

CDAF Task Team

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The CDAF

- Climate Data Assessment Framework

- A CDR is "a time series of measurements of sufficient length, consistency and continuity to determine climate variability and change" (NRC, 2004), ideally traceable to SI standards.
- The CDAF is intended to be used to support users of sea surface temperature (SST) datasets to understand the suitability of GHRSSST datasets for use as Climate Data Records (CDRs).
 - Will provide authoritative, comparable information about GHRSSST datasets that will allow users to make their own judgment about the use of the datasets as CDRs for their application.

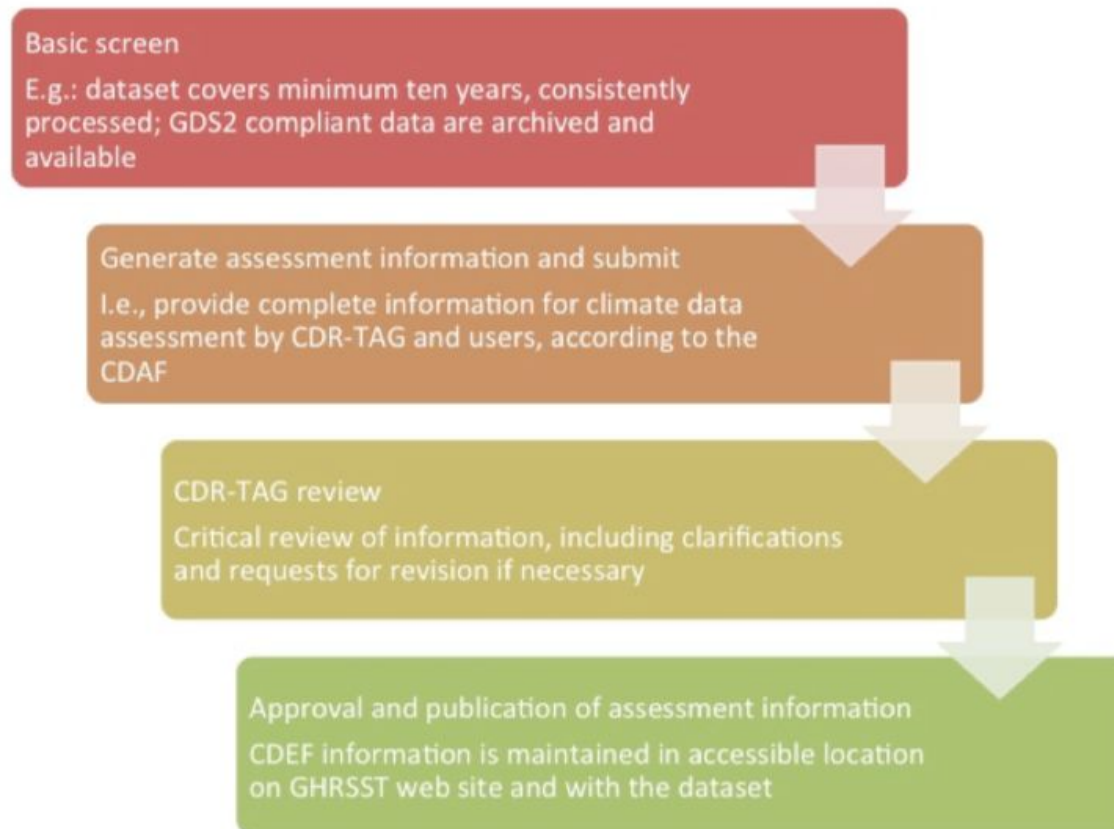
- Task Team

- Has been in existence for several years but other pressures/projects have meant that progress has been slow to date
- Progress has been made this year on the coding side
 - Last report discussed MMD work which has been on hold for the past year

