Quantitative Assessment of Climate Change Impacts On Forest Ecosystem

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Quantitative Assessment of Climate Change Impacts on Forest Ecosystem

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Abstract:

Characterizing and predicting the response of terrestrial ecosystems to global change is one of the key challenges of contemporary ecology and ecological conservation. The impact of climate change on forest ecosystem has been widely studied, but it rarely uses method of multi-index fusion for quantitative evaluation. In this study, forest ecosystem in Heilongjiang Province was investigated. Based on remote sensing, meteorological observation, ground survey, geographic information, MAXENT model, CASA model, carbon sequestration potential model of Zhou Guangsheng-Zhang Xinshi, pixel dichotomy model and Savitzky Golay Filter model were used. On this basis, we analysed the change characteristics of forest distribution, net primary productivity and vegetation coverage. We also established a model for evaluating the impact of forest ecosystem change on climate, and made a quantitative assessment of the impact on climate. Our results indicate the following: (1) From 2001 to 2019, the forest area in Heilongjiang Province ranged from 2.34×10^5 to 2.46×10^5 km^2, the forest NPP ranged from 40.48 to 555.32 $gC/m^2/a$, and the vegetation coverage ranged from 42.42% to 67.64%, both of which showed a significant upward trend; (2) The values of forest ecological role were significantly positively correlated with the climatic potential; (3) The results of climate impact assessment of forest ecosystem change showed the contribution rate of climate change to forest ecosystem change was negatively correlated with forest coverage, which varied from 4.79% to 18.07% in different regions (cities) of the province. This study contribute to improving evaluating influence of climate change on forest ecosystem.

KEYWORDS

Forest; Net primary productivity; vegetation coverage; climate change

1. Introduction

Global environmental change and sustainable development have always been the major challenges facing mankind. It is an indisputable fact that the global change marked by the increase of temperature and the change of precipitation pattern (Chair et al, 2015). Climate change may trigger interactions between global terrestrial and marine ecosystem processes (Williamson et al, 2009), resulting in global forest and grassland degradation (Underwood et al, 2018; Cusack et al, 2016; Hedwall et al, 2016), land desertification (Huang et al, 2020; Li et al, 2021) or desertification reversal (Yue et al, 2019), migration of vegetation zones (Myers-Smith et al, 2019; Bjorkman et al, 2018; Carboin et al, 2018), sharp decline in biodiversity (Trew et al, 2021) and so on. Forest ecosystem is one of the main terrestrial ecosystems, and it is also the most complex terrestrial ecosystem. It has high biological productivity and biomass (Melillo et al, 1993), as well as rich biodiversity (Tilman et al, 1996; Nadrowski et al, 2010; Yu et al, 2008). Ecosystem distribution is an important signal of forest ecosystem status. There are large areas of forest vulnerability in Northeast and Southwest China. The subtropical evergreen deciduous broad-leaved mixed forest, cold temperate mountain coniferous forest and temperate deciduous broad-leaved mixed forest become more vulnerable under climate Change (Wan et al, 2018). The effect of temperature on distributing plant species in forest-steppe ecotone of northern (Liu et al, 2015) and boreal forest (Wu et al, 2017) in northern China was greater than that of precipitation. Air temperature

increasing obviously effected the ecotone of alpine coniferous forests. The areas of suitable distribution regions for alpine tundra, subalpine forest, cold-temperate coniferous forest, and temperate mixed forest decreased continuously; however, the areas for warm-temperate deciduous broad-leaved forest and temperate grassland increased (Liu et al, 2017). And if the climate continues to warm, it will cause the transition zone between *Pinus tabulaeformis* and *Picea crassifolia* to move to higher elevations (Wang et al, 2021).

Net primary productivity (NPP) is an important signal of vegetation biomass accumulation and carbon sink capacity, and climate has a direct impact on the global ecosystem NPP (Leith, 1975; Taiz et al, 2015; Gillman et al. 2015; Chu et al, 2016). Global warming, the increase of CO2 concentration and increased nitrogen deposition will increase plant photosynthetic rate and carbon uptake to some extent (Schippers et al, 2015; Gang et al, 2015). But also stimulate the activities of soil microorganisms, improve soil heterotrophic respiration rate, and increase soil carbon release (Allison et al, 2008; Ma et al, 2018). Since the 1990s, the NPP of terrestrial vegetation in China has been increasing in general (Fang et al, 2003). However, because of the obvious regional differences in climate change, the impacts on the NPP of forest ecosystems in different regions are also different. The results show that climate warming has a negative effect on forest NPP in southern China, but a positive effect on northern China (Li et al, 2017; Wang et al, 2017). There is a good correlation between Normalized Difference Vegetation Index (NDVI) and vegetation growth (Piao et al, 2015; Ghebrezgabhera et al, 2020; Dearborn et al, 2021; Shen et al, 2021;), and the time series of vegetation index extracted by remote sensing can be used to study the response of vegetation to climate change at a large regional scale. The size of the time window can affect the results of the vegetation cover change trend study. Both long-term and short-term changes are relative, and different models (such as linear and nonparametric models) will also significantly affect the results (De Jong, et al, 2011; 2012).

The impact of climate change on forest ecosystem is often assessed qualitatively or quantitatively by analyzing the relationship between NDVI, NPP and climate factors. These studies have made important contributions to understanding the long-term evolution of forest ecosystems and revealing the impact of meteorological and human on terrestrial vegetation. However, the changes of vegetation coverage and NPP may not be consistent (Ding et al, 2020), so the study of the climate driving of forest ecosystem change trend by a single indicator may increase confuses the results. It is necessary to assess the impact of meteorological conditions on forest ecosystem comprehensively and accurately before the government draws up ecological measures, protection plans and financial investment to cope with climate change (Aldieri et al, 2020). Therefore, it is important to comprehensively evaluate the climate influence of vegetation growth with different biophysical properties.

Heilongjiang Province, the northernmost province in China, has a forest coverage rate of nearly 50% which is an important ecological security barrier in Northeast Asia. How to ensure the sustainable development of the forest ecosystem in this region and mitigate the adverse effects of global change is important. The province situates in the East Asian monsoon region with the largest rate of environmental change on earth. It spans the cold temperate and temperate climate zones from north to south, and the semi-arid and semi-humid climate zones from west to east. It's environmental variability, sensitivity and vulnerability of ecosystem are in the forefront of the country and even in East Asia (Martel et al, 2018; Zhao et al, 2020; Wu et al, 2016; Li et al, 2018; Xia et al, 2017). This combination of climate and geography across thermal and humid climate zones, as well as diverse types of forest ecosystems, makes this region an ideal choice for studying how climate change affects boreal forest ecosystems.

The objective of this study is to quantitatively evaluate the comprehensive contribution rate of climate conditions to forest ecosystem change. In this study, we analyzed the change characteristics of forest distribution, NPP and vegetation coverage in Heilongjiang Province and their climate impact. We also established a model for evaluating the impact of forest ecosystem change on climate to solve the problem of single quantitative assessment index of climate impact on forest ecosystem.

2. The study area

Heilongjiang Province (121°11'-135°05'N, 43°26'—53°33'E), located in the northeast of China, is the northernmost province in China with the highest latitude, with a land area of about 460,000 km^2 (Figure 1). The study area belongs to the continental monsoon climate from the middle temperate zone to the cold temperate zone. The annual average temperature is between -3.80 ℃ and 5.85 ℃, and the temperature decreases gradually from southeast to northwest. The annual average precipitation is 397.60 ~ 656.40 mm (data source: dataset of daily climate data from Chinese surface stations V3.0). The precipitation in the southwest is low, and the precipitation in the central and eastern parts is high. The terrain of the study area is high in the northwest, north and southeast, and low in the northeast and southwest which is mainly composed of mountains, platforms, plains and water. Mountains account for about 24.7% and plain 37.0% of the province.

