Chin. Geogra. Sci. 2014 Vol. 24 No. 6 pp. 631–646
doi: 10.1007/s11769-014-0662-9
Springer Science Press
www.springerlink.com/content/1002-0063

Examining Forest Net Primary Productivity Dynamics and Driving Forces in Northeastern China During 1982–2010

MAO Dehua[1, 2], WANG Zongming[1], WU Changshan[3], SONG Kaishan[1], REN Chunying[1]

(1. *Key Laboratory of Wetland Ecology and Environment*, *Northeast Institute of Geography and Agroecology*, *Chinese Academy of Sciences*, *Changchun* 130102, *China*; 2. *University of Chinese Academy of Sciences*, *Beijing* 100049, *China*; 3. *Department of Geography*, *University of Wisconsin-Milwaukee*, *Milwaukee WI* 53201, *USA*)

Abstract: Forest net primary productivity (NPP) is a key parameter for forest monitoring and management. In this study, monthly and annual forest NPP in the northeastern China from 1982 to 2010 were simulated by using Carnegie-Ames-Stanford Approach (CASA) model with normalized difference vegetation index (NDVI) sequences derived from Advanced Very High Resolution Radiometer (AVHRR) Global Inventory Modeling and Mapping Studies (GIMMS) and Terra Moderate Resolution Imaging Spectroradiometer (MODIS) products. To address the problem of data inconsistency between AVHRR and MODIS data, a per-pixel unary linear regression model based on least squares method was developed to derive the monthly NDVI sequences. Results suggest that estimated forest NPP has mean relative error of 18.97% compared to observed NPP from forest inventory. Forest NPP in the northeastern China increased significantly during the twenty-nine years. The results of seasonal dynamic show that more clear increasing trend of forest NPP occurred in spring and autumn. This study also examined the relationship between forest NPP and its driving forces including the climatic and anthropogenic factors. In spring and winter, temperature played the most pivotal role in forest NPP. In autumn, precipitation acted as the most important factor affecting forest NPP, while solar radiation played the most important role in the summer. Evapotranspiration had a close correlation with NPP for coniferous forest, mixed coniferous broadleaved forest, and broadleaved deciduous forest. Spatially, forest NPP in the Da Hinggan Mountains was more sensitive to climatic changes than in the other ecological functional regions. In addition to climatic change, the degradation and improvement of forests had important effects on forest NPP. Results in this study are helpful for understanding the regional carbon sequestration and can enrich the cases for the monitoring of vegetation during long time series.

Keywords: forest; net primary productivity (NPP); Carnegie-Ames-Stanford Approach (CASA) model; normalized difference vegetation index (NDVI); northeastern China

Citation: Mao Dehua, Wang Zongming, Wu Changshan, Song Kaishan, Ren Chunying, 2014. Examining forest net primary productivity dynamics and driving forces in northeastern China during 1982–2010. *Chinese Geographical Science*, 24(6): 631–646. doi: 10.1007/s11769-014-0662-9

1 Introduction

As one of the largest land cover types, forests play a significant role in the regional climate and global carbon cycle (Fang *et al*., 2001a). There is general agreement that global forest is a large and persistent carbon sink for atmospheric CO_2 (Pan *et al*., 2011). Forest in China is also a centre to the global and national carbon sink for atmospheric CO_2 (Fang *et al*., 2001b; Piao *et al*., 2009). Forests transform atmospheric carbon from CO_2 to

Received date: 2012-11-27; accepted date: 2013-03-11
Foundation item: Under the auspices of Key Program of Chinese Academy of Sciences (No. KZZD-EW-08-02), CAS/SAFEA (Chinese Academy of Science/State Administration of Foreign Experts Affairs) International Partnership Program for Creative Research Teams (No. KZZD-EW-TZ-07), Strategic Frontier Program of Chinese Academy of Sciences—Climate Change: Carbon Budget and Relevant Issues (No. XDA05050101)
Corresponding author: WANG Zongming. E-mail: zongmingwang@neigae.ac.cn

woody biomass with the process of photosynthesis, while at the same time some energy is lost through respiration and mortality. The balance between the light energy fixed through photosynthesis and the energy lost through respiration and mortality is termed forest net primary productivity (NPP). The NPP represents the net carbon input from the atmosphere to the terrestrial vegetation (Melillo *et al*., 1993), and it is one of the important biophysical variables presenting vegetation activities, and is the first step of the biogeochemical carbon cycle (Tan *et al*., 2007). The studies of spatio-temporal dynamics of NPP and factors that impact such dynamics have become a new research focus and have attracted much attention recently. These research activities were spurred by global issues, such as global change, indirect sustainable management, and conservation of biodiversity (Yuan *et al*., 2006). As an essential component of the global change study, examining the spatio-temporal dynamics of forest NPP and factors that lead such changes have played an important role in forest monitoring and management. And the study on forest NPP is helpful to understand the global or regional carbon cycle.

Remote sensing can provide important information for simulating forest NPP and examining its spatio-temporal dynamics. For instance, remote sensing can supply a synoptic view of large geographic regions with multiple spectral bands and repetitive coverage. The spatial resolutions of remote sensing imagery range from meter-level to kilometer-level with the coverage area from local to global scale. The temporal coverage of remote sensing imagery ranges from hours to several years. Through applying remote sensing technology, Nemani *et al*. (2003) reported a global NPP increase of 6% from 1982 to 1999, and pointed out that such increase was mainly due to the reduced cloud cover and associated increase in solar radiation. Piao *et al*. (2003; 2005) estimated the NPP dynamic from 1982 to 1999 based on normalized difference vegetation index (NDVI) and detected seasonal dynamics of terrestrial NPP in response to climatic changes in China. Based on remote sensing datasets, numerous related studies were also conducted to simulate NPP values and applied to different regions with a number of models (Tagesson *et al*., 2009; Yu *et al*., 2009b; Huang *et al*., 2010).

For a better examination of the NPP dynamic and its response to climatic changes and human disturbances, time-series NPP datasets are essential. For example, the NDVI from advanced very high resolution radiometer (AVHRR) provided by the National Oceanic and Atmospheric Administration (NOAA), with a spatial resolution of 8 km and a time sequence from 1982 to 2006, have been widely applied in estimating forest NPP. Comparatively, the NDVI with a spatial resolution of 1 km, from moderate resolution imaging spectroradiometer (MODIS) data, have been available since 2000. Although remote sensing imagery are available for a certain time span, it is still very difficult to find a single remote sensing dataset with consistent spatial/spectral resolution and covering a long time for accurate NPP simulation. To date, scientists always limit the spatial resolution and time series to a certain degree such that a single remote sensing data source can be utilized. For many study areas, however, a consistent simulation of NPP at the same spatial resolution over a long time is particularly important. The Carnegie-Ames-Stanford Approach (CASA) model, one of the most important and widely used light-use efficiency models, was utilized to study the dynamics of forest NPP and its responses to climatic changes and land cover changes (Potter *et al*., 2012).

The northeastern China has abundant forest resources, and its forest area is approximately 31% of the total forest area in China (EBVMC, 2001). The role in carbon sink of forest in the northeastern China can not be ignored. However, forests in the northeastern China have experienced significant changes due to climatic and anthropogenic impact over the past decades. In particular, increased temperature and decreased precipitation have had significant impacts on forests (Guo *et al*., 2007; Yao *et al*., 2011). Land cover changes due to human activities, including farming reclamation or other deforestation activities over the last century, urbanization in recent decades, also significantly affect forest distribution and quality (Xu *et al*., 2004a; Liu *et al*., 2009).

Therefore, we studied the forest in the northeastern China based on NPP. The objectives of the present study are: 1) to simulate long-term (from 1982 to 2010) monthly and annual forest NPP in the northeastern China through integrating AVHRR GIMMS (Global Inventory Modeling and Mapping Studies) NDVI, TERRA MODIS NDVI and meteorological datasets, 2) to investigate the spatio-temporal dynamic of forest NPP across the study area over 29 years, and 3) to explore the impact of climatic change and human activities (forest-land degradation or improvement) on the dynamics of forest NPP, and provide guidance to forest management and ecological restoration in the northeastern China.

2 Data and Methods

2.1 Study area

In this study, the northeastern China (38°42′–53°35′N, 115°32′–135°09′E) is selected as the study area. It covers three provinces (Heilongjiang, Jilin, and Liaoning) and four prefecture-level administration divisions of Inner Mongolia Autonomous Region (i.e., Hulun Buir City, Xing′an League, Tongliao City, and Chifeng City) (Fig. 1). The study area is surrounded by medium and low mountains along three directions, including the Changbai Mountains in the southeast, the Da Hinggan Mountains in the northwest, and the Xiao Hinggan Mountains in the northeast. This study area is an important forest zone and timber production base in China, with a forest area of approximately 4.73×10^5 km^2. Native forest types include cold-temperate mixed broad-leaved deciduous forest and needle-leaved forest, as well as cold-temperate coniferous forest. A large portion of the study area is characterized by a temperate monsoon continental climate, except for areas located at the latitude of 50°N or higher, which are dominated by the cold monsoon. Winter is long and cold, while summer is short. Air temperature in this study area increases from north to south, with a mean annual temperature of –4℃–12℃. Precipitation has significant seasonal and annual changes. And approximately 70%–80% of total precipitation occurred between mid-June and mid-August. Annual precipitation decreases from 1100 mm in the east to 250 mm in the west.

