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Research on spatial distribution characteristics and dynamic monitoring of forest resources based on multi-source remote sensing data

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Abstract As a core component of terrestrial ecosystems, forests play a crucial role in global ecological balance, climate regulation and biodiversity conservation. In this paper, the spatial distribution characteristics and dynamic changes of forest resources in Jiangxi Province were studied through multi-source remote sensing data. The methodology utilizes spatial distribution pattern analysis, Gini coefficient, kernel density estimation method, and buffer analysis method, and combines with the forest productivity remote sensing model (VPM) to analyze the distribution characteristics of forest resources in the province in depth. The results showed that the forest resources in Jiangxi Province showed obvious geographical differences, and the distribution types in different areas ranged from aggregated to stochastic. According to the analysis, the north and west of Gan are randomly distributed, while the central area of Gan is of aggregated type distribution. The dynamic monitoring results showed that the overall forest area in Jiangxi Province showed an increasing trend between 2014 and 2024, but the rate of forest loss was still high, especially in areas with low rainfall. Specifically, arid regions with an average annual rainfall of less than 400 millimeters have a forest loss rate of 43.81%, whereas wet regions have a lower loss rate of 25.43%. These findings provide important data support for rational conservation and utilization of forest resources.

Index Terms Forest resources, remote sensing technology, spatial distribution, dynamic monitoring, Gini coefficient, forest productivity

I. Introduction

As an important part of terrestrial ecosystems, forest resources play an irreplaceable role in maintaining ecological balance, protecting biodiversity and promoting sustainable socioeconomic development [1], [2]. Remote sensing technology, with its macro, dynamic and rapid characteristics, has become an important means of forest resources investigation and monitoring [3].

In Germany, forest resources monitoring is implemented together with integrated ecological environment monitoring, and forest resources monitoring is carried out with high-resolution remote sensing images as the base map, which reduces a large amount of field investigation workload [4]. In the 1970s, China started the continuous national forest resources inventory [5]. The traditional forest resources monitoring mainly relies on manual field investigation, which is a heavy workload and at the same time increases the danger of field personnel. Nowadays, the use of multi-source remote sensing technology has greatly improved the monitoring efficiency. At the same time, primitive forests mountainous areas and other areas that are difficult to rely on manual monitoring, multi-source remote sensing can play its data advantages, making monitoring possible, greatly reducing the workload and reducing the danger [6]-[8].

Forest resource monitoring is a complex and systematic project, which requires the comprehensive utilization of multiple remote sensing data sources to obtain comprehensive and accurate forest resource information [9], [10]. Different types of remote sensing data have their own advantages in forest monitoring. For example, optical remote sensing data, such as Landsat and Sentinel-2, can provide information on the spatial distribution and species composition of forests, while synthetic aperture radar (SAR) data, such as ALOS PALSAR and TerraSAR-X, can penetrate the cloud layer to obtain the structural parameters of forests, such as tree heights, biomass, etc. [11], [12]. In addition, LiDAR point cloud data can directly reflect the three-dimensional structural characteristics of forests, which has a unique advantage for the extraction of forest vertical structural parameters [13]. The fusion application of multi-source remote sensing data can comprehensively portray the spatial and temporal characteristics of forest resources from different perspectives and levels, and realize the high-precision inversion of forest parameters [14], [15]. At the same time, the comparison and analysis of multi-temporal remote sensing data can accurately monitor the dynamic change process of forest resources, and provide scientific basis for the sustainable operation and management of forest resources [16], [17]. In general, multi-source remote sensing data provide a new technical means for forest resources monitoring, greatly enhance the capacity and efficiency of forest resources monitoring, and provide a strong support for the dynamic supervision of forest resources and scientific decision-making.

This paper mainly studies the spatial distribution characteristics of forest resources and their dynamic changes in Jiangxi Province through the integration and analysis of multi-source remote sensing data. Firstly, the spatial distribution type and equilibrium of forest resources were analyzed by the nearest neighbor index method and Gini coefficient. Secondly, the spatial density of forest resources was evaluated by using the kernel density estimation method, and the influence of natural factors on the distribution of resources was explored by combining with the buffer zone analysis method. And the spatial and temporal change law of forest productivity was studied through the forest productivity remote sensing model. In addition, this paper analyzed the impact of precipitation on the growth and loss of forest resources by combining the relationship between rainfall and forest dynamics. Ultimately, based on the results of these analyses, scientific support is provided for the protection and rational utilization of forest resources.

