The effect of driving climate data on the simulated terrestrial carbon pools and fluxes over North America

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ABSTRACT: Dynamic vegetation models provide the ability to simulate terrestrial carbon pools and fluxes and a useful tool to study how these are affected by climate variability and climate change. At the continental scale, the spatial distribution of climate, in particular temperature and precipitation, strongly determines surface vegetation characteristics. Model validation exercises typically consist of driving a model with observation-based climate data and then comparing simulated quantities with their observation-based counterparts. However, observation-based datasets themselves may not necessarily be consistent with each other. Here, we compare simulated terrestrial carbon pools and fluxes over North America with observation-based estimates. Simulations are performed using the dynamic vegetation model Canadian Terrestrial Ecosystem Model (CTEM) coupled to the Canadian Land Surface Scheme (CLASS) when driven with two reanalysis-based climate datasets. The driving ECMWF reanalysis data (ERA40) and NCEP/NCAR reanalysis I data (NCEP) show differences when compared to each other, as well as when compared to the observation-based climate research unit (CRU) data. Most simulated carbon pools and fluxes show important differences, particularly over eastern North America, primarily due to differences in precipitation and temperature in the two reanalysis. However, despite very different gross fluxes, the model yields fairly similar estimates of the net atmosphere-land CO₂ flux when driven with the two forcing datasets. The ERA40 driven simulation produces terrestrial pools and fluxes that compare better with observation-based estimates. These simulations do not take into account land use change or nitrogen deposition, both of which have been shown to enhance the land carbon sink over North America. The simulated sink of 0.5 Pg C year⁻¹ during the 1980s and 1990s is therefore lower than inversion-based estimates. The analysis of spatial distribution of trends in simulated carbon pools and fluxes shows that the simulated carbon sink is driven primarily by NPP enhancements over eastern United States.

KEY WORDS carbon pools; carbon fluxes; climate datasets; dynamic vegetation

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1. Introduction

The spatial distribution of vegetation, and terrestrial carbon pools and fluxes, at the continental to global scales is governed primarily by climate in particular temperature and precipitation (Walter and Box, 1976; Woodward, 1987; Stephenson, 1990; Prentice et al., 1992). Terrestrial carbon fluxes are also sensitive to decadal and inter-annual variability in climate. Nemani et al. (2003) showed that a decreased cloud cover, and the resulting increase in solar radiation, led to an increase in net primary production (NPP) in Amazon rain forests during the 1982–1999 period. Gobron et al. (2005) studied the impact of the 2003 drought on plant productivity in Europe using remote-sensing data. They found that the drought affected the growth of vegetation but that the effects of the drought were temporally limited. Zhao et al. (2011) studied the effect of changing climate on vegetation in the arid region of north-western China during 1982–2003 and noted an increase in productivity which was well correlated to precipitation increase during the growing season and the preceding winter.

The development of Dynamic Global Vegetation Models (DGVMs) (Peng, 2000; Cox, 2001; Cramer et al., 2001; Quillet et al., 2010; Van den Hoof et al., 2011) has allowed to model changes in vegetation structure in response to climate variability and climate change in earth system models. As the climate changes, a DGVM can simulate the changes in structural vegetation attributes and its spatial distribution. Consequently, vegetation becomes a dynamic component of the earth system that interacts with and provides feedback to other earth system components. The changes in vegetation structure affect the biophysical processes at the land surface and changes in terrestrial carbon pools and fluxes affect the biogeochemical processes through carbon cycle feedbacks (Cox et al., 2000; Myneni et al., 2001; Foley et al., 2003). DGVMs represent vegetation in terms of plant functional types (PFTs). This approach
broadly classifies vegetation according to its form and function into functionally similar types (Box, 1996) such as broadleaf and needleleaf trees and their deciduous and evergreen types; crops and grasses are separated into C3 and C4 types according to their photosynthetic pathways. This classification does not take into account species level differences that become important at local scales but is expected to capture continental scale variability in terrestrial carbon pools and fluxes.