Overview of the CDAF

- There are a number of sources of information that are needed

Climate Data Assessment Framework



CDAF Tool metrics

- Primarily to be used to provide information for section 2
 - Generate assessment information (Quantitative measures)
 - Systematic differences referenced to drifting buoys
 - *Global median difference*
 - *Bin SST to buoy differences on a $10^{\circ} \times 10^{\circ}$ scale and estimate standard deviation of subsets (filter out bins with too few matches first)*
 - Systematic differences referenced to Argo measurements
 - *Global median difference*
 - *Bin SST to buoy differences on a $20^{\circ}(\text{lat}) \times 90^{\circ}(\text{lon})$ scale and estimate standard deviation of subsets (filter out bins with too few matches first)*
 - Non-Systematic effects
 - *Calculate robust standard deviations after median values (including geographic variations) have been removed using above statistics*
 - Stability
 - Use the GTMBA using simplified method from Merchant et al. (2012)
 - SST Sensitivity
 - Calculated SST sensitivities based on retrieval algorithm characteristics (provided by data provider)

Example of current output form

KEY DESCRIPTIVE FEATURES	INFORMATION	
Period covered		
Geographic range		
Spatial resolution		
Temporal resolution		
Timeliness of new data		
Dataset volume		
Valid data fraction		
Data level / grid		
Observation technology		
Dependence on other data		
Type(s) of SST		
Traceability		
Uncertainty info in product		
QUANTITATIVE MEASURES	VALUE	COMMENTS
Difference relative to drifting buoys		Global median difference of satellite minus drifting buoy SST, across full dataset. The satellite SSTs are SST_{skin} with no skin-effect adjustment, so a skin-effect difference of order -0.2 K is to be expected.
Difference relative to Argo		Global median difference of satellite minus upper Argo float SST, across full dataset. The satellite SSTs are SST_{skin} with no skin-effect adjustment, so a skin-effect difference of order -0.2 K is to be expected.
Geographical variation in difference relative to drifting buoys		Geographical variation in difference, as described by the standard deviation of median satellite minus drifting buoy SST differences on space scales of ~1000 km, across the full dataset.
Geographical variation in difference relative to Argo measurements		Geographical variation in bias, as described by the standard deviation of median satellite minus upper Argo float SST differences on space scales of 20° latitude by 90° longitude, across the full dataset.
Dispersion relative to		Spread of differences associated with non-

drifting buoys		systematic effects as quantified by a robust standard deviation of differences of satellite and drifting buoy data, after removing the geographical variations in differences quantified above
Stability		95% confidence interval for the relative multi-year trend between satellite SSTs and the Global Tropical Moored Buoy Array
Sensitivity to true SST		Average weight of the satellite observations in determining SSTs in the dataset, the difference from 100% representing the weight of prior information in the SSTs

AVAILABILITY, DOC'N, FEEDBACK	
Data URL / ftp / DOI	
Primary peer reviewed reference	
Source of technical documents	
Dataset restrictions	
Facility for user feedback	
Other documentation	
OTHER PRINCIPLES (GCOS)	COMMENTS
2. and 12. Overlaps between sensors exist and are exploited to harmonize the dataset	
3. Detailed history of methods/ algorithms is available	
11. Constant sampling within diurnal cycle	

Workplan

- **Get reference data**
- **Produce Matchups**

Together with Matchup Task Team ([Jean-Francois](#))
Matchup production coordinate with Matchup TT
(Felyx based)

Initial data produced but not integrated

- **Create Statistics**

As much as possible this will use already existing code/processes.

- Currently have rewritten (Python) versions of some of Gary Corlett's IDL code, work ongoing

