# Detecting the anthropogenic influences on recent changes in ocean carbon uptake

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## 1- Models and simulations description

### 1-1- The reconstructions: RECCAP simulations

The pseudo-observations or reconstructions datasets have been provided by the RECCAP project [*Canadell et al.*, 2011]. In this project, reconstructions of the evolution of the carbon uptake by the oceans have been performed by seven ocean biogeochemical models forced by NCEP atmospheric reanalyses [*Kalnay et al.*, 1996] from 1959 to 2005. These seven models are listed in Table S1.

| Model name | Available variables | References |
|---|---|---|
| MICOM-HAMOCCv1 | $fgCO_2$, $pCO_2$ | [*Assmann et al.*, 2010] |
| CCSM-BOGCM | $fgCO_2$, $pCO_2$ | [*Matear and Lenton*, 2008] |
| CCSM-BEC | $fgCO_2$, $pCO_2$ | [*Doney et al.*, 2009] |
| CCSM-ETHk15 | $fgCO_2$, $pCO_2$ | [*Graven et al.*, 2012] |
| CCSM-ETHk19 | $fgCO_2$, $pCO_2$ | [*Graven et al.*, 2012] |

| | | |
|---|---|---|
| NEMO-PISCES | $fgCO_2$ | [*Aumont and Bopp*, 2006] |
| NEMO-Planktom5 | $fgCO_2$, $pCO_2$ | [*Buitenhuis et al.*, 2010] |

**Table S1**: Ensembles of ocean biogeochemical models forced with atmospheric observations used as reconstructions of oceanic carbon uptake from 1959 to 2005. Simulated ocean carbon fluxes ($fgCO_2$) and partial pressure of $CO_2$ ($pCO_2$) used in this study are provided on the RECCAP website (http: //www.globalcarbonproject.org/reccap/products.htm) or the OCMIP5 website (http://ocmip5.ipsl.fr).

Trends estimated from these seven ocean biogeochemical models have been assessed in several studies combining atmospheric and ocean in situ data as well as reconstructions provided by inverse modeling [*Schuster et al.*, 2013; *Wanninkhof et al.*, 2013; *Tjiputra et al.*, 2014].

**1-2- The fingerprints simulations: CMIP5 simulations**

In this study, we have employed outputs from several Earth System Models that have contributed to CMIP5. The geochemical ensemble (GEO) gathers all of the available esmFixClim2 simulation of the CMIP5 database. In this kind of simulation, carbon dioxide is treated as a non-radiative gas implying only the geochemical response to rising $CO_2$ on marine biogeochemistry is considered. The climate ensemble (CLIM) gathers on the other hand all of the available esmFdbk2 simulation of the CMIP5 database. For these ensembles of simulations, the geochemical response of $CO_2$ is shunted down by fixing atmospheric $CO_2$ seen by biogeochemistry at its preindustrial level. The coupled ensemble (ALL) combines these two responses. It is composed by all of the available historical simulation of the CMIP5 database. The last ensemble gathers all of the preindustrial control simulation (piControl and esmControl) of the CMIP5 database. This dataset allows us to characterize the internal variability (IV). The number of models and their name are given in Table S2 for each ensemble of simulations.

