To those who have been supporting me selflessly and to those who love science
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LIST OF ABBREVIATIONS

BNF  Biological nitrogen fixation
CMIP5 Coupled model intercomparison project phase 5
DNDC DeNitrification-DeComposition
ESMs Earth system models
FACE Free air CO₂ enrichment experiment
GPP Gross primary production
LAI Leaf area index
NEP Net ecosystem production, the difference between NPP and Rₜ
NPP Net primary production
PDSI Palmer drought severity index
Rₜ Heterotrophic respiration
SOM Soil organic matter
SPEI Standardized precipitation evapotranspiration index
SPI Standardized precipitation index
SMAs Soil moisture anomalies
TBM Terrestrial biosphere models
WFPS Water filled pore space
PFT Plant functional type
Nr Reactive nitrogen
TERRESTRIAL SOIL NITROUS OXIDE EMISSIONS AND RESPONSES OF CARBON CYCLING TO DROUGHT

By

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December 2015

Chair: Stefan Gerber
Major: Soil and Water Science

Terrestrial carbon, water and nitrogen cycles are coupled at multiple scales and are crucial to future greenhouse gas concentration and thus climate change. Concerns on climate feedbacks through nitrogen originate from both nitrous oxide (N₂O) and from interactions with the carbon cycle. This study adopts Terrestrial Biosphere Models (TBMs) to explore soil N₂O emissions and carbon-drought responses in the context of C-N interaction. Key questions tackled here include: spatiotemporal dynamics of global soil N₂O emission; sensitivity of N₂O emission to soil moisture regimes, step rises in atmospheric CO₂ and temperature; response of N₂O emission to historical global enviromental changes (climate change, atmospheric nitrogen deposition and CO₂) and land cover transitions; how well do current TBMs represent carbon-drought response; and what is the role of nitrogen in carbon-drought response. I added a N₂O emission module to LM3V-N and found that N₂O fluxes were highly sensitive to soil moisture regime indicated by water filled pore space. The global response of N₂O to step rise of CO₂ was largely determined by tropical emissions which reduces N₂O fluxes in the first few decades, while the extratropical response was weaker and positive, highlighting the need to expand field studies in tropics. Although land cover transition alone had a minor
impact on N2O emissions over 1970-2000, its contribution varied spatiotemporally and peaked in the 1920s, balanced between positive responses in temperate regions and negative responses in the tropics. To investigate the performance of current TBMs in the response to water anomalies, I evaluated 9 Earth System Models from the historical experiment of the Coupled Model Intercomparison Project Phase 5 (CMIP5). Models are on average more responsive to meteorological drought indicated by the Standardized Precipitation Index (SPI) compared to the FLUXNET upscaled gross primary productivity and satellite derived leaf area index. The over-response is less obvious based on soil moisture drought indicated by surface (less than 10cm) soil moisture anomalies (SMAs). Nevertheless, nitrogen is found to buffer (reduce sensitivity) vegetation’s response (net primary productivity and net ecosystem productivity) to precipitation anomalies based on simulations that include C-N interactions in LM3V-N and that do not.
CHAPTER 1
GENERAL INTRODUCTION

Background

Nitrogen and Climate Change

Nitrogen (N) is an essential element in living organisms. Most of the unperturbed or "natural" ecosystems are scarce in available N (ammonium, nitrate and other oxidized nitrogen forms), referred as reactive N (Nr), due to high energetic costs of biological fixation of atmospheric N₂ and N losses to volatilization, denitrification and/or leaching (Vitousek and Howarth, 1991a). Thus terrestrial ecosystem productivity is often constrained by limited N supply, especially in mid- and high-latitude ecosystems (Gruber and Galloway, 2008). Human activities have more than doubled Nr fluxes into Earth’s ecosystems through agricultural fertilizer application and fossil fuel combustion since the late 19th century (Galloway et al., 2004). While perhaps alleviating N constraints in forests and grasslands (Zaehle and Dalmonech, 2011), these large Nr fluxes have caused various urgent environmental problems such as photosmog, tropospheric ozone depletion, eutrophication of water bodies, declination of biodiversity, global acidification and warming (Galloway et al., 2003; Galloway et al., 2008). Among these, the perturbation of climate system is of critical importance. Concerns on the feedback to climate through terrestrial N cycle originate mainly from two areas: interactions with carbon (C) cycle and nitrous oxide (N₂O) emissions.

Nitrogen Influences on Terrestrial Carbon Fluxes

C and N are tightly coupled as organisms require both of these elements (Gruber and Galloway, 2008). Plants and microbes require N for growth and maintenance of tissues. The majority of N supporting biological activities is supplied via the
decomposition of plant litter and soil organic matter (SOM) that is regulated by nutrient/N availability, resulting in a strong dependence of plant activity and heterotrophic respiration on ecosystem N status. At the global scale, a growing number of TBMs have accounted for C-N interactions, with an emphasis in the regulation of N on carbon sequestration in terrestrial ecosystems in response to climate change, atmospheric CO$_2$ increase, atmospheric Nr deposition and land use change (Sokolov et al., 2008; Jain et al., 2009; Thornton et al., 2009; Gerber et al., 2010; Zaehle et al., 2010b; Xu-Ri and Prentice, 2008; Churkina et al., 2009; Jain et al., 2013; Gerber et al., 2013).

Overall, introducing C-N coupling in models showed a significantly reduction in the strength of the so called CO$_2$ fertilization effect and a decrease in the warming induced global C source (Sokolov et al., 2008; Thornton et al., 2009). CO$_2$ fertilization effect refers to the enhancement of photosynthesis and thus primary productivity by elevated atmospheric CO$_2$ levels (Reich and Hobbie, 2013; Kimball, 1983). The enhancement of biomass accumulation and CO$_2$ uptake is not unlimited but constrained by shortage of resources such as nutrients and water. Despite soil N availability has been reported to decrease, unchange or increase from manipulative CO$_2$ enrichment experiments (e.g. the Free Air CO$_2$ Enrichment experiment, FACE) and ecosystem responses to CO$_2$ enrichment vary widely, from no enhancement to transient or sustained net primary production (NPP) enhancement (Reich et al., 2006; Drake et al., 2011; Reich and Hobbie, 2013; Oren et al., 2001; Langley et al., 2009), the current generation of global C-N models agree that biomass accumulation and CO$_2$ uptake from
CO$_2$ fertilization are reduced by N constraints at the global scale (Zaehle and Dalmonech, 2011).

TBMs that do not consider C-N interaction (C-only models) show that increasing temperature increases NPP and heterotrophic respiration. Most of the C-only models produce a stronger temperature effect on heterotrophic respiration compared to NPP, which creates a positive climate-carbon feedback, where CO$_2$ induced warming weakens the uptake of anthropogenic carbon (Friedlingstein et al., 2006). However, temperature enhances SOM decomposition, increases ecosystem N availability and therefore plant growth. This effect is large enough that the land becomes a source by the year 2100 in some models (Thornton et al., 2009; Sokolov et al., 2008), and thus more terrestrial C storage with a warming climate. Models agree on enhanced vegetation growth due to N released from SOM decomposition under warming despite differing in magnitudes (Zaehle et al., 2010a; Jain et al., 2009).

**Drought and Terrestrial Carbon Cycle**

Among various factors that affect terrestrial C cycling, water related climate extremes, such as drought and intense precipitation, can substantially affect regional and global carbon cycle (Keenan et al., 2012; Reichstein et al., 2013) and is growingly important since the future is predicted to experience more frequent and intense droughts (Dai, 2011).

Drought is a complex climate event which causes extended period of deficiency in water supply. Observational data (e.g. FLUXNET), remote sensing and models have been used to quantify the effects of drought on C cycling. Most of the studies focused on primary productivity have revealed the negative impacts of drought globally, although responses might be different regionally (Chen et al., 2013; Chen et al., 2012; Zhao and
Running, 2010; Ciais et al., 2005). Fewer studies focused on ecosystem respiration suggested divergent responses (Meir et al., 2008; Metcalfe et al., 2010; Shi et al., 2014). For example, drought can stimulate soil respiration via reductions in soil anoxia (Cleveland et al., 2010), and decrease soil respiration via reductions in substrate (C) availability (Borken et al., 2006). Nevertheless, compared to primary productivity, respiration is reported to be less sensitive to drought based on FLUXNET data (Schwalm et al., 2010), and modeling (Shi et al., 2014). Despite FLUXNET data, remote sensing and models agree on the direction of drought’s impact on ecosystem productivity (GPP or NPP), it remains largely unknown how modeled drought-carbon relationship matches empirical drought-carbon response such as in terms of drought vulnerability, resistance and resilience at the global scale.

Drought also alters terrestrial N cycle and affects N availability for vegetation growth. Field level studies revealed the complex impacts of drought on N mineralization (Townsend et al., 2011), nitrification (Emmett et al., 2004), leaching (Lodge et al., 1994), gaseous losses (Wood and Silver, 2012; Davidson et al., 2008; Davidson et al., 2004; Wieder et al., 2011; Cleveland et al., 2010), and biological N fixation (Wurzburger and Miniat, 2014), and thereby also on the availability of N. One the other hand, N constraints on photosynthesis is linked to canopy water flux (i.e. transpiration) through leaf stomata, which might regulate soil moisture availability. Models without N component might bias estimations of vegetation’s drought response, although to my knowledge, no study is available to quantify the role of N constraints on global scale carbon-drought response.
**Nitrous Oxide Emissions**

$N_2O$ is one of the most important greenhouse gas contributing to climate change (Ciais et al., 2013). In addition, it is suggested to be the single most important ozone-depleting substance (Ravishankara et al., 2009). The concentration of atmospheric $N_2O$ has been increasing considerably since the industrial revolution (Ciais et al., 2013). The high growth rate is attributed mainly to applications of synthetic fertilizer and manure during agriculture intensification (Butterbach-Bahl et al., 2013).

Approximately 70% of global $N_2O$ emissions originate from microbial mediated processes in managed and unperturbed soils (mostly nitrification and denitrification) (Butterbach-Bahl et al., 2013; Syakila and Kroeze, 2011). Nitrification is an aerobic process that oxidizes ammonia or ammonium ($NH_4^+$) to nitrite followed by further oxidation of nitrite to nitrate ($NO_3^-$). Denitrification is an anaerobic process that reduces nitrate ($NO_3^-$) ultimately to $N_2$ through a sequential of intermediate steps involving nitrogen oxides such as nitrite ($NO_2^-$), nitric oxide (NO), nitrous oxide ($N_2O$). Nitrification and denitrification allow for gaseous N transferring from soil to atmosphere, which is an important mechanism through which ecosystem loses its biological available N (Houlton and Bai, 2009). Nitrifying microbes need oxygen as electron acceptor and ammonia or ammonium as the electron donor, while denitrifying microbes normally require organic carbon for electron donor and low oxygen concentration. Therefore, soil texture, soil moisture conditions, N turnover rate, temperature and oxygen concentration are all well-known regulators of nitrification and denitrification $N_2O$ fluxes (Li et al., 2000; Parton et al., 1996; Parton et al., 2001). Among these regulators, soil moisture is one of the most frequently reported factors with the hotspots and hot-moments of $N_2O$ emissions tightly coupled to water dynamics (Galloway et al., 2003; Schlesinger, 2009).
Soil moisture not only influences nitrification and denitrification rates through its regulations on substrate availability and O\textsubscript{2} supply, but also controls on the gaseous partition among various N gases (e.g. N\textsubscript{2}, N\textsubscript{2}O and NO).

In addition to biotic denitrification, researchers have reported chemical decomposition of nitrite (chemodenitrification) to be important for NO emissions from acidic soils (Ciais et al., 2013), however its role for N\textsubscript{2}O production is not well studied (Li et al., 2000). Abiotic decomposition of ammonium nitrate in the presence of light, associated with appropriate relative humidity and a surface, is reported as another mechanism of N\textsubscript{2}O production (Ciais et al., 2013; Rubasinghege et al., 2011), and its role has not yet been assessed globally.

Over the last three decades, considerable efforts have been dedicated to estimate the magnitude of soil N\textsubscript{2}O sources and their regulators, but large uncertainties still remain. Inverse modeling (‘top down’) based on observation networks is questioned by poor understanding of the variability of stratosphere-troposphere exchanges that affect N\textsubscript{2}O sinks (Ciais et al., 2013). Empirical-driven estimation ("bottom up") by combining average measured fluxes with vegetation and soil information is not capable of capturing seasonal or interannual variability or responses to environmental drivers (Ciais et al., 2013). Advance in process based land modeling brings the flexibility of separating and quantifying soil emissions at different temporal scales, assessing its transient response to environmental drivers and projecting into future environmental changes (Stocker et al., 2013; Xu-Ri et al., 2012; Zaehle et al., 2011; Saikawa et al., 2013).
Earlier process-based models, for example, the application of the “hole-in-pipe” concept (Firestone and Davidson, 1989a) in the Carnegie-Ames-Stanford (CASA) Biosphere model, calculated the sum of NO, N\textsubscript{2}O and N\textsubscript{2} fluxes as a constant portion of gross mineralized N, and the relative ratios of N trace gases (NO\textsubscript{x}:N\textsubscript{2}O:N\textsubscript{2}) as a function of soil moisture (Potter et al., 1996). Recent global N\textsubscript{2}O models take advantage of global dynamic land models with more sophisticated processes, such as microbial dynamics (Saikawa et al., 2013; Stocker et al., 2013; Zaehle et al., 2011; Xu-Ri et al., 2012). Simulations performed with O-CN model demonstrated a positive response of N\textsubscript{2}O emissions to historical warming and a negative response to historical CO\textsubscript{2} increase, globally (Zaehle et al., 2011). Although CO\textsubscript{2} and interaction with climate change resulted in an increase in historical and future N\textsubscript{2}O emissions in the LPJ-DyN (Xu-Ri et al., 2012) and LPX-Bern (Stocker et al., 2013) models, historical CO\textsubscript{2} change alone caused a slight decrease in historical N\textsubscript{2}O emissions from LPJ-DyN (Xu-Ri et al., 2012). This negative CO\textsubscript{2} response seems to be in disagreement with one meta-analysis of manipulative field experiments showing an increase in N\textsubscript{2}O emissions at elevated levels of CO\textsubscript{2} (Zaehle et al., 2011; Xu-Ri et al., 2012; van Groenigen et al., 2011). In addition to CO\textsubscript{2} and climate change, global N\textsubscript{2}O emissions are further complicated by response to other global change factors, such as increasing Nr deposition and land cover transitions. Only O-CN (Zaehle et al., 2011) is applied to study the land cover impact on soil N\textsubscript{2}O emissions. However, from their study, it is unclear separately to what extent conversions of forests to croplands or pastures and changes in harvest or regrowth cycles in secondary vegetation alter large scale soil N\textsubscript{2}O.
emissions. And it is also unknown how land cover transitions interact with environmental factors (CO₂, climate change, nitrogen deposition) in shaping historical N₂O emissions.

**LM3V/LM3V-N**

Much of the work in this dissertation is based on the terrestrial biosphere model LM3V-N. LM3V-N is the land model of the Geophysical Fluid Dynamics Laboratory (GFDL) that is capable of simulating ecosystem dynamics and interactions between land and atmosphere (Shevliakova et al., 2009) and entails a prognostic N cycle (Gerber et al., 2010). More detailed description of LM3V and LM3V-N is available in Appendix A and B, respectively. Within each grid cell, the coexistence of different land cover types are possible, and are represented as tiles (sub-grid unit). Each tile assumes 4 land cover types: primary or potential land undisturbed by human activities, cropland, pasture and secondary lands that are harvested at least once. Primary, cropland and pasture each occupy one tile per grid cell. Secondary vegetation is represented by a series of tiles within one grid cell to indicate the size/age classes of vegetation since the last land use disturbance. For computation reasons, secondary vegetation tiles are combined under the following conditions: a) the biomass is within the same biomass size class (0.5, 1, 2, 3, 4, 5, 6, 8, 10 kgC m⁻²); and b) biological N fixation (BNF) rates per unit leaf mass are within 50% of each other (Gerber et al., 2013). LM3V-N includes five plant functional types (PFTs): C3 and C4 grasses, tropical, temperate deciduous and cold evergreen trees. A tile can only be occupied by a single PFT. Each PFT has five vegetation C pools (leaves, fine roots, sapwood, labile, and heartwood), two litter and two soil organic C pools and their corresponding N pools based on the specific C/N ratios.
Photosynthesis is based on stomatal conductance with the Farquhar scheme (Farquhar et al., 1980) and further improvements (Collatz et al., 1992; Collatz et al., 1991a). Plants can adjust their uptake of N from soil inorganic pools to maintain their specific C/N ratios in tissues based on Liebig’s Law of the Minimum. Meanwhile, an additional N storage pool in plant buffers diurnal and seasonal asynchronies between N supply and demand. BNF is one of the most uncertain processes in C-N models. Instead of empirically relating BNF to ecosystem variables such as evapotranspiration (Jain et al., 2009; Zaehle and Friend, 2010) or net primary productivity (Thornton et al., 2007), BNF in LM3V-N is dynamically simulated based on plant N availability, demand and light condition. This scheme mimics the successional development of BNF with high N fixation in the early stage and decreasing fixation as vegetation develops. Organic matter decomposition is based on a modified CENTURY approach (Bolker et al., 1998). Mineral N can both stimulate “light” organic matter decomposition and contribute to “heavy” SOM stabilization. The fate of soil mineral N depends on the relative strength of the competing sinks, with the order of soil immobilization > plant uptake > leaching/denitrification. Denitrification so far has been lumped with leaching losses and not simulated explicitly. N losses occur through leaching from mineral N and dissolved organic N, natural fires and removal from live vegetation pools (clearance, harvest and grazing) in land use activities.

LM3V-N has been demonstrated to be capable of reconstructing historical land C and N sinks, recreating spatial variations in C and N dynamics, reasonably responding to step changes in atmospheric CO₂, and capturing C-N interactions following disturbance (Gerber et al., 2010; Bernal et al., 2012; Gerber et al., 2013). Consistent with
succession theory, C-N interactions are weak in LM3V-N when the modeled system is approaching steady state, and strong following disturbance. Over the long term, losses of N from fire and dissolved organic nitrogen are critical factors limiting ecosystem N accumulation and maintaining N limitation (Gerber et al., 2010; Gerber et al., 2013).

Objectives of This Dissertation

C-N interactions are known to be important in global biogeochemical cycles and climate change. LM3V-N has its unique features that are not captured by other C-N models such as the dynamic BNF scheme and realistically tracking of the secondary vegetation succession with explicitly resolved C-N interactions. It has been applied to study the impact of N cycle on terrestrial C dynamics, and been further extended to study the terrestrial and aquatic nitrogen (LM3-TAN) cycling at the watershed level (Lee et al., 2014). It has not yet been applied to explore soil N\textsubscript{2}O emissions at the global scale and a comparison to earlier models is thus warranted. Studies on large scale terrestrial N\textsubscript{2}O emissions from C-N interaction perspective are limited. Therefore, one of the objectives is to embed a new N\textsubscript{2}O emission module into LM3V-N (Chapter 2), evaluate modeled N\textsubscript{2}O emissions against field observations and previous modeling studies, test its sensitivity to the general N cycling, soil moisture regimes and the parameterization of nitrification and denitrification. Special focus is placed on the response of modeled N\textsubscript{2}O emissions to elevated atmospheric CO\textsubscript{2} concentration and temperature where field manipulative experiments provide the base for comparison. I further take advantage of this model to resolve contributions from multiple global change factors, especially involving land cover transition, that shape historical N\textsubscript{2}O emissions (Chapter 3). The goal is to fill the gaps in the study of global scale land cover transition impacts on N\textsubscript{2}O emissions.
In addition to $\text{N}_2\text{O}$ emissions, C-N interactions in the plant-soil system also alter carbon cycling. I took the carbon-drought response as my example to illustrate the specific role of N on carbon cycling. I first evaluate results from multiple models participated in the historical experiment of the Coupled Model Intercomparison Project Phase 5 (CMIP5) to answer the question: how well do modeled drought-carbon responses match the empirical drought-carbon relationships (Chapter 4). I further compare simulation results from LM3V-N with nitrogen interaction (C-N) vs. that without nitrogen interaction (C-ONLY) to reveal the role of N in carbon-drought response (Chapter 5).
CHAPTER 2
GLOBAL SOIL NITROUS OXIDE EMISSIONS IN A DYNAMIC CARBON-NITROGEN MODEL

Introduction

Nitrous oxide (N$_2$O) is a major reactant in depleting stratospheric ozone as well as an important greenhouse gas (Ravishankara et al., 2009; Butterbach-Bahl et al., 2013; Ciais et al., 2013). With a global warming potential of 298 times more (per unit mass) than that of carbon dioxide (CO$_2$) over a 100-year period (Forster et al., 2007), the contributions of N$_2$O emissions to global radiative forcing and climate change are of critical concern (Zaehle and Dalmonech, 2011). The concentration of atmospheric N$_2$O has been increasing considerably since the industrial revolution with a linear rate of 0.73±0.03 ppb yr$^{-1}$ over the last three decades (Ciais et al., 2013). Although applications of synthetic fertilizer and manure during agriculture intensification have been identified as the major causes of this increase which has resulted in an increase of the radiative forcing by 0.125 W m$^{-2}$ (Davidson, 2009; Zaehle and Dalmonech, 2011), nonagricultural (natural) soil is still an important N$_2$O source (Ciais et al., 2013; Syakila and Kroeze, 2011). N$_2$O fluxes from nonagricultural soils are highly heterogeneous, which limits my ability to estimate and predict global scale budget, and quantify its response to global environmental changes (Butterbach-Bahl et al., 2013; Ciais et al., 2013).

Most of the N$_2$O fluxes from soil are produced by microbial nitrification and denitrification (Braker and Conrad, 2011; Syakila and Kroeze, 2011). Nitrification is an aerobic process that oxidizes ammonium (NH$_4^+$) to nitrate (NO$_3^-$), during which some N is lost as N$_2$O. Denitrification reduces nitrate or nitrite to gaseous N (i.e. NO$_x$, N$_2$O and N$_2$), a process that is fostered under anaerobic conditions. N$_2$O is generated in intermediary steps during denitrification and a small portion can escape from soil before
further reduction to N$_2$ takes place. Soil texture, soil NH$_4^+$, soil water filled pore space (WFPS), mineralization rate, soil pH, and soil temperature are well-known regulators of nitrification N$_2$O fluxes (Parton et al., 1996; Li et al., 2000; Parton et al., 2001). Denitrification and associated N$_2$O emissions depend primarily on carbon supply, the redox potential and soil NO$_3^−$ (Firestone and Davidson, 1989b; Parton et al., 1996). Soil moisture has a particularly strong impact (Galloway et al., 2003; Schlesinger, 2009) as it influences nitrification and denitrification rates through its regulations on substrate availability and soil redox potential (as oxygen diffusion proceeds at much slower rate in water filled than in air filled pore space), thereby also controlling the partitioning among various denitrification products (i.e. NO$_x$, N$_2$O and N$_2$) (Firestone and Davidson, 1989b; Parton et al., 2001). Although emissions are known to be sensitive to soil moisture, quantitative understanding of its role in terrestrial N$_2$O fluxes and variability is limited (Ciais et al., 2013).

At regional to global scale, the application of the “hole-in-pipe” concept (Firestone and Davidson, 1989b) in the CASA biosphere model pioneered one of the earliest process-based estimation of natural soil N$_2$O fluxes. The model calculated the sum of NO, N$_2$O and N$_2$ fluxes as a constant portion of gross mineralized N, and the relative ratios of N trace gases (NO$_x$:N$_2$O:N$_2$) as a function of soil moisture (Potter et al., 1996). While the early models of nitrification and denitrification are primarily conceptual driven, recent global N$_2$O models combine advancements in global dynamic land models with more detailed processes, including microbial dynamics. Xu and Prentice (2008) simplified nitrification and denitrification modules from DNDC (i.e., DeNitrification-DeComposition) (Li et al., 1992; Li et al., 2000) in their global scale dynamic N scheme
(DyN) and incorporated DyN into the LPJ dynamic global vegetation model. In the
DNDC approach, nitrification and denitrification were allowed to happen simultaneously
in aerobic and anaerobic microsites. Zaehle et al. (2011) incorporated a nitrification-
denitrification scheme into the O-CN land model following largely the LPJ-DyN with
minor modifications and additions of the effects of soil pH and chemo-denitrification that
originated from DNDC (Li et al., 2000). Stocker et al. (2013) embedded the LPJ-DyN
approach into an Earth System Model and investigated the feedbacks of N₂O emissions,
together with CO₂ and CH₄, to climate. Compared to LPJ-DyN approach, Saikawa et al.
(2013) retained the explicit simulation of nitrifying and denitrifying bacteria from DNDC
in their CLMCN-N₂O module based on CLM V3.5 land model. Simulations with O-CN
demonstrated a positive response of N₂O emissions to historical warming and a
negative response to historical CO₂ increase, globally. While CO₂ and interaction with
climate change resulted in an increase in historical and future N₂O emissions from LPJ-
DyN (Xu-Ri et al., 2012) and its application in LPX-Bern (Stocker et al., 2013),
respectively, historical CO₂ change alone, i.e. single factor of Xu-Ri et al. (2012),
caused a slight decrease in historical N₂O emissions. The negative CO₂ response
seems to be in disagreement with one meta-analysis of manipulative field experiments
showing an increase in N₂O emissions at elevated levels of CO₂ (Zaehle et al., 2011;Xu
et al., 2012;van Groenigen et al., 2011). The discrepancy in response to global change
factors needs to be addressed both in models and in the interpretation of manipulative
field experiments.

Here I add a N₂O gas emission module to LM3V-N, a land model developed at
the Geophysical Fluid Dynamics Laboratory (GFDL). In this chapter, I will first briefly
introduce LM3V-N and describe the added N$_2$O emission module. I then subject the model to historic changes in CO$_2$, N deposition, and recent climate change to infer natural N$_2$O emissions in the past few decades. I test the model’s sensitivity to soil water regime, by addressing the parameterization of soil WFPS, and by replacing the model soil moisture with two different soil moisture reanalysis products. I also conduct sensitivity tests with regard to the general N cycling and parameterization of N$_2$O emissions. Since I build largely on existing parameterization of nitrification-denitrification processes, my focus relies on the evaluation of these processes if transferred to a different model. Finally, I subject the model to step changes in atmospheric CO$_2$ and temperature to understand modeled reponses to CO$_2$ fertilization/climate change.

**Methods**

**Model Description**

General introduction of LM3V and LM3V-N is provided in Chapter 1 and Appendix A and B. Further details are available in the references cited in these sections. Gaseous losses so far were not differentiated from hydrological leaching in LM3V-N. I add a soil nitrification-denitrification module which accounts for N gaseous losses from NH$_3$ volatilization, nitrification and denitrification. The nitrification-denitrification scheme implemented here combines features from both the DNDC model (Li et al., 1992; Li et al., 2000) and the CENTURY/DAYCENT (Parton et al., 1996; Parton et al., 2001; Del Grosso et al., 2000). In this part, I provide details on the nitrification-denitrification module which explicitly simulates N gaseous losses from nitrification and denitrification, as well as other process modifications compared to the original LM3V-N.
Nitrification-denitrification

Transformation among mineral N species (ammonium and nitrate) occurs mainly through two microbial pathways: nitrification and denitrification. Although ongoing debate exists in whether nitrification rates may be well described by bulk soil ammonium concentration or soil N turnover rate (Parton et al., 1996; Zaehle and Dalmorech, 2011), I adopt the donor controlled scheme (ammonium concentration). In addition to substrate, soil texture, soil water filled pore space (WFPS, the fraction of soil pore space filled with water), and soil temperature are all well known regulators of nitrification. As a first order approximation, nitrification rate \( (N, \text{in unit, kgN m}^{-2} \text{ year}^{-1}) \) is simulated as a function of soil temperature, \( \text{NH}_4^+ \) availability and WFPS,

\[
N = k_n f_n(T) f_n(WFPS) \frac{N_{NH_4^+}}{b_{N,NH_4^+}} \tag{2-1}
\]

where \( k_n \) is the base nitrification rate \( (11000 \text{ year}^{-1}, \text{the same as in LM3V-N}) \) (Gerber et al., 2010); \( N_{NH_4^+} \) is ammonium content (in unit, kgN m\(^{-2}\)); \( b_{N,NH_4^+} \) is the buffer or sorption parameter for \( \text{NH}_4^+ \) (unitless, 10 in LM3V-N) (Gerber et al., 2010); \( f_n(T) \) is the temperature response function following Li et al. (2000), with an optimum temperature for nitrification at 35\(^\circ\)C; and \( f_n(WFPS) \) is the soil water response function. The effect of WFPS on nitrification is texture dependent, with most of the reported optimum value around 0.6 (Parton et al., 1996; Linn and Doran, 1984). I adopt the empirical WFPS response function from Parton et al. (1996) with medium soil texture.

\[
f_n(T) = \left( \frac{60-T_{soil}}{25.78} \right)^{3.5} 0.03 \times e^{\frac{3.5 \times 0.0 \times (T_{soil}-34.22)}{25.78}} \tag{2-2}
\]

\[
f_n(WFPS) = \left( \frac{WFPS-1.27}{-0.67} \right)^{1.9 \times 0.28} \times \left( \frac{WFPS-0.0012}{0.5 \times 9988} \right)^{2.04} \tag{2-3}
\]

where \( T_{soil} \) is the soil temperature in degree Celsius.
Denitrification is controlled by substrate NO\textsubscript{3}\textsuperscript{−} (electron acceptor), labile C availability (electron donor), soil moisture and temperature. Labile C availability is estimated by soil heterotrophic respiration (HR). Following LPJ-DyN Xu and Prentice (2008), denitrification is assumed to have a Q\textsubscript{10} value of 2 when the soil temperature is between 15 and 25 °C. The soil moisture response function is adopted from Parton et al. (1996). Soil pH is reported to be an important indicator of chemodenitrification which occurs predominantly in acidic soils (pH<5) under conditions of high nitrite concentration (Li et al., 2000). However, its role for N\textsubscript{2}O production is not well studied (Li et al., 2000) and I do not model the chemodenitrification explicitly.

\[ D = k_d f_d(T) f_d(WFPS) f_g NO_3^- \]  \tag{2-4}

And

\[ f_g = \frac{HR}{HR+K_c NO_3^-+K_n} \]  \tag{2-5}

\[ NO_3^- = \frac{N_{NO_3^-}}{b_{NO_3^-}} \]  \tag{2-6}

where \( D \) is the denitrification rate (in unit, kgN m\textsuperscript{-2} year\textsuperscript{-1}); \( k_d \) is the base denitrification rate (8750 year\textsuperscript{-1}); \( f_g \) mimics the impact of labile C availability and substrate (nitrate) on the growth of denitrifiers, adapted from Li et al. (2000); \( K_c \) and \( K_n \) are half-saturation constants taken from Li et al. (2000) (0.0017 and 0.0083 kgN m\textsuperscript{-2} respectively, assuming an effective soil depth of 0.1m); \( b_{NO_3^-} \) is the buffer or sorption parameter for NO\textsubscript{3}\textsuperscript{−} (unitless, 1 in LM3V-N) (Gerber et al., 2010); \( N_{NO_3^-} \) and \( NO_3^- \) are nitrate content before and after being buffered (in unit, kgN m\textsuperscript{-2}), respectively; and \( f_d(T) \) and \( f_d(WFPS) \) are empirical soil temperature and water response function for denitrification, adopted from Xu-Ri and Prentice (2008) and Parton et al. (1996), respectively.

\[ f_d(T) = e^{308.5 \times \left( \frac{1}{6.80 + 2 \times T_{soil} + 46.6} \right)} \]  \tag{2-7}
\[
\frac{f_d(WFPS)}{12.0}^{0.6} = \frac{1.5}{20^{(x \times 2.5 \times WFPS)}}
\]

(2-8)

**Gaseous partitions from nitrification-denitrification**

\(\text{N}_2\text{O}\) is released as a byproduct from both nitrification and denitrification. The fraction of \(\text{N}_2\text{O}\) lost from net nitrification is uncertain (Li et al., 2000; Xu and Prentice, 2008). Here I set this fraction to be 0.4%, which is higher than Goodroad and Keeney (1984a), but at the low end provided by Khalil et al. (2004a). \(\text{N}_2\text{O}\) and \(\text{NO}_x\) emissions from nitrification are based on the \(\text{NO}_x: \text{N}_2\text{O}\) ratio \(R_{\text{NO}_x: \text{N}_2\text{O}}\) which is updated at every time step and for each grid cell. \(R_{\text{NO}_x: \text{N}_2\text{O}}\) varies with relative gas diffusivity \(D_r\), the relative gas diffusivity in soil compared to air (Parton et al., 2001), which is calculated from air filled porosity \((\text{AFPS, i.e., the portion of soil pore space that is filled by air})\) (Davidson and Trumbore, 1995)

\[
R_{\text{NO}_x: \text{N}_2\text{O}} = 15.2 + \frac{35.5 \times \text{ATAN}(0.68 \times \pi \times (10 \times D_r - 1.68))}{\pi}
\]

(2-9)

\[
D_r = 0.209 \times \text{AFPS}^{\frac{4}{3}}
\]

(2-10)

where \(\text{ATAN}\) stands for the trigonometric arctangent function; \(\text{AFPS}\) is the air filled porosity \((1-\text{WFPS})\), and \(\pi\) is the mathematical constant, approximately 3.14159.

During denitrification, the gaseous ratio between \(\text{N}_2\) and \(\text{N}_2\text{O}\) \(R_{\text{N}_2: \text{N}_2\text{O}}\) is calculated following the empirical function derived by Del Grosso et al. (2000), which combines the effects of substrate \(\text{(NO}_3^-\text{)}\) to electron donor \((HR, the proxy for labile C)\) ratio and \(\text{WFPS}\). \(R_{\text{N}_2: \text{N}_2\text{O}}\) is updated at every time step and for each grid cell.

\[
R_{\text{N}_2: \text{N}_2\text{O}} = Fr\left(\frac{\text{NO}_3^-}{HR}\right) \cdot Fr(WFPS)
\]

(2-11)

With

\[
Fr\left(\frac{\text{NO}_3^-}{HR}\right) = \max(0.16 \times k, k \times e^{-0.8 \times \frac{\text{NO}_3^-}{HR}})
\]

(2-12)
\[ Fr(WFPS) = \max(0.1, 0.015 \times WFPS - 0.32) \]  \hspace{1cm} (2-13)

where \( k \) is a texture dependent parameter (Table 2-1) estimated from Del Grosso et al. (2000). \( k \) controls the maximum value of the function \( Fr \left( \frac{NO_3}{HR} \right) \).

