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Using Bayesian model averaging to estimate terrestrial evapotranspiration in China

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SUMMARY

Evapotranspiration (ET) is critical to terrestrial ecosystems as it links the water, carbon, and surface energy exchanges. Numerous ET models were developed for the ET estimations, but there are large model uncertainties. In this study, a Bayesian Model Averaging (BMA) method was used to merge eight satellite-based models, including five empirical and three process-based models, for improving the accuracy of ET estimates. At twenty-three eddy covariance flux towers, we examined the model performance on all possible combinations of eight models and found that an ensemble with four models (BMA_Best) showed the best model performance. The BMA_Best method can outperform the best of eight models, and the Kling–Gupta efficiency (KGE) value increased by 4% compared with the model with the highest KGE, and decreased RMSE by 4%. Although the correlation coefficient of BMA_Best is less than the best single model, the bias of BMA_Best is the smallest compared with the eight models. Moreover, based on the water balance principle over the river basin scale, the validation indicated the BMA_Best estimates can explain 86% variations. In general, the results showed BMA estimates will be very useful for future studies to characterize the regional water availability over long-time series.

1. Introduction

Evapotranspiration (ET) is one of the most important variables of terrestrial ecosystems as it links water, carbon, and surface energy exchanges. Therefore, accurate estimations of ET in large scale is crucial for understanding the interactions between land surfaces and the atmosphere (Keane et al., 2002), drought and land resource management (Raupach, 2001), and coupling water cycling and ecosystem carbon exchange (Eamus, 2003). Over the past several years, there have been substantial efforts to retrieve ET over large areas. Zeng et al. (2012) estimated global ET with a spatial regression model by integrating precipitation, temperature and satellite-derived normalized difference vegetation index (NDVI) data. Xia et al. (2014) calculated ET over grassland ecosystems of dryland East Asia using regression tree method. Shu et al. (2011) estimated the regional ET over the North China Plain using the data from Chinese geostationary satellite Fengyun-2C and found spatial variations of ET compare very well to the land use types. However, ET is still the component with the most problem in the water cycle processes because of the complex controlling factors and heterogeneity of the landscape (Lettenmaier and Famiglietti, 2006; Yuan et al., 2010a).

Numerous models are developed for quantifying spatiotemporal variations of ET using remote sensing observations (Cleugh et al., 2007; Mu et al., 2007; Fisher et al., 2008; Leuning et al., 2008; Jung et al., 2009; Yuan et al., 2010b; Zhang et al., 2010; Mu et al., 2011; Vinukollu et al., 2011a; Yang et al., 2012; Baik and Choi, 2015; French et al., 2015; Liu et al., 2015; Tang and Li, 2015). Satellite-based modeling has been an important tool for accurately parameterizing surface biophysical variables because remotely sensed data provide temporally and spatially continuous information over heterogeneous surfaces. In previous studies, the net radiation products, remotely sensed variables (e.g., vegetation index) and meteorological measurements (e.g., vapor pressure and air temperature) were used to calculate the special

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evapotranspiration. For example, the global land ET was estimated by Vinukollu et al. (2011) using a set of remote sensing and observational based radiation and meteorological forcing datasets such as International Satellite Cloud Climatology Project (ISCCP), Advanced Very High Resolution Radiometer (AVHRR) and Global Meteorological Forcing Data set from Princeton University (PU).

However, there are large model uncertainties revealed by the inter-comparisons of ET estimates (Vinukollu et al., 2011b). For example, Jiménez et al. (2011) indicated that the global annual mean ET between different models and datasets had 50% uncertainties, which induced large uncertainties for the global water and energy cycles. The mean annual ET in China calculated by different models ranged from 535 to 852 mm/year. The major reason for the different models estimations were the differences in model structures and their dominant variables (Chen et al., 2014).

The multi-model ensembles method has increasingly been used to improve model estimations (Hagedorn et al., 2005). The Bayesian Model Averaging (BMA) method, a statistical scheme based on multi-model ensemble, was originally developed as a way to combine different models or forecasts (Hoeting et al., 1999). The contribution of each individual model in the BMA method is weighted by its posterior weight of evidence (Ellison, 2004). BMA has been widely used to study the climate change (Duan and Phillips, 2010), improve the predictions accuracy of hydrology (Duan et al., 2007), weather (Raftery et al., 2005; Wu et al., 2012), forest biomass (Li et al., 2008) and economics (Fernandez et al., 2001). Previous studies indicated better estimations of BMA than other multi-model ensemble methods (Viallefont et al., 2001; Ellison, 2004; Raftery et al., 2005; Sloughter et al., 2007). For example, Wang et al. (2012) merged seasonal rainfall forecasts from multiple models using BMA and improved effectively skills of the models. Similarly, BMA method also was used to merge estimates of hydrological flows from multi-model and BMA ensembles decreased estimates bias value and increase correlation coefficient compared with the single best model (Jiang et al., 2012). Moreover, BMA method can quantify the uncertainties from the inputs, model structure and parameters and improve the model accuracy (Najafi et al., 2011). For example, Najafi et al. (2011) used BMA to merge the hydrologic models variance and quantify the uncertainties, which were useful in evaluating the regional water resources.

