Modelling the integrated effects of land use and climate change scenarios on forest ecosystem aboveground biomass, a case study in Taihe County of China

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Abstract: Global and regional environmental changes such as land use and climate change have significantly integrated and interactive effects on forest. These integrated effects will undoubtedly alter the distribution, function and succession processes of forest ecosystems. In order to adapt to these changes, it is necessary to understand their individual and integrated effects. In this study, we proposed a framework by using coupling models to gain a better understanding of the complex ecological processes. We combined an agent-based model for land use and land cover change (ABM/LUCC), an ecosystem process model (PnET-II), and a forest dynamic landscape model (LANDIS-II) to simulate the change of forest aboveground biomass (AGB) which was driven by land use and climate change factors for the period of 2010–2050 in Taihe County of southern China, where subtropical coniferous plantations dominate. We conducted a series of land use and climate change scenarios to compare the differences in forest AGB. The results show that: (1) land use, including town expansion, deforestation and forest conversion and climate change are likely to influence forest AGB in the near future in Taihe County. (2) Though climate change will make a good contribution to an increase in forest AGB, land use change can result in a rapid decrease in the forest AGB and play a vital role in the integrated simulation. The forest AGB under the integrated scenario decreased by 53.7% (RCP2.6 + land use), 57.2% (RCP4.5 + land use), and 56.9% (RCP8.5 + land use) by 2050, which is in comparison to the results under separate RCPs without land use disturbance. (3) The framework can offer a coupled method to better understand the complex and interactive ecological processes, which may provide some supports for adapting to land use and climate change, improving and optimizing plantation structure and function,

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and developing measures for sustainable forest management.

1   Introduction

Land use and climate change are the two prongs of global change and global ecology, contributing to changes in both local environment and forest ecosystem services (Hansen *et al*., 2001; Schroter *et al*., 2005). Multiple human-induced global changes, such as climate change, land use change, deforestation and other global environmental changes are complex and are interacting in the context of a multi-system (e.g., climate system, land system, forest ecosystem). These changes are modifying the atmospheric composition and the land surface's landscape, resulting in a complex impact on the forest ecosystem (Karl and Trenberth, 2003; Foley *et al*., 2005). Traditionally, climate, land use, and forest ecological response studies have been operated relatively separately, dealing with specific questions in respective research fields on different space and time scales (Parmesan and Yohe, 2003; Drummond and Loveland, 2010; Rounsevell *et al*., 2012). However, as research continues, these factors separating studies cannot satisfy the needs of human-earth system coupling and multidisciplinary integrated development, nor can they keep up with the policy makers' overall planning (Schindler and Hilborn, 2015). Therefore, to better adapt to and mitigate the future global change, it is necessary to explore and anticipate the individual and combined impacts of land use and climate change on forest.

As a result of continued anthropogenic disturbances, climate change has and will continue to affect the forest ecosystem from species to communities, including tree species richness, forest productivity, forest composition and distribution, and forest biomass (Boisvenue and Running, 2006; Bertrand *et al*., 2011; Michaletz *et al*., 2014; Dai *et al*., 2016). Among them, the change of forest biomass is the most significant criterion for evaluating the quality of the forests and has been widely used in the studies of forest ecological responses to climate change and other disturbances (Fearnside, 2000; Mickler *et al*., 2002). In general, climate change and its impact on forest ecosystems show a long-term process (Payette *et al*., 1989). Much attention has been focused on the interaction between atmospheric composition changes (e.g., CO_2, N) and the tree species or forest communities (Medlyn *et al*., 2001; Xu *et al*., 2007). However, compared with the long-term effects caused by climate change, land use change (such as urbanization, deforestation, farmland expansion and transition, and engineering construction) can bring more direct, short-term effects on forest landscape and forest biomass (Rudel *et al*., 2005). Due to the complex relationships between forest ecosystem, climate system and land system, it is difficult to explore and predict the key ecosystem characteristics except by going through coarse estimates (Gustafson *et al*., 2010). In recent years, however, multi-scale and multi-model approaches have provided a new method for some organizations, communities and researchers to deal with these comprehensive issues. For example, global land project (GLP) presented a framework that incorporates human behavior processes in land use and climate system models to quantitatively analyze dynamic changes in terrestrial ecosystems by using agent-based land use and land cover change models (ABM/LUCC) and some dynamic global vegetation models (DGVMs) (Rounsevell *et al*., 2012). And for another example, the European advanced terrestrial eco-

system analysis and modeling (ATEAM) project proposed using multiple internally consistent scenarios and models to assess the vulnerability of agriculture, forestry, and other human sectors that rely on ecosystem services with respect to global change (Schröter *et al*., 2004). In terms of more specific issues for forest ecosystems, many studies have also been conducted at the regional or landscape levels. Nepstad *et al*. (2008) used global circulation models (GCMs), dynamic vegetation models and economic models to explore the interactions among ecosystems, economy and climate to make prospects for a near-term forest tipping point in the Amazon. Thompson *et al*. (2011) used the LANDIS-II model to evaluate regional forest growth and composition change in Massachusetts, USA over a period of 50 years. They found that, while climate change may enhance growth rates, it will be more than offset by land use, primarily by forest conversion for developed use. ABM has many advantages in simulating land use change and it is designed to integrate human decision processes into a location-specific context in order to explain patterns of land use and test the understanding of land use functions (Matthews *et al*., 2007). For forest landscape simulation, the LANDIS-II model is a forest disturbance and succession model that can simulate significant ecological characteristics of forested landscapes, such as tree composition, distribution, disturbances, and seed dispersal, as well as the spatial arrangement of aboveground biomass (AGB) (Scheller *et al*., 2007). Meanwhile, this model was specifically designed to address the effect of land use and climate change on forest landscape (Xu *et al*., 2007, 2011; Thompson *et al*., 2016). Based on the above, we combined an ABM/LUCC model, an ecosystem process model (PnET-II) and the LANDIS-II to simulate and analyze the variations in forest AGB under various land use and climate scenarios.