### Other modified processes

To complete the N loss scheme in LM3V-N, I also added NH\(_3\) volatilization into LM3V-N. NH\(_3\) volatilization in soil results from the difference between the equilibrium NH\(_3\) partial pressure in soil solution and that in the air. Dissolved NH\(_3\) is regulated by ammonium concentration and pH. The net flux of NH\(_3\) from soil to the atmosphere varies with soil NH\(_3\), moisture, temperature, therefore

\[
NH_3 = k_{nh} f(pH) f_{NH3}(T)(1 - WFPS) \frac{N_{NH_3}}{b_{N,NH_4}} \]  \hspace{1cm} (2-14)

where \( NH_3 \) is the net ammonia volatilization flux (in unit, kgN m\(^{-2}\) year\(^{-1}\)); \( k_{nh} \) is the base ammonia volatilization rate (365 year\(^{-1}\)); \( f(pH) \) is the pH factor and \( f(T) \) is the temperature factor which are given by the following two equations:

\[
f(pH) = e^{2 \times (pH_{soil} - 10)} \]  \hspace{1cm} (2-15)

\[
f_{NH3}(T) = \min(1, e^{308.5 \times (\frac{1}{10} - \frac{1}{T_{soil} + 46.0})}) \]  \hspace{1cm} (2-16)

where \( pH_{soil} \) is the soil pH which is prescribed instead of simulated dynamically. \( f(pH) \) and \( f(T) \) follow largely on the NH\(_3\) volatilization scheme implemented in the dynamic global vegetation model LPJ-DyN (Xu and Prentice, 2008).
Model Experiments

Global hindcast with potential vegetation

To understand the model performance and compare with other models and observations, I conducted a hindcast simulation with potential vegetation. The model resolution was set to 3.75 degrees longitude by 2.5 degrees latitude. I forced the model with 3 hourly reanalysis weather data based on Sheffield et al. (2006). I used a 17 year recycled climate of 1948-1964 for the spin-up and simulation years prior to 1948. Atmospheric CO\textsubscript{2} concentration was prescribed with 284 ppm for model spin-up and based on ice core and atmospheric measurements for transient simulations (Keeling et al., 2009). N deposition was set as natural background for simulations before 1850 (Dentener and Crutzen, 1994a), and interpolated linearly between the natural background and a snapshot of contemporary (1995) deposition (Dentener et al., 2006) for simulations after 1850. Soil pH was prescribed and derived from the Harmonized World Soil Database (HWSD) version 1.1, the same as NACP model driver data (Wei et al., 2014).

The model was spun up from bare ground without C-N interactions for the first 68 years and with C-N interactions for the following 1200 years to develop and equilibrate C and N stocks. To speedup the spin-up process, slow litter and soil C and N pools were set to the equilibrium values based on litterfall inputs and decomposition/leaching rates every 17 years. I determined the model to reach a quasi-equilibrium state by confirming the drift to be less than 0.03 PgC yr\textsuperscript{-1} for global C storage and 0.2 TgN yr\textsuperscript{-1} for global N storage. From this quasi equilibrium state, I initialized the global hindcast experiment starting from 1850 using the corresponding climatic forcings, CO\textsubscript{2} and N
deposition data. In the following analysis, I will focus mostly on the last three decades (1970-2005).

**Sensitivity to soil water filled pore space (WFPS)**

While LM3V-N carries a simplified hydrology, I bracketed effects of soil moisture by exploring the parameterization of WFPS and by substituting the predicted soil moisture with 3-hourly re-analysis data. Levels of soil water (in unit kg m\(^{-2}\)) therefore stem from: (1) the simulated water content based on LM3V-N soil water module, hereafter LM3V-SM (2) the Global Land Data Assimilation System Version 2 with the land surface model NOAH 3.3 (Rodell et al., 2004), hereafter NOAH-SM, and (3) the ERA Interim reanalysis dataset from European Center for Medium range Weather Forecasting (ECMWF) (Dee et al., 2011), hereafter ERA-SM. The latter two datasets integrate satellite and ground based observations with land surface models. When overriding soil moisture, I linearly interpolated the 3 hourly data onto the 30 minutes model time step. In these simulations, I allowed soil C and N dynamics to vary according to different soil moisture datasets, but kept the model prediction of soil water to use for plant productivity and evapotranspiration.

Parameterization of the soil moisture effect on nitrification and denitrification are based on WFPS. LM3V-N uses the concept of plant available water, where water that is available to plants varies between the wilting point and field capacity. Water content above the available water capacity (i.e., the difference between field capacity and wilting point) leaves the soil immediately (Milly and Shmakin, 2002), and thus WFPS does not attain high values typically observed during denitrification. To explore the effect of WFPS – soil moisture relationship on N\(_2\)O emissions, I calculated WFPS using three methods. Method 1 assumes WFPS is the ratio of available water and the available
water capacity in the rooting zone. In Method 2 I assume, WFPS is the ratio of the water filled porosity and total porosity which is derived from bulk density (BD, in unit kg m\(^{-3}\)). BD was obtained from the Harmonized World Soil Database (HWSD) version 1.1 (Wei et al., 2014). The calculation is given by

\[
WFPS = \frac{\theta}{\frac{\rho h_r}{BD} \left(1 - \frac{BD}{PD}\right)}
\]

where \(\theta\) (kg m\(^{-2}\)) is the root zone soil water; \(h_r\) (m) is the effective rooting depth of vegetation; \(\rho\) is the density of water (1000 kg m\(^{-3}\)); and \(PD\) is the particle density of soil (2650 kg m\(^{-3}\)). Method 1 generally leads to an overestimation of WFPS because the available water capacity is smaller than total pore space. In contrast, the use of Method 2 with LM3V-SM creates an underestimation since water is not allowed to accumulate beyond field capacity and misses high WFPS to which nitrification and denitrification are sensitive. Meanwhile, for NOAH-SM and ERA-SM data, Methods 2 is more close to the “real” WFPS and is the default method when using these data sets. In a third approach, which is also the default method with LM3V-SM that is applied in the global hindcast experiment, the subsequent elevated CO\(_2\) and temperature responses experiment, and sensitivity tests with regard to N cycling, calculates WFPS as the average of the previous two methods.

For each soil moisture dataset (3 in total, 2 replacements and 1 simulated by LM3V-N), I calculated WFPS using three methods mentioned above. I conducted transient simulations with the nine different WFPSs (3 datasets \(\times\) 3 methods) starting from the near equilibrium state obtained in the global hindcast experiment in 2.2.1. The use of less realistic method for WFPS for each soil moisture driver (LM3V-SM, NOAH-SM and ERA-SM) offers insights of the sensitivity of N\(_2\)O emissions to soil moisture.
The simulation procedure was the same as that in global hindcast experiment except for the WFPS. ERA-SM is only available starting from 1979, prior to which simulations were conducted with model default soil moisture (LM3V-SM). Results from ERA-SM were analyzed starting from 1982, leaving a short period for adjustment.

**Sensitivity to N cycling processes and parameterization**

$N_2O$ emission is constrained by ecosystem availability of mineral N, which is linked to different N cycling processes in addition to nitrification and denitrification processes. To test the sensitivity of modeled $N_2O$ emission to the larger plant-soil N cycle, I conducted the following sensitivity analyses, in form of a one at a time perturbation. I replaced the dynamic BNF scheme with empirically reconstructed preindustrial fixation rates (Cleveland et al., 1999), removing the negative feedback between BNF and plant N availability. I further shut off N loss pathways through DON leaching and fire volatilization (with $ash\_fraction$ =1). I expect that these three modifications alleviate N limitation: Prescribed BNF may continuously add N beyond plant N demand. Further eliminating fire and DOM N losses leave loss pathways that have to pass the available N pool thereby opening the possibility of increasing gaseous losses. Further, removing these plant-unavailable pathways (Thomas et al., 2015) increases N retention and opens the possibility of alleviating N limitation. In addition, I modified key parameters related to general N cycling and $N_2O$ emissions one-at-a-time. I multiplied several parameters that directly affect ammonium and nitrate concentration or $N_2O$ fluxes by 10 (x10) or 0.1 (x0.1), while kept other parameters as defaults. These parameters control the active root N uptake rate ($v_{max}$), nitrification rate ($k_n$), denitrification rate ($k_d$, $Kc,Kn$) and the fraction of net nitrification lost as $N_2O$ ($frac$).
Responses to elevated CO\textsubscript{2} and temperature

Responses of N\textsubscript{2}O emissions to atmospheric CO\textsubscript{2} and global warming have been reported at field scale (Dijkstra et al., 2012; van Groenigen et al., 2011). Here, I evaluate the model’s response to a doubling of preindustrial CO\textsubscript{2} level (284 ppm to 568 ppm) and a 2K increase in atmospheric temperature. Starting from the same quasi-equilibrium state with potential vegetation as in the global hindcast experiment in 2.2.1, I conducted four transient model runs: (1) the CONTROL run with the same drivers as spin-up; (2) the CO\textsubscript{2}FERT run with the same drivers as the CONTROL except a doubling of atmospheric CO\textsubscript{2} level; (3) the TEMP run with the same drivers as the CONTROL except a 2K rise in atmospheric temperature; and (4) the CO\textsubscript{2}FERT×TEMP run with both the doubling of CO\textsubscript{2} and 2K rise in temperature. For each experiment, I ran the model for 100 years and evaluated the corresponding results.

Comparisons with Observations

I compared my model results for annual N\textsubscript{2}O gas loss with field data: I compiled annual N\textsubscript{2}O emissions from peer-reviewed literature (see Appendix A for more information). To increase the representativeness of the measurements, I included only sites with more than 3 months or 100 days experimental span. I limited my datasets where there was no reference to a disturbance of any kind. Only locations with at least 50 years non-disturbance history for forests and 10 years for vegetation other than forests were included. The compiled 61 measurements cover a variety of spatial ranges with vegetation types including tropical rainforest, temperate forest, boreal forest, tundra, savanna, perennial grass, steppe, alpine grass and desert vegetation. Multiple measurements falling into the same model grid cell were averaged. If the authors had indicated the dominant vegetation or soil type, I used the values reported for the
dominant type instead of the averaged. For multiyear measurements, even if the authors gave the individual year’s data, I averaged the data to avoid overweighting of long term studies. If the location was between borders of different model grid cells, I averaged across the neighboring grid cells.

I also compared monthly N2O fluxes at a group of sites: (a) the Tapajós National Forest in Amazonia (3°S, 55°W), taken from Davidson et al. (2008); (b) the Hubbard Brook Experimental Forest in New Hampshire, USA (44°N, 72°W), as described in Groffman et al. (2006); (c) the cedar forest from Oita, Japan (33°N, 131°E), as described in Morishita et al. (2007); (d) the Leymus chinensis (LC) and Stipa grandis (SG) steppe in Inner Mongolia, China (44°N, 117°E), taken from Xu-Ri et al. (2003); (e) the cedar forest in Fukushima, Japan (37°N, 140°E), taken from Morishita et al. (2007); and (f) the primary (P1 and P2) and secondary (L1 and L2) forests located at the Pasir Mayang Research Site (1°S, 102°E), Indonesia, taken from Ishizuka et al. (2002). In addition, daily measurements of soil temperature, soil moisture and N2O emissions were compared at four German forest sites located in the same grid cell (50°N, 8°E), as described in Schmidt et al. (1986).

**Results**

**Global Budget, Seasonal and Inter-Annual Variability**

My modeled global soil N2O flux is $6.69 \pm 0.32$ TgN yr$^{-1}$ (1970-2005 mean and standard deviation among different years) (Figure 2-1) with LM3V-SM (Method 3, default method for LM3V-N calculated soil moisture), $5.61 \pm 0.32$ TgN yr$^{-1}$ with NOAH-SM (Method 2) and $7.47 \pm 0.30$ TgN yr$^{-1}$ with ERA-SM (1982-2005, Method 2) which is within the range of reported values: The central estimation of N2O emission from soils under
natural vegetation is 6.6 TgN yr\(^{-1}\) based on the Intergovernmental Panel on Climate Change (IPCC) AR5 (Ciais et al., 2013) (range, 3.3–9.0 TgN yr\(^{-1}\)) for the mid-1990s. Mean estimation for the period of 1975-2000 ranged from 7.4 to 10.6 TgN yr\(^{-1}\) with different precipitation forcing data (Saikawa et al., 2013). Xu et al. (2012) reported the decadal-average to be 8.3-10.3 TgN yr\(^{-1}\) for the 20th century. Potter and Klooster (1998) reported a global mean emission rate of 9.7 TgN yr\(^{-1}\) over 1983-1988, which is higher than the earlier version of their model (6.1 TgN yr\(^{-1}\)) (Potter et al., 1996). Other estimates includes 6-7 TgN yr\(^{-1}\) (Syakila and Kroeze, 2011), 6.8 TgN yr\(^{-1}\) based on the O-CN model (Zaehle et al., 2011), 3.9-6.5 TgN yr\(^{-1}\) for preindustrial periods from a top-down inversion study (Hirsch et al., 2006), 1.96-4.56 TgN yr\(^{-1}\) in 2000 extrapolated from field measurements by an artificial neural network approach (Zhuang et al., 2012), 6.6-7.0 TgN yr\(^{-1}\) for 1990 (Bouwman et al., 1995), and 7-16 TgN yr\(^{-1}\) (Bowden, 1986) as well as 3-25 TgN yr\(^{-1}\) (Banin, 1986) from two earlier studies.

Following Thompson et al. (2014), El Niño years are set to the years with the annual multivariate ENSO index (MEI) greater than 0.6. 1972, 1977, 1982, 1983, 1987, 1991, 1992, 1993, 1994, 1997 and 1998 were chosen as El Niño years. I detected reduced emissions during most of the El Niño years (Figure 2-1), in line with the global atmospheric inversion study of Thompson et al. (2014) and the process based modeling study from Saikawa et al. (2013).

Figure 2-2 shows the simulated global natural soil N\(_2\)O emissions in 4 seasons averaged over the period of 1970-2005 based on LM3V-SM (Method 3). The northern hemisphere displays a large seasonal variability, with the highest emissions in the northern summer (JJA, June to August) and lowest in winter (DJF, December to
February. Globally, northern spring (MAM, March to May) has the highest emission rate (2.07 TgN) followed by summer (1.89 TgN). The smaller emissions in summer compared to spring stems from a reduced contribution of the southern hemisphere during northern summer.

As expected, a large portion (more than 60%) of the soil N₂O fluxes have tropical origin (23.5 S to 23.5N), while emissions from cooler regions are limited by temperature and arid/semi-arid regions by soil water. My modeling results suggested year-round high emission rates from humid zones of Amazonia, east central Africa, and throughout the islands of Southeast Asia, with small seasonal variations (Figure 2-2). Emissions from tropical savannah are highly variable, with locations of both high fluxes (seasonal mean > 30 mgN m⁻² month⁻¹ or 3.6 kg ha⁻¹ yr⁻¹) and low fluxes (seasonal mean < 1.3 mgN m⁻² month⁻¹ or 0.16 kg ha⁻¹ yr⁻¹). The simulated average tropical emission rate is 0.78 kgN ha⁻¹ yr⁻¹ (1970-2005), within the range of estimates (0.2-1.4 kgN ha⁻¹ yr⁻¹) based on site-level observations from the database of Stehfest and Bouwman (2006), but smaller than a more detailed simulation study (1.2 kgN ha⁻¹ yr⁻¹) carried out by Werner et al. (2007). My analysis here excluded land cover, land use changes and human management impacts, while most of the observation-based or regional modeling studies did not factor out those impacts. My modeling result in natural tropics is comparable with another global modeling study (average emission rate, 0.7 kgN ha⁻¹ yr⁻¹) (Zaehle et al., 2010b), in which the authors claimed they may underestimate the tropical N₂O sources compared to the inversion estimates from the atmospheric transport model TM3 (Hirsch et al., 2006).
**Sensitivity to Water Filled Pore Space**

The different parameterization of WFPS and the use of different soil moisture modeling data allows to test the sensitivity of soil N\textsubscript{2}O emissions to variable WFPS. Globally, emissions generally increase with WFPS (Figure 2-3). WFPS derived from Method 1 is higher than that based on Method 2. Data-derived soil moisture datasets combined with different calculation methods together produced a range of 0.15-0.72 for the global mean WFPS (1982-2005). While mean values greater than 0.6 (approximately field capacity) are less realistic, these high WFPS values provide the opportunity to test the model’s response to the soil moisture-based parameterization of redox conditions in soils. Global soil N\textsubscript{2}O emissions are highly sensitive to WFPS, with approximately 0.25 TgN per year per 0.01 change in global mean WFPS in the range 0 to 0.6. The spatial and temporal characteristic of WFPS also matters. Emission rate from LM3V-SM (Figure 2-3 green cycle) is 1.13 TgN yr\textsuperscript{-1} higher than that from NOAH-SM (Figure 2-3 blue triangle), while both model configuration have the same mean WFPS (ca 0.21), highlighting effects of regional and temporal differences between the soil moisture products.

**Model-Observation Comparisons**

Modeled N\textsubscript{2}O emissions capture the average of cross-site observed annual mean emissions (0.54 vs. 0.53 kgN ha\textsuperscript{-1} yr\textsuperscript{-1} based on LM3V-SM) reasonably (Appendix A and Figure 2-4a), but spread considerably along the 1:1 line. The points deviating the most are from tropical forests, with overestimations from montane tropical forest and underestimations from lowland tropical forests if those measurements are representative of gridcell emissions. These patterns are similar as results from NOAH-SM (Appendix A and Figure 2-4b) and ERA-SM (Appendix A and Figure 2-4c), except
that the application of WFPS from NOAH-SM slightly underestimates the observed global mean (0.54 vs. 0.47 kgN ha\(^{-1}\) yr\(^{-1}\) from NOAH-SM with WFPS based on Method 2).

At the Tapajós National Forest, results from LM3V-SM capture some of the variations in N\(_2\)O fluxes, but the model is not able to reproduce the high emissions observed during spring (Panel (a), Figure 2-5). At the Hubbard Brook Experimental Forest, the correlations between model results and observations are 0.51 (LM3V-SM), 0.56 (NOAH-SM) and 0.62 (ERA-SM) for yellow birch, 0.66 (LM3V-SM), 0.68 (NOAH-SM) and 0.70 (ERA-SM) for sugar maple, However, the model is less robust in reproducing the magnitude of emission peaks. Groffman et al. (2006) suggested high emissions of N\(_2\)O in winter were associated with soil freezing. However, the model assumes little emissions when soil temperature is under 0 °C. In addition, observations suggested N\(_2\)O uptake (negative values in Panel (b), Figure 2-5) while the model does not incorporate mechanisms to represent N\(_2\)O uptake. At the Oita cedar forest, model reproduces the seasonality of N\(_2\)O emissions accurately (Panel (c), Figure 2-5). ERA-SM overestimates the magnitude of N\(_2\)O fluxes from Inner Mongolia grassland, while the magnitudes produced from LM3V-SM and NOAH-SM are comparable with observations. However, the timing of the emission peaks are one or two month in advance from model output compared to observations (Panel (d), Figure 2-5). At the Fukushima cedar forest, similar as at the Oita cedar forest, models are less robust at capturing the magnitude of high peaks despite the seasonality produced by the model are good (Panel (e), Figure 2-5). Emissions from the primary and secondary tropical rainforest at the Pasir Mayang Research Site are highly variable, which makes the
comparison difficult (Panel (f), Figure 2-5). LM3V-SM (but not ERA-SM and NOAH-SM) reproduces the low emissions in September-November 1997 and the increase of emissions from secondary forests in December, 1997. Overall, modeled variability is smaller compared to observation.

The strong variability of measured N\textsubscript{2}O emissions is further illustrated in Figure 2-6. Difference in measured N\textsubscript{2}O fluxes between different forest sites within one grid cell is large, reflecting the heterogeneity that is not captured within one grid cell. In addition, the error bars, which represent the standard deviation of measured N\textsubscript{2}O fluxes at three different plots of the same forest, are large. The standard deviation is as high as 49.27 \( \mu \text{gN m}^{-2}\text{h}^{-1} \), indicating the strong variability of measured N\textsubscript{2}O fluxes at the plot scale. Modeled N\textsubscript{2}O fluxes are generally within the range of measured N\textsubscript{2}O emissions. Model outputs slightly underestimate N\textsubscript{2}O emissions largely due to the underestimation of soil water content (Panel (b) Figure 2-6).

**Sensitivity to Nitrogen Cycling Processes**

Disallowing of N losses through DON and fire volatilization enhance ecosystem N accumulation and availability to plants and microbes, and therefore increases N\textsubscript{2}O emissions (Panel (a), Figure2-7). The gain in N\textsubscript{2}O emissions from disallowing DON loss is small (0.12 TgN yr\(^{-1}\)). However, N\textsubscript{2}O emission is on average (1950-2005) increased by 3.63 TgN yr\(^{-1}\) in the absence of fire volatilization N loss (I note, that fires do occur, but N is retained as ash in the litter). The gain is most evident in tropical regions (not shown), indicating the importance of fire in regulating ecosystem N status. Simulated preindustrial BNF is smaller than the empirical reconstructed BNF (72 in LM3V-N vs. 108 TgN yr\(^{-1}\) from empirical based data). However, BNF in LM3V-N increases with time.
under historical varying climate, increasing atmospheric CO₂ level and N deposition. The global average BNF during 1950-2005 is 100 TgN yr⁻¹, close to the empirical value. Nevertheless, substitution of BNF in LM3V-N by empirical preindustrial value increased N₂O flux by 1.2 TgN yr⁻¹ (Panel (a), Figure 2-7).

Among the specific parameters tested, N₂O emission is most sensitive to the 10 times change (x10) of the fraction of net nitrification lost as N₂O gas. The relative magnitude of N₂O flux on average (1950-2005) reaches 6.5 times of the default (Panel (b), Figure 2-7). Reduction (x0.1) of maximum active plant N uptake strength (vₘₐₓ) strongly increases N₂O emissions (ca. by 3 times of the default). Meanwhile, enhancement of vₘₐₓ also increases N₂O fluxes, reflecting the non-linear response of N₂O emissions to vₘₐₓ. x10 in the maximum nitrification rate kₙ and denitrification rate kₜ increase N₂O emissions, while x0.1 decrease N₂O flux. N₂O increases more with increasing kₜ than with increasing kₙ, whereas reduction of kₙ (x0.1) produces a stronger response than reduction of kₜ. The half-saturation constant that represents the regulation of labile carbon availability on denitrification rate, Kc, is the least sensitive parameter. Meanwhile, reduction (x0.1) of the half-saturation constant Kn that represents the regulation of substrate availability on denitrification rate on average increased N₂O fluxes by 4.5 TgN yr⁻¹ (Panel (b), Figure 2-7).

**CO₂ and Temperature Responses**

Globally, N₂O emissions respond to a step CO₂ increase first with a decline to ultimately increased levels after approximately 40 years (Figure 2-8a, black line). The simulated global response follows largely the behaviour as simulated for tropical forests (Figure 2-8a, yellow line). The shift from a negative to a positive response indicates possible competing mechanisms operating on different time scales. Field level
experiments revealed the highly variable effects of CO₂ fertilization on N₂O emissions. Based on a meta-analysis, van Groenigen et al. (2011) suggested that elevated CO₂ significantly increased N₂O emission by 18.8%, while Dijkstra et al. (2012) argued for a non-significant response in non-N-fertilized studies. In contrast to observation studies, the global C-N cycle model analyses from O-CN suggested negative CO₂ fertilization effects on N₂O emissions (Zaehle et al., 2011). The negative impacts (reduced N₂O flux), which are also reported in manipulative experiments, are likely from increased plant N and immobilization demand under CO₂ fertilization, reducing N availability for nitrifiers and denitrifiers (Dijkstra et al., 2012). CO₂ fertilization on average (over 100 years) increased the global mean plant nitrogen uptake rate by 10.02 kgN ha⁻¹ yr⁻¹, as shown in Figure 2-9 (Panel (b)). Modeled soil inorganic N content (ammonium and nitrate) is reduced at first, but the reduction is not sustained. One mechanism to alleviate CO₂ fertilization caused N limitation is through BNF, which is on average (over 100 years) more than doubled (Figure 2-9 Panel (e)). Similar as manipulative field experiments (Dijkstra et al., 2012), positive effects (increase N₂O fluxes) can result from the impacts of elevated CO₂ level to increase litter production (Figure 2-9 Panel (a)) and consequently C sources for denitrifiers, and to increase soil moisture (Figure 2-9 Panel (d)) from reduced stomatal conductance and leaf transpiration (Figure 2-9 Panel (c)). With both positive and negative mechanisms embedded in my model, the net effects depend on the relative strength of the opposing forces.

Temperate deciduous forests, where most of the forest CO₂ fertilization experiments are conducted, respond positively to elevated CO₂ level (Figure 2-8a, green line). The slight increase in modeled N₂O emission are comparable with the mean
response of field data compiled for temperate forests (ca. 0.01-0.03 kgN yr\(^{-1}\) ha\(^{-1}\)) (Dijkstra et al., 2012). A similar positive response was detected for cold evergreen forests (Figure 2-8a, pink line) with stronger magnitude compared to temperate deciduous forests. For grasslands, Dijkstra et al. (2012) reported small negative mean response from northern mixed prairie (\(\Delta N_2O\), ca. -0.01 to -0.03 kgN yr\(^{-1}\) ha\(^{-1}\)), zero mean response from shortgrass steppe and positive mean response from annual grassland (ca. 0.03-0.06 kgN yr\(^{-1}\) ha\(^{-1}\)). My model shows a small negative mean response from C4 grassland (Figure 2-8a, cyan line) with the similar magnitude of that reported for the Northern mixed prairie, where the composition of C4 grass varies (Dijkstra et al., 2012). A CO\(_2\) increase in C3 grassland initially reduces N\(_2\)O emission (Figure 2-8a, blue line). However, this slight negative response turns into a small positive within one decade.

Elevated temperature generally increases N\(_2\)O emissions except for the slight negative effect in C4 grass (Figure 2-8b). Overall the response to a 2 degree warming is bigger than that of doubling of CO\(_2\). The simulated temperature effects are more pronounced in the first decade and decrease over time in tropical forests (Figure 2-8b, yellow line), while for the temperate deciduous forests (Figure 2-8b, green line) and boreal forests (Figure 2-8b pink line), the temperature effects become more pronounced over time. Simulated temperate forest response (in the first decade) is close to that of observed mean (ca. 0.2-0.5 kgN yr\(^{-1}\) ha\(^{-1}\)) (Dijkstra et al., 2012). My modeled slight negative response in C4 grass and positive in C3 grass are in alignment with data compiled by Dijkstra et al. (2012) who reported both positive and negative responses in grasslands.
The results of combining CO₂ and temperature are similar to the CO₂ effect alone (Figure 2-8c), despite the fact, that the individual effect of temperature is much stronger than that of CO₂. This antagonistic interaction (i.e. the combined enhancement in N₂O flux from elevated CO₂ and temperature are smaller than the summary of their individual effects) is also evident for C3 grass (first 50 years), temperate deciduous tree and cold evergreen forests (Figure 2-8d).

Discussion

My model combines two of the most widely applied biogeochemical models (DNDC and CENTURY) with current advancements in field level studies. The model is capable of reproducing the global mean natural N₂O emissions from other modeling and inverse methods, and the average of observed cross-site annual mean behavior. By focusing on the role of soil moisture in N₂O emissions, I find a global scale high dependence of simulated N₂O emissions on soil moisture (WFPS), mainly driven by emissions from tropical regions. The model broadly reproduces the magnitude and direction of responses to elevated CO₂ and temperature from manipulative field experiments where data is avilable. The global responses to elevated CO₂ and temperature follow largely the response of tropical forests, where a noted absence of field experiments exist.

Evaluation of global simulations against field measurements is susceptible to scale mismatches. The complexity of microscale interactions for N₂O production creates notorious large spatial and temporal variabilities which are undoubtedly difficult to constraint even at the stand level (Butterbach-Bahl et al., 2013). Daily measurements from the German forest sites (Figure2-6) illustrate the large variability in N₂O emissions. Further improvement in soil moisture simulation will improve my estimation of N₂O
fluxes at the German forest sites. However, the homogeneous representation of environmental drivers within model grid cells casts doubt on site-specific model-observation comparison in global simulations. For example, N$_2$O emissions vary with topography which are not treated explicitly in most of the global C-N models. 3.8 times difference was detected in a montane forest (Central Sulawesi, Indonesia) moving from 1190 m to 1800m (Purbopuspito et al., 2006), and 4.3 times difference was found from a tropical moist forest (Brazilian Atlantic Forest) with the altitude change from 100m to 1000m (Sousa Neto et al., 2011). However, comparison against field data revealed, that the model’s variability is smaller compared to observation for both across field sites (Figure 2-4), and at different sites (Figures 2-5 and 2-6). One of the reason for this shortcoming may be that fast transitions, such as freeze-thaw cycle (Groffman et al., 2006) and pulsing (Yienger and Levy, 1995) are not sufficiently captured.

Soil moisture is a key variable in climate system but difficult to derive or measure at the global scale (Seneviratne et al., 2010). My modeled fluxes are highly sensitive to WFPS, which is in agreement with observation and model synthesis studies (Heinen, 2006; Butterbach-Bahl et al., 2013). The large range when calculating WFPS from different methods resulted in a difference of more than 5 TgN yr$^{-1}$ in global soil N$_2$O fluxes. Saikawa et al. (2013) found an up to 3.5 TgN yr$^{-1}$ gap induced by different precipitation forcing data from CLMCN-N2O. It is difficult to single out the difference caused by soil moisture alone from their results. Nevertherless, those two studies did suggest the importance of improving the dynamics of soil water and representation of WFPS for the purpose of predicting soil N$_2$O emission and climate feedbacks.
The root zone soil water in LM3V-N is based on a single layer bucket model. This simplified treatment of soil water dynamics may increase the difficulty in reproducing the temporal and spatial dynamics of WFPS. As a first step, I used the average between the original analog in LM3V-N and that is derived from soil total porosity to account for actual soil moisture and the possibility of soil water above field capacity. Meanwhile, overriding soil moisture with data-derived products (NOAH-SM and ERA-SM), suggests that the most realistic average (1970-2005) soil N\textsubscript{2}O emission is in the range of 5.61-7.47 TgN yr\textsuperscript{-1}. A more realistic root zone water module, such as multilayer representations of biogeochemistry and soil water dynamics, would refine models of soil N\textsubscript{2}O emissions. El Niño events trigger reduced soil emissions in my results similar as proposed by Saikawa et al. (2013) and Thompson et al. (2014). El Niño events are known to have induced several of the most well known large scale droughts and alters soil moisture dynamics (Schwalm et al., 2011). Tropical forests N\textsubscript{2}O emissions are highly correlated with root zone soil water content and contribute strongly to the global-scale fluxes of N\textsubscript{2}O in my model. Whether there is a strong link between soil N\textsubscript{2}O emission anomalies and El Niño induced soil moisture deviations needs further investigation with improved soil hydrology.

Globally, N\textsubscript{2}O emissions from nitrification-denitrification are similar to O-CN and LPJ-DyN as they are all derived from DNDC. Embedding an established N\textsubscript{2}O emission module into LM3V-N enables evaluation of the response of N\textsubscript{2}O emissions under different assumptions across models with respect to the dynamics of the larger plant-soil N cycle. Generally higher inputs from BNF or constraints on losses through organic N (fire, DON) enhance N\textsubscript{2}O emissions. The representation of of BNF in models requires
improvement but I show here that different implementations are globally important for N\textsubscript{2}O emissions. Similarly, the magnitude of N lost through fire impacts N\textsubscript{2}O emissions in fire prone regions, while N emission factors are poorly constrained globally (Andreae and Merlet, 2001). The strength of plant uptake of N poses a strong constraint on the availability of N for nitrification-denitrification losses as it can draw down N substantially (Gerber and Brookshire, 2014). A reduction of plant uptake strength allows for relatively more N allocated for denitrification. More surprising was the positive effect of a stronger plant uptake capacity on N\textsubscript{2}O emissions: Enhanced plant uptake allow increased vegetation production, and an throughput through litterfall and mineralization in the long run, which ultimately may allow higher N\textsubscript{2}O losses in lieu of other export pathways. In addition to those N cycling processes N\textsubscript{2}O emission is highly sensitive to the fraction of N lost as N\textsubscript{2}O from net nitrification. The fraction of N\textsubscript{2}O lost from net nitrification is uncertain. Goodroad and Keeney (1984b) suggested a value of 0.1-0.2%, while Khalil et al. (2004b) reported a range of 0.16%-1.48% depending on the O\textsubscript{2} concentration. I applied a global constant of 0.4% in my default simulation, bearing in mind the large uncertainties associated with this parameter.

Globally, the tropical fluxes contribute with more than 60% to the global soil N\textsubscript{2}O fluxes. Also, global responses to elevated CO\textsubscript{2} and temperature are dominated by the tropical response. In contrast to temperate and boreal forests, tropical forests respond negatively to elevated CO\textsubscript{2} in the first few decades. My results therefore suggest caution when extrapolating from current manipulative field studies to the globe: The postive response to CO\textsubscript{2} enrichment as obtained from (mostly) extratropical field study may be overestimated, when the studies’ fluxes are scaled up to the globe. Moreover, I
found strong interaction of elevated CO$_2$ and temperature, acting to reduce soil N$_2$O emission compared to the sum of individual responses, highlighting the non-linear impacts of CO$_2$ and temperature on N$_2$O emissions. My results from step increases of CO$_2$ and temperature is different from Xu-Ri et al. (2012) in which CO$_2$ and climate change act synergistically to increase historical N$_2$O emissions, especially in tropical regions. CO$_2$ fertilization plus interaction with temperature rise reduce tropical N$_2$O fluxes in the first several decades from my model. I realize that this interaction is likely to be different when incorporating other factors (Brown et al., 2012), such as N deposition, precipitation and land use change (disturbance). In addition, step changes in atmospheric CO$_2$ and temperature compared to gradual and sustained increases may also lead to differences, and may explain the discrepancy between the previous modeling study and meta-analysis of manipulative field experiments with regard to CO$_2$ fertilization responses (Xu et al., 2012; Zaehle et al., 2011). However, step changes mimic most closely manipulative experiments. Nevertheless, the largest uncertainties lie in the tropical region where my model indicated strongest responses and strongest nonlinear interactions of elevated CO$_2$ and temperature.

