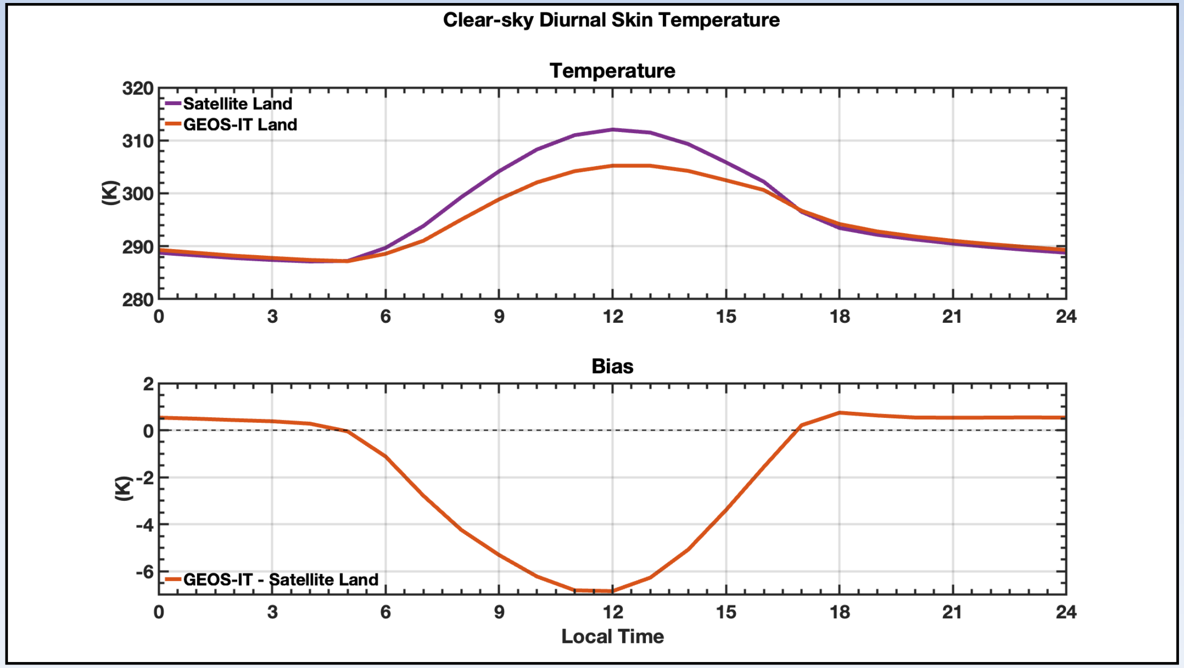
Global Evaluation of Reanalysis Surface Temperatures and Station Observations in All-sky Conditions for use in CERES

B. Scarino[1], W. L. Smith[1], Jr., S. Kato[1], S.-H. Ham[2], and S. Sun-mack[2]

[1]NASA Langley Research Center, Hampton, VA
[2]Analytical Mechanics Associates, Hampton, VA

Background

- Cloud mask threshold approaches rely on cloud-free skin temperature (T_s) estimate
- T_s in cloudy condition necessary for optical depth and height retrievals
- Downstream radiation budget calculations rely clouds and on model T_s in cloudy condition
- Need for stability in T_s estimates for clear and cloudy skies
- T_s and surface air temperature (T_a) estimates vary significantly between different reanalyses
- Differences between reanalyses and satellite-derived T_s can be extreme



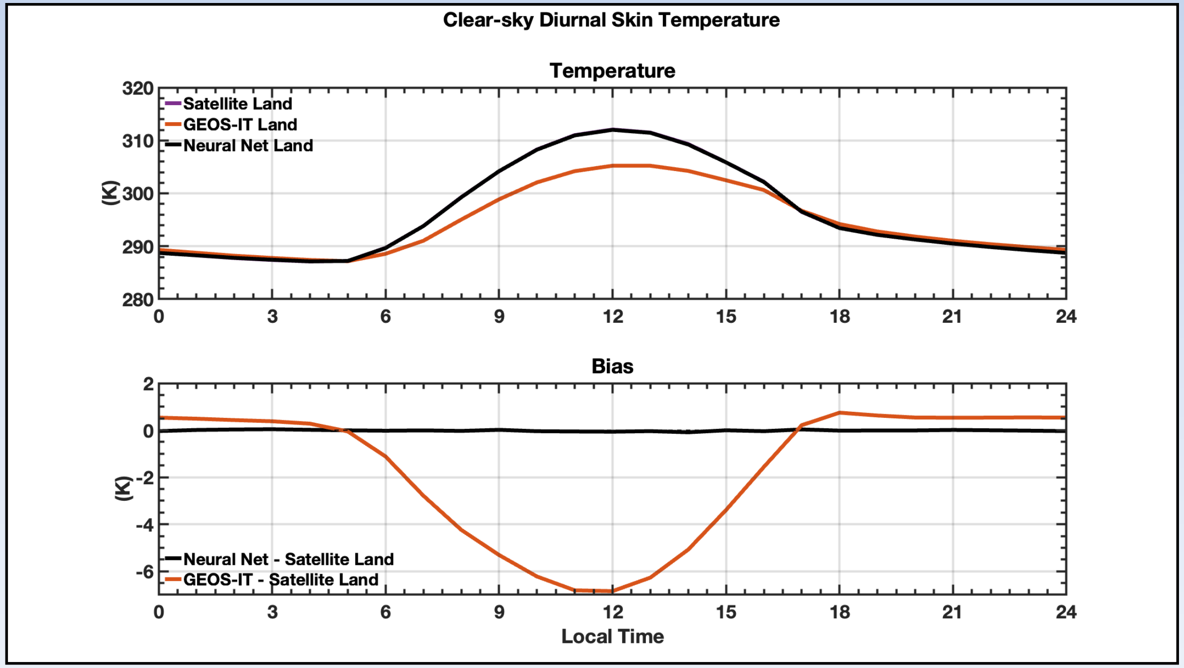
Large diurnal dependence in reanalysis land T_s bias

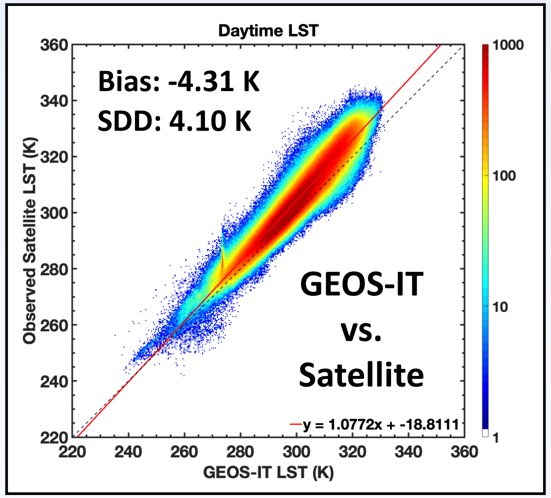
Objectives

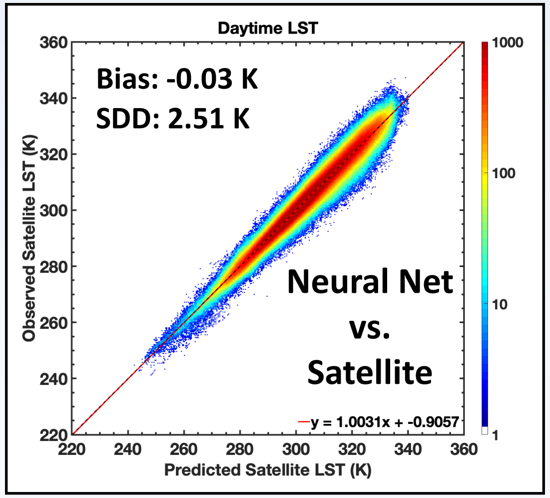
- Explore the consistency of T_s and T_a temperature across different reanalysis datasets, relative to…
  - …one-another
  - …global surface station observations
  - …satellite

- Explore deep neural network (DNN) approach to produce consistent T_s estimates given any reanalysis dataset
  - Estimate one reanalysis dataset from another
  - Estimate satellite observation from reanalysis

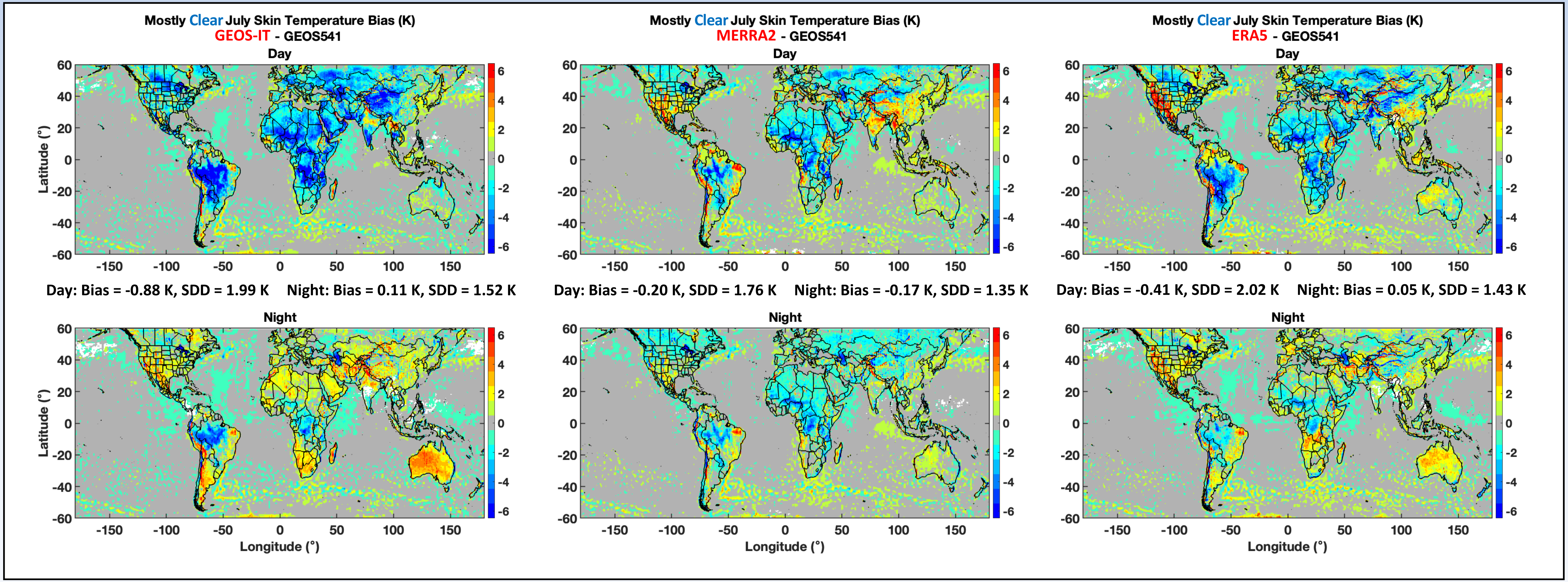
Desire for consistent initial T_s regardless of reanalysis source







