

A Strategy for Assimilating Data from Microsats

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Utilizing MicroSats to Improve Atmospheric Prediction

Project Aims

- **Maximize the information extracted from microsats** to improve the environmental characterization, particularly in regions of interest
- Develop a capability to **rapidly implement** and **optimally utilize** meteorological data from microsats to improve atmospheric prediction by using informed **data selection** and properly accounting for their spatially and temporally varying **observation uncertainty**
 - Both **data selection** (thinning) and **observation error variances** will be **dynamic in space and time**
- Apply this generic approach developed for microsats **to other observing systems** to further improve forecasts
- Early success
 - Available SmallSats : **COWVR** and **TEMPEST** (on ISS), and the **TROPICS** pathfinder.
 - We are **among the first in the world** to assimilate **COWVR** data and evaluate its performance with an operational model (NAVGEM)
 - Initial trials show **similar beneficial impact to** legacy sensors such as **SSMIS**

The Challenge

Our DA systems use outdated approximations for **sampling** and **weighting** of satellite observations, **leading to sub-optimal forecast quality**

Current Practice

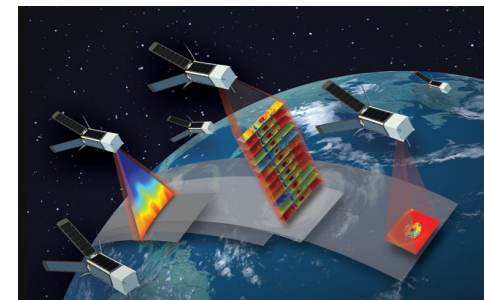
- **Globally uniform sampling**
 - Observations fall on a **uniform grid**, regardless of observation quality or atmospheric flow
- **Static observation uncertainty**
 - Each observation is assigned a **fixed uncertainty** (weight)



A Better Way

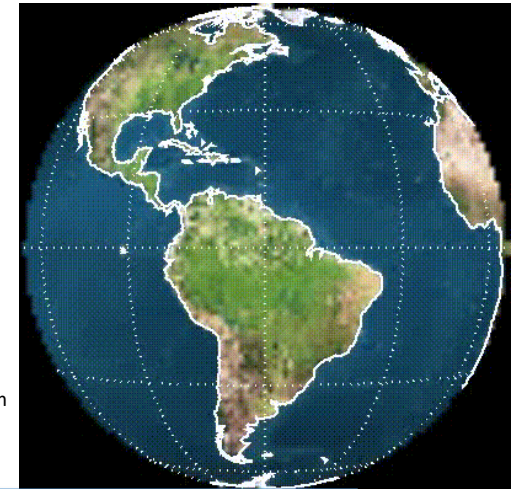
- **Dynamic sampling** in regions of interest
- **Adaptive observation uncertainty**

Sampling Approach: Predict where observations will be beneficial based on e.g. FSOI, then sample them accordingly



TROPICS Image credit: NASA/TROPICS
(Time-Resolved Observations of Precipitation structure and storm Intensity with a Constellation of Smallsats)

TROPICS
nadir field of view (FOV) per day



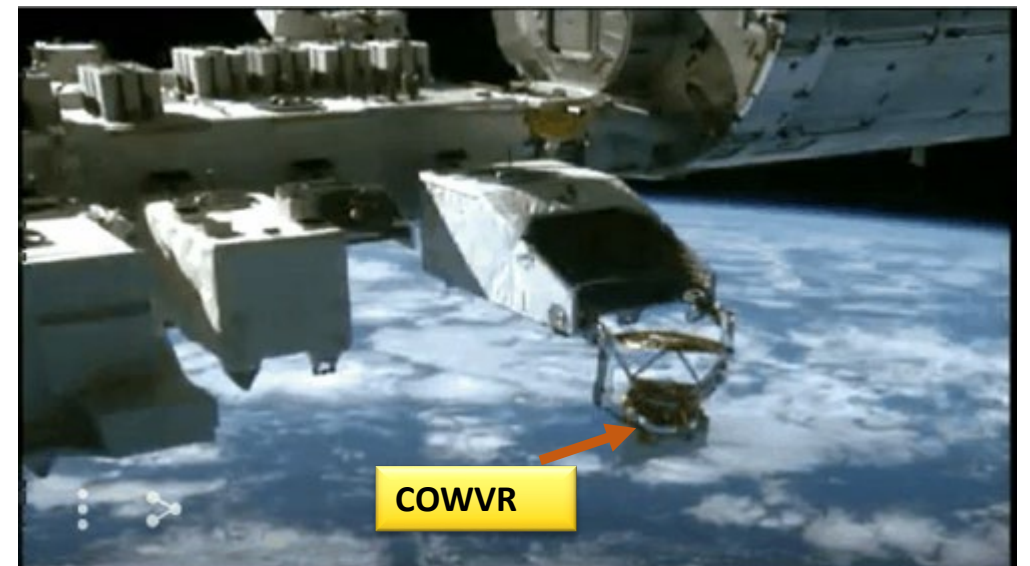
Credit:
R. Bennartz
Vanderbilt
University

- SmallSats provide a **high** volume of high temporal **resolution** data, fill data gaps, mitigate risk via **data redundancy**
- SmallSats exhibit **shorter lifetimes, higher uncertainty, larger variability** in sensor performance, and **unknown biases**

Compact Ocean Wind Vector Radiometer (COWVR)

COWVR measures ocean surface wind vector, precipitable water vapor, precipitation rate

- STP-H8 (Space Test Program - Houston 8) mission to demonstrate new low-cost microwave technologies for weather
- Launched Dec. 22, 2021 to the International Space Station (ISS), installed Jan. 7, 2022, plan to operate 3 years
- **Conical fore/aft imaging**
 - **12 channels:**
 - **V, H, 3rd and 4th Stokes at three frequencies (18.7 GHz (1-4), 23.8GHz (5-8), 33.9GHz (9-12))**
 - Spatial resolution:
 - 18.7 GHz: 30x19 km
 - 23.8 GHz: 23x15 km
 - 33.9 GHz: 16x10 km
 - Swath width: 890 km
 - **Data spans approximately 60S to 60N**



COWVR Radiance Assimilation

Experiment Design

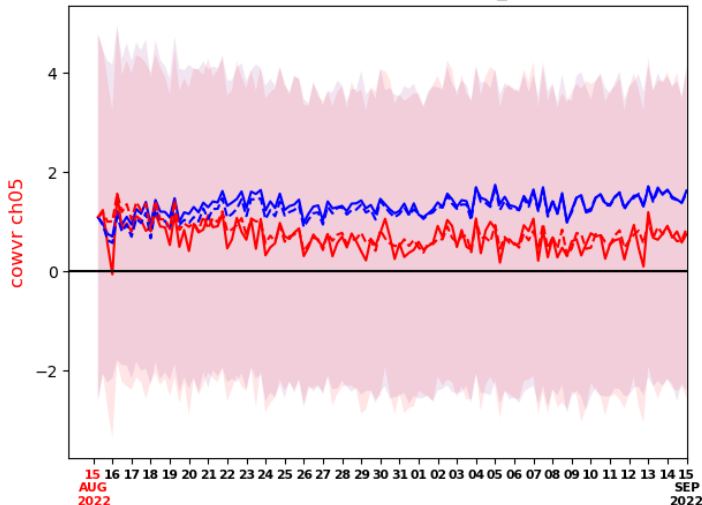
- NAVGEM Model Resolution: T425L60, Surface to 0.04 hPa
- NRL Atmospheric Variational Data Assimilation System – Accelerated Representer (NAVDAS-AR) : 4DVar hybrid (Kuhl et al. 2013)
- VarBC with cte, 2 airmass, and 0 (dashed) or 13 (solid) scan bias predictors (blue is raw, red is bias-corrected, shading is rmse)
- We used a logistic predictor to simultaneously fit/correct the separate fore/aft scan biases

COWVR Composite FOV from EDR

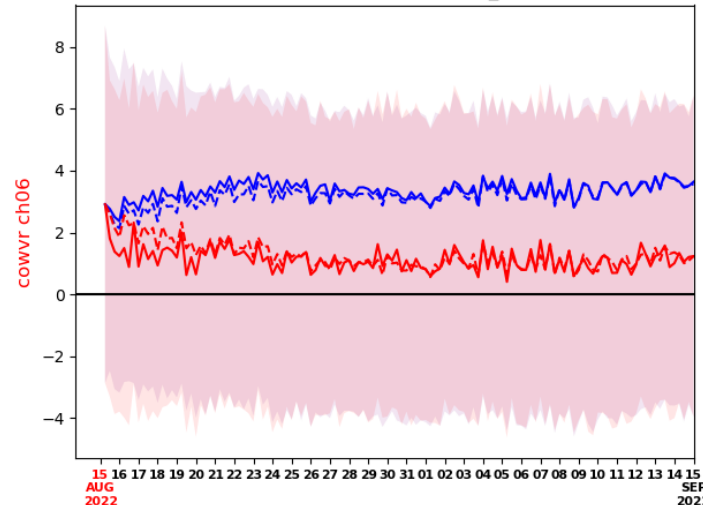
- COWVR radiance at CFOVs added in addition to all Obs data operationally assimilated
- COWVR Tb from 18, 23 and 34 GHz V/H were thinned to 1.75° lat/lon box per 30m
- Within each lat/lon box, both Fore and Aft looks are kept
- COWVR Tb Obs errors set to 4.5K (V) and 5.5K (H)
- COWVR QC:
 - Currently using obs_qual_flag ==0
 - Ocean only scenes
 - CLW <= 0.18 mm
 - 3-σ innovation check
- All of the above is still being refined, including the VarBC predictors

