

# Net primary productivity (NPP) dynamics and associated urbanization driving forces in metropolitan areas: a case study in Beijing City, China

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## Abstract

*Context* Eco-environmental effects of urbanization are a focus in landscape ecology.

*Objective* The influences of population, economic and spatial development during the urbanization process in Beijing City, China on net primary productivity (NPP) were analyzed. The responding mechanism of NPP in different urbanization stages was also examined to develop advice about eco-environmental sustainability of urban development.

*Methods* Using the Carnegie Ames Stanford Approach model, we estimated NPP. Using linear regression and polynomial regression analysis, we analyzed NPP responses to stages of urbanization.

*Results* High NPP areas were located in northeast Yanqing, northwest Miyun, northern Huairou and Pinggu. The distribution of NPP generally occurred in the following order from high NPP to low NPP: outer suburbs, inner suburbs, encircled city center, and inner city. Because of the heat island effect in winter, the estimated NPP in the encircled city center and inner

city was higher in 2009 than in 2001. There was a negative correlation between NPP and both economic and spatial urbanization, but an increase in population did not necessarily lead to an immediate decrease in NPP. An analysis of NPP dynamics in five kinds of urban development zones showed that urbanization resulted in a lasting and observable loss of NPP over time and space, although there was some promotion of NPP in highly urbanized zones.

*Conclusion* There are three stages in the response of NPP to urbanization: damage stage, antagonistic stage, and coordination stage. The stage threshold depends on local eco-environmental management and urban planning interventions.

**Keywords** NPP dynamics · Urbanization process · Impervious surface area · Beijing City, China

## Introduction

Urbanization, which is the most significant feature of human development since 20th century, refers to a population shift from rural to urban areas. Urbanization includes at least three aspects: migration, economic development, and spatial expansion (Li et al. 2013a, b; Liu et al. 2014). As a result of migration and economic development, urban land cover has been significantly changed, which integrally has had a dramatic impact on regional ecosystems (Wu et al.

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2014a). Urbanization changes biogeochemical cycles, soil quality and biodiversity (Islam and Weil 2000; Crist et al. 2000; He et al. 2014), as well as reconstructs the water, heat, and carbon balances of regional ecosystems (Chen et al. 2009; Sun and Chen 2012; Zhang et al. 2012). Therefore, the study of changes in urban landscape patterns during urbanization and their ecological impacts have become an important topic for clarifying the interactions between population growth, economic development, landscape transformation and their ecological effects (Imhoff et al. 2004). Net primary productivity (NPP) directly reflects the production capacity of vegetation and is the basis of organic material and energy cycles in the global ecosystem (Field et al. 1998; Houghton et al. 1999; Field 2001). NPP is usually defined as “NPP = Photosynthesis – Respiratory action” or “NPP = Plant growth + Litterfall” (Lieth and Whitaker 1975). The formation of NPP is a typical natural ecosystem function and can effectively indicate the ecological response of urbanization. The land cover transformations into townscapes from rural landscapes can usually result in an overall decline of NPP (DeFries et al. 1999; Wu et al. 2014b; Lu et al. 2015).

However, there are some controversies regarding this reasoning. Imhoff et al. (2000) found that urbanization of areas in poor natural conditions improved photosynthetic productivity, and Milesi et al. (2003) suggested that concentrated urban forest planning could alleviate the decrease in NPP. Imhoff et al. (2004) showed that the amount of NPP significantly increased in cold-region urbanized areas in winter. Buyantuyev and Wu (2009) found that the productivity of vegetation in urbanized areas could be improved by introducing high-productivity populations of vegetation, carrying out artificial cultivation, and fertilization. Therefore, the environmental problems resulting from urbanization may be phasic. To identify differences in the stages of urbanization, it is necessary to recognize that urbanization is not just land construction. It often involves complex internal mechanisms, such as towns changing to streets and villages changing to communities (Li et al. 2012b). However, present studies often lack a comprehensive measure associated with NPP relating to population urbanization and economic urbanization, and ignore any phasic differences in NPP at the different stages of urbanization.

Metropolitan areas are ideal for investigating the ecological effects of urbanization, given that the rate

of urbanization and size of the affected area are often high and their ecological impacts are prominent. Also, because of the large spatial extent of such areas, there are often more significant urbanization differences inside a metropolitan area (Tian et al. 2010). The urbanization differences can be utilized in quantifying the ecological effects of urbanization not only at the same point in time, but also along the same time series. China, which experienced fast urbanization in the recent 30 years, has suffered significant negative impacts on NPP, even in the centers of cities (Xu et al. 2007; Tan et al. 2015). As a metropolitan center, Beijing City is the capital of China. The large-scale increase in construction over the past two decades has promoted significant economic development and population growth, resulting in great demand for construction land. The urbanization of Beijing City has led to a decrease in the amount of natural landscapes and an increase in mixed-use areas. The negative effect on NPP in the urbanization of Beijing City should be highlighted.

In this study, we used Beijing City as a case study area to clarify the dynamic changes in NPP from 2001 to 2009 and associated driving mechanisms of urbanization. Our objectives were to: (i) estimate NPP using the CASA model and clarify temporal and spatial changes of NPP; (ii) investigate the relationships between NPP and spatial urbanization, economic urbanization, and population urbanization using linear and nonlinear regressions; and (iii) reveal the effect of different urbanization stages on NPP in Beijing City.

## Study area and data

### Study area

Beijing City is located in the northwest of the North China Plain, boarded by the Huanghuaihai Plain to the south, the Yanshan Mountains and Inner Mongolia plateau to the north, the Taihang Mountains to the west, and the Songliao plain to the northeast. It is an area of 16,807.8 km<sup>2</sup> that crosses 115°25′–117°30′E and 39°28′–41°05′N. Beijing City has a typical warm subhumid continental monsoon climate, with four seasons: a dry and windy spring, a hot and rainy summer, a sunny and mild autumn, and a cold and snowy winter. As a result of the vertical differentiation in terms of the terrain, water, heat and soil types, there

are different vegetation zones associated with elevation.

Since the 1980s, the economy in Beijing City has developed rapidly, with substantial population growth resulting in the merger of the suburbs with the city center. In addition, industry and manufacturing businesses have moved to the suburbs. At present, there are four kinds of functional area in Beijing City: (i) the city center; (ii) expanding areas; (iii) new development areas; and (iv) biological conservation areas.

#### Data source

Data sources were as follows: (i) LANDSAT images 20010831R123L32, 20010831R123L33, 20090922R123L32 and 20090922R123L33 from 2001 and 2009, supplied by Chinese Academy of Sciences; (ii) a SPOT/VGT image every 10 days from 2001 and 2009; (iii) vegetation types in Beijing (1:1,000,000), used to calculate photosynthetic radiation and maximum light-energy utilization; (iv) meteorological data supplied by the Chinese meteorological data-sharing service (<http://cdc.cma.gov.cn/>), including the highest, lowest and average temperatures, rainfall and sun radiation daily from Beijing meteorological stations; (v) data relating to population, manufacture and GDP in 16 counties within Beijing City from 2001 and 2009 from the *Beijing Statistics Yearbook*, *Beijing Economy and Social Development Statistical Bulletin*, and Beijing Statistical Information Net (<http://www.bjstats.gov.cn/>); (vi) borders of the administrative districts and data of natural elements e.g. river and water areas in the form of Arc/INFO Coverage; and (vii) the grain yield at a county scale from the *Beijing Statistics Yearbook*, and the NPP Product of MOD17A3H estimated by Moderate Resolution Imaging Spectroradiometer (MODIS) images ([https://lpdaac.usgs.gov/dataset\\_discovery/modis/modis\\_products\\_table](https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table)).

