Scientific Analysis of VOSClim Data

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Overview

- Climate quality datasets and VOSClim
  - Requirements for climate datasets
  - Use of VOSClim data
  - Uncertainty in gridded fields
- Systematic biases and manual vs automatic reports
- Increasing the use of VOSClim data
- Summary

Climate datasets: requirements and the role of VOSClim

- 3 Key Requirements for climate quality dataset (amongst others)
  - Long time series of observations (multi-decadal)
  - Data characterized in terms of uncertainties
  - Estimates of systematic bias and impact of changing observing system

Climate datasets: requirements and the role of VOSClim

- 3 Key Requirements for climate quality dataset (amongst others)
  - Long time series of observations (multi-decadal)
  - Data characterized in terms of uncertainties
  - Estimates of systematic bias and impact of changing observing system
- VOSClim aids characterizing the observations and source of uncertainty
  - Extensive metadata
  - Model parameters co-located with observations
  - Additional parameters

Uncertainty and biases in VOS observations

- **Four main sources of uncertainty and bias in VOS observations:**
  - **Sampling or representativeness errors (e.g. is temperature report representative of the temperature 100 km to the East?).**
  - **Random errors (e.g. errors reading thermometer scale, coding and transmission errors).**
  - **Biases specific to individual ship or platform (e.g. calibration errors, poorly positioned instruments).**
  - **Systematic biases due to environmental conditions (e.g. heating errors)**
- All of these need to be understood to estimate the uncertainty in gridded datasets:
  - Sampling errors will depend on amount of data and how well distributed the observations are
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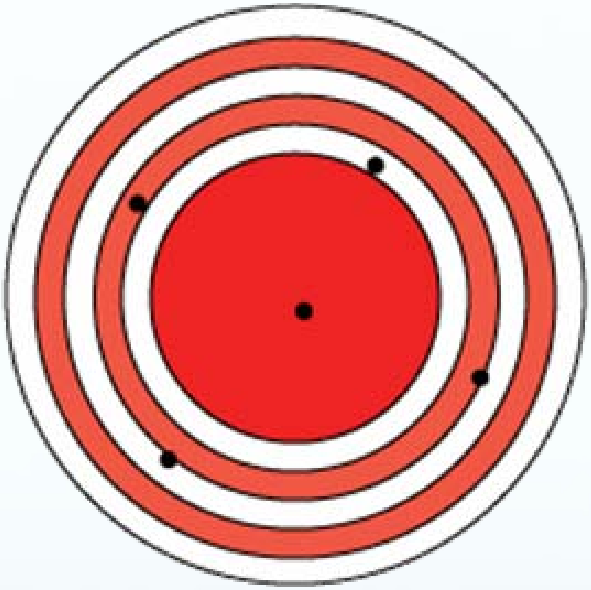
Example of accurate (centered on the bulls eye) but imprecise data



Observations have large scatter or random errors but with mean value close to center (i.e. small or no mean bias).

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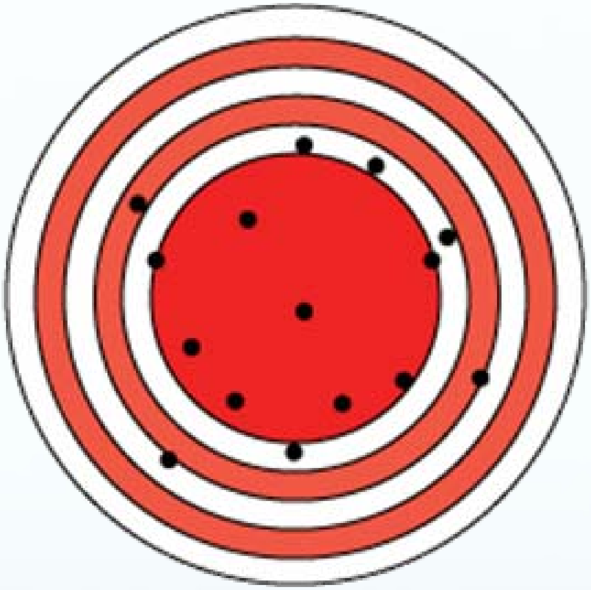

- As the number of observations increases the errors average out and the mean value is closer to the center.

- Difficult to estimate mean distance from center due to lack of ‘ground truth’. However, we can estimate the uncertainty that this introduces on average based on the number of observations and how scattered they are.

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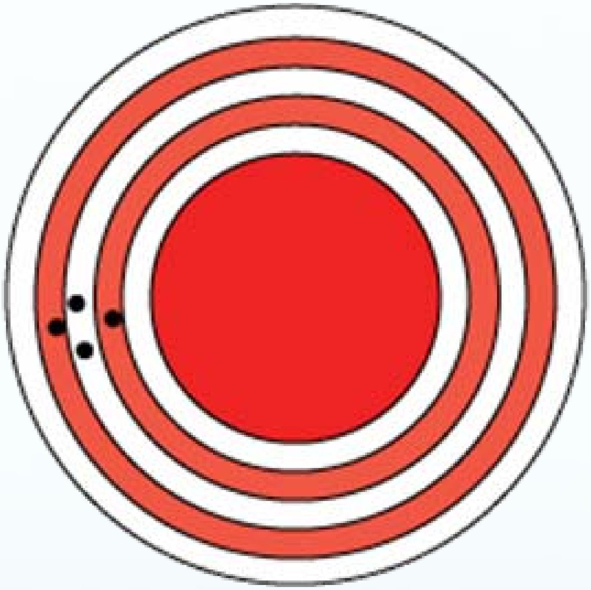
Example of precise (clustered close together) but inaccurate (far from middle) data



Observations from individual platform may be biased for variety of reasons (e.g. position of sensors, calibration errors)

