Predicting the responses of forest distribution and aboveground biomass to climate change under RCP scenarios in southern China

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Abstract

In the past three decades, our global climate has been experiencing unprecedented warming. This warming has and will continue to significantly influence the structure and function of forest ecosystems. While studies have been conducted to explore the possible responses of forest landscapes to future climate change, the representative concentration pathways (RCPs) scenarios under the framework of the Coupled Model Intercomparison Project Phase 5 (CMIP5) have not been widely used in quantitative modeling research of forest landscapes. We used LANDIS-II, a forest dynamic landscape model, coupled with a forest ecosystem process model (PnET-II), to simulate spatial interactions and ecological succession processes under RCP scenarios, RCP2.6, RCP4.5 and RCP8.5, respectively. We also modeled a control scenario of extrapolating current climate conditions to examine changes in distribution and aboveground biomass (AGB) among five different forest types for the period of 2010–2100 in Taihe County in southern China, where subtropical coniferous plantations dominate. The results of the simulation show that climate change will significantly influence forest distribution and AGB. (i) Evergreen broad-leaved forests will expand into Chinese fir and Chinese weeping cypress forests. The area percentages of evergreen broad-leaved forests under RCP2.6, RCP4.5, RCP8.5 and the control scenarios account for 18.25%, 18.71%, 18.85% and 17.46% of total forest area, respectively. (ii) The total AGB under RCP4.5 will reach its highest level by the year 2100. Compared with the control scenarios, the total AGB under RCP2.6, RCP4.5 and RCP8.5 increases by 24.1%, 64.2% and 29.8%, respectively. (iii) The forest total AGB increases rapidly at first and then decreases slowly on the temporal dimension. (iv) Even though the fluctuation patterns of total AGB will remain consistent under various future climatic scenarios, there will be certain responsive differences among various forest types.

Keywords: CMIP5, forest distribution and aboveground biomass, LANDIS-II, PnET-II, RCPs, southern China, subtropical plantation, Taihe County

Introduction

Earth’s surface has experienced the strongest warming in history due to anthropogenic disturbances (Jones et al., 2001); especially during the last three decades, global mean surface temperatures were likely the warmest as they have been in the last millennium (Jones et al., 2001), and perhaps for far longer (Marcott et al., 2013). According to the Fifth Assessment Report (AR5) of Intergovernmental Panel on Climate Change (IPCC), it is certain that the global mean surface temperature has increased by 0.85 [0.65–1.06] °C since the late 19th century and that average precipitation has increased in the mid-latitude land areas of the Northern Hemisphere since the early 20th century (IPCC, 2013). However, the effects of global climate change do not exhibit themselves in a uniform way due to anthropogenic disturbances and the complexity of the earth’s surface (Karl & Trenberth, 2003). In China, annual mean surface air temperature showed a warming trend of 1.52 °C/100a during the period of 1909–2010 (Cao et al., 2013), and bidecadal oscillation in precipitation variability was apparent during the 20th century (Wang et al., 2004a; Ge et al., 2007; Qian et al., 2007).

Global climate change is dominated by human-induced changes in atmospheric composition, and continual emission of greenhouse gases (Karl & Trenberth, 2003). The continuation of these behaviors will cause further changes in the global climate system (Ash et al., 2013). To improve the understanding of the complex interactions of the climate system, ecosystem and human activities, research communities have developed sequential scenarios, including the IS92 scenarios (Goodale et al., 2002), and the scenarios from the
Special Report on Emissions Scenarios (SRES) (Nakicenovic et al., 2000). Although these scenarios provide crucial support in climate change research, they do not incorporate the human-derived reduction in emissions under climate policy and cannot satisfy the needs of climate change research. Therefore, climate change researchers from different disciplines and scientific communities have established a newly coordinated parallel process for developing new scenarios, representative concentration pathways (RCPs) (Moss et al., 2010). According to the IPCC, the new set of RCPs was used in the new climate model simulations carried out under the framework of the Coupled Model Intercomparison Project Phase 5 (CMIP5) of the World Climate Research Programme (WCRP) (IPCC, 2013). A set of four new pathways, RCP8.5, RCP6.0, RCP4.5 and RCP2.6, were defined according to the radiative forcing target level from 2.6 to 8.5 W m$^{-2}$ for 2100 (Van Vuuren et al., 2011a). For RCP2.6, the emission pathway leads to very low greenhouse gas concentration levels (Van Vuuren et al., 2011c). RCP4.5 is a stabilization scenario where total radiative forcing is stabilized before 2100 (Thomson et al., 2011). For RCP6.0, the radiative forcing level is at 6.0 W m$^{-2}$ in the year 2100 without having exceeded that value in prior years (Masui et al., 2011). RCP8.5 leads to high greenhouse gas concentration levels (Riahi et al., 2011). Further description of the RCPs has been documented in a special issue in the Journal of Climate Change (Van Vuuren et al., 2011b).