Based on the vegetation map and ecological functional region map (Fu *et al*., 2001), climatic and topographic information, forests in the northeastern China were classified into four ecological functional regions, namely, the Da Hinggan Mountains, the Xiao Hinggan Mountains and Wanda Mountains, the Changbai Mountains, and the Inner Mongolia semi-arid zone. Spatial distribution of different forest types of and four ecological functional regions are shown in Fig. 1.

2.2 Data source and data processing

2.2.1 Remote sensing data

Remote sensing data employed in this study consist of AVHRR GIMMS NDVI and TERRA MODIS NDVI. The AVHRR GIMMS NDVI dataset (from 1982 to 2006)

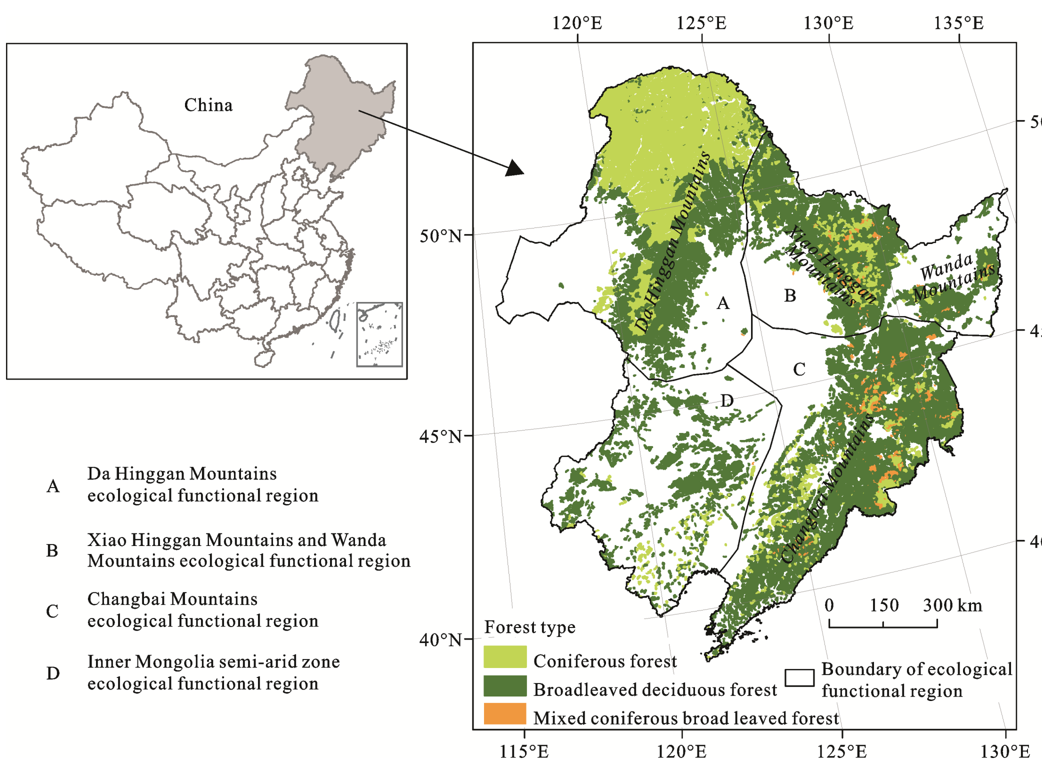

Fig. 1 Spatial distribution of forest types and ecological functional regions in northeastern China

at a spatial resolution of 8 km × 8 km and every half month was derived from the NOAA/AVHRR imagery. The TERRA MODIS NDVI dataset with a spatial resolution of 1 km × 1 km from 2000 to 2010 was downloaded from the National Aeronautics and Space Administration′s (NASA) Earth Observing System. The NDVI data for every month were obtained by using the Maximum Value Composite (MVC) method with which the highest observed value for each pixel from a predefined compositing period is employed to represent the NDVI value for that period.

2.2.2 Meteorological data

Meteorological data, including mean monthly temperature, monthly cumulative precipitation and daily sunshine duration from 1982 to 2010, were extracted from the China Meteorological Data Sharing Service System (http://cdc.cma.gov.cn/). In the study area, meteorological data from 95 stations were recorded and employed after removing the records with deficiencies. Monthly solar radiation data for all meteorological stations were calculated from daily sunshine duration, the latitudes of meteorological stations, as well as other parameters (Allen *et al*., 1998; Seaquist *et al*., 2003). To be consistent with the spatial resolution of the constructed NDVI dataset, these monthly data were then interpolated into raster format at an 8 km spatial resolution by using the universal Kriging method. Further, evaportranspiration data were calculated from temperature and precipitation raster data by using the regional evaportranspiration model. Expressions for actual evaportranspiration used for correlation analyses in this paper were referenced from previous study by Zhou and Zhang (1995). In the regional evaportranspiration model, the potential evaportranspiration and net radiations in surface need to be calculated, firstly. All the data were projected into the Albers Equal Area Conic projection system using the ArcGIS-9.3 software.

2.2.3 Forest distribution and actual observed NPP

Forest distribution data were extracted and edited from the land cover data covering the northeastern China in 2000. The land cover data were derived from Landsat Thematic Mapper (TM) images through computer classifications and visual interpretations. Details on data processing can be found in Wang *et al*. (2009). As shown in Fig. 1, forests in the study area were classified into coniferous forest, mixed coniferous broadleaved forest, and broadleaved deciduous forest. The actual observed forest NPP data used to validate the simulated results were contained from the results of Luo (1996). Those observed NPP with a unit of g C/(m^2·yr) were calculated from forest biomass in 2006 (Luo, 1996). And the data were obtained by harvest and widely used in many studies (Zhu *et al*., 2006a). Based on the geographical position of observed data, there are 74 samples retained after calculating the mean value of samples in the same pixel.

2.2.4 Frame of data processing

For achieving the objectives, data processing and analysis were carried out as a frame presented in Fig. 2. First, based on the remote sensing data and meteorological data, a geographical database consisting of monthly NDVI, temperature, precipitation, and solar radiation were prepared. Second, monthly and annual NPP for different forest types from 1982 to 2010 were simulated by CASA model and validated by observed data. Third, estimated forest NPP was applied to investigate its spatio-

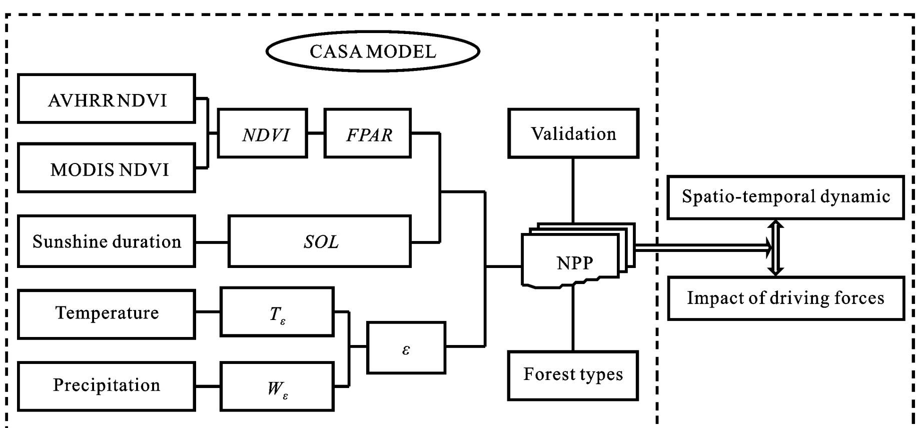

Fig. 2 Frame for data processing and analysis. *SOL*: solar radiation; *FPAR*, fraction of photosynthetically active radiation; T_ε: effect of temperature on plant photosynthesis; W_ε: impact of water on plant photosynthesis; ε: active light-use efficiency

temporal dynamic and impacts from climatic factors and human activities.

2.3 Simulation of forest NPP using CASA model

The CASA model developed by Potter *et al*. (1993) is a light efficiency process-based model, which has the ability of mitigating problems associated with limited and inconsistent data from meteorological stations in large scale studies (Yuan *et al*., 2006). The CASA model has been widely applied in different regions and at different scales. With the CASA model, forest NPP can be calculated by using the following equation (Potter *et al*., 1993; Zhu *et al*., 2007b:

$$NPP(x,t) = APAR(x,t) \times \varepsilon(x,t) \quad (1)$$

where $NPP(x, t)$ refers to the forest NPP of a pixel at location x and time t; $APAR$ is the absorbed photosynthetically active radiation, which refers to canopy-absorbed incident solar radiation over a time period (MJ/m^2), and ε is the actual light-use efficiency. The process for simulating forest NPP was accomplished through programming using the Arc Macro Language provided by the ArcInfo Worksation software. The details of deriving monthly APAR and ε are described as follows.