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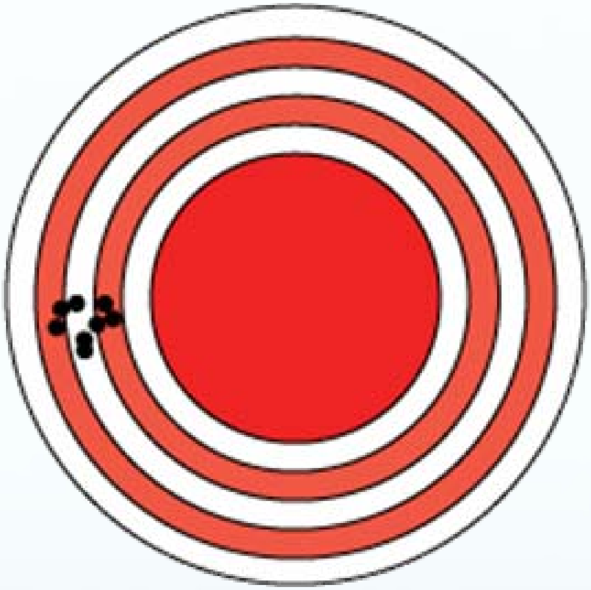

Increasing number of observations from a single ship will not reduce the error this introduces (additional observations still far from center)

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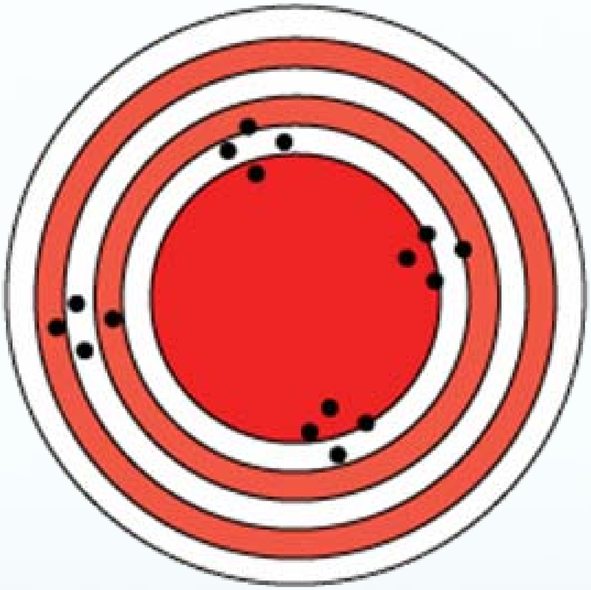

- However, if we have data from multiple ships the mean biases will, on average, cancel each other out and the average of the cluster will be close to the center.
- Again, difficult to estimate mean distance from center but we can estimate the uncertainty that this introduces based on number of ships making observations.

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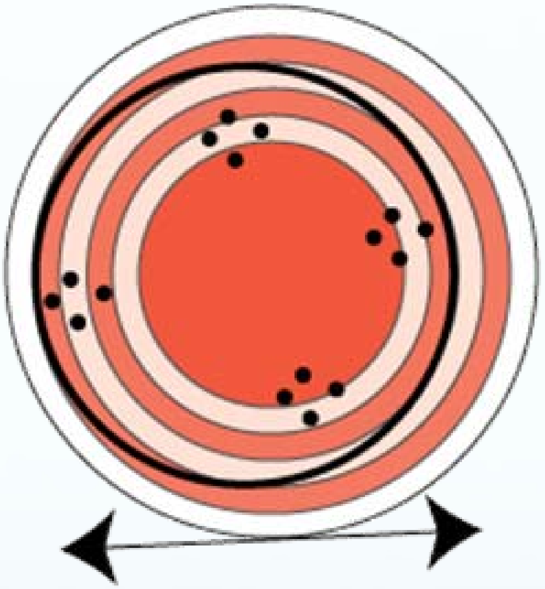
Estimating the random and bias uncertainties

- From VOSClim we have observations and co-located model values in same dataset
- Differences between observations and model calculated
- Mean and standard deviation of differences calculated for each individual ship, month and ocean region
- The mean of the standard deviations across the ships gives an indication of the random uncertainty (or precision)
- How the mean difference varies across the platforms gives a measure of the bias uncertainty (or accuracy)

Estimating the random and bias uncertainties



From VOSClim, we can estimated the uncertainty due to both the **bias uncertainty (how spread out the different clusters are)** and the random errors (how spread out the observations are for each platform)

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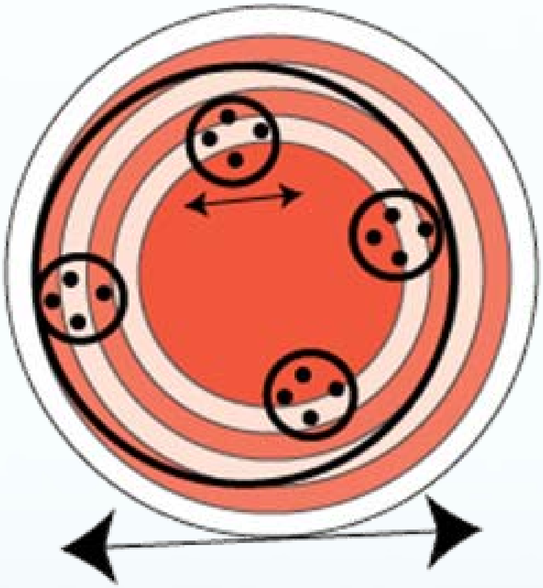

