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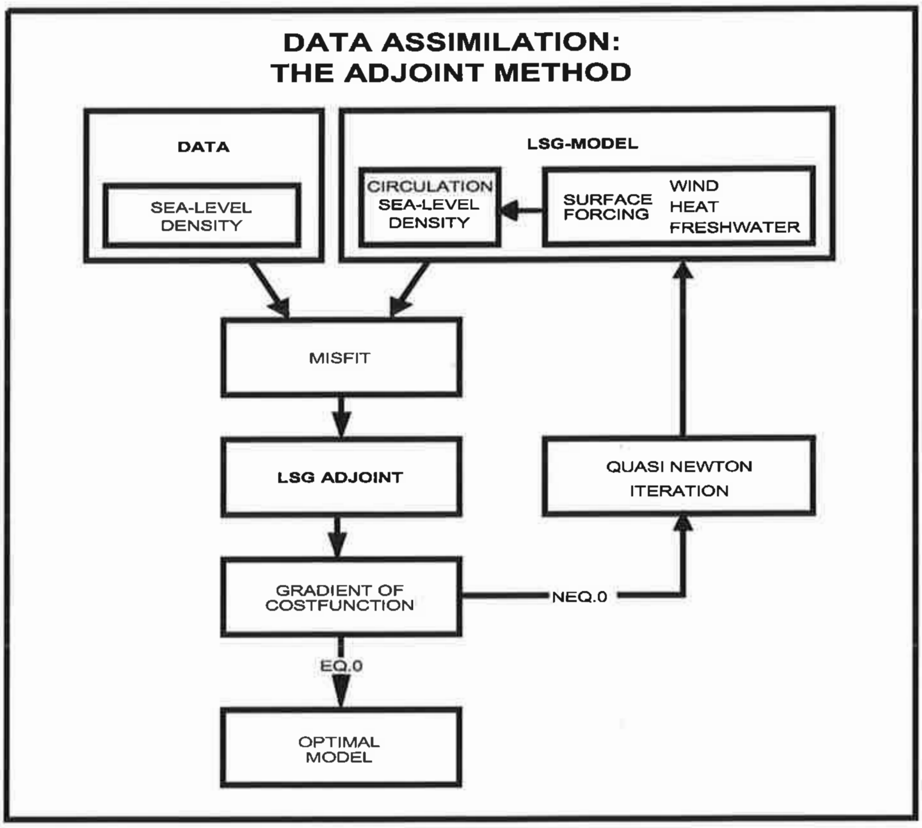

CYCLOSTATIONARY CIRCULATION ESTIMATION WITH A GLOBAL OCEAN ASSIMILATION SYSTEM

by

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Abstract

A coarse version of the Global Ocean Assimilation System (GOAS) is applied to estimate the mean cyclostationary global ocean circulation. This version of the state estimation system is based on the Hamburg LSG Model and its adjoint. Here, a mean seasonal cycle of Levitus'raw station hydrography is assimilated into the ocean model. The adjoint hydrography assimilation improves the model's wind-driven circulation as well as its representation of the dynamically controlled generation and distribution of observed water masses. An improvement of buoyancy-driven transports remains limited by coarse-model characteristics. Altogether, results demonstrate reliable and efficient model dynamics as well as GOAS' flexibility in the exploration of the model's phase space. Hence, the coarse version of GOAS finds application in estimating the substance inventories of the global ocean in view of climate change issues.

1.) Introduction

Recent developments in climate observation and modelling have raised the prospect of a comprehensive climate monitoring system (CLIVAR, 1997). These advances result from the recognition of the ocean as the primary memory of the climate system, fundamental changes of the observational basis of large-scale oceanography during the past two decades and the advent of dynamically consistent numerical models of the global ocean circulation. State estimation and prediction of the ocean and climate take advantage of these new capacities with the combination of observations and model dynamics through the process of data assimilation. Assimilated data products provide the optimal resource for studies of climate dynamics and the global ocean circulation and are of discriminating assistance for the design of continuing climate observations. A climate monitoring system with comprehensive data assimilation at its core will be able to deliver the high quality data crucial to the detection and prediction of climate variability and change. This paper reports the assembly of a Global Ocean Assimilation System (GOAS) for climate research and monitoring and its pilot application to estimating the mean, cyclostationary global ocean circulation.

Two decades ago, a general data paucity of large-scale oceanography left little alternative to averaging sparse observations and associating them with a mean cyclostationary ocean circulation. Now, the TOGA-TAO array in the tropical Pacific is continuously providing data for El Nino prediction with impact on extended range weather prediction in remote regions of the globe. Extensive observational efforts during the WOCE field phase indicate a great wealth of ocean variability consistent with a red frequency spectrum (WOCE, 1997), while satellites yield information on the ocean surface with increasing detail and precision at global coverage. With the recognition of the ocean as the primary memory of the climate system, climate dynamics distinguish phenomenologically three major time scales of the ocean circulation. Climate variability due to unstable air-sea interactions and stochastic atmospheric forcing (Hasselmann, 1976) involves the upper, wind-affected layers of the ocean and exhibits interannual and interdecadal time scales. Stability and variability of the thermohaline circulation govern time scales from decades to centuries, while the issue of climate change is intimately related to the conveyor belt and abyssal circulation with response times ranging from centuries to millenia. On all of these time scales the spatially global nature of the ocean circulation is essential.

A growing observational record of oceanic large-scale variability and the identification of several major time scales have led to a wider discussion of the concept of a mean equilibrium circulation. The International Project Office of WOCE finds "that the concept of a 'mean' circulation is elusive" at this time (WOCE, 1997). In fact, it can hardly be expected that the wealth of information gathered during the WOCE field phase can be interpreted solely in terms of a concept that was formed and developed in the Pre-WOCE-Era under conditions of a notorious data shortage. Unquestionably, analysis and interpretation of new data will give rise to new concepts and views of the ocean's large-scale features. However, these new perspectives do not replace the classical concept of a mean equilibrium circulation. Much of the problem of anthropogenically forced climate change, namely its long-term consequences, depends closely on storage and transport processes in the abyssal ocean with very long time scales. A mean equilibrium circulation is a physically appropriate approximation for these aspects of ocean dynamics. Furthermore, an indispensible prerequisite of convincing stability studies is the ability to simulate an albeit hypothetical equilibrium circulation. In general, demonstration of the ability to simulate a realistic cyclostationary circulation for given atmospheric forcing (provided the ocean is statistically stable) is of major significance for the confidence in all model results. Beyond their fundamental relevance, model equilibria certainly require additional clarification of their relation to the long-term mean of the ocean circulation.

Models with varying characteristics accomodate a wide range of oceanic large-scale dynamics. While a large number of models is based on the Primitive Equations for a Boussinesq fluid on the rotating sphere, they differ with respect to their spatial and temporal resolution. Coarse resolution models simulate the turbulent ocean essentially as a laminar fluid. While the model circulation in this class never resembles a snapshot of the ocean circulation, simulated tracer distributions agree broadly with observations. On this basis, coarse resolution models are expected to reproduce integral circulation parameters realistically. Due to their numerical efficiency they are furthermore particularly appropriate for long-term integrations, coupling to atmospheric circulation models and as the simulation component in comprehensive ocean assimilation systems. Nevertheless, in spite of some recent advances, the issue of subscale transfers has not yet been solved satisfactorily. For one, the complete tensor character of momentum- and tracer-diffusion seems to be of significance to facilitate diffusive spreading along isopycnals. Secondly, subscale turbulence also appears to provide pronounced non-diffusive contributions. Unlike the exclusively diffusive parametrisation of microscopic transports for the Navier-Stokes Equations, turbulent transports obviously emerge also as additional advection and propagation. The closer investigation of these questions by assimilation with coarse resolution models is not yet under way.

On the other hand, higher resolution non-eddy resolving models simulate and predict interannual and interdecal climate variability with increasing skill. The basis for this success is the adequate resolution of dispersive and waveguide properties of tropical and basinwide ocean waves. These wave dynamics are essential for climate variability due to unstable air-sea interactions and its predictability. Certainly, the issue of a satisfactory parametrisation of subscale transports is less pressing at higher resolution. In fact, the statistical properties of fine-grid model circulations resemble considerably closer observations of the large- and meso-scale circulation in the upper ocean. Nevertheless, an increase in numerical resolution alone merely postpones the problem temporarily. Frequently, a resolution of about 10 km is considered desirable, corresponding in essence to the first baroclinic Rossby radius. While such a resolution will stress the available computer capacity for some time to come, it is barely sufficient to represent adequately the horizontal mesoscale variability of a 2-layer model. Obviously, such a coarse vertical structure is an unrealistically poor representation of the ocean's baroclinicity. Furthermore, it is unclear at this time when computer capacities will be available permitting a dynamic linkage of mesoscale spatial variability with long time scales of the abyssal circulation. A comprehensive picture of the ocean circulation is currently provided by the combined application of complementary model types.

