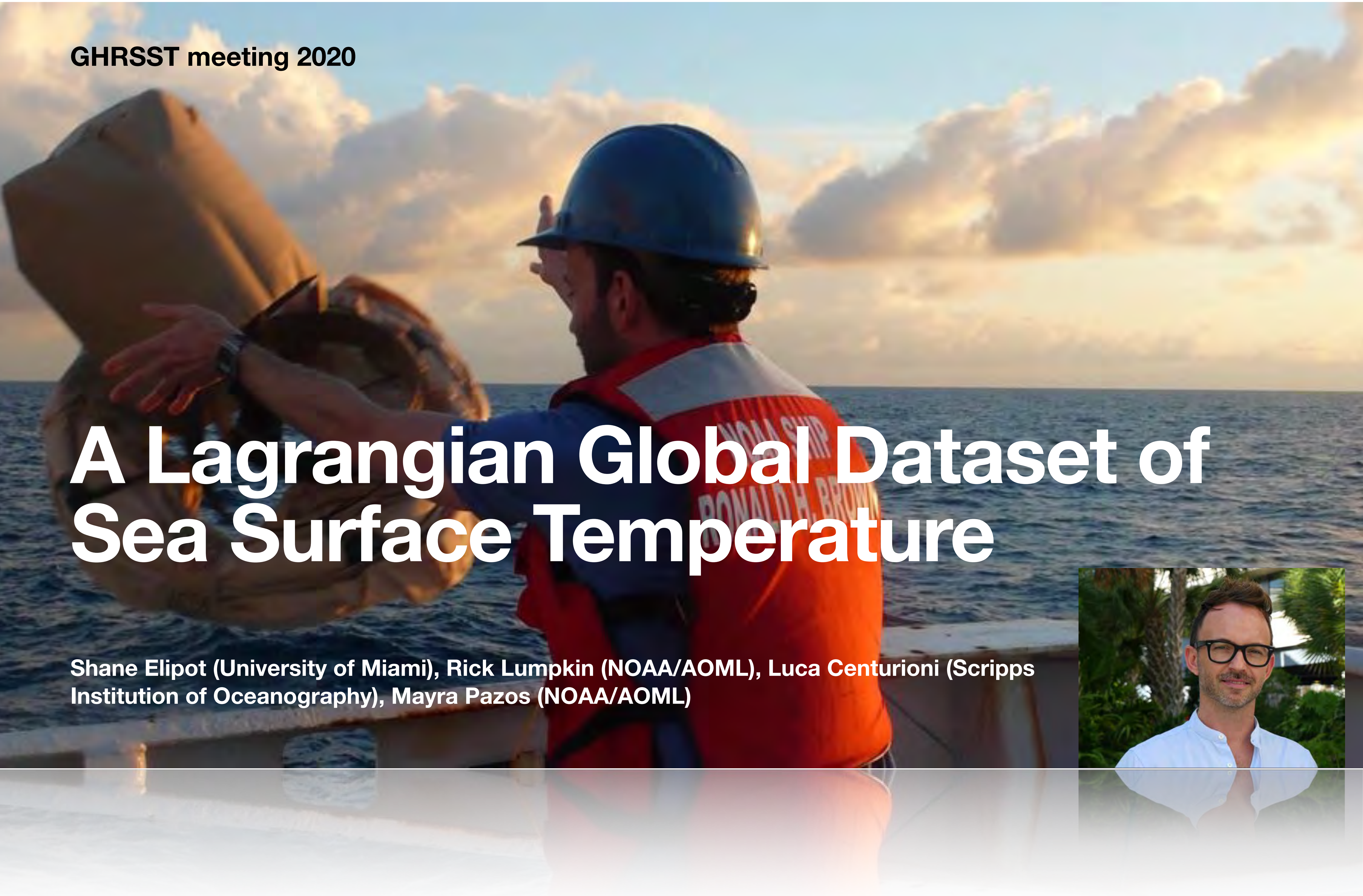
GHRSST meeting 2020

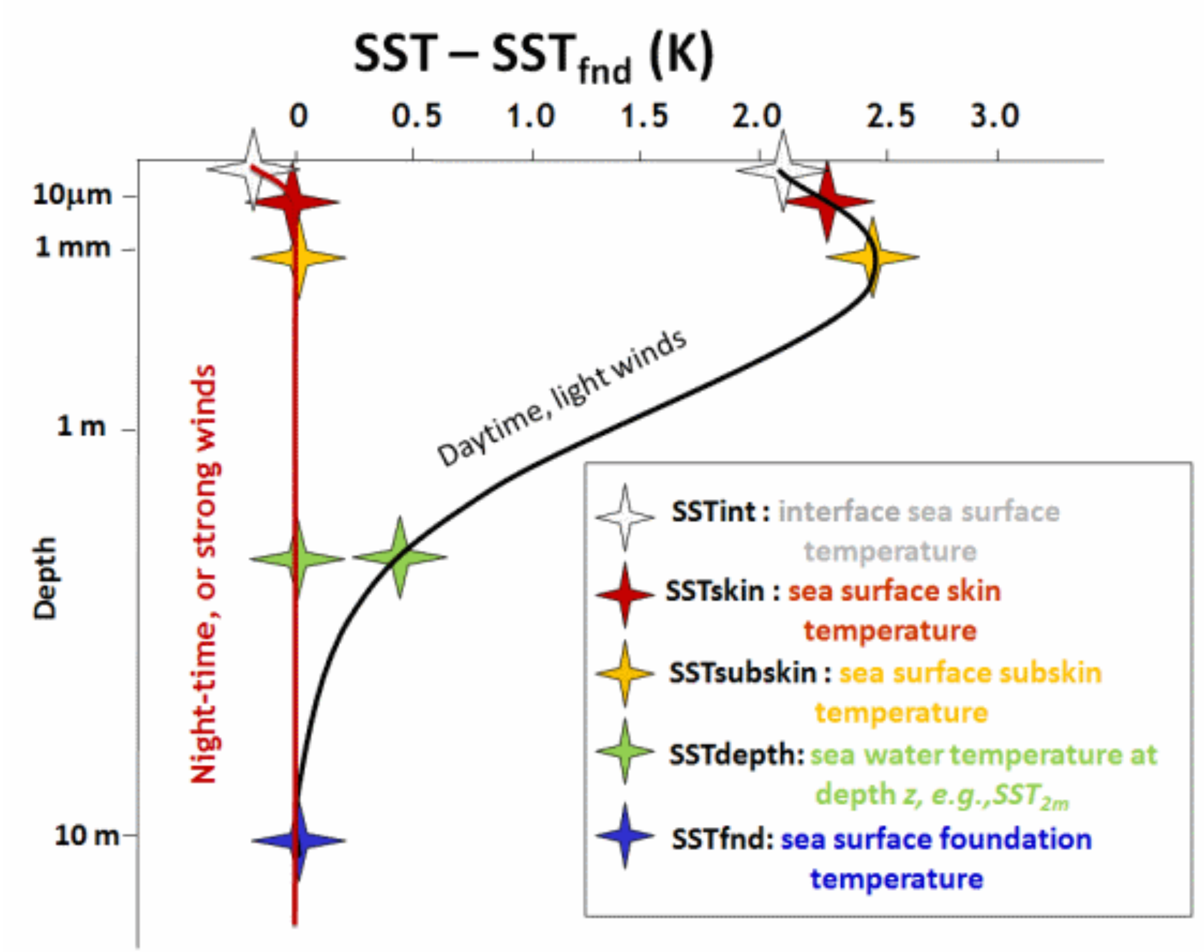


A Lagrangian Global Dataset of Sea Surface Temperature

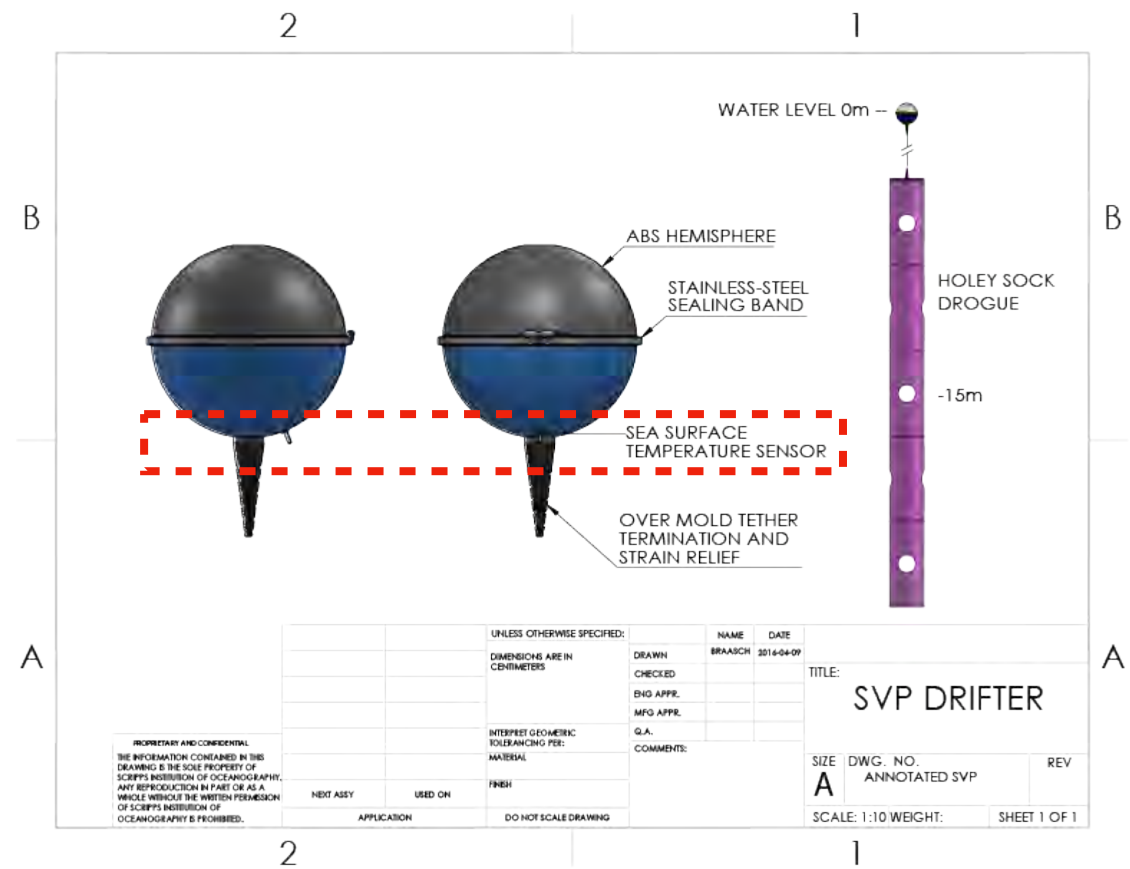
Shane Elipot (University of Miami), Rick Lumpkin (NOAA/AOML), Luca Centurioni (Scripps Institution of Oceanography), Mayra Pazos (NOAA/AOML)

Is a Global Drifter Program (SVP) drifter measuring SST?

<u>My understanding</u>: probably not

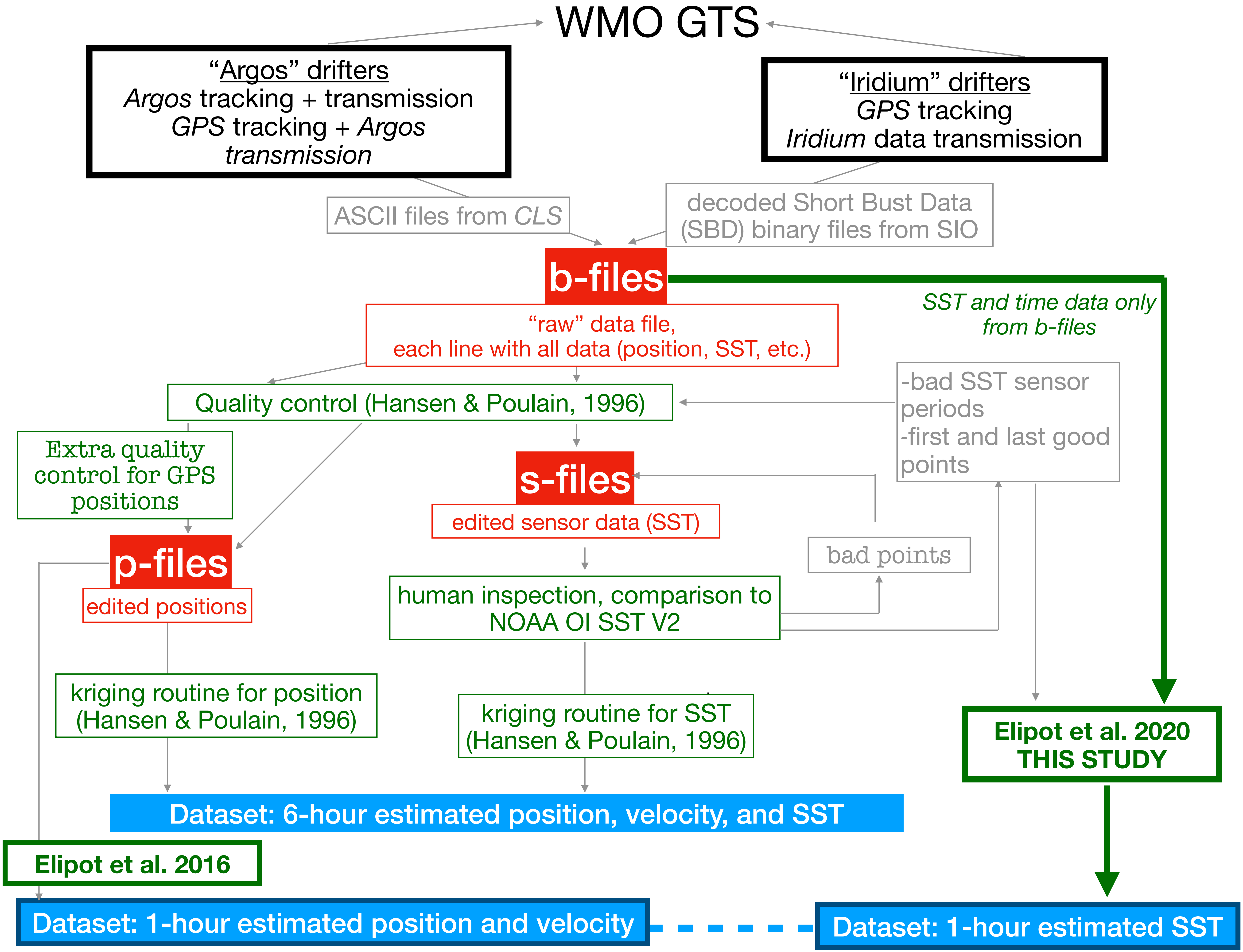


from Group for High Resolution SST (GHRSST)
https://www.ghrsst.org/



Source: Scripps Lagrangian Drifter Laboratory
http://gdp.ucsd.edu/ldl_drifter/instruments/svp.html

A GDP drifter is measuring **sea water temperature at depth** (18 cm?),
However I will use the term “SST” from now on



WMO GTS
"Argos" drifters
Argos tracking + transmission
GPS tracking + Argos transmission
"Iridium" drifters
GPS tracking
Iridium data transmission
ASCII files from CLS
decoded Short Bust Data (SBD) binary files from SIO
b-files
SST and time data only from b-files
"raw" data file, each line with all data (position, SST, etc.)
Quality control (Hansen & Poulain, 1996)
-bad SST sensor periods
-first and last good points
Extra quality control for GPS positions
s-files
edited sensor data (SST)
p-files
edited positions
bad points
human inspection, comparison to NOAA OI SST V2
kriging routine for position (Hansen & Poulain, 1996)
kriging routine for SST (Hansen & Poulain, 1996)
Elipot et al. 2020 THIS STUDY
Dataset: 6-hour estimated position, velocity, and SST
Elipot et al. 2016
Dataset: 1-hour estimated position and velocity
Dataset: 1-hour estimated SST

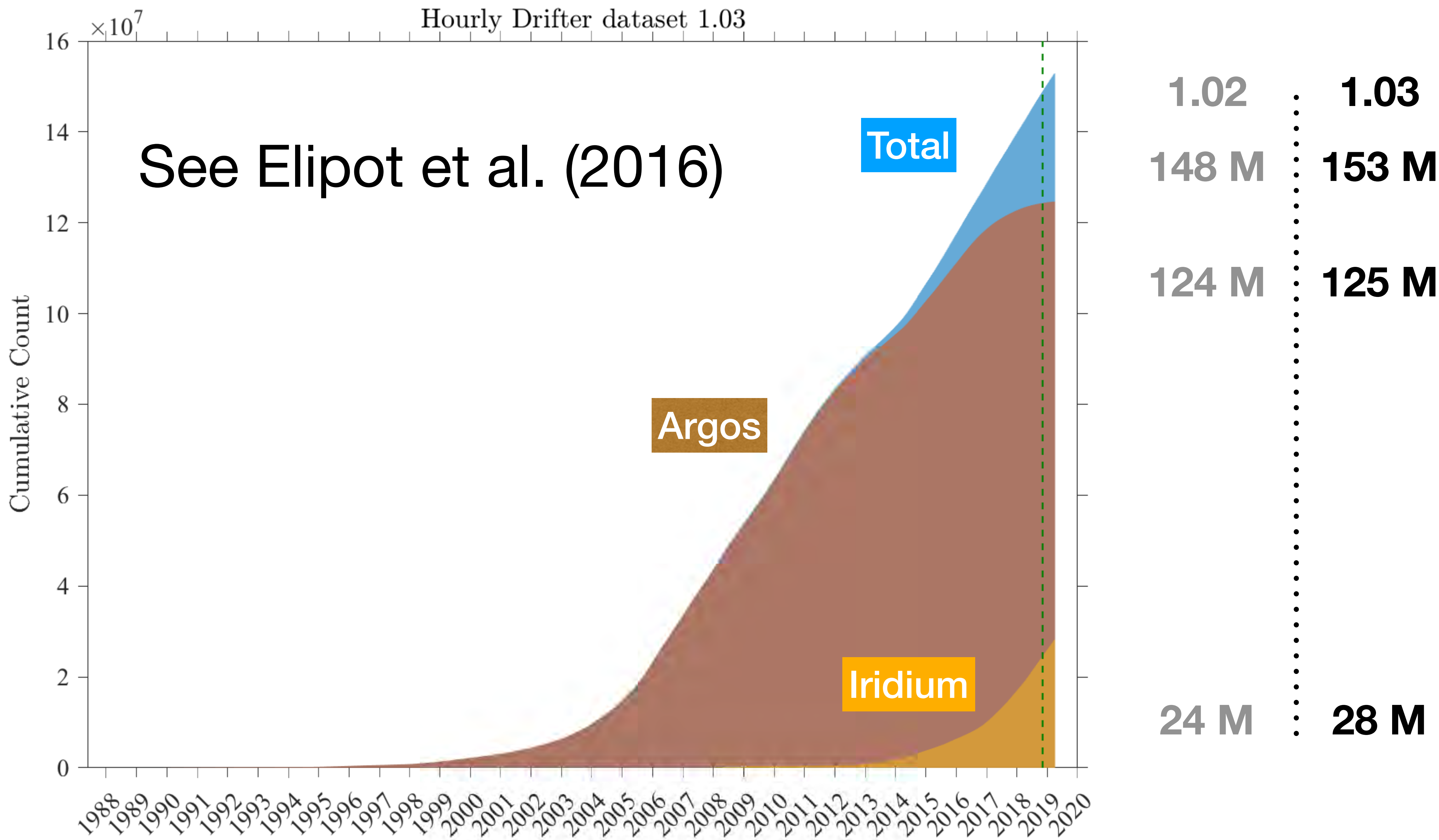
Drifter hourly dataset (position and velocity)

