Impact of precipitation levels on vegetation in ecologically fragile karst areas in the Guangxi (China) karst region

~~The impacts of different levels of precipitation on vegetation in the karst ecological fragile areas vary significantly~~

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Abstract

To investigate the distribution pattern of regional rainstorm disasters and its impact on vegetation in the karst region of Guangxi, two vegetation parameters, fractional vegetation cover (FVC) and net primary productivity (NPP), were selected to analyze the spatial response characteristics and forest species differences of different vegetation parameters to five levels of rainfall in Karst region of Guangxi. ~~, namely moderate rainfall, heavy rainfall, heavy rainfall, heavy rainfall and very heavy rainfall.~~ Normalized Difference Vegetation Index (NDVI), fractional vegetation cover (FVC), and net primary productivity (NPP), to analyze the spatial response characteristics of different vegetation remote sensing parameters to five levels of rainfall, namely, moderate rain, heavy rain, heavy rain, heavy rain, and very heavy rain, and the differences of forest species in the karst region of Guangxi. The results show: (1) The effects of exceptionally heavy rainfall on vegetation NDVI, FVC and NPP were significantly greater than those of other classes of rainfall. (2) The southwestern and central parts of the study area are the concentration of high negative impacts of very heavy rainfall and heavy rainfall on the remote sensing indices of vegetation. (3) Different levels of rainfall had a greater negative effect on NDVI and FVC in economic and broadleaf forests in the study area, while eucalyptus forests had a lesser effect. The results suggest ~~targeting~~ focusing vegetation protection efforts based on ~~according to~~ geographical and species-specific differences~~species differences~~, particularly ~~especially~~ in areas with ~~aof~~ high incidence of exceptionally heavy rainfall and regions dominated by ~~in areas of~~ economically value and ~~broad-leaved~~ types of vegetation ~~forests~~.

Keywords: karst areas; rainstorm; vegetation cover; net primary productivity

Introduction

Karst is one of the four major ecologically fragile ~~areas~~ regions in China. Karst landforms are ~~is~~ widely distributed in Guangxi, where these ~~karst~~ areas are characterized by ~~have~~ prominent rocky desertification landscape (*Chen et al., 2018*) and shallow soil layer. In ~~the special~~this unique habitat, vegetation has weak ability to bear meteorological disasters (*Xu et al., 2012*). Under the background of climate warming, meteorological disasters happen and develop at a high frequency and ~~high~~ intensity (*Zhai et al., 2012*;

Comentado [PI1]: The title seems like a research hypothesis

Comentado [PI2]: What is the difference between the three? It would be more important to call them differently

Con formato: Resaltar

Lim et al., 2023; *Pandey et al., 2022*), posing a great threat to the ecological environment protection. ~~Rainstorm is~~Rainstorms are one of the most significant ~~important~~ meteorological disasters in karst areas (*Huang et al., 2015*; *Cahyadi et al., 2021*). Assessing their impact in these ~~, and it is of great significance to assess the impact of rainstorm in these areas~~regions is crucial for controlling ~~the control of~~ rocky desertification, ~~vegetation~~ protection and restoration vegetation, and managing the ecological environment ~~control~~.

At present, a variety of remote sensing vegetation indexes have been developed, among which normalized difference vegetation index (NDVI) is the most widely used (*Khoroshev et al., 2023*; *Mazengo et al., 2023*). Fractional vegetation cover (FVC) means the percentage of the vertical projection area of the above-ground portion of vegetation on the ground in the total statistical area within a unit area (*Gitelson et al., 2002*). Net primary productivity (NPP) is the amount of organic matter accumulated by green plants per unit area and time, namely the deduction of respiration consumption of plants from organic carbon fixed by photosynthesis (*Pu et al., 2001*). As a spatially explicit indicator (*Donmez et al., 2024*), it has been ~~proved~~ proven to be ~~highly~~a highly effective indicator ~~indicative in reflecting~~of the lushness of plant community growth and its ecological quality (*Qian et al., 2020*). Meteorological conditions are indispensable and important factors affecting vegetation growth (*Uffia et al., 2021*; *Tian et al. 2024*; *Nabizada et al., 2023*), and scholars have carried out many studies using remotely sensed vegetation indices and meteorological data, which mainly include two major categories of the effects of climatic factor averaging and non-averaging (meteorological hazards)~~.~~. In the research on the average state, it is generally believed that temperature exerts a significant effect on vegetation in temperate and cold regions, while precipitation exerts a significant effect on vegetation in arid and semi-arid regions or areas with obvious differences between dry and wet seasons. In terms of the impact of meteorological disasters on vegetation, researchers mainly focus on the impact of drought (*Li et al., 2019*; *Liu et al., 2021*; *Zhao et al., 2015*; *Orimoloye et al., 2021*; *Ali et al., 2024*).

Comentado [PI3]: What does this term refer to?

