Comments

Ecology, 91(3), 2010, pp. 921–923
© 2010 by the Ecological Society of America

Global potential net primary production predicted from vegetation class, precipitation, and temperature: comment

Luke P. Shoo[1,2] and Vanessa Valdez Ramirez[1]

Terrestrial vegetation acts as a reservoir for significant amounts of carbon and is involved in annual processing of carbon through photosynthesis and respiration (Clark 2007). Empirical study of contemporary patterns of terrestrial net primary production (NPP) is therefore critical for understanding how the global carbon budget will be affected by ongoing climate change (Clark et al. 2003). Field-based measurements of NPP are necessary to calibrate process-based models and remote sensed surrogates of productivity (Chen et al. 2004, Nightingale et al. 2008) as well as to build algorithms that link NPP to climate at global scales (Lieth 1975, Schuur 2003).

In a recent analysis, Del Grosso et al. (2008) present an updated model of the global relationship between NPP and climate. The Del Grosso et al. (2008) model was considered to be an improvement on previous algorithms in two main respects. First, the model allowed for separate fitting of climate–NPP relationships for tree- and non-tree-dominated systems. For a given level of precipitation, non-tree-dominated systems were shown to exhibit significantly lower NPP than tree-dominated systems so it would seem sensible to parameterize equations for the two systems separately. Second, the new model drew upon a greatly expanded data set of NPP compiled as part of the Ecosystem Model–Data Intercomparison (EMDI) project (Olson et al. 2001) supported by the National Center for Ecological Analysis and Synthesis (NCEAS) in Santa Barbara, California, USA. The worldwide synthesis of data is expected to improve coverage, representation and replication of data from vegetation types, climates, and soils used to parameterize models. Here we raise some concerns about the methodological approach used to derive the "improved" models and their application in the retrospective reconstruction of past global trends in NPP in response to 20th-century climate change.

The authors state that the analysis benefited from "approximately 5600 global data points with observed mean annual NPP" (Del Grosso et al. 2008). This is a large step up from just 100 sites across six continents employed in the next most recent analysis (Schuur 2003). Closer inspection, however, reveals that ~4500 (about 80%) of the global points used in the analysis were not direct observations but rather estimates derived from spatial interpolations of smaller subsets of field measurements. This issue is particularly important for two of the three data compilations that cover continental Australia (Barrett 2001) and the Great Plains of the United States (Sala et al. 1988). In these cases, the interpolations themselves were dependent on local modeling of NPP that utilized information on mapped environmental variables such as precipitation. Clearly, the application of such derived input data to test coarser resolution models of climate–NPP relationships is an example of circular reasoning.

The problem of circularity in this context has been noted previously. Zheng et al. (2003) warned that due caution should be exercised when attempting to use derived data to validate more general models. Unfortunately no guidelines were given as to what should constitute "due caution" and, in any case, these important limitations were not reiterated by Del Grosso et al. (2008). Clearly, the benefits and shortcomings of using point and regionally interpolated data in such applications need to be debated. We believe that regionally interpolated data do not improve model algorithms but instead introduce extra, unwanted problems in analyses that complicate interpretation of results. Here, we describe some of the main issues (in addition to circularity).

First, regionally specific interpolations introduce geographic inconsistencies in approaches used to generate NPP data. For example, in the EMDI data set, NPP in one region was interpolated using precipitation regressions (i.e., U.S. Great Plains) while in another case, regressions that account for precipitation, soil fertility, and other ecosystem parameters were used (i.e., continental Australia). This is not consistent with the goal of developing a global NPP data set that has been derived from a standard set of methodologies (e.g., Clark et al. 2001*a*, Chave et al. 2005). Second, regionally interpolated data is likely to generate undue confidence in the model by artificially inflating sample size and removing real spatial variability in NPP data. Interpolated estimates of NPP in one cell are influenced by estimates of NPP in neighboring field plots. As such,

Manuscript received 30 October 2008; revised 16 March 2009; accepted 2 April 2009. Corresponding Editor: M. A. Arthur.

[1] Centre for Tropical Biodiversity and Climate Change, School of Marine and Tropical Biology, James Cook University of North Queensland, Townsville, Queensland 4811 Australia.