Goal: to add SST hourly estimates

available at https://www.aoml.noaa.gov/phod/gdp/hourly_data.php

Latest release of hourly dataset, 1.03

spans 02-Oct-1987 13:00:00 to 04-Apr-2019 01:00:00

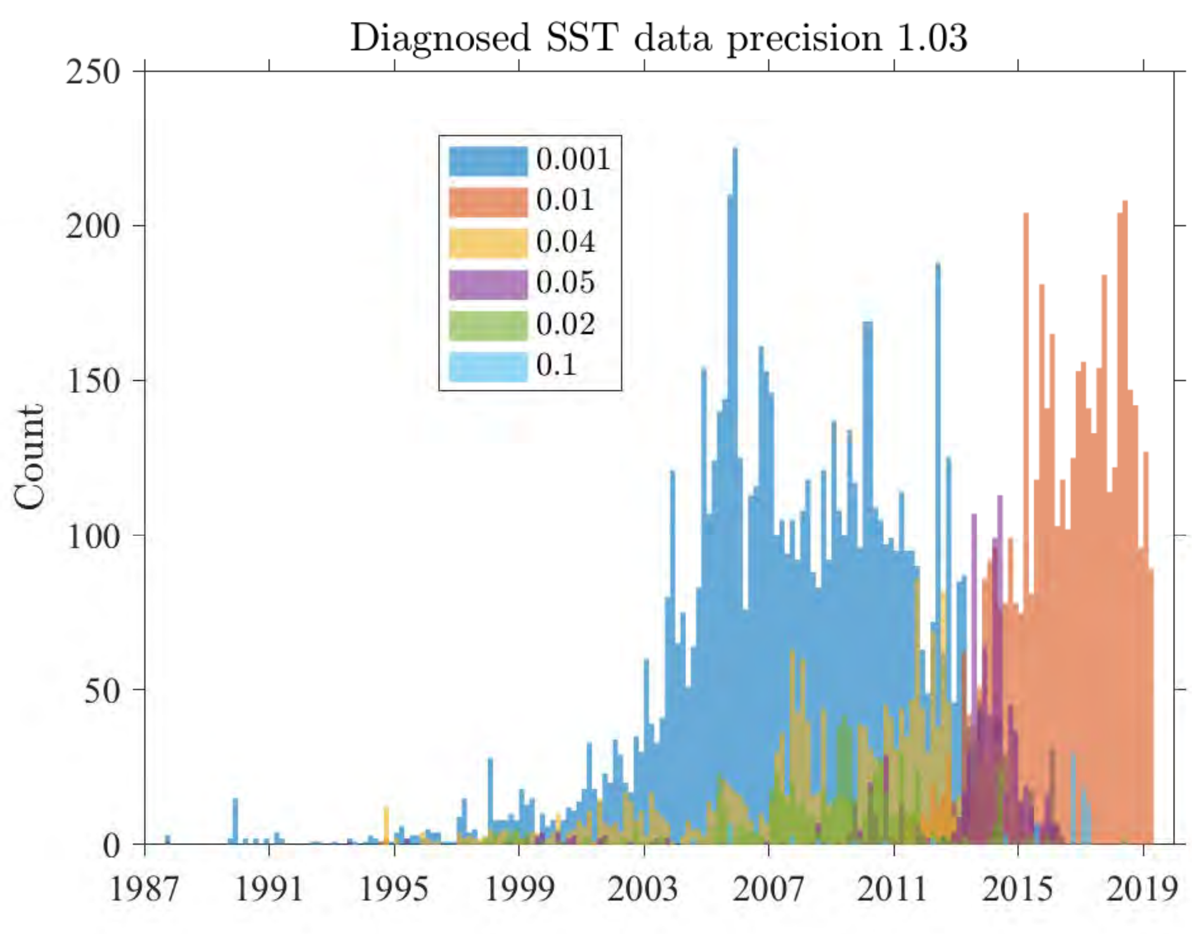


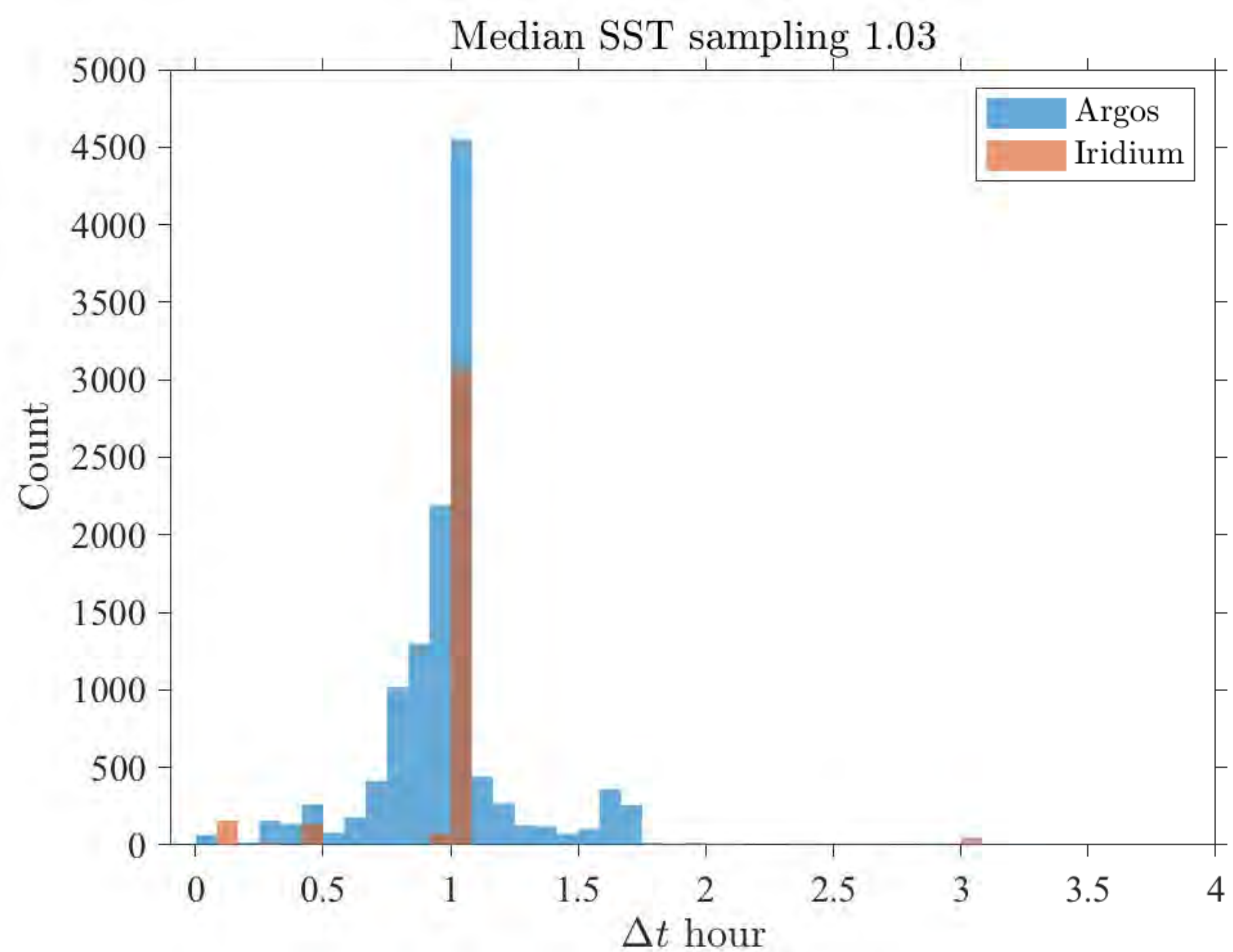
(The hourly dataset is a subset of the complete drifter dataset)

Add ~ 1M estimates/month

Methodology for new SST product

Consider SST data for drifters of product release 1.03



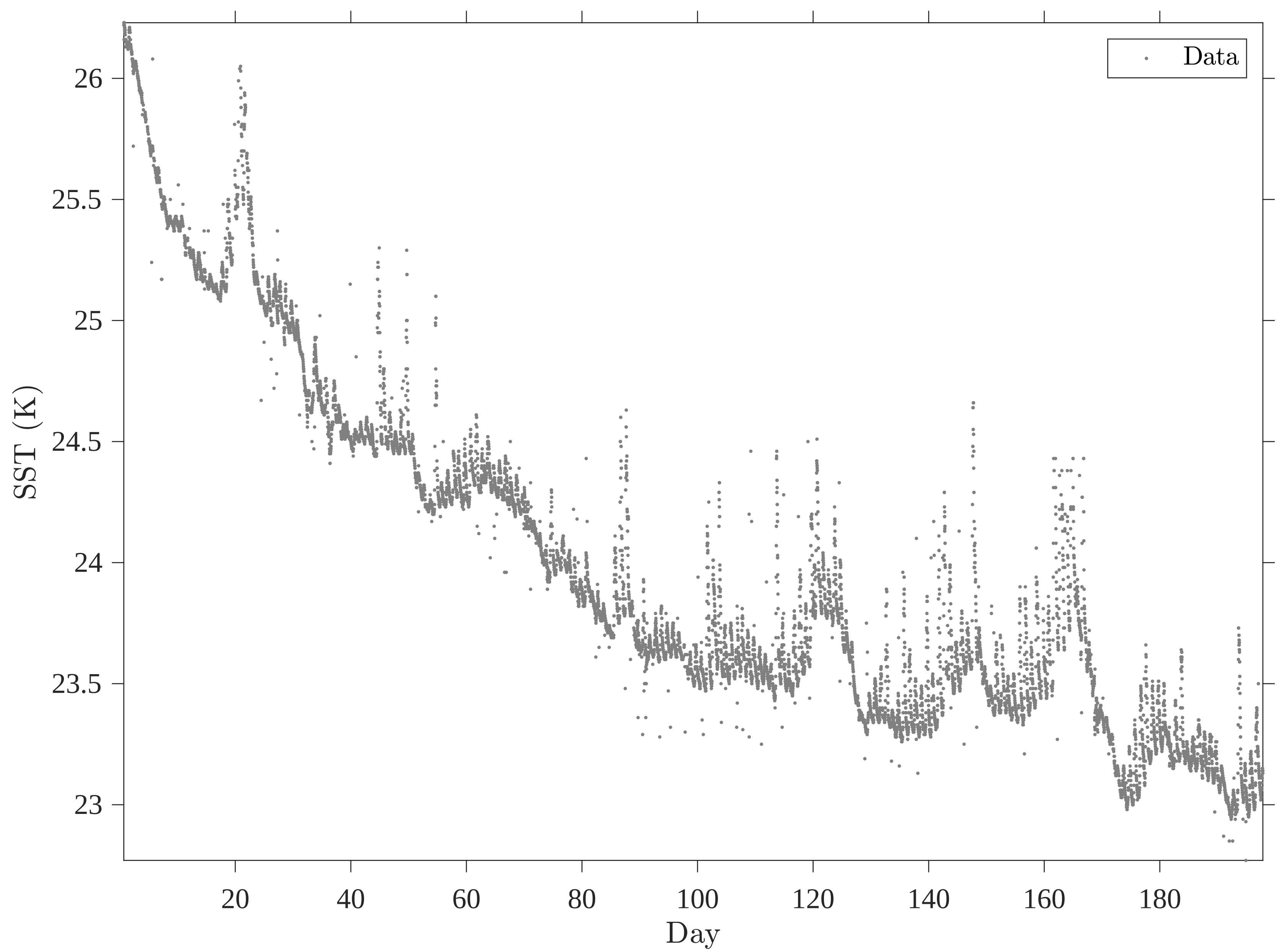


"Raw" SST drifter data are **very** heterogeneous …

Methodology

Step 1: estimation at original sampling times

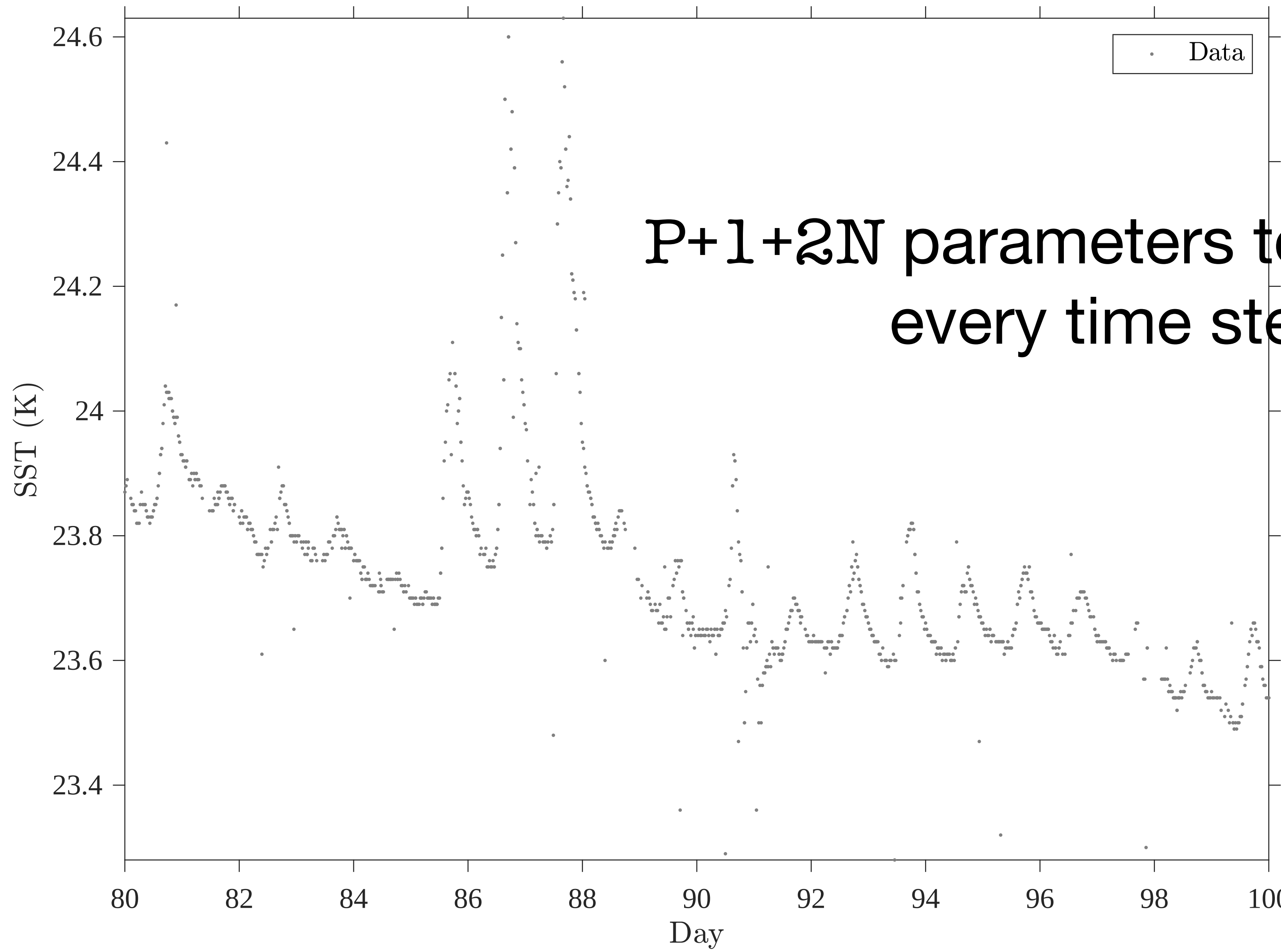
Example from a SPURS drifter (Δt≈30min)



Methodology: local model in time

Low frequency, non-diurnal evolution + diurnal oscillation

$$s_m(t;t_k) = \sum_{p=0}^{P} s_{p,k}(t-t_k)^p + \sum_{n=1}^{N} A_{n,k}\cos[n\omega(t-t_k)+\phi_{n,k}]$$



