EOSense

AUTOMATED CALIBRATION AND DATA QUALITY CONTROL

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QUESTION 1

- What are the key data quality parameters you wish to measure?

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- Signal to Noise Ratio
- Relative gain
- Non-linearity
- Focus / MTF
- Absolute calibration drift

QUESTION 2

- How often **would you like** to update the information on data quality?

Image by image? Hourly? Daily? Monthly?

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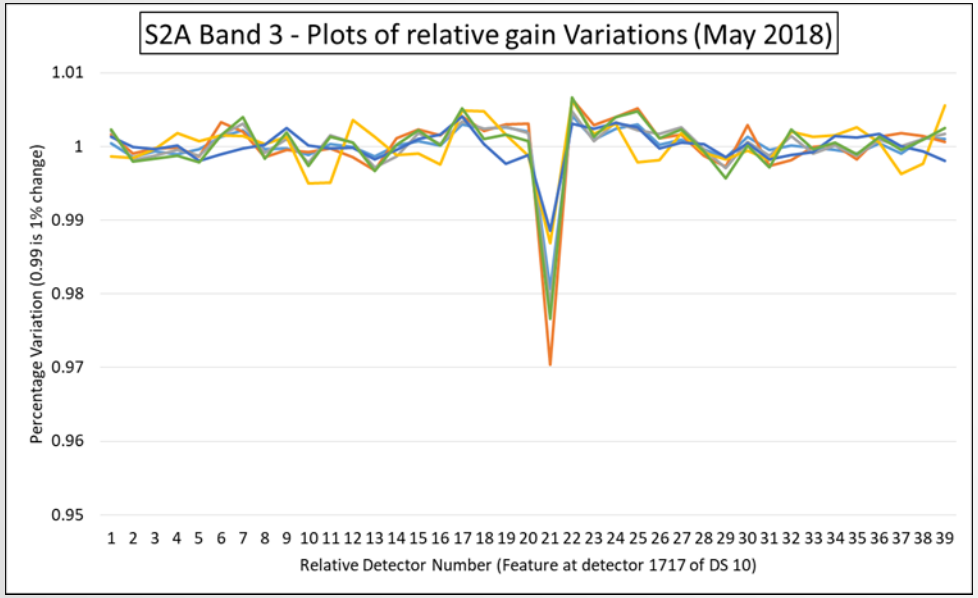
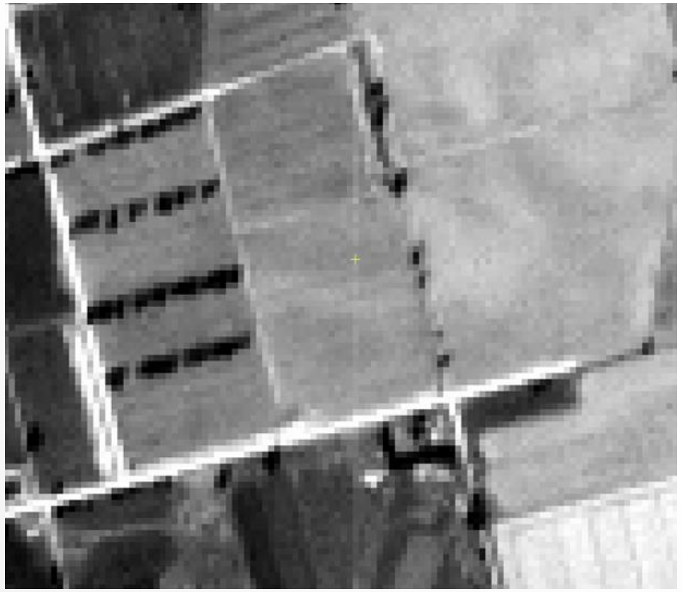
- How often **would you like** to update the information on data quality?
- Using vicarious methods we are limited by target availability (orbit, season and clouds)
- Using on-board calibration devices we are limited by the cycle time between acquisitions (two weeks?, one month?)





QUESTION 3

- How can I make data quality a task that is **not** resource hungry?

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- How can I make data quality a task that is **not** resource hungry?
- Most systems can be automated in part, whether its data collection, data processing and to some degree analysis.
- However, most groups still have a large manual element, especially in the analysis and correction areas (see reference to SNR estimate from EO data in the monthly cyclic reports on OLCI below).

2.4.2.2 OLCI-B

The SNR assessment from EO data has not been applied to OLCI-B considering a) that SNR estimates from RC data have been proved more reliable for OLCI-A and b) that it requires a significant amount of human and machine resources that can be more efficiently used for other tasks.

QUESTION 4

- What would be your ideal system?

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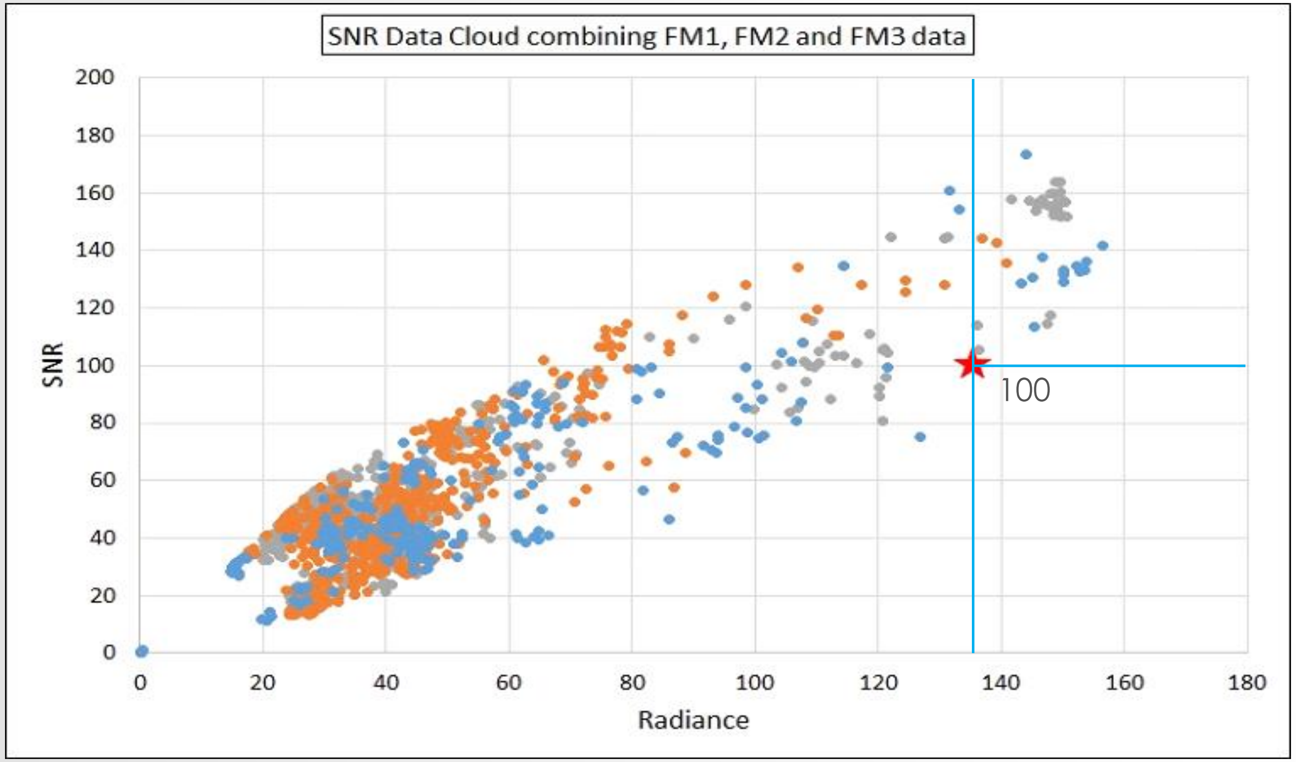
- What would be your ideal system?
- No need to select data to collect, uses any data.
- No cloud screening.
- No complex models applied, simple processing.
- Data quality assessments as often as possible (every image?)
- Totally automated analysis
- Self-correcting (errors corrected without human intervention)

WHAT DO WE MEAN BY AUTOMATED METHODS?

- Entirely automated with no human intervention in deriving the radiometric calibration and data quality measures.
- Uses heterogeneous images (Level 0 and Level 1 data depending on methodology)
- Has very high temporal sampling, a single image in some cases is enough to derive some measures.
- Essentially works on the statistical variations within a single scene or multiple scenes to determine the quality measures.

