Estimation of terrestrial carbon cycle in Asia using a machine learning and satellite data

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Gross Primary Productivity (GPP) and Ecosystem Respiration (RE) play an important role in the terrestrial carbon cycle. For large-scale estimation, empirical upscaling by machine learning using observation data is becoming one methodology because of expansion of ground observation network, improvement of satellite data, and development of machine learning [Yang et al. 2007; Jung et al. 2011; Kondo et al., 2015]. In Asia, spatio-temporal variations in terrestrial carbon fluxes were estimated using support vector regression by integrating ground observation network including JapanFlux [Ichii et al., 2017].
MODIS sensor data onboard Terra and Aqua satellite are one of the most widely used data for upscaling. The MODIS dataset used in many of the previous studies was an older version, Collection 5 (C5). C5 data was not able to adequately account for the secular change of sensor sensitivity, and it was improved by the new version, Collection 6 (C6) [Wang et al., 2012]. C5 data were mainly used in the large-scale estimation by machine learning so far. Therefore, we need to upgrade the dataset from C5 to C6.
In this study, we upgraded the MODIS data (from C5 to C6) from the existing study [Ichii et al. 2017]. We upgraded only MODIS data for site-level training and testing and large-scale model application. The satellite data used as input variables include the surface temperature, leaf area index, the vegetation index and the water index. GPP and NEE (Net Ecosystem Exchange) were estimated as output variables.
In the site-level model training and testing, there was no overall big difference in the result of the model (GPP, NEE) between C5 and C6. Spatial variations in GPP and NEE averaged over 2000-2015 were similar except for Southeast Asia. We also found differences in long-term trends in GPP and NPP over Asia. GPP and NEE using C6 shows more increase trends from 2000-2015. We need to evaluate which GPP and NEE changes are more realistic by comparing with other independent datasets.

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