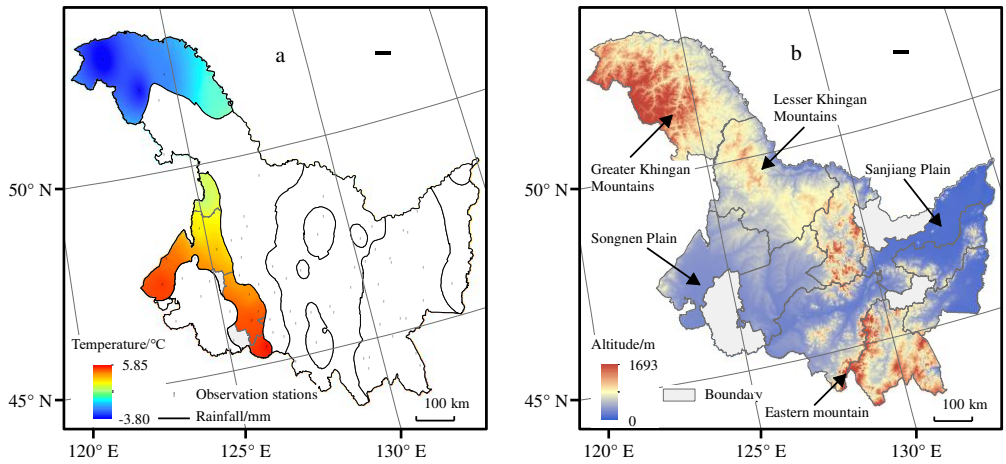

Figure 1 Average yearly temperature, precipitation (a) and topography (b) in the study area

3. Data collection and methodology

3.1 NDVI data set reconstruction

In this study, we used the Global MOD13Q1 data as the basic data source of land use classification. The data come from EOS data center of NASA LPDAAC (The Land Processes Distributed Active Center). Which is level-3 product in the Sinusoidal projection with 250-meter resolution. The coverage of each area is 10°×10° lat/long, and the data areas used in Heilongjiang Province are h25v03, h25v04, h26v03 and h26v04. The data contains Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) data sets. In this study, MODIS Reprojection Tool was used for stitching and projection conversion (conversion to WGS-1984-UTM projection).

The temporal spectral data of vegetation index can reflect the dynamic of vegetation growth, and high quality NDVI time series data is of great significance for regional and global ecological and environmental applications. However, Although MOD13Q1/NDVI uses Maximum Value Composite to synthesize data, solar elevation angle and observation angle, interference of cloud, water vapor, aerosol, soil background can effect the data acquisition and processing. In this study, we used the Savitzky Golay Filter (Savitzky et al, 1964) to reconstruct the NDVI dataset from 2001 to 2019. Savitzky Golay Filter is a simplified least squares fitting convolution for smoothing and calculating derivatives of continuous values, which can be understood as a weighted moving

average filter with a polynomial of a given degree. It can effectively retain the relative maximum, minimum and width of the data set, and has been applied in winter wheat distribution and phenology monitoring (Chu et al, 2016), satellite data performance evaluation (Kandasamy et al, 2015), vegetation temporal and spatial change analysis (Li et al, 2017) and so on.

Figure 2 shows there are fluctuations in the NDVI curve in the original sequence, with obvious peaks and troughs in most years, and the general change law conforms to the law of vegetation growth. But the curve has many sawteeth and obvious noise, which is not conducive to the trend analysis of vegetation change. The NDVI curve filtered by Savitzky Golay Filter can clearly show the fluctuation rule of NDVI in a year, and the effect of removing dryness is obvious. It is in line with the law of vegetation growth and can be used as the analysis of vegetation change trend.

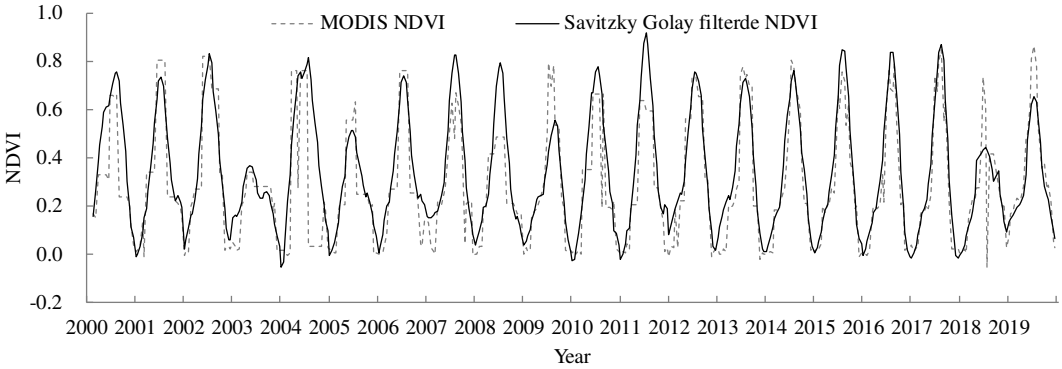

Figure 2 Randomly selected pixels (126.35 ° E, 46.48 ° N): Comparison of original sequence NDVI from 2000 to 2019 with reconstruction using Savitzky Golay filter

3.2 Meteorological data

3.2.1 Preprocessing of meteorological observation data

The meteorological data derived from the daily data of 80 meteorological stations in Heilongjiang Province from 1951 to 2019, including daily average temperature, daily precipitation, daily average relative humidity and other basic meteorological. Climate change research must be based on reliable data. However, due to the influence of station migration and others, most of the measured data are not uniform in sequence, which will cover up the reality and produce false climate change. It is necessary to check the uniformity and quality control of the data before conducting climate change analysis to maximize the reliability of the data (WEI F, 1999; REN et al, 1998).

We used SPSS 22 to conduct normal test for the daily temperature and relative humidity data in each climate zone. The significance level was $P \geq 0.05$ which indicating most of the daily temperature and relative humidity data in each climate zone were approximately normal distribution, and no standardized processing was required in the analysis. The change of daily precipitation does not have gradual and continuous characteristics. It's not the independent variable to judge whether the precipitation data obey the normal distribution, but the monthly precipitation is the independent variable. The test results show that most of the temperature and precipitation data used in this study are subject to normal distribution. Therefore, no standardization is done when further analysis is not required.

3.2.2 Climate index selection

Climate largely determines the geographical distribution and characteristics of vegetation types,

and both low and high temperatures restrict the geographical distribution of plants. Most tropical and subtropical woody plants cannot survive when the minimum temperature in the coldest month is below 5℃ and the average temperature is below 10℃ in the hottest month. Deciduous woody plants in frigid zone cannot survive when the maximum temperature is higher than 5℃ in the coldest month and the average temperature is higher than 21℃ in the hottest month. We

According to the results of screening bioclimatic variables (bioclimatic variables are specifically defined in WorldClim, http://worldclim.rog) by Yu et al (2019) and the classification method of main factors affecting plant growth and geographical distribution by Woodward. We divided into seven bioclimatic variables with clear ecological significance. These are as follows: (1) The minimum temperature of the coldest month represents the lowest temperature that plants can tolerate; (2)The annual temperature and the mean temperature of the warmest quarter represent the supply of heat needed to complete a life cycle; (3)Annual precipitation and precipitation of the driest quarter represent the water supply needed to sustain plant growth; (4)The mean diurnal range of temperature represents the range of temperature, and the precipitation seasonality represents the range of precipitation.

