

Asian Dust Emissions under Climate Change

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ABSTRACT: Amid global warming and desertification expansion, East Asia is experiencing a surge in dust activity, yet the mechanisms behind this trend remain unclear. Here, we explored spatiotemporal changes in dust activity and their driving factors across East Asia using machine learning method, with particular focus on the role of vegetation dynamics. Our analyses reveal significant regional heterogeneity from 2010 to 2023, while a synchronous upsurge in dust activity has occurred since 2020, primarily modulated by vegetation changes. Vegetation shifts dominated dust activity in areas with vegetation recovered or deteriorated, explaining more than 45% of the total dust emissions, whereas climatic drivers chiefly influenced dust variations in persistently bare lands. These findings highlight vegetation restoration as a critical strategy to mitigate the surge in dust activity. Notably, the vegetation degradation in parts of Mongolia in recent years calls for urgent transboundary cooperation to mitigate the increasing dust emissions and their far-reaching impacts.

KEYWORDS: Asia; Dust or dust storms; Vegetation; Climate change

1. Introduction

Dust activity primarily occurs in the arid and semiarid regions (Goudie and Middleton 2006; Huang et al. 2010). Since the 1960s, the drylands have been expanding in semiarid regions and are projected to account for 50% of the global land surface by the end of this century (Huang et al. 2016a,b). The warming rate is higher in drylands than in humid regions, indicating that drylands will face more severe warming risk, such as desertification (Huang et al. 2017a,b). Consequently, dust activity in these regions would increase, which in turn modulates the atmospheric radiation balance, thereby influencing regional climate (Alam et al. 2014; Huang et al. 2014). Beyond their climatic influence, frequent dust events exert profound environmental, health, and economic impacts. They facilitate the long-range transport of pollutants, degrade ecosystems, and pose substantial threats to human health, including respiratory impairments and elevated risks of cardiovascular and oncological diseases (Martinelli et al. 2013; Hong et al. 2010; Wang et al. 2005). Furthermore, dust events can lead to significant economic losses by affecting agricultural productivity, damaging infrastructure, and disrupting transportation systems (Middleton 2017). Many countries have implemented proactive measures to mitigate these adverse impacts of dust activity. For example, following the Dust Bowl of the 1930s, which was caused by drought and excessive land cultivation, the United States launched a series of initiatives, including the establishment of the National Grasslands, the initiation of the Prairie States Forestry Project, among other measures

(Lee and Gill 2015). Similarly, China has advanced large-scale ecological restoration programs in recent years, such as the Three-North Shelter Forest Program and the Natural Forest Protection Program (Bryan et al. 2018). These initiatives are of great significance for vegetation restoration and desertification control (C. Chen et al. 2019).

As the second largest dust source globally (Shao et al. 2011), East Asia is undergoing an increase in dust activity (Tan et al. 2025). In 2021 and 2023, the region experienced some of the most severe dust events in recent decades, with 2023 witnessing 13 unprecedented large-scale dust events (Chen et al. 2023). However, dust activity in this region also exhibits pronounced regional heterogeneity. In Mongolia, dust activity has shown a significant increase (Bao et al. 2023), with its frequency nearly fourfold relative to the 1960s (Ministry of Environment and Tourism of Mongolia 2018). In contrast, as the downstream weather region of Mongolia, China has experienced a decrease in dust activity (Bao et al. 2023). Notably, approximately 50% of the total dust days in China were transboundary events originating from Mongolia (Bao et al. 2021). This regional divergence, coupled with intensified cross-border dust transport, has led to inconsistent changes in dust activity across East Asia, underscoring the urgency of analyzing the spatiotemporal changes in dust activity with distinct subregions of East Asia.

Although regional differences are significant, most studies have focused on investigating the driving factors of dust variations at the entire East Asia region. Prior research has attributed dust activity changes in East Asia to variations in wind speed (Wu et al. 2022), variations in Mongolian cyclones intensity (Mu and Fiedler 2025), and climate factors such as precipitation and temperature (Lee and Sohn 2011). Vegetation dynamics, particularly those modulated by large-scale ecological restoration, have also been recognized as key influences (Tan and Li 2015; Wang et al. 2021). While these findings collectively suggest that dust

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variations in East Asia are driven by multiple factors, the relative importance of these factors has rarely been quantified. Given the divergent regional trends across East Asia, it is essential to resolve the dominant driving factors within distinct subregions to improve mechanistic understanding and guide effective mitigation.

Accurately simulating dust emission is a critical foundation for quantifying the contribution of these drivers to dust activity, as it represents the initial and essential process of dust activity (Shao et al. 2011). Over the past several decades, significant advances in wind erosion physics have greatly improved the understanding of dust aerosol emission, thereby enhancing the accuracy of dust emission modeling. Early studies primarily relied on empirical relationships between wind speed and dust emission (Gillette and Passi 1988). In contrast, recent developments have incorporated more physically based processes that account for the effects of soil properties, aerodynamic forces, and threshold friction velocity (Kok 2011; Shao 2001, 2004). These improvements have greatly enhanced the ability of reanalysis datasets to reproduce dust emission processes (Chin et al. 2002; Colarco et al. 2010), providing crucial support for an in-depth exploration of the driving mechanisms of dust activity under climate change.