DGVMs are typically validated against observation-based estimates of terrestrial carbon pools and fluxes when driven with observation-based climate data. However, observation-based climate datasets themselves may not necessarily be consistent with each other with consequences for model validation. The objective of this article is to study the effect of driving climate data on the simulated terrestrial carbon pools and fluxes over North America, a region that covers several climatic zones and consequently biomes, using the Canadian Terrestrial Ecosystem Model (CTEM) (Arora, 2003; Arora and Boer, 2003, 2005) coupled to the Canadian Land Surface Scheme (CLASS) (Verseghy, 1991, 2011; Verseghy and Boer, 2003, 2005). Coupled CLASS/CTEM are driven offline at 0.5° (45 km) resolution over North America using the European Center for Medium range Weather Forecast’s (ECMWF) ERA40 reanalysis (Uppala et al., 2005) and the National Center for Environmental Prediction’s NCEP/NCAR reanalysis I data (Kalnay et al., 1996) from 1958 to 2001. Both simulations, one driven by ERA40 data and the other driven by NCEP data, are then evaluated by comparing CLASS/CTEM simulated terrestrial carbon pools and fluxes to observation-based estimates.

CTEM has been validated at selected sites and different PFTs in earlier studies (Arora and Boer, 2005; Li and Arora, 2011) and also at the global scale when implemented in an earth system model (Arora et al., 2009) but coupled to earlier versions of CLASS. The CLASS version 3.5. used here better simulates the hydraulic and thermal regimes by incorporating an improved treatment of soil evaporation, a new canopy conductance formulation, and an enhanced snow density and snow interception.

This article is organized as follows. Section 2 of the article gives a brief overview of the coupled land surface and terrestrial ecosystem models, CLASS and CTEM, along with the description of the experimental set up and the methodology. In Section 3, the effect of different driving data sets on vegetation growth and productivity is analysed by comparing them with observed and modelled data. Section 3 assesses the spatial and temporal evolution of the simulated biosphere in the recent past. A brief summary of the results and conclusions are given in Section 4.

2. Models, experimental set-up and data sets

2.1. Coupled land surface and terrestrial ecosystem model

The configuration used here is comprised of CTEM (Arora and Boer, 2005) coupled to the CLASS (version 3.5) (Verseghy, 2011). In its standard formulation, CLASS uses three soil layers, 0.1 m, 0.25 m and 3.75 m thick, corresponding approximately to the depth influenced by the diurnal cycle, the rooting zone and the annual variations of temperature, respectively (Poitras et al., 2011). CLASS includes prognostic equations for energy and water conservation for the three soil layers and a thermally and hydrologically distinct snowpack where applicable (treated as a fourth variable-depth layer). The energy balance and temperature calculations are performed over the three soil layers, but the hydrological balance calculations are performed only for layers above the bedrock. In an attempt to crudely mimic subgrid-scale variability, CLASS adopts a ‘pseudo-mosaic’ approach and divides each grid cell into a maximum of four sub-areas: bare soil, vegetation, snow over bare soil and snow with vegetation. The energy and water balance calculations are first performed for each sub-area separately, and then averaged over the grid cell, using averaged structural attributes and physiological properties of the four PFTs in CLASS: needleleaf trees, broadleaf trees, crops and grasses. These structural attributes include leaf area index (LAI), roughness length, canopy mass and rooting depth, which have to be specified if they are present in a grid cell. When coupled to CTEM, these structural vegetation attributes are dynamically simulated by CTEM as a function of environmental conditions.

CTEM is a process-based ecosystem model (Arora, 2003; Arora and Boer, 2003, 2005, 2006; Li and Arora, 2011) designed to simulate terrestrial ecosystem processes. It is able to grow vegetation from bare ground and simulates several vegetation structural attributes including LAI, vegetation height, root distribution and canopy mass. It includes processes of photosynthesis, autotrophic and heterotrophic respiration, phenology, turnover, allocation, fire and land use change. The photosynthesis sub-module uses the biogeochemical approach as described by Farquhar et al. (1980) and Collatz et al. (1991, 1992). CTEM simulates two dead carbon pools, litter and soil organic carbon, and three live vegetation pools (stems, leaves and roots). The structure of CTEM is shown in Figure 1 along with the prognostic equations for carbon in the five model pools. Terrestrial ecosystem processes in CTEM are modelled for nine different PFTs: evergreen and deciduous needleleaf trees, broadleaf evergreen and cold and drought deciduous trees, and C3 and C4 crops and grasses. The vegetation structural attributes of CTEM’s nine PFTs are averaged for four PFTs (needleleaf trees, broadleaf trees, crops and grasses) when they are passed to CLASS. Figure 2 shows the manner in which CLASS and CTEM are coupled to each other. CLASS and CTEM’s photosynthesis sub-module, simulating the fast biophysical processes, such as photosynthesis, canopy conductance and leaf respiration, operate at a 30 min timestep while other biogeochemical processes are modelled at a daily timestep. Once coupled, CLASS and CTEM simulate energy, water and CO2 fluxes across the land–atmosphere boundary. However, CTEM does not include the coupling of carbon with nitrogen and

