Calibration of Radiances

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From Steve Bilanow's Presentation at March 2011 X-CAL meeting
TMI Pointing Uncertainty Effects

- "Prelaunch measure of TMI 10 V and10H boresight alignment offsets from a 49 degrees scan cone were reported at 0.555 and 0.185 degrees respectively*. This corresponds to ~ 1.3 K and -0.2 K bias shifts.

* Memorandum from Jim Shiue, 12/11/97"

When you do the trigonometry, this translates to *increases* of the Earth Incidence Angle for the two 10.7 GHz channels of 0.649° and 0.216°. (OK, a few too many significant figures)

Is it real?
Does it matter?

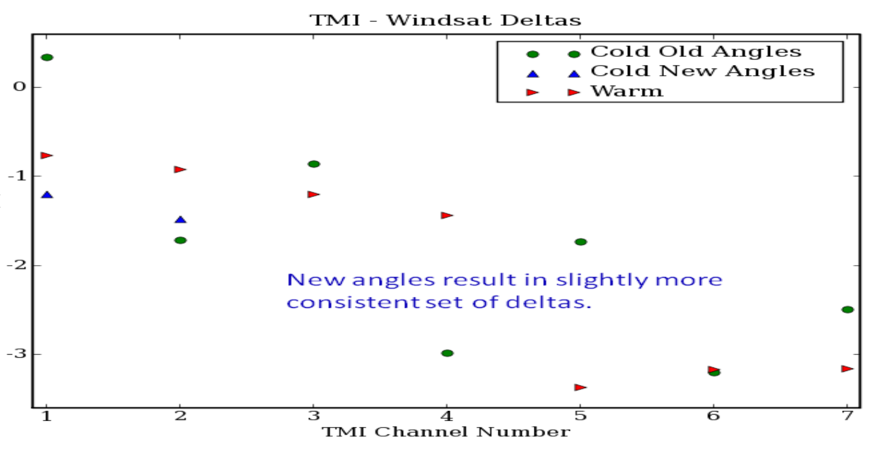
Use TAMU Model to Calculate TMI-WS Differences
Warm End Differences < 0.05K /Ignore

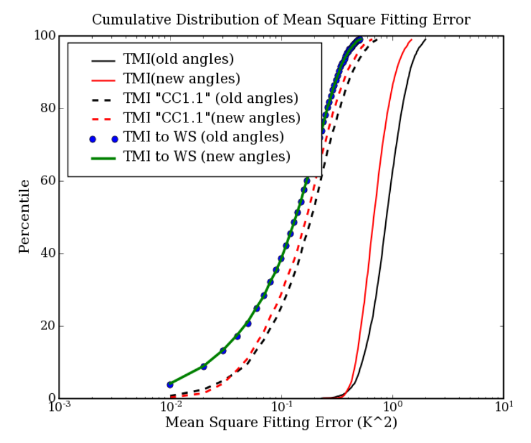
Deltas Computed with TAMU Model

	10V	10H	19V	19H	21V	37V	37H
	0.34	-1.71	-0.86	-2.98	-1.73	-3.20	-2.49
	-1.20	-1.48	Including Jim Shiue's Angles				
@	171K	89	202	137	200	216	156
	-0.76	-0.92	-1.20	-1.43	-3.37	-3.17	-3.16
@	281	280	285	284	284	281	281

Deltas are more self-consistent using Jim Shiue's angles.

