

**Climate Change** 



# Modelling observation errors for historical datasets

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**CECMWF** 

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# EUMETSAT





- Historical data records
- Revisiting historical observation errors (climate reanalysis)
- On the importance of references: bias terminology & a simulation
- Better understanding of uncertainties in reprocessed data records
- Conclusions





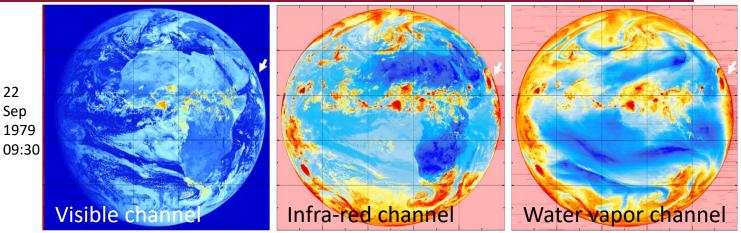


# Meteosat-1 (launched in 1977)

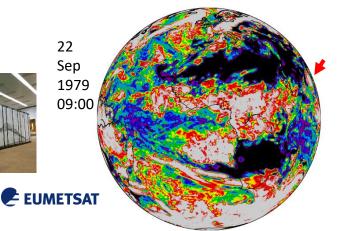


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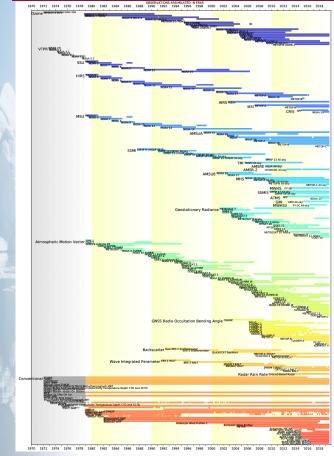


### **ERA5 Total Cloud Cover**





# Historical data records



Satellite observations in reanalyses span a half-century
 → Additional satellite data records exist, though not in "ready-form" for assimilation (reprocessing required).

→ Historical data records pose specific challenges:

### Todays' instruments:

- improve design upon legacy instruments,
- generally well-characterized before launch, (and sometimes even after, *cf.* NPP, METOP manoeuvers),
- include in-flight calibration systems

# Today's **data**:

- processing generally well-documented,
- often inter-compared (cf. GSICS talk by T. Hewison),
- contextually well-described (other satellites),
- supported by simul. models developed since mission onset

Furoneau

### Today's metadata:

central system: WMO Oscar/Space





# Data & methods used in this talk

### Observations, and models!

### + At the intersection: Data assimilation observation feedback

- From 2 reanalyses (cf. talk by B. Bell), using ECMWF ODB-API to decode the data
  - ERA-Interim (1979-2019)
  - ERA5 (1972-2019), ERA5.1 for years 2000-2006
- Contains:
  - Observation departures from background and from analysis
  - Data assimilation flags
  - Bias estimates, for bias-corrected observations
  - Observation random error assumed by the assimilation (sigo)
  - Background (random) error assumed by the assimilation (sigb)
- This is further complemented by computing Desroziers' diagnostics
  - Yields new estimates of sigo, sigb
- Drawing here examples from satellite data, in-situ data

#### Reprocessed satellite data records

'Observation data':

HIRS and SSM/T-2 brightness temperature plus 'ancient' data: VTPR, MRIR, THIR...

- 'Model data': simulated brightness temperatures, based on ERA-Interim or ERA5, using 4D fields of temperature, humidity (+ ozone, CO<sub>2</sub> for HIRS), using RADSIM v2.2 and RTTOV v12.3







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# Observation 'errors' in ERA5 (1