In this study, we focused on dust activity in China and Mongolia within East Asia, using reanalysis data to investigate the spatiotemporal characteristics of dust activity from 2010 to 2023. Subsequently, we examined vegetation cover changes in dust activity hotspots. Finally, we quantified the relative contributions of 13 driving factors to dust activity changes in these regions using the extreme gradient boosting (XGBoost) algorithm and Shapley additive explanations (SHAP). Our aims are to 1) reveal the spatiotemporal patterns and correlations between dust activity and vegetation cover in East Asia and 2) quantify the contribution of vegetation and elucidate the dominant drivers of dust activity changes across different subregions.

2. Materials and methods

a. Data collection

The Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-2), is generated by the National Aeronautics and Space Administration (NASA) Global Modeling and Assimilation Office (GMAO) based on the Goddard Earth Observation System Model, version 5 (Colarco et al. 2010). It provides long-term reanalysis data spanning from 1980 to the present with a spatial resolution of $0.5^\circ \times 0.625^\circ$ (Gelaro et al. 2017). Multiple studies have highlighted the reliability of MERRA-2 in estimating dust emissions, with its interannual variations and extreme values presenting high consistency with satellite observations (Wang et al. 2023; Shi et al. 2021), and demonstrating remarkable advantages in capturing intense dust events (Jing et al. 2017; Yao et al. 2020). Additionally, the MERRA-2 temperature and precipitation fields present agreement with observations (S. Chen et al. 2019), and variables such as wind speed and geopotential height are highly consistent with those from other reanalysis datasets (Alghamdi 2020; Carvalho 2019). Thus, monthly data on dust emission flux (EMFLX), 2-m air temperature (temperature),

land total precipitation (precipitation), temperature and geopotential height at the 500- and 850-hPa levels (i.e., temp850hPa, temp500hPa, hgt850hPa, and hgt500hPa), specific humidity, surface pressure (pressure), near-surface wind speed, wind speed at 850 hPa (wind850hPa), and soil moisture data were obtained from MERRA-2.

The normalized difference vegetation index (NDVI) data were derived from the *Terra* Moderate Resolution Imaging Spectroradiometer (MODIS) vegetation indices monthly (MOD13C2), version 6.1 product, with a spatial resolution of $0.05^\circ \times 0.05^\circ$ (Didan 2015). The leaf area index (LAI) data were obtained from the MCD15A3H version 6 product, also based on MODIS observations, with a spatial resolutions of 500 m and a temporal frequency of 4 days (Myneni et al. 2015). Given the inconsistent temporal resolutions of these datasets, all variables were aggregated to annual means to ensure temporal consistency. This approach also helps filter out seasonal variability and episodic extremes, thereby highlighting climate-scale variations (Wu et al. 2022; Zhao et al. 2025). However, we also acknowledge its limitations, particularly the potential loss of short-term variability, which may reduce the model's ability to capture the triggering mechanisms of dust activity and associated nonlinear processes. Subsequently, to ensure consistency with the horizontal resolution of MERRA-2, the NDVI and LAI datasets were interpolated to a spatial resolution of $0.5^\circ \times 0.625^\circ$ using linear interpolation.

b. Drivers of dust activity

In this study, EMFLX was utilized as the dependent variable to represent dust activity from 2010 to 2023. The remaining 13 variables introduced above were treated as independent variables, representing the main driving factors of dust activity.

Previous findings (Lee and Sohn 2011; Mu and Fiedler 2025; Wang et al. 2021; Wu et al. 2022) demonstrated that wind speed, large-scale weather systems, climate change, and vegetation dynamics are the main drivers of dust activity in East Asia. We categorized these 13 independent variables into four groups accordingly. Temperature, precipitation, and soil moisture were employed as indicators to represent climate change (climate factors), while near-surface wind speed and wind850hPa were introduced to characterize wind speed factors (wind factors). To represent the characteristics of large-scale weather systems (weather factors), six variables were selected: temp850hPa, temp500hPa, hgt850hPa, hgt500hPa, specific humidity, and pressure. Since no single index can comprehensively reflect vegetation dynamics (Ding et al. 2020), NDVI and LAI were selected to represent vegetation cover changes (vegetation factors). NDVI reflects vegetation density, and LAI represents vegetation structural changes (Chen et al. 2025; Lv et al. 2025).

c. XGBoost and SHAP models

Extreme gradient boosting (XGBoost) is an advanced, regularized implementation of gradient boosting algorithms that has demonstrated superior performance by enabling fast computation and effectively handling sparse datasets (Chen and Guestrin 2016). It addresses the common problem of overfitting in traditional boosting methods through a stepwise shrinkage process (Chen and Guestrin 2016). Additionally,

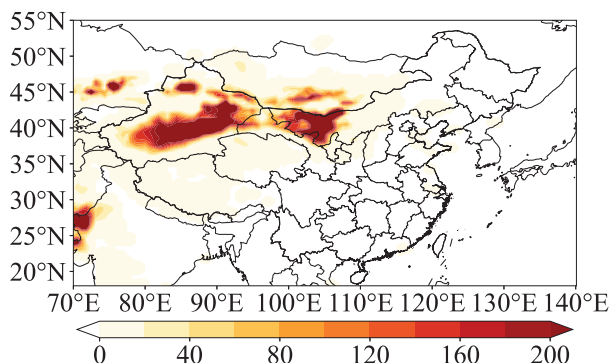


FIG. 1. Distribution of dust emissions. The average value of EMFLX ($\text{mg m}^{-2} \text{day}^{-1}$) in East Asia from 2010 to 2023.

