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Hydroclimatic Controls on the Means and Variability of Vegetation Phenology and Carbon Uptake  
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Hydroclimatic Controls on the Means and Variability of Vegetation Phenology and Carbon Uptake

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Abstract

Long-term, global offline (land-only) simulations with a dynamic vegetation phenology model are used to examine the control of hydroclimate over vegetation-related quantities. First, with a control simulation, the model is shown to capture successfully (though with some bias) key observed relationships between hydroclimate and the spatial and temporal variations of phenological expression. In subsequent simulations, the model shows that: (i) the global spatial variation of seasonal phenological maxima is controlled mostly by hydroclimate, irrespective of distributions in vegetation type, (ii) the occurrence of high interannual moisture-related phenological variability in grassland areas is determined by hydroclimate rather than by the specific properties of grassland, and (iii) hydroclimatic means and variability have a corresponding impact on the spatial and temporal distributions of gross primary productivity (GPP).
1. Introduction

Recognition that the Earth’s energy and water cycles are intrinsically entwined is longstanding (e.g., Budyko 1971). The land surface energy and water balances both feature evapotranspiration as a dominant term, and the generation of rainfall (a key component of the water cycle) has a profound effect on the heat budget of the atmosphere. The inseparability of the energy and water cycles underlies their joint treatment in numerous analyses (e.g., Trenberth et al. 2011) and the formation of international research projects addressing their linkage, such as GEWEX (the Global Energy and Water Exchanges Project, part of the World Climate Research Programme, or WCRP).

The Earth’s carbon cycle is in turn intrinsically entwined with the energy and water cycles. Vegetation health (and associated carbon uptake) is affected by water availability; deserts, for example, tend not to be carbon sinks. Conversely, carbon affects the water and energy cycles; the transpiration of water from vegetation and the associated cooling of the land surface are in large part controlled by the efficiency of the vegetation’s uptake of carbon dioxide (e.g., Berry et al. 2010), and the build-up of vegetation through carbon uptake has a direct impact on land surface albedo – how much of the sun’s radiation is absorbed by the surface. Carbon dioxide is, of course, also a greenhouse gas. The basic connection between the surface fluxes of water, energy, and carbon is appropriately recognized in numerous studies (e.g., Leuning et al. 2004; Bowling et al. 2010), and it is a motivation for such international research projects as ILEAPS (the Integrated Land Ecosystem Atmosphere Study, another component of WRCP).

In this paper, we focus in particular on the carbon-water linkage at the land surface. A number of relevant studies in the literature have shared this focus. Using data collected at a number of flux tower sites in North America, Knapp and Smith (2001) provided a powerful,
A modeling framework is a natural venue for studying the connections between carbon and water. Wang and Eltahir (2000), using a simple coupled biosphere-atmosphere model, showed how the interaction between vegetation and precipitation can lead to multiple equilibria for vegetation state. Zeng et al. (1999) showed, again with a simple coupled model, how vegetation-climate interactions may affect the nature of precipitation variability in the Sahel. Puma et al. (2013) used a modeling framework to compare the impacts of meteorological variability and phenological variability on the simulation of surface moisture and carbon fluxes. Complex and relatively complete models of vegetation behavior, models that indeed tie together explicitly the interactions between carbon, energy, and water fluxes at the land surface and accordingly allow the prediction of vegetation state, are arguably the new state-of-the-art in numerical climate modeling. Sellers et al. (1997) pointed to the explicit treatment of carbon as a
logical step in the evolution of land surface treatments in Earth system models; dynamic
vegetation models (DVMs) following this evolutionary path are already being used at major
climate modeling centers (e.g., Lawrence et al. 2010, Krinner et al. 2005, Boussetta et al. 2012,
Dunne et al. 2013).

An advantage of using a modeling framework for carbon-water studies is the potential for
doing unique analyses that isolate and illustrate the mechanisms that control the transfers of
water and carbon across the land surface. Carefully formulated modifications of a physical
process treatment or of a variable that forces it can be imposed, and the resulting impacts on
surface fluxes can be quantified and analyzed, thereby elucidating the role of the process
examined. A second important advantage of such models is their ability to provide data fields
that are unattainable with in situ measurement networks or even satellite-based sensors. Gross
primary productivity (GPP), for example, can only be measured directly at a limited number of
flux tower sites. A DVM, however, if driven with observations-based meteorological forcing,
can potentially produce estimates of GPP at high spatial and temporal resolution across the
globe. Such estimates would be biased relative to nature, of course, due to deficiencies in model
formulation and forcing data; still, if care is given to their interpretation, the estimates do have
scientific value.

