

Dynamical prediction of terrestrial ecosystems and the global carbon cycle: A 25-year hindcast experiment

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[1] Using a 25-year hindcast experiment, we explore the possibility of seasonal-interannual prediction of terrestrial ecosystems and the global carbon cycle. This has been achieved using a prototype forecasting system in which the dynamic vegetation and terrestrial carbon cycle model VEGAS was forced with 15-member ensemble climate predictions generated by the NOAA/NCEP coupled climate forecasting system (CFS) for the period 1981–2005, with lead times up to 9 months. The results show that the predictability is dominated by the ENSO signal with its major influence on the tropical and subtropical regions, including South America, Indonesia, southern Africa, eastern Australia, western United States, and central Asia. There is also important non-ENSO related predictability such as that associated with midlatitude drought. Comparison of the dynamical prediction results with benchmark statistical prediction methods such as anomaly persistence and damping show that the dynamical method performs significantly better. The hindcasted ecosystem variables and carbon flux show significantly slower decrease in skill at longer lead time compared to the climate forcing variables, partly because of the memories in land and vegetation processes that filter out the higher-frequency noise and sustain the signal.

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1. Introduction: Prospect for Ecosystem and Carbon Prediction

[2] An age-old method of environmental prediction that society relies heavily on is the assumption that the seasonal cycle repeats itself each year. A prominent example is the seasonal shifting agricultural practice involving planting in the spring, crop growth in the summer, and harvest in the fall, an invention that dates back to the dawn of civilization. However, interannual climate variability renders one year different from another. The interannual climate anomalies (deviations from an average seasonal cycle) tend to be less predictable, often with adverse effects on human activities.

[3] Recently, forecasts of climate anomalies have been used to predict certain ecosystem characteristics such as

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crop yield and malaria epidemics, and the focus has been on end-user applications such as farmers operating at regional or smaller scales [e.g., *Cane et al.*, 1994; *Hammer et al.*, 2000; *Hansen and Indeje*, 2004; *Palmer et al.*, 2004]. The methodology is typically statistical: observed correlation between climate anomalies and a certain application indicator, for example, crop yield, is used to predict this indicator, provided that climate anomalies can be predicted either statistically or dynamically. On the carbon cycle side, several projects focusing on carbon data assimilation are under way in which error propagation in observations and model parameters is quantified and optimized to produce the best analysis, thus laying the foundation for running a model in prediction mode [*Rayner et al.*, 2005; *Scholze et al.*, 2007].

[4] Here we develop a system for prediction of carbon cycle variability on seasonal-interannual timescales within an organized, quantitative framework.

[5] Distinction is made here between prediction and projection. While projection of future ecosystem and carbon cycle change in response to long-term climate change has been considered in numerous studies, in particular Intergovernmental Panel on Climate Change (IPCC) working group II related activities, the work reported here aims at a deterministic prediction on the shorter seasonal-to-interannual timescales. In this case the prediction is deterministic

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for climate timescales, not weather timescales (which is predictable only up to 1-2 weeks).

[6] What does one expect from seasonal-interannual ecocarbon prediction? A main target is to predict spatial patterns and temporal variability of carbon fluxes and pool sizes (note that ecosystem productivity is typically expressed as a carbon flux) a few months ahead of time. Specific examples include reduced productivity and enhanced fire and CO₂ flux from Amazon to Indonesia when a drought is predicted, say in response to an upcoming El Niño event, and concurrent reduced CO₂ outgassing and phytoplankton production in the eastern Equatorial Pacific Ocean. Such linkages have been documented by observational and modeling studies [e.g., Jones et al., 2001; Zeng et al., 2005a; Patra et al., 2005; Turk et al., 2001]. Another example is to predict atmospheric CO₂ concentration and growth rate, say at Mauna Loa, or global total land-atmosphere carbon flux. Although varying by only 2-3 ppmv on interannual timescales which has little impact on greenhouse effect, atmospheric CO₂ is an integrated indicator of the global biosphere and carbon cycle (recall how the Keeling Curve of Mauna Loa CO₂ concentration clearly depicts the seasonal cycle of the Northern Hemisphere biosphere) [Keeling et al., 1995]. Analogous to NINO3 as an index for climate anomalies associated with ENSO, atmospheric CO2 can be used as a broad index for anomalies in the ecosystem function and the global carbon cycle. Therefore, we will use global total land-atmospheric CO₂ flux as a key indicator in measuring the prediction skill, while also assessing the spatial distribution in ecosystem productivity and carbon fluxes.

