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Key Points:

- SSH has an obvious elevationdependent increasing trend in vegetation greenness, stronger at higher elevations
- Increasing warming promotes vegetation growth in highlands but resulting in heat stress in lowlands of the Central and Western Himalayas
- Precipitation helps in vegetation growth at middle elevated areas across the region, while the Eastern Himalaya faces waterlogging stress

Supporting Information:

Supporting Information may be found in the online version of this article.

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Elevation-Dependent Vegetation Greening and Its Responses to Climate Changes in the South Slope of the Himalayas

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Abstract The South Slope of the Himalayas (SSH) is witnessing dynamic shifts in vegetation greenness driven by climatic conditions across elevation variability. Here, we analyzed greening patterns of natural vegetated surfaces along the elevational gradient and examined their connection to climate changes from 2000 to 2022. Over 50% area of SSH exhibited significant greening, with higher rates in Central Himalayas (CH) and Western Himalayas (WH) compared to Eastern Himalayas (EH). The relative change rate (RCR) showed a notable increasing vegetation greenness from ~2,600 to ~5,000 m, followed by a decreasing trend in all subregions. Results showed that air temperature promoted the vegetation greening significantly in the high mountains but caused heat stress in lowlands of CH and WH. Precipitation supported growth in the middle mountains across the region except EH, which faced waterlogging stress. These findings are valuable for understanding vegetation changes under future climate changes and advancing our knowledge of ecosystem responses.

Plain Language Summary The South Slope of the Himalayas (SSH), known for its unique biodiversity and complex role in climate regulation, is undergoing noticeable changes in vegetation due to climate change. Due to diverse climatic environments and abrupt elevational variations, this region has different vegetation zones. However, there remains a gap in comprehensive studies addressing these changes. To fill this gap comprehensively, we utilized Normalized Vegetation Difference Index (NDVI) from 2000 to 2022 to analyze variations in naturally vegetated surface across the elevation and their correlation with climate. Our results revealed a significant increase in vegetation greenness across SSH and subregions (except Eastern Himalaya (EH)). The relative change rate (RCR) of NDVI indicated stronger vegetation growth at higher elevations from ~2,600 to ~5,000 m, followed by a decline in all subregions. Interestingly, further analyses revealed a warming induced vegetation growth in highland areas across the region, while lowland region faced heat stress in the Central Himalay (CH), and Western Himalaya (WH). Conversely, precipitation promoted vegetation in the middle-elevated areas, although EH faced waterlogging stress. These contrasting responses, patterns, and trends in vegetation changes in the Himalayas highlight the need for a comprehensive understanding of specific spatial variations when devising climate change adaptation strategies.

1. Introduction

Mountains at higher elevations are experiencing a faster rate of warming than lower elevations or in plain areas (Nogués-Bravo et al., 2007; Pepin et al., 2015; Yang et al., 2021). The Himalayas, as one of the largest mountain ecosystems in the world, face a considerably high warming rate about three times greater than the global average (Shrestha et al., 2012), and this ongoing warming intensifies the hydroclimate cycle, changes in snow cover, leading to strong shifts in precipitation patterns (Deng et al., 2017; Palazzi et al., 2013; Shekhar et al., 2010). Generally, the Indian summer monsoon and westerly winter belt are the major sources of precipitation in the Himalayas mountains (Palazzi et al., 2013), but variations in their timing, frequency, and intensity have led to more erratic distribution (He et al., 2022; Kapnick et al., 2014). These climatic shifts have a direct impact on biodiversity, vegetation phenology, and vegetation cover (Chakraborty et al., 2018; Feldman et al., 2024; Gu et al., 2020; Manish et al., 2016; Mishra & Chaudhuri, 2015; Wang & Sun, 2023).

In this context, the susceptibility of mountain vegetation to climate change has gained increasing attention over the past few decades (Baker & Moseley, 2007; Liu et al., 2023; Pepin et al., 2015; Schickhoff et al., 2016). Studies



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Methodology: Hamza Mukhtar, Mengijao Xu, Wei Zhao have shown that northern high-latitude regions experience more pronounced warming than low-latitude regions, resulting in increased vegetation growth in the northern high-latitude regions (Chen et al., 2022; Park et al., 2020). However, it is essential to recognize that other environmental limitations, such as water availability, may modulate the impact of temperature on vegetation growth (Liu et al., 2019; Piao et al., 2014), and this process is also influenced by other factors including biome type, hydraulic strategies, water use efficiency, and geographical context (Anderegg et al., 2018; Jiao et al., 2021; Vicente-Serrano et al., 2013). For instance, the faster warming rates at higher elevations may be conducive to vegetation growth, but it might be constrained by limited water availability (Jiao et al., 2021; Liu et al., 2019).

