New Stratospheric Temperature Climate Data Records by Merging SSU with AIRS

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ITSC-25 May 8-14 2025 at Resort Rio, Goa, India; 16:00 - 17:00, , May 9 2025, P8.05

Content

- Importance of long-term stratospheric temperature climate data records
- NOAA long-term stratospheric temperature satellite observations
- Reprocessing efforts for historic Stratospheric Sounding Unit Data
- From SSU to AIRS/CrIS hyperspectral data series
  - An approach to convert AIRS level1c data to equivalent SSU data
  - Removing the trend due to CO2 increasing
  - Microwave vs. Infrared datasets
- Conclusion

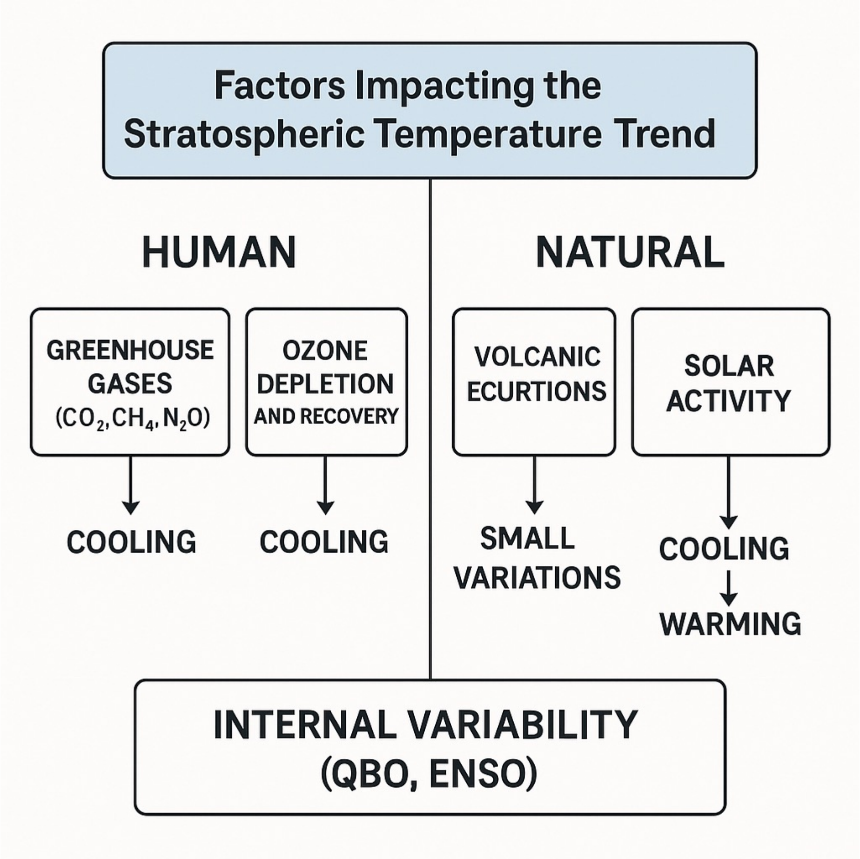
Importance of Long-Term Stratospheric Temperature Climate Data Records

- Human-induced climate change
  - Greenhouse Gas effect
  - Ozone Layer Monitoring

- Volcanic and Solar Influences: Captures responses to volcanic eruptions and solar cycles

- Weather and Climate Models Validation

- Global, Consistent Coverage: Satellite data provides uniform global observations unavailable from ground stations.



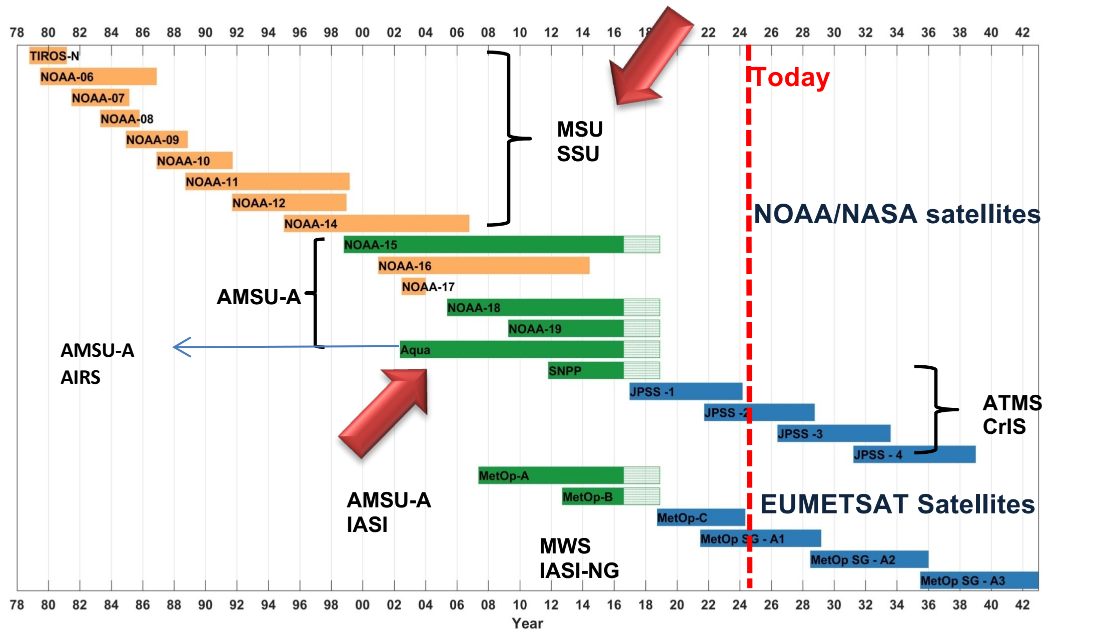
Satellite Series for SSU Related Observations

- SSU and its successors are the only means available to provide stratospheric temperature observations with global coverage for long-term monitoring

- NOAA satellites have been continuously observing stratosphere for over 40 years

- JPSS Program carries the NOAA operational temperature sounding capability into the future

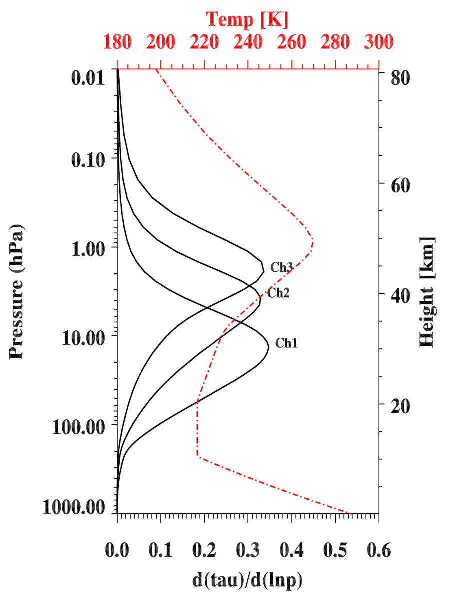
- Inter-satellite calibration and satellite merging are needed to develop climate data record for long-term monitoring



SSU Instruments

- One of the TOVS instruments (MSU, HIRS, SSU) onboard NOAA TIROS-N polar-orbiting satellite series from 1978-2006
- Provided by UK Met Office
- Infrared radiometer using pressure modulation technique to measure atmospheric radiation from CO_2 15-μm v_2 band
- Three cells of CO_2 gas were placed in the optical path with different pressure which allowed three channels for a single CO_2 band

$P(peak) \sim P(cell)/[CO_2]^{1/2}$,

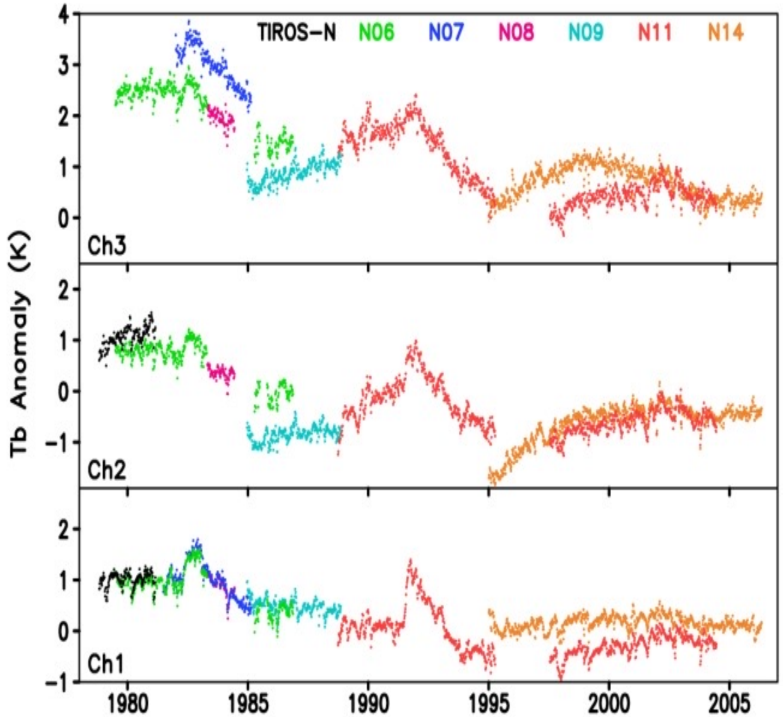


SSU channel weighting functions determined by cell pressure values

SSU Channel	1	2	3
Channel Peak (hPa)	15.0	5.0	1.5

Issues in Raw SSU Dataset

- Insufficient documentation– lost or no record of many calibration parameters
- Bad data from bad calibration (NOAA-7 channel 2)
- Space view anomaly—directly affects level-1c radiances
- Gas leaking in the CO_2 cell→ weighting function variation
- atmospheric CO_2 variations
- limb-effect
- diurnal drift effect→ semi-diurnal tides in the stratosphere
- Residual biases



