

Dynamic vegetation change response to topography based on Landsat observations in the Tianshan Mountains, China during 2000-2022 Post-print

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Abstract

In the arid regions of Northwest China, vegetation cover plays a crucial role in maintaining unique terrestrial ecosystems. Vegetation growth is highly sensitive to variations in topographical factors, and the influence of topography on vegetation cover has attracted increasing attention. This study analyzed vegetation dynamics and their relationship with topography in the Tianshan Mountains of China using Landsat Normalized Difference Vegetation Index (NDVI) data during 2000-2022 and Shuttle Radar Topography Mission (SRTM)-derived topographical factors (elevation, slope, and aspect). Theil-Sen slope estimation and Mann-Kendall trend tests were applied to quantify temporal changes in vegetation, while a terrain area correction coefficient (K) was used to assess spatial associations of vegetation with topography. Random Forest (RF) regression and SHapley Additive exPlanations (SHAP) analysis evaluated the relative importance of topographical factors in shaping vegetation cover (multi-year mean NDVI) distribution. Key findings included that over the 23-a period, 59.46% of the vegetated area exhibited significant improvement ($P < 0.05$), with the southern Tianshan Mountains showing the most pronounced increase (70.59%), whereas vegetation degradation (3.10%) was primarily concentrated in river valleys with intensive human activities. RF-SHAP analysis revealed that elevation is the primary driver of vegetation cover patterns, explaining 52.00% of the NDVI variation. The peak NDVI (0.42) occurred at elevations between 2800 and 3200 m. Slope and aspect also significantly influenced vegetation distribution, and higher NDVI values and greater improvement trends were observed on shady (north-facing) slopes compared to sunny (south-facing) slopes. K-index analysis indicated pronounced vegetation change—both degradation and improvement—in areas with elevations between 1100 and 2800 m and slopes exceeding 5° , par-

ticularly on sunny slopes. Low-elevation desert areas in the southern Tianshan Mountains were highly susceptible to degradation. This study underscores the critical role of topography in regulating vegetation cover and its spatiotemporal dynamics, providing a scientific basis for sustainable management of arid mountain ecosystems.

Full Text

Preamble

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Dynamic vegetation change response to topography based on Landsat observations in the Tianshan Mountains, China during 2000-2022 WEN Di^{1,2}, LI Jun^{1,2,3*}, XU Weifeng^{1,2}, CHEN Zhixiang^{1,2}, PENG Dailiang⁴

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Abstract

In the arid regions of Northwest China, vegetation cover plays a crucial role in maintaining unique terrestrial ecosystems. Vegetation growth is highly sensitive to variations in topographical factors, and the influence of topography on vegetation cover has attracted increasing attention. This study analyzed vegetation dynamics and their relationship with topography in the Tianshan Mountains of China using Landsat Normalized Difference Vegetation Index (NDVI) data during 2000-2022 and Shuttle Radar Topography Mission (SRTM)-derived topographical factors (elevation, slope, and aspect). Theil-Sen slope estimation and Mann-Kendall trend tests were applied to quantify temporal changes in vegetation, while a terrain area correction coefficient (K) was used to assess spatial associations of vegetation with topography. Random Forest (RF) regression and SHapley Additive exPlanations (SHAP) analysis evaluated the relative importance of topographical factors in shaping vegetation cover (multi-year mean NDVI) distribution. Key findings included that over the 23-a period, 59.46% of the vegetated area exhibited significant improvement ($P < 0.05$), with the southern Tianshan Mountains showing the most pronounced increase (70.59%), whereas vegetation degradation (3.10%) was primarily concentrated in river valleys with intensive human activities. RF-SHAP analysis revealed that elevation is the primary driver of vegetation cover patterns, explaining 52.00% of the NDVI variation. The peak NDVI (0.42) occurred at elevations between 2800 and 3200 m. Slope and aspect also significantly influenced vegetation distribution,

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Keywords

topography; vegetation dynamics; Normalized Difference Vegetation Index (NDVI); Random Forest (RF); SHapley Additive exPlanations (SHAP); Tianshan Mountains Citation: WEN Di, LI Jun, XU Weifeng, CHEN Zhixiang, PENG Dailiang. 2026. Dynamic vegetation change response to topography based on Landsat observations in the Tianshan Mountains, China during 2000-2022. *Journal of Arid Land*, 18(3): 501-523. <https://doi.org/10.1016/j.jaridl.2026.03.008>; <https://cstr.cn/32276.14.JAL.20250294>

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Introduction

Vegetation plays a fundamental role in terrestrial ecosystems (Yan et al., 2021) and links the atmosphere, soil, and hydrosphere. Changes in vegetation significantly influence climate regulation and the hydrological cycle (Piao et al., 2020; Zhou et al., 2020). Analyzing the spatial distribution of vegetation and its responses to various drivers enables effective assessment of regional ecosystem dynamics (Novillo et al., 2019; Jin et al., 2020; Shi et al., 2020; Lan and Dong, 2022). Advances in remote sensing technology facilitate large-scale monitoring of vegetation dynamics, particularly in mountainous regions where field observations are limited (Zhang et al., 2023a). High-resolution data, especially the Normalized Difference Vegetation Index (NDVI), provide accurate information on vegetation change and are widely used for monitoring at global and regional scales (Jiang et al., 2021; Li et al., 2021b; Hu et al., 2023).

Vegetation dynamics are governed by complex interactions among climatic con-

ditions, human activities, and topographical factors. Among these, climatic drivers—particularly temperature and precipitation variability—exert primary control over vegetation growth by regulating water availability and thermal conditions (Jiang et al., 2021; Gao et al., 2022). Numerous studies indicate that rising temperatures significantly alter vegetation phenology, such as advancing the onset of the growing season in temperate grasslands under warming conditions (Liu et al., 2021).

Additionally, altered precipitation patterns, particularly reduced spring rainfall, have been shown to limit vegetation productivity in water-limited environments (Ren et al., 2023). Concurrently, human activities profoundly influence vegetation patterns through agricultural expansion, grazing intensity, urbanization, and ecological restoration programs (Bashir et al., 2020). Overgrazing pressure has been identified as a major driver of grassland degradation in arid regions (Bi et al., 2020), whereas conservation measures have promoted vegetation recovery in many areas. In addition, agricultural intensification has triggered local degradation in vulnerable regions such as the Ili River Valley in China (Li et al., 2021b).