"TMI_CC_1.1" based on TAMU model only @ Cold End, U. Mich at Warm End.
75% Weight for Windsat, 25% TMI



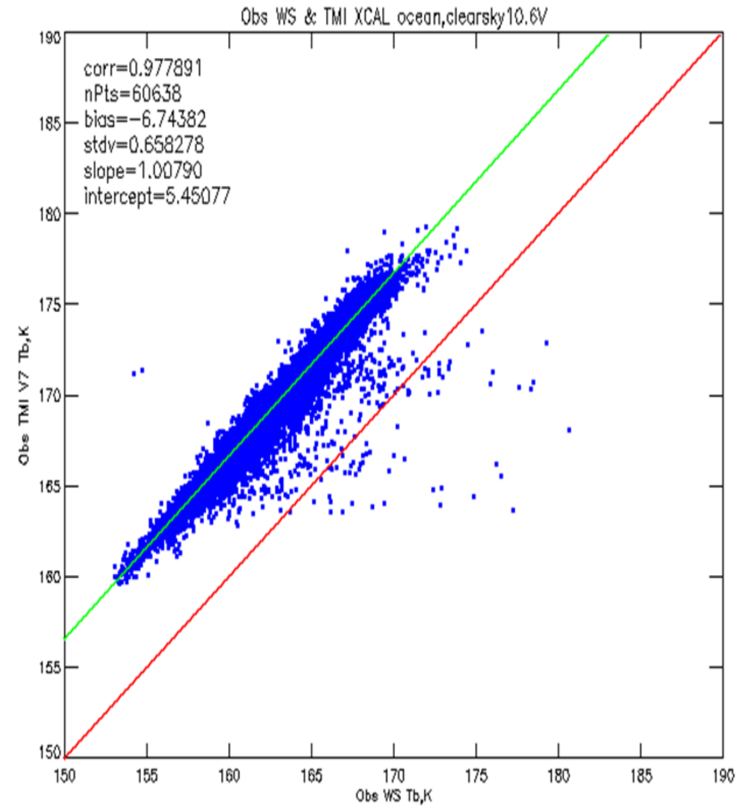


Conclusions

TMI 10 GHz Angle Issue is real
It Matters (a little)
Will be treated explicitly for TMI
Similar Issues Will Recur
Explicit Treatment Where Known
Intercalibration will cover where not Known

Steve Bilanow unearthed an ancient memo from Jim Shiue pointing out that the 10.7 GHz beams of TMI are not co-aligned with the other TMI beams, nor even with one another. The Earth Incidence Angle impact actually exceeds a half a degree. This raises two issues: "Is it real?" and if so, "Does it matter?" The TAMU algorithm has been used to gain some insight here. First the TMI-Windsat differences have been calculated for approximately 10,000 coincident TMI/Windsat observations using both the original and corrected sets of incidence angles. The deltas are given numerically and graphically in two figures above. The 10V offset was always odd; it was the only positive difference. With the new set of angles, all differences are negative and somewhat more self-consistent. The TAMU algorithm also provides a measure of consistency with the radiative transfer models through the penalty function (Mean square fitting error). The S-shaped curves above show the distribution of the penalty function values over the roughly 10K fits. The solid red and black curves represent the TMI version-7 unadjusted values as the source sensor. Even though the version 7 calibration contains some voodoo based on the old angles, using the new angles improves the fit slightly. These two threads suggest that the new 10V angles are, in fact, closer to reality than the old ones. If we generate a TAMU-only Consensus Calibration 1.1 (analogous to the X-CAL team CC_1.1, but based entirely on the TAMU model) the two dashed lines result. The new angles generate calibrations somewhat more consistent with the models than the old angles. Thus, for any sensor used as part of the calibration standard or as a transfer standard, we need to get the angles right.

On the other hand, if TMI is recalibrated to agree with Windsat, the fit improves and there is no discernable difference between the angle assumptions. Thus, the X-CAL process could paper over this angle issue, and presumably other similar issues. While, on philosophical grounds, we should treat any such issue explicitly if it is known, there are likely to be similar issues among the constellation instruments that we do not know. The X-CAL process will keep them from wrecking the GPM ship.



