Simulation of Maximum Light Use Efficiency of Typical Reed Communities in the Liaohe River Delta Estuarine Wetlands: Postprint

Authors: Chen Jilong, Li Guosheng, Liao Huajun, Wang Bingliang, Cui Linlin

Date: 2017-04-18T00:00:00+00:00

Abstract

The CASA model is one of the most widely used models for investigating macroscale net primary productivity. Maximum light use efficiency constitutes the most critical parameter in the CASA model; however, it cannot be readily obtained through direct measurement and experimentation, but must be derived through simulation. This study retrieved the maximum light use efficiency for typical reed (Phragmites australis) communities in the Liaohe Delta estuarine wetland using the CASA model, and performed a sensitivity analysis on how potential errors in remote sensing and meteorological data affect the maximum light use efficiency. Simulation results demonstrate that reed communities exhibit exceptionally high carbon conversion capacity, with maximum light use efficiency reaching 1.667 g C/MJ and actual conversion rates ranging from 0.957 to 1.102 g C/MJ. Sensitivity analysis reveals that simulated maximum light use efficiency shows strong sensitivity to total radiation and NDVI; the relative variation range in maximum light use efficiency induced by total radiation error is merely -4.14% to 4.56%; the sensitivity of simulation results to NDVI decreases as NDVI increases, and even when considering a 30% error, the simulated values remain relatively concentrated within the variation range of sample points. These findings indicate that the simulated maximum light use efficiency for reeds possesses considerable stability and reliability.

Full Text

Simulation of Maximum Light Conversion Efficiency for a Phragmites Salt Marsh in the Liaohe River Estuarine Wetland

Jilong Chen[1], Guosheng Li[2],*, Huajun Liao[2], Bingliang Wang[2], Linlin Cui[3]

[1]Chongqing Institute of Green and Intelligent Technology, Chinese Academy of Sciences, Chongqing 400714, China
[2]Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China
[3]Key Laboratory of Coastal Wetland Biogeosciences, China Geological Survey, Qingdao 266071, China

Abstract: Maximum light conversion efficiency (MLE) is a critical parameter for the Carnegie-Ames-Stanford Approach (CASA) model, which is widely used for modeling net primary productivity (NPP) globally. However, MLE is difficult to parameterize using experiments and field observations. Since MLE is fundamental in ecological studies, modeling MLE is of vital importance and significance. The present study determined the MLE of a Phragmites salt marsh in the Liaohe River estuarine wetland in China. The main objectives were to: (1) determine the MLE of a Phragmites marsh, and (2) investigate the sensitivity of MLE to environmental factors. Factors included in the CASA model comprised Absorbed Photosynthetically Active Radiation (APAR) using sunshine duration obtained from the National Meteorological Information Center; Fraction of Absorbed Photosynthetically Active Radiation (FAPAR) calculated using the Normalized Difference Vegetation Index (NDVI) determined from 16-day Moderate Resolution Imaging Spectroradiometer (MODIS) data; temperature and water stress coefficients calculated using MODIS reflectance data; and meteorological variables including air temperature, precipitation, sunshine duration, air pressure, water vapor pressure, wind velocity, and relative humidity. Field observations of the NPP of the salt marsh were conducted at 54 sampling areas with a size of 250 m × 250 m, of which 27 sites were used for modeling and the remaining for validation.

The results showed that the Phragmites salt marsh had a relatively high carbon conversion efficiency, with an average MLE of 1.667 g C/MJ, varying between 1.112 and 2.611 g C/MJ, which was much higher than the proposed value of 0.389 g C/MJ by Potter. It was even higher than that of broad-leaved, coniferous, and theropencrymion forests. The simulated MLE was sensitive to global solar radiation and NDVI, decreasing with their increase, which was more pronounced at lower values. This indicated that it is important to check data quality and increase the data accuracy of global solar radiation. In the present study, global solar radiation was estimated using sunshine duration with an accuracy of 95%. The relative range of MLE affected by the error of global solar radiation was from -4.14% to 4.56%. MLE became less sensitive as NDVI increased, whereas the simulated values still fell into the MLE range, but the NDVI error increased by 30%. In practical applications, the differences in MODIS NDVI data were much smaller, suggesting that our results are universal and could be used for other satellite images with different spatial resolutions. The air temperature and precipitation errors had little effect on the simulated results, as MLE was not sensitive to them. The results of the sensitivity analysis increased the reliability and confidence of the simulated MLE for the Phragmites salt marsh, which is of great significance when studying the carbon sink and sequestration potential

of wetlands in China and other regions globally.

