SST and SSES in ACSPO v2.41

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Objectives

- ACSPO v. 2.41 generates two SST products:
  1. Baseline SST (BSST): global regression
  2. De-biased SST (DSST): DSST= BSST – SSES bias

- SSES are the Single Sensor Error Statistics - the estimates of BSST bias and SD wrt *in situ* SST at every L2 pixel

- The ACSPO SSES were designed to facilitate assimilation of ACSPO L2/L3U SST in the "foundation" L4 analyses in two ways:
  - ✓ De-biased SST should minimize the need for bias correction during the L4 analyses
    (already tested by L4 producers, currently used in CMC and OSTIA)
  - ✓ SSES SDs should improve weighting DSST with other data by characterizing its real precision under variable conditions
    (not tested yet)

- This presentation describes the current ACSPO SST algorithms and compares the performance of SSES bias correction in ACSPO and in other SST systems

References

1. Petrenko, B., A. Ignatov, Y. Kihai, P. Dash, Sensor-Specific Error Statistics for SST in the Advanced Clear-Sky Processor for Oceans. *J. Atmos. Ocean. Technol.,* **2016**, 33, 345–359, doi: 10.1175/JTECH-D-15-0166.1

2. Kramar, M. A. Ignatov, B. Petrenko, Y. Kihai, and P. Dash, Near real time SST retrievals from Himawari-8 at NOAA using ACSPO system. *Proc. of SPIE,* **9827**, doi: 10.1117/12.2229771

3. Petrenko, B., A. Ignatov, M. Kramar, and Y. Kihai, Exploring new bands in multichannel regression SST algorithms for the new generation infrared sensors at NOAA. *Proc. of SPIE,* **9827**, doi: 10.1117/12.2229578

Baseline SST equation for AHI/ABI

The BSST equation employs four AHI bands centered at 8.6, 10.4, 11.2, 12.3 µm:

$$T_S = a_0 + a_1 T_{13} + a_2(T_{13}-T_{15}) + a_3(T_{11}-T_{10}) + a_4(T_{11}-T_{12}) +$$
$$+ [a_5 + a_6 T_{11} + a_7(T_{11}-T_8) + a_8(T_{11}-T_{10}) + a_9(T_{11}-T_{12})]S_\vartheta +$$
$$+ [a_{10}(T_{11}-T_8) + a_{11}(T_{11}-T_{10}) + a_{12}(T_{11}-T_{12})]T_S^0$$

$T_8, T_{10}, T_{11}, T_{12}$	observed BTs in bands 11, 13, 14 and 15
$S_\vartheta = 1/\cos(\vartheta) - 1$	ϑ is VZA
T_S^0	L4 SST in °C (currently Canadian Meteorological Center – CMC, v3, daily 0.10°)
a's	regression coefficients trained on global datasets of matchups (MDS)

- The equation provides stable BSST estimates with:
  - ✓ global precision wrt *in situ* SST of ~0.4 to 0.5 K
  - ✓ mean sensitivity to "skin" SST ≈ 0.95
- Produces significant regional biases depending on observational conditions

The concept of ACSPO SSES

- In order to account for non-uniformity of BSST biases, SSES should be defined for separate segments of the SST domain, relatively uniform in terms of retrieval errors
- ***The question is: How to define “relatively uniform segments”?***
- The straightforward approach is to represent SST errors as functions of some physical variables (TPW, VZA, latitude, wind speed, aerosol, etc. – e.g., *Castro et al., 2008; Minnett, 2014, Petrenko and Ignatov, GHRSST, 2014*)
- In ACSPO, this approach was found inefficient because it is difficult to account for all physical factors (if at all possible)
- Starting with ACSPO v2.40, SST errors are analyzed in the space of regressors (***R***-space), rather than in the space of physical variables.
  - ✓ The number of SSES arguments is limited with the number of regressors
  - ✓ The definition of the ***R***-space may be linked to the statistics of BSST errors

The link between BSST errors and the statistics of regressors within the MDS

- The least-squares estimate of the vector of regression coefficients is constructed from the statistics of regressors within the training MDS :

$$\boldsymbol{C}=\boldsymbol{D}^{-1}\langle(\boldsymbol{R}-\langle\boldsymbol{R}\rangle)^{T}(T_{IS}-\langle T_{IS}\rangle)\rangle \qquad (1)$$

$\boldsymbol{C}$	vector of regression coefficients
$\boldsymbol{R}$	vector of regressors
T_{IS}	*in situ* SST
$\langle * \rangle$	denotes averaging over the MDS
$\boldsymbol{D}=\langle(\boldsymbol{R}-\langle\boldsymbol{R}\rangle)(\boldsymbol{R}-\langle\boldsymbol{R}\rangle)^{T}\rangle$	covariance matrix of regressors within the MDS

- The variance of BSST error is also the function of $\boldsymbol{R}$, $\langle\boldsymbol{R}\rangle$ and $\boldsymbol{D}$:

$$\boldsymbol{V}(\boldsymbol{R})=[(\boldsymbol{R}-\langle\boldsymbol{R}\rangle)^{T}\boldsymbol{D}^{-1}(\boldsymbol{R}-\langle\boldsymbol{R}\rangle)] \qquad (2)$$

Using $\boldsymbol{\rho}=\boldsymbol{V}^{0.5}$ (aka Fisher distance) as a metric links the definition of the ***R***-space to retrieval errors

The definition of the space of regressors (*R*-space)

- <u>Origin</u>: <***R***> - mean ***R*** within the MDS
- <u>Metric</u>: ***ρ(R)*** - Fisher distance
- <u>Basis</u>: Eigenvectors {$\boldsymbol{\varphi}_{i}$, i=1,2,…,N} of the regressors' covariance matrix ***D***

- ✓ The SSES may be defined for the limited part of the ***R***-space close to <***R***>
- ✓ The metric ***ρ(R)*** is directly linked to the variance of the SST retrieval error
- ✓ Since the coordinates of ***R*** are statistically independent, with the variance of each coordinate being equal to the corresponding eigenvalue of D, the dimensionality of the ***R***-space can be reduced by dropping the eigenvectors corresponding to the least significant eigenvalues.

Generation of SSES LUT and using it in L2 processing

Off-line SSES LUT generation

First n (out of N) eigenvectors of $\boldsymbol{D}$ are used as a basis in the $\boldsymbol{R}$-space

Each orthant of the basis is subdivided into 10 segments in terms of $\boldsymbol{\rho}$:
$i-1< \rho <=i+1$, i=0,1,…8; ρ>9 for $i=9$

- Regression coefficients for each segments are calculated from the matchups belonging to this segment
- SSES SD is defined as SD of local regression wrt matchups

On-line SSES calculation

Each pixel is ascribed to a specific segment, based on $\boldsymbol{R}$

Regression coefficients and SSES SDs are selected from LUT

Piecewise-Regression SST (PWR SST) is calculated using local coefficients

SSES Bias=BSST-PWR SST

- Currently, for AHI, N=12 and n=9, which corresponds to 2^9*10=5120 segments
- De-biased SST is an equivalent of PWR SST: DSST= PWR SST

Global Bias and SD wrt in situ SST for AHI Baseline SST and De-biased SST

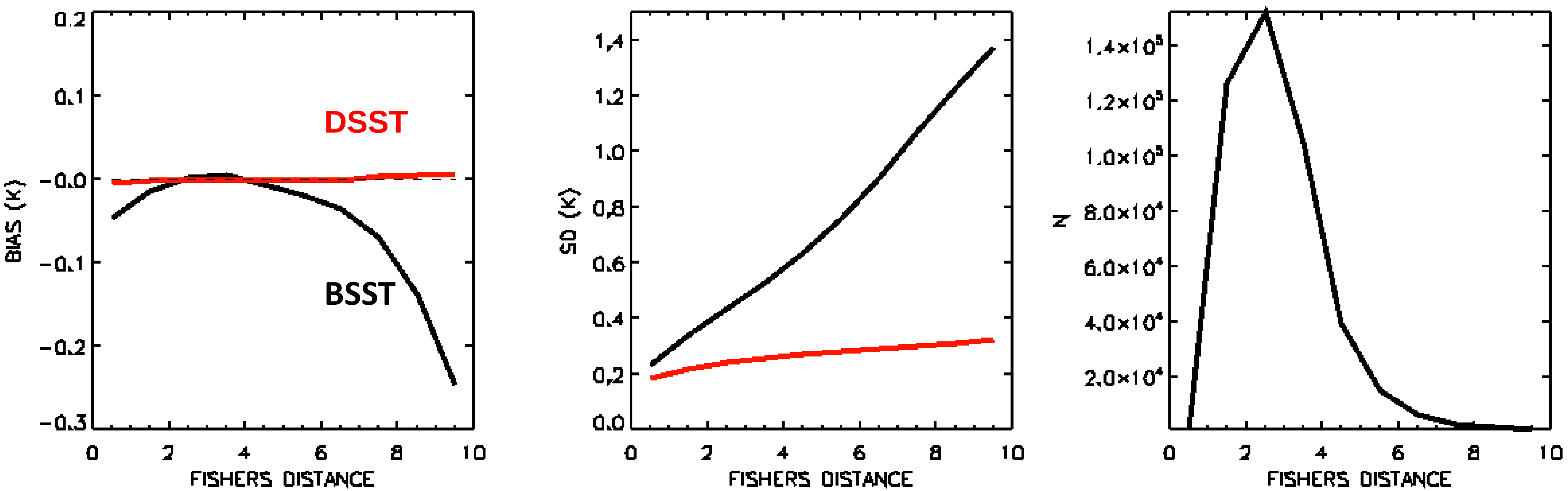
- Training MDS: 510298 matchups for January-December 2016
- Validation MDS: 103064 matchups for January-March 2017

SST	Training MDS		Validation MDS	
	Bias	SD	Bias	SD
Baseline	0.00 K	0.48 K	-0.07 K	0.43 K
De-biased	0.00 K	0.25 K	-0.02 K	0.25 K