Both of these advantages come into play in the present paper, in which we use the
dynamic phenology component of an established DVM together with the water and energy
balance framework of a hydrology-focused LSM to characterize, on a global scale, the controls
of precipitation means and variability on GPP – both on its spatial distribution and on its
temporal variability across the globe. The modeling system used (described in Section 2) is
indeed found to be effective in capturing the key hydroclimatic controls on phenology that
operate in nature (as demonstrated in Section 3). The simulated GPP distributions from the thus-validated system are analyzed jointly with global precipitation data in Section 4. The model experiments provide new insights into the relative impacts of precipitation means, precipitation variability, and vegetation type in determining GPP distributions.

2. Dynamic Phenology Model

The dynamic phenology model used in this study is in essence a merger of the carbon physics of the NCAR/DOE CLM4 dynamic vegetation model (Oleson et al. 2010) with the energy and water balance formulations of the NASA Global Modeling and Assimilation Office (GMAO) Catchment land surface model (LSM) (Koster et al. 2000). We provide here a brief description of these two components and the technique used to merge them into a new model, hereafter referred to as the Catchment-CN LSM (i.e., the Catchment LSM with carbon and nitrogen physics).

The NCAR/DOE Community Land Model, version 4 (CLM4), represents prognostic coupled energy, water, carbon, and nitrogen cycles in a framework that permits global-scale as well as regional and site-level simulation. The global-scale parameterization used here includes specification of sub-grid heterogeneity in plant functional type (PFT) distributions, with multiple PFTs assigned fractional area coverage within each grid cell, where they compete with one another for available soil moisture and mineral nitrogen resources. In this prescribed biogeography mode the fractional areas occupied by individual PFTs do not change, but vegetation growth, soil heterotrophic activity, carbon stocks, and other ecosystem states (such as leaf area index) do vary prognostically (Thornton et al. 2009).
The GMAO Catchment land surface model is a state-of-the-art surface energy and water budget model designed for use with global Earth system models. As with most other LSMs, the Catchment LSM employs complex treatments of land surface flux generation, tying the efficiency of evaporation and runoff generation to the moisture and temperature states of the land surface, and it includes parameterizations of vegetation impacts on transpiration, canopy interception, albedo, and surface roughness. Relatively unique to the Catchment LSM is its treatment of the subgrid variability of soil moisture and temperature, which is explicitly tied to a description of the topographic variability in the region modeled – in the Catchment LSM, valley bottoms within a given grid element are explicitly modeled as being wetter, and the hilltops are explicitly modeled as being drier. Runoff and evaporation are calculated independently in the different hydrological regimes, using regime-specific physics.

In essence, in merging the two models, we retain the Catchment LSM’s energy and water balance calculation framework while using the NCAR/DOE CLM4 carbon balance calculations. The approach is illustrated in Figure 1. In the original Catchment LSM (Figure 1a), the model uses forcing from the atmosphere along with prescribed vegetation phenology (LAI and greenness fraction) and the current values of LSM temperature and moisture prognostic variables to compute the canopy conductance, the parameter describing the ease with which the plants transpire water. The canopy conductance, computed separately for each hydrological regime, is then used in each regime’s energy balance and water balance calculations, which in turn provide the fluxes of heat and moisture to the atmosphere.

Figure 1b shows the approach used by the merged system, the Catchment-CN LSM. The atmospheric inputs are now fed first into the components of the NCAR/DOE model that update the carbon states and compute, as a matter of course, canopy conductances that reflect an explicit
treatment of photosynthesis physics. These canopy conductances, along with the leaf area
indices diagnosed from the new carbon prognostic variables, are fed into the energy and water
balance calculations of the original Catchment LSM. The output fluxes with the merged system
include a net carbon flux.

The merger of the two models allows the Catchment-CN LSM to follow 19 distinct
vegetation types, a significant increase from the six independent types followed with the original
Catchment LSM. Furthermore, the unique character of the original Catchment LSM allows for
the independent monitoring of carbon variables in the different topographically-defined
hydrological regimes. Figure 2 describes our methodology. Each land surface element is
subdivided into three static carbon zones defined by topography, through analysis of the
distribution of the compound topographic index (Moore et al., 1993). The first zone, covering a
fixed 10% of the area, represents the valley bottoms; this zone tends to be generally wet. The
second and third zones represent the lower (drier) hillslopes and upper (even drier) hillslopes,
respectively. Through areal weighting, soil moisture and temperature information from the
dynamically-varying hydrological zones are combined for use by the carbon physics in the fixed
vegetation zones, as indicated in the figure. Separate sets of carbon prognostic variables are
followed in each vegetation zone, and thus each zone generates a different manifestation of
phenology. When examining the model results, we find that green vegetation indeed tends to be
densest in the valley bottoms.