23.8GHz V (Ch 5) and H (Ch 6) Radgrams

Innovation ISS COWVR ch05 23.8 GHz V
bias=1.3 mean=0.68 stdv=3.1 exp:exp_13preds
bias=1.2 mean=0.77 stdv=3.1 exp:exp_3preds(dashed)



Innovation ISS COWVR ch06 23.8 GHz H
bias=3.4 mean=1.1 stdv=5 exp:exp_13preds
bias=3.2 mean=1.3 stdv=5 exp:exp_3preds(dashed)

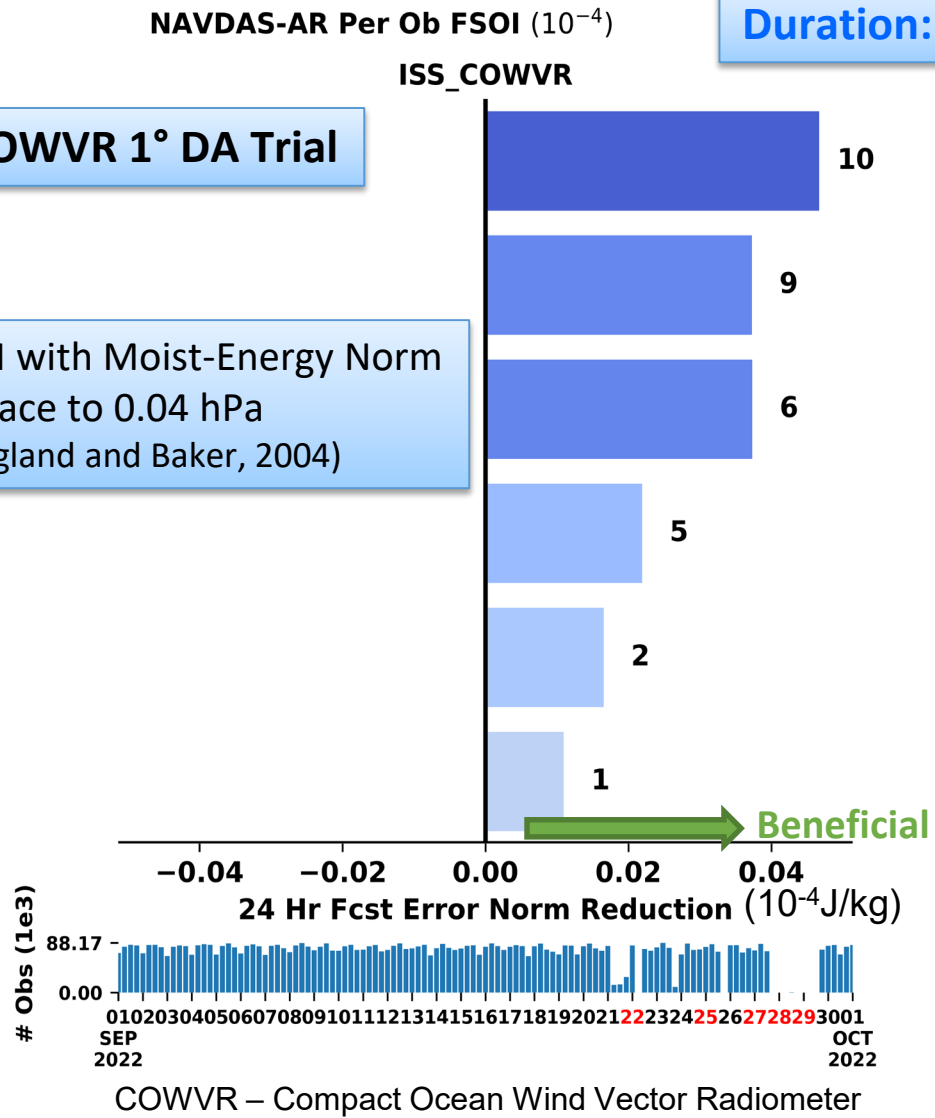


FSOI Per Ob: COWVR vs SSMIS

Duration: 1-30 September 2022

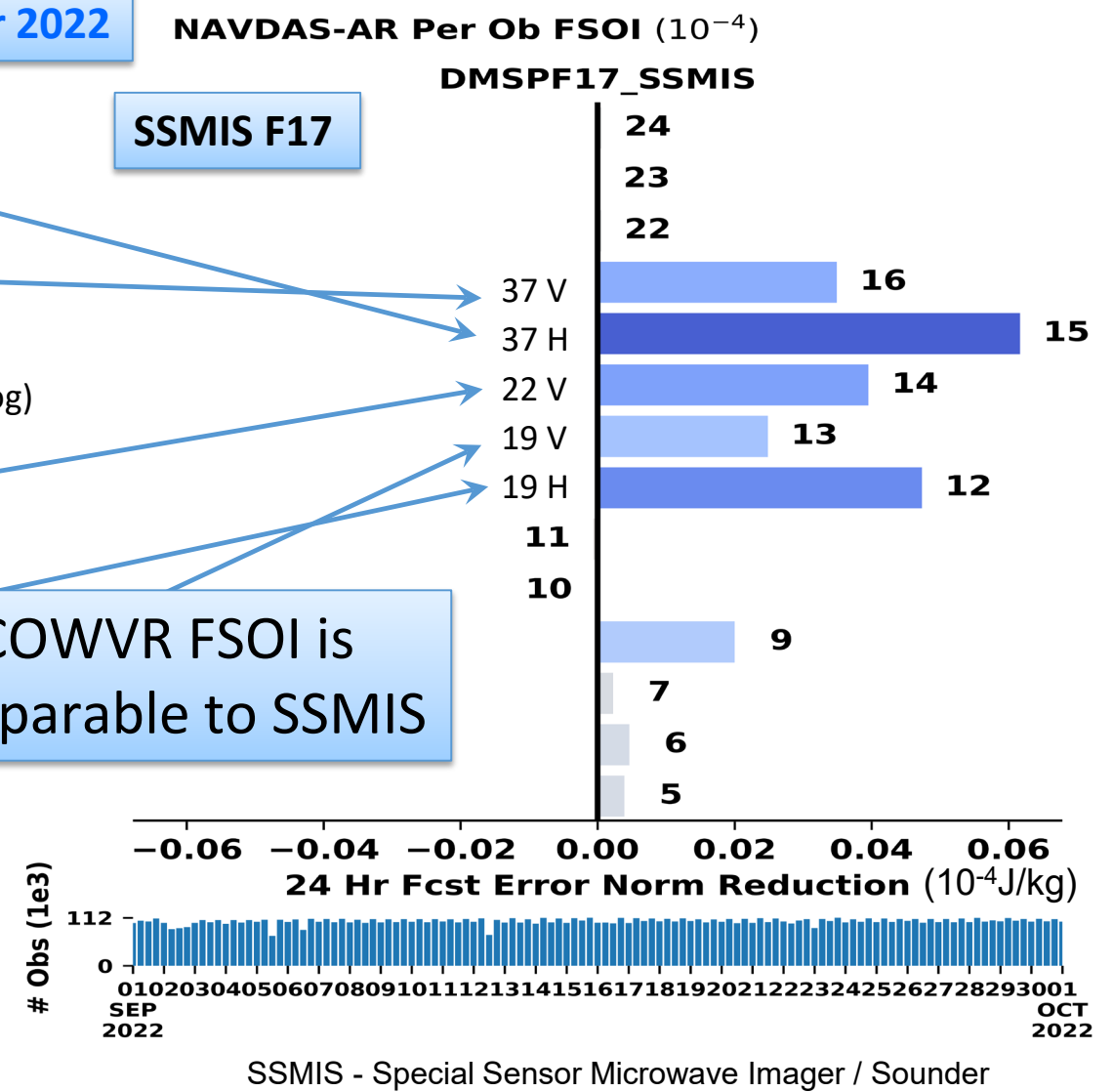
COWVR 1° DA Trial

FSOI with Moist-Energy Norm Surface to 0.04 hPa (Langland and Baker, 2004)



