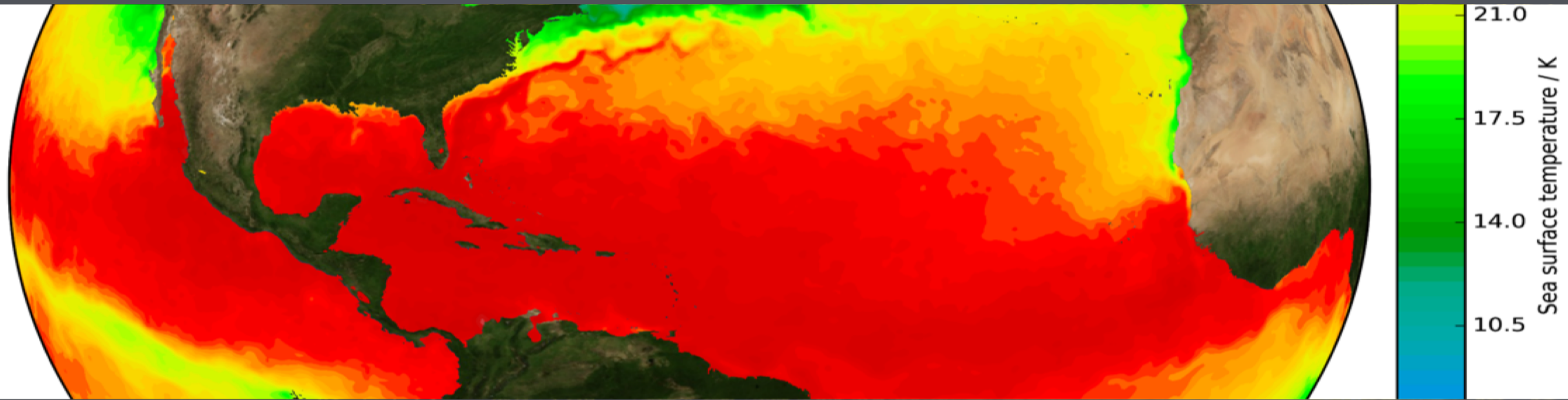
Earth Observation and Space
Department of Meteorology

