Uncertainty in Surface Turbulent Fluxes from ICOADS

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Introduction

The size of the surface turbulent exchange of heat at the ocean surface is not well known. In situ ocean surface heat flux datasets typically contain a global heat flux imbalance of around 30 Wm^{-2} (da Silva et al. 1994, Josey et al. 1999). Reanalysis fluxes contain large biases in some regions and satellites have particular problems retrieving the sensible heat flux (WGASF, 2000).

Researchers have therefore tried to either improve the in-situ fluxes using measurements of ocean heat transport to constrain and balance the heat fluxes (Grist and Josey, 2003) or by synthesis of the fluxes from a range of data sources in an attempt to exploit the strengths of each (Yu et al., 2004a,b).

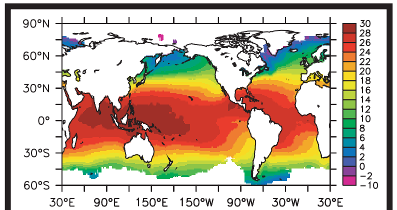
Here we take a different approach to improving the in situ fluxes from ICOADS using an improved method of flux calculation which allows the calculation of uncertainty estimates for the fluxes.

Data: ICOADS

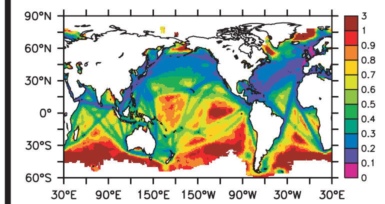
The International Comprehensive Ocean-Atmosphere Data Set (ICOADS, Worley et al. 2005) was used to construct the flux data set. ICOADS contains the routine weather reports from ships, buoys, drifters and fixed platforms. These measurements of sea surface temperature (SST), air temperature, near surface humidity, winds and pressure can be used with parameterisations known as "bulk formulae" to estimate the surface turbulent exchange of heat and moisture, the sensible and latent heat fluxes.

The OI Meteorological Fields

Using ICOADS individual ship reports we have calculated daily fields of SST, air temperature, near surface humidity, winds and pressure on a 1˚x1˚ area grid. We largely followed the methodology of Reynolds (Reynolds 1988, Lorenc 1981). Random error estimates for the ship data were taken from Kent and Berry (2005). The previous day's analysis, incremented to allow for a seasonal cycle, has been used for the background field. The background error field is the previous day's analysis error relaxed towards the climatological intra-monthly standard deviation using a 3 day time scale. The spatial scale chosen was 300 km. In the absence of data, anomalies are allowed to persist, but the uncertainty increases towards the climatological variability.



Annual average air temperature (˚C) for 1990 calculated from ICOADS-derived daily OI fields. Ocean regions which are blank either contain sea ice or are so poorly sampled that not even a climatological air temperature estimate can be calculated.



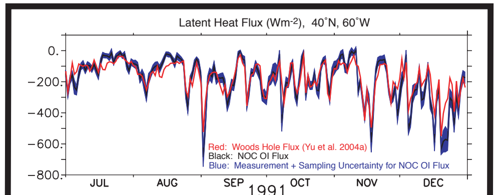
Annual average monthly air temperature uncertainty (measurement plus sampling, ˚C) for 1990 from ICOADS calculated from daily OI fields.

Flux Calculation

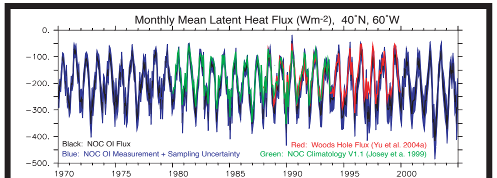
We have chosen to use the flux parameteration of Smith (1980, 1988) to calculate the fluxes, as did Josey et al. (1999). More recent versions of the bulk formulae do exist, for example the COARE algorithm (Fairall et al. 2003). However the COARE algorithm is designed for use with research vessel data where a time series of observations is typically available and which are used to model both warm surface layer and cool skin effects. More research is needed before we can apply this type of parameterisation to the ICOADS reports.

There has been much discussion in the literature about the best averaging method to use to calculate monthly-mean fluxes (summarised by Josey et al. 1995). The choice is whether to calculate fluxes from averages of the input meteorological variables (the "classical method", advantage: computationally simple, uses all available data; disadvantage: important correlations between the variables missed) or to average fluxes calculated from individual co-incident reports (the "sampling method", advantage: important correlations between variables captured; disadvantage: computationally expensive, does not use all available data). Most recent studies have taken the latter sampling approach but research has suggested that this could cause random errors to bias the fluxes due to the non-linearity of the bulk formulae (Berry 2004).

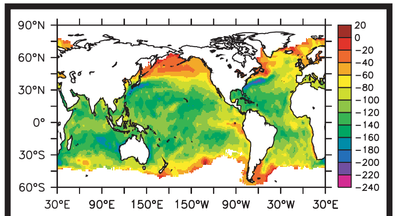
We therefore take a different approach which should largely avoid these problems. Firstly we generate daily fields of the input meteorological variables using Optimal Interpolation (OI) which include uncertainty estimates. These daily fields are then used with the bulk formulae to produce daily flux estimates, again with uncertainty estimates. This approach should capture most of the correlations between variables (as in the sampling method) yet reduce any bias due to large random errors in the input variables to non-linear bulk formulae.