Vegetation responds sensitively to the changes in precipitation and air temperature (*Ahmad et al., 2023*). ~~, especially i~~In the karst region, air temperature and precipitation are important meteorological factors affecting the growth of vegetation ~~in the region~~, and it has been found that the response of ~~vegetation~~ NDVI to precipitation is significantly higher than that of air temperature (*Wei et al., 2013*). In the context of climate change, the frequency and intensity of meteorological disasters have increased significantly (*Zhu and Xiong 2018*; *Maryono et al., 2023*; *Putri, 2021*), and rainfall, ~~a meteorological element,~~ is often presented in the form of torrential rainfall disasters, and it is a frequent, high and heavy situation, which is more destructive to soil and water conservation and vegetation growth in the karst region, but there are fewer studies on the impact of torrential rainfall on the vegetation ~~in the karst region~~. In this study, based on long-time series satellite remote sensing data and precipitation observation data in karst areas of Guangxi, three vegetation remote sensing parameters of normalized difference vegetation index (NDVI), fractional vegetation cover (FVC) and net primary productivity (NPP) and five levels of rainfall (moderate rain, heavy rain, rainstorm, heavy rainstorm and extremely heavy rainstorm) were inverted and calculated, and the temporal and spatial distribution characteristics of effects of different levels of rainfall on vegetation in the study ~~area~~ region were analyzed. At the same time, the differences in the effects of different levels of rainfall on different forest species were studied to provide a scientific basis for the assessment of impact of rainstorm and vegetation protection and restoration in karst areas.

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Materials and Methods

Overview of the study area

The Guangxi Autonomous Region is situated in the southeastern part of southern China, with a latitude range of 20°54'-36°20' north and a longitude range of 104°28'-112°04' east. This area, situated to the west of the Yun-Gui Plateau, features intricate topography primarily characterized by mountains and hills. Karst landforms are prevalent throughout the region, encompassing 40.9% of the total land area.

The vegetation in Guangxi Province exhibits a remarkable diversity, with shrub forests being the most widespread (63.40%), followed by broad-leaved forests (17.20%), and bamboo forests being the least prevalent (0.88%). The distribution of various forest species in the study area is shown in *Fig. 1*.

Data

~~The data of d~~Daily temperature and precipitation data from 69 meteorological stations spanning the period from ~~during~~ 1961-2020, provided by the ~~which were provided by~~ Guangxi Meteorological Information Center, ~~was~~ were used to calculate rainstorm disaster indicators ~~of rainstorm~~ (*Table 1*).

Satellite remote sensing data were obtained from the MODIS (Moderate-~~resolution~~ Resolution ~~imaging~~ Imaging ~~spectro~~Spectro-radiometer) product MOD13Q1 (MODIS/Terra Vegetation Indices 16-Day L3 Global 250 m SIN Grid), provided by the National Aeronautics and Space Administration (NASA). ~~inversion of the National Aeronautics and Space Administration (NASA), MOD13Q1 (MODIS/Terra Vegetation Indices 16 - Day L3 Global 250m SIN Grid), a~~ This dataset features a spatial ~~250 m spatial~~ resolution of 250 m and a temporal resolution of 16 d, offering high-quality ~~interval~~ synthesized ~~tic high~~ time-series ~~phase~~ data. The data used corresponds to version V006 and covers the period from 2000 to 2021. ~~Vegetation index product MOD13Q1 (MODIS/Terra Vegetation Indices 16 - Day L3 Global 250m SIN Grid), 250 m spatial resolution 16 d interval synthesized high temporal phase data, version V006, data time period 2000-2021.~~ The MOD13Q1 remote sensing dataset of Guangxi Karst region was preprocessed through a series of steps, ~~(~~including band extraction, ~~mosaicing~~mosaicking, projection transformation, region extraction, and data format conversion~~, etc.)~~. This process resulted in a high-quality NDVI ~~to obtain the NDVI~~ dataset, which was ~~th reliable quality and monthly~~ further synthesized on a ~~to obtain the~~ monthly basis to create a monthly NDVI dataset. Additionally, the ~~and to find the~~ yearly average NDVI values were calculated from this dataset.

Geographic information data ~~include~~includes Digital Elevation Model (DEM) data of Guangxi, administrative boundaries of cities and counties in Guangxi, latitude and longitude coordinates of meteorological stations in Guangxi, vector boundaries of ~~informative Guangxi~~ karst areas, and data on the distribution of forest species within the~~in~~ Guangxi karst areas.

Methods

~~Through the use of~~Using terrestrial ecosystem carbon budget (TEC) models, ~~it is possible to compute~~ the net primary productivity (NPP) can be calculated (*Chen et al., 2023*). The formulas are as follows:

$$\mathrm{NPP}_{ij} = \mathrm{GPP}_{ij} - R_{ij} \tag{1}$$

$$\mathrm{GPP}_{ij} = \varepsilon_{ij} \times \mathrm{FPAR} \times \mathrm{PAR}_{ij} \tag{2}$$

$$\mathrm{NPP}_i = \sum_{j=1}^{n} \mathrm{NPP}_{ij} \tag{3}$$

~~In the formulas,~~ Where, NPP_{ij}, GPP_{ij} and R_{ij} ($\mathrm{gC\cdot m^{-2}}$) are respectively net primary productivity, total primary productivity and respiratory consumption of vegetation in the j^{th} month of the i^{th} year; ε_{ij}($\mathrm{gC\cdot MJ^{-1}}$) is the actual utilization rate of light energy in the j^{th} month of the i^{th} year, reflecting the influence of temperature, water and other factors on photosynthesis; FPAR is the proportion of photosynthetic active radiation absorbed by vegetation; PAR_{ij} ($\mathrm{MJ\cdot m^{-2}}$) is the incident photosynthetic active radiation in the j^{th} month of the i^{th} year; NPP_i ($\mathrm{gC\cdot m^{-2}}$) is the net primary productivity of vegetation in the i^{th} year; n is the total number of months in a year, n=12.