In the data processing, the 10-day SPOT/VGT NDVI was combined into monthly images using the maximum value composite, with a spatial resolution of 1 km. Then the NDVI of LANDSAT images was extracted, with a spatial resolution of 30 m. Using the image sharpening method in ENVI 5.0 (Vijayaraj et al. 2006), the SPOT/VGT NDVI had been down-scaled to 30 m by merging the texture of LANDSAT NDVI, which made the data acceptable for city scale analysis.

## Methods

### Estimating NPP using the CASA model

The NPP estimation model can be divided into three components, i.e. a statistical-model, process-model, and parameter-model. The parameter model is better suited to large areas than to small areas (Field et al. 1995). In 1972, Monteith was the first to estimate NPP through absorbed photosynthetic active radiation (APAR) and efficiency of light energy utilization. He also suggested taking the effect of water, temperature and nutrition into account. Potter et al. (1993) put forward the Carnegie Ames Stanford Approach model based on GIS and RS, and studied the spatial distribution of global terrestrial NPP and net ecosystem production using this model. Ruimy and Saugier (1994) assigned efficiencies of light in different ecosystems based upon the original CASA model, which has become an important means of using remote sensing to monitor NPP dynamics because of the operability of parameter gain and the applicability of representing the annual change in NPP (Field et al. 1995; Paruelo et al. 1997; Bradford et al. 2005).

NPP is determined by APAR and the efficiency of light energy utilization in the CASA model. Photosynthetically active radiation is a driving force of plant photosynthesis, and APAR represents part of the absorbed vegetation canopy. Efficiency of light energy utilization ( $\varepsilon$ ) is the ratio of the potential chemical energy in dry production to the photosynthetic effective radiation energy of a leaf in a certain period per unit area. APAR is determined by solar radiation and FPAR (Fraction of Photosynthetic Active Radiation), whereas efficiency of light energy utilization is determined by the temperature stress coefficient, the water stress coefficient, and the maximum efficiency of light energy utilization (Los 1998; Zhu et al. 2006). NPP was calculated using the following formulae:

$$NPP(x, t) = APAR(x, t) \times \varepsilon(x, t)$$

$$APAR(x, t) = SOL(x, t) \times FPAR(x, t) \times 0.5$$

$$FPAR(x, t) = \alpha FPAR_{NDVI} + (1 - \alpha) FPAR_{SR}$$

$$SR(x, t) = \frac{1 + NDVI(x, t)}{1 - NDVI(x, t)}$$

$$FPAR(x, t) = \frac{(NDVI(x, t) - NDVI_{i, \min})}{(NDVI_{i, \max} - NDVI_{i, \min})} \times (FPAR_{\max} - FPAR_{\min}) + FPAR_{\min}$$

$$FPAR(x, t) = \frac{(SR(x, t) - SR_{i, \min})}{(SR_{i, \max} - SR_{i, \min})} \times (FPAR_{\max} - FPAR_{\min}) + FPAR_{\min}$$

$$\varepsilon(x, t) = T_{\varepsilon 1}(x, t) \times T_{\varepsilon 2}(x, t) \times W_{\varepsilon}(x, t) \times \varepsilon_{\max}$$

$$T_{\varepsilon 1}(x, t) = 0.8 + 0.02T_{opt}(x, t) - 0.0005[T_{opt}(x, t)]^2$$

$$T_{\varepsilon 2}(x, t) = 1.1814 / \{1 + e^{[0.2(T_{opt}(x, t) - T(x, t) - 10)]}\} \times 1 / \{1 + e^{[0.3(-T_{opt}(x, t) - T(x, t) - 10)]}\}$$

$$W_{\varepsilon}(x, t) = 0.5 + 0.5E(x, t) / E_p(x, t)$$

where  $NPP(x, t)$  is  $NPP$  ( $\text{gC m}^{-2} \text{ month}^{-1}$ );  $APAR(x, t)$  is effective radiation ( $\text{gC m}^{-2} \text{ month}^{-1}$ );  $\varepsilon(x, t)$  is the actual light energy utilization ( $\text{gC MJ}^{-1}$ );  $x$  is the position in space;  $t$  is the study period;  $SOL(x, t)$  is solar radiation ( $\text{MJ m}^{-2} \text{ month}^{-1}$ ), referring to the average value of northern China;  $FPAR(x, t)$  is the fraction of the incoming solar radiation in the photosynthetically active radiation spectral region that is absorbed by a photosynthetic organism; '0.5' is the ratio of effective radiation to the total solar radiation;  $SR_{i, \min}$  and  $SR_{i, \max}$  represent the maximum and the minimum NDVI simple ratio SR, respectively;  $FPAR_{\min} = 0.001$ ,  $FPAR_{\max} = 0.95$ , and  $\alpha$  is 0.5;  $T_{\varepsilon 1}(x, t)$  and  $T_{\varepsilon 2}(x, t)$  represent the temperature stress coefficient;  $W_{\varepsilon}(x, t)$  represents the water stress coefficient;  $\varepsilon_{\max}$  represents the highest efficiency of light energy utilization,  $\text{gC MJ}^{-1}$  (Zhu et al. 2007).  $T_{opt}(x, t)$  is the average temperature when NDVI peaks.  $T_{\varepsilon 1}(x, t)$  is 0 if the average temperature is at or below  $-10^\circ$ ; and  $T_{\varepsilon 2}(x, t)$  is the half of the  $T_{\varepsilon 2}(x, t)$  value when the optimum temperature is equal to the average temperature, if the average temperature is  $10^\circ$  above or  $13^\circ$  below the optimum temperature.  $E(x, t)$  represents actual evapotranspiration (mm); and  $E_p(x, t)$  represents the potential evapotranspiration (mm) (Zhou and Zhang 1996).

### Characterizing urbanization

Urbanization can be characterized by people, finance aggregation, and the expansion of dwellings. Therefore, this study quantitatively analyzed the urbanization

process as population urbanization, economic urbanization, and spatial urbanization. Population urbanization and economic urbanization were quantified through the index of population density and GDP per capita, and the indicators to analyze spatial urbanization were impervious surface area (ISA).

Impervious surface area was also used to represent the intensity of urban spatial expansion on sub-pixel scale. ISA extracted by a vegetation-impervious surface soil (V-I-S) model is a type of continuous spatial data that can be used to comprehensively measure urban land-use intensity and magnitude dynamics on a gradient. ISA usually is extracted using a linear spectral mixture model (LSMM) for spectral mixture analysis. Linear trends models, which have been widely used, are preferred to nonlinear trends models, because of the simple calculations involved (Wu and Murray 2003; Small 2004):

$$R = \sum_{i=1}^n f_i R_{ij} + e_i, \quad f_i \geq 0; \quad \sum_{i=1}^n f_i = 1, \\ i = 1, 2, 3, \dots, n; \quad j = 1, 2, 3, \dots, p$$

where  $R_i$  represents the pixel reflectivity when the band is  $i$ ;  $i$  represents the spectral band;  $p$  represents the number of end members;  $R_{ik}$  represents the end member  $k$ 's reflectivity of band  $i$ ; and  $e_i$  represents the error of band  $i$ . In the study, the number of end members was 3, representing vegetation, imperviousness, and soil, respectively (Ridd 1995).

To test the validity and accuracy of the model, the study analyzed the error of ISA by root-mean-square error (RMSE). The calculating expressions were as follows:

$$RMSE = \sqrt{\left( \sum_{i=1}^m \varepsilon_{in}^2 \right) / m},$$

where  $RMSE$  represents the mean square covariance error, which is a measure of differences between the values predicted and the values observed;  $\varepsilon_{in}$  is the residual of pixel  $i$  when the band is  $n$ , and  $m$  represents the number of pixels. After inspection, the average RMSE of Beijing inner city in 2001 and 2009 was 0.021 and 0.018, respectively. The RMSE of Beijing suburbs in 2001 and 2009 were 0.025 and 0.012, respectively. As all RMSE values were less than 0.1, the ISA model could be regarded to be of acceptable accuracy (Liu et al. 2013).

