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Spatio-temporal variations of vegetation carbon use efficiency and potential driving meteorological factors in the Yangtze River Basin

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Abstract: Understanding of vegetation dynamics is essential for addressing the potential threats of terrestrial ecosystem. In recent years, the vegetation coverage of the Yangtze River basin (YRB) has increased significantly, yet how about the spatio-temporal variations and potential driving meteorological factors of carbon use efficiency (CUE) under the context of global warming are still not clear. In this study, MODIS-based public-domain data during 2000–2015 was used to analyze these aspects in the YRB, a large river basin with powerful ecological functions in China. Spatio-temporal variations of CUE in different sub-basins and land cover types were investigated and the correlations with potential driving meteorological factors were examined. Results of this study revealed that CUE in the YRB had strong spatio-temporal variability and varied remarkably in different land cover types. For the whole YRB, average CUE of vegetated land was 0.519, while the long-term change trend of CUE was obscure. Along the rising altitude, CUE generally showed an increasing trend until the altitude of 3900m and then followed by a decreasing trend. CUE of grasslands was generally higher than that of croplands, and then forest lands. The inter-annual variation of CUE in the YRB is likely to be driven by precipitation as a strong positive partial correlation between the inter-annual variability of CUE and precipitation was observed in most of sub-basins and land cover types in the YRB. The influence of temperature and relative humidity is also outstanding in certain regions and land cover types. Our findings are useful from the view point of carbon cycle and reasonable land cover management under the context of global warming.

Keywords: Carbon use efficiency; Climate variability; MODIS; Altitude; Land cover type; Precipitation

Introduction

Terrestrial ecosystem is considered to be a major carbon sink in the global carbon cycle (Zhao and Running 2010). Gross primary production (GPP), Net primary production (NPP) and respiration are three basic components of carbon cycle. Among which, Gross primary production (GPP) represents the capacity of the plants in an ecosystem to capture energy and carbon. Net primary production (NPP), the reduction of GPP after autotrophic respiration, is the net carbon stored as new plant material in an ecosystem (Zhang et al. 2009). Carbon use efficiency (CUE), defined as the ratio of NPP to GPP, represents a convenient way to analyze the Carbon allocation at the stand level at ecosystem scale (Chambers et al. 2004). As an important ecological parameter in regional and global carbon cycle research, CUE not only reflects the ability of vegetation in transferring carbon from the atmosphere to the terrestrial biomass and the potential of carbon sequestration, but also determines the impact of respiration on vegetation productivity (Ryan et al. 1997; DeLucia et al. 2007; Manzoni et al. 2012). In terrestrial carbon cycle modeling, small changes of CUE can cause significant changes in carbon budget evaluation results. Examining the variability of CUE is thus important for climate change and CO_2 emissions studies (Chen et al. 2013). In the context of global warming, the response of terrestrial ecosystem to climate change is the key issue of the International Geosphere-Biosphere Program (IGBP) (Bradford and Crowther 2013; Chen et al. 2018, 2019). Scientific understanding of the change characteristics of vegetation CUE and potential influencing factors is of great significance to accurately assess ecosystem status of carbon source or sink and predict regional carbon budget under global change and human disturbance.

Vegetation dynamics of terrestrial ecosystem are influenced by many factors such as climatic change, land-use change, ecological engineering, and urbanization in different regions (Qu et al. 2018; Jiang et al. 2020). Study revealed that temperature has a positive influence on vegetation coverage in China (Yu and Hu

2013), while the relationship between precipitation and vegetation growth varied depends on the wetness of the area (Xu et al. 2014). In recent years, researches on vegetation CUE under different environmental regimes and global change scenarios have received increasing attention (e.g., Metcalfe et al. 2010; Zhu 2013; Khalifa et al. 2018). Geographically, Piao et al. (2010) pointed out that CUE increases with altitude. Climatically, Zhang et al. (2009) revealed that the CUE exhibited a decreasing trend along enhanced precipitation when it was less than 2300 mm year^{-1} and a static trend when the annual precipitation was over 2300 mm. The CUE showed a decreasing trend along temperature when it was between -20°C and -10°C, and showed an increasing trend along rising temperature when it was between -10°C and 20°C. Zhang et al. (2014b) revealed a decreasing trend of CUE of global terrestrial ecosystem during 2000-2009, which was strongly controlled by temperature and precipitation. Different terrestrial ecosystems differ in their responses to external environment and CUE shows significant spatio-temporal variability (Kwon and Larsen, 2013; Zhang et al. 2014b). CUE varied with ecosystem types, being the highest in wetlands and lowest in grassland, and CUE decreased with latitude with the lowest CUE in tropics, and the highest CUE in higher latitude regions (Tang et al. 2019). Campioli et al. (2011) revealed that CUE of leaves and wood significantly correlated with environmental condition. In addition, soil nutrition and management may also have influences on CUE. For example, plants grown on the barren soil, and under low temperature and drought conditions, may have larger changes in CUE than plants grown under near-optimal conditions (van Iersel 2003). Forest managements such as irrigation, fertilization, and selective logging can also affect ecosystem CUE (e.g., Giardina et al. 2003). Due to the complexity of driving mechanism of CUE, investigation on the dynamics and potential influencing factors of CUE is quite necessary to achieve a better land cover management.

In recent years, the measurement of carbon fluxes between the ecosystem and the atmosphere based on eddy covariance flux tower has been widely applied (e.g., Chen et al. 2018; Rambal et al. 2012). Although, the accuracy of flux tower observation is high, the limitation of the quantity and spatial distribution of flux tower hinders the analysis of carbon flux dynamics at regional or global scales (Khalifa et al. 2018). Fortunately, satellite remote sensing based public-domain data sources provide continuous spatial observation of environmental variables on a large scale (e.g., NDVI, biomass, soil moisture, etc.). Among which, the high spatio-temporal resolution MODIS primary productivity product (MOD17) based on the TERRA polar orbiting Environment Satellite is the most popular one. The MOD17 is part of the NASA Earth Observation System (EOS) program and is the first satellite-driven dataset to monitor vegetation productivity on global scale. The goal of the MOD17 MODIS project is to provide continuous estimates of GPP/NPP across Earth's entire vegetated land surface (Heinsch et al. 2003). Outputs of MOD17 GPP/NPP are very useful in natural resource and land management, global carbon cycle analysis, ecosystem function assessment and environmental change monitoring. With the MOD17 data, the variability of primary productivity as well as

CUE of different land cover types and their association with climate conditions can be detected (e.g., Khalifa et al. 2018; Chen 2019).

