

## Impacts of urbanization on net primary productivity in the Pearl River Delta, China

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Received 8 May 2015; Accepted after revision 2 August 2015; Published online 28 September 2015

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### Abstract

Great changes in land use/land cover from rapid urbanization have occurred in the Pearl River Delta, China. As the primary cause of land development in the urbanization process, urban expansion has mostly occurred on land with higher NPP, significantly impacting the regional ecosystems. The primary purpose of this study was to reveal the impacts of urban expansion on the regional NPP. The land cover datasets and three types of urban lands (urban, peri-urban and non-urban areas) were obtained to quantify the urban expansion of the Pearl River Delta from 2000 to 2010. The Carnegie-Ames-Stanford-Approach (CASA) model was driven by the land cover types, NDVI data and climate data to calculate the NPP for the study area and analyze its spatial-temporal variations, as well as the impacts on NPP from urban expansion. The results showed: cropland and forest with higher NPP values and wetland were the major source of urban expansion, which generally reduced the regional NPP values, primarily by replacing vegetation with urban land. The conversion of land to urban use resulted in a reduction of 0.103TgC from 2000 to 2005 and 0.034TgC from 2005 to 2010, cropland and forest accounted for the largest proportion of the total NPP losses. In spatial distribution, the NPP losses occurring in urban and peri-urban areas accounted for 89.63% and 75.04%, respectively, which was primarily a result of the massive vegetation with high productivity being replaced with impervious surfaces during the rapid urbanization process. These results provided an indicator to understand and evaluate ecosystem changes in urban regions.

**Keywords:** NPP loss; Urbanization; Urban expansion; CASA model; Pearl River Delta.

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### Introduction

In conjunction with the development of human society, the world is undergoing considerable changes in land use/land cover. It's estimated that between one third to one half of the earth's land surface has been transformed by human activities (Vitousek et al., 1997; Imhoff et al., 2004). As the most extreme anthropogenic land use/land cover transformation, urbanization is associated with urban expansion, population growth and economic development and has become an important theme in ecological research (Buyantuyev et al., 2010; Lu et al., 2010). Urbanization altered the composition and structure of urban ecosystems through transforming the natural landscape of urban land

surface (McDonnell et al., 1997; Alberti, 2005; Yu et al., 2009). Non-urban lands have been rapidly transformed into urban lands as a result of urban expansion, encroaching upon large areas of highly productive forest and fertile cropland, not only leading to losses in vegetation and soil carbon sequestration capacity and a functioning carbon cycle, but also generating great pressure on natural resources and food security (Burke et al., 1991; Houghton et al., 1999; Nizeyimana et al., 2001; Imhoff et al., 2004). Chen et al. (2006) estimated that the carbon fixing capacity from vegetation decreased by two thirds when suburban areas were transformed into urban areas. Forest and grassland being converted to cropland directly reduced vegetation and soil carbon stocks (Burke et al., 1991). Thus, urbanization significantly influenced the function and process of urban ecosystems and brought lots of potential eco-environmental problems, which have become one of the most important aspects of global change (McDonnell et al., 1997; Alberti, 2005; Tian and Qiao, 2014).

As an important part of the terrestrial carbon cycle, net primary productivity (NPP) is the remaining amount of solar energy converted to chemical energy through photosynthesis and represents the primary source of food for human beings and other heterotrophic organisms (Oke et al., 1989; Imhoff et al., 2004). NPP directly reflects the productivity of vegetation in specific environment and ecosystem health, which is the main component of carbon budget of ecosystems (Field et al., 1998). A NPP loss results in changes of an ecosystem's structure and function, changes in the atmospheric composition, a reduction in biodiversity and food supply (Houghton et al., 1999; DeFries et al., 1999; Pimm and Raven, 2000; Field, 2001; Imhoff et al., 2004). Therefore, NPP is useful as a "common currency" for quantifying the impact of urbanization on the terrestrial ecosystem (Xu et al., 2007).

Some studies on how urbanization impacts on NPP have been carried out in China and abroad at the regional or national scale (Milesi et al., 2003; Imhoff et al., 2000; Imhoff et al., 2004; Xu et al., 2007; Yu et al., 2009; Lu et al., 2010; Pei et al., 2013; Tian and Qiao, 2014). Imhoff et al. (2000, 2004) found urbanization has a variable but an overall negative impact on NPP in the United States. Pei et al. (2013) studied the NPP variations caused by urban land development in China during 2000-2006 and found the NPP was reduced at an accelerating rate of  $0.31 \times 10^{-3} \text{ PgCyr}^{-1}$  in the urbanization process. The loss of NPP caused by urbanization reached 45.93 Gg during 1999-2005 in Shenzhen (Yu et al., 2009). With the accelerating urbanization, the influences of urbanization on NPP are still very important for regional carbon balance and deserve further detailed investigation.

As the first area of China's reform and opening up, the Pearl River Delta has become one of the fastest developing regions in China in terms of its population and economy. According to the Guangdong Statistical Yearbook (<http://www.gdstats.gov.cn/>), population in the Pearl River Delta increased from 18.68 million in 1982 to 56.16 million in 2010 with more than twice growth rate, contributing to 4.19% of China's total population in 2010. GDP in the Pearl River Delta increased from 7.01 billion US\$ in 1987 to 556.51 billion US\$ in 2010 and its proportion in Guangdong province increased from 30.81% to 82.17% from 1987 to 2010. This region is bordered with Hong Kong, a largely urbanized city, which had higher GDP than each city of the Pearl River Delta, but its GDP growth rate during 1978-2010 was lower than that in the Pearl River Delta. Over past decades, the Pearl River Delta's preferential policy has attracted investment from Hong Kong, Taiwan and some developed countries. The constant population growth and economic development have resulted in an accelerated urbanization process and the corresponding regional eco-environmental problems are worsening. In this study, we quantified the impact of urban expansion on the regional

NPP in the Pearl River Delta, China and addressed the following issues: (1) the temporal-spatial variations of urban expansion and NPP values and (2) the regional differences of NPP variations and NPP losses in urban lands with the various levels of urbanization.

## Materials and Methods

### Study area

The Pearl River Delta lies in the southeast of Guangdong province, China and is close to the South China Sea ( $21^{\circ} 27' N \sim 23^{\circ} 56' N$  and  $111^{\circ} 59' E \sim 115^{\circ} 26' E$ ) (Figure 1). It includes the cities of Guangzhou, Shenzhen, Zhuhai, Dongguan, Zhongshan, Jiangmen and Foshan, as well as parts of Huizhou and Zhaoqing city, with a total area of 41,700 km<sup>2</sup>. The Pearl River Delta belongs to the subtropical marine monsoon climate zone, characterized by abundant rainfall and warm environment; the average annual temperature is approximately 22 °C and the mean annual precipitation is 1,600~2,000 mm. The main soil types are latosolic red soil and cultivated paddy soil. Forest and cropland comprise the dominant vegetation types, of which the main forest type is the subtropical monsoon evergreen broad-leaved forest. However, this native vegetation type has almost been eliminated by the long-term disturbance from human activities.