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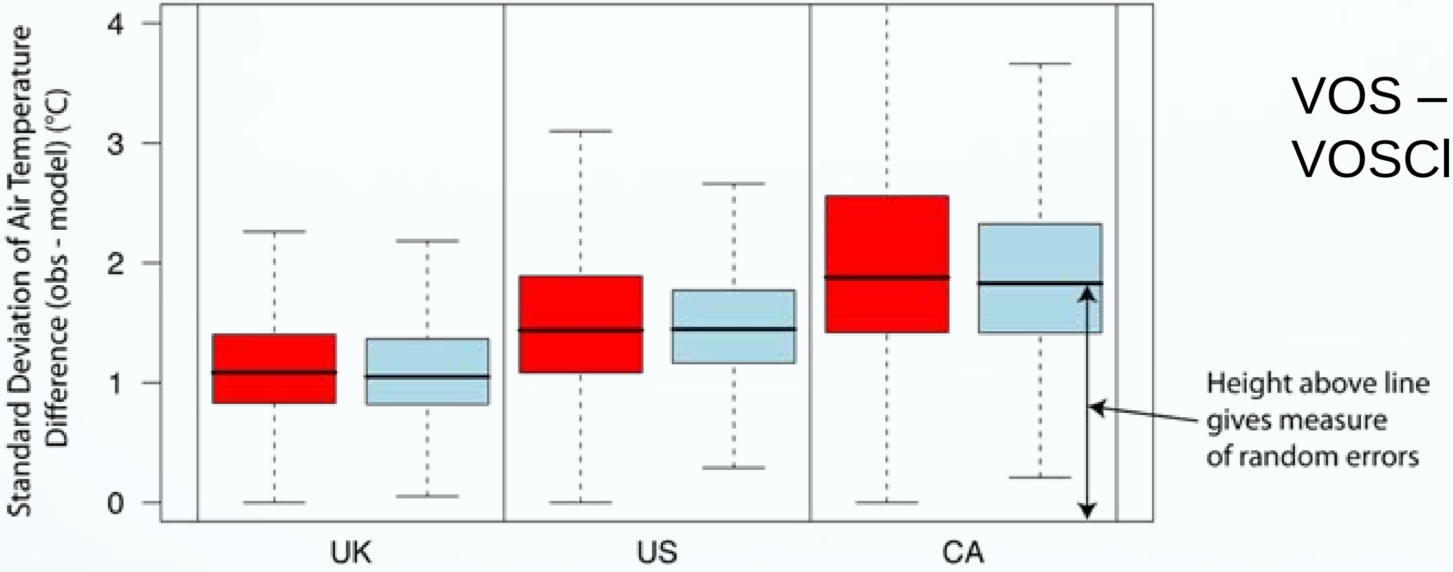
Example: estimating the random uncertainty



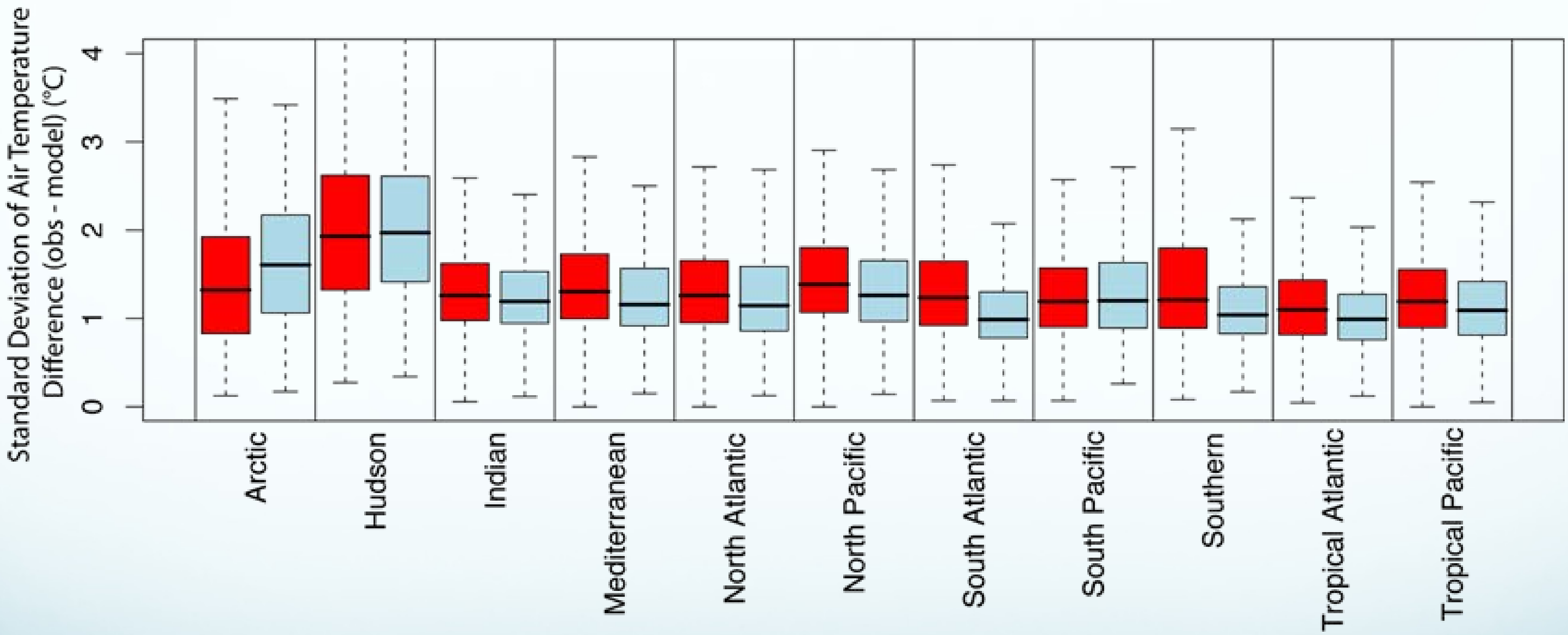
VOS – Red
VOSClim – light blue

Standard deviation of ship – model differences (i.e. random uncertainty) calculated for each individual ship.

