NEWS

Global-Scale Drought Caused Atmospheric CO_2 Increase

PAGES, 178, 181

Identifying the mechanisms driving interannual fluctuations of atmospheric carbon dioxide is necessary for predicting future CO_2 concentrations and climate change [*Prentice et al.*, 2001]. A possible clue comes from a well-established positive correlation between atmospheric CO_2 growth rates and the El Niño–Southern Oscillation phenomenon [*Keeling et al.*, 1989; *Bousquet et al.*, 2000]. Most tropical droughts are also linked to El Niño [*Lyon*, 2004], suggesting carbon losses from drought as a major cause for interannual CO_2 variations.

A lag correlation between 7-month running means (see Figure 1) of monthly atmospheric CO_2 concentrations [*Cooperative Atmospheric Data Integration Project*, 2004] and Niño 3 sea surface temperatures (available at http://www.cpc.noaa.gov/data/indices/) for the period 1979–2003 peaks at a lag of four months with a correlation of 0.49, and a significance level above 99.9% (assuming 42 independent measurements).

Simulations of the balance between photosynthesis and ecosystem respiration with the Biosphere Energy Transfer Hydrology model (BETHY), driven by observed climate data, capture most of the timing and magnitude of the observed CO_2 growth rate anomalies during the time of the latest two El Niño events, 1998 and 2002, and closely follow interannual changes in land precipitation (Figure 1). Observed growth rates for 1998, however, were higher than simulated; this could be attributed to unusually large emissions from tropical forest fires during 1998, which did not occur during the 2002 El Niño [*Page et al.*, 2002; see also http://dup.esrin.esa.int/ionia/wfa/index.asp].

For the period October 1999 to September 2003, satellite observations of the fraction of absorbed photosynthetically active radiation (fAPAR) [*Gobron et al.*, 2005] from the Sea-viewing Wide Field-of-view Sensor (SeaWiFS) reveal a temporary negative trend in vegetation activity, especially in the semi-arid tropics (Figure 2a). The patterns are well reproduced by BETHY (Figure 2b), which simulates the response of vegetation to the increasingly dry conditions during this period (see Figure 1). An exception is the positive trend for Borneo seen in SeaWiFS data that may have been caused by regrowth after the 1998 fires reported by *Page et al.* [2002], a process not incorporated into BETHY.

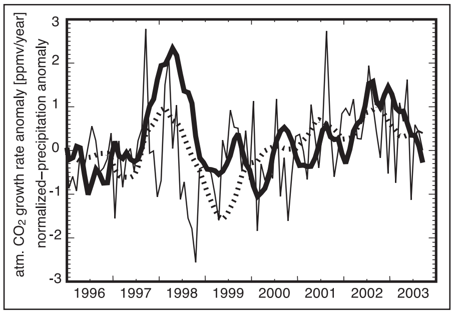

*Fig. 1. Growth rate anomalies of atmospheric CO_2 derived from the average of the concentrations at Mauna Loa, Hawaii, and the South Pole [*Cooperative Atmospheric Data Integration Project, *2004], in ppmv yr^{-1}. Anomalies were derived by subtracting the 1979 to 2003 mean of 1.6 ppmv yr^{-1} and the average seasonal cycle. Curves were smoothed by a 7-month running mean, and then the first and last three months were removed. Shown are observations (bold curve) and simulations (dashed curve) using the BETHY terrestrial vegetation model coupled to the TM2 transport model [*Knorr and Heimann, *2001]. The thin curve shows anomalies of negative global land precipitation [*Chen et al., *2002] in units of their standard deviation. Anomalies were derived by subtracting the 1979–2002 mean and the average seasonal cycle.*

Whether droughts on average cause carbon loss of the land biosphere will require further studies. Also, some of the variability may have been caused by generally small variations in ocean carbon fluxes [*Bousquet et al.*, 2000], emissions from fossil fuel burning, or contributions from burning events outside tropical forests. However, a dominant impact of El Niño–related drought on the rate of increase of atmospheric CO_2 can be simulated on the basis of the natural processes of photosynthesis and respiration alone. A detailed analysis of the available data using CO_2 flux inversions and carbon cycle data assimilation should help confirm the mechanisms causing the recent and possible future accelerations of atmospheric CO_2 growth rates.

References

Bousquet, P., P. Peylin, P. Ciais, C. Le Quéré, P. Friedlingstein, and P. Tans (2000), Regional changes in carbon dioxide fluxes of land and oceans since 1980, *Science, 290*, 1342–1346.

