Algorithms for geostationary sea surface temperatures: Differences and Challenges

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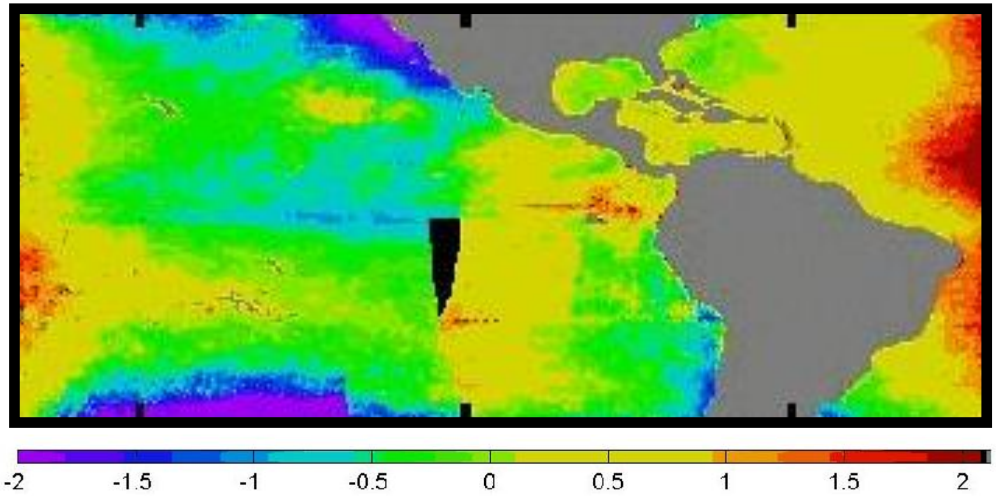
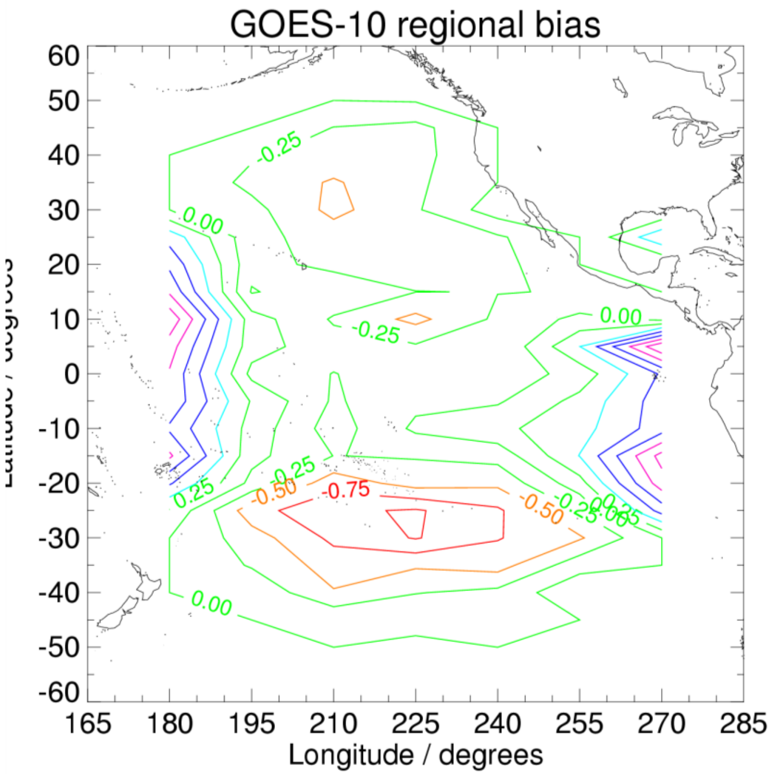
Outline

- **A little history**
  - The original GOES-SST (1999…)
  - Updated Physical-Statistical
  - Cloud detection
    - Threshold vs Bayesian
- **The move to fully physical retrieval**
  - Deterministic vs. stochastic
  - Error estimation
- **Next-generation sensors**
  - The revival of linear regression
  - Diurnal studies
- **Summary**

Pattern of TMI / GOES differences

Fixed viewing geometry of GOES emphasizes that single "global" linear retrieval equation is regionally sub-optimal



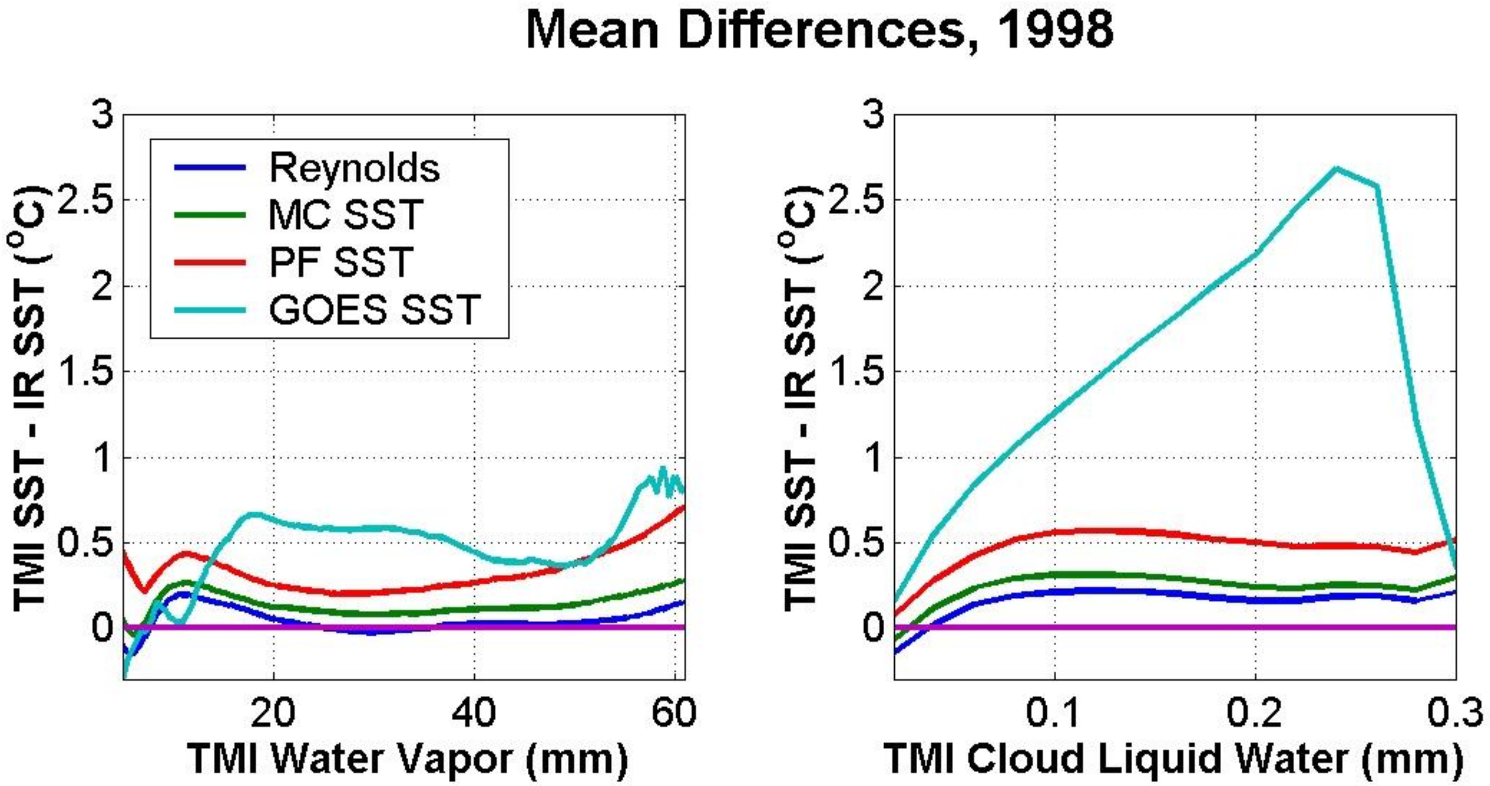


Bias pattern for GOES-W similar to that predicted by radiative transfer

Sources of TMI – IR SST retrieval bias

Water vapor

Cloud liquid water



DIRECT REGRESSION OR RADIATIVE TRANSFER?

- What’s good about direct regression?
  - *Eliminates radiative transfer modeling and calibration errors*
  - *Implicitly includes errors due to imperfect cloud screening, sensor noise, etc.*
  - *Straightforward, and guaranteed to produce the optimum result in the absence of other information*
- This looks great. Any disadvantages?

DIRECT REGRESSION OR RADIATIVE TRANSFER?

- What is the main advantage of remote sensing?
  - *Provides data in remote regions where in situ observation are sparse or non-existent*
- To utilize remotely-sensed data to an optimum level, we need to be able to specify accuracy in these remote regions
  - *This requires independent data in order to gain the necessary confidence*
- Can retrieval accuracy be improved by the addition of other data sources?
  - *Inclusion of water vapor can probably only be done at a very rudimentary level using direct regression. Studies have demonstrated little actual improvement*

DIRECT REGRESSION OR RADIATIVE TRANSFER?

•The chief advantage of radiative transfer is that it allows specification of the retrieval algorithm without bias towards the data-rich regions

•The in situ data can then act as a random independent sampling of the retrieval conditions.

•If the observed errors agree with the modeled ones, then high confidence can be placed on the modeled errors in data-sparse regions

•Additional advantage is that other sources of error can be accounted for explicitly, and external data (e.g. atmospheric profiles) can be incorporated

This doesn’t mean it’s easy to do…

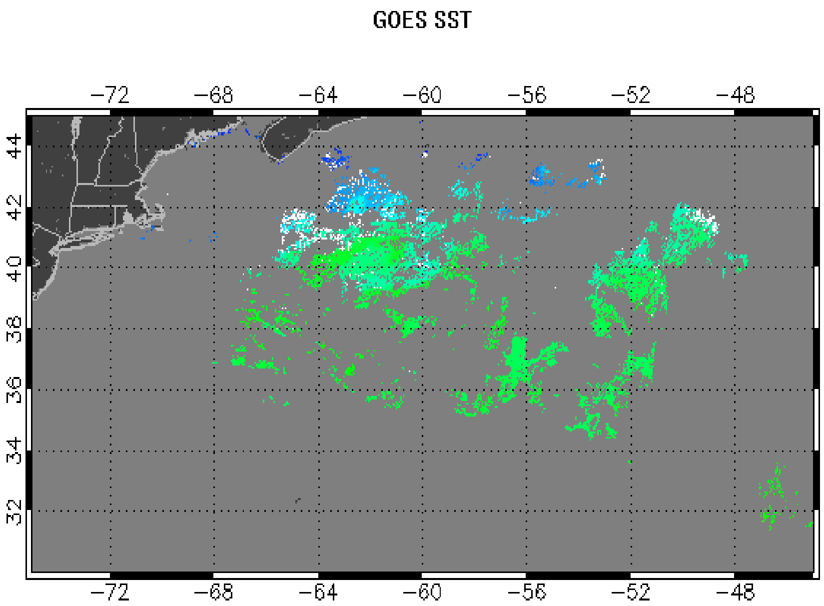
Physical retrieval for GOES

- **GOES SST retrieval adopted "physical-statistical" – linear retrieval coefficients derived by regression on simulated data:**