De-biased SST significantly reduces the global SD wrt in situ SST, which suggests efficient suppressing of regional SST biases

Bias and SD of AHI Baseline SST and De-biased SST wrt *in situ* SST as functions of Fisher distance

Training MDS

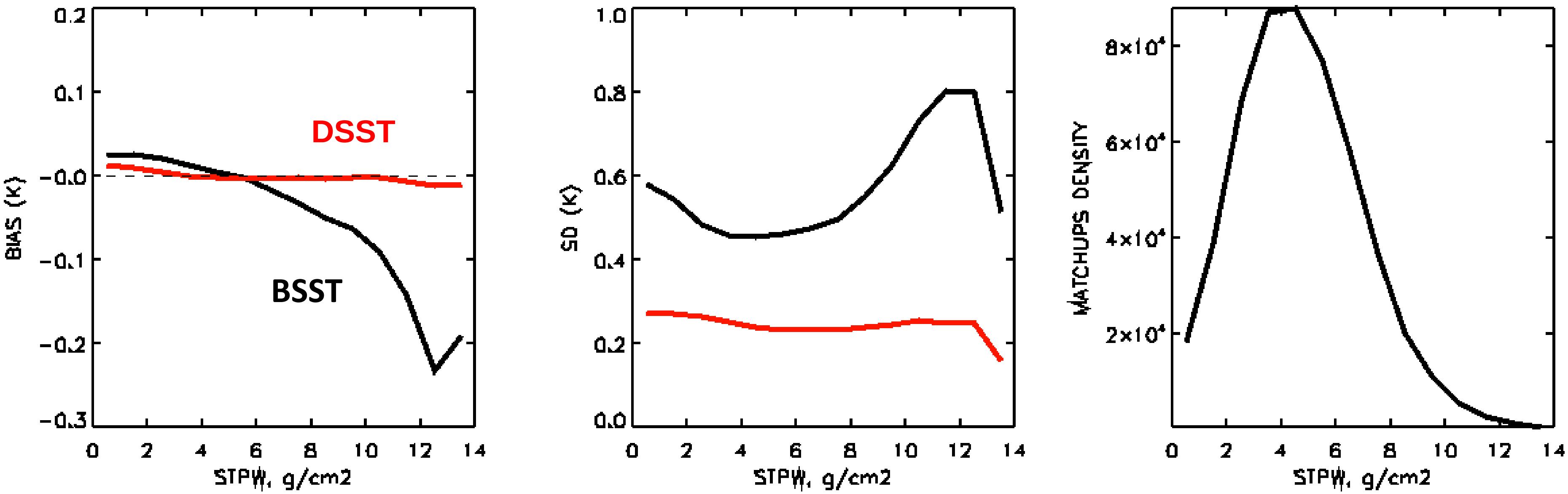


- The matchups are concentrated within the interval of Fisher distances $0.5 < \rho < 10$
- BSST bias is the smallest at the maximum of the matchups density, strongly non-uniform
- BSST SD monotonically increases with Fisher distance
- DSST bias and SD are smaller and almost flat as functions of Fisher distance

Bias and SD of AHI Baseline SST and De-biased SST wrt *in situ* SST as functions of “slant” TPW (STPW)

Training MDS

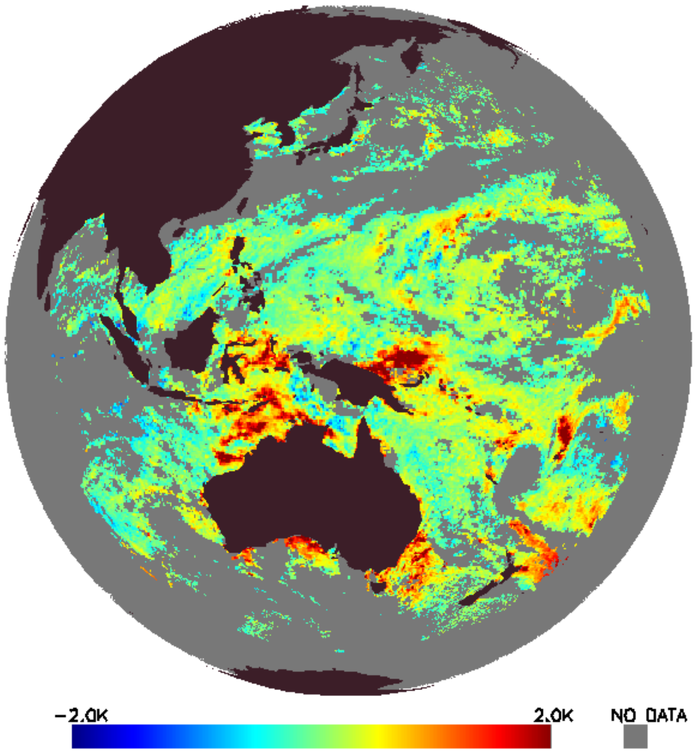
STPW=TPW/cos(VZA), characterizes the precipitable water vapor content along the line of sight



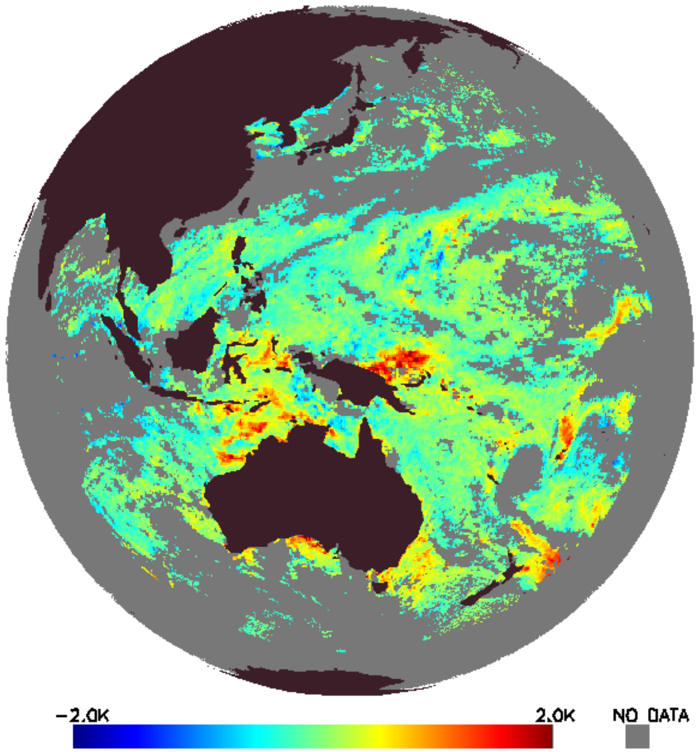
- BSST accuracy and precision are the best at the maximum of the matchups density and degrade with the distance from this maximum
- DSST bias and SD are smaller and more uniform

AHI: Baseline SST - CMC and SSES bias, 2016-01-10, 3:00 UTC

Baseline SST-CMC, Bias=0.36 K, SD=0.54 K



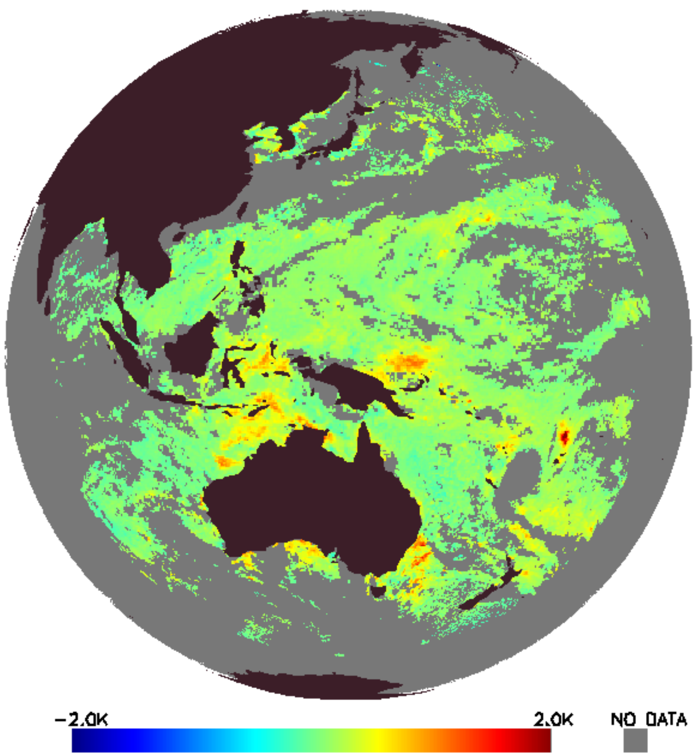
SSES Bias



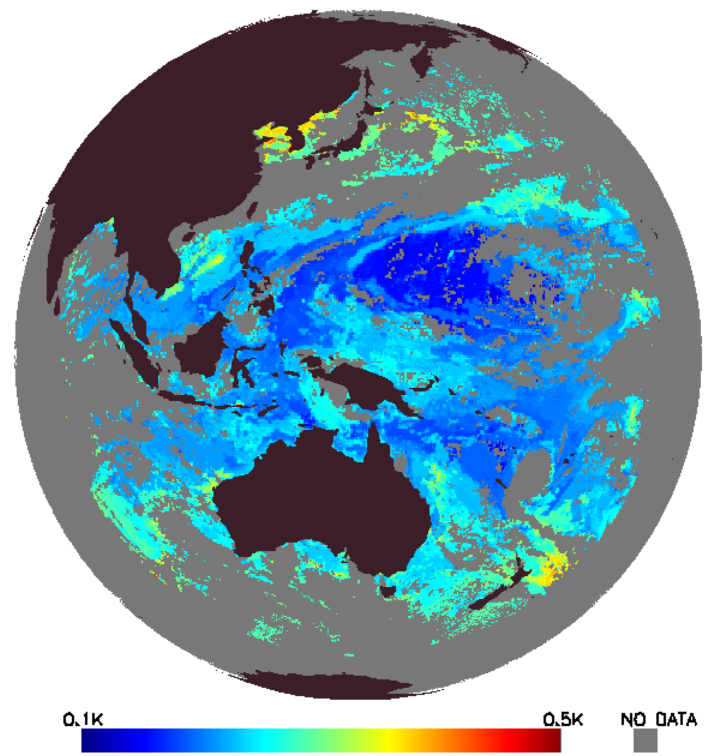
SSES bias is sensitive to daytime warming effects and cloud leakages in Baseline SST