Climate change has and will continue to significantly influence the structure and function of forest ecosystems (Lasch et al., 2002; Kulakowski et al., 2011; Grimm et al., 2013). Specifically, climate change may affect tree species richness (Iverson & Prasad, 2001), distribution (Kelly & Goulden, 2008), forest community composition (Bertrand et al., 2011) and forest productivity (Fung et al., 2005; Boisvenue & Running, 2006). Meanwhile, ecological responses to climate change alter the biogeophysical functions of forests and also provide climate feedback (Hansen et al., 2001; Walther et al., 2002; Bonan, 2008). Although climate change is affecting forest ecosystems in numerous facets, previous studies of forest distribution and biomass were focused on the representing interactions between forests and climate. Examples of the concern include representing spatial patterns, processes and dynamics in forests at the local, regional and global scales (Melillo et al., 1993; Mickler et al., 2002; Kelly & Goulden, 2008; Thompson et al., 2011). Variation in forest structure is expected as a result of the change in plant distribution (Grimm et al., 2013) and represented as the polar ward shift in response to climate change (Parmesan & Yohe, 2003; Hughen et al., 2004). This shift of and change in plant distribution also appear in the vertical band (Davis & Shaw, 2001; Kelly & Goulden, 2008). Variation in forest biomass, including both living and dead, may be affected by soils, climate, species composition and succession. This could lead to changes in forest carbon stocks and net primary productivity (Michaletz et al., 2014). Much focus has been concentrated on the variation in forest biomass attributed to the change in forest productivity and driven by climate factors (Scheller & Mladenoff, 2004; Gustafson et al., 2010; Thompson et al., 2011).

It is generally quite arduous to quantify the complex effects on forest ecosystems caused by climate change at the landscape scale; however, spatial simulation models offer an efficient way to simulate forest dynamics under climate change. To date, many models have been developed and applied to exploring forest responses to climate change, including GAP models (Pastor & Post, 1988; Prentice et al., 1993; Keane et al., 2001), spatially dynamic forest landscape models (Mladenoff, 2004; Lischke et al., 2006; Scheller et al., 2007), statistical analysis of current species distribution against climate variables using regression tree analysis (Iverson & Prasad, 1998; Iverson et al., 2008) and response surface analysis (Shafer et al., 2001). LANDIS-II is a forest landscape disturbance and succession model that operates on landscapes mapped out as cells. Many significant ecological characteristics of forested landscapes can be simulated over long periods of time, such as tree composition, distribution, disturbances, seed dispersal and the spatial arrangement of aboveground biomass (AGB) (Mladenoff, 2004; Scheller et al., 2007). LANDIS-II was specifically designed to address the effect of climate change on forests and has been widely applied in analyzing complex interactions. Xu et al. (2007, 2009) assessed the potential effects and uncertainties of global climatic change on forest landscapes. In recent years, plentiful studies have also been conducted on adaptive and restorative responses to climate change (Ravenscroft et al., 2010; Steenberg et al., 2011; Duveneck et al., 2014). Nevertheless, most of them examined the effects of climate change on forest landscapes under SRES (Gustafson et al., 2010; Thompson et al., 2011; Steenberg et al., 2012; Kretchun et al., 2014). Not as much can be found regarding the use of a new set of scenarios (RCPs) to explore the complex interactions between forests and the changing climate. In China, researchers have applied the LANDIS models on boreal forests (He et al., 2005; Liang et al., 2011; Zhao et al., 2013), but little attention is being paid to the plantation in southern China.
In the last two decades, plantations have expanded rapidly and contributed significantly to global industrial production and ecosystem services (Carle & Holmgren, 2008). China has played an important role in global plantation, accounting for around 23% of the total planted forest area in the world (FAO, 2010). Plantations are widely distributed in southern regions of China where the climatic condition showing as warm and wet under the Asian monsoon climate, while it occupied 63% of the total area and 62% of the total stocking volume of those in the whole China (Liu et al., 2014a). However, the predominance of very few tree species in the plantations, uneven spatial distribution and low volumes in growing stock have generated several major challenges regarding plantations in China (Liu et al., 2011, 2014a). Furthermore, climate change is also a crucial element that is likely to hinder the ability of forest managers and influence the sustainable development of plantations (Millar et al., 2007; Booth, 2013; Pawson et al., 2013). For this reason, investigating the various responses of different forests to climate change is beneficial for designing more effective adaptive treatments to mitigate climate change impacts.

In this study, we used LANDIS-II, a forest dynamic landscape model, and coupled with a forest ecosystem process model, PnET-II, to simulate spatial interactions and ecological succession processes under various climate change scenarios. The objectives of the study were to (i) clarify the forest distribution and quantify AGB of different forest types, (ii) explore the dynamic patterns of forest distribution and AGB in four forest types from 2010 to 2100 under three RCP scenarios and a control scenario and (iii) make a case for designing more effective adaptive treatments to climate change in south China’s planted forests.

Materials and methods

Study area

Our study area is Taihe County, located in south-central Jiangxi Province, China (Fig. 1), which extends across 26.45°-26.98°N, 114.95°-115.33°E, and has a total area of around 266,700 ha. This area lies on subtropical monsoon climate with mild winters (mean January temperature: 6.5 °C) and warm summers (mean July temperature: 29.7 °C). The average annual precipitation is 1,370 mm, most of which...
The forests within the study area are comprised of eighteen dominant species (Table S1), including Masson’s pine (Pinus massoniana), slash pine (Pinus elliottii), Chinese fir (Cunninghamia lanceolata), Chinese weeping cypress (Cupressus funebris), camphor tree (Cinnamomum camphora), zhennan (Phoebe zehn-nan), crenate guger tree (Schima superba), beautiful sweet gum (Liquidambar formosana), Chinese sassafras (Sassafras tzumu), evergreen chinkapin (Castanopsis eugiei), myrsina leaf oak (Cyclobalanopsis gracilis), fortune chinabells (Aihiphylum fortunei), farges evergreen chinkapin (Castanopsis fargesii), long-peduncled alder (Alnus cremastogyne), faber oak (Quercus fabri), shinybark birch (Betula luminifera), chinaberry (Melia azedarach) and poplar (Populus deltoids).

