

The impact of calibration errors on 21 cm global experiments: a bayesian case study with EDGES

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EDGES calibration

Bayesian model selection

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Global signal constraints

Conclusions

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How accurately do we need to be able to model the instrument during calibration to achieve an unbiased detection of the 21 cm absorption trough at Cosmic Dawn?

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Answer depends on:

- Beam chromaticity
- Foreground model accuracy

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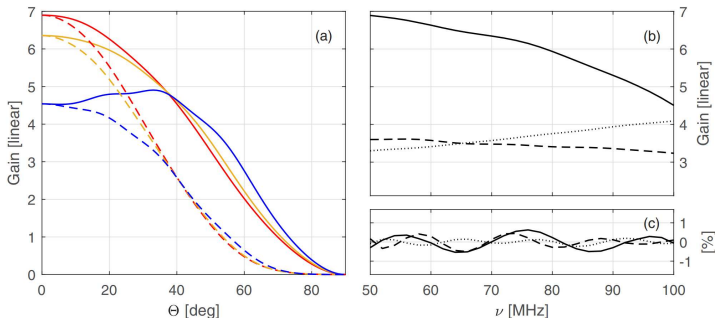
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Extended Data Figure 4 | Antenna beam model. a, Beam cross-sections showing the gain in the plane containing the electric field (dashed) and in the plane containing the magnetic field (solid) from FEKO for the H2 antenna and ground plane over soil. Cross-sections are plotted at 50 MHz (red), 70 MHz (yellow) and 100 MHz (blue). b, Frequency dependence of the gain at zenith angle $\Theta = 0^\circ$ (solid) and the 3-dB points at 70 MHz in the electric-field plane (dashed) and magnetic-field plane (dotted). c, Small

undulations with frequency, after a five-term polynomial (equation (2)) has been subtracted from each of the curves, are plotted as fractional changes in the gain. Simulated observations with this model yield residuals of 0.015 K (0.001%) to the five-term fit over the frequency range 52–97 MHz at GHA = 10 and residuals of 0.1 K (0.002%) at GHA = 0, showing that the cumulative beam yields less chromaticity than the approximately 0.5% variations in the individual points plotted.

- Figure credit: Bowman et al. (2018), Nature volume 555, pages 67–70

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‘Adjustment for beam chromaticity’ in EDGES data calibration (Mozdzen et al. 2017, 2019):

- divide out the effect of beam chromaticity in the measured spectra using electromagnetic simulations of the beam and a model for the sky
- Beam correction factor:

$$B_{\text{factor}}(\nu) = \frac{\int_{\Omega} T_{\text{sky-model}}(\nu_{75}, \Omega) * B(\nu, \Omega) d\Omega}{\int_{\Omega} T_{\text{sky-model}}(\nu_{75}, \Omega) * B(\nu_{75}, \Omega) d\Omega} . \quad (1)$$

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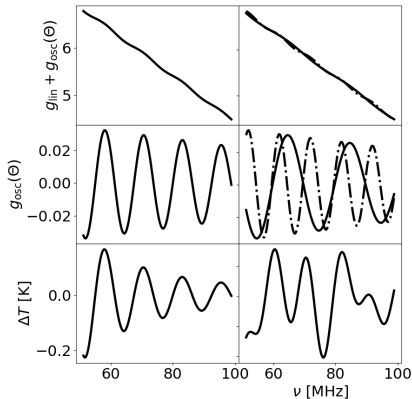
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- Mock mis-calibration scenario
- Assume perfect model for smooth component but 1% uncertainty on amplitude of undulating component of gain model
- Perfect sky model
- Result: ~ 200 mK structure in the data (statistically significant relative to order 10 mK noise level)

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Are there calibration systematics of this type in the publicly available EDGES low-band data?

