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Research article

Study on the influence of meteorological elements on growing season vegetation coverage in Xinjiang, China

Huimin Bai[1], Li Li[2], Yongping Wu[3], Chen Liu[4], Zhiqiang Gong[5], Guolin Feng[3,5,*] and Gui-Quan Sun[1,6,*]

[1] Complex Systems Research Center, Shanxi University, Taiyuan, Shanxi, China

[2] School of Computer and Information Technology, Shanxi University, Taiyuan, Shanxi, China

[3] College of Physics Science and Technology, Yangzhou University, Yangzhou, Jiangsu, China

[4] Center for Ecology and Environmental Sciences, Northwestern Polytechnical University, Xi'an, Shaanxi, China

[5] Laboratory for Climate Studies, National Climate Center, China Meteorological Administration, Beijing, China

[6] Department of Mathematics, North University of China, Taiyuan, Shanxi, China

* **Correspondence:** Email: fenggl@cma.gov.cn, gquansun@126.com.

Abstract: Xinjiang is a typical arid and semi-arid Mountain basin system, which make the regional ecosystem extremely fragile. Studying the influence of climate on vegetation is conducive to qualitatively analyze the change trend of vegetation coverage in this region. Therefore, utilizing vegetation coverage and main meteorological elements (temperature, precipitation, relative humidity, sunshine hours) data in Xinjiang province, this paper carried out the influence of multiple meteorological elements on vegetation coverage changes, and constructed a model of the impact of multiple meteorological elements on the growing season vegetation coverage based on random forest. The model can better simulate the vegetation coverage in 2017 and 2018, with an average error of 0.027, in consequence it can well forecast whether the vegetation is high-density or low-density in this area. Correlation analysis and variable importance show that the critical meteorological factors affecting vegetation cover change are relative humidity and sunshine hours, accounting for 73% of the vegetation coverage area. The results are helpful to understand how meteorological factors affect the vegetation coverage, and then provide a theoretical reference for the construction of ecological security in Xinjiang.

Keywords: vegetation; arid and semi-arid region; climate change; machine learning

1. Introduction

Ecological security is not only an important part of national security construction, but also the guarantee of human sustainable development [1]. In recent years, global warming, sea level rise [2], glacier melting [3] and extreme drought events occur more frequently and intensely [4] through review [5], observation and simulation [6], which have brought challenges to human survival and development. As an important part of the terrestrial ecosystem and a key element connecting land and atmosphere, vegetation has the advantages of mitigating climate warming, preventing wind and fixing sand and purifying air [7]. As everyone knows, vegetation growth requires photosynthesis, transpiration and respiration: Photosynthesis is a process in which green plants absorb water and CO_2 to produce O_2 and organic matter under the action of visible light and enzyme catalysis, namely vegetation growth depends on temperature [8], water [9], CO_2 [10] and visible light; Transpiration absorbs water from the soil through the roots, a small part of it is supplied for photosynthesis, and most of it is evaporated into the air through the leaf stomata [11], thereby increasing the air humidity [12]; Respiration is the process of oxidative decomposition of plant organisms to release energy, water and CO_2, which is closely related to temperature [13]. It can be derived that the vegetation growth depends on the temperature, precipitation, light, carbon dioxide, humidity and so on.

Based on station and reanalyzed climate data (temperature, precipitation, light (radiation)) and satellite remote sensing vegetation index data, scholars at home and abroad have carried out many studies on global and regional scales [14–19]. They jointly revealed that the critical factors affecting vegetation growth depend on local climate characteristics, land use, etc. According to Net Primary Productivity (NPP) data for 1982–1999, Nemani et al. [14] demonstrated that vegetation growth in the northern hemisphere is limited by temperature, precipitation in arid areas and radiation in tropical areas. Zhao et al. [15] analyzed the relationship between meteorology and vegetation based on Normalized Difference Vegetation Index (DNVI) data from 1982 to 2013, and reached a consistent conclusion. Using DNVI data from 1982 to 1999, Zhou et al. [16] showed that there was a statistically significant relationship between vegetation and temperature change in the northern high latitude area. Northern of North America is subarctic climate with cold climate all the year round [20], therefore the increase of temperature promotes its vegetation growth [21]. For vegetation growing in arid areas, especially grasslands and open shrubs under water shortage environment [22], the increase of precipitation is conducive to its growth [23], such as Inner Mongolia, China [24] and New Mexico, USA [25]. Hickler et al. [26] analyzed the influencing factors of vegetation greening in arid areas based on ecosystem model, and showed that precipitation was the main reason to control the greening trend of Sahel. Zhao et al. [27] applied statistical methods to analyze the relationship between vegetation and climate in the arid region of Northwest China, indicating that NDVI was highly correlated with precipitation and evaporation, and had nothing to do with temperature. Mild and humid Europe and Southeast Asia, especially in evergreen broad-leaved forests, the key factor restricting vegetation growth is solar radiation [14]. However, there are few studies on quantifying the impact of multiple factors on vegetation. With the increase of quantitative vegetation growth data, more and more scholars study the impact of regional and global climate on vegetation based on statistical methods and machine learning methods. Shi et al. [17] utilized image data and support vector machine method to dichotomy whether there is vegetation in China's ecological construction areas, and then used random forest regression method to quantitatively evaluate the vegetation in vegetated areas. Zheng et al. [19] used the method of stepwise clustering regression to simulate the vegetation in the Three-River Headwaters region, and then used the Coupled Model Intercomparison Project 5 (CMIP5) to predict the vegetation change in this area under different scenarios. Bai et al. constructed a model for predicting the future vegetation growth trend utilizing regression [28] and support vector machine [29] method, and found that the key factor affecting the growth of vegetation in North China is relative humidity, that is, the synergistic effect of temperature and precipitation. The above methods can simulate the vegetation well, so this paper uses the random forest regression method to study.