AHI: De-biased SST - CMC and SSES SD, 2016-01-10, 3:00 UTC

De-biased SST-CMC: Bias=0.21 K, SD=0.20 K



SSES SD



De-biasing:
- ✓ Significantly reduces global SD wrt CMC
- ✓ During day, retains warm bias wrt CMC, consistently with the warm bias in *in situ* SST

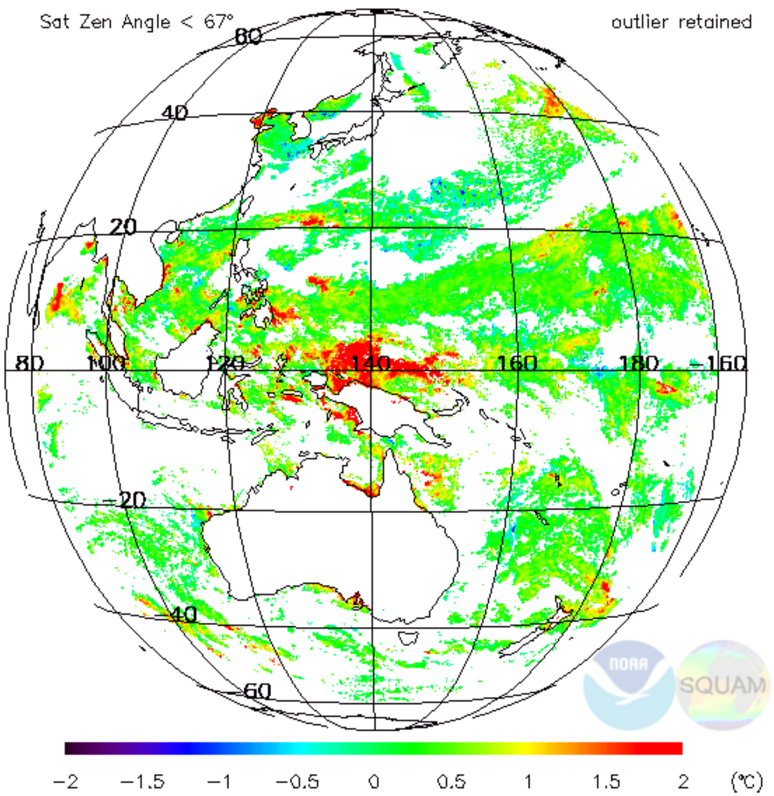
SSES SD varies from ~0.1 K to ~0.4 K

The performance of SSES bias correction in ACSPO and other SST systems

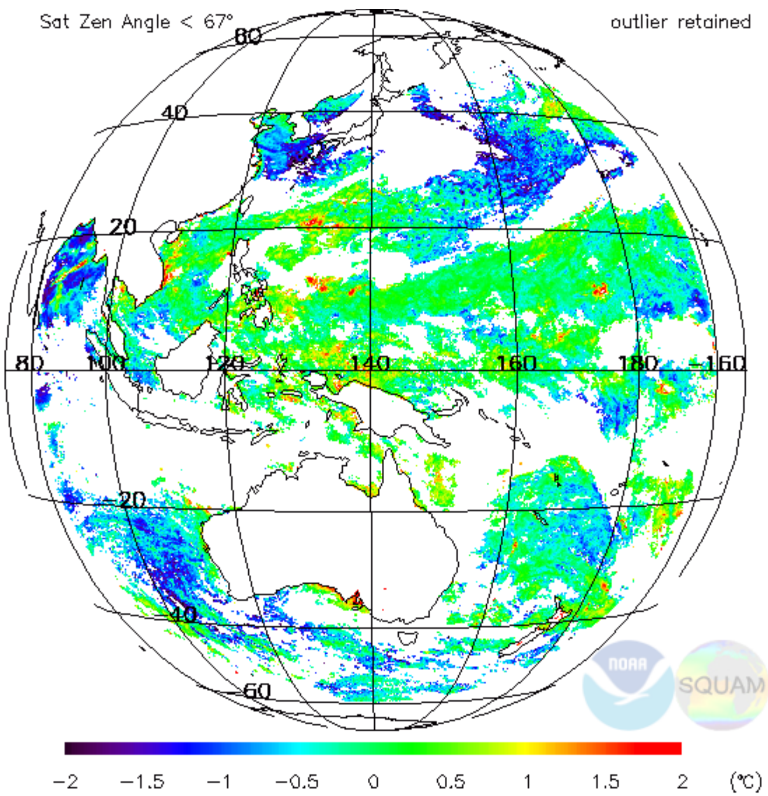
- The GHRSST Data Specification format 2.0 does not specify the way of SSES estimation.
- The renovated GHRSST web site, https://www.ghrsst.org/ , does not provide any further information on SSES
- We interpret SSES as the estimates of biases and SD of retrieved SST with respect to *in situ* SST, considering that *in situ* SST is the only available source of reference data.
- We also assume that the efficiency of SSES bias correction means its capability of reducing regional SST biases and global SD wrt *in situ* SST
- In the next slides, we compare the efficiency SSES bias correction in ACSPO and other available products

AHI: ACSPO and JAXA BSST-CMC, 21 March 2017, 14:00 Local Solar time (Day)

ACSPO: Bias=0.52 K, SD=0.56 K



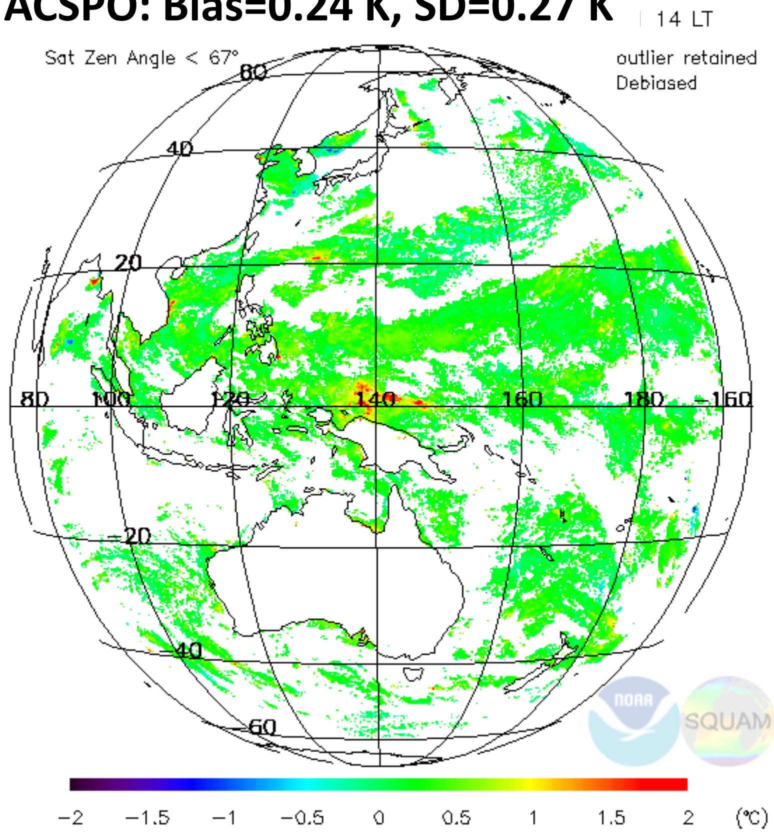
JAXA: Bias=-0.16 K, SD=0.64 K



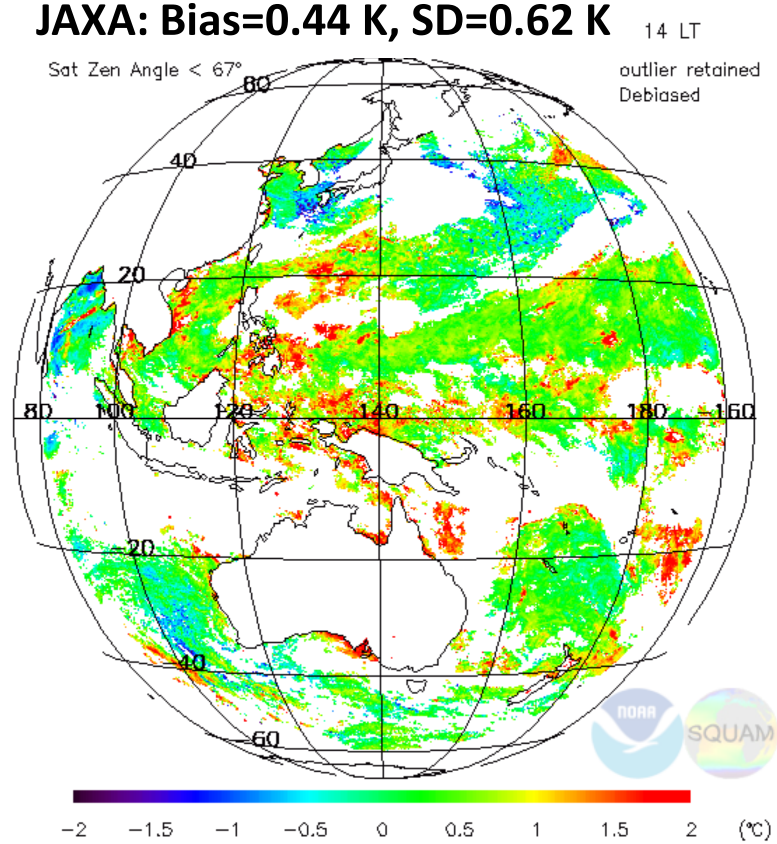
The statistics are calculated for |VZA|<67°