In southern China, the forested regions are vast, and the plantations are widely distributed in the hilly red soil region, which accounts for 63% of the total area and 62% of the total stocking volume of those in the whole of China (Liu *et al*., 2014). In the past decades, though the rapid expansion of plantations has made a significant contribution to industrial production and ecosystem services, several issues and challenges always exist, such as unitary tree species, low volumes in growing stock, etc. (Liu *et al*., 2011). At the same time, the development of plantations is under pressure from both changes. With the acceleration of urbanization and township in China nowadays, the demand for land is increasing and the corresponding climate change will exert intense pressure on the regional forest management (Rudel *et al*., 2005). In this paper, our objectives were (1) to estimate the land use changes, including the town expansion, deforestation and forest conversion in Taihe County, Jiangxi Province, China, (2) to build a research framework to explore the integrated and relative effects by using simply coupled models, and (3) to simulate the integrated effects of climate change and land use change on forest AGB under various scenarios over the next 40 years from 2010 to 2050. We chose this period for simulation based on following aspects. Firstly, land use changes are greatly influenced by policy which may change with economy, population and other environmental factors. In this study, we chose the relative recent period of 2010–2050 to simulate the land use change. Secondly, this period can also reflect an overall trend of climate change in the near future. So, we chose this period by considering the tradeoff of temporal scale effects between land use and climate change to simulate the integrated effects on forest ecosystem.

2 Materials and methods

2.1 Study area

Our study area is Taihe County (26.45°–26.98°N, 114.95°–115.33°E),which is located in south-central Jiangxi Province, a typical hilly red soil region of southern China (Figure 1). The total area of the study area is 266,700 ha, and the study area is a major component of the Jitai Basin. This area has a subtropical monsoon climate with mild winters (with a mean January temperature of 6.5°C) and warm summers (with a mean July temperature of 29.7°C), and the average annual temperature is 18.6°C. The average annual precipitation is 1370 mm, most of which (approximately 60%) falls between March and June (Wang *et al*., 2011). The main land use type in the study area includes forest land, town land, farmland, river, and the other land. The total forest area is 163,200 ha, contributing 61.2% to the study area, and the area of plantations is 73,292 ha, which accounts for 44.9% of the total forested area according to forestry resource survey data in Jiangxi Province in 2009. The forests within the study area are comprised of 18 dominant species including: masson pine (*Pinus massoniana*), slash pine (*Pinus elliottii*), Chinese fir (*Cunninghamia lanceolata*), Chinese weeping cypress (*Cupressus funebris*), camphor tree (*Cinnamomum camphora*), zhennan (*Phoebe zhennan*), crenate gugertree (*Schima superba*), beautiful sweetgum (*Liquidambar formosana*), Chinese sassafras (*Sassafras tzumu*), eyer evergreenchinkapin (*Castanopsis eyrei*), myrsinaleaf oak (*Cyclobalanopsis gracilis*), fortune chinabells (*Alniphyllum fortunei*), farges evergreenchinkapin (*Castanopsis fargesii*), longpeduncled alder (*Alnus cremastogyne*), faber oak (*Quercusfabri*), shinybark birch (*Betula luminifera*), chinaberry (*Melia azedarach*) and poplar (*Populus deltoids*). The Qianyanzhou Experiment Station for Comprehensive Development of Natural Resources in the Red Earth Hilly Area (QYZ ecological station, see Figure 1) is also located within our study area.
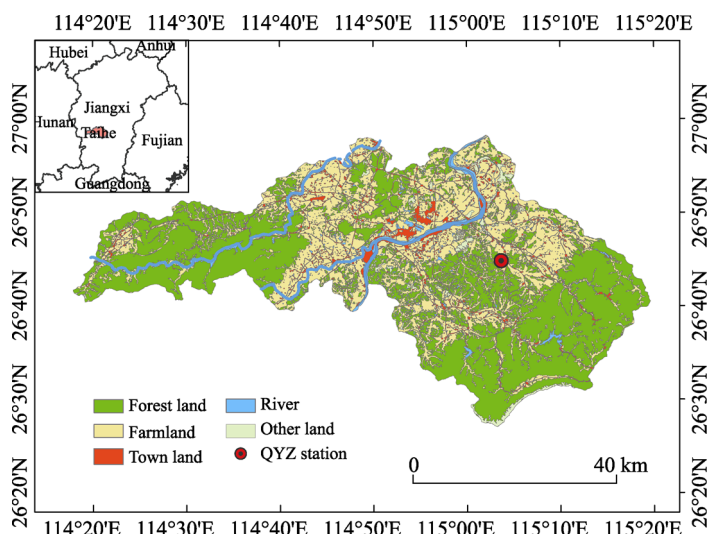

Figure 1 Location and land use types of Taihe County, Jiangxi Province, China. QYZ station: Qianyanzhou ecological station

2.2   Climate change

The future climatic data were compiled from the projections of 21 climate models in the Coupled Model Intercomparison Project Phase 5 (CMIP5) of the World Climate Research Programme (WCRP) multi-model dataset, which was provided by the National Climate Center of China Meteorological Administration (http://www.climatechange-data.cn). The main climatic factors include monthly mean temperature, monthly maximum temperature, monthly minimum temperature, and monthly precipitation. In this study, the climatic data were under the Representative Concentration Pathways (RCPs) scenarios, including the RCP2.6, RCP4.5 and RCP8.5 scenarios from 2010 to 2050. From the climate prediction dataset, it can be found that the annual mean temperature will have a 1.09–1.73°C increase in our study area in all RCPs scenarios (Figure 2). However, due to the subtropical monsoon climate, the inter-annual variation of precipitation shows a slightly increasing trend and obvious fluctuation from 2010–2050 under various RCPs scenarios. In addition, we designed a control scenario by extrapolating current climate conditions, whereby the temperature and precipitation data were the means of the observations during the last 10 years (2001–2011) from the QYZ ecological station in our study area.
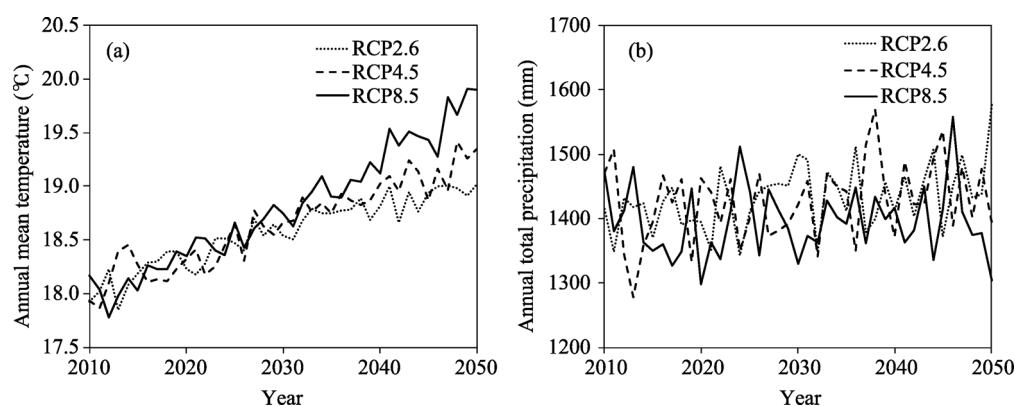

