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Combining vegetation index derived from PhenoCam with EVI to estimate daily GPP in semi-arid grassland of northeastern China

Hesong Wang (1), Gensuo Jia (2), Huichen Zhao (2), and Anzhi Zhang (2)

(1) College of Forestry, Beijing Forestry University, Beijing 100083, China; wanghs119@126.com, (2) Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing 100029, China; jiong@tea.ac.cn (G.J.); zhaohc@tea.ac.cn (H.Z.); zhanganzhi@tea.ac.cn (A.Z.)

Accurate estimation of temporal continuous gross primary production (GPP) plays an important role in mechanistic understanding of global carbon budget and exchange between atmosphere and terrestrial ecosystems. Ground based PhenoCam can provide near surface observations of plant phenology with high temporal resolution and have great potential in modeling seasonal dynamics of GPP. However, due to the empirical approaches for estimating fAPAR, there still exist some uncertainties of adopting PhenoCam images into GPP modeling. Here, in semi-arid grassland of northeastern China, we combined Green Excess Index (GExI) derived from PhenoCam and EVI retrieved from MODIS to generate daily time-series of fAPAR (fAPARcam), and then to estimate daily GPP (GPPpre) with a light use efficiency model from 2012 to 2014. Among the three continuous years, daily fAPARcam exhibited similar temporal behaviors with eddy covariance observed GPP (GPPobs). The overall determination coefficients (R2) were all greater than 0.81. GPPpre agreed well with GPPobs and these agreements showed highly statistically significant (p <0.01). R2 ranged from 0.80 to 0.87, RE ranged from -2.9% to 2.81% and RMSE ranged from 0.83 (gC/m2d-1) to 0.98 (gC/m2d-1). GPPpre was then resampled to 8-day temporal resolution and further evaluated by comparing with MODIS GPP products and VPM modeled GPP. Validation showed the variance explained by GPPpre is still the highest. RMSE and RE were also lower than the other two in general. Explanatory power of inputs in GPP modeling was also explored: fAPAR is the most influential input and PAR takes the second place. Contributions of Tscalar and Wscalar are lower than PAR. These results highlight the potential of PhenoCam images in high temporal resolution GPP modeling. Our GPP modeling method will help to reduce uncertainties of using PhenoCam images in monitoring of seasonal development of vegetation production.