[7] Seasonal-interannual ecosystem and carbon cycle predictions have become possible due mainly to two strands of research and development in recent years: (1) significantly improved climate prediction systems, such as the National Oceanic and Atmospheric Administration/National Centers for Environmental Prediction (NOAA/NCEP) coupled Climate Forecast System (CFS) [Saha et al., 2006], and similar efforts such as the European DEMETER and EUROSIP project [Palmer and Shukla, 2000; Palmer et al., 2004]; and (2) development of global dynamic vegetation and terrestrial carbon cycle models on the land side and carbonecosystem models on the ocean side that, when forced offline by observed climate variables, are capable of simulating the major interannual variability in CO₂ fluxes associated with phenomena such as ENSO and drought episodes [Zeng et al., 2005a, 2005b; Peylin et al., 2005].

[8] Here we report a prototype prediction system where the NCEP/CFS climate prediction is used to drive the vegetation/terrestrial carbon model Vegetation-Global-Atmosphere-Soil (VEGAS). The system is dynamical in two important aspects: (1) the CFS predicts the evolution of the physical climate system based on the basis of the internal dynamics of the coupled atmosphere-land-ocean system; and (2) the dynamic vegetation model represents vegetation growth and decay, competition, and the full terrestrial carbon cycle from photosynthesis to carbon allocation and decomposition.

[9] Seasonal-interannual climate prediction has so far relied heavily on ENSO prediction. For instance, major teleconnections are seen across the tropics, as well as some midlatitude regions such as western United States, southern Africa, and central Asia. Such statistical linkage has been employed for agricultural prediction, typically at regional scale. Yet a state-of-the-art climate-carbon prediction system may be able to capture other changes that may or may not be associated with known modes of climate variability. One example is the 1998–2002 midlatitude drought resulting from unusual synergistic anomalies in sea surface temperatures in the Pacific, Indian, and Atlantic oceans [*Hoerling and Kumar*, 2003; *Zeng et al.*, 2005b]. Such changes are difficult, if not impossible, for statistical method to predict, but in principle are predictable in a dynamical prediction system.

2. Design of the Eco-carbon Prediction System

2.1. Setup of the Prediction System

[10] We set up a prototype eco-carbon prediction system using the dynamic vegetation and terrestrial carbon cycle model VEGAS [*Zeng*, 2003; *Zeng et al.*, 2004, 2005a] forced by the predicted climate from the NCEP Climate Forecast System [*Saha et al.*, 2006]. This proposed framework does not include ecosystem feedback to the climate because current climate prediction systems are not set up to do so. Since interannual climate variability arises largely from the coupling between physical ocean, atmosphere, and land, such a "one-way" approach will capture most of the variability.

[11] Potential ambiguity warrants some explanation of the key terminology:

[12] 1. Operational forecast: Predicting what will happen in the future using dynamical or statistical methods, initialized (dynamical) or trained (statistical) by observational input from the past and present.

[13] 2. Hindcast or Retrospective Forecast: Similar to operational forecast, except that the models are applied to past situations, but using only observations to initialize before the period the hindcast is issued for, i.e., even though later observations are already available but are not used. This retrospective approach is useful when the system can be applied to a long period of time to test model skill. Thus, in essence, hindcasting is not different from forecasting and we will use the term "forecast" to describe a procedure applicable to both when there is no ambiguity and "operational forecast" verus "hindcast" when distinction is needed, while "prediction" is used similar to forecast but in an even more general sense.

[14] 3. Validation versus Observation: Ideally, one should use various observations to test the skill of the hindcast as these events already took place. Unfortunately, unlike climate variables such as precipitation and temperature, there are only limited observations of the major ecosystem and carbon variables with sufficient spatiotemporal resolution. The approach here is to use the results from an "offline" simulation in which the vegetation model was forced with observed (as opposed to predicted) climate. Such results for VEGAS had been previously compared with CO_2 fluxes derived using atmospheric inversion of observed CO_2 concentrations and satellite vegetation index



Figure 1. Global total land-atmosphere carbon flux simulated by the vegetation-carbon model VEGAS forced by observed climate (black), compared to that derived from an inversion of a network of atmospheric CO_2 concentrations (red lines with each line representing an inversion using different number of stations [*Rodenbeck et al.*, 2003]), and the Mauna Loa CO_2 growth rate (green). The results were smoothed by a 12 month running mean to remove the seasonal cycle. This offline VEGAS simulation is termed the "validation" and used here to validate the hindcasts in a "tier-2" validation approach [*Morse et al.*, 2005].