Dry land, in which the annual potential evaporation far exceeds the annual precipitation [30], has the climatic characteristics of sparse precipitation, high surface temperature, abundant solar radiation and low humidity [31]. Feng et al. [32] have shown that dry lands will continue to expand, which leads to the reduction of carbon sequestration and the intensification of regional warming [33]. The reduction of carbon sequestration and regional warming are synergistic [34]. In addition, the increasing trend of drought also does great harm to crops, and then affects human survival [35]. Therefore, the expansion of dry land has a great harm to the ecosystem, making the ecosystem pattern change [36]. However, sand dams may improve the adaptability of dry lands to climate change [37]. Mountain basin system is a geographical complex in which the basin is embedded in the mountain system. It has formed a unique ecological landscape pattern due to its unique natural geographical environment and the transformation of material and energy between regions [38]. Xinjiang, located in the Northwest of China, has formed a unique mountain-basin system in arid and semi-arid areas since Tarim Basin is embedded in Tianshan and Kunlun Mountains and Junggar Basin is embedded in Altai Mountains and Tianshan Mountains [39]. As a result, the region's ecosystems are fragile and extremely sensitive to climate change. The southern and northern Xinjiang are separated by the Tianshan Mountains, and the climate of the two regions is quite different. Among them, the climate of Northern Xinjiang can be the representative of the climate of the northern hemisphere, and Southern Xinjiang can be the representative of the southern hemisphere [40]. How to find the key factors affecting vegetation stability and predict future vegetation trends through the model of meteorological elements affecting vegetation coverage is a challenge for scientists and decision makers.

Focusing on the scientific problem of how climate change affects the ecosystem, taking the typical arid and semi-arid Mountain basin system in Xinjiang as the research object, using meteorological elements and vegetation coverage data, this paper analyzes the temporal and spatial characteristics of climate and vegetation, and the response of vegetation to climate. Predict the evolution law of ecological landscape pattern of mountain basin system and reveal the future evolution law of large-scale vegetation from the perspective of small scale. Part 2 introduces the data and methods. Part 3 introduces the geographical location of the study area. Part 4 analyzes the temporal and spatial distribution characteristics of meteorological elements and vegetation coverage. Part 5 analyzes the correlation between meteorological elements and vegetation coverage, and constructs the regression model of meteorological factors affecting vegetation coverage change based on random forest. Part 6 is discussion and conclusions.

2. Materials and methods

2.1. Materials

Vegetation coverage (VC): vegetation coverage is a index which denote situation of regional vegetation cover, widely applies on ecological, hydrological and climatic studies [41]. Moderate Resolution Imaging Spectroradiometer (MODIS) monthly NDVI data is obtained from National Aeronautics and Space Administration (NASA) (https://www.nasa.gov/ [2022-5-23]) with a spatial resolution of 1km. The vegetation coverage data can be calculated by formula (2.1),

$$\mathrm{VC} = \frac{\mathrm{NDVI} - \mathrm{NDVI_S}}{\mathrm{NDVI_V} - \mathrm{NDVI_S}}. \tag{2.1}$$

Where, $\mathrm{NDVI_S}$ indicates the NDVI value of pixels without vegetation, $\mathrm{NDVI_S} = 0.05$. $\mathrm{NDVI_V}$ represents the NDVI value of pixels completely covered by vegetation, $\mathrm{NDVI_V} = 0.96$. Firstly, ArcGIS is used to extract vegetation coverage data in Xinjiang and resample the spatial resolution of VC to 0.1. Finally, spatial distribution value and time series value of growing season vegetation coverage ($\mathrm{VC_{gs}}$) from 2000 to 2018 is calculated.

Meteorological elements: The daily observation data of more than 2400 stations with temperature, precipitation, relative humidity and sunshine hours are provided by the National Meteorological Center. Station information can be browsed (http://data.cma.cn [2022.2.25]). We select the stations in Xinjiang, calculate the annual average temperature (T_a), annual average relative humidity (RH_a), annual average sunshine hours (SH_a) and annual cumulative precipitation (P_c) of the region, and interpolate the meteorological data to match the spatial resolution of VC_{gs}.