The Yangtze River Basin (YRB) located in 90°13′–122°19′E, 24°27′–35°54′N, is one of the most important large river basins in the world (Figure 1a). It covers an area of 180×10^4 km^2, accounting for 18.75% of the land territory of China. Because of its rich natural resources, numerous tributaries and lakes, the Yangtze River feeds the south of China and forms an important modern economic Belt of some 3000 km from the East to the West. The YRB is a unique and complete natural ecosystem with powerful functions in water and soil conservation, biology breeding, oxygen release and carbon sequestration, and environmental purification. However, due to the effects of global climate change and rapid development of social economy, the ecological environment problems in the YRB have become increasingly prominent, such as the degradation of surface vegetation, the aggravation of soil erosion, the continuous environmental pollution and the reduction of biodiversity (e.g., Li et al. 2001; Cui et al. 2008). "Eco-environment first" and "green development" are the latest national formulating strategies for the construction of the Yangtze River Economic Belt and the development of YRB (Du 2016). In recent years, the vegetation coverage of the YRB has increased significantly (e.g. Qu et al. 2018; Cui et al. 2019), yet how about the spatio-temporal variations and potential driving meteorological factors of carbon use efficiency (CUE) under the context of global warming are still not clear.

This study attempts to examine the spatio-temporal patterns of CUE change in the YRB and how they are affected by the ongoing climate change. Specifically, the objectives of this study are: (1) to investigate the spatio-temporal variations of vegetation CUE in the YRB; (2) to examine the difference of CUE between different land cover types; and (3) to reveal the relative effects of major meteorological factors on the change of CUE in different regions and land cover types. The results of this study will contribute to better understand the dependence of the vegetation CUE on climates, as well as the carbon sink function of ecosystem in the YRB under the context of increasing levels of atmospheric CO_2 concentrations and climate change. Also, the results are essential to the promotion of reasonable land cover management and ecological resources utilization in the YRB.

1 Material and Methods

1.1 Study area

The Yangtze River is the largest river in China and the third longest river in the world. The river originates from the Tanggula Snow Mountains of the Qinghai-Tibet Plateau and flows about 6300 km eastwards to the East China Sea. The terrain of the basin is high in the west and low in the east, with a total drop of about 6000 m from the source of the river to the estuary. There are many types of landforms in the YRB, among which mountains, plateaus and hills account for 84.7%, plains account for 11.3%, rivers, lakes and other waters account for 4% (Figure 1b).

Climatically, the YRB belongs to the subtropical monsoon region of East Asia. According the observations applied in the study, the calculated mean annual temperature of the YRB is about 14.5°C and mean annual precipitation is about 1100 mm. However, due to great differences in landscape topography and the distance to sea across the YRB, mean annual temperature and precipitation in the basin vary remarkably between -5.2°C–21.5°C, and 288.7–2311.4 mm, respectively. Specific differences of mean annual climate conditions in the sub-basins are shown in Table 1. Among the major land cover types, woodland (WL), wet cropland (WC) and dry cropland (DC) are the top three in percentage of area (Figure 1c).

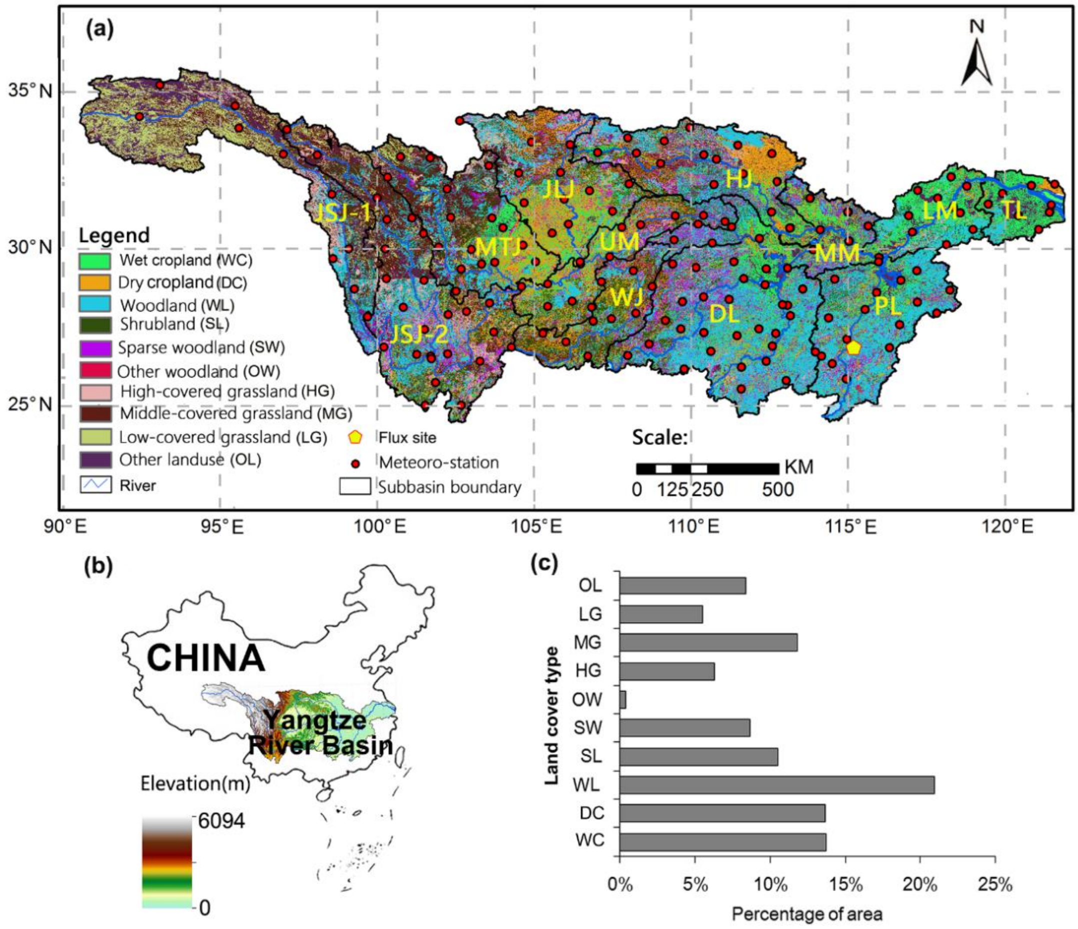

Figure 1 Basic geographical characteristics of the Yangtze River Basin: (a) distribution of land cover types, secondary water resources areas and meteorological stations across the Yangtze River basin; (b) the location and DEM of the Yangtze River Basin; and (c) area percentage of different land cover types.

Abbreviations for sub-basins: JSJ-1, Jinsha River sub-basin above Shigu; JSJ-2, Jinsha River sub-basin below Shigu; MTJ, Mintuo River sub-basin; JLJ, Jialing River sub-basin; WJ, Wujiang River sub-basin; UM, Yibin-Yichang section of the Yangtze River mainstream; DL, Dongting Lake sub-basin; HJ, Hanjiang River sub-basin; PL, Poyang Lake sub-basin; MM, Yichang-Hukou section of the Yangtze River mainstream; LM, Lower Yangtze River mainstream Interval; TL, Taihu Lake sub-basin.