Need for 3σ filter

n working with the TMI/Windsat matchup data set generated by UCF for algorithm team purposes, Sid Boukabara found a great many wild points. He was reading this data set with the TAMU program which included the standard deviation tests. It was thought that these limits (2K for all Vpol channels and 3K for all Hpol channels) would eliminate all RFI problems; clearly this is not so. Based on this we have introduced an additional filter into the programs which use the matchup data set. We take a first pass through the data and note the average and standard deviation of the differences between corresponding Windsat and TMI channels. For subsequent passes we reject all points for which the difference departs from this mean by more than 3 times the standard deviation. We find roughly an order of magnitude more such points than one would expect for a Gaussian distribution. Eliminating these wild points shifts the means by a few hundredths of a Kelvin. An equivalent filter has also been implemented for the TMI/AMSR-E matchup and will be implemented for all future matchup data sets.

Texas A&M University Algorithms

The Texas A&M University (TAMU) algorithm adjusts 4 parameters of a geophysical model to match the over-ocean radiances of the source sensor. It matches in the sense of minimizing a penalty function which is simply a weighted average of the squares of the differences between the observed and computed radiances. The set of geophysical parameters that minimizes this penalty function is then used to compute the radiances of the target sensor.

The penalty function allows choices of which channels are used and with what weight. For the present, only binary values (*i.e.* 0 or 1) have been used in the weight vector but other values are possible. In fitting Windsat to predict TMI radiances the 7 channels having closely corresponding TMI channels have unit weight and the remaining channels (6.8GHz H&V, 23GHz V). For predicting AMSR-E from TMI the algorithm is run twice. Once with only the low frequency channels for predicting the low frequency channels of AMSR-E and again with all channels to predict the 89 GHz channels of AMSR-E

The geophysical parameters adjusted are sea surface wind, sea surface temperature, cloud liquid water content, and, in an indirect sense, precipitable water. The atmospheric profile assumes the cloud to be distributed between 4 and 5 km, the lapse rate to be 6.26K/km and a fixed relative humidity profile (See the error model discussion). The lapse rate and the relative humidity profile are averages from the GDAS data set associated with the niversity of Central Florida matchup data set. There is no reliable information as to the height of the cloud (if any) so the height used is arbitrary but roughly in the center of the possible range. The atmospheric temperature at the lowest level is the actual parameter adjusted but it modulates the precipitable water via the fixed relative humidity profile. Comparison of the retrieved atmospheric and sea surface temperatures is a test of the reasonableness of this assumption. The position of the cloud is not important as long as it is at a temperature warmer than -40C, the temperature of spontaneous nucleation.

The absorption coefficients and emissivities used are those agreed upon by the X-CAL team with modification. They have been translated from Fortran 77 to Fortran 90. The cloud liquid water and sea surface emissivity models have been modified to permit negative values of the cloud liquid water and surface wind speed. While this seems nonsensical on a physical basis it is computationally important. At low values of the parameters radiance fluctuations (e.g. NEDT) can cause some negative apparent values. If these are rejected or converted to some non-negative value, a bias will result. Also, if the source sensor has a calibration error, that too can cause negative values. The aim here is to transfer the calibration of one sensor to another for comparison purposes and clipping the values would contaminate the results. The modification of the cloud liquid water absorption is simple. Any discontinuity at zero can also interfere with the iterative solution to match the brightness temperatures.

The nested grid search algorithm is used. It computes the brightness temperature for the first guess set of parameters (SST and T_0 (the lowest level of the atmosphere) = 285K, Wind Speed = 10 m/s, and Cloud liquid water = 5 mg/cm^2). The initial step size is chosen to give on the order of 1K of brightness temperature change in at least one channel (1K for SST and T_0, 0.5 m/s of wind speed and 0.5 mg/cm^2 of CLW) and no change large compared to 1K. The brightness temperature computations are performed for 250m thick layers with an explicit correction for the temperature change across the layer. The parameters that minimize the penalty function are found at this resolution and then the step size is then halved and the process is repeated through 7 halvings, *i.e.* until the step size corresponds to approximately 0.01K. Less would make neither numerical nor physical sense. After the minimum penalty function has been found for this last step size, the radiances for the target sensor are computed.