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Figure 1. The structure of the terrestrial ecosystem model and the rate change equations for carbon in five model pools: leaves (L), stem (S), root (R), litter or debris (D), and soil organic matter or humus (H).

\[
\begin{align*}
\frac{dC_L}{dt} &= G - A_S - A_R - R_{gl} - R_{gl}, - D_L \\
\frac{dC_S}{dt} &= A_S - R_{gS} - R_{mS} - D_S \\
\frac{dC_R}{dt} &= A_R - R_{gR} - R_{ur} - D_R \\
\frac{dC_D}{dt} &= D_L + D_S + D_R - R_{AD} - C_{D\rightarrow H} \\
\frac{dC_H}{dt} &= C_{D\rightarrow H} - R_{CH}
\end{align*}
\]

Figure 2. The manner in which the land surface scheme CLASS and the terrestrial ecosystem module CTEM are coupled to each other. CTEM sub-modules are shown with a thick dark outline.

CLASS

- Albedo and transmittivity calculations
- Photosynthesis, leaf respiration, and canopy conductance
- Surface energy and water balance
- Soil heat and moisture dynamics

\( \Delta t = 30 \text{ minutes} \)

CTEM

- Autotrophic respiration
- Heterotrophic respiration
- Allocation
- Phenology
- Turnover, mortality
- Conversion of biomass to structural attributes

\( \Delta t = 1 \text{ day} \)
phosphorus cycles and so, nutrient limitation of photosynthesis is not explicitly modelled. Nevertheless, CTEM implicitly models nutrient limitation by ‘downregulating’ photosynthesis as CO₂ increases using an empirical formulation that is calibrated on the basis of plants grown in elevated and ambient CO₂ environments (Arora et al., 2009).

2.2. Experimental set-up

The coupled CLASS and CTEM models are run offline over the North American domain shown in Figure 3, at a horizontal resolution of 0.5° and a timestep of 30 min. The input data required to run the model include the incident solar and longwave radiation, air temperature, relative humidity, wind velocity, surface pressure and total precipitation. The soil texture information, i.e. percentage of sand and clay, for the three layers (see Section 2.1.) is specified from Webb et al. (1991). Finally, the fractional coverage of CTEM’s nine PFTs (Figure 3) for the 0.5° grid cells are specified from Arora and Boer (2010) who use the HYDE 2 crop area data set (Wang et al., 2006) to reconstruct historical land cover. The land cover is specified at its 1960 values so land use change is not taken into account. It should be noted that, even though the geographical distribution of PFTs is fixed, the vegetation attributes (LAI, land-atmosphere CO₂ fluxes and carbon pools) are simulated as dynamic functions of driving climate.

Two simulations are performed with CLASS/CTEM models using different driving climate data. The first uses ERA40 reanalysis data (Uppala et al., 2005), and the second uses NCEP reanalysis (Kalnay et al., 1996). ERA40 data is available for the 1957–2002 period at 2.5° (250 km) resolution, while NCEP data is available for the 1948-present period at 200 km resolution. These two simulations driven by ERA40 and NCEP for the common 1958–2001 period are referred to as RPERA and RP_NCEP, respectively.

Initial conditions for prognostic variables in CLASS and CTEM (including structural vegetation attributes) for the RPERA and RP_NCEP simulations are obtained by

Figure 3. Fractional coverage (%) of the nine PFTs modelled by CTEM for the North American domain.
spinning the model from zero vegetation for 400 years, driven by repeated 1958–1977 ERA40 and NCEP climate data, respectively. Similarly to the CMIP5 modelling protocol (Taylor et al., 2009, 2012), a constant CO2 concentration value corresponding to the year 1765 is used for the first 207 simulation years for the spin up, followed by transient CO2 concentrations corresponding to the years 1765–1957 for the remaining 193 years. The transient 1958–2001 simulations RP_ERA and RP_NCEP are forced with evolving CO2 concentrations from the Mauna Loa Observatory (Keeling et al., 1976; Thoning et al., 1989). Because the soil carbon is much slower to reach equilibrium than any other carbon pool (Figure 1), an accelerator is used to allow the soil carbon pool to reach equilibrium at a similar rate as the vegetation and the litter, so that all carbon pools have stabilized within the first part of the spin-up (constant CO2).