P+1+2N parameters to estimate at every time step t_k

… it turns out we choose P=1 and N=3

Model parameters estimated by an adaptation of the **LOcally WEighted Scatter plot Smoothing estimator** (**LOWESS**, Cleveland, 1979)

local model around t_k →

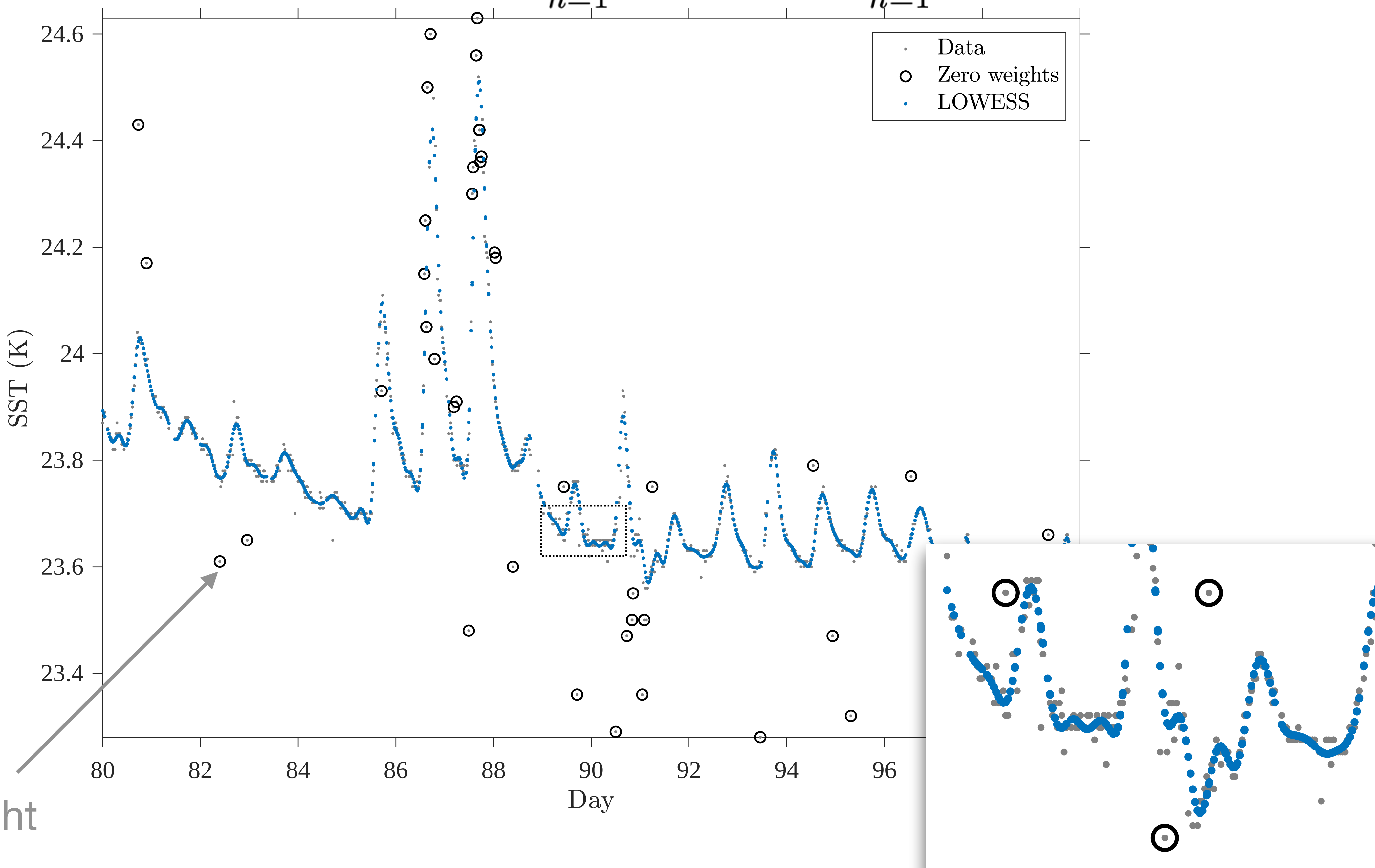
$$s_m(t;t_k) = \sum_{p=0}^{1} s_{p,k}(t-t_k)^p + \sum_{n=1}^{3}\left[\alpha_{n,k}\cos\omega_n(t-t_k) + \beta_{n,k}\sin\omega_n(t-t_k)\right]$$

SST estimate at t_k for $t = 0$ →

$$\widehat{s}_{m,k} \equiv s_m(t_k;t_k) = s_{0,k} + \sum_{n=1}^{3}\alpha_{n,k} = s_{0,k} + \sum_{n=1}^{3} A_{n,k}\cos\phi_{n,k}.$$

Algorithm:

- Estimation in a 2-day window around t_k
- 4 iterations on a whole trajectory, sequentially downweighting data points with large residuals



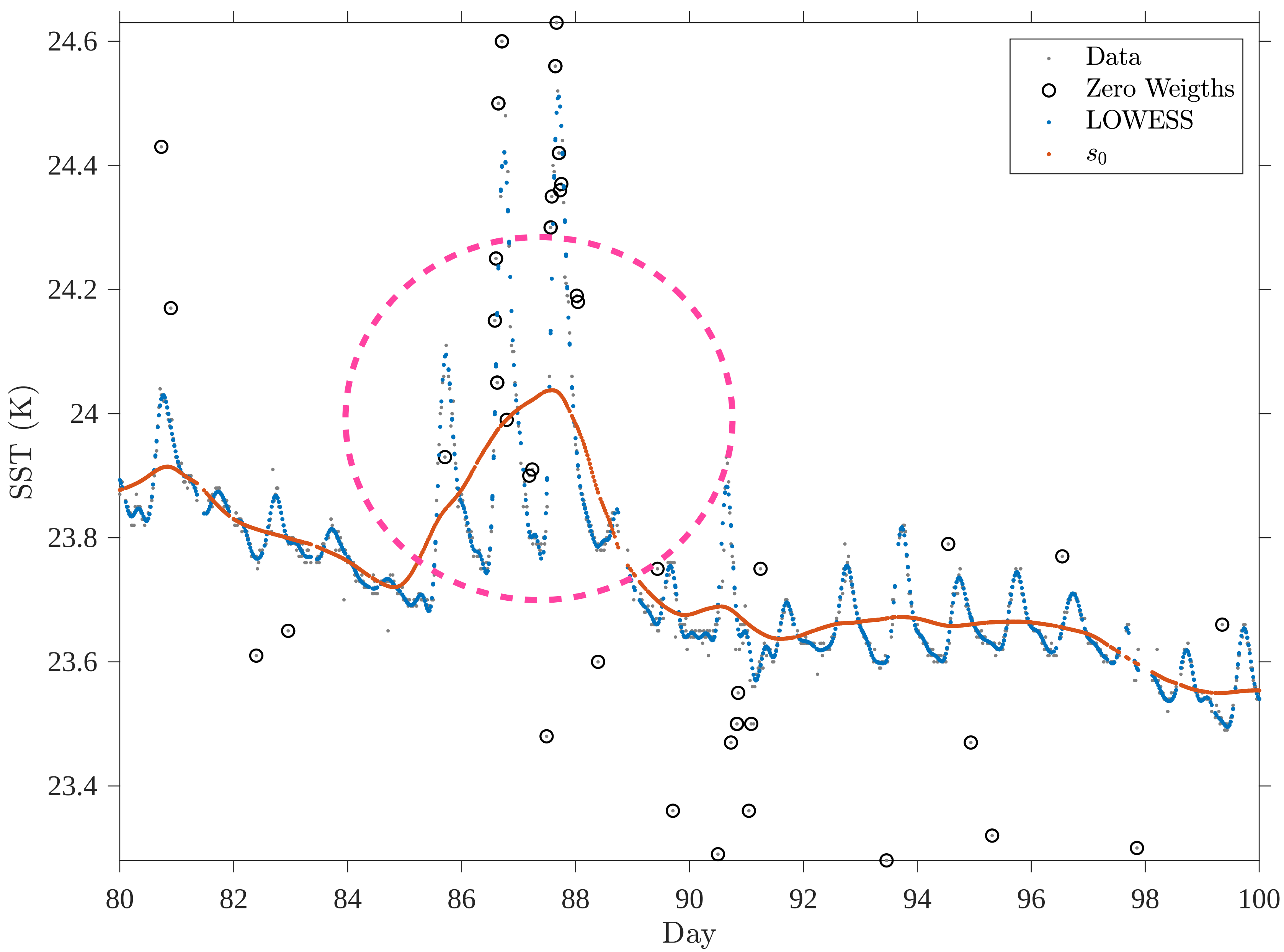
zero-weight points

Methodology

separation of non-diurnal and diurnal signals

$$\widehat{s}_{m,k} \equiv s_m(t_k; t_k) = s_{0,k} + \sum_{n=1}^{3} \alpha_{n,k}$$

diurnal signal has zero-mean by construction



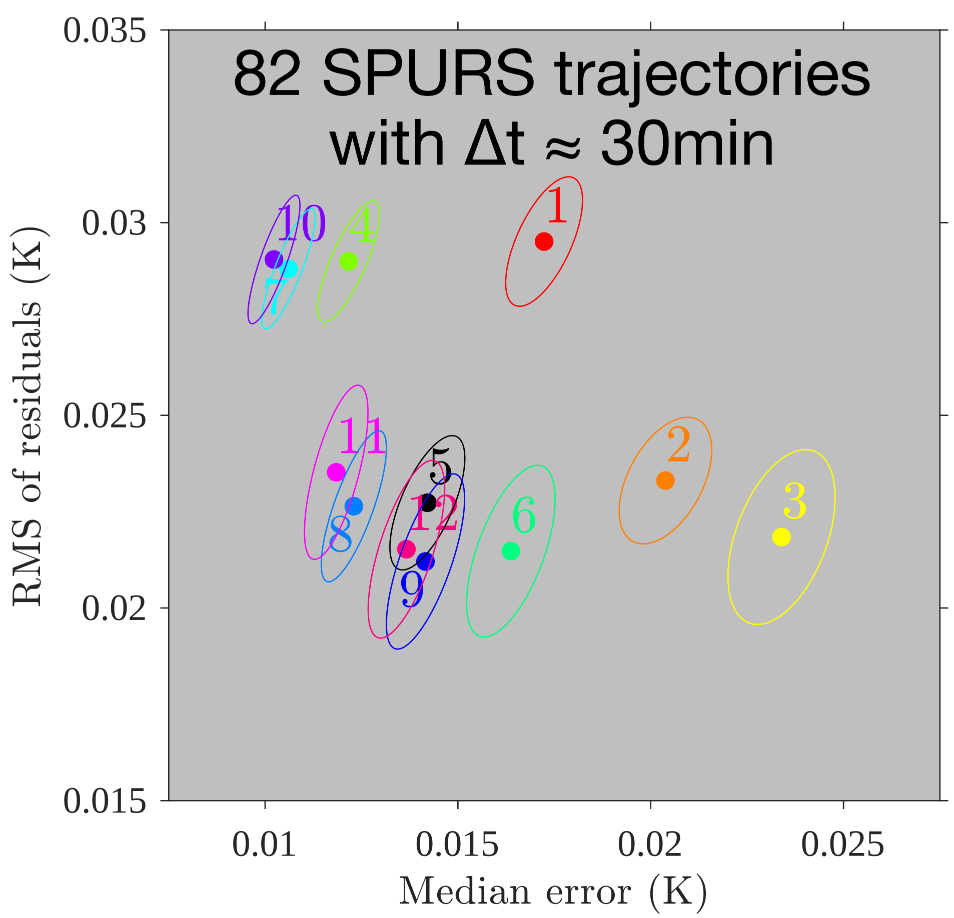
Performances of model orders

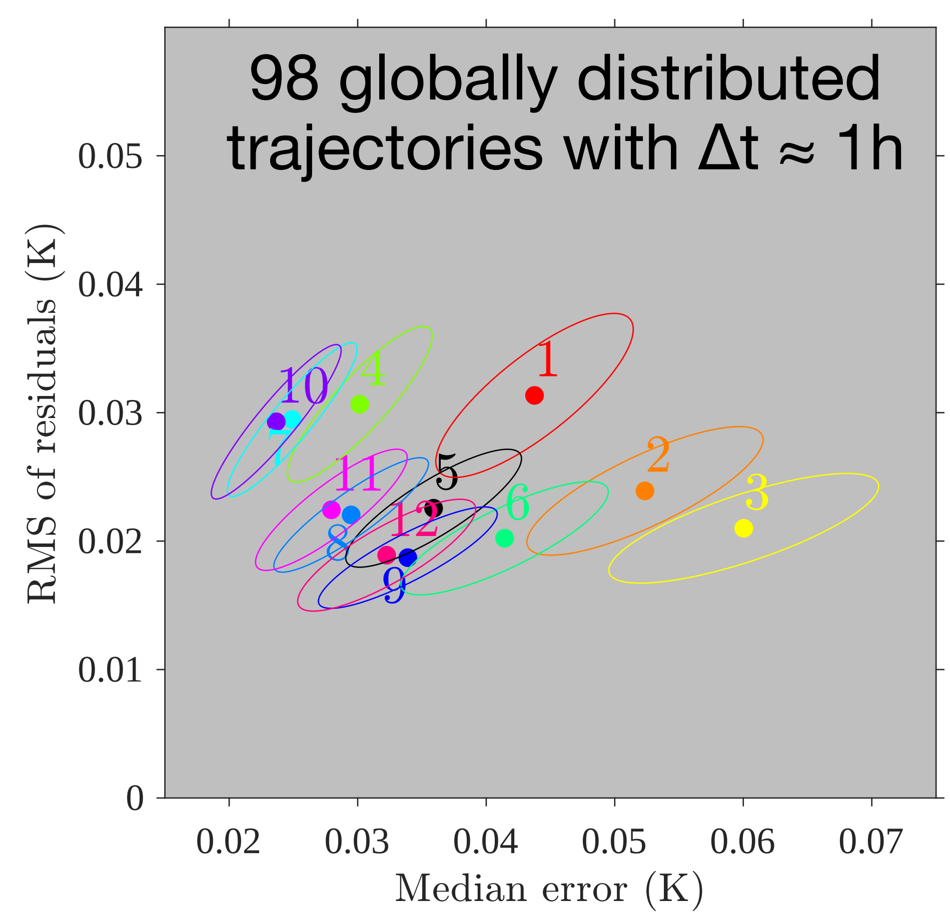
We choose P = 1 and N = 3

Table 1: Table of model numbers

Polynomial order (P)	0	1	2	3
Number of diurnal harmonics (N)				
1, 2	1	4	7	10
1, 2, 3	2	5	8	11
1, 2, 3, 4	3	6	9	12

≅ model errors





≅ variance of estimates (data density, data scatter, …)

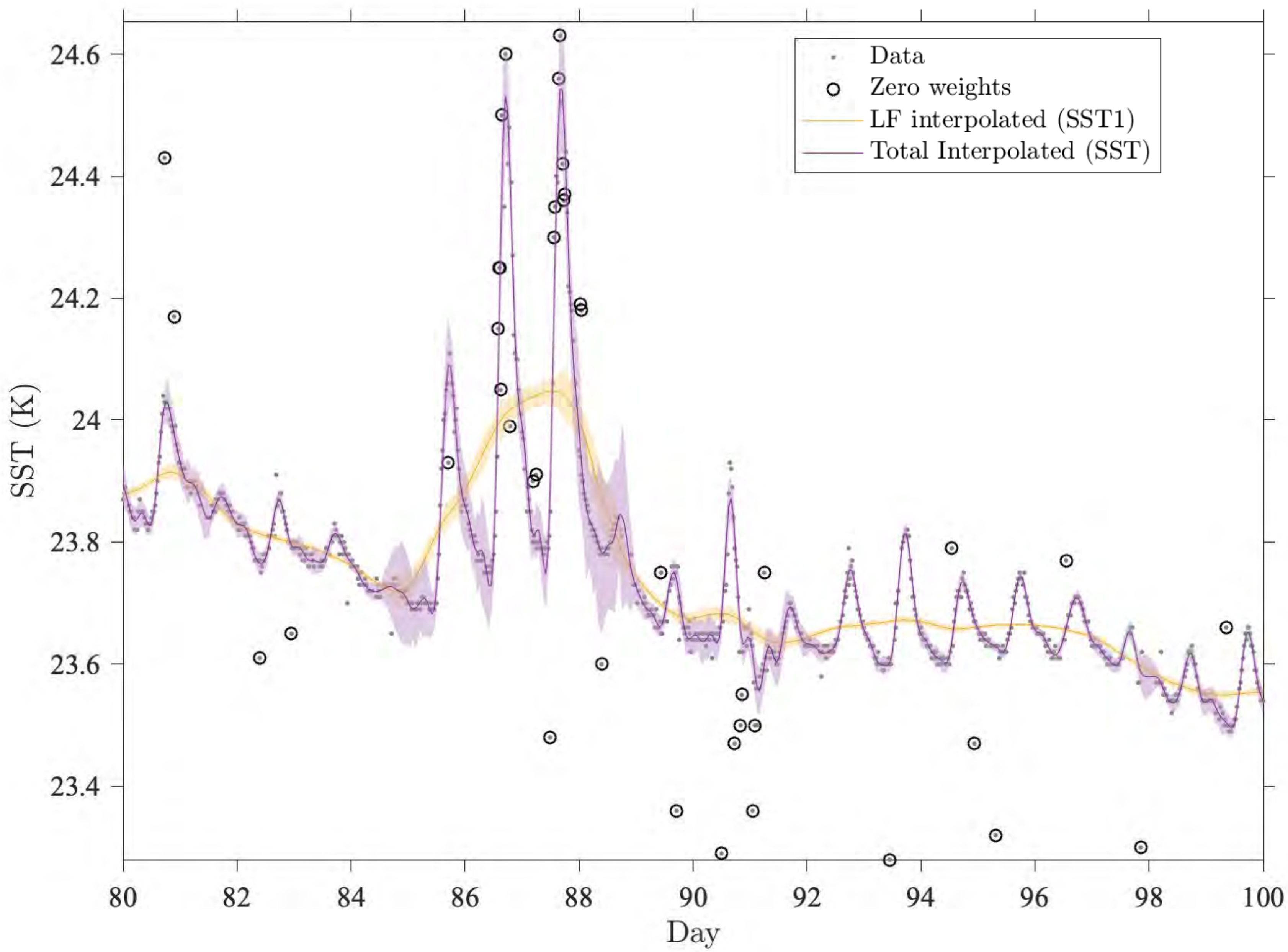
Methodology

model: $s_m(t) = s_P(t;t_k) + s_D(t;t_k)$

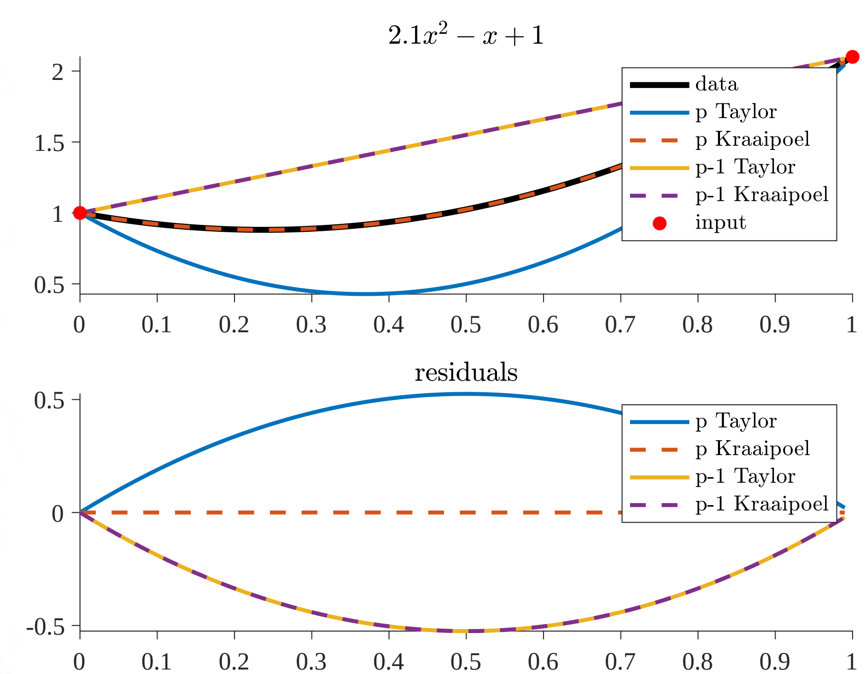
Step 2: interpolation to top-of-the-hour