SSMIS F17

COWVR FSOI is comparable to SSMIS

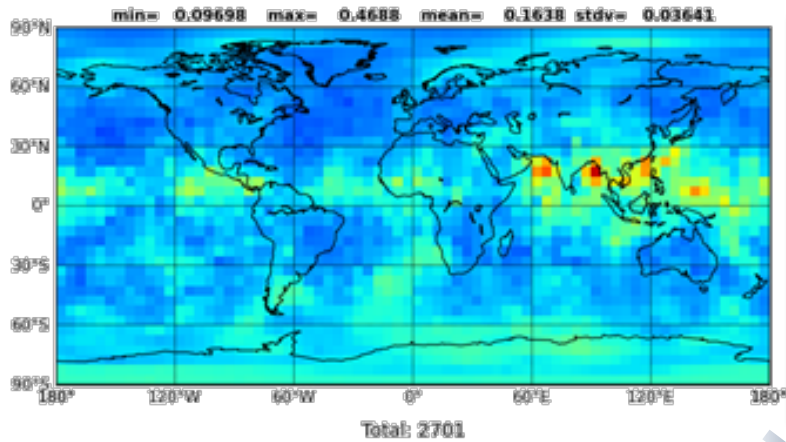


Machine Learning's Role in the Project

PostDoc
needed!

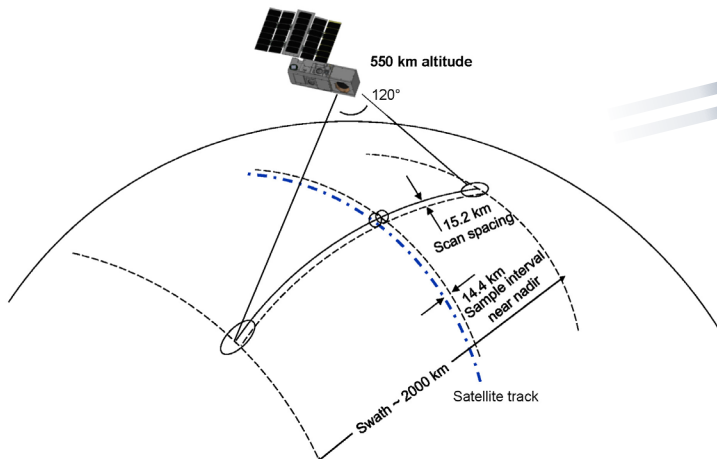
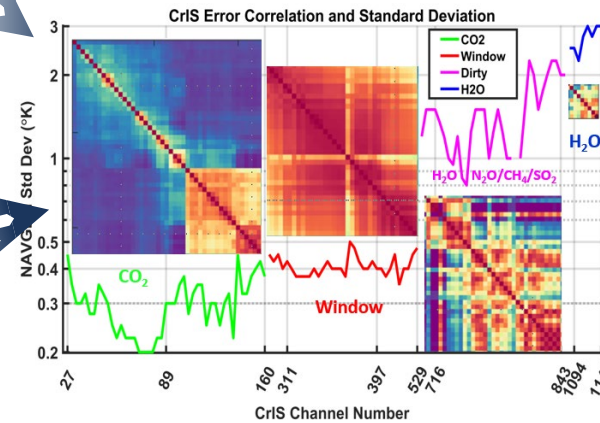
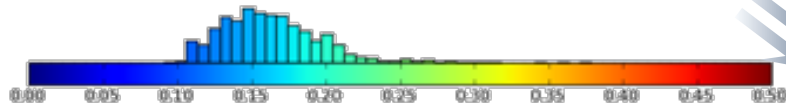
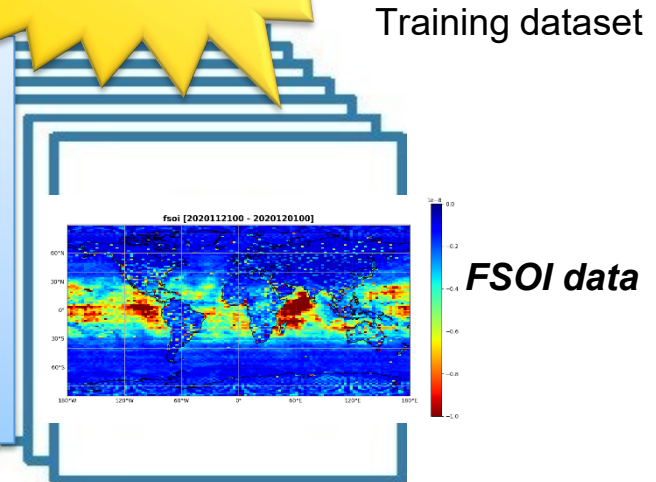
Training dataset

CRIS Global STDV Innovation for ch0059 14.572um 2014061900



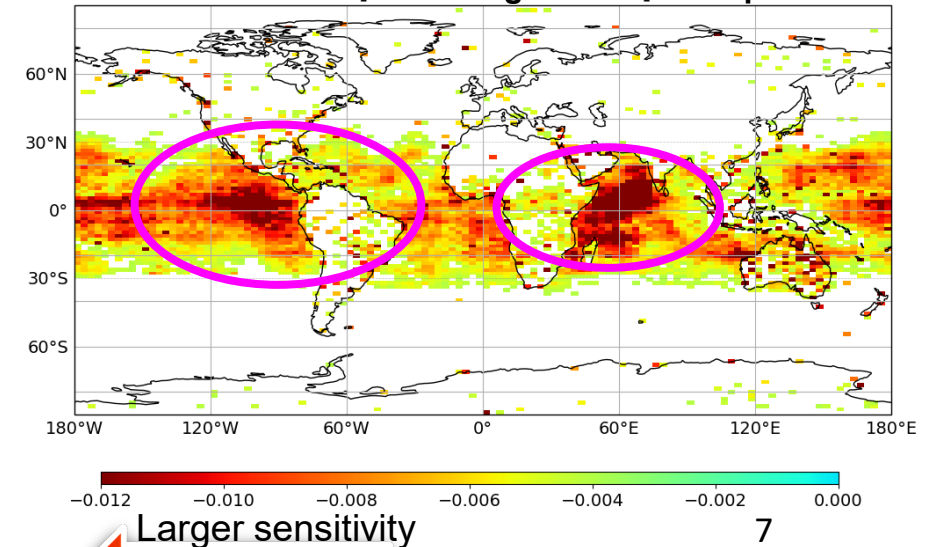
Use supervised ML methods (e.g. CNN, XG-BOOST) to predict **observation uncertainty** characteristics

Use unsupervised ML methods (e.g. K-means clustering) to identify features of interest *a priori* for **adaptive sampling**



Cross-track Infrared Sounder (CrIS)
Convolutional neural network (CNN)
eXtreme Gradient Boosted trees (XG-BOOST)

