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Research paper

Quantification of the response of global terrestrial net primary production to multifactor global change

Peng Li[a], Changhui Peng[a,b,*], Meng Wang[a], Weizhong Li[a], Pengxiang Zhao[a], Kefeng Wang[a], Yanzheng Yang[c], Qiuan Zhu[a,*]

[a] Center for Ecological Forecasting and Global Change, College of Forestry, Northwest A&F University, Yangling, Shaanxi 712100, China
[b] Department of Biology Sciences, Institute of Environment Sciences, University of Quebec at Montreal, C.P. 8888, Succ. Centre-Ville, Montreal H3C 3P8, Canada
[c] Center for Earch System Science, Tsinghua University, Beijing 100084, China

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ABSTRACT

Based on an updated and comprehensive global NPP database, an artificial neural network (ANN) data mining approach was used to investigate the spatial and temporal patterns and control factors on global terrestrial ecosystem NPP between 1961 and 2010. Five variables (precipitation, air temperature, leaf area index, fraction of photosynthetically active radiation and atmospheric CO_2 concentration) were selected and integrated to develop a three-layer back-propagation (BP) ANN model. The results indicated that the ANN method is capable of simulating and predicting the NPP of the global terrestrial ecosystem, yielding a simulation accuracy of 0.72 and a prediction accuracy of 0.60. The estimated global mean annual NPP was approximately 61.46 Pg C between 1961 and 2010, with an annual increase of 0.23 Pg C and a total increasing of 10.14 Pg C. The middle and high latitudinal zones made the major contribution to the total NPP increasing with percentage of 87.5% (8.87 Pg C), whereas the low latitude zone made the remaining contribution (1.27 Pg C). The atmospheric CO_2 concentration was found to be the dominant factor that controlled the interannual variability and to be the major contribution (45.3%) of global NPP. Leaf area index, climate and fraction of photosynthetically active radiation resulted in NPP increases of 21.8%, 18.3% and 14.6%, respectively. Overall, multiple factors jointly control the variation in global NPP, and it is vital to consider the underlying mechanisms of combined environmental effects on NPP in future studies.

1. Introduction

Net primary production (NPP) is a principal component in the global biosphere carbon cycle and it represents the net carbon fixed by the global plant community (Chapin et al., 2002). As a fundamental attribute of the global biosphere, NPP plays an essential role in providing humans with necessary food, timber and fibre (Vitousek et al., 1986; Costanza et al., 1998; Running et al., 2004). Because NPP is a composite reflection of the combined climatic, geochemical, ecological and human effects on the biosphere (Nemani et al., 2002, 2003), it is sensitive to multiple environmental changes such as climate and atmospheric changes (Chapin et al., 2002). Therefore, to assess the spatial and temporal patterns of NPP and to quantitatively analyse the relationships between NPP and its related environmental factors, these factors have received increasing attention in global change studies during the past several decades (Piao et al., 2005; Hsu et al., 2012; Liang et al., 2015; Pan et al., 2016).

Previous studies have indicated that the variability of NPP is controlled by a broad range of biotic and abiotic factors operating mainly through changes in plant physiological activities and phenology (Geider et al., 2001; Richardson et al., 2010; Stoy et al., 2014; Xia et al., 2015). Climate change and increasing CO_2 concentrations were recognized as the key factors in the change in global terrestrial NPP (Melillo et al., 1993). Rising air temperatures, altered precipitation patterns and elevated atmospheric CO_2 interact with each other and exert a combined impact on ecosystem structure and function (Canadell et al., 2007). In addition to climate change and the fertilization effects of rising atmospheric CO_2, land use change, such as afforestation and deforestation (Zhou et al., 2015),

* Corresponding authors at: Center for Ecological Forecasting and Global Change, College of Forestry, Northwest A&F University, Yangling, Shaanxi 712100, China
E-mail addresses: peng.changhui@uqam.ca (C. Peng), qiuan.zhu@gmail.com (Q. Zhu).

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and anthropogenic nitrogen deposition (Stevens et al., 2015) also have an important effect on terrestrial NPP. Therefore, the complex interactions between these factors in the global terrestrial ecosystem pose a considerable challenge for NPP modelling studies. In general, these interactions are not well known, and it is difficult to attribute the relative contribution of multifactor global changes.

Empirical models have been used to quantify the relationship between NPP and related environmental variables (Zaks et al., 2007; Del Grosso et al., 2008; Cleveland et al., 2015), and it assume that effects of environmental variables on NPP change are linear and independent of each other. However, evidences from both field experiment and theoretical analysis have shown nonlinear ecosystem responses to the environmental changes (Berry and Bjorkman, 1980; Peng et al., 2013a), and highlighted the potential limitations from the linear regression analysis. A considerable number of ecosystem process models also have been applied to analyse the spatiotemporal patterns of NPP and its responses to global change in terrestrial ecosystems (Cramer et al., 1999; Pan et al., 2014). However, huge uncertainties remain in the different ecosystem models in estimating global NPP. Siegenthaler and Sarmiento (1993) quantified the annual global NPP to be 51.97 Pg C, which was much lower than the estimation of Sundquist (1993), who estimated global NPP to be 60 Pg ; Cramer et al. (1999) conducted a comparison of 17 process-based models, and the estimated global NPP had a wide range of 44–66 Pg C yr^{-1}, resulting from how the water balance was represented in the models. Similarly, Friedlingstein et al. (2006) found the differences in the same 17 global NPP models were due largely to the belowground processes that cause different responses of NPP to multifactor global change. Thus, the limitations of NPP estimation are largely attributed to complicated processes in the biosphere, and the process models have been unable to consider all of the complicated nonlinear relationships involving ecosystem and environmental variables. Compared with empirical models and process-based models, the artificial neural network (ANN) method has the greatest potential to address the nonlinear problems because of its accurate mapping capability (Liu et al., 2010). The ANN method is known for its strengths in handling many types of prediction and classification complexities. This method has been used successfully to map global terrestrial N_2O emissions (Zhuang et al., 2012) and to simulate methane emissions (Dengel et al., 2013; Zhu et al., 2013), the soil organic carbon dynamics (Dai et al., 2014; Yang et al., 2014; Were et al., 2015), and the C flux of a Chinese fir plantation in subtropical China (Wen et al., 2014).