In this study, we selected representative subtropical forests, mainly including broad-leaved forests (evergreen broad-leaved forests [EBF], deciduous broad-leaved forests [DBF] and coniferous forests [Masson’s pine forests [MF], slash pine forests [SF], Chinese fir and Chinese weeping cypress forests [CCF]). We did not take bamboo forests and economic forests into consideration because their physiological characteristics are much different from what was selected above. According to the forestry resource survey data, the subtropical coniferous forests occupy the largest share, accounting for 69% of the total forest area. Dominated by Chinese fir, Masson’s pine and slash pine, the coniferous forests are distributed in lower mountain areas with elevations under 1000 m. The broad-leaved forests are mainly distributed along lower hills (100–900 m). Farges evergreen chinkapin forests are located at an elevation of around 350–700 m. Evergreen chinkapin forests are distributed on hillsides or ridges (400–1000 m). Camphor tree forests are mainly distributed along river banks or shoal areas. In the study area, the area of subtropical forests is 73,292 ha and accounts for 44.9% of the total forested area. The plantations are dominated by Chinese fir and slash pine. A multitude of plantations have made our study area as a representative to investigate the responses of forest distribution and AGB to climate change in the hilly red soil regions of southern China.

LANDIS-II model

The LANDIS-II model is a cell-based spatially dynamic forest landscape model of disturbance, succession and management (Scheller & Mladenoff, 2004; Scheller et al., 2007; Xi et al., 2009). It can simulate forest dynamics by tracking species-age cohorts (cohorts of trees within the same age range) (Mladenoff et al., 1996; Mladenoff & He, 1999). Developing from the LANDIS model, forest landscape change is driven by species life-history attributes, species’ establishment probability (SEP), maximum aboveground net primary production (ANPP), disturbances and spatial heterogeneity (Scheller et al., 2007). Many extensions (modules) have been developed for the LANDIS-II models (He & Mladenoff, 1999b; Gustafson et al., 2000; Scheller & Mladenoff, 2004) and are widely applied in climate change and forest management researches (Scheller & Mladenoff, 2005, 2008; Xu et al., 2009; Gustafson et al., 2010). In this study, we used the LANDIS-II model which included the biomass succession extension (Scheller & Mladenoff, 2004). With this extension, LANDIS-II can address climate change effects on forested ecosystems (Xu et al., 2007, 2009; Scheller & Mladenoff, 2008). The calculating results on ANPP and SEP for each species by the PnET-II model (detailed explanation in following part) entered the LANDIS-II model (Scheller & Mladenoff, 2005), by which we can analyze the effects of climate change to forest succession. We coupled these two models to simulate the forest succession process under different climate scenarios.

PnET-II model

The PnET-II is a process-based model for carbon and water balance in forest ecosystem (Aber & Federer, 1992; Aber et al., 1995b; Ollinger et al., 2002). It utilizes a nested set of modular approaches to predict effects of climate change at stand and regional levels (Aber et al., 1995b). The PnET-II model is based on two principal relationships, including maximum photosynthetic rate and foliar nitrogen concentration, as well as stomatal conductance and realized photosynthetic rate (Aber & Federer, 1992). This model can simulate the effect of climate change on forest photosynthesis by applying adjustable factors, including light (dependent on the input of photosynthetically active radiation [PAR]), temperature (dependent on the input of temperature), water availability (dependent on the input of precipitation), water vapor deficit and CO2 concentration (Botkin et al., 1972; Xu et al., 2009). In this study, we applied PnET-II model version 5.1 (Xu et al., 2009) to calculate ANPP and SEP of eighteen tree species under RCPs and a control scenario.

Parameterization

Climate change. The future climate change data were derived from the WCRP’s CMIP5 multimodel dataset, provided by the National Climate Center of China Meteorological Administration (http://wwwclimatechange-data.cn). The data were compiled from the projections of 21 climate models in CMIP5 average under RCPs (RCP2.6, RCP4.5 and RCP8.5) scenarios and interpolated into consolidated grids (1° × 1°). We did not do the statistically downscaled but rather treated the entire study area as homogeneous in terms of climatic conditions in the simulation period. The climatic data are comprised of the mean monthly temperature and precipitation from 2006 to 2100 without recycling any of the meteorological forcing. The main climate factors include monthly mean temperature, monthly maximum temperature, monthly minimum
temperature and monthly precipitation. In this study, we simulated the effect of climate change under RCP2.6, RCP4.5 and RCP8.5, while RCP6.0 data were not available. PAR data are based on the observations by the Qianyanzhou Experiment Station for Comprehensive Development of Natural Resources in the Red Earth Hilly Area (QYZ ecological station, see Fig. 1) and Chinese FLUX Observation and Research Network (http://www.chinaflux.org/enn/). As the limited variability of PAR in our study area over the last 50 years (1961–2007) (Zhu et al., 2010), we hypothesized that PAR would be consistent under various future climate scenarios. CO2 concentration data were derived from the RCPs database (http://tntcat.iiasa.ac.at:8787/RcpDb). By the year 2100, the CO2 concentration is projected to reach 420.90 ppm under RCP2.6, 538.36 ppm under RCP4.5 and 935.87 ppm under RCP8.5, respectively.

Analyzing the climate prediction dataset, it can be found that the general trend of annual mean temperature and precipitation will increase in our study area under all RCP scenarios (Fig. 2), while the slope of the temperature is steeper than that of precipitation. Owing to the subtropical monsoon climate, the interannual variation in precipitation is obvious. There is about 1.1–4.7 °C increase in annual mean temperature (Fig. 2a) and 76.3–97.29 mm increase in annual precipitation (Fig. 2b–d) during the period 2010–2100 under RCP scenarios. In addition, we designed a control scenario (no climate change), which its temperature and precipitation data were compiled from ten-year (2001–2011) averages. The other long-term climate parameters, including CO2 concentration and PAR, were obtained from the QYZ ecological station in our study area.