| Name of CMIP5 simulations | piControl and esmControl | historical | esmFixClim2 | esmFdbk2 |
|---|---|---|---|---|
| Response induced on Ocean carbon uptake and abbreviation | Internal variability (**IV**) | Coupled (**ALL**) | Geochemical (**GEO**) | Climate (**CLIM**) |
| Number Of Models | 21 | 21 | 7 | 5 |
| CMIP5 Earth system models | bcc-csm1-1, bcc-csm1-1-m, CanESM2, CMCC-CESM, CNRM-CM5, inmcm4, IPSL-CM5A-LR, IPSL-CM5A-MR, IPSL-CM5B-LR, MIROC-ESM-CHEM, MIROC-ESM, HadGEM2-CC, HadGEM2-ES, MPI-ESM-LR, MPI-ESM-MR, GISS-E2-H-CC, GISS-E2-R-CC, NorESM1-ME, GFDL-ESM2G, GFDL-ESM2M, CESM1-BGC | bcc-csm1-1, bcc-csm1-1-m, CanESM2, CMCC-CESM, CNRM-CM5, inmcm4, IPSL-CM5A-LR, IPSL-CM5A-MR, IPSL-CM5B-LR, MIROC-ESM-CHEM, MIROC-ESM, HadGEM2-CC, HadGEM2-ES, MPI-ESM-LR, MPI-ESM-MR, GISS-E2-H-CC, GISS-E2-R-CC, NorESM1-ME, GFDL-ESM2G, GFDL-ESM2M, CESM1-BGC | bcc-csm1-1, CanESM2, IPSL-CM5A-LR, MIROC-ESM, HadGEM2-ES, GFDL-ESM2M, CESM1-BGC | bcc-csm1-1, CanESM2, IPSL-CM5A-LR, HadGEM2-ES, GFDL-ESM2M |

**Table S2**: Ensembles of Earth system models simulations used for evaluating the response to external forcings. The CMIP5 name of each ensemble, the number of runs available and the external forcings accounted for are specified for each ensemble.

## 2- Methods

### 2-1- Detection & Attribution algorithm

The method used in this study for climate change attribution is an adaptation of the regularized optimal fingerprint method detailed in [*Allen and Tett*, 1999; *Ribes et al.*, 2009; 2010]. State-of-the-art optimal fingerprints, first introduced by [*Allen and Tett*, 1999], have been largely used in the context of the IPCC. Optimal fingerprint methods consist in a generalized linear regression. It usually relies on a strong assumption considering that models represent accurately the responses to external forcings (i.e., the fingerprints). Here, the uncertainty related to the models response to an external forcing has been estimated from the simulated internal variability. In this framework, proposed by [*Ribes et al.*, 2009; 2010; 2013], best fit is estimated by minimizing "Total least squares" (TLS) of the statistical model detailed as follows:

$$Y = \sum_{i=1}^{N} \beta_i g_i + \varepsilon_Y \qquad (1)$$

$$\tilde{g}_i = g_i + \varepsilon_g \qquad (2)$$

where $Y$ are the observations, $g_i$ is the response of ocean carbon uptake to the i$^{th}$ external forcing, $\beta_i$ is an unknown scaling factor and $\varepsilon_Y$ denotes the internal climate variability. The response $\tilde{g}_i$ simulated by the various Earth System Models is composed by the "true" response $g_i$ —considered unknown— and a noise $\varepsilon_g$ corresponding to simulated internal variability.

Therefore, statistical inference performed with the model (1) requires additional assumptions with respect to the internal variability ($\varepsilon_Y$) and the uncertainties related to external forcing responses ($\varepsilon_g$). It is first assumed that $\varepsilon_Y$ follows a Gaussian distribution, with a covariance C. This matrix C is estimated from control simulations as in [*Ribes et al.*, 2009; 2010]. In this study, the covariance matrix C has been estimated from more than 13 000 years of control simulations.

### 2-2- Trends analysis

In this study, climate impacts include simultaneously the contribution of the natural variability (e.g., volcanoes, solar constant) and the contribution of the anthropogenic forcing (e.g., greenhouse gases, aerosols). The contribution of the natural variability has little consequences on the ocean carbon fluxes [*Tjiputra and Otterå*, 2011] compared to those of the anthropogenic forcings which induce substantial long-term changes [*Friedlingstein and Prentice*, 2010].

On this assumption, we have proceeded to an analysis of a long-term trend of each ensemble (RECCAP, ALL, GEO and CLIM) to identify the contribution of the anthropogenically-induced climate forcing on ocean carbon uptake.

