Vegetation Change and Its Stress Analysis in the Pearl River Basin (2004-2013): Postprint

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Abstract

Vegetation plays a crucial role in regional climate regulation and hydrological cycling. Against the backdrop of increasingly frequent extreme climate events in southern China in recent years, investigating vegetation dynamics and associated stressors is of paramount significance. This study takes the Pearl River Basin as the research area, utilizing MODIS EVI to analyze vegetation change patterns, and explores the stresses imposed by human activities and the natural environment on vegetation changes through DMSP night light data from US military meteorological satellites and meteorological data. The results demonstrate that: from 2004 to 2013, the annual mean EVI in the Pearl River Basin ranged between 0.33 and 0.38, with EVI values decreasing in the following order: evergreen broadleaf forest > mixed forest > wooded grassland > evergreen coniferous forest > grassland. The EVI change trends among different vegetation types were essentially consistent, while interannual variations of EVI for the same vegetation type were relatively minor. Specifically, the maximum interannual changes for mixed forest and grassland were 0.07 and 0.04, respectively, whereas those for evergreen broadleaf forest, evergreen coniferous forest, and wooded grassland were all 0.06. During 2004–2013, the urbanization level increased by approximately 71%, with its annual development trend being opposite to that of EVI. Comparative analysis reveals that human activities exert a greater influence on vegetation changes in the Pearl River Basin than the natural environment, as evidenced by the correlation coefficient between DMSP night light changes and EVI changes being significantly higher than those for temperature and precipitation.

Full Text

Preamble

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Analysis of Vegetation Variation and Stress Factors in the Pearl River Basin from 2004 to 2013

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Abstract

Vegetation plays a crucial role in regional climate regulation and hydrological cycling. Against the backdrop of increasingly frequent extreme climate events in southern China in recent years, studying vegetation dynamics and their driving stresses is of significant importance. This research selected the Pearl River Basin as the study area and analyzed vegetation variation patterns using MODIS Enhanced Vegetation Index (EVI) data. The study examined stresses from both human activities and natural environments, utilizing Defense Meteorological Satellite Program (DMSP) nighttime light data and meteorological data.

The results show that the annual average EVI in the Pearl River Basin ranged from 0.33 to 0.38 during 2004–2013. Across vegetation types, EVI values decreased in the following order: evergreen broad-leaved forest > mixed forest > woody savannas > evergreen coniferous forest > grassland. Interannual variation was relatively small for all vegetation types, with maximum annual variations of 0.04 for mixed forests and grasslands, and 0.06 for evergreen broad-leaved forests. Urbanization levels increased by approximately 71% during this period. Comparative analysis revealed that human activities exerted a stronger influence on vegetation changes than natural environmental factors. Nighttime light changes showed opposite trends to EVI changes, with correlation coefficients significantly higher than those for temperature and precipitation. This indicates that human activity is the dominant stress factor driving vegetation changes in the Pearl River Basin.

Keywords: EVI; DMSP; vegetation change; Pearl River Basin

1. Introduction

Vegetation changes significantly impact energy balance, climate, and biochemical environments, serving as a sensitive indicator of environmental responses to climate and human activities [1-3]. Studying the patterns of natural vegetation change and their influencing factors is therefore of great significance.

Current research primarily focuses on spatiotemporal vegetation variations and their relationships with natural elements [4-8]. Zhou et al. [9] used MODIS data to analyze urbanization impacts on vegetation phenology, providing robust evidence for vegetation responses to global warming. Zhang et al. [10] analyzed global carbon cycles through precise estimation of net primary productivity. Zhang et al. [11] examined spatiotemporal changes in vegetation coverage and biomass in temperate deserts using remote sensing. Zhang et al. [12] studied the effects of summer drought on vegetation growth, which is crucial for predicting impacts of future extreme climate events on vegetation ecosystems. Tian et al. [13], Su et al. [14], and others used remote sensing to monitor vegetation dynamics. Suepa et al. [15] investigated spatiotemporal variations in vegetation phenology and seasonal precipitation in Southeast Asia.

However, few studies have determined which factor—natural or anthropogenic—dominates vegetation changes. In recent years, extreme climate events have become frequent globally, with droughts occurring even in humid southern China, significantly impacting regional vegetation growth. This underscores the urgent need to strengthen research on vegetation dynamics and influencing factors in southern China.

This study analyzes vegetation changes in the Pearl River Basin from 2004 to 2013 using MODIS EVI data, meteorological precipitation and temperature data from the China Meteorological Data Network, and DMSP nighttime light data to examine stresses from human activities and natural environments.