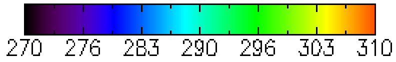
$$SST = (a_0 + a_1 S) + \sum (a_i + a_i' S) T_i$$

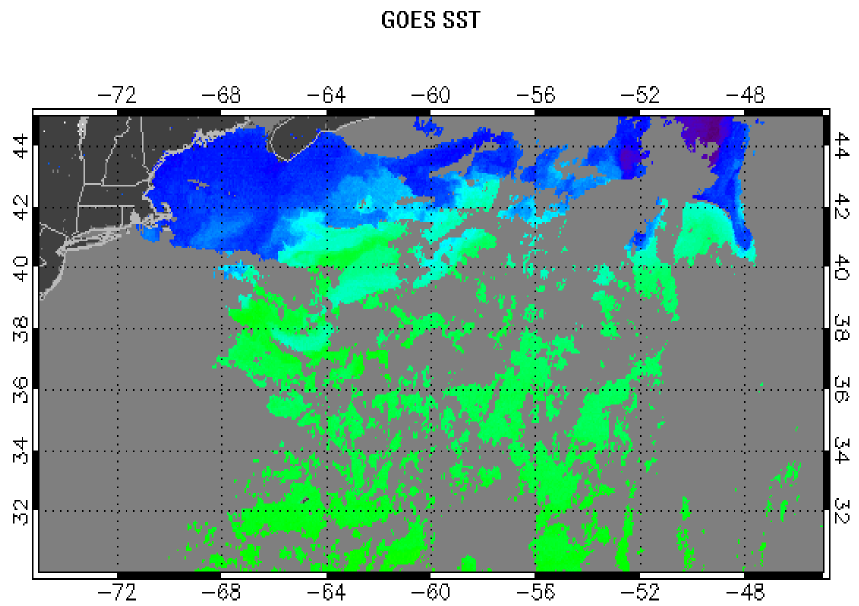
- **A.k.a. "OSI-SAF" formulation**
- **Had to overcome loss of 12 micron channel for GOES-12+**
- **Use 3.9 micron channel in daytime**
  - Required model of solar contribution
  - Atmospheric scattering and sunglint

Bayesian Cloud Mask *cf.* Thresholds

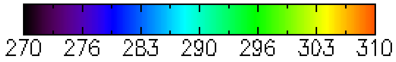


Conventional threshold-based cloud mask





Bayesian cloud mask



Significant increase in good SST retrievals in oceanographically important areas

Physical Retrieval

- **Reduces the problem to a local linearization**
  - Dependent on ancillary data (NWP) for an initial guess
  - More compute-intensive than regression – not an issue nowadays
    - Especially with fast RTM (*e.g.* CRTM)
- **Widely used for satellite sounding**
  - More channels, generally fewer (larger) footprints
- **Initially, start with a simple reduced state vector**
  - $\boldsymbol{x} = [\mathrm{SST}, \mathrm{TCWV}]^T$
  - *N.B.* Implicitly assumes NWP profile shape is more or less correct
- **Selection of an appropriate inverse method**
  - Ensure that satellite measurements are contributing to signal
  - Avoid excessive error propagation from measurement space to parameter space
    - If problem is ill-conditioned

History of Inverse Model

- **Forward model:** $\mathbf{Y} = \mathbf{KX}$
- **Simple Inverse:** $\mathbf{X} = \mathbf{K}^{-1}\mathbf{Y}$ **(measurement error)**

- **Legendre (1805) Least Squares:**

$$\mathbf{X} = \mathbf{X}_{ig} + (\mathbf{K}^{T}\mathbf{K})^{-1}\mathbf{K}^{T}(\mathbf{Y}_{d} - \mathbf{Y}_{ig})$$

- **MTLS:** $\mathbf{X} = \mathbf{X}_{ig} + (\mathbf{K}^{T}\mathbf{K} + / \mathbf{R})^{-1}\mathbf{K}^{T}(\mathbf{Y}_{d} - \mathbf{Y}_{ig})$

- **OEM:** $\mathbf{X} = \mathbf{X}_{a} + (\mathbf{K}^{T}\mathbf{S}_{e}^{-1}\mathbf{K} + \mathbf{S}_{a}^{-1})^{-1}\mathbf{K}^{T}\mathbf{S}_{e}^{-1}(\mathbf{Y}_{d} - \mathbf{Y}_{a})$

Uncertainty Estimation

Physical retrieval

Normal LSQ Eqn: $\Delta x = (K^T K)^{-1} K^T \Delta y \quad [= G\Delta y]$

MTLS modifies gain: $G' = (K^T K + \lambda I)^{-1} K^T$

Regularization strength: $\lambda = (2 \log(\kappa)/||\Delta y||)\sigma^2_{end}$

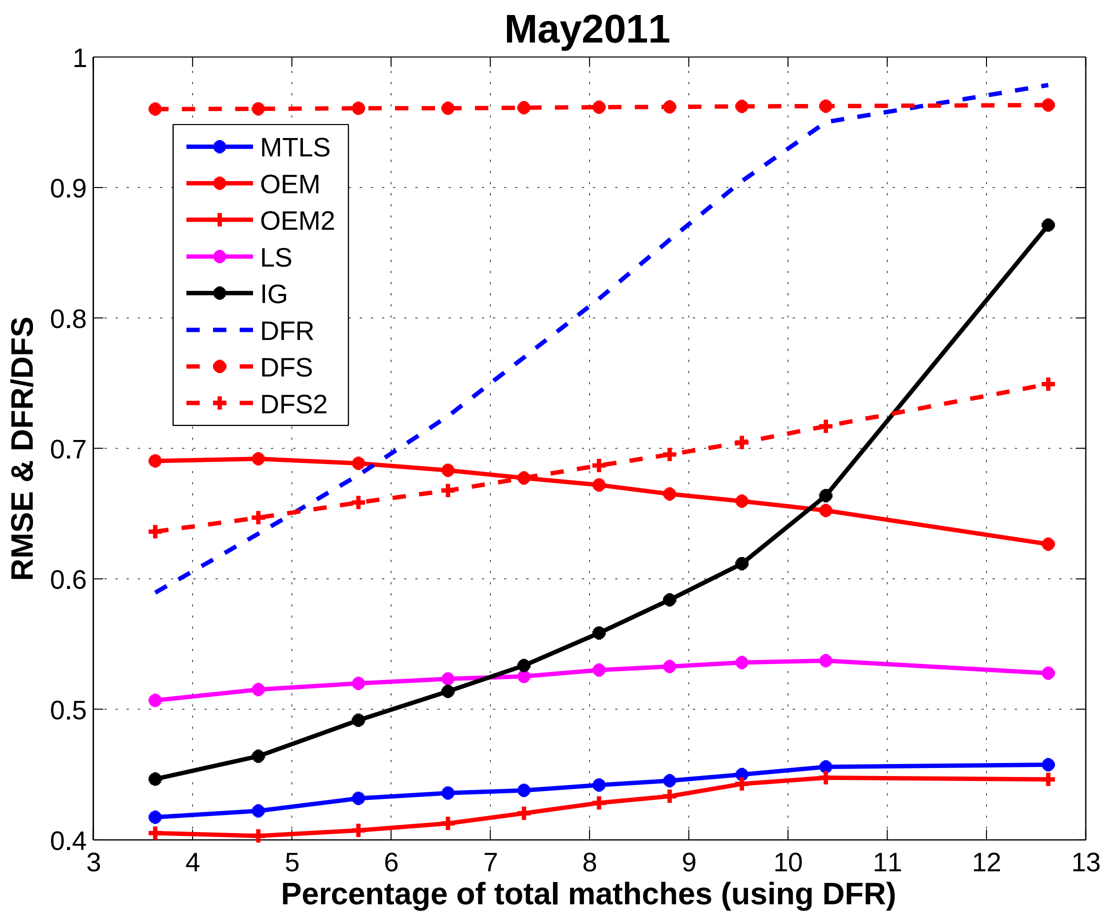
(σ^2_{end} = lowest singular value of $[K\ \Delta y]$)

Total Error

$$||e|| = ||(MRM - I)\Delta x|| + ||G'||\langle||(\Delta y - K\Delta x)||\rangle$$

***N.B.* Includes TCWV as well as SST**

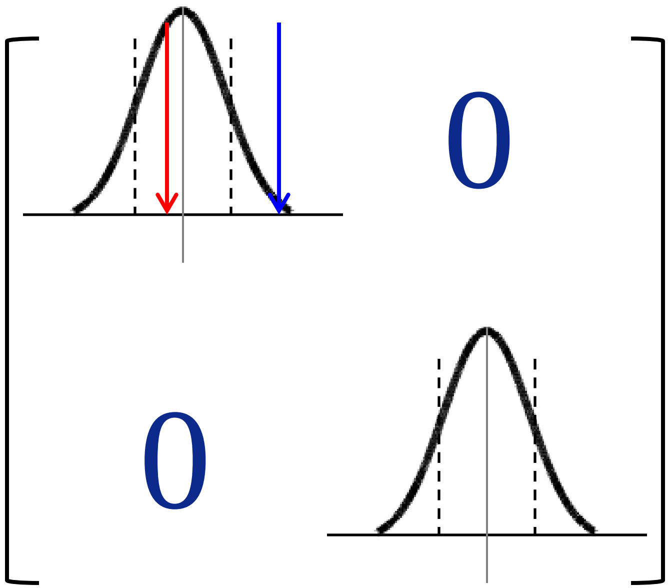
DFS/DFR and Retrieval error



- ❑ Retrieval error of OEM higher than LS
- ❑ More than 75% OEM retrievals are degraded w.r.t. *a priori* error
- ❑ DFR of MTLS is high when *a priori* error is high

