Dynamical Prediction of the Terrestrial Ecosystem and the Global Carbon Cycle: A 25-year Hindcast Experiment

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ABSTRACT

Using a 25-year hindcast experiment, we explore the possibility of seasonal-interannual prediction of the terrestrial ecosystem 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 consisting of lead times up to 9 months from the NCEP/CFS climate forecast system. 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 US and central Asia. There is also important non-ENSO related predictability such as that associated with mid-latitude 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 compared to the climate variables, partly due to the memories in land and vegetation processes that filter out the higher frequency noise and sustain the signal.

1. Prospect for eco-carbon prediction

Recently, forecasts of climate anomalies have been used to predict certain ecosystem characteristics such as 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; 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 the information on climate anomalies can be predicted either statistically or dynamically. However, predicting ecosystem and carbon cycle at global scale, whether dynamical or statistical, has not been made quantitatively at interannual timescale.

What does one expect from seasonal-interannual eco-carbon prediction? A main target is to predict spatial patterns and temporal variability of carbon fluxes and pool sizes (note that ecosystem productivity is a flux) a few months ahead of time. Specific examples include reduced productivity and enhanced fire and CO_2 flux from Amazon to Indonesia when a drought is predicted, say in response to an upcoming El Nino event, and concurrent reduced CO_2 outgasing and phytoplankton production in the eastern Equatorial Pacific Ocean. Such linkages have been documented by numerous observational and modeling studies (e.g., Jones et al., 2001; Zeng et al., 2005a; Turk et al., 2001). Another example is to predict atmospheric CO_2 concentration and growth rate, say at Mauna Loa, or global total land-atmosphere carbon flux. While varying by only 2-3 ppmv on interannual timescales which has little impact on greenhouse effect, atmospheric CO_2 is an integrated indicator of the global biosphere and carbon cycle (recall how the Keeling Curve of Mauna Loa CO_2 concentration clearly depicts the seasonal cycle of the Northern Hemisphere biosphere; Keeling et al., 1995). Analogous to NINO3 as an index

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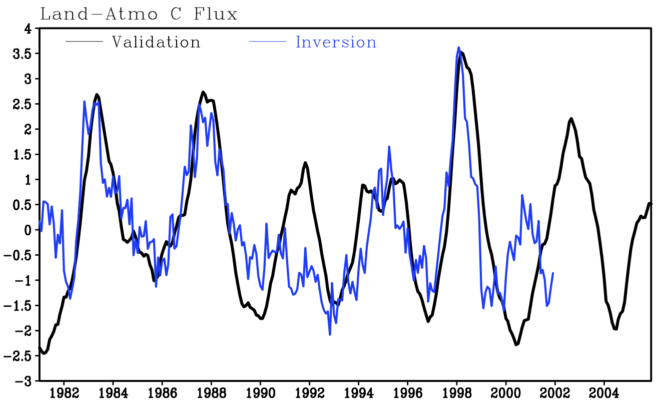

Figure 1 Global total land-atmosphere carbon flux simulated by the VEGAS forced by observed climate (black), compared to that derived from an inversion of a network of atmospheric CO_2 concentrations (blue; Rodenbeck et al., 2003) with a 12 month running mean to remove the seasonal cycle.

for climate anomalies associated with ENSO, atmospheric CO_2 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 CO_2 flux as a key indicator in measuring the prediction skill, and also assess the spatial distribution in ecosystem productivity and carbon fluxes.

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 NOAA/NCEP (National Oceanic and Atmospheric Administration/ National Centers for Environmental Prediction) coupled Climate Forecast System (CFS; Saha et al., 2006), and similar efforts such as the European DEMETER and EUROSIP project (Palmer et al.,2004), (2) development of global dynamic vegetation and terrestrial carbon cycle models on the land side and carbon-ecosystem models on the ocean side that, when forced offline by observed climate variables, are capable of simulating the major inter-annual variability in CO_2 fluxes associated with phenomena such as ENSO and drought episodes (Zeng et al., 2005a,b).

