

Detecting ASCAT sensor drift

- **ASCAT**: microwave radar instrument on Metop satellites, designed for wind speed and direction over open ocean. Also capable for observing sea ice extent and surface soil moisture changes.

- Regular calibration campaigns using active transponders provide ongoing quality monitoring, but infrequently due to requirements to halt data collection during calibration passes over the transponders.

- Natural targets like tropical rainforests have been used for calibration campaigns that don't rely on active transponders.

- Upcoming EUMETSAT H SAF ASCAT Surface Soil Moisture (SSM) products categorized as Climate Data Record (CDR), Intermediate CDR (ICDR), and Near Real-Time (NRT).

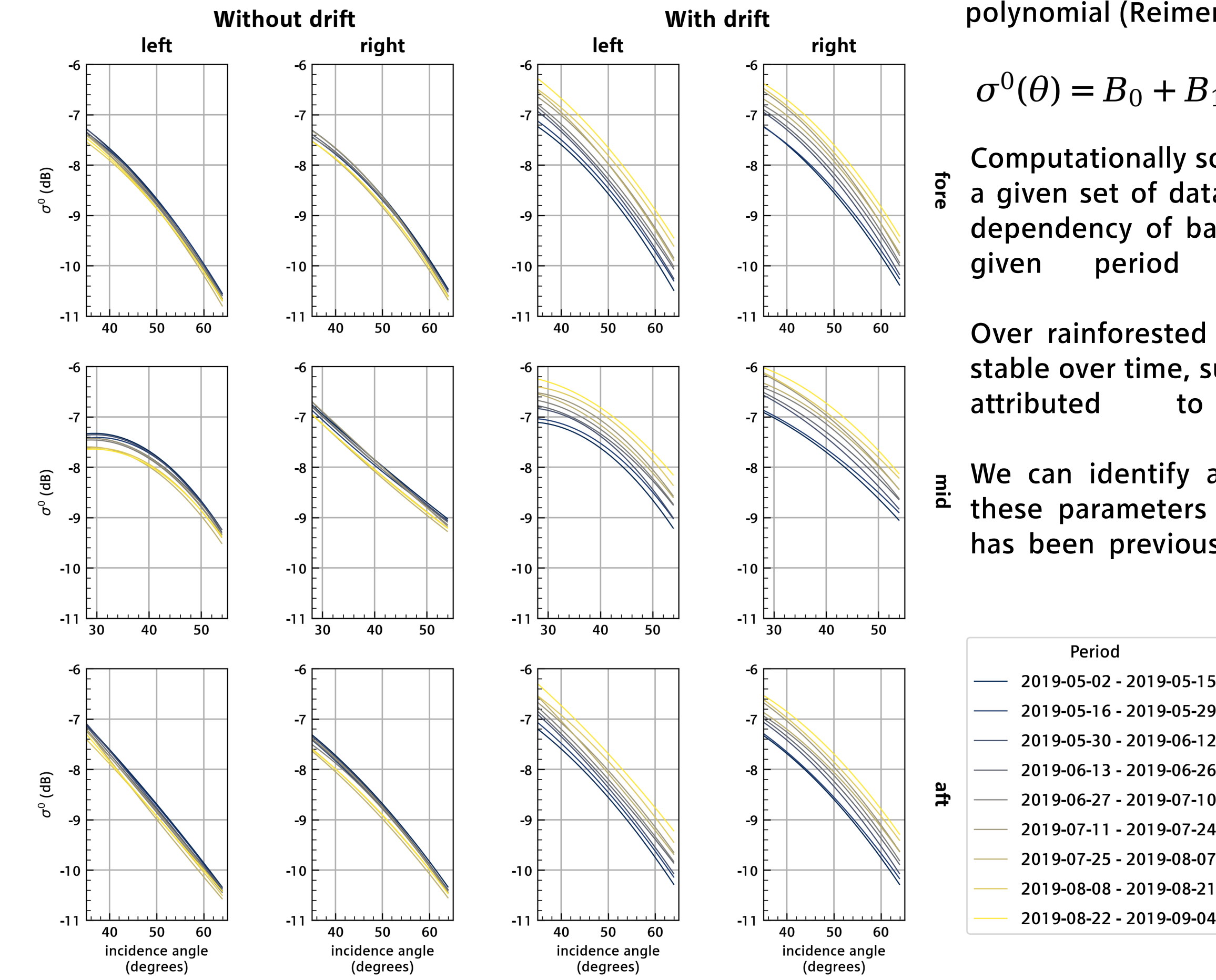
- ICDR products introduced to maintain consistency between historic data and NRT products, which may be subject to intentional or unintentional changes.