*PnET-II configuration.* The PnET-II model was used to simulate ANPP and SEP with the input of climate data, site condition parameters and the species-specific parameters (Aber & Federer, 1992; Aber et al., 1995b). We used monthly climate

![Fig. 2](https://example.com/figure2.png)  
**Fig. 2** The variation trend of annual mean temperature and precipitation under RCP scenarios. (a) Annual mean temperature (°C); (b) annual total precipitation (mm) under RCP2.6; (c) annual total precipitation (mm) under RCP4.5; (d) annual total precipitation (mm) under RCP8.5.
data under three RCP scenarios and a control scenario. To simulate regional ANPP, the water-holding capacity (WHC) of the soil is an important site condition parameter of the water balance simulation in the PnET-II model (Webb et al., 1993), and this parameter for site specific was observed by the QYZ ecological station. The species-specific parameters were obtained from the literature published in the study region. The foliar nitrogen concentration (FolNCon) is a crucial parameter in the process of ANPP calculation, leading to changes in the maximum net photosynthetic rate. This variable referenced from the publication by Yu et al. (2014). Some important parameters for each species were acquired from the literature published, including minimum temperature for photosynthesis (PsnTMin) (Wu, 1984; Editorial Committee of Forest of China, 2000), optimum temperature for photosynthesis (PsnTOpt) (He & Liu, 1989; Editorial Committee of Forest of China, 2000), water use efficiency (WUE) (Sheng et al., 2011). In addition, some fixed parameters were from the literature (Aber & Federer, 1992; Aber et al., 1995b; Aber & Driscoll, 1997; Ollinger et al., 2002; Liu et al., 2014b).

**LANDIS-II configuration.** The main inputs for LANDIS-II include spatial inputs (initial species map and ecoregion map) and nonspatial inputs (species life-history attributes, ANPP and SEP). Spatial inputs for LANDIS-II take the form of raster maps with 100-m cell size in this study. The initial species map, including the species and age cohort’s information at each cell, is derived from forestry resource survey data by the subcompartment division of Jiangxi Province in 2009. The ecoregion map is divided into five ecoregions, four forested regions and one nonforested region, which are based on the relatively homogeneous geomorphic form (Fig. 3). In detail, ecoregion 1 is nonforestland and inactive in our simulation. Ecoregion 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. In this study, we simulated eighteen dominant tree species (Table S1). Species life-history attribute parameters were mainly compiled from the literature, published LANDIS parameterization, plot investigation data and consultations with local forestry experts (He & Liu, 1989; Chen et al., 1996, 2009; Editorial Committee of Forest of China, 2000; Wang et al., 2004b; Chen, 2010; Li et al., 2011) (Table S1). The ANPP and SEP inputs were obtained from the PnET-II model. Moreover, the modeling was based on the assumption that the species life-history attribute parameters and the landscape heterogeneity (e.g., elevation, soil texture, phenology and land use type) would not change with time.

**Model output.** In this study, we simulated eighteen dominant tree species in the LANDIS-II and PnET-II models over the period of 90 years (2010–2100) under three climate change scenarios (RCP2.6, RCP4.5 and RCP8.5). A control scenario of extrapolating current climate conditions was also set to compare the responses of forest distribution and AGB to climate
change. To address more clearly the differences on the responses of forest types, we reclassified the simulated forest resulting from the LANDIS-II model into five forest types, including EBF (farges evergreen chinkapin, eyer evergreen chinkapin, zhennan, camphor tree, creane guger tree and myrsina leaf oak), DBF (beautiful sweet gum, fortune chinabells, Chinese sassafras, long-peduncled alder, poplar, faber oak, chinaberry and shinybark birch), CCF (Chinese fir and Chinese weeping cypress), MF (Masson’s pine) and SF (slash pine). The outputs of species’ AGB are at the end of every simulation time step (10 years) in the LANDIS-II biomass extension with 3 replications.

**Model validation.** The results of AGB from the LANDIS-II model have been evaluated for the uncertainty analyses, sensitivity analyses and structural analyses by previous literature (Mladenoff & He, 1999; Xu et al., 2009). However, due to the lack of long-term observational data for the whole region of this work, it is difficult to validate the simulated results from spatially landscape models. Fortunately, we have collected the observational stand volume at each forest subcompartment from the forestry inventory data. The conversion method between AGB and stock volume is referenced from the study of 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 forest type (Fang et al., 2001). These variables for specific forest type were obtained through field measurements and the previous studies in this area (Fang et al., 2001; Wu et al., 2011). For the validation, we first chose all the forest subcompartments in the study area and then randomly selected five hundred subcompartments based on the distribution of main species for validation. We compared the simulated and investigated values at the initial year. The distribution of the verification points is shown in Fig. S1. The results showed a positive linear correlation between the simulated and investigated values ($R^2 = 0.6456$, $P < 0.001$), which indicated that there were no apparent biases of different dominant forest types in our study region (Fig. 4).

