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On the impact of gap-filling algorithms on variability patterns of reconstructed oceanic surface fields

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Abstract. The variability and consistency of oceanic surface fields (SST, pressure, air-sea fluxes) from different sources are studied. The sources are reconstructions using available observations and the NCEP-NCAR and ECMWF reanalysis. It is shown that the variabilities of different reconstructions differ widely from each other and from those of the reanalyses. Some reconstructed fields are shown to lack internal consistency. It is concluded that variability patterns inferred from gappy data have to be used with great caution. EOF-based methods are found to yield more reliable results than those based on the method of successive correction.

1. Introduction

To study climate dynamics the development of the climate system over time must be known. Observations, however, are inhomogenously distributed in space and time. Over the oceans observations are concentrated along the main shipping routes with large gaps in between them, most notable in the Southern Ocean. Several authors (e.g., [*DaSilva et al.*, 1994; *Kaplan et al.*, 1998]) have tried to reconstruct the past ocean surface climate by filling these gaps using sophisticated interpolation methods. Recently, the reanalyses of NCEP-NCAR [*Kalnay et al.*, 1996] and ECMWF (ERA15) [*Gibson et al.*, 1997] have produced global sets of meteorological fields. Reanalysis can be regarded as gap-filling using a model. Data gaps are known to influence variability patterns [*Gulev et al.*, 2000], while the gap-filling algorithm may affect variability even in well-sampled regions [*Kent et al.*, 2000] by propagating information from adjacent under-sampled regions. In this paper the impact of different gap-filling algorithms on variability patterns and internal consistency of the different datasets is investigated.

2. Data and Method

Four variables are considered: sea surface temperature (SST), surface level pressure (SLP), zonal component of wind stress (τ_x), and latent heat flux (Q_{lat}). These variables are taken from four sources, [*Kaplan et al.*, 1998] and [*Kaplan et al.*, 2000] (SST and SLP, respectively), [*DaSilva et al.*, 1994] (all variables), as well as both the NCEP-NCAR and the ECMWF reanalyses (all variables). For shortness these datasets will be denoted by Kaplan, DaSilva, NCEP, and ERA15. For each dataset the detrended monthly mean anomalies from the annual cycle over the period 1958 to 1993 (1979 to 1993 if ERA15 is involved) are considered. The results do not change when seasonally stratified data are considered.

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The DaSilva data are reconstructions based on *in situ* observations made from ships. Data gaps are filled using an inter-/extrapolation method called successive correction. The two Kaplan reconstructions are also based on *in situ* observations. However, gaps are filled using an EOF technique that retains known spatial coherences. The dataset denoted here as Kaplan SST is a combination of the Kaplan reconstruction [*Kaplan et al.*, 1998] before 1981 and the optimal interpolation data [*Reynolds and Smith*, 1994] obtained by blending satellite-derived temperatures with *in situ* observations after 1981. Similar SST products enter the reanalyses as the lower boundary condition, while the other quantities are calculated from the atmospheric model. However, SLP is restricted by the assimilation of observed winds. Both in DaSilva and the reanalysis, τ_x and Q_{lat} are parameterized from basic quantities (wind speed, SST, and specific humidity).

The variability of two datasets is compared by calculating correlation maps [*Hurrell and Trenberth*, 1999]. At each grid point they display the correlation between the corresponding time series. A high correlation indicates that both datasets exhibit the same variability. It should be noted here that even small correlations may be statistically significant. Assuming a decorrelation time of 12 months, which is an upper limit for the variables considered, a correlation of

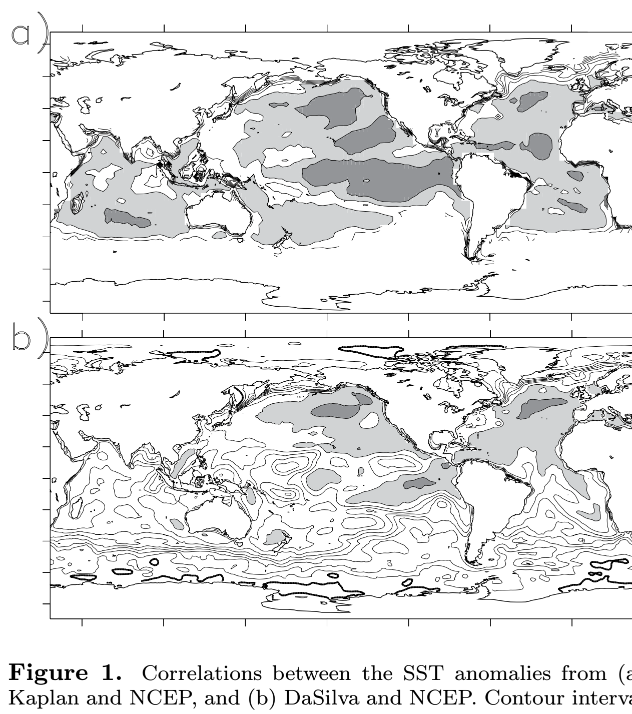

Figure 1. Correlations between the SST anomalies from (a) Kaplan and NCEP, and (b) DaSilva and NCEP. Contour interval = 0.1, shading above 0.8, zero line thick.