2.3. Data sets and methods

While the reanalysis data provide the sub-daily resolution of meteorological data needed for driving the CLASS and CTEM models, they are not ‘observation-based’ in a strict sense. Thus, prior to studying the impact of the climate data on vegetation, the ERA40 and NCEP seasonal mean temperature and precipitation used to drive CLASS/CTEM are compared to the gridded observational-based data from the climate research unit (CRU) (Mitchell and Jones, 2005). The CRU TS 2.1 data set covers the period 1901–2002 and has a resolution of 0.5°. This comparison helps identify biases in the two reanalysis datasets.

The simulated terrestrial pools and fluxes are analysed by comparing green LAI, NPP, GPP and woody biomass with observation-based estimates and multi-model results from other studies. The observation-based green LAI were obtained from the International Land Surface Climatology Project Initiative (ISLSCP II) FASIR-adjusted NDVI Biophysical Parameter Fields measured by the satellite mounted AVHRR sensor (Los et al., 2000; Hall et al., 2006; Sietse, 2010). These monthly global data are available for the 1982–1998 period at 1° × 1° resolution. The NPP data are from the MODIS NPP/GPP project (MOD17) (Zhao et al., 2005), a part of the NASA/EOS project. It is a continuous satellite-driven data available from 2000 to 2006 at 1 km resolution. The algorithm used in MOD17 is based on the original logic of Monteith, suggesting that NPP under non-stressed conditions is linearly related to the amount of absorbed photosynthetically active radiation (PAR) during the growing season. The MOD17 product also combines the complex effects of temperature, water and radiation on the productivity and corrects the data contaminated by cloudiness or severe aerosol. The GPP data were obtained from observation-based estimations of global GPP for the 1998–2005 period using eddy covariance flux data and various diagnostic models from the Beer et al. (2010) study. Finally, the woody biomass data are from an AVHRR GIMMS NDVI data set with an 8-km resolution and forest inventory data for stem wood volume (Dong et al., 2003). An equation that relates the forest inventory data with the satellite NDVI data as a function of latitude, was developed and tested by Dong et al. (2003) in order to estimate the woody biomass with a high resolution across the northern hemisphere in the early 1980s and the late 1990s. The observation-based and multi-model mean data used for validation come from different sources and need not necessarily be consistent with each other.

Both RP_ERA and RP_NCEP simulations are also investigated for spatial and temporal variability of primary carbon fluxes and trends in the carbon pools in North America. To limit the effect of initial conditions, this analysis is restricted to the last 32 years (1970–2001) of the simulation. Trends are calculated using Sen’s slope method (Sen, 1968) and the statistical significance of these trends is estimated using the Mann–Kendall test (Kendall, 1975; Khaliq et al., 2009) at 5% significance level.

3. Results and discussion

3.1. Driving data validation

The seasonal mean temperature and precipitation differences between the two reanalysis and the CRU dataset for the period 1958–2001 are shown in Figure 4. For the winter precipitation, both NCEP and ERA40 reanalysis show similar differences compared to the CRU. There are two main regions of underestimation: up to 5 mm/d on the West Coast and in the Canadian Rocky Mountains and up to 2 mm/d in southeast United States. The NCEP and ERA40 summer precipitation compare differently to the CRU data. NCEP tends to overestimate precipitation by up to 5 mm/d in southeast United States and Mexico and by 4 mm/d in Alaska. It underestimates summer precipitation in some parts of northeast Canada and northwest Mexico by up to 4 mm/d. ERA40 tends to generally underestimate summer precipitation, particularly over the United States, by 1 or 2 mm/d, but as high as up to 4 mm/d in southeast United States and up to 5 mm/d in Mexico (Figure 4(a)). Overall, ERA40 precipitation appears to compare better with the CRU data set, especially during summer when most of the vegetation growth occurs.

In Figure 4(b), ERA40 generally overestimates the seasonal mean winter temperature by 1–2 °C in the southern half of North America, and by up to 10 °C in the high-latitude regions of northwest Canada and Alaska. NCEP generally tends to underestimate the winter temperatures, especially in the highlands of western United States (up to 6 °C). For seasonal mean summer temperature, ERA40 shows a constant overestimation of between 2 and 6 °C that is enhanced over the highlands in western United States (up to 10 °C). Similar to ERA40, NCEP tends to overestimate the temperatures in summer except along the Canadian West Coast where it underestimates the temperature by up to 10 °C.
Figure 4. Comparison of the 1958–2001 NCEP and ERA40 (a) precipitation (mm/d) and (b) mean air temperature (°C) with that of CRU for the winter (DJF) and summer (JJA) periods.

