J Arid Land (2026) 18(6): 928-948

WANG Yongliang[*], ZHANG Weijiang

2026-06-18

ChinaRxiv

Abstract

The Shaanxi-Gansu-Ningxia (SGN) border region, as a typical transitional zone between the East Asian monsoon and the westerlies, features a fragile ecological environment. In this study, the spatiotemporal evolution and multiscale driving mechanisms of surface winds in this ecologically fragile transition zone were investigated by integrating trend analysis, empirical orthogonal function (EOF) decomposition, and geographic detector method. The results indicated that from 1980 to 2022, the annual mean surface wind speeds in the SGN border region significantly increased, with a linear growth rate of 0.003 m/(s•a). However, the anomaly series revealed a clear interdecadal transition: surface wind speed anomalies were predominantly negative from 1980 to 1999 and shifted to persistently positive and increasing anomalies after 2000. Consistent strengthening was observed in summer, autumn, and winter, with the most pronounced increase occurring in autumn. The spatial distribution generally followed a pattern of higher values in the northwest and lower values in the southeast. Spring presented the strongest surface wind speeds and the most extensive areas with high values. EOF analysis revealed two dominant spatial modes: the first mode (variance contribution >73.40%) reflected regionally consistent changes, and its temporal coefficients increased continuously, corresponding to the overall strengthening trend of surface wind speed; and the second mode exhibited an east-west dipole oscillation pattern, dominated by interannual fluctuations. The geographic detector results revealed that fractional vegetation cover (FVC), temperature, and topographic elevation were key factors influencing the spatial differentiation of surface wind speeds, with all the factors exhibiting enhanced interactive effects—especially the synergistic effect between vegetation cover and temperature. Background circulation analysis indicated that enhanced westerlies and decreased geopotential height in the mid-to-upper troposphere provided favourable dynamic conditions for increased surface wind speeds. This study advances the understanding of surface wind speed changes in climate transition zones, providing a scientific basis for regional wind energy planning, ecological protection, and wind erosion control.

Full Text

J Arid Land (2026) 18(6): 928–948
doi: 10.1016/j.jaridl.2026.06.002; CSTR: 32276.14.JAL.20250623

Mechanisms driving surface wind speed increases in an ecologically fragile region of Northwest China: Insights from circulation anomalies and geographical detector analysis

WANG Yongliang*, ZHANG Weijiang

School of Civil and Hydraulic Engineering, Ningxia University, Yinchuan 750021, China

Abstract: The Shaanxi-Gansu-Ningxia (SGN) border region, as a typical transitional zone between the East Asian monsoon and the westerlies, features a fragile ecological environment. In this study, the spatiotemporal evolution and multiscale driving mechanisms of surface winds in this ecologically fragile transition zone were investigated by integrating trend analysis, empirical orthogonal function (EOF) decomposition, and geographic detector method. The results indicated that from 1980 to 2022, the annual mean surface wind speeds in the SGN border region significantly increased, with a linear growth rate of 0.003 m/(s • a). However, the anomaly series revealed a clear interdecadal transition: surface wind speed anomalies were predominantly negative from 1980 to 1999 and shifted to persistently positive and increasing anomalies after 2000. Consistent strengthening was observed in summer, autumn, and winter, with the most pronounced increase occurring in autumn. The spatial distribution generally followed a pattern of higher values in the northwest and lower values in the southeast. Spring presented the strongest surface wind speeds and the most extensive areas with high values. EOF analysis revealed two dominant spatial modes: the first mode (variance contribution>73.40%) reflected regionally consistent changes, and its temporal coefficients increased continuously, corresponding to the overall strengthening trend of surface wind speed; and the second mode exhibited an east-west dipole oscillation pattern, dominated by interannual fluctuations. The geographic detector results revealed that fractional vegetation cover (FVC), temperature, and topographic elevation were key factors influencing the spatial differentiation of surface wind speeds, with all the factors exhibiting enhanced interactive effects—especially the synergistic effect between vegetation cover and temperature. Background circulation analysis indicated that enhanced westerlies and decreased geopotential height in the mid- to upper-troposphere provided favourable dynamic conditions for increased surface wind speeds. This study advances the understanding of surface wind speed changes in climate transition zones, providing a scientific basis for regional wind energy planning, ecological protection, and wind erosion control.

Keywords: surface wind speed; Shaanxi-Gansu-Ningxia (SGN) region; empirical orthogonal function (EOF) analysis; geographical detector; atmospheric circulation

Citation: WANG Yongliang, ZHANG Weijiang. 2026. Mechanisms driving surface wind speed increases in an ecologically fragile region of Northwest China: Insights from circulation anomalies and geographical detector analysis. Journal of Arid Land, 18(6): 928–948. https://doi.org/10.1016/j.jaridl.2026.06.002; http://cstr.cn/32276.14.JAL.20250623

*Corresponding author: WANG Yongliang (E-mail: ylwangdo@outlook.com)
Received 2025-12-16; revised 2026-04-14; accepted: 2026-06-01

KeAi Communications Co. Ltd.

http://jal.xjegi.com; https://www.keaipublishing.com/en/journals/journal-of-arid-land/

This version posted 2026-06-18.

1 Introduction

As a critical parameter for surface energy exchange and material transport, surface wind speed variations are jointly modulated by natural factors (i.e., temperature, pressure gradients, and topography) and anthropogenic activities (i.e., land use change and urbanization). Previous studies have reported a significant decrease in global surface wind speeds over the past few decades (Azorin-Molina et al., 2018; Diao et al., 2020; Wang et al., 2025). Furthermore, surface wind speed variations have profound effects on both societal systems and climate processes, such as water vapour evaporation, hydrological cycles (He et al., 2025), and surface energy balance (Wu et al., 2025). Previous research has attributed the reduction in atmospheric evaporative demand to diminished surface wind speeds (Woolway et al., 2020). For instance, Akinsanola et al. (2021) demonstrated that a 29.00% decrease in surface wind speeds could reduce annual evapotranspiration by 1.00%–3.00%.