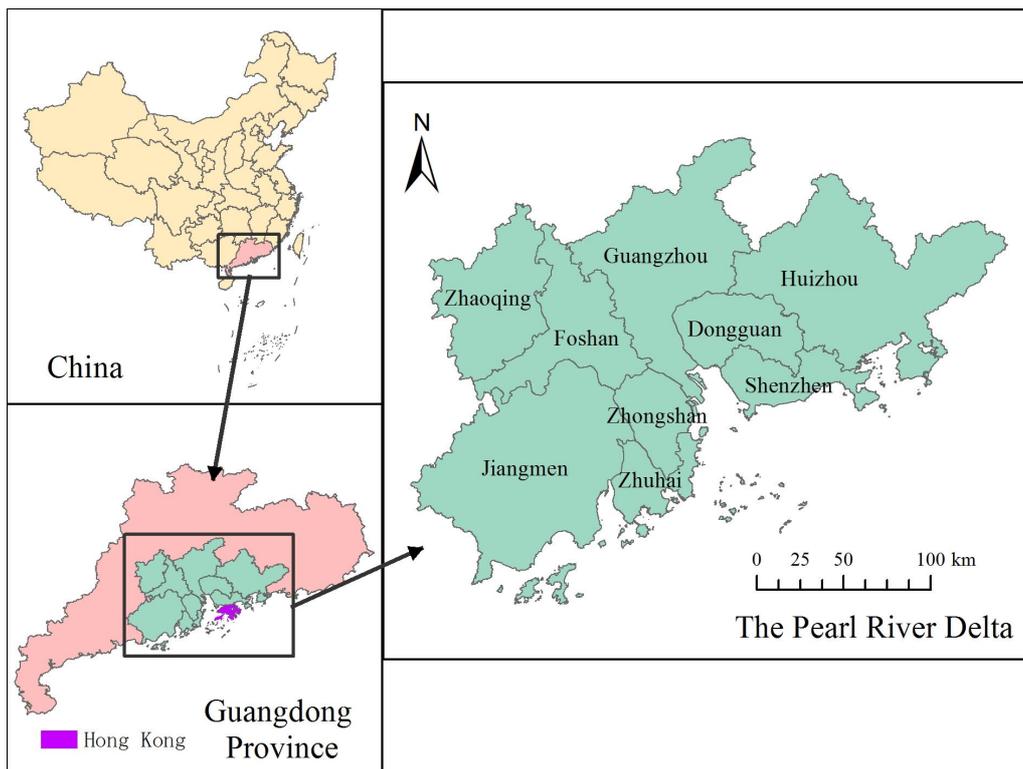


Figure 1. The scope and location of the Pearl River Delta.

### Methods

Nighttime images from the Defense Meteorological Satellite's Operational Linescan system (DMSP/OLS) and land cover datasets were used to measure the process of urban expansion. We used the Carnegie Stanford Ames Approach (CASA) terrestrial carbon

model to estimate NPP. Land cover types, Normalized Difference Vegetation Index (NDVI) derived from the Moderate-resolution Imaging Spectroradiometer (MODIS) data and climate datasets (<http://cdc.nmic.cn/home.do>) were combined to run CASA model and the ground measured NPP were used to evaluate the simulated results. We used the methods of zonal analysis and conversion matrix of land covers to quantify the impacts of urban expansion on regional NPP.

#### *Data pre-processing*

Landsat TM/ETM+ images acquired in 2000, 2005 and 2010 were interpreted to extract the land cover data sets based on FAO LCCS land cover types. To meet with the vegetation types in the CASA model, the land cover types were recorded and merged into new classes: forest (EBF, evergreen broad-leaf forest; ENF, evergreen needle-leaf forest; DBF, deciduous broad-leaf forest; DNF, deciduous needle-leaf forest; MF, mixed forest; Shrub), cropland, urban land, grassland, wetland and unused land.

Monthly NDVI data were derived from the MODIS 16 day NDVI product (MOD13Q1) and the MODIS day NDVI in China (MODND1D) from the TERRA satellite with a grid size of 250m×250m for the year 2000, 2005 and 2010. We produced a 12-layer map of monthly maximum NDVI values by using the algorithm of MVC (maximum value composite).

The required climate data as inputs for the CASA model are monthly total solar radiation, monthly mean temperature and monthly total precipitation in 2000, 2005 and 2010, which were collected from 65 meteorological stations of Guangdong and nearby provinces and 22 solar radiation observation stations of the fifth geographic zone in China including Guangdong and surrounding provinces according to Wen et al. (2008) (Figure 2). We need to rasterize these site-based climate elements to acquire their spatial distribution. The simple interpolation approach (e.g., Kriging, Inverse Distance Weighting) generally takes into account the locations and values of the climate element, but not considering its environmental influence factors, the simulated results would have a higher accuracy by building regression models between the climate element and its influence factors (Zhu et al., 2005). Thus, based on some reported studies, a multi-nonlinear regression model between the observed monthly solar radiation and its influence factors (latitude, elevation and monthly sunshine hours) was established to simulate the solar radiation (Zhu et al., 2005); a multi-nonlinear regression model between the observed monthly mean temperature and its influence factors (latitude, longitude and elevation) was established to simulate the temperature (Liao et al., 2003); a combination of a multi-nonlinear regression model between the observed monthly total precipitation and its influence factors (latitude, longitude and elevation) with the Kriging interpolation method were used to simulate the precipitation (Liu et al., 2009). The spatial distribution of these climate data were on a level surface comprised of a 250 m×250 m grid cell made to fit the spatial resolution of the NDVI data.

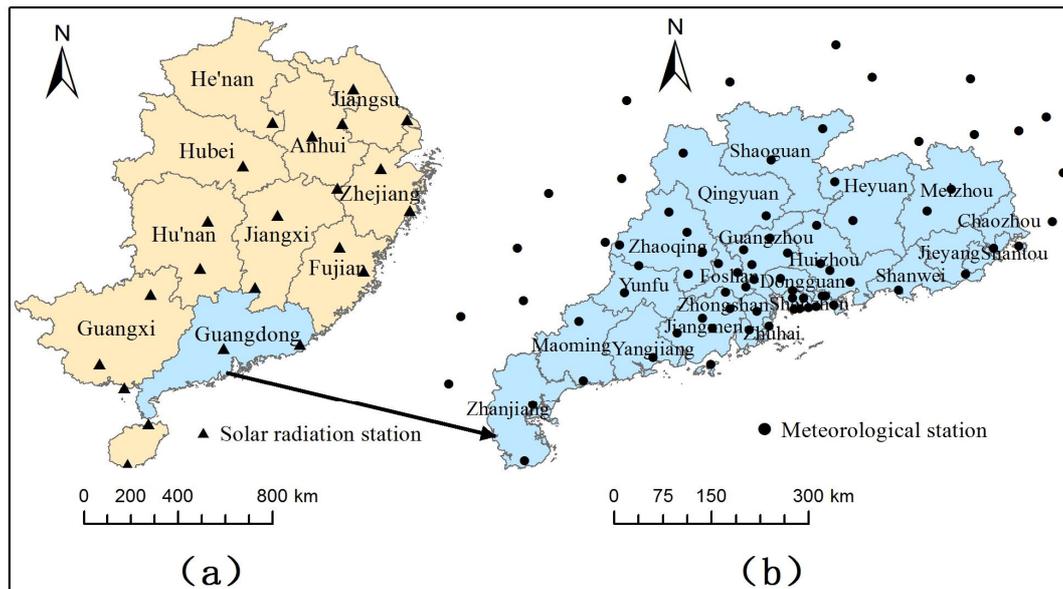


Figure 2. The spatial distribution of solar radiation station (a) and meteorological station (b).

Forest volumes and crop harvest data for the year 2000, 2005 and 2010 are from the agricultural statistical yearbook of Guangdong. According to Lu et al. (2012) and Kang et al. (2014), we estimated regional forest NPP by using the biomass expansion regression equation based on forest volumes data; we estimated regional cropland NPP by using the specific transformation formula between cropland NPP and crop harvest based on crop harvest data; the regional NPP are on the prefecture-level city scale in Guangdong province. The measured ground NPP data were compiled from the continuous measurement of biomass on 6 sample plots from 1999 to 2010 in the national forest eco-station of Dinghushan and Heshan in the Pearl River Delta (<http://rs.cern.ac.cn/index.jsp>).

#### *Satellite mapping of urban expansion*

We used the Shannon entropy theory representing landscape diversity and nighttime images from the DMSP/OLS to create three forms of urban lands with various levels of urbanization: urban, peri-urban and non-urban areas.

The Shannon entropy expression is as follows:

$$H = -\sum_{i=1}^n p_i \ln p_i \quad (1)$$

where  $i$  is equal to the number of land cover types and  $n$  equals the maximum number;  $p_i$  corresponds to the area percentage of the number of  $i$  land cover types in one evaluation cell and  $H$  represents the diversity and homogeneity of distribution for all land cover types. A larger value for  $H$  represents more even distribution patterns. The land cover types used in this expression include urban land, forest, cropland, grassland, swags and unused land. According to the relevant studies (Huang et al., 2012), the evaluation cell is 960 m×960 m (corresponding to 32×32 grid cells with a size of 30 m×30 m each). The scope of the peri-urban land is the area with a value of  $H$  greater than 0.7.