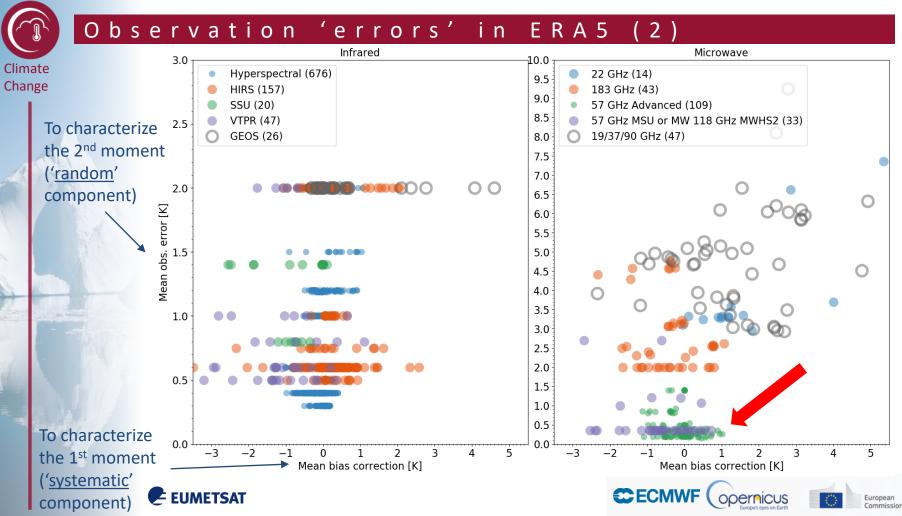
- Consider here all radiance satellite obs. actively assimilated
- Compute, per instrument and per channel:
  - (estimated) systematic error = monthly average (biascorr) in ODB jargon
  - (assumed) random error = monthly average (obserror) in ODB jargon
    - Considering the monthly timescale smooths out short events, visible with occasional spikes in individual assimilation cycle results
  - Then consider the average over all months when the data are available
- For all distinct satellites/channels assimilated:
  - 1,172 entries
  - Group the various instrument channels for plotting,
     by technology (instrument type) and/or frequency band



