Home Search Collections Journals About Contact us My IOPscience

The terrestrial carbon budget of South and Southeast Asia

This content has been downloaded from IOPscience. Please scroll down to see the full text.

View the table of contents for this issue, or go to the journal homepage for more

Download details:

IP Address: 130.126.152.72

This content was downloaded on 19/10/2016 at 15:43

Please note that terms and conditions apply.

Environmental Research Letters



OPEN ACCESS

RECEIVED

7 April 2016

REVISED

6 September 2016

ACCEPTED FOR PUBLICATION 4 October 2016

PURIISHED

19 October 2016

Original content from this work may be used under the terms of the Creative Commons Attribution 3.0 licence.

Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI



LETTER

The terrestrial carbon budget of South and Southeast Asia

Matthew Cervarich¹, Shijie Shu¹, Atul K Jain^{1,15}, Almut Arneth², Josep Canadell³, Pierre Friedlingstein⁴, Richard A Houghton⁵, Etsushi Kato⁶, Charles Koven⁷, Prabir Patra⁸, Ben Poulter⁹, Stephen Sitch¹⁰, Beni Stocker¹¹, Nicolas Viovy¹², Andy Wiltshire¹³ and Ning Zeng¹⁴

- ¹ Department of Atmospheric Sciences, University of Illinois, Urbana, IL 61801, USA
- ² Karlsruhe Institute of Technology, Institute of Meteorology and Climate Research/Atmospheric Environmental Research, Garmisch-Partenkirchen, Germany
- Global Carbon Project, CSIRO Oceans and Atmosphere Flagship, GPO Box 3023, Canberra, ACT, 2601, Australia
- Ollege of Engineering, Mathematics and Physical Sciences, University of Exeter, Exeter EX4 4QF, UK
- Woods Hole Research Center, 149 Woods Hole Road, Falmouth, MA 02540-1644, USA
- Institute of Applied Energy, 105-0003 Tokyo, Japan
- Earth Sciences Division, Lawrence Berkeley National Laboratory, Berkeley, CA 94720, USA
- ⁸ Department of Environmental Geochemical Cycle Research, JAMSTEC, Yokohama 2360001, Japan
- ⁹ Institute on Ecosystems and the Department of Ecology, Montana State University, Bozeman, MT 59717, USA
- College of Life and Environmental Sciences, University of Exeter, Exeter EX4 4RJ, UK
- Department of Life Sciences, Imperial College, Ascot SL5 7PY, UK
- Laboratoire des sciences du climat et de l'environnement, CEA Saclay, F-91191 Gif-sur-Yvette Cedex, France
- Met Office Hadley Centre, Fitzroy Road, Exeter EX1 3PB, UK
- Department of Atmospheric and Oceanic Science and Earth System Science Interdisciplinary Center, University of Maryland, College Park, MD 20742, USA
- ⁵ Author to whom any correspondence should be adressed.

E-mail: jain1@illinois.edu

Keywords: terrestrial carbon, land surface model, carbon budget

Supplementary material for this article is available online

Abstract

Accomplishing the objective of the current climate policies will require establishing carbon budget and flux estimates in each region and county of the globe by comparing and reconciling multiple estimates including the observations and the results of top-down atmospheric carbon dioxide (CO₂) inversions and bottom-up dynamic global vegetation models. With this in view, this study synthesizes the carbon source/sink due to net ecosystem productivity (NEP), land cover land use change (E_{LUC}), fires and fossil burning (E_{FIRE}) for the South Asia (SA), Southeast Asia (SEA) and South and Southeast Asia (SSEA = SA + SEA) and each country in these regions using the multiple top-down and bottom-up modeling results. The terrestrial net biome productivity (NBP = NEP $-E_{LUC} - E_{FIRE}$) calculated based on bottom-up models in combination with E_{FIRE} based on GFED4s data show net carbon sinks of 217 \pm 147, 10 \pm 55, and 227 \pm 279 TgC yr $^{-1}$ for SA, SEA, and SSEA. The top-down models estimated NBP net carbon sinks were 20 \pm 170, 4 \pm 90 and 24 \pm 180 TgC yr⁻¹. In comparison, regional emissions from the combustion of fossil fuels were 495, 275, and 770 TgC yr⁻¹, which are many times higher than the NBP sink estimates, suggesting that the contribution of the fossil fuel emissions to the carbon budget of SSEA results in a significant net carbon source during the 2000s. When considering both NBP and fossil fuel emissions for the individual countries within the regions, Bhutan and Laos were net carbon sinks and rest of the countries were net carbon source during the 2000s. The relative contributions of each of the fluxes (NBP, NEP, E_{LUC} , and E_{FIRE} , fossil fuel emissions) to a nation's net carbon flux varied greatly from country to country, suggesting a heterogeneous dominant carbon fluxes on the country-level throughout SSEA.



1. Introduction

South and Southeast Asia (SSEA) is characterized by a faster than global average population growth and is increasing its food and energy production for the growing population by expanding agricultural land and burning more fossil fuels. A carbon budget, the net gain or loss of carbon, for this region will enable the constraining of other neighboring regional fluxes and act as an overall constraint on the global carbon budget. A full carbon budget, as the one presented here is also important to support the development of climate mitigation policies, and project future climate change.

Geographically, SSEA occupies one of the largest areas of tropical forests. These forests account for about 20% of the potential global terrestrial net primary productivity (NPP) and play an important role in regulating the Earth's carbon cycle and climate (Tian et al 2003). Studies suggest tropical land carbon fluxes exhibit, on average, a larger variability than temperate carbon fluxes (Tian et al 1998, Foley et al 2002, Peylin et al 2005, Zeng et al 2005, Ahlström et al 2015), due to the influence of climatic events, such of El Niño and La Niña events on ecosystem processes, and the subsequent ecosystem disturbance such as large scale forest fires (Patra et al 2005). Specifically, studies suggest that enhanced sources occur during El Niño episodes and abnormal sinks during La Niña (Gérard et al 1999, Jones et al 2001). The large variability in land source and sink fluxes makes it difficult to determine longterm trends in the net terrestrial carbon flux. Therefore, a better understanding of how the SSEA ecosystems respond to natural variability will reduce uncertainties in understanding the long-term trends and the magnitude and sign of the carbon-climate feedbacks.

The region has a history of land use land cover change (LULCC) activity such as intensive cultivation and overgrazing of pasturelands (Canadell 2002) and transitioning forestland to agricultural land. Globally, SEA had the highest deforestation rate (FAO 2010) between 1990 and 2010 with the forests of SEA contracting in size by just less than 33 million hectares (FAO 2010). A great deal of concern has been raised regarding to what extent such rapid changes in LULCC and management practices have affected the amount of carbon in vegetation, soil organic matter, and litter pools, thereby impacting the net land-atmosphere carbon flux, which is essential to ecosystem sustainability in SSEA.

Forest fires also contribute to the carbon budget by rapidly releasing carbon from vegetation. van der Werf *et al* (2010) estimated global biomass burning emitted 2.0 PgC yr⁻¹ with substantial interannual variability from 1997 to 2009. Fires caused by both natural and human sources impact biomass emission, sometimes in tandem. For example, in SEA it is economically advantageous to clear land via fire (Dennis *et al* 2005).

