Exploring the response of net primary productivity variations to urban expansion and climate change: A scenario analysis for Guangdong Province in China

Fengsong Pei a, Xia Li b,*, Xiaoping Lii b,**, Chunhua Laob, Gengrui Xiaa

a School of Urban and Environmental Sciences, Jiangsu Normal University, Xuzhou, 221116, PR China
b Guangdong Key Laboratory for Urbanization and Geo-simulation, School of Geography and Planning, Sun Yat-sen University, 135 West Xingang RD., Guangzhou, 510275, PR China

ABSTRACT

Universal land development alters landscapes and carbon cycle, especially net primary productivity (NPP). Despite projections that NPP is often reduced by urbanization, little is known about NPP changes under future urban expansion and climate change conditions. In this paper, terrestrial NPP was calculated by using Biome-BGC model. However, this model does not explicitly address urban lands. Hence, we proposed a method of NPP-fraction to detect future urban NPP, assuming that the ratio of real NPP to potential NPP for urban cells remains constant for decades. Furthermore, NPP dynamics were explored by integrating the Biome-BGC and the cellular automata (CA), a widely used method for modeling urban growth. Consequently, urban expansion, climate change and their associated effects on the NPP were analyzed for the period of 2010-2039 using Guangdong Province in China as a case study. In addition, four scenarios were designed to reflect future conditions, namely baseline, climate change, urban expansion and comprehensive scenarios. Our analyses indicate that vegetation NPP in urban cells may increase (17.63 gC m⁻² C₀⁻¹ e 23.35 gC m⁻² C₀⁻¹) in the climate change scenario. However, future urban expansion may cause some NPP losses of 241.61 gC m⁻² C₀⁻¹, decoupling the NPP increase of the climate change factor. Taking into account both climate change and urban expansion, vegetation NPP in urban area may decrease, minimally at a rate of 228.54 gC m⁻² C₀⁻¹ to 231.74 gC m⁻² C₀⁻¹. Nevertheless, they may account for an overall NPP increase of 0.78 TgC year⁻¹ to 1.28 TgC year⁻¹ in the whole province. All these show that the provincial NPP increase from climate change may offset the NPP decrease from urban expansion. Despite these results, it is of great significance to regulate reasonable expansion of urban lands to maintain carbon balance.

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1. Introduction

Northern terrestrial ecosystem' acted as a carbon sink, as inferred from some inventory-based analyses and atmospheric inversion models (Fan et al., 1998; Gielen et al., 2013). However, the ecosystem could become a carbon source owing to some disturbances, such as climatic droughts (Ciais et al., 2005), insect outbreaks (Kurz et al., 2008) and urban expansion (Seto et al., 2012). It is crucial to explore the consequences of various ecological disturbances for elucidating carbon cycling and other ecosystem processes.

Climate change frequently occurs on a large extent, and has a critical impact on carbon cycling. By contrast, urban expansion occurs on a local scale. However, it has a greater impact on the ecosystem because of severe human interruption. Particularly, global urban area has expanded dramatically over the past decades. It is expected to experience more urban land expansion by 2030, nearly tripling the urban lands in 2000 (Angel et al., 2011; Seto et al., 2012). As a typical land use/cover change, urban expansion alters the compositions, structures and functions of terrestrial ecosystem (Alberti, 2008; Seto et al., 2012). Many studies investigated the process of urban expansion (Liu et al., 2010; Li et al,
climate change, and the impacts of climate change on carbon cycle (Mu et al., 2008; Zhao and Running, 2010; Wu et al., 2012; Piao et al., 2013). However, researchers paid less attention to the coupling effects of urban expansion and climate change on carbon cycle, especially net primary productivity (NPP). Understanding the relationship among urban expansion, climate change and carbon cycle is crucial for regulating urban development by city managers.

NPP refers to production of organic compounds, principally through the photosynthesis. It reflects not only the production capability of vegetation but also the ecological processes directly (e.g., carbon source/sink). Terrestrial NPP is dominated by climate change, nitrogen limits, and some human-induced factors (e.g., urban expansion) (Cramer et al., 1999; Wang and Houlton, 2009; Wu et al., 2014). In terms of climate change, Mu et al. (2008) assessed the contributions of increasing CO2 and climate change to the carbon cycle by taking China as a case study. They found that the climate change reduced carbon storage of China’s ecosystems without incorporating CO2 fertilization effects. Zhao and Running (2010) found a reduction of the global NPP (about 0.55 PgC) in the period of 2000–2009. This reduction was mainly induced by droughts that occurred during this time. As to urban expansion, Xu et al. (2007) assessed the impacts of urbanization on the NPP in limited areas in the Yangtze Delta. Yu et al. (2016) updated the land use/cover by each urban sprawl on the regional NPP of Shenzhen, China. They pointed out that NPP is often decreased by urban land transformation in the process of rapid urbanization. Seto et al. (2012) estimated the losses of vegetation biomass to be 1.38 PgC (0.05 PgC year−1) based on the areas with high probability of urban expansion within the tropics. However, Imhoff et al. (2004) and Pei et al. (2013) found a small increase of NPP concerning urbanization in some areas. In addition, Wu et al. (2014) assessed the contributions of urbanization and climate change to the NPP variations in the Yangtze River Delta in China over the last decade based on the DMSP/OLS (Defense Meteorological Satellite Program Operational Linescan System) nighttime light imagery data. Earlier studies frequently focused on spatial consequences of NPP to urban land development, either at present or in the past, by using diagnostic analysis. Little is known about the locations, magnitudes, and frequencies of NPP changes under future urban expansion and climate change. It remains uncertain what is the relative contributions of climate change and urban expansion to the global carbon cycle.

