

JGR Atmospheres

RESEARCH ARTICLE

10.1029/2025JD045250

Special Collection:

Climate and weather extremes in a warming climate: Processes, Prediction and Projection

Key Points:

- Dust storms (DSs) have decreased nationally since the 1960s, but severe and extreme events have risen sharply since the early 2000s
- Low-intensity DSs are driven by large-scale dynamics, while severe DSs respond more to surface aridity
- Intensified drought and winds in northwest China sustain severe DS, while wetting and weaker winds reduce DSs on the Tibetan Plateau

Supporting Information:

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

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Citation:

Li, J., Hao, X., Lyu, Z., Wang, X., Jin, J., & Liao, H. (2026). Frequency-intensity decoupling and drivers of China's dust storms from 1961 to 2024. *Journal of Geophysical Research: Atmospheres*, 131, e2025JD045250. <https://doi.org/10.1029/2025JD045250>

Received 27 AUG 2025

Accepted 5 FEB 2026

Frequency-Intensity Decoupling and Drivers of China's Dust Storms From 1961 to 2024

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Abstract Dust storms (DSs) have significant impacts on human health, air quality, and terrestrial ecosystems. In recent years, the increasing frequency of extreme DSs has underscored the urgent need to better understand their historical characteristics and dominant drivers. Here, we examined a 64-year observational record (1961–2024) of springtime DS in China, emphasizing the spatiotemporal variations of DS across different intensities. A significant nationwide decrease in the frequency of DSs has been observed, primarily attributed to a reduction in lower-intensity (ODS; ordinary DS) events. The proportion of severe and extreme dust storms (SEDS) has significantly increased since the early 2000s, suggesting a transition toward fewer but more intense occurrences. Using machine learning with interpretable methods, we show that ODS are primarily driven by synoptic-scale dynamics, whereas SEDS are more sensitive to land-surface deficits. SEDS frequency increases sharply when evaporation reaches extremely low values (<50 mm) and top-layer soil temperature exhibits rapid warming (exceeding 290 K). These conditions indicate a precipitation-limited surface state, with strong winds serving as the final trigger for SEDS. The increases in SEDS since 1990 in northwestern China coincide with intensifying spring drought and strengthening wind extremes, while in North China, despite only modest increases in wind speed, persistent surface drying has sustained elevated SEDS activity. In contrast, the eastern Tibetan Plateau exhibits a clear decline, consistent with progressive wetting and a notable weakening of near-surface winds. Our findings identify early-warning predictors that can improve the interpretation and development of future dust-storm projections under climate change.

Plain Language Summary Dust storms (DSs) harm air quality, ecosystems, and public health. This study analyzes over 60 years of spring DS records across China to understand how their frequency and intensity have changed. While total DSs have declined, mainly due to fewer ordinary dust storms (ODS), severe and extreme events (SEDS) have become more common since the early 2000s. Using machine learning, we find that ODS are mainly driven by large-scale weather systems, whereas SEDS are more sensitive to dry surface conditions. When precipitation is scarce, leading to reduced evaporation and elevated soil temperatures, strong winds can more easily trigger SEDS. Since 1990, worsening drought and wind extremes have increased SEDS in northwestern China, while fewer SEDS have occurred on the eastern Tibetan Plateau due to wetter and calmer conditions. These insights can support better forecasts and planning under future climate change.

1. Introduction

Dust storms (DSs) are severe meteorological hazards characterized by strong winds that mobilize large amounts of loose surface material, resulting in visibility reductions below 1 km. They frequently impact arid and semi-arid regions (Shepherd et al., 2016). East Asia contains several major dust source regions and frequently experiences DSs (Y. Shao & Dong, 2006). These events lead to severe impacts on human health, the economy, ecosystems, and climate (Fussell & Kelly, 2021; Han et al., 2012; Kang et al., 2021). Understanding their dynamics is essential for enhancing early warning systems, evaluating the efficacy of mitigation policies, and guiding strategies to minimize risks associated with DS among ongoing climatic and land-surface changes.

DSs in East Asia exhibit significant spatiotemporal variability, influenced by climatic factors and surface conditions. DS hotspots are primarily located in northern China deserts, where average wind speeds exceed 2 m s^{-1} , annual precipitation is typically below 450 mm, and mean temperatures range from 5 to 10°C (Guan et al., 2017). These regions are closely linked to major dust-source areas in southern Mongolia and the Taklamakan Desert (S. Chen et al., 2017). Spring (March–May) is recognized as the season with the highest occurrence of DSs in China, contributing to over 80% of the annual DS frequency (Z. Zhou & Zhang, 2003). During this period, large quantities of dust are generated in northern China due to cyclonic activities and cold surges originating from Siberia (X. Liu et al., 2004).

Long-term records indicate a notable decrease in springtime DS frequency in northern China from the 1960s through the early 2000s (Guan et al., 2017). This overall downward trend, however, has been punctuated by notable anomalies; most prominently, the early 2000s saw an abrupt resurgence in dust activity, with the 2000–2002 period exhibiting markedly more frequent outbreaks than the preceding years (X. Wang et al., 2008). Regional trajectories also exhibit divergence: in northwestern China, DS frequency has reportedly increased since approximately 2013 (Y. Wang et al., 2024), in contrast to the ongoing reduction observed in most of the other regions of East Asia. Importantly, trends can differ according to event intensity. Guo et al. (2018) reported an increasing incidence of large-scale, high-intensity storms (visibility $<200 \text{ m}$) during 1996–2007. Recent episodes further highlight this extremity, with the mid-March 2021 event among the strongest of the past decade (Hu et al., 2022) and spring 2023 witnessing the most frequent DS days in 10 years (Y. Chen et al., 2024), and 2025 outbreaks reported to affect an exceptionally broad area, reaching as far south as Hainan, China's southernmost province (<https://www.news.cn/politics/20250413/2bef9dffe65341649f8190b4dee0cda8/c.html>). Therefore, a systematic, intensity-classified assessment of the spatiotemporal evolution of DSs is needed.

The mechanisms underlying DS occurrences are influenced by the interaction of climate forcing, land surface conditions, and atmospheric circulation. Among meteorological drivers, near-surface WS provides the kinetic energy for dust uplift and serves as the primary trigger for dust events (Y. Liu et al., 2022; W. Zhou et al., 2024). Precipitation and snowmelt suppress dust emissions by enhancing soil cohesion and surface moisture (X. Liu et al., 2004; Tanaka et al., 2011). Air temperature exerts a complex and generally indirect influence on the occurrence and intensity of spring DSs by affecting soil conditions, vegetation, and synoptic weather patterns (Li et al., 2022; L. Liu et al., 2024). The land-surface conditions, as indicated by vegetation cover, soil water content, and snow cover, further govern dust availability and the stability of the source region (Hao et al., 2024; Kim et al., 2017). Identifying the dominant drivers of DS activity is critical for understanding its underlying mechanisms and improving prediction, but remains challenging due to the nonlinear and regionally heterogeneous interactions between atmospheric dynamics and land surface conditions. Traditional approaches have primarily relied on numerical models to simulate dust emissions and transport, with most efforts focusing on the relationship between meteorological factors and dust emissions. For example, recent modeling studies have suggested that the long-term decline in East Asian dust emissions since the early 2000s has been mainly attributed to weakened surface winds, with secondary contributions from increasing vegetation cover and soil moisture content, while the influence of ecological restoration remains limited (C. Wu et al., 2022). A few studies have quantitatively analyzed the contribution of meteorological and ecological factors through statistical methods, indicating that WS reduction was the dominant driver in decadal dust declines, while changes in vegetation had a more localized impact (Gui et al., 2023; D. Wu et al., 2021). Nevertheless, systematic assessments of the relative importance of various drivers of DS frequency, particularly those distinguishing between different intensity categories, remain scarce. The development of machine learning techniques offers a promising tool to capture complex and nonlinear relationships, enabling more robust identification of dominant predictors across different regions and storm intensities.

This study investigated DS activity in East Asia from 1961 to 2024, detailing its variability in terms of seasonality, spatial distribution, and intensity. A national surface observation network is utilized to classify sites based on DS frequency, while regional regimes are identified through clustering analysis. Machine learning models are constructed to quantify the relative importance of synoptic and land-surface conditions, with interpretable techniques used to map spatial patterns of key predictors across DS intensities.