University of Reading

INFERENCES FROM DISTRIBUTIONS OF DIFFERENCE IN SST VALIDATION DATA

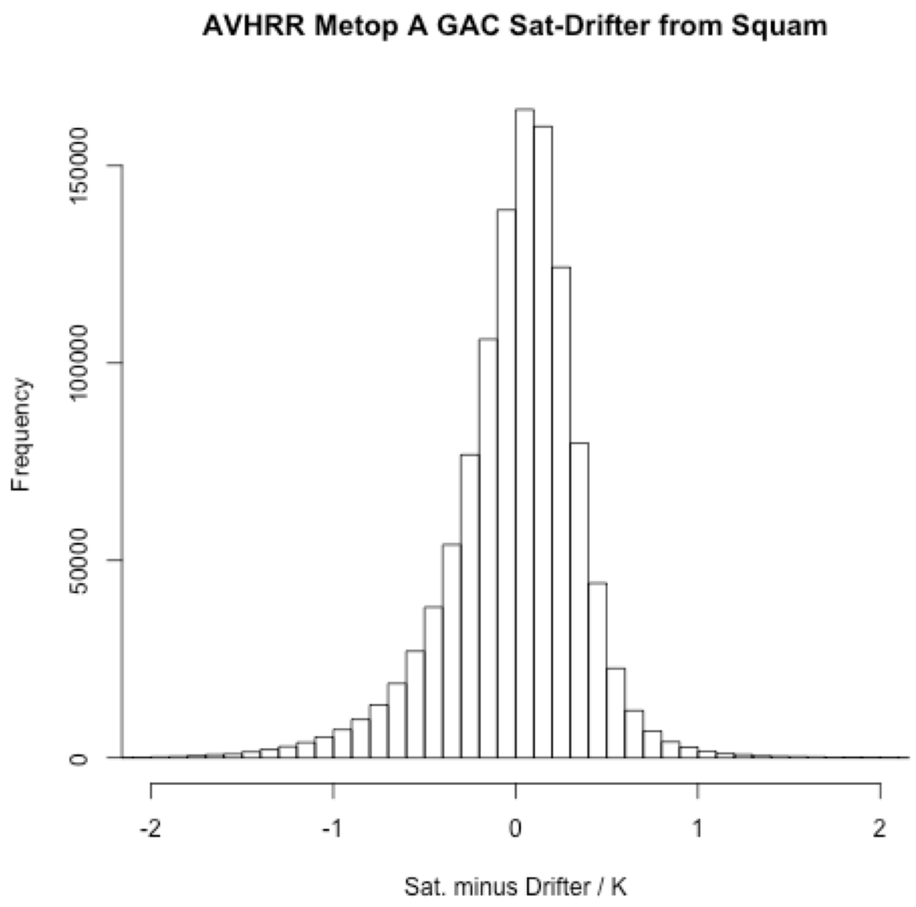


Christopher Merchant
Department of Meteorology
University of Reading

National Centre for Earth Observation
NATURAL ENVIRONMENT RESEARCH COUNCIL

QUESTION

- Drifting buoy numbers, coverage and reporting frequencies over the past decade+
- We now obtain very statistically robust distributions of satellite-in-situ matches
- Is there more information in these distributions than we have hitherto extracted?



LOGIC OF STUDY

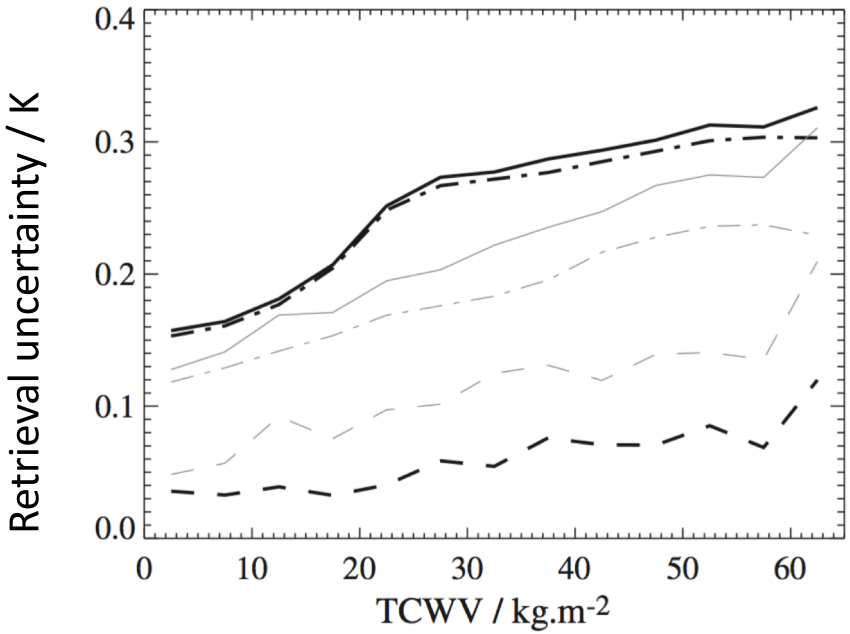
- Consider how to model satellite-drifter SST differences
  - In nominal conditions (“clear skies”)
  - In contaminated conditions
    - e.g., cloud, aerosol – hereafter will just say “cloud”
- Propose a distributional model and its parameters
- Fit this to examples of match-up data
- Interpret the parameters in physical terms

