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CARBON CYCLE & OCEAN MODELLING

The capability to model the complete carbon cycle and its climatic feedback will enable us to make informed choices about climate change mitigation. At C-MMACS we have carried out a comprehensive study of this by integrating high precision data with sophisticated models of the oceanic circulation, carbon cycle, transport and inversion for robust flux estimation.

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1.1 Robust Estimation of Carbon Fluxes over Temperate Asia

Estimates of carbon sources and sinks are poorly known over Asia and the Indian Ocean, especially because of the sparsely of the spatial data that lowers the resolvability of inverse solutions. The oceanic and land components of carbon cycle and transport of carbon from sources are causes for uncertainty. We need robust estimates of carbon fluxes from India to formulate our country's response to mitigate climate change. In our continuing programme of robust estimation of carbon fluxes, we have added data from the Pondicherry station in addition to Hanle to our observation network. The data spans the 2007-2009 period and we have performed an inversion for interannual fluxes in this period. From these fluxes we have constructed a monthly climatology and added this to the background Net Ecosystem Productivity (NEP) which is the difference between Net Primary Productivity and respiration.

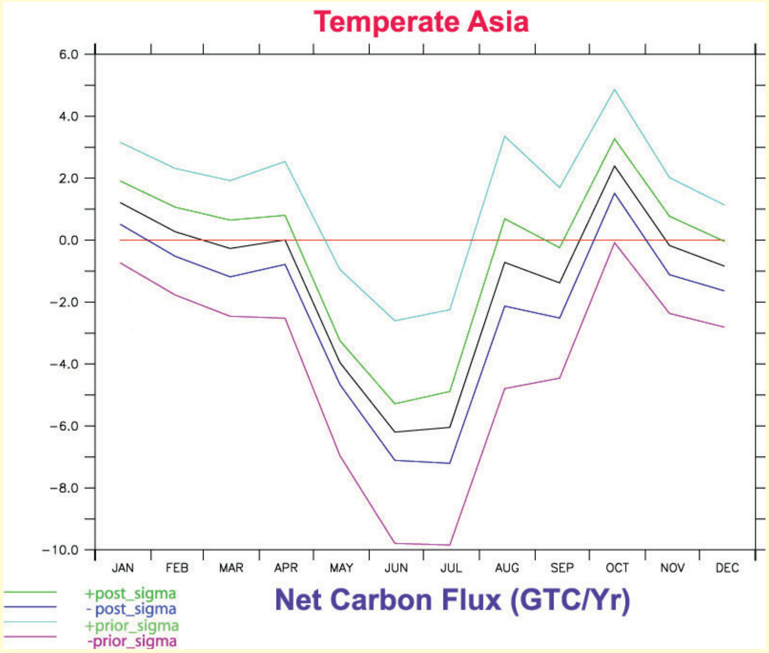

Figure 1.1 Net carbon flux from Temperate Asia (black line), a-posteriori uncertainty envelope (green and blue) and a-priori envelope (cyan and magenta). Note enhanced uptake during June-Aug which results in a net uptake of 1.3 GtC/yr.

The results of this net flux for the Temperate Asia region are shown in Figure 1.1. The black line denotes the net flux after inversion, the green and blue lines denote the +/- 1-sigma a-posteriori errors, and cyan and magenta denote a-priori errors. It is immediately apparent that there is a considerable reduction in the errors due to the inclusion of Indian stations. There is also a shift of maximum productivity from July to June. In addition, Temperate Asia is a net sink of 1.3 GTC/yr. In summary, our efforts towards expanding the CO2 measurement network and the application of a rigorous procedure to invert this data have considerably improved the robustness of flux estimates from temperate Asia.

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1.2 Biogeochemical Cycles of the Indian Ocean using Ocean Model Simulations and Observations

Marine biota plays an extremely important role in the global carbon cycle. The biological pump transfers a considerable amount of carbon from the atmosphere and the euphotic zone to the deep ocean as organic matter, the basic mechanism being fixation of inorganic carbon into organic molecules during photosynthesis. This has an important bearing on the long-term climate response to increase in atmospheric carbon dioxide arising from anthropogenic emissions. Only a comprehensive modeling of the biogeochemical cycles and synthesis of data will yield insight into the physical, chemical and biological processes which influence the carbon cycle on wider spatial and temporal scales.

