ESA Climate Change Initiative Phase-II

Sea Surface Temperature (SST) (www.esa-sst-cci.org)

Uncertainty Estimates in Remotely Sensed Surface Temperature

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Provision of uncertainty estimates in the retrieval of geophysical parameters from satellite data is fundamental to ensuring the correct usage of the data. Often uncertainties in remote sensing datasets are expressed in relation to in-situ observations; for example the GHRSST requirements for sea surface temperature data are to provide single sensor error statistic bias and standard deviations (GHRSST Science Team, 2010). Uncertainty is inherent in the retrieval process and can be calculated independently of in-situ observations, enabling it to be validated in its own right. Several different sources of uncertainty in the retrieval process will contribute to the total uncertainty budget. In general terms the following sources of uncertainty can be identified which are likely to be common to most geophysical retrievals. For all satellite observations there will be some degree of noise in the observation that needs to be propagated into the geophysical parameter retrieval (uncorrelated or random effects). Some uncertainty will be inherent in the retrieval process itself and this will be correlated on synoptic scales as Earth surface properties are retrieved through the atmosphere (locally systematic effects). Uncertainty can also be correlated over larger scales as the result of residual biases, which may arise from calibration processes or brightness temperature harmonisation across different sensors (large scale effects). Finally, where data are provided as averaged products at a reduced spatial resolution this can introduce sampling uncertainty if data points are missing due to bad data, or often in the case of visible and infrared data due to cloud cover. Here we demonstrate how to estimate these individual uncertainty components and construct an uncertainty budget with reference to sea surface temperature (SST).

1. Uncertainties from Random Effects

Coefficient based SST retrieval is calculated as a linear combination of two brightness temperatures (BTs) in the 11 and 12 µm channel. These BTs have an associated error due to instrument noise which propagates into the SST retrieval. Figure 1 shows a simulated error field propagated into a two-channel nadir (N2) and dual view (D2) retrieval. The magnitude of the D2 error field is greater than for the N2 retrieval as it uses twice as many observations. In practice, we only know an estimate of the measurement uncertainty (the standard deviation of the measurement errors). Propagating the measurement uncertainty in the SST retrieval gives a value dependent on the number of observations available.