2. Data and Methods

2.1. Dust Event Observations

The dust weather records were derived from in situ observations archived by the National Meteorological Information Center of the China Meteorological Administration. The network includes 719 meteorological stations across China, with monthly occurrences of dust weather in spring from 1961 to 2024, including floating dust, blowing dust, DSs, severe DSs, and extreme DSs. According to the China Meteorological Administration (<https://www.cma.gov.cn/zfxgk/gknr/flfgbz/bz/202209/P020220921579209244330.pdf>), DSs are subdivided into three intensity levels based on horizontal visibility. A DS is defined as when surface winds lift large quantities of dust and sand, leading to severely reduced visibility below 1 km. A severe dust storm (SDS) occurs when visibility drops below 500 m. An extreme-severe dust storm (EDS) is the most intense category, characterized by exceptionally dense airborne dust and sand, reducing horizontal visibility to less than 50 m. To avoid confusion with the general term “DS,” we refer to events with horizontal visibility between 1 km and 500 m as ordinary DSs (ODS) throughout this study. SEDS is defined as the combined frequency of SDS and EDS. These definitions were adopted in our analysis to distinguish events of varying severity.

2.2. Meteorological Data Sets

The meteorological predictors employed in this study were obtained from the ERA5-Land reanalysis data set, developed by the European Center for Medium-Range Weather Forecasts. ERA5-Land provides global land surface variables at a spatial resolution of $0.1^\circ \times 0.1^\circ$, enhancing the depiction of land–atmosphere interactions relative to the commonly used ERA5. A total of 14 surface variables were used in this study, including surface pressure, leaf area index (LAI), volumetric soil water in the top layer (0–7 cm), snow depth, top-layer soil temperature, skin temperature, 2 m air temperature, relative humidity (RH), near-surface (10 m) WS, maximum near-surface WS (WSmax), surface evaporation, total precipitation, surface reservoir content, and snow cover. Among these, RH was derived from 2 m air temperature and dew point temperature. All variables used in this study were at monthly temporal resolution. Monthly WS and WSmax were calculated from daily 10 m zonal and meridional wind components, as ERA5-Land monthly products do not provide absolute WS directly. The LAI was calculated as the sum of the high- and low-vegetation LAI components. The selection of these variables was based on their established physical linkages concerning dust emission, transport, and surface-atmosphere coupling mechanisms. Wind speed is the primary driver of DSs (Lee & Sohn, 2009). Soil moisture, soil temperature, and vegetation conditions (LAI) regulate dust emission by determining friction velocity and erodible surface availability (Marticorena & Bergametti, 1995; Shao, 2008). Surface pressure and air temperature influence boundary-layer stability and cyclone activity (Guan et al., 2017). Air humidity influences the WS threshold by modifying near-surface soil moisture and the cohesive forces between sand particles (Yang et al., 2019). Hydrological variables, including evaporation, precipitation, snow cover, and reservoir content, capture the land–atmosphere coupling conditions that modulate soil erodibility and vegetation dynamics (Hao et al., 2024; X. Liu et al., 2004; Tanaka et al., 2011). The predictors were used as inputs to station-specific XGBoost (eXtreme Gradient Boosting) models.

The Standardized Precipitation–Evapotranspiration Index (SPEI) covering the period 1980–2023 was retrieved from the SPEIbase v2.7 data set, maintained by the Spanish National Research Council (CSIC). This global gridded product provides multi-scalar drought indices derived from monthly precipitation and potential evapotranspiration (PET). The underlying SPEI calculations follow the method of Vicente-Serrano et al. (2010): PET is first estimated using the Thornthwaite approach, which converts monthly mean temperature into atmospheric evaporative demand. A monthly climatic water balance (precipitation minus PET) is then computed and aggregated over the target time scale. The resulting water-balance series is then fitted to a three-parameter log-logistic distribution, and the cumulative probability is standardized to obtain the final SPEI. For this study, we selected the 1-month accumulation scale, which is particularly suited for capturing short-term soil moisture anomalies and surface dryness relevant to dust emission processes. The data set spans 1961–2024 at a 0.5° spatial resolution.

2.3. K-Means Clustering

We utilized the *k*-means clustering algorithm to classify observational stations based on their similar temporal patterns of DS frequency, aiming to characterize regional variations in long-term DS activity. The clustering input

matrix was constructed with stations as rows and the number of DS days during March–May from 1961 to 2024 as columns, thereby reflecting interannual variability at each site over six decades. The optimal number of clusters (k) was evaluated for values between 2 and 7. For each k , we computed the mean inter-cluster Pearson correlation by first deriving the composite time series for each cluster and then calculating the pairwise correlation coefficients among them (Li et al., 2021). The mean of the upper triangle (excluding the diagonal) of the correlation matrix was used as an indicator of the distinctiveness of temporal signals among clusters. This analysis enabled the selection of a k -value that balanced within-cluster coherence and between-cluster separation, providing a data-driven basis for identifying coherent dust climate regimes across China.

2.4. XGBoost Regression Algorithm and SHAP Analysis

To quantify the relative contributions of meteorological factors to DS activity, we developed station-specific regression models based on the XGBoost algorithm, a gradient-boosted tree ensemble method suitable for structured environmental data. We separately developed models for ODS and SEDS, with the response variable defined as the total number of DS events recorded at each station during spring of each year, aggregated from monthly observational data. To improve predictive skill and reduce the risk of overfitting, model hyperparameters were optimized via Bayesian search using 50 iterations of BayesSearchCV. The search space covered key structural parameters, including tree depth (3–12), learning rate (0.01–0.3), number of estimators (100–500), subsampling ratios for rows and columns (0.5–1.0), regularization terms (α and λ , ranging from 10^{-3} to 10), and minimum loss reduction (γ). The data set was randomly divided into an 80% training set and a 20% independent test set. Five-fold cross-validation was conducted on the training set for hyperparameter tuning, and the final optimized model was evaluated on the 20% test set.

To reduce redundancy among correlated predictors and enhance model interpretability, pairwise correlation coefficients were computed among these features, and variables with absolute correlations exceeding $|r| > 0.9$ were iteratively screened by retaining the predictor with higher importance. This procedure resulted in a final subset of 11 variables for both ODS and SEDS, which were used for model training and subsequent interpretation. The reduced feature set effectively minimized multicollinearity while preserving key factors, facilitating a more robust identification of dominant meteorological drivers across stations.

To interpret the model outputs, SHapley Additive exPlanations (SHAP) were applied to quantify the marginal contribution of each predictor to the predicted output at each station. This approach has been widely used in environmental and geoscientific modeling to enhance interpretability and identify dominant drivers (Yi et al., 2025; W. Zhou et al., 2024; L. Zhu et al., 2024). Mean absolute SHAP values were calculated per station and per variable to assess the spatial heterogeneity in feature importance, enabling the identification of dominant drivers for both DS and SEDS.

3. Results

3.1. Spatiotemporal Evolution of Springtime DSs Over China

Figure 1 shows the evolution of springtime DS activity in China from 1961 to 2024, categorized by month (March, April, and May) and classified by event intensity, which includes ODS, SDS, and EDS. A marked decline in the frequency of total DS days was evident from the early 1960s to the early 2000s, consistently observed across all spring months. Among the spring months, April consistently records the highest frequency of DS occurrences, highlighting its critical role as the peak of seasonal DS activity (S. Wang et al., 2005). Since the early 2000s, total occurrences of DSs have remained relatively low. However, intermittent resurgences in event frequency, particularly in April and May, suggest a shift toward later-season peaks in DS activity (Guo et al., 2018).

