OPTIMIZATION OF FOREST AGE-DEPENDENT LIGHT-USE EFFICIENCY AND ITS IMPLICATIONS ON CLIMATE-VEGETATION INTERACTIONS IN CHINA

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ABSTRACT:

Forest's net primary productivity (NPP) is a key index in studying interactions of climate and vegetation, and accurate prediction of NPP is essential to understand the forests' response to climate change. The magnitude and trends of forest NPP not only depend on climate factors (e.g., temperature and precipitation), but also on the succession stages (i.e., forest stand age). Although forest stand age plays a significant role on NPP, it is usually ignored by remote sensing-based models. In this study, we used remote sensing data and meteorological data to estimate forest NPP in China based on CASA model, and then employed field observations to inversely estimate the parameter of maximum light-use efficiency (ε_{max}) of forests in different stand ages. We further developed functions to describe the relationship between maximum light-use efficiency (ε_{max}) and forest stand age, and estimated forest age-dependent NPP based on these functions. The results showed that ε_{max} has changed according to forest types and the forest stand age. For deciduous broadleaf forest, the average ε_{max} of young, middle-aged and mature forest are 0.68, 0.65 and 0.60 gC MJ^{-1}. For evergreen broadleaf forest, the average ε_{max} of young, middle-aged and mature forests are 1.05, 1.01 and 0.99 gC MJ^{-1}. For evergreen needleleaf forest, the average ε_{max} of young, middle-aged and mature forests are 0.72, 0.57 and 0.52 gC MJ^{-1}.The NPP of young and middle-aged forests were underestimated based on a constant ε_{max}. Young forests and middle-aged forests had higher ε_{max}, and they were more sensitive to trends and fluctuations of climate change, so they led to greater annual fluctuations of NPP. These findings confirm the importance of considering forest stand age to the estimation of NPP and they are significant to study the response of forests to climate change.

1. INTRODUCTION

The vegetation is the main body of the biosphere, and it is significant to regulate the global carbon balance (Piao et al., 2001). Net Primary Production (NPP) is one of the main components of the carbon cycle (Piao et al., 2008; Liang et al., 2015) and also an indicator to the ecosystem performance (Lobell et al., 2002). Climate change has deeply affected the ecosystem and NPP has become a significant tool to reflect the variation of the ecosystem (Hao et al., 1998; Liu et al., 2015). In general, the forest ecosystem NPP accounted for 35% of the global and 65% of the terrestrial ecosystem NPP (Gower et al., 1996; Waring and Schlesinger, 1985). The variation in forest NPP will change the atmospheric CO_2 concentration and further affect the climate change (Want et al., 2011). The difference in the forest stand ages and forest types are critical factors to the forest ecosystem, and it is essential to investigate the variation of the forest NPP with the forest stand ages among forest types (Chen et al., 2003; Song and Woodcock, 2003; Kashian et al., 2006). The Carnegie-Ames-Stanford Approach (CASA) model (Potter et al., 1993) based on the remote sensing data is widely used to simulate the spatial distribution of the NPP and it can also be employed to monitor NPP at different scales (Li et al., 2009). The accuracy of the estimated NPP based on the CASA model has been mostly affected by the maximum light-use efficiency (ε_{max}), and it exists differences among forest types and the forest stand ages (Zhu et al., 2006; Hui et al., 2012). The maximum light-use efficiency could influence the carbon sink of the ecosystem, and reflect the forest ecosystem productivity (Zhou et al., 2010). Potter and Field think that the maximum light-use efficiency of all the vegetation types around the world is 0.389 gC/MJ, and Raymond et al believe that the upper limit of the maximum light-use efficiency is 3.5 gC MJ^{-1}. Thus, it is essential to determine the maximum light-use efficiency based on the forest stand ages among forest types (Potter et al., 1993; Raymond et al., 1994; Field et al., 1995, 1998). In this study, the CASA model was employed to estimate NPP in China from 1982 to 2005. We calculated the maximum light-use efficiency of forests in the forest stand ages based on the estimated NPP and the field observation NPP. The relationship between the maximum light-use efficiency and the forest stand ages could be developed to reflect the impact of change in the forest stand ages on the maximum light-use efficiency, and the estimated age-dependent NPP could also be calculated based on the relationship.

