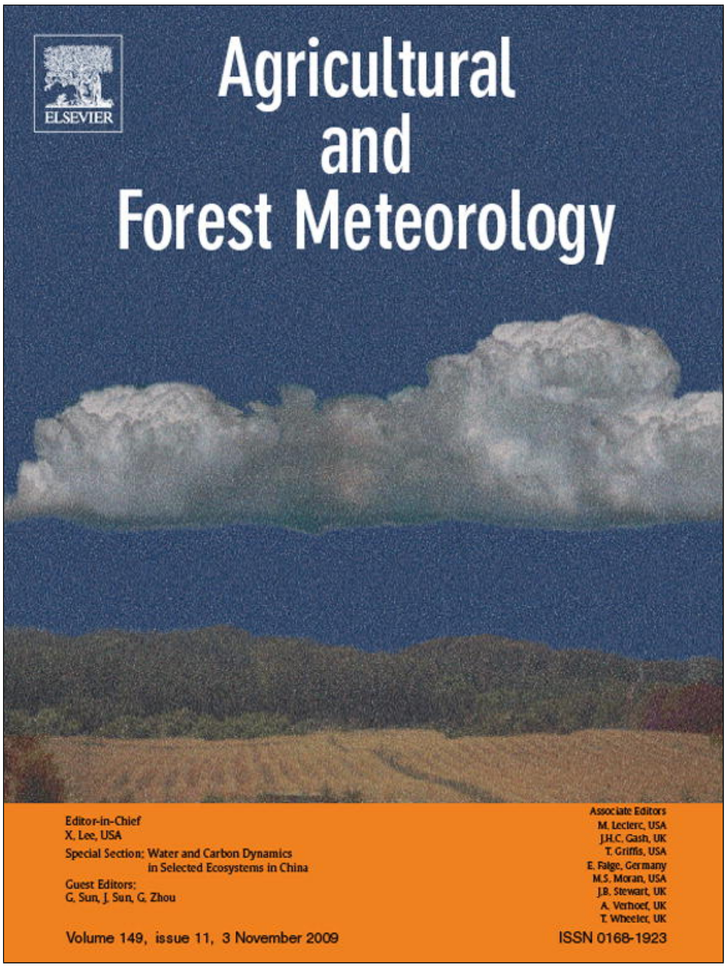
ELSEVIER
Agricultural and Forest Meteorology
Editor-in-Chief
X. Lee, USA
Special Section: Water and Carbon Dynamics in Selected Ecosystems in China
Guest Editors:
G. Sun, J. Sun, G. Zhou
Associate Editors
M. Leclerc, USA
J.H.C. Gash, UK
T. Griffis, USA
E. Falge, Germany
M.S. Moran, USA
J.B. Stewart, UK
A. Verhoef, UK
T. Wheeler, UK
Volume 149, issue 11, 3 November 2009
ISSN 0168-1923

Agricultural and Forest Meteorology 149 (2009) 2054–2060

Contents lists available at ScienceDirect

Agricultural and Forest Meteorology

journal homepage: www.elsevier.com/locate/agrformet

How does the conversion of land cover to urban use affect net primary productivity? A case study in Shenzhen city, China

Yu Deyong [a], Shao Hongbo [b,c,d,*], Shi Peijun [a,*], Zhu Wenquan [a], Pan Yaozhong [a]

[a] State Key Laboratory of Earth Surface Processes and Resource Ecology, Key Laboratory of Environment Change and Natural Disaster, MOE/Academy of Disaster Reduction and Emergency Management, Beijing Normal University, Beijing 100875, China
[b] State Key Laboratory of Soil Erosion and Dryland Farming on the Loess Plateau, Institute of Soil and Water Conservation, Chinese Academy of Sciences, Yangling 712100, China
[c] Yantai Institute of Costal Zone Research for Sustainable Development, Chinese Academy of Sciences (CAS), Yantai 264003, China
[d] Institutes of Life Sciences, Qingdao University of Science & Technology, 266042 Qingdao, China

ARTICLE INFO

Article history:
Received 4 January 2008
Received in revised form 15 July 2009
Accepted 24 July 2009

Keywords:
Urbanization
Net primary productivity
NDVI
Environmental monitoring
Land use

ABSTRACT

China has made great economic achievements since the Reform and Opening policy implementation. Shenzhen as the representative city has experienced rapid urbanization and population growth. Urbanization strongly changes the nature of the land surface and has a large influence on the regional ecosystems. In the process of urbanization, fertile cropland and original forest are often destroyed. It is important to regularly monitor the effect of urbanization on the natural environment so as to allow us to control the encroachment to a reasonable extent. Net primary productivity (NPP) is an important productivity indicator of the ecosystem. We obtained land covers from Landsat TM images to quantify urbanization of Shenzhen between 1999 and 2005. We used the Moderate Resolution Imaging Spectroradiometer (MODIS-based) Normalized Difference Vegetation Index (NDVI) data, Landsat-based land cover map, meteorological data and other field data to drive the CASA productivity model and obtain net primary productivity for the study area. Finally, we estimated the effect of urban sprawl on regional NPP. The study on Landsat-based land cover maps indicated that a move towards urban is the most significant landscape change in Shenzhen City and urbanization has irreversibly transformed about 20.21% of Shenzhen's surface during 1999–2005. NPP loss mainly resulted from urbanization during 1999–2005 and totaled to 321.51 Gg of carbon, an average annual reduction of 45.93 Gg of carbon. For every square km of Shenzhen area, NPP was on average reduced by 0.0017 Gg of carbon during 1999–2005. The loss of NPP is equivalent to a reduction in absorption of 520.85 Gg CO_2 and release of 385.81 Gg O_2, so urbanization has a large influence on the regional net primary productivity.