SST ERROR DISTRIBUTIONS

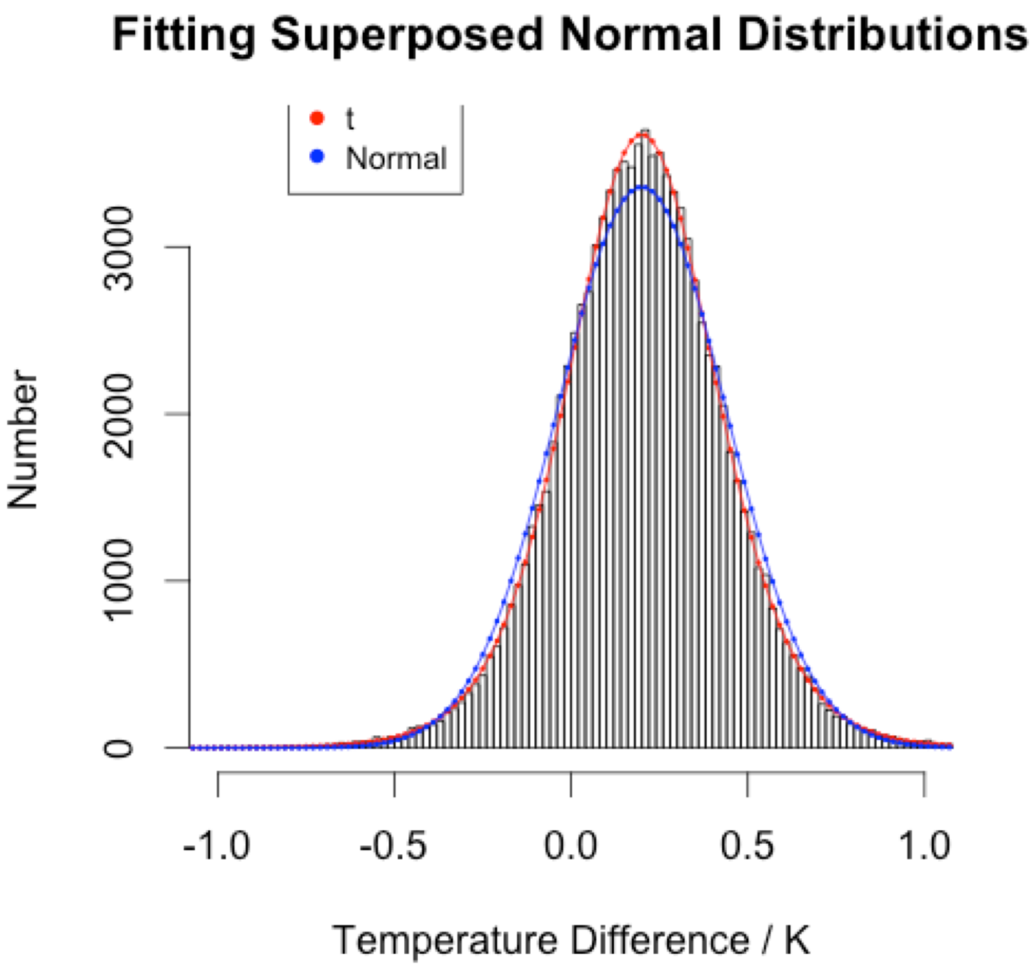
- Part of the satellite-drifter difference arises from their errors
- We typically assume the errors should be normally distributed
- But … uncertainty is not constant
- A sum of different normal distributions is not a normal distribution

Solid lines: ARC SST retrieval uncertainty as a function of atmospheric water vapour, different channel combos, simulated.