In the Himalayas, several studies have recently examined vegetation changes and their responses to climate change across different elevation gradients at the local level (Kumari et al., 2021; Li et al., 2016; Qamer, Xi, et al., 2016; Qamer, Shehzad, et al., 2016; Wu et al., 2020). For example, Mishra and Mainali (2017) observed predominant greening at lower elevations and browning trends at higher elevations across the region. However, there remains a big gap in understanding the elevation-dependent patterns of long-term vegetation changes across the entire Himalayan region. Therefore, there is an urgent need for more comprehensive studies focused on the long-term monitoring of vegetation dynamics in response to climate change across different elevation zones throughout the entire Himalayan region.

Satellite remote sensing is a powerful approach for monitoring large-scale vegetation dynamics due to its global coverage, long time series, and high spatial-temporal resolution availability (de Jong et al., 2011; Wang, Xie, et al., 2020). Normalized difference vegetation index (NDVI) is widely used vegetation indices, which exhibits a high correlation with vegetation phenology, productivity, canopy area, and biomass (Shen et al., 2024; Sweet et al., 2015; Tucker & Sellers, 1986). Although, several NDVI data sets have been produced, but due to sensor shifts and variations among platforms (Tian et al., 2015; Zhang et al., 2017), most of them face uncertainties in long-term monitoring vegetation trends. Comparatively, the Moderate Resolution Imaging Spectroradiometer (MODIS) (Huete et al., 2002) products offer a long-term and consistent measurements since 2000, showing good performance for vegetation change monitoring.

Herein, based on the MODIS-Terra NDVI product, this study selected the south slope of the Himalayas (SSH) to perform trend analysis on vegetation greenness to detect its spatial variation across elevation gradients from 2000 to 2022 and to examine how these trends vary for different vegetation types within the same elevation gradients, as well as the elevation-dependent influence of temperature and precipitation on vegetation greenness patterns in the SSH and its subregions. By addressing the gaps in existing research, this study contributes to a more comprehensive understanding of how climate change is impacting vegetation dynamics across the Himalayas, with implications for the conservation and sustainable management of these critical ecosystems.

2. Material and Methods

2.1. Study Area

The SSH, as a major part of the Greater Hindu-Kush Himalayan region, is geographically located in the lower middle part of this region with a range of $26^{\circ} 22'$ and $36^{\circ} 0'$ North and $72^{\circ} 60'$ and $97^{\circ}40'$ East (Figure S1a in Supporting Information S1). It covers about $481,000 \text{ km}^2$ area of five countries: China, Pakistan, Nepal, Bhutan, and India, where the elevation ranges from 60 to >8,000 m, with an average elevation of 2,386 m (Figure 1b). The region is divided into three subregions: EH, CH, and WH, which are drained by the Brahmaputra, Ganges, and Indus River systems, respectively. Due to its large extent and physiographic modifications, the climate varies from western to eastern and southern to northern. The SSH receives substantial rainfall, supporting dense vegetation except at higher elevations. Due to diverse climatic environments, and abrupt elevational variation, this region has tropical, subtropical, temperate, subalpine forests and alpine grasslands (Figure S1c in Supporting Information S1).

2.2. Data Source and Processing

The study used the NDVI data set from the MODIS-Terra vegetation index product MOD13A2 collection 6 (version 6.1) to conduct the analysis. The spatial and temporal resolutions of this data set are 1 km and 16 days, respectively. The study period is from 2000 to 2022. To de-noise impurities, we applied the Savitzky–Golay (SG) filter approach to smooth the NDVI time series. For this purpose, the quality control band of MOD13A2 product



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Figure 1. Spatial distribution of $NDVI_{MA}$ from 2000 to 2022 and areal proportion of each normalized difference vegetation index level (a) Based on Theil-Sen median trend analysis and Mann-Kendall test, trends of $NDVI_{MA}$ over the SSH from 2000 to 2022 with the areal percentage of each trend type (b) in the whole region and subregions.

was used to weight each pixel point of each image of the NDVI time series on the following conditions: pixel with value 0 (good data) was assigned to full weight (1), pixel with values 1–2 (marginal data) was assigned to half weight (0.5), and pixel with value 3 (cloudy) was assigned to minimal weight (0.1). The whole pre-procedure was done using the TIMESAT software package in the MATLAB environment (Jönsson & Eklundh, 2004).