2.3.1 Estimation of APAR

The algorithm of calculating $APAR$ at location x and time t was detailed in equations 2, 3 and 4, respectively (Zhu *et al*., 2007b; Piao *et al*., 2001).

$$APAR(x,t) = SOL(x,t) \times FPAR(x,t) \times 0.5 \quad (2)$$

$$FPAR(x,t) = \min\left[\frac{SR - SR_{\min}}{SR_{\max} - SR_{\min}}, 0.95\right] \quad (3)$$

$$SR(x,t) = \frac{1 + NDVI(x,t)}{1 - NDVI(x,t)} \quad (4)$$

where SOL is the total solar radiation over a time period (MJ/m^2). $FPAR(x, t)$ is the fraction of photosynthetically active radiation at position x and time t, which is calculated from the simple ratio (SR) of vegetation indices. Further, SR is calculated from the NDVI sequence, $SR_{\max}$ is the maximum value of SR, and $SR_{\min}$ is the minimum value of SR (e.g., unvegetated land areas). The fixed values of $SR_{\max}$ are different for various forest types. The value for $SR_{\max}$ is obtained from the previous study by Zhu *et al*. (2007b).

In this study, monthly AVHRR GIMMS NDVI dataset differ from monthly TERRA MODIS NDVI dataset in terms of spatial and spectral resolution. Hence, a per-pixel unary linear regression model method integrating the two datasets from different sensor sources was used to construct a consistent and successive NDVI sequence dataset from 1982 to 2010 with the same spatial resolution. The structure form of the model for different data is shown as follow:

$$G_i = a + bV_i + \varepsilon_i \quad (5)$$

where G_i represents the GIMMS NDVI value for the ith month, V_i is the converted MODIS NDVI value at the 8 km × 8 km resolution for the ith month, parameters a and b are calculated with the ordinary least squared method, and ε_i is the random error term. This model was constructed and calibrated with the GIMMS NDVI and MODIS NDVI from 2000 to 2006, when both datasets are available. The model was constructed with a spatial resolution of 8 km, and the monthly MODIS NDVI sequences from 2000 to 2010 were translated to 8 km spatial resolution to be consistent with those of the AVHRR GIMMS NDVI data. Good consistency between GIMMS and MODIS NDVI were discussed and the annual changes of NDVI during the three decades were compared. And this per-pixel unary linear regression model appeared to be the most appropriate regression equation for each pixel, and more details about the process of constructing long time-series NDVI data were described in Mao *et al*. (2012). The correlation coefficient of GIMMS NDVI and expanded GIMMS NDVI is 0.991, and R^2 is 0.995 and 0.982 for the regional and pixel consistency check, respectively.

2.3.2 Estimation of ε

The algorithm of actual light use efficiency (ε) can be expressed by Equation (6) (Field *et al*., 1995; Zhou and Zhang, 1995; Peng *et al*., 2010):

$$\varepsilon(x,t) = T_{\varepsilon 1}(x,t) \times T_{\varepsilon 2}(x,t) \times W_{\varepsilon}(x,t) \times \varepsilon_{\max} \quad (6)$$

where, $T_{\varepsilon 1}(x, t)$ and $T_{\varepsilon 2}(x, t)$ are temperature stress coefficients which reflect the restriction from temperature on light use efficiency at position x and in time t, and $W_{\varepsilon}(x, t)$ is the moisture stress coefficient which suggests the reduction of light use efficiency caused by moisture factor at position x and in time t. $\varepsilon_{\max}$ is the maximum light-use efficiency of vegetation under ideal conditions. The values of $\varepsilon_{\max}$ for different forest types in China were obtained following the simulated results from Zhu *et al*. (2006b).

2.4 Validation for estimated forest NPP

In order to assess the effectiveness of estimated forest NPP, we made a validation by calculating the mean relative error (MRE) and correlation coefficient between estimated forest NPP and observed forest NPP. The comparison among various estimated forest NPP using different models was employed to support the validation for forest NPP from CASA model in this study.

2.5 Examination of spatio-temporal dynamics of forest NPP

With the estimated forest NPP for each 8 km × 8 km pixel in the northeastern China from 1982 to 2010, we conducted a spatio-temporal analysis on forest NPP. For spatial analysis, we divided the forest NPP into six grades, and examined their spatial distribution. Moreover, the spatial distribution of forest NPP in the four forest ecological functional regions was explored. To explore the temporal dynamics, we examined the time series forest NPP data categorized by forest types, seasons, and ecological functional regions. For analyzing the spatio-temporal patterns of forest NPP, correlation analysis, regression analysis, and variation analysis were conducted in the present study. Variation analysis was employed to investigate spatial differences among the temporal variability of NPP during the 29 years. The variation coefficient (*C.V.*) is calculated by Equation (7):

$$C.V. = \frac{\sqrt{[\sum_{i=1}^{n}(NPP_i - \overline{NPP})^2]/29}}{\overline{NPP}} \tag{7}$$

where NPP_i is the mean NPP for the year i (i = 1, ..., 29), and $\overline{NPP}$ is the mean NPP value for all the years (from 1982 to 2010).

2.6 Evaluation for impact of climatic factors on forest NPP

We also examined the climatic factors that correlate with such spatial and temporal patterns. In particular, the climatic factors employed in analyses include temperature, precipitation, solar radiation, and evaportranspiration. Similarly, the impact of climatic factors on the dynamic of forest NPP was evaluated based on different forest types, growth seasons, and ecological functional regions. Correlation analysis was performed to examine whether a statistically significant association existed for each climatic factor.

3 Results and Analyses

3.1 Simulation results of forest NPP

Using the CASA model, we simulated the monthly and annual forest NPP values in the northeastern China from 1982 to 2010. For each year, the forest NPP values were calculated for each 8 km × 8 km pixel (7123 pixels total for the study area). Intending to validate the accuracy, we made a comparison between forest NPP from the simulated result and actual observation. As shown in Fig. 3, the forest NPP value from observation is higher than that from model simulation. However, a clear linear relation exists between forest NPP value from estimation by using CASA model and actual observation by harvest method. The correlation coefficient is 0.736 ($p < 0.01$) between the NPP from estimated result by CASA model and from observed result by field investigation. The value of mean relative error is 18.97%. It means 81.03% of the estimated accuracy for forest NPP using CASA model in the northeastern China. Also, the fluctuation range of the simulated forest NPP is lower than that of the observed forest NPP. Based on those results and other′s estimated accuracy (Zhu *et al*., 2006a), forest NPP from simulation is considered as reliable and can be used to do further analyses.

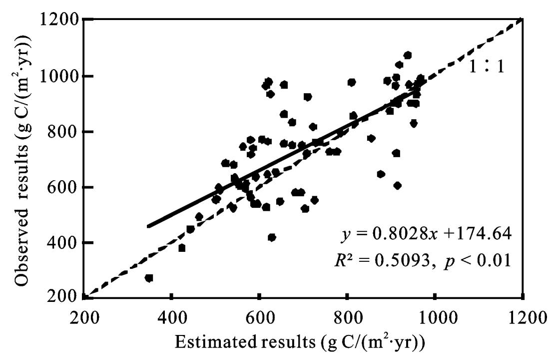

Fig. 3 Comparison of forest NPP from estimation using CASA model and actual observation using harvest method

Total forest NPP in the northeastern China over the study period was approximately 300 Mg C/yr, and the mean forest NPP over the study period ranged from 200 g C/(m^2·yr) to 985 g C/(m^2·yr). A comparison with results obtained in other studies is also reported in Table 1. In particular, the simulated results from 1982 to 1999 were compared with the results reported by Zhu *et al*.

Table 1 Comparison of simulated forest NPP for different forest types with findings from other studies

Study	Model and scale	Study period	Forest type (g C/(m^2·yr))		
			Broadleaved deciduous forest	Coniferous forest	Mixed coniferous broadleaved forest
Zhu *et al*. (2006a)	CASA/8 km	1982–1999	663	447	469
Present study	CASA/8 km	1982–1999	691	534	613
Guo *et al*. (2008)	BOIME-BGC/1 km	2000–2006	474	454	573
Zhao *et al*. (2011)	CEVSA/1 km	2000–2008	638	460	722
Present study	CASA/8 km	2000–2008	646	547	720

(2006a), and the results from 2000 to 2008 were compared with the results reported by Guo *et al*. (2008) and Zhao *et al*. (2011). We found that differences of forest NPP values exist among different models, but the general trend is consistent. There was a change from increasing trend to decreasing trend. The low diversity for different studies may be the results of different scales and study periods (e.g. a large pixel resolution may smooth small variations).

