TOWARDS OPTIMAL RECONSTRUCTION OF OCEAN SURFACE FLUX FIELDS: EXPLORING WIND STRESS – SEA LEVEL HEIGHTS CONSTRAINT

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1. INTRODUCTION

We approach the problem of analysis of historical ocean-atmosphere flux fields as a general problem of the least squares based analysis of time-evolving fields. The typical sources of information for such analyses are imperfect models (prognostic models for time transitions or diagnostic constraints) and incomplete and erratic observations. This problem is central in two areas of climate research which traditionally are considered separately: assimilation of data into numerical models and objective analyses (reconstructions) of data sets of historical observations. (In fact the main difference between these two types of problems is in a relative amount of information brought by the model vs observations: it is low in the latter problem and high in the former.)

Least squares procedures of optimal estimation, when applied to gappy and erratic data, result in the solutions which predominantly project onto the most energetic patterns of a priori error covariance. This property of the solution allows to combine the classical least squares technique with the approach of a space reduction in order to develop a computationally effective procedure of objective analysis for observed historical climate fields, which are characterized by comparatively precise data and good coverage in the last few decades, and poor observational coverage prior (Kaplan et al., 1997, 2001). Recent applications of the procedure to the historical ship-based data for such flux-related variables as sea surface temperature (SST) and sea level pressure (SLP) resulted in near-global monthly reconstruction from 1850s to present accompanied by verified error bars (Kaplan et al., 1998, 2000). We believe that a modification of the same approach can be used successfully for objective analyses of interannual variability of surface flux fields, at least for the areas where climatological normals are considered known.

We attempt to evaluate a potential of multivariate analyses of surface momentum fluxes with explicit model constraints of local (e.g. geostrophic balance equations) or non-local nature (e.g. dynamical ocean models converting wind stress fields into sea level height observations). For illustration of prospects and difficulties of such applications we compare 4 versions of the tropical Pacific surface zonal wind stress: a successive correction analysis by Da Silva et al. (1994) (DS), our own trial reduced space optimal interpolation (OI) of global surface winds, surface (10 m) winds from the NCEP-NCAR reanalysis (Kalnay et al., 1996) (RA), and Florida State University (FSU) subjective analysis (Goldenberg and O'Brien, 1981). Our trial OI analysis of surface winds was produced by application of the technique by Kaplan et al. (2000) to to the set of COADS observations (Woodruff et al., 1987) corrected by Da Silva et al. (1994) for systematic biases. The wind stress product was obtained by multiplying the analyzed values of wind vector anomalies by climatological wind speed from Da Silva (1994) atlas. Results of comparison based on various criteria are presented in Sec. 2. Our conclusions are given in Sec. 3, and recommendations for the methodological approach to a historical analysis of the interannual variability of surface fluxes are in Sec. 4.

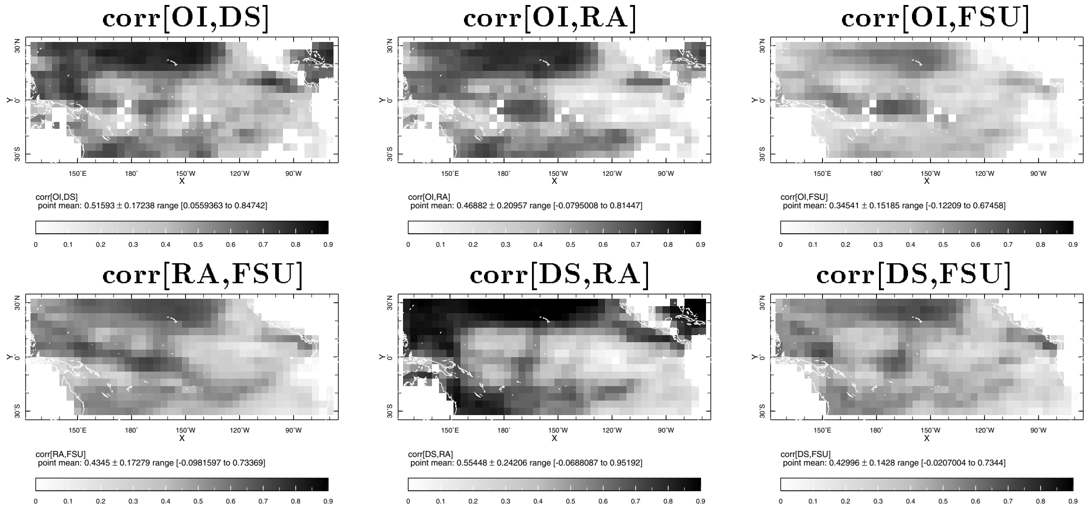

Figure 1: Pairwise correlation fields between four wind stress products, 1964-1993.

