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Challenges and opportunities to reduce uncertainty in projections of future atmospheric CO_2: a combined marine and terrestrial biosphere perspective

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Abstract

Atmospheric CO_2 and climate projections for the next century vary widely across current Earth system models (ESMs), owing to different representations of the interactions between the marine and land carbon cycle on the one hand, and climate change and increasing atmospheric CO_2 on the other hand. Several efforts have been made in the last years to analyse these differences in detail in order to suggest model improvements. Here we review these efforts and analyse their successes, but also the associated uncertainties that hamper the best use of the available observations to constrain and improve the ESMs models. The aim of this paper is to highlight challenges in improving the ESMs that result from: (i) uncertainty about important processes in terrestrial and marine ecosystems and their response to climate change and increasing atmospheric CO_2; (ii) structural and parameter-related uncertainties in current land and marine models; (iii) uncertainties related to observations and the formulations of model performance metrics. We discuss the implications of these uncertainties for reducing the spread in future projections of ESMs and suggest future directions of work to overcome these uncertainties.

1 Introduction

The inclusion of the carbon cycle in recent generations of Earth system models (ESMs) has enabled further examination of synergies and interactions within the climate system (Cox et al., 2000; Friedlingstein et al., 2006; Fung et al., 2005). However, the increased complexity of the ESMs has also led to new challenges, in particular related to the magnitude of future climate-carbon cycle interactions during the next century: ESM projections made for the Coupled Carbon Cycle Climate Model Intercomparison Project (C^4MIP) varied greatly in their projected atmospheric CO_2 concentrations in the year 2100, although they were driven by the same emission scenario (Friedlingstein et al., 2006). In these simulations, the largest contributor to the model spread was the spread

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in the land carbon trend, which resulted from diverging representations of land carbon processes and their sensitivity to changes in atmospheric CO_2 and climate (Friedlingstein et al., 2006, 2014). Despite reduced uncertainty in the ocean projections, results from the subsequent fifth phase of Coupled Model Intercomparison Project (CMIP5, Taylor et al., 2012) also show a significant spread of land and ocean carbon future projections (Arora et al., 2013; Jones et al., 2013; Friedlingstein et al., 2014), as illustrated in Fig. 1. Note that for the land carbon projections, the spread due to model differences is larger than difference across scenarios, highlighting again substantial uncertainty in the projections because of land model uncertainties.

Following Friedlingstein et al. (2003), the change in atmospheric CO_2 given anthropogenic fossil fuel emissions (FF) is the result of the combined effects of the sensitivity of the carbon cycle to climatic change (carbon-climate interaction, described as γ_L, γ_O, [D1]which are the land and ocean sensitivities, respectively) and the sensitivity of the carbon cycle to changes in the atmospheric CO_2 concentration (carbon-concentration interaction; described as β_L, β_O, which are the land and ocean sensitivities, respectively; Friedlingstein et al., 2006; Gregory et al., 2009). While it has been long established that ambiguities in the representations of the physical aspects of the climate system contributes significantly to the overall uncertainties in climate projections (e.g. Bony et al., 2006; Knutti et al., 2008; Soden and Held, 2006), the C^4MIP and CMIP5 results clearly demonstrate the importance of carbon-cycle climate interactions for climate projections (Gregory et al., 2009; Huntingford et al., 2009).

These carbon-cycle sensitivities have been used to characterise the climate-carbon feedback strength and have also been employed as a diagnostic tool to compare ESMs projections. For a given scenario, the land carbon-climate feedbacks for the CMIP5 models have been shown to be more uncertain than ocean feedback (Arora et al., 2013). In the same study, the contribution of the generally negative carbon-concentration interaction to the overall carbon-cycle climate feedback was shown to be significantly larger and more uncertain than the generally positive carbon-climate interactions. The wide variability of sensitivities across models, being one of the dominant causes for the large spread in carbon-climate projections (Arora et al., 2013; Friedlingstein et al., 2006; Jones et al., 2013; Sitch et al., 2008), calls for a better understanding of the "real-world" carbon cycle sensitivities and their improved representation in Earth system models.

The terrestrial and marine biogeochemical components of Earth system models rely on "empirically-based" process representations to describe complex ecological processes at the larger spatial scale of these models. This adds significant uncertainties to an Earth system model, compared to the representation errors of physical atmosphere and ocean models, which are mainly associated with the parameterisation of physical processes occurring at subgrid-scale levels (Fig. 2). These ecological models require extensive parameterization and/or upscaling procedures, however, despite considerable efforts, there are significant challenges to extrapolating empirical evidence from controlled field or mesocosm experiments, which can address the carbon-cycle sensitivities of a particular ecosystem to the global scale (e.g. Zaehle et al., 2014). Parameter and structural uncertainties of biological processes can be as much important as physical-related uncertainties to the projected climate as indicated by single-model studies (e.g. Booth et al., 2012; Yurova et al., 2010).

In order to reduce uncertainties in coupled climate-carbon cycle model projections, these biogeochemical models need to be constrained by observational data, in a similar way as climate projections have been constrained in the past (e.g. Collins et al., 2012; Knutti and Tomassini, 2008; Knutti et al., 2006; Sanderson and Knutti, 2012) ("methods" in Fig. 2). The key challenge is to turn the results and insights obtained due to the current trend to developing comprehensive benchmarking systems to evaluate the terrestrial (Anav et al., 2013a; Cadule et al., 2010; Dalmonech and Zaehle, 2013; Luo et al., 2012; Piao et al., 2013; Randerson et al., 2009) and marine (Anav et al., 2013a; Friedrichs et al., 2009; Stow et al., 2009) components of Earth system models into improved model skill. This requires a sound understanding not only of the conceptual and methodological issues that might limit our ability to make the best use

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of current observational dataset (see Fig. 2), but also in-depth understanding of the processes and structures of the models under investigation.

The aim of this review is to assess and list key-issues and challenges that need to be taken into consideration if the uncertainties in future carbon-climate projections are to be reduced; with particular focus on the terrestrial and marine ecosystems component of ESMs. We begin by discussing selected process uncertainties (Sects. 2 and 3). Key issues which impact the use of observations to constrain models are discussed in Sect. 4. Next, we discuss different levels of uncertainty that impact our ability to infer future reliability of models based on their past/present-day performances (Sect. 5). Finally, we summarise key challenges and opportunity that can provide potential direction of work.

2 Uncertainty in the marine ecosystem carbon cycle

2.1 Process uncertainties

The ocean-atmosphere net carbon exchange is primarily modulated by the physico-chemical reactions governing the solution of CO_2 in water, and therefore the ocean circulation, while biological processes play only a secondary role (Chavez et al., 2011; Le Quéré, 2010). A small fraction of the marine primary productivity of 40–50 $\mathrm{Pg\,C\,yr^{-1}}$ (PP; Behrenfeld and Falkowski, 1997; Longhurst et al., 1995) is exported to deeper ocean layers through sedimentation of dead biomass, providing a "biological pump" of CO_2 into the ocean. Since marine production is limited by the availability of nitrogen, phosphorus and silicon, this biological pump provides a coupling between the global cycle of silicon, nitrogen and phosphorus and the level of atmospheric CO_2.

Currently, oceans take up roughly a quarter of the anthropogenic CO_2 emissions, primarily via the solution pump (Le Quéré et al., 2013). This ocean carbon sink over is likely to be altered in the next few decades due to the effects of climate changes on the ocean circulation (Fung et al., 2005; Riebesell et al., 2009; Sarmiento et al.,

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1998), resulting in ocean surface warming and enhanced ocean stratification. These changes will impact the physico-chemical ocean C uptake, but also affect marine PP through to altered nutrient and light availability associated with the direct effects of temperature changes on production as well as the altered ocean circulation (Doney et al., 2004; Hallegraeff, 2010; Riebesell et al., 2009; Steinacher et al., 2010). While there is generally consensus among several models on the leading role of the physico-chemical mechanisms, there remains substantial uncertainty as to the response of the biological related C uptake to e.g. temperature (e.g. Bopp et al., 2001; Steinacher et al., 2010).

There is substantial uncertainty in the understanding of the temperature response of phytoplankton. Sarmiento et al. (2004) used an empirical model based on observational constraints to predict a range of PP increase between 0.7–8.1 % by 2050 relative to pre-industrial conditions, depending on the algorithm used to describe the temperature sensitivity of PP. Using the UVic Earth System model, Taucher and Oschlies (2011) investigated the effect of the temperature sensitivity of PP relative to the contribution of temperature-induced circulation changes. They showed that accounting for the temperature sensitivity of PP led to a different sign of the projected PP change.

One reason for the uncertainty on the temperature response of marine PP is that it is unclear, how temperature will affect the structure of the phytoplankton communities. Thomas et al. (2012) suggested that phytoplankton might show adaptive behaviour with respect to optimum of temperature. Recent attention has therefore moved towards understanding the impact of changes in the community structure and its impact along the food chain. However, uncertainty for instance related to different temperature sensitivities within the community, in terms of growth rate and grow efficiency and interacting effects, does not allow to quantify the strength and the persistence of feedbacks with climate (Riebesell et al., 2009). While therefore potential changes are to be expected for the future, the net effect on the total functionality is still unknown.

The other important effect of increasing atmospheric CO_2 levels, and thus the accumulation of anthropogenic CO_2 in the ocean, is the reduction of ocean pH and con-

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current a shift in the seawater carbonate chemistry, shifting inorganic carbon from carbonate toward more bicarbonate and CO_2 (Doney et al., 2009a). The biological consequences of ocean acidification are not well understood globally, as both positive and negative responses have been observed among different groups of marine organisms in biological data (Langdon et al., 2003; Malakoff, 2012; Riebesell et al., 2007). The number of ocean acidification studies conducted at relevant CO_2 levels is still limited (Fabry et al., 2008). Furthermore, the currently available experiments are limited to short term laboratory experiments, hence not compatible with expected rate of change in concentration of CO_2. This is relevant because of the potential for the community to adapt to new pH conditions at the time-scale of the anthropogenic CO_2 perturbation (Doney et al., 2009a). Furthermore, simulating future impacts of ocean acidification on marine biology requires assumptions to be made on changing C : N : P stoichiometry (see next paragraph), which cannot be accounted for in current generation models that assume fixed C : N : P ratios (Tagliabue et al., 2011). As research on ocean acidification is a relatively new field of research, predicting its impacts still presents a challenge to the biogeochemical modelling community.

The marine nitrogen cycle plays a central role in ocean biogeochemistry as a limiting nutrient for PP. Global PP depends on the amount of bioavailable nitrogen, which in turn depends on the biological processes of nitrogen-fixation and denitrification. While feedbacks within the marine nitrogen cycle are mediated by the phosphorus cycle, through the N : P ratio in surface water (Gruber, 2008), uncertainties in future evolution of the marine nitrogen cycle will also centre on the possibility of a decrease in oxygen concentration in the ocean interior, which would increase denitrification and subsequently lower PP (Gruber, 2008). The future evolution of the marine nitrogen cycle will depend on ocean circulation and on changes in aeolian iron availability (Berman-Frank et al., 2008).

It is clear that the physical change and the solubility pump will have a significant contribution in determining the ocean net CO_2 fluxes for the decades to come (Denman et al., 2007). Nevertheless, Sarmento et al. (2010) pointed towards a likely important

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role that marine bacterial community could play in the future, if climate-change induced changes in the rate of marine PP propagates into significant changes of the biological pump. For instance, Schmittner et al. (2008) have demonstrated in a modelling experiment that changes in the marine PP affecting the biological pump may become important for the net ocean carbon uptake on centennial to millennial time scale.

2.2 Intra- and inter-model uncertainties

The spread in the projections of the ocean carbon cycle and its climate-CO_2 feedbacks in current ESMs has been shown to be not negligible, but less large than the spread of projections of the corresponding land models (Arora et al., 2013). Uncertainties arise in simulating future ocean biogeochemical cycles for a wide variety of reasons, linked to how the physics and the biology of the system is represented (Doney et al., 2004; Gnanadesikan et al., 2004; Sarmiento et al., 2004). Efforts toward the development of a more process-based representation of ocean trophic dynamics have increased in the last decade, allowing linkages to be made between the ocean physical process of transport and the process of marine primary productivity (Dutkiewicz et al., 2009; Le Quere et al., 2005). Previously, few studies used prognostic models to determine the response of ocean biology to warming (e.g. Bopp et al., 2001; Boyd and Doney, 2002).

Ocean physics and biology are tightly coupled and uncertainties in the physic of the system translate in uncertainties in the biological counterpart. Figure 3 reports the global scores computed by Anav et al. (2013a) and used to rank the ESMs participating to the CMIP5. These scores represent the global performance under present-day conditions with respect to climate and ocean global variables and component of the carbon cycle (we excluded the net carbon fluxes) for ocean and land. Seasonalities, interannual variability and stocks of key-variables are considered. For each variable Fig. 3a reports the standard deviation computed among the models performances. Since all the scores range between 0 and 1 (skilful model), the standard deviation can be compared and indicates for which variables the models differ the most in terms of performances, and are hence more uncertain. Figure 3a shows that both physical vari-

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ables of the systems (i.e. sea-surface temperature, SST; mixing-layer depth, MLD) and biological variables (i.e. PP) are important to explain the between-model differences. In the same figure, the lower panel reports also the actual scores for each ESM realization (Fig. 3c).

Biogeochemical ocean models show a large disagreement on projected changes in future PP, with uncertainties in the magnitude of change. Even when models agree globally on the sign of change, regional differences in projected PP exist (Steinacher et al., 2010). A multi-model study by Steinacher et al. (2010) using four ESMs showed a decrease in global mean PP of between 2 and 20 % by 2100 relative to pre-industrial conditions under SRES A2 emission scenario, while Schmittner et al. (2008) using another ESM (UVic) found that global PP increases by 2100 following the same emission scenario. Bopp et al. (2013) showed that the differences of the CMIP5 projections of global and regional changes in PP are not as robust across ESMs, as sea surface temperature and pH.

One cause of the diverging projections are model parameterisations of processes, which cannot be represented explicitly at the spatial and temporal scale of the model (e.g. meso-scale eddies), or for which insufficient knowledge is available to explicitly model these processes (e.g. effects of marine biodiversity on carbon cycling). The way in which mesoscale eddies are modelled has a significant effect on the vertical supply of nutrients, and therefore, biological activity and PP (Chelton et al., 2011; Oschlies and Garçon, 1998).

Biogeochemical cycling is also highly dependent upon specific plankton functional types (PFTs) and the explicit inclusion of PFTs in models is needed to take ecological changes into account (Le Quere et al., 2005). However, incorporating PFTs into models may add further uncertainty to the model if additional model parameters remain insufficiently constrained (Anderson, 2005; Matear, 1995). Manizza et al. (2010) showed that the representation of ecosystem structure plays a pivotal role in linking ocean carbon uptake and export production, and thus determining the best model structure is one of the main challenges in marine biogeochemical modelling. Hashioka et al. (2012) and

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Sailley et al. (2013) showed that the model structure in four different models that include PFTs has a large effect on the governing mechanisms responsible for variations in plankton biomass. Oschlies (2001) showed that different ecosystem model configurations have a large effect on primary production based on element recycling, and thus total PP. However Friedrichs et al. (2009) showed that increasing model complexity does not increase the model skill in simulating PP.

Compared to ocean physical dynamics and ocean chemistry, less is known about the response of marine biology to climate and atmospheric CO_2 and changes. This is reflected by a lower degree of complexity in ocean biological models, compared to the richness of interacting biological processes in terrestrial ecosystem models. Table 1 identifies common sub-components of the models used in the CMIP5 project, as for instance same ocean circulation models for some ESMs or similar food-web structures. Due to better predictability of the physico-chemical effects and the lower importance of biological processes, the future patterns of ocean-atmosphere are relatively more comparable among models and the spread is smaller compared to land models, as shown in Fig. 1. There is a potential that the simplicity of the ocean biological models prevents a full assessment of the possible feedbacks between $p\mathrm{CO}_2$, temperature and biological C uptake, hence when and with which degree the marine biological component can provide a feedback in the carbon-climate system is still hence an open issue.

3 Uncertainty in the terrestrial carbon cycle

3.1 Process uncertainties

The net CO_2 exchange of terrestrial ecosystems is controlled by the activity of vegetation and soil organisms and their respective responses to climate and CO_2 concentration perturbations (Chapin III et al., 2009; Davidson and Janssens, 2006). Anthropogenic land-use and land-use change (Houghton et al., 2012), and natural disturbances also affect the store of carbon in the land biosphere (Sitch et al., 2013),

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which currently absorbs about a quarter of the anthropogenic CO_2 emission (Le Quere et al., 2013).

Here we focus on the most important, biologically controlled processes, which shape the macroscopic, decadal to century scale evolution of the net land carbon balance, because of their strong dependence of climate and atmospheric CO_2 levels, and thus their potential to give rise to land-atmospheric CO_2 feedbacks: (i) the response of photosynthesis to elevate CO_2 and its potential down-regulation (Lloyd and Farquhar, 2008) ; (ii) acclimation of plant carbon uptake and release to increasing temperature (Lloyd and Farquhar, 2008); (iii) acclimation of soil fauna, microbial and fungal activity to temperature (Craine et al., 2012).

The gross assimilation of carbon into plants responds strongly positive to elevated CO_2 at short-time scales (Ainsworth and Long, 2005). This short-term response is encoded into current ESMs and the cause for the large negative land carbon-concentration feedback (Arora et al., 2013). However, plants may down-regulate photosynthesis under increasing CO_2 acting on physiological and biochemical adjustments. In addition, changes in the allocation of the assimilated carbon between short-lived (leaves, fine roots) and longer-lived (wood) tissues may alter the net C storage of plants (and ecosystems) to elevated CO_2 (Körner et al., 2005; Luo et al., 2003). Next to the carbon balance of the plants, these changes in allocation, specifically the total belowground carbon flux affect also the soil organic matter dynamics. However, these characterized by significant complexity and the mechanisms explaining the interactions between these fluxes with variability in soil moisture and temperature are at the current state not enough understood (Chaplin et al., 2009).

Consequently, experimental studies indicate a wide range of responses of plant biomass to increasing atmospheric CO_2, dependent on species and experimental conditions (e.g. Poorter and Navas, 2003). Differences in CO_2 response can in some cases be related to growth sink limitations (Sala et al., 2012; Kirschbaum, 2011), suggesting that incorporation of plant internal feedback mechanisms, such as nutrient limitations (Zaehle and Dalmonech, 2011) and merismeric control (Fatichi et al., 2013) into mod-

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els could improve realism and reduce uncertainties. However, the complexity of the responses of plants to elevated CO_2 make difficult to identify the overarching mechanisms, and thus to sufficiently constrain the response of the net plant carbon balance to CO_2 (Zaehle et al., 2014).

Photosynthesis, as well as plant and soil respiration increase instantaneously with temperature as long as the temperature remains below a critical temperature threshold (e.g. Lloyd and Taylor, 1994). This response is implemented in the current regeneration of ESMs, and gives rise to the positive carbon-climate interaction (Arora et al., 2013). However, acclimation of the response has been observed in many cases, involving several mechanisms at the tissue-level and organ level (see the review of Smith and Dukes, 2013). Acclimation of photosynthesis to temperature has been observed in several species (Kositsup et al., 2008; Way and Sage, 2008) and may strongly attenuate the plant's temperature response. However no general pattern of photosynthesis–temperature relationships has emerged, as data are available only at local scale and vary strongly between experiments. Consequently, few models have included such parameterisation (see e.g. Smith and Dukes, 2013).

Similarly to photosynthesis, plants might adjust their respiratory rate in response to changes in temperature, influenced also by other factors such as light or availability of nutrients (Atkin and Tjoelker, 2003; Atkin et al., 2005). The fairly poor understanding of acclimation and adaptation mechanisms at biochemistry level due to potential confounding factors (i.e. vapour pressure deficit), contributes to the lack of robust predictability (Lin et al., 2012). Nevertheless, Ziehn et al. (2011) identified temperature acclimation of photosynthesis and respiration, as well as the stomatal response to CO_2 as explaining factors for the residual variation in the net photosynthetic rate after the assimilation of leaf-trait in the BETHY model, highlighting the importance of constrain these mechanisms.