3.2 Spatial variation of mean forest NPP

Through spatial analysis, we found that the spatial variations of forest NPP are consistent with forest types and ecological functional regions (Fig. 4). Broadleaved deciduous forests had the highest NPP values exceeding 700 g C/(m^2·yr), when compared with that of the coniferous forests and mixed coniferous broadleaved forests. On the contrary, coniferous forests had the lowest NPP due to a short growth period. For the four forest ecological functional regions, the Changbai Mountains had the highest forest NPP values, followed by the Xiao Hinggan Mountains and Wanda Mountains, then the Da Hinggan Mountains. Forests in the Inner Mongolia semi-arid zone had the lowest amount of forests and the worst environment for vegetation growth among the four regions.

For examining the variations of forest NPP for different forest types, we grouped the forests into four grades based on the forest NPP values, and these grades are: 1) less than 600 g C/(m^2·yr), 2) 600–700 g C/(m^2·yr), 3)700–800 g C/(m^2·yr), and 4) higher than 800 g C/(m^2·yr). The percentage of forest areas covered by each grade for each forest type is shown in Fig. 5. It can

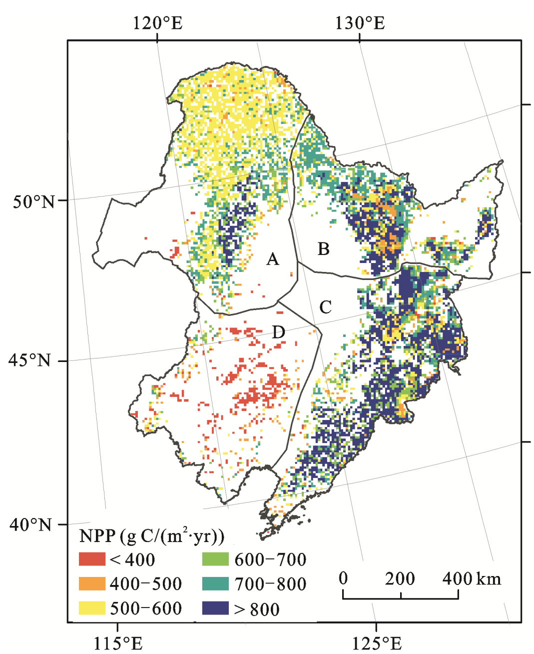

Fig. 4 Spatial pattern of mean forest NPP from 1982 to 2010. A: Da Hinggan Mountains ecological functional region; B: Xiao Hinggan Mountains and Wanda Mountains ecological functional region; C: Changbai Mountains ecological functional region; D: Inner Mongolia semi-arid zone ecological functional region

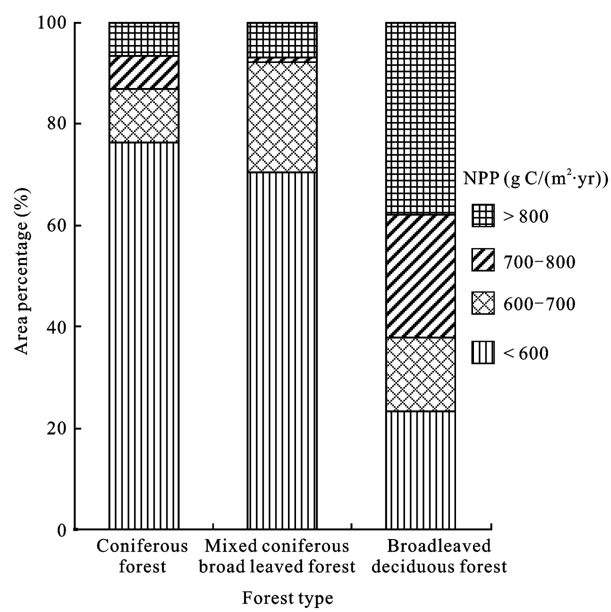

Fig. 5 Area percentages of forest NPP at different grades for different forest types

be observed that the forest NPP differs significantly for different forest types. For coniferous forest, over 75% of the pixels had a forest NPP value lower than 600 g C/(m^2·yr). Mixed coniferous broadleaved forests, which only occupy a small area in the northeastern China, had around 70% of the pixels with a forest NPP value less than 600 g C/(m^2·yr), and less than 1% of the pixels with a forest NPP value ranging from 700 g C/(m^2·yr) to 800 g C/(m^2·yr). Broadleaved deciduous forests, on the other hand, had the highest forest NPP values, and the pixels with a forest NPP value higher than 800 g C/(m^2·yr) comprise a large percentage. As a summary, the distribution of forest NPP in the northeastern China had a clear spatial heterogeneity and obvious disparity pattern among different forest types.

3.3 Temporal dynamics of forest NPP for different forest types

Annual forest NPP values and their changes for different forest types are shown in Fig. 6. Forest NPP values for all types of forests exhibited a significantly increasing trend ($p < 0.05$, standard deviation 37–44) from 1982 to 2010, and coniferous forests showed the most notable increase in the forest NPP values as indicated in the regression coefficient. Although there was a clear trend, some variations exist. The maximum and the second highest forest NPP values over the study period can be found in 2010 and 1996, respectively. And the minimum forest NPP values for broadleaved deciduous forests and mixed coniferous broadleaved forests can be found in 1983 and 1994. For coniferous forests, the minimum and the second lowest forest NPP values are found in 1983 and 1998. It can also be observed that, in general, coniferous forests had lower forest NPP values, and broadleaved deciduous forests were likely to have higher forest NPP values.

3.4 Trends of forest NPP in different seasons

To further investigate the dynamic of forest NPP over the study period, the changing trends in different seasons from 1982 to 2010 were analyzed. Results show that forest NPP values in summer (from June to August) and winter (January, February, and December) did not have a clear trend of increasing or decreasing (Fig. 7). However, the forest NPP values in spring (from March to May) and autumn (from September to November) were found to have significantly increased trends. For a particular year, the highest values of forest NPP (over 400 g C/(m^2·yr)) were found in summer, while the lowest forest NPP values (e.g., lower than 0.4 g C/(m^2·yr)) were found in winter. As a growing cycle, spring marks the beginning of vegetation growth, and the forest NPP reaches its peak value in the summer, then autumn marks the end of the growing season. Forest NPP in winter was almost zero because of the low temperature and the lack of leaves in deciduous forests.

3.5 Disparity of forest NPP in different ecological functional regions

In this study, the spatial variations of forest NPP were also examined among the four forest ecological functional regions which have obvious climatic differences. As shown in Fig. 4, discrepant grades were found in different forest ecological functional regions because of variation in forest types and climatic conditions. The changing trends of forest NPP values were investigated

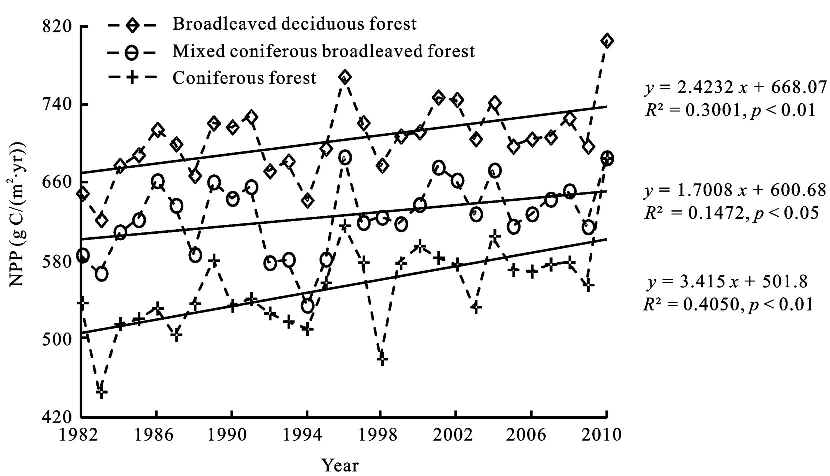

Fig. 6 Annual changing trends of forest NPP for different forest types from 1982 to 2010

for the four regions. Results indicate that significantly increased trends of forest NPP from 1982 to 2010 were found in the Da Hinggan Mountains, the Xiao Hinggan Mountains and Wanda Mountains, and the Inner Mongolia semi- arid zone ecological functional regions (Fig. 8). Mean annual forest NPP in the Changbai Moutains ecological functional region had no obviously changing trends. Figure 8 also shows a difference in mean forest NPP for these forest eclogical functional regions. Although forest NPP in the Changbai Mountains ecological functional regions had no clear trends over the study period, a typical amplitude of fluctation was observed with the biggest standard divation of 44 g C/(m^2·yr).