AHI: De-biased ACSPO and JAXA SST - CMC, 21 March 2017, 14:00 Local Solar time (Day)

ACSPO: Bias=0.24 K, SD=0.27 K



JAXA: Bias=0.44 K, SD=0.62 K

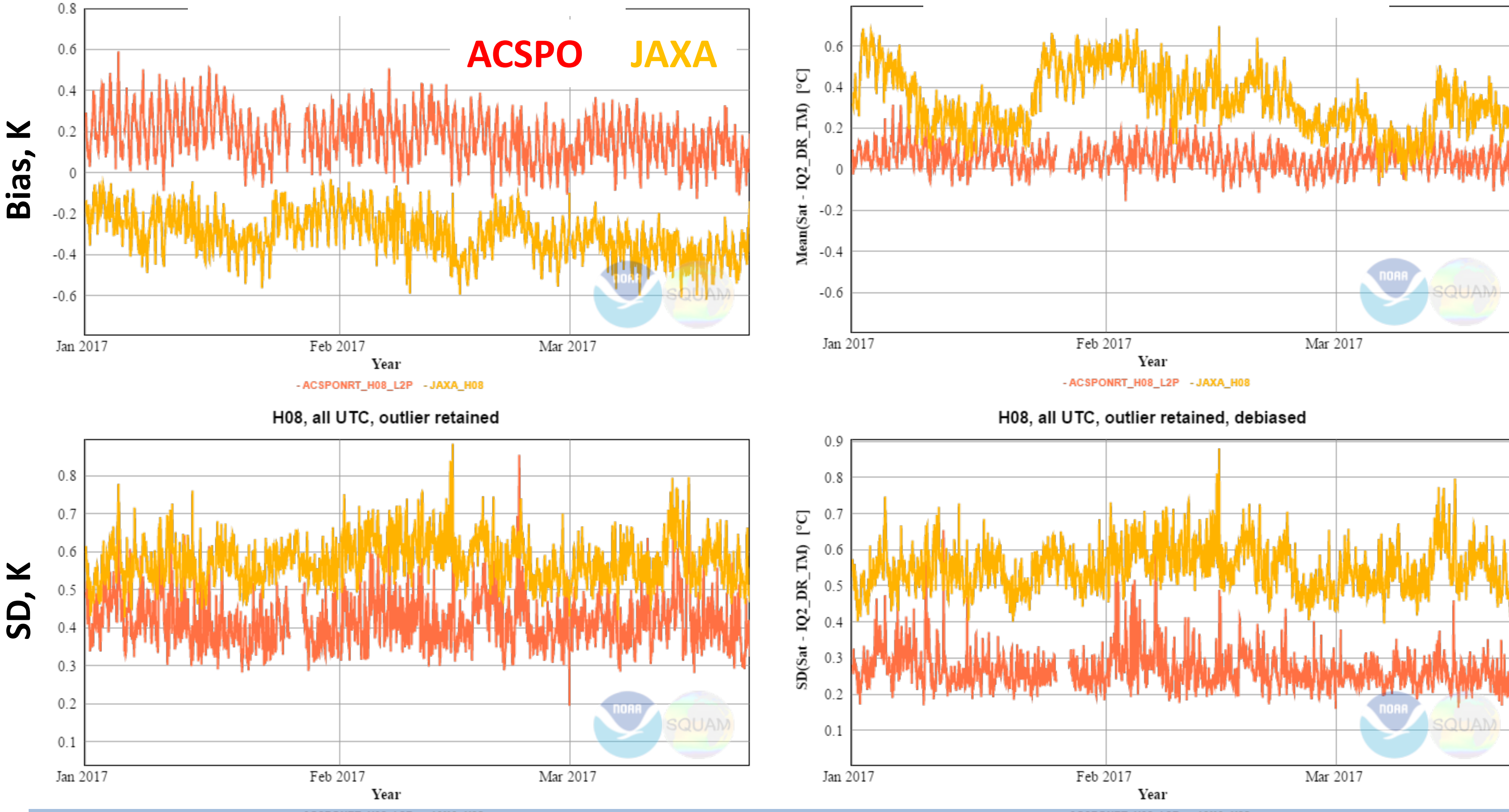


ACSPO DSST: Warm bias reduced; SD reduced from 0.56 K to 0.27 K

JAXA DSST: Bias warmed up; SD slightly reduced from 0.64 K to 0.62 K

AHI: Time series of bias and SD of Baseline SST and De-biased SST wrt *in situ* SST

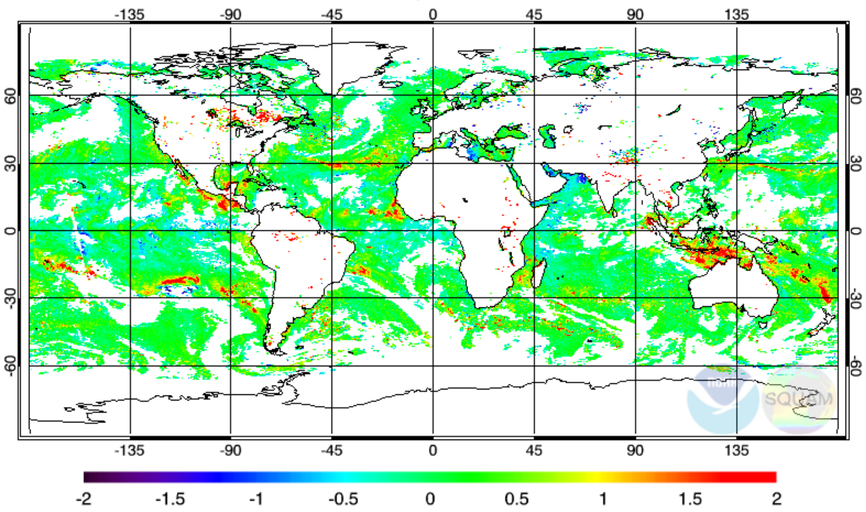
Baseline SST-*in situ* SST | **De-biased SST-*in situ* SST**



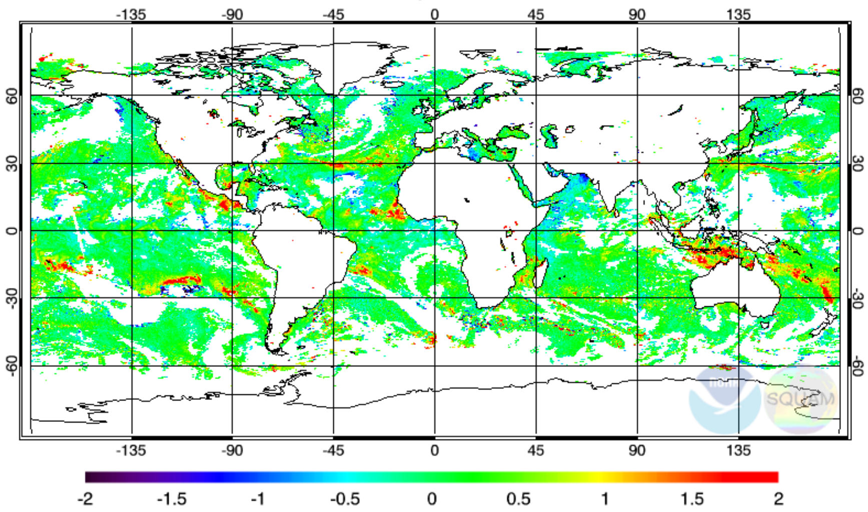
- ACSPO DSST: Reduces magnitude of variations in bias, reduces SD
- JAXA DSST: Warms up bias, makes it more non-uniform, slightly changes SD

VIIRS , day : Baseline SST minus CMC by ACSPO and NAVO (2016-10-01)

ACSPO: Bias=0.30 K, SD=0.52 K



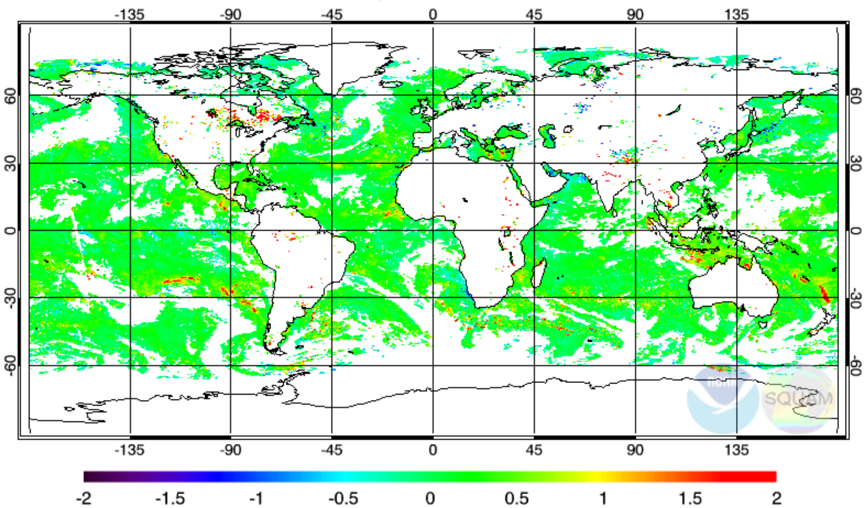
NAVO: Bias=0.29 K, SD=0.51K



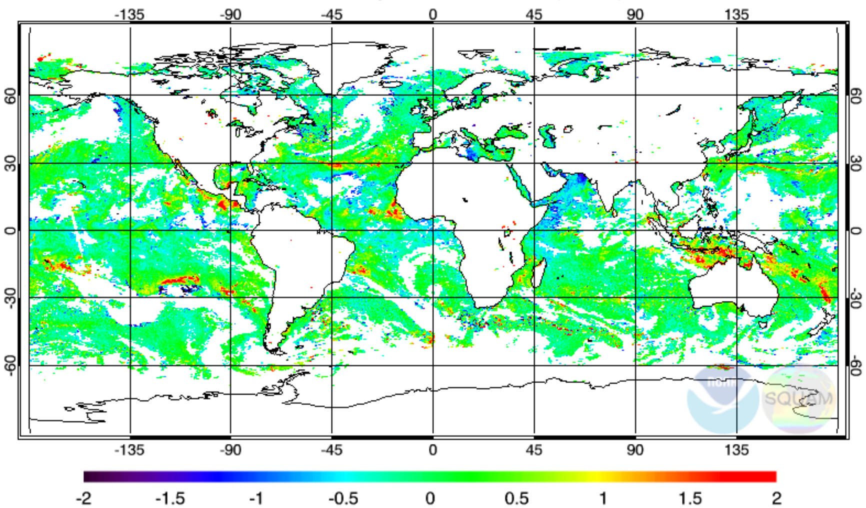
- The statistics for ACSPO and NAVO BSST are similar

