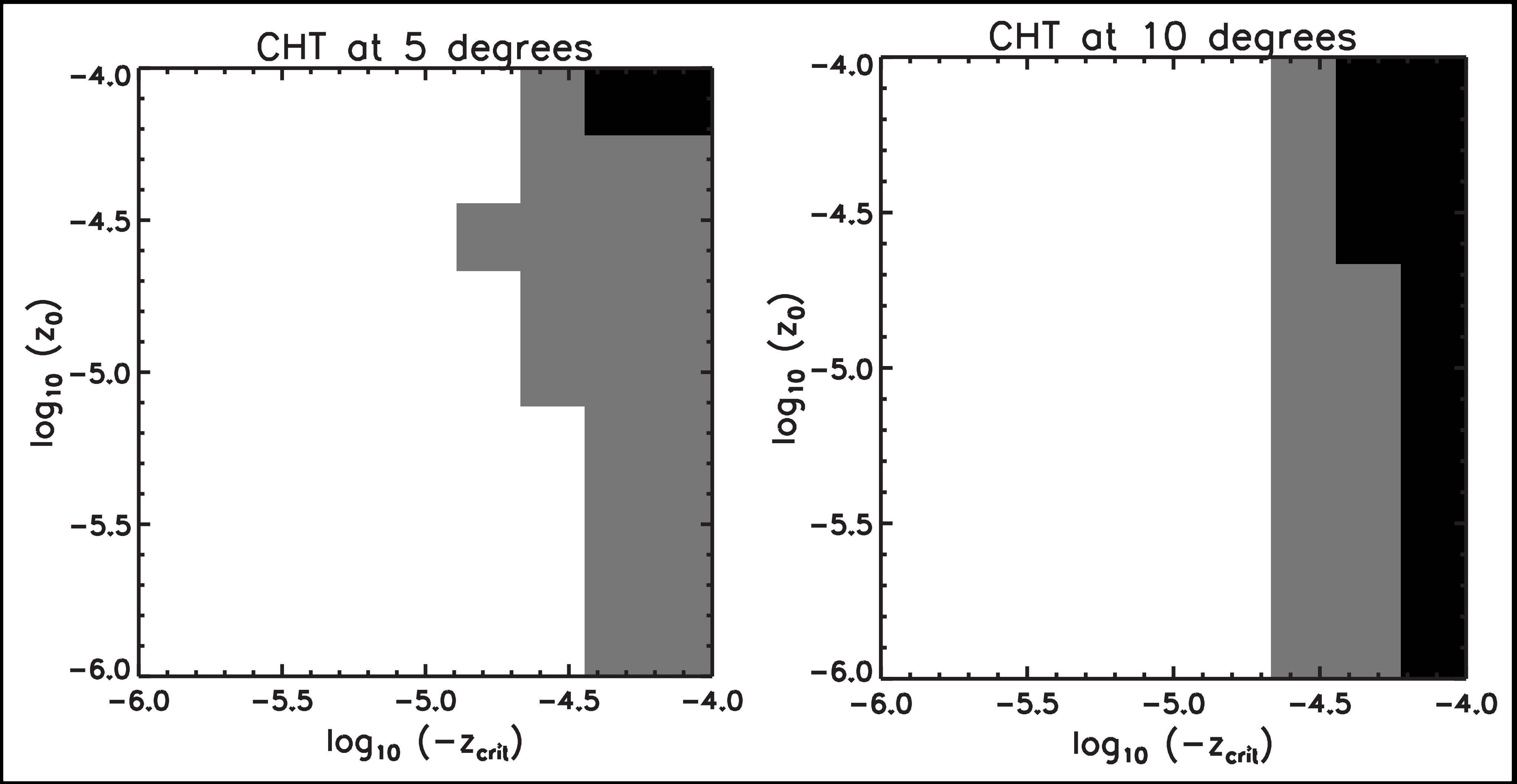
210 CMB+spatially varying noise+beam simulations of 5, 10, 25 degree collisions, sampling 35 representative parameter combinations with 3 CMB realizations each, placed at high/low noise locations