Topographical factors also impose critical constraints on vegetation distribution by modulating local microclimates, soil conditions, and hydrological processes (Wang et al., 2022). The Tianshan Mountains provide a compelling context for studying these relationships. As the largest mountain system in Central Asia's arid temperate zone, they serve as a vital climatic boundary (Li et al., 2022a). In China, they span over two-thirds of the range and connect the Junggar Basin and Tarim Basin. Their unique topography creates a distinct continental climate with pronounced vertical temperature gradients (Li et al., 2022b). An elevation difference of approximately 4000 m supports diverse vertical natural zones, including desert, mountain forest, and alpine glacier zones (Zhang et al., 2023b). For example, in the Tomur Peak region (Fig. 1a [Figure 1: see original paper]), vegetation increases with elevation, arranged as warm temperate desert, temperate desert steppe, mountain steppe, subalpine meadow, alpine meadow, and alpine cushion vegetation (Li et al., 2021b). In the Bogda Peak region (Fig. 1b), vegetation follows this sequence: temperate desert, mountain meadow, mountain coniferous forest, subalpine shrub meadow, alpine meadow, and alpine cushion vegetation. This results in a unique vertical zonation pattern, highlighting the complexity of vegetation distribution in the Tianshan Mountains (Zhang et al., 2021). Within this system, variations in elevation, slope, and aspect generate substantial spatial heterogeneity in solar radiation, water availability, and wind exposure, thereby forming complex water-energy gradients that support diverse plant communities (Adams et al., 2021; Hua et al., 2022). Elevation gradients in the Tianshan Mountains typically correspond to predictable changes in temperature and precipitation, leading to distinct vertical zonation of plant communities. Slope and aspect further modulate these effects by regulating incident radiation, water runoff patterns, and soil retention capacity, resulting in markedly different vegetation conditions between sunny (south-facing) and shady (north-facing) slopes (Jing et al., 2024).

Although the influence of topography is widely acknowledged, most previous studies in the Tianshan Mountains have prioritized climatic and anthropogenic drivers, often treating topography as a secondary or control variable (Gao et al., 2022; Lin et al., 2022; Hou et al., 2023). While

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Vertical natural belts of Tomur Peak (a) and Bogda Peak (b) in the Tianshan Mountains, China

some studies have incorporated basic topographic parameters (Meng et al., 2020; Zhang et al., 2024), comprehensive assessments using high-resolution data across extended spatiotemporal scales remain limited. Moreover, interactions among multiple topographical factors and their combined effects on vegetation dynamics are poorly quantified. Conventional analytical methods—including correlation analysis, linear regression, and geographic detectors—though valuable, often fail to capture complex nonlinear relationships and interactions among driving factors (Jia et al., 2020; Han et al., 2023). Recent advances in remote sensing and machine learning offer transformative opportunities to address these limitations. The availability of high-resolution Landsat NDVI data enables unprecedented monitoring of vegetation dynamics across complex terrains. Meanwhile, machine learning algorithms—particularly Random Forest (RF) and SHapley Additive exPlanations (SHAP)—provide powerful tools for quantifying factor importance, resolving complex nonlinear relationships and revealing interaction effects that are often overlooked by traditional methods (Bao et al., 2021). These technological advancements create new opportunities for a more comprehensive examination of vegetation–topography relationships in the Tianshan Mountains.

This study leveraged these technological advances to systematically investigate vegetation–topography relationships in the Tianshan Mountains from 2000 to 2022, using high-resolution Landsat NDVI and Shuttle Radar Topography Mission (SRTM) topographical data. We developed an integrated analytical framework combining statistical methods (Theil-Sen trend analysis and Mann-Kendall trend test) with machine learning approaches and topographical factors to achieve the following objectives: (1) quantifying the spatiotemporal trends in vegetation cover across topographical gradients; (2) evaluating the individual and synergistic effects of elevation, slope, and aspect on vegetation distribution and dynamics; and (3) identifying the topographically sensitive areas requiring priority conservation or restoration. By addressing these objectives, this study provides a comprehensive understanding of the controlling role of topography in vegetation dynamics within arid mountain ecosystems, thereby informing targeted conservation strategies and sustainable land management practices in these areas.

Materials and methods

Study area

The Tianshan Mountains in central Xinjiang Uygur Autonomous Region, China,

extend 1700 km from east to west, with an average elevation of 2300 m and peaks exceeding 7300 m. This mountain system separates northern and southern Xinjiang, bordered by the Taklimakan Desert to the south and the Gurbantungut Desert to the north (Fang et al., 2019). It consists of three parallel ranges: southern Tianshan (STS), central Tianshan (CTS), and northern Tianshan (NTS), separated by intermontane basins (Fig. 2 [Figure 2: see original paper]). The STS features rugged topography and peaks over 6000 m, including Tomur Peak at 7443 m. The CTS traverses the Ili River Basin, while the NTS

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extends from Mingshui Town to Alashankou City in Xinjiang, with Bogda Peak reaching 5445 m as its highest point.

The Tianshan Mountains exhibit a continental climate, with temperature and precipitation decreasing from northwest to southeast. Precipitation occurs predominantly during summer months. Annual precipitation ranges from a minimum of approximately 150 mm to a maximum of 600–800 mm, with a regional average of 250–300 mm. Temperature variation is pronounced, with an annual mean of approximately 5.0°C. The sunny slopes have a significantly higher annual average temperature (7.5°C–10.0°C) compared to the shady slopes (2.5°C–5.0°C) (Cai et al., 2021). Water vapor is mainly transported by westerly winds, fostering a relatively humid alpine climate and earning the region the designation of ‘water tower of Central Asia’ (Sorg et al., 2012).

This climatic regime supports diverse, arid-adapted vegetation cover, predominantly comprised of grassland, meadow, mountain vegetation, and desert, forming the most complete mountainous vertical vegetation belt in temperate arid regions (Immerzeel et al., 2020).

2 Overview of the elevation distribution (a) and vegetation type distribution (b) in the Tianshan Mountains and three subregions. STS, CTS, and NTS represent the southern Tianshan, central Tianshan, and northern Tianshan, respectively.