Figure 2   Variation trend of annual mean temperature and precipitation in the study area under RCPs scenarios from 2010 to 2050. (a) annual mean temperature (°C); (b) annual total precipitation (mm) under RCPs scenarios

2.3   Land use change simulation

In our study area, there are mainly four types of land use, including town land, forest land, farmland and other land. The land use data in 1990, 1995, 2000, 2005, and 2010 were obtained from the land and resources survey by the department of land and resources of Jiangxi Province, China. Based on these, we found that the land use types did not change dramatically, and land use changes mainly occurred as town land sprawl and forest land loss. Therefore, farmland and other land were not modeled in the future land use simulation, with their changes depending on the simulated results of forest land and town land. The town land sprawl was of interest in our study, as it had a close relationship with human activities and human decisions. In this study, we used a GIS-based agent based model built by Agent Analyst software. Agent Analyst is an open-source software developed to integrate an ABM development platform – the Recursive Porous Agent Simulation Toolkit (Repast) – within a

GIS (ArcGIS). Agent Analyst is a mid-level integration tool that takes advantage of both modeling environments. Specifically, we used the modified and simplified urban growth model to investigate how the behavior of residential household agents affects landscape sprawl for Taihe County. In this model, there is a town center agent placed in the center of Chengjiang Town, which is the center of economy, politics and population in the study area. Residential household agents evaluated the utility by calculating a score for each sample cell's distance from the town center, the probability of development, and the importance of the resident agent placed on distance and development probability. The utility was calculated from several environmental variables. First of all, the distance from each cell to the town center (*tcdist*) was selected because the resident agent would give priority to the cells which were close to the town center. Secondly, the development probability for each cell was calculated by evaluating the physical condition and population. In this study, the development of town land use is limited by surroundings. For example, the development has a slope-limiting under 15 degrees, and land use type is not the water body in general. In the meantime, the area that is close to the roads may get a higher probability. We made a buffer of 30 m from the main roads, which have a higher development probability of town land use. In addition, the population in different zones had been considered. The population of different administrative division of the town units was standardized. These variables above, including slope, roads, and population, were weighted them equally and were overlaid to a map of development probability (*devpro*). Finally, we assumed that all the resident agents had the equal preference on the distance and development probability. This method can simplify the model code, as well as achieve our study objectives more directly. As a result, the agents may prefer cells that are closer to the town center and have a higher development probability. The utility formula is shown in Eq. 1:

$$\text{Utility} = (1 - |\beta_p - devpro|^{\alpha_p}) \times (1 - |\beta_d - tcdist|^{\alpha_d}) \tag{1}$$

where *devpro* stands for the development probability, *tcdist* stands for the distance from each cell to the town center; β_d represents that the resident agents prefer the cells closer to the town center, β_p means that they prefer a higher development probability. Here, β_d, β_p=1. The importance resident agents place on development probability (α_p) and the distance to the town center (α_d), $\alpha_p + \alpha_d = 1$. For the sake of simplicity code, all resident agents have the same utility function and parameter values in this model. In terms of the inputs of the model, the land use map and the development probability map take the form of raster maps with a 100-m resolution. The initial land use map is the rasterized land use data from 2010. The development probability map is calculated by some limiting factors, as shown in Eq. 2:

$$\text{Development probability} = f(\alpha_p, \beta_s, \gamma_w, \lambda_r) \tag{2}$$

where α_p stands for the standardized population in respective administrative towns in Taihe County, and β_s stands for the slope. In this study, we limited the developed cells' slope to less than 15 degrees. When the slope is above 15 degrees, the development probability is set to zero; γ_w stands for the water body area, which is also defined as undeveloped area and the development probability set to 0. λ_r stands for the buffer of the roads, which is frequently affected by human activities, and the probability is set to 0.8. The development probability is within the range of 0–1, and the development probability map is shown in Figure 3.
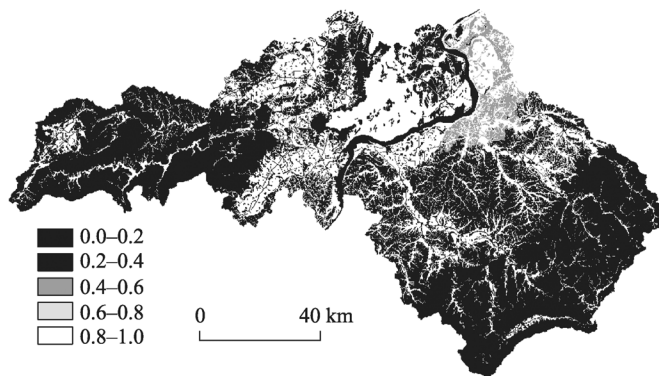
Figure 3   The map of development probability for resident agents to settle, where 0.0 means no development at all and 1.0 means full development

Based on the overall plans for land use in Taihe County from 2006 to 2020, we determined how many cells to develop for the resident agents in the future simulation. The overall plan for land use in part reflects the land use change policy in the near future, which indicates the choice tendency of the local government. The overall plan has a binding effect and a guiding function on the implementation of land use policies. Especially in China, the land use plan has a more profound effect and the local government plays a predominant role in the process of land use. Therefore, the land use plan data is relatively reliable to use as the basic data for the model in our study. The area of town land was 14,773 ha in 2010, and the total town planning area will reach 17,173 ha in 2020 according to the overall plan goal. Accordingly, about 240 new cells were selected at each time step (one year) for the resident agents to settle in and turn into town land. In this study, we assumed that the land use policy and developing rate will sustain and extrapolate current conditions in the coming decades up until 2050.