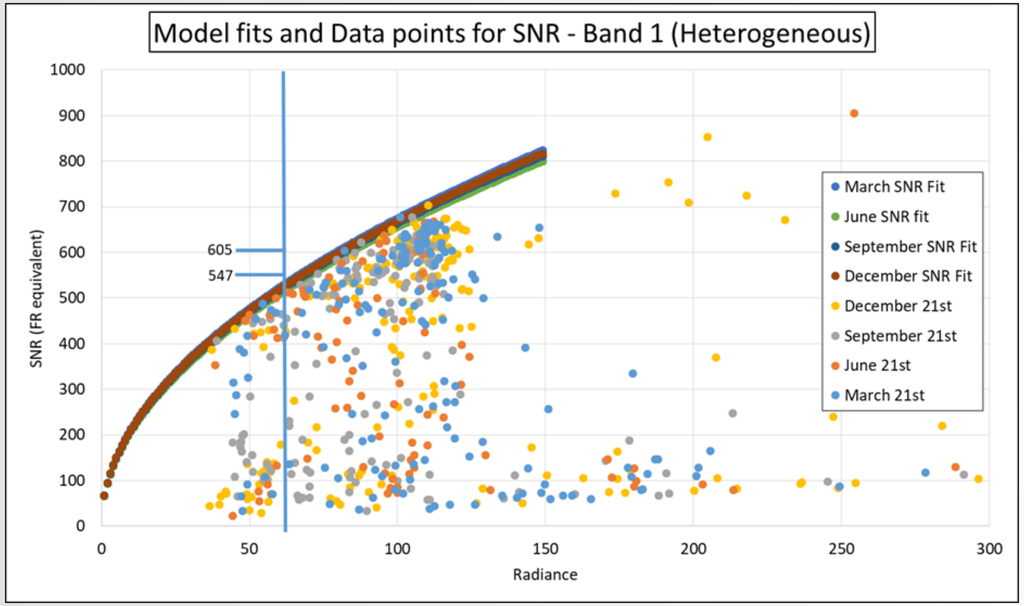
EXAMPLE 1 – SIGNAL TO NOISE RATIO

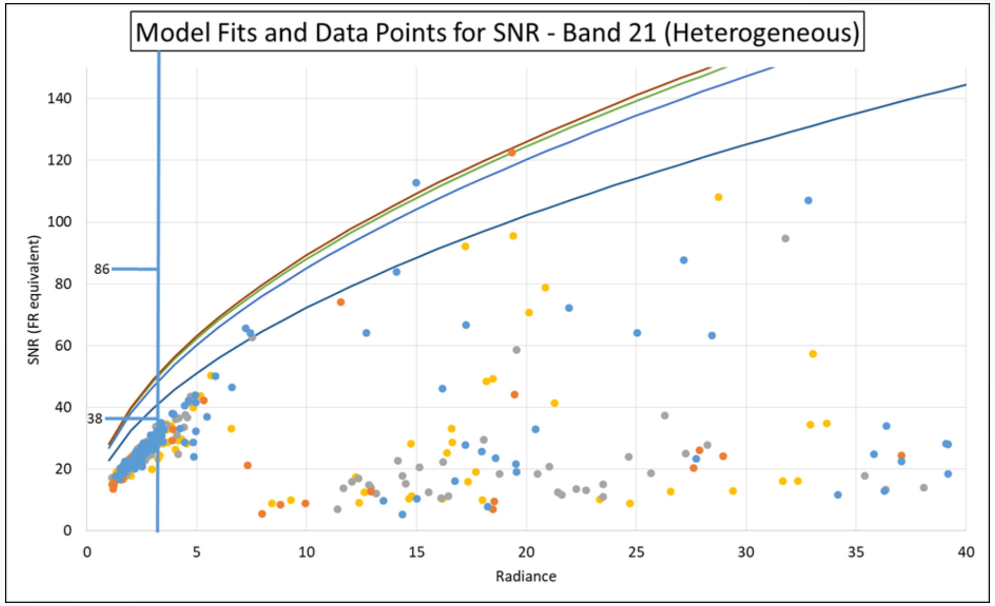


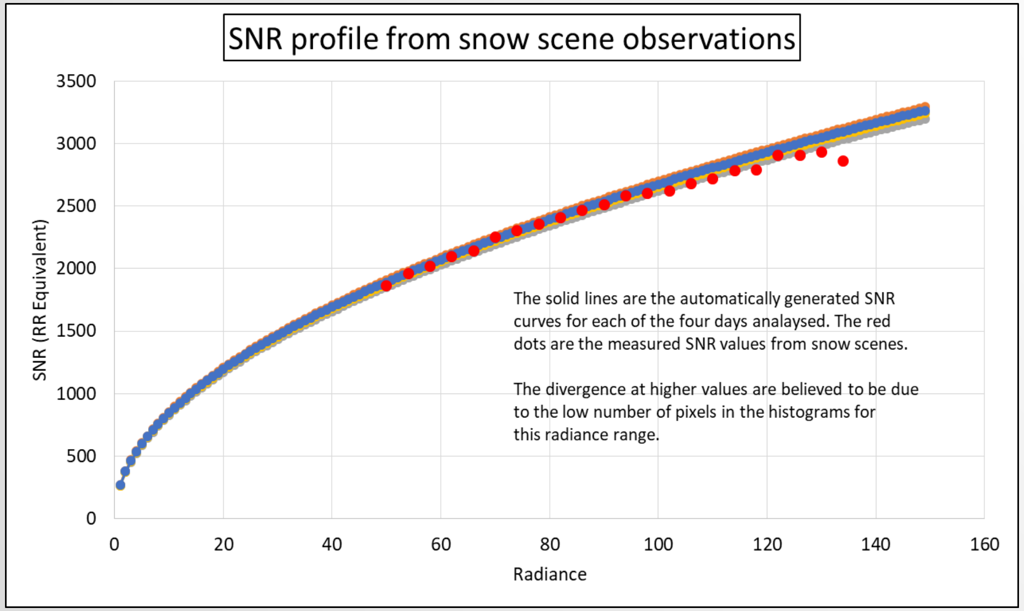
Uses a statistical approach based on either a moving window or column and row based values

- Each dot is a separate image
- Upper edge of the data cloud provides an estimate of the "true" SNR.
- Red star is the requirement
- Lower part of cloud shows the effect of surface mixtures.
- Can be applied to get detector to detector variations in SNR

EXAMPLE 1 – SIGNAL TO NOISE RATIO



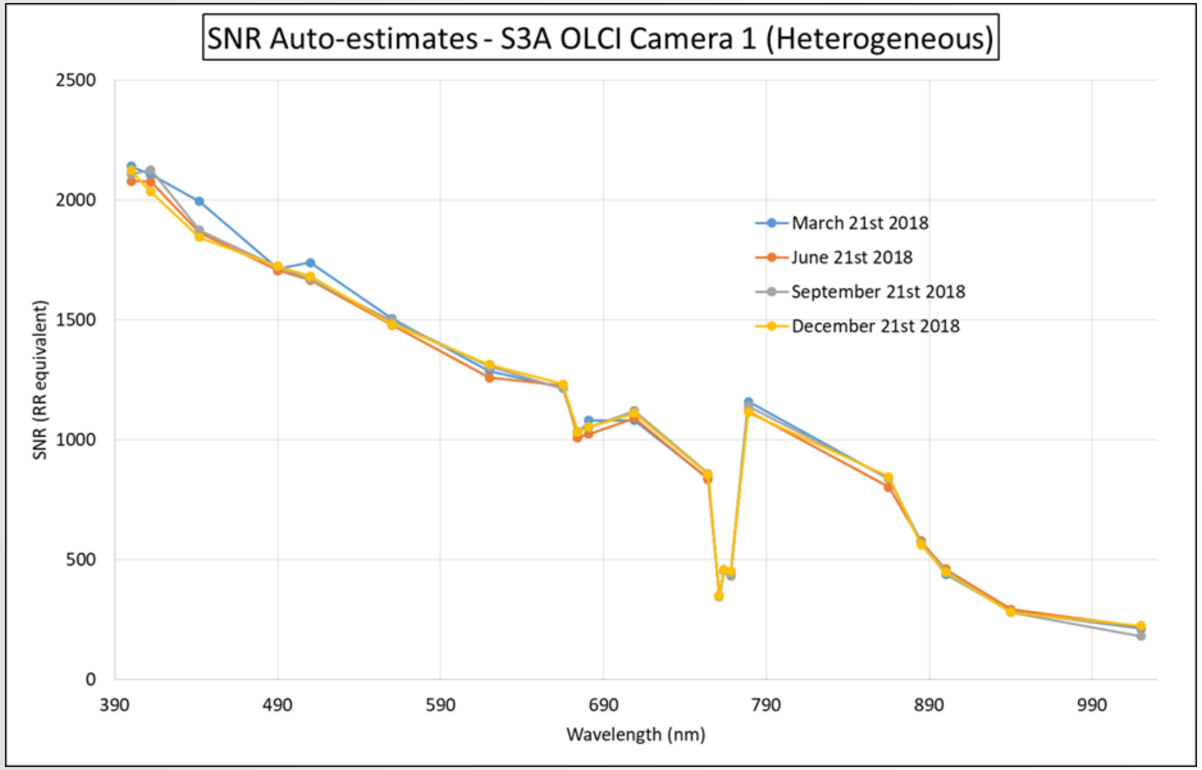


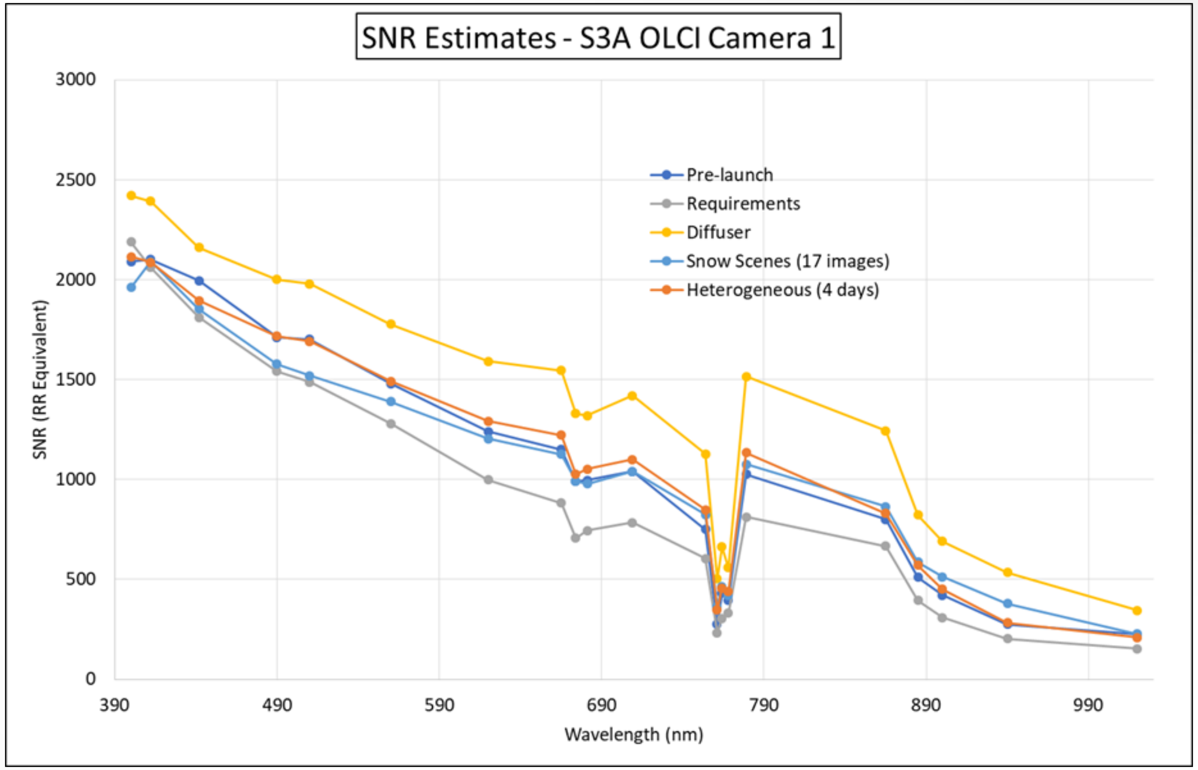


We can use a shot-noise limited model to see how our data behaves.