For comparison purposes, an additional algorithm has been implemented. Each matchup box in the UCF data set includes surface and atmospheric parameters from GDAS. These are used to compute brightness temperatures directly for both the target and source sensors. But for minor implementation choices, this algorithm is quite similar to the UCF algorithm and yields almost identical results.

TMI(Version 7) – Windsat (7 channels) Deltas

	10V	10H	19V	19H	21V*	37V	37H
Fit	0.30	-1.68	-1.58	-3.08	-1.72	-3.20	-2.48K
GDAS	0.22	-1.66	-1.79	-2.95	-1.81	-3.22	-2.53K
@	170	88	200	133	203	214	153K

AMSR-E – TMI(CC_1.1)

	10V	10V	18V	18H	23V*	23H*	37V	37H	89V	89H
Fit 9	0.13	0.55	-0.53	-0.15	-0.07	0.11	-2.01	-0.33	-0.05	0.61K
Fit 7	0.04	0.55	-0.42	0.16	-0.17	-0.01	-2.09	-0.41	0.05	0.60K
GDAS	-0.02	0.56	-0.69	-0.09	-0.25	1.7	-2.1	-0.35	0.27	0.97K
@	176	89	202	131	213	151	220	157	267	239K

- Based in lowest quartile of TMI 21V data

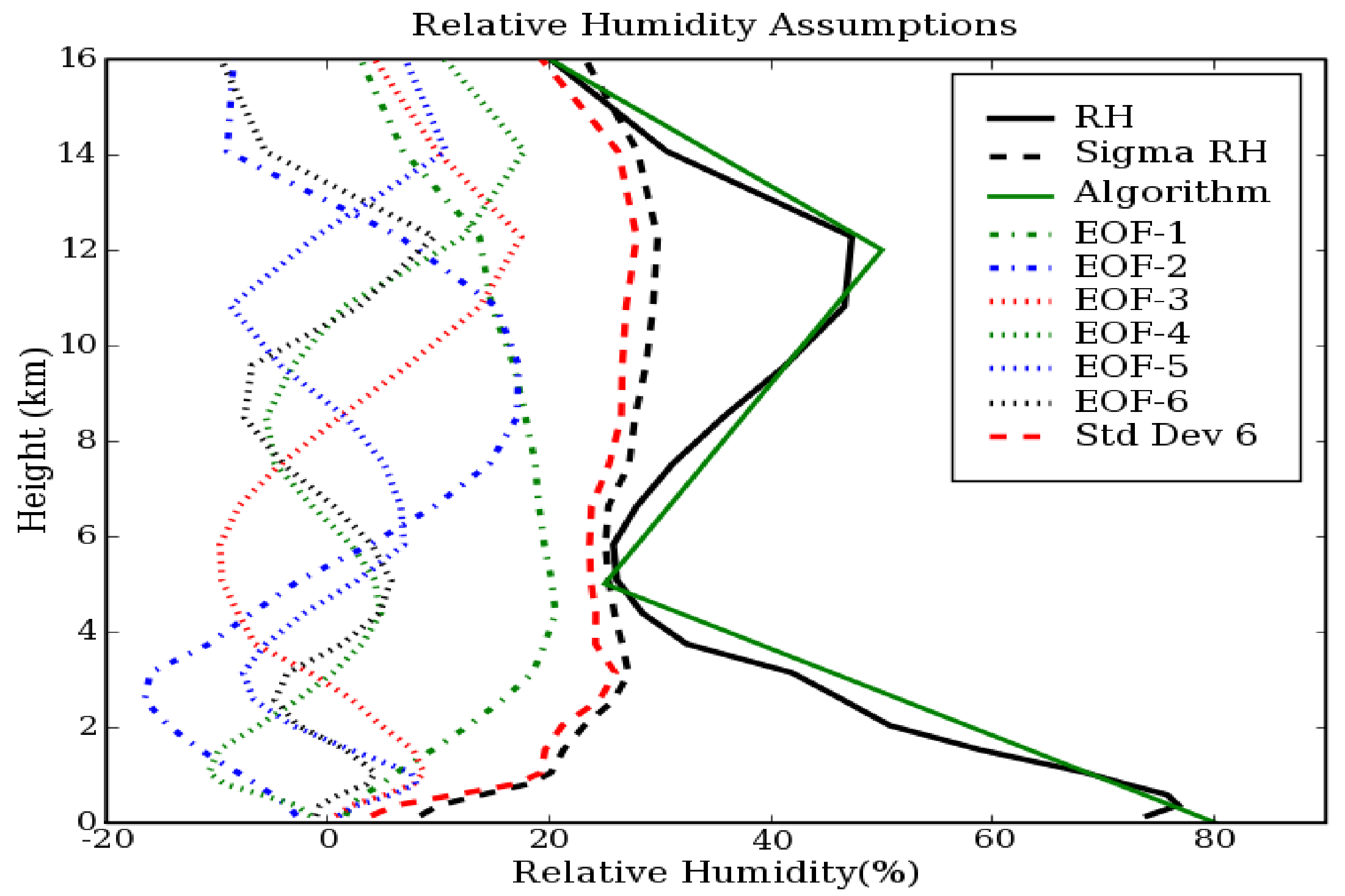
23H based on double difference wrt TMI 21V