The nighttime imagery from the DMSP/OLS provides a tool for monitoring the tempo-spatial dynamics of the urban expansion (Imhoff et al., 1997; Chen et al., 2003; He et al., 2005; Yang et al., 2011). The threshold technology is the most commonly used method for extracting the urban areas from the nighttime imagery (Yang et al., 2011). Yearly static nighttime images were used in this study and urban areas generally exhibit high levels of nighttime light emissions. According to previous research and actual repeated trials, urban land was determined by that which had a threshold of DN greater than 50 (MilesI et al., 2003; Shu et al., 2011).

### Calculation of NPP

One year's worth of MODIS NPP data are available and distributed by the EROS Data Center Distributed Active Archive Center (EDC DAAC) with the product name of MOD17A3; however, urban areas and water bodies are masked out in this datasets (Milesi et al., 2003). As a result, we need to generate our own NPP for the study area. Estimating the NPP based on light use efficiency has been broadly used on regional and global scales (Potter et al., 1993; Hicke et al., 2002; Lobell et al., 2002; Zhu et al., 2007). The CASA model is a type of static parameter model to estimate NPP and the simulated results represent the existing actual NPP. In CASA model, the NPP is estimated as the product of the amount of photosynthetic active radiation absorbed by vegetation and the actual light use efficiency ( $\epsilon$ ) (Potter et al., 1993; Zhu et al., 2007), the flow chart is shown in Figure 3. We firstly estimated the NPP for the year 2000, 2005 and 2010 on a monthly time scale at 250 m spatial resolution in Guangdong province and then summed the monthly NPP to provide a map of annual NPP with the unit of grams C per square meters ( $\text{gCm}^{-2}\text{yr}^{-1}$ ). The NPP in the Pearl River Delta was extracted within a mask of the boundary map of the Pearl River Delta.

According to Potter et al. (1993), PAR is the product of the total solar radiation ( $\text{MJm}^{-2}\text{mon}^{-1}$ ) and the constant 0.5, which accounts for the fact that approximately half of the incoming solar radiation is in the photo synthetically active radiation (0.4~0.7  $\mu\text{m}$ ). As shown in Figure 3, FPAR is determined by the land cover types and the fraction of vegetation covers and is defined as a linear function of the NDVI or the simple ratio (SR) (Zhu et al., 2007). The light use efficiency ( $\epsilon$ ) can be determined as the product of the maximum light use efficiency ( $\epsilon_{\text{max}}$  ( $\text{gC MJ}^{-1}$ ), the temperature stress coefficient ( $T_{\epsilon}$ ) and the moisture stress coefficient ( $W_{\epsilon}$ ). According to Zhu et al. (2007),  $T_{\epsilon}$  was estimated based on the land cover types and temperature;  $W_{\epsilon}$  was determined by the climatic conditions and the corresponding geographical factors and was the function of EET (Regional Actual Evapotranspiration) and PET (Regional Potential Evapotranspiration), the detailed description refers to correlative research (Potter et al., 1993; Zhang, 1989; Zhou and Zhang, 1995; Zhou and Zhang, 1996; Zhu et al., 2007).

It's worth noting the calculation of  $\epsilon_{\text{max}}$ . Zhu et al. (2006) and Pei et al. (2013) simulated  $\epsilon_{\text{max}}$  of some typical vegetation types in China using a modified least squares function based on simulated NPP and measured ground NPP. Due to the limited samples of measured ground NPP during 2000-2010 in Guangdong province, we used the estimated regional cropland NPP of 21 prefecture-level cities as the samples. According to the method proposed by Zhu et al. (2006), we simulated  $\epsilon_{\text{max}}$  of the cropland in 2000, 2005 and 2010, which is 0.455, 0.505 and 0.546, respectively. The

spatial distribution of forest NPP was calculated using the  $\epsilon_{\max}$  simulated by Zhu et al. (2006) and Pei et al. (2013), respectively; zonal statistical method was used to acquire the regional forest NPP of 21 prefecture-level cities, which were then compared with the estimated regional forest NPP of 21 prefecture-level cities based on forest volumes. According to the principle of minimum error, we took the average values of  $\epsilon_{\max}$  proposed by Zhu et al. (2006) and Pei et al. (2013) as  $\epsilon_{\max}$  of land covers except for cropland in this study. The  $\epsilon_{\max}$  of EBF, ENF, DBF, DNF, MF, shrub, urban land, grassland, wetland and unused land was 0.808, 0.378, 0.585, 0.434, 0.461, 0.389, 0.482, 0.482, respectively.

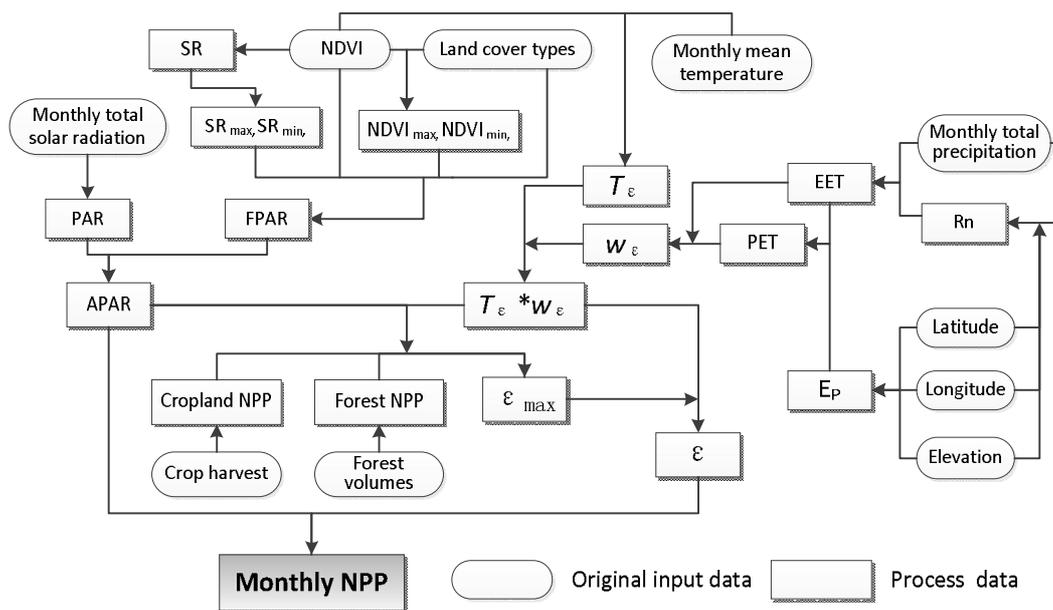


Figure 3. The flow chart of CASA model used to estimate the monthly NPP. The CASA model has four key inputs: (1) monthly total solar radiation which is used to estimate PAR (Photosynthetic Active Radiation); (2) remote sensing inputs (NDVI, land cover types) which are used to estimate FPAR (Fractional of PAR); (3) monthly mean temperature which is used to estimate the temperature stress coefficient ( $T_{\epsilon}$ ), monthly total precipitation and geographical variables (latitude, longitude and elevation) which are used to estimate the moisture stress coefficient ( $W_{\epsilon}$ ); (4) crop harvest and forest volumes which are used to estimate the maximal light use efficiency ( $\epsilon_{\max}$ ). The algorithm to estimate the NPP can be expressed as:  $NPP = (PAR * FPAR) * (\epsilon_{\max} * T_{\epsilon} * W_{\epsilon})$ . The implementation of the algorithm was completed in the software Envi4.8 and ArcGIS10.1. APAR, Absorbed Photosynthetic Active Radiation; SR, Simple Ratio; PET, Regional Potential Evapotranspiration; EET, Regional Actual Evapotranspiration;  $E_p$ , Reference Potential Evapotranspiration;  $R_n$ , Net Radiation. (We portrayed this figure based on Yu et al. (2009)).