1. Introduction

Studies on terrestrial ecology indicate that about half of the land surface of the Earth has changed in an unsustainable way due to human activities (Vitousek et al., 1997). Man consumes 10–55% of dry matter produced by vegetation photosynthesis per year (Vitousek et al., 1986; Rojstaczer et al., 2001). DeFries et al. (1999) estimated that the potential photosynthesis ability of global ecosystems decreased by 5% due to land cover change in the past two centuries. Recently, people have started to pay more attention to the potential environmental problems caused by urbanization (Berry et al., 1990; McDonnell et al., 1997). From an ecological viewpoint, urbanization accompanied by land use changes has a large impact on the ecosystem, altering its composition and structure, and consequently affecting ecosystem processes and functioning (Alberti, 2005). Land use and land cover changes alter the natural matter and energy cycles of the ecosystem (Wackernagel and Yount, 1998; Pielke et al., 1999; Imhoff et al., 2000). In the course of urbanization, the conversion of land to urban use notably decreases photosynthesis of the ecosystem in regions with productive forests (Wear and Greis et al., 2001; Nizeyaimana et al., 2001).

The world is undergoing urban sprawl and experiencing rapid population growth, which is transforming regional natural landscapes. For example, large patches of fertile cropland and forests tend to be fragmentized due to rapid urbanization (Imhoff et al., 1997; Folke et al., 1997). In some regions, loss of cropland has an

* Corresponding authors. Dr. Professor Shao Hong-Bo, Institute of Life Sciences, Qingdao University of Science & Technology, 266042 Qingdao, China. Tel.: +86 53284023984.
E-mail addresses: shaohongbochu@126.com (S. Hongbo), dyyucas@163.com (S. Peijun).

0168-1923/$ – see front matter © 2009 Elsevier B.V. All rights reserved.
doi:10.1016/j.agrformet.2009.07.012

important influence on food security, climate conditions and the environment (Yu et al., 2006). Researchers have carried out many studies on the effect of urbanization on matter cycles, energy flow and ecosystem service (Schimel et al., 2000).

Net primary productivity (NPP) is the amount of solar energy converted to chemical energy through the process of photosynthesis (production minus respiration) and represents the primary source of food for Earth's heterotrophic organisms (organisms that require preformed organic compounds for food energy) including human beings (Imhoff et al., 2004). Quantitative investigations on the influence of urbanization on NPP, net ecosystem productivity (NEP) and net biosphere productivity (NBP) are important in the context of earth system science and global change studies (Postel et al., 1996). NPP loss may affect the composition of the atmosphere (Pimm and Raven, 2000), fresh water availability (Sala et al., 2000), biodiversity (DeFries et al., 1999; Field, 2001) and the ecological adjusting mechanism of energy supply and distribution (Houghton et al., 1999). Hence, NPP is a sensitive indicator of climatic and environmental changes (Schimel et al., 1995). Studying the impact of urbanization on NPP is crucial to understand the change of ecosystem structure and function and to predict future global carbon cycle trends.

In the past, researchers mainly focused on the impact of urbanization on net primary productivity on a large scale. Cristina et al. (2003) used the MODIS data, land cover map and night light extent data, derived from the Defense Meteorological Satellite's Operational Linescan system (DMSP/OLS) to estimate the extent of urban development and its impact on NPP in the southeastern United States. Imhoff (2004) used nighttime images from the DMSP/OLS data to portray the extent and spatial distribution of the urbanized area and estimate urbanization impact on NPP by using the NDVI data as the input to the Carnegie Ames Stanford Application (CASA) productivity model in the United States. These studies were conducted at coarse resolution (1 km or larger). The methods are suitable for regions on a large spatial scale, but give inaccurate NPP patterns for regions on a fine scale. So far, only a small number of studies based on fine data resolution have been carried out to study how the conversion of land to urban use affects net primary productivity. This paper studies the influence of urban sprawl on fine-resolution NPP in a rapid urbanization region.

2. Study area

Shenzhen City, which is one of the important cities of the Guangdong province, China, is located between 22°27′ N and 22°52′ N latitude and between 113°46′ E and 114°37′ E longitude. Its location is shown in Fig. 1. The total area is approximately 1968.79 km^2. It is located in the subtropical marine climate zone. Annual temperature values for Shenzhen during 1990–2005 are 36.6 °C (average maximum), 22.4 °C (mean), and 1.4 °C (average minimum). Mean annual precipitation and total sunshine hours are 1933 mm and 2011 h, respectively. Its total mean annual solar radiation is 5404.9 MJ m^{-2}. The main soil types are yellow soil and lateritic red soil. The dominant vegetation types of Shenzhen are evergreen broad-leaved mixed forests, garden forests and cropland. Shenzhen was established in 1979 and is the first experimental zone of Chinese Reform and Open-Door Policy. Its astonishing development rate has made it famous throughout the world. During the twenty-five years since its establishment, Shenzhen's economy has increased at an annual mean rate of 30% and the total economy has increased by 1800 times (Shenzhen Statistical Yearbook, 2006). In 2005, GDP of Shenzhen city was 495.1 billion RMB yuan and the permanent resident number reached 8.28 million. As a result, Shenzhen experienced rapid urbanization, with urbanization rates over 78% until 2005.

3. Methods

We chose the combination of satellite data, geo-spatial meteorological data and ground observational data of NPP to carry out the study. Except observational NPP, all other data were reproduced at 30 m spatial resolution and projected to Universal Transverse Mercator (UTM) zone 49, by using World Geodical System-84 (WGS84) datum. We used land cover maps both to track land cover changes due to recent urban sprawl in Shenzhen and to guide the estimation of NPP from MODIS-based data. Two 30 m spatial resolution land cover maps obtained by Landsat Thematic Mapper images (TM) for the year 1999 and 2005, respectively, are used to portray the extent and spatial distribution of land cover changes caused by urbanization in Shenzhen during 1999–2005. We downloaded the available MODIS albedo products (the red-band and the near infrared-band for the year 1999 and 2005) from the EROS Data Center Distributed Active Archive Center (EDC DAAC) to compute MODIS-based NDVI. These albedo data are 16-day composites of atmospherically corrected maximal values at 250 m spatial resolution. We produced a 32-day composite product of the maximal value for a time series and reprojected the composite to Universal Transverse Mercator (UTM), and WGS84 datum from the original Integerized Sinusoidal Projection. In this study, the period of a time series or monthly data means 32 days, so one year includes about 11 time series of composite product of maximal value and other inputs. We calculated NPP by using the MODIS-based NDVI data as the input to the CASA productivity model to evaluate the effect of the conversion of land to urban use.