The current set of metrics are fairly simple

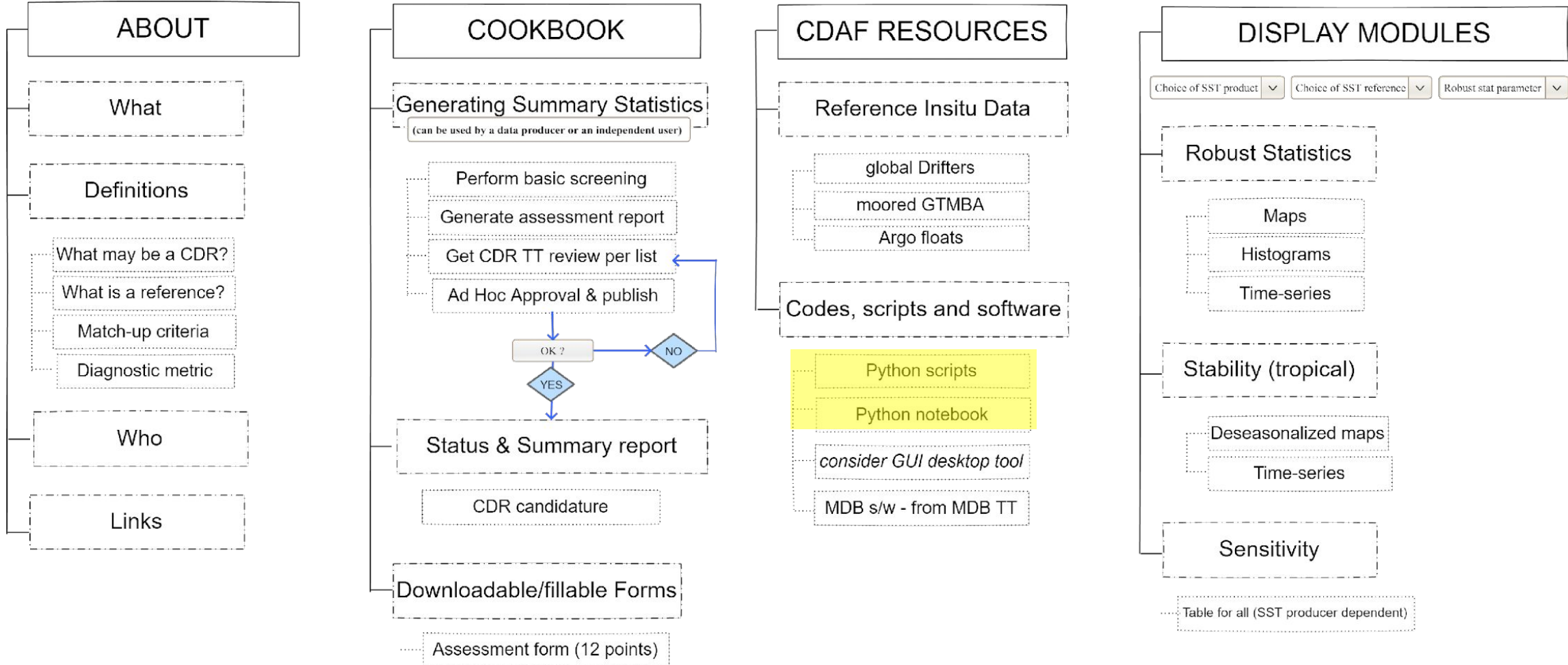
- Means/Medians
- Standard Deviation/Robust Standard Deviations
- Geographic binning code

- **Web/Form output**

Initial designs ideas created
([Prasanjit](#))

Web Workflow Design

Sitemap: Climate Data Assessment Framework (CDAF) web



IDL to Python Conversion

IDL codes' names (Gary C.)	Python Notebooks (new)
<p>Main program cci_val_plot_master_timeseries_cdaf.pro</p> <p>subroutines/functions cci_cdaf_assessment_l4.pro rsd.pro stratify_data.pro calc_histogram.pro mpfitfun.pro cci_cdaf_assessment.pro</p>	<p>cci_val_plot_master_timeseries_cdaf.ipynb</p>
<p>Main program cci_stability_plot_main.pro</p> <p>subroutines/functions cci_cdaf_fit_trend.pro</p>	<p>cci_stability_plot_main.ipynb</p>

In scripts and will also be available as Python notebooks
Extra statistics beyond original code available

