

Supplementary Information

Ocean circulation reconstructions from ϵ_{Nd} : A model-based feasibility study

T. Friedrich¹, A. Timmermann¹, T. Stichel², and K. Pahnke³

¹ International Pacific Research Center, School of Ocean and Earth Sciences and Technology, University of Hawaii at Manoa, East-West Rd. 1680, POST Bldg, Honolulu, HI 96822, USA

² Department of Geology and Geophysics, School of Ocean and Earth Sciences and Technology, University of Hawaii at Manoa, East-West Rd. 1680, POST Bldg, Honolulu, HI 96822, USA

³ Institute for Chemistry and Biology of the Marine Environment, Carl von Ossietzky University, Carl-von-Ossietzky-Strasse 9-11, D-26129, Oldenburg, Germany

1 Model Configuration

To study the response of ϵ_{Nd} to changes in ocean circulation we conducted a series of idealized freshwater perturbation experiments under preindustrial climate conditions using the atmosphere-ocean-sea ice-carbon cycle model LOVECLIM [Goosse *et al.*, 2010]. LOVECLIM is based on the ECBilt-CLIO Earth system model of intermediate complexity extended by vegetation and marine carbon cycle components. The marine carbon cycle component has been deactivated for our study.

The sea ice-ocean component (CLIO) [Goosse *et al.*, 1999] of LOVECLIM consists of a primitive equation level model with a horizontal resolution of $3^\circ \times 3^\circ$ and 20 levels in the vertical with thicknesses ranging from 10 m to ~ 700 m. CLIO uses a free surface and is coupled to a thermodynamic-dynamic sea ice model. Mixing along isopycnals, the effect of mesoscale eddies on transports and mixing as well as downsloping currents at the bottom of continental shelves are parametrized (Goosse *et al.*, 2010). The strength of vertical mixing is coupled to the roughness of bottom topography [Declodt *et al.*, 2010] as presented in Friedrich *et al.* [2011] .

The atmosphere component (ECBilt) is a spectral T21 model, based on quasigeostrophic equations with 3 vertical levels and a horizontal resolution of about $5.625^\circ \times 5.625^\circ$. Ageostrophic forcing terms are estimated from the vertical motion field and added to the prognostic vorticity equation and thermodynamic equation. Diabatic heating due to radiative fluxes, the release of latent heat and the exchange of sensible heat with the surface are parametrized. The seasonally and spatially varying cloud cover climatology is prescribed in ECBilt. It should be noted that an interactive atmospheric component is crucial for the simulation of large-scale ocean circulation changes. Some of the major climatic feedbacks associated with AMOC reductions require atmosphere-ocean-sea ice coupling [Krebs and Timmermann, 2007] .

The ocean, atmosphere and sea ice component of the ECBilt-CLIO model are coupled by exchange of momentum, heat and freshwater fluxes. The hydrological cycle over land is closed by a bucket model for soil moisture and a simple river runoff scheme. Due to the weakness of the tropical trade winds simulated by the model, the moisture transport from the Atlantic to the Pacific is too weak. To generate an Atlantic salty enough for a stable AMOC, a freshwater flux adjustment is prescribed which redirects snow- and rainfall over the Atlantic to the North Pacific.

Details on the performance of LOVECLIM under different climate conditions can be found in Rennsen *et al.* [2002], Justino *et al.* [2005], Menviel *et al.* [2008a], Timmermann *et al.* [2009], Goosse *et al.* [2010] and Friedrich *et al.* [2011] .

2 Non-parametric regression methods

The ACE algorithm is a multiple nonparametric regression based on an iterative procedure to define optimal transformations (f) between the p-dimensional data vector (X_1, X_2, \dots, X_p) and the response

Y so that the mismatch (e) is minimized:

$$Y = \sum_{i=1}^p f_i(X_i) + e \quad (1)$$

In our case the respective simulated overturning streamfunction (Ψ^j) is the target value and the simulated ϵ_{Nd} data at the core locations in Table 1 are the predictors:

$$\Psi^j = \sum_{i=1}^p f_i^j(\epsilon_{Nd}^i) \quad (2)$$

with ϵ_{Nd}^i being the i-th simulated ϵ_{Nd} time series at one of the core locations. Details on the ACE algorithm can be found in *Breiman and Friedman (1985)* and *Timmermann et al. (2001)*.