Some additional modifications to the NCAR/DOE vegetation model were needed to
optimize its performance in the GMAO system. To prevent some occasional singular behavior –
namely, the catastrophic shutdown of vegetation during cold spells and a resulting overgrowth of
the vegetation during the subsequent year – we replaced a particular set of vegetation types (crop
and temperate shrubs/grass) that feature a strong response to temperature stress by a mix of two
different types: one that is seasonally deciduous and one that is not. Neither of the replacement
types employ the temperature stress shutdown, though both respond to moisture stress; the
proportion of the mix applied is defined by latitude, and the replacement is indeed limited to the
latitude band 32°-42° in both hemispheres. Outside of this latitudinal band, we limit the number
of coexisting PFTs in each static carbon zone to two. Also, we modified the NCAR/DOE
vegetation physics to allow half of the new carbon assimilated by deciduous types to be
displayed during the current year rather than in the following year, which brings certain
measures of our interannually-varying phenology more in line with observations. Finally,
whereas the NCAR/DOE vegetation model uses the previous year’s annual mean temperature to
determine certain onset triggers, we use a climatological mean temperature.

In our main (“control”) application of the model, the prescribed distributions of
vegetation type follow those used by the default 0.5°×0.5° version of CLM4 (Oleson et al. 2010).
Vegetation phenology and carbon states, however, evolve freely. The model is run globally
offline (i.e., disconnected from an atmospheric model) on high-resolution catchments (roughly
20-30 km in size) over the period 1948-2008, using the observations-based meteorological
forcing of Sheffield et al. (2006); the simulation loops over this period more than 30 times to
ensure spin-up and equilibration of the carbon storage reservoirs. The output data examined
(phenological variables, carbon fluxes, etc.) are aggregated to 2°×2.5° for processing.

3. Evaluation Against Observations

To test the realism of the model’s connections between hydroclimate and vegetation
variables, we focus on two distinct aspects of global phenological expression: the global spatial
pattern of long-term phenological means and the interannual variability of phenology at a given location. These are discussed in turn following a brief description of the observations.

a. Observations used

We examine satellite-based products of NDVI (normalized difference vegetation index) and FPAR (fraction of absorbed photosynthetically active radiation), both of which increase with green vegetation cover. The NDVI data is a subset of the latest version of the Global Inventory and Mapping Studies, or GIMMS, data (Tucker et al. 2005). The data’s native resolution is semiweekly at 8 km, and the data span the period July 1981-present. For our analyses we aggregate these data to a 2.5°×2.5° degree, monthly resolution for the period 1982-2010. The data are derived from the Advanced Very High Resolution Radiometer (AVHRR) instrument with known limitations compared to the more advanced MODIS instrument (Kaufman et al. 1998). However, the longer temporal coverage of GIMMS relative to MODIS (29 versus 11 years) and the good correspondence between their measurements (Tucker et al. 2005, Beck et al. 2011) makes it well suited to the analysis presented here.

The FPAR data are derived directly from the NDVI data using the method of Los et al. (2000). The method combines the NDVI-based FPAR estimation technique of Sellers et al. (1996) with that of Choudhury (1987) and Goward and Huemmrich (1992); the combination provides estimates that are well behaved relative to available in-situ observations. The relationship between NDVI and FPAR underlying this combined approach is monotonic but nonlinear. Note that it is also somewhat vegetation dependent, so that the conversion of global
NDVI data to global FPAR data requires a global field of vegetation types. Thirteen years of FPAR data are available, spanning the period 1997-2009.

As will be seen below, the sensitivities of the NDVI and FPAR data to hydroclimatic variation are similar in many ways. Both are worth illustrating here. The NDVI values are constructed directly from spectral reflectance measurements and thus represent a raw form of the observations. While the construction of the FPAR values requires some additional assumptions regarding vegetation behavior, FPAR has the distinct advantage of representing a physically meaningful phenological variable, one that can be compared directly to output from the Catchment-CN model.