To investigate the driving factors of vegetation dynamic changes across the elevational gradient, we selected nearsurface air temperature and precipitation as the primary climatic drivers based on their significant spatiotemporal changes and direct influence on vegetation dynamics, as highlighted in prior studies conducted in SSH (Abbas et al., 2015; Baniya et al., 2018; Shrestha et al., 2012; Wang, Peng, et al., 2020; Wang, Xie, et al., 2020). Additionally, vegetation cover types and surface elevation were included to capture spatial heterogeneity. Climatic data with 1-hr temporal and 0.1° spatial resolution were sourced from ERA5-Land to ensure high accuracy and reliability of the data (Muñoz-Sabater et al., 2021). The MODIS 500-m landcover type data set (MCD12Q1) Version 6.1 was sourced from the Land Processes Distributed Active Archive Center (LP DAAC). The 30-m SRTM (Shuttle Radar Topography Mission) DEM (digital elevation model) data was also sourced from LP DAAC. To match the spatial resolution, land cover data was resampled by the nearest neighbor interpolation method, and the bilinear interpolation method was used to resample the climate data, and DEM data to a 1-km scale. To reduce the influence of seasonal variations and phenological differences across vegetation types, we used the mean annual NDVI (NDVI_{MA}) to highlight long-term trends, which can avoid uncertainties from vegetation growing season definitions at different elevations and latitudes. For climatic variables, we adopted mean annual near-surface air temperature and total annual precipitation to provide a more consistent representation of climatic influences. Further, NDVI_{MA} values <0.1 were masked out to omit sparse and non-vegetated areas (Li et al., 2019). Additionally, to avoid the impact of human activities, land cover data was reclassified into three major classes: grassland, savannas, and forest. Finally, DEM data was divided into 29 elevation zones with an interval of 200 m.

2.3. Methods

2.3.1. Trend Analysis

To detect the changing pattern of the vegetation cover, the commonly used Mann-Kendall (MK) test (Kendall, 1975; Mann, 1945) was employed on 23-year NDVI_{MA} images. As a non-parametric statistical test, the MK test is often used in combination with the Theil-Sen Slope Estimator (Sen, 1968; Theil, 1950) to evaluate the significance of the time series trend (Fernandes & Leblanc, 2005; Neeti & Eastman, 2011).

For pixels with significant trends, the Theil-Sen Slope Estimator was applied to derive the changing rate as shown in Equation 1, this method is insensitive to measure errors and outliers in the time series data:

$$S_{\text{NDVI}} = \text{median}\left(\frac{\text{NDVI}_j - \text{NDVI}_i}{j - i}\right), 2000 \le i < j \le 2022$$
(1)

where, S_{NDVI} denotes the Theil–Sen median which is also often recognized as the changing rate, while *i* and *j* represent the number of time series, and NDVI_i and NDVI_j represent the NDVI values at moments *i* and *j*, respectively. When $S_{\text{NDVI}} > 0$, the NDVI exhibits an increasing trend in that period, and vice versa.

2.3.2. Partial Correlation Analysis

Correlation analysis is a useful statistical method to measure the influence of one variable on another. To measure the comprehensive influence of multiple factors, partial correlation is a good option to measure the relationship between two variables while eliminating the influence of other variables. The positive and negative coefficients indicate whether the vegetation and climatic factors correlate positively or negatively. The format is shown below:

$$R_{xy} = \frac{\sum_{i=1}^{n} \left[(x_{ij} - \overline{x_j}) \left(y_{ij} - \overline{y_j} \right) \right]}{\sqrt{\sum_{i=1}^{n} (x_{ij} - \overline{x_j})^2 \sum_{i=1}^{n} \left(y_{ij} - \overline{y_j} \right)^2}}$$
(2)