Based on the seasonal variations of the physical and biological properties of the mixed layer of different regions of the Indian ocean (30oS-27oN, 35oE-110oE), we have divided the ocean for this study into three components viz. Arabian sea, Bay of Bengal and South Indian Ocean. In this research work we study the interannual and seasonal variations of mixed layer properties and plankton biomass using an OGCM (MOM4p1, GFDL) which is coupled to a sea-ice model embedded with biology. The global ocean model was spun up with climatological forcing for 150 years and then forced with CORE interannual fluxes for the period 1948-2007.

Spatial and temporal variations of chlorophyll primary productivity, nitrate and zooplankton and mixed layer of the Indian Ocean have been studied in detail using model simulations and validated with U.S JGOFS Arabian Sea process cruises observations for Arabian Sea (1994-1995) and Bay of Bengal process studies (BOBPS) cruise observations for Bay of Bengal (2001-2003). We have also used remote sensing data from various sources such as sea surface temperature from TMI, chlorophyll-a from SeaWIFS . We have extracted chlorophyll from SeaWiFS (Sea viewing Wide Field of view Sensor) and MODIS (Moderate Imaging Spectroradiometer) satellite data using SEADAS image processing software. We have compared model simulated chlorophyll variations at a few locations in the Arabian Sea with satellite derived chlorophyll (Figure 1.2). The agreement between the model and the data is reasonably good.

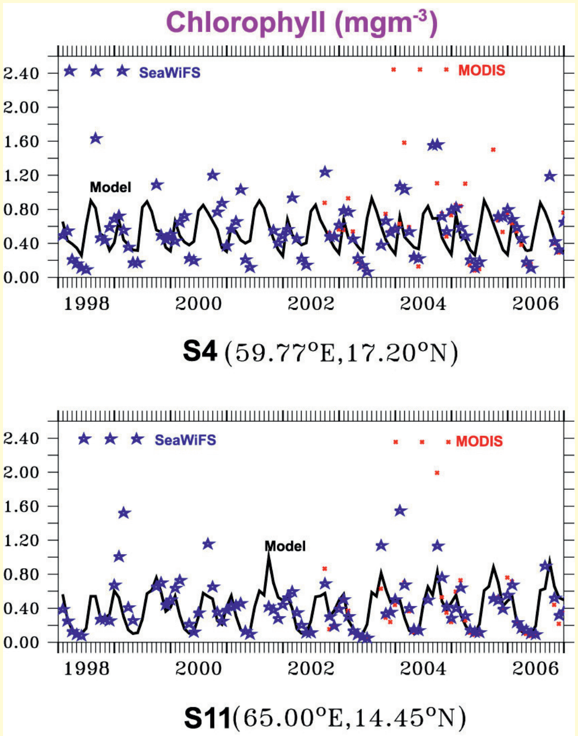

Figure 1.2 Comparison of model derived chlorophyll variations at S4 (top panel) and S11 (bottom panel) stations of JGOFS studies in the Arabian sea with satellite data.

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1.3 Southern Ocean Biogeochemical Cycles

The Southern Ocean (SO) is the least explored and least accessible basin compared to other oceans but it forms an important component of the global climate system. The SO is a region of high inorganic nutrient concentrations and low phytoplankton biomass and is considered to have a large CO2 uptake potential if the nutrients could be utilised. In this study we have used mom4p1 climatological model simulations along with observations to examine the seasonal variability of mixed layer. The model derived temperature and salinity at various depths has been compared with a few of the available atlases and shown to be in good agreement.