The ocean state estimation system GOAS has two global circulation models available: the coarse Hamburg LSG Model (Maier-Reimer et al., 1993) and the finer-resolving HOPE Model (Frey and Latif, 1997). The Hamburg LSG Model is a coarse resolution model for the study of global long-term aspects of storage and transport processes of the oceanic climate component. It has been extensively used for simulations of the conveyor belt circulation (Drijfhout et al. 1996) and of distributions of geochemical and biological tracers (Maier-Reimer, 1993). The HOPE Model is primarily designed for use in coupled models for the study of air-sea interactions. Hence the model uses a fairly high vertical resolution near the surface and simulates mixed-layer physics in terms of an entrainment algorithm depending on the Richardson-number. To adequately reproduce tropical wave dynamics, horizontal resolution increases towards the equator. The model has been extensively used for studies of interannual ocean-atmosphere variability and its coupling to the seasonal cycle. With both models, GOAS addresses essential climate aspects of the global ocean circulation.

In general the notion of data assimilation refers to any measure to operate a model in the vicinity of observations. Direct models usually require an observation-based forcing, whereas inverse models (Wunsch, 1977; Olbers et al., 1985) reverse the conventional role of model input and output. While both approaches combine model and data, they lack the option to filter and interpolate the observations: data errors and model-data incompatibilities are dynamically propagated into the model (Sarmiento and Bryan, 1982). While Optimal Interpolation provides such a filter, it is unable to extrapolate data information onto the entire system (Fischer, 1996). Comprehensive data assimilation filters and interpolates observations dynamically, tunes the model to realistic conditions and extrapolates dynamically the impact of specific observations onto the entire system. With variable control parameters at the model input and weighted data at the model output these procedures yield an optimal solution "between" the direct solution, which plays the role of a first guess in most assimilation applications, and the inverse result. Comprehensive data assimilation utilises the Kalman Filter or the Adjoint Method. Both approaches are formally equivalent (Ghil and Malanotte-Rizzoli, 1991) and apply with particular advantage in different practical situations. While the Kalman Filter provides direct access to the complete statistical structure of the estimate (Evensen, 1994), this wealth of statistical detail also hampers the estimation itself at large numbers of degrees of freedom. If the number of data to be assimilated becomes very large - as for global ocean modeling - storage requirements become prohibitive.

The Adjoint Method minimises a cost function by variation of control parameters. The cost function is formed essentially by the misfit of model output and data while control parameters can be chosen as initial values, forcing parameters or internal model parameters such as diffusion coefficients. For this variational problem the dynamical equations may play the role of a strong or a weak constraint. Imposing the model equations as a strong constraint formally ignores a model error and permits determination of the optimal solution without evaluating the storage-intensive error covariance matrix. While this option provides a significant practical advantage of the Adjoint Method over the Kalman Filter, it also impairs strongly error estimates for the optimal solution.

Minimisation of the cost function requires determination of the zero of the gradient of the cost function with respect to the control parameters. For a global ocean model the number of control parameters is generally very large and an accurate and numerically efficient method of evaluating this gradient is the backward integration of the adjoint model. Besides model and data, the adjoint model is hence the crucial member of a comprehensive adjoint assimilation system. In essence, the coding of the adjoint of a complex model is no lesser task than coding the model itself. As model development proceeds from continuous equations through discretised equations to the final code, adjoint formulation is possible on all three levels of this process. With complex models the most effective approach compiles adjoint code directly from the model code (Thacker, 1991; Talagrand, 1991) under observation of stringent rules for the formulation of adjoint statements (Giering and Kaminski, 1997). Utilising this procedure the uncompromised adjoint of the Hamburg LSG Model has been developed (Giering, 1996a). Moreover, the formal simplicity of the rules for adjoint code construction allows the automatisation of adjoint code compilation, which has been exploited in the design and implementation of a Tangent Linear Adjoint Model Compiler (Giering, 1996b). This software compiles the adjoint code for a given model much the same way a FORTRAN compiler produces a machine-readible version of a FORTRAN code. In application of this compiler the uncompromised adjoint of the HOPE model has been obtained (Oldenborgh et al., 1997). Hence, GOAS is based on two models with supplementing characteristics and their adjoints. In the present pilot study the LSG version of GOAS is utilised to estimate the mean, cyclostationary global ocean circulation.

There are several studies to date estimating the mean circulation by assimilation of hydrography with coarse resolution models. At a time when high resolution models demonstrate improving skill in simulating and predicting shorter term climate variations, these studies have met with some difficulty (see Marotzke and Willebrand, 1996, for a review). So far it has been impossible to determine major integral circulation parameters with satisfactory accuracy. Marotzke and Willebrand fundamentally question the feasibility of such an estimate in the framework of coarse resolution models. Others have suspected possibly large errors in pre-WOCE hydrography measurements as the main obstacle. Both of these conclusions may be somewhat premature. There are certainly limits to the simulation of the global ocean circulation with coarse models and pre-WOCE hydrography may indeed be erroneous on occasion. Nevertheless, coarse resolution models reproduce global tracer distributions realistically and this clearly suggests that these models are capable to provide realistic, dynamically established water mass inventories. On the other hand, already a superficial comparison of hydrographic observations with direct model results demonstrates large-scale discrepancies well beyond a scattered lack of precision. At this time, the hydrography of simulated or assimilated equilibrium circulations of coarse models does not generally represent all major observed large-scale features. Among others, this applies to aspects of Mediterranean Water in the North Atlantic or to intermediate salinity minima in the Pacific. Such discrepancies are well within the realm of coarse-resolution modeling, and data assimilation is evidently the appropriate approach to an improved coarse-model representation of oceanic water masses. So far, assimilation studies have often remained in close vicinity of the first guess. In fact, a large fraction of these studies was based on compromised models and/or compromised assimilation procedures (Marotzke and Willebrand, 1996), with serious limitations for phase space exploration. Typically, present assimilated circulations are far from inverse solutions. A claim of fundamental inconsistency of coarse resolution models will have to demonstrate that the model adaption of observed hydrography inevitably leads to a circulation and forcing which are irreconcilable with information from other sources. So far, this is not the case. While it is clear that assimilation cannot overcome inherent model limitations, it will be shown here that sufficiently flexible formulations for the model and its adjoint increase data acceptance and induce improved model dynamics producing an improved water mass inventory.

This paper is organised as follows. Section 2 introduces the basic elements of the coarse version of GOAS, i.e. the ocean circulation model, its adjoint and the data used in the present estimation. In section 3 details of this estimation and its results are discussed, while section 4 summarises the estimate and the performance of GOAS.

2.) The Global Ocean Assimilation System

The major components of the the coarse version of the state estimation system GOAS are the Hamburg LSG Model and its adjoint. The Hamburg LSG Model goes back to a concept by Hasselmann (1982) and addresses long-term aspects of the global ocean circulation. The present model formulation has been developed by Maier-Reimer et al. (1993).

The model is based on the Primitive Equations for a Boussinesq fluid near the surface of the rotating sphere and utilises the UNESCO (1981) formula

$$\rho = \rho(p, T, S)$$

as state equation for seawater. This equation provides a diagnostic relation between density ρ (specifying the weight per unit volume for a Boussinesq fluid), pressure p, temperature T and salinity S. Potential temperature ϑ, defined in terms of in situ temperature T and depth z (i.e. pressure) according to

$$\vartheta = \vartheta(T, z) = T - z * (0.12K/km)$$

is used as a proxy for heat. Prognostic model variables are sea level ζ, potential temperature ϑ, salinity S and the horizontal velocity-field with covariant components $v_n = a(u\,cos\varphi, v)$, where φ denotes latitude and a the Earth's radius (for details on co- and contravariant vectors in spherical coordinates, see Hasselmann, 1982). Using index notation with Greek indices $\mu, \nu, \ldots = 1,2,3$ running over all three spatial coordinates, Latin indices $m, n, \ldots = 1,2$ over horizontal coordinates only and the usual summation convention, the equations of motion are the continuity equation

$$\partial^\nu v_\nu = 0$$

and the horizontal momentum budget

$$\partial_t v_n + \epsilon_{mn} f v^m + \frac{1}{\rho_0} \partial_n p = A \Delta v_n$$

where momentum advection is neglected. Furthermore, the equations of motion include the hydrostatic equilibrium condition in the vertical

$$p = g\rho_0(\zeta + \frac{1}{\rho_0} \int_z^0 dz' \rho)$$

and the buoyancy budgets

$$\partial_t B + \partial^\nu (B v_\nu + I_\nu) = 0$$

valid for both potential temperature and salinity: $B = (\vartheta, S)$. This system is closed by the linearised kinematic boundary condition

$$\partial_t \zeta = v_3(z=0)$$

with vertical velocity v_3, requiring that the free surface be a material surface. Here, $\epsilon_{mn} = a^2(n-m)cos\varphi$ denotes the antisymmetric Levi-Cevita tensor, $f = 2\Omega sin\varphi$ the Coriolis-parameter and ρ_0 a constant reference density. Diffusively parametrised subscale transfers are explicitely taken into account only in the horizontal with $A = 3. \times 10^5\, m^2/s$ and

$$I_\nu = -K(\partial_n, 0)B$$

where $K = 200\, m^2/s$. These equations are supplemented by a convective mixing algorithm which maintains stable stratification under conservation of heat and salt. A thermodynamic budget accounts for the freezing and melting of sea-ice.