In recent years, the potential causes of surface wind speed variations have garnered widespread attention (Laurila et al., 2021; Wang et al., 2024a; Zha et al., 2024). Furthermore, numerous studies have proposed advanced physical mechanisms to interpret surface wind speed changes in China, including the weakening of monsoonal circulations (Zhang and Wang, 2020), the impact of urbanization on surface roughness (Öztürk et al., 2024), and the role of large-scale atmospheric oscillations, such as the Arctic Oscillation and the Pacific Decadal Oscillation (Zhang et al., 2021a; Li et al., 2025). However, while multiple theories exist to explain surface wind speed changes, particularly in inland regions, such as the Shaanxi-Gansu-Ningxia (SGN) border region, a consensus on the dominant mechanisms—especially those integrating both natural and anthropogenic drivers—remains elusive. Surface winds are fundamentally driven by large-scale atmospheric circulation patterns and the pressure gradient force, which are modulated by both natural climatic factors and anthropogenic activities. However, traditional research has focused predominantly on single meteorological processes and wind erosion effect analysis, and there are still gaps in the understanding of multifactor interactions and their driving mechanisms with spatial heterogeneity, particularly the hierarchical influence of large-scale circulations on local modulation. For instance, Zhou et al. (2021) revealed that surface wind speeds decline most rapidly in spring, whereas winter contributes most significantly to the reversal of the annual trend following abrupt temperature changes. However, the physical mechanisms underlying such seasonal differences remain unclear. Moreover, at the regional scale, the spatially heterogeneous characteristics of decreased surface wind speeds in core areas and surrounding regions imply potential impacts of topography, fractional vegetation cover (FVC), and anthropogenic activities. Nevertheless, existing studies have not yet systematically quantified the relative weights of these local and surface factors and their interactive effects against the backdrop of dominant large-scale circulation patterns.

Many scholars have conducted preliminary explorations into the driving mechanism of surface wind speed changes. Zhang et al. (2024a) reported that surface wind speed variations on the Qinghai-Xizang Plateau are closely related to changes in pressure gradients induced by asymmetric warming between high- and low-latitude zones. Moreover, studies in the sandy areas of the northern Loess Plateau revealed that interannual surface wind speed fluctuations are correlated with phased achievements in sand fixation projects (Guo et al., 2019). However, existing studies have focused predominantly on single-factor statistical analyses and lack a systematic evaluation of multifactor interactions. As an ecological transition zone, the variation in surface wind speeds in the SGN border region may be influenced by the complex geographical environment and anthropogenic activities (Chen et al., 2021; Li et al., 2022; Sun et al., 2022), although related research is still insufficient. Traditional statistical methods (i.e., correlation analysis, the Mann-Kendall test, and residual analysis) struggle to reveal the spatially heterogeneous contributions of driving factors; and spatial analysis tools, such as geographical detectors, are urgently needed to quantify the independent and interactive effects of local-scale natural and anthropogenic factors on the spatial pattern of surface wind speeds.

However, the mechanisms are likely region-specific and modulated by local geography and

human intervention. The SGN border region presents a compelling and unique case: it is a quintessential ecologically fragile transitional zone between the East Asian monsoon and the midlatitude westerlies (Wang et al., 2024b). This geographical setting renders it exceptionally sensitive to oscillations in large-scale circulation and surface changes induced by both climate warming and regional ecological restoration policies. Consequently, the SGN border region serves as a natural laboratory for examining the synergistic forcing of multiscale drivers on surface wind speeds, with findings that can provide insight into similar vulnerable ecotones globally.

Therefore, focusing on the SGN border region as the study area and on the basis of long-term meteorological observation data, reanalysis datasets, and remote sensing products from 1980 to 2022, this research integrated trend analysis, spatial interpolation, empirical orthogonal function (EOF) decomposition, and geographic detector analysis, aiming to achieve the following objectives: (1) to reveal the spatiotemporal trends, spatial distribution patterns, and dominant spatial modes of surface wind speeds along with their temporal evolution characteristics in the SGN border region from 1980 to 2022; (2) to quantitatively analyse the effects of natural and anthropogenic factors on surface wind speed changes and their interactions; and (3) to explore the underlying mechanisms of surface wind speed variations from the perspectives of circulation patterns, climate warming, and synergistic surface processes. These findings provide a scientific basis for wind energy planning, ecological restoration, and wind erosion control in the SGN border region and offer case references and theoretical support for studies on surface wind speed changes in similar climate transition zones worldwide.

2 Methods

2.1 Study area

The SGN border region ($34°30'–37°50'$N, $105°02'–108°55'$E) is located in the inland of Northwest China, covering 31 cities and counties (or districts) in northern Shaanxi Province, eastern Gansu Province, and south-central Ningxia Hui Autonomous Region, with a total area of 6.9×10^4 km^2 (Fig. 1). This region lies in the transition zone between the East Asian monsoon and the midlatitude westerlies, representing an ecologically fragile area in northern China, with frequent extreme winds that pose a serious threat to agriculture, transportation, and ecological security. Owing to monsoon influences, the climate in the southeastern part of the study area is humid, while the northwestern regions are predominantly arid (Yu et al., 2008). The multi-year average temperature ranges from 6.00°C–10.00°C, and the multi-year average precipitation is approximately 250–500 mm, with most rainfall concentrated from July to September (accounting for more than 60.00% of the annual total). The seasonal and interannual variability is high, making water availability a key factor restricting ecosystem stability.

2.2 Data source and processing

The climate data used in this study were sourced from the National Cryosphere Desert Data Center (http://www.ncdc.ac.cn/). This dataset features high spatial resolution (1 km) and a complete time series (monthly data from 1980 to 2022), covering key meteorological variables, such as the surface wind speed and temperature. Surface wind speed data refer to measurements at 10.00 m height above ground level. The data underwent rigorous quality control during production, including internal consistency checks and outlier screening (Zhang et al., 2021b; Hu and Zhang, 2024).

Changes in surface wind speeds are influenced by both natural climate factors and anthropogenic activities (You et al., 2014; Zha et al., 2017; Diao et al., 2020). To systematically investigate the driving mechanisms, in this study, considering the actual ecological and natural conditions of the region and referring to existing research Zhang et al. (2024b), we selected seven potential drivers from two aspects: natural climate and human activities, including temperature, elevation, slope (terrain gradient), roughness, FVC, land use type (based on the China Land Cover Dataset (CLCD; https://zenodo.org/record/4417810), and urban built-up area. Slope refers to the terrain slope, which is calculated from a digital elevation model (DEM). Urban built-up area data

Fig. 1 Topographical map of the study area

are available from 1992 onwards. To assess potential bias, we conducted a sensitivity analysis using the overlapping period (1992–2022) and compared the q values with those from the full-period analysis. The relative ranking of factors remained consistent, suggesting that incomplete coverage did not substantially alter the main conclusions. To verify the reliability of the urban built-up area data, we compared it with nighttime light data (NTL) from the same period. The high spatial correlation ($R^2 > 0.85$) supported the consistency and reliability of the urban built-up area dataset. The selection of these factors was grounded in their physical relationship with surface wind speeds: temperature directly affects atmospheric stability and pressure gradients; elevation and slope modulate local wind fields through topographic dynamic effects; roughness length directly affects surface wind speed by modulating the frictional drag force, larger roughness generally leads to greater momentum loss and reduced near-surface wind speeds; and FVC, land use type, and urban built-up area reflect the frictional and blocking effects of underlying surface properties on airflow (Ge et al., 2021; Yan et al., 2023).