mean sensitivity
for observations with large beneficial impacts

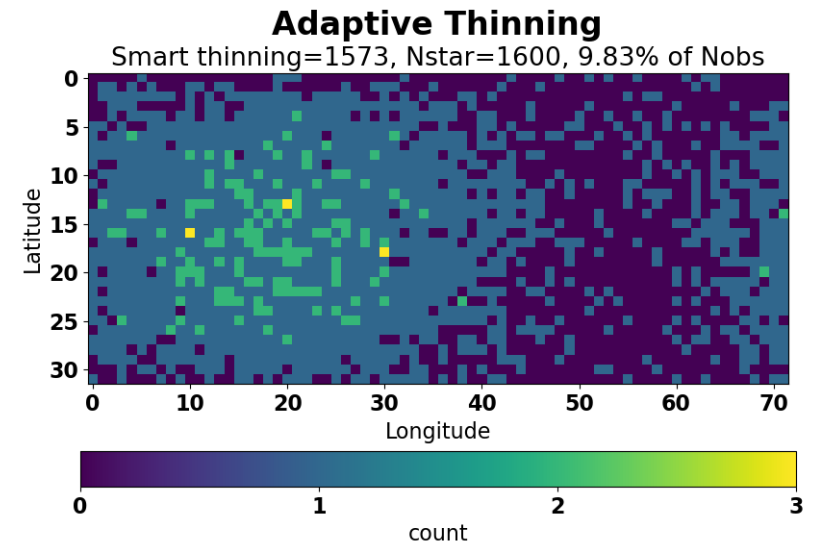
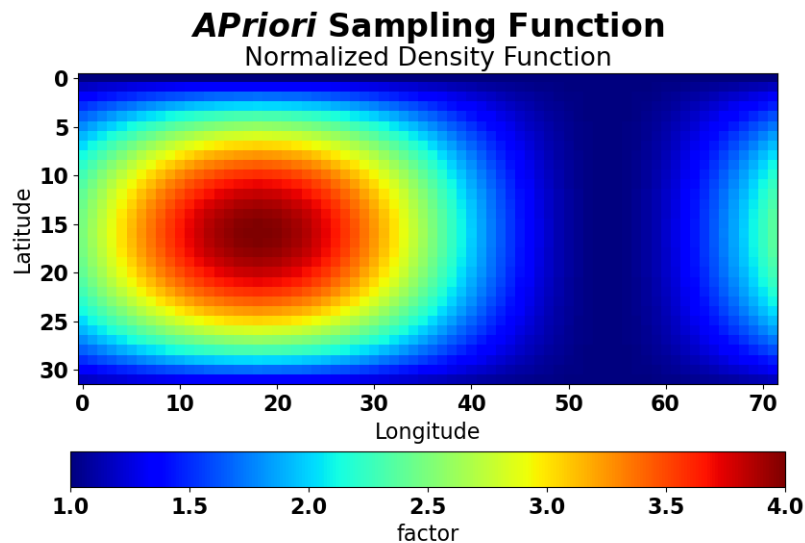
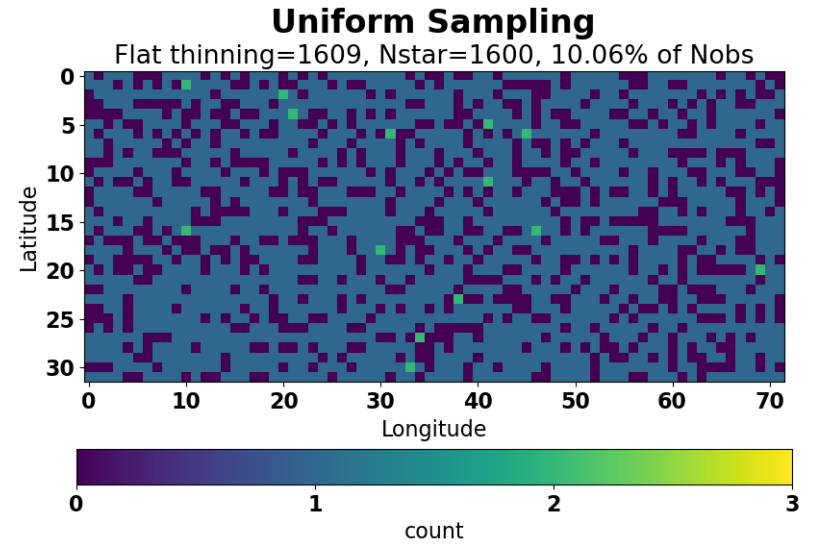
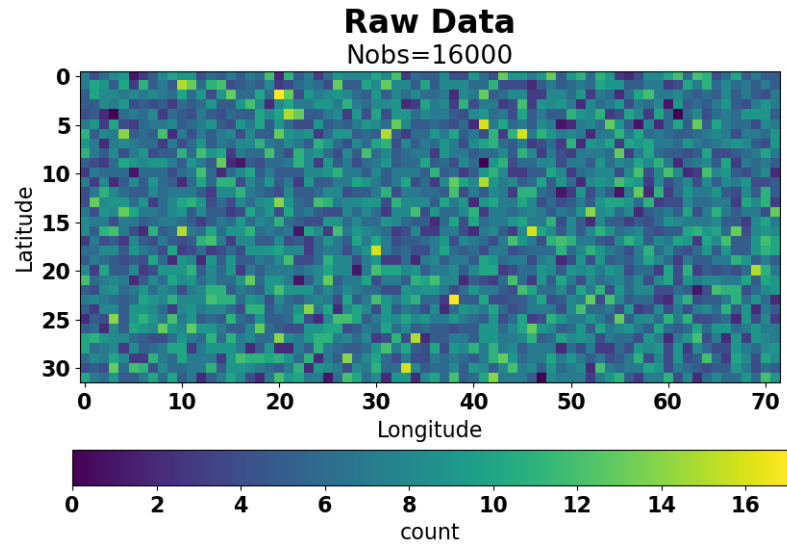


Adaptive Sampling Strategy

- Construct a **candidate density function** for adaptive thinning, e.g. spatial map of time mean FSOI or abs(FSOI), or Eady index (Bauer et al, 2011), etc.
- If the function is not available *a priori*, we may need a statistical or **machine learning** model to predict it
- Perform data sampling based on the **candidate density function**, *retaining more data where the function is greater, and less data where it is lesser*
- Compare forecasts with data sampled from that **density function** vs. a control run with **standard uniform** sampling, keeping the **data count** relatively **constant**
- Evaluate (standard forecast scores, fit2obs, etc.)
- Look at **combinations** of those **density functions** for further improvement
- **Hybridization** of climatological and flow-of-the-day functions may be the most promising. **Density functions** can vary with time as well.

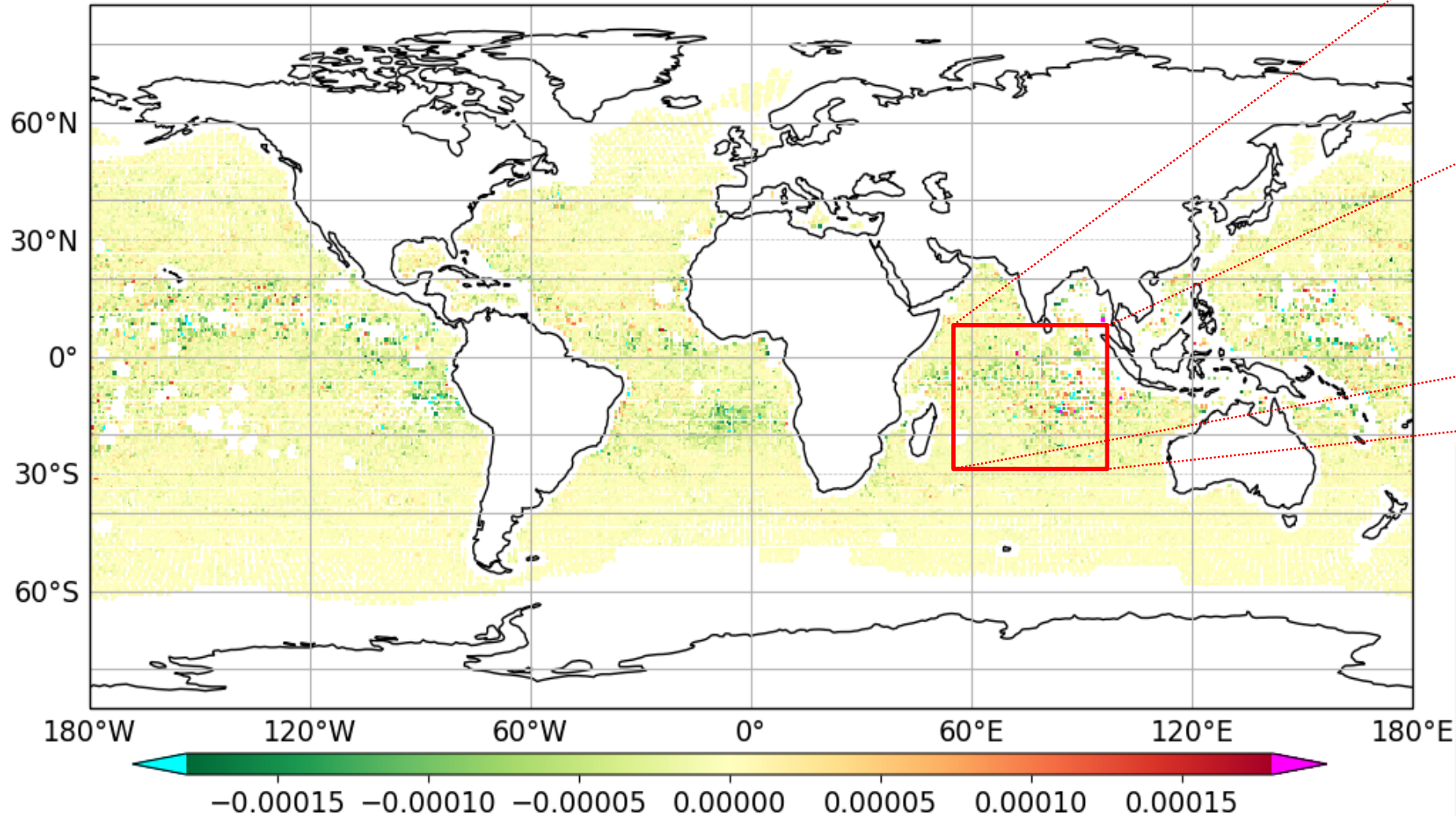
Adaptive Data Sampling Conceptual Model

- Start with a **large** number of data **Nobs** from a given source,
- And suppose we are **constrained** to use only **$N^* \ll Nobs$**
- We can **sample uniformly** to meet that constraint,
- Or we can **sample** based on a **relative density function**
- May need a **machine learning** model to predict this '*a priori*' function