For deforestation and forest conversion modeling, we used the land use extension and biomass harvest extension from the LANDIS-II model. Land use extension can incorporate a sequence of maps depicting land use or land cover change into LANDIS-II simulations. Maps were developed from the output of the urban sprawl model in Agent Analyst. With this extension, the model can simulate how cohorts will be removed if changes in the land use or land cover results in forest loss. In addition, land use extension is integrated into the biomass harvest extension, resulting in corresponding land use and AGB changes. The harvest experiment in the simulation was designed to match the current forest management policy, which keeps ten percent for different forest management area at each time step (ten years) for the LANDIS-II model.

2.4   Forest AGB simulation

In this study, we used LANDIS-II and PnET-II to conduct the simulation of forest AGB. The LANDIS-II model is a cell-based spatially dynamic forest landscape model of disturbance, succession and management (Scheller *et al*., 2007). It can simulate forest dynamics by tracking the changes in species age cohorts, which is driven by species life history attributes, species establishment probability (SEP), maximum aboveground net primary production (ANPP), and spatial heterogeneity (Mladenoff and He, 1999). LANDIS-II is specifically designed to address the effects of climate change on forests and has been widely applied in

analyzing complex interactions (Scheller and Mladenoff, 2005; Xu *et al*., 2009). In this study, we used the LANDIS-II model with the biomass succession extension, land use extension, and biomass harvest extension. With these extensions, LANDIS-II can address climate change and land use change effects on forest AGB (Gustafson *et al*., 2010; Thompson *et al*., 2011). The main inputs for LANDIS-II include spatial inputs (initial species maps, ecoregion maps and land use maps) and non-spatial inputs (species life history attributes, ANPP and SEP). The initial species map was derived from forestry resource survey data by the sub-compartment division of Jiangxi Province in 2009. The ecoregions map was divided into five ecoregions, four forested regions and one non-forested region, which were based on relatively homogeneous geomorphic forms (Figure 4). The parameters of the species life history attributes were mainly compiled from literature, plot investigation and consultations with local forestry experts (Chen *et al*., 1996; ECFC, 2000) (Table 1).
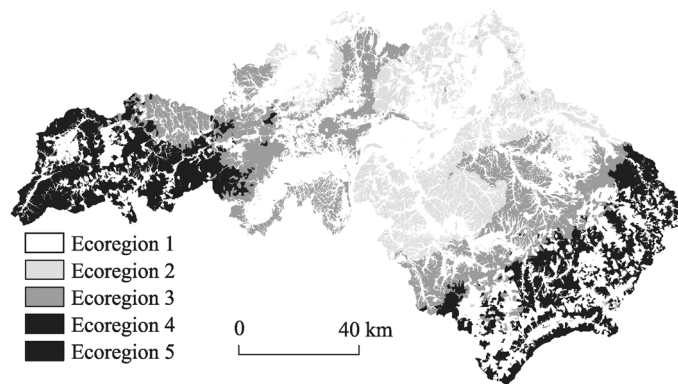

Figure 4   Ecoregions of the study area. Ecoregion 1 is non-forestland and un-active in our simulation. Ecoregions 2 to 5 stand for low hills (under 100 m), medium hills (100–250 m), high hills (250–500 m) and mountains (above 500 m), respectively

The ANPP and SEP for each species were derived from the PnET-II model. The PnET-II is a process based model for carbon and water balance in forest ecosystems (Aber and Federer, 1992). It can simulate the effect of climate change on forest photosynthesis by applying adjustable factors, including light, temperature, water availability, water vapor deficit and CO_2 concentration (Xu *et al*., 2009). In this study, we applied version 5.1 of the PnET-II model to calculate the ANPP and SEP of 18 tree species under RCPs and a control scenario. The most primary parameters in PnET-II, such as the water-holding capacity (WHC) and photosynthetically active radiation (PAR), were based on observation in the QYZ ecological station. The other parameters were obtained from literature published for this area, including foliar nitrogen concentration (FolNCon) (Yu *et al*., 2014), minimum temperature for photosynthesis (PsnTMin) (Wu, 1984), optimum temperature for photosynthesis (PsnTOpt) (ECECA, 1989), and water use efficiency (WUE) (Sheng *et al*., 2011).

2.5   Modelling framework

To explore the integrated and relative effects of land use and climate change on forest AGB, we simply coupled the ABM/LUCC model, the PnET-II model and the LANDIS-II to build a framework and to combine the human system and the climate system (Figure 5). Firstly, we

Table 1   Species life history attributes in Taihe County, Jiangxi Province, China

Species	Common name	Longev-ity (year)	Sexual maturity (year)	Shade tol.	Seed dispersal dist.	
					Effec-tive (m)	Maxi-mum (m)
Cunninghamia lanceolata	Chinese fir	200	10	1	200	500
Cupressus funebris	Chinese weeping cypress	500	35	2	70	200
Pinus massoniana	Masson pine	200	10	1	200	500
Pinus elliottii	Slash pine	200	10	1	200	500
Schima superba	Crenate gugertree	300	20	5	20	200
Cinnamomum camphora	Camphor tree	1000	15	4	50	120
Phoebe zhennan	Zhennan	1000	50	5	40	120
Castanopsis eyrei	Eyer evergreenchinkapin	200	20	5	50	120
Castanopsis fargesii	Farges evergreenchinkapin	150	30	5	60	250
Quercus fabri	Faber oak	120	15	4	20	200
Cyclobalanopsis gracilis	Myrsinaleaf oak	200	7	4	20	50
Liquidambar formosana	Beautiful sweetgum	130	8	3	100	375
Betula luminifera	Shinybark birch	100	15	2	150	400
Alnus cremastogyne	Longpeduncled alder	125	5	3	15	60
Alniphyllum fortunei	Fortune Chinabells	120	15	2	250	500
Sassafras tzumu	Chinese sassafras	120	20	3	50	150
Melia azedarach	Chinaberry	80	5	2	200	400
Populusdeltoids	Poplar	90	10	2	150	500

