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Optimizing the photosynthetic parameter V_{cmax} by assimilating MODIS-f_{PAR} and MODIS-NDVI with a process-based ecosystem model

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ABSTRACT

Combination of satellite remote sensing data and an ecosystem model provides an opportunity to monitor net ecosystem production, water cycle and energy balance at the regional scale. Photosynthesis is a critical ecological process that is coupled to the carbon and water cycle and energy balance. Therefore, an accurate description of its spatiotemporal pattern is essential when simulating an ecosystem at the regional scale. To determine the spatial distribution of the maximum Rubisco catalytic capacity (V_{cmax}), we have developed a scheme that optimizes the photosynthetic parameter from a remotely sensed f_{PAR} (the fraction of photosynthetically active radiation absorbed by the plant canopy) and NDVI (normalized difference vegetation index) using the VIP ecosystem model. It integrates the interval estimation method and a one-dimensional searching algorithm, in which the samples include randomly selected pixels, the photosynthetic capabilities are optimized with the golden section search algorithm in the randomly sampled pixels to derive the prior probability of V_{cmax}, and then the search interval of V_{cmax} is narrowed to a confidence interval. We verified this scheme on the North China Plain (NCP) to determine the V_{cmax} pattern in winter wheat at a 1-km resolution. The simulation results by the VIP model with the derived V_{cmax} pattern were indirectly validated using census data for grain yield, field evapotranspiration (ET) measurements, the MODIS leaf area index (MODIS-LAI) and daily MODIS land surface temperatures (MODIS-LST). The validation results demonstrated a satisfactory agreement between the simulated and measured data with R^2 of 0.63, 0.82, 0.29 and 0.92 for yield, ET, LAI and LST, respectively. It is suggested that the proposed V_{cmax}-retrieving method is practical for regional crop growth predictions.

1. Introduction

The combination of satellite remote sensing and ecosystem models provides an opportunity for monitoring net ecosystem production, the water cycle, and energy balance on a regional level (Dorigo et al., 2007). Photosynthesis is a critical ecological process that is coupled to the ecosystem's carbon cycle, water cycle and energy balance. Therefore, an accurate description of its spatiotemporal pattern is essential when simulating an ecosystem at the regional scale.

Biophysical processes, which include CO_2 transport through the leaf and stomata, and biochemical processes in the chloroplast thylakoid membranes, stroma, mitochondria and cytosol of the cell determine the net rate of CO_2 assimilation (A). These biophysical and biochemical processes in conjunction with environmental variables, such as light intensity and temperature, confer different effects on A; thus, it is difficult to predict how A will be affected by genetics, epigenetics and the environment. Therefore, certain canopy-state variables, such as the leaf area index (Doraiswamy et al., 2004; Moulin et al., 2003) and plant chlorophyll concentration (Haboudane et al., 2002; Zhao et al., 2004), which are closely related to the plant photosynthetic capability, are frequently used to describe A. The canopy state variables can be easily retrieved from remote sensing data using the canopy reflectance model (Shabanov et al., 2000; Schlerf and Atzberger, 2006) or the statistical relationship between the spectral signature and biophysical (or biochemical) variables (Atzberger et al., 2003; Huang et al., 2004). Thus, the retrieved state variables are directly used to replace variables in the model because the observed data are presumably more reliable than simulated data. This approach is widely employed in studies that range from sub-regional (Bastiaanssen and Ali, 2003) to regional (or continental) scales (Mo et al., 2005) due to its excellent performance and its simplicity. However, the observed errors in the

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remote sensing state variables are propagated into the model when the remote sensing state variable is used directly (Dorigo et al., 2007). This shortcoming can be avoided by adjusting the model parameters to determine the optimal consistency between the simulated and observed remote sensing state variables (Launay and Guerif, 2005). Parameter adjusting is more flexible for assimilating remote sensing state variables and their associated error in the model because a physical description of the underlying process is an acceptable representation of the natural system, and the adjusted model parameter is expected to improve model prediction. Therefore, using remote sensing data to adjust the model parameters has been the more frequent approach instead of direct use of remote sensing state variables in a model. This practice was confirmed by the following groups. Dente et al. (2008) used remotely sensed LAI to improve wheat yield simulation and determine an optimal set of input parameters, including sowing data, soil wilting point and field capacity. Fang et al. (2008) utilized the MODIS-LAI to re-initialize planting data, planting density and row spacing as well as improve the model's performance in simulating the corn yield. Hazarika et al. (2005) successfully simulated net primary productivity using the re-initialized leaf area index. However, no reports have described photosynthetic parameters for re-initialization due to the complexity of the photosynthetic process.