Large uncertainties in the evolution of soil heterotrophic activity emerge from the gaps in our knowledge in terms of potential for the soil microbial community to acclimate and adapt to temperature changes (Allison and Martiny, 2008; Wieder et al., 2013;

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Zhou et al., 2011). The response is further complicated changes in substrate availability for soil organic matter decomposition, as substrate limitation might cause apparent lower temperature sensitivity e.g. (Holland et al., 2000). Progress has been made to simulate the response of microbial activity to altered substrate availability (Wielder et al., 2013). Similarly, the role of soil vertical transport of organic matter might have important implications for the stock of carbon on the long term through stabilisation mechanisms along soil depth (Braakhekke et al., 2011). However, the implication of these processes for global carbon storage has not been fully explored by global models. Soil incubation experiments are typically not long enough to strongly support either hypothesis and thus to provide a constraint for soil C models. There is hence the need to provide more comprehensive studies on the interactive effect of temperature and labile carbon availability on soil respiration (Davidson and Janssens, 2006).

Uncertainties in the future response of terrestrial C store to climate change arise also from other processes. Thawing permafrost will potentially release a large amount of carbon due to warming, however, there is large uncertainty about the timing and magnitude of this C flux (e.g. MacDougall et al., 2012). Although globally applicable permafrost soil models exist, none of the CMIP5 models include a representation of permafrost carbon and its potential positive climate-carbon feedback. Hence the role of carbon release from permafrost areas due to warming is still to be quantified in a coupled setting.

Despite the fact that functional biodiversity is better represented in terrestrial than marine ecosystem models, current global vegetation models typically fail to realistically consider demographic processes and the true diversity of plant types (Purves and Pacala, 2008; Friend et al., 2013). Rates of recruitment, competitive interactions, and rates of mortality are all likely to change as a result of future environmental change, with implications for carbon fluxes, particularly under transient conditions but also at equilibrium. However the emphasis in current models is on the description of basic physiological processes such as photosynthesis. Clearly the turnover of vegetation is as important as net primary production in determining the carbon balance of vegeta-

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tion, and mortality rates in particular are strongly dependent on species and environmental conditions (Lines et al., 2010). There is therefore an urgent need to explore approaches for incorporating more realistic demographic approaches into global vegetation models, and investigating their consequences.

The constraints on carbon cycling imposed by the cycles of macro-nutrients such as nitrogen and phosphorus have been shown to limit the potential of land to sequester more carbon in response to increasing atmospheric CO_2 (Oren et al., 2001; Norby et al., 2010; Hungate et al., 2013; Zaehle et al., 2014), while alleviating only little of terrestrial N limitation in response to warming (Melillo et al., 2011; Zaehle and Dalmonech, 2011). However, carbon-nitrogen interactions and feedbacks are only included in few ESMs (Zaehle and Dalmonech, 2011). Also, the impact of tropospheric ozone on vegetation (Anav et al., 2011; Sitch et al., 2007) is not yet simulated by ESMs.

3.2 Intra- and inter-model uncertainties

Terrestrial ecological dynamics are currently represented with diverging degree of detail in terms of structures, terrestrial-climate biophysical interactions and response to disturbances. Contrary to marine ecosystems (Sect. 2.2), in which physics and biology of the ocean are tightly linked, differences amongst terrestrial ecosystem models in ESMs are caused primarily because of alternative representations of carbon-cycle processes, rather than the representation of land biophysics. Similarly to ocean models, Fig. 3b shows for which global land variables the models performance diverge the most. Most of the spread in the model performances is associated to global land C-related variables across ESMs (i.e. GPP, global soil and vegetation C stocks), while for climate variables, models are relatively closer in terms of performance, hence less uncertain compared to C-related variables. The spread of performance referred to soil C stock is related to a clear cluster of model realizations as also emerging from Fig. 3d.

Anav et al. (2013a) found that the range of GPP simulated by ESMs for the present day varies between 113 and 178 $Pg\,C\,yr^{-1}$. Piao et al. (2013) obtained a similar result when analysing the outputs of 10 terrestrial ecosystem models forced by observed cli-

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mate, which ranged between 110 and 150 $Pg\,C\,yr^{-1}$. For two particular models, Piao et al., 2013 show that the difference in GPP between offline and online varied up to 20 $Pg\,C\,yr^{-1}$ as result of the bias in the simulated climate and as result of the coupling. Large variability at the present day is also reported for soil carbon content, with some ESMs having a low limit of about 500 $Pg\,C\,yr^{-1}$ and other having values up to 3000 $Pg\,C\,yr^{-1}$ (Anav et al., 2013a; Todd-Brown et al., 2012).

These differences depicted for present-day conditions must translate in differences under future scenario. Model responses under future scenarios have been already shown to vary largely amongst terrestrial models outcome in both offline (e.g. Cramer et al., 2001; Sitch et al., 2008) and within ESMs (Arora et al., 2013; Friedlingstein et al., 2006), as several of these terrestrial ecosystem models are also included in coupled climate models.

Previous analysis of the C^4MIP models output showed strong model divergence in predicted trajectories of land carbon storage, in some cases with disagreement on the sign of changes in vegetation and soil carbon pools response globally (Friedlingstein et al., 2006) and regionally (e.g. Qian et al., 2010; Sitch et al., 2008). Arora and Matthews (2009) fitted the global parameters of a carbon box model to each ESMs of the C^4MIP project, in order to provide a common standard to compare processes, otherwise differently modelled in each single ESM. Despite the fitted parameters contain implicitly the information on the modelled climate of each ESMs, the analysis revealed the lack of consensus among models in terms of magnitude of response of NPP to CO_2 and climate change, but also of vegetation and soil carbon turnover rate.

At regional scales, several published modelling studies agree on the pivotal role of the tropical latitudinal band in the global carbon cycle in response to climate variability both at present e.g. (Jones et al., 2001; Zeng et al., 2005) and in the future (Cox et al., 2000; Raddatz et al., 2007). Uncertainties in the processes governing ecosystem dynamics in these areas might lead in turn to significant uncertainties in terms of climate-carbon feedbacks strengths (Matthews et al., 2007).

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However, land surface models differ in the simulation of the impact of occurrence of drought conditions on tropical vegetation. Under strong drying of the Amazon Basin, several vegetation models showed that the chance for a forest dieback will increase in the future. However, the likelihood of occurrence of this tipping point depends strongly on the model of vegetation (Huntingford et al., 2008; Poulter et al., 2010), the plant physiological responses (Fisher et al., 2010; Galbraith et al., 2010; Huntingford et al., 2013) and the extend of predicted drying (Huntingford et al., 2013; Malhi et al., 2009; Shiogama et al., 2011).

Similarly to Hungtinford et al. (2013), several studies indicate the dominance of uncertainties attributable to parameters such as temperature-photosynthesis response, in tropical areas (e.g. Matthew et al., 2007; Booth et al., 2012). Booth et al. (2012) in particular found a large range of possible values of the parameters regulating the optima in the temperature–photosynthesis relationship compatible with the atmospheric CO_2 for present day.

Modelled soil carbon processes are also key contributors to the uncertainty of carbon patterns, both between models (e.g. Qian et al., 2011) and within model (e.g. Zaehle et al., 2005). The experiments of (Jones et al., 2005) and (Thum et al., 2011), in which different soil model structures were explored in terms of response to climate change, showed how a difference in the model might affect the magnitude of the carbon-climate feedback strength of the carbon sensitivity and climate-carbon feedbacks affecting the response of soil respiration and hence the magnitude of the carbon release. Yurova et al. (2009) used three different soil structures, according to three different conceptual, state-of-the-art approaches. They showed that the resultant uncertainty in projected climate change are comparable to the modelled temperature differences, which are due to the carbon-climate interaction in C4MIP models (Zeng et al., 2004).

As for marine ecosystem models, Tables 2 and 3 report how processes such as soil respiration and the temperature and drought effects on photosynthesis and canopy conductance follow a similar parameterisation amongst sub-set of models. For example most of the current ESMs use also the soil dynamics represented in the Century model (Parton et al., 1993).

It is not possible to obtain full descriptions of the main structures and key parameterisations for all the models. Tables 2 and 3 report the main sub-units, and key-models used as reference for parameterization or structures. The degree of common model structures indicated in Tables 2 and 3 shows that the projections of these models might not be completely independent information. Given the above discussion, it clearly emerges that the current ensemble used in CMIP5 does not sample the entire possible space of climate responses of soil processes.

4 Constraining future projections based on observations: data and metrics

Given the divergence of model outcomes for the contemporary period (Anav et al., 2013) and in the future (e.g. Bopp et al., 2013; Jones et al., 2013), it is imperative to have a good understanding of the available, appropriate datasets and methodology to evaluate models (Foley et al., 2013). The development of a constraint based on observations should benefit from the richness of available datasets. Nevertheless, uncertainties of the data set and their use as a constraint may limit the application of a particular data set as a constraint. Some of these uncertainties and/or limits are also common to the general model evaluation and calibration problems, such as data uncertainties (see the review of Foley et al., 2013). In this section we discuss examples and key-issues related to (i) observational constraint; (ii) selection of the appropriate dataset; and (iii) performance metrics.

4.1 Observational constraints

Terrestrial and marine ecosystem models are expected to return characteristics of the system such as the average state of the system (hereafter “climatology”), and evaluation exercise targeting this climatology are fundamental to pinpoint model weaknesses

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and consecutively improve the model. However, such an evaluation does not necessarily translate into a constraint for the model's capacity to make projections. An observational constraint should have a strong relationship with a forecast quantity of interest (e.g. the carbon storage in 2100) and should contain a detectable trend or predictable variability, such as an anthropogenic-induced signal (Allen et al., 2000). In other words, model evaluation has to be performed with respect not only to climatology, but also the carbon dynamics that are likely to be important to predict the impact of climate change and increasing atmospheric CO_2 on land and marine ecosystems. An example for this would be an observational constraint, which has a clear relationship between the measure of model error (here indicated with the general term "model-data" distance) and the magnitude of the carbon-climate feedback.

The point related to the anthropogenic-induced signal can be solved having long temporal series of the observed quantity, where it is possible to assess that apparent trends in the data are not caused by long-time scale, but natural and system inherent variability. That is the case for long-term records of temperature (Gillett et al., 2012; Rowlands et al., 2012) but is a challenge for shorter datasets, as demonstrated by (Henson et al., 2010). Nevertheless, it is important to detect features in the data that highlight underlying trends, such as the sensitivity of processes/variables to particular drivers, that we know they will be impacted in the future, as for instance evidenced in ecosystem manipulation studies. This approach assumes that the ecosystem will have a response in the future, which is comparable to its present-day sensitivity to that driver.

Atmospheric CO_2 records from ice cores and monitoring stations (continuous and flask data), Table 4, are one of the observational datasets most commonly used to evaluate and constrain the simulated carbon cycle in terms of climatology, but also trends and sensitivities (Cadule et al., 2010; Dalmonech and Zaehle, 2013; Dargaville et al., 2002; Heimann et al., 1998). For example, Cadule et al. (2010) and Dalmonech and Zaehle (2013) used the CO_2 growth rate to provide a constrain on the sensitivity of carbon fluxes to SST anomalies and land temperature anomalies respectively, at interannual-decadal time scales. The global carbon-cycle feedback to climate, i.e. the change in atmospheric CO_2 as response to a change in global temperature can be used as a combined constraint on $\gamma[D2]$ and β (Cox and Jones, 2008; Gregory et al., 2009; Scheffer et al., 2006).

Longer-time scale constraints require indirect measurements of changes in atmospheric CO_2, such as derived from ice-cores. Using records of the temperature and CO_2 drop during the little ice age, 1500–1750 AD Cox and Jones, (2008) estimated values of the global carbon-cycle sensitivity to climate as high as 40 ppmv °C^{-1}. Frank et al. (2010) instead, using ensemble reconstructions of the past millennium, estimated the range as 1.7–21.4 ppmv °C^{-1} (median of 7.7 ppmv °C^{-1}), against the estimated modeled range of 2.1–15.6 ppmv °C^{-1} from the C^{4}MIP models. The values calculated by Cox and Jones (2008) are assumed to be representative of the global sensitivity at centennial to multi-centennial scales, hence comparable to the carbon-climate projections for the next century. (Frank et al., 2010) instead used the values as representative of the 20th century climate perturbation (the historical 0.7 °C increase of temperature).

However, these sensitivities could show a time scale-dependency (Friedlingstein and Prentice, 2010; Woodwell et al., 1998; Willeit et al., 2014). In other words, the response to external drivers has its own temporal scale, which is the result of aggregated subcomponent responses of the ecosystems that act differently with different time response. This may also depend with magnitude of change, for instance on the rate of warming, the rate of CO_2 increase and the initial conditions, hence the state of the system e.g. (Gregory et al., 2009; Shaver et al., 2000). These points might have several implications:

Firstly, the evaluation is often performed at a specific level of aggregation of the modelled process (i.e. land NPP or ocean PP response to a particular stressor). However, these data do not always detect only the signal of interest (e.g. a pure climate or pure CO_2 effect) on the specific process, because of internal feedbacks or confounding effects, depending for example on the experimental design and the variables monitored (Zaehle et al., 2014).

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Secondly, if the sensitivities are state-dependent, it will be important for models to also correctly return the state of the system along to the slope of the sensitivity, which will be difficult in the case of processes acting on longer time scales, such as vegetation rebound from past disturbance, the extent of nutrient limitation, or gradual changes in the biophysical boundary conditions.

Lastly, the occurrence of different ecological response time scales indicates that the model evaluation and the formulation of model constraints needs to address the dynamics at the process level, and a relevant temporal and spatial scales, which help assess internal feedbacks of the system (Cox et al., 2013). Due to inherent non-linearities in the system, the short scale processes can have hence an impact also on longer temporal scales relevant for the future carbon-climate evolution (Cox et al., 2013, see Sect. 5.2.1).

4.2 Global dataset

4.2.1 Terrestrial dataset

There is a large data-base of derived datasets, benefitting of extensive spatial and temporal coverage (Table 4, see also Luo et al., 2012 for terrestrial data sets). Along to the already mentioned dataset, a CO_2 net land and ocean fluxes database based on inversions (Table 4), is available as a result of the TransCom3 project (Gurney et al., 2002) and it has been recently used to evaluate the ESMs participating to the CMIP5 (Anav et al., 2013a). Satellite-based dataset have been successfully used to evaluate marine and terrestrial ecosystem in several regions and over the globe (Anav et al., 2013b; Dalmonech and Zaehle, 2013; Friedrichs et al., 2009; Guenet et al., 2013; Kelley et al., 2013; Randerson et al., 2009) and we can benefit of record of up to almost 30 yr of data.

Compared to most of the satellite dataset, that are related mainly to phenology or leaf development, the new chlorophyll datasets might a be promisingly record (Frankenberg et al., 2011), as it is more directly related to photosynthesis and hence to a specific

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carbon-process. While satellite-based datasets provide information only for the surface layer and for limited biological properties, they could be used in combination with other datasets such as vegetation height measurements (Simard et al., 2011).

Global up-scaled records as the GPP-product by (Jung et al., 2011), soil respiration (e.g. Bond-lamberty and Thomson, 2010), soil carbon (e.g. Nachtergaele et al., 2012; FAO 2009) and vegetation carbon stocks (e.g. Gibbs et al., 2006) are valuable datasets to evaluate the "climatology" of the carbon cycle. Nevertheless caution has to be used when these dataset are implemented for a quantitative constraint, due to the inherent uncertainties associated to the upscaled procedure and the lack of a temporal dimension with which to assess current trends.

Currently, tropical areas lack of extensive in situ "observational" records, including manipulative experiments (Luo et al., 2006) and leaves traits (Kattge et al., 2011). This is fundamental in order to e.g. understand how fertilisation effect might counteract the direct effect of temperature on plant physiological response, and hence supporting plant resilience.

Satellite based data are also affected by high uncertainties in tropical areas (Asner and Alencar, 2010). As an example, Fig. 4 reports the standardised seasonal signal of selected satellite-based datasets of vegetation activity aggregated over the Amazon area (Appendix A). The figure shows the lack of agreement between different records in depicting the same underlying process and obstacles the selection of the most suitable dataset and hence the evaluation and constrain exercise. Similarly, derived dataset of net CO_2 fluxes obtained by inversions, despite their usefulness to highlight differences when aggregated by latitudinal band, might be a poor constrain on the tropical latitudinal band due to the paucity of CO_2 monitoring stations used in the inversion processes. For instance, Koffi et al. (2012) assimilated data of atmospheric CO_2 to constrain GPP and NEP in a terrestrial ecosystem model. Along to other results they found an overestimation of GPP in the tropical area as result of poor coverage of observational constrain.

4.2.2 Marine dataset

Similarly as for land, TransCom 3 provides ocean air–sea CO_2 fluxes database (Table 4). The new Surface ocean CO_2 Atlas (SOCAT) aims to provide a comprehensive, publicly available, regularly updated global dataset of marine CO_2 which is independent from the Takahashi database (Pfeil et al., 2012) (Table 4).

Global scale estimates of variables such as chlorophyll *a* and diffuse attenuation coefficient are available from remotely sensed measurements from the Coastal Zone Color Scanner (1978–1986), Sea-viewing Wide Field-of-view Sensor (1997–2010) and Aqua Modis (2002–2012). For marine ecosystems, the physical and the biological parts are tightly coupled and this makes the evaluation and constrain of the biological subcomponents difficult. For example, in Fig. 5 the timing of the blooming of chlorophyll concentration has been computed for SeaWifs-based dataset. Although this is a robust observational feature linked to the phenology of marine PP, such information is linked not only to the marine ecosystem but also to the modelled physical ocean system via the vertical mixing. Therefore, this biogeochemical metric can be viewed as a way to support a joint constrain of circulation and biogeochemistry models.

New marine dataset will allows to explore, along to stock data, information at community structural level and physiological level. The new MAREDAT (MARine Ecosystem DATa) database (Buitenhuis et al., 2013) provides one of the first comprehensive biomass datasets to validate plankton in the ocean. The initiative provides global gridded data for 11 plankton functional types (PFTs) including 9 of the PFTs that have been proposed as essential in simulating important biogeochemical processes in the oceans (Le Quéré et al., 2005). In addition new dataset providing information such phytoplankton physiological parameters are becoming available (Barton et al., 2013; Litchman and Klausmeier, 2008; Thomas et al., 2012).

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4.3 Metrics

Evaluation metrics can be used to synthesise the complexity of model-data comparison, and thereby to facilitate comparing and ranking the models, as well as formulating weights to provide probabilistic forecast in multi-model ensemble and perturbed ensemble (Sects. 5.2.1 and 5.2.2). Several evaluation analysis of the recent years differ in data used and metric proposed for marine e.g. (Doney et al., 2009b; Gleckler et al., 2008; Jolliff et al., 2009) and terrestrial ecosystems e.g. (Blyth et al., 2011; Dalmonech and Zaehle, 2013; Kelley et al., 2013). This evidences how the choice of dataset and metric carries a partial but inevitable degree of subjectivity and hence uncertainty. Although this demonstrates that we are still far from a common standard of evaluation, Foley et al. (2013) showed how it is possible to formalise and group metrics according to the concept of data-model distance and the aspects of observations that we want to depict (e.g. statistics of the populations, functional relationships) providing examples of robust choice and use of the metrics.

The use of different metrics in the evaluation analysis, might also limit the interpretability of the numerical scores and the final global performance if, for instance, the metrics range between different values or the upper and lower limits of the scores are not clear. (Abramowitz, 2005) and Dalmonech and Zaehle (2013) demonstrated that the use of a reference baseline reduces ambiguities in the numerical interpretation and use of the metric, and can thereby help to reduce this problem. It remains pivotal, nevertheless, to make use of several metrics, because of the complexity of modelled system. It is ascertain a robust interpretation of model-data differences based on only one metric, or expressing data-model difference in one specific field.