VIIRS , day: De-biased SST minus CMC by ACSPO and NAVO (2017-10-01)

ACSPO: Bias=0.27 K, SD=0.34 K



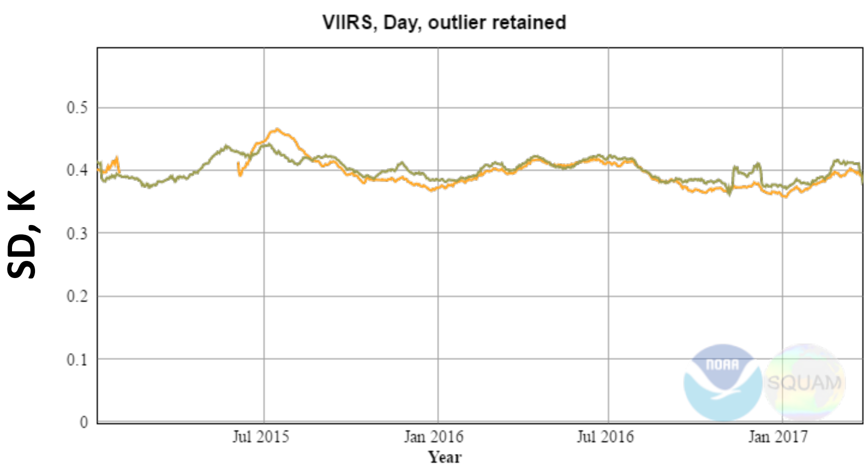
NAVO: Bias=0.15 K, SD=0.50K



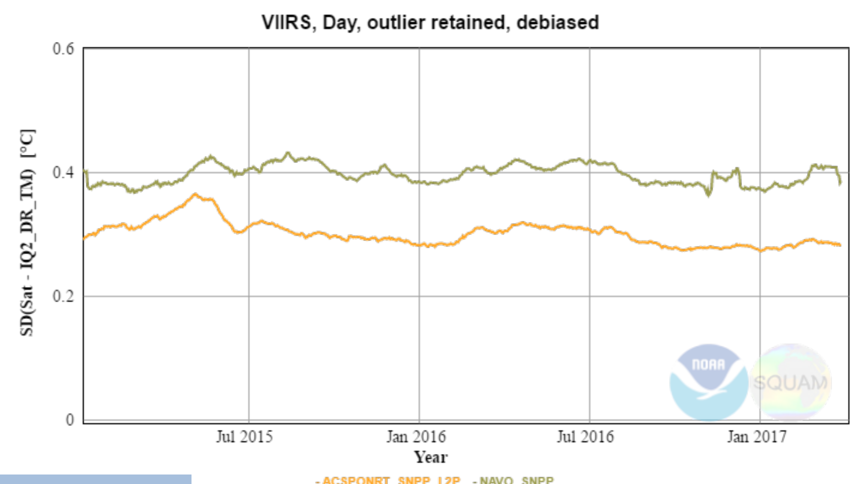
- ACSPO DSST: reduces SD from 0.52 K to 0.34 K
- NAVO DSST: reduces SD from 0.51 K to 0.50 K

VIIRS, day: bias and SD of BSST and DSST wrt *in situ* SST by ACSPO and NAVO

Baseline SST-*In situ* SST



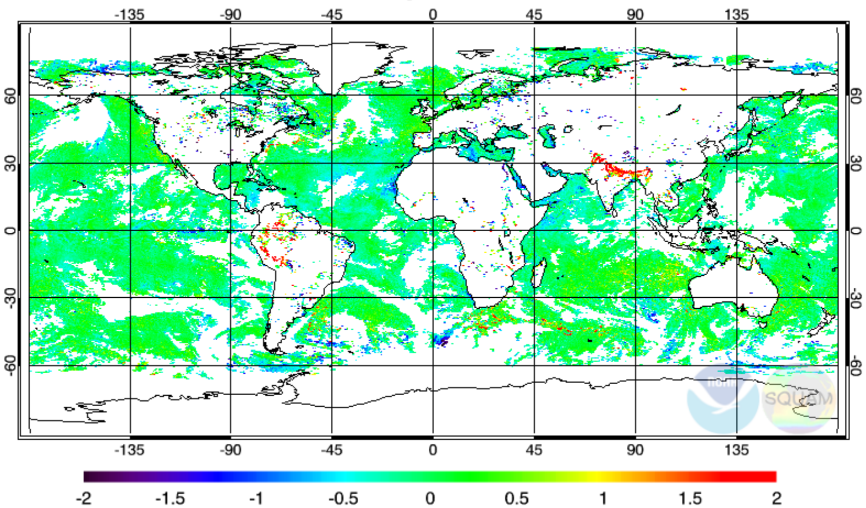
De-biased SST-*In situ* SST



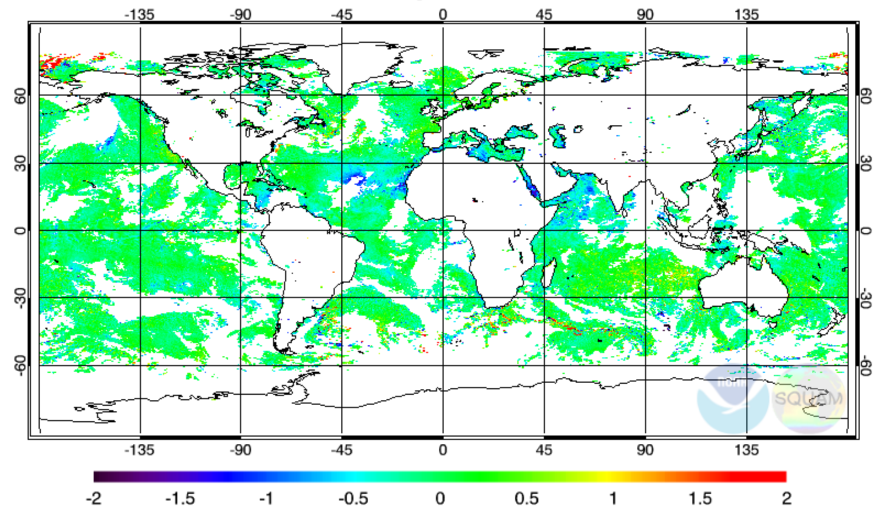
- ACSPO: DSST reduces SD
- NAVO: DSST leaves SD almost the same

VIIRS , night: Baseline SST minus CMC by ACSPO and NAVO (2017-10-01)

ACSPO: Bias=0.05 K, SD=0.36 K



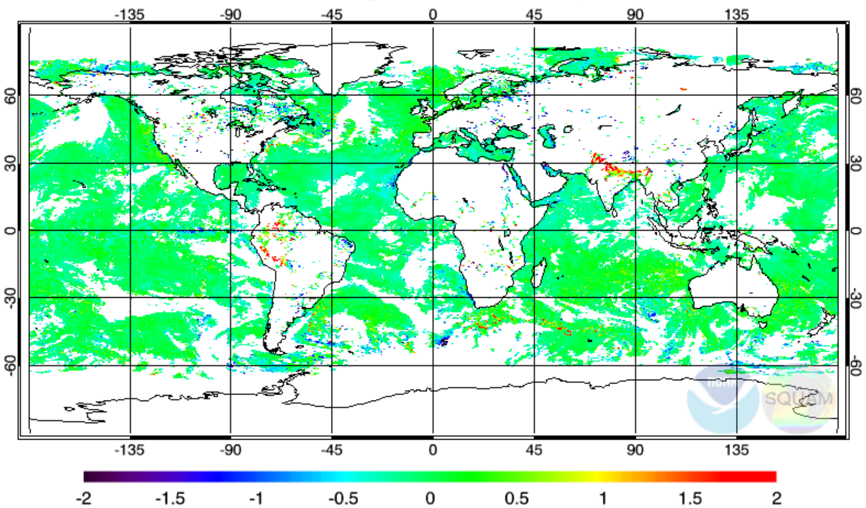
NAVO: Bias=0.01 K, SD=0.34K



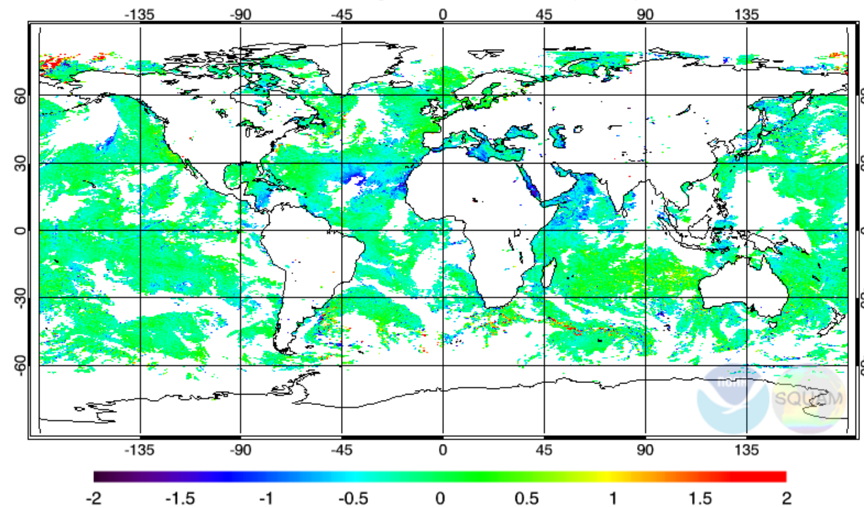
- ACSPO and NAVO BSST statistics are close