Based on ~~According to~~ the image element linear decomposition model, ~~the~~ vegetation cover is estimated ~~by~~ using NDVI, and the pixel ~~image element~~ dichotomy method, i.e., the NDVI value of each ~~image~~ pixel~~element~~ can be expressed as a combination of ~~the information contributed~~contributions from ~~by the~~ two components: ~~parts of the~~ vegetation cover and ~~the~~ non-vegetation cover. This relationship is

Comentado [PI5]: It is important information that should not be in parentheses.

Comentado [PI6]: Reorganizing information. Related ideas were grouped together to avoid repetition and improve clarity.
Eliminating redundancies
Correcting terms, improving flow. Connectors such as "This dataset features" and "offering" were added to improve the cohesion of the text.

Con formato: Fuente: (Predeterminada) Times New Roman, 11 pto quantified through ~~, which can be computed by the~~ a transformation of the vegetation cover fraction [32]. FVC can be calculated as follows:

$$\mathrm{FVC}_{ij} = \left(\mathrm{NDVI}_{ij} - \mathrm{NDVI}_{\mathrm{s}}\right)/\left(\mathrm{NDVI}_{\mathrm{v}} - \mathrm{NDVI}_{\mathrm{s}}\right) \tag{4}$$

$$\mathrm{FVC}_{i} = \frac{1}{n}\sum_{j=1}^{n} \mathrm{FVC}_{ij} \tag{5}$$

~~In the formulas~~Where, $\mathrm{FVC}_{ij}(\%)$ is the vegetation cover in the j^{th} month of the i^{th} year; NDVI_{ij} is the NDVI in the j^{th} month of the i^{th} year; $\mathrm{NDVI}_{\mathrm{s}}$ and $\mathrm{NDVI}_{\mathrm{v}}$ are the NDVI of full soil cover and like meta-vegetation full coverage, respectively, namely $\mathrm{NDVI}_{\mathrm{s}}=0.05$, and $\mathrm{NDVI}_{\mathrm{v}}=0.95$, which is set based on the characteristics of vegetation in China; FVC_{i} is the vegetation cover in the i^{th} year. According to this formula, when NDVI < 0.05, vegetation cover is negative, and there is no vegetation in the area.

This study ~~utilizes~~ employs Pearson's correlation analysis to examine the ~~method to investigate the~~ relationship between remotely sensed indicators (such as FVC and NPP) ~~of~~ for different vegetation types ~~with~~ under varying rainfall conditions ~~levels of rainfall~~ (*Chen et al., 2023*). The calculation formula is as follows:

$$\mathrm{R} = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2\sum_{i=1}^{n}(y_i-\bar{y})^2}} \tag{6}$$

~~In the formula~~Where, R is the correlation coefficient of variables x and y; x_i is the vegetation remote sensing parameters in the i^{th} year; $\bar{x}$ is the mean of multi-year vegetation remote sensing parameters; y_i is the rainfall in the i^{th} year; $\bar{y}$ is the mean of multi-year rainfall. The value range of correlation coefficient R is [-1, 1]. The larger the R is, the stronger the correlation between variables is. ~~Significance~~The significance test was conducted by t statistic.

Results and Discussions

Responses of vegetation remote sensing parameters to different levels of rainfall

Fractional vegetation cover (FVC)

The average absolute values of correlation coefficients between FVC and the ~~different~~different rainfall levels ~~of rainfall~~ (extremely heavy rainstorm, heavy rainstorm, rainstorm, heavy rain and moderate rain) were 0.24, 0.19, 0.17, 0.17 and 0.19, respectively. Overall, ~~, and there~~these results ~~was generally a~~ indicate a weak correlation (including R and P values). The negative correlation areas accounted for 63.0%, 61.3%, 39.8%, 41.1% and 44.50%, of which there was a significant negative correlation in 23.3%, 1.58%, 0.61%, 1.16% and 1.00% of the areas (p<0.05). FVC was mostly negatively correlated with extremely heavy ~~rainstorm~~rainstorms and heavy ~~rainstorm~~rainstorms (including R and P values), and mainly positively correlated with heavy rain and moderate rain (including R and P values). The correlations between FVC and ~~different levels of~~ rainfall levels were significantly different in space. By analyzing the regional distribution characteristics of the negative correlation between FVC and rainfall, it was found ~~is found~~ that the high-value areas varied by rainfall intensity. Specifically, ~~of~~ the negative correlation between FVC and extremely heavy rainstorms was predominantly concentrated in ~~mainly distributed in~~ ~~, the southwest,~~ while for ~~and~~ heavy rainstorm, it was ~~concentrated in~~ mainly observed in the central region. In contrast, the correlations for rainstorms and moderate rain exhibited similar patterns, primarily appearing in the southwest, north, and localized areas of the northeast. ~~the middle, while rainstorm and moderate rain were similar, mainly appearing in the southwest, north and local northeast~~. Moreover, the distribution range of heavy rain was slightly larger than ~~that of~~ rainstorms. Moderate rain was primarily concentrated in ~~mainly distributed in local~~localized areas of the north, with a ~~and the distribution was also~~ scattered distribution pattern (*Fig. 2*). The analysis revealed that ~~It is~~

Comentado [PI7]: ?

Comentado [PI8]: The types of forest vegetation that were analyzed must be included.

Con formato: Resaltar

Comentado [PI9]: I think this is what they meant, so sorry but I didn't understand:
The areas with negative correlation represent 63.0%, 61.3%, 39.8%, 41.1% and 44.50%, of which there was a significant negative correlation in 23.3%, 1.58%, 0.61%, 1.16% and 1.00% of the areas (p<0.05).

Comentado [PI10]: describe them including R and P values

Comentado [PI11]: I think that's what they meant, it's very difficult to read the document.