Snippets

IDL code

```
function cci_cdaf_fit_trend, x, y, range, plot=plot, thick=thick, col=col

COMPILE_OPT idl2

years = ((1./12.)*INDGEN(480)) + 1978

id = where(years ge range[0] and years le range[1] and finite(x) and finite(y), c)
result = LINFIT(x[id], y[id], sigma = sigma)

if keyword_Set(plot) then begin

    fit = result[0] + x[id]*result[1]
    oplot, x[id], fit, color=col, thick=thick
    oplot, x[id], fit+(1.96*sigma[1]*12), color=col, thick=thick, linestyle=1
    oplot, x[id], fit-(1.96*sigma[1]*12), color=col, thick=thick, linestyle=1
endif

return, [result[1] - 1.96*sigma[1], result[1]+1.96*sigma[1]]*12

END
```

Python code

```
def cci_cdaf_fit_trend(x, y, x_range, plot=False, thick=1, col='b', axes=None):
    years = (1.0 / 12.0) * np.arange(480) + 1978
    valid_indices = np.where((years >= x_range[0]) & (years <= x_range[1]) & np.isfinite(x) & np.isfinite(y))
    x_valid = x[valid_indices]
    y_valid = y[valid_indices]
    result = linregress(x_valid, y_valid)

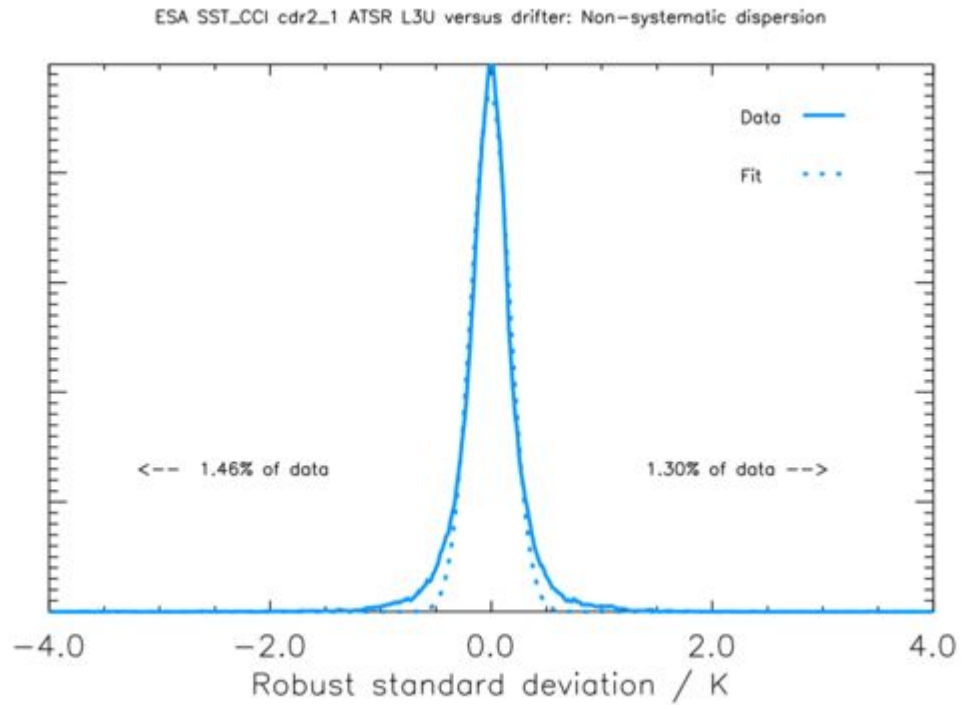
    if plot:
        fit = result.intercept + x_valid * result.slope
        if axes is None:
            plt.plot(x_valid, fit, color=col, linestyle='--', linewidth=thick)
        else:
            axes.plot(x_valid, fit, color=col, linestyle='--', linewidth=thick)

        upper_bound = fit + 1.96 * result.stderr * 12
        lower_bound = fit - 1.96 * result.stderr * 12

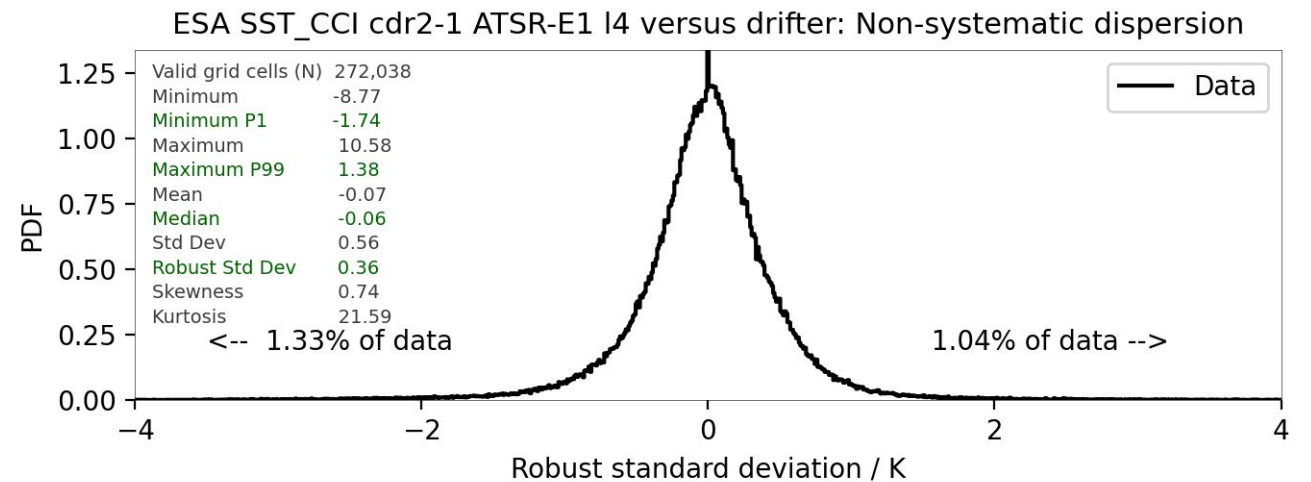
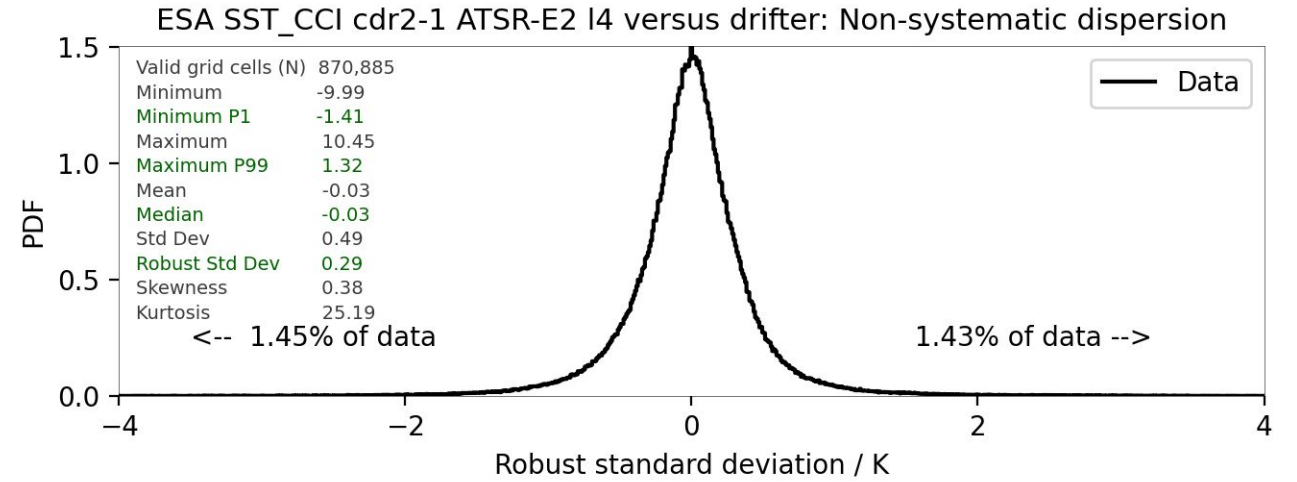
        if axes is None:
            plt.fill_between(x_valid, upper_bound, lower_bound, color=col, alpha=0.2)
        else:
            axes.fill_between(x_valid, upper_bound, lower_bound, color=col, alpha=0.2)

    trend_range = [12 * (result.slope - 1.96 * result.stderr), 12 * (result.slope + 1.96 * result.stderr)]
    return trend_range
```

