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PU	Public	✓
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D4.1.5: Assessments of the role of climate-carbon cycle feedbacks in future climate scenarios and report on how to reduced uncertainty in the processes involved

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Atmospheric CO_2 concentration is one of the most important factors likely to determine the climate of the 21st century. In projecting the future climate changes, the majority of experiments with comprehensive ocean-atmosphere general circulation models (OAGCMs) still use prescribed CO_2 concentration scenarios, derived a priori from an offline carbon cycle models driven by an emission scenario. Doing so, the climate change simulated by the OAGCM has no impact on the carbon cycle and therefore on the atmospheric CO2 trajectory. However, the atmosphere-land and atmosphere-ocean fluxes of CO_2 are known to be sensitive to climate. For example, the growth-rate of atmospheric CO_2 varies with the El Nino Southern Oscillation (eg. Bousquet et al. 2000), and is also believed to have been affected by the climate perturbation arising from the Pinatubo volcanic eruption (Jones and Cox, 2001, Lucht et al. 2002). In the context of future climate change, offline carbon cycle simulations have been extensively performed (e.g. Prentice et al. 2001). There is a general agreement that future climate change will reduce both land and ocean carbon uptake.

Coupled climate-carbon cycle models have been developed by several climate centres across the world. Within the umbrella of the Analysis Integration and Modelling of the Earth System (AIMES) programme of the International Geosphere Biosphere Programme (IGBP), an intercomparison project of these climate-carbon cycle models has been launched since 2001. The coupled Climate Carbon Cycle Model intercomparison Project (C4MIP) compared 11 models, all following the same simulation protocol. Key results of the project are (Friedlingstein et al., 2006):

- An agreement amongst models the climate carbon cycle feedback is positive
- A large uncertainty of the magnitude of this feedback, ranging for very low (0.05) to very large (0.3)
- A dominant role of the terrestrial biosphere in driving the feedback, and hence the associated uncertainty

Indeed, most ‘C^4MIP’ models attribute their carbon-climate change response primarily to a reduction in land carbon uptake in the tropics, and a widespread, climate-driven, loss of soil carbon, and to a lesser extent to a decrease of CO_2 uptake by the oceans, caused both by ocean warming and by a shrinking volume of the surface mixed layer. Nevertheless, the broad range in carbon cycle-climate feedback among models reflects divergences in model representations of basic carbon cycle processes and their interactions (e.g. Sitch et al. 2008; Le Quéré et al. 2005).

Since the publication of the C4MIP paper, a large effort has been devoted to evaluate the Dynamic Global Vegetation Models (DGVMs) that are now used in ESMs (eg. Randerson et al., 2009). Combination of satellite, atmospheric, and surface datasets, spanning from the recent decades to the full 20th century allow to evaluate the models on seasonal, interannual and centenial time scale. Of particular interest in the context of future climate-carbon cycle feedback is the development of metrics based on the multiple characteristics of the spatial and time evolution of atmospheric CO_2. In the context of ENSEMBLES, a comparison of the Hadley Centre and IPSL models has been performed for their capability to simulate atmospheric CO2 (Cadule et al., 2009].

Cadule et al., (2009) evaluated three global models of the coupled carbon-climate system against atmospheric CO2 concentration measured at a network of stations (Figure 1). These three models, HadCM3LC, IPSL-CM2-C and IPSL-CM4-LOOP participated to the C4MIP experiment and to various other simulations of the future climate impacts on the land and ocean carbon cycle. A new set of performance metrics is defined, and applied to quantify each model's ability to reproduce the global growth rate (Figure 2), the seasonal cycle (Figure 3), the ENSO forced interannual variability of atmospheric CO2 and the sensitivity to climatic variations (Figure 4). Knowing that the uncertainty on the amplitude, in 2100, of the climate carbon feedback is mainly due to the uncertainty of the response of the terrestrial biosphere to the climate change, our new metrics primarily target the evaluation of the land parameterisation of the carbon cycle. The modelled fluxes are prescribed to the same global atmospheric transport model LMDZ4, and the simulated concentrations compared to available observations. We found that the IPSL-CM4-LOOP model is best able to reproduce the phase and amplitude of the atmospheric CO2 seasonal cycle in the Northern hemisphere, while the other two models generally underestimate the seasonal amplitude (Figure 3). This points to some shortcomings in describing the vegetation phenology and heterotropic respiration response to climate. We also found that IPSL-CM2-C produces a climate-driven abnormal source of CO2 to the atmosphere in response to El Ninõ anomalies. Here, a good model performance rests upon a realistic simulation of ENSO type climate variability and the subsequent tropical carbon cycle response. The three climate models underestimate the SST warm anomaly during an El Ninõ, but HadCM3LC does best in reproducing the inter-annual CO2 variability (Figure 4). All together, 10 different traits were developed and applied at 12 atmospheric CO2 stations in order to evaluate the three models (Figure 5).