## Results and Discussions

### *The spatial-temporal patterns of urban expansion*

Urban expansion was the most important landscape change in the Pearl River Delta, as shown in Figure 4, indicating the expanding urban areas and peri-urban areas. Urban areas significantly expanded from 4594 km<sup>2</sup> in 2000 to 6686 km<sup>2</sup> in 2010 with an

annual increase rate of 210 km<sup>2</sup> between 2000 and 2010 and the annual increase rate of change in peri-urban areas was 168 km<sup>2</sup> during the same period. During the 10-year period, urban areas mainly expanded as infilling and edge-expansion growth, the impervious surfaces in the Pearl River Mouth Rim came together creating a megalopolis and the urban expansion became more aggregated and compact (Li and Yeh, 2004; Sun et al., 2013).

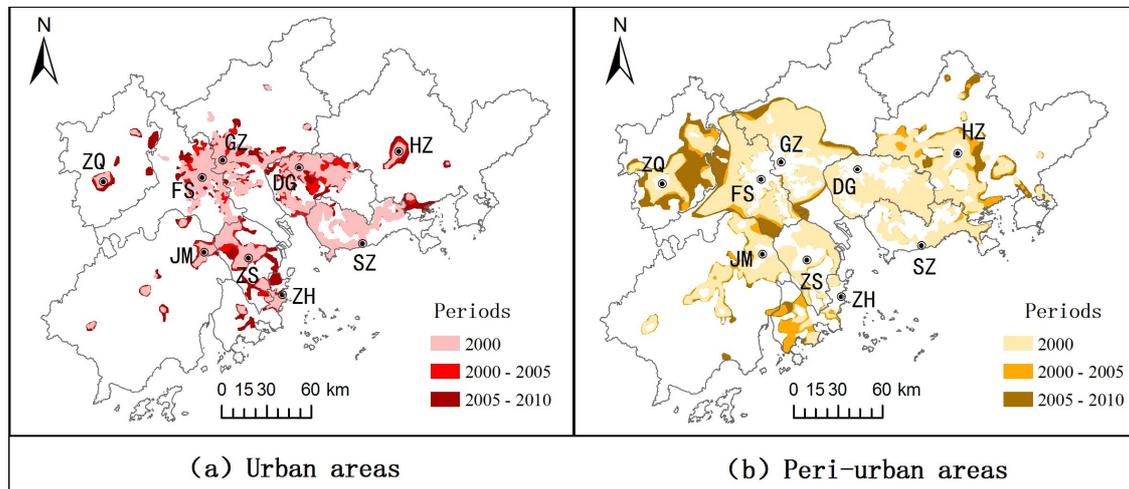


Figure 4. Urban expansion from 2000 to 2010 in the Pearl River Delta. The period was divided into 2 periods of five years. (a) indicates urban areas, (b) indicates peri-urban areas. DG=Dongguan; FS=Foshan; GZ=Guangzhou; HZ=Huizhou; JM=Jiangmen; SZ=Shenzhen; ZH=Zhuhai; ZQ=Zhaoqing; ZS=Zhongshan.

Table 1 indicates the conversion area and percentage of urban land use from non-urban land covers during 2000-2010. The newly expansion area of urban land use was 851.78 km<sup>2</sup> during 2000-2005 and 941.49 km<sup>2</sup> during 2005-2010, revealing a faster urbanization process. Cropland was the primary source of urban expansion, accounting for 55.16% of the urban expansion during 2000-2005 and 48.49% during 2005-2010, which is a slight decrease between periods primarily because of the implementation of a national farmland protection policy. Forest accounted for 18.05% of the urban expansion during 2000-2005 and increased to 25.92% during 2005-2010, which indicated increasingly serious deforestation. Wetland was an important landscape in the Pearl River Delta and played a significant role in ecological regulation; it accounted for 25.92% of the urban expansion during 2000-2005 and decreased to 12.91% during 2005-2010, indicating that the existence and protection of wetland are attracting broad attention. Unused land greatly increased to 9.3% during 2005-2010. Grasslands accounted for a lower proportion on account of their small land area. Anyway, cropland was the primary source of urban expansion, followed by forest and wetland, which indicated a substantial increase in human activities with time. Special economic development zones and high-tech industry zones were constructed to attract more foreign investments (Sun et al., 2013) and the encroachment of cropland and forests by urban expansion has significantly influenced the regional NPP.

Table 1. The conversion area and percentage of urban land use from non-urban land covers in the Pearl River Delta during 2000-2010 (km<sup>2</sup>, %). UL, urban land.

Periods	Forest →UL	Cropland →UL	Grassland →UL	Wetland →UL	Unused land →UL	Total New UL
2000-2005	153.75 (18.05)	469.84 (55.16)	0.46 (0.05)	220.74 (25.92)	6.98 (0.82)	851.78 (2.08)
2005-2010	274.69 (29.18)	456.53 (48.49)	1.22 (0.13)	121.52 (12.91)	87.53 (9.30)	941.49 (2.29)

### The NPP variations of different land covers in 2000, 2005 and 2010

#### Validation of the NPP Calculations

We compared the annual mean NPP values in this study with the measured ground NPP values and other domestic simulation results (Figure 5 and Table 2). As shown in Figure 5, the mean relative error was 23.69% and the correlation coefficient (r) was 0.78, the simulated NPP values were slightly lower than the measured ground NPP that mainly attributed to the difference between the spatial resolution of remote sensing data and the sample size of the measured ground data.

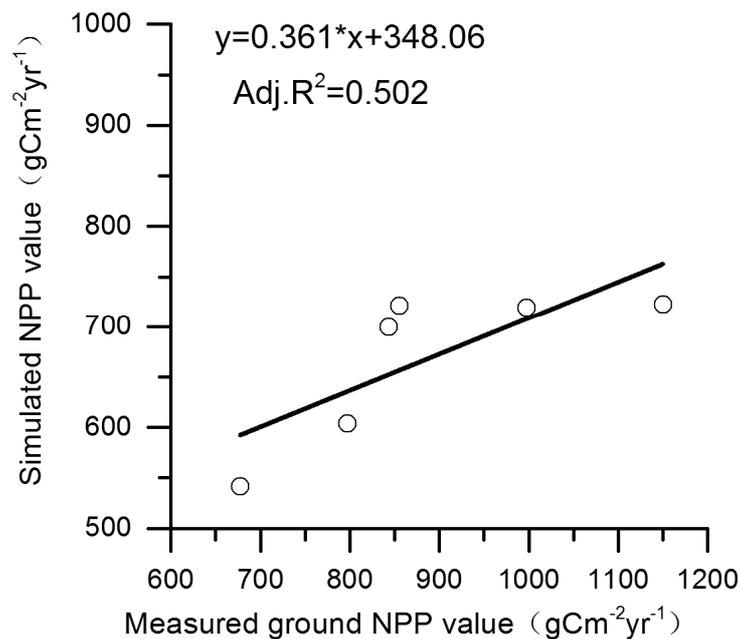


Figure 5. Correlation between simulated NPP values and measured ground NPP values.

As shown in table 2, the simulated NPP values of different land cover types presented some variations. The simulated results of evergreen broad-leaf forest and deciduous broad-leaf forest in this study are lower than site-based data calculated by Luo (1996), and that of other vegetation types were higher or close to MOD17A3 and other simulated results in given references, these differences may be caused by the model itself, data source and study area, as well as the vegetation types and their

classification accuracy (Zhu et al., 2007). At a resolution of 250 m×250 m, most of the urban cover is a mosaic of trees with vegetation beneath and buildings, especially in Guangdong province with high rates of urban greening, constructive land in mountain counties scattered, some vegetation also grows in and around ponds, swamps and other wetlands, thus, the NPP value is generally greater than zero.

Table 2. Comparison of annual mean NPP simulated in this paper with other research results ( $\text{gCm}^{-2}\text{yr}^{-1}$ ). EBF, evergreen broad-leaf forest; ENF, evergreen needle-leaf forest; DBF, deciduous broad-leaf forest; DNF, deciduous needle-leaf forest; MF, mixed forest. “-” indicates “no data”.