In the past decades, many ecosystem models were developed while modeling the NPP. These models can be categorized into three major groups: statistical models, parametric models, and process models (Ruiny et al., 1994). The statistical models are simple but lack of generality (Matsushita et al., 2004). Given the advantage of remote sensing for direct observation, the parametric models can reliably assess vegetation productivity. This has been confirmed in several prior studies (Veroustraete et al., 2004; Maselli et al., 2013). However, parametric models have difficulty in evaluating future NPP for the lack of corresponding satellite observation in future periods. The process models describe the biogeochemical cycling process (e.g., photosynthesis, respiration, assimilation and allocation) for natural vegetation. This type of model is commonly limited by the high complexity, difficult calibration, and high computational cost when it is applied on a regional scale (Ruiny et al., 1994; Chiesi et al., 2007). For reflecting the climate change over the next few decades, the vegetation NPP was modeled by using one of the process models, Biome-BGC. Despite the predictive capability of Biome-BGC, the model has limited effects on the simulation of non-natural vegetation in urban lands. Urban NPP are frequently modeled by using: (1) top-down models; (2) bottom-up models; (3) hybrid models (Grimm et al., 2008; Trusilova and Churkina, 2008; Chen et al., 2014). In this paper, future urban NPP was modeled by using cellular automata (CA), Biome-BGC, Carnegie-Ames-Stanford approach (CASA) and NPP-fraction method (Potter et al., 1993; Running and Hunt, 1993). In terms of land use/cover change, many methods were developed to capture their dynamics. These methods can be categorized as two kinds: non-spatial and spatial models (Huang and Cai, 2007). As one of the temporal—spatial modeling approaches, CA has been widely employed in simulating land cover/use change. This is particularly effective in the simulation of urban expansion, from a single city to megalopolitan cluster area (Li et al., 2011; Kuang, 2011; He et al., 2013). In this paper, the effects of urban expansion and climate change on NPP were investigated by using several model simulations. The urban expansions in Guangdong Province in China were simulated and predicted by using the CA model. Future climate change was projected by using downscaling methods based on outputs from general circulation models (GCM). Terrestrial NPP was modeled based on Biome-BGC. A method of NPP-fraction was designed for modeling future urban NPP. Consequently, the relative contributions of urban expansion and climate change to future NPP were evaluated by using scenario analysis.

2. Materials and methods

2.1. Study area

The study area, which covers approximately 179,800 km², is located in Guangdong Province in southern China (Fig. 1). The predominant climate in this region is subtropical, with an annual rainfall of 1700 mm and average annual temperature of 19 °C. The province mostly belongs to the monsoon climate region, with rainfall and heat energy in the same seasons, which provide a favorable environment for plant growth. The main ecosystem types encompass evergreen broadleaf forest (EBF), evergreen needleleaf forest (ENF), mixed forest, alpine shrub and so on. Since the economic reform in 1978, Guangdong has witnessed rapid and unprecedented urbanization, accompanied by massive urban land development. In 2010, Guangdong became one of the largest urban areas at the provincial level in China, with urban areas five times larger than in 1990 (Wang et al., 2012).

2.2. Data preparation and preprocessing

Daily meteorological data (e.g., maximum temperature, minimum temperature, precipitation and solar radiation), which covers the period of 1961–2009, were obtained from the Chinese National Meteorological Information Center. Data continuity and consistency were validated by screening and eliminating suspicious and missing records. Vapor pressure deficit (VPD) and day length were simulated by using the MTClim (Hungerford et al., 1989). In addition, spatial distributions of various vegetation were obtained from a digitized map of China at a scale of 1:1,000,000 (Editorial Board of Vegetation Map of China, 2001). To fit the Biome-BGC model properly, original categories of the vegetation types in Guangdong Province were reclassified into several classes: evergreen needle-leaf forest (ENF), evergreen broadleaf forest (EBF), shrub and grass. In terms of urban areas, urban lands were extracted by using geographic information system (GIS) from three land use/cover datasets across China, which cover the years 2000, 2005 and 2008. The land use/cover dataset in 2000 was obtained from a digitized map at a 1:100,000 scale, which was interpreted and produced based on 512 scenes of Landsat TM/ETM+ images in 1999/2000 (Liu et al., 2005). In addition, the land use/cover data in 2005 and 2008 were derived from the updated survey of land use/cover by each province in China (Jing, 2009; Liu et al., 2005). For improving the computational efficiency and capturing the dynamics of urban landscape, all the land use data were aggregated to a cell size of
500 m (1548 columns, 1176 rows). As to the soil-related data (e.g., percent of sand, silt and clay, soil depth), they were obtained from the Harmonized World Soil Database (Freddy et al., 2008). A digital elevation data with a 90 m resolution from the shuttle radar topography mission (SRTM) was used to derive the elevation and slope map. For validating and checking the NPP simulation, some field-based biomass/NPP records, which were widely used in previous studies (Ni, 2004; Feng et al., 2007), were collected from Luo’s (1996) study. The data were primarily compiled based on the national forest inventories from 1989 to 1993, and other published literature (Ni, 2004; Jin et al., 2007).