Despite the overall decline in DS frequency since the 1960s, the proportion of high-intensity events, defined as (SDS + EDS) relative to total DS, has increased markedly over the past two decades. This trend is apparent across all spring months (Figures 1b–1d). Notably, in May (Figure 1d), a month typically associated with reduced DS activity due to increasing vegetation cover (Li et al., 2022), the fraction of SDS + EDS events has frequently exceeded 60% in recent years, despite the low absolute frequency of total DS days. This shift to a higher prevalence of severe events during a reduction in overall DS activity suggests a decoupling between the frequency and intensity of DSs. Such intensification may indicate an increasing impact of meteorological extremes in a warming

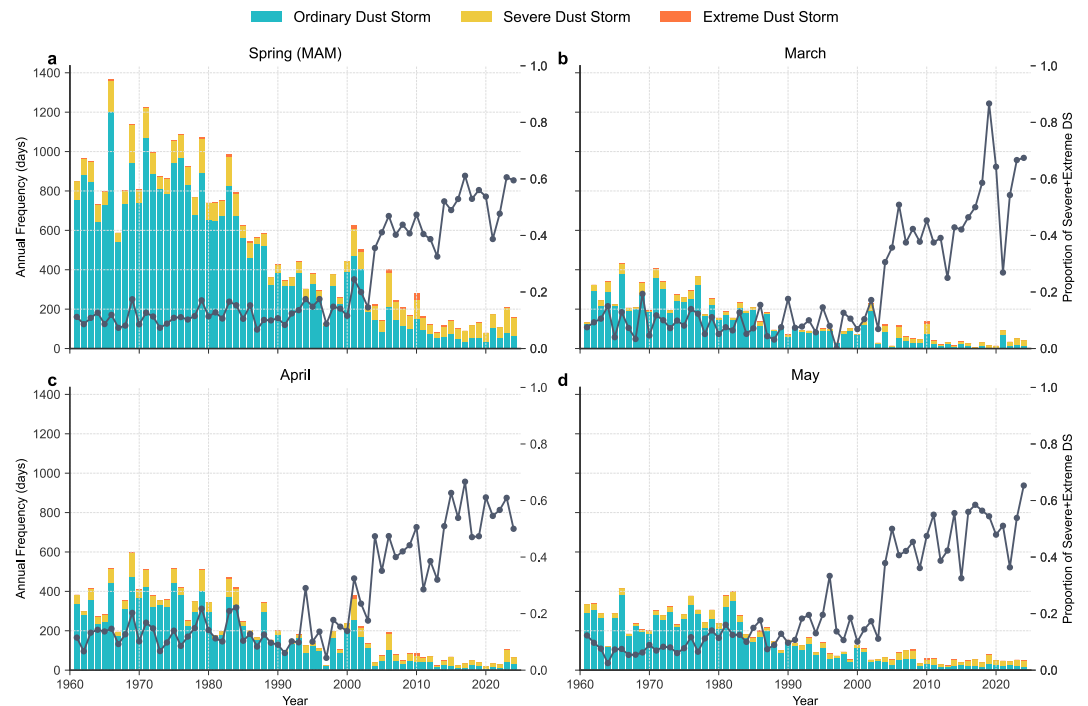


Figure 1. Long-term evolution of springtime dust storm (DS) frequency and intensity in East Asia from 1961 to 2024. Stacked bars show annual counts of DS days categorized by intensity: ordinary (blue), severe (yellow), and extreme (red). The overlaid black line represents the proportion of severe and extreme events relative to total DS days.

climate, including enhanced surface aridity, intensified synoptic-scale wind systems, and land–atmosphere interactions that promote the occurrence of fewer but more severe DS outbreaks.

Figure 2 illustrates the spatial distribution of long-term trends in DS across China, also separated by intensity categories. The annual trends for ODS (Figure 2a) show widespread declines throughout northern and north-western China, especially in eastern Xinjiang, central Inner Mongolia, and the North China Plain, with trend slopes below -0.10 days per year at many stations. However, the trends observed in SDS (Figure 2b) are generally weak and spatially scattered. For SDS, a limited number of stations, one located in the western Inner Mongolia and along the southern edge of the Taklimakan Desert, exhibit statistically significant increasing trends. When all categories are combined (Figure 2c), the spatial trend pattern closely resembles that of ODS. This

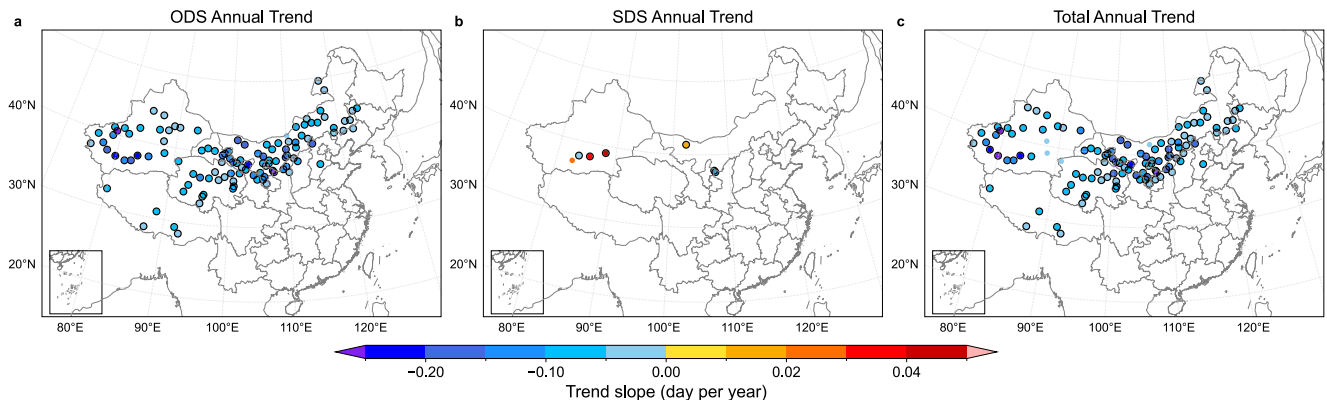


Figure 2. Spatial distribution of annual trends in (a) ordinary dust storm (ODS), (b) severe dust storm (SDS), and (c) total DS (ODS + SDS + extreme-severe dust storm (EDS)) occurrences across China for 1961–2024. Trends are computed at each station using the Mann–Kendall test; only stations with non-zero trends are shown. Colored circles indicate the magnitude of the trend (day per year), and stations with statistically significant ($p < 0.05$) non-zero trends are outlined in black. The EDS category is not shown because all stations exhibit zero trends.

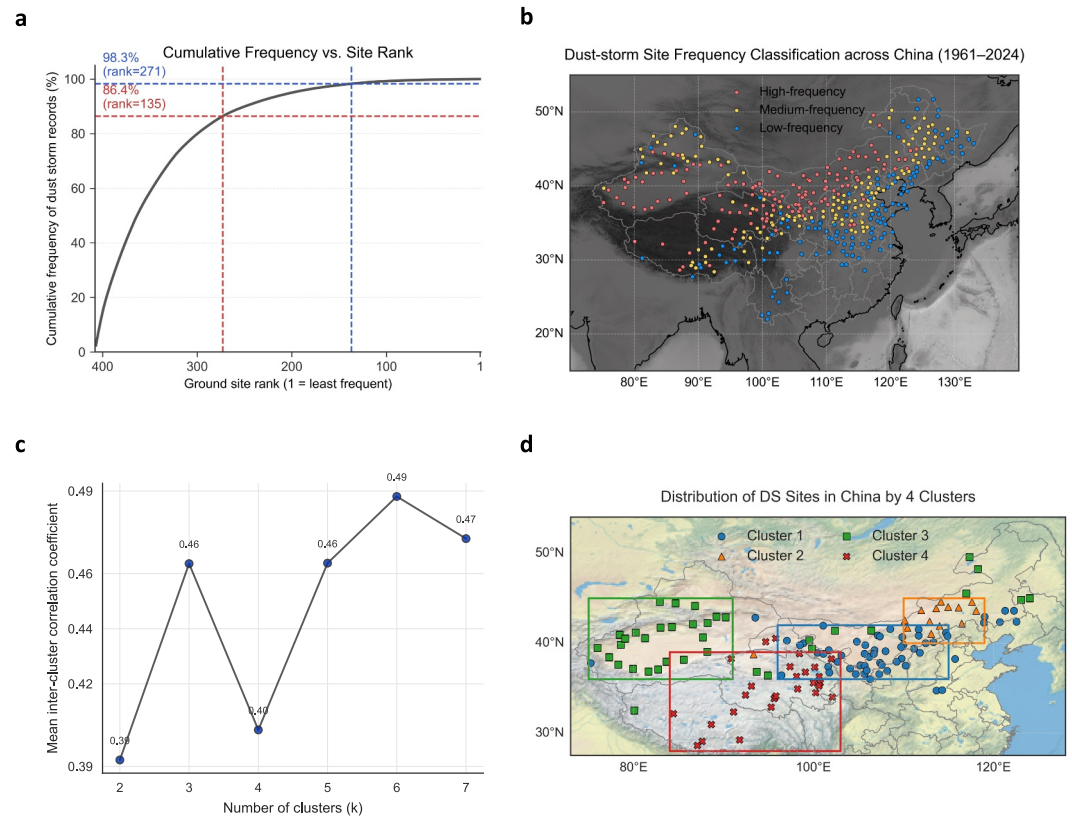


Figure 3. Spatial classification and clustering of total dust storm (DS) across China during 1961–2024. (a) Cumulative percentage of total DS events as a function of ranked observation sites. Thresholds for high-frequency (top 135 sites, accounting for 85.4% of DS events) and medium-frequency sites (top 271 sites, 98.3% cumulative coverage) are indicated by dashed lines. (b) Geographic distribution of classified DS sites: high-frequency (red), medium-frequency (yellow), and low-frequency (blue). (c) Internal validation of clustering solutions based on mean inter-cluster correlation coefficient. (d) Spatial distribution of DS sites by four regional clusters.

consistency underscores that the observed national-scale decline in DS frequency is primarily due to reductions in ODS, while the spatial footprint of SDS and EDS has remained relatively stable or has only seen localized increases.