According to the Chinese national water resources management regionalization, the whole YRB is divided into 12 secondary water resources areas: Jinsha River sub-basin above Shigu (JSJ-1), Jinsha River sub-basin below Shigu (JSJ-2), Mintuo River sub-basin (MTJ), Jialing River sub-basin (JLJ), Wujiang River sub-basin (WJ), Yibin-Yichang section of the Yangtze River mainstream (UM), Dongting Lake sub-basin (DL). Hanjiang River sub-basin (HJ), Poyang Lake sub-basin (PL), Yichang-

Hukou section of the Yangtze River mainstream (MM), Lower Yangtze River mainstream Interval (LM) and the Taihu Lake sub-basin (TL) (Figure 1a). In the following analysis, the spatial difference of CUE and its response to climate variables were specifically examined according to this hydrological subdivision.

Table 1 Basic climate conditions and carbon use efficiency (CUE) related variables in the Yangtze River Basin (YRB)

Sub-basin		Area ($\times 10^4 km^2$)	Mean Precipitation (mm)	Mean Temperature (°C)	Mean CUE	CUE Std Dev	Spatial C_v	Trend of CUE (β)
Secondary water resources area	JSJ-1	21.42	451.7	2.8	0.650	0.041	0.066	0.0012
	JSJ-2	28.78	799.8	11.6	0.637	0.040	0.063	-0.0001
	MTJ	16.30	979.5	11.9	0.634	0.034	0.053	0.0001
	JLJ	15.98	999.1	17.0	0.566	0.071	0.124	0.0004
	WJ	8.79	1068.7	15.4	0.536	0.060	0.110	-0.0010
	UM	9.30	1060.3	17.4	0.519	0.079	0.150	-0.0001
	DL	26.28	1374.9	17.2	0.459	0.078	0.167	-0.0009
	HJ	15.90	898.2	14.7	0.436	0.108	0.244	-0.0005
	PL	16.22	1665.3	18.3	0.438	0.097	0.214	-0.0011
	MM	8.97	1279.7	16.6	0.456	0.081	0.175	0.0006
	LM	8.46	1283.8	16.2	0.466	0.085	0.178	0.0019**
	TL	3.69	1197.3	16.9	0.526	0.062	0.115	0.0035***
The whole YRB		180.09	1049.8	14.0	0.519	0.123	0.216	0.0000

Notes: C_v, Coefficient of Variation; ** and *** indicate $p<0.05$ and $p<0.01$ significance level, respectively. The abbreviations for sub-basins refer to Figure 1.

1.2 Available data

1.2.1 MODIS GPP and NPP products

Annual GPP and NPP of the Yangtze River basin from 2000 to 2015 were downloaded from NTSG MOD17 v55 dataset which provided by the Numerical Terradynamic Simulation Group, University of Montana (http://files.ntsg.umt.edu/data/NTSG_Products/MOD17/). The dataset contains continuous global monitoring of primary productivity from 2000 to 2015 with a spatial resolution of 1 km and a temporal resolution of 8-day, monthly, and annual intervals. Updates are provided on an annual basis. With comparison to the NASA/USGS LPDAAC 8-day and annual v5 product, NTSG MOD17 v55 contains the following two improvements: temporal infilling of cloud-contaminated pixels and a consistent forcing meteorology (NCEP/NCAR Reanalysis II). Details of version 55 improvements can be found in Zhao and Running (2010) and Zhao et al. (2005).

The accuracy and applicability of MOD17 products were evaluated from a flux tower of Qianyanzhou Ecosystem Observation station in the YRB in this study. The Qianyanzhou flux tower (115°03′29.2″E, 26°44′29.1″N), a member of ChinaFLUX, is located in the south hilly area of the Poyang Lake sub-basin (Figure 1a). The flux tower is surrounded by planted forest with a coverage > 90%. The observed GPP from flux tower at time scales of daily, monthly and yearly during 2003-2010 was opened for public research (http://www.cnern.org.cn/). We extracted the MOD17 GPP values from one pixel where the flux tower was installed, although this may introduce errors for the comparison owing to different spatial resolutions. The comparison of MOD17 GPP with flux tower delivered GPP indicates that correlation coefficient of annual GPP is 0.77 (P < 0.05) and the fluctuation of monthly GPP is highly consistent. The MOD 17 data slightly under-estimates GPP with comparison to the measured result of flux tower. These results are consistent with previous studies (e.g., Zhao et al. 2005; Turner et al. 2006). This deviation of NTSG MODIS GPP products probably come from the influences of some factors in the calculation algorithm. This is also the reason why so many scholars have been working hard to make continuous improvement to the MODIS NPP/GPP products.

1.2.2 DEM and Land cover data

Digital Elevation Model (DEM) and land cover data of the YRB were derived from Resource and Environment Data Cloud Platform of the Chinese Academy of Sciences (http://www.resdc.cn) (Figure 1). Spatial resolution of both the data is 1 km. The land cover data of the YRB were extracted from remote sensing monitoring of land cover in China in 2010. According to the sub-category classification of LUCC, there are 10 land cover types including Wet cropland (WC), Dry cropland (DC), Woodland (WL), Sparse woodland (SW), Shrubland (SL), Other woodland (OW), High-covered grassland (HG), Middle-covered grassland (MG), Low-covered grassland (LG), Other land cover (OL) can be obtained in the basin (Figure 1a). It should be noted that the surface of “Other land cover (OL)” is not vegetated, including waters and barren lands where no biomass were considered in these land cover types.

1.2.3 Meteorological data

Monthly meteorological data from 152 weather stations inside the YRB (see in Figure 1a) were obtained from National Climate Centre of China Meteorological Administration (CMA) (http://data.cma.cn/). The data include monthly pan evaporation (ET), precipitation (P), temperature (T), relative humidity (RH), sunshine duration (SD) and wind speed (WS), among others during the period 2000–2015. All the climate variables provided by CMA had gone through a standard quality control process before delivery. According to these observations, yearly data of P and ET were aggregated from monthly data, while yearly data of the other meteorological variables (T, RH, SD and WS) were averaged from monthly data.

1.3 Methodology

According to the objectives, research scheme of this study was designed like this: Firstly, we calculated annual CUE series of the YRB from 2000 to 2015 based on the obtained NTSG MODIS GPP/ NPP products. Secondly, we calculated linear trend of annual CUE by applying the Sen’s slope method at each pixel across the YRB. At basin scale of the secondary water resources subdivision, the significance of change trend and the degree of CUE variability in time and space was further examined by the Mann-Kandell test and the statistic Coefficient of Variation, respectively. Thirdly, based on the land cover data of the YRB, the changes of CUE in different land cover types were analyzed. Finally, main driving meteorological factors to the annual variations of CUE in different sub-basins and different land cover types in the YRB were examined by using the Spearman partial correlation analysis. Details of relevant methods are described as follows:

(1) In this study, carbon use efficiency (CUE) of land vegetation is defined as the ratio of NPP to GPP:

$$\mathrm{CUE} = \mathrm{NPP}/\mathrm{GPP}, \tag{1}$$

where NPP and GPP are the vegetation Net Primary Productivity and Gross Primary Productivity, respectively. Both the variables are derived from the NTSG MOD17 v55 dataset. The unit of both the NPP and GPP is gC/m^2, while CUE is dimensionless.