We have computed linear long-term trend from the time series of ocean carbon uptake of each member of the four ensembles. Of these trends, we have estimated the probability density function (pdf) presented on the Figure 3 based on the assumption of a Gaussian distribution. The p-value (panel g of Figure 3) results from a consistency test comparing a set of trends, $y$, of a given ensemble to a reference distribution, $X$, as follows:

$$\frac{y - \bar{x}}{\sigma_x \sqrt{\frac{n+1}{n}}} \sim T_{n-1}$$

where $\bar{x}$ and $\sigma_x$ are the mean and standard deviation of the sample $X$.

## 3- Detection of the ALL forcing

In this section, we apply a 1-forcing D&A analysis, in order to estimate the anthropogenic influence (ALL forcing) from the RECCAP pseudo-observations. The analysis is based on the CMIP5 historical simulations multi-model mean, and the RECCAP multi-model mean. Figure S1 shows the scaling factors best estimated (diamond) and their associated 5%-95% confidence interval (90% significance level). p-values bracketed indicate if the linear fits performed with the TLS algorithm pass a residual consistency test (which consists in comparing the distribution of residuals of the fit to the distribution of the internal variability).

It appears that all scaling factors are significantly different from zero and positive, translating that the representation of the evolution of the carbon uptake by the oceans as simulated by the 21 CMIP5 models is comparable in average with that reconstructed by the 7 RECCAP models. Yet, only scaling factors of two oceanic domains are statistically equal to 1. It demonstrates that the representations of the ocean carbon uptake evolution between the CMIP5 models and the RECCAP reconstructions are similar in amplitude in the high-latitude Atlantic and the low-latitude Pacific. In other regions, scaling factors are smaller than 1. This means that CMIP5 models overestimate in average the ocean carbon uptake between 1960 and 2005 compared to the RECCAP ensemble mean. Nonetheless, scaling factor's confidence intervals get larger and include 1 if each CMIP5 model is taken individually.

**4- Evaluation of the fits as estimated by the TLS algorithm**

Figure S2 compares evolution of ocean carbon uptake anomalies as fitted by the TLS algorithm to those represented by the ensemble mean of GEO (in green), CLIM (in red) and RECCAP (in black). This allows us to assess the accuracy of the TLS regression and to better understand why the residuals consistency test fails in the low-latitude Pacific. Figure S2 shows, in addition, that the TLS regressions fit closely to the RECCAP ensemble mean in most cases. Yet, discrepancies between the TLS fit and the RECCAP ensemble mean have to be regarded with respect to internal variability. Our results suggest that these discrepancies are well within the range of internal variability except over the low-latitude Pacific, where the residual consistency test is (moderately) rejected with a p-value of 0.08.

To test the robustness of the TLS fit to the spatiotemporal information, we have re-played our detection and attribution procedure by considering two regional time series together in the optimal fingerprints analysis (instead of only one as performed for

Figure 2). In this spatio-temporal analysis, we have combined the regions zonally, i.e., the high-latitude Pacific with the high-latitude Atlantic and the low-latitude Pacific with the low-latitude Atlantic (with a spatial dimension of 2). The Southern Ocean (South of 30°S) has been divided in two oceanic basins corresponding respectively to the Atlantic and Pacific oceans before the zonal combination.

Figure S3 illustrates the robustness of our results since the optimal fingerprints analysis performed with this pre-processing leads to the same conclusions. That is, the climate influence on the ocean carbon uptake is only detected within the low-latitude oceans, while the influence of rising atmospheric CO2 is detected at global scale.

**5- Sensitivity of D&A results to data pre-processing**

In this section, we evaluate the sensitivity to D&A analysis to the ensemble size. For this purpose, we have re-run TLS algorithm with different estimate of the ensemble mean increasing step by step the size of the ensemble size.