The response to increases in temperature and CO$_2$ is a consequence of both the direct effect of temperature on nitrification and denitrification, and indirect effects via water and mineral N availability. The initial negative response of N$_2$O emissions to CO$_2$ fertilization from tropical forests produced by LM3V-N stems largely from the increased demand and uptake of mineral N due to enhanced vegetation growth under elevated atmospheric CO$_2$ level. Despite soil N availability has been reported to decrease, unchanged or increase from manipulative CO$_2$ enrichment experiments across
extrotropical ecosystems (Reich et al., 2006; Drake et al., 2011; Reich and Hobbie, 2013), no empirical evidence is available in tropical forests. LM3V-N produced, on average, a reduced soil mineral N concentration in tropical forests initially. Consequently, less N is available for gaseous losses. If gross mineralization is used as an indicator of the rate of N flow in the “hole-in-the-pipe” concept and gaseous losses are proportional to mineralization, the initial negative response is unlikely to be detected. I found increased mineralization rate with increased litterfall under elevated CO₂, while N availability is reduced from LM3V-N. The mineralization based approach is likely to predict an increase of losses regardless of N limitation. In LM3V-N, N availability recovers as N cycling processes adjust to CO₂ fertilization, especially from BNF, but also via higher transient retention of N from deposition.

In addition to the uncertainties mentioned above, I simplified N₂O sources and processes, ignoring other microbial metabolic pathways and abiotic processes that produce or consume N₂O. The global magnitude of those ignored process remains largely unexplored. I do not incorporate explicit mechanisms for N₂O emissions from freeze-thaw cycle or poorly drained soils (e.g. wetlands), the uptake of organic N etc., which might be globally important, especially with future climate changes. Considering those uncertainties and gaps, more studies are in needed in order to understand the terrestrial N₂O emissions.

Conclusions

I present estimates of terrestrial soil N₂O fluxes under natural vegetation (1970 to 2005) based on existing N₂O emission formulations embedded into the global C-N cycle model LM3V-N. To determine the sensitivity of the modeling result to soil water (WFPS), I replaced the root zone soil water with two other derived datasets and altered the way
in which WFPS is calculated. My best estimate of modeled global natural soil N₂O flux is 5.61-7.47 TgN yr⁻¹ (1970-2005), within the range of current understanding of soil N₂O emissions, but highly sensitive to WFPS, general N cycling and parameterization of N₂O losses through nitrification and denitrification. Improvement of soil hydrology is likely to significantly reduce the large uncertainties associated with soil N₂O emission estimates. Although the simulated mean responses are in agreement with manipulative field studies where effects of elevated CO₂ and temperature were investigated, I found that the global response to elevated CO₂ was dominated by tropical forest (reduce N₂O fluxes in the first few decades), where my model suggest a different response than the field studies carried out in temperate ecosystems (increase N₂O fluxes), highlighting the need to expand field studies in tropical ecosystems. Warming generally enhanced N₂O efflux, and the enhancement was greatly dampened when combined with elevated CO₂, although CO₂ alone had a small effect. My analysis suggests caution when extrapolation from current field CO₂ enrichment and warming studies to the global scale.
Table 2-1. Texture dependent parameter $k$ estimated from Del Grosso et al. (2000).

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<tr>
<th>Soil Texture</th>
<th>Coarse</th>
<th>Medium</th>
<th>Fine</th>
<th>Coarse/medium</th>
<th>Coarse/fine</th>
<th>Medium/fine</th>
<th>Coarse/medium/fine</th>
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</table>
Figure 2-1. Simulated annual global soil $\text{N}_2\text{O}$ emissions based on potential vegetation (1970-2005). Shaded grey area indicates El Niño years with the annual multivariate ENSO index (MEI) greater than 0.6. Colours refer to different soil moisture dataset used in the estimation: red for LM3V-SM (with WFPS calculated by Method 3); blue for NOAH-SM (Method 2) and green for ERA-SM (Method 2). Details for these soil moisture dataset and WFPS calculating methods is available in the main text.
Figure 2-2. Global seasonal mean soil N$_2$O emissions (LM3V-SM, Method 3) averaged over the years 1970-2005. DJF (December, January and February), stands for Northern Hemisphere Winter; MAM (March, April and May) for Spring; JJA (June, July and August) for Summer; and SON (September, October and November) for Autumn.
Figure 2-3. Sensitivity of simulated global soil N2O emissions (with potential vegetation) to water filled pore space (WFPS). The x-axis is the WFPS averaged globally over 1982-2005; the y-axis represents the corresponding global total N2O fluxes. A total of nine sets of WFPS are obtained through either different soil water datasets (symbols) or varied calculation methods (colours). Maximum water, porosity and average correspond to method 1, method 2 and method 3 in the main text, respectively. Coloured symbols represent interannual means and error bars indicate interannual standard deviations.
Figure 2-4. Observed vs. simulated annual N$_2$O emissions from natural soils. Dashed green lines are the 1:1 lines. The solid circles represent the overall means. Different panels represent simulations with different soil moisture data: (a) LM3V-SM (simulated by LM3V-N); (b) NOAH-SM (based on land surface model NOAH 3.3 in Global Land Data Assimilation System Version 2); and (c) ERA-SM (reanalysis data from ECMWF). Water filled pore space (WFPS) is calculated using the average of the one based on available water capacity and the one based on the total porosity (Method 3, see the main text for detailed description) for panel (a); and using the total porosity (Method 2) for panel (b) and (c).
Figure 2-5. Observed vs. simulated monthly N\textsubscript{2}O emissions at (a), the Tapajós National Forest in east-central Amazonia (3°S, 55°W), taken from Davidson et al. (2008); (b), the Hubbard Brook Experimental Forest in New Hampshire, USA (44°N, 72°W), taken from Groffman et al. (2006); (c), a cedar forest at Oita, Japan (33°N, 131°E), taken from Morishita et al. (2007); (d), the *Leymus chinensis* (LC) and *Stipa grandis* (SG) steppe in Inner Mongolia, China (44°N, 117°E), taken from Xu-Ri et al. (2003); (e), a cedar forest in Fukushima, Japan (37°N, 140°E), taken from Morishita et al. (2007); and (f), the primary (P1 and P2) and secondary (L1 and L2) forests located at the Pasir Mayang Research Site, Indonesia, taken from Ishizuka et al. (2002) (1°S, 102°E). Shown are modeled results from three WFPS schemes (LM3V-SM, NOAH-SM and ERA-SM) the same as in Figure 2-4.
Figure 2-6. Comparison between observations and model outputs at four forest sites from German (50°N, 8°E). Panel (a) indicates soil temperature (2cm from observation and 1 cm from model) in °C; (b) soil moisture (2cm from observation and root zone from model) in % and (c) soil N₂O emissions in μgN m⁻² h⁻¹. Observations are taken from Schmidt et al. (1986). Shown are modeled results from two WFPS schemes (LM3V-SM and NOAH-SM) similar as in Figure 2-4.
Figure 2-7. Changes in simulated global average N\textsubscript{2}O (1950-2005) emissions from modifying general N cycling processes (a) and model parameters one-at-a-time (b). Altered processes include disallowing N losses through dissolved organic matter (DON in (a)) and fire volatilization (Ash in (a)), and replacing simulated biological N fixation with preindustrial N fixation rate (BNF in (a)). Parameters include: $v_{\text{max}}$, the maximum active N uptake rate per unit root biomass; $k_n$, the base nitrification rate; $k_d$, the base denitrification rate; $K_c$ and $K_n$, the half saturation constants for labile C availability and nitrate respectively; and $\text{frac}$ is the fraction of net nitrification lost as N\textsubscript{2}O. Parameters are either increased by multiplying 10 (lightblue) or reduced by multiplying 0.1 (lightgreen) relative to the defaults.
Figure 2-8. Soil N₂O emissions in response to step increases in atmospheric CO₂ and temperature. Panel (a) is the response to CO₂ fertilization alone, expressed as the difference between CO₂ increased run and the control run (CO₂_FERT - CONTROL), the inset zooms into the y axis (flux difference) around zero; Panel (b) is the response to temperature increase alone (TEMP-CONTROL); Panel (c) is the combined response to both CO₂ enrichment and temperature rise (CO₂_FERT×TEMP-CONTROL); and Panel (d) is the interactive effect of CO₂ and temperature responses, which is the difference between the combined (results from Panel (c)) and minus the individual responses (results from Panel (a) and (b)). Results are shown as annual values (thin dashed lines) and as running average with a moving window of 17 years (period of recycled climate forcing, thick solid lines). The black lines represent the global average response. Coloured lines indicate responses for biome as represented by each plant functional type (PFT) considered in LM3V-N: C4 grass (cyan), C3 grass (blue), tropical forest (yellow), temperate deciduous forest (green) and cold evergreen forest (pink). Dashed red line represents the zero line.
Figure 2-9. CO₂ fertilization effects (no temperature change) on litter pool size (Panel (a)), plant nitrogen uptake rate (Panel (b)), canopy transpiration rate (Panel (c)), soil water content in the root zone (Panel (d)) and biological nitrogen fixation (BNF) rate (Panel (e)). Shown are the 100-year average of global means (spatial) from control (284 ppm, red) and with elevated CO₂ (568 ppm, blue).
CHAPTER 3
THE IMPACT OF LAND-COVER TRANSITION ON SOIL NITROUS OXIDE EMISSIONS

Introduction

Nitrous oxide (N\textsubscript{2}O), commonly known as the laughing gas, is a biogenic greenhouse gas that is also suggested to be the single most important ozone-depleting substance (Ravishankara et al., 2009). Atmospheric N\textsubscript{2}O concentration has increased 20% since the industrial revolution (Ciais et al., 2013). Most of this increase is attributable to anthropogenic addition of reactive nitrogen (Nr), including atmospheric Nr deposition and agricultural fertilization. Although terrestrial ecosystems are major sources of N\textsubscript{2}O emissions, terrestrial N\textsubscript{2}O budgets are known to be highly variable both temporally and spatially, and current estimations are afflicted with large uncertainties (Ciais et al., 2013).

Most of the soil N\textsubscript{2}O is produced through microbial facilitated nitrification and denitrification (Braker and Conrad, 2011; Syakila and Kroeze, 2011). Ammonia-oxidizers can generate N\textsubscript{2}O during oxidation of ammonia to nitrite. N\textsubscript{2}O is also produced as byproducts through denitrifying microbes during the reduction of nitrite or nitrate ultimately to N\textsubscript{2}, known as denitrification. Nitrifying and denitrifying microbial communities vary strongly in their responses to environmental conditions (Hayatsu et al., 2008; Syakila and Kroeze, 2011), indicating the strong variability of N\textsubscript{2}O production in response to environmental factors. N\textsubscript{2}O emissions are frequently attributed to nitrification in well-aerated soils while denitrification is the more important contributor in saturated soils (Firestone and Davidson, 1989b; Parton et al., 1996; Li et al., 1992). In addition, soil temperature, inorganic N and labile carbon availability are all well-known
regulators of nitrification and denitrification (Firestone and Davidson, 1989b; Parton et al., 1996; Li et al., 1992).

Global environmental changes, such as climate change, atmospheric Nr deposition, CO₂ fertilization, play an important role in shaping historical N₂O emissions, although their individual contribution or even the sign remains largely uncertain at the global scale (Ciais et al., 2013). Previous modeling studies revealed a small increase of non-agricultural N₂O sources over the 20th century, mostly due to the rise of land temperature (Xu-Ri et al., 2012; Zaehle et al., 2011). Stocker et al. (2013) also suggested the amplification of land N₂O emissions by the future climate change (mostly warming) with the consideration of anthropogenic Nr addition. Although land models suggested an overall enhancement of N₂O emissions by warming, both positive and negative effects of warming were reported regardless of N fertilization treatments from field manipulative experiments (Dijkstra et al., 2012). As with temperature, CO₂ fertilization is reported to increase as well as reduce N₂O emissions from manipulative field experiments. A meta-analysis carried out by van Groenigen et al. (2011) suggested an overall positive impact of CO₂ fertilization on N₂O emissions, while a similar meta-analysis by Dijkstra et al. (2012) revealed non-significant effects of CO₂ fertilization in non-fertilized studies. Results from process based models showed the negative response of N₂O emissions to historical CO₂ increase (Xu-Ri et al., 2012; Zaehle et al., 2011), although the combined effect of CO₂ and climate change increases N₂O emissions (Xu-Ri et al., 2012). In addition to warming and CO₂ fertilization, soil N₂O fluxes are known
to be sensitive to moisture dynamics. However, the responses of N\textsubscript{2}O emission to changes in precipitation, especially seasonal and frequency distribution, are less well studied (Ciais et al., 2013).

Understanding how multiple global environmental changes affect N\textsubscript{2}O emissions is important since these changes are happening simultaneously. The review of field studies from Brown et al. (2012) pointed to a general dampening of interactive effects involving heat, elevated CO\textsubscript{2}, enhanced Nr input and elevated precipitation, although amplification of N\textsubscript{2}O emission was suggested when environmental changes were combined with disturbance such as fire. Considering the complexity of multiple level interactions, upscaling current limited number of field level results to the global scale may be inadequate. Nevertheless, field level studies point to the potential importance of interactions in regulating large scale N\textsubscript{2}O emissions.

As one of the most important disturbance throughout the globe, land cover change is linked, directly or indirectly, to N\textsubscript{2}O emissions through biophysical and biogeochemical mechanisms. With about 38% of the total ice free land area being used for cropland and pasture (Foley et al., 2011; Ciais et al., 2013), land cover change alters surface albedo, roughness, energy and water balance, biogeochemical cycles, and therefore plays an important role in climate changes (Ciais et al., 2013). Land cover transitions reset the states and conditions that control land C and N cycles, with transient behavior that is sensitive to interactions with local conditions (Gerber et al., 2013; McVicar and Kellman, 2014). Pulse emissions of N\textsubscript{2}O are frequently observed following clear-cutting or
harvest of forests (Steudler et al., 1991; Page et al., 2011; McVicar and Kellman, 2014) with increased N availability for nitrification and denitrification partly due to changes in rates of mineralization or/and plant uptake. Cleared forests generally have higher soil temperatures compared to non-disturbed forests due to alternations of surface radiative balance (Chen et al., 1993). Reduced evapotranspiration through vegetation due to the removal of aboveground biomass alters soil moisture conditions and therefore N$_2$O emissions (Zerva and Mencuccini, 2005). The impacts of land cover transitions are multifaceted and rely strongly on the time-span following disturbance. Nevertheless, pulses of N$_2$O fluxes are expected to be relatively short lived as plant and soil recover from disturbance (McVicar and Kellman, 2014). The initial increases might decline to background values (McVicar and Kellman, 2014; Keller and Reiners, 1994), but could also sustain different levels over longer timescales, depending on various factors such as the land cover characteristics and the nonlinear interactions with local conditions. For example, conversions of tropical forests to pastures are reported to decrease N$_2$O fluxes (Verchot et al., 1999; Neill et al., 2005; Melillo et al., 2001), although higher emission rates are possible with large amount of N fertilizers or N-fixing crops (Neill et al., 2005).

At the global scale, Zaehle et al. (2011) reported a slight negative land cover impact on N$_2$O emissions, with an on average overall reduction of 0.07 TgN yr$^{-1}$ over 1981-1990 from the O-CN model. It remains unknown separately to what extent conversions of forests to croplands or pastures and changes in harvest or regrowth cycles in secondary vegetation alter large scale soil N$_2$O
emissions. Old pastures and secondary forests are reported to have lower emission rates compared to primary vegetation in the tropics (Neill et al., 2005; Verchot et al., 1999; Keller et al., 1993; Keller and Reiners, 1994), while young pastures are suggested to generate more N$_2$O gas shortly after transition (e.g. <10 years) (Luizao et al., 1989; Keller et al., 1993). Net N$_2$O fluxes due to deforestation depend on the magnitude of the emission pulses shortly after conversion, and the resulting long-term changes in the physical environment (soil temperature and soil water) and the biogeochemical cycles. However, it is unclear as for the relative role played by shorter term pulse and longer term response in shaping historical N$_2$O emissions. In addition, how interactions of land cover transition with other global change factors, such as enhanced atmospheric CO$_2$ concentration, Nr deposition and climate change, alter N$_2$O emissions at the global scale need to be further studied (Zaehle et al., 2011).

To fill the gaps, I make use of a global land model (LM3V-N) with subgrid land cover transitions among primary vegetation, secondary vegetation, cropland and pasture, and explicitly resolved C-N interactions along the successional path following land cover transitions (Shevliakova et al., 2009; Gerber et al., 2010; Gerber et al., 2013; Huang and Gerber, 2015) to explore the individual as well as interaction contributions of land cover transition, climate, CO$_2$ fertilization and Nr deposition to terrestrial N$_2$O budget. I further evaluate N$_2$O emission in different land cover classes, thereby, tracking secondary vegetation as a different land cover category. Land management practice, such as N fertilization and
irrigation, which can significantly change N\textsubscript{2}O emissions, is, however, not explicitly considered in this study.

**Methods**

**Model Description**

Description of the model is available from Chapter 1, 2, Appendix A and B.

**Simulations**

I carried out two series of simulations starting from the steady state. To bring the model to the steady state, I spun up the model from bare ground without C-N interactions for 68 years and then with C-N interactions for the later 1600 years to develop the potential vegetation. The model is assumed to reach the steady state with the global C storage drift smaller than 0.03 PgC yr\textsuperscript{-1} and global N storage drift less than 0.2 TgN yr\textsuperscript{-1} respectively. I used 3 hourly reanalysis weather data to drive the model (Sheffield et al., 2006). I recycled 17 years of weather data (1948-1964) for spin-up. During the spin-up, atmospheric CO\textsubscript{2} concentration was set at 284ppm, and Nr deposition was set as natural background (Dentener and Crutzen, 1994a).

I started transient simulations in year 1700 and ran the model with different combinations of corresponding forcing. Historical atmospheric CO\textsubscript{2} concentration was based on ice core and atmospheric measurements (Keeling et al., 2009). For simulations prior to 1850, natural background Nr deposition was applied (Dentener and Crutzen, 1994a). For simulations after 1850, I interpolated between the natural background and one year's contemporary data (1995) (Dentener et al., 2006) to approximate Nr deposition. Historical land cover transitions, including shifting cultivation and forestry, were implemented annually.
(Hurtt et al., 2006). To explore the individual impact of land cover, CO₂, climate and Nr deposition on historical N₂O emissions, I turned on the time-variant model forcing one at a time, as described in Table 3-1, and compared to a reference simulation that is the continuation of the spinup. For example, the individual effect of land cover can be inferred from the difference between the run with land cover change turned on (+Lc) and the reference run (Ref), i.e., \( F(+Lc) - F(\text{Ref}) \). I define the difference from including one forcing for each run as the single factor effect. In a second series (Table 3-2), I ran the model with all of these 4 forcing turned on (the Full run), and then excluding one corresponding forcing for each run. In this way, the impact of land cover change and its interaction with 3 other global change factors can be inferred from the difference between the Full run and the run that excludes land cover change (-Lc), i.e., \( F(\text{Full}) - F(-Lc) \). I call the difference from excluding one forcing for each run the overall effect. Finally I define the interaction effect as the difference between the overall and the single effect. Similarly, the single, overall and interaction effects of CO₂, climate and Nr deposition can be inferred from these two series of model simulations.

To compare the typical responses of N₂O emissions to land cover transitions between tropical and temperate ecosystems, I picked up a typical tropical forest (0, 65W) and a temperate forest (46N, 76W). I brought the tropical forest run and the temperate forest run into steady states following the same spin-up scheme as implemented in the previous global runs. From the steady states, I mimic a clear-cutting of the forest by removing 95% of the above ground biomass. I then tracked the evolution of N₂O fluxes following the clear-cutting.
Results

Global Effects

Figure 3-1 shows the simulated global soil N$_2$O emissions from including one forcing each time and the reference (Panel a) and excluding one forcing each time and the Full run (Panel b). Total soil N$_2$O fluxes are in the range of 5.5-8.5 TgN yr$^{-1}$. Figure 3-2 shows the cumulative single (Panel a), overall (Panel b) and the interaction (Panel c) effects of historical land cover transition, climate change, CO$_2$ fertilization and Nr deposition over 1850-2000. Since the weather of 1948-1964 is recycled for model spin-up and simulations prior to 1948, the climatic impact is effective only after the year 1964. Climatic impact is the strongest with regard to the annual mean and interannual variability over the period of 1970-2000 (0.94±0.60TgN yr$^{-1}$, mean±standard deviation of annual impact) for the single factor effect. The strong climatic impact is dampened (reduced to 0.32±0.31TgN yr$^{-1}$) by the interaction with land cover, CO$_2$ and Nr deposition. CO$_2$ alone has a minor impact on global soil N$_2$O fluxes since the industrialization (-0.09±0.1TgN yr$^{-1}$, or -14.21 TgN accumulated over1850-2000) (Figure 3-2a, red). However, the slight negative effect of CO$_2$ is magnified by the interaction with other global change factors. And the overall effect of CO$_2$ reaches -67.97 TgN accumulated over 1850-2000 (Figure 3-2b, red). Nr deposition increases N$_2$O fluxes, with the average single factor effect of 0.16±0.12 TgN yr$^{-1}$ and the overall effect of 0.21±0.12 TgN yr$^{-1}$ (1850-2000). The interaction of Nr deposition with other factors is small throughout the period of 1850-2000, with a cumulative increase of N$_2$O flux by 7.85 TgN (Figure 3-2c,
orange). Land cover transition alone enhances soil N$_2$O emissions in the late 19$^{\text{th}}$ century and most of the 20$^{\text{th}}$ century. The rate of enhancement increases with time prior to ca. 1923, with a slope of 0.01 TgN yr$^{-1}$, and decreases thereafter. However, during the last decade of the 20$^{\text{th}}$ century, land cover alone brings about a negative effect on land N$_2$O fluxes (Figure 3-2a, green). A similar pattern is obtained for the overall impact of land cover transition, with an earlier and stronger negative effect (Figure 3-2b). The peak of land cover effect is 1.10 and 0.94 TgN yr$^{-1}$ for single factor and overall respectively. Accumulatively, the single effect of land cover transition increases N$_2$O fluxes by 60.13 TgN and the overall effect is lower, 31.66 TgN (1850-2000) (Figure 3-2a,b, green).

**Regional Contributions**

Figure 3-3 displays the single and overall effects of each global change factors (land cover, CO$_2$, climate and Nr deposition) for each continent (Europe, Asia, Australia, South America and North America) and the globe over the period of 1970-2000 (means and interannual standard deviations). Climatic effects (both single and overall) show a similar pattern for each continent as that of the globe, with strong interannual variability and reduced fluxes due to interaction (Figure 3-3 blue). Interaction for Nr deposition is stronger in Europe compared to other continents (Figure 3-3 orange). And the interaction increases, from 0.06±0.02 (single effect) to 0.11±0.02 (overall effect) TgN yr$^{-1}$, N$_2$O emissions caused by Nr deposition in Europe. CO$_2$ alone has a small negative effect in North America (-0.02±0.03 TgN yr$^{-1}$), South America (-0.04±0.08 TgN yr$^{-1}$), Africa (-0.11±0.07 TgN yr$^{-1}$) and Australia (-0.01±0.02 TgN yr$^{-1}$), and a slight positive effect in
Europe (0.004±0.01 TgN yr⁻¹) and Asia (0.01±0.05 TgN yr⁻¹). The overall effect of 
CO₂ (single + interaction) acts to decrease historical N₂O emissions for all 
continents, with the strongest negative overall effect from Asia (-0.39±0.22 TgN 
yr⁻¹). Land cover transitions result in a diverse pattern of N₂O emissions in 
different continents. North America and Europe display a similar pattern, with a 
stronger positive response from the single factor effect and reduced positive 
response when interaction is included. Land cover conversions from South 
America, Africa and Australia act to reduce soil N₂O fluxes based on both the 
single effect and the overall effect. The magnitude of reductions is bigger in the 
overall effect compared to that of single effect. In Asia, land cover change alone 
increases N₂O fluxes while the overall impact is negative. Among the 4 global 
change factors, land cover has the strongest single and overall effects in Europe, 
Africa and South America, although the directions differ: positive in Europe and 
negative in Africa and South America.

**Decomposition of Impacts Involving Land Cover Transitions**

I decomposed the land cover impacts into transitions associated with 
secondary vegetation, cropland and pasture (see Appendix D for detailed 
algorithm). The single effect from land cover transition ended as secondary 
vegetation (or cropland, pasture) corresponds to the difference in N₂O emission 
rate (without environmental impacts) in secondary vegetation (or cropland, 
pasture) compared to the potential primary vegetation. And the overall effect from 
land cover transition ended as secondary vegetation (or cropland, pasture) is the 
difference in the N₂O emission rate that accounts for environmental drivers in
secondary vegetation compared to the primary vegetation. Conversions to
cropland contribute to most of the N$_2$O emissions caused by land cover
transitions (Figure 3-4), although cropland area is no larger than other categories
(Figure 3-5). Conversions to secondary vegetation slightly increase N$_2$O fluxes
with the cumulative single effect of 8.65 TgN and overall effect of 2.60 TgN
(1850-2000), while conversions to pasture reduce historical N$_2$O fluxes by 16.65
TgN or by 22.52 TgN if interaction is counted.

The interactive effect of land cover transition is linked to the differential
response to environmental drivers between the post- and pre-converted land
cover categories. A negative interaction effect (-6.05 TgN) from secondary
vegetation (Figure 3-4c) indicates a reduction in the response (or N$_2$O emissions)
to environmental drivers in secondary vegetation compared to the corresponding
primary vegetation. Similar as the secondary vegetation, responses to
environmental drivers are reduced for both cropland (-16.39 TgN) and pasture (-
5.88 TgN).

In addition to separate the interactive effect of land use transitions, I also
decomposed the interactive effects of each environmental factors (see Appendix
D for detailed algorithm). For example, the interactive effect of CO$_2$ can be
decomposed into 4 components associated with the 4 land cover classes: the
interactive effect of CO$_2$ on primary vegetation ($V_{co2,p}$), the interactive effect of
CO$_2$ on secondary vegetation plus the gain in response to CO$_2$ (single effect)
from conversion of primary vegetation to secondary vegetation ($V_{co2,s}$), the
interactive effect on cropland plus the gain from transition ($V_{co2,c}$), and the
interactive effect on pasture plus the transition gain ($V_{\text{co2\_pa}}$). All of the components for CO$_2$, climate and Nr deposition effects are listed in Table 3-3. The negative component from primary vegetation for CO$_2$ effect indicates that interaction with climate and Nr deposition reduces N$_2$O fluxes caused by CO$_2$ fertilization by 8.82 TgN (1850-2000). In addition to primary vegetation, interactive effects from secondary vegetation, cropland and pasture plus transition gains all contributed to the negative interactive effect from CO$_2$. Similar as for CO$_2$, components from primary, secondary, cropland and pasture all contributed to the reduction of N$_2$O fluxes caused by climate change interacting with CO$_2$ and Nr deposition, with the largest contribution from primary vegetation (5.49 TgN accumulated over 1970-2000). Primary vegetation and conversion into pasture reduce N$_2$O fluxes from the interaction of Nr deposition with climate, CO$_2$, while conversions into secondary vegetation and cropland increase N$_2$O fluxes from interactive Nr deposition effect.

**Tropical vs. Temperate Land Cover Transition Response**

Land cover transition responses differ between tropical (23.5S-23.5N) and temperate (23.5N-66.5N and 23.5S-66.5S) regions. Land cover changes in tropical regions reduce annual soil N$_2$O fluxes, and the reduction strength grows with time, especially after the 1950s (Figure 3-6a). Land cover conversions in temperate zones trigger N$_2$O emissions (Figure 3-6b). The strength of the enhancement in temperate zones increases with time until ca. 1920 and then decreases. The global budget of land cover effect is balanced between positive contribution from temperate region and negative response from tropical region. Over 1850-2000, temperate regions emit 159.30 TgN (single effect) or 135.20
TgN (overall effect) due to land cover transitions (Figure 3-7) while tropical emissions are reduced by 97.2 TgN (single effect) or 101.21 TgN (overall effect) (Figure 3-7). Conversions to secondary vegetation, cropland and pasture all contribute to enhanced temperate emissions, with the dominant contribution from cropland (Figure 3-7d,e,f). On the other hand, conversions ended as secondary vegetation, cropland and pasture all contribute to reduced tropical emissions, with the largest share goes to the cropland again (Figure 3-7a,b,c). However, the dominant role of cropland is less obvious in tropical compared to temperate zone.

Temperate and tropical ecosystems differ in various ways in N$_2$O emissions following land cover conversions. The peak of the emission pulse after clear-cutting of a typical temperate forest is higher than that of a typical tropical forest, as illustrated in Figure 3-8. The timing of the emission pulse from temperate site lags behind the tropical site, indicating a delay of positive impact of forest transitions on N$_2$O emissions from temperate region compared to the tropical region. With the aboveground biomass constituting a considerable portion of total N from tropical forest and relative high N availability, losses of N through biomass removal, gaseous and leaching pathways create an overall deficit of available N which reduces N$_2$O flux after the pulse emission, and takes a long time (more than 100 years) to recover to the pre-cutting level. However, reduction in N$_2$O emission in the recovery process is not seen in temperate forest because of low N availability in the control, and the fraction of N removed during clearcutting is smaller as much of the N stocks in temperate forests are found in
soil organic matter (0.69 vs. 0.02 kg m\(^{-2}\) in soil organic matter compared to aboveground biomass in this temperate site).

In addition, without land management practice such as N fertilization and irrigation, old grasslands emit less N\(_2\)O compared to forests. I illustrate the difference in state transition by picking out forest grid cell that is adjacent to grass grid cell, and comparing the average N\(_2\)O emissions in steady state (from the model spin-up run) between forest grid cells and the adjacent grass grid cells (Figure 3-9). The reduction is significant (\(P<0.01\)) for both tropical and temperate regions but is much stronger from the tropical compared to temperate regions.

**Discussion**

Historical soil N\(_2\)O emissions respond to multiple changes simultaneously. While chronic global changes, such as climate change, Nr deposition and rise in atmospheric CO\(_2\), have been studied earlier, it remains largely unknown how land cover transitions involving cropland, pasture and secondary vegetation affect N\(_2\)O emissions, and how land cover impacts interact with chronic global changes. I applied the global land model (LM3V-N) with two series of combinations of land cover, CO\(_2\), Nr deposition and climatic forcing to explore the potential importance of each of the global change factor and their interactions in shaping historical soil N\(_2\)O emissions. In the following section, I will further discuss the contribution from each of these factors.

The response to Nr deposition increases with time starting from 1850, but is smaller compared to other two process based models which reported a response of 0.80±0.14 TgN yr\(^{-1}\) for the 20\(^{th}\) century (Xu-Ri et al., 2012) or 0.8
TgN yr⁻¹ since 1860 (Zaehle et al., 2011). The role of increasing Nr deposition might be partially offset by BNF adjusting according to ecosystem N status. Compared to these two models in which biological nitrogen fixation (BNF) are either not simulated explicitly or empirically related to ecosystems evapotranspiration, BNF in LM3V-N is dynamically simulated based on ecosystem N status. The declining trend of BNF in simulations with only Nr deposition indeed suggests the compensation of BNF to Nr deposition, a mechanism not captured in earlier model simulations. Accumulatively, BNF with Nr deposition is reduced by 638.73 TgN (1850-2000) compared to the spin-up (reference) run. My results thus show that uncertainty in the representation of BNF in global models may result in large uncertainties in N₂O budget estimation as well as responses to environmental factors. In addition to difference in the representation of N cycling, uncertainties in Nr deposition dataset may also contribute to the difference in Nr deposition response compared to other models. Globally, the interaction of Nr deposition with land cover change, CO₂ and climate change is small but positive. Europe, where Nr deposition rates are high, displays the strongest interaction. It is likely that the positive interaction from Nr deposition will increase in the future with higher Nr deposition rates.

The large contribution of recent climate change to the interannual variability of terrestrial N₂O flux is in line with Zaehle et al. (2011). The reduced impact of climate when interacts with other factors (land cover transition, CO₂ and Nr deposition), points to mechanisms that prevent climate-induced N₂O production, e.g. by reducing available Nr in soils. Xu-Ri et al. (2012) revealed the
enhancement of the positive climatic effect when interacts with CO\textsubscript{2} based on potential vegetation during the 20\textsuperscript{th} century. It is difficult to compare with their result since my interactive term incorporates the impact of land cover change and Nr deposition. CO\textsubscript{2} fertilization alone slightly reduces global N\textsubscript{2}O fluxes (cumulative 14.21 TgN over 1850-2000); however, CO\textsubscript{2}, too, shows strong interaction with other anthropogenic drivers, resulting a reduction of the N\textsubscript{2}O flux by 67.97 TgN over 1850-2000. The negative CO\textsubscript{2} fertilization impact relies partly on the limitation of N availability for nitrifiers and denitrifiers caused by enhanced vegetation growth and plant N uptake (Huang and Gerber, 2015). The stronger reductions of the interactive CO\textsubscript{2} effect from secondary vegetation and cropland (note N fertilization is not considered) compared to natural vegetation indicates more serious N limitation in post-disturbance dynamics. Land cover transitions normally cause an initial loss of nitrogen through erosion, emissions of trace gases, harvesting of biomass and leaching of mineral and dissolved organic N (Steudler et al., 1991; Page et al., 2011; McVicar and Kellman, 2014). Losses of N further tightens the N cycle and limits N availability for nitrification and denitrification, which is magnified by rising CO\textsubscript{2} levels.