Transitioning of land from tropical forest or peatland to agricultural or other commercial uses is driving SEA to have the highest deforestation rate worldwide (Langner and Siegert 2009). Langner and Siegert (2009) showed fire events are three times more frequent during El Niño years than non-El Niño.

Fossil fuel burning is another important source of carbon emissions. Globally, fossil fuels have emitted 9.0 PgC yr⁻¹ during 2000s and are the greatest source of carbon (Le Quéré *et al* 2015). SSEA is also likely to have a large source of carbon emissions from the combustion of fossil fuels due to the rapidly expanding population and gross domestic product growth, both of which are closely related to fossil fuel emissions (Raupach *et al* 2007).

Carbon budgets for the globe (Le Quéré et al 2015), South Asia (Patra et al 2013, Thompson et al 2016), and SEA (Thompson et al 2016) have been established. Additionally, Pan et al (2011) and Adachi et al (2011) evaluated the carbon budget of tropical forests in SEA and Tao et al (2013) estimated the carbon exchange due to changes in cropland coverage and management in SSEA. This study builds upon and extends the previous budget studies by further investigating the terrestrial carbon budget and its components for SSEA region and each country of SSEA region. By quantifying the country-specific terrestrial carbon budget and related carbon fluxes, this study will help to determine how much carbon is being stored or released in its forests and other ecosystems toward its budgeted reduction in carbon dioxide. Country-level estimates are particularly relevant e.g., in the context of the 2015 Paris Climate agreement (UNFCCC 2015), which requires quantifiable biosphere sources and sinks of carbon dioxide (CO₂) and other greenhouse gases at country level in order to enable successful implementation of climate policy. Further division of the sectorial carbon budget for large countries like India is desired for preparing efficient emission mitigation policy.

The specific objectives of this study are: (1) to estimate the terrestrial carbon budget components; net ecosystem productivity (NEP), LULCC emission (E_{LUC}) , and fire emissions due to non-land use change activities (E_{FIRE}); of South Asia (SA) and Southeast Asia (SEA), the two sub-regions of SSEA, and that of each contributing country of SA (Bangladesh, Bhutan, India, Nepal, PakistanSri Lanka,) and SEA (Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Singapore, Thailand, and Vietnam) regions for the period 2000-2013; (2) estimate NEP and its interannual variability for the period 1980-2013; (3) compare the terrestrial carbon budget, in terms of net biome production (NBP = NEP $-E_{LUC} - E_{FIRE}$) of SA and SEA and the countries within these two regions to the fossil fuel emissions. We use multiple data products; including fossil fuel inventory data and remote sensing data products for E_{FIRE} ; the results of dynamic global vegetation models (DGVMs) (or bottom-up



models), atmospheric inversion models (or top-down models) and a book-keeping model to estimate the carbon fluxes and terrestrial carbon budget.

2. Data and methods

The study region is SSEA. We report here carbon fluxes for SA, SEA and entire SSEA and for those countries whose areas occupy twelve or more $0.5^{\circ} \times 0.5^{\circ}$ pixels, which is the standard resolution for the bottom-up models being used in this study. Singapore and Brunei are the only two countries whose areas do not satisfy our criteria; therefore we do not report carbon emissions for these two countries, but account for their carbon fluxes in regional total estimates. In the following we describe the methods and the data we used to estimate the terrestrial carbon budget (carbon sink and source terms), and the fossil fuel emissions for comparison purpose.

2.1. Net ecosystem production (NEP) and LULCC emissions estimated based on TRENDY models (or bottom-up models)

We use an ensemble of nine dynamic global vegetation models (DGVMs: CLM4.5 Oleson et al 2013, ISAM Jain et al 2013, JULES Clark et al 2011, LPJ Sitch et al 2003, LPJ GUESS Ahlström et al 2012, LPX Stocker et al 2014, ORCHIDEE Krinner et al 2005, VEGAS Zeng et al 2005 and VISIT Ito and Inatomi 2012) results for carbon fluxes over for SSEA region. Model simulations follow the protocol as described by the carbon cycle model intercomparison project (TRENDY) (Sitch et al 2015), where each model was run from its pre-industrial equilibrium (assumed at the beginning of the 1860) to 2013. Here we use the TRENDY model results for NEP (=NPP (net primary productivity)—Rh (heterotrophic respiration)) based on two different simulation scenarios, S2 (S2 NEP) and S3 (S3 NEP). For S2 simulations, the models were forced with changing CO₂ (Dlugokencky and Tans 2014), CRU-NCEP reanalysis climate forcing (Harris et al 2014) and timeinvariant pre-industrial (year 1860) HYDE land use (Klein Goldewijk et al 2011) data sets over the period 1860–2013. The S3 simulations assume the same input for CO₂ and climate as for S2 case, but the land use varies with time based on HYDE land use data set (figure 1). All models account for nitrogen deposition. Model parameterizations are summarized in table S1. For each simulation NPP and Rh are spatially integrated at the regional and country level for further analysis. Land use change emissions (E_{LUC}) are estimated by subtracting S2 NEP from S3 NEP (S3 NEP -S2 NEP).

2.2. Fire emissions due to non-LULCC activities

The E_{LUC} term already accounts for fire emission due to LULCC activities, such as deforestation. In order to

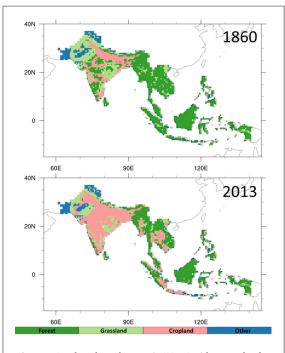


Figure 1. South and Southeast Asia (SSEA) with HYDE land cover data (Klein Goldewijk *et al* 2011) in 1860 and 2013.

account for fire emissions due to non-LULCC activities (E_{FIRE}), such as lightning induced fires, we obtained carbon emissions from fires from the Global Fire Emissions Database version 4.1, which includes small fire burned area (GFED4s) as described in van der Werf et al (2010) but with updated burned area (Giglio et al 2013). The burned area information is used as input data in a modified version of the satellitedriven Carnegie-Ames-Stanford Approach (CASA) biogeochemical model to estimate carbon emissions associated with fires, both LULCC- and non-LULCC related (see van der Werf et al 2010). To calculate E_{FIRE} , we subtract GFED4s-estimated fire emissions due to land use change from the fire emissions due to all fire activities (land use change and non-land use related fire activities). In this way, E_{FIRE} also accounts for emissions from peat land, which has also not been accounted for in TRENDY model results. We analyze E_{FIRE} emission data from 1997 to 2013 in this study.

2.3. Net biome production (NBP) calculated based on bottom-up modeling approach

We estimate NBP after accounting for disturbances due to LULCC and forest fire (excluding fire emissions due to deforestation) such that NBP = S2 NEP – E_{LUC} – E_{FIRE} . The E_{LUC} and E_{FIRE} terms are described in sections 2.1 and 2.2.

The variables are averaged for the 1980s, 1990s, and 2000–2013 (hereafter, referred to as the 2000s) to evaluate the change in the NEP and NBP over the past three decades. To study the impact of climate variability on NEP anomalies we detrended the NEP and climate data (temperature and precipitation) by removing the linear trend. Negative NBP values



represent net C release to the atmosphere and positive values represent net C sequestered by the terrestrial biosphere.