[Zeng et al., 2005a; Rodenbeck et al., 2003]. Similar comparisons have been conducted using other models and inversions and the broad-scale interannual variability in carbon fluxes have been found consistent with inversion and other indicators [Peylin et al., 2005]. An example is shown in Figure 1 for the total land-atmosphere carbon flux. An overall agreement between the forward model and the inversion is seen, although both have large uncertainty. The uncertainty for the inversion can be seen in the differences when different number of CO₂ stations are used, although the actual uncertainty is likely much higher. Such offline forecast is what one would get if the climate prediction is "perfect" (exactly like the observed climate) and will be referred to as "the validation". Thus the skill assessed here originates solely from climate prediction, not from the vegetation model, and the difference between this validation and the hindcast shows how errors in climate prediction propagates into carbon cycle prediction. Nevertheless, this is fundamentally different from simply comparing the CFS predicted climate variables with their observed counterparts, because the eco-carbon model is a nonlinear transformation of the predicted climate information. As we will show in our results, the skill in eco-carbon prediction is actually higher than that of the climate forcing because of many important ecosystem processes. Since the model in its offline mode has been validated with inversion, vegetation index, and other data, one has certain confidence that the exercise here is not purely "mathematical", but suggests real potential for prediction; that is, the hindcasted ecosystem and carbon variables should have some realism compared to their observational counterparts if available.

[15] Such a validation approach has been formally proposed recently by *Morse et al.* [2005] in application to malaria prediction where it is referred to as "tier-2"

validation, while the kind using observed ecosystem and carbon variables would be termed "tier-3" validation. However, there is the possibility of some degree of tier-3 validation with currently available data such as site carbon flux measurements. We chose the tier-2 approach here as a key first step toward full validation without being hampered by complication from data quality and other compounding issues.

[16] The forecast procedure of our prototype system includes a few major steps described below and illustrated in Figures 2 and 3. It uses the hindcast setup with VEGAS and CFS as an example, but can be done similarly in operational forecast or for the ocean.

[17] 1. A 25-year (1981–2005) hindcasted climate data set from NCEP/CFS [*Saha et al.*, 2006] was preprocessed. To avoid any bias to which the carbon model may be sensitive, the monthly anomalies (deviations from the 25-year mean climatology) of precipitation/temperature were derived. These anomalies were then added to an observed climatology of CRU [*Mitchell and Jones*, 2005] to produce full-valued climate forcings.

[18] 2. Spin up the vegetation model to equilibrium using January 1981 climate forcing to avoid any "shock" to the vegetation state at model startup.

[19] 3. Run VEGAS for 9 months into future forced by CFS forecasts climate processed from step 1. This is a continuous run from current to 9 months into future forced by the continuous climate forcing. This is done 15 times using 15 CFS ensemble members. The monthly forcing is interpolated to the vegetation model's daily time step. The 9 month and 15 member output of the ecosystem and carbon cycle variables are saved as the hindcast output predicted at this month.

[20] 4. The vegetation state variables such as leaf carbon predicted at the end of the first month above are saved and



Figure 2. Schematic diagram of a prototype forecast system, showing its configuration of model and forcing.

averaged over the 15 member ensemble to serve as the initial condition for the next month's forecast.

[21] 5. Repeat steps 3 and 4, but for the next month, until the end of the hindcast period.

[22] Compared to typical state-of-the-art climate prediction in which sophisticated data assimilation is used for initialization, step 4 is a simple way of initializing the prediction. Carbon data assimilation has only been attempted recently [*Rayner et al.*, 2005] and is not yet ready for application to the prediction problem. However, an attempt has been made in expanding a data assimilation system for prediction by *Scholze et al.* [2007], although the focus there is different from ours. Future research should explore ways to assimilate ecosystem variables such as vegetation structure for prediction purpose. [23] For a significant fraction of the land surface, especially in midlatitude regions, human management such as agriculture, forestry and fire suppression has major impacts on carbon fluxes. To avoid complications, our prototype experiment here only considers natural variability and potential vegetation. Useful results are expected despite of this simplification because human management tends to alleviate adverse climate effects such as drought, but not to reverse them.