At the surface the model is forced by momentum- and buoyancy-fluxes. At this time, surface stresses include a wind contribution only, while a stress component due to swell is not taken into account. Winds are represented by the Hellermann-Rosenstein data set (1983). Surface buoyancy transfers are represented as Newtonian fluxes with fixed time constants. Radiative and turbulent contributions to the heat flux are parametrised as sensible heat flux controlled by a fictious air-temperature with a restoring time of 60 days

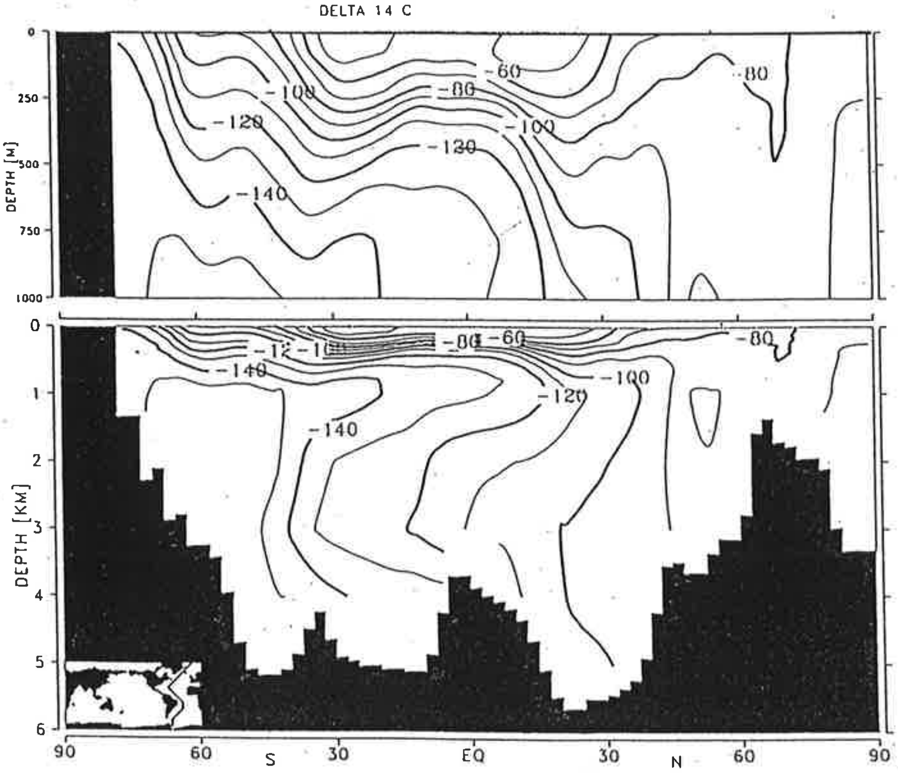


Fig.1a: LSG Simulation

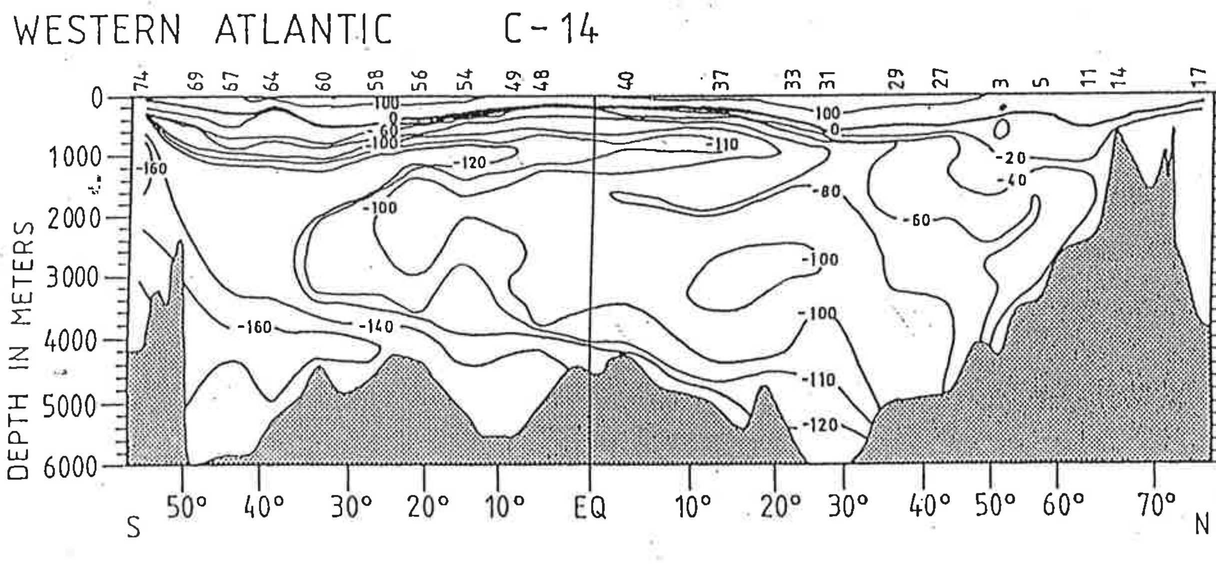


Fig.1b: GEOSECS Observation

Fig.1: Distribution of radiocarbon $\Delta^{14}C$ in the Western Atlantic.

and monthly mean air-temperatures are taken from the COADS data set (Woodruff et al., 1987). In view of the coarse spatial resolution a particular "cold air advection" parametrisation (Maier-Reimer et al., 1993) is frequently used in LSG simulations to account for the spatially and temporally intermittent occurence of convective events. In the present assimilation application this specific coarse-model parametrisation will be dropped in the expectation that ocean buoyancy data provide the corresponding information. Similar to the heat flux, the freshwater flux at the ocean surface is expressed in terms of a restoring salinity with a restoring time of 40 days (Maier-Reimer et al., 1993). As restoring values, Levitus sea surface salinities are chosen. The Newtonian formulation of surface buoyancy fluxes ensures a unique cyclostationary model equilibrium for given surface forcing. In the assimilation application of the LSG Model in the framework of GOAS these forcing fields play the role of a first guess.

The model is discretised on an Arakawa E-grid with a horizontal resolution of $3.5° \times 3.5°$ and 11 levels in the vertical. Buoyancy advection is represented in terms of an upstream differencing scheme with pronounced implicit diffusion. On the basis of this formulation explicit diffusion can be kept as low as given above. The model includes realistic topography and resolves the annual cycle with a time-step of one month.

Fig.1 shows a simulation of the radiocarbon ^{14}C distribution in the western Atlantic with the Hamburg LSG Model (Fig.1a) and the corresponding GEOSECS section (Stuiver and Östlund, 1980). Radiocarbon ^{14}C is a radioactive isotope of carbon with a lifetime of 8367 years, which has proven as an effective constraint of ocean circulation models. Its natural source are collisions of cosmic rays and nitrogen in the upper atmosphere and tree-ring reconstructions indicate that its atmospheric abundance varies only by 2 percent with an oscillation period of a few centuries. Radiocarbon is usually measured in terms of

$$\Delta^{14}C = \delta^{14}C - 2\delta^{13}C$$

where δ denotes deviations from a given standard. Subtraction of the stable isotope $\delta^{13}C$ removes fractionation effects due to photosynthesis and gasexchange at the air-sea interface and $\Delta^{14}C$ can be considered as an exclusively physical tracer providing direct information on circulation speeds through radioactive decay. In this sense, natural $\Delta^{14}C$ provides an approximate measure for the age of the corresponding water mass. Abyssal values of temperature and salinity, on the other hand, reflect primarily the mixing ratio of the main deep water sources.

It is seen from Fig.1 that the LSG simulation of the Atlantic circulation captures quantitative as well as major qualitative features of the observed carbon distribution.

Radiocarbon values are in broad quantitative agreement and the $\Delta^{14}C$ distribution due to Antarctic intermediate water is well represented. The figure also shows that the simulation of abyssal radiocarbon is less satisfactory. The large-scale features of these discrepancies are not inherently outside the capacities of the LSG Model and the primary goal of coarse-resolution assimilation is the minimisation of mismatches of this type.

Adjoint assimilation is a variational technique of state estimation with least-square optimality. Given a set of observations d_N, the best model fit m_N to these data is to be determined by variation of parameters x_p controlling the model integration. Here, capital indices $M, N, \ldots$ label the data space while indices $p, q, \ldots$ refer to parameter space. For the present global ocean circulation estimation, data are given as a climatological annual cycle of global temperature- and salinity-observations, with data space dimension of order 10^8. The independent variables in this optimisation problem are model parameters which control the initial model density as well as surface momentum-, heat- and freshwater-fluxes. For the LSG Model, these controls span a parameter space with dimension of order 10^5. The optimal least-square fit of the model is thus obtained as the minimum of the quadratic cost function

$$J(x) = \frac{1}{2} C^{MN} Y_M(x) Y_N(x) + \frac{1}{2} X_{pq}\, y^p(x) y^q(x)$$

with respect to the control variables $x = x_p$. The first term of this cost function involves the model-data misfit

$$Y_N = m_N(x) - d_N$$

and the inverse of the data covariance matrix

$$C_{MN} =< \delta d_M \delta d_N >$$

with data error δd_N as weights. The second so-called penalty term is quadratic in the deviation of the control parameters from their first guess x_0^p