3.3 Land cover classification based on remote sensing

The forest distribution range in the study area was extracted based on the classification results of "IGBP Global Vegetation Classification Scheme" of MODIS MCD12Q1 data. Forests consist of the following nine categories: (1) Dominated by evergreen conifer trees (canopy >2m). Tree cover >60%, (2) Dominated by evergreen broadleaf and palmate trees (canopy >2m). Tree cover >60%, (3) Dominated by deciduous needleleaf (larch) trees (canopy >2m). Tree cover >60%, (4) Dominated by deciduous broadleaf trees (canopy >2m). Tree cover >60%, (5) Dominated by neither deciduous nor evergreen (40-60% of each) tree type (canopy >2m). Tree cover >60%, (6) Dominated by woody perennials (1-2m height) >60% cover, (7) Dominated by woody perennials (1-2m height) 10-60% cover, (8) Tree cover 30-60% (canopy >2m), (9) Tree cover 10-30% (canopy >2m).

Landsat series data of the same period were used to test the classification accuracy of the combined data. We analyzed the classification accuracy of land use types (forest and other land use types) from 2001 to 2019 by using error matrix and Kappa analysis method based on LANDSA data of the year. The overall classification accuracy was more than 85%, and the Kappa coefficient was more than 0.82.

3.4 Maximum Entropy model

3.4.1 Model operation parameters and variable

Maximum Entropy Model (MAXENT) was originally proposed in the Center for Biological Diversity and Conservation (AMNH) of the American Museum of Natural History. It is a model based on the principle of niche, which derives constraints from the records of species occurrence points and the corresponding characteristics of environmental variables. The maximum entropy principle and machine learning technology are used to establish the niche and distribution model of species, and to explore the possibility of species distribution under this constraint (Steven et al, 2006; 2018). It is widely used because of its good performance in the comparison of species distribution modeling methods (Elith et al, 2011; Moya et al, 2017).

The parameters required for the operation of MAXENT model are determined according to the evaluation method of Yu et al (2019b). When the sample size of Maxent model is 121, the prediction accuracy is better. The characteristic parameters have great influence on the response curve of environmental variables, while the control frequency and the maximum background point have little influences. The AUC is the highest which the characteristic parameter is “threshold”

and the control frequency is 1. Jackknife test showed that the main temperature factors affecting forest distribution were the average temperature of the warmest season, the annual average temperature and the lowest temperature of the coldest month. And the main water factors were annual precipitation, seasonal variation of precipitation and the driest season precipitation.

3.4.2 Simulation of suitable area of forest distribution

According to the calculation principle of half peak width, about 76% of the distribution points are included in the optimal range when the environmental factors and the frequency distribution curve accord with the normal distribution. Generally, when the sample of plant geographical distribution is enough, the distribution curve of species existence frequency with climate conforms to normal distribution (Gunasekaran et al, 1982; Saha, 2001; Yam et al, 2016). The range of optimum climatic calculated by this method can explain 76% of the species distribution, that is, the climate guarantee rate to ensure the production capacity, stability and sustainability of vegetation or terrestrial ecosystem is 76%. If the data of number of climatic factors (n) affecting the geographical distribution and function of terrestrial ecosystems are statistically independent, the threshold of the existence probability (p) of the distribution boundary of terrestrial ecosystems is 0.76^n (based on 76% climate guarantee rate and n climatic factors) (Wan et al, 2016). According to the simulation results of MAXENT model, the contribution rate of 7 climatic factors affecting forest potential distribution was more than 0, the classification criteria of forest potential distribution was: suitable (existence probability ≥ 14. 65%), unsuitable (0 ≤ existence probability < 14. 65%).

3.5 NPP model screening

The vitality of an ecosystem reflects its carrying capacity and anti-disturbance ability. We selected NPP as an evaluation index of the productivity of the ecosystem because the material basis of the existence of all ecosystems. NPP climate potential estimated by Zhou Guangsheng -- Zhang Xinshi model (Zhou et al, 1995) which based on the vegetation CO_2 flux equation and water vapor flux equation. The model was used to simulate the vegetation productivity by Zhang et al (2011) and the results of simulating the vegetation productivity of Zhalong wetland in China were also verified (Yu et al, 2021). The actual NPP was monitored using the CASA model (Potter et al, 1993).

3.6 Vegetation coverage model

Based on NDVI and dimidiate pixel model (Li et al, 2004), the actual vegetation coverage of forest was calculated. The vegetation climatic potential coverage was calculated based on comprehensive eco-meteorological, and the model of vegetation climatic potential coverage is as follows:

(1) Monthly vegetation coverage simulation model based on integrated eco-meteorological:

$$\mathrm{VC}_{\mathrm{M,i}} = k_1 \times M_{\mathrm{c,i}} + k_2 \times \mathrm{VC}_{\mathrm{M,i\text{-}1}} + b$$

Where, VC_M is vegetation coverage; the i is month; the i-1 is the month prior to month i; M_c is the comprehensive ecological-meteorological factor; k_1、k_2 and b are equation coefficients obtained by model calibration. The specific method is to calibrate the parameters of the Monthly vegetation coverage simulation model by using the remote sensing monthly vegetation coverage (FC) and monthly comprehensive eco-meteorological factor (Mc) data set in 2000, and to obtain the pixel-by-pixel k_1、k_2 and b.

(2) Calculation Model of Mc based on meteorological factors of light, temperature, water and carbon dioxide.

$$M_{\mathrm{c}} = \mathrm{PAR} \times T_{\varepsilon} \times W \times F_{\mathrm{CO2}}$$

$$F_{CO2} = 1 + 0.6 \times \mathrm{Ln}([CO_2]/369.29)$$

Where, Mc is comprehensive eco-meteorological factor; PAR is photosynthetically active radiation; Tε is temperature stress coefficient; W is water stress coefficient; FCO_2 is Carbon dioxide fertilization factor; $[CO_2]$ is Surface carbon dioxide concentration（Unit: ppm）.

(3) Photosynthetically active radiation

Solar global radiation on the earth's surface (Rs) and PAR were estimated according to sunshine duration. RS is calculated from the Monthly average sunshine duration by the method recommended by Food and Agriculture Organization of the United Nations, and the calculation formula is as follows:

$$R_s = (a + b\frac{n}{N})R_a$$

Where, n is actual sunshine duration; N is maximum sunshine duration; Ra is exoatmospheric solar radiation; a and b are fitting coefficient。

PAR was calculated according to the ratio of PAR to RS of 0.48:

$$\mathrm{PAR} = 0.48 \times R_s$$

(4) Temperature stress coefficient

$$T_\varepsilon = \left((T_a - T_{min})(T_a - T_{max})\right) \div \left((T_a - T_{min})(T_a - T_{max}) - (T_a - T_{opt})^2\right)$$

Where, Tε is temperature stress coefficient; Ta is average monthly temperature (Unit: oC); Tmin、T_{max} and T_{opt} are the minimum, maximum and optimum temperatures for photosynthesis, respectively (Melillo et al，1993).

(5) Water Stress Coefficient

The ratio of monthly actual evapotranspiration (E) to potential evapotranspiration (PET) was used to estimate the water stress coefficient (W), and the calculation formula is as follows:

$$W = E / \mathrm{PET}$$

$$\mathrm{PET} = 1.35\frac{\Delta R_n}{\Delta + \gamma}$$

Where, Δ is saturation vapor pressure gradient; γ is humidity calculation constant; R_n is monthly net radiation，and the calculation formula is as follows:

$$R_n = (1 - \alpha)R_s - R_{nl}$$

Where, α is surface albedo; R_{nl} is net long-wave radiation

3.7 Evaluation model of meteorological impact of forest ecosystem change

3.7.1 Model Construction

The meaning of the determination coefficient is that the variation of the dependent variable can be explained according to the variation of the independent variable. Therefore, this study took the actual observed value as the dependent variable and the climate potential value as the independent variable to establish the determination coefficients of NPP, FVC and forest distribution area respectively. Based on the determination coefficients of each variable, an impact evaluation model of meteorological conditions for ecological civilization construction was established.

$$M = \frac{\left(a \cdot \left|NPP_c\right| + b \cdot \left|VC_c\right| + c \cdot \left|LUC_c\right|\right)}{3} \times 100\%$$

Where, M is contribution rate of climate change; NPP_c is determination coefficient between actual NPP and NPP climate potential for 2001 – 2019; $VC_c$is determination coefficient between actual vegetation cover and potential vegetation cover for 2001 – 2019; LUC_c is determination coefficient between actual forest land cover and potential suitable forest area from 2001 to 2019; *a, b* and c are weights.