Keywords: maximum light conversion efficiency; Phragmites salt marsh; CASA model; net primary productivity; Liaohe River estuarine wetland

Introduction

Estuarine wetlands are a special type of wetland ecosystem that can be compared with farmland ecosystems in terms of their high carbon sequestration capacity. Salt marsh and mangrove wetlands can sequester much higher carbon per unit area than even mature tropical rainforests. Located at the interface of marine and river ecosystems, they are among the most productive ecosystems and play an important role in the global carbon cycle. Site-based measured data with high precision are indispensable basic materials for model calibration and validation. Traditional plot observations are fundamental methods for wetland productivity research, but due to the special natural environment of wetlands, field measurements are difficult. At regional or global scales, the CASA model based on light conversion efficiency is widely used. The maximum light conversion efficiency is one of the most critical parameters in the CASA model, directly affecting the total net primary productivity. Under ideal conditions, it represents the maximum total dry matter fixed by vegetation per unit of photosynthetically active radiation absorbed through photosynthesis.

The maximum light conversion efficiency varies significantly across ecosystems. Harvard and Raymond proposed that forest maximum light conversion efficiency can reach 1.1-1.4 g C/MJ, while Heimann and McGuire estimated global vegetation NPP using 1.25 g C/MJ. Raich estimated that forest maximum light conversion efficiency is about 0.55 g C/MJ, with a narrower range for crops. Potter simulated a maximum light conversion efficiency of 0.389 g C/MJ using group NPP data, but this widely used value has been reported to underestimate net productivity. These results indicate that local calibration or simulation of maximum light conversion efficiency is crucial for accurate NPP estimation. Due to limited measured data, there are few related studies. Running simulated different vegetation types using the BIOME-BGC ecophysiological process model, obtaining maximum light conversion efficiencies of 0.542-0.985 g C/MJ. Zhu Wenquan used Chinese forestry census data and Pathfinder data to simulate maximum light conversion efficiencies of 0.389-1.259 g C/MJ for major Chinese forest vegetation types. However, forest ecosystem simulation values cannot be simply applied to wetland ecosystems.

The Liaohe River estuarine wetland is one of China' s important estuarine wetlands, located at the southern end of the Liaohe Plain at the top of Liaodong Bay in the Bohai Sea. The interaction between marine and terrestrial forces and the mixing of fresh and salt water creates complex and diverse wetland types and ecological environments, developing wetland plant communities dominated by Phragmites, Typha, and rice paddies. The Phragmites area reaches 756 km^2, making it Asia' s largest temperate coastal wetland and the world' s second-largest reed field. Various oil development surface engineering projects have altered the natural hydrological patterns and severely damaged the original habitat, causing significant changes in vegetation and NPP patterns. Despite some NPP research in the Liaohe Delta, most studies remain limited to finite sampling points or landscape-level applications. Accurately determining the maximum light conversion efficiency of Phragmites communities is a prerequisite for NPP research and is important for understanding estuarine wetland carbon sink functions, assessing carbon sequestration potential, and improving wetland ecosystem management.

Methods

1.1 CASA Model Parameterization

Based on the light conversion efficiency principle and considering water, temperature, and nutrient stress, Monteith proposed using absorbed photosynthetically active radiation and light conversion efficiency to estimate terrestrial NPP. Potter and Field implemented the NPP estimation based on this principle. The theoretical framework can be expressed as:

$$NPP(x,t) = APAR(x,t) \times \varepsilon(x,t)$$

where $APAR$ is absorbed photosynthetically active radiation, ε is the actual light conversion efficiency, x represents space, and t represents time.

The actual light conversion efficiency is the most critical component of the CASA model. Potter proposed that vegetation has maximum light conversion efficiency under ideal conditions, but actual light conversion efficiency is regulated by environmental factors such as temperature, water status, and atmospheric water vapor pressure deficit. Therefore, temperature and water availability are used to adjust it, expressed as:

$$\varepsilon(x,t) = T_\varepsilon(x,t) \times W_\varepsilon(x,t) \times \varepsilon_{\max}$$

where T_ε is the temperature stress coefficient, W_ε is the water stress coefficient, and $\varepsilon_{\max}$ is the maximum light conversion efficiency.