needlet sensitivity/exclusion region



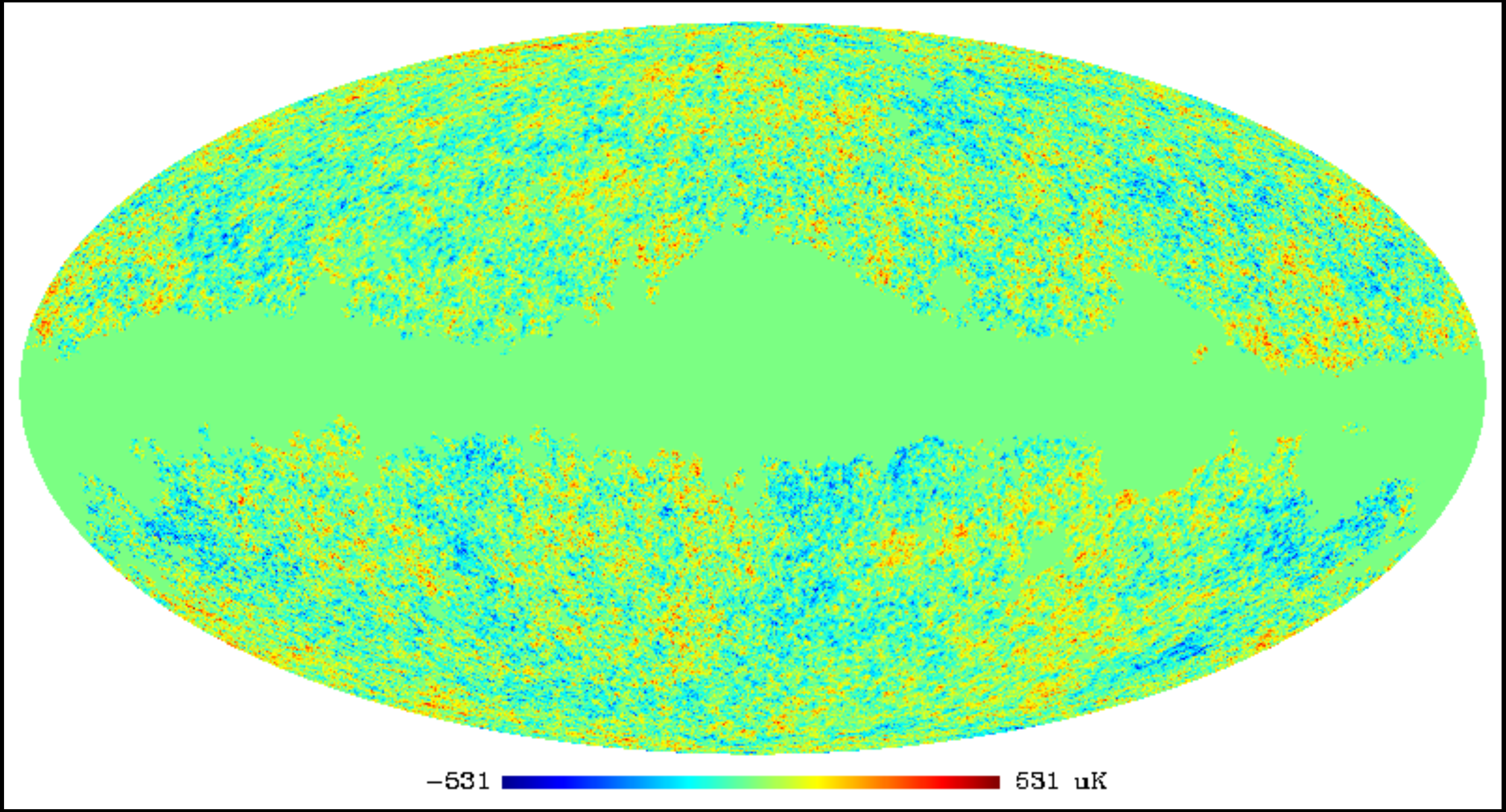
- Bayesian step would detect anything in needlet exclusion region; sensitive to needlet sensitivity region.

CHT sensitivity/exclusion region



- Limited by 1 degree CMB “realization noise” as well as experimental sensitivity/resolution.

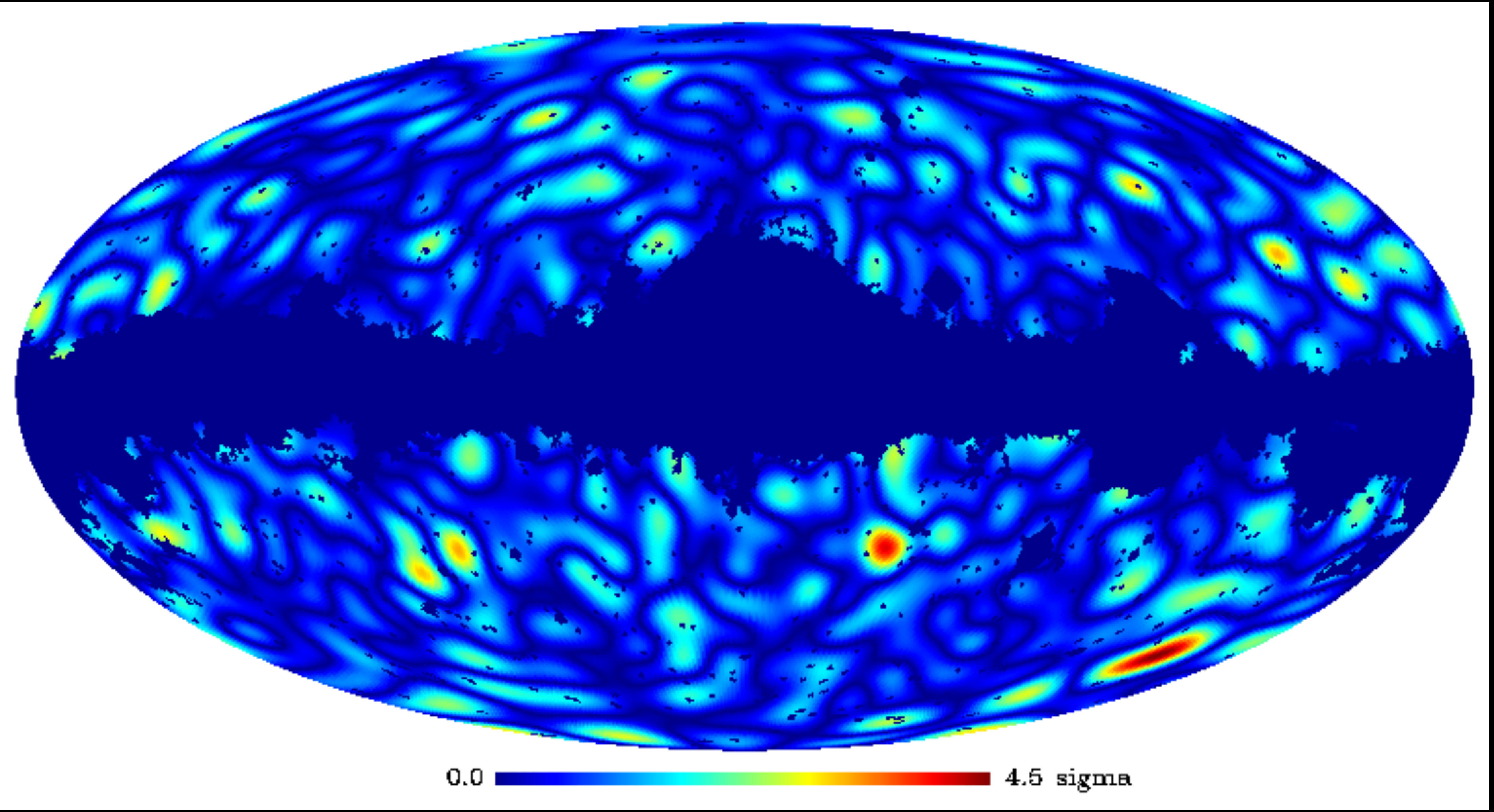
WMAP7 W band (94 GHz)