This work shows that multiple time scales are needed to evaluate models, and that a model which does best on seasonal scales may not necessarily be outperforming others on inter-annual time scales. The advantage of defiing a single metrics, although the procedure is a bit rigid and looks tedious to implement, is that it allows for testing future structural improvements of models and inclusion of new processes in the same rigorously defined framework. Here we have shown that the signal of atmospheric CO2 concentration, despite being a coarse scale and process-integrated signal, has a great useful in falsifying models against observations.

It is not yet clear to what extent, if at all, these metrics will constrain future model projections but their consistent use to evaluate late 20th century ESM simulations will provide valuable guidance on model performance and avenues for future model development and improvement. An ultimate goal would be to link such observed quantities with future behaviour in ESMs and hence be able to derive constraints, e.g. through weighting of individual members within an ensemble of future projections. Analysis of multi-model ensembles that exist already (e.g. from C4MIP, Friedlingstein et al. [2006]) or are planned (e.g. for IPCC AR5, Hibbard et al. [2007]) and perturbed parameter ensembles of single models (e.g. with HadCM3C; Booth et al. [2009]) will enable progress towards this goal.

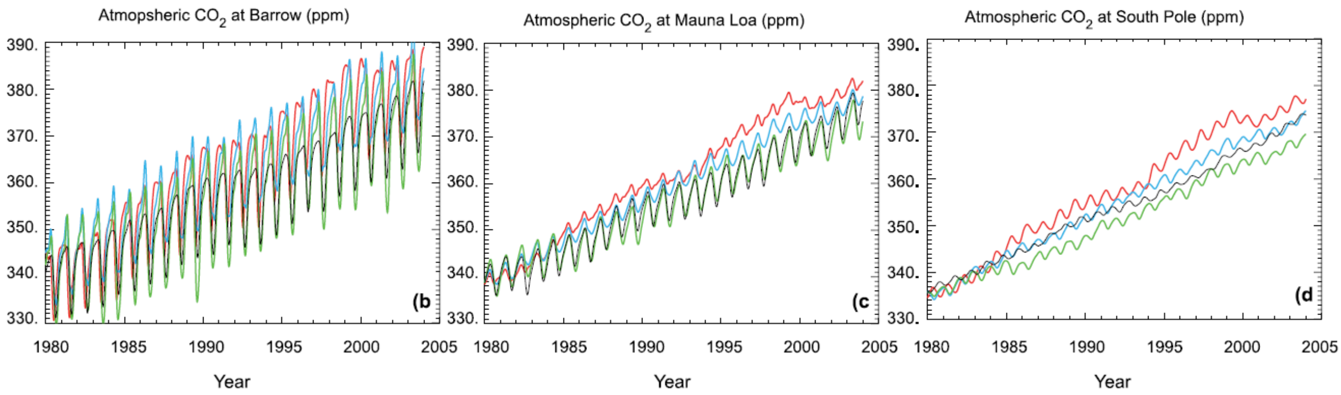

Figure 1. a) Atmospheric CO2 concentration at Point Barrow (BRW), Alaska, simulated by the 3 coupled models HadCM3LC (red), IPSL-CM2-C (blue) and IPSL-CM4-LOOP (green). Observed CO2 concentration is shown in black. b) and c) Same as a) for Mauna Loa (MLO), Hawaii, and South Pole (SPO) respectively.