2.4. Estimates of NBP based on atmospheric CO₂ inverse models (or top-down models)

In order to compare TRENDY models estimated NBP for the 2000-2013 period, which uses bottom-up modeling approach, we used NBP estimates based on the following 5 atmospheric inversion or top-down models: ACTM (Patra et al 2011), CCAM (Rayner et al 2008), GELCA (Ganshin et al 2011), JMA_CDTM (Sasaki et al 2003), and CarbonTracker-Europe (Peters et al 2007). Atmospheric inversion models used here inferred NBP by applying Bayesian statistics to observed atmospheric CO₂ concentrations, the carbon flux due to fossil fuels and simulated atmospheric transport. Fossil fuel fluxes were based on data from CDIAC and PBL. The inversion models are forced with atmospheric data from JCDAS, ECMWF, NCEP2, NCEP, or JRA-25. The inverse models are run at a relatively coarse resolution (>1.8 $^{\circ}$ × 1.8 $^{\circ}$ spatial resolution only have 11 divisions of global land) and therefore cannot be applied at the country level.

2.5. Estimates of LULCC emissions based on the bookkeeping model

Additionally, country specific LULCC emissions estimated based on TRENDY models are compared with a bookkeeping method (Houghton 2003 and 2010), which uses the following two data types to calculate annual sources and sinks of carbon from LULCC: first, rates of land use (e.g., wood harvest) and land-cover change (e.g., conversion of forest to cropland) and, second, carbon densities (MgC ha⁻¹) in four pools of carbon: living biomass, above- and below-ground; dead biomass, including coarse woody debris; harvested wood products; and soil organic carbon. The effects of environmental change (e.g., the concentration of CO₂ in the atmosphere, changes in climate, and N deposition) were not included in the defined changes. Rates of forest growth and rates of decay varied with type of ecosystem, type of land use, and region, but they did not vary through time in response to changing environmental conditions. Changes in the areas of croplands and pastures used in bookkeeping model calculation were obtained from FAOSTAT (2015) from 1961 to 2013. After 1990, rates of deforestation and reforestation were obtained from the FRA 2015 (FAO 2015). Earlier changes were compiled from data and assumptions similar to those used in previous analyses (Houghton 1999, 2003, 2010). The bookkeeping model results for SA, SEA and SSEA presented in this study are part of a new global estimate (Houghton and Nassikas 2016). Although bookkeeping model results are available from period 1850 to 2015, we are using the results for the period

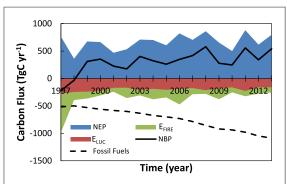


Figure 2. Cumulative components of the terrestrial carbon budget (NEP, $E_{\rm LUC}$, $E_{\rm FIRE}$) NBP, and fossil fuels for the period 1997–2013. Positive values are a land sink of carbon and negative values are emissions to the atmosphere. Net ecosystem productivity (NEP; dark blue) and land use change emissions ($E_{\rm LUC}$; red) are the average of TRENDY models estimates. Fire emission estimates due to non-land use change activities ($E_{\rm FIRE}$; green) are from the Global Fire Emissions Database version 4 (van der Werf *et al* 2010). Net biome productivity (NBP; solid line) is the difference between emissions from the land sink, NEP, and the land sources, $E_{\rm LUC}$, and $E_{\rm FIRE}$. Fossil fuel emission (dashed line) is sourced from the Carbon Dioxide Information Analyses Center (CDIAC) database.

1980–2013 for comparing two modeling approaches (DGVMs and bookkeeping).

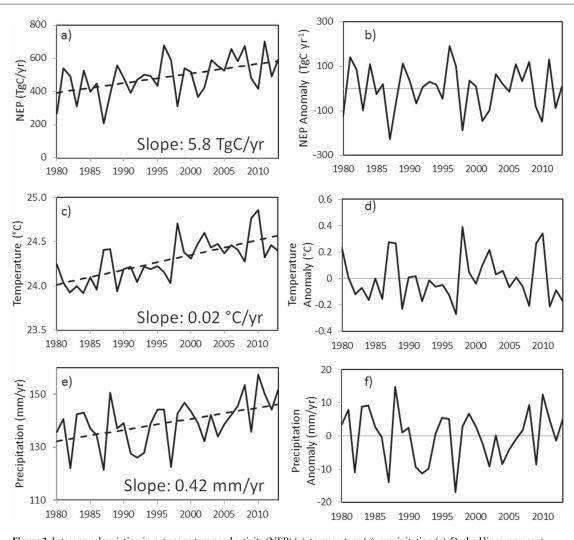
2.6. Emissions from fossil fuel consumption and cement production

We also compare country specific NBP estimates with the emissions from fossil fuel burning and cement production. Carbon emissions from fossil fuel consumption were retrieved from Le Quéré et al (2015), which were compiled from many sources, including the Carbon Dioxide Information Analysis Center (CDIAC) (Boden et al 2015), BP statistical review of world energy the International Energy Agency (IEA), the United Nations (UN) (2014), the United States Department of Energy (DOE), Energy Information Administration (EIA), and more recently also the Planbureau voor de Leefomgeving (PBL) Netherlands Environmental Assessment Agency. Here the fossil fuel emissions at national and regional levels include emissions from gas flaring and cement production (US Geological Survey 2013). Data is available at a country level from 1959 to 2013. In this study we analyze data from 1980 to 2013.

3. Results

3.1. NEP

The TRENDY model results based on the S2 experiment, which does not consider land use change over time, suggests that NEP for SSEA increased from a sink of 414 TgC yr⁻¹ in the 1980s to 489 TgC yr⁻¹ and 542 TgC yr⁻¹ in the 1990s, and the 2000s, respectively, and had a 1980–2013 absolute C sink growth rate of 5.8 TgC yr⁻¹ (figures 2 and 3(a), table S2). The increase in NEP over the period 1980–2013 has mainly been



 $\textbf{Figure 3.} \ Interannual \ variation \ in \ net \ ecosystem \ productivity \ (NEP) \ (a), temperature \ (c), precipitation \ (e). \ Dashed \ lines \ represent \ least \ squared \ linear \ fit \ with \ slope \ shown \ in \ text. \ Detrended \ interannual \ variation \ in \ NEP \ (b), temperature \ (d), \ and \ precipitation \ (f).$

attributed to the carbon dioxide fertilization effect due to the incremental increase in atmospheric carbon dioxide concentrations (Sun *et al* 2014). For the 1980–2013 period, SSEA coefficient of variation (CV), the standard deviation divided by the mean, is relatively large (25%) compared to the growth rate (115 TgC yr⁻¹) (table S2), suggesting there is substantial interannual variability.

All countries had positive absolute growth rates (increasing sink; decreasing source) except Bangladesh, Bhutan, and Nepal. Bangladesh had the least absolute growth rate ($-0.04 \, \mathrm{TgC} \, \mathrm{yr}^{-1}$) and the Indonesia had the greatest normalized growth rate ($3 \, \mathrm{TgC} \, \mathrm{yr}^{-1}$) (table S2). Sri Lanka had a highest variation relative to the mean as shown by a CV greater than 100% (112%), while Bangladesh had the lowest (CV = 24%) (table S2). The growth rates, which are increasing due to CO_2 fertilization, describe the trend in NEP, but the relatively high CVs suggest there is considerable year-to-year variability in every country.