## Analyzing the correlations between NPP variation and urbanization

The statistical measurement of urbanization is usually based on administrative units. Thus, focusing on population urbanization and economic urbanization, the statistical analysis of Beijing administrative units can better reflect the municipal regulation of urbanization. A large number (181) of township units in Beijing City were selected for evaluation in this study. The northern and southwestern mountain areas have a low level of urbanization whose ISA is  $<0.2$ . In this study, we used areas for which the average ISA of the villages and towns was  $>0.20$  to analyze NPP dynamics related to population urbanization, economic urbanization, and spatial urbanization.

As a common research technique in geography and macroscopic ecology, replacing the different time periods with the spatial differences for multi-temporal data can reduce the shortage of time length. The developmental stage determines the spatiotemporal diversity of urbanization and NPP. Therefore, the first task was to divide the study area into relevant urban development types and stages. We used the method of “trading space for time” to represent different developmental stages in Beijing City by different urban development zones. That is to say, the study area was divided into different urban development types based on state values (ISA2001, ISA2009) and rate of change values (ISA2009/2001). Three classes of “high”, “middle” and “low” values were combined from ISA using every two adjacent thresholds of Fig. 1. Urban development usually accompanies a change from a less urbanized zone to a more urbanized zone, and in Beijing City the more urbanized zone scarcely changed to a less urbanized zone. For example, low and middle classes in 2001 increased to high class in 2009, while high class in 2001 seldom decreased to middle or low class in 2009. Thus, Beijing City was divided into five zones (Fig. 2): (i) highly urbanized zone with low development speed (HUZLDS), namely a zone that remained high class from 2001 to 2009; (ii) moderately urbanized zone with high development speed (MUZHDS), namely a zone that advanced from middle class in 2001 to high class in 2009; (iii) moderately urbanized zone with low development speed (MUZLDS), namely a zone that remained middle class from 2001 to 2009; (iv) lowly urbanized

zone with high development speed (LUZHDS), namely a zone that advanced from low class in 2001 to middle or high class in 2009; and (v) lowly urbanized zone with low development speed (LUZLDS), namely a zone that remained low class from 2001 to 2009. According to this division, the urbanization process of 181 township units during 2001–2009 was identified and mapped (Fig. 2). Based on these divisions, we selected 450 sample points at random in the study area, calculated ISA and NPP in a 1-km grid, analyzed the relation between ISA and NPP, and further investigated the influence of the spatial urbanization process on NPP.

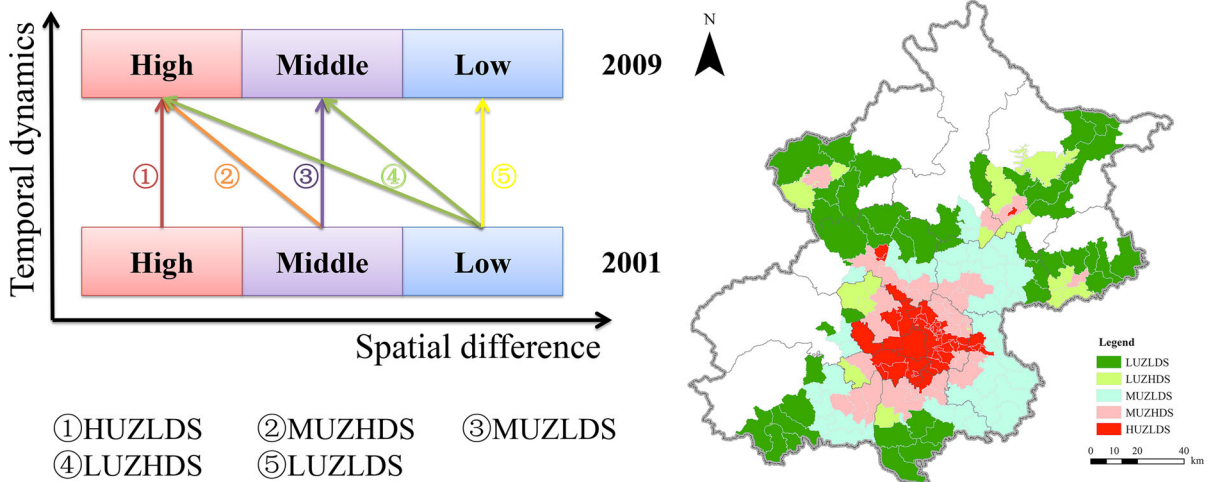
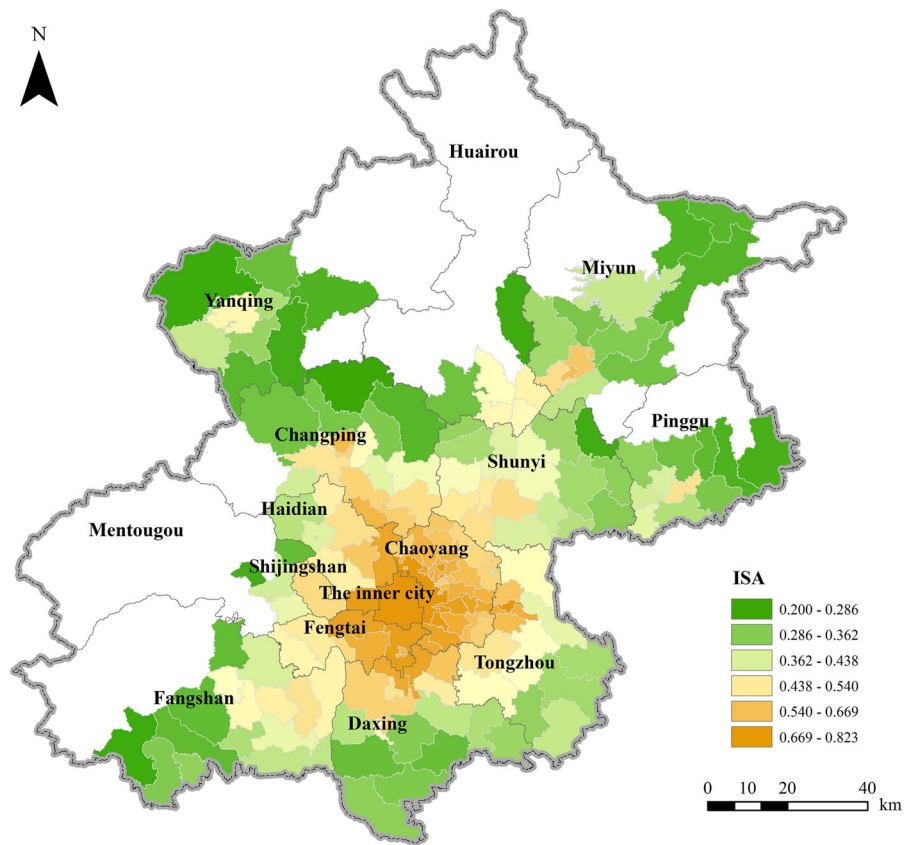
## Results

### Spatial–temporal dynamics of NPP

Figure 3 shows that the average NPP of Beijing City in 2001 was  $505 \text{ gC m}^{-2}$ , and  $447 \text{ gC m}^{-2}$  in 2009. The spatial pattern of unit NPP was uneven, and the order of NPP from high to low levels was woodland areas in the north and northeast, the southwest mountain area, and plains and urban centers. Highest-value NPP (higher than  $515 \text{ gC m}^{-2}$ ) was found in woodland, which included deciduous and coniferous forests, shrub, and shrub-grassland, located in the important biological conservation area of Beijing City. Mid-value NPP ( $180\text{--}515 \text{ gC m}^{-2}$ ) was found in crop-growing areas, which included farmland, woodland in towns, meadows and orchards, located in southeast Fangshan, eastern and southern Daxing and Tongzhou, most of Shunyi, southeastern Changping, and Yanqing. Low-value NPP (lower than  $180 \text{ gC m}^{-2}$ ) was found in areas dominated by urban landscape, with only a few green spaces.