Notes: Shade tol. stands for the species' tolerance to shade. The value is an integer between 1and 5, where 1 means the least tolerance and 5 means the most tolerance. Seed dispersal dist. stands for the species' effective or maximum distance for dispersing seeds.
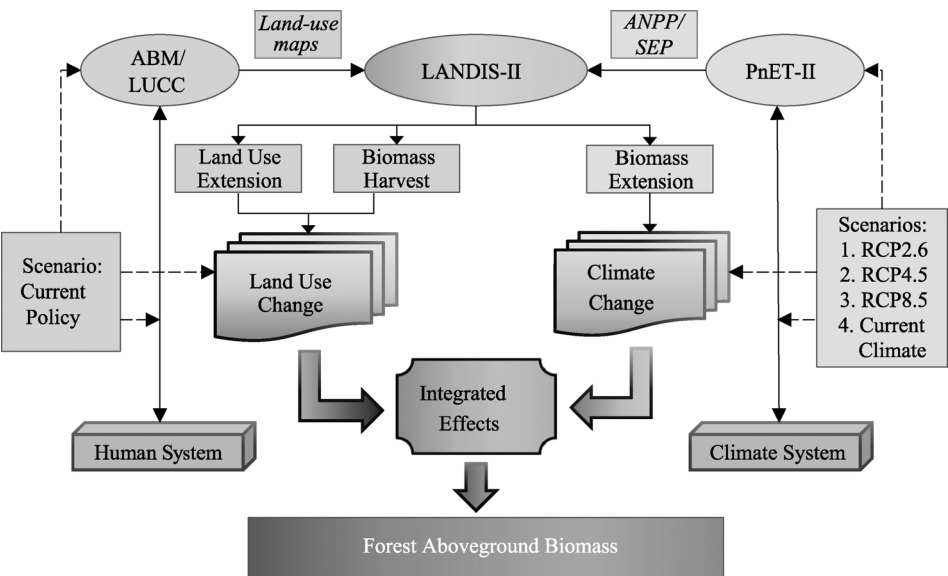

Figure 5   The framework for the integrated effects of land use and climate change on forest AGB

used the ABM/LUCC model to simulate the development of town land under the current land use policy. A series of land use maps were created from the output of the ABM model, as well as the input for land use extension for LANDIS-II. Secondly, we used the PnET-II

model to calculate the ANPP and SEP for tree species under various climate scenarios, including RCP2.6, RCP4.5, RCP8.5, and a current climate (CC) scenario, as well as the inputs for the biomass succession extension of LANDIS-II. Finally, the LANDIS-II model was used as the core of the framework to simulate the forest AGB change under the pressure of human and climate factors. This framework offers a coupled method to better understand the interaction of ecological processes, and it may give some supports for improving and optimizing the plantations' structure and function.

3 Results

3.1 Land use change modelling

The results of the town land change under the ABM/LUCC model is shown in Figure 6. In this section, we are only interested in the town land sprawl, so the output maps are shown as town land over the upcoming 40 years. The results show area percentages of town land in 2020, 2030, 2040 and 2050 account for 6.4%, 7.3%, 8.2% and 9.0% of the total area, respectively. Rapid town land expansion is built on the current town center, which forms an overall sprawling trend of the town center into the surrounding area. The development of town land occurs in Chengjiang Town, which has the highest population in Taihe County. In addition, the results show that urban and town fringe is the transition belt, which is the most active portion of the town land sprawl process. The spatial pattern of the town land development reflects the rules and behaviors of the decision-making of the resident agents. They prefer to settle in areas closer to the town center.
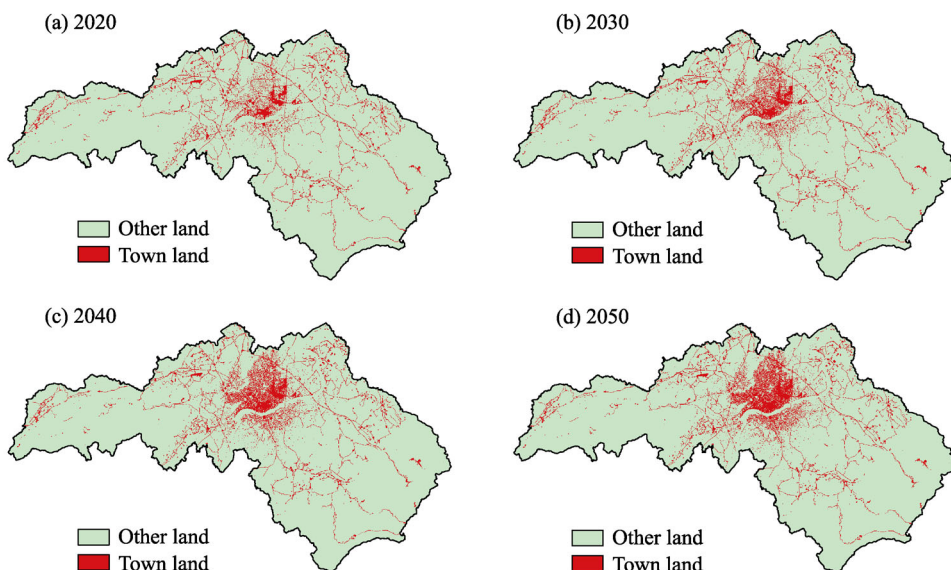