Embury & Merchant, 2011
10.1016/j.rse.2010.11.020



FIT CLEAR SKY DIFFERENCES USING T-DIST

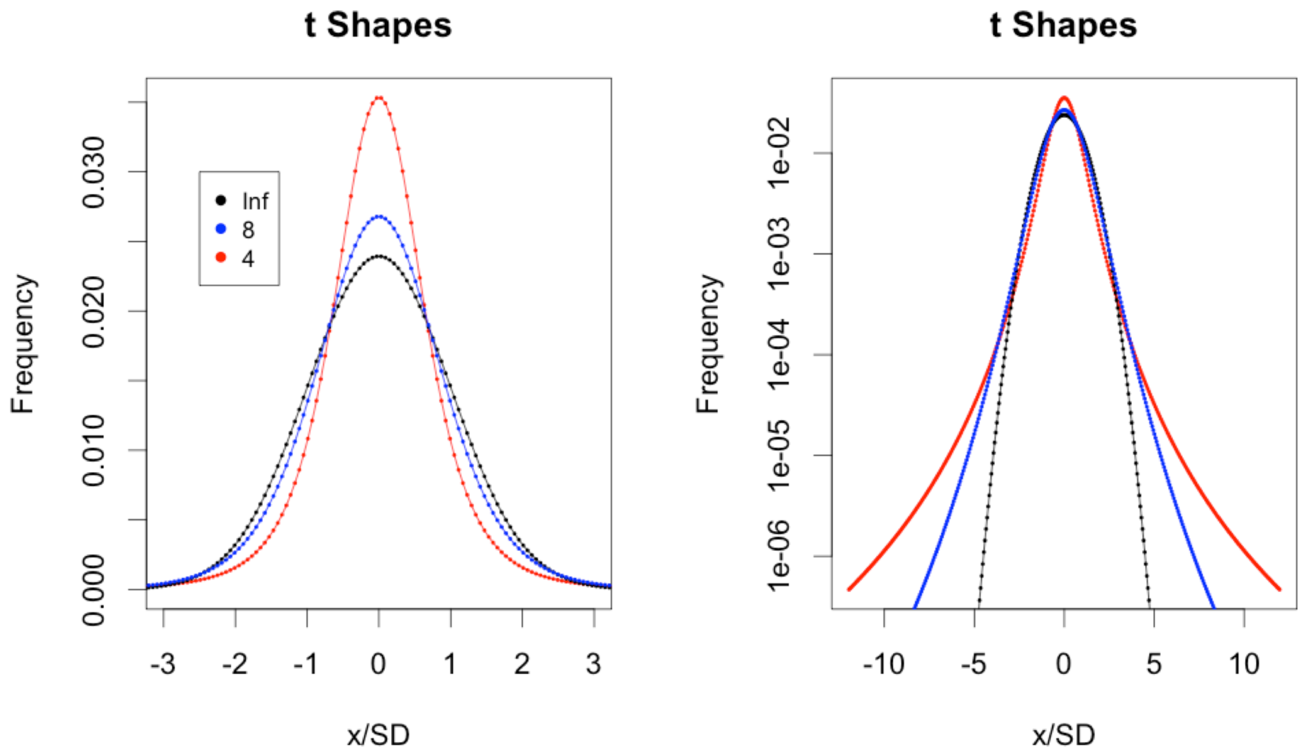


- Synthetic data combining two normal distributions
- Student’s t distribution can better capture the shape

STUDENT T DISTRIBUTION

University of Reading

- Generalized normal distribution function, with a shape parameter than can put more weight into the wings and peak
- Three t distributions with zero mean and unit standard deviation:



RESIDUAL CLOUD ERRORS

- When clear-sky retrievals are applied to contaminated pixels (e.g., residual cloud) the result is usually cold => “cold tail”

- Choose a distribution that focusses on errors ≳ the clear-sky uncertainty, $\boldsymbol{\sigma}$ (reduces degeneracy of the solution)

$$f(\epsilon \geq 0) = 0 \qquad f(\epsilon < 0) \propto \exp\left(-\frac{|\epsilon|}{\boldsymbol{\tau}}\right)\left(1 - \exp\left(-\left(\frac{\epsilon}{\boldsymbol{\sigma}}\right)^2\right)\right)^2$$

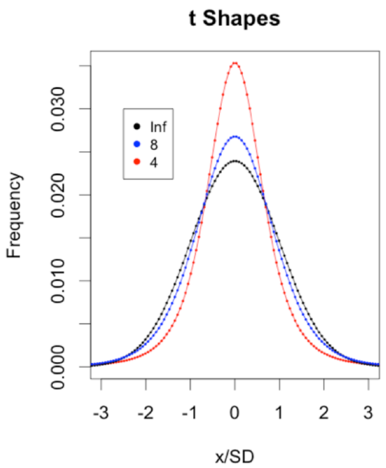
Only cold errors are modelled

Extreme errors are less common

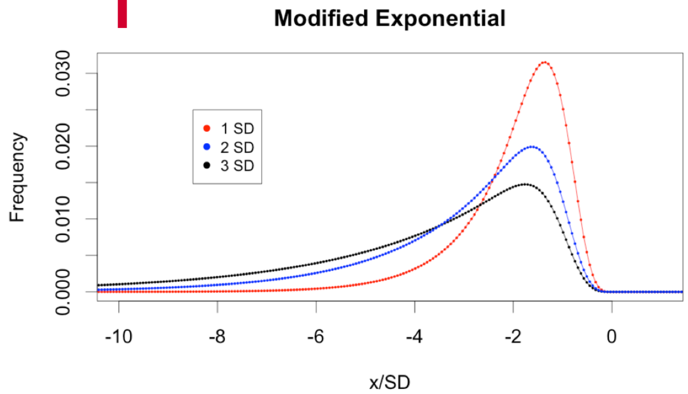
Only characterize errors beyond the main peak with this term

SAT-BUOY DIFFERENCE MODEL

$$d = \epsilon_{buoy} + \epsilon_{match} + \epsilon_{clear} + \delta_{x<f}\epsilon_{contam}$$