3.1. NPP ecosystem model

Many models have been developed to estimate NPP, which can be divided into three categories (Ruimy and Saugier, 1994): (1) statistical models, (2) parameter models, (3) process-based models. The CASA ecosystem model, based on estimating light use efficiency (LUE), is a process-based model and appropriate to estimate NPP on a global or regional scale. The CASA ecosystem model is robust in describing spatial and temporal NPP patterns (Potter et al., 1993).

In the CASA model, NPP is the product of modulated absorbed photosynthetically active radiation (APAR) and a light use efficiency factor, namely (Potter et al., 1993):

$$\mathrm{NPP}(x,t) = \mathrm{APAR}(x,t)\varepsilon(x,t) \quad (1)$$

where NPP(x, t) represents NPP in the geographic coordinate of a given location x and time t. APAR(x, t) (MJ m^{-2} mon^{-1}) is the APAR absorbed by the vegetation. $\varepsilon(x, t)$ is the light use efficiency (g C MJ^{-1}) of the vegetation. The algorithm of light use efficiency can be expressed as:

$$\varepsilon(x,t) = T_{\varepsilon1}(x,t)T_{\varepsilon2}(x,t)W_{\varepsilon}(x,t)\varepsilon_{\max} \quad (2)$$

where $T_{\varepsilon1}$ (x, t) and $T_{\varepsilon2}$ (x, t) are temperature stress coefficients; $W_{\varepsilon}(x, t)$ is a moisture stress coefficient and $\varepsilon_{\max}$ is a biome-specific light use efficiency factor that is estimated from daily meteorological conditions. $\varepsilon_{\max}$ means the maximal light use efficiency of the specific biome under ideal conditions (minimum temperature and vapor pressure deficit). In this model, the moisture stress coefficient ($W_{\varepsilon}(x, t)$) is simultaneously related to many soil parameters such as field moisture capacity, wilting coefficient, the percentage of soil sand and clay particles, depth of the soil, etc. However, these parameters are difficult to obtain in Shenzhen because of the lack of fundamental soil data. In this study, we used monthly meteorological data (monthly total solar radiation, monthly average temperature and monthly total precipitation)

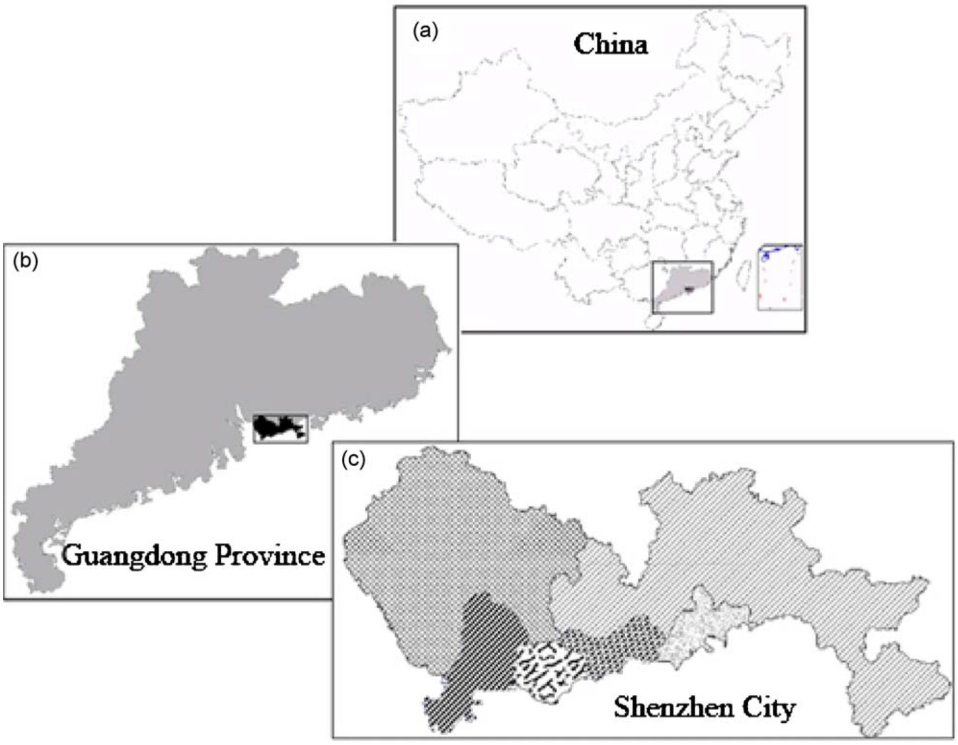

Fig. 1. The location of Shenzhen city (c) in China (a) and Guangdong province of China (b), respectively. Shenzhen city is divided into six districts: Yantian, Nanshan, Luohu, Longgang, Futian and Baoan.

and used the regional evapotranspiration model of Zhou and Zhang (1995, 1996) to estimate the regional moisture stress coefficient. It has been proved that its accuracy is over 90%. The regional moisture stress coefficient (r) can be defined by:

$$r = \frac{E_1(x,t)}{E_2(x,t)} \tag{3}$$

where E_1 (x, t) is the estimated evapotranspiration (see Eq. (4)) and E_2 (x, t) is potential evapotranspiration.

$$E_1(x,t) = \frac{P(x,t) \times R(x,t) \times [P(x,t)^2 + (R(x,t))^2 + P(x,t) \times R(x,t)]}{P(x,t) + R(x,t)] \times [P(x,t)^2 + R(x,t)^2} \tag{4}$$

In Eq. (4), $R(x, t)$ expresses net solar radiation (MJ m^{-2} mon^{-1}) and $P(x, t)$ is monthly precipitation (mm mon^{-1}). The potential evapotranspiration is given by:

$$E_2(x,t) = \frac{E_1(x,t) + E_0(x,t)}{2} \tag{5}$$

where $E_0(x,t) = 16 \times [10 \times T(x,t)/I(x)]^{a(x)}$. $\alpha(x)$ and $I(x)$ can be computed by the following Eq. (6):

$$a(x) = (0.675I(x)^3 - 77.1I(x)^2 + 17920I(x) + 492390) \times 10^{-6}$$
$$\text{with } I(x) = \sum_{i=1}^{12}[T(x,t)/5)]^{1.514} \tag{6}$$

where $I(x)$ is the total heat index in a year and $T(x, t)$ is the monthly average temperature per area.