[2] E-mail: luke.shoo@jcu.edu.au

interpolated data do not represent truly independent data but instead are pseudoreplicates. As an intermediate analytical step, regional interpolations are also expected to preemptively "smooth" out some of the real spatial variability in NPP. Both of these issues are likely to yield an overly optimistic impression of the degree of congruence between input data and the model algorithm. Third, regionally interpolated data exacerbate geographic sampling bias in the global data set by inflating replication in just two regions (continental Australia, Great Plains of United States). This is important because the optimized global algorithm is then heavily driven by data from only a small set of "over-sampled" regions. Finally, the procedure of substituting point data with regionally interpolated data in global data compilations is expected to make it more difficult to revisit and update global NPP models as better resolution climate data become available.

The use of interpolated data to indirectly estimate NPP represents a trade-off between increasing replication and representativeness of global NPP data and generating data that result in self-fulfilling tests of mechanistic drivers or correlates of NPP. Arguably, the cons of the later outweigh any perceived benefits. That is, forecasting change in terrestrial NPP has implications for the global carbon budget which is critical to preempting feedbacks in atmospheric CO_2 accumulation and the climate system. We run the very real risk of building models that are both misleading in terms of predictions but also the degree of uncertainty associated with those predictions. Given these risks, we recommend that data sets only be used to address such ecological questions where NPP has been directly measured in the field.

A further issue concerns the temporal mismatch between data on NPP and climate used to parameterize models. Del Grosso et al. (2008) reconciled NPP estimates that spanned single growing seasons through to multiple years against long term averages of climate (i.e., annual means from 1961–1990). Census dates for NPP data also varied widely among studies. For example, some tropical NPP data points from the Clark et al. (2001*b*) compilation were determined 30–40 years ago which stands in stark contrast to the timing of other more contemporary studies used in the analysis (e.g., Schuur 2003). By adopting a 30-year climate average, Del Grosso et al. (2008) do not account for significant changes in climate that have occurred in the later half of the preceding century and year-to-year variability in environmental conditions when parameterizing their models. This is important because ecosystems could reasonably be expected to respond to climate variability through temporal adjustments in productivity. For example, canopy tree growth in one tropical plot has been shown to vary more than twofold among years and was negatively correlated with minimum temperatures over a 16-year period (Clark et al. 2003). Productivity of grasslands, croplands and tropical savannahs is also known to vary on an interannual basis (Zheng et al. 2003).

This shortcoming is not unique to the Del Grosso et al. (2008) analysis. However, it is an important caveat given that the resulting models were subsequently used to reconstruct trends in NPP over the 20th century. The problem is that much of the variability in NPP (see Del Grosso et al. 2008: Figs. 1 and 2) used to parameterize the models may in fact be attributable to temporal change in response to fluctuating climates that do not reflect the long term average condition. The broad temporal spread of NPP observations is not insignificant because it covers a period of time that overlaps substantially with the reconstruction period. It is possible that this methodological issue may even partly explain why a minority of data points classified as non-tree-dominated in the Del Grosso et al. (2008) analysis had NPP values greater than most trees for a given level of precipitation. That is, the NPP for the non-tree points may have been assessed in unusually good years with the reverse being true for the tree-dominated systems.

To adequately address the issue of mismatched data it will be necessary to disentangle the effects of time and space in analyses of patterns of observed productivity. This represents a significant challenge because the underlying data points are often less than ideal. Census dates are not available for all point estimates of NPP. The same is true for historical estimates of climate particularly in regions where the density of weather stations has been low or in areas of complex terrain where climate can vary enormously over small distances (New et al. 2002). It is also not obvious what relative influences short term and long-term climate processes have on realized NPP in any given year. For example, immediate water availability can affect plant growth directly though plant water balance but it is also expected to modify productivity via soil weathering and chronic reductions in nutrient availability (Schuur 2003). Furthermore, there may be time lags between water availability and productivity such that plant growth may respond to water from the previous year.

Given the above, we recommend that future analyses include a more comprehensive treatment of temporal matching between climate and NPP data. Specifically, we suggest a tiered analytical approach that will enable short term processes to be disentangled from long term processes. That is, we suggest compiling climate data at multiple temporal levels including: actual concurrent climate for the year(s) that NPP was measured; short-term climate averages (e.g. concurrent climate and the proceeding five years); and, long-term climate averages (e.g., 30-year mean). By relating the pattern of NPP to each of these data sets it will be possible to determine

which, if any, temporal window of climate is best for explaining the global pattern of NPP. Such an analysis offers considerable opportunity to gain valuable insights into the relative importance of temporal processes that can inform development of future global models.