1.2 Calculation of APAR

Vegetation-absorbed photosynthetically active radiation depends on total solar radiation and the fraction of photosynthetically active radiation absorbed by vegetation, expressed as:

$$APAR(x,t) = SOL(x,t) \times \alpha \times FPAR(x,t)$$

where SOL is total solar radiation at pixel x, α represents the proportion of solar effective radiation usable by vegetation (generally about 0.45-0.50 of total solar radiation energy), and $FPAR$ is the fraction of photosynthetically active radiation absorbed.

Since solar radiation stations are scarce, the Ångström-Prescott (A-P) model and sunshine duration are often used to calculate total radiation. The fraction of absorbed photosynthetically active radiation depends on vegetation type and coverage. Studies show that FPAR has a linear relationship with the Normalized Difference Vegetation Index (NDVI), which can be determined based on the maximum and minimum NDVI values and corresponding FPAR values for a vegetation type:

$$FPAR(x,t) = \frac{NDVI(x,t) - NDVI_{i,\min}}{NDVI_{i,\max} - NDVI_{i,\min}} \times (FPAR_{\max} - FPAR_{\min}) + FPAR_{\min}$$

where $NDVI_{i,\max}$ and $NDVI_{i,\min}$ are the maximum and minimum NDVI values for vegetation type i, and $FPAR_{\min}$ and $FPAR_{\max}$ are the corresponding minimum and maximum FPAR values (typically 0.001 and 0.95, respectively).

Further research indicates that FPAR also has a good linear relationship with the Ratio Vegetation Index (RVI). Considering that NDVI-based estimates tend to be higher than measured values while RVI-based estimates are lower but with smaller errors, this study combines both methods and uses their average as the final result.

1.3 Stress Coefficients

The temperature stress coefficient T_ε is calculated as:

$$T_\varepsilon(x,t) = 0.02 \times T_{opt}(x) - 0.0005 \times T_{opt}(x)^2$$

where T_{opt} is the optimal temperature for vegetation growth, defined as the mean air temperature of the month when NDVI reaches its maximum. When monthly average temperature is -10°C, photosynthetic production is considered zero. When temperature equals the optimal temperature, T_ε equals 1.

The water stress coefficient W_ε reflects the influence of water conditions on light conversion efficiency:

$$W_\varepsilon(x,t) = 0.5 + 0.5 \times \frac{EET(x,t)}{PET(x,t)}$$

where PET is potential evapotranspiration calculated using the Penman-Monteith equation, and EET is actual evapotranspiration calculated using the complementary relationship proposed by Bouchet.

1.4 Maximum Light Conversion Efficiency Calculation

From the formula, when NPP, $APAR$, T_ε, and W_ε are known, the maximum light conversion efficiency for vegetation at a sample point can be calculated. Since model estimation inevitably simplifies certain processes and different data errors may be introduced, the maximum light conversion efficiency simulated from different sample points may vary. This study uses the principle of minimum error to fit the maximum light conversion efficiency for Phragmites.

1.5 Net Primary Productivity Allocation

Part of NPP is allocated to roots during the growing season, accumulating to form belowground biomass. Since NPP includes both aboveground and belowground components, and due to the special conditions of wetlands and Phragmites'well-developed deep root systems, belowground NPP measurement is more difficult than aboveground. This study only measured aboveground biomass in field plots. To separate aboveground NPP from the CASA model results, Pierre's model of leaf dynamic allocation is used to allocate carbon to different organs based on resource availability:

$$NPP_{root} = NPP \times \frac{N_r \times L \times W \times N}{K + L \times W \times N}$$
$$NPP_{stem} = NPP \times \frac{N_s \times W \times N}{K + L \times W \times N}$$
$$NPP_{leaf} = NPP - NPP_{root} - NPP_{stem}$$

where N_r and N_s represent allocation ratios to roots and stems under no resource limitation, L is light availability estimated using leaf area index, W is the water factor depending on soil moisture and texture, N is the nutrient factor estimated using humidity and temperature, and K is the extinction coefficient (default value of 2).

Data Collection and Processing

Modeling vegetation NPP involves extensive meteorological data, remote sensing data, and other basic materials. Data quality directly affects result reliability. During data collection and processing, every effort was made to reduce inherent errors and standardize the data.

2.1 Meteorological Data

Meteorological data included daily total radiation, air temperature, precipitation, sunshine duration, air pressure, water vapor pressure, wind speed, and relative humidity from 2009-2011. All data were obtained from the China Meteorological Data Sharing Network. Since regional NPP modeling requires grid-based meteorological data, meteorological elements from stations were spatially interpolated to the entire region. To reduce edge interpolation errors, data from 26 meteorological stations across Liaoning Province were downloaded and interpolated using the ANUCLIM method, then clipped to the study area boundary.