All the driver data were standardized to the period 1980–2022 and underwent corresponding spatiotemporal consistency processing. The land use type and FVC data were obtained from the National Qinghai-Xizang Plateau Data Center (http://data.tpdc.ac.cn/) at a spatial resolution of 1 km. The roughness data were sourced from the European Space Agency (ESA; https://panda.copernicus.eu/) with a spatial resolution of 0.1°. The DEM data were acquired from the Geospatial Data Cloud (https://www.gscloud.cn/) at a resolution of 30.00 m.

To explore the influence of the background atmospheric circulation on surface wind speeds, this study also used monthly mean European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis v5 (ERA5) reanalysis data from the ECMWF, including geopotential height and wind vectors at 500 and 200 hPa, covering the period 1980–2022 (Hersbach et al., 2020).

Notably, some human activities (e.g., urban built-up area) are not fully covered over the entire study period (1980–2022), which may introduce uncertainty in the geographical detector analysis. If the trend of such factors strongly coincides with surface wind speed changes during overlapping periods, the explanatory power of shorter-period factors (e.g., FVC) could be

overestimated. This issue was assessed and discussed in the subsequent analysis of this study. Furthermore, the geographical detector factors selected in this study primarily characterize surface and underlying surface properties. Although these factors, especially temperature, are direct manifestations of climatic conditions, the geographical detector quantifies the explanatory power of the factors for the spatial pattern of surface wind speeds. Therefore, the analysis in this section aims to reveal the dominant surface factors influencing the spatial differentiation of surface wind speeds and their interactions, whereas the long-term trends in surface wind speeds, particularly the underlying dynamic mechanisms, require comprehensive diagnosis by integrating large-scale circulation background analysis.

2.3 Theil-Sen median slope

The Theil-Sen median slope method is a nonparametric statistical approach used to estimate linear trends in data. It does not rely on data distribution assumptions and is insensitive to outliers, making it suitable for trend analysis of long time series (Ma et al., 2025):

$$Slope = \frac{n \times \sum_{i=1}^{n}(i \times y_i) - \sum_{i=1}^{n} i \sum_{i=1}^{n} y_i}{n \times \sum_{i=1}^{n} i^2 - \left(\sum_{i=1}^{n} i\right)^2}, \tag{1}$$

where *Slope* is the interannual rate of change in the surface wind speed (m/(s · a)); i is the index of the observation year ($i = 1, 2, \dots, 43$); n is the number of years ($n = 43$); and y_i is the value of the surface wind speed during year i (m/s).

2.4 Mann-Kendall test

The Mann-Kendall test is a nonparametric statistical method widely used to analyse whether a monotonic trend occurs in time series data. To address potential autocorrelation in the time series, we applied pre-whitening before conducting the Mann-Kendall test, following the approach recommended by Ahmed et al. (2020). Its key advantage lies in not requiring data to follow a specific distribution, and it has been extensively applied in fields such as environmental science, hydrological analysis, and ecology. For a detailed introduction, refer to Zuo et al. (2022).

2.5 EOF analysis

EOF analysis is a statistical method used for dimensionality reduction and pattern extraction in spatiotemporal data. It is widely applied in many fields, including meteorology, oceanography, and environmental sciences (Liu et al., 2024). By decomposing the data matrix, this method extracts dominant spatial modes and their corresponding temporal coefficients, revealing the principal structures and dynamic patterns inherent in the dataset. The formulas are as follows:

$$F_{jt} = \sum_{k=1}^{m} v_{jk} z_{kt}, \tag{2}$$

$$\mathrm{EOF}_k = (v_{1k}, v_{2k}, \cdots, v_{mk}), \tag{3}$$

$$\mathrm{PC}_k = (z_{k1}, z_{k2}, \cdots, z_{kn}), \tag{4}$$

where j represents the spatial points ($j = 1, 2, \ldots, m$); t represents the temporal points ($t = 1, 2, \ldots, n$); k represents the index of spatial modes ($k = 1, 2, \ldots, K$, where K is the total number of retained modes); F_{jt} represents the t^{th} observation at the j^{th} spatial point; v_{jk} represents the j^{th} spatial function of the k^{th} column; z_{kt} represents the t^{th} temporal function of the k^{th} row; EOF_k represents the k^{th} spatial mode; and PC_k represents the k^{th} temporal coefficient (referred to as the k^{th} principal component (PC)).

2.6 Geographical detector

In this study, all the continuous variables (e.g., temperature, elevation, and FVC) were discretized into five categories using the natural breaks (Jenks) method, which optimizes the classification by minimizing the within-class variance and maximizing the between-class differences (Wang et al., 2016). This approach is widely used in geographical detector applications to ensure robust factor

stratification (Deng et al., 2022b). Details of the discretization thresholds (Jenks breakpoints) are provided in Table S1.

Notably, Table S1 includes only the continuous factors (elevation, slope, roughness, temperature, and FVC). The remaining two factors—CLCD and urban built-up area—are categorical variables. As such, they do not require discretization and are directly input into the geographical detector model using their original categorical codes. Therefore, they are not listed in Table S1.

Additionally, for temperature and roughness, the Jenks natural breaks method resulted in only four distinct categories instead of five (as applied to other continuous variables). This is due to the relatively limited variability in their spatial distributions within the study area, which led to a lower number of naturally separable classes. Using fewer than four categories would fail to capture the internal heterogeneity, while more than four categories would result in unstable stratification with negligible variance gain. Thus, retaining four categories balances explanatory power and statistical robustness for these two factors.

2.6.1 Factor detection

Factor detection was used to examine the degree of spatial differentiation of the effects of driving factors on surface wind speed variations. The q statistic, which measures the proportion of surface wind speed variance explained by a given factor, was employed to describe the explanatory power of driving factors in accounting for the spatial heterogeneity of surface wind speeds. The formula is as follows:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2}, \tag{5}$$

where q is the explanatory power of the selected factor for the spatial variability of surface wind speeds; $h = 1, 2, \ldots, L$, is the stratification of the selected factor; N and N_h are the numbers of samples in the entire zone and h^{th} layer, respectively; and σ and σ_h refer to the variance in the entire zone and h^{th} layer, respectively.