2.2. Model Description: Vegas and CFS

[24] The terrestrial carbon model VEGAS [Zeng, 2003; Zeng et al., 2004, 2005a] simulates the dynamics of vegetation growth and competition among different plant



Figure 3. Schematic diagram of a prototype forecast system, showing the temporal structure in real time (horizontal axis, t from Jan1981 to Dec2005 at monthly interval) and forecast lead time (vertical axis, L = 1 to 9 months). The ensemble mean of 1 month lead (L = 1) forecast of state variables is used to initialize the model at the next month.

functional types (PFTs). It includes four PFTs: broadleaf tree, needleleaf tree, cold grass, and warm grass. The different photosynthetic pathways are distinguished for C3 (the first three PFTs above) and C4 (warm grass) plants. Phenology is simulated dynamically as the balance between growth and respiration/turnover. Competition is determined by climatic constraints and resource allocation strategy such as temperature tolerance and height-dependent shading. The relative competitive advantage then determines fractional coverage of each PFT with possibility of coexistence. Accompanying the vegetation dynamics is the full terrestrial carbon cycle, starting from photosynthetic carbon assimilation in the leaves and the allocation of this carbon into three vegetation carbon pools: leaf, root, and wood. After accounting for respiration, the biomass turnover from these three vegetation carbon pools cascades into a fast soil carbon pool, an intermediate, and finally a slow soil pool. Temperature and moisture-dependent decomposition of these carbon pools returns carbon back into the atmosphere, thus closing the terrestrial carbon cycle. A fire module includes the effects of moisture availability, fuel loading, and PFT-dependent resistance. The vegetation component is coupled to land and atmosphere through a soil moisture dependence of photosynthesis and evapotranspiration, as well as dependence on temperature, radiation, and atmospheric CO₂.

[25] The NCEP Climate Forecast System (CFS) is the fully coupled ocean-land-atmosphere dynamical seasonal prediction system that became operational at NCEP in August 2004 [Saha et al., 2006] (http://cfs.ncep.noaa.gov/). The atmospheric component of the CFS is a lower-resolution version of the Global Forecast System (GFS) that was the operational global weather prediction model at NCEP during 2003. The ocean component is the GFDL Modular Ocean Model version 3 (MOM3). The land component is that of Mahrt and Pan [1984]. There are several important improvements inherent in the new CFS relative to the previous dynamical forecast system. These include (1) the atmosphere-ocean coupling spans almost all of the globe (as opposed to the tropical Pacific only); and (2) the CFS is a fully coupled modeling system with no flux correction (as opposed to the previous uncoupled tier-2 system, which employed multiple bias and flux corrections) [Kanamitsu et al., 2002].

[26] The CFS provides important advances in operational seasonal prediction on a number of fronts [Saha et al., 2006]. For the first time in the history of U.S. operational seasonal prediction, a dynamical modeling system has demonstrated a level of skill in forecasting U.S. surface temperature and precipitation that is comparable to the skill of the statistical methods used by the NCEP Climate Prediction Center (CPC). This represents a significant improvement over the previous dynamical modeling system used at NCEP. Furthermore, the skill provided by the CFS spatially and temporally complements the skill provided by the statistical tools. The availability of a dynamical modeling tool with demonstrated skill should result in overall improvement in the operational seasonal forecasts and have significant practi-

cal implications for land climate variability relevant to this project.

3. Results From the 25-Year Hindcast Experiment

[27] An implementation of the forecast procedure described in section 2.1 yielded a large hindcast product even at monthly output frequency. It includes 300 (25 year \times 12 month) forecasts with each forecast consisting of 9 month lead time and 15 ensemble members, in addition to the 2 dimensionality (latitude and longitude), thus essentially a 5-dimensional data set for all the vegetation and carbon variables. The simulation is equivalent to a single model run of 40,500 months (3375 years). As a prototype, VEGAS was run at a relatively coarse resolution of $2.5^{\circ} \times 2.5^{\circ}$.