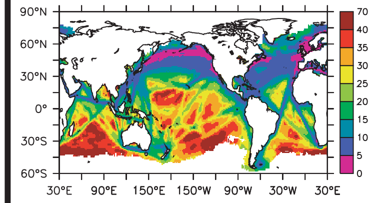
Comparison of daily latent heat fluxes (Wm^{-2}) for July to December 1991 from OI Fluxes (black/blue) and from the WHOI Fluxes (red, Yu et al. 2004a) at 40˚N, 60˚W. In this well-sampled region the OI Fluxes seem to do a good job of capturing variability on the synoptic timescale. Note that the OI Fluxes have not yet had corrections for known biases applied so we cannot verify whether the larger fluxes from the in situ data are realistic..



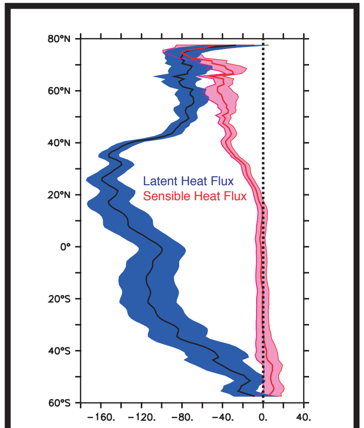
Comparison of monthly latent heat fluxes (Wm^{-2}) for 1970 to 2004 at 40˚N, 60˚W from OI Fluxes (black/blue), WHOI Fluxes (red, Yu et al. 2004a) and NOC v1.1 (Josey et al. 1999). The blue shaded area indicates the estimated random plus sampling uncertainty in the OI monthly mean flux.



Annual average latent heat flux (Wm^{-2}) for 1990 calculated from ICOADS-derived daily OI fields of the basic meteorological variables.



Annual average monthlatent heat flux uncertainty (measurement plus sampling, Wm^{-2}) for 1990 from ICOADS calculated from daily OI fields.

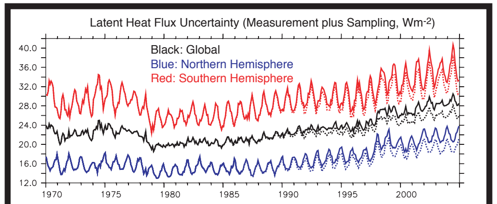


Zonal average monthly mean heat fluxes for January 1991 (Wm^{-2}) including estimates of uncertainty (measurement plus sampling, shaded regions). Latent heat flux (black/blue), sensible heat flux (red/pink).

Fluxes and Uncertainties

There are 3 different types of uncertainty, random, sampling and bias. All are important but we have so far only considered the random and sampling uncertainties in the meteorological variables and surface fluxes. Gleckler and Weare (1993) presented a framework for the calculation of random and bias error estimates for fluxes based on known errors in the input meteorological fields. We here adapt the method of Gleckler and Weare, assuming that the random errors in all the variables are uncorrelated and that uncertainties in the bulk formulae themselves contribute to the bias uncertainty.

The input to the Gleckler and Weare formulation is the random uncertainty for the input OI fields. The extension to calculate the bias uncertainty is trivial, however the input bias uncertainties are presently poorly known and their determination requires futher research. The contribution to sampling uncertainty is accounted for by the relaxation of the random uncertainty to the climagological variability (described earlier).



Estimate of monthly mean latent heat flux uncertainty (Wm^{-2}) over the period 1970 to 2004. The black line shows a Global average, the blue line a Northern Hemisphere average and the red line a Southern Hemisphere average. The solid lines are calculated using ship data only, the dotted lines also include buoy data.

Conclusions and Future Work

The latent and sensible heat fluxes calculated from the ICOADS daily OI fields have not yet been rigourously validated. However comparisons with flux products, such as WHOI and NOC V1.1, show broad similarities and interesting differences. The flux and uncertainty estimates will be validated after we have applied corrections for biases and inhomogenities in the ship data.

o A new approach to the calculation of surface turbulent heat fluxes from in situ data has been developed which allows uncertainty estimates to be made for the fluxes.

o The new method calculates fluxes from daily fields of the basic meteorological variables which should reduce biases in the flux inherent in either the sampling or classical method of flux calculation.

o Inititial comparisons with other fluxes on a variety of time scales suggests that the new approach works.

o So far only the random (measurement plus sampling) component of the flux uncertainty has been calculated. The bias component to the error can be calculated once the input data have been corrected for known biases and an estimate of the residual bias uncertainty has been made.

o The flux uncertainty, as expected, is strongly depended on the sampling of the ship data in ICOADS, outside the main shipping lanes the errors can be very large.

o However in well-sampled regions (largely the Northern mid-latitudes) there are enough data to make high-quality daily estimates of sensible and latent heat flux.

o The reduction in the amount of ship data (rather than data from moored or drifting buoys) in ICOADS has meant that our estimates of sensible and latent heat flux over the ocean are getting worse with time, despite the huge increase in data quantity from autonomous systems in recent years.

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