3.7.2 Determination of weights

We combine the Analytic Hierachy process (AHP) (Saaty, 1977; 1980) and Shannon Entropy Index (Shannon, 1948) to determine the model weight. Which not only avoids the subjectivity of the subjective weighting method, but also avoids the randomness of the objective weighting method. Perform consistency test on the weight results calculated by the above two methods, and calculate the combination weight after passing the consistency test. See Table 1 for the calculation results.

Table 1 The weights of Analytic Hierachy process, Shannon Entropy Index and combination weighting method

Ecological variables	Analytic Hierachy Process	Shannon Entropy Index	combination weighting
NPP	0.5584	0.3670	0.5195
vegetation cover	0.3196	0.3353	0.3228
forest land cover	0.1220	0.2977	0.1577

3.7.2.1 Consistency test of weighting method. The Spearman rank correlation coefficient was used for consistency test.

$$d\left(W^{(1)}W^{(2)}\right) = \left[\frac{1}{2}\sum_{j=1}^{n}\left(W^{(1)} - W^{(1)}\right)^2\right]^{\frac{1}{2}}$$

When $0 \le d\,(W^{(1)}, W^{(2)}) \le 1$, the weighted results are in good consistency. The smaller $d\,(W^{(1)}, W^{(2)})$ is, the closer the two weighted results are. If the weights obtained by the two weighting methods are consistent, the calculation of the combination weight is carried out. If the consistency of the two weights is not good, the evaluation factors or factor scores in the Analytic Hierarchy Process are adjusted until the consistency of the two weighting methods is checked. In this study, d(W(1),W(2))=0.2532, indicating that the weight calculated by AHP and entropy method has a good consistency.

3.7.2.2 Combination weighting.This research refers to the method of Xi et al (2010) to carry on the combination weight, the method is as follows:

$$W_i = \alpha a_i + \left(1 - \alpha\right) b_i$$

$$\alpha = \frac{n}{n-1} G_{AHP}$$

$$G_{AHP} = \frac{2}{n}\left(1p_1 + 2p_2 + \mathrm{L}\ np_n\right) - \frac{n+1}{n}$$

Where, a_i is Objective weight of the jth attribute; b_i is Subjective weight of the jth attribute; w_i is Final weight of the jth attribute; α is Coefficient to be determined; n is Number of indicators; p_1、p_1、…、p_n are W_1, W_2,..., W_n reorder the components from small to large.

3.8 Geographic information data

Digital Elevation Model (dem) is the data of SRTM terrain product v4.1, which comes from the international scientific data mirror website (http://www.gscloud.cn) of the Computer Network Information Center of the Chinese Academy of Sciences, with the spatial resolution of 90m.

The provincial administrative division data required by the study comes from the 1:250000 basic geographic information issued by the China Meteorological Administration. It's topologically checked to remove the gaps between provincial boundaries and county boundaries. The provincial administrative division data and the location data of meteorological observation stations are from the China Meteorological Administration.

4. Results

4.1 Characteristics of forest distribution change

The forest area was between 2.34 × 10^5 and 2.46 × 10^5 km^2 from 2001 to 2019 in Heilongjiang Province (Figure 3). The change of forest area can be divided into two stages taking 2014 as the boundary. It increased significantly with an average annual increase of 903. 20 km^2 in the early stage (2001 – 2014) and decreased significantly of 1389. 97 km^2 in the later stage (2014 – 2019).

The suitable distribution area of the forest was between 3. 72 × 10^5 and 4. 14 × 105 km^2, with an average of 3. 93 × 10^5 km^2, which had no significant change trend and no significant correlation with the actual distribution area of the forest. The actual distribution area of forest in the study area may be affected by both meteorological and non-meteorological conditions.

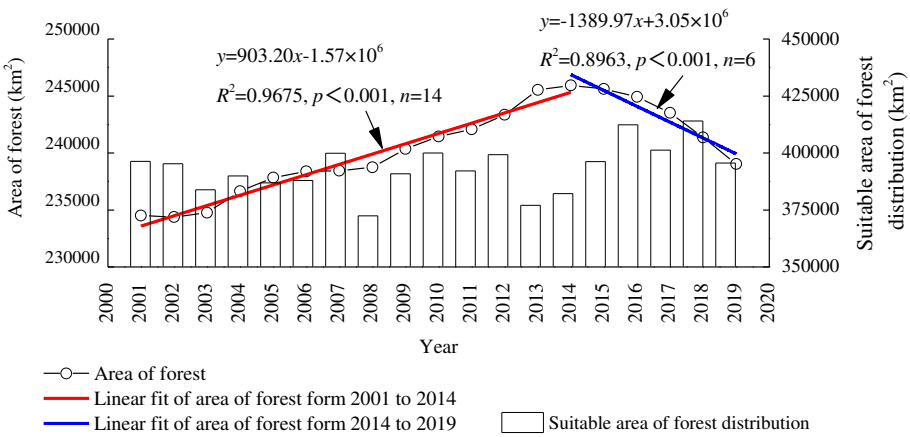

Figure 3 Temporal variation of forest area and suitable area of forest in Heilongjiang Province from 2001 to 2019.

The forest area in Heilongjiang Province took 2014 as the demarcation point, which showed a trend of increasing first and then decreasing as the curve shown in the figure. The bar chart shows that the suitable area of forest fluctuates greatly, and there is no significant change trend.

The forests mainly distributed in the Greater Kingan Mountains, Lesser Kingan Mountains and most of the Eastern Mountainous areas. There are 50.90% area of the whole province has maintained forest vegetation for a long time (11 – 19 years). The unstable areas of forest vegetation are mainly distributed in the edge of the Greater Kingan Mountains, the Lesser Kingan Mountains and the Eastern mountain, and some areas of Sanjiang Plain, accounting for 2.66% of the province

(Figure 4-a and Figure 4-b). Figure 4-c shows that most areas of the province, except the southwest, are suitable for forest distribution. And that all the forests in the province are distributed in the suitable distribution area, with 82.82% of the area suitable for forest distribution in the long term (11 – 19 years) (Figure 4-d). And the actual distribution area of forests is highly consistent with the potential distribution area.