$$R_{xy,z} = \frac{R_{xy} - R_{xz}R_{yz}}{\sqrt{(1 - R_{xz}^2)}\sqrt{(1 - R_{yz}^2)}}$$
(3)

where R_{xy} is Pearson's correlation. *n* represents the period length (23), x_{ij} and y_{ij} denote the individual values of the drivers and NDVI, respectively, in the *i*th year, while $\overline{x_j}$ and $\overline{y_j}$ are the mean values of the drivers and NDVI, respectively, over the 23 years. While $R_{xy,z}$ is the partial correlation coefficient between variable *x* and *y* after eliminating the effect of *z*. Further, the T-test method was used to test the significance of both correlation coefficients.

3. Results and Discussion

3.1. Spatio-Temporal Variation Pattern of Vegetation Cover

To understand the general distribution of vegetation cover across the study area, the average value of the NDVI_{MA} from 2000 to 2022 is shown in Figure 1a. NDVI_{MA} values <0.1, along with cropland and urban land areas, are masked to exclude non-vegetated areas and human-induced activities, thereby focusing exclusively on naturally vegetated areas, as the complexity of the process and spatial variability of human activity creates significant

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Figure 2. Elevation-dependent pattern of multi-year average normalized difference vegetation index (NDVI) and the greening rate with the relative changing rate (RCR) of NDVI at different elevation ranges. (a, b) In the whole region, (c, d) Eastern Himalaya, (e, f) Central Himalaya, and (g, h) Western Himalaya. The dashed line and dash-dot line indicate the decline of NDVI_{MA} values and the rising range of the greening rate at high elevation ranges, respectively. The RCR was calculated by dividing the slope of the greening rate by the NDVI_{MA} at each elevation zone.

uncertainty on their influence on vegetation greenness (Wang et al., 2016). Within the SSH, 77.21% of the area exhibits high NDVI_{MA} values ranging from 0.5 to 0.9, predominantly covered with forest types, indicating healthy vegetation cover across the whole region. Further, a declining trend in NDVI_{MA} values is observed from south (lowlands) to north (highlands). Comparatively, the east-to-west gradient reveals a decline in highly vegetated surfaces (NDVI_{MA} >0.9), coinciding with an increase in areas with lower vegetation cover (NDVI_{MA} <0.3).

Further analysis, employing the Theil-Sen slope and MK test, confirmed that 51.19% of the total vegetation cover exhibited a significantly increasing trend in vegetation greenness across the SSH (Figure 1b). Only 0.99% of the area exhibited a significantly decreased trend. For the different subregions, the WH showed the highest increase with a 52.72% area of significance increase, followed by the CH (51.19%) and EH (33.36%). The difference is highly related to the original vegetation cover. Because the existing vegetation cover was already robust in the EH, in turn, the vegetation changes were not significant compared to the WH, which had relatively worse vegetation cover. Meanwhile, the vegetation greening percentage in the SSH surpasses previous findings, both regionally (Mishra & Mainali, 2017), and within subregions of the EH (Kumar et al., 2022; Wang et al., 2022), CH (Baniya et al., 2018; Wu et al., 2020) and WH (Abbas et al., 2015; Kumari et al., 2021), likely due to differences in the study region selection. Additionally, previous studies used mean NDVI of multiple seasons to calculate vegetation greenness. Conversely, we used NDVI_{MA} to enhance the temporal representativeness and reduce seasonal variation and short-term fluctuations induced by the big climatic differences of this region due to abrupt elevational changes (Sabin et al., 2020).

Regarding the greening rates, the SSH showed a significant increasing trend with a greening rate of 0.00169 yr⁻¹ (Figure S2 in Supporting Information S1), corresponding to a relative change (RC) of 9.56%, consistent with previous studies (Baniya et al., 2018; Wang et al., 2022). Among the subregions, the WH exhibited the highest rate of 0.00198 yr⁻¹, representing a RC of 11.35%, followed by the CH with a rate of 0.00180 yr⁻¹ and a RC of 9.08%. The EH showed the lowest rate of 0.00111 yr⁻¹, with a RC of 8.34%, only passing the 0.05 significant test. These variations in the greening rates and RC percentages at different subregions align with the overall spatial distribution of significant change areas shown in Figure 1b.