2.2. Methods

2.2.1. Time series trend estimation

In order to observe the change trend of VC_{gs} and meteorological elements (T_a, P_c, RH_a and SH_a), the least square method is used for linear regression. The change trend is β in formula (2.2).

$$y = \alpha + \beta x + \varepsilon, \tag{2.2}$$

where

$$\begin{cases} \beta = \dfrac{\sum_{i=1}^{n} i \times y_i - \frac{1}{n}\sum_{i=1}^{n} i \sum_{i=1}^{n} y_i}{\sum_{i=1}^{n} i^2 - \frac{1}{n}\left(\sum_{i=1}^{n} i\right)^2} \\ \alpha = \bar{y} - \beta\bar{t} \end{cases}, \bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i, \bar{t} = \frac{1}{n}\sum_{i=1}^{n} t_i.$$

n represents the number of study years, y_i represents the VC_{gs} and meteorological element (T_a, P_c, RH_a and SH_a) value in the i-th year, α represents the intercept, β represents the slope, and ε represents the residual error. When $\beta > 0$, y shows an upward trend, and when $\beta < 0$, y shows a downward trend.

The correlation coefficient can reflect whether the linear relationship between variables and time is close. The formula of correlation coefficient between time and variables is

$$r = \sqrt{\frac{\sum_{i=1}^{n} t_i - \frac{1}{n}\left(\sum_{i=1}^{n} t_i\right)^2}{\sum_{i=1}^{n} y_i - \frac{1}{n}\left(\sum_{i=1}^{n} y_i\right)^2}}.$$

The significance test should be carried out on the correlation coefficient (r) to judge whether the degree of change trend is significant.

2.2.2. Detrend fluctuation analysis

This paper mainly analyzes the impact of climate on vegetation change, the linear increase of vegetation and climate is regarded as the influence of human factors [42]. Therefore, the human activities are removed by the method of detrend to analyze the impact of climate change on vegetation coverage in the next research.

$$dx_i = x_i - \hat{x}_i, \tag{2.3}$$

where, dx_i represents the value of vegetation and climate factors after the trend is removed in the i-th year, x_i represents the observed value, and $\hat{x}_i$ represents the fitting value of linear regression.

2.2.3. Time series turning point

Cumulative anomaly is an intuitive method to judge the change trend of variables according to the curve trend. For the sequence of variable x, the cumulative anomaly at time t is expressed as

$$\hat{x}_t = \sum_{i=1}^{t} (x_i - \bar{x}), t = 1, 2, \cdots, n, \tag{2.4}$$

where,

$$\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i.$$

The rise of cumulative anomaly curve indicates the increase of anomaly value, the decline indicates the decrease of anomaly value, and the fluctuation up and down is regarded as the turning point of time series.

2.2.4. Pearson correlation coefficient

Calculate the correlation coefficient of x and y through Pearson, where $x = (x_{n1}, x_{n2}, x_{n3}, x_{n4})$ represents meteorological elements (T_a, P_c, RH_a and SH_a) , y represents VC_{gs}, n represents sample numbers and r represents the correlation coefficient between them. The calculation formula of correlation coefficient is

$$r = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^{n} (y_i - \bar{y})^2}}, \tag{2.5}$$

$\bar{x}$, $\bar{y}$ represents the average of x and y, respectively. Whether the correlation between the two variables is significant or not must be tested for significance according to the significance test table.

2.2.5. Random forest

Random forest is a method of ensemble learning. The basic principle of ensemble learning is to aggregate multiple single models into a new model through some criteria [43]. Random forest, single model is decision tree, is a data-driven nonparametric model with strong tolerance to outliers and noise and no prior knowledge [44]. Based on the nonparametric advantages of random forest, we propose a prediction model of vegetation coverage affected by multiple meteorological elements. The workflow of random forest is shown in Figure 1. The data set S is obtained by taking the annual average temperature, annual cumulative precipitation, annual average relative humidity and annual average sunshine hours as independent variables and growing season vegetation coverage as dependent variables. Randomly select k data sets $S_i(i = 1, 2, ..., k)$ with the same size as the original data set from the data set S through bootstrap. k decision tree models were obtained by training. The vegetation coverage and meteorological element data from 2000 to 2016 are used to train the model, and the meteorological data in 2017 and 2018 are used to predict the vegetation coverage value. The root mean square error (RMSE) is used to evaluate the quality of the model.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_i - f(x_i))^2},$$

where N represents the number of grids, Y_i indicates vegetation observation value, $f(x_i)$ indicates vegetation simulation value.