To investigate model response to internal climate variability we first removed the linear trend from NEP model estimates time series (figure 3(b)), which is influenced by non-internal climate factors, such as CO₂ fertilization. We also de-trend the temperature and precipitation to remove the confounding climate change effects (figures 3(d) and (f)). The first order trend for temperature and precipitation was 0.02 °C yr^{-1} and 0.42 mm yr^{-1} (figures 3(c) and (e)). Detrended SSEA NEP had statistically significant correlation with detrended temperature (r = -0.71, P < 0.5) (table S3) and a statistically significant correlation with detrended precipitation (r = -0.15, P > 0.5) (table S3) suggesting the year to year variability in NEP was driven mainly by changes in temperature. The strong negative correlation of temperature to NEP suggests NEP in the region decreases carbon uptake or increases carbon emissions in warmer years due to the increase in heterotrophic respiration in warmer environments (Moncrieff and Fang 1999). Although the relationship of CO₂ emission and sink change with climate variability is well accepted, the relative effects of rainfall and temperature are debated (Wang et al 2014). The DGVM simulated interannual variations are often much weaker than those estimated by the inverse models (e.g., Patra et al 2005), suggesting



Table 1. Terrestrial carbon fluxes for the countries in South Asia (SA), Southeast Asia (SEA) and South and Southeast Asia (SSEA = SA + SEA) (listed in alphabetic order) for the 2000–2013 period based on the average of the nine TRENDY models. NBP for SSEA for 2000–2013 Positive values are sink of carbon and negative values are source of carbon. Uncertainty is estimated with the 1- σ standard deviation from the terrestial ecosystem models. Fossil fuel emissions are from the Carbon Dioxide Information Analysis Center (CDIAC) database and averaged over the 2000–2013 period.

| Country | NEP (TgC yr ⁻¹) | LULCC (TgC yr ⁻¹) | FIRE (TgC yr ⁻¹) | NBP (TgC yr ⁻¹) | Fossil Fuels (TgC yr ⁻¹) |
|-------------|-----------------------------|-------------------------------|------------------------------|-----------------------------|--------------------------------------|
| Bangladesh | 10.6 ± 8.8 | -1.4 ± 4.6 | -0.0 ± 0.0 | 9.3 ± 9.2 | -12.2 |
| Bhutan | 2.2 ± 1.9 | -0.4 ± 1.1 | -0.5 ± 0.0 | 1.2 ± 2.3 | -0.1 |
| India | 200.6 ± 137.7 | -6.2 ± 44.4 | -8.5 ± 0.6 | 185.9 ± 145.6 | -439.9 |
| Nepal | 9.2 ± 7.6 | -0.2 ± 2.8 | -1.0 ± 0.1 | 8.0 ± 8.4 | -0.9 |
| Pakistan | 14.2 ± 7.7 | -1.1 ± 2.8 | -0.4 ± 0.0 | 12.7 ± 10.9 | -38.2 |
| Sri Lanka | 3.6 ± 1.6 | -3.1 ± 2.2 | -0.2 ± 0.0 | 0.4 ± 3.2 | -3.3 |
| SA | 240.6 ± 138.4 | -12.4 ± 44.8 | -10.6 ± 0.6 | 217.5 ± 146.6 | -494.6 |
| Cambodia | 11.5 ± 3.61 | -5.8 ± 6.6 | -8.1 ± 0.5 | -2.3 ± 7.4 | -0.9 |
| Indonesia | 106.3 ± 48.9 | -94.9 ± 76.5 | -49.6 ± 49.2 | -38.2 ± 17.8 | -101.4 |
| Laos | 24.8 ± 11.1 | -6.8 ± 8.0 | -10.3 ± 0.7 | 7.7 ± 16.0 | -0.4 |
| Malaysia | 22.2 ± 11.9 | -14.6 ± 16.6 | -4.5 ± 0.4 | 3.1 ± 26.4 | -49.4 |
| Myanmar | 53.1 ± 18.7 | -10.9 ± 12.4 | -17.3 ± 1.9 | 24.9 ± 25.9 | -2.9 |
| Philippines | 16.2 ± 5.3 | -13.2 ± 9.4 | -1.3 ± 1.1 | 1.8 ± 13.4 | -20.5 |
| Thailand | 37.4 ± 13.3 | -10.1 ± 16.5 | -11.2 ± 0.8 | 16.1 ± 24.2 | -70.0 |
| Vietnam | 34.7 ± 16.6 | -19.1 ± 14.1 | -18.6 ± 1.3 | -3.0 ± 17.5 | -29.5 |
| SEA | 306.2 ± 59.2 | -175.4 ± 83.4 | -120.9 ± 49.3 | 9.8 ± 55.4 | -274.9 |
| SSEA | 546.6 ± 200.6 | -187.7 ± 192.2 | -131.6 ± 3.5 | 227.3 ± 278.9 | -769.5 |

that either the DGVM NEP estimates are relatively less sensitive to environmental conditions or the variability of upper tropospheric CO₂, which is used to drive the top-down models, is not representative variability of the boundary layer CO₂ which is interacting with the vegetation.

3.2. LULCC emissions

The TRENDY models estimated E_{LUC} for SSEA were a net source in the 1980s, 1990s, and 2000s with mean annual emissions of 199 TgC yr⁻¹, 304 TgC yr⁻¹, and 244 TgC yr⁻¹, respectively. Every country, except Indonesia and Sri Lanka, had lower carbon emissions in the 2000s than in the 1990s (figure S1). In all three decade, Indonesia had the highest E_{LUC} with increasing trend (figure S1) and the emissions contributed to 32%, 30%, and 39% of the total SSEA emissions for the 1980s, 1990s, and 2000s, respectively. Malaysia had the second largest E_{LUC} in the 1980s (24 TgC yr⁻¹, 12%) and 2000s (14 TgC yr⁻¹, 6%) (table 1). In the 1990s, India had the second highest E_{LUC} (32 PgC yr⁻¹, 10%). However, India experienced the greatest decrease in E_{LUC} (26 TgC yr⁻¹, 80%), whereas Indonesia experienced greatest increase in E_{LUC} $(3 \, \text{TgC yr}^{-1}, 4\%)$ between the 1990s and 2000s. Indonesian and Malaysian deforestation is primarily due to logging and the expansion of oil palm plantations (Wicke et al 2011, FAO 2010). From 1980 to 2013, 11 Mha or 6% of Indonesia's total land area had been converted from forest to cropland (Klein Goldewijk et al 2011). In contrast, in India reforestation/ afforestation policies practiced by India's Ministry of the Environment and Forests in the 2000s have decelerated the rate of deforestation (Reddy et al 2015). On the regional scale, deforestation (due to conversion of forest to cropland and pasturelands) was

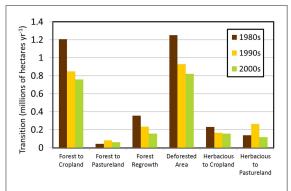


Figure 4. Decadal average rate of conversions of land in South and Southeast Asia (SSEA).

the major driving factor of LULCC emission over the last three decades. The deforestation rates for SSEA region in the 1980s, 1990s, and 2000s were 1.25, 0.93, and 0.82 Mha⁻¹. Part of the deforestation effect is compensated by the forest regrowth in the regions which were the greatest in the 1980s (0.36 Mha yr⁻¹) (figure 4) mitigating part of the carbon emissions associated deforestation. Likewise, the 2000s had a forest regrowth of 0.16 Mha yr⁻¹ with a majority (81%) of regrowth due to the abandonment of cropland.