"Optimized" OE

- $[S_e]$, S_a =

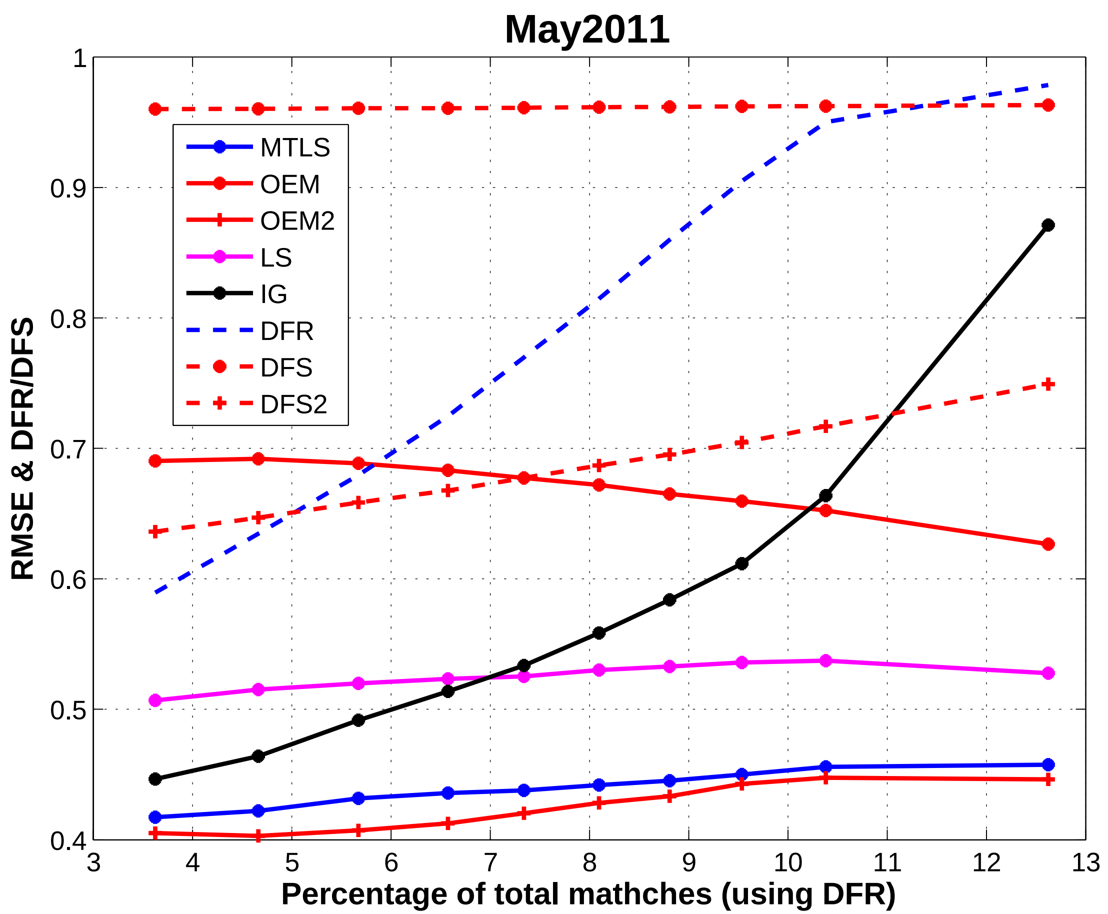


σ^2 is an overestimate…

…or an underestimate

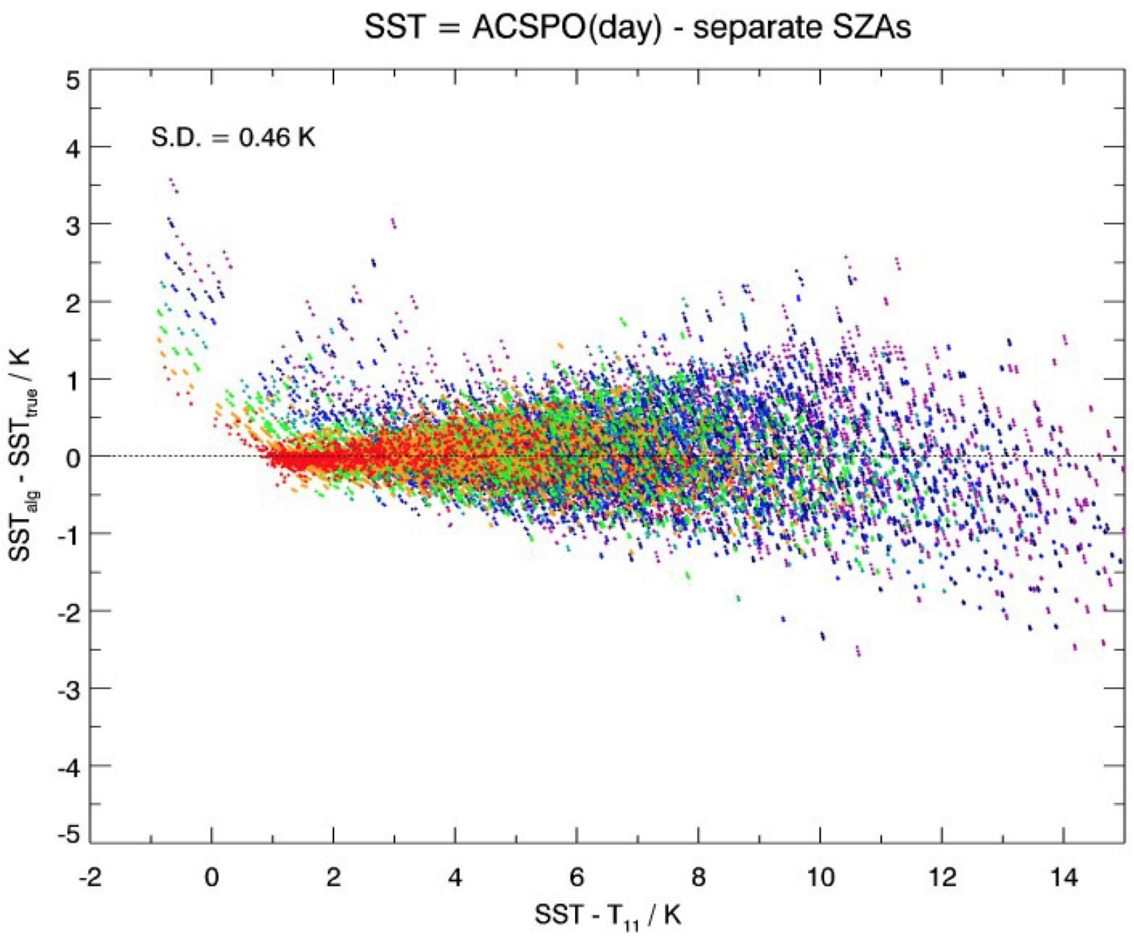
- **Perform experiment – insert "true" SST error into S_a^{-1}**
  - Can only be done when truth is known, *e.g.* with matchup data

DFS/DFR and Retrieval error



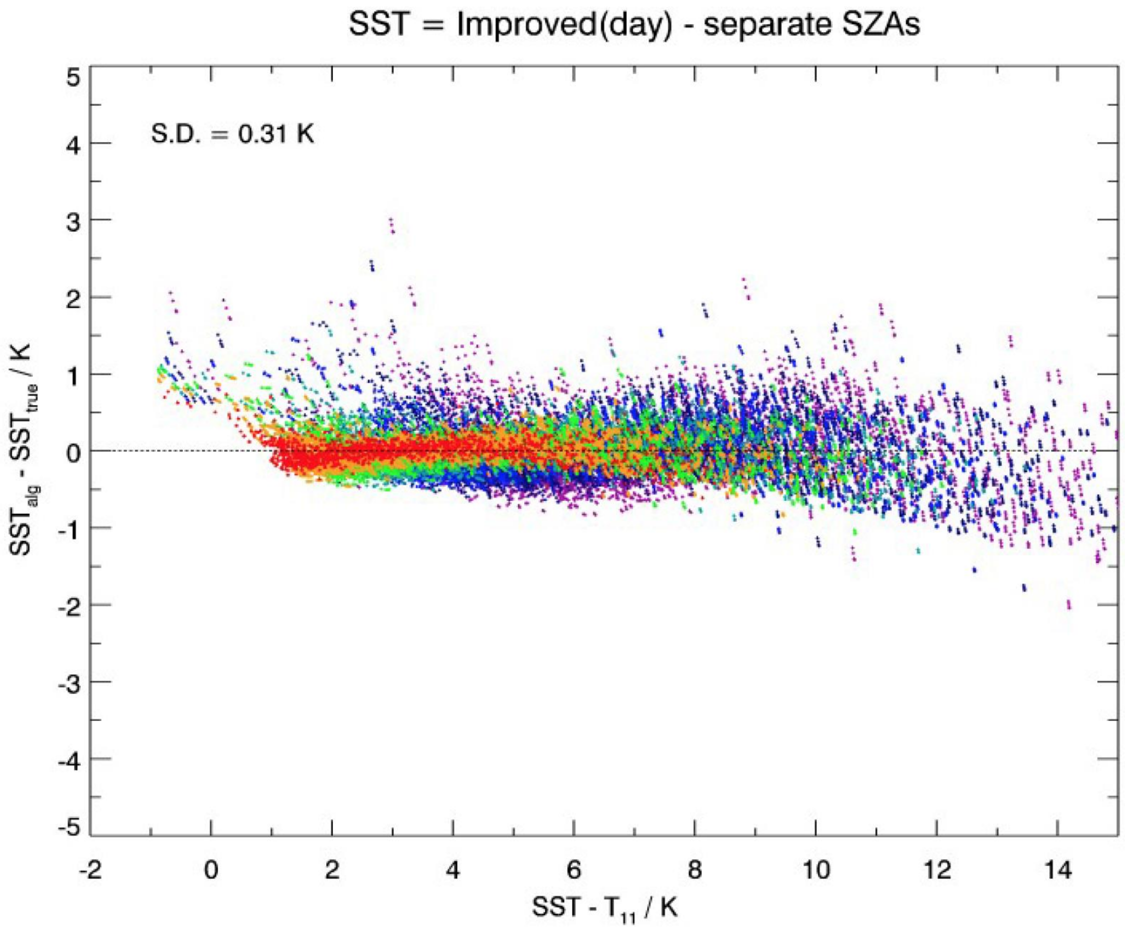
- ❑ Retrieval error of OEM higher than LS
- ❑ More than 75% OEM retrievals are degraded w.r.t. *a priori* error
- ❑ DFR of MTLS is high when *a priori* error is high
- ❑ The retrieval error of OEM is good when *a priori* SST is perfectly known, but DFS of OEM is much lower than for MTLS