II. Research Data Sources and Methodology

As a major component of terrestrial ecosystems, forests play an important role in enhancing human wealth, maintaining ecological balance and protecting biodiversity. For a long time, due to population growth and people's irrational exploitation of forest resources, forest resources have been subjected to large-scale logging and reclamation, resulting in the reduction of forest resources and a series of natural disasters and ecological and environmental problems such as floods, droughts, acid rain, haze and land desertification. In recent years, the protection and rational utilization of forest resources have received more and more attention. The spatial distribution characteristics and dynamic monitoring of forest resources based on multi-source remote sensing data are of great significance for the protection and rational utilization of forest resources and the maintenance of a good ecological environment.

II. A. Data sources

In this paper, we selected the forest resources of Jiangxi Province, China, including "China Forest People", "National Forest Base", "Jiangxi National Forest Park", "Jiangxi Provincial Forest Park" and other objects, and removed the duplication points, and as of July 2024, a total of 346 forest resources were selected. Among them, there are 14 in Nanchang City, 55 in Ganzhou City, 32 in Ji'an City, 33 in Yichun City, 40 in Shangrao City, 20 in Jingdezhen City, 32 in Fuzhou City, 26 in Jiujiang City, 20 in Pingxiang City, 8 in Xinyu City and 13 in Yingtan City.

II. B. Research methodology

II. B. 1) Analysis of spatial distribution patterns

In this paper, we will analyze the spatial distribution characteristics of forest resources in Jiangxi Province from two aspects: spatial distribution type and distribution balance.

1) Nearest-neighbor index method [18]

Considering forest resources as point elements, the nearest neighbor index is applied to measure and assess the distribution type of selected resources in the provincial area. The formula is as follows:

$$r_i = \sum_{i=1}^{m} \frac{r_i}{m}, r_E = \frac{1}{2\sqrt{m/A}}, R = \overline{r_1} / \overline{r_E} \tag{1}$$

where r_i denotes the average actual distance between the i th brand resource and the closest brand resource, $\overline{r_1}$ denotes the average actual distance between each forest resource and the closest forest resource, $\overline{r_E}$ denotes the theoretical closest distance between each brand resource, m is the total number of brand resources, A is the area of Jiangxi Province, and R is the closest neighbor index of forest resources. $R < 1$, indicating that it is in the aggregated distribution situation, and the spatial structure is cohesive; $R = 1$, indicating that it is in the random distribution situation, and the spatial structure is stochastic; $R > 1$, indicating that it is in the uniform distribution situation, and the spatial structure is homogeneous.

2) Gini coefficient

In this paper, the Gini coefficient is used to describe the degree of balance in the distribution of forest resources in Jiangxi Province. The formula is as follows:

$$G_{ini} = \frac{-\sum_{i=1}^{n} P_i \ln P_i}{\ln N}, C = 1 - G_{ini} \tag{2}$$

where R_i is the proportion of the number of forest resources in the i th prefecture and city to the total number of forest resources in Jiangxi Province, N is the number of cities, and C is the degree of uniform distribution. Where G_{ini} takes the value range of 01, and its larger value indicates a lower degree of distributional balance.

II. B. 2) Kernel density estimation methods

Kernel density estimation is mainly used to analyze the density of the study object in its surrounding spatial region [19]. The formula is as follows:

$$f(x_0) = \frac{1}{ph} \sum_{i=1}^{p} K\left(\frac{x_0 - x_{0i}}{h}\right) \tag{3}$$

where $(x_0 - x_{0i})$ is the distance from the element point x_0 to the location of the event x_{0i}, h is the bandwidth, which is usually greater than $0, k$ is the kernel function, p is the number of all observation points, and $f(x_0)$ is the kernel density, whose value is higher indicates the higher density of the distribution of the forest resources in that location. distribution is more dense.