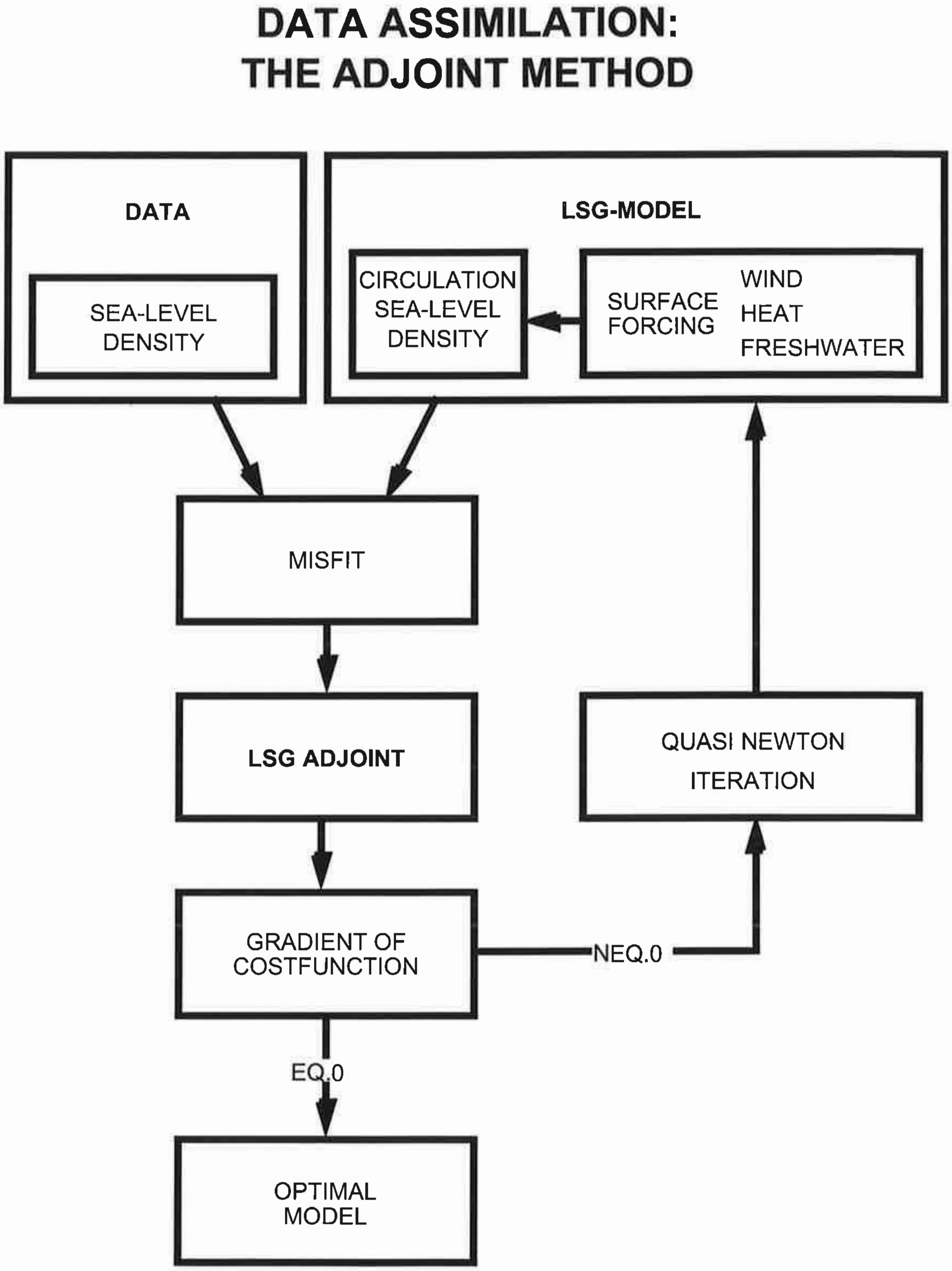
$$y^p = x^p - x_0^p$$

weighed by the covariance matrix

$$X_{pq} =< \delta x_p \delta x_q >$$

of the a priori assigned control uncertainty δx_p. In the present application only the variances of data and control parameters will be used and the off-diagonal elements of these covariance matrices are assumed to vanish. Optimal values for the control variables

Fig. 2: Adjoint assimilation with GOAS/LSG. Flow chart of cost gradient minimisation.



are now determined in the minimum of the cost function given by the requirement that its gradient

$$\partial_p J(x) = (\partial_p m_M) C^{MN} Y_N(x) + X_{pq}\, y^q \tag{1}$$

with respect to the control variables y^p vanishes. The matrix $\partial_p m_M$ is called the adjoint model and due to the structure of the first term on the r.h.s. of (1) adjoint assimilation is often considered as the temporally backward integration of the adjoint model forced by the model-data misfit. The second term represents variations of the control parameters starting from their first guess. During the minimisation of the cost function, contributions from this term will generally increase. For well posed problems this increase does not affect the overall decrease of the cost function.

The key ingredient for this approach to optimisation is the adjoint model. Generally, this component can be obtained from the continuous model equations, their discretised version or directly from the model code. In either case, the model can be considered as a chain of algorithms - in particular as a chain of commands in case of the numerical model code - which maps the control variables into the model output and through (1) ultimately into the cost function. According to the chain rule of differentiation, the gradient of the cost function with respect to the control variables is obtained by differentiating each member of this chain with respect to its argument. On the level of the numerical code, this allows the fairly transparent adjoint code construction even for complex models. The adjoint code is obtained from the model code as line-by-line construction of adjoint commands systematically applying elementary "recipes" of adjoint code construction (Giering and Kaminsky, 1997). In this manner, the adjoint code of the Hamburg LSG model has been derived (Giering, 1996). Moreover, the simplicity of these recipes permits coding the adjoint code construction itself: corresponding software is now available as Tangent Linear and Adjoint Model Compiler (TAMC) (Giering, 1996b). This adjoint model compiler has been applied in the adjoint code construction for the higher resolving GOAS/HOPE version (Oldenburgh et al., 1997). A particular advantage of this approach is its flexibility with respect to changes in the model and the inclusion of further model control parameters. With the help of the TAMC it is possible to update the adjoint model quick and efficiently.

A schematic representation of the course of the adjoint assimilation is shown in Fig.2. Data and model-output form the misfit which forces the "backward integration" of the adjoint model. The result of this integration is the gradient of the cost function with respect to the control variables. If this gradient vanishes, the optimal solution has been obtained. Otherwise, a quasi-Newtonian iteration procedure defines improved values for

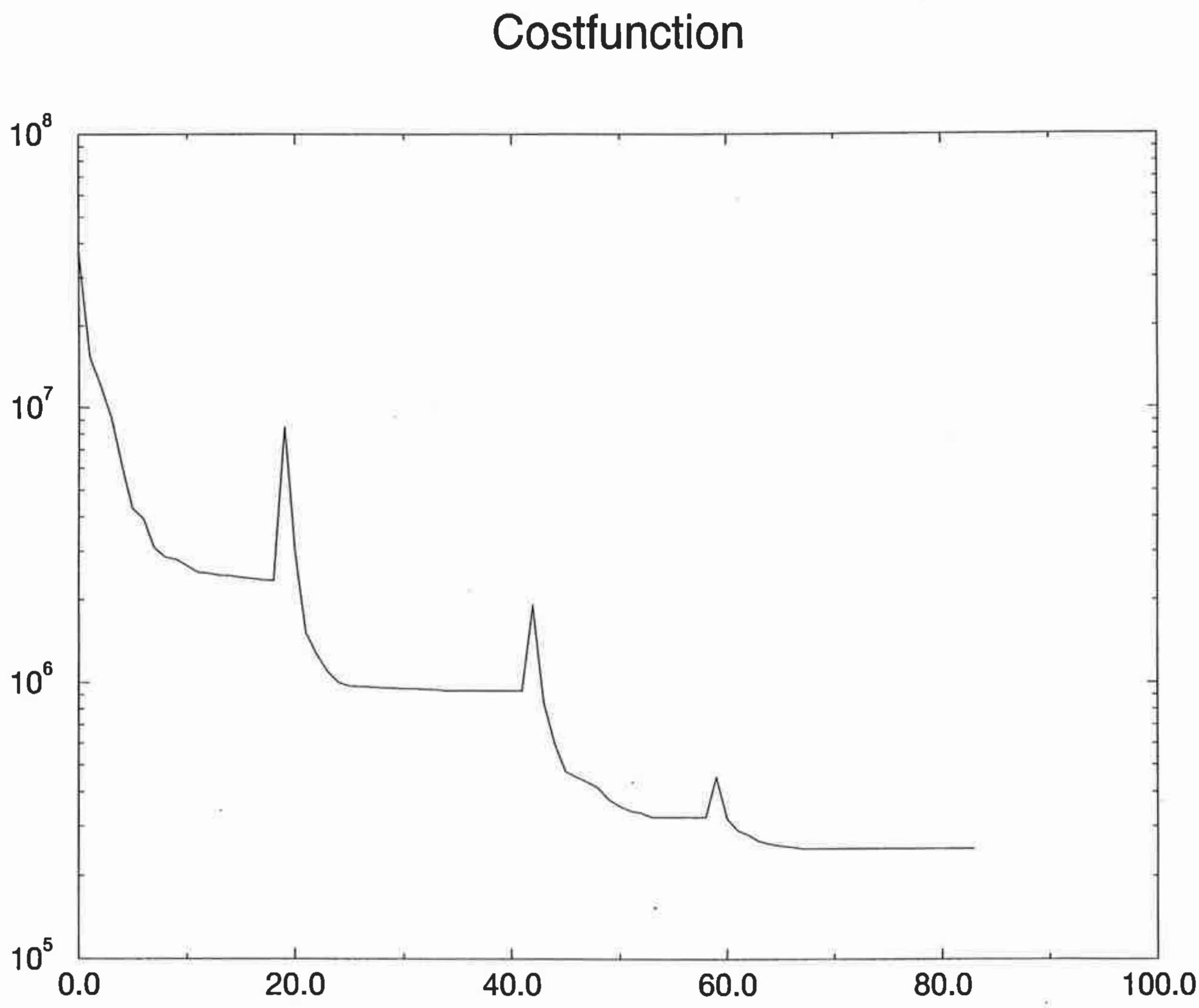


Fig.3: Costs as function of iteration. Spikes between assimilation cycles indicate cost increase during forward integration without assimilation.

the control parameters, and the loop is restarted until a minimum of the cost function is reached. In practice, a zero of the cost gradient is generally not found. Rather, the cost function approaches asymptotically a value which is significantly smaller than its initial value, indicating that there are no major gradients in the phase space vicinty of this model state. While this suggests that a global minimum may not have been found, the corresponding model state will here be considered as an acceptable representation of the optimal solution. Primarily, this is justified by the significantly higher data similarity of the corresponding model state.