~~found that~~ FVC– exhibited ~~had~~ the strongest correlation with extremely heavy rainstorm, and extremely heavy rainstorm which also had the most pronounced ~~had the most obvious~~ negative impact on vegetation ~~in~~ within the study area. Both ~~E~~extremely heavy ~~rainstorm~~rainstorms and heavy ~~rainstorm~~rainstorms negatively affected a wide range of ~~areas~~regions. When rainfall levels increased ~~changed~~ from rainstorm to heavy rainstorm and from heavy rainstorm to extremely heavy rainstorm, the correlation between FVC and rainfall underwent significant changes. ~~had a great change,~~ Notably, ~~and even~~ there was even a shift between positive and negative ~~correlation~~correlations in some regions.

Comentado [PI12]: describe them including R and P values

Comentado [PI13]: Idem P and R values

Net primary productivity (NPP)

In the study area, the absolute values of correlation coefficients (R) between vegetation NPP and different ~~levels of~~ rainfall levels (extremely heavy rainstorm, heavy rainstorm, rainstorm, heavy rain and moderate rain) were 0.23, 0.19, 0.22, 0.21 and 0.27, respectively. Overall, these values indicate ~~and there was~~ generally a weak correlation. The proportion of areas exhibiting a negative correlation ~~areas~~ was 40.7%, 21.1%, 7.45%, 7.28% and 1.69%, respectively. Among these, ~~among which the~~ negative correlation was significant ($p<0.05$) in 0.44%, 0.29%, 0.01%, 0% and 0% of the areas. ~~($p<0.05$).~~ In the study area, NPP was mainly positively correlated with different rainfalls levels ~~of rainfall~~. However, ~~, but~~ the negative correlation areas of extremely heavy ~~rainstorm~~rainstorms were relatively wide, though their ~~but the~~ proportion did not ~~was no more than~~exceed –50%. Notably, t~~T~~here were clear ~~–was an obvious~~ spatial differences in the correlation between NPP and different rainfalls levels ~~of rainfall~~. The high-value areas of ~~the~~ negative correlation between NPP and extremely heavy ~~rainstorm was~~rainstorms were distributed in the central and north-central ~~parts~~ regions of the study area. For ~~, and~~ heavy ~~rainstorm was~~rainstorms, these areas were –concentrated in the south-central and north-eastern regions, ~~parts of the study area,~~ while rainstorms, they –appeared in a few localized areas of ~~parts of~~ the south-central ~~parts~~region. Heavy rain was distributed in the east-central and north-eastern zones ~~parts~~ of the study area, while ~~and~~ the negative correlation areas of moderate rain were scattered across ~~in~~ the north, southwest, and east (*Fig. 3*). The analysis revealed ~~It is found~~ that the correlation between NPP and moderate rain was the ~~largest~~strongest, with ~~, and~~ moderate rain exhibiting ~~had~~ almost entirely ~~–all~~ positive effects on vegetation across ~~in~~ the study area. In contrast, t~~T~~he negative effects of extremely heavy ~~rainstorm~~rainstorms ~~was~~ were the most ~~obvious~~pronounced. The ~~negative effect~~ areas showing negative effects of different rainfalls levels ~~of rainfall~~ on vegetation NPP were ~~concentrated~~ predominantly concentrated in the central region ~~area of~~of the study area.

Comentado [PI14]: P value es missing

Responses of various forest species to different levels of rainfall

The responses of FVC ~~of~~ in different forest vegetation types ~~forest species~~ to ~~different~~ varying levels of rainfall were significantly different (*Fig. 4*). In general, ~~with the increase of~~as rainfall levels increased, the negative correlation between FVC and ~~–of different forest species and~~ rainfall also increased. This was particularly evident ~~Especially~~ when ~~rainfall~~ rainfall levels changed from heavy rainstorms to extremely heavy rainstorms, where the correlation between FVC and rainfall increased significantly. However, the effects of different rainfalls levels on NDVI ~~of rainfall had various effects on NDVI~~ varied across ~~of~~ different forest ~~species~~vegetation. For extremely heavy rainstorm, the effects were most pronounced in ~~on~~ broad-leaved forest (-0.42) and bamboo forest (-0.40), ~~–were obvious,~~ while the impact on ~~it had a small effect on~~ eucalyptus (-0.26) and Chinese fir (-0.27) was relatively small. For heavy ~~rainstorm~~rainstorms, the effects on most ~~difference of other~~ forest vegetation types ~~species~~ were ~~was~~ not significant, except for bamboo forest (-0.13). In the case of ~~For~~ rainstorm, ~~it had an obvious effect on~~ Chinese fir (-0.20) showed a notable response, while ~~and a small effect on~~ eucalyptus (-0.12) was less affected. ~~).~~ For heavy rain and moderate rain, the responses of ~~different~~ forest types ~~species~~ were consistent: ~~, that is, the effects on~~ economic forest (-0.19) and broad-leaved forest (-0.18) ~~were obvious,~~exhibited stronger effects, while ~~–while the effect on~~ eucalyptus (-0.11, and -0.12) showed

Comentado [PI15]: Use contrasting colors for vegetation types minimal impact~~was small~~.