Vegetation Types	This study	MOD17A3	Luo (1996)	Piao et al. (2001)	Liu (2001)	Tao et al. (2003)	Zhu et al. (2007)
EBF	833.06	721.86	1016.5	525	945	721	985.8
ENF	519.34	696	395.5	354	587	515	367.1
DBF	533.49	517.07	671.8	304	928	517.6	642.9
DNF	467.06	381.14	490	432	585	379.1	438.8
MF	744.7	739.21	-	-	-	-	-
Shrub	470.04	636.31	364	283	-	272	367.7
Grassland	524.25	602.72	230.6	-	271	414.6	226.2
Cropland	534.74	538.75	532.9	216		648.8	426.5
Urban Land	384.04	480.84	-	-	-	-	-
Wetland	395.18	438.22	-	-	-	-	-
Unused Land	514.47	629.54	-	-	-	-	-

#### *The NPP variations of different land covers*

Table 3 shows the estimated value of the annual mean NPP and total NPP simulated by the CASA model in 2000, 2005 and 2010. Among all the land cover types, forest had generally the highest mean NPP (approximately  $700 \text{ gCm}^{-2}\text{yr}^{-1}$ ), followed by cropland and grassland, with a mean NPP value of approximately  $500 \text{ gCm}^{-2}\text{yr}^{-1}$ . The mean NPP of wetland and urban land use was lower, with a value of approximately  $400 \text{ gCm}^{-2}\text{yr}^{-1}$ . The unused land had the lowest mean NPP (approximately  $350 \text{ gCm}^{-2}\text{yr}^{-1}$ ). The overall annual mean NPP decreased by  $53.06 \text{ gCm}^{-2}$  from 2000 to 2005 and increased by  $33.57 \text{ gCm}^{-2}$  from 2005 to 2010. The annual total NPP of forests was the highest, accumulating approximately  $14 \text{ TgCyr}^{-1}$  ( $1\text{Tg}=10^{12}\text{g}$ ). Cropland had a lower total NPP than forest, accumulating approximately  $4\text{TgCyr}^{-1}$  during 2000-2010 and the total NPP of urban land use and wetland were equivalent, approximately  $2 \text{ TgCyr}^{-1}$ . Grassland and unused land had the lowest total NPP, approximately  $0.05 \text{ TgCyr}^{-1}$ . The total NPP of each land cover type exhibited a similar trend as the mean NPP, decreased by  $1.86 \text{ TgC}$  from 2000 to 2005 and increased by  $1.2 \text{ TgC}$  from 2005 to 2010. On an annual basis, the change in NPP was impacted by both climate and human disturbances. Climate was the more influential factor; human disturbances caused by urban expansion increased the change rates of NPP in the climatic context (Zhu et al., 2007).

Table 3. The estimated value of annual mean NPP and total NPP in 2000, 2005 and 2010.

Time	Forest	Cropland	Grassland	Urban land	Wetland	Unused land	Total area
Annual mean NPP (gCm <sup>-2</sup> yr <sup>-1</sup> )							
2000	684.90	505.02	485.87	395.79	414.38	383.10	573.29
2005	650.44	447.04	466.94	309.28	351.52	261.28	520.23
2010	700.66	484.86	509.42	324.04	362.62	371.64	553.80
Annual total NPP (TgCyr <sup>-1</sup> )							
2000	14.1860	4.3571	0.0350	2.1530	1.8865	0.0552	22.67
2005	13.6218	3.5755	0.0332	1.9564	1.5694	0.0505	20.81
2010	14.3914	3.6405	0.0334	2.3271	1.6004	0.0175	22.01

### *The impacts of urban expansion on regional NPP*

#### *The NPP variations due to urban expansion*

We calculated the monthly and seasonal NPP values for all land cover types over the course of a year in 2000, 2005 and 2010 and averaged the NPP values in three years. To assess the impact of urban expansion on the variations of the NPP values, we compared monthly and seasonal values of NPP for urban, peri-urban and non-urban areas, as well as the annual NPP difference between urban and peri-urban areas (urban-peri-urban), urban and non-urban areas (urban-non-urban).

The mean NPP showed monthly and seasonal variations among urban, peri-urban and non-urban areas throughout the year (Figure 6a and b). The mean NPP exhibited an overall increase from March to July when it reached a maximum value and then exhibited a continuous decrease from August to February when it reached a minimum value. The accumulation period of NPP primarily occurs between May and October when precipitation and heat conditions are ideal, accounting for 77.19% of the annual mean NPP. From perspective of seasonal dynamics, the NPP values in urban, peri-urban and non-urban areas were significantly different ( $P < 0.05$ ) in the four seasons. The mean NPP value in spring (March to May) was 102.34 gCm<sup>-2</sup>. As planted vegetation became more active the mean NPP value increased to 208 gCm<sup>-2</sup> in summer (June to August). The mean NPP value in autumn (September to November) was 125.82 gCm<sup>-2</sup> and decreased to 37.77 gCm<sup>-2</sup> in winter (December to February). The decrease of urban NPP from fall to winter is believed to be a result of reduced precipitation and heat. The mean NPP values in spring, summer, fall and winter accounted for 21.55%, 43.99%, 26.5% and 7.96% of the total annual NPP, respectively.

As shown in Figure 6c, the mean NPP was lower in urban areas than peri-urban areas and non-urban areas throughout the year. These NPP differences between urban and peri-urban areas, urban and non-urban areas had the temporal patterns of seasonal symmetries, but were much less significant than the NPP differences in arid and semi-humid/arid regions (Imhoff et al., 2004; Pei et al., 2013), which may primarily depend on the local prevailing climate and land use/covers conditions. The Pearl River Delta is characterized by a warm and humid subtropical marine climate with abundant rainfall and heat throughout the year, there was greater plant growth in urban areas compared to non-urban environments (Gregg et al., 2003; Wen et al., 2010). Nonetheless, these increased NPP gains in urban areas are not enough to offset the NPP losses caused by urban expansion in the rapid urbanization process. It was estimated that the total NPP

decreased by 0.173 TgC when peri-urban areas had been changed to urban areas from 2000 to 2010, which generally agree with Chen et al. (2006). But in the regions with an arid and semi-humid/arid climate, urban areas generally exhibited higher NPP than non-urban areas primarily through human-sponsored resource augmentation (e.g., management practices, irrigation and fertilization) and the introduction of faster growing exotic tree species (Imhoff et al., 2004; Buyantuyev and Wu, 2009; Pei et al., 2013). Our findings are in agreement with those reported studies (Imhoff et al., 2004; Chen et al., 2006; Wen et al., 2010; Pei et al., 2013) wherein urbanization has a generally negative effect on the NPP in humid regions with higher rainfall, especially during the peak-growing season. That is, urban expansion reduced the NPP of vegetation even under favorable climatic conditions, primarily by replacing vegetation with impervious surfaces. In these cases, human-sponsored resource augmentation in urban areas did not have a significant advantage over the natural prevailing conditions found in the surrounding non-urban areas (Imhoff et al., 2004; Pei et al., 2013) and, therefore, did not have a dominant effect on the NPP in urban areas. On the contrary, the reduction of fractional vegetation cover had a mostly negative effect on the NPP.

#### *The NPP loss caused by urban expansion from 2000 to 2010*

The overall NPP difference during 2000-2010 shows that the Pearl River Delta has experienced great NPP losses over large areas (Figure 7). To understand the effects of urban expansion on the NPP, we concentrated on the conversion of non-urban land to urban land use and calculated the loss of regional NPP as the area weighted sum of the NPP difference between 2000 and 2005, 2005 and 2010 (Table 4). On the whole, the conversion of land to urban use in the Pearl River Delta has resulted in an annual reduction of 0.103 Tg of photo synthetically fixed carbon during 2000-2005 and 0.034 Tg of carbon during 2005-2010. The NPP losses occurring in urban and peri-urban areas accounted for 89.63% and 75.04%, respectively, which was primarily a result of the massive vegetation with high productivity being replaced with impervious surfaces during the rapid urbanization process.

Table 4. Loss of the total NPP from urban expansion during 2000-2010 (TgC). PRD, Pearl River Delta; UL, urban land. “-” indicates “no data” or “the value is too small”.