This method does not only keep the plant physiological and ecological basis of the original CASA ecosystem model, but also simplifies the input parameters and widens its applicability.

Potter et al. (1993) assumed that vegetation has maximal light use efficiency (ε_{max}) under ideal conditions. However, in reality it is easily affected by actual temperature and moisture conditions. Many researchers (Potter et al., 1993; Field et al., 1995, 1998; Jeffrey, 2006) set ε_{max} to a sole value for different vegetation types. However, the maximal light use efficiency, which is mainly affected by temperature, water availability, soil type, plant nutrition, diseases, individual development, gene difference and energy distribution (Prince, 1991), differs greatly in the real situation (Goetz and Prince, 1996; Paruelo et al., 1997; McCrady and Jokela, 1998). In the current paper, according to the principle of minimal error between the modeled NPP and the observed NPP, Eq. (7) is used to model the maximal light use efficiency for different vegetation types. The observed NPP data related to seven major biomes were provided by the former Ministry of Forestry of China. Latitude, longitude, elevation, leaf area index, total biomass, and total NPP are documented for each observed site. ε_{max} can be estimated in three steps: (1) by computing for each pixel the values of APAR, temperature and water stress factors; (2) by selecting observed NPP data; (3) development of an equation (see Eq. (7)) and computing ε_{max} for different vegetation types. For each vegetation type, the error between the observed NPP and the estimated NPP can be expressed by:

$$E(x) = \sum_{i=1}^{j}(m_i - n_i\varepsilon_{max})^2, \quad \varepsilon_{max} \in [l, u] \tag{7}$$

where i expresses the sample number of the vegetation, m_i is the observed NPP and n_i is the product of APAR, temperature and water stress factors. ε_{max} is the maximal light use efficiency modeled for the vegetation. l and u are the lower and the upper light use efficiency of the vegetation, respectively. Eq. (7) can be expanded as:

$$E(x) = \sum_{i}^{j} n_i^2 \varepsilon_{max}^2 - 2\sum_{i=1}^{j} m_i n_i \varepsilon_{max} + \sum_{i=1}^{j} m_i^2, \quad x \in [l, u] \tag{8}$$

Eq. (8) is a hyperbolic equation, so it must have a minimum value between l and u. In this case, the error between the observed

NPP and the estimated NPP is at its minimum and ε_{max} is just the estimated maximal light use efficiency for the vegetation.

The flow chart of the CASA model algorithm used to calculate NPP is shown in Fig. 2.

3.2. Input requirements and data processing for the NPP model

3.2.1. Mapping Shenzhen land cover

We chose two cloud-free Landsat TM images representative of the growing season to describe Shenzhen land cover in 1999 and 2005. One image was taken in September 1999 and the other one in August 2005. We used global positioning system (GPS) instruments to obtain the exact location of ground control points (GCPs) while at the same time investigating the features of different land covers at these locations. One hundred and ninety-six evenly distributed GCPs were used to make geometric corrections of each TM image, with a root mean square error (RMSE) of less than 0.5 pixel. The TM images were masked using the geographical boundary of Shenzhen County. Visual interpretation of remote sensing images is an effective way to map regional land cover/land use types (Wilson and Sader, 2002). A supervised classification approach was chosen for mapping the land cover using the maximum likelihood method. The classification result was verified and modified according to ground survey. Finally, land cover maps for 1999 and 2005 were classified into five categories: (1) urban, (2) cropland, (3) forests, (4) water body, (5) wetland. Accuracy of the images was assessed using the ground truth data collected during field survey. The overall accuracy was 90.2% for the 1999 map and 89.5% for the 2005 map.

3.2.2. MODIS-based NDVI

Compared to Landsat TM images, the spatial resolution of MODIS red-band or near-infrared-band albedo images (250 m × 250 m) is crude. A MODIS image pixel is equivalent to about 69 Landsat TM pixels, which belong to different land covers. At a 250 m resolution, most of the MODIS pixels are corresponding to a mosaic of trees with grass underneath, buildings or other land covers. If these Landsat TM pixels are allocated the same albedo value, this may cause more systematic errors. We used a linear model to decompose MODIS albedo image pixels to the Landsat TM scale. A linear equation group is used to derive the red-band or near-infrared-band MODIS-based albedo value for the five land covers corresponding to a pixel of MODIS image data:

$$\begin{cases} N_1 = N_{11}P_{11} + N_{12}P_{12} + N_{13}P_{13} + N_{14}P_{14} + N_{15}P_{15}\% \\ N_2 = N_{21}P_{21} + N_{22}P_{22} + N_{23}P_{23} + N_{24}P_{24} + N_{25}P_{25}\% \\ N_3 = N_{31}P_{31} + N_{32}P_{32} + N_{33}P_{33} + N_{34}P_{34} + N_{35}P_{35}\% \\ N_4 = N_{41}P_{41} + N_{42}P_{42} + N_{43}P_{43} + N_{44}P_{44} + N_{45}P_{45}\% \\ N_5 = N_{51}P_{51} + N_{52}P_{52} + N_{53}P_{53} + N_{54}P_{54} + N_{55}P_{55}\% \end{cases} \quad (9)$$

where N_m (m = 1, 2, ..., 5) is the red-band or near-infrared-band albedo value of the mth pixel of the MODIS image data and N_{mn} is the red-band or near-infrared-band albedo value of the n (n = 1, 2,