A SOM is a subtype of artificial neural networks that works as an associative memory by recognizing and exploiting relationships in the data. Here, the SOM is composed of nodes or neurons which are arranged in a two-dimensional mesh and performs a non-linear projection from the high-dimensional input data onto this two-dimensional grid. During the self-organizing process the training data (in our case simulated ϵ_{Nd} time series at the core locations) are presented to this mesh. The Euclidian distance between the input and the value of each node is calculated and the “winning neuron” is defined by the shortest distance. The value of the “winning neuron” and those of its neighborhood are then updated by adjusting them towards the training vector whereas the magnitude of adjustment is defined by a “learning rate”. The neighborhood radius and the “learning rate” are decreasing over the course of the training process. After several learning cycles the nodes become organized in a map that contains the topographic features of the input data. After the training process the SOM is labeled. A target value (here the respective simulated overturning streamfunction Ψ) is assigned to every node following a minimum distance criterion between the SOM and the simulated vector $(\epsilon_{Nd}^{i,1}, \epsilon_{Nd}^{i,2}, \dots, \epsilon_{Nd}^{i,p}, \Psi_i)$ with p being the number of cores used for the MOC reconstruction and i being the time step of the simulated data. Details on SOMs can be found in *Kohonen (1982)* and *Friedrich and Oeschlies (2009a,b)*.

It should be noted that our MOC-reconstruction from simulated ϵ_{Nd} values is based on the simplifying assumption that transport changes are the major driver for variations in watermass distributions and thus ϵ_{Nd} anomalies. The fact that watermass volumes can also be altered through changes in upwelling and mixing is neglected here.

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Core name	AMOC variability		SOMOC variability	
	AMOC \pm^m (millennial-scale) correlation/lag [yr]	AMOC \pm^c (centennial-scale) correlation/lag [yr]	SOMOC \pm^m (millennial-scale) correlation/lag [yr]	SOMOC \pm^c (centennial-scale) correlation/lag [yr]
North Atlantic:				
ODP-980	0.96 / 70	0.87 / 80	0.76 / 50	0.86 / 40
MD01-2454G	0.83 / 10	0.81 / 10	0.83 / 290	0.80 / 40
BOFS 8K	0.96 / 200	0.80 / 100	0.88 / 400	0.66 / 110
OCE326-GGC6 (ODP-1063)	-0.98 / 150	-0.92 / 90	-0.81 / 170	-0.95 / 80
12JPC	-0.99 / 140	-0.95 / 90	-0.83 / 180	-0.94 / 80
KNR166-2-26JPC	-0.98 / 40	-0.98 / 10	-0.41 / 820	-0.30 / 10
KNR166-2-31JPC	-0.97 / 40	-0.97 / 20	-0.33 / 790	-0.47 / 10
MD99-2198	-0.87 / 120	-0.67 / 60	-0.77 / 10	-0.85 / 20
VM12-107	-0.85 / 150	-0.92 / 30	-0.90 / 30	-0.94 / 30
KNR197-3-25GGC	-0.20 / 40	-0.59 / 10	0.93 / 10	0.97 / 10
KNR197-3-46CDH	-0.95 / 90	-0.89 / 40	-0.83 / 20	-0.90 / 20
KNR197-3-9GGC	-0.94 / 120	-0.89 / 50	-0.86 / 20	-0.88 / 20
South Atlantic:				
KNR159-5-36GGC	-0.51 / 290	0.83 / 80	0.94 / 10	0.94 / 20
RC11-83	-0.98 / 190	-0.84 / 70	-0.77 / 770	-0.91 / 60
TNO57-21	-0.98 / 190	-0.86 / 70	-0.77 / 770	-0.91 / 60
MD07-3076	-0.98 / 230	-0.88 / 120	-0.84 / 1000	-0.94 / 50
North Pacific:				
BOW-8A	-0.94 / 490	-0.68 / 200	0.91 / 170	0.77 / 60
MV99-MC19/ GC31/PC08	0.59 / 300	-0.85 / 25	-0.93 / 30	-0.95 / 20
South Pacific				
ODP-1123	-0.98 / 50	-0.82 / 70	-0.75 / 960	-0.66 / 100
CHAT3K	0.95 / 20	0.92 / 50	0.87 / 80	0.94 / 10
CHAT5K	0.91 / 20	0.94 / 50	0.90 / 40	0.95 / 10
CHAT10K	-0.98 / 60	-0.85 / 70	0.95 / 10	0.86 / 0
CHAT16K	-0.95 / 370	-0.81 / 100	0.26 / 200	0.61 / 50
Indian Ocean:				
SK129CR2	-0.97 / 550	0.38 / 90	-0.67 / 840	-0.95 / 80

Supplementary Table 1. Name of cores, correlation and lag for maximum of explained variance derived from lagged correlation between simulated ϵ_{Nd} and simulated MOC-indices at the model's grid point corresponding to the core location. See column header for experiments. Please note that the two core locations OCE326-GGC6 and ODP1063 are identical on the model grid. See also Figure 1 and Table 1 of the main manuscript for core locations and Figure 4h-k for MOC-indices of the different experiments.