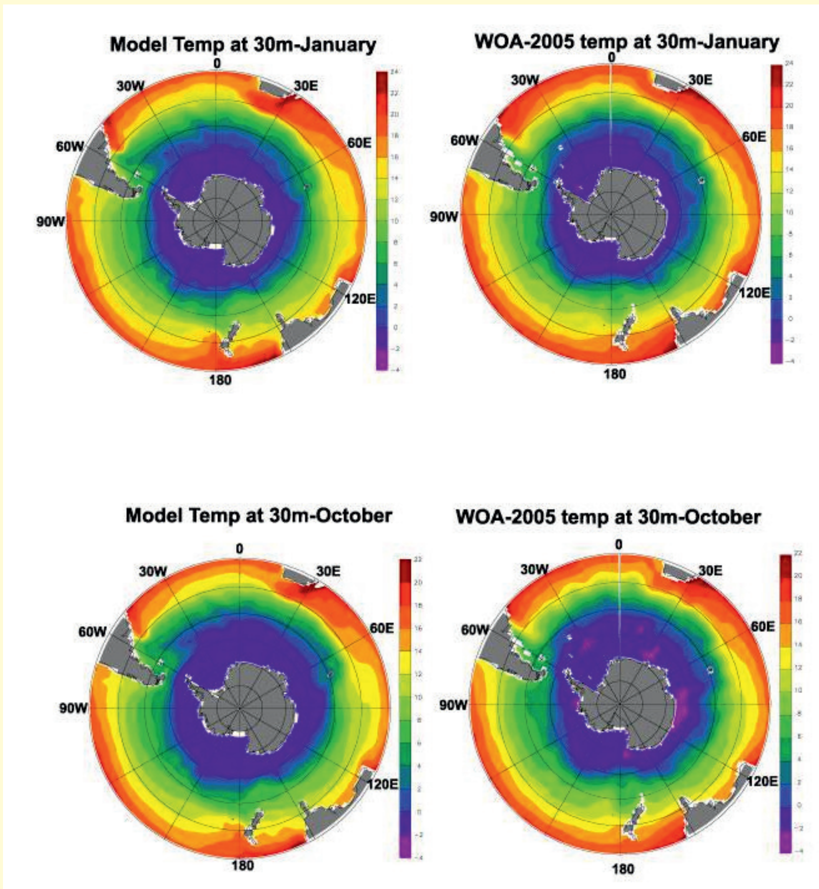

Figure 1.3 Comparison of Model Temperature with WOA-2005.

Figure 1.3 shows the comparison of model simulated temperature at 30m depth with World Ocean Atlas-05 (WOA05) for the months of January and October. The left panel shows the model derived temperature (deg C) at 30m depth and the right panel from the WOA05 atlas. Similarly the model derived salinity (Figure 1.4) is compared with WOA05 for the months of January and October. Salinity is one of the crucial parameters for the seasonal variation of ice coverage. The model derived salinity shows minor differences compared to observations. These differences are due to errors in forcing fluxes which we are in the process of refining in our new simulations.

