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Sterna Inter-calibration Study

Spectral Band Adjustment Functions

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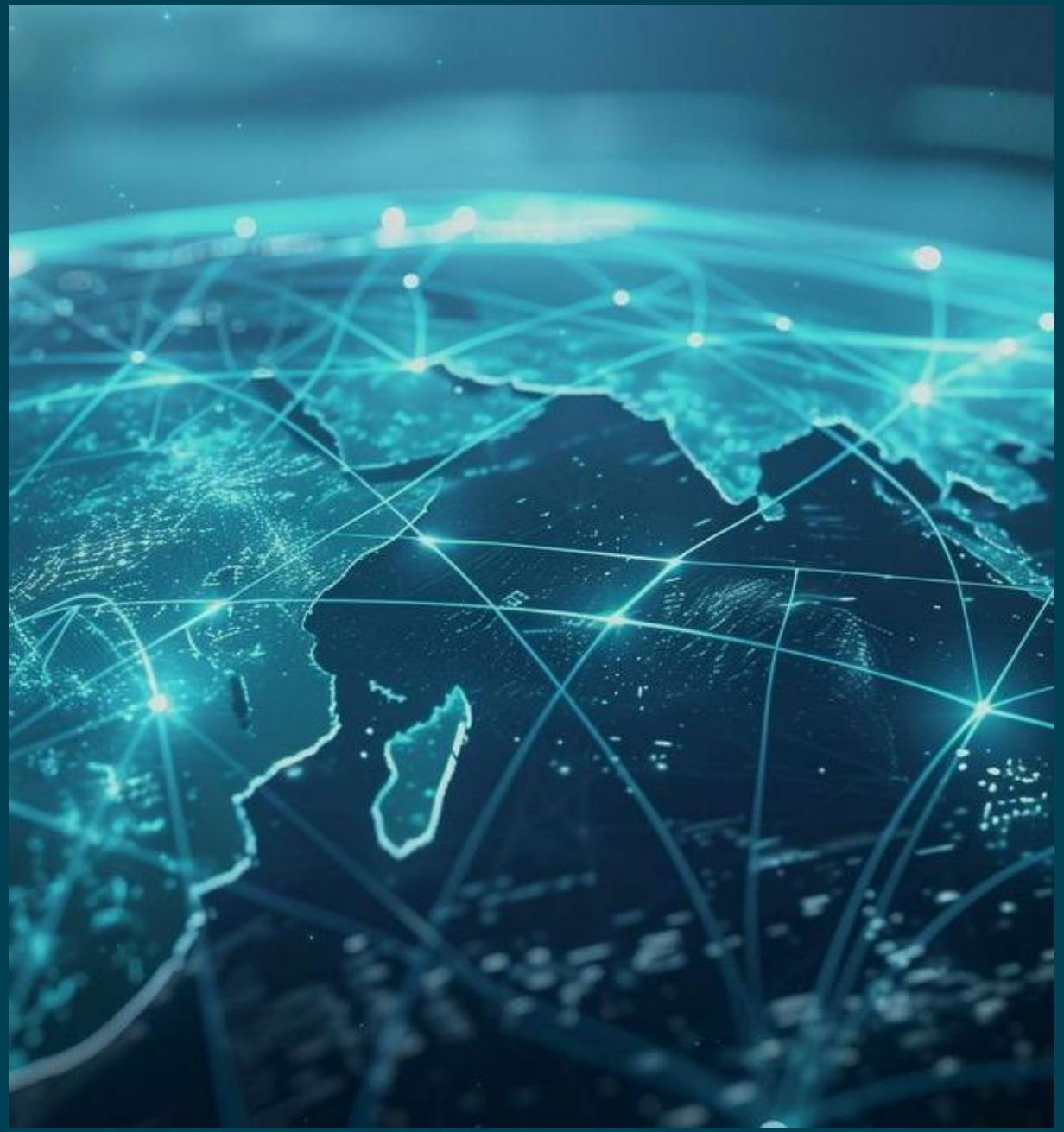
13 November 2025



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Summary

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01

RTTOV Simulations

Simulations: RTTOV dataset summary

“Under identical ground, atmospheric, and viewing conditions, any differences in simulated brightness temperature arise solely from variations in simulated sensor characteristics.”

Simulations generated by EUMETSAT

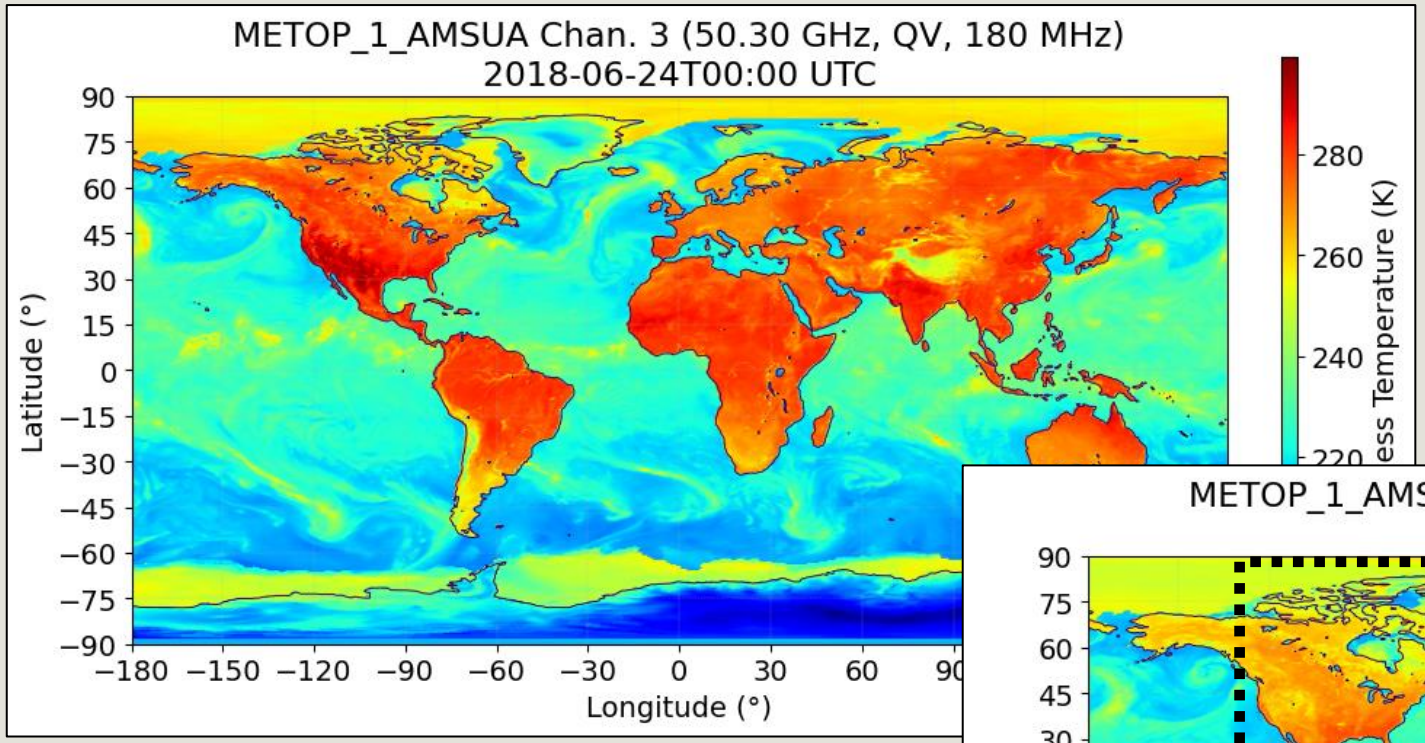
- Based on ERA5 reanalysis data
- Simulations available for clear-sky and all-sky conditions. **Clear-sky used**.
- Both **real** and **top-hat** (boxcar) spectral response functions (SRFs) were used [1]
- Viewing zenith angle (VZA) of 0º, and 53º to represent the ICI conical scanner geometry
- **Global** samples taken the **1st, 12th** and **24th** of each month at **00:00 UTC** and **12:00 UTC**
- Period: **One year** starting 2018-03-01
- Total samples per channel: ~5.5 x 10^7

Platform	Sensor	VZA (º)
MetOp-1 (= MetOp-B)	MHS	0
MetOp-1 (= MetOp-B)	AMSU-A	0
JPSS (= SNPP)	ATMS	0
AWS	AWS	0 and 53
MetOp-SG-1 (= MetOp-SG-A)	MWS	0
MetOp-SG-2 (= MetOp-SG-B)	ICI	53

- Real SRFs used when available
- No real SRFs for MHS → *Top-hat* used
- *Top-hat* simulations **identical** for these channels:
  - ATMS-6, AMSUA-5, and MWS-6
  - ATMS-3 and MWS-3

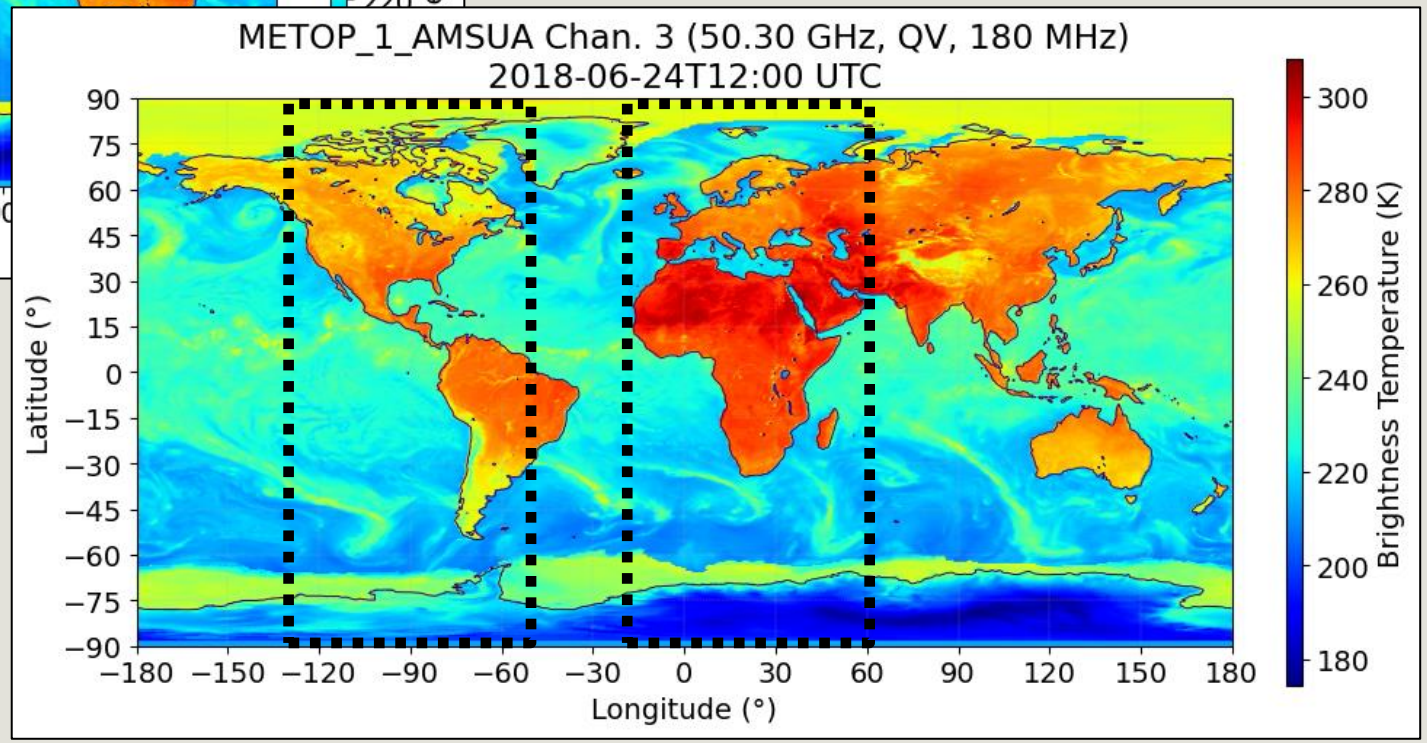
[1] https://nwp-saf.eumetsat.int/site/software/rttov/download/coefficients/spectral-response-functions/

Simulations: RTTOV samples



RTTOV simulations for ERA5 for 2018-06-24

At 00:00 UTC and 12:00 UTC



Daily cycle-**location bias →**

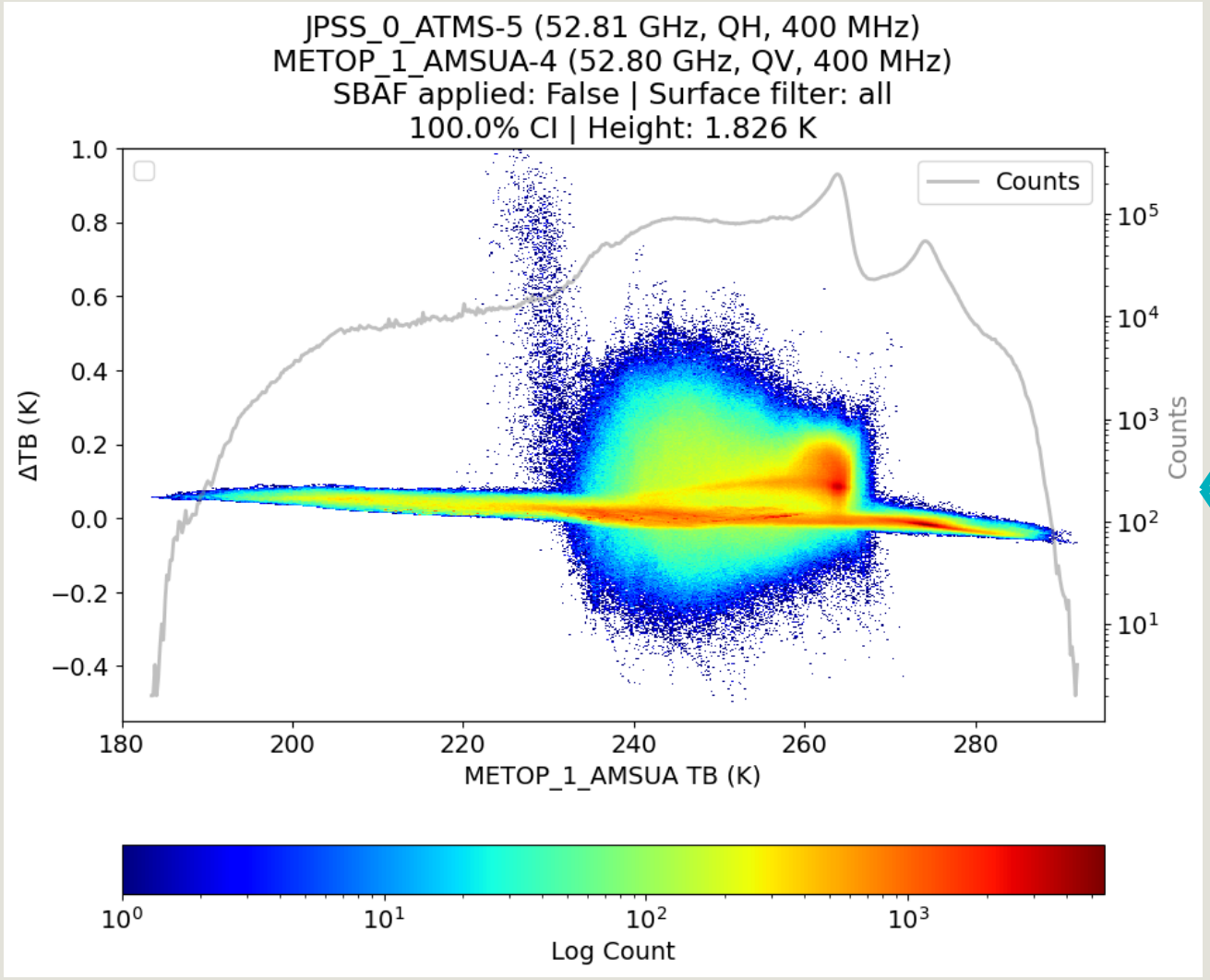
Channel Equivalence: ATMS vs. AMSU-A and MHS

Monitored Sensor	Channel Name	Frequency [GHz]	Bandwidth [MHz]	Polarisation	Reference Sensor	Channel Name	Frequency [GHz]	Bandwidth [MHz]	Polarisation
ATMS	5	52.81	400	QH	**AMSU-A**	4	52.80	400	**QV**
ATMS	6	53.58	170	QH	**AMSU-A**	5	53.60	170	QH
ATMS	7	54.40	400	QH	**AMSU-A**	6	54.40	400	QH
ATMS	8	54.94	400	QH	**AMSU-A**	7	54.94	400	**QV**
ATMS	9	55.48	330	QH	**AMSU-A**	8	55.50	330	QH
ATMS	10	57.29	155	QH	**AMSU-A**	9	57.29	330	QH
ATMS	18	183.31	2000	QH	**MHS**	5	190.31	2200	**QV**
ATMS	20	183.31	1000	QH	**MHS**	4	183.31	1000	QH
ATMS	22	183.31	500	QH	**MHS**	3	183.31	500	QH