II. B. 3) Scale index

Due to the differences in the distribution of forest resources of different ranks in each city, in order to reflect the scale of the distribution of forest resources in each prefecture-level city in Jiangxi Province, the scale degree index can be derived by comparing the number of forest resources that each city has with the area of the city in which it is located [20]. The formula is as follows:

$$G_i = \frac{n_i}{s_i} \tag{4}$$

where G_i is the scale degree of forest resources in the i city, n_i is the number of forest resources in the i city, and s_i is the area of the i city, and the larger the value of G_i is, the larger is the scale of the distribution of forest resources in the region.

II. B. 4) Buffer analysis method

In order to explore the natural factors of the spatial distribution of forest resources in prefecture-level cities in Jiangxi Province, this paper adopts the buffer zone analysis method. Buffer analysis is a spatial analysis method based on three types of points, lines and surfaces to establish polygons with different radius widths to analyze the scope and degree of association and influence between spatial objects and the surrounding things, environment and other aspects. The formula is as follows:

$$M_i = \{x : d(x, O_i) \le R\} = \{O_i : i = 1, 2, 3, \cdots, n\} M = cup_{i=1}^{n} M_i \tag{5}$$

The principle is that given an object M_i in a space, the radius R determines the size of its neighborhood. Where R is the longest radius of the object M_i, d is the radius of the polygon taking the Euclidean distance, M_i is the set of all points within the polygonal buffer with d as the radius, o is the multi-object set of the spatial target, and M is the buffer of the multi-object merged set with radius R.

II. B. 5) Remote sensing models of forest productivity

In this study, forest productivity was estimated using the Vegetation Photosynthesis Model (VPM), which is a light energy utilization model developed based on satellite remote sensing data and flux observation data, and the VPM model expression is:

$$GPP = \varepsilon_g \times FPAR_{chl} \times PAR \tag{6}$$

$$\varepsilon_g = \varepsilon_0 \times T_{scalar} \times W_{scalar} \times P_{scalar} \tag{7}$$

1) Linear fitting method

Firstly, based on the linear correlation between the annual forest productivity NPP data and the vegetation index EVI data at medium spatial resolution, we constructed a linear functional equation between the pure image element NPP data and the vegetation index EVI data, and secondly, we used all the cloud-free 30m spatial resolution Landsat-EVI summed and averaged during the growing season as the input data, and then calculated the 30m resolution annual forest productivity data with the help of the linear functional equation constructed above. The linear functional relationship equation constructed above is used to calculate the annual value data of forest productivity at 30m resolution. The specific steps include:

(1) Extraction of pure image elements

Based on the 30m-resolution vegetation type map (the first-level classification system of the vegetation type data includes cropland, woodland, grassland, etc.), determine whether the NPP is a pure image element by image element, i.e., if the vegetation types corresponding to the range of an intermediate-resolution NPP image element are the same, then the NPP image element is regarded as a pure image element. Iterate through all image elements and extract the pure image element NPP and its corresponding EVI image element value as a set of data.

(2) Construct correlation function

Several sets of pure image element data corresponding to each vegetation type are used as input data, and linear fitting is performed using the linfit function of ENVIUDL to obtain the fitting formula between NPP and EVI corresponding to each vegetation type, respectively:

$$NPP_c = a \times EVI_p + b \tag{8}$$

where, NPP_c is the vegetation productivity corresponding to the pure image element; EVI_p is the EVI value corresponding to the pure image element; a,b are the parameters to be fitted.

(3) Calculation of forest productivity at 30m resolution

Based on the parameters obtained from the fitting equation and the average value of Landsat_EVI at 30m resolution during the vegetation growing season, the estimation of NPP at 30m resolution in the experimental area was realized:

$$NPP_d = a \times Landsat_{EVI} + b \tag{9}$$

where, NPP_c is the calculated 30m spatial resolution vegetation productivity data; Landsat_EVI is the average of all cloud-free 30mEVI values during the vegetation growing season; a,b are the fitting parameters.

2) Time series fitting method

The linear fitting method cannot calculate the forest productivity data in time series, and cannot realize efficient, fast and real-time monitoring during crop growth. Therefore, this study utilizes a data fusion method estimated from MODIS data based on the trend of forest productivity changes in adjacent time series. The specific steps include:

(1) Extracting pure image elements: the extraction method is the same as the pure image element extraction method in the linear fitting method;

(2) Constructing the correlation function

Linear fitting is performed using the linfit function of ENVINDL to obtain the fitting formula between the pure image element NPP and its corresponding EVI value for each vegetation type, respectively:

$$mNPP_p(t_1,k_i) = a \times EVI_p(t_1,k_i) + b \tag{10}$$

where, $mNPP_p(t_1,k_i)$ is the pure image element NPP at 500m spatial resolution on day k_i of year t_1; The $EVI_p(t_1,k_i)$ is the EVI value corresponding to the pure image element NPP on day k_i of year t_l; a,b are the parameters to be fitted.