Data sources

2.2.1 NDVI data

The NDVI data used in this study comprised the 30-m annual maximum NDVI dataset in China from 2000 to 2022 (<https://nesdc.org.cn/sdo/detail?id=60f68d757e28174f0e7d8d49>), provided by the Land Use and Global Change Remote Sensing Team, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences (Yang et al., 2019). This dataset, generated using the Google Earth Engine platform, is based on Landsat 5/7/8/9 satellite imagery.

Effective observation values were obtained through cloud and shadow masking, followed by linear interpolation and Savitzky-Golay filtering to determine the

annual maximum NDVI value for each pixel. Pixels with NDVI values below 0.10 were excluded from analysis as non-vegetated areas (Piao et al., 2014).

2.2.2 Topographical data

This study utilized the topographical data (elevation, slope, and aspect) derived from the SRTM, a joint project by National Aeronautics and Space Administration (NASA) and the National Geospatial-Intelligence Agency (NGA) launched in February 2000 (<https://earthexplorer.usgs.gov>).

The mission employed radar interferometry to produce global land elevation data at approximately 30 m spatial resolution, which has demonstrated excellent performance in quantitative terrain analysis within complex mountainous environments (Li et al., 2023). Elevation was classified into six categories: ≤ 1100 , 1100-1550, 1550-2800, 2800-3200, 3200-3600, and >3600 m (Zhang et al., 2023b). Slope was categorized into five classes: 0° - 5° , 5° - 15° , 15° - 25° , 25° - 35° , and $>35^\circ$ (Li

WEN Di et al.: Dynamic vegetation change response to topography based on... et al., 2019). Aspect was classified into five categories: flat terrain (-1.0°), shady slope (0.0° - 67.5° and 337.5° - 360.0°), sunny slope (157.5° - 247.5°), semi-shady slopes (67.5° - 112.5° and 292.5° - 337.5°), and semi-sunny slopes (112.5° - 157.5° and 247.5° - 292.5°) (Wang et al., 2014), as illustrated in Figure 3 [Figure 3: see original paper].

3 Spatial distribution of elevation (a), slope (b), and aspect (c) in the Tianshan Mountains and three subregions

Methods

2.3.1 Theil-Sen trend analysis and Mann-Kendall trend test The Theil-Sen trend analysis method, also known as Sen's slope estimator, is a robust nonparametric technique for trend analysis. It effectively handles missing data, non-normal distributions, and outliers, making it particularly suitable for long-term, per-pixel analysis of vegetation dynamics in remote sensing time series. This method estimates the median slope of pairwise data points over time, as defined in Equation 1:

$$SNDVI_j - NDVI_i \quad S \quad NDVI \quad Median \quad , \quad j \quad i \quad ,$$

where SNDVI represents the median trend of the NDVI time series; Median denotes the median operator; and NDVI_i and NDVI_j are the NDVI values at time points *i* and *j*, respectively. A positive SNDVI indicates an increasing trend in vegetation over time, while a negative value indicates a decreasing trend.

The Mann-Kendall trend test is a nonparametric statistical test used to detect significant trends in long-term time series data. It does not assume a normal distribution and is robust to missing values and outliers, which makes it widely

applicable in climate and hydrological studies (Xiong and Wang, 2022; Fan et al., 2023). The null hypothesis H0 states that the time series $X=(x_1, x_2, \dots, x_n)$ consists of n independent and identically distributed samples. The alternative hypothesis H1 is two-tailed, indicating that the distribution of x_i differs from that of x_j for all $i \leq n$ and $j \leq n$, where $i \neq j$. The test statistic S is computed using Equation 2:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(x_j - x_i)$$

The function $\text{sgn}()$ is the sign function, defined in Equation 3: $\text{sgn}(x) = 1$ if $x > 0$, $\text{sgn}(x) = 0$ if $x = 0$, and $\text{sgn}(x) = -1$ if $x < 0$.

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The variance $\text{Var}(S)$ is calculated using the formula as follows:

$\text{Var}(S) = \frac{p(p-1)}{2}$ where q is the number of tied groups; and t_p is the number of data points in the pth tied group.

The significance of the trend is evaluated using the standardized test statistic Z, calculated using the formula as follows: $Z = S / \sqrt{\text{Var}(S)}$. $Z \geq 1.96$ if $S \geq 0$ and $Z \leq -1.96$ if $S < 0$. For vegetation trend analysis, a $|Z|$ value exceeding 1.96 or 2.58 indicates statistical significance at the 95.00% or 99.00% confidence level ($\alpha=0.05$ or 0.01), respectively. Based on the magnitude of the NDVI trend and its statistical significance, vegetation change trends can be further categorized into five classes, as detailed in Table 1.

Vegetation change classification table

SNDVI

Vegetation change type

SNDVI

$Z \leq -2.58$

Highly significant decrease

$1.96 < Z < 2.58$

$-2.58 < Z < -1.96$

Significant decrease

$Z \geq 2.58$

$-1.96 < Z < 1.96$

Nonsignificant change

Vegetation change type Significant increase Highly significant increase

Note: SNDVI represents the median trend of the Normalized Difference Vegetation Index (NDVI) time series; Z is the standardized test statistic.

2.3.2 Correction for differences in terrain area Vegetation change is influenced by topographical conditions. A specific vegetation change type may be restricted to certain terrains but still significantly affect the overall study area, introducing uncertainty when assessing the influence of topography on vegetation dynamics (Li et al., 2021a).

Therefore, to eliminate this bias caused by differences in absolute terrain area and to objectively assess the impact of different topographical conditions on vegetation change, this study applied a terrain area correction coefficient (K) to correct for terrain area differences, thereby reducing uncertainty in vegetation change assessment. The formula for K is as follows: $K = \frac{A_m / A_e}{A_m / A}$ where A_m refers to the area of vegetation change type m under topographical condition e (m^2); A_e refers to the total area of under topographical condition e (m^2); A is the total area of the study area (m^2); A_m/A_e represents the area ratio of vegetation change type m under topographical condition e; and A_m/A denotes the area ratio of vegetation change type m across the entire study area. When $K > 1.00$, the vegetation change type m is dominantly distributed under topographical condition e, with higher values indicating greater dominance; when $K = 1.00$, the distribution of vegetation change type m is stable under topographical condition e; and when $K < 1.00$, the vegetation change type m is non-dominantly distributed under topographical condition e.