Validation uses snow scenes and a different approach to the analysis based on modelling of the statistical outputs

RECENT RESULTS 1 – OLCI SNR





SNR derived automatically for four different days using heterogeneous images

Heterogeneous image SNR compared to snow, pre-launch, diffuser and requirements.

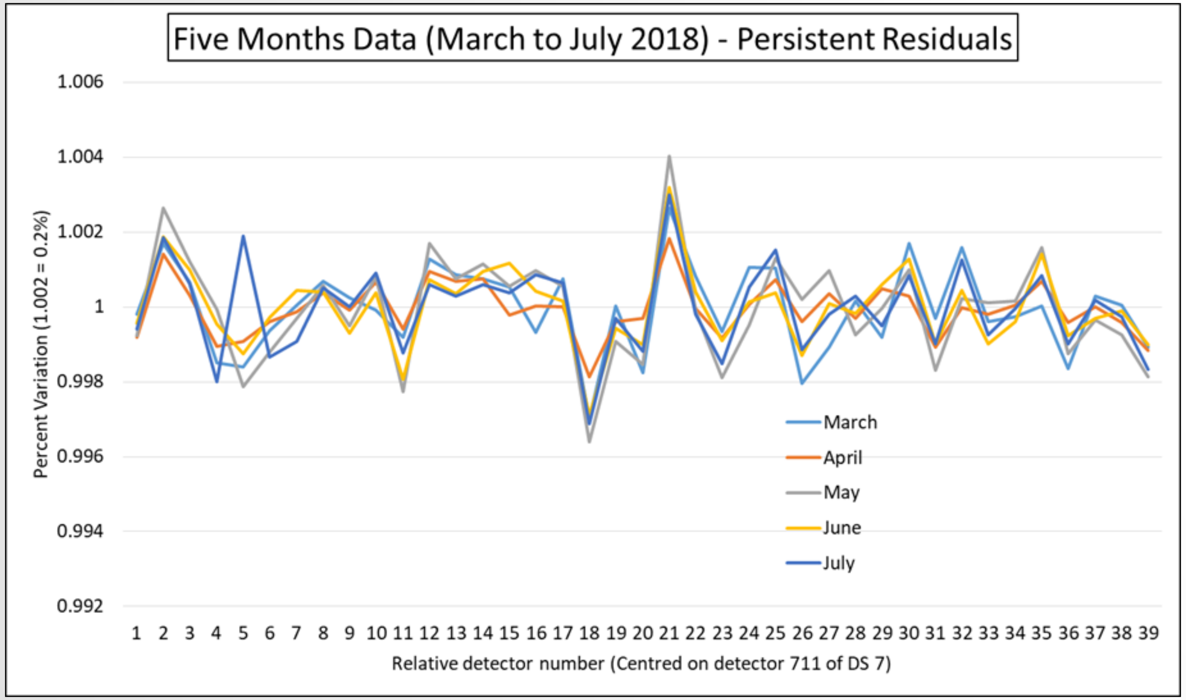
EXAMPLE 1 – S3 OLCI

- Although we cannot provide details of the analysis we have noted some discrepancies between the SNR calculated using the on-board diffuser and those determined from heterogeneous images, snow scenes and pre-launch data.
- We hope to release these results once we receive clearance from Eumetsat.

EXAMPLE 2 – RELATIVE GAIN

- This is effectively the detector to detector variation one can see over (for example) a homogeneous surface. When we equalise the detectors, we remove any residuals between detectors of a pushbroom system that may induce striping.
- Any residuals remaining can cause visual striping if they are greater than about 0.2% of the signal level.

PERSISTENT RESIDUALS – SENTINEL 2A



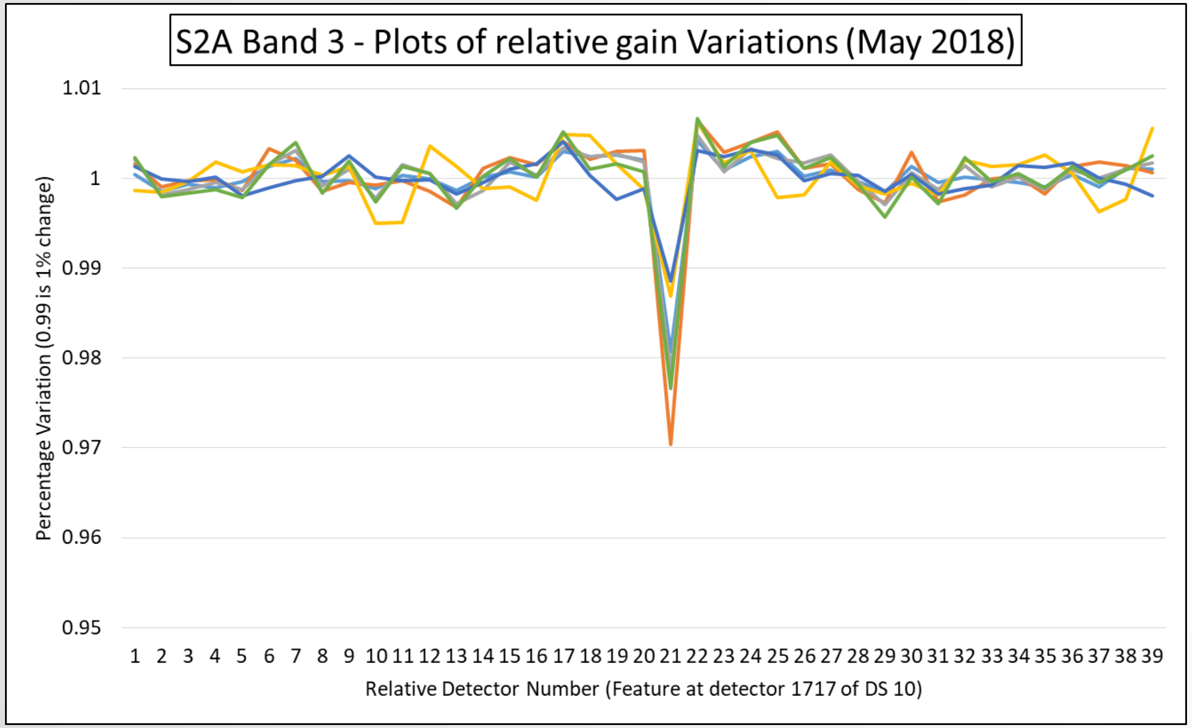
These small, often persistent residuals can be detected and in the case on the left, exceed 0.4% of the signal level.

In this case for S2A they were persistent for the five months analysed.

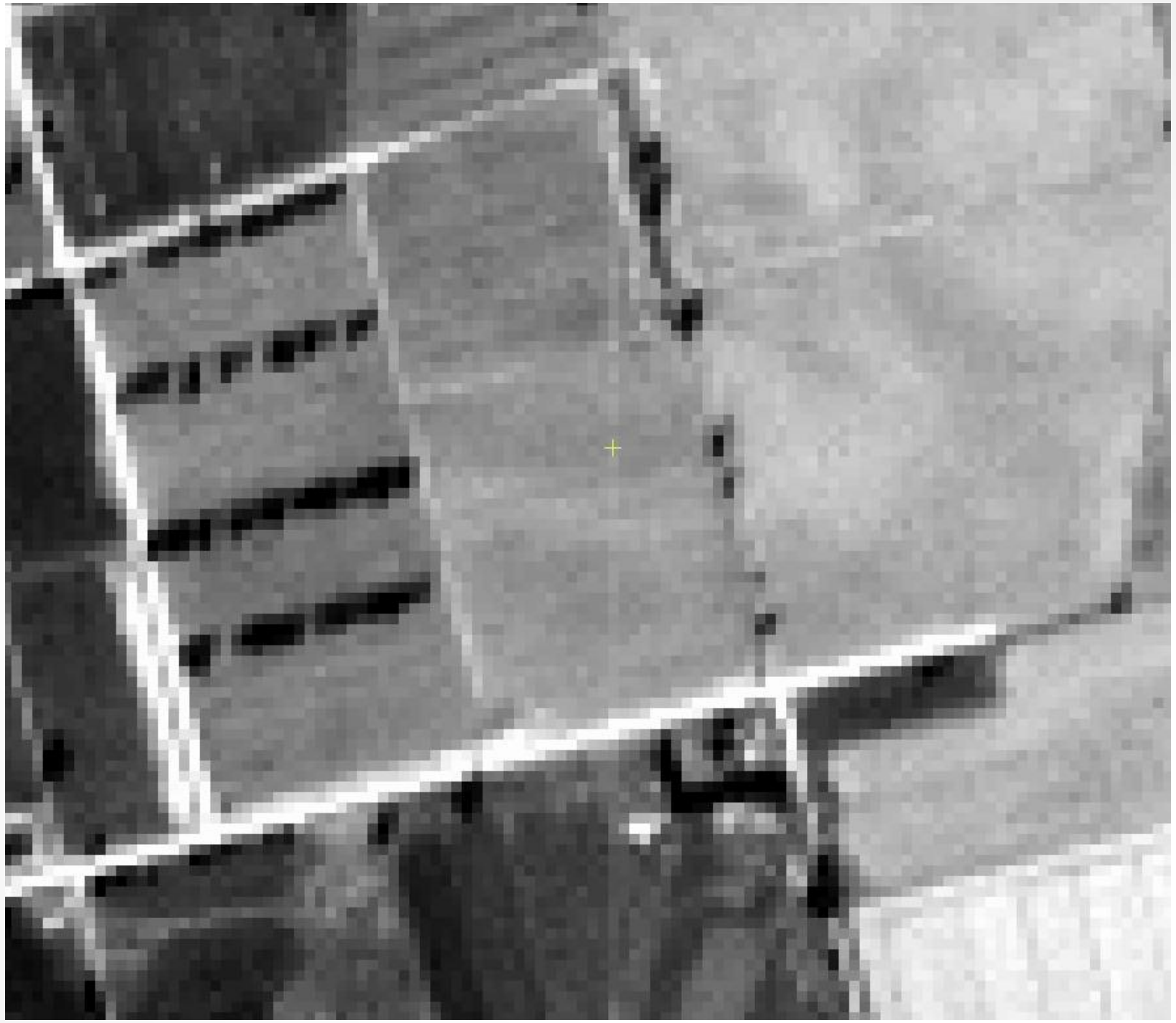
Similar persistent residuals have been observed in S3A, generally of a lower magnitude, but increasing throughout 2018.