VIIRS , night: De-biased SST minus CMC by ACSPO and NAVO (2017-10-01)

ACSPO: Bias=0.03 K, SD=0.27 K



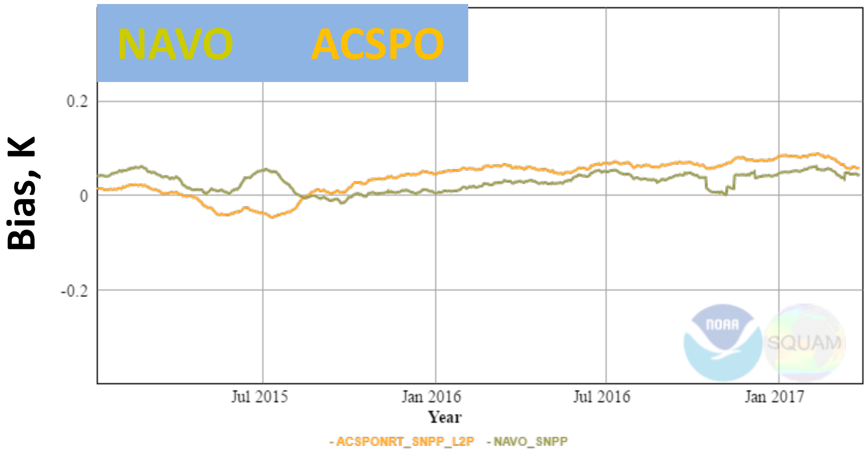
NAVO: Bias=-0.10 K, SD=0.34K



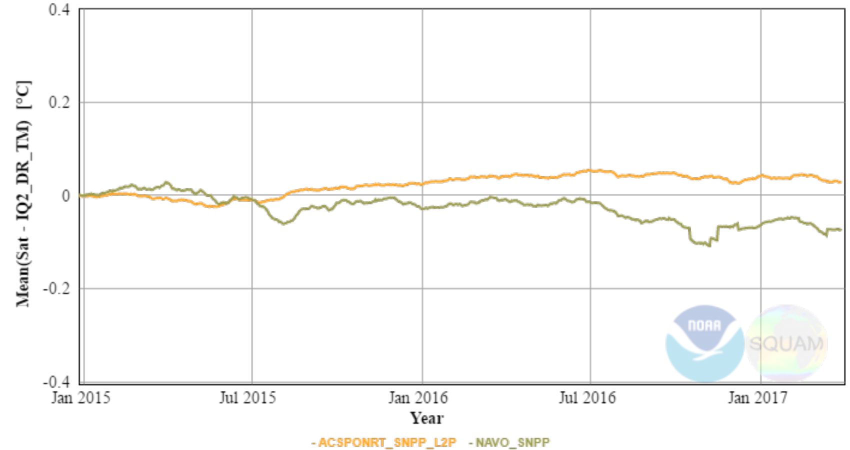
- ACSPO DSST reduces SD from 0.36 K to 0.27 K
- NAVO DSST: SD does not change

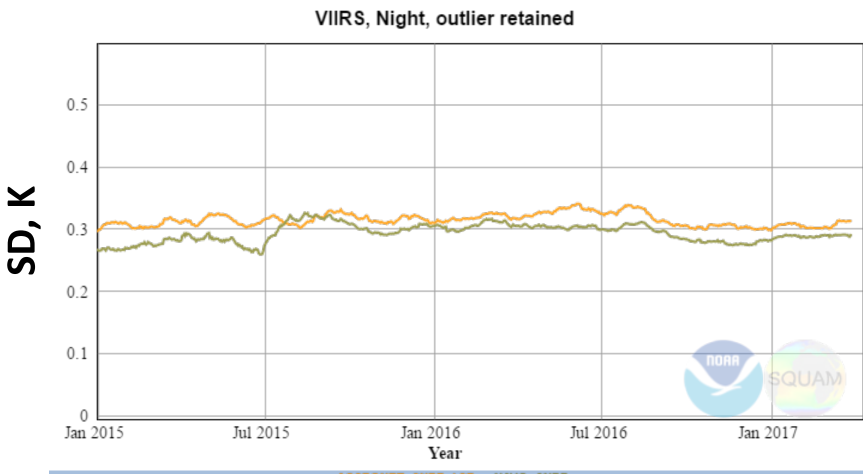
VIIRS, night: bias and SD of BSST and DSST wrt *in situ* SST by ACSPO and NAVO

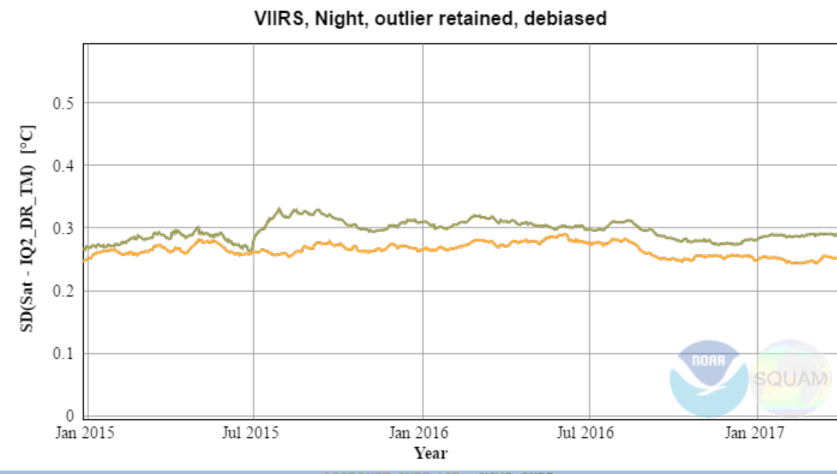
Baseline SST-In situ SST



DE-biased SST-In situ SST



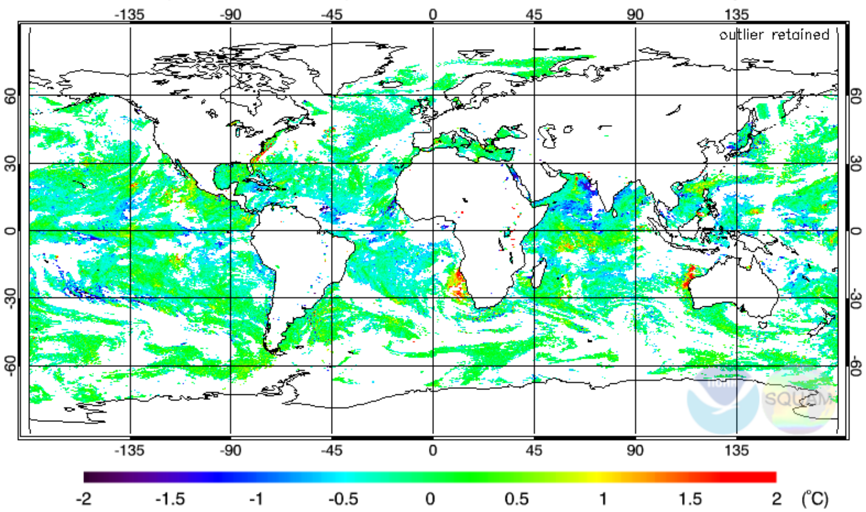




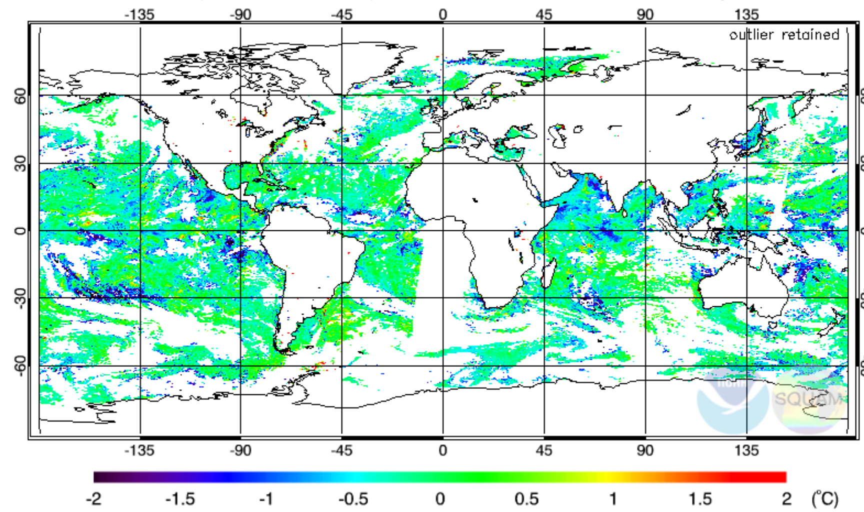
- ACSPO: DSST reduces SD
- NAVO: DSST increases SD or keeps it unchanged

MetOp-B FRAC, day : Baseline SST minus CMC by ACSPO and OSI-SAF (2017-03-20)

