



## Geographical statistical assessments of carbon fluxes in terrestrial ecosystems of China: Results from upscaling network observations

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### ABSTRACT

Accurate quantifying the magnitudes and distributions of carbon budgets is helpful for strategies in mitigating global climate change. Based on spatial patterns of carbon fluxes (gross ecosystem productivity (GEP), ecosystem respiration (ER) and net ecosystem productivity (NEP)) and their drivers, we constructed geographical statistical assessment schemes and quantified the magnitudes of carbon fluxes in China. The optimal assessment scheme was then validated with observed eddy covariance data to analyze the spatial distributions of carbon fluxes. Using climate-based geographical statistical assessment schemes, our estimates of GEP, ER and NEP in China during 2000s were  $7.51 \pm 0.51$ ,  $5.82 \pm 0.16$  and  $1.91 \pm 0.15$  PgC yr<sup>-1</sup>, corresponding to 4.29%–6.80%, 5.65%–6.06% and 9.10%–12.73% of global annual carbon fluxes, respectively. The spatial distributions of GEP, ER and NEP, generated from the optimal scheme, were similar, following a southeast–northwest decreasing gradient. The maximum values for GEP, ER and NEP were 1790, 1300 and 490 gC m<sup>-2</sup> yr<sup>-1</sup>, respectively, which occurred in Central subtropics and Southern subtropics. Climate-based geographical statistical assessment schemes provided an independent dataset for the regional carbon budget assessment, which can be deemed as the potential carbon fluxes. Meanwhile, most areas in China were potential carbon sink especially Eastern China and the largest potential carbon sink appeared in Central subtropics and Southern subtropics.

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### 1. Introduction

Increased atmosphere CO<sub>2</sub> concentration, partly resulting from human activities, has been regarded as one of the main forces causing the global climate change (Solomon et al., 2007). Terrestrial ecosystems were deemed as a major sink of atmosphere CO<sub>2</sub> (Tans et al., 1990;

Ballantyne et al., 2012), therefore, enhancing the strength of carbon sink in terrestrial ecosystem has been regarded as a feasible way to mitigate the climate change (Liu et al., 2008). Accurate quantification of the terrestrial ecosystem carbon sink and its increasing potential will provide a scientific basis for carbon management in climate change mitigation.

Located in the mid-high latitude in the Northern Hemisphere, terrestrial ecosystems in China serve as a sink of atmosphere CO<sub>2</sub> and play an important role in maintaining the global carbon balance (Fang et al., 2007; Piao et al., 2009a; Piao et al., 2011). Furthermore, to meet the need of its economic growth, China has consumed huge energy

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resources with high carbon emission rates, which will likely keep increasing (Boden et al., 2010). Therefore, accurate quantifying the magnitude, the spatial distribution and the increasing potential of carbon sink for terrestrial ecosystems in China is also important for strategies in carbon management aiming at the global climate change mitigation.

The magnitude and distribution of carbon sink in China have been intensively investigated through the inventory approach and various models (Fang et al., 2007; Piao et al., 2009a; Piao et al., 2011; Tian et al., 2011a; Tian et al., 2011b), while there were some uncertainties among investigations. Meanwhile, the magnitude and distribution of carbon sink are affected by those of various carbon fluxes, including gross ecosystem productivity (GEP), net primary productivity (NPP), and ecosystem respiration (ER) and so on. Many studies have quantified carbon fluxes in China, such as GEP (Feng et al., 2007; Li et al., 2013), NPP (Fang et al., 2003; Tao et al., 2003; He et al., 2005; Feng et al., 2007; He et al., 2007; Gao and Liu, 2008; Gao et al., 2012), and net ecosystem productivity (NEP) (Cao et al., 2003; Tao et al., 2007; Ji et al., 2008; Sun, 2009) using various models, while there were substantial disagreements, e.g. NPP in China ranged from 1.43 to 4.73 PgC yr<sup>-1</sup> (Gao et al., 2012), and NEP floated from 0.0625 to 0.12 PgC yr<sup>-1</sup> (Cao et al., 2003; Tao et al., 2007; Ji et al., 2008; Sun, 2009). Moreover, the potential level of carbon fluxes, which was the base for calculating the potential increment of carbon sink, was still unsolved.

The eddy covariance technique, measuring the net exchange of CO<sub>2</sub> between the biosphere and the atmosphere at the ecosystem scale, is widely used all over the world (Baldocchi, 2008). In conjunction with remote sensing (RS) and climate data, eddy covariance measurements were upscaled to continental (Papale and Valentini, 2003; Xiao et al., 2008, 2010, 2011, 2012) or global scales (Jung et al., 2011) using the machine learning technique, which was regarded as an important forward step in assessing carbon fluxes (Jung et al., 2011). China has conducted eddy covariance observations since 2002 and establishes a national network of eddy covariance towers covering 17 sites (Yu et al., 2013), which experiences little disturbance especially fire and thinning and provides a valuable platform for calculating the potential level of carbon fluxes. However, there was no attempt in upscaling observations to the national scale.

By integrating ChinaFLUX observations and published carbon flux data (GEP, ER and NEP) from other sites in China, we constructed geographical statistical assessment schemes of carbon fluxes and selected the optimal scheme to examine the spatial distributions of GEP, ER and NEP. The specific objectives were: 1) to develop carbon flux assessment schemes; 2) to quantify the total annual carbon fluxes in China, and 3) to characterize the spatial distributions of mean annual

biosphere–atmosphere carbon fluxes. As our assessment schemes were based on sites experiencing little disturbance and mainly dependent on climate, to some extent, our estimated carbon fluxes may be regarded as the potential carbon fluxes in China.

## 2. Data and methods

### 2.1. Integration of carbon flux data

Through integrating ChinaFLUX observations and published data in literatures, we built a dataset containing 52 site data (Yu et al., 2013), which covered most kinds of ecosystem types in China (Fig. 1a) and were fairly representative of typical Chinese climate types (Fig. 1b). Some sites from literature included NEP, GEP or ER incompletely, which made the site number used to develop assessment schemes unequal. In addition, the positive GEP and NEP indicate a carbon uptake from the atmosphere, while the positive ER represents a carbon release to the atmosphere.