3.2. Regional Classification and Temporal Trends by Cluster

To characterize the spatial heterogeneity of total DS (ODS + SDS + EDS) activity across China from 1961 to 2024, we first ranked all observation sites based on cumulative total DS frequency and identified groupings using a threshold-based classification and clustering approach (Figure 3). The cumulative frequency distribution (Figure 3a) reveals a highly skewed pattern: the top 135 sites (ranked from most to least active) account for 85.4% of all recorded total DS events, while 271 sites capture 98.3% of total occurrences. Based on these thresholds, we categorized sites into three classes: high-frequency (top 135), medium-frequency (ranks 136–271), and low-frequency (remaining sites). Their spatial distribution (Figure 3b) shows that high-frequency sites are primarily concentrated in two key source regions: the Gobi Desert along the China–Mongolia border, including central and eastern Inner Mongolia, and the periphery of the Taklamakan Desert in southern Xinjiang. Medium-frequency sites are mainly situated to the south of these dust source regions, with a few sites in northern Xinjiang. Low-frequency sites are widely scattered over central, eastern, and northeastern China, where DSs are limited due to higher precipitation and increased vegetation cover.

K-means clustering was employed to analyze regional patterns in dust activity by utilizing the total DS frequency time series from 135 high-frequency observation sites. Internal validation using mean inter-cluster correlation (Figure 3c) indicated that the four-cluster configuration was the most optimal. We also evaluated clustering

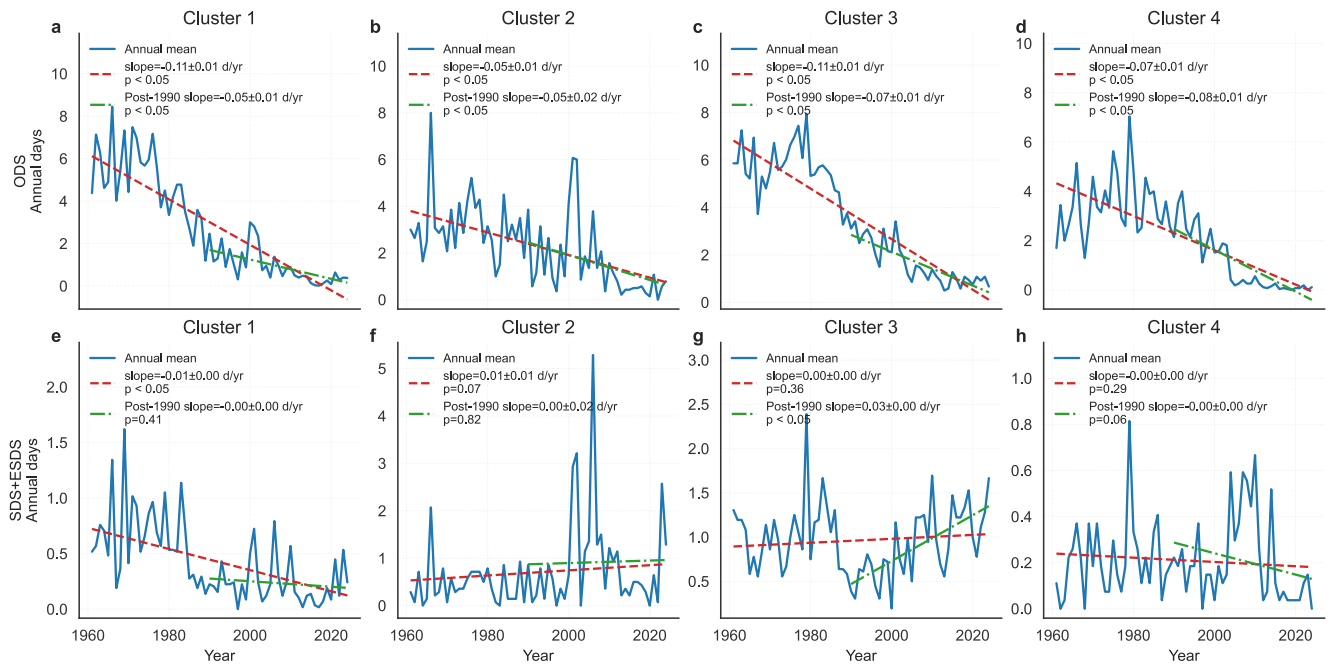


Figure 4. Temporal evolution of annual dust storm activity across the four regional clusters during 1961–2024. Panels (a–d) show annual mean occurrences of ordinary dust storm for each cluster, with linear trends fitted for the full period (red dashed lines) and the post-1990 period (green dashed lines). Panels (e–h) display the corresponding trends in the combined frequency of SEDS (SDS + EDS). Trend slopes are expressed in days per year, and statistical significance is based on linear regression (p -values shown).

robustness using silhouette scores and Gap Statistics (Figure S1 in Supporting Information S1). These diagnostics collectively confirm that the four clusters provide the most coherent and stable representation of regional dust climatology. The spatial distribution of the four clusters (Figure 3d) revealed distinct dust regimes across China. Cluster 1 spans the Hexi Corridor, the Loess Plateau, and central Inner Mongolia. Cluster 2 is concentrated in eastern Inner Mongolia. Cluster 3 encompasses the Taklamakan Desert and adjacent basins, as well as parts of northern Xinjiang. Cluster 4 is confined to the Tibetan Plateau.

Figure 4 presents the temporal evolution of ODS and SEDS frequency across the four regional clusters from 1961 to 2024. Linear trends are estimated for the entire period and the post-1990 sub-period to evaluate potential changes in trend. For ODS (Figures 4a–4d), all clusters exhibit statistically significant decreasing trends over the full analysis period (1961–2024). Clusters 1 and Cluster 3 show the strongest long-term declines in ODS frequency, both at $-0.11 \text{ days yr}^{-1}$ ($p < 0.05$). After 1990, the rate of decline lessens but remains significant, with trends of -0.05 and $-0.07 \text{ days yr}^{-1}$ ($p < 0.05$). Cluster 4 displays a moderate long-term trend of $-0.07 \text{ days yr}^{-1}$, which intensifies slightly in the post-1990 period to $-0.08 \text{ days yr}^{-1}$ ($p < 0.05$). Cluster 2 exhibits the weakest decline among all regions, with a consistent but smaller reduction of $-0.05 \text{ days yr}^{-1}$ across both periods ($p < 0.05$).

The temporal evolution of SEDS (Figures 4e–4h) reveals weak and generally non-significant trends across all clusters. In Cluster 1, although the long-term trend is negative ($-0.01 \text{ days yr}^{-1}$, $p < 0.05$), no significant change is observed after 1990. Cluster 2 shows a weakly significant long-term increase in SEDS frequency ($+0.01 \text{ days yr}^{-1}$, $p = 0.07$) though no discernible trend is evident after 1990. In Cluster 3, a statistically significant post-1990 increase is observed ($+0.03 \text{ days yr}^{-1}$, $p < 0.05$), despite the absence of a significant long-term trend. Cluster 4 is characterized by persistently low annual frequencies and shows no statistically significant trends over either the full period or the post-1990 period, although the latter suggests a weakly negative trend ($p = 0.065$). While high-intensity DS activity has largely remained stable or fluctuated, three of the four clusters (Clusters 1–3) have experienced a notable resurgence in SEDS frequencies since 2020, indicating a potential shift toward more variable and intense springtime DS in recent years.