ATMS-18, worth remembering

SNPP/ATMS vs. METOP-B/AMSU-A and MHS

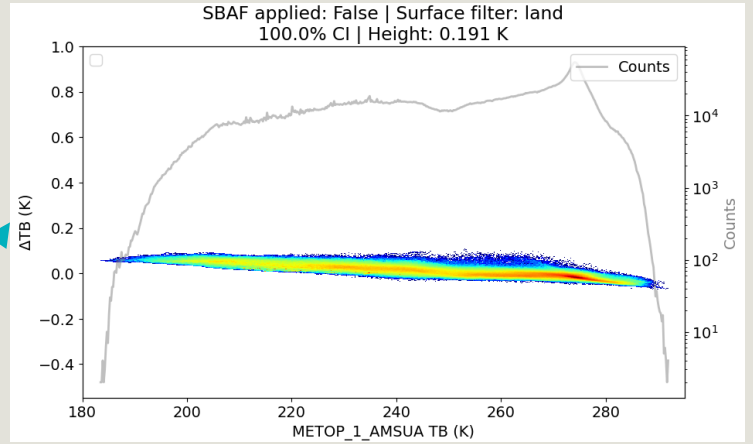
Simulations: Surface Classes I

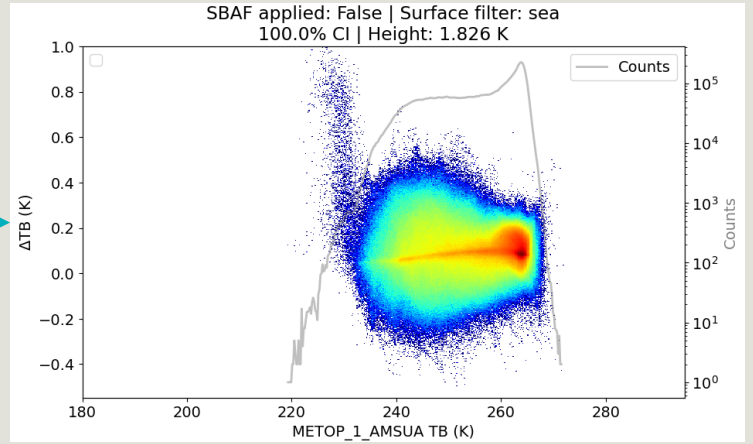


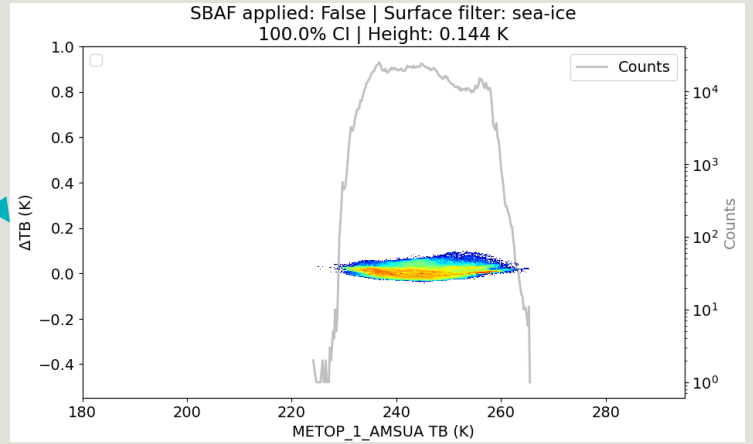
Land

Sea

Sea-Ice

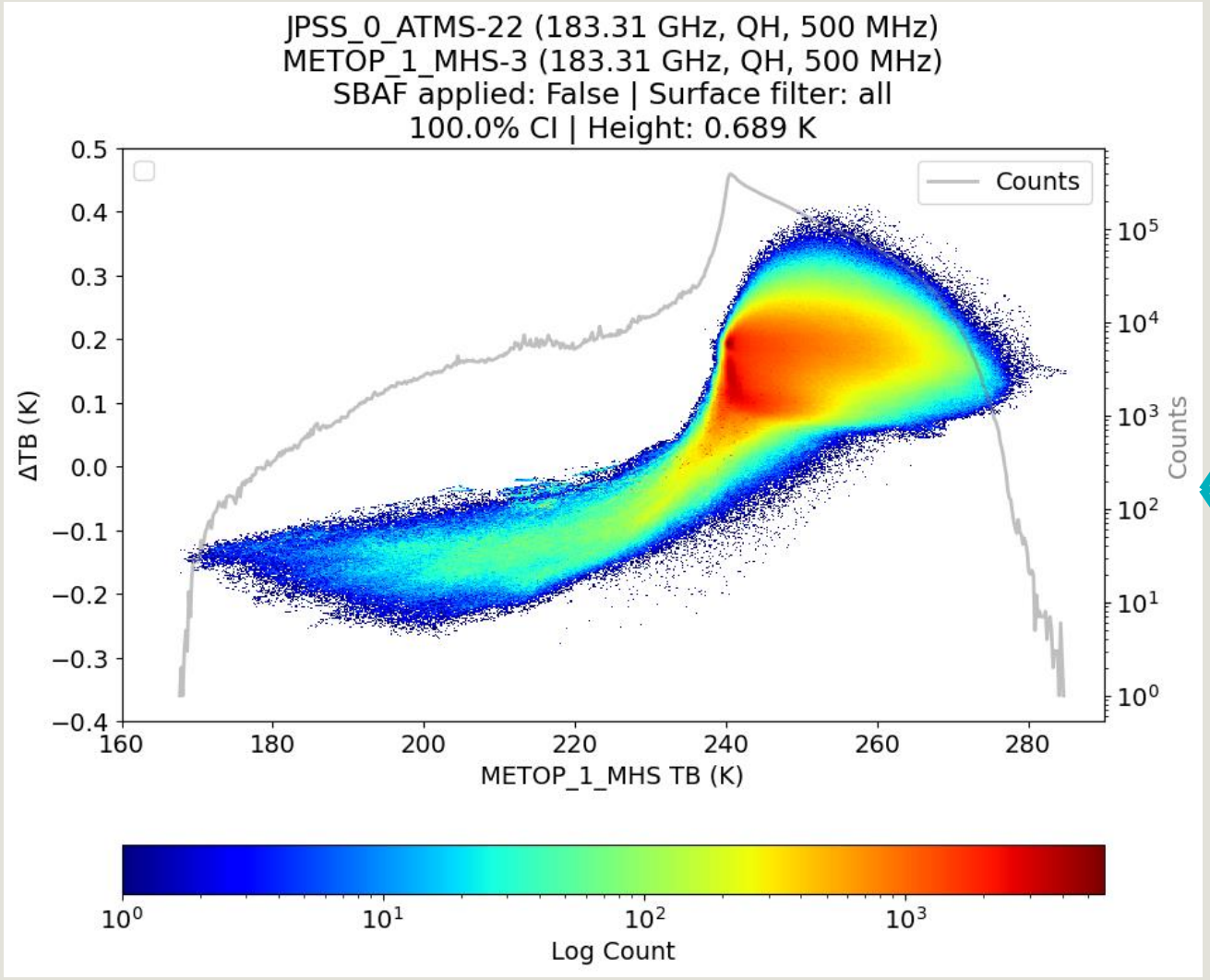






ATMS-5: Atmospheric temperature sounding channel near a window band

Simulations: Surface Classes II

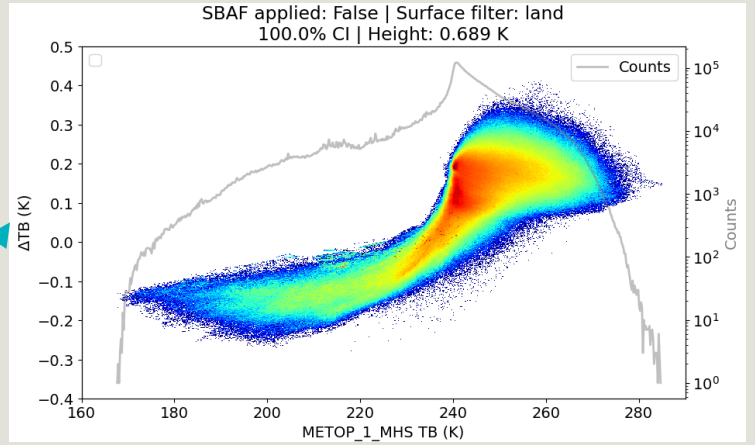


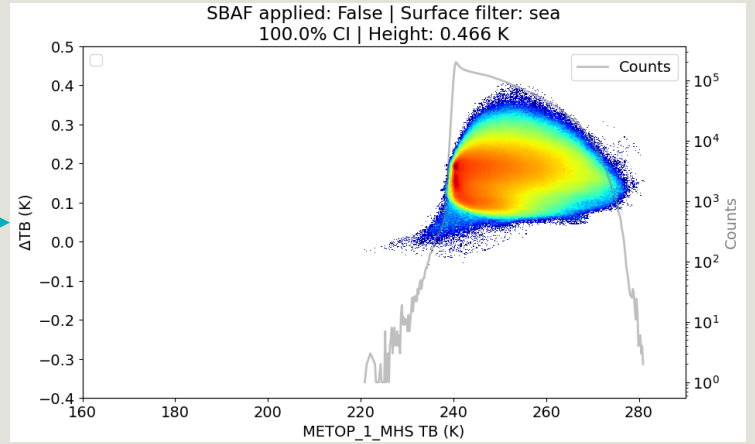
ATMS-22: Humidity sounding channel

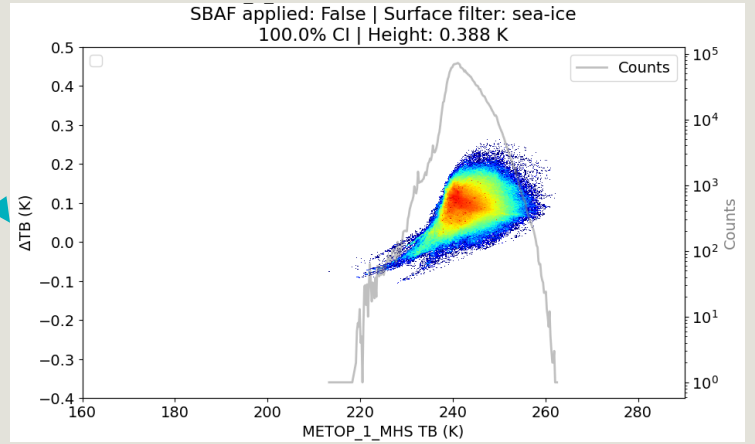
Land

Sea

Sea-Ice







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02

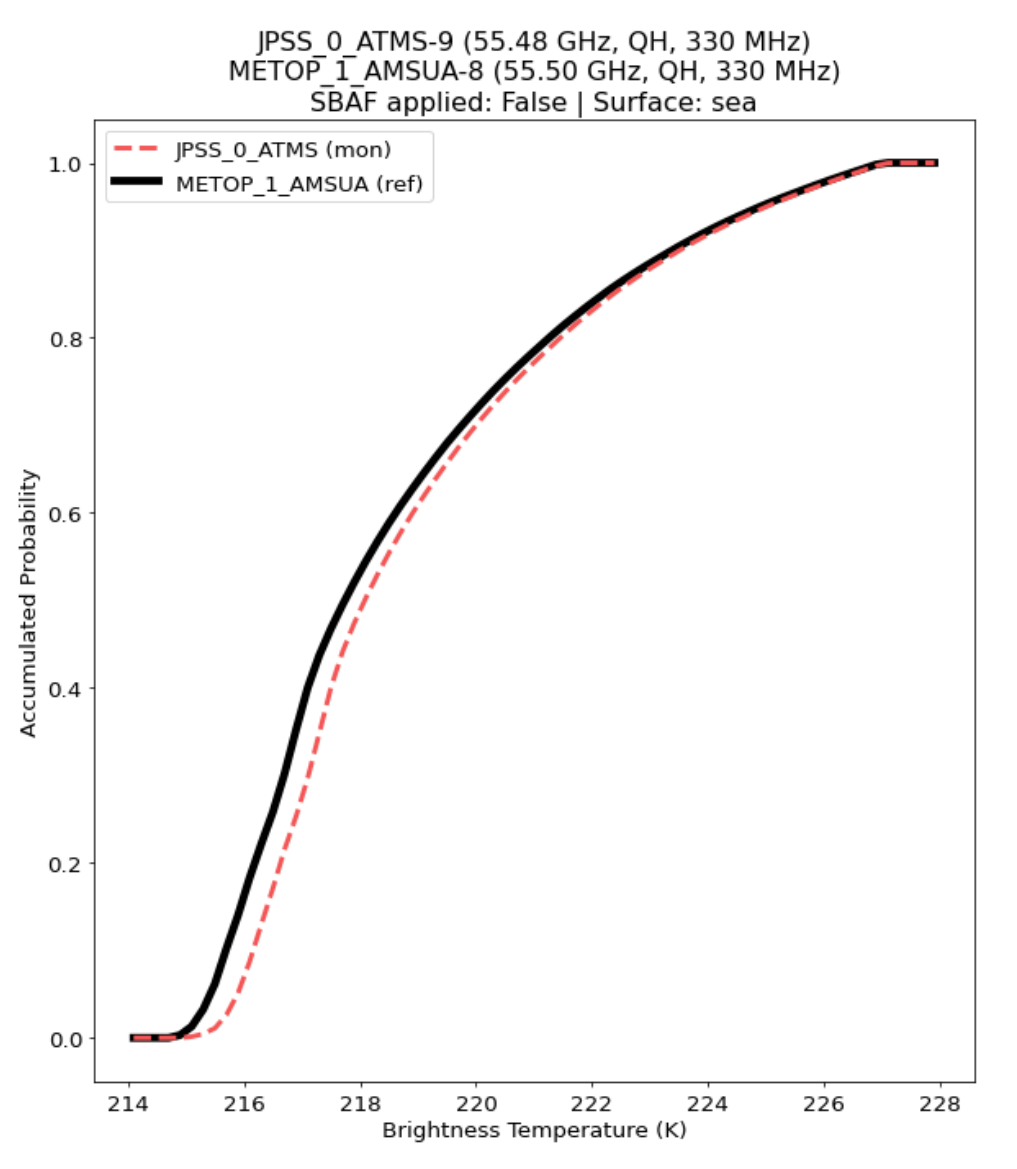
SBAF Construction
CDF Matching

Spectral Band Adjustment Functions: Piecewise Linear

$$SBAF_\lambda(x) = y_i + \frac{y_{i+1} - y_i}{x_{i+1} - x_i}(x - x_i), \qquad x \in [x_i, x_{i+1}), \qquad i = 1, \ldots, N$$

- Piecewise linear function
- Discrete and finite ranges
- $2\,N + 1$ parameters per range $(x_i, y_i) \ll$ Number of samples
- Not a direct Look Up Table (LUT), but a simple model

Cumulative Distribution Function (CDF) Matching

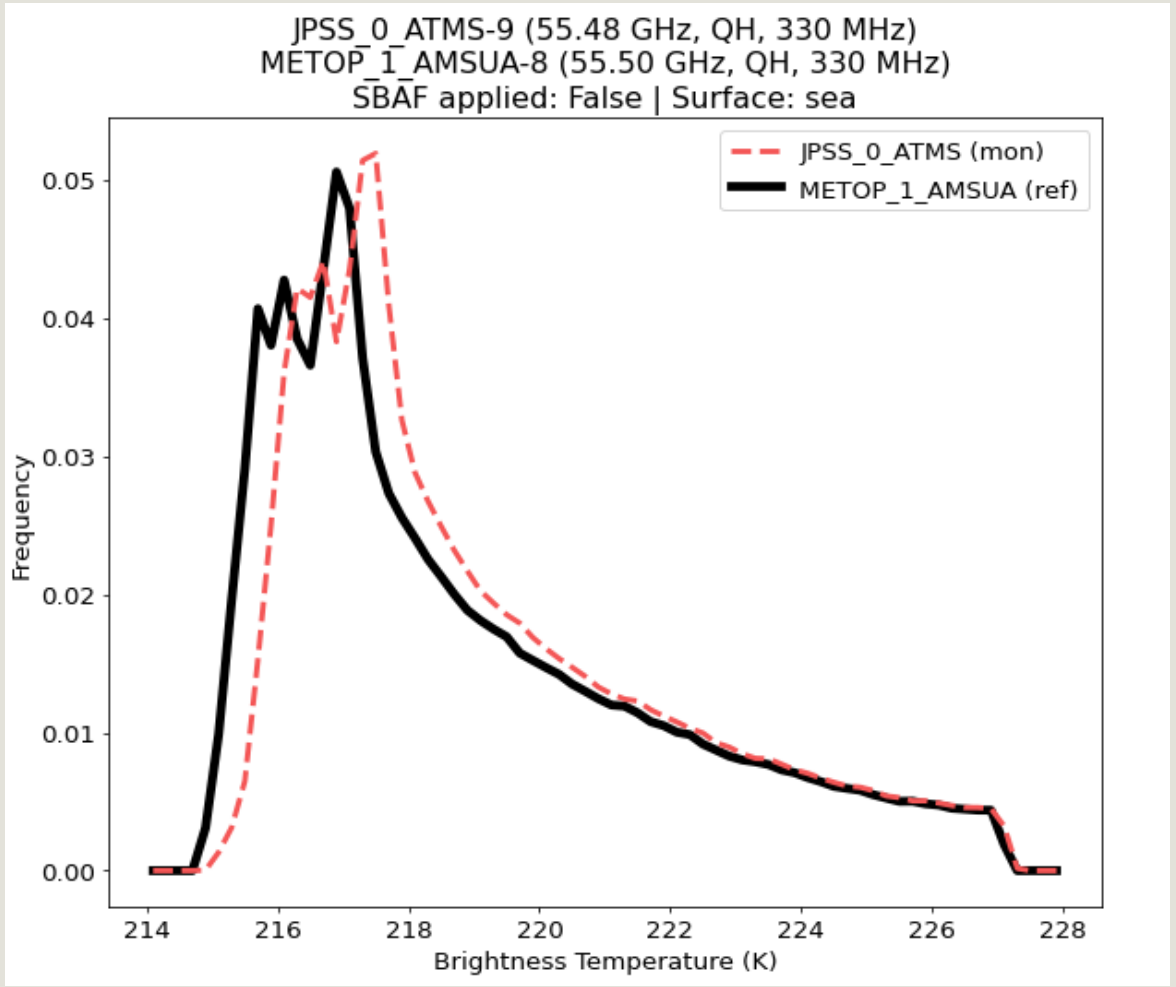


$$TB'_{mon} = \overbrace{CDF_{ref}^{-1}\left(CDF_{mon}(TB_{mon})\right)}^{SBAF}$$