The percentage of geographic area covered by each forest NPP grade is shown in Fig. 9. It can be observed that the forest NPP values in the most areas of the Da Hinggan Mountains ecological functional region had a value lower 600 g C/(m^2·yr). In the Xiao Hinggan Mountains and Wanda Mountains ecological functional region, where broadleaved deciduous forests and mixed coniferous broadleaved forests were widely distributed, forest NPP exceeding 700 g C/(m^2·yr) were found. The Changbai Mountains ecological functional region, characterized by broadleaved deciduous forests and few evergreen coniferous forests, had over 55% of the total area with forest NPP values over 800 g C/(m^2·yr). Finally, forest NPP in the Inner Mongolia semi-arid zone ecological functional region varied under 600 g C/(m^2·yr)

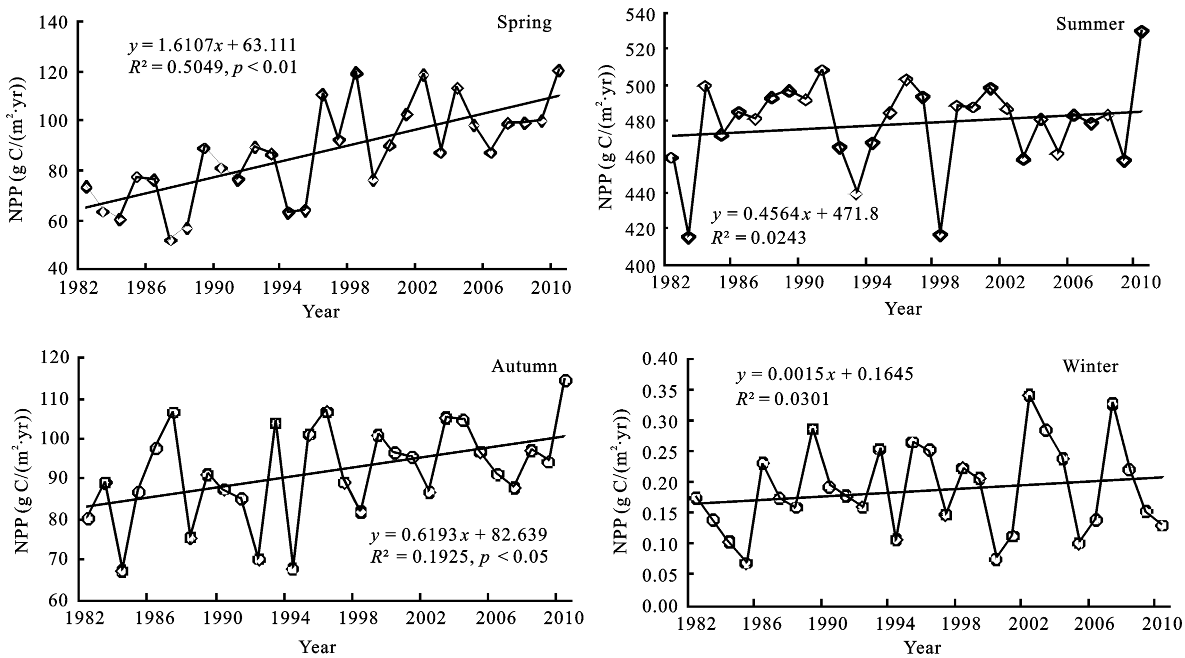

Fig. 7 Changing trends of annual forest NPP in different seasons from 1982 to 2010

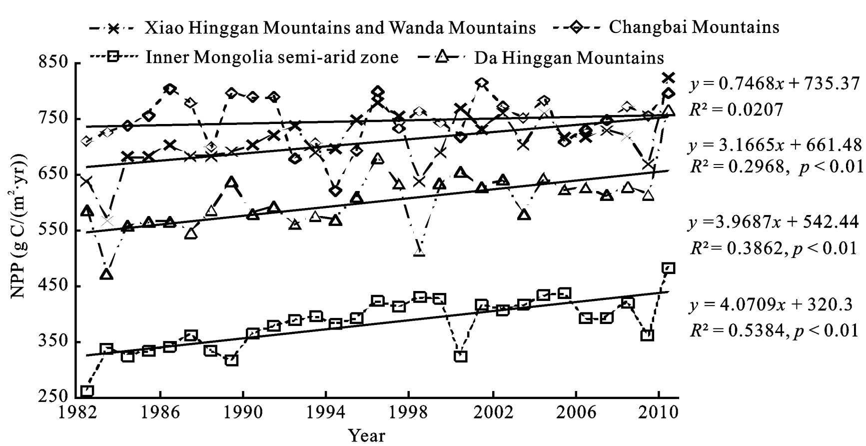

Fig. 8 Changing trends of annual forest NPP in different ecological functional regions from 1982 to 2010

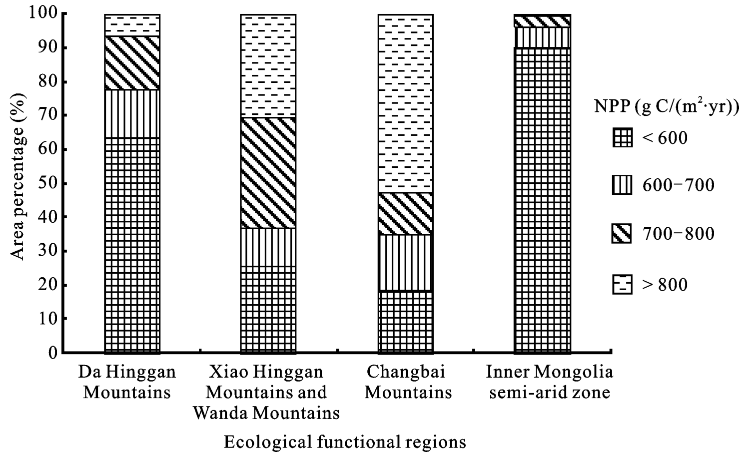

Fig. 9 Area percentages of forest NPP at difenernt grades for different ecological functional regions

because of the severe environment and scattered patches.

3.6 Temporal coefficient of variation analysis

For a better assessment on the changes of forest NPP in the northeastern China, temporal variation analysis was also conducted. The spatial pattern of variation coefficients (*C.V.*) (Equation 7) at pixel scale are shown in Fig. 10. The forest NPP in the Inner Mongolia semi-arid zone ecological functional region had the highest variation coefficients, varying from 0.10 to 0.69. A higher variation coefficient indicates more obvious variation trends. Therefore, the forest NPP in the Inner Mongolia semi-arid zone had a significantly increasing trend. This may be due to the Three North Shelter Forest projects, which has played an important role in the improvement of forest NPP in the semi-arid zone (Yan *et al*., 2011).

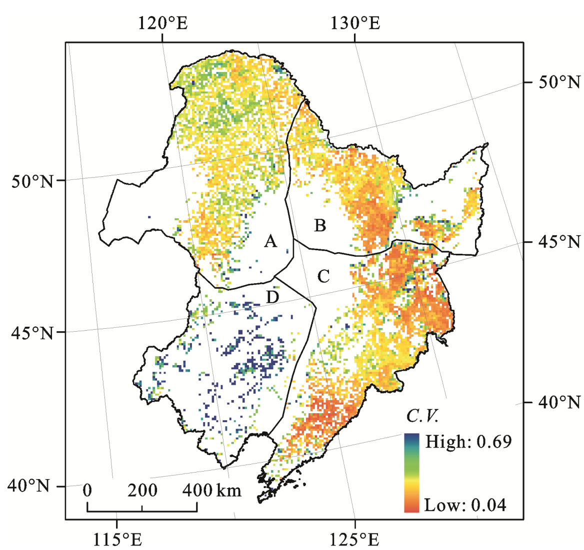

Fig. 10 Spatial pattern of variation coefficients (*C.V.*) for forest NPP in northeastern China. A: Da Hinggan Mountains ecological functional region, B: Xiao Hinggan Mountains and Wanda Mountains ecological functional region, C: Changbai Mountains ecological functional region, D: Inner Mongolia semi-arid zone ecological functional region

3.7 Effects of climatic factors on forest NPP

Climatic factors are important determinants of vegetation and play a crucial role in shaping spatial patterns and temporal dynamics of forest NPP. Results of correlation analysis between annual forest NPP of different forest types and annual climatic factors (e.g., temperature, precipitation, solar radiation, evaportranspiration) are shown in Table 2. This enables an exploration of the impact of climatic changes on forest NPP and their variations for different forest types. Positive correlations between forest NPP and mean temperature (TEM), and between forest NPP and solar radiation (SOL) were found for all types of forests. Positive correlations indicate that rising temperature and increasing solar radiation in the northeastern China were associated with the increase of forest NPP. On the contrary, negative correlations were found between forest NPP and annual precipitation (PRE), and between forest NPP and evaportranspiration (ET). A large amount of precipitation reduced the opportunity for forests to receive solar radiation for photosynthesis (Piao *et al*., 2003). In 1998, flood damage made great negative effects on forests in the northeastern China, so a low value of forest NPP was found for the year, especially in autumn. Moreover, a large amount of evaportranspiration reduced available moisture content. The moisture for vegetation growth in the northeastern China was not only derived from pre-

Table 2 Correlation coefficients between forest NPP and climatic factors in different forest types ($n = 29$)

Forest type	NPP and TEM	NPP and PRE	NPP and SOL	NPP and ET
Coniferous forest	0.228	–0.405*	0.626**	–0.659**
Mixed coniferous broadleaved forest	0.101	–0.138	0.121	–0.440*
Broadleaved deciduous forest	0.112	–0.157	0.210	–0.609**

Notes: * means significant, $p < 0.05$; ** means extremely significant, $p < 0.01$. NPP, net primary productivity; TEM, mean annual temperature; PRE, annual cumulative precipitation; SOL, annual total solar radiation; ET, annual cumulative evaportranspiration

cipitation, but also from thawed snow and frozen soil. Evaportranspiration is the synthetical and direct character of the intensity of temperature, precipitation, and solar illuminance. Therefore, forest NPP and evaportranspiration had the closest and negative correlation.