Only five images per month were used to generate the plot above, so a fraction of an orbit in each case.

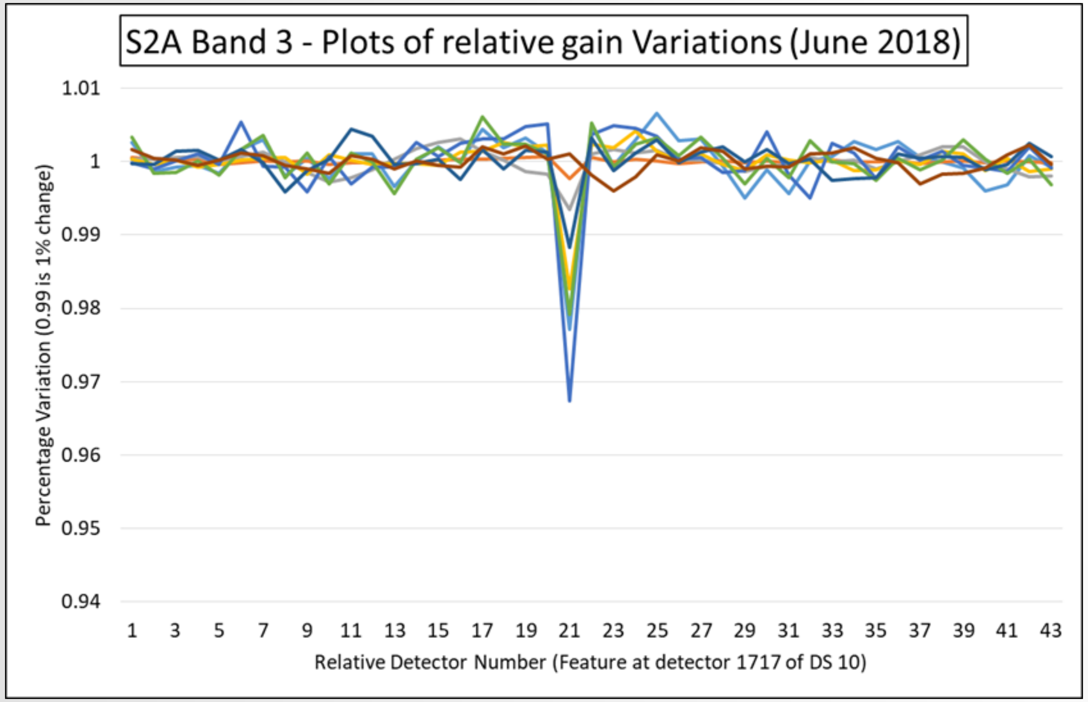
LARGE ERROR SEEN IN MAY 2018

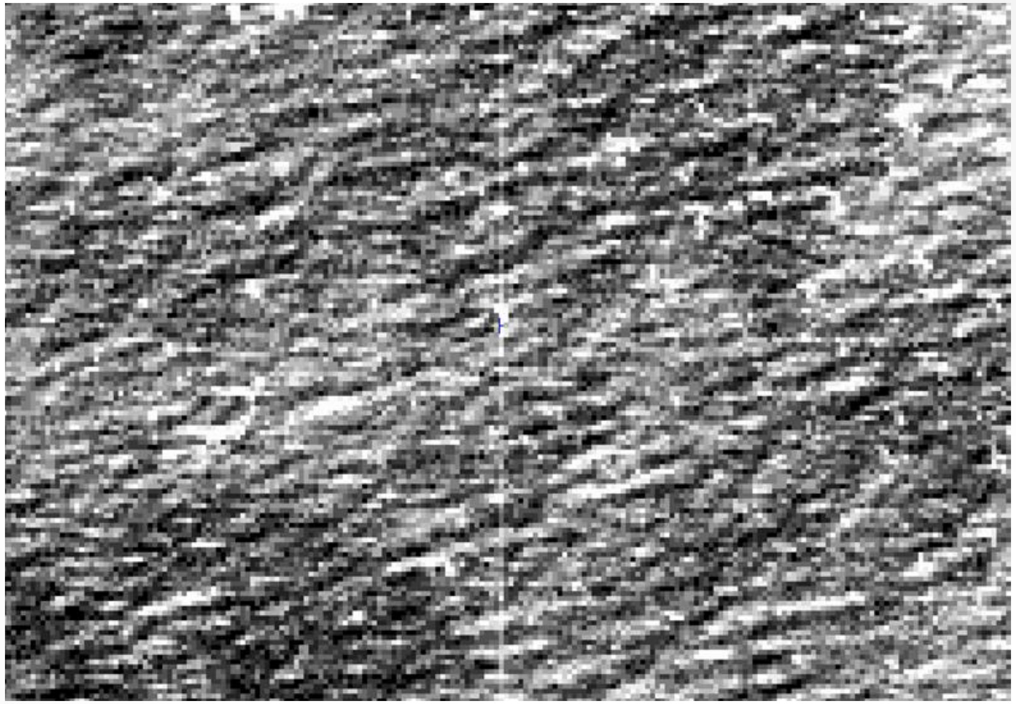


A 2-3% error residual seen in all images processed in May, producing visible artefacts. Green band DS 10.



STILL THERE IN JUNE 2018 !

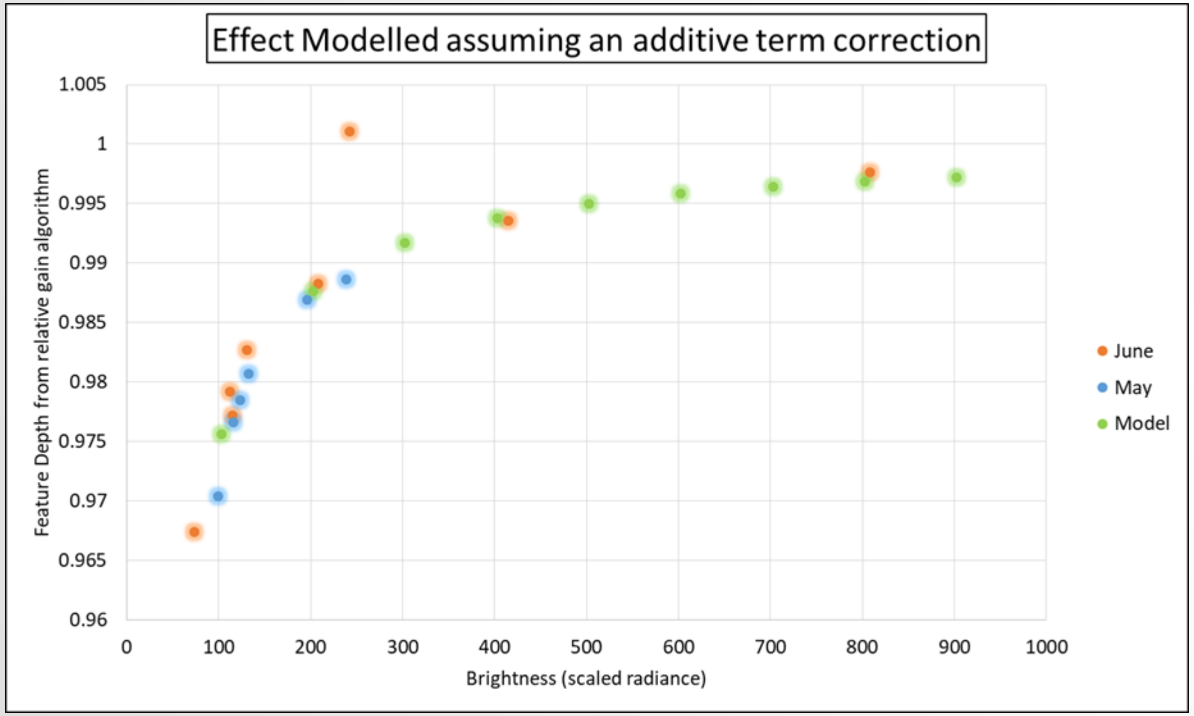




The same feature persists throughout June, until the 21st June, then it disappears. Note the variation in the depth of the feature, are the changes related to brightness variations?

Feature returned in early July and disappeared finally in August 2018.