2. Study Area

The Pearl River Basin is located in southern China (102°14 -115°53 E, 21°31 -26°49 N) and represents a crucial economic zone. The region features a south subtropical climate with abundant water resources, abundant sunshine, and annual precipitation of 1,400–2,000 mm in most areas. The basin is predominantly mountainous and hilly, with small, scattered plains. The coldest month average temperature is 10°C, and extreme minimum temperatures are -4°C. Vegetation community types are diverse, mainly including evergreen broad-leaved forests, evergreen coniferous forests, mixed forests, woody savannas, and grasslands, with high overall vegetation coverage.

[Figure 1: see original paper] Location of study area and meteorological stations

3. Data and Processing

3.1 Vegetation Data

Vegetation data were derived from MODIS vegetation index products (MOD13Q1) at 250 m spatial resolution, covering tiles h27v06, h27v07, h28v06, and h28v07 for 2004–2013. Vegetation type data were obtained from MODIS LANDUSE products at 500 m resolution, using the University of Maryland land cover classification system. The main vegetation types in the study area are evergreen broad-leaved forest, evergreen coniferous forest, mixed forest, woody savannas, and grasslands.

3.2 Nighttime Light Data

For urbanization level analysis, DMSP/OLS (Defense Meteorological Satellite Program/Operational Linescan System) nighttime light data were used. These data have a spatial resolution of 1 km and strong correlations with population and economic levels, making them effective for monitoring urbanization and human activities [18-20].

3.3 Meteorological Data

Daily precipitation and mean temperature data from 44 national basic meteorological stations within the Pearl River Basin were obtained for 2004–2013. Data preprocessing included image reprojection and clipping to the study area boundary.

3.4 Enhanced Vegetation Index

Common vegetation indices include NDVI and EVI. However, NDVI suffers from saturation issues in high vegetation cover areas [17]. EVI addresses this limitation and effectively reduces atmospheric interference. Given that the study area in southern China has relatively high vegetation coverage and complex climate conditions, EVI was selected for comprehensive vegetation analysis. The EVI calculation formula is:

$$EVI = 2.5 \times \frac{band2 - band1}{band2 + 6 \times band1 - 7.5 \times band3 + 1}$$

where band1 represents the red band, band2 the near-infrared band, and band3 the blue band.

EVI data were aggregated to monthly, quarterly, and annual scales using the following formulas:

- Monthly EVI: $EVI_m = EVI_i + EVI_j$ (where EVI_i is the first half-month EVI and EVI_j is the second half-month EVI)
- Quarterly EVI: $EVI_s = EVI_{mi} + EVI_{mj} + EVI_{mk}$ (for spring, summer, and autumn respectively)
- Annual EVI: $EVI_y = EVI_{si}+EVI_{sj}+EVI_{sk}+EVI_{sh}$ (for spring, summer, autumn, and winter)

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4. Methods

4.1 Vegetation Change Analysis

The study calculated annual average EVI values for the Pearl River Basin from 2004–2013 and performed statistical analysis. Results show that annual average EVI experienced a gradual increase from 2004 to 2008, followed by a fluctuating decline from 2008 onward, though the downward trend was not statistically significant. The overall range was 0.33–0.38.

[Figure 2: see original paper] The EVI evolution from 2004 to 2013

Analysis of different vegetation types revealed consistent trends across types, with small interannual variations. Maximum interannual variations were 0.04 for mixed forests and grasslands, and 0.06 for evergreen broad-leaved forests, evergreen coniferous forests, and woody savannas.

[Figure 3: see original paper] The statistic of mean yearly EVI from 2004 to 2013

Seasonal analysis of the five vegetation types showed: - **Spring (March–May)**: EVI values ranked as evergreen broad-leaved forest > mixed forest > woody savannas > evergreen coniferous forest > grassland, with relatively high values and small differences between types. - **Summer (June–August)**: Similar ranking, with values at their annual peak and minimal interannual variation. - **Autumn (September–November)**: Similar ranking, with moderate values and small fluctuations. - **Winter (December–February)**: Similar ranking, but with the lowest annual values.

Overall, evergreen broad-leaved forests showed small seasonal variations, while grasslands exhibited large seasonal changes.

[Figure 4: see original paper] The EVI of different vegetation types changes from 2004 to 2013
[Figure 5: see original paper] The EVI changes from 2004 to 2013 in different seasons

4.2 Urbanization Stress Analysis

Rapid urban development, heat island effects, and increased carbon emissions affect regional climate and vegetation growth. This study used DMSP/OLS data to calculate annual average light values for each pixel in the Pearl River Basin as a measure of urbanization intensity, where higher values indicate greater urbanization.