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

2. Design of the eco-carbon prediction system

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 by 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 (Zeng et al., 2005a; Rodenbeck et al., 2003). An example is shown in Fig.1 for the total land-atmosphere carbon flux. Such an offline simulation 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 will be the skill solely from climate prediction, not from the vegetation model. Nevertheless, this is fundamentally different from simply comparing the CFS predicted climate variables with their observed counterparts, because the eco-carbon model is a non-linear transformation of the

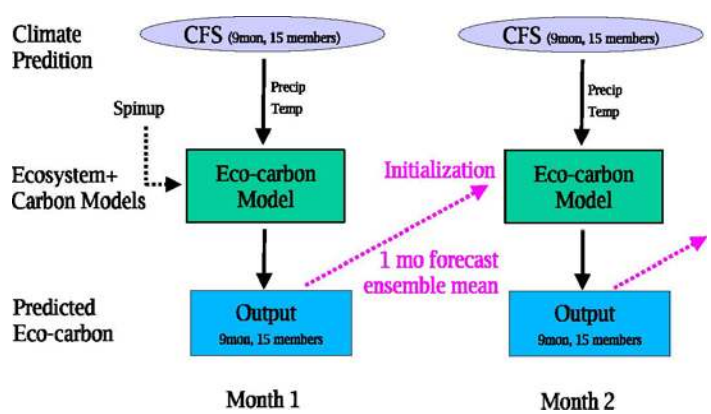

Figure 2 Schematic diagram of a prototype forecast system, showing its configuration of model and forcing.

predicted climate information.

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

1. A 25-year (1981-2005) hindcasted climate dataset 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 Climatic Research Unit (CRU) dataset (Mitchell and Jones, 2005) to produce full-valued climate forcings.
2. Spin-up the vegetation model to equilibrium using January1981 climate forcing, to avoid any 'shock' to the vegetation state at model startup.
3. Run VEGAS for 9 month into future forced by CFS forecasts climate processed from Step 1. 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 outputs of the ecosystem and carbon cycle variables are saved as the hindcast output predicted at this month.
4. The vegetation state variables such as leaf carbon predicted at the end of the first month above are saved, and averaged over the 15 member ensemble to serve as the initial condition for the next month's forecast.
5. Repeat Steps 3 and 4, but for the next month, until the end of the hindcast period.

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. Nevertheless, future research should explore ways to assimilate ecosystem variables such as vegetation structure for prediction purpose.

For a significant fraction of the land surface, especially in mid-latitude regions, Human management such as agriculture, forestry and fire suppression have major impacts on carbon fluxes. To avoid complications, our proto type 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. Also, as a prototype, our forecast output is at a relatively coarse resolution of 2.5°×2.5°.

3. Results from a 25-year hindcast experiment

To aid in analyzing the results, we define a total land-atmospheric carbon flux as

$$Fta = Rh - NPP, \quad (1)$$

where NPP is the Net Primary Productivity, and Rh is the heterotrophic or soil respiration. Fta is sometimes termed Net Ecosystem Exchange (NEE). While precipitation exerts strong control on NPP (growth), temperature has a major control on Rh