2.2 Remote Sensing Data

Remote sensing data are indispensable for regional NPP research. MODIS multi-band data provide vegetation and temperature information with high temporal resolution and short repeat cycle, making them very important for regional NPP studies. This study used MODIS data products to simulate Phragmites community NPP, including MOD13 vegetation index products, MOD15 leaf area index products, and MOD09 reflectance products from 2009-2011. These products from NASA have undergone strict quality control and verification, with proven accuracy sufficient for such research.

2.3 Net Primary Productivity Measurement Data

NPP was measured using the harvest method. Continuous, uniformly growing typical Phragmites communities were selected, with 27 large plots (250 m × 250 m) used for simulating maximum light conversion efficiency and the other 27 for validation. In each large plot, five 2 m × 2 m subplots were established at the corners and center. All Phragmites in the subplots were harvested at ground level, separated by organ, weighed fresh, and sampled (300-500 g). Litter was also collected. Samples were oven-dried at 80°C to constant weight, and total dry weight per subplot was calculated based on dry matter ratios and total fresh weight. The average of five subplots was used to calculate plot-level biomass, then converted to carbon content per unit area using a carbon conversion coefficient of 0.45.

Results

3.1 Simulation Results

The simulated maximum light conversion efficiency for Phragmites ranged from 1.112 to 2.611 g C/MJ, with a mean value of 1.667 g C/MJ (1.656 ± 0.43). This is significantly higher than the 0.389 g C/MJ proposed by Potter and higher than values for broad-leaved, coniferous, and mixed forests. Using the simulated maximum light conversion efficiency, the actual light conversion efficiency of Phragmites communities was calculated to be 0.957-1.102 g C/MJ.

The temporal dynamics of light conversion efficiency showed a clear unimodal seasonal pattern. Due to low temperature constraints, Phragmites begins growth when temperature rises to suitable levels, and light conversion efficiency increases. As the growing season progresses with increasing temperature and precipitation favoring photosynthesis, leaf area and coverage increase, reaching maximum light conversion efficiency (1.524 g C/MJ) in late July when temperature and precipitation peak. Subsequently, efficiency decreases with declining temperature and precipitation and leaf senescence.

3.2 Simulation Validation

Since maximum light conversion efficiency cannot be measured directly, validation was performed indirectly by comparing simulated aboveground NPP with measured values using the simulated MLE of 1.667 g C/MJ. The correlation coefficient between simulated and observed values was 0.63 ($p < 0.001$), with root mean square error of 24% and mean values of 619.9 g C/m² (simulated) and 627.3 g C/m² (observed), showing good consistency. When using Potter's value of 0.389 g C/MJ, simulated aboveground NPP was only 112.8-184.6 g C/m², significantly underestimating the carbon sequestration capacity.

3.3 Sensitivity Analysis

To simulate vegetation MLE, remote sensing and meteorological data are used to calculate APAR, FPAR, T_ε, and W_ε. Errors in these data propagate to the final results. The main error sources include: APAR error from estimating total radiation using sunshine duration, FPAR error from NDVI, and T_ε and W_ε dependence on temperature and precipitation.

Single-factor analysis was conducted by varying each factor within ±30% of actual 2009-2011 values. Results showed different factors affected simulations differently:

- **Total radiation and NDVI**: Strong sensitivity, with simulated MLE decreasing as they increased. MLE ranged from 1.239-2.568 g C/MJ (1.752 ± 0.409) and 1.313-2.276 g C/MJ (1.716 ± 0.308) respectively. Sensitivity was more pronounced at lower values, with first derivatives of -1.351 to -0.642 and -1.218 to -0.708 respectively. However, even with ±30% error, simulated values remained within the sample range (1.112-2.611 g C/MJ).
- **Temperature and precipitation**: Low sensitivity, with MLE ranges of 1.547-1.801 g C/MJ (1.669 ± 0.08) and 1.586-1.774 g C/MJ (1.672 ± 0.06) respectively. First derivatives were small (-0.12 to 0.134 and -0.08 to 0.107), indicating stable results.

Total radiation was estimated using sunshine duration with 95% accuracy (relative root mean square error < 5% for all 27 samples). With this error estimate, simulated MLE ranged from 1.598-1.743 g C/MJ, with absolute change of -0.069 to 0.076 g C/MJ and relative change of only -4.14% to 4.56%, demonstrating stability and reliability.