Although land cover changes alone have a minor effect (0.04±0.28 TgN yr\textsuperscript{-1}) on N\textsubscript{2}O emissions over 1970-2000, comparable with -0.07±0.25 TgN yr\textsuperscript{-1} averaged over 1981-1990 and -0.09±0.25 TgN yr\textsuperscript{-1} averaged over 1991-2000 from Zaehle et al. (2011), the impact of land cover change varies with time and space. Land cover change has the strongest single and overall effects in Europe (positive), South America (negative) and Africa (negative) compared to CO\textsubscript{2},
climate and Nr deposition in the period of 1970-2000. Over the longer period of 1850-2000, the single effect of land cover transition can be as high as 1.10 TgN yr\(^{-1}\) and the overall effect reaches 0.94 TgN yr\(^{-1}\). The continental variability of land cover transition to N\(_2\)O emission is further visible if separating between tropical and extra-tropical regions, where N\(_2\)O emissions increase in response to land cover changes in temperate region and are reduced in tropical regions over the historical period.

Global scale impact of land use transition is a combination of various positive and negative responses. The net global response to land cover changes depends on factors such as transition types (Figure 3-4), the extent (area) of transitions, the time spans after transitions (Figure 3-8) as well as the characteristics of the ecosystems been converted (Figure 3-9). Positive responses with pulses of emissions occur following conversion of the natural forests, and my simulations are in line with field level studies (Steudler et al., 1991; Page et al., 2011; McVicar and Kellman, 2014), and may be modified with respect to and timing based on the initial state of the system at the time of the disturbance (here I considered steady state), as well as climate defining ecosystem type and storage of N above-ground vs. belowground. Reductions of emissions can occur during secondary forest succession as available N decreases (Keller and Reiners, 1994; Verchot et al., 1999; Davidson et al., 2001), or due to the lower emissions from old grassland when converted from forests (Keller et al., 1993). The temperate ecosystems are dominated by the positive emission pulses following land cover transitions over 1850-2000, while the
tropical ecosystems are dominated by the longer term negative impacts. Luizao et al. (1989) suggested a N₂O emission rate of 1 TgN yr⁻¹ in the Amazon basin during the conversion of forest to pasture while Keller et al. (1993) argued for an overestimation from Luizao et al. (1989) since Luizao et al. (1989) based their results on emission pulses from the young pasture, while pasture emissions actually vary with age and can be even lower than the original forest emissions. Luizao et al. (1989) suggested a threefold increase in N₂O emissions during the initial transition of tropical forest, and the emission pulse captured from my model (Figure 3-9) is comparable with their threefold increase. However, my results suggest a reduction of N₂O fluxes over 1850-2000 when land use history and the whole path of post-disturbance succession is considered.

It is critical to note that I do not include fertilizer input in my models nor account explicitly for N₂ fixing crops. It is unknown whether manure application will turn the reduction of N₂O emissions into an enhancement through transitions of forest to pasture. Nevertheless, the strong positive responses from temperate region following land cover transition suggest the importance of land cover change in N₂O emission in temperate landscapes even though manure and mineral N fertilization are not considered.

Conclusions

Using the process based land model LM3V-N, I found the contribution of land cover transition to land N₂O emission is different regionally and temporally. Globally, land cover transition first increases and then decreases N₂O emissions with a peak in the 1920s. In the last 30 years of the 20th century land cover transition has the strongest single and overall effects among CO₂, climate and Nr
deposition in Europe (positive), South America (negative) and Africa (negative).
Specially, the global response of N$_2$O emission to land cover transition is a combination of positive responses such as from temperate regions, with emissions of 159.30 TgN, or 135.20 TgN when interaction is considered over 1850-2000, and negative responses such as from the tropical regions, with reduced emissions by 97.2 TgN (single effect) or 101.21 (single + interaction effect) over 1850-2000. In addition, interactions involving land cover transition, climate change, CO$_2$ fertilization and Nr deposition reduce the strong positive climatic effect and enhance the negative effect of elevated atmospheric CO$_2$ concentration on soil N$_2$O emissions.
Table 3-1. Summary of forcing for model simulations to investigate the individual effect of land cover, CO$_2$, climate and Nr deposition.

<table>
<thead>
<tr>
<th></th>
<th>Land Cover</th>
<th>CO$_2$</th>
<th>Climate</th>
<th>N Deposition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ref</td>
<td>1700</td>
<td>1700</td>
<td>1948-1964</td>
<td>1850</td>
</tr>
<tr>
<td>+Land cover</td>
<td>1700-2000</td>
<td>1700</td>
<td>1948-1964</td>
<td>1850</td>
</tr>
<tr>
<td>+CO$_2$</td>
<td>1700</td>
<td>1700-2000</td>
<td>1948-1964</td>
<td>1850</td>
</tr>
<tr>
<td>+Clim</td>
<td>1700</td>
<td>1700</td>
<td>1948-2000</td>
<td>1850</td>
</tr>
<tr>
<td>+NDep</td>
<td>1700</td>
<td>1700</td>
<td>1948-1964</td>
<td>1850-2000</td>
</tr>
</tbody>
</table>

Note: Each model run with one time-variant forcing is compared to the reference (Ref) simulation with the preindustrial forcing. +Land cover indicates the simulation with land cover transition, while other forcing keeps the same as the spin-up. Similarly, +CO$_2$ indicates the simulation with the time-variant atmospheric CO$_2$ concentration; +Clim with the time variant climate conditions instead of recycling, and +NDep with the transient Nr deposition instead of the natural background.

Table 3-2. Summary of forcing for model simulations to investigate the overall effect (individual + interaction) of land cover, CO$_2$, climate and Nr deposition.

<table>
<thead>
<tr>
<th></th>
<th>Land Cover</th>
<th>CO$_2$</th>
<th>Climate</th>
<th>N Deposition</th>
</tr>
</thead>
</table>

Note: The Full run is the simulation with all of the forcing (Land cover, CO$_2$, climate and Nr deposition) turned on. The overall effect for each of the forcing is the difference from the Full and the corresponding model run that excluding that forcing. –Land cover is the simulation with no land cover change; -CO$_2$ is the simulation with preindustrial (constant) atmospheric CO$_2$ concentration; -Clim refers to simulation with the recycling climate as the spin up run, and –NDep indicates simulation with natural background Nr deposition.

Table 3-3. Components of the interactive environmental effects.

<table>
<thead>
<tr>
<th></th>
<th>Primary (TgN)</th>
<th>Secondary (TgN)</th>
<th>Crop (TgN)</th>
<th>Pasture (TgN)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CO$_2$</td>
<td>-8.82</td>
<td>-10.09</td>
<td>-29.77</td>
<td>-4.38</td>
</tr>
<tr>
<td>Clim</td>
<td>-5.49</td>
<td>-3.65</td>
<td>-4.14</td>
<td>-4.68</td>
</tr>
<tr>
<td>NDep</td>
<td>-1.73</td>
<td>0.50</td>
<td>11.87</td>
<td>-2.60</td>
</tr>
</tbody>
</table>

Note: Each row corresponds to one environmental driver: CO$_2$ indicates atmospheric CO$_2$; Clim is climate and NDep means the atmospheric Nr deposition. Each column displays one component of the interactive term: Primary for interactive effect from primary vegetation; Secondary is the interactive effect from secondary vegetation plus the transition effect; Crop for interactive effect from cropland plus the transition gain and Pasture for interactive effect from pasture plus the transition gain. Values are shown as the cumulative value for CO$_2$ and Ndep over 1850-2000 and for Clim over 1970-2000.
Figure 3-1. Global annual soil N$_2$O emissions. Panel (a) shows soil N$_2$O budgets from including one forcing each time compared to the reference. Ref indicates reference simulation with the spin-up forcing; +Land cover indicates the simulation with land cover transition, while other forcing keeps the same as the spin-up. Similarly, +CO2 indicates the simulation with the time-variant atmospheric CO$_2$ concentration; +Clim with the time variant climate conditions instead of recycling, and +NDep with the transient Nr deposition instead of the natural background. Panel (b) shows results from excluding one forcing each time compared to the Full run. The Full run is the simulation with all of the forcing (Land cover, CO$_2$, climate and Nr deposition) turned on. – Land cover, -CO2,-Clim and –Ndep indicate simulations excluding the corresponding forcing compared to the Full run. Details on forcing are available in Table 3-1 and 3-2. Dashed lines indicate yearly N$_2$O budget and filled line are 17-year running means.
Figure 3-2. Cumulative global soil N\textsubscript{2}O emissions caused by global changes (1850-2000). Panel (a) is the single factor effect through including one time variant forcing compared to the reference simulation (see Table 3-1 for more details); Panel (b) is the overall effect by excluding the corresponding forcing from the full simulation (Table 3-2); and Panel (c) is the interaction effect, i.e. the difference between the overall effect and the single factor effect. Color lines represent global change factors: land cover (green), atmospheric CO\textsubscript{2} (red), climate (blue) and Nr deposition (orange). The dashed black line is the zero line. Since the weather of 1948-1964 is recycled for model spin-up and simulations prior to 1948, the climatic impact is effective only after the year 1964.
Figure 3-3. Global and continental changes of N₂O emissions caused by land cover transition (green), atmospheric CO₂ (red), climate (blue) and Nr deposition (orange) over 1970-2000. Dashed bars represent the single factor effect (Table 3-1), and filled bars stand for the overall effect (Table 3-2). Error bars (black line) are the standard deviation of the annual variability over the time period.
Figure 3-4. Decomposition of land cover transition impact on global soil N$_2$O emissions (1850-2000). Panel (a), (b) and (c) correspond to the single, overall and interaction effect as mentioned in Figure 3-2, respectively. Blue lines indicate the total land cover transition effect; green lines are contributions due to conversion of natural vegetation to secondary vegetation (Scnd); red lines are contributions due to conversion of natural vegetation to cropland (Crop); orange lines are contributions due to conversion of natural vegetation to pasture (Pasture); and the black dashed line is the zero line.
Figure 3-5. Land areas (in unit of $10^6$ km$^2$) of four land cover types.
Figure 3-6. Annual soil N$_2$O emissions caused by land cover transitions in tropical (panel (a), 23.5S-23.5N) and temperate (panel (b), 23.5N-66.5N and 23.5S-66.5S) regions over 1850-2000. Black lines represent the single factor effect (Table 3-1), and green lines stand for the overall effect (refer to Table 3-2).
Figure 3-7. Decomposition of the cumulative land cover transition impact on soil N$_2$O emission in tropical (23.5S-23.5N) and temperate (23.5N-66.5N and 23.5S-66.5S) zones over 1850-2000. Panels correspond to the single, overall and interaction effect as mentioned in Figure 3-2. Legend is the same as in Figure 3-4.
Figure 3-8. Differential responses of a typical tropical forest (0, 65W) and a temperate forest (46N, 76W) following clear-cutting. Blue (tropical forest) and green (temperate forest) lines are the steady states (with the same forcing as Ref from Table 3-1) before disturbance. Clear-cutting is mimicked by removing 95% of the above ground biomass. Red (tropical forest) and black (temperate forest) lines represent the dynamics of N₂O fluxes following clear-cutting.
Figure 3-9. N$_2$O fluxes from forests and adjacent grasslands. I approximate the alteration of N$_2$O fluxes due to the state change (from forest to grassland) by picking out forest grid cell that is adjacent to grass grid cell, and comparing the average throughout the tropical (23.5S-23.5N) and temperate (23.5N-66.5N and 23.5S-66.5S) regions. Values are taken from the steady states of the spin-up run. Red bars represent the average from forests and blue bars for the adjacent grasslands. Error bars (black line) are the standard deviations across grid cells. Different letters indicate the differences are statistical significant ($P<0.01$) in tropical and temperate regions, respectively.
CHAPTER 4
ELUSIVE RESPONSE OF VEGETATION TO DROUGHT: EVALUATION OF CMIP5 MODELS

Introduction

The global carbon cycle and climate system are tightly coupled. Anthropogenic carbon dioxide (CO$_2$) emission into the atmosphere is one of the main drivers of recent climate change (Ciais et al., 2013) and is of critical importance for future climate projections. Terrestrial ecosystems have been absorbing ca. 25-30% of anthropogenic CO$_2$ emissions in the past several decades, acting as an important negative feedback mechanism in the carbon-climate system (Le Quere et al., 2009). The primary pathway of terrestrial carbon uptake is through plant growth. Vegetation growth depends on a multitude of factors, including climate, atmospheric CO$_2$ concentration and nutrient supply, which leads to large uncertainties in the prediction of the terrestrial carbon sink. Earth system models (ESMs) are vital tools to understand the variability of terrestrial carbon sink and its feedback to future climate change especially at the global scale. As the most recent coupled carbon-climate experiment, the Coupled Model Intercomparison Project Phase 5 (CMIP5) incorporates mechanisms affecting vegetation dynamics and terrestrial carbon cycling through climate change and variability, CO$_2$ fertilization and in a few models, nitrogen fertilization (Taylor et al., 2011). It is important to critically evaluate modeled vegetation activities against observations considering the large spread of future projections of atmospheric CO$_2$ concentration (Friedlingstein et al., 2014).

Water is a primary resource limiting terrestrial biological activities. Water related climate extremes, such as drought, have been reported to significantly
alter large scale vegetation activities, reducing the terrestrial carbon sink strength or even turning terrestrial ecosystems into carbon sources temporarily (Ciais et al., 2005; Phillips et al., 2009; Zhao and Running, 2010). Vegetation CO$_2$ uptake anomalies induced by climate extremes are reported to add up to the similar magnitude of that of terrestrial carbon sink, with most of the contributions from water scarcity (Zscheischler et al., 2014b; Zscheischler et al., 2014a; Reichstein et al., 2013). The importance of drought impacts on vegetation activities and terrestrial carbon cycle has been widely recognized, and has been shown by recent intensive studies through observation (e.g. FLUXNET), remote sensing and process based models (Chen et al., 2013; Zscheischler et al., 2014b; Potter et al., 2011; Liu et al., 2014; Zhao and Running, 2010; Schwalm et al., 2010; Vicente-Serrano et al., 2013), especially in the face of the potential of more frequent and intense droughts in the future (Dai, 2011). However, it remains largely unknown how realistic CMIP5 models represent drought impacts on vegetation activity. For example, Piao et al. (2013) pointed to an over-estimation of the slope of gross primary productivity (GPP) in response to precipitation from 10 process-based terrestrial biosphere models, which only reflects partly the drought sensitivity of vegetation.

Drought is roughly defined as an extended period of water scarcity. Drought responses of the carbon cycle are complex partly due to the multifaceted nature of drought. Precipitation can be used as an indicator of dryness/wetness conditions since precipitation is one of the determinants of soil water. However, simple precipitation metric is not sufficient in characterizing various aspects of
drought, such as the duration, extent, cumulative severity and timing (Chen et al., 2013; McKee et al., 1993). Thus, droughts are frequently quantified by drought indices, combining other variables that adjust precipitation. The Palmer drought severity index (PDSI) (Palmer, 1965) and the standardized precipitation index (SPI) (McKee et al., 1993) are two of the mostly widely used indices. PDSI is based on the soil water balance that takes into account water supply (precipitation), demand (potential evapotranspiration) as well as loss (e.g. runoff), but is complicated and sometimes inconsistent among several calculation methods (Trenberth et al., 2014). SPI is an index based solely on precipitation, but its simplicity and consistency with more complicated indices (e.g. PDSI) have won itself growing popularity among drought studies (Sims et al., 2002; Ji and Peters, 2003; Mueller and Seneviratne, 2012; WMO, 2012; Orlowsky and Seneviratne, 2013). Most importantly, it can be used to characterize droughts at multiple temporal scales.

The concept of drought time-scale of response indicates the time lag between the initialization of water scarcity and the detection of its impacts (Vicente-Serrano et al., 2014). The lagged or legacy impacts of drought are frequently documented in literature (Reichstein et al., 2013). For example, lagged tree mortality was reported some period after severe droughts (Anderegg et al., 2013; Bigler et al., 2007; Phillips et al., 2010); and grasslands are reported to have lower above-ground net primary production following dry years despite normal precipitation (Sala et al., 2012). Drought time-scale of response is linked to the resistance of vegetation to droughts, or the ability of vegetation to adapt and
acclimate to water anomalies. Vegetation with longer drought time-scale of response is expected to be more resistant to drought impacts. Realistic representation of biome specific characteristic time scales of drought responses is important since it is common in drought responses (Reichstein et al., 2013; Niu et al., 2014). Responses to drought incorporate various aspects of vegetation activity from molecular to phenological, physiological or ecological processes (Niu et al., 2014; Reyer et al., 2013) and can be characterized by different metrics in addition to the time-scale. For example, the vulnerability refers to the susceptibility of vegetation to adverse effects caused by water anomalies (Reyer et al., 2013), while the resilience to drought indicates capacity of vegetation to restore pre-disturbance structure and function (Herrero and Zamora, 2014).

Although meteorological drought indices, such as SPI, are useful indicators of water deficits and surpluses, the dryness or wetness faced by plants are more directly linked to soil moisture conditions. Factors other than meteorological conditions, such as soil characteristics, affect soil moisture dynamics and subsequently vegetation activities (Weng and Luo, 2008; Porporato et al., 2004). Previous global scale studies are constrained by the availability of observation based data since soil moisture is known to be highly variable from daily to interannual timescales and is difficult to measure (Seneviratne et al., 2010). Recent soil moisture products from space borne passive and active microwave have become available for 30+ years (Dorigo et al., 2014), although these data are limited to the surface soil column (less than 10 cm) (Liu et al., 2011) which might become “decoupled” from root zone soil moisture in some
occasions (Seneviratne et al., 2010; Capehart and Carlson, 1997). Nevertheless, information obtained from soil moisture drought provides us additional perspective of drought-carbon responses.

Complementary to previous CMIP5 evaluations which either focus on terrestrial carbon cycling and simple relationship with climate variables (Shao et al., 2013) or drought alone (Orlowsky and Seneviratne, 2013), I confronted the modeled drought response of vegetation, as indicated by GPP and leaf area index (LAI) against that derived from empirical data, emphasizing on the overall sensitivities as well as different facets of drought responses, such as the time-scale, vulnerability, excursions and sensitivities to extreme dry/wet events, starting season and duration. I chose SPI as the drought index due to its temporal flexibility as well as the availability of CMIP5 output data. In addition, I also compared soil moisture drought responses, but are cautious on the conclusions draw from soil moisture droughts.

Methods

Data

CMIP5 models and experiments

CMIP5 provides a standard set of model simulations based on common protocols and enables evaluations of model performance from different perspectives (Taylor et al., 2011). I selected 9 ESMs from the historical experiment (esmHistorical), which represents the evolving of current climate through the twentieth century. Model forcing for historical runs are consistent with observations and concentrations of well-mixed greenhouse gases are prescribed. Criteria for model selections are based mainly on the availability of monthly GPP,
LAI and relevant climate and soil moisture data. Only one model configuration
was randomly selected from each climate center, since the configurations within
a climate center are likely to be similar. For models with multiple realizations,
only the first ensemble member (“r1i1p1”, “r1” stands for the first run under the
first set of initial conditions (“i1”), and the first set of physical parameters (“p1”))
(Taylor et al., 2011) was used. Model output data was downloaded from the
Program for Climate Model Diagnosis and Intercomparison (PCMDI) data server.
Models used in this study, as well as their complete name expansions are listed
in Table 4-1.

The land carbon components of these ESMs differ in their representations
of plant function types (PFTs), land use changes, soil characteristics, carbon and
nitrogen pools, and the latitudinal and longitudinal resolutions, which are reported
in Table 4-2. Despite differences in model structure and parameterization, they
share similarities in treatments of terrestrial carbon and water cycles. Plant
species with similar characteristics are grouped into PFTs. For each PFT, GPP is
the accumulation of leaf photosynthesis during a certain period of time.
Photosynthesis is simulated generally following the biochemical based
Farquhar’s scheme or its modified version for C3 (Farquhar et al., 1980;Collatz
et al., 1991a) and Collatz et al. (1992) for C4 plant, except in SEIB-DGVM where
photosynthetic rate is simplified as a Michaelis-type function of the intensity of
photosynthetic active radiation (PAR) and takes into account of light use
efficiency (Sato et al., 2007). After accounting for the autotrophic respiration (Ra,
typically the sum of the maintenance and growth respirations), the net primary
production (NPP, the difference between GPP and Ra) is allocated to different vegetation pools, such as leaves, roots and stems. LAI can be derived from leaf carbon content (kgC m\(^{-2}\)) and the specific leaf area (SLA, m\(^2\) kgC\(^{-1}\)) which might be PFT specific constant (e.g. ORCHIDEE, Krinner et al. (2005)), or vary with leaf longevity (e.g. LM3V, Shevliakova et al. (2009)) or the vertical gradient of canopy (e.g. CLM4-CN, Thornton and Zimmermann (2007)). One exception is from TRIFFID in which LAI is solved from the allometrical relationships with leaf, root and total stem carbon (Cox, 2001). Carbon from leave, root and stem turnovers, mortality and local disturbance enters litter or soil pools and are subjected to decomposition, which are represented as first-order decay processes that are modified by soil moisture and temperature (Todd-Brown et al., 2013).

Coupling between vegetation dynamics and water is reflected in the link between photosynthesis and stomatal conductance and the down-regulation of GPP by soil water stress. Stomatal opening regulates the exchange of carbon and water vapor (transpiration) and the latter is linked to atmospheric demand and surface energy budget. The formulation of stomatal conductance generally adopts the Ball-Woodrow-Berry model (Ball et al., 1987) or its modified version (Leuning, 1995), semi-empirically relating stomatal conductance to carbon assimilation. Soil water stress functions that down-regulate GPP vary with models and detailed information is provided in Appendix E. In addition, water availability also affects processes such as plant phenology, establishment, allocation, respiration and mortality etc., which differ among models.
I chose 1982-2005 as my reference period based on the availability of model and observation data. All global model output and reference data were regridded to a common resolution of 1°×1° and a common land mask (i.e., from the reference GPP dataset) using the nearest neighbor method which I assume conserves drought responses.

**Observation-driven data**

To compare observation-driven and ESMs simulated drought-carbon relationships, I used four global monthly precipitation datasets based on observations, remote sensing or combination of these to derive reference meteorological drought index (Table 4-3). Observation-based monthly precipitation data is used from CRU TS 3.21 (Climatic Research Unit at the University of East Anglia) (Jones and Harris, 2013), covering 1901-2012 on a 0.5°×0.5° grid; from GPCC v6 (Global Precipitation Climatology Centre) (Schneider et al., 2014; Schneider et al., 2011), covering 1901-2012 on a 0.5°×0.5° grid; and from University of Delaware v3.01 (DELA in short), which combines dataset from GHCN2 (Global Historical Climate Network) and, more extensively, from the archive of the creators, covering 1901-2010 on a 0.5°×0.5° grid (Willmott, 2012), and from GPCP v2.2 (Global Precipitation Climatology Project) consisting of monthly means of precipitation derived from both satellite and gauge measurements since 1979 on a 2.5°×2.5° grid (Adler et al., 2003).

Direct GPP measurements at the global scale do not exist for my reference period (1982-2005), although satellite derived GPP datasets are becoming available in recent years (Mao et al., 2012). I chose the dataset that up scales the FLUXNET flux tower GPP from training of a model tree ensemble
(MTE) at site level as described in Jung et al. (2011). The MTE upscaling approach consists of a set of trained regression trees and 29 candidate predictors, such as the global fraction of absorbed photosynthetic active radiation (FARAP, derived from remote sensing), climate and land cover. Although uncertainties remain in MTE-GPP, the data-oriented approach provided us an avenue to evaluate land models and has been applied in several studies (Anav et al., 2013; Piao et al., 2013; Zscheischler et al., 2014a).

I used two global datasets of LAI in this study. The first one is from the GlobalMapping Website (GLOBMAP in short), which fuses the MODIS and historical AVHRR LAI products (Liu et al., 2012). MODIS and AVHRR LAI are extracted from MOD09A1 (the MODIS land surface reflectance dataset) and GIMMS NDVI respectively. MODIS LAI is derived based on the GLOBCARBON LAI algorithm (Liu et al., 2012; Deng et al., 2006), and AVHRR LAI is derived from grid cell level SR-LAI relationship, in which SR stands from the ratio of the near-infrared to red band land surface reflectance from AVHRR and LAI comes from MODIS. The two derived LAI products have been shown to be in good consistence and the fused product has been validated against field measurements with good agreements (Liu et al., 2012). Different from the empirical retrieving method applied in GLOBMAP, a second global product GLASS is generated from more physical based inversion techniques using the general regression neural networks (GRNNs) method (Xiao et al., 2014). The GRNNs are trained with fused MODIS and CYCLOPES LAI products and the
MODIS reflectance values for each of the MODIS biome. LAI is then retrieved from MODIS reflectance data based on the trained GRNNs.

A global representative soil moisture dataset based on in situ measurement is not available. Satellite observations are capable of providing global scale soil moisture estimations, and several quasi-global datasets have been generated either from scatterometer (e.g., ERS AMI and MetOp ASCAT) or various multi-frequency radiometers (e.g., AMSR-E, SMMR, SSM/I and WinSat) (Dorigo et al., 2014). Each of these datasets has its pros and cons with regard to spatiotemporal coverage or quality, for example, radiometers generally perform better in dry regions while scatterometers are superior in more densely vegetated regions (Dorigo et al., 2014). Taking advantage of merging the passive or/and active microwave products, the recently generated multi-decadal soil moisture dataset, ECV_SM, expanded the spatiotemporal coverage and preserved the short term (e.g., seasonal and inter-annual) as well as long term dynamics of the original soil moisture products. ECV_SM has been evaluated against the GLDAS-Noah land surface model, the land surface component of MPI-ESM (JSBACH) and the ERA-Interim reanalysis data with respect to the trend (1988-2010) and anomalies (Dorigo et al., 2012; Loew et al., 2013), and against ground measurements for the inter- and intra- annual dynamics in different regions (Liu et al., 2011; Dorigo et al., 2014; Zeng et al., 2015; Pratola et al., 2014). These assessments demonstrated the robustness of ECV_SM and provided confidence in studies making use of this global dataset.
The new version of ECV-SM (v02.1) used in this study combines retrievals of soil moisture from six passive (SMMR, SSM/I, TMI, AMSR-E, WindSat and AMSR2) microwave sensors and the scatterometers on board of ERS-1, ERS-2 and METOP-A into a global dataset covering the period 1979-2013. I chose the merged product as my reference surface soil moisture (not deeper than 10 cm, (Liu et al., 2011)). The original daily soil moisture is aggregated to a monthly time window in line with other datasets.

**Drought Indices**

I used monthly series of two standardized drought indices to quantify meteorological and soil moisture drought. SPI is a commonly used index of meteorological drought, indicating precipitation surpluses or deficits over different time scales. For each month, precipitation over the previous \( n \) (the time-scale of SPI, 1-24 in this study) months is summed. These new monthly precipitation time series are then fitted by a two-parameter Gamma distribution for each SPI time-scale respectively. The fitted Gamma distribution is then transformed into the standard normal distribution according to the cumulative distribution function to yield the SPI. SPI is therefore normalized to a mean of 0 and a standard deviation of 1. More details on the algorithms can be found in Lloyd-Hughes and Saunders (2002).

Soil moisture drought is indicated by surface soil moisture anomalies (SMAs). To obtain SMAs, I removed the mean seasonality from the monthly soil moisture time series \( x_{y,m} \) where \( m \) (1,2,…,12) indicates the month and \( y \) the year. The deseasonalized monthly time series \( x'_{y,m} \) is given by
\[ x'_{y,m} = x_{y,m} - \frac{1}{n} \sum_{i=1}^{n} x_{i,m} \]  

(4-1)

where \( n \) is the number of years used in this study. \( x'_{y,m} \) is further standardized to zero mean and unity standard deviation for each grid cell to yield SMAs. Prior to removing the seasonality, a linear detrending was performed in grid cells with significant trend (\( P<0.05 \)) to avoid correlations caused by a long term trend. The standardization takes into account soil moisture difference between observation and ESMs simulations and makes comparison with SPI feasible. While SPIs are calculated with varying time-scales, the time-scale information is not taken into account for SMAs. Months with soil temperature below 0 °C are excluded from this analysis since the observation data is constrained to temperature above 0 °C. Models have different soil layers and depths. Soil temperature used to exclude data points for each model is calculated as depth-weighted average temperature to the layer that is closest to 10 cm to match ECV-SM which represents soil moisture no deeper than 10 cm.

**Quantifications of Drought Response**

At the global scale I calculated the correspondence between annual GPP and SPI anomalies over timescales from \( k=1-24 \) months for the period 1982-2005. Anomalies were calculated by first determining the global annual means and then removing the linear trends. The Pearson correlation coefficient was used to quantify the magnitude of correlations between GPP and SPI anomalies. Similar procedure was applied to LAI for both models and references.

The meteorological drought index depends strongly on precipitation and inaccuracy in precipitation data set contributes to uncertainties in drought
quantification, especially after 1991 when less observation stations are available compared to 1950-1990 (Trenberth et al., 2014). While models are driven by their corresponding precipitation and therefore no errors in SPI that drivers GPP/LAI anomalies, errors in observation-based SPI lead to biased estimation of drought responses. To illustrate the impact caused by uncertainties in SPI, I estimated SPI errors from observations at the global scale and calculated regression slopes taking SPI as the explanatory variable (x) through measurement error models (MEMs, (Fuller, 1987)). MEMs take into account errors in the explanatory variable (commonly known as “error-in-x”) and correct the bias towards zero when “error-in-x” is accounted compared to the slope estimated from ordinary least squares regression. For each year, the uncertainty of the global SPI is estimated as the standard deviation among the 4 SPIs derived from GPCC, GPCP, DELA and CRU. The error is then estimated as the standard deviation of the mean of SPIs among different years. I also fitted MEMs with a 50% reduction of the error as the low end, and 50% increases as the high end. Although upscaling of the observed GPP to the global scale relies partly the on earlier version of GPCC precipitation (Jung et al., 2011), I assumed the same error in driving both GPP and LAI, taking MET-GPP and satellite LAI as the true GPP and LAI respectively.

To understand the regional pattern of vegetation in response to water anomalies and the characteristic time-scales of responses, I first removed the linear trend and the mean annual cycle, and normalized GPP and LAI to obtain the anomalies at each grid cell, similar as the procedure to obtain SMAs in
section *Drought Indices*. I then separated GPP (or LAI) anomalies into 12 series (one per month) and correlated each series with 1- to 24-months SPIs, respectively. I obtained a maximum of 288 (24 SPI time-scales by 12 months per year) statistically significant correlation coefficients ($P<0.05$) for each grid cell. I focused on the highest monthly correlation coefficients as an indirect indicator of the vulnerability of vegetation activity to water anomalies. I also extracted the SPI time-scales at which these highest correlations were obtained to understand the time-scale of responses and infer the resistance of vegetation activity to water anomalies. I further divided the global land into different zones based on the main climates and the precipitation/temperature regimes according to the Köppen-Geiger climate classification (Kottek et al., 2006), and focused on the arid vs. humid (Figure E-1) regional responses.

To separate dry and wet responses, I defined extreme dry condition with the 3-months SPI smaller than -2 and extreme wet condition with the 3-months SPI bigger than 2 (McKee et al., 1993). The 3-months SPI can be considered as a short term drought indicator and is a common temporal scale in drought assessment (Zscheischler et al., 2014b; Ji and Peters, 2003; WMO, 2012). I further aggregated the extreme dry (or wet) conditions that are adjacent in space and time into extreme dry (or wet) events (3 dimensional, longitude × latitude × time) following Lloyd-Hughes (2012) and Zscheischler et al. (2014b). By adjacent, I refer to the 26 neighbors in a 3×3×3 (latitude × longitude × time) voxel. The size of an extreme event and its impact are the integration of SPIs and GPP (or LAI) anomalies over the spatiotemporal domain of that event,
respectively. The GPP (or LAI) anomaly here is treated as the original value removing the linear trend and mean annual cycle to obtain the absolute deviations. The mean ratio between GPP (or LAI) anomalies and SPI in extreme dry events is used as an indicator of the global dry sensitivity, and the extreme wet events for the global wet sensitivity. In a “backward” analysis, I defined the GPP (or LAI) reduction extreme with the standardized GPP (or LAI) anomalies smaller than -2, and increase extreme with the standardized anomalies bigger than 2, in line with the definition of extreme dry/wet conditions. I spanned the single reduction/increase extremes into 3-dimensional extreme reduction/increase events (voxels), similar as to extreme dry/wet events. I further compared the start season and duration of the extreme dry events with the extreme reduction events, or the extreme wet events with the extreme increase events, to investigate the timing of responses.

For the soil moisture - drought analysis, I separated monthly GPP (or LAI) anomalies into 12 series (one per month) and correlated each series with corresponding SMAs. Similar as in SPI, I focused on the highest correlations. I also defined extreme dry conditions with SMAs smaller than -2 and extreme wet conditions with SMAs bigger than 2, and conducted extreme event analysis similarly as the SPI.

**Results**

**Global Annual Sensitivity and Uncertainty Associated with SPI**

Figure 4-1 displays correlations between global annual GPP (or LAI) anomalies and SPIs across 1-24 months drought timescales. The upscaling approach generated MTE-GPP relies partly on the GPCC precipitation (Jung et
Therefore, correlations are calculated only for SPIs derived from GPCC precipitation. Satellite derived LAI products are not directly dependent on precipitation, and correlation coefficients are calculated for all of the 4 reference SPIs. CMIP5 models generally overestimate the global correspondence between annual GPP and water anomalies with higher multi-model mean correlation coefficients (black, Panel (a) in Figure 4-1) compared to that of MTE-GPP (red, Panel (a)). However, the difference diminishes as SPI time-scale increases and approaches zero with the SPI time-scale of 24-months. In addition, differences among models indicated by 95% confidence intervals increase with SPI time-scale. LAI is generally less responsive to water anomalies than GPP. The correlation coefficients are smaller from LAI compared to GPP for each SPI time-scale and in both models and observations (Figure 4-1). Correlations between reference (i.e. data-based) LAIs and SPIs are weak with the mean correlation coefficients less than 0.2 for each SPI time-scale and most of the reference correlations showing non-significant ($P>0.05$) relationships. Similar to GPP, the mean correlation coefficients are higher for modeled LAI (black, Panel (b) in Figure4-1) compared to reference (red, Panel (b)) across SPI time-scales. However, the mean difference is not statistically significant ($P>0.05$) for short SPI time-scales (1- and 2-months). In contrast to the GPP analysis, the mean difference does not approach zero as SPI time-scale increases and variability within models or references does not increase with SPI time-scale.