Global mean anomaly TB time series for each satellite before adjustment and merging (raw data)

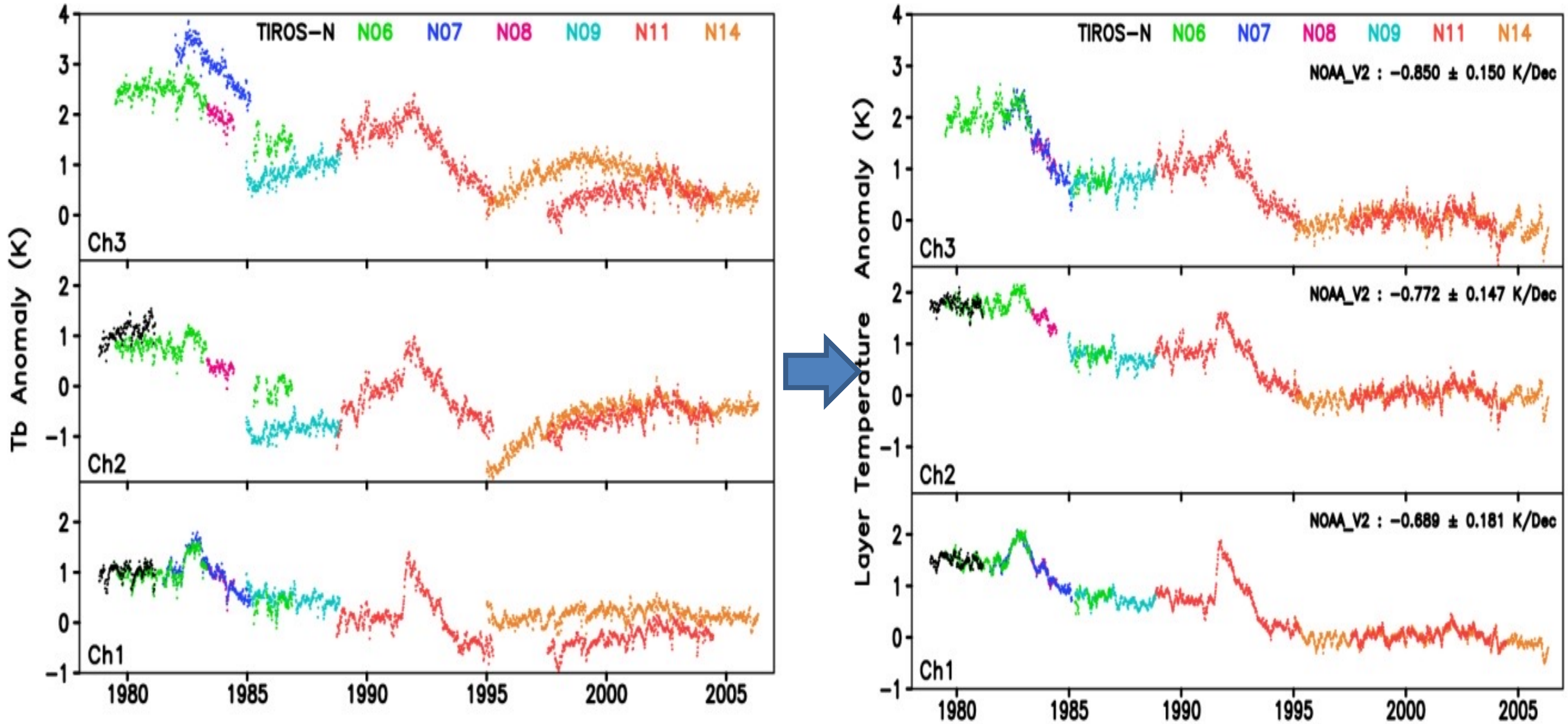
NOAA SSU Processing History

- Raw SSU data and satellite orbital information were operationally processed at NOAA/NESDIS for each satellite along with other TOVS instruments and saved in operational level-1b files
- Operational level-1b files were distributed to world-wide users and archived in NOAA/NCEI Comprehensive Large Array-data Stewardship System (CLASS) ; other centers may also have archives after receiving the data
- SSU data were not used in NWP forecasting since NWP models were not high enough to assimilate SSU data in early days
- UK Met Office conducted instrument testing and developed its version of SSU time series **(Nash and Forrester 1986)**
- Technical notes available for NOAA operational processing and UKMO instrument testing, but information for instrument calibration was insufficient and sometimes even missing
- NOAA/STAR began to develop SSU temperature time series using level-1c radiances derived from operational level-1b data in 2008
- STAR released its first version of SSU time series in 2011 **(Wang et al. 2012)**
- **Thompson et al. (2012)** demonstrated large SSU trend differences between STAR and Met Office versions and between climate model simulations and SSU observations and called for re-investigation of the SSU problems
-
- The SPARC temperature trend group organized a meeting at London in 2013 with participation from both NOAA and Met Office SSU groups to discuss technical issues in SSU processing
- STAR recalibrated the SSU raw data using improved information and developed SSU FCDR and Version 2 SSU temperature time series in 2014 **(Zou et al. 2014)**
- STAR merged the SSU V2 data with AMSU-A observations and extended the SSU data to present **(Zou and Qian 2016)**. This version is still being used by the climate community for climate change investigation in the stratosphere

NOAA Version 2.0 SSU Time Series

Before Adjustment and Merging

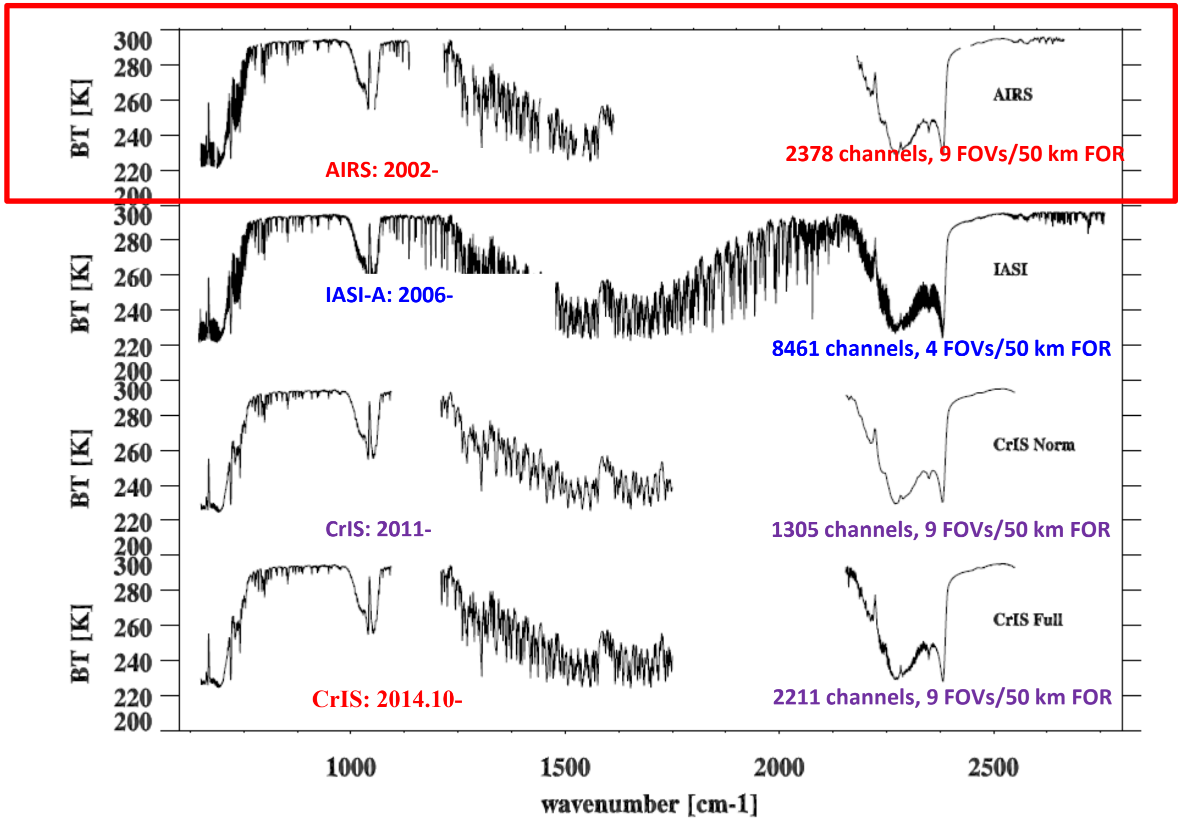
After Adjustment and Merging



Recalibration successfully rehabilitated the SSU data record, making the inconsistent raw SSU time series with large time-varying biases between satellites before correction (left) to a consistent, well-intercalibrated and -merged satellite time series suitable for climate change studies after correction (right).