MODELLED ADDITIVE EFFECT

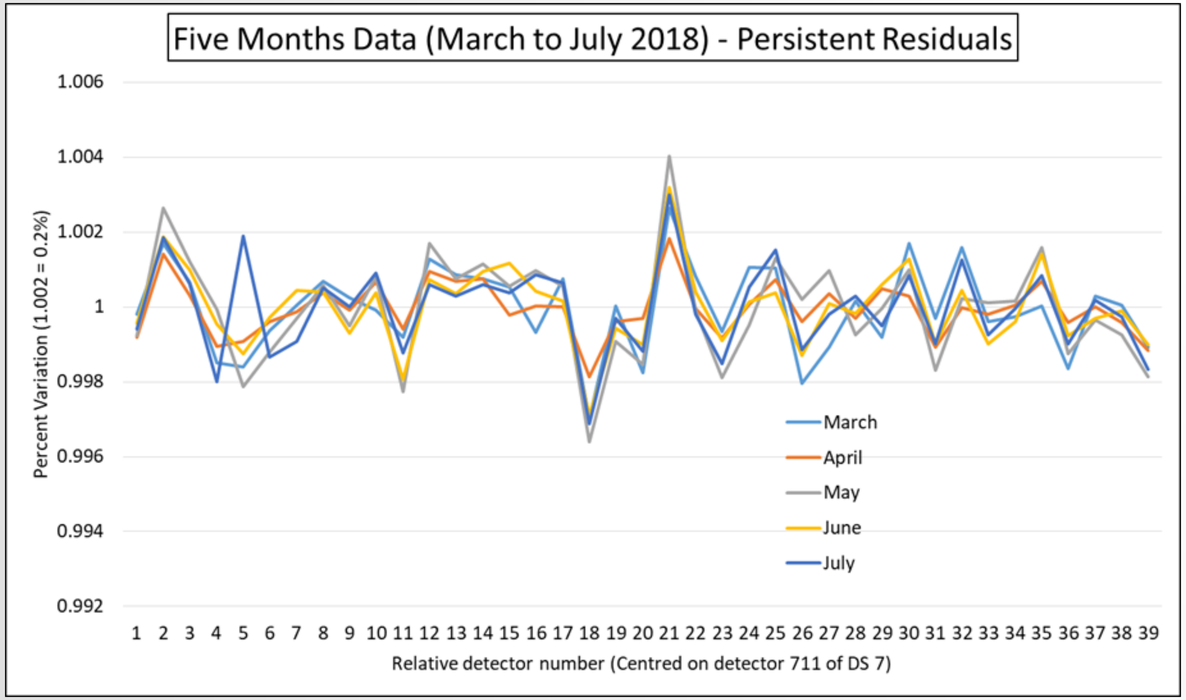


We created a very simple model assuming an additive term of 2.5 scaled radiance units (green dots) which accounted for almost all the variation seen.

Therefore we can distinguish quite clearly between additive terms where the model converges towards one, and multiplicative effects.

PERSISTENT RESIDUALS – VARIABLE DEPTHS

- Finding persistent residuals means we have to ask the question…

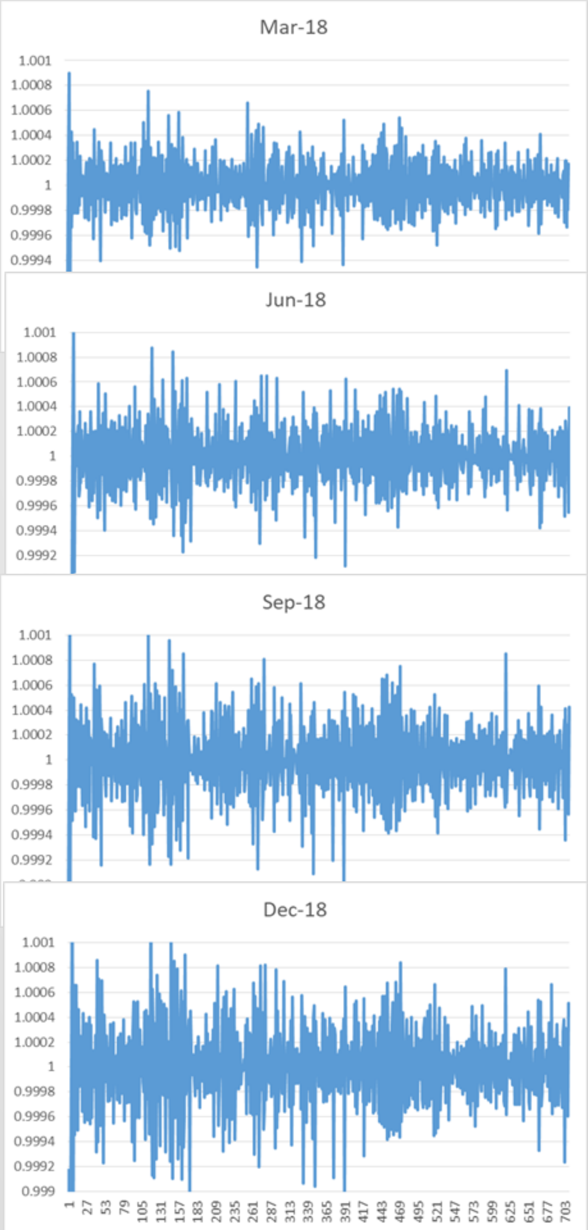


Why can we see these features in normal images but the MPC can not see them in diffuser images?

A clue to why could be what we see in the plot (left). Note that the grey line extremes are greater than the orange line extremes with the dark blue line extremes in-between.

We considered that this sort of behaviour, along with the fact that the MPC saw nothing could be related to a non-linearity error.

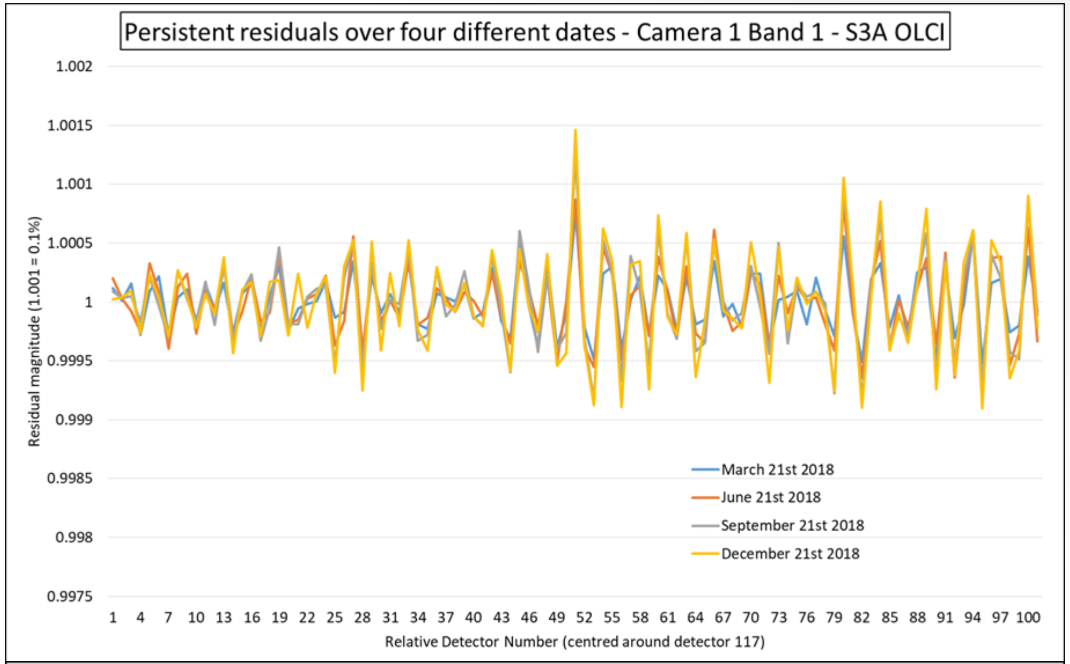
RECENT RESULTS 3 – OLCI REL. GAIN

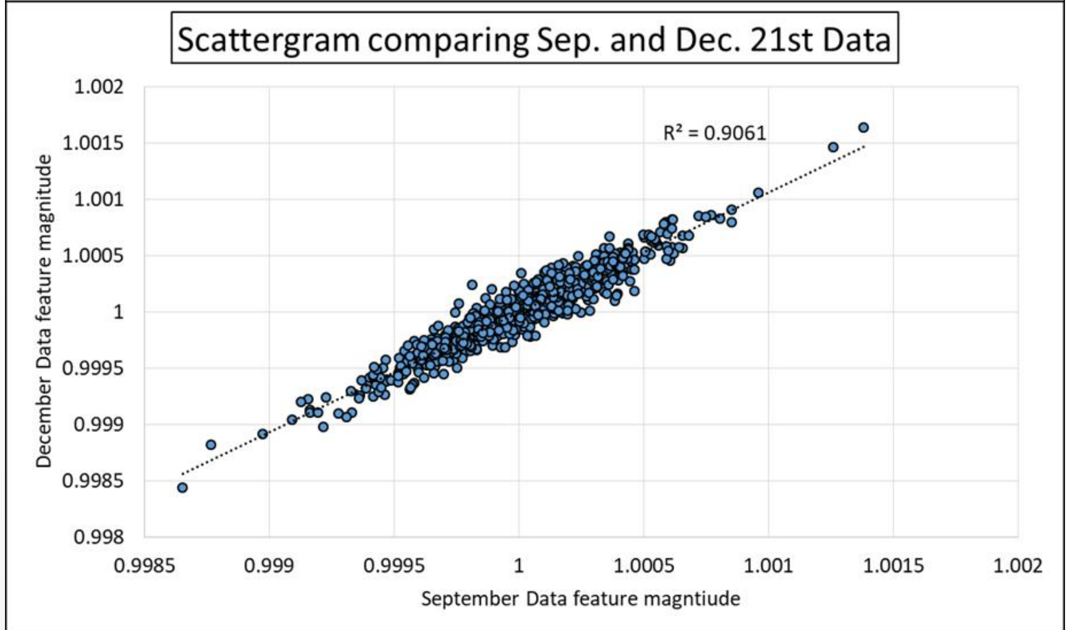


Variation in relative gain with time (left).