The global precipitation data used here consist of monthly precipitation totals for 1979-present at 2.5°×2.5° degree resolution, as produced by the Global Precipitation Climatology Project as part of their Version 2 Satellite-Gauge dataset (Adler et al. 2003; see also ftp://precip.gsfc.nasa.gov/pub/gpcp-v2.2/doc/V2.2_doc). Satellite-based data contributing to the product, in varying capacities and over various periods and regions, include Special Sensor Microwave/Imager (SSM/I) passive microwave estimates, Television-Infrared Observation Satellite (TIROS) Operational Vertical Sounder (TOVS) estimates, and the Adjusted Geostationary Operational Environmental Satellite (GOES) Precipitation Index (Adler et al. 1994). A wealth of surface rain gauges is used to adjust the multi-sensor precipitation estimates over land. Hall et al. (2006) provide background on the accuracy of the GPCP product; of note is the higher uncertainty of the product over mountains, deserts, high latitudes, and undeveloped areas due in large part to a lower density of rain gauges.
b. Impact of hydrological variations on the mean spatial distributions of phenological variables

To deal with the fact that NDVI shows significant seasonal variability, with different regions having different peak months for the index, we examine a quantity we will call $\text{NDVI}_{\text{max}}$. We compute, at each $2.5^\circ \times 2.5^\circ$ grid cell, the average seasonal cycle of NDVI from the GIMMS data and then identify the month for which the average NDVI is highest. $\text{NDVI}_{\text{max}}$ is set to the average value for the 3-month period centered on this peak month. (Note that under this definition, the values for $\text{NDVI}_{\text{max}}$ in adjacent grid cells may be taken from different 3-month periods.) Figure 3a shows the global distribution of $\text{NDVI}_{\text{max}}$ as derived from the spatially aggregated GIMMS data. The distribution mirrors known vegetation distributions, with large values in tropical, deciduous, and boreal forests, intermediate values in grassland and shrubland areas, and small values in the deserts.

Figure 4a shows how the spatial distribution of $\text{NDVI}_{\text{max}}$ in Figure 3a correlates with various meteorological quantities. The first four bars of each panel show the square of the spatial correlation ($r^2$, across land surface grid cells) of $\text{NDVI}_{\text{max}}$ with, respectively, annual mean precipitation, the standard deviation of annual precipitation, annual mean air temperature, and annual mean net radiation. (The base-10 logarithms of the precipitation quantities are in fact used here. Temperature and net radiation information are derived from the full period of the Sheffield et al. (2006) dataset. The outgoing longwave component of the net radiation is estimated using the surface air temperature in that dataset.) The salient result from the figure is the dominance of the two precipitation quantities in determining the spatial structure of NDVI. Multiple regression of $\text{NDVI}_{\text{max}}$ on the mean and variability of precipitation produces an $r^2$ of about 0.55 (fifth bar), and adding the temperature and net radiation information to the multiple
regression does not significantly increase the $r^2$ (sixth bar). These results underlie the
importance of hydroclimate in determining the spatial distribution of phenological maxima.

Figure 5a shows more directly how $NDVImax$ is related to precipitation means and
variability. Each dot in Figure 5a corresponds to a 2.5°×2.5° land grid cell. The size and color
of the dot is determined by the local value of $NDVImax$, as indicated by the legend. The dot’s
abscissa is determined by the mean annual precipitation at that grid cell, and the dot’s ordinate
refers to the interannual variability of precipitation there. (Note the logarithmic scales.) The
precipitation and NDVI quantities are computed over consistent time periods; for example, if a
grid cell’s peak NDVI, as computed from the GIMMS data for 1982-2010, occurs in July, then
precipitation means and variances are computed from nineteen September-August yearly totals
starting with the total for the period September 1981-August 1982.

Two features of the scatter plot stand out. The first reflects an expected result: a
minimum average precipitation must be achieved to attain moderately high $NDVImax$ levels. The
plot shows this minimum value to be roughly 1 mm/day; the dots to the left of this threshold
(which include, of course, all desert points) show low values of $NDVImax$. The second, and more
intriguing, feature of the scatter plot is the tendency for $NDVImax$ to decrease as the standard
deviation of precipitation increases. This feature is illustrated more clearly in Figure 5b, which
shows a binned version of the scatter plot data; to generate this plot, an array of boxes is overlain
on Figure 5a, and the $NDVImax$ values for the points within each box are averaged. For a given
value of the mean precipitation, especially for values above 1 mm/day, $NDVImax$ clearly tends to
decrease with increasing $\sigma_p$. This presumably reflects the reduced ability of vegetation to
flourish when the year-to-year supply of water is less stable.
We also examine in this context the analogous variable $\text{FPAR}_{\text{max}}$, the average value of a grid cell’s FPAR for the 3-month period centered on the peak FPAR month, as determined from the local climatological cycle. Figure 3b shows the distribution of $\text{FPAR}_{\text{max}}$ as computed from the GIMMS data. As might be expected, given that FPAR in GIMMS is derived from NDVI, the spatial distributions in Figures 3a and 3b are very similar, as are the spatial correlations with the meteorological forcing variables (Figure 4b). Figures 5c and 5d show the precipitation-based scatter plots for the $\text{FPAR}_{\text{max}}$ values. Average water supply (mean precipitation) and water supply stability ($\sigma_p$) are seen to impose dual control over $\text{FPAR}_{\text{max}}$ as well; the sensitivity of FPAR to hydroclimate is indeed very similar to that of NDVI.