### 2.2. Carbon flux assessment schemes

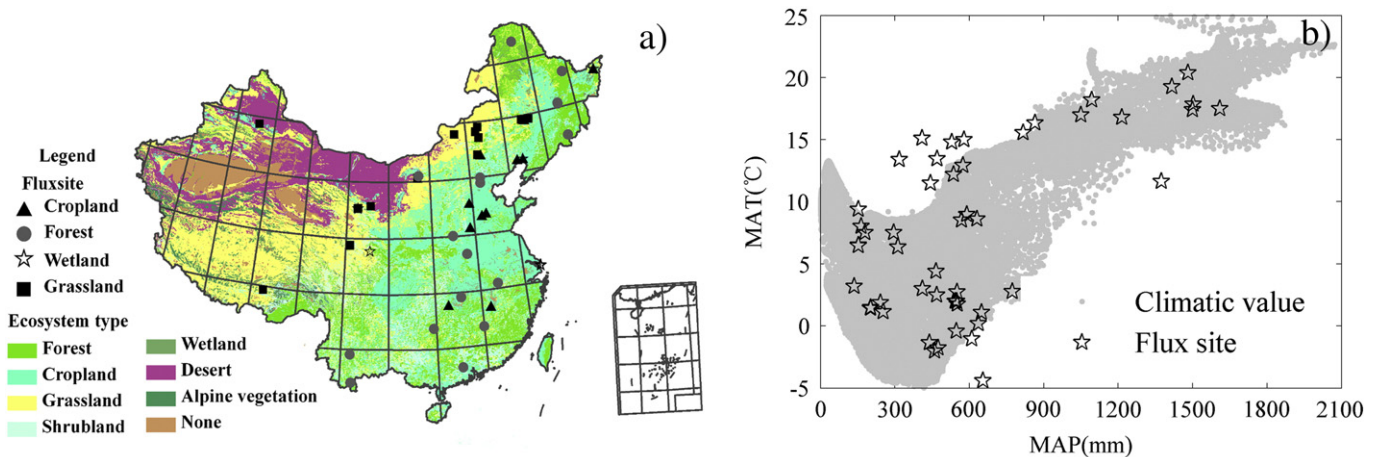
Yu et al. (2013) found that mean annual temperature (MAT) and mean annual precipitation (MAP) affected the spatial patterns of carbon fluxes (GEP, ER and NEP) among terrestrial ecosystems in China. GEP, ER and NEP also exhibited strict positive coupling correlations in their spatial patterns. Based on results from Yu et al. (2013), we developed three kinds of assessment schemes to assess carbon fluxes of terrestrial ecosystems in China.

#### 2.2.1. Schemes based on the effects of MAT and MAP

Yu et al. (2013) found that GEP and NEP increased linearly while ER increased exponentially with the increasing MAT, and the  $R^2$  was 0.57, 0.49 and 0.48 for GEP, ER and NEP, respectively. Furthermore, with the increasing MAP, GEP, ER and NEP grew significantly in a linear way, the  $R^2$  was 0.61, 0.51 and 0.32, respectively. In addition, carbon fluxes were only limited by the most limited factor (Chapin et al., 2012). Therefore, a carbon flux assessment scheme was recommended as follows:

$$Cflux = \min\{f(MAT), f(MAP)\} \quad (1)$$

where  $Cflux$  is GEP, ER or NEP, respectively,  $f(MAT)$  and  $f(MAP)$  are regression equations between  $Cflux$  and MAT and MAP, and “min” indicates the smaller value referring to the  $f(MAT)$  and  $f(MAP)$ . The



**Fig. 1.** The distribution of eddy covariance observations in China used in this study among ecosystem types (a) and mean annual climate space (b) in China. In panel (a), the background is the vegetation map according to the Editorial Committee of Vegetation Map of China (2007). In panel (b), climate parameters are the mean annual precipitation (MAP, x-axis) and temperature (MAT, y-axis) over a 50-year period of record (1961–2010), obtained from the China Meteorological Bureau database. Gray points represent the spatial distribution of the climatic data in China at a 20 km resolution.

regression equations between *Cflux* and MAT and MAP were listed in Supplement Table 1.

Results from Yu et al. (2013) suggested that MAT and MAP not only independently, but also jointly affected the spatial variations of carbon fluxes. Comparing with the single-factor's contribution, the combined contribution of MAT and MAP significantly increased. Though ER increased exponentially with the increasing MAT, there was no difference between the linear function and the exponential function of ER and MAT when considering the combined contribution of MAT and MAP. Therefore, another carbon flux assessment scheme was suggested as:

$$Cflux = A + B \times MAT + C \times MAP \quad (2)$$

where *Cflux* is GEP, ER or NEP, respectively, A, B and C are regression coefficients between *Cflux* and climate variables (MAT and MAP). The regression equations between *Cflux* and climate variables (MAT and MAP) were listed in Supplement Table 2.

Yu et al. (2013) also found that the interaction between MAT and MAP significantly affected the spatial patterns of carbon fluxes in China. Thus, the scheme containing the interaction item was recommended as:

$$Cflux = A + B \times MAT + C \times MAP + D \times MAT \times MAP \quad (3)$$

where *Cflux* is GEP, ER or NEP, respectively, while A, B, C and D are regression coefficients between *Cflux* and MAT, MAP and their interaction. The detailed equations were listed in Supplement Table 3.