3.2. Elevation-Dependent Variation Pattern

To analyze the distribution and variation of the greening rate along the elevation gradient, Figure 2 shows a common decreasing trend for the $NDVI_{MA}$ with the increase in elevation. However, the starting points of the

decreasing trend in the whole region and subregions were quite similar (around 2,400 m), as shown by the purple dashed line. In contrast, the greening rate revealed diverse features with the variation of surface elevation. At the regional level, the greening rate fluctuated at lower elevations, stabilized at mid-elevations, gradually increased between 3,600 and 4,600 m, as shown by the green dash-dot lines, and then sharply declined (Figure 2a). For the EH, the changes were quite stable below 2,600 m, which gradually increased to 0.0037 yr⁻¹ at 4,800 m and then sharply decreased to 0.0025 yr⁻¹ at 5,400 m (Figure 2c). Comparatively, the CH and WH showed somewhat similar patterns, with a general decreasing trend in the greening rate, but both experienced an abrupt, a short increase at the high elevations: 4,000–4,600 m for the CH and 4,200–4,600 m in the WH (Figures 2e and 2g). Both regions shared a similar vegetation cover compared to the EH, resulting in different patterns. These differences could be partly attributed to the varying responses of different vegetation types to the distinct climatic conditions for different elevations across the region (see Figure S3 and Text S1 in Supporting Information S1).

In addition, relative changing rate (RCR) of the greening rate along the elevation gradient, showed an obvious increasing trend from middle mountains to high mountains (Figure 2), which was a different pattern compared to the greening trends. All parts of the SSH exhibit similar trends, with RCR rising around ~2,600 m, peaking near ~5,000 m, and then declining. These patterns highlight the elevation-dependent features of vegetation, showing that the high-altitude vegetation is more responsive to climate change with faster RCR than the lowland vegetation. Recently similar increasing greening patterns in higher elevations have been reported at the global level (Gao et al., 2019) and regional level (Tao et al., 2018; Wang, Peng, et al., 2020). However, the RCR statistics in this study provide a more nuanced and clear greening at higher elevations, which offers a more comprehensive understanding of changing features in a mountainous environment. Overall, the RCR value increases at a rate of 0.10% yr⁻¹/200 m in the higher elevation zones (2,600–5,200 m) (Figure 2b). Among the subregions, the EH exhibits the fastest RCR increase at a value of 0.14% yr⁻¹/200 m, compared to the CH (0.08% yr⁻¹/200 m) and WH (0.07% yr⁻¹/200 m) (Figures 2d, 2f, and 2h).

3.3. Diverse Responses Among Different Vegetation Cover Types

Based on Figures 5 and 6, NDVI changes varied at regional and subregional levels, likely due to differences in vegetation cover types. To investigate this further, we compared the NDVI_{MA}, greening rates, and RCR for three vegetation types (forest, savannas, and grassland) (Table S1 in Supporting Information S1). Forest showed the highest NDVI_{MA}, followed by savannas and grassland. However, the greening rate was inversely ordered across subregions, with grassland showing the highest RCR values, particularly in the EH (1.03% yr⁻¹).

Furthermore, an elevation-dependent analysis revealed that forests consistently had the highest mean NDVI values, followed by savannas and grasslands across most elevation ranges, while grasslands only became dominant at higher altitudes across the region and subregions. Interestingly, below 2,800 m elevation, savannas and grassland exhibited decreasing greening rates, whereas forests remained stable; between 2,800 and 4,600 m, the greening rate gradually increased for all types, where grassland eventually experienced a decline (Figure S4a in Supporting Information S1). Previously, the weakest grassland productivity in the alpine zone was reported by Qamer, Shehzad, et al. (2016) in Pakistan's Hindu Kush Karakoram area, where growth was influenced due to temperature (Abbas et al., 2015). The EH showed similar greening patterns as shown in the entire region, with some fluctuations (Figure S4b in Supporting Information S1), while in the CH and WH, greening rates decreased across all vegetation types, with a slight increase at higher elevations (linked with grassland) (Figures S4c and S4d in Supporting Information S1). A possible reason behind higher forest fluctuation (deforestation and reforestation) at lower elevations in the Himalayas (Gu et al., 2020), is peak human influences (Sandel & Svenning, 2013), and increasing road infrastructure at intermediate elevations (Mann et al., 2019). In contrast, a stronger and faster forest gain at higher elevations is highly influenced by warming temperatures (Wang et al., 2022). These varying greening patterns of vegetation types underscore the crucial role of climate change in shaping vegetation dynamics across the elevations.