Extra channels in new sensors



- **No longer dependent on just split-window in daytime**

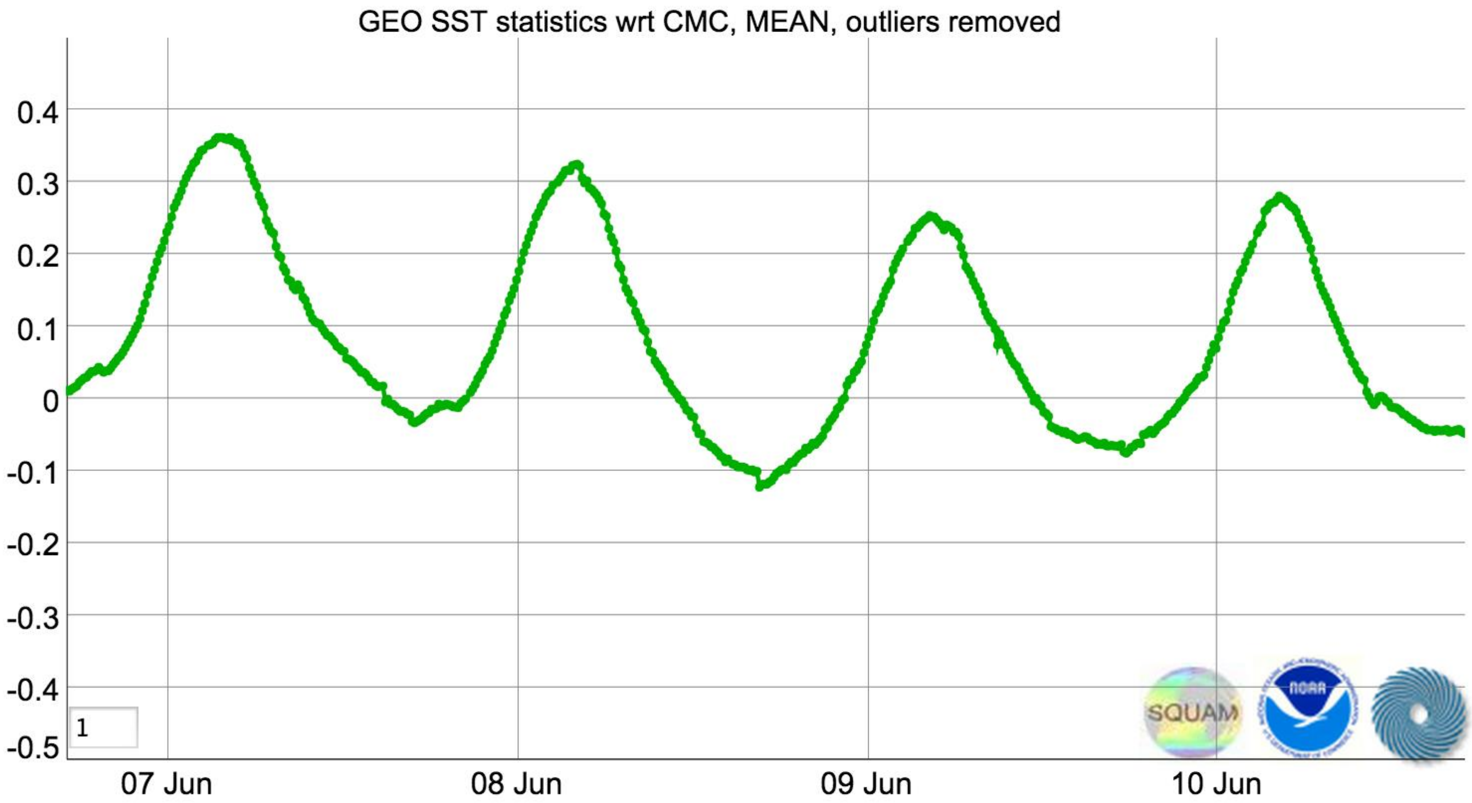
Extra channels in new sensors



- **No longer dependent on just split-window in daytime**
- **Regression can work well if cloud screening is "good"**

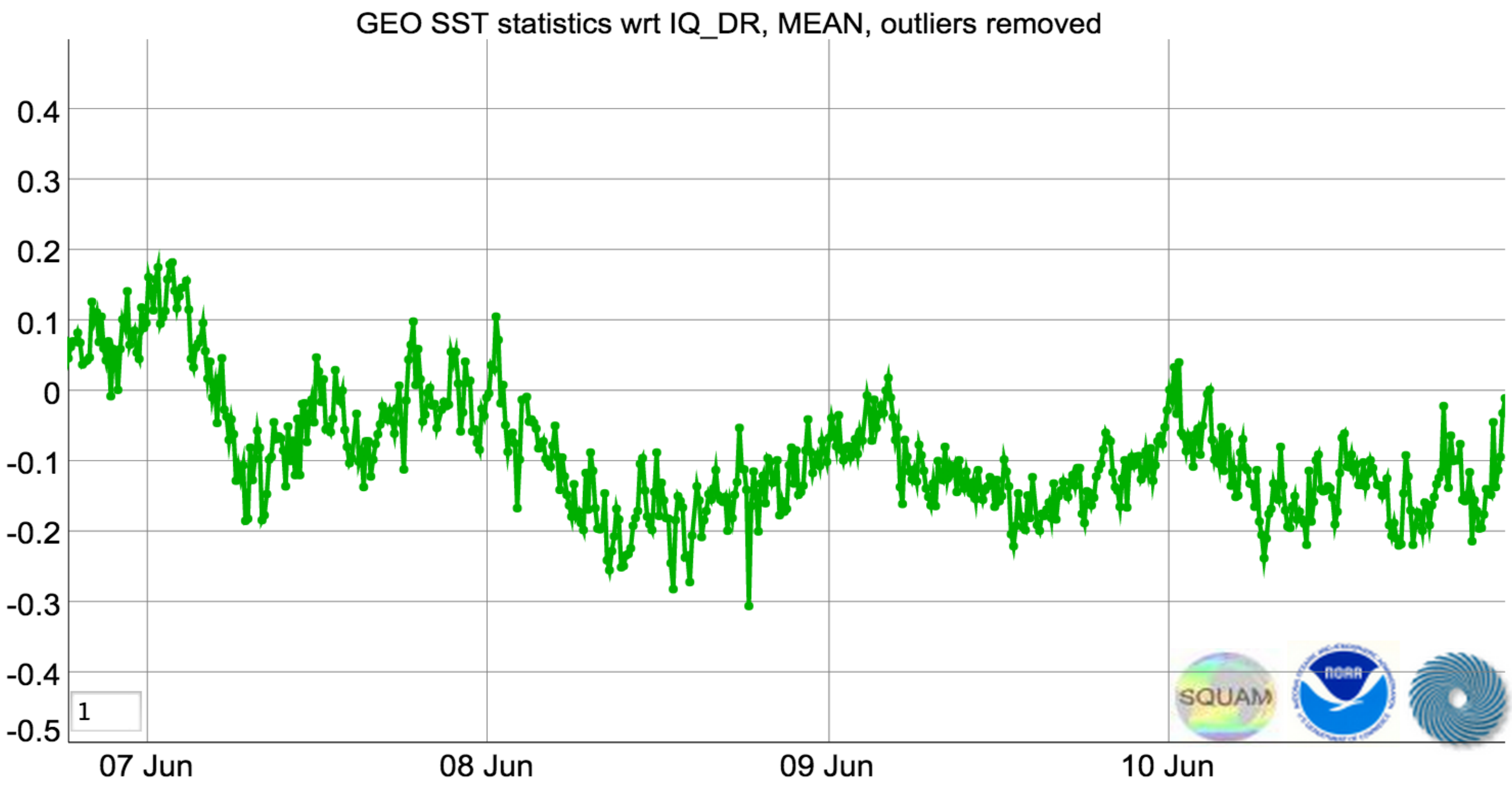
H-8 ACSPO – CMC foundation

- **Small jumps as daily reference analysis changes (0Z ➔ ~10AM local time @nadir)**

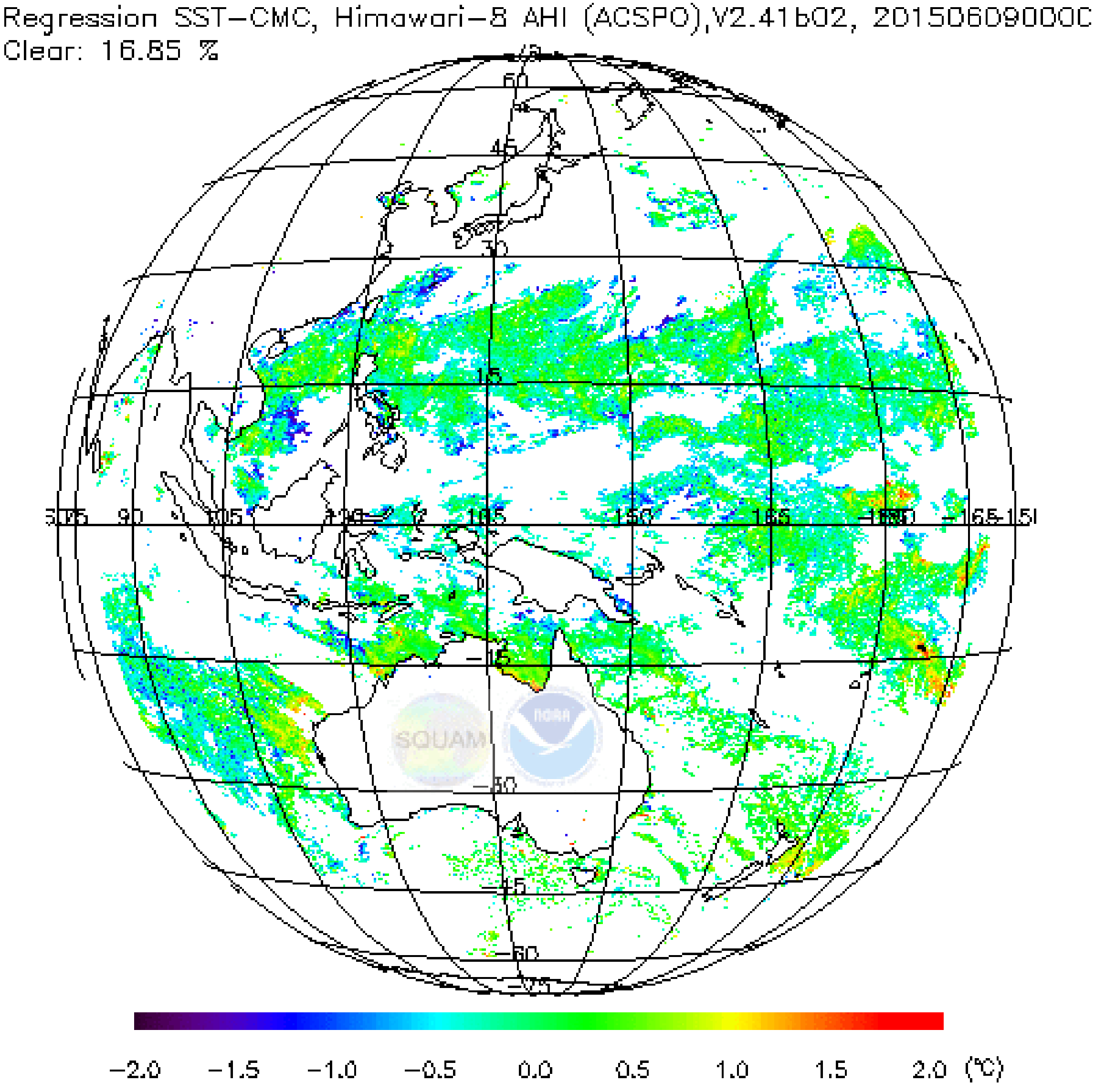


Difference from drifting buoys

- Much less excursion (drifters are shallow)
- See initial separation and then mixed



