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A continuous measure of gross primary production for the conterminous United States derived from MODIS and AmeriFlux data

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ABSTRACT

The quantification of carbon fluxes between the terrestrial biosphere and the atmosphere is of scientific importance and also relevant to climate-policy making. Eddy covariance flux towers provide continuous measurements of ecosystem-level exchange of carbon dioxide spanning diurnal, synoptic, seasonal, and interannual time scales. However, these measurements only represent the fluxes at the scale of the tower footprint. Here we used remotely sensed data from the Moderate Resolution Imaging Spectroradiometer

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(MODIS) to upscale gross primary productivity (GPP) data from eddy covariance flux towers to the continental scale. We first combined GPP and MODIS data for 42 AmeriFlux towers encompassing a wide range of ecosystem and climate types to develop a predictive GPP model using a regression tree approach. The predictive model was trained using observed GPP over the period 2000–2004, and was validated using observed GPP over the period 2005–2006 and leave-one-out cross-validation. Our model predicted GPP fairly well at the site level. We then used the model to estimate GPP for each 1 km × 1 km cell across the U.S. for each 8-day interval over the period from February 2000 to December 2006 using MODIS data. Our GPP estimates provide a spatially and temporally continuous measure of gross primary production for the U.S. that is a highly constrained by eddy covariance flux data. Our study demonstrated that our empirical approach is effective for upscaling eddy flux GPP data to the continental scale and producing continuous GPP estimates across multiple biomes. With these estimates, we then examined the patterns, magnitude, and interannual variability of GPP. We estimated a gross carbon uptake between 6.91 and 7.33 Pg C yr^{-1} for the conterminous U.S. Drought, fires, and hurricanes reduced annual GPP at regional scales and could have a significant impact on the U.S. net ecosystem carbon exchange. The sources of the interannual variability of U.S. GPP were dominated by these extreme climate events and disturbances.

1. Introduction

The quantification of ecosystem carbon fluxes for regions, continents, or the globe can improve our understanding of the feedbacks between the terrestrial biosphere and the atmosphere in the context of global change and facilitate climate-policy decisions (Law et al., 2006). Gross primary productivity (GPP) is the amount of carbon fixed by vegetation through photosynthesis and a key component of ecosystem carbon fluxes and the carbon balance between the biosphere and the atmosphere (Mäkelä et al., 2008). The accurate estimation of GPP is essential for the quantification of net ecosystem carbon exchange (NEE) as the latter is often a small difference of two large carbon fluxes — GPP and ecosystem respiration (R_e). The estimation of GPP for regions, continents, or the globe, however, can only be made by using ecosystem models (e.g., Prince & Goward, 1995) and/or remotely sensed data (e.g., Running et al., 2004).

Eddy covariance flux towers have been providing continuous measurements of ecosystem-level exchange of carbon, water, and energy spanning diurnal, synoptic, seasonal, and interannual time scales since the early 1990s (Baldocchi et al., 2001; Wofsy et al., 1993). At present, over 500 eddy covariance flux towers are operating on a long-term and continuous basis around the world (FLUXNET, http://daac.ornl.gov/FLUXNET). This global network encompasses a large range of climate and biome types (Baldocchi et al., 2001), and provides probably the best estimates of ecosystem-level carbon fluxes. The flux towers directly measure NEE that can be separated into two major components: GPP and R_e (Desai et al., 2008; Reichstein et al., 2005). However, these estimates only represent fluxes at the scale of the tower footprint with longitudinal dimensions ranging between a hundred meters and several kilometers depending on homogeneous vegetation and fetch (Göckede et al., 2008; Schmid, 1994). To quantify the exchange of CO_2 between the terrestrial biosphere and the atmosphere, significant efforts are needed to upscale flux tower measurements from the stand scale to landscape, regional, continental, or global scales.

Satellite remote sensing is a potentially valuable tool for upscaling efforts (Running et al., 1999; Xiao et al., 2008). Several studies have integrated flux data with remote sensing data to quantify GPP over large areas. Zhang et al. (2007) estimated GPP for the Northern Great Plains grasslands using satellite and flux tower data. Yang et al. (2007) linked satellite observations to flux tower GPP data for the estimation of GPP for two broad vegetation types in the U.S. using a machine learning approach. Despite these efforts, to our knowledge, no study has upscaled AmeriFlux GPP data to the continental scale to produce spatially-explicit estimates of GPP across multiple biomes and to examine the patterns, magnitude, and interannual variability of GPP over the conterminous U.S.

Here we used a regression tree approach and remotely sensed data from the Moderate Resolution Imaging Spectroradiometer (MODIS) to upscale flux tower GPP data to the continental scale and produced wall-to-wall GPP estimates for multiple biomes across the conterminous U.S. First, we developed a predictive GPP model based on site-specific MODIS and flux tower GPP data, and validated the model using eddy flux data in both temporal and spatial domains. Second, we applied the model to estimate GPP for each 1 km × 1 km cell across the conterminous U.S. for each 8-day interval over the period 2000–2006 using wall-to-wall MODIS data. Third, we examined the patterns, magnitude, and interannual variability of GPP across the conterminous U.S.

2. Data and methods

2.1. Regression tree approach

We used a modified regression tree approach implemented in the commercial software, Cubist, to upscale flux tower GPP to the continental scale. Regression tree algorithms typically predict class membership by recursively partitioning a dataset into more homogeneous subsets. The partitioning process splits each parent node into two child nodes, and each child node is treated as a potential parent node. Regression tree models can account for a nonlinear relationship between predictive and target variables and allow both continuous and discrete variables. Previous studies showed that regression tree methods are not only more effective than simple techniques including multivariate linear regression, but also easier to understand than neural networks (e.g., Huang & Townshend, 2003).

Cubist constructs an unconventional type of regression tree, in which the terminal nodes or leaves are linear regression models instead of discrete values (Minasny & McBratney, 2008). Cubist produces rule-based models containing one or more rules, each of which is a set of conditions associated with a multivariate linear submodel. Cubist is a powerful tool for generating rule-based predictive models. A Cubist model resembles a piecewise linear model, except that the rules can overlap with one another (RuleQuest, 2008). Details on regression tree approaches and Cubist were described in Yang et al. (2003), Wylie et al. (2007), and Xiao et al. (2008). In our previous study, we used Cubist to develop a predictive NEE model and upscaled NEE estimates to the continental scale for the conterminous U.S. (Xiao et al., 2008). In this study, we used Cubist to construct a predictive GPP model based on MODIS and AmeriFlux GPP data. Cubist uses three statistical measures to evaluate the quality of the constructed predictive model, including mean absolute error (MAE), relative error (RE), and product-moment correlation coefficient (Xiao et al., 2008; Yang et al., 2003). MAE is calculated as:

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |y_i - \hat{y}_i| \quad (1)$$