How well does the Catchment-CN model perform? The model produces diagnostics for both the incident and absorbed photosynthetically active radiation; we take the ratio of these quantities to produce the model’s FPAR values. Figure 3c shows the global distribution of simulated FPAR in the peak 3-month period; note that for a given location, this peak period may differ from that for the observations. Two features of the simulated FPAR distribution stand out. First, the simulated spatial patterns agree well with the observed patterns in Figure 3b. Second, there are, nonetheless, apparent biases in the simulated FPAR values, with the highest simulated values being too large and the lowest being too small. Such biases presumably reflect deficiencies in the model, though they may also stem partially from limitations in the forcing data or in the observational FPAR values themselves. The biases must be kept in mind throughout our analysis.

The square of the spatial correlation of simulated FPAR with meteorological forcing variables (Figure 4c) agrees quite well with the corresponding values found for observed FPAR (Figure 4b). The simulated $r^2$ values with the temperature and net radiation variables are slightly
higher, but these values are still quite low. Figure 4 shows that, in strong agreement with the observations, variations in hydroclimate explain most of the FPAR variability seen in the model.

The agreement in spatial pattern with a presence of bias also manifests itself in the precipitation-based scatter plot in Figure 5e and the corresponding binned version of the plot in Figure 5f. In agreement with the observations, the model clearly shows an increase in FPAR with increasing precipitation and with decreasing precipitation variability. Overall, the model, though biased, does appear to simulate realistic controls of hydroclimatic variation over phenological means.

c. Impact of hydrological variations on the interannual variability of phenological variables

As a second and somewhat independent test of the ability of the Catchment-CN model to capture observed links between carbon and water variables, we examine the interannual variability of vegetation phenology. Rather than examining the total variance of a variable such as summertime NDVI, we focus instead on a modified quantity, one that captures the carbon-water connection:

\[
\text{Var(NDVI)*} = \text{Var(NDVI)} \cdot \text{Corr}^2(\text{NDVI,P}),
\]

where \(\text{Var(NDVI)}\) is the interannual variance of 3-month NDVI averages (again centered on the peak NDVI month, based on the climatological seasonal cycle), \(\text{Corr}^2(\text{NDVI,P})\) is the correlation between these individual NDVI averages and the corresponding yearly precipitation totals (with the end of the precipitation averaging period corresponding to the end of the 3-month NDVI averaging period), and \(\text{Var(NDVI)*}\) is interpreted as the portion of the NDVI variance associated with variations in moisture availability. That is, we are employing here the standard
interpretation of $\text{Corr}^2(\text{NDVI}, P)$ as the fraction of the variance of NDVI “explained” by variations in $P$. Equation (1) allows us to isolate this part of NDVI variability from that associated with other sources, such as variations in radiation or nutrients as well as interference from clouds, water vapor, and aerosols (Los et al. 2000).

A few notes are required regarding the estimation of $\text{Var(NDVI)}^*$. First, by using the annual totals for precipitation, we are assuming that a given year’s precipitation represents the water available that year for growth. Of course, other averaging periods for the precipitation could have been employed (e.g., Zeng et al. 2013). The patterns in $\text{Corr}^2(\text{NDVI}, P)$ obtained with these other averaging periods, however, turn out to be the same, to first order; correlation maps generated using 6-month or 9-month precipitation averages (not shown) are very similar to those generated with the annual precipitation. Note that using the annual precipitation rather than the contemporaneous 3-month precipitation has an important advantage: it reflects the fact that antecedent precipitation can provide water to vegetation growth through storage in ground reservoirs and snowpack (Milly, 1994).

Second, the observations are known to be subject to significant contamination from clouds in high latitudes and from pollution in Southeast Asia (Fensholt and Proud, 2012), the upshot being that small and artifactual negative correlations between NDVI and precipitation are often seen in these regions. These negative correlations are problematic for our analysis. We zero them out before computing $\text{Corr}^2(\text{NDVI}, P)$, making the explicit assumption that any such negative correlations represent noise. Note that even on the off chance that the negative correlations are real, they would not represent the physical relationship we are after in this paper, namely, the ability of water limitations to limit vegetation growth.
Figure 6a shows the distribution of Var(NDVI)*, as computed with (1). The patterns are quite interesting: the regions for which moisture-related NDVI variability is high tend to coincide with the Earth’s grassland regimes – in the Great Plains of the U.S., the Nordeste region of Brazil, the African Sahel, the Asian steppes, and eastern and northern Australia (see Figure 7). The Var(NDVI)* patterns do miss grassland areas in India and China, but as shown in Figure 7, these areas are subject to extensive irrigation (Siebert et al. 2005), a supply of water not accounted for in the Corr^2(NDVI,P) diagnostic. Figure 6 demonstrates that, aside from such irrigated areas, the locations of the Earth’s grassland areas can be identified reasonably well from the joint analysis of NDVI and precipitation data. The same patterns, and thus the same connections to grassland regimes, are seen for Var(FPAR)*, the portion of the interannual variance in 3-month FPAR averages related to moisture variations.

