Estimating the net ecosystem exchange for the Dayekou Guantan forest by integrating MODIS and Flux data

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Abstract: Estimating net ecosystem carbon exchange (NEE) on regional and global scales is important for the carbon cycle and the greenhouse effect. The eddy covariance technique provides long-term continuous monitoring of site-specific NEE at the tower footprint scale. Remote sensing technology can continuously and systematically monitor multiple information of terrestrial ecosystem at regional scale, and it becomes an important tool to extend NEE to large scale combining with flux data. In present study, according to TG model, we established several new NEE models (using linear regress method based on single variable or multiple variables) that are suitable for Dayekou Guantan forest station with Moderate-resolution Imaging Spectroradiometer (MODIS) products. Variables include enhanced vegetation index (EVI), land surface water index (LSWI) and land surface temperature (LST, including daytime LST and nighttime LST’). Compared with models based on single variable, models based on EVI, LSWI and LST have the best effect. Results showed that this method had good precision (2008) ($R^2$ and RMSE reached 0.8014 and 0.7364, respectively) and generally captured the expected seasonal patterns of NEE. We validated the model using independent flux (2009), which demonstrated this method performed well for estimating NEE ($R^2$ and RMSE reached 0.8618 and 0.5538, respectively). In addition, during the whole process, variables had obvious seasonal dynamical characteristics and closely related to NEE seasonal dynamics. However, uncertainty still existed in this method. In future research, more influencing factors should be selected to simulate NEE more accurately and extend the scope of research to a larger extent.

1. Introduction

Net ecosystem carbon exchange (NEE), the difference between photosynthetic uptake and release of CO$_2$ by respiration from autotrophs (vegetation) and heterotrophs (free-living and fauna in the soil and symbiotic microorganisms), represents the net exchange of CO$_2$ between terrestrial ecosystems and the atmosphere[1]. In recent years, the increase of greenhouse gas concentration has led to global greenhouse effect, of which carbon dioxide has a 60% impact on global warming[2]. An accurate estimation of the spatial patterns and temporal dynamics of NEE in terrestrial ecosystems at the regional and global scale is of great interest to human society[3-5]. At the same time, long-term continuous observation of CO$_2$ fluxes between ecosystems and atmosphere can promote people's understanding of the impact of global carbon cycle process.

Eddy covariance has been widely used to measure CO$_2$/H$_2$O and energy fluxes in ecosystems. NEE data obtained are used to represent the carbon exchange between the whole ecosystem and the atmosphere, and to provide the necessary basic data for the estimation of carbon budget and the construction of carbon cycle model in China[2]. However, these NEE only represent fluxes at the tower footprint scale, with longitudinal dimensions ranging from a hundred meters to several
kilometers relying on homogeneous vegetation and fetch[6]. To quantify the net exchange of CO\textsubscript{2} over regions or continents, flux tower measurements from distributed points need to be scaled up to spatially continuous estimates[4-5]. Satellite remote sensing technology can monitor multiple information of terrestrial ecosystem continuously and systematically at the regional scale[7-9], at the same time, the ecosystem can be sampled at fixed intervals. Moderate-resolution Imaging Spectroradiometer (MODIS) are useful for monitoring the carbon flux, as reflectance can be converted into biophysically meaningful descriptors of the land surface[10]. Therefore, new approaches are critically needed to extend the role of field plots to capture regional variation and to bridge a major gap between field and satellite observations[11]. Tang X G et al[1] proposed a new NEE model solely based on MODIS data, including enhanced vegetation index(EVI), land surface water index (LWSI), land surface temperature (LST), and Terra nighttime (LST\textsuperscript{\textdegree}). The results showed that this method could further improve the precision and generally capture the expected seasonal patterns of NEE[1]. In 2012, Tang X G et al[3] selected eight eddy flux sites to represent the major forest ecosystems in the northern United States, the results showed that simpler model based entirely on MODIS products promised well to estimate NEE by the eddy covariance technique.

Forest ecosystems account for 31\% of terrestrial ecosystems[12] and play an important role in terrestrial ecosystem carbon cycle and climate change mitigation[13]. The Dayekou Guantan (GT) Forest Station is a forest flux site in the Heihe Watershed Allied Telemetry Experimental Research. However, little research has been done on the flux of the ecosystem. So, we investigated the GT site, the objectives of this study are: (1) according to the TG model of predicting NEE in earlier study, with MODIS and flux data, a model based on remote sensing parameters was established to estimate NEE of GT, (2) to validate biophysical performance of vegetation indices (EVI and LSWI) and land surface temperature (LST) in relation to seasonal dynamics of NEE fluxes, (3) deficiencies of the analysis model and references for future research.