Global (non-polar) Reanalysis Skin Temperature Differences



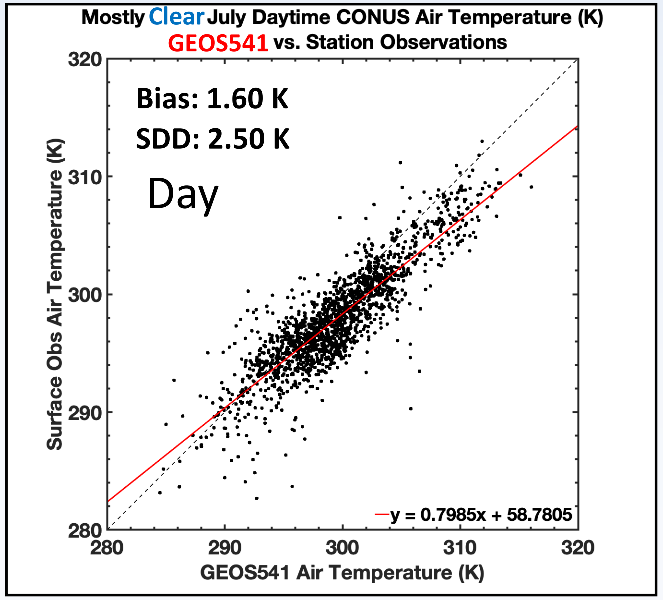
- Seasonal, regional, and diurnal dependencies complicate reanalysis T_s bias accounting
- Land difference can easily swing by 1 K on average – easily more than 6 K instantaneously

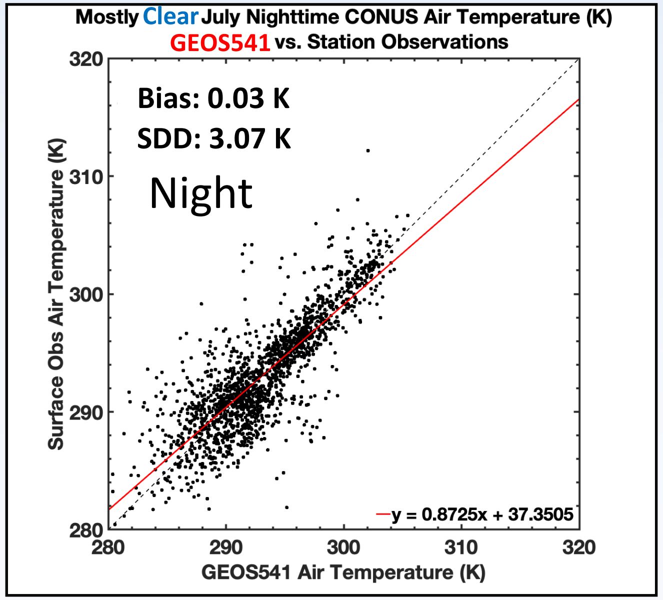
A change in reanalysis T_s will influence the cloud mask

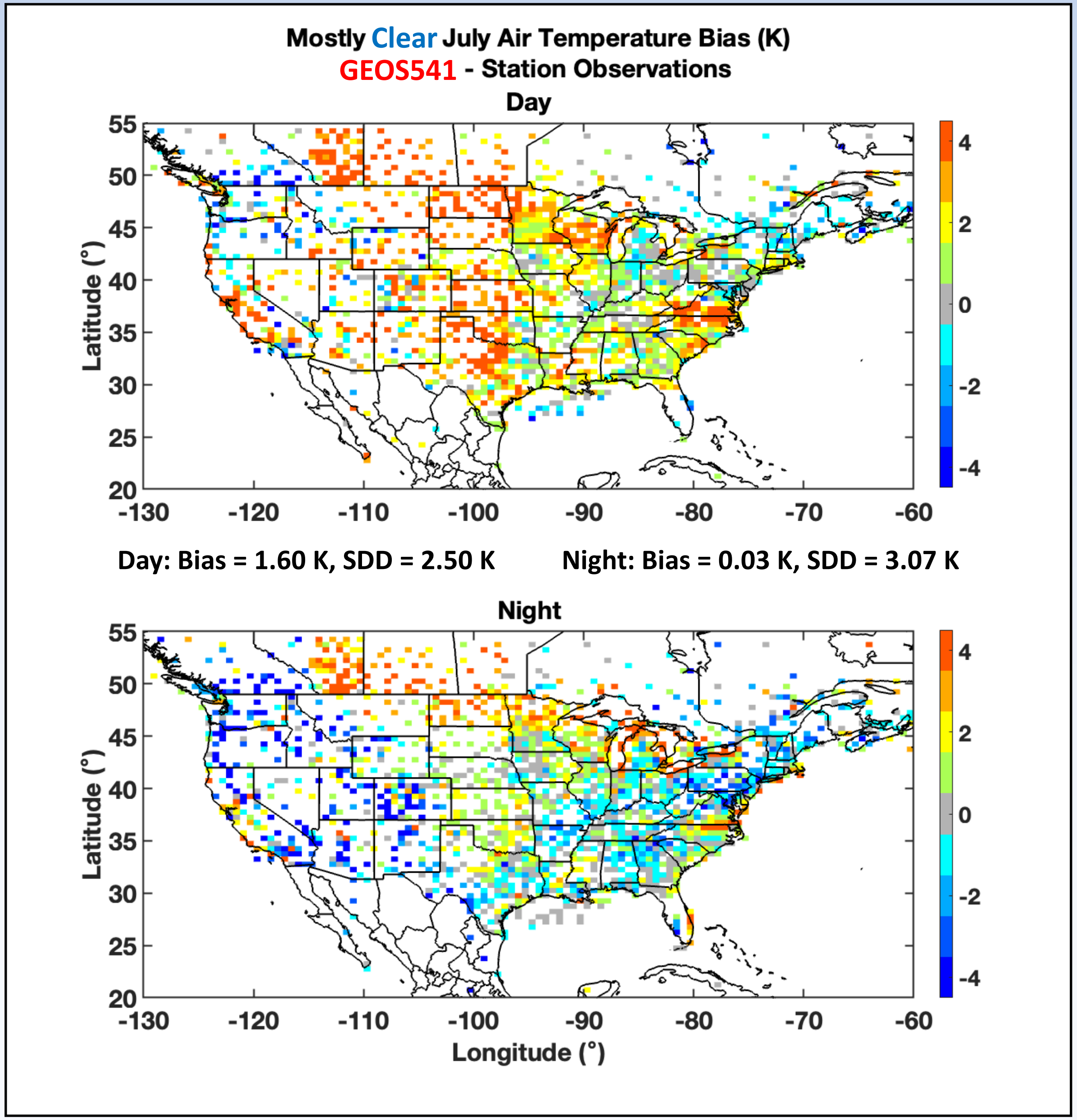
Reanalysis vs. Observed Air Temperature

- Ground validation of T_s is limited, but surface T_a observations are global
- GMAO does not assimilate station T_a – T_s and T_a tied to numerical models of near-surface processes