- This study presents a strategy to monitor ASCAT Level 1b backscatter stability over tropical rainforests and discusses its implementation as an early-warning system for the ASCAT SSM ICDR product.

- Discovering problems that undermine coherence between CDR and ICDR products is critical for applications like drought monitoring and climate studies, which rely on consistent time series data.

Monitoring changes in σ^0 incidence angle dependence

Second-degree polynomial fit to σ^0 as a function of incidence angle (Metop A, ascending passes only)



The relationship between incidence angle and backscatter at a calibration target can be modeled by a second-degree polynomial (Reimer et al., 2014):

$$\sigma^0(\theta) = B_0 + B_1(\theta - 40) + B_2(\theta - 40)^2$$

Computationally solving for parameters B_0 , B_1 , and B_2 with a given set of data, we can describe the incidence angle dependency of backscatter over a location or area for a given period of time.

Over rainforested areas, these parameters remain quite stable over time, such that any significant variation can be attributed to calibration/instrument errors.

We can identify a period as anomalous by checking if these parameters fall outside an acceptable range that has been previously established by well-calibrated data.

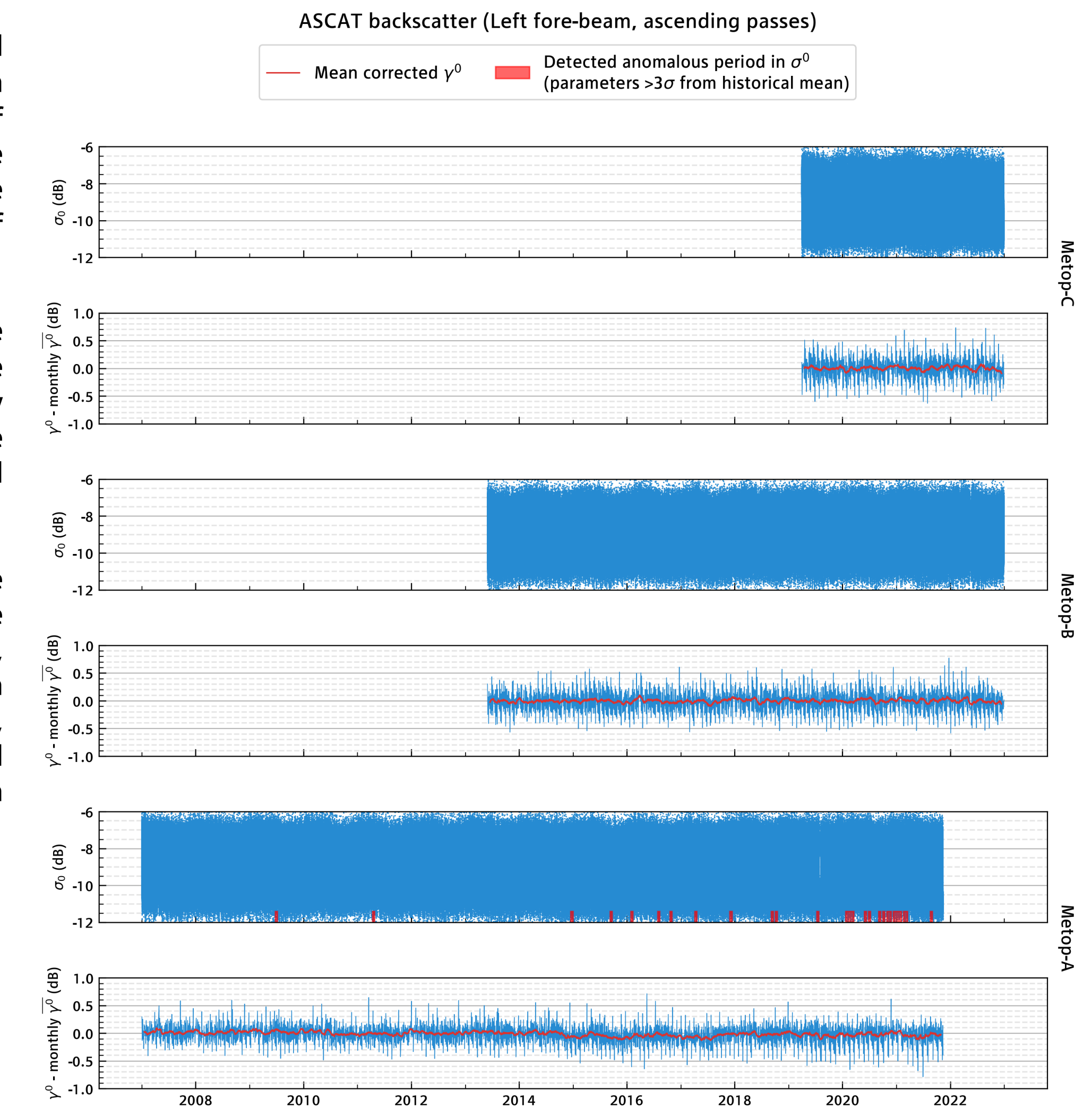
In this experiment, the mean and standard deviation of parameters B_0 , B_1 , and B_2 were calculated for each satellite over a reference period split into two-week-long chunks. The acceptable range for each satellite was defined as three standard deviations from its mean.