Intrapolant: $$\mathcal{I}_P[s_P(t)](t;t_k,t_{k+1}) = \frac{t_{k+1}-t}{t_{k+1}-t_k}\mathcal{D}_P\left[s_P(t,t_k)\right] + \frac{t-t_k}{t_{k+1}-t_k}\mathcal{D}_P\left[s_P(t,t_{k+1})\right]$$

extrapolation term: $$\mathcal{D}_P\left[s_m(t,t_k)\right] \equiv \sum_{j=0}^{P}\left(1-\frac{j}{P+1}\right)\frac{1}{j!}(t-t_k)^k \widehat{s}_{P,k}^{(j)}.$$



hybrid method of 2-point linear interpolation and extrapolation using a Dutch Taylor expansion by Kraaipoel (2003)



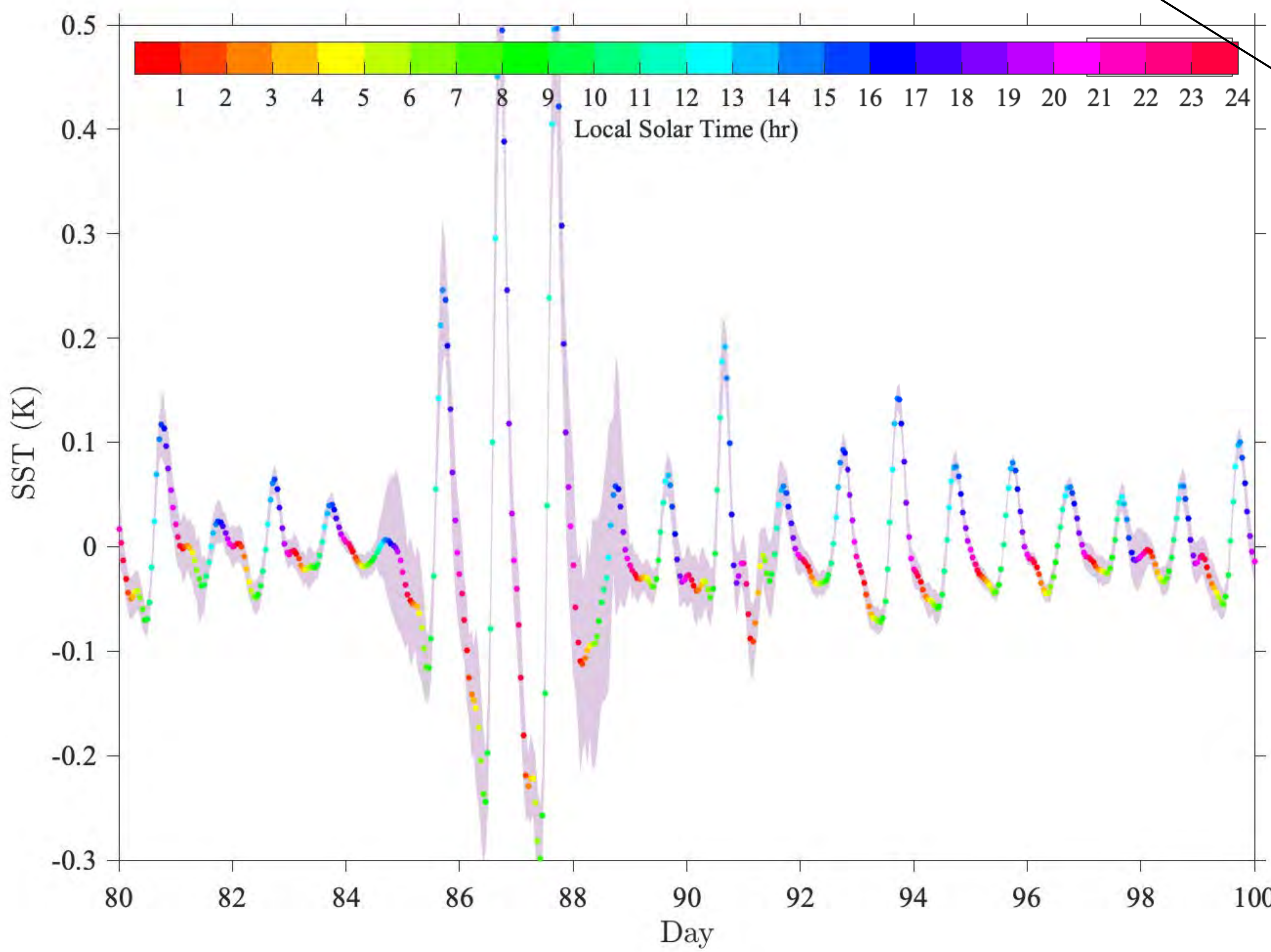
Methodology

model: $s_m(t) = s_P(t; t_k) + s_D(t; t_k)$

Step 2: interpolation to top-of-the-hour

LOWESS estimates: $\widehat{s}_{D,k} \equiv s_D(t_k; t_k) = \sum_{n=1}^{N} \alpha_{n,k} = \sum_{n=1}^{N} A_{n,k} \cos\phi_{n,k}.$

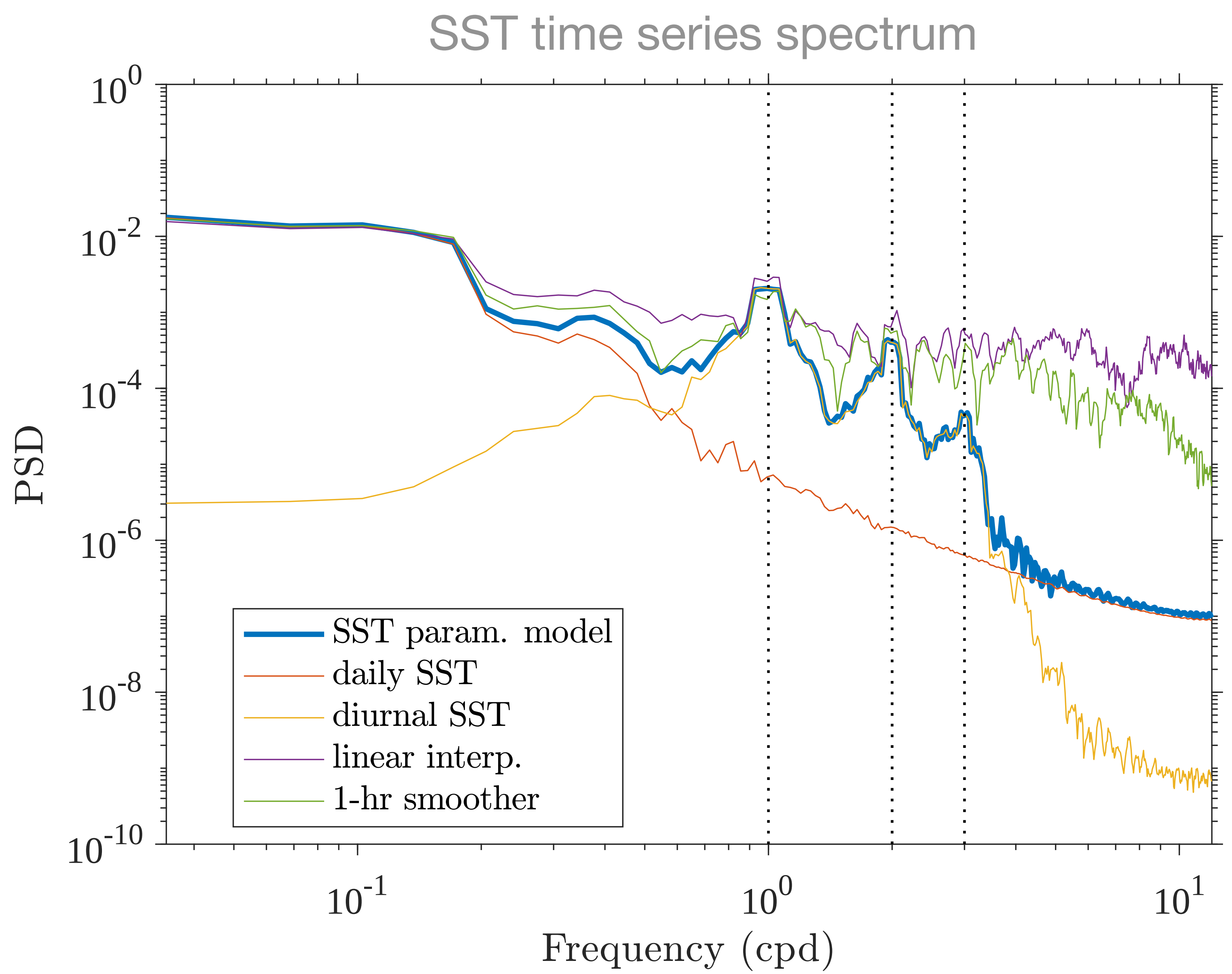
Extrapolant: $\mathcal{I}_D[s_D(t)](t; t_k, t_{k+1}) = \frac{t_{k+1} - t}{t_{k+1} - t_k} s_D(t, t_k) + \frac{t - t_k}{t_{k+1} - t_k} s_D(t, t_{k+1}).$



linear extrapolation terms

Methodology

Method is effectively a data filter:



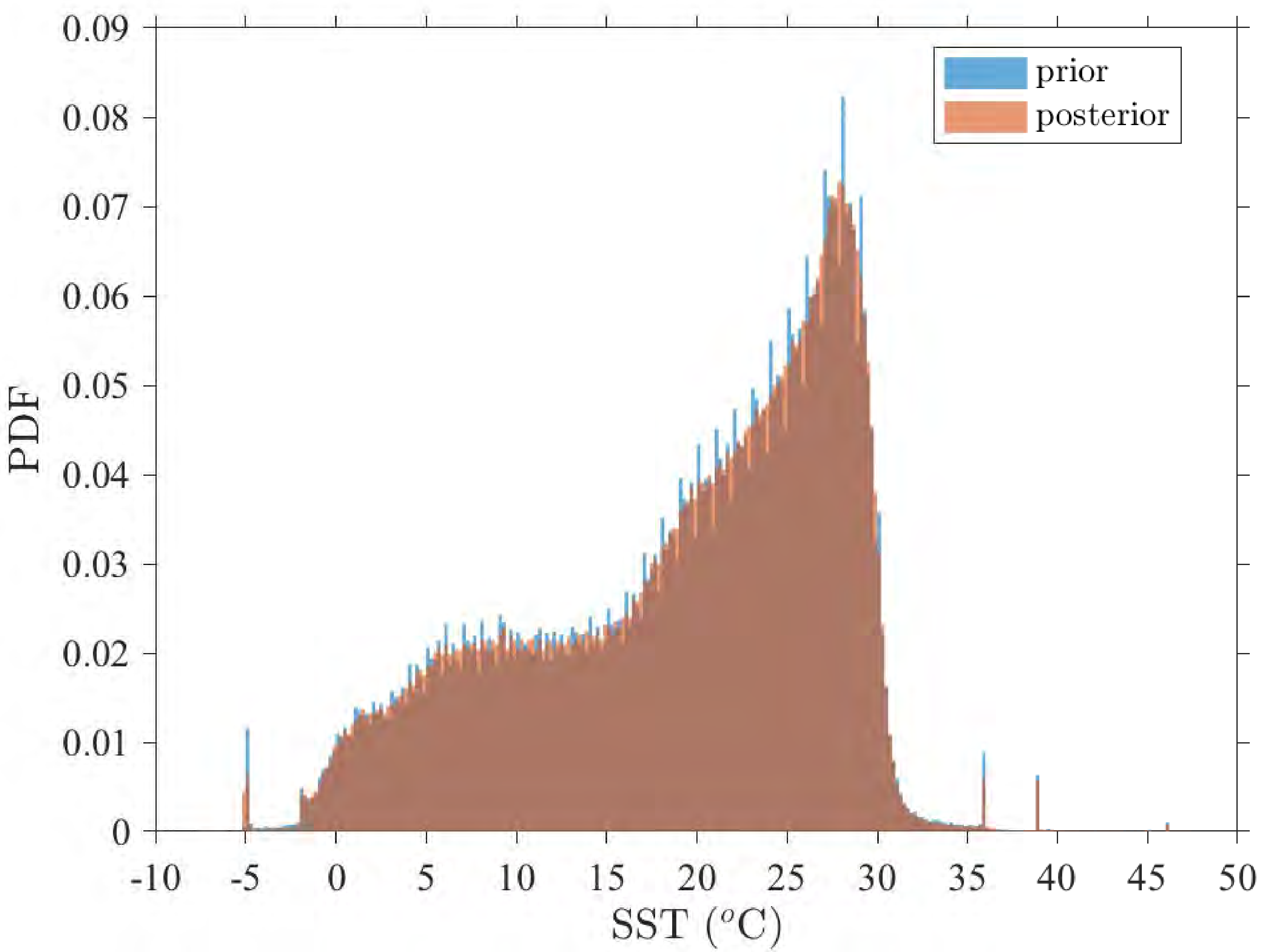
Note high frequency noise for alternative methods : linear interpolation and 1-h smoother

Global Results

prior (raw) and posterior (after LOWESS)

Applied the method to 15,707 trajectories, totaling 178,002,728 data points: 99.50% : $-2<SST_{prior}<40$

Histograms of SST values before and after processing



Method fails for 126,007 data points (0.07%)