XGBoost minimizes training losses and reduces classification errors while developing the final model (Abdullah et al. 2019; Dong et al. 2018). However, it carries inherent uncertainties as a data-driven approach because it quantifies statistical relationships between inputs and outputs without verifying whether the identified features respect underlying physical principles (Naser 2025). Nevertheless, this limitation is common to most machine learning approaches, and it does not preclude the extraction of meaningful insights. To better interpret the predictions of XGBoost and understand the contributions of individual features, we employed SHAP, which are grounded in the concept of the Shapley value from game theory (Lundberg and Lee 2017; Lundberg et al. 2020). It offers a novel approach to enhance the interpretability of complex predictive models and visualize the complex causal relationships between dependent variables and their driving factors (Lundberg and Lee 2017; Lundberg et al. 2020). SHAP values not only indicate the degree to which a given feature alters the prediction but also enable the model builder to decompose any prediction into the sum of the effects of each feature value and explain it (Lundberg and Lee 2017). When a SHAP value is greater than 0 (or less than 0), the corresponding feature value is interpreted as having a positive (or negative) contribution to the prediction. The computation of SHAP values can be conveniently implemented using the SHAP library in Python.

XGBoost and SHAP models are widely used in Earth science research (Batunacun et al. 2021; Ghafarian et al. 2022; Silva et al. 2022; Wang et al. 2022; Yan et al. 2024a), for SHAP can interpret the complex nonlinear relationships hidden within the black-box XGBoost model and quantify the magnitude and direction (positive or negative) of multiple driving factors' impacts (Rodríguez-Pérez and Bajorath 2020; Yan et al. 2024a). Thus, based on 13 independent variables and one dependent variable (EMFLX), we employed the XGBoost model to construct a predictive model of dust activity. SHAP model was subsequently applied to explore the influence of each variable on dust activity, quantify their relative importance, and identify the dominant driving factors.

Before fitting the XGBoost and SHAP models, missing values in all variables were processed. It should be noted that the following data processing steps were applied exclusively to

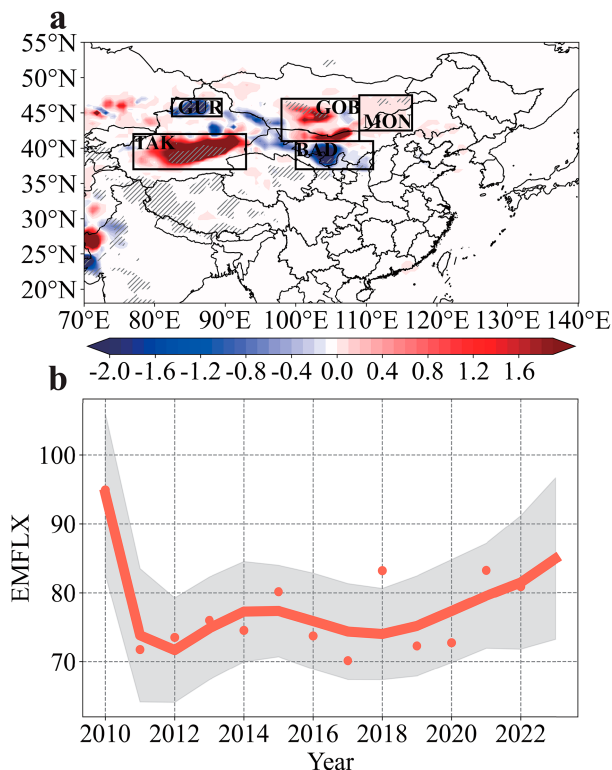


FIG. 2. Dust emissions interannual changes in East Asia from 2010 to 2023. (a) Linear trends of EMFLX ($\text{mg m}^{-2} \text{day}^{-1} \text{yr}^{-1}$) and their spatial distribution of significance. The gray lines mean passing the 90% significance test. (b) The interannual variations of EMFLX ($\text{mg m}^{-2} \text{day}^{-1}$) in East Asia. The pink line is the fitted line, and the gray shaded area means the 95% prediction interval. The average EMFLX in East Asia was calculated for the five regions listed in Table 1.

the machine learning analysis. In regions where LAI values were missing, NDVI values were observed to be zero. Therefore, the missing LAI values were considered to represent non-vegetated areas and were replaced with zero. In contrast, missing values in the other variables were removed before analysis. After data cleaning, the number of valid data points used as input for the machine learning model in each region was as follows: Each variable has 1006 data points for the GUR region, 2947 for the TAK region, 2619 for the GOB region, 1728 for the BAD region, and 1848 for the MON region. Then, the input dataset was randomly split into 70% training and 30% testing sets. Regression analysis between the predicted and observed values of the test dataset was performed to calculate the coefficient of determination (R^2) and root-mean-square error (RMSE), which were used to evaluate the model performance. During training, fivefold cross validation was implemented to optimize key hyperparameters of the XGBoost model, including the number of estimators, the learning rate (learning_rate), and the maximum tree depth (max_depth). However, it should be emphasized that the results may have limited generalizability to other regions or time periods due to the limited sample size.

TABLE 1. Geographical information of the five representative regions.