State estimation in this framework exhibits four major benefits. First, the optimisation procedure recognises poor data quality and provides via the model dynamics a quality check for the observations. Secondly, the model substitutes missing data and thus interpolates data gaps with dynamical consistency. Thirdly, the information of physically, temporally or spatially restricted data is dynamically extrapolated onto the entire model domain. And finally, the model is fine-tuned to operate in the vicinity of the observations.

The data base for the present state estimation are the raw station temperature and salinity data of the World Ocean Atlas (Levitus et al., 1994) for the period from 1970 to 1993. These data are discretised on a $2^\circ \times 2^\circ$ grid with 29 levels in the vertical and monthly means are taken at each data grid point. The monthly mean temperature- and salinity-profiles are checked for static stability and discarded if unstable. Additional filtering or smoothing is not applied. These data provide a statically stable, mean annual cycle of the global oceanic buoyancy field at a time-step of one month. Furthermore, data-variances are calculated from the raw data and the Atlas-average is substituted wherever only one datum is available. Model-data misfit and the cost function are calculated by projection of the model hydrography onto the data grid to minimise the corruption of data information in the essential link of model and data.

3.) Hydrography Assimilation

The present study assimilates hydrographic data into the model under variation of the surface forcing. The task is to find surface buoyancy fluxes and wind stresses such that the model dynamics yield a model buoyancy field in close vicinity of the data. To this end a fluid particle has to explore the dynamical consequences of a given surface forcing over the entire conveyor belt. Basically, this requires assimilation times of the order of the ocean's turnover time, i.e. several centuries, and storage of the model's phase space trajectory for this period. Even for a model numerically as efficient as the Hamburg

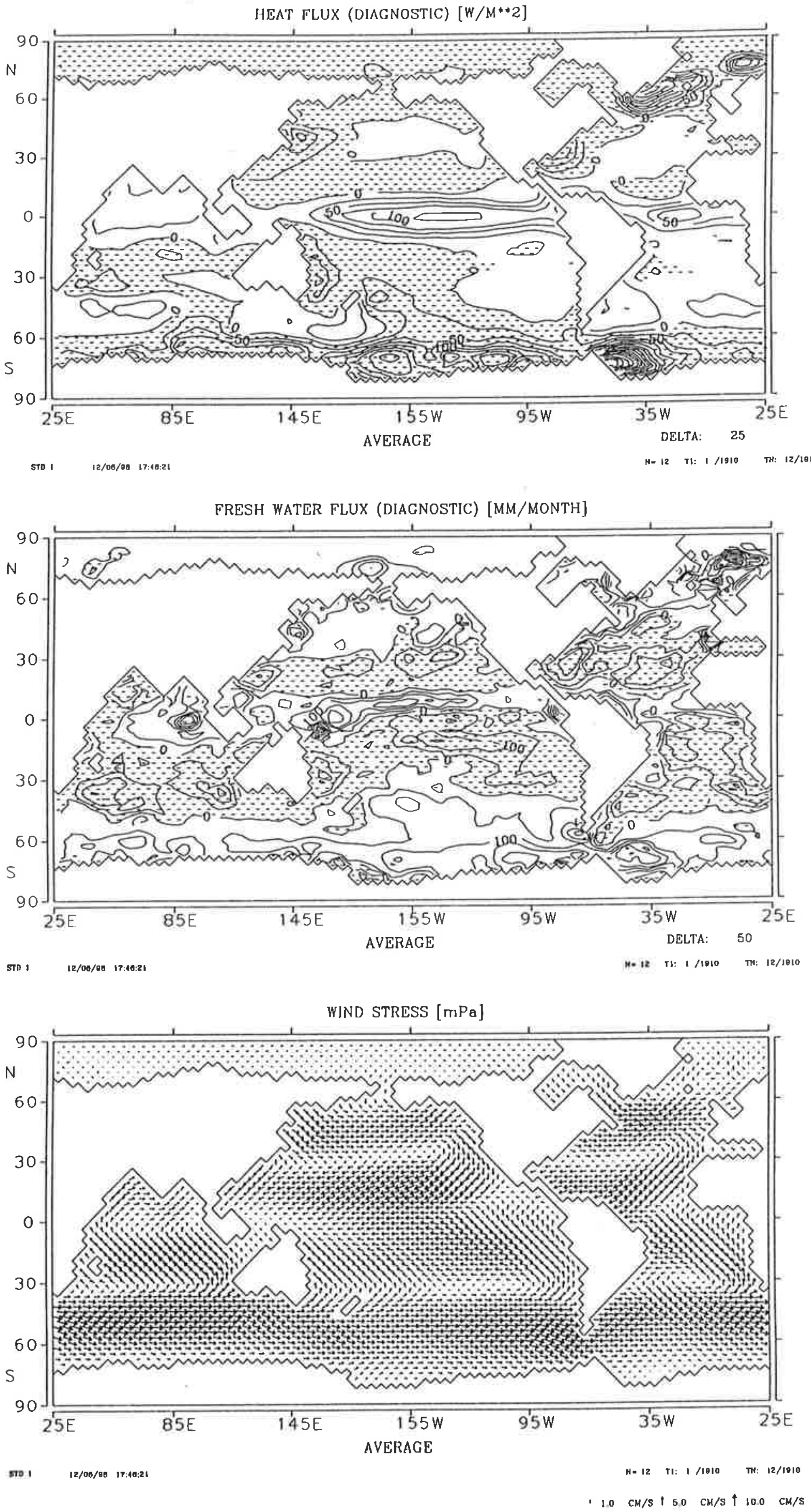


Fig.4: Surface forcing of optimal solution. Top: Heat Flux. Middle: Freshwater Flux. Bottom: Wind Stress.

LSG Model storage requirements of this magnitude are prohibitive. With the available computer resources assimilation times of the order of 10 years are practical.

For assimilation times of the order of a decade only the uppermost ocean layers respond directly to varied surface forcing. If in addition deviations from cyclostationarity are penalised, the optimal solution of the assimilation problem will remain in close vicinity to the first guess, with only a minor decrease of the cost function. To facilitate greater flexibility for the phase space exploration, the trend penalty is thus dropped and non-cyclostationary model states are accepted as optimal solution. This leads indeed to a more pronounced variation of control parameters, accompanied by a significant decrease in costs. To obtain a cyclostationary estimate of the ocean circulation, the LSG Model is subsequently integrated forward in time for a period of 1000 years using the surface forcing of the optimal solution. After this integration the model is essentially cyclostationary but the cost function has increased again. However, this increase remains well below the first guess and below values which are typically obtained for assimilation with trend penalty. This behaviour of the cost function is shown in Fig.3 for four assimilation cycles. It is also seen from Fig.3 that during forward integrations of successive cyles the cost increase itself decreases. In the present case, additional cycles do not lead to further improvement of the cost function. The cyclostationary model state after 4 assimilation cycles is taken here as the optimal solution.

Moreover, with decadal assimilation times wind- and buoyancy-driven dynamics compete to establish data-contraints in the upper ocean, particularly so since the time-scale of the wind-driven circulation on basin scale is just of the order of decades. At such assimilation periods the system is thus unable to recognise the buoyancy dominance on longer time-scales and non-cyclostationary "optimised" surface wind stresses appear unrealistically stochastic. This problem vanishes if the model buoyancy field is sufficiently close to the data initially. To accomodate the physical time-scale separation of the wind- and buoyancy-driven circulation, the first assimilation cycle varies surface buoyancy fluxes only and brings the buoyancy field in closer vicinity to the data. After this preliminary assimilation, the wind is included into the control parameters for the remaining 3 cycles. The result of this assimilation run is discussed in the following.

