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Remote Sensing-Based Study of Plant Cover and Urbanization in Kunming from 2000 to 2022

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Abstract: Reduced vegetation cover due to accelerated urbanization can lead to many ecological problems, and whether ecological conservation measures can effectively mitigate this effect remains to be assessed. This paper explores the influence of urbanization on vegetation cover and the performance of related ecological protection measures in Kunming. This paper reveals the significant negative correlation between NDVI and NDBI data during the period of 2000-2022 through linear regression analysis and Pearson correlation analysis, and combines spatial analyses to demonstrate the changes of vegetation cover in Kunming during the urbanization process. The study results indicated that the NDVI in Kunming City as a whole had a slow increasing trend, with 0.0020 per year, and NDBI had a slow decreasing trend with 0.0014 per year. And they are significantly negatively correlated with a Pearson correlation coefficient of -0.6168. In addition, the vegetation cover in non-urban areas and the area around Dianchi Lake has increased considerably, indicating that the ecological protection measures in the region are effective, but the vegetation cover in urban areas has still declined. The study provides an important scientific basis for ecological protection policies and sustainable urban planning in similar cities, and promotes urban ecological protection and green development.

Keywords: NDVI, NDBI, Kunming

1. Introduction

Urban expansion changes the land use pattern, which usually leads to a decrease in vegetation cover, and there is a significant negative correlation between the two [1]. This change not only affects the regional ecological balance but also may exacerbate environmental problems, such as biodiversity reduction and soil erosion [2]. In the context of rapid urban development, ecological conservation and restoration measures have emerged and are widely used to mitigate the negative impacts of urban expansion on vegetation [3]. Therefore, it is important to study the impacts of urbanization on vegetation cover and the effectiveness of related treatment programs to develop sustainable urban planning and ecological strategies.

Recent studies utilizing remote sensing have advanced in exploring the link between urbanization and changes in vegetation cover. Some studies have revealed the negative impact of urbanization on vegetation cover by analyzing Normalized Difference Vegetation Index (NDVI) and Normalized Difference Built-up Index (NDBI) data [4]. However, most of these studies focus on economically developed and rapidly urbanizing regions, and studies on regions adopting ecological policies are on the low side. Kunming, an important city in southwest China, has experienced rapid urban expansion

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in recent years, prompting the municipal government to adopt various ecological measures aimed at reducing urbanization's adverse effects on vegetation [5,6]. However, the actual effects of these measures have not been fully evaluated, and this study will fill this gap.

This study will take Kunming as an example, and linear regression and Pearson correlation analysis were used to examine the quantitative relationship between NDVI and NDBI from 2000 to 2022 in Kunming. In addition, the spatial analysis method was used to compare the NDVI and NDBI change maps in 2000 and 2022 to visualize the spatial change of vegetation cover during urbanization. This study aims to reveal the effects of urbanization on vegetation cover and assess the actual effects of ecological protection measures, which will provide scientific basis for ecological protection and urban planning in Kunming and other similar cities, and promote sustainable urban development.

2. Data and methods

2.1. Study area

This paper takes Kunming City as the study area, which is located in the central part of Yunnan Province, China, with a longitude of 102°10′-103°40′E, a latitude of 24°23′-26°33′N, and a total area of 21,012.54 km^2. It has a low-latitude highland mountainous monsoon climate, with an average annual sunshine of about 2,200 hours and the average annual precipitation is about 1,000 mm, which makes the city famous as the ‘Spring City’ [5]. Figure 1 shows the land use types in Kunming, from which it can be seen that the study area is dominated by vegetation cover. There is a large natural lake, Dianchi, in the southwest, and major urban clusters are built around it. And there is more agricultural land in the east of the study area. Due to the long term presence of water bloom in Dianchi Lake, which has a significant effect on the remote sensing data, the area of Dianchi Lake and other water body areas are excluded from this study[7].