2.3. CA model for simulation of urban expansion

Recent years have witnessed a growing trend of using CA to investigate complex urban dynamics (Batty and Xie, 1994; Li and Yeh, 2002; Li et al., 2011). In this paper, urban land development probability \( P(s_{ij}) \) of location \((i,j)\) was simulated by using a logistic-CA model (Wu, 2002; Li et al., 2008):

\[
P(s_{ij}) = \left(1 + \frac{1}{1 + \exp(-z_{ij})} \right)^{-1} CON_{ij} \cdot \Omega_{ij}
\]

\[
z_{ij} = a + \sum_k b_k x_k
\]

where \( \gamma \) is a stochastic factor within the range \((0, 1)\); \( a \) is a parameter to control the stochastic degree; \( z_{ij} \) is the suitability score for urban land development; \( a \) is a constant from the logistic regression model, \( b_k \) is coefficients of the \( k \)th spatial variable concerning accessibility or proximity (e.g., distances to urban centers, transport lines), \( a \) and \( b_k \) are calibrated by using a logistic regression model based on several spatial variables (Wu, 2002). The term \( CON_{ij} \) is a combined physical constraint, and \( \Omega_{ij} \) refers to the development density of developed cell \((i,j)\).

The function \( CON_{ij} \) is defined as a conditional function, which converts the state of all land cells into a binary variable. This term reflects the combined physical constraint for urban land development. For instance, the value of zero will be assigned to all unavailable cells for urban development (e.g., water, protected areas).

The neighborhood function \( \Omega_{ij} \) is calculated as:

\[
\Omega_{ij} = \frac{\sum 3 \times 3 \{ \text{cond}(s_{ij} = \text{urban}) \}}{3 \times 3 - 1}
\]

where \( \text{cond}(s_{ij} = \text{urban}) \) is a conditional function that returns true if the state \( s_{ij} \) is urban area. The neighborhood of a cell \((i,j)\) is defined as eight neighboring cells.

At each iteration of the CA simulation, the development probability \( P(s_{ij}) \) is compared with a threshold value \( (P_{\text{threshold}}) \) to decide if a non-urban cell is to convert into an urbanized cell according to equation (4). In this study, urban expansion was simulated by using the logistic-CA model components of geographical simulation and optimization system (GeoSOS) (Li et al., 2011).
2.4. Downscaling methods for projecting climate change

GCM model is one of the important tools used to assess global climate change. However, their resolution are too coarse to resolve sub-grid-scale features, such as topography, hydrology, and urban expansion (Salathé, 2005). In past decades, many downscaling techniques have been developed for adapting the fine-scale application of GCM. To reduce the uncertainty of downscaling methods, an ensemble of simulations was executed with two independent realizations of downscaling, as discussed below.

2.4.1. Change factor (CF)

In the core algorithm of CF, daily temperature (precipitation) is calculated by combining the monthly difference (ratio) of temperature (precipitation) from climate model with the observed values. As to maximum and minimum temperature, a difference of monthly temperature is calculated between the future horizon ($T_{\text{max}}^{\text{ref},2020}$ and $T_{\text{min}}^{\text{ref},2020}$, °C) and reference period ($T_{\text{max}}^{\text{hadcm},2000}$ and $T_{\text{min}}^{\text{hadcm},2000}$, °C) of the climate model outputs. Daily maximum and minimum temperature at the future horizon ($T_{\text{max}}^{2020}$ and $T_{\text{min}}^{2020}$, °C) is then retrieved by adding this difference to the observed daily temperature ($T_{\text{obs},d}^{\text{max}}$ and $T_{\text{obs},d}^{\text{min}}$, °C) (Chen et al., 2011).

$$\begin{align*}
T_{\text{max}}^{2020} &= T_{\text{obs},d}^{\text{max}} + (T_{\text{max}}^{\text{hadcm},2000} - T_{\text{max}}^{\text{hadcm},2020}) \\
T_{\text{min}}^{2020} &= T_{\text{obs},d}^{\text{min}} + (T_{\text{min}}^{\text{hadcm},2000} - T_{\text{min}}^{\text{hadcm},2020})
\end{align*}$$

