Estimating Random Errors in Marine Air Temperatures

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1. Introduction

Routine weather observations made by Voluntary Observing Ships (VOS) have been used in numerous studies ranging from air-sea interaction to validation of model output and satellite data. In order to understand the trends and variability seen in these observations and to understand the differences between the VOS observations and data from other sources we need uncertainty estimates for each source together with estimates of the systematic biases.

In this poster new estimates of the random uncertainties in individual VOS marine air temperature (MAT) observations are made using the semi-variogram method. A number of different variogram models are explored and the effect of height and bias adjustment on the resulting uncertainty estimates shown.

2. Data Sources

VOS observations for the period 1970 - 2006 from the Intenational Comprehensive Ocean-Atmosphere Data Set ICOADS (Worley et al., 2005) combined with measurement metadata (Kent et al., 2007) have been used. The ICOADS 3.5σ trimming limits have been applied to remove outliers and mis-positioned reports identified following Kent and Challenor (2006).

3. The Semi-Variogram Method

The semi-variogram method (e.g. Lindau, 1995; Kent and Berry, 2005) estimates the random errors as a function of the squared differences between pairs of observations and as a function of separation distance. i.e. the sample variogram is given by

$$2\hat{\gamma}(h) = \frac{1}{|N(h)|}\sum_{N(h)}\left(Z(s_i) - Z(s_j)\right)^2$$

Where $2\hat{\gamma}(h)$ is the variogram between separation distances of h-Δh and h+Δh. $Z(s_i)$ is the value of the variable at location s_i and $Z(s_j)$ the value of the variable at location s_j. The sum is over all

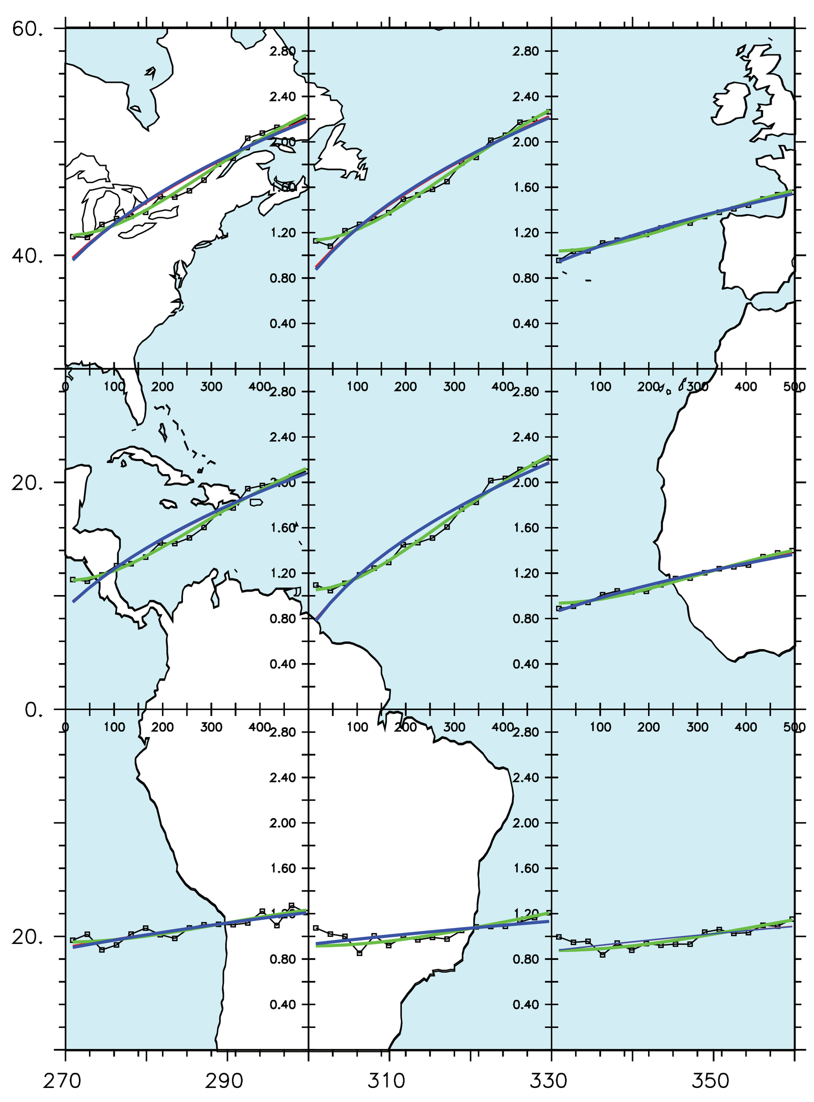
$$N(h) \equiv \{(i,j) : h - \Delta h < |s_i - s_j| \le h + \Delta h\}$$