**Results**

**ANPP**

The variation in mean ANPP for the five forest types under future climate change is shown in Fig. 5. These grouped mean values are calculated by the mean values in four active ecoregions, say from ecoregion 2–5 (more detail can be found in Fig. S2 for a complete trend of SEP and ANPP of each ecoregion). The results from the PnET-II simulation show that ANPP of all forest types first increases and then decreases under all climate scenarios, compared with the stable condition under the control scenario. For each ecoregion, the trend of the mean ANPP gradually decreases with altitude increase, from ecoregion 2–5 (shown as histogram in Fig. S2). It can be found from Fig. 5 that the mean ANPP of broad-leaved forests is significantly higher than that of coniferous forests. For EBF and DBF, our results show little difference in the variation trend, but the mean ANPP for EBF is higher than that of DBF. The mean ANPP under RCP8.5 scenario is relatively higher than that under the other RCP scenarios (Fig. 5a, b). For MF, the mean of ANPP is mostly between the range of 550 and 600 g cm$^{-2}$ yr$^{-1}$. Under RCP8.5 scenario, the mean ANPP begins to decrease dramatically in 2080 and drop to 455 g cm$^{-2}$ yr$^{-1}$ by 2100 (Fig. 5c). For SF, the variation trend is more dramatic than that of MF, especially under RCP8.5 scenario (Fig. 5d). For CCF, the mean ANPP shows a small increase before 2080 and then a dramatic decrease afterward, especially for RCP4.5 and RCP8.5 scenarios. The decline of the mean ANPP under RCP8.5 scenario is more severe than that of RCP4.5 scenario (Fig. 5e).

**SEP**

The variation in mean SEP of five forest types under future climate change is shown as Fig. 6. The grouped mean SEP is also calculated by the mean values across the four active ecoregions, say from ecoregion 2–5 (more detail can be found in Fig. S2 for a complete trend of SEP and ANPP of each ecoregion). Overall, the variation in SEP shows that all forest types show a different degree of enhancement, except for RCP8.5 and the control scenario. Under RCP8.5 scenario, SEP of the EBF begins to decrease dramatically in 2080 and that of the other forest types begins to decrease earlier around 2050. That means EBF have relatively high establishment probabilities and experience the fastest growth than the others (Fig. 6a). For the other forest types, the variation trend on SEP is similar under all climate
scenarios from 2010 to 2100 (Fig. 6b–e). By 2100, the mean SEP under RCP4.5 scenario has the highest establishment probabilities for all forest types. For each ecoregion, mean SEP has a slight difference for each forest type under various climate scenarios (shown as line chart in Fig. S2).
Fig. 6 Species’ establishment probability (SEP) simulated by PnET-II under RCP2.6, RCP4.5, RCP8.5 and control scenarios. (a–e) Stand for the grouped mean SEP for species of EBF, DBF, MF, SF and CCF across the four active ecoregions, respectively.
Forest composition

The area percentages and the rate of interannual variation in various forest types resulting from the LANDIS-II model are shown in Figs 7 and S3. It can be found that the area percentages of EBF increase significantly than those of the other forest types. The area percentages of CCF show a slight increase before 2040, followed by a falling trend. Under various scenarios setting in this work, the variation in area percentages shows similar trend for all forest types, while with weak differences. For EBF, the area percentages under RCP2.6, RCP4.5, RCP8.5 and the control scenarios account for 18.25%, 18.71%, 18.85% and 17.46% of total forest area, respectively. It can be concluded that the forest landscape composition is markedly altered by climate change. EBF would substitute CCF as the second most dominant forest type. SF is still the dominant forest type in our study area under the various climate scenarios. The area percentages of CCF and MF are similar, holding approximately 10% of the total forest area. In terms of spatial distribution of forest types, the results show similar patterns under various climate scenarios on temporal dimension (Fig. S4). However, the spatial patterns show an obvious change for specific forest types, especially EBF. We found that broad-leaved forests show more adaptive capability than that of coniferous forests to future climate warming in this area.

![Fig. 7](image-url) The area percentages of five forest types under four climate scenarios. (a–d) Stand for area percentages under RCP2.6, RCP4.5, RCP8.5 and the control scenarios, respectively.

Forest AGB

The forest AGB of the different forest types and tree species simulated by the LANDIS-II model is shown in Fig. 8 and Table 1. Compared with the control scenario, the results of the total AGB under RCP2.6, RCP4.5 and RCP8.5 increase by 24.1%, 64.2% and 29.8%, respectively, by 2100. At the forest type level, our results show

Fig. 8 Forest AGB of different forest types under various climate scenarios. (a) EBF; (b) DBF; (c) MF; (d) SF; (e) CCF; (f) Total AGB.
Table 1 Changes in forest AGB (g m⁻²) between 2010 and 2100 for eighteen species and five forest types as simulated by the LANDIS-II model under four climate scenarios

<table>
<thead>
<tr>
<th>Species</th>
<th>Current climate</th>
<th>RCP2.6</th>
<th>RCP4.5</th>
<th>RCP8.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total AGB</td>
<td>1540.7</td>
<td>1911.8</td>
<td>2529.9</td>
<td>1999.5</td>
</tr>
<tr>
<td>Evergreen</td>
<td>6526.5</td>
<td>6905.6</td>
<td>7635.5</td>
<td>7752.6</td>
</tr>
<tr>
<td>broad-leaved forests</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Crenate guger tree</td>
<td>2186.0</td>
<td>1744.9</td>
<td>1640.7</td>
<td>1963.2</td>
</tr>
<tr>
<td>Camphor tree</td>
<td>3319.7</td>
<td>3520.2</td>
<td>3919.1</td>
<td>4272.5</td>
</tr>
<tr>
<td>Zhennan</td>
<td>5434.6</td>
<td>5321.4</td>
<td>5042.3</td>
<td>5899.0</td>
</tr>
<tr>
<td>Eye evergreen chinakipin</td>
<td>-362.0</td>
<td>-261.1</td>
<td>-65.0</td>
<td>35.2</td>
</tr>
<tr>
<td>Farges evergreen chinakipin</td>
<td>-1010.6</td>
<td>-1059.8</td>
<td>-917.0</td>
<td>-970.7</td>
</tr>
<tr>
<td>Myrsina leaf oak</td>
<td>4472.7</td>
<td>4644.4</td>
<td>5146.0</td>
<td>5743.0</td>
</tr>
<tr>
<td>Deciduous</td>
<td>1446.0</td>
<td>2349.2</td>
<td>2996.6</td>
<td>2933.0</td>
</tr>
<tr>
<td>broad-leaved forests</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Faber oak</td>
<td>-1265.5</td>
<td>-1099.5</td>
<td>-161.0</td>
<td>1189.9</td>
</tr>
<tr>
<td>Beautiful sweet gum</td>
<td>-226.7</td>
<td>-423.8</td>
<td>160.9</td>
<td>1272.4</td>
</tr>
<tr>
<td>Shiny bark birch</td>
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<td>-1102.3</td>
<td>-867.6</td>
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<tr>
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<td>2365.2</td>
<td>2613.4</td>
<td>2827.8</td>
</tr>
<tr>
<td>Longpeduncled alder</td>
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<td>-150.1</td>
<td>132.5</td>
</tr>
<tr>
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<tr>
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</tr>
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<td>-4319.8</td>
<td>-4023.8</td>
<td>-4421.1</td>
</tr>
<tr>
<td>Masson’s pine</td>
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<tr>
<td>Slash pine forests</td>
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<td>-2107.0</td>
<td>-1666.2</td>
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<tr>
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<td>-2107.0</td>
<td>-1666.2</td>
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</table>