Table 2 also shows that the correlation between climatic factors and NPP is different for different forest types. Comparatively, the forest NPP of coniferous forests was more sensitive to climatic change than two other types of forests. Coniferous forests are distributed in the northern part of the study area, with higher latitude, shorter growing days, less solar radiations, and lower temperature, and therefore more sensitive to climatic changes. Overall, this finding showed stronger correlation existed between forest NPP and climatic factors, and some of them are highly significant. Different from other studies, in which correlation analyses were only conducted between NPP and temperature and precipitation (Sun and Zhu, 2001), the results of this study indicated that there was a stronger correlation between evaportranspiration and NPP for all types of forests in the northeastern China. This result, therefore, contributes to the understanding of the influence of climatic factors on forest NPP.

To investigate effects of seasonal climatic factors on seasonal forest NPP, correlation analyses between forest NPP in four seasons and seasonal meteorological factors were conducted. As shown in Table 3, seasonal temperature was closely associated with forest NPP in spring, summer, and winter. As spring is the start of growing cycle for trees and increased temperature yields long growth period (Zhu *et al.*, 2007a), therefore, temperature is associated with a higher value of forest NPP. Summer is associated with stronger photosynthetic rate and a warmer winter can facilitate the growth of evergreen coniferous forests. Therefore, increasing temperature in the three seasons improved forest NPP and resulted in a significantly positive correlation between forest NPP and temperature. Negative correlations were found between forest NPP and precipitation in spring, summer, and autumn. This is expected as the growing season of forests is from April to October, and precipitation had much more effect on forest NPP in the growing season (summer and autumn) by reducing solar radiation or sunshine duration (Nemani *et al.*, 2003). Further, forest NPP was significantly and positively correlated to solar radiation in spring and summer. This is reasonable as trees have more leaves in spring and summer, and solar radiation strengthens productivities. Finally, evaportranspiration was negatively associated with forest NPP in summer and autumn seasons and positively correlated to forest NPP in spring and winter. In summer and autumn, increasing evaportranspiration reduced soil moisture for vegetation growth, thereby reducing forest NPP. In winter, the northeastern China has a freezing temperature, and ground is covered by snow for over 100 days. Therefore, increasing evaportranspiration may be beneficial to forest NPP by improving soil conditions.

We also conducted similar analysis at the scale of ecological functional regions, and results are listed in Table 4. Forest NPP in the Inner Mongolia semi-arid zone with lower precipitation had the highest correlation coefficient with temperature because increased temperature resulted in droughts by reducing soil moisture (Long *et al.*, 2010). The arid environment led to grassland degradation or transform to farmland for acquiring more economic benefits. This phenomenon also occurred in forestland. A significantly negative correlation

Table 3 Correlation coefficients between forest NPP and climatic factors in different seasons ($n = 29$)

Season	NPP and TEM	NPP and PRE	NPP and SOL	NPP and ET
Spring	0.533**	–0.029	0.505**	0.094
Summer	0.422*	–0.372*	0.502**	–0.265
Autumn	0.096	–0.366*	–0.026	–0.308
Winter	0.861**	0.188	–0.102	0.398*

Notes: * means significant, $p < 0.05$; ** means extremely significant, $p < 0.01$. NPP, net primary productivity; TEM, mean seasonal temperature; PRE, seasonal cumulative precipitation; SOL, seasonal total solar radiation; ET, seasonal cumulative evaportranspiration

Table 4 Correlation coefficients between forest NPP and climatic factors in different ecological functional regions (n = 29)

Ecological functional region	NPP and TEM	NPP and PRE	NPP and SOL	NPP and ET
Da Hinggan Mountains	0.175	-0.376^{*}	0.698^{**}	-0.617^{**}
Xiao Hinggan Mountains and Wanda Mountains	0.205	–0.277	0.130	-0.509^{**}
Changbai Mountains	–0.050	0.044	0.250	–0.271
Inner Mongolia semi-arid zone	0.307	0.111	0.518^{**}	–0.130

Notes: * means significant, $p < 0.05$; ** means extremely significant, $p < 0.01$. NPP, net primary productivity; TEM, mean annual temperature; PRE, annual cumulative precipitation; SOL, annual total solar radiation; ET, annual cumulative evaportranspiration

between forest NPP and precipitation in the Da Hinggan Mountains was found, possibly because precipitation under low-temperature surroundings resulted in less solar duration and radiation for tree growth (Piao *et al*., 2003). Solar radiation played the most important role in forest NPP in the Da Hinggan Mountains and the Inner Mongolia semi-arid zone, while evaportranspiration served as the most important climatic factor affecting the forest NPP in the northern part of the study area, comprising the Da Hinggan Mountains, the Xiao Hinggan Mountains and Wanda Mountains. Evaportranspiration reduced soil moisture content and was likely to negatively affect forest NPP. Thus, negative correlations between forest NPP and evaportranspiration were found, especially in the northern part of the study area, which had lower temperature and less precipitation. Forest NPP in the Da Hinggan Mountains was thus found to be more sensitive to climatic changes than in other three regions during the past three decades.

4 Discussion

4.1 Uncertainty of forest NPP simulation

In this study, the CASA model was applied to simulate the forest NPP with an accuracy of 81.03% in Northeastern China over 29 years. And the significant correlation was found between estimated forest NPP and actually observed forest NPP. After the validation and statistical analysis, effective estimation of forest NPP was obtained. It is important to be aware that a few major errors may lead to the uncertainty of the estimates. First, the forest NPP was simulated at a large spatial scale (8 km × 8 km) with most pixels containing numerous types of forests. Therefore, the resultant forest NPP values may be subject to estimation errors, especially in the Inner Mongolia semi-arid zone. Secondly, errors from the input data of the CASA model were also non-negligible. Although the MVC method was used to derive monthly NDVI to reduce the effects of clouds, atmosphere, and solar elevation angle, errors still exist in these processes of data acquisitions. The estimation of solar radiation and interpolation of meteorological data also yielded simulation errors of forest NPP estimates. Nevertheless, optimal approaches were adopted in this study to reduce possible errors. These approaches include employing the preferable Kriging interpolation method and proper parameters suitable for Northeastern China. Accuracy of integrating AVHRR GIMMS and TERRA MODIS datasets to construct a long-time sequence NDVI dataset were discussed in detail and successfully verified through the consistency check presented by Mao *et al*. (2012). The forest NPP value from actual observation is a little higher than the value from model simulation. It mainly resulted from an accumulation from many years of the actual observation forest NPP value. Through model comparison, differences among various models or at diverse spatial resolutions were determined. When compared with the results from Zhu *et al*. (2006a), a higher mean forest NPP was found in this study. This is likely due to the differences in the study area, as Zhu *et al*. only employed the Northeastern China Transect. The transect covers geographic regions with lower vegetation abundance. The mean forest NPP from 2000 to 2008 obtained in this study is similar to the CEVSA modeling results reported by Zhao *et al*. (2011), and is slightly higher than the value obtained in Guo *et al*. (2008). In summary, no significant differences exist among these results. Therefore, the results, based on the root mean square error and comparisons among several models, reported in the present study were credible and scientific for such a large study area (Northeastern China) and long-time sequence (nearly three decades).

4.2 Spatial pattern and temporal dynamics of forest NPP

The evident climatic changes and intense human disturbances resulted in great changes in forest NPP in

Northeastern China. Our results indicate that forest NPP in the Northeastern China over the past decades exhibited an obvious spatial pattern and temporal dynamics. Spatially, coniferous forests dominated by Dahurian Larch (*Larix gemelinii*) and Pinus sylvestris (*Pinus sylvestris* var. *mongolicalitv*) were primarily distributed in the Da Hinggan Mountains with a lower temperature and longer winter. The Da Hinggan Mountains region is the second biggest permafrost zone in China and is covered by snow more than half a year (Zhou *et al*., 2000). Thus, the short growing days and small needle-shaped leaves resulted in lower forest NPP when compared with other types of forests. Mixed coniferous broadleaved forests and broadleaved deciduous forests are primarily distributed in the Changbai Mountains and the Xiao Hinggan Mountains and Wanda Mountains, where higher forest NPP values can be attributed to the abundant precipitation and higher temperature, resulting in more growing days. The forest NPP value in the Inner Mongolia semi-arid zone is the lowest when compared to other regions. It is not only due to the lack of precipitation, but also because of much evaportranspiration in the area. The forest NPP of similar forest types had different grades, which can be attributed to climatic conditions and the ages of the trees (Huang *et al*., 2010).