[28] To facilitate the analysis of the results, we define a total land-atmospheric carbon flux as

$$F_{ta} = R_h - NPP \tag{1}$$

where NPP is the Net Primary Productivity and R_h is the heterotrophic or soil respiration. F_{ta} is sometimes termed Net Ecosystem Exchange (NEE), but the ecological literature is not always consistent on the definitions of these terms [Chapin et al., 2006], e.g., whether fire should be included. For simplicity here, the carbon loss due to fire is lumped into autotrophic respiration (aboveground biomass burned; thus in NPP) and R_h (litterfall burned) because both fire and respiration lose carbon via oxidation, so that F_{ta} is zero under steady state, i.e., no net accumulation of carbon over large spatial and long timescales. While precipitation exerts strong control on NPP (growth), temperature has a major control on R_h [Schlesinger, 1991; Zeng et al., 2005a]. From the point of view of ecosystem prediction, NPP is most relevant. For the purpose of predicting atmospheric CO₂, the net carbon flux F_{ta} is most relevant. While important variables such as leaf biomass, fire carbon flux, R_h , and soil carbon are all available, results will only be shown for NPP and F_{ta} here.

[29] A "plume" chart (Figure 4) shows the hindcasted NPP at one grid point in the Amazon and another in southeastern United States for a 3.5-year period during 1996-1999. When compared with the validation, the hindcast NPP captures the large changes associated with the 1997-1998 El Niño. Each member of the ensemble forecast starts from a slightly different initial condition in the climate forecast while the initial vegetation state is the same for each member as described above. The multiple ensemble members (plumes) clearly demonstrate the power of ensemble forecasting. For instance, some members from the September 1997 Amazon forecast overpredict the decreased NPP, some others predict increased NPP, but many others, as well as the ensemble mean correctly predict decreased NPP. In the March 1998 forecast for southwestern United States, the model predicts an initial increase followed by a decrease after 3 months, very similar to the validation, suggesting skill in transitional events with long lead time.



Figure 4. A time section of the predicted NPP anomalies (kgC $m^{-2} a^{-1}$) for two grid points, one over the Amazon, the other one southwestern United States, compared to the validation (black line). Each line represents one individual member of a 15-member ensemble forecast. For clarity, the forecasts were "thinned" to show only every 6 months and for a 6 month long forecast while the actual forecasts were monthly and 9 months long. The top two panels are for anomalies while the lower panels include seasonal cycle.

On the other hand, the transition after December 1998 was only captured by few ensemble members. It is interesting that southwestern United States has much larger scatter across the ensemble members than the Amazon, and its interannual variability is also larger relative to its seasonal amplitude.

[30] Figure 5a shows the global total land-atmosphere carbon flux from the hindcast compared to the validation. The hindcasts reproduce the major interannual variability, including two major El Niño events in 1982-1983 and 1997-1998, although the amplitude is underestimated for 1997-1998. A surprising yet good result is that the forecast deteriorates relatively slowly as a function of lead time L (L = 1 month is the average of the first month and so on); that is, a forecast 9 months into future still carries significant amount of predictability compared to, for example, a 1 month lead forecast. This is partly due to the spatial averaging, partly due to the skill in the CFS predicted climate, and also importantly due to the memory in the hydroecosystem such as soil moisture which tends to filter out higher-frequency noise. Such skill stems from the good climate prediction skill in the tropics as CFS captures the major interannual anomalies in precipitation and temperature there (Figures 5b and 5c), as long established by observational and modeling work [Rayner et al., 1998; Zeng et al., 2005a; Patra et al., 2005].

[31] Figure 6 shows anomaly correlation between the hindcast and the validation land-atmosphere carbon flux F_{ta} for three lead times L = 1, 3, and 6 months.

Anomaly correlation is a commonly used skill indicator defined as

$$r = \frac{\overline{x'y'}}{\sigma_x \sigma_y} \tag{2}$$

where σ is variance, prime denotes anomaly, overline denotes average, *x* is any variable from the hindcast while *y* is the corresponding variable from the validation. Many land regions have some skill, with correlation greater than 0.5 in many places in the first month. A summary of statistics (Figure 7) shows that for F_{ta} at L = 1 month, 15% of the land area has correlation higher than 0.5, and 62% of the land area has correlation higher than 0.3 (statistically significant at 95% level based on student t-test). At L = 3 months, 25% of the land area has correlation higher than 0.3.

[32] The area with high skill tends to be in the tropics, including the Amazon, Indonesia, and Australia, but also midlatitude regions such as southern Africa, the U.S. West and southwest/central Asia. This is not surprising, as these regions all have well established teleconnection with ENSO, the dominant interannual climate mode in precipitation and temperature [e.g., *Ropelewski and Halpert*, 1987].