The $E_{\rm LUC}$ from the bookkeeping model for the 2000s are within the uncertainty range of the bottom-up models for SSEA region and for 11 of 14 countries (figure S1). Additionally, the bookkeeping model is consistent with bottom-up models with respect to the decadal trend for SSEA—an increase from the 1980s to the 1990s followed by a decrease from the 1990s to the 2000s. Differences may be due to different LULCC inputs and different modeling approaches to estimate emissions due to land use changes.



3.3. Fire emissions

The estimated average SSEA E_{FIRE} for 1997–2013 were $132 \pm 4 \text{TgC yr}^{-1}$. Forest fires from Indonesia accounted for $50 \pm 49 \,\mathrm{TgC} \,\mathrm{yr}^{-1}$. Indonesia employs peatland fires as a land clearing technique before the planting of crops. Cambodia, Laos, Thailand, Myanmar, and Vietnam collectively contribute to 31% of the region total with rates of $8 \pm 1 \,\mathrm{TgC}\,\mathrm{yr}^{-1}$, $10 \pm 1 \,\mathrm{TgC} \,\mathrm{yr}^{-1}$, $11 \pm 1 \,\mathrm{TgC} \,\mathrm{yr}^{-1}$, $17 \pm 1 \,\mathrm{TgC} \,\mathrm{yr}^{-1}$, and $18 \pm 1 \, \text{TgC yr}^{-1}$, respectively. These countries are the region's maxima for lightning activity (Christian et al 2003) and, in conjunction with periods of low precipitation, may be one of the causes of forest fires. Additionally, man-made fires have extensively been used to clear land for agricultural and other economic purposes (Fox 2000) and may have a higher tendency to spread during dry conditions. On the regional scale, rates of are decelerating at 12 TgC yr⁻² (7.3% yr⁻¹) with substantial country to country variation (figure S2). Indonesia's emissions are estimated to be decreasing $14 \,\mathrm{TgC}\,\mathrm{yr}^{-2}$ (11.2% yr^{-1}), whereas India's are increasing by 1.4 TgC yr⁻² (0.12% yr⁻¹). Bangladesh, Cambodia, Myanmar, Pakistan, and Sri Lanka all have rates of change of less than 1 TgC yr⁻¹. Additionally, there is substantial year to year variability. The CV was 86% for SSEA. The large interannual variability suggests that fire emissions are impacted by the variables that have high interannual variations, such as precipitation. During El Nino years, a descending branch of the Walker circulation is established over the western pacific and suppresses convection in Southeast Asia (Julian and Chervin 1978), resulting in a low precipitation that leads to drying of the biomass and increases the potential to ignite a fire due to lightening. Other countries also experience fire emission variability due to changes in precipitation, but the countries that experience the greatest variability have greater forest area (figure 1), and therefore emit carbon during fire events and have larger amplitudes in fire emissions.

3.4. NBP emissions

Figures 5 and S3 and table 1 show the bottom-up models estimated mean NBP for the period 2000-2013 and its components, including S2 NEP, E_{LUC} and E_{FIRE} for SA, SEA and SSEA regions and individual countries within SA and SEA, respectively. The bottom-up models estimated NBP for SA, SEA and SSEA (SA + SEA) were $217 \pm 147 \,\mathrm{TgC} \,\mathrm{yr}^{-1}$, $10 \pm 55 \,\mathrm{TgC} \,\mathrm{yr}^{-1}$, and $227 \pm 279 \,\mathrm{TgC} \,\mathrm{yr}^{-1}$ (1- σ standard deviation of the 9 DGVM models (table 1), compared to the topdown estimated NBP of $20 \pm 170 \,\mathrm{TgC}\,\mathrm{yr}^{-1}$, $4 \pm 190 \,\mathrm{TgC}\,\mathrm{yr}^{-1}$ and $24 \pm 180 \,\mathrm{TgC}\,\mathrm{yr}^{-1}$ (1- σ standard deviation of the five inverse models). Clearly, the bottom-up models and top-down models both suggest the terrestrial biosphere for SA and SEA regions acted as a net sink for the period 2000-2013, but the sink estimated with the bottom-up models is about many

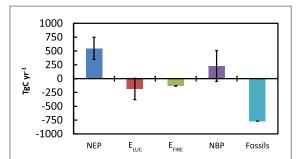


Figure 5. Mean carbon fluxes for the period 2000–2013. Error bars represent the first standard deviation of the model results. Fire emissions due to non-LUC related fire activities, $E_{\rm FIRE}$, are from Global Fire Emissions Database version 4 s (van der Werf *et al* 2010) and fossil fuel emissions are from the Carbon Dioxide Information Analysis Center (CDIAC) database. NEP, $E_{\rm LUC}$, and NBP are estimated from the TRENDY models. Positive values are a land sink of carbon and negative values are emissions to the atmosphere.

times the estimate from the atmospheric inversion models for both regions. However, the atmospheric inversion models estimate was within one standard deviation of the bottom-up models. Multi-model syntheses suggest large uncertainties in the estimated CO₂ fluxes by both the top-down and bottom-up approaches. Contributing to the found discrepancy is the incomplete accounting of all relevant carbon fluxes inherent in these modeling approaches. For example, the budget estimated by top-down models for the Asian regions is only weakly constrained by atmospheric observations and may be reflected as weak or no increase in uptake over SSEA, as this region is largely missing atmospheric CO₂ measurement data (Patra et al 2016). Another possible reason for the lower estimates of carbon uptake may be the underestimate of the increase in fossil fuel emissions in this region, which is assumed a posteriori and is subtracted from the total optimized CO_2 flux (Thompson et al 2016). At the same time bottom-up models may have overestimated the CO2 sink amount due to overestimation of the CO₂ fertilization effect, as most models do not include nitrogen and phosphorous-limitation on gross primary production, and/or the LULCC database may have underestimated rates of deforestation. Uncertainties from initial/ boundary conditions such as climate variability (monsoons, droughts), model parameters and land use cover data can increase the inter-model variability. A recent study analyzing TRENDY project model outputs on global scale supports the large variability of the estimated land-atmosphere carbon exchange in tropical regions (figure 3, Zhao et al 2016).

The estimated $E_{\rm FIRE}$ for SA, SEA and SEA are 11 ± 1 , 121 ± 49 and $132 \pm 4\,{\rm TgC\,yr^{-1}}$, which are approximately the same as the estimated $E_{\rm LUC}$ emissions for SA, but about 50 TgC yr⁻¹ lower than $E_{\rm LUC}$ emissions for SEA and SSEA regions (table 1), suggesting that $E_{\rm LUC}$ emissions influence the terrestrial carbon budget of SEA and SSEA more than $E_{\rm FIRE}$ emissions.



For the 2000s period, the estimates of the carbon sink due to S2 NEP SA, SEA and SSEA are 240 ± 45 (CV = 18%), 306 ± 83 (27%) and $547 \pm 201 \, \text{TgC} \, \text{yr}^{-1}$ (CV = 37%). The estimates of E_{LUC} for three regions are 12 ± 45 (CV = 375%), 175 ± 83 (CV = 47%) $188 \pm 192 \, \text{TgC} \, \text{yr}^{-1}$ (CV = 88%) (table 1). The relatively high CV values in E_{LUC} , particularly for SA, suggest uncertainty in estimates of NBP based on bottom-up models is, in part, caused by representation of LULCC and varying parameterizations of plant function types across the numerical models.