that AGB of broad-leaved forests is significantly higher than that of coniferous forests. There existed difference on the AGB among various climate scenarios. For EBF, AGB first increases dramatically and then remains stable over time (Fig. 8a). The relative magnitude of the response to the various climate change scenarios is also different. At the end-of-time of the simulation period, AGB of EBF ranked as RCP8.5 > RCP2.6 > RCP4.5 > control scenario. For DBF, AGB first increases and then decreases (Fig. 8b). While for MF, SF and CCF, it experiences a weak rise before 2040, followed by a rapid decline (Fig. 8c–e). For CCF, AGB under RCP8.5 scenario is significantly lower than that under other climate scenarios in the last three decades (Fig. 8e). For the whole region, total AGB first experiences a rapid increase and then decrease at a relatively slow rate during the simulation periods (Fig. 8f). Total AGB ranked as RCP4.5 > RCP2.6 > RCP8.5 > control scenario by 2100.

At the species level, the dynamic changes on AGB are more complex and responded differently among various climate scenarios (Table 1). Between 2010 and 2100, the variations for most broad-leaved species show positive values under various climate scenarios. However, for some specific species, such as evergreen chinkapin, faber oak, beautiful sweet gum and longpeduncled alder, different values existed. They show negative values under the current climate, RCP2.6 and RCP4.5 scenarios, while positive value for RCP8.5 scenario. The AGB for all the coniferous species (except for Chinese weeping cypress) decreases during the simulated period and shows differences among the various climate scenarios. As the dominant tree species of plantations, changes in AGB for Chinese fir is more significant under RCP8.5 scenario, while for pine forests, the variation under RCP4.5 is weaker compared with other scenarios.

The spatial distribution of forest AGB is shown in Fig. 9. It can be found that the spatial pattern variations in AGB are consistent with forest types. The high values zone on AGB is located at the broad-leaved forests, while relative low values zone covers coniferous forests, especially CCF. During the simulation period, the total AGB under these climate scenarios presents similar spatial patterns. At the end of the simulation year, the low values zone under RCP8.5 is significantly lower than that of other climate scenarios.

**Discussion**

**Interpretation of results**

Our results suggest that the climate change will have important effects on ANPP, forest distribution and AGB. Spatial pattern variations show that ANPP is consistent with AGB for different forest types. Nevertheless, driven by species-specific physiological characteristics of climatic factors tolerance and site conditions, the responses of different forest types and tree species to climate changes are different across the simulating four active ecoregions in this study. We found that forest productivity increased with the increment of temperature and precipitation in subtropical monsoon climate zone, which shows the consistence with the results of Nemani et al. (2003), Fang et al. (2003) and Mi et al. (2008). However, our results also show decreases in ANPP under different climate scenarios in the later
Fig. 9 The spatial distribution of forest AGB under four climate scenarios.
ANPP decreases gradually from ecoregion 2 forest productivity. In addition, our results show that physiological processes of tree species and in turn affect physiological processes of tree species and in turn affect et al. For RCP8.5, there is about a 4.7°C increase in annual mean temperature, and maximum and minimum temperature increase accordingly, which may affect most tree growth. Our results of mean SEP under RCP8.5 for broad-leaved forests, especially for DBF, decrease so dramatically, but the variation is not for all species. For example, beautiful sweet gum and long-peduncled alder also show a little increase in SEP during the simulation. For the coniferous planted forests, we think that much greater warming may be not conducive to these non-native species (including some deciduous species) establishment, especially without any human intervention.