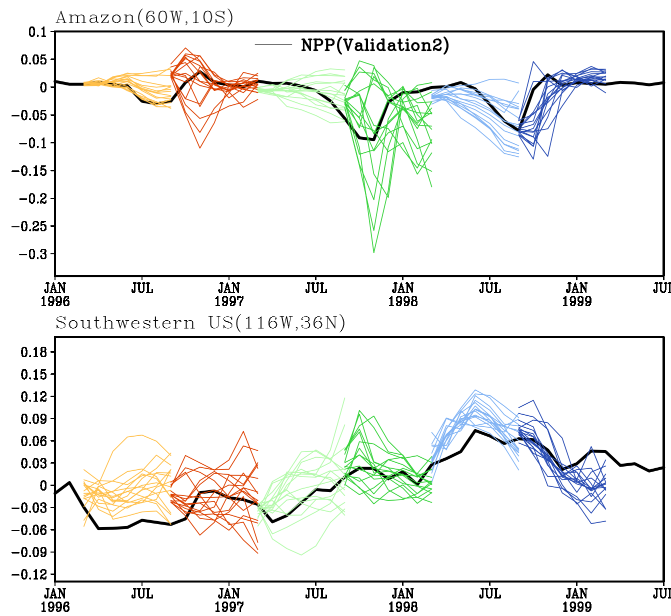

Figure 3 A time section of the predicted NPP (kg $cm^{-2}y^{-1}$) anomalies for two grid points, one over the Amazon and the other over south-western US, compared to the validation (black line; seasonal cycles removed). Each colored line represents one individual member of a 15-member ensemble forecast. Different colors represent forecasts made at different time. 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 for 9 month lead.

(Schlesinger 1991; Zeng et al., 2005a). From the point of view of ecosystem prediction, NPP is most relevant. For the purpose of predicting atmospheric CO_2, the net carbon flux Fta is most relevant. While results will be shown for NPP and Fta, other variables such as leaf biomass, fire carbon flux, Rh, soil carbon are all available.

A 'plume' chart (Fig. 3) shows the hindcasted NPP at one grid point in the Amazon and another in southeastern US for a 3.5 year period during 1996-1999. When compared with the validation, the hindcast NPP captures the large changes associated with the 1997-98 El Nino. Each member of the ensemble forecast starts from a slightly different initial condition in the climate forecast while the initial vegetation state is 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 over predict the decreased NPP, some others predict increased NPP, many others and the ensemble mean correctly predict decreased NPP. In the March 1998 forecast for southwestern US, 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. On the other hand, the transition after December 1998 was only captured by few ensemble members.

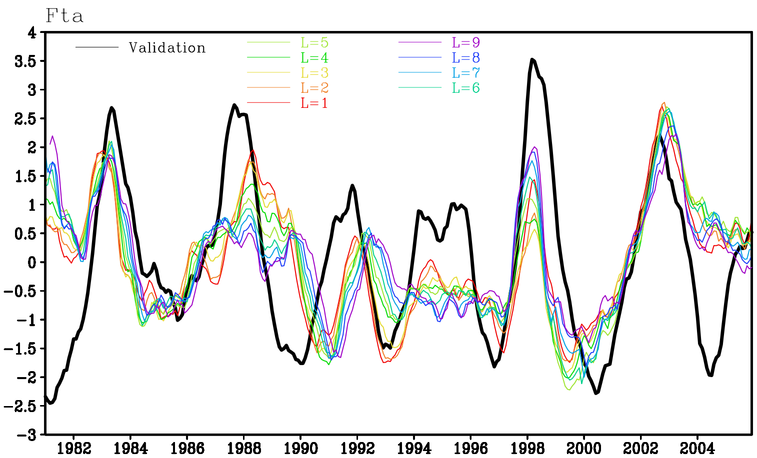

Figure 4 Global total land-atmosphere carbon flux (PgCy-1) predicted by the hindcast experiment compared to the validation (solid black line). Each colored line represents the 15-member ensemble mean of the forecasts for a particular lead time (from 1 to 9 months), obtained by combining all the forecasts for that lead time. Seasonal cycle has been removed.

Figure 4 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 Nino events in 1982-83 and 1997-98, although the amplitude is underestimated for 1997-98. 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 1-month lead forecasts and so on), i.e., 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 skill in the CFS predicted climate, and also importantly due to the memory in the hydro-ecosystem such as soil moisture which tends to filter out higher frequency noise.