Taking into account errors in SPI in regression analysis increases the sensitivity of GPP (or LAI) to SPI (Figure 4-2). For the 1-month time-scale (SPI1),
the sensitivity of MTE-GPP now exceeds the mean of the model. Indeed, the slope is highly sensitive to the error of SPI, with more than 20 times increase when the error is increased by 50%. Similar as GPP, LAI from GLOBMAP and GLASS show higher sensitivity to 1-month SPI compared to the mean of models if errors in SPI are considered (Figure 4-2).

**Highest Sensitivity and SPI Time-Scale**

The highest correlations among 24 SPI timescales and 12 months (total of 288 correlations) provide information on vulnerabilities of vegetation to droughts. Responses to water anomalies in models are stronger compared to reference data (Figure 4-3). For modeled GPP, CMIP5 models are characterized by higher multi-model mean highest correlations across a large portion of the global land, such as the Southeastern United States, Southeastern China, Equatorial Africa and America, and a large portion of Europe and South Asia, but is less obvious in large parts of the Northern High Latitudes (north of 60°N) and the Southeast Asia tropical islands (Panel (a) vs. (b), Figure 4-3). For each individual model, the overestimation is consistent despite regional differences (Figure E-2). Among the models, MIROC are most close to MTE-GPP if evaluated based on the highest correlations (Figure E-2). The overestimation is further shown through the higher multi-model mean highest correlations averaged over the globe (Panel (a), Figure 4-4), but also if split into arid vs. humid regions (Panel (a), (b), Figure 4-5).

The regional pattern of a stronger vulnerability of modeled GPP generally holds for LAI, with small differences such as in part of the West Coast of United States. In this region, observations show smaller vulnerability compared to the multi-model mean leaf area, which is not detected from GPP (Figure 4-3). Further
averaged across globe or averaged over arid or humid regions, modeled highest correlations between LAI and water anomalies are higher than those for data-based reference (Figure 4-4, 4-5). Among the individual models, INMCM4 exhibits the strongest highest correlations (> 0.6) over most of grid cells, while highest correlations are relatively weaker in MIROC compared to other models and MIROC resembles the referential (i.e. data-inferred) correlations most. Compared to GLOBMAP, GLASS derived referential correlations show weaker highest correlations with mostly non-significant correlation ($P>0.05$, blank in Figure E-3) over the Northern High Latitudes (north of 60°N).

The SPI time-scales at which the highest correlations are obtained are averaged across models or references and displayed in Figure 4-6. Highest correlation between GPP and SPI are for many gridcells at longer SPI time scales in the reference (e.g. >18 months). As a result, timescales with strongest correlations are shorter in models compared to data-based references when SPI time scales are averaged across the globe (models: mean, 6.45 months; 95% confidence interval, 5.25-7.65 months; MTE-GPP: 8.22 months, Panel (b), Figure 4-4). However, LAI has a longer average time-scale in CMIP5 models (mean, 10.02 months; 95% confidence interval, 7.69-12.35 months) compared to the mean of the references (8.63 months; 95% confidence interval, 8.28-8.98 months) (Panel (b), Figure 4-4). The overall shorter mean time-scale of modeled GPP response holds for both arid and humid regions (Panel (c), Figure 4-5), and the longer mean time-scale of response from modeled LAI is also consistent between arid and humid regions (Panel (d), Fig 4-5). Among the individual
models, INMCM4 shows the fastest response of GPP to water anomalies with the mean response time-scale of 3.8 months, followed by BCC (Figure E-4). Individual models varied strongly with respect to LAI response time-scale (Figure E-5). The mean response time-scale of LAI is as low as 3.5 months from INMCM4 and as high as 13.1 months from NOR, indicating large uncertainties in model derived LAI response time-scale.

GPP and LAI in arid regions are on average more vulnerable to water anomalies (higher highest correlations) compared to humid regions from both CMIP5 models and observations (Panel (a), (b) in Figure 4-5). The gap of correlations (arid vs. humid) is slightly bigger in observations compared to CMIP5 models. While biomes in arid regions take longer time to respond compared to humid regions from CMIP5 models (7.04±2.52 months from arid vs. 6.41±1.41 months from humid regions for GPP, and 10.77±3.80 months from arid vs. 10.04±2.78 months from humid region for LAI), a slightly shorter response time of arid biomes is detected in the data-based reference (8.15 months in arid vs. 8.44 months from humid regions for GPP, and 8.61±0.83 months in arid vs. 8.72±0.84 months in humid region for LAI) (Panel (a), (b) in Figure 4-5), although the differences are not statistically significant (P>0.05) based on Student’s t-test.

**Extreme Event Analysis Based on SPI**

GPP reductions integrated over all extreme dry events (1982-2005) ranges from -5.30 (CAN) to -30.28 GtC (GFDL), which are larger than that of MTE-GPP (-3.00 GtC) (Figure 4-7). The integrated increase of GPP during extreme wet events is also higher from models (range, 3.64 (CAN)-14.90 (BCC)
GtC) compared to MTE-GPP (1.61 GtC) (Figure 4-7). Higher excursions of modeled GPP during extreme events compared to data-derived product are not attributable to difference in the magnitude of extreme events. The mean total volume of extreme dry events is 16.36×10⁸ km² month (95% confidence interval, 15.21×10⁸ km² month to 17.51×10⁸ km² month) from models compared to 17.88×10⁸ km² month for reference GPP during the period 1982-2005. And the mean total volume of extreme wet events is 11.83×10⁸ km² month (95% confidence interval, 10.92×10⁸ km² month to 12.74×10⁸ km² month) in models compared to 12.75×10⁸ km² month for the GPP reference. Overall, the sensitivity (total GPP excursions divided by total volume of extreme dry or wet events) is smaller for the data-based reference compared to each of the 9 models under study (Figure 4-8). GPP in the GFDL model is the most sensitive to extreme dry conditions (-16.77 gC m⁻² month⁻¹), while HAD is the most sensitive to extreme wet conditions (12.31 gC m⁻² month⁻¹) (Figure 4-8). In addition, the over-sensitivities are unlikely to be explained only by difference in the magnitude of means and standard deviations of GPP, since the over-reduction or increase of modeled GPP in extreme events holds when GPP anomalies are normalized for each grid cell (Figure E-6).

Globally, the reduction of leaf area is -11.58×10⁷ km² month (95% confidence interval, -8.21×10⁷ to -14.95×10⁷ km² month) if integrated over extreme dry events, higher than the mean of references, -3.86×10⁷ km² month (95% confidence interval of -2.53×10⁷ to -5.19×10⁷ km² month from 8 LAI-SPI combinations) (Figure 4-7). Further, the mean cumulative increase of leaf area
from extreme wet events is $6.37 \times 10^7$ km$^2$ month (95% confidence interval of $3.70 \times 10^7$ to $9.04 \times 10^7$ km$^2$ month), again higher than the reference of $1.56 \times 10^7$ km$^2$ month (95% confidence interval, $0.40 \times 10^7$ to $2.72 \times 10^7$ km$^2$ month) (Figure 4-7). Similar as GPP, the over reduction or increase of leaf area is associated with the sensitivity to extreme events (Figure 4-8). However, the difference in sensitivities derived from the two referential LAI datasets (GLOBMAP vs. GLASS) is large, especially during extreme wet events, reflecting large uncertainties in observations (Figure 4-8). However, the sensitivity gap in observed LAI is largely reduced when LAI anomalies are normalized to 0 means and 1 standard deviations (Figure E-7). Despite a higher mean in models, the sensitivities analyzed for normalized leaf area anomalies is not statistically different from data-based references ($P>0.05$, Student’s t test) (Figure E-7).

When referential leaf area responses are characterized by a range of values considering uncertainties in SPIs and observed LAI, there are models showing lower cumulative leaf area excursions or sensitivities compared to observations. For example, the cumulative reduction of leaf area in drought is $-4.45 \times 10^7$ km$^2$ month in the HAD model, which is lower than the response from GLASS with drought index derived from GPCC ($-5.04 \times 10^7$ km$^2$ month), GPCP ($-5.14 \times 10^7$ km$^2$ month), DELA ($-5.17 \times 10^7$ km$^2$ month) and CRU ($-5.96 \times 10^7$ km$^2$ month) (Figure 4-7).

Models are generally in line with data-based references with regard to the start season of extreme events. Both models and references pointed to the highest frequency of drought (Figure 4-9) or extreme wet event (Figure E-8)
occurring in northern hemisphere summer, while winter has the lowest counts. In line with extreme dry/wet events, most of the GPP reduction (Figure 4-10) or increase (Figure E-9) of extreme events occurred in summer, and least in winter. However, the relative allocations to 4 seasons differ between extreme dry and GPP reduction extreme events (or extreme wet vs. GPP increase extreme events). The relative difference in counts of the start season between summer and winter is smaller in extreme dry conditions compared to GPP reduction extreme events. Reference LAI reduction (Figure 4-11) or increase (Figure E-10) extreme events are most likely to occur in summer, while winter has the least counts. Models generally agree with references, with exceptions, for example BCC has the least counts in autumn, CESM and INMCM4 have the most counts of LAI increase extreme events in spring (Figure 4-11 and Figure E-10).

In models, the mean duration of extreme dry events is 1.61±0.03 months (multi-model mean ± standard deviation), which is not bigger than the average duration of 1.64 month for the reference. However, the mean duration of GPP reduction extreme events in models is 1.69±0.17 months, which is longer than the reference with 1.42 months. Similarly, the mean duration of extreme wet events is 1.62±0.03 months in models, which is not longer than the duration of 1.69 in the data-based reference. However, the mean duration of GPP increase extreme events is 1.74±0.08 months, which is longer than the reference of 1.38 months. For LAI, the average duration between the two referential data sets (GLOBMAP vs. GLASS) varies largely. The mean duration of LAI reduction extreme events is 2.17±0.25 months in models, longer than the duration of 1.52
months for GLOBMAP but shorter than 2.99 months for GLASS. The mean duration of LAI increase extreme events is 2.31±0.30 months in models and again longer than the duration of 1.47 months for GLOBMAP data and 2.70 months for GLASS.

**Response to Soil Moisture Anomalies**

Figure 4-12 shows the highest correlations (among 12 months, averaged among models or observations) between GPP (or LAI) anomalies and surface soil moisture anomalies (SMAs). Remote sensing soil moisture dataset is known to be less robust in densely vegetated area (Dorigo et al., 2010), and I found largely non-significant correlations \((P>0.05)\) between GPP (or LAI) anomalies and SMAs in tropical forests. The multi-model mean highest correlations from GPP are slightly higher than reference in area such as the Southeastern United States, India and Southeastern China. Meanwhile, correlations from the reference are comparable with models over Australia and a large portion of Africa (Figure 4-12). Individually, the highest correlation coefficients vary among models and regions (Figure E-11). Compared to the response to SPI, larger portions of grid cells display negative or weak positive correlations (Figure 4-3, 4-12, E-11). Most of the negative correlations are located in the Northern high latitudes, but this varies among models (Figure 4-3, E-11). Instead of overestimation as found for the LAI-SPI relationship, the multi-model mean highest LAI-SMA correlations are underestimated over a large portion of the land while correlations are significant \((P<0.05)\), such as in the Southeastern United States, Africa, India and Australia. Models vary greatly in the spatial pattern of the highest LAI-SMA
correlations (Figure E-12). While highest correlations from INMCM4 are predominantly positive and strong, MIROC produces negative correlations over a large portion of the global land (Figure E-12).

The inconsistency in responses of leaf area to SMAs compared to SPI is further demonstrated through extreme events. In extreme dry events indicated by SPI, leaf area is reduced in both models and in the data-based reference with cumulative leaf area expressed in negative values (Panel (c), Figure 4-7). However, 3 (GFDL, IPSL, MIROC) out of 9 models show an increase in leaf area (Panel (c), Figure 4-13) during drought as indicated by SMAs. Likewise, 2 (CESM and MIROC) out of 9 models are associated with reductions of leaf area in extreme wet events with SMAs as the indicator (Panel (d), Figure 4-13). The cumulative leaf area changes over 1982-2005 range from an increase of $3.18 \times 10^7$ km$^2$ month to a reduction of $-5.15 \times 10^7$ km$^2$ month during droughts, and from an increase of $10.70 \times 10^7$ km$^2$ month to a reduction of $-5.93 \times 10^7$ km$^2$ month during extreme wet conditions. Reductions of leaf area during droughts are smaller in the observations ($-0.60 \times 10^7$ km$^2$ month from GLOBMAP and $-0.92 \times 10^7$ km$^2$ month from GLASS) compared to models ($-3.23 \pm 1.37 \times 10^7$ km$^2$ month, multi-model mean ± standard deviation). And for increases of leaf area during wet extreme events, GLASS is within the range spanned by models. The overall pattern is similar in the analysis of sensitivity to droughts (total leaf area excursions divided by total volume of extreme dry/wet events) (Figure 4-14). However, GLASS (0.015) shows a much stronger sensitivity to wet extremes than GLOBMAP (0.002) despite the volume of extreme wet events being close
(9.37 vs. 9.10 ×10^8 km^2 month from GLOBMAP and GLASS respectively). The stronger sensitivity for GLASS compared to GLOBMAP stems largely from differences in the means and variances in these two datasets, since the sensitivity is comparable between GLASS and GLOBMAP when leaf area anomalies are expressed in normalized anomalies (Figure E-14). Normalization of leaf area anomalies does not rule out the inconsistent responses of models to extreme soil moisture events. For example, CAN, GFDL, IPSL and MIROC show increases in leaf area during dry anomalies while other models indicate reductions (Figure E-13, E-14).

Modeled GPP reduction during extreme dry events ranges from -0.82 (GFDL) to -25.93 GtC (HAD), which is more severe than the reference of -0.68 GtC (Panel (a), Figure 4-13). Consequently, all of the models have higher sensitivity to drought (range, -1.5 to -19.34 gC m^-2 month^-1) compared to the reference of -1.28 gC m^-2 month^-1 (Panel (a), Figure 4-14). The mean increase in wet extreme events is higher from models, but the enhancement from MTE-GPP is within the 95% confidence interval of models. MTE-GPP shows higher enhancement compared to MIROC and CAN, with CAN showing a slight reduction (-0.6 GtC) (Panel (a), Figure 4-13). When GPP anomalies are expressed as normalized anomalies, mean excursions in carbon budgets or sensitivities are still stronger in models compared to reference (Figure E-13, E-14). However, GFDL and IPSL indicate slight enhancements during droughts instead of reductions.
Discussion

Understanding and modeling the response of vegetation to drought is challenging due to the multifaceted nature of drought and markedly varied sensitivities to drought across land biomes and time-scales. Here I evaluated the drought response of CMIP5 models from various perspectives: the overall correlations between global annual GPP (or LAI) anomalies vs. the drought index SPI across time-scales from 1 month to two years; the maximum correlation and time-scale of maximum response from each grid cell and aggregated regionally or globally; during 3-dimensional (longitude × latitude × time) extreme events; and based on soil moisture drought.

Response to Meteorological Drought

I quantified meteorological drought with SPI. GPP in the CMIP5 models is generally more responsive (or less buffered) to water anomalies than the reference based GPP data. This over-response of modeled GPP compared to observation is in line with findings of Piao et al. (2013) which showed an overestimation of GPP-precipitation relationship in models. However, the overestimation is time-scale dependent, and I found correlations between SPI and GPP are similar at longer time-scales. The over-response also means more vulnerable and less resistant to drought in models compared to observation. The highest correlations between SPI and GPP are also elevated in models compared to the data indicating higher vulnerability to drought in models, with the exception of Northern High Latitudes. Models revealed overall shorter response time-scales to meteorological drought, indicating less resistance and perhaps a lack of mechanisms that alleviate drought impacts. The insufficiency in modeled
drought response time-scale is further confirmed by the difference in arid vs. humid regions. In models, arid regions on average need longer lasting dry condition to exhibit a maximum response (indicated by the time-scale at which the correlation between SPI and GPP is highest) compared to humid regions, while humid regions exhibit a slightly higher resistance in data compared to arid regions. My classification of arid and humid regions is broad, and did not differentiate between arid and semi-arid or humid vs. semi-humid which might obscure the characteristic time-scale of drought response across different biomes. Vicente-Serrano et al. (2013) pointed to the biome dependent time-scale of drought responses, however, direct biome by biome comparison is not possible due to differences in the numbers and types of PFTs simulated in CMIP5 models. Nevertheless, my broad classification of arid vs. humid biomes revealed potential gaps in models in capturing time-scale of drought impacts.

The over-response of GPP to SPI in models is also revealed in the analysis of GPP in extreme dry and wet events (events outside 2 standard deviations from the mean). Previous studies revealed that CMIP5 models tend to overestimate global mean GPP and LAI (Shao et al., 2013), and possibly the magnitude of absolute GPP (or LAI) anomalies. It is possible that the variability of MTE-GPP is underestimated (Jung et al., 2011; Piao et al., 2013). However, the higher GPP reduction in models compared to data persisted even if GPP anomalies were standardized. This suggests that extreme dry/wet events are more likely to produce GPP excursions in models than in data. In addition, the spread of GPP reductions and increases in extreme dry and wet extreme events
is large among models, with a 5.72 times difference in GPP reductions and 4.13 times in GPP increases, respectively. This large spread points to large uncertainties in capturing meteorological drought responses among models.

LAI depends on GPP and the allocation of GPP to leaf, while GPP is regulated by leaf area through the amount of leaf that performs photosynthesis. The strong link between GPP and LAI explains their large similarities in response to water anomalies. For example, similar as GPP, modeled LAI is on average more responsive to SPI compared to reference, indicated by higher mean global annual correlations, higher mean vulnerability over a large area of the global land, stronger mean excursions and sensitivities to extreme dry or wet events. The analysis of LAI-SPI relationship provides complementary evidence to my findings, since sources of referential LAI data are different from GPP. Despite similarities, the global annual correlation and the highest monthly correlation with SPI are weaker for LAI compared to GPP, indicating precipitation anomalies play a less important role in leaf area anomalies. LAI responds to water anomalies on longer time-scale compared to GPP, and is thus more resistant to immediate changes of water. Some differences between LAI and GPP responses are expected since leaf area is constrained by other factors or processes such as the strategy of carbon allocation and leaf phenology, but also lag effects from via leaf turnover. Compared to observations, models produced less resistance of GPP but more resistance of LAI to water anomalies. This discrepancy indicates stronger resistance to droughts in plants in other processes (e.g. leaf longevity or drought deciduousness). However, the markedly different resistant pattern among
individual models revealed lack of agreement in LAI response time-scale derived from models. Further improvement in capturing the drought response of LAI is important in simulating and predicting carbon flux anomalies during droughts.

**Response to Soil Moisture Drought**

GPP and LAI generally respond stronger to meteorological drought in models compared to data. The stronger response to hydrological anomalies in models is less obvious when soil moisture anomalies are used instead of SPI. Drought responses of modeled GPP stem largely from the water stress functions and should also reflect plant water availability. The large spread of the modeled sensitivity of GPP to extreme dry events indicates either a big difference in water stress functions or a large range of modeled soil moisture availability that regulate plant activity, or both. These water stress functions vary in their formulations and parameterizations. Some of them down-regulate the leaf level maximum carboxylation capacity of Rubisco while some scale the potential photosynthetic rate; some of them are based on soil water conditions alone while there is model which also takes into account of the leaf water demand; some of them are parameterized based on soil matrix potential while some are based on volume soil water content (see Appendix A for detailed information). These various forms of water stress functions reflect my limited understanding of the universal mechanism that down-regulate GPP when water is limited. Modeled leaf area responds to SPI coherently with reductions in droughts, but SMAs droughts are associated with both reductions and enhancements in different models. The highest correlations between LAI and SPI are predominantly positive, but some of the models are characterized by highest correlations with
SMAs being negative over a large area of the global land. Divergent responses of modeled LAI to SMAs detected in my study may stem from various processes, such as difference in the representation of surface soil moisture vs. plant available water, soil water stress functions, GPP allocation to leaf biomass, leaf phenology and functions to derive leaf area.

One of the impediments towards mechanistic understanding of vegetation’s drought response is the limitation of knowledge and empirical data on plant available water. While I found an overestimation of the response of vegetation to meteorological drought, Rebel et al. (2012) suggested a possible underestimation of the response of vegetation to drought in ORCHIDEE land surface model based on the slower decrease of root zone soil moisture after rain compared to surface soil moisture derived from remote-sensed AMSR-E (LPRM), with the true plant available moisture remains unknown. Although the strong link between surface and root-zone soil moisture is frequently documented from in-situ measurements (e.g., (Albergel et al., 2008; Rebel et al., 2012; Ford et al., 2014)), it is unclear to what extent soil water anomalies experienced by plants are captured by surface soil moisture anomalies since the variability and availability of soil moisture changes with depth (Hirschi et al., 2014). Root zone water availability is a better proxy of the dry/wet stress experienced by plant, however, observation-based root zone water is not available in large scale. SPI is widely used as a drought indicator and short term SPI has been shown to have good correlations with soil moisture availability/anomaly (Sims et al., 2002; Scaini et al., 2015), but only reflect one side of the multiple processes (e.g., interception,
drainage) regulating soil water dynamics. Remotely sensed soil moisture anomalies have been shown to be in line with SPI at specific locations, and have a high response to precipitation (Scaini et al., 2015). Nevertheless, the inconsistence between evaluation of the response to SPI and SMAs in this study calls for improvement in understanding of plant available water. The over-response of vegetation to meteorological drought in this study may incorporate uncertainties in the treatment of precipitation that ultimately ends up as water that is available for plant uptake.

**Uncertainties**

Results from SPI and SMAs revealed different vegetation response patterns. In fact, responses to SPI alone are afflicted with large uncertainties if errors in meteorological drought quantification and reference datasets are accounted for. I roughly explored the impact of possible errors in SPI on the model-observation comparison. Sensitivity of vegetation to drought is enhanced when errors in the explanatory variable SPI is included. The enhancement is large enough to alter the result of model-observation comparison for short SPI time-scales. Ignoring driver errors in observations can lead to biased result especially when driver errors are large (Lichstein et al., 2014). Considering this error-in-x in SPI put the modeled over-response to SPI into question. Further, results for tropical forest derived from MTE-GPP are less reliable: MTE-GPP is obtained from training the FLUXNET flux tower observations with a large number of sites in temperate ecosystems and few located in the tropics. The satellite FAPAR, based on which flux tower measurements are extrapolated, is subject to contamination by cloud especially in tropical forests. In addition, the confidence
in the interannual variability of MTE-GPP is lower than the mean annual and mean seasonal cycle of GPP (Jung et al., 2011; Piao et al., 2013), thus evaluation of drought response based on longer time-scales is afflicted with larger uncertainties. I use LAI as a complementary variable to evaluate drought response. However, LAI errors cannot be excluded, particularly in tropical forest with the satellite based LAI (Fang et al., 2012). Nevertheless, my result of an over-response to SPI in models is relative robust for some extra-tropical region such as a large portion of Europe without explicit consideration of measurement error derived for SPI.

The referential soil moisture, ECV_SM, also subjects to perturbation by dense vegetation especially in tropical forest (Dorigo et al., 2010; Liu et al., 2011). ECV_SM has more missing data gaps compared to models and other references. It is unclear to what extent responses are affected by data gaps. ECV_SM is known to be afflicted with errors but difficult to quantify. In addition to uncertainties mentioned above, various sources such as model implementations of disturbance regimes (e.g., land use change and fire), model resolution and regridding method, contribute to uncertainties in drought response of vegetation and need to be treated with caution.

**Implications for Future Studies**

An important application of this study is to identify knowledge gaps and facilitate model improvement with regard to vegetation’s drought response. Several implications can be drawn from this study. First, multiple perspective evaluation is helpful in providing a thorough picture on the performance of modeled vegetation’s drought response. Drought is a complex phenomenon and
drought impacts are complicated. Although modeled GPP is more sensitive to short-term meteorological drought, the over-sensitivity does not hold for long-term meteorological drought. Although modeled LAI is more responsive to meteorological drought, the over-response is not true based on soil moisture drought. Therefore, single point evaluation of model’s response to drought might be misleading. Second, further new efforts are required to improve mechanistic understandings of how water stress affect vegetation’s activity. Models vary in their water stress functions which may result in difference in model performance. Third, more focus need to be put on LAI. I found distinct response pattern of LAI among individual models, such as the time-scale of highest correlations (SPI), the highest correlations with SMAs, the cumulative changes and sensitivities to extreme SMAs events. Since LAI is a common parameter that upscale leaf level productivity to the ecosystem level, accurate simulation of LAI response is beneficial for carbon cycling studies. Finally, empirical global dataset with low uncertainty is essential in benchmarking models and identifying model insufficiency. Observation datasets are afflicted with uncertainties which might mislead the evaluation of model’s performance and should be taken into account in future studies. Especially important and urgent is the generation of the global dataset of plant available water. It is unclear from my study whether models are more sensitive to drought or not compared to observation since SPI and SMAs pointed to different answers. While SPI and SMAs are commonly used but indirect indicators of water stress faced by plants, the empirical based plant
available water dataset is important to reveal the actual water stress that regulate vegetation’s response and identify model’s performance.

Conclusions

I compared drought responses of vegetation activities derived from 9 CMIP5 models with observations based on meteorological drought index SPI and surface soil moisture anomalies (SMAs). The less buffered or over response of vegetation to SPI from models is demonstrated through higher mean global annual correlation, higher reduction/increase in extreme events, higher vulnerability and lower resilience for both GPP and LAI, despite patterns are less consistent between GPP and LAI for time related indicator. However, the over response from models is less obvious based on surface SMAs for GPP and even in contradictory when it comes to leaf area. The inconsistency comes partly from limitations of SPI and surface SMAs in reflecting water stress experienced by plants. In addition, potential errors in referential SPI, SMAs as well as GPP and LAI contribute to the uncertainties in derived referential drought response and model-data comparison.
Table 4-1. CMIP5 models used with complete model expansions

<table>
<thead>
<tr>
<th>Models</th>
<th>Model expansion</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Earth system models</strong></td>
<td></td>
</tr>
<tr>
<td>BCC-CSM1.1</td>
<td>Beijing Climate Center, Climate System Model version 1.1</td>
</tr>
<tr>
<td>CanESM2</td>
<td>Second Generation Canadian Earth System Model</td>
</tr>
<tr>
<td>CESM1-BGC</td>
<td>Community Earth System Model, version 1.0-Biogeochemistry</td>
</tr>
<tr>
<td>GFDL-ESM2G</td>
<td>Geophysical Fluid Dynamics Laboratory Earth System Model with GOLD ocean component (ESM2G)</td>
</tr>
<tr>
<td>HadGEM2-ES</td>
<td>Hadley Centre Global Environmental Model, version 2 (Earth System)</td>
</tr>
<tr>
<td>INM-CM4.0</td>
<td>Institute of Numerical Mathematics Coupled Model, version 4.0</td>
</tr>
<tr>
<td>IPSL-CM5A-LR</td>
<td>L’Institut Pierre-Simon Laplace Coupled Model, version 5A, coupled with NEMO, low resolution</td>
</tr>
<tr>
<td>MIROC-ESM</td>
<td>Model for Interdisciplinary Research on Climate, Earth System Model</td>
</tr>
<tr>
<td>NorESM1-ME</td>
<td>Norwegian Earth System Model, version 1 (intermediate resolution)</td>
</tr>
<tr>
<td><strong>Land surface models or vegetation models</strong></td>
<td></td>
</tr>
<tr>
<td>BCC-AVIM1.0</td>
<td>Beijing Climate Center Atmosphere Vegetation Interaction Model Version 1.0</td>
</tr>
<tr>
<td>CLASS</td>
<td>Canadian Land Surface Scheme</td>
</tr>
<tr>
<td>CTEM</td>
<td>Canadian Terrestrial Ecosystem Model</td>
</tr>
<tr>
<td>CLM4</td>
<td>Community Land Model, version 4</td>
</tr>
<tr>
<td>CLM4CN</td>
<td>Community Land Model, version 4, with the Coupled Carbon–Nitrogen Cycle</td>
</tr>
<tr>
<td>LM3</td>
<td>Land Model, version 3</td>
</tr>
<tr>
<td>LM3V</td>
<td>Land Model, version 3, with Vegetation and Carbon Cycling</td>
</tr>
<tr>
<td>JULES</td>
<td>Joint United Kingdom Land Environment Simulator</td>
</tr>
<tr>
<td>TRIFFID</td>
<td>Top-down Representation of Interactive Foliage and Flora Including Dynamics</td>
</tr>
<tr>
<td>LSM</td>
<td>Land Surface Model</td>
</tr>
<tr>
<td>ORCHIDEE</td>
<td>Organizing Carbon and Hydrology in Dynamic Ecosystems</td>
</tr>
<tr>
<td>MATSIRO</td>
<td>Minimal Advanced Treatments of Surface Interaction and Runoff</td>
</tr>
<tr>
<td>SEIB-DGVM</td>
<td>Spatially Explicit Individual-Based Dynamic Global Vegetation Model</td>
</tr>
</tbody>
</table>
Table 4-2. Primary characteristic of the land carbon cycle component of the 9 participating models in this study. DGVM refers to the dynamic change of vegetation coverage with plant competition; No. PFTs stands for the number of plant functional types implemented in models; No. soil layers refers to the number of soil layers.