(2) The Sen's slope (Sen 1968), also known as the "Nonparametric linear regression slope", was applied to estimate the linear trend. As an alternative to the standard linear regression slope, the Sen's slope is the most popular nonparametric technique in the earth sciences (meteorology, hydrology, ecology, climatology). It is a method that is insensitive to outliers. It can be significantly more accurate than simple linear regression for skewed and heteroskedastic data, and competes well against simple least squares even for normally distributed data. The formula for Sen's slope is given as:

$$\beta = median\left(\frac{x_j - x_i}{t_j - t_i}\right) \qquad 1 < i < j < n, \tag{2}$$

where β is the linear change trend; i and j are time variables, x_i and x_j are the sequential data values in the CUE time series. A positive value of β indicates an increasing trend, and a negative value of β indicates a decreasing trend.

(3) The significance of the long-term change trend of CUE was further examined by the Mann-Kandell (MK) test. The MK test is a rank-based non-parametric method which has been widely applied for trend detecting in hydro-climatic time series due to its robustness against the influence of abnormal data and especially its reliability for biased variables (e.g., Chen et al. 2007; Yin et al. 2016). According to the method, the null hypothesis of no trend is rejected if standardized statistics $|Z| \geq 1.64$, $|Z| \geq 1.96$ and $|Z| \geq 2.32$ at 0.1, 0.05 and 0.01 significance levels, respectively.

(4) Coefficient of Variation (C_v) is a statistical measure of the dispersion of data points in a data series around the mean. C_v represents the ratio of the standard deviation to the mean, and it is a useful statistic for comparing the degree of variation from one data series to another. We use C_v to examine the degree of spatial and temporal variability of CUE in the YRB.

(5) In multivariate correlation analysis, the relationships between different variables are very complex. They may be affected by more than one variable. Simple linear correlation coefficient cannot truly reflect the essential relationship between two variables. Partial correlation analysis, also known as net correlation analysis, is used to analyze the linear correlation between two variables under the condition of controlling the linear influence of other variables (Ye et al. 2018). In this study, Spearman partial correlation coefficient was calculated to analyze the influence of major climatic factors on the change of vegetation CUE. Specifically, when we performed the calculation of partial correlation coefficient between CUE and a certain climate variable, for example CUE and precipitation, other climate variables

such as ET, RH, SD and WS were regarded as control variables in the analysis. The significance of the partial correlation was further examined by the two-sided *t*-test.

2 Results

2.1 Spatial distribution of CUE across the basin

From visual inspection in Figure 2, it is clear that CUE in the YRB shows obvious spatial difference from east to west. CUE is generally high in the west and low in the east and middle of the YRB. Statistics indicate that the average CUE of vegetated land of the whole YRB was 0.519 with maximum value of 0.749 and minimum value of 0.016 during the study period. The sub-plot in the lower left corner of Figure 2 further indicates that CUE in 68% area of the YRB was ranged in 0.5–0.7, and 26% area was ranged in 0.3–0.5. This result indicates that in most area of the YRB, surface vegetation has relatively high efficiency in transferring productivity into biomass stored in the ecosystem. For the secondary water resources areas, the basic statistical characteristics of CUE related variables are listed in Table 1. Results indicate that the multi-year averages of CUE of the sub-basins were ranged in 0.436–0.650. Mean annual CUE of the top three sub-basins are JSJ-1 (0.650), JSJ-2 (0.637) and MTJ (0.634). The HJ and PL sub-basins have the lowest CUE, and the values were 0.436 and 0.438. Values of CUE of TL and LM in the lower YRB were a little higher than that in the middle YRB. In addition, according to the value of C_v, it can be concluded that CUE in the HJ and PL sub-basins has the strongest spatial variability, while CUE in the MTJ sub-basin has the smallest spatial variability.

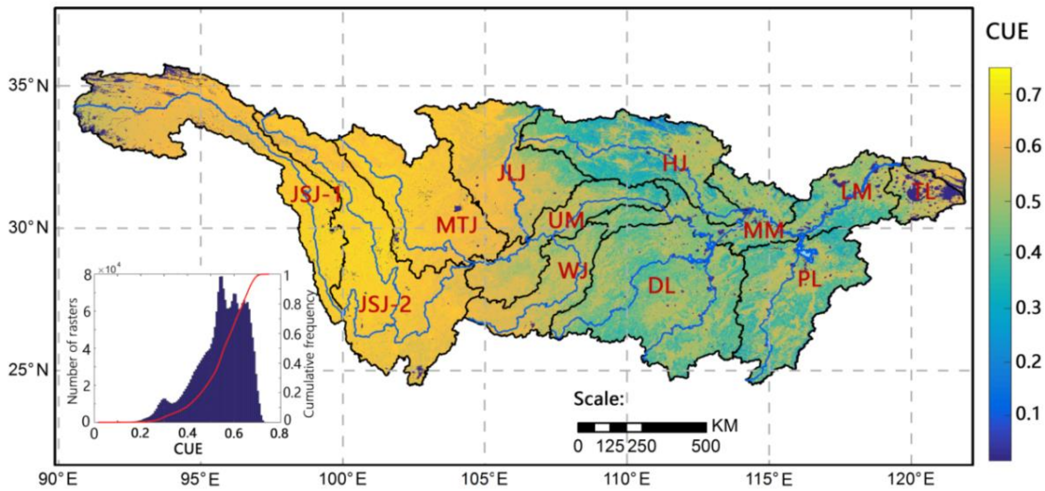

Figure 2 Spatial distribution of the average annual carbon use efficiency (CUE) across the Yangtze River basin (YRB). The abbreviations for sub-basins refer to Figure 1.

Figure 3 displays the variation characteristics of GPP, NPP and CUE in the YRB along altitude. It is noted from the figure that both the GPP and NPP show the similar pattern with rising altitude. Both fluctuate and peak at 2300 m a.m.s.l. and after that decrease rapidly. When the altitude is over 5000 m a.m.s.l., both the GPP and NPP have dropped below 80gC/m². However, as the ratio of the two variables, the variation of CUE is much complex. CUE fluctuates greatly below 800 m a.m.s.l. along rising altitude with a decreasing trend below 300 m a.m.s.l., an increasing trend between 300 and 500 m a.m.s.l. and then followed by a decreasing trend between 500 and 800 m. From the altitude of 800 m, CUE begins to increase steadily with rising altitude, and peaks at 3900 m a.m.s.l. However, the increasing slope is relatively larger between 1200 m and 2800 m a.m.s.l., and then the increasing slope decreases obviously. Above 3900 m a.m.s.l., CUE begins to decrease with rising altitude. In contrary to the former stage, the decreasing slope is relatively smaller between 3900 m and 4600 m a.m.s.l., and then the decreasing slope increases obviously.