The average pixel brightness reflects economic development and urbanization levels, but its development is gradual and constrained by development stage and space. Using 2004 as the baseline year, the average brightness decreased in 2005, indicating initial development stages with low overall levels despite spatial expansion. As development deepened, levels increased, reaching a new plateau in 2013. Overall, urbanization levels increased by approximately 71% from 2004–2013, with an average annual growth of 7.1%.

[Figure 6: see original paper] The light data of DMSP from 2004 to 2013
[Figure 7: see original paper] The average lights from 2004 to 2013

4.3 Natural Environment Change Analysis

Using daily precipitation and temperature data from 44 meteorological stations, the study constructed 12×44 matrices for monthly precipitation and temperature, then calculated seasonal and annual averages.

Annual precipitation showed large fluctuations, with the lowest precipitation in 2011. Years below the average accounted for 40% of the study period (2004, 2007, 2009, 2011), coinciding with major drought events in Guangdong and Guangxi. Seasonal precipitation ranked as summer > spring > autumn > winter, with consistent seasonal patterns across years. However, interannual precipitation variation was inconsistent with vegetation changes, indicating that vegetation dynamics result from combined natural and anthropogenic factors rather than precipitation alone.

Annual mean temperature also showed large variations, with a difference exceeding 1°C between the highest and lowest years. Half of the years had temperatures below the long-term average. Seasonal temperature fluctuations were largest in winter, while summer and autumn showed relatively high and stable temperatures.

[Figure 8: see original paper] The average annual precipitation from 2004 to 2013 of rain gauging stations
[Figure 9: see original paper] The quarter average precipitation from 2004 to 2013 of rain gauging stations
[Figure 10: see original paper] The average annual temperature from 2004 to 2013
[Figure 11: see original paper] The quarter average temperature from 2004 to 2013

5. Discussion

To further explore relationships between vegetation change and human activities/natural environment, this study used 44 meteorological stations as sampling points, extracting corresponding EVI, DMSP, temperature, and precipitation values.

Results show that from 2004–2013, EVI generally decreased while DMSP values showed an upward trend. Precipitation remained relatively stable with a slight increase, and temperature showed a decreasing trend with fluctuations.

To determine the dominant factor, correlation analysis was performed on annual change rates of EVI, DMSP, temperature, and precipitation. Results show: - Precipitation and temperature changes were positively correlated with vegetation changes - Human activity intensity changes were negatively correlated with vegetation changes - The correlation coefficient for human activity impact was highest ($R^2 = 0.4205$), followed by temperature ($R^2 = 0.4150$) and precipitation ($R^2 = 0.2184$)

[Figure 12: see original paper] The 44 sample data in study area from 2004 to 2013
[Figure 13: see original paper] Relationship between precipitation and vegetation
[Figure 14: see original paper] Relationship between temperature and vegetation
[Figure 15: see original paper] Relationship between DMSP and vegetation

These findings indicate that human activity is the dominant factor driving vegetation changes in the Pearl River Basin, with natural environmental factors playing a secondary role. Among natural factors, temperature has a greater impact on vegetation growth than precipitation.

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6. Conclusions and Outlook

Vegetation changes are influenced by both human activities and natural environments. Current quantitative research on their relative contributions remains limited. This study demonstrates that:

1. **Human activity is the primary driver** of vegetation changes in the Pearl River Basin, while natural environmental factors are not dominant.
2. **Temperature effects exceed precipitation effects** among natural factors influencing vegetation growth.
3. **Annual average EVI showed a weak declining trend** from 2004–2013, with consistent patterns across vegetation types and small interannual variations.
4. **Climate variability was substantial**, with large fluctuations in annual precipitation and temperature. Precipitation was concentrated in summer,

while temperature fluctuations were most pronounced in winter.

Vegetation change is a complex process. This study focused on human activities and natural environment, but future research should further explore relationships between regional CO concentration changes and vegetation dynamics.

References

[1] Albani M, Medvigy D, Hurtt G C, Moorcroft P R. The contributions of land-use change, CO fertilization, and climate variability to the Eastern US carbon sink. Global Change Biology, 2006, 12(12): 2370-2390.

[2] Parmesan C, Yohe G. A globally coherent fingerprint of climate change impacts across natural systems. Nature, 2003, 421(6918): 37-42.