Figure 4 details the changes in NPP from 2001 to 2009. The average unit NPP in the outer suburban areas in 2001 and 2009 was both above  $470 \text{ gC m}^{-2}$ , but declined sharply by 2009. The estimated NPP in Huairou decreased the most, from  $642 \text{ gC m}^{-2}$  in 2001 to  $495 \text{ gC m}^{-2}$  in 2009, whereas NPP in Yanqing and Miyun decreased, respectively, from  $588$  to  $457 \text{ gC m}^{-2}$  and from  $604$  to  $472 \text{ gC m}^{-2}$ . The estimated NPP in Changping, Tongzhou, Shunyi, and Daxing also decreased, of which the biggest decrease was  $87 \text{ gC m}^{-2}$  (from  $521$  to  $434 \text{ gC m}^{-2}$  in Changping), and the smallest variation (in Daxing) was just

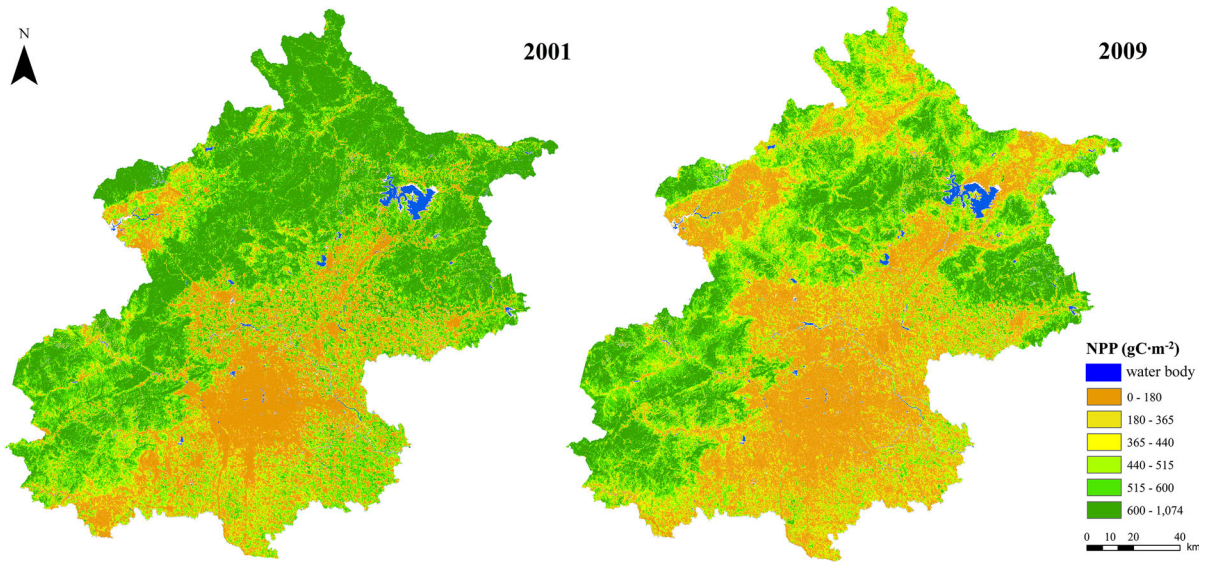
**Fig. 1** Map of the study area showing the levels of urbanization classified according to impervious surface area fraction in 2009



**Fig. 2** Methods of determining the division of urbanization types (*left*), and their spatial patterns (*right*) in Beijing City

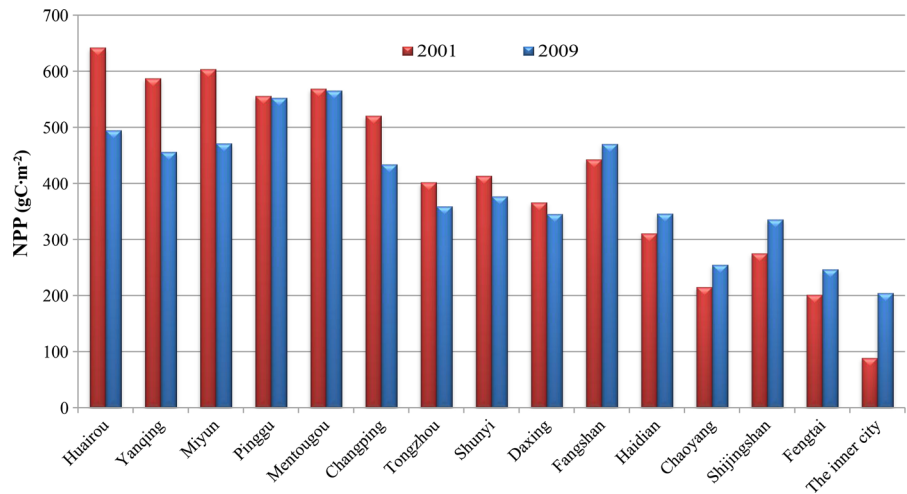
21 gC m<sup>-2</sup>. In contrast, the estimated NPP in all city center locations increased. In terms of the degree of NPP increase, the biggest increase was from 89 to 205 gC m<sup>-2</sup> in the inner city from 2001 to 2009. The

pattern overall shows that the order of the dynamic changes in yearly NPP from high to low was, in turn, outer suburbs, inner suburbs, encircle the city center, and inner city.



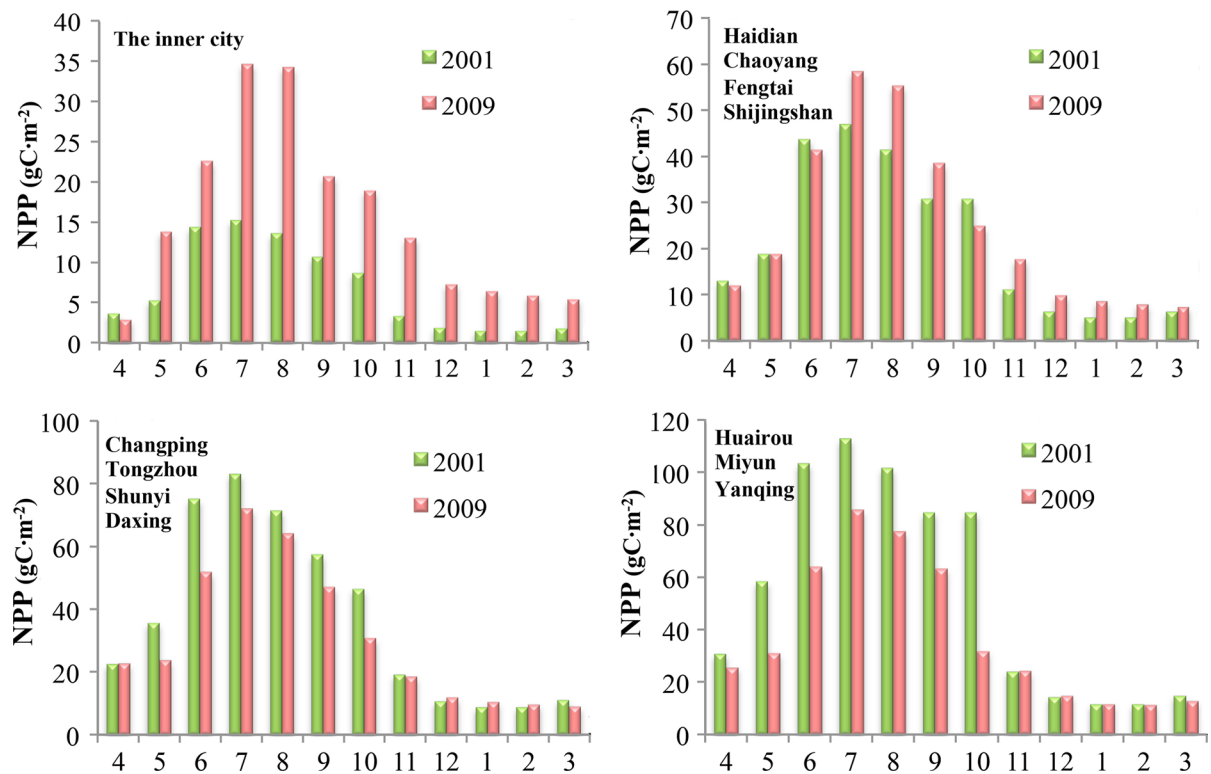
**Fig. 3** Spatial pattern of NPP in Beijing City