<table>
<thead>
<tr>
<th>ESMs</th>
<th>BCC_CSM1</th>
<th>CanESM</th>
<th>CESM1-BGC</th>
<th>GFDL_ESM2G</th>
<th>HadGEM2-ES</th>
<th>INM-CM4.0</th>
<th>IPSL-CM5A-LR</th>
<th>MIROC-ESM</th>
<th>NorESM1-ME</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abbreviation</td>
<td>BCC</td>
<td>CAN</td>
<td>CESM</td>
<td>GFDL</td>
<td>HAD</td>
<td>INMCM4</td>
<td>IPSL</td>
<td>MIROC</td>
<td>NOR</td>
</tr>
<tr>
<td>Land model</td>
<td>BCCAVIM1.0</td>
<td>CLASS</td>
<td>CLM4</td>
<td>LM3</td>
<td>JULES</td>
<td>LSM</td>
<td>ORCHIDEE</td>
<td>MATSIRO</td>
<td>CLM4</td>
</tr>
<tr>
<td>Vegetation model</td>
<td>CTEM</td>
<td>CLM4CN</td>
<td>LM3V</td>
<td>TRIFFID</td>
<td>-</td>
<td>-</td>
<td>SEIB-DGVM</td>
<td>CLM4CN</td>
<td></td>
</tr>
<tr>
<td>DGVM</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>N cycle</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>No. PFTs</td>
<td>15</td>
<td>9</td>
<td>15</td>
<td>5</td>
<td>11</td>
<td>13</td>
<td>13</td>
<td>15</td>
<td></td>
</tr>
<tr>
<td>No. soil layers</td>
<td>10</td>
<td>3</td>
<td>15</td>
<td>20</td>
<td>4</td>
<td>23</td>
<td>7</td>
<td>6</td>
<td>15</td>
</tr>
<tr>
<td>Soil depth</td>
<td>3.4</td>
<td>4.1</td>
<td>43.7</td>
<td>10</td>
<td>3</td>
<td>15</td>
<td>3.9</td>
<td>14</td>
<td>43.7</td>
</tr>
<tr>
<td>Fire</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Human activities</td>
<td>Crop</td>
<td>Crop</td>
<td>Crop, pasture, wood harvest</td>
<td>Crop, pasture, wood harvest</td>
<td>Deforestation</td>
<td>Crop, pasture</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Land use emissions</td>
<td>Prescribed</td>
<td>Computed</td>
<td>Computed</td>
<td>Computed</td>
<td>Prescribed</td>
<td>Computed</td>
<td>Computed</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Resolution (lat×lon)</td>
<td>2.8°×2.8°</td>
<td>2.8°×2.8°</td>
<td>0.9°×1.3°</td>
<td>2.0°×2.5°</td>
<td>1.3°×1.9°</td>
<td>1.5°×2°</td>
<td>1.9°×3.8°</td>
<td>2.8°×2.8°</td>
<td>0.9°×1.3°</td>
</tr>
<tr>
<td>Reference</td>
<td>(Wu et al., 2013; Ji et al., 2008)</td>
<td>(Arora and Boer, 2010)</td>
<td>(Gent et al., 2011; Thornton et al., 2002)</td>
<td>(Dunne et al., 2012; Shevliakova et al., 2009)</td>
<td>(Cox, 2001; Jones et al., 2010; Bona n, 1996)</td>
<td>(Volodin et al., 2001; Bonna ni et al., 2005; Dufres ne et al., 2013)</td>
<td>(Krinner et al., 2005; Watane be et al., 2011)</td>
<td>(Sato et al., 2007; Watanes be et al., 2002; Tjiput ra et al., 2013)</td>
<td></td>
</tr>
</tbody>
</table>
Table 4-3. Observational data used for CMIP5 model evaluations. GPP stands for gross primary production; LAI refers to leaf area index; PRE refers to precipitation and SM stands for soil moisture.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Temporal resolution</th>
<th>Spatial resolution</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>MTE_GPP</td>
<td>Monthly, 1982-2011</td>
<td>0.5°×0.5°</td>
<td>(Jung et al., 2011)</td>
</tr>
<tr>
<td>GLASS_LAI</td>
<td>8 day, 1981-2012</td>
<td>0.05°×0.05°</td>
<td>(Liang and Xiao, 2012; Xiao et al., 2014)</td>
</tr>
<tr>
<td>GLOBMAP_LAI</td>
<td>Half month/8 day,</td>
<td>0.07°×0.07°</td>
<td>(Liu et al., 2012)</td>
</tr>
<tr>
<td></td>
<td>1981-2011</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CRU_PRE</td>
<td>Monthly 1901-2012</td>
<td>0.5°×0.5°</td>
<td>(Jones and Harris, 2013)</td>
</tr>
<tr>
<td>DELA_PRE</td>
<td>Monthly 1901-2010</td>
<td>0.5°×0.5°</td>
<td>(Willmott, 2012)</td>
</tr>
<tr>
<td>GPCP_PRE</td>
<td>Monthly, 1979-current</td>
<td>2.5°×2.5°</td>
<td>(Adler et al., 2003)</td>
</tr>
<tr>
<td>GPCC_PRE</td>
<td>Monthly 1901-2010</td>
<td>0.5°×0.5°</td>
<td>(Schneider et al., 2011)</td>
</tr>
<tr>
<td>ECV_SM</td>
<td>Daily, 1978 to 2013</td>
<td>0.05°×0.05°</td>
<td>(Liu et al., 2011)</td>
</tr>
</tbody>
</table>
Figure 4-1. Pearson correlation coefficients between detrended global annual GPP (or LAI) and the Standardized Precipitation Index (SPI) over 1982-2005. X axes are SPI timescales indicating drought severity at different temporal scales (1-24 months). Black dots represent result from CMIP5 models (multi-model mean) and red dots from observations. Shaded areas correspond to the 95% confidence limits among models (9 in total) or for the data-based LAI responses (8 in total, 2 LAI datasets by 4 precipitation datasets).
Figure 4-2. GPP and LAI responses to SPI. Model Mean (filled in blue) indicates GPP (or LAI) responses with the multi-model mean ordinary least squares regression slope from 9 CMIP5 models; OLS (filled in red or green) indicates the ordinary least squares regression slope from the reference; Base, 50%Plus and 50%Minus are slopes of reference estimated from the measurement error model (MEM). The error of SPI is estimated as the standard deviation of the mean annual SPI among the 4 precipitation derived SPIs. To increase the robustness of the analysis, the error estimated above (Base) is enlarged by 50% (50%Plus) and reduced by 50% (50%Minus), respectively. For GPP (left panel), the reference is MTE-GPP, and for LAI (right panel), reference are from GLASS and GLOBAMP Results are shown for SPI with 1-month (SPI1) time-scales.
Figure 4-3. Spatial map of the highest correlations obtained from 288 (at most, 24 SPI time-scales by 12 months per year) possible statistically significant correlation coefficients ($P<0.05$) between GPP (or LAI) anomalies and SPI. Shown are averages among models or observations.
Figure 4-4. Global average of the highest correlations and the SPI time-scales (in months) at which the highest correlations are obtained. Highest correlations are chosen from 288 (at most, 24 SPI time-scales by 12 months per year) possible statistically significant correlation coefficients ($P<0.05$) between GPP (or LAI) anomalies and SPI for each grid cell. Shown are means and 95% confidence limits among 9 global averages for models or 8 (2 LAI datasets by 4 precipitation datasets) for the referential LAI responses. For the referential GPP, only 1 dataset is used. Therefore, results are shown for only global averages.
Figure 4-5. Arid and humid regional averages of the highest correlations and the SPI time-scales (in months) at which the highest correlations are obtained. Highest correlations are chosen from 288 (at most, 24 SPI time-scales by 12 months per year) possible statistically significant correlation coefficients ($P<0.05$) between GPP (or LAI) anomalies and SPI for each grid cell. Shown are means and 95 confidence limits among 9 global averages for models or 8 (2 LAI datasets by 4 precipitation datasets) for the referential LAI responses. For the referential GPP, only 1 dataset is used. Therefore, results are shown for only global averages. The differentiation between arid vs. humid regions is based on the Köppen-Geiger climate classification (Kottek et al., 2006), and details is provided in supplementary Figure 4-1.
Figure 4-6. SPI time-scales (in months) at which the highest correlations in Figure 4-3 are obtained. Shown are averages among models or observations.
Figure 4-7. Cumulative GPP (or leaf area) reductions and increases during extreme dry and wet events, respectively. Extreme dry events are 3-dimensional (latitude × longitude × time) voxel spanned from adjacent single dry extreme (SPI < -2). Likewise, extreme wet events are spanned from single wet extreme with SPI > 2. For each panel, in-box lines show the cumulative values from the largest 760 extreme events and the outside lines indicate the total. Error bars and dots correspond to the 95% confidence intervals and means among models (blue) or references (red). Solid lines are based on models and dashed lines based on observations.
Figure 4-8. Sensitivities of GPP (top) and leaf area (bottom) reductions and increases to the total volume of extreme dry and wet events, respectively. Positive values in dry indicate reduction and in wet indicate increases. Color filled bars are from models and lined bars from observations. Error bars and dots correspond to the 95% confidence intervals and means among models (blue) or observations (red).
Figure 4-9. Counts of the start season of extreme dry events (1982-2005). Panels with black titles are from models, and red from reference. Different colors represent categories of the length of extreme dry events.
Figure 4-10. Counts of the start season of extreme reduction events of GPP (1982-2005). Panels with black titles are from models, and red from reference. Different colors represent the length categories of extreme reduction events.
Figure 4-11. Counts of the start season of extreme reduction events of LAI (1982-2005). Panels with black titles are from models, and red from reference. Different colors represent length categories of extreme reduction events.
Figure 4-12. Spatial distribution of the highest correlations between GPP (or LAI) anomalies and surface soil moisture anomalies (SMAs). The highest correlation is derived from the 12 possible statistically significant ($P<0.05$) correlation coefficients (one for each month within a year).
Figure 4-13. Cumulative reductions or increases of GPP and LAI in surface soil moisture anomalies (SMAs). The difference from Figure 4-7 is that the dry extreme is defined with surface soil moisture anomalies (SMAs) smaller than -2, and wet extreme with SMAs bigger than 2. Negative values indicate reductions and positive values mean increases. Solid lines are from models and dashed lines from observations. Error bars and dots correspond to the 95% confidence intervals and means among models (blue) or references (red).
Figure 4-14. Sensitivities of GPP (or leaf area) to the total volume of extreme dry and wet events. The difference from Figure 4-8 is that the dry extreme is defined with surface soil moisture anomalies (SMAs) smaller than -2, and wet extreme with SMAs bigger than 2. Positive values in dry indicate reduction and in wet indicate increases. Color filled bars are from models and lined bars from observations. Error bars and dots correspond to the 95% confidence intervals and means among models (blue) or references (red).
CHAPTER 5
NITROGEN RESTRICTIONS BUFFER MODELED INTERACTIONS OF WATER WITH THE CARBON CYCLE

Introduction

Climate extremes such as droughts, intense rainfall events, or heat waves can substantially alter regional or global carbon cycle (Reichstein et al., 2013; Keenan et al., 2012). Zscheischler et al. (2014a) showed the dominant role of extreme events in the interannual variability in gross primary productivity (GPP), with most of the negative GPP extremes over the period of 1982-2011 being attributable to water scarcity. Drought has significant impacts (mostly negative) on terrestrial ecosystems, which have been intensively investigated in recent years through observation (e.g. FLUXNET), remote sensing, and terrestrial biosphere models (TBMs). By analyzing the FLUXNET data, Schwalm et al. (2010) found that GPP is more sensitive to drought events than ecosystem respiration, which is in line with other modeling and synthesis studies (Shi et al., 2014; Zscheischler et al., 2014b). Zhao and Running (2010) suggested a global declining net primary productivity (NPP) trend over 2000-2009 due to drought induced reduction of NPP in the Southern Hemisphere, although the approach applied to derive NPP from satellite products has been questioned (Medlyn, 2011; Samanta et al., 2011). Several TBMs have been applied to assess the impact of droughts on ecosystem primary productivity for North America (Chen et al., 2012), Amazonia (Potter et al., 2011), Europe (Ciais et al., 2005; Reichstein et al., 2007; Vetter et al., 2008), Asia (Liu et al., 2014; Xiao et al., 2009), and the globe (Chen et al., 2013; Zscheischler et al., 2014b). These models generally revealed the negative effect of moisture scarcity on primary productivity, although
non-significant or positive correlations are possible in certain regions (Chen et al., 2013).

Capturing the mechanisms of how the terrestrial carbon cycle responds to changes in precipitation and the hydrologic cycle at the continental to global scale remains a challenge for TBMs (Moyano et al., 2013; Piao et al., 2013; Carvalhais et al., 2014; Powell et al., 2013). For example, results from the most recent Coupled Model Intercomparison Project, CMIP5, generally do not successfully reproduce the observation-based strong relationships between terrestrial carbon turnover and precipitation and predict faster turnover in many semiarid areas (Carvalhais et al., 2014), while 9 out of 10 TBMs from another study are reported to be oversensitive to precipitation compared to the slope of the observed residue land sink (RLS) vs. precipitation (Piao et al., 2013).

Water constraints on plant growth also have the potential to interact with nutrient limitation. Nutrients were considered only in a few CMIP5 simulations, but C-N interactions are now incorporated in a number of TBMs (Sokolov et al., 2008; Xu and Prentice, 2008; Thornton et al., 2009; Jain et al., 2013; Gerber et al., 2010; Zaehle and Friend, 2010; Churkina et al., 2009). In these models, nutrients can limit carbon uptake during times of otherwise favorable growth conditions (Thomas et al., 2015). Further, the downregulation of photosynthesis by nitrogen limitation can potentially alter evapotranspiration (ET) directly via stomatal conductance, possibly reducing ET losses of water from soils (Lee et al., 2013; Gerber et al., 2010; Thomas et al., 2015), or indirectly via a reduced biomass with smaller vegetation size and reduced plant water demand.
resulting alteration in soil moisture has the potential to feed back into the carbon cycle because of corresponding changes in plant growth (Huxman et al., 2004; Ponce Campos et al., 2013), decomposition of organic matter and mineralization of soil nitrogen (Stanford and Epstein, 1974), nitrification and denitrification (Emmett et al., 2004), nitrogen leaching (Gordon et al., 2008), thereby also affecting future levels of N availability.

Using LMV3-N, a global TBM with coupled carbon-nitrogen cycle, I investigate how the additional limitation posed by nitrogen affects the response to water anomalies. I determine the water anomalies based on the standardized precipitation evapotranspiration index (SPEI), such that dryness is represented relative to local means and variances. In this paper, I focus my analysis on 3 major carbon flux variables, namely NPP, heterotrophic respiration \((R_h)\) and net ecosystem productivity \((NEP, \text{the difference between NPP and } R_h)\), and juxtapose model simulations that include nitrogen interactions \((C-N)\) and simulations that do not \((C-ONLY)\).

**Methods**

**Model Description and Simulations**

The coupled land surface model LM3V/LM3V-N is described in Chapter 1 and Appendix A and B with the soil N\(_2\)O emission module described in Chapter 2. In the coupled mode, N availability feeds back onto plant productivity by mechanisms that lead to down-regulation of photosynthesis when the projected long-term (ca. annual) carbon stoichiometry cannot be met. A further, though less pronounced feedback is occurring in soil where litter decomposition elevated but stabilization of organic matter is lower at increased levels of mineral N forms.
Here, I ran the model with (C-N) and without (C-ONLY) nitrogen having an effect on carbon cycles, on a spatial resolution of 3.75 degrees latitude and 2.5 degree longitude. Both of the C-ONLY and C-N were forced by the 3 hourly reanalysis meteorological data (Sheffield et al., 2006). A 17 year climate data of 1948-1964 was repeated for the spin-up and simulations before 1948. Atmospheric CO$_2$ level was set at 284 ppm for spin-up and based on instrumental measurements for transient runs (Keeling et al., 2009). Spatially explicit nitrogen deposition was prescribed as natural background for simulations prior to 1850 (Dentener and Crutzen, 1994b), and interpolated linearly between the natural background and current levels (Dentener et al., 2006) for simulations after 1850.

In the C-ONLY configuration, the model was spun up from bare ground to develop the potential vegetation and carbon stocks for 800 years. In the C-N configuration, the spin-up started from bare ground without C-N interactions for the first 68 years and then included C-N coupling for the subsequent 1200 years to develop and equilibrate carbon and nitrogen pools. To speed up the spin-up process in both C-ONLY and C-N, slow litter and slow soil carbon and nitrogen stocks were set to the steady state values every 17 years based on litterfall, decomposition and dissolved organic leaching rates. Simulations were considered to reach the quasi-equilibrium state if a drift of the total global carbon stock was less than 0.03 PgC yr$^{-1}$ and the global nitrogen stock was less than 0.2 TgN yr$^{-1}$. Subsequent historical runs starting from 1850 were initialized from the quasi-equilibrium state using the corresponding climatic forcing, CO$_2$ and N
deposition. Model outputs over the period of 1950-2005 were used for the following analysis.

**Drought Index, SPEI**

Drought indices can quantitatively describe the characteristic of water anomalies. A variety of drought indices have been developed with different emphases on the multifaceted extreme dry/wet conditions. I chose the standardized precipitation evapotranspiration index (SPEI) (Vicente-Serrano et al., 2010). SPEI combines features from two of the mostly widely used indices: the Palmer drought severity index (PDSI) (Palmer, 1965) and the standardized precipitation index (SPI) (McKee et al., 1993). PDSI is based on the soil water balance that considers soil water holding capacity and anomalies of water supply (precipitation), demand (potential evapotranspiration) and loss (runoff), while SPI relies solely on precipitation, but is typically calculated at multiple temporal scales. SPEI takes advantage of the multi-temporal characteristic of SPI and the sensitivity of the PDSI to changes in evapotranspiration demand (with the role of temperature) in addition to precipitation.

I based the SPEI calculation on monthly precipitation (PR) and potential evapotranspiration (PET) using R 3.0.1 with the SPEI package (Beguería and Vicente-Serrano, 2013). I performed SPEI calculations on the same climatological data that was used to drive the model. I estimate PET data based on the Penman-Monteith method, following the description in Sheffield et al. (2012), who showed the importance of physical based PET in deriving drought indices. SPEIs can be obtained for different time-scales representing the
cumulative water balance over the previous months. The difference between PR and PET was calculated for each grid cell and month \(j\) following:

\[
D^k_j = \sum_{i=0}^{k-1} (PR_{j,i} - PET_{j,i}), \quad j \geq k
\]  

(5-1)

where \(D^k_j\) is the difference over a timescale \(k\) (in months). \(D\) series for each grid cell were then fitted by a log-logistic distribution function according to Vicente-Serrano et al. (2010) as the best distribution function given by

\[
F(x) = \left[1 + \left(\frac{x-\gamma}{\alpha}\right)^\beta\right]^{-1}
\]  

(5-2)

where \(\alpha\), \(\beta\), and \(\gamma\) are parameters indicating scale, shape and origin (Vicente-Serrano et al., 2010; Chen et al., 2013). SPEI is then obtained by standardizing \(F(x)\), with mean and standard deviation of 0 and 1, respectively.

**Comparison of Model Results**

I calculated the global correspondence between carbon flux anomalies and the SPEI index over timescales from \(k=1\) to 24 months for the period 1950-2005. Carbon flux anomalies investigated were net primary productivity (NPP), heterotrophic respiration (\(R_h\)) and net ecosystem productivity (NEP, the difference between NPP and \(R_h\)). I calculated anomalies by first determining the global annual means of SPEI, NPP, \(R_h\) and NEP and removed the linear trend from each of these time series. Pearson correlation coefficient is used to quantify the correlation between carbon flux anomalies (NPP, \(R_h\) and NEP) and the SPEI index anomalies for each SPEI time scale (24 in total) at the global scale for both C-ONLY and C-N.

To understand the spatial pattern of carbon fluxes in response to water anomalies, I first removed the linear trend and the mean annual cycle, and
normalized the carbon flux variables to obtain the carbon flux anomalies at each grid cell. I then separated each carbon flux anomaly into 12 series (one per month) and correlated each series with 1- to 24-month SPEI. For each grid cell and each carbon flux variable, I obtained at most 288 (24 SPEI time-scales by 12 months per year) correlation values that were statistically significant ($P<0.05$). I then obtained the highest monthly correlation coefficient for each grid cell (Vicente-Serrano et al., 2013). I further divided the land surface into different zones and focused on 12 regions (Figure F-6) based on the main climates and the precipitation/temperature regimes according to the Köppen-Geiger climate classification (Kottek et al., 2006).

To separate dry and wet responses, I first defined climate extreme events (extreme dry and extreme wet). At the grid cell scale, I define a single dry extreme with SPEI smaller than -2 or wet extreme with SPEI bigger than 2; recall that SPEIs are anomalies with 0 mean and 1 standard deviation. The SPEI time-scales typically used are 1-, 3-, 6-, 12- and 24-month (Chen et al., 2013). In my analysis of extreme events, I focus on the 3-month SPEI which can be considered as a short term drought index and is a common temporal scale in drought assessment (Zscheischler et al., 2014b; Chen et al., 2013; Begueria et al., 2010). The thresholds of 2 and -2 are also widely chosen for other drought studies (Lloyd-Hughes, 2012; Zscheischler et al., 2014b). I aggregated extremes that are adjacent in space and time into voxels (3 dimensional, longitude × latitude × time ) following Lloyd-Hughes (2012) and Zscheischler et al. (2014b). By adjacent, I refer to the 26 neighbors in a 3×3×3 (longitude × latitude × time)
cube excluding the central cell at a given time. The size of an extreme event is the integration of SPEIs over the spatiotemporal domain of that event.

In the forward analysis, I calculated the responses to extreme dry/wet events by integrating carbon flux anomalies (NPP, Rₙ and NEP) over the spatiotemporal domain of an extreme event for C-ONLY and C-N respectively. Following the suggestion of Zscheischler et al. (2013), carbon flux anomalies for each grid cell and each model configuration were obtained from subtracting the linear trend and mean annual cycle. To test the robustness of my results, I also analyzed the case with the detrended variables normalized to zero mean and one standard deviation at each grid cell. I applied two normalization schemes: one by the combined results of the C-ONLY and C-N model configuration; and the other by the individual standard deviation of each model configuration. Without normalization, I obtain absolute flux anomalies (in unit of GtC). While normalization by the individual model standard deviation may be suitable to analyze the anomalies in individual model configuration (C-N or C-ONLY), it makes it difficult to compare the configurations against each other.

To explore the contributions of water anomalies to carbon flux anomalies, I conducted backward analysis by computing the SPEIs across the spatiotemporal domain spanned by an extreme event in carbon fluxes (NPP, Rₙ and NEP), similar as Zscheischler et al. (2014b). I define a single negative (reduction) extreme in carbon fluxes with the carbon flux anomalies (the same as the forward analysis that normalized to a common standard deviation) smaller than -2 or a positive (increase) extreme with carbon flux anomalies bigger than 2. I also used
two thresholds for extreme events (1.5, or 2.5 x standard deviation) to test the
sensitivity of the backward analysis to looser or tighter criteria of extreme carbon
flux event. Similar as in the forward analysis, I further test the robustness of the
result with carbon flux anomalies normalized to the individual standard deviation
of each model configuration. I aggregated point scale extremes into extreme
events into 3 dimensional voxels by the same scheme applied in the forward
analysis. I then integrated the SPEIs over the spatiotemporal domain (the size of
the voxel) for each carbon flux extreme event. In an additional analysis I
calculated the integrated SPEIs of the 100 largest positive/negative spatio-
temporal carbon flux anomalies and fitted the density distribution with a Gaussian
fit.

Results

Global Mean Correlations between Annual Carbon Fluxes and SPEI

Figure 5-1 shows that on a global scale, correlations between detrended
carbon fluxes and SPEIs on timescales from 1 to 24 months. Overall, the
correlations between carbon flux anomalies and SPEIs are weaker in the C-N
model configuration (circles in Figure 5-1) compared to C-ONLY (squares). A
smaller correlation coefficient indicates the smaller sensitivity of carbon fluxes to
water anomalies. The higher sensitivity of production compared to respiration
over short timescales is in line with previous observational and modeling studies
(Schwalm et al., 2010; Shi et al., 2014). However, correlations between NPP and
SPEI diminish, whereas the sensitivity of Rₙ increases as the timescale of SPEI
increases. As a consequence, Rₙ is more sensitive relative to production (NPP)
on the longest, 24-month timescale. NEP-SPEI correlations decrease with
increasing SPEI timescales following the pattern of NPP. This indicates that on a global scale the response to moisture anomaly might be stronger tied to variability in NPP as opposed to $R_h$.

**Spatial Pattern of Correlations between Monthly Carbon Fluxes and SPEI**

Next, I explored the spatial pattern of carbon flux anomalies in response to water anomalies. Figure 5-2 shows the highest correlation coefficients between simulated monthly carbon fluxes and SPEIs over the period 1950-2005 for each grid cell based on C-ONLY (left side of the Figure 5-2), and the differences compared to C-N (right hand of Figure 5-2, excluding grid cells with the highest correlations being negative in the left side). The values represent the maximum correlations, among the 288 possible combinations of SPEI index and month. Without nitrogen constraints (C-ONLY), the correlation maxima of NPP-SPEI and NEP-SPEI are overall positive and strong, indicating high dependence of vegetation activity on water availability at least during certain periods of a year (Figure 5-2a and e). The overall global positive maximum responses do not exclude negative correlations in individual gridcells in the northern high latitudes and humid regions such as the Amazonia and the islands of Southeast Asia (Figure 5-2a and e). $R_h$ displays both positive and negative highest correlations with SPEI (Figure 5-2c), with positive correlations over much of Northern Asia and North America polewards of 50 degree. And tropical responses are inconsistent with the maximum correlations being negative and positive in humid and in dryer systems. Across all timescales and months, typically less than 50% of the correlations between NPP and SPEI are positive, with most of the positive
relationships occurring in temperate and subtropical and seasonally wet tropical regions (Figure F-1, left side).

The overall positive maximum correlation between NPP and SPEI is maintained in C-N, but C-N interactions significantly reduce the highest positive response of NPP to drought in the equatorial summer dry (Köppen-Geiger class Aw in Table 5-1, $P<0.001$), arid steppe (BS in Table 5-1, $P<0.001$), humid temperate (Cf in Table 5-1, $P<0.001$), boreal humid (Df in Table 5-1, $P<0.001$) and boreal winter dry (Dw in Table 5-1, $P<0.05$), which are regions where N limitations are common. No strong difference can be detected for tropical humid and monsoonal forests (Af and Am in Table 5-1) primarily due to the strong fixation responses counteracting N restrictions in LM3V-N. N constraints increase the maximum correlations with SPEI in the summer dry boreal ecosystems (Ds in Table 5-1) and polar tundra (ET in Table 5-1), though the increases are not statistically significant ($P>0.05$). Nitrogen coupling results in a similar pattern for NEP (Figure 5-2b, f, Table 5-1), despite differences in local responses. For gridcells where the maximum correlations are positive, the difference in the highest correlation for $R_h$ is small, with a global mean difference of 0.008 (C-ONLY minus C-N, $P<0.001$). Significant reductions in correlations by nitrogen constraints for $R_h$ are found in tropical humid region (Af in Table 5-1, $P<0.05$), the arid steppe (BS in Table 5-1, $P<0.001$), humid temperate region (Cf in Table 5-1, $P<0.05$), while increase in the correlations from C-ONLY to C-N appears in the humid boreal ecosystem (Df in Table 5-1, $P<0.05$). The fractions of correlations that are positive ($P<0.05$) across the 288 SPEI timescales-month combinations
are significantly ($P<0.001$) reduced in C-N at the global scale (global mean difference of 0.02), despite smaller for $R_h$-SPEI relationship to begin with. In comparison the fraction of positive correlation reduces by 0.04 globally from C-ONLY to C-N for both NPP and NEP (Figure F-1). An additional analysis which instead of the maximum across 288 month-timescale combinations takes into account the highest absolute correlation generally reproduces the regional pattern for NPP (Table F-1 and Figure F-2). However, the difference (C-ONLY minus C-N) turns into small negative and non-significant at the global scale for $R_h$ ($P >0.05$), and both the signs and magnitudes are altered across several regions (Table F-1 and Figure F-2).

**Forward and Backward Analysis of Extreme Events**

Extreme dry conditions at the 3 months timescale (3-month SPEI<-2, and evaluated as integrals over time and space) are associated with both positive and negative NPP (Figure 5-3a), $R_h$ (Figure 5-3b) and NEP (Figure 5-3c) anomalies. Extreme dry conditions lead to an overall reduction in NPP, as evidenced by stronger negative anomalies, and more events displaying a negative response of NPP to drought. Deviations of NPP anomalies from the 1:1 line (C-ONLY vs. C-N, Figure 5-3a, red) reveal a smaller response of NPP to drought in C-N compared to the C-ONLY configuration under dry conditions. On the other hand, extreme wet conditions (3-month SPEI >2) are more likely to enhance NPP in both C-ONLY and C-N, although there are cases of negative NPP anomalies (Figure 5-3d). Compared to C-ONLY, the enhancement of NPP is dampened in C-N with most of the points falling below the 1:1 line when anomalies in C-ONLY are positive (right side of the vertical zero line). Dry
extreme events are more likely to increase $R_h$ (Figure 5-3b), and the magnitude of increases is damped when nitrogen interactions are considered (the majority of points below the 1:1 line). Wet extremes can both reduce and increase $R_h$, but the magnitude of changes is again dampened by the nitrogen component (Figure 5-3e). NEP, as the difference between NPP and $R_h$, follows largely the patterns of NPP, again showing smaller sensitivity to moisture anomalies in C-N compared to C-ONLY. Patterns are similar if carbon flux anomalies are normalized by the common standard deviation (Figure F-3). Responses of NPP and NEP to dry and wet events show similar patterns if normalized by individual standard deviation, although the differences between C-ONLY and C-N become weak, especially for $R_h$ (Figure F-4).

In the backward analysis I chose the 100 strongest carbon flux extreme event voxels and determined the corresponding area-weighted SPEIs. NPP reductions are more likely to be associated with dry conditions, with the means of the SPEIs in the 100 largest events less than 0 for both C-ONLY (Figure 5-4a, blue) and C-N (Figure 5-4a, red). The distribution of SPEIs in C-ONLY in NPP reduction events shift to the drier end compared to that of C-N, indicating NPP anomalies are less affected by droughts, or attributed to mechanisms other than droughts in C-N. Similarly, positive NPP extremes (NPP increase events, Figure 5-4d) are more likely to be associated with wet conditions. The distribution of the SPEIs in C-ONLY in high NPP events shifts to the wetter end compared to that of C-N, indicating that in the C-N configuration NPP anomalies are less affected by the extreme wet conditions, or high NPP is more likely to be caused by another
factor instead of water availability. NEP follows largely the pattern of NPP (Figure 5-4a,c,b,d). Patterns of NPP and NEP hold when fluxes are normalized by their individual standard deviations (Figure F-5), although shifts to extremes of dry and wet in C-ONLY vs. C-N are less pronounced, as expected. Patterns of $R_h$ are different than NPP and NEP. The means of SPEIs are bigger than 0 for both C-ONLY (Figure 5-4b blue) and C-N (Figure 5-4b red) in $R_h$ reduction events, and smaller than 0 in $R_h$ increase events. In both, the increase and reduction events, the distributions of SPEIs are closer to 0 in C-N compared to C-ONLY (Figure 5-4 and Figure F-5), except for $R_h$ increase event with individual normalization (Figure F-5e), suggesting that extreme fluxes in NPP, $R_h$ and NEP are less influenced by water anomalies.

**Contributions of N Availability and Soil Moisture Gain to C Flux Anomalies**

Carbon-nitrogen interactions reduce the correlations between carbon flux anomalies and water anomalies (section 3.1) and dampen the negative impacts of droughts as well as the enhancement of water surplus (section 3.3), buffering the carbon cycle against water anomalies. Figure 5-5 shows that the instantaneous nitrogen limitation in the C-N model configuration is higher in wet events than in dry events ($P<0.05$). Instantaneous nitrogen limitation refers to the direct reduction in gross primary production (GPP) due to down-regulation of photosynthesis because of plant nitrogen deficit.

Perhaps equally important is that in C-N, GPP is reduced (by an average of $\sim 33\%$ globally) under N limitation. The reduction in GPP with the associated decline of stomatal conductance under N limitation, decreases transpiration and ultimately results in higher soil moisture in C-N compared to C-ONLY (Figure 5-
Transpiration is on average 9.6% smaller in C-N compared to C-ONLY (Figure F-6a), while the root zone soil water content is 5.8% (Figure F-6b) higher compared to C-ONLY, globally over the period of 1950-2005. Thus, under the same meteorological drought as indicated by the SPEIs, vegetation from C-N experiences less severe soil moisture shortage compared to C-ONLY.

**Discussion**

I assessed the role of nitrogen in drought-carbon response of a global dynamic land model from different perspectives: from the correlation between global annual means of carbon fluxes (NPP, R_h, and NEP) against global annual means of SPEIs on different timescales (1-24 month), by relating carbon flux anomalies to monthly SPEIs at the grid cell scale or regionally, by analyzing carbon flux anomalies under extreme dry and wet conditions (3 months SPEI < -2 or > 2), by evaluating the SPEIs under the 100 largest carbon flux anomalies, and ultimately by comparing water and nitrogen availability for a simulation that does account for N interactions vs. a simulation that does not. Overall, the model results point to a reduced impact of water anomalies on carbon flux anomalies when effects of nitrogen are considered in LM3V. While the buffering role of nitrogen is found for all of the 3 carbon fluxes studied, I find that the response to water anomalies is stronger in NPP than R_h, at least for shorter SPEI timescales. Next, I will further discuss the role of the N cycle in buffering moisture responses, and address the divergent moisture response of NPP and R_h, and ultimately NEP.

Two mechanisms contribute to nitrogen constraints acting as buffer for NPP in the model: the alternation of the relative importance of N-limitation vs.
water-limitation, and the soil moisture gain from curbed transpiration under N limitation. Under well watered conditions, N limitation acts as an extra constraint on carbon assimilation and thus vegetation growth. In contrast, N limitation is less severe with the reduced vegetation N demand that occur in water limiting conditions. My reported relative increase of N availability in droughts vs. extreme wet conditions is indirectly supported by a meta-analysis which reported the increase of soil available nitrogen by drought stress (He and Dijkstra, 2014). A second mechanism is an overall increased soil water, arising from reduced transpiration in the C-N model configuration. The reduced transpiration is caused by a reduced leaf area but also to reduced stomatal conductance under N limited conditions. The reduction in transpiration further allows a carry-over of water from wet conditions into droughts. Thus while, drought indices are the same for C-ONLY and C-N, water limitation is less severe in C-N. This result is in line with an earlier hypothesis that that increasing N deposition onto N-limited forests may increase foliar biomass and therefore increased the risk of tree water deficit (Aber et al., 1989).

Effects of water anomalies on $R_h$ are weaker compared to NPP. Heterotrophic respiration, as a microbial mediated process performed by a wide range of microbes covering a large span of ecophysiological optima (Schimel and Schaeffer, 2012), can operate at lower water potentials compared to most plants, and the soil matrix may alleviate harsh conditions (Orchard and Cook, 1983). Therefore, it is reasonable for respiration being less sensitive to dryness/wetness conditions compared to production, which has been reported by other studies.
(Shi et al., 2014; Zscheischler et al., 2014b; Schwalm et al., 2010; Anderson-Teixeira et al., 2011; Misson et al., 2010). The higher resilience of heterotrophic respiration to wet/dry conditions compared to NPP manifested itself by a weaker correlation between $R_h$ and water anomalies globally at shorter SPEI timescales (Figure 5-1), by smaller global mean difference in maximum positive correlations (Figure 5-2 and Table 5-1) as well as the fractions of positive correlations (Figure F-1) and by less pronounced $R_h$ excursion under extreme water conditions (Figure 5-3). Further, the $R_h$ extremes are not associated with consistent negative or positive SPEIs (Figure 5-4 and Figure F-5). However, the introduction of N constraints also buffered the respiration response to extreme events, although to a lesser degree than in NPP (Figure 5-3). A likely mechanism is that the C-N configuration has smaller excursions in soil moisture, a critical determinant of the respiration coefficient.

Overall, my results show, that $R_h$ is less sensitive to water anomalies, which also suggests that N mineralization is relatively resilient to drought. As a consequence N supply via mineralization may fluctuate less than N demand by plants (as evidenced by stronger response of NPP under C-ONLY). This differential response contributes to patterns of reduced plant N limitation in dry conditions compared to wet conditions (Figure 5-5). However, the lack of sensitivity of $R_h$ to water availability is timescale dependent (Figure 5-1). Shi et al. (2014) reported diminishing differences in reductions in NPP and $R_h$ under droughts in grassland, due to the decline in soil carbon stocks (therefore, substrate availability for respiration) over time with reduction of production and
consumption of SOM pool. Extreme wet conditions are suggested to result in a strong lagged response in carbon fluxes (Zscheischler et al., 2014b), and possibly lagged carbon inputs into soils. My results show a stronger response if moisture anomalies are persistent, supporting the idea that associated changes in productivity will create a lagged response in \( R_h \).

NEP is the difference between NPP and \( R_h \), and is a key variable to understand the contributions of land ecosystems to atmospheric \( CO_2 \) dynamics. Responses of NEP to water anomalies follow largely on that of NPP. Extreme dry (wet) events decrease (increase) NPP, and the excursions are less pronounced if C-N interactions are considered. Since the \( R_h \) response to extremely dry/wet conditions is substantially smaller than NPP (Figure 5-3), it is reasonable that NPP dominates the responses of NEP to moisture anomalies. As shown in the global analysis, the responses of NPP and \( R_h \) to water anomalies are time scale dependent. I applied 3-month SPEI in the extreme event analysis, which may not reflect the whole characteristic of NEP response across time scales, especially for long time scales (e.g. > 24 month). The spatial pattern of maximum positive correlations between NEP and SPEI is generally similar as NPP, partly due to the dependence of \( R_h \) on NPP for substrate in addition to the less sensitivity of \( R_h \) compared to NPP.

Within the overall buffer effect, I found spatially varied capabilities of N acting to reduce the moisture sensitivity, partly due to the extent of N limitation as well as ecosystems’ capability to respond to water anomalies. In moist tropical systems where N limitation is alleviated by up-regulation of biological \( N_2 \) fixation,
N induced buffering is small. This is evidenced by small differences in the correlations between water anomalies and productivity when evaluated for C-ONLY and C-N. In contrast, strong N buffering effects occur in humid temperate, arid steppe and humid boreal regions, biomes that are typically associated with considerable N limitation (Vitousek and Howarth, 1991b). The buffering effect is inconsistent with respect to differences in maximum correlations vs. the strongest (the bigger of the absolute value of the positive and negative maxima) for $R_h$ across several regions (Table 5-1 and Table F-1). The inconsistency is attributable to the complex response of $R_h$ to water anomalies. The moisture function of soil organic matter decomposition has a hump, thus the decrease in moisture can both positively and negatively affects soil respiration. Negative soil moisture anomalies from water saturated locations might increase soil respiration with more oxygen available and less constraint on microbial activities, at the same time reduce soil respiration from water limited locations (Wang et al., 2014; Cleveland et al., 2010). Drought associate warming triggers microbial activities in cold region (Karhu et al., 2014) while low moisture availability might limit soil respiration. While it is unclear from my analysis what mechanisms dominant the response of $R_h$ in different regions, correlations of $R_h$ with moisture anomalies are overall weaker and less consistent.

I realize the limitation of drawing conclusions from a single model. Nevertheless, my results provide insights beyond the configuration specific to LM3V-N. The buffering effect of nitrogen constraints to dry and wet events detected in my model relies partly on the curbed transpiration from C-N.
compared to C-ONLY. If the carbon and water coupling in stomata is not constrained by nitrogen limitation, or the plants adopt the strategy of opening stomata even if nitrogen is limited, for example, the scheme implemented in the Fixation and Uptake of Nitrogen (FUN) model (Fisher et al., 2010), the buffering capacity of nitrogen is likely to be weaker. Lee et al. (2013) modified the unconstraint scheme from the Community Land Model with coupled Carbon and Nitrogen cycles (CLM4-CN), and linked the carbon and water coupling in stomata to nitrogen limitation. Similar as in my result, they found a downregulation of 9.2% due to nitrogen limitation on canopy transpiration. In addition, they demonstrated the improvement in the simulation of carbon, water and energy fluxes (e.g. runoff, latent heat) with the leaf-level constraints of nitrogen. In addition to the modified version of CLM4-CN, OCN also incorporates reduced stomatal conductance (Zaehle and Friend, 2010). To specifically pin down how nitrogen constraints are affecting drought responses, a multi-model study would be helpful in confirming the robustness of my results.

Water anomalies can potentially alter ecosystem nitrogen availability and nitrogen feedbacks to carbon cycle through multiple processes, such as plant N uptake (He and Dijkstra, 2014; Rillig, 2004), soil organic matter decomposition (Cleveland et al., 2010; Bonal et al., 2008), N mineralization (Auyeung et al., 2013), N losses (Wood and Silver, 2012; Wieder et al., 2011; van Haren et al., 2005; Lodge et al., 1994; Gordon et al., 2008) and biological N₂ fixation (Wurzburger and Miniat, 2014). While LM3V-N incorporates mechanisms to represent these processes, their relative contributions are not clear, and may
depend on the timescale and local conditions. The buffering effects found in my study rely partly on the soil moisture gain from reduced transpiration loss due to N limitation. In this study, water stress is expressed in meteorological terms (SPEI derived from the forcing data), which therefore is not the most direct stresses vegetation experience. Further studies with direct focus on the soil moisture based drought and plant physiology would be helpful in revealing the impact of N cycling processes on vegetation’s response to moisture anomalies. In addition, the treatments of plant and microbial dynamics are simplified in my model. In fact, multiple factors and processes, such as acclimation (Smith and Dukes, 2013), adaptation of vegetation and microbes (Jones et al., 2014), mortality (Powell et al., 2013), changes in plant allocation pattern (Pereira and Chaves, 1993), shifts in plant and microbial communities (Fuchslueger et al., 2014; Balser and Firestone, 2005) are all involved in the adjustment of plant activities and soil respirations to moisture anomalies, and linked to N dynamics. I broadly point to the buffering role of N in one of the current generation of global carbon models, realizing the detailed understanding of carbon-water-nitrogen interactions will advance quickly as model improves.

Conclusions

I compared anomalies of SPEI and carbon flux relationship between two model configurations, one that captures carbon-nitrogen interaction and one that does not. I found that the responses of carbon fluxes to dry and wet extremes are buffered and dampen the variability in carbon fluxes, when N constraints are considered. That is NPP, NEP, and \( R_h \) excursions during extreme wet and dry events are less pronounced. One reason is that reduced transpiration under N
limitation leads a carry-over effect of water into dry conditions, and to smaller transpiration in drier conditions. A second reason is that wet anomalies typically yield higher potential for productivity and growth, which increases the likelihood of being constrained by limited N supply. Many of the mechanisms leading to an increased resilience to water anomalies if N cycles are included are also considered in other terrestrial models. Therefore, the combined effect of nutrient and water availability requires care when predicting drought effects on carbon sequestration under future climate scenarios.
Table 5-1. Differences in the maximum Pearson correlation coefficients (monthly anomalies of carbon fluxes vs. SPEI) between C-ONLY and C-N globally, and the 12 land regions following the Köppen-Geiger Climate Classification.

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Köppen-Geiger Climate Classification</th>
<th>NPP Mean</th>
<th>95% conf.</th>
<th>Rh Mean</th>
<th>95% conf.</th>
<th>NEP Mean</th>
<th>95% conf.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Global</td>
<td>Global</td>
<td>0.030**</td>
<td>[0.026, 0.034]</td>
<td>0.006**</td>
<td>[0.003, 0.012]</td>
<td>0.027**</td>
<td>[0.023, 0.031]</td>
</tr>
<tr>
<td>Af</td>
<td>Equatorial Humid</td>
<td>-0.000</td>
<td>[-0.003, 0.002]</td>
<td>0.021*</td>
<td>[0.007, 0.036]</td>
<td>-0.001</td>
<td>[-0.003, 0.002]</td>
</tr>
<tr>
<td>Am</td>
<td>Equatorial Monsoonal</td>
<td>-0.000</td>
<td>[-0.005, 0.005]</td>
<td>0.015</td>
<td>[-0.012, 0.043]</td>
<td>-0.001</td>
<td>[-0.005, 0.004]</td>
</tr>
<tr>
<td>As</td>
<td>Equatorial summer dry</td>
<td>0.058</td>
<td>[-0.011, 0.127]</td>
<td>0.015</td>
<td>[-0.050, 0.080]</td>
<td>0.057</td>
<td>[-0.007, 0.122]</td>
</tr>
<tr>
<td>Aw</td>
<td>Equatorial winter dry</td>
<td>0.020**</td>
<td>[0.010, 0.030]</td>
<td>0.013</td>
<td>[-0.005, 0.031]</td>
<td>0.019**</td>
<td>[0.009, 0.029]</td>
</tr>
<tr>
<td>BS</td>
<td>Arid Steppe</td>
<td>0.038**</td>
<td>[0.025, 0.050]</td>
<td>0.034**</td>
<td>[0.019, 0.049]</td>
<td>0.040**</td>
<td>[0.027, 0.053]</td>
</tr>
<tr>
<td>Cf</td>
<td>Warm temperate humid</td>
<td>0.058**</td>
<td>[0.044, 0.073]</td>
<td>0.016*</td>
<td>[0.004, 0.028]</td>
<td>0.059**</td>
<td>[0.045, 0.074]</td>
</tr>
<tr>
<td>Cs</td>
<td>Warm temperate summer dry</td>
<td>0.021</td>
<td>[-0.002, 0.045]</td>
<td>-0.014</td>
<td>[-0.042, 0.0147]</td>
<td>0.021</td>
<td>[-0.001, 0.044]</td>
</tr>
<tr>
<td>Cw</td>
<td>Warm temperate winter dry</td>
<td>0.013</td>
<td>[-0.006, 0.032]</td>
<td>-0.008</td>
<td>[-0.044, 0.029]</td>
<td>0.011</td>
<td>[-0.007, 0.029]</td>
</tr>
<tr>
<td>Df</td>
<td>Snow humid</td>
<td>0.049**</td>
<td>[0.041, 0.058]</td>
<td>-0.007*</td>
<td>[-0.013, -0.000]</td>
<td>0.033**</td>
<td>[0.026, 0.041]</td>
</tr>
<tr>
<td>Ds</td>
<td>Snow summer dry</td>
<td>-0.008</td>
<td>[-0.039, 0.024]</td>
<td>0.023</td>
<td>[-0.024, 0.070]</td>
<td>0.015</td>
<td>[-0.023, 0.052]</td>
</tr>
<tr>
<td>Dw</td>
<td>Snow winter dry</td>
<td>0.027*</td>
<td>[0.004, 0.049]</td>
<td>0.006</td>
<td>[-0.007, 0.019]</td>
<td>0.036*</td>
<td>[0.014, 0.058]</td>
</tr>
<tr>
<td>ET</td>
<td>Polar tundra</td>
<td>-0.016</td>
<td>[-0.048, 0.016]</td>
<td>-0.007</td>
<td>[-0.047, 0.033]</td>
<td>-0.024*</td>
<td>[-0.045, -0.003]</td>
</tr>
</tbody>
</table>

Note: Abbreviations in the first column represent the Köppen-Geiger Climate Classes (first 2 letters), indicating the main climate and precipitation/temperature regimes. NPP stands for net primary productivity; Rh is the heterotrophic respiration; and NEP is the net ecosystem exchange. Values are shown in means and 95% confident intervals based on paired Student's t-test. * represents a significant difference between C-ONLY and C-N at $P < 0.05$ and ** at $P < 0.001$. The Köppen-Geiger climate map is provided in Figure F-6.
Figure 5-1. Pearson correlation coefficients between detrended global annual carbon fluxes and global drought index (SPEI) over 1950-2005. X axes are SPEI timescales indicating drought severity at different temporal scales (1-24 months). Squares represent results obtained from the model configuration without nitrogen interaction (C-ONLY), and circles with nitrogen interaction (C-N). Filled symbols indicate correlations are significant ($P<0.05$) and while open symbols indicate not significant relationship. NPP is the net primary productivity (left); $R_h$ is the heterotrophic respiration (middle); and NEP is the net ecosystem exchange (i.e. the difference between NPP and $R_h$, right).
Figure 5-2. Spatial pattern of the Pearson correlation coefficients ($r$) between the drought index SPEI, and the simulated monthly carbon flux anomalies (1950-2005). The left column shows results for the C-ONLY model configuration. Values represent the maximum (not strongest) correlation for each grid cell, across months and SPEI timescales. The right column is the corresponding difference between C-ONLY and C-N (C-ONLY minus C-N if the maxima in the left column are a positive, otherwise in blank) for each of the carbon flux. Panel (a) and (b) are for net primary productivity (NPP); Panel (c) and (d) for heterotrophic respiration ($R_h$); and Panel (e) and (f) for net ecosystem productivity (NEP). Blank areas in each panel represent either polar frost/ arid desert according to the Köppen-Geiger climate classification, or locations with no significant correlations ($P>0.05$), or the maximum correlations being negative in the right column.
Figure 5-3. Carbon flux anomalies in C-ONLY vs. C-N during dry extreme events (3-month SPEI < -2, upper 3 panels) and wet extreme events (3-month SPEI > 2, lower 3 panels). Panel (a) and (d) are for net primary productivity (NPP); Panel (b) and (e) for heterotrophic respiration ($R_h$); and Panel (c) and (f) for net ecosystem productivity (NEP). Carbon flux anomaly for each of the dry/wet extreme event is the cumulative carbon flux anomaly (weighted by grid cell area) in the three-dimensional space (longitude × latitude × time) spanned by a dry/wet extreme event (see detailed definition in the main text). Carbon flux anomalies in each grid cell are calculated based on de-trended and deseasonalized values. The solid red line is the 1:1 line; the solid blue line shows the least squares fit to the data points; and the red dashed lines are zero lines.
Figure 5-4. Distribution of SPEIs in carbon flux extreme events with reductions in NPP, \( R_h \) and NEP in the upper panel and increases in the lower 3 graphs. Extreme events are aggregation of single grid cell extremes across three-dimensional domain (longitude × latitude × time) into voxels. Single grid extreme refers to those with carbon flux anomaly (detrended, deseasonalized and normalized by a common standard deviation) smaller than -2 or bigger than 2, respectively. The y-axes represent the number of extreme events in for a given SPEI interval out of the total of 100 voxels with the strongest reduction or increases, respectively. Lines denote a Gaussian fit to the histogram. Panel a and d are for net primary productivity (NPP); Panel b and e for heterotrophic respiration \( (R_h) \); and Panel c and f for net ecosystem productivity (NEP). Blue bars and lines denote C-ONLY, and red C-N.
Figure 5-5. Nitrogen limitation during 100 largest dry and wet extremes. The ratio between GPP that is nitrogen limited and the potential GPP without N limitation (GPP_POT) is used as the indicator of instantaneous N constraints on productivity. The difference between wet and dry is significant ($P<0.05$).
Figure 5-6. Comparisons of annual canopy transpiration (Panel a) and annual mean root zone soil water content (Panel b) between model configuration without nitrogen interaction (C-ONLY) and with nitrogen interaction (C-N). Blue line indicates result from C-ONLY and red line from C-N.
CHAPTER 6
SUMMARY

Nitrogen cycle plays an important role in both CO$_2$ and N$_2$O emissions by the terrestrial biosphere. I added a soil N$_2$O emission module to the dynamic global land model LM3V-N, compared modeled N$_2$O emissions with field observations and previous modeling results, and tested its sensitivity of the general N cycling, parameterization of nitrification and denitrification, soil moisture conditions and step rises in atmospheric CO$_2$ and temperature. I also focused on the role of multiple global change factors, especially involving land cover transitions, in shaping historical N$_2$O emissions. The impact of nitrogen cycle on CO$_2$ sequestration is multifactored. I focused specifically on the role of nitrogen in carbon-drought response. I first evaluated carbon-drought relationship from CMIP5 models against FLUXNET derived GPP-drought response and satellite based LAI-drought response. After getting a general picture of the performance of current TBMs with regard to carbon-drought response, I illustrated the role of N in carbon-drought response through comparing simulation results with C-N interaction in LM3V-N against that without C-N interaction.

The model is capable of reproducing the global mean natural N$_2$O emissions from other modeling and inverse methods, and the average of observed cross-site annual mean behavior. However, the model's variability is smaller compared to observation for both across field sites (Figure 2-4), and at different sites (Figures. 2-5 and 2-6), which indicates possible model insufficiency in capturing fast transitions, such as freeze-thaw cycle and pulsing. Processes, such as plant N uptake and N loss through fire volatilization, that regulate N availability for nitrification-denitrification have strong controls on N$_2$O fluxes in addition to the parameterization of N$_2$O loss through
nitrification and denitrification. Modeled N$_2$O fluxes were highly sensitive to WFPS, with a global sensitivity of approximately 0.25 TgN per year per 0.01 change in WFPS. I found that the global response of N$_2$O emission to CO$_2$ fertilization was largely determined by the response of tropical emissions which reduces N$_2$O fluxes in the first few decades and increases afterwards. The initial reduction was linked to N limitation under higher CO$_2$ level, and was alleviated through feedbacks such as biological N fixation. The extratropical response was weaker and generally positive, highlighting the need to expand field studies in tropical ecosystems. This different response pattern between tropical and extratropical ecosystems may partly explain the discrepancy between global models and meta-analysis of manipulative CO$_2$ enrichment experiments since no such manipulative studies are availabe in tropical forests.

Warming generally enhanced N$_2$O efflux, and the enhancement was greatly dampened when combined with elevated CO$_2$, although CO$_2$ alone had a small effect. My analysis suggests caution when extrapolation from current field CO$_2$ enrichment and warming studies to the global scale.

Although land cover transition alone had a minor impact on soil N$_2$O emissions over 1970-2000, its contribution varied with time and space. The positive impact of land cover transition on N$_2$O fluxes peaked in the 1920s, balanced between positive responses in temperate regions and negative responses in the tropics. In temperate systems, land cover transitions resulted in an increase of soil N$_2$O emissions by 159.30 TgN over 1850-2000, or 135.20 TgN when interaction with other environmental drivers was considered, while the tropical emission was reduced by 97.2 TgN (single effect) or 101.21 TgN (single + interaction effect) over 1850-2000. Climate change alone
increased soil N$_2$O emissions by 0.94±0.60TgN yr$^{-1}$ over 1970-2000 and the strong climatic impact was dampened (reduced to 0.32±0.31TgN yr$^{-1}$) by the interaction with land cover, CO$_2$ and Nr deposition. One the other hand, the slight negative effect of CO$_2$ was magnified through interacting with other global change factors, resulting a reduction of soil N$_2$O fluxes by 67.97 TgN over 1850-2000. N$_2$O emissions associated with Nr deposition increased with time, and were small for both the single and interaction effects, partly due to compensation by the dynamic biological nitrogen fixation implemented in LM3V-N. Altogether, although land cover transitions contribute to a small amount of N$_2$O fluxes averaged over the global or over certain period, they are temporally or spatially important. Large amount of N$_2$O emissions following land cover transitions are detected in temperate regions, even in absence of fertilizer additions.

Models are on average more responsive to meteorological drought (indicated by SPI) compared to empirical data if uncertainties in observations are neglectable. Over-response in models is revealed through higher mean correlations between global annual anomalies of gross primary productivity (GPP) and SPI, stronger vulnerability indicated by the highest correlation among 288 combinations of SPI time-scales (1- to 24- months) and months within a year (12 in total), weaker resistance derived from the SPI time-scale at which the maximum correlations are obtained, stronger excursions and sensitivities of GPP to extreme dry or wet events. Responses derived from leaf area index (LAI) also generally point to an overestimation in models. However, the time-scale of response (resistance) is inconsistent between humid vs. arid regions, or from GPP vs. LAI when evaluated against the reference. The markedly different resistance patterns among models indicate lack of agreement in current understanding of
responses and their time-scales. The over-response is less obvious for GPP based on soil moisture drought indicated by surface (less than 10cm) soil moisture anomalies (SMAs). More importantly, instead of over-estimation, LAI responses might be underestimated based on SMAs and are inconsistent among models. Both overall reductions and enhancements of leaf area are detected from soil moisture drought, and large area of the global land has the highest correlations being both positive and negative. While both SPI and surface SMA are taken as proxies of available water to plant, the discrepancy of responses derived from SPI and surface SMA calls for improvement in understanding of plant available water in addition to vegetation’s response. Besides, uncertainties in referential data sets further obscure differences between models and observations, leaving the evaluation of modeled vegetation’s response to drought elusive.

I further assessed the effect of nitrogen limitation on the response of the terrestrial carbon cycle to moisture anomalies using LM3V-N. I analyzed the response of the three carbon fluxes: net primary productivity (NPP), heterotrophic respiration ($R_h$) and net ecosystem productivity (NEP, i.e. the difference between NPP and $R_h$) and how these fluxes are altered under anomalies SPEI. I detected the temporal scale dependent correlations between each of the carbon flux and SPEI, globally, with a strong legacy effect of anomalies on $R_h$. The consideration of nitrogen constraints buffered the carbon fluxes anomalies in response to extreme dry and wet events. The nitrogen induced buffer constrained the growth of plants under wet extremes and allowed for less reduced growth during drought. Extra gain of soil moisture from the downregulation of canopy transpiration by nitrogen limitation, and the shift in relative
importance of water and nitrogen limitation during dry and wet extreme events are possible mechanisms contributing to the buffer effect of nitrogen on modeled NPP and NEP. The response of R_{h} to moisture anomalies was much weaker compared to NPP, and buffer effects of the N cycle less evident. Nevertheless, the N buffering effect is likely to reduce the over-sensitivity of modeled vegetation activity to meteorological drought detected from CMIP5 models.

Altogether, I showed that carbon and nitrogen cycling’s contribution to greenhouse gas emissions is regulated by recent climate change. Climatic factor and its interactions with other global changes shape the historical variation in soil nitrous oxide emissions. Meanwhile, CO_{2} fluxes between the atmosphere and the terrestrial ecosystem response to climate variability (especially drought in this study) and the response is buffered by N limitation. Both CO_{2} and N_{2}O fluxes are interlinked with various processes and factors, such as nitrogen availability, dryness or wetness conditions and land cover transition. Therefore, greenhouse gas mitigation strategies should take into account the complex interlink among carbon, water and nitrogen cycling processes as well as the interaction with anthropogenic activities. Process based models are important tools to investigation large scale biogeochemical cycles. However, interpretation and application of modeling results requires caution especially for complex phenomenon such as drought. Based on this study, I suggest future modeling studies on greenhouse gas emission and climate change taking a multiple perspective approach to understand the tradeoff and interactions among various elements.
Here I provide an overview of the main simulated processes and general assumptions applied in the global dynamic land model, LM3V. Further details can be found in the literatures cited below. In this part, I do not include soil organic matter decomposition, which is overviewed in Appendix B.

**Plant Functional Types and Biogeography**

LM3V simulates the distribution of 5 plant functional types (PFTs) (C3 grasses, C4 grasses, tropical, temperate deciduous and cold evergreen trees) based on physiology, leaf longevity and allocation pattern. The bioclimatic constraints are derived from the ecosystem demography model (ED) (Moorcroft et al., 2001). To be specific, a grid cell is occupied by grass PFTs if the biomass is less than 1 kgC m$^{-2}$; otherwise by tree PFTs. C3/C4 photosynthetic pathway is determined by an empirical function of average annual mean temperature and precipitation. Grid cells with 9-11 cold months (mean canopy air temperature lower than 283 K) are occupied by the cold evergreen tree type. Tropical tree type includes grids with mean canopy air temperature of the coldest month greater than 278 K. More details is available in Shevliakova et al., (2009).

**Vegetation Growth and Allocation**

LM3V simulates 5 vegetation C pools: leaves (C$_l$), sapwood (C$_{sw}$), wood (C$_w$), fine roots (C$_r$), and labile C pool (Shevliakova et al., 2009). Vegetation C pools other than wood form the living C pool (C$_{liv}$). The living C pool is calculated daily based on the balance between net primary production (NPP) and turnover losses.

\[
\frac{dC_{liv}}{dt} = \begin{cases} 
NPP - \alpha_l C_l - \alpha_r C_r - \alpha_{sw} C_{sw} - \mu C_{liv} & \text{Leaf \textit{- on season}} \\
NPP - \alpha_{sw} C_{sw} - \mu C_{liv} & \text{Leaf \textit{- off season}} 
\end{cases}
\]  

(A-1)
where $\alpha_l$ and $\alpha_r$ represents the turnover rates of leaves and fine roots, respectively. $\alpha_{sw}$ is sapwood to wood conversion rate and $\mu$ is the mortality rate. NPP is calculated from the balance between photosynthesis and respiration, similar as the IBIS model (Foley et al., 1996). The living C pool is then divided among the four C pools daily with corresponding ratios $p_x(h)$ ($x=l, r, vl, sw$) defined as

\[
Leaf - on\ season \quad Leaf - off\ season
\]

\[
p_l(h) = \frac{1}{1 + c_1 + c_2 h}, \quad p_l(h) = 0,
\]

\[
p_r(h) = \frac{c_1}{1 + c_1 + c_2 h}, \quad p_r(h) = 0,
\]

\[
p_{vl}(h) = 0, \quad p_{vl}(h) = \frac{1+c_1}{1+c_1+c_2 h},
\] (A-2)

And

\[
p_{sw}(h) = 1 - p_l(h) - p_r(h) - p_{vl}(h)
\] (A-3)

where $h$ is vegetation height, $c_1$ is a PFT specific parameter standing for root:leaf biomass ratio, and $c_2$ is a PFT specific parameter representing the ratio of sapwood biomass (per unit vegetation height) and leaf biomass. The height $h(b)$ is derived from results of the age-height structured ED model, and formulated empirically on vegetation total biomass

\[
h(b) = h_{max}(1 - \exp(-h_1 b))
\] (A-4)

where $h_{max}$ is the maximum canopy height, $h_1$ is an empirical parameter and $b$ is the total biomass. $c_1$ and $c_2$ were estimated from the following 2 equations

\[
c_1 = \frac{\bar{c}_r \cdot \sigma_l}{LAI}
\] (A-5)

\[
c_2 = \frac{\bar{c}_{sw}}{h_{Cr}} = f \sigma_l \rho_{wc} \frac{A_{sw}}{A_l}
\] (A-6)
where $C_l$, $C_r$, $C_{sw}$ are equilibrium biomass densities of fine roots, sapwoods and leaves derived from literature; $s_l$ is the specific leaf area; $f$ stands for the form factor relating the product of basal area and height to biomass; $\rho_{wc}$ is the wood carbon density; $A_{sw}/A_l$ is sapwood area to leaf area ratio.

$C$ in wood biomass is the difference between sapwood conversion into wood and wood losses through branch fall and mortality

$$\frac{dC_w}{dt} = \alpha_{sw}C_{sw} - (\mu + \frac{1}{\tau_f})C_w$$  \hspace{1cm} (A-7)

where $\mu$ is the mortality rate and $\tau_f$ is the fire return interval.

**Phenology**

The treatment of phenology in LM3V is based on the ED model and capable of capturing the seasonal cycle of both drought and cold deciduous vegetation. When the mean monthly canopy air temperature goes below 10 °C or the mean monthly plant available soil water drops to below 10% of its maximum possible value, leaves and fine roots are dropped. During leaf drops, 50% of leaf and fine root $C$ is allocated into soil $C$ pools, and the remaining is maintained as labile $C$. On the other hand, when the mean monthly canopy air temperature goes above 10 °C and the mean monthly plant available soil water is more than 10% of its maximum possible value, leaf and fine root grow out consuming the living $C$ pools and the labile $C$ storage is set to zero. Under leave on condition, LAI is simulated as a function of leaf $C$ pool and the specific leaf area which depends on leaf longevity (Reich et al., 1997).

**Disturbance**

Disturbances represented in LM3V are natural mortality and fire. Mortality losses from leaf, roots, sapwood, wood and labile $C$ pools are updated annually and added to
the soil C pools. Mortality rates $\mu$ represent the effects of herbivores, extreme events and competition etc. $\mu$ is assumed to be constant for each PFT and approximated from the quasi-equilibrium values of net primary production ($\text{NPP}_{eq}$), biomass ($C$), and leaf and root litter ($L$) from literature.

$$\mu = \frac{\text{NPP}_{eq} - L}{c}$$  \hfill (A-8)

Fire disturbance is simulated following the ED model. Fire potential is a function of the historical fire return rate ($1/\pi$), the adjusting factor proportional to fuel size (aboveground biomass) and the drought indicator. Fire losses are calculated annually with the annual fire mortality rates $\frac{1}{\tau_f}$ given by:

$$\frac{1}{\tau_f} = \frac{1}{\pi} \left( \frac{\sum_{j=1}^{2} \delta_j c_{abg}}{\sum_{j=1}^{2} s_j c_{abg}} \right)$$  \hfill (A-9)

and $c_{abg_j} = C_t + f_{abg}(C_w + C_{sw} + C_{vl})$  \hfill (A-10)

where $\overline{c_{abg}}$ is the equilibrium aboveground biomass; $c_{abg_j}$ is the aboveground biomass in month $j$; $f_{abg}$ is the aboveground fraction of wood, sapwood, and labile biomass. $\delta_j$ is a drought index, which indicates the occurrence of drought (1 for drought months and 0 for none drought) when the average monthly plant available water is smaller than 10% of its maximum value. $C_{abg}$ and $\pi$ values derived from literature for each PFTs are available from Shevliakova et al. (2009).

**Water Balance and Soil Hydrology**

Vegetation canopy exchanges $\text{CO}_2$ and water vapour through photosynthesis which is coupled with stomatal conductance on the basis of the Collatz et al., (1991,1992) simplification of the Farquhar scheme (Farquhar et al., 1980). Stomatal conductance is the minimum of two values: the non-water-limited verse water-limited
value. Non-water-limited stomatal conductance is calculated following (Leuning, 1995), while the water-limited value is based on the balance between transpiration and hypothetical root water uptake driven by water potential. The flow of water along the potential gradient is determined primarily by root density, plant height, sapwood biomass, root permeability and xylem resistance.

Soil hydrology in LM3V follows partly on Land Dynamics (LaD) with further improvements (Shevliakova et al., 2009; Milly and Shmakin, 2002; Milly et al., 2014). A grid cell can be either glaciered or non-glaciered. For non-glaciered cell, water is stored as snowpack, root-zone water, groundwater and canopy intercepted water. Root zone is defined between the land surface and the effective rooting depth at which the root biomass decays to certain threshold.
APPENDIX B
PROGNOSTIC NITROGEN CYCLE

LM3V-N expands the LM3V land model by pairing each of the vegetation and soil C pool with a corresponding N pool and extending the decomposition model in LM3V with two additional belowground pools (Gerber et al., 2010). N enters the ecosystem through atmospheric N deposition and biological N fixation (BNF), losses via fire and leaching of dissolved organic N (DON) as well as mineral N. Major characteristics of LM3V-N include the following 5 aspects, and details are available in (Gerber et al., 2010).

C-N Coupling in Vegetation

Plants adjust their uptake of C and N to maintain their tissue specific C:N ratios, which are PFT dependent constants (Gerber et al., 2010). Instead of varying C:N ratios, short-term asynchronies in C and N assimilations or temporary imbalances in stoichimetry are buffered by additional N storage pool (S) in which N is allowed to accumulate once plant N demand is satisfied. The optimum storage size $S_{target}$ is based on tissue turnover $Q_{N,liv}$,

$$S_{target} = t_h Q_{N,liv} \quad (B-1)$$

where $t_h$ is the time span that buffer plant N losses (currently set as 1 year). Plant N status ($x$) is defined as the fraction of the actual N storage compared to the target storage: $x = S / S_{target}$. Consequently, N constraints on photosynthesis and soil N assimilation are based on plant N status:

$$A_{g,N} = A_{g,pot} (1 - e^{-x \varphi}) \quad (B-2)$$

$$U_{N,P} = U_{N,P,pot} \begin{cases} 1 & x < 1 \\ 0 & \text{else} \end{cases} \quad (B-3)$$
where $A_{g,N}$ indicates N constrained gross photosynthesis rate ($\mu$molC m$^{-2}$ s$^{-1}$) and $A_{g,pot}$ corresponds to the potential photosynthesis rate without N limitation. The parameter $\varphi$ mimic the metabolic deficiency as plant N decreases. $U_{N,P,pot}$ is the potential inorganic N uptake rate from soil available ammonium and nitrate pools. The actual inorganic N uptake rate ($U_{N,P}$) is run at its potential and drops to zero when N storage reaches its target size.

**Soil C-N Interactions in Organic Matter Decomposition**

Organic matter decomposition is based on a modified CENTURY approach (Bolker et al., 1998), and amended with formulation of N dependent C and N mineralization rates. N can both trigger the decomposition of “light” organic matter and stabilize C in “heavy” organic matter in LM3V-N. Sustained positive effect of available N on organic matter decomposition relies on the persistence of microbial N limitation during decomposition, which is realized through the combination of available N supply to microbial organisms and their respiration rate. Therefore, the decomposition rate $F_L$ is given by:

$$F_L = kL(1 + \xi[N_{av}])$$  \hspace{1cm} (B-4)

where $k$ stands for the first order decomposition rate, $L$ is the organic matter pool size, $[N_{av}]$ is the soil available N concentration (ammonium plus nitrate), and $\xi$ is a parameter (m$^3$ kgN$^{-1}$).

LM3V-N incorporates the negative effects of N on organic matter decomposition through increasing the fraction of C and N fluxes into the recalcitrant pool:

$$q = \frac{q_{max}[N_{av}]}{k_{5,1/2} + [N_{av}]}$$  \hspace{1cm} (B-5)
where \( q \) is the fraction of organic matter stabilized, \( q_{\text{max}} \) is the maximum fraction that can be stabilized, and \( k_{s,1/2} \) is the half saturation constant.

**Competing Sinks of Available Nitrogen**

The fate of soil mineral N (i.e. ammonium and nitrate) depends on the relative strength of the competing sinks, with the hierarchy order of sorption > soil immobilization > plant uptake > leaching/denitrification. Denitrification thus far is lumped with leaching losses and summed into a generic N loss term. Sorption/desorption buffers available N and is assumed to be at steady state in each model time step. N immobilization into organic matter occurs during transfers among litter and soil organic matter pools. Leaching losses of available N are simulated on the basis of drainage rate. Plant uptake of mineral N is a combination of both active and passive processes. The active uptake is modeled as a Monod function, and the passive transport is a function of available N and plant transpiration.

\[
U_{N,P,pot,i} = \frac{v_{\text{max}}C_{r,N,av}}{n_0(k_{p,1/2} + [N_{av}])] + [N_{av}]Q_{W,T}}
\]  

(B-6)

where \( v_{\text{max}} \) (yr\(^{-1}\) kgC\(^{-1}\)) stands for the maximum uptake rate per unit root mass \( C_r \), \( k_{p,1/2} \) is the half saturation constant, and \( Q_{W,T} \) represents the transpiration flux of water.

**Nitrogen Losses from Organic Pools**

Over the long term, losses of N from fire and DON are critical factors limiting the ecosystem N accumulation and maintaining N limitation in LM3V-N. N volatilized from fire is approximated as a function of C released from fire, stoichiometric ratio of burned tissues and a global retention factor (0.45) which accounts for the concentration of N remained in the ash. DON leaching is linked to hydrologic losses of dissolved organic
matter \((L_{DOM})\) by the C:N ratio. And \(L_{DOM}\) is based on drainage rate and a buffer parameter \(b_{DOM}\).

\[
L_{DOM} = \frac{q_{W,D}}{h_s b_{DOM}} DOM
\]  
(B-7)

where \(DOM\) is the amount of dissolve organic matter in the soil column. Soil volume \((h_s)\) is used to convert DOM mass to concentration. Production of DOM (in units of kgC m\(^{-2}\)) is assumed to be proportional to the decomposition flux of the structural litter and soil water content.

**Biological Nitrogen Fixation**

BNF in LM3V-N is dynamically simulated on the basis of plant N availability, N demand and light condition. BNF is turned on only when plant N requirement is failed to be satisfied by root uptake. The change rate of BNF, \(df_{fix}/dt\), is simulated on the basis of current N demand (\(\psi\)), establishment (\(\lambda_f\)) and decay (\(\sigma_f\)) rates of nodules,

\[
\frac{df_{fix}}{dt} = \lambda_f \frac{\psi}{C_L} - \sigma_f f_{fix}
\]  
(B-8)

where \(C_L\) is the amount of C in leaf. LM3V-N differentiates extratropical from tropical ecosystems in BNF through the dependence of nodule establishment on light availability. \(\lambda_f\) is constrained by light availability in extratropical ecosystems, and is independent on light for tropical trees where N fixers commonly occupy the canopy .

\[
\lambda_f = \begin{cases} 
\lambda_{f,0,PFT} e^{-\tau LAI} & \text{Extratropical} \\
\lambda_{f,0,PFT} & \text{Tropical}
\end{cases}
\]  
(B-9)

where \(\lambda_{f,0,PFT}\) is the establishment rate without light limitation, \(\tau\) stands for the light extinction constant, and LAI is the leaf area index.

N demand (\(\psi\)) is calculated on the basis of the accumulating plant N deficit \((D, \text{in units of kgN m}^{-2} \text{ yr}^{-1})\) and plant N status (\(x\)): 
\[ \psi = D \frac{q e^{-x_0}}{1 - e^{-x_0}} \]  

(B-10)

\( D \) is the daily averaged difference between N demand and total N obtained by plant:

\[ D = \max \left[ \frac{NPP_{pot} - Q_{C, liv}}{r_{p, target}} - \left( f_{fix} C_l + U_{N, P} - Q_{N, liv} \right), 0 \right] \]  

(B-11)

where \( NPP_{pot} \) is the potential NPP without N limitation, \( Q_{C, liv} \) and \( Q_{N, liv} \) are the combined leaf, root and sapwood turnover losses of C and N, respectively, and \( r_{p, target} \) is the combined C:N ratio of living plant.
APPENDIX C
OBSERVED ANNUAL N₂O EMISSION DATA

Annual N₂O fluxes data were compiled from peer-reviewed literature. I applied simple selection criteria (see the main text) to reduce the mismatches between model outputs and field measurements, bearing in mind the gaps between complex field conditions and idealized model forcing. Latitudes (Lat) and longitudes (Lon) in Table C-1 are based on model grids.
## Table C-1. Observed annual N₂O emission data for model comparison

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<th>No</th>
<th>Country</th>
<th>Lon</th>
<th>Lat</th>
<th>Location</th>
<th>Veg Type</th>
<th>N₂O kgN ha⁻¹ yr⁻¹</th>
<th>Reference</th>
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<td></td>
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<td>0.15</td>
<td>0.25</td>
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<td>133.1</td>
<td>-12.3</td>
<td>Douglas Daly region</td>
<td>Savanna</td>
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<td>Temperate forest</td>
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<td>0.64</td>
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<td>Achenkirch</td>
<td>Temperate forest</td>
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<td>0.54</td>
</tr>
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<td>151.9</td>
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<td>South-east Queensland</td>
<td>Tropical forest</td>
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<td>Innsbruck</td>
<td>Temperate forest</td>
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<td>48.2</td>
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<td>Temperate forest</td>
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Decomposition of Land Cover Transition Effects

The single effect of land cover transition \( (V_{\text{single}}) \) is calculated as the difference between \( \text{N}_2\text{O} \) fluxes from simulation with only land cover transitions, \( F(+Lc) \), and the reference simulation without environmental or land cover transitions, \( F(\text{ref}) \). \( \text{N}_2\text{O} \) flux from \( F(+Lc) \) is comprised by flux \( (N) \) from each land cover category multiplied by the corresponding fractional area. Total fractional area \( (a) \) of the 4 land cover categories (subscript \( p \) for primary, \( s \) for secondary, \( c \) for cropland and \( pa \) for pasture) is

\[
V_{\text{single}} = F(+Lc) - F(\text{ref}) = a_p N_p + a_s N_s + a_c N_c + a_{pa} N_{pa} - N_p
\]

\[
= a_p N_p + a_s N_s + a_c N_c + a_{pa} N_{pa} - (a_p + a_s + a_c + a_{pa})N_p
\]

\[
= a_s (N_s - N_p) + a_c (N_c - N_p) + a_{pa} (N_{pa} - N_p)
\]

Equation D-1 tells us that the single effect of land cover transition is the summary of flux differences from the transferred land cover categories (secondary, cropland and pasture) compared to their corresponding potential (primary) land cover type.

The overall impact of land cover transition \( (V_{\text{over}}) \) is taken as the difference between \( \text{N}_2\text{O} \) fluxes from the complete model run \( (\text{Full}) \) with both land cover transitions and environmental drivers \( (\text{CO}_2, \text{climate and Nr deposition}) \), \( F(+A+Lc) \), and from the simulation excluding the land cover transition, \( F(+A) \). I use \( +A \) to indicate environmental drivers \( (\text{CO}_2, \text{climate and Nr deposition}) \) and \( N' \) to indicate \( \text{N}_2\text{O} \) flux that incorporates environmental impacts.

Similarly, the overall impact of land cover transition can be decomposed into three components that each represent the difference in \( \text{N}_2\text{O} \) flux (with environmental impacts...
effects) between the transferred land cover categories (secondary, cropland and pasture) and their corresponding primary vegetation, as in the following Equation D-2.

\[ V_{over} = F(+A + Lc) - F(+A) = a_p N'_p + a_s N'_s + a_c N'_c + a_{pa} N'_{pa} - N'_p \]

\[ = a_p N'_p + a_s N'_s + a_c N'_c + a_{pa} N'_{pa} - (a_p + a_s + a_c + a_{pa}) N'_p \]

\[ = a_s (N'_s - N'_p) + a_c (N'_c - N'_p) + a_{pa} (N'_{pa} - N'_p) \]  

(D-2)

The interaction effect of land cover transition \((V_{inter})\) is calculated as the difference between the overall and the single impacts.

\[ V_{inter} = V_{over} - V_{single} \]

\[ = F(+A + Lc) - F(+A) - F(+Lc) + F(ref) \]  

(D-3)

The interaction impact can also be taken as the total effect of land cover transition and environmental drivers \((F(+A+Lc) - F(ref))\) subtracted by effects from land-cover only \((F(+Lc) - F(ref))\) and environmental drivers only \((F(+A) - F(ref))\).

Mathematically, it is the same as Equation D-3.

After substituting and rearrangement from D-3, I decomposed the interaction term again into three components, each representing the difference in the response to environmental drivers for the three transferred land use categories compared to their corresponding primary vegetation (D-4).

\[ V_{inter} = a_s [(N'_s - N_s) - (N'_p - N_p)] + a_c [(N'_c - N_c) - (N'_p - N_p)] + a_{pa} [(N'_{pa} - N_{pa}) - (N'_p - N_p)] \]  

(D-4)
Decomposition of Environmental Effects Involving Land Cover Transitions

The mathematical form is similar for each of the environmental drivers used in this study (CO<sub>2</sub>, climate and Nr deposition). So I only take CO<sub>2</sub> as an example to illustrate the decomposition of environmental factors.

Similar as in previous section, the single effect of CO<sub>2</sub> ($V_{CO2\_single}$) is calculated as the difference between N<sub>2</sub>O fluxes from simulation with only CO<sub>2</sub>, $F(+CO2)$, and the reference simulation with no historical environmental or land cover transitions, $F(ref)$. I use $N^c$ to indicate N<sub>2</sub>O flux from CO<sub>2</sub>-only run and $N^o$ for the reference run

$$V_{co2\_single} = F(+CO2) - F(ref) = N^c_p - N^o_p$$

$$= a_p(N^c_p - N^o_p) + a_s(N^c_p - N^o_p) + a_c(N^c_p - N^o_p) + a_{pa}(N^c_p - N^o_p)$$ (D-5)

The overall impact of CO<sub>2</sub> is the difference between N<sub>2</sub>O fluxes from the complete model run (Full), $F(+B+Lc+CO2)$, and from the simulation excluding CO<sub>2</sub>, $F(+B+Lc)$. I use $+B$ to indicate N<sub>2</sub>O flux with environmental drivers other than CO<sub>2</sub> (i.e., climate and Nr deposition). Superscript $B'$ corresponds to flux with environmental effects from CO<sub>2</sub>, climate and Nr deposition while superscript $B$ indicate N<sub>2</sub>O flux with the effects of climate and N (excluding CO<sub>2</sub>). The overall impact of CO<sub>2</sub> ($V_{co2\_over}$) is therefore decomposed into 4 components: the overall effect of CO<sub>2</sub> on primary vegetation, secondary vegetation, cropland and pasture.

$$V_{co2\_over} = F(+B + Lc + CO2) - F(+B + Lc)$$

$$= a_p N^B_p + a_s N^B_s + a_c N^B_c + a_{pa} N^B_{pa} - (a_p N^B_p + a_s N^B_s + a_c N^B_c + a_{pa} N^B_{pa})$$

$$= a_p (N^B_p - N^B_p) + a_s (N^B_s - N^B_s) + a_c (N^B_c - N^B_c) + a_{pa} (N^B_{pa} - N^B_{pa})$$ (D-6)

The interaction impact of CO<sub>2</sub> ($V_{co2\_inter}$) is calculated as the difference between the overall and the single impacts. $V_{co2\_inter}$ is comprised by 4 components: the
interactive effect of CO2 on primary vegetation \( V_{\text{co2}_p} \) and effects on secondary vegetation \( V_{\text{co2}_s} \), cropland \( V_{\text{co2}_c} \) and pasture \( V_{\text{co2}_pa} \).

\[
V_{\text{co2}\text{inter}} = F(+B + Lc + CO2) - F(+CO2) - F(+B + Lc) + F(\text{ref})
\]

\[
= a_p \left[ \frac{(N_p^{B'} - N_p^B) - (N_p^c - N_p^o)}{V_{\text{co2}_p}} \right] + a_s \left[ \frac{(N_s^{B'} - N_s^B) - (N_s^c - N_s^o)}{V_{\text{co2}_s}} \right] + \\
\frac{a_c \left[ (N_c^{B'} - N_c^B) - (N_c^c - N_c^o) \right]}{V_{\text{co2}_c}} + a_{pa} \left[ \frac{(N_{pa}^{B'} - N_{pa}^B) - (N_{pa}^c - N_{pa}^o)}{V_{\text{co2}_pa}} \right]
\]  \hspace{1cm} (D-7)

\( V_{\text{CO2}_s} \) can be further decomposed into interactive effects of CO2 on secondary vegetation and the gain in response to CO2 (single effect) from transition of primary vegetation to secondary vegetation (D-8), and the same for \( V_{\text{CO2}_c} \) (D-9) and \( V_{\text{CO2}_pa} \) (D-10).

\[
V_{\text{co2}_s} = a_s \left[ \frac{(N_s^{B'} - N_s^B) - (N_s^c - N_s^o)}{V_{\text{co2}_s}} \right] + a_s \left[ \frac{(N_c^c - N_c^o) - (N_p^c - N_p^o)}{V_{\text{co2}_s}} \right] \hspace{1cm} \text{Interactive effect on secondary} \\
\text{Gain from transition}
\]  \hspace{1cm} (D-8)

\[
V_{\text{co2}_c} = a_c \left[ \frac{(N_c^{B'} - N_c^B) - (N_c^c - N_c^o)}{V_{\text{co2}_c}} \right] + a_c \left[ \frac{(N_c^c - N_c^o) - (N_p^c - N_p^o)}{V_{\text{co2}_c}} \right] \hspace{1cm} \text{Interactive effect on crop} \\
\text{Gain from transition}
\]  \hspace{1cm} (D-9)

\[
V_{\text{co2}_pa} = a_{pa} \left[ \frac{(N_{pa}^{B'} - N_{pa}^B) - (N_{pa}^c - N_{pa}^o)}{V_{\text{co2}_pa}} \right] + a_{pa} \left[ \frac{(N_{pa}^c - N_{pa}^o) - (N_p^c - N_p^o)}{V_{\text{co2}_pa}} \right] \hspace{1cm} \text{Interactive effect on pasture} \\
\text{Gain from transition}
\]  \hspace{1cm} (D-10)
APPENDIX E
SUPPLEMENTARY INFORMATION TO CHAPTER 4

Soil Moisture Stress Function

Water stress functions that down-regulate GPP are given in Table E-2 and associated symbols are explained in Table E-1. CLM4, ORCHIDEE and LSM scaled the leaf-level maximum carboxylation capacity of Rubisco ($V_{cmax}$), while SEIB-DGVM, CTEM, LM3V and TIFFID constraint the potential photosynthetic rates. CLM4 is unique by parameterization for soil matrix potential ($\psi$), and LSM is one of the precursors of CLM4. The water stress function applied in LM3V differed from other models by incorporating the leaf water demand. Some of the models linked soil water availability to the root biomass or root biomass fractions, and LSM, CLM4 and CTEM took into account layered soil water and root distribution.

Table E-1. Explanation of model variables, parameters and constants used in water stress functions.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
<th>Value</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_{si}$</td>
<td>Degree of soil saturation in soil layer $i$ in CTEM</td>
<td>0-1</td>
<td>unitless</td>
</tr>
<tr>
<td>$\beta_i$</td>
<td>Soil water-stress factor for soil layer $i$</td>
<td>0-1</td>
<td>unitless</td>
</tr>
<tr>
<td>$\beta_r$</td>
<td>Root zone soil water-stress factor</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_t$</td>
<td>Total soil water-stress factor integrated over the soil column</td>
<td>0-1</td>
<td>unitless</td>
</tr>
<tr>
<td>$\theta_c$</td>
<td>Critical soil water content at which photosynthesis first falls below potential rate in TRIFFID</td>
<td></td>
<td>m$^3$ m$^{-3}$</td>
</tr>
<tr>
<td>$\psi_c$</td>
<td>Soil matrix potential when stomata are fully closed</td>
<td>PFT dependent</td>
<td>mm</td>
</tr>
<tr>
<td>$\theta_{dry}$</td>
<td>Soil water content when evapotranspiration ceases</td>
<td></td>
<td>m$^3$ m$^{-3}$</td>
</tr>
<tr>
<td>$\theta_f$</td>
<td>Soil water content at field capacity</td>
<td></td>
<td>m$^3$ m$^{-3}$</td>
</tr>
<tr>
<td>$\theta_i$</td>
<td>Soil water content in soil layer $i$</td>
<td></td>
<td>m$^3$ m$^{-3}$</td>
</tr>
<tr>
<td>$\psi_i$</td>
<td>Soil water matric potential in soil layer $i$</td>
<td></td>
<td>mm</td>
</tr>
<tr>
<td>$\theta_{ice,i}$</td>
<td>Ice fraction in soil layer $i$</td>
<td>0-1</td>
<td>Unitless</td>
</tr>
<tr>
<td>$\psi_o$</td>
<td>Soil matrix potential when stomata are fully open</td>
<td>PFT dependent</td>
<td>mm</td>
</tr>
<tr>
<td>$\theta_{opt}$</td>
<td>Optimal soil water content for evapotranspiration</td>
<td></td>
<td>m$^3$ m$^{-3}$</td>
</tr>
<tr>
<td>$\theta_r$</td>
<td>Root zone available soil water content</td>
<td></td>
<td>m$^3$ m$^{-3}$</td>
</tr>
<tr>
<td>$\theta_{sat,i}$</td>
<td>Total porosity in soil layer $i$</td>
<td>0-1</td>
<td>unitless</td>
</tr>
<tr>
<td>$\theta_w$</td>
<td>Soil water content at the wilting point</td>
<td></td>
<td>m$^3$ m$^{-3}$</td>
</tr>
<tr>
<td>$A_p$</td>
<td>Leaf-level potential C assimilation</td>
<td></td>
<td>$\mu$mol CO$_2$ m$^{-2}$ s$^{-1}$</td>
</tr>
</tbody>
</table>
Table E-1. Continued

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
<th>Value</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A_s$</td>
<td>Stressed leaf-level C assimilation</td>
<td></td>
<td>$\mu$mol CO$_2$ m$^{-2}$ s$^{-1}$</td>
</tr>
<tr>
<td>$A_{sat}$</td>
<td>Leaf-level photosynthetic rate under light saturation</td>
<td></td>
<td>$\mu$mol CO$_2$ m$^{-2}$ s$^{-1}$</td>
</tr>
<tr>
<td>$B_{ri}$</td>
<td>Fraction of root biomass in soil layer $i$</td>
<td>0-1</td>
<td>unitless</td>
</tr>
<tr>
<td>$D$</td>
<td>Total canopy demand for soil water in LM3V</td>
<td></td>
<td>$\mu$mol H$_2$O m$^{-2}$ s$^{-1}$</td>
</tr>
<tr>
<td>$f(CO_2)$</td>
<td>CO$<em>2$ dependent function for $A</em>{sat}$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$f(DYL)$</td>
<td>Day length scaling function</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$f(N)$</td>
<td>Nitrogen limitation function</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$f_w$</td>
<td>Fraction of available water for plant ($f_w = 0$ at wilting point and $f_w = 1$ at field capacity)</td>
<td>0-1</td>
<td>unitless</td>
</tr>
<tr>
<td>$f_{w0}$</td>
<td>Soil water fractions inducing closure of the stomatal</td>
<td>0.028</td>
<td>unitless</td>
</tr>
<tr>
<td>$f_{w1}$</td>
<td>Soil water fractions inducing maximum opening of the stomatal</td>
<td>0.5</td>
<td>unitless</td>
</tr>
<tr>
<td>$i$</td>
<td>Index of vertical soil layer</td>
<td></td>
<td>unitless</td>
</tr>
<tr>
<td>$q_{vmax}$</td>
<td>Q10 of $V_{c25}$ (CLM4 and LSM)</td>
<td>2.4</td>
<td>unitless</td>
</tr>
<tr>
<td>$S$</td>
<td>Supply of available water</td>
<td></td>
<td>$\mu$mol H$_2$O m$^{-2}$ s$^{-1}$</td>
</tr>
<tr>
<td>$stattwater$</td>
<td>Status of water availability in SEIB-DGVM</td>
<td>0-1</td>
<td>unitless</td>
</tr>
<tr>
<td>$T_f$</td>
<td>Freezing temperature</td>
<td>273.15</td>
<td>K</td>
</tr>
<tr>
<td>$T_i$</td>
<td>Soil temperature in soil layer $i$</td>
<td></td>
<td>K</td>
</tr>
<tr>
<td>$T_l$</td>
<td>Leaf temperature</td>
<td></td>
<td>K</td>
</tr>
<tr>
<td>$V_{c25}$</td>
<td>Value of $V_{cmax,0}$ at 25 °C</td>
<td>76.1</td>
<td>$\mu$mol CO$_2$ m$^{-2}$ s$^{-1}$</td>
</tr>
<tr>
<td>$V_{cmax}$</td>
<td>Maximum carboxylation capacity of Rubisco</td>
<td></td>
<td>$\mu$mol CO$_2$ m$^{-2}$ s$^{-1}$</td>
</tr>
<tr>
<td>$V_{max}$</td>
<td>Maximum rate of RuBP regeneration at quantum-saturation</td>
<td></td>
<td>$\mu$mol CO$_2$ m$^{-2}$ s$^{-1}$</td>
</tr>
<tr>
<td>$V_{cmax,0}$</td>
<td>Potential maximum carboxylation capacity of Rubisco</td>
<td></td>
<td>$\mu$mol CO$_2$ m$^{-2}$ s$^{-1}$</td>
</tr>
<tr>
<td>$V_{max,0}$</td>
<td>Potential maximum rate of RuBP regeneration at quantum-saturation</td>
<td></td>
<td>$\mu$mol CO$_2$ m$^{-2}$ s$^{-1}$</td>
</tr>
<tr>
<td>$v_w$</td>
<td>Plant response to soil water</td>
<td>1</td>
<td>unitless</td>
</tr>
</tbody>
</table>
Table E-2. Formulations for the soil water-stress functions. Explanations of symbols are given in Table E-1.

<table>
<thead>
<tr>
<th>Model</th>
<th>Soil water-stress functions ($\beta$)</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>LM3V</td>
<td>$A_s = \beta_r A_p$</td>
<td>(Shevliakova et al., 2009; Moorcroft et al., 2001)</td>
</tr>
<tr>
<td></td>
<td>$\beta_r = \begin{cases} \frac{S}{D} &amp; \text{if } S &gt; D \ \frac{1}{S} &amp; \text{if } S \leq D \end{cases}$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$A_s = \beta_r A_p$</td>
<td></td>
</tr>
<tr>
<td>TRIFFID</td>
<td>$\beta_r = \begin{cases} \frac{1}{\theta - \theta_w} &amp; \text{if } \theta_r &gt; \theta_c \ \frac{1}{\theta_w - \theta_r} &amp; \text{if } \theta_r &lt; \theta &lt; \theta_c \ 0 &amp; \text{if } \theta_r &lt; \theta_w \end{cases}$</td>
<td>(Cox, 2001; Clark et al., 2011)</td>
</tr>
<tr>
<td>ORCHIDEE</td>
<td>$\beta_r = \begin{cases} 1 &amp; \text{if } f &gt; f_{w1} \ 1 - \frac{f_{w1} - f_{w0}}{f_{w1} - f_{w0}} &amp; \text{if } f_{w0} &lt; f &lt; f_{w1} \ 0 &amp; \text{if } f &lt; f_{w0} \end{cases}$</td>
<td>(Krinner et al., 2005)</td>
</tr>
<tr>
<td>ORCHIDEE</td>
<td>$V_{cmax} = V_{cmax,0} \beta_r$</td>
<td></td>
</tr>
<tr>
<td>ORCHIDEE</td>
<td>$V_{jmax} = V_{jmax,0} \beta_r$</td>
<td></td>
</tr>
<tr>
<td>LSM</td>
<td>$\beta_t = \sum_i \beta_i B_{fr1}$</td>
<td>(Bonan, 1996)</td>
</tr>
<tr>
<td></td>
<td>$\beta_t = \begin{cases} \left( \frac{\theta_r - \theta_{dry}}{\theta_{opt} - \theta_{dry}} \right)^{w} &amp; \text{for } T_i &gt; T_f \ 0.01 &amp; \text{for } T_i \leq T_f \end{cases}$</td>
<td></td>
</tr>
<tr>
<td>ORCHIDEE</td>
<td>$V_{cmax} = V_{c25}(q_{vmax})^{\frac{T_{lf}-25}{10}} f(T_{lf}) \beta_t f(N)$</td>
<td></td>
</tr>
<tr>
<td>ORCHIDEE</td>
<td>$\beta_t = \sum_i \beta_i B_{fr1}$</td>
<td></td>
</tr>
<tr>
<td>CLM4</td>
<td>$\beta_t = \begin{cases} \frac{\psi_c - \psi_i}{\psi_c - \psi_{sat,i}} &amp; \text{for } T_i &gt; T_f - 2 \ \frac{\theta_{sat,i} - \theta_{ice,i}}{\theta_{sat,i}} &amp; \text{for } T_i \leq T_f - 2 \end{cases}$</td>
<td>(Oleson et al., 2010)</td>
</tr>
<tr>
<td>ORCHIDEE</td>
<td>$V_{cmax} = V_{c25}(q_{vmax})^{\frac{T_{lf}-25}{10}} f(T_{lf}) \beta_t f(N) f(DYL)$</td>
<td></td>
</tr>
<tr>
<td>ORCHIDEE</td>
<td>$\beta_t = \sum_i \beta_i B_{fr1}$</td>
<td></td>
</tr>
</tbody>
</table>

$\text{total } i = 6$  

$\text{total } i = 15$
Table E-2. Continued

<table>
<thead>
<tr>
<th>Model</th>
<th>Soil water-stress functions ($\beta$)</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>CTEM</td>
<td></td>
<td>(Arora, 2003)</td>
</tr>
<tr>
<td></td>
<td>$A_s = \beta_t A_p$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\beta_t = \sum_i \beta_i B_{fr_i}$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\beta_i = 1 - (1 - \beta_{di})^2$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\beta_{di} = \text{max}[0, \text{min}(1, \frac{\theta_i - \theta_w}{\theta_f - \theta_w})]$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>total $i = 3$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$A_{sat} = \beta_r f(T_{if}) f(CO_2) A_p$</td>
<td></td>
</tr>
<tr>
<td>SEIB-DGVM</td>
<td>$\beta_r = \sqrt{\text{stat}_{water}}$</td>
<td>(Sato et al., 2007)</td>
</tr>
<tr>
<td></td>
<td>$\text{stat}<em>{water} = \frac{\text{max}(\theta</em>{i1}, \theta_{i2}) - \theta_w}{\theta_f - \theta_w}$</td>
<td></td>
</tr>
</tbody>
</table>
Figure E-1. Arid vs. Humid regions according to the Köppen-Geiger climate classification (Kottek et al., 2006). Arid region corresponds to equatorial summer dry (As), arid steppe (BS), warm temperate summer dry (Cs) and snow summer dry (Ds) from Köppen-Geiger climate classification. And humid regions are from equatorial fully humid (Af), warm temperate fully humid (Cf) and snow fully humid climates.
Figure E-2. Spatial map of the highest correlations between GPP anomalies and SPI for each model (black title) and observation (red title). The highest correlations are obtained from 288 (at most, 24 SPI time-scales by 12 months per year) possible statistically significant correlation coefficients ($P<0.05$).
Figure E-3. Spatial map of the highest correlations between LAI anomalies and SPI for each model (black title) and observation (red title). The highest correlations are obtained from 288 (at most, 24 SPI time-scales by 12 months per year) possible statistically significant correlation coefficients ($P<0.05$).
Figure E-4. SPI time-scales (in months) at which the highest correlations are obtained for GPP in Figure E-2 for each model (black title) and observation (red title).
Figure E-5. SPI time-scales (in months) at which the highest correlations are obtained for LAI in Figure E-3 for each model (black title) and observation (red title).
Figure E-6. Cumulative GPP or leaf area excursions during extreme dry or wet events, respectively. The same as Figure 4-7, except that GPP anomalies and leaf area anomalies are the standardized for each grid cell.
Figure E-7. Sensitivities of GPP (or leaf area) excursions to the total volume of extreme dry or wet events, respectively. The same as Figure 4-8, except that GPP anomalies and Leaf Area anomalies are the standardized for each grid cell.
Figure E-8. Counts of the start season of extreme wet events (1982-2005). Panels with black titles are from models, and red from reference. Different colors represent categories of the length of extreme wet events.
Figure E-9. Counts of the start season of extreme increase events of GPP (1982-2005). Panels with black titles are from models, and red from reference. Different colors represent categories of the length of extreme increase events. The legend is the same as in Figure E-8.
Figure E-10. Counts of the start season of extreme increase events of LAI (1982-2005). Panels with black titles are from models, and red from reference. Different colors represent categories of the length of extreme increase events.
Figure E-11. Spatial distribution of the highest correlations between GPP anomalies and surface soil moisture anomalies for each model (black title) and observation (red title). The highest correlation is derived from the 12 possible statistically significant ($P<0.05$) correlation coefficients (one for each month within a year).
Figure E-12. Spatial distribution of the highest correlations between LAI anomalies and surface soil moisture anomalies for each model (black title) and observation (red title). The highest correlation is derived from the 12 possible statistically significant ($P<0.05$) correlation coefficients (one for each month within a year).
Figure E-13. Cumulative excursions of GPP and LAI in surface soil moisture anomalies (SMAs). The same as in Figure 4-13, except that GPP and leaf area anomalies are the standardized for each grid cell.
Figure E-14. Sensitivities of GPP (or leaf area) excursions to the total volume of extreme dry and wet events. The same as in Figure 4-14, except that GPP anomalies and Leaf Area anomalies are the standardized.
APPENDIX F
SUPPLEMENTARY FIGURES AND TABLES TO CHAPTER 5

This section provides supplementary figures and tables of Chapter 5.
Table F-1. Differences in the strongest Pearson correlation coefficients. The same as Table 5-1 in the main text, except that the strongest correlations are chosen from the bigger absolute value of the positive maxima and the negative maxima. The strongest sensitivity takes into account both the positive and negative responses.

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Köppen-Geiger Climate Classification</th>
<th>NPP</th>
<th>95% conf.</th>
<th>Rn</th>
<th>95% conf.</th>
<th>NEP</th>
<th>95% conf.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Global</td>
<td>Global</td>
<td>0.027**</td>
<td>[0.022, 0.031]</td>
<td>-0.002</td>
<td>[-0.006, 0.001]</td>
<td>0.025**</td>
<td>[0.021, 0.029]</td>
</tr>
<tr>
<td>Af</td>
<td>Equatorial humid</td>
<td>0.002</td>
<td>[-0.002, 0.006]</td>
<td>0.003</td>
<td>[-0.004, 0.010]</td>
<td>0.003*</td>
<td>[0.000, 0.006]</td>
</tr>
<tr>
<td>Am</td>
<td>Equatorial monsoonal</td>
<td>0.005</td>
<td>[-0.005, 0.015]</td>
<td>-0.005</td>
<td>[-0.022, 0.013]</td>
<td>0.005</td>
<td>[-0.003, 0.014]</td>
</tr>
<tr>
<td>As</td>
<td>Equatorial summer dry</td>
<td>0.051</td>
<td>[-0.013, 0.115]</td>
<td>-0.004</td>
<td>[-0.056, 0.048]</td>
<td>0.060</td>
<td>[-0.003, 0.123]</td>
</tr>
<tr>
<td>Aw</td>
<td>Equatorial winter dry</td>
<td>0.008</td>
<td>[-0.004, 0.021]</td>
<td>-0.006</td>
<td>[-0.016, 0.005]</td>
<td>0.013*</td>
<td>[0.002, 0.025]</td>
</tr>
<tr>
<td>BS</td>
<td>Arid steppe</td>
<td>0.037**</td>
<td>[0.024, 0.050]</td>
<td>0.026**</td>
<td>[0.013, 0.039]</td>
<td>0.036**</td>
<td>[0.024, 0.049]</td>
</tr>
<tr>
<td>Cf</td>
<td>Warm temperate humid</td>
<td>0.067**</td>
<td>[0.052, 0.081]</td>
<td>-0.008</td>
<td>[-0.018, 0.001]</td>
<td>0.063**</td>
<td>[0.049, 0.076]</td>
</tr>
<tr>
<td>Cs</td>
<td>Warm temperate summer dry</td>
<td>0.011</td>
<td>[-0.009, 0.032]</td>
<td>-0.005</td>
<td>[-0.025, 0.015]</td>
<td>0.017</td>
<td>[-0.005, 0.038]</td>
</tr>
<tr>
<td>Cw</td>
<td>Warm temperate winter dry</td>
<td>0.025</td>
<td>[-0.001, 0.050]</td>
<td>-0.015</td>
<td>[-0.039, 0.008]</td>
<td>0.022</td>
<td>[-0.001, 0.045]</td>
</tr>
<tr>
<td>Df</td>
<td>Snow humid</td>
<td>0.038**</td>
<td>[0.031, 0.045]</td>
<td>-0.012**</td>
<td>[-0.017, -0.007]</td>
<td>0.027**</td>
<td>[0.020, 0.0337]</td>
</tr>
<tr>
<td>Ds</td>
<td>Snow summer dry</td>
<td>0.004</td>
<td>[-0.033, 0.041]</td>
<td>-0.023</td>
<td>[-0.079, 0.033]</td>
<td>0.009</td>
<td>[-0.028, 0.046]</td>
</tr>
<tr>
<td>Dw</td>
<td>Snow winter dry</td>
<td>0.029*</td>
<td>[0.008, 0.049]</td>
<td>0.011</td>
<td>[-0.010, 0.031]</td>
<td>0.034*</td>
<td>[0.014, 0.054]</td>
</tr>
<tr>
<td>ET</td>
<td>Polar tundra</td>
<td>-0.025</td>
<td>[-0.055, 0.004]</td>
<td>-0.019</td>
<td>[-0.044, 0.006]</td>
<td>-0.021</td>
<td>[-0.051, 0.009]</td>
</tr>
</tbody>
</table>
Figure F-1. The fractions of significant positive correlation ($P<0.05$) across the 288 SPEI timescales-month combinations (24 SPEI time-scales by 12 months per year) from C-ONLY (left side) and the differences in fractions between C-ONLY and C-N (C-ONLY minus C-N, right columns). Panel (a) and (b) are for net primary productivity (NPP); Panel (c) and (d) for heterotrophic respiration ($R_h$); and Panel (e) and (f) for net ecosystem productivity (NEP).
Figure F-2. Spatial pattern of the strongest Pearson correlation coefficients ($r$) between SPEI and simulated monthly carbon flux anomalies. The same as Figure 5-2 in the main text except that the strongest correlations are chosen from the bigger absolute value of the positive maxima and the negative maxima, instead of the maximum correlations. The strongest sensitivity takes into account both the positive and negative responses.
Figure F-3. Carbon flux anomalies (with common normalization) in C-ONLY vs. C-N during dry and wet extreme events. The same as Figure 5-3 in the main text except that the variabilities of carbon fluxes are normalized to a common standard deviation (combined results from C-ONLY and C-N) in each grid cell.
Figure F-4. Carbon flux anomalies (with individual normalization) in C-ONLY vs. C-N during dry and wet extreme events. The same as Figure 5-3 in the main text except that carbon fluxes are normalized by the individual standard deviation from each model configuration.
Figure F-5. Distribution of SPEIs in carbon flux extreme events with individual normalization. The same as Figure 5-4 in the main text except that carbon fluxes are normalized by the individual standard deviation from each model configuration.
Figure F-6. Köppen-Geiger climate zones regridded to model resolution using the nearest neighbor method. The first letter in the legend key stands for main climates (A, equatorial; B, arid; C, warm temperate; D, snow and E, polar), and the second letter represents precipitation or temperature regimes (W, desert; S, steppe; f, fully humid; s, summer dry; w, winter dry; m, monsoonal; F, polar frost and T, polar tundra) in the Köppen-Geiger climate classification systems. Arid desert (BW) and polar frost (EF) were excluded from my regional analysis. Information of the original 0.5 degree latitude/longitude map can be found in Kottek et al. [2006], or at http://koeppen-geiger.vu-wien.ac.at/present.htm (accessed at December 2014).
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BIOGRAPHICAL SKETCH

Yuanyuan Huang was born in Yichang, located in the midstream of Yangtze River in China. She got her bachelor’s degree in environmental science from Wuhan University in China. Later on, she went to the Research Center for Eco-Environmental Sciences, Chinese Academy of Sciences to study Ecology, focusing on the eco-evolution between plant and soil quality, and how to facilitate restoration of arid vegetation. Yuanyuan’s passionate for natural science drove her to pursue a Doctor of Philosophy from Department of Soil and Water Science, University of Florida. Her doctoral research focuses on the interactions among terrestrial carbon, water and nitrogen cycles.