2. DATA AND METHODS

2.1 Remote sensing data

Many vegetation indices based on the remote sensing data have been developed to monitor vegetation dynamics, and the most widely used is the Normalized Difference Vegetation Index (NDVI). The NDVI dataset used in this study was obtained from the Global Inventory Modelling and Mapping Studies inventory (Tucker et al., 2005) during the period 1982 to 2005. This dataset has a long time series and it is helpful to be applied to reflect the vegetation information (Beck et al., 2011). The spatial resolution of the dataset is 8 km, and the temporal resolution is 15 days. To match with other data, the GIMMS NDVI dataset is composited based on the maximum value composite (MVC). The MVC technique retains the highest value for each pixel, and the images are relatively cloud-free, with the ability to reflect the vegetation dynamics (Eidenshink, 1992; Holben, 1986).

2.2 Meteorological data and the land cover map

This study employed the monthly average temperature, the monthly precipitation data and the monthly total solar radiation data during the period 1982 to 2005 from the National Climate Centre of the Chinese Meteorological Administration (CMA). The homogeneity and reliability of the monthly meteorological data have been previously checked and controlled by the CMA (Yu et al., 2014). The related longitude, latitude and the altitude of the meteorological stations are also used in this study to interpolate the meteorological data based on the GIS methods. The cell size matches with the NDVI dataset. The Land Cover map used in this study was originated from the MODIS Landcover dataset, and the classification of the vegetation type was chosen type 1 (ISTP).

2.3 Field observation data of NPP

The NPP field observation data originates from the forest inventory data and Luo's study based on the 1266 forest plots from 1982 to 2005. It includes the forest stand age, the LAI, the total biomass, the longitude, latitude and altitude of the observation sites. It is used to correct the maximum light-use efficiency (ε_{max}) of the CASA model among different forest types in the forest stand ages. Based on the available field observation of the NPP, the forest types that considered in this study include the deciduous broadleaf forest (DBF), the evergreen needleleaf forest (ENF) and the evergreen broadleaf forest (EBF).

2.4 CASA model

Carnegie-Ames-Stanford Approach (CASA) model (Potter et al., 1993) can estimate monthly NPP with satellite data, monthly temperature, precipitation and soil properties (Liu et al., 2015; Zhang et al., 2015). The CASA model can simulate the spatial distribution and the variation of NPP on a regional scale and it has been widely used to monitor the NPP for various spatial scales. In CASA model, the NPP is the function of Absorbed Photosynthetic Active Radiation (APAR), the maximum light-use efficiency (ε_{max}), the effect of the temperature stress index (T_ε) and the moisture stress factor (W_ε). For a given geographic coordinate (x) at month t, NPP is calculated as,

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

$$\mathrm{APAR(x,t)} = \mathrm{FPAR(x,t)} * R_s(x,t) * 0.5 \quad (2)$$

$$\varepsilon(\mathrm{x,t}) = \varepsilon_{max}(x,t) * T(x,t) * W(x,t) \quad (3)$$

where R_s is the incoming shortwave radiation, FPAR is the fraction of photosynthetic active radiation absorbed by vegetation, which is determined from the satellite data (NDVI). Other model parameters, such as the annual maximum and minimum NDVI for each vegetation type, are considered corresponds to the 95% and 5% quantiles of the probability distribution of the monthly NDVI in each vegetation type (Liang et al., 2015).

2.5 Statistical methods

The estimate NPP based on the CASA model is largely affected by the maximum light-use efficiency (ε_{max}). In this study, we employed the field observation NPP to correct the ε_{max} for the forest stand ages among forest types.

$$\varepsilon_{max} = \frac{NPP * \varepsilon_a}{NPP_m} \quad (4)$$

where NPP is the field observation data of NPP, NPP_m is the estimated NPP based on the meteorological data and the remote sensing data (NDVI), ε_a is the fixed value for all the vegetation types and all the forest age, and here the value is 0.43.
The NPP_m is separated by the forest types and the forest stand ages, thus the ε_{max} for different forest types and the forest stand ages have different values. The ε_{max} of various field observation sites are grouped by the forest types and the forest stand ages.
To investigate the relationship between the forest stand ages and the ε_{max}, the forest stand ages were separated into 12 groups. The forest stand ages that less than 15 years are regarded as group 1, and the forest stand ages between the 15years and the 30 years were regarded as group 2,⋯, and the forest stand ages more than 165 years are regarded as group 12.