(3) Calculation of forest productivity at 30m resolution

With the help of the parameter a,b obtained from the above fitting method and the 30 mLandsat_EVI data, the 30 m spatial resolution of $mNPP_{30}(t_1,k_i)$ was calculated for day k_i of year t_1 with the following equation:

$$mNPP_{30}(t_1,k_i) = a \times EVI_{30}(t_1,k_i) + b \tag{11}$$

where, $mNPP_{30}(t_1,k_i)$ is the spatially resolved vegetation productivity data at 30m on day k_i of year t_1, as computed in equation (6); The $EVI_{30}(t_1,k_i)$ is the EVI for day t_1 of year k_i, obtained by banding the preprocessed Landsat data; a,b are the parameters obtained using the fitting function.

Based on the assumption that the temporal trends in vegetation productivity are similar for the same period, for the same vegetation type, and for different spatial resolutions, Eq:

$$\frac{mNPP_{500}(t_1,k_i)}{mNPP_{500}(t_1,k_j)}=\frac{mNPP_{30}(t_1,k_i)}{mNPP_{30}(t_1,k_j)}i,j\in[1,365] \tag{12}$$

where, $mNPP_{500}(t_1,k_i)$ is the 500m spatially resolved vegetation productivity on day k_i of year t_1; $mNPP_{500}(t_1,k_j)$ is the 500m spatially resolved vegetation productivity on day k_j of year t_1; $mNPP_{30}(t_1,k_i)$ is the 30m spatially resolved vegetation productivity on day k_i in year t_1, and $mNPP_{30}(t_1,k_j)$ is the t_l year to be calculated. 30m spatially resolved productivity on day k_j; i,j is a variable denoting any day from 1 to 365. Knowing the 500m spatial resolution productivity data for the time series of day k_i,k_j in year t_1 and the 30m spatial resolution productivity data for day k_i in year t_1, Equation (7) yields the t_1 year k_j day 30m spatial resolution productivity data as shown in equation (13):

$$mNPP_{30}(t_1,k_j)=\frac{mNPP_{30}(t_1,k_i)\times mNPP_{500}(t_1,k_j)}{mNPP_{500}(t_1,k_i)}i,j\in[1,365] \tag{13}$$

Based on the above method to traverse the 500m spatial resolution productivity data on day k_j of year t_1, calculate the time-series 30m spatial resolution vegetation productivity data on day k_j of year t_1, and finally accumulate all the 30m NPP data of year t_1 for the period of 8d. The annual 30m spatially resolved vegetation productivity data for year t_1 can be obtained.

III. Spatial distribution and dynamic analysis of forest resources in Jiangxi Province

This chapter will analyze the spatial distribution characteristics of forest resources in Jiangxi Province from the aspects of spatial distribution type, spatial distribution structure and dynamic changes of forest resources.

III. A. Analysis of spatial distribution types

Combined with the significance level P value and critical value Z of the nearest neighbor index, the distribution types of counties and districts in Jiangxi Province were further analyzed, and the results are shown in Table 1. The spatial distribution types corresponding to the significance level P value and critical value Z are as follows:

1) When P > 0.1 and -1.65 ⩽ Z ⩽ 1.65, the type of distribution does not significantly tend to be random.
2) When 0< P <0.1 and Z <-1.65, the distribution tends to be aggregated.
3) When 0< P <0.1 and Z >-1.65, the distribution type tends to disperse.

From the calculation results in the table, it can be seen that the North Gan, West Gan and South Gan regions are random types, the North-East Gan region is decentralized type, and the Central Gan region is aggregated type. Obviously, the distribution of each region in Jiangxi Province varies greatly.