Figure 6   The results of town land change from the ABM/LUCC model

3.2 ANPP

The ANPP from the PnET-II model is an important parameter and offers important input for

forest AGB calculation in the LANDIS-II model. Therefore, the ANPP change is of interest in this section and the ANPP change for the 18 tree species under the three RCPs scenarios is shown in Figure 7. The ANPP under the current climate scenario is unchanged during the simulation, so the results were not shown here. The mean values of the ANPP are calculated from the mean values in four active ecoregions from ecoregion 2 to 5. The results of the simulation show that the overall trend of the ANPP for all species increases during 2010–2050, and the ANPP of broad-leaved species is significantly higher than that of coniferous species. Under different climate change scenarios, the variation in the ANPP shows a significant difference between species, especially for certain broad-leaved species, such as crenate gugertree, eyer evergreenchinkapin and farges evergreenchinkapin. Under the RCP2.6 scenario, the range of the ANPP for all species is 489 g m^{-2}·yr^{-1} (Chinese weeping cypress) to 1043 g m^{-2}·yr^{-1} (eyer evergreenchinkapin). By 2050, the percentage of the increase for each species is in the range of 5.7% (Chinese fir) to 12.5% (eyer evergreenchinkapin). Under RCP4.5 scenario, the range of the ANPP for all species is 483 g m^{-2}·yr^{-1} (Chinese weeping cypress) to 1097 g m^{-2}·yr^{-1} (eyer evergreenchinkapin). By 2050, the percentage of increase for each species is in the range of 7.7% (Chinese fir) to 23.4% (eyer evergreenchinkapin). Under the RCP8.5 scenario, the range of the ANPP for all species is 483 g m^{-2}·yr^{-1} (Chinese weeping cypress) to 1143 g m^{-2}·yr^{-1} (eyer evergreenchinkapin). By 2050, the percentage of increase for each species is in the range of 6.9% (Chinese fir) to 26.5% (eyer evergreenchinkapin). The forest AGB is influenced by many factors, such as ANPP, spatial distribution and SEP. The variation on ANPP is the dominant factor to affect the forest biomass, reflecting the AGB accumulation rate for different species. In terms of 18 species in our study area, the rate of change for each species from 2010 to 2050 was selected to show the effect of ANPP on forest AGB. The main tree species includes eyer evergreenchinkapin, chinaberry, longpeduncled alder, shinybark birch, faber oak and camphor tree. The effect degree of ANPP on forest AGB for these tree species gradually increase under RCP2.6, RCP4.5 and RCP8.5 scenarios.

3.3   Forest AGB

In order to ensure that the simulated result of forest AGB is relatively correct, we first compared the simulated and investigated values with the first year in order to validate the LANDIS-II simulation results.The investigated values come from the observational stand volume at each forest sub-compartment from the forestry inventory data. The method for converting between AGB and stock volume is referenced from Fang *et al*. (2001). The biomass expansion factor (BEF) was calculated as a function of stand timber volume (x), BEF = a + b/x, where a and b are constants for a specific forest type (Fang *et al*., 2001). These variables for specific species were obtained through field measurements and from previous studies in the area (Wu *et al*., 2011). Specifically, five hundred sub-compartments were randomly selected as the verification points, which were based on the distribution of the main species in our study area (Figure 8a). The results showed a positive linear correlation between the simulated and investigated values (R^2=0.6463, p<0.001), which indicated that the method's feasibility and the simulation results can be considered reliable (Figure 8b).
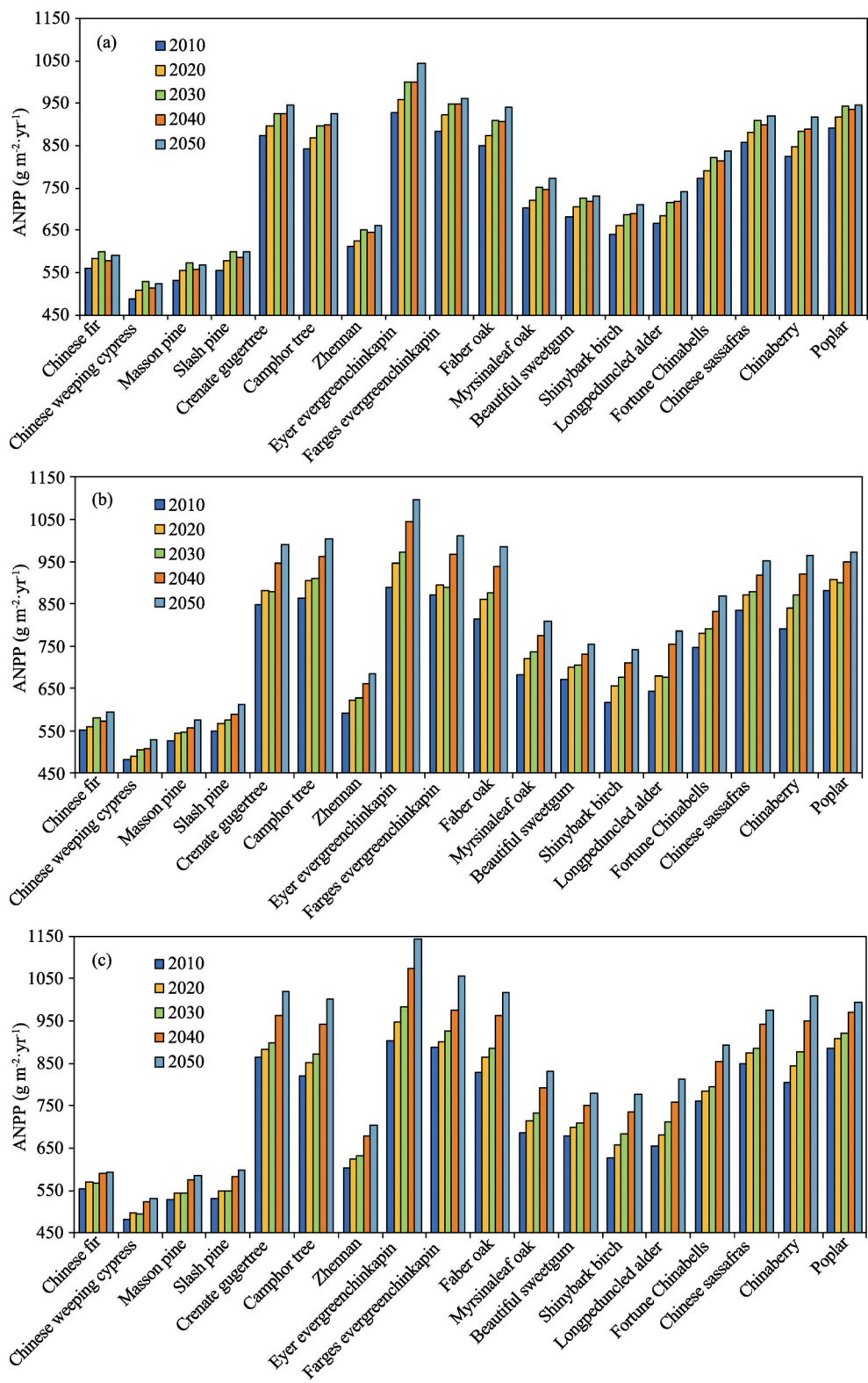
Figure 7 Aboveground net primary production (ANPP) for 18 species simulated by PnET-II under RCPs scenarios. (a) RCP2.6; (b) RCP4.5; (c) RCP8.5
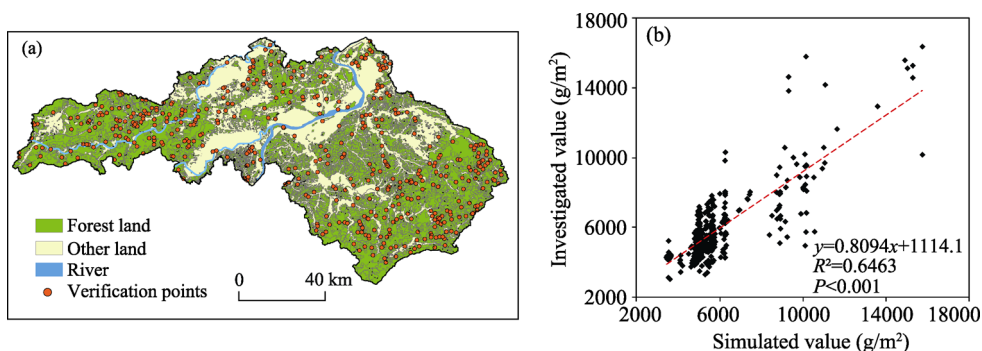
Figure 8 Spatial distribution of the points for model validation and the comparison between simulated and investigated values of forest AGB