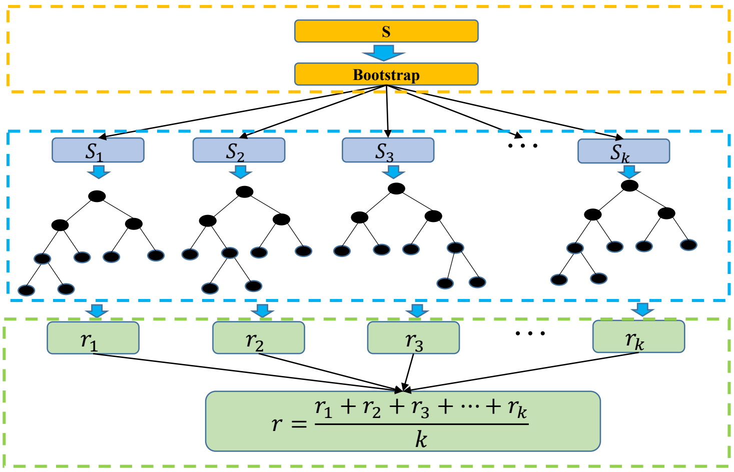

Figure 1. Random forest workflow.

3. Study area

Xinjiang, located in the core area of Central Asia and Northwest China, is one of the driest areas in the world due to far from the sea. Xinjiang, from northern to southern, Altai Mountain, Jungar Basin, Tianshan Mountain, Tarim Basin, Kunlun Mountain, respectively, that is "three mountains and two basins", form a unique mountain basin system. These geomorphic features make different regions in Xinjiang have different climate patterns. There are large areas of grassland and forest vegetation in Altay, Tianshan and Kunlun Mountains in Xinjiang. In 2000, 2010, 2020, the grassland and forest area in Xinjiang accounted for 37.5, 31.1 and 31.3% of the regional area respectively, mainly grassland (Figure 2, Table 1). The land area of grassland and forest decreased by 6.4% from 2000 to 2010, and

Table 1. The proportion of different land uses in Xinjiang.

	2000(%)	2010(%)	2020(%)
Framland	4.3	4.2	5.5
Forest	2.8	2.3	1.7
Grassland	34.7	28.9	29.6
Water	3.8	3.17	2.15
City	0.3	0.3	0.6
Unused land	54.2	61.1	60.6

the area did not change much from 2010 to 2020 [45]. The mountain basin system and drought are extremely sensitive to global warming, extreme climate and other events, which makes the vegetation in Xinjiang extremely sensitive to climate [40].

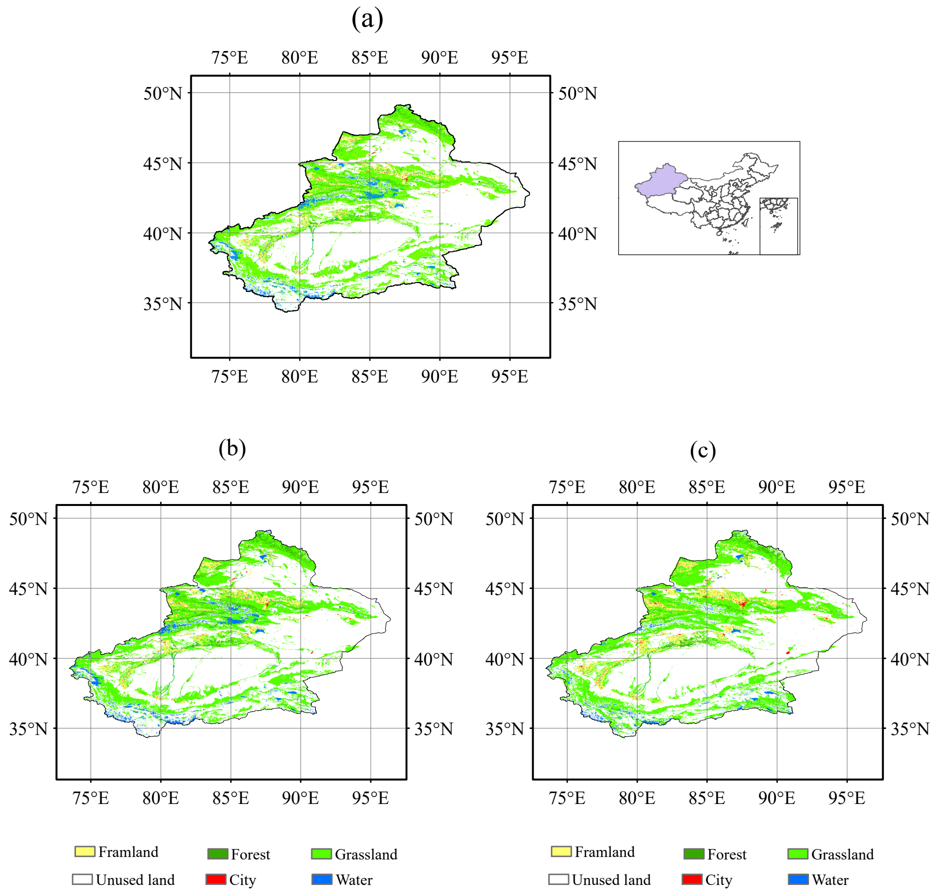

Figure 2. Location of the study area and land use in Xinjiang. (a) 2000, (b): 2010,(c) 2020.