**Fig. 4** Variation in NPP from 2001 to 2009 in Beijing City



As shown in Fig. 5, the inverted U-shaped volatility of mensal changes demonstrated that NPP dynamics correlated with the monthly water and heat status of the temperate continental climate, being highest in summer (accounting for 64.65 and 62.88 % of total annual NPP in 2001 and 2009, respectively) and lowest in winter (accounting for 8.93 and 11.00 % of total annual NPP in 2001 and in 2009, respectively). Summer and autumn (April to November) levels of NPP in 2009 were lower than in 2001, but there was no difference in winter and spring NPP levels (December to May) between the 2 years.

But the annual change was not greater than that in summer and autumn (April to November). From the view of monthly change in different regions, the NPP changes were mainly from May to October in the outer suburbs, decreasing from 53 to 20 gC m<sup>-2</sup>; however, the changes from May to October in the inner suburbs were lower than those in the outer suburbs, even if the inner suburbs were the area experiencing urban development most rapidly. The monthly changes in the encircled center and inner city were mainly rising. The main growth in the encircled center was concentrated in July and August,



**Fig. 5** Variation in NPP from January to December in 2001 and 2009 in different counties in Beijing City

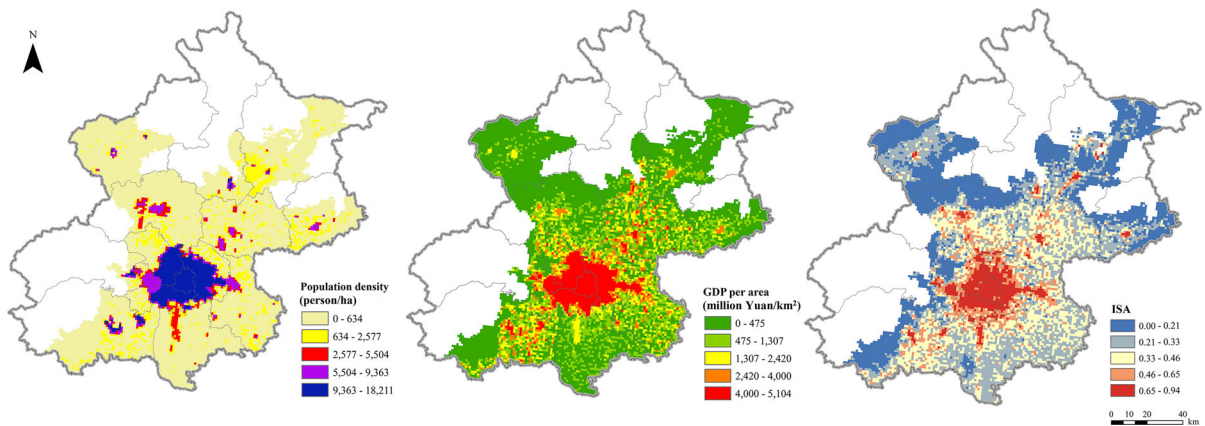
(11.6 and  $13.9 \text{ gC m}^{-2}$ , respectively), and the changes from November to February in the encircled center were more obvious than in the inner suburbs. At the same time, the monthly NPP in the inner city increased significantly (by more than 100 % both from May to August and from November to February). Interestingly, compared with the overall decline in NPP during the winter (December to March), NPP increased closer to the city center despite the increased level of urbanization. This could be explained by the heat island effect, whereby the buildings maintain the temperature at a level higher than in less urbanized areas (Imhoff et al. 2004, 2010).

#### Spatial patterns of urbanization

From 2001 to 2009, GDP in Beijing City increased by 10 %, presenting exponential growth trend, while there was an increasing linear trend in population, from 13,851,000 in 2001 to 17,550,000 in 2009. Compared to GDP in 2001 (281.77 billion yuan), the GDP in 2009 increased four times; meanwhile, compared to per

capita GDP in 2001 (25,300 yuan), the per capita GDP in 2009 increased about three times. Population urbanization and economic urbanization showed spatial characteristics similar to those of spatial urbanization (Fig. 6), with a decreasing trend from the city center to more peripheral areas. In addition, the high-value zones of population urbanization, economic urbanization, and spatial urbanization were almost identical, mainly distributed in the inner city, encircled center, and built-up areas of surrounding counties. However, the polarization of population distribution were marked, with  $>93.63$  person/ha in highly concentrated areas in 2001, but  $<6.34$  person/ha in low-concentration areas. Moreover, the spatial polarization characteristics of economic urbanization were significant. For example, the central town was the most important economic development zone in Beijing City, with a GDP of  $>40$  million Yuan/ $\text{km}^2$ ; by contrast, southeastern Tongzhou, northeastern Shunyi, southwestern Fangshan and northwestern Changping were the important expanding zones, with a GDP  $<40$  million Yuan/ $\text{km}^2$ , although they could be seen as representing the suburb urbanization process.





**Fig. 6** Spatial patterns of urbanization in Beijing City. The figure shows the mean population density, GDP per area, and ISA in 2001

From 2001 to 2009, the amount of urban built-up land in Beijing City expanded rapidly from 1398.36 to 2204.42 km<sup>2</sup>. Of the various land use types that changed to construction land, farmland was the most affected, with 560.19 km<sup>2</sup> being converted. Simultaneously, the average ISA increased from 24.44 % in 2001 to 29.28 % in 2009. In particular, the average ISA of the central city increased from 52.42 % in 2001 to 61.45 % in 2009, which showed the gradual increase in the density of construction in the central city of Beijing. In addition, from 2001 to 2009, the amount of urban sprawl decreased gradually from the center to the periphery. Urban construction land expanded significantly and green land reduced markedly, which indicated that the urbanization “hot spots” were moving from the central city to the suburbs.