[3] Schimel D, Melillo J, Tian H Q, McGuire A D, Kicklighter D, Kittel T, Rosenbloom N, Running S, Thornton P, Ojima D, Parton W, Kelly R, Sykes M, Neilson R, Rizzo B. Contribution of increasing CO and climate to carbon storage by ecosystems in the United States. Science, 2000, 287(5460): 2004-2006.

[4] Su W, Yu D Y, Sun Z P, Zhan J G, Liu X X, Luo Q. Vegetation changes in the agricultural-pastoral areas of northern China from 2001 to 2013. Journal of Integrative Agriculture, 2016, 15(5): 1145-1156.

[5] Storey E A, Stow D A, O' leary J F. Assessing postfire recovery of chamise chaparral using multi-temporal spectral vegetation index trajectories derived from Landsat imagery. Remote Sensing of Environment, 2016, 183: 53-64.

[6] Liu X Y, Zhou W, Bai Z K. Vegetation coverage change and stability in large open-pit coal mine dumps in China during 1990-2015. Ecological Engineering, 2016, 95: 447-451.

[7] Keating M P Jr, Ochs C A, Balachandra D, Holland M M, Lizotte R E Jr, Yu K W. Spatial variation related to hydrologic patterns and vegetation in greenhouse gas fluxes from the Mississippi Delta agricultural region. Applied Soil Ecology, 2016, 98: 278-281.

[8] Sun W Y, Song X Y, Mu X M, Gao P, Wang F, Zhao G J. Spatiotemporal vegetation cover variations associated with climate change and ecological restoration in the Loess Plateau. Agricultural and Forest Meteorology, 2015, 209-210: 87-99.

[9] Zhou D C, Zhao S Q, Zhang L X, Liu S G. Remotely sensed assessment of urbanization effects on vegetation phenology in China's 32 major cities. Remote Sensing of Environment, 2016, 176: 272-281.

[10] Zhang Y, Xiao X M, Jin C, Dong J W, Zhou S, Wagle P, Joiner J, Guanter L, Zhang G L, Qin Y W, Wang J, Moore B. Consistency between sun-induced

chlorophyll fluorescence and gross primary production of vegetation in North America. Remote Sensing of Environment, 2016, 183: 154-169.

[11] Zhang C, Lu D S, Chen X, Zhang Y M, Maisupova B, Tao Y. The spatiotemporal patterns of vegetation coverage and biomass of the temperate deserts in Central Asia and their relationships with climate controls. Remote Sensing of Environment, 2016, 175: 271-281.

[12] Xu H J, Wang X P, Zhang X X. Decreased vegetation growth in response to summer drought in Central Asia from 2000 to 2012. International Journal of Applied Earth Observation and Geoinformation, 2016, 52: 390-402.

[13] Tian F, Brandt M, Liu Y Y, Verger A, Tagesson T, Diouf A A, Rasmussen K, Mbow C, Yang Y J, Fensholt R. Remote sensing of vegetation dynamics in drylands: Evaluating vegetation optical depth (VOD) using AVHRR NDVI and in situ green biomass data over West African Sahel. Remote Sensing of Environment, 2016, 177: 265-276.

[14] Ju J C, Masek J G. The vegetation greenness trend in Canada and US Alaska from 1984-2012 Landsat data. Remote Sensing of Environment, 2016, 176: 1-16.

[15] Detsch F, Otte I, Appelhans T, Hemp A, Nauss T. Seasonal and long-term vegetation dynamics from 1-km GIMMS-based NDVI time series at Mt. Kilimanjaro, Tanzania. Remote Sensing of Environment, 2016, 178: 70-83.

[16] Suepa T, Qi J G, Lawawirojwong S, Messina J P. Understanding spatio-temporal variation of vegetation phenology and rainfall seasonality in monsoon Southeast Asia. Environmental Research, 2016, 147: 621-629.

[17] Huete A, Didan K, Miura T, Rodriguez E P, Gao X, Ferreira L G. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sensing of Environment, 2002, 83(1/2): 195-213.

[18] Wang X H. Land use changes and its impact on land surface temperature of Yancheng City from 2000 to 2009 analysis // Selected Papers from Conferences of the Photoelectronic Technology Committee of the Chinese Society of Astronautics: Optical Imaging, Remote Sensing, and Laser-Matter Interaction. Suzhou: SPIE, 2014.

[19] Simulation of China’ s population density based on nighttime light data. Journal of Beijing Normal University (Natural Science), 2005, 60(2): 266-276.

[20] Application of DMSP/OLS light data in urbanization monitoring. Journal of Beijing Normal University (Natural Science), 2014, 50(4): 407-413.

Note: Figure translations are in progress. See original paper for figures.