Table 1: The nearest neighbor index and distribution type of forest resource points

Region	North Jiangxi	Northeast Jiangxi	West Jiangxi	Central Jiangxi	Gannan
Average observation distance (km)	3.0444592	5.598376	4.24799	3.290296	2.594112
Expected average distance (km)	2.5275458	3.04009	3.96135	4.125046	2.624769
The nearest neighbor ratio R	1.204938	1.840559	1072400	0.79683	0.988696
Z score	1.56524	3.942882	0.437277	-1.73192	-0.10474
P	0.118257	0.00043	0.006624	0.082166	0.917271
Distribution type	Random	Dispersed	Random	Gathering	Random

III. B. Analysis of spatial distribution structure

III. B. 1) Spatial distribution hotspot analysis

The hotspot map of spatial distribution of forest resources in Jiangxi Province is specifically shown in Figure 1. According to Kenks's natural discontinuity method, the distribution of forest town resource points in east Fujian is categorized into four levels, with 1~3 as hotspots, -1~1 as sub-hotspots, -2~-1 as sub-coldspots, and -3 or less as coldspots. It can be seen that the distribution trend of forest resource points in Jiangxi Province is relatively obvious, with hotspots relatively concentrated and sub-hotspots, sub-coldspots and coldspots relatively dispersed.

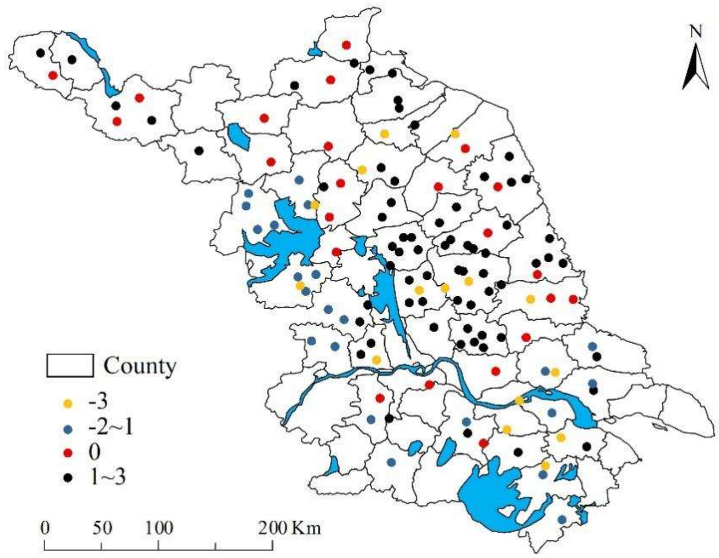

Figure 1: Hot spot distribution of forest resources

III. B. 2) Distance analysis of spatial distribution

1) Distance between forest resource points and county (district) centers

Take the city and county center point as the source market, analyze the law of different spatial distances on the change of the increase or decrease of the number of forest resource points. The fitted distance of forest resource points from county (district) government is specifically shown in Figure 2. The fitting curve is Y. The buffer distance of 15~25km accounted for 76.36% of the total number of resource points, and with the increase of the spatial buffer distance, the number of resource points showed a trend of increasing and then decreasing, forming a high-density ring, and the fitting value $R^2=0.9435$, which is a good fit.

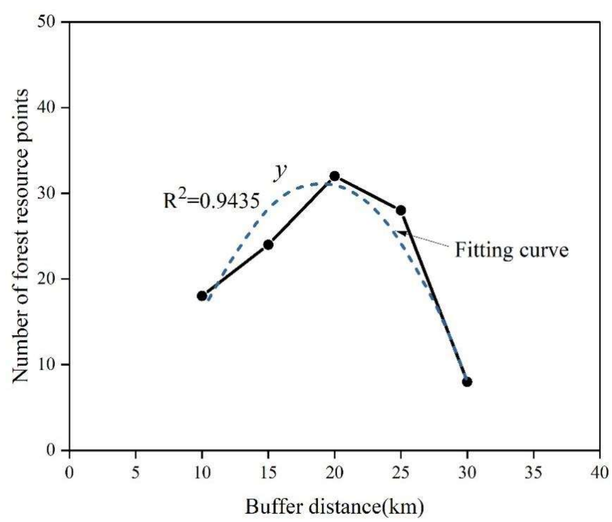

Figure 2: Distance between forest resource point and county center

2) Distance of forest resource points from prefecture-level city centers

Taking Nanchang People's Government as the center, the distance of forest resource points from prefecture-level city center was fitted, as shown in Figure 3. The fitting curve is Y. With the increase of spatial buffer distance, the number of resource points shows a trend of increasing and then decreasing, and the buffer distance of 40~80km accounts for 75.4% of the total number of resource points, forming a high-density ring, with the fitting value of $R^2=0.9231$, which is a good degree of fitting.