Wang et al. 2012; Zou et al. 2014

Hyperspectral Instruments: AIRS/IASI/CrIS

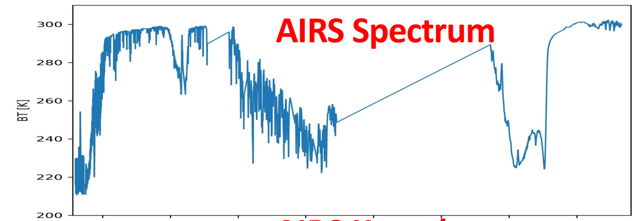


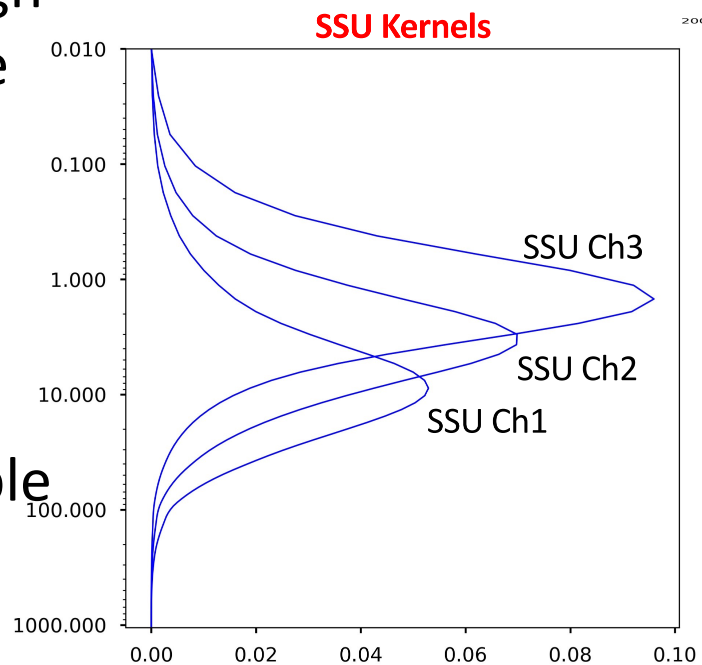
AIRS the is key to bridge SSU between JPSS/CrIS

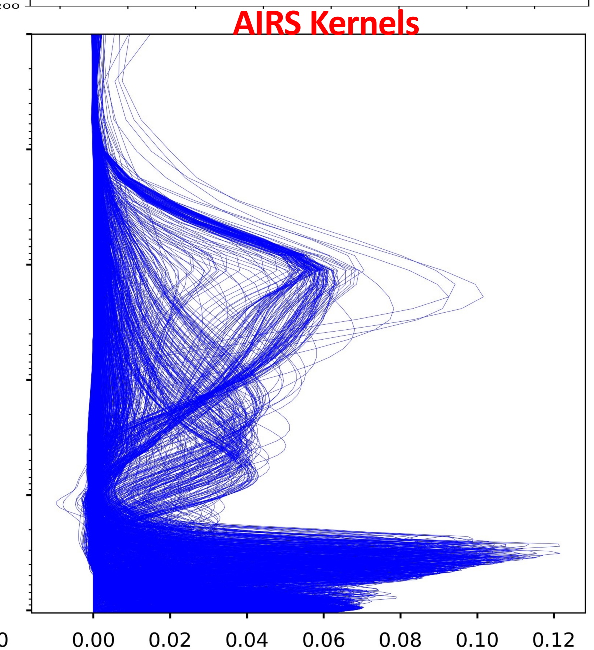
Owing to their hyperspectral nature and accurate radiometric and spectral calibration, AIRS/CrIS/IASI have several longwave and shortwave channels providing 3D measurements of stratospheric temperature with high data quality.

From AIRS to equivalent SSU

- AIRS overlapped with SSU during 2002-2006
- AIRS/CrIS have enough channels to cover the three SSU channels
- Plan to generate equivariant SSU channels from multiple AIRS/CrIS channels
- Merge the equivalent SSU channels with the original SSU channels







Problem Definition and Challenges

- **Linear Regression**: select several AIRS channels and use linear regression to combine these channels into SSU
- **Training Datasets for Regression**: large variability but not redundant
- **Constrains**
  - Representativeness: Using weight function as constrains
  - Noise:
    - ❑ Cannot use too many channels (10-13)
    - ❑ The coefficients for each channels is less than 0.5
- **AIRS data**
  - Level 1B: very noisy but has RTM support
  - Level 1C: reconstructed from level 1B but with new spectral grids
  - Using Level1C data but choosing the spectral channels that both level1C and level1B have common spectral grid
  - Longwave channels with high priority

Regression Problems with Constraints

For SSU BT at each channel:

$$y = \sum_i \beta_i X_i$$

X: AIRS channel BT (LW+SW)
y: SSU channel BT
β: weights for each channels, sum(β_i) = 1
For each $\beta_{i,}$ less than 0.5

The goal is to find an assignment β to that minimizes the cost function:

$$f(\beta) = \underline{\|\mathbf{X}\,\beta - \mathbf{Y}\|_2^2} + \underline{\lambda\|\mathbf{W}^x\,\beta - \mathbf{W}^y\|_2^2}$$

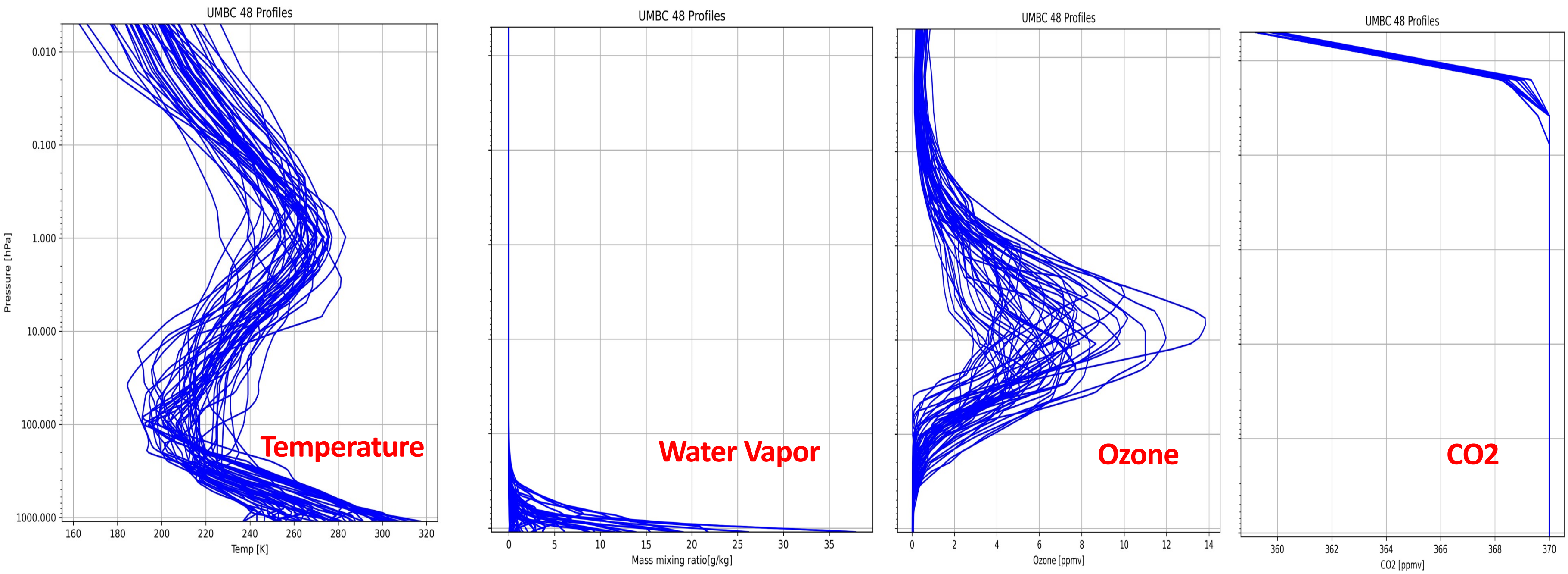
X: Training Dataset from AIRS selected channels , Y: Training Dataset of SSU BT
W^x: Weighting function of AIRS selected channels, W^y: Weighting function of SSU
λ: a hyperparameter that controls the balance between BT and weighting function fitting

The problem is solved using CVXPY, a domain-specific language for convex optimization embedded in Python
Citing CVXPY — CVXPY 1.3 documentation

Steven Diamond and Stephen Boyd. 2016. CVXPY: a python-embedded modeling language for convex optimization. J. Mach. Learn. Res. 17, 1 (January 2016), 2909–2913. https://doi.org/10.48550/arXiv.1603.00943

Goldberg, M. D., and H. E. Fleming, 1995: An Algorithm to Generate Deep-Layer Temperatures from Microwave Satellite Observations for the Purpose of Monitoring Climate Change. *J. Climate*, **8**, 993–1004, https://doi.org/10.1175/1520-0442(1995)008<0993:AATGDL>2.0.CO;2.