ACSPO: Bias=0.00 K, SD=0.42 K

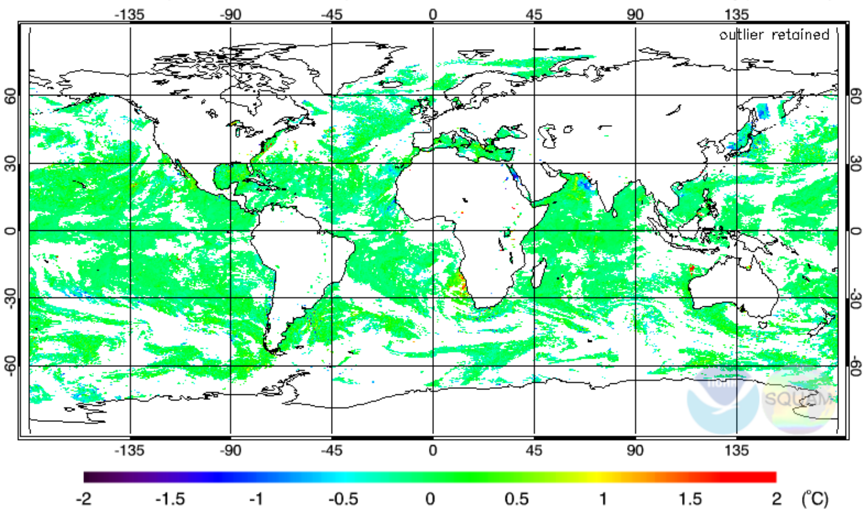


OSI-SAF: Bias=-0.08 K, SD=0.44K

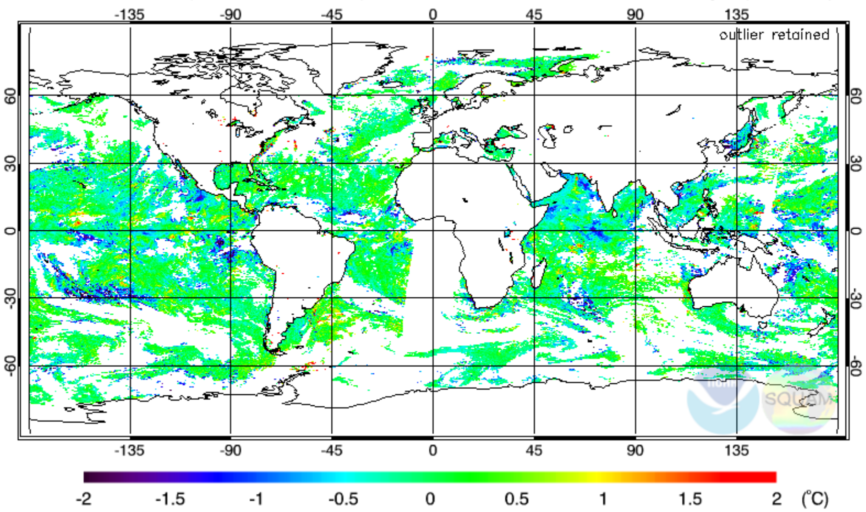


MetOp-B FRAC, day: De-biased SST minus CMC by ACSPO and OSI-SAF (2017-03-20)

ACSPO: Bias=0.04 K, SD=0.21 K



OSI-SAF: Bias=0.01 K, SD=0.44K

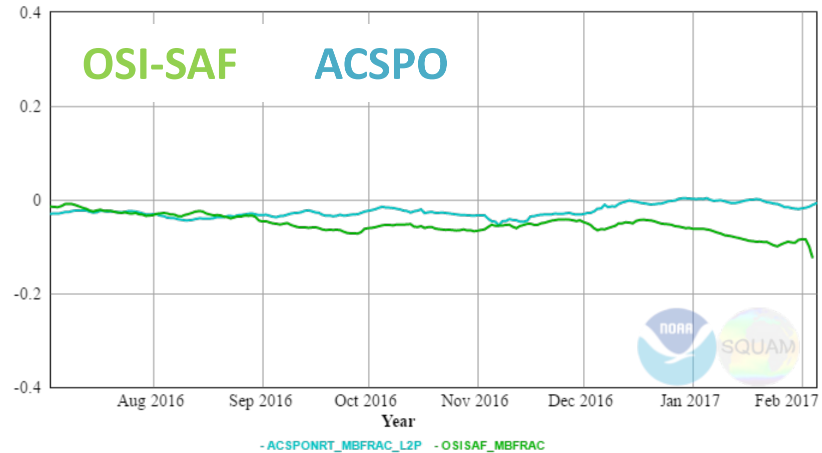


- ACSPO DSST: reduces SD from 0.42 K to 0.21 K
- OSI-SAF DSST: SD remains the same

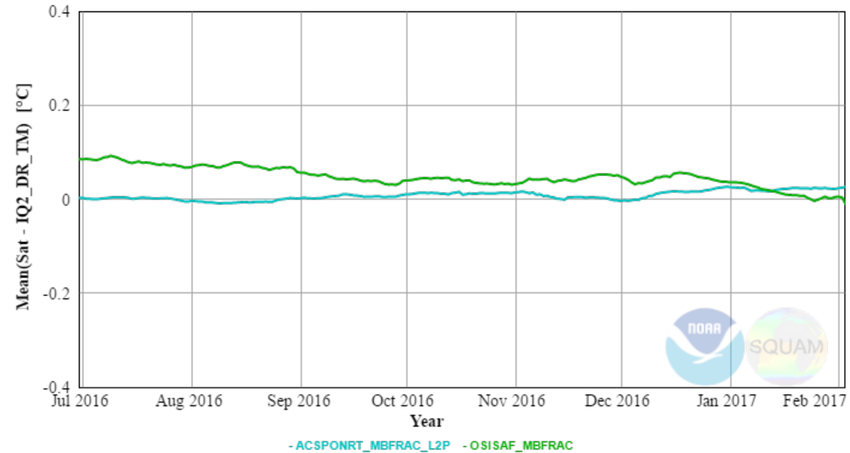
MetOp-B FRAC, day: bias and SD of BSST and DSST wrt *in situ* SST by ACSPO and OSI-SAF

Bias, K

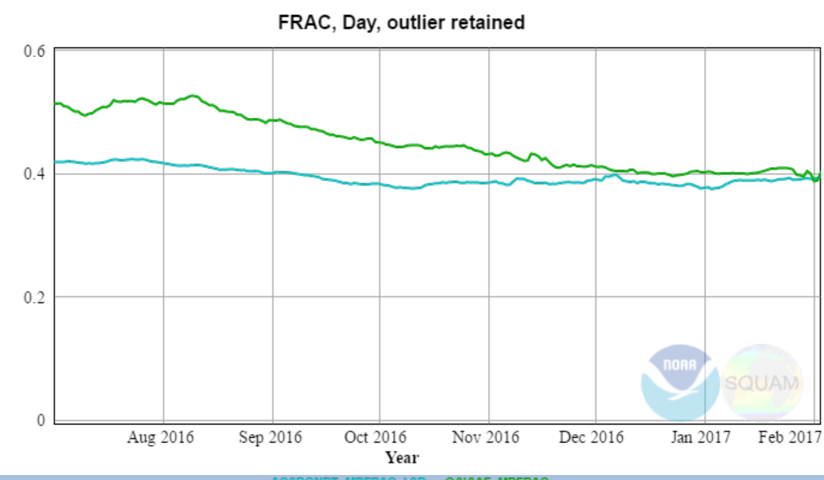
Baseline SST-In situ SST

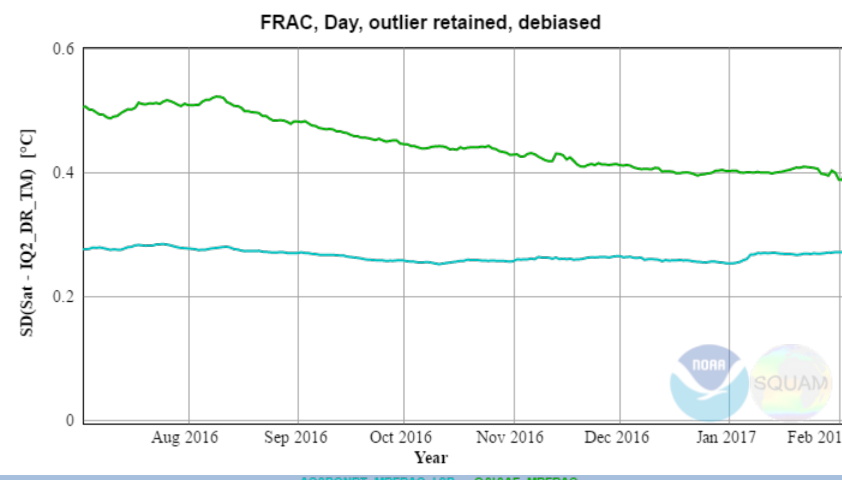


De-biased SST-In situ SST



SD, K

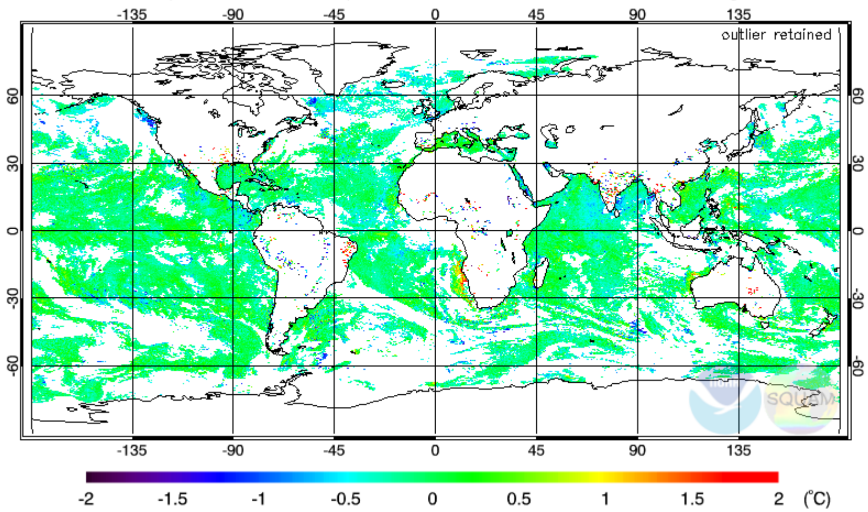




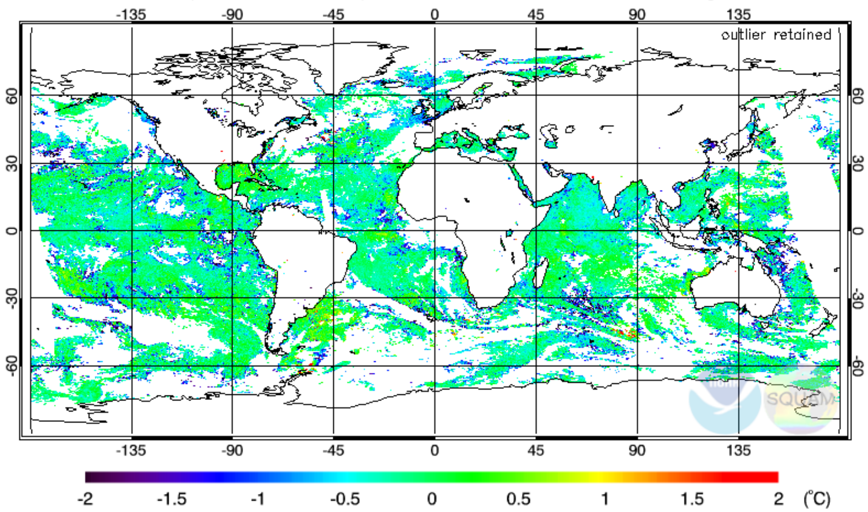
- ACSPO: DSST reduces bias and makes it more uniform; reduces SD from ~0.4 K to ~0.3 K
- NAVO: DSST warms up bias, does not change SD