The forest NPP values in different ecological functional regions and seasons, as well as in different forest types, had various characteristics over the study period. During the past 29 years, there was a general increasing trend of forest NPP due to many climatic factors, including increased temperature, decreased precipitation, less cloudy and rainy days, and more solar radiations, all of which provided a better growing environment for forests (Jin *et al*., 2000; Mao *et al*., 2010; Yang *et al*., 2010). Fang *et al.* (2001b) found that the changes of NPP are owing to the difference of precipitation. The annual changes of forest NPP are the most correlated to variability of annual precipitation, such as the difference between 2009 and 2010. Strong precipitation in 1998 resulted in the low NPP because reduced the solar radiation for vegetation photosynthesis (Piao *et al*., 2003). Furthermore, a seasonal analysis on dynamics of forest NPP shows that the forest NPP value increased significantly in spring and autumn, which cover the growing season of forests. As a result of the forest fire over the Da Hinggan Mountains in the spring of 1987, the forest NPP in spring in 1987 decreased significantly (Fig. 7). Moreover, the temporal analysis results of forest NPP for the four ecological functional regions show that all regions except the Changbai Mountains region had a clear increasing trend of forest NPP. It is because that the forests in the Changbai Mountains region have been significantly impacted by human activities, such as deforestation, farmland reclamation. Therefore, effective forest managements are imperative for the Changbai Mountains ecological functional region.

4.3 Effects of forest degradation and conservation on forest NPP

Forests play a vital role on regional environment and ecological equilibrium. However, in the past several decades, forests in Northeastern China have undergone significant human-induced changes (Liu *et al*., 2003; Xu *et al*., 2004b; Liu *et al*., 2009). Although a large number of forest parks and reserves have been established in the past three decades, large areas of primary forests were damaged, especially the coniferous forests. Bai and Dent (2005) argued that land degradation and improvement in China significantly affected NPP. Xu *et al.* (2004a) found that a total of 9.006×10^5 ha forests were degraded during 1985–1995 and 4.869×10^5 ha forests were degraded during 1995–2000 in Northeastern China. Liu *et al*. (2005) found that 1.023×10^5 ha forests were converted into other land use types in the Da Hinggan Mountains and Xiao Hinggan Mountains and in the eastern part of Northeastern China. These degraded areas were mainly distributed in the forest-grassland and forest-cropland transitional zones. The conversion from forestland into other land cover types resulted in a decrease in NPP. To date, deforestation is still ongoing, resulting in reduced productivity and degraded regional environments, such as aggravated soil erosion in the Inner Mongolia semi-arid zone. Forests in the Inner Mongolia semi-arid zone are scattered, and the enhancement of forest quality and expansion of forest area are necessary to control the sandstorm and stabilize the sands in the Inner Mongolia semi-arid zone. Moreover, the Grain to Green Program (GTGP) must be effectively implemented in this sub-region, especially in the Horqin desert zone which includes the serious desertification of lands (Yan *et al*., 2011). Some forests disappeared in the past three decades, especially in the Changbai Mountains, because of urbanization and land degradation. Yu *et al*. (2009a) and Lu *et al*. (2010) emphasized that urbanization had significant effects on the change of NPP. In light of this, economic development policy in Northeastern China, including the 'Revitalizing old industrial base of Northeast China' policy (Zhang, 2008), may also negatively affect the forests and forest NPP values.

Chinese central and local governments have gradually realized the importance of sustainable utilization of forests in Northeastern China. The Natural Forest Conservation Program (NFCP) and the GTGP (Liu *et al.*, 2008) were implemented for improving and protecting forests. Northeastern China, as one of the typical region which has luxuriant forest resources and at the same time experiencing significant deforestation, is the key region for the implementation of these two programs. The area of plantations increased significantly in Northeastern China. A total of 5.242×10^5 ha forests were returned from croplands in Northeastern China from 1990 to 2000 (Liu *et al.*, 2005). Moreover, about 8.28×10^4 ha of grassland was returned to forestland in the Da Hinggan Mountains and Xiao Hinggan Mountains from 2000 to 2005 (Liu *et al.*, 2009). Results from the seventh forest inventory (from 2004 to 2008) showed that areas of tree plantation obviously increased in Northeastern China, and therefore increased forest NPP in this area. As the major lumber production base in China, effective conservation and management on forests in Northeastern China will be implemented. Thus, the forest NPP values in Northeastern China will maintain the increasing trends with reasonable forest conservation and management practices.

5 Conclusions

Forest NPP in Northeastern China from 1982 to 2010 is simulated using the CASA model by integrating AVHRR and MODIS remote sensing data. Simulation results are employed to investigate the spatial patterns and temporal dynamics of forest NPP during these 29 years. Further, the impact of climatic factors and human activities, including degradation and plantation activities, on the dynamics of forest NPP is examined for the past three decades. Climatic changes and human activities exert obvious effects on forest NPP in Northeastern China. In addition, we find that forest NPP increased significantly over the past decades. The increasing trends in forest NPP are found stastically significant in spring and autumn and in different ecological functional regions including the Da Hinggan Mountains, the Xiao Hinggan Mountains and Wanda Mountains, and the Inner Mongolia semi-arid zone.

Meanwhile, stronger correlations are found between evaportranspiration and forest NPP for coniferous forest, mixed coniferous broadleaved forest, and broadleaved deciduous forests in Northeastern China, when compared with other climatic factors. Forest NPP in the Da Hinggan Mountains ecological functional region is more sensitive to climatic changes than that in other three regions over the study period. Coniferous forests, which are the most sensitive to climatic changes, merits further investigations in the future work.

References

Allen R G, Pereira L S, Raes D, 1998. Crop evapotranspiration-Guidelines for computing crop water requirements. In: *FAO Irrigation and Drainage*. Rome: FAO, 13–56.

Bai Z, Dent D, 2009. Recent land degradation and improvement in China. *AMBIO*, 38(3): 150–156. doi: 10.1579/0044-7447-38.3.150

EBVMC (Editorial Board of Vegetation Map of China, Chinese Academy of Sciences), 2001. *Vegetation Regionalization Map of China*. Beijing: Science Press. (in Chinese)

Fang J, Chen A, Peng C *et al.*, 2001a. Changes in forest biomass carbon storage in China between 1949 and 1998. *Science*, 292(5525): 2320–2322. doi: 10.1126/science.1058629

Fang J, Piao S, Tang Z *et al.*, 2001b. Interannual variability in net primary production and precipitation. *Science*, 293(5536): 1723. doi: 10.1126/science.293.5536.1723a

Field C B, Randerson J T, Malmstrom C M, 1995. Global net primary production: Combining ecology and remote sensing. *Remote Sensing of Environment*, 51(1): 74–88. doi: 10.1016/0034-4257(94)00066-V

Fu Bojie, Liu Guohua, Chen Liding *et al.*, 2001. Scheme of ecological regionalization in China. *Acta Ecologica Sinica*, 21(1): 1–6. (in Chinese)

Guo Zhixing, Wang Zongming, Song Kaishan *et al.*, 2007. Correlations between forest vegetation NDVI and water-thermal condition in Northeast China forest regions in 1982–2003. *Chinese Journal of Ecology*, 26(12): 1930–1936. (in Chinese)

Guo Zhixing, Wang Zongming, Zhang Bai *et al.*, 2008. Analysis of temporal-spatial characteristics and factors influencing vegetation NPP in Northeast China from 2000 to 2006. *Resources Science*, 30(8): 1226–1235. (in Chinese)

Huang N, Niu Z, Wu C *et al.*, 2010. Modeling net primary production of a fast-growing forest using a light use efficiency model. *Ecological Modelling*, 221(24): 2938–2948. doi: 10.1016/j.ecolmodel.2010.08.041

Jin H, Li S, Cheng G *et al.*, 2000. Permafrost and climatic change in China. *Global and Planetary Change*, 26(4): 387–404. doi:

10.1016/S0921-8181(00)00051-5

Liu J, Li S, Ouyang Z *et al*., 2008. Ecological and socioeconomic effects of China′s policies for ecosystem services. *PNAS*, 105(28): 9477–9482. doi: 10.1073/pnas.0706436105

Liu Jiyuan, Zhang Zengxiang, Xu Xinliang *et al*., 2009. Spatial patterns and driving forces of land use change in China in the early 21st century. *Acta Geographica Sinica*, 64(12): 1411–1420. (in Chinese)

Liu Jiyuan, Zhang Zengxiang, Zhuang Dafang *et al*., 2003. A study on the spatial-temporal dynamics changes of land-use and driving forces analyses of China in the 1990s. *Geographical Research*, 22(1): 1–12. (in Chinese)