3. RESULTS

3.1 The estimated NPP of the forest types

Based on the remote sensing data and the meteorological data, the NPP of China from 1982 to 2005 was estimated. Based on the available filed observation data of NPP, the selected forest types include the evergreen needleleaf forest (ENF), the evergreen broadleaf forest (EBF) and the deciduous broadleaf forest (DBF). The spatial distribution of the forest types is shown in Fig.1.

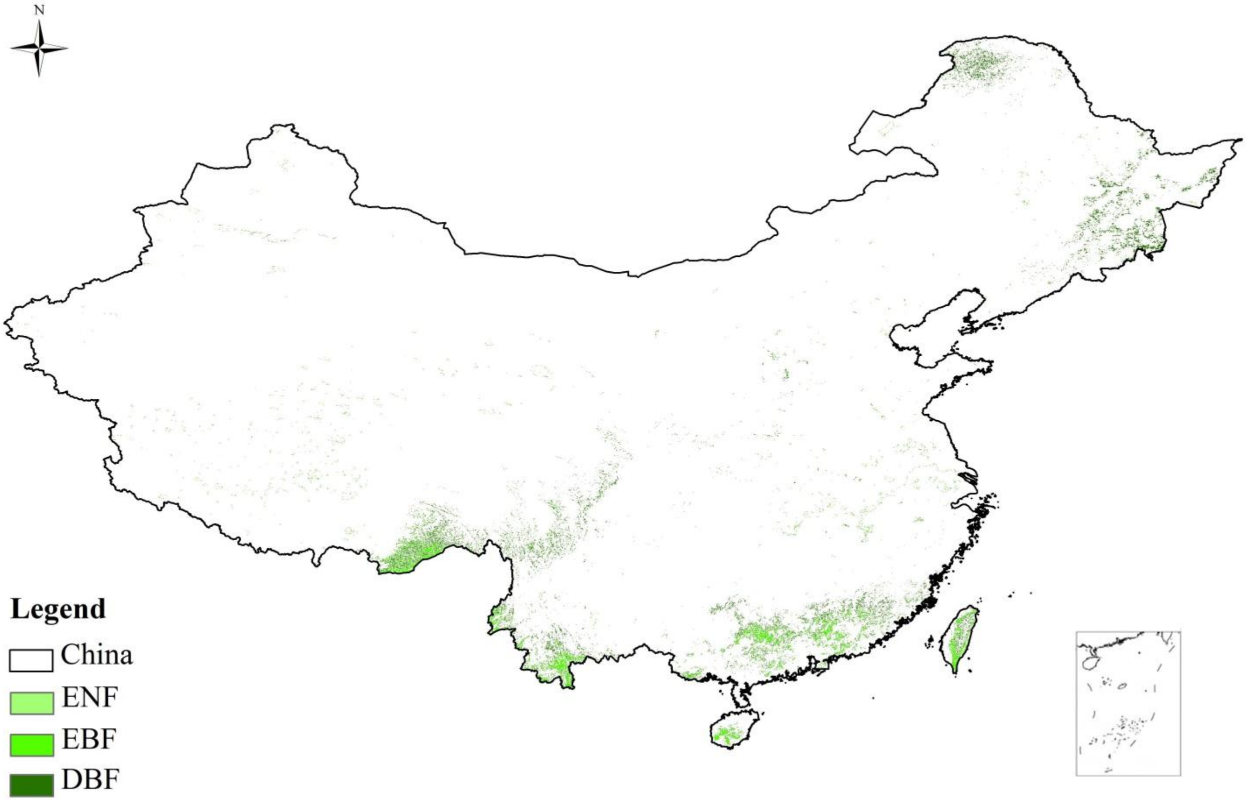

Figure 1. The spatial distribution of three selected forests in China

The forest types	NPP(gC $m^{-2}a^{-1}$)
ENF	388
EBF	438
DBF	420

Table 1 The estimated NPP based on the constant ε_{max} for three forest types

The forest is major in South China, and there are still some forests in Northeast China. The evergreen needleleaf forest mainly distributes in the east of China, and some north regions in China. The evergreen broadleaf forest is mainly in the South China, and also some places in the east China. The deciduous broadleaf forest is usually located in South China, and the northeast China.