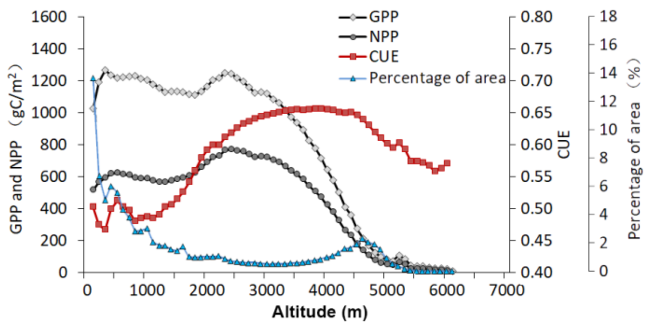

Figure 3 Variations of Gross primary production (GPP), Net primary production (NPP), carbon use efficiency (CUE) and area percentage along rising altitude in the Yangtze River basin (YRB).

2.2 Inter-annual variation of CUE across the basin

Figure 4 shows the spatial distribution of linear change rate (β) of CUE in the YRB during 2000~2015. Result from the figure indicates that major increasing regions of CUE are concentrated in the lower YRB of LM and TL sub-basins, the upper reaches of HJ sub-basin and the central of MTJ sub-basin. In contrast, the decreasing regions of CUE are mainly concentrated in the southern parts of the YRB, especially in DL and PL sub-basins. Statistical result in the lower left sub-plot in Figure 4 indicates that change rate of CUE across the YRB presents a normal distribution characteristic. The areas of CUE increase and decrease are basically half to half. Linear change rates of more than 80% area were ranged in -0.003–0.003 $gC{\cdot}m^{-2}{\cdot}a^{-1}$.

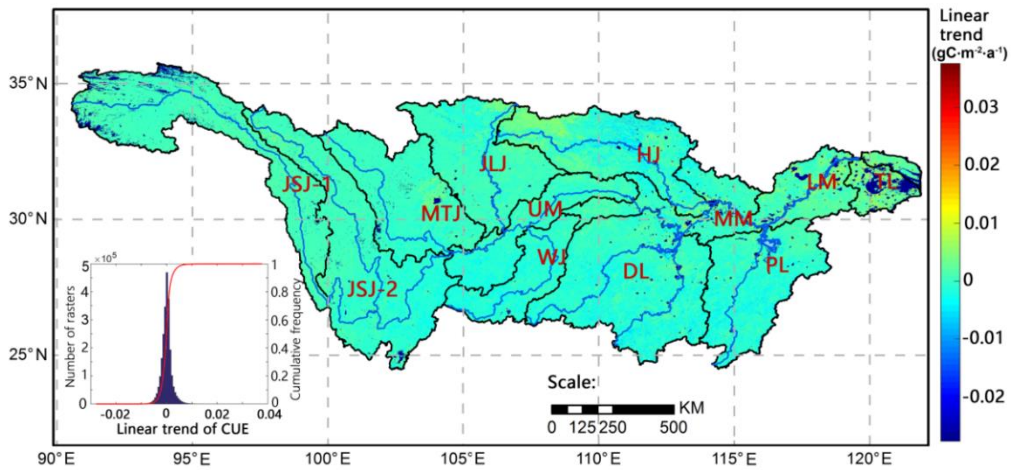

Figure 4 Spatial pattern of change trend of carbon use efficiency (CUE) over the Yangtze River basin (YRB) during 2000~2015. The abbreviations for sub-basins refer to Figure 1.

For different secondary water resource areas, it can be seen from Figure 5a that inter-annual variations of the CUE are much different. CUE of the LM sub-basin shows the greatest temporal variability, followed by HJ sub-basin and TL sub-basin. CUE of the JSJ-2 sub-basin shows the smallest temporal variability in the YRB (Figure 5b). Overall, CUE of the sub-basins of JSJ-1, MTJ, JLJ, MM, LM and TL shows an increasing trend during the study period, while the other sub-basins show a decreasing trend. However, only the increasing trend of CUE in the LM and TL sub-basins reached 0.05 significance level (Figure 5c).

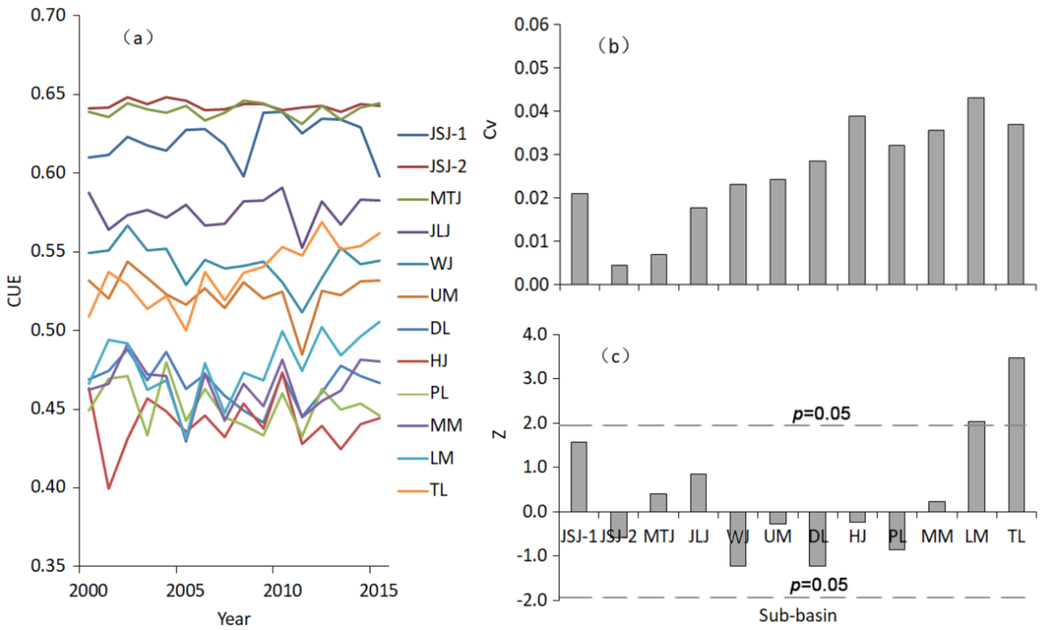

Figure 5 Inter-annual variation of carbon use efficiency (CUE) in different sub-basins in the Yangtze River basin (YRB): (a) annual fluctuation processes of CUE; (b) temporal variability of CUE and (c) significance test of the change rate. The abbreviations for sub-basins refer to Figure 1.