Can Time Mean FSOI Maps Predict Beneficial Obs?

mean fsoi per profile [2022100100 - 2022101018]
51293 bins, min=-0.000389964, max=0.000265754



- 10-day SSMIS mean FSOI *per profile* (0.5° bins) for ch 12-16 only, as a proxy for COWVR
- Negative values are beneficial, positive are non-beneficial, white indicates no data
- Extreme outliers (0.01%) were discarded before binning

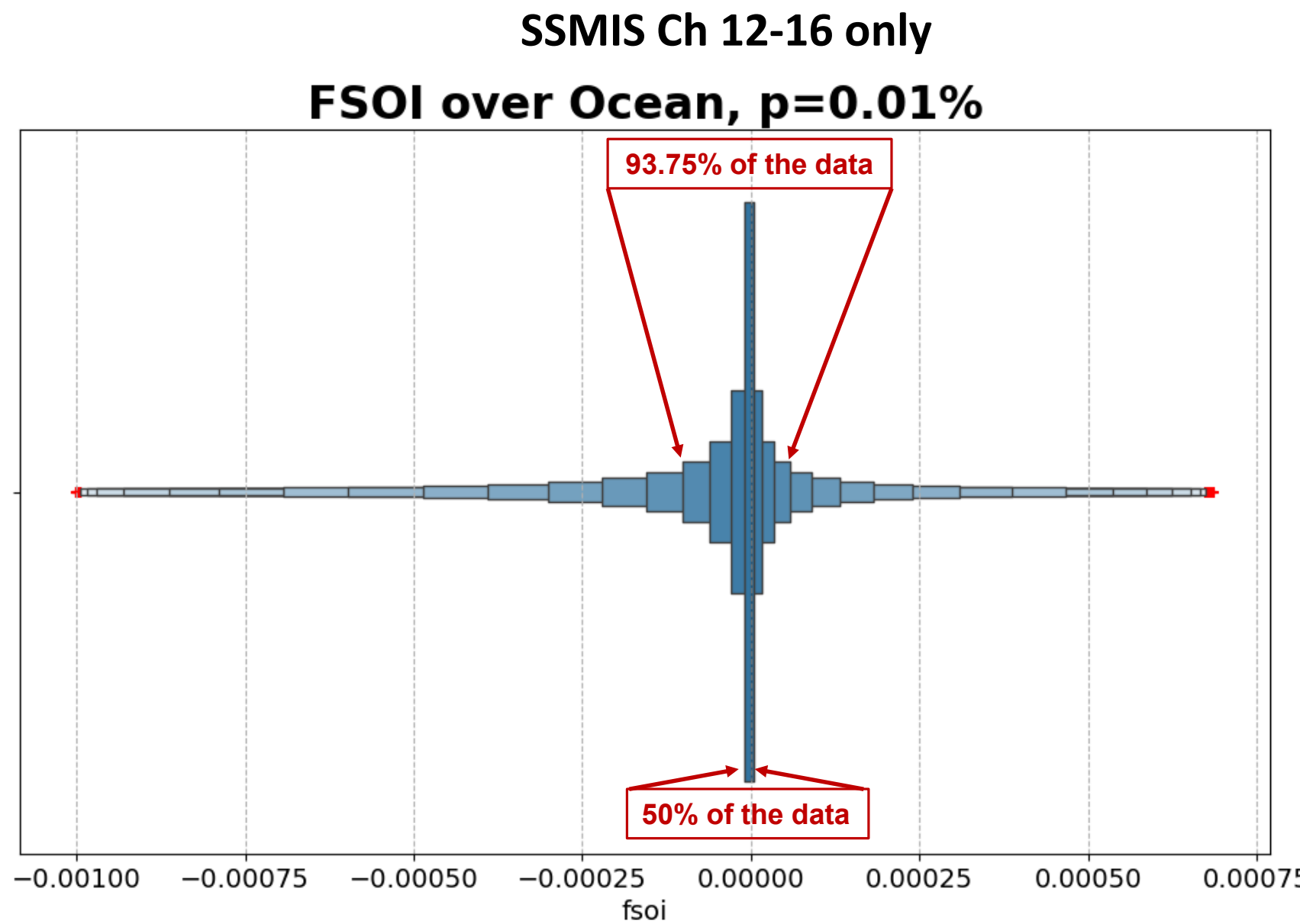
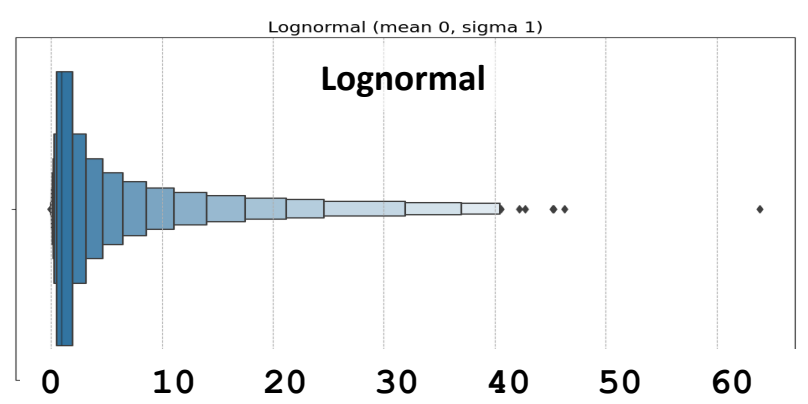
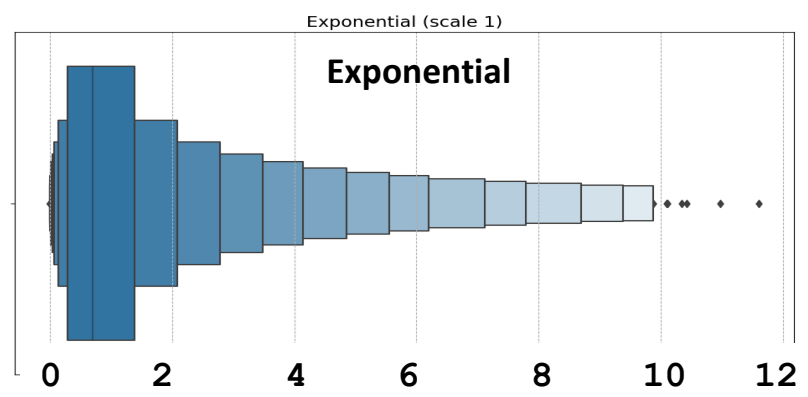
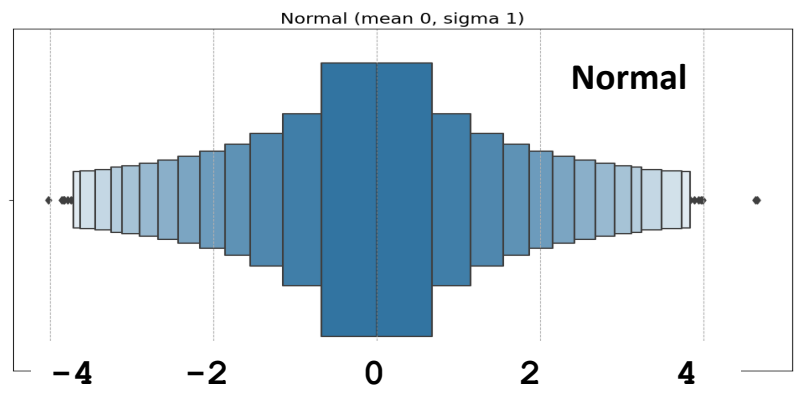
Examining the PDF of Per Profile FSOI

For large datasets, even if the data is normally distributed, traditional box of whiskey plots are inadequate