Most of the field measurements of NPP have been conducted and published for global terrestrial ecosystems during the past several decades. The detailed observational data and the ANN method may offer an opportunity to analyse the effects of multiple environmental factors on global terrestrial NPP. In this study, we synthesized 2196 measurements from a global compilation of NPP data on global terrestrial ecosystems. We chose a three-layer back-propagation neural network (BPNN) method (Svozil et al., 1997; Saxén and Pettersson 2006; Liu et al., 2012) to estimate NPP and selected five key variables: including precipitation (Hsu et al., 2012), air temperature (Clark et al., 2003), leaf area index (Schloss et al., 1999), fraction of photosynthetically active radiation (Bicheron and Leroy, 1999) and atmospheric CO_2 concentration (Norby et al., 2005), which are considered to be main factors controlling the NPP dynamics of global terrestrial ecosystem (Chapin et al., 2002). The main objectives of this study were to (1) examine the performance of the ANN model in estimating the NPP of the global terrestrial ecosystem, (2) analyse the spatiotemporal patterns of global NPP during the period 1961–2010, and (3) quantify the relative contributions of major environmental factors controlling the change in global NPP.

2. Materials and methods

2.1. Data

We have collected and complied most of the available observational NPP data from the Oak Ridge National Laboratory (ORNL) Distributed Active Archive Center database (http://daac.ornl.gov/NPP/npp home.shtml). These study sites contain NPP measurements from more than 30 countries and cover a range of vegetation types and biomes. Each site contains a collection of NPP observational records (Bailey, 1989; Jager et al., 2000). These NPP observed values were originally recorded as yearly measurements per unit area.

To examine the potential effects of multifactor global change on the variation of NPP, we collected environmental factors to develop the ANN model, including climate, atmospheric CO_2 concentrations (CO_2), fraction of photosynthetically active radiation (fPAR), and leaf area index (LAI) for each site. These site-level data were first retrieved from original records in ORNL and then complemented with other spatially explicit data sets based on the geographic coordinates and experiment dates of the measurements. For climate data (monthly, half degree spatial resolution), we used precipitation (P) and air temperature (T), which were derived from newly available CRU-TS climate forcing data (http://www.cru.uea.ac.uk/). The half degree monthly atmospheric CO_2 concentration (CO_2) data and the fraction of photosynthetically active radiation (fPAR) data were derived from the Multi-scale Synthesis and Terrestrial Model Intercomparison Project (MsTMIP) (http://nacp.ornl.gov/MsTMIP.shtml). The leaf area index (LAI) dataset used in this study was from Global Land Surface Satellite (GLASS) LAI dataset, which consists of time-series reflectance data generated from MODIS and AVHRR (Xiao et al., 2014). Then, the global 0.5° LAI were generated by aggregating three-hour intervals of 0.05° data from the GLASS LAI dataset. To aggregate from a 0.05° cell size to 0.5° cell size, the LAI data values for each 10×10 pixel block were then averaged to create a single 0.5° pixel of new values. The maps of global major biomes in this study (Fig. 1) were a combination of (1) the Terrestrial Ecoregions of the World database (http://worldwildlife.org/publications/terrestrial-ecoregions-of-the-world), which includes forest (including the three subtypes tropical, temperate, boreal forest and mixed forest), grassland, savanna, shrubland, tundra, desert and cropland, and (2) global land cover maps (http://due.esrin.esa.int/globcover/; 2009 version), which defines croplands and other areas (including artificial surfaces and associated areas, water bodies, and permanent snow and ice).

Finally, a total of 2196 datasets with complete records, containing both NPP values and the selected five environmental variables, were used for developing the ANN model. The geographic distribution of the collected 2196 datasets were presented in Fig. 1. The detailed statistics on the NPP, P, T, LAI, fPAR and CO_2 for each biome type were summarized in Table S1.

2.2. Artificial neural networks

Neural networks use machine learning based on the concept of the self-adjustment of the internal control parameter (Bishop, 1995; Rojas, 1996). Similar to the human brain, an ANN learns from past experiences to solve new problems. When modelling non-parametric relationships, a neural network uses the knowledge gained from past experiences to build a codex of "neurons" to make new decisions, classifications and forecasts (Lek and Guégan, 1999). Because of excellent data-mining ability, the ANN often has a better performance than conventional experience methods (Moffat et al., 2007; Moffat et al., 2010). In this paper, a back-propagation network was used to conduct the relationship between the output variable (NPP) and the input variables (five environmental factors).