2.3 Changes of CUE in different land cover types

As shown in Figure 6, CUE varied remarkable in different land cover types. Overall, CUE of grasslands is higher than that of croplands, and then forest lands. Specifically, the land cover type of LG has the highest CUE (0.621), followed by MG (0.580), DC (0.546), HG (0.544), SW (0.532), WC (0.515), SL (0.503), OW (0.502) and WL (0.477). Inter-annual variation of the CUE of different land cover types shows high consistency except for the LG. As shown in Figure 7a, CUE of most land cover types experienced a decreasing trend during 2000–2011 and reached the lowest in 2011. In the following several years, CUE of most land cover types turned to increase. According to the calculated C_v, CUE of the WL shows the largest temporal variability, followed by WC and SL. CUE of the MG shows the smallest temporal variability (Figure 7b). During the study period, values of CUE of WC, HG and LG show an increasing trend, while the other six land cover types show a decreasing trend. Further test indicated that the linear trend of CUE of all land cover types was not significant at 0.05 significance level (Figure 7c).

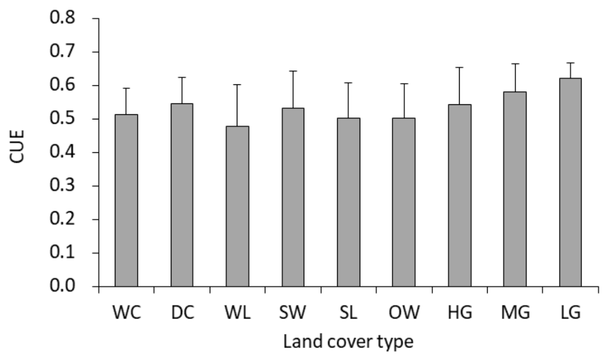

Figure 6 Mean and standard deviation of carbon use efficiency (CUE) for different land cover types in the Yangtze River basin (YRB). Abbreviations for land cover types: WC, wet cropland; DC, dry cropland; WL, woodland; SW, sparse woodland; SL, shrubland; OW, Other woodland; HG, high-covered grassland; MG, middle-covered grassland; LG, low-covered grassland.

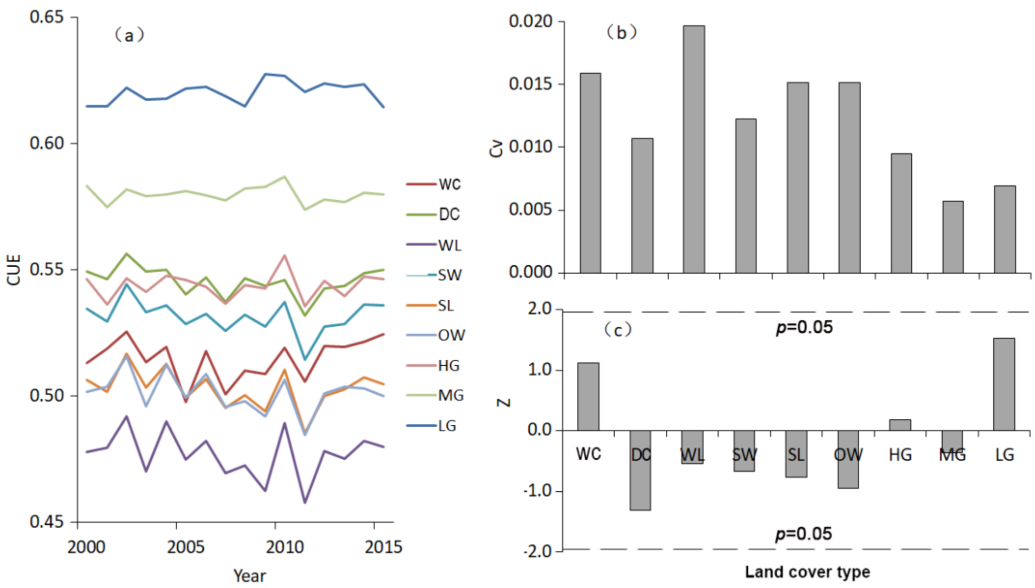

Figure 7 Inter-annual variation of carbon use efficiency (CUE) for different land cover types in the Yangtze River basin (YRB): (a) annual fluctuation processes of CUE; (b) temporal variability of CUE and (c) significance test of the change rate. Abbreviations for land cover types: WC, wet cropland; DC, dry cropland; WL, woodland; SW, sparse woodland; SL, shrubland; OW, Other woodland; HG, high-covered grassland; MG, middle-covered grassland; LG, low-covered grassland.

2.4 Partial correlation with meteorological driving factors

Climate condition is an important environmental factor that affects the variation of CUE of terrestrial ecosystem. In this paper, six variables including ET, P, RH, SD, WS and T were selected as the potential meteorological driving factors of CUE in the YRB. Statistic result indicated that mean values of the six variables are 974 mm, 1050 mm, 67%, 4.03 h, 1.57 m/s and 14.05°C during the study period 2000–2015. Linear trends (β) of the six variables are 11.8 mm/a ($p<0.01$), 0.73 mm/a, -0.002/a ($p<0.05$), -0.009 h/a, 0.008 m/s·a ($p<0.01$) and 0.007 °C/a, respectively. However, the basic characteristics of the six meteorological variables are quite different among the sub-basins.

Table 2 lists the partial correlation coefficients between inter-annual variability of CUE and major meteorological factors in different regions of the YRB. The partial correlation coefficients above 0.1 significance level are shown in bold fonts. The result from the table indicated that annual CUE in half of the sub-basins, such as MTJ, JLJ, UM, PL, MM and LM, has little correlation with all the meteorological factors. Annual CUE in the other half sub-basins was greatly affected by certain meteorological factor, showing a high partial correlation coefficient. For example, temperature (T) showed a positive high partial correlation with CUE in the JSJ-1 sub-basin ($p<0.01$). Pan evaporation (ET) showed a negative high partial correlation with CUE in the JSJ-2 sub-basin ($p<0.1$). Precipitation (P) showed a positive high partial correlation with CUE in the sub-basins of WJ, DL, HJ and TL ($p<0.1$). There was also some special case in the WJ sub-basin where annual CUE showed positive high partial correlation with precipitation (P) and temperature (T), and negative high partial correlation can also be found for the relative humidity (RH) and wind speed (WS). For the whole YRB, annual CUE was mainly affected by precipitation as a significant positive partial correlation ($p<0.01$) can be observed between them. Besides, the effect of other meteorological factors was obscure.