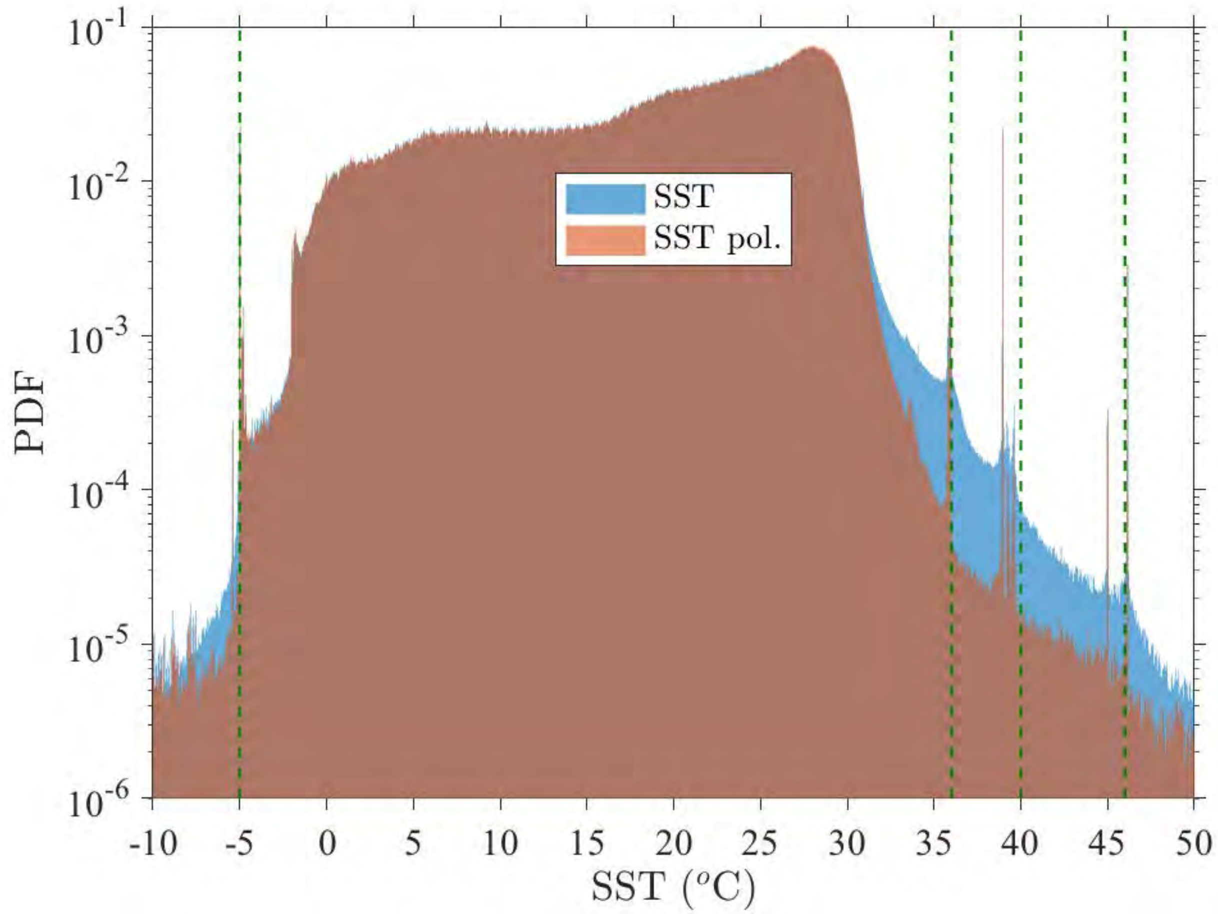
99.58% : $-2<SST_{posterior}<40$

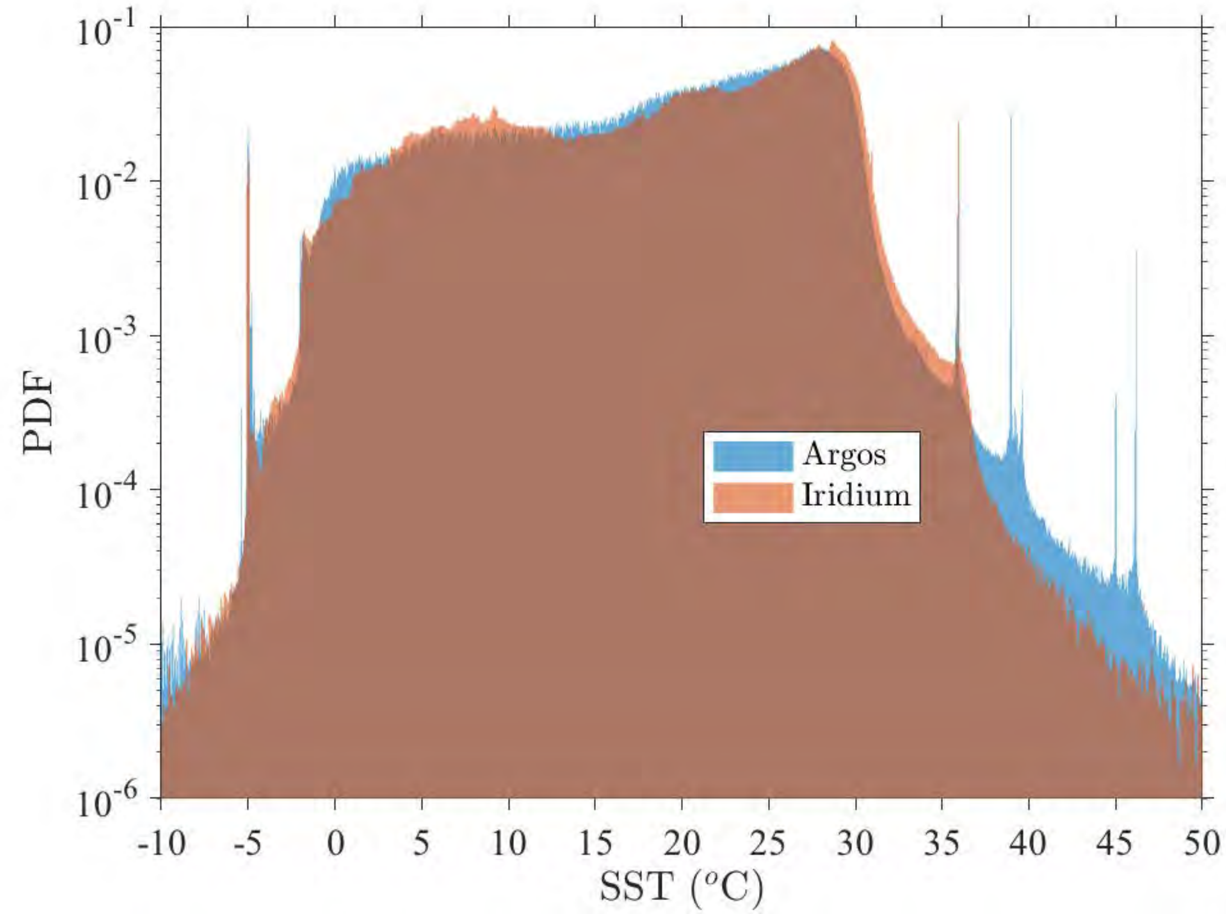
→ 99.98% success rate

Global results
Posterior SST

99.58% : $-2<SST_{posterior}<40$

99.42%: $-2 \leqq SST_{posterior} \leqq 36.92$

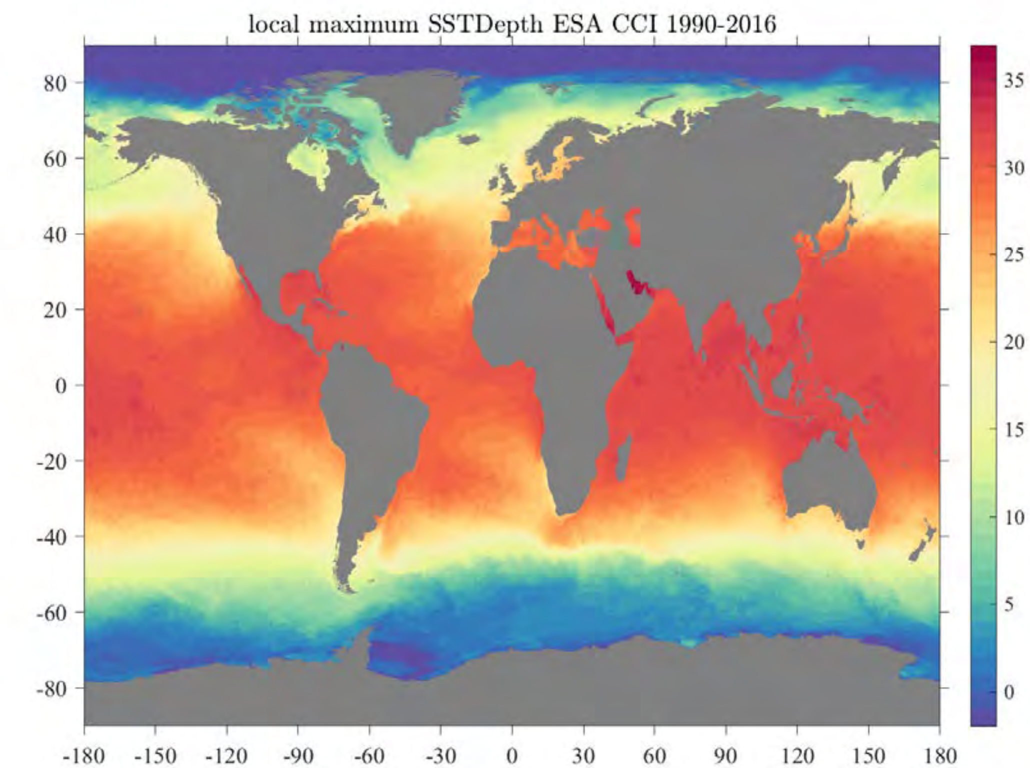


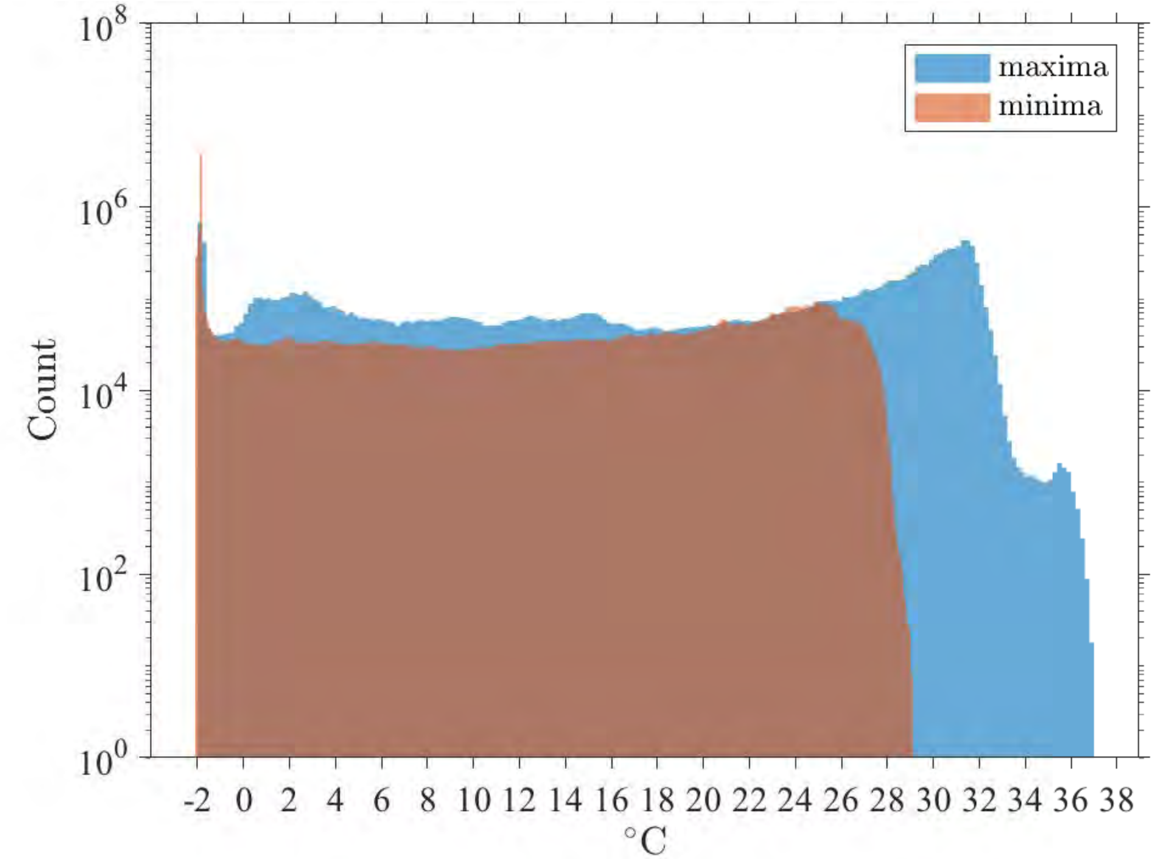


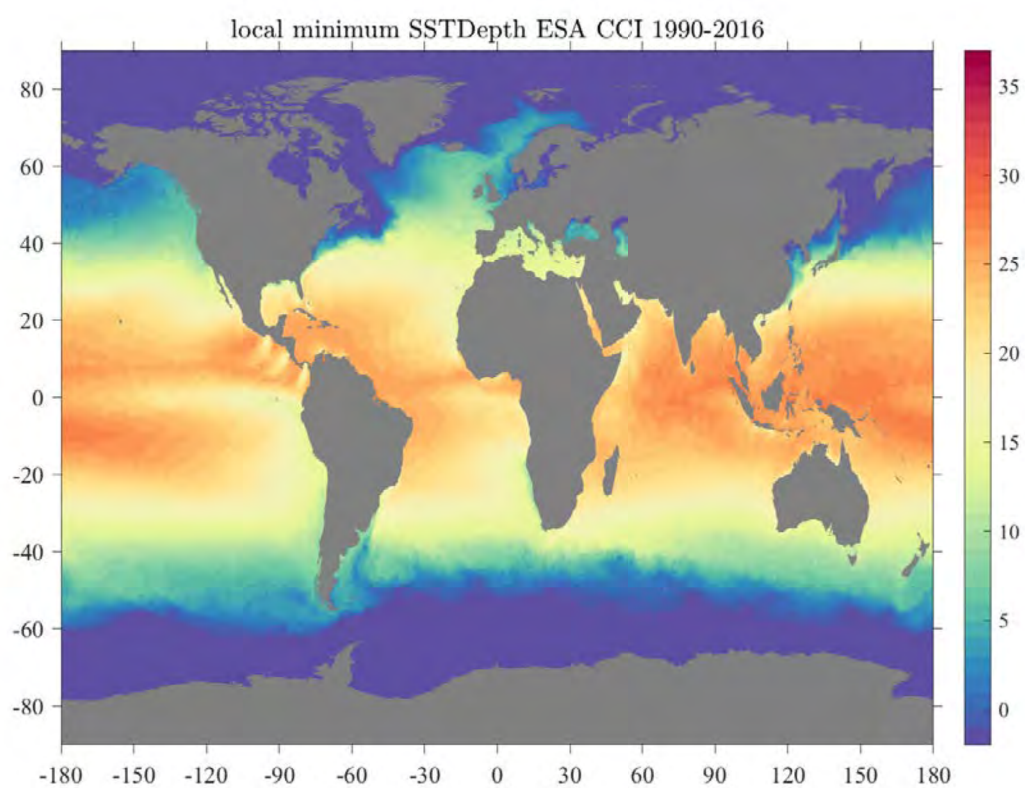
local peaks in PDF are minima and maxima bit counts of SST sensors

What “physical” cut-off temperatures?

Comparison to ESA SST CCI OSTIA L4 product; Merchant et al. (2019)







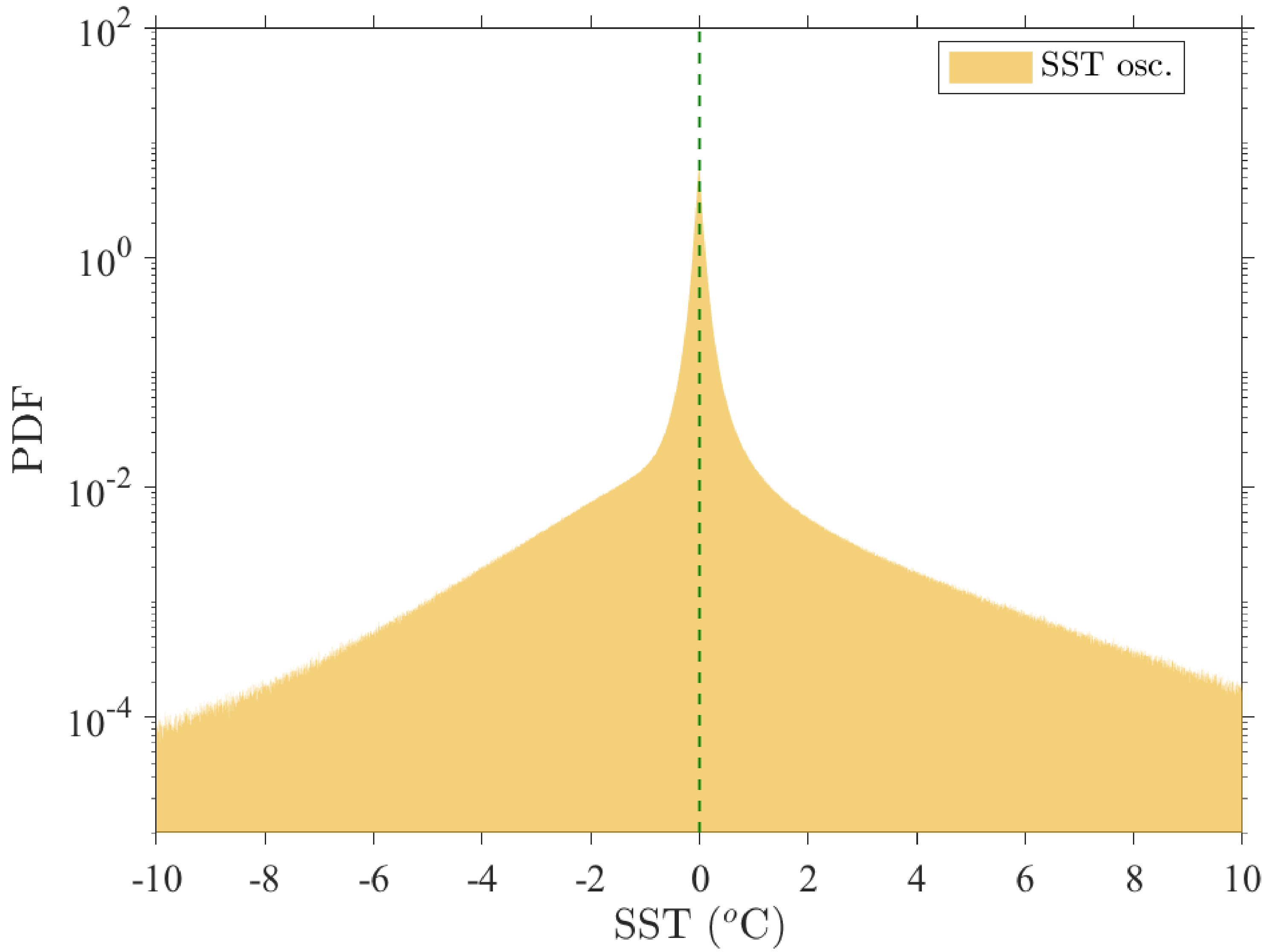
Local maxima and minima for daily SST adjusted to 20 cm depth

Global extremum values are -2 and 36.92 (1990-2016)