Highest resolution WMAP channel (beam 0.22 deg)

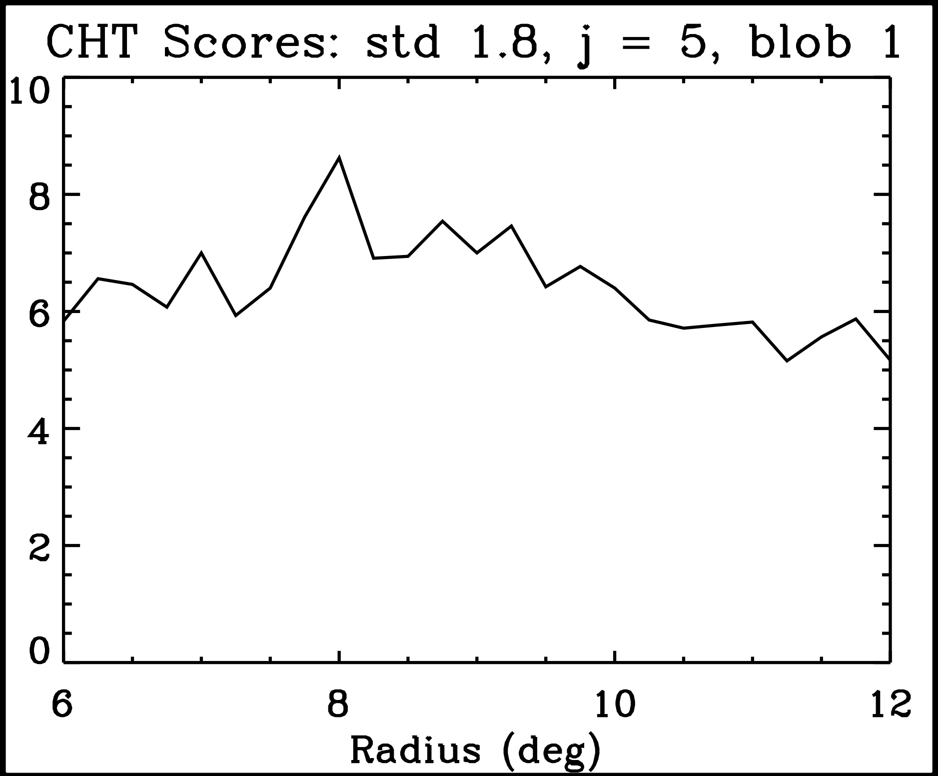
WMAP7 W band example: std needlet 2.5 j=3

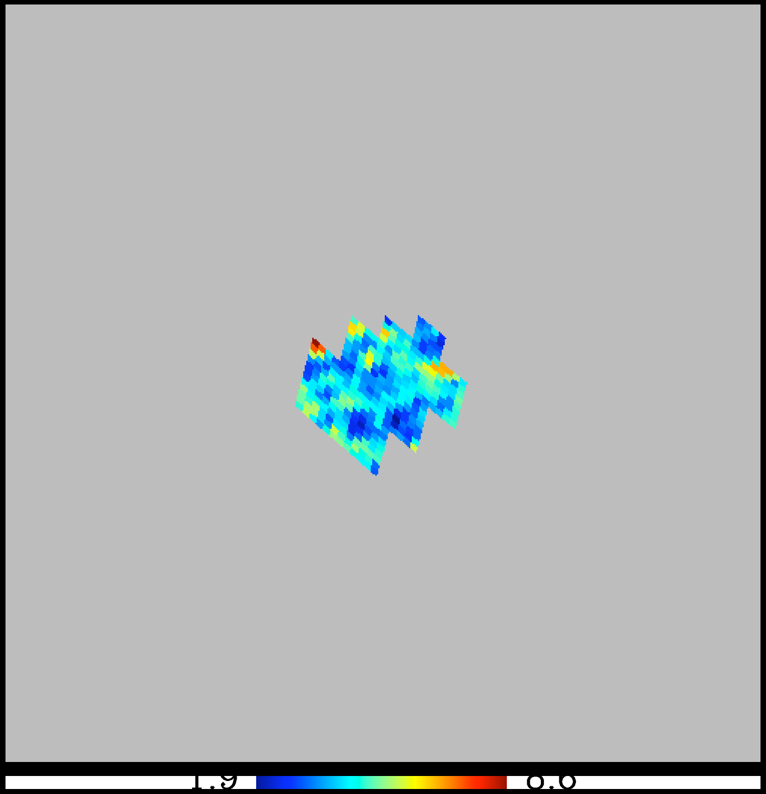
significances (sensitive to 5 - 14 degrees)



11 features pass thresholds, with detections in multiple needlet types/frequencies

WMAP7 W band: CHT response





- "peakiest" CHT response found in W band data
- no circular temperature discontinuities detected
- no conclusive detection can be claimed