Parameters: μ, σ, s



Parameter: τ

$$x \sim U(0,1)$$

$$\delta_{x<f} = \begin{cases} 1 \text{ for } x < f \\ 0 \text{ for } x \geq f \end{cases}$$

$$\therefore \delta_{x<f}\epsilon_{contam} \neq 0 \text{ for a fraction } f$$

ESTIMATING PARAMETERS

- Use Bayes theorem – but hard problem:
  - Multivariate, nonlinear, integration across peaky functions

- Calculate

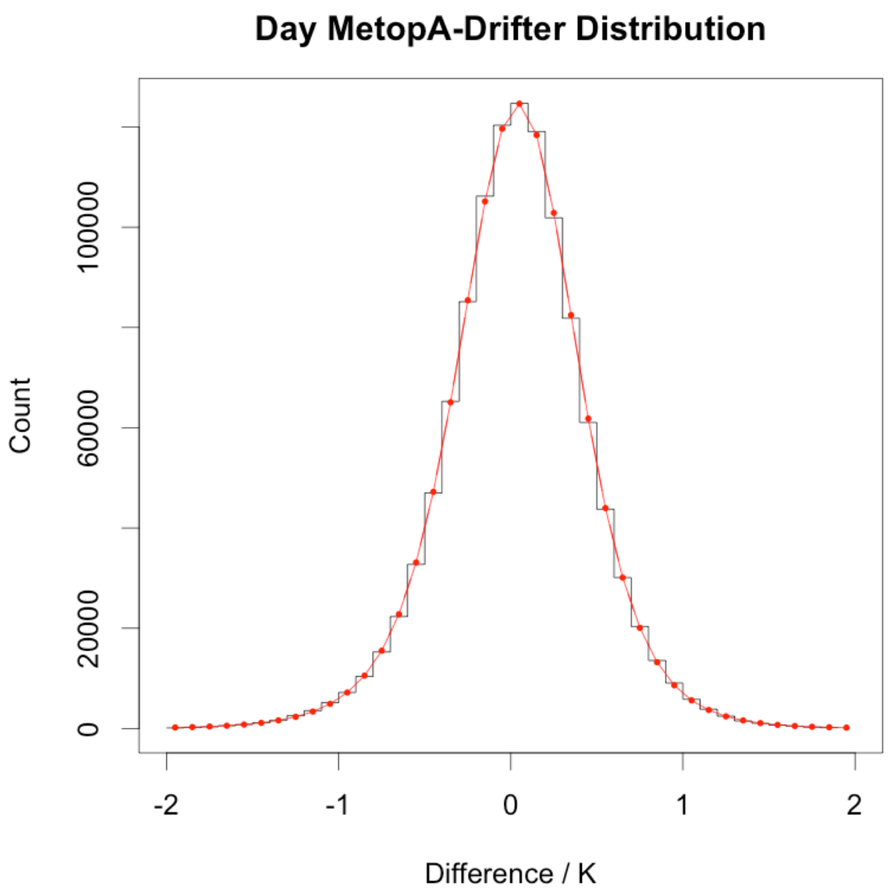
$$P(\theta|D) \propto P^*(D|\theta)P(\theta)$$

- Sample the parameter space, θ, using **Markov Chain Monte Carlo**

- Minimally informative priors
  - Mostly uniform
  - Contamination fraction is a-priori <<100%