2. COMPARISON RESULTS

The four data sets included into the comparison have a common 30-year-long time period 1964-1993. For each product we computed its seasonal cycle for this period, and by subtraction calculated anomaly values with regards to it. All comparisons hereby are presented for those anomalies.

We start by comparing all products pairwise in terms of local correlations (Figure 1). All products are using pretty much the same data. The DS and OI are based on the identical sets of wind observations (the difference between them being in the analysis techniques only), while the FSU complements observations by the intelligence of a human analyst, and the RA employs the intelligence of primitive equations and constraints which they carry from other kinds of observational data. The lack of coherency between these products is stunning: an area averaged correlation coefficient between any two products does not exceed 0.56 (this maximum is achieved by the DS and RA correlation; next best is between OI and DS, 0.52; the lowest mean correlation, 0.35, is between OI and FSU). Note that our correlation maps show all non-positive and missing values in white (no shading). The 7 white grid boxes in the Central Pacific and a white inclusion in the South East corner of the domain visible in the OI correlation maps are considered missing because they were excluded from our analysis due to too poor observational data.

Despite many differences between correlation maps of Figure 1, there are certain common features: relatively high correlations in the western, northern, and south-western parts of the basin, low correlations in the 15^oS-15^oN equatorial band, except for the 180^o-160^oW segment, and very low correlations in the south-eastern corner of the domain. These features can be readily explained via the OI analysis theoretical error estimate in Figure 2: areas of low correlation roughly correspond to the areas of the high theoretical error (note that the error values in Figure 2 represent only the large-scale component of the error; the full error includes small-scale components, which are not resolved by this analysis). High analysis error is being caused by the two factors: low number of observations (high $1/N_{\rm obs}$ values) and high local small-scale variability in the wind (Figure 2). The inverted number of observations clearly reconfirms the same spatial features of the error. However, many details of this pattern, including ship tracks, are seen in the COADS-based estimate of small-scale variability as well. Comparison with satellite-based estimates shows that the COADS-based values are too low in the areas of low sampling. That suggests a certain inadequacy of our OI analysis which uses COADS-based estimates of small-scale variability: we underestimate the error

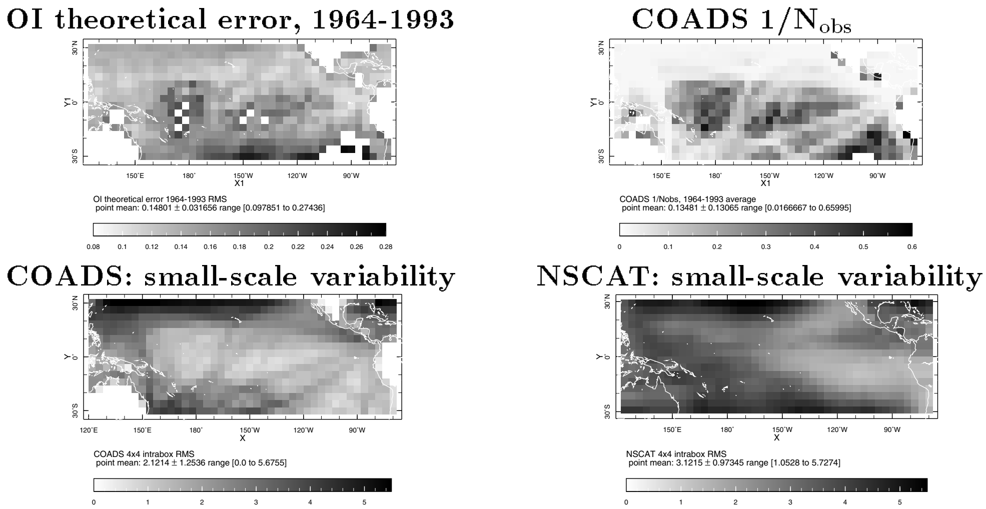

Figure 2: Zonal wind analysis error and small-scale variability estimates from ships (COADS) and the satellite scatterometry (NSCAT).