H-8 ACSPO Animation



- **SQUAM web page (low res!); half-hourly**

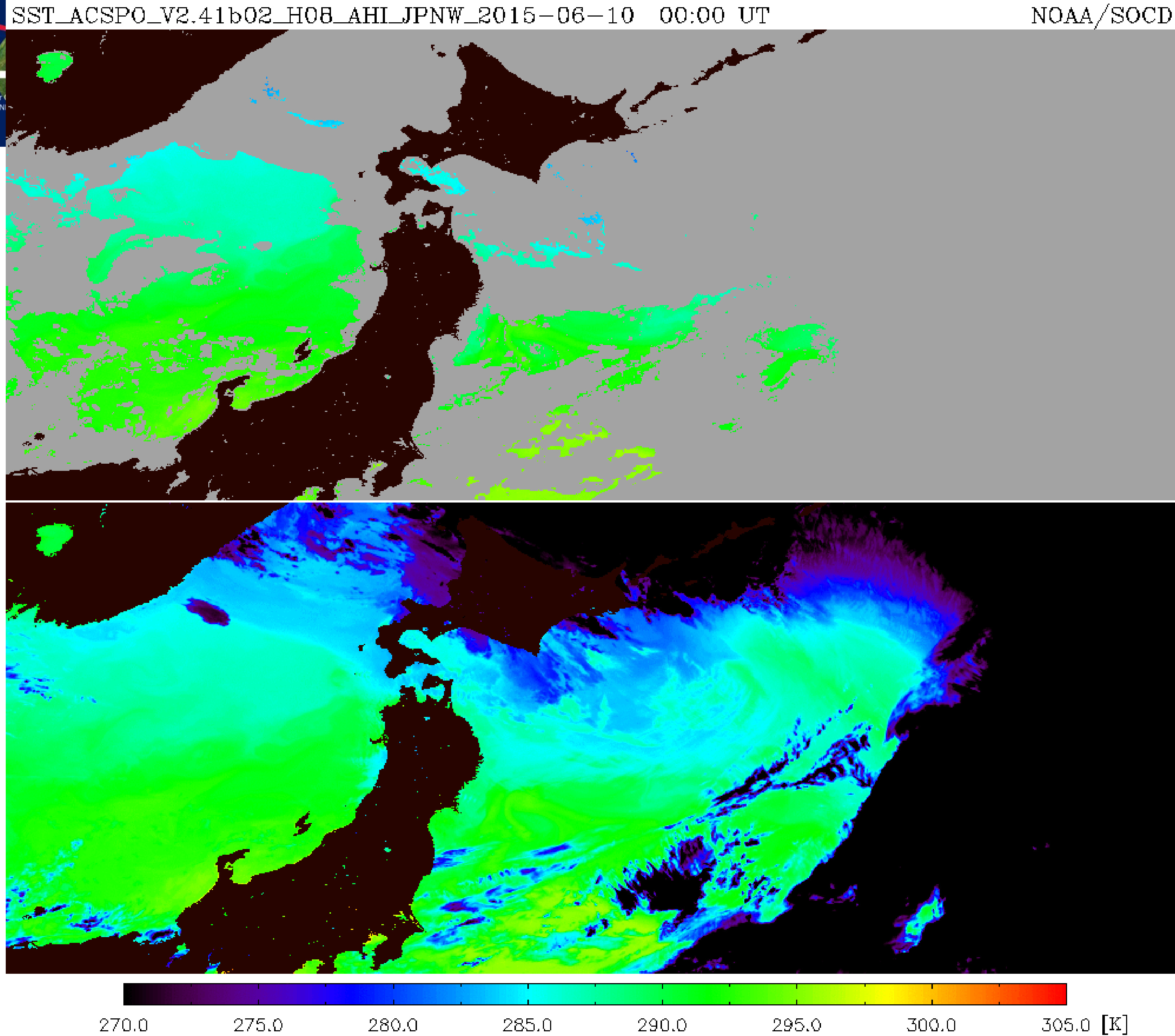
Improved cloud detection

- **Use a combination of spectral differences and RT**
  - Envelope of physically reasonable clear-sky conditions
- **Relaxed spatial coherence (3×3)**
- **Also check consistency of single-channel retrievals**
- **Flag excessive TCWV adjustment & large MTLS error**
- **Increased coverage w.r.t. GHRSST QL3+, but with reduced cloud leakage**

Summary

- **New physical retrievals (including aerosol) and cloud detection**
  - Dynamic error calculation
- **Latest sensors are very good (multiple channels, low noise) so if cloud detection is good, linear regression retrieval will work rather well**
  - Piecewise regression can ameliorate a lot of issues
- **Reprocessing**
  - A lot of data. Physical methods need auxiliary (including aerosol…)
    - Where to get aerosol profiles?
  - Now recognized as necessary for anomaly-based products
  - The above has translated to funding!

Backup slides


SST_ACSPO_V2.41b02_H08_AHI_JPNW_2015-06-10 00:00 UT
NOAA/SOCD
270.0
275.0
280.0
285.0
290.0
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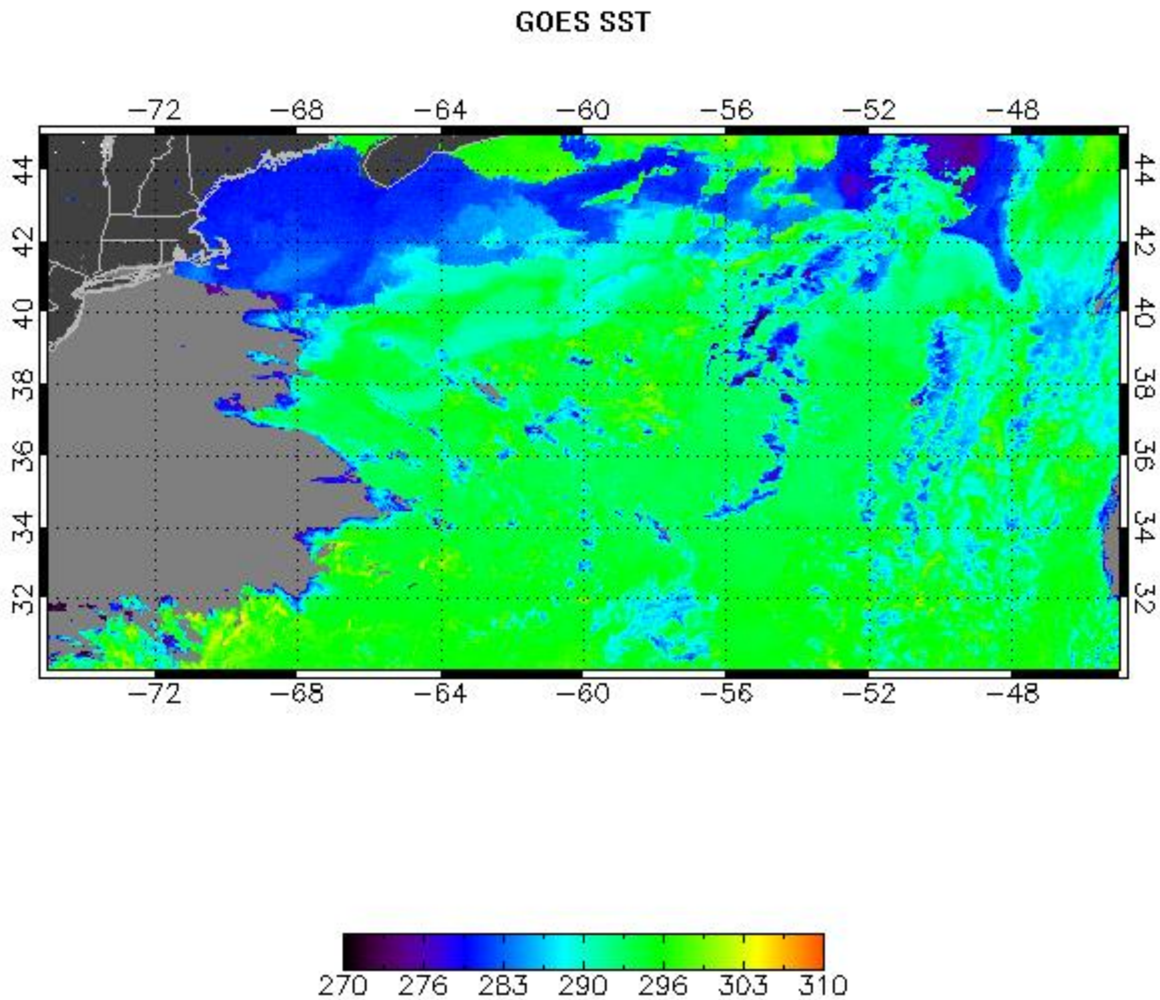
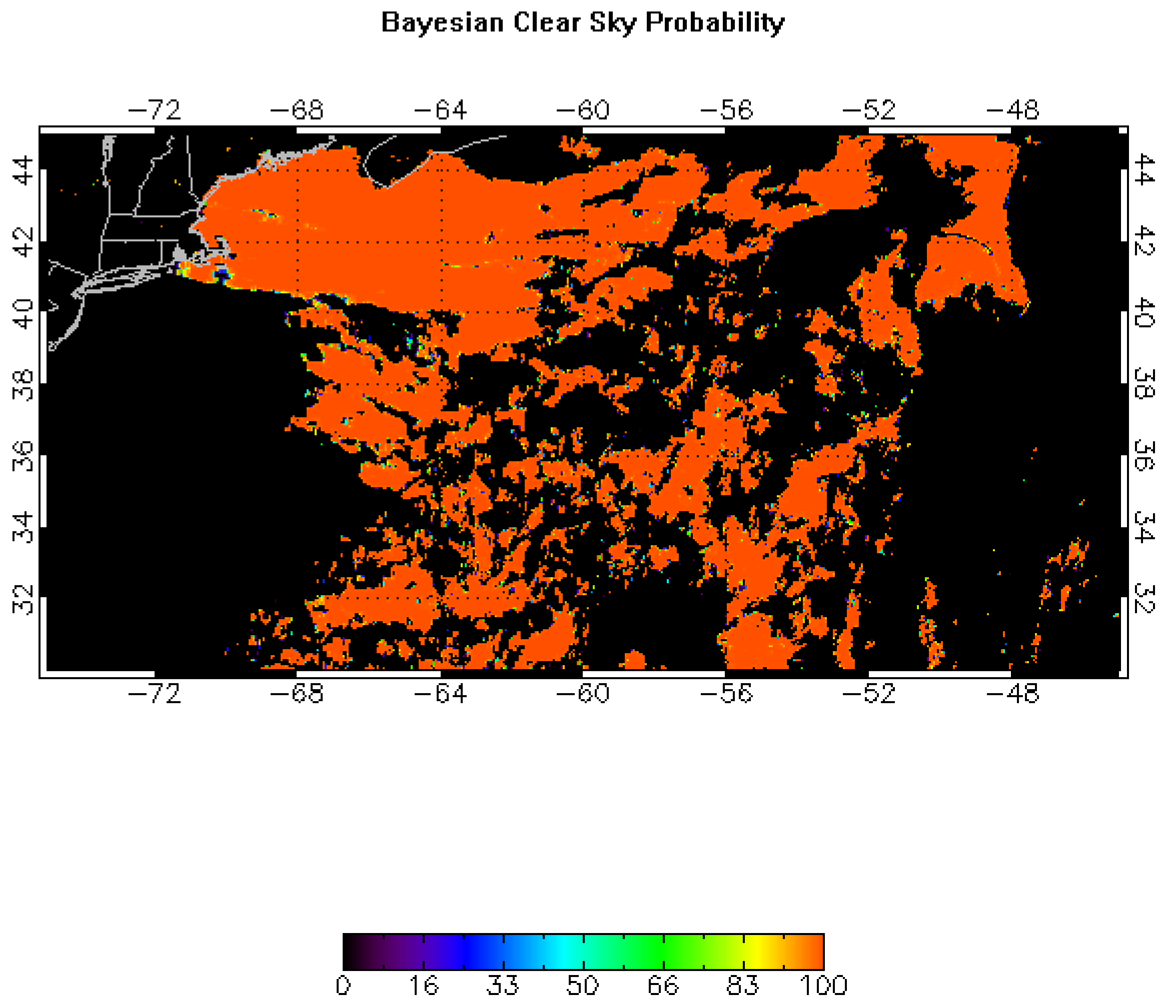
300.0
305.0
[K]