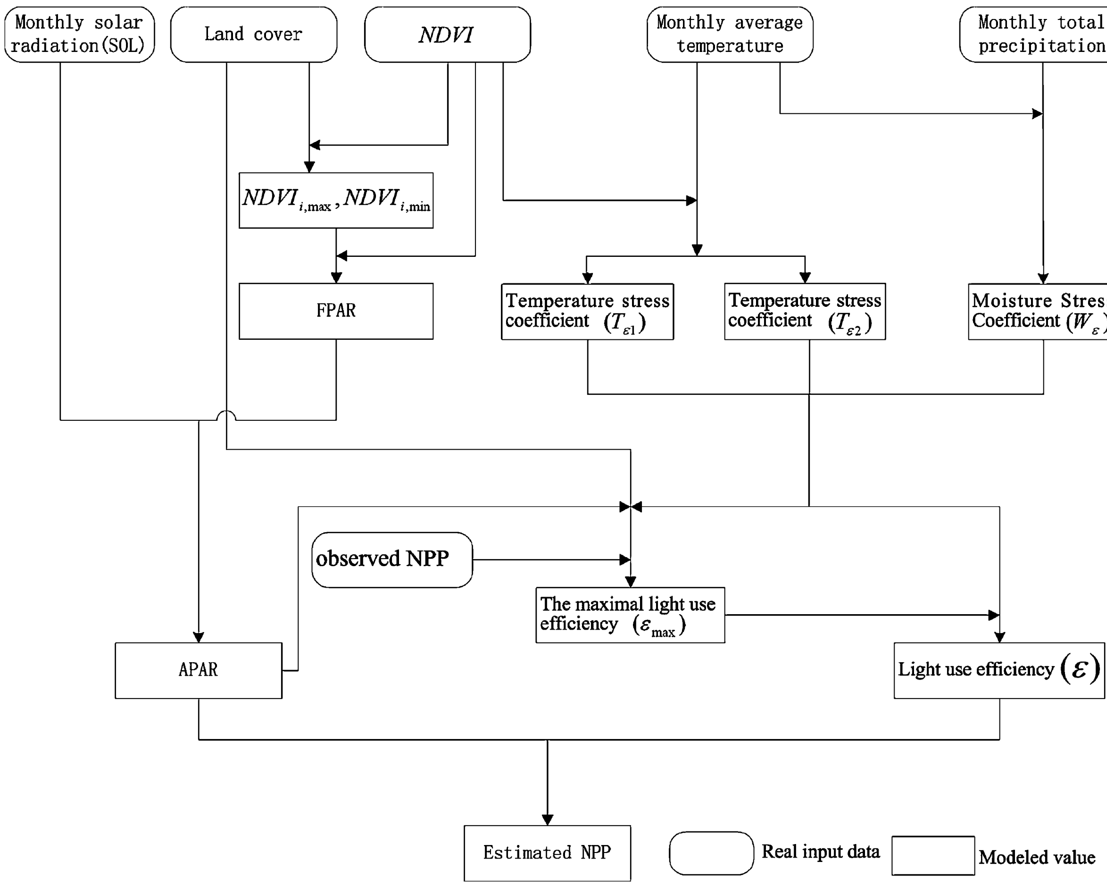

Fig. 2. The flow chart of the CASA model used to estimate NPP. The CASA model has three key inputs: (1) remote sensing inputs (land cover, NDVI), (2) monthly surface meteorological inputs (monthly solar radiation (SOL) which is used to estimate APAR; monthly average temperature and monthly total precipitation which are used to estimate temperature stress coefficients ($T_{\varepsilon1}$, $T_{\varepsilon2}$) and moisture stress coefficient (W_ε)), (3) biome-specific coefficients (observed NPP, ε_{max} and ε). Based on the land cover, observed NPP, temperature stress coefficients and moisture stress coefficient, the maximal light use efficacy (ε_{max}) of the vegetation type is estimated to produce light use efficiency (ε) of the vegetation type, which is then used with the absorbed photosynthetic active radiation (APAR) to predict monthly net primary productivity (NPP), namely, NPP = APAR × ε, where APAR = SOL × FPAR × r and r is the ratio of the solar radiation (with wavelength range of 0.38–0.71 μm) that can be utilized by the vegetation with the total solar radiation. Final estimation of annual NPP is obtained by adding the 11 time series of NPP in a year.

..., 5) types of land covers of TM image included in the mth pixel of MODIS data. P_{mn}% stands for the area percentage of the nth land cover to the mth pixel of the MODIS image. Each group of five MODIS pixels can build a linear equation group as in Eq. (9) and can be used to compute the red-band or near-infrared-band albedo value of different land covers. We can obtain new red-band or near-infrared-band albedo values for different land covers after linear decomposition by a 5 × 5 MODIS-pixel slide window that floats across the whole MODIS image. In the overlap area, the original albedo values are replaced by the calculated albedo values. A NDVI map was generated for all the images by using:

$$\mathrm{NDVI} = \frac{\mathrm{Red} - \mathrm{NIR}}{\mathrm{Red} + \mathrm{NIR}} \tag{10}$$

where Red and NIR represent the red-band and near-infrared-band MODIS albedo after pixel decomposition.

In theory, the value of NDVI of a water body should be zero. Urban generally means very little vegetation, so NDVI values of water bodies and urban areas were set to zero when they were used to calculate NPP.

3.2.3. Monthly meteorological data

The meteorological data required as input for the CASA ecosystem model are the monthly mean air temperatures, monthly total precipitation and monthly total solar radiation, in 1999 and 2005. These data were recorded by seven weather stations of Shenzhen and nearby regions. They were bilinearly interpolated into an image with 30 m × 30 m resolution to match MODIS-based NDVI data and Landsat TM image data.

3.2.4. Selecting the observed NPP from NPP databases

The observed NPP data are mainly used to estimate the maximal light use efficiency and verify the estimated NPP. The observed NPP data were compiled from two sources: (1) the former Ministry of Forestry of China, (2) by continuous measurement of NPP on 48 sample plots from 1999 to 2005 for the vegetation types under study.

4. Results and discussion

4.1. Land cover changes based on remote sensing images during the process of urban sprawl

The surface area and percentage change in each land cover per district between 1999 and 2005 is shown in Table 1. Compared to the other land covers, the increase area of urban land is the largest with the biggest increase being 11,045 hm^2, or 15.89% of the total land cover change in the Baoan district. The area occupied by crops was reduced in all the districts, with the largest decrease having taken place in the Baoan district. Forested area increased by 1473 hm^2 in Longgang district; this may be caused by the urban green land increase. It decreased in all other districts between 1999 and 2005. The area covered by water bodies decreased in all the districts indicating that many river tributaries were sacrificed in the process of urban sprawl. Wetland occupies a small percentage only of the total surface area, and changed minimally. Land covers of the Baoan district showed the most substantial change, with about 33.04% of its surface having changed its land use during the 7 years of our study. Urban area increased by 18,841 hm^2, or 9.78% of the total surface in Shenzhen city, it being the most significant landscape change for this district. Cropland, forest and area occupied by water bodies all decreased during the seven years. Between 1999 and 2005, land development irreversibly transformed about 20.21% of Shenzhen's surface. About half of this is due to new urban developments (48.4%) and about 31.7% is due to cropland reduction. All these indicated the substantial increase in human activity.