Correlation of all four days (top right)

Correlation of September 21st and December 21st (bottom right)





RELATIVE GAIN OLCI

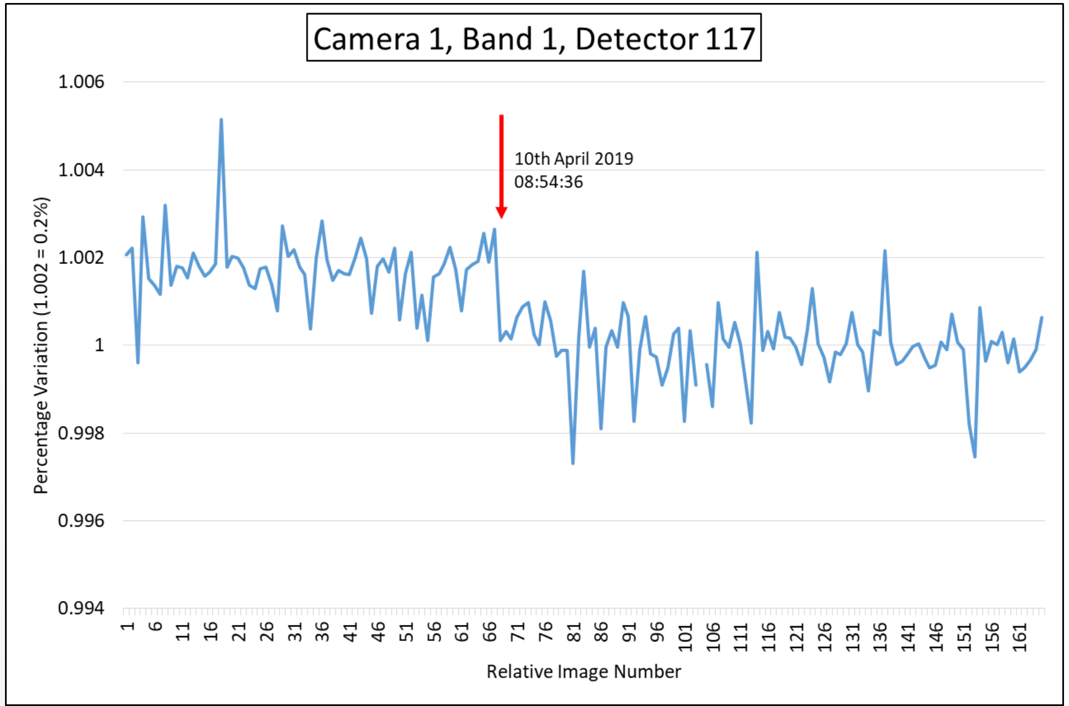
Unfortunately we cannot present our results at this time without the permission of Eumetsat. However, we did see persistent residuals in OLCI data with lower magnitudes than S2A, which were present throughout 2018 and into 2019.

A key date which may be of interest to those who calibrate S3A, is the 10th of April 2019. This is the date that new coefficients were used based on our analyses of Camera 1, Band 1, which removed many of the persistent residuals seen for this band. Other bands however, still show the same features after this date, some of the features outside requirements.

2.2.4 Updating of calibration ADF [OLCI-L1B-CV-260]

Two OL_1_CAL_AX ADFs have been provided to PDGS during the previous period, one for OLCI-A and one for OLCI-B. OLCI-A version includes an update of the Radiometric Gain Model (RGM) with a revised trending correction; OLCI-B version includes the first complete RGM for OLCI-B (i.e. with a trending correction, and based on in-flight BRDF model), as well as an update of the Geometric Calibration Models.

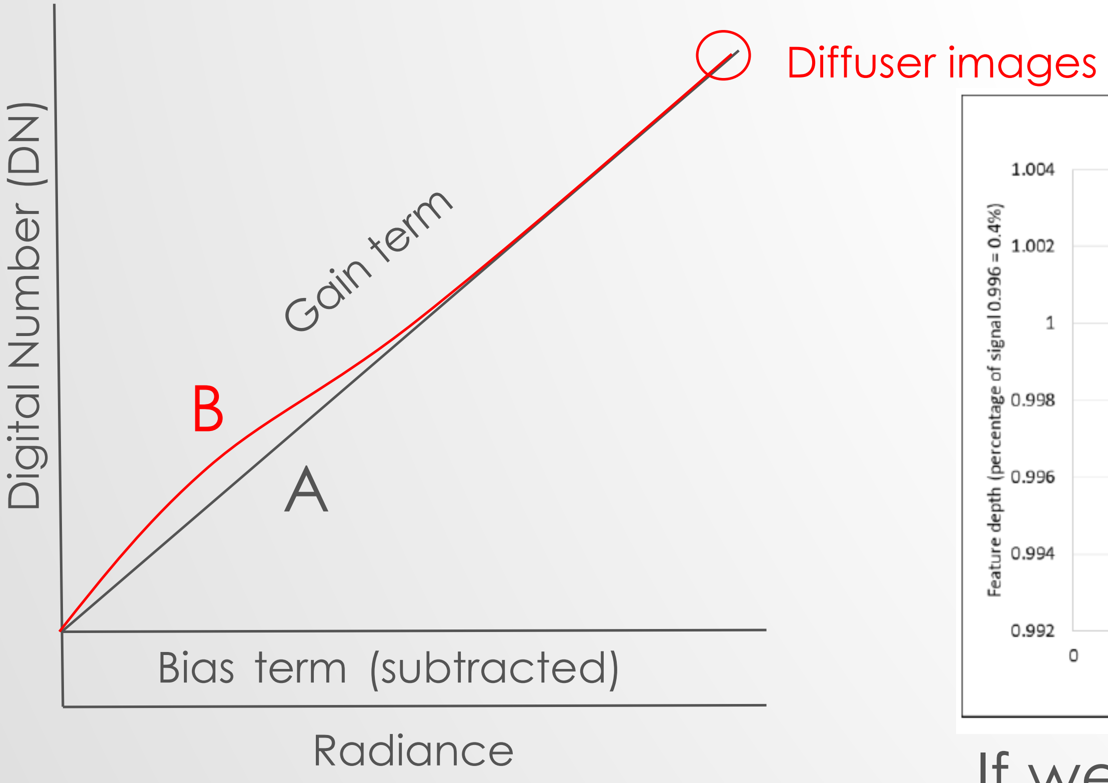
They have been deployed in PDGS on 11th April 2019 (S3A) and 12th April 2019 (S3B) as part of respectively Processing Baseline 2.48 and Processing Baseline 1.20.



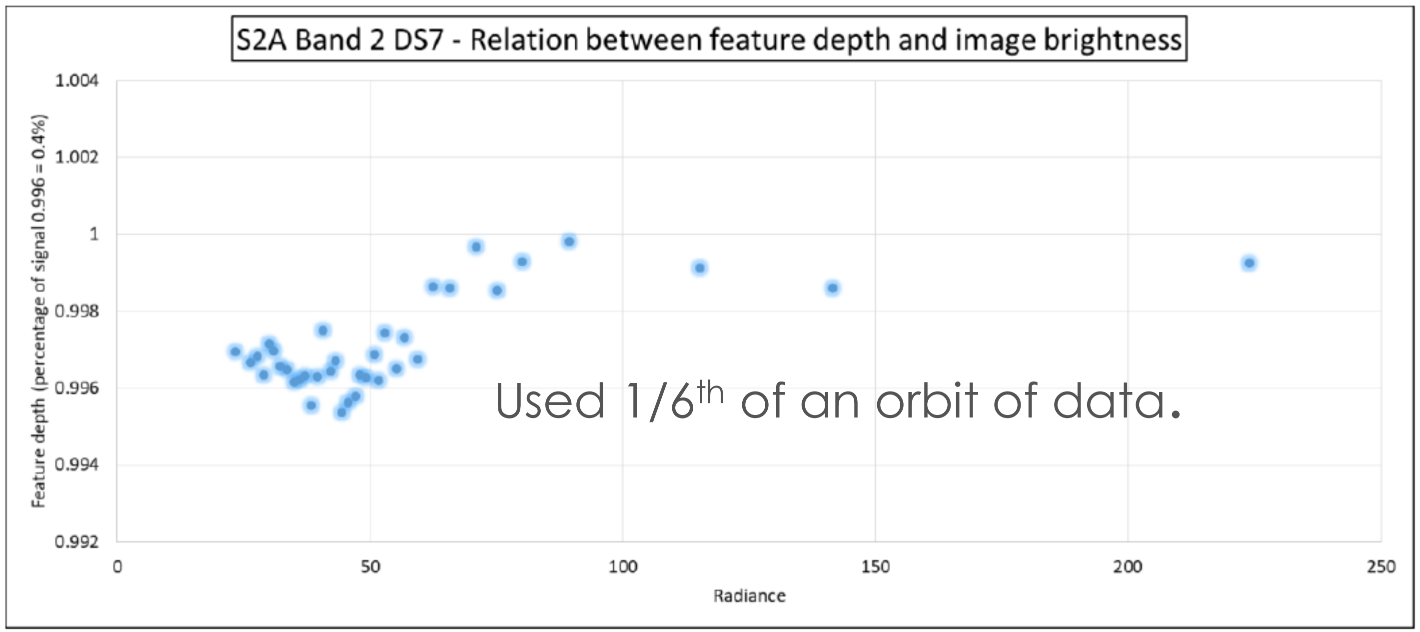
EXAMPLE 3 – NON-LINEARITY

- The nesting of the persistent residual curves for S2A pointed to perhaps some form of signal dependence, which could explain why these features are not being corrected.
- If there are no features at the diffuser brightness, but due to non-linearity there are features at normal earth target brightness, then these sort of effects could be seen.

EXAMPLE OF NON-LINEARITY IN S2A?



Assuming our non-linearity correction is not perfect (B)



If we ratio the values A/B we get a distinct pattern of behaviour which shows the correction required to remove the persistent residuals