Brightness Temperature Deltas

The algorithm described above has been applied to two matchup data sets. The University of Central Florida has created data sets of TMI coincidences with both Windsat and AMSR-E for the year July 2005 through June 2006. The data were averaged over one degree boxes and observations coincident within one hour were retained. They appended GDAS surface and atmospheric data to each box. The TAMU algorithms were applied to the boxes that passed the standard deviation and 3s tests described above with the additional requirements that the Tbs be consistent with ocean, that the GDAS data appeared to be good and that GDAS also considered the box to be ocean (*i.e.* salinity > 30PPT). After a given box was accepted and processed, we skipped forward in the data set so that the time of the TMI observation differed by at least 3 minutes to assure independence.

The TAMU algorithms were applied to both matchup data sets. First we used the Windsat data to predict TMI Tbs; these results were included in the generation of a consensus calibration based on both Windsat (75%) and TMI (25%). This consensus calibration (CC_1.1) was applied to TMI and the resulting Tbs used to predict the observations of AMSRE. For fitting to Windsat to predict TMI we only used the 7 channels of Windsat corresponding to the low frequency channels of TMI. The AMSRE fits were done in two ways, with the 7 low frequency channels of TMI and with all 9 channels.

One can see the differences between the Fit and GDAS algorithms are generally modest, of the order of 0.1K or less. These differences represent nudging of the Tbs by the fitting algorithm to be more consistent with the radiative transfer models used. If we look at the correlation between cloud liquid water and precipitable water in the retrieved atmospheres, we find a correlation coefficient near -75% both for the WS-TMI and AE-TMI data. For comparison if we look at the GDAS data directly, there is only a small positive correlation. This large negative correlation is clearly non-physical and results from the fitting routine compensating for incompatibilities between the radiances of Windsat in one case and TMI in the other case and the radiative transfer models. One can also see that for the AMSR-E/TMI fits, there is little difference in the results for the low frequency channels whether or not we use the 85 GHz TMI channels in the fit.