Periods	Regions	Forest →UL	Cropland →UL	Grassland →UL	Wetland →UL	Unused land→UL	Total loss of NPP
2000→2005	urban	-0.010826	-0.024778	-	-0.010787	-0.000054	-0.046445
	peri-urban	-0.009505	-0.028820	-0.000001	-0.007956	-0.000019	-0.046302
	non-urban	-0.002980	-0.006375	-0.000019	-0.001408	0.000051	-0.010731
	PRD	-0.023312	-0.059973	-0.000020	-0.020151	-0.000023	-0.103478
2005→2010	urban	-0.008775	-0.004807	-	-0.002055	0.003742	-0.011895
	peri-urban	-0.011546	-0.004738	0.000031	0.002723	-0.000007	-0.013537
	non-urban	-0.008483	-0.000615	-0.000038	-0.000057	0.000733	-0.008460
	PRD	-0.028804	-0.010160	-0.000008	0.000611	0.004469	-0.033892

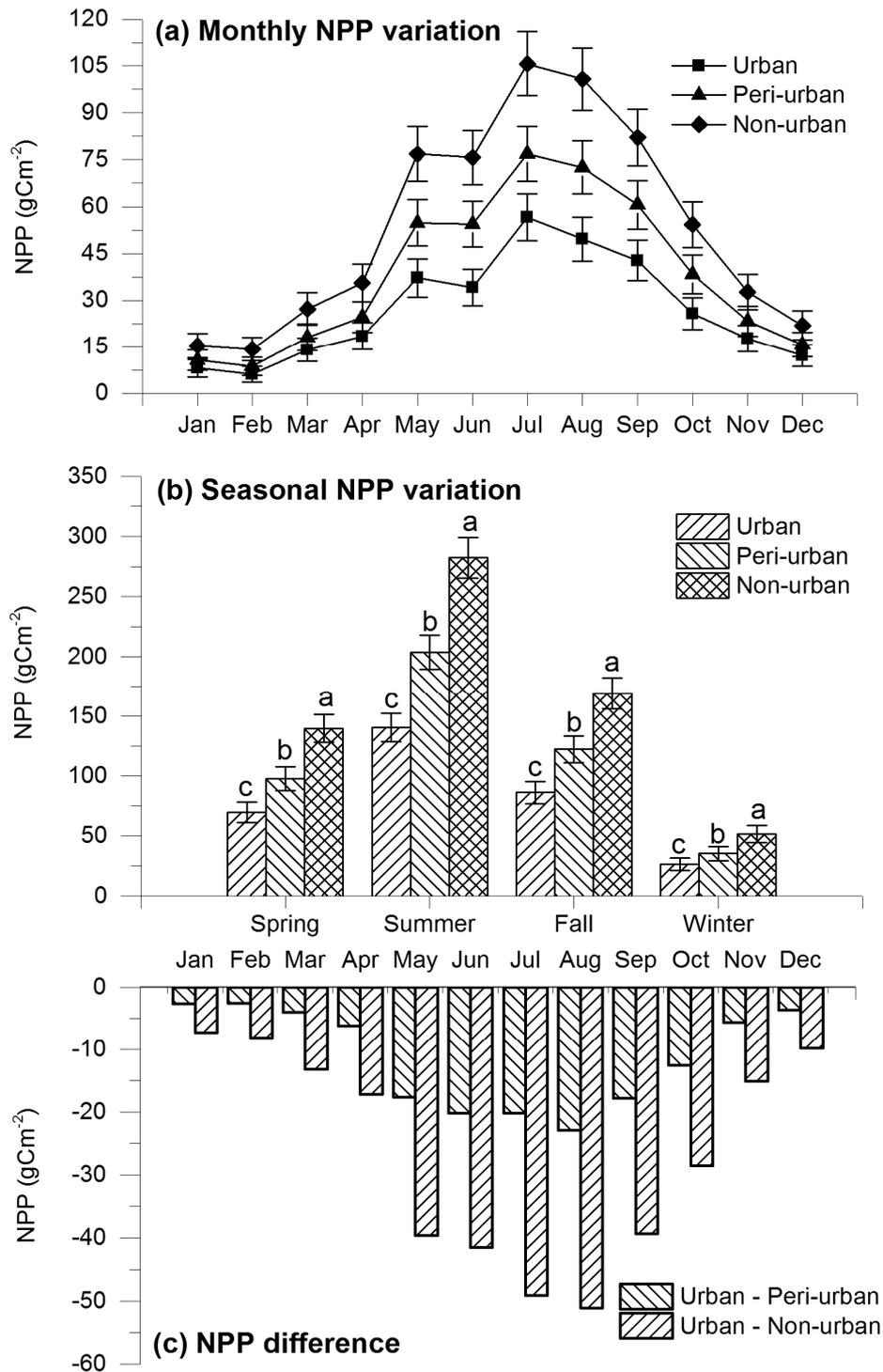


Figure 6. (a) Variations of the monthly NPP for urban (squares), peri-urban (triangles) and non-urban (diamonds) areas. (b) Variations of the seasonal NPP for urban, peri-urban and non-urban areas. Error bars represent standard error. Bars with different letters are significantly different at the  $\alpha=0.05$  level. (c) NPP difference between urban and peri-urban areas (urban-peri-urban), urban and non-urban areas (urban-non-urban).

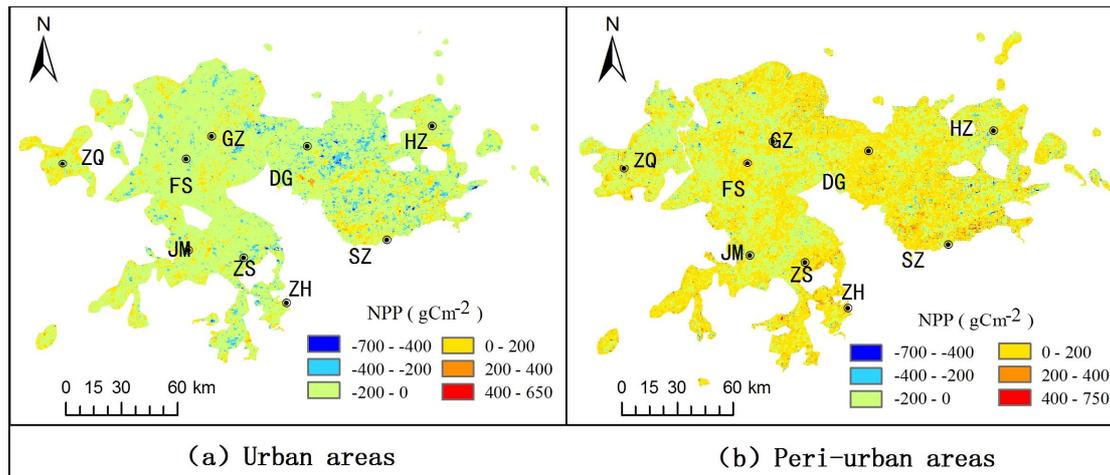


Figure 7. NPP difference in urban areas and peri-urban areas between 2000 and 2005 (a) and 2005 and 2010 (b) showing the NPP loss (negative value) or gain (positive value). DG=Dongguan; FS=Foshan; GZ=Guangzhou; HZ=Huizhou; JM=Jiangmen; SZ=Shenzhen; ZH=Zhuhai; ZQ=Zhaoqing; ZS=Zhongshan.

As for the various conversion types to urban land use, the loss of NPP had significant temporal and spatial heterogeneity. During 2000-2005, the loss of NPP caused by the conversion from cropland was the highest and reached 0.06 TgC, accounting for 57.96% of the total NPP loss resulting from urban expansion. The loss of NPP caused by the conversion from forest and wetland was 0.023 TgC and 0.02 TgC, accounting for 22.53% and 19.47%, respectively. The NPP loss caused by the conversion from unused land and grassland only accounted for 0.04% of the total loss. During 2005-2010, the total loss of NPP decreased by 67.25% compared with the total loss of NPP during 2000-2005, primarily a result of the increased mean NPP of all land cover types and urban green area during 2005-2010. The loss of NPP caused by the conversion from forest increased to 0.029 TgC, accounting for 84.99% of the total NPP loss of urban expansion. The loss of NPP caused by the conversion from cropland decreased by 0.01 TgC, accounting for 29.98%. The conversion from wetland and unused land to urban land increased the NPP to 0.001 TgC and 0.005 TgC, respectively.