i.e. over all pairs of observations with separation distances between h-Δh and h+Δh. |N(h)| gives the number of distinct elements of N(h).

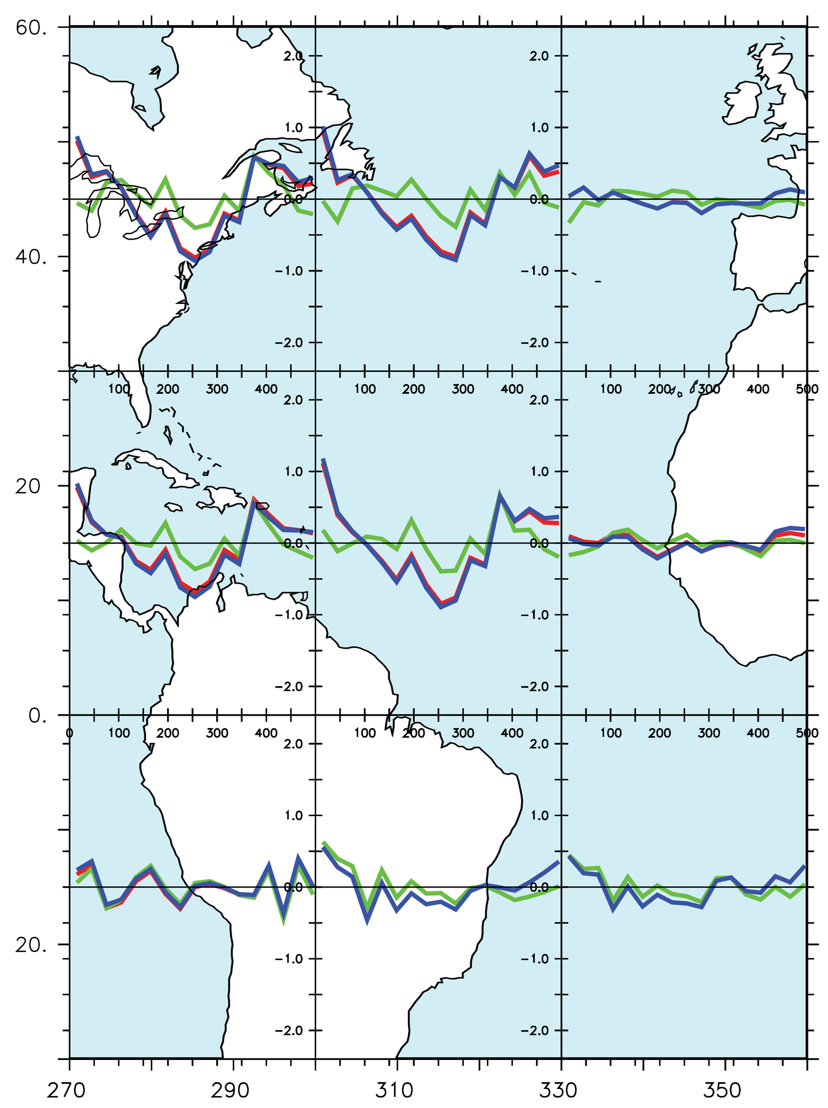
The differences between pairs of observations are a result of measurement errors in the observations and real differences due to spatial and temporal variability. By limiting the pairs of observations to the same nominal reporting time and extrapolating to zero separation distance the natural variability is minimised and any difference remaining is due to random errors. The random error can then estimated as the square root of half the squared difference at zero separation, i.e. $\sqrt{\hat{\gamma}(0)}$