From Gary's IDL code



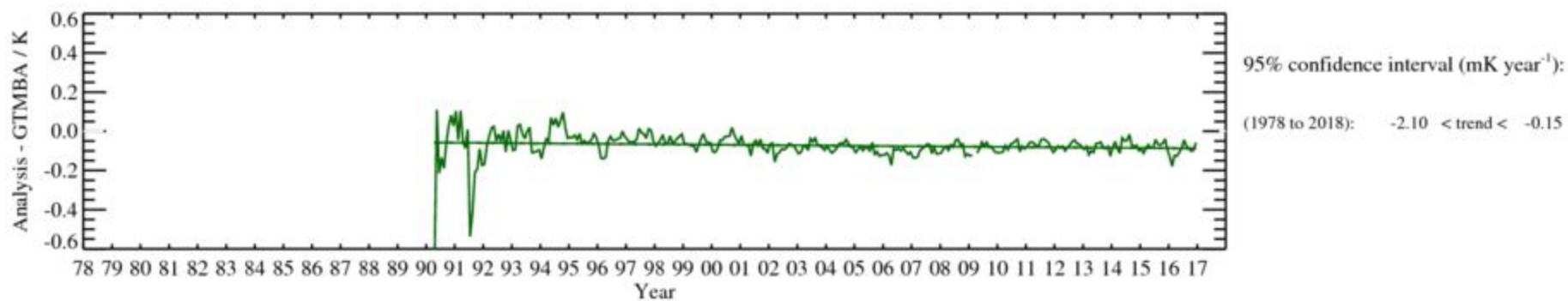
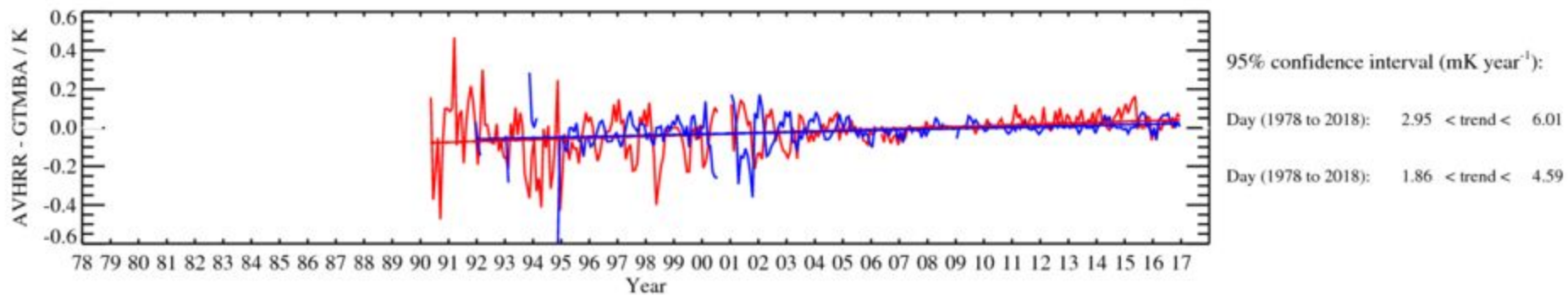
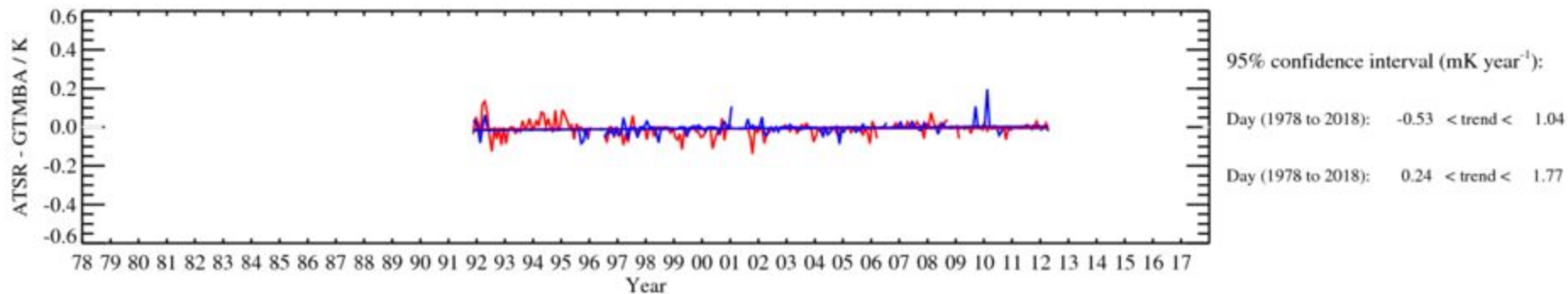
From Python code (newer)