As to precipitation, a ratio is calculated based on GCM output for the future horizon ($P_{\text{hadcm},2020}$) and reference period ($P_{\text{hadcm},2000}$). Daily precipitation for future horizon ($P_{2020,d}$) is obtained by multiplying this ratio with the observed daily precipitation ($P_{\text{obs},d}$) (Chen et al., 2011).

$$P_{2020,d} = P_{\text{obs},d} \times \frac{T_{\text{hadcm},2000}}{T_{\text{hadcm},2020}}$$

2.4.2. Statistical downscaling model (SDSM)

The SDSM, which was developed by Wilby et al. (2002), is a useful tool to downscale climate change. This algorithm is best categorized as a hybrid of stochastic weather generator and regression-based downscaling methods (Wilby and Wigley, 1997). The downscaling process is either unconditional (e.g., wet-day occurrence and temperature), or conditional (as with rainfall amount) on an event.

In terms of precipitation, the downscaled process can be performed in two steps: (1) estimating wet-day occurrence; (2) simulating total precipitation. For wet-day occurrence ($W_i$), a linear dependency is employed based on some predictor variables ($X_{ij}$):

$$W_i = \beta_0 + \sum_{j=1}^{n} \beta_j X_{ij}, \quad 0 \leq W_i \leq 1$$

By generating a random number, precipitation is supposed to occur if the uniform random number $\tau \leq W_i$. If a wet-day occurrence is obtained, total precipitation $P^k_i$ is given by:

$$P^k_i = \gamma_0 + \sum_{j=1}^{m} \gamma_j X_{ij} + e_i$$

With regard to temperature, a direct linear relationship was assumed between the predictand ($U_i$) and the chosen predictors ($X_{ij}$):

$$U_i = \alpha_0 + \sum_{j=1}^{n} \alpha_j X_{ij} + e_i$$

where $e_i$ represents the model error. This parameter, which is assumed to follow a Gaussian distribution, is stochastically generated from normally distributed random numbers.

No matter precipitation or temperature ($X_{ij}$), all predictors ($V_{ij}$) are standardized based on their climatological mean ($\overline{V}_j$) and standard deviation ($\sigma_j$) calculated from the 40-year climatic data (1961–1990):

$$X_{ij} = \frac{V_{ij} - \overline{V}_j}{\sigma_j}$$

In this paper, least squares calibration was performed to obtain the downscaled parameters ($\alpha$, $\beta$ and $\gamma$) by using the re-analysis data for the period of 1961–1990 from the National Center for Environmental Prediction (NCEP) (Kalnay et al., 1996). A detailed description of SDSM can be found in Wilby et al. (1999), Wilby and Dawson (2012).

2.5. Simulation of NPP using Biome-BGC

2.5.1. Model description

Biome-BGC is a process-based model designed to simulate the energy and material cycle within terrestrial ecosystems (Running and Hunt, 1993; White et al., 2000). This model requires input of daily meteorological data, eco-physiological parameters and general environmental information (e.g., soil and vegetation). Many biogeochemical and hydrological processes, including evapotranspiration, soil evaporation, photosynthesis and respiration by plant, can be simulated for various biomes.

For water vapor flux, Penman–Monteith equation is used to calculate the evaporation of soil water, the evaporation of canopy-intercepted water, and the transpiration of water from leaves:

$$\epsilon = \frac{s \cdot \text{RAD} + \frac{e_{\infty} \cdot VPD_{\infty}}{r_{\text{lu}}}}{1 + \frac{e_{\infty} \cdot VPD_{\infty}}{r_{\text{lu}}}} + s$$

where $\epsilon$ is the evaporation rate (W m$^{-2}$ s$^{-1}$); RAD is the incident radiant flux density (W m$^{-2}$); $e_\infty$ is the ratio of molecular weights of water vapor and air; $r_l$ is the resistance to water vapor flux (s m$^{-1}$); $r_{\text{lu}}$ defines the combined resistances to convective and radiative heat (s m$^{-1}$); $\rho$ is the density of air as a function of temperature; $c_p$ is the specific heat of air (J kg$^{-1}$ °C$^{-1}$); AirPa is the air pressure (Pa).

Photosynthesis is a process in which CO$_2$ water molecules and solar energy are combined to generate simple sugars by vegetation. In Biome-BGC, this reaction is characterized by using three equations, which represent different controls on photosynthesis rate, respectively. First, diffusion constraint of CO$_2$ on photosynthetic rate is represented as:

$$A_{\text{nec}} = \frac{G_{\text{Nec}} \cdot (C_a - C_i)}{G_i}$$

where $C_a$ represents the atmospheric concentration of CO$_2$ (Pa); $C_i$ is the intercellular concentration of CO$_2$ (Pa); $G_{\text{Nec}}$ is the CO$_2$ conductance converted from stomatal conductance to water vapor. In addition, photosynthesis rate is constrained by regulation of the carboxylation rate of photosynthesis reaction in equation (14).