Assessing bias in T_a can help interpret bias in T_s



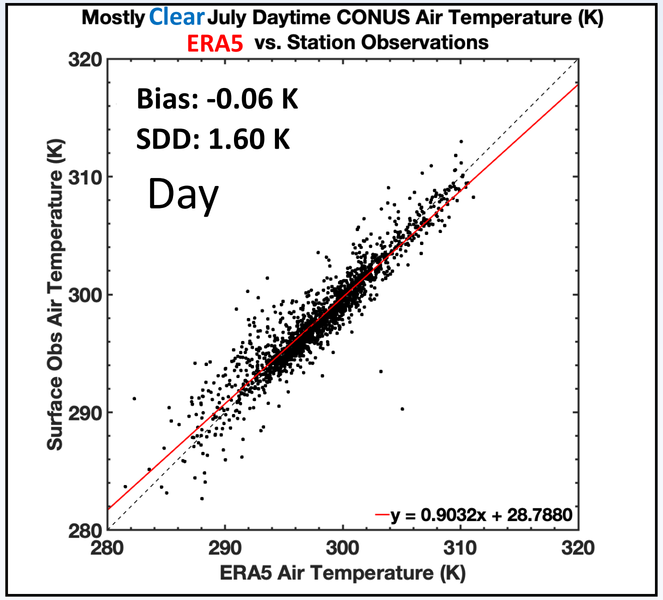


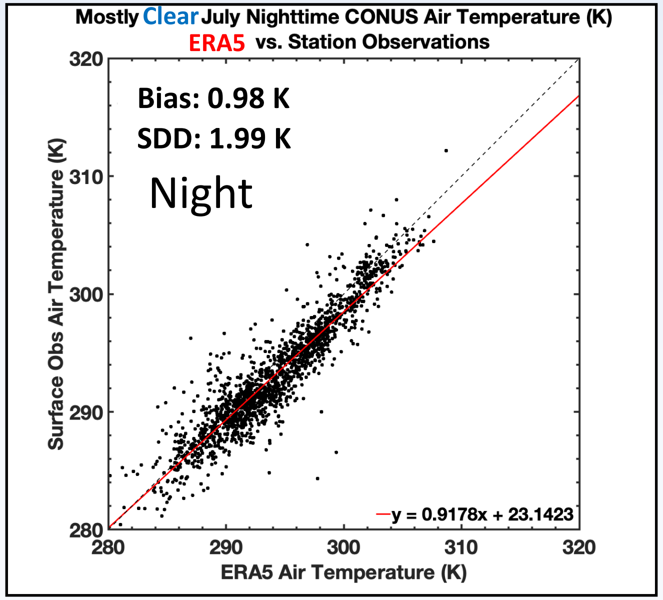


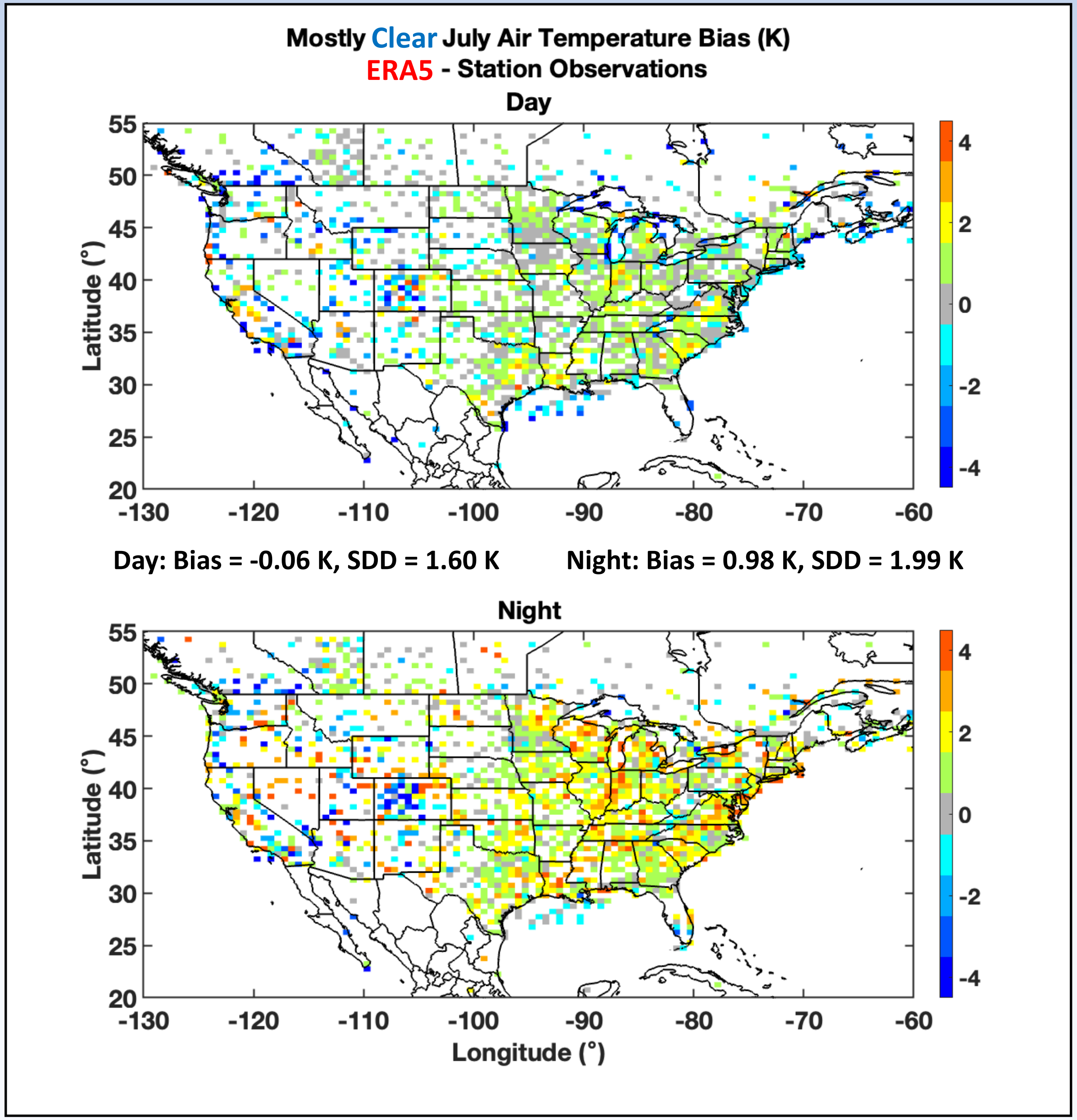
Reanalysis vs. Observed Air Temperature

- ERA5 assimilates station T_a over land
- Variation reduced by 1 K for day and night

Neural Net efforts initially focused on T_a input rather than T_s





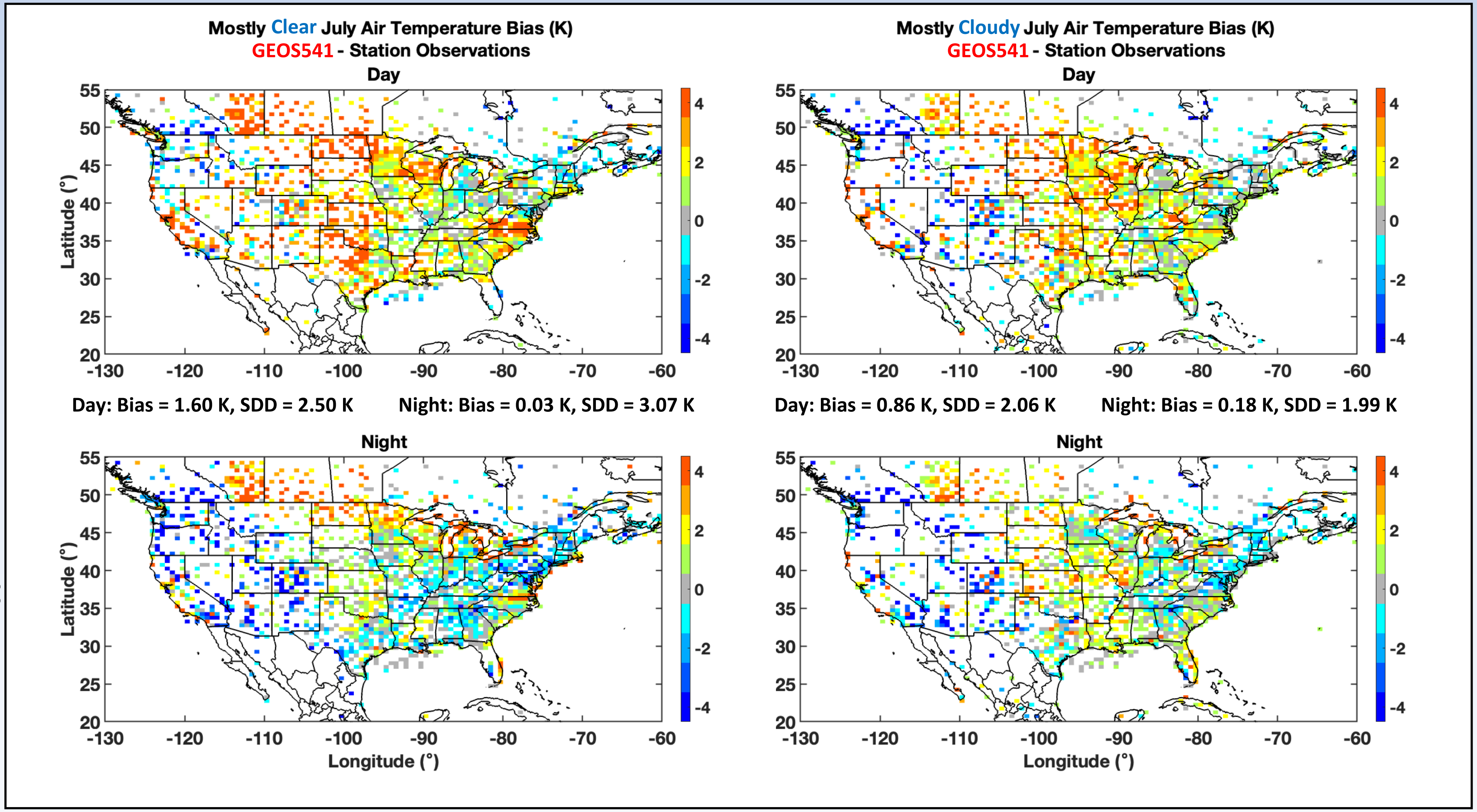


Reanalysis vs. Observed Air Temperature

Clear | Cloudy

Day

Night

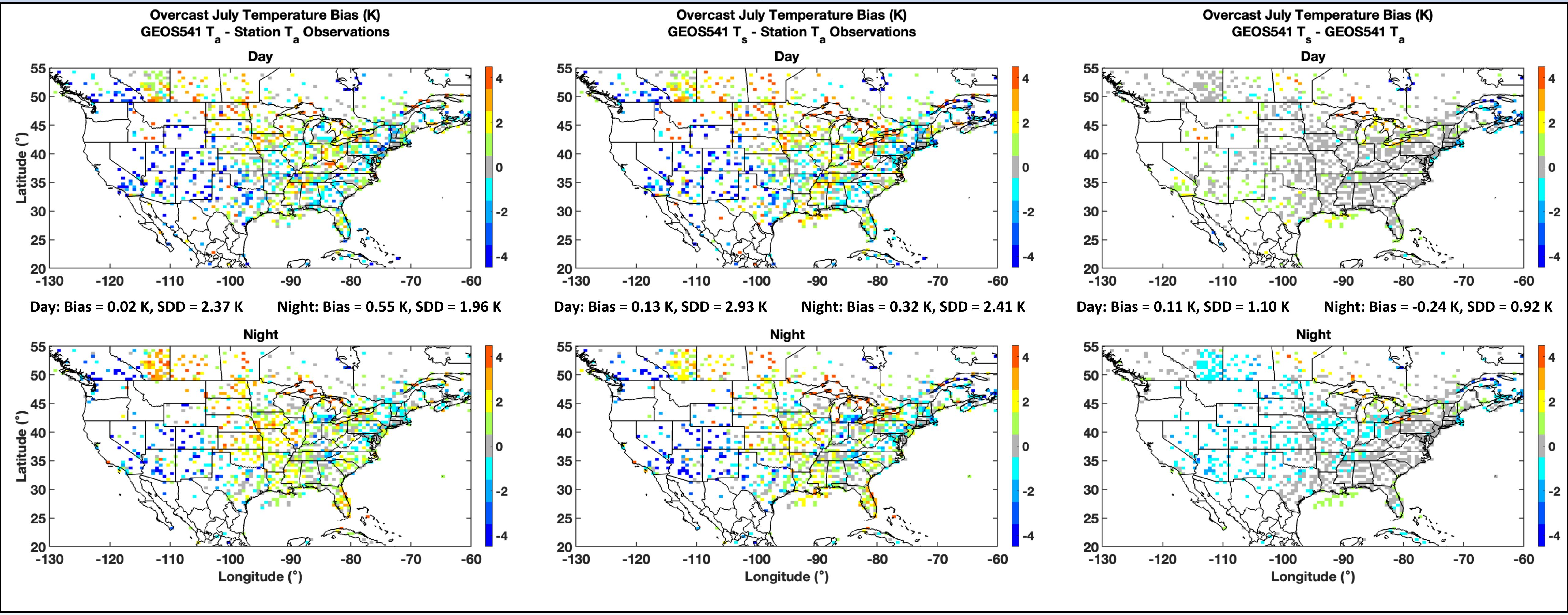


- Strong biases in both clear and cloudy conditions
- Overcast bias nearly as bad as clear because station T_a not assimilated

Clear and cloudy differences in T_a may inform expected T_s bias in cloudy conditions

Overcast Temperature Biases

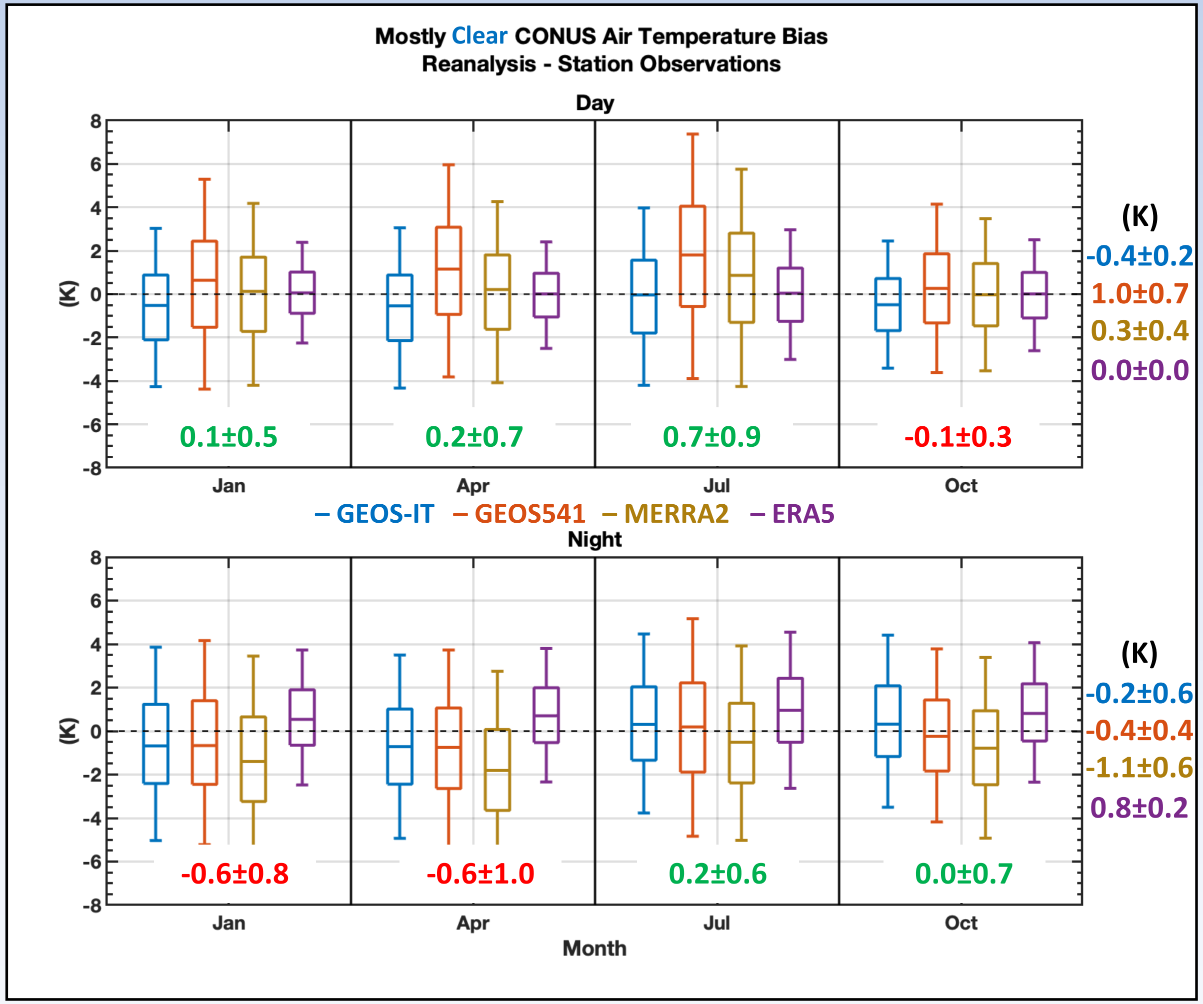
GEOS541 T_a – Observed T_a | **GEOS541 T_s – Observed T_a** | **GEOS541 T_s – GEOS541 T_a**