4. Spatial and temporal distribution characteristics of vegetation coverage and meteorological elements.

4.1. Time series characteristics of meteorological elements and vegetation coverage

The monthly average vegetation coverage in Xinjiang (Figure 3), the peak value reached 0.36 in July, and the minimum value appeared from January to March. The study shows that the growing season of vegetation is April to October in Xinjiang, and the vegetation coverage increases significantly from April to June, with an increase of 0.18 from 0.16 in March to 0.34 in June. The relationship between vegetation and climate factors in growing season was studied.

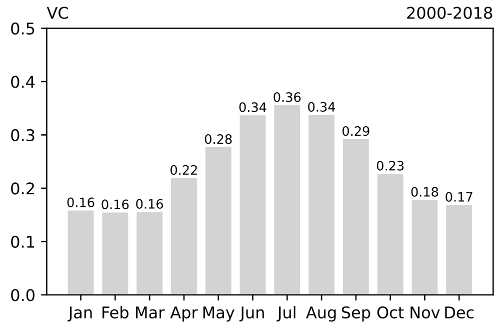

Figure 3. Monthly mean vegetation coverage during 2000 to 2018 in Xinjiang.

By analyzing the change trend of vegetation coverage and climate factors in Xinjiang, it can be seen that vegetation coverage (increased by 0.01/10a) shows a significant upward trend. The temperature (increased by 0.13 °C / 10a), precipitation (increased by 12.9 mm / 10a) showed an upward trend (consistent with the trend of changing to warm and humid in the northwest). The relative humidity (decreased by 1.7 % / 10a) and sunshine hours (decreased by 0.03 h / 10a) showed a downward trend (Figure 4(a1)– (e1)). From anomaly value after detrend, we found that when the vegetation fluctuates, the meteorological elements will also change accordingly, so there is a good corresponding relationship between vegetation and climate (Figure 4(a2)–(e2)). From the cumulative anomaly between vegetation coverage and climate factors, it can be found that 2005, 2009 and 2015 are the turning points of vegetation coverage, and the meteorological elements have also changed accordingly in the vicinity of these years (Figure 4(a3)–(e3)).

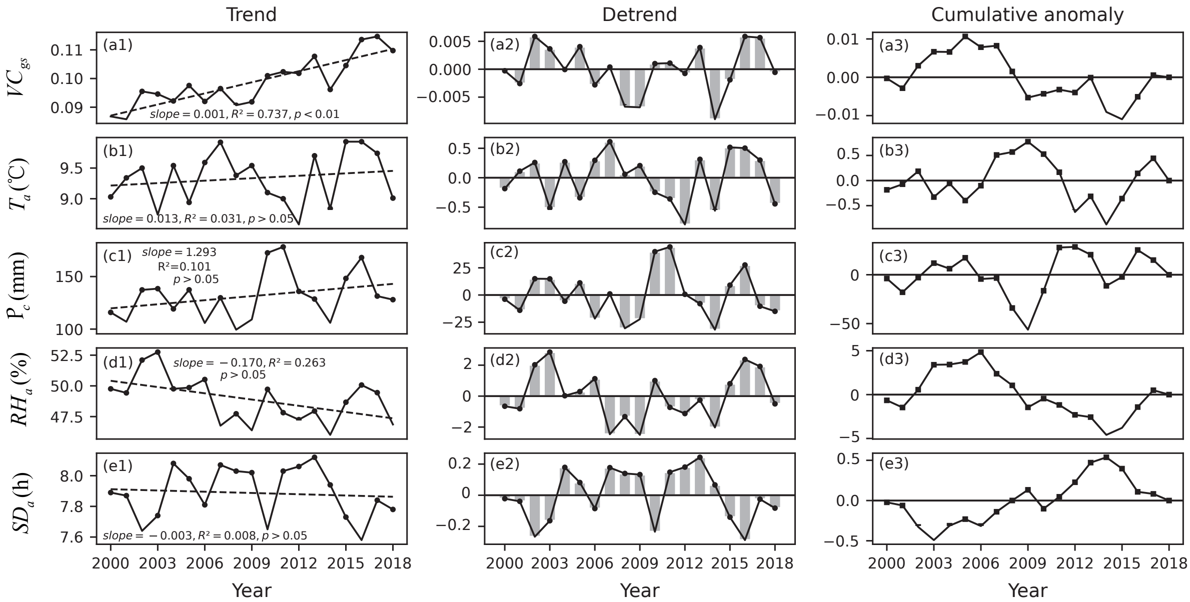

Figure 4. Time series characteristics of vegetation and meteorological elements in Xinjiang during 2000 to 2018: (a1)–(e1) is the change trend, (a2)–(e2) is anomaly value after detrend, (a3)–(e3) is the cumulative anomaly value.