The estimated NPP based on the constant maximum light-use efficiency (ε_{max}) vary for different forest types. For the evergreen needleleaf forest, the average NPP during the period 1982 to 2005 is about 388 gC m^{-2} a^{-1}. For the evergreen broadleaf forest, the average NPP is about 438 gC$m^{-2}a^{-1}$. For the deciduous broadleaf forest, the average NPP is about 420 gC$m^{-2}a^{-1}$ (Table 1). The evergreen broadleaf forest has the largest NPP than the other two forest types, and the evergreen needleleaf forest has the least NPP based on the constant ε_{max}.

3.2 The relationship between the maximum light-use efficiency (ε_{max}) and the forest stand ages

The maximum light-use efficiency (ε_{max}) of different stand ages is based on the field observation data NPP. The field observation data NPP is separated by different forest types, and then grouped by the forest stand ages. The number of the study sites in different forest stand ages is also summed up. Here we investigate three forest types including the evergreen broadleaf forest (EBF), the deciduous broadleaf forest (DBF) and the evergreen needle forest (ENF). The relationship between the ε_{max} and the forest stand ages for three forest types ate shown in Fig. 2.

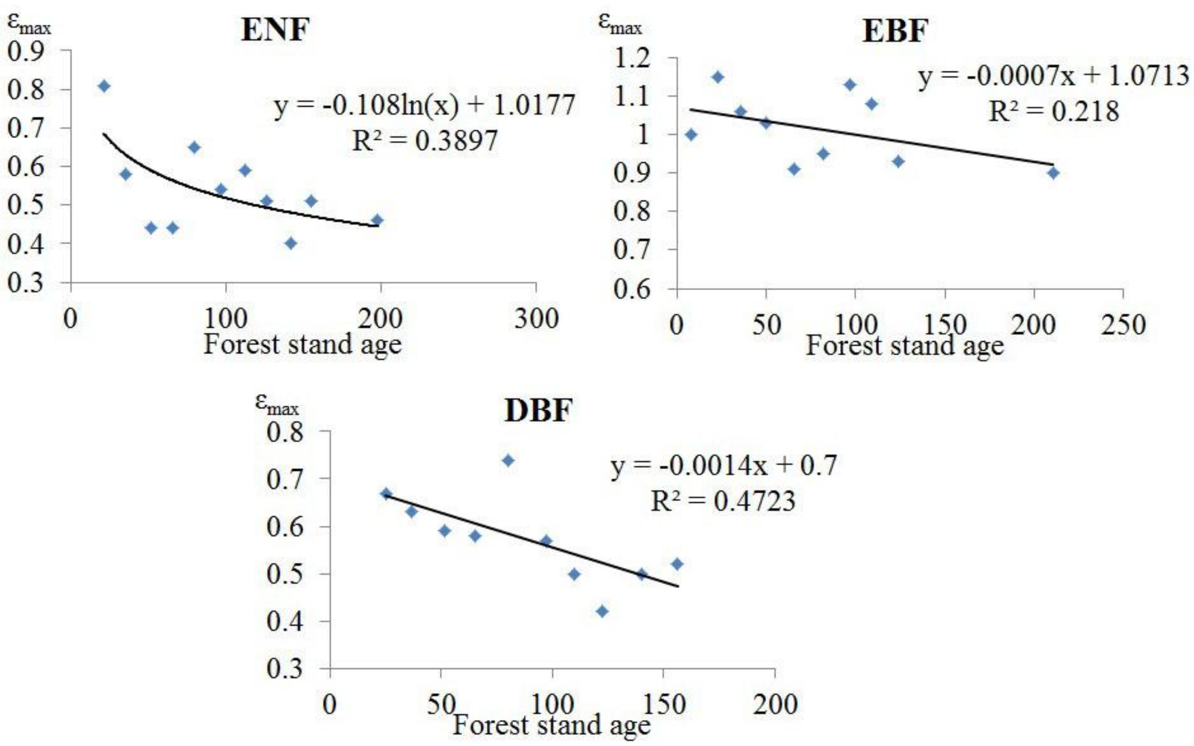

Figure 2 The relationship between the forest stand age and the maximum light-use efficiency (ε_{max}) of three forest types

From Fig.2, The regression equation of the evergreen needleleaf forest is y=-0.108 * ln(x) + 1.0177. The determination of the correlation coefficients (R^2) is 0.3897. The ε_{max} has decreased as the forest ages increase, but the relationship between the ε_{max} and the forest stand ages are non-linear. The regression equation of the evergreen broadleaf forest is y=-0.0007 * x + 1.0713. The R^2 is 0.218. The ε_{max} has decreased as the forest stand ages increase, and the relationship is linear. The regression equation of the deciduous broadleaf forest is y=-0.0014 * x + 0.7. The R^2 is 0.4723. The ε_{max} has decreased as the forest ages increase, and the slope is higher than the evergreen broadleaf forest. The relationship between the ε_{max} and the forest stand ages are also linear.