University of Reading

METOP-A GAC FROM SQUAM



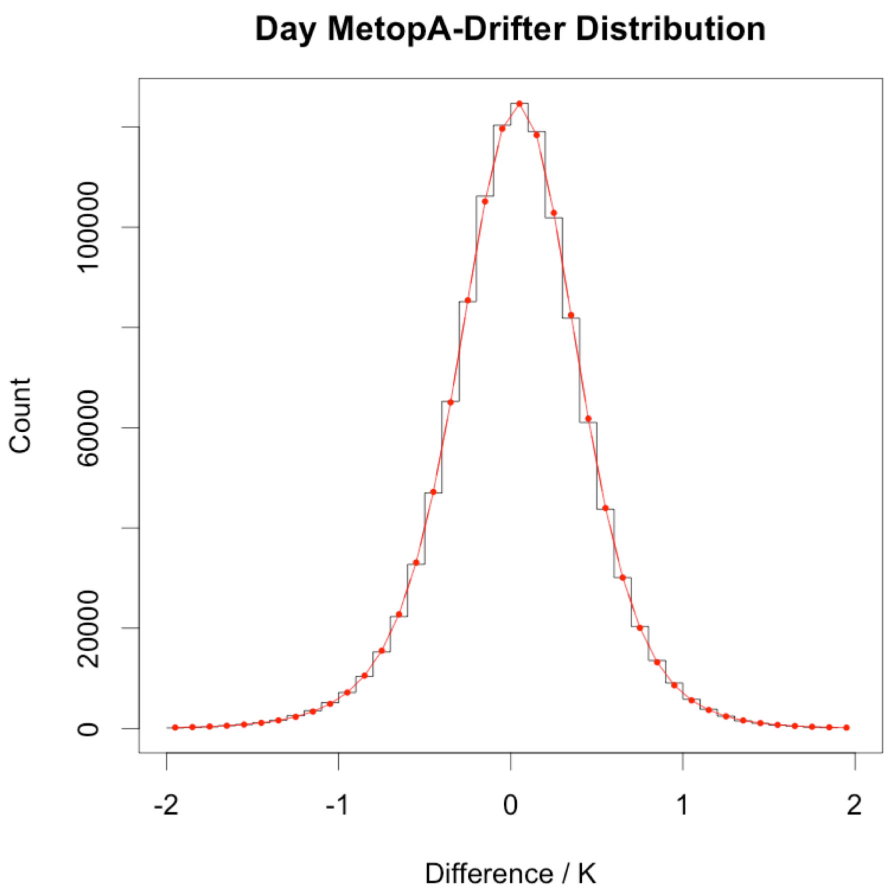
DAY

Parameter	Estimate	± 90% CI
Clear-sky mean / K	0.047	0.001
Clear-sky St.Dev / K	0.416	0.001
Shape	6.8	0.1
Cloud %	2.6	0.2
Cloud scale / K	0.25	0.02

The “clear sky” bias is small (0.047 K) and slightly more positive than the distribution mean (0.033 K). The “clear sky” standard deviation is smaller than the distribution SD (0.43 K).

Squam histogram data provided by Xinjia Zhou and Sasha Ignatov

METOP-A GAC FROM SQUAM



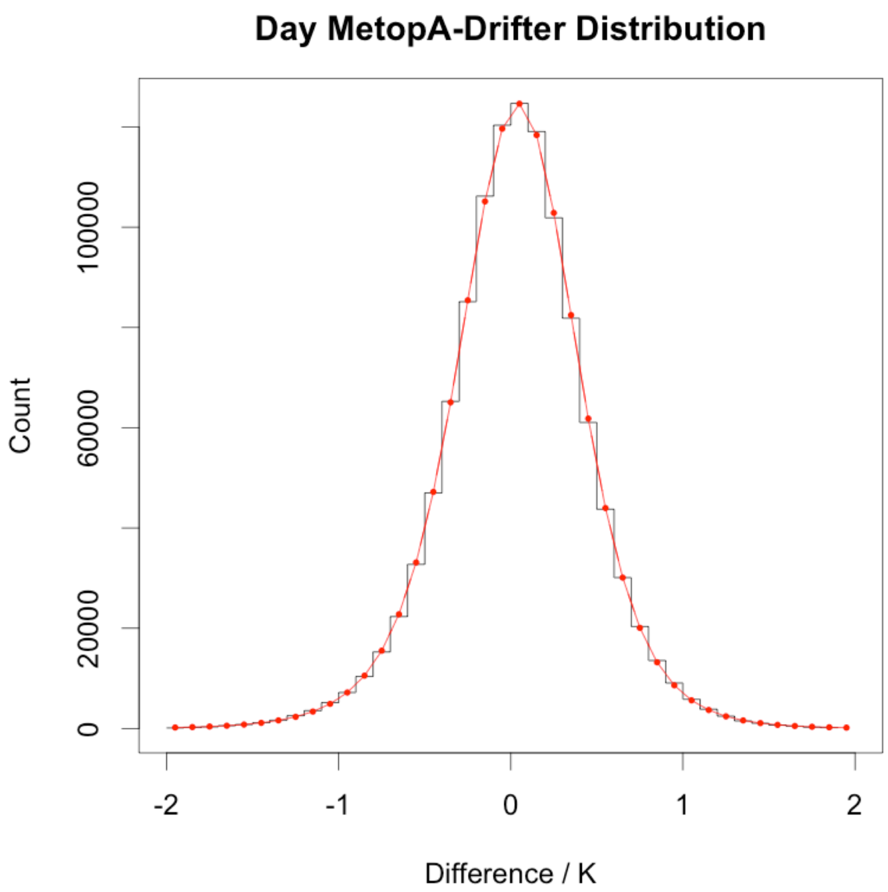
DAY

Parameter	Estimate	± 90% CI
Clear-sky mean / K	0.047	0.001
Clear-sky St.Dev / K	0.416	0.001
Shape	6.8	0.1
Cloud %	2.6	0.2
Cloud scale / K	0.25	0.02