Fig.4 shows the annual mean of the surface heat- and freshwater-fluxes and the surface wind stress for the optimal solution. These parameters reflect primarily the variation of the control parameters necessary to obtain the optimal solution. Changes relative to the first guess are generally small and do not exhibit a pronounced pattern. Similar to the first guess, the optimal forcing is well compatible with current direct observations of air-

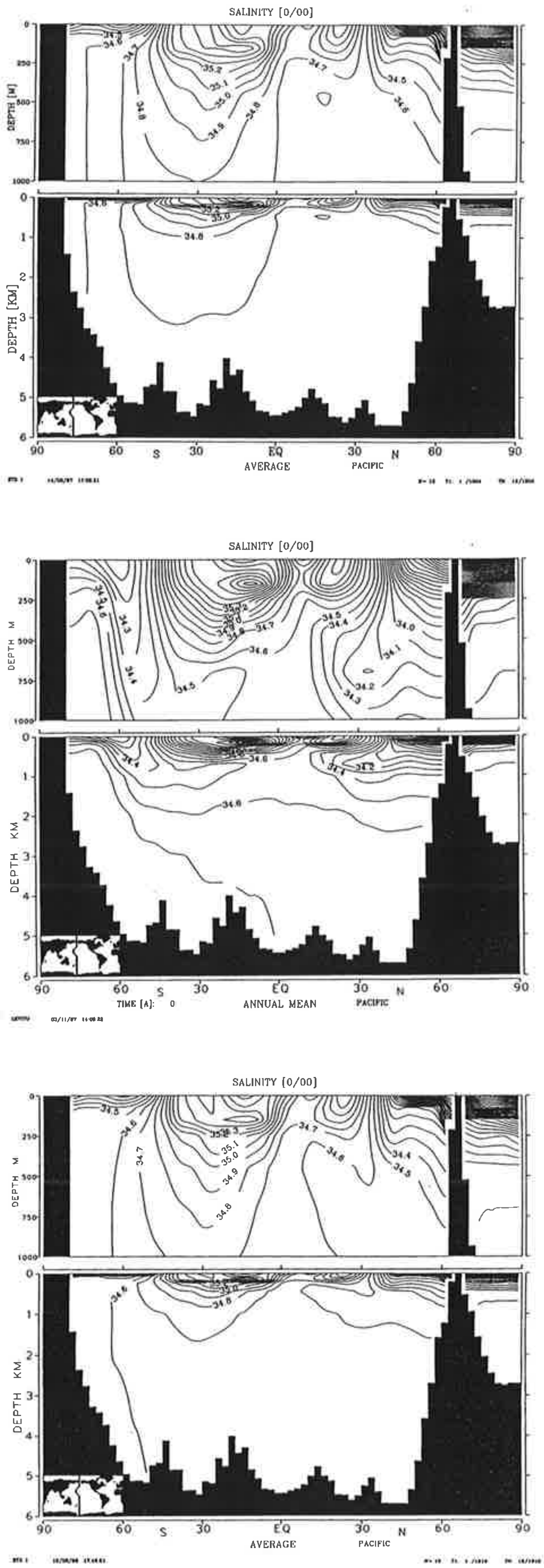


Fig.5: Annual mean salinity section in the Pacific. Top: Simulation. Middle: WOA. Bottom: Optimal Solution.

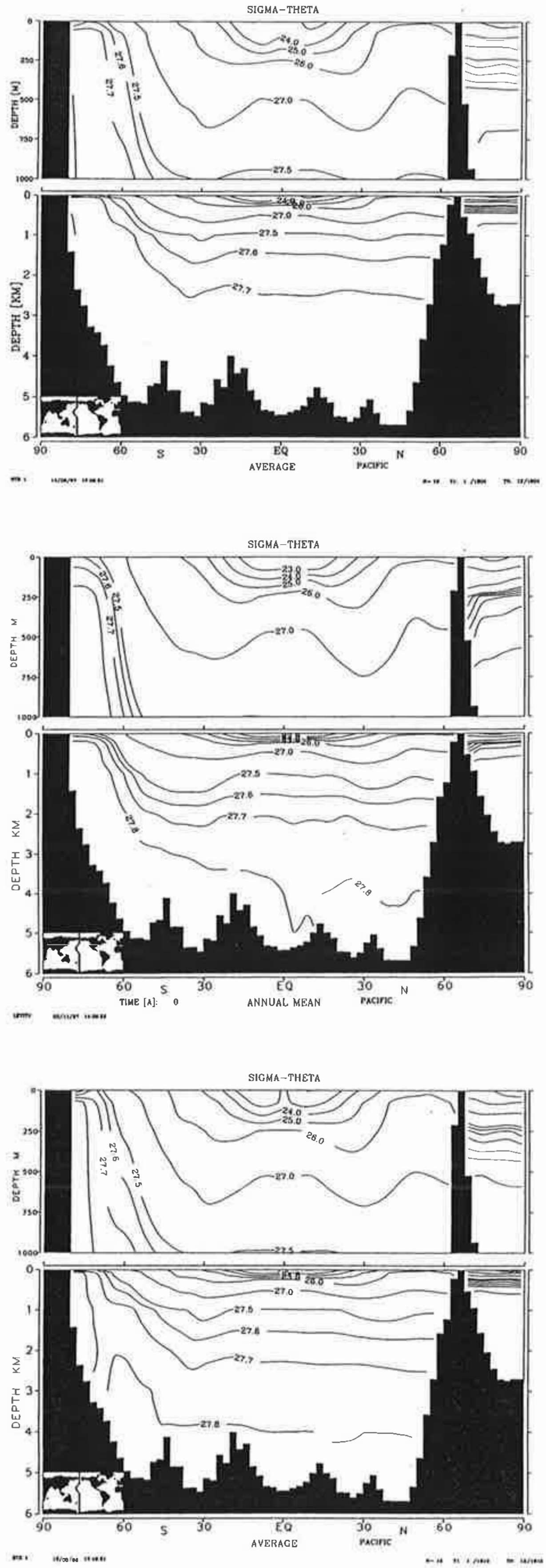


Fig.6: Annual mean density (σ_Θ) section in the Pacific. Top: Simulation. Middle: WOA. Bottom: Optimal Solution.

sea exchange processes. As a detail of the annual mean surface heat flux (Fig.4a) it may be noted that the model is able to reproduce a fairly localised region of positive heat flux off Newfoundland which is well known from observations. Strictly stationary solutions of coarse circulation models are known to have difficulties in this region (Schiller, 1996). The general understanding of this problem points to the limited capacity of coarse models to represent strong gradients characterising the ocean buoyancy field in this region. The present result suggests rather that the resolution of seasonal variations - albeit in the framework of a coarse model - suffices to capture this feature. It is furthermore noted that changes in the wind stress pattern (Fig.4c) are minimal and the major variation with respect to the first guess is a quantitative increase in windspeeds at high southern latitudes. The cyclostationary model circulation to be discussed below corresponds directly to the forcing of Fig.4: a specific coarse-model parametrisation of surface heat fluxes in terms of cold air advection, as sometimes used in conjunction with the LSG Model, is not employed.

Fig.5 shows a salinity cross section in the Pacific for the model simulation (Fig.5a), the observations (Fig.5b) and the optimal solution of the assimilation (Fig.5c). Overall, simulated and observed salinities are quantitatively comparable assuming a value of approximately 34.7 psu in the abyssal Pacific. With respect to the pattern there are two major differences. For one, particularly in the Southern Pacific simulated saline surface waters penetrate to greater depths than observed. Secondly, the observed salinity minimum at intermediate depths ($\sim 1000m$) is absent from the simulation. The corresponding salinity section of the optimal solution (Fig.5c) demonstrates that the assimilation indeed conveys these large-scale features of the data at least partially to the model. In better agreement with the data, the model thermocline is now shallower than in the simulation, and the intermediate salinity minimum is clearly represented in the North Pacific. In the South the salinity minimum remains absent. Here, the number of available data is considerably smaller than in the Northern Hemisphere, so that the the global cost function is less sensitve to improvements in this region. In principal, GOAS permits a remedy of this hemispheric asymmetry by assigning artificially large weights to Southern salinity observations. However, artificial salinity weights without corresponding temperature modifications will generally affect the model density unfavourably, and hence the pressure forces and ultimately the model circulation. Temperature modifications corresponding to an artificial salinity weight are essentially determined by the salinity-temperature covarianes of the data. In the present application, these covariances have been neglected and are thus not available. An alternative is the incorporation of further salinity data, as