The most sensitive photosynthetic parameters in the photosynthesis process are V_{cmax} (the maximum rate of Rubisco carboxylase activity) and J_{max} (the maximum rate of photosynthetic electron transport). V_{cmax} describes a photosynthesis limitation, the photosynthetic Rubisco enzyme system, which dominates under light saturation as regulated by the photosynthetically active radiation (PAR) effectively absorbed by photosystem II (von Caemmerer and Farquhar, 1981). V_{cmax} and J_{max} are tightly coupled, and the fixed ratio of J_{max}/V_{cmax} at 25 °C is typically assumed in large-scale modeling schemes. Therefore, specifying V_{cmax} is critical and substantially contributes to terrestrial GPP (gross primary productivity) sensitivity to the atmospheric CO_2 concentration and the overall uncertainties of model-predicted carbon fluxes. In wheat, a 40% decrease in V_{cmax} led to a 34% decrease in GPP (Lei et al., 2011), and a 10% increase in V_{cmax} led to a 4% increase in yield in NCP (Mo et al., 2005). Although both parameters are tightly correlated with a plant's photosynthetic capacity, carboxylation capacity (V_{cmax}) has been measured and studied more extensively (Wullschleger, 1993; Leuning, 1997; Kattge and Knorr, 2007). At the leaf scale, the key photosynthetic parameters, V_{cmax} and J_{max}, can be calculated by fitting the CO_2 response curve to the measured photosynthetic rate and intercellular CO_2 concentration (Muller et al., 2005; Alonso et al., 2009).

At the regional scale, the photosynthetic rate and intercellular CO_2 concentration are unavailable for each pixel; thus, it is impossible to obtain photosynthetic parameter patterns using a CO_2 response curve. V_{cmax} is affected by factors that determine the level of activated enzyme (Rubisco), which is determined by the foliar chlorophyll concentrations. These factors include temperature (Sage, 2002), water stress (Flexas et al., 2006), leaf nitrogen content (Maroco et al., 2002; Gonzalez-Real and Baille, 2000), radiation intensity (Choi and Roh, 2003), salt stress (Centritto et al., 2003) and a combination of the aforementioned factors. Under environmental stress, chlorophyll levels decrease and induce a decrease in V_{cmax} (Houborg et al., 2013), because leaf chlorophyll levels are the primary factor that control spectral reflectance variation in the visible light regions and dominantly control the solar radiation levels that a leaf absorbs. The decrease in chlorophyll levels affects the abilities of green vegetation to reflect incident solar radiation; this response can be detected using the remote sensing data, such as: MODIS-f_{PAR} and MODIS-NDVI (Dawson et al., 2003; Huang et al., 2010). Therefore, stressed vegetation or vegetation with a low photosynthetic capability has a reduced f_{PAR} value (or NDVI value), which suggests that some remote sensing data are reliable indicators of photosynthetic capability in specific vegetation. Therefore, developing an empirical or theoretical transfer function between V_{cmax} and remote sensing data (such as: MODIS-f_{PAR} or MODIS-NDVI) could be an approach for obtaining spatial patterns for photosynthetic parameters.

The quantitative relationship between V_{cmax} and remote sensing data recently has been the subject of interest. Many of the conditions that affect plant development and grain yield either favorably or adversely (i.e. fertilization treatment, rust infection, drought or precipitation events) result in a corresponding increase or reduction of the crop's photosynthetically active biomass at the canopy scale, and this response can often be captured though spectral measures such as the normalized difference vegetation index (NDVI) (Tucker, 1979). However, the NDVI often fails to reflect plant photosynthetic capacity accurately, especially when the time of NDVI collection does not coincide with the flourishing stage of the crop's photosynthetically active biomass. Most authorities recommend collection of spectral data when the crop canopy is full (Basnyat et al., 2004; Becker-Reshef et al., 2010), because image acquisition before full crop canopy coverage results in spectral information that includes the contribution from the soil surface rather than from just the crop itself. Usually, the cumulative NDVI in the flourishing stage is a good indicator of plant photosynthetic capability (Basnyat et al., 2004), since it provides the aggregated assessment of plant photosynthetic capacity over time. Hu and Mo (2012) derived a regression between the accumulated NDVI during the growing season and the county-level statistic grain yield, and then V_{cmax} estimated using the process-based ecosystem model VIP with the assumption that the model has good performance in yield simulation at regional scale. This practice is similar to a statistical approach, it is restricted by the census data quality as well as heterogeneity of the soil and vegetation at the county level. In the data sparse region which lack of grain census data, the relationship between remote sensing data and photosynthetic capacity is hard to establish, and limited the use of the statistical approach.

This study aims to develop a new scheme to retrieve the photosynthetic parameter (V_{cmax}) for winter wheat over the NCP by assimilating MODIS-f_{PAR} and MODIS-NDVI data with the VIP ecosystem model. This approach is trying to resolve the photosynthetic capacity pattern retrieval problem in data sparse region. The model predictions with the retrieved V_{cmax} pattern were evaluated using the census data for grain yield, measured ET, MODIS-LST and MODIS-LAI. Finally, the simulation error of the model with the retrieved V_{cmax} pattern and the difference between this scheme and other V_{cmax} retrieval approaches are discussed.

2. Methods

2.1. Model description

The VIP model used in this study is a dynamic ecosystem model that simulates radiation, water, heat and CO_2 transfer processes during the crop-growing season (Mo et al., 2012; Mo and Liu, 2001). The water cycle incorporates the total above-canopy evapotranspiration and soil moisture transfer. Energy fluxes are described with a two-source scheme that individually discerns the canopy and the soil surface. The temperatures of the canopy (T_c) and soil surface (T_g) which were used to calculate land surface temperature (Appendix A, Eq. (A3)) are governed by the two-sources soil-canopy energy balance sub-model (Shuttleworth and Wallace, 1985; Mo et al., 2012). The carbon cycle includes assimilation via photosynthesis, crop growth and soil organic matter decomposition schemes. The leaf photosynthesis rate is primarily restricted by the carboxylation rate, which is limited by the