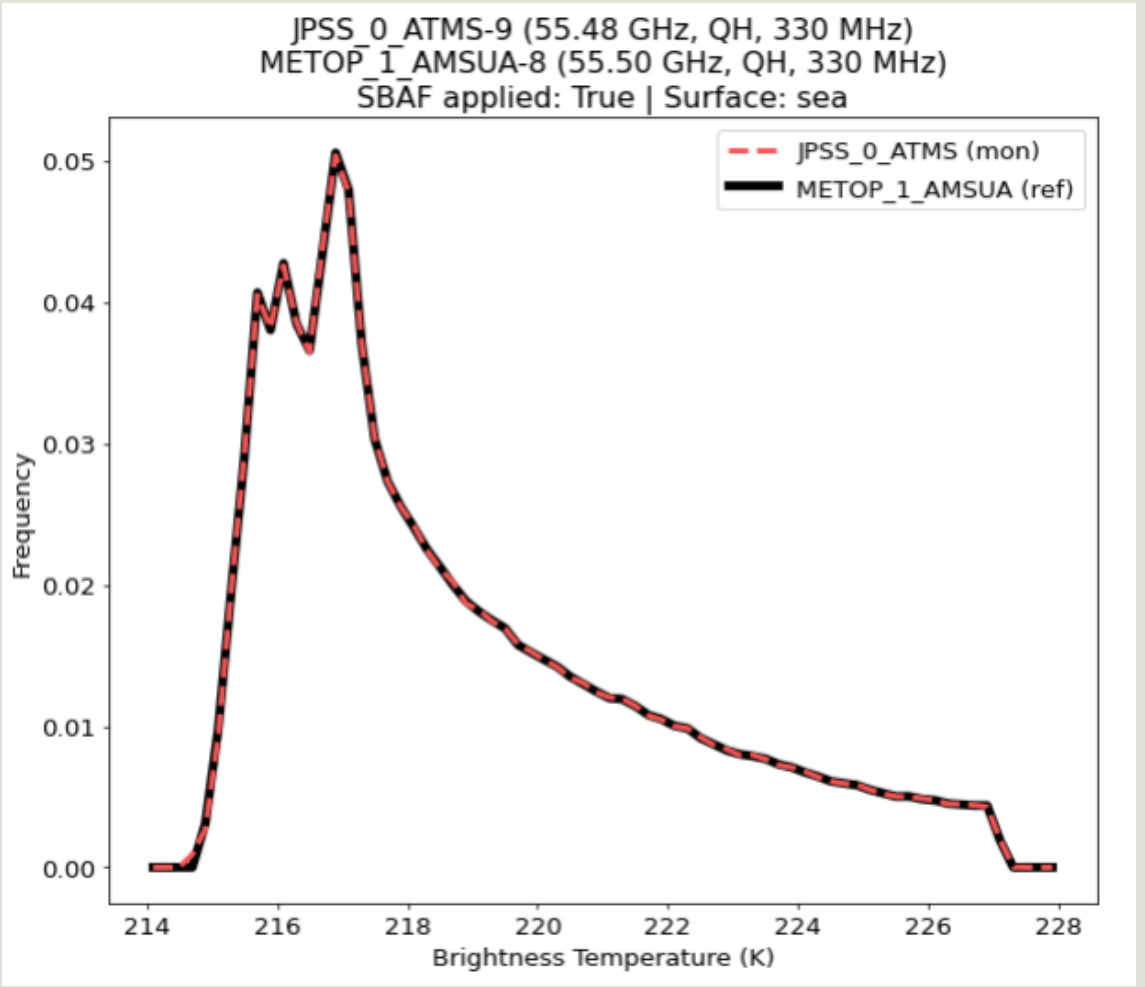
$$\Rightarrow \mathbb{E}[TB'_{mon} - TB_{\text{ref}}] = 0$$

- TB (mon, ref) pairs decoupled. Only the distribution is used
- Monotonic non-decreasing (forced increasing)
- Parametric representation (piecewise linear interpolation)
- Number of ranges: 10/100 per K (more on this later)
- Number of parameters << number of samples
- Ambiguity: $tb_i^{mon} \cong tb_j^{mon}$ but $tb_i^{ref} \neq tb_j^{ref}$

Cumulative Distribution Function Matching: Adjustment



$$\overline{\Delta \mathrm{TB}} = 3.20 \times 10^{-1}\ \mathrm{K}$$



$$\overline{\Delta \mathrm{TB}} = -1.04 \times 10^{-4}\ \mathrm{K}$$

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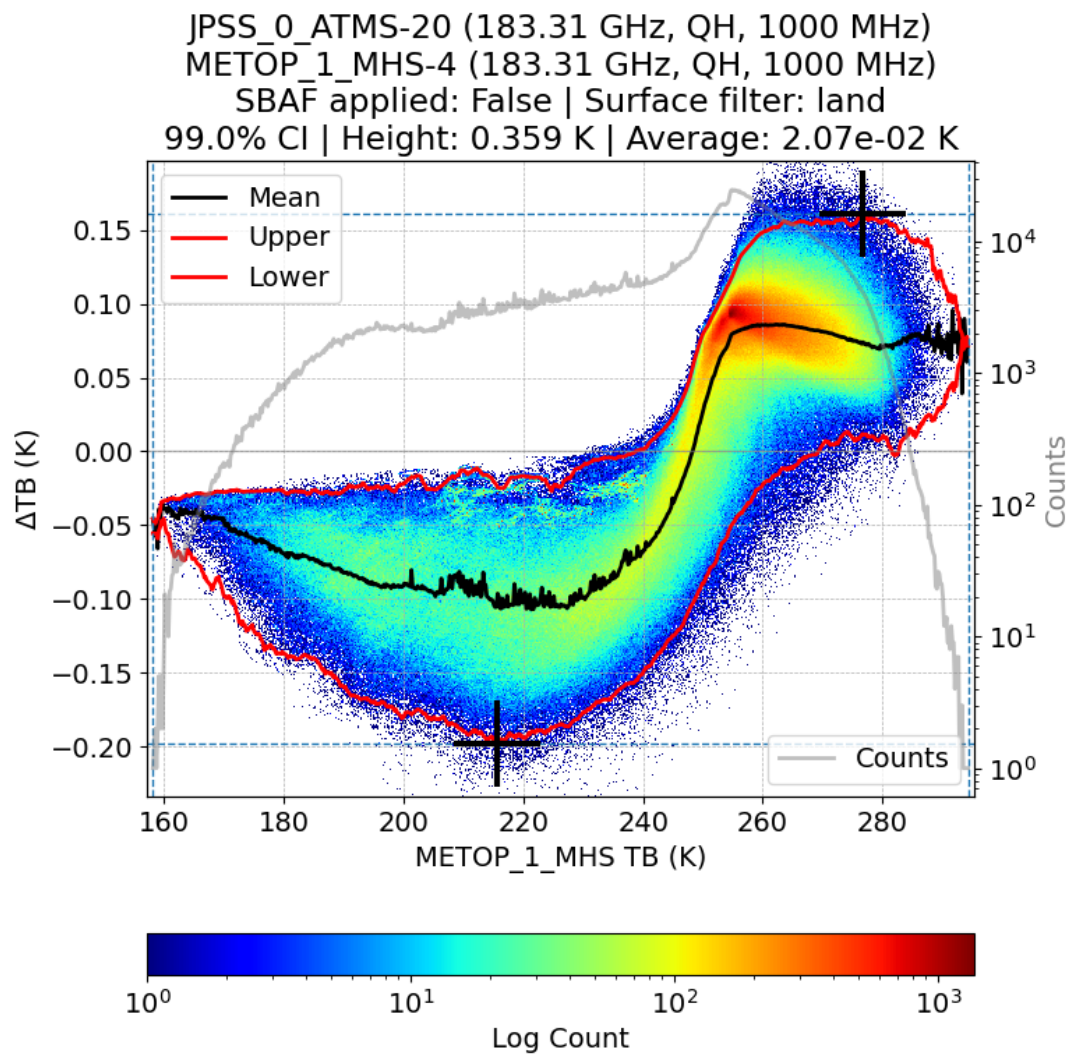
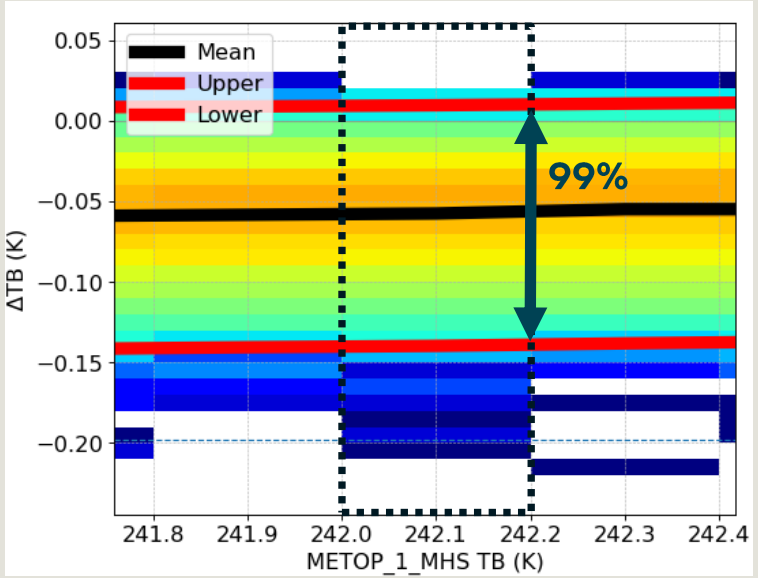
03

SBAF Application
Density Heatmaps Sample Results

Heatmap Histogram: Description

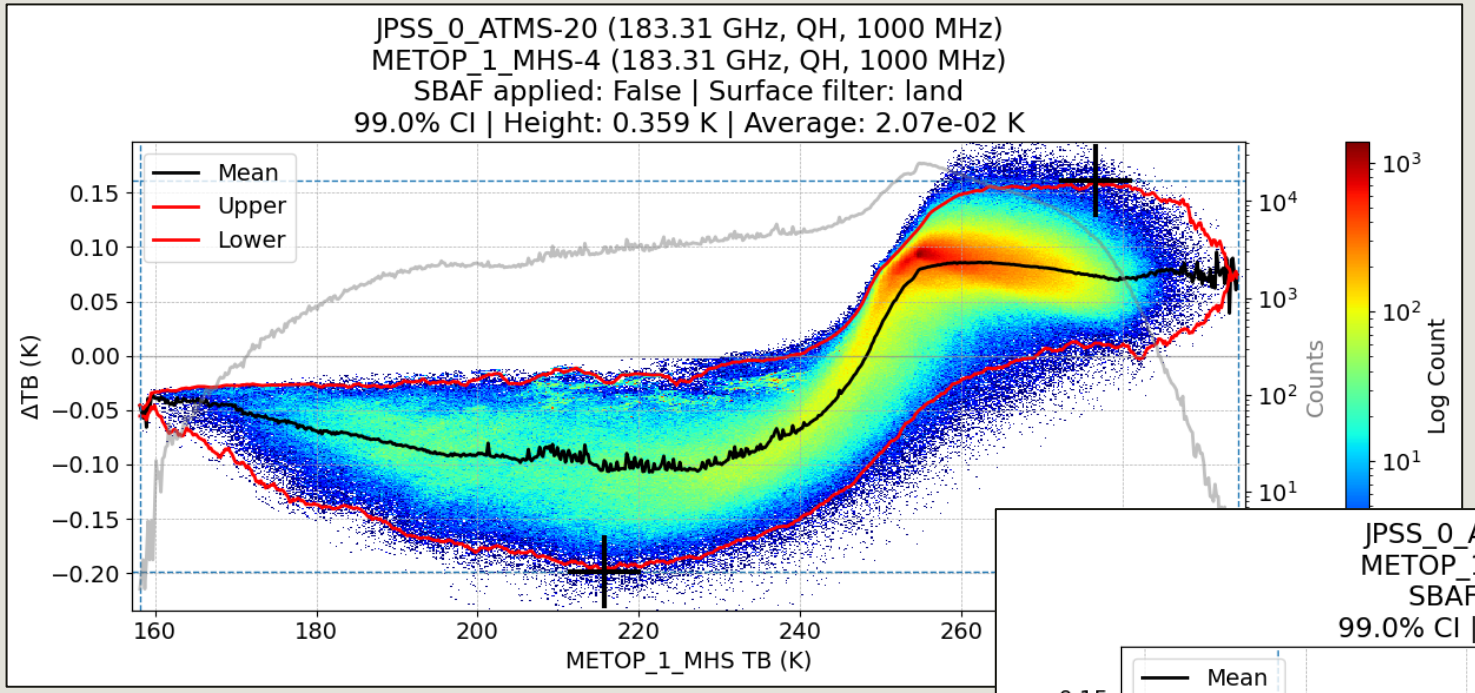




- Discrete ΔTB vs. monitored TB rectangular bins
- Bin sizes: 0.2 K (TB) 1e-3 K (ΔTB, only meaningful for plotting)
- In plots: TB percentiles (0.5, 99.5, red solid lines) and mean (black solid line) are calculated ***binwise***

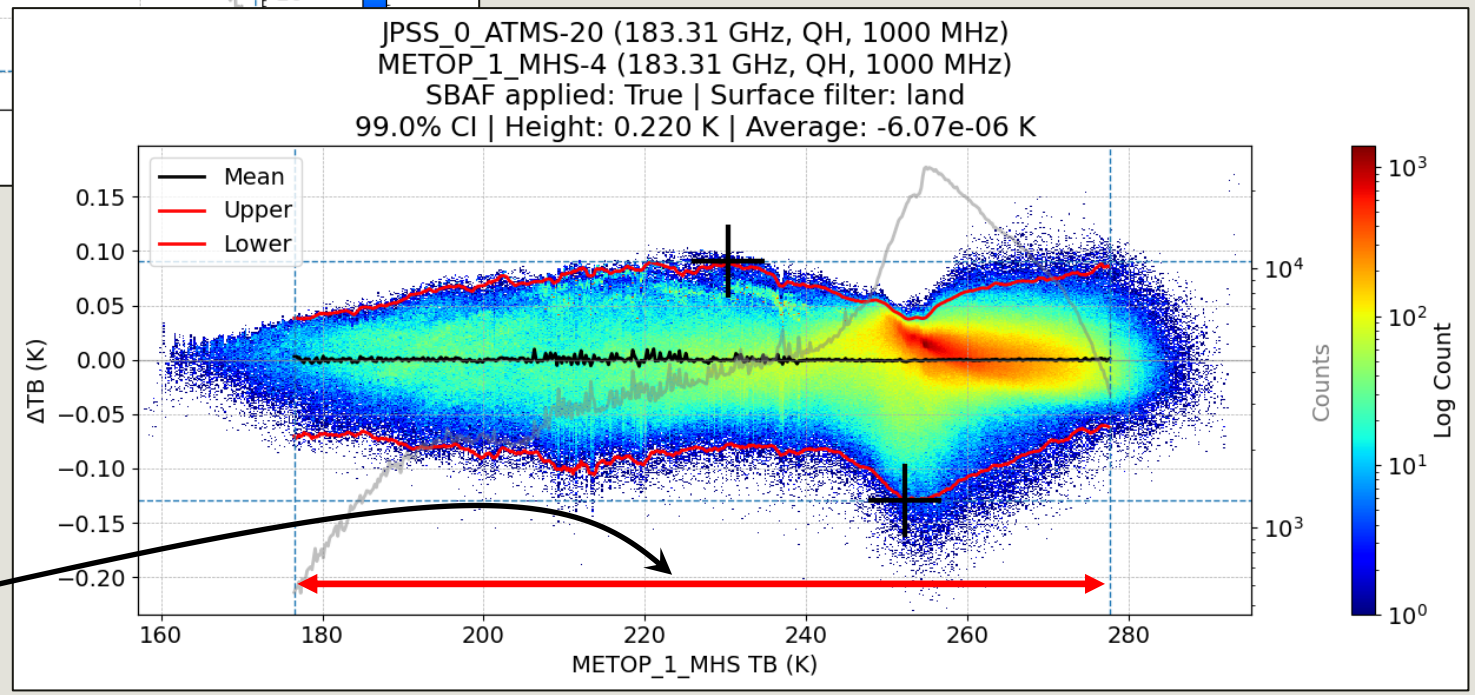
- ┼ Markers at minimum and maximum percentiles (0.5 and 99.5) define the binwise worst cases for the entire distribution (minimum of binwise minimums and vice-versa)
- *Height* is the ΔTB range between markers (horizontal blue dotted lines). This is larger than the 99% CI of the distribution
- Reference TB validity interval (100% in this case): Vertical blue dotted lines
- In the metrics: **The average value is global**, not *binwise*

SBAF: Sample results I – Adjustment



Original

- Random dataset split 50%/50% **CDF matching/error analysis**
- All results are from the error analysis split
- Removed 0.5% lower and 0.5% higher reference TBs (validity range)