$$A_v = \frac{V_{\text{max}} \cdot (C_i - G_i)}{C_i + K_i \cdot (1 + \frac{G_i}{K_i})} - MR_{\text{vegday}}$$

where $V_{\text{max}}$ is the maximum rate of carboxylation of photosynthesis (mol m$^{-2}$ s$^{-1}$); $C_i$ is the intercellular CO$_2$ concentration (Pa); $K_i$ is the half-velocity constant for CO$_2$ (Pa); $MR_{\text{vegday}}$ is the daily maintenance respiration of vegetation (mol m$^{-2}$ day$^{-1}$).
where $V_{\text{max}}$ is the maximum rate of carboxylation; $I^*$ is the CO$_2$ compensation point; $K_e$ and $K_r$ are the kinetic constants for rubisco carboxylation and oxygenation (Pa); $MR_{\text{leaf/day}}$ is the daytime leaf maintenance respiration; $f$ is the maximum rate of electron transport. Moreover, the photosynthesis rate is manipulated through the electron transport limitation of RuBP regeneration as in equation (15). The smaller of the two results is then used as the rate of carbon assimilation.

As to the respiration, Biome-BGC simulates all the processes of autotrophic (growth and maintenance) and heterotrophic (decomposition). For the growth respiration, it is assumed to be a constant proportion for all new tissues. In addition, maximum rate for decomposition and biomass loss are defined as constants. The rate is adjusted based on temperature and water availability. There is no decomposition if temperature is below −10 °C. As to the maintenance respiration ($MR$, a Q10 relationship with temperature ($T$) as well as nitrogen content ($N$) of tissues is used to determine the rate as follows:

$$MR = 0.218 \times N \times Q_{10}^{(T - 20)/10}$$  (16)

The details of the Biome-BGC model can be found in the Biome-BGC project page: http://www.ntsg.umt.edu/project/biome-bgc.

2.5.2. Model run and parameterization

An equilibrium of initial state is often required by Biome-BGC to ensure the balance between input and output fluxes. Firstly, a spin-up run was performed to bring state variables in this model into dynamic equilibrium by using meteorology data during 1980–2009 and a CO$_2$ concentration of 372 ppm (Houghton et al., 2001). By using the spin-up endpoint as an initial condition, vegetation NPP was simulated for the period of 1980–2039.

With the use of prescribed parameters concerning site conditions, meteorology, and eco-physiological values, Biome-BGC simulates the flux and storage of energy, water, carbon, and nitrogen. For distinguishing different biomes, 42 parameters are required in the core algorithm of Biome-BGC. It is a difficult task to determine these generalized biome parameterizations in regional and global modeling. In this paper, these parameters were assigned in the following way: (1) For each parameter, we conducted a literature search of published studies for each biome; (2) A sensitivity analysis was performed by varying all the parameters to their potential NPP of natural vegetation remains constant in future decades. Considering the simulating capability of ecological processes, Biome-BGC was selected to model future NPP. Despite its predictive capability, Biome-BGC has limited effects on the simulation of artificial vegetation in urban lands (Zhao et al., 2006). Thus, one of remote sensing-based models, CASA, was also used to calculate the vegetation NPP of non-natural vegetation, assuming that the CASA can faithfully estimate vegetation productivity, at least on a regional scale (Imhoff et al., 2004; Pei et al., 2013; Maselli et al., 2013).

The NPP-fraction was calculated in two steps. First, the NPP after urbanization (NPP$_{\text{urb.2000–2009}}$) in recent years (2000–2009) was evaluated by using CASA based on satellite data (Pei et al., 2013). Second, the potential NPP in urban lands (NPP$_{\text{potential.2000–2009}}$) during this period was calculated using Biome-BGC. Finally, an NPP-fraction (NPP$_{\text{urb.2000–2009}}$/NPP$_{\text{potential.2000–2009}}$) was calculated by performing a division of the potential NPP by the NPP after urbanization. Consequently, urban NPP (NPP$_{\text{urb.2010–2039}}$) could be calculated through a combination of the NPP-fraction and the potential NPP calculated by Biome-BGC (NPP$_{\text{potential.2010–2039}}$). The detailed expression can be shown as follows:

$$NPP_{\text{urb.2010–2039}} = NPP_{\text{potential.2010–2039}} \times \frac{NPP_{\text{urb.2000–2009}}}{NPP_{\text{potential.2000–2009}}}$$  (17)

2.6. Scenario design for future conditions

A scenario analysis technique was applied for future periods (2010–2039) to elucidate the relative contributions of urban expansion and climate change to the NPP variations. Four scenarios were designed and simulated according to the drivers they represented (Table 1), namely, baseline scenario, climate change scenario, urban expansion scenario, and comprehensive scenario.

2.6.2.1. Baseline scenario. The baseline scenario was designed as a reference scenario. It was established to describe future conditions without any climate change and urban expansion. In other words, this scenario reflects a continuation of present climatic conditions and urban areas in future decades. In detail, the temperature and precipitation data were recycled by using the historical climate (1980–2009). CO$_2$ concentration was fixed at the level of 2000 (i.e., 372 ppm) (Houghton et al., 2001). In addition, urban area was set in accordance with the urban lands in 2006 in both present and future periods.