Fig. 3(a) indicates the change in urbanization during 1999–2005 in the Shenzhen district. The darker the area, the larger the change. Many previously scattered urban patches became connected with each other and urban patches are increasing in size. It is clear that in the seven years the intensity and frequency of human activities have greatly increased, much beyond the original urban fringe. The population of Shenzhen city increased by almost 100%, from 4.32 million in 1999 to 8.28 million in 2005. Fig. 3(a) shows that urbanization greatly sprawled in the region. However, the lower right region in Fig. 3(a) changed relatively little and this is the main forest region. During the seven years, urbanization encroached on cropland and forested area, thereby impacting on the regional NPP values.

4.2. The effect of urban sprawl on net primary productivity

Table 2 shows the estimated value of mean and total NPP for Shenzhen as calculated using the CASA model. The estimated mean NPP for cropland, forest and wetland decreased considerably between 1999 and 2005. Absolute values of mean forest NPP decreased most, about 184.52 g C m^{-2} per year. The largest percentage change in mean NPP was found for wetland, a change of 30%.

Total NPP of Shenzhen in 1999 was 1811.0 Gg C (1 Gg = 10^9 g) per year and 1489.49 Gg C per year in 2005. Total cropland NPP exhibited the highest decrease, only being 68.36% of that in 1999. Total NPP of Shenzhen decreased by 321.51 Gg of carbon, in which cropland NPP makes up 44.4% and forest NPP occupies 55.6% of the reduction. As a result of the area increasing by 644 hm^2, although mean wetland NPP decreased, total wetland NPP slightly increased by 0.26 Gg of carbon. Total NPP in Shenzhen decreased by 17.75 % compared to that in 1999.

The difference of Shenzhen NPP derived from CASA model between 1999 and 2005 is shown in Fig. 3(b). Urban sprawl in the region caused an evident decline in NPP. Fig. 3(b) also indicated that NPP decreased more in those regions that had no significant urban patches. By overlaying the difference map of land cover between 1999 and 2005 with Fig. 3(b), it can be concluded that NPP reduction mainly resulted from natural forest being transformed to fruit garden and shrub land. Although fruit tree and shrub fall into

Table 1
Change in land cover area expressed in hm^2 and as a percentage of total area changed (numbers in parentheses), between 1999 and 2005.[a].

District	Urban	Cropland	Forest	Water body	Wetland	Total change
Baoan	11,045 (15.89)	−5,380 (−7.74)	−1294 (1.86)	−4777 (−6.87)	471 (0.68)	22,967 (33.04)
Futian	638 (8.6)	−75 (−1.01)	−479 (−6.45)	−73 (−0.99)	−11 (−0.15)	1,277 (17.19)
Longgang	5,097 (5.99)	−5,934 (−6.97)	1473 (1.73)	−743 (−0.87)	107 (0.13)	13,355 (15.69)
Luohu	366 (4.67)	−163 (−2.08)	−166 (−2.12)	−65 (−0.83)	28 (0.36)	789 (10.07)
Nanshan	1,433 (9.36)	−764 (−4.99)	−99 (−0.65)	−600 (−3.92)	31 (0.2)	2,929 (19.11)
Yantian	260 (3.51)	−33 (−0.44)	−169 (−2.27)	−73 (−0.98)	14 (0.19)	549(7.4)
Shenzhen	18,841 (9.78)	−12,350 (−6.41)	−734 (−0.38)	−6364 (−3.3)	640 (0.33)	38,929(20.21)

[a] Negative values mean a decrease between 1999 and 2005.