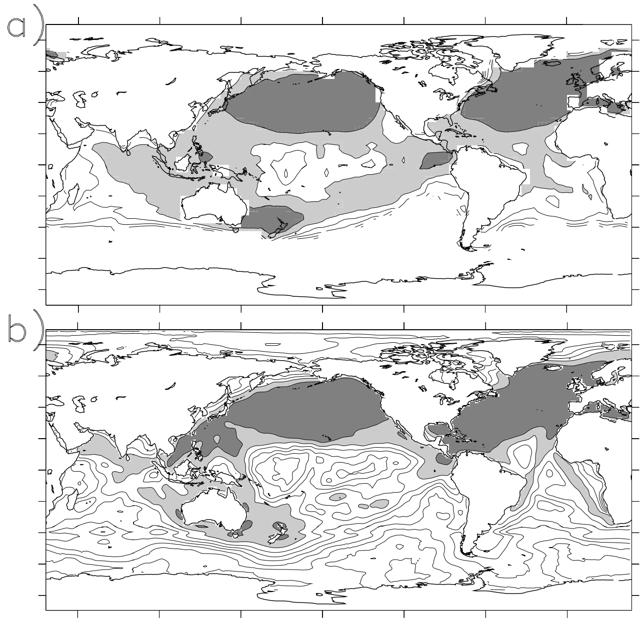

Figure 2. As Figure 1, but for SLP anomalies.

0.3 is still significant at the 99% level with 45 years of data. In a second step the internal consistency of the datasets is assessed by investigating patterns of common variability of different quantities.

3. Results

3.1. Correlations between datasets

3.1.1. SST Figure 1 shows two examples of correlation maps between SST anomalies. While the correlation between the Kaplan reconstruction and that used for NCEP is fairly high and relatively uniform, that between DaSilva and NCEP is much lower away from the main shipping routes. For instance, the routes through the South Atlantic are clearly visible. The SST products used for both reanalyses are mainly identical and therefore highly correlated (not shown). The correlations between Kaplan and DaSilva (not shown) resemble those between DaSilva and NCEP.

As explained above, the main differences between Kaplan and NCEP on one hand and DaSilva on the other are the technique used to fill data gaps and the use of satellite data after 1981. To test whether the latter is the reason for the differences the correlation maps have been recalculated for the pre-satellite period 1958-1979. All these maps (not shown) are qualitatively equal to those displayed here. Therefore, the different gap-filling algorithms make the difference. The EOF-based algorithms used in Kaplan and NCEP retain known large scale variability structures. Obviously, the successive correction method used by DaSilva is much less capable in doing so. A similar conclusion has been reached by [*Smith et al.*, 1996].

3.1.2. SLP Figure 2 shows that correlations between SLP anomalies are generally higher than those for SST, exceeding 0.9 in large parts of the Northern Hemisphere. However, shipping lanes show up even more pronounced. The variability of the two reanalyses is nearly identical (not shown) with correlations exceeding 0.9 almost everywhere.

The low correlation between DaSilva and NCEP (Figure 2b) away from the shipping routes comes as a surprise. As SLP patterns are large-scale structures with a typical length-scale of 1000 km, one would expect much broader regions of high correlations along the shipping routes. This suggests problems with either the gap-filling algorithm used in DaSilva or the internal physics of the NCEP model. The latter, however, seems unlikely as the independent ERA15 model displays the same variability, while the former is in accordance with the findings from the analysis of the SST fields.

The SLP reconstruction of Kaplan is independent of the reanalysis. Nevertheless, it exhibits similar variability (Figure 2a), while DaSilva does not (Figure 2b). Thus for SLP EOF-based methods are better suited to reconstruct fields than the successive correction method. It is supposed that this conclusion is also valid for other variables.

3.1.3. Q_{lat} and τ_x For Q_{lat} the large-scale correlation patterns between DaSilva and NCEP mainly resemble those found for SST and SLP (Figure 3a), with high correlation in data-rich areas and clearly visible ship routes. The absolute value of the correlations, however, is generally lower. As Q_{lat} is parameterized from three quantities, this is not surprising. The pattern for τ_x (not shown) resembles that for Q_{lat} with slightly higher values.