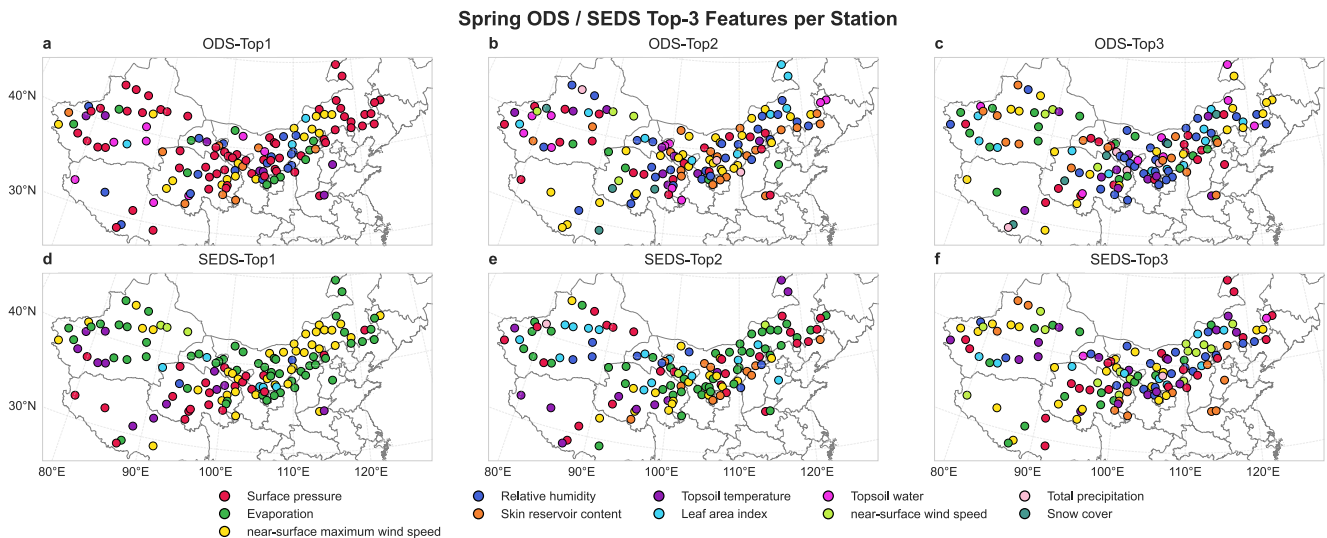


Figure 5. Spatial distribution of the top three meteorological predictors for ordinary dust storm (panels a–c) and severe and extreme dust storms (panels d–f) occurrences at 135 high-frequency monitoring stations across China, based on SHapley Additive exPlanations analysis applied to eXtreme Gradient Boosting models. Each colored dot represents the most important (Top 1; a, d), second-most (Top 2; b, e), and third-most (Top 3; c, f) influential variable for a given station. The legend indicates the corresponding predictors and their color coding.

3.3. Divergent Drivers of DS and SEDS Across China

To identify the dominant drivers of ODS and SEDS, we applied SHAP analysis to XGBoost models trained on a data set combining all 135 high-frequency stations. The model performance was generally robust. The models demonstrate reliable out-of-sample performance, with a test R^2 of 0.62 for ODS and 0.47 for SEDS, comparable to results in prior research (Ebrahimi-Khusfi et al., 2021). Figure 5 shows the spatial distributions of the top three predictors for each station. For ODS (Figures 5a–5c), the surface pressure and WSmax emerged as dominant predictors at nearly 60% of high-frequency stations across northern China, highlighting the critical role of synoptic systems driving the outbreak of DSs. At the remaining stations, evaporation and RH were the most frequently ranked top features. The distributions of Top-2 and Top-3 features (Figures 5b and 5c) show increasing spatial heterogeneity in comparison to Top-1 features. Although WSmax and RH emerged as key variables in some stations, land-surface indicators (such as LAI, skin reservoir content, and topsoil water) appear more prominently. This indicates that synoptic weather dominated the development of ODS when local land conditions were favorable.

For SEDS (Figures 5d–5f), the spatial distribution of key predictors differs markedly from that of ODS. While the surface pressure and WSmax remain influential at some northern sites, evaporation becomes increasingly prominent, especially across northern Xinjiang and central-eastern Inner Mongolia. Notably, evaporation ranks among the top three predictors at 84.3% of high-frequency stations, underscoring its widespread role in modulating surface conditions favorable for SEDS. In comparison to ODS, the significance of land-surface proxies (e.g., LAI and skin reservoir content) is significantly reduced.

To integrate the station-level SHAP results, we analyzed the mean feature importance by regional cluster (Figure 6). For Clusters 1, 2, and 4, surface pressure, WSmax, and RH are the top four predictors of ODS. For Cluster 3, source-related land surface indicators such as topsoil water and skin reservoir content are significant, showing that antecedent dryness plays an important role in modifying emission potential. SEDS exhibit marked regional differences (Figures 6e–6h). In Cluster 1, the combination of evaporation, WSmax, and surface pressure points to a regime where antecedent dryness and intense winds synergistically contribute to the initiation of SEDS events. For Cluster 2, WSmax emerged as the most influential predictor, highlighting the critical role of both locally driven dust emissions under strong winds and the contribution of long-range dust transport. In Clusters 3 and 4, the top five predictors are identical.

Figures 7 and 8 present the SHAP dependence plots for key predictors associated with the occurrence of ODS and SEDS, respectively. Surface pressure exhibits a complex multimodal pattern for ODS (Figure 7a), with SHAP



Figure 6. Regional differences in dominant drivers of ordinary dust storm (ODS) and severe and extreme dust storms (SEDS) revealed by cluster-mean SHapley Additive exPlanations (SHAP) values. Bar plots show the mean absolute SHAP values of 10 meteorological variables for ODS (top row) and SEDS (bottom row) events across four spatial clusters.

values peaking across several distinct pressure intervals, reflecting the diverse synoptic drivers of DSs in northern China, including cold fronts, the Siberian High, and cyclonic systems. Notably, SEDS are confined to a narrower pressure range between 800 and 900 hPa (Figure 8a), suggesting more specific dynamical conditions. WSmax demonstrates a quasi-monotonic enhancement of DS risk for both ODS and SEDS, characterized by a nearly linear amplification in SHAP values beyond 6 m s^{-1} . Hydrometeorological indicators, including topsoil water content, precipitation, skin reservoir content, and snow cover, exhibit consistent negative SHAP responses, indicating their suppressive effects on DS probability. A reduction in LAI also corresponds with enhanced dust activity; both ODS and SEDS show marked SHAP increases when LAI drops below 1, signaling the importance of land-surface degradation in dust mobilization.

For both ODS and SEDS, the risk increases as evaporation approaches zero, but the sensitivity range is notably narrower for SEDS (Figure 8d). When evaporation falls below approximately 50 mm, SHAP values rise sharply, indicating a stronger response to suppressed evaporation. This behavior is characteristic of a supply-limited regime, where limited precipitation and depleted near-surface soil moisture reduce latent heat fluxes, leading to rapid surface warming (Figure 9). Once the topsoil temperature exceeds $\sim 290 \text{ K}$ (Figure 8h), the inferred risk of SEDS increases nonlinearly. Under these dry and warm antecedent conditions, strong WS further enhances the likelihood of SEDS. This mechanism also explains the markedly low RH ($< 20\%$) associated with SEDS (Figure 8c), in contrast to the higher RH during ODS (Figure 7c), which often occurs alongside frontal cooling or precipitation.