Table 2 Partial correlation coefficients between annual carbon use efficiency (CUE) and major meteorological factors during 2000–2015 in different regions of the Yangtze River Basin (YRB)

Sub-basin		Meteorological factors					
		ET	P	RH	SD	WS	T
Secondary water resources area	JSJ-1	-0.294	0.439	0.417	0.488	-0.07	0.754***
	JSJ-2	-0.560*	-0.010	0.353	0.015	0.088	0.114
	MTJ	-0.161	0.139	0.184	-0.252	-0.068	0.291
	JLJ	-0.093	0.101	0.357	-0.316	-0.129	0.231
	WJ	0.168	0.649**	-0.683**	-0.118	-0.631**	0.632**
	UM	-0.076	0.287	0.290	0.009	-0.211	0.241
	DL	0.192	0.572*	0.017	0.233	-0.325	0.260
	HJ	-0.275	0.529*	0.438	0.348	0.138	-0.103
	PL	0.158	0.380	0.148	0.317	0.010	-0.031
	MM	-0.179	0.343	0.415	0.326	0.106	0.132
	LM	0.346	0.498	0.126	0.200	-0.224	-0.218
	TL	-0.139	0.581*	-0.211	0.084	-0.057	-0.148
The whole YRB		180.09	0.111	0.752***	-0.276	0.217	-0.316

Notes: *, **, *** indicate ρ<0.1, ρ<0.05, and ρ<0.01 significance level, respectively. The abbreviations for sub-basins refer to Figure 1. Abbreviations for meteorological factors: ET, pan evaporation (mm); P, precipitation (mm); RH, relative humidity (%); SD, sunshine duration (h); WS, wind speed (m/s); T, temperature (°C).

For different land cover types, the partial correlation coefficients between annual CUE and major meteorological factors were also calculated. As listed in Table 3, significant positive partial correlation ($p<0.05$) between CUE and precipitation can be found in most of the land cover types, such as WC, WL, SW, SL, OW and HG. Relatively high but not significant positive partial correlation between CUE and precipitation can also be found in the DC and MG land cover types. However, for the land cover type of LG, the effect of relative humidity (RH) was most important for annual variation of CUE. A significant negative partial correlation was found for the two variables ($p<0.05$). In addition to the above, the partial correlation of CUE and the other meteorological factors were not obvious in all the land cover types.

Table 3 Partial correlation coefficients between **annual** carbon use efficiency (CUE) and major meteorological factors in different Land Cover Types (LCT) in the Yangtze River basin (YRB)

LCT	Meteorological factors					
	ET	P	RH	SD	WS	T
WC	0.105	0.644**	-0.032	0.346	0.041	-0.026
DC	-0.068	0.492	0.197	0.219	-0.264	0.157
WL	0.360	0.780***	-0.356	0.145	-0.318	0.188
SW	0.050	0.682**	-0.054	0.073	-0.384	0.357
SL	0.108	0.684**	-0.100	0.269	-0.312	0.187
OW	0.362	0.748***	-0.363	0.197	-0.434	0.340
HG	-0.072	0.643**	-0.177	0.144	0.009	-0.220
MG	0.049	0.404	-0.185	-0.140	-0.179	0.159
LG	0.091	0.299	-0.607**	-0.374	0.494	0.428

Notes: ** and *** indicate $\rho<0.05$ and $\rho<0.01$ significance level, respectively. The abbreviations for land cover types refer to Figure 6. The abbreviations for meteorological factors refer to Table 2.

3 Discussion

Previously, some of the earliest studies held the conception that CUE of land vegetation in different environments equals to a constant value of 0.5 (e.g., Ryan et al. 1997; Gifford 2003; DeLucia et al. 2007). However, most of the recent studies revealed that CUE has strong spatio-temporal variability (e.g., Zhang et al. 2009; Piao et al. 2010; Khalifa et al. 2018; Tang et al. 2019). The result of our investigation confirms to this view point. In fact, CUE should not be considered as a constant value since the driving processes of photosynthesis and respiration are nonlinearly governed by different environmental drivers (Khalifa et al. 2018). Knowledge of the spatial pattern of CUE and how it is related to local geographical, topographic and climatic factors is critical for understanding carbon cycling of regional or global ecosystems and its response to climate change (DeLucia et al. 2007; Zhang et al. 2009).

It is known that plant growth depends on local water and energy conditions. Previously, Xu et al. (2016) found that vegetation was particularly sensitive to climate change in the arid regions of China due to low precipitation and relatively high evapotranspiration. In the YRB, Qu et al. (2018) revealed that temperature is a controlling factor determining the vegetation greenness, while the response of vegetation to precipitation is relatively lower because of the abundant water. These researches demonstrate that temperature and precipitation are the two essential meteorological factors for plant growth although their relative effects may vary in different regions. The spatial difference of CUE in the YRB and its variation along altitude are the results of such direct meteorological factors of temperature and precipitation, among others. However, specific influence mechanism of temperature and precipitation on CUE under different environment are quite complex. The changes of temperature will affect the ratio of photosynthesis and respiration, thus affecting the CUE (Giardina et al. 2003). Available water is important for plants growth, the decrease of precipitation may lead to the increase of plants total respiration, GPP, as well as respiration of leaves and roots (Metcalfe et al. 2010). Whereas, redundant precipitation can affect other critical environmental factors for plant growth, such as radiation input, nutrient leaching or soil oxygen (Schuur et al. 2001). Due to these reasons, CUE is normally higher in the environments characterized by a shortage of precipitation and lower temperature relative to wet and warm environments (Teskey et al. 1995). Climatically, the east and middle regions of YRB are relatively wet and warm, and so CUE values in these regions are commonly lower. The climate becomes dryer and colder in the west parts of YRB due to distance from sea and increasing altitude, and so CUE increased accordingly.

Along the rising altitude, many studies have shown an overall increasing trend of CUE on regional scale (e.g., Piao et al. 2010). However, our investigation indicates that CUE didn't increase all the time in the YRB, but peaked at some 3900 m a.m.s.l. Previously, Zhang et al. (2009) also pointed out that CUE follows a globally increasing trend along rising altitude while decreasing trend can be found in a certain altitude range of 3600–4750 m a.m.s.l. According to the rising altitude, both the temperature and precipitation in the YRB show a decreasing trend (Figure 8). It should be noted that the decrease in precipitation along altitude is more affected by the increasing distance from sea and direction of moisture inflow in a large region. The corresponding temperature and precipitation to the peak value of CUE at 3900 m a.m.s.l are 8.26℃ and 720 mm, respectively. In consideration of the changes of temperature, precipitation and CUE along rising altitude, our investigation may imply that the increasing CUE along rising altitude below 3900 m was mainly affected by the decreasing precipitation in the YRB, while the decreasing CUE along rising altitude above 3900 m a.m.s.l was more affected by the decreasing temperature. In addition, the large fluctuation of CUE below 800 m a.m.s.l obviously deviated from the effect of precipitation and temperature, which is possibly affected by the different combination of land cover types below this altitude. The slight variation of CUE between the altitudes of 2800 and 4600 m a.m.s.l may indicate that CUE was not sensitive to the corresponding environmental precipitation and temperature at these areas.