2.3.3 RF model with SHAP analysis

This study employed a RF model integrated with the SHAP method to evaluate the impact of topographical factors on vegetation cover. The RF model uses Bootstrap resampling to generate training samples, constructs individual decision trees, and aggregates predictions through ensemble voting. This approach can effectively capture complex nonlinear relationships, assess variable importance, and mitigate overfitting and computational complexity (Wang et al., 2021;

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Yadav et al., 2021). The dataset, comprising both NDVI values and topographical factors (elevation, slope, aspect, profile curvature, etc.) was partitioned into training and testing sets at a 7:3 ratio. Model performance was evaluated using coefficient of determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). To further ensure robustness, we performed 5-fold cross-validation, where the training set was split into five equal subsets. In each fold, four subsets were used for training and one for validation (Xiao et al., 2023). Feature importance was assessed using permuted importance (threshold > 0.01)

and SHAP values to quantify individual contributions. SHAP analysis further elucidated nonlinear effects and interaction patterns through dependency plots. The combined RF-SHAP framework enhanced the interpretability of ensemble learning while minimizing overfitting risks (Hong et al., 2025) and capturing intricate relationships between topographical factors and vegetation cover. To statistically validate the relative importance of topographical factors, we first computed SHAP values based on the RF model. Then, we applied the Friedman test to determine whether global differences existed among feature importance values. For features showing significant differences ($P < 0.05$), we conducted pairwise comparisons using the Wilcoxon signed-rank test, a non-parametric method suitable for paired data. All analyses were performed using the scikit-learn and SHAP libraries in Python 3.8, with hyperparameter optimization via grid search.

To complement the machine learning analysis, we also examined linear relationships between topographical factors and NDVI using traditional statistical methods. Pearson correlation coefficients were calculated to assess the strength and direction of linear associations.

Subsequently, partial correlation analysis was conducted to control for potential confounding effects among topographical variables, thereby isolating the unique contribution of each factor to NDVI variation. These analyses were implemented in Python 3.8.

Results

Vegetation dynamics in the Tianshan Mountains during 2000-2022

An analysis of vegetation change in the Tianshan Mountains during 2000-2022 indicated that average NDVI is ranked as $CTS > NTS > STS$ (Fig. 4 [Figure 4: see original paper]). Overall, vegetation exhibited an increasing trend, with NDVI values ranging from 0.37 to 0.43 and a decadal trend of 0.6×10^{-3} . The maximum NDVI value of 0.43 was recorded in 2017. Among subregions, vegetation growth rates followed the order $NTS > CTS > STS$, with the STS showing the slowest rate of increase.

4 Interannual variation of Normalized Difference Vegetation Index (NDVI) in the Tianshan Mountains and three subregions during 2000-2022. Shaded areas indicate 95% confidence intervals, while dashed lines represent time-series trend lines.

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Slope estimation and significance tests (Fig. 5 [Figure 5: see original paper]) revealed that the Tianshan Mountains contain more pixels exhibiting improvement than degradation. Specifically, 59.46% of the area showed significant veg-

etation improvement (Fig. 6 [Figure 6: see original paper]), whereas only 3.10% exhibited significant degradation. The STS region constituted the primary area of improvement, with highly significant improvement covering 70.59% of the total STS area, indicating effective ecological restoration. In contrast, significant degradation was concentrated in the Ili River Valley and in areas with intense human activities, including Hejing County, Dabankou District, and Tekes County. This spatial heterogeneity highlighted the complex interplay among climate change, human activities, and local topography in shaping vegetation dynamics.

Statistical significance of vegetation change trends in the Tianshan Mountains during 2000–2022

6 Area proportion for different vegetation change types in the Tianshan Mountains and three subregions during 2000–2022

Spatial patterns of vegetation change across topographical gradients

3.2.1 Vegetation change patterns along the elevation gradient inverted V-shaped relationship with elevation, peaking at 0.42 in the high elevation zone between 2800 and 3200 m. This pattern was primarily governed by the vertical zonation of hydrothermal

WEN Di et al.: Dynamic vegetation change response to topography based on... conditions. Below 1100 m, NDVI values remained low due to water stress caused by limited precipitation and high potential evapotranspiration—characteristic of low-elevation desert ecosystems. The optimal combination of sufficient moisture and favorable temperatures in mid-to-low elevation zone can create the most suitable ecological niche for vegetation growth, supporting mountain meadow and forest ecosystems. Above 3200 m, NDVI values declined sharply due to constraints imposed by low temperatures, short growing seasons, and persistent snow and ice cover.

The spatial distribution of vegetation change trends further highlighted the ecological sensitivity of different elevation zones. Analysis of vegetation dynamics in the Tianshan Mountains revealed the following sequence in areal extent: highly significant increase>nonsignificant change>significant increase, with minimal areas showing decline. Above 3200 m, regions with significant greening substantially exceeded those with nonsignificant changes, whereas below 3200 m, the differences between significant increase and nonsignificant change were relatively small. The degradation hotspots were predominantly concentrated in low-elevation river valleys, illustrating how intense human activities—such as agricultural expansion and urbanization—can counteract the benefits of a relatively humid climate, leading to vegetation degradation. In contrast, the NTS exhibited an intermediate condition: significant greening primarily occurred at higher elevations, while lower-elevation areas appeared more stable.

7 Area proportion of each vegetation change type at different elevation zones in the Tianshan Mountains (a) and three subregions of STS (b), CTS (c), and

NTS (d) during 2000-2022

3.2.2 Vegetation change patterns along the slope gradient Slope significantly influences vegetation distribution and dynamics by regulating human accessibility and soil stability. The Tianshan Mountains exhibited the lowest multi-year average NDVI values on flat slopes (0° - 5°), a pattern consistent with extensive agricultural and construction land conversion driven by high human accessibility (Fig. 8 [Figure 8: see original paper]). Conversely, NDVI values peaked on moderate slopes (15° - 25°), indicating superior vegetation growth conditions—

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likely due to reduced human activities compared to flatter terrain. Notably, when the slope exceeded 15° , NDVI values changed little and tended to stabilize. Trend analysis revealed distinct shifts in vegetation change patterns along the slope gradient (Fig. 8). The overall trend distribution across the Tianshan Mountains followed: highly significant increase>nonsignificant change>significant increase, and there were minimal degraded areas. Although steep slopes ($>25^{\circ}$) exhibited lower overall NDVI averages, the proportion of areas showing significant vegetation growth had markedly increased. This spatial mismatch indicated that steeper slopes, despite lower vegetation cover, are undergoing the strongest recovery—potentially facilitated by ecological restoration projects and natural succession due to their inaccessibility.