Regions	Land-use type	Geographical range	Annual amounts of EMFLX (kg yr ⁻¹)	Contribution to East Asian dust variations (%)
GUR	Gurbantungut Desert	44.5°–47.0°N 82.5°–89.5°E	1.29	5.88
TAK	Taklamakan Desert	37°–42°N 77°–93°E	11.73	53.31
GOB	Gobi Desert	41°–47°N 98°–109°N	5.04	22.90
BAD	Badanjaran Desert, Tenge Desert, Ulanbuhe Desert, Kubuqi Desert, Mu Us Sandy Land	37°–41°N 100°–111°E	3.84	17.44
MON	Mongolian–Manchurian grassland	42.5°–47.5°N 109°–116.5°E	0.10	0.47

3. Spatiotemporal characteristics of dust activity

We analyzed EMFLX values to assess dust activity from 2010 to 2023. Within the study area, the annual average EMFLX value during this period was $19.22 \text{ mg m}^{-2} \text{ day}^{-1}$. However, the spatial distribution of dust activity was highly heterogeneous. Dust activity was primarily concentrated in northwest China and southern Mongolia, where EMFLX values were substantially higher than the regional average. Notably, the Tarim Basin and the Gobi Desert experienced the most frequent dust activity, with average EMFLX values exceeding $200 \text{ mg m}^{-2} \text{ day}^{-1}$. In contrast, the areas surrounding the deserts and sandy lands, as well as the southwestern Tibetan Plateau, exhibited significantly lower EMFLX values, averaging less than $20 \text{ mg m}^{-2} \text{ day}^{-1}$ (Fig. 1). This regional distribution pattern aligns with findings from previous studies (Zhao et al. 2006; Wang et al. 2021).

In recent years, dust activity trends have exhibited significant spatial variability across northwest China and southern Mongolia. Areas exhibiting increasing dust activity were mainly located in the Taklamakan Desert (TAK) in southern Xinjiang of China, the Gobi Desert (GOB) in southern Mongolia, and the Mongolian–Manchurian Grassland (MON) in eastern Mongolia, where EMFLX displayed a clear upward trend and passed the 90% significance level (Fig. 2a). The most pronounced increase occurred in the TAK region, with a trend slope of 1.5701 ($p < 0.1$). Conversely, the Gurbantungut Desert (GUR) in northern Xinjiang, China, and the desert regions in western Inner Mongolia, China (BAD), experienced a significant downward trend in dust activity, as indicated by a decline in EMFLX (Fig. 2a). The steepest decline was observed in the GUR region, with a trend slope of -1.2240 ($p < 0.05$). Based on these findings, these five regions exhibiting significant EMFLX interannual changes over the past decade were selected as representative areas for subsequent analysis (Table 1).

Given the pronounced spatial heterogeneity across East Asia, quantifying the relative contributions of these five representative regions was essential for understanding the overall dust variations in East Asia. The contributions of these five regions varied substantially. The TAK region was the

dominant source, accounting for 53.31% of the total dust variations, with an annual EMFLX of 11.73 kg yr^{-1} (Table 1). The GOB and BAD regions were secondary contributors at 22.90% and 17.44% (Table 1), respectively, while the contributions from GUR and MON were minimal, at 5.88% and 0.47% (Table 1). Therefore, recent variations in dust activity

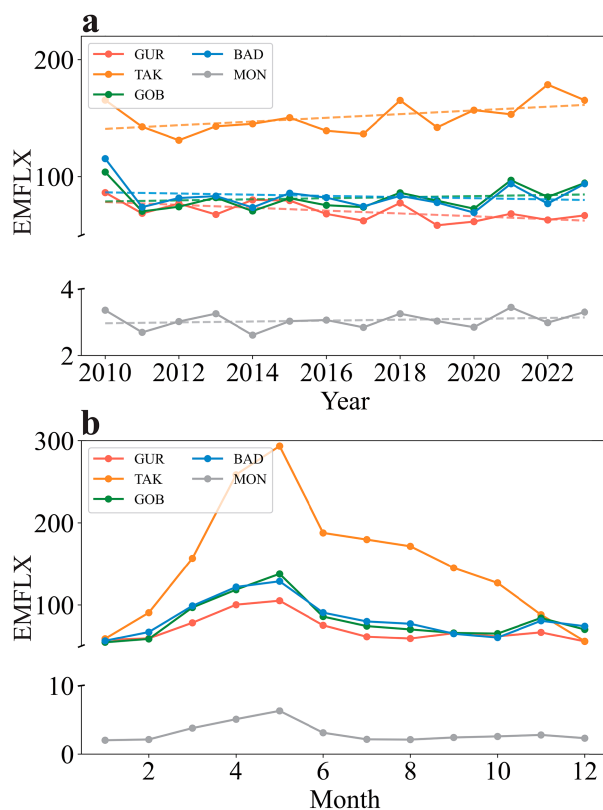


FIG. 3. Variations in dust emissions from 2010 to 2023. (a) Comparison of interannual variations in EMFLX ($\text{mg m}^{-2} \text{ day}^{-1}$) among five representative regions. (b) Comparison of intramonthly variations in EMFLX ($\text{mg m}^{-2} \text{ day}^{-1}$) among five representative regions.