2.6.2.2. Climate change scenario. When representing future climate change in Guangdong Province, one of the medium-emission scenarios from the fourth assessment report (AR4) of IPCC (Intergovernmental Panel on Climate Change), SRES (special report on emissions scenarios) B2 was used, assuming a local solution to economic, social, and environmental sustainability in future decades (Bernstein et al., 2007). The climate change scenario

<table>
<thead>
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<th>Categories</th>
<th>CO$_2$ concentration</th>
<th>Temperature/precipitation</th>
<th>Urban lands (year)</th>
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<td>Historical</td>
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<td>Future</td>
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<td>Climate change scenario</td>
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<td>Comprehensive scenario</td>
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addresses only conditions of climate change, but no urban land development. This scenario projects a fluctuation of temperature, precipitation and CO2 concentration, according to the IPCC SRES B2 emission. In this paper, the temperature and precipitation data were downscaled by using CF/SDSM based on the IPCC GCM output. The CO2 concentration was linearly interpolated based on Johns et al. (2003). However, no urban expansion was identified in this scenario. That is, the urban area in 2006 was applied in future periods.

2.6.2.4. Comprehensive scenario. The comprehensive scenario portrays a future condition with changed temperature, precipitation, Meteorological data, CO2 concentration and urban lands were all tackled the impacts of both climate change and urban expansion. The change scenario, comprehensive scenario and baseline period were set up as shown in Table 1.

2.6.3. Scenario analyses for the relative contributions of future urban expansion and climate change to NPP variations

To isolate the contribution of a single factor to future NPP variations, NPP differences between urban expansion scenario, climate change scenario, comprehensive scenario and baseline scenario were calculated by using the NPP results from various scenarios (Table 3). The factor of climate change was accounted by calculating the difference between model outputs of climate change scenario and baseline scenario. To account for both urban expansion and climate change, the difference was also calculated between the comprehensive scenario and baseline scenario. All these results were then analyzed at the cell level in urban area and at the regional scale in the whole Guangdong Province, respectively.

3. Results and discussions

3.1. Simulated urban expansion

3.1.1. Calibration of the CA model

Several spatial variables were retrieved by calculating distances to urban centers, roads, expressways, and railways with GIS. Suitability of urban land development was computed by using logistic regression (i.e., the CA model is calibrated) (Wu and Webster, 1998). By using this calibration method, \( z_{ij} \) in equation (2) was thus specified as follows:

\[
    z_{ij} = 2.744 - 5.229x_{\text{DIStown}} - 0.995x_{\text{DISroad}} - 2.336x_{\text{DISrailway}} - 2.179x_{\text{DISexpressway}} - 14.796x_{\text{slope}}
\]

(18)

where \( x_{\text{DIStown}} \), \( x_{\text{DISroad}} \), \( x_{\text{DISrailway}} \) and \( x_{\text{DISexpressway}} \) represent the distances to town centers, main roads, railways, and expressways, respectively. \( x_{\text{slope}} \) is the slope.

In the CA simulation, numerous iterations are required to obtain subtle patterns of urban expansion. Despite no accordance on how many iterations should be used, 100–200 iterations are quite normal (Li and Yeh, 2004). When calibrating the CA model, we performed 200 iterations for producing a realistic pattern.

3.1.2. Validation and simulation of the CA model

The CA model requires a validation when applied to the simulation of a real city. Its accuracy, which is measured from land use confusion matrix, is shown in Table 2. The predictions of urban development simulations are 78.13% and 72.22% correct for the years 2005 and 2008, respectively. In addition, the kappa coefficients are 0.77 and 0.78, respectively. These results show conformity between the simulated and actual patterns of land use.

Fig. 2a shows the actual spatial distribution of urban lands in 2000. Future land use patterns in 2020 were simulated, assuming the continuation of current trends and dynamics of urban land development. Consequently, the urban lands of Guangdong Province may increase by about 126% in 2020, compared with the initial urban lands in 2000 (Fig. 2b). The urban expansions are mainly distributed around the urban centers because of their high transition suitability.

3.2. Projected climate change

Future climate conditions were projected based on the outputs of HADCM3 by using two downscaling techniques (SDSM and CF). To understand future climatic trends, we examined the climate change for two periods (baseline vs. future). First, a baseline period (1961–1990) was defined in line with the recommendations of the World Meteorological Organization. Second, a 30-year average (2010–2039) of the projected climatic factors was calculated from the model outputs of two downscaling techniques (Diaz-Nieto and Wilby, 2005). Seasonal and spatial dynamics were investigated for these two periods.

3.2.1. Seasonal dynamics

To elucidate the trends of future climate change, the difference between future and reference period was calculated by month. As shown in Fig. 3, both maximum and minimum temperatures in future climate projection exhibit an increase in comparison with the reference period in most months. For the maximum temperature, the amount of increase varies between 0.97 (± 0.35) °C (for SDSM) and 0.96 (± 0.50) °C (for CF). When it concerns the minimum temperature, the variation shows a slight increase, from 1.09 (± 0.32) °C (for SDSM) to 0.83 (± 0.46) °C (for CF). These results indicate an increase of future temperature, and are approximate to the findings of Leung et al. (2006).