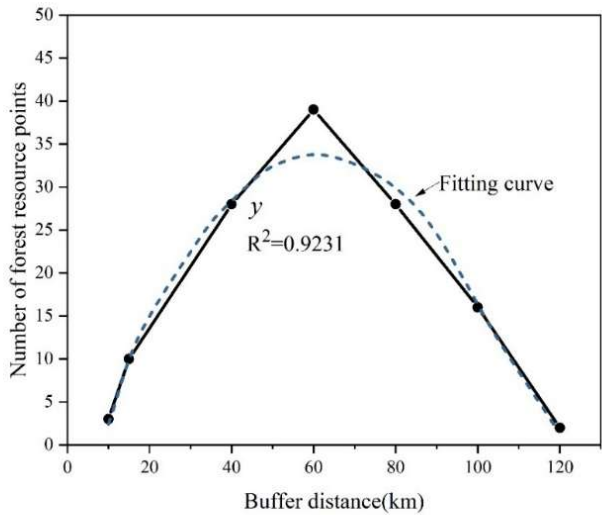

Figure 3: Distance between forest resource points and prefecture-level city centers

III. C. Analysis of changes in forest resource dynamics

In order to better integrate the ecological background of the study area, this study analyzed the spatial combination of rainfall and forest dynamics. The forest area in Jiangxi Province in 2014 and 2024 within different rainfall gradients is shown in Figure 4. It can be seen that most of the forests in Jiangxi Province are distributed in areas where the average annual rainfall is greater than 400 mm, and 89% and 86% of the forests are distributed in areas where the average annual rainfall is between 400 mm and 800 mm in 2014 and 2024, respectively.

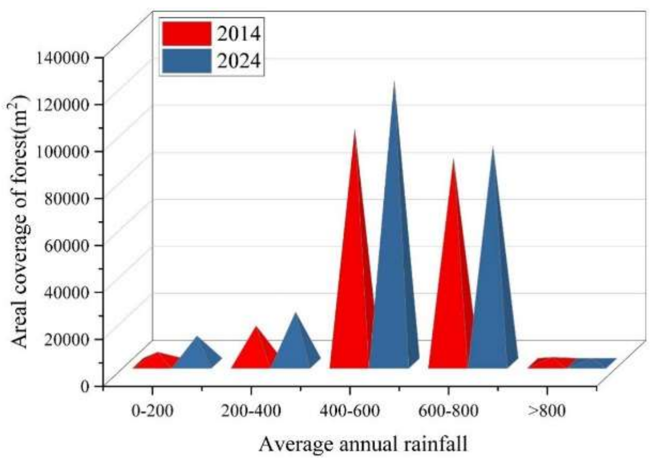

Figure 4: Forest area in different precipitation gradient zones in 2014 and 2024

For each rainfall gradient zone, this study calculated the area of forest growth, area of forest loss, forest loss rate, and forest growth rate. Here, the forest loss rate refers to the ratio of the area of forest loss to the area of forest in 2014-2024, the forest growth rate refers to the ratio of the area of forest growth to the area of forest in 2014-2024, and the net growth rate is the ratio of the area of forest growth minus the area of forest loss to the area of forest in 2014-2024 and to the area of forest in 2014. The area of forests within different rainfall gradient zones in Jiangxi Province as well as the dynamic changes are specifically shown in Table 2. In terms of forest growth, it can be found that there are different degrees of forest growth within each rainfall gradient zone, and the growth rate of forests in humid areas with average annual rainfall greater than 400 mm is 13.64%, with a lower net growth rate than that in arid and semi-arid areas with average annual rainfall less than 400 mm (61.2%). In addition, forest loss in Jiangxi Province cannot be ignored, with more than 20% forest loss in each rainfall gradient area in the whole study area, and the rate of forest loss in the area with an average annual rainfall of less than 200 mm amounted to 43.81%, that is to say, more than 40% of forests in the rainfall gradient area were turned into non-forests in 2007. The rate of forest loss in areas with an average annual rainfall of less than 400 millimeters (i.e., arid and semi-arid areas) was 34.86 per cent, which is higher than in humid and semi-humid areas with an average annual rainfall of more than 400 millimeters (25.43 per cent).