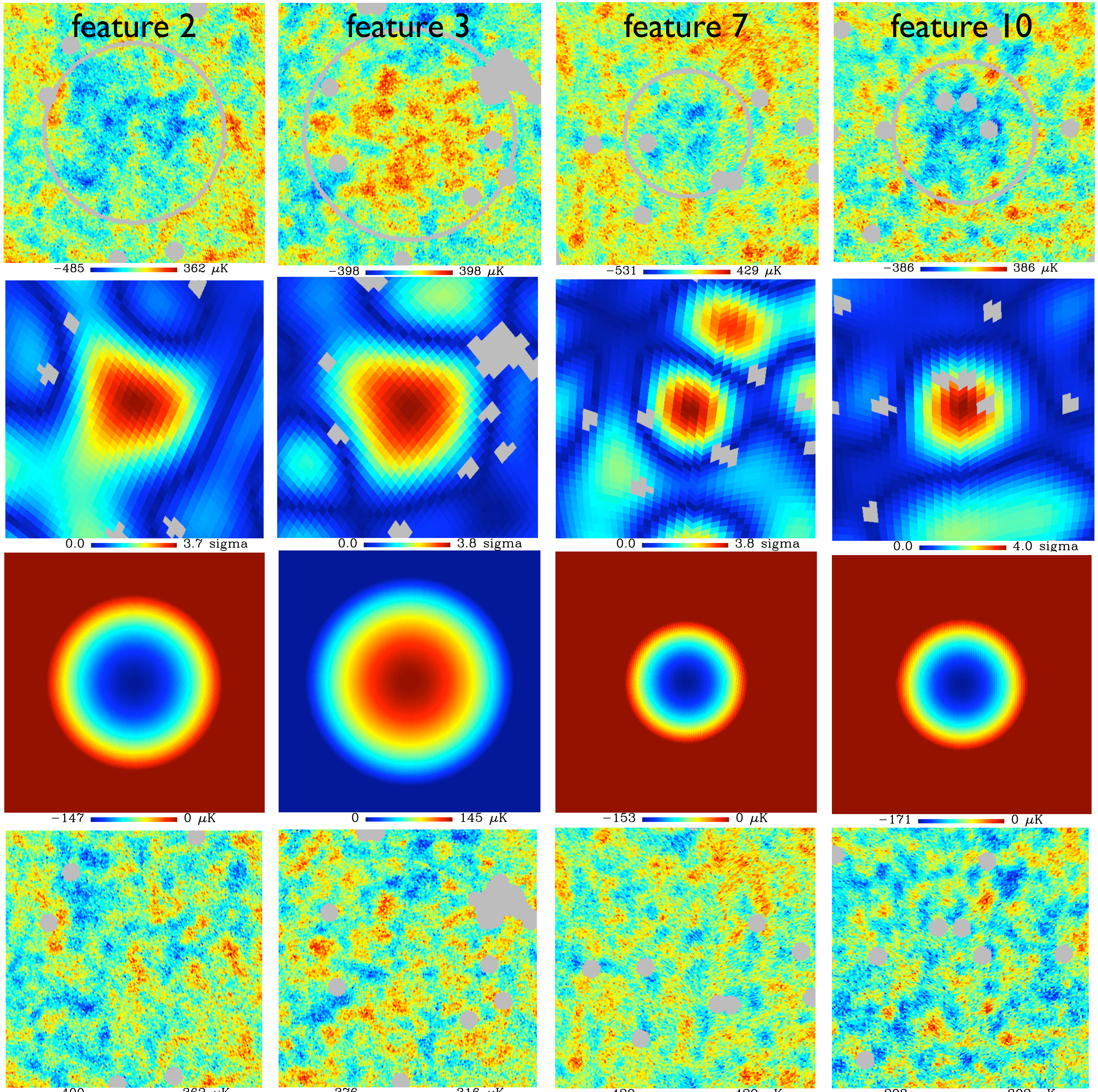
Bayesian model selection

- Find four features with no detectable temperature discontinuity (at WMAP quality data) but with evidence ratios significantly higher than false detection threshold evidence ratio.

- Evidence ratios consistent with simulated collisions using marginalized parameters.

- Cannot claim a conclusive detection.

- All four features are at about our angular size CHT detection threshold of 5 deg, and within the needlet sensitivity region.