4. Random Errors in VOS Observations

Previous work used a linear variogram model to extrapolate the variograms to zero separation distance in order to estimate the random errors in VOS observations. However, there are other variogram models (e.g. Cressie 1993) and these may provide a better fit to the sample variograms. The left panel shows an example of the estimated sample semi-variograms (black) plotted against separation distance for different 30° grid boxes over the North Atlantic and during July 1993. 50 km separation bins have been used (Δh=25 km). Also shown are a number of the more commonly used variogram models. These are the linear (red), Gaussian (green) and exponential (blue) variogram models.



Semi-variograms (°C) (black) plotted against separation distance (km) for July 1993. Also shown are the linear (red), Gaussian (green) and exponential (blue) variogram models.

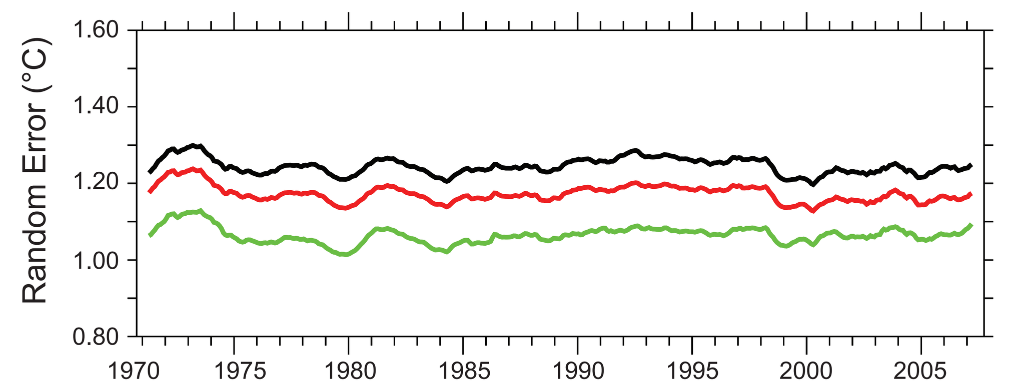


Residual semi-variograms (°C) plotted against distance (km) for the linear (red), Gaussian (green) and exponential (blue) variogram models for July 1993

The right panel shows the residuals of the model fitting. This clearly shows that over the western tropical and north Atlantic both the linear and exponential models underestimate the semi-variogram at low separation distances. As the separation increases these models then overestimate the semi-variograms. In contrast, the Gaussian model (green) gives a better fit over all separation distances. Over the remainder of the North Atlantic there is little to distinguish between the different models.

5. Global Error Estimates and Bias Correction

Based on the results shown for the different variogram models, sample variograms have been estimated globally on a 30° grid for each month between 1970 and 2006 and the variograms extrapolated to zero separation distance using the Gaussian variogram model. The plot below shows a time series, with a 12 month running mean filter applied, of the estimated random errors using the Gaussian variogram model (black). Also shown are estimates of the random errors after the observations have been height corrected (red) and height and bias corrected (green). The bias correction corrects for day time heating errors in VOS observations (Berry et al., 2004). Over the 37 year period all three random error estimates are relatively constant from one year to the next. Each adjustment made to the observations reduces the random error estimates, with the height adjustment reducing the error estimates by 0.1 °C and the bias and height adjustment reducing the error estimates by 0.2 °C.