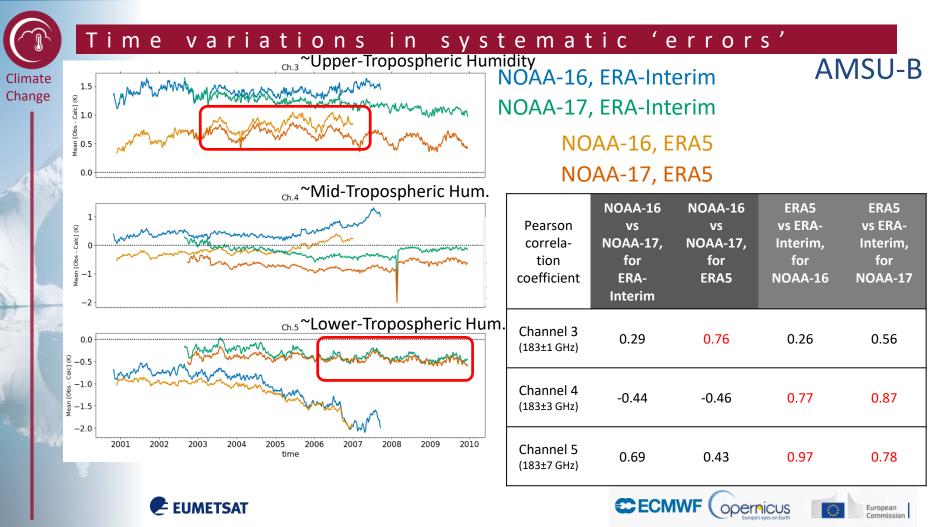


Climate

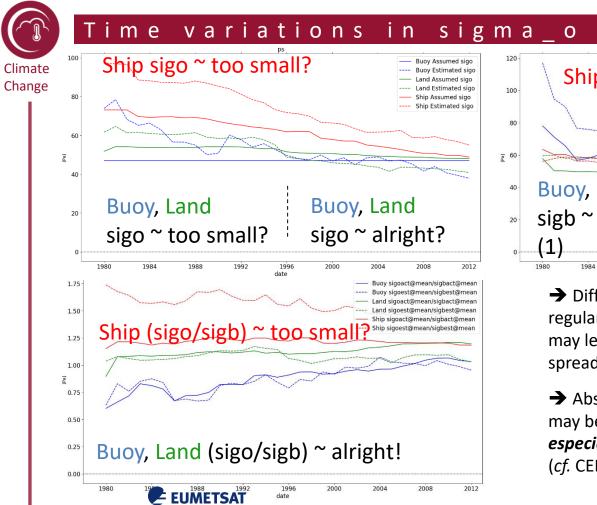
Change

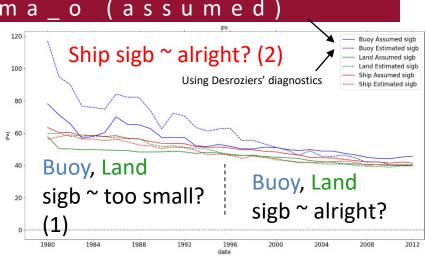


Brightness temperature observations assimilated in ERA5 (feedback 1972-2011); Diagnostics on a monthly basis, subjected then to average over all available months



AMSU-B brightness temperature observations assimilated in ERA-Interim, ERA5 (feedback 1979-2011); Diagnostics on a daily basis, subjected then to 10-day moving average





→ Difference between (1) and (2): greater regularity/stationarity of observations in (1) may lead to collapse the analysis ensemble spread for the next background

→ Absence of time variation in sigma\_o may be sub-optimal for reanalysis especially in poorly-observed areas and times (cf. CERA-20C, Laloyaux et al.)

opernicus

European

Surface pressure observations assimilated in ERA5 (feedback 1979-2011); All diagnostics, including Desroziers', estimated on a yearly basis; Results shown on 31 Dec. of each year



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# Vocabulary

Climate Change

# Bias: "our" term for the systematic component of the error

#### Rarely can we assert systematicity

... since we rarely have enough independent samples to assert the systematic nature, and we can generally not replicate the measurement in the same conditions

Rarely do we know exactly the <u>error</u> ... since we rarely know the true value, however we can measure distances between two estimates, or their projection(s)

#### International Vocabulary of Metrology (VIM guide) defines systematic error as

"component of measurement error that in replicate measurements remains constant or varies in a predictable manner"

The Bureau International des Poids et Mesures (BIPM):

- has the mission of establishing worldwide uniformity of measurements, traceable to the International System of Units (SI);
- is under the authority of the General Conference on Weights and Measures (CGPM), which has the authority for approving the definitions of the SI (first approved 1960).

Knowing what biases to expect... may help us better estimate them...







# Instrument network simulation

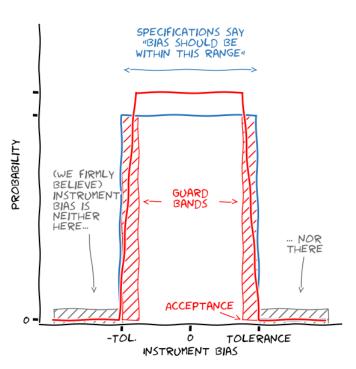
Change

# Hypothetical population of 100,000 instruments

- All calibrated with | systematic error |  $< \varepsilon$ (arbitrary unit)
  - Assuming a *uniform distribution*  $[-\varepsilon, +\varepsilon]$
  - Considering also that acceptance occurs within a narrower band (because of verification uncertainty *u*)
- 'Guaranteed' with
- | drift | < D(arb. unit, per year)
- Assuming a *uniform distribution* [ *D*, + *D* ]
- Recommended calibration cycle:
  - Every  $N = (\varepsilon / D)$  years
- For this population of instruments, we investigate the distribution of biases:
  - Right after calibration, if one considers uncertainties in the calibration (and does not apply acceptance guard bands)
  - After *N* years, just before re-calibration
  - Mix of ages, recalibration every N years
  - Mix of specs. (e.g., different manufacturers):  $\varepsilon$  to  $3\varepsilon$ , D to 3D
  - Mix of specs., mix of ages, delayed recalibration cycle
  - Mix of specs., mix of ages, mix of recalibration cycles