With regard to the individual country's terrestrial carbon fluxes, the terrestrial ecosystems of acted as a sink for atmospheric CO_2 with India had the greatest sink (NBP = $185 \pm 146 \,\mathrm{TgC}\,\mathrm{yr}^{-1}$) with relatively higher estimates of NEP ($201 \pm 138 \,\mathrm{TgC}\,\mathrm{yr}^{-1}$) and lower estimates of E_{LUC} ($-6 \pm 44 \,\mathrm{TgC}\,\mathrm{yr}^{-1}$) and E_{FIRE} ($-9 \,\mathrm{TgC}\,\mathrm{yr}^{-1}$) (figure S3). On the other hand, terrestrial ecosystems of three countries in SEA acted as source. Indonesia, Cambodia and Vietnam had estimated NBPs that were a source of carbon (table 1 and figure S3), primarily due to large emissions due to fires.

Uncertainty in NBP arises from the 9 TRENDY models representing LULCC activities and NEP differently. Major differences among the models are the inclusion/exclusion of carbon-nitrogen interactions, fire simulations, cropland harvest, shifting cultivation, and wood harvest and forest degradation (table S1). It is difficult to tease out relative contribution of each of the processes to the total uncertainty because controlled sensitivity simulations with each model are not available.

3.5. Comparison of NBP flux with fossil fuel emissions

Carbon emissions due to fossil fuel burning increased in every country within SA and SEA (figure S4). Overall, the total regional emissions (SA, SEA and SSEA) increased from the 1980s (179, 72 and 221 TgC yr^{-1}) to the 1990s $(278, 153 \text{ and } 431 \text{ TgC yr}^{-1})$, and from the 1990s to the 2000s (2000–2013) (493, 275 and 768 TgC yr^{-1}). Fossil fuel emissions are largely connected to economic activity. India had the fastest absolute growth rates and Bhutan had the slowest absolute growth rates at 16 TgC yr⁻², and 0.005 TgC yr⁻², respectively. India, which contributed greater than half of the regions fossil fuel emissions, has expanded its gross domestic product 10-fold from 1980 to 2013 (World Bank 2015). SSEA fossil fuel emissions increased every year except for in 1998 when the regions GDP decreased by 32% during the East Asian Financial crisis (World Bank 2015).

While the SA and SEA terrestrial biosphere during the 2000s acted as the net carbon sink for atmospheric CO₂, the magnitudes of the NBP sinks for both regions are less than the magnitude of the source due to fossil fuels (table 1).

India was a net source of carbon, when fossil fuel emissions (441 TgC yr⁻¹) are also considered. In Cambodia, Laos, Myanmar, Thailand, and Vietnam (collectively called Mainland Southeast Asia (MSEA)), non-deforestation fire emissions were of similar magnitude or of greater magnitude than fossil fuel emissions. This suggests the net land to atmosphere carbon emissions in MSEA is equally or more-so driven by emissions due to fires than fossil fuels. Bhutan, Laos, Myanmar, and Nepal were net sink of carbon when considering NBP and fossil fuels. NBP estimates for Myanmar are $25 \pm 26 \, \text{TgC yr}^{-1}$ and fossil fuel emissions estimates are 3 TgC yr⁻¹ (table 1, figure S3). The SSEA region has emissions due fossil fuel burning which are more than 4 times higher than the region's NBP. In contrast, the varying magnitudes of carbon sources in the countries of SSEA are different from each other and different from SSEA. This suggests the carbon budget of each country is determined by factors unique to the given country, possibly including land cover type, economic activity, climate, forest fire frequency, and management.

Our analysis suggests that the distribution of carbon emissions is not homogenous for the countries that make up SA and SEA (table 1). This suggests carbon emission reduction strategies should consider the sources at the country level.

4. Discussion and summary

Our assessment of the terrestrial carbon budget and fossil fuel emissions for SSEA and its countries provides insight into the trends and fluxes of NBP and its components. Additionally, our use of fossil fuel emissions data allows us to make quantitative comparisons between the NBP and the emission from fossil fuel burning. NBP of SSEA region was a net sink of carbon in the 2000s.

The NBP determined from the average of the nine TRENDY models' estimates, was $227 \,\mathrm{TgC} \,\mathrm{yr}^{-1}$ and based on average of atmospheric inverse models is $24 \,\mathrm{TgC} \,\mathrm{yr}^{-1}$. In comparison, fossil fuel emissions were $700 \,\mathrm{TgC} \,\mathrm{yr}^{-1}$. Fossil fuel emissions grew at $27 \,\mathrm{TgC} \,\mathrm{yr}^{-2}$, whereas the growth of NBP sink was $9 \,\mathrm{TgC} \,\mathrm{yr}^{-2}$, indicating that fossil fuel emissions grew about three times faster than the growth of the NBP sink. The NBP sink is increasing steadily due to higher atmospheric CO_2 and its effect on plant growth (CO_2 fertilization effect), while atmospheric CO_2 source is increasing due to E_{LUC} , E_{FIRE} and fossil fuel emissions.

NEP, the largest component of the terrestrial carbon budget, had an average sink of 545 TgC yr⁻¹ and grew at 12 TgC yr⁻² in the 2000s. Unlike fossil fuel emissions, NEP has a large interannual variation negatively correlated with temperature suggesting that increased heterotrophic respiration in warm years increases carbon emissions or decreases carbon sink.



On yearly timescales, the land sink was sensitive to changes in fire emissions and variations in the local temperature. Warm and dry anomalies, typically associated with El Niño events, triggered less NEP and hence weaker carbon sink. Countries in MSEA had the greatest correlation with temperature (table S2). The interannual variability of NEP is consistent with the warming of MSEA during El Niño events and associated decrease in NEP via an increase in Rh, which is particularly sensitive to temperature increases in MSEA (Zhou et al 2009).

The interannual variability of NEP is greater in DGVM than in top-down models. Top-down models are driven by tropospheric CO_2 sampled from aircraft in the upper atmosphere. Stephens *et al* (2007) showed the seasonal variability of upper tropospheric CO_2 is less than the seasonal variability of boundary layer CO_2 . Further investigation is needed into interannual variability of the vertical distribution of CO_2 to better constrain the top-down models.

 $E_{\rm LUC}$ increased from the 1980s to 1990s then reversed the trend from the 1990s to the 2000s. The reversing of the trend is attributed to human and policy factors such as the afforestation efforts in India. $E_{\rm LUC}$ was 244 TgC yr⁻¹ and decreased at 1.6 TgC yr⁻² in the 2000s, with relatively low interannual variability suggesting the E_{LUC} is seldom influenced by environmental factors. Furthermore, E_{LUC} decreased in nearly every country, with the exception of Laos and Indonesia, from the 1990s to the 2000s (figure S1). Land use change practices in Indonesia have been well-documented and attributed to the expansion of palm oil plantations at the expense of tropical forests (FAO 2010, Wicke et al 2011), and in Laos due to the expansion of agriculture, deforestation for timber, and expansion of cities (Fox and Vogler 2005).

Fire emissions due to non-LULCC fire activities, $E_{\rm FIRE}$ in SSEA are primarily from Indonesia and MSEA. In MSEA, there is a local maxima of lightening that triggers fires in vegetated areas, including forest fires.