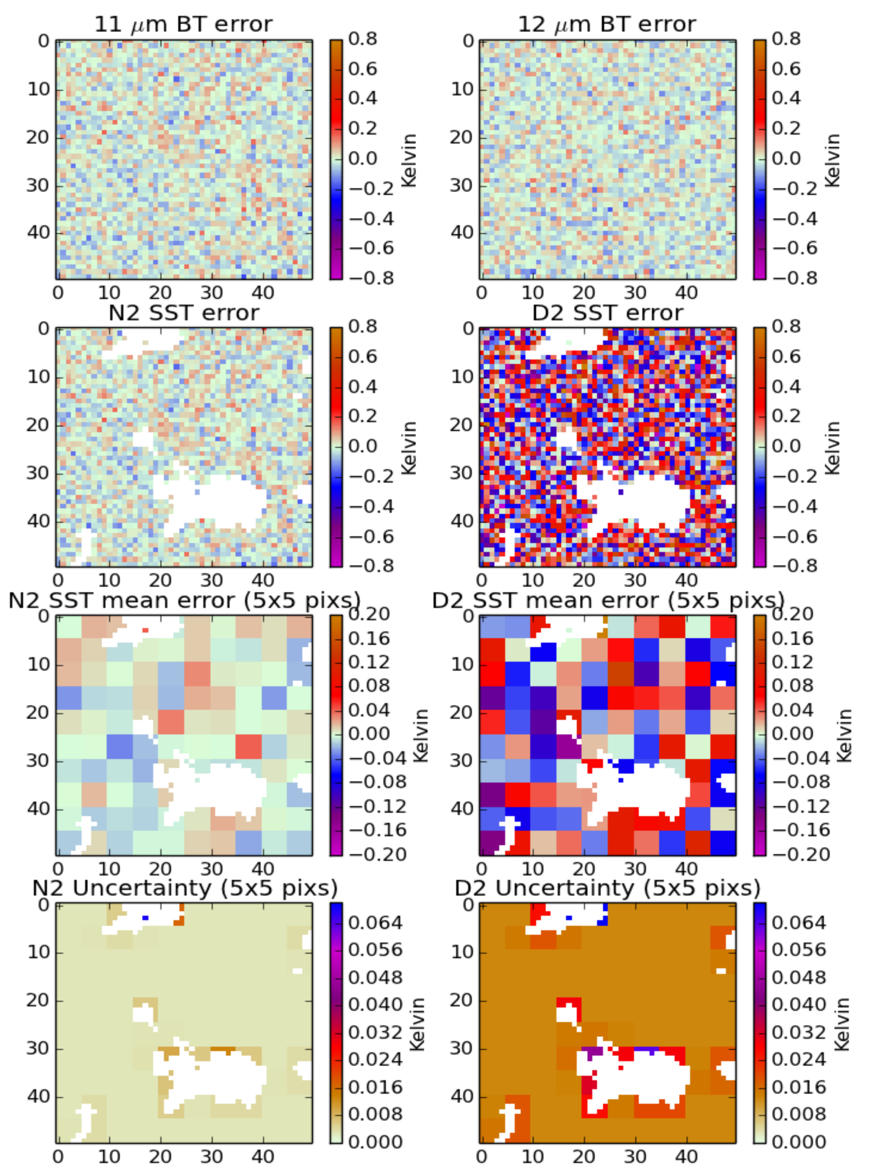


Figure 1: Error and uncertainty propagation into sea surface temperature retrieval.

2. Uncertainties from Locally Systematic Effects

Uncertainties from locally systematic effects (LSE) in SST are inherent in the retrieval system and are correlated over synoptic scales. Figure 2 shows uncertainties from LSE for a coefficient based retrieval as a function of the atmospheric total column water vapor (TCWV). For the two-channel retrieval, the uncertainty increases with TCWV and is higher for larger viewing angles. For a three-channel retrieval the same difference between the forward (cyan) and nadir (green) views is seen but the overall uncertainties are lower, peaking at ~20 kg m^{-3} TCWV. The dual view retrievals give the lowest uncertainties from LSE.

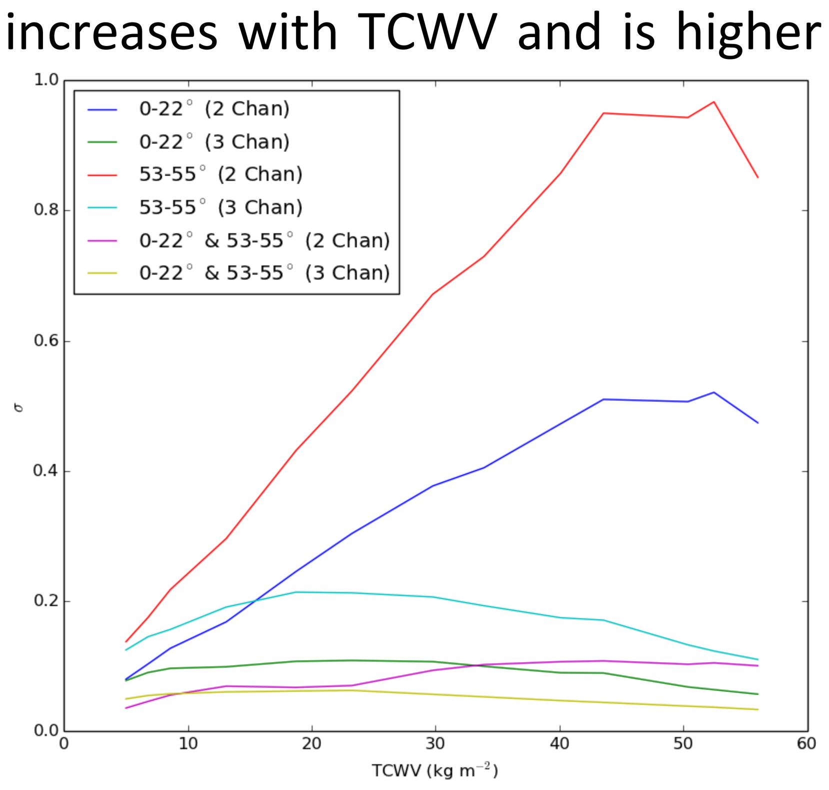
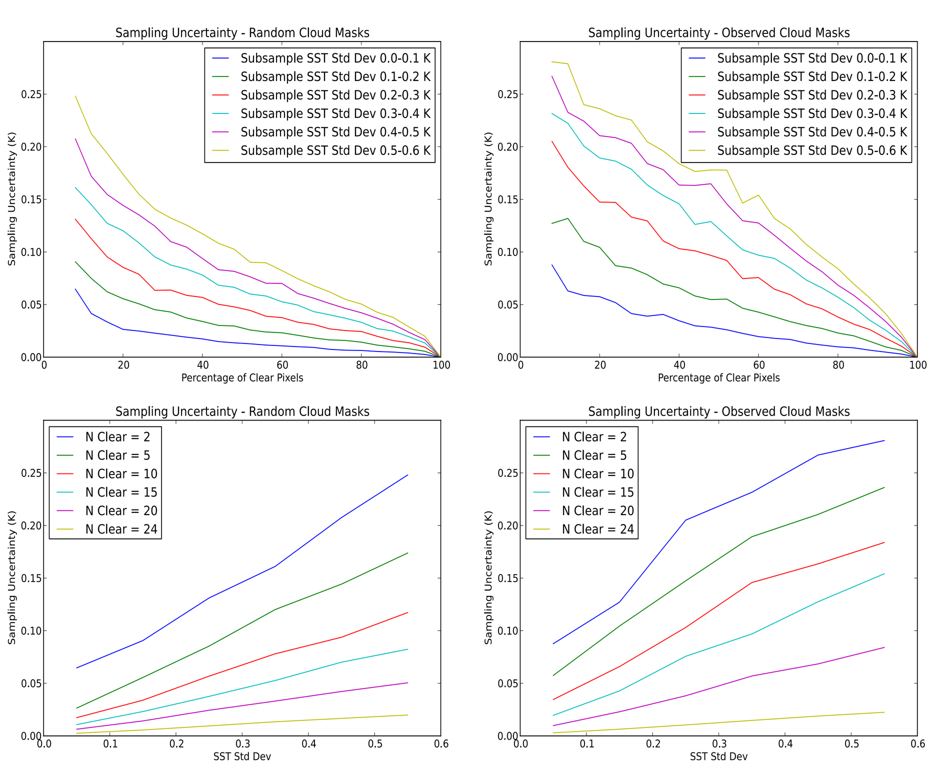