#### 2.2.2. The scheme based on the spatial positive coupling correlations among carbon fluxes

Yu et al. (2013) found that the spatial patterns of GEP, ER and NEP in China exhibited an obvious "positively coupling correlation". In terms of the spatial variations, 68% of the per-unit GEP contributed to ER and 29% to NEP. Therefore, a carbon flux assessment scheme was recommended as:

$$ER = 0.68 \times GEP + 81.90, R^2 = 0.90, n = 41 \quad (4)$$

$$NEP = 0.29 \times GEP - 37.22, R^2 = 0.57, n = 39 \quad (5)$$

where GEP is calculated from the optimal equation among Eqs. (1), (2) and (3).

#### 2.2.3. The scheme based on the relation among carbon fluxes

NEP is the difference of GEP and ER (Chapin et al., 2006), providing another approach to assess NEP as:

$$NEP = GEP - ER \quad (6)$$

where GEP is calculated from the optimal equation among Eqs. (1), (2) and (3), while ER is calculated from the optimal equation among Eqs. (1), (2), (3) and (4).

The mean of all schemes by each carbon flux was then calculated. In summary, the number of assessment schemes for GEP, ER and NEP was 4, 5 and 6, respectively (Table 1).

### 2.3. Data processing

#### 2.3.1. Carbon flux data

By summarizing long-term ChinaFLUX observations and published data (GEP, ER and NEP) from other sites in China, we aggregated 52 site observations (Yu et al., 2013) and developed carbon flux assessment schemes. If sites have data longer than 1 year, we calculated the mean of carbon fluxes and climatic variables for the measuring period, which may exclude the effect of the inter-annual variation. We used

**Table 1**

Assessment schemes for GEP, ER and NEP in China.

<i>Cfluxes</i>	Assessment schemes					
	I	II	III	IV	V	VI
GEP	(1)	(2)	(3)	–	–	Mean
ER	(1)	(2)	(3)	(4)	–	Mean
NEP	(1)	(2)	(3)	(5)	(6)	Mean

Note: numbers in the table were the equation number described above, and mean indicates the average value of all schemes for GEP, ER and NEP, which were the abbreviation of gross ecosystem productivity, ecosystem respiration and net ecosystem productivity, respectively.

multi-year average climatic data as the substitution if sites have missing climate data (Yu et al., 2013).

Each scheme was then calibrated using the leave-one-out cross-validation. One site data were excluded at a time, and the remaining sites were used to train the scheme and to predict the excluded site value. The calibration was then done at each site, respectively. Therefore, the data used for developing and calibrating the scheme were independent (Xiao et al., 2010).

#### 2.3.2. Climate data

Annual climate data (MAT and MAP) at a 1 km × 1 km spatial resolution were generated from data of 756 climate stations from China Meteorological Administration (CMA) during 2000s, using the interpolation software of ANUSPLIN (Hutchinson, 1995; Hutchinson, 2002).

The schemes were built using the mean carbon fluxes and climatic variables, which neglected the inter-annual variation and represented the carbon fluxes under the long-term mean climate. Therefore, mean climate data of 2000s (from 2001 to 2010) were used to generate the magnitudes of carbon fluxes and their spatial distributions.

#### 2.3.3. Ecosystem type and climate zone data

The ecosystem type data with a 1 km × 1 km spatial resolution were obtained from the Vegetation Map of China (Editorial Committee of Vegetation Map of China, 2007), which included 11 vegetation type groups of coniferous forest, mixed forest, broadleaved forest, scrub, desert, steppe, grass-forb community, meadow, swamp, alpine vegetation and planted vegetation. These vegetation type groups were then reclassified into 7 ecosystem types: forest, grassland, cropland, shrubland, wetland, desert and alpine vegetation. Specifically, coniferous forest, mixed forest, and broadleaved forest were merged to forest; steppe, meadow and grass-forb community to grassland; planted vegetation to cropland, and swamp, scrub, desert and alpine vegetation to wetland, shrubland, desert and alpine vegetation, respectively.

Using the Vegetation Map of China (Editorial Committee of Vegetation Map of China, 2007), we also obtained the distribution of climate zones based on the Vegetation Regionalization.

#### 2.3.4. LAI data

To find out the effect of LAI on the performance of each scheme, we extracted LAI data of each site from validated MODIS dataset (Liu et al., 2012). Using the 8-day temporal resolution LAI, we calculated the mean LAI of each pixel at each year. The mean LAI from 2001 to 2010 was then used to test the effect of LAI on the performance of our schemes.

### 2.4. Statistical analyses

Under Matlab 7.7 (Math Works Inc., Natick, MA, USA), the Taylor Diagram (Taylor, 2001) was used to select the optimal assessment scheme for each carbon flux, and the performance of the optimal scheme and its uncertainties was evaluated using the generalized linear model (GLM) of regstats. The relationship between the regression residual of the optimal scheme and LAI was also evaluated using the generalized linear model (GLM) of regstats, and the difference in the regression



residual of the optimal scheme among ecosystem types was tested using the one-way analysis of variance (ANOVA). Under ArcGIS 10.0 (ESRI, Redlands, CA, USA), we used the spatial analyst tools to analyze average annual carbon fluxes (GEP, ER and NEP) in various climate zones of China.

### 3. Results

#### 3.1. The total annual carbon fluxes

Based on carbon flux assessment schemes, we calculated the total annual GEP, ER and NEP during 2000s. The estimated total annual GEP, ER and NEP differed among schemes (Table 2), while the standard deviations of carbon fluxes among schemes were small. The coefficients of variation (CV) among schemes for GEP, ER and NEP were 6.79%, 2.75% and 7.85%, respectively. Based on our assessment schemes, the mean total annual GEP, ER and NEP were  $7.51 \pm 0.51$ ,  $5.82 \pm 0.16$  and  $1.91 \pm 0.15$  PgC yr<sup>-1</sup>, respectively.