EXAMPLE S3A - OLCI

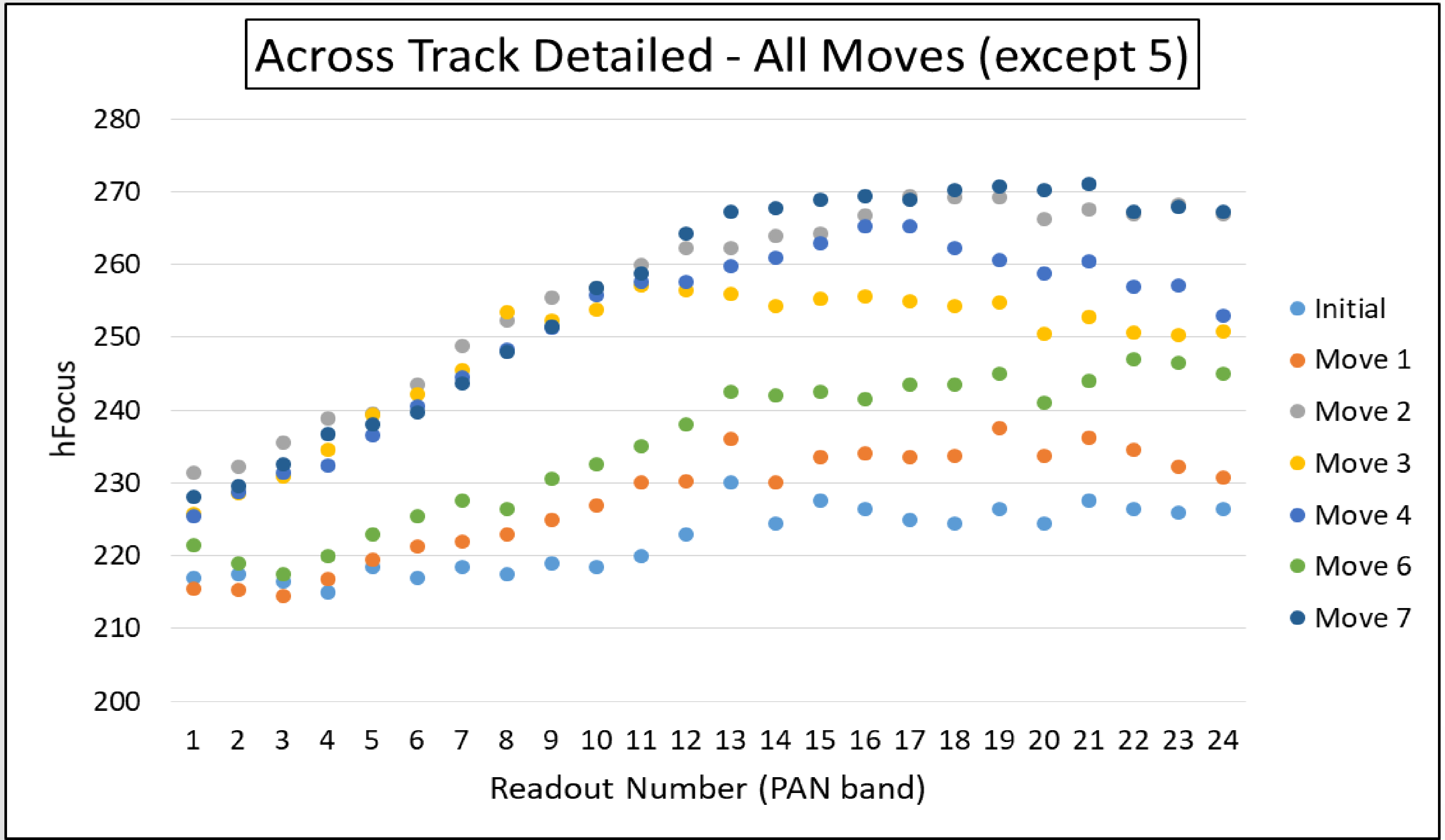
- Again we are awaiting clearance from Eumetsat to present these results. Initial studies seem to suggest much smaller variations and no sudden changes at specific wavelengths, which is different from S2. Although some offsets observed exceed 0.2%.

EXAMPLE 4 – FOCUS (MTF)

- This algorithm uses statistics of each scene to estimate how sharp the imagery is, in other words the focus, which has a direct relationship to the MTF.
- The type of image used has little impact on the overall result, except in extreme cases. A snow scene with little textural information and few edges is less effective than an agricultural area.

Small satellite example of focus changes

- Instrument with four CCD's each with 6 readouts so 24 readouts in total for the whole swath. The focus has been changed to determine the best position. Notice the across track variation meaning poorer focus on the left side of the instrument (this has been confirmed visually)



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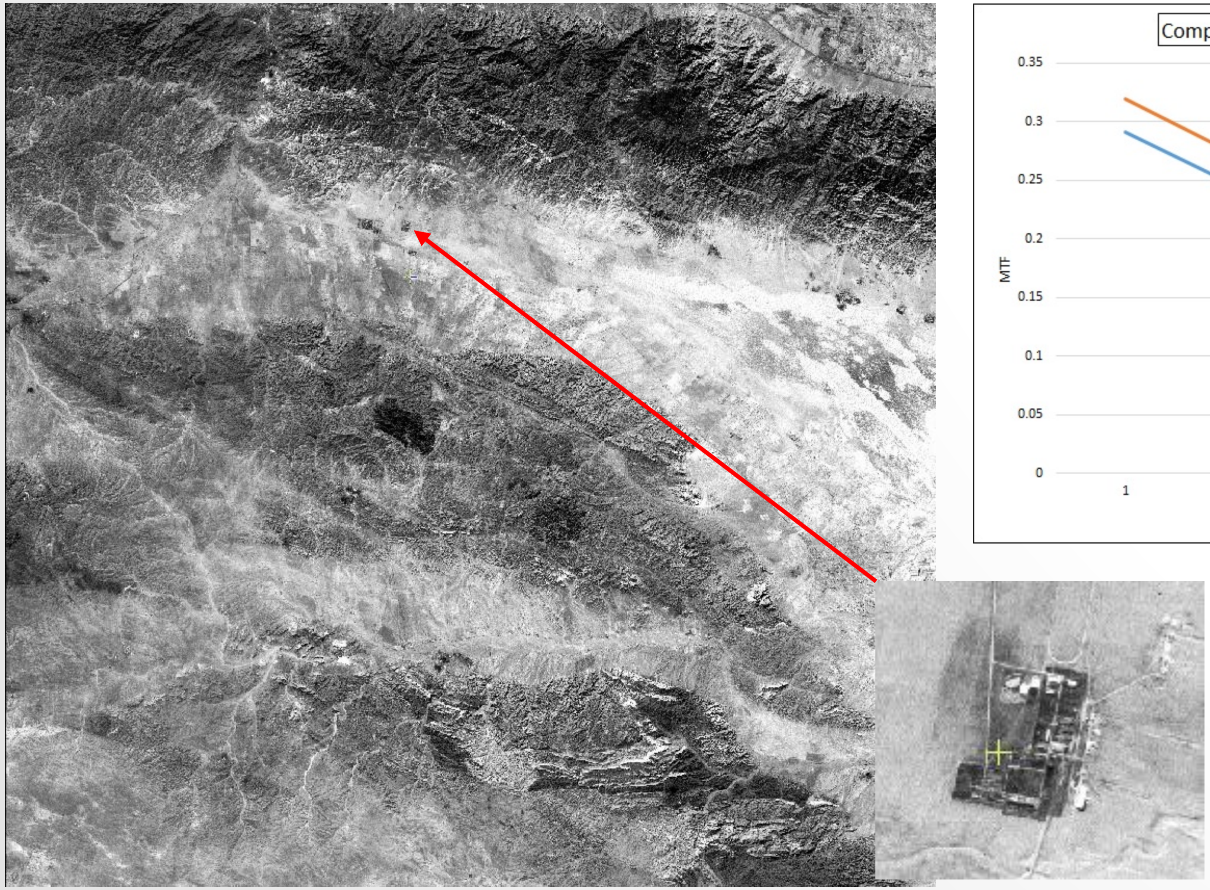
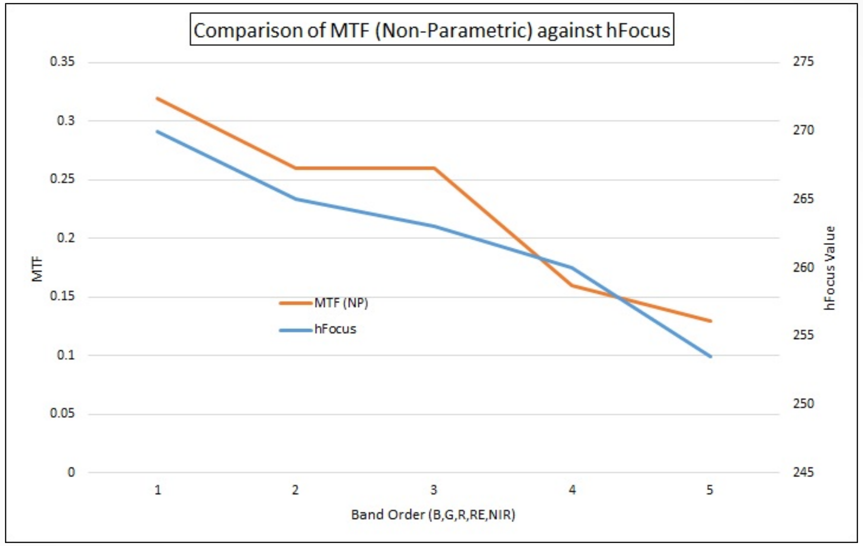
Instrument focus and MTF – Comparison Image 1





Roll (11.65°)

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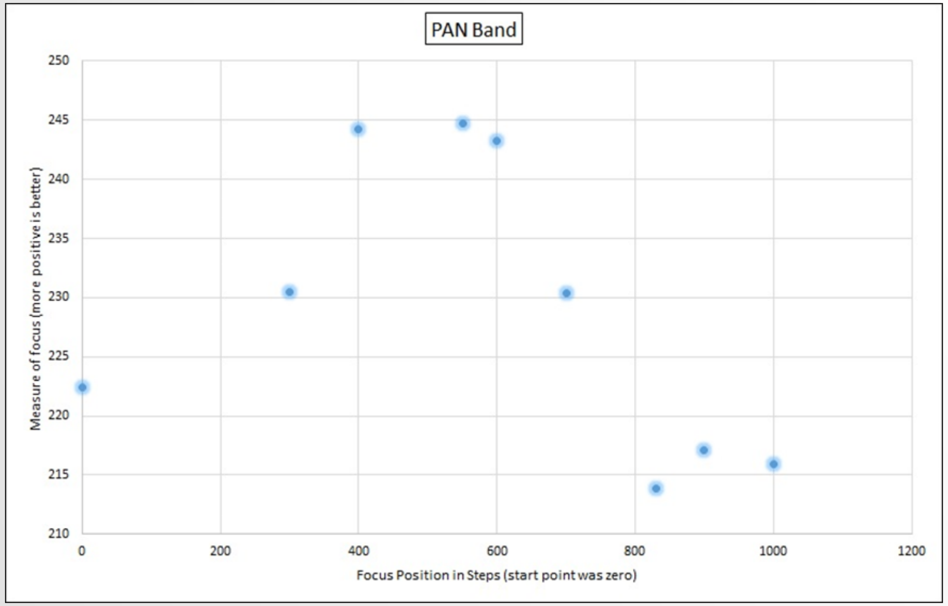
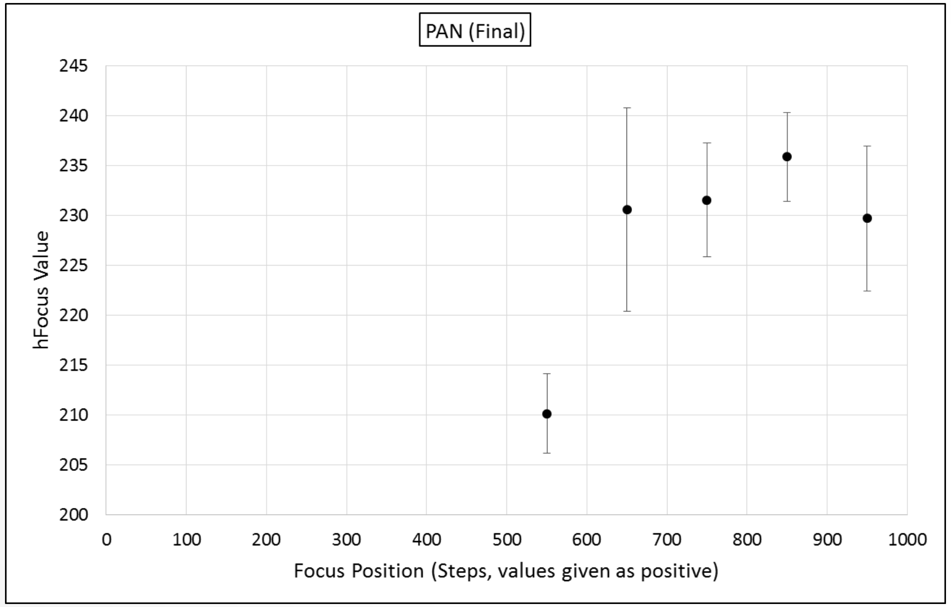
Monitoring changes in focus with time