2.6.2 Interaction detection

Interaction detection was used to identify whether the combined effect of $X1$ and $X2$ enhances (or diminishes) the explanatory power for surface wind speeds. The interaction q value between two factors $X1$ and $X2$, denoted as $q(X1 \cap X2)$, was calculated by overlaying the stratified layers of both factors and computing the combined explanatory power. The classification of the interaction types is provided in Table 1.

Table 1 Criteria of the interaction types

Interaction criteria	Interaction type
$q(X1 \cap X2) < \text{Min}(q(X1), q(X2))$	Nonlinear weakening
$\text{Min}(q(X1), q(X2)) < q(X1 \cap X2) < \text{Max}(q(X1), q(X2))$	Univariate weakening
$q(X1 \cap X2) > \text{Max}(q(X1), q(X2))$	Bivariate enhancement
$q(X1 \cap X2) = q(X1) + q(X2)$	Independent
$q(X1 \cap X2) > q(X1) + q(X2)$	Nonlinear enhancement

2.6.3 Ecological detection

Ecological detection was applied to assess whether two driving factors exhibit a statistically significant difference in their spatial distribution effects on surface wind speeds, quantified through the F statistic:

$$F = \frac{N_{X1}(N_{X2} - 1) \sum_{h=1}^{L1} N_h \sigma_h^2}{N_{X2}(N_{X1} - 1) \sum_{h=1}^{L2} N_h \sigma_h^2}, \tag{6}$$

where N_{X1} and N_{X2} are the samples of the selected factor $X1$ and $X2$, respectively; and $L1$ and $L2$ are the numbers of categories in $X1$ and $X2$, respectively.

2.7 Circulation background analysis method

To identify the circulation changes associated with the shift from the wind stilling phase to the recovery phase, we compared the differences in these circulation fields between two periods: 1980-1999 (earlier period, corresponding to the wind stilling phase) and 2000-2022 (late period, corresponding to the wind recovery and strengthening phase). Composite difference analysis was employed to calculate the difference in each circulation variable between the later and earlier periods, and statistical significance was assessed using a t test at the 90% confidence level.

3 Results

3.1 Spatial distribution characteristics of surface wind speeds

Surface wind speeds exhibited distinct seasonal and regional spatial variations in the study area from 1980 to 2022 (Fig. 2). Overall, the annual surface wind speeds showed significant spatial heterogeneity across the region, which is generally characterized by relatively high surface wind speeds in the northwestern parts and low wind speeds in the southeastern parts. Surface wind speeds were generally stronger in spring, with the most extensive coverage of high-value zones (>3.0 m/s), which is particularly notable in the west-central and northern parts of the study area. Surface wind speeds decreased overall in summer, although localized high-wind speed areas still existed. Surface wind speeds further decreased in autumn and winter, with most areas falling within the range of 1.5-3.0 m/s. Among these, the 1.5-2.0 m/s category accounted for more than 50.00% in both autumn and winter (Fig. 2f). This distribution pattern is closely related to regional topography, variations in monsoon circulation intensity, and underlying surface properties, reflecting the complexity and sensitivity of the transitional climate.

(a) Annual
Surface wind speed (m/s): 3.13-1.42

(b) Spring
Surface wind speed (m/s): 3.43-1.64

(c) Summer
Surface wind speed (m/s): 3.21-1.48

(d) Autumn
Surface wind speed (m/s): 2.98-1.22

(e) Winter
Surface wind speed (m/s): 3.03-1.33

(f) Pixel percentage (%)
Period: Annual, Spring, Summer, Autumn, Winter
Surface wind speed categories (m/s): <1.50; 1.50-2.00; 2.00-2.50; 2.50-3.00; >3.00

Fig. 2 Spatial (a–e) and percentage (f) distribution of the annual and seasonal surface wind speeds in the study area from 1980 to 2022

3.2 Temporal trends in surface wind speeds

Figure 3 presents the time series, anomalies, and trends of the annual and seasonal surface wind speeds in the study area from 1980 to 2022. Overall, the annual surface wind speeds in the study area significantly increased ($P < 0.05$), with a linear growth rate of 0.003 $\mathrm{m/(s \cdot a)}$ (Fig. 3a). To further investigate whether this increase is characterized by a nonmonotonic, phase-like transition, we applied piecewise linear regression to the annual time series and used the cumulative anomaly method to assist in identifying the breakpoint. Piecewise linear regression revealed a breakpoint at approximately 2000 ($P < 0.05$). Specifically, the surface wind speed series exhibited a weak downward trend ($Slope = -0.007\ \mathrm{m/(s \cdot a)};\ P < 0.05$) from 1980 to 1999, followed by a pronounced upward trend ($Slope = 0.029\ \mathrm{m/(s \cdot a)};\ P < 0.05$) from 2000 to 2022.

Fig. 3 Temporal variation in the annual (a), spring (b), summer (c), autumn (d), and winter (e) surface wind speeds in the study area from 1980 to 2022

At the seasonal scale, the surface wind speeds in spring slightly increased, with a growth rate of 0.001 $\mathrm{m/(s \cdot a)}$ ($P < 0.05$) (Fig. 3b). The anomaly series revealed small amplitude fluctuations throughout the study period, without a clear long-term bias. The surface wind speeds in summer noticeably increased, with a rate of increase of 0.004 $\mathrm{m/(s \cdot a)}$ ($P < 0.05$) (Fig. 3c). The anomalies remained relatively stable before 2000, after which they shifted to predominantly positive values and have remained consistently high in recent years. The surface wind speeds in autumn showed the most pronounced increasing trend, with a growth rate of 0.006 $\mathrm{m/(s \cdot a)}$ ($P < 0.05$) (Fig. 3d). The anomaly series turned from negative to positive in the late 1990s, followed by a fluctuating upward trend. The surface wind speeds in winter also significantly increased, with a growth rate of 0.004 $\mathrm{m/(s \cdot a)}$ ($P < 0.05$) (Fig. 3e). The anomaly series shifted from negative to positive in the

mid-to-late 1990s and thereafter displayed a fluctuating upward trend, with high values emerging in the late 2010s.