An exception to this general picture are the tropical regions, especially the Pacific, where correlations between DaSilva and NCEP are significantly lower for Q_{lat} (and τ_x) than they are for SST and SLP. Rather than being caused by inadequate gap-filling, this is probably caused by problems within NCEP, which is known to have a South Pacific Convergence Zone (SPCZ) that is oriented too zonally [*Arpe*, 1997]. In Figure 3b this wrongly-placed SPCZ shows up as a band of low correlation south of the equator in the eastern Pacific. Outside the tropics, however, both reanalyses show a remarkable agreement in the variability of Q_{lat} (Figure 3b)

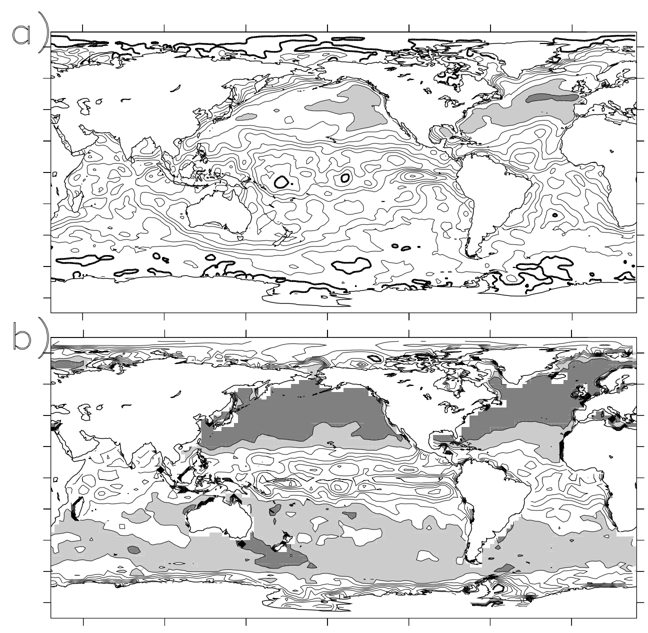

Figure 3. Correlations between the latent heat flux anomalies from (a) DaSilva and NCEP, and (b) ERA15 and NCEP. Contours as in Figure 1.

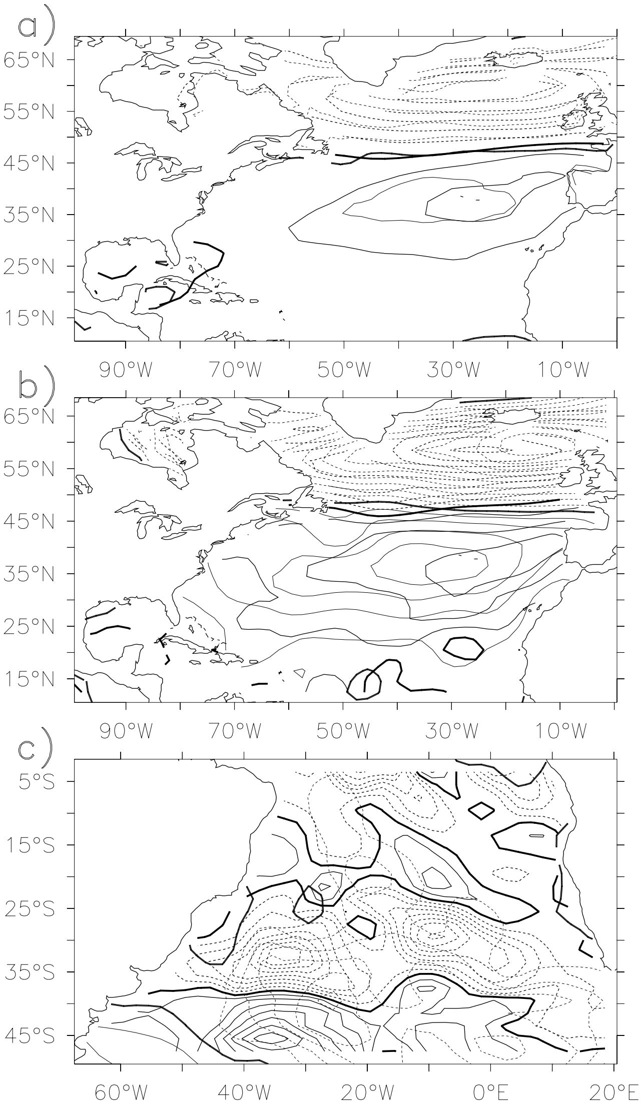

Figure 4. $-\partial_y p/f$ (thick) and τ_x (thin) from the first SVD of p and τ_x for (a) NCEP and (b) DaSilva in the North Atlantic, and (c) DaSilva in the South Atlantic (arbitrary units).

and τ_x (not shown), supporting the view that differences between DaSilva and NCEP in these regions are indeed caused by the gap-filling.