99.42%: $-2 \leqq SST_{posterior} \leqq 36.92$

Global results for LOWESS estimation
Diurnal SST anomalies

Histograms of diurnal SST anomalies

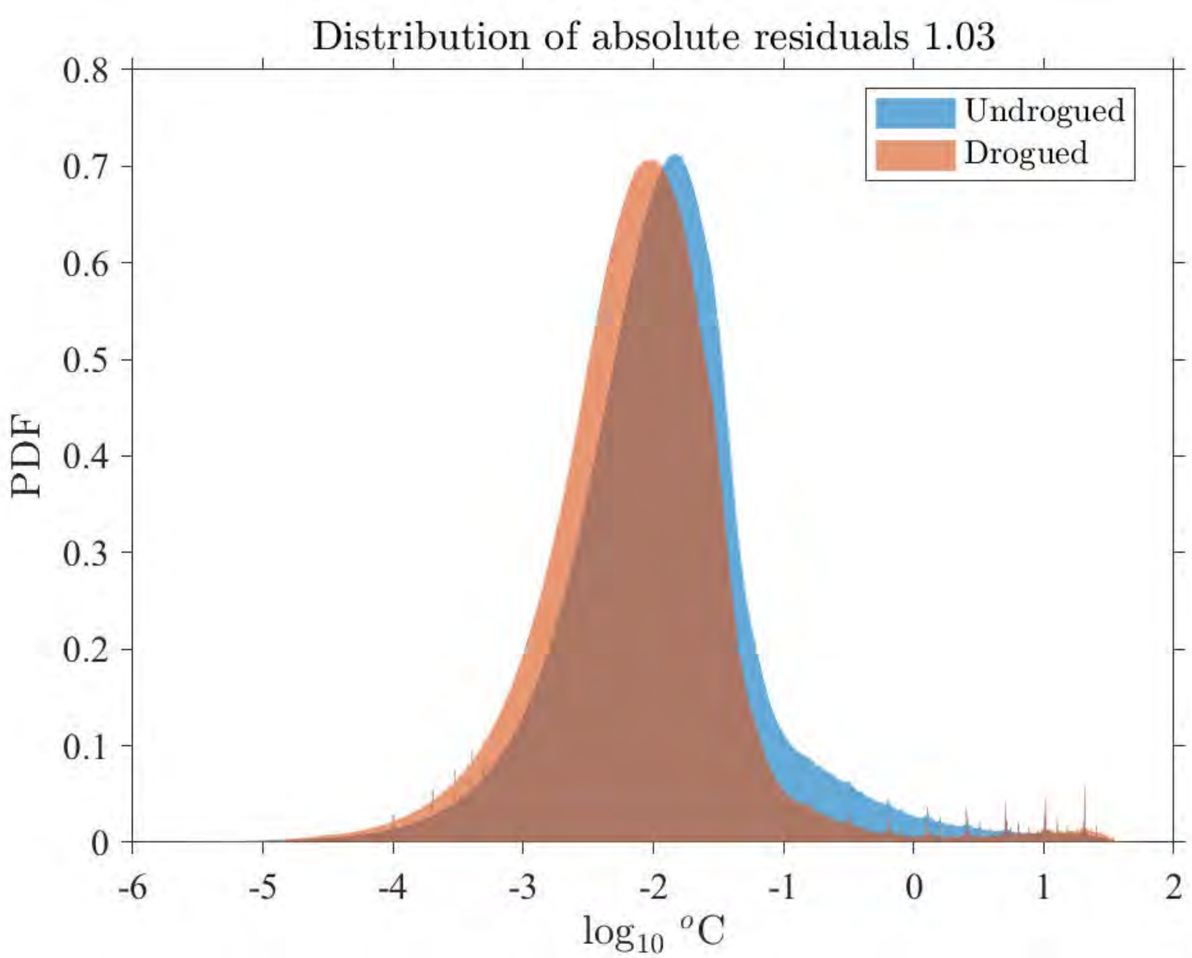


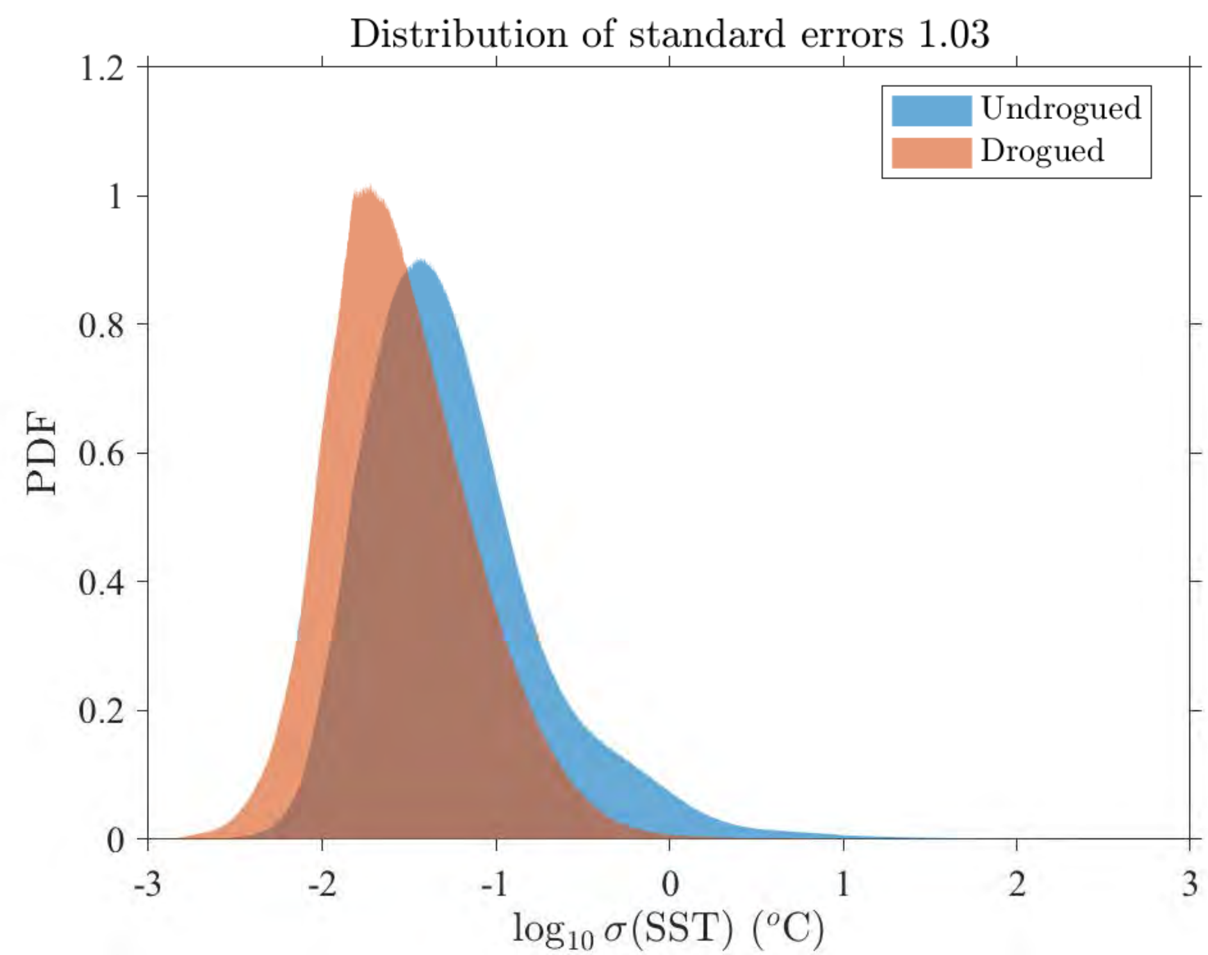
95.76% : abs(ΔSST)≦1

97.70% : abs(ΔSST)≦2

Global results for LOWESS estimation

Residuals and standard error distributions





Typical formal standard error is 0.027°C

Larger residuals and errors for undrogued estimates (~0.037°C) than for drogued estimates (~0.018°C).

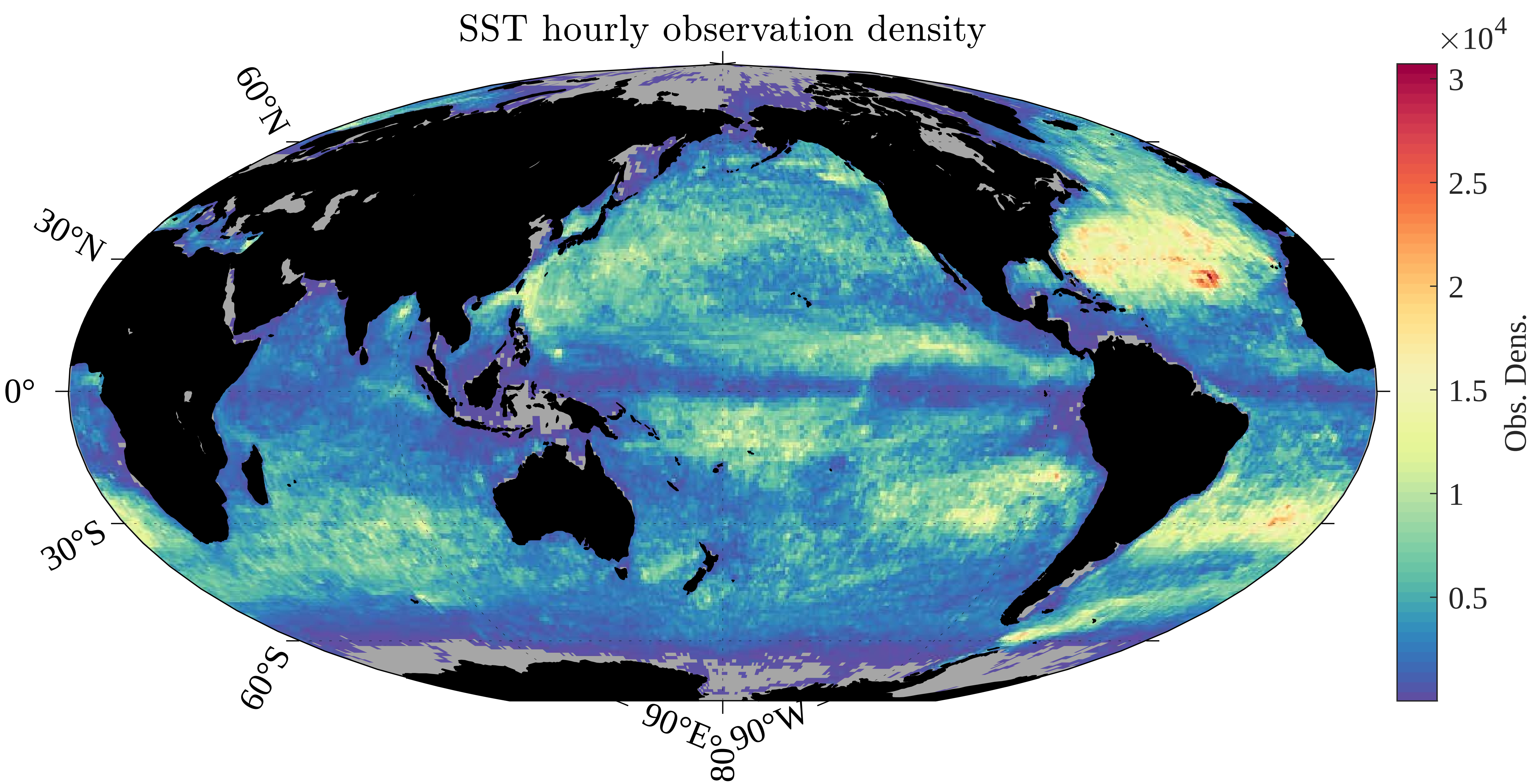
Global results for hourly interpolated estimates

(Oceanographic results)

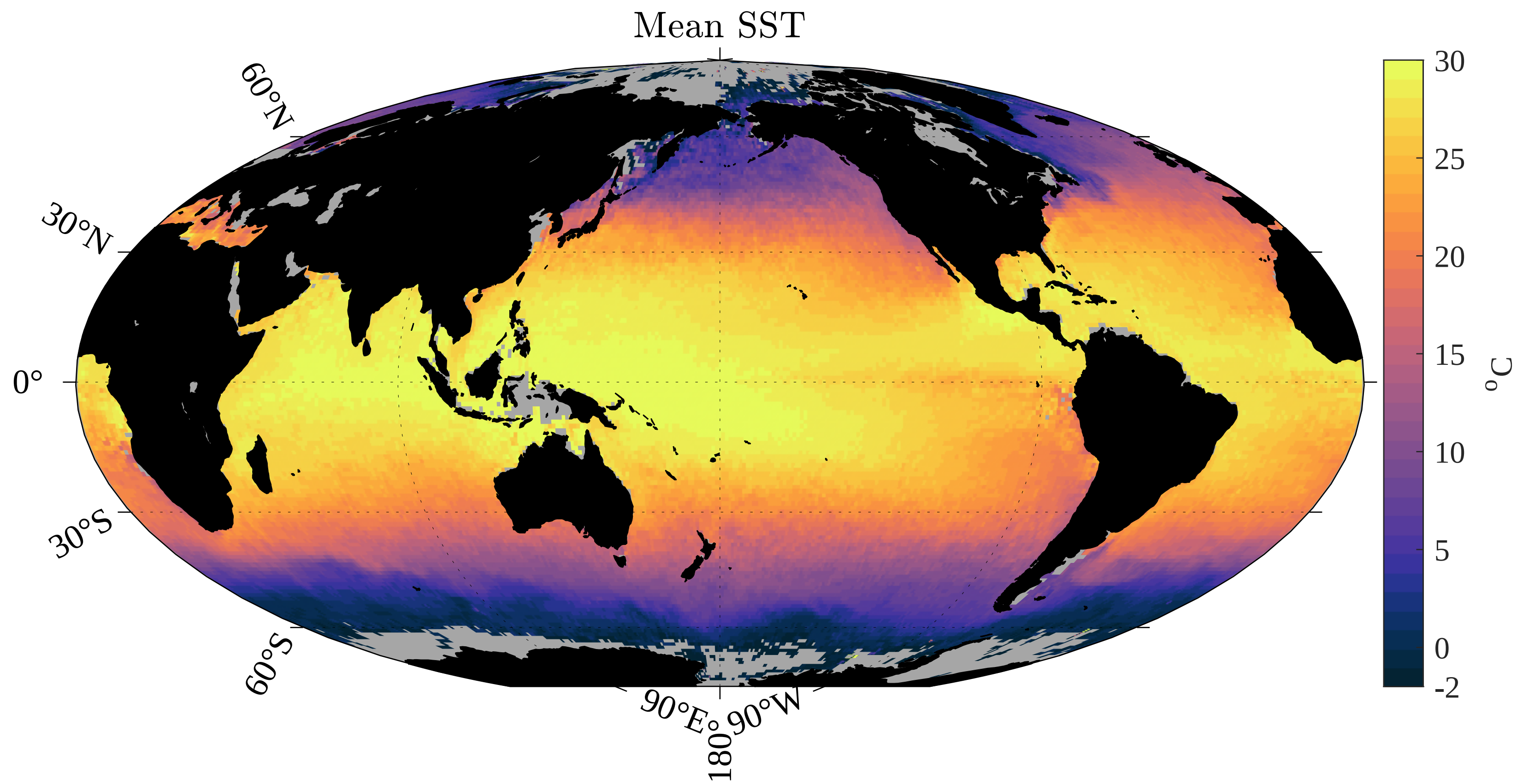
Hourly observation density

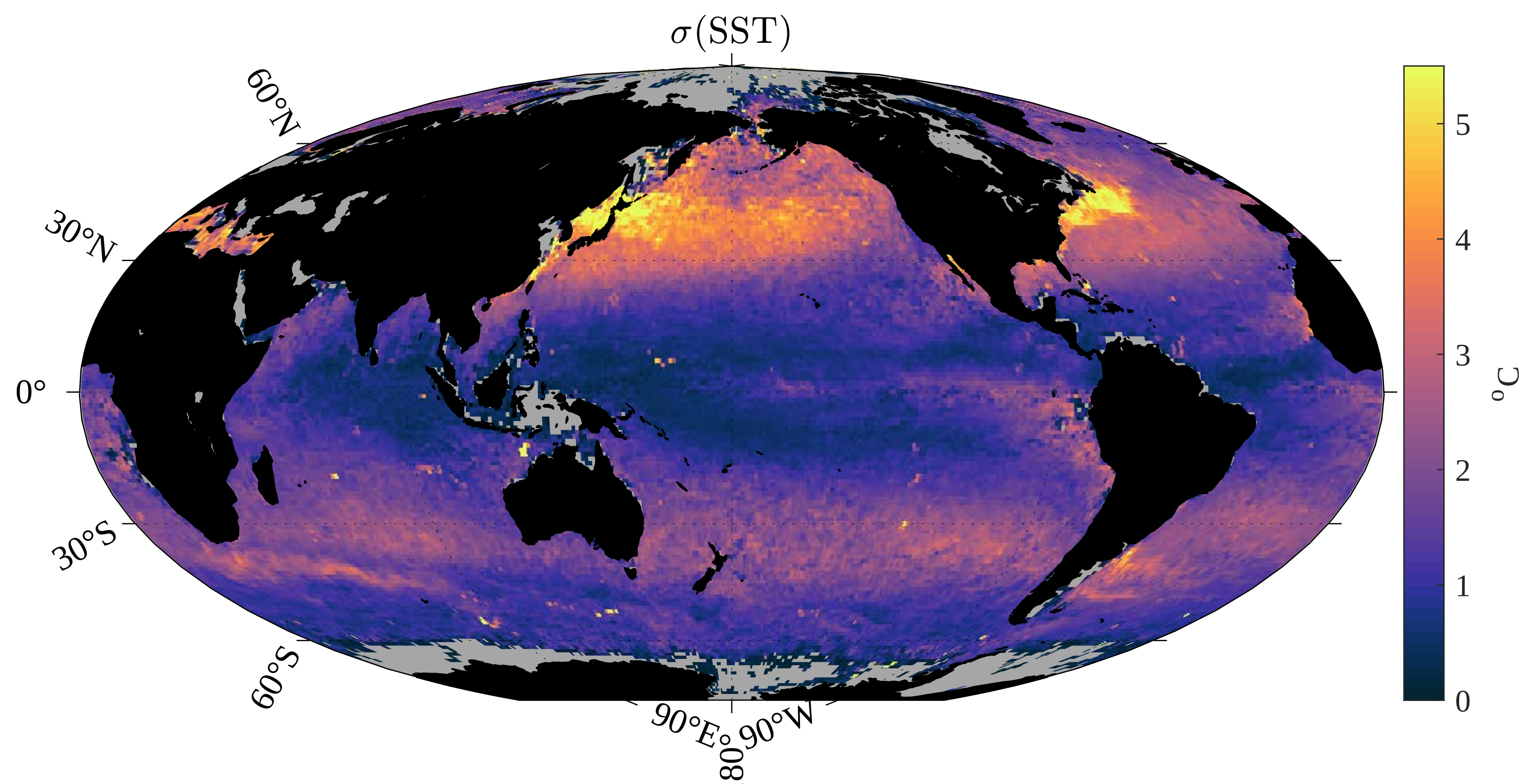
After interpolation we obtain 146,323,140 hourly estimates (95.7% of the position dataset) of 14 variables (23GB dataset):

diurnal SST anomaly, non-diurnal SST, SST tendency, and all associated standard errors; amplitude and phase of 3 diurnal harmonics, size of interpolation gap,