Table 2: Forest area and changes in different precipitation zones

-	0–200mm	200–400mm	400–600mm	600–800mm	>800mm	0–400mm	>400mm
Forest surface in 2014(m2)	4793	16016	99618	87258	2098	20848	189250
Forest surface in 2024(m2)	11617	21901	120527	92304	2114	33607	215055
Forest growth(m2)	8924	11135	46756	26716	490	20027	73929
Forest growth rate	186.19%	69.52%	46.94%	30.62%	23.36%	96.06%	39.06%
Forest loss(m2)	2100	5250	25847	21670	474	7268	48124
Forest loss rate	43.81%	32.78%	25.95%	24.83%	22.59%	34.86%	25.43%
Net forest change(m2)	6824	5885	20909	5046	16	12759	25805
Net forest growth rate	142.37%	36.74%	20.99%	5.78%	0.76%	61.20%	13.64%

In order to better explore the statistical relationship between forest loss and rainfall in Jiangxi Province from 2014 to 2024, this study used a finer average annual rainfall interval of 20 mm, and then generated 43 rainfall gradient zones such as 0-20,20-40,40-60. Similarly, this study calculated the forest loss rate for each rainfall gradient zone and analyzed the variation of forest loss rate along the rainfall gradient. Finally, this study conducted a linear least squares regression analysis between the forest loss rate values and the mean annual rainfall values for the period from 2014 to 2024. The results of the regression analysis between the forest loss rate values and the mean annual rainfall values are shown in Fig. 5, and it was found that there was a significant negative correlation between the forest loss rate and the mean annual rainfall, with a slope of 0.04%/mm, where the p-value was less than 0.01, and the R^2 was 0.41. That is to say, the forest loss rate of the areas with a mean annual rainfall of less than 400 mm (i.e., the arid and semi-arid areas) was significantly higher than that of the areas with a mean annual rainfall of more than 400 mm. In other words, the rate of forest loss was significantly higher in the humid and semi-humid areas where the average annual rainfall was higher than 400 mm.

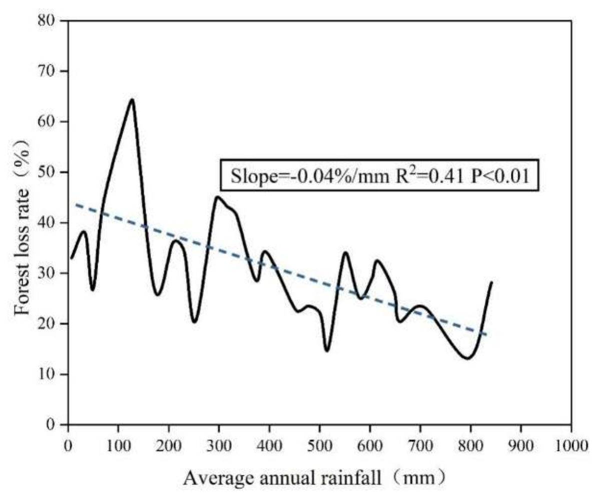

Figure 5: Linear regression analysis between annual precipitation and ratio of forest

IV. Conclusion

The study shows that the forest resources in Jiangxi Province show an overall growth trend during the period from 2014 to 2024, especially the growth of forest area in humid areas is more significant. The growth rate of forests in regions with higher average annual precipitation, such as wet regions with annual precipitation between 400 and 800 mm, is 13.64%. In arid regions, on the other hand, the forest growth rate was lower, with a net growth rate of only 61.2%. Through dynamic monitoring, it was found that the rate of forest loss within different rainfall gradient zones showed significant differences. In particular, the forest loss rate in the zones with average annual precipitation below 400 mm was as high as 43.81%, showing that the forest resources in these zones are facing greater ecological threats. Forest productivity estimation using remote sensing technology also showed a significant positive correlation between precipitation and forest productivity. In the future management of forest resources, more attention must be paid to forest protection in arid and semi-arid regions and to strengthening the monitoring of sustainable development in humid regions.

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