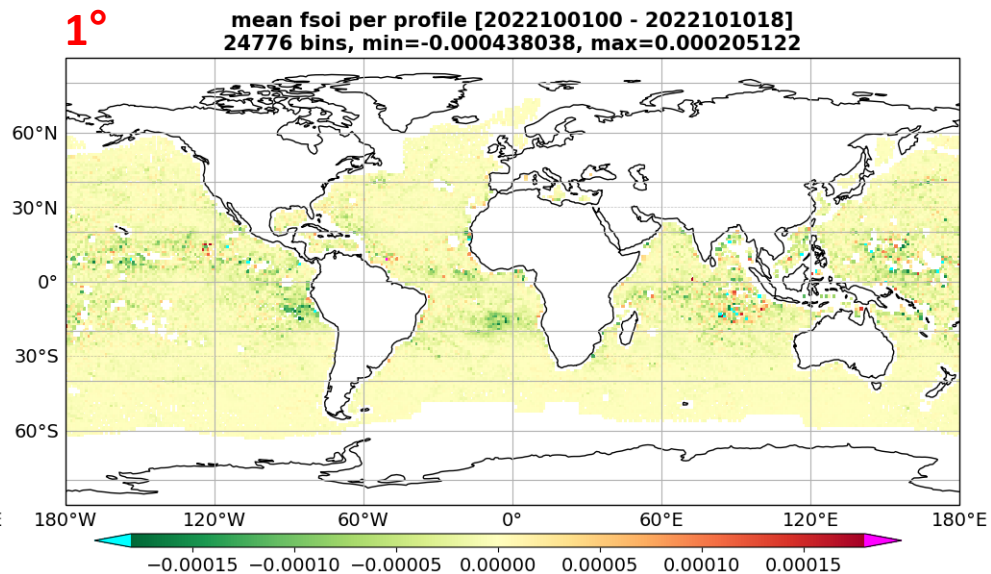
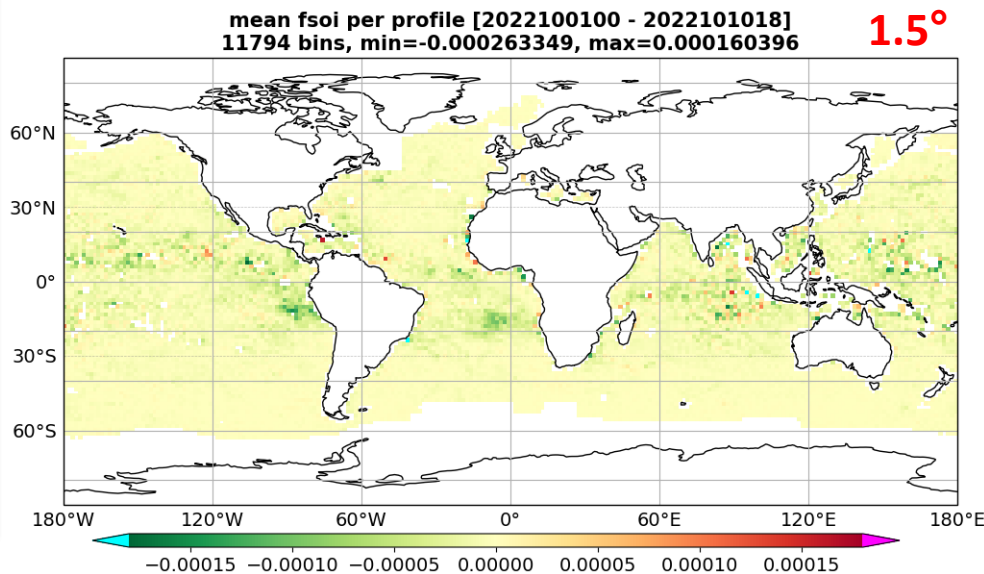
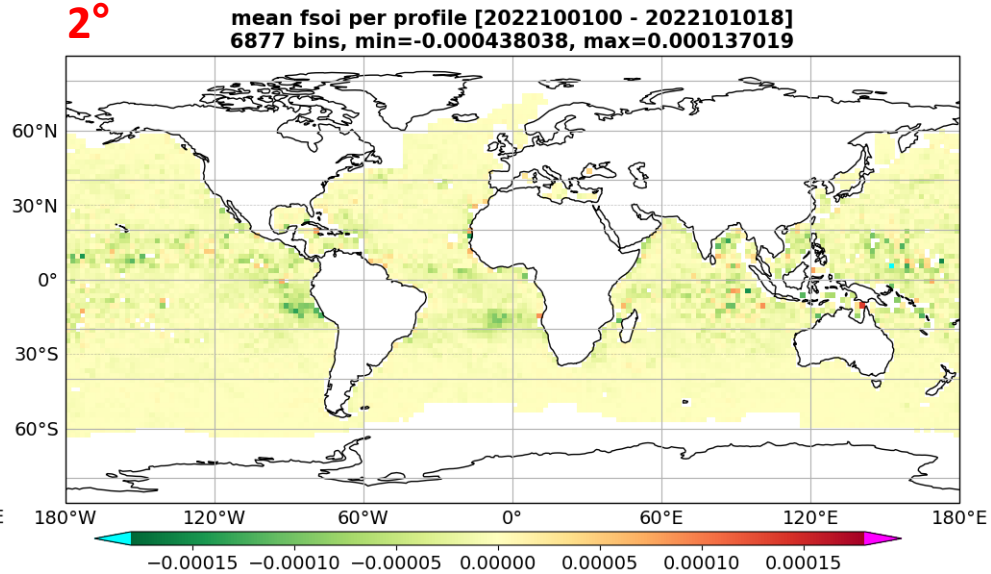
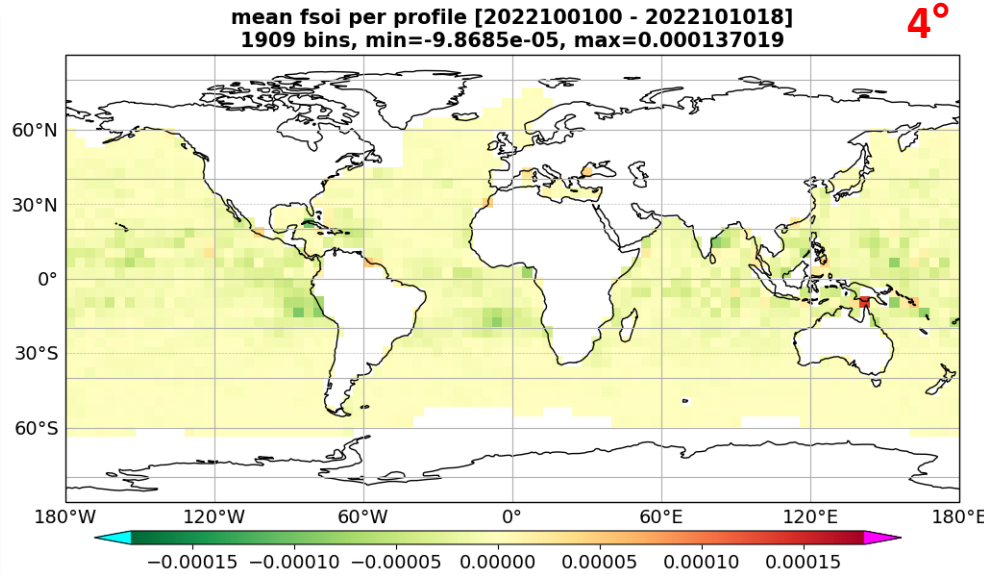
Happy St. Patrick's Day