We found that contribution of the geochemical forcing is not sensitive to the ensemble size demonstrating how strong is the response of ocean carbon uptake to rising anthropogenic $CO_2$. This is not the case for the climate forcing, which requires an ensemble of 3 members minimum to detect its contribution to the recent changes in the carbon uptake by the low-latitude oceans. For this forcing, the ensemble size does not play in other regions demonstrating the robustness of our findings.

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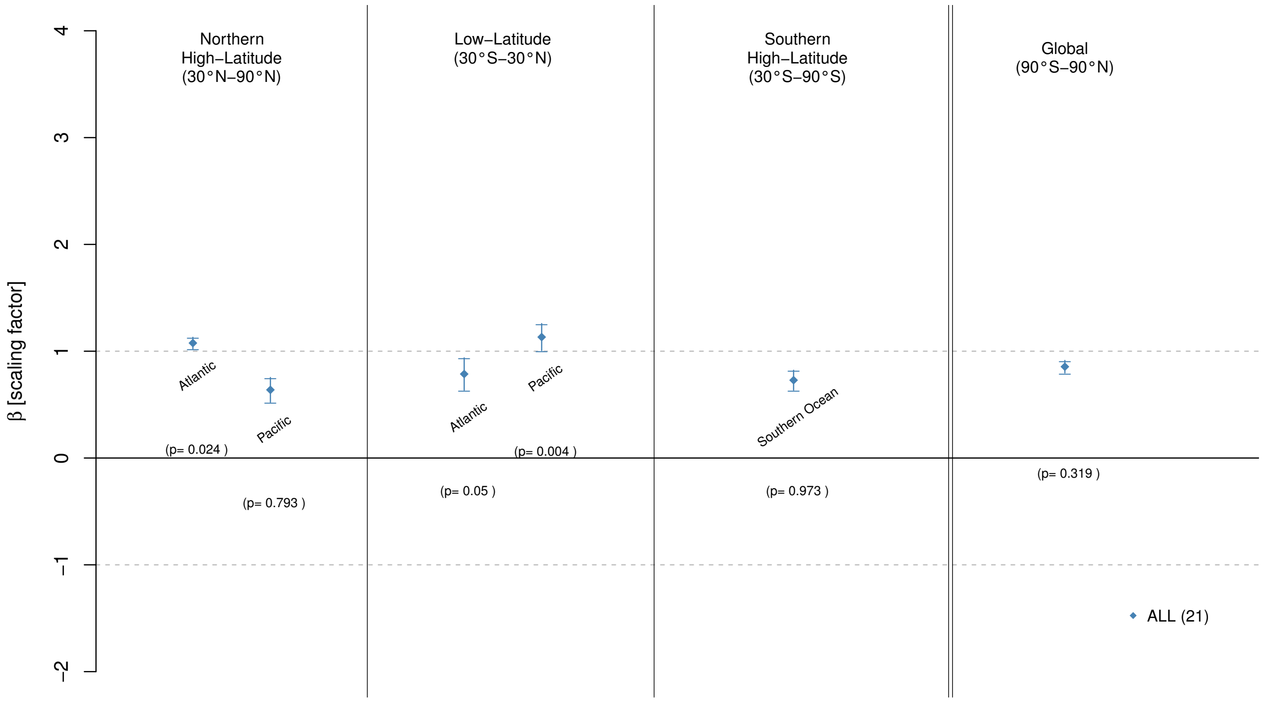


Figure 1: **Evaluation of the historical (ALL) ocean $CO_2$ uptake evolution over the 1960-2005 period as estimated by the ensemble mean of the 21 CMIP5 models.** Scaling factors ($\beta$) best estimates and their 5%-95% confidence intervals as computed from the optimal fingerprint analysis applied at regional and global scale. Regional scaling-factors are estimated from time series of ocean carbon uptake anomalies, while global scaling factor integrates spatiotemporal information by performing all of the regional time series at once in the ROF analysis. Bracketed p-values give information of the accuracy of the fit; if p is larger than 0.2, fit passes the residual consistency test.