3.3 Dominant spatial patterns and time series of surface wind speeds

To reveal the dominant spatial modes and temporal evolution characteristics of surface wind speed changes in the SGN border region, we conducted an EOF analysis. The first mode of empirical orthogonal function (EOF1) explained the major portion of the variance in surface wind speeds. Specifically, its variance contribution rates were 78.19% at the annual scale and 78.34%, 81.10%, 73.40%, and 77.99% for spring, summer, autumn, and winter, respectively, indicating that this mode was the most dominant spatial pattern of regional surface wind speed variations (Fig. 4). The spatial pattern of EOF1 exhibited uniform positive values across the entire study area at the annual scale and in spring, summer, and autumn, suggesting a high degree of spatial coherence in surface wind speed changes—i.e., the region generally experienced in-phase strengthening or weakening of wind speeds. However, the spatial pattern of EOF1 in winter showed uniform negative values across the region, reflecting that surface wind speed changes in winter were also spatially coherent. The sign of an EOF mode was mathematically reversible; the opposite sign in winter did not imply a physically opposite variation but rather indicated that the spatial structure was consistent, with the sign convention chosen arbitrarily.

The first principal component (PC1) series clearly captured the temporal evolution of this coherent pattern. PC1 values were generally low from the 1980s to the early 1990s, after which they began to fluctuate upward, peaking in the late 2010s. Its 5 a moving average curve (black dashed line) further highlighted this long-term shift from a low-value period to a high-value period, which aligns closely with the significant upward trend in the annual surface wind speeds. The sustained positive-phase growth of PC1, particularly since the mid-1990s, directly corroborated the overall strengthening of surface winds in the study area.

The second mode of empirical orthogonal function (EOF2) represents a secondary spatial pattern of surface wind speed variations, with variance contributions much lower than those of EOF1. The contributions were 11.75% at the annual scale and 11.29%, 7.87%, 18.85%, and 11.75% for spring, summer, autumn, and winter, respectively (Fig. 5). Notably, the variance contribution of EOF2 in autumn was relatively high, suggesting that this mode plays a more important role in autumn surface wind speed variations. The spatial pattern of EOF2 exhibited a clear dipole-like out-of-phase distribution between the east and west, revealing differential wind speed changes within the region. At the annual scale and in spring, summer, and winter, the spatial pattern was "positive in the west and negative in the east", indicating that the surface wind speed trends in the western and eastern parts of the study area are opposite. However, in autumn, the pattern exhibited a reversed dipole structure ("negative in the west and positive in the east") compared with that in the other seasons, suggesting a seasonally unique configuration of the east-west contrast pattern.

The second principal component (PC2) series fluctuated frequently and did not show a single long-term trend that is similar to PC1; its 5 a moving average also oscillated around zero. This finding indicated that the out-of-phase relationship between the eastern and western surface wind speeds represented by EOF2 was characterized mainly by interannual and interdecadal oscillations rather than long-term unidirectional changes.

A comprehensive analysis indicated that surface wind speed changes in the SGN border region from 1980 to 2022 were primarily controlled by two typical spatial modes: the first mode (EOF1) dominated the long-term coherent strengthening trend across the entire region; and the second mode (EOF2) captured the out-of-phase oscillatory relationship between surface wind speed changes in the eastern and western parts of the region, with the spatial phase varying seasonally and characterized mainly by interannual fluctuations. The high variance contribution of EOF1 further confirmed that regional surface wind speed changes were fundamentally dominated by coherent and region-wide variations.

Fig. 4 Spatial distribution (a) and temporal coefficient (b) of the first eigenvector field in the study area from 1980 to 2022. EOF1, first mode of empirical orthogonal function; PC1, first principal component (temporal coefficient). The black dashed line represents the 5 a moving average of the PC1 temporal coefficient. The value in the lower-left corner denotes the variance contribution of the first mode.

Panel labels and visible annotations:

- (a1) Annual; EOF1; 0–60 km; N
- (b1) Annual; PC1; 78.19%; Year
- (a2) Spring; EOF1
- (b2) Spring; PC1; 78.34%; Year
- (a3) Summer; EOF1
- (b3) Summer; PC1; 81.10%; Year
- (a4) Autumn; EOF1
- (b4) Autumn; PC1; 73.40%; Year
- (a5) Winter; EOF1
- (b5) Winter; PC1; 77.99%; Year

(a1) Annual EOF2
(b1) Annual PC2 11.75%

(a2) Spring
(b2) Spring PC2 11.29%

(a3) Summer
(b3) Summer PC2 7.87%

(a4) Autumn
(b4) Autumn PC2 18.85%

(a5) Winter
(b5) Winter PC2 11.75%

Fig. 5 Spatial distribution (a) and temporal coefficient of the second eigenvector field in the study area from 1980 to 2022. EOF2, second mode of empirical orthogonal function; PC2, second principal component (temporal coefficient). The black dashed line represents the 5 a moving average of the PC2 temporal coefficient. The value in the lower-left corner denotes the variance contribution of the second mode.

3.4 Geographic detection analysis of surface wind speed changes

3.4.1 Factor detection analysis We applied factor detection to quantify the importance of each selected factor using q values (Fig. 6). The factors were ranked in descending order of their explanatory power: FVC>temperature>elevation>CLCD>slope>roughness>urban built-up area. Among them, FVC, temperature, and elevation were the dominant influencing factors, with explanatory powers exceeding 45.00%. However, roughness and urban built-up area had minimal influences on surface wind speed changes in the investigated region, with explanatory powers less than 18.00%. Notably, the geographic detector quantifies the spatial explanatory power of each factor and does not directly attribute temporal trends.

Fig. 6 q value of each factor to surface wind speed in the Shaanxi-Gansu-Ningxia (SGN) border region. FVC, fractional vegetation cover; CLCD, China Land Cover Dataset.

The high explanatory power of temperature, a proxy for thermal conditions affecting atmospheric stability and large-scale pressure gradients, underscored the role of climate warming. The significance of static factors, such as elevation and slope, highlighted their persistent control on the spatial distribution of surface wind speeds by shaping local airflow patterns, even if they did not explain the temporal increase.

3.4.2 Ecological detection analysis Ecological detection was applied to evaluate the significant differences in the spatial distribution of surface wind speeds caused by the selected factors (Fig. 7). The results indicated that there was no significant difference in elevation or CLCD, but these factors significantly differed when they interacting with other factors. Slope exhibited no significant differences with roughness and CLCD, but significant variations in its influence on surface wind speeds were observed compared with those of other factors. FVC, temperature, and urban built-up area played critical roles in the spatial distribution of surface wind speeds. The spatial patterns and evolutionary trends of surface wind speeds were influenced by both natural climate and anthropogenic activities.