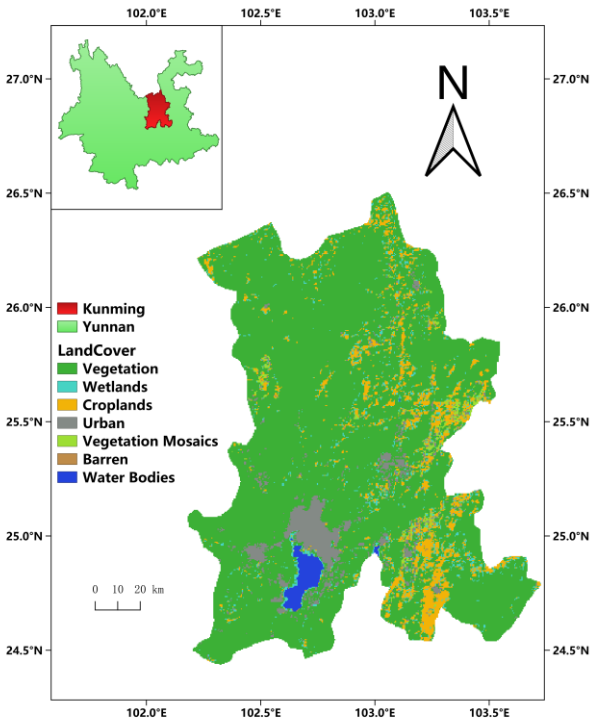

Figure 1: Land use types in Kunming

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2.2. Data sources and data pre-processing

In this paper, the annual data of the study area for 22 years from January 2000 to December 2022 were selected, and the remotely sensed image data were derived from the MODIS-NDVI vegetation index product and MODIS-NDBI building index product, which were acquired via Google Earth Engine. NDVI is a widely used indicators of vegetation cover, which is primarily because green vegetation exhibits higher reflectance in the near-infrared band (NIR) and lower reflectance in the red band (RED), and is calculated by the following formula:

$$\mathrm{NDVI} = \frac{\mathrm{NIR-RED}}{\mathrm{NIR+RED}} \tag{1}$$

The NDVI data used in this paper were derived from the MODIS MOD13Q1 dataset with a spatial resolution of 250 m and a temporal resolution of 1 year [8]. NDBI is commonly used for urbanization level and construction land identification, which is mainly based on the fact that urban construction materials have high reflectance in the short-wave infrared band (SWIR) and low reflectance in the near-infrared band (NIR), and is calculated by the following formula:

$$\mathrm{NDBI} = \frac{\mathrm{SWIR-NIR}}{\mathrm{SWIR+NIR}} \tag{2}$$

The NDBI data utilized in this research were extracted from the MODIS MOD09A1 dataset, which has a temporal resolution of 1 year and spatial resolution of 500 m [9,10].

Both NDVI data and NDBI data were processed in the Google earth engine using the maximum value synthesis method (3) for both NDVI data and NDBI data for cloud cover and missing values.

$$\mathrm{I_{composite}}(\mathrm{t}) = \max\left(\mathrm{I_1(t), I_2(t), \ldots, I_n(t)}\right) \tag{3}$$

where $\mathrm{I_{composite}}(\mathrm{t})$ denotes the value of the synthesized image at time t. The maximum value of each pixel during the time period is selected. Specifically, for each pixel point, the value is calculated using equation (4).

$$\mathrm{I_{composite}}(\mathrm{x,y}) = \max\left(\mathrm{I_1(x,y), I_2(x,y), \ldots, I_n(x,y)}\right) \tag{4}$$

where (x, y) are the spatial coordinates in the image. The maximum value synthesis method selects the maximum value of each year's data to be synthesized into the remote sensing image data for that year, minimizing the interference of cloud cover. Both NDVI and NDBI remotely sensed images were cropped and masked in Google earth engine using the administrative boundaries provided by the FAO/GAUL/2015/level2 dataset and hand-drawn Dianchi boundary. A numerical scaling of 1:10,000 was carried out to make the values of the NDVI and NDBI data between -1 and 1.

In this paper, the time series aggregation of .tiff images of NDVI data and NDBI data was processed based on the mean value formula (5), so that the remotely sensed image maps were transformed into a time series of the mean values of NDVI and NDBI in the study area for subsequent analysis.

$$\mathrm{Mean} = \frac{1}{\mathrm{N}} \sum_{\mathrm{i=1}}^{\mathrm{N}} \mathrm{x_i} \tag{5}$$

where N represents the number of pixels in the image and x_i is the value of each pixel.