Boxenplots Can Handle Large Datasets



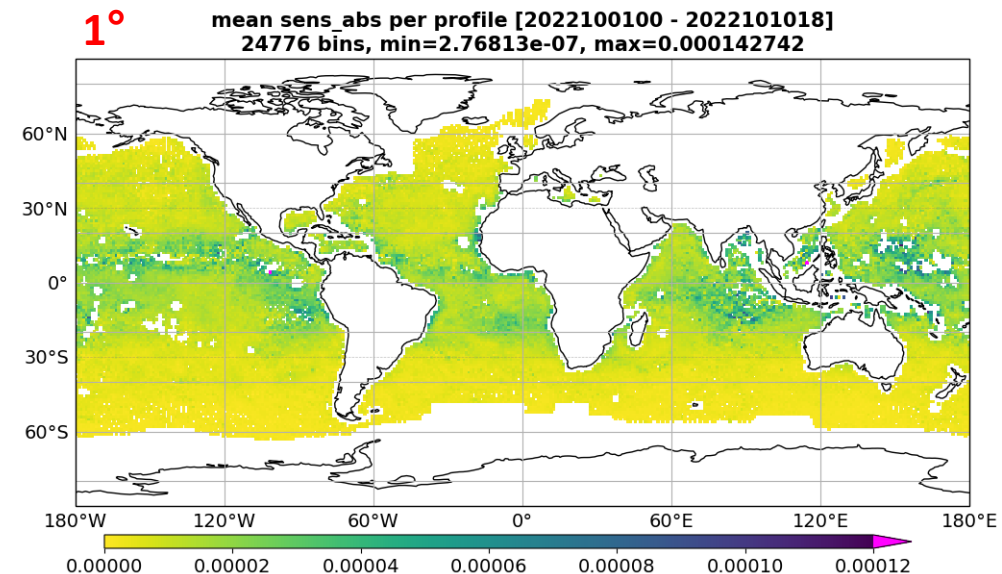
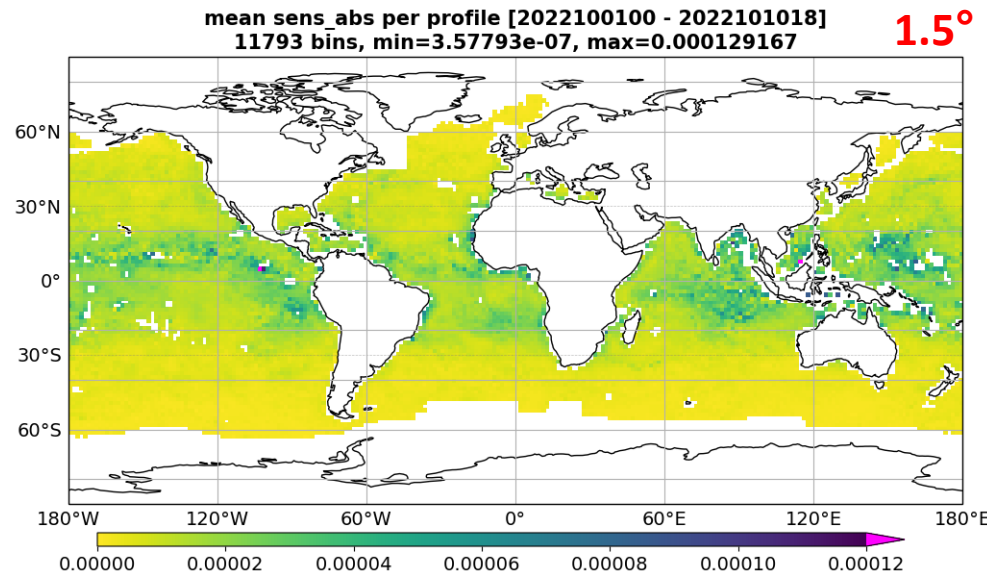
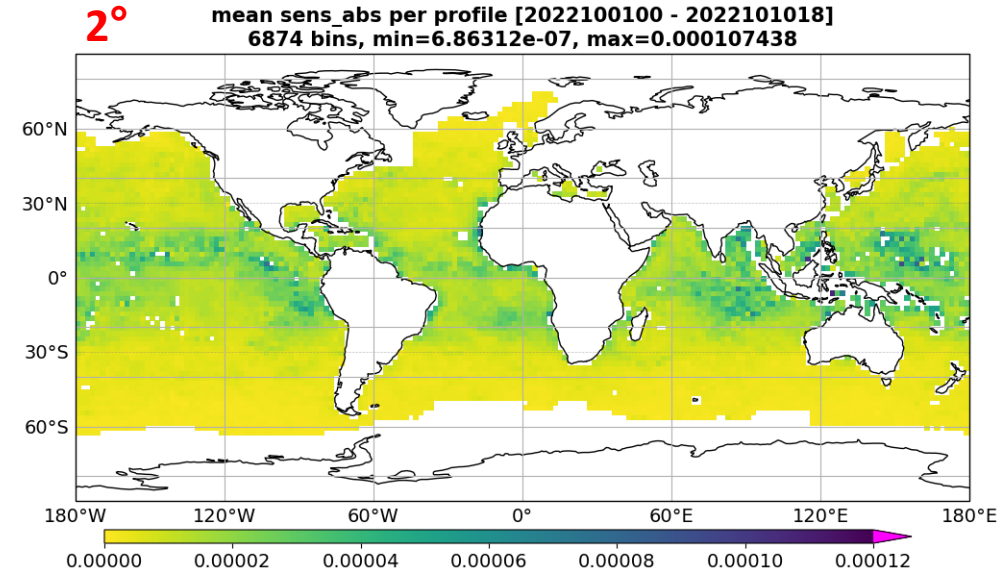
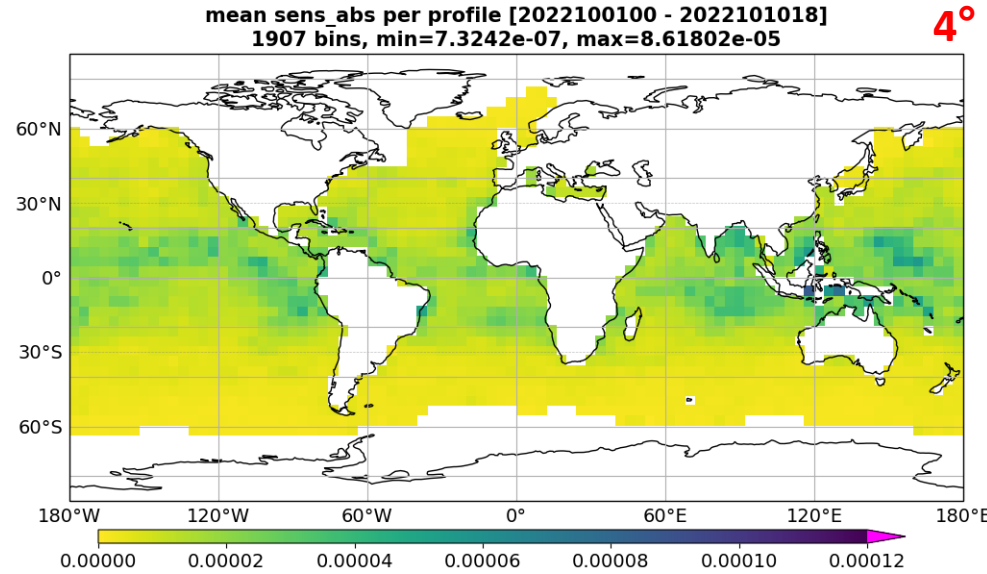
Drawbacks of Mean FSOI as a Data Density Function

- Although [patterns are **persistent** across **larger** scales,
- there is small scale mixing of ben/nonben obs that may be related to errors of **displacement**
- This suggest it may be **better** to look at the **absolute value** of FSOI or sensitivity



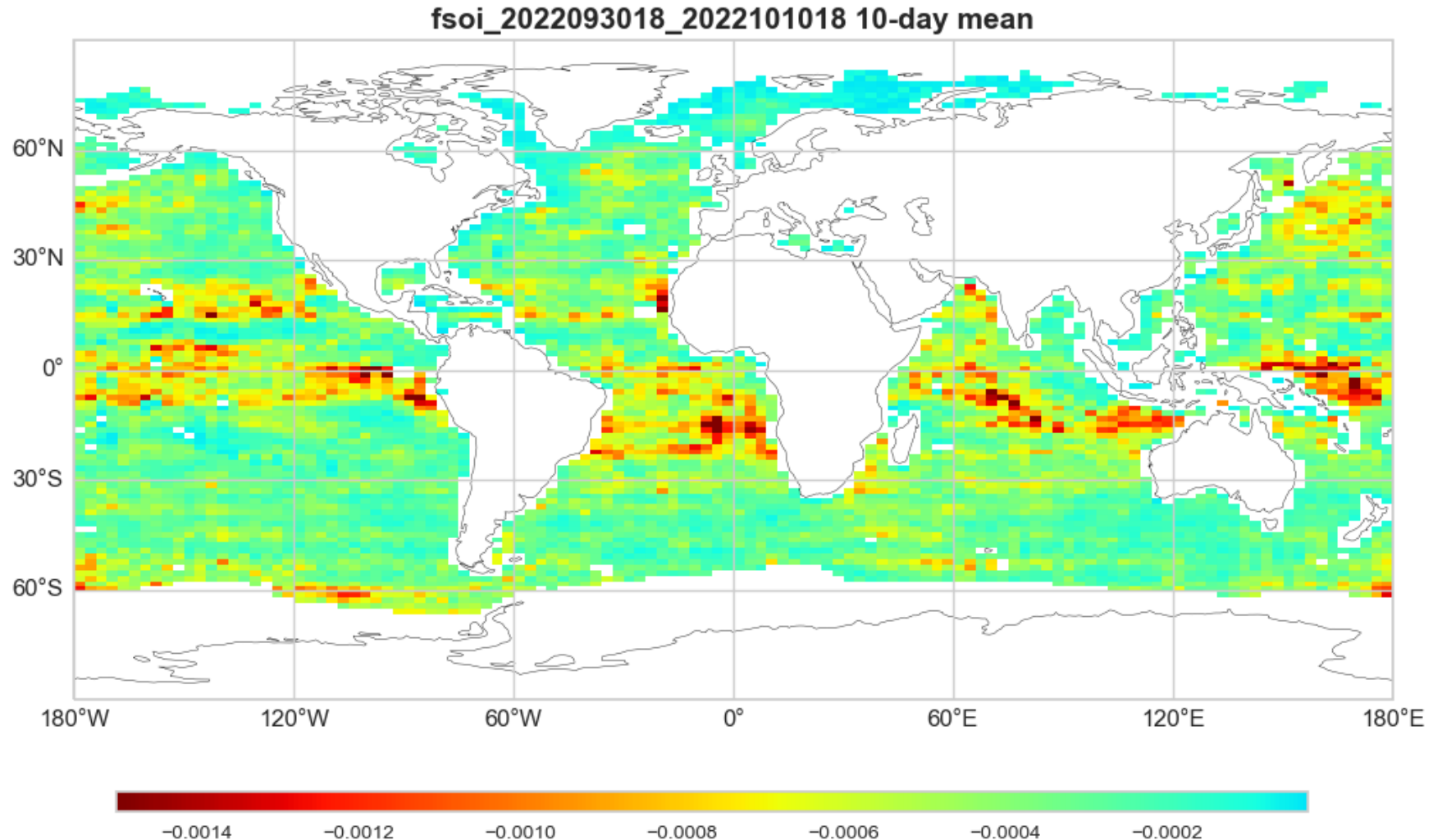
Absolute Sensitivity is Better Behaved

- Patterns are **persistent** across **all** scales
- This suggests **the pattern is real**, and might be suitable for prediction