3.4.3 Interaction detection analysis To identify the synergistic effects between any two selected factors and their effects on the spatial heterogeneity of surface wind speeds, we conducted an interaction detection analysis (Fig. 8). The findings revealed that the q values of the interactions between any two factors were generally greater than those of the individual factors, indicating that dual and nonlinear enhancement effects occur, with no independent interactions. The interactions between any two factors, i.e., elevation, slope, roughness, temperature, urban built-up area, FVC, and CLCD, were bidirectionally enhanced. In the investigated region, FVC exhibited the strongest interactions with the other factors, with an explanatory power greater than 0.719. The interaction strengths revealed the following ranking: FVC temperature (q=0.857)>FVC elevation (q=0.800)>FVC slope (q=0.799)>FVC CLCD (q=0.782)>FVC roughness (q=0.763)>FVC urban built-up area

($q = 0.719$). Notably, the interaction detection results further substantiated the significant influences of FVC, temperature, and elevation on surface wind speeds. In conclusion, the interactions between selected factors collectively enhanced their effects on surface wind speed variations.

Fig. 7 Ecological detection in the SGN border region. In the matrix, 'Y' indicates a statistically significant difference ($P < 0.05$) between the effects of the two factors on surface wind speeds, whereas 'N' indicates no significant difference.

Fig. 8 Interaction detection between factor-pairs in the SGN border region. The error bars represent the 95% confidence intervals of the q values based on 1000 bootstrap resamples.

3.5 Characteristics of circulation background changes

To explore the possible background circulation underlying the significant upward trend in surface wind speeds in the study area, we compared and analysed the differences in geopotential height and horizontal wind fields at the 500 and 200 hPa pressure levels between 1980–1999 and 2000–2022 (Figs. 9 and 10).

(a) Annual (b) Spring

(b) Summer (d) Autumn

(c) Winter

Scale: 0–1500 km

Legend:
- Study area
- International boundary
- Coastline
- Horizontal wind vector (m/s)
- Approved: GS(2023)2763

Geopotential height anomaly (dagpm): −1.6, −1.2, −0.8, −0.4, 0.0, 0.4, 0.8, 1.2, 1.6

Fig. 9 Composite differences in the annual (a), spring (b), summer (c), autumn (d), and winter (e) 500-hPa geopotential height and horizontal winds in the SGN border region from 2000–2022 minus 1980–1999. Stippling represents the statistical significance of the 500-hPa geopotential height exceeding the 90% confidence level. The light green vectors refer to the 500-hPa horizontal wind differences exceeding the 90% confidence level.

The characteristics of the 500-hPa circulation field revealed that on both annual and seasonal (spring, summer, autumn, and winter) scales, the geopotential heights over the study area and its key upstream regions generally decreased during the later period compared with those during the earlier period (the shaded areas indicate significant differences at the 90% confidence level) (Fig. 9). A decrease in geopotential height typically implied enhanced trough activity or a deepening of cyclonic circulation over the region, which favours an increase in the surface pressure gradient. Moreover, the difference field of the horizontal wind vectors indicated that the westerly component at mid-tropospheric levels strengthened in most seasons (especially in spring, summer, and autumn) during the later period (light green vectors). Such an intensification of mid-level westerly circulation can effectively drive an increase in surface wind speeds through downward momentum transfer. Therefore, the configuration of the 500 hPa circulation field—characterized by decreased geopotential height accompanied by enhanced westerly flow—provided favourable mid-level dynamic conditions for increasing surface wind speeds.

The characteristics of the 200-hPa circulation field mainly reflect changes in the upper-level westerly jet stream (Fig. 10). The analysis revealed that during the later period, the intensity of the westerly jet stream at 200 hPa over the study area tended to increase during multiple seasons, particularly in spring and winter. Strengthening of the upper-level westerly jet was often associated with an enhanced meridional temperature gradient and increased baroclinicity in the middle and lower troposphere; and through dynamic coupling across the entire troposphere, it can influence lower-level winds. Such changes in the 200 hPa wind field, which are consistent with the circulation changes at 500 hPa, together formed a vertical structure of enhanced westerly circulation from the upper to the middle troposphere. This provided a deep atmospheric circulation background conducive to long-term increases in surface wind speeds.

(a) Annual

(b) Spring
Scale: 0–1500 km

(c) Summer

(d) Autumn

(e) Winter

Legend: Study area; International boundary; Coastline; Horizontal wind vector (m/s).
Approved: GS(2023)2763.

Geopotential height anomaly (dagpm): −1.8, −1.2, −0.6, 0.0, 0.6, 1.2, 1.8.

Fig. 10 Composite differences in the annual (a), spring (b), summer (c), autumn (d), and winter (e) 200-hPa geopotential height and horizontal winds in the SGN border region from 2000–2022 minus 1980–1999. Stippling represents the statistical significance of the 200-hPa geopotential height exceeding the 90% confidence level. The light green vectors refer to the 200-hPa horizontal wind differences exceeding the 90% confidence level. In panel e (winter), the white areas indicate that the absolute difference in 200-hPa geopotential height between the two periods is near zero, implying little to no change in the mean geopotential height.

4 Discussion

4.1 The dominant role of large-scale atmospheric circulation

The analysis presented in Section 3.5 clearly reveals systematic adjustments in the circulation background. The significant upward trend in surface wind speeds in the study area during 1980–2022 was closely related to these systematic changes in mid- and upper-tropospheric atmospheric circulation. These changes were manifested mainly as follows: (1) a decrease in the 500-hPa geopotential height, indicating more active cyclonic circulation or trough activity, which directly favoured an increase in the surface pressure gradient—the most direct dynamic driver of enhanced wind speeds; and (2) an increase in the westerly circulation at both 500 and 200 hPa, resulting in the formation of a vertically coherent background of strengthened westerly momentum transfer. Via downward momentum transport, this strengthened westerly circulation provided sustained dynamic support for increased surface wind speeds. The above-described shift in circulation patterns was likely associated with the adjustment of mid- and high-latitude atmospheric circulation under global warming, changes in land-sea thermal contrast and interdecadal variations in large-scale climate modes, such as the Arctic Oscillation. The coordinated changes in these circulation factors collectively strengthened the influence of the wind systems on the study area, thereby serving as the primary large-scale circulation background driving the long-term upward trend in surface wind speeds across the region.