Grouped and averaged based on country

Box plot shows median random error for each country and spread of values (inter-quartile range)

Example: estimating the random uncertainty (by region)



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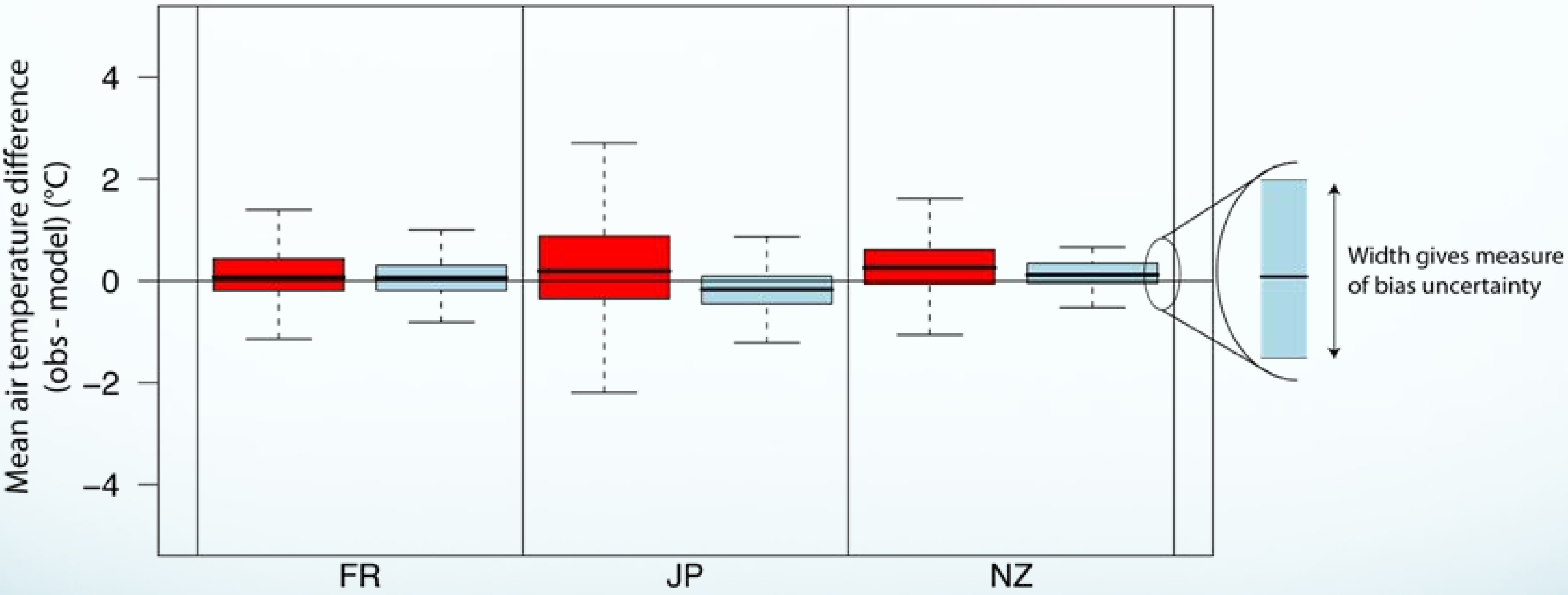
Example: estimating the bias uncertainty



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Comparison of VOS and VOSClim (example for North Atlantic and US Ships)

	Bias Uncertainty		Random Uncertainty		Total	
Variable (units)	**VOS**	**VOSClim**	**VOS**	**VOSClim**	**VOS**	**VOSClim**
Air Temperature (° C)	0.69	0.48	1.07	0.98	1.27	1.09
Relative humidity (%)	4.37	N/A	4.51	N/A	6.28	N/A
Wind Speed (m/s)	0.92	0.76	1.57	1.54	1.82	1.72
Sea Level Pressure (hPa)	1.03	0.48	0.76	0.66	1.28	0.81
Sea Surface Temperature (° C)	1.08	0.89	0.89	0.89	1.40	1.26

Estimating the uncertainty in gridded fields

- For a given grid box, uncertainty given by a function of
  - Natural variability (sampling errors)
  - Number of platforms making observations (bias uncertainty)
  - Number of observations (random uncertainty)
- Random and bias uncertainties estimated using the VOSClim dataset
- Natural variability estimated using the VOS

Estimating the uncertainty in gridded fields

$$\text{Grid-box uncertainty} = \frac{\text{Variance due to natural variability}}{\text{Effective number of days sampled}} + \frac{\text{Variance due to random uncertainty}}{\text{Number of observations}} + \frac{\text{Variance due to bias uncertainty}}{\text{Number of individual platforms}}$$

- Increase number of days sampled
  - Most effective in highly variable regions and where sampling is poor.
- Increase number of platforms (and number of observations)
  - Reduces effect of bias uncertainty.
  - Where # observations increases, random uncertainties reduced.
- Increase accuracy (and precision) of data
  - In many regions platform bias dominates monthly means.

Reducing the sources of uncertainty

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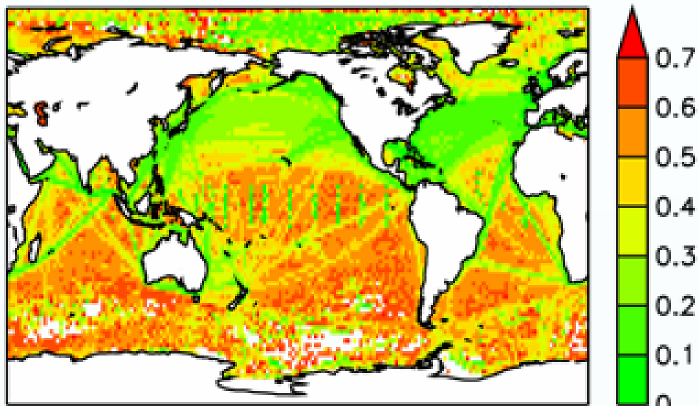
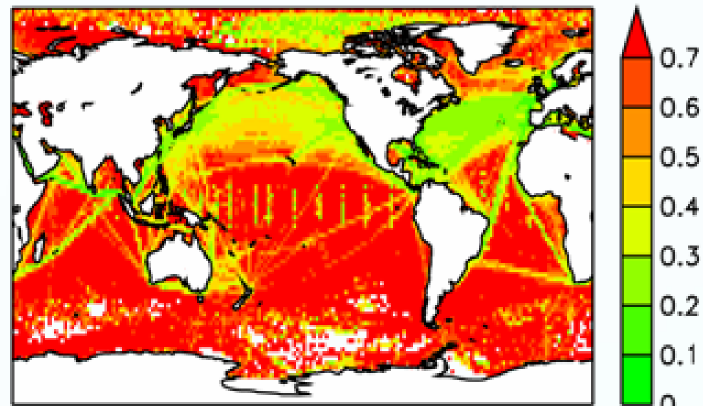
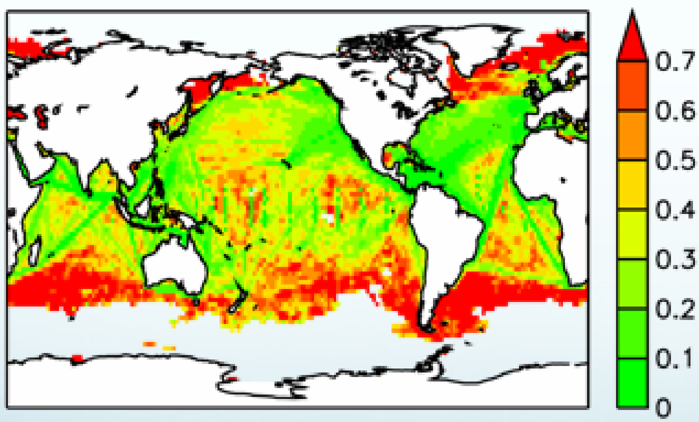
Adequacy of the observing system – contribution of different uncertainty components