The variation in the loss of NPP was also a factor of the level of urbanization. During 2000-2010, the NPP losses caused by the conversion from forest and cropland were the highest in urban areas, which were slightly higher than that in peri-urban areas, but much higher than that in non-urban areas. The conversion of grassland to urban land increased the NPP in urban areas, but reduced the NPP in peri-urban and non-urban areas. The NPP losses caused by the conversion from wetland and unused land had similar spatial patterns as that of forest and cropland. The NPP loss was highest in urban areas and lowest in non-urban areas.

The overall reduction of the photosynthetic carbon sink caused by urban expansion was only one aspect of the NPP losses/gains. The impacts of urban expansion on NPP are complicated and could be positive or negative, primarily depending on the local environments (Pouyat et al., 2007; Buyantuyev et al., 2009; Lu et al., 2010). On the one hand, the conversion from highly productive vegetation to urban land with low productivity would result in losses in the NPP (Imhoff et al., 2004; Buyantuyev et al., 2009). On the other hand, the warmer prevailing climate and urban heat island, resource augmentation and the replacement of native plant species with faster growing exotics

might also enhance the NPP (Imhoff et al., 2004; Buyantuyev et al., 2009; Lu et al., 2010; Pei et al., 2013). In this study, the NPP gains appeared lower relative to the NPP losses, especially in urban and peri-urban areas during 2000-2005. However, during 2005-2010, the overall gains in the NPP were much higher relative to the overall NPP losses across the Pearl River Delta. This indicated that the NPP values are also influenced by other factors, except for the relative alternation of the urban ecosystem, such as the fractional vegetation cover, the regional prevailing climate and the seasonal patterns of photosynthetic activity (Imhoff et al., 2004). Wen et al. (2010) found that the losses in carbon absorption caused by land occupation could be offset by improving the fractional vegetation cover. With the expansion of urban areas in the Pearl River Delta, the growth rates of the fractional vegetation cover increased from 7.37% during 2000-2005 to 29.10% during 2005-2010 and to some extent these NPP gains offset the NPP losses caused by urban expansion. To further explore the mechanics of the NPP variations, Pei et al. (2013) studied the effects of the Urban Heat Island (UHI) in the Pearl River Delta during 2001-2010. The results indicated that the land surface temperature (LST) of the urban land use was slightly higher than the vegetation. Actually, the difference between the growing ability of the same vegetation type inside and outside the UHI areas might be more capable of reflecting the effects of the UHI. Our finding of the effect of the UHI on the NPP appeared to be small relative to the local prevailing climate conditions in the Pearl River Delta. Gregg et al. (2003) found that higher urban temperatures could not account for plant growth in urban areas, which provides guidance and references for our further studies. Although previous studies and this study have drawn certain meaningful conclusions regarding the effects of urban expansion on vegetation NPP, there are still some uncertainties such as the assimilation and combination among different data sources, the specific composition of the urban land use, the precision of NPP calculation and the relative contributions of urban expansion and climate change. Researchers should further consider these questions in subsequent studies, accounting for climate change in NPP calculations and focusing primarily on the true effects of the UHI on NPP in the Pearl River Delta.

## Conclusions

As a representative region, the Pearl River Delta has undergone great changes in land use/land cover as a result of rapid urbanization and population growth, urban expansion is the primary form of land development in the urbanization process. During the 10-year period, the urban land area expanded by 851.78 km<sup>2</sup> during 2000-2005 and 941.49 km<sup>2</sup> during 2005-2010, exhibiting a faster urbanization process. Cropland and forest with higher NPP values and wetland were the major source of urban expansion, which would significantly influence the regional NPP. Our findings of the overall effects of urbanization on the NPP was that urban expansion generally reduced the NPP values even under favorable climate conditions, primarily by replacing vegetation with urban land. The conversion of land to urban use resulted in a reduction of 0.103 TgC during 2000-2005, cropland and forest accounted for about 57.96% and 22.53% of the total reduction, respectively. During 2005-2010, the total reduction of NPP was 0.034TgC, cropland and forest accounted for 29.98% and 84.99% of the total reduction, respectively; it's worth noting that the conversion from wetland and unused land to urban land increased NPP. The encroachment of cropland and forest will threaten the food security, ecosystem functions and biodiversity. In terms of spatial distribution, the losses of NPP occurring in urban and peri-urban areas accounted for 89.63% and

75.04%, respectively, which was primarily a result of the massive vegetation with high productivity being replaced with impervious surfaces during the rapid urbanization process. Our results have important implications for predicting the long-term eco-environmental impacts, urban planning and management, local food security and maintaining the carbon balance of urban ecosystems in the face of accelerating urbanization and future climate changes.

## Acknowledgments

This work was funded by the project of the National Natural Science Foundation of China (41171446, 31170445). Special thanks to the reviewers for their helpful comments and suggestions.

## References

- Alberti, M., 2005. The effects of urban patterns on ecosystem function. *Int. Reg. Sci. Rev.* 28, 168-192.
- Burke, I.C., Kittel, T.G.F., Lauenroth, W.K., Snook, P., Yonker, C.M., Parton, W.J., 1991. Regional analysis of the Central Great Plains. *Bioscience*. 41, 685-692.
- Buyantuyev, A., Wu, J.G., 2009. Urbanization alters spatiotemporal patterns of ecosystem primary production: a case study of the Phoenix metropolitan region, USA. *J. Arid Environ.* 73, 512-520.
- Buyantuyev, A., Wu, J.G., Gries C., 2010. Multiscale analysis of the urbanization pattern of the Phoenix metropolitan landscape of USA: Time, space and thematic resolution. *Landscape Urban Plan.* 94, 206-217.
- Chen, J., Zhou L., Shi, P.J., Ichinose, T., 2003. The study on urbanization process in China based on DMSP/OLS data: development of a light index for urbanization level estimation. *J. Remote Sens.* 7, 168-175.
- Chen, Y.J., Guan, D.S., Peart, M.R., 2006. Impacts of rapid urbanization on carbon fixing and oxygen production of vegetation in the Pearl River Delta. *Acta Sci. Nat. Univ. Sunyatseni.* 45, 98-102.
- DeFries, R.S., Field, C.B., Fung, I., Collatz, G.J., Bounoua, L., 1999. Combining satellite data and biogeochemical models to estimate global effects of human-induced land cover change on carbon emissions and primary productivity. *Global. Biogeochem. Cy.* 13, 803-815.
- Field, C. B., 2001. Global change-Sharing the garden. *Science.* 294 (5551), 2490-2491.
- Field, C.B., Behrenfeld, M.J., Randerson, J.T., Falkowski, P., 1998. Primary production of the biosphere: integrating terrestrial and oceanic components. *Science.* 281, 237-240.
- Gregg, J.W., Jones, C.G., Dawson, T.E., 2003. Urbanization effects on tree growth in the vicinity of New York City. *Nature.* 424, 183-187.
- He, C.Y., Li, J.G., Chen, J., Shi, P.J., Pan, Y.Z., Li, J., Zhuo, L., Ichinose, T., 2005. The urbanization model and process in Bohai sea surrounding area in the 1990s by using DMSP/OLS data. *Acta Geogr. Sin.* 60, 409-417.
- Hicke, J.A., Asner, G.P., Randerson, J.T., Tucker, C., Los, S., Birdsey, R., Jenkins, J.C., Field, C., 2002. Trends in North American net primary productivity derived from satellite observations, 1982-1998. *Global. Biogeochem. Cy.* 16, 1-14.
- Houghton, R.A., Hackler, J.L., Lawrence, K.T., 1999. The U.S. carbon budget contributions from land-use change. *Science.* 285, 574-578.
- Huang, J.Y., Zhou, Q.M., Wu, Z.F., 2012. Recognition of Urban Fringe Area based on Remote sensing image: A Case Study of Guangzhou-Foshan Metropolitan Area. *Proceedings of the 33<sup>rd</sup> Asian Conference on Remote Sensing*, Nov 26-30: Pattaya, Thailand.
- Imhoff, M.L., Bounoua, L., DeFries, R., Lawrence, W.T., Stutzer, D., Tucker, C.J., Ricketts, T., 2004. The consequences of urban land transformation on net primary productivity in the United States. *Remote Sens. Environ.* 89, 434-443.
- Imhoff, M.L., Lawrence, W.T., Stutzer, D.C., 1997. A technique for using composite DMSP/OLS 'city lights' satellite data to accurately map urban areas. *Remote Sens. Environ.* 61, 361-370.
- Imhoff, M.L., Tucker, C.J., Lawrence, W.T., Stutzer, D.C., 2000. The use of multi source satellite and geospatial data to study the effect of urbanization on primary productivity in the United States. *IEEE. T. Geosci. Rem.* 38, 2549-2556.