The forest AGB of the different tree species simulated by the LANDIS-II model under various scenarios is shown in Figure 9. The results show that all the forest AGB increase under the CC, RCP2.6, RCP4.5 and RCP8.5 scenarios from 2010 to 2050 (shown as the blue histogram in Figure 9). However, the results of the forest AGB show initial increase and then decrease under all land use and integrated scenarios (shown as the red histogram in Figure 9). As to the climate change, variation in the AGB shows a difference between various climate scenarios. By 2050, the forest AGB under CC, RCP2.6, RCP4.5 and RCP8.5 increases by 2965.9 g m^2, 3163.1 g m^2, 3281.1 g m^2 and 3416.4 g m^2, respectively. As to the isolated effect of land use, the forest AGB increases to 8109.3 g m^2 in 2020, then decreases to 6441.2 g m^2 by 2050 only under the land use scenario. In terms of the integrated effect of land use and climate change, the results show an increase first, and then show a decreasing trend after 2020 under land use that is integrated with RCPs scenarios. When compared to the results under separate RCPs without land use disturbance, the forest AGB under the integrated scenario decreases by 53.7% (RCP2.6+land use), 57.2% (RCP4.5+land use), and 56.9% (RCP 8.5+land use), respectively by 2050. Land use change plays a vital role in the integrated simulation. It has a more significant effect on forest AGB than climate change, and this effect will become more noticeable as the simulation time progresses.
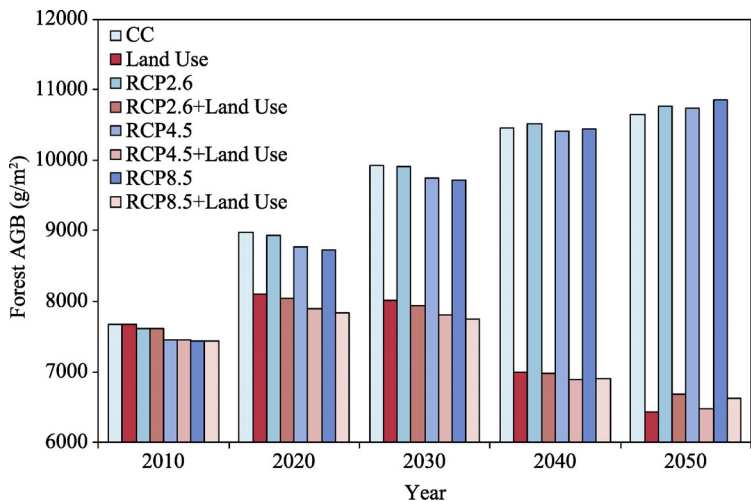

Figure 9 Forest AGB of the total forest area under various scenarios. CC: current climate scenario

4   Discussion

4.1   Results interpretation

Our results suggest that land use and climate change is likely to significantly change forest AGB in our study area under various scenarios. Land use change, including town sprawl and harvest, makes a great contribution to the integrated effects and becomes the dominant factor in the simulation. These simulation results show consistence with the results of Thompson *et al*. (2011) and Gustafson *et al*. (2010). Thompson *et al*. (2011) found in Massachusetts, USA, while climate change may enhance growth rates, this will be more than offset by land use. Gustafson *et al*. (2010) also found that the direct effects of climate change in south-central Siberia are not as significant as timber harvest and other disturbances. For the simulation results of land use change, primarily forest conversion is the town land sprawl. We used the simplified ABM/LUCC model to simulate this conversion process of land use. The results help to specify the behavioral rules of individuals, identify the situations in which the agents reside, and determine possible outcomes according to the appropriate contexts. From an object-oriented point of view, these resident agents are self-directed objects, and their evaluation of the utility of the landscape location will influence their actions. The environmental factor is also an important contributor to ABM in this study. This method can directly represent the interior driving factors of land use change. According to our results, population and the physical environment are the two main factors that influence the agents' decisions. For the ANPP results, we found that forest productivity increased with temperature and precipitation in the subtropical monsoon climate zone under RCPs, which shows consistence with the result of Mi *et al*. (2008). Except for temperature and precipitation, change in other environmental factors also leads to ANPP change. For example, the changing atmospheric concentrations, such as CO_2 (Wittig *et al*., 2005), O_3 (Cojocariu *et al*., 2005) and N (Huang *et al*., 2014), may also affect forest productivity. In our study, we incorporated the effect of CO_2 concentrations on the stomata conductance of different species. However, we did not consider the effects of CO_2 fertilization on ANPP.