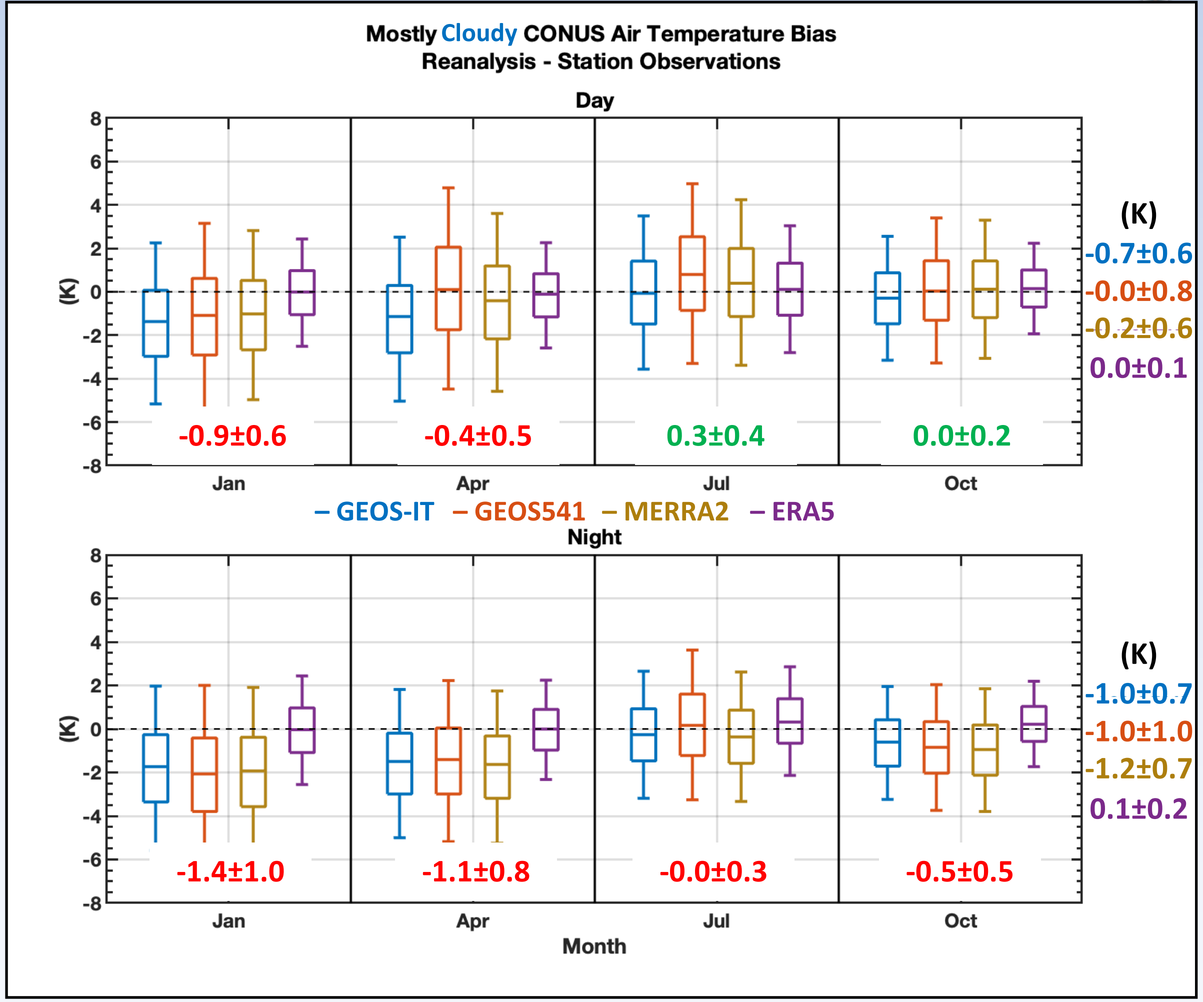


- Cloudy bias needs consideration
  - Influences flux calculations
  - No satellite truth
- GMAO T_s and T_a are reasonably close in overcast conditions

Further Study: Can T_a observations lead to reliable T_s estimates in cloudy conditions?