4.2. Spatial distribution characteristics

4.2.1. Spatial distribution characteristics of meteorological elements

There are great differences in the climate between Southern and Northern Xinjiang. The annual average temperature in Northern Xinjiang is between 3 and 9 °C, and that in southern Xinjiang is between 10 and 13 °C, and the daily temperature difference is large. The temperature in southern Xinjiang is higher than that in Northern Xinjiang. The annual precipitation of Northern Xinjiang is 100–500 mm, which of Southern Xinjiang is 20–100 mm. The annual average humidity of Southern Xinjiang is 39–50 %, and that of Northern Xinjiang is 50–64 %. The precipitation of Southern Xinjiang is lower than that of Northern Xinjiang, of which the precipitation and relative humidity of Tianshan Mountains are higher than those of Altai mountains and Kunlun Mountains. The sunshine is abundant in Xinjiang, showing a distribution pattern gradually increasing from east to west. The temperature, precipitation and relative humidity in Ili Valley are higher than those in Altay area (Figure 5(a)–(d)).

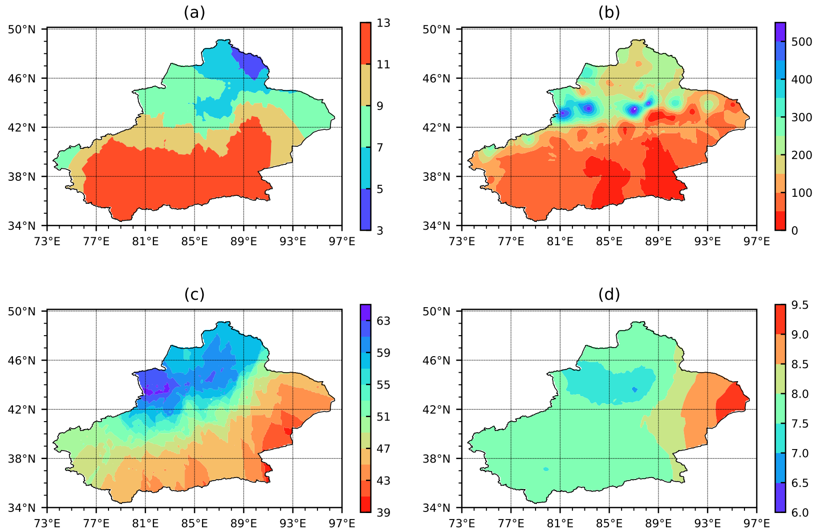

Figure 5. Average value of climate during 2000 to 2018 in Xinjiang : (a) temperature (unit: °C), (b) precipitation (unit: mm), (c) relative humidity (unit:%), (d) sunshine hours (unit: h).

4.2.2. Spatial distribution characteristics of vegetation coverage

According to the spatial distribution of growing season vegetation coverage in Xinjiang, the vegetation coverage in the Ili River Valley (Tianshan Mountains) and Altay is significantly higher than that in the Kunlun Mountains (Figure 6(a)). The vegetation coverage of Ili River Valley is higher than that of other areas. Vegetation grows well in areas with high temperature, precipitation and relative humidity. The change trend coefficient of vegetation coverage is shown in Figure 6(c),(d). Observing the change of vegetation coverage, the vegetation coverage in Xinjiang generally showed an increasing trend from 2000 to 2018. After segmented calculation of the trend of vegetation coverage, it was found that the vegetation coverage in Ili River Valley and other areas in Xinjiang showed a decreasing trend in 2000 s (2000–2009), but the vegetation coverage in Ili River Valley showed an increasing trend, and the vegetation coverage in Altai Mountain showed a decreasing trend in 2010 s (2010–2018). Through the analysis of temporal and spatial characteristics and trend in Xinjiang, it can be found that the change trend and climate characteristics of Altay and Ili River Valleys in Xinjiang are very different.