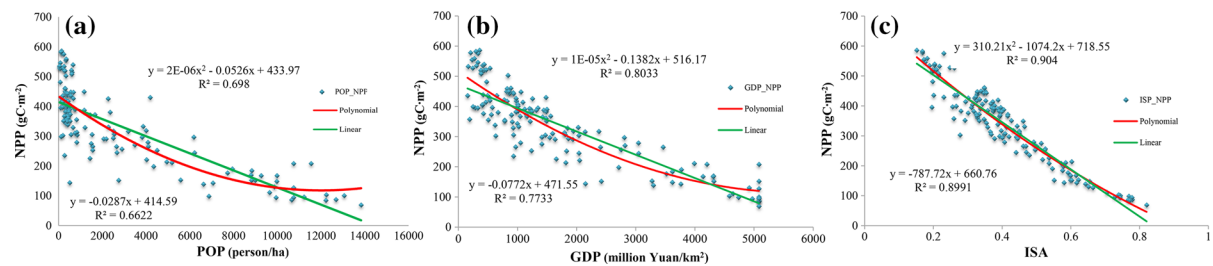
#### Correlation between urbanization and NPP

Although population urbanization, economic urbanization, and spatial urbanization had a significant negative relation with NPP, this relation was not consistent (Fig. 7). The negative relation between population urbanization and NPP occurred in two stages. In towns with a population density less than 20 persons/ha, population aggregation and non-agricultural population shift had little relation with NPP. However, in towns where the population density was greater than 20 persons/ha, the increase in population directly led to a decline in NPP. Judging from the slope of the linear regression, population urbanization did not influence the decline of NPP severely, which indicated that the interaction between NPP and population was low in densely populated towns. This

might be because the limited amount of ecological land such as parks and green belt was nearly stable in highly populated areas, which would be little affected by newly added population.

Figure 7 shows an obviously negative relation between economic urbanization and NPP. On the one hand, with economic development, NPP in central towns was lower than in the surrounding ones. On the other hand, the counties with high economic output might have had high NPP. From an analysis of NPP and GDP per area, economic urbanization appeared not only as the transformation from agricultural activity to nonagricultural activity and the resulting economic growth, but also as the adjustment of industrial structure. In regions where GDP per area was low, along with the rapid development of nonagricultural activity, the urban ecological land was gradually occupied and led to a decrease in NPP. By contrast, intensive use of the land, local eco-environmental management and urban planning all could result in an increase in NPP in regions where GDP per unit area was high.

Figure 7 also shows an obviously negative relation between spatial urbanization and NPP. This observation means that with the expansion of urban construction land and increase of building intensity, there was a sharp drop in the NPP. The effect was more remarkable than the rise of population or GDP. Nevertheless, the inner city and Chaoyang district were above the line of the scatter chart, which indicated that spatial urbanization caused only a small decrease in NPP. In general, the complicated relation between spatial urbanization and NPP was shown as follows: at first, with the expansion of urban areas, ecological land was gradually occupied,



**Fig. 7** Correlation between urbanization and NPP: **a** population density (POP); **b** GDP per area; **c** ISA

which led to a decrease in NPP. The images showed that 46.1 % of new urban construction land came from farmlands and 38.66 % came from green land between 2001 and 2009. Second, urbanization promoted the discrete distribution of ecological land. Finally, the NPP increases occurred in highly developed urban zones, which depended to some extent on the growth of green land, local eco-environmental management and urban planning.

#### NPP variation contrast in different urbanization zones

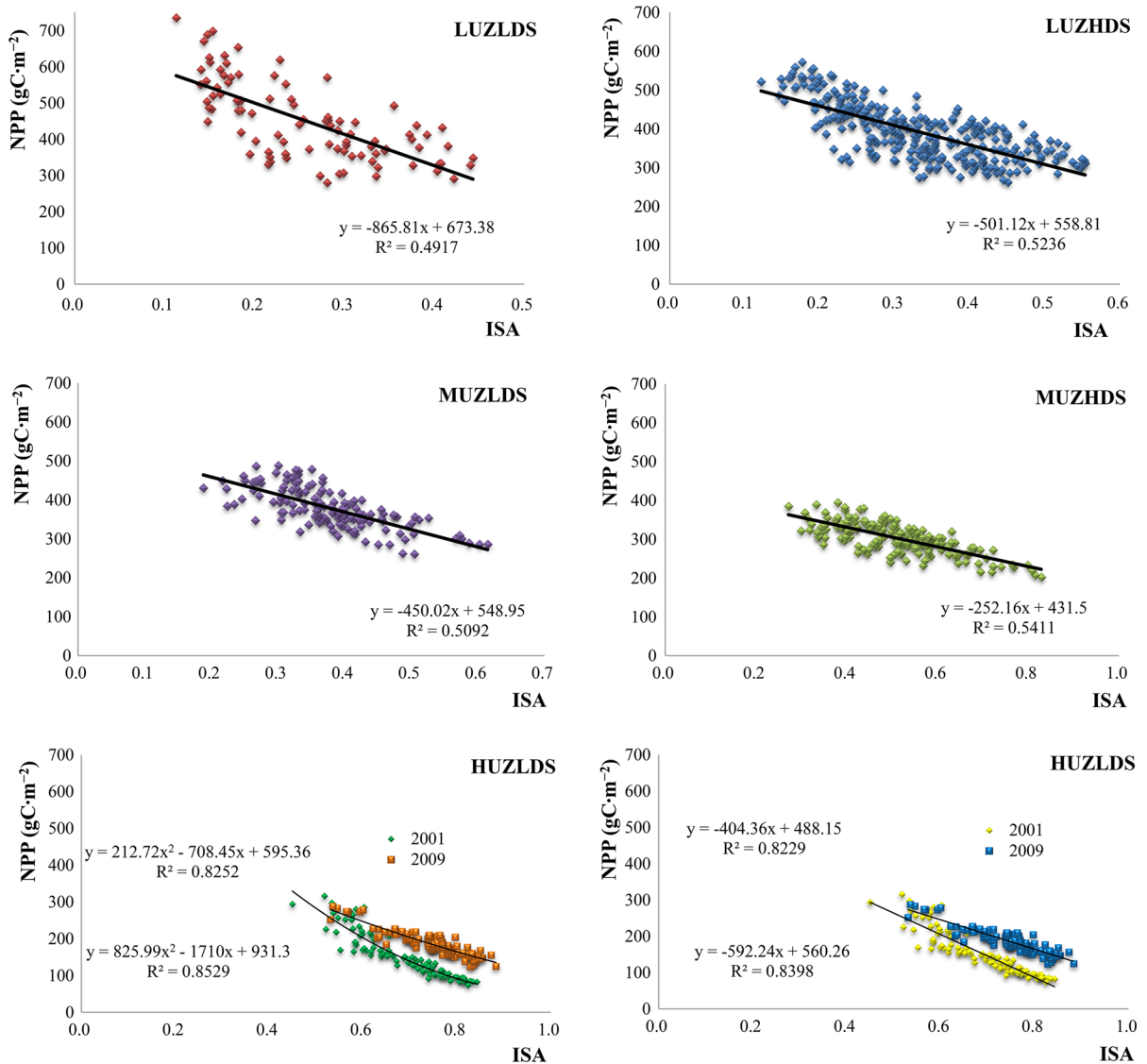
There were 94 samples of LUZLDS, 302 samples of LUZHDS, 138 samples of MUZLDS, 176 samples of MUZHDS, and 200 samples of HUZLDS in Beijing City. Based on the process from LUZLDS to MUZLDS and from LUZHDS to MUZHDS, the results indicated that, with an increase in intensity and speed of urbanization, the decline of NPP would become increasingly obvious (Fig. 8). Furthermore, the slopes of linear regression equations gradually became increased, which indicated that the change in NPP had phased characteristics. The data showed that the slope of ISA\_NPP was between  $-865.81$  and  $-252.16 \text{ gC m}^{-2}$ . However, in HUZLDS, the relation between ISA\_NPP was more complicated. As ISA improved, NPP first decreased and then increased weakly.

Thus, there was a weak relation between ISA and NPP ( $R^2 = 0.49$  and  $0.52$ , respectively) in the low-degree urban development zones. The ecosystem functions are directly related to the land-cover indicators such as vegetation coverage and ISA (Zhang et al. 2013). The results based on developmental speed showed that the newly increased construction land and increased construction intensity caused lasting and observable losses of NPP in time and space.