Liu Yansui, Peng Liuying, Chen Yufu, 2005. Conversion of land use types and ecological effect in Northeast China. *Transactions of the CSAE*, 21(10): 175–178. (in Chinese)

Long Huiling, Li Xiaobing, Wang Hong *et al*., 2010. Net primary productivity (NPP) of grassland ecosystem and its relationship with climate in Inner Mongolia. *Acta Ecologica Sinica*, 30(5): 1367–1378. (in Chinese)

Lu D, Xu X, Tian H *et al*., 2010. The effects of urbanization on net primary productivity in southeastern China. *Environment Management*, 46(3): 404–410. doi: 10.1007/s00267-010-9542-y

Luo Tianxiang, 1996. *Patterns of Biological Production and Its Mathematical Models for Main Forest Types of China*. Beijing: Graduate School, Chinese Academy of Sciences. (in Chinese)

Mao D, Wang Z, Luo L *et al*., 2012. Integrating AVHRR and MODIS data to monitor NDVI changes and their relationships with climatic parameters in Northeast China. *International Journal of Applied Earth Observation and Geoinformation*, 18: 528–536. doi: 10.1016/j.jag.2011.10.007

Mao Dehua, Wang Zongming, Luo Ling *et al*., 2010. Growing-season normalized difference vegetation index, NDVI, response to climate changes and increased carbon dioxide concentration in frozen areas of Northeast China during 1982–2008. *Acta Scientiae Circumstantiae*, 30(11): 2332–2342. (in Chinese)

Melillo J M, McGurie A D, Kicklighter D W *et al*., 1993. Global climate change and terrestrial net primary production. *Nature*, 363(6426): 234–240. doi: 10.1038/363234a0.

Nemani R R, Keeling C D, Hashimoto H *et al*., 2003. Climate-driven increases in global terrestrial net primary production from 1982 to 1999. *Science*, 300(5625): 1560–1563. doi: 10.1126/science.1082750

Pan Y, Birdsey R, Fang J *et al*., 2011. A large and persistent carbon sink in the world′s forests. *Science*, 333(6045): 988–993. doi: 10.1126/science.1201609

Peng D, Huang J, Huete A R *et al*., 2010. Spatial and seasonal characterization of net primary productivity and climate variables in southeastern China using MODIS data. *Journal of Zhejiang University*, 11(4): 275–285. doi: 10.1631/jzus.B0910501

Piao S, Fang J, Ciais P *et al*., 2009. The carbon balance of terrestrial ecosystems in China. *Nature*, 458(7241): 1009–1014. doi: 10.1038/nature07944

Piao S, Fang J, Zhou L *et al*., 2003. Interannual variations of monthly and seasonal normalized difference vegetation index (NDVI) in China from 1982 to 1999. *Journal of Geophysical Research*: *Atmospheres*, 108(D14). doi: 10.1029/2002JD002848

Piao S, Fang J, Zhou L, 2005. Changes in vegetation net primary productivity from 1982 to 1999 in China. *Global Biogeochemical Cycles*, 19(2): GB2027. doi: 10.1029/ 004GB002274

Piao Shilong, Fang Jingyun, Chen Anping, 2003. Seasonal dynamics of terrestrial net primary production in responses to climate changes in China. *Acta Botanica Sinica*, 45(3): 269–275. (in Chinese)

Piao Shilong, Fang Jingyun, Guo Qinghua, 2001. Application of CASA model to the estimation of Chinese terrestrial net primary productivity. *Acta Phytoecologica Sinica*, 25(5): 603–608. (in Chinese)

Potter C S, Klooster S, Genovese V, 2012. Net primary production of terrestrial ecosystems from 2000 to 2009. *Climatic Change*, 115(2): 365–378. doi: 10.1007/s10584-01200460-2

Potter C S, Randerson J T, Field C B *et al*., 1993. Terrestrial ecosystem production: A process model based on global satellite and surface data. *Global Biogeochemical Cycles*, **7**(4): 811–841. doi: 10.1029/93GB02725

Seaquist J W, Olsson L, Ardo J, 2003. A remote sensing based primary production model for grassland biomass. *Ecological Modeling*, 169(1): 131–155. doi: 10.1016/S0304-3800(03)00267-9

Sun Rui, Zhu Qijiang, 2001. Effect of climate change of terrestrial net primary productivity in China. *Journal of Remote Sensing*, 5(1): 58–61. (in Chinese)

Tagesson T, Smith B, Lofgren A, 2009. Estimating net primary production of Swedish forest landscapes by combining mechanistic modeling and remote sensing. *AMBIO*, 38(6): 316–324. doi: 10.1579/08-A-513.1

Tan K, Piao S, Peng C *et al*., 2007. Satellite-based estimation of biomass carbon stocks for northeast China′s forests between 1982 and 1999. *Forest Ecology and Management*, 240(1): 114–121. doi: 10.1016/j.foreco.2006.12.018

Wang Zongming, Zhang Bai, Song Kaishan *et al*., 2009. Land use changes in Northeast China driven by human activities and climatic variation. *Chinese Geographical Science*, 19(3): 225–230. doi: 10.1007/s11769-009-0225-7

Xu Xinliang, Liu Jiyuan, Zhuang Dafang *et al*., 2004a. Analysis on spatial-temporal characteristics and driving factors of woodland change in Northeastern China based on 3S technology. *Scientia Geographica Sinica*, 24(1): 55–60. (in Chinese)

Xu Xinliang, Liu Jiyuan, Zhuang Dafang *et al*., 2004b. Spatial-Temporal characteristics and driving factors of woodland resource changes in China. *Journal of Beijing Forest University*, 26(1): 41–46. (in Chinese)

Yan Q, Zhu J, Hu Z *et al*., 2011. Environmental impacts of the shelter forests in Horqin sandy land, Northeast China. *Journal of Environmental Quality*, 40(3): 815–824. doi: 10.2134/jeq2010.0137

Yang Z, Ouyang Y, Xu X *et al*., 2010. Effects of permafrost degradation on ecosystems. *Acta Ecologica Sinica*. 30(1): 33–39. doi: 10.1016/j.chnaes.2009.12.006

Yao J, He X, Li X *et al*., 2011. Monitoring responses of forest to climate variations by MODIS NDVI: A case study of Hun River upstream, northeastern China. *European Journal of Forest Research*, 131(3): 705–716. doi: 10.1007/s10342-011-0543-z

Yu D, Shao H, Shi P *et al*., 2009a. How does the conversion of land cover to urban use affect net primary productivity? A case study in Shenzhen City, China. *Agricultural and Forest Meteorology*, 149(11): 2054–2060. doi: 10.1016/j.agrformet.2009.07.012

Yu D, Shi P, Shao H *et al*., 2009b. Modeling net primary productivity of terrestrial ecosystems in East Asia based on an improved CASA ecosystem model. *International Journal of Remote Sensing*, 30(18): 4851–4866. doi: 10.1080/01431160802680552

Yuan Jinguo, Niu Zheng, Wang Chenli, 2006. Vegetation NPP distribution based on MODIS data and CASA model—A case study of Northern Heibei Province. *Chinese Geographical Science*, 16(4): 334–341. doi: 10.1007/s11769-006-0334-5

Zhang Pingyu, 2008. Revitalizing old industrial base of Northeast China: Process, policy and challenge. *Chinese Geographical Science*, 18(2): 109–118. doi: 10.1007/s11769-008-0109-2

Zhao Guoshuai, Wang Junbang, Fan Wenyi *et al*., 2011. Vegetation net primary productivity in Northeast China in 2000–2008: Simulation and seasonal change. *Chinese Journal of Applied Ecology*, 22(3): 621–630. (in Chinese)

Zhou Guangsheng, Zhang Xinshi, 1995. A natural vegetation NPP model. *Acta Phytoecologica Sinica*, 19(3): 193–200. (in Chinese)

Zhou Youwu, Guo Dongxin, Qiu Guoqing *et al*., 2000. *Geocryology in China*. Beijing: Science Press, 26–30, 40–42. (in Chinese)

Zhu W, Pan Y, Liu X *et al*., 2006a. Spatio-temporal distribution of net primary productivity along the Northeast China transect and its responses to climatic change. *Journal of Forestry Research*, 17(2): 93–98. doi: 10.1007/s11676-006-0022-4

Zhu Wenquan, Pan Yaozhong, He Hap *et al*., 2006b. Simulation of the maximum light use efficiency for typical vegetation in China. *Chinese Science Bulletin*, 51(6): 700–706. (in Chinese)

Zhu Wenquan, Pan Yaozhong, Yang Xiaoqiong *et al*., 2007a. Influence analysis of climatic changes on terrestrial vegetation net primary productivity in China. *Chinese Science Bulletin*, 52(21): 2535–2541. (in Chinese)

Zhu Wenquan, Pan Yaozhong, Zhang Jinshui, 2007b. Estimation of net primary productivity of Chinese terrestrial vegetation based on remote sensing. *Journal of Plant Ecology*, 31(3): 413–424. (in Chinese)