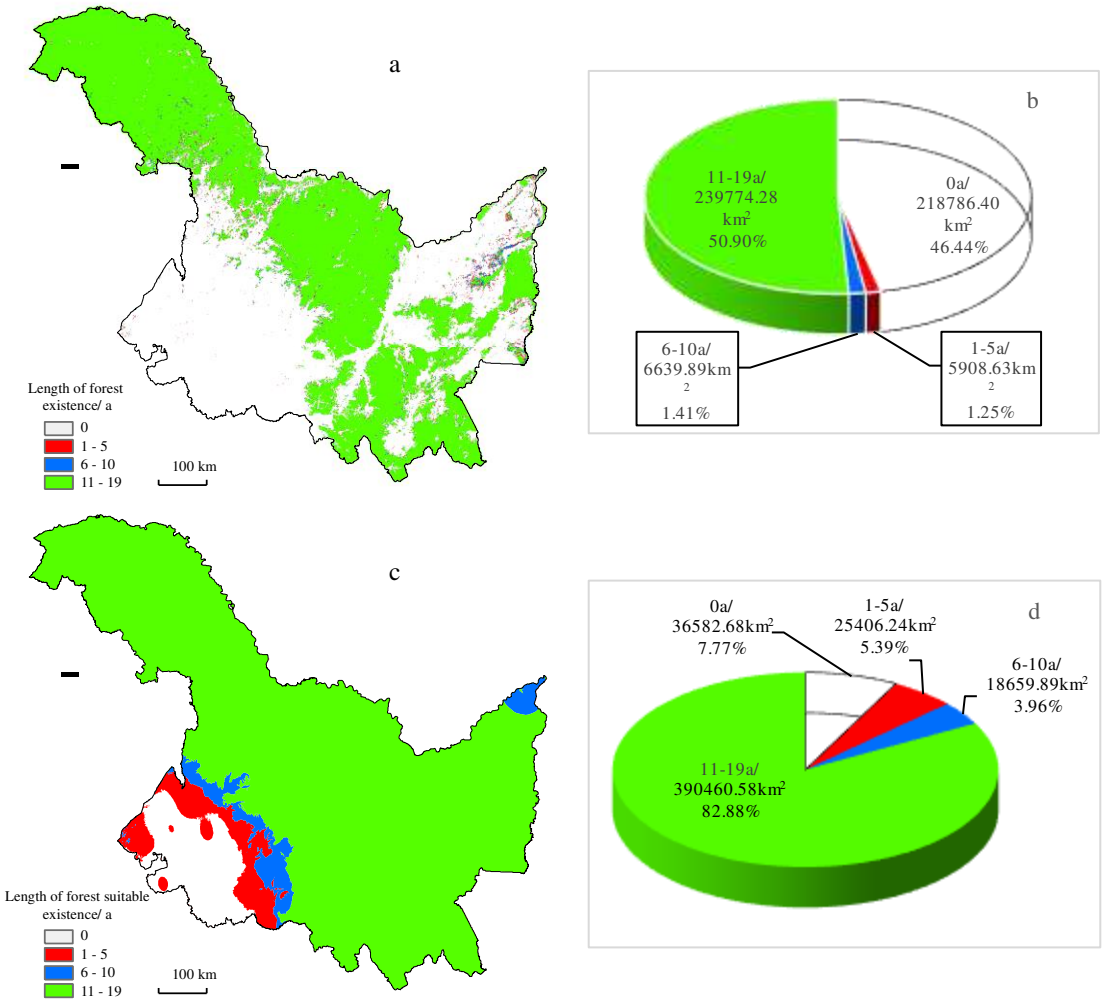

Figure 4 Sketch map of forest distribution in Heilongjiang Province from 2001 to 2019

(a, c): The number of years that each pixel of forest has existed (a) or suitable existence (c). Green, blue, and red pixels represent forests that have existed (a) or suitable existence (c) for 11-19 years, 6-10 years, and 1-5 years, respectively. The white pixels in the study area represent a forest that never existed (a) or unsuitable existence between 2001 and 2019. (b, d): There are different years of forest pixel area and the proportion of the total area of the study area.

4.2 Variation characteristics of forest NPP

The NPP (ranges from 440.48 to 555.32gC/m^2/a with an average of 507.05gC/m^2/a) is generally slightly lower than the NPP climate potential (ranges from 460.38 to 577.62gC/m^2/a with an average of 515.67gC/m^2/a,). They all showed a significant increase trend of 4.71 gC/m^2/a and 3.92gC/m^2/a respectively (Figure 5).

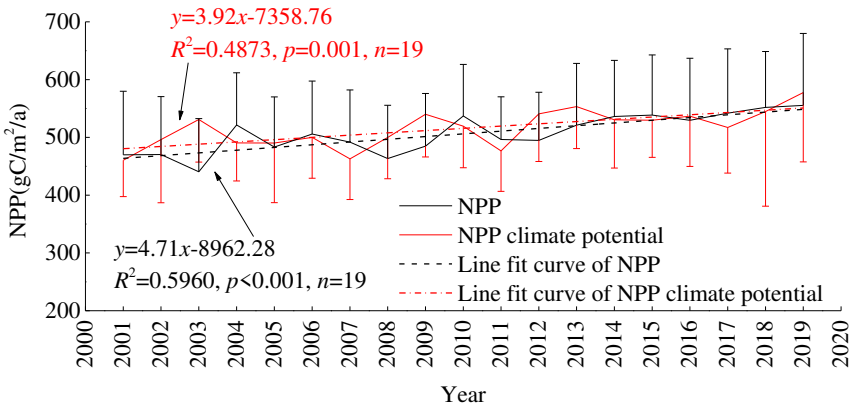

Figure 5 Temporal variation of forest NPP in Heilongjing Province from 2001 to 2019

The spatial variation of forest NPP was obvious ranges from 359.59 to 868.45gC/m^2/a of which about 469.49gC/m^2/a was the most. The NPP in the Eastern Mountains was generally larger than that in the Greater Kingan Mountains and the Lesser Kingan Mountains (Figure 6-a). The regional distribution characteristics of NPP climate potential (Figure 6-b) was consistent with the forest NPP. The climatic potential of NPP ranged from 392.64 to 628.23gC/m^2/a and mainly concentrated in the vicinity of 462.13gC/m^2/a, followed 560gC/m^2/a.

The forest NPP in most regions is lower than the NPP climatic potential (Figure 6-e), but some regions of the eastern mountains exceeds the climatic potential which is calculated based on meteorological observation data. One of the reason may be that the interpolation accuracy of meteorological data will be affected under the condition of complex terrain, which will affect the estimation accuracy of NPP. The NPP (Figure 6 – C) and NPP climatic potential (Figure 6 – d) of most forests showed increasing trends, with the largest increasing trends at 4.21 gC/m2/a and 2.98 gC/m2/a, respectively. the increasing trend of forest actual NPP was greater than the increasing trend of NPP climate potential in most areas (Figure 6 – f).