4.2 Interaction between climate warming and local thermal effects

The significant upward trend in surface wind speeds observed in the SGN border region from 1980 to 2022 aligns with findings of wind speed recovery reported in other regions following periods of decline (Kim and Paik, 2015; Li et al., 2018; Zhang and Wang, 2020). The distinct and important contribution of this study, therefore, is not merely reporting an increase but also providing a detailed and multifaceted mechanistic diagnosis of how and why this recovery and strengthening occurred within this specific ecologically fragile transition zone. The results of the integrated analysis reveal a combination of distinct processes: pronounced autumn intensification, a dominant synergistic interaction between vegetation coverage and warming identified by the geographical detector, and coevolution with specific mid- to upper-tropospheric circulation adjustments. This shift in focus—from trend documentation to process-based explanations—offers a foundational understanding of the evolution of wind speeds in sensitive climate transition zones.

On the one hand, against the backdrop of global warming, the study area has experienced significant temperature increases (Deng et al., 2022a), leading to an enhanced surface-atmosphere temperature gradient. This may intensify local thermal circulations (such as mountain-valley winds or oasis-desert circulations), thereby promoting increases in wind speeds under certain seasonal and topographic conditions. On the other hand, ecological restoration projects implemented in recent decades (e.g., returning farmland to forestland and grassland) have significantly increased vegetation coverage in the study area, and FVC was identified as the primary factor influencing wind speeds in this study. Increased vegetation may modify surface roughness, albedo, and evapotranspiration processes, regulating the thermal structure of the local boundary layer and consequently affecting the surface wind speed distribution and trend.

The strongest interaction between FVC and temperature ($q = 0.857$) suggests a critical biogeophysical feedback loop. Increased vegetation coverage enhances surface roughness and evapotranspiration. The former tends to dissipate near-surface momentum, whereas the latter cools the surface and increases the latent heat flux, potentially stabilizing the boundary layer (Piao et al., 2020). However, in a warming climate, this surface cooling effect may be moderated or counteracted. The resulting altered surface-atmosphere temperature gradient can modify local pressure fields and thermally driven circulations (e.g., slope winds). Furthermore, vegetation growth itself is temperature dependent. Thus, warming can promote a higher FVC, which in turn can modify surface energy partitioning and roughness in ways that either amplify or dampen the response of the wind to large-scale forcing, creating a tightly coupled "climate-vegetation-wind" system specific to this transitioning landscape.

Notably, the geographical detector analysis in this study revealed that the interaction between temperature and FVC had the strongest explanatory power for wind speed variation ($q = 0.857$), indicating that the coupled effect of climate warming and vegetation restoration is a mechanism that cannot be ignored in terms of driving regional surface wind speed changes. Furthermore, in the monsoon-westerlies transition zone, the study area may experience synergistic enhancement between large-scale circulation changes (e.g., intensified westerly circulation) and local thermal adjustments, resulting in a more pronounced upward trend in wind speeds.

Therefore, the long-term change in surface wind speeds in the SGN border region is not a direct outcome of climate warming alone but rather the product of combined effects from large-scale circulation adjustments, regional responses to global warming, and local underlying surface changes induced by anthropogenic activities. This understanding is important for understanding the coupling mechanisms within the climate–vegetation–wind erosion system of fragile ecological zones and for predicting future trends in wind resource evolution.

4.3 Synergistic effects of surface and anthropogenic factors

The geographic detector analysis in this study indicated that changes in surface wind speeds are not solely driven by individual climatic factors but are also the product of synergistic interactions between natural surface attributes and human activities. Natural factors such as FVC, topography (elevation and slope), and land surface temperature fundamentally control the spatial

differentiation of wind speeds. Moreover, human activities further modulate the spatiotemporal dynamics of the surface wind field by altering land use types (as reflected by land cover changes in datasets, such as CLCD), surface roughness, and urban heat island effects.

The interaction detection results revealed that the interaction between any two factors enhances wind speeds, particularly for FVC $\cap$ temperature ($q = 0.857$) and FVC $\cap$ elevation ($q = 0.800$). This suggested that against the background of climate warming, human interventions such as vegetation restoration may be coupled with topographic dynamic effects—through changes in surface albedo, evapotranspiration, and roughness—to jointly enhance or buffer the response of wind speeds to climate change. For example, in hilly areas with better ecological restoration (higher FVC and complex topography), increased surface roughness may reduce surface wind speeds. In contrast, in high-elevation areas with sparse vegetation, the acceleration effect of topography on airflow may combine with enhanced local circulation because of warming, leading to a further increase in wind speeds (Meng et al., 2018; Zhang et al., 2022).

4.4 Comparison with previous studies and methodological insights

In this study, EOF analysis, geographic detector, and circulation analysis were integrated to investigate surface wind speed changes in the SGN border region, offering both methodological and mechanistic advancements over previous methods. Earlier studies on wind speed trends in China often relied on linear trend analysis (Zhang et al., 2019), correlation with large-scale indices or single-factor attribution (Zhang et al., 2021a). Our EOF analysis not only confirmed a dominant regionally coherent mode of increased wind speeds (consistent with large-scale circulation forcing) but also revealed a secondary east-west dipole mode, which aligns with the results of studies highlighting regional heterogeneity due to topography and land cover (Li et al., 2022). The geographic detector extends beyond traditional regression by quantifying the spatial explanatory power and, crucially, the interactions among factors. This approach addresses a gap noted in reviews calling for more integrated and multi-driver assessments (Zha et al., 2024). Our finding that the FVC-temperature interaction has the greatest explanatory power underscores the value of examining coupled natural-human systems, a perspective less common in earlier wind speed studies focused solely on circulation or urbanization. The circulation analysis in this study explicitly links mid- to upper-tropospheric changes (weakened geopotential height and strengthened westerlies) to the surface trend, providing a dynamic framework that complements the statistical surface factor analysis. This integrated approach—combining spatiotemporal decomposition, spatial statistical detection, and dynamical diagnostics—offers a more comprehensive understanding than studies using only one of these methods do. This particularly benefits research in transitional zones, such as the SGN border region, where both large-scale forcing and local heterogeneity are pronounced.

4.5 Limitations and future perspectives

By integrating station observations, reanalysis data, and geographic detector methods, this study systematically revealed the spatiotemporal evolution patterns and driving mechanisms of surface wind speeds in the SGN border region from 1980 to 2022, providing empirical evidence for understanding changes in the wind environment in ecologically fragile areas. However, certain limitations remain in terms of data, methods, and mechanistic interpretation, which should be addressed and refined in future research.