The parameters in Green are robust parameters

ESA SST_CCI Version CDR 2.0 Stability Assessment

From Gary's IDL code



Daytime ATSR/AVHRR



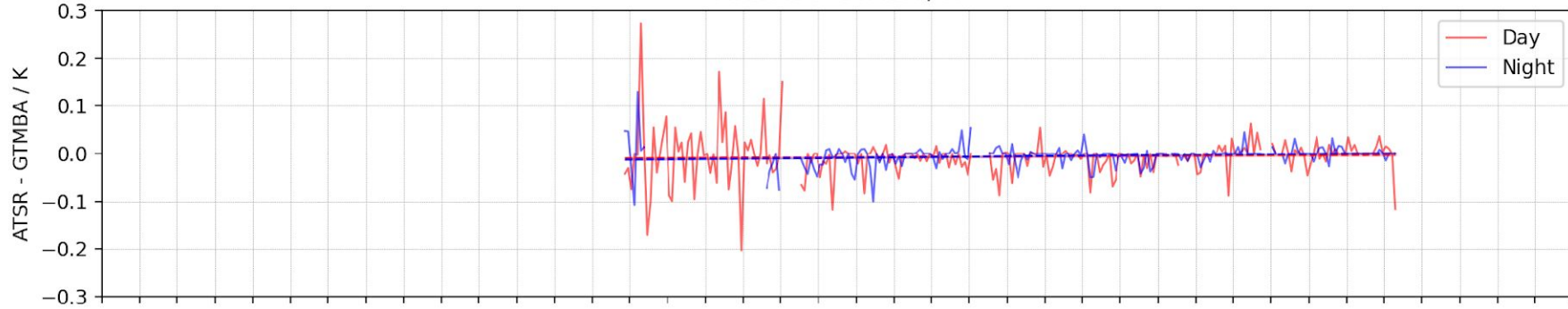
Nighttime ATSR/AVHRR



Analysis



ESA SST_CCI Version CDR 2.0 Stability Assessment
ATSR I3c- GTMBA / K



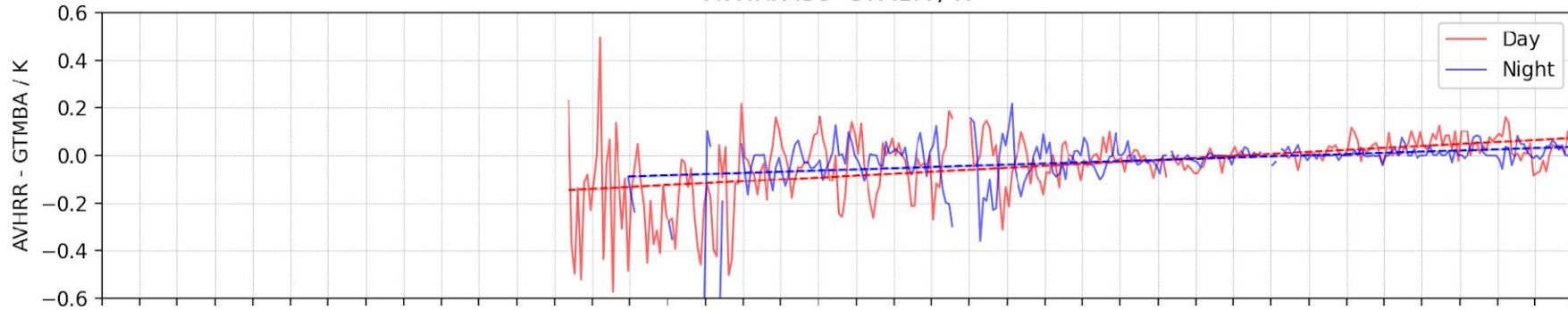
From Python code (newer)

95% confidence interval (mK year⁻¹):

Day (1978 to 2018): -0.61 < trend < 1.28

Night (1978 to 2018): 0.07 < trend < 1.32

AVHRR I3c- GTMBA / K

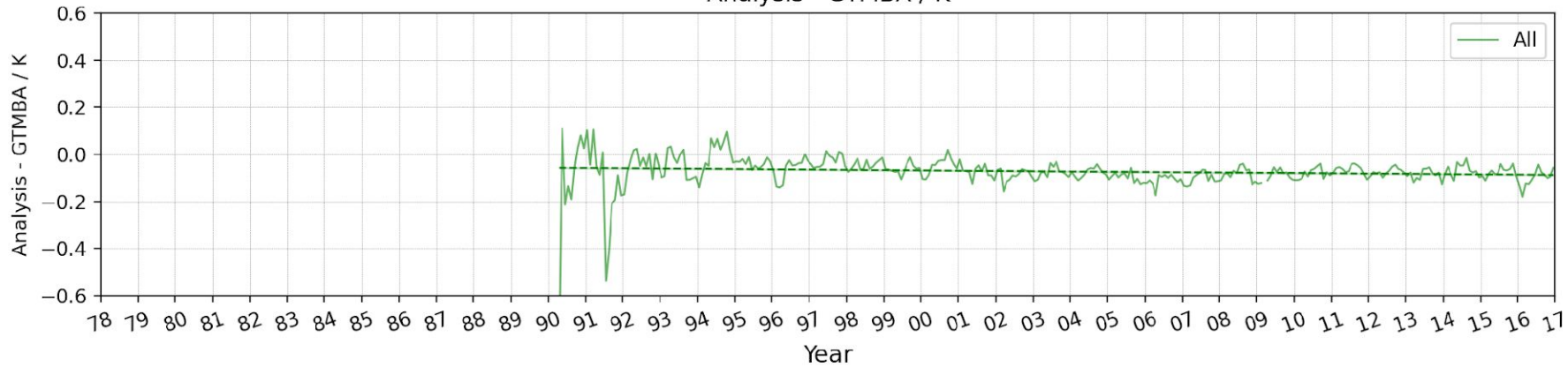


95% confidence interval (mK year⁻¹):

Day (1978 to 2018): 6.49 < trend < 9.93

Night (1978 to 2018): 3.27 < trend < 6.51

Analysis - GTMBA / K



95% confidence interval (mK year⁻¹):

(1978 to 2018): -2.10 < trend < -0.15

Next steps

- Remaining IDL2Py conversion as needed (12 months)
- Interface new code with new matchup data including extra statistics
 - Interface with Felyx generated MMDs
 - Analyze geo-spatial variations
 - Stability analysis
- Setup initial interface
 - Design already in progress
 - Start working on interfaces/code
 - Output structure to CDAF database