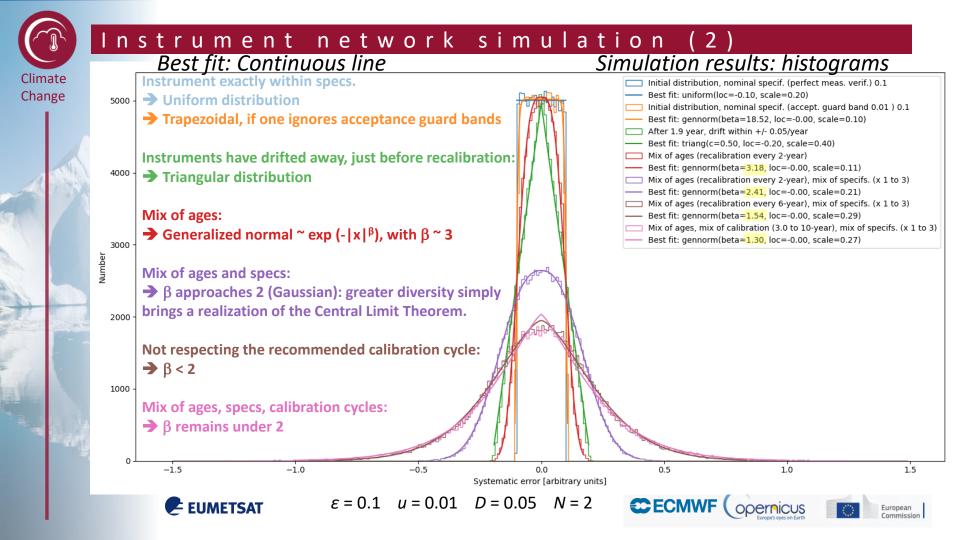
Methodology reference: Monte-Carlo method as described in the Joint Committee for Guides in Metrology (JCGM) 101:2008 Evaluation

of measurement data — Supplement 1 to the "Guide to the expression of uncertainty in measurement" - Propagation of distributions using a Monte Carlo method, p. 15

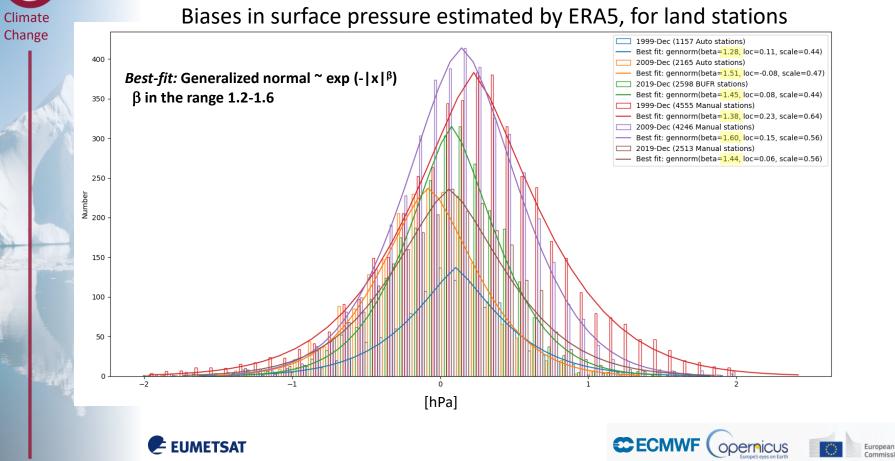


European

**ECMW** 



# What about real data?



Surface pressure observations assimilated in ERA5; obs. feedback; monthly estimates for Dec. 1999, Dec. 2009, Dec. 2019



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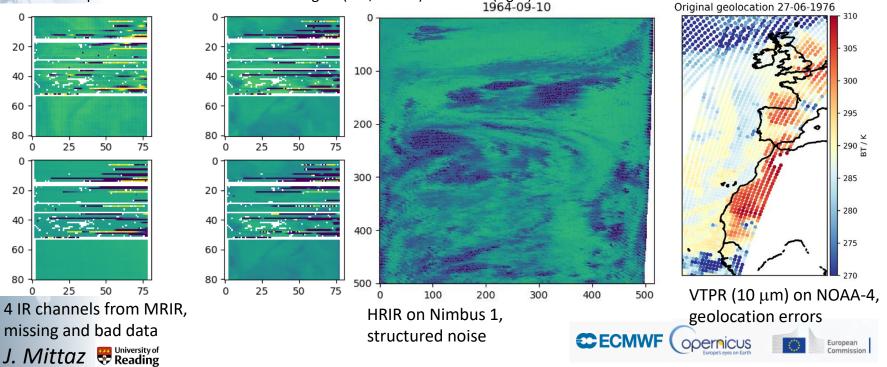




# Identifying quality issues

Climate General aspects: Limited knowledge/documentation, Limited telemetry for most sensors, Significant amount of bad data, Change Can be quite noisy, Geolocation issues possible...