Figure 2: Uncertainties from LSE as a function of TCWV and view angle.

3. Sampling Uncertainty in SST

Sampling uncertainty arises in reduced resolution data where some observations are unavailable, for example due to the presence of cloud. Figure 3 shows sampling uncertainty for observations over 5x5 pixel domains at 1 km resolution as a function of the percentage of clear sky pixels and the standard deviation of the SST. The plots show that sampling uncertainty cannot be modeled by applying a random mask as uncertainties using observed masks are significantly higher.

Figure 3: Sampling uncertainties across 5x5 pixel domains for random and observed cloud masks.



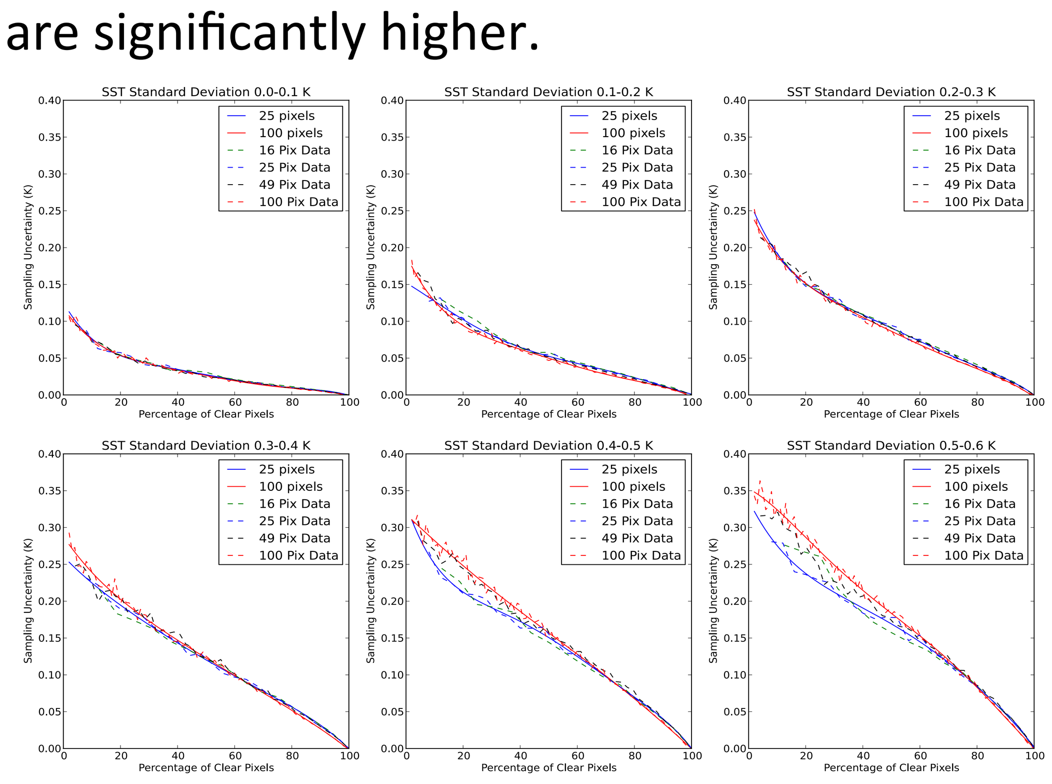


Figure 4: Sampling uncertainty modeled as a function of SST variability.