2. Materials and methods

2.1 Study site description

The analysis was based on the data from Dayekou Guantan Station (100°15′E and 38°32′N, 2835 m elevation). The Dayekou Guantan tower is located in the horseshoe area of Sunan Yugur Autonomous County, Zhangye City, Gansu Province, and belongs to the Dayekou Basin, relying on the Heihe Watershed Allied Telemetry Experimental Research of Cold and Arid Regions Environmental and Engineering Research Institute, Chinese Academy of Sciences (Figure 1). Forest composition is dominated by coniferous forests, mainly 15-20 meters of Picea crassifolia, mostly middle-aged and near-mature forests with a canopy density of about 0.6. The ground is covered with moss about 10cm and the vegetation grows well. Dayekou Guantan Forest Station is a typical semi-humid forest steppe climate, with mean annual temperature 1.62°C and mean precipitation 374.06mm.
2.2 MODIS products and processing

Compared with NDVI, EVI contains blue-band information, and corrects vegetation indices such as atmospheric and surface conditions[14]. EVI has been successfully applied to temperate forests[15], and the impact of aerosols on EVI is not as significant as that on NDVI[16]. The shortwave infrared (SWIR) spectral band is sensitive to vegetation water content and soil moisture, a combination of NIR and SWIR bands have been used to derive water-sensitive vegetation indices[3]. A few studies have demonstrated that the satellite-derived LST is strongly correlated with ecosystem respiration (Re) as both autotrophic and heterotrophic respirations are significantly affected by air/surface temperature[3,17-19].

The 8-day Land Surface Reflectance (MOD09A1, with resolution of 500 m) and LST data (MOD11A2, with resolution of 1 km) were obtained from the National Aeronautics and Space Administration (NASA) (https://ladsweb.modaps.eosdis.nasa.gov/). The reflectance values of these four spectral bands – blue (459-479nm), red (620-670nm), near infrared (841–875 nm), and shortwave infrared (1628–1652 nm) in 2008-2009 were used to calculate EVI and LSWI. Some studies had shown that for evergreen coniferous forests, reflectance data extraction using a single pixel and 3×3, 5×5 pixels had no significant difference in the calculation of vegetation index[15]. Therefore, based on the longitude and latitude information of the study site[15], the reflectance and surface temperature data of 3 km × 3 km centered on the flux tower were extracted from MOD09A1 and MOD11A2 products. HUete et al[14] had developed a global EVI product from MODIS data for the period 2000 to present, defined as:

\[
EVI = 2.5 \times \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + 1 + 6.0 \times \rho_{red} - 7.5 \times \rho_{blue}}
\]  

(1)

and Gao B C et al[20] developed the LSWI from satellite data to measure vegetation liquid water[1]:

\[
LSWI = \frac{\rho_{NIR} - \rho_{SWIR}}{\rho_{NIR} + \rho_{SWIR}}
\]  

(2)

where \(\rho_{nir}, \rho_{red}, \rho_{blue}\) and \(\rho_{swir}\) are the spectral reflectance in MODIS bands 2,1,3 and 6.

2.3 Eddy covariance data

Flux and meteorological data[21-22] were obtained from Cold and Arid Regions Environmental and Engineering Research Institute, Chinese Academy of Sciences (http://westdc.westgis.ac.cn/). The Dayekou Guantan Forest Station dataset began on December 27, 2007 and ended on March 21, 2012. The height of instrument is 20.25 m, the azimuth angle of the ultrasound is 74°, and the sampling frequency of the data is 10 Hz/s. The original flux of this study is 30 minutes flux data in 2008 and 2009. The data process includes outlier removal, coordinate rotation, frequency response correction,
WPL correction and initial quality control. Complete NEE flux data were obtained by Artificial Neural Network (ANN) method using meteorological data and converted into eight-day NEE data (gCm\(^{-2}\)day\(^{-1}\)) to match the composting intervals of MODIS products. Meteorological data, including air temperature, soil temperature, relative humidity and short-wave downward radiation, were also measured and recorded at a frequency of half an hour.

2.4 Model development

In this study, we established a model to estimate NEE according to TG model[1] based on MODIS and flux data. The explanatory variables included EVI, LSWI and LST (including Terra daytime LST and nighttime LST\(^{'}\)). The target variable was NEE. We split the flux data into a training set (2008) and a test set (2009). After analyzing the correlation between these parameters and NEE observed, based on linear regression method, the model with the maximum coefficient of determination (R\(^2\)) and the minimal root mean square error (RMSE) was chosen as the best model.