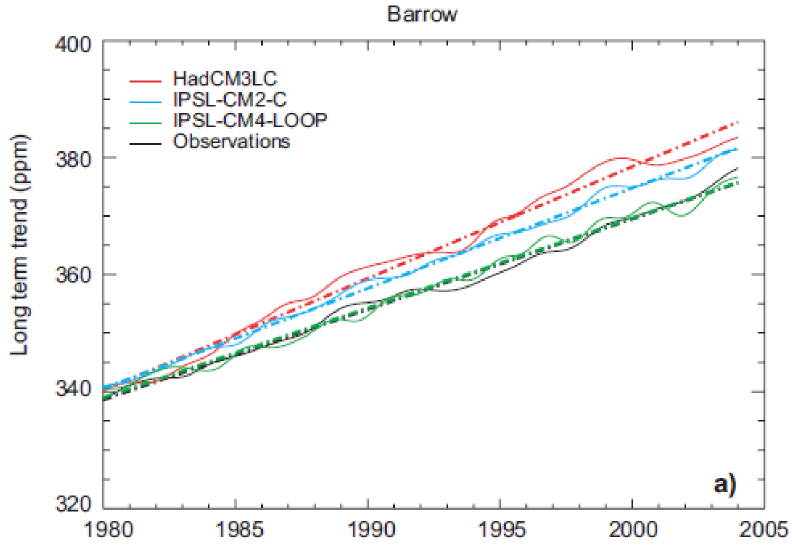

Figure 2. Observed and simulated long term trend of atmospheric CO2 at the BRW. The deseasonalized annual CO2 concentration is shown in solid line, while its averaged value over the 1979-2003 period is shown in dotted line. Modelled CO2 are set to the observation value for January 1979. Color code is as in Figure 1.

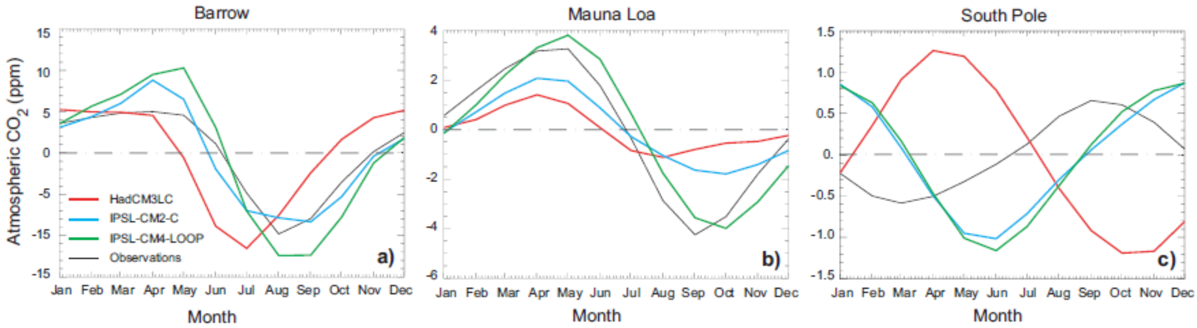

Figure 3. Simulated and observed climatologic averaged CO2 seasonal cycle at BRW, MLO and SPO.