UMBC 48 Atmospheric Profiles

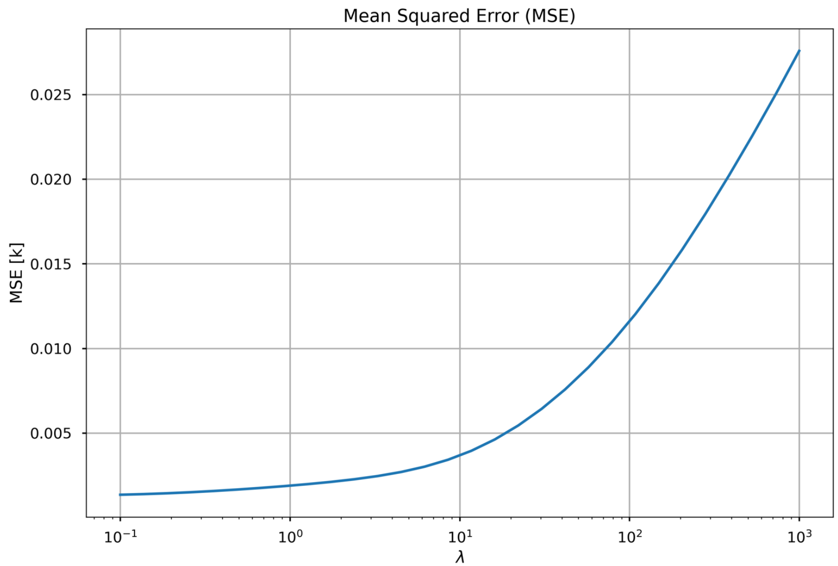


UMBC 48 profiles, which contain typical atmospheric profiles in different location and season, are used for CRTM.

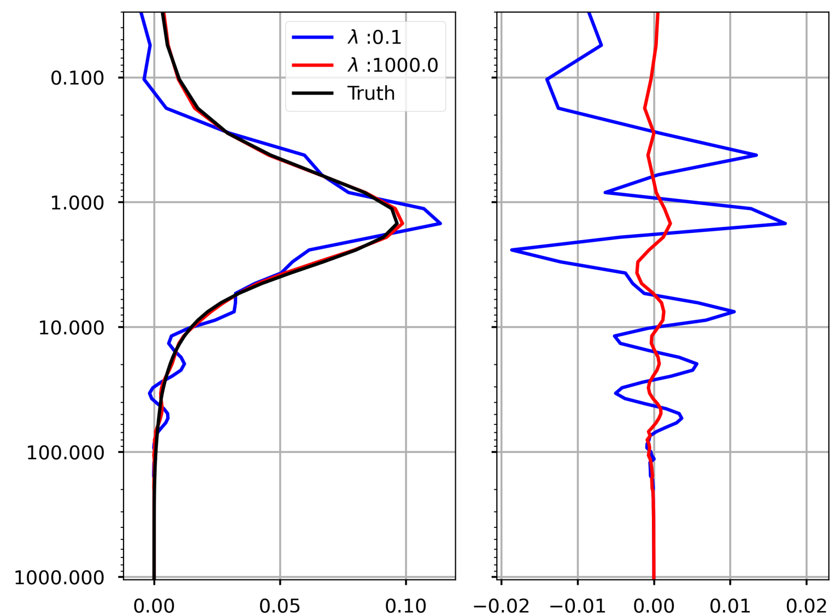
We uses them to simulate both AIRS and SSU observations.

SSU channel 3: Example

Brightness Temperature MSE varying with penalty factor



Weighting Function Fitting varying with penalty factor

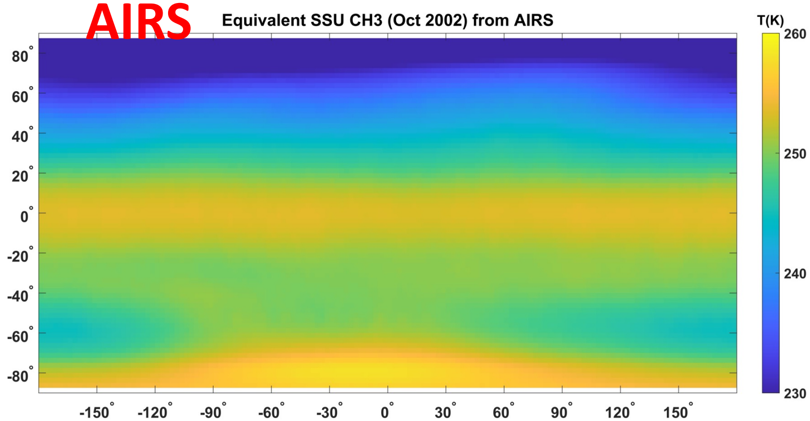


The goal is to find an assignment β to that minimizes the cost function:

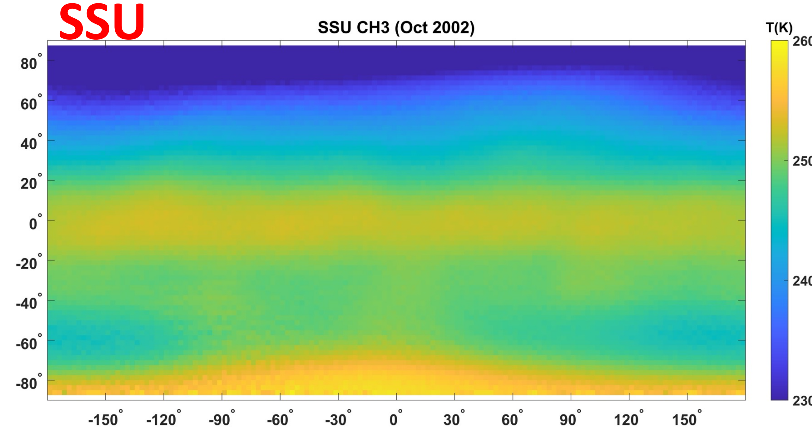
$$f(\beta) = \|\mathbf{X}\,\beta \;-\mathbf{Y}\|_2^2 + \;\lambda\|\mathbf{W}^x\,\beta \;-\mathbf{W}^y\|_2^2$$