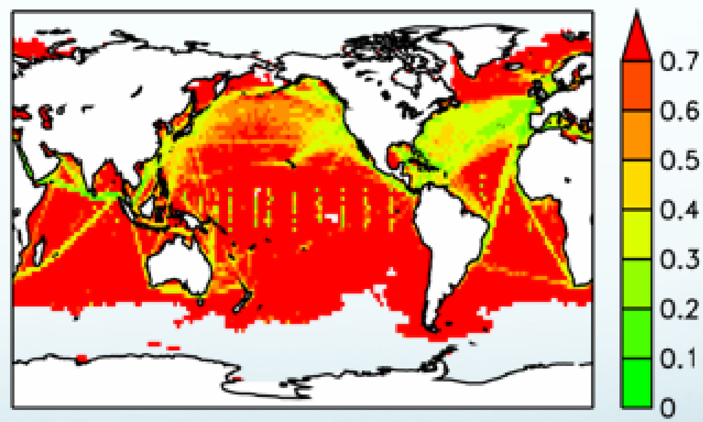
Average monthly random uncertainty
(air temperature, °C)



Average monthly bias uncertainty
(air temperature, °C)

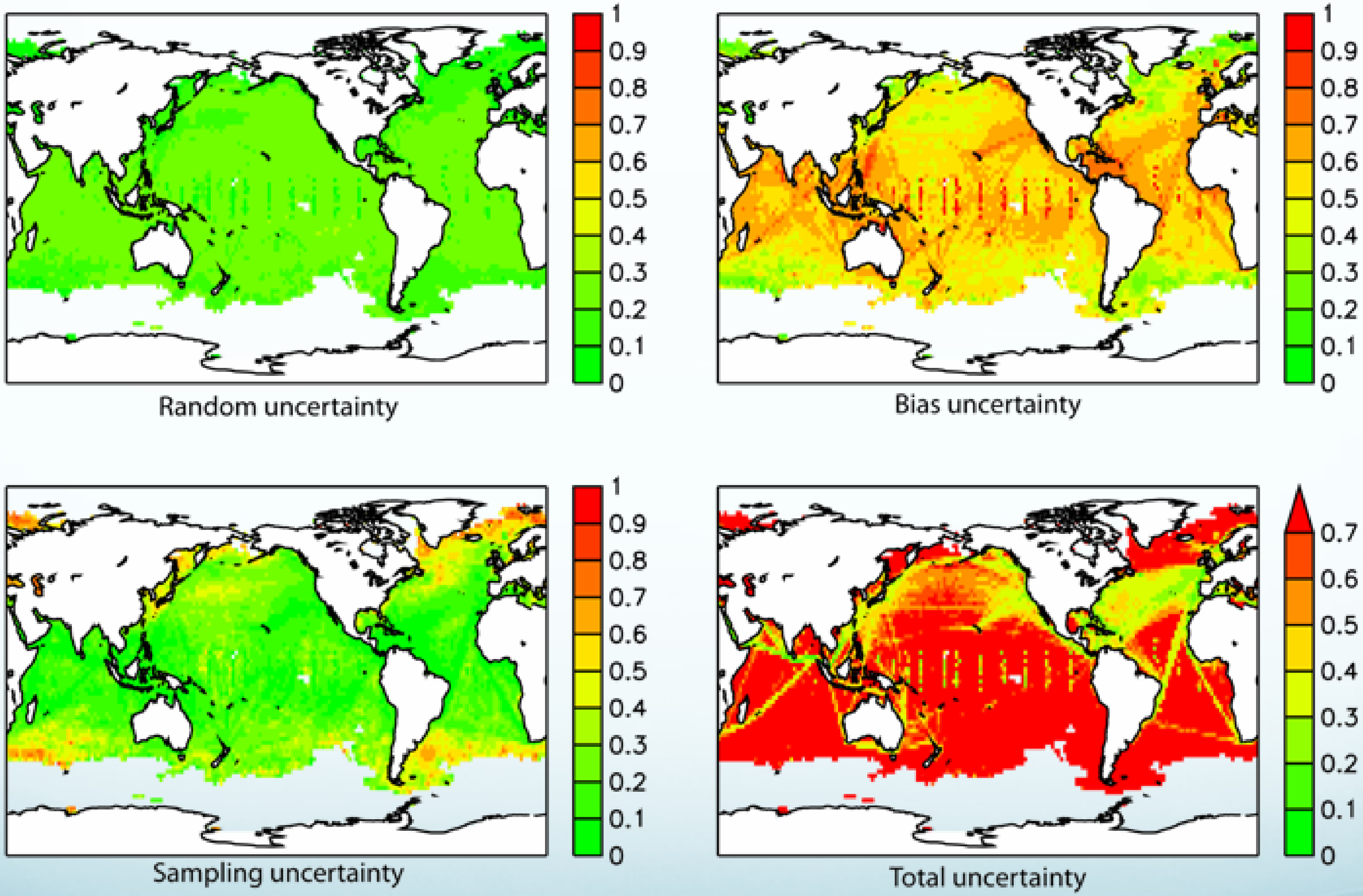


Average monthly sampling uncertainty
(air temperature, °C)