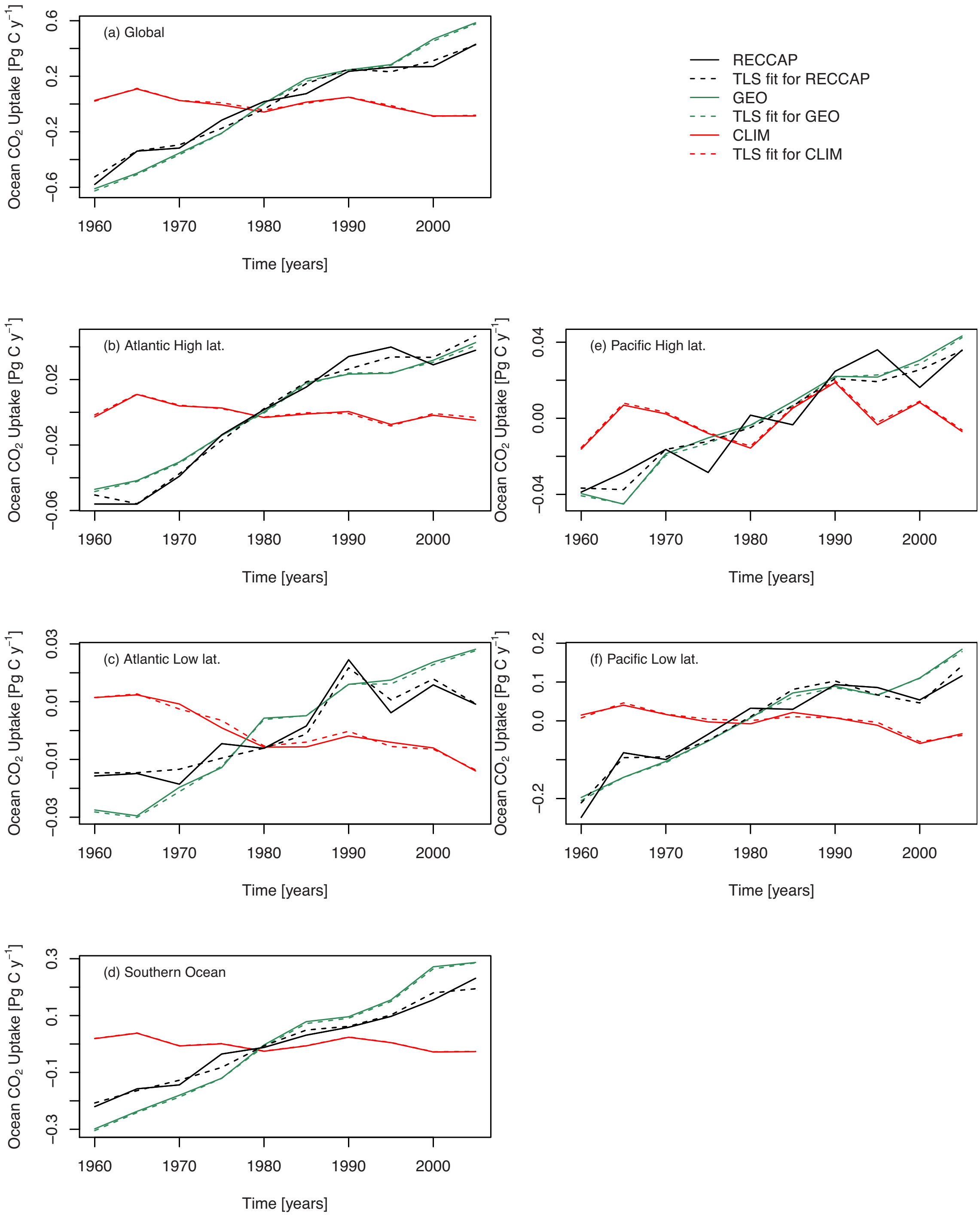


Figure 2: **Evaluation of reconstructed time-series of ocean $CO_2$ uptake anomalies over the 1960-2005 period.** Annual anomalies (in Pg C $y^{-1}$) averaged over 10 non-overlapping periods of the RECCAP ensemble mean and the ensemble mean of simulation accounting solely geochemical forcing (GEO) and solely the climate forcings (CLIM) as used in the optimal fingerprint analysis are given in solid black, green and red lines. Time-series fitted by TLS algorithm for the RECCAP, GEO and CLIM ensemble mean are respectively given in dashed black, green and red lines.