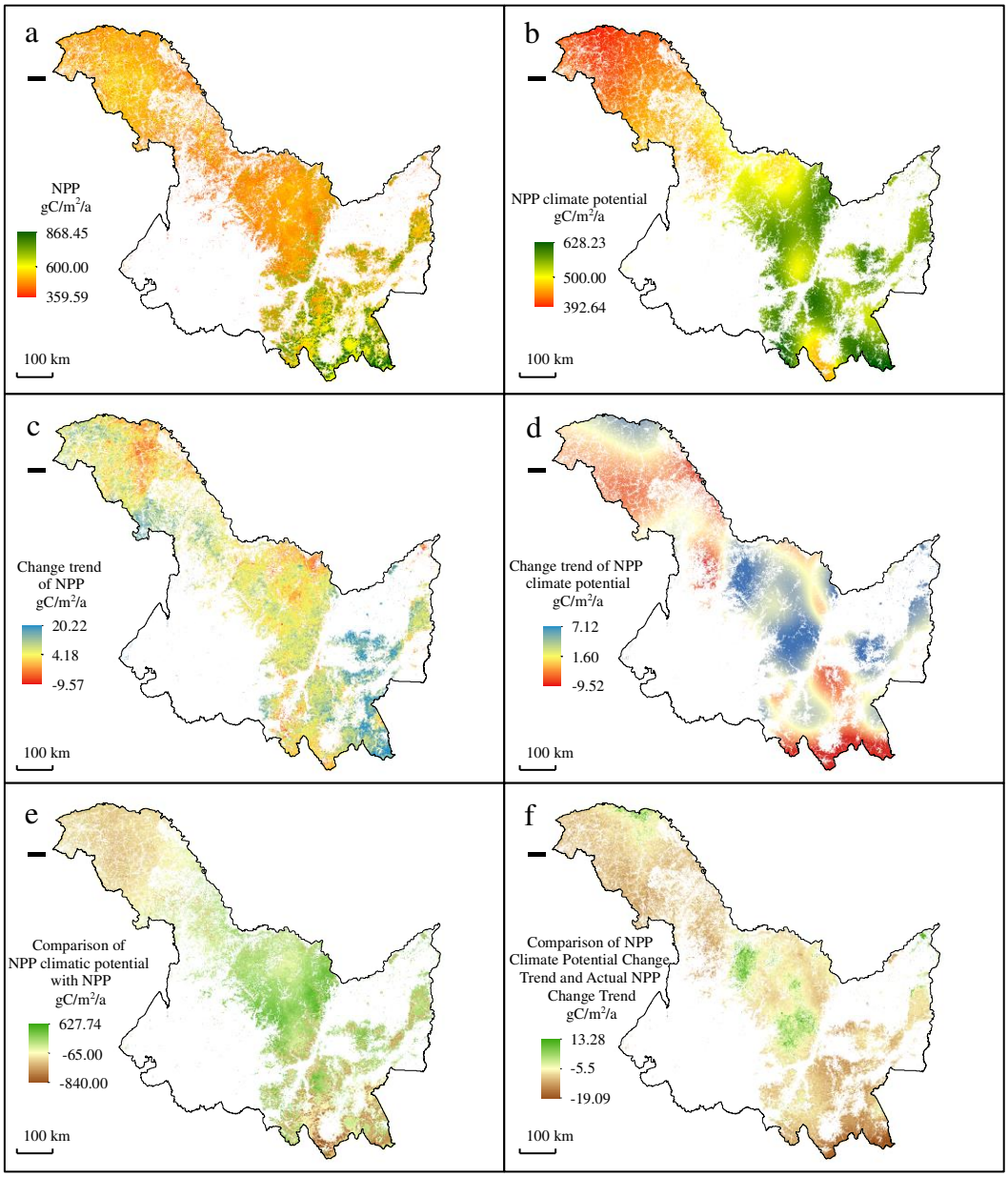

Figure 6 Comparison of NPP climate potential and NPP in Heilongjiang Province from 2001 to 2019 a: Distribution map of mean NPP of forest from 2001 to 2019; b: Distribution map of average climate potential of forest NPP from 2001 to 2019; c: Distribution of linear trend of NPP change in real forest from 2001 to 2019, in which the value of each pixel is the slope obtained by linear fitting; d: Distribution of linear trends in forest NPP climatic potential change from 2001 to 2019, where the values for each pixel are the slopes of the linear fit; e: A comparison diagram of the climate potential of forest NPP and the real forest NPP, calculated as the climate potential of forest NPP (Fig. 6-b) minus the real forest NPP (Fig. 6-a); f: A comparison diagram of the changing trend of climate potential of forest NPP and the changing trend of real forest NPP, calculated as the changing trend of climate potential of forest NPP (Figure 6-d) minus the changing trend of real forest NPP (Figure 6-c).

4.3 Change characteristics of forest vegetation coverage

The vegetation coverage (ranged from 42.42% to 67.64%) was generally lower than the climate potential of vegetation coverage (ranged from 58.34% to 72.71%). And there was a significant upward trend of 0.51%/a and 0. 49%/a respectively.

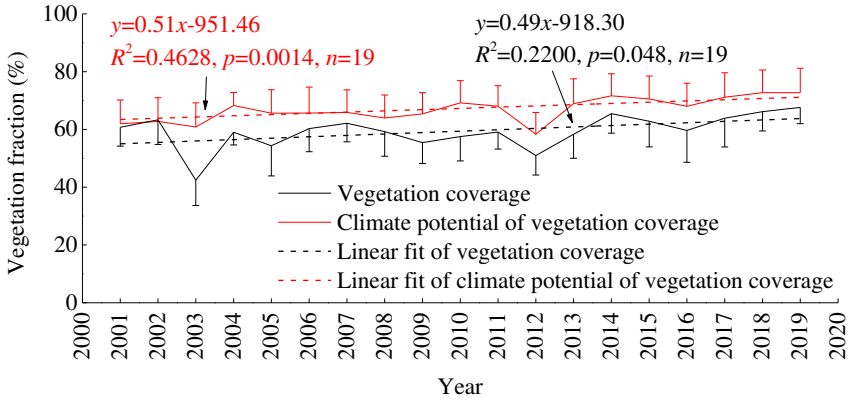

Figure 7. Temporal change of forest vegetation coverage in Heilongjiang Province from 2001 to 2019

The forest vegetation coverage (Figure 8-a) and the climatic potential of vegetation coverage (Figure 8-b) showed the same distribution characteristic. The Eastern Mountains and the southeastern part of the Lesser Khingan Mountains was higher than that in the Greater Khingan Mountains and the northern part of the Lesser Khingan Mountains. The forest coverage was lower than the climate potential (Figure 8–e), in which the vegetation coverage in the northern slope of Lesser Kingan Mountains and Eastern Mountains were different from the climate potential.

Most of the forest vegetation coverage (Figure 8-c) and the climatic potential of vegetation coverage (Figure 8-d) were increasing. The climate potential of vegetation coverage change trend was less than that of realistic coverage in most of the province, but the opposite has occurred in parts of the Lesser Khingan Range (Figure 8-f).