During simulation, the forest AGB accumulation is calculated by the ecosystem process rates and the quantity of aboveground living biomass for each tree species-age cohort without regard to disturbances (Scheller and Mladenoff, 2004). The biomass module conducted three process rates, ANPP, aboveground mortality, and woody biomass decomposition (Scheller and Mladenoff, 2005). These critical calculations and assumptions can help to implement the coarse simulation at the forest landscape scale (Scheller *et al*., 2007). As to the disturbances in our simulation, they are land use change (primarily town land sprawl and forest transition), climate change (primarily temperature and precipitation) and forest harvest (biomass removal). In the simulation, the biomass accumulation has a positive correlation with the increase of temperature and precipitation, irrespective of the land use change. This increasing trend of AGB is consistent with the results of Wu *et al*. (2011). Under all land use scenarios, the total forest AGB first experiences a slight increase and then quickly decreases. Forest transition and tree species removal that is caused by town land sprawl, and by plantation timber harvest done every ten years have resulted in a sharp decrease in the total forest AGB. These human-induced actions can result in even more direct influence on the forest AGB than climate change and biomass accumulation.

4.2   Uncertainties and limitations of simulating the integrated effects

Land, climate and forest are interacting and are in the process of mutual restraint in the multisystem. Land system change is mainly caused by anthropogenic activity, which is accompanied by a series of forest landscape changes, including forest transitions, deforestation, forest conversion and reforestation (Rudel *et al*., 2005). Climate system change is also affected by anthropogenic activity and land use change, and it has effect and feedback mechanisms involved with the forest and the climate (Karl and Trenberth, 2003). For the forest ecosystem, spatial interactive processes, succession, disturbances, migration and transition occurred simultaneously (Hansen *et al*., 2001; Cottenie, 2005). Therefore, it is difficult to study longtime successive responses of this integrated effect on the forest at the landscape scale.

In this study, we offer a framework to explore the integrated and relative effects by using some simply coupled models. This framework can help us to assemble the models for different systems to conduct the integrated effects on forests, and to gain a better understanding of the complex, interacting ecological processes. However, there are also uncertainties and limitations of simulating the integrated effects in our study. Firstly, uncertainties exist in the data and in the parameterization process, which is limited by the available data and the literature. For climate data, the RCPs dataset resulting from the multi-model ensemble is still an important issue, though it is more acceptable than a single model (Tebaldi and Knutti, 2007). In addition, the accuracy of climate data is hard to obtain by spatial resolution at the regional and landscape scale. As to parameterization for the PnET-II and LANDIS-II, a large amount of tree species life history parameters may potentially arouse some uncertainty in the simulation. Even though these uncertainties and limitations are inevitable in the simulation process, our results are still credible based on the forestry survey data, plot investigation, model validation, and consultation with local forestry experts. Secondly, the limitations in the simulation were derived from the models. In this study, we used the highly simplified ABM/LUCC model. ABM is based on the complexity theory and can represent feedback in multilevel systems where the higher and lower levels simultaneously influence and limit one another (Yu *et al*., 2011). Meanwhile, the agents in the modeling are intelligent, so they can be influenced by the environment and by changes in the behavior of other agents. In order to simplify the code in the Agent Analyst and easily achieve our goals, we only concentrated on the resident agents and the town land change. The humans are the main actors in land use and other activities, and they are as well as the main sources of uncertainty in the simulation. The selection mechanism of human activities to land use will change with the physical condition and the relationship between different agents. In our study, we ignored some complex interaction process between agents which may lead to some uncertainty. However, this method can bring some conveniences for modeling in turn, and can make our study objectives to be achieved. The future studies should be improved to reduce uncertainty. (1) Differences of agent types should be considered to simulate the real world as much as possible. The main agent types should be selected depending on the specific research goals. (2) The key selection activities of different agents should be screened based on the research goals. We should consider the interaction and mutual influence between the agents. (3) The environmental and economic factors will change over time. This point should also be included

and the extreme events can be added in the future simulation. (4) We should build the agent's self-learning mechanism according to the change of the agents and the environment, so as to find a balance between the reality and simulation to reduce uncertainty. For the other ecological models, the PnET-II and LANID-II models are also the simplifications of complex ecosystem processes. In terms of LANDIS-II, the model simulates broad spatial and long temporal scale dynamics for cells that incorporate species not with individual stems but with cohorts (Scheller *et al*., 2007). Finally, the coupled simulation that dealt with the integrated effects was based on some reasonable assumptions. For example, the species life-history attribute parameters and the landscape heterogeneity (e.g. landform, soil texture hydrologic conditions and phenology) would not change with time. Moreover, although the RCPs scenarios were developed from human activities like land use effect, we assumed that land use change was not affected by climate change, which could lead to some uncertainties in the simulation. Though there are cumulative uncertainties and limitations in simulating the integrated effects, we considered these to be trade-offs between the technical and ecological insights. Our objective is not to predict the forest biomass precisely in the near future, but to explore the change of forest landscape under multiple factors, which is a new exploration for the comprehensive simulation. This framework has scientific significance in the study of the effect of land use and climate change on forest landscape.

5   Conclusions

From our study we can draw the following conclusions. (1) Land use (including town expansion, deforestation and forest conversion) and climate change are likely to influence forest AGB in the near future in Taihe County. (2) Though climate change will make a good contribution to the forest AGB increase, land use change can result in a rapid decrease in the forest AGB and play a vital role in the integrated simulation. Under the integrated scenario, forest AGB decreased by 53.7% (RCP2.6+land use), 57.2% (RCP4.5+land use), and 56.9% (RCP8.5+land use) by 2050, which is in comparison to the results under separate RCPs. (3) The framework for simulating the integrated effects on forest AGB can offer a coupled method to gain a better understanding of the complex, interacting ecological processes.

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