In their comparison of ERA40 and NCEP reanalyses to CRU over the 1958–2001 period, Simmons et al. (2004) have shown that there is a warm bias in the surface temperature in the middle and high latitudes, especially prior to the 1970s due to the lack of satellite observations. Their study also showed that when comparing ERA40 to the NCEP reanalysis, ERA40 is closest to the CRU analysis for all but the earliest years (prior to 1967).

3.2. CLASS/CTEM evaluation and analysis

The simulated terrestrial carbon pools and fluxes from the offline CLASS and CTEM simulations (RP_ERA and RP_NCEP) for the 1958–2001 period are compared with observations where possible and also analysed to investigate the trends for the 1970–2001 period.

3.2.1. Evaluation of the mean state

Simulated NPP, GPP, woody biomass and green LAI, are compared with observation-based where available or with multi-model mean data as described in Section 2.3. In Figure 5(a), RP_ERA GPP compares reasonably well with the observation-based estimate from Beer et al. (2010). The model captures the spatial distribution of GPP relatively well, with high values located mostly in southeast United States and along the coasts of Mexico. The model also somewhat captures the high GPP values along the West Coast. The simulated higher GPP for the RP_NCEP case over southeast United States is the result of higher summer precipitation in the NCEP reanalysis (Figure 4(a)). While simulated GPP compares well with its observation-based estimate, simulated NPP for the RP_ERA case (Figure 5(b)) is higher over the eastern United States and generally lower elsewhere when compared to the satellite-based NPP from MODIS (Zhao et al., 2005). Similar to GPP, NPP for the RP_NCEP case is too high compared to the estimate from Zhao et al. (2005), especially over eastern United States, again due to higher than observed summer precipitation. CTEM uses a single-leaf photosynthesis approach and the coupling between photosynthesis and canopy conductance is based on vapour pressure deficit (Leuning, 1995). The effect of water stress on maximum potential temperature-based photosynthetic rate is taken into account by reducing the potential photosynthetic rate via a non-linear soil moisture function, which takes into account the degree of soil saturation, the wilting point and the field capacity soil moisture contents and the fraction of roots in the three soil layers (Arora, 2003). The coefficient of determination ($R^2$) and root mean square error (RMSE) of both NPP and GPP values against their respective evaluation data are shown in Table 1. For both net and gross primary productivities, the RMSE values confirm that RP_NCEP has the larger errors. Interestingly, the $R^2$ values show that the spatial patterns are better captured by RP_NCEP. In Figure 6(a), simulated woody biomass for the RP_ERA case is generally higher than its observation-based estimate except in the Pacific northwest region of the United States and interior British Columbia. This is possibly related to only one PFT dedicated to needleleaf evergreens. Validation of CTEM over British Columbia (BC) in another project at a 40 km resolution shows that an additional needleleaf evergreen PFT, with higher leaf life span as well as higher drought and cold resistance, is needed for interior BC to simulate realistic spatial distribution of LAI (Dr. Yiran Peng, CCCma, personal communication). Finally, the use of the NCEP reanalysis leads to even higher simulated woody biomass.

Even though the simulated GPP (Figure 5(a)) compares reasonably well with its observation-based estimate, the simulated NPP (Figure 5(b)) is overestimated compared to the MODIS estimates from Zhao et al. (2005) and woody biomass (Figure 6(a)) is overestimated compared to observation-based estimates from Dong et al. (2003). These inconsistencies are most likely the result of different sources of the validation data.

With its warmer temperatures and greater precipitation in summer, compared to the CRU data set, the NCEP reanalysis yield values of GPP and NPP (Figure 5(a) and
Figure 5. The spatial plots correspond to the mean annual (a) GPP (kgC m\(^{-2}\) year\(^{-1}\)) (1998–2001 or 1998–2005) and (b) NPP (kgC m\(^{-2}\) year\(^{-1}\)) (2000–2001) for RP_ERA (2nd column), RP_NCEP (4th column) and their respective validation data (3rd column) from Beer et al. (2010) and Zhao et al. (2005). Zonal distributions along the northern latitudes of the studied variable are shown in the 1st column.