Subregional patterns revealed differing pressures. In the STS, vegetation across the slope gradient predominantly exhibited significant improvement, particularly on flat slopes (0° - 5°), indicating widespread recovery. In the CTS, nonsignificant changes were most prevalent.

However, active greening also occurred on gentle slopes (5° - 15°)—possibly linked to regional conservation measures. The NTS exhibited a pattern similar to the CTS. For slopes exceeding 5° , the proportion of areas showing significant increase in NDVI generally rose with slope steepness, while the proportion of areas showing nonsignificant change decreased correspondingly. Thus, the degree of vegetation improvement was positively correlated with slope steepness.

Collectively, these findings indicated that slope steepness is not only a determinant of baseline vegetation cover but also a key predictor of vegetation change trajectories. Throughout the study period, steep slopes exhibited the most pronounced positive trend in vegetation recovery.

8 Area proportion of vegetation change types along the slope gradient in the Tianshan Mountains (a) and three subregions of STS (b), CTS (c), and NTS (d) during 2000-2022

3.2.3 Vegetation change patterns across the aspect gradient Aspect fundamentally regulates vegetation dynamics in the Tianshan Mountains by shaping mi-

croclimate conditions through differential solar radiation. Figure 9 [Figure 9: see original paper] clearly illustrates the spatial distribution patterns of multi-year average NDVI values and vegetation change types across different aspects. The overall pattern revealed that shady slopes exhibited significantly higher vegetation cover, with average NDVI values ranging from 0.40 to 0.50, whereas sunny slopes showed markedly lower values (<0.30). This disparity primarily stemmed from differences in

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solar radiation: shady slopes provided more favorable growth conditions due to reduced evapotranspiration and enhanced soil water retention; conversely, sunny slopes experienced water stress from intense solar radiation and higher temperatures. Additionally, regarding vegetation change, the dominant trend on shady slopes was highly significant increase, followed by nonsignificant change and significant increase, with only minimal areas undergoing significant decrease. Flat terrain exhibited the highest improvement potential, with over 65.00% exhibiting highly significant increase, followed by shady, semi-shady, and semi-sunny slopes. Sunny slopes showed the lowest improvement potential, with more than 40.00% displaying nonsignificant change.

Subregional analysis revealed notable variations. In the STS, shady slopes exhibited slightly higher NDVI values than flat terrain, reflecting the greater dependence of arid-zone vegetation on aspect for water regulation. Vegetation change patterns aligned with regional trends, with over 50.00% of flat terrain showing significant improvement and negligible degradation. The CTS displayed a distinct pattern: flat terrain had the highest NDVI values (>0.50), attributed to developed river systems and oasis agriculture. Vegetation predominantly exhibited nonsignificant change ($>50.00\%$ of the CTS area), with only flat terrain showing significant improvement (of which $>40.00\%$ showed highly significant increase), indicating relatively stable vegetation conditions. In the NTS, the highest NDVI values (about 0.40) occurred on shady and semi-shady slopes, with overall NDVI slightly exceeding those in the STS, likely due to more favorable precipitation patterns. Vegetation growth on shady slopes in the NTS was greater than that in the CTS, suggesting greater potential for forest restoration.

In summary, the spatial distribution and dynamic changes of vegetation across different aspects in the Tianshan Mountains were jointly determined by hydrothermal conditions and existing vegetation characteristics. Flat terrain and shady slopes emerged as core zones for vegetation improvement, whereas sunny slopes required targeted conservation measures to maintain existing vegetation stability.

9 Area proportion of vegetation change types along the aspect gradient in the Tianshan Mountains (a) and three subregions of STS (b), CTS (c), and NTS (d) during 2000-2022. , , , and represent flat terrain, shady slope, semi-shady slope, semi-sunny slope, and sunny slope, respectively.

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Impact of topographical factors on vegetation change

3.3.1 Impact of elevation on vegetation change K-value analysis revealed distinct elevational distribution patterns for vegetation change types across the Tianshan Mountains and three subregions (Fig. 10 [Figure 10: see original paper]). The K value quantitatively identified the spatial concentration of specific vegetation change types (e.g., degradation or improvement) relative to regional averages.

Across the entire Tianshan Mountains, a distinct pattern emerged: vegetation degradation was highly concentrated in the elevation zone of 1550-2800 m, where the maximum K value reached

1.23. This indicated that the probability of vegetation degradation occurring within this elevation

zone is significantly higher than the regional average, identifying it as a key ecologically vulnerable zone. This concentration of degradation may stem from the region's high sensitivity to climate change. In contrast, high elevation zones (>2800 m) and the low elevation zone (<1100 m) emerged as dominant elevation zones for significant vegetation improvement. The improvement trend in high elevation zones suggested reduced human disturbance, while warming-induced snowmelt may create favorable conditions for vegetation growth. The greening trend in the low elevation zone primarily benefits from ecological restoration projects targeting desert-oasis transition zones.

Subregional analysis revealed notable differences across Tianshan subzones. In the STS, significant improvement occurred in both high elevation zone (>3600 m) and mid-to-low elevation zones (<2800 m). The CTS and NTS exhibited more synchronized response patterns, with the most pronounced degradation concentrated at elevations between 1550 and 2800 m. In both subregions, high elevation zones (>3200 m for the CTS and >2800 m for the NTS) were the

10 Variation of terrain area correction coefficient (K) with elevation depending on vegetation change types in the Tianshan Mountains (a) and three subregions of STS (b), CTS (c), and NTS (d). The dotted line indicates K=1.00.

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primary elevation zones for significant improvement. This north-south divergence indicated that the optimal altitudinal range for vegetation recovery is modulated by regional hydrometeorological conditions: in the relatively humid CTS and NTS, greening is favored at higher elevations, whereas in the arid STS, it shifts toward lower elevations.

In summary, K-value analysis clearly identified mid-to-low elevation zones as the core vulnerable areas for vegetation degradation in the Tianshan Mountains. However, the elevation range of vegetation recovery was not uniform but

exhibited systematic variation along regional hydrometeorological gradients—occurring at higher elevations in the more humid northern and central regions and shifting to lower elevations in the arid southern areas. 3.3.2 Impact of slope on vegetation change K-value analysis indicated that the dominant distribution of vegetation change types influenced by slope exhibited certain patterns across the Tianshan Mountains and three subregions (Fig. 11 [Figure 11: see original paper]).

