ON THE IMPACT OF GAP-FILLING ALGORITHMS ON VARIABILITY PATTERNS OF RECONSTRUCTED OCEANIC SURFACE FIELDS - AN UPDATE

Andreas Sterl
Royal Netherlands Meteorological Institute, P.O. Box 201, NL-3730 AE De Bilt, Netherlands
sterl@knmi.nl

ABSTRACT

In a recent paper Sterl (2001) investigated the impact of different gap-filling algorithms on variability patterns and the internal consistency of reconstructed fields by calculating correlation maps between monthly anomalies of quantities from different datasets. This analysis is extended here by considering two satellite-derived data sets. Additional evidence is presented for the assumption that the NCEP-NCAR reanalysis exhibits realistic variability.

1. INTRODUCTION

To study climate dynamics the development of the climate system over time must be known. Observations, however, are inhomogeneously 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., Da Silva 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.

In a recent paper Sterl (2001) investigated the impact of different gap-filling algorithms on variability patterns and the internal consistency of reconstructed fields by calculating correlation maps between monthly anomalies of SST (sea surface temperature), SLP (sea level pressure) and Q_{lat} (latent heat flux) of different datasets. The gap-filling algorithms considered were (i) reconstructions from observations using EOF-techniques (Kaplan et al., 1998 and 2000; SSTs as used as lower boundary condition in reanalyses) (ii) reconstructions using successive correction (Da Silva et al., 1994), and (iii) reanalyses (NCEP-NCAR and ERA15).

For all quantities the correlations were found to be high in areas of high data density. However, those between the DaSilva reconstruction and the other datasets drop off rapidly away from major shipping routes, leading to the conclusion that the method of successive correction is inadequate to fill the gaps in the observations. Further support for this conclusion came from the fact that the DaSilva data were found to lack known physical relations in data-poor regions. For instance, SLP and wind stress were found not to be related by geostrophy.

This paper extends the analysis of Sterl (2001). The same technique of correlation maps is used and additional satellite-derived datasets that are independent of the reanalyses are considered. Additional evidence is found for the assumption that the reanalyses display the correct variability. This assumption was implicitly made by Sterl (2001) when he concluded that the EOF-based method of Kaplan was better suited to fill gaps than the successive correction method of DaSilva. It is further shown how the sparsity of observations influences the variability of the reconstructed SST field that were used as the lower boundary condition for the NCEP-NCAR reanalysis and consequently the physics of air-sea interaction inferred from the reanalysis data.

2. CORRELATIONS BETWEEN REANALYSIS AND SATELLITE DATA

Sterl (2001) showed that in terms of variability SLP as reconstructed by Kaplan et al. (2000) agreed well with those produced by the NCEP-NCAR reanalysis, while the agreement between NCEP and the DaSilva reconstruction was poor in data-sparse regions. This led him to conclude that the EOF-based method of Kaplan is better suited for the reconstruction of meteorological fields than is the successive correction method of DaSilva. This conclusion rests on two assumptions, namely (i) that the Kaplan and the reanalysis SLP data are independent, and (ii) that the variability displayed by the reanalysis is correct. The first assumption is not completely true as marine wind observations have been assimilated into the reanalysis, and the second could only be supported by the fact that ERA15 displayed the same variability as NCEP.