Chen, M., P. Xie, J. E. Janowiak, and P. A. Arkin (2002), Global land precipitation: A 50-yr monthly analysis based on gauge observations, *J. Hydrometeorol., 3*, 249–266.

Cooperative Atmospheric Data Integration Project (2004), GLOBALVIEW-CO2, NOAA Clim. Monit. and Diagn. Lab., Boulder, Colo.

Gobron, N., et al. (2005), The state of vegetation in Europe following the 2003 drought, *Int. J. Remote Sens.*, in press.

Keeling, C. D., R. B. Bacastow, A. F. Carter, S. C. Piper, T. P. Whorf, M. Heimann, W. G. Mook, and H. Roeloffzen (1989), A three-dimensional model of atmospheric CO_2 transport based on observed winds: 1. Analysis of observational data, in *Aspects of Climate Variability in the Pacific and Western Americas*, Geophys. Monogr. Ser., vol. 55, edited by D. H. Peterson, pp. 165–236, AGU, Washington D. C.

Knorr, W., and M. Heimann (2001), Uncertainties in global terrestrial biosphere modeling: 2: Global constraints for a process-based vegetation model, *Global Biogeochem. Cycles, 15*(1), 227–246.

Lyon, B. (2004), The strength of El Niño and the spatial extent of tropical drought, *Geophys. Res. Lett., 31*, L21204, doi:10.1029/2004GL020901.

Page, S. E., F. Siegert, J. O. Rieley, H.-D. V. Boehm, A. Jayak, and S. Limink (2002), The amount of carbon released from peat and forest fires in Indonesia during 1997, *Nature, 420*, 61–65.

Prentice, I. C., et al. (2001), The carbon cycle and atmospheric carbon dioxide, in *Climate Change 2001*, edited by J. T. Houghton et al., pp. 185–225, Cambridge Univ. Press, New York.

—WOLFGANG KNORR and MARKO SCHOLZE, QUEST, Department of Earth Sciences, University of Bristol, U.K.; NADINE GOBRON and BERNARD PINTY, Global Vegetation Monitoring Unit, IES, EC Joint Research Centre, Ispra, Italy; and THOMAS KAMINSKI, FastOpt, Hamburg, Germany

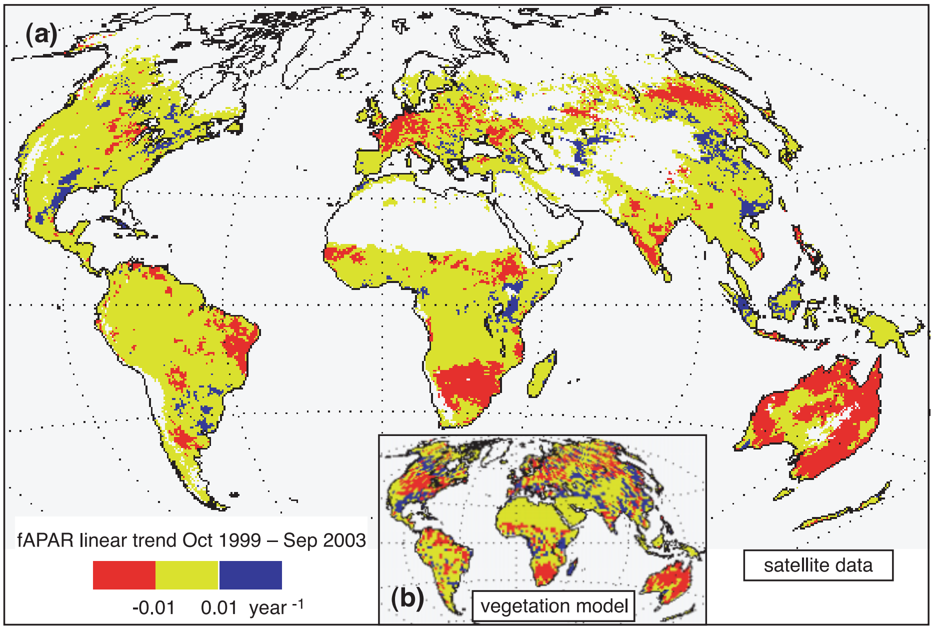

Fig. 2. (a) Linear trends in fAPAR derived from annual mean values for the period October 1999 to September 2003 retrieved from SeaWiFS satellite data. White areas indicate pixels with less than 50% temporal coverage each year. (b) The same trend in fAPAR predicted by the BETHY model.