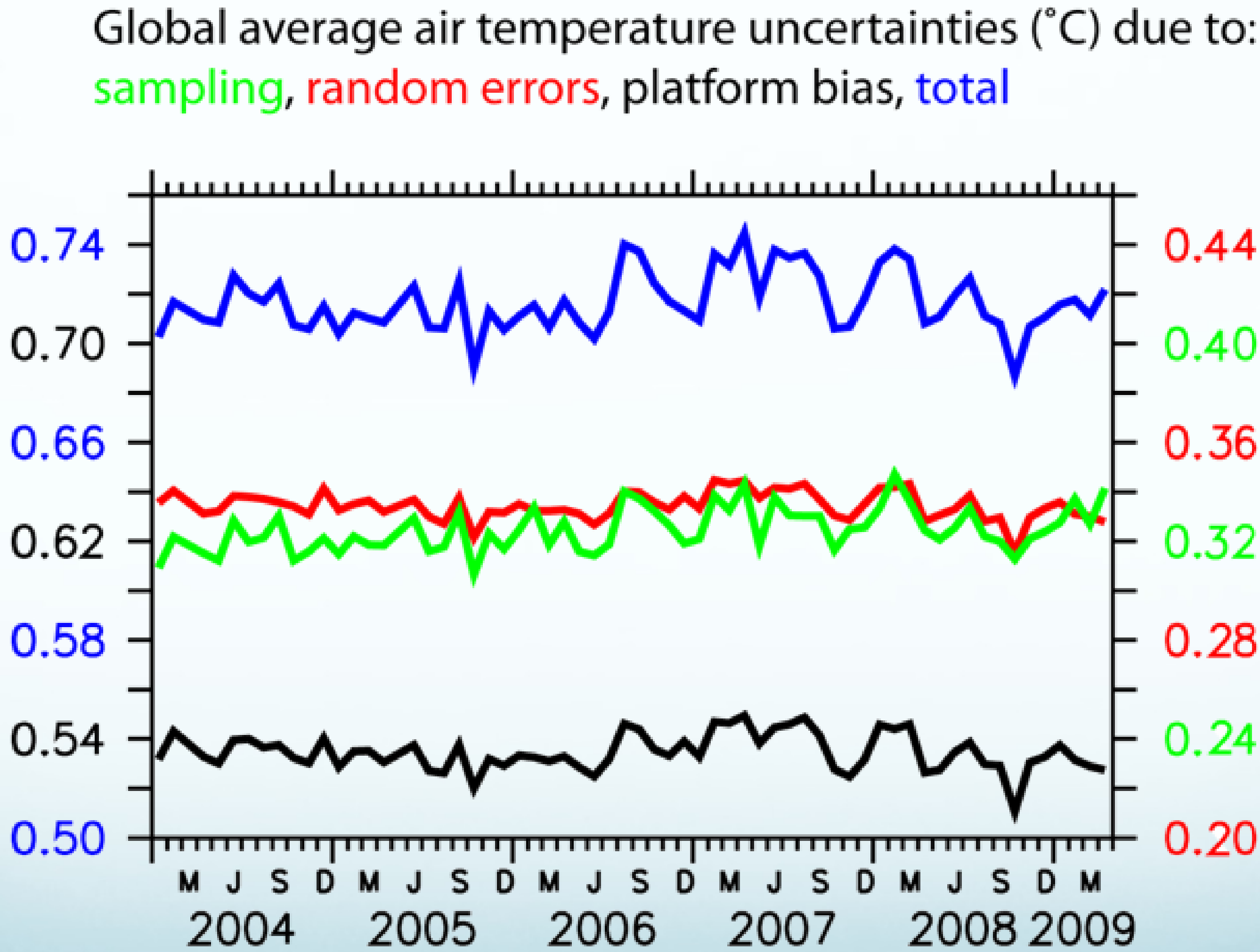


Average monthly total uncertainty
(air temperature, °C)

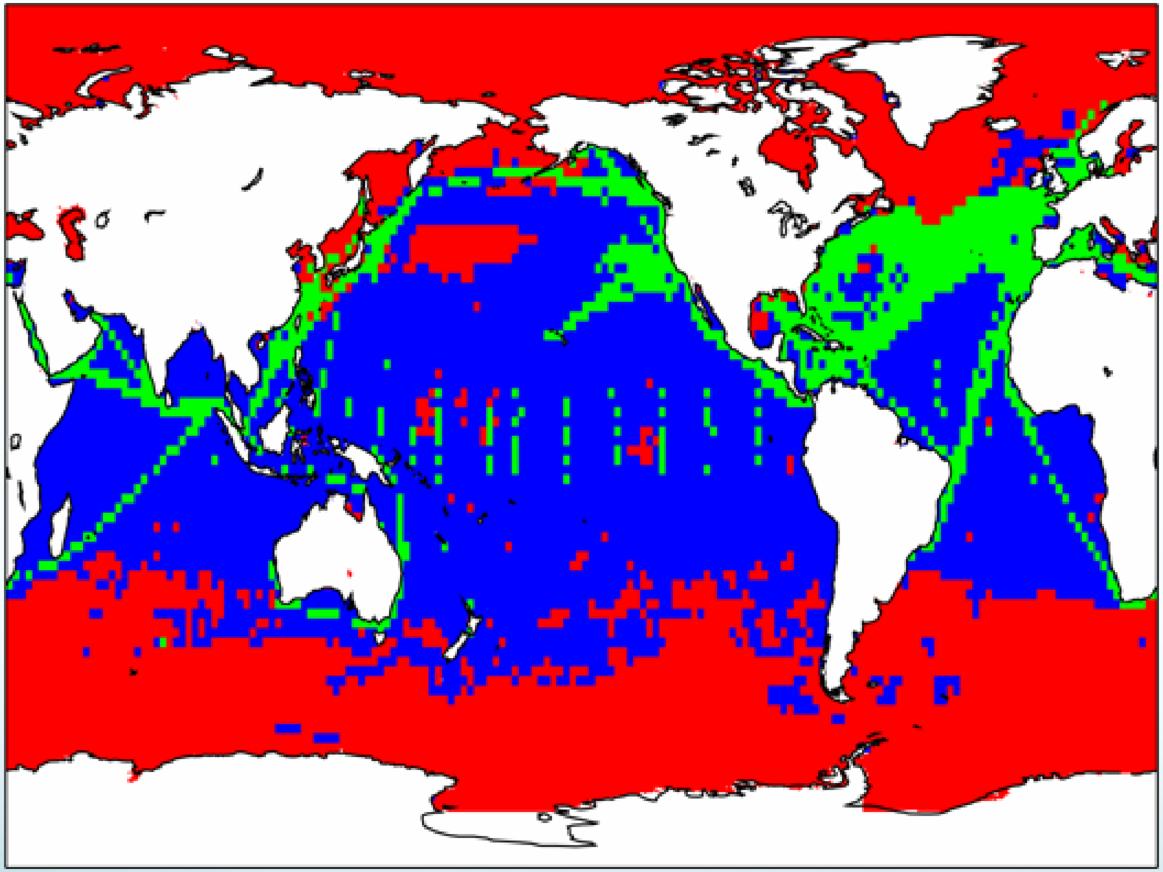
Adequacy of the observing system – fractional contribution of different uncertainty components