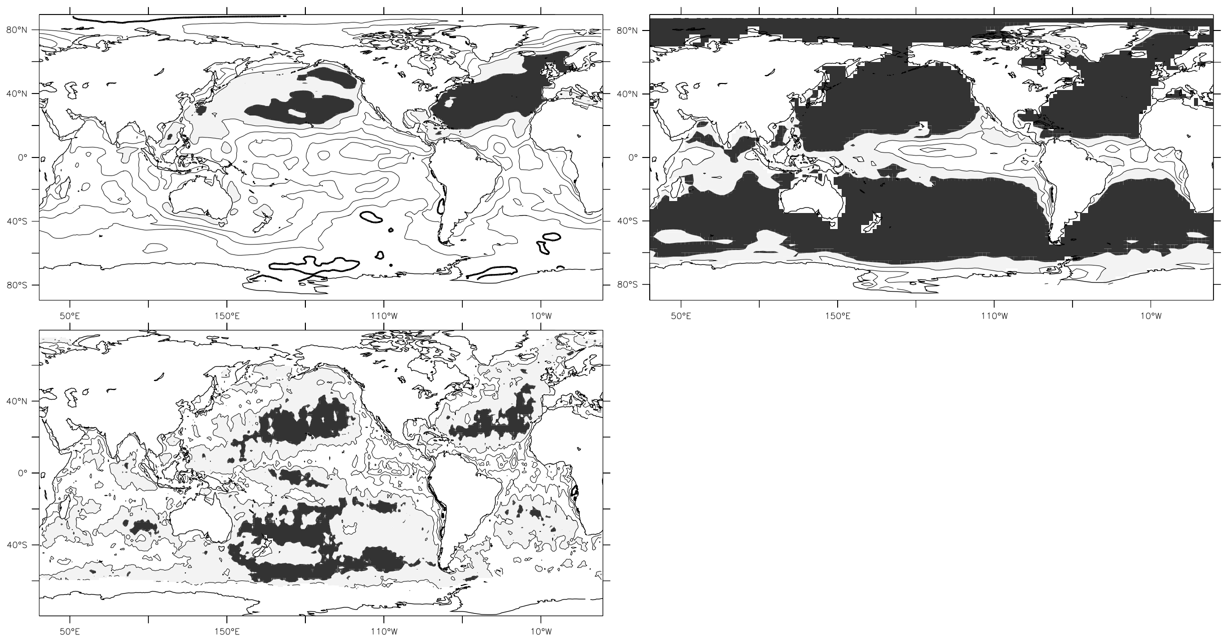

Figure 1: Correlations between the τ_x anomalies from DaSilva and NCEP (upper left), ERA15 and NCEP (upper right), and ERS1/2 and NCEP (lower left). Light (dark) shading above 0.8 (0.9); contour interval 0.2. Values exceeding 0.25 are well above the 99% significance level. This also holds for the other figures.

A quantity closely related to SLP is the wind stress. For this quantity a truly independent product exists in the form of fields derived from the ERS-1 and 2 scatterometers as produced and distributed by Ifremer/CERSAT (http://www.ifremer.fr/cersat/SERVICES/ARFTP/E_ARFTP.HTM). They are available from September 1991 onwards. Figure 1 shows the correlation maps of the east-west component of wind stress (τ_x) between DaSilva and NCEP, ERA15 and NCEP, and ERS-1/2 and NCEP. Not surprisingly, the pattern of the DaSilva/NCEP correlation very much resembles that of the respective SLP correlation (Sterl, 2001, Figure 2b). The two reanalyses agree well outside the tropics, but show large discrepancies within. This is in accordance with similar results for Q_{lat} (Sterl, 2001, Figure 3b). Finally, the correlation between ERS-1/2 and NCEP is very high, exceeding 0.8 in most regions, the exception being the tropics and parts of the Southern Hemisphere storm tracks. As both are truly independent this means that the wind stress variability is realistic in NCEP. As wind stress is closely related to SLP this also means that SLP variability in NCEP is realistic.

Another data set that is independent of the reanalysis is HOAPS (Grassl et al., 2000). It is a satellite-derived data set of air-sea interaction parameters spanning the time form mid-1987 to December, 1997. Figure 2 shows the correlations between Q_{lat} form HOAPS and from NCEP along with those between DaSilva and NCEP and between ERA15 and NCEP. As can be seen the HOAPS/NCEP correlations are lower in the Northern Hemisphere than those between DaSilva and NCEP and much lower than those between the two reanalyses.

Generally, the DaSilva reconstruction was found by Sterl (2001) to give good results in data-rich areas like the Northern Hemisphere, a result that is recovered here for τ_x (Figure 1), and is was just shown that the reanalyses exhibit a realistic variability. Together, the relatively low correlation between HOAPS and NCEP point to some deficiencies in the former data set.

3. SPARSITY-INDUCED VARIABILITY CHANGES IN NCEP REANALYSIS

The tendency of SST, $\partial SST/\partial t$, is known to be highly correlated with Q_{lat} in the Northern Hemisphere extra tropics (Cayan, 1992). As shown in Sterl (2001) this relationship also holds in the Southern Hemisphere as evidenced by the NCEP data, but could not be extracted from the DaSilva data due to their sparseness. However, caution is also needed when dealing with the NCEP data. Figure 3 shows the correlation between $\partial SST/\partial t$ and Q_{lat} for two periods of time, namely 1958-1972 (left) and 1988-1997 (right). Apparently, the relationship between the two quantities has changed over time. Especially in the Southern Ocean they are not correlated during the earlier period.