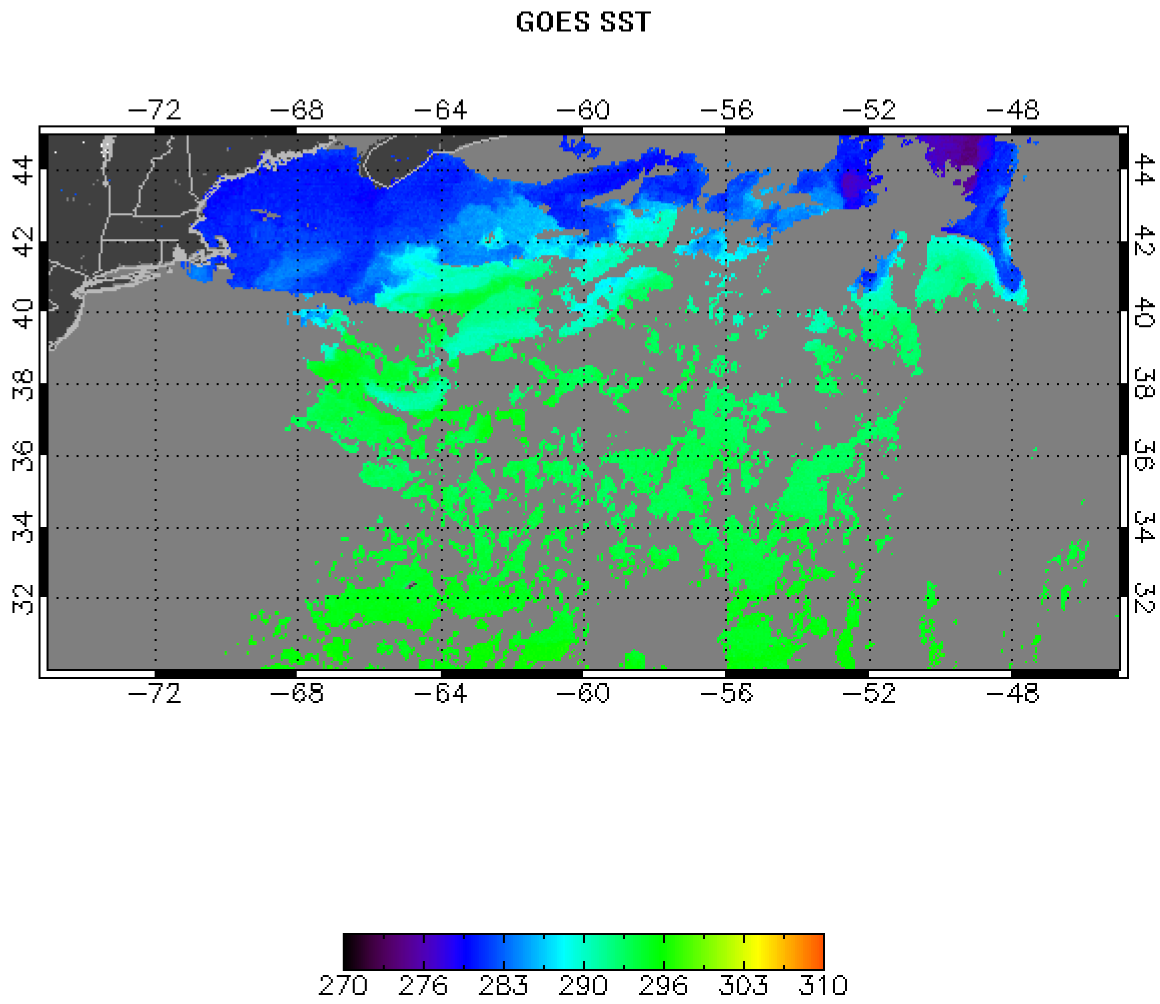
Unmasked SST 2005–325–15



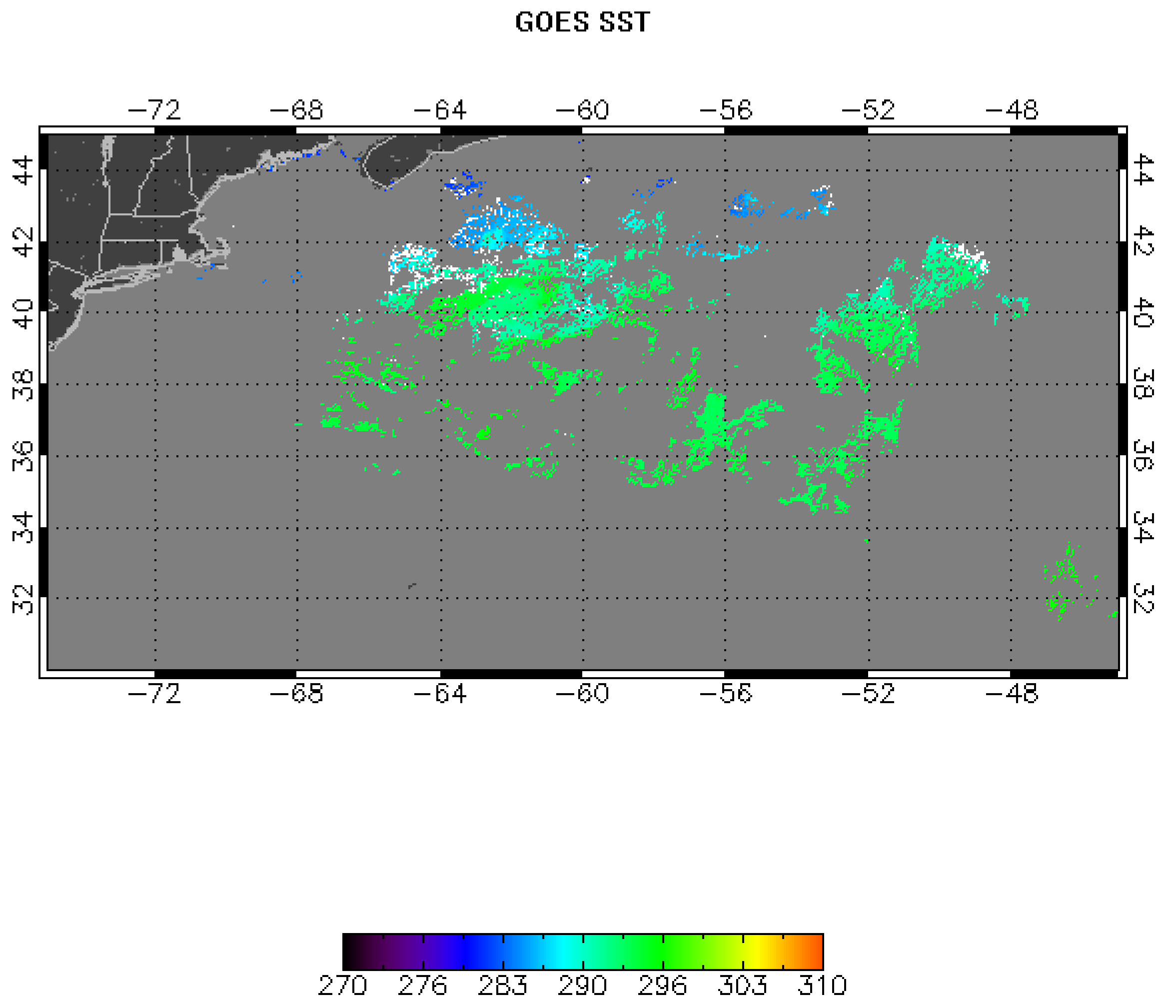
P(clear) 2005–325–15



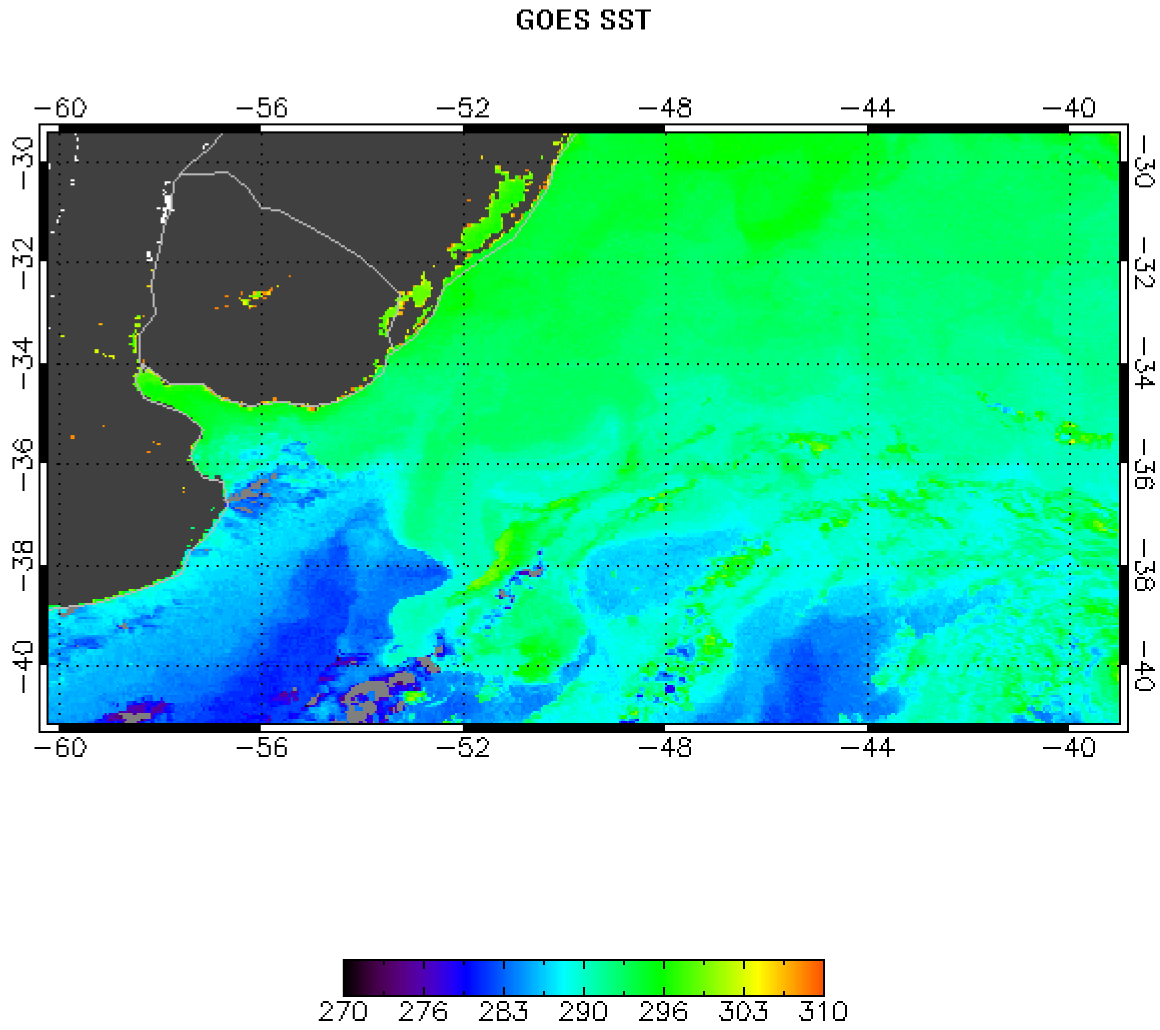
Masked Bayesian SST for P_{clear} ≥95% 2005–325–15