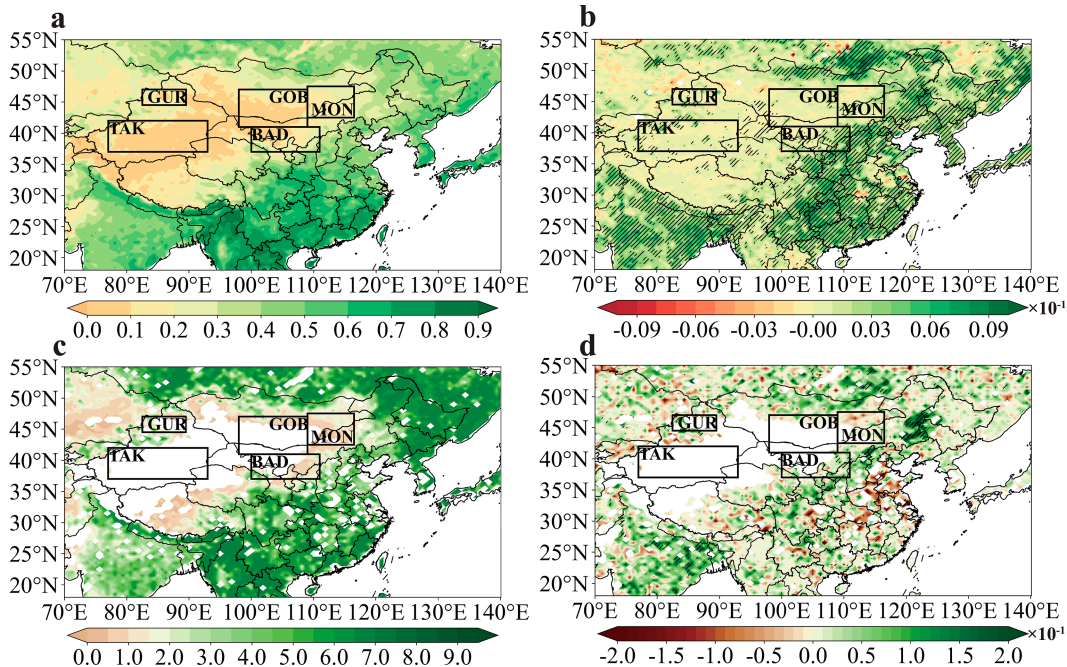


FIG. 4. Vegetation cover and interannual change trend in East Asia from 2010 to 2023. (a) The average value of NDVI (dimensionless). (b) Linear trends of NDVI and their spatial distribution of significance. (c),(d) As in (a) and (b), but for LAI (dimensionless). The black lines mean passing the 90% significance test.

across East Asia have been primarily controlled by the TAK region, while also being co-influenced by the synergistic influences of other regions. Recently, the enhanced EMFLX from the TAK and GOB regions (Fig. 2a) has driven an overall increasing trend in East Asian dust activity (Fig. 2b). However, this upward trend has been partially offset by the weakening of dust activity in the GUR and BAD regions (Fig. 2a), thus slowing the overall rising trend in East Asia (Fig. 2b).

However, dust activity across all five representative regions exhibited synchronous and consistent fluctuations despite regional differences in overall trends. Dust activity in East Asia has generally exhibited a fluctuating upward trend from 2010 to 2023, with a notable increase around 2020 (Fig. 2b). A similar pattern was observed across the five representative regions, all of which experienced an increase in EMFLX around 2020 (Fig. 3a). This consistency suggests that dust activity in these regions fluctuated synchronously with the overall trend in East Asia. Such consistent fluctuations indicated that their interannual variations may exhibit a similar periodicity. Dust activity in these regions also showed consistent seasonal variability, with peaks in spring and troughs in winter, characterized by the highest EMFLX values in April and May, and the lowest in December and January (Fig. 3b).

4. Vegetation dynamics in dust activity hotspots

The bare lands were primarily located in northwest China and southern Mongolia, characterized by absent LAI values and low NDVI (Figs. 4a,c). These bare lands were consistent with the hotspots of dust activity (Fig. 1). However, vegetation cover

across these regions exhibited substantial regional variation in both extent and temporal trends. Most areas in the GUR, TAK, and GOB regions lacked vegetation cover, as reflected by NDVI values close to zero and by minimal or missing LAI (Figs. 4a,c). In contrast, vegetation cover is extensive in the BAD and MON regions, with relatively higher NDVI and LAI than GUR, TAK, and GOB regions (Figs. 4a,c). Most areas in the GUR region remained predominantly bare from 2010 to 2023, though slight vegetation recovery was observed in the southwestern part, where NDVI and LAI showed an increase (Figs. 4b,d). TAK and GOB regions remained persistently bare land, with consistently low NDVI and LAI values (Figs. 4b,d). The BAD region exhibited signs of vegetation recovery, particularly in the eastern part of region, as reflected in increasing trends in both NDVI and LAI (Figs. 4b,d). Conversely, the MON region experienced slight vegetation degradation, particularly in the northern part of this region, as indicated by a modest decline in NDVI and LAI (Figs. 4b,d). These spatial heterogeneity was broadly consistent with previous studies (Fu et al. 2024; Yan et al. 2024b).