#### 3.2. The optimal assessment scheme

Though the estimated total annual carbon fluxes differed little, the generated spatial distributions of carbon fluxes varied among schemes. Using the Taylor Diagram, the performances of assessment schemes, which were indicated by the proximity to the benchmark, were evaluated (Fig. 2A1–A3). Among all schemes, the third scheme, fully considering the effect of MAT, MAP and their interaction, was the optimal approach to describe the spatial distribution of GEP (Scheme III, Fig. 2A1), while the optimal approach for ER was based on the spatial positive coupling correlation between GEP and ER (Scheme IV, Fig. 2A2). However, the scheme, which was based on the relation among carbon fluxes (Scheme V, Fig. 2A3), i.e. NEP was the difference between GEP and ER, described the spatial variation of NEP better than other schemes. The optimal equations were:

$$\text{GEP} = 107.02\text{MAT} + 2.18\text{MAP} - 0.10\text{MAT} \times \text{MAP} - 544.35 \quad (7)$$

$$\text{ER} = 0.68 \times \text{GEP} + 81.90 \quad (8)$$

$$\text{NEP} = \text{GEP} - \text{ER}. \quad (9)$$

The performances of the optimal scheme were also evaluated in detail (Fig. 2B1–B3). Despite carbon fluxes simulated by the optimal scheme deviated some from observations, the data evenly distributed along the 1:1 line except for some extreme data, indicating that the optimal scheme well documented the variability of carbon fluxes.

The performances of the optimal scheme differed among carbon fluxes. The optimal scheme had a great consistency with the observed GEP ( $y = 0.77x + 221.21$ ,  $R^2 = 0.74$ ,  $p < 0.001$ ), with the RMSE of  $303.07 \text{ gC m}^{-2} \text{ yr}^{-1}$  (Fig. 2B1). The estimated ER from the optimal scheme also agreed well with observations ( $y = 0.64x + 266.14$ ,

$R^2 = 0.55$ ,  $p < 0.001$ ), with the RMSE of  $275.79 \text{ gC m}^{-2} \text{ yr}^{-1}$  (Fig. 2B2). The optimal scheme for NEP also well documented the variation of NEP ( $y = 0.61x + 79.33$ ,  $R^2 = 0.62$ ,  $p < 0.001$ ), and the RMSE was  $112.4 \text{ gC m}^{-2} \text{ yr}^{-1}$  (Fig. 2B3).

#### 3.3. The spatial distributions of carbon fluxes

The spatial distributions of carbon fluxes (GEP, ER and NEP) in China, generated from the optimal scheme, were similar. All carbon fluxes exhibited a decreasing gradient from southeast to northwest. The largest value for GEP occurred in the middle and lower reaches of Yangtze River, while that for ER appeared in areas between the southern Yangtze River and the Tropic of Cancer, and the maximum NEP occurred in Yunnan–Guizhou Plateau, Sichuan Basin and Yangtze–Huaihe Valley. Moreover, most areas in China had a positive NEP, which indicates a large potential carbon sink in China.

In theory, desert and alpine vegetation regions should have small carbon fluxes as the limited water or temperature, while our assessment schemes generated a high carbon sequestration and emission rate in Northwest China and Qinghai–Tibetan Plateau. These poor predictions may result from the fact that there were no sufficient observations in these areas. Therefore, when calculating the total annual carbon budget, we set carbon fluxes (GEP, ER and NEP) of desert and alpine vegetation regions to zero (Fig. 3a–c), which seems to be more reasonable.

#### 3.4. Carbon fluxes of different climate zones

Based on their spatial distributions (Fig. 3), we averaged the carbon fluxes of different climate zones (Fig. 4).

Carbon fluxes varied largely among climate zones. The values of GEP, ER and NEP in Central subtropics and Southern subtropics were 1790, 1300 and  $490 \text{ gC m}^{-2} \text{ yr}^{-1}$ , respectively, which were higher than those in other climate zones. The values of GEP, ER and NEP in Northern subtropics and Tropics were similar, which were lower than values in Southern subtropics and higher than values in Warm temperate forest and Temperate forest. Carbon fluxes in Cold temperate forest, Temperate desert and Alpine vegetation were the lowest, with values lower than 300, 280 and  $20 \text{ gC m}^{-2} \text{ yr}^{-1}$ , respectively.

### 4. Discussions

#### 4.1. The methods of carbon flux assessments in China

Quantifying the regional carbon budget is one of key issues in ecological science, and provides a theoretical basis for carbon management (Solomon et al., 2007). Many approaches, including process-based models, the inventory approach and the observation-based geographical statistical model, have been used in quantifying the regional carbon fluxes (Yu et al., 2011).