At the data and methodological level, although the spatial distribution of meteorological stations covers the entire region, the density remains insufficient in complex terrain areas, which may affect the local accuracy of spatial interpolation and EOF modes. Moreover, the grid-scale analysis of the geographic detector is unable to fully capture the fine-scale modulation of wind speeds by underlying surface details, such as microtopography and vegetation canopy structure. The background circulation analysis focused on the mid-to-upper troposphere and did not explore in depth the direct contributions of boundary-layer dynamic processes (e.g., low-level jets and vertical wind shear). Although key natural and anthropogenic factors were considered, other variables, such as aerosol concentration, soil moisture, and seasonal snow cover—which may affect wind speeds by altering surface thermal properties—were not included. Human activities

were represented mainly by static or indirect indicators, and the interactive mechanisms between their dynamic processes and wind speeds need further clarification. Furthermore, the geographical detector analysis in this study focused primarily on explaining the spatial patterns of wind speeds. Although we complemented this with circulation analysis to explore potential causes of temporal trends, future research should attempt to incorporate spatially explicit indicators that directly represent circulation intensity or monsoon/westerly indices (e.g., pressure gradient force and jet stream indices) into attribution frameworks to more directly link large-scale dynamics with local surface wind speed variations. In terms of a mechanistic explanation, this study preliminarily illustrated the synergistic relationships among circulation adjustment, climate warming, and underlying surface changes. However, specific biogeophysical feedback processes among these factors—such as how vegetation restoration modulates local circulation by altering roughness and albedo—lack quantitative modelling and attribution analysis. The deeper dynamic causes underlying the difference between the regional upward wind speed trend and the "wind stilling" phenomenon observed in other parts of the world also need to be clarified through broader comparative studies.

Future research could proceed in the following directions. First, integrating higher-spatiotemporal-resolution reanalysis data, satellite-retrieved wind fields, and wind-profile radar observations would improve the characterization of wind fields over complex terrain. Future studies could incorporate surface pressure gradient data to more directly quantify its role in near-surface wind speed changes. Second, developing or applying regional climate models coupled with detailed surface-process and boundary-layer schemes to conduct multi-scenario simulations and factor-separation experiments could quantitatively disentangle the contributions of different driving elements. Furthermore, constructing a coupled "climate–vegetation–wind erosion" system model would help assess the long-term impacts of different ecological restoration and land-use scenarios on the regional wind environment. Finally, extending the research perspective to broader climate transition zones and conducting multiregional comparisons and long-time-series analyses would deepen the understanding of the spatiotemporal differentiation patterns and unified mechanisms of surface wind speed responses under global change. By exploring these directions, it is hoped that the current limitations can be further overcome, providing a more solid scientific foundation for the sustainable utilization of regional wind energy resources, wind erosion prevention, and the optimization of ecological security patterns.

5 Conclusions

With a focus on the ecologically fragile SGN border region—a transition zone between the East Asian monsoon and the midlatitude westerlies—in this study, an integrated trend analysis, EOF decomposition, a geographic detector analysis, and circulation diagnostics were performed to investigate surface wind speed changes from 1980 to 2022. The annual wind speeds increased significantly at 0.003 $m/(s \cdot a)$, with a phase shift from negative anomalies in 1980–1999 to positive anomalies after 2000, indicating early stilling followed by recovery and strengthening. The increase was most pronounced in autumn, whereas it changed little in spring. Geographic detector analysis revealed that the spatial heterogeneity in wind speeds arises from nonlinear interactions among factors, with FVC, temperature, and elevation as the dominant drivers. The strongest synergism occurred between FVC and temperature ($q = 0.857$), suggesting that ecological restoration and regional warming jointly modulate wind regimes by altering surface roughness, albedo, and boundary-layer stability. At the large scale, post-1990s circulation adjustments—including a reduced 500-hPa geopotential height and enhanced westerlies at 500 and 200 hPa—strengthened the pressure gradients and downward momentum transfer, providing a dynamic background for the increase in wind speeds. By integrating spatial heterogeneity analysis, temporal mode decomposition, and dynamic assessment, this study offers a mechanistic explanation for the evolution of wind speeds in a fragile ecological transition zone, emphasizing the coevolution of circulation, climate change, and human-induced land surface modifications. Future work should use process-based models to quantify this feedback and extend

the framework to other transitional regions.

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.

Acknowledgements

This work was funded by Key Research and Development Plan of Ningxia Hui Autonomous Region (2023BEG02054). Special thanks are due to the anonymous reviewers and the editors for their helpful comments that improved the manuscript substantially.

Author contributions

Writing - original draft preparation: WANG Yongliang; Visualization: WANG Yongliang; Software: WANG Yongliang; Methodology: WANG Yongliang, ZHANG Weijiang; Formal analysis: WANG Yongliang; Data curation: WANG Yongliang; Writing - review & editing: WANG Yongliang; Supervision: ZHANG Weijiang; Funding acquisition: ZHANG Weijiang. All authors approved the manuscript.

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Appendix

Table S1 Classification thresholds for continuous factors

Factor	Unit	Class boundaries (thresholds)	High-risk stratification
Elevation	m	619.00–1290.00	1540.00–1780.00
Elevation	m	1290.00–1430.00	1540.00–1780.00
Elevation	m	1430.00–1540.00	1540.00–1780.00
Elevation	m	1540.00–1780.00	1540.00–1780.00
Elevation	m	1780.00–2020.00	1540.00–1780.00
Slope	°	1.03–3.19	1.03–3.19
Slope	°	3.19–8.41	1.03–3.19
Slope	°	8.41–13.60	1.03–3.19
Slope	°	13.60–18.90	1.03–3.19
Slope	°	18.90–22.50	1.03–3.19
Roughness	m	1.12–13.50	13.50–25.80
Roughness	m	13.50–25.80	13.50–25.80
Roughness	m	25.80–38.20	13.50–25.80
Roughness	m	38.20–50.50	13.50–25.80
Temperature	°C	6.64–7.74	7.74–9.29
Temperature	°C	7.74–9.29	7.74–9.29
Temperature	°C	9.29–10.80	7.74–9.29
Temperature	°C	10.80–14.00	7.74–9.29
FVC		0.260–0.680	0.260–0.680
FVC		0.680–0.850	0.260–0.680
FVC		0.850–0.945	0.260–0.680
FVC		0.945–0.990	0.260–0.680
FVC		0.990–1.000	0.260–0.680

Note: FVC, fractional vegetation cover.

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