∞ = normal
2 = extreme non-normal
6.8 = > tails are quite heavy

Squam histogram data provided by Xinjia Zhou and Sasha Ignatov

METOP-A GAC FROM SQUAM



DAY

Parameter	Estimate	± 90% CI
Clear-sky mean / K	0.047	0.001
Clear-sky St.Dev / K	0.416	0.001
Shape	6.8	0.1
Cloud %	2.6	0.2
Cloud scale / K	0.25	0.02

Cold-tail ("cloud/aerosol") affects ~2.6% of matches. For the affected matches, mean additional bias is -0.6 K, which implies -0.015 K bias in the whole distribution – very small.

Squam histogram data provided by Xinjia Zhou and Sasha Ignatov

ACSPO – CCI COMPARISONS

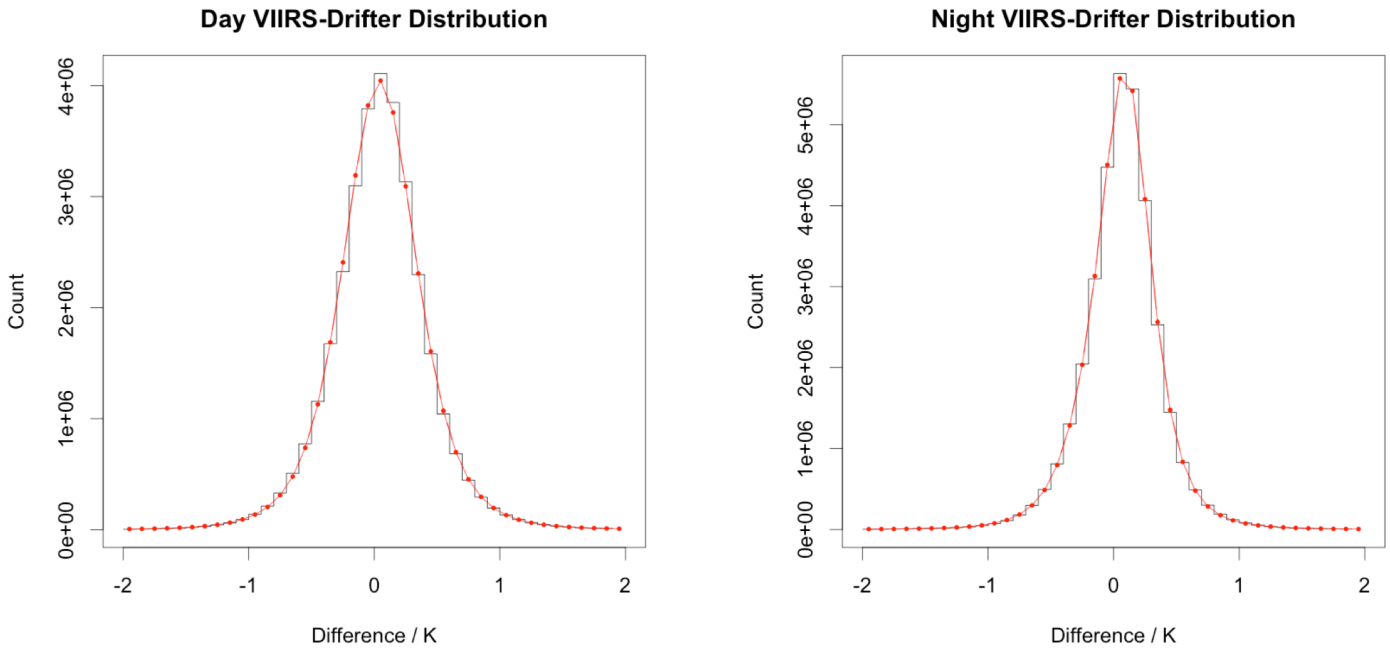
University of Reading

Case	Project	Clear-sky mean / K	Clear-sky SD / K	Shape	Cloud %	Cloud scale / K	Cloud bias overall / K
		μ	σ	s	f	τ	β
Metop A Day	ACSPO	0.047	0.42	6.8	3%	0.25	-0.015
	CCI	0.043	0.35	6.4	11%	0.26	-0.06
Metop A Night	ACSPO	0.091	0.29	4.7	20%	0.26	-0.09
	CCI	0.073	0.27	3.7	26%	0.42	-0.17