3.3 The maximum light-use efficiency (ε_{max}) of forests in different stand ages

The corrected maximum light-use efficiency (ε_{max}) has indicated that the great differences exist among different forest types. Based on the research data about the forest stand ages in China, the forest stand ages are first separated by the forest types, and then grouped by the young forest, middle-aged forest and the mature forest. For the deciduous broadleaf forest, the average ε_{max} of young, middle-aged and mature forest are 0.68, 0.65 and 0.60 gC MJ^{-1}. For the evergreen broadleaf forest, the average ε_{max} of young, middle-aged and mature forests are 1.05, 1.01 and 0.99 gC MJ^{-1}. For the evergreen needleleaf forest, the average ε_{max} of young, middle-aged and mature forests are 0.72, 0.57 and 0.52 gC MJ^{-1}. In general, the average ε_{max} of evergreen broadleaf forest is larger than the deciduous broadleaf forest, and the minimum of the average ε_{max} is the evergreen needleleaf forest. The average ε_{max} of young forest is higher than the middle-aged forest, and the mature forest has the lowest ε_{max}.

3.4 The estimated forest age-dependent NPP

The maximum light-use efficiency (ε_{max}) of the young, middle-aged and the mature forests are separated by the forest stand ages, and the forest types including the evergreen needleleaf forest, the evergreen broadleaf forest and the deciduous broadleaf forest are also considered in the study. Based on the estimated NPP of forest types and the ε_{max} of different stand ages, the estimated NPP of different stand ages are calculated. For the evergreen needleleaf forest, the estimated NPP of young, middle-aged and mature forest are about 650 gC $m^{-2}a^{-1}$, 514 gC $m^{-2}a^{-1}$ and 469 gC $m^{-2}a^{-1}$. For the evergreen broadleaf forest, the estimated NPP of young, middle-aged and mature forest are about 1069 gC $m^{-2}a^{-1}$, 1028 gC $m^{-2}a^{-1}$ and 1008 gC $m^{-2}a^{-1}$. For the deciduous broadleaf forest, the estimated NPP of young, middle-aged and mature forest are about 664 gC $m^{-2}a^{-1}$, 635 gC $m^{-2}a^{-1}$ and 586 gC m^{-2} a^{-1}.