The results obtained with the dynamic phenology model are remarkably similar. A comparison of Figures 6b and 6c shows that the model captures very well the observed spatial pattern Var(FPAR)*, though again with a bias, as indicated by the different scaling factors used for the plotting. Overall, the model successfully captures the role of hydroclimate in determining the spatial distribution of interannual variability in phenology.

4. Model Experiments

Having demonstrated the Catchment-CN model’s ability to capture the basic hydroclimatic controls on phenology seen in the observations, we now use model experiments to address key questions regarding the connections between hydroclimate and vegetation.
a. Influence of vegetation type on phenological variability

Clouding the interpretation of the Catchment-CN model’s performance relative to observations in Section 3 above is the possibility that its use of prescribed vegetation types is somehow guaranteeing correct model behavior. Given, for example, that the observed distribution of Var(FPAR)* in Figure 6b captures well the locations of the world’s grasslands (Figure 7), we must consider the possibility that high values of Var(FPAR)* are encouraged by the unique properties of grassland and discouraged by the properties of forests and shrubs, so that by imposing the observed vegetation distributions in the model, we artificially guarantee high simulated values of Var(FPAR)* in the correct areas (Figure 6c). The more intriguing possibility to consider, however, is that a specific hydroclimatic regime is responsible for high Var(FPAR)* values, a regime for which only grasslands happen to survive. With this second possibility, the vegetation type does not cause the Var(FPAR)* value; rather, the vegetation type and the Var(FPAR)* value are together controlled by something else, namely, the local moments of precipitation.

To examine this issue, we performed a repeat of the simulation described above, but with a twist: grassland vegetation was imposed on all land surfaces, and no other vegetation types were allowed to exist. Thus, in this experiment, vegetation type could not affect in any way the simulated spatial and temporal distributions of FPAR. Note that in this experiment, grassland is placed even in the driest deserts and in the wettest tropical areas; if the local climate is not conducive to grassland’s survival, the grass is accordingly allowed to die out.

Figure 8c shows the spatial distribution of Var(FPAR)* for the all-grassland simulation. The plot captures, to first order, the features seen in the original model plot, supporting the
second possibility noted above. That is, the presence of grassland does not lead to high 
Var(FPAR)\* values; the high values are instead indicative of a hydroclimatic regime that also 
happens to support grassland best. Similarly, the all-grassland simulation shows a relationship 
between FPAR maxima, mean precipitation, and precipitation variability (Figure 8a) that agrees 
to first order with that seen in the original model simulation (Figure 5f). The fact that FPAR 
tends to be highest in very wet conditions, for example, is not simply the result of the presence of 
dense forests in wet areas; the wet conditions themselves encourage the high FPAR values, and 
wet areas also tend to be where dense forests tend to flourish.

We repeated the simulation still again, this time after prescribing a deciduous forest 
vegetation type everywhere. The results, shown in Figures 8b and 8d, are essentially the same. 
Hydroclimatic variability, more than vegetation type, appears to dominate phenological 
variability – in the model and, we can infer, in nature.

b. Hydroclimate and the global carbon cycle

As noted in the introduction, a unique advantage of a model that can simulate phenology 
is its ability to provide information on additional, difficult to measure quantities. While carbon 
fluxes such as gross primary productivity (GPP), net primary productivity (NPP), and net 
ecosystem exchange (NEE) have been measured at various tower sites (Baldocchi 2008), directly 
observed global distributions of land-atmosphere carbon exchange are nonexistent. Model 
simulations, however, can readily provide these fields, and many examples of such simulated 
distributions already appear in the literature (e.g., Friedlingstein 2006). (We note that other
approaches for inferring global fields, such as machine learning algorithms that upscale from the site measurements, are also available [Jung et al. 2011].