Considering both NBP and fossil fuels, both for SA and SEA were net sources of atmospheric CO₂ $(276 \text{ and } 265 \text{ TgC yr}^{-1})$ in the 2000s. Fossil fuel emissions increased at an exponential rate throughout the 2000s, simultaneously the NBP sink also increased, but at a slower rate. If the trends continue the NBP sink will further increase, but many factors may complicate future projections. For example, increased temperatures may further weaken the carbon sink, in terms of NEP, in the region due to the lager enhancement of ecosystem respiration comparing to the increment of carbon assimilation, which is expected to be water-limited under the drier future climate. LULCC has been a source over the 2000s, but this source term is shrinking in magnitude since the 1990s and therefore is helping to increase the NBP sink through the legacy effect of slower rate of deforestation. The E_{FIRE} emissions are approximately

constant over the last three decades (figure S2), but the emission rates may grow in the future, as the environmental conditions grow drier and hotter due to climate change.

This study presents the terrestrial carbon budget estimates, in terms of NBP, at regional and country levels. While fine scale carbon budget information can be used to inform decision-makers regarding carbon management or policy-related activities, the uncertainty in estimated regional and country specific NBP based on top-down and bottom-up modeling approaches are large, represented here as the 1 σ standard deviation of the model derived estimates (figures 5 and S3, and tables 1 and S2). The magnitude of the terrestrial carbon source terms, including deforestation and other disturbances, for countries within SSEA are probably less reliable than that of the CO₂ emissions from fossil-fuel burning. Additional uncertainty in the carbon budget estimates arises from sinks associated with post disturbance recovery and interannual variations due to climate anomalies. Clearly, the current approaches to model carbon dynamics need improvements to account for subgrid scale level processes and feedbacks. Future carbon budget analyses will require data for environmental variables, such as LULCC activities, at higher resolutions accounting for detailed decisions on land management at a sub-national scale, given that most countries have different land classes, different commodities and multiple options for managing commodities (West et al 2013). This can be accomplished by using satellite-based land products to improve spatial representation, and supported by highly accurate ground-based estimates. Higher resolution data in combination with extending the DGVMs to account for carbon and other nutrient dynamics at higher resolutions will be useful for informing policy decisions, because of their ability to connect carbon and other nutrient stocks and flows to ground-based physical processes.

Acknowledgments

This research was partly supported by the NASA Land Cover and Land Use Change Program (NNX14AD94G) and the US National Science Foundation (No. NSF-AGS-12-43071).

References

Adachi M, Ito A, Ishida A, Kadir W R, Ladpala P and Yamagata Y 2011 Carbon budget of tropical forests in Southeast Asia and the effects of deforestation: an approach using a processbased model and field measurements *Biogeosciences* 8 2635–47

Ahlström A et al 2015 The dominant role of semi-arid ecosystems in the trend and variability of the land CO_2 sink Science 348 895–9

Ahlström A, Schurgers G, Arneth A and Smith B 2012 Robustness and uncertainty in terrestrial ecosystem carbon response to



- CMIP5 climate change projections *Environ. Res. Lett.* 7 044008
- Boden T A, Marland G and Andres R J 2015 Global, Regional, and National Fossil-Fuel CO₂ Emissions (Oak Ridge, Tenn., USA: Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, US Department of Energy) (doi:10.3334/CDIAC/00001_V2015)
- Canadell J G 2002 Land use effects on terrestrial carbon sources and sinks Sci. China C 45 (suppl.) 1–9
- Christian H J et al 2003 Global frequency and distribution of lightning as observed from space by the optical transient detector J. Geophys. Res.: Atmos. 108 ACL-4
- Clark D B et al 2011 The joint UK land environment simulator (JULES), model description: II. Carbon fluxes and vegetation dynamics Geosci. Model Develop. 4 701–22
- Dennis R A et al 2005 Fire, people and pixels: linking social science and remote sensing to understand underlying causes and impacts of fires in Indonesia Hum. Ecology 33 465–504
- Dlugokencky E and Tans P 2014 Trends in atmospheric carbon dioxide, National Oceanic & Atmospheric Administration, Earth System Research Laboratory (NOAA/ESRL)(http:// esrl.noaa.gov/gmd/ccgg/trends)
- FAO, U 2010 Global Forest Resource Assessment (Rome: UN Food and Agriculture Organisation)
- FAO 2015 Global Forest Resource Assessment 9 pp
- FAOSTAT 2015 Food and Agriculture Organization Statistics
 Division (http://faostat3.fao.org/home/E) (Accessed:
 March 2016)
- Foley J A, Botta A, Coe M T and Costa M H 2002 El Niño—Southern oscillation and the climate, ecosystems and rivers of Amazonia Glob. Biogeochem. Cycles 16 79–1
- Fox J 2000 How blaming 'slash and burn' farmers is deforesting mainland southeast Asia *Analysis from East West Center*, *Report No.* 47, 1601 East-West Rd, Honolulu
- Fox J and Vogler J B 2005 Land-use and land-cover change in montane mainland southeast Asia *Environ. Manage.* 36 394–403
- Ganshin A et al 2011 A global coupled eulerian-lagrangian model and 1×1 km CO Geosci. Model Develop. Discuss. 4 2047-80
- Gérard J C, Nemry B, Francois L M and Warnant P 1999 The interannual change of atmospheric CO₂: contribution of subtropical ecosystems? *Geophys. Res. Lett.* **26** 243–6
- Giglio L, Randerson J T and Werf G R 2013 Analysis of daily, monthly, and annual burned area using the fourthgeneration global fire emissions database (GFED4) J. Geophys. Res.: Biogeosci. 118 317–28
- Harris I, Jones P D, Osborn T J and Lister D H 2014 Updated highresolution grids of monthly climatic observations—the CRU TS3.10 Dataset *Int. J. Climatol.* 34 623—42
- Houghton R A 2003 Revised estimates of the annual net flux of carbon to the atmosphere from changes in land use and land management 1850–2000 *Tellus* B 55 378–90
- Houghton R A 2010 How well do we know the flux of CO_2 from land-use change? *Tellus* B **62** 337–51
- Houghton R A, Hackler J L and Lawrence K T 1999 The US carbon budget: contributions from land-use change *Science* 285
- Houghton R A and Nassikas A A 2016 Global and regional fluxes of carbon from land use and land-cover change 1850–2015, submitted
- Ito A and Inatomi M 2012 Use of a process-based model for assessing the methane budgets of global terrestrial ecosystems and evaluation of uncertainty *Biogeosciences* 9 759–73
- Jain A K, Meiyappan P, Song Y and House J I 2013 CO₂ emissions from land-use change affected more by nitrogen cycle, than by the choice of land-cover data Glob. Change Biol. 19 2893–906
- Jones A, Roberts D L, Woodage M J and Johnson C E 2001 Indirect sulphate aerosol forcing in a climate model with an interactive sulphur cycle J. Geophys. Res.: Atmos. 106 20293–310