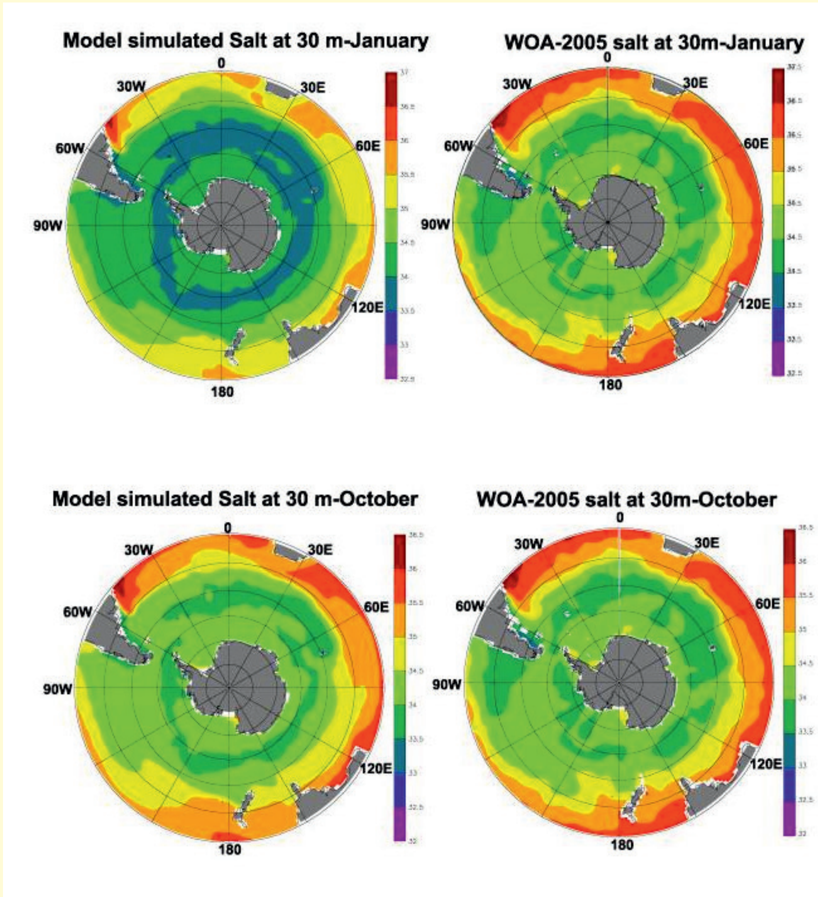

Figure 1.4 Comparison of model simulated salinity with WOA-2005.

We are also analyzing satellite derived chlorophyll and primary productivity at a few locations in the region where an Indo-German iron fertilization experiment (LOHAFEX) was carried out. We are in the process of comparing this with in-situ observations in an effort to understand the comprehensive effects of iron fertilization on the circulation and biology of the Southern Ocean.

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1.4 Factor Loadings Of Interannual Variability of Sea Surface Temperature in Indian Ocean: A Novel Method of Extraction

Factor analysis (FA) is widely used for the identification of fundamental (coupled) modes in a set of variables. In other words, the factor solutions identify latent variables that explain why the variables are correlated to each other. One major advantage of FA is that factor solutions are resistant to noise: an unavoidable part of any measurements. If noise represents a significant portion of the total variance, then FA is an appropriate diagnostic tool to extract coupled modes. The most widely used methods of estimation of factors solutions are based on either Minres or Maximum Likelihood (ML) algorithm. Nevertheless the existing Minres algorithms heavily depends on iterative computation to minimize a certain error-residual. Hence the computing time required to find optimal factor solutions increases exponentially with the dimension of a residual-matrix. On the other hand, the theory behind ML assumes that input data is normally distributed. This is not true, in general. Another more severe limitation, common to both these algorithms, originates from the need of an inversion of a certain correlation matrix. These methods, hence, fail when the estimated correlation matrix is non-positive definite (hereafter dirty correlation matrix). The causes of such an aberration in a correlation matrix are many, but one which is of more concern in the present study is the measurement-noise. Though there are several mathematical laundries to clean such a dirty correlation matrix, how far they distort the hidden reality in data is debatable. Therefore, an important issue is how to extract fundamental modes from a noisy data with minimal distortion. It is also desirable to use an algorithm which assumes nothing about the statistical properties of input data; Minres algorithm qualifies in this aspect.