Alternative Density Functions

- Can we use FSOI **indirectly** to create an **alternative density function**?
- In this example, we start with the **beneficial-only** FSOI 3° lat x 1.5° lon over the same 10 days of SSMIS data, using all available channels
- **Clustering algorithms** leap to mind

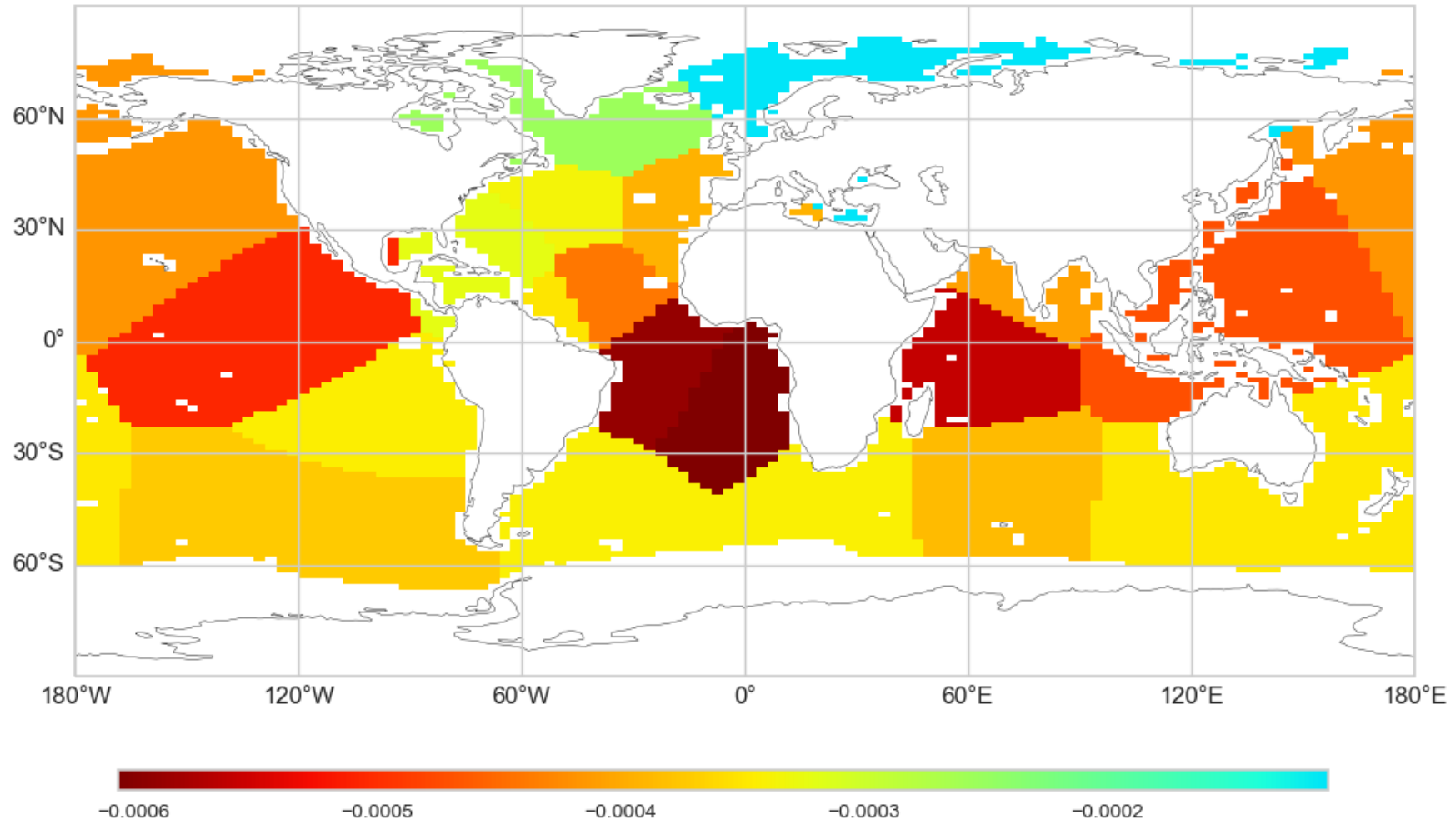


K-means with Custom Metric and Single Parameter α

- Clustering algorithms can also provide candidate density patterns
- K-means with $K=20$ and the custom metric is shown, and reflects both the underlying fsoi and true great circle distance
- Many other clustering algorithms could be applied

$$D(p1, p2) = \sqrt{\left(\frac{GCD(p1, p2)}{10800 Nm}\right)^2 + \alpha \left(\frac{fsoi_{p1} - fsoi_{p2}}{fsoi_{max} - fsoi_{min}}\right)^2}$$

fsoi-based cluster



Conclusions

- The age of microsats is coming, and we need to be prepared
- There may be higher uncertainty, shorter lifetimes, larger variability in sensor performance, and unknown biases that we have not had to contend with for legacy satellites
- Adaptive uncertainty estimation and adaptive data sampling will help us get the most out of these future instruments, and also apply to legacy instruments
- We showed an approach to adaptive sampling with candidate data density functions derived from metrics such as FSOI by applying traditional statistics and machine learning
- Great care must be taken with data that have statistical properties far from normal
- Now we need to test these ideas, and see what works



RO# 64.16.66.B3063 Location

Monterey, CA 939435502

Description

Data assimilation research is greatly enhanced by co-location of NRL with the Fleet Numerical Meteorological and Oceanographic Center (FNMOC), one of the world's leading operational forecast centers. Researchers have **ready access to operational global and regional data assimilation systems developed at NRL and complete real-time global data bases maintained by FNMOC**. The NRL Atmospheric Variational Data Assimilation System-Accelerated Representer (NAVDAS-AR) was transitioned to operations in 2009 and further upgraded to Hybrid 4D-Var in 2016. Research opportunities exist to contribute to further improvement of the mesoscale and global data assimilation systems as well as the development of coupled and next generation data assimilation systems. Research areas include treatment of nonlinearity for both prediction and observation models, efficient computational algorithms for high resolution data assimilation suitable for operational use, direct assimilation of all sky radiances, use of artificial intelligence, initialization of tropical cyclones, coupled data assimilation, observation bias and covariance estimation, forecast and model error estimation, preconditioning techniques, Kalman filters/smoothers, adaptive ensemble covariance localization, inflation and hybridization, particle filters, and Monte-Carlo-Markov-Chains.

Strong emphasis is placed on developing techniques for

(1) utilizing new types of atmospheric data (e.g., satellite, Doppler radar, high resolution mesoscale observations, unmanned platforms, observations of opportunity), (2) initializing models with cloud and moisture information (including soil moisture and precipitation), (3) analyzing mesoscale features in the coastal zone, (4) directly assimilating all-sky (cloudy radiance) assimilation MW and IR, (5) the use of artificial intelligence in detecting/correcting errors in conventional and satellite observations, (6) improving the initialization of tropical cyclones including examining data selection for dropsonde data, (7) data assimilation in the polar (especially Arctic) regions, (8) observation bias and covariance estimation, forecast and model error estimation, (9) aerosol and trace constituent assimilation, (10) coupled data assimilation for Earth System of system that includes atmosphere, ocean, land, sea-ice, waves, upper-atmosphere, aerosols and trace gases, and improved land surface components

Keywords:

Data assimilation; Data quality control; Meteorology; Moisture initialization; 4D optimal estimation; Representer methods; Ensemble data assimilation methods; Satellite radiance assimilation; Variational analysis; Ensemble; Nonlinearity; Kalman filter;

Eligibility

Citizenship: Open to U.S. citizens and permanent residents

Level: Open to Postdoctoral applicants

Stipend

Base Stipend

\$94,523.00

Travel Allotment

\$3,000.00

Contact Nancy Baker, Hui Christopherson, or William Campbell at this meeting if you are eligible and interested in this opportunity, or know someone who might be.