Vegetation dynamics contributes to the multi-decadal variability of precipitation in the Amazon region

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1] Precipitation in most of the Amazon shows multi-decadal fluctuations that were linked to oceanic forcing in the Atlantic. This modeling study shows that vegetation dynamics may play a major role in such low-frequency variability in the Amazon. Despite the large amount of annual precipitation, the presence of a dry season (albeit short) facilitates a strong impact of dynamic vegetation on precipitation persistence in the model. The year-to-year variation of net primary productivity (NPP) is dominated by that of the dry season NPP. As a result, above-normal (below-normal) precipitation in a particular year can enhance (suppress) vegetation growth, leading to widespread increase (decrease) of vegetation density in the subsequent year. Precipitation in the subsequent year is therefore more likely to be above (below) normal. This damping effect of vegetation enhances low-frequency variability of precipitation and leads to recurrent droughts or floods, a result previously considered characteristic of arid and semi-arid regions. Citation: Wang, G., S. Sun, and R. Mei (2011), Vegetation dynamics contributes to the multi-decadal variability of precipitation in the Amazon region, Geophys. Res. Lett., 38, L19703, doi:10.1029/2011GL049017.

1. Introduction

[2] Precipitation in the Amazon region is characterized by multi-decadal fluctuations, with recent regime shifts around 1940s and 1970s [Marengo, 2004]. Although El Nino Southern Oscillation is an important factor influencing the inter-annual variability of precipitation in the Amazon [e.g., Grimm and Tedeschi, 2009], this low-frequency variability seems more related to sea surface temperature in tropical and subtropical Atlantic [Marengo [2009] and the reviews therein]. While oceanic forcing is an important driver for precipitation variability, soil moisture and vegetation feedback may also play a major role in regions like the Amazon where climate is sensitive to land surface conditions [e.g., Costa et al., 2007]. This study explores the role of vegetation dynamics in the low-frequency variability of precipitation in the Amazon region.

[3] Numerical modeling studies using climate models of various complexities coupled with dynamic global vegetation models (DGVMs) repeatedly demonstrated that vegetation dynamics is an important mechanism for decadal and multi-decadal variability of precipitation in several regions. For example, Zeng et al. [1999] and Wang and Eltahir [2000a] using reduced form climate models found that feedback from dynamic vegetation contributes to perpetuating precipitation anomalies and enhances low-frequency variability of rainfall in the Sahel region. This finding is confirmed by studies using general circulation models (GCMs) coupled with DGVMs [e.g., Wang et al., 2004; Delire et al., 2004, 2011]. Delire et al. [2004] further demonstrated that this enhancement of low-frequency variability by vegetation dynamics is most likely to occur in the transition zone between dry and wet climates, i.e., semi-arid regions, which is consistent with the locality of strong soil moisture-precipitation coupling [Koster et al., 2006].

[4] Here, this study presents evidence from a numerical model that vegetation dynamics may have contributed to the observed low-frequency variability of precipitation in the Amazon, a region much wetter than the “hotspots” of land-atmosphere coupling identified in previous studies. Despite the large amount of annual precipitation in this region, the presence of a dry season facilitates a strong feedback between vegetation and precipitation.

2. Model and Experimental Design

[5] The model used here is the NCAR Community Atmosphere Model version 3 coupled with the Community Land Model version 3 including dynamic global vegetation model (CAM3-CLM3-DGVM). Descriptions of the different model components are given by Collins et al. [2004], Oleson et al. [2004], and Levis et al. [2004]. At each time step of the coupled model, CAM3 simulates the atmospheric processes and provides atmospheric forcing to CLM3-DGVM, while CLM3-DGVM simulates the land surface biophysical, physiological, biogeochemical processes and ecosystem dynamics and provides surface fluxes to CAM3. Consistent with the very strong soil moisture-precipitation coupling in CAM3-CLM3 [Koster et al., 2006; Guo et al., 2006; Wang et al., 2007], precipitation in the model is highly sensitive to prescribed evapotranspiration (ET) changes [Mei and Wang, 2010; Sun and Wang, 2011]. However, the sensitivity of ET to prescribed vegetation changes in CLM3 is very low, which limits the response of precipitation to vegetation changes [Sun and Wang, 2011]. As a result, in most of the Amazon region in the model, precipitation increases only slightly with prescribed increase of vegetation density [Mei and Wang, 2010; Sun and Wang, 2011].