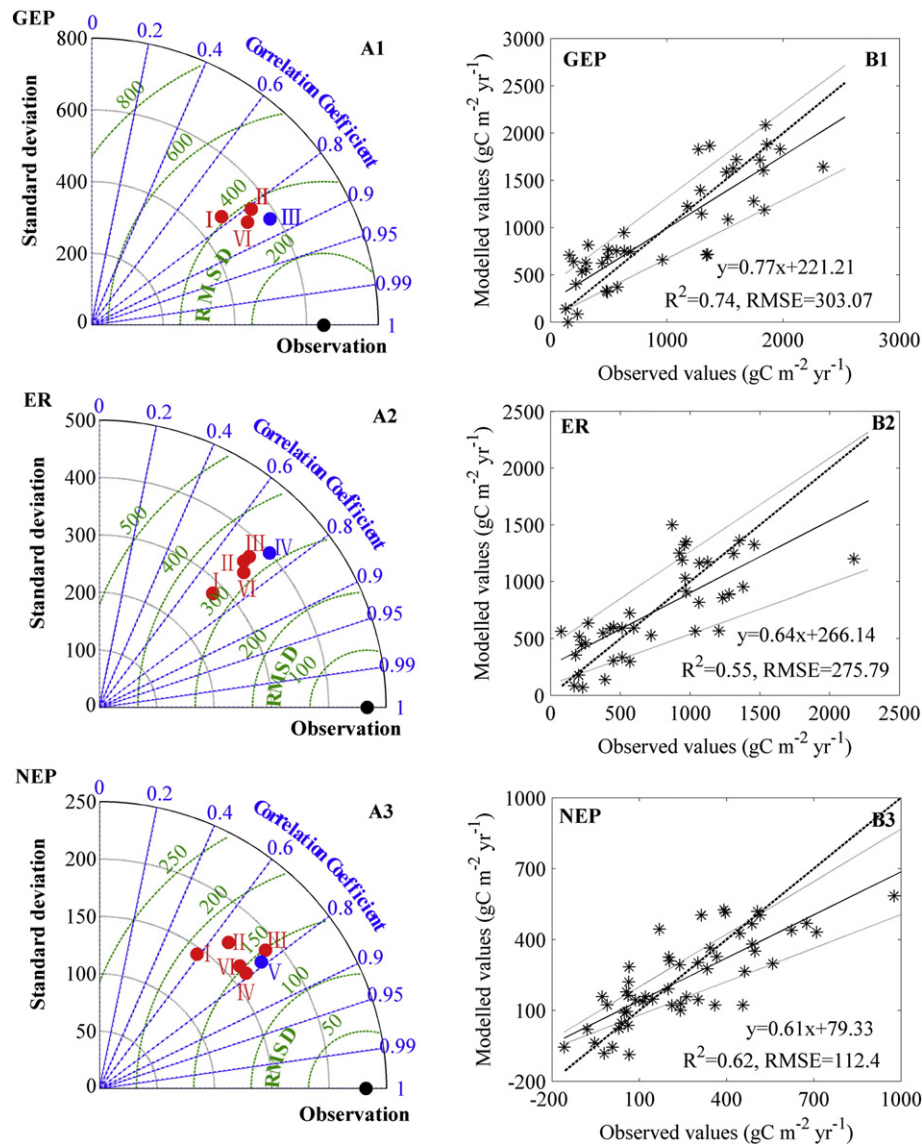
Each approach has both strengths and weaknesses. Process-based models need site-specific parameters as inputs, which are usually validated using limited eddy covariance observations and have large uncertainties. The inventory approach, a widely applied method in evaluating the regional carbon budget, calculates the carbon budget by subtracting the current carbon storage from that in the former stage, while it is limited by the frequency and uncertainties of the inventory (Fang et al., 2007). Upscaling network eddy covariance observations to the regional scale provides valuable information for analyzing the regional carbon budget, which also satisfies the need of scientists. If observations were sufficient enough and had the full representativeness, it is easy to up-scale observations to the regional scale using the geostatistical interpolating technique. Though current eddy covariance observations do have enough representativeness, the site number inhibits the direct application of the observation-based method with the geostatistical interpolating technique. However, it may be feasible to evaluate carbon fluxes

**Table 2**  
The total annual GEP, ER and NEP with different assessment schemes (PgC yr<sup>-1</sup>).

Cfluxes	Assessment schemes <sup>b</sup>						Mean (std)
	I	II	III	IV	V	VI	
GEP <sup>a</sup>	6.79	7.95	7.78	–	–	7.51	7.51 ± 0.51
ER	5.75	6.05	5.65	5.89	–	5.75	5.82 ± 0.16
NEP	1.79	2.15	1.71	1.99	1.89	1.91	1.91 ± 0.15

<sup>a</sup> GEP, ER and NEP were the abbreviation of gross ecosystem productivity, ecosystem respiration and net ecosystem productivity, respectively.

<sup>b</sup> The schemes were developed to assess the carbon fluxes in China based on results from Yu et al. (2013), which were described in detail in Carbon flux assessment schemes section and Table 1.



**Fig. 2.** The difference in the performances of carbon flux assessment schemes (A1–A3) and the performances of the optimal scheme (B1–B3). The schemes were developed to assess the carbon fluxes in China based on results from Yu et al. (2013), which were described in detail in Carbon flux assessment schemes section and Table 1. The difference in the performances of various schemes was evaluated using the Taylor Diagram (A1–A3), which drew standard deviation of the scheme outputs (the black line), centered root mean square difference (RMSD, the green dot line), and correlation coefficient (the scales on the arch, the blue line) together in one plot (Taylor, 2001). The observation was the observed value, while other dot meant various schemes. The performances of the optimal scheme were analyzed in B1 to B3, where the dot line was the 1:1 line and the solid line was the fitting line between the observation and the optimal scheme. GEP, ER and NEP were the abbreviation of gross ecosystem productivity, ecosystem respiration and net ecosystem productivity, respectively.