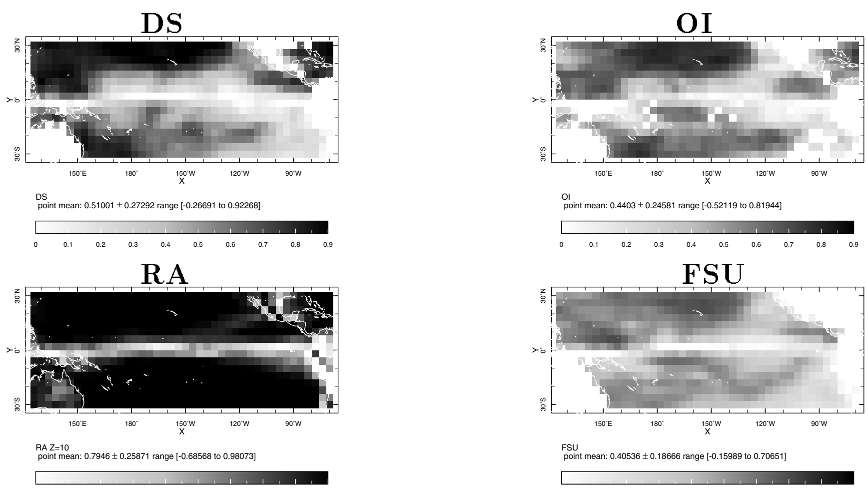

Figure 3: Correlation coefficient between $-\frac{\partial P}{\partial y}$ and fu, 1964-1993. P is the SLP from the reanalysis (Kalnay et al., 1996), f is a Coriolis parameter.

in poorly sampled locations, and this affects both analyzed fields and their error estimates.

There are other ways to evaluate quality of a wind data set besides simple local least squares comparison. For example, one could expect a good data set not to violate too strongly certain local dynamical constraints, like geostrophic or frictional balance (e.g. Kushnir and Kaplan, 1994). As a simplest possible example of such kind of test in Figure 3 we show correlations of the two terms in the meridional geostrophic balance ($-\frac{\partial P}{\partial y}$ and fu) for all four products. The SLP P was taken from the reanalysis (Kalnay et al., 1996), and RA zonal wind is in a much better balance with it than all other products. But even when this calculation is repeated with Da Silva et al. (1994) SLP (not shown), the RA wind still has the best balance among all data sets, even though the difference in performances is far from being that remarkable. Moreover, all wind products show better geostrophic balance with reanalysis SLP than with Da Silva SLP. This demonstrates how imposing an internal dynamical constraint on the analysis stage (Reanalysis) can affect all dynamically connected variables in a consistent way.

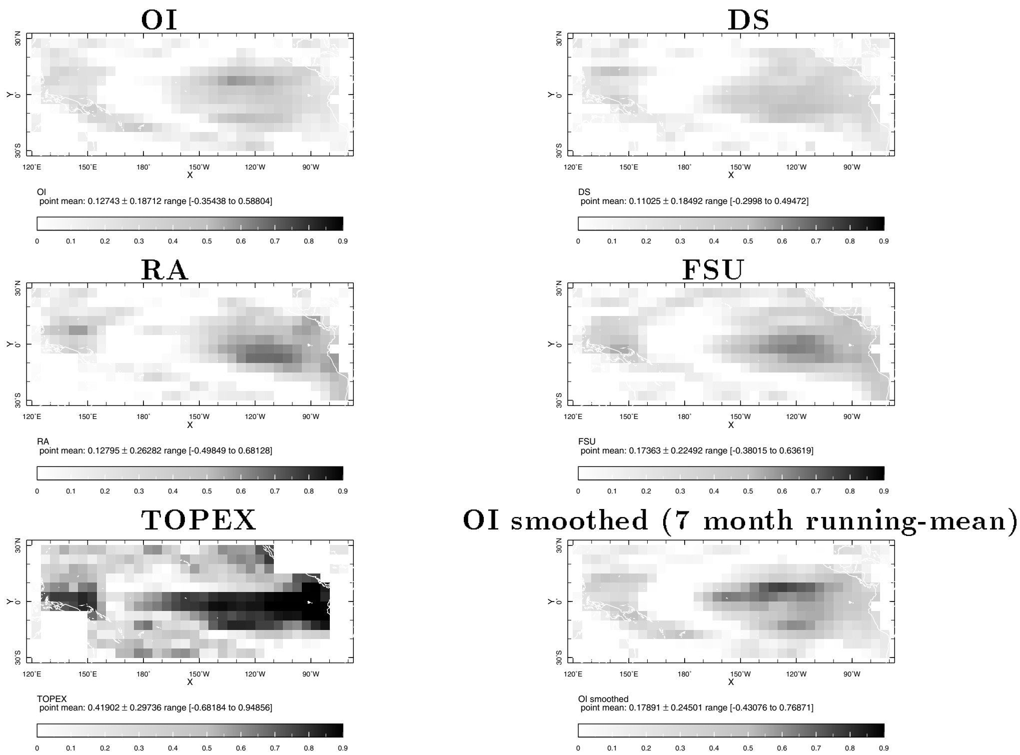

Figure 4: Correlations between sea level height and SST. Periods: 1992-2000 for TOPEX, 1964-1993 for the model output.