In regard to forest distribution, the results of percentage area show that the EBF will increase and the CCF will decrease under climate change scenarios. That is mainly because of the distribution of evergreen broad-leaved forests being the typical vegetation in subtropical forests (Hou, 1983). In the forest successional stages, evergreen broad-leaved forests have been considered the climax vegetation in humid subtropical regions (Walker, 1985). Without considering anthropogenic disturbances (e.g., deforestation, reforestation and afforestation), forests will develop in the direction to the climax state. Meanwhile, tree distribution is influenced by climatic factors (Fang & Yoda, 1991). Expanding on the area percentage of EBF shows that it is more adaptive to future variation in climate by RCPs. This is also in agreement with a previous study suggesting that broadleaf trees can adapt to higher temperatures better than conifers, which may lead to a variation in forest distribution (Ni, 2011). In addition, the reduction in the CCF percentage area is in agreement with a study by Liu et al. (2014b). They found that the distribution of Chinese fir will increase in south-central China, but the mean probability of establishment will decrease in the 2050s. Comparing with other coniferous species (Masson’s pine and slash pine), Chinese fir is more sensitive to a temperature increase and requires better site conditions (Wu, 1984; Chi, 1992; Zhang & Xu, 2002). Change in forest distribution is also associated with tree species composition. For example, some pioneer species, particularly northern species (poplar), may be extinct because of climate change (Walker et al., 2002). In summary, tree species migration and forest distribution are controlled by integrated factors (Scheller & Mladenoff, 2008). Seed dispersal limitation, species competition, ecological succession and habitat heterogeneity may primarily contribute to altering spatial patterns and species coexistence in the subtropical forest under future climate change (Fang & Yoda, 1991; He & Mladenoff, 1999a; Liang et al., 2014; Svenning et al., 2014). In our study, we only simulated the consequences of climate change in the near future. If we run the model for a longer time period, the coniferous forests may eventually be replaced by the broad-leaved forests.
For forest AGB, our results show that total AGB first experiences a rapid increase and then decrease at a relatively slow rate under future climate scenarios. This is in agreement with previous studies (Scheller & Mladenoff, 2004; Steenberg et al., 2011; De Bruijn et al., 2014; Ma et al., 2014), which indicate that forest AGB will not keep increasing during forest succession. We calculated the quantity of the aboveground living biomass for each tree species-age cohort. Without disturbance, the aboveground living biomass at each time step is a function of the existing biomass, ANPP and aboveground mortality (Acker et al., 2002). The result suggests that AGB will increase at the same pace of productivity, which is in agreement with the findings of Mickler et al. (2002). Nevertheless, aboveground mortality increases logistically as AGB increases, until equilibrium is reached with ANPP. After that point, the AGB would be removed due to the age-related mortality which would begin at one half of a species’ lifespan (Scheller & Mladenoff, 2004). The AGB of broad-leaved forests reaches the dynamic equilibrium later and experiences longer accumulation than that of coniferous forests. For EBF, AGB does not experience a decrease in our simulation. The reason could be that some native species in longevity (e.g., camphor tree, zhennan) will not reach their natural mortality before the simulating year 2100. Our results also suggest that although the fluctuation of total AGB is generally consistent under different future climatic scenarios, some important differentiation do appear along temporal dimension, which reflects the different responses of various forest types to climate change.

Uncertainties and caveats

We used three climate change scenarios as well as a control scenario of extrapolating current climate conditions to explore the different effects on forest distribution and AGB. These RCP scenarios were projected using a multimodel ensemble from CMIP5 (Taylor et al., 2012), and the performances of simulating the climatic characteristics over China have already been assessed by Xu & Xu (2012a). The projected results showed that climate simulating models can effectively reflect the warming tendency in China, but showed limited ability in terms of precipitation (Xu & Xu, 2012b). This may influence the site condition and change the population dynamics in the forest ecosystem. Uncertainties and limitations in projecting the regional-scale climate changes are unavoidable. First, uncertainties in projections resulting from the multimodel ensemble are still an important issue, although it is more acceptable than a single model (Zhou & Yu, 2006; Tebaldi & Knutti, 2007). Second, the accuracy of climate data is hard to obtain by spatial resolution at the regional and landscape scales (Mears et al., 1999, 2001). In this study, due to the limitations of spatial resolution, the entire area was treated as homogeneous in terms of climatic conditions which may affect heterogeneity. Finally, with the restrictions of data sources, we were only able to access climate data (RCP2.6, RCP4.5 and RCP8.5) up until the end of this century. All of these elements mean that the projection of climate change is uncertain. However, our study is not trying to accurately predict the forest landscape under the future exact climate conditions, but to compare it with the different effects of these scenarios on forests. We focused on exploring the responses of forests to regional climate change as a whole. Therefore, using these climate data could suffice for our study purposes.

Forest response to climatic change occurs on many levels and is a complex and long-term process. Spatial interactive processes, succession, disturbances, migration and transformation occurred simultaneously in the forest ecosystem from species to communities (Cottee-nie, 2005; Wang et al., 2010). Based on traditional plot observation and forest inventory methods, it is difficult to study long-time successive responses of forests at the landscape scale. Forest landscape models can be used for exploring the response to future climatic change (Scheller & Mladenoff, 2005; Xu et al., 2012). On the one hand, compared with the GAP models and mathematics empirical models (Friend et al., 1993; Logofet & Lesnaya, 2000), spatially dynamic forest landscape models can trace the variation characteristics of forest landscapes and simulate spatial interactions among species (Scheller et al., 2007; Dai et al., 2015b; Xi et al., 2016). On the other hand, the simulating results are limited by inherent uncertainties in the response of forest landscape to climatic change (Xu et al., 2009). For LANDIS-II, the model simulates broad spatial and long temporal scale dynamics at cells which incorporate species not with individual stems but with age-defined cohorts (Scheller et al., 2007). A large number of tree species life-history parameters determine succession behavior, and also arouse some uncertainties in the simulation. Moreover, modeling predictions rely on various reasonable assumptions. One major assumption in the uncertainty is that we simulate the effect of climate change without considering other disturbances. However, other anthropogenic and natural disturbances, such as land cover transitions, deforestation, fire, wind and insect, may also affect the forest landscapes significantly (He & Mladenoff, 1999b; Dale et al., 2001; Cairns et al., 2008; Drummond & Loveland, 2010). Additionally, in terms of forest biomass, we only focused on the AGB in this study. But the belowground biomass comprises a significant fraction of total forest biomass.
which could lead to some uncertainty in the simulation. Finally, we did not incorporate the biogeophysical feedback of forests to climate change which may enhance or diminish climate forcing, and then in turn affect the forest landscape (Bonan, 2008).