3.4. Driving Mechanism of the Elevation-Dependent Changing Feature

Behind the vegetation changes, climate change has been revealed to be the main component in modulating vegetation greenness along the elevation gradient (Gao et al., 2019; Jiang et al., 2017; Körner & Hiltbrunner, 2018). Significantly increasing temperature and decreasing precipitation trends in higher elevated areas of the SSH (Figure S3 and Text S1 in Supporting Information S1), which are dominated by grassland and highly





Figure 3. (a) Elevation-dependent partial correlation coefficients of the NDVI_{MA} with air temperature and total precipitation in different subregions. *, **, *** indicate significance at p < 0.05, p < 0.01, and p < 0.0001, respectively. (b) Spatial and temporal distributions of the partial correlation between NDVI_{MA} and climate factors (air temperature and precipitation).

sensitive to both variables (Sun et al., 2015), may offset the benefits of warming, and caused in reduced greening of grassland (Figure S4 in Supporting Information S1) (Liu et al., 2019, 2021). In addition, partial correlation analysis of the NDVI_{MA} with these climate factors revealed different patterns with elevation (Figure 3a). At lower elevations, the $NDVI_{MA}$ showed a negative correlation with temperature and a positive at higher elevations, suggesting warming-induced vegetation greening in higher elevations. Specifically, the shift from negative to positive effect of temperature on NDVI from lower to higher elevation was stronger in the CH and WH compared to the EH, which mostly showed a positive correlation across elevations. This indicates that temperature takes precedence once precipitation meets vegetation's water demand, whereas precipitation becomes more influential when temperature hits the vegetation's tolerance limit (Cong et al., 2017; Guo et al., 2015). Conversely, a negative relationship was observed across all elevations of the EH, indicating that water is not the constraining factor in the EH (Kad & Ha, 2023). However, precipitation played a non-significant positive role across all elevations of the CH, except between 3,000 and 4,200 m, and in the WH. Both region's lowlands belong to the Siwalik Hills, which experience dry conditions for most of the year (Ganjoo & Ota, 2012), where increased precipitation enhances

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vegetation growth and the expansion of the growing season (Du et al., 2019). In contrast, a negative correlation at higher elevations indicates that water shortages are not strong.

To further examine key driving factors, partial correlation analysis was used to define nine categories based on significance test at p < 0.05 and correlation values across the study area (Table S2 in Supporting Information S1). Figure 3b shows the distribution of these categories. Clearly, (T+)* accounted for the highest area percentage (15.39%), predominantly in highly elevated areas, indicating that the faster warming rate at higher elevations (Dimri et al., 2018; Pepin et al., 2015) can directly promote vegetation growth by speeding up the breakdown of plant debris, soil organic material, nitrogen conversion (Li et al., 2019), and increased water availability through earlier snowmelt (Dye & Tucker, 2003; Harpold & Molotch, 2015). Conversely, (T-)* covered 8.52% area, mainly distributed in lower elevated areas of the CH and WH, suggesting heat stress due to faster evaporation (Piao et al., 2014) and causing a limit to vegetation growth (Guo et al., 2018; Xie et al., 2024) across all vegetation types (Figure S4 in Supporting Information S1). Continued warming can lead to drought stress in the future (Mastrotheodoros et al., 2020), which can partially offset the benefits of increased carbon sequestration due to warming in higher elevations (B. He et al., 2023; Lian et al., 2020). This is further exacerbated by widespread heat stress in lowland regions (van Oldenborgh et al., 2018), where human activities intensify the pressure on vegetation. In lower and middle elevated areas, human activities like agricultural expansion and road construction have led to deforestation and forest fragmentation, exacerbating heat stress by altering surface properties and reducing evapotranspiration (Gu et al., 2020; Mann et al., 2019; Pandey et al., 2014). Additionally, in lowland tropical regions, intensified land use changes and biodiversity loss further diminish vegetation resilience to extreme heat, which amplifies heat stress by reducing ecosystem stability, disrupting water cycles, and limiting the capacity of vegetation recovery from heatwaves (Mann et al., 2019; Munsi et al., 2010).