Example of simulated SSU CH3 with AIRS

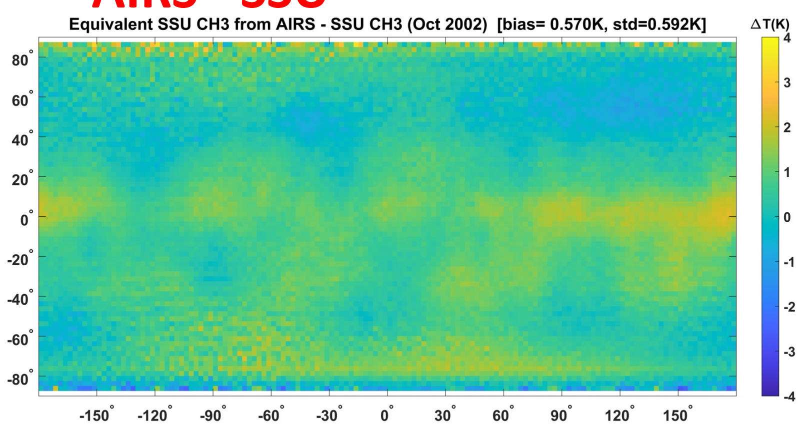
AIRS



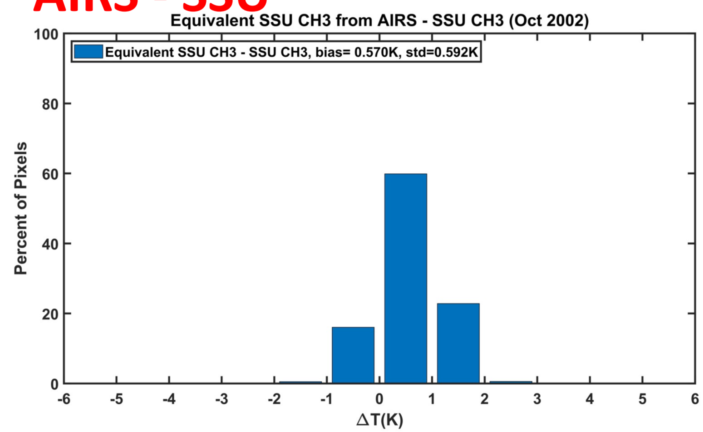
SSU



AIRS - SSU



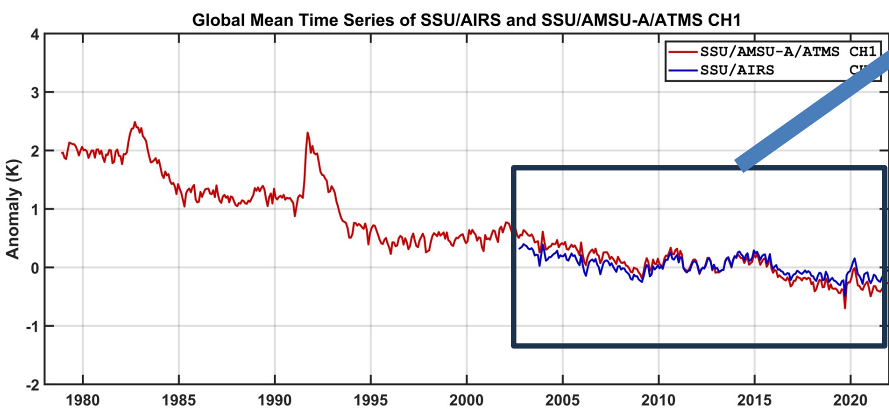
AIRS - SSU

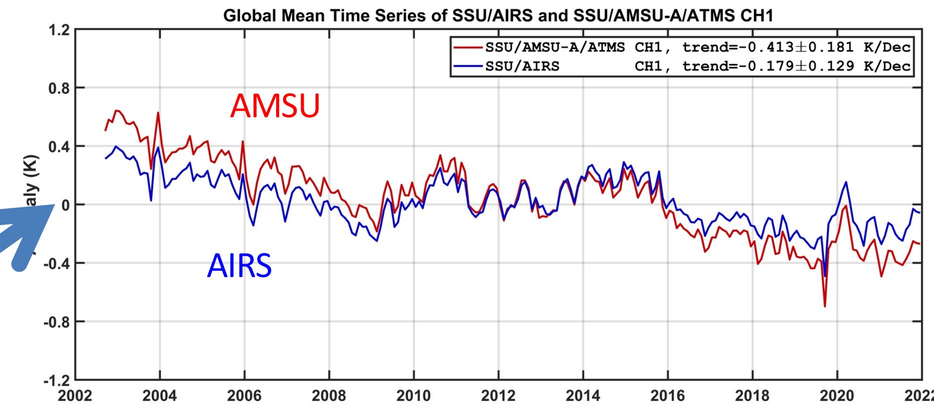


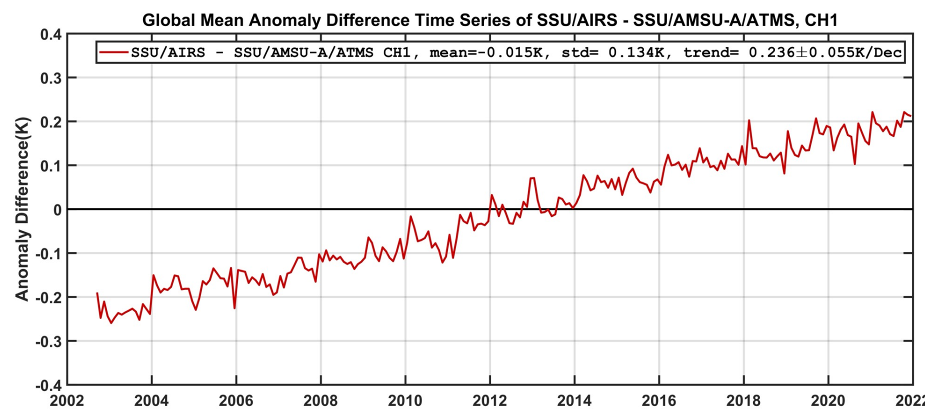
Global Mean Anomaly Time Series
SSU/AIRS vs SSU/AMSU-A/ATMS CH 1

The trend of Infrared Sounder data:

- Stratospheric temperature cooling
- **CO_2 increasing effects**



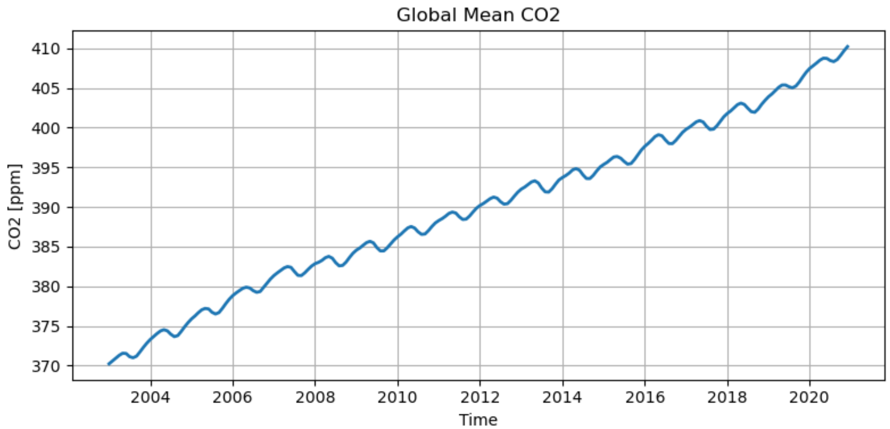




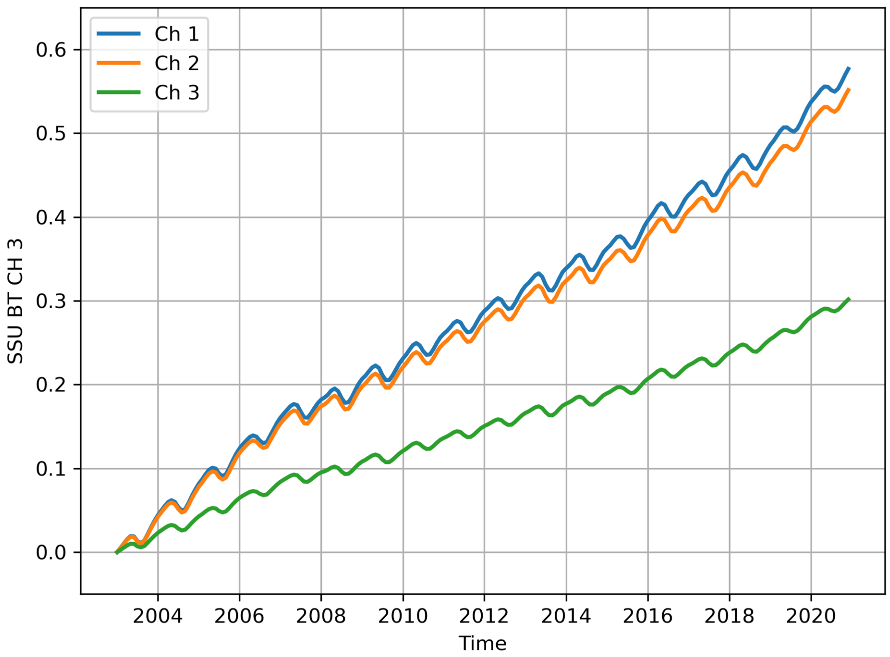
The trend difference is caused by the CO_2 increasing effects