Similarly, in our "data-rich" world, it is important to select datasets in a way such as to avoid potential for correlation between data of the same type. Non-independent datasets may provide metrics that contain redundant information, leading a biased assessment of the reliability of the models. All the mentioned evaluation studies are quite recent, hence there is not yet a formalisation of the metrics to constrain or how to for-

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mulate e.g. weights, nevertheless in first instance should be demonstrated that metrics are related and how to future projections.

In the field of climate change prediction, M. Collins et al. (2011) indicated that it was not possible to find a simple and direct emergent relationship between climate model "errors" and future climate change trends. Instead, there was a need to explore several metrics formulations of the "model error" or multivariate metrics. Murphy et al. (2004) used a likelihood weight based on a "global metric" formulated on several present-day climate variables, as estimates of the relative reliability of model versions. It appears likely that the same approach can also be applied also to the evaluation of coupled carbon-cycle climate models.

There is an emergent class of studies that explicitly uses present-day observations to formulate constraints for climate and carbon variables projections and the quantification of uncertainties (Sect. 5.2), in terms of model-data misfit functions (e.g. Booth et al., 2012; Gregg et al., 2009; Rayner et al., 2011; Rowlands et al., 2012) – the most simplest being the root mean square error. These misfit-functions provide a means of including error estimates, when they are known e.g. (e.g. Friedrichs et al., 2007; Kidston et al., 2011; Raupach et al., 2005), but the specification of structural errors in observations is yet unresolved (Raupach et al., 2005). In these studies it has been also shown how it is possible extend the formulation of the misfit-function to more than one dataset (e.g. Model data fusion approach, Keenan et al., 2012), and increase the potential to constrain the model parameters and the process of interest.

5 Constraining future projections based on models and observations

5.1 The philosophical viewpoint: the validity of constraining future projections

When designing approaches to constrain future projections, a number of philosophical issues relating to the nature of the climate-carbon system must be considered in order

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to design as robust a methodology as possible, and account for remaining uncertainties in the future projection.

Firstly, it is important to recall that when a model is used to make future projections, it is simulating a state that has not previously been encountered. ESMs contain numerous parameterisations of processes not explicitly represented in the models, which are derived from the current state of knowledge. While applicable under past and present conditions, these parameterisations may not necessarily be applicable under different climate forcings. Acknowledging that complex models cannot be validated per se, but only evaluated given a set of observations and a specific task the model is set to undertake (Rykiel, 1995; Refsgaard and Henriksen, 2003), the merit of an evaluation score obtained under present conditions hinges in the adequacy of the models parameterisations under future conditions. Since judging this adequacy is extremely difficult, the ability of present-day constraints for future projections can be generally questioned (Stainforth et al., 2007). Simulating past climates, for which suitable observations exist, provide an alternative test to the models' ability to simulate alternative climate states (e.g. Annan et al., 2005; Braconnot et al., 2012), but uncertainty in the forcing data used to drive models and in the proxy data used for evaluation (Cane et al., 2006) prevent this from being a very strong constraint.

A second issue concerns the current lack of consensus about an objective way to select specific metrics to quantify model-data differences. The climate-carbon system is very complex, with multiple temporal and spatial scales of variability and trends, which overlay each other. The observational constraint of the entire system is necessarily incomplete, considering that (i) the observational target is the (small) sum of a number of (large, but uncertain) fluxes, (ii) uncertainties in measurement techniques result in ambiguous observations of similar properties. As a result, there is no single data-set or metric that best measures the skill of an ESM to simulate the carbon-climate system (Foley et al., 2013). So far, no consensus has emerged, as to the objective selection of different metrics to integrate the multiple currently available observations.

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A third critical consideration when developing methodologies to constrain future projections is that while some uncertainties can be quantified or characterised in some way, depending on the basis for probabilities (Foley, 2010), there are "unknown unknowns", i.e. processes or feedbacks, of which "we do not even know that we do not know" them (Curry, 2011). It is impossible to address this lack of understanding in a comprehensive, quantitative way and to include this into an assessment of a models predictive capacity (Van Asselt et al., 2002). Nonetheless, it is important to discuss and communicate the possibility of unexpected outcomes, outside of those predicted by the models, as failing to address them could result in overconfidence into the projections (Petersen, 2002).

5.2 Methodologies

Given the uncertainties associated with modelled physical and biogeochemical processes, basing the future behaviour of the Earth system on a single model experiment would be highly unreliable. As such, ensemble approaches, either perturbed parameters or multi-model, are widely used to explore and reduce uncertainties in future projections in climate modelling (M. Collins et al., 2011a; Tebaldi and Knutti, 2007) and are suitable also for carbon-climate models.

5.2.1 Multi-model ensembles

The multi-model method assumes that any existing model represents a plausible representation of the system under investigation. Thus, based on the application and analysis of projections made by many different models, one may learn about the potential future state of the system (and the likelihood of that state). Within climate science, many studies have demonstrated an improvement in prediction skill when multiple models are employed, compared with a single model (e.g Chikamoto et al., 2012; Reichler and Kim, 2008). Hagedorn et al. (2005) argued that the increased skill of multi-model ensemble predictions compared to single models is related to error cancellation. The

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improvement in skill can also arguably be attributed to the use of different models and the increased ensemble size (Doblas-Reyes et al., 2005).

A method to use observations of the current system's state to reduce the spread in an ensemble is to weight models according to their capacity to reproduce relevant observations. Systematic model evaluation studies can generate quantitative metrics based on the capacity of each individual models to reproduce current processes and trends (see Sect. 4.3). Model intercomparison projects (e.g. CMIP5: Arora et al., 2013; PMIP: Braconnot et al., 2011) provide insights into the level of relative agreement between the models. Incorporating such information into the generation of ensemble-mean projections can account for some uncertainty relating to the models' predictive skill and therefore increase the confidence of the ensemble. However, as discussed before, a high model skill to simulate past and present processes cannot be considered a necessary guarantee of a high predictive skill (Reichler and Kim, 2008).

The often-reported effective gain in predictive skills by means of model ensembles is only valid if ensemble members are truly independent. This is especially a concern in "ensembles of opportunity" (Stone et al., 2007), where models are chosen more for ease of availability than demonstrated skill (Masson and Knutti, 2011). However, assessing model independence is difficult, and often not quantified (Abramowitz, 2010). For instance, current ESMs as the ones used in the CMIP5 simulations, share subunits, use similar process parameterisations and in some cases share the entire module (as discussed in Sect. 2). The problem of independence is particular relevant to ensemble-weighting schemes, which rely on model convergence in ensembles next to the agreement with observed data to constrain future projections by weighting ensemble members according to their similarity (Giorgi and Mearns, 2001; Tebaldi et al., 2004, 2007), because such an approach may weight similar models as more skilful compared to independent ones, leading to overconfidence in structurally similar models.

Another application of the multi-model ensemble approach to constraining future patterns relies on the use of "emergent constraints" instead of direct model evaluation. This approach attempts to find a correlation/relationship across a set of models be-

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tween a simulated quantity in the present-day period and its predicted change in the future. If such relationships exists, the ability of the model to correctly simulate this quantity at present-day could be taken as indicative of a "correct" prediction of the change. If good observational constraints for this quantity for the present day are available, this in turn allows to constrain the correlated variable in the future. This approach has been successfully applied in the field of climate prediction (e.g. Knutti et al., 2006; Hall et al., 2006; Hewitt et al., 2001). Recently, Cox et al. (2013) have demonstrated it may be possible to constrain the terrestrial carbon-climate interaction (γ_L) in the tropical area using current observations of the interannual variability of the CO_2 growth rate.

Another example of such a teleconnection is the relationship between γ_L and pre-industrial soil carbon content in the CMIP5 ensemble (Arora et al., 2013) as depicted in Fig. 6. There is a clear tendency for models with higher initial soil carbon content to also have higher land carbon-climate sensitivity at the time of CO_2 doubling. The initial soil carbon content suggests that the ESMs might have a lower turnover time, allowing for more carbon accumulation in the soil under increasing CO_2. This large soil carbon store is susceptible to be lost under warming, leading to a higher land carbon-climate sensitivity. The correlation between the two quantities suggests how the sensitivity could also depend on the initial state of the system (see also Willeit et al., 2014).

The main challenge to the use of emerging constraints is that it is nearly impossible to ascertain that the existence of a correlation between a present-day and future process is not a structural error common to all models but an expression of teleconnections of the real Earth system.

5.2.2 Perturbed-parameters ensemble

Perturbed-parameter ensemble experiments consist of several runs of the same model, in which relevant parameters, or combinations thereof, are sampled to cover a the range of plausible values (Booth et al., 2012; Hemming et al., 2011; Lermusiaux, 2006;

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Rowlands et al., 2012; Zaehle et al., 2005). Perturbed-parameter ensemble experiments provide a way to explore the sensitivity of the model to specific parameters and associated uncertainties in the model outcome.

However, due to computational limitations, analyses of this type have often been restricted to the use of simplified models such as box-models, Earth system models of intermediate complexity (EMIC). Nonetheless, some attempts have been made to use this approach with comprehensive ESMs, by calibrating a simple model to an ESM, and then perturbing the parameter space of the simplified model to explore the sensitivity of carbon-climate feedback strengths to model parameters e.g. (Eliseev and Mokhov, 2006; Jones et al., 2006).

Probabilistic approaches such as Bayesian inference to assess the likelihood of certain parameter combinations, based on perturbed-parameter ensembles and a comparison to suitable observations, have been shown to be successful in constraining site-level simulations of ecosystems models (Ricciuto et al., 2011) as well as projections of climate-related variables (Goldstein and Rougier, 2009; Schmittner et al., 2011; Tebaldi et al., 2004) and global carbon cycle e.g. (Ricciuto et al., 2008; Smith et al., 2013; Urban and Keller, 2010). Application of the perturbed-parameter ensemble approach to CO_2 projections has demonstrated, however, that observed changes in atmospheric CO_2, as well as derived quantities, such as the airborne fraction of anthropogenically emitted CO_2 and the global carbon budget, are not a strong constraint on future projections the global carbon balance, due to their poor constraint on the carbon-climate interaction strength (Jones et al., 2003, 2006; Melnikov and O'Neill, 2006). Rayner et al. (2011) showed that 20 yr of observations of the CO_2 growth rate were enough to constrain a simple land surface model with respect to net land carbon fluxes. However, slower processes acting on longer time scales, as they are relevant for the climate system, could not be adequately constrained. This partly results from processes and parameters, which are highly correlated under current conditions, so called "equifinality" leading to similar projections for different sets of parameter combinations

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(e.g. Ricciuto et al., 2008), even though these different parameter combinations give rise to different trajectories in the future.

A potential way around the equifinality problem is the use of multiple constraints (metrics), as recent work involving data-fusion methods to constrain a land ecosystem model and its future projections (Ricciuto et al., 2011; Keenan et al., 2012) have demonstrated the potential of a few years of multiple datasets to substantially reduce uncertainties over simulations of the ecosystem, in addition to identifying model structural errors.

Perturbed-parameter ensembles have been shown to exhibit a lower compared to multi-model ensembles, at least as far as physical climate variables are concerned (Yokohata et al., 2013). One way to overcome this limitation is to include structural uncertainties in a single model, additionally to parameter uncertainties (Watanabe et al., 2012; Yokohata et al., 2013). These so-called multi-physics ensembles allow to explore the effect of different parameterisations for selected processes on the model projections. The great advantage of such an approach is that single processes or modules can be evaluated thoroughly with the rest of the model remaining the same. This is not the case for multi-model ensembles, where confounding effects are introduced by the variety of differing sub-components of the models.

6 Concluding remarks and future directions

6.1 Data and process uncertainties

Earth system model development currently tends to be directed towards increased model complexity by adding more ecological processes (e.g. nutrient interactions, permafrost soils) and diversity (e.g. plant and soil community dynamics as well as marine population dynamics), conceptually known to be highly relevant. The inclusion of such complexity provides additional feedback mechanisms in the models and generally increases the “realism” of the representation of the Earth system in ESMs. The increased

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complexity may contribute to reduced model spread, where compensating feedbacks exist (see e.g. Zaehle and Dalmonech, 2011 for the terrestrial N cycle). However, the increased complexity may prove detrimental, where there are not enough observations to suitably constrain the emergent feedback mechanisms (e.g. Luo et al., 2011). Furthermore, the inclusion of data constraints does not improve the reliability of projections, if there is incomplete understanding about the scaling of feedback mechanisms observed in particular ecosystems to a wider range of species (or for plant-functional type/plankton functional types). Nevertheless, the spread between models will not be reduced sufficiently, if currently unconstrained biological processes in the current generation of ESMs are not equally scrutinised, constrained by data, and in particular, the adequacy of empirical parameterisations under changed environmental conditions, investigated. This will be more important for models of the terrestrial biosphere than the oceans, because uncertainty in the projected changes of the ocean circulation and their effect on the net atmosphere–ocean CO_2 flux is likely to be of a larger magnitude compared to other biogeochemical effects, at least over the next few decades.

6.2 Data-model constraints

The question of whether observations of present day carbon-cycle processes can provide useful constraints on future model projections remains challenging to answer. Model evaluation using observations from the historical period allows for the identification of strengths and weaknesses of individual models and potentially also their components in general, which may be used as an indicator for the level of trust one may wish to place into the model's prediction. The challenges that need to be addressed to corroborate the assessment of the model's predictive capacity are two-fold: (i) to which extent do the differences in future predictions of Earth system models relate to differences in ecosystem processes simulated by these models for the present-day, and can we define "emergent" constraints based on contemporary observations, which allow to evaluate precisely these present-day processes or patterns? (ii) Which additional observations do we need to better constrain the relevant processes that drive

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the model's sensitivities to date? These additional observations may be derived from an in-depth assessment of the spatio-temporal dynamics observed with current monitoring networks. Given the inherent variability of the Earth system and the concurrent changes in multiple drivers of environmental change, it is unlikely that this alone will provide a sufficient constraint. New manipulative experiments in key geographic regions are required that simultaneously perturb different ecosystem drivers, as well as sophisticated model-data intercomparison methodologies, to benefit fully from these multifactorial observations.

6.3 Model evaluation

The usefulness of an evaluation exercise strongly depends on the correct interpretation of the observational uncertainty. Failure to account for this uncertainty in the evaluation metric, for instance by ignoring alternative data sources describing the same phenomena, may lead to erroneous conclusions about model performances. Similarly, where possible, complementary data constraining component processes of the process under investigation can be extremely useful to ensure that a good model performance is not achieve by compensating errors in underlying process formulations. It is imperative that there is a transparent documentation of the evaluation methodology, such that the consequences of any inevitably subjective decision-making can be understood by potential end-users of the model projections.

As a fraction of the spread in the ESMs' projections of atmospheric CO_2 results from biases in the predicted present-day climate in combination with the diverging predictions of the rate and the spatial pattern of climate change predicted by these models, given the same radiative forcing, a further point is important to consider: using current carbon-cycle observations to evaluate and calibrate Earth system models components bears the risk of introducing compensating errors, if the evaluation metric is sensitive to the ESM's climate biases. Conversely, if the ESMs model's component is evaluated when driven with observed boundary conditions ("offline"), the "optimal" model performance when calibrated against observations might not be preserved when the ESM

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component is employed within the Earth system model itself. In both cases, proper formulation of the evaluation metrics to be independent of such climate biases, e.g. by evaluating correlation patterns, can be helpful to avoid an "apparent" constraint and thus a wrong assessment of the confidence in the ESM models predictive capacity.

6.4 Model uncertainties

Our review shows that the different ESMs are not independent in their structure – a fact, which is easily forgotten in sight of the diverging predictions. It is important to understand these structural similarities, which could be promoted by more clarity in the communication regarding model structures and parameterisations (through papers or accessible technical reports). Structural errors are likely to be similar across models that share the same code or modules and are hence likely to be persistent. Model independence is difficult to quantify. Suitable metrics would be useful to better characterise and communicate the confidence associated with ensemble predictions.

While knowledge of structural similarities is beneficial, the sensitivity of model output to the shared characteristics may also be important for determining independence. Perturbed parameter ensembles of different terrestrial and marine ESM components would be helpful to separate parametric and structural uncertainty. In this context, systematic testing of a specific model sub-unit in a modelling framework could help to identify the impact of structural uncertainties on the model's future predictions and to diagnose the most reasonable model structure given presently available data. If the currently available data were not permitting to tell model structures apart despite diverging future predictions of the models, this approach may still yield insight into the data needed to reduce model structural uncertainty.

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Appendix A

Data used in Fig. 4 include: EVI-MODIS (biweekly), data of quality good and marginal. Seawif-FAPAR (about 10 days temporal window) considers only good quality data according to (REF-report). LAI data consider filled based on correlation with adjacent pixel and filled based on linear interpolation. Temporal window interests years 2000–2005, common to all the datasets. Data have been thereinafter regridded to 1° × 1° of resolution. Before the aggregation over the South American tropical (94.5° W–41.5° E; 24.5° N–15.5° S), where gaps below 10 % occurred, data have been interpolated by mean of a cubic spline. Despite the screening of grid cells is not accurate, the pattern of Fig. 4 capture the main findings reported in (Dahlke et al., 2012).

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References

Abramowitz, G.: Towards a benchmark for land surface models, Geophys. Res. Lett., 32, L22702, doi:10.1029/2005GL024419, 2005.

Abramowitz, G.: Model independence in multi-model ensemble prediction, Australian Meteorological and Oceanographic Journal, 59, 3–6, 2010.

Ainsworth, E. A. and Long, S. P.: What have we learned from 15 years of free-air CO_2 enrichment (FACE)? A meta-analytic review of the responses of photosynthesis, canopy properties and plant production to rising CO_2., New Phytol., 165, 351–371, doi:10.1111/j.1469-8137.2004.01224.x, 2005.

Allen, M., Stott, P., Mitchell, J., Schnur, R., and Delworth, T.: Quantifying the uncertainty in forecasts of anthropogenic climate change, Nature, 407, 617–620, doi:10.1038/35036559, 2000.

Allison, S. D. and Martiny, J. B. H.: Resistance, resilience, and redundancy in microbial communities, P. Natl. Acad. Sci. USA, 105, 11512–11519, 2008.

Anav, A., Menut, L., Khvorostyanov, D., and Výovy, N.: Impact of tropospheric ozone on the Euro-Mediterranean vegetation, Glob. Change Biol., 17, 2342–2359, doi:10.1111/j.1365-2486.2010.02387.x, 2011.

Anav, A., Friedlingstein, P., Kidston, M., Bopp, L., Ciais, P., Cox, P., Jones, C., Jung, M., Myneni, R., and Zhu, Z.: Evaluating the land and ocean components of the global carbon cycle in the Cmip5 Earth system models, J. Climate, 26, 6801–6843, doi:10.1175/JCLI-D-12-00417.1, 2013a.

Anav, A., Murray-Tortarolo, G., Friedlingstein, P., Sitch, S., Piao, S., and Zhu, Z.: Evaluation of land surface models in reproducing satellite derived leaf area index over the high-latitude Northern Hemisphere – Part 2: Earth system models, Remote Sens., 5, 3637–3661, doi:10.3390/rs5083637, 2013b.

Anderson, T. R.: Plankton functional type modelling: running before we can walk?, J. Plankton Res., 27, 1073–1081, 2005.

Annan, J. D., Hargreaves, J. C., Ohgaito, R., Abe-Ouchi, A., and Emori, S.: Efficiently constraining climate sensitivity with paleoclimate simulations, Sci. Online Lett. Atmos., 1, 181–184, 2005.

Arora, V. K. and Matthews, H. D.: Characterizing uncertainty in modeling primary terrestrial ecosystem processes, Global Biogeochem. Cy., 23, 1–14, doi:10.1029/2008GB003398, 2009.

Arora, V. K., Scinocca, J. F., Boer, G. J., Christian, J. R., Denman, K. L., Flato, G. M., Kharin, V. V., Lee, W. G., and Merryfield, W. J.: Carbon emission limits required to satisfy future representative concentration pathways of greenhouse gases, Geophys. Res. Lett., 38, 3–8, doi:10.1029/2010GL046270, 2011.