In the middle-degree urban development zones, the regression slopes of ISA\_NPP were higher than those in low-degree urban development zones. Compared with different development speeds of the moderately urbanized zone, the NPP in low-speed urban development zones varied from 261 to  $488 \text{ gC m}^{-2}$ , whereas NPP in high-speed urban development zones varied only from 202 to  $394 \text{ gC m}^{-2}$ . Furthermore, the regression slope of ISA\_NPP in low-speed urban development zones was lower than that in high-speed urban development zones. Thus, the negative ecological effect of newly increased construction land and construction intensity in low-speed urban development zones was more than that in high-speed urban development zones. During 2001–2009, the newly increased construction land in the middle-degree urban development zones was  $262.32 \text{ km}^2$ , accounting for 32.54 % of the total. The changed range of ISA was 12.21 %, which was more than the average level of the whole city.

Unlike the variation that occurred in other urban development zones, ISA\_NPP varied greatly in HUZLDS. The slopes of ISA\_NPP ( $-592.24$ ) were between MUZLDS and LUZLDS. This indicated that NPP in HUZLDS was not seriously influenced by urbanization. In comparison with linear analysis, quadratic polynomial provided a better fit. During 2001–2009, NPP increased in highly developed urban zones, which depended to some extent on the increase in green areas in the inner city ( $3.26 \text{ km}^2$ ) and the decrease in urban area ( $4.51 \text{ km}^2$ ).

NPP variation was obvious in different urbanization zones. In highly developed urban zones, NPP had not dropped substantially between 2001 and 2009, which suggested that the negative ecological effect had relatively eased. However, the NPP decreased substantially in lowly developed urban zones, although the negative ecological effect was uncertain,



**Fig. 8** Correlation between urbanization and NPP in different development zones in Beijing City

because of its low  $R^2$ . By contrast, moderately developed urban zones had an obvious negative ecological effect on NPP.

## Discussion

### NPP estimation validation

Compared with previous research focused on NPP change during China's urbanization, the NPP estimation of this study was in accord with the

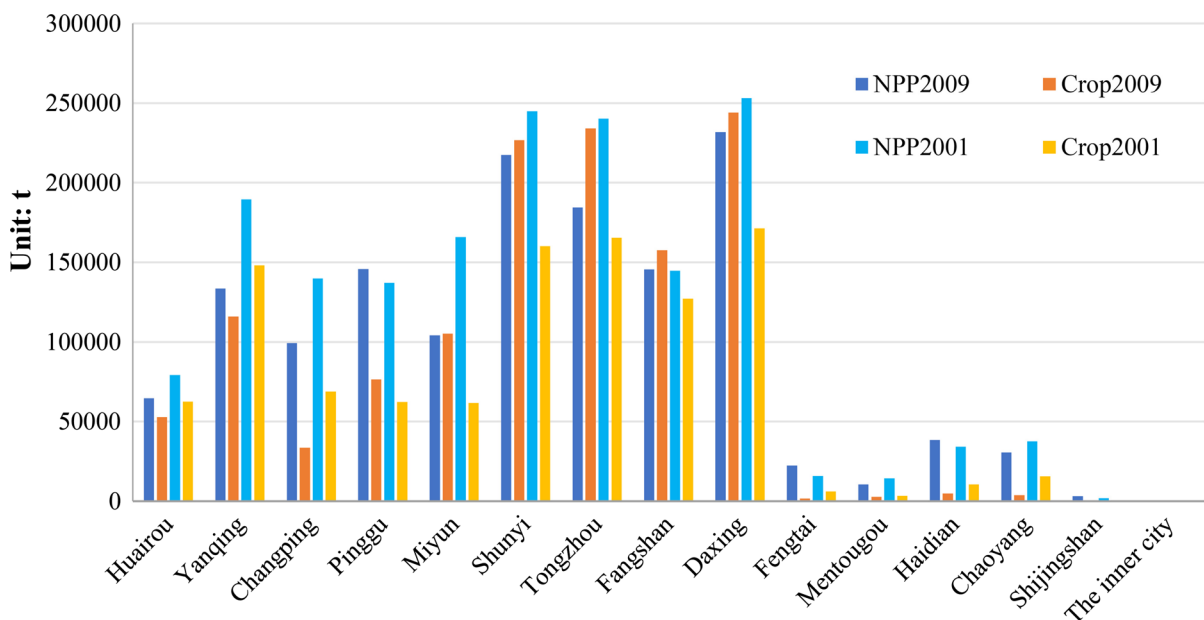
estimation in Xuzhou, China (Tan et al. 2015). However, the values were lower than the similar estimation in Jiangyin, China (Xu et al. 2007). The differences are probably due to Beijing being a northern city of China with colder climate than the other two cities, which negatively impacted vegetation growth. Because the ground based site observations of biomass were usually limited in a certain city, to further validate the estimation of NPP from the CASA model, the grain yield on a county scale and the MODIS NPP Product were introduced as the comparison.

As Fig. 9 shows, the NPP estimation on cropland has been extracted. Most of the spatial distributions between the NPP estimation and the crop production were similar at the country scale. In Changping and Pinggu, although the absolute values varied widely, the range of changes was similar. Nevertheless, in some suburban counties such as Daxing, Tongzhou and Miyun, crop production was greatly increased in the urbanization process. This increase had not been detected by NPP estimation because the improvement of crop biomass was a complex process that was not simulated in the CASA crop model.

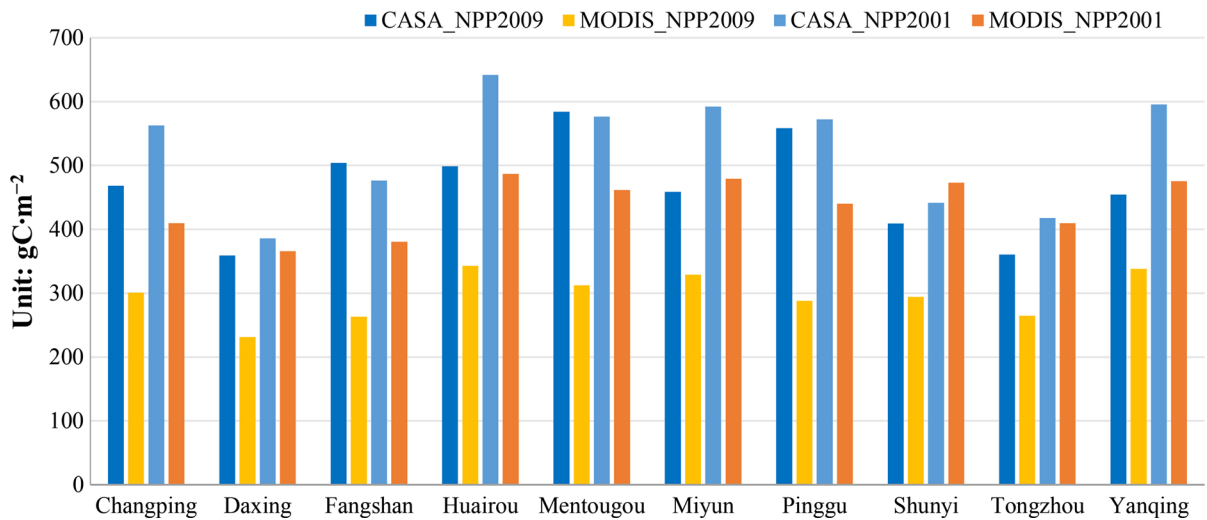
The mean estimation values of CASA and the MODIS Product were extracted from 1000 random points. Because the NPP on building land was not estimated in the MODIS Product, the districts in the central city were excluded. As Fig. 10 shows, although the absolute value of CASA estimation was higher than that from the MODIS Product, the rank of the general distribution was similar. Furthermore, the decrease of NPP detected in this study also appeared in the MODIS Product, which exhibited a larger decline than did the CASA model. Because the meteorological parameters used in these two models were different, it could not be affirmed that one model is better than the other. In future studies, more multisource data validation will be needed to enhance the accuracy of estimation.