- Kang, T.T., Gao, P., Ju, W.M., Huang, J.L., 2014. The spatial and temporal variations of maximum light use efficiency and possible driving factors of croplands in Jiangsu province. *Acta. Ecol. Sin.* 34, 410-420.
- Li, X., Yeh, A., 2004. Analyzing spatial restructuring of land use patterns in a fast growing region using remote sensing and GIS. *Landscape Urban Plan.* 69, 335-354.
- Liao, S.B., Li, Z.H., Yong, S.C., 2003. Comparison on methods for rasterization of air temperature data. *Resour. Sci.* 25, 83-88.
- Liu, J.S., Chen H., Yang S.Y., Wang W., Xiang, Y., Zhao, C., 2009. Comparison of interpolation methods on annual mean precipitation in Hebei Province. *Acta. Ecol. Sin.* 29, 3493-3500.
- Liu, M.L., 2001. Land-use/land-cover change and terrestrial ecosystem phytomass carbon pool and production in China. Ph.D. Thesis. Chinese Academy of Sciences. pp. 96-111.
- Lobell, D.B., Hicke, J.A., Asner, G.P., Field, C.B., Tucker, C.J., Los, S.O., 2002. Satellite estimates of productivity and light use efficiency in United States agriculture, 1982-98. *Glob. Change Biol.* 8, 722-735.
- Lu, D.S., Xu, X.F., Tian, H.Q., Moran, E., Zhao, M.S., Running, S., 2010. The effects of urbanization on net primary productivity in Southeastern China. *Environ. Manage.* 46, 404-410.
- Lu, J.L., Liang, S.L., Liu, J., 2012. Study on estimation of forest biomass and storage of Shanxi province. *Chinese. Agr. Sci. B.* 28, 51-56.
- Luo, T.X., 1996. Patterns of net primary productivity for Chinese major forest types and their mathematical models, Ph.D. Thesis. Chinese Academy of Sciences. pp. 45-170.
- McDonnell, M.J., Pickett, S.T.A., Groffman, P., Bohlen, P., Pouyat, R.V., Zipperer, W.C., Parmelee, R.W., Carreiro, M.M., Medley, K., 1997. Ecosystem progress along an urban-to-rural gradient. *Urban. Ecosys.* 1, 21-36.
- Milesi, C., Elvidge, C.D., Nemani, R.R., Running, S.W., 2003. Assessing the impact of urban land development on net primary productivity in the southeastern United States. *Remote Sens. Environ.* 86, 401-410.
- Nizeyimana, E., Petersen, G.W., Imhoff, M.L., Sinclair, H.R., Waltman, S.W., Reed-Margetan, D.S., Levine, E.R., Russo, J.M., 2001. Assessing the impact of land conversion to urban use on soils with different productivity levels in the USA. *Soil Sci. Soc. Am. J.* 65, 391-402.
- Oke, T.R., Crowther, J.M., McNaughton, K.G., Monteith, J.L., Gardiner, B., 1989. The micrometeorology of the urban forest[and discussion]. *Phil. Trans. R. Soc. Lond. B.* 324, 335-349.
- Pei, F.S., Li, X., Liu, X.P., Wang, S.J., He, Z.j., 2013. Assessing the differences in net primary productivity between pre- and post-urban land development in China. *Agr. Forest Meteorol.* 4, 174-186.
- Piao, S.L., Fang, J.Y., Guo, Q.H., 2001. Application of CASA model to the estimation of Chinese terrestrial net primary productivity. *Acta. Phytoecol. Sin.* 25, 603-608.
- Pimm, S. L., Raven, P., 2000. Biodiversity-Extinction by numbers. *Nature.* 403, 843-845.
- Potter, C.S., Randerson, J.T., Field, C.B., Matson, P.A., Vitousek, P.M., Mooney, H.A., Klooster, S.A., 1993. Terrestrial ecosystem production: a process model based on global satellite and surface data. *Global. Biogeochem. Cy.* 7, 811-841.
- Ran, Y., Li, X., 2011. Plant functional types map in China. Cold and Arid Regions Science Data Center at Lanzhou. doi:10.3972/westdc.001.2013.db.
- Shu, S., Yu, B.L., Wu, J.P., Liu, H.X., 2011. Methods for deriving urban built-up area using night-light data: assessment and application. *Remote Sens. Technol. Appl.* 26, 170-176.
- Sun, C., Wu, Z.F., Lv, Z.Q., Yao, N., Wei, J.B., 2013. Quantifying different types of urban growth and the change dynamic in Guangzhou using multi-temporal remote sensing data. *Int. J. Appl. Earth Obs. Geoinform.* 21, 409-417.
- Tian, G.J., Qiao, Z., 2014. Assessing the impact of the urbanization process on net productivity in China in 1989-2000. *Environ. Pollut.* 184, 320-326.
- Tao, B., Li, K.R., Shao, X.M., Cao, M.K., 2003. Temporal and spatial pattern of net primary production of terrestrial ecosystems in China. *Acta. Geogr. Sin.* 58, 372-380.
- Vitousek, P.M., Mooney, H.A., Lubchenco, J., Melillo, J.M., 1997. Human domination of Earth's ecosystems. *Science,* 277, 494-499.
- Wen, J.S., Ge, Y., Jiao, L., Deng, Z.P., Peng, C.H., Chang, J., 2010. Does urban land use decrease carbon sequestration? A case study in Taizhou, China. *Chin. J. Plant Ecol.* 34, 651-660.
- Wen, X.H., Shang, K.Z., Wang, S.G., Yang, D.B., Fan, W.Y., 2008. Primary study on regional characteristics of solar radiation in China during 1961-2000. *J. Desert. Res.* 28, 554-561.
- Xu, C., Liu, M., An, S., Chen, J.M., Yan, P., 2007. Assessing the impact of urbanization on regional net primary productivity in Jiangyin County, China. *J. Environ. Manage.* 85, 597-606.

- Yang, Y., He, C.Y., Zhao, Y.Y., Li, T., Qiao, Y.W., 2011. Research on the layered threshold for extracting urban land using the DMSP/OLS stable nighttime light data. *J. Image Graph.* 16, 666-672.
- Yu, D.Y., Shao, H.B., Shi, P.J., Zhu, W.Q., Pan, Y.Z., 2009. How does the conversion of land cover to urban use affect net primary productivity? a case study in Shenzhen city, China. *Agr. Forest Meteorol.* 149, 2054-2060.
- Zhang, X.S., 1989. The potential evapotranspiration (PE) index for vegetation and vegetation-climatic classification (2)- an introduction of main methods and PEP program. *Acta Phytoecol. Et. Geobot. Sin.* 13, 197-207.
- Zhou, G.S., Zhang, X.S., 1995. A natural vegetation NPP model. *Acta Phytoecol. Sin.* 19, 193-200.
- Zhou, G.S., Zhang, X.S., 1996. Study on climate-vegetation relationship. *Acta Phytoecol. Sin.* 20, 113-119.
- Zhu, L.F., Tian, Y.Z., Yue, T.X., Fan, Z.M., Ma, S.N., Wang, Y.A., 2005. Simulation of solar radiation on ground surface based on 1km grid cells. *Transactions of the CSAE.* 21, 16-19.
- Zhu, W.Q., Pan, Y.Z., He, T., Yu, D.Y., Hu, H.B., 2006. Simulation of maximum light use efficiency for some typical vegetation types in China. *Chinese. Sci. Bullet.* 51, 457-463.
- Zhu, W.Q., Pan, Y.Z., Zhang, J.S., 2007. Estimation of net primary productivity of Chinese terrestrial vegetation based on remote sensing. *Chinese. J. Plant Ecol.* 31, 413-424.