In light of the identified importance of near-surface wind and land-surface drought in modulating SEDS, we further assess the spatial correspondence between long-term trends in these drivers and observed changes in SEDS frequency. Figure 10 presents trends in mean and maximum 10-m WS for three distinct periods (1961–1990, 1991–2024, and 1961–2024), while Figure 11 depicts springtime trends in the SPEI, a widely used indicator of surface drought severity. Clusters 1 and 2, covering portions of northern China and Inner Mongolia, show slightly increased mean WS and maximum WS since 1990 (Figures 10b and 10e), accompanied by intensifying spring drought (Figure 11h). These signals are consistent with the observed stagnation in SEDS frequency during recent decades (Figures 4e and 4f). For Cluster 3, the marked post-1990 increase in SEDS (Figure 4g) appears to be driven by a combination of significantly enhanced WSmax (Figure 10e) and intensified surface drought

SHAP Dependence with LOWESS (95% CI) for ODS

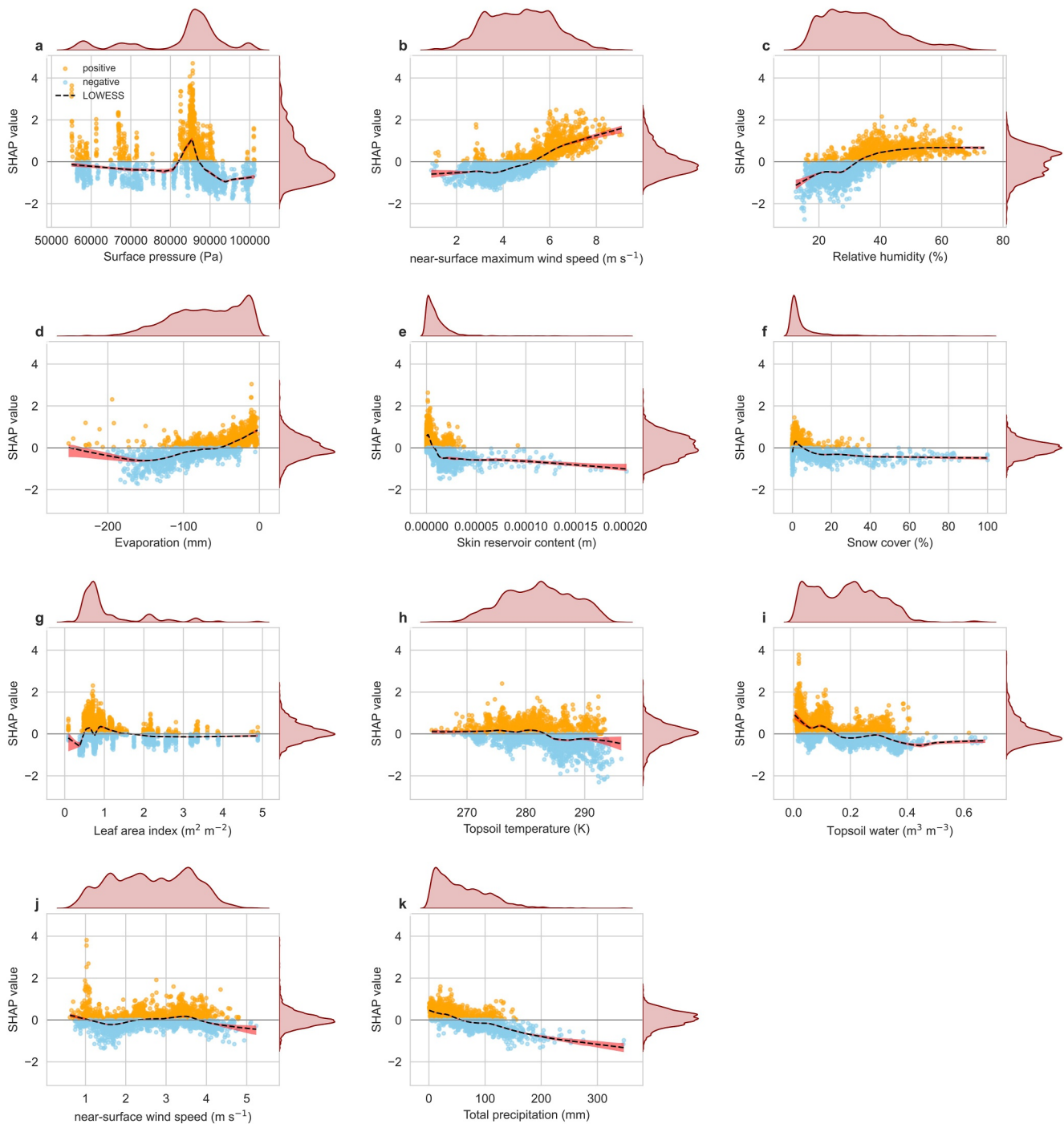


Figure 7. SHapley Additive exPlanations (SHAP) dependence plots for key predictors of ordinary dust storm, generated using eXtreme Gradient Boosting and smoothed with locally weighted scatterplot smoothing (LOWESS). Each panel depicts the marginal effect of an individual variable on the model output (SHAP value), with warmer-colored points representing stronger positive SHAP contributions. Distributions along the top and right margins indicate the value density of each predictor across all samples. Shaded envelopes show 95% confidence intervals for the LOWESS curves, derived from bootstrap resampling.

(Figure 11h). Conversely, Cluster 4, which covers the Tibetan Plateau, has experienced a notable decline in SEDS frequency since 1990 (Figure 4h). This decrease coincides with a pronounced wetting trend in spring SPEI (Figures 11h–11i) and a sustained weakening of WS during the same period (Figures 10b and 10e).

SHAP Dependence with LOWESS (95% CI) for SEDS

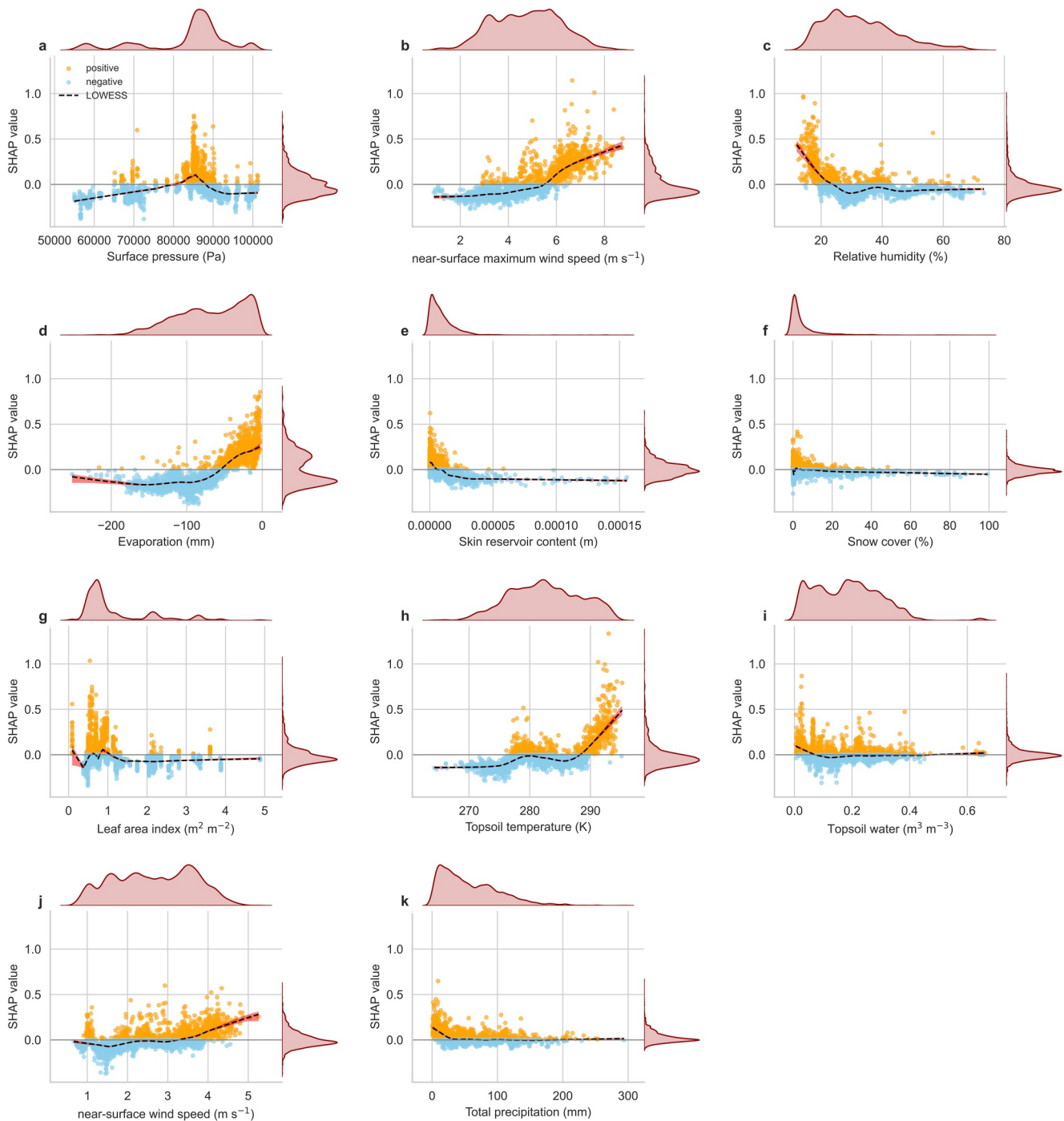


Figure 8. Same as Figure 7, but for features of severe and extreme dust storms.