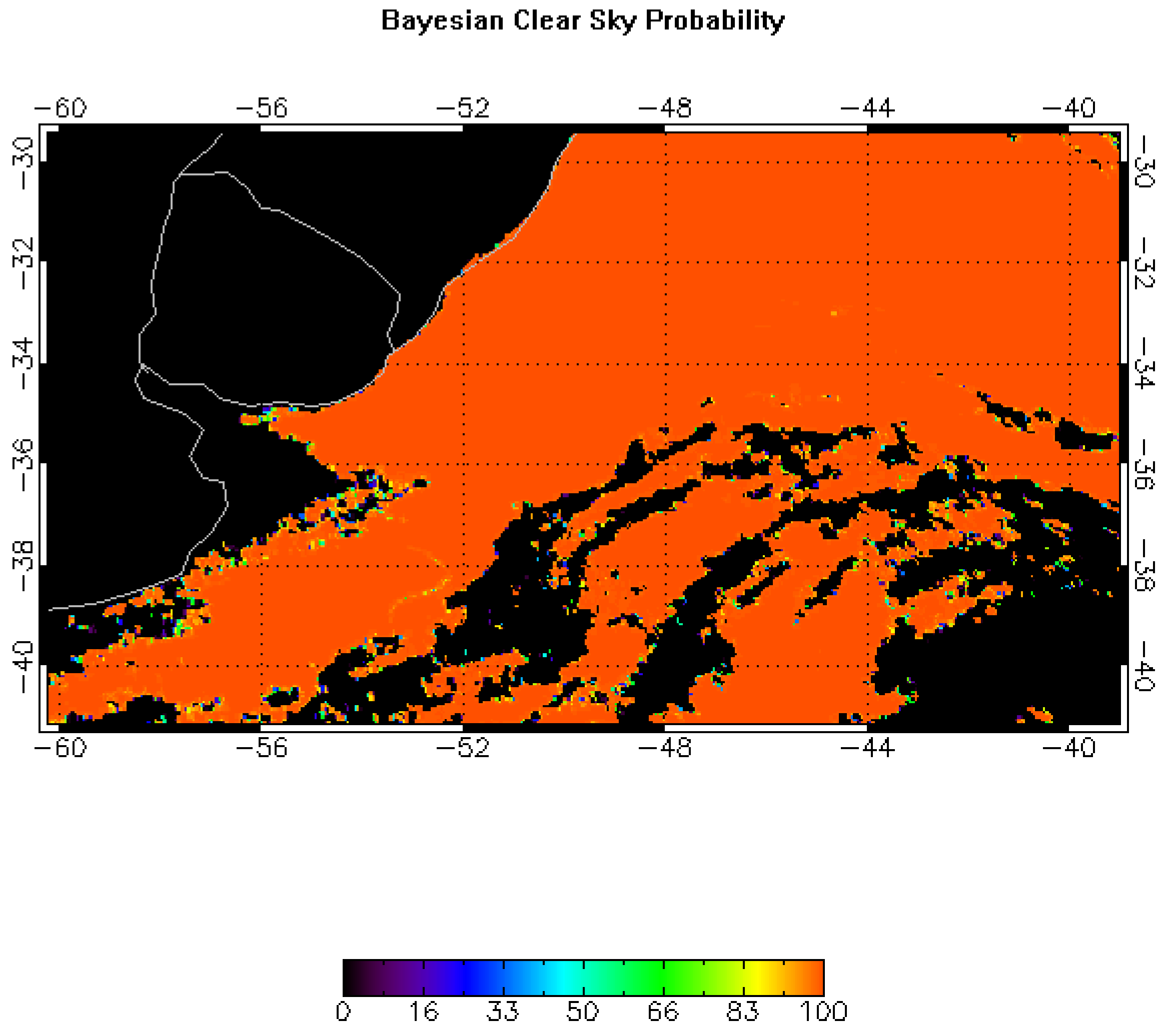
Conventional SST 2005–325–15



Unmasked SST 2005–330–14



P(clear) 2005–330–14



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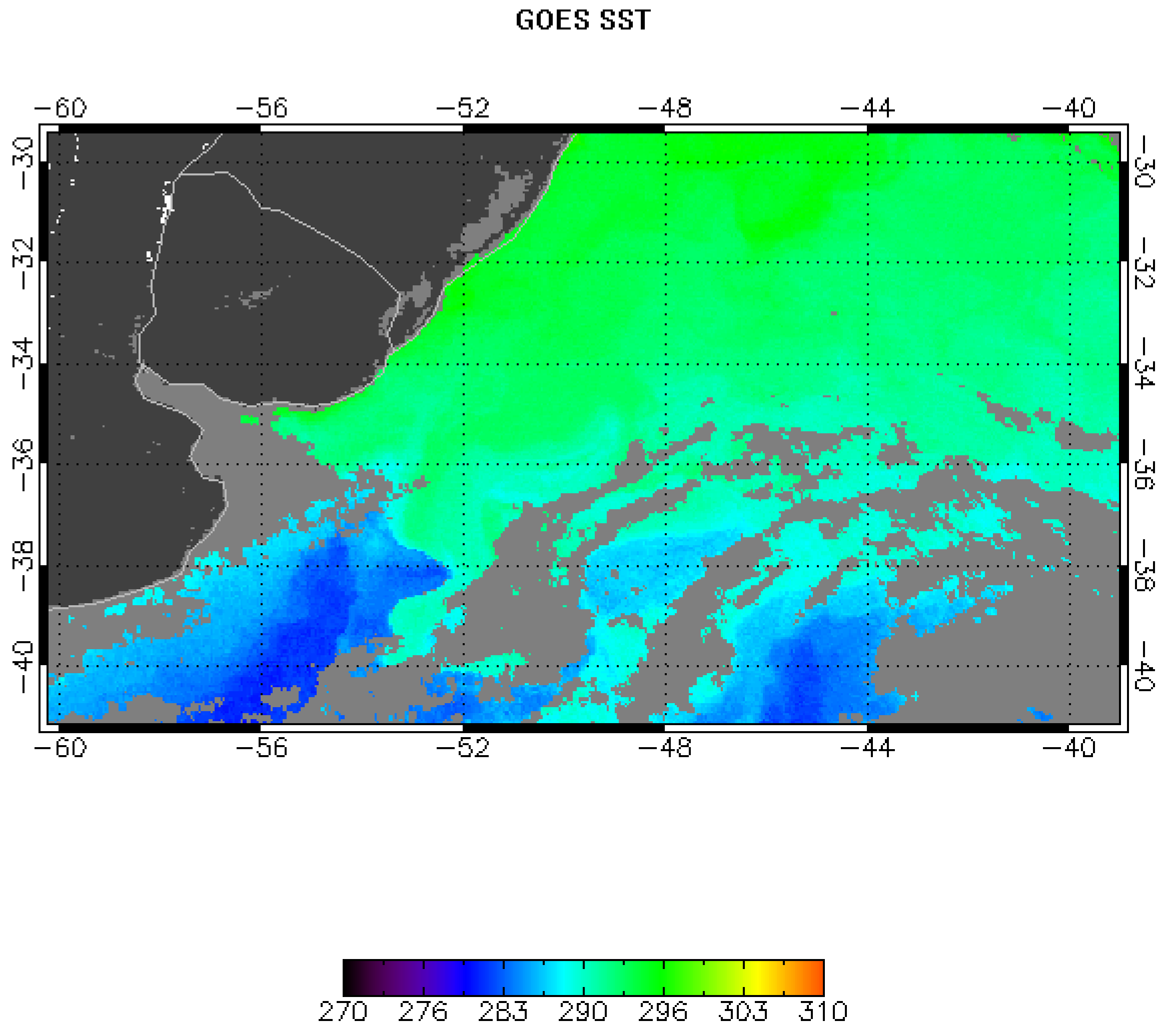
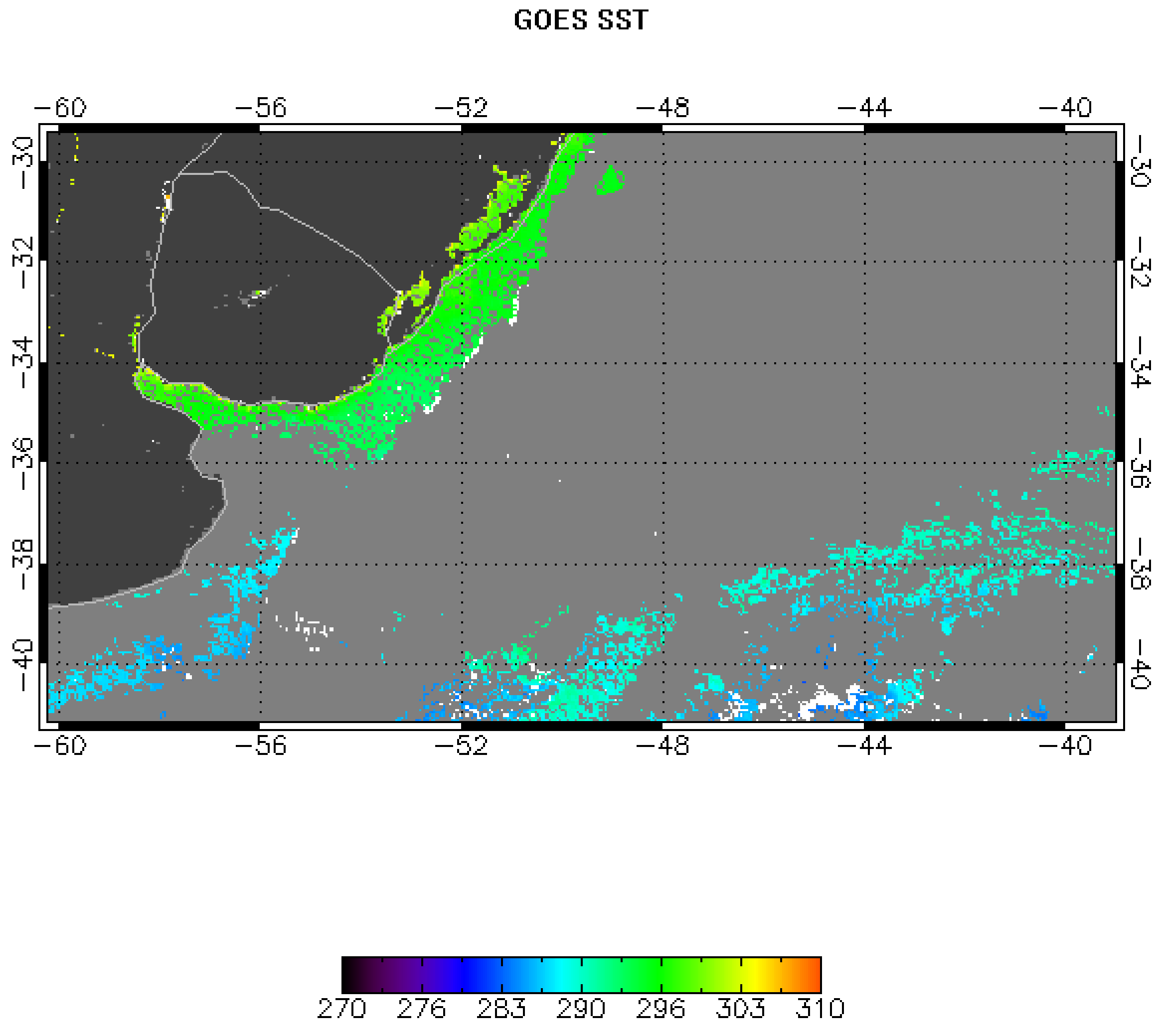