Arora, V. K., Boer, G. J., Friedlingstein, P., Eby, M., Jones, C. D., Christian, J. R., Bonan, G., Bopp, L., Brovkin, V., Cadule, P., Hajima, T., Ilyina, T., Lindsay, K., Tjiputra, J. F., and Wu, T.: Carbon-concentration and carbon-climate feedbacks in CMIP5 Earth system models, J. Climate,26, 5289–5314, doi:10.1175/JCLI-D-12-00494.1, 2013.

Asner, G. P. and Alencar, A.: Drought impacts on the Amazon forest: the remote sensing perspective, New Phytol., 187, 569–578, doi:10.1111/j.1469-8137.2010.03310.x, 2010.
Atkin, O. K. and Tjoelker, M. G.: Thermal acclimation and the dynamic response of plant respiration to temperature, Trends Plant Sci., 8, 343–351, 2003.
Atkin, O. K., Bruhn, D., Hurry, V. M., and Tjoelker, M. G.: Evans Review No. 2: the hot and the cold: unravelling the variable response of plant respiration to temperature, Funct. Plant Biol., 32, 87–105, doi:10.1071/FP03176, 2005.
Barton, A. D., Pershing, A. J., Litchman, E., Record, N. R., Edwards, K. F., Finkel, Z. V., Kiørboe, T., and Ward, B. A.: The biogeography of marine plankton traits, Ecol. Lett., 16, 522–534, doi:10.1111/ele.12063, 2013.
Behrenfeld, M. J. and Falkowski, P. G.: Photosynthetic rates derived from satellite-based chlorophyll concentration, Limnol. Oceanogr., 42, 1–20, 1997.
Berger, J. O., De Oliveira, V., and Sanso, B.: Objective Bayesian analysis of spatially correlated data, J. Am. Stat. Assoc., 96, 1361–1374, 2001.
Berman-Frank, I., Chen, Y., Gao, Y., Fennel, K., Follows, M. J., Milligan, A. J., and Falkowski, P.: Feedback between the nitrogen, carbon and oxygen cycles, in: Nitrogen in the Marine Environment, Elsevier Inc, Amsterdam, the Netherlands, 1539–1563, 2008.
Blyth, E., Clark, D. B., Ellis, R., Huntingford, C., Los, S., Pryor, M., Best, M., and Sitch, S.: A comprehensive set of benchmark tests for a land surface model of simultaneous fluxes of water and carbon at both the global and seasonal scale, Geosci. Model Dev., 4, 255–269, doi:10.5194/gmd-4-255-2011, 2011.
Bony, S., Colman, R., Kattsov, M. V., Allan, R. P., Bretherton, C. S., Dufresne, J.-L., Hall, A., Hallegatte, S., Holland, M. M., Ingram, W. J., Randall, D. A., Soden, B. J., Tselioudis, G., and Webb, M. J.: How well do we understand and evaluate climate change feedback processes?, J. Climate, 19, 3445–3482, 2006.
Booth, B. B. B., Jones, C. D., Collins, M., Totterdell, I. J., Cox, P. M., Sitch, S., Huntingford, C., Betts, R. A., Harris, G. R., and Lloyd, J.: High sensitivity of future global warming to land carbon cycle processes, Environ. Res. Lett., 7, 024002, doi:10.1088/1748-9326/7/2/024002, 2012.
Bopp, L., Monfray, P., Aumont, O., Dufresne, J.-L., Treut, H. Le, Madec, G., Terray, L., and Orr, C. J.: Potential impact of climate change on marine export production, Global Biogeochem. Cy., 15, 81–99, 2001.

BGD
11, 2083–2153, 2014

Bopp, L., Resplandy, L., Orr, J. C., Doney, S. C., Dunne, J. P., Gehlen, M., Halloran, P., Heinze, C., Ilyina, T., Séférian, R., Tjiputra, J., and Vichi, M.: Multiple stressors of ocean ecosystems in the 21st century: projections with CMIP5 models, Biogeosciences, 10, 6225–6245, doi:10.5194/bg-10-6225-2013, 2013.

Boyd, P. W. and Doney, S. C.: Modelling regional responses by marine pelagic ecosystems to global climate change, Geophys. Res. Lett., 29, 1–4, 2002.

Braakhekke, M. C., Beer, C., Hoosbeek, M. R., Reichstein, M., Kruijt, B., Schrumpf, M., and Kabat, P.: SOMPROF: a vertically explicit soil organic matter model, Ecol. Model., 222, 1712–1730, doi:10.1016/j.ecolmodel.2011.02.015, 2011.

Braconnot, P., Harrison, S. P., Otto-Bliesner, B., Abe-Ouchi, A., Jungclaus, J., and Peterschmitt, J.-Y.: The Paleoclimate Modeling Intercomparison Project contribution to CMIP5, CLIVAR Exchanges, No. 56, International CLIVAR Project Office, Southampton, UK, 15–19, 2011.

Braconnot, P., Harrison, S. P., Kageyama, M., Bartlein, P. J., Masson-Delmotte, V., Abe-Ouchi, A., Otto-Bliesner, B., and Yan Zhao, Y.: Evaluation of climate models using palaeoclimatic data, Nature Clim. Change, 2, 417–424, doi:10.1038/NCLIMATE1456, 2012.

Buitenhuis, E. T., Vogt, M., Moriarty, R., Bednaršek, N., Doney, S. C., Leblanc, K., Le Quéré, C., Luo, Y.-W., O'Brien, C., O'Brien, T., Peloquin, J., Schiebel, R., and Swan, C.: MAREDAT: towards a world atlas of MARine Ecosystem DATa, Earth Syst. Sci. Data, 5, 227–239, doi:10.5194/essd-5-227-2013, 2013.

Cadule, P., Friedlingstein, P., Bopp, L., Sitch, S., Jones, C. D., Ciais, P., Piao, S. L., and Peylin, P.: Benchmarking coupled climate-carbon models against long-term atmospheric CO_2 measurements, Global Biogeochem. Cy., 24,GB2016, doi:10.1029/2009GB003556, 2010.

Cane, M. A., Braconnot, P., Clement, A., Gildor, H., Joussaume, S., Kageyama, M., Khodri, M., Paillard, D., Tett, S., and Zorita, E.: Progress in paleoclimate modeling, J. Climate, 19, 5031–5057, doi:10.1175/JCLI3899.1, 2006.

Chapin III, F. S., McFarland, J., David McGuire, A., Euskirchen, E. S., Ruess, R. W., and Kielland, K.: The changing global carbon cycle: linking plant-soil carbon dynamics to global consequences, J. Ecol., 97, 840–850, doi:10.1111/j.1365-2745.2009.01529.x, 2009.

Chavez, F. P., Messi, M., and Pennington, J. T.: Marine Primary production in relation to climate variability and change, Annu. Rev. Mar. Sci., 3, 227–260, doi:10.1146/annurev.marine.010908.163917, 2011.

Chelton, D. B., Gaube, P., Schlax, M. G., Early, J. J., and Samelson, R. M.: The influence of nonlinear mesoscale eddies on near-surface oceanic chlorophyll, Science, 334, 328–332, 2011.

Chikamoto, Y., Kimoto, M., Ishii, M., Mochizuki, T., Sakamoto, T., Tatebe, H., Komuro, Y., Watanabe, M., Nozawa, T., Shiogama, H., Mori, M., Yasunaka, S., and Imada, Y.: An overview of decadal climate predictability in a multi-model ensemble by climate model MIROC, Clim. Dynam., 40, 1201–1222, doi:10.1007/s00382-012-1351-y, 2012.

Coleman, K. and Jenkinson, S.: ROTHC-26.3, a model for the turnover of carbon in soils, Herts, Rothamsted Research, Harpenden, Hertfordshire, UK, available online at: http://www.uni-kassel.de/w_dec/Modellierung/wdec-rothc_manual.pdf, 1999.

Collatz, G. J., Ball, J. T., Grivet, C., and Berry, J. A.: Physiological and environmental regulation of stomatal conductance, photosynthesis and transpiration: a model that includes a laminar boundary layer, Agr. Forest Meteorol., 54, 107–136, 1991.

Collatz, G. J., Ribas-Carbo, M., and Berry, J. A.: Coupled photosynthesis-stomatal conductance model for leaves of C4 plants, Funct. Plant Biol., 19, 519–538, 1992.

Collins, M., Booth, B. B. B., Glen, B. B., James, R. H., Sexton, D. M. H., and Webb, M. J.: Climate model errors, feedbacks and forcings: a comparison of perturbed physics and multi-model ensembles, Clim. Dynam., 1737–1766, doi:10.1007/s00382-010-0808-0, 2011.

Collins, M., Chandler, R. E., Cox, P. M., Huthnance, J. M., Rougier, J., and Stephenson, D. B.: Quantifying future climate change, Nature Clim. Change, 2, 403–409, doi:10.1038/nclimate1414, 2012.

Collins, W. J., Bellouin, N., Doutriaux-Boucher, M., Gedney, N., Halloran, P., Hinton, T., Hughes, J., Jones, C. D., Joshi, M., Liddicoat, S., Martin, G., O'Connor, F., Rae, J., Senior, C., Sitch, S., Totterdell, I., Wiltshire, A., and Woodward, S.: Development and evaluation of an Earth-System model – HadGEM2, Geosci. Model Dev., 4, 1051–1075, doi:10.5194/gmd-4-1051-2011, 2011.

Cox, P. and Jones, C.: Illuminating the modern dance, Nature, 321, 19–21, 2008.

Cox, P. M., Betts, R. A., Jones, C. D., Spall, S. A., and Totterdell, I. J.: Acceleration of global warming due to carbon-cycle feedbacks in a coupled climate model, Nature, 408, 184–187, doi:10.1038/35041539, 2000.

Cox, P. M., Pearson, D., Booth, B. B., Friedlingstein, P., Huntingford, C., Jones, C. D., and Luke, C. M.: Sensitivity of tropical carbon to climate change constrained by carbon dioxide variability, Nature, 494, 341–344, doi:10.1038/nature11882, 2013.

Craine, J. M., Fierer, N., McLauchlan, K. K., and Elmore, A. J.: Reduction of the temperature sensitivity of soil organic matter decomposition with sustained temperature increase, Biogeochemistry, 113, 359–368, doi:10.1007/s10533-012-9762-8, 2012.

Cramer, W., Bondeau, A., Woodward, F. I., Prentice, I. C., Betts, R. A., Brovkin, V., Cox, P. M., Fisher, V., Foley, J. A., Friend, A. D., Kucharik, C., Lomas, M. R., Ramankutty, N., Sitch, S., Smith, B., White, A., and Young-Molling, C.: Global response of terrestrial ecosystem structure and function to CO_2 and climate change: results from six dynamic global vegetation models, Glob. Change Biol., 7, 357–373, doi:10.1046/j.1365-2486.2001.00383.x, 2001.

Curry, J.: Reasoning about climate uncertainty, Climatic Change, 108, 723–732, doi:10.1007/s10584-011-0180-z, 2011.

Dahlke, C., Loew, A., and Reick, C.: Robust identification of global greening phase patterns from remote sensing vegetation products, J. Climate, 25, 8289–8307, doi:10.1175/JCLI-D-11-00319.1, 2012.

Dalmonech, D. and Zaehle, S.: Towards a more objective evaluation of modelled land-carbon trends using atmospheric CO_2 and satellite-based vegetation activity observations, Biogeosciences, 10, 4189–4210, doi:10.5194/bg-10-4189-2013, 2013.

Dargaville, R. J., Heimann, M., McGuire, A. D., Prentice, I. C., Kicklighter, D. W., Joos, F., Clein, J. S., Esser, G., Foley, J., Kaplan, J., Meier, R. A., Melillo, J. M., Moore, B., Ramankutty, N., Reichenau, T., Schloss, A., Sitch, S., Tian, H., Williams, L. J., and Wittenberg, U.: Evaluation of terrestrial carbon cycle models with atmospheric CO_2 measurements: results from transient simulations considering increasing CO_2, climate, and land-use effects, Global Biogeochem. Cy., 16, 1092, doi:10.1029/2001GB001426, 2002.

Davidson, E. A. and Janssens, I. A.: Temperature sensitivity of soil carbon decomposition and feedbacks to climate change, Nature, 440,165–173, doi:10.1038/nature04514, 2006.

Denman, K. L., Brasseur, G., Chidthaisong, A., Ciais, P., Cox, P. M., Dickinson, R. E., Hauglustaine, D., Heinze, C., Holland, E., Jacob, D., Lohmann, U., Ramachandran, S., da Silva Dias, P. L., Wofsy, S. C., and Zhang, X.: Couplings between changes in the climate system and biogeochemistry, in: Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, edited by: Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K. B., Tignor, M., and Miller, H. L., Cambridge University Press, Cambridge, UK, New York, NY, USA,499–587, 2007.

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11, 2083–2153, 2014

Challenges and opportunities to reduce uncertainty in projections

D. Dalmonech et al.

Doblas-Reyes, F. J., Hagedorn, R., and Palmer, T. N.: The rationale behind the success of multi-model ensembles in seasonal forecasting – Part 2: Calibration and combination, Tellus A, 57, 234–252, 2005.

Doney, S. C., Lindsay, K., Caldeira, K., Campin, J.-M., Drange, H., Dutay, J.-C., Follows, M., Gao, Y., Gnanadesikan, A., Gruber, N., Ishida, A., Joos, F., Madec, G., Maier-Reimer, E., Marshall, J. C., Matear, R. J., Monfray, P., Mouchet, A., Najjar, R., Orr, J. C., Plattner, G.-K., Sarmiento, J., Schlitzer, R., Slater, R., Totterdell, I. J., Weirig, M.-F., Yamanaka, Y., and Yool, A.: Evaluating global ocean carbon models: the importance of realistic physics, Global Biogeochem. Cy., 18, GB3017, doi:10.1029/2003GB002150, 2004.

Doney, S. C., Fabry, V. J., Feely, R. A., and Kleypas, J. A.: Ocean acidification: the other CO_2 problem, Annu. Rev. Mar. Sci., 1, 169–192, doi:10.1146/annurev.marine.010908.163834, 2009a.

Doney, S. C., Lima, I., Moore, J. K., Lindsay, K., Behrenfeld, M. J., Westberry, T. K., Mahowald, N., Glover, D. M., and Takahashi, T.: Skill metrics for confronting global upper ocean ecosystem-biogeochemistry models against field and remote sensing data, J. Marine Syst., 76, 95–112, doi:10.1016/j.jmarsys.2008.05.015, 2009b.

Dufresne, J., Foujols, M. A., Denvil, M., Caubel, S., Benshila, H., Bony, R., Bopp, S., and Braconnot, L.: Climate change projections using the IPSL-CM5 Earth system model: from CMIP3 to CMIP5, Clim. Dynam., 40, 2123–2165, 2013.

Dunne, J. P., John, J., Adcroft, A. J., Griffies, A. M., Hallberg, R. W., Shevliakova, E., Stouffer, R. J., Cooke, W., Dunne, K. A., Harrison, M. J., Krasting, J. P., Makyshev, S. L., Milly, P. C. D., Phillipps, P. J., Sentman, L. T., Samuels, B. L., Spelman, M. J., Winton, M., Wittenberg, A. T., and Zadeh, N.: GFDL's ESM2 global coupled climate – carbon Earth system models – Part 1: Physical formulation and baseline simulation characteristics, J. Climate, 25, 6646–6665, doi:10.1175/JCLI-D-11-00560.1, 2012.

Dutkiewicz, S., Follows, M. J., and Bragg, J. G.: Modeling the coupling of ocean ecology and biogeochemistry, Global Biogeochem. Cy., 23, 1–15, doi:10.1029/2008GB003405, 2009.

Eliseev, A. V. and Mokhov, I. I.: Carbon cycle–climate feedback sensitivity to parameter changes of a zero-dimensional terrestrial carbon cycle scheme in a climate model of intermediate complexity, Theor. Appl. Climatol., 89, 9–24, doi:10.1007/s00704-006-0260-6, 2006.

Fabry, V. J., Seibel, B. A., Feely, R. A., and Orr, J. C.: Impacts of ocean acidification on marine fauna and ecosystem processes, ICES J. Mar. Sci., 65, 414–432, 2008.

FAO/IIASA/ISRIC/ISSCAS/JRC: Harmonized World Soil Database (version 1.1), FAO, Rome, Italy, IIASA, Laxenburg, Austria, 2009.
Fatichi, S., Leuzinger, S., and Körner, C.: Moving beyond photosynthesis: from carbon source to sink-driven vegetation modeling, New Phytol.,doi:10.1111/nph.12614,2013.
Farquhar, G. D., von von Caemmerer, S., and Berry, J. A.: A biochemical model of photosynthetic CO_2 assimilation in leaves of C3 species, Planta, 149, 78–90, 1980.
Fisher, R., Mcdowell, N., Purves, D., Moorcroft, P., Sitch, S., Cox, P., Huntingford, C., Meir, P., and Woodward, F. I.: Assessing uncertainties in a second-generation dynamic vegetation model caused by ecological scale limitations, New Phytol., 187, 666–681, 2010.
Foley, A. M., Dalmonech, D., Friend, A. D., Aires, F., Archibald, A., Bartlein, P., Bopp, L., Chappellaz, J., Cox, P., Edwards, N. R., Feulner, G., Friedlingstein, P., Harrison, S. P., Hopcroft, P. O., Jones, C. D., Kolassa, J., Levine, J. G., Prentice, I. C., Pyle, J., Vázquez Riveiros, N., Wolff, E. W., and Zaehle, S.: Evaluation of biospheric components in Earth system models using modern and palaeo observations: the state-of-the-art, Biogeosciences Discuss., 10, 10937–10995, doi:10.5194/bgd-10-10937-2013, 2013.
Frank, D. C., Esper, J., Raible, C. C., Buentgen, U., Trouet, V., Stocker, B., and Joos, F.: Ensemble reconstruction constraints on the global carbon cycle sensitivity to climate, Nature, 463, 527–530, doi:10.1038/nature08769, 2010.
Frankenberg, C., Fisher, J. B., Worden, J., Badgley, G., Saatchi, S. S., Lee, J.-E., Toon, G. C., Butz, A., Jung, M., Kuze, A., and Yokota, T.: New global observations of the terrestrial carbon cycle from GOSAT: Patterns of plant fluorescence with gross primary productivity, Geophys. Res. Lett., 38, L17706, doi:10.1029/2011GL048738, 2011.
Friedlingstein, P. and Prentice, I. C.: Carbon – climate feedbacks: a review of model and observation based estimates, Current Opinion in Environmental Sustainability, 2, 251–257, doi:10.1016/j.cosust.2010.06.002, 2010.
Friedlingstein, P., Cox, P., Betts, R., Bopp, L., von Bloh, W., Brovkin, V., Cadule, P., Doney, S., Eby, M., Fung, I., Bala, G., John, J., Jones, C., Joos, F., Kato, T., Kawamiya, M., Knorr, W., Lindsay, K., H. D., M., Raddatz, T., Rayner, P., Reick, C., Roeckner, E., Schnitzler, K.-G., Schnur, R., Strassmann, K., Weaver, A. J., C., Y., and Zeng, N.: Climate – carbon cycle feedback analysis: results from the C 4 MIP model intercomparison, J. Climate, 19, 3337–3353, 2006.