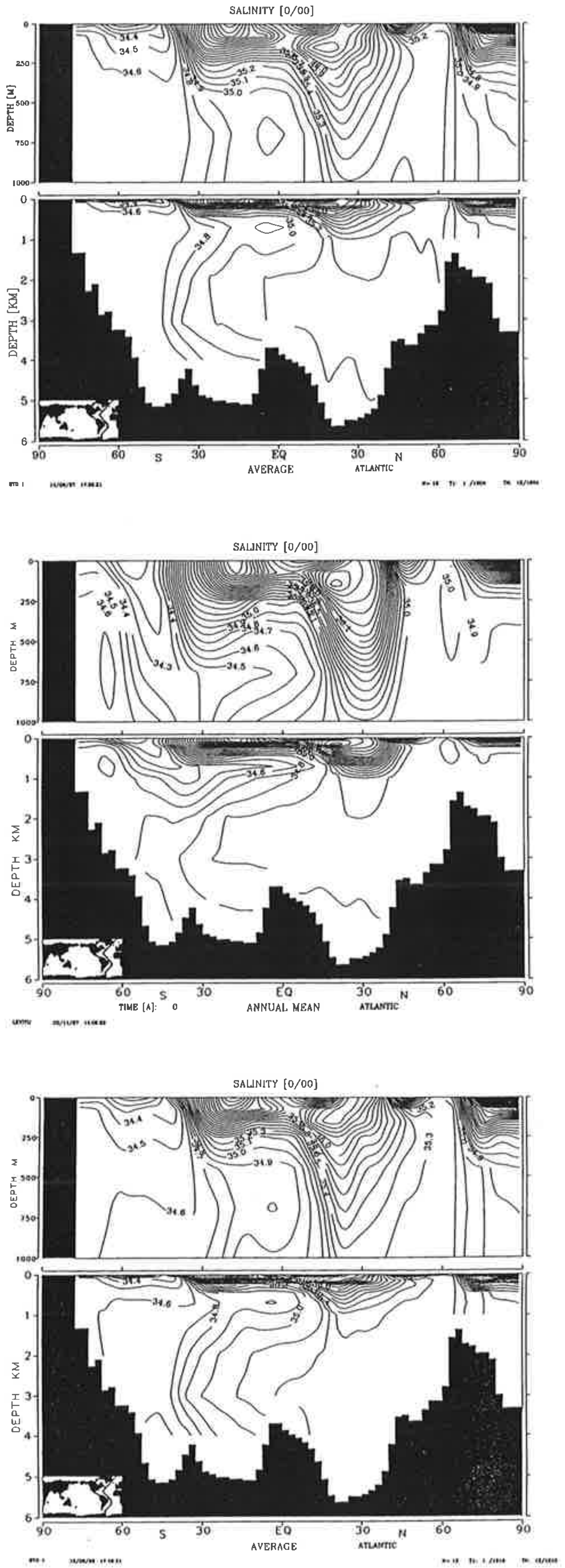


Fig.7: Annual mean salinity section in the Atlantic. Top: Simulation. Middle: WOA. Bottom: Optimal Solution.

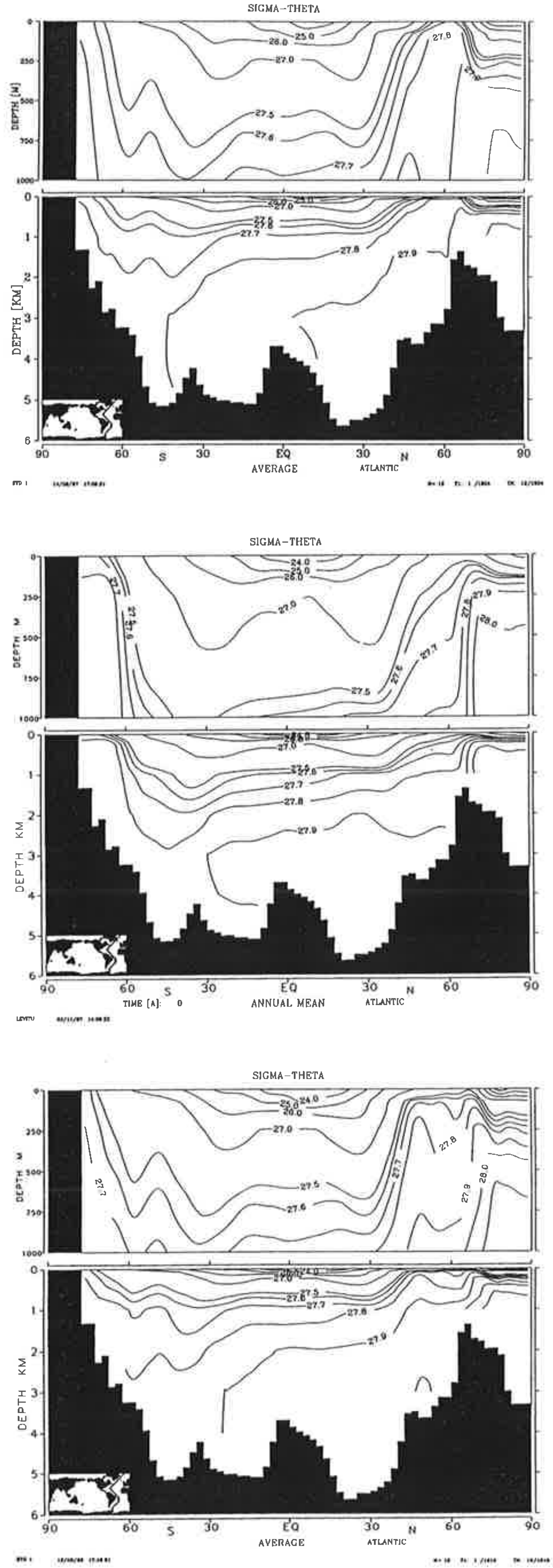


Fig.8: Annual mean density (σ_Θ) section in the Atlantic. Top: Simulation. Middle: WOA. Bottom: Optimal Solution.

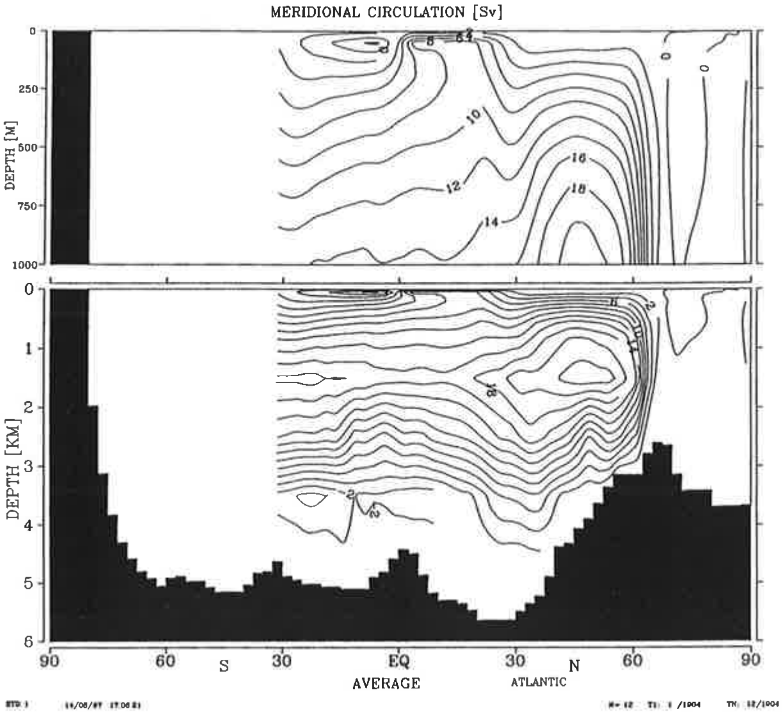
provided for example by the WOCE Hydrographic Program - Special Analysis Center (1998). Both approaches will be considered in the future. It may furthermore be noted that the dynamics and thermodynamics of these fresher intermediate waters are not well understood at this time.

Nevertheless, even in the present framework the hydrography assimilation clearly improves the model density, not least in the Southern Pacific. This is seen from Fig.6, showing a Pacific section of sigma-theta for the simulation (Fig.6a), the Levitus data (Fig.6b) and the optimal solution (Fig.6c). The simulation (Fig.6a) does not produce Antarctic Bottom Water heavier than $\sigma_\Theta = 27.8$, which is clearly present in the observations (Fig.6b). In the optimal solution (Fig.6c), however, this mass of Bottom Water is well represented in the model, originating near Antarctica in agreement with the data. It is emphasised that this model improvement has to be considered primarily a result of model dynamics rather than a direct effect of the assimilation. At decadal assimilation times, the direct influence of abyssal data on the optimisation is small. However, since this water is generated near the surface, the assimilation is able to set the corresponding conditions in the model and thus transfer the surface-data information dynamically to the abyss. Moreover, it is mentioned that these considerable differences in the density fields of the first guess and the optimal solution are due to essentially minor changes in the surface forcing (Fig.4).

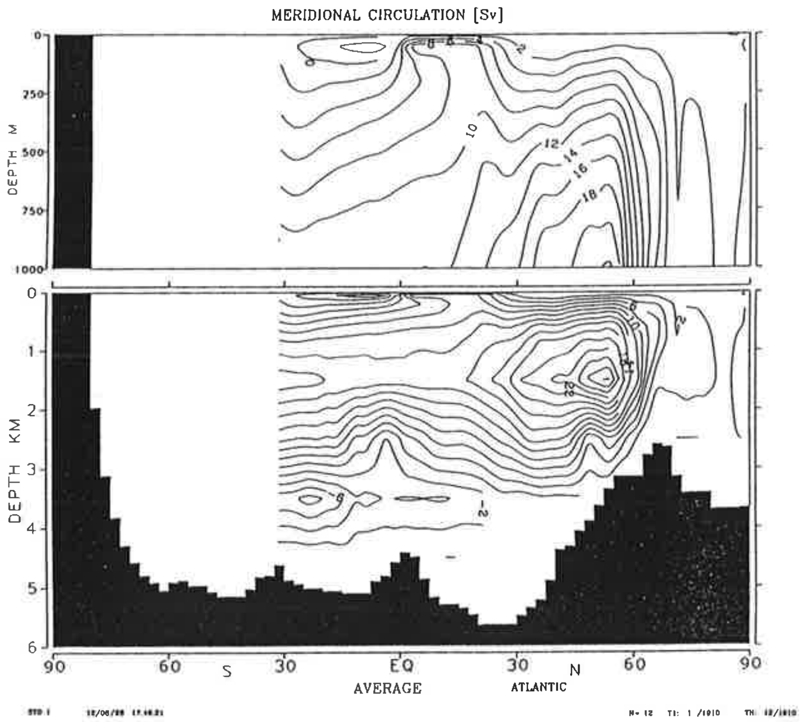
Fig.7 represents a salinity cross section in the Atlantic, again for simulation (Fig7.a), data (Fig.7b) and for the optimal solution (Fig.7c). As for the Pacific, simulated and observed salinities are quantitatively comparable, and the simulation resembles the data with respect to major large-scale features. The dominant result of the assimilation is here also the improved representation of intermediate fresher water mainly in the South Atlantic.