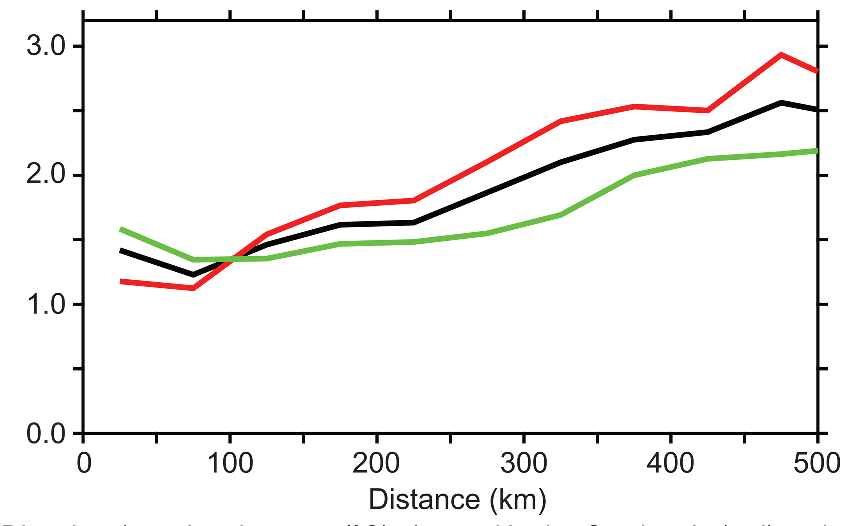


Globally average random error estimates for uncorrected (black), height corrected (red) and bias and height corrected air temperature observations. A 12 month running mean filter has been applied

6. Anisotropy and Future Work

The variogram estimates shown, together with previous studies, assume the spatial variability is isotropic and use omnidirectional variogram estimates. However, over some highly anisotropic regions such as the Gulf Stream this assumption will be invalid. The figure below shows the square root of two directional sample semi-variograms estimated over the Gulf Stream region (30N - 45N, 75W-60W) along a North - South axis (red) and along an East - West axis (green) together with the square root of the omnidirectional semi-variogram (black). As expected in this region, the semi-variogram aligned along the East - West axis increases at slower rate than the variogram aligned along the North South axis. This is due to the lower spatial variability across a zonal region compared to the meridional spatial variability.

The results suggest that not taking the isotropy into account will overestimate the random errors in some regions. The next step to improving the random error estimates will be to calculate the sample variograms along different axis and find the axis along which the value at zero separation distance is a minimum. This should then give an estimate of the random error in the observations with the effects of anisotropy removed.



Directional semi-variograms (°C) along a North - South axis (red) and East - West axis (green) plotted against separation distance (km) over the Gulf Stream (30N - 45N, 75W - 60W) during July 1993. Also shown is the omnidirectional semi-variogram (black)

7. Summary and Conclusions

Following previous authors, random errors have been estimated for MAT observations using the semi-variogram method. However, the variogram model used by previous authors has been shown to be unsuitable for MAT observations, with a Gaussian variogram model shown to be more suitable. Applying bias adjustments to account for the varying observing height and for day time heating, reduces the random uncertainty estimates. Each adjustment reduces the random uncertainty estimate by approximately 8%. Finally, the effects of anisotropy on the variogram and error estimates have been shown in an example, suggesting that the error estimates could be further improved by taking these effects into account.

References

Berry, D. I., E. C. Kent, and P. K. Taylor, 2004: An analytical model of heating errors in marine air temperatures from ships. *Journal of Atmospheric and Oceanic Technology*, **21**, 1198-1215.

Cressie, N. A. C., 1993: Statistics for Spatial Data. *Wiley Series in Probability and Mathematical Statistics*, Wiley and Sons, 900 pp.

Kent, E. C. and D. I. Berry, 2005: Quantifying random measurement errors in Voluntary Observing Ship meteorological observations. *International Journal of Climatology*, **25**, 843 - 852.

Kent, E. C. and P. G. Challenor, 2006: Towards Estimating Climatic Trends in SST. Part II: Random Errors. *Journal of Atmospheric and Oceanic Technology*, **23**, 476 - 486.

Kent, E. C., S. D. Woodruff, and D. I. Berry, 2007: Metadata from WMO Publication No. 47 and an Assessment of Voluntary Observing Ship Observation Heights in ICOADS. *Journal of Atmospheric and Oceanic Technology*, **24**, 214 - 234.

Lindau, R., 1995: A new Beaufort Equivalent Scale. International COADS Winds Workshop, Kiel, Germany, Institut fur Meereskunde, Kiel, and NOAA, 232 - 252.

Worley, S. J., S. D. Woodruff, R. W. Reynolds, S. J. Lubker, and N. Lott, 2005: ICOADS Release 2.1 Data and Products. *International Journal of Climatology*, **25**, 823 - 842.

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