MetOp-B FRAC, night: Baseline SST minus CMC by ACSPO and OSI-SAF (2017-03-20)

ACSPO: Bias=0.02 K, SD=0.33 K

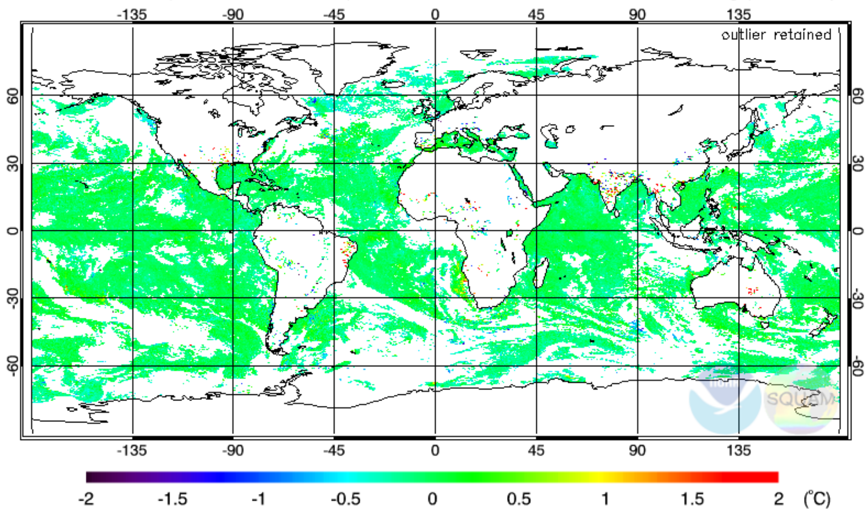


OSI-SAF: Bias=-0.05 K, SD=0.43K

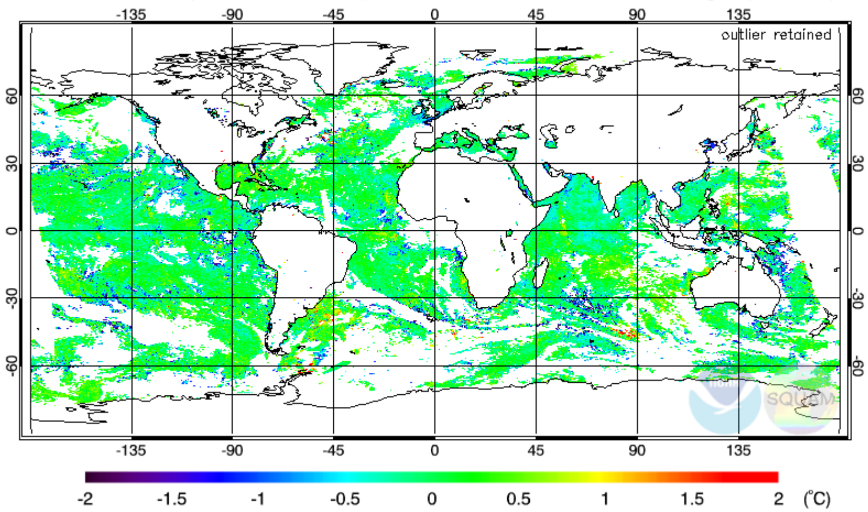


MetOp-B FRAC, night: De-biased SST minus CMC by ACSPO and OSI-SAF (2017-03-20)

ACSPO: Bias=0.06 K, SD=0.20 K

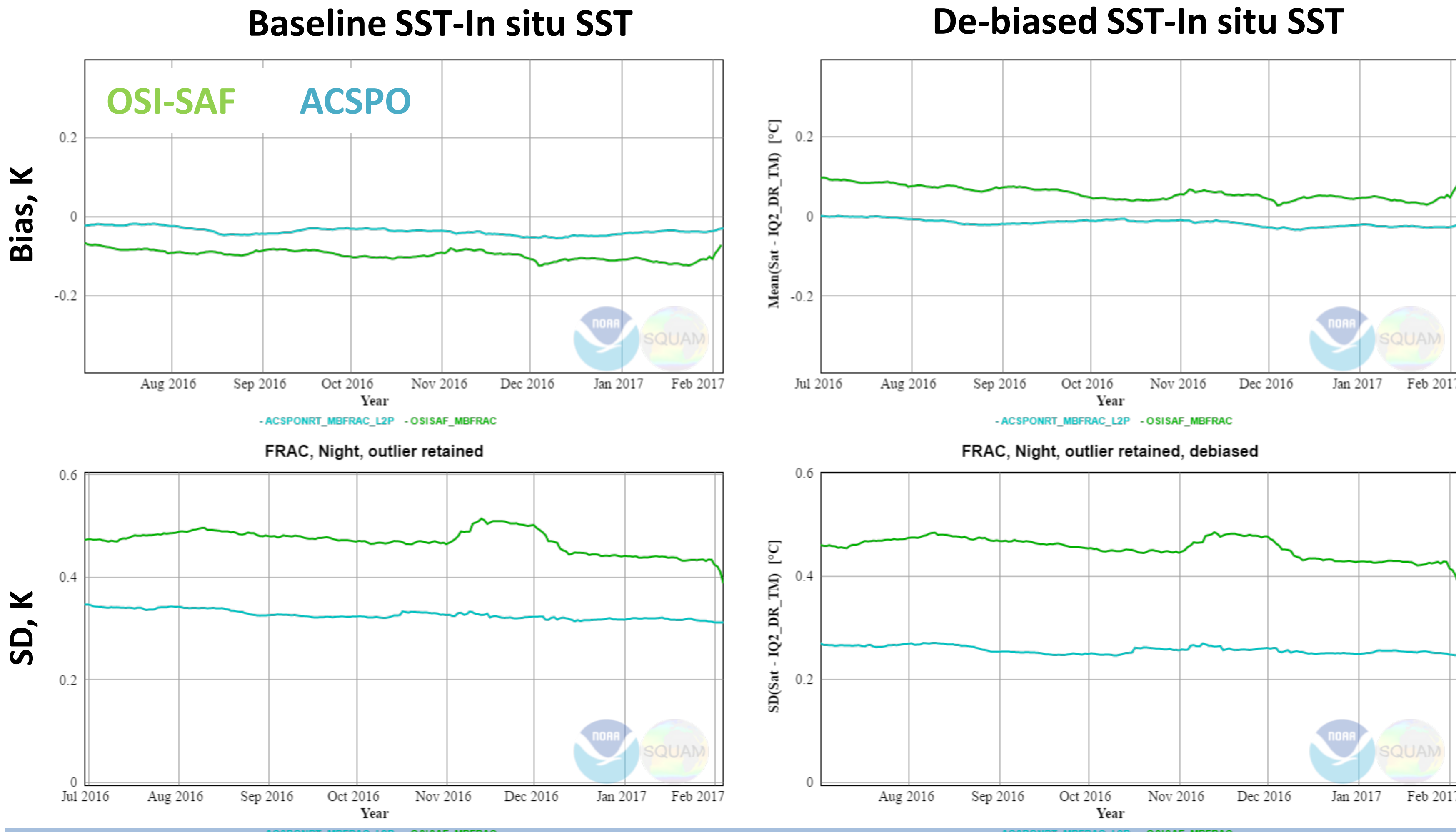


OSI-SAF: Bias=0.08 K, SD=0.41K



- ACSPO DSST: reduces SD from 0.33 K to 0.20 K
- OSI-SAF DSST: SD slightly changes from 0.43 K to 0.41 K

MetOp-B FRAC, night: bias and SD of BSST and DSST wrt *in situ* SST by ACSPO and OSI-SAF



- ACSPO: DSST brings bias closer to 0; reduces SD from ~0.35 K to ~0.25 K
- OSI-SAF: DSST warms up bias, slightly changes SD

Summary

- The ACSPO SSES algorithm analyzes SST errors as functions of statistics of regressors within the training MDS, rather than as functions of certain physical variables
- This makes the ACSPO the only SST system, in which SSES bias correction efficiently suppresses instant regional SST biases and substantially improves the global precision with respect to *in situ* SST.
- Starting with v.2.40 the ACSPO generates two SST products:
  - Baseline SST: Sufficiently precise wrt *in situ* SST and sensitive to SST_{skin};
    - available in the GDS2 format as a separate level
  - De-biased SST: highly precise wrt *in situ* SST (SST_{depth}) ;
    - obtained by subtracting SSES bias from Baseline SST
- De-biased ACSPO VIIRS SST has been already extensively tested and used as input to CMC and OSTIA. However, nobody have tried yet to use ACSPO SSES SDs to facilitate data assimilation.
- The further modifications of the ACSPO SST will be focused at more accurate approximations of “skin” and “bulk” SST. The upcoming modifications will be discussed in the tomorrow’s presentation

Thank you