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Answer:

- Use Bayesian model selection to choose between models with components designed to model systematics and those that exclude systematic model components
- Bayesian evidence automatically implements Occam's razor: a simpler theory with a compact parameter space will have a larger evidence than a more complicated one, unless the latter is significantly better at explaining the data.
- If there are not systematic effects in the data, Bayesian evidence will favour simpler models

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Model components:

- δT_b (4 models) - no detectable global signal, or one of the three global signal parametrisations: a flattened Gaussian, Gaussian or ARES simulation
- \bar{T}_{Fg} (8 models) - log-polynomial models between 3rd and 10th order. 3rd order = minimum complexity model for the intrinsic foregrounds and negligible calibration errors. higher orders = intrinsic foregrounds + contamination by certain classes of calibration systematics
- T_{cal} (2 models) - we consider models both with and without the inclusion of an explicit damped sinusoidal systematic component.
- N (2 models) - generalised radiometric + white noise covariance model of flat noise model

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Model number	Global signal model, δT_b	Log-poly. order, \bar{T}_{Fg}	Systematic, T_{cal}	Noise model, N	log(evidence)	Residual RMS [mK]
111	flattened Gaussian	6	Y	R+W+w	332.17 ± 0.24	20.4
112	Gaussian	6	Y	R+W+w	332.21 ± 0.24	21.0
113	flattened Gaussian	8	Y	R+W+w	332.37 ± 0.22	19.7
114	flattened Gaussian	5	Y	R+W+w	332.63 ± 0.24	20.4
115	Gaussian	8	Y	R+W+w	332.81 ± 0.23	20.7
116	flattened Gaussian	9	Y	R+W+w	333.58 ± 0.22	19.6
117	ARES	10	Y	R+W+w	334.07 ± 0.20	20.7
118	-	9	Y	R+W+w	334.08 ± 0.24	20.8
119	-	10	Y	R+W+w	334.08 ± 0.23	20.7
120	Gaussian	5	Y	R+W+w	334.18 ± 0.24	21.1
121	ARES	9	Y	R+W+w	334.25 ± 0.21	20.8
122	ARES	7	Y	R+W+w	334.28 ± 0.22	20.9
123	ARES	8	Y	R+W+w	334.40 ± 0.21	20.8
124	-	8	Y	R+W+w	334.48 ± 0.25	20.7
125	-	7	Y	R+W+w	334.64 ± 0.26	20.9
126	flattened Gaussian	10	Y	R+W+w	334.97 ± 0.22	19.7
127	Gaussian	7	Y	R+W+w	335.09 ± 0.23	20.9
128	flattened Gaussian	7	Y	R+W+w	336.17 ± 0.23	19.8

- model number in ascending order of evidence
- $\Delta \log(E) = 3$ constitutes strong evidence for one model over another (rel. probability 20:1; Kass & Raftery (1995))
- T_{cal} and high order poly. decisively preferred; RMS > theoretical noise estimate

Global signal parameters

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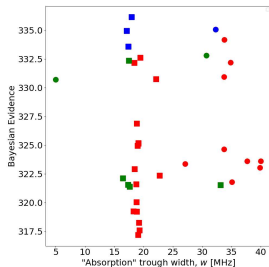
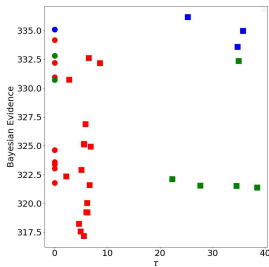
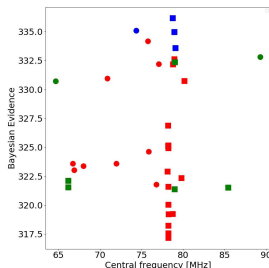
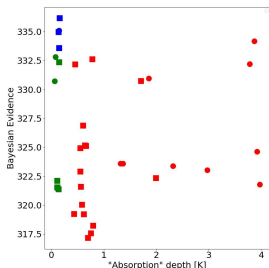
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- Gaussian (circles) and flattened Gaussian (squares) MAP parameter values (amplitude, central frequency, flattening factor, width) as a function of model evidence

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- The publicly available EDGES low-band data is not well described by models for foreground emission and a global signal, alone
- Models including T_{cal} and high order polynomials (greater than 5th order) decisively preferred by Bayesian evidence relative to those excluding them
- Residual RMS significantly in excess of theoretical thermal noise estimate
- Covariance between model component limits constraints on shape of global 21 cm signal (width, flatness). The best constrained parameter is the absorption depth with the highest evidence models favouring $A < 209$ mK, consistent with standard cosmological expectation

MAP global signal realisations

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