BGD
11, 2083–2153, 2014

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Friedlingstein, P., Meinshausen, M., Arora, V., Jones, C., Anav, A., Liddicoat, S., and Knutti, R.: Uncertainties in CMIP5 climate projections due to carbon cycle feedbacks, J. Climate, 27, 511–526, doi:10.1175/JCLI-D-12-00579.1, 2014.
Friedrichs, M. A. M., Dusenberry, J. A., Anderson, L. A., Armstrong, R. A., Chai, F., Christian, J. R., Doney, S. C., Dunne, J., Fujii, M., Hood, R., McGillicuddy, D. J., Moore, J. K., Schartau, M., Spitz, Y. H., and Wiggert, J. D.: Assessment of skill and portability in regional marine biogeochemical models: role of multiple planktonic groups, J. Geophys. Res., 112, C08001, doi:10.1029/2006JC003852, 2007.
Friedrichs, M. A. M., Carr, M.-E., Barber, R. T., Scardi, M., Antoine, D., Armstrong, R. A., Asanuma, I., Behrenfeld, M. J., Buitenhuis, E. T., Chai, F., Christian, J. R., Ciotti, A. M., Doney, S. C., Dowell, M., Dunne, J., Gentili, B., Gregg, W., Hoepffner, N., Ishizaka, J., Kameda, T., Lima, I., Marra, J., Mélin, F., Moore, J. K., Morel, A., O'Malley, R. T., O'Reilly, J., Saba, V. S., Schmeltz, M., Smyth, T. J., Tjiputra, J., Waters, K., Westberry, T. K., and Winguth, A.: Assessing the uncertainties of model estimates of primary productivity in the tropical Pacific Ocean, J. Marine Syst., 76, 113–133, doi:10.1016/j.jmarsys.2008.05.010, 2009.
Friend, A. D., Lucht, W., Rademacher, T. T., Keribin, R., Betts, R., Cadule, P., Ciais, P., Clark, D. B., Dankers, R., Falloon, P. D., Ito, A., Kahana, R., Kleidon, A., Lomas, M. R., Nishina, K., Ostberg, S., Pavlick, R., Peylin, P., Schaphoff, S., Vuichard, N., Warszawski, L.,Wiltshire, A. and Woodward, F. I.: Carbon residence time dominates uncertainty in terrestrial vegetation responses to future climate and atmospheric CO_2, P. Natl. Acad. Sci. USA, in press, doi:10.1073/pnas.1222477110, 2013.
Fung, I. Y., Doney, S. C., Lindsay, K., and John, J.: Evolution of carbon sinks in a changing climate, P. Natl. Acad. Sci. USA, 102, 11201–11206, 2005.
Galbraith, D., Levy, P. E., Sitch, S., Huntingford, C., Cox, P., Williams, M., and Meir, P.: Multiple mechanisms of Amazonian forest biomass losses in three dynamic global vegetation models under climate change., New Phytol., 187, 647–665, doi:10.1111/j.1469-8137.2010.03350.x, 2010.
Gibbs, H. K.: Olson's major world ecosystem complexes ranked by carbon in live vegetation: an updated database using the GLC 2000 land cover product, available online at: http://cdiac.ornl.gov/epubs/ndp/ndp017/ndp017b.html, 2006.

Gillett, N. P., Arora, V. K., Flato, G. M., Scinocca, J. F., and Von Salzen, K.: Improved constraints on 21st-century warming derived using 160 years of temperature observations, Geophys. Res. Lett., 39, 1–5, doi:10.1029/2011GL050226, 2012.

Giorgi, F. and Mearns, L. O.: Probability of regional climate change based on the Reliability Ensemble Averaging (REA) method, Geophys. Res. Lett., 30, 1629,doi:10.1029/2003GL017130, 2003.

Gleckler, P. J., Taylor, K. E., and Doutriaux, C.: Performance metrics for climate models, J. Geophys. Res., 113, D06104, doi:10.1029/2007JD008972, 2008.

Gnanadesikan, A., Dunne, J. P., Key, R. M., Matsumoto, K., Sarmiento, J. L., Slater, R. D., and Swathi, P. S.: Oceanic ventilation and biogeochemical cycling: Understanding the physical mechanisms that produce realistic distributions of tracers and productivity, Global Biogeochem. Cy., 18, GB4010, doi:10.1029/2003GB002097, 2004.

Gobron, N., Pinty, B., Taberner, M., Mélin, F., Verstraete, M. M., and Widlowski, J.-L.: Monitoring the photosynthetic activity of vegetation from remote sensing data, Adv. Space Res., 38, 2196–2202, doi:10.1016/j.asr.2003.07.079, 2006.

Goldstein, M. and Rougier, J.: Reified Bayesian modelling and inference for physical systems, J. Stat. Plan. Infer., 139, 1221–1239, doi:10.1016/j.jspi.2008.07.019, 2009.

Gregg, W. W. and Casey, N. W.: Global and regional evaluation of the SeaWiFS chlorophyll data set, Remote Sens. Environ., 93, 463–479, 2004.

Gregg, W. W., Friedrichs, M. A. M., Robinson, A. R., Rose, K. A., Schlitzer, R., Thompson, K. R., and Doney, S. C.: Skill assessment in ocean biological data assimilation, J. Marine Syst., 76, 16–33, doi:10.1016/j.jmarsys.2008.05.006, 2009.

Gregory, J. M., Jones, C. D., Cadule, P., and Friedlingstein, P.: Quantifying carbon cycle feedbacks, J. Climate, 22, 5232–5250, doi:10.1175/2009JCLI2949.1, 2009.

Gruber, N.: The marine nitrogen cycle: overview and challenges, Nitrogen in the marine environment, 1–50, 2008.

Guenet, B., Cadule, P., Zaehle, S., Piao, S. L., Peylin, P., Maignan, F., Ciais, P., and Friedlingstein, P.: Does the integration of the dynamic nitrogen cycle in a terrestrial biosphere model improve the long-term trend of the leaf area index?, Clim. Dynam.,40, 2535-2548,2013.

Gurney, K. R., Law, R. M., Denning, A. S., Rayner, P. J., Baker, D., Bousquet, P., Bruhwiler, L., Chen, Y.-H., Ciais, P., Fan, S., Fung, I. Y., Gloor, M., Heimann, M., Higuchi, K., John, J., Maki, T., Maksyutov, S., Masarie, K., Peylin, P., Prather, M., Pak, B. C., Randerson, J., Sarmiento, J., Taguchi, S., Takahashi, T., and Yuen, C.-W.: Towards robust regional esti-

BGD
11, 2083–2153, 2014

mates of CO_2 sources and sinks using atmospheric transport models, Nature, 415, 626–630, doi:10.1038/415626a, 2002.

Hagedorn, R., Doblas-Reyes, F. J., and Palmer, J. R.: The rationale behind the success of multi-model ensembles in seasonal forecasting – I. Basic concept, Tellus A, 57, 219–233, 2005.

Hallegraeff, G. M.: Ocean climate change, phytoplankton community responses, and harmful algal blooms: a formidable predictive challenge, J. Phycol., 235, 220–235, doi:10.1111/j.1529-8817.2010.00815.x, 2010.

Harrison, S. P. and Prentice, C. I.: Climate and CO_2 controls on global vegetation distribution at the last glacial maximum: analysis based on palaeovegetation data, biome modelling and palaeoclimate simulations, Glob. Change Biol., 9, 983–1004, 2003.

Hashioka, T., Vogt, M., Yamanaka, Y., Le Quéré, C., Buitenhuis, E. T., Aita, M. N., Alvain, S., Bopp, L., Hirata, T., Lima, I., Sailley, S., and Doney, S. C.: Phytoplankton competition during the spring bloom in four Plankton Functional Type Models, Biogeosciences Discuss., 9, 18083–18129, doi:10.5194/bgd-9-18083-2012, 2012.

Heimann, M., Esser, G., Haxeltine, A., Kaduk, J., Kicklighter, D. W., Knorr, W., Kohlmaier, G. H., Mcguire, A. D., Melillo, J., Moore III, B., Otto, R. D., Prentice, I. C., Sauf, W., Schloss, A., Sitch, S., Wittenberg, U., and Wurth, G.: Evaluation of terrestrial carbon cycle models through simulations of the seasonal cycle of atmospheric First results of a model intercomparison study, Global Biogeochem. Cy., 12, 1–24, 1998.

Hemming, D., Betts, R., and Collins, M.: Sensitivity and uncertainty of modelled terrestrial net primary productivity to doubled CO_2 and associated climate change for a relatively large perturbed physics ensemble, Agr. Forest Meteorol.,180,79–88, doi:10.1016/j.agrformet.2011.10.016, 2011.

Henson, S. A., Sarmiento, J. L., Dunne, J. P., Bopp, L., Lima, I., Doney, S. C., John, J., and Beaulieu, C.: Detection of anthropogenic climate change in satellite records of ocean chlorophyll and productivity, Biogeosciences, 7, 621–640, doi:10.5194/bg-7-621-2010, 2010.

Holland, E. A., Neff, J. C., Townsend, A. R., and McKeown, B.: Uncertainties in the temperature sensitivity of decomposition in tropical and subtropical ecosystems: implications for models, Global Biogeochem. Cy., 14, 1137–1151, doi:10.1029/2000GB001264, 2000.

Houghton, R. A., House, J. I., Pongratz, J., van der Werf, G. R., DeFries, R. S., Hansen, M. C., Le Quéré, C., and Ramankutty, N.: Carbon emissions from land use and land-cover change, Biogeosciences, 9, 5125–5142, doi:10.5194/bg-9-5125-2012, 2012.

Huntingford, C., Fisher, R. A., Mercado, L., Booth, B. B. B., Sitch, S., Harris, P. P., Cox, M., Jones, C. D., Betts, R. A., Malhi, Y., Harris, G. R., Collins, M., Cox, P. M., and Moorcroft, P.: Towards quantifying uncertainty in predictions of Amazon " dieback ", Philos. T. Roy. Soc. B, 363, 1857–1864, doi:10.1098/rstb.2007.0028, 2008.

Huntingford, C., Lowe, J. A., Booth, B. B. B., Jones, C. D., Harris, G. R., Gohar, L. K., and Meir, P.: Contributions of carbon cycle uncertainty to future, Tellus B, 61, 355–360, doi:10.1111/j.1600-0889.2009.00414.x, 2009.

Huntingford, C., Jones, P. D., Livina, V. N., Lenton, T. M., and Cox, P. M.: No increase in global temperature variability despite changing regional patterns, Nature, 500, 327–330, doi:10.1038/nature12310, 2013.

Hungate, B. A., Dijkstra, P., Wu, Duval, B. D., Day, F. P., Johnson, D. W., Megonigal, J. P., Brown, A. L. P., and Garland, J. L.: Cumulative response of ecosystem carbon and nitrogen stocks to chronic CO_2 exposure in a subtropical oak woodland, New Phytol., 200, 753–766, 2013.

Ilyina, T., Six, K. D., Segschneider, J., and Maier-reimer, E.: Global ocean biogeochemistry model HAMOCC: model architecture and performance as component of the MPI-Earth system model in different CMIP5 experimental realizations, Journal of Advances in Modeling Earth Systems, 5, 287–315, doi:10.1029/2012MS000178, 2013.

Jolliff, J. K., Kindle, J. C., Shulman, I., Penta, B., Friedrichs, M. A. M., Helber, R., and Arnone, R. A.: Summary diagrams for coupled hydrodynamic-ecosystem model skill assessment, J. Marine Syst., 76, 64–82, doi:10.1016/j.jmarsys.2008.05.014, 2009.

Jones, B. C. D., Cox, P., Huntingford, C., Centre, H., and Office, M.: Uncertainty in climate – carbon-cycle projections associated with the sensitivity of soil respiration to temperature, Tellus B, 55, 642–648, 2003.

Jones, C. D., Collins, M., Cox, P., and Pall, S. A.: The carbon cycle response to ENSO: a coupled climate – carbon cycle model study, J. Climate, 14, 4113–4129, 2001.

Jones, C. D., Cox, P. M., and Huntingford, C.: Climate-carbon cycle feedbacks under stabilization: uncertainty and observational constraints, Tellus B, 58, 603–613, doi:10.1111/j.1600-0889.2006.00215.x, 2006.

Jones, C., McConnell, C., and Coleman, K.: Global climate change and soil carbon stocks; predictions from two contrasting models for the turnover of organic carbon in soil, Glob. Change Biol., 11, 154–166, doi:10.1111/j.1365-2486.2004.00885.x, 2005.

Jones, C., Robertson, E., Arora, V., Friedlingstein, P., Shevliakova, E., Bopp, L., Brovkin, V., Hajima, T., Kato, E., Kawamiya, M., Liddicoat, S., Lindsay, K., Reick, C. H., Roelandt, C., Segschneider, J., and Tjiputra, J.: Twenty-first-century compatible CO_2 emissions and airborne fraction simulated by CMIP5 Earth system models under four representative concentration pathways, J. Climate, 26, 4398–4413, doi:10.1175/JCLI-D-12-00554.1, 2013.

Jung, M., Reichstein, M., Margolis, H. A., Cescatti, A., Richardson, A. D., Arain, M. A., Arneth, A., Bernhofer, C., Bonal, D., Chen, J., Gianelle, D., Gobron, N., Kiely, G., Kutsch, W., Lasslop, G., Law, B. E., Lindroth, A., Merbold, L., Montagnani, L., Moors, E. J., Papale, D., Sottocornola, M., Vaccari, F., and Williams, C.: Global patterns of land-atmosphere fluxes of carbon dioxide, latent heat, and sensible heat derived from eddy covariance, satellite, and meteorological observations, J. Geophys. Res., 116, G00J07, doi:10.1029/2010JG001566, 2011.

Kattge, J., Díaz, S., Lavorel, S., Prentice, I. C., Leadley, P., Bönisch, G., Garnier, E., Westoby, M., Reich, P. B., Wright, I. J., Cornelissen, J. H. C., Violle, C., Harrison, S. P., Van Bodegom, P. M., Reichstein, M., Enquist, B. J., Soudzilovskaia, N. A., Ackerly, D. D., Anand, M., Atkin, O., Bahn, M., Baker, T. R., Baldocchi, D., Bekker, R., Blanco, C. C., Blonder, B., Bond, W. J., Bradstock, R., Bunker, D. E., Casanoves, F., Cavender-Bares, J., Chambers, J. Q., Chapin Iii, F. S., Chave, J., Coomes, D., Cornwell, W. K., Craine, J. M., Dobrin, B. H., Duarte, L., Durka, W., Elser, J., Esser, G., Estiarte, M., Fagan, W. F., Fang, J., Fernández-Méndez, F., Fidelis, A., Finegan, B., Flores, O., Ford, H., Frank, D., Freschet, G. T., Fyllas, N. M., Gallagher, R. V., Green, W. A., Gutierrez, A. G., Hickler, T., Higgins, S. I., Hodgson, J. G., Jalili, A., Jansen, S., Joly, C. A., Kerkhoff, A. J., Kirkup, D., Kitajima, K., Kleyer, M., Klotz, S., Knops, J. M. H., Kramer, K., Kühn, I., Kurokawa, H., Laughlin, D., Lee, T. D., Leishman, M., Lens, F., Lenz, T., Lewis, S. L., Lloyd, J., Llusià, J., Louault, F., Ma, S., Mahecha, M. D., Manning, P., Massad, T., Medlyn, B. E., Messier, J., Moles, A. T., Müller, S. C., Nadrowski, K., Naeem, S., Niinemets, Ü., Nöllert, S., Nüske, A., Ogaya, R., Oleksyn, J., Onipchenko, V. G., Onoda, Y., Ordoñez, J., Overbeck, G., Ozinga, W. A., Patiño, S., Paula, S., Pausas, J. G., Peñuelas, J., Phillips, O. L., Pillar, V., Poorter, H., Poorter, L., Poschlod, P., Prinzing, A., Proulx, R., Rammig, A., Reinsch, S., Reu, B., Sack, L., Salgado-negret, B., Sardans, J., Shiodera, S., Shipley, B., Siefert, A., Sosinski, E., Soussana, J. F., Swaine, E., Swenson, N., Thompson, K., Thornton, P., Waldram, M., Weiher, E., White, M., White, S., Wright, S. J., Yguel, B., Zaehle, S., Zanne, A. E.

BGD

11, 2083–2153, 2014

and Wirth, C. : TRY – a global database of plant traits, Glob. Change Biol., 17, 2905–2935, doi:10.1111/j.1365-2486.2011.02451.x, 2011.

Keenan, T. F., Davidson, E., Moffat, A. M., Munger, W., and Richardson, A. D.: Using model-data fusion to interpret past trends, and quantify uncertainties in future projections, of terrestrial ecosystem carbon cycling, Glob. Change Biol., 18, 2555–2569, doi:10.1111/j.1365-2486.2012.02684.x, 2012.

Kelley, D. I., Prentice, I. C., Harrison, S. P., Wang, H., Simard, M., Fisher, J. B., and Willis, K. O.: A comprehensive benchmarking system for evaluating global vegetation models, Biogeosciences, 10, 3313–3340, doi:10.5194/bg-10-3313-2013, 2013.

Kidston, M., Matear, R., and Baird, M. E.: Parameter optimisation of a marine ecosystem model at two contrasting stations in the Sub-Antarctic Zone, Deep-Sea Res. Pt. II, 58, 2301–2315, doi:10.1016/j.dsr2.2011.05.018, 2011.

Kirschbaum, M. U. F.: Does enhanced photosynthesis enhance growth: lessons learned from CO_2 enrichment studies, Plant Physiol., 155, 117–124, 2011.

Knorr, W.: Annual and interannual CO_2 exchanges of the terrestrial biosphere: process-based simulations and uncertainties, Global Ecol. Biogeogr., 9, 225–252, 2000.

Knutti, R. and Tomassini, L.: Constraints on the transient climate response from observed global temperature and ocean heat uptake, Geophys. Res. Lett., 35, 1–5, doi:10.1029/2007GL032904, 2008.

Knutti, R., Meehl, G. A., Allen, M. R., and Stainforth, D. A.: Constraining climate sensitivity from the seasonal cycle in surface temperature, J. Climate, 19, 4224–4233, 2006.

Knutti, R., Allen, M. R., Friedlingstein, P., Gregory, J. M., Hegerl, G. C., Meehl, G. A., Meinshausen, M., Murphy, J. M., Plattner, G.-K., Raper, S. C. B., Stocker, T. F., Stott, P. A., Teng, H., and Wigley, T. M. L.: A review of uncertainties in global temperature projections over the twenty-first century, J. Climate, 21, 2651–2663, doi:10.1175/2007JCLI2119.1, 2008.

Koffi, E. N., Rayner, P. J., Scholze, M., and Beer, C.: Atmospheric constraints on gross primary productivity and net ecosystem productivity: results from a carbon-cycle data assimilation system, Global Biogeochem. Cy., 26,GB1024, doi:10.1029/2010GB003900, 2012.

Körner, C., Asshoff, R., Bignucolo, O., Hättenschwiler, S., Keel, S. G., Peláez-Riedl, S., Pepin, S., Siegwolf, R. T. W., and Zotz, G.: Carbon flux and growth in mature deciduous forest trees exposed to elevated CO_2, Science, 309, 1360–1362, doi:10.1126/science.1113977, 2005.

Kositsup, B., Montpied, P., Kasemsap, P., Thaler, P., Améglio, T., and Dreyer, E.: Photosynthetic capacity and temperature responses of photosynthesis of rubber trees (Hevea brasiliensis Müll. Arg.) acclimate to changes in ambient temperatures, Trees, 23, 357–365, doi:10.1007/s00468-008-0284-x, 2008.
Langdon, C., Broecker, W. S., Hammond, D. E., Glenn, E., Fitzsimmons, K., Nelson, S. G., Peng, T.-H., Hajdas, I., and Bonani, G.: Effect of elevated CO_2 on the community metabolism of an experimental coral reef, Global Biogeochem. Cy., 17,1011, doi:10.1029/2002GB001941,2003.
Lengaigne, M., Menkes, Æ. C., Andre, J., and Madec, Æ. G.: Influence of the oceanic biology on the tropical Pacific climate in a coupled general circulation model, Clim. Dynam., 28, 503–516, doi:10.1007/s00382-006-0200-2, 2007.
Lermusiaux, P. F. J.: Uncertainty estimation and prediction for interdisciplinary ocean dynamics, J. Comput. Phys., 217, 176–199, 2006.
Lines, E. R., Coomes, D. A., and Purves, D. W.: Influences of forest structure, climate and species composition on tree mortality across the eastern US, PLoS ONE, 5, e13212, doi:10.1371/journal.pone.0013212, 2010.
Litchman, E. and Klausmeier, C. A.: Trait-based community ecology of phytoplankton, Annu. Rev. Ecol. Evol. S., 39, 615–639, doi:10.1146/annurev.ecolsys.39.110707.173549, 2008.
Lloyd, J. and Farquhar, G. D.: Effects of rising temperatures and [CO_2] on the physiology of tropical forest trees, Philos. T. Roy. Soc. B, 363, 1811–1817, doi:10.1098/rstb.2007.0032, 2008.
Lloyd, J. and Taylor, J.: On the temperature dependence of soil respiration, Funct. Ecol., 8, 315–323, 1994.
Long, M. C., Lindsay, K., Peacock, S., Moore, J. K., and Doney: Twentieth-century oceanic carbon uptake and storage in CESM1 (BGC), J. Climate, 1, 6775–6799, doi:10.1175/JCLI-D-12-00184.1, 2013.
Longhurst, A., Sathyendranath, S., Platt, T., and Caverhill, C.: An estimate of global primary production in the ocean from satellite radiometer data, J. Plankton Res., 17, 1245–1271, 1995.
Lu, J. and Ji, J.: A simulation and mechanism analysis of long-term variations at land surface over arid/semi-arid area in north China, J. Geophys. Res., 111, 1–19, doi:10.1029/2005JD006252, 2006.