Across the entire mountain range, vegetation showing highly significant increase predominated on steep slopes ($>25^\circ$) and flat slopes ($<5^\circ$), with the greatest dominance observed on slopes exceeding 35° ($K=1.22$). This indicated that steeper slopes have a higher probability of significant vegetation improvement compared to the regional average, suggesting their potential as core zones for ecological restoration. This pattern can be primarily attributed to limited human accessibility, which facilitates natural vegetation recovery. In contrast, vegetation change types of highly significant decrease ($K=1.41$) and significant decrease ($K=1.37$) were dominant across the broad 5° - 35° slope gradient, peaking in the 15° - 25° range. This reflected dual pressures on 5° - 35° slope zones: intensified soil erosion combined with human disturbances from grazing and cultivation.

Subregional analysis revealed notable spatial variations: unlike other subregions, vegetation in the STS exhibited a dominant pattern of highly significant increase on slopes below 15° .

However, in areas steeper than 15° , vegetation degradation types began to emerge and dominate.

Specifically, types of highly significant decrease were most dominant in the 0° - 5° slope range ($K=1.16$), while significant decrease exhibited relative dominance in the 25° - 35° range ($K=1.26$).

In the CTS, vegetation exhibiting highly significant increase showed clear dominance on flat

11 Variation of K with slope depending on vegetation change types in the Tianshan Mountains (a) and three subregions of STS (b), CTS (c), and NTS (d). The dotted line indicates $K=1.00$.

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slopes ($<5^\circ$) and extremely steep slopes ($>35^\circ$). Conversely, vegetation degradation types were more dominant within the 15° - 35° range, peaking between 15° and 25° . The NTS displayed a response pattern similar to CTS: the 5° - 35° slope range represented the primary terrain for vegetation degradation, whereas significant increase type showed dominance on slopes $<25^\circ$ and maintained a clear advantage on steep slopes ($>25^\circ$).

The north-south gradient differences highlighted that vegetation response to slope is modulated by regional aridity levels. In the extremely arid STS, gentle slopes became core areas of ecological degradation, whereas in the relatively moisture-rich CTS and NTS, the conventional pattern of “gentle slopes being more susceptible to disturbance while steep slopes recover” was more pronounced.

In summary, K-value analysis clearly identified the 5°-35° slope zones as the core areas of vegetation degradation in the Tianshan Mountains, while steep slopes (>25°) and certain flat slopes (<5°) emerged as key zones of ecological recovery in the region. The relationship between vegetation change and slope was not uniform but varied systematically along the regional aridity gradients.

3.3.3 Impact of aspect on vegetation change K-value analysis revealed distinct patterns in the dominant distribution of vegetation change types influenced by aspect across the Tianshan Mountains and three subregions (Fig. 12 [Figure 12: see original paper]). Across the entire mountain range, significant decrease type was predominant on sunny slopes, indicating a higher probability of vegetation degradation on sunny slopes, and highlighting sunny slopes as ecologically vulnerable surfaces. This phenomenon can be attributed to the stronger solar radiation received by sunny slopes, which intensifies soil evaporation and increases water stress, thereby suppressing vegetation resilience. Conversely, areas with vegetation showing highly significant increase were concentrated on shady slopes and flat terrain, with this predominance decreasing progressively from shady to sunny slopes. The reduced transpiration and enhanced soil moisture retention on shady slopes created more humid and shaded microclimatic conditions that promoted vegetation recovery and growth.

12 Variation of K with aspect depending on vegetation change types in the Tianshan Mountains (a) and three subregions of STS (b), CTS (c), and NTS (d). , , , and represent flat terrain, shady slope, semi-shady slope, semi-sunny slope, and sunny slope, respectively. The dotted line indicates K=1.00.

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Subregional analysis revealed notable differences: the STS exhibited a pattern contrasting with the overall trend, where vegetation decline occurred primarily on semi-shady and semi-sunny slopes, while flat terrain, shady slopes, and sunny slopes were dominated by vegetation improvement—albeit with lower statistical dominance. This suggested that under conditions of extreme aridity, the hydrological contrast between sun- and shade-facing slopes diminishes, making microtopographic water redistribution processes potentially more influential. In contrast, the CTS and NTS exhibited responses highly consistent with the overall pattern. Vegetation degradation was overwhelmingly predominant on sunny slopes in both subregions, peaking on these aspects in the CTS and reaching a K value of 1.27 in the NTS. Conversely, significant vegetation improvement was concentrated on shady slopes, semi-shady slopes, and flat terrain.

Moreover, in the NTS, vegetation improvement was most pronounced on flat terrain, achieving maximum dominance (K=1.86). This highlighted that in

areas with relatively favorable hydrological and thermal conditions, flat terrain—particularly when combined with human irrigation management—can support exceptionally strong vegetation recovery and ecological restoration in vulnerable regions.

In summary, K-value analysis clearly demonstrated that sunny slopes represent generally vulnerable areas for vegetation degradation in the Tianshan Mountains, whereas shady slopes and flat terrain constitute advantageous areas for ecological restoration.

3.3.4 Synergistic effect of topographical factors on vegetation cover

A comprehensive analysis of the K-value revealed the influence of topography on vegetation cover in the Tianshan Mountains. Specific combinations of elevation, slope, and aspect synergistically shaped local hydrothermal niches (Fig. 13 [Figure 13: see original paper]). The K-value clearly demonstrated the dominant distribution of different vegetation cover levels across various topographical combinations. Across the entire mountain range, topographical control patterns were pronounced: low-cover vegetation ($NDVI < 0.20$) dominated in combination of high elevations ($> 3600\text{m}$), extremely steep slopes ($> 35^\circ$), and sunny slopes, consistent with cold, high-radiation, and thin-soil environment. Moderate-cover vegetation ($0.20 < NDVI < 0.40$) thrived optimally in combination of low elevations ($< 1100\text{m}$), gentle slopes ($5^\circ-15^\circ$), and sunny slopes in arid climate conditions. High-cover vegetation ($NDVI > 0.40$) was closely associated with high elevations (2800–3200 m), flat slopes ($< 5^\circ$), and shady slopes, which provide ample moisture from precipitation and snowmelt, suitable temperatures, and reduced water transpiration—constituting the most favorable hydrothermal configuration for vegetation growth.