### NPP variation in urbanization

Urbanization is characterized by people, finance aggregation, and the increased artificial land-covers. The latter can result in substantial decreases in vegetation biomass. However, the positive demand for urban green space from people and finance aggregation generated positive ecological effects. The negative effect will be countered by the positive demand for urban green space (Liu et al. 2015). Space-for-time substitutions are often used to develop quantitative predictions of ecological responses with limited observations (Lester et al. 2014). Because only two different years were considered in this study, the five urbanization development zones were regarded as different urbanization stages. The ecological functions are non-linearly correlated to the land-cover indicator such as vegetation fraction and ISA fraction (Kuang et al. 2015). In the initial low-intensity built-up areas, the ecological functions are sensitive to changes in land cover, and the NPP and other ecological functions degraded faster when the urbanization degree intensified. In moderate-intensity built-up areas, the ecological degradation slowed, exhibiting an early stagnant and later rapid ecological restoration. After the intensity of a built-up area becomes high, the degradation of ecological functions will be controlled and thriving new urban ecosystems develop.



**Fig. 9** Comparison of NPP estimation on cropland and the crop production in 2001 and 2009



**Fig. 10** Comparison of NPP estimations between CASA and MODIS with the values of 1000 random points

NPP variation in different urbanization stages could be extended to the ecological effects on other elements of urbanization. Based on this study, we propose that there were three stages in the response of NPP to urbanization: damage stage, antagonistic stage, and coordination stage (Fig. 11). These three stages were rather a deduction from the NPP variation of the five urbanization development zones than a quantitative conclusion. In the first stage, NPP was obviously negatively influenced by stress under the low levels of urbanization. In the second stage, substantial ecological changes occurred under the influence of rapid urbanization, and the increase of construction land speeded up the occupation of ecological land; however, there was also ecological restoration due to the increasing demand of urban dwellers for green space and corresponding ecosystem services. In the third stage, the negative urbanization stress on NPP weakened and coordination developed between urbanization and ecological functions such that ecosystem services were realized.

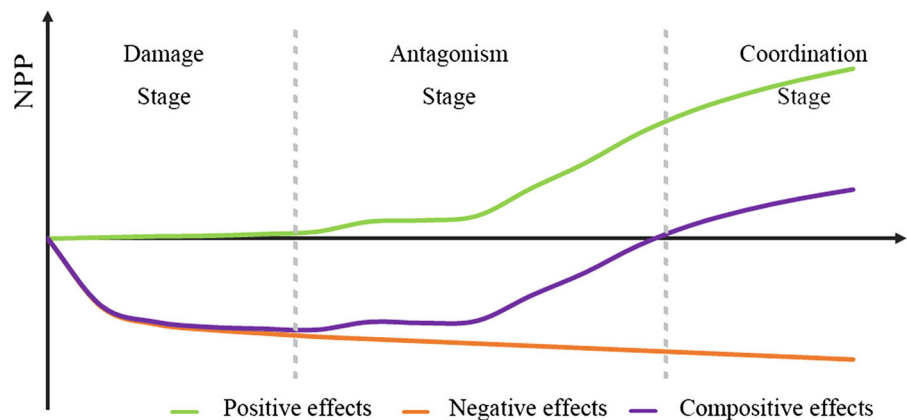
Under consistent management in urban areas, the urban ecosystem can be renewed with some key ecosystem processes being restored. Thus adaptive urban planning in an urbanized area may bring benefits to the urban ecosystem. For example, green space maintenance and water landscape layout could have positive cooling and refreshing effects on the urban thermal environment (Li et al. 2012a; Zhou et al. 2014). However, it should be noted that evaluating

human benefits of ecosystem services and their trade-offs in urban management is complicated, such as the requirements for water availability in various ecological processes (Jenerette et al. 2011). Therefore, although the ideal situation can be realized at a local scale, the negative effect of urbanization will still exist and the positive effect has an upper limit, even in the coordination stage. Further exploration of the key factors that influence trade-offs between ecosystem services is greatly needed.

#### Limitations and future research directions

In the estimation of NPP, meteorological parameters in the basic data from the CASA model can affect the accuracy of the model. At the same time, extrapolating the meteorological parameters that came from 15 weather stations in the Beijing area might cause some uncertainty. In other driving force analyses, meteorological factors have been acknowledged as a dominant influence on biomass accumulation and carbon dynamics (Yu et al. 2013; Piao et al. 2015). In this study focusing on the NPP response to urbanization, the effect of meteorological factors has been excluded. In urban studies on a local scale, it is often assumed that climate change is a factor influencing the NPP value rather than altering the spatial pattern, because the spatial variation of meteorological parameters is often similar (Xu et al. 2007; Tan et al. 2015). That is to say, the significant spatial variance of NPP

**Fig. 11** Urbanization stage and its effect on NPP dynamics



dynamics in the urban environment usually results from land use change. However, it does not mean that the meteorological driving force can be neglected in comprehensive urban ecosystem studies.

Furthermore, in the regions where ISA >20 %, we assumed that the effects of urbanization were more obvious than those of meteorological factors, such as precipitation, temperature, and radiation. However, this was not in line with reality on the municipal scale. Using discrete and continuous data relating to landscape to illustrate NPP dynamic responses to population urbanization, economic urbanization, and spatial urbanization could not reveal the mechanism of interaction between urban ecosystems and urbanization. Therefore, to achieve a more in-depth picture of urban ecosystem variation in different stages of urbanization, we need to: (i) distinguish the leading role of urbanization versus meteorological factors on a regional basis; and (ii) consider indirect factors such as urban landscape design and urban heat island effect on NPP (Zhang et al. 2014).

## Conclusions

NPP is one of the most significant factors characterizing ecosystem structure and function. In Beijing City, the spatial pattern of NPP was uneven, being higher in the northern and northwestern mountains than on the plains or in cities. In urbanized areas, yearly NPP was highest in the outer suburbs, followed by inner suburbs, and encircled city center, and was the lowest in the inner city. The high-value zones of NPP were located in the northeast of Yanqing,

northwest of Miyun, north of Huairou and Pinggu, and a low-value zone was in the inner city. In the city center the estimated NPP of green land, cultivated land and woodland decreased, but a contrary response occurred in built-up areas. From the view of monthly change, NPP declined from outer suburban to inner city. NPP dynamics were found to correlate with precipitation and temperature, although NPP levels were higher in the city centers during the winter months than might be expected, perhaps as a result of the heat island effect and urban heating.

The results also showed that nonlinear trends were more appropriate than linear trends when describing the relation between urbanization and NPP. Population urbanization affected NPP as a result of the demand for construction land and ecological land from urban residents, but in regions where the vegetation resources were abundant, NPP was not seriously affected. Economic urbanization affected NPP via GDP and industrial structure, whereby increases in GDP led to a decrease in NPP because of clearance of vegetation for construction. In terms of spatial urbanization, the expansion of built-up land reduced the productivity of vegetation, although in some highly urbanized areas, increasing the number or size of green areas improved the estimated NPP. Meanwhile, results based on different types of urban development zones indicated that, with increases in the intensity and speed of urbanization, the decline in NPP would be clearer. However, as ISA improved, NPP in HUZLDS decreased initially, but then increased weakly. Overall, urbanization causes a lasting and observable loss of NPP in both time and space. Nevertheless, the promotion of NPP does also exist in highly developed

urban zones. To sum up, in Beijing City, there were three stages in the response of NPP to urbanization: a damage stage, an antagonistic stage, and a coordination stage, although this division depended on local eco-environmental management and urban planning.

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