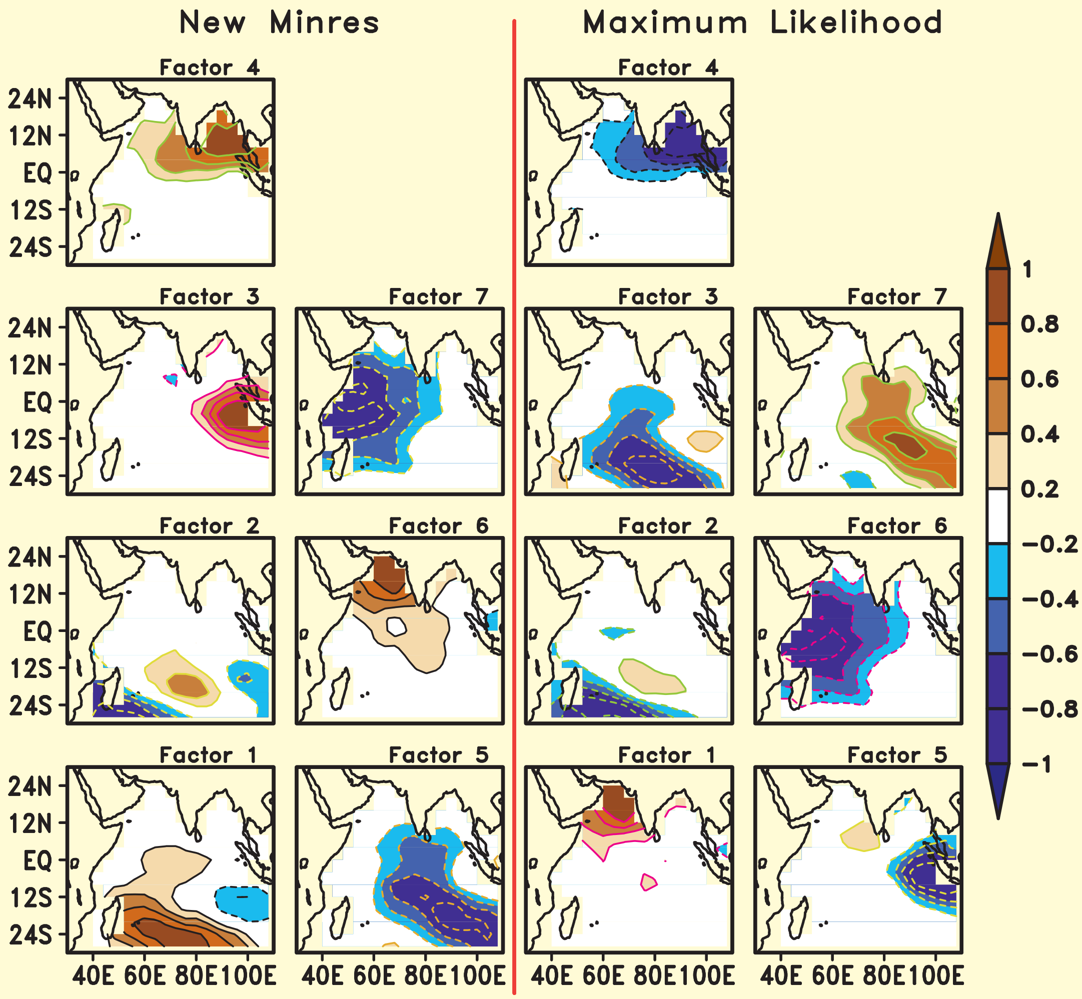

Figure 1.5 Factor loadings of interannual variability of Sea Surface temperature in Indian Ocean estimated via Maximum Likelihood methods (right side of red line) and via new Minres methods (left side of red line). The matching pairs are (1 -> 3), (2 -> 2), (3 -> 5), (4 -> 4), (5 -> 7), (6 -> 1) and (7 -> 6). The integers in parenthesis indicate mode-indices of New Minres and ML algorithms respectively.

The numerical iterations in existing Minres algorithms could be grouped broadly into two categories. Those in the first category, for convenience are termed internal iteration (II), are associated with matrix computations (e.g., inversion of correlation matrix). The iterations in the second category, called external iteration (EI), are related to the dimensionality of the factor-model. Moreover, note that solutions from II are often not robust when the size of correlation matrix is large and all existing factor analysis algorithms fail when a dirty correlation matrix is encountered. The mathematical steps in II, hence, are modified in such a manner that the need for a matrix inversion is minimized or even completely bypassed. This considerably saves the computational time as well as delivers more robust factor solutions irrespective of the nature of correlation matrix. However, the details of this modification are temporarily withheld for securing a copy right for this new and faster Minres algorithm for Factor analysis.

The fidelity of this new method is established by comparing the factor loadings with those from the ML algorithm. For this purpose, the factor loadings of the observed sea surface temperature in Indian Ocean based on these two methods are estimated and displayed in Figure 1.5. Note that only the interannual variability is examined. In this study, we have used global monthly sea surface temperatures from Extended Reconstructed Sea Surface Temperature V3b from National Oceanic and Atmospheric Administration. The factor loadings, unlike in principal component analysis, do not have any order of importance; instead they highlight regions or a set of variables that contributes significantly towards the total co-variability. The similarity among the structures of factor loadings from the two methods is remarkable. Nevertheless, they may differ in term of polarity due to the inherent sign indeterminacy of factor solutions.