Table 1. Coefficient of determination (\(R^2\)) and root mean square error (RMSE) values from the NPP and GPP values against the respective evaluation data for both RP_ERA and RP_NCEP simulations.

|       | NPP          | GPP          |
|-------|--------------|--------------|
|       | \(R^2\)      | RMSE         | \(R^2\)      | RMSE         |
| RP_NCEP | 0.5307      | 0.2338       | 0.6483      | 0.3546       |
| RP_ERA  | 0.5630      | 0.2924       | 0.6716      | 0.4392       |

(b)) that are much too high in southeast United States. This overestimation is, indeed, well correlated with the higher summer precipitation shown in Figure 4(a). The woody biomass (Figure 6(a)) is, as a result, also overestimated when compared to observations. These patterns are also seen in the zonal distribution of GPP, NPP and woody biomass in Figures 5(a), (b) and 6(a), respectively. The zonal distribution of both GPP and NPP, for the RP_ERA case, compares well the observation-based estimates from Beer et al. (2010) and satellite-driven data from Zhao et al. (2005), respectively, while for the RP_NCEP case both quantities are overestimated in the tropics and mid-latitudes regions. In regard to the woody biomass, both simulations yield values that are higher than the observation-based estimates although the RP_ERA case is closer to the observations.

In Figure 6(b), CTEM tends to underestimate the green LAI when driven by the ERA40 reanalysis. The underestimation, when compared to the observation-based data, is greatest in areas covered mostly by forests such as the boreal forest in central and western Canada and the temperate forests covering most of eastern United States. This is most likely a model limitation, although satellite-based LAI products also have their limitations. Many different approaches are used to calculate the normalized difference vegetation index (NDVI), used to derive LAI, and this leads to different results, as shown by Alcaraz-Segura et al. (2010). Furthermore, Garrigues et al. (2008) have shown that LAI datasets derived from remote-sensing data all have their weaknesses. Most datasets agree over croplands and grasslands, but large differences appear over forests ‘where differences in vegetation structure representation between algorithms and surface reflectance uncertainties lead to substantial discrepancies between products’ (Garrigues et al., 2008).

The RP_NCEP case shows similar spatial pattern to that for RP_ERA, but it tends to overestimate the LAI especially in southeast United States. The zonal distribution of the LAI shows that both simulations tend to overestimate LAI between 25 and 35\(^\circ\)N but tend to underestimate LAI north of 50\(^\circ\)N, similarly to what found Gibelin et al. (2006) when comparing their LAI, simulated by ISBA terrestrial ecosystem model, with the ISLSCP data (their Figure 2). In addition, Gibelin et al.
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Figure 6. The spatial plots correspond to the mean annual (a) woody biomass (kgC m\(^{-2}\)) (1995–1999) and (b) green LAI (m\(^2\)/m\(^2\)) (1995–1998) for RPERA (2nd column), RP_NCEP (4th column) and their respective validation data (3rd column) from Dong et al. (2003) and from ISLSCP (Los et al., 2000; Hall et al., 2006; Sietse, 2010). Zonal distributions along the northern latitudes of the studied variable are shown in the 1st column.

(2006) show that ISLSCP values of LAI are generally rather high compared to MODIS and ECOCLIMAP (Champeaux et al., 2005) data.

The different sources of observation-based data and inconsistencies between them make it difficult to draw firm conclusions about model behaviour. For example, the simulated GPP in the RP ERA case over the southeastern United States (Figure 5(a)) compares well with its observation-based estimate but simulated woody biomass is higher compared to observation-based estimates and simulated LAI is lower. Nevertheless, despite the differences in the absolute magnitude of simulated GPP, NPP, woody biomass and LAI, the spatial patterns of these quantities and their zonal distributions compare reasonably well to those from the observation-based analysis. However, the productivity and the LAI in the Yucatan peninsula are underestimated by both simulations (RP ERA and RP_NCEP). This could be due to a combination of the low resolution of both climate dataset, and its impact on the quality of the datasets, and of problems with model performance in tropical regions.