Seasonal Station Observation Comparisons



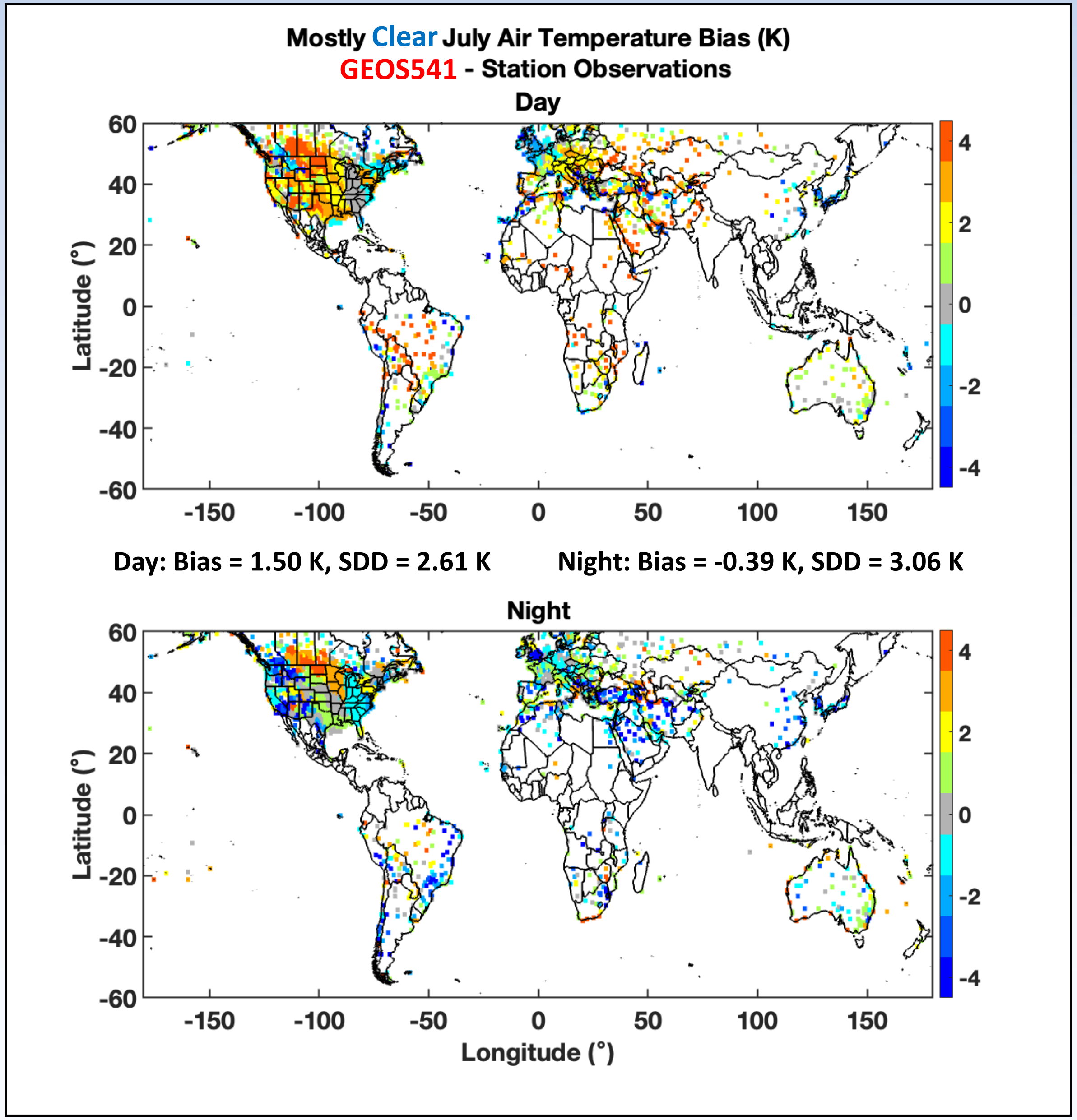


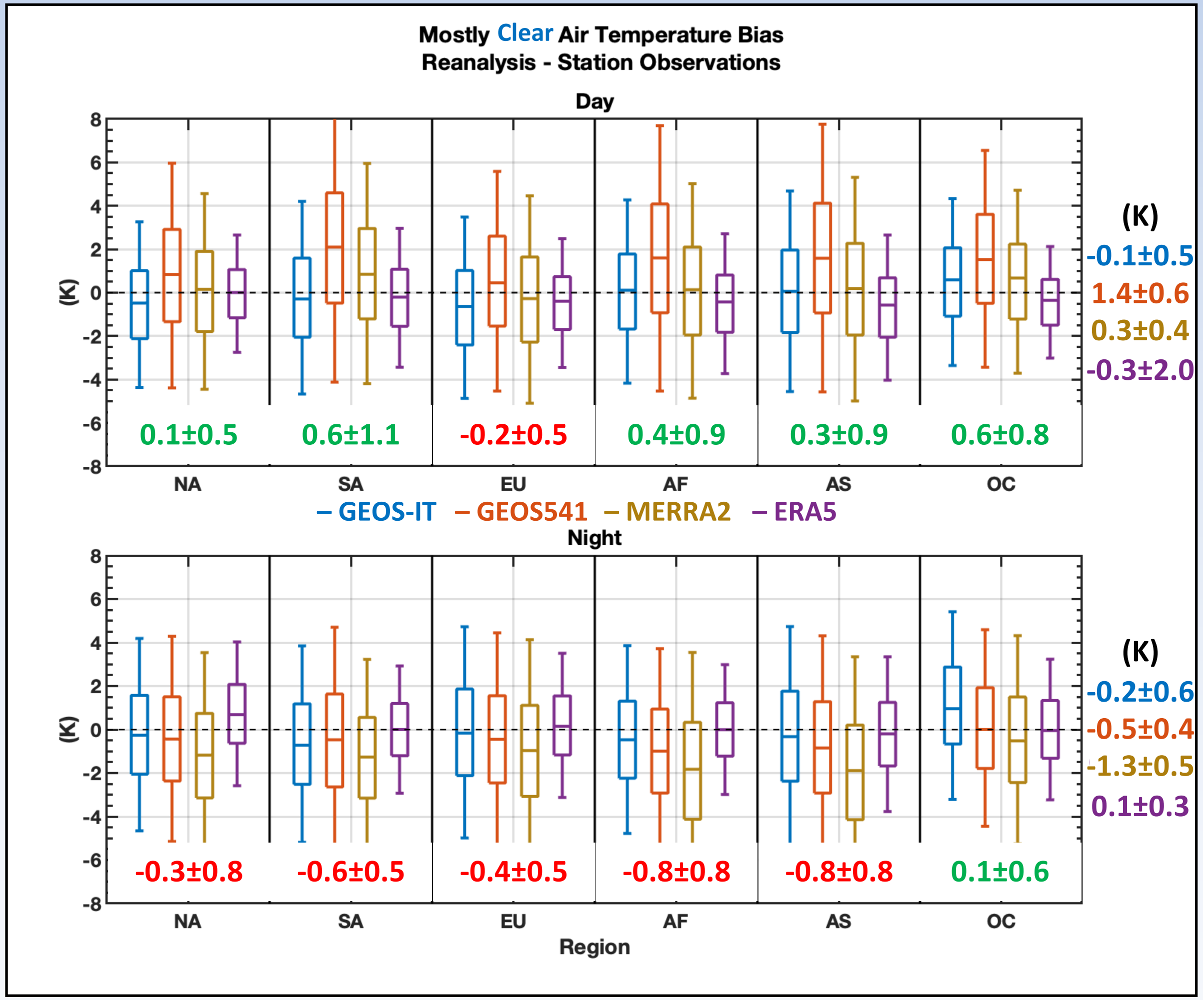
- Large average bias and seasonal variation in GEOS541 daytime clear-sky
- MERRA2 1+ K too cold at night with ~0.6-K month-to-month variance
- ERA5 is the most certain and consistent – although too warm at night

- Overall larger month-to-month variation in cloudy conditions
- GMAO too cold in Jan and Apr – Oct at night
- Nighttime ERA5 improved when cloudy – daytime accuracy remains

GEOS-IT and GEOS541 diurnal relationships consistent with changes in heat capacity – seasonal relative distributions more consistent in clear conditions

Regional Station Observation Comparisons



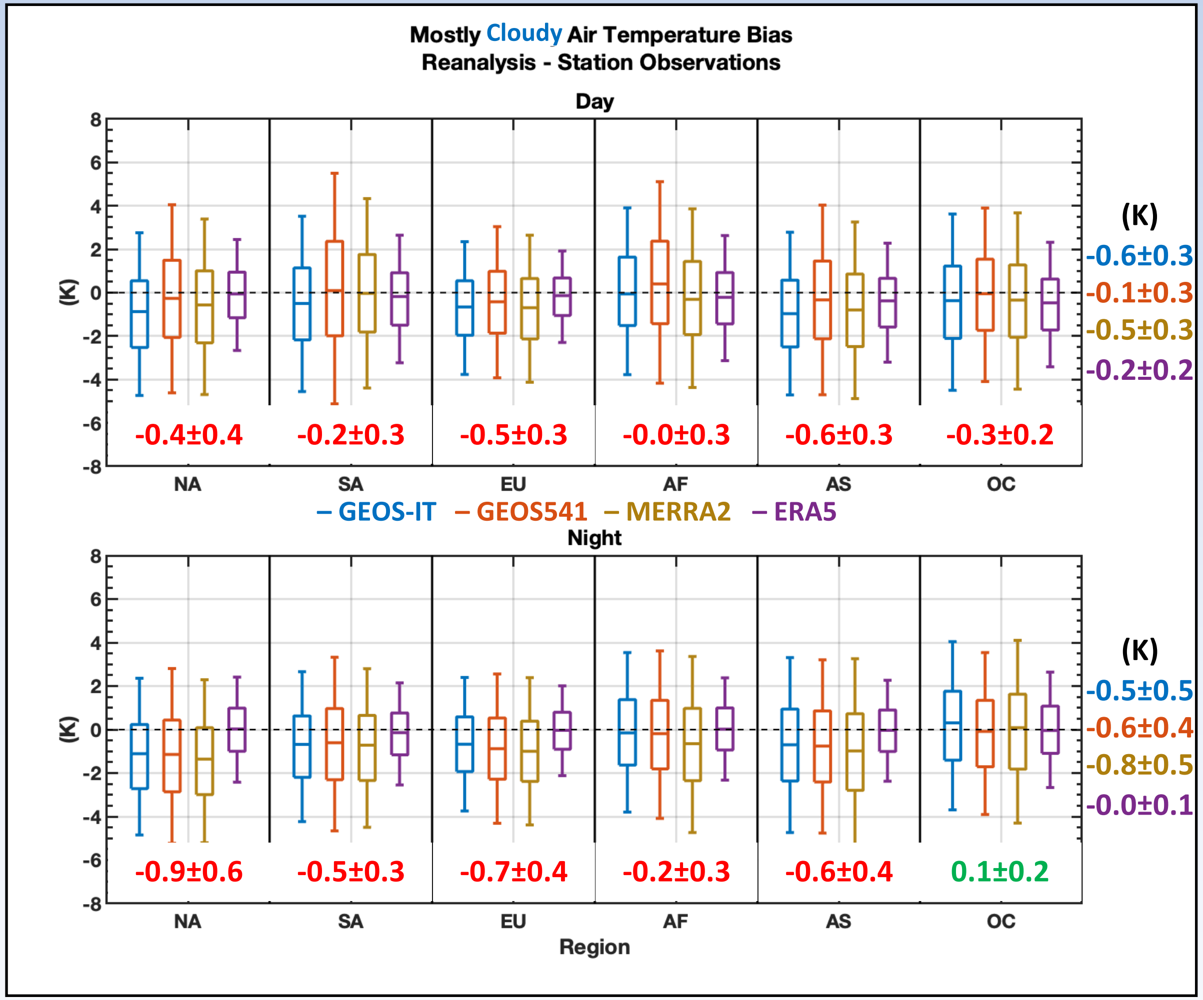


- GEOS-IT overall small bias and uncertainty compared to GEOS541 and MERRA2
- ERA5 fairly consistent – although NA seems out-of-family (especially at night)

Regional Station Observation Comparisons

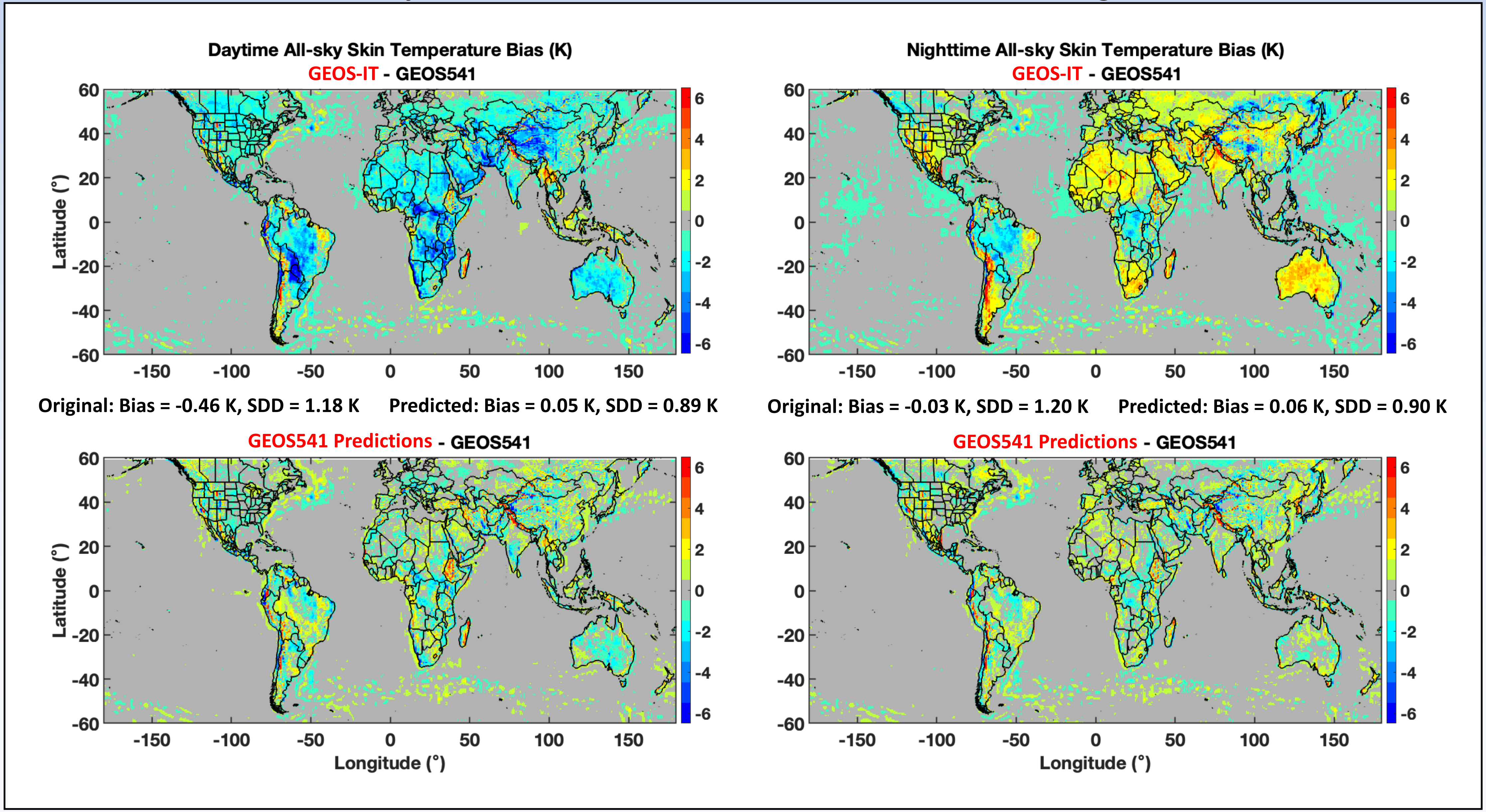
- Overall smaller region-to-region variation in cloudy conditions
- GEOS-IT less consistently accurate when cloudy
- GMAO largely too cold over land
- Relatively good ERA5 regional consistency, especially at night – although daytime AS and OC are noticeably too cold