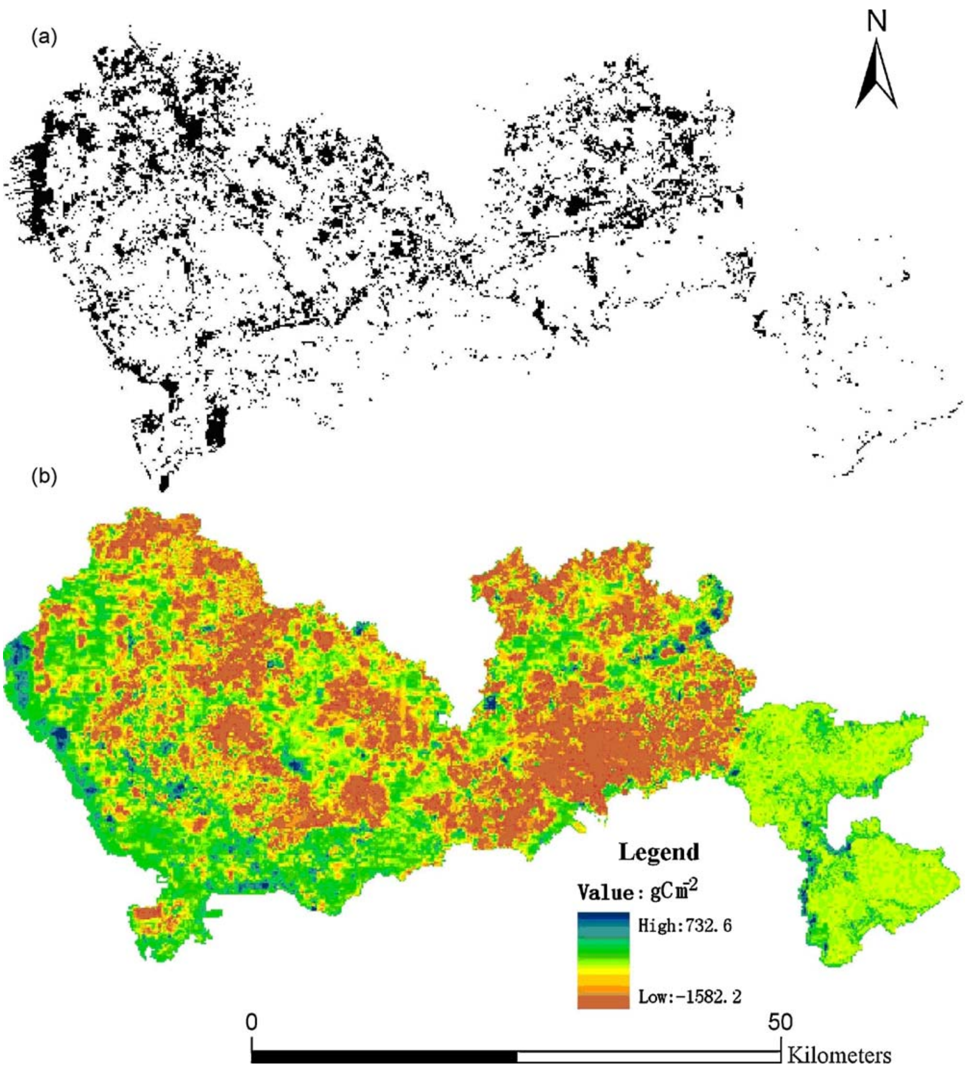

Fig. 3. The difference of urban area (a) and NPP (b) for Shenzhen between 1999 and 2005.

the forest category, their productivity is far lower than that of natural forest.

There are many factors that can influence NPP, such as soil type, climate (solar radiation, precipitation, temperature) and human disturbance, etc. During a short period (in our case seven years), the soil type tends to be unchanged and in a stable status, but the meteorological conditions may fluctuate. In order to filter the influence of climate fluctuations on NPP, we use the 7 years of average monthly total solar radiation, temperature and precipitation during 1999–2005 to drive the CASA ecosystem model with the other inputs unchanged. The results showed that total NPP of Shenzhen was 1859.71 Gg of carbon in 1999 and 1434.08 Gg of carbon in 2005, overestimating by 2.69% and underestimating by 3.72% compared to that in 1999 and 2005, respectively. Therefore, climate fluctuation only has a slight influence on regional NPP variation in a short period. It was also proved by Elmore et al. (2008) that, compared to climate factors, land use change has a larger impact on NPP in China. So, NPP reduction of Shenzhen is mainly caused by human disturbance, especially urban sprawl encroaching on forests and cropland.

Table 2
Estimated value of mean and total NPP in 1999 and 2005, for Shenzhen.

	Cropland	Forest	Wetland	Total
Mean NPP ($g\,C\,m^{-2}\,yr^{-1}$)				
1999	1086.99	1764.95	187.91	
2005	961.33	1580.43	131.72	
Unit change in NPP ($g\,C\,m^{-2}$)	−125.66	−184.52	−56.19	
Percent change (%)	11.56	10.45	29.90	
Total NPP (Gg C)				
1999	209.03	1600.03	1.94	1811.00
2005	66.14	1421.15	2.20	1489.49
Total change in NPP (Gg C)	−142.89	−178.88	0.26	−321.51
Percent change (%)	68.36	11.18	13.61	17.75

According to the reaction equations of photosynthesis and respiration, vegetation absorbs 1.62 g CO_2 to produce 1 g carbon of dry matter and releases 1.2 g O_2 in the process. Between 1999 and 2005, the ecosystems of Shenzhen lost 321.51 Gg of carbon that is equivalent to reducing absorption of CO_2 by 520.85 Gg and a reduction in release of 385.81 Gg O_2. The heat contained in 1 g carbon of dry matter equals that contained in 0.00067 g standard coal, so 321.51 Gg NPP is equivalent to the heat loss contained in 2.15×10^6 ton of standard coal. This is a considerable loss in NPP and hence in carbon sequestration potential. This loss is accompanied by an increase in emissions of CO_2 due to the significant growth in population, rapid development of industry and fossil fuel combustion. Hence, the total carbon release in the area must have increased in the 7-year period. The sharp reduction in cropland area and productivity must weaken food and fruit supply. According to Shenzhen's 2005 statistical reports, over 95%

of food was imported from other regions. Urbanization also weakens the ability of ecosystems to mitigate natural disasters. In recent years, with vegetation destroyed by urban sprawl, flood frequency has evidently increased in Shenzhen (Gao et al., 2005). It is fortunate that Shenzhen now recognizes the situation, and many remediation policies are being put into place.

5. Conclusions

China has made great economic achievements since the Reform and Opening policy implementation. Shenzhen, as a representative city, has experienced rapid urbanization and population growth. Urbanization intensely changes the status and nature of land surface. NPP is an important productivity indicator of ecosystems. Studying the change of NPP in the process of urbanization is helpful to understand the feedback mechanism of the ecosystem to human activities and to ensure that the natural resources are used as efficiently as possible. This paper provides a method for understanding the regional effects of urbanization on net primary productivity.

Urbanization is the most significant landscape change for Shenzhen. Land development has irreversibly transformed about 20.21% of Shenzhen's surface; 80.1% of the surface variation is due to the urban increase and cropland reduction. The intensity and frequency of human activities have greatly increased much beyond the original urban fringe.

The estimated total NPP for Shenzhen was 1811.0 Gg C in 1999 and 1489.49 Gg C in 2005, respectively. Total NPP of Shenzhen decreased by 321.51 Gg C during 1999–2005. For every square km of Shenzhen land, NPP was, on average, reduced by 0.0017 Gg of carbon that was not sequestered during 1999–2005. Crop NPP makes up 44.36% and forest NPP is responsible for 55.64% of the reduction. During the seven years, urban sprawl, not climate fluctuation, was the main cause of regional NPP reduction, again underlining that urbanization has a large influence on the regional net primary productivity.

Acknowledgments

This research was funded by the Program of National Natural Science Foundation of China (40801211), Project of State Key Laboratory of Earth Surface Processes and Resources Ecology (070106, 2008-ZZ-05), the National Science Fund Project for Distinguished Young Scholars of the National Natural Science Foundation of China (No. 40425008), International Cooperative Partner Plan of Chinese Academy of Sciences, and One Hundred-Talent Plan of Chinese Academy of Sciences. Special thanks are given to the referees and the associate editor for their instructive comments and suggestions and editing for the revised manuscript, respectively.

References

Alberti, M., 2005. The effects of urban patterns on ecosystem function. Int. Region. Sci. Rev. 28, 168–192.

Cristina, M., Christopher, D.E., Ramakrishna, R.N., Steven, W.R., 2003. Assessing the impact of urban land development on net primary productivity in the southeastern United States. Remote Sens. Environ. 86, 401–410.