Quantitative validation of simulating results through comparing forest inventory data at large spatial and long-time scales may be very difficult, especially for the prediction study. However, we still have confidence in our results based on (i) the LANDIS-II model, which has been applied previously in many studies around the world (Scheller & Mladenoff, 2008; Gustafson et al., 2010; Steenberg et al., 2011). The analysis of the uncertainty and sensitivity has been carried out as well in many studies (Xu et al., 2009; Gustafson et al., 2010). The validity of PnET models has also been verified in our study area of China (Yan et al., 2011; Liu et al., 2014b). The validity of both PnET-II and the LANIDS-II models strongly supports our results in this paper. (ii) The ecological input parameters are from previous published references and long-term sequenced filed investigations, which are supported by the Qianyanzhou ecological station in the Taihe County. The input of initial community map was derived from forestry inventory data which has made a big contribution to forest studies (Lexer et al., 2002; Corona et al., 2011). (iii) The outputs of our simulation are reasonable, and in accordance with expert knowledge. We also have tried to validate the results of AGB by comparing the simulated and investigated values at the initial year. In addition, our results are consistent with previous studies in the same study area (Ma et al., 2008; Mi et al., 2008; Wu et al., 2011). In summary, the points mentioned above strongly support our results in this paper.

Adaptation to climate change for regional forest management

Climate change is likely to obstruct the implementation of forest management goals in the future. Therefore, incorporating knowledge of adaptation to climate change into forest management is necessary, especially for plantations (Canadell & Raupach, 2008). In this paper, we chose Taihe County as the typical area to study the regional responses of forests to climate change based on some reasonable points. First and foremost, there are various forests in this area, which include almost all the major forest types (evergreen broad-leaved forests, deciduous broad-leaved forests and coniferous forests) in southern China. In particular, our study area is covered by a large area of plantations, such as Chinese fir plantations, Masson’s pine and slash pine plantations. From a plantation management perspective, these forest types are the significant representatives and spread widely in southern China (Xiang et al., 2011; Liu et al., 2014b). Moreover, the natural conditions of our study area, such as the soil (red soil), the terrain (hilly), and especially the climate (sub-tropical monsoon climate), are very typical in southern China. Last but not least, a long-term ecological station (QYZ ecological station) in our study provides substantial support for our model parameterization to ensure the credibility of our simulation results. Based on the above points, we believe that the Taihe County area is a very typical representation of southern China for studying the responses of forests to future climate change. We also understand that our results in the study area have some degree of universalities for regional forest management, which can be extended to the other areas in southern China.

In terms of regional forest management, climate change adaptation strategies can be viewed as a risk management component of sustainable forest management (Spittlehouse & Stewart, 2003). Numerous adaptive strategies and actions have been developed to adapt and mitigate climate change in other studies, such as resistance and resilience options, stand management, change rotation age and modified wood processing technology (Spittlehouse, 2005; Millar et al., 2007; Xi et al., 2008). For our study area or even the whole of southern China, the research on adaptation to climate change for sustainable forest management is relatively insufficient. Based on this condition, several adaptability suggestions are proposed for regional forest management in southern China. Firstly, suitable tree species selection should be considered on the premise of ensuring timber production. For example, some fast growing broadleaf species (e.g., fortune chinabells and long-peduncled alder) can be invaded to pure plantations in some specific areas to promote the climatic adaptability and vulnerability. Secondly, forestry partition management would become an effective way to cope with climate change. According to our results, the spatial diversity was shown in different ecoregions. As a consequence, appropriate adaptive strategies and actions concentrated in different management zones would be needed in the future forest management planning. Finally, forestry policy should be revised to consider climatic adaptation. In China, especially in the southern forest region, public forest is the main component of the forest resources, which is more directly affected by the forestry policy. Central and local governments should encourage and guide adaptation strategies of forest management according to the local conditions, and finally practice sustainable development of forestry.

Based on the above, if we want to successfully cope with climate change, we need first to evaluate and
predict the long-term effects on forests, and from there determine what should be done now and in the future to adapt to this threat (Spittlehouse & Stewart, 2003). In this study, we focus on the trends, interactions and the relative magnitude of the response to multiple climate change situations. Although there are cumulative uncertainties in the modeling, it is the trade-offs between the technical and the conceptual models (Mladenoff, 2004). In the future, multimodel methods should be integrated to improve the accuracy of the models. Furthermore, land use change, deforestation and other disturbances should also be incorporated to cope with global climate change.

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References
Aber JD, Ollinger SV, Federer CA et al. (1995b) Predicting the effects of climate change on water yield and forest production in the northeastern United States. Climate Research, 5, 207–222.


He HS, Mladenoff DJ (1999b) Spatially explicit and stochastic simulation of forest landscape fire disturbance and succession. Ecology, 80, 81–99.


Supporting Information

Additional Supporting Information may be found in the online version of this article:

Figure S1. The distribution of the points for model validation.
Figure S2. The variation trend of aboveground net primary production (ANPP) and species’ establishment probability (SEP) simulated by PnET-II under RCP2.6, RCP4.5, RCP8.5 and control scenarios across the four active ecoregions.
Figure S3. The rate of inter-annual variation of area for the five forest types under four climate scenarios.
Figure S4. The spatial distribution of five forest types under four climate scenarios.
Table S1. Species life-history attributes in the Taihe County, Jiangxi Province, China.