SSU Trend due to CO2 increasing

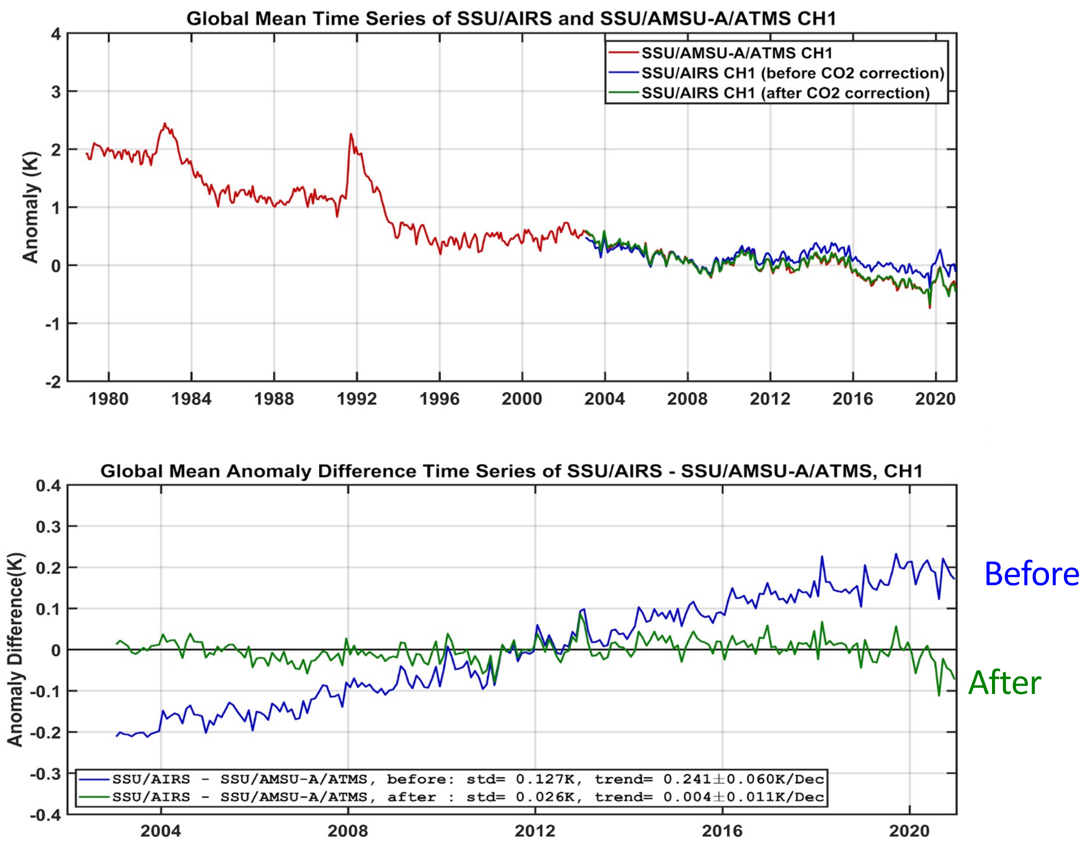
Global Mean CO_2

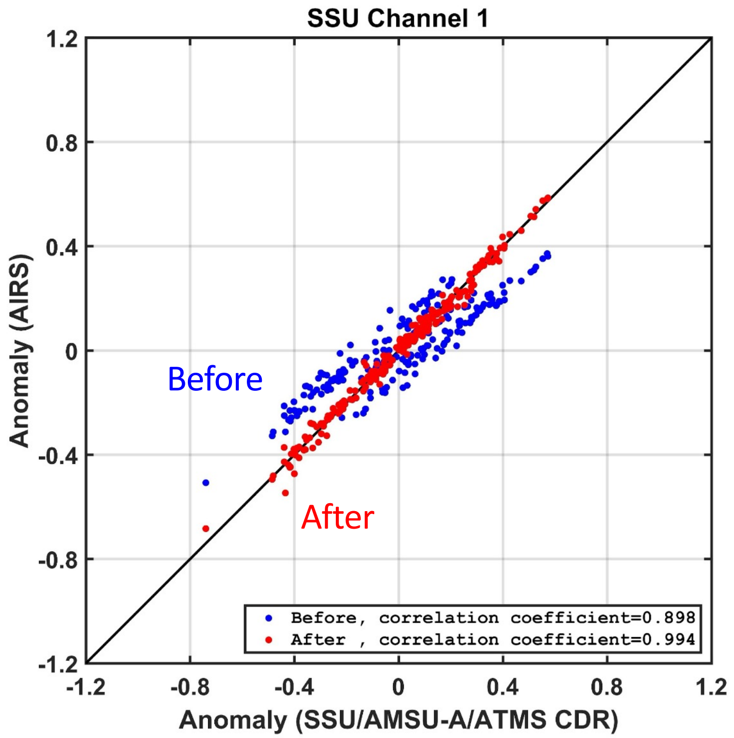


SSU BT changes due to CO_2

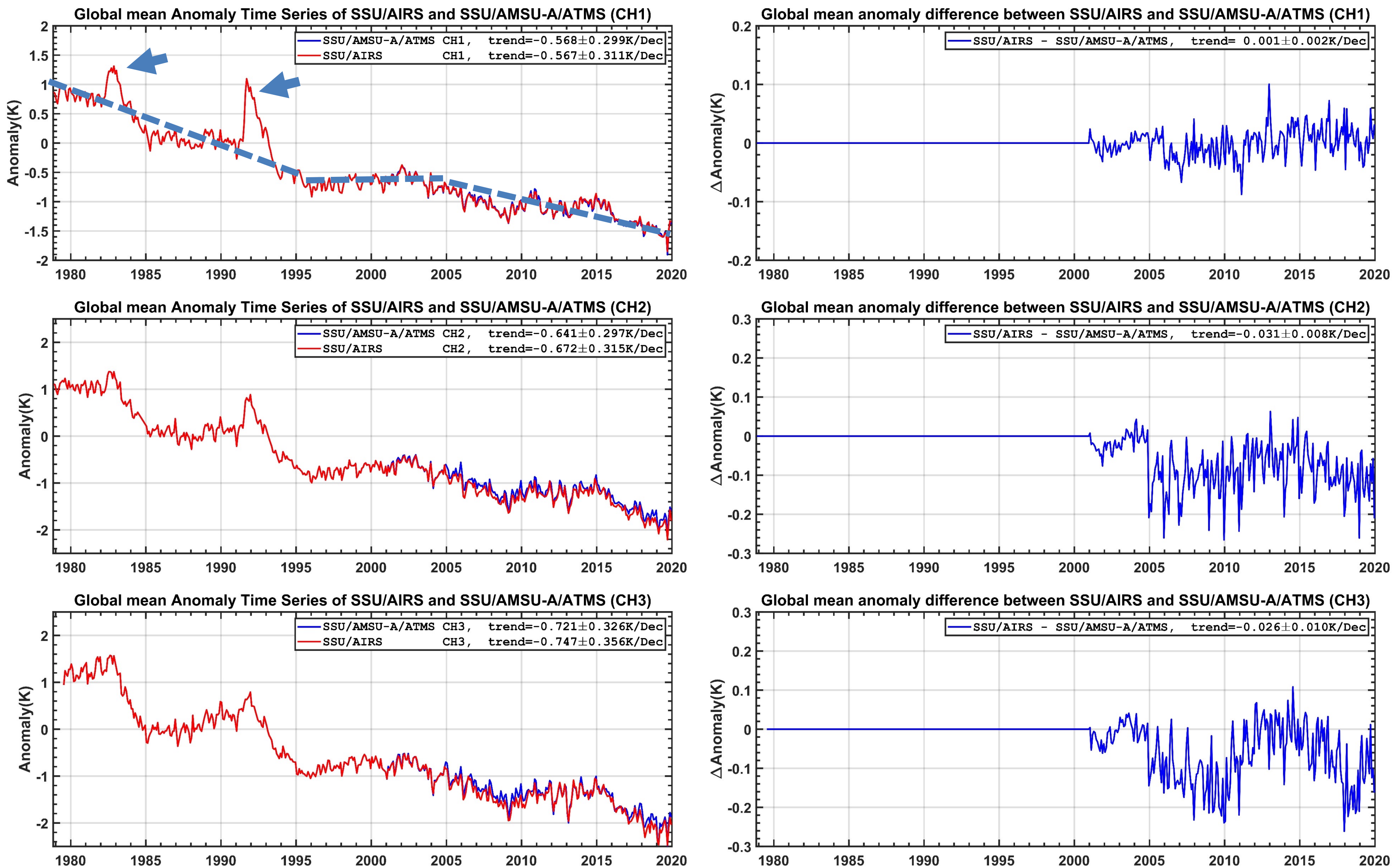


Global Mean Anomaly Time Series
SSU/AIRS vs SSU/AMSU/ATMS CH 1





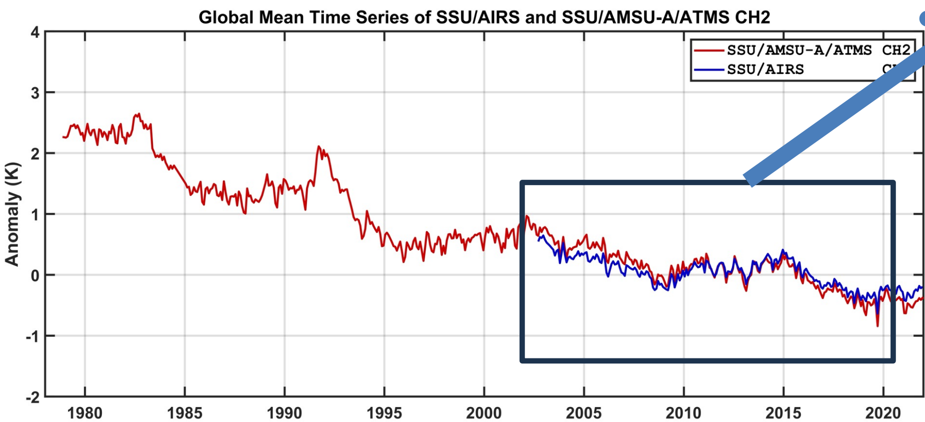
Global Mean Anomaly Time Series
SSU/AIRS vs SSU/AMSU/ATMS