4. Conclusions

The recurrence of extreme DSs in spring, particularly in 2021 and 2023 (Figure S2 in Supporting Information S1), has aroused increasing attention due to their substantial environmental and societal impacts. Long-term records of DSs from 1961 to 2024 indicate a significant decrease in the frequency of springtime DSs in China, primarily attributed to a drop in ODS events. This downward trend was most evident between the early 1960s and early

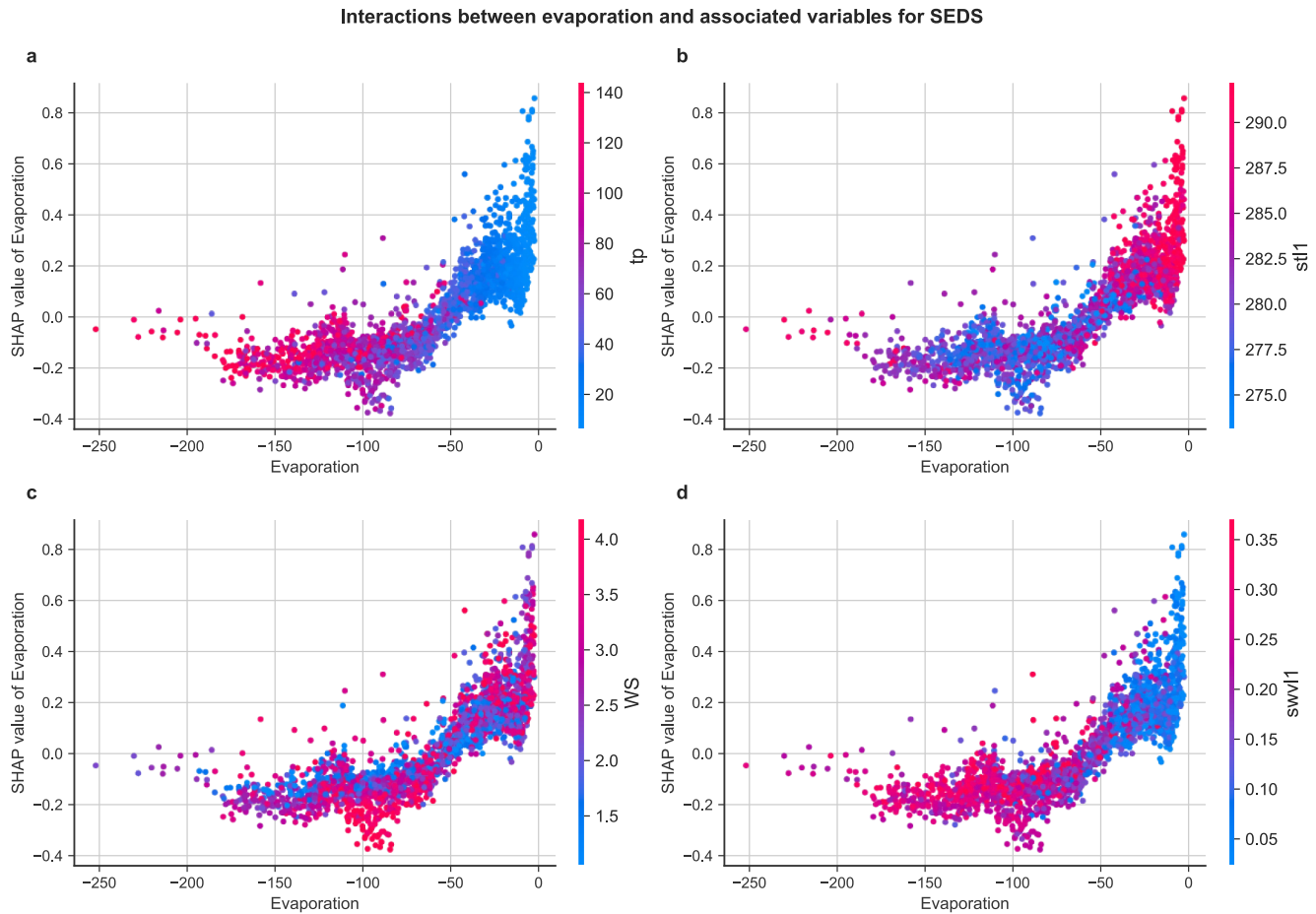


Figure 9. SHapley Additive exPlanations dependence plots illustrate the interaction effects between evaporation and selected environmental variables on the occurrence of severe and extreme dust storms. Each subplot is colored by a different interacting feature: (a) total precipitation (tp), (b) topsoil temperature (stl1), (c) near-surface wind speed, and (d) topsoil water content (swvl1).

2000s, with statistically significant declines in all four regional clusters. Since the early 2000s, DS activity has stabilized at relatively low levels, albeit interspersed with episodic resurgences. The relative contribution of SEDS has risen notably during this period, exceeding 60% of total DS occurrences over the past 10 years (2015–2024). This shift indicates a potential decoupling between overall event frequency and intensity, with high-intensity DSs becoming increasingly dominant. Spatially, high-frequency DS activity remains concentrated along the Gobi and Taklimakan peripheries, while low-frequency regions extend into eastern and southern China.

Cluster-based analysis of high-frequency stations reveals four distinct types. All clusters show statistically significant long-term declines in ODS frequency since 1961, with the most pronounced reductions in Cluster 1 (Hexi Corridor and central Inner Mongolia) and Cluster 3 (Taklamakan and northern Xinjiang), both at $-0.11 \text{ days yr}^{-1}$ ($p < 0.05$). Conversely, SEDS activity exhibits weak or non-significant long-term trends, yet a post-2020 resurgence is evident in Clusters 1–3, suggesting a recent shift toward more intense but less frequent events under evolving environmental conditions.

Attribution based on machine learning indicates a marked difference in the dominant factors of ODS versus SEDS. For ODS, large-scale dynamic factors dominate, with surface pressure consistently ranking among the top two predictors across all four clusters. In contrast, SEDS events are more sensitive to land-surface hydrometeorological deficits. In addition to WSmax, evaporation emerged as the most influential predictor, ranking among the top three at 85.1% of high-frequency stations, suggesting that prolonged dryness, combined with synoptic forcing, promotes the development of severe outbreaks. These findings are further supported by SHAP dependence analyses, which show an abrupt increase in SEDS risk when evaporation falls within the range of 0–50 mm and topsoil temperature exceeds 290 K, indicating a precipitation-limited evaporative condition. Moreover,

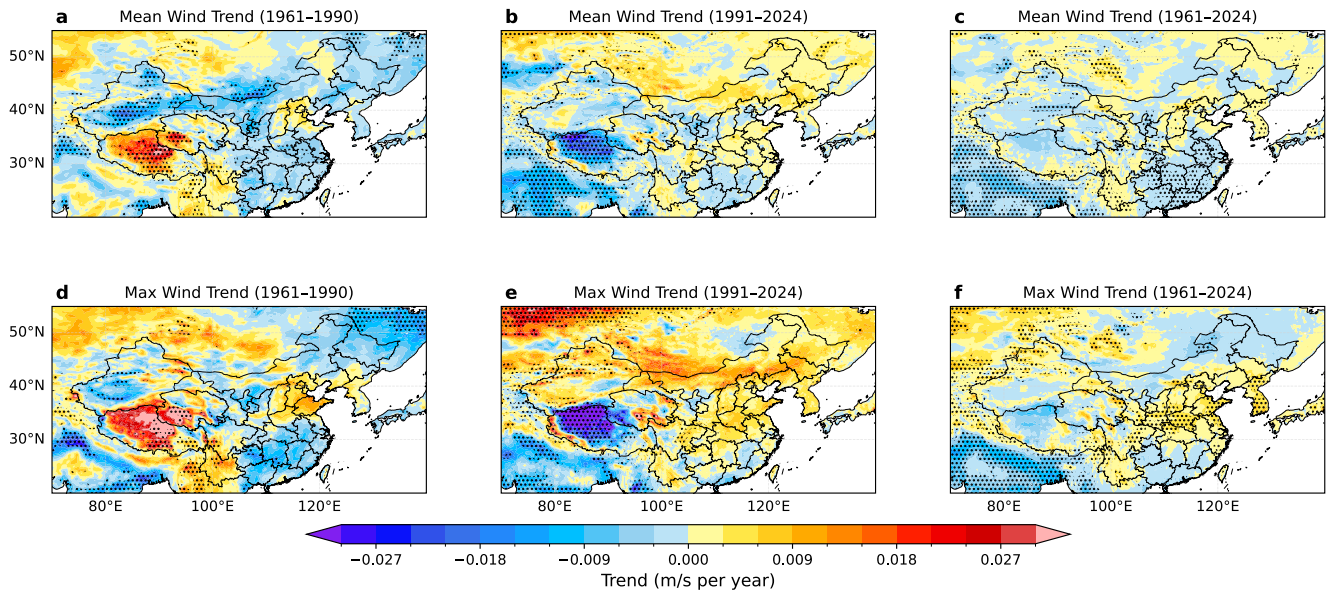


Figure 10. Linear trends in spring near-surface wind speed (WS) over East Asia during different periods. Panels (a–c) show trends in seasonal mean WS for 1961–1990, 1991–2024, and the full period 1961–2024, respectively. Panels (d–f) display trends in seasonal maximum daily WS for the same three time intervals. Stippling indicates grid points where trends are statistically significant at the 95% confidence level.