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2.3. Analytical method

2.3.1. Linear regression analysis

In this study, linear regression analysis was used to quantify the trend of vegetation cover in the study area from 2000 to 2022. Linear regression assumes a linear relationship between time and NDVI. The specific model is expressed as:

$$y = \beta_0 + \beta_1 x \tag{6}$$

where y represents the mean value of NDVI in the study area for each year; x is the year for each year; β_0 represents the intercept of the regression equation; and β_1 represents the change in NDVI in the study area for each year, and is the magnitude of the change in vegetation cover from one year to the next. β_1 is calculated from equation (7).

$$\beta_1 = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sum_{i=1}^{n}(x_i - \overline{x})^2} \tag{7}$$

where x_i and y_i are the year and NDVI value, $\overline{x}$ and $\overline{y}$ are the mean of the year and NDVI value, respectively, and n is the total number of years of data.

In this paper, the coefficient of determination R^2 was used to measure the goodness of fit of the regression model. The closer the value of R^2 is to 1, the better the model fits the data, and the more the independent variable, year, explains the dependent variable, NDVI. The specific calculation formula is as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y})^2} \tag{8}$$

where y_i is the actual NDVI data for each year, $\hat{y}_i$ is the NDVI value predicted by the regression equation, $\overline{y}$ is the mean of all actual NDVI data, and n is the total number of years of data.

This method also was used to analyze the trend of NDBI in the study area from 2000 to 2022 in this paper.

2.3.2. Pearson correlation analysis

In order to further examine the correlation between NDVI and NDBI in the study area between 2000 and 2022, this paper conducted Pearson's correlation analysis on the series of annual mean values of both [4]. This paper utilized the Pearson correlation coefficient to assess the linear correlation between NDVI and NDBI. The Pearson correlation coefficient assesses the strength of the linear association between two sets of variables, with values spanning from -1 to 1. A coefficient near 1 or -1 suggests a strong correlation, whereas a coefficient of 0 implies no linear relationship. The Pearson correlation coefficient is calculated by this equation:

$$r = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2} \cdot \sqrt{\sum_{i=1}^{n}(y_i - \overline{y})^2}} \tag{9}$$

where x_i and y_i denote the NDVI and NDBI values for year i, respectively, $\overline{x}$ and $\overline{y}$ are the annual average values of NDVI and NDBI, respectively, and n represents the total number of years of data. In addition, in order to determine whether the correlation is statistically significant, this paper also calculates the significance level of the correlation, which is the p-value. The p-value is employed to determine the validity of the null hypothesis, which posits that there is no connection between NDVI and NDBIWhen the p-value falls below the significance threshold of 0.05, it means that the correlation is statistically significant and the null hypothesis is rejected as there is a significant correlation between the two.

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2.3.3. Spatial analysis

In order to analyze the spatial changes of vegetation cover and urbanization process in the study area, only NDVI and NDBI remote sensing image maps of 2000 and 2022 were selected for the spatial scale comparative analysis in this paper, and based on Eq. (10) and Eq. (11), this variable was calculated for NDVI and NDBI in the study area from 2000 to 2022 respectively, which was plotted as a map to be used for analyzing NDVI and NDBI in the area where the change in NDVI and NDBI occurred.

$$\mathrm{NDVI_{change}} = \mathrm{NDVI_{2023}} - \mathrm{NDVI_{2000}} \tag{10}$$

$$\mathrm{NDBI_{change}} = \mathrm{NDBI_{2023}} - \mathrm{NDBI_{2000}} \tag{11}$$

3. Results

3.1. Linear regression analysis

Figure 2 (a) shows the trend of annual mean NDVI values in the study area from 2000 to 2022. It is evident from the figure that the annual mean NDVI values in the study area fluctuated between 0.7512 and 0.8128, and the overall trend showed a slow increase, indicating that the vegetation cover in the study area showed a slow improvement during the study period. 2008, 2015 to 2022 were years of lush vegetation with high overall vegetation cover, with the highest NDVI value reaching 0.8128 in 2022; the lowest was 0.7512 in 2000. The red line in Figure 2 (a) is a linear regression line, and the slope of regression is 0.0020, indicating that the annual mean NDVI value increases by about 0.0020 per year; $R^2 = 0.7034$, indicating that the regression model can explain about 70.34% of the variation of NDVI.

Figure 2 (b) shows the trend of annual mean value of NDBI in the study area during the period from 2000 to 2022. It is evident from the figure that the annual mean value of NDBI in the study area fluctuates between 0.0310 ~ 0.0789, and the overall trend shows a slow decline, indicating that the overall building density in the study area had a downward tendency during the study period of time. The overall building density was the highest in the year 2001, with an NDBI value of 0.0789, and the lowest in the year 2022, with an NDBI value of 0.0310, and the NDBI fluctuated more significantly between 2007 and 2017. The red line in Figure 2 (a) is a linear regression line, and the slope of regression is -0.0014, indicating that the annual mean NDVI value decreased by about 0.0014 per year; $R^2 = 0.5884$, indicating that the regression model can explain about 58.84% of the variation of NDBI.