Simulated results may also be assessed on the basis of vegetation carbon use efficiency (CUE), the ratio of net to GPP, which describes the ability of plants to transfer carbon from the atmosphere to terrestrial biomass (DeLucia et al., 2007). CUE may also be used to assess the consistency between the NPP and GPP data used for validating simulated results. DeLucia et al. (2007) show that the CUE of forests can vary from 0.23 to 0.83, with an average value of 0.53, depending on the tree type, their stand age and leaf mass to total mass ratio. Figure 7 shows the simulated mean CUE for the 1990–1999 period obtained from both RP ERA and RP_NCEP simulations, together with two observation-based CUE calculated using NPP estimates from Zhao et al. (2005) and GPP estimates from Beer et al. (2010) and Zhao et al. (2005). The comparison between the two observation-based CUE demonstrates the lack of consistency that can occur between ‘observational’ datasets. The CUE calculated using Beer et al. (2010) GPP generally has much higher values than those suggested by DeLucia et al. (2007) and obtained with Zhao et al. (2005). Simulated CUE values vary between 0.15 and 0.80, with an average of 0.573 over North America for the RP ERA case and 0.585 for the RP_NCEP case. Terrestrial ecosystem models that do not model autotrophic respiration explicitly usually assume a constant value of 0.5 for the CUE for all types of plants (DeLucia et al., 2007). The values of CUE obtained from our recent past experiments (RP ERA and RP_NCEP) are generally similar to that suggested by DeLucia et al. (2007), though the RP NCEP case gives somewhat
higher values than RP\_ERA. In addition, simulated values of CUE are greatest for temperate deciduous forests and lowest for boreal forests, similar to DeLucia et al. (2007). The areas covered mostly by crops show higher values of CUE, consistent with the observations made by Frantz and Bugbee (2005) and Choudhury (2000), the latter stating that in general the CUE values for forests are about 30% lower than those for crops and grasses.

### 3.2.2. Trends in biospheric fluxes and pools

Both RP\_ERA and RP\_NCEP simulations are further analysed to investigate trends in terrestrial carbon pools and fluxes. To limit the effect of initial conditions, results from the last 32 years (1970–2001) of the simulations are averaged to investigate trends in terrestrial carbon pools and fluxes. To limit the effect of initial conditions, results from the last 32 years (1970–2001) of the simulations are used.

Figure 8 shows the trends in the driving data (CO$_2$, precipitation and temperature), in simulated fluxes (net atmosphere-land CO$_2$ flux, GPP, NPP, autotrophic and heterotrophic respiration) and in carbon pools (LAI and woody biomass). The temperature and precipitation data, and the GPP, NPP, both respiration fluxes and LAI are shown for total carbon in the system that includes both LAI and woody biomass, which yields the simulated sink, is associated with an increase in woody biomass (Figure 8(i)). There is also a marginal contribution from the soil carbon (figure not shown). However, CTEM only includes a single soil carbon pool and studies show that multi-pool models are able to capture the response to soil warming experiments more realistically (Knorr et al., 2005). The simulated LAI also increases over the 1970–2001 period (Figure 8(i)). The increase in LAI and woody biomass, which yields the simulated sink, is associated with an increase of about 22% in GPP and NPP over the 1970–2001 period (Figure 8(e) and (f)).

Figures 9 and 10 show the spatial distribution of trends associated with the live (stem and roots) and dead (litter and soil) carbon pools for the 1970–2001 period for RP\_ERA and RP\_NCEP simulations, respectively, computed using Sen’s slope method. Trends are also shown for total carbon in the system that includes these four pools in panel (a) of both figures. For both simulations, most of North America shows an increasing trend, except for parts of the central United States, the high latitudes of Canada and segments along the southern West Coast, mostly due to the decreasing trend in the soil carbon pool in these regions, especially for the RP\_NCEP case. The marginal decrease in soil carbon is explained by the positive trend in temperature that results in greater heterotrophic respiration rates that overwhelms the increase in NPP, causing a net loss of soil carbon. The simulated general positive trend of carbon uptake averaged over the 1970–2001 period is strongest in eastern United States, where NPP and GPP are generally the highest (Figure 5). The simulated trends are highest for the stem component, followed by soil carbon, roots and the litter components.

Figure 11 shows the simulated trends in NPP (in gC m$^{-2}$ year$^{-1}$) for the 1970–2001 for the RP\_ERA and RP\_NCEP simulations. The trend in NPP is either not significant or positive over the North American domain. Most regions which show increase in NPP are similar to those found in the observation-based study from Hicke et al. (2002), except the area east of the Great Lakes. Hicke et al. (2002) found that northeast North America
4. Summary and conclusions

The effect of driving climate data on the simulated terrestrial carbon pools and fluxes over North America is assessed using CTEM coupled to CLASS. The offline simulations are driven with NCEP and ERA40 reanalysis data from 1958 to 2001 over North America and simulated quantities are compared with observation- and model-based estimates.