- → Work ongoing to improve/categorize quality and uncertainty, and flag accordingly
- Examples at EUMETSAT with an anomaly database for MVIRI
- Examples below for ancient Nimbus imagers (left, center) and VTPR (right)



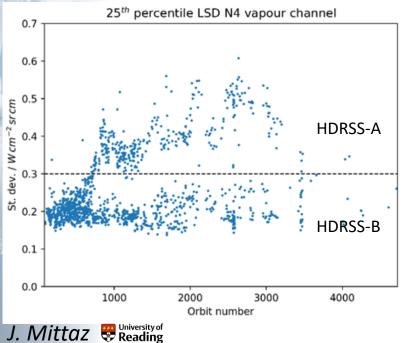


# Noise estimates

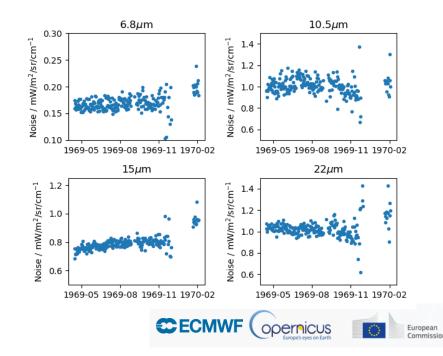
Change

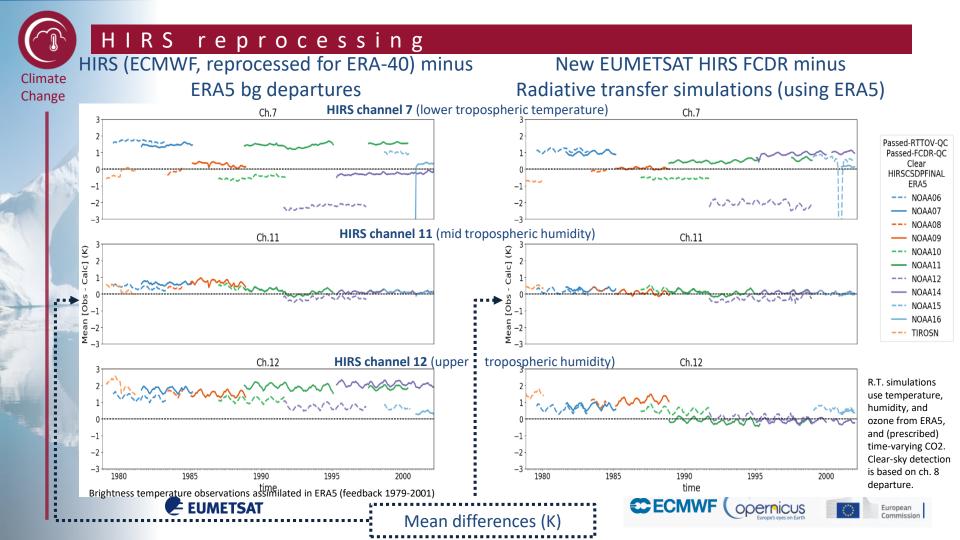
Vary due to a number of causes (random component of uncertainty)