TAMU ALGORITHM (WS →TMI)
COMPONENTS OF UNCERTAINTY
(All Cold End Data)

	10V	10H	19V	19H	21V	37V	37H
@TB	172	90	206	143	231	219	160
EOF1	-.02		.02	-.04	-.26		
EOF2				.02	-.09		
EOF3					.16		
EOF4					.10		
EOF5					.05		
EOF6	all < 0.02						
RH	.03		.02	.05	.34		
CLHT			.02	.03			
LR					.10		
NET	.03		.04	.06	.36		

NOTES: ALL VALUES IN KELVINS
VALUES LESS THAN 0.02K LEFT BLANK

TAMU ALGORITHM (WS →TMI)
COMPONENTS OF UNCERTAINTY
(Lowest Quartile Only)

	10V	10H	19V	19H	21V	37V	37H
@TB	170	88	198	131	219	213	151
EOF1	-.02		.02		-.16		
EOF2					-.04		
EOF3					.09		
EOF4					-.06		
EOF5					.03		
EOF6	all < 0.02						
RH	.02		.03		.20		
CLHT	-.02		.05	.06			
LR					-.06		
NET	.03		.06	.06	.20		

NOTES: ALL VALUES IN KELVINS/
VALUES LESS THAN 0.02K LEFT BLANK

TAMU ALGORITHM TMI(9) →AMSRE
COMPONENTS OF UNCERTAINTY

	10V	10H	18V	18H	23V	23H	36V	36H	89V	89H
@TB	176	89	202	131	213	151	220	157	267	239
EOF1	.05			.15	.18	.08	.02	.03	.21	.19
EOF2	.04		.03	.04	.06	.05	.02	.02	.09	.06
EOF3			.05	.07	.11	.04			.04	.06
EOF4			.04	.04	.07					.02
EOF5			.03	.05	.03	.04			.03	.04
EOF6	all < 0.02									
RH	.06		.08	.18	.23	.11	.03	.04	.23	.21
CLHT			.23	.29	.03	.74		.03	.07	.09
LR			.03	.04	.08	.04			.03	.03
NET	.06		.25	.34	.25	.75	.03	.05	.24	.23

NOTES: ALL VALUES IN KELVINS
VALUES LESS THAN 0.02K LEFT BLANK
23 GHz channels based on lowest quartile of TMI 21V

Error Models

We have also tried to estimate the uncertainties in the deltas. We first identified the critical assumptions in the fitting routine. We assume a constant lapse rate of 6.26K/km but the GDAS data show a standard deviation of 0.30K/km about this value. We recomputed with a lapse rate of 6.26-0.30 K/km to estimate this component of the uncertainty. Similarly we place the cloud between 4 and 5km altitude, roughly the midpoint of the possible range. We recomputed with the cloud placed from the surface to 1km altitude to estimate this component. We assume a relative humidity profile given by the green line in the graph which is a close approximation to the average RH profile in the GDAS data set. We also decomposed the variability of the RH profile into Empirical Orthogonal Functions (EOFs), the first six of which are shown in the graph with the actual rather than normalized amplitudes. The black dashed line shows the total standard deviation of the RH profile and the dashed red line, the part contribute by the first 6 EOFs. We added each of the EOFs to the RH profile and recomputed to estimate the impact of water vapor variability. The results are shown in several tables. The statistics were compiled for the full data set and for the lowest quartile of the TMI Tbs. This latter choice was to facilitate comparisons with the University of Michigan results which were heavily weighted towards the low Tbs.

Looking at the WS→TMI results we only see a few significant contributions to uncertainty. The cloud height assumption seems to have very little impact. The lapse rate only impacts the 21V results. We can see that 6 EOFs is enough as the sixth one has very little impact. As one might expect, the primary impact of the relative humidity profile is on the 21V channel. Going to the lowest quartile has little impact except at 21V where the modeled uncertainty is significantly lower. Thus, the X-CAL working group has decided to use the bottom quartile of TMI Tb for channels on the 22 GHz water vapor line and all the data otherwise.

Going to the TMI→AMSR-E matchups first using all 9 TMI channels we a generally similar pattern with one surprise. We find an unexpectedly large sensitivity to the cloud height assumption. While this is probably an overestimate because we chose the extreme value rather than the 1s value (which in unknown), it is still uncomfortably large. If we compare with the computations using only the 7 low frequency channels this sensitivity is more reasonable. The cloud height sensitivity comes from the 85 GHz channels. Fortunately, the 7 and 9 channel results do not differ by much.