In addition, vegetation dynamics across these regions were temporally inconsistent as well. Across East Asia, although NDVI and LAI have slightly declined since 2018, vegetation cover has maintained a long-term growth trend (Figs. 5a,c). However, the five representative regions displayed distinct temporal patterns. In the GUR region, vegetation may have slightly recovered since 2014, as NDVI remained relatively stable while LAI exhibited an overall increasing trend after 2014 (Figs. 5b,d). In contrast, the TAK and GOB regions have long been characterized by sparse or nearly absent vegetation, with NDVI and

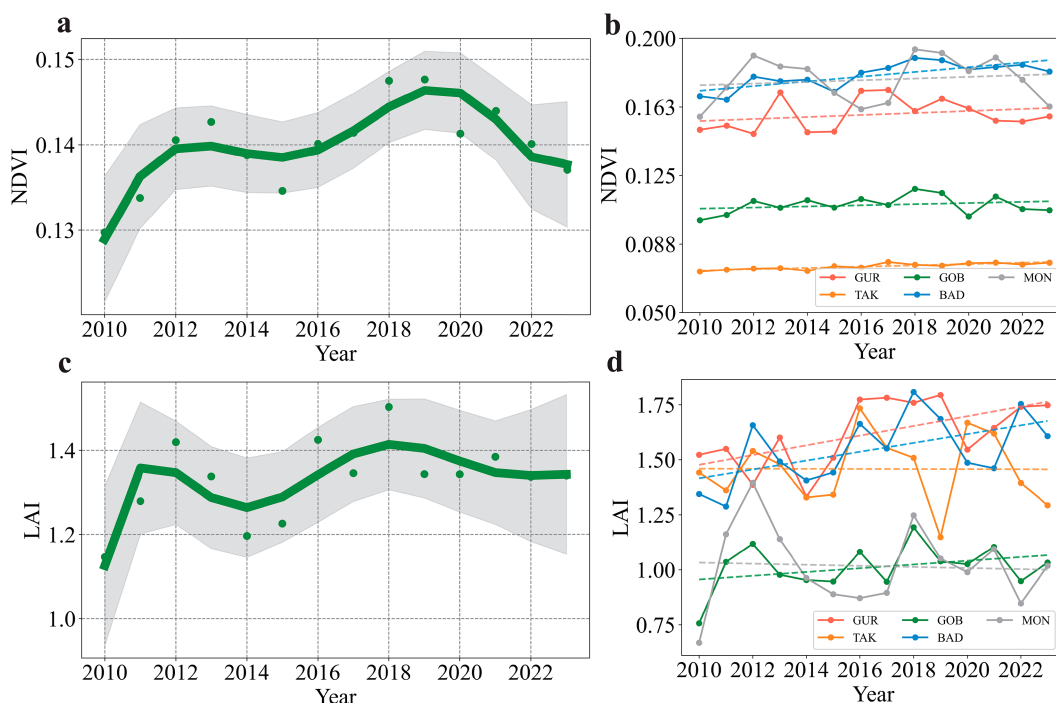


FIG. 5. Interannual changes in vegetation cover from 2010 to 2023. (a) Interannual variations of NDVI (dimensionless) in East Asia. (b) Interannual variations of NDVI in five representative regions. (c),(d) As in (a) and (b), but for LAI (dimensionless). The green line in (a) and (c) is the fitted line, and the gray shaded area means the 95% prediction interval. The average NDVI and LAI in East Asia were calculated for the five regions listed in Table 1. Missing values were excluded from the calculation of the average LAI in (c) and (d).

LAI remaining relatively low and showing little temporal variation (Figs. 5b,d). The BAD region showed a general recovery trend in vegetation, as reflected by increases in both NDVI and LAI (Figs. 5b,d). Conversely, the MON region exhibited a fluctuating downward trend in NDVI and LAI following 2018, indicating vegetation degradation during this period (Figs. 5b,d).

It is worth noting that an inverse relationship was observed between vegetation dynamics and dust variations in several regions. Since 2020, dust activity has intensified across East Asia (Fig. 2b), while vegetation has slightly degraded (Figs. 5a,c). Meanwhile, dust activity has decreased markedly (Figs. 2a and 3a) in regions showing a vegetation recovery pattern (Figs. 4b,d and 5b,d), such as the BAD and GUR regions. Conversely, the MON region, which has experienced slight vegetation degradation (Figs. 4b,d and 5b,d), exhibited an increasing trend in dust activity (Figs. 2a and 3a). However, dust activity does not appear to exhibit a clear inverse relationship with vegetation interannual changes in the TAK and GOB regions, where vegetation has remained persistently sparse or nearly absent (Figs. 4b,d and 5b,d).

5. Regional differences in drivers of dust activity

Given the distinct trends of dust activity and vegetation cover across different regions of East Asia, we conducted separate analyses for the five representative regions. We employed a combination of XGBoost and SHAP models to assess the

effects of 13 driving factors on regional dust activity variations. The models exhibited satisfactory performance, characterized by relatively high coefficients of determination (R^2) and low RMSE (Fig. 6). The main factors identified in the XGBoost algorithm were climate factors (including temperature, precipitation, and soil moisture), weather factors (including temp850hPa, temp500hPa, hgt850hPa, hgt500hPa, specific humidity, and pressure), wind factors (including near-surface wind speed and wind850hPa), and vegetation factors (including NDVI and LAI). Here, the dust activity was approximated with EMFLX.