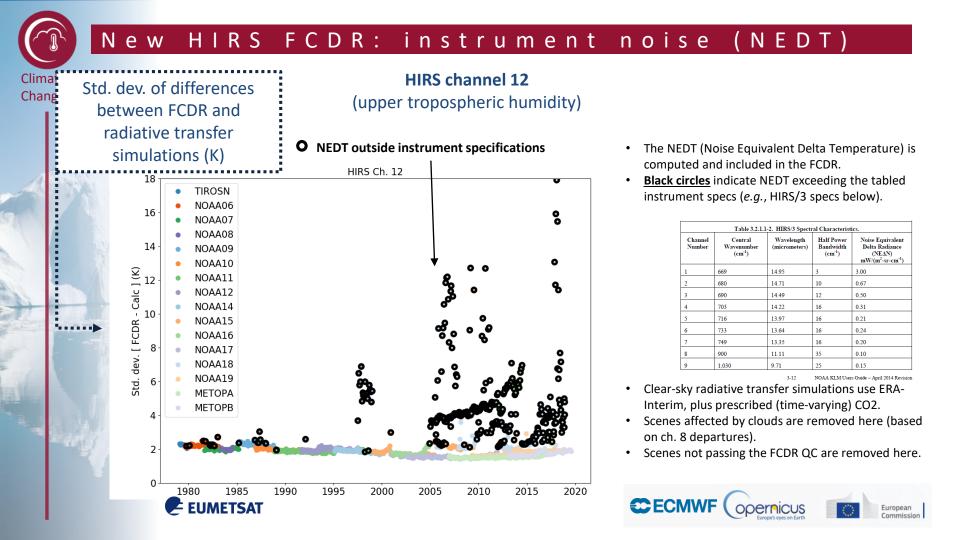
# THIR noise varies dependent on which on-board tape is used



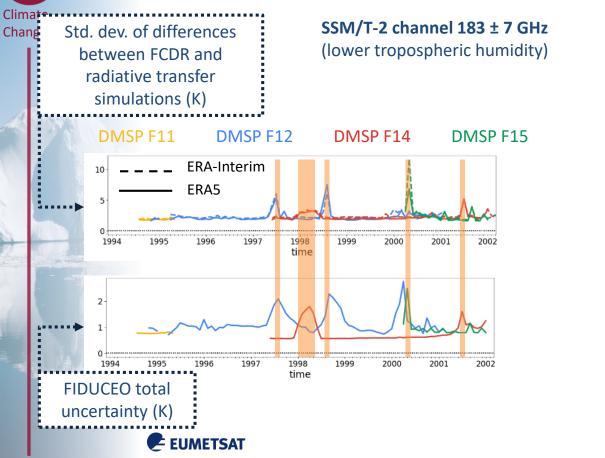
# MRIR noise estimates







# SSM/T-2 FCDR: FIDUCEO uncertainties



- SSM/T-2 predates AMSU-B, MHS.
- FCDR contains FIDUCEO uncertainties (cf. *talk by C. Merchant*).
- FCDR Release 2: adds flags on cloud/rain contamination (based on SSM/I, HOAPS) and quality controls.
- Scenes affected by rain/clouds or not passing FCDR QC are removed here (based on FCDR Release 2 quality flags).
- Further intercomparisons required with traceable measurements, accounting for representativeness (cf. talk by X. Calbet)





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# Conclusions and perspectives

### Systematic part of the observation errors (bias)

Know what/when references are used for calibration,

if one could know more about actual calibration tolerance and cycle, may tell us more about what biases to expect? For in situ, WMO OSCAR/Surface (will eventually) do this

 For satellite data: share predictors between satellites with same instruments, when biases appear to follow similar patterns?

### Random part of the observation errors (sigma\_o)

- Revisit estimates for old instruments, in reanalysis?

### **Observation reprocessing**

- Provide uncertainties in FCDRs, to help users make informed decisions?

### Instrument/network specifications:

 Link between WMO/OSCAR and RTTOV, including noise specifications?
 e.g., as done for the SRF/spectral characteristics? This would help users exploit readily NEDT (sometimes) provided in the data

Not solely for documenting past missions, but also for future missions (potentially: many small satellites, dev. and launched quickly)

knowns ~ *Negligence* (Un)published studies, manufacturers' results, (known somehow) model limitations...

Observations and models

(deterministic, physical)...

Knowledge

Known

knowns

Unknown

Unveiled when looking at new data, or at old data under a new light...

Instrument specifications

and actual performance, ensemble physical models...

Wisdom

Known

unknowns