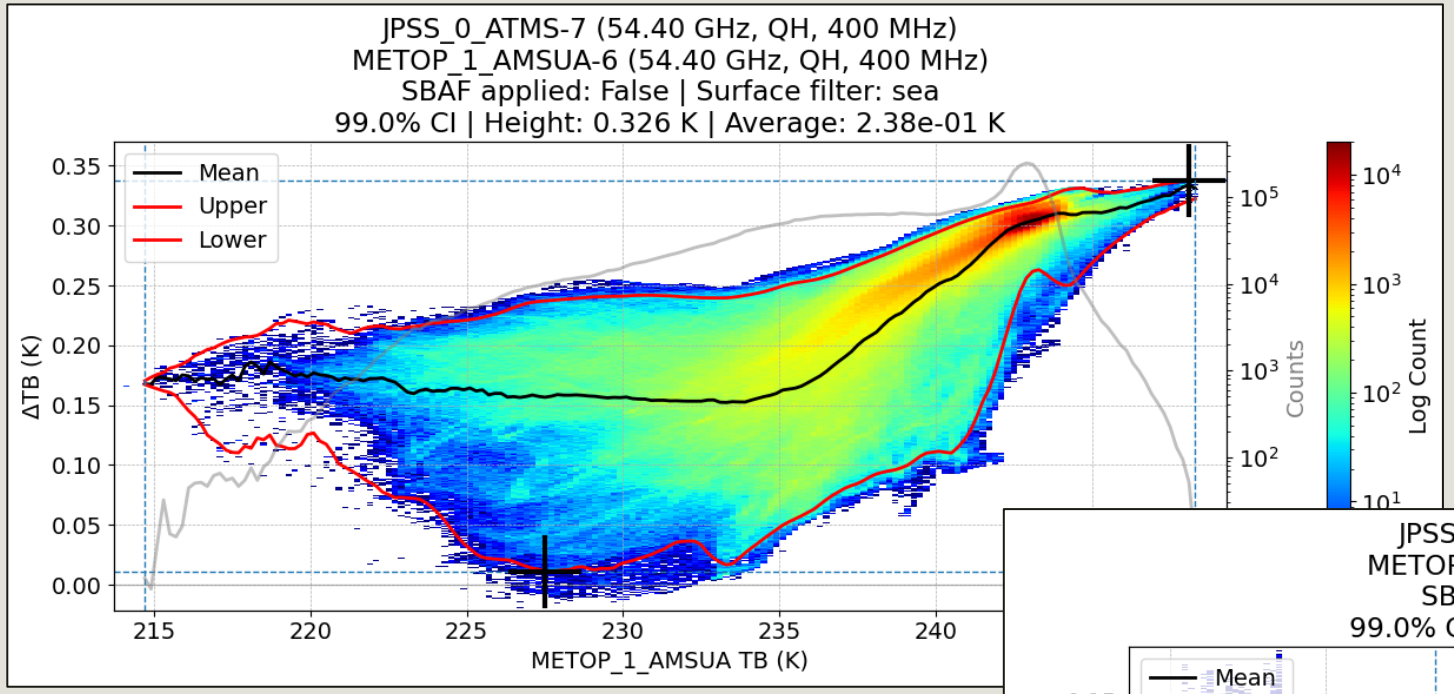


Adjusted

- Less heteroscedastic
- Smaller average
- Narrower CI, in general

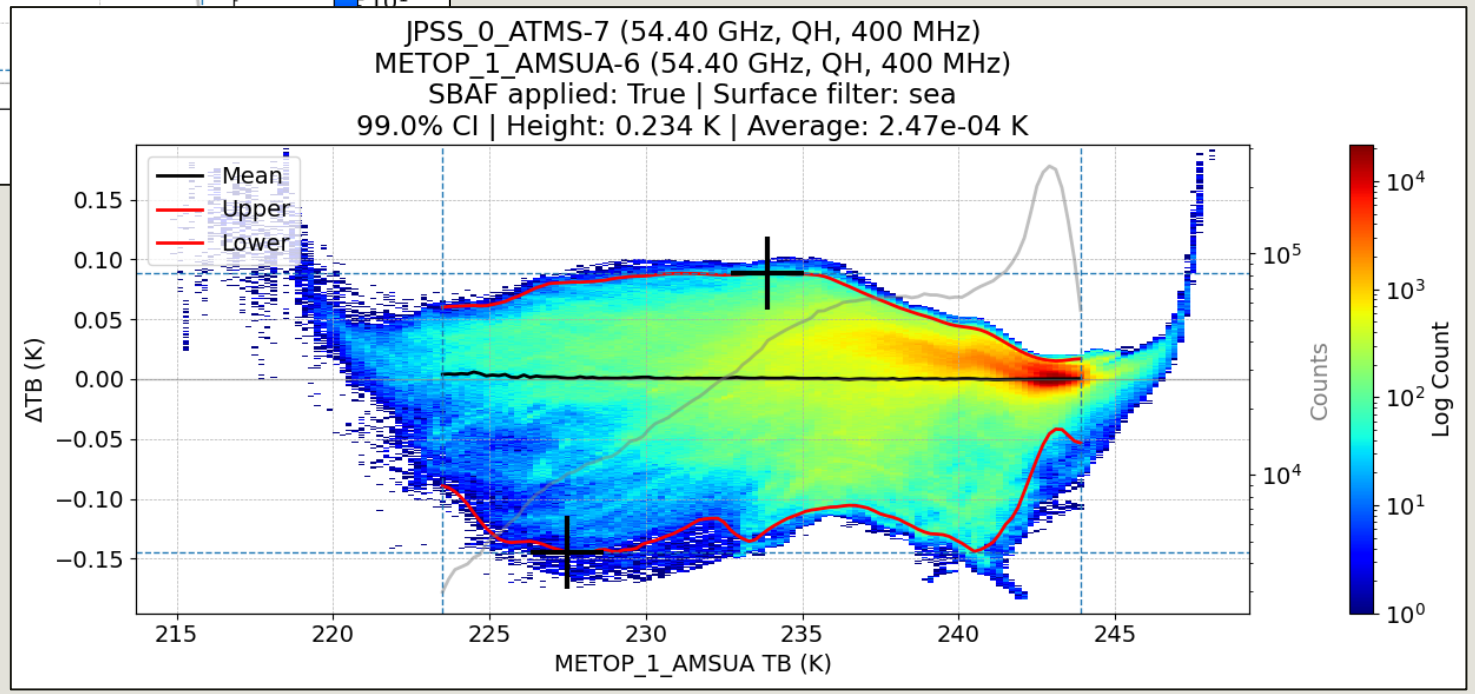
Validity range (99%)

SBAF: Sample results II – Extrapolation



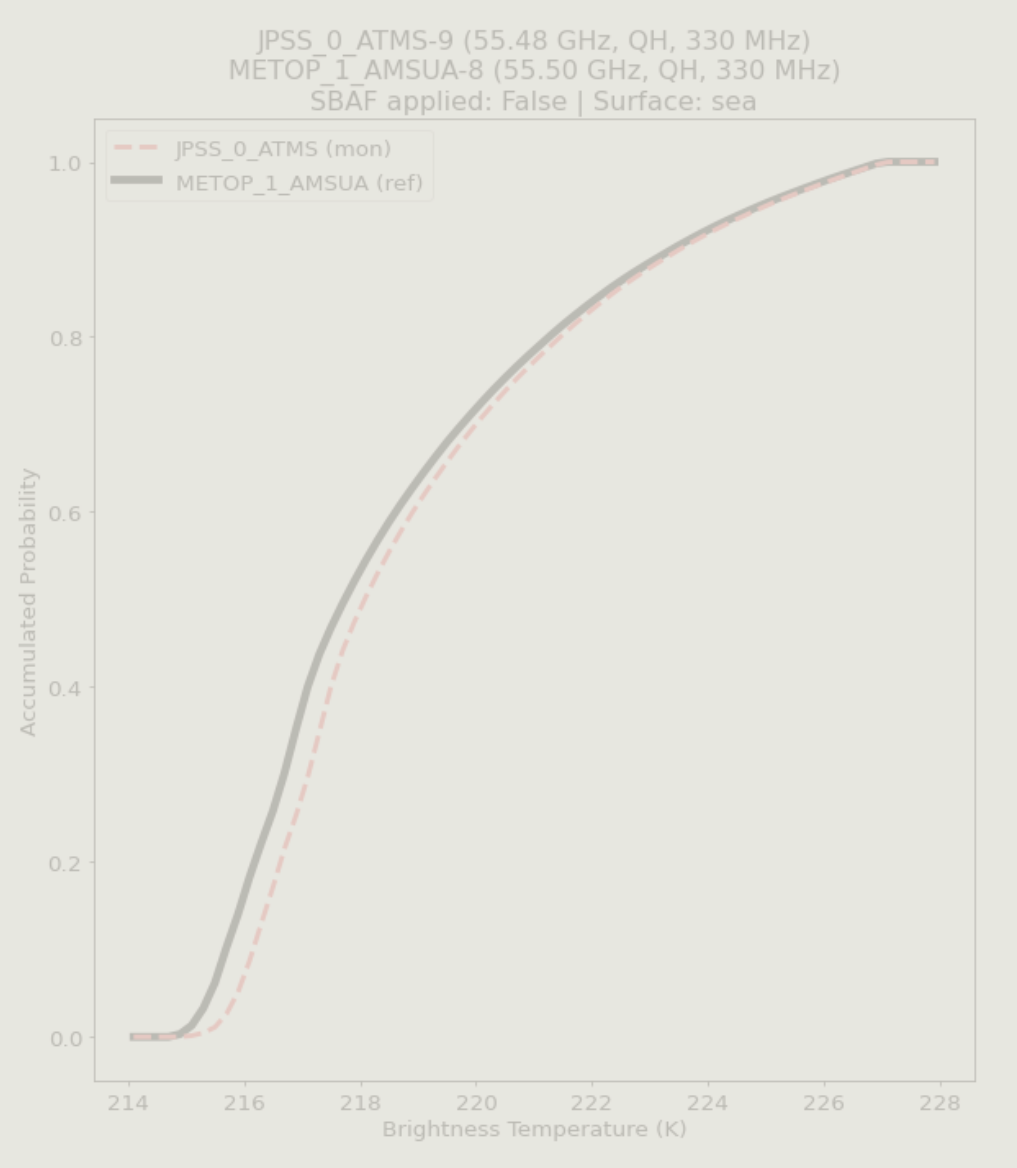
Original

No extrapolatable, in general



Adjusted

CDF Matching: Fixed-size bins



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$$\Rightarrow \mathbb{E}[TB'_{mon} - TB_{\text{ref}}] = 0$$

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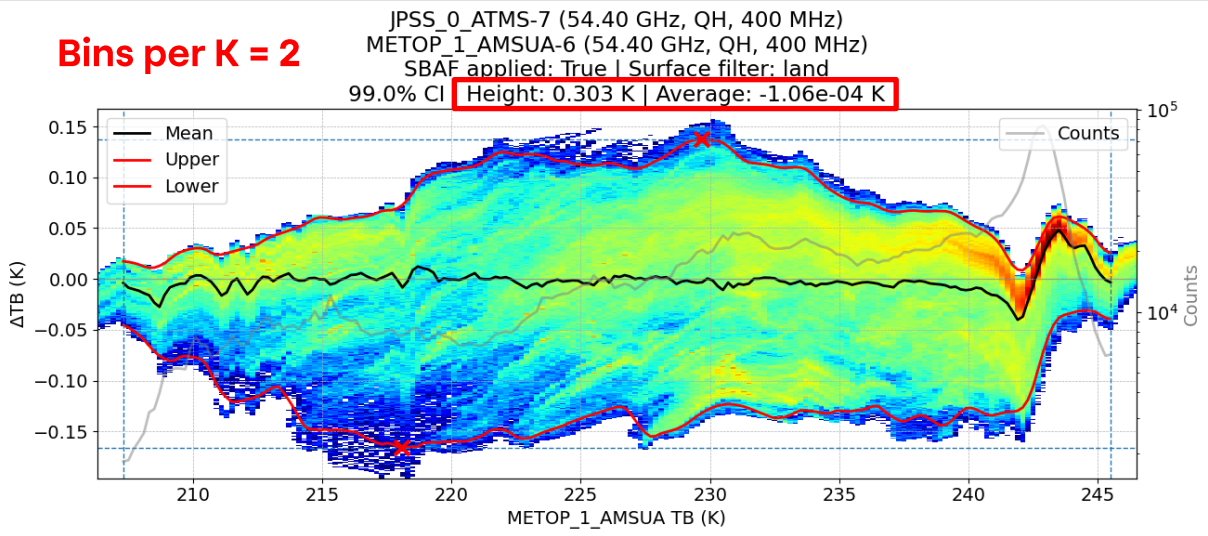
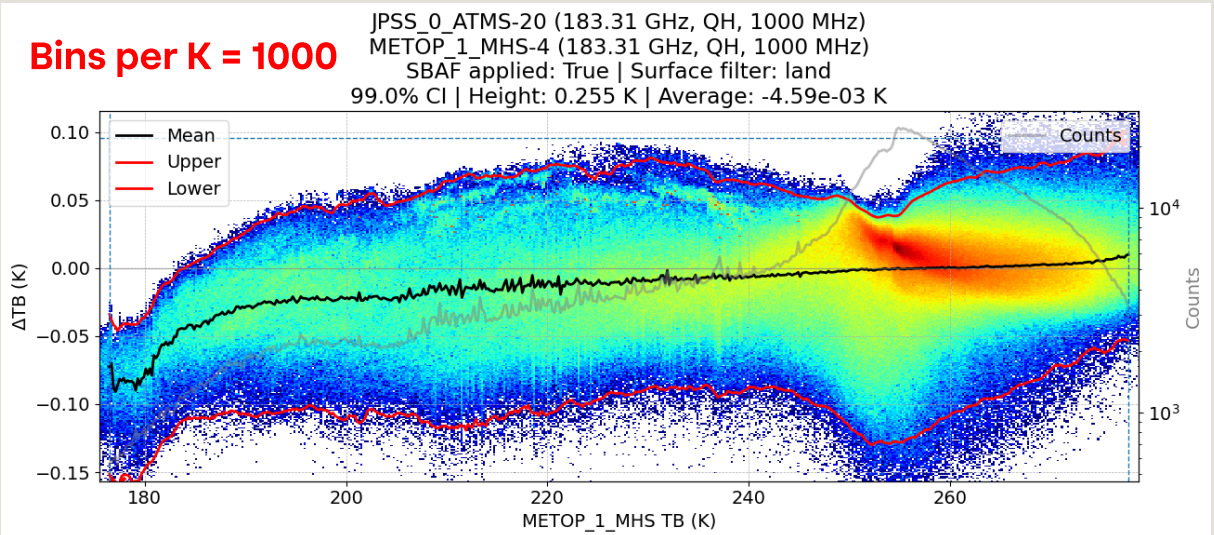
- Monotonic non-decreasing (forced increasing)
- Parametric representation (piecewise linear interpolation)
- Number of ranges: 10/100 per K (more on this later)
- Number of parameters << number of samples
- Ambiguity: $tb_i^{mon} \cong tb_j^{mon}$ but $tb_i^{ref} \neq tb_j^{ref}$

CDF Matching: Fixed-size bins

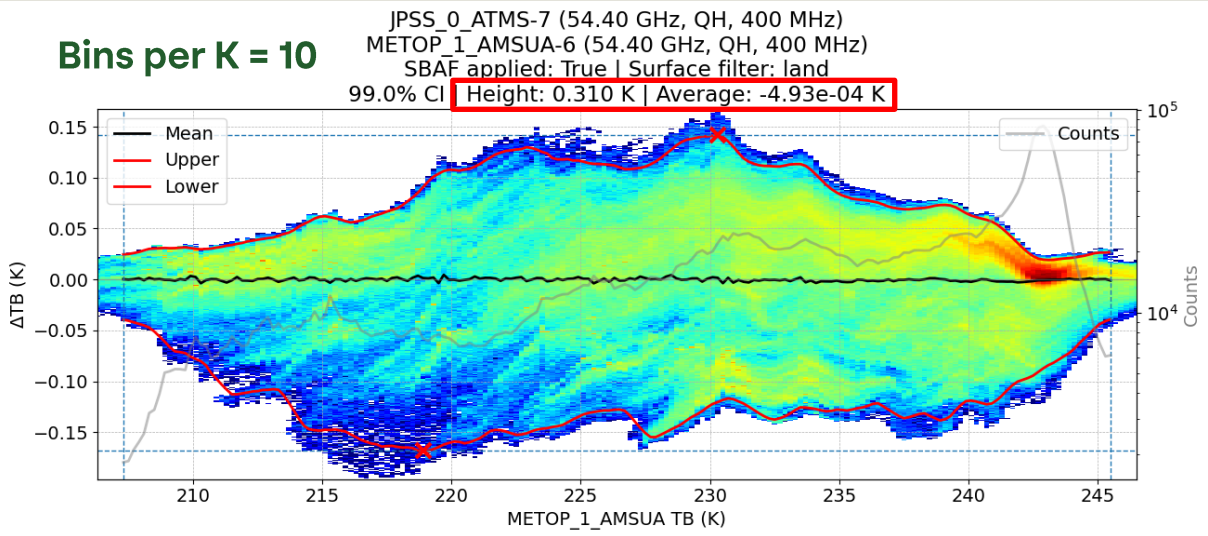
Bins per K = 2



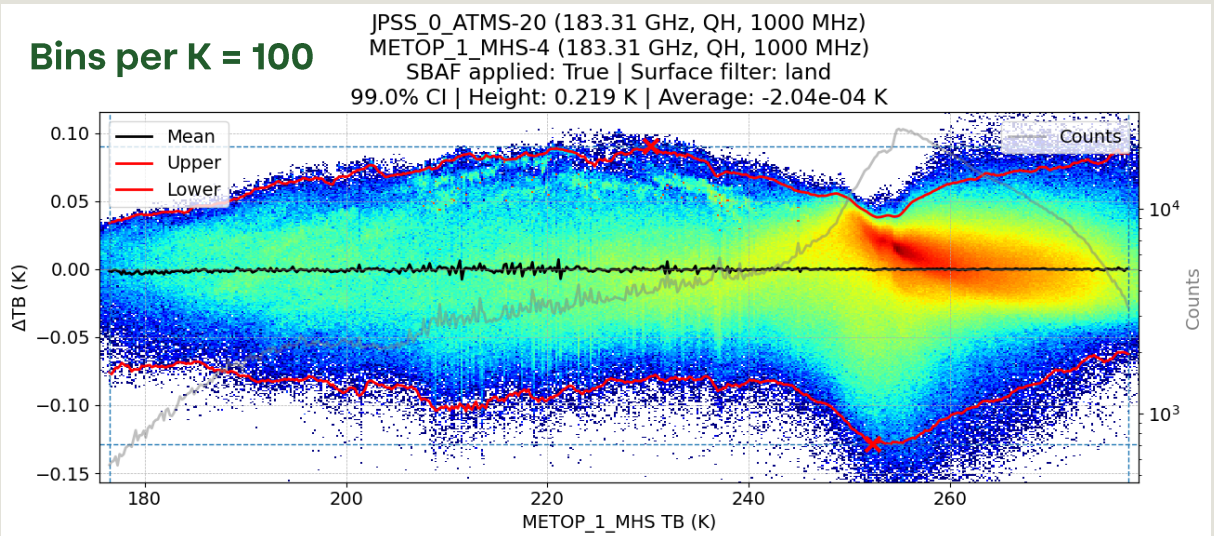
Bins per K = 1000



Bins per K = 10



Bins per K = 100



Other discarded methods: No CDF matching

1. The SBAF as a linear regression model (slope and intercept)
   - Ordinary Least Squares (OLS), without and with Heteroscedasticity-Robust Covariance
   - Generalized least Squares (GLS)
   - Weighted Least Squares (WLS)
   - Robust Linear Models (RLM) with different windows (Huber's T, Andrew's Wave)
   - **Slightly reduced the spread** of the bias distribution
   - **Not satisfactory results** → the mean bias is not reduced enough