The responses of NPP of different forest vegetation types ~~forest species~~ to ~~different levels of~~varying rainfall levels ~~were~~ also showed significan~~tly~~ ~~different~~differences. Overall, ~~with the increase of~~as rainfall levels increased, the negative correlation between NPP and ~~of different forest species and~~ rainfall increased. ~~,~~ and the correlation between NPP and rainfall increased more significantly as rainfall level changed from heavy rainstorm to extremely heavy rainstorm. The effects of different levels of rainfall on NPP of different forest species were not consistent. For extremely heavy ~~rainstorm~~rainstorms, the impact on ~~effect on~~ eucalyptus forests (-0.21) ~~was~~were ~~obvious~~notable, while ~~but~~ the effects on economic ~~forest~~forests and broad-leaved ~~forest~~forests (-0.13) were relatively small. Heavy ~~rainstorm~~rainstorms had a ~~n obvious~~more pronounced effect on ~~effect on~~ pine forests (-0.14) and a ~~small~~ lesser effect on eucalyptus forests (-0.09). In the case of ~~For rainstorm~~rainstorms, ~~the effect on~~ broad-leaved forest (-0.11) showed a stronger response, ~~was big,~~ while ~~that on~~ eucalyptus forests (-0.07) were less affected ~~was small~~. For heavy rain and moderate rain, the sensitivity of different forest ~~species~~ vegetation was ~~basically the same~~consistent.

In conclusion, the comparison of different remote sensing parameters of vegetation shows that there was a weak correlation between varying ~~different levels of~~ rainfalls levels and three vegetation remote sensing parameters ~~of vegetation~~. Among these, ~~and~~ the negative correlation was highest with NDVI, ~~was the highest,~~ followed by FVC, and lowest with ~~while the negative correlation with~~ NPP ~~was the lowest~~. Across ~~Among~~ different rainfalls levels ~~of rainfall~~, the negative ~~effect~~effects of extremely heavy ~~rainstorm~~rainstorms ~~was~~were the most ~~obvious~~pronounced, followed by heavy ~~rainstorm~~rainstorms. In contrast, ~~,~~the effects ~~while that~~ of ~~rainstorm~~rainstorms, heavy rain, and moderate rain were ~~was~~ weaker and showed ~~had~~ little difference. Among different forest ~~species~~vegetation type, the negative effects of ~~different~~ varying ~~levels of~~ rainfall levels on NDVI and FVC were more pronounced in ~~of~~ economic forest and broad-leaved forest, while the impact ~~were more obvious, and the negative effect~~ on eucalyptus forest was small. However, ~~while there was no big difference in~~ the negative effects on NPP showed minimal differences across forest vegetation type~~of different forest species~~.

There was a certain difference in the negative impact areas of different ~~levels of~~ rainfalls levels ~~–~~on FVC of various forest ~~species~~ vegetation types (*Fig. 5*). As rainfalls level increased ~~changed~~ from rainstorm to heavy rainstorm, the proportion of negatively impact ~~area~~areas for~~of~~ different forest ~~species~~ vegetation types rose ~~obviously~~. However, this trend ~~change~~ was less ~~not obvious in the changing process of other levels of~~pronounced during other transitions of rainfall, such as ~~rainfall from~~ moderate rain to heavy rain, heavy rain to rainstorm, and heavy rainstorm to extremely heavy rainstorm. The average negative impact area across ~~of different levels of rainfall on~~ all forest ~~species~~ vegetation types due to different rainfalls levels ranged from ~~accounted for~~ 45%-61%~~.~~. In terms of severity,~~on average,~~ the negative impact followed this hierarchy: namely heavy rainstorm > extremely heavy rainstorm > moderate rain > heavy rain > rainstorm. During ~~For~~ extremely heavy rainstorm, the negative impact was greater on ~~area of~~ eucalyptus (69%) and broad-leaved forests (66%) compared to ~~was larger than that of~~ Chinese fir forest (48%). For heavy ~~rainstorm~~rainstorms, ~~that of~~ broad-leaved forest (66%) experienced a higher impact than ~~was larger than that of~~ eucalyptus (57%) and bamboo forests (58%). Under~~For~~ rainstorm conditions, ~~that of~~ Chinese fir forest (61%) showed a greater ~~was larger than that of~~ negative impact than bamboo forests (26%). In the case of ~~For~~ heavy rain, ~~that of~~ economic forests (71%) were more affected ~~was larger~~ than ~~that of~~ eucalyptus forests (18%). Finally, ~~For~~ under moderate rain, both ~~that of~~ economic ~~forest~~ (58%) and Chinese fir forests (56%) experienced a greater impact than ~~was larger than that of~~ eucalyptus forests (39%).

The areas negative impacted ~~areas of~~ by different ~~levels of~~ rainfalls level on NPP varied across ~~of various~~ forest vegetation type ~~species had a certain difference~~. In general, as ~~with the change of~~ rainfall levels increased from moderate rain to heavy rainstorm, ~~there was an obvious increase in~~ the proportion of negative impacted area for most ~~of different~~ forest vegetation type rose significantly. ~~species,~~ However,

Comentado [PI16]: I suggest changing to: This trend was particularly pronounced when rainfall levels shifted from heavy rainstorms to extremely heavy rainstorms, where the correlation between NPP and rainfall increased significantly. However, the effects of different rainfall levels on NPP varied across of vegetation type.

Comentado [PI17]: Obvious is not a suitable word for a scientific paper and is used a lot throughout the document.

Comentado [PI18]: If the results are not finished yet, why is it concluded?