For precipitation, $(P+)^*$ pixels accounted for 6.37% area and contributed to vegetation growth due to suitable water availability, primarily in middle elevated areas of the CH and WH. In contrast, $(P-)^*$ pixels represented 3.17% of the area, concentrated in the lowlands of the EH, highlighting the destructive effect of reduced solar radiation caused by excessive moisture (Y. He et al., 2023), which likely leads to waterlogging stress on vegetation growth (Manghwar et al., 2024), due to extreme rainy monsoons in the EH (Kad & Ha, 2023), emphasizing the need for suitable temperature conditions for vegetation resilience. Meanwhile, $(T+ \& P+)^*$ pixels, covered 0.80% highlands of the region, indicating a synergistic effect of warmth and moisture in enhancing vegetation growth (Maina et al., 2022). Conversely, the $(T- \& P-)^*$ category, which covered 0.45% of the area, highlighted combined stress from both factors, leading to unfavorable vegetation conditions in the lowlands where human activities also exacerbate these stresses (Mann et al., 2019). Pixels with $(T+ \& P-)^*$, covered 0.82% area at highlands, implying that a warmer and drier condition might have improved vegetation health due to earlier snowmelt and enough water availability (Dye & Tucker, 2003). Lastly, $(T- \& P+)^*$ pixels, covering 0.67% of the lower WH area, underscored the importance of water in mitigating the effects of increasing temperature (Du et al., 2019). These patterns revealed complex elevation-specific interactions between climate and vegetation, illustrating diverse impacts of temperature and precipitation on vegetation greenness in the SSH.

Though our study provides a more comprehensive analysis of vegetation change dynamics and their sensitivity to climate changes across elevations in the SSH, future studies could improve the understanding of these effects by incorporating additional factors such as extreme weather events, changes in snow cover, and soil moisture. Meanwhile, the changes in the temporal patterns of precipitation frequency and intensity should be crucial for further investigation (Feldman et al., 2024; Zhang et al., 2025; Zhou et al., 2021), especially for the elevation-dependent precipitation distribution feature in this region. Additionally, it would be particularly valuable to examine vegetation conditions under projected climate change scenarios for exploring the carbon cycle and its feedback mechanisms within the Earth's climate system. For the methodology, different machine learning methods and high-resolution data may offer a better understanding of the intricate relationships between climatic factors and vegetation responses, helping to refine predictions and guide effective conservation strategies.

4. Conclusion

This study provides a detailed analysis of elevation-dependent variation in the spatial pattern of vegetation greenness, land cover types, and the influence of climatic factors in the Himalaya Mountains from 2000 to 2022. Our findings indicate a significant increase in NDVI_{MA} across all subregions. Temporal trends show significant vegetation greening with an overall relative change of 9.56%. Vegetation greening trends exhibit distinct patterns

along elevation gradients, with fluctuating greening rates across vegetation types. Notably, RCR highlights the strongest change in vegetation greening at higher elevations.

Additionally, elevation-dependent partial correlation between climatic variables and vegetation suggests that higher warming promotes vegetation growth at higher elevations, while lower elevations experience heat stress that limits vegetation growth. Conversely, precipitation shows diverse patterns, with positive correlations at lower and middle elevations (except EH). The observed patterns underscore the complex interactions between climate variables and elevation, suggesting that future ecological responses in the Himalayas will likely vary by region and elevation. Future research should focus on long-term monitoring and modeling to predict how these trends may evolve, particularly in the context of ongoing climate change.

Data Availability Statement

The MODIS data sets for NDVI (Didan, 2021) and Land cover types (Friedl & Sulla-Menashe, 2022), provided by NASA, are accessed through the Application for Extracting and Exploring Analysis-Ready Samples (AppEEARS), hosted by the Land Processes Distributed Active Archive Center (LP DAAC, https://appeears. earthdatacloud.nasa.gov/). The ERA5-Land (Muñoz Sabater, 2019) reanalysis data are downloaded from the Copernicus Climate Data Store (https://cds.climate.copernicus.eu/datasets/reanalysis-era5-land?tab=download). The 30m-SRTM data set, originally produced by NASA, is available for download from CGIAR-CSI (http://srtm. csi.cgiar.org).

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