BGD
11, 2083–2153, 2014

Lu, M., Yang, Y., Luo, Y., Fang, C., Zhou, X., Chen, J., Yang, X., and Li, B.: Responses of ecosystem nitrogen cycle to nitrogen addition: a meta-analysis, New Phytol., 189, 1040–1050, 2011.
Luo, Y. Q., Hui, D. F., and Zhang, D. Q.: Elevated CO_2 stimulates net accumulations of carbon and nitrogen in land ecosystems: a meta-analysis, Ecology, 87, 53–63, 2006.
Luo, Y., Ogle, K., Tucker, C., Fei, S., Gao, C., LaDeau, S., Clark, J. S., and Schimel, D. S.: Ecological forecasting and data assimilation in a data-rich era, Ecol. Appl., 21, 1429–1442, 2011.
Luo, Y. Q., Randerson, J. T., Abramowitz, G., Bacour, C., Blyth, E., Carvalhais, N., Ciais, P., Dalmonech, D., Fisher, J. B., Fisher, R., Friedlingstein, P., Hibbard, K., Hoffman, F., Huntzinger, D., Jones, C. D., Koven, C., Lawrence, D., Li, D. J., Mahecha, M., Niu, S. L., Norby, R., Piao, S. L., Qi, X., Peylin, P., Prentice, I. C., Riley, W., Reichstein, M., Schwalm, C., Wang, Y. P., Xia, J. Y., Zaehle, S., and Zhou, X. H.: A framework for benchmarking land models, Biogeosciences, 9, 3857–3874, doi:10.5194/bg-9-3857-2012, 2012.
Luo, Y.-W., Doney, S. C., Anderson, L. A., Benavides, M., Berman-Frank, I., Bode, A., Bonnet, S., Boström, K. H., Böttjer, D., Capone, D. G., Carpenter, E. J., Chen, Y. L., Church, M. J., Dore, J. E., Falcón, L. I., Fernández, A., Foster, R. A., Furuya, K., Gómez, F., Gundersen, K., Hynes, A. M., Karl, D. M., Kitajima, S., Langlois, R. J., LaRoche, J., Letelier, R. M., Marañón, E., McGillicuddy Jr., D. J., Moisander, P. H., Moore, C. M., Mouriño-Carballido, B., Mulholland, M. R., Needoba, J. A., Orcutt, K. M., Poulton, A. J., Rahav, E., Raimbault, P., Rees, A. P., Riemann, L., Shiozaki, T., Subramaniam, A., Tyrrell, T., Turk-Kubo, K. A., Varela, M., Villareal, T. A., Webb, E. A., White, A. E., Wu, J., and Zehr, J. P.: Database of diazotrophs in global ocean: abundance, biomass and nitrogen fixation rates, Earth Syst. Sci. Data, 4, 47–73, doi:10.5194/essd-4-47-2012, 2012.
Luo, Y., White, L. W., Canadell, J. G., DeLucia, E. H., Ellsworth, D. S., Finzi, A., Lichter, J., and Schlesinger, W. H.: Sustainability of terrestrial carbon sequestration: a case study in Duke Forest with inversion approach, Global Biogeochem. Cy., 17, 1021, doi:10.1029/2002GB001923, 2003.
MacDougall, A. H., Avis, C. A., and Weaver, A. J.: Significant contribution to climate warming from the permafrost carbon feedback, Nat. Geosci., 5, 719–721, doi:10.1038/ngeo1573, 2012.
Malakoff, D.: Researchers struggle to assess responses to ocean acidification, Science, 338, 27–28, 2012.

Malhi, Y., Aragao, L. E. O. C., Galbraith, D., Huntingford, C., Fisher, R., Zelazowski, P., Sitch, S., Mcsweeney, C., and Meir, P.: Exploring the likelihood and mechanism of a climate-change-induced dieback of the, P. Natl. Acad. Sci. USA, 106, 20610–20615, 2009.

Manizza, M., Buitenhuis, E. T., and Le Quéré, C.: Sensitivity of global ocean biogeochemical dynamics to ecosystem structure in a future climate, Geophys. Res. Lett., 37,L13607, doi:10.1029/2010GL043360,2010.

Masson, D. and Knutti, R.: Climate model genealogy, Geophys. Res. Lett., 38, L08703, doi:10.1029/2011GL046864, 2011.

Matear, R. J.: Parameter optimization and analysis of ecosystem models using simulated annealing: a case study at Station P, J. Mar. Res., 53, 571–607, 1995.

Matthews, H. D., Eby, M., Ewen, T., Friedlingstein, P., and Hawkins, B. J.: What determines the magnitude of carbon cycle-climate feedbacks?, Global Biogeochem. Cy., 21, 1–12, doi:10.1029/2006GB002733, 2007.

Melillo, J. M., Butler, S., Johnson, J., Mohan, J., Steudler, P., Lux, H., Burrows, E., Bowles, F., Smith, R., Scott, L., Vario, C., Hill, T., Burton, A., Zhou, Y.-M., and Tang, J.: Soil warming, carbon-nitrogen interactions, and forest carbon budgets., P. Natl. Acad. Sci. USA, 108, 9508–9512, doi:10.1073/pnas.1018189108, 2011.

Melnikov, N. B. and O'Neill, B. C.: Learning about the carbon cycle from global budget data, Geophys. Res. Lett., 33, L02705, doi:10.1029/2005GL023935, 2006.

Moore, J., Lindsay, K., Doney, S., Long, M., and Misumi, K.: Marine ecosystem dynamics and biogeochemical cycling in the Community Earth System Model [CESM1(BGC)]: comparison of the 1990s with the 2090s under the RCP4.5 and RCP8.5 Scenarios, J. Climate, 26, 9291–9312, doi:10.1175/JCLI-D-12-00566.1, 2013.

Murphy, J. M., Sexton, D. M. H., Barnett, D. N., Jones, G. S., Webb, M. J., Collins, M., and Stainforth, D. A.: Quantification of modelling uncertainties in a large ensemble of climate change simulations, Nature, 430, 768–772, doi:10.1038/nature02770.1., 2004.

Nachtergaele, F., van Velthuizen, H., Verekst, L., and Widberg, D.: Harmonized World Soil Database v1.2., 2012.

Norby, R. J., Warren, J. M., Iversen, C. M., Medlyn, B. E., McMurtrie, R. E.: CO_2 enhancement of forest productivity constrained by limited nitrogen availability, P. Natl. Acad. Sci. USA, 107, 19368–19373, 2010.

Oleson, K. W., Lawrence, D. M., Gordon, B., Flanner, M. G., Kluzek, E., Peter, J., Levis, S., Swenson, S. C., Thornton, E., Dai, A., Decker, M., Dickinson, R., Feddema, J., Heald, C. L., Lamarque, J., Niu, G., Qian, T., Running, S., Sakaguchi, K., Slater, A., Stöckli, R., Wang, A., Yang, L., Zeng, X., and Zeng, X.: Technical Description of version 4.0 of the Community Land Model (CLM), 2010.

Oren, R., Ellsworth, D. S., Johnsen, K. H., Phillips, N., Ewers, B. E., Maier, C., Schäfer, K. V., McCarthy, H., Hendrey, G., McNulty, S. G., and Katul, G. G.: Soil fertility limits carbon sequestration by forest ecosystems in a CO_2-enriched atmosphere, Nature, 411, 469–472, 2001.

ORNL-DAAC, Global Soil Data Task Group: Global Gridded Surfaces of Selected Soil Characteristics (IGBP-DIS). [Global Gridded Surfaces of Selected Soil Characteristics (International Geosphere-Biosphere Programme – Data and Information System)]. Data set, available at: http://www.daac.ornl.gov from Oak Ridge National Laboratory Distributed Active Archive Center, Oak Ridge, Tennessee, USA, doi:10.3334/ORNLDAAC/569, 2000.

Oschlies, A.: Model-derived estimates of new production: new results point towards lower values, Deep-Sea Res. Pt. II, 48, 2173–2197, 2001.

Oschlies, A. and Garçon, V.: Eddy-induced enhancement of primary production in a model of the North Atlantic Ocean, Nature, 394, 266–269, 1998.

Palmer, J. R. and Totterdell, I. J.: Production and export in a global ocean ecosystem model, Deep-Sea Res. Pt. I, 48, 1169–1198,2001.

Parton, W. J., Scurlock, J. M. O., Ojima, D. S., Scholes, R. J., Kirchner, T., Seastedt, T., and Garcia, E.: Observations and modeling of biomass and soil organic matter dynamics for the grassland biome worldwide, Global Biogeochem. Cy., 7, 785–809, 1993.

Petersen, A. C.: The Precautionary Principle, Knowledge Uncertainty, and Environmental Assessment, Paper for NOB/NIG workshop "Knowledge Uncertainty", 30–31 October 2002, Erasmus University Rotterdam, available online at: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.108.721&rep=rep1&type=pdf, 2002.

Pfeil, B., Olsen, A., Bakker, D. C. E., Hankin, S., Koyuk, H., Kozyr, A., Malczyk, J., Manke, A., Metzl, N., Sabine, C. L., Akl, J., Alin, S. R., Bates, N., Bellerby, R. G. J., Borges, A., Boutin, J., Brown, P. J., Cai, W.-J., Chavez, F. P., Chen, A., Cosca, C., Fassbender, A. J., Feely, R. A., González-Dávila, M., Goyet, C., Hales, B., Hardman-Mountford, N., Heinze, C., Hood, M., Hoppema, M., Hunt, C. W., Hydes, D., Ishii, M., Johannessen, T., Jones, S. D., Key, R. M., Körtzinger, A., Landschützer, P., Lauvset, S. K., Lefèvre, N., Lenton, A., Lourantou, A., Merlivat, L., Midorikawa, T., Mintrop, L., Miyazaki, C., Murata, A., Nakadate, A., Nakano, Y., Nakaoka, S., Nojiri, Y., Omar, A. M., Padin, X. A., Park, G.-H., Paterson, K., Perez, F. F., Pierrot, D., Poisson, A., Ríos, A. F., Santana-Casiano, J. M., Salisbury, J., Sarma, V. V. S. S., Schlitzer, R., Schneider, B., Schuster, U., Sieger, R., Skjelvan, I., Steinhoff, T., Suzuki, T., Takahashi, T., Tedesco, K., Telszewski, M., Thomas, H., Tilbrook, B., Tjiputra, J., Vandemark, D., Veness, T., Wanninkhof, R., Watson, A. J., Weiss, R., Wong, C. S., and Yoshikawa-Inoue, H.: A uniform, quality controlled Surface Ocean CO_2 Atlas (SOCAT), Earth Syst. Sci. Data, 5, 125–143, doi:10.5194/essd-5-125-2013, 2013.

Piao, S., Sitch, S., Ciais, P., Friedlingstein, P., Peylin, P., Wang, X.,Ahlström, A., Anav, A., Canadell, J. G., Cong, N., Huntingford, C., Jung, M., Levis, S., Levy, P. E., Li, J., Lin, X., Lomas, M. R., Lu, M., Luo, Y., Ma, Y., Myneni, R. B., Poulter, B., Sun, Z., Wang, T., Viovy, N., Zaehle, S. and Zeng, N. :Evaluation of terrestrial carbon cycle models for their response to climate variability and to CO_2 trends, Glob. Change Biol.,19, 2117–2132, doi:10.1111/gcb.12187, 2013.

Post, W. M., Emanuel, W. R., Zinke, P. J., and Stangenberger, A. G.: Soil carbon pools and world life zones, Nature, 298, 156–159, 1982.

Poulter, B., Hattermann, F., Hawkins, E. D., Zaehle, S., Sitch, S., Restrepo-Coupe, N., Heyder, U., and Cramer, W.: Robust dynamics of Amazon dieback to climate change with perturbed ecosystem model parameters, Glob. Change Biol.,16(9), 1–19, doi:10.1111/j.1365-2486.2009.02157.x, 2010.

Poorter, H. and Navas, M. L.: Plant growth and competition at elevated CO_2: on winners, losers and functional groups, New Phytol., 157, 175–198, 2003.

Purves, D. and Pacala, S.: Predictive models of forest dynamics, Science, 320, 1452, doi:10.1126/science.1155359, 2008.

Qian, H., Joseph, R., and Zeng, N.: Enhanced terrestrial carbon uptake in the northern high latitudes in the 21st century from the coupled carbon cycle climate model intercomparison project model projections, Global Biogeochem. Cy., 16, 641–656, doi:10.1111/j.1365-2486.2009.01989.x, 2010.

Le Quéré, C.: Trends in the land and ocean carbon uptake, Current Opinion in Environmental Sustainability, 2, 219–224, doi:10.1016/j.cosust.2010.06.003, 2010.

Le Quere, C., Harrison, S. P., Prentice, I. C., Buitenhuis, E. T., Aumont, O., Bopp, L., Claustre, H., Cotrim Da Cunha, L., Geider, R., Giraud, X., Klaas, C., Kohfeld, K., Legendre, L., Manizza, M., Platt, T., Rivkin, R. B., Sathyendranath, S., Uitz, J., Watson, A. J., and Wolf-Gladrow, D.: Ecosystem dynamics based on plankton functional types for global

BGD
11, 2083–2153, 2014

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ocean biogeochemistry models, Glob. Change Biol., 11, 2016–2040, doi:10.1111/j.1365-2486.2005.01004.x, 2005.
Le Quéré, C., Andres, R. J., Boden, T., Conway, T., Houghton, R. A., House, J. I., Marland, G., Peters, G. P., van der Werf, G. R., Ahlström, A., Andrew, R. M., Bopp, L., Canadell, J. G., Ciais, P., Doney, S. C., Enright, C., Friedlingstein, P., Huntingford, C., Jain, A. K., Jourdain, C., Kato, E., Keeling, R. F., Klein Goldewijk, K., Levis, S., Levy, P., Lomas, M., Poulter, B., Raupach, M. R., Schwinger, J., Sitch, S., Stocker, B. D., Viovy, N., Zaehle, S., and Zeng, N.: The global carbon budget 1959–2011, Earth Syst. Sci. Data, 5, 165–185, doi:10.5194/essd-5-165-2013, 2013.
Raddatz, T. J., Reick, C. H., Knorr, W., Kattge, J., Roeckner, E., Schnur, R., Schnitzler, K.-G., Wetzel, P., and Jungclaus, J.: Will the tropical land biosphere dominate the climate–carbon cycle feedback during the twenty-first century?, Clim. Dynam., 29, 565–574, doi:10.1007/s00382-007-0247-8, 2007.
Randerson, J. T., Hoffman, F. M., Thornton, P. E., Mahowald, N. M., Lindsay, K., Lee, Y.-H., Nevison, C. D., Doney, S. C., Bonan, G., Stöckli, R., Covey, C., Running, S. W., and Fung, I. Y.: Systematic assessment of terrestrial biogeochemistry in coupled climate-carbon models, Glob. Change Biol., 15, 2462–2484, doi:10.1111/j.1365-2486.2009.01912.x, 2009.
Raupach, M., Rayner, P. J., Barrett, D. J., Defries, R. S., Heimann, M., Ojima, D. S., Quegan, S., and Schmullius, C. C.: Model – data synthesis in terrestrial carbon observation: methods, data requirements and data uncertainty specifications, Glob. Change Biol., 11, 378–397, doi:10.1111/j.1365-2486.2005.00917.x, 2005.
Rayner, P. J., Koffi, E., Scholze, M., Kaminski, T.,and Dufresne, J., L.: Constraining predictions of the carbon cycle using data, Philos. T. Roy. Soc. A, 369, 1955–1966, doi:10.1098/rsta.2010.0378, 2011.
Refsgaard, J. C. and Henriksen, H. J.: Modelling guidelines – terminology and guiding principles, Adv. Water Resour., 27, 71–82, doi:10.1016/j.advwatres.2003.08.006, 2004.
Reichler, T. and Kim, J.: How well do coupled models simulate today's climate?, B. Am. Meteorol. Soc., 89, 303–311, 2008.
Ricciuto, D. M., Davis, K. J., and Keller, K.: A Bayesian calibration of a simple carbon cycle model: the role of observations in estimating and reducing uncertainty, Global Biogeochem. Cy., 22, 1–15, doi:10.1029/2006GB002908, 2008.

BGD
11, 2083–2153, 2014

Ricciuto, D. M., King, A. W., Dragoni, D., and Post, W. M.: Parameter and prediction uncertainty in an optimized terrestrial carbon cycle model: effects of constraining variables and data record length, J. Geophys. Res., 116, 1–17, doi:10.1029/2010JG001400, 2011.
Riebesell, U., Schulz, K. G., Bellerby, R. G. J., Botros, M., Fritsche, P., Meyerhoefer, M., Neill, C., Nondal, G., Oschlies, A., Wohlers, J., and Zoellner, E.: Enhanced biological carbon consumption in a high CO_2 ocean, Nature, 450, 545–549, doi:10.1038/nature06267, 2007.
Riebesell, U., Koertinger, A., and Oschlies, A.: Sensitivities of marine carbon fluxes to ocean change, P. Natl. Acad. Sci. USA, 106, 20602–20609, 2009.
Rowlands, D. J., Frame, D. J., Ackerley, D., Aina, T., Booth, B. B. B., Christensen, C., Collins, M., Faull, N., Forest, C. E., Grandey, B. S., Gryspeerdt, E., Highwood, E. J., Ingram, W. J., Knight, S., Lopez, A., Massey, N., Mcnamara, F., Meinshausen, N., Piani, C., Rosier, S. M., Sanderson, B. M., Smith, L. A., Stone, D. A., Thurston, M., Yamazaki, K., Yamazaki, Y. H., and Allen, M. R.: Broad range of 2050 warming from an observationally constrained large climate model ensemble, Nat. Geosci., 5, 256–260, doi:10.1038/ngeo1430, 2012.
Saatchi, S. S., Houghton, R. A., Alvala, R. C. D. S., Soares, J. V., and Yu, Y.: Distribution of aboveground live biomass in the Amazon basin, Glob. Change Biol., 13, 816–837, 2007.
Sailley, S. F., Vogt, M., Doney, S. C., Aita, M. N., Bopp, L., Buitenhuis, E. T., Hashioka, T., Lima, I., Le Quéré, C., and Yamanaka, Y.: Comparing food web structures and dynamics across a suite of global marine ecosystem models, Ecol. Model., 261–262, 43–57,
Sala, A., Woodruff, D. R., and Meinzer, F. C.: Carbon dynamics in trees: feast or famine?, Tree Physiol., 32, 764–775, doi:10.1093/treephys/tpr143, 2012.
Sanderson, B. M. and Knutti, R.: On the interpretation of constrained climate model ensembles, Geophys. Res. Lett., 39,L16708, doi:10.1029/2012GL052665, 2012.
Sarmento, H., Montoya, J. M., Vázquez-Domínguez, E., Vaqué, D., and Gasol, J. M.: Warming effects on marine microbial food web processes: how far can we go when it comes to predictions?, Philos. T. Roy. Soc. B, 365, 2137–2149, doi:10.1098/rstb.2010.0045, 2010.
Sarmiento, J. L., Hughes, T. M. C., Stouffer, R. J., and Syukuro, M.: Simulated response of the ocean carbon cycle to anthropogenic climate warming, Nature, 393, 1–2, 1998.
Sarmiento, J. L., Slater, R., Barber, R., Bopp, L., Doney, S. C., Hirst, A. C., Kleypas, J., Matear, R., Mikolajewicz, U., Monfray, P., Soldatov, V., Spall, S. A., and Stouffer, R.: Response of ocean ecosystems to climate warming, Global Biogeochem. Cy., 18,GB3003,doi:10.1029/2003GB002134, 2004.