Regional differences were observed in the relative importance of these driving factors. Specifically, vegetation factors were not the primary drivers in GUR, TAK, and GOB regions with bare land for a long time (18.7%, 5.4%, and 15.3%, respectively) (Figs. 7a,d,g). Conversely, these three regions were mainly influenced by climate factors and wind factors (Figs. 7a,d,g). In the GUR region, EMFLX variation was primarily driven by climate factors (42.4%), with soil moisture identified as the most influential variable, followed by NDVI (Fig. 7a). SHAP value analysis revealed higher soil moisture could substantially lower the EMFLX value and EMFLX decreasing sharply as NDVI increased (Figs. 7b,c). In the TAK region, wind factors and climate factors were the primary contributors to EMFLX variation, accounting for 37.8% and 31.5%, respectively (Fig. 7d). Near-surface wind speed and soil moisture were identified as the two most important variables, contributing the most to

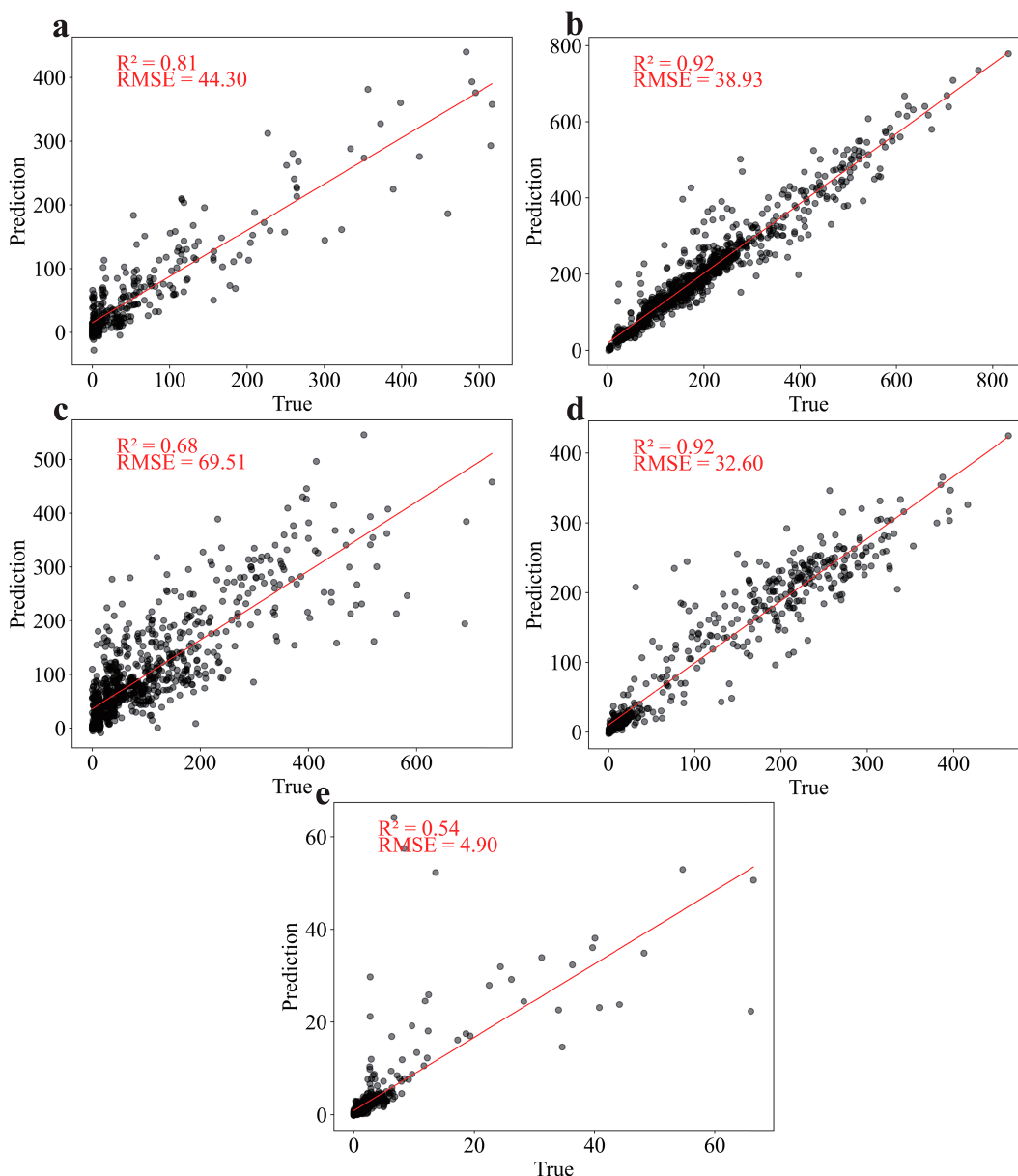


FIG. 6. The simulation performance of the models in five representative regions. Comparison of EMFLX ($\text{mg m}^{-2} \text{ day}^{-1}$) estimation results against real value in (a) the GUR region, (b) the TAK region, (c) the GOB region, (d) the BAD region, and (e) the MON region. The red line is the fitted straight line.

explaining of EMFLX variations (Fig. 7d). Specifically, EMFLX increased sharply with rising near-surface wind speed, whereas it decreased significantly as soil moisture increased (Figs. 7e,f). The GOB region was mainly influenced by climate factors, with their relative contribution to dust variations reaching 44.5% (Fig. 7g). The two most influential variables were temperature and temp500hPa, with higher values of both corresponding to increased EMFLX (Figs. 7h,i).