[33] The skill generally decreases at longer lead time (larger L), as expected. At 3 month lead, the land area with correlation higher than 0.5 in F_{ta} dropped to 10% while it decreased to slightly below 30% for correlation higher than 0.3. At 6 month lead, the skill decreases more, but signif-



Figure 5. (a) Global total land-atmosphere carbon flux (PgC a^{-1}) predicted by the hindcast experiment compared to the validation (solid black line); (b) Tropical mean precipitation (mm d^{-1}) from CFS compared to the observation; (c) Tropical mean temperature (Celsius) from CFS compared to the observation. Each line represents the 15-member ensemble mean of the forecasts for a particular lead time (from 1 to 9 months), obtained by combining all the forecasts for that lead time. Seasonal cycle has been removed.

icant correlation is still seen in the regions identified above such as the Amazon and U.S. West, with only a few regions having negative correlations (i.e., prediction is on average opposite of what happened) that are not statistically significant.

[34] From the viewpoint of predicting global total ecosystem productivity or CO_2 , anomaly correlation may not be the best indicator because regions with high correlation may have small amplitude that contributes little to the global total. A better measure for this purpose is regression as shown in Figure 8. In this case, regression is defined as

$$R = \frac{\overline{x'y'}}{\sigma_v} \tag{3}$$

Compared to Figure 6b, the regression pattern shown in Figure 8 is dominated by the same regions with higher and longer predictability such as the Amazon and southwestern United States.



Anomaly Correlation

Figure 6. Anomaly correlation of net land-atmosphere carbon flux between validation and the forecasts for lead time 1, 3, and 6 months.

[35] A well known "spring barrier" exists in ENSO prediction as prominently seen in the CFS precipitation and the forecasted NPP, as the forecast made in the spring has much lower correlation (Figure 9a) [e.g., *Webster and Yang*, 1992; *Saha et al.*, 2006]. This spring barrier in climate prediction manifests itself in the ecosystem prediction as a "summer barrier" with a delay of about one season due to the memory in land and vegetation (Figure 9b).

[36] Because ENSO dominates the interannual CO₂ signal, statistical skill analysis inevitably depicts how the system performs with ENSO which tends to be dominated

by the tropics [Zeng et al., 2005a]. Because of this, any statistical prediction will also be dominated by the ENSO signal [e.g., Rayner et al., 1998; Jones and Cox, 2005; Patra et al., 2005]. However, there are other important variabilities a dynamical prediction system can also capture. For instance, during the period of 1998–2002, much of the midlatitude Northern Hemisphere was in the grip of a wide-spread drought caused by an unusual pattern of the tropical ocean temperature anomalies [Hoerling and Kumar, 2003]. Zeng et al. [2005b] suggested that this drought played a key role in the consecutive large CO₂



Figure 7. Summary of correlation skill for Figure 6, showing the cumulative percentage area that have correlation between forecasted and the validation F_{ta} higher than a given value (horizontal axis). Correlation values smaller than 0.1 (including negative correlations) are not shown. Note the rapid decrease in skill at $L \ge 2$ in the CFS forecasted climate (precipitation and temperature), but the significantly higher skill in the carbon model forecasted NPP and F_{ta} .

growth in 2002–2003. Figure 10 shows the hindcasted net carbon flux averaged over 1998–2002 compared to the validation. The hindcast captures much of the drought-

induced carbon flux in North America and Eurasia. Since the hindcasts are only for 9 months, the 3.5-year average shown in Figure 10 includes both the skill of the seasonal



Figure 8. Regression between the forecasts and the validation land-atmosphere carbon flux F_{ta} for lead time of 3 months (kgC m⁻² a⁻¹). Compared to the correlation in Figure 6b, large flux anomalies remain only in regions with strong ENSO teleconnection which are also the main contributors to global total carbon flux.



Figure 9. Seasonal dependence of the forecast skill (correlation between forecast and the validation for precipitation and F_{ta} averaged over the tropics). The vertical axis is lead time L while the horizontal axis is the month the forecast was issued. A so-called "spring barrier" is prominent in the CFS precipitation and the forecasted F_{ta} as the forecast made in the spring has much lower correlation. Note that the spring barrier in climate prediction manifests itself in F_{ta} as a "summer barrier" with a delay of about one season due to the memory in land and vegetation.

forecast and the persistence of the drought. Nonetheless, the persistence ultimately comes from SST that provides useful information for predicting the biosphere. In the case of long-lasting climate anomalies, even if the seasonal climate prediction itself has no skill, the dynamic vegetation model would carry past climate information into future because its initial condition reflects cumulative effect of the past.