Sato, H., Itoh, A., and Kohyama, T.: SEIB – DGVM: A new Dynamic Global Vegetation Model using a spatially explicit individual-based approach, Ecol. Model., 200, 279–307, doi:10.1016/j.ecolmodel.2006.09.006, 2007.

Savtchenko, A., Ouzounov, D., Ahmad, S., Acker, J., Leptoukh, G., Koziana, J., and Nickless, D.: Terra and aqua MODIS products available from NASA GES DAAC, Adv. Space Res., 34, 710–714, doi:10.1016/j.asr.2004.03.012, 2004.

Scheffer, M., Brovkin, V., and Cox, P. M.: Positive feedback between global warming and atmospheric CO_2 concentration inferred from past climate change, Geophys. Res. Lett., 33, 2–5, doi:10.1029/2005GL025044, 2006.

Schiebel, R. and Movellan, A.: First-order estimate of the planktic foraminifer biomass in the modern ocean, Earth Syst. Sci. Data, 4, 75–89, doi:10.5194/essd-4-75-2012, 2012.

Schmittner, A., Oschlies, A., Matthews, H. D., and Galbraith, E. D.: Future changes in climate, ocean circulation, ecosystems, and biogeochemical cycling simulated for a business-as-usual CO_2 emission scenario until year 4000 AD, Global Biogeochem. Cy., 22, 1–21, doi:10.1029/2007GB002953, 2008.

Schmittner, A., Urban, N. M., Shakun, J. D., Mahowald, N. M., Clark, P. U., Bartlein, P. J., Mix, A. C., and Rosell-Melé, A.: Climate sensitivity estimated from temperature reconstructions of the last glacial maximum, Science, 334, 1385–1388, doi:10.1126/science.1203513, 2011.

Shaver, G. R., Canadell, J. G., Chapin III, F. S., Gurevitch, J., Harte, J., Henry, G., Ineson, P., Jonasson, S., Melillo, J., Pitelka, L., and Rustasd, L.: Global warming and terrestrial ecosystems: a conceptual framework for analysis, BioScience, 50, 871–882, doi:10.1641/0006-3568(2000)050[0871:GWATEA]2.0.CO;2, 2000.

Shevliakova, E., Pacala, S. W., Malyshev, S., Hurtt, G. C., Milly, P. C. D., Caspersen, J. P., Sentman, L. T., Fisk, J. P., Wirth, C., and Crevoisier, C.: Carbon cycling under 300 years of land use change: importance of the secondary vegetation sink, Global Biogeochem. Cy., 23, 1–16, doi:10.1029/2007GB003176, 2009.

Shiogama, H., Emori, S., Hanasaki, N., Abe, M., Masutomi, Y., and Takahashi, K.: Observational constraints indicate risk of drying in the Amazon basin, Nature Communications, 3, 253–257, doi:10.1038/ncomms1252, 2011.

Simard, M., Pinto, N., Fisher, J. B., and Baccini, A.: Mapping forest canopy height globally with spaceborne lidar, J. Geophys. Res.-Biogeo., 116, G04021, doi:10.1029/2011JG001708, 2011.

Sitch, S., Cox, P. M., Collins, W. J., and Huntingford, C.: Indirect radiative forcing of climate change through ozone effects on the land-carbon sink, Nature, 448, 791–794, doi:10.1038/nature06059, 2007.
Sitch, S., Huntingford, C., Gedney, N., Levy, P. E., Lomas, M., Piao, S. L., Betts, R., Ciais, P., Cox, P., Friedlingstein, P., Jones, C. D., Prentice, I. C., and Woodward, F. I.: Evaluation of the terrestrial carbon cycle, future plant geography and climate-carbon cycle feedbacks using five Dynamic Global Vegetation Models (DGVMs), Glob. Change Biol., 14, 2015–2039, doi:10.1111/j.1365-2486.2008.01626.x, 2008.
Sitch, S., Friedlingstein, P., Gruber, N., Jones, S. D., Murray-Tortarolo, G., Ahlström, A., Doney, S. C., Graven, H., Heinze, C., Huntingford, C., Levis, S., Levy, P. E., Lomas, M., Poulter, B., Viovy, N., Zaehle, S., Zeng, N., Arneth, A., Bonan, G., Bopp, L., Canadell, J. G., Chevallier, F., Ciais, P., Ellis, R., Gloor, M., Peylin, P., Piao, S., Le Quéré, C., Smith, B., Zhu, Z., and Myneni, R.: Trends and drivers of regional sources and sinks of carbon dioxide over the past two decades, Biogeosciences Discuss., 10, 20113–20177, doi:10.5194/bgd-10-20113-2013, 2013.
Smith, M. J., Purves, D. W., Vanderwel, M. C., Lyutsarev, V., and Emmott, S.: The climate dependence of the terrestrial carbon cycle, including parameter and structural uncertainties, Biogeosciences, 10, 583–606, doi:10.5194/bg-10-583-2013, 2013.
Smith, N. G. and Dukes, J. S.: Plant respiration and photosynthesis in global-scale models: incorporating acclimation to temperature and CO_2, Glob. Change Biol., 19, 45–63, doi:10.1111/j.1365-2486.2012.02797.x, 2013.
Soden, B. J. and Held, I. M.: An assessment of climate feedbacks in coupled ocean – atmosphere models, J. Climate, 19, 3354–3360, 2006.
Stainforth, D. A., Allen, M. R., Tredger, E.R, Smith, L. A.: Confidence, uncertainty, and decision-support relevance in climate prediction, Philos. T. Roy. Soc. A, 365, 2145–2161, 2007.
Stauffer, B., Fluckiger, J., Monnin, E., Schwander, J., Barnola, J. M., and Chappellaz, J.: Atmospheric CO_2, CH_4 and N_2O records over the past 60 000 years based on the comparison of different polar ice cores, Ann. Glaciol., 35, 202–208, 2002.
Steinacher, M., Joos, F., Frölicher, T. L., Bopp, L., Cadule, P., Cocco, V., Doney, S. C., Gehlen, M., Lindsay, K., Moore, J. K., Schneider, B., and Segschneider, J.: Projected 21st century decrease in marine productivity: a multi-model analysis, Biogeosciences, 7, 979–1005, doi:10.5194/bg-7-979-2010, 2010.

Stow, C. A., Jolliff, J., McGillicuddy, D. J., Doney, S. C., Allen, J. I., Friedrichs, M. A. M., Rose, K. A., and Wallhead, P.: Skill assessment for coupled biological/physical models of marine systems, J. Marine Syst., 76, 4–15, doi:10.1016/j.jmarsys.2008.03.011, 2009.

Tagliabue, A., Bopp, L., and Gehlen, M.: The response of marine carbon and nutrient cycles to ocean acidification: large uncertainties related to phytoplankton physiological assumptions, Global Biogeochem. Cy., 25, GB3017,doi:10.1029/2010GB003929, 2011.

Takahashi, T., Sutherland, S. C., and Kozyr, A.: Global ocean surface water partial pressure of CO_2 database: measurements performed during 1968–2008 (version 2008), ORNL/CDIAC-152, NDP-088r, 2009.

Taylor, K. E., Stouffer, R. J., and Meehl, G. A.: An overview of CMIP5 and the experiment design, B. Am. Meteorol. Soc., 93,485–498,doi:10.1175/BAMS-D-11-00094.1, 2011.

Taucher, J. and Oschlies, A.: Can we predict the direction of marine primary production change under global warming?, Geophys. Res. Lett., 38, 1–6, doi:10.1029/2010GL045934, 2011.

Taylor, K. E., Stouffer, R. J., and Meehl, G. A.: An overview of CMIP5 and the experiment design, B. Am. Meteorol. Soc., 93, 485–498, doi:10.1175/BAMS-D-11-00094.1, 2012.

Tebaldi, C. and Knutti, R.: The use of the multi-model ensemble in probabilistic climate projections, Philos. T. Roy. Soc. A, 365, 2053–2075, doi:10.1098/rsta.2007.2076, 2007.

Tebaldi, C., Mearns, L., Nychka, D., and Smith, R.: Regional probabilities of precipitation change: a Bayesian analysis of multimodel simulations, Geophys. Res. Lett., 31, L24213, doi:10.1029/2004GL021276, 2004.

Thomas, M. K., Kremer, C. T., Klausmeier, C. A., and Litchman, E.: A global pattern of thermal adaptation in marine phytoplankton, Science, 338, 1085–1088, doi:10.1126/science.1224836, 2012.

Thum, T., Räisänen, P., Sevanto, S., Tuomi, M., Reick, C., Vesala, T., Raddatz, T., Aalto, T., Järvinen, H., Altimir, N., Pilegaard, K., Nagy, Z., Rambal, S., and Liski, J.: Soil carbon model alternatives for ECHAM5/JSBACH climate model: evaluation and impacts on global carbon cycle estimates, J. Geophys. Res., 116, G02028, doi:10.1029/2010JG001612, 2011.

Tjiputra, J. F., Roelandt, C., Bentsen, M., Lawrence, D. M., Lorentzen, T., Schwinger, J., Seland, Ø., and Heinze, C.: Evaluation of the carbon cycle components in the Norwegian Earth System Model (NorESM), Geosci. Model Dev., 6, 301–325, doi:10.5194/gmd-6-301-2013, 2013.

Todd-Brown, K. E. O., Randerson, J. T., Post, W. M., Hoffman, F. M., Tarnocai, C., Schuur, E. A. G., and Allison, S. D.: Causes of variation in soil carbon simulations from

CMIP5 Earth system models and comparison with observations, Biogeosciences, 10, 1717–1736, doi:10.5194/bg-10-1717-2013, 2013.
Tucker, C., Pinzon, J., Brown, M., Slayback, D., Pak, E., Mahoney, R., Vermote, E., and El Saleous, N.: An extended AVHRR 8-km NDVI dataset compatible with MODIS and SPOT vegetation NDVI data, Int. J. Remote Sens., 26, 4485–4498, doi:10.1080/01431160500168686, 2005.
Urban, N. M. and Keller, K.: Probabilistic hindcasts and projections of the coupled climate, carbon cycle and Atlantic meridional overturning circulation system: a Bayesian fusion of century-scale observations with a simple model, Tellus A, 62, 737–750, doi:10.1111/j.1600-0870.2010.00471.x, 2010.
Van Asselt, M. B. A. and Rotmans, J.: Uncertainty in integrated assessment modelling, Climatic Change, 54, 75–105, 2002.
Volodin, E. M., Dianskii, N. A., and Gusev, A. V: Simulating Present Day Climate with the INMCM4. 0 Coupled Model of the Atmospheric and Oceanic General Circulations, Izv. Atmos. Ocean. Phy.+, 46, 414–431, doi:10.1134/S000143381004002X, 2010.
Watanabe, M., Shiogama, H., Yokohata, T., Kamae, Y., Yoshimori, M., Ogura, T., Annan, J. D., Hargreaves, J. C., Emori, S., and Kimoto, M.: Using a multiphysics ensemble for exploring diversity in cloud–shortwave feedback in GCMs, J. Climate, 25, 5416–5431, doi:10.1175/JCLI-D-11-00564.1, 2012.
Watanabe, S., Hajima, T., Sudo, K., Nagashima, T., Takemura, T., Okajima, H., Nozawa, T., Kawase, H., Abe, M., Yokohata, T., Ise, T., Sato, H., Kato, E., Takata, K., Emori, S., and Kawamiya, M.: MIROC-ESM 2010: model description and basic results of CMIP5-20c3m experiments, Geosci. Model Dev., 4, 845–872, doi:10.5194/gmd-4-845-2011, 2011.
Way, D. A. and Sage, R. F.: Thermal acclimation of photosynthesis in black spruce [Picea mariana (Mill.) B. S. P.], Plant Cell Environ., 31, 1250–1262, doi:10.1111/j.1365-3040.2008.01842.x, 2008.
Wieder, W. R., Bonan, G. B., and Allison, S. D.: Global soil carbon projections are improved by modelling microbial processes, Nature Clim. Change, 3, 909–912, 2013.
Willeit, M., Ganopolski, A., Dalmonech, D., Foley, A. M., and Feulner, G.: Time-scale and state dependence of the carbon-cycle feedback to climate, Clim. Dynam., in review, 2014.
Woodwell, G. M., Mackenzie, F. T., Houghton, R. A., Apps, M., Gorham, E., and Davidson, E.: Biotic feedbacks in the warming of the earth, Clim. change, 40, 495–518, 1998.

Wu, Z., Dijkstra, P., Koch, G. W., Penuelas, J., and Hungate, B. A.: Responses of terrestrial ecosystems to temperature and precipitation change: a meta-analysis of experimental manipulation, Glob. Change Biol., 17, 927–942, 2011.
Yokohata, T., Annan, J. D., Collins, M., Jackson, C. S., Shiogama, H., Watanabe, M., Emori, S., Yoshimori, M., Abe, M., Webb, M. J., and Hargreaves, J. C.: Reliability and importance of structural diversity of climate model ensembles, Clim. Dynam.,41,2745–2763, doi:10.1007/s00382-013-1733-9, 2013.
Yurova, A. Y., Volodin, E. M., I. G., A., Chertov, O. G., and Komarov, A. S.: Effects of variations in simulated changes in soil carbon contents and dynamics on future climate projections, Glob. Change Biol., 16, 823–835, doi:10.1111/j.1365-2486.2009.01992.x, 2010.
Zaehle, S. and Dalmonech, D.: Carbon–nitrogen interactions on land at global scales: current understanding in modelling climate biosphere feedbacks, Current Opinion in Environmental Sustainability, 3, 311–320, doi:10.1016/j.cosust.2011.08.008, 2011.
Zaehle, S., Sitch, S., and Smith, B.: Effects of parameter uncertainties on the modeling of terrestrial biosphere dynamics, Global Biogeochem. Cy., 19, GB3020, doi:10.1029/2004GB002395, 2005.
Zaehle, S., Friedlingstein, P., and Friend, A. D.: Terrestrial nitrogen feedbacks may accelerate future climate change, Geophys. Res. Lett., 37, L01401, doi:10.1029/2009GL041345, 2010.
Zaehle, S., Medlyn, B. E., De Kauwe, M. G., Walker, A. P., Dietze, M. C., Hickler, T., Luo, Y., Wang, Y.-P., El-Masri, B., Thornton, P., Jain, A., Wang, S., Warlind, D., Weng, E., Parton, W., Iversen, C. M., Gallet-Budynek, A., McCarthy, H., Finzi, A., Hanson, P. J., Prentice, I. C., Oren, R., and Norby, R. J.: Evaluation of eleven terrestrial carbon-nitrogen cycle models against observations from two temperate free-air CO_2 enrichment studies, New Phytol., in press, doi:10.1111/nph.12697, 2014.
Zahariev, K., Christian, J. R., and Denman, K. L.: Preindustrial, historical, and fertilization simulations using a global ocean carbon model with new parameterizations of iron limitation, calcification, and N_2 fixation, Prog. Oceanogr., 77, 56–82, doi:10.1016/j.pocean.2008.01.007, 2008.
Zeng, N., Qian, H., Munoz, E., and Iacono, R.: How strong is carbon cycle-climate feedback under global warming?, Geophys. Res. Lett., 31, 1–5, doi:10.1029/2004GL020904, 2004.
Zeng, N., Mariotti, A., and Wetzel, P.: Terrestrial mechanisms of interannual CO_2 variability, Global Biogeochem. Cy., 19, GB1016,doi:10.1029/2004GB002273, 2005.

Zhou, J., Xue, K., Xie, J., Deng, Y., Wu, L., Cheng, X., Fei, S., Deng, S., He, Z., Nostrand, J. D. Van and Luo, Y.: Microbial mediation of carbon-cycle feedbacks to climate warming, Nature Clim. Change, 2, 106–110, doi:10.1038/nclimate1331, 2011.

Zhu, Z., Bi, J., Pan, Y., Ganguly, S., Anav, A., Xu, L., Samanta, A., Piao, S., Nemani, R., and Myneni, R.: Global data sets of Vegetation Leaf Area Index (LAI)3g and Fraction of Photosynthetically Active Radiation (FPAR)3g derived from Global Inventory Modeling and Mapping Studies (GIMMS) Normalized Difference Vegetation Index (NDVI3g) for the period 1981 to 2011, Remote Sens., 5, 927–948, doi:10.3390/rs5020927, 2013.

Ziehn, T., Kattge, J., Knorr, W., and Scholze, M.: Improving the predictability of global CO_2 assimilation rates under climate change, Geophys. Res. Lett., 38, L10404, doi:10.1029/2011GL047182, 2011.

Table 1. Marine ecosystem models in current ESMs: main structure.

ESM	reference	OGCM	biochemistry model	food-web representation	PP response to temperature
BCC-CSM1.1	na	MOM4	OCMIP-2	no explicit food-web	na
CESM1-BGC	Moore et al. (2013), Long et al. (2013)	POP2	BEC	multiple functional groups	Q10
NorESM1	Ilyina et al. (2012)	MICOM	HAMOCC5	extended NPZD	Michaelis-Menten kinetics
BNU-ESM	na	MOM4	IBGC	na	na
GFDL-ESM2	Dunne et al. (2013)	MOM4	TOPAZ	3 phytoplankton groups	na
HadGEM2	Palmer and Totterdell, (2001)	HadGOM2	diat-HadOCC	few functional groups	Q10
CanESM2	Zahariev et al. (2008)	CanOM4	CMOC1.2	NPDZ	Arrhenius
IPSL-CM5	Lengaigne et al. (2007)	NEMO3.2	PISCES	few functional groups	na
MIROC-ESM	Watanabe et al. (2011)	COCO	NPZD type	NPDZ	
MPI-ESM	Ilyina et al. (2012)	MPIOM	HAMOCC5	extended NPZD	Michaelis-Menten kinetics
inmcm4	Volodin et al. (2010)	na	na	na	na

OGCM: ocean global circulation model; NPZD: nutrient-phytoplankton-zooplankton-detritus structure type; Q10 or Arrhenius: models of temperature dependence of primary productivity PP (for the functions see Lloyd and Taylor, 1994). na: not available.

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Table 2. Terrestrial ecosystem models (TEM) in current ESMs: key-structure and -parameterizations for soil dynamics. Names of the models that have been used as reference for parameterization or structures are also reported.

ESM	Reference	LSM-TEM	soil dynamics (respiration) structure	response to temperature	response to moisture
BCC-CSM1.1	Lu et al. (2006)	BCC-AVIM	na	na	na
CESM1-BGC	Oleson et al. (2004)	CLM4-CN	first order kinetic	Arrhenius	increases to a maximum and decreases
NorESM1	Tjiputra et al. (2012)	CLM4	CENTURY	Arrhenius	increases
BNU-ESM	na	BNU-ColM3	na	na	na
GFDL-ESM2	Shevliakova et al. (2009)	LM3	CENTURY	increases with T	increases
HadGEM2	W. J. Collins et al. (2011b)	MOSES2-TRIFFID	ROTHC	Q10	increases
CanESM2	Arora et al. (2011)	CLASS2.7-CTEM1	first order kinetic	Q10	increase with soil matric potential, increases to a maximum and decreases
IPSL-CM5	Dufresne et al. (2013)	ORCHIDEE	CENTURY	Q10	increase (quadratic function)
MIROC-ESM	Watanabe et al. (2011), Sato et al. (2007)	MATSIRO-SEIB-DVGM	ROTHC	Q10	increases as function of ET
MPI-ESM	Knorr et al. (2000), Raddatz et al. (2007)	JSB ACH	first order kinetic	Q10	increase
inmcm4	Volodin et al. (2010)	INMCM4.0	na	na	na

CENTURY (Parton et al., 1993); Roth-C (Coleman and Jenkinson, 1999); Q10 or Arrhenius: models of temperature dependence of soil respiration according to Lloyd and Taylor (1994); LSM: Land surface models; ET: evapotranspiration; na: not available.