The corresponding density field sigma-theta is shown in Fig.8. The most significant feature in the data (Fig.8b) is the "nose" of North Atlantic Deep Water with $\sigma_\Theta \geq 27.9$. In the simulation (Fig.8a) this is only partially captured and less pronounced in the assimilation (Fig.8c).On the other hand, the assimilation clearly improves on the level of the $\sigma_\Theta = 27.8$ isopycnal, which rises again in the South Atlantic.

Fig.9 shows the meridional circulation of the North Atlantic before (Fig.9a) and after (Fig.9b) assimilation. It is seen that the North Atlantic overturning circulation has slightly intensified relative to the simulation. This is due primarily to enhanced contributions from the wind-driven circulation in this region of the North Atlantic. On the other hand, there are now only 14 Sverdrups leaving the domain shown while there were 18 Sverdrups in



a)Simulation



b) Optimal Solution

Fig.9: Annual mean meridional circulation in the Atlantic.

the simulation. This is a well-known feature of coarse-resolution assimilation: at coarse resolution data-like buoyancy-fields generally exhibit weak gradients and thus result only in weak geostrophic mass transports. Nevertheless, for the North Atlantic the major change due to the assimilation is the enhanced presence of Antarctic Bottom Water, with 8 Sverdrups for the optimal solution compared to 4 Sverdrups in the simulation, and the further penetration of this water mass into the Northern Hemisphere. It will have to be evaluated in detail if this circulation overcomes the simulation-data mismatches shown for instance in Fig.1. However, it is already obvious from Fig.9 that the circulation of the optimal solution wil improve the agreement of model and data such as those shown in Fig.1a.

The meridonal heat transport for the annual mean circulation is shown in Fig.10. Vanishing of the global heat transport at both the northern and the southern boundary is primarily a measure for the stationarity of the annual mean circulation and is seen to be well satisfied. However, with a maximum of less than 1 Petawatt for the North Atlantic, poleward heat transports remain on the lower end of observational estimates (Isemer et al., 1989).

Assimilation of hydrographic observations into the Hamburg LSG Model clearly improves the model's water mass inventory. These improvements are by no means exclusively detrimental to the model circulation. Overall, geostrophic transports are indeed weaker than suggested by other observational sources. At the same time, however, model dynamics are sufficiently realistic to generate and maintain major large-scale features of the observed buoyancy field. Noteworthy in this respect are the realistic model seasonality, an improved wind-driven circulation, and a more realistic buoyancy field in the upper and intermediate ocean.

4.) Conclusion

The coarse version of GOAS combines information from data sources with the dynamics of the Hamburg LSG Model for an estimate of the mean cyclostationary global ocean circulation. With the adjoint assimilation method the information of physically, geographically and temporally restricted data is dynamically extrapolated onto the entire system. The assimilation of hydrographic data yields a surface forcing which improves on the model representation of the generation, distribution and age of water masses. This forcing is compatible with contemporary observations of air-sea exchange processes and does not invoke special coarse-model parametrisations like cold air advection. The re-

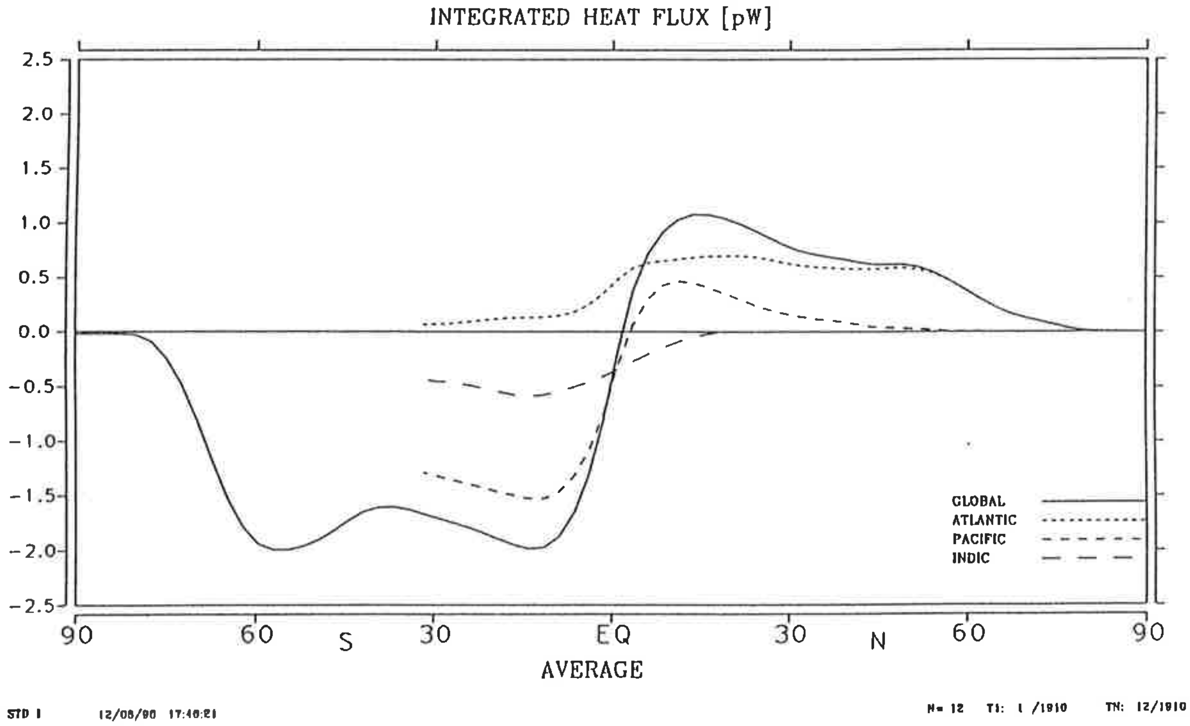


Fig.10: Annual mean heat transports for the optimal solution.

dundancy of cold air advection alone has to be considered as an improvement in model performance.

Optimisation of the global cost function by integration of the adjoint model poses high storage requirements. For the coarse version of GOAS, this can partially be compensated by shorter assimilation times. At decadal assimilation times upper ocean data information dominates the optimisation of the cost function. Nevertheless, the optimal solution also exhibits a significantly more data-like abyssal ocean. This is due to the fact that the ocean is forced at the surface and it is here that the conditions for water mass formation are set. Once these conditions are conveyed to the model by assimilation, it will generate these water masses in accordance with its dynamics. The present results demonstrate that the dynamics of the LSG Model are realistic in producing a water mass distribution in the deep ocean which is compatible with the data. With the presence of these water masses the optimal solution differs considerably from the first guess. This in turn provides a measure for the flexibility of GOAS to explore the model's phase space.

The partial success of incorporating previously lacking water masses into this model depends to a large extent on the resolution of the seasonal cycle. On both hemispheres, water mass formation is a process of pronounced seasonality which is difficult to accomodate in a strictly stationary model. With its cyclostationarity, the optimal LSG solution is able to account for this periodicity. In view of the atmospheric input of geochemical and biological tracers, the seasonality of the involved model features warrants further investigation.

With respect to the wind-driven circulation, assimilation results are ambivalent. Unquestionably, there is considerable room for improvement in the present framework. On the other hand, a realistic representation of buoyancy fields at coarse spatial resolution generally exhibits weak gradients and thus induces only weak geostrophic mass transports. For associated heat transports it is an additonally complicating factor that much of the warm water is concentrated near the surface. At low vertical model resolution these contributions tend to be underestimated. These inherent restrictions of coarse resolution models have been pointed out previously by Toggweiler et al. (1989) and are also emphasized by Marotzke and Willebrand (1996). Two approaches are considered to overcome these limitations in the coarse-model framework. For one, an increase in vertical resolution will improve the representation of the vertical distribution of heat in the ocean. Secondly, a special coarse-model parametrisation of subscale transports may improve the overall transports of heat and fresh water.

What can be achieved? With an improved wind-driven circulation and an extended data-base also including data-covariances, the coarse version of GOAS is expected to yield a complete, dynamically maintained water mass inventory of the global ocean. In this respect, model dynamics are not unrealistic and the phase space exploration by the adjoint model is sufficiently flexible. Whether transports can be improved to a degree that they are critically comparable with information from other sources remains to be seen. But with characteristics as summarized here, the coarse version of GOAS is a reliable and efficient tool for the study of substance inventories of the global ocean which are central to the issue of climate change.

Acknowledgement

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