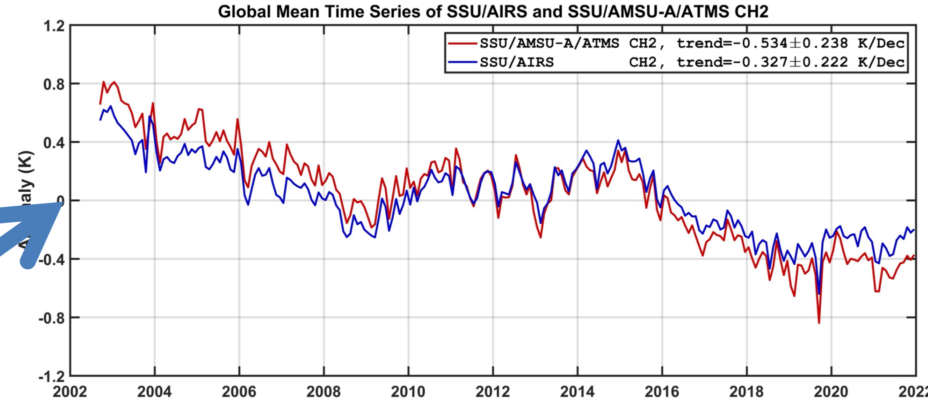


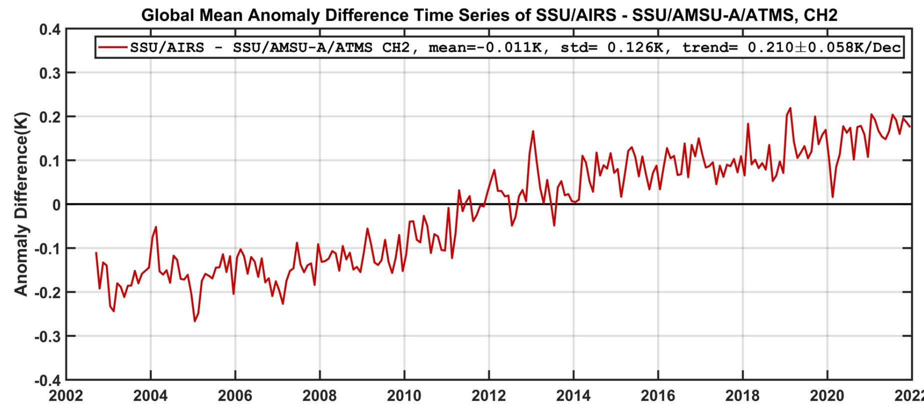
Conclusion

- The efforts has been made to reprocess the SSU data sets for climate data records for stratospheric temperature monitoring in NOAA/NESDIS/STAR.
- The AIRS datasets is the key to carry the NOAA operational temperature sounding capability into the future by linking SSU to AIRS/CrIS.
- A method has been successfully developed to convert AIRS hyperspectral data into equivalent SSU observations.
- Global Mean Anomaly Time Series of SSU/AIRS vs. SSU/AMSU-A/ATMS agree very well.
- The new data SSU/AIRS data will be released soon.

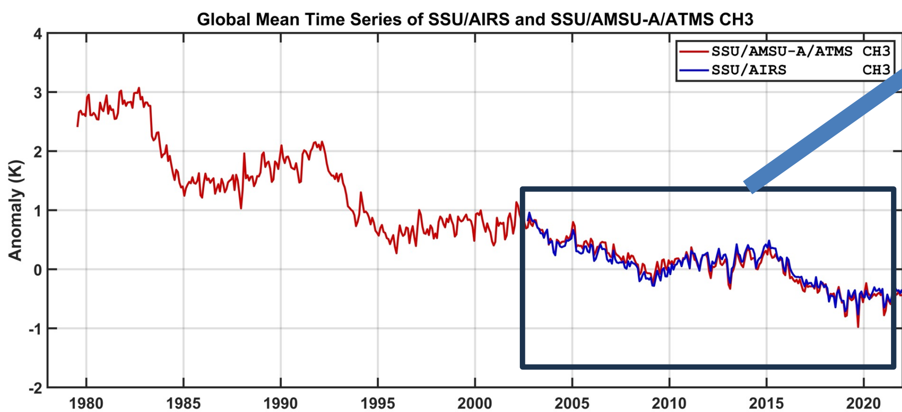
Global Mean Anomaly Time Series
SSU/AIRS vs SSU/AMSU-A/ATMS Ch 2

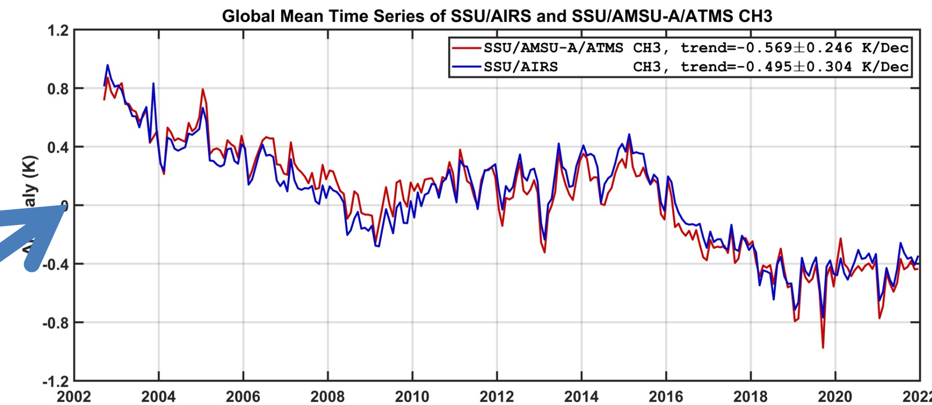


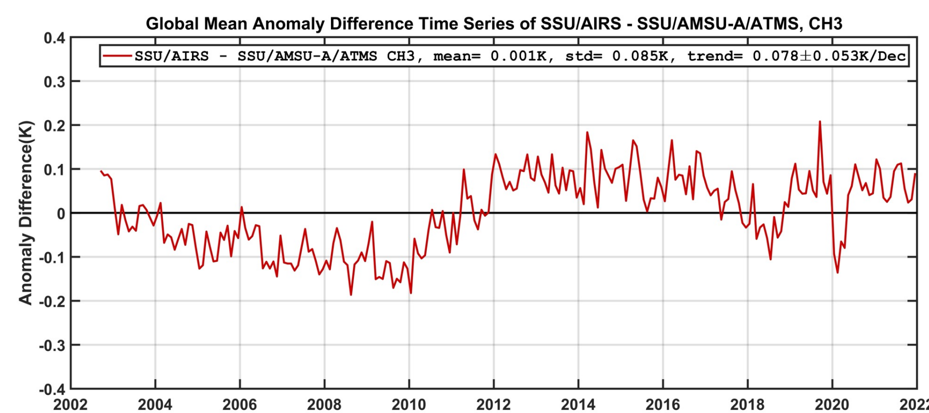


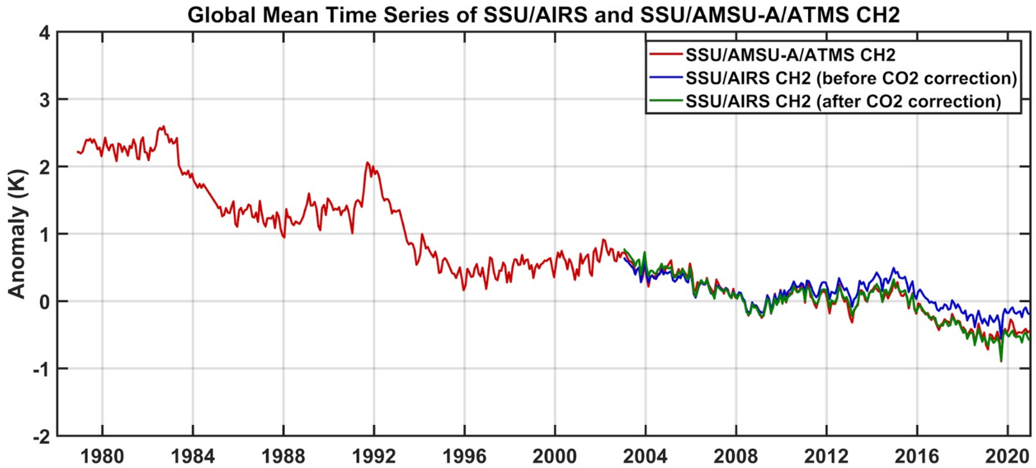


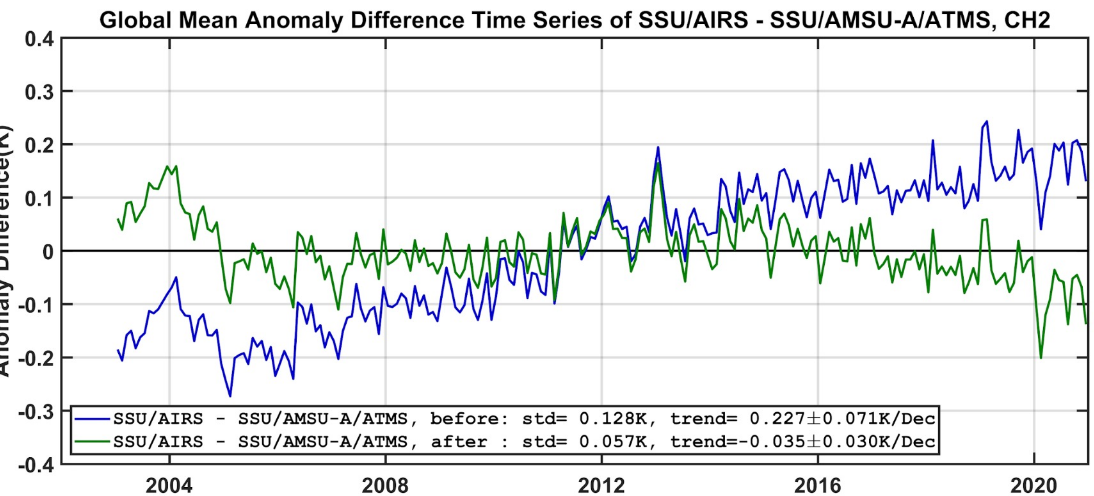
Global Mean Anomaly Time Series of SSU/AIRS vs SSU/AMSU-A/ATMS Ch 3