Figure 4 shows sampling uncertainty modeled for a range of SST standard deviations. The polynomial fit corresponds to 25 and 100 pixel domains (blue and red lines respectively). At low SST standard deviations (< 0.4 K) a single fit is sufficient to describe sampling uncertainty for domain sizes of 0.05-0.1°. For regions of higher SST variability domain size is more important.

4. Validating Uncertainty Budgets

Where uncertainty budget estimates are derived within the retrieval scheme these can be validated independently using in-situ observations. Figure 5 shows a validation of single pixel uncertainties for 1 year of AATSR matchup data, comprised of components from uncorrelated and locally systematic effects for N2 and D2 retrievals. The retrieved uncertainty should follow the 1:1 line when plotted against the standard deviation of the retrieved minus in-situ SST difference. A lower limit to this relationship is found below a retrieval uncertainty of 0.2 K due to uncertainties in the in-situ measurement.

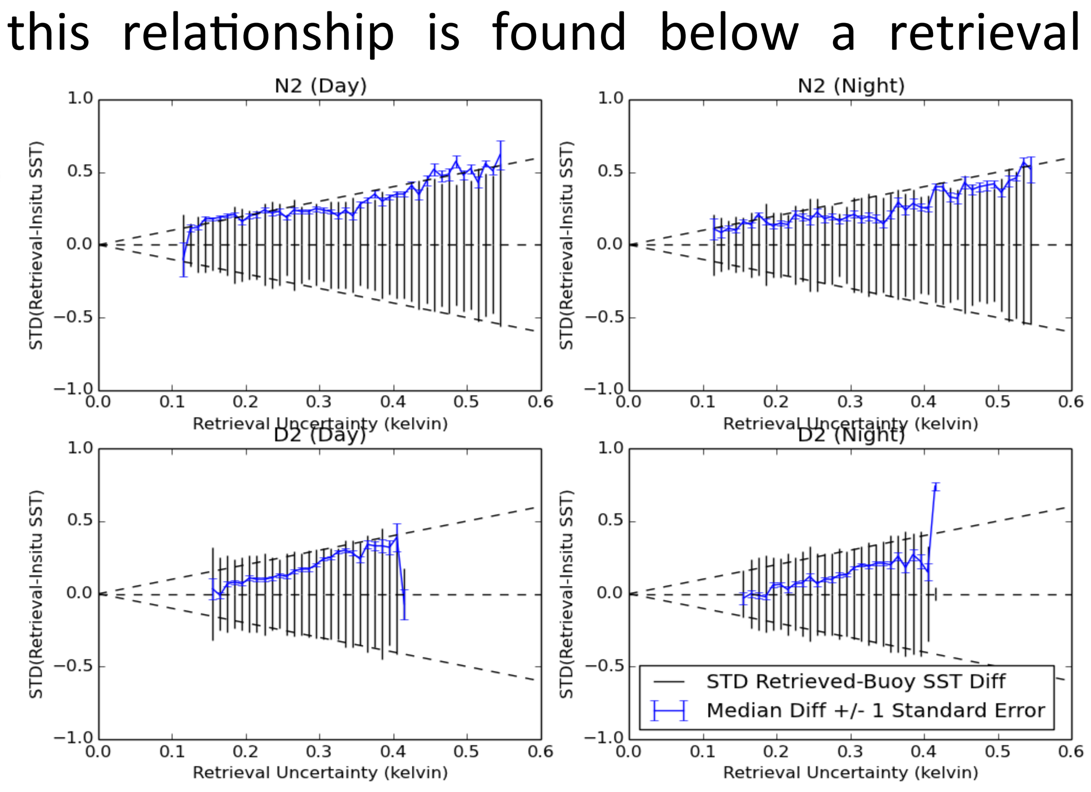


Figure 5: Single pixel uncertainty budget validation for N2 and D2 retrievals for 2005 matchup data.

References

GHRSST Science Team (2010), The Recommended GHRSST Data Specification (GDS) 2.0, document revision 4, available from the GHRSST International Project Office, 2011, pp 123.