Finally, we employ a non-local dynamical criterium to evaluate wind products: we use them as a forcing for a linear model of the tropical Pacific Ocean (Cane and Patton, 1984) and would like to check how realistic is its sea level height anomaly response. However, since there are not enough of good coverage and quality sea level height data in the period of comparison (1964-1993), we use the SST anomaly as a proxy for the tropical Pacific sea level height. A comparison of the SST anomaly (Kaplan et al., 1998) with the TOPEX altimetry (Cheney et al., 1994) for 1992-2000 shows significant positive correlations in almost entire equatorial and Panama coastal regions (Figure 4). The RA and FSU fare much better in this comparison than the OI and DS. At the same time the latter products show much more of month-to-month variability in the central equatorial region (5^oS-5^oN, 160^oE-120^oW) than the former two, even though on longer terms they all show similar variability which also matches that of the SST NINO3 index (Figure 5). When we apply a 7 month running-mean filter to our OI product, the comparison improves to the level of no lower than that of the RA and FSU.

3. CONCLUSIONS

We have applied our reduced space optimal estimation technique (a computationally effective way to approximate the full-grid optimal solution) to zonal surface winds from the COADS corrected by Da Silva et al. (1994). Interannual variability for 1964-1993 for the resulting trial analysis (OI) was compared in the tropical Pacific region with that in three other wind analyses (DS, RA, and FSU). We used performance measures of three types: local least-squares comparison, a local dynamical constraint, and a non-local dynamical constraint. Results show that a good performance of a product by one of criteria does not necessarily imply a good performance by others and vice

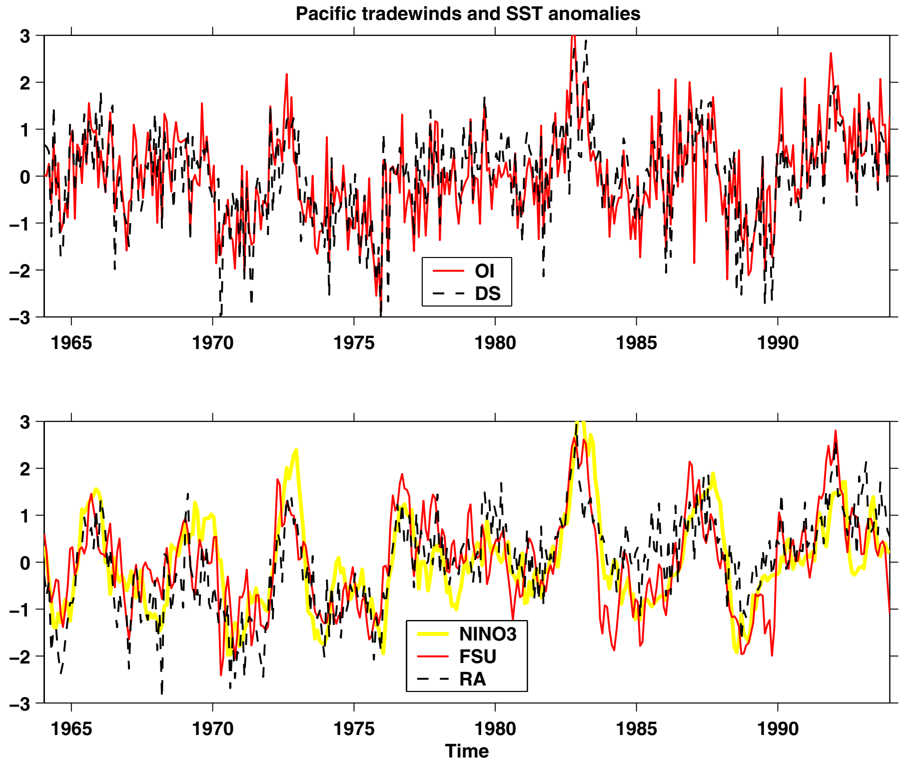

Figure 5: Central Pacific tradewinds and NINO3.

versa. A dynamical constraint imposed at the analysis stage is a useful tool to improve quality of flux estimation. At the same time, leaving a constraint out may result in the product which is optimal in many senses but not particularly consistent with that constraint. The reduced space optimal estimation technique easily allows incorporating linear (or linearized) constraints into the cost function.

4. RECOMMENDATIONS

Our work allows to make some recommendations regarding the use of satellite data for the analyses of flux fields based on the in situ data: (1) In computing observational error variance (which allows the analysis to distinguish between poor and high quality observations) we use COADS-based estimates of small-scale variability. Comparison with satellite data suggests that in many places small-scale variability is heavily underestimated by ship data even during the best sampling periods. The satellite data (even for the relatively short time periods) is an invaluable source of information for the variability on those small scales which are still larger than the instrument footprint; variability on even smaller scales (including random instrumental error) has to be estimated from in situ data in the style of Kent et al. (1999) technique.

(2) When satellite data are available for longer than a few years period, the analyses which blend it with in situ data (e.g. Reynolds and Smith, 1994) can be used as the source data set for estimating spatial covariance of the target field and its dominant structures – the most important information for setting up an objective analysis procedure.

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