2. The SBAF as a Neural Network regression model
   - Excellent training and validation results with simulated data
   - **Catastrophic failure** when applied to real data

Other discarded methods: CDF matching

1. Empirical cumulative distribution function (ECDF)
   - **No bins required**
   - Number of parameters ≈ number of collocations of the CDF matching dataset → sampling problem → **bins required**
   - If small CDF matching dataset is chosen → Not robust (pointwise)

2. Constant probability
   - Equiprobable ranges
   - Denser distribution → smaller ranges, and vice-versa
   - In most cases leads to **sensitivity when robustness is required** and vice-versa (empirical)

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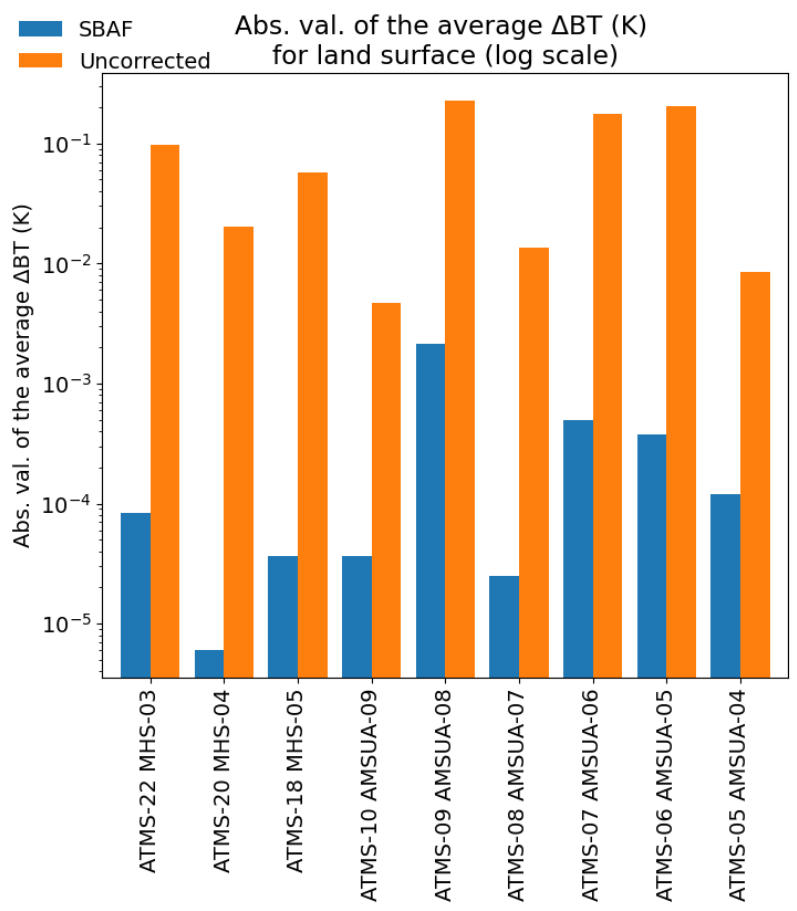
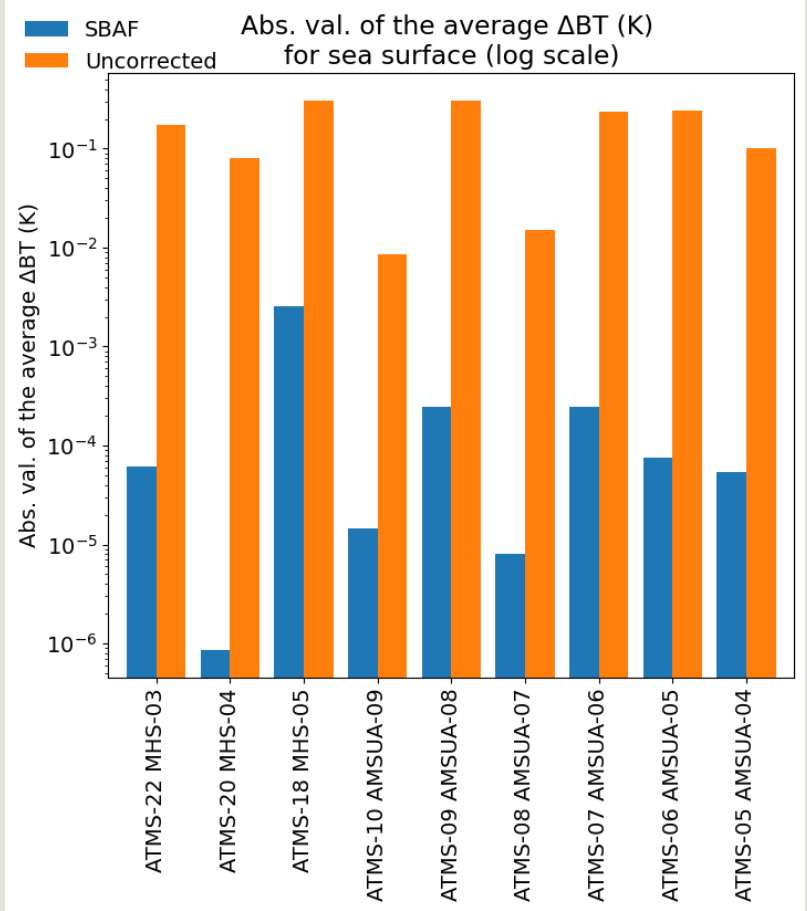
04

SBAF Errors
Error Propagation

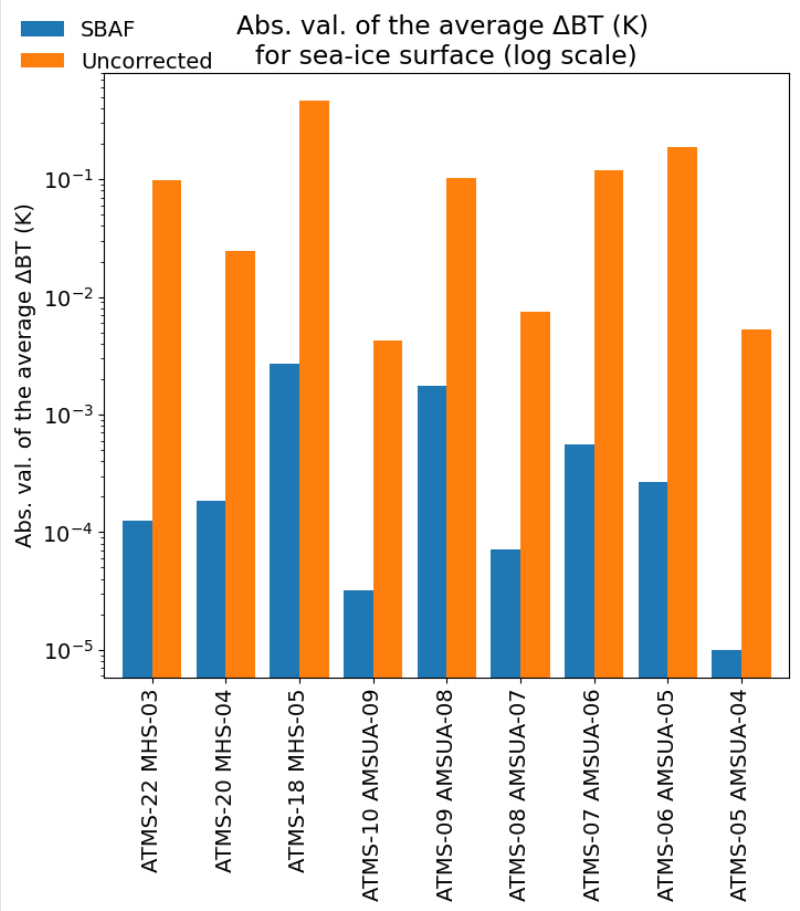
Errors: Results Summary I – $|\overline{\Delta TB}|$ per surface type



Land

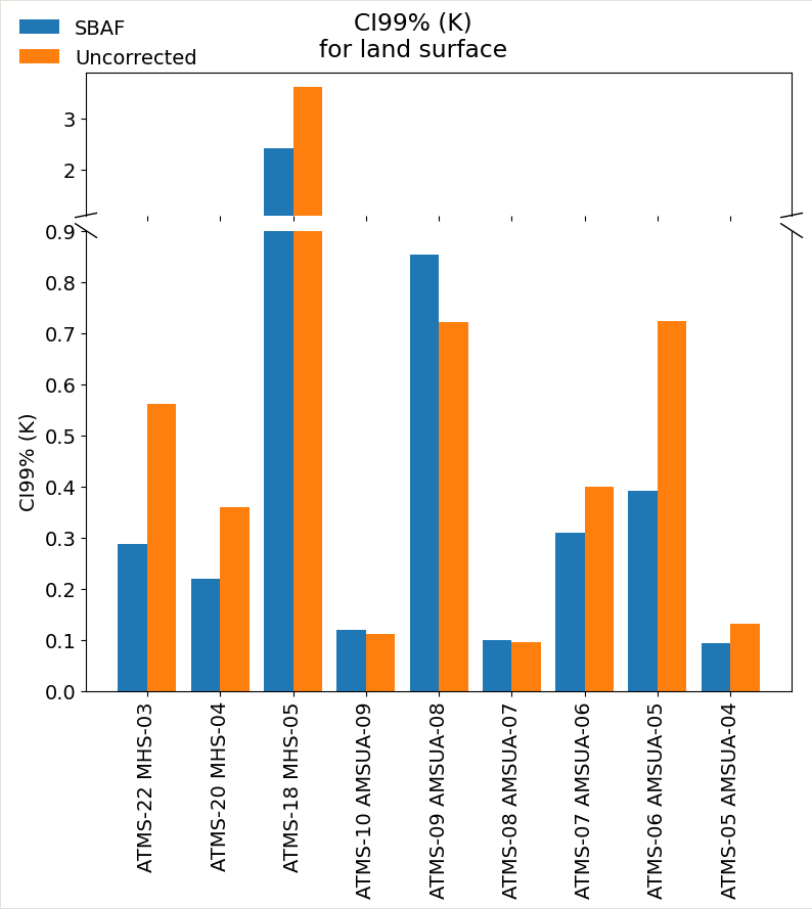


Sea

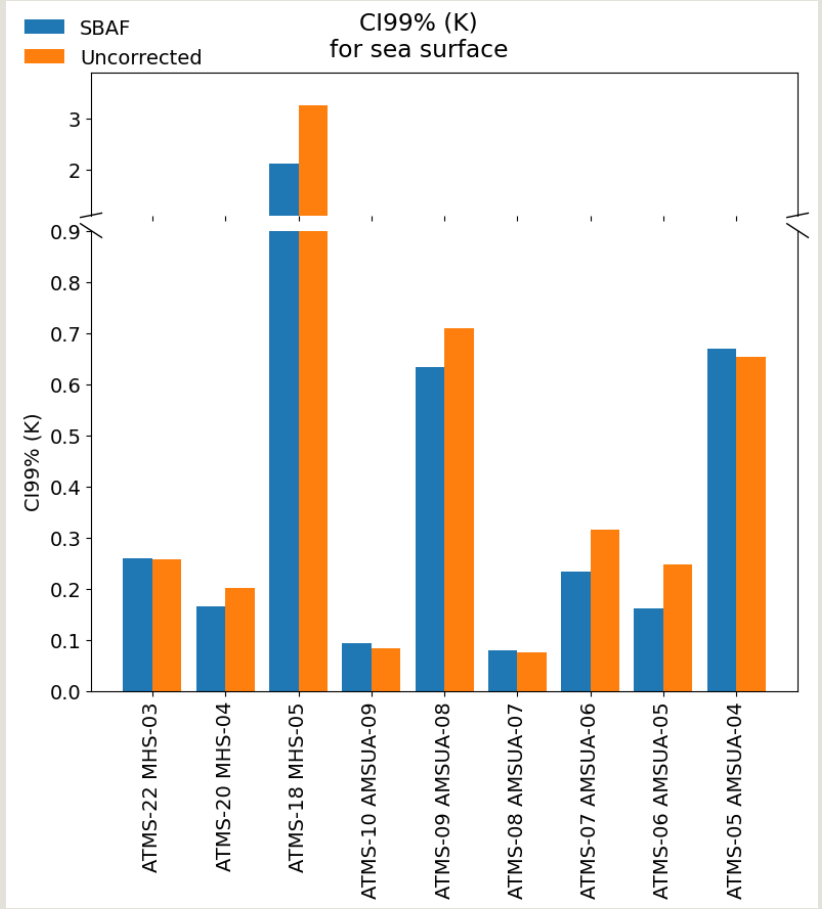


Sea-Ice

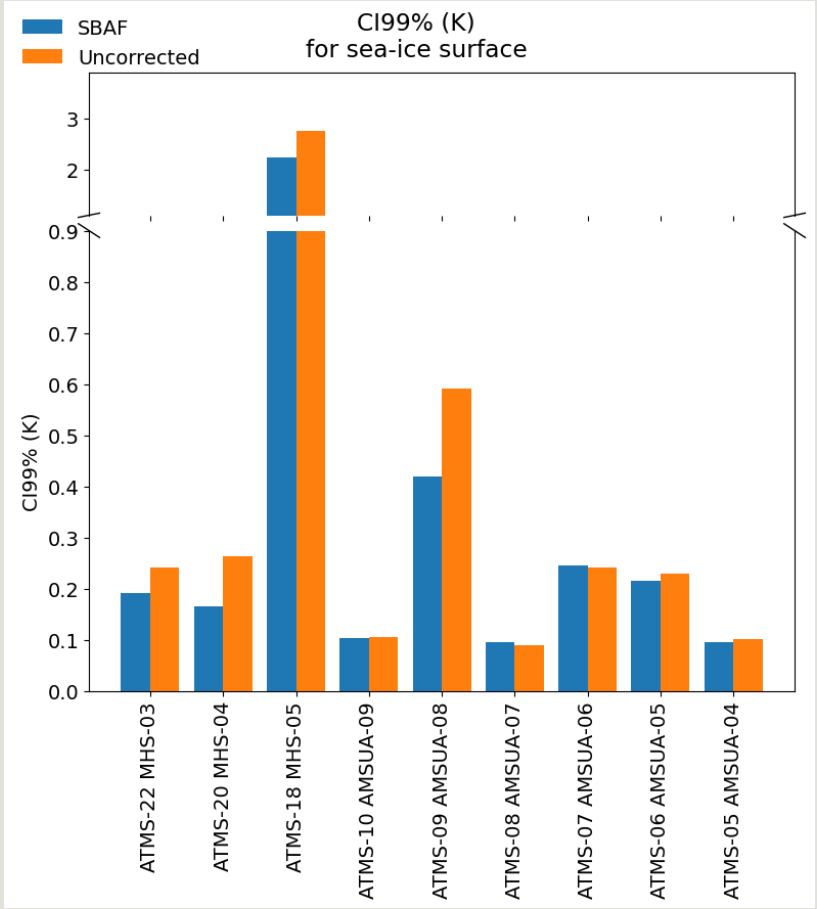
Errors: Results Summary II – CI99 per surface type