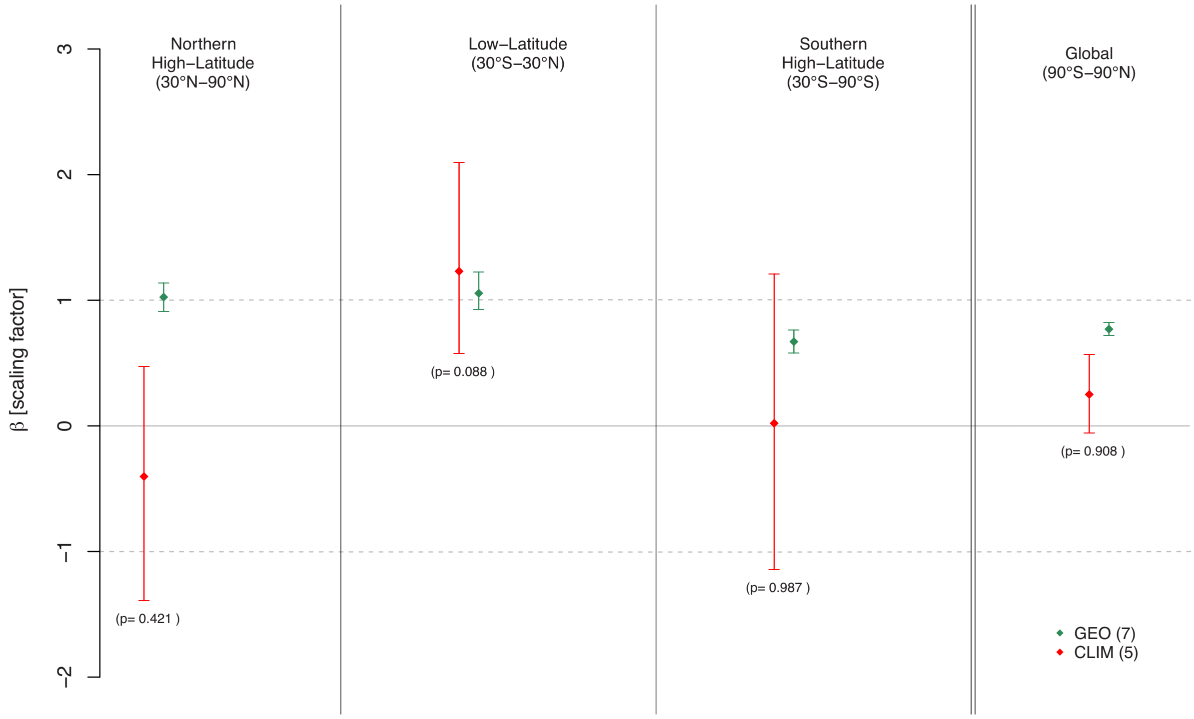


Figure 3: **Scaling factors ($\beta$) best estimates and their 5%-95% confidence intervals as computed from the optimal fingerprints analysis applied to the RECCAP datasets.** Scaling-factors are estimated zonally from regional time series of ocean carbon uptake anomalies. These estimations integrates spatiotemporal informations by performing at least two regional time series at once in the optimal fingerprints analysis. Optimal fingerprints analysis were used on the 1960-2005 ensemble mean time series (The number of models for each ensemble used is bracketed). p-values assess if residuals of the regression fit pass a residual consistency test.