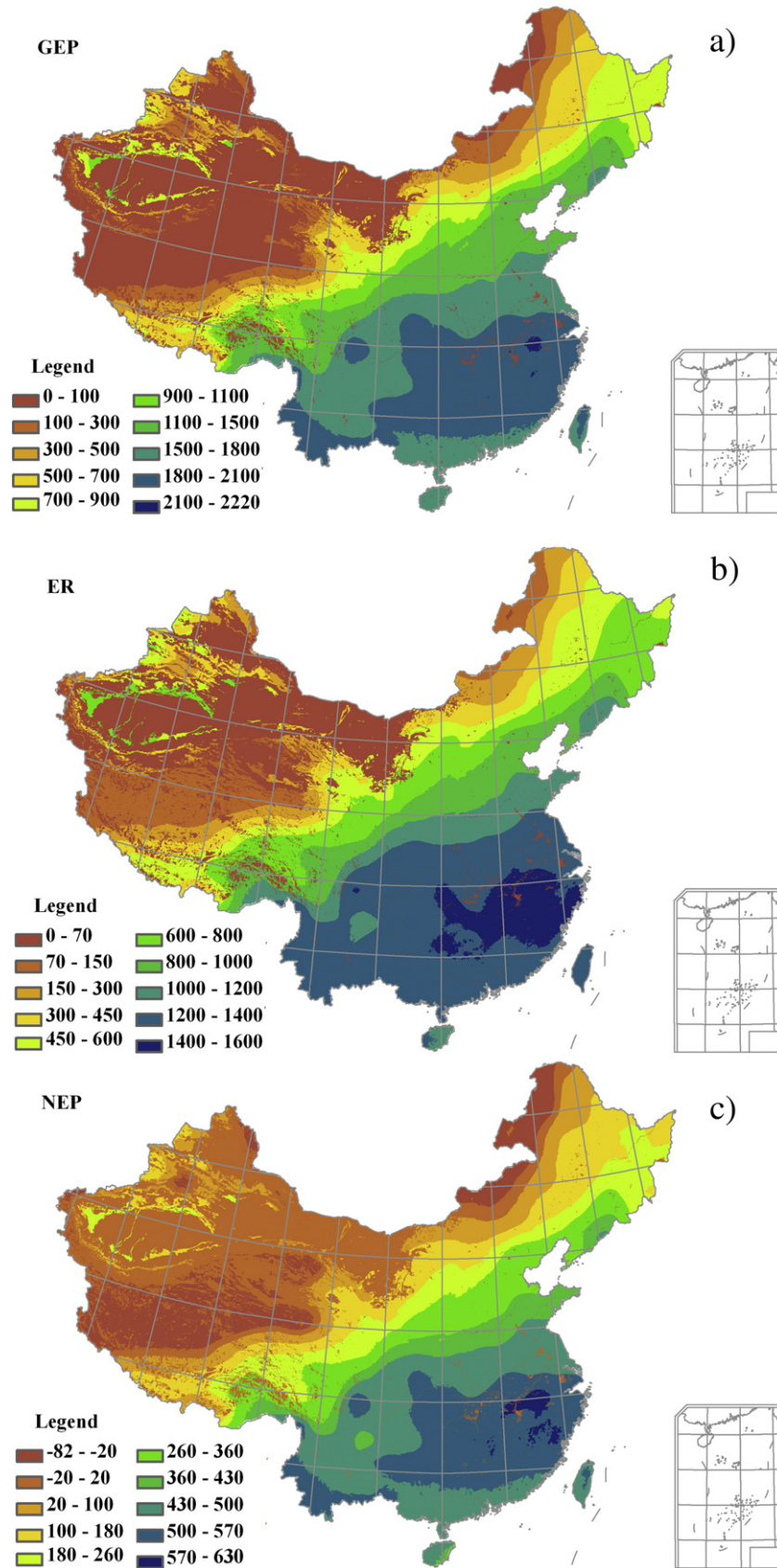
with the geographical statistical regression method using limited representative observations. Based on spatial patterns and drivers of carbon fluxes in China, we constructed geographical assessment schemes and evaluated the magnitudes of carbon fluxes in China. The optimal scheme was then selected using the Taylor Diagram to evaluate the spatial distributions of carbon fluxes. The generated carbon fluxes matched well with observations (Fig. 2B1–B3) and the magnitudes differed little among schemes (Table 2). Therefore, our climate-based geographical statistical schemes were practicable and provided an independent and alternative dataset for the regional carbon budget assessment.

However, our estimates of carbon fluxes were dependent on climate variables. Meanwhile, our estimates neglected the effect of vegetation types or vegetation cover, and there was also no significant difference in regression residuals of the optimal scheme among vegetation types ( $F > 0.05$ ). Moreover, eddy covariance observations in China were mainly conducted in natural vegetations without the effect of land use changes. The residual analysis showed that there was no correlation

between the regression residual and LAI. Furthermore, our estimated carbon fluxes were based on eddy covariance measurements of CO<sub>2</sub> fluxes and did not include emissions from other sources such as volatile organic compounds (VOCs) and burnings, different from results of the inventory approach and models. Therefore, our estimates should be regarded as climate-based potential carbon fluxes of the carbon sink or source, which may overestimate the actual carbon fluxes (Beer et al., 2010).

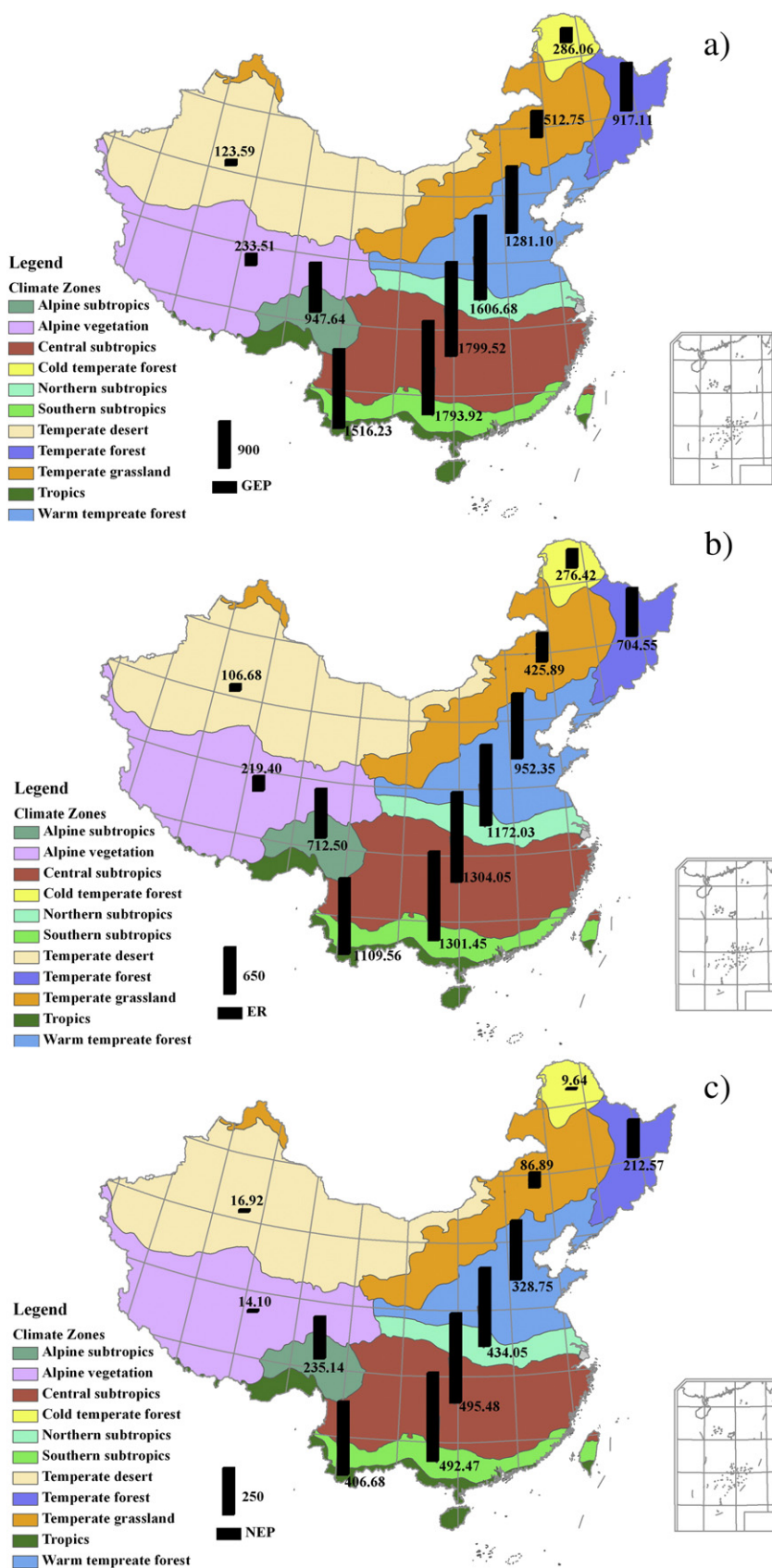
#### 4.2. The total annual carbon fluxes in China and their global role