Assimilation most beneficial where overcast



Deep Neural Network to Estimate Reanalysis Skin Temperature

Day | **Night**

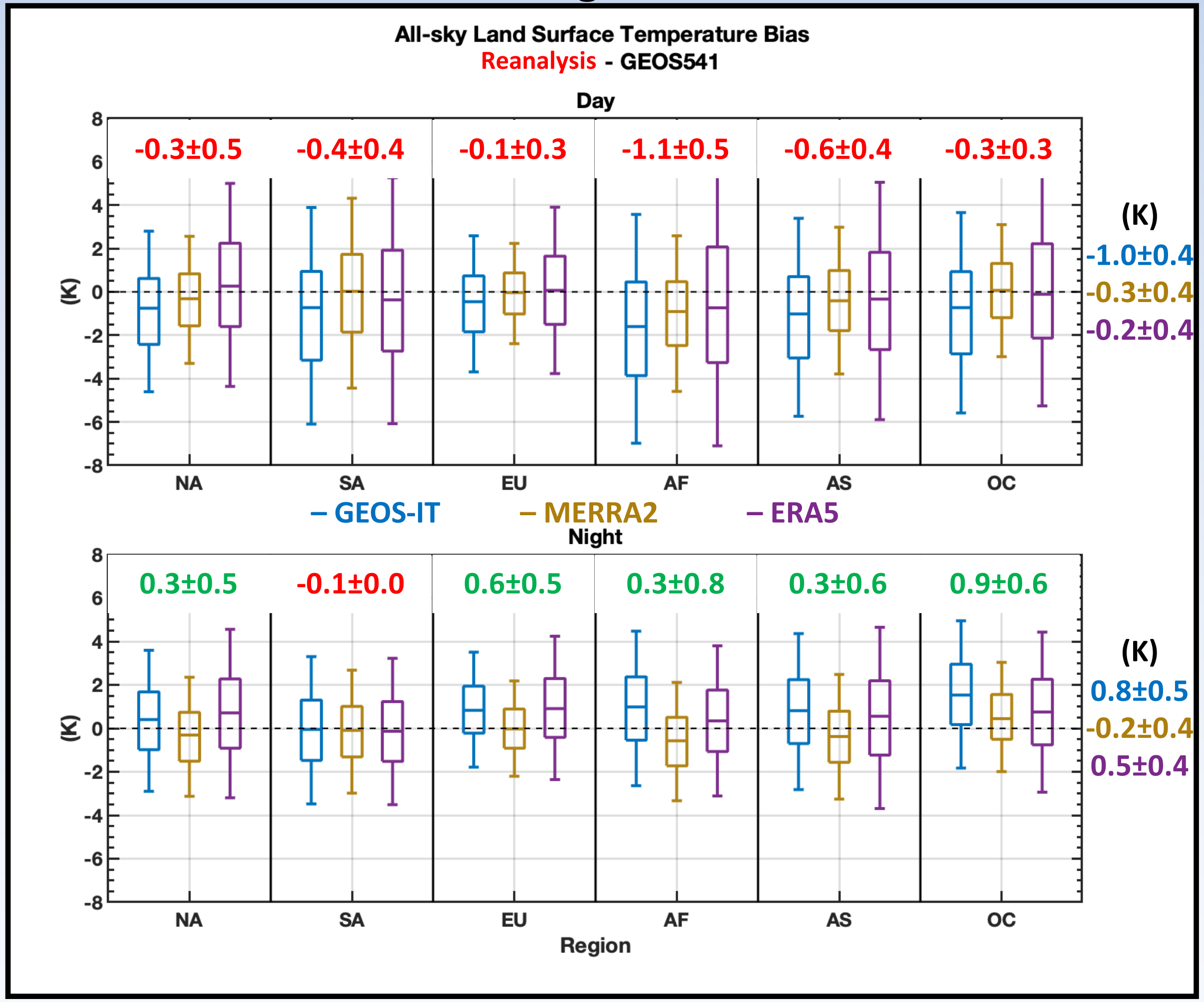


Original

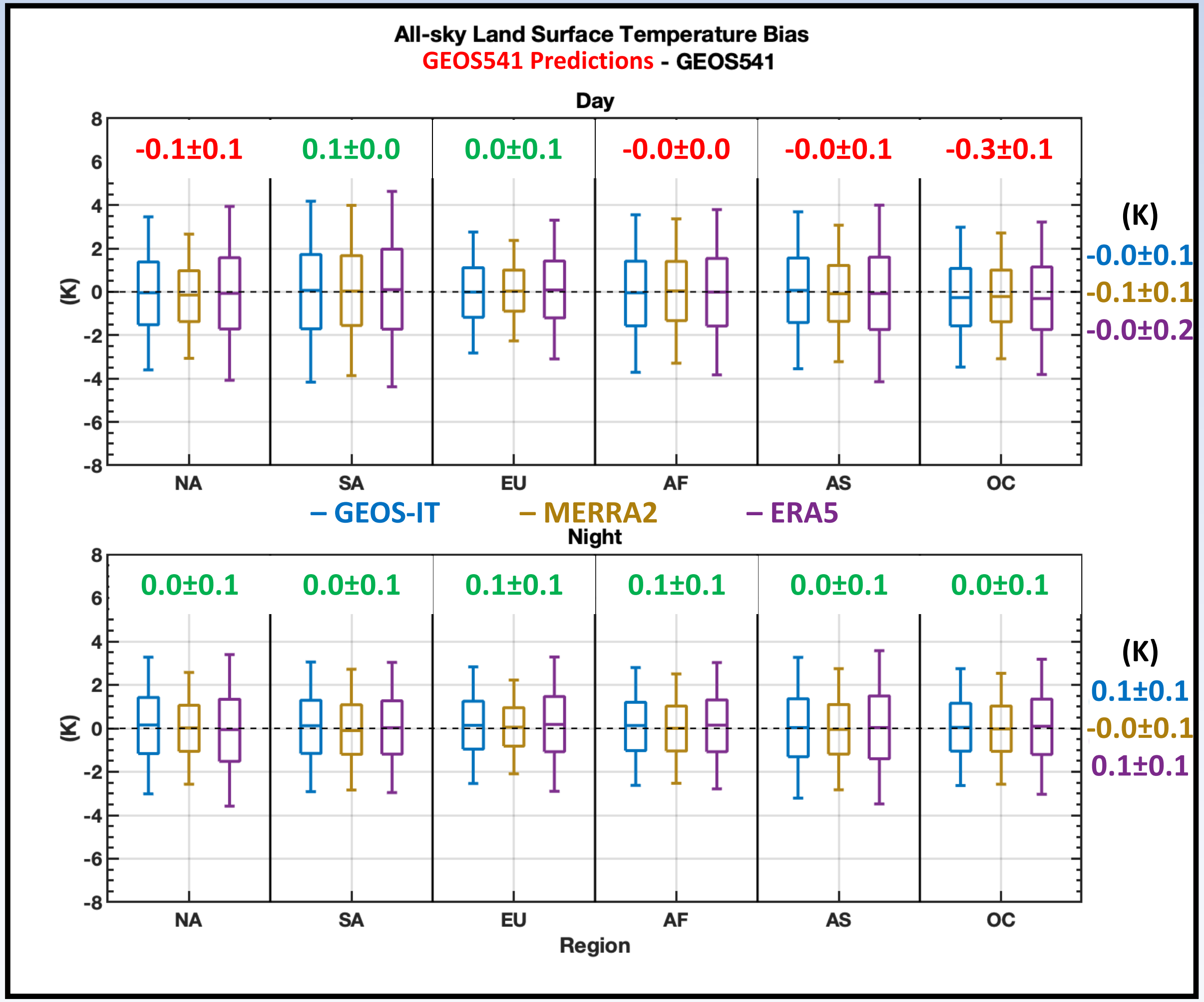
With DNN

Deep Neural Network to Estimate Reanalysis Skin Temperature

Original



With DNN



- Model relationships are multi-variate and complex
- DNN can help unravel and more consistently simulate all-sky GEOS541 T_s from different GMAO inputs

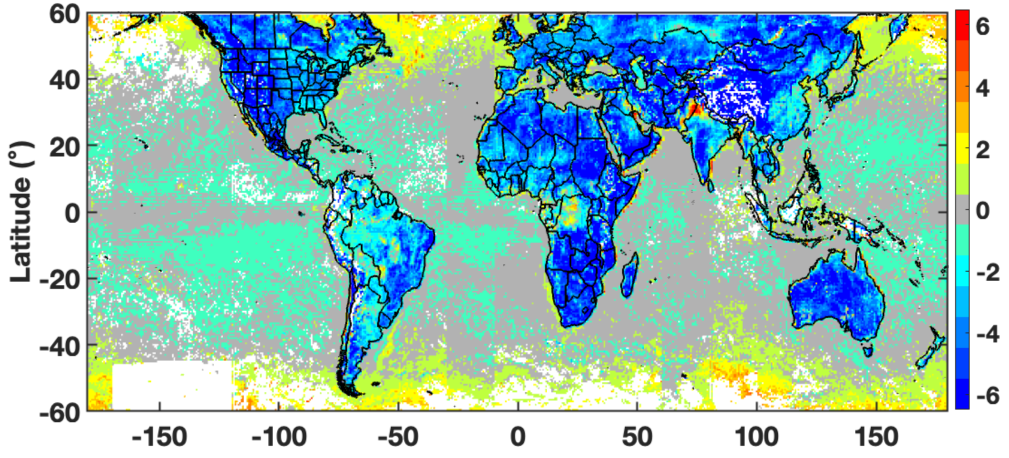
Note: Yet to prove that this DNN approach will result in more consistent cloud retrievals