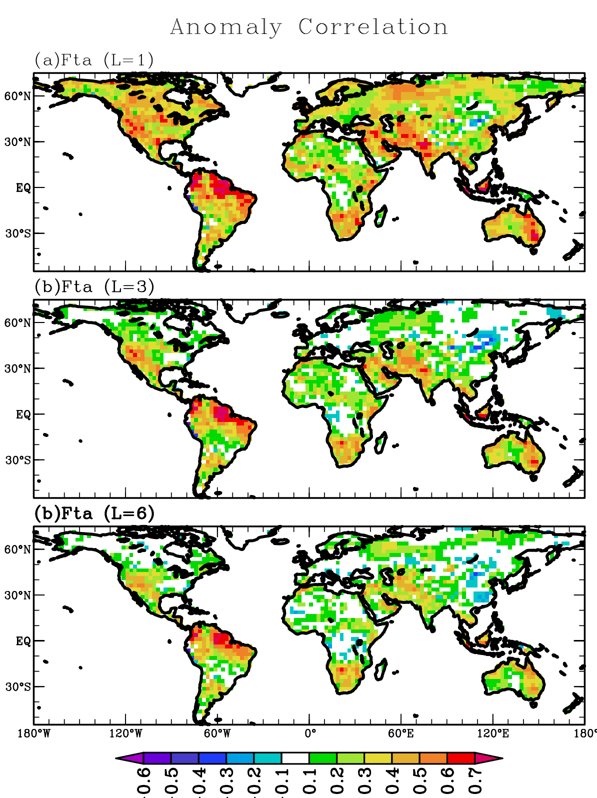

Figure 5 Anomaly correlation of net land-atmosphere carbon flux between validation and the forecasts for lead time of 1, 3, 6 months.

The upper panel of Fig.5 shows anomaly correlation between the hindcast and the validation land-atmosphere carbon flux Fta for three lead times L=1, 3, and 6 month. Many land regions have some skill, with correlation greater than 0.5 in many places in the first month. The area with high skill tends to be in the tropics, including the Amazon, Indonesia and Australia, but also mid-latitude regions such as southern Africa, the US 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, 1986).

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 to. 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 assumed to decrease at a rate defined by the de-correlation timescale of the variable (e.g., precipitation). An auto-correlation analysis using the observed precipitation and temperature was conducted with the seasonal cycle pre-removed (not shown), and the de-correlation 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) de-correlation 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.

Figure 6 shows the anomaly correlation of tropical Fta. These two benchmark methods have similar skill that is 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. 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.

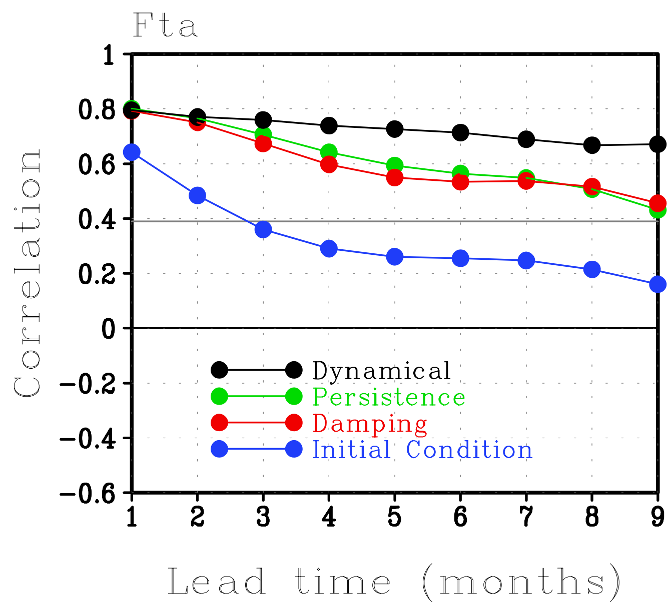

Figure 6 The correlation skill between the hindcast and the validation of tropically averaged land-atmosphere carbon flux for four forecasting methods: Dynamical, Persistence, Damping, and Initial Condition only.

4. Conclusions

Using a 25-year hindcast experiment, we demonstrate the feasibility of seasonal-interannual prediction of terrestrial ecosystem 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 month from the NCEP/CFS climate forecast system.

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 mid-latitude 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 extra-tropics. 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 US and central Asia.

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 due to the memories in land and vegetation processes that filter out the higher frequency noise and sustain the signal. 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.

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; (2) The initialization used is simplistic and can be improved in the future with observed climate variable and in conjunction with carbon data assimilation; (3) Furthermore, improvement in model physics for both climate and terrestrial carbon cycle simulation and predictions are necessary.

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