Though our estimate of GEP was in the range of that estimated by Gao et al. (2012), assuming that NPP is about half of GEP (DeLucia et al., 2007), our estimated total annual GEP in China was higher than previous studies based on the processed-based model (Feng et al., 2007) and the light use efficiency (LUE) model (Li et al., 2013). This may partly be due to the fact that our estimated GEP was a



**Fig. 3.** The spatial distributions of carbon fluxes in China from 2001 to 2010 (Unit:  $\text{gC m}^{-2} \text{yr}^{-1}$ ). a, b and c were the distribution of GEP, ER and NEP, respectively, where GEP, ER and NEP were the abbreviation of gross ecosystem productivity, ecosystem respiration and net ecosystem productivity, respectively.





**Fig. 4.** The spatial carbon fluxes of different climate zones in China from 2001 to 2010 (Unit: gC m<sup>-2</sup> yr<sup>-1</sup>), a, b and c were the distributions of GEP, ER and NEP, respectively, where GEP, ER and NEP were the abbreviation of gross ecosystem productivity, ecosystem respiration and net ecosystem productivity, respectively. Climate zones were classified based on the Vegetation Regionalization from Editorial Committee of Vegetation Map of China (2007).

climate-based potential GEP. Meanwhile, to the best of our knowledge, there was no estimate of ER in China. Yu et al. (2010) found that the total annual soil respiration was  $3.84 \text{ PgC yr}^{-1}$  from 1998 to 2008, which was 65.98% of our estimated total annual ER. This ratio was smaller than that of the global (Yuan et al., 2011), which may partly be due to the lower content of soil organic carbon in China (Wu et al., 2003). Moreover, our estimate of the total annual NEP was also more than 10 times higher than the values (ranged from 0.0625 to  $0.12 \text{ PgC yr}^{-1}$ ) from published literatures (Cao et al., 2003; Tao et al., 2007; Ji et al., 2008; Sun, 2009). This huge difference may be due to the difference in the definition of NEP. NEP used here was defined as the difference of GEP and ER, which was the climate-based potential carbon flux without the effect of land use changes and other factors, whereas NEP in literatures (Cao et al., 2003; Tao et al., 2007; Ji et al., 2008; Sun, 2009) resulted from eco-physiological process models, which was considered as the carbon sink (Tao et al., 2007). Furthermore, our estimated NEP was also higher than the carbon sink from the inventory approach or models (Fang et al., 2007; Piao et al., 2009a, 2011; Tian et al., 2011a, 2011b) as the distinct difference between NEP and carbon sink at the regional scale (Chapin et al., 2012).

The proportion of the world's carbon fluxes in China estimated in our study was similar to that of land area. Given the global total annual GEP floated from 110.5 to  $175 \text{ PgC yr}^{-1}$  (Alton et al., 2009; Beer et al., 2010; Yuan et al., 2010; Welp et al., 2011; Chen et al., 2012; Koffi et al., 2012), our estimated GEP in China accounted for 4.29%–6.80% of the global total GEP. Over the same period, the estimated total annual ER in China accounted for 5.65%–6.06% of the global total ER, which ranged from 96 to  $103 \text{ PgC yr}^{-1}$  (Jung et al., 2011; Yuan et al., 2011). Our estimated total annual NEP occupied 9.10%–12.73% of the global total NEP ( $15\text{--}21 \text{ PgC yr}^{-1}$ , Jung et al., 2011).

#### 4.3. The spatial distributions of carbon fluxes in China

GEP, ER and NEP had similar spatial distributions, showing a decreasing gradient from southeast to northwest. The higher carbon fluxes appeared in Eastern China, including Temperate forest, Warm

temperate forest, Subtropics and Tropics, and the highest carbon fluxes occurred in Central subtropics and Southern subtropics, while most areas in Western China showed low carbon fluxes, in accordance with the former study (Yu et al., 2013). This indicates that Eastern China had a large potential carbon sink, especially Central subtropics and Southern subtropics.