4. DISCUSSION

The NPP is the key indicator to reflect the ecosystem performance to the climate change, and the accurate estimate of NPP is significant to regulate the global carbon balance. The forest ecosystem is essential to the world carbon cycle, and the NPP of forest ecosystem has explained about 65% of the terrestrial ecosystem. The CASA model is widely used to monitor NPP, and the factor that has the largest effect on the estimated NPP based on the CASA model is the maximum light-use efficiency (ε_{max}). The ε_{max} varies for different vegetation types which have been investigated by many studies, but the ε_{max} can also be different for the various stand ages of forest types. This study focused on the maximum light-use efficiency of the different stand ages among three forest types in China. The evergreen needleleaf forest and the evergreen broadleaf forest have the linear relationship between the forest stand ages and the ε_{max}, and the deciduous broadleaf forest has the non-linear relationship. The determination of the relationship is based on the R^2 of the equation, and the deciduous broadleaf forest has better result when applied the non-linear relationship. The evergreen broadleaf forest has the higher ε_{max} than the evergreen needleleaf forest and the deciduous broadleaf forest. The ε_{max} of evergreen broadleaf forest is always underestimated by the constant ε_{max}, which will also lead to the underestimate of NPP. The evergreen broadleaf forest has the maximum deviation of the NPP for the young, middle-aged and the mature forest. The ε_{max} of the evergreen broadleaf forest among the young, middle-aged and the mature forest change little, but it also has the decreased trend as the forest stand ages increase. The ε_{max} of evergreen needleleaf forest is a little estimated by the constant ε_{max}, and the NPP is also underestimated. The ε_{max} of the evergreen broadleaf forest among the young, middle-aged and the mature forest has the decreased trend, and the change is higher than the other two forest types. The ε_{max} of deciduous broadleaf forest is underestimated, and it also has the decreased trend from the young forest to the mature forest. In general, the estimated NPP based on the constant ε_{max} are underestimated especially for the young and middle-aged forest. For the evergreen needleleaf forest, the deviation of the NPP in young and middle-aged forest is about 262 gC $m^{-2}a^{-1}$ and 126 gC $m^{-2}a^{-1}$. For the evergreen broadleaf forest, the deviation of the NPP is about 600 gC $m^{-2}a^{-1}$ for the young and middle-aged forest. For the deciduous broadleaf forest, the deviation of the NPP in young and middle-aged forest is about 240 gC $m^{-2}a^{-1}$. The evergreen broadleaf forest has the largest deviation in NPP, and the young forest for the forest types have higher deviation of NPP than the middle-aged forest and the mature forest. Young forests and middle-aged forests had higher ε_{max}, and they are more sensitive to climate change. The NPP of young and middle-aged forest should consider the variation of the forest stand age.

5. CONCLUSION

This study employed both the meteorological data and the remote sensing data to estimate the NPP of three forest types including the evergreen needleleaf forest (ENF), evergreen broadleaf forest (EBF) and deciduous broadleaf forest (DBF) based on the CASA model. The original CASA model based on the fixed maximum light-use efficiency (ε_{max}) does not consider the effect of the forest stand ages among forest types, and it will lead to the deviation in the estimate of NPP. This study first estimate the NPP based on the CASA model and then employed field observations to inversely estimate the parameter of maximum light-use efficiency of forests in different stand ages. The relationship between maximum light-use efficiency and the forest stand ages was functioned to estimate forest age-dependent NPP. The results showed that ε_{max} has changed according to forest types and forest stand ages. The deciduous broadleaf forest, evergreen broadleaf forest and evergreen needleleaf forest all have decreased trend as the forest stand ages increase. The evergreen broadleaf forest has the higher ε_{max} than the other two forest types. For deciduous broadleaf forest, the average ε_{max} of young, middle-aged and mature forest are 0.68, 0.65 and 0.60 gC MJ^{-1}. For evergreen broadleaf forest, the average ε_{max} of young, middle-aged and mature forests are 1.05, 1.01 and 0.99 gC MJ^{-1}. For evergreen needleleaf forest, the average ε_{max} of young, middle-aged and mature forests are 0.72, 0.57 and 0.52 gC MJ^{-1}. The evergreen broadleaf forest has the largest deviation in NPP, and the young forest for the forest types have higher deviation of NPP than the middle-aged forest and the mature forest. Young forests and middle-aged forests had higher ε_{max}, and they were more sensitive to trends and fluctuations of climate change, so they led to greater annual fluctuations of NPP. These findings confirm the importance of considering the forest stand ages to the estimation of NPP and they are significant to study the response of forests to climate change.

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