Land



Sea

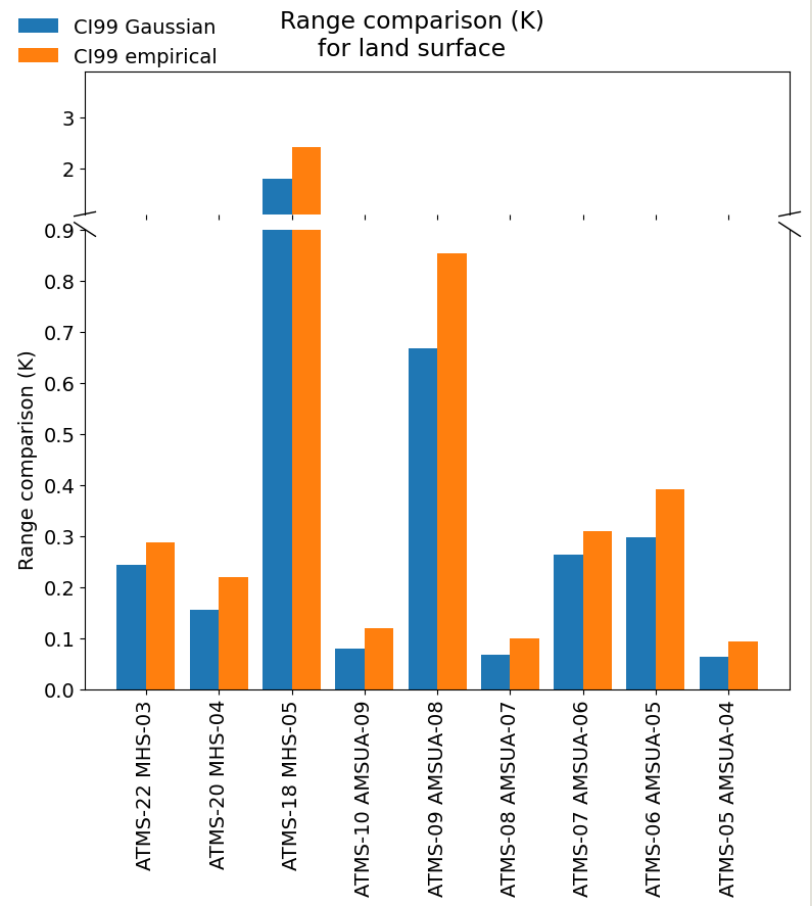


Sea-Ice

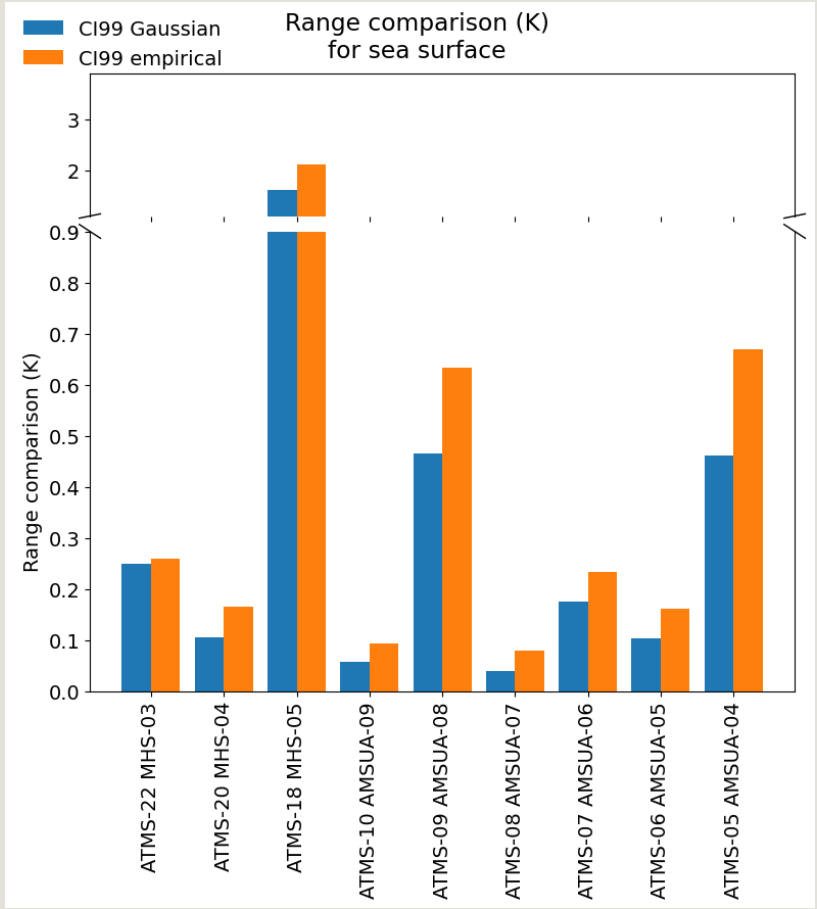
* If not negligible average, the CIs will require re-calculation for binwise zero mean

Errors: Results Summary III – Comparison with Gaussian

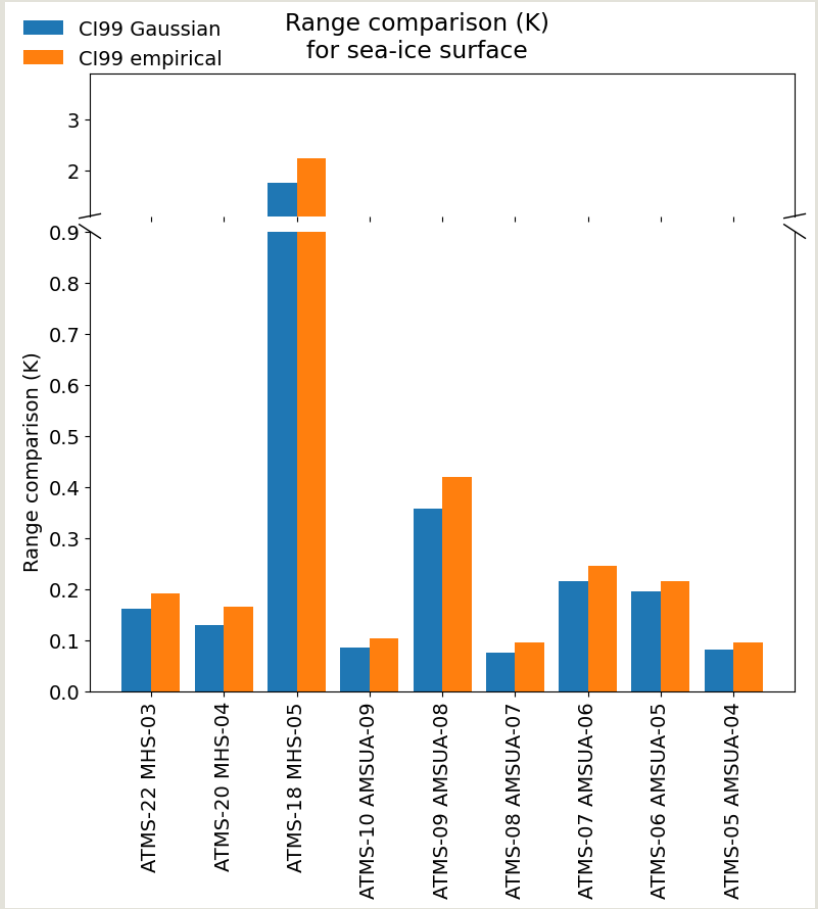
CI99 Gaussian: 2 x 2.576 x **global** standard deviation



Land

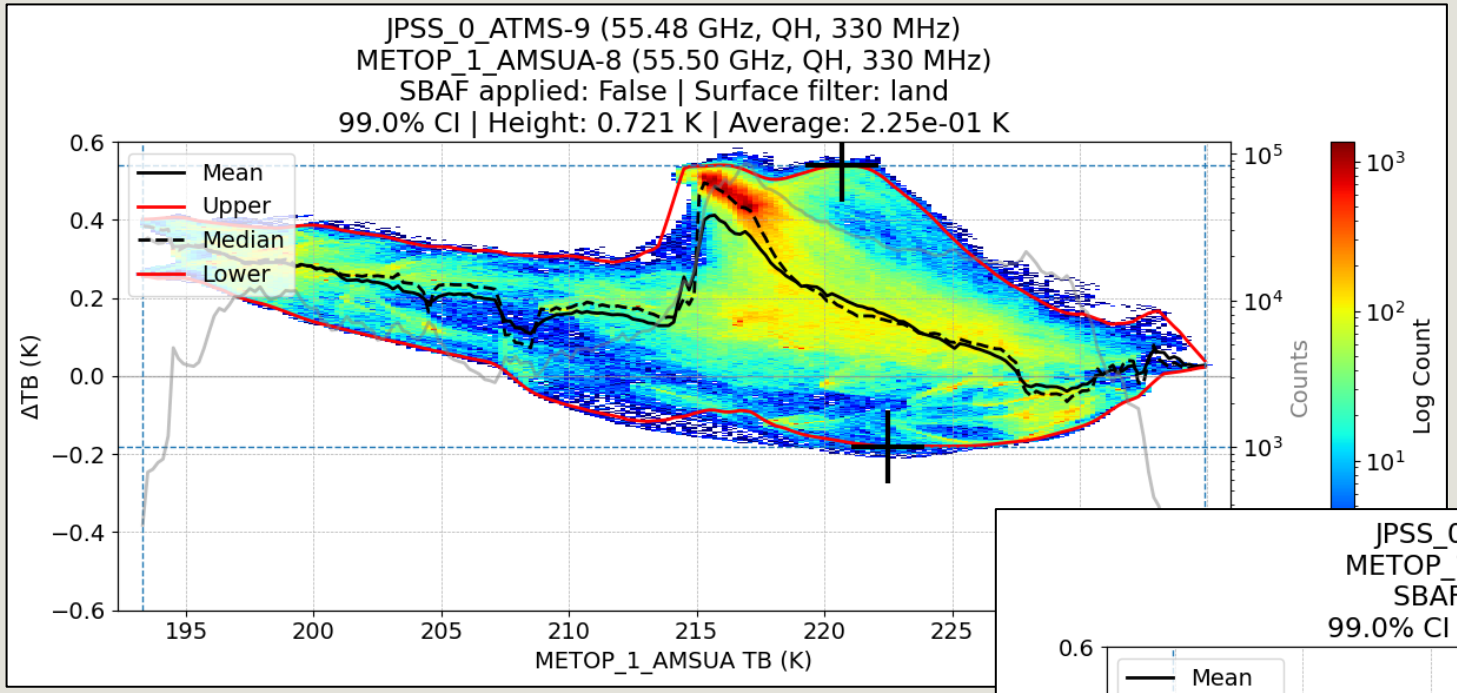


Sea



Sea-Ice

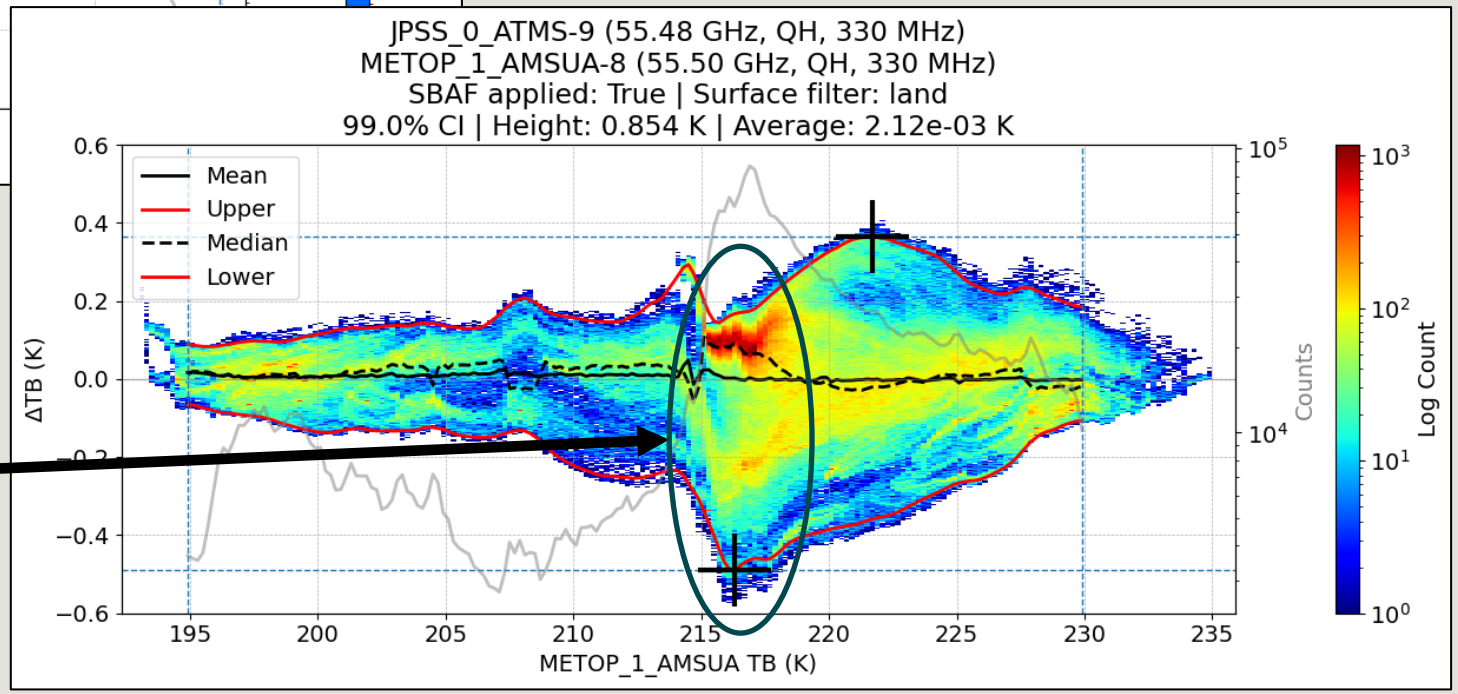
Errors: Average vs. CI trade-off



Original

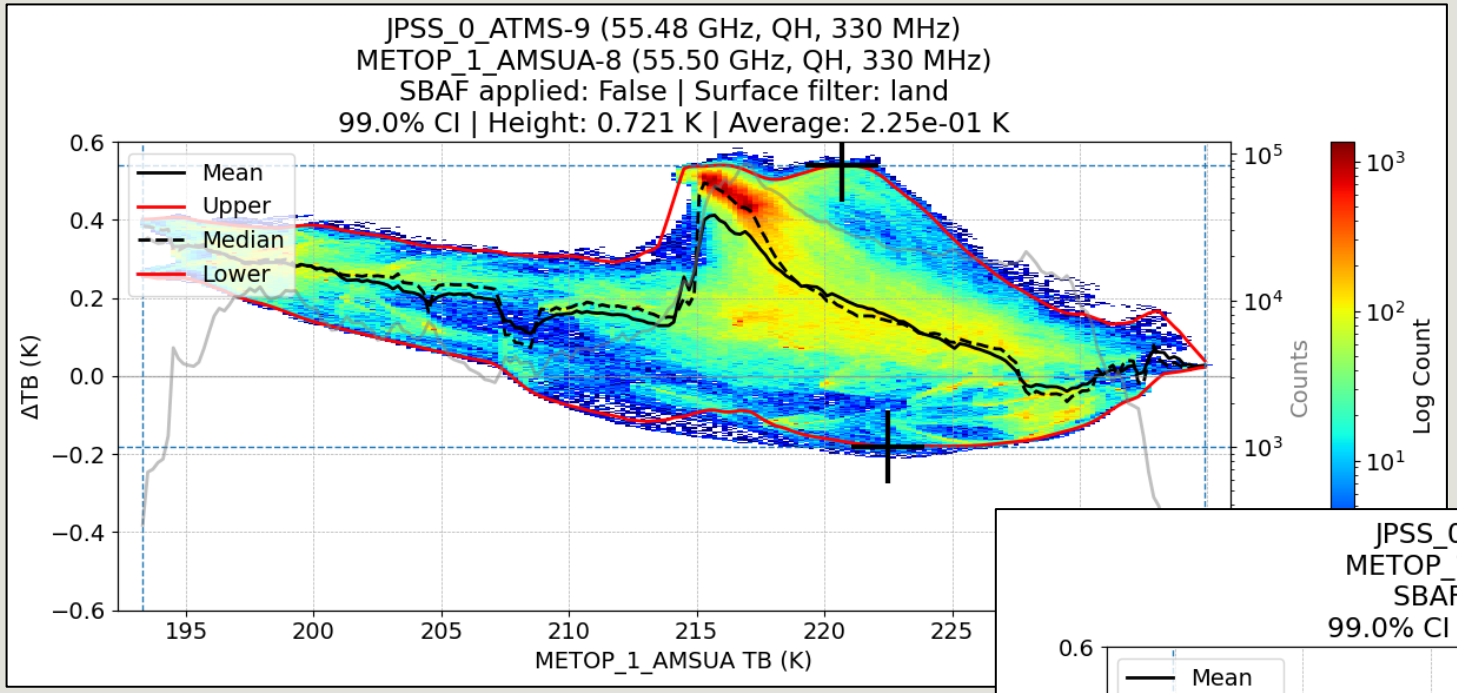
- Average: **2.25×10^{-1} K → 2.12×10^{-3} K**
- But CI 99%: **0.721 K → 0.854 K**