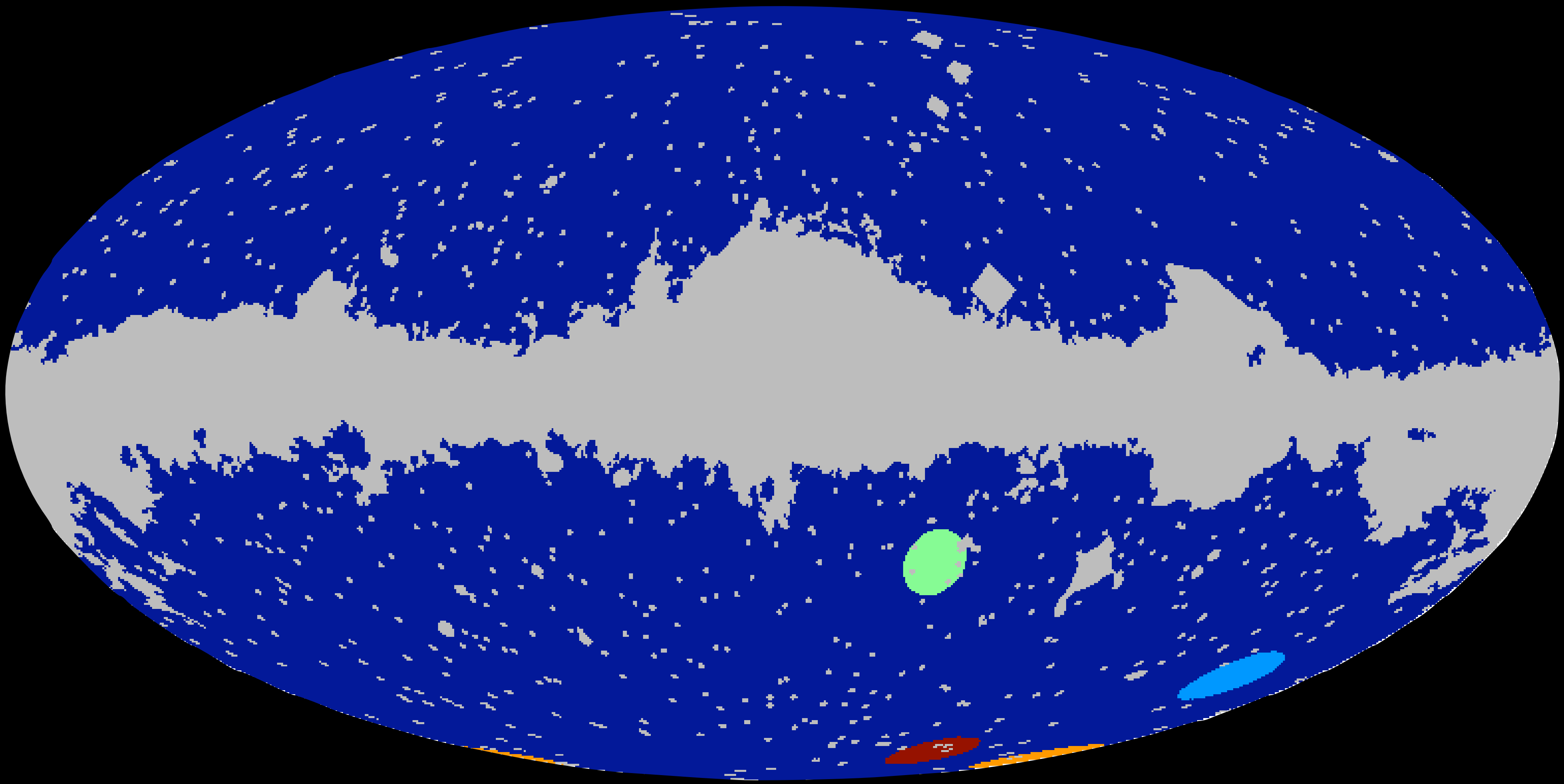
data

needlet significance

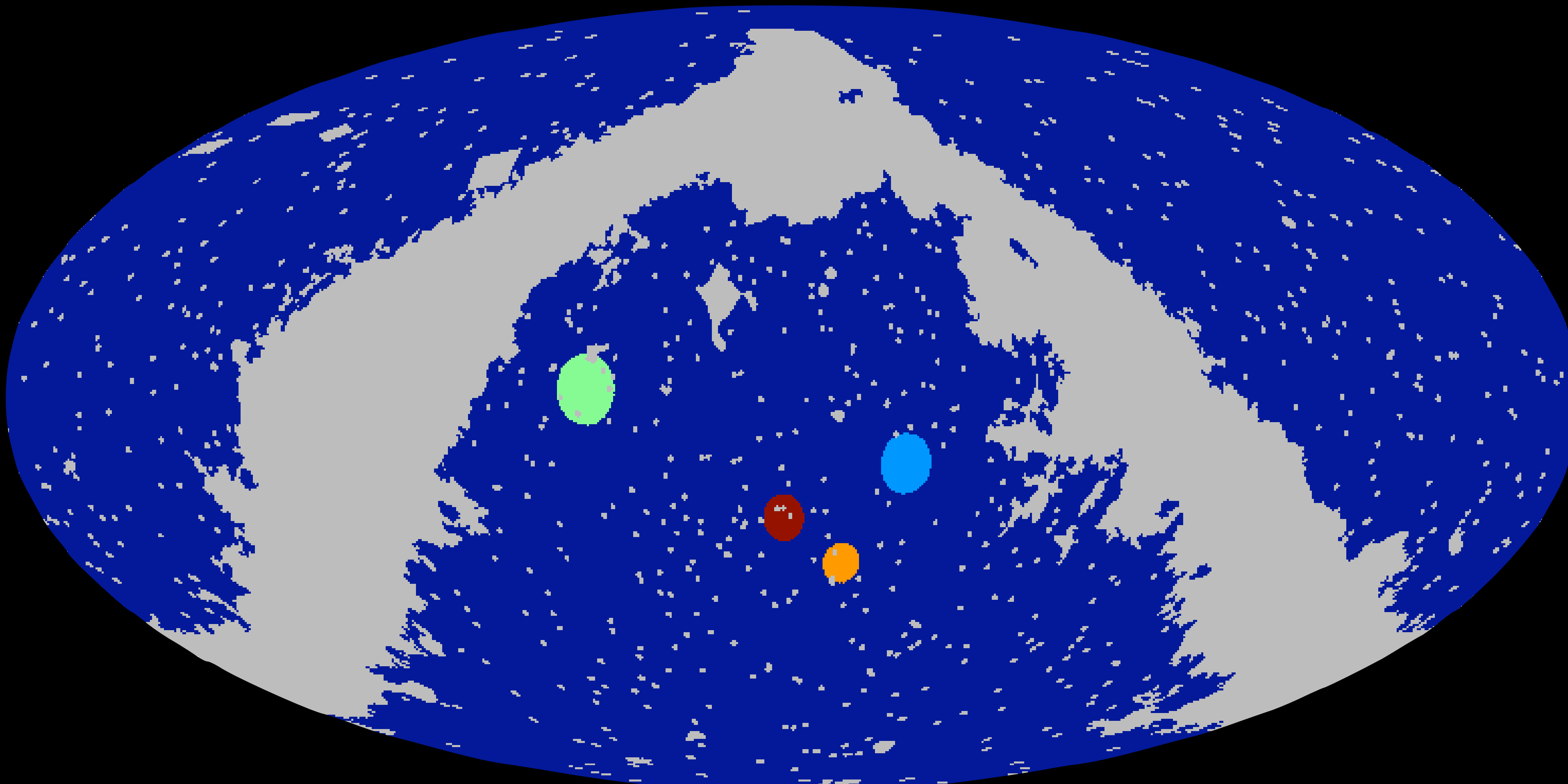
template

data minus template

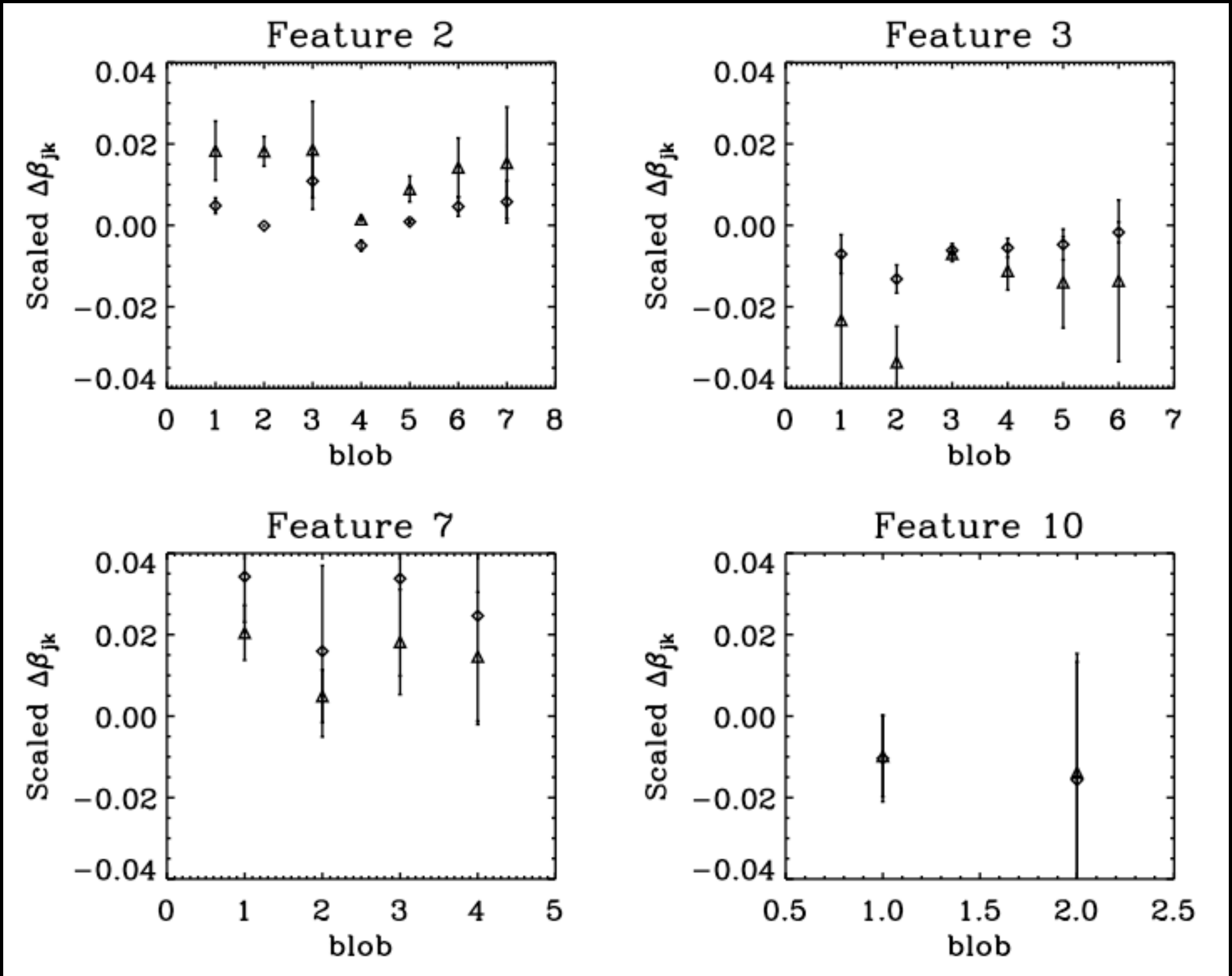
feature locations - Galactic coords