Here we provide model-based estimates of the connection between carbon exchange and hydroclimatic variability, focusing mainly on GPP. We first provide in Figure 9a this particular model’s vision of the global distribution of GPP. Because GPP is a flux rather than a manifestation of vegetation state, we present it in terms of annual averages rather than for a 3-month maximum period. The distributions have the expected maxima in the densely forested tropics, with swaths of high values in the boreal forests of the north. Figures 9b and 9c show the corresponding GPP fields from the simulations prescribing grassland and deciduous tree types, respectively. The three panels show some differences but are, to first order, very similar, indicating that vegetation type alone is not the main source of spatial variations in GPP; both GPP and vegetation distributions are apparently controlled in tandem by something else.

Naturally, that “something else” is water availability. Figure 10 shows, in analogy to Figure 4, the square of the spatial correlation between GPP and various meteorological forcing variables. For all three simulations (control, “all grass”, and “all trees”), precipitation mean and variability have the dominant impact on GPP, with an $r^2$ of about 0.55 for the multiple regression of GPP on $\log_{10} P$ and $\log_{10} \sigma_P$. Adding in the annual temperature and net radiation information increases the $r^2$ to about 0.65. The fact that the $r^2$ values do not increase by much for the uniform vegetation experiments suggests once again that variations in vegetation type do not by themselves contribute significantly to spatial variations in GPP; the remaining unexplained variance in Figure 10a presumably results from spatial variability in, for example, the seasonal cycles and shorter-term temporal structure of the forcing quantities.
Figure 11 shows how precipitation means and variability control the spatial distribution of GPP using scatter plots analogous to those shown in Figure 5. As with FPAR, GPP tends to increase with increasing moisture availability (x-axis) and decreasing interannual variability (y-axis), regardless of which vegetation types are assigned at the surface.

In contrast to Figure 5, Figure 11 uses a nonlinear scale for the shading, a scale that shows the dominance of precipitation means over precipitation variability in determining GPP. The impact of precipitation variability on GPP, however, is nevertheless significant. This is demonstrated with a supplemental model simulation ("ClimP") in which we prescribed standard, spatially varying vegetation types (as in the control simulation) but a modified precipitation forcing: at each grid cell in ClimP, we scaled the precipitation forcing in each month of each year so that the seasonal cycle of monthly totals for the year matched the long-term (climatological) seasonal cycle. Thus, in ClimP, we artificially removed the monthly-scale year-to-year temporal variability in the precipitation forcing – at each grid cell, the mean precipitation applied was identical to that used in the control simulation, whereas the interannual variability of monthly precipitation was, by construction, set to zero.

Figure 12 shows the difference between the mean annual GPP produced in ClimP and that in the control simulation. Regions with large positive differences appear in the southeast U.S., along the eastern coasts of South America and Australia, in the Indian subcontinent, in northeastern China, and in various other regions of South America and Africa. Negative differences do not appear anywhere. In effect, Figure 12 illustrates where GPP in the real world would be larger if the year-to-year precipitation supply were more dependable – i.e., where the interannual variability of precipitation holds down the land surface’s carbon uptake. Note, however, that human activities can mitigate the effects of this variability. India, southeast Asia,
and northeastern China in particular are known to undergo extensive irrigation (Figure 8). Because irrigation is effectively a means of providing a more dependable water supply, these particular areas may, in the real world, be capturing the larger GPP rates.

With Figure 13, we focus on the interannual variability of GPP at each grid cell rather than on the spatial distribution of its mean. Figure 13a shows the variance of annual GPP. Figure 13b shows the spatial distribution of $\text{Corr}^2(\text{GPP}, P)$, where $P$ is the annual precipitation; that is, Figure 13b shows the fraction of the total GPP variance that is associated with, or can be “explained by”, variations in annual water supply. The fractions are reasonably large across the globe, even in some areas considered to be not strongly water-stressed, such as the southeastern United States. In contrast, the fields of $\text{Corr}^2(\text{GPP}, T)$ and $\text{Corr}^2(\text{GPP}, R_{\text{net}})$, where $T$ is the yearly-averaged temperature and $R_{\text{net}}$ is the yearly-averaged net radiation, show significantly lower values (Figures 13c and 13d). While interannual temperature variations do have some impact on high latitude GPP variations (perhaps through their effects on snowcover duration), they have little impact anywhere else. Interannual net radiation variations appear to contribute more, especially in Africa; it is quite possible, however, that these particular “contributions” are not real and instead simply reflect known existing correlations between precipitation and net radiation there (not shown).