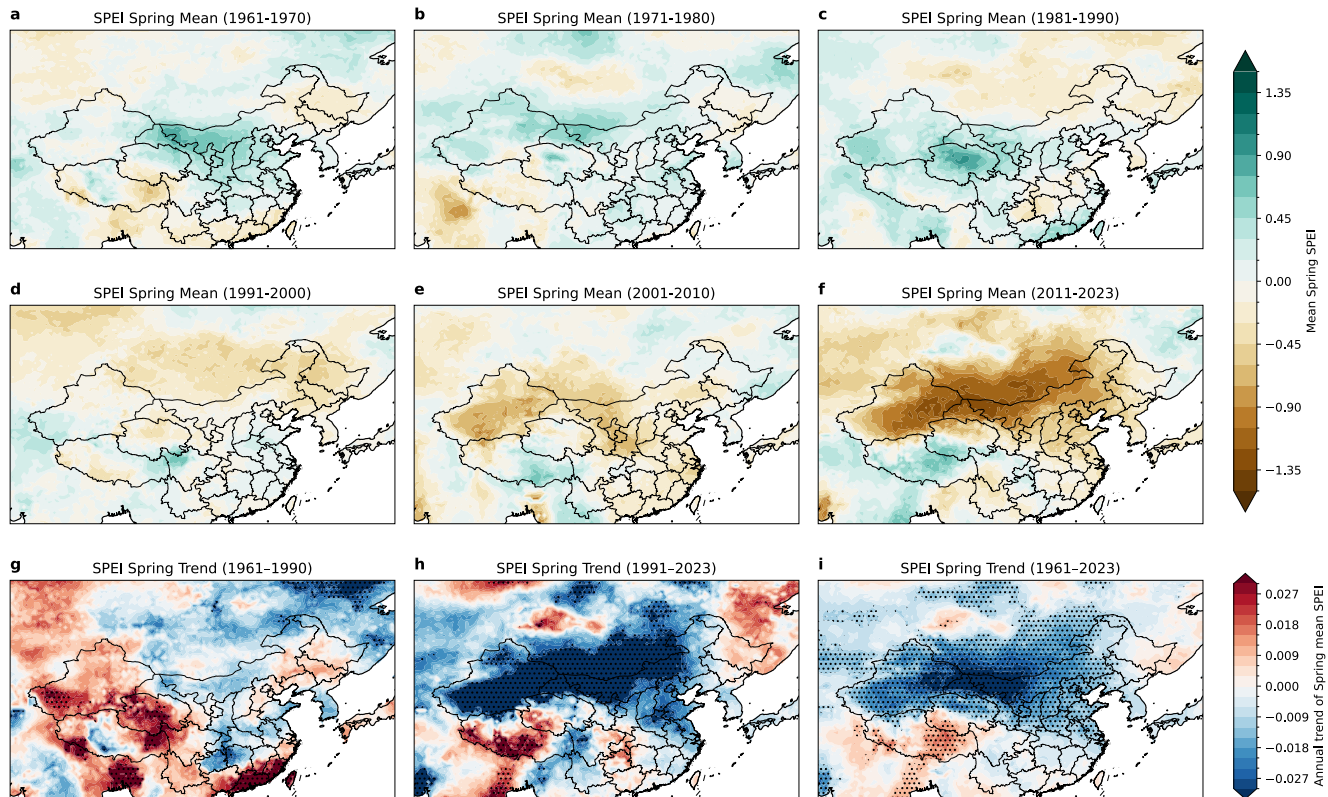


Figure 11. Spatial distribution of spring standardized precipitation-evapotranspiration index (SPEI) over East Asia. Panels (a)–(f) show decadal means of spring SPEI from 1961–1970 to 2011–2023. Panels (g)–(i) present linear trends in spring SPEI for three periods: 1961–1990, 1991–2023, and the full record (1961–2023). Stippling indicates grid points with statistically significant trends at the 95% confidence level.

regional trend analyses show that SEDS-prone clusters with increasing WS_{max} and intensifying drought (e.g., Cluster 3) have experienced elevated SEDS frequency since the early 1990s, while regions with wetting and wind weakening (e.g., Cluster 4) exhibit notable declines. The post-1990 increase in SEDS in northwestern China reflects a typical water-deficit dust-emission regime, in which prolonged spring drought suppresses surface evaporation, collapses latent-heat fluxes, and markedly reduces the threshold friction velocity required for dust entrainment. Under these conditions, rapid warming of the topsoil temperature strengthens sensible-heat fluxes, deepens the boundary layer, and increases turbulent mixing. This facilitates the downward transfer of mid-tropospheric momentum and may promote the development of extreme near-surface wind events. When strong synoptic systems occur, the co-existence of intensified wind extremes, elevated topsoil temperatures, and highly erodible surface conditions implies that even relatively modest dynamical disturbances can trigger disproportionately large SEDS outbreaks. Although North China exhibits only weak intensification in near-surface winds, persistent surface drying has markedly reduced soil cohesion and weakened vegetation protection, thereby lowering the threshold friction velocity for dust entrainment. Consequently, synoptic winds of moderate strength, which were previously insufficient to generate high-intensity events, can now more readily trigger severe outbreaks. As a result, dust episodes that once remained in the ordinary category are increasingly able to intensify into SEDS. These results align with satellite-based assessments of extreme spring DSs over the Gobi, which suggest a shift in dominant precursors, evolving from wind-dominated outbreaks (e.g., April 2001) to events primarily amplified by antecedent drought (e.g., March 2021) (Q. Zhu & Liu, 2024).

Although this study identifies robust statistical linkages between land-surface deficits, wind extremes, and the occurrence of SEDS, an important limitation is that our analysis is based primarily on monthly aggregated variables. Extreme DSs, however, are inherently synoptic-scale phenomena driven by sub-daily to multi-day processes, including frontal passages, cyclone development, and short-lived wind surges. Monthly means may smooth out these transient features, weakening the direct physical interpretability of dynamical triggers associated with individual high-intensity events. Likewise, land-surface anomalies such as soil drying or evaporative suppression often evolve on weekly timescales, and their interaction with short-duration wind extremes may not be fully resolved in a monthly framework. Therefore, while the monthly products enable a long-term, spatially consistent assessment of the climatological impact on SEDS, they cannot fully capture event-scale dynamics such as boundary-layer instability, turbulence bursts, or the timing of synoptic forcing. Future work should integrate higher-frequency reanalysis and process-based dust models to refine the attribution of extreme events and resolve how land–atmosphere coupling evolves at the timescales relevant for dust mobilization.

Our study highlights a shift in the characteristics of DS activity across China: while the frequency of ordinary events has declined, the high-intensity events have increased, with SEDS increasingly governed by the compound effects of surface aridity and intensified wind forcing. Quantifying these patterns through interpretable machine learning provides an empirical basis for future monitoring and predictive modeling. As climate variability and land use continue to evolve, understanding the distinct drivers of high-intensity DS events remains essential for early warning, impact assessment, and regional adaptation strategies.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

The ERA5-Land monthly averaged data from 1950 to present are provided by the Copernicus Climate Change Service (Muñoz Sabater, 2019). The monthly SPEI can be downloaded from the Global SPEI database (Vicente-Serrano et al., 2024). The dust storm records used in this study can be obtained from the China Meteorological Administration data service at <https://data.cma.cn/> with registration.

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Acknowledgments

This work is supported by the National Natural Science Foundation of China (Grant 42205031) and the National Key Research and Development Program of China (Grant 2024YFE0113700).

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