Precipitation is the most complex aspect of the downscaling problem (Wilks, 2010). Fig. 4 shows the seasonal variations of

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Note: number in each category refers to number of pixels in that category.

Table 2

Confusion matrix between actual and simulated land use.

<table>
<thead>
<tr>
<th>Category</th>
<th>2005</th>
<th>2008</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simulated</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Accuracy</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Simulated</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Accuracy</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: number in each category refers to number of pixels in that category.

Table 2

Confusion matrix between actual and simulated land use.
3.2. Future precipitation downscaled by using SDSM and CF. They indicate a fluctuation in monthly precipitation, from 9.29 (± 20.47) mm (for SDSM) to 11.64 (± 32.51) mm (for CF). However, SDSM and CF both indicate a summer increase in precipitation (June to August). The results are in accordance with the findings of Leung et al. (2006).

3.2.2. Spatial patterns of climate change
Aside from the seasonal variations, spatial heterogeneity in future climate change was investigated by calculating the difference between future and reference period. As for the maximum and minimum temperatures, the outputs of both SDSM and CF show an obvious increase. As shown in Fig. 5a and b, the maximum temperature exhibits some increases between 0.79 °C and 1.12 °C. The minimum temperature is similar to that of the maximum temperature, about 0.72 °C to 1.20 °C. In terms of the spatial heterogeneity, both the maximum and minimum temperature decrease from the southwest to the southeast. In addition, precipitation increases from 53.63 mm to 198.82 mm (Fig. 5c and d). The spatial distribution of precipitation is also identical for the two downscaling methods. That is, the precipitation shows a decrease from north to south in Guangdong Province.

3.3. Variations of the NPP

3.3.1. Validation of the NPP calculations
The observed NPP and some other literature were used to test the reliability of the Biome-BGC simulations. We performed a comparison between the model results and other studies. An agreement was found between our results and the CASA-derived value by Pei et al. (2013). In addition, our results were slightly lower than those of Luo and Wang (2009) (i.e., 103.5 TgC year⁻¹—166.8 TgC year⁻¹). This may probably be caused by the large light-use efficiency they used.

A general coincidence was also found between the simulation results and field data from Luo (1996) (Fig. 6). Our results are within the observed range of 520.26 gC m⁻² year⁻¹ and 966.46 gC m⁻² year⁻¹.

![Fig. 2. Patterns of urban lands in 2000 and 2020: (a) Actual land use in 2000; (b) Simulated land use in 2020.](image)

![Fig. 3. Comparisons of maximum and minimum temperature between future and reference periods: (a) maximum temperature; (b) minimum temperature.](image)

Note: REF represents the outputs from reference periods; CF represents the outputs by change factor method; SD represents the outputs by statistical downscaling model.
3.3.2. Interannual variations of the NPP

Fig. 7 shows the anomalies of annual NPP in Guangdong Province from 1981 to 2009. It exhibited some NPP fluctuation of about 100 gC m$^{-2}$ year$^{-1}$ in this period. Particularly, it was decreased to −158 gC m$^{-2}$ year$^{-1}$ in 2004. This could be mainly caused by the droughts in this period (Zheng et al., 2010).

3.3.3. Scenario simulations of future NPP

For each scenario, we calculated the distributions and amounts of average NPP in Guangdong Province during 2010–2039. Fig. 8a–f illustrate the spatial distribution of vegetation NPP under the following scenarios: reference, climate change, urban expansion and comprehensive scenarios. In the reference scenario, the total NPP is 97.71 TgC year$^{-1}$. This exhibits a slight increase of 3.00 TgC year$^{-1}$ in comparison with current carbon uptake during 2000–2009. This can be explained by the forest age of less than 40 years in Guangdong Province (Wang et al., 2011).

In the climate change scenario, two simulations were performed by using the outputs from SDSM and CF, respectively. However, future NPP show a spatial accordance between the two simulations (Fig. 8b and c). It exhibits a slight increase, with total NPP of 100.28 PgC year$^{-1}$ to 100.80 PgC year$^{-1}$. This is probably correlated.
with CO₂ fertilization, climate change, and forest age (Mu et al., 2008; Wang et al., 2011). As shown in Fig. 8d, urban expansions reduce the NPP in Guangdong Province in comparison with the baseline scenario, about 175 PgC year⁻¹ (1.79% of total NPP). This may be caused by the growing urban expansion in Guangdong Province by replacing vegetation with an impervious surface.

Both urban expansion and climate change are addressed in the comprehensive scenario. The average NPP in this scenario varies between 98.49 TgC year⁻¹ and 98.99 TgC year⁻¹ during 2010—2039 (Fig. 8e and f). This shows a slight increase compared with the value in the reference scenario.