3. Results and discussion

3.1 Modelling and model validation

After analyzing the relationships between EVI, daytime LST, nighttime LST\(^{'}\), and LSWI with NEE measured at Dayekou Guantan Forest site from 2008 (data missing for 233-297 days and was too long to interpolated), we established the regression model based on each single variable and multiple variables. Compared with the others (Table 1), we got the best model with the maximum R\(^2\) of 0.8014 and the minimal RMSE of 0.7364(Figure 2.a). The new empirical model for NEE was defined as:

\[
NEE = 0.2131 - 10.4008 \times EVI - 2.1540 \times LSWI - 0.0731 \times LST (R^2 = 0.8014, \text{RMSE} = 0.7364)(3)
\]

Table 1. model parameters

| variables | R\(^2\) | RMSE(gCm\(^{-2}\)d\(^{-1}\)) |
|-----------|--------|---------------------------|
| LSWI      | 0.0060 | 1.8410                    |
| LST       | 0.5868 | 1.8700                    |
| EVI       | 0.7637 | 0.8975                    |
| LST\(^{'}\)| 0.6922 | 1.0240                    |
| EVI, LSWI | 0.7660 | 0.8930                    |
| EVI, LST  | 0.7883 | 0.8495                    |
| LSWI, LST | 0.7338 | 0.9526                    |
| EVI, LST\(^{'}\)| 0.7909 | 0.8442                    |
| LSWI, LST\(^{'}\)| 0.7615 | 0.9016                    |
| EVI, LSWI, LST | 0.8014 | 0.7364                    |
| EVI, LSWI, LST\(^{'}\)| 0.7989 | 0.8280                    |

The model was run at eight-day time scale using the site-specific EVI, daytime LST, and LSWI to estimate NEE. Because the correlation between LST and LST\(^{'}\) was more than 0.9, LST/LST\(^{'}\) was selected separately to simulate with other parameters. Then model performance was evaluated using scatter plots of estimated (NEE\(_{mod}\)) versus measured NEE (NEE\(_{obs}\)) in 2008-2009 (1-7 months) (Figure 2). And we validated the performance using 2009 data (Figure 2.b). Results showed that the model simulated NEE in 2009 agreed reasonably well with observed with R\(^2\) of 0.8618, RMSE of 0.5538. Figure 2 indicated that the residuals were not randomly distributed. In absolute magnitude, low NEE values were generally associated with lower prediction errors, whereas high NEE values were associated with higher prediction errors[1]. This suggests that the uncertainties of carbon flux measurements are directly proportional to the magnitude of the fluxes, the conclusion is consistent with Tang X G et al[3].
Figure 2. A linear comparison between the predicted and measured NEE values during the periods 2008 (a) and 2009 (b) at the Dayekou Guantan Forest site. NEE_{mod} values are from simulations of TG model using eight-day MODIS composites.

Figure 3. A comparison of the seasonal dynamics of 8-days NEE at the Dayekou Guantan Forest site during the period 2008-2009. Predicted NEE is from the TG model, and measured NEE is from the CO_{2} flux tower site. For x-axis, the data refer to day of year ranging from 1 to 365(366).

3.2 Seasonal dynamics of NEE with EVI, LSWI, LST and LST

Figure 3. showed that measured NEE was consistent with predicted NEE in changing trend. This study used predicted values to analyze the annual dynamic changes of NEE from 2008 to 2009 because the measured NEE values were partly missing.
Figure 4. showed that the NEE, EVI, LSWI and LST time series in 2008-2009 at the Dayekou Guantan Forest site had distinct seasonal cycles. Figure 4d demonstrated the changes of NEE during 2008-2009, the values were negative and the forest ecosystem of Dayekou Guantan was characterized by carbon sink all year round, and reached its peak during July, which was consistent with Tong X J [13]. The seasonal dynamics of NEE can be explained in part by the change of land surface temperature, the interannual change of forest ecosystem respiration is 40% of the interannual change of photosynthesis [13]. In the non-growing season of winter, because low temperature inhibited the respiration of the forest ecosystem more than photosynthesis, and EVI increased with time, the photosynthesis efficiency of the whole forest ecosystem were stronger than that of respiration. Thus, the NEE value of the forest ecosystem was negative and showed a slight carbon sink. With the increasing of temperature, vegetation began to grow and photosynthesis increased gradually. In absolute magnitude, NEE increased gradually, both in 2008 and 2009. After peaking in July and August, the NEE value gradually decreased with the decrease of temperature.

EVI (Figure 4c) directly reflected the growth status of the Dayekou Guantan forest ecosystem during 2008-2009 and had strong seasonal dynamics. The vegetation indices derived from MODIS data captured well the beginning and ending of the plant growing season[1] in 2008–2009. The correlation with NEE was 0.7637. EVI began an abrupt increase on end of June, and reached its peak during July and August. Subsequently, EVI gradually declined and remained low after 300 days.

In the winter months, LSWI (Figure 4b) values were high, which was attributed to the snow cover on and under the forest canopy. Snow reflects strongly in visible and near-infrared bands, but weakly in short-wave infrared bands, which leads to the increase of LSWI in non-growing season. As snow melted in the spring, LSWI gradually declined, then increased again with the progress of plant growth season, and gradually decreased in the late growing season. Overall, the LSWI time series data can be easily recognized with a spring trough and a fall trough[1].