NDVI sensitivity decreased with increasing vegetation cover. Even with maximum NDVI error, simulated results (1.313-2.276 g C/MJ) remained concentrated within the sample range. MODIS NDVI data from different resolutions (250 m and 1000 m) showed small differences (0.016 g C/MJ), proving the universality of results across satellite images with different spatial resolutions.

Conclusion

Accurately determining maximum light conversion efficiency is fundamental for studying regional vegetation NPP using light use efficiency models. This study combined remote sensing technology with ground meteorological observations and productivity field monitoring to invert the maximum light conversion efficiency of typical Phragmites communities in the Liaohe River estuarine wetland using the CASA model.

The results show that Phragmites communities have very high carbon conversion capacity, with maximum light conversion efficiency reaching 1.667 g C/MJ and actual conversion efficiency of 0.957-1.102 g C/MJ. Sensitivity analysis reveals that simulated MLE is strongly sensitive to total radiation and NDVI, decreasing as these factors increase, with sensitivity more pronounced at lower values. Controlling total radiation precision is particularly important, though this study achieved 95% simulation accuracy. With this error estimate, the relative change amplitude of simulated MLE is only -4.14% to 4.56%, indicating stability and reliability. Sensitivity decreases with increasing NDVI, and even with 30% error, simulated values remain within the sample range. MODIS NDVI data are widely used for regional NPP research, and different resolutions yield similar results, making them comparable. Simulated Phragmites MLE shows low sensitivity to temperature and precipitation, with minimal impact from their errors.

References

[1] Odum W E, Odum E P, Odum H T. Nature' s pulsing paradigm. Estuaries, 1995, 18(4): 547-555.

[2] Parton W J, Scurlock J M O, Ojima D S, Gilmanov T G, Schlesles R J, Schimel D S, Kirchner T, Menaut J C, Seastedt M T, Moya E G, Kamnalrut A, Kinyamario J I. Observations and modeling of biomass and soil organic matter dynamics for the grassland biome worldwide. Global Biogeochemical Cycles, 1993, 7(4): 785-890.

[3] Potter C S, Randerson J T, Field C B, Matson P A, Vitousek P M, Mooney H A, Klooster S A. Terrestrial ecosystem production: a process model based on global satellite and surface data. Global Biogeochemical Cycles, 1993, 7(4): 811-841.

[4] Field C B, Randerson J T, Malmström C M. Global net primary production: combining ecology and remote sensing. Remote Sensing of Environment, 1995, 51(1): 74-88.

[5] Raymond E, Hunt J R. Relationship between woody biomass and PAR conversion efficiency for estimating net primary production from NDVI. International Journal of Remote Sensing, 1994, 15(8): 1725-1729.

[6] Wofsy S C, Goulden M L, Munger J W, Fan S M, Bakwin P S, Daube B C,

Bassow S L, Bazzaz F A. Net exchange of CO in a mid-latitude forest. Science, 1993, 260(5112): 1314-1317.

[7] Russell G, Jarvis P G, Monteith J L. Absorption of radiation by canopies and stand growth // Russell G, Marshall B, Jarvis P G, eds. Plant Canopies: Their Growth, Form and Function. Cambridge: Cambridge University Press, 1989: 21-39.

[8] Heimann M, Keeling C. A three-dimensional model of atmospheric CO transport based on observed winds: 2. model description and simulated tracer experiments. American Geophysical Union, 1989, 55: 237-275.

[9] Raich J W, Rastetter E B, Melillo J M, Kicklighter D W, Steudler P A, Peterson B J, Grace A L, Moore III B, Vörösmarty C J. Potential net primary productivity in South America: application of a global model. Ecological Applications, 1991, 1(4): 399-429.

[10] McGuire A D, Melillo J M, Joyce L A, Kicklighter D W, Grace A L, Moore III B, Vorosmarty C J. Interactions between carbon and nitrogen dynamics in estimating net primary productivity for potential vegetation in North America. Global Biogeochemical Cycles, 1992, 6(2): 101-124.

[11] Lobell D B, Hicke J A, Asner G P, Field C B, Tucker C J, Los S O. Satellite estimates of productivity and light use efficiency in United States agriculture, 1982-98. Global Change Biology, 2002, 8(8): 722-735.

[12] Goetz S J, Prince S D. Remote sensing of net primary production in boreal forest stands. Agricultural and Forest Meteorology, 1996, 78(3/4): 149-179.