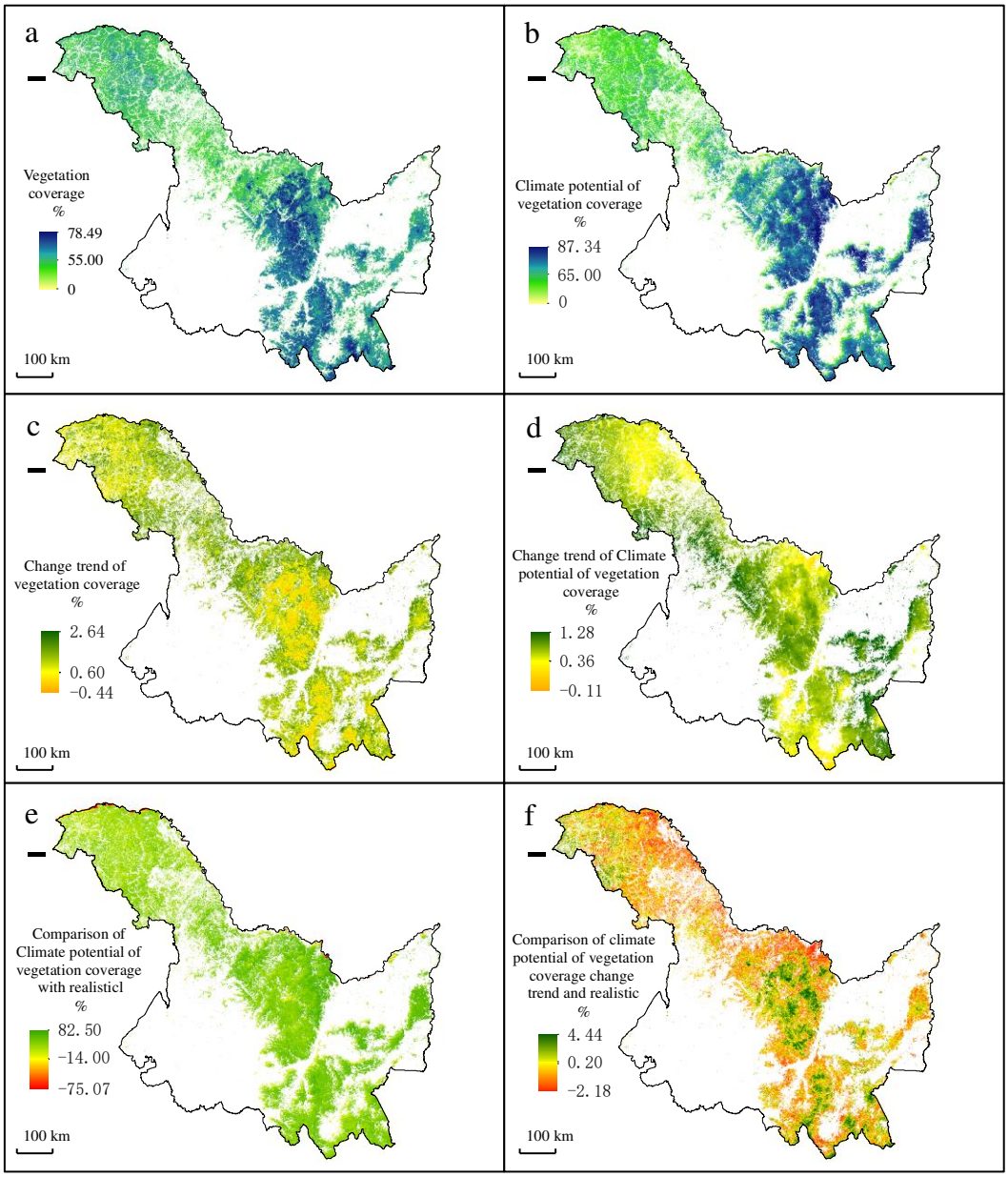

Figure 8 Comparison of climatic potential and forest vegetation coverage in Heilongjiang Province from 2001 to 2019 a: Distribution map of actual average forest vegetation coverage from 2001 to 2019; b: Distribution map of mean climatic potential of forest vegetation coverage from 2001 to 2019; c: Distribution of linear trend of actual forest vegetation coverage change from 2001 to 2019, in which the value of each pixel was the slope obtained by linear fitting; d: Distribution map of linear trend of climatic potential change of forest vegetation coverage from 2001 to 2019, in which the value of each pixel was the slope obtained by linear fitting; e: A comparison of climate potential of vegetation coverage and vegetation coverage, calculated as the climate potential of forest vegetation coverage (Fig. 8-b) minus the vegetation coverage (Fig. 8-a); f: A comparison diagram of the changing trend of climate potential of vegetation coverage and the changing trend of vegetation coverage. The calculation method was the changing trend of climate potential of vegetation coverage (Figure 8-d) minus the changing trend of real forest vegetation coverage (Figure 8-c).

4.4 Impact of meteorological conditions on forest ecosystem changes

4.4.1 Meteorological influence of ecosystem change

Because the NPP climate potential, vegetation coverage climate potential and potential distribution area of forest are all calculated based on meteorological factors, which can represent the climate potential of each ecological function driven by meteorological factors, this study analyzed the relationship between the actual value of each ecological function and the potential climate potential.

Fig. 9 shows that the actual values of forest ecological function elements are significantly positively correlated with the climate potential. The NPP climate potential was calculated based on annual precipitation and average daily temperature from 0℃ to 30℃. Therefore, the actual value of forest NPP was positively correlated with the coupling effect of the above two basic meteorological factors, and the contribution rate of NPP change was 16.31%. Climate potential of vegetation coverage is base on that calculation model of comprehensive eco-meteorological factors base on sunshine hours, monthly average temperature, evapotranspiration and carbon dioxide fertilization, so there was a positive correlation between the actual value of forest vegetation coverage and the comprehensive effect of the above three meteorological factors; According to the analysis results of potential distribution area of forest simulated by MAXENT model, the comprehensive contribution rate of precipitation in the driest season and annual precipitation to the potential distribution of forest was 69. 96% (average value from 2001 to 2019), which showed that there was a positive correlation between actual distribution area of forest and the coupling effect of precipitation in the driest season and annual precipitation.

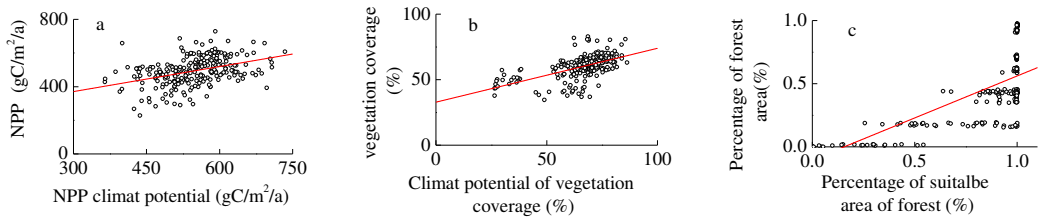

Figure 9 Relationship between NPP and climatic productivity potential (a), between vegetation coverage and climate potential of vegetation coverage (b), and between percentage of forest in district and percentage of suitable area of forest in district (c) in Heilongjiang province

The linear fitting relation of NPP climat potential and realistic NPP was y=0.49x+221.81, Coefficient of determination (Figure 9-a) was 0.1631, Prob＜0.001. The linear fitting relation of cliamate potential of vegetation coverage and realistic vegetation coverage (Figure 9-b) was y=0.41x+32.82, Coefficient of determination was 0.3261, Prob＜0.001. The linear fitting relation of suitiale are of forest distribution and area of forest (Figure 9-c) was y=0.66x-0.10, Coefficient of determination was 0.5161, Prob＜0.001. All the sample points participating in linear fitting were 247.

The data of sample points is the average value of each city in Heilongjiang Province. The province is divided into 13 cities, and the sample points are 13 cities ×19 years (2001-2019) =247.

4.4.2 Impact assessment of meteorological conditions

The contribution rate of meteorological conditions to forest ecosystem changes is 11.08% in the province, and the contribution rate is between 4.79% (Mudanjiang) and 18.07% (Daqing). Considering the forest coverage and location of each city, it can be seen that the forest coverage in Songnen Plain (0.01% -43.22%) and Sanjiang Plain (17.24% -42.37%) is relatively low, and

the contribution rate of meteorological conditions to forest ecosystem change is relatively high, with an average of 14.29% and 11.25%, respectively. However, the urban forest coverage in the Greater Kingan Mountains (96. 36%), Lesser Kingan Mountains (44. 38% – 91. 92%) and Eastern Mountains (71. 09%) was higher, and the contribution rate of meteorological conditions was relatively low, averaging 8. 96%, 8.27% and 4. 79%, respectively.

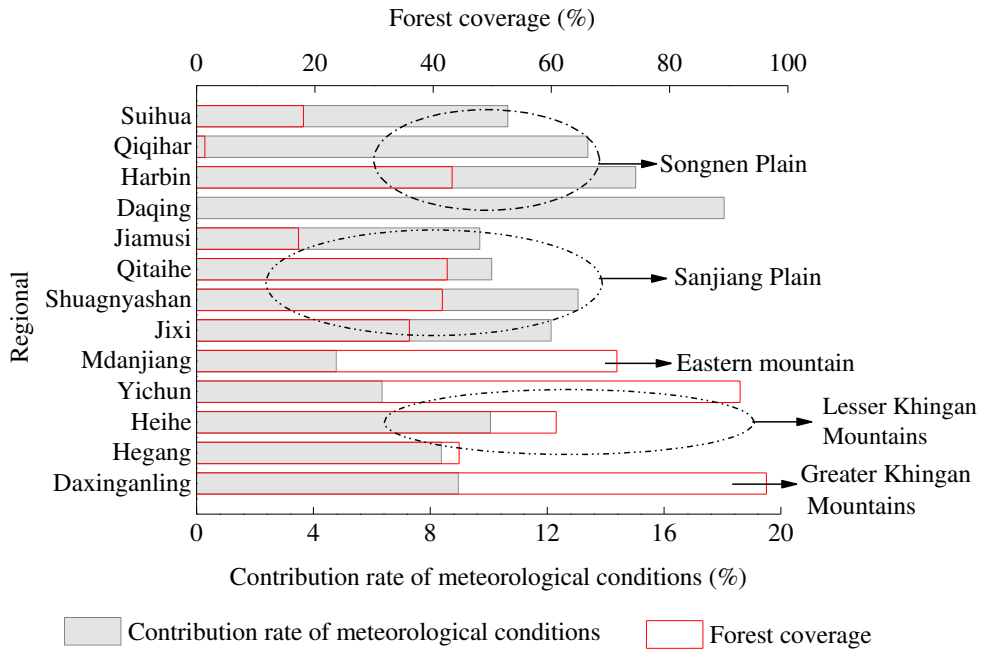

Figure 10 Contribution rate of meteorological conditions (gray Bar) and forest coverage (red Bar) of forest ecosystems in 13 cities of Heilongjiang Province

Forest coverage is calculated as the percentage of forest area in the total area of a region. There was a significant negative correlation between the contribution rate of meteorological conditions (y) and forest coverage (X), and the linear regression equation was y = -5.94x + 107.67. Coefficient of determination was 0.4748, Prob=0.009, and sample points participating in linear fitting were 13.