Deep Neural Network to Estimate Satellite Skin Temperature

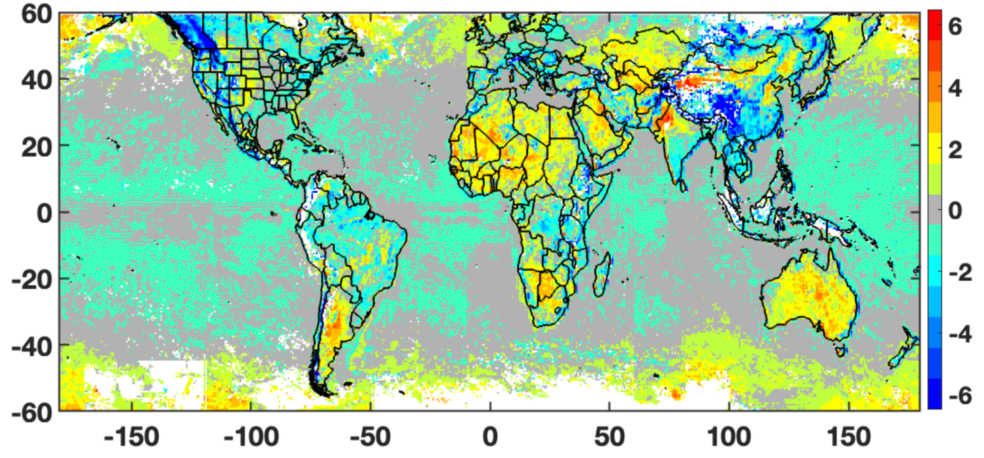
Day | **Night**

Original

Daytime Clear-sky Skin Temperature Bias (K)
GEOS-IT - Satellite Observations



Nighttime Clear-sky Skin Temperature Bias (K)
GEOS-IT - Satellite Observations

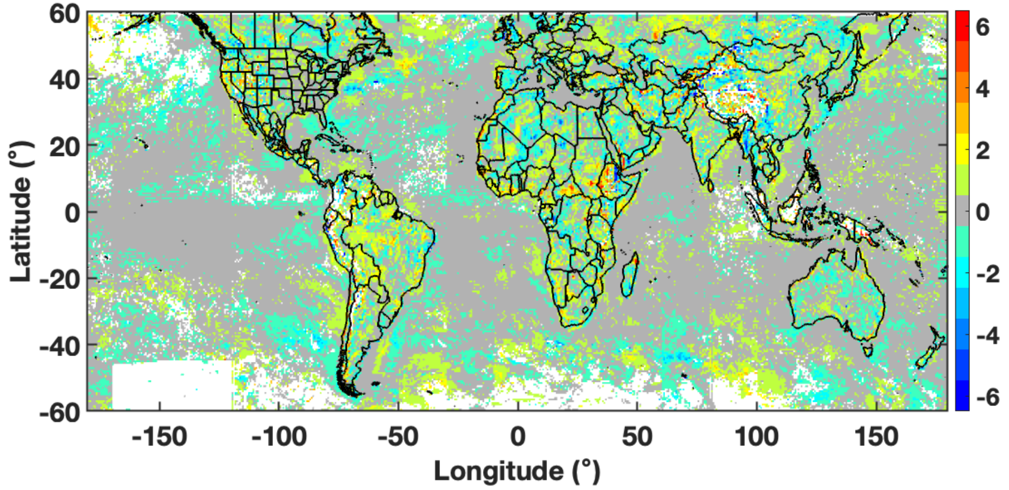


Original: Bias = -2.64 K, SDD = 2.70 K Predicted: Bias = -0.03 K, SDD = 1.01 K

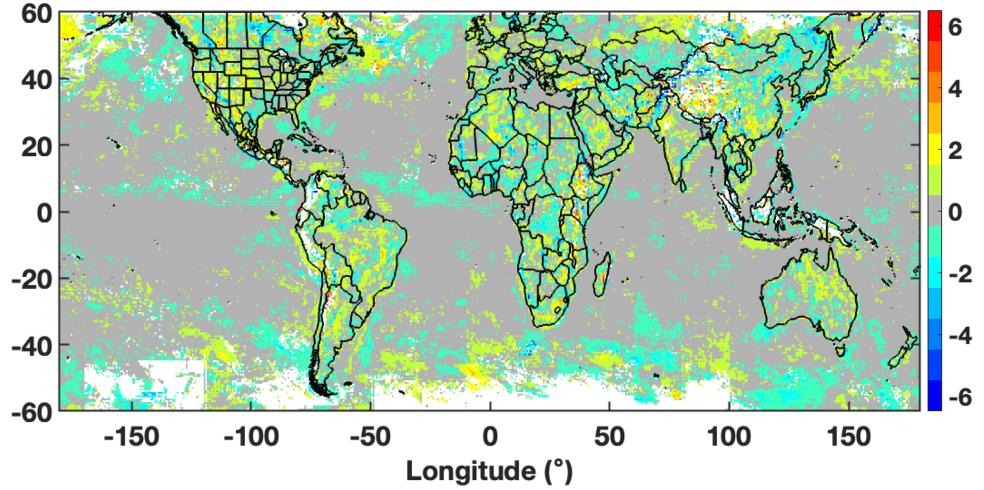
Original: Bias = 0.13 K, SDD = 1.55 K Predicted: Bias = -0.00 K, SDD = 0.82 K

With DNN

Satellite Predictions - Satellite Observations

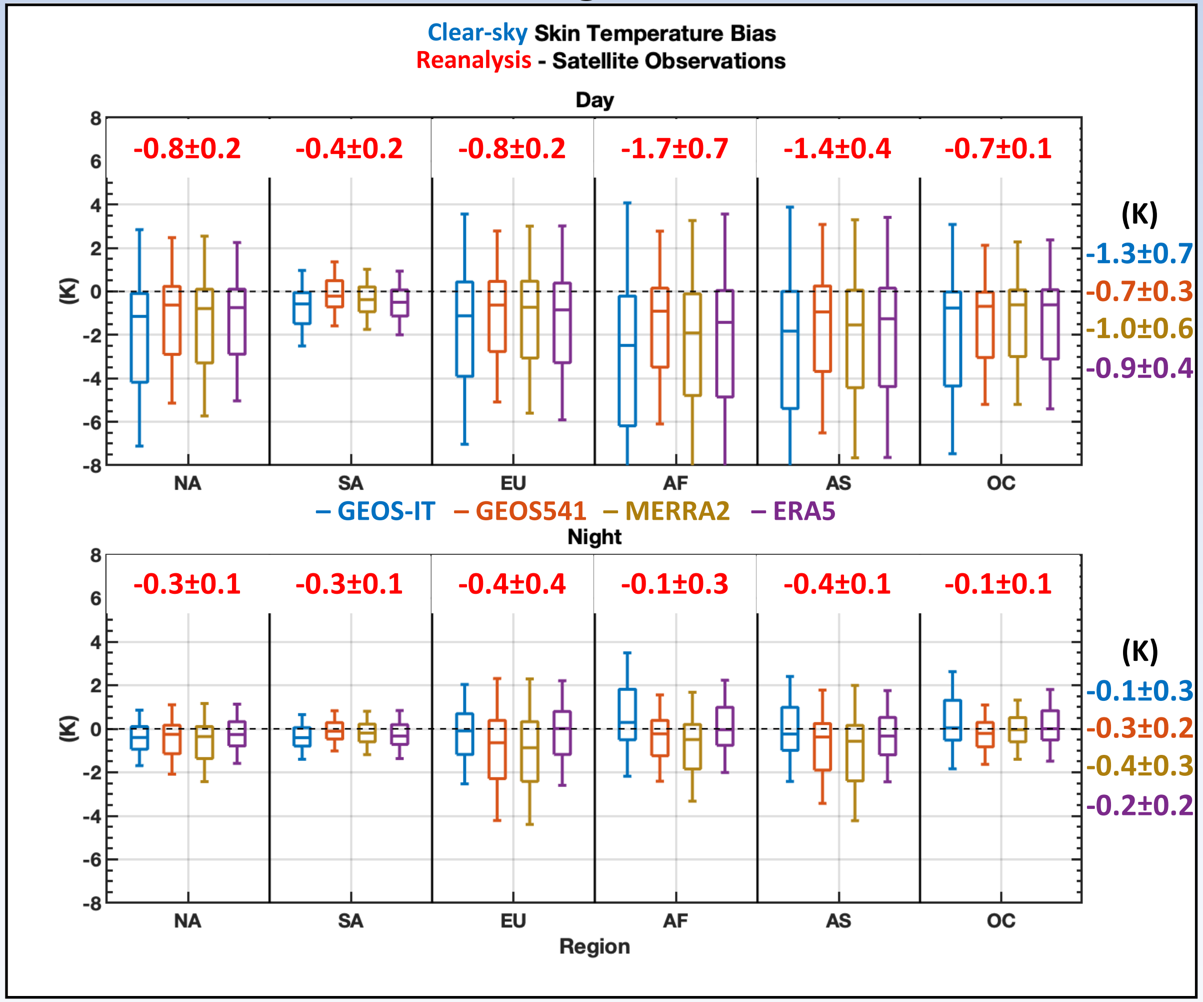


Satellite Predictions - Satellite Observations

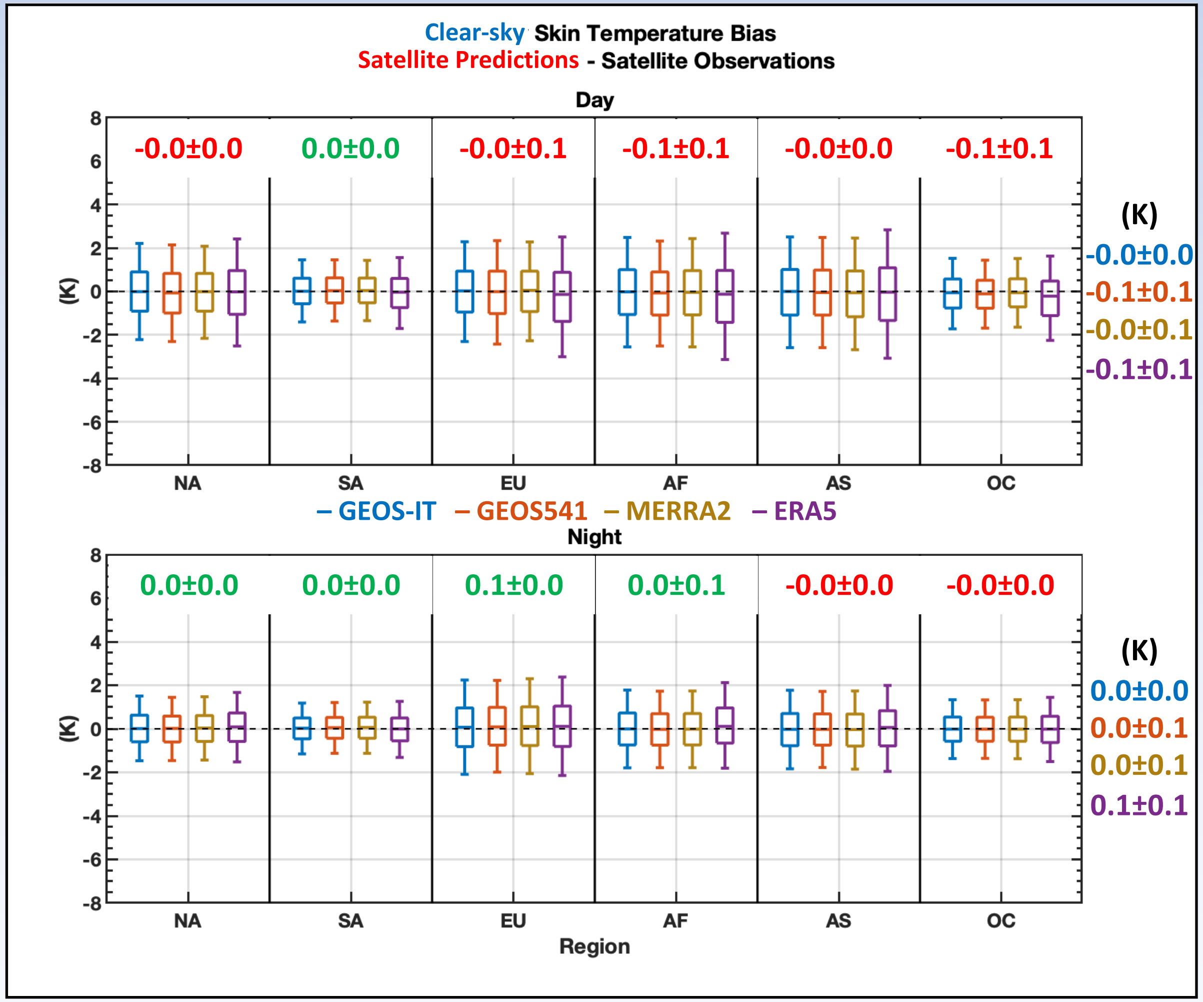


Deep Neural Network to Estimate Satellite Skin Temperature

Original



With DNN



- Observation relationships show greater complexity
- DNN can exploit predictor correlations to arrive at a consistent, observations-based answer

Reanalyses T_s not designed to match Satellite T_s, but a deep neural network can help achieve that