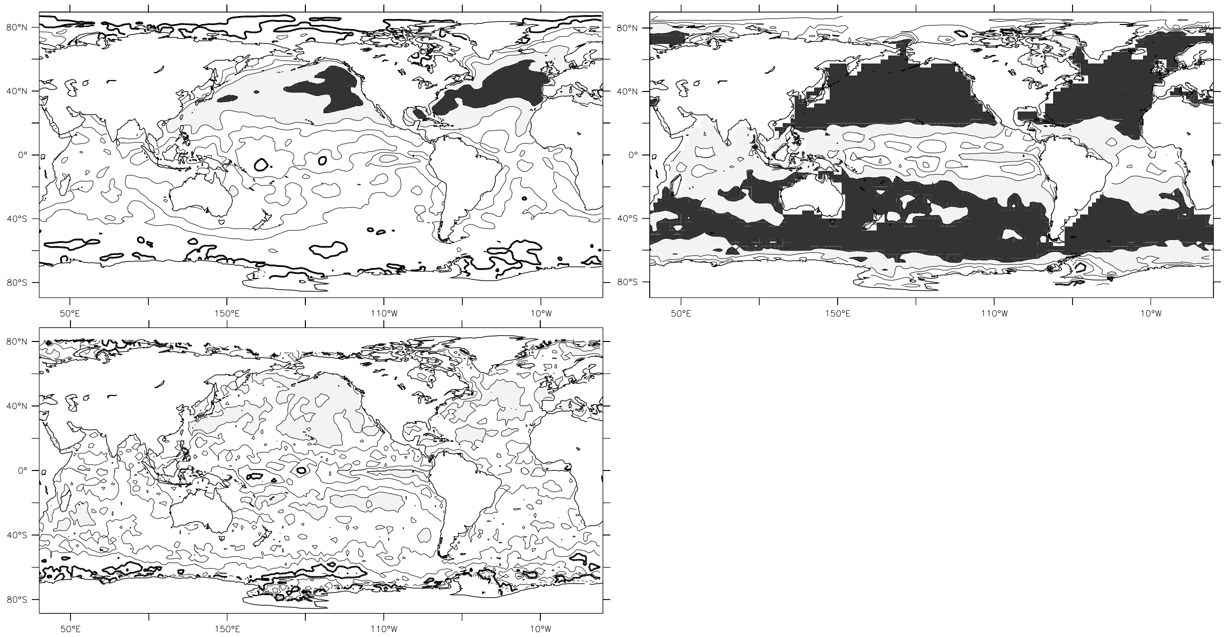

Figure 2: Correlations between the Q_{lat} anomalies from DaSilva and NCEP (upper left), ERA15 and NCEP (upper right), and HOAPS and NCEP (lower left). Light (dark) shading above 0.6 (0.8); contour interval 0.2.

The reason is again data sparseness. Figure 4 (left) shows that apparently SST varies much more after 1981 than before. Obviously the introduction of a satellite-derived SST product after 1981 caused this jump in variability and thus changed the apparent relation between SST tendency and Q_{lat}. The latter, on the other hand, seems not to be influenced by the faster varying SST, as it does not show a change in variability after 1981 (Figure 4, right). This can only be explained by assuming that the variability of Q_{lat} is mainly determined by internal variability of the atmosphere and not by that of SST. Latent heat flux variability thus *drives* SST variability in nature (see also Cayan, 1992), a feature that is prevented by the set-up of the reanalysis with its prescribed SSTs. Putting it the other way around: The fact that in NCEP $\partial SST/\partial t$ and Q_{lat} correlate so well after 1981 although they are essentially *unrelated* in the reanalysis model is again an indication that natural variability is captured quite well in the NCEP model.

4. SUMMARY AND CONCLUSIONS

Extending the work of Sterl (2001) by considering satellite-derived datasets that are independent of the reanalyses it has been shown that the reanalyses display the correct variability. This strengthens the earlier conclusion that EOF-based methods are better suited to fill gaps in observations than is the successive correlation method.