[37] The pillar of seasonal-interannual climate prediction is the predictability related to the tropical ENSO SST anomalies which generally weakens outside the tropics. The fact that the forecasted ecosystem response is similar to the validation indicates that significant predictability also exists in regions outside the tropics. Since these variabilities are not always related to ENSO, other variations captured by the CFS forecast system are also useful for eco-carbon prediction.

4. Comparison of the Dynamical Method With Some Statistical Methods

[38] While the hindcast experiments discussed above demonstrate significant skill in seasonal prediction, it is important to establish benchmarks to which the dynamical prediction can be compared. Two statistical methods are used here in the absence of information on future climate. The first is the persistence method in which the climate anomaly at the time of forecast is simply assumed to persist into future (Persistence). The second is a damping method in which the climate anomaly at the time of forecast is



Figure 10. Land-atmosphere carbon flux (kgC m⁻² a⁻¹) averaged for the midlatitude drought period of 1998–2002 from (a) the hindcast at L = 6; and (b) the validation.



Figure 11. The correlation skill between hindcast and the validation of tropically averaged land-atmosphere carbon flux for four forecasting methods: Dynamical, Persistence, Damping, and Initial Condition only. Values above 0.39 as indicated by the horizontal line are statistically significant at 95% level.

assumed to decrease at a rate defined by the decorrelation timescale of the variable (e.g., precipitation). An autocorrelation analysis using the observed precipitation and temperature was conducted with the seasonal cycle preremoved (not shown), and the decorrelation timescale ranges from 3-7 months. Then climate anomalies for the "future" were allowed to decrease exponentially from the current values to zero at the (spatially varying) decorrelation timescale (Damping). An additional experiment was also conducted in which climate forcing anomalies were set to zero in the 9 month forecast, thus showing only the decay of the initial condition (Initial Condition) which reflects the cumulative effect of past anomalies.

[39] Figure 11 shows the anomaly correlation of tropical F_{ta} . These two benchmark methods have skill comparable to the dynamical prediction at L = 1 and 2. Not surprisingly, their skills deteriorate faster than the dynamical prediction. At L = 9, the anomaly correlation for the dynamical prediction is still over 0.6 while the two statistical benchmark methods have about 0.4. These are all statistically significant at 95% level.

[40] Another issue of interest is how much of the predictability comes from the memory in the eco-carbon system (Initial Condition). If no information on climate anomaly is used, as in the case of Initial Condition only, the skill drops much more rapidly. While this is expected, an interesting finding is the memory effect in land and vegetation that nonetheless gives rise to a correlation of 0.4 at L = 3 and 0.2 at L = 9.

[41] Anomaly correlation depicts the skill in phase relationship, but it does not compare magnitude of the changes. For this purpose, we use the Taylor diagram [*Taylor*, 2001], a method originating from atmospheric model intercomparison that depicts simultaneously in a 2-D plot the magnitude, phase, and root-mean-square errors. Figure 12 shows the following for tropical carbon flux:

[42] 1. The fully dynamical prediction has a correlation that decreases slowly from 0.8 to 0.65 as lead time increases from 1 to 9 months, while Persistence and Damping decrease more rapidly from 0.8 to 0.4 (more clearly seen in Figure 11).

[43] 2. The amplitude (standard deviation or variance) changes only slightly from L = 1 to 9 for the dynamical method (1.1 of validation at L = 9). In contrast, Persistence amplitude increases rapidly and reaches 1.7 (70% higher) of validation at L = 9. Instead, the Damping method has an amplitude that decreases to 0.4 of validation at L = 9. Neither is surprising in that Persistence maintains the anomaly, while the signal decreases toward zero in Damping.