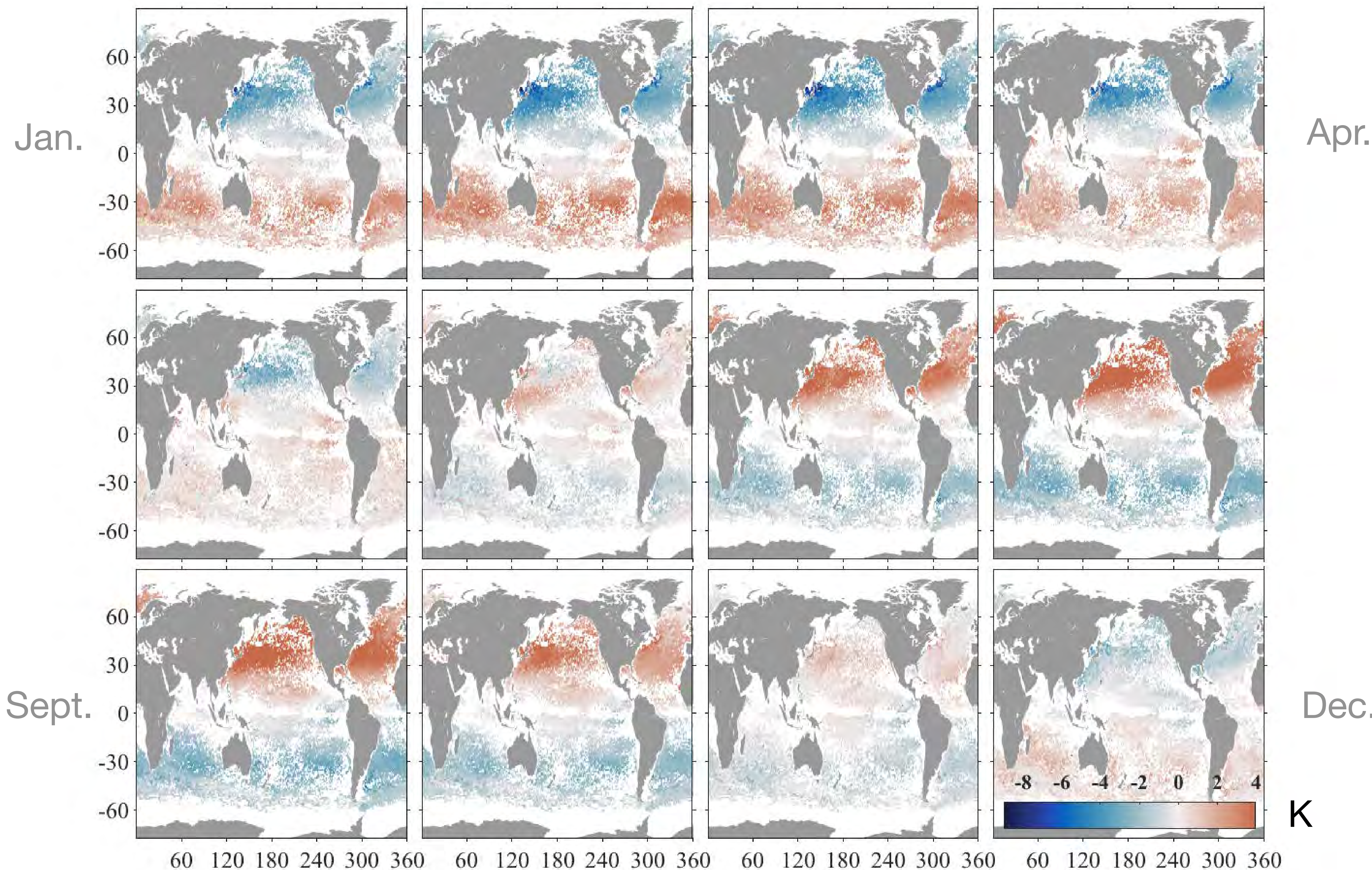


Eulerian mean and standard deviation



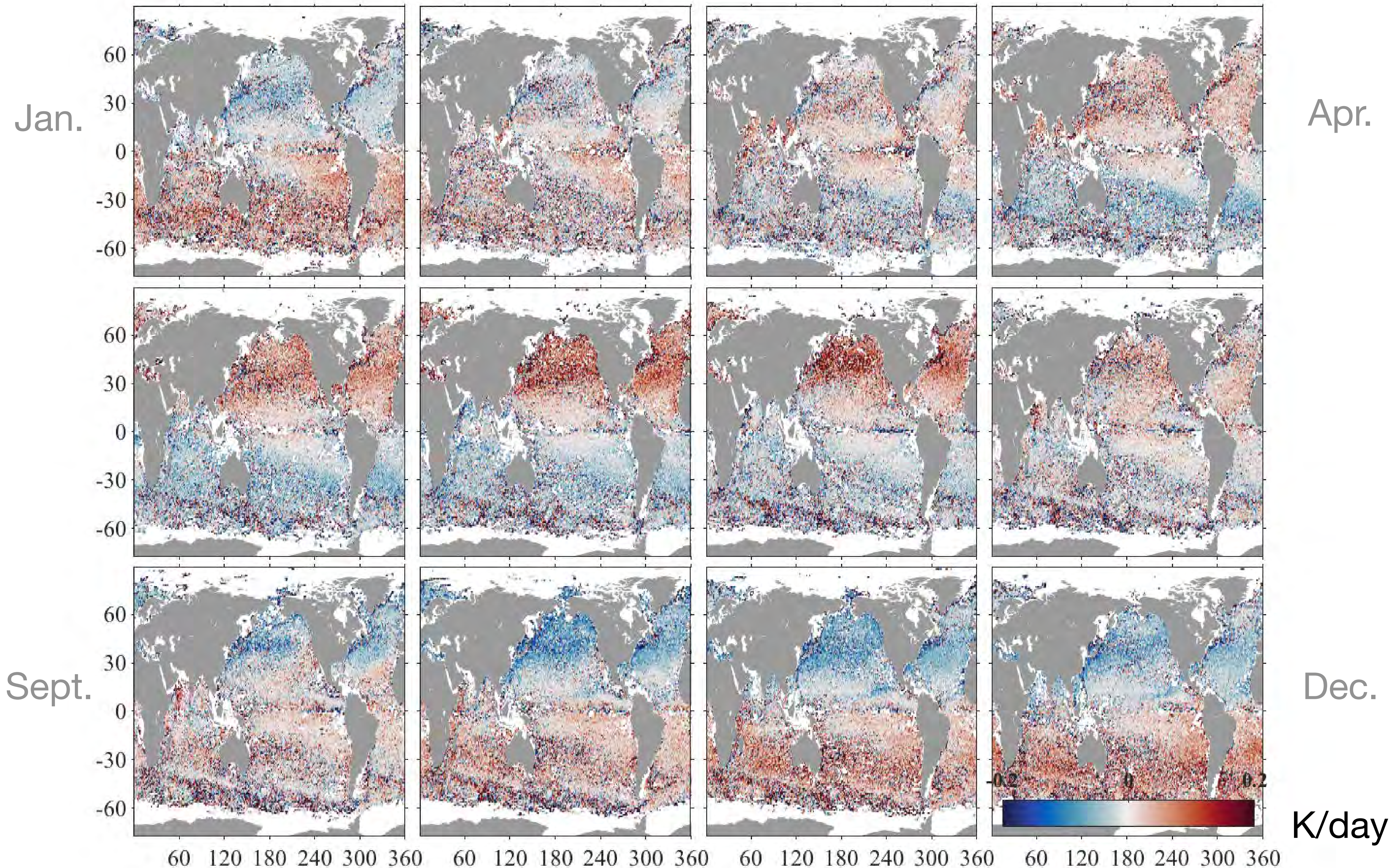


Monthly SST anomalies



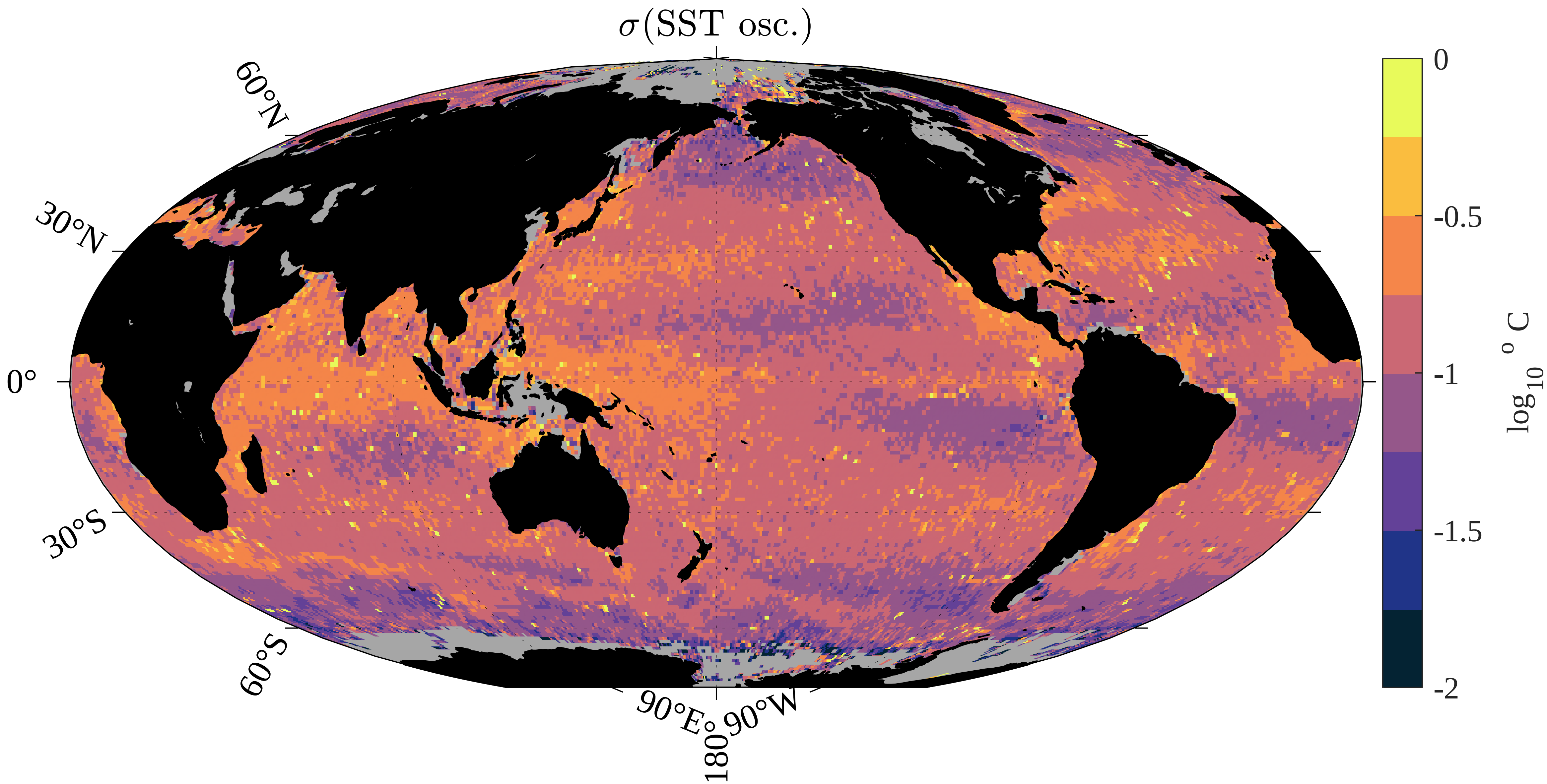
Data density is sufficient to study seasonal variability

SST tendency



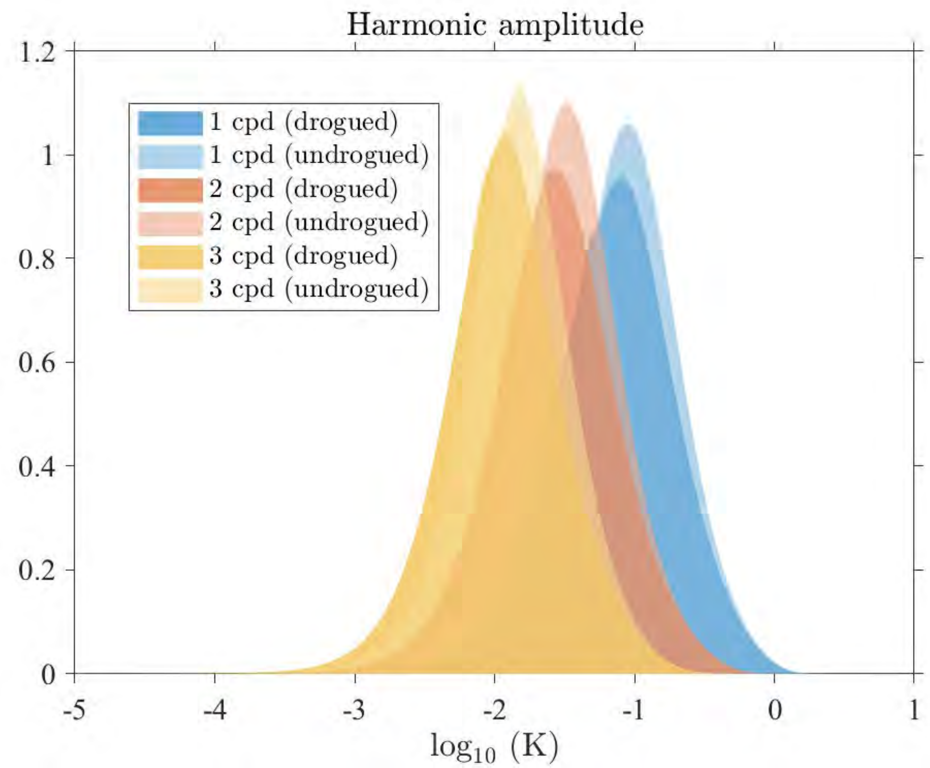
SST tendency is the combined result of air-sea fluxes and ocean circulation

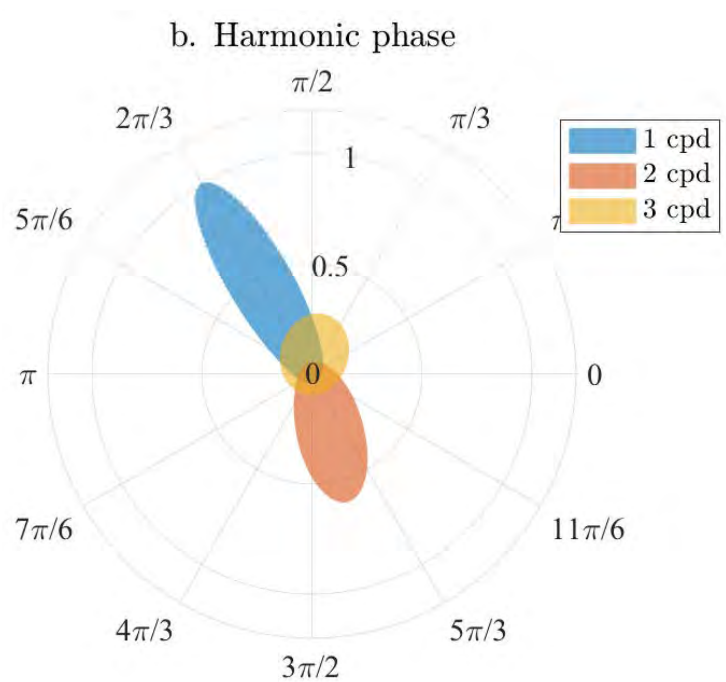
Diurnal SST standard deviation

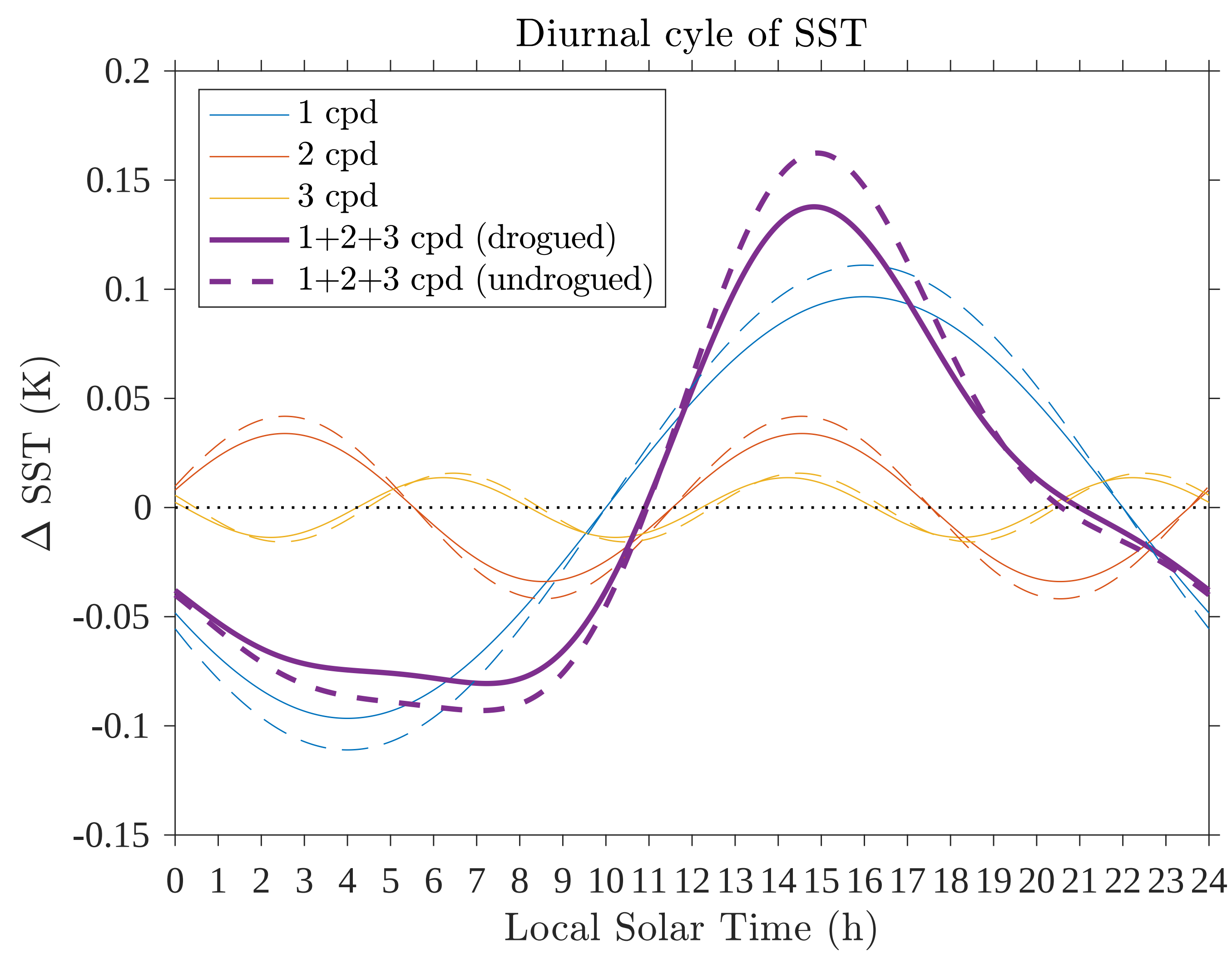


Diurnal variance varies by orders of magnitude, with latitude, and a east-west asymmetry