However, variations in EMFLX were primarily governed by vegetation factors in the BAD and MON regions with changing vegetation cover (59.3% and 46.0%, respectively) (Figs. 8a,d). In the BAD region, the two dominant factors

influencing EMFLX were NDVI and LAI (Fig. 8a). When NDVI and LAI were low, EMFLX rose with the decrease in NDVI and LAI (Figs. 8b,c), suggesting that bare or sparsely vegetated surfaces strongly promote dust emission. Conversely, as NDVI and LAI increased, EMFLX decreased sharply (Figs. 8b,c). In the MON region, LAI and temperature emerged as the two most important driving factors, exerting opposite effects on EMFLX (Fig. 8d). Specifically, LAI exhibited a similar effect to that observed in the BAD region, with higher LAI significantly reducing EMFLX, whereas EMFLX increased rapidly with rising temperature (Figs. 8e,f).

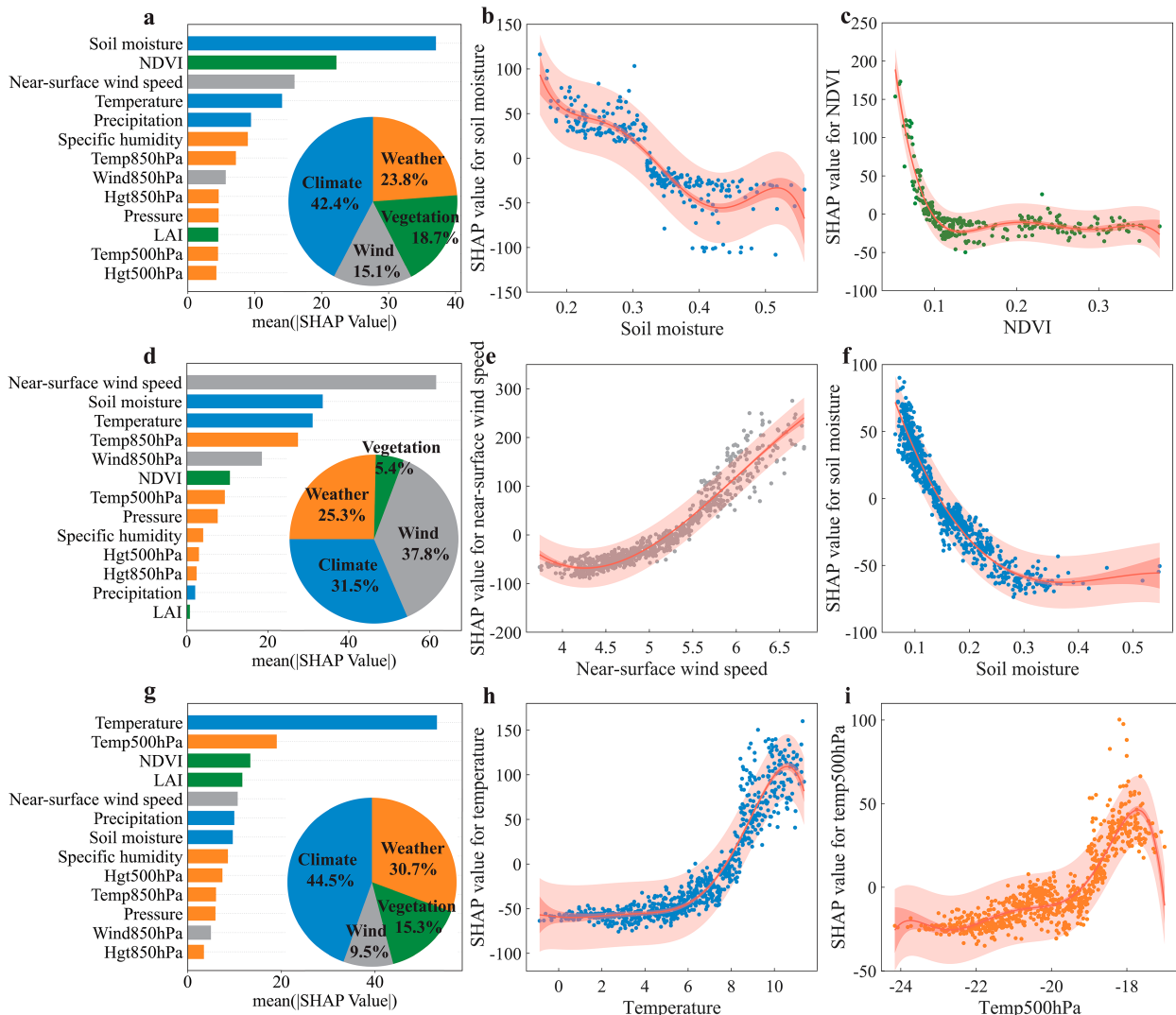


FIG. 7. Drivers of EMFLX (mg m⁻² day⁻¹) variations in persistently bare land areas. The importance of driving factors arranged in descending order in (a) GUR, (d) TAK, and (g) GOB regions. The importance of each variable is evaluated based on its mean |SHAP| value. Inset pie charts display the contributions of vegetation, weather, climate, and wind factors. (b), (c