The only assumption from this analysis that applies to the GDAS approach is the cloud height assumption. This sensitivity was also computed and is included in the final results.

Another approach to the uncertainty was statistical. We subdivide the data by month and computed the deltas on a month-by-month basis. By standard statistical procedures, we computed the uncertainty in the mean from these. If there is a seasonal component, (not obvious in looking at plots) it would make this error estimate too large. However, these estimates are quite small. Except for the cloud height assumption, all of the error sources we modeled should be included in the statistical error. Nevertheless, we have estimated total error by a root sum square of the modeled and statistical error. In no case, is the contribution from both large, so the sum is modestly pessimistic as one would want an error estimate to be.

TAMU ALGORITHM TMI(7) →AMSRE
COMPONENTS OF UNCERTAINTY

	10V	10H	18V	18H	23V	23H	36V	36H	89V	89H
@TB	176	89	202	131	213	151	220	157	267	239
EOF1				.07	.21	.13			.18	.19
EOF2				.04	.05	.17			.07	.05
EOF3					.12	.05			.05	.08
EOF4					.07	.07				.04
EOF5					.06				.03	.05
EOF6	all < 0.005									
RH				.08	.26	.23			.20	.22
CLH T					.03				.03	.03
LR					.08	.02			.02	.03
NET				.08	.28	.23			.24	.23

NOTES: ALL VALUES IN KELVINS
VALUES LESS THAN 0.02K LEFT BLANK
23 GHz channels based on lowest quartile of TMI 21V

TAMU ALGORITHM (WS →TMI)
UNCERTAINTY
All Cold End Data

	10V	10H	19V	19H	21V	37V	37H
@TB	172	90	206	143	231	219	160
Mod	.03		.04	.06	.36		
Stat/M	.02	.03	.06	.05	.04	.06	.03
Net/M	.04	.03	.07	.08	.36	.06	.03
Stat/QR	all below 0.02						
Net/QR	.03	.02*	.04	.06	.36	.02*	.02*

NOTES: ALL VALUES IN KELVINS
VALUES LESS THAN 0.02K LEFT BLANK

TAMU MODEL UNCERTAINTY (WS →TMI)
Lowest Quartile Only

	10V	10H	19V	19H	21V	37V	37H
@TB	170	88	198	131	219	213	151
Mod	.03		.06	.06	.20		
Stat/M	.07	.05	.04	.04	.05	.06	.03
Net/M	.08	.05	.07	.07	.21	.06	.03
Stat/QR	all < 0.02						
Net/QR	.03		.06	.07	.20		

NOTES: ALL VALUES IN KELVINS
VALUES LESS THAN 0.02K LEFT BLANK

TAMU ALGORITHM (TMI →AMSRE)
UNCERTAINTY

9 CHANNEL

	10V	10H	18V	18H	23V	23H	37V	37H	89V	89H
Mod	.06		.25	.34	.25	.75	.03	.05	.24	.23
Stat	.03	.02	.02	.04	.06	.08	.03	.02	.04	.04
Net	.07	.02	.25	.34	.26	.75	.04	.05	.24	.23

7 CHANNEL

	10V	10H	18V	18H	23V	23H	37V	37H	89V	89H
Mod				.08	.28	.23			.24	.23
Stat	.04	.04	.04	.04	.06	.09	.05	.03	.06	.06
Net	.04	.04	.04	.09	.29	.25	.05	.03	.25	.24

GDAS

	10V	10H	18V	18H	23V	23H	37V	37H	89V	89H
Mod	(cloud height only)					.10			.04	.05
Stat	.04	.03	.03	.04	.07	.09	.05	.03	.06	.05
Net	.04	.03	.03	.04	.07	.13	.05	.03	.07	.07

NOTES: ALL VALUES IN KELVINS
VALUES LESS THAN 0.02K LEFT BLANK
LOWEST QUARTILE OF TMI 21V FOR 23 GHz CHANNELS