Comentado [PI19R18]: should go in the conclusion section

~~but~~ the proportion of negatively impacted areas for~~of~~ economic ~~forest~~, Chinese fir and pine forests decreases ~~declined with the change of~~when rainfall levels shifted from heavy rainfalls ~~from heavy rain~~ to rainstorm. On average, ~~T~~the negatively impacted areas for all ~~of different levels of rainfall on all~~ forest ~~species~~ vegetation types ranged from ~~accounted for~~ 2%-39% ~~on average~~, following the order: ~~namely~~ extremely heavy rainstorm > heavy rainstorm > rainstorm > heavy rain > moderate rain. For extremely heavy rainstorms, the negative impact area of eucalyptus (62%) was larger than that of economic forest (20%). Similarly, ~~F~~for heavy ~~rainstorm~~rainstorms, ~~that of~~of the impacted area of bamboo forest (45%) exceeded ~~was larger than~~ that of broad-leaved forest (17%) and economic forest (14%). For rainstorm, the negative impacted area ~~that of~~of bamboo forests (26%) was larger than that of pine forests (3%), ~~Economic~~ economic forest (2%) and Chinese fir forest (1%). For heavy and moderate rain, the negatively impacted areas across ~~of different~~ forest vegetation types ~~species~~ were relatively ~~was~~ small, with ~~and the~~ proportion ranging ~~ed~~ from 3% to 9% for heavy rain and from 1% to 3% for moderate rain.

In summary, ~~from~~ the comparison of different remote sensing vegetation parameters ~~of vegetation~~ revealed significant differences ~~, it is found that there was a large difference~~ in the proportion of negative impacted areas across varying ~~between different levels of~~ rainfall levels and three vegetation remote sensing ~~parameters of vegetation~~. The proportion of negatively affected ~~area~~areas ~~of~~ for FVC was 53%, while ~~; the proportion of negatively affected area of~~for NPP, it was smaller, ~~with an~~ averaging~~e of~~ 16%. For FVC, heavy rainfall had the largest proportion of negative impacted areas, followed ~~by heavy and~~ moderate rainfall, while the proportions for heavy and ~~heavy~~ moderate rainfall ~~had~~ were the smallest and relatively similar. ~~proportion of negative impact area.~~ In contrast, ~~F~~for NPP, the amount of rainfall was proportional to the size of the impacted area ~~of impact~~. Regarding forests vegetation type, the proportions ~~For FVC, the proportion~~ of negatively impacted ~~area~~areas for FVC ~~was~~were higher ~~for~~ in economic and broad-leaved~~leaf~~ forests but~~and~~ lower in ~~for~~ eucalyptus and bamboo forests. Conversely, ~~F~~for NPP, the proportion were ~~of~~ higher ~~negatively affected area was higher for~~ eucalyptus and bamboo forests~~,~~ and lower ~~for~~ in economic and broad-leaved forests.

Discussion

~~Generally speaking, areas~~Areas with sparse vegetation have poor water and soil retention ~~ability~~capacity, making them more susceptible ~~and heavy rainfall is not conducive to vegetation growth but will aggravate~~to soil and water loss during heavy rainfall events, which can further hinder vegetation growth (*Chen et al., 2015*; *Block and Richter, 2000*). In this study, it ~~is~~ was found that ~~the~~ vegetation in the northeast, northwest and southeast of the study area exhibited a ~~had an obvious~~ significant negative correlation with moderate rain and heavy rain. This suggests that ~~That is to say, in~~in the ecologically sensitive and fragile karst areas, moderate ~~rain~~ and heavy rain may also have an ~~obvious~~ notable impact on vegetation, in addition to the effects ~~except for other levels~~ of higher rainfall levels such as ~~above rainstorm~~rainstorms. Rainfall in the karst areas of Guangxi is ~~mainly~~ primarily concentrated in spring and summer. ~~, and the spacial~~ The spatial distribution of high-value areas ~~of~~ for annual extremely heavy rainstorms, heavy rainstorm, and rainstorms showed significant ~~had great~~ similarity, as did ~~and that of~~the high-value areas for ~~of~~ annual moderate ~~rain~~ and heavy rain. ~~also had great similarity.~~ The northeast region (Guilin City) and the central and western region (Hechi City) of the study area were identified as the main rainstorm centers and rainfall concentration ~~areas~~ regions (*Fig. 6*) (*Huang et al., 2012*). The spatio-temporal distribution of areas highly sensitive to vegetation responses ~~areas of vegetation~~ to extremely heavy rainstorm, heavy rainstorm, and rainstorms in the study area ~~was significantly different~~ differed significantly from that of ~~areas~~ regions with frequent rainstorm (the center and southwest). This indicates that, in addition ~~indicating that apart from the~~to spatio-temporal differences in precipitation (*Sun et al. 2021*), other factors such as variations ~~the differences~~ in bedrock exposure rate across ~~in various~~ karst areas (*Chen et al., 2018*) and the complex composition of

Comentado [PI20]: No need to repeat

Comentado [PI21]: I think this is what they meant vegetation types (*Pan et al., 2021*), –are also key contributors to the pronounced ~~important reasons for the large~~ spatio-temporal heterogeneity of vegetation responses to ~~precipitation~~ rainfalls in these regions. ~~he areas.~~

Conclusion

The results of this study suggest ~~paper show~~ that extremely ~~extraordinarily~~ heavy rainfall has the most ~~obvious~~ pronounced negative impacts on ~~different~~ the remotely sensed vegetation indices (FVC and NPP) in the Guangxi karst region. Among the two ~~remotely sensed vegetation~~ indices, the negative effects of varying ~~different levels of~~ rainfall levels –on FVC ~~was~~were significantly greater than ~~that of~~ those on NPP. The ~~effects~~effects of different rainfall amounts on the two remotely sensed vegetation indices showed significant spatial differences, as well as substantial variations in their impacts ~~large differences in the effects~~ on different tree species in the study area. Notably, ~~, with generally larger~~ the negative effects on ~~the~~ FVC were generally greater ~~s of~~ for economic and broad-leaved~~leaf~~ forests. Additionally, ~~There is also a lag effect of~~ rainfall has a lag effect on vegetation, which was not addressed in ~~is not addressed in~~ this study but ~~paper and~~ will be explored in future ~~studies~~research.