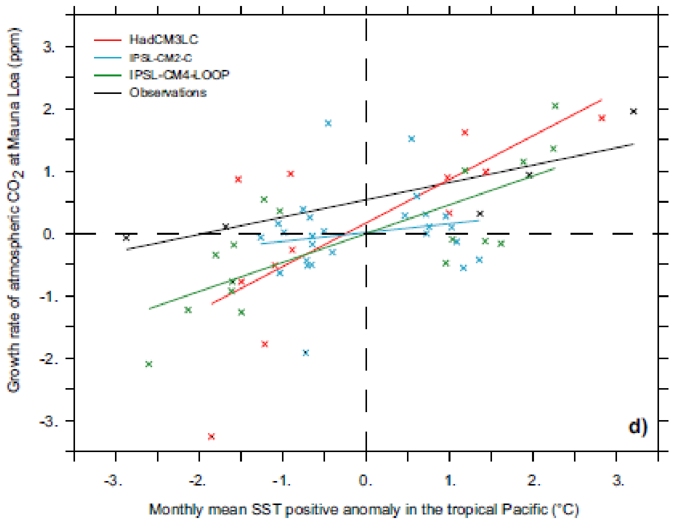

Figure 4 CO2-Temperature diagram showing the positive and negative anomalies of atmospheric CO2 growth rate at MLO as a function of anomalies of Eastern Tropical Pacific SST.

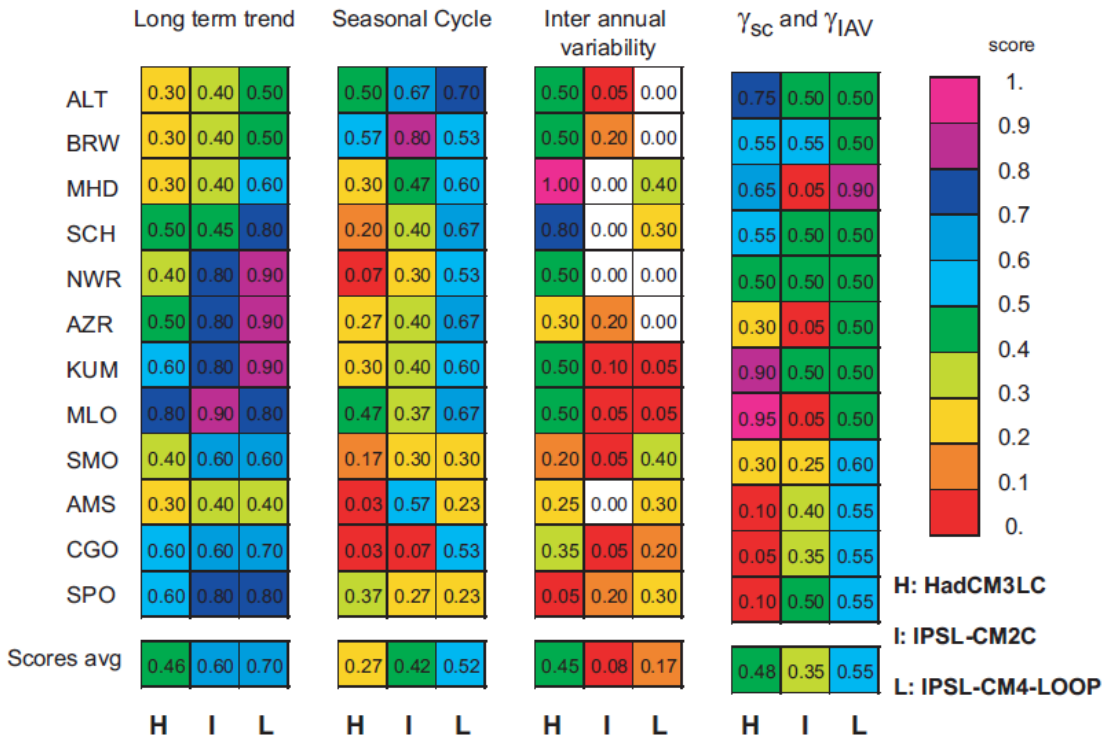

Figure 5. Matrix displaying the three models (H: HadCM3LC, I: IPSL-CM2-LC, and L: IPSL-CM4-LOOP) scores (see color bar) at all stations. Long term trend score is the average of 2 traits: the trend in growth rate and the trend in inter-hemispheric gradient. Seasonal Cycle score is the average of 3 traits: climatic average traits (phase and amplitude), and the trend in the peak to peak amplitude. Inter-annual variability score is the average of 2 traits: the El Niño and La Niña CO2 variability. "SC and IAV " is the average of 2 traits: (seasonal and inter-annual) CO2-temperature sensitivity.

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