Both daytime LST and nighttime LST’ had strong correlations with NEE(LST was 0.5868, LST’ was 0.6922) and daytime LST(Figure 4d) was more closely correlated with NEE than nighttime LST’. But combining NEE and EVI, the fitting effect of LST and NEE was better. Temperature not only affects autotrophic and heterotrophic respiration, but also affects canopy photosynthesis, thereby it controls CO$_2$ fluxes in ecosystems[13]. Because carbon exchange in ecosystems is mainly regulated by respiration and photosynthesis, and temperature has an impact on their efficiency, the annual variation of temperature indirectly reflects the change of NEE.

4. Discussion
Eddy covariance method can directly measure the carbon exchange between ecosystem and atmosphere, and is widely used to monitor the changes of carbon flux in ecosystem sites, which provides a basis for model validation[23]. However, the NEE estimating still contains significant uncertainties.
Uncertainty of eddy covariance measurement. The measurement is influenced by environment and instruments, such as expensive equipment, time-consuming construction of observation system, stringent requirements on observation underlying surface, and difficult maintenance of instruments. In addition, the observed data need to be converted into 30-minute flux data after strict follow-up processing before they can be used. These processes often have impacts on data.

Uncertainty of data gap-filling. In this study, the 30-minute data were filled based on meteorological data and would bring some errors to the results. Some studies have shown that the effect of filling technology on data may reach ±2.5 g/m²year⁻¹ [24].

Uncertainty of model. We selected only EVI, LSWI and LST as explanatory variables to estimate NEE. However, the factors controlling CO₂ exchange are complicated[1]. NEE can be calculated by ecosystem respiration (Re) and gross primary productivity (GPP). GPP is controlled by temperature, moisture and light efficiency et al. Field studies of Re have identified temperature, soil moisture, nutrient availability, stocks of living and dead biomass, ecosystem productivity, and seasonal carbon allocation as the controlling factors[1,25-26]. Other studies have shown that environmental factors (such as solar radiation, temperature, precipitation, soil temperature and humidity) play direct and indirect roles in the seasonal, annual and interannual changes of net carbon exchange of ecosystems, and these effects vary with the changes of ecological space[13]. Therefore, it is not very accurate to simulate the true value of NEE by selecting some factors in the influencing factors data set as input variables to build the model. In addition, the inability of our model to account for transient carbon pools could introduce uncertainties to the NEE estimates[3]. Thus, in future research, additional explanatory variables should be selected to better account for live and dead vegetation carbon pools, as well as other factors that influence the decomposition of woody detritus and soil respiration[3].

Figure 3a is a comparison between estimated and measured NEE in 2008. Around the 100 days, measured NEE increased in absolute value and decreased around 120 days. This may be due to the trend of decrease and increase of EVI values in the vicinity of 100 days during this period. EVI can directly reflect the growth of ecosystem, and NEE is closely related to vegetation growth. Therefore, the change of NEE in this period may be caused by the change of EVI. Figure 3a also showed that we can only get the approximate annual change of NEE by using the model, but it could not show the change more accurately. When we built the model, it would often weaken the obvious change trend of the actual change sometimes.

In the present study, carbon sink was observed throughout the year in the study site, which might be due to the fact that the photosynthetic efficiency of the forest ecosystem was always higher than that of respiration. The satellite-derived LST was strongly correlated with ecosystem respiration (Re) as both autotrophic and heterotrophic respirations are significantly affected by air/surface temperature [3,17-19]. Due to the Picea crassifolia, which belongs to evergreen needleleaf forests are green around the whole year, MODIS parameters are less than NEE than the other remotely sensed variables. In addition, average values for the central 3 × 3 km area cannot represent the whole Dayekou Guantan flux. Thus, in future research, we should consider expanding the site scale to the regional scale as well as provide more accurate carbon exchange influence for China even the world.

5. Conclusions
According to the TG model proposed by Tang X G et al, the NEE estimated model of the ecosystem was established based on the observed flux of the Dayekou Guantan Forest site in 2008 and MODIS-derived parameters such as EVI, LSWI and LST, and good simulation results were obtained. Results showed that variables had distinct seasonal dynamics. During the whole process, EVI directly reflected the growth status of vegetation in the ecosystem. In addition, NEE had a good correlation with MODIS parameters except LSWI. Compared with models based on single variable, models based on EVI, LSWI and LST have the best effect. Therefore, the interannual dynamics of NEE can be simulated accurately based on MODIS variables. Nevertheless, there are some uncertainties in the model. In future research, more influencing parameters should be selected to better simulate and predict NEE of ecosystem and the approach has great potential for scaling up plot-level NEE of CO₂ to
large areas.

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