3.2. Internal consistency

It has been shown that time variability differs between datasets. This may translate into serious errors when studying the combined variability of the atmosphere-ocean system. Suppose we are interested in the relation between SST and Q_{lat}. One often-used approach (e.g., [*Czaja, Frankignoul*, 1999]) is to perform an SVD analysis of the cross-covariance matrix of the two fields and from the resulting SVD patterns infer the physics of the underlying air-sea interaction processes. To show that this approach might fail when data with improperly filled gaps are used, we consider two fields with known relation, namely SLP and τ_x. Through geostrophy they are related as $\tau_x \sim -\partial_y p/f$, where p stands for SLP and f is the Coriolis parameter.

It is of course the x-component of the wind rather than the stress that is proportional to $\partial_y p/f$. However, patterns of u_x and τ_x are very similar, so that for the purpose of this exercise they can be interchanged. Furthermore, as both τ_x and SLP are surface quantities, some deviation from geostrophy is to be expected.

To make the point we consider two regions, the North Atlantic as an example of an area with high data density, and the South Atlantic as one with low data density. Figure 4a shows the result of the SVD analysis for the North Atlantic using NCEP. The expected geostrophic relation clearly shows up. Figure 4b shows that in this data-rich area also DaSilva gives the expected result. In the data-sparse South Atlantic, however, the patterns of τ_x and $-\partial_y p/f$ as obtained from DaSilva are quite different (Figure 4c), while NCEP (not shown) confirms that geostrophy is also valid here. Thus the gap filling algorithm employed in DaSilva destroys a known physical relationship between variables. Therefore, any search for unknown relationships should be performed with great caution.

This may be illustrated by looking at the relation between Q_{lat} and the tendency of SST, $\partial SST/\partial t$. These two quantities are known to be highly correlated in the extratropical Northern Hemisphere [*Cayan*, 1992], and one would expect the same to be true in the Southern Hemisphere. While the two reanalyses indeed confirm this expectation (not shown) DaSilva does not (Figure 5). High correlations are only found in data-rich areas, around Australia and in the south-eastern Atlantic. So from DaSilva alone one would conclude air-sea interaction physics to differ between both hemispheres. It should be noted that [*Cayan*, 1992] only uses Northern Hemisphere winter. Therefore his correlations are much higher than those displayed here. However, comparing the two winter hemispheres separately does not change the conclusions.

4. Summary and Conclusions

Several datasets of monthly anomalies of SST, SLP, τ_x, and Q_{lat} have been intercompared with respect to their variability by calculating correlation maps. The datasets fall into three classes, (i) reconstructions from observations using EOF-techniques, (ii) reconstructions using successive correction, and (iii) reanalyses. While for all quantities the correlations are high in areas of high data density, those between the DaSilva reconstruction and the other datasets drop off rapidly away from major shipping routes. It is concluded that the method of successive correction is inadequate to fill the gaps in the observations. This conclusion

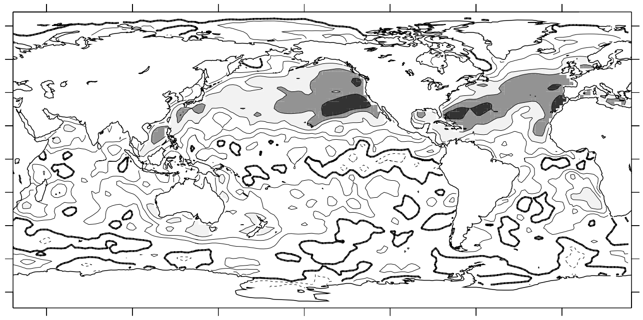

Figure 5. Correlation between $\partial SST/\partial t$ and Q_{lat} for DaSilva. Shading above 0.3 ($\approx$ 99% significance).

is further supported by showing that the DaSilva data lack known physical relations in data-poor regions.

As the SLP field from the EOF-based method [*Kaplan et al.*, 2000] is highly correlated with those of the independently derived fields from the two reanalyses, this method seems better suited to fill gaps. It is therefore desirable to try to apply it to other quantities than only SST and SLP.

In terms of variability the two reanalyses are generally found to agree well. An exception are Q_{lat} and τ_x in the tropics where the reanalyses (NCEP more so than ERA15) are known to have problems with the positions of both the Intertropical and the South Pacifc Convergence Zone.

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