Air temperature uncertainty time series



Assessment of the observing system (air temperature - requirements)



Red – More data (sampling error dominates)

Blue – Reduce measurement error (either through increasing number of independent platforms or decreasing errors)

Green – Regions of best sampling, adequacy depends on user requirements

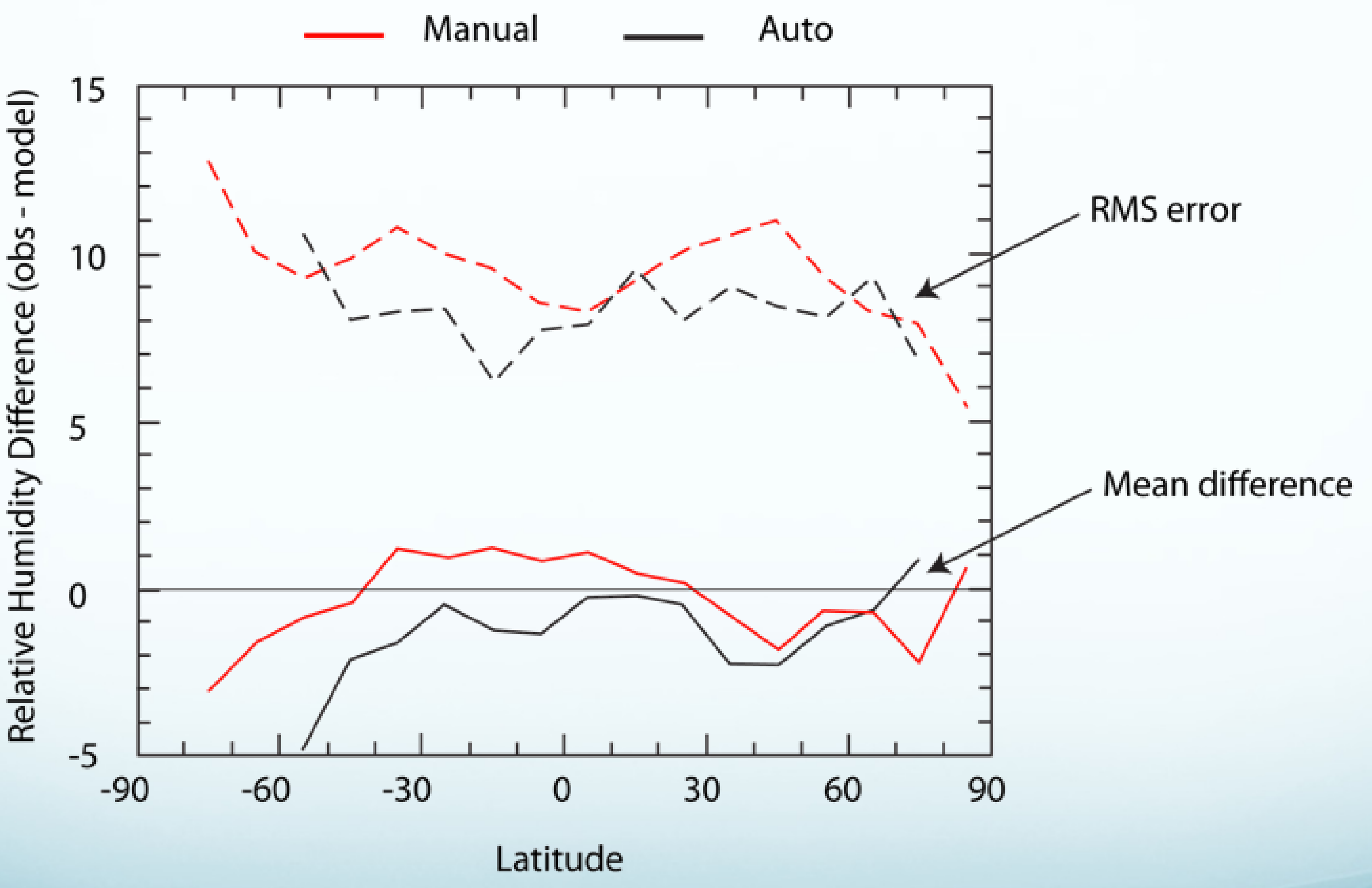
Reducing the uncertainty in gridded datasets based on VOS data

- All variables
  - Improve sampling in data sparse and highly variable regions
- Air temperature, SST, humidity
  - Increase number of platforms or decrease measurement errors
- SLP
  - Increase sampling outside of tropics, improve accuracy in tropics
- Wind speed and cloud cover
  - Increase sampling everywhere outside most heavily sampled shipping lanes