At launch, best focus. Focus was changed in "steps" from zero, peaks at 550. Our best focus coincided with that determined by satellite manufacturer

Launch plus five years. Focus has changed, now peaks at around 830 "steps"



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SENTINEL-2 FOCUS

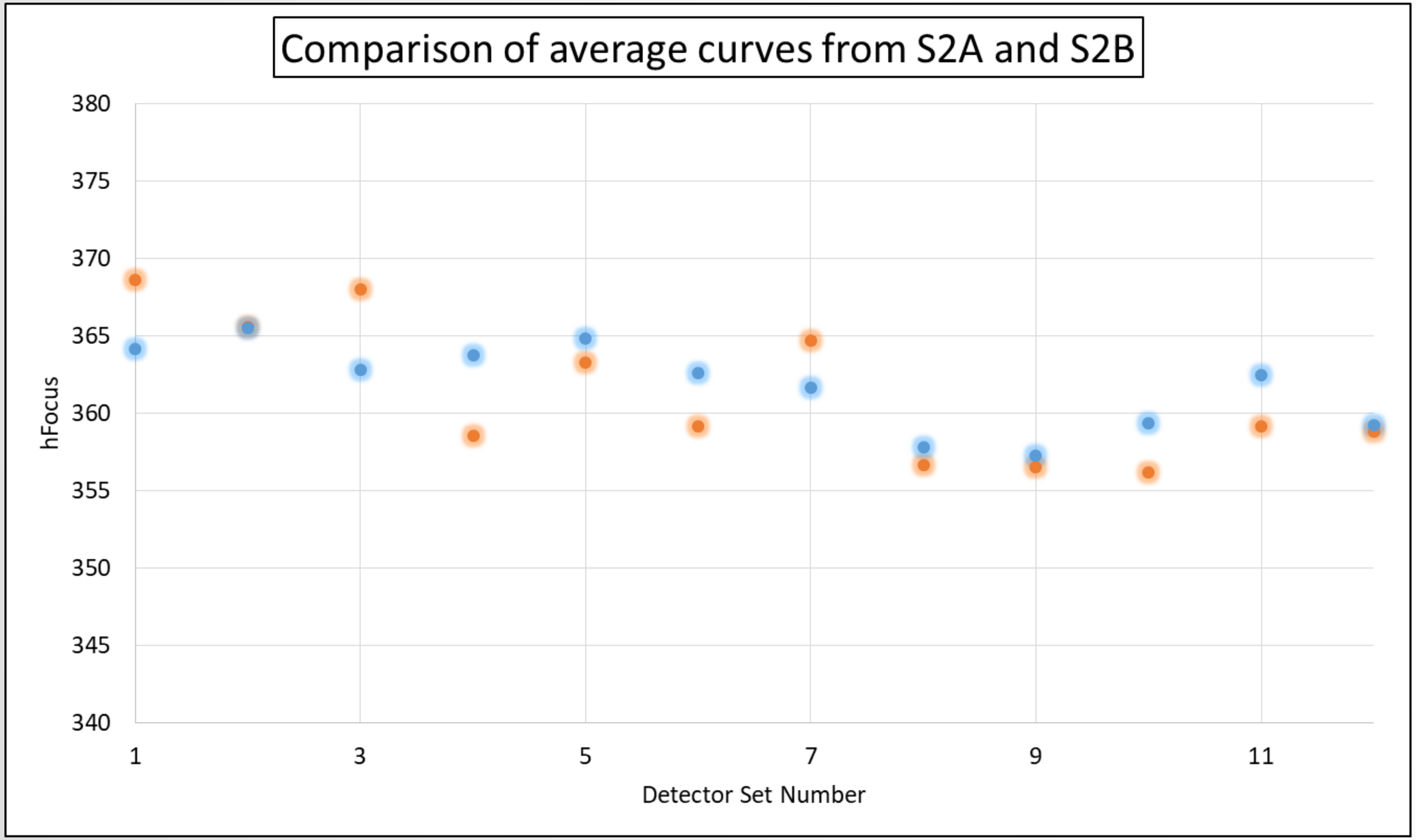


Figure 4: Average curves generated using 27 S2A images and 21 S2B images

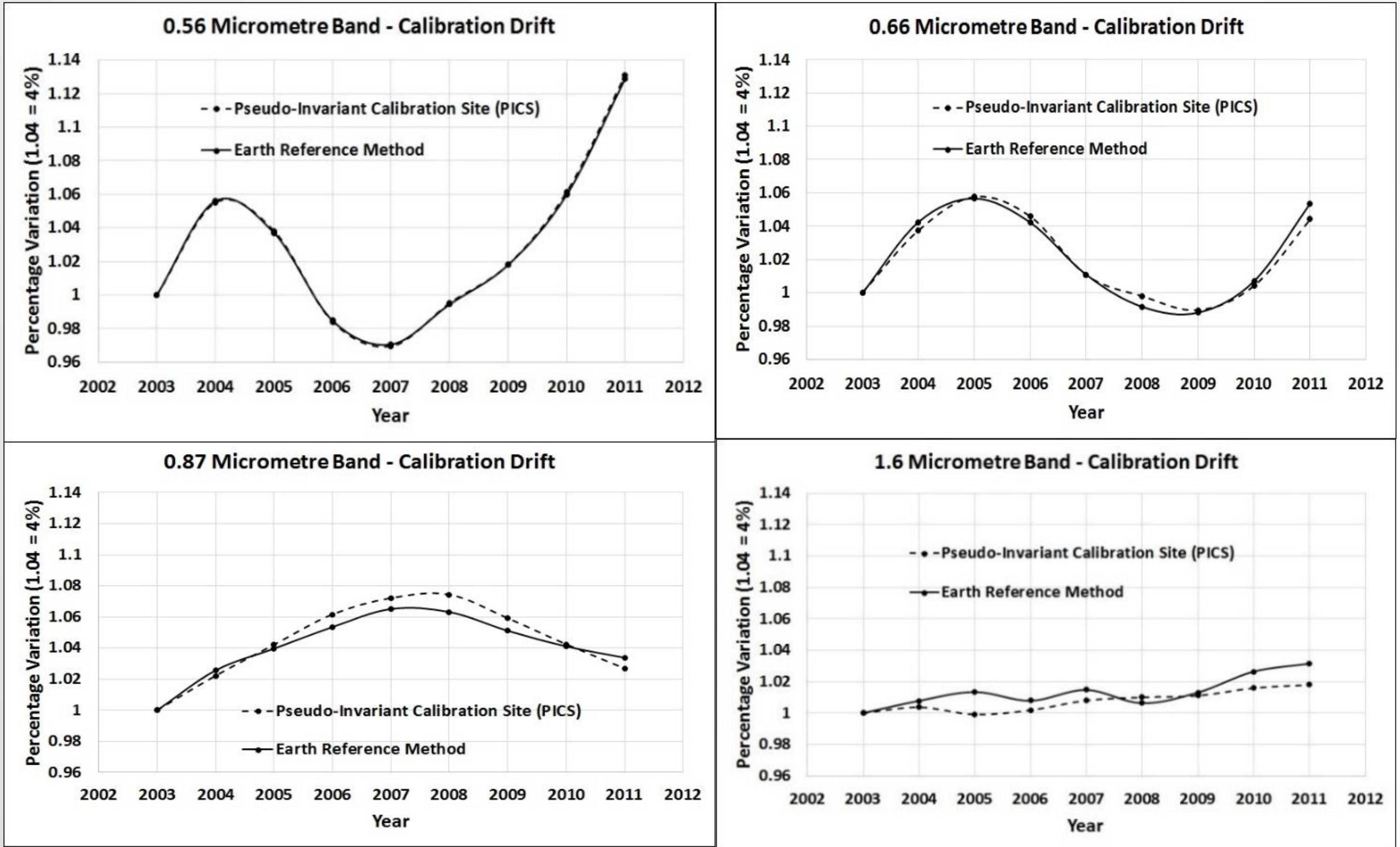
We were also able to assess the across-track focus variation across the twelve detector sets

Some asymmetry can be seen, higher on the left (S2A blue, S2B orange).

Ideal would be a whole days worth of data from each sensor.

Possibility of trending focus change with time.

EXAMPLE 5 – ABSOLUTE CALIBRATION DRIFT



CONCLUSIONS

- The statistical methods used not only seem to be very effective, but provide an alternative way of assessing data quality values
- The methods have revealed some differences from the currently applied “standard” methods including those using on-board devices, which we believe require further investigation.
- It should be possible to use these methods in an automated way alongside those currently being used to provide additional robust data quality assessments.