Summary

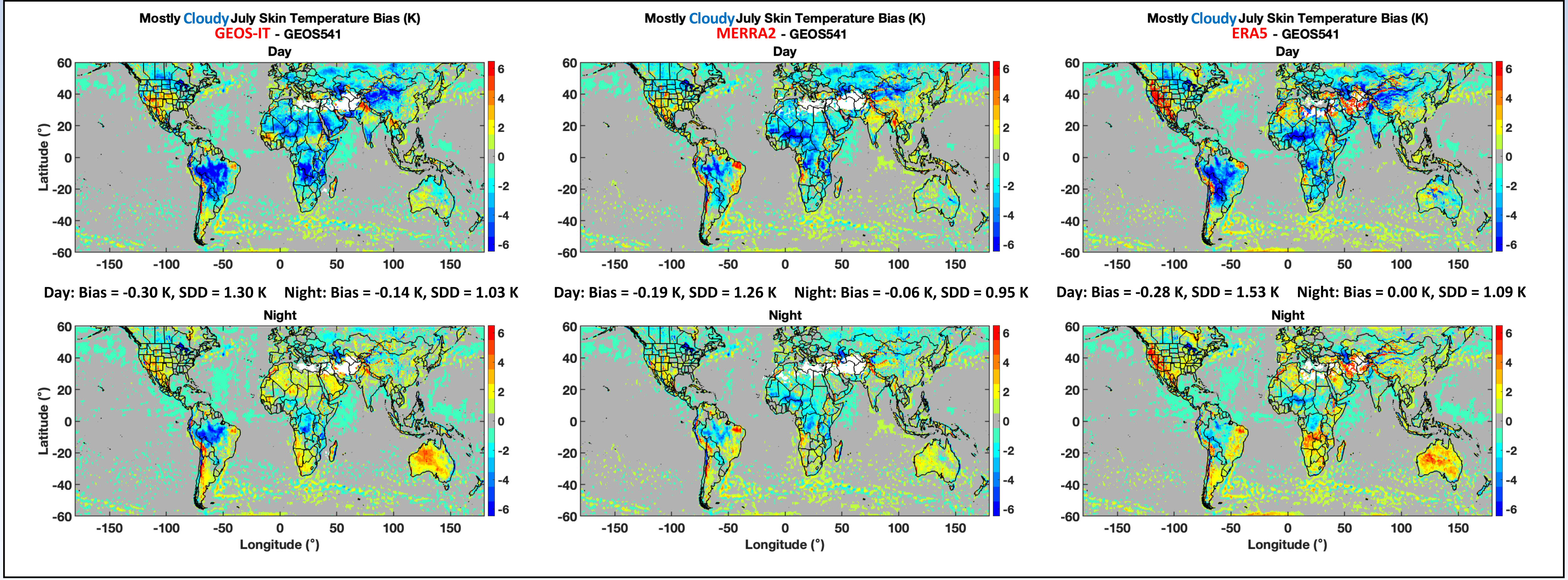
- Clear and cloudy differences in T_a may inform expected T_s bias in cloudy conditions
- Varying relative performance between GMAOs across different seasons, regions, day+night, and cloud condition complicates T_s bias accounting
- ERA5 T_a is seasonally and (mostly) globally consistent
  - Except nighttime clear over NA and daytime AS and OC
  - Overcast conditions are especially accurate
- A deep neural network is effective at simulating a reference T_s that is consistent given any reanalysis dataset

Next Step: Use a DNN with GMAO inputs to correct GMAO T_a to observed T_a in sufficiently cloudy conditions

– i.e., use T_a-informed estimated T_s for better cloud optical depth and height retrievals and flux calculations

Additional Slides

Global Reanalysis Skin Temperature Differences

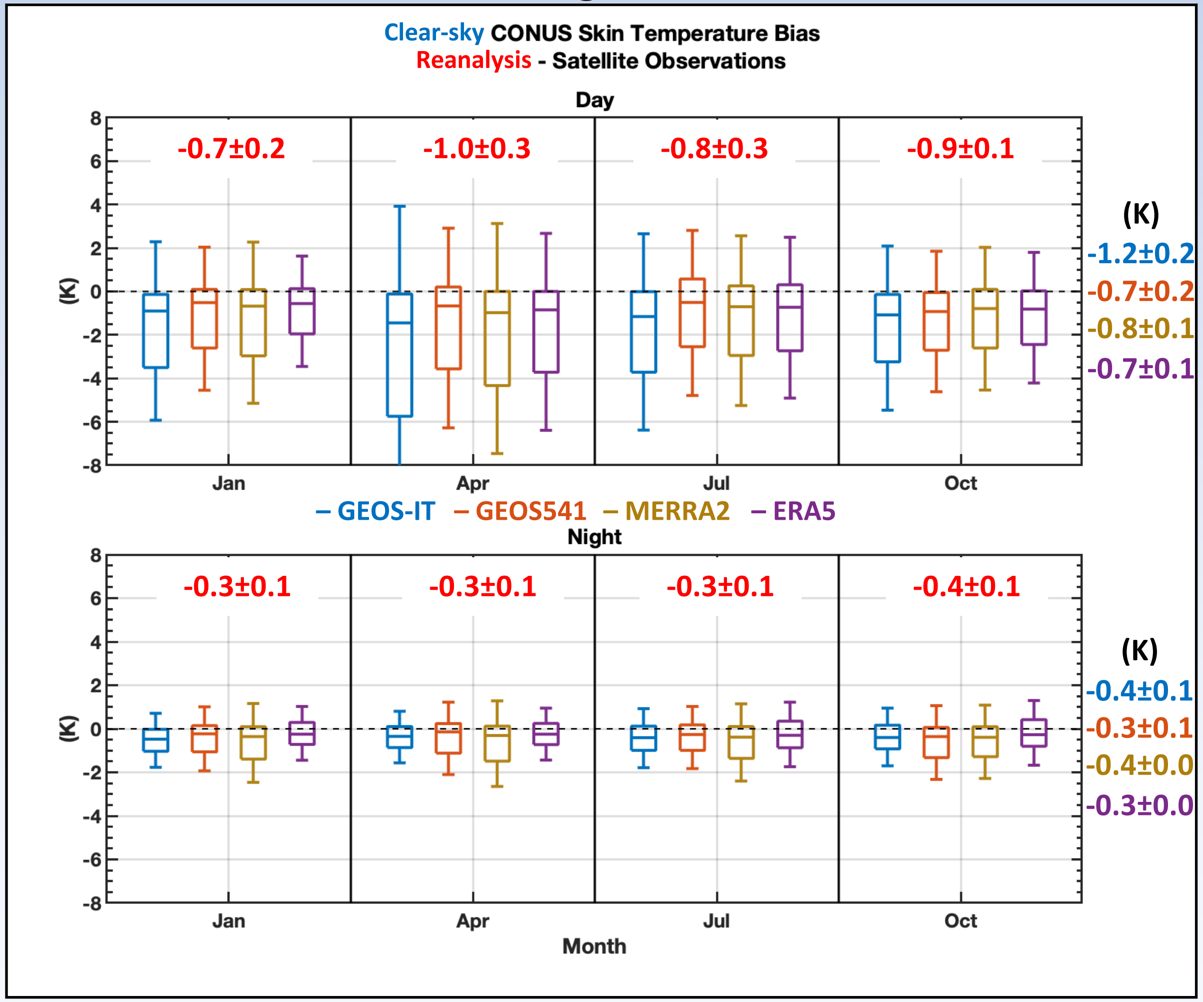


- Relationships change depending the reanalysis cloud conditions
- T_s tied to model's accuracy in predicting clouds

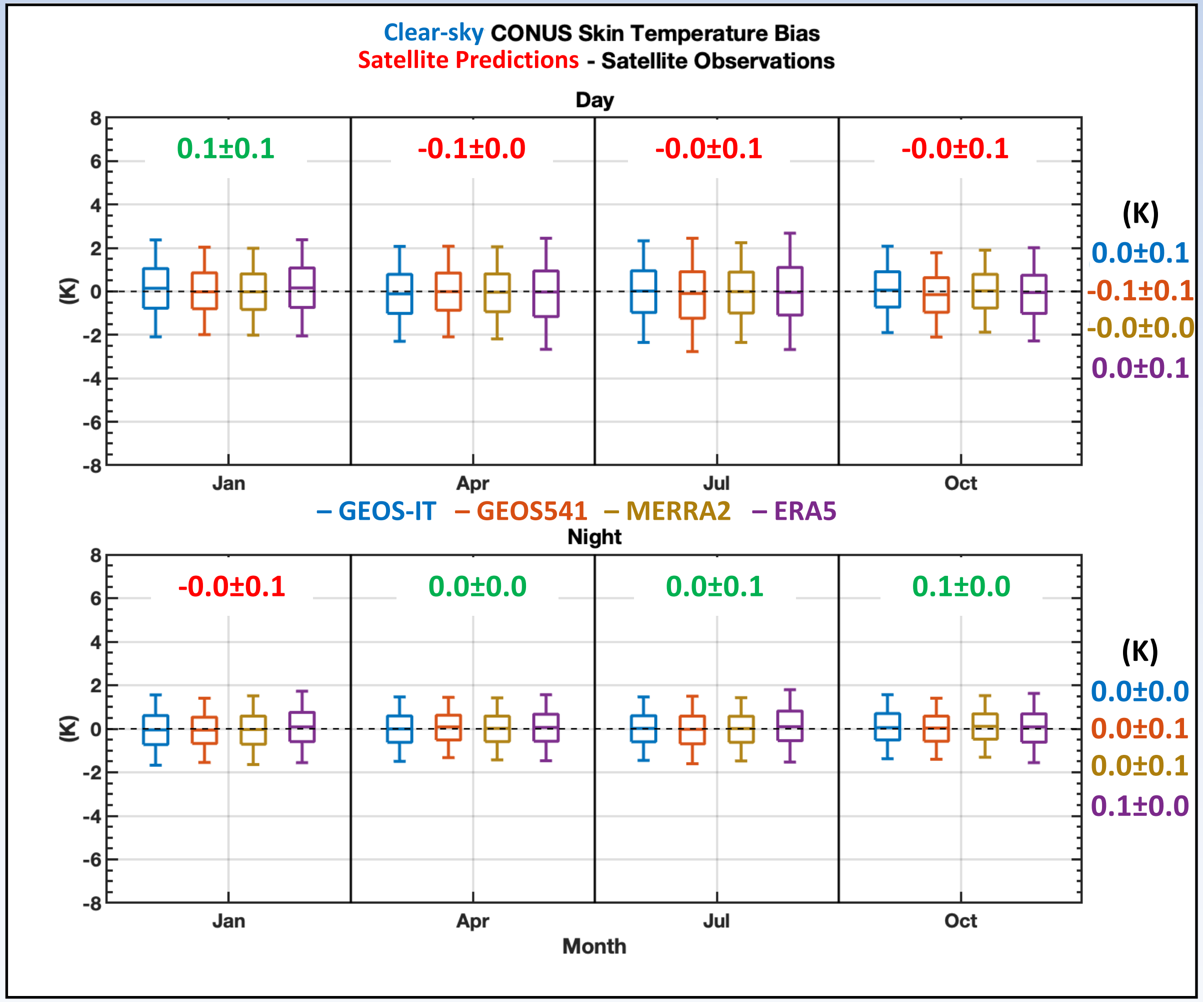
Resolving these degrees of freedom is a nonlinear consideration

Deep Neural Network to Estimate Satellite Skin Temperature

Original



With DNN



A DNN can consistently simulate satellite T_s from GMAO inputs