Conventional SST 2005–330–14



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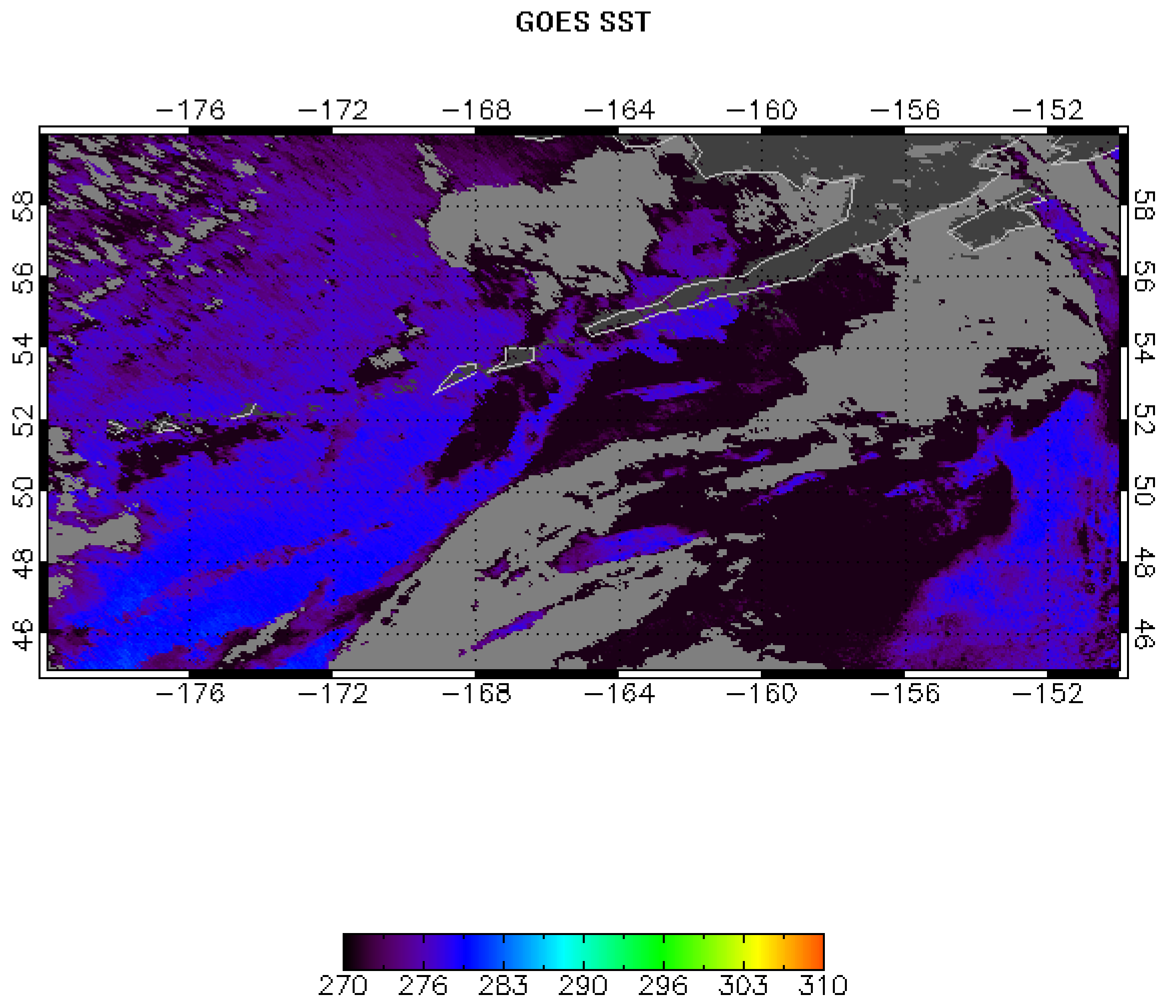
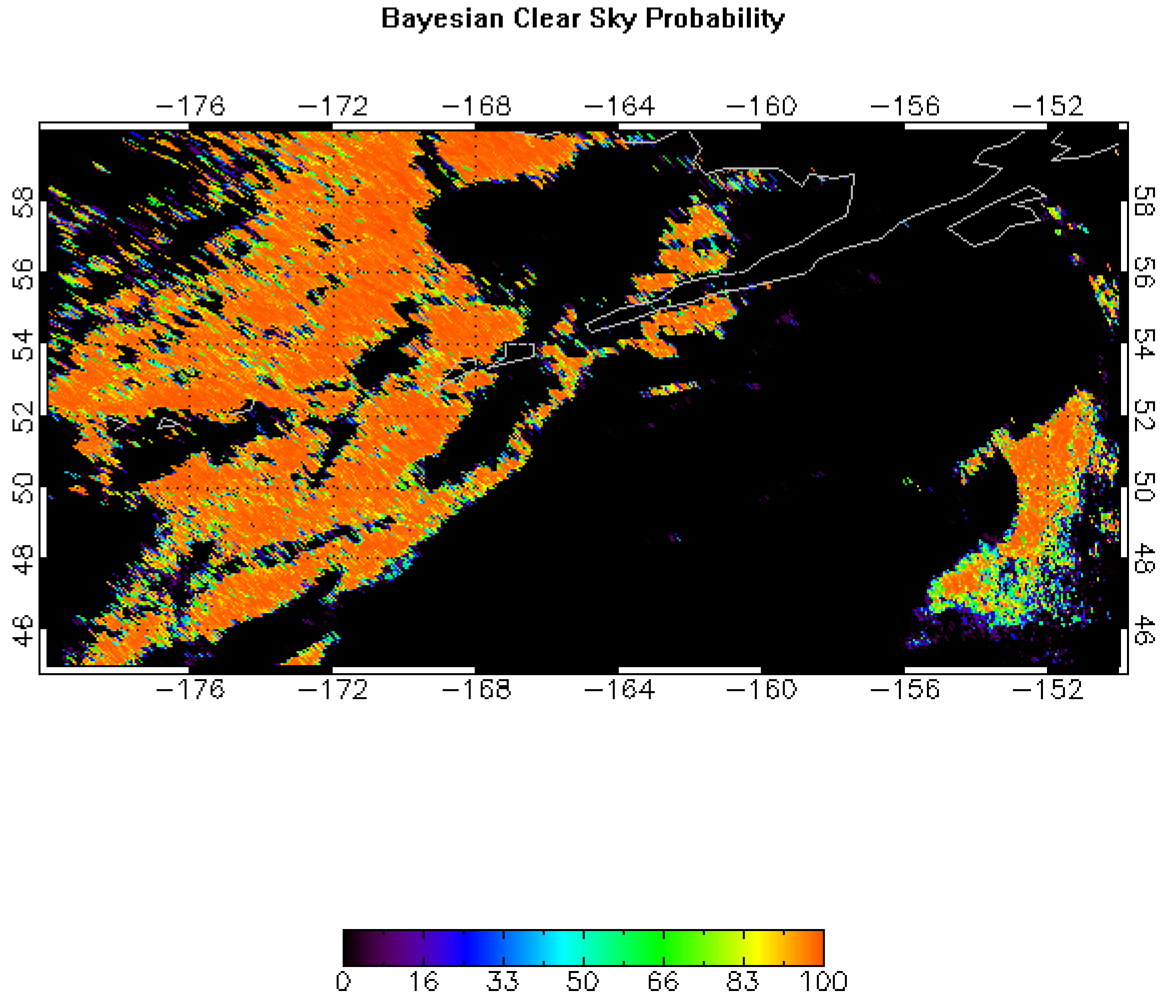


P(clear) 2005–332–15



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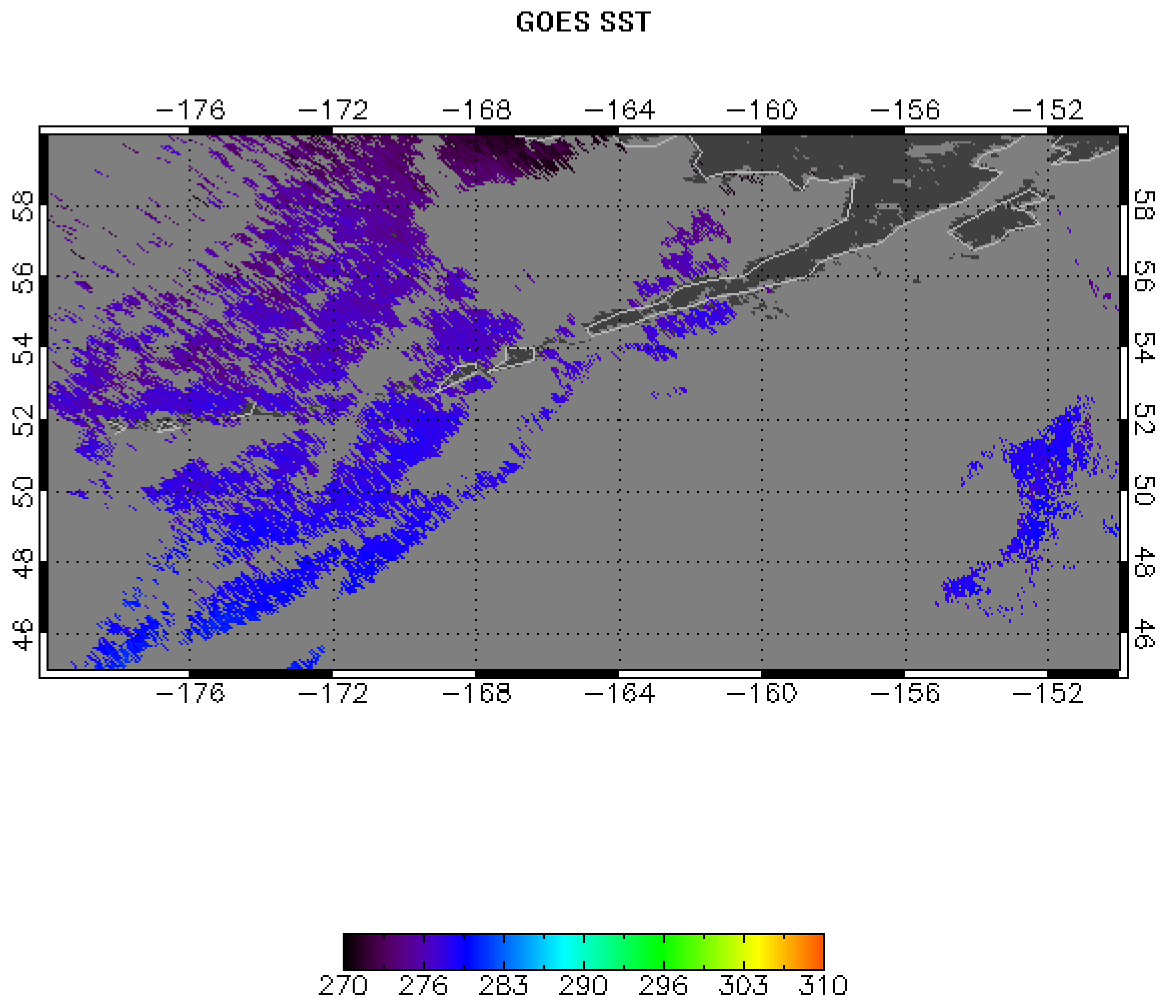

Conventional SST 2005–332–15