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1.5 A Data Adaptive Temporal Filter for Climate Variability Analysis: An Innovative Approach

The spatio-temporal filtering is one of the central diagnostic tools used to explore the characteristics of a complex dynamical system. A number of filtering methodologies are in use. But each one has its own merits and demerits. A researcher has to choose prudently the appropriate one so that the outcome reveals the underlying realty in a least distorted manner. While designing such filters with reduced distortion, it is helpful to have a fair degree of prior understanding of the system's dynamic characteristics, without which the broth is likely to be spoiled by over- or under- filtering. Generally, filtering is done either by considering only some temporally local characteristics in a time series or by a global optimization of a certain metric. A typical example for the first (hereafter LF) is the Running Mean whereas the filtering by Fourier Transform falls in the second category (hereafter GF). In the case of LF, the characteristics are truly local in nature irrespective of the behavior of time series at other time points. This is not the case with GF; the characteristics of the filtered time series are sensitive to the total duration of a time series and outliers present. The latter deserves more attention. . At this point, it is instructive to note that embedded in a phenomenon having longer time-scale and larger space-scale are multitudes of higher amplitude events having shorter time-scales and smaller space-scales. Though these faster events (i.e., outliers) are the inevitable part of dynamics of the climate, they are not necessarily the essential features of a longer time-scale and larger-space scale event

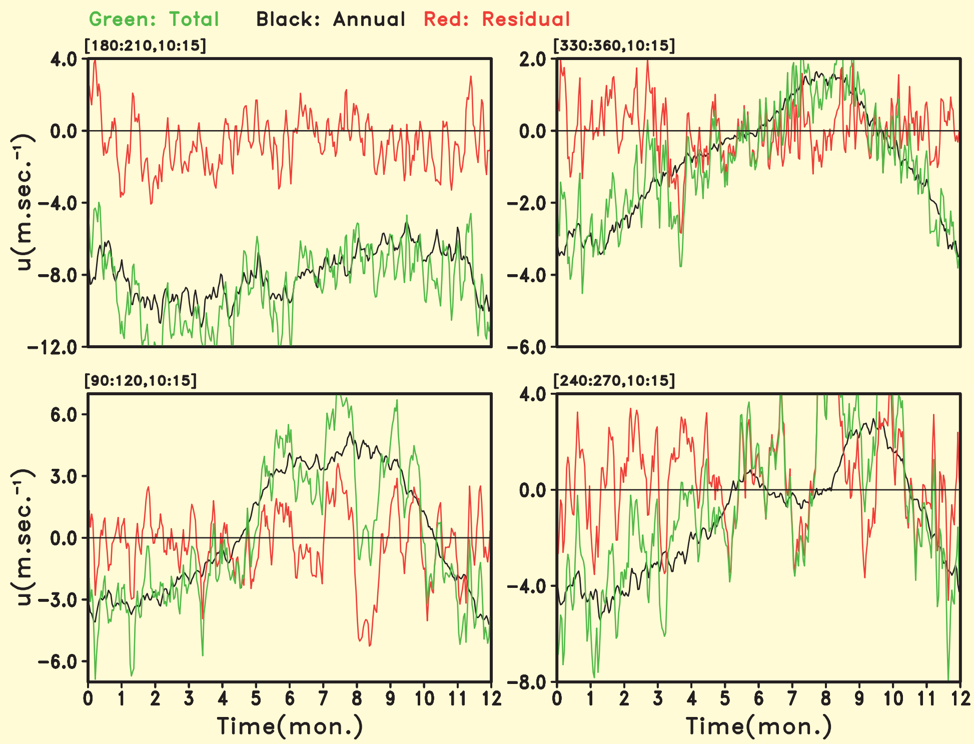

Figure 1.6 One-year segment of zonal wind over four regions as indicated. The total wind (Green line), its non-linear annual cycle (Black line) and the residual (Red line) are shown in each panel.

that one wishes to understand. Moreover, these outliers are often clustered in space and time. Our experiences show that the affect of such unwanted features on an output can be reduced by taking into consideration the nature of variability at nearby spatial locations. Some preliminary results of applying such an innovative filter on the daily zonal component of wind (NCEP/NCAR Reanalysis) are shown in Figure 1.6.

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