This study uses BMA method to improve China terrestrial ET estimates based on eight ET models. The objectives of this study are to: (1) use the BMA method to improve the accuracy of ET estimates; (2) compare two ensemble strategies: ensemble with all models and ensemble with the selected models; (3) examine the performance of the BMA method through a water balance analysis; and (4) analyze the spatiotemporal patterns of ET calculated by the BMA method over China from 1982 to 2009.

2. Data

2.1. Data at eddy covariance (EC) site

Twenty-three EC sites (Fig. 1, Table 1) were used to examine model performance. The data were collected from Arid/Semi-arid experimental observation synergy and integration, ChinaFlux, AsiaFLUX and LathuileFLUX. The sites included seven major biomes, evergreen needleleaf forests, evergreen broadleaf forests, deciduous needleleaf forests, deciduous broadleaf forests, mixed forests, grasslands and croplands. The eight ET models are driven by 8-day net radiation (R_n), solar radiation (R_g), relative humidity (R_h), air temperature (T_a), maximum air temperature (T_{max}), atmospheric pressure (Pr), wind speed (W_s), vapor pressure deficit (VPD) and Minimum air temperature (T_{min}) (see Table 2).

It has been recognized that the sum of latent heat (LE) and sensible heat (H) as measured in EC towers is generally less than the available energy (Foken, 2008). LE observations can be corrected with the following formulas (Jung et al., 2010),

$$\mathrm{LE}_{cor} = (R_n - G)/(H_{uncor} + \mathrm{LE}_{uncor}) \times \mathrm{LE}_{uncor} \quad (1)$$

where R_n is the net radiation, G is the soil heat flux, H_{uncor} is uncorrected sensible heat, LE_{uncor} is uncorrected latent heat and LE_{cor} is corrected latent heat.

The leaf area index (LAI) and normalized difference vegetation index (NDVI) for the eddy covariance towers were from

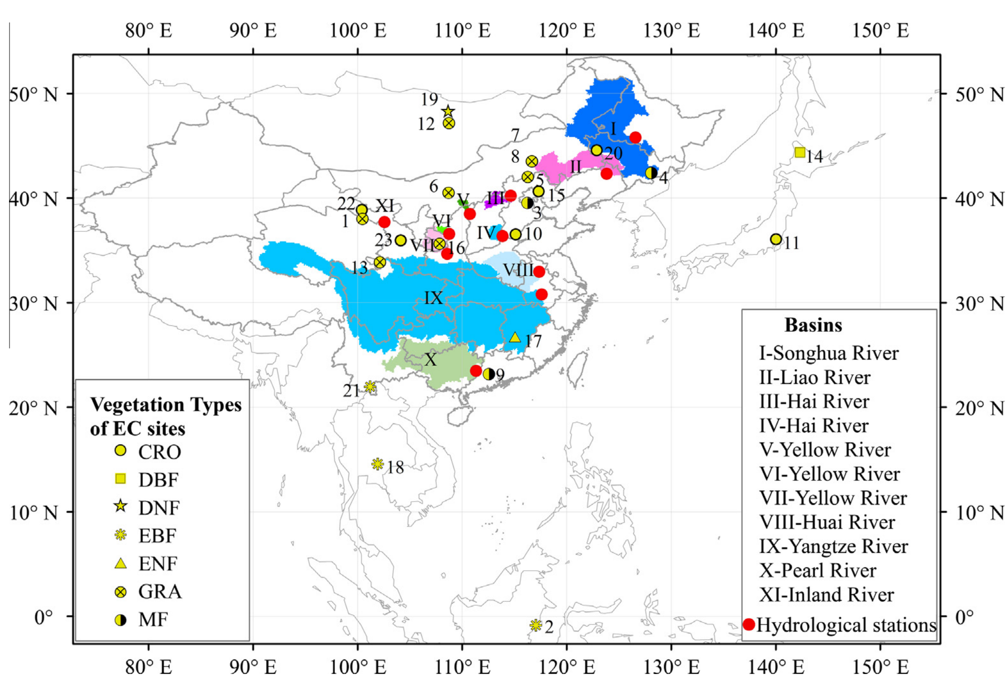

Fig. 1. Locations of the twenty-three EC sites and eleven hydrological stations. Numbers match with the sites ID in Tables 1 and 3. DBF: deciduous broadleaf forests; DNF: deciduous needleleaf forests; EBF: evergreen broadleaf forests; ENF: evergreen needleleaf forests; CRO: croplands; GRA: grasslands; MF: mixed forests.