Kernel Change Detection in γ^0 time series

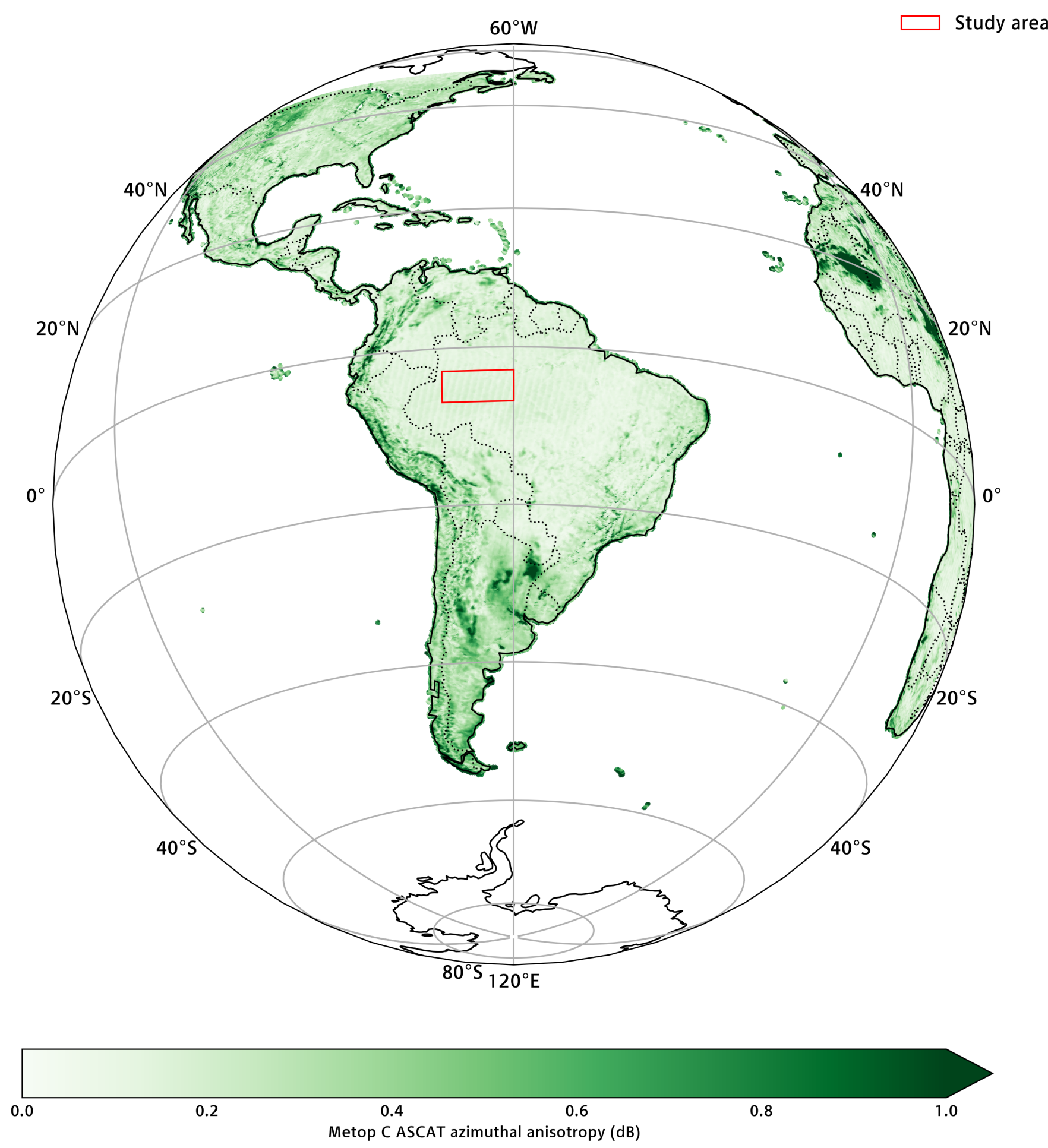
Gamma nought (γ^0) is calculated by dividing sigma nought (σ^0) (in the linear scale) by the cosine of the incidence angle of the observations, normalizing the short-term time-domain effects of this dependence.