Both the NCEP and ERA40 reanalysis data differ from each other, especially in terms of summer precipitation, as well as with the observation-based CRU climate data and both reanalysis data show generally warmer temperatures also during summer. Overall, the ERA40 reanalysis data compares better with the observation-based CRU climate data than the NCEP. The observation-based GPP, LAI and woody biomass data and the model-based NPP data, that are used to validate simulated quantities, are not derived from the same source so are expected to be inconsistent with each other. The inconsistency between Zhao et al. (2005) NPP estimates and Beer et al. (2010) GPP estimates is reflected in large CUE values that generally do not compare well with the observation-based estimates from DeLucia et al. (2007).

Both the limitations in the driving climate data as well as the inconsistencies in the data used for model validation make the task of model assessment somewhat difficult. However, the simulations are able to provide broad insight into the behaviour of the CTEM model. The model is able to reproduce the broad spatial patterns of LAI, woody biomass, NPP and GPP as well their zonal distributions. The range in the simulated values of CUE and its average value also compare reasonably well with observation-based estimates of DeLucia et al. (2007). Limitations, however, remain in simulated quantities. In particular, the simulated LAI is low compared to the ISLSCP satellite-based estimates, although Gibelin et al. (2006) show that the LAI estimates in this product are higher than other satellite-based estimates, especially in the boreal forest, and the model does not capture the GPP of the productive needleleaf evergreen forests along
the interior of west coast of the United States. This model limitation is also obvious in the comparisons of simulated woody biomass with their observation-based estimates. Despite its generally higher than observed woody biomass, the model is not able to simulate enough woody biomass along the United States west coast as well as in the interior BC. Both the interior BC and the interior west coast of the United States are characterized by drier summers and colder winters than at the coast. Results from another study under progress (Dr. Yiran Peng, CCCma, personal communication) show that, while the only needleleaf evergreen PFT of the model performs well at the coast of BC, it yields lower than observed GPP in the interior of the province. These results indicate that while the broad classification of PFTs in CTEM is sufficient to capture terrestrial ecosystem process at the global scale, it is insufficient for representing continental scale processes and another needleleaf evergreen PFT is required.

The simulations are also used to assess the land carbon sink over the North American domain. Despite very different gross fluxes, the model yields fairly similar estimates of the net atmosphere-land CO₂ flux with the two forcing datasets. The simulated sink of 0.5 Pg C year⁻¹ during the 1980s and 1990s compares well with another model-based estimates during the 1980s (Pacala et al., 2001) but is lower than the inversion-based estimates which vary from 0.81 to 1.26 Pg C year⁻¹ during the 1990s. This is expected since our simulations do not include land use change and the effect of nitrogen deposition. The analysis of
spatial distribution of trends in simulated carbon pools and fluxes shows that the simulated carbon sink is driven primarily by NPP enhancements over eastern United States and the resulting carbon sequestration in the woody biomass. Future efforts will attempt to include land use change, which will help to quantify the contribution of cropland abandonment in eastern United States on the simulated sink.

The choice of ECMWF’s ERA40 and ERA-Interim as the driving data in this study was based on how far back in time each of them went. Ideally, the spin-up simulation should be performed with climate that shows minimal warming trends. Although the ERA-Interim reanalysis is available at a higher resolution, we chose ERA40 given its availability since 1958 allowing us to perform our spin-up simulation with repeated 1958–1977 climate followed by the recent past simulation from 1958 to 2001. Preliminary analysis of a simulation using ERA40 for the 1958–1978 period, followed by ERA-Interim during the 1979–2001 period, suggests similar spatial patterns (figures not shown) as in the case RP_ERA. However, the use of ERA-Interim data tends to overestimate the productivity and the biomass in areas that were already overestimated (mainly southeastern United States) in RP_ERA when compared to observations.

Our simulations do not take into account competition between PFTs and as a result the fractional coverage of PFTs does not change in time. As shown by Smith et al. (2011), competition is important to model vegetation shifts and changing tree line which can have non-negligible effects on temperature and precipitation through biophysical feedbacks, particularly in the context of a changing climate. Work is in progress to implement competition in CTEM based on competition parameterisation of Arora and Boer (2006), and we expect to be able to use it in future simulations.

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