Typical diurnal cycle



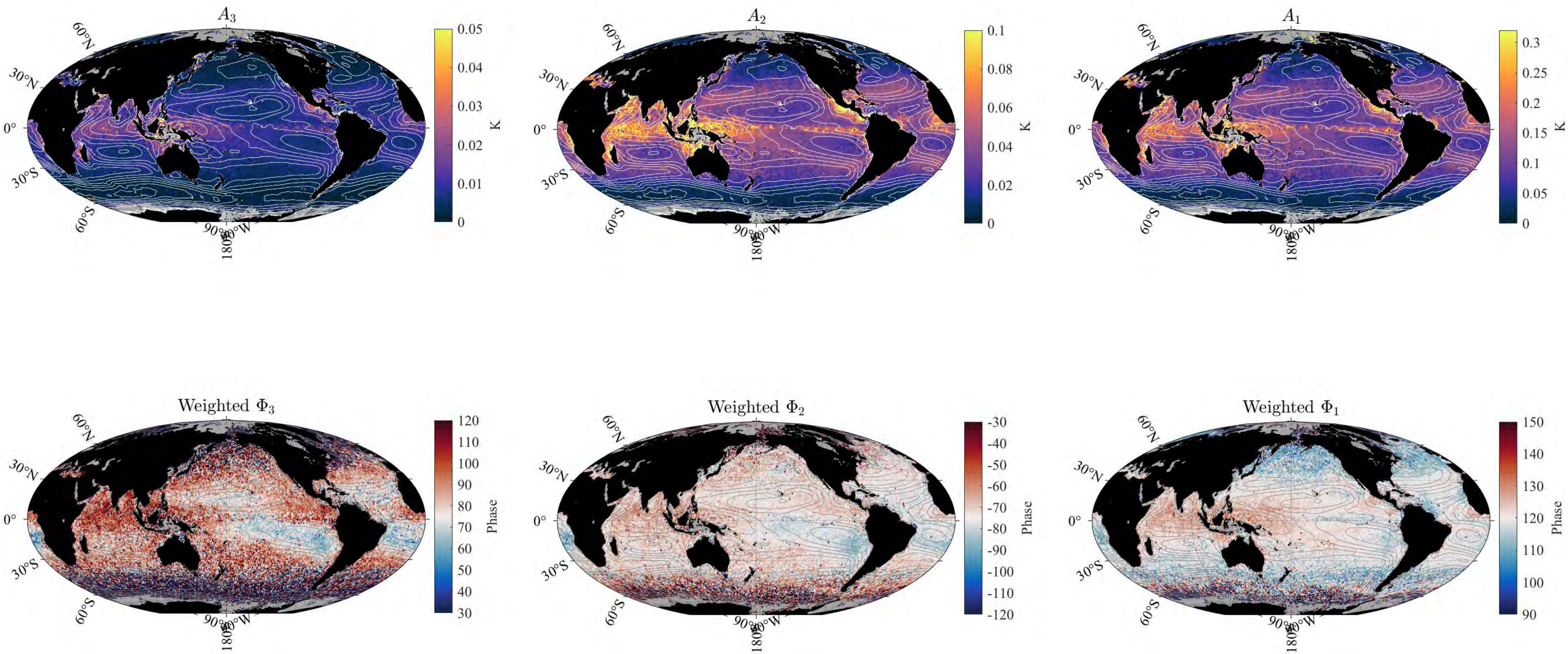




Diurnal amplitude is dependent on drogue status!

Diurnal SST harmonics

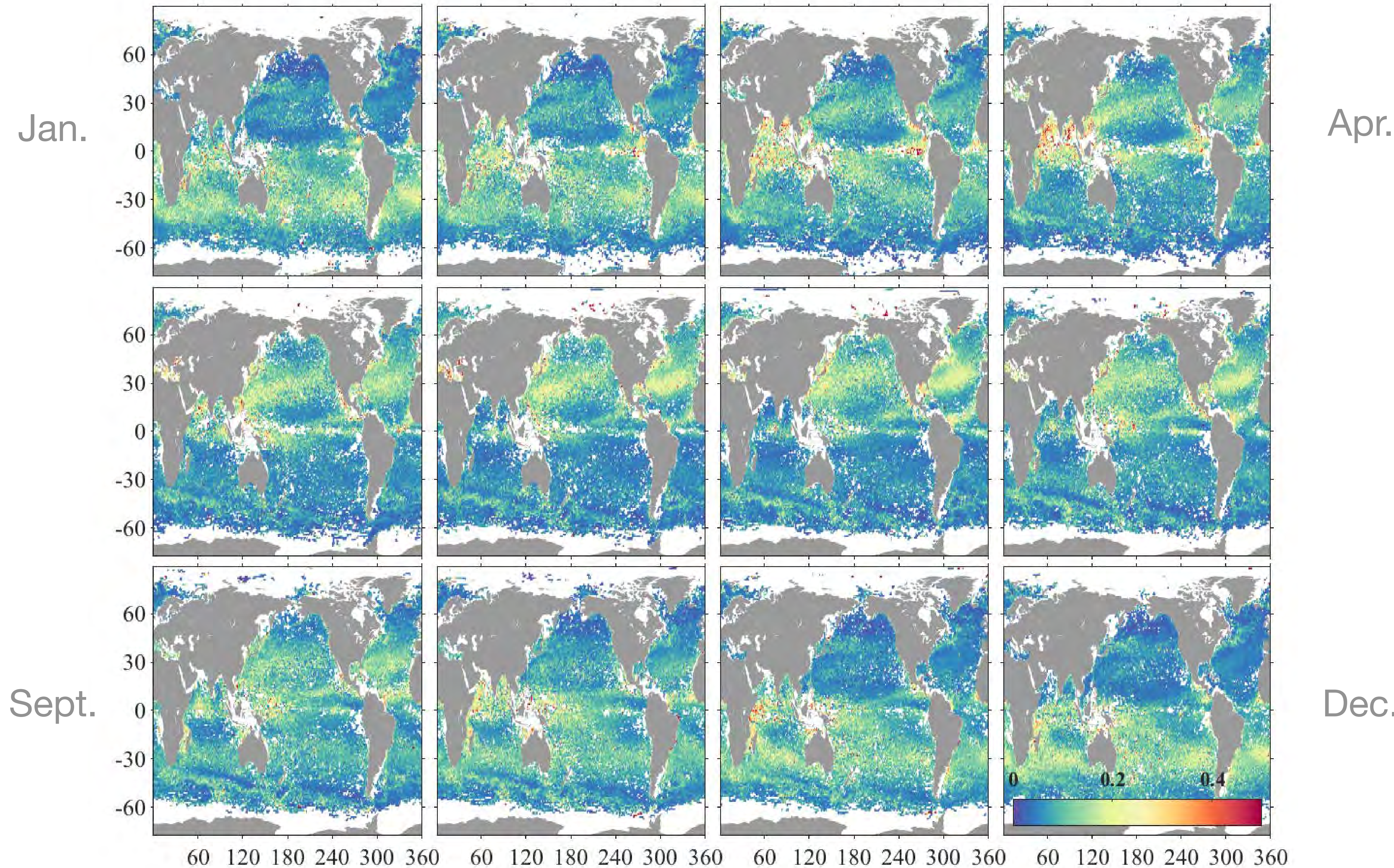
Harmonic amplitude, with mean wind speed contours



Harmonic phase, with mean wind speed contours

Monthly diurnal amplitude

$$\sqrt{\sum_{n=1}^{3} \frac{A_n^2}{2}}$$



Diurnal amplitude varies with seasons; and is dampened in Western Boundary Current and high EKE regions

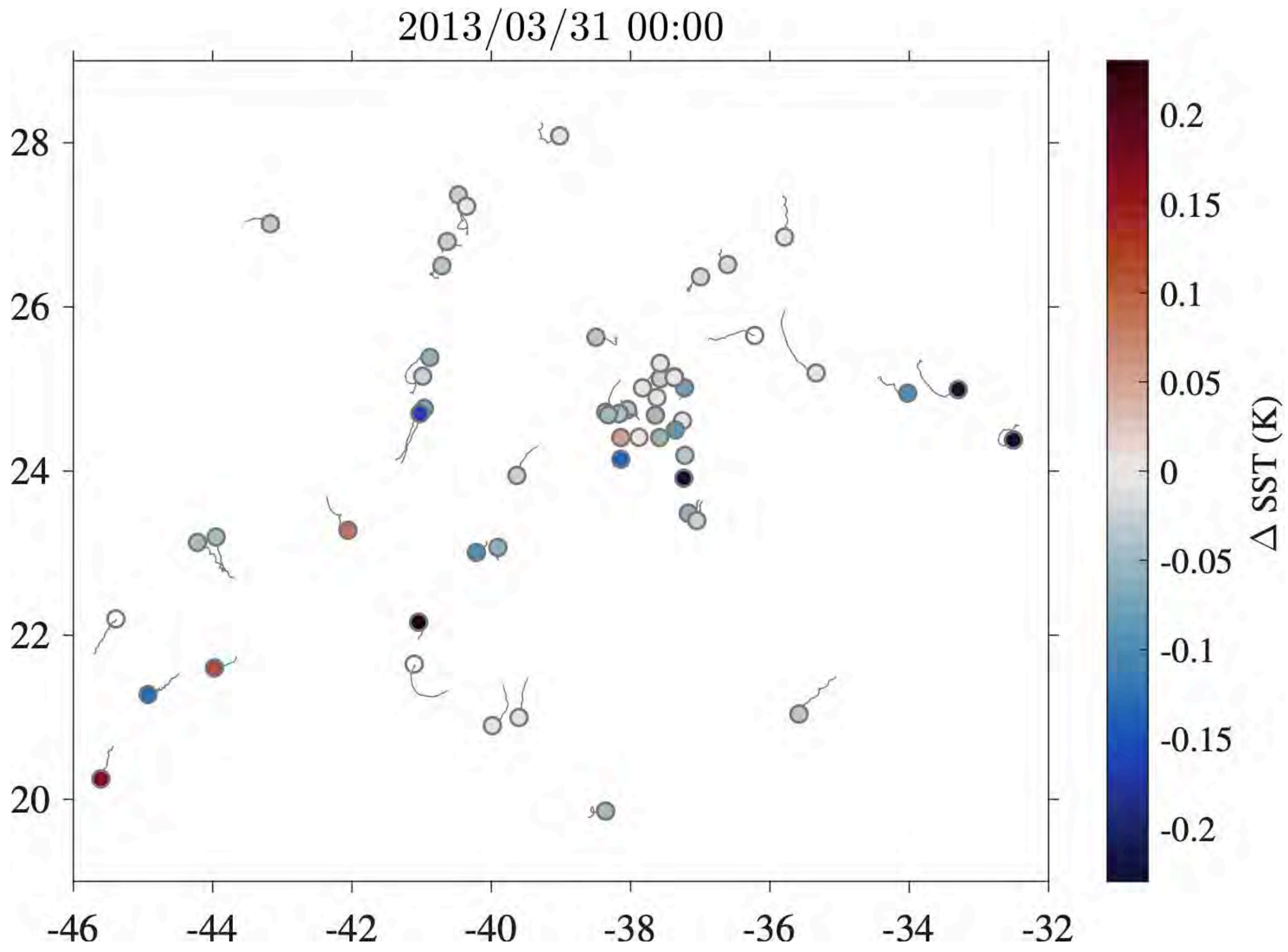
Summary

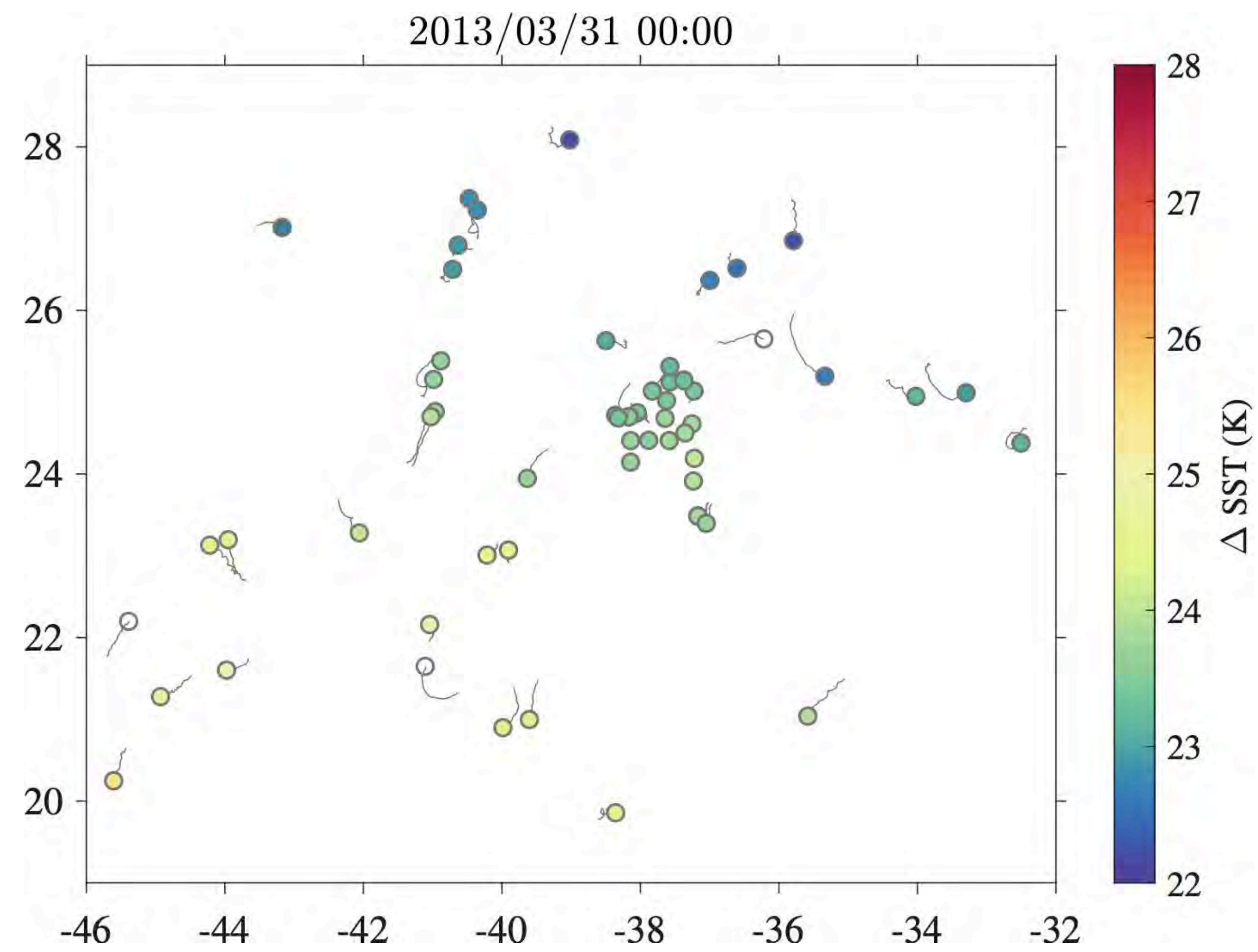
- A new Lagrangian SST dataset has been developed to accompany the on-going hourly drifter product from the GDP (SST available 2020?).

- Along-trajectory SST temporal evolution is modeled as a sum of a daily mean + a tendency term + a diurnal oscillation with 3 harmonics

- New global tool for studying air-sea interactions and general circulation.

Questions? Shane Elipot selipot@miami.edu





Thank you!

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twitter.com/ShaneKahn