Due to geographical and ~~species~~ forest vegetation differences, targeted vegetation protection is ~~of great importance~~crucial, particularly ~~especially~~ in areas with a~~of~~ high incidence of extremely heavy rainfall and in ~~areas~~ regions dominated by~~of~~ economic and broad-leaved forests.

Conflicts of interest

The authors declare that there is no conflict of interest.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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References

Ahmad MH, Abubakar A, Ishak MY, Danhassan SS, Jiahua Z, Alatalo JM. 2023. Modeling the influence of daily temperature and precipitation extreme indices on vegetation dynamics in Katsina State using statistical downscaling model (SDM). *Ecological Indicators* 155:110979. https://doi.org/10.1016/j.ecolind.2023.110979

Ali S, Basit A, Umair M, Makanda TA, Shaik MR, Ibrahim M, Ni J. 2024. The Role of Climate Change and Its Sensitivity on Long-Term Standardized Precipitation Evapotranspiration Index, Vegetation and Drought Changing Trends over East Asia. *Plants (Basel, Switzerland)* 13(3):399. https://doi.org/10.3390/plants13030399

Block M, Richter M. 2000. Impacts of heavy rainfalls in ElNiño 1997/98 on the vegetation of Sechura Desert in Northern Peru (Apreliminary report). *Phytocoenologia* 30(3-4):491-517.

Cahyadi A, Haryono E, Adji TN, Widyastuti M, Riyanto IA, Muhammad DTN, Tastian NF. 2021. Rainfall Variability in Gunungsewu Karst Area, Java Island, Indonesia. *Indonesian Journal of Forestry Research* 8(1):23-35. DOI: 10.20886/ijfr.2021.8.1.23-35

Chen YL, Mo WH, Luo YM. 2015. EVI simulation of vegetation in Karst rocky area using climatic factors. *Transactions of the Chinese Society of Agricultural Engineering (Transactions of the CSAE)*, 31(9):187-194. DOI:10.11975/j.issn.1002-6819.2015.09.029

Chen YL, Mo JF, Mo WH, Zhong SQ, Wang JH, Ding MH, Hu BQ. 2018. Temporal and spatial distributions of rocky desertification in Guangxi karst area in the past 30 years. *Guangxi Sciences* 25(5):625-631. DOI: 10.13656/j.cnki.gxkx.20181031.001

Chen YL, Xie Y, Li MZ, Xie M, Mo WH. 2023. Effects of Different Grades of Drought on Vegetation in Ecologically Fragile Karst Areas of Guangxi. *Available at Research Square*, https://doi.org/10.21203/rs.3.rs-3179753/v1

Donmez C, Sahingoz M, Paul C, Cilek A, Hoffmann C, Berberoglu S, Helming K. 2024. Climate change causes spatial shifts in the productivity of agricultural long-term field experiments. *European Journal of Agronomy*, 155:127121. https://doi.org/10.1016/j.eja.2024.127121

Gitelson AA, Kaufman YJ, Stark R, Rundquist D. 2002. Novel algorithms for remote estimation of vegetation fraction. *Remote Sensing of Environment*, 80(1):76–87. https://doi.org/10.1016/S0034-4257(01)00289-9

Huang HH, Lin KP, Gao AN, et al. 2012. Weather forecasting techniques and methods in Guangxi. Beijing: China Meteorological Press.

Huang XS, Lu H, Liao XP, Huang Z, Xie M. 2015. The distribution characteristics and defense strategies of droughts and floods of typical stony desertification area in Guangxi. *Journal of Meteorological Research and Application*, 36(2):59-61+126.

Khoroshev AV, Kalmykova OG, Dusaeva GK. 2023. Evaluation of the Normalized Differential Vegetation Index as a Source of Information on Aboveground Phytomass in Steppes. Izvestiya, *Atmospheric and Oceanic Physics*, 59(9):1166-1179. https://doi.org/10.1134/S0001433823090116

Li YJ, Ding JL, Zhang JY, Wu PF. 2019. Response of vegetation cover to drought in the northern slope of the Tianshan Mountains during 2001-2015 based on the land-use and land-cover change. *Acta Ecologica Sinica*, 39(17):6206- 6217.

Lim KK, Kim JM. 2023. Financial Loss Assessment for Weather-Induced Railway Accidents Based on a Deep Learning Technique Using Weather Indicators. *Applied Sciences*, 13(18):10418. https://doi.org/10.3390/app131810418

Liu JR, Zhao J, Wang JB. 2021. Response of vegetation cover to drought in the Qilian Mountains Region from 2001 to 2016. *Pratacultural Science*, 38(3):419-431.