High-density cluster forces larger interval amplitude



Adjusted

Errors: Random and systematic



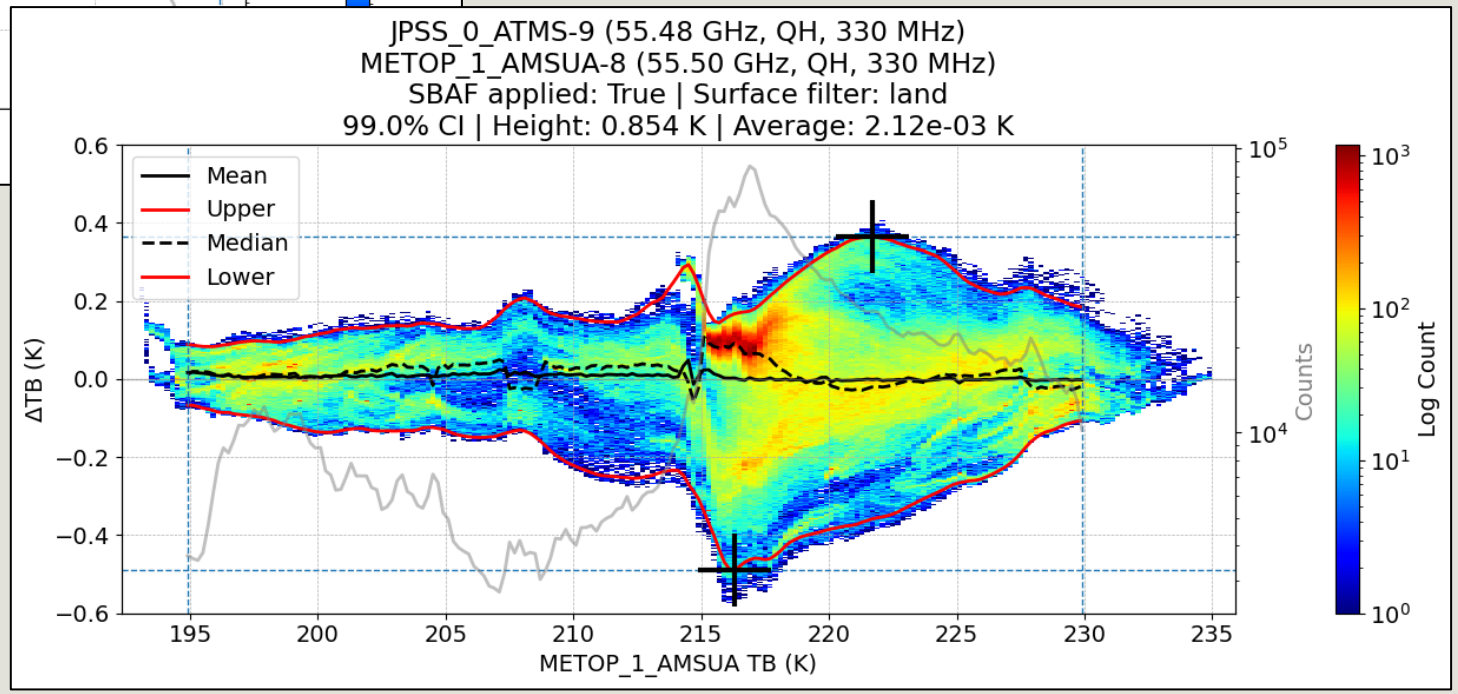
Original

$SBAF_{\lambda}(BT_{mon\_sensor})$ is a **new sensor** with its intrinsic:

- Systematic and random errors propagated from the monitored sensor
- Characterized bias and CI w.r.t. the reference sensor

In the cross-calibration context:

- The *average* is a **systematic** error contribution
- CI characterize the total residual variability (if avg << CI)



Adjusted

Error Propagation: SBAF

$$\widehat{tb}_{mon} = SBAF_{\lambda}(tb_{mon}) = \alpha_i + \beta_i tb_{mon}, \qquad tb_{mon} \in [x_i, x_{i+1}), \qquad i = 1, \dots, N$$

$$u(\widehat{tb}_{mon}) = u(tb_{mon}) \sum_{i=1}^{N} \beta_i p_i$$

- Some errors of the physical sensor are not represented by the simulations (e.g., NEΔT)
- They must be propagated to the modelled sensor through the SBAF
- The sensitivity is the weighted sum of the slopes of the piecewise linear elements of the SBAF
- The probability p_i is global and distributed along a year, sampled daily at 00:00 and 12:00 UTC
- Sun-synchronous platforms → Daily cycle – longitude correlation?

Backup Slides

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B0

RTTOV Simulations: Top hat vs real SRF

Top-hat vs. Real SRFs: Worst cases I

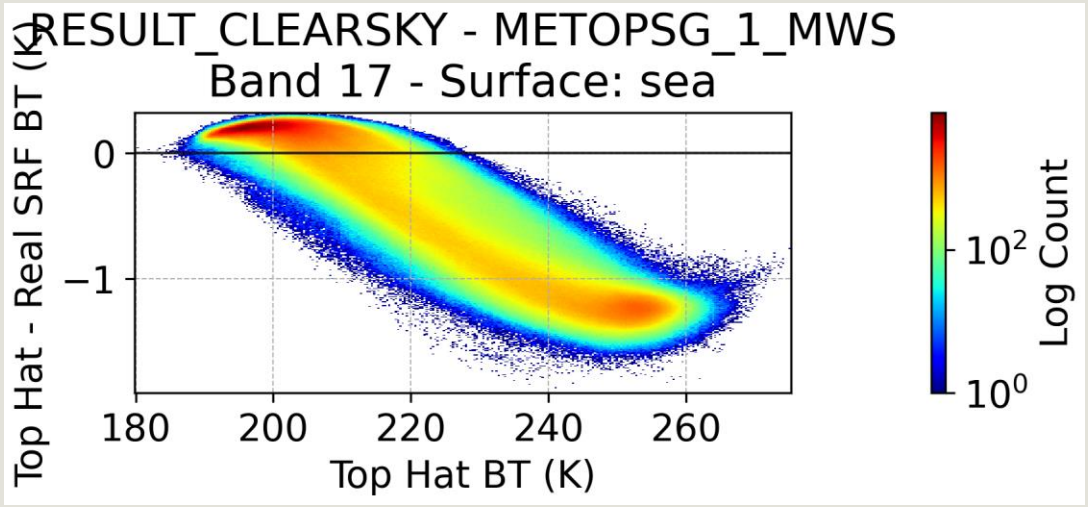
Clear sky simulations with filtered surface

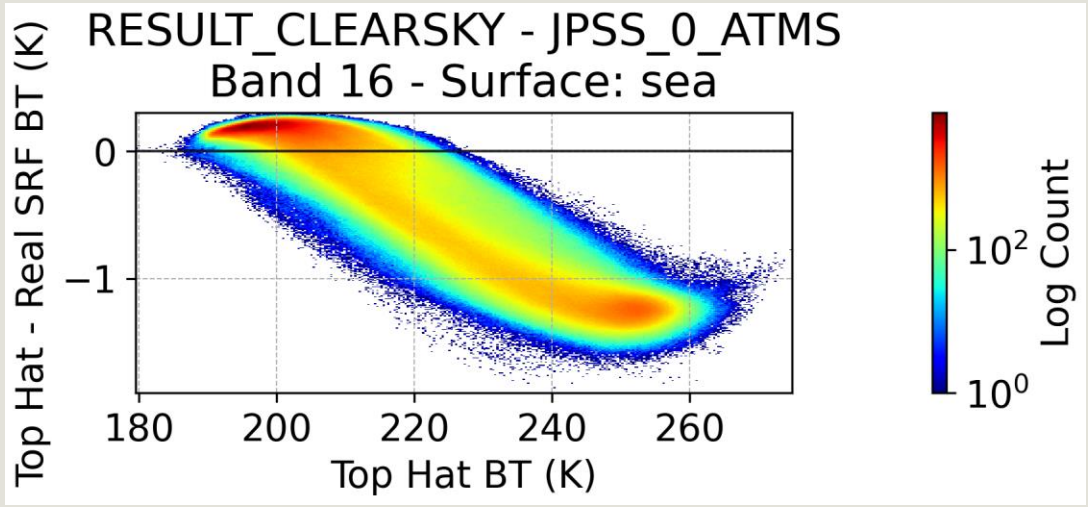
Sensors and channels with residual standard deviation > 0.2 K

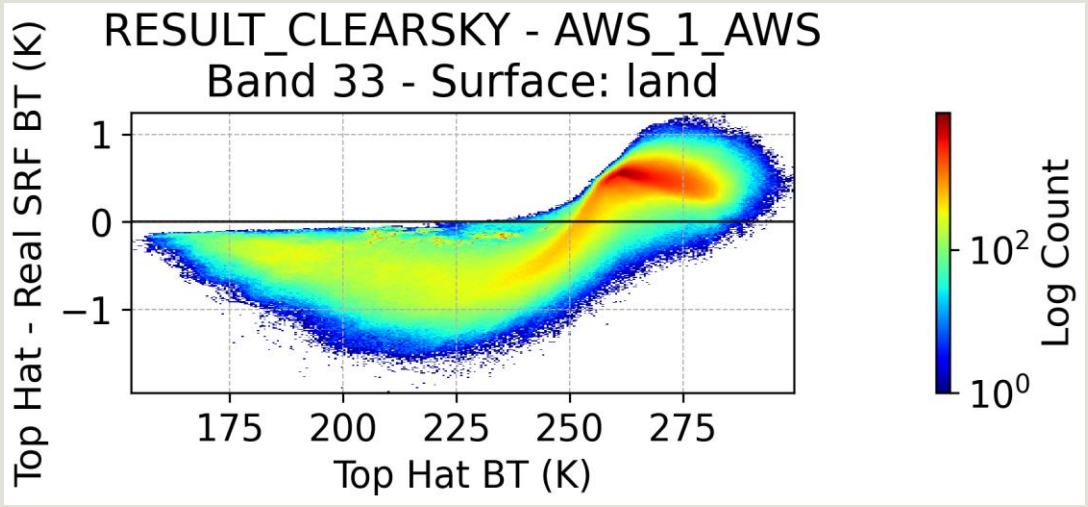
Only paired channels are shown

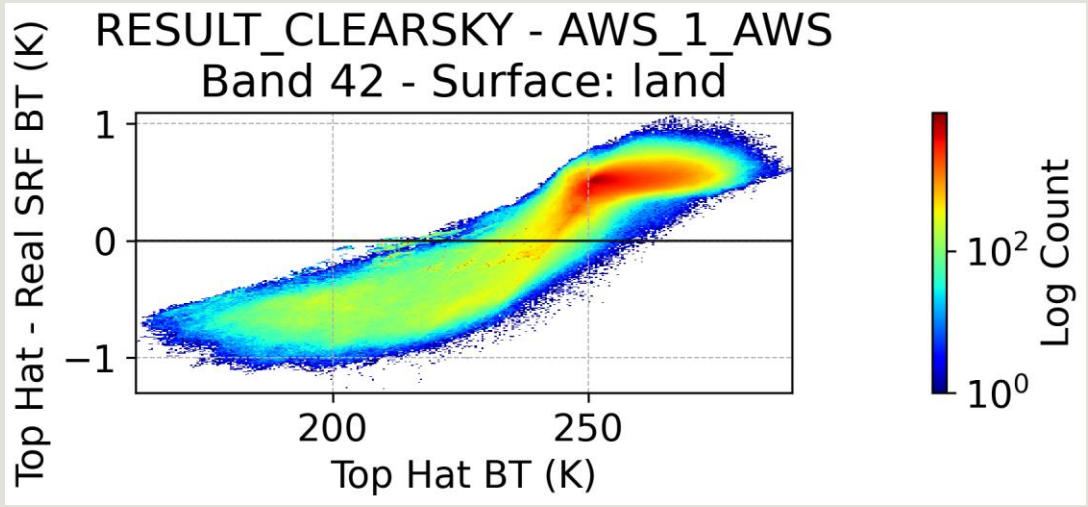
			TB residual statistics (K)				TB range (K)	
Sensor	Channel	Surface	min	max	mean	std	min	max
MWS	17	sea	-1.906	0.323	-0.412	**0.568**	179.8	275.2
ATMS	16	sea	-1.900	0.307	-0.418	**0.565**	179.5	274.8
AWS	33	land	-1.949	1.249	0.046	**0.523**	153.2	299.5
AWS	42	land	-1.303	1.097	0.240	**0.420**	161.4	289.9
ATMS	22	land	-0.997	1.310	-0.193	**0.399**	167.6	285.1
AWS	33	sea-ice	-1.507	0.746	-0.042	**0.393**	199.4	277.1
AMSUA	3	sea	-1.491	-0.020	-0.373	**0.316**	178.2	257.5
ATMS	3	sea	-1.468	-0.002	-0.345	**0.316**	178.1	258.0
MWS	3	sea	-1.480	-0.013	-0.360	**0.316**	178.1	258.0
MWS	21	land	-0.547	1.044	-0.019	**0.256**	156.3	295.1
AWS	44	land	-0.957	0.608	0.016	**0.239**	156.3	297.9
AWS	32	land	-1.101	0.581	-0.022	**0.232**	151.4	305.9
MWS	23	land	-0.454	0.978	-0.032	**0.232**	167.6	285.1