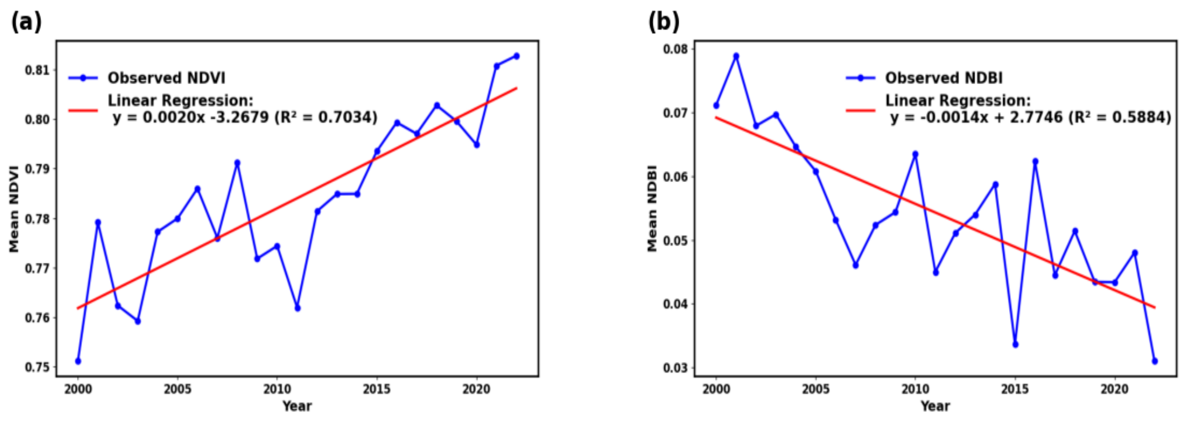

Figure 2: (a) NDVI trend (2000-2022) in Kunming (b) NDBI trend (2000-2022) in Kunming

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3.2. Correlation analysis

Figure 3 illustrates the correlation between the annual mean values of NDVI and NDBI in the study area from 2000 to 2022. The Pearson correlation coefficient of NDVI and NDBI from 2000 to 2022 is -0.6168, which implies that there is a moderately strong negative correlation between the two. That is, with the advancement of urbanization, the vegetation cover in the study area shows an increasing trend year by year, while the level of urbanization gradually decreases. The significance level of 0.0017, much less than the commonly used significance level of 0.05, further verifies the statistical significance of the negative correlation between NDVI and NDBI. Therefore, it can be concluded that the negative correlation between vegetation cover and urbanization level is significant in urbanization process of the survey region, suggesting that ecological conservation measures may have mitigated the adverse effects of urbanization on vegetation to a certain extent.