Then, seasonal effects in γ^0 are corrected by normalizing the entire time series by monthly mean values, creating a stable time series that can be analyzed for breakpoints.

Breakpoints in the time series are identified using Kernel Change Detection with a Gaussian kernel, as implemented in the Python package "Ruptures" (Truong et al., 2020), with no prespecified number of breakpoints and a penalty value of 20.



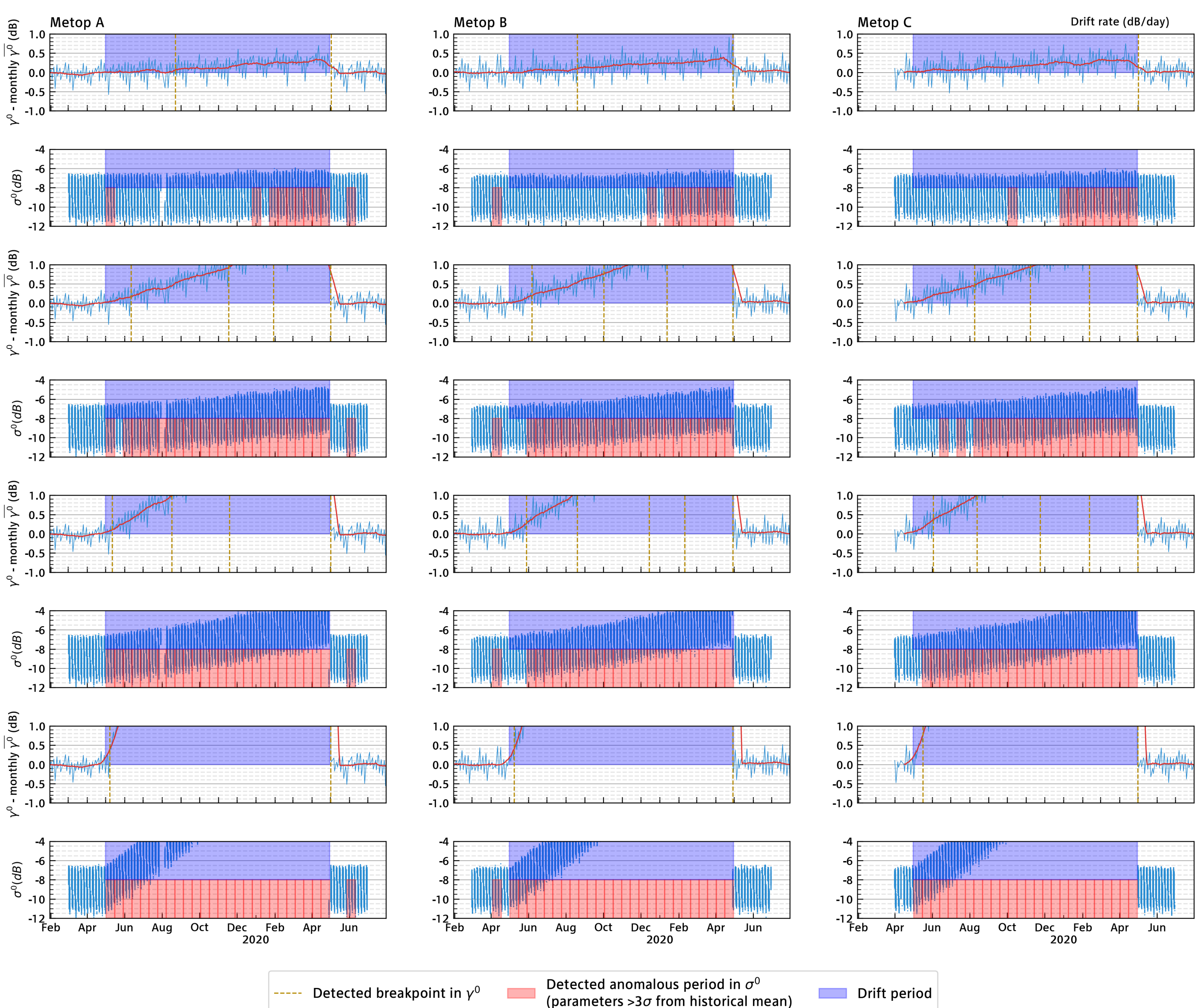
Rainforests as stable calibration targets



