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

Ning Zeng[1,2], Jin-Ho Yoon[1], Augustin Vinzileos[3], G. James Collatz[4], EugeniaKalnay[1], Annarita Mariotti[2,5], Arun Kumar[6], Antonio Busalacchi1[1,2], Stephen Lord[3]

[1]Dept. of Atmospheric and Oceanic Science, University of Maryland, College Park, MD, USA, [2]Earth System Science Interdisciplinary Center, University of Maryland, [3]NOAA Environmental Modeling Center, Camp Springs, MD, [4]NASA Goddard Space Flight Center, Greenbelt, MD, [5]ENEA Casaccia, Rome, Italy, [6]NOAA Climate Prediction Center, Camp Springs, MD, Correspondence to: zeng@atmos.umd.edu

1. Prospect for Eco-Carbon Prediction

Climate prediction has in the past been applied to crop yield, malaria and other applications, typically based on statistical correlation. Here we test the feasibility of predicting ecosystems and carbon cycle on seasonal-interannual timescales using dynamical models both in climate and ecosystem/carbon cycle.

Two strands of recent research made this a real possibility

- Significantly improved skill in atmosphere-ocean prediction system, such as CFS at NCEP
- Development of dynamic ecosystem and carbon cycle models that are capable of capturing major interannual variabilities, when forced by observed climate anomalies

A prototype prediction system where the NCEP/CFS climate prediction is used to drive the dynamic vegetation/carbon model VEGAS (Fig.1)

2. Major forecasting steps

1. A25-year (1981-2005) hindcasted climate dataset from NCEPCFS (Saha et al., 2006) was preprocessed.
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 done15 times using 15 CFS ensemble members (Fig.1).
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.

3. Results from a 25-year hindcast experiment

- Power of ensemble forecasting in capturing the likelihood of change (Fig.2)
- 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 (Fig.4).
- 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 (Fig.3,4).
- 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.

Many land regions have some skill (Fig.3), 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.

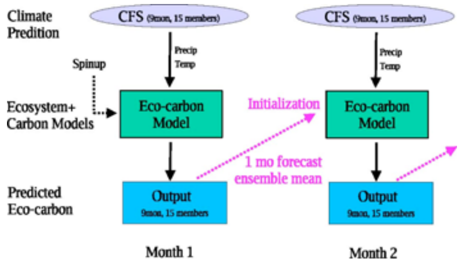

Figure 1: Schematic diagram of a prototype forecast system, showing its configuration of model and forcing.

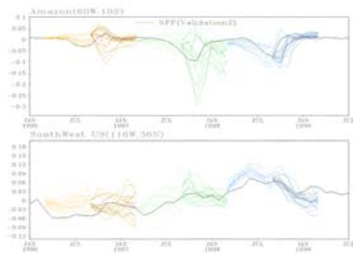

Figure 2: A time section of the predicted NPP anomalies (kgC/m2/y) for two grid points over the Amazon and southwestern US, compared to the validation (black line; seasonal cycles removed). Each line represents one individual member of a 15-member ensemble forecast. For clarity, the forecasts were `thinned' to show only every 6 months and for a 6-month long forecast while the actual forecasts were monthly and 9 month long.

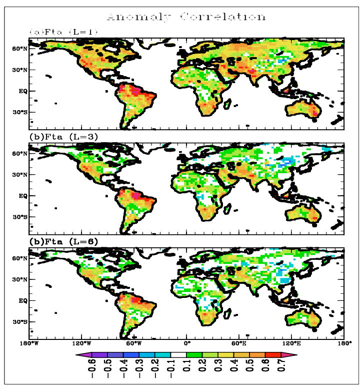

Figure 3: Anomaly correlation of net land-atmosphere carbon flux between validation and the forecasts for lead time 1, 3, 6 months.

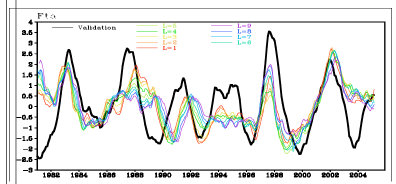

Figure 4: Global total land-atmosphere carbon fux (PgCy-1) predicted by the hindcast experiment compared to the validation (solid blackline).

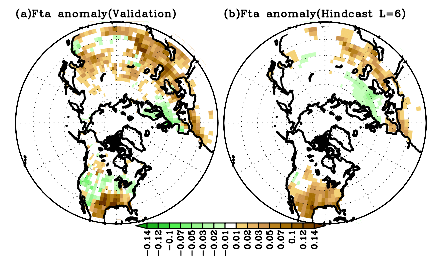

Figure 5: Land-atmosphere carbon flux averaged for the midlatitude droughtperiod of 1998-2002 from (a) the hindcast at L=6; (b) the validation.

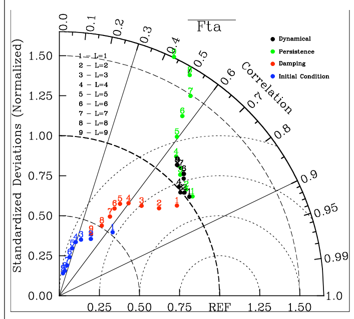

Figure 6. Taylor diagram (Taylor, 2001) showing the skill of the fully dynamical prediction (Dynamical) compared to Persistence, Damping and Initial Condition only.

Both the skill of the seasonal forecast and the persistence in 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 such as this long-lasting drought, 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.

- The fully dynamical prediction has a correlation that decreases slowly, while Persistence and Damping decrease more rapidly. Also, the amplitude changes only slightly for dynamical method. In contrast, Persistence amplitude increases rapidly. Instead, the Damping method has an amplitude that decreases.
- The Initial Condition only case correlation and amplitude decreases, thus the signal is 'forgotten' much more rapid than the other methods.
- Persistence maintains the anomaly, while the signal decreases towards zero in Damping. The persistence method also makes the climate anomaly last longer, while the damping method relaxes the anomaly to zero.

4. Conclusions

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 results show that the predictability is dominated by the ENSO signal for its major influence on the tropical and subtropical regions. Much of the predictability comes from regions with major ENSO teleconnection such as the Amazon, Indonesia, western US and central Asia. However, there is also important non-ENSO related predictability such as that associated with mid-latitude drought. 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.

5. References

Saha, S., S. Nadiga, C. Thiaw, and others, 2006: The NCEP Climate Forecast System. J. Climate, 19 (15), 3483-3517.
Taylor, K. E., 2001: Summarizing multiple aspects of model performance in a single diagram. J.Geophys. Res., 106(D7), 7183-7192, 10.1029/2000JD900719
Zeng et al. (2008); Dynamical Prediction of the Terrestrial Ecosystems and the Global Carbon Cycle: a 25-year Hindcast Experiment., *Global Biogeochem Cycles.*