- Julian P R and Chervin R M 1978 A study of the Southern oscillation and walker circulation phenomenon Mon. Weather Rev. 106 1433–51
- Klein Goldewijk K, Beusen A, Van Drecht G and De Vos M 2011 The HYDE 3.1 spatially explicit database of human-induced global land-use change over the past 12 000 years *Glob*. *Ecology Biogeography* 20 73–86
- Krinner G, Viovy N, de Noblet-Ducoudré N, Ogée J, Polcher J, Friedlingstein P, Ciais P, Sitch S and Prentice I C 2005 A dynamic global vegetation model for studies of the coupled atmosphere-biosphere system Glob. Biogeochem. Cycles 19 GB1015
- Langner A and Siegert F 2009 Spatiotemporal fire occurrence in Borneo over a period of 10 years *Glob. Change Biol.* 15 48–62
- Le Quéré C et al 2015 Global carbon budget 2014 Earth Syst. Sci. Data 7 47–85
- Moncrieff J B and Fang C 1999 A model for soil ${\rm CO_2}$ production and transport: II. Application to a Florida Pinus elliotte plantation *Agric. Forest Meteorol.* **95** 237–56
- Oleson K 2013 Technical description of version 4.5 of the Community Land Model (CLM) NCAR Technical Note NCAR/TN-503+STR 420 pp (doi:10.5065/D6RR1W7M)
- Pan Y et al 2011 A large and persistent carbon sink in the world's forests Science 333 988–93
- Patra P K et al 2013 The carbon budget of South Asia Biogeosciences $10\,513-27$
- Patra P K, Canadell J G, Thompson R L, Kondo M and Poulter B 2016 Sources and Sinks of Carbon Dioxide in Populous Asia, APN Project Reference: ARCP2013-01CMY-Patra/ Canadell/ (http://apn-gcr.org/resources)
- Patra P K, Maksyutov S and Nakazawa T 2005 Analysis of atmospheric CO₂ growth rates at Mauna Loa using CO₂ fluxes derived from an inverse model *Tellus* B 57 357–65
- Patra P K, Niwa Y, Schuck T J, Brenninkmeijer C A M, Machida T, Matsueda H and Sawa Y 2011 Carbon balance of South Asia constrained by passenger aircraft ${\rm CO_2}$ measurements *Atmos. Chem. Phys.* 11 4163–75
- Peters W *et al* 2007 An atmospheric perspective on North American carbon dioxide exchange: carbon tracker *Proc. Natl Acad. Sci.* **104** 18925–30
- Peylin P, Bousquet P, Le Quéré C, Sitch S, Friedlingstein P, McKinley G, Gruber N, Rayner P and Ciais P 2005 Multiple constraints on regional CO₂ flux variations over land and oceans Glob. Biogeochem. Cycles 19 GB1011
- Raupach M R, Marland G, Ciais P, Le Quéré C, Canadell J G, Klepper G and Field C B 2007 Global and regional drivers of accelerating CO₂ emissions *Proc. Natl Acad. Sci.* 104 10288–93
- Rayner P J, Law R M, Allison C E, Francey R J, Trudinger C M and Pickett-Heaps C 2008 Interannual variability of the global carbon cycle (1992–2005) inferred by inversion of atmospheric CO_2 and $\delta 13CO_2$ measurements Glob. Biogeochem. Cycles 22 GB3008
- Reddy C S, Rajashekar G, Krishna P H, Jha C S and Dadhwal V K 2015 Multi-source and multi-date mapping of deforestation in Central India (1935–2010) and its implication on standing phytomass carbon pool *Ecological Indicators* 57 219–27
- Sasaki T, Maki T, Oohashi S and Akagi K 2003 Optimal sampling network and availability of data acquired at inland sites *Global Atmosphere Watch Report Series No. 148* World Meteorological Organization Global Atmosphere Watch pp 77–9
- Sitch S et al 2015 Recent trends and drivers of regional sources and sinks of carbon dioxide *Biogeosciences* 12 653–79
- Sitch S *et al* 2003 Evaluation of ecosystem dynamics, plant geography and terrestrial carbon cycling in the LPJ dynamic global vegetation model *Glob. Change Biol.* **9** 161–85
- Stephens B B et al 2007 Weak northern and strong tropical land carbon uptake from vertical profiles of atmospheric CO₂ Science 316 1732–5
- Stocker B D, Feissli F, Strassmann K M, Spahni R and Joos F 2014
 Past and future carbon fluxes from land use change, shifting
 cultivation and wood harvest *Tellus* B 66 23188



- Sun Y, Gu L, Dickinson R E, Norby R J, Pallardy S G and Hoffman F M 2014 Impact of mesophyll diffusion on estimated global land ${\rm CO}_2$ fertilization *Proc. Natl Acad. Sci.* 111 15774–9
- Tao B, Tian H, Chen G, Ren W, Lu C, Alley K D, Xu X, Liu M, Pan S and Virji H 2013 Terrestrial carbon balance in tropical Asia: contribution from cropland expansion and land management Glob. Planet. Change 100 85–98
- Thompson R L et al 2016 Top-down assessment of the Asian carbon budget since the mid 1990s Nat. Commun. 7 10724
- Tian H, Melillo J M, Kicklighter D W, McGuire A D, Helfrich J V, Moore B and VoÈroÈsmarty C J 1998 Effect of interannual climate variability on carbon storage in Amazonian ecosystems *Nature* 396 664–7
- Tian H, Melillo J M, Kicklighter D W, Pan S, Liu J, McGuire A D and Moore B 2003 Regional carbon dynamics in monsoon Asia and its implications for the global carbon cycle Glob. Planet. Change 37 201–17
- UNFCCC 2015 Adaptation of the Paris agreement, FCCC/CP/ 2015/L.9/Rev.1, 12 December 2015 (https://unfccc.int/ resource/docs/2015/cop21/eng/l09r01.pdf)
- United Nations 2014 2011 Energy Statistics Yearbook (New York: United Nations Department for Economic and Social Information and Policy Analysis, Statistics Division)
- US Geological Survey 2013 Mineral Commodity Summaries 2013 (Reston, VA: US Geological Survey) 198 pp

- van der Werf G R, Randerson J T, Giglio L, Collatz G J, Mu M, Kasibhatla P S, Morton D C, DeFries R S, Jin Y V and van Leeuwen T T 2010 Global fire emissions and the contribution of deforestation, savanna, forest, agricultural, and peat fires (1997–2009) *Atmos. Chem. Phys.* 10 11707–35
- Wang X $et\,al\,2014\,A$ two-fold increase of carbon cycle sensitivity to tropical temperature variations $Nature\,506\,212-5$
- West T O, Brown M E, Duren R M, Ogle S M and Moss R H 2013 Definition, capabilities and components of a terrestrial carbon monitoring system *Carbon Manage*. 4 413–22
- Wicke B, Sikkema R, Dornburg V and Faaij A 2011 Exploring land use changes and the role of palm oil production in Indonesia and Malaysia *Land Use Policy* 28 193–206
- World Bank Group 2015 World Development Indicators 2015 (World Bank Publications)
- Zeng N, Mariotti A and Wetzel P 2005 Terrestrial mechanisms of interannual CO₂ variability *Glob. Biogeochem. Cycles* **19** GB1016
- Zhao F et al 2016 Role of CO₂, climate and land use in regulating the seasonal amplitude increase of carbon fluxes in terrestrial ecosystems: a multimodel analysis *Biogeosci. Discuss.* 2016 1-22
- Zhou T, Shi P, Hui D and Luo Y 2009 Global pattern of temperature sensitivity of soil heterotrophic respiration (Q10) and its implications for carbon-climate feedback *J. Geophys. Res.: Biogeosci.* 114 G02016