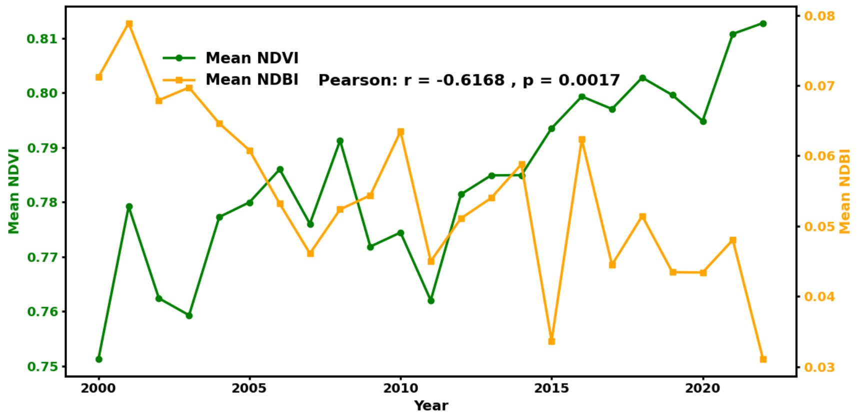

Figure 3: Correlation of NDVI&NDBI (2000-2022) in Kunming

3.3. Spatial analysis

Figure 4 (a) shows the difference in the values of NDVI in the survey region during 2000 and 2022. It is evident that in the urban areas of the survey region, there is a significant decrease in the NDVI, which is shown in red color, indicating that these areas may have been deforested with a lot of vegetation due to urban development. Figure 4 (b) shows the variation among the NDBI of the study region in the year 2000 and in the year 2022, and it is evident that in the urban centers of the survey region and its surrounding areas, there is a significant increase in the NDBI values. These areas are shown in red, indicating that these areas have become more urbanized and may have experienced a lot of building development, infrastructure construction, and land transformation. Areas of increased NDBI tend to correspond to areas of decreased NDVI, suggesting that the urbanization process in the study area is still resulting in decreased vegetation cover in urban areas. However, the NDVI in non-urban areas and along Dianchi Lake increased significantly, and the NDBI in the corresponding areas also decreased significantly. Combined with the correlation analysis of the overall NDVI and NDBI above, it can be seen that the local government's afforestation project in non-urban areas and the wetland construction project along Dianchi Lake still offset the negative impacts of urban development on the vegetation cover on the overall scale, and its vegetation cover is still growing slowly. However, the construction of green belts in urban areas has still not been able to offset the effects of urbanization on plant cover. This may also be due to the low spatial resolution of the MODIS sensors, thus ignoring the effect of small-scale green belt construction within the city.

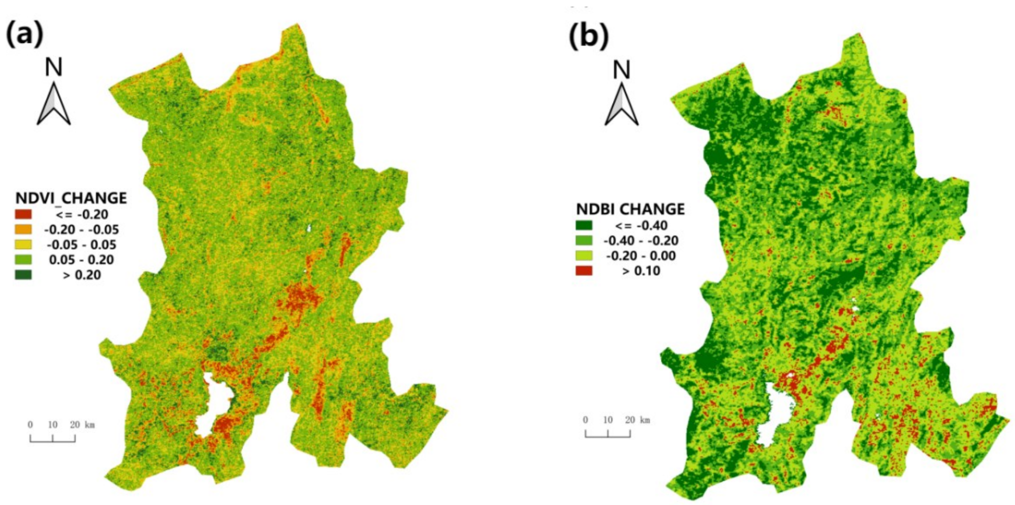

Figure 4: (a) NDVI change (2000-2022) (b)NDBI change (2000-2022)

4. Conclusion

This paper used linear regression analysis and Pearson correlation analysis to analyze the NDVI and NDBI data of Kunming City from 2000 to 2022, and found that the NDVI showed a slow increasing trend, about 0.0020 per year, and the study could explain 70.34% of the NDVI changes, the NDBI showed a slow decreasing trend, about 0.0014 per year, and the study could explain 58.84% of the changes in NDBI, and the changes in NDVI and NDBI demonstrated a significant negative correlation, and the correlation coefficient is -0.6168. In addition, this paper also used spatial analysis method to compare the maps of the changes in NDVI and NDBI of Kunming City in the year 2000 and the year 2022, and found that the NDVI in the urban area was significantly lower and the NDBI was significantly higher, and that in the non-urban area as well as along the Dianchi Lake, the NDVI increased and NDBI decreased. However, the remote sensing data are greatly affected by atmospheric and other factors, as well as the low spatial resolution of the MODIS sensors, which has a certain impact on the accuracy of this study. In future studies, remote sensing data from sensors with higher spatial resolution, such as Landsat, can be used to study the main urban areas where buildings are more concentrated, so as to further assess the role of ecological construction measures, such as the construction of green belts in urban areas, in mitigating the impacts of urbanization on plant cover.

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