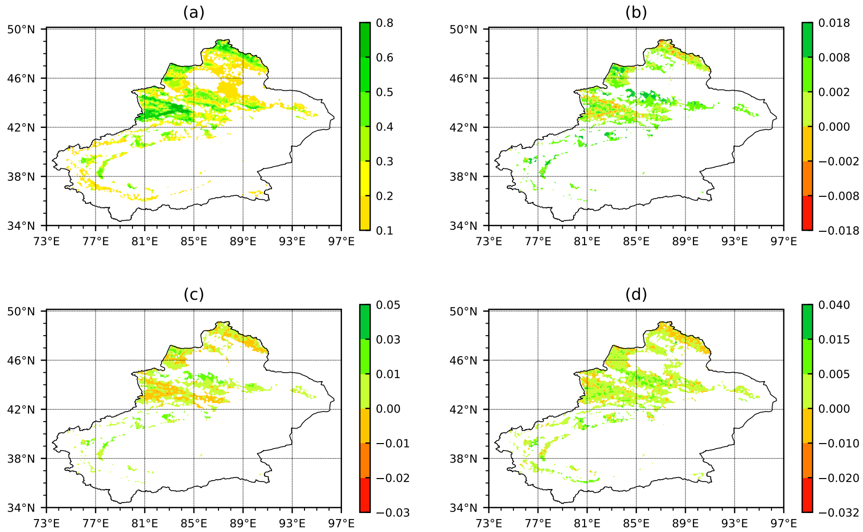

Figure 6. Spatial distribution characteristics of vegetation coverage: (a) growing season mean vegetation coverage from 2000 to 2018 (unit: dimensionless), (b) change trend of growing season mean vegetation coverage from 2000 to 2018, (c) change trend of growing season mean vegetation coverage from 2000 to 2009, and (d) change trend of growing season mean vegetation coverage from 2010 to 2018.

Table 2. Correlation coefficients between vegetation coverage and meteorological elements.

Variable	T_a	P_c	RH_a	SH_a
Correlation coefficients	0.18	0.64*	0.72*	-0.36

* means passing the significance test of 99%.

5. Relationship between vegetation coverage and meteorological elements

5.1. Correlation analysis between vegetation coverage and meteorological elements

Correlation coefficient between regional average meteorological elements and vegetation coverage in Xinjiang (Table 2). Temperature, precipitation and relative humidity are positively correlated with vegetation coverage, and sunshine hours are negatively correlated with vegetation coverage, which are consistent with the work in Reference [45]. The main climatic characteristics of Xinjiang province are drought, little rain and long sunshine hours. Because of this, the growing season mean vegetation coverage is positively correlated with the annual average temperature, and is significantly positively correlated with the annual cumulativel precipitation and the annual average relative humidity, and has different correlations with the sunshine hours in different regions (Figure 7). The correlation between vegetation coverage and sunshine duration is opposite to that of precipitation.

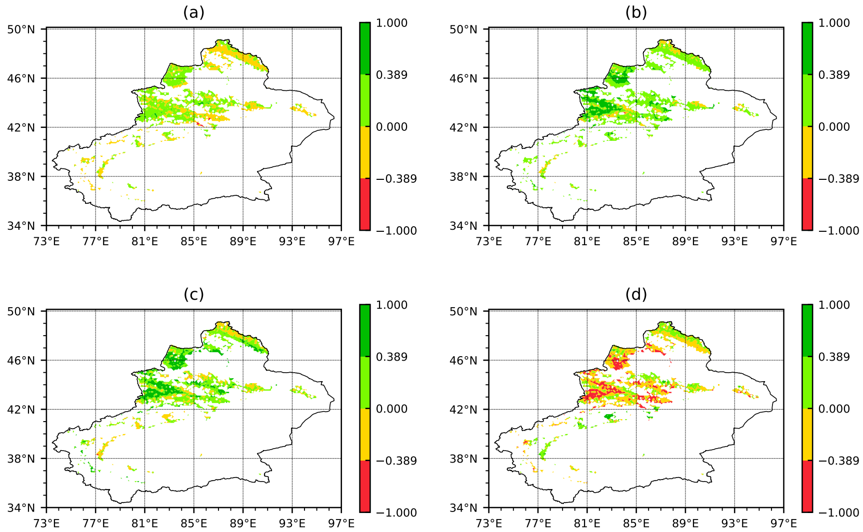

Figure 7. Correlation coefficient (PCC) between vegetation coverage (VC_{gs}) and meteorological elements (T_a, P_c, RH_a and SH_a), where $|PCC| > 0.389$ means passing the significance test of 90%.

5.2. *Meteorological factors affect vegetation coverage model*

The random forest regression model of meteorological elements affecting vegetation coverage is obtained through RandomForestRegressor in Python sklearn library, and the number of trees is set to 500. The meteorological element data in 2017 and 2018 are used to test the constructed vegetation coverage model affected by meteorological elements, and compared with the real observation values. It is found that the model can well model whether the vegetation in this area is high-density or low-density (Figure 8). There is also a certain error between the simulated value and the real value, with an average error of 0.027. The importance of each meteorological element variable to vegetation coverage is obtained by random forest regression model, and the most important factor is selected at each grid point (Figure 9). The calculation shows that the temperature accounts for 6.8%, the precipitation accounts for 20.1%, the relative humidity accounts for 45.8%, and the sunshine hours account for 27.3%. In general, the key factor affecting vegetation growth in Xinjiang is humidity, followed by sunshine hours.