[44] 3. In the Initial Condition only case, correlation decreases from 0.64 to near 0.1 while the amplitude from

Figure 12. Taylor diagram [*Taylor*, 2001] showing the skill of the fully dynamical prediction (Dynamical) compared to Persistence, Damping, and Initial Condition only. The radial distance indicates standard deviation of each method normalized by that of the validation, while the azimuth angle represents the anomaly correlation between each forecast and the validation. The distance to the REF point (the validation, or where a perfect forecast would be) is the root-mean-square (RMS) error. Plotted dots are for tropical total carbon flux. The numbers indicate lead time L in months. The Dynamical method has high skill that decays slowly with lead time. Persistence deteriorates modestly in correlation but with rapid amplitude overprediction, while Damping leads to rapidly underpredicted amplitude. Initial Condition only has lower but non-negligible skill.

0.5 to 0.1 of validation, thus the signal is "forgotten" much more quickly than the other methods. This is not surprising as the persistence method makes the climate anomaly last longer, while the damping method relaxes the anomaly to zero. In many ways, the initial condition only case is an extreme of the damping method, but with the climate anomaly damped to zero instantaneously. Its skill is the lowest both in amplitude and phase in Figure 12. Despite this, as discussed previously, the spatial patterns show that in certain regions where the ENSO influence is strong, the memories in land and vegetation have significant contribution to the eco-carbon predictability. In summary, although some signal is carried along by the initial condition, simple statistical methods such as persistence and damping assumption of climate anomalies improve significantly, but dynamical prediction is much better especially at long lead time.

5. Discussion and Conclusion

[45] Using a 25-year hindcast experiment, we demonstrate the feasibility of seasonal-interannual prediction of terrestrial ecosystems and the global carbon cycle variables. This has been achieved using a prototype forecasting system in which the dynamic vegetation and terrestrial carbon cycle model VEGAS was forced with the 15-member ensemble climate prediction with lead time up to 9 months from the NCEP/CFS climate forecast system.

[46] The results show that the predictability is dominated by the ENSO signal for its major influence on the tropical and subtropical regions, but there is also important non-ENSO related predictability such as that associated with midlatitude drought. The correlation between global total land-atmospheric carbon flux from the hindcast with that from a validation experiment in which observed climate was used to drive the carbon model is higher than 0.42 at 3 month lead time. The correlation is higher at 0.79 for the tropical flux, while it is only 0.56 for the Northern Hemisphere extratropics. The anomaly correlation is higher than 0.3 for 25% of the land area at 3 month lead. Much of the predictability comes from regions with major ENSO teleconnection such as the Amazon, Indonesia, western United States, and central Asia.

[47] Compared to the CFS predicted precipitation and temperature where skill deteriorates rapidly at longer lead time, the hindcasted NPP and carbon flux show significantly slower decrease in skill, especially for the global or tropical total carbon flux, likely because of the memories in land and vegetation processes that filter out the higher-frequency noise and sustain the signal.

[48] Comparison of the dynamical prediction results with benchmark statistical methods show that the dynamical method is significantly better than either anomaly persistence or damping of the current climate anomalies. Using initial condition only also leads to some predictability, consistent with the notion of a land-vegetation memory. Given the high correlation between ENSO and MLO CO₂, it is expected that a simple regression on ENSO will have good skill in prediction MLO CO₂ [*Jones and Cox*, 2005; *Patra et al.*, 2005]. Our test shows that the dynamical prediction has better skill (correlation 0.55 compared to 0.46 for ENSO regression). Of course the dynamical method also gets the geographical distribution as well as changes not related to ENSO.

[49] The validation of the hindcasts described here uses a tier-2 approach [*Morse et al.*, 2005]; that is, the validation is from an offline model rather than direct observations of the ecosystem and carbon variables. However, since the model in its offline mode has been validated with fluxes from atmospheric inversion, vegetation index, and other data (Figure 1) [*Zeng et al.*, 2005a, 2005b; *Qian et al.*, 2008]; our results suggest real potential for prediction in that the hindcasted ecosystem and carbon variables do represent nature to a certain degree. Obviously, in-depth evaluation will be needed in the future.

[50] We conclude that seasonal-interannual prediction of the ecosystem and carbon cycle is feasible. Such prediction will be useful for a suite of activities such as ecosystem management, agriculture, and fire preparedness. The current system can be improved in several ways including (1) combination of statistical and dynamical methods; for instance, statistically correcting the systematic bias in the climate prediction; and (2) the initialization used is simplistic and can be improved in the future with observed climate variable and in conjunction with carbon data assimilation [*Rayner et al.*, 2005; *Scholze et al.*, 2007].

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