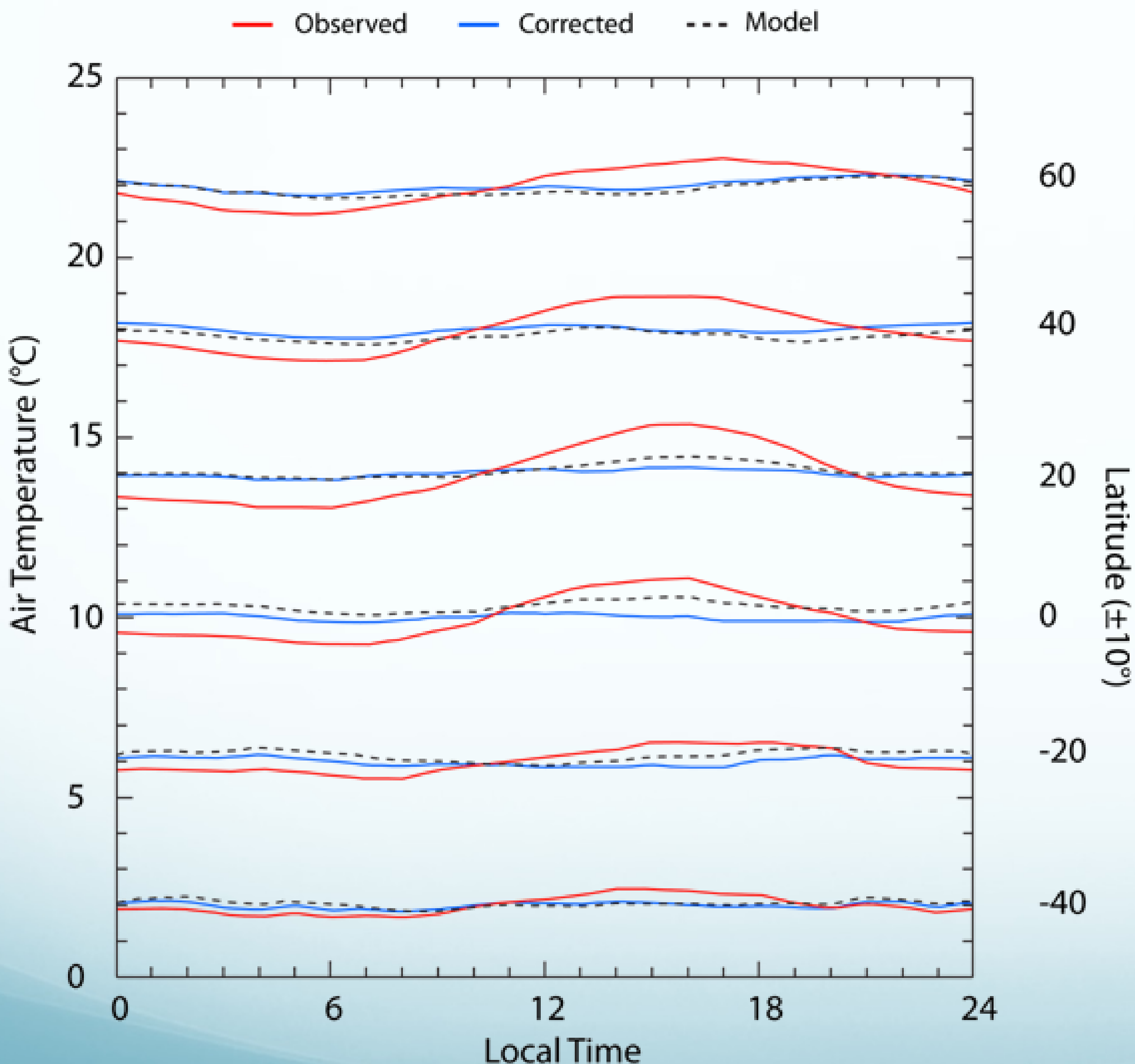
Systematic Biases and Manual vs Automatic Reports

- Independent study at UK Met Office characterizing VOS observations (as well buoys and fixed platforms) (Ingleby 2009)
- Mean differences between model and observations and RMS errors calculated
- Results broken down on subsets
  - Platform (VOS, VOSClim, buoy, rig)
  - Manual vs Automatic (AWS)
  - Observing method
  - Country

Relative Humidity Biases



Air Temperature Biases



- Air temperature diurnal range shown for different latitude bands
- Warm bias clearly seen in observations (relative to model)
- After correction, observations and model in better agreement

Manual vs Automatic RMS errors

Variable (units)	Manual VOS	Automatic
Air temperature (° C)	1.62 (VOSClim – 1.43)	1.42
Relative humidity (%)	9.82	8.59
SLP (hPa)	1.50	0.87
SST (° C)	1.24 (VOSClim – 1.13)	0.9

- Automatic observations have lower RMS errors than manual observations
- VOSClim performs better than VOS

Manual vs Automatic Wind speed ratios

- Ratio of observed wind speed to model wind speed gives better estimate of quality (ratios > 1 indicate observed wind greater than model)

	Manual	Automatic
Wind speed	1.21	1.19
Height Corrected Wind Speed	1.08	1.07

- Results similar between manual and automatic observations for wind speed

Increasing the use of VOSClim data

- So far, use of VOSClim data not very visible
  1. Lack of visibility in scientific community
  2. Misunderstanding of aims of VOSClim
  3. Complex to associate metadata with observations

- Need to address each of these three issues
  - Scientific paper highlighting benefits of VOSClim data and aims of VOSClim project (addresses 1 and 2)
  - Subset of metadata now included routinely as part of ICOADS (making use of metadata easier for individuals)
  - Additional VOSClim parameters in ICOADS

Summary

- Primary use of VOSClim data is to characterize the observations. Several examples shown
  - Estimation of different sources of uncertainty
  - Estimation of systematic biases
  - Manual vs AWS
- Expanding VOSClim to all ships will reduce overall uncertainty in gridded data.
  - Better characterization of data
  - Need to ensure improving one component of the observing system (e.g. sensor accuracy) is not at the expense of another (e.g. number of observations)
- Need to raise visibility of VOSClim data in scientific community