Top-hat vs. Real SRFs: Worst cases II

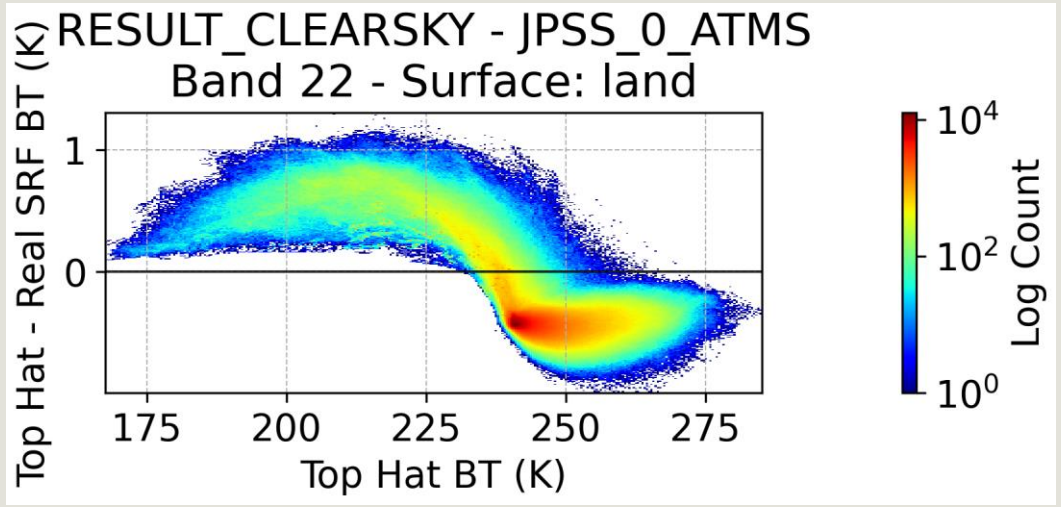


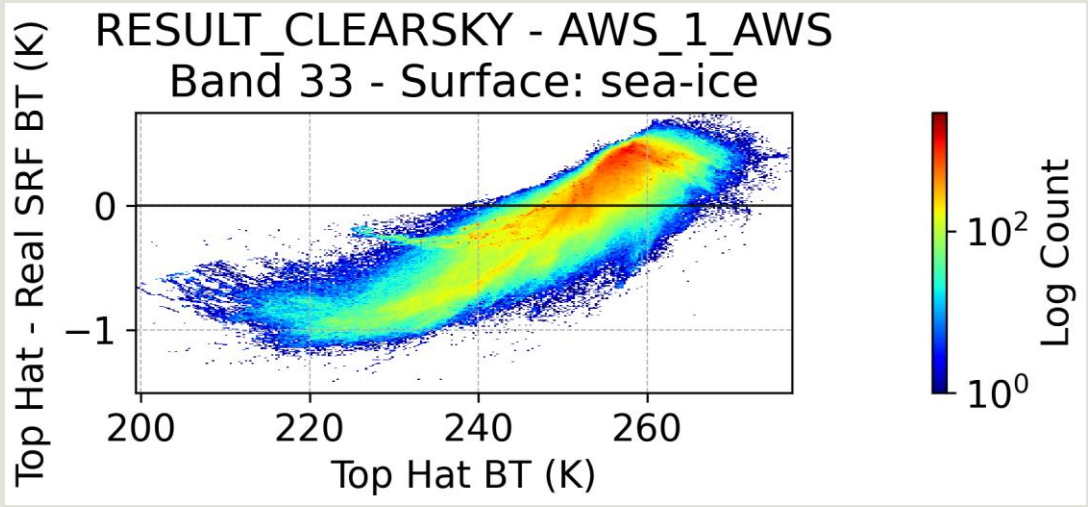


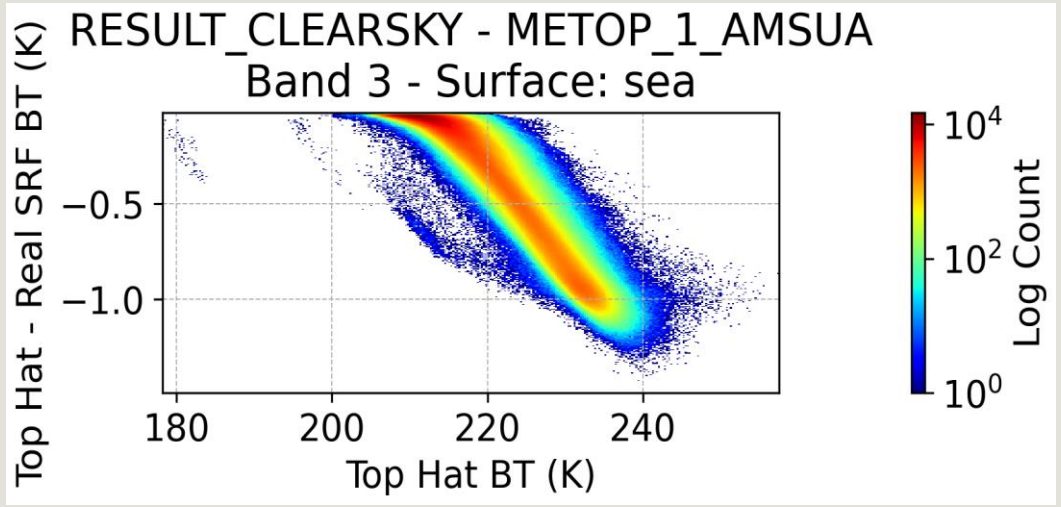


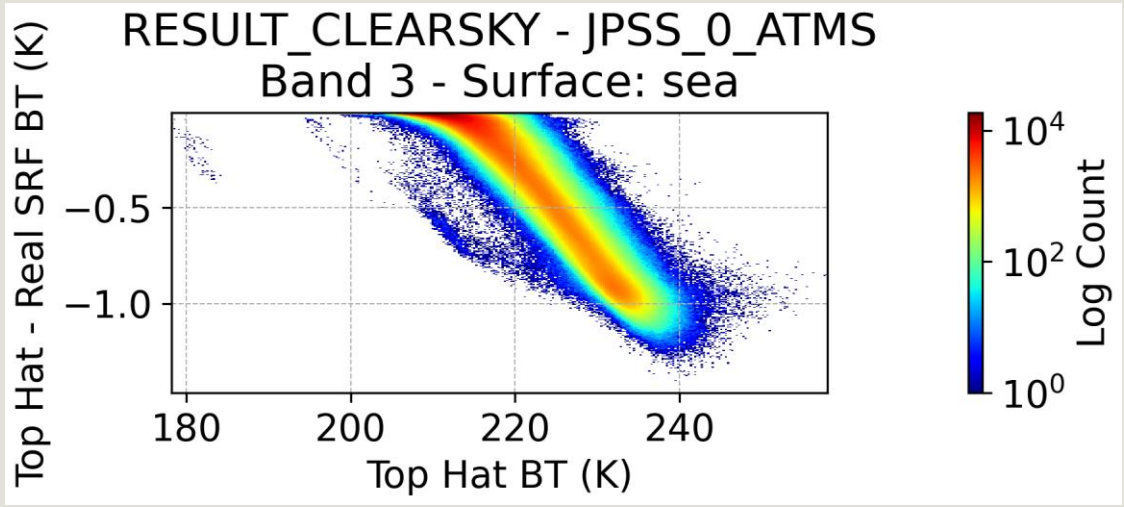


Top-hat vs. Real SRFs: Worst cases III









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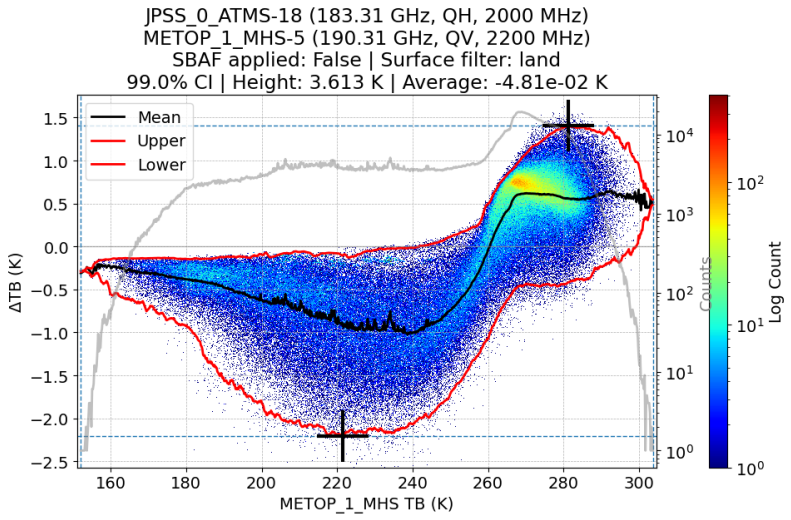
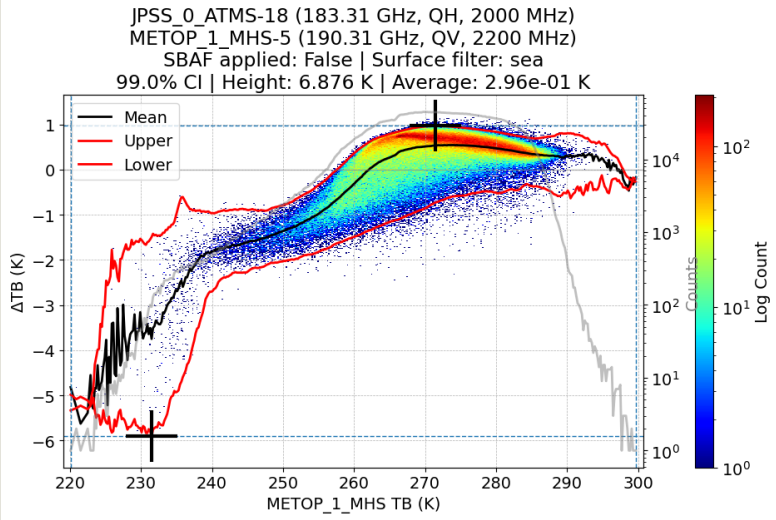
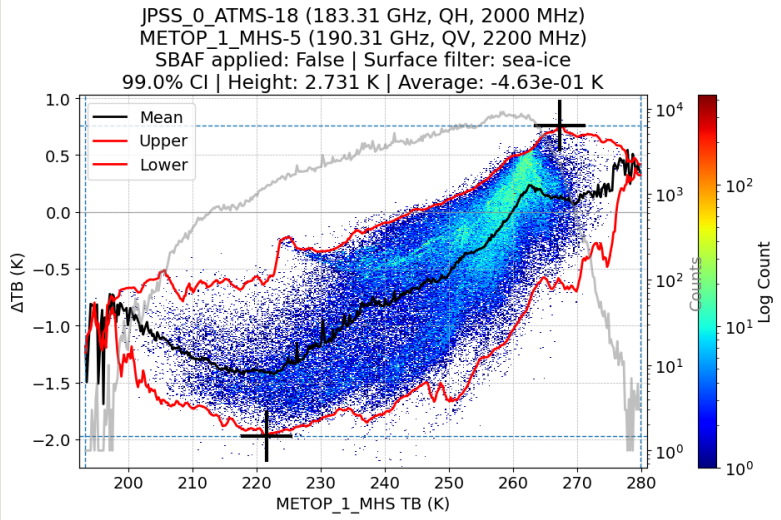
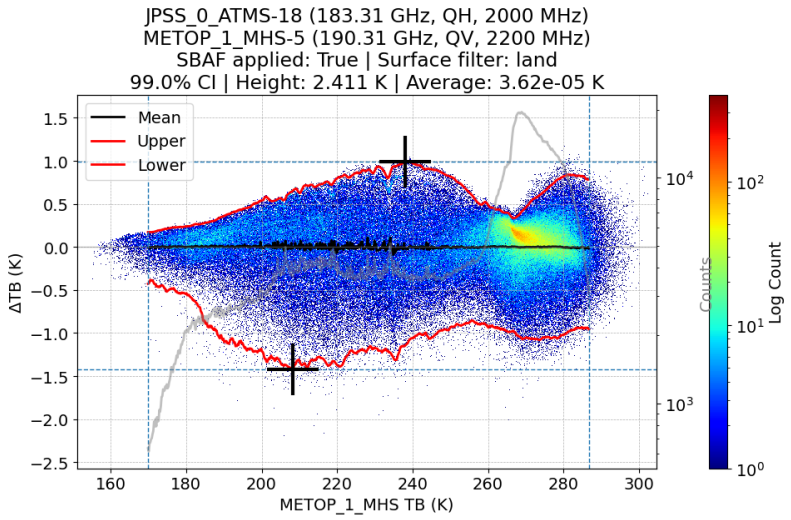
Extra Figures

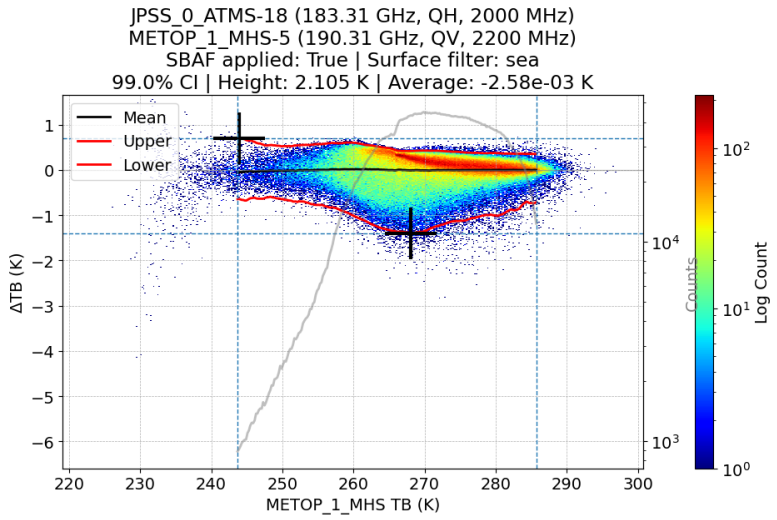
SBAF: Results Summary – ATMS-18 & MHS-5

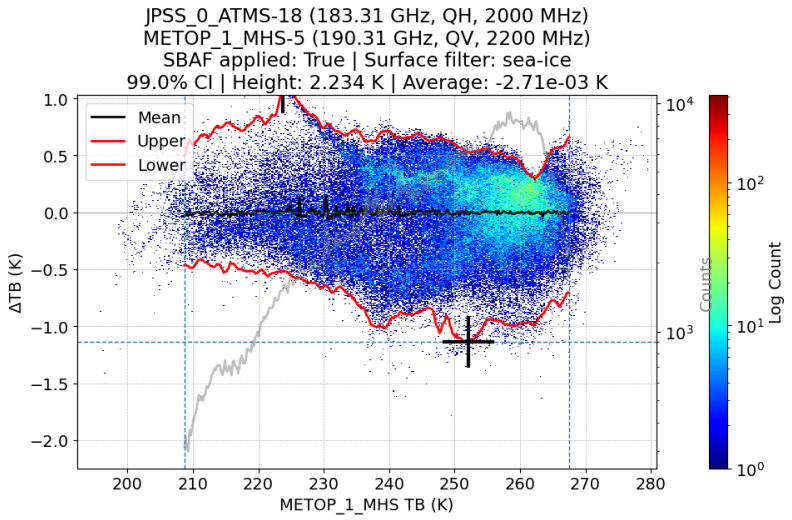










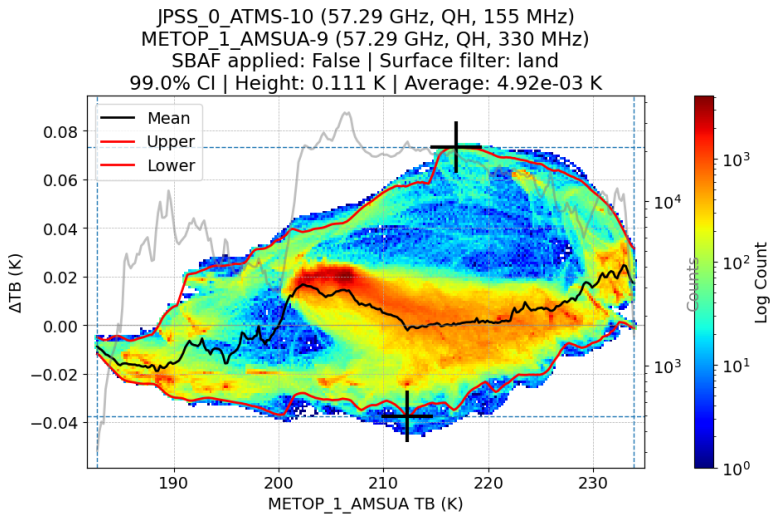


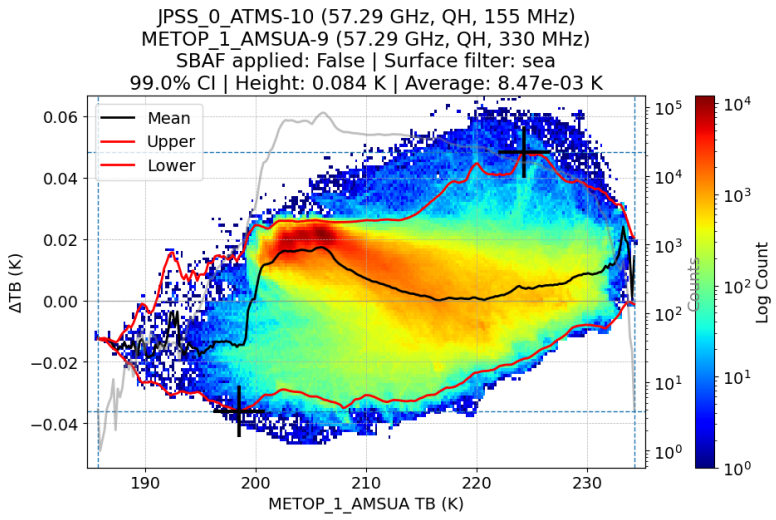
Land

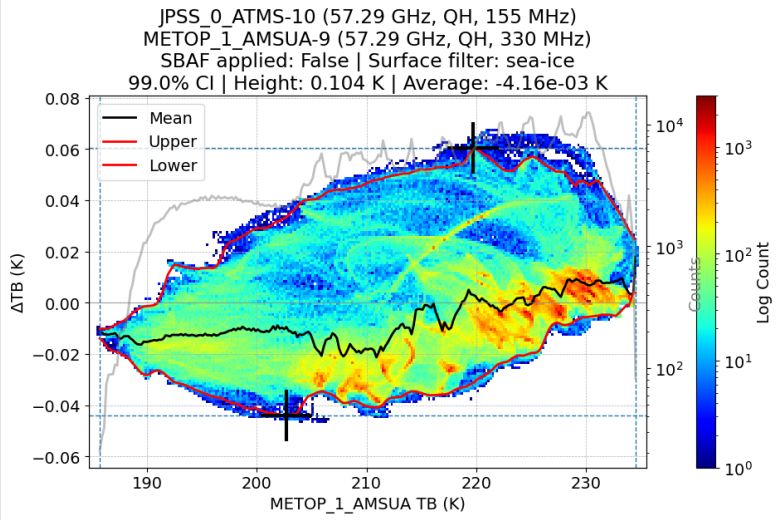
Sea

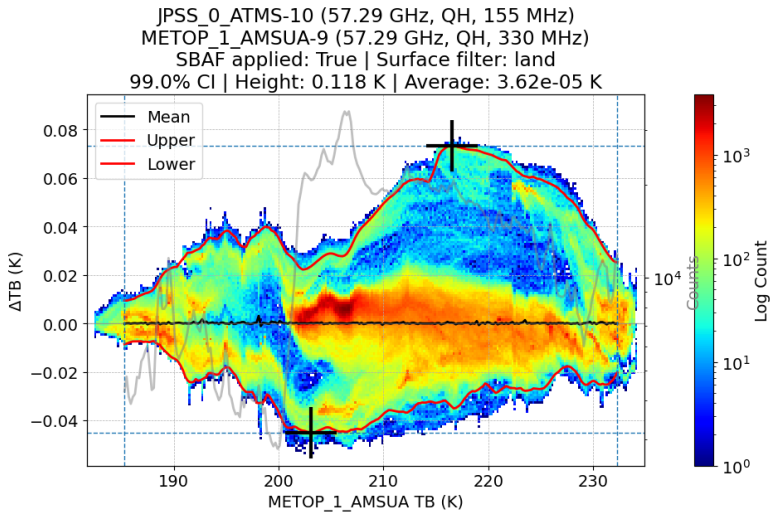
Sea-Ice

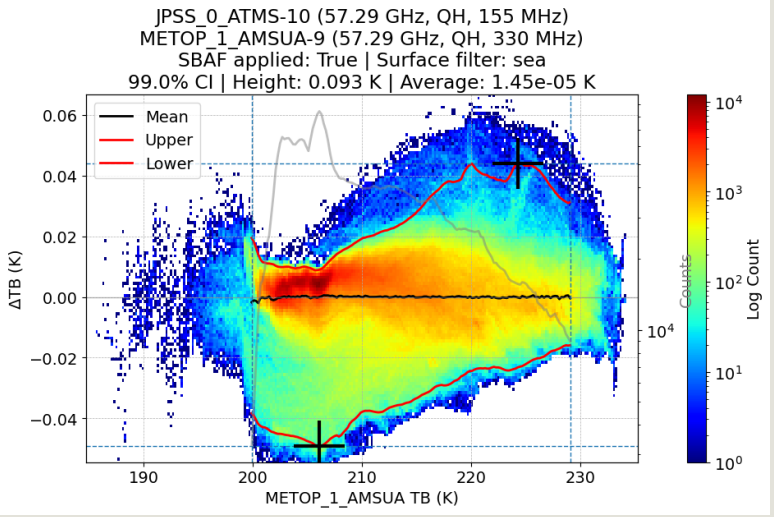
SBAF: Results Summary – ATMS 10 & AMSU-A 9

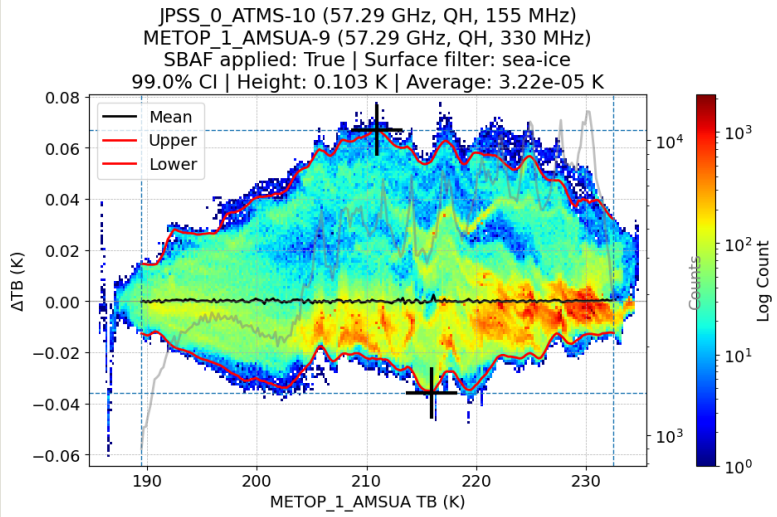












Land

Sea

Sea-Ice