Together, annual precipitation, temperature, and net radiation do not explain all of the simulated GPP variability. As before, presumably a significant part of the variability stems from year-to-year variations in (for example) the sub-annual timing of the precipitation and associated variations in infiltration and runoff.
Figure 14 shows one final interesting result regarding the interannual variability of GPP. The shading shows $\text{Var}(\text{GPP})$ for a 3-month averaging period (centered, at each grid cell, around the month of maximum GPP). Overlaid on the plot are black dots indicating where $\text{Var}(\text{FPAR})$ for 3-month averages (centered around the local monthly maximum for FPAR) exceeds a value of 0.003, an arbitrary threshold chosen for plotting convenience. The figure shows that $\text{Var}(\text{GPP})$ and $\text{Var}(\text{FPAR})$ tend not to be maximized in the same regions; $\text{Var}(\text{GPP})$ maxima tend to lie on the wetter sides of the $\text{Var}(\text{FPAR})$ maxima. The same basic result (not shown) is found for comparisons of the water-limited portions of the variances (i.e., $\text{Var}(\text{GPP})^*$ versus $\text{Var}(\text{FPAR})^*$), and it is also found (not shown) for the all-grassland and all-deciduous-trees simulations, suggesting that variations in vegetation type are not responsible for such spatial offsets in the maxima. The spatial offsets are instead induced by the carbon physics built into the modeling system. Assuming these physical treatments are accurate, then similar offsets would apply to the real world’s distributions of $\text{Var}(\text{GPP})$ and $\text{Var}(\text{FPAR})$. In other words, given estimates of $\text{Var}(\text{FPAR})$ attained, for example, through the processing of the GIMMS data, knowledge of the offsets could potentially help in the construction of an estimated spatial field of $\text{Var}(\text{GPP})$.

4. Summary and Discussion

Using the Catchment-CN model, a merger of the dynamic phenology components of the CLM4 dynamic vegetation model with the water and energy budget framework of the GMAO Catchment LSM, we examine the connections across the globe between hydroclimate and vegetation variables. Justification for the use of this model in such a study is provided by its demonstrated ability to reproduce observed connections between FPAR and precipitation moments (Section 3), namely, the increase in FPAR with increasing mean precipitation and
decreasing precipitation variability and the proper geographical placement of spatial maxima in the global field of moisture-related FPAR variance.

Our model results can be summarized as follows. First, based on our supplemental simulations with globally uniform vegetation type, we find that the aforementioned relationships between FPAR and precipitation moments are largely independent of vegetation type; the fact that trees grow in wet regimes, grass grows in drier regimes, and shrubs grow in even drier regimes has only a second-order impact on the spatial distribution of FPAR and its interannual variability at each location. Instead, hydroclimatic moments appear to be the dominant determinants of both vegetation type and phenological expression, as represented by FPAR. Our second basic result is that hydroclimatic moments provide a similarly dominant control over the spatial and temporal variability of gross primary productivity (GPP), again with only a second-order contribution from vegetation type.

Such a global scale description of GPP connections to hydroclimate is achievable with a DVM but is not possible with observations, which are much more spatially and temporally limited. Knapp and Smith (2001) used observations collected across eleven tower sites to show that aboveground net primary production (ANPP) tends to increase with increasing annual precipitation, and our global scale results (for GPP, a related variable) are consistent with this. We do see some inconsistencies, however, with their study. For example, Knapp and Smith (2001) find that ANPP has its maximum interannual variability in grassland areas. We find that while the interannual variability of FPAR is maximized in grassland areas, the maxima for GPP variability tend to be spatially offset from these FPAR variance maxima (Figure 14), slightly toward the wetter (forested) side. The offset is minor, however, and the apparent inconsistency, while certainly a possible result of model deficiencies, may also relate to the limited number of
tower sites they examined. More importantly, Knapp and Smith (2001) find that “interannual variability in ANPP [is] not related to variability in precipitation”. Results from our control simulation (not shown) indicate that the square of the spatial correlation coefficient between Var(GPP) and Var(P) across land points is of the order of 30%, which disagrees with their conclusion; indeed, when we limit the calculation to values at the grid cells containing the LTER sites they studied, the square of correlation coefficient increases. We also find a reasonably strong relationship between the time series of GPP and precipitation (Figure 13b) at individual locations.

While interpretations of DVM-based results must be tempered by knowledge of model biases and limitations, DVM experiments, if properly interpreted, open the door to a wealth of potential studies of the global carbon cycle and its interactions with the global water and energy cycles. This paper provides one such study. Another example of note is provided by Guan et al. (2012), who show with DVM simulations over Africa that the statistical character of precipitation forcing (e.g., rainfall intensity) manifests itself in the GPP produced. The advantages of using DVMs – their provision of comprehensive (and often unmeasurable) data and their ability to be modified at will to allow the examination of the impacts of individual physical processes – stand them in good stead for future carbon analyses. Our understanding of global carbon-water-energy connections should continue to increase as researchers continue to use ever-improving versions of these tools.
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