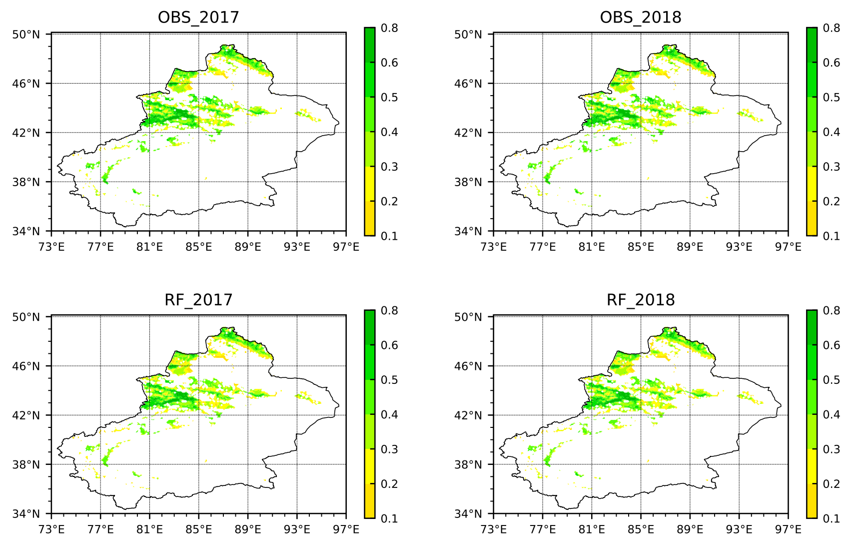

Figure 8. Observed (OBS) value of vegetation coverage and simulated value of random forest (RF) model in 2017 and 2018.

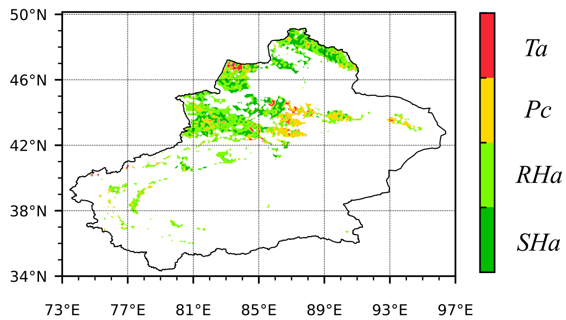

Figure 9. The most important climatic factor (annual average temperature (T_a), annual cumulative precipitation (P_c), annual average relative humidity (RH_a) and annual average sunshine hours (SH_a)) for predicting growing season vegetation coverage.

6. Discussion and conclusions

Xinjiang is a typical arid and semi-arid Mountain basin system in China, the ecosystem in this region is fragile due to the unique terrain. Therefore, the vegetation is extremely sensitive to climate change in this region. Considering the lack of effective models to quantitatively analyze the impact of meteorological elements on vegetation coverage, this paper qualitatively analyzes the impact of meteorological elements on vegetation coverage using simple statistical methods, and quantitatively describes the impact of meteorological elements on vegetation coverage using machine learning methods. The main conclusions are as follows: There are obvious differences in climate between Southern and Northern Xinjiang due to the particularity of geographical location, and the vegetation in Northern Xinjiang is more dense than that in Southern Xinjiang. From the time series and spatial distribution of vegetation coverage, the vegetation coverage has an obvious increasing trend, but the land use area of grassland and forest decreases. Vegetation coverage is positively correlated with temperature, precipitation and relative humidity, and negatively correlated with sunshine duration (Figure 7). The vegetation coverage model based on random forest can well simulate the vegetation coverage (Figure 8), and the average error is less than 0.03. Variable importance shows that the key meteorological factors affecting vegetation cover change in Xinjiang are relative humidity and sunshine hours, accounting for 73% of the vegetation coverage area (Figure 9).

The interaction between climate and vegetation should be a process of mutual feedback [46]. This paper mainly constructs a model for the impact of climate on vegetation, ignoring the impact of vegetation growth on climate. Therefore, it is necessary to consider the impact of vegetation on climate in the next research, and then analyze the interaction between climate and vegetation qualitatively and quantitatively. Recently, based on the interaction mechanism between vegetation and water, some authors have constructed a coupling dynamic model of vegetation and climate with time delay. Li et al. [47,48] finds that time delay is the key factor to induce occurrence of periodic oscillation pattern. In addition, Sun et al. found that small changes in rainfall can make the vegetation system experience different steady states, which may be used as an indicator of the vulnerability of the vegetation system [49].

Human activities, such as afforestation, deforestation, etc., affect the vegetation cover in the region. Some researches regard human activities as a linear trend, and study the impact of climate on vegetation coverage change through residual analysis [42]. Meanwhile, other researches quantify the contribution of human activities to vegetation increase through residual analysis [17]. It is relatively scarce to use real human activity data to study the impact of human activities on vegetation. Human activity data will be collected to analyze the impact of human factors on vegetation, such as economic development, ecological construction and urban construction. Artificial intelligence methods, such as machine learning, deep learning and dynamics, will be utilized to establish a vegetation coverage prediction model for the synergistic effect of climate and human.

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Conflict of interest

The authors declare there is no conflicts of interest.

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