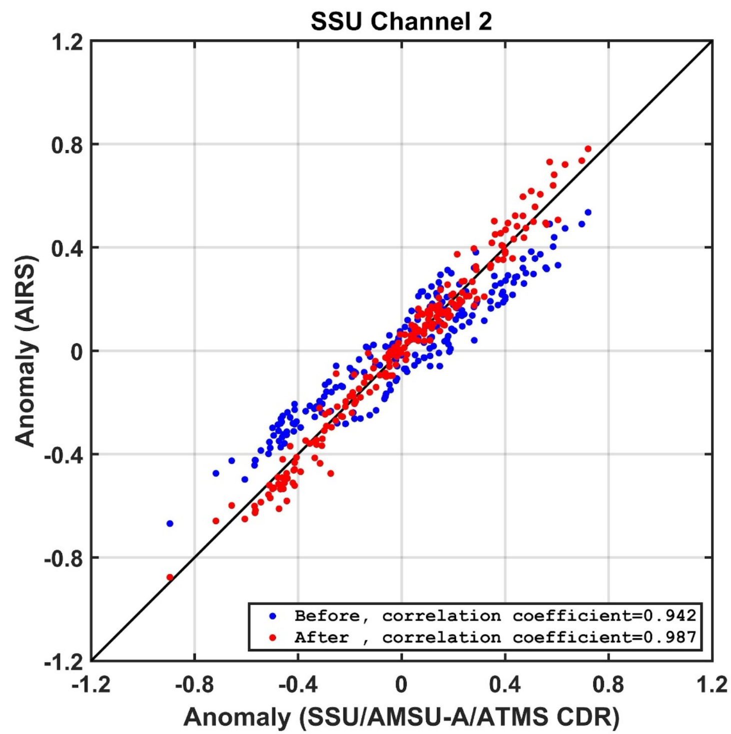


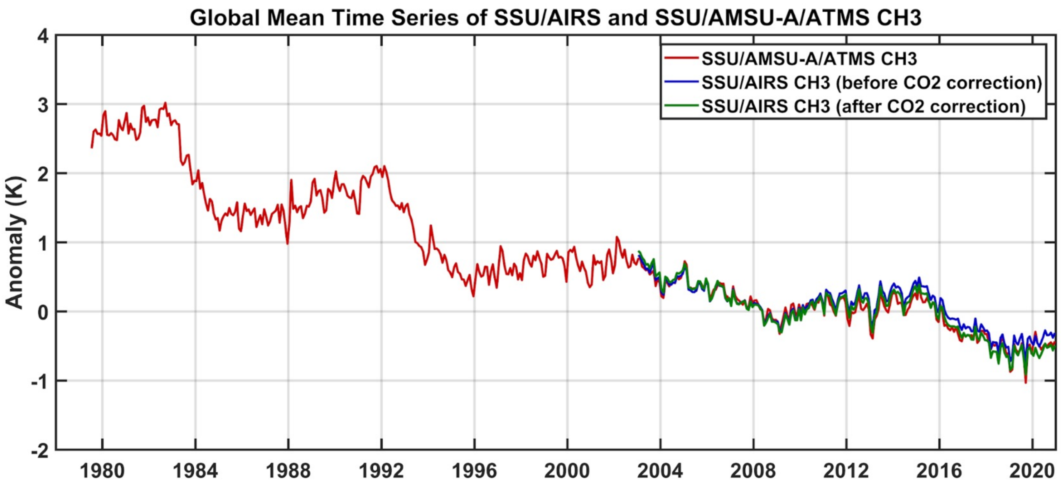


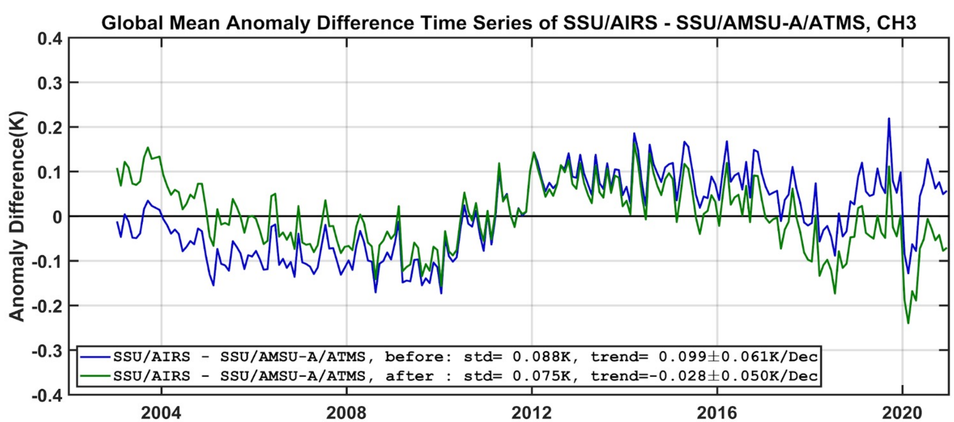


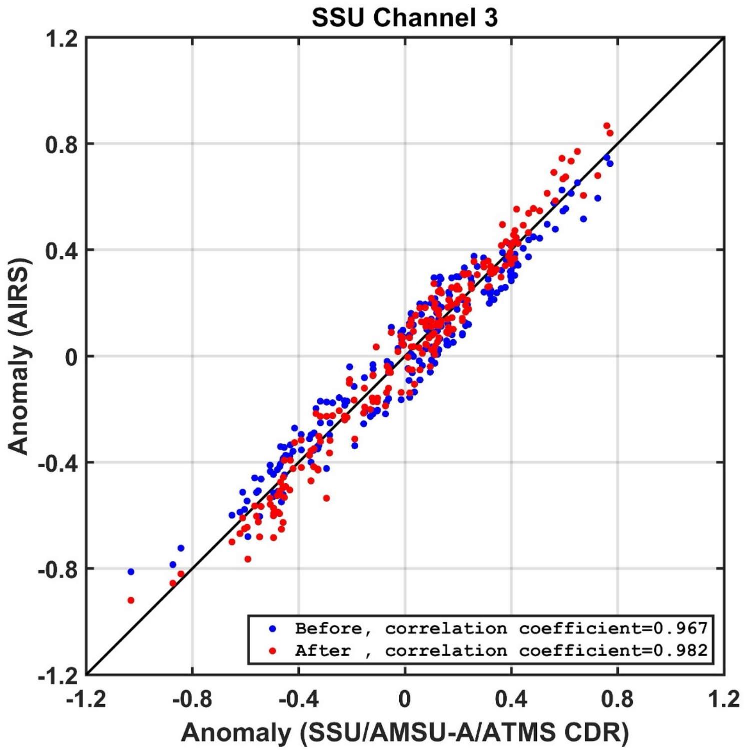

Global Mean Time Series of SSU/AIRS and SSU/AMSU-A/ATMS CH2
SSU/AMSU-A/ATMS CH2
SSU/AIRS CH2 (before CO2 correction)
SSU/AIRS CH2 (after CO2 correction)
Anomaly (K)
4
3
2
1
0
-1
-2
1980
1984
1988
1992
1996
2000
2004
2008
2012
2016
2020


Global Mean Anomaly Difference Time Series of SSU/AIRS - SSU/AMSU-A/ATMS, CH2
SSU/AIRS - SSU/AMSU-A/ATMS, before: std= 0.128K, trend= 0.227±0.071K/Dec
SSU/AIRS - SSU/AMSU-A/ATMS, after : std= 0.057K, trend=-0.035±0.030K/Dec
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
2004
2008
2012
2016
2020


SSU Channel 2
Anomaly (AIRS)
Anomaly (SSU/AMSU-A/ATMS CDR)
Before, correlation coefficient=0.942
After , correlation coefficient=0.987
1.2
0.8
0.4
0
-0.4
-0.8
-1.2
-1.2
-0.8
-0.4
0
0.4
0.8
1.2


Global Mean Time Series of SSU/AIRS and SSU/AMSU-A/ATMS CH3
SSU/AMSU-A/ATMS CH3
SSU/AIRS CH3 (before CO2 correction)
SSU/AIRS CH3 (after CO2 correction)
Anomaly (K)


Global Mean Anomaly Difference Time Series of SSU/AIRS - SSU/AMSU-A/ATMS, CH3
Anomaly Difference(K)
SSU/AIRS - SSU/AMSU-A/ATMS, before: std= 0.088K, trend= 0.099±0.061K/Dec
SSU/AIRS - SSU/AMSU-A/ATMS, after : std= 0.075K, trend=-0.028±0.050K/Dec


SSU Channel 3
Anomaly (AIRS)
Anomaly (SSU/AMSU-A/ATMS CDR)
Before, correlation coefficient=0.967
After , correlation coefficient=0.982