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 net primary productivity. Global Biogeochem. Cy. 13 (3), 803–815.

Elmore, A.J., Shi, X., Gorence, N.J., Li, X., Jin, H.M., Wang, F., Zhang, X.H., 2008. The spatial distribution of agricultural residue from rice for potential biofuel production in China. Biomass Bioenerg. 32, 22–27.

Field, C.B., 2001. Sharing the garden. Science 294, 2490–2491.

Field, C.B., Behrenfeld, M.J., Randerson, J.T., Falkowski, P., 1998. Primary production of the bio sphere: integrating terrestrial and oceanic components. Science 281, 237–240.

Field, C.B., Randerson, J.T., Malmstrom, C.M., 1995. Global net primary production: combining ecology and remote sensing. Remote Sens. Environ. 51, 74–88.

Folke, C., Jannson, A., Larsson, J., Costanza, R., 1997. Ecosystem appropriation by cities. AMBIO 26, 167–172.

Gao, Z.L., Feng, X.P., Cong, H.J., 2005. Study on the effect of urbanization on floodwater—taking the Shenzhen city as an example. Chin. Agric. Sci. Bull. 21 (8), 380–383.

Goetz, S.J., Prince, S.D., 1996. Remote sensing of net primary production boreal forest stands. Agr. Forest Meteorol. 78, 149–179.

Houghton, R.A., Hackler, J.L., Lawrence, K.T., 1999. The U.S. carbon budget contributions from land-use change. Science 285, 574–578.

Imhoff, M.L., Tucker, C.J., Lawrence, W.T., Stutzer, D.C., 2000. The use of multisource satellite and geospatial data to study the effect of urbanization on primary productivity in the United States. IEEE Trans. Geosci. Remote 38 (6), 2549–2556.

Imhoff, M.L., Lawrence, W.T., Stutzer, D.C., Elvidge, C.D., 1997. Using nighttime DMSP/OLS images of city lights to estimate the impact of urban land use on soil resources in the US. Remote Sens. Environ. 59, 105–117.

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.

Jeffrey, A.H., 2006. NCEP and GISS solar radiation data sets available for ecosystem modeling: description, differences, and impacts on net primary production. Global Biogeochem. Cy. 19, 1–18.

McCrady, R.L., Jokela, E.J., 1998. Canopy dynamics, light interception, and radiation use efficiency of selected loblolly pine families. Forest Sci. 44, 64–72.

McDonnell, M.J., Pickett, S.T.A., Pouyat, R.V., Zipperer, W.C., Parmelee, R.W., Carreiro, M.M., Medley, K., 1997. Ecosystem processes along an urban-to-rural gradient. Urban Ecosyst. 1, 21–36.

Nizeyaimana, E., Petersen, G.W., Imhoff, M.L., Sinclair, H., Waltman, S., Reed-Margetan, D.S., Levine, E.R., Russo, P., 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.

Paruelo, J.M., Epstei, H.E., Lauenroth, W.K., Burkei, C., 1997. ANPP estimates from NDVI for the central grassland region of the United States. Ecology 78, 953–958.

Pielke, S.R.A., Walko, R.L., Steyaert, L.T., Vidale, P.L., Liston, G.E., Lyons, W.A., Chase, T.N., 1999. The influence of anthropogenic landscape changes on weather in south Florida. Mon. Weather Rev. 127, 1663–1673.

Pimm, S.L., Raven, P., 2000. Biodiversity-extinction by numbers. Nature 403 (6772), 843–845.

Postel, S.L., Daily, G.C., Ehrlich, P.R., 1996. Human appropriation of renewable fresh water. Science 271 (5250), 785–788.

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.

Prince, S.D., 1991. A model of regional primary production for use with coarse resolution satellite data. Int. J. Remote Sens. 12, 1313–1330.

Rojstaczer, S., Sterling, S.M., Moore, N.J., 2001. Human appropriation of photosynthesis products. Science 294 (5551), 2549–2552.

Ruimy, A., Saugier, B., 1994. Methodology for the estimation of terrestrial net primary production from remotely sensed data. J. Geophys. Res. 97, 18515–18521.

Sala, O.E., Chapin, F.S., Armesto, J.J., 2000. Biodiversity—global biodiversity scenarios for the year 2100. Science 287 (5459), 1770–1774.

Schimel, D., Enting, I.G., Heimann, M., 1995. CO_2 and the carbon cycle. In: Climate Change 1994 (Intergovernmental Panel on Climate Change), Cambridge University Press, Cambridge.

Schimel, D., Melillo, J., Tian, H.Q., 2000. Contribution of increasing CO_2 and climate to carbon storage by ecosystems in the United States. Science 287 (5460), 2004–2006.

China Statistics Press, pp. 6–8.

Vitousek, P.M., Ehrlich, P., Ehrlich, A., Matson, P.M., 1986. Human appropriation of the products of photosynthesis. BioScience 36, 368–373.

Vitousek, P.M., Mooney, H.A., Lubchenco, J., Melillo, J.M., 1997. Human domination of Earth's ecosystems. Science 277, 494–499.

Wackernagel, W., Yount, D., 1998. The ecological footprint: an indicator of progress toward ecological sustainability. Environ. Monit. Assess. 51, 511–529.

Wear, D. N., Greis, J. G., 2001. The Southern Forest Resource Assessment Draft Summary Report. http://www.srs.fs.fed.us/sustain.

Wilson, E.H., Sader, S.A., 2002. Detection of forest harvest type using multiple dates of Landsat TM imagery. Remote Sens. Environ. 80, 385–396.

Yu, D.Y., Pan, Y.Z., Liu, X., Wang, Y.Y., Zhu, W.Q., 2006. Ecological capital measurement by remotely sensed data for Huahou and its socio-economic application. J. Plant Ecol. 30 (3), 404–413 (in Chinese, with English abstract).

Zhou, G.S., Zhang, X.S., 1995. Natural vegetation NPP model. Acta Phytoecol. Sin. 19, 193–200.

Zhou, G.S., Zhang, X.S., 1996. Study on NPP of natural vegetation on China under global climate change. Acta Phytoecol. Sin. 20 (1), 11–19.