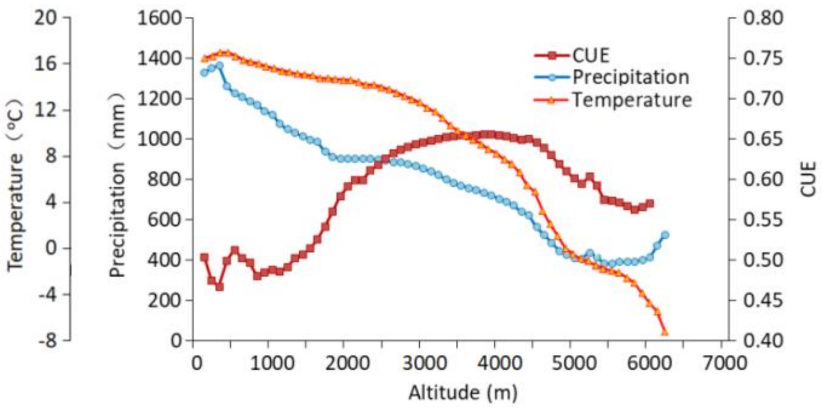

Figure 8 Variations of precipitation, temperature and carbon use efficiency (CUE) along rising altitude in the Yangtze River basin (YRB).

This study further confirms that the CUE is variable for different land cover types although the variation of the CUE is not always consistent among studies (Zhang et al. 2009; Kwon and Larsen 2013). In the YRB, CUE of different land cover types ranges in 0.477–0.621. CUE of grasslands is generally higher, followed by croplands and forest lands. This result is highly consistent with previous studies. Major reasons may lie in the different vegetation structure, physiological characteristics and age

(Zhu 2013). For example, due to higher hydraulic resistance in their stems and branches, tall trees have lower specific rates of photosynthesis and lower productivity with reference to the sparse vegetation (Hubbard et al. 1999). Zhang et al. (2009) also revealed that CUE of dense vegetation is generally lower than that of sparse vegetation, and the CUE of forest was lower than that of shrub and grassland. Due to this reason, CUE of the four sub-category forest lands in the YRB is SW>SL>OW>WL in descending order. In addition, with comparison to natural vegetation, the cultivated crops generally have higher CUE (Amthor 1989). This is probably correlated to the status of soil nutrient under human management. Observational experiment from Bowen. (2007) showed that CUE of *Pinus radiate* increased with the increase supply of soil nitrogen and phosphorus nutrition. CUE was 0.42 under low nutrition supply while 0.51 under high nutrition supply, indicating that plant respiration would consume a large proportion of carbon assimilation products in poor soil environment. Giardina et al. (2003) also observed that the CUE of planted forest of *Eucalyptus saligna* with fertilization was 0.53, which is slightly higher than that of the sample without fertilization (0.51). In the YRB, intensive planting of dry cropland is common. In order to increase yield of seasonal economic crops, more and more fertilizer is applied to the farmland (Xie et al. 2018). That is why CUE of the croplands, especially the land cover type of DC was relatively high.

Temporally, the evolution of CUE in the YRB varied in different sub-basins and different land cover types. CUE of the grasslands has the smallest temporal variability, and then croplands and forest lands. Due to this reason, CUE of the upstream sub-basins with more area of grassland in the YRB has smaller temporal variability, while CUE of the middle-lower sub-basins with less area of grassland has bigger temporal variability (see in Figure 6). In terms of long-term trend, CUE of the whole YRB has changed little during the study period 2000–2015. Previously, Zhang et al. (2014b) revealed a decreasing trend of CUE of global terrestrial ecosystem during 2000–2009. They attributed this temporal dynamic of CUE to the effects of temperature and precipitation: increased temperature lowered the CUE, while increased precipitation led to a higher CUE. Khalifa et al. (2018) showed an insignificant correlation between the variations in CUE and precipitation in Ethiopia, however, they concluded that the inter-annual variation of CUE is likely to be driven by a drought of time scale of three months. Our investigation shows a significant positive partial correlation between the annual variations of CUE and precipitation for most sub-basins and land cover types in the YRB. This may suggest that the change of precipitation in the YRB is the most critical meteorological factor that affecting the annual variation of CUE, although the influence of temperature and relative humidity is also outstanding in certain regions and land cover types. Other meteorological variables, such as ET, RH and WS would found to have less influence than precipitation and air temperature on plant growth in the study region. Recent work from Chen (2019) also revealed that the increase of annual precipitation was the main factor driving the increasing forest CUE in Northeast China during 2000–2015.

It should be mentioned that some limitations were existed. In this study, we used only one scenario of land cover data of 2010 to identify the changes of CUE in different land cover types. Theoretically, it is not reliable to compare the CUE value in different years by using the land cover data of the same year, since land cover in the YRB has been changed during the period 2000-2015 due to climate change and human activities. According to recent research from Cheng et al. (2017), total area of changed land use in the YRB from 2000 to 2010 was about 16162 km^2, which account for 0.9% area of the whole YRB. Therefore, this small change of land use in the YRB, to a large extent, will not affect the results of this study. In addition, previous studies have revealed that vegetation dynamics in the YRB also affected by increasing human activities, such as ecological restoration and urbanization (Zhang et al. 2014a; Qu et al. 2018). However, this paper focused on the investigation of meteorological driving factors on the change of CUE in the YRB, the impacts of human activities were not involved and leave for future studies.

4 Conclusions

In this study, we investigated spatio-temporal variations in MODIS-based vegetation carbon use efficiency and potential driving meteorological factors in the YRB during 2000–2015. Several findings can be obtained as follows:

(1) Spatially, CUE is generally high in the west and low in the east and middle of the YRB. The average CUE of vegetated land of the whole YRB was 0.519. Along the rising altitude, CUE generally shows an increasing trend until the altitude of 3900 m and then followed by a decreasing trend. In addition, CUE fluctuates greatly below 800 m while varied slightly between 2800 m and 4600 m. Temporally, although the long-term change trend of CUE of the YRB was obscure, CUE in the LM and TL sub-basins of the lower YRB showed a significant increasing trend during the study period.

(2) CUE varied remarkably in different land cover types. Generally, CUE of grassland is higher than that of cropland, and then forest land. Annual variations of the CUE of different land cover types show high consistence except for the LG. CUE of the WL shows the largest temporal variability, while MG shows the smallest temporal variability. During the study period, CUE change trends of all the land cover types were not significant.

(3) There is a strong positive partial correlation between the inter-annual variability of CUE and precipitation in most of sub-basins and land cover types in the YRB. This suggests that the change of precipitation in the YRB is the most critical meteorological factor that affecting the inter-annual variation of CUE.

Generally, the results of the current study confirm that CUE has strong spatio-temporal variability and varied remarkably in different land cover types. Inter-annual variation of CUE is highly correlated with certain critical meteorological factor. It is anticipated that climate will continue to change in the future under the context of increasing levels of atmospheric CO_2, how about the impact of climate change on the carbon sequestration capacity of land cover types as sinks for atmospheric carbon deserves attention. In addition, the YRB is expected undergoing large-scale land use change and ecological restoration due to climate change and socioeconomic development, more researches on the subsequent eco-environmental impacts are required in order to provide scientific basis to support the sustainable management.

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