The purpose of this comment is not to detract from the value of studies such as Del Grosso et al. (2008) that aim to scale up point observations of NPP (i.e., from small field plots) to estimate components of the carbon cycle across the entire land surface of the Earth. Rather, we simply caution against the use of interpolated estimates of NPP as independent observations of NPP when testing climate based models at course spatial scales. Likewise, we emphasize that temporal variability in climate needs to be taken into account if we are to properly parameterize models that seek to reconstruct historical trends in NPP.

Acknowledgments

This work was supported by a Marine and Tropical Sciences Research Facility funded Fellowship and the Research Advancement Program from James Cook University.

Literature cited

Barrett, D. J. 2001. NPP multi-biome: VAST calibration data, 1965–1998. Data set. Available on-line from Oak Ridge National Laboratory Distributed Active Archive Center, Oak Ridge, Tennessee, USA. ⟨http://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=576⟩

Chave, J., et al. 2005. Tree allometry and improved estimation of carbon stocks and balance in tropical forests. Oecologia 145:87–99.

Chen, Z. M., I. S. Babiker, Z. X. Chen, K. Komaki, M. A. A. Mohamed, and K. Kato. 2004. Estimation of interannual variation in productivity of global vegetation using NDVI data. International Journal of Remote Sensing 25:3139–3159.

Clark, D. A. 2007. Detecting tropical forests' responses to global climatic and atmospheric change: current challenges and a way forward. Biotropica 39:4–19.

Clark, D. A., S. Brown, D. W. Kicklighter, J. Q. Chambers, J. R. Thomlinson, and J. Ni. 2001*a*. Measuring net primary production in forests: concepts and field methods. Ecological Applications 11:356–370.

Clark, D. A., S. Brown, D. W. Kicklighter, J. Q. Chambers, J. R. Thomlinson, J. Ni, and E. A. Holland. 2001*b*. Net primary production in tropical forests: an evaluation and synthesis of existing field data. Ecological Applications 11: 371–384.

Clark, D. A., S. C. Piper, C. D. Keeling, and D. B. Clark. 2003. Tropical rain forest tree growth and atmospheric carbon dynamics linked to interannual temperature variation during 1984–2000. Proceedings of the National Academy of Sciences (USA) 100:5852–5857.

Del Grosso, S., W. Parton, T. Stohlgren, D. Zheng, D. Bachelet, S. Prince, K. Hibbard, and R. Olson. 2008. Global potential net primary production predicted from vegetation class, precipitation, and temperature. Ecology 89:2117–2126.

Lieth, H. 1975. Modeling the primary productivity of the world. Pages 237–263 *in* H. Lieth and R. H. Whittaker, editors. Primary productivity of the biosphere. Springer-Verlag, Berlin, Germany.

New, M., D. Lister, M. Hulme, and I. Makin. 2002. A high-resolution data set of surface climate over global land areas. Climate Research 21:1–25.

Nightingale, J. M., M. J. Hill, S. R. Phinn, I. D. Davies, A. A. Held, and P. D. Erskine. 2008. Use of 3-PG and 3-PGS to simulate forest growth dynamics of Australian tropical rainforests: I. Parameterisation and calibration for old-growth, regenerating and plantation forests. Forest Ecology and Management 254:107–121.

Olson, R. J., K. R. Johnson, D. L. Zheng, and J. M. O. Scurlock. 2001. Global and regional ecosystem modeling: databases of model drivers and validation measurements. ORNL/TM-2001/196. Oak Ridge National Laboratory, Oak Ridge, Tennessee, USA.

Sala, O. E., W. J. Parton, L. A. Joyce, and W. K. Lauenroth. 1988. Primary production of the central grassland region of the United States. Ecology 69:40–45.

Schuur, E. A. G. 2003. Productivity and global climate revisited: the sensitivity of tropical forest growth to precipitation. Ecology 84:1165–1170.

Zheng, D., S. Prince, and R. Wright. 2003. Terrestrial net primary production estimates for 0.5 deg grid cells from field observations: a contribution to global biogeochemical modeling. Global Change Biology 9:46–64.