Except for the total NPP, relative contributions of urban expansion and climate change were also analyzed at the cell level and at the provincial scale for future decades. As to urban cells influenced by urban land use and climate change, future NPP exhibits some decrease by the former in urban expansion scenario, and some increase by the latter in climate change scenario (Table 3). Concretely, climate change may cause an NPP increase of 17.63 gC m⁻² year⁻¹ to 23.35 gC m⁻² year⁻¹, in comparison with the decrease of 241.61 gC m⁻² year⁻¹ for urban expansion. The decrease from urban expansion is more than ten times greater than the increase from climate change. Take the two factors as a whole, they may account for an NPP decrease of 228.54 gC m⁻² year⁻¹ to 231.74 gC m⁻² year⁻¹ in comprehensive scenario. As to the regional consequence at the provincial scale, NPP increases (2.57—3.09 TgC year⁻¹), which are caused by the climate change factor, may be found in climate change scenario. However, urban expansion may reduce the NPP of 1.75 TgC year⁻¹ in urban expansion scenario. While integrating the two factors in the comprehensive scenario, they may account for a slight NPP increase of 0.78 TgC year⁻¹ to 1.28 TgC year⁻¹, in contrast to the NPP decrease at the cell level for urban area. This can be correlated with the dominant roles of accumulative effects of NPP increase induced by climate change for the whole province. For the non-linear

<table>
<thead>
<tr>
<th>Scenario analyses of the vegetation NPP in future decades.</th>
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<tr>
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<td></td>
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<tr>
<td>Vegetation NPP for urban cells (gC m⁻² year⁻¹)</td>
</tr>
<tr>
<td>Total NPP at provincial scale (TgC year⁻¹)</td>
</tr>
</tbody>
</table>

Note: CF represents the outputs by change factor method; SDSM represents the outputs by statistical downscaling model.
relationship among urban expansion, climate change and carbon uptake by vegetation, the total effects of urban expansion and climate change on NPP variations are not equal to the sum of the individual effects from single factors.

Our results show that the NPP increase from climate change may offset the NPP decrease from urban expansion in Guangdong Province. However, appropriate policy guidance of urban expansion is in urgent need for reducing the negative impacts on carbon sequestration at local, regional and even global scales.

4. Conclusions

In this paper, the probable impacts of climate change and urban expansion on NPP in future decades were explored by using a combination of CA, downscaling GCM, and Biome-BGC models. For modeling future urban NPP, an NPP-proportion method was proposed, assuming the ratio of real NPP in urban areas to their potential NPP will be constant in future decades. The relative contributions of urban expansion and climate change to the NPP were investigated by using scenario analysis. Four scenarios were designed according to whether or not they represent the drivers of climate change and urban expansion.

Consequently, urban lands in Guangdong Province were projected as some increases in 2020 (about 126% greater than the urban lands in 2000), based on the trends of urban expansion from 2000 to 2005. In addition, both maximum and minimum temperatures in this region reveal a slight increase than in the reference period. As to precipitation, it may exhibit a fluctuation in most months in future decades. Moreover, an obvious increase of precipitation could be found in summer. According to scenario analyses, both urban expansion and climate change exhibit noticeable effects on the NPP. At the cell levels, urban expansion may reduce the NPP of 241.61 gC m$^{-2}$ year$^{-1}$, decoupling the NPP increase from climate change (17.63 gC m$^{-2}$ year$^{-1}$–23.35 gC m$^{-2}$ year$^{-1}$). At the provincial scale, urban expansion may reduce the NPP of 1.75 PgC year$^{-1}$. However, the factor of climate change may promote the NPP, which varies between 2.57 PgC year$^{-1}$ and 3.09 PgC year$^{-1}$. Colligating the two factors upward, they may cause an NPP increase of 0.78 PgC year$^{-1}$ to 1.28 PgC year$^{-1}$. This indicates that the NPP increase induced by climate change may offset the NPP decrease from urban expansion in the whole province. Despite those results, a regulation of urban expansion is necessary in future periods.

The objectives of this paper are to explore the relative contributions of climate change and urban expansion to NPP variations. However, this study addresses only the IPCC SRES B2 emission scenario concerning climate change. Future work will involve extending the study to a wide range of emission scenarios while representing the probable climate change in future decades. This includes some other scenarios used in IPCC AR4 (e.g., SRES A1, A2, B1 and B2). In addition, this study used Guangdong Province, one of the earliest economic reform regions in China, as a case study. It is essential to extend the exploration to a broad spatial scale, such as continental or global scale. As to the calculation of urban NPP, the processes of urban expansion on carbon cycling are complex, and not well simulated by many ecological models. In this study, urban expansion was modeled by using CA model, one of the bottom-up methods. Particularly, we assumed that future urban expansion will follow an inertial trend, which was calibrated using historical data. It is uncertain how well these parameters represent future urban development. In addition, a loose coupling was conducted between CA and Biome-BGC. In our future work, one of the challenging aspects is to develop a method for better representing the process between land use and carbon cycle.

Acknowledgments

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jenvman.2014.11.002.

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