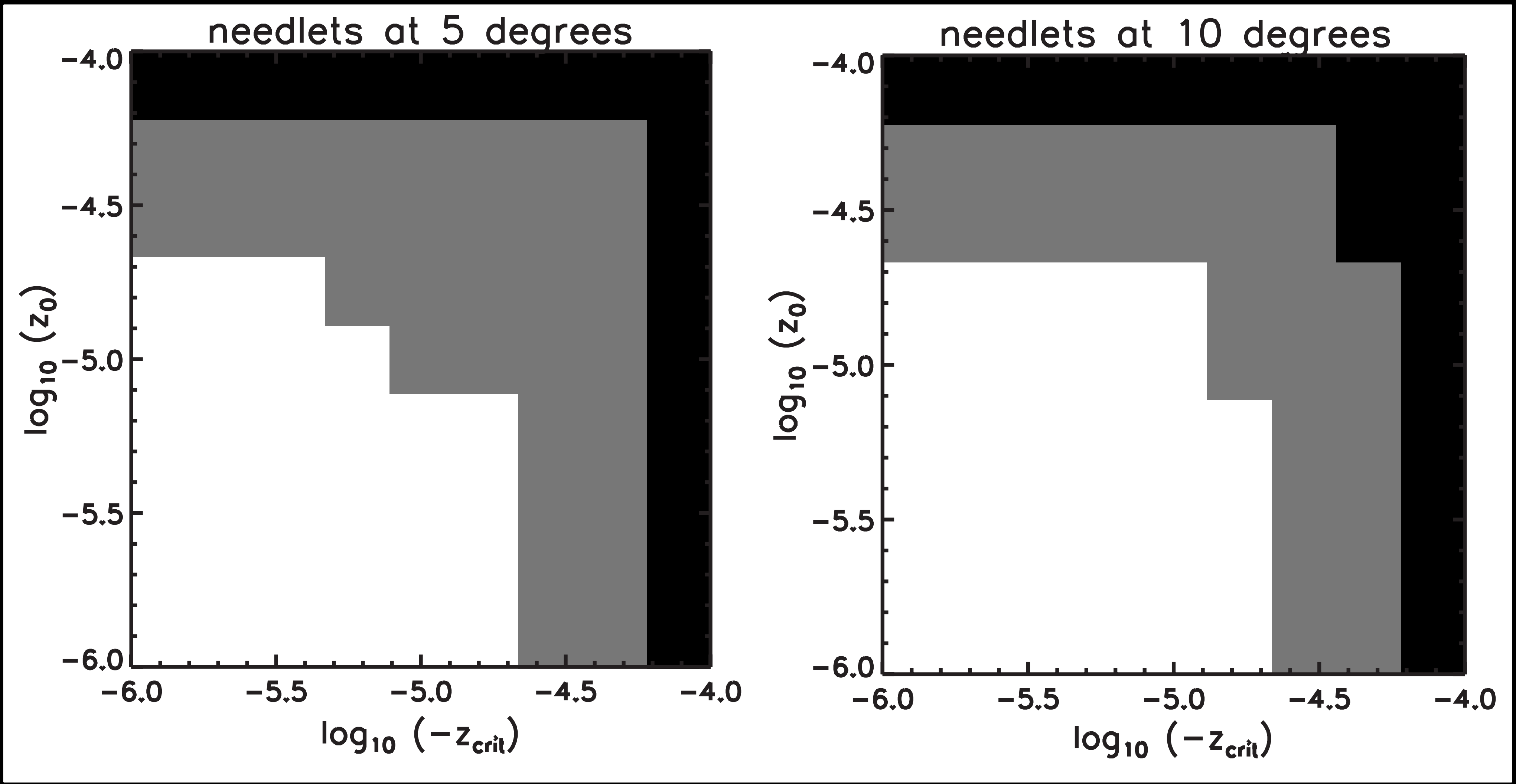
feature locations - rotated



Checking for foreground residuals

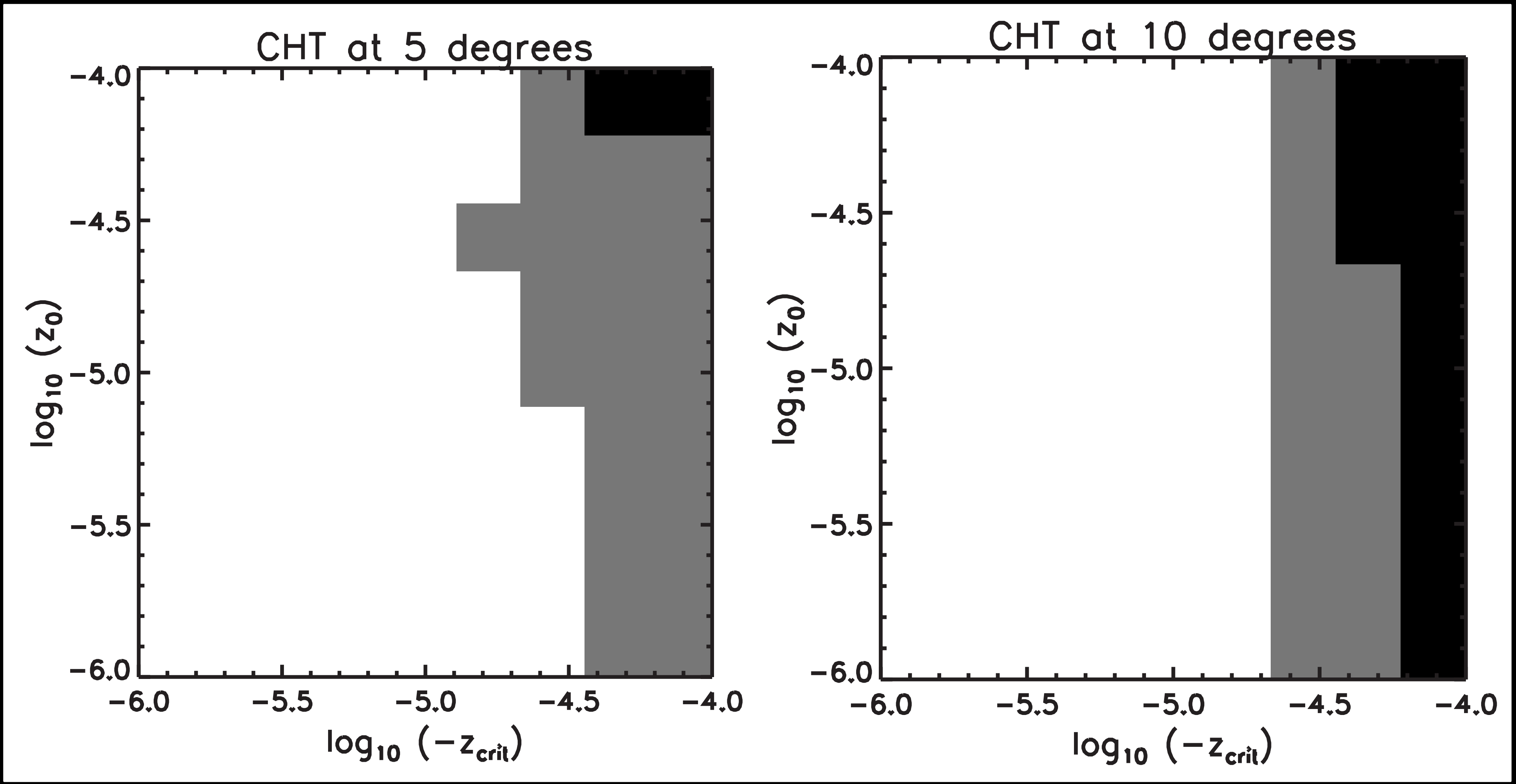


needlet sensitivity/exclusion region



- Bayesian step would detect anything in needlet exclusion region; sensitive to needlet sensitivity region.

CHT sensitivity/exclusion region



- Limited by 1 degree CMB “realization noise” as well as experimental sensitivity/resolution.