Subregional analysis further revealed that this optimal topographical configuration is strongly modulated by regional climate, resulting in systematic differentiation. In the STS, influenced by an arid-dominated climate, the optimal topography for high-cover vegetation growth occurred at high elevations (2800–3200 m) on sunny slopes, indicating that vegetation growth in this region prioritizes light and heat availability over water conservation. In contrast, the CTS and NTS exhibited distinct patterns: under more humid conditions, the optimal topographical configuration for high-cover vegetation shifted to higher elevations (3200–3600 m) on shady slopes. This highlighted the critical role of shady slopes in moisture retention and the greater availability of water sources—such as orographic precipitation and snowmelt—at higher elevations.

This systematic differentiation demonstrated that while the topographical mechanisms governing vegetation distribution—such as aspect regulating moisture gradients and slope influencing material stability—are universal, the resulting optimal habitat patterns are ultimately determined by regional hydrothermal conditions. In arid regions, vegetation tends to occur at lower elevations with greater solar radiation (sunny slopes), whereas in more humid areas, it favors higher elevations where moisture retention is enhanced (shady slopes).

In summary, K-index analysis clearly indicated that topographical control over vegetation is fundamentally the result of multidimensional factors acting syner-

gistically.

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13 Distribution of NDVI across various topographical combinations in the Tianshan Mountains (a1-f1) and three subregions of STS (a2-f2), CTS (a3-f3), and NTS (a4-f4). , , , and represent flat terrain, shady slope, semi-shady slope, semi-sunny slope, and sunny slope, respectively.

Relative importance of topographical factors

3.4.1 Model validation and robustness assessment To ensure the robustness and generalizability of the RF model, we implemented a rigorous

WEN Di et al.: Dynamic vegetation change response to topography based on... validation framework. To assess regional variability, the RF model was independently trained and tested for three subregions: STS, CTS, and NTS. The model demonstrated stable performance across the entire mountain range, with a cross-validated R2 of 0.522 and a test set R2 of 0.506.

Predictive accuracy varied across subregions: STS (R2=0.515), CTS (R2=0.516), and NTS (R2=0.522), reflecting the differential influence of topography on vegetation dynamics along the hydro-climatic gradient. In the arid STS, non-topographical factors—such as extreme water stress and soil salinity—likely dominated, weakening the apparent topographical signal. This cross-regional validation underscores that while topography is a significant driver, its influence is modulated by broader climatic conditions. These results confirmed the model's robustness and applicability across diverse topographical and ecological contexts. 3.4.2 SHAP analysis of topographical factors SHAP analysis ranked the importance of factors as follows: elevation>slope>aspect>planar curvature>profile curvature (Fig. 14 [Figure 14: see original paper]). The SHAP dependence plots revealed the specific, often nonlinear, functional relationships between each factor and NDVI.

NDVI. SHAP values peaked at approximately 0.080 in the elevation zone of 2000–3000 m, whereas low elevations (<1500 m) and high elevations (>3500 m) exhibited negative effects (SHAP -0.300). The positive influence of elevation was most pronounced in the 20°–40° slope range, consistent with the optimal ecological niche theory. This nonlinear response suggested threshold effects in vegetation distribution, driven by the optimal water-heat balance in mid-elevation areas. relationship indicated that gentle to moderate slopes (5°–25°) are most favorable for vegetation growth. Extremely steep slopes (>35°) were associated with increased soil erosion and reduced soil depth, limiting water and nutrient retention. In contrast, flat slopes (<5°), particularly in low-elevation valleys, were often subject to human disturbance (e.g., agriculture, urbanization) and potential soil salinization, explaining the negative SHAP values observed.

peaked near 0.100 at 320° (northwest-facing slopes), indicating superior vegetation cover on shady slopes. In steep areas (slope>30°), aspect significantly influenced NDVI, suggesting that terrain interactions govern vegetation distribution. This highlighted the role of aspect in regulating solar radiation and soil moisture, with significant implications for modeling mountain ecosystems. a weak negative effect, as convex areas promote runoff and erosion. Planar curvature (indicating flow convergence or divergence) exhibited a clearer signal: negative values (concave areas) positively influenced NDVI, particularly at lower elevations, by enhancing water accumulation and creating mesic microsites in an otherwise arid environment. 3.4.3 Importance ranking of topographical factors Elevation was the most influential variable in the RF model, with an average absolute SHAP value of 0.053 (Fig. 15a [Figure 15: see original paper]). Slope ranked second in importance at 0.027, followed by aspect, planar curvature, and profile curvature, with average absolute SHAP values of 0.023, 0.008, and 0.006, respectively. In the NDVI correlation analysis, slope exhibited the strongest Pearson correlation ($r=0.08$), indicating a significant linear relationship, whereas aspect, planar curvature, and profile curvature showed weaker correlation (Fig. 15b). Partial correlation analysis corroborated these results, underscoring the significance of elevation and slope in model predictions and their associations with NDVI, likely due to their influence on hydrological and thermal regimes, soil erosion processes, and vegetation distribution patterns.

Discussion

Topographical control and spatial heterogeneity in vegetation dynamics

The dynamic changes in vegetation within the Tianshan Mountains from 2000 to 2022 presented a

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14 SHAP dependence plot for elevation (a), slope (b), aspect (c), profile curvature (d), and planar curvature (e). The aspect in Figure 14c is indicated by an angle, ranging from 0° to 360°.

15 Important ranking of topographical factors to NDVI (a) and correlation coefficient between topographical factors and NDVI (b)

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complex interplay of topographical control, climatic influence, and anthropogenic pressure. Our high-resolution analysis not only confirms the previously reported greening trend in northwestern China (Zhang et al., 2023a), but more importantly, reveals the profound spatial heterogeneity underlying this pattern. This fine-scale understanding enables a deeper exploration of the mechanisms driving these vegetation dynamics.