Maryon A, Zulaekhah I, Nurendyastuti AK. 2023. Gradual changes in temperature, humidity, rainfall, and solar irradiation as indicators of city climate change and increasing hydrometeorological disaster: a case study in Yogyakarta, Indonesia. *International Journal of Hydrology Science and Technology*, 15(3):304-326. https://doi.org/10.1504/IJHST.2023.130161

Mazengo TER, Guo Z, Liu X, Wu Y, Li Y, Gwandu C. 2023. Effects of irrigation and rainfed practices on Normalized Difference Vegetative Index of Wheat (Triticum aestivum L.) and its Implications on Grain Yield in Northern China. *Environmental Systems Research*, 12(1):36. https://doi.org/10.1186/s40068-023-00303-w

Nabizada AF, Rousta I, Mozaffari G, Dalvi M, Olafsson H, Siedliska A, Krzyszczak J. 2023. A remotely sensed study of the impact of meteorological parameters on vegetation for the eastern basins of Afghanistan. *Earth Science Informatics*, 16(2):1293-1312.https://doi.org/10.1007/s12145-023-00965-1

Orimoloye IR, Belle JA, Ololade OO. 2021. Drought disaster monitoring using MODIS derived index for drought years: A space-based information for ecosystems and environmental conservation. *Journal of Environmental Management*, 284:112028.https://doi.org/10.1016/j.jenvman.2021.112028

Pan FG, Sun JF, Wang AH. 2021. Vegetation restoration of the karst rocky desertification areas in Duokan region, Tiandeng County, Guangxi. *Forest Science and Technology*, (4):15-19. DOI: 10.13456/j.cnki.lykt.2020.05.29.0001

Pandey D, Tiwari AD, Mishra V. 2022. On the occurrence of the observed worst flood in Mahanadi River basin under the warming climate. *Weather and Climate Extremes*, 38:100520. https://doi.org/10.1016/j.wace.2022.100520

Pu SL, Fang JY, Guo QH. 2001. Terrestrial net primary production and its spatio-temporal patterns in China during 1982—1999. *Acta Scientiarum Naturalium Universitatis Pekinensis*, 15(4):563-569.DOI:

10.13209/j.0479-8023.2001.102
Putri IHS. 2021. Preliminary Study of Land Use Change and Hydro-meteorological Disaster in The North Coast of Central Java. *IOP Conference Series: Earth and Environmental Science*, 750(1):012035. DOI: 10.1088/1755-1315/750/1/012035
Qian S, Yan H, Wu MX, Cao Y, Xu LL, Cheng L. 2020. Dynamic monitoring and evaluation model for spatio-temporal change of comprehensive ecological quality of vegetation. *Acta Ecologica Sinica*, 40(18):6573-6583.
Sun GK, Du T, Yang AP, Liu SY, Mo CX, Ruan YL. 2021. Spatial and temporal variation of extreme precipitation in Guangxi. *Journal of Guangxi University (Natural Science Edition)*, 46(2):327-335. DOI: 10.13624/j.cnki.issn.1001-7445.2021.0327
Tian R, Liu L, Zheng J, Li J, Han W, Liu Y. 2024. Combined Effects of Meteorological Factors, Terrain, and Greenhouse Gases on Vegetation Phenology in Arid Areas of Central Asia from 1982 to 2021. *Land,* 13(2):180. https://doi.org/10.3390/land13020180
Uffia ID, Akachuku CO, Udofia OE, Nsien IB. 2021. Meteorological influences on some melliferous plant species: Nectar nutritional composition and honey yield in mangrove vegetation zone of Akwa Ibom State, Nigeria. *Global Journal of Pure and Applied Sciences*, 27(4):361-366. DOI:10.4314/gjpas.v27i4.2
Wei ZF, Ren ZY, Zhang C. 2013. Analysis on the time-lag correlation between vegetation and climatic factors——Take Guangxi as an example. *Ecology and Environmental Sciences*, 22(11):1757-1762. DOI: 10.16258/j.cnki.1674-5906.2013.11.004
Xu JY, Hu YC, Wang HY. 2012. Landscape patterns of rocky desertification land in karst region of Guangxi Zhuang Autonomous Region in recent 10 years. *Bulletin of Soil and Water Conservation*, 32(1):181-184+267+263. DOI: 10.13961/j.cnki.stbctb.2012.01.015
Zhai PM, Liu J. 2012. Extreme weather/climate events and disaster prevention and mitigation under global warming background. *Strategic Study of CAE*, 14(9):55-63+84.
Zhao SY, Gong ZN, Liu XY. 2015. Correlation analysis between vegetation coverage and climate drought conditions in North China during 2001-2013. *Acta Geographica Sinica*, 70(5):717-729.
Zhu DY, Xiong KN. 2018. Influence of climatic factors on treatment of stony desertification in China's karst area: a review. *Jiangsu Agricultural Sciences*, 46(7):19-23. DOI: 10.15889/j.issn.1002-1302.2018.07.004

Figure Captions

Figure 1 Distribution of forest species and meteorological stations in the study area

Figure 2 Spatial distribution of correlation between FVC and different levels of rainfall in karst areas of Guangxi

(a) Extremely heavy rainstorm; (b) Heavy rainstorm; (c) Rainstorm (d) Heavy rain (e) Moderate rain

Figure 3 Spatial distribution of correlation between vegetation NPP and different levels of rainfall in karst areas of Guangxi

(a) Extremely heavy rainstorm; (b) Heavy rainstorm; (c) Rainstorm; (d) Heavy rain; (e) Moderate rain

Figure 4 Negative correlation between various forest species and different levels of rainfall in the study area

Figure 5 Proportion of the negative correlation between different forest species and different levels of rainfall in the study area

Figure 6 Spatial distribution of different levels of rainfall in the study area

(a) Extremely heavy rainstorm; (b) Heavy rainstorm; (c) Rainstorm; (d) Heavy rain; (e) Moderate rain

Table Captions

Table 1 Indicators of rainstorm levels