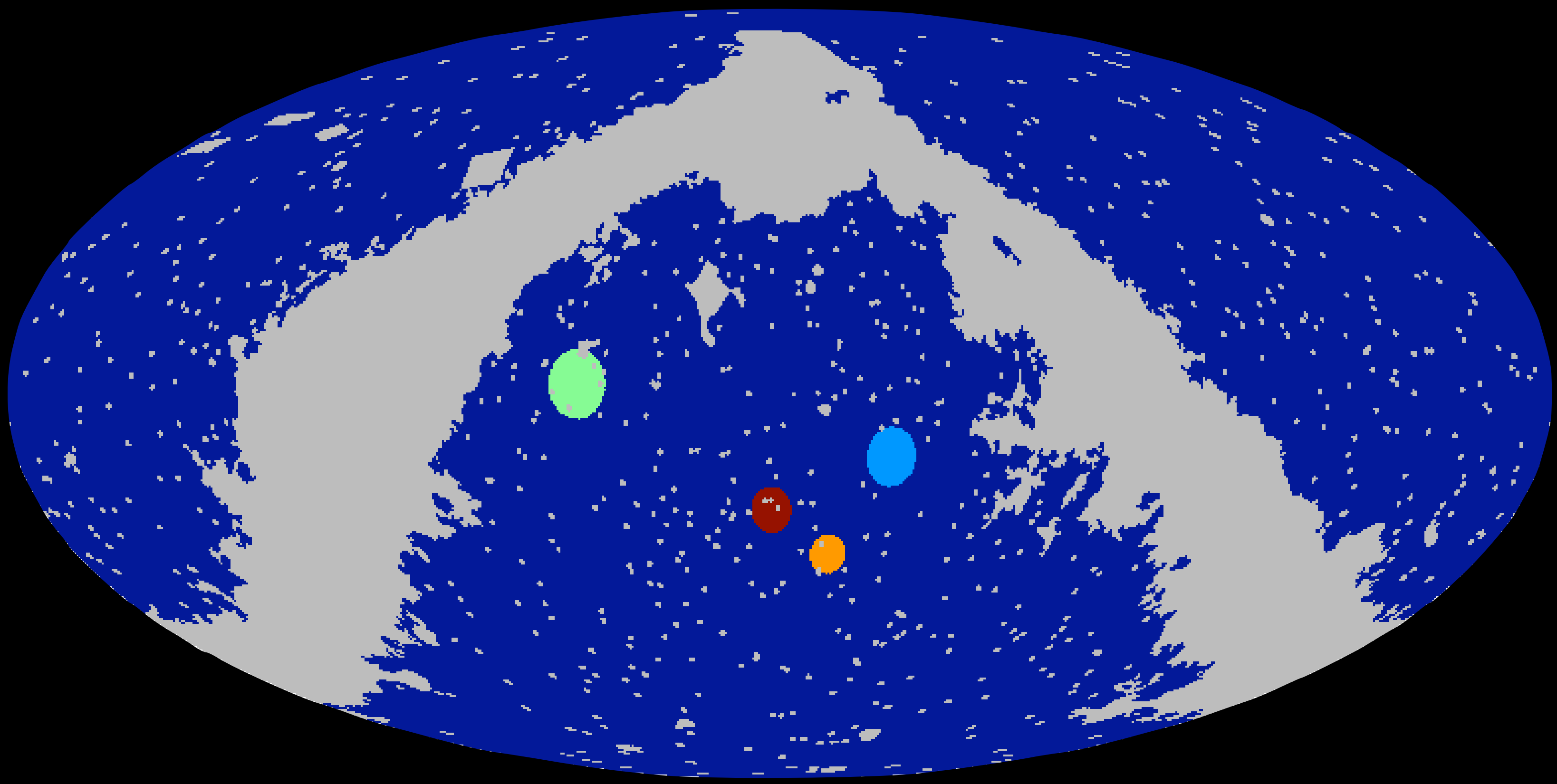
What would we learn about eternal inflation?

- Theory predicts number of expected collisions and strength of each collision given:
  - properties of underlying potential (energy scales of minima and potential barriers)
  - number of e-folds of inflation inside our bubble.

$$N \propto \frac{\lambda}{H_F^4}\left(\frac{H_F}{H_I}\right)^2 \sqrt{\Omega_\kappa}$$

Work In Progress I

- Evidence ratios are currently confined to patches



- Theories will predict number on full-sky (LCDM)

Work In Progress II

- How do we relate patch evidences to full-sky?

- In the case of one blob only:

$$\Pr(\bar{N}_\mathrm{s}|1, \boldsymbol{d}, f_\mathrm{sky}) = \Theta(\bar{N}_\mathrm{s})\, f_\mathrm{sky} e^{-f_\mathrm{sky}\bar{N}_\mathrm{s}} \frac{1 + f_\mathrm{sky}\bar{N}_\mathrm{s} E_b/L_b(\mathbf{0})}{1 + E_b/L_b(\mathbf{0})}$$

- More generally:

$$\Pr(\bar{N}_\mathrm{s}|N_\mathrm{b}, \boldsymbol{d}, f_\mathrm{sky}) \propto$$

$$\Theta(\bar{N}_\mathrm{s})\, e^{-f_\mathrm{sky}\bar{N}_\mathrm{s}} \sum_{N_\mathrm{s}=0}^{N_\mathrm{b}} \frac{(f_\mathrm{sky}\bar{N}_\mathrm{s})^{N_\mathrm{s}}}{N_\mathrm{s}!} \sum_{b_1, b_2, \ldots, b_{N_\mathrm{s}}=1}^{N_\mathrm{s}} \left\{ \prod_{s=1}^{N_\mathrm{s}} \frac{E_{b_s}}{L_{b_s}(\mathbf{0})} \prod_{i,j=1}^{N_\mathrm{s}} (1 - \delta_{s_i, s_j}) \right\}$$

Summary

- Detecting bubble collisions in CMB: dramatic signature of pre-inflationary physics and the Multiverse.

- An automated pipeline to look for bubble collisions in the CMB without being biased by *a posteriori* selection effects.

- Applied to WMAP7 data, no "smoking gun" causal edge signature found: leads to bounds on parameter space.

- Four features consistent with bubble collisions identified.

- Planck will be able to corroborate through increased resolution (3X) and sensitivity (order of magnitude) and counterpart polarization signal (Czech et al 2010).