[13] Running S W, Thornton P E, Nemani R, Glassy J M. Global terrestrial gross and net primary productivity from the earth observing system // Sala O E, Jackson R B, Mooney H A, Howard R W, eds. Methods in Ecosystem Science. New York: Springer-Verlag, 2000: 44-57.

[14] Zhu Wenquan. Simulation of maximum light utilization efficiency of typical vegetation in China. Chinese Science Bulletin, 2006, 51(6): 700-706.

[15] Li Guosheng. Landscape change analysis of Liaohe Delta wetland. Chinese Journal of Ecology, 1996, 16(3): 260-265.

[16] Wang Bingliang. Patterns and controlling factors of aboveground net primary productivity of vegetation in Liaohe Delta region. Chinese Journal of Eco-Agriculture, 2010, 19(10): 2269-2274.

[17] Liao Huajun. Wetland resources and regional sustainable development in Liaohe Delta. Chinese Journal of Ecology, 2000, 20(6): 545-551.

[18] Chen J L, Li G S, Xiao B B, Wen Z F, Lv M Q, Chen C D, Jiang Y, Wang X X, Wu S J. Assessing the transferability of support vector machine model for estimation of global solar radiation from air temperature. Energy Conversion and Management, 2015, 89: 318-329.

[19] Roujean J L, Breon F M. Estimating PAR absorbed by vegetation from bidirectional reflectance measurements. Remote Sensing of Environment, 1995, 51(3): 375-384.

[20] Sellers P J, Berry J A, Collatz G J, Field C B, Hall F G. Canopy reflectance, photosynthesis, and transpiration. III. A reanalysis using improved leaf models and a new canopy integration scheme. Remote Sensing of Environment, 1992, 42(3): 187-216.

[21] Peng Shaolin. Biomass, productivity and light use efficiency of zonal vegetation in Dinghushan. Acta Phytoecologica Sinica, 1994, 24(5): 497-502.

[22] Los S O. Linkages between global vegetation and climate: an analysis based on NOAA advanced very high resolution radiometer data [D]. Washington: National Aeronautics and Space Administration (NASA), 1998.

[23] Allen R G, Pereira L S, Raes D. Crop evapotranspiration: guidelines for computing crop water requirements. FAO irrigation and drainage paper 56. Rome: FAO, 1998.

[24] Chen J L, Li G S. Parameterization and mapping of solar radiation in data sparse regions. Asia-Pacific Journal of Atmospheric Sciences, 2012, 48(4): 423-431.

[25] Friedlingstein P, Joel G, Field C B, Fung I Y. Toward an allocation scheme for global terrestrial carbon models. Global Change Biology, 1999, 5(7): 755-770.

[26] Peng Shaolin. Estimation of light use efficiency of vegetation in Guangdong. Chinese Journal of Ecology, 2000, 20(6): 903-909.

[27] Schubauer J P, Hopkinson C S. Above- and belowground emergent macrophyte production and turnover in a coastal marsh ecosystem, Georgia. Limnology and Oceanography, 1984, 29(5): 1052-1065.

[28] Yang Shilun. Carbon storage and sequestration function of typical wetland vegetation in Yangtze River estuary: a case study of Phragmites zone in Chongming Dongtan. Chinese Journal of Eco-Agriculture, 2008, 16(2): 269-272.

[29] Ahearn D S, Viers J H, Mount J F, Dahlgren R A. Priming the productivity pump: flood pulse driven trends in suspended algal biomass distribution across a restored floodplain. Freshwater Biology, 2006, 51(8): 1417-1433.

[30] Liu Liangming. Study on the relationship between MODIS and AVHRR vegetation indices. Geomatics and Information Science of Wuhan University, 2004, 29(4): 307-310.

[31] Trishchenko A P, Cihlar J, Li Z Q. Effects of spectral response function on surface reflectance and NDVI measured with moderate resolution satellite sensors. Remote Sensing of Environment, 2002, 81(1): 1-18.

[32] Huete A, Justice C, Van Leeuwen W. MODIS vegetation index (MOD 13). Version 3. Algorithm theoretical basis document. ATBD-MOD-13, NASA, 1999.

[33] Discussion on carbon sequestration potential of Phragmites wetland ecosystems in China. Chinese Agricultural Science Bulletin, 2010, 26(18): 320-323.

[34] Chen J L, Li G S. Parameterization and mapping of solar radiation in data sparse regions. Asia-Pacific Journal of Atmospheric Sciences, 2012, 48(4): 423-431.

Note: Figure translations are in progress. See original paper for figures.