5. Discussions

Influence of climatic factors on NPP

One of the concerns of our research is the impact of climate factors on NPP. The results showed that the forest NPP in Heilongjiang Province increased significantly from 2001 to 2019. The coupling effect of annual precipitation and daily mean temperature (0-30 ℃) was the main meteorological factors of forest NPP change in the province, and the contribution rate was 16. 31%. This result was much lower than the conclusion reached by Wang et al (2017) that 66% of NPP variation in Northeast China was attributable to climate factors. The main reason for this difference is the different calculation methods of NPP climate driving effect. The statistical object of Wang et al was the pixel with significant inter-annual variation of NPP. However, the object of this study is the whole forest pixels (including the pixels with significant inter-annual changes in NPP, but also including the pixels without significant changes in NPP). In addition to meteorological, there are many others that affect the change of vegetation NPP, such as the characteristics of vegetation itself, atmospheric CO_2 concentration, atmospheric nitrogen

deposition, artificial afforestation (or deforestation), etc. Among them, the dynamics of carbon cycle in forest ecosystems largely depends on the age of forests, which is the key factor to determine the carbon storage and carbon flux of ecosystems. The characteristics of carbon exchange between forest and atmosphere vary with stand age, and have significant forest age effect (Schwalm et al, 2007; Pregitzer et al, 2004). The forest dominant species in Heilongjiang Province are mainly Larix gmelinii, Pinus koraiensis, Quercus mongolica, Betula platyphylla, Picea asperata, Pinus sylvestris var.mongolica and so on, and the forest age is mainly middle-aged forest and near-mature forest (Dai et al, 2011). The NPP of the forest in this study period is in the stage of rapid growth (He et al, 2012; Goulden et al, 2011), which may be one of the reasons for the significant increasing trend of forest NPP in Heilongjiang Province. Zhang et al (2014) studied the changes of forest biomass in Northeast China through satellite observation, and found that forest biomass increased significantly from 2001 to 2010, in which forest development was the most important contributor to forest biomass growth, followed by climate control.

Influence of climatic factors on vegetation distribution

Climate impact is a long-term and permanent process, which has a decisive impact on vegetation distribution (Raich et al, 1992, Parmesan et al, 2003). As for that boreal forest in China, the influence of temperature on the forest is greater than that of precipitation, which may be due to the physiological and ecological characteristics of the boreal forest. Boreal forests are also more sensitive to global warming than other ecosystems (Wilmking, et al, 2005; Buermann et al, 2014). Due to the impact of climate change, boreal coniferous forest in Heilongjiang Province will face the severe challenge of being replaced by other biological communities, and the distribution area may be reduced, but this does not mean that the potential distribution area of boreal forest ecosystem will be reduced (Liu et al, 2017). In recent years, rising temperatures have led to a sustained and island-like degradation of permafrost in northeastern China. This change is pushing northern ecosystems into an unbalanced state, which may affect the relative role of climate factors and fire in determining vegetation distribution. The results of this study showed that although the actual distribution area of forest in Heilongjiang Province was distributed in the potential distribution area (4.1.2 Figure 4), there was a significant correlation between the proportion of actual distribution area and the proportion of potential distribution area (4.4.1 Figure 9-c). However, the actual distribution area of forests in the province is not consistent with the potential distribution area (Figure 3 of Section 4.1.1). This shows that the actual distribution area of forest is not only affected by meteorological conditions, but also strongly disturbed by fire, outbreak of pests and diseases, human production activities and so on, but the results of such disturbances are not enough to completely change the distribution trend of forest ecosystem in a larger area.

Influence of climatic factors on vegetation coverage

The results show that the average vegetation coverage of the province has a significant increasing trend from 2001 to 2019, and the contribution rate of climate change to the change of vegetation coverage is 32.61%. On the one hand, climate warming can promote vegetation growth in cold areas or high altitude areas in the north; On the other hand, the increase of vegetation cover will also have an adverse effect on land surface temperature. The increase of vegetation coverage reduces the background (no snow) and snow-covered surface albedo, resulting in a significant increase in surface absorption of solar radiation, and amplifies the feedback between snow cover, surface albedo and absorbed solar radiation (Zhang et al, 2007). Snow- vegetation interaction warms northern land in spring, resulting in a rapid increase of vegetation coverage in spring and prolongs the length of growing season (Peng et al, 2011). From the point of view of heat, it provides favorable conditions for the improvement of vegetation coverage. In addition, although the increase of vegetation coverage reduces the intensity of soil evaporation, it increases the vegetation transpiration, even if there is no significant impact on the total precipitation, but it may

change the pattern of precipitation, so that the precipitation in some areas decreases, resulting in the reduction of vegetation coverage. Which may also be one of the reasons for the decrease of a small amount of forest vegetation coverage in the southern part of the Lesser Kinggan Mountains and the northern slope of the Eastern Mountains (Figure 8-c).

Influence of climatic factors on forest ecosystem

Climate is one of the main factors affecting the distribution pattern and functional characteristics of terrestrial vegetation types, which affects the composition of biological communities in ecosystems by affecting physiological processes such as photosynthesis, respiration and phenology of vegetation, thus changing vegetation distribution, NPP and vegetation coverage. Due to the inconsistency of vegetation coverage and NPP changes, there is great uncertainty in assessing the climate driving effect by using a single index (Ding et al, 2020). In this study, the impacts of climate change on forest ecosystems were assessed with different weights by integrating forest distribution, NPP and vegetation coverage indexes, which reducing the uncertainty generated by single index assessment to a certain extent. The results showed that the contribution rate of meteorological conditions to forest ecosystem change ranged from 4. 79% to 18. 07%, and there was a significant negative correlation between climate contribution rate and forest coverage. From the perspective of landscape ecology, the larger the patch area of the forest type, the more conducive it will be to the abundance and quantity of species, the extension and interconnection of the food chain, and the reproduction of the secondary species, so as to gain greater anti-interference and restoration ability. Therefore, for the same external disturbance, areas with higher forest cover rate have a lower impact on their ecological functions than those with lower forest cover rate.

6. Conclusion

From 2001 to 2019, the forest area in Heilongjiang Province showed a trend of increasing first and then decreasing, and both NPP and vegetation coverage showed a significant upward trend. The contribution rate of meteorological conditions to forest ecosystem change varies from 4.79% to 18.07% in different cities. There was a negative correlation between the impact of meteorological conditions on forest ecosystem and forest coverage, that is, the higher the forest coverage, the lower the impact of meteorological conditions, and vice versa.

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Authors contributions: Dan Liu: Writing and analysis; Hao Yan: analysis; Chenglong Yu: analysis and supervision; Shiping Yin: analysis; Chengwei Wang: analysis; Lijuan Gong: analysis.

Declarations

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Consent to publish: Agree to publish

Competing interests: The authors declare no competing interests.

ORCID

Dataset of daily climate data from Chinese surface stations V3.0. Id: http://data.cma.cn/

MODIS MCD12Q1 and MODIS MOD13Q1. Id: https://ladsweb.modaps.eosdis.nasa.gov/

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