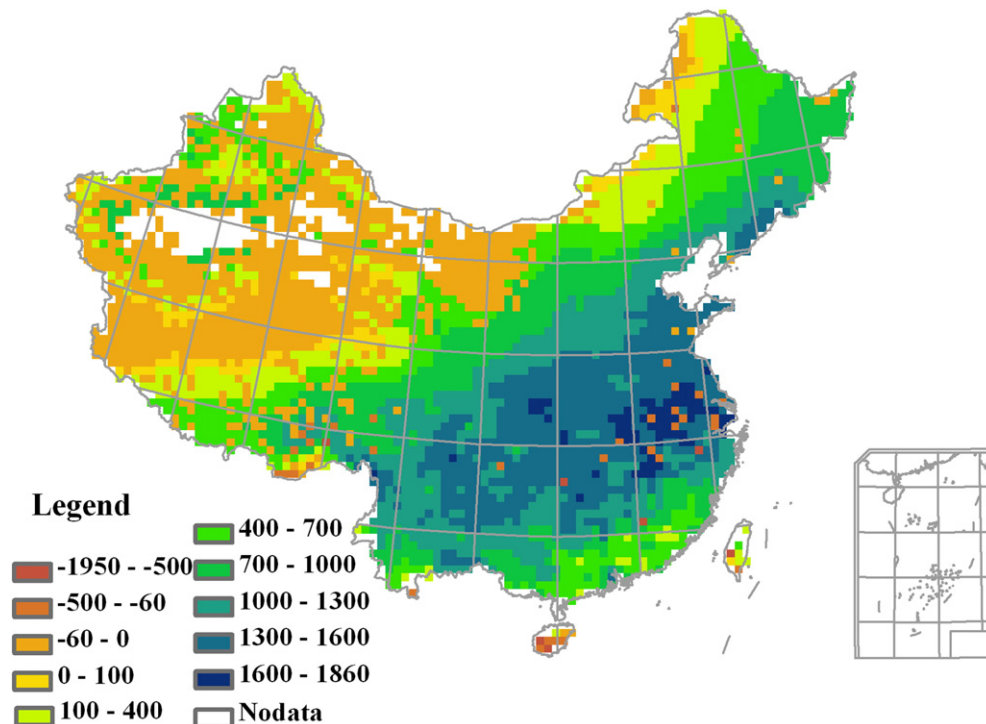
Former study also suggests a decreasing gradient from southeast to northwest for carbon fluxes (GEP and ER) in China (Jung et al., 2011), while the highest values appeared in Tropics, which was different from our estimates. Furthermore, the difference between our estimates and results from Jung et al. (2011) showed large spatial variability. The largest difference in GEP occurred in Central subtropics and Northern subtropics (Fig. 5), which may be due to the distinct climate in Chinese subtropics owing to the effect of Qinghai–Tibet Plateau (Wu et al., 2007). The spatial distributions of our estimated carbon fluxes were more reasonable and matched well with observations (Fig. 2B1–B3) as our estimates were explored using observations of Chinese terrestrial ecosystems with strong representativeness of Subtropics. Therefore, experiencing the distinct climate, Subtropics had the highest carbon fluxes and should be paid more attention. Our estimates also provided a useful supplementary to the global carbon flux distributions.

#### 4.4. Uncertainties in carbon flux estimates of China

Though our schemes successfully described the spatial distributions of carbon fluxes in China, there were some uncertainties, especially in NEP estimates.

Firstly, carbon fluxes used in this study were derived from the observed net ecosystem exchange (NEE) by the eddy covariance technique, which contained some uncertainties (Richardson et al., 2008), and NEE-based NEP would be overestimated in terrestrial ecosystems (Chapin et al., 2006).

Secondly, the representativeness of observations is essential when using the observation-based geographical statistical regression method, while some areas such as desert and alpine vegetation regions had no observations in our study. Though we can estimate the values of carbon



**Fig. 5.** The spatial distribution of the difference in GEP between our estimate and result from Jung et al. (2011). The positive value indicates a higher GEP in our estimate. GEP was the abbreviation of gross ecosystem productivity.



fluxes in these regions using geographical statistical regressions, the results had certain uncertainties and overestimated the real values. In fact, the carbon fluxes and the total annual values in desert and alpine vegetation regions were small, and setting carbon fluxes in desert and alpine vegetation regions to zero had little effect on the magnitudes and the distributions of the estimated carbon fluxes.

Furthermore, our estimates were climate-based potential carbon fluxes, while many factors, including the past temperature changes (Piao et al., 2009b) and human activities (Chapin et al., 2012; Tao et al., 2013; Zhang et al., 2013), were not considered. We also made no comprehensive analyses about how climate, biotic factors (LAI, ecosystem types) and human activities affected the spatial variability of carbon fluxes, which may lead to some uncertainties in our estimates. Therefore, further studies should develop new assessment schemes incorporating geographical statistics and remote sensing or integrating geographical statistics with ecological processes.

## 5. Conclusions

Integrating 52 site eddy covariance observations in China, we developed geographical statistical assessment schemes to evaluate the magnitudes of GEP, ER and NEP. The optimal scheme was then selected to assess the spatial distributions of carbon fluxes.

The climate-based assessment schemes successfully evaluated the regional carbon fluxes in China, which can be deemed as the potential carbon fluxes. The estimated GEP, ER and NEP in 2000s were  $7.51 \pm 0.51$ ,  $5.82 \pm 0.16$  and  $1.91 \pm 0.15$  PgC yr<sup>-1</sup>, respectively, accounting for 4.29%–6.80%, 5.65%–6.06% and 9.10%–12.73% of the corresponding global annual carbon fluxes, respectively.

Based on the optimal assessment scheme, the estimated carbon fluxes in China showed a southeast–northwest decreasing gradient. Eastern China, including Temperate forest, Warm temperate forest, Subtropics and Tropics, had higher carbon fluxes.

Most areas in China occupied a positive NEP, indicating a potential carbon sink. Central subtropics and Southern subtropics, with the largest NEP values, had the highest potential carbon sink.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at <http://dx.doi.org/10.1016/j.gloplacha.2014.04.003>.

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