- ASCAT backscatter shows low azimuthal anisotropy and spatio-temporal variability in rainforested regions.
- Stable relationship between backscatter measurements and incidence angles.
- Stable γ^0 backscatter signal after correcting for seasonal effects.
- Study area was selected from a region of the Amazon which exemplifies these properties.

Comparison

Detection of artificially introduced drift in ASCAT backscatter data (Left fore-beam, ascending passes only)



- Artificial drift was introduced to the ASCAT backscatter product at several different rates (0.001, 0.005, 0.01, and 0.05 dB/day).
- Both detection methods were applied to the resulting timeseries data.
- The time each method took to detect the drift at each rate was recorded.
- The Kernel Change Detection method usually detected the drift earlier than the incidence-angle-dependence method, especially at lower (and more realistic) drift rates, except on Metop C data.
- Both methods were also applied to the entire unaltered timeseries of all three backscatter products.
- Kernel Change Detection picked up some known anomalies in the historical Metop-A timeseries (e.g. in October 2014).
- The incidence-angle-dependence method did not pick up on any known anomalies in unaltered historical data, and flagged many false positives in Metop A data.

Drift rate (dB/day)	Number of days until drift detected					
	Metop A		Metop B		Metop C	
	γ^0 breakpoints	σ^0 polynomials	γ^0 breakpoints	σ^0 polynomials	γ^0 breakpoints	σ^0 polynomials
0.05	7	15	8	15	16	15
0.01	11	15	28	43	33	29
0.005	42	15	37	43	100	57
0.001	114	253	111	239	N/A	253

Takeaways

- Detection of anomalies by measuring variance from historical data is highly sensitive to the data used to calculate the historical mean and standard deviation and the properties of that data.
- Kernel Change Detection shows promise for live detection of instrument miscalibration in Metop/ASCAT, although analysis of incidence angle dependence could also serve this purpose well with further parameter tuning.

Moving forward

Time-series stability should be increased by analyzing only specific grid locations where azimuthal anisotropy and spatio-temporal variability are historically low.

One or both methods will be implemented in a process that runs weekly on live data.

Results from live monitoring should be evaluated after the system has been in place for a period of time.

Acknowledgements

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References

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