Extending and refining existing research, our findings on the dominant role of elevation align with the global recognition of mountain regions as biodiversity hotspots and ecologically sensitive areas (Liang et al., 2024). NDVI in the Tianshan Mountains exhibited an inverted U-shaped relationship with elevation, peaking between 2800 and 3200 m. This pattern corresponds to vertical elevational zonation, where mid-to-low elevations (<2800 m) offer optimal hydrothermal conditions by balancing lowland water stress and high-elevation thermal limitations (Gao et al., 2019). Furthermore, this study employed SHAP values to quantify the contribution of topographical factors to vegetation cover, revealing that elevation alone accounts for 52.00% of NDVI variance—substantially exceeding the combined influence of other topographical elements. This elevational control was not static but interacted strongly with factors such as slope. The positive effect of flat slopes (<5°) was most evident at low elevations (<1100 m), likely due to deeper soil development and reduced erosion rates—both critical for vegetation in arid regions (Wang et al., 2022). Conversely, the influence of aspect was amplified on steep slopes (>25°), where microclimatic and soil moisture conditions diverge markedly due to variations in solar radiation. This finding is consistent with results from other semi-arid mountain systems (Yang et al., 2020).

This study revealed that vegetation degradation is concentrated in areas with mid-to-low elevations (1100–2800 m), moderate to steep slopes (15°–35°), and sunny slopes, indicating that these topographical settings are ecologically vulnerable. These areas face dual pressures from climate change and human activities. Sunny slopes experience heightened evapotranspiration due to increased solar radiation, leading to soil moisture deficits (García-Gamero et al., 2021).

Meanwhile, gentler topography facilitates human activities such as urban development and grazing (e.g., Yili River Valley). In contrast, steep slopes (>25°) exhibited significant vegetation recovery despite lower baseline NDVI values. This reflects the effectiveness of ecological restoration initiatives like the Three-North Shelterbelt Program in these less accessible areas, and may also indicate natural recovery following reduced anthropogenic pressure (Li et al., 2021a). These complex interactions suggest that future vegetation trajectories in the Tianshan Mountains will be shaped by fine-scale topographical niches, potentially driving broader environmental changes.

Climatic and anthropogenic drivers of vegetation change

While topography provides the foundational template, climatic and anthropogenic factors are also key drivers of vegetation change (Xiong and Wang, 2022). The widespread greening trend is closely linked to regional warming and humidification in Northwest China. Rising temperatures—particularly at high elevations—may extend growing seasons and accelerate snowmelt, temporarily enhancing water availability. However, this study also identified underlying risks supported by prior research (Bhambri et al., 2023): the accelerated retreat of snowlines (reduction in snow-covered area) may compromise long-term water security for downstream oasis ecosystems—the foundation supporting both

natural vegetation and human societies. Furthermore, localized degradation in low-elevation river valleys and urban centers bears clear signatures of human impacts. Agricultural expansion, urbanization, and overgrazing can override local climatic advantages, resulting in vegetation decline (Cao et al., 2025). This coexistence of greening and browning underscores humanity's dual role: as a driver of degradation in accessible areas, and as an agent of ecological recovery through conservation policies in remote, topographically complex regions.

Limitations and prospects

Despite its significant findings, this study has several limitations that warrant acknowledgment.

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First, while NDVI is a reliable indicator of vegetation greenness, it tends to saturate in high-biomass areas and is sensitive to soil background effects in sparsely vegetated regions.

Future studies could employ physiological indicators such as solar-induced chlorophyll fluorescence to directly monitor photosynthetic activity. Second, our assessment of human activity impacts relies on indirect inference. Integrating explicit geospatial datasets—such as precise boundaries for grazing intensity, infrastructure expansion, and conservation programs (e.g., the Three-North Shelterbelt Program)—would enable more robust attribution of observed changes. Third, while 30 m resolution represents an improvement over coarser datasets, finer ecological processes and understory dynamics may still be unresolved. Ultra-high-resolution imagery from drones or Planet Labs satellites could capture these details. Finally, although our machine learning approach (RF-SHAP) successfully identified key topographical drivers and their nonlinear associations with vegetation cover, correlation does not imply causation. To strengthen causal inference, our spatiotemporal analysis incorporated elements of “natural experiments” by dividing the study area into distinct hydrometeorological subregions (STS, CTS, and NTS).

Within these diverse zones, the consistent and disproportionate concentration ($K > 1.00$) of vegetation degradation in specific topographical settings—such as mid-to-high elevations ($> 1100\text{m}$) and sunny slopes—provides tentative, though inferential, evidence for causal linkages.

This design effectively controls for large-scale climatic confounding factors. Nevertheless, to fully validate these causal pathways, more explicit causal inference techniques are required, such as quantifying direct and indirect effects through Structural Equation Modeling (SEM) (Fu et al., 2025; Yao et al., 2025) or applying Granger Causality Tests (Xiao et al., 2023) to long-term data integrated with high-resolution environmental variables. Such approaches would help confirm the causal mechanisms suggested by SHAP analysis.

Conclusions

This study utilized 30 m resolution Landsat NDVI data from 2000 to 2022, employing trend analysis, K-value analysis, and a RF-SHAP modeling framework to systematically assess vegetation dynamics in the Tianshan Mountains and their relationship with topographical factors.

Vegetation across the Tianshan Mountains exhibited a significant greening trend over the 23-a period, with the most pronounced improvement observed in the STS. Nevertheless, localized degradation persisted. These degraded patches were highly concentrated, primarily occurring in low-elevation desert-oasis ecotones and anthropogenically disturbed piedmont zones, including irrigation districts such as the Ili River Valley. Topography emerged as the dominant driver of vegetation distribution and change. Elevation was the most influential factor, with optimal vegetation conditions occurring in mid-elevation zones (1100–2800 m). Slope and aspect were also significant predictors. Notably, shady slopes consistently supported higher vegetation cover and stronger greening trends compared to sunny slopes. Analysis of topographical combinations identified distinct optimal habitats for different vegetation cover classes. This clear ecological partitioning highlights a strong adaptation of vegetation to microclimatic conditions shaped by topography. These findings enhance our understanding of how topography shapes vegetation patterns in arid mountain ecosystems. The identification of degradation hotspots provides valuable references for targeted ecological conservation and restoration efforts in the Tianshan Mountains. Future research could further incorporate climatic variables to disentangle the combined effects of topography and climate on vegetation dynamics under changing environmental conditions.

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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WEN Di; Validation: WEN Di, LI Jun; Visualization: WEN Di; Supervision: WEN Di, LI Jun, XU Weifeng, CHEN Zhixiang, PENG Dailiang. All authors approved the manuscript.

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

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