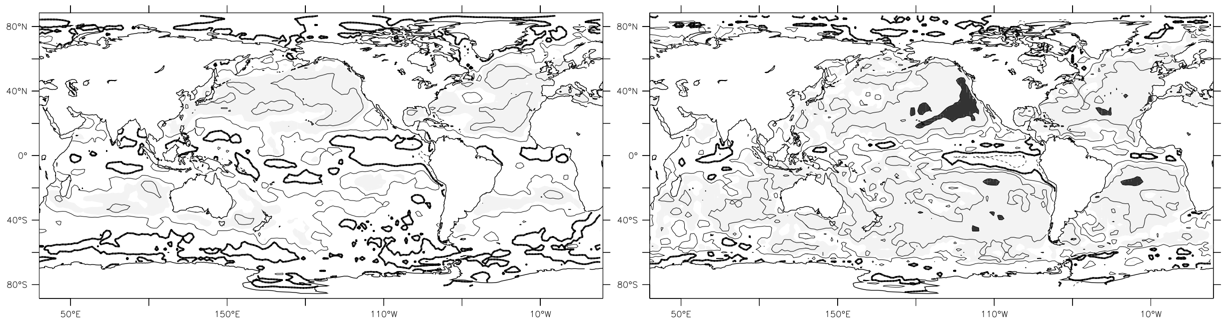

Figure 3: Correlation between $\partial SST/\partial t$ and Q_{lat} from NCEP for the periods 1958-1972 (left) and 1988-1997 (right). Light (dark) shading above 0.3 (0.6); contour interval 0.2.

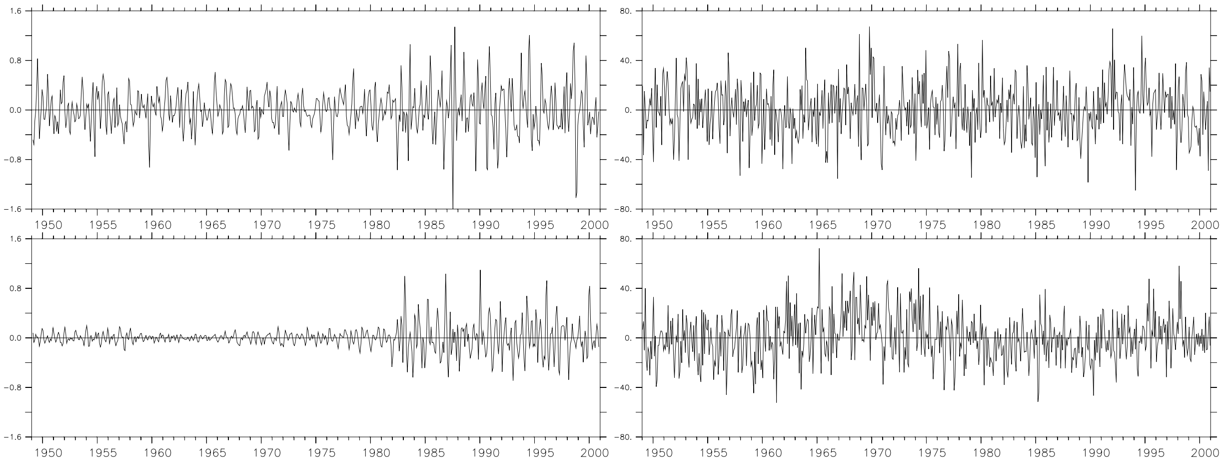

Figure 4: Time series of $\partial SST/\partial t$ (left column) and Q_{lat} (right column) from NCEP at 180°W, 40°N (upper row) and 120°W, 40°S (lower row).

At the same time it was found that the satellite-derived latent heat flux from HOAPS differs in variability from the reanalyses and also from DaSilva in data-rich areas, leading to the presumption that this data set misses some of the true variability.

The SST used as the lower boundary condition in the NCEP-NCAR reanalysis has become much more variable since the introduction of satellite-derived SSTs in 1981. It has been shown that this influences the inferred physical relationship between SST variations and latent heat flux. From this apparent change in physics it is concluded hat Q_{lat} is mainly determined by atmospheric variability and that it is the cause for SST changes.

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