SST CCI retrievals compare favourably, but ACSPO cloud detection looks to be better.

sst cci

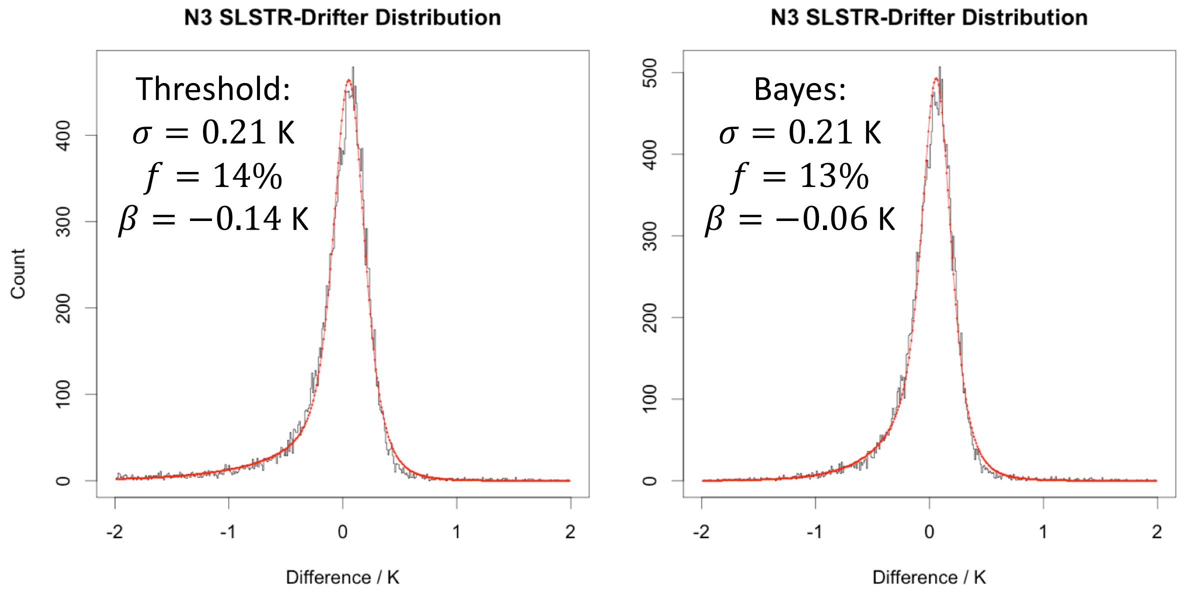
VIIRS FROM SQUAM



- Highly symmetric – “extra” tail <0.1% of data (negligible)
- Highly non-Gaussian – shape parameter ~4 in both cases
  - Heavy symmetric tails

SLSTR AND CLOUD DETECTION

- Initial operations of SLSTR used solely a threshold-based mask
- Since April 2018, the operational data also have a Bayesian clear-sky probability estimate (Merchant et al., 2005)
- Use of the Bayesian reduces cloud-related bias of whole distribution by 0.08 K



Single view
3-channel
Night time SST

Histogram data provided by Gary Corlett (SLSTR Mission Performance Centre)

CONCLUSIONS

- Five parameter model can be fitted to observed validation distributions
- Model has physical interpretation
  - Central peak, described by Student t distribution, interpreted as the difference distribution under ideal retrieval conditions (clear sky) where uncertainty varies between different “families” within the data
  - Exponential cold tail (usually attributed to cloud, perhaps also aerosol)
    - The cold-tail fraction in the case of GAC night-time is high but plausible given compositing of pixels in GAC
- Parameters describing distribution fit with physical expectations
  - Night-time SSTs better than day-time
  - Less cloud contamination in day scenes
- **Allows more insightful and objective assessment of relative performance of retrievals and cloud screening**