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Table 3. Terrestrial ecosystem models (TEM) in current ESMs: key-structure and -parameterizations for vegetation dynamics. Names of the models that have been used as reference for parameterization or structures are also reported. For the reference of the ESMs, see Table 2.

ESM	LSM-TEM	vegetation Dynamics: name of the model	Photosynthesis+ conductance	Photosynthesis: response to soil moisture
BCC-CSM1.1	BCC-AVIM	na	na	na
CESM1-BGC	CLM4-CN	CNDV (common to CLM3-DVGM)	Farquhar-A	linear function applied to Vcmax
NorESM1	CLM4	CLM3-DVGM (IBIS,LPJ)	Farquhar-A	linear function applied to Vcmax
BNU-ESM	BNU-ColM3	BNU-DGVM (LPJ)	na	na
GFDL-ESM2	LM3	LM3v (ED, Demography Model)	Farquhar-B	non linear
HadGEM2	MOSES2-TRIFFID	TRIFFID-DVGM	Farquhar-B	linear
CanESM2	CLASS2.7-CTEM1	CTEM-dvgm	Farquhar-B	non linear
IPSL-CM5	ORCHIDEE	LPJ	Farquhar-A	linear function applied to Vcmax
MIROC-ESM	MATSIRO-SEIB-DVGM	SEIB-DVGM, gap model, (LPJ)	LightUseEfficiency-A	linear
MPI-ESM	JSBACH	JSBACH-dynveg	Farquhar	Effect on conductance
inmcm4	INMCM4.0	na	na	na

Farquhar: photosynthetic model according to Farquhar et al. (1980),Collatz et al. (1991),Collatz et al. (1992); A = conductance function of relative humidity (Ball et al., 1987); B = conductance function of VPD (Leuning et al., 1995); LPJ (Sitch et al., 2003); IBIS (Foley et al., 1996); ED (Moorcroft et al., 2001) ; Vcmax: photosynthetic capacity; LSM: Land surface models; ET: evapotranspiration; na: not available.

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Table 4. Datasets widely and recently used in evaluation of terrestrial and marine ecosystems. Newly datasets are also reported (see also Foley et al., 2013; Luo et al., 2012).

Dataset: Terrestrial Ecosystems	Reference
FAPAR (fraction of absorbed photosynthetically active radiation)	Gobron et al. (2006)
LAI (leaf area index)	Zhu et al. (2013)
NDVI/EVI (normalized difference vegetation index, Enhanced vegetation index)	Tucker et al. (2005)
GPP (gross primary productivity, upscaled, gridded, global)	Jung et al. (2011)
Soil C (upscaled, gridded, global)	Harmonized World Soil Database: Nachtergaele et al. (2012); Post et al. (1982); ORNL-DAAC (2000)
Vegetation C (upscaled, gridded, global, regional)	NDP-017b:Gibbs (2006); Saatchi et al. (2007)
Soil Respiration (upscaled, gridded, global)	Bond-Lamberty and Thomson (2011)
Site level manipulative experiments	Luo et al. (2006); Wu et al. (2011); Lu et al. (2011)
GPP-based on Fluorescence data (potential dataset)	Frankenberg et al. (2011)
Leaves trait dataset	Kattge et al. (2011)
Dataset: Marine Ecosystems	**Reference**
climatologies of pCO_2 (partial pressure)	Takahashi et al. (2009)
Primay Productivity (PP) based on chlorophyll dataset: Aqua Modis/Coastal Zone Color Scanner/SeaWifs	Savtchenko et al. (2004); Gregg and Casey, (2004)
MAREDAT (biomass dataset)	Buitenhuis et al. (2013), Luo et al. (2012), Schiebel and Movelian (2012)
Surface ocean CO_2 Atlas (SOCAT)	Pfeil et al. (2012)
Trait-based Community Ecology of Phytoplankton	Litchman and Klausmeier (2008)
Common Datasets	**Reference**
atmospheric CO_2 (ice core, remote stations)	ice-core: Stauffer et al., 2002; NOAA/Globalview, CDIAC: cdiac.ornl.gov
land–atmosphere and ocean–atmosphere CO_2 fluxes from GCP (global)	Global Carbon Project: Le Quaere et al. (2013)
land–atmosphere and ocean–atmosphere CO_2 fluxes from inversion (global, regional)	TRANSCOM3 project: Gurney et al. (2002)

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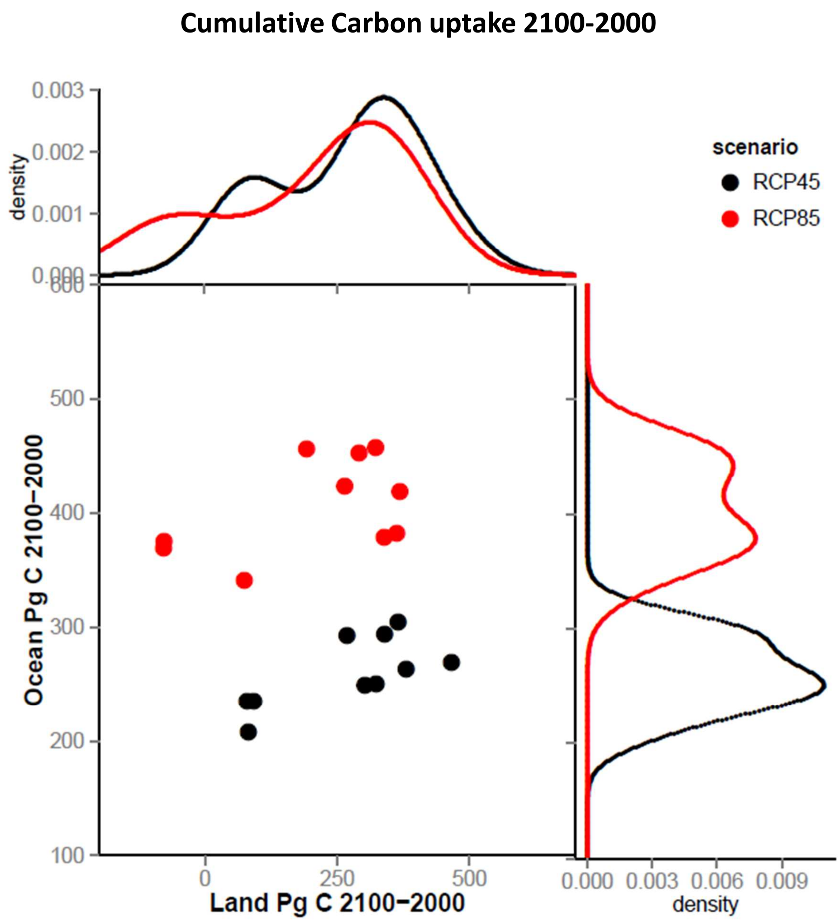

Fig. 1. Cumulative carbon uptake in land and ocean in ESMs with respect to year 2000 under two different RCP scenarios. Probability density functions are also reported.

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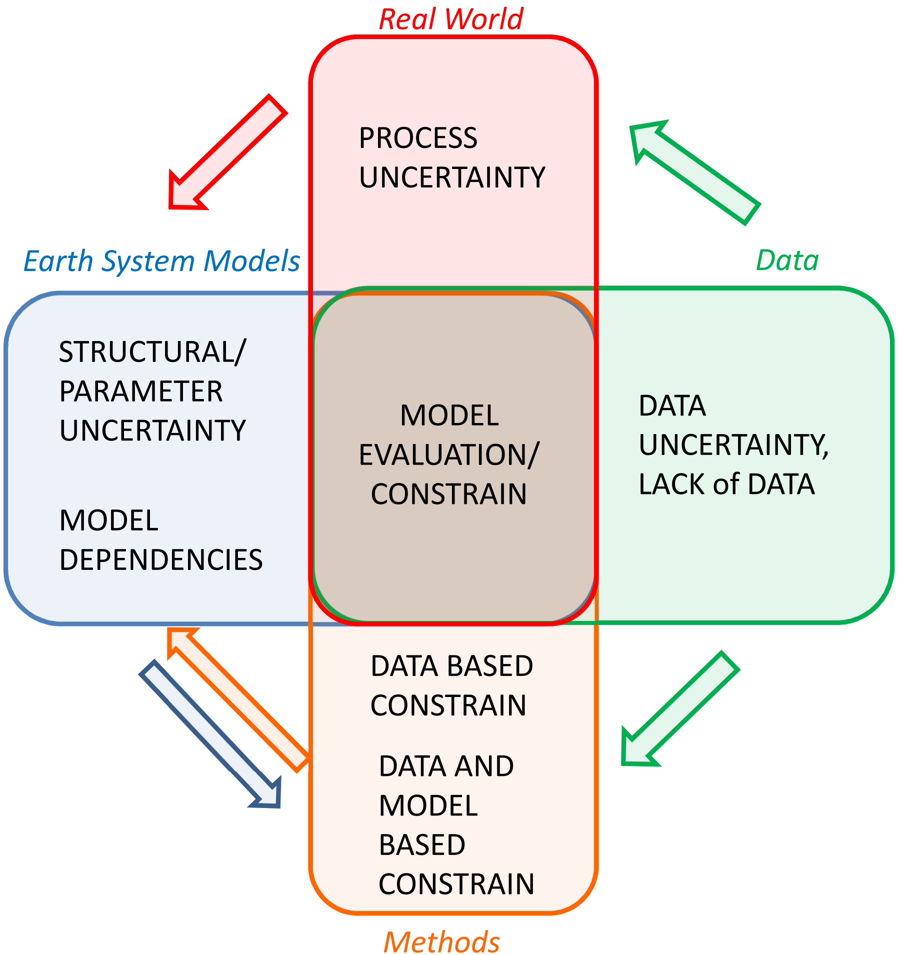

Fig. 2. Framework of uncertainties, related to the ESM carbon-projections constrains, as they are structured in the work.

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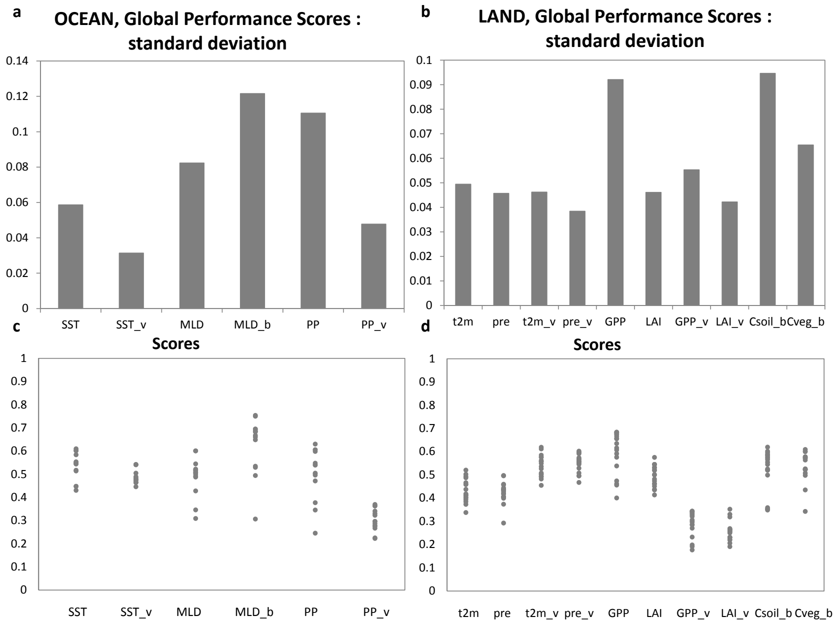

Fig. 3. Performance scores computed for climate- and carbon- related variables across the CMIP5 EMSs according to Anav et al. (2013). **(a)** Standard deviation of the skill scores for ocean variables and **(b)** for land variables; **(c)** skill scores for each individual ESM realization for ocean variables and **(d)** for land variables. The scores refer to global performances for: *P*, precipitation on land; *T*, temperature at 2 m on land; GPP, gross primary productivity; PP, ocean primary productivity; SST, sea surface temperature; MLD, mixing-layer depth; Csoil, soil carbon stock; Cveg, vegetation carbon stock; LAI, leaf area index. The metrics are based on the mean annual cycle (no index, correspondence of phase and amplitude); similarity between data and observations (index v: comparison of both the mean state and the interannual variability), and bias (index b: the score is based on the normalized mean bias between the model and the reference data).

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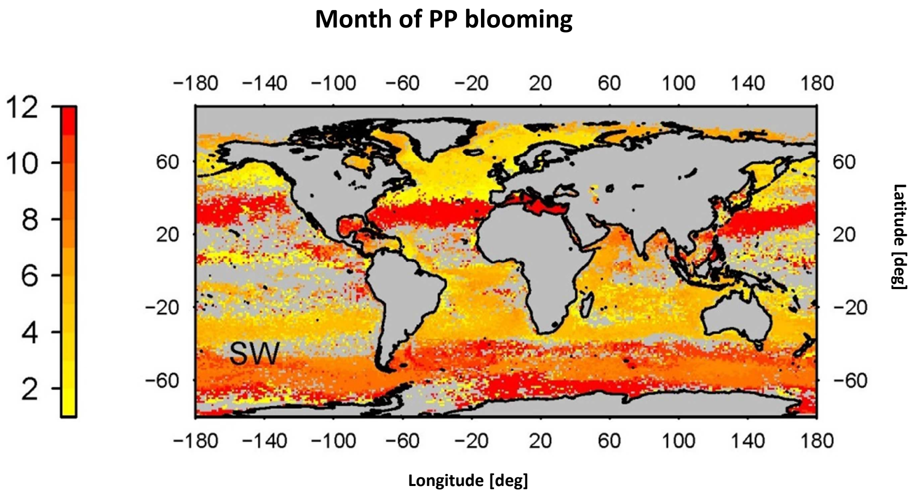

Fig. 4. Most frequent month of time of blooming computed on primary productivity, PP, data based on SeaWifs dataset.

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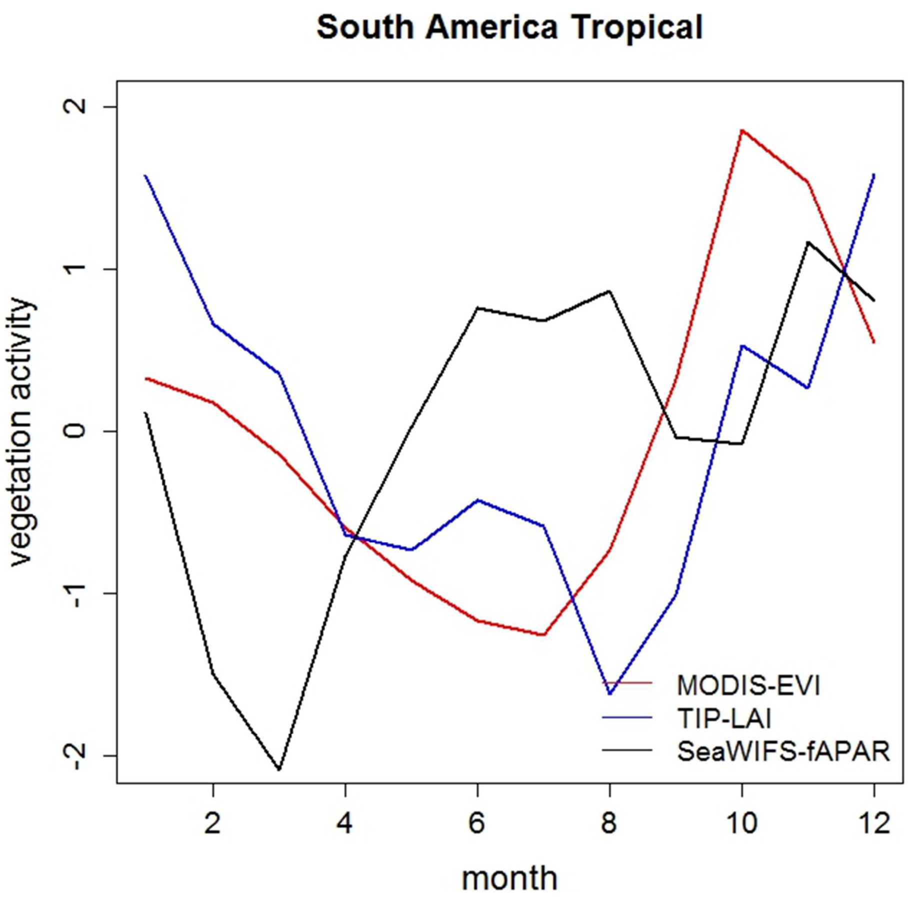

Fig. 5. Standardized data of seasonal vegetation activity in three satellite based datasets aggregated over the South America tropical area over years 2000–2005.

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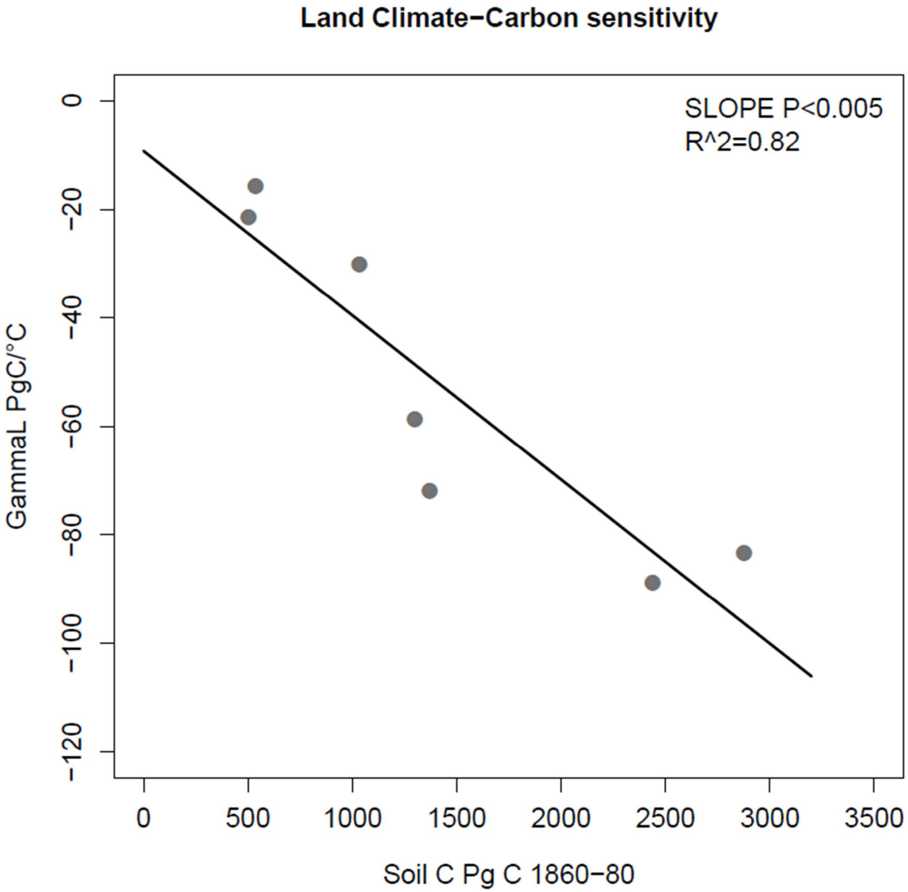

Fig. 6. Soil carbon stock computed during the preindustrial period for the ESMs (CMIP5 experiments) plotted vs. the climate-carbon land sensitivity of the same models reported in Arora et al. (2013). Only CMIP5 models with explicit modeling of Land use change were considered. The solid black diagonal line shows the best fit estimate between the two variables.