[6] In this study, two main experiments (“Dynamic” and “Static”) are designed to examine the impact of vegetation dynamics on precipitation variability using the CAM3-CLM3-DGVM model. Both experiments are 108 years long, driven with the Hadley Center sea ice and sea surface temperature data (HadISST) [Rayner et al., 2003] during the period 1901–2008. In “Dynamic”, the model functions in its normal mode, predicting the year-to-year changes of
vegetation distribution and structure; in “Static”, DGVM is turned off and vegetation is prescribed with no inter-annual variation. To ensure consistency with the CAM3-CLM3-DGVM climatology, this prescribed vegetation is derived from the last year of a 200-year CAM3-CLM3-DGVM simulation driven with climatological SST forcing. This vegetation state is also used to initialize the model for the “Dynamic” experiment. With SST varying as observed during 1901–2008, the difference between “Static” and “Dynamic” in precipitation variability results from vegetation dynamics modulating the effects of global oceanic forcing. To quantify the magnitude of low-frequency variability in precipitation, we use the fraction of precipitation variance with time scales longer than a certain threshold (e.g., \( N \) years). First, the power spectrum of annual precipitation time series is estimated. The power spectrum is then integrated over the whole frequency domain \([0, 1]\) to derive a representation for the total variance \( (V_{tot})\), and the power spectrum integration over the frequency range \([0, \frac{1}{N}]\) reflects the variance with time scales longer than \( N \) years \( (V_N)\). We use the ratio \( \frac{V_N}{V_{tot}} \) as a measure for the fraction of low-frequency variability. In this study we examine the low-frequency fractions for \( N = 5 \) and \( N = 10 \), respectively. The CRU TS 3.0 precipitation at spatial resolution of \( 0.5 \times 0.5 \) degrees during the period 1901–2006 is used as the observational reference.

3. Results

[7] Based on the low-frequency fraction estimated for the CRU precipitation, three “hotspots” of low-frequency variability stand out in the Tropics and Subtropics, including portions of the Amazon, the African Sahel region, and central Australia. Of these three, Amazon is the only wet climate regime, for which the details are shown in Figure 1. Fractions of variance at times scales longer than 5 years and 10 years both identify an area of strong low frequency variability in the equatorial Amazon and an area further south.

[8] The model-simulated precipitation variability in “Static” (i.e., with SST varying as observed but with static vegetation) shows a much weaker low-frequency signal than the CRU data (Figure 2, left). For example, CRU data indicates vast areas where over 70% of the total precipitation variance comes from components with time scales longer than 5 years, and this value is less than 50% in the model with static vegetation. With dynamic vegetation added to the model, the signal of low-frequency variability becomes much stronger (Figure 2, middle, compared to Figure 2, left), and the strength of this signal is comparable with observations. While the enhancement of low-frequency variability by dynamic vegetation takes place across all South America (Figure 2, right), the most significant impact is found in the area between the equator and 10°S, which overlaps with the observed equatorial “hotspot” in Figure 1.

[9] The substantial underestimation of low-frequency variability by the model without dynamic vegetation indicates that oceanic forcing alone is not enough to cause the observed low-frequency variability of precipitation. Despite differences in the detailed spatial distribution of the low-frequency fraction, the reasonable agreement between the model with dynamic vegetation and the CRU data suggests that terrestrial biosphere-atmosphere interactions may have significantly contributed to the low-frequency variability of precipitation in the Amazon region.

[10] Despite the large amount of annual precipitation in the areas of Amazon where the model indicates a strong impact of dynamic vegetation, the region experiences a dry season of several months in boreal summer. During the late dry season and even in the early rainy season, water availability becomes the limiting factor for vegetation productivity. During the rest of the year, water is abundant and productivity is limited primarily by light availability. The modeled year-to-year variation of net primary productivity (NPP) in the region is dominated by that of the dry season NPP. For example, averaged over the area (60–70°W, 0–10°S), 86% of annual NPP variance can be explained by NPP during the July-August-September (JAS) season (which is the late dry season)

Figure 1. Fraction of precipitation variance with time scale longer than (top) 5 years and (bottom) 10 years, based on CRU data over land during the period 1901–2006.
and transition to rainy season for this specific area in the model), while 81% of year-to-year variance of the JAS NPP can be explained by soil moisture during the same season (Figure 3). Note that results in Figure 3 are from the 108-year “Static” experiment. Here the “Static” experiment is chosen over “Dynamic” to minimize the influence of low-frequency signal, since low-frequency variability (which is strong in “Dynamic”) in both NPP and soil moisture can lead to spurious linear correlation. It is clear from Figure 3 that dry season water availability, which depends on precipitation in both the preceding rainy season and the current dry season, is the main controlling factor for the inter-annual variation of NPP therefore for vegetation growth. This establishes the pathway for precipitation to influence vegetation structure and density in the model.

As vegetation density increases, ET increases during seasons when light is not limiting (typical of dry season and dry-to-wet transition season), which favors precipitation. This is the main pathway for vegetation to influence precipitation in the model. Despite the existence of other offsetting mechanisms, the overall response is a precipitation increase with the increase of vegetation density, although the sensitivity is rather low [Mei and Wang, 2010; Sun and Wang, 2011]. Combined with the water-limited vegetation growth, this enhances the persistence of precipitation anomalies.

Figure 2. Fraction of precipitation variance with time scale longer than (top) 5 years and (bottom) 10 years simulated by CAM3–CLM3-DGVM (left) with static vegetation and (middle) with dynamic vegetation during 1901–2008, and (right) the difference between the two.

Figure 3. (a) Dependence of annual NPP on the dry season (July–August–September) NPP. (b) Dependence of dry season NPP on soil water in the top five soil layers (summed up to ~30 cm). NPP and soil moisture are both averaged over the region (60–70°W, 0–10°S).
lengthening both wet and dry episodes. Transitions between wet and dry are likely triggered by large scale oceanic forcing and/or internal atmospheric variability.

4. Discussion

[12] In this study, using the NCAR CAM3–CLM3–DGVM model we demonstrate that vegetation dynamics can enhance the low-frequency variability of precipitation in the Amazon, contributing to the observed multi-decadal fluctuation of precipitation in this region. This result indicates that the impact of biosphere–atmosphere interactions on precipitation variability bears relevance not only in semi-arid regions (as previously found) but also in wet tropical climate with a distinct dry season.

[13] The found impact of vegetation feedback in CAM3–CLM3–DGVM results from the water-limited vegetation growth during the dry season on one hand and the increase of precipitation with vegetation density on the other. Based on both modeling and observational studies, macro-scale deforestation (often basin-wide and hypothetical) in the Amazon would reduce precipitation [e.g., Dickinson and Kennedy, 1992; Zhang et al., 1996; Werth and Avisar, 2002; Fu and Li, 2004; Sampaio et al., 2007], while meso-scale deforestation (which is more realistic in spatial extent) tends to enhance convection, cloudiness, and even precipitation over deforested areas due to mesoscale circulation triggered by land surface heterogeneity [e.g., Cutrim et al., 1995; Wang et al., 2000, 2009; Baidya Roy and Avisar, 2002]. The year-to-year variation of vegetation in CAM3–CLM3–DGVM is naturally induced by climate variations, in the form of slow changes in vegetation density or coverage (as opposed to naturally induced by climate variations, in the form of slow changes in vegetation density or coverage (as opposed to complete transition from forest to grassland or to agricultural land in macroscale deforestation studies). It spans the whole domain, which is similar to the spatial extent of changes imposed in macroscale deforestation studies. The direction of precipitation response to the year-to-year vegetation variation in the model is thus consistent with the response found in macroscale deforestation studies.

[14] A much discussed topic in ecosystem and climate sciences is the potential for abrupt shift (a.k.a. the “runaway” behavior) and the underlying mechanism of a positive feedback between the biotic and abiotic components of the system [e.g., Scheffer et al., 2001; Foley et al., 2003]. It is worth pointing out that the combination of water-limited vegetation growth and precipitation decrease induced by vegetation degradation found in this study is not sufficient to cause a positive feedback between vegetation and precipitation. For example, in the drying phase of a positive feedback, the magnitude of precipitation reduction induced by vegetation degradation has to be large enough to cause further degradation of vegetation, leading to a runaway behavior [e.g., Wang, 2004]. In CAM3–CLM3–DGVM however, the system is locked to a single equilibrium state due to the low sensitivity of precipitation to vegetation changes in the model [Sun and Wang, 2011]. The enhancement of low-frequency variability found in this study is therefore not a result of positive feedback leading to transitions between two different equilibrium states, as was the case in some models [Wang and Eltahir, 2000b; Oyama and Nobre, 2003; Wang, 2004]. Instead, in CAM3–CLM3–DGVM, following an event leading to vegetation degradation (which can be a drought or logging), the precipitation amount, although reduced, is still enough to support the maintenance and further growth of the post-perturbation vegetation, which leads to a negative feedback and vegetation recovery. During such negative feedback, vegetation acts as a damper for the inter-annual variation in the system, contributing to climate persistence. For example, in the year following an El Nino drought that leads to vegetation reduction, due to the long time scale (ranging from years to decades) of vegetation, vegetation is likely to be still less than normal, which favors less-than-normal precipitation even though the large scale oceanic forcing may have gone back to its normal state. Such damping effects by vegetation on fast (inter-annual) processes in the climate system are responsible for the vegetation-induced increase of low-frequency variability found in this study.

[15] Due to the damping effects of vegetation, the several years following a severe drought in a region may be more prone to recurrent droughts, making it more likely for drought years to occur as a cluster. A similar statement holds for flood years. In the Amazon region, the past decade witnessed two extreme droughts, one in 2005 and a much more severe one in 2010 that coincided with the local dry season [e.g., Marengo et al., 2008, 2011; Lewis et al., 2011, Xu et al., 2011]. The drought in 2010, a “once-in-a-century” event, caused substantial reduction of vegetation greenness across the Amazon basin south of the equator that did not recover when the rainy season precipitation returned to normal [Xu et al., 2011]. Results from our study suggests that, in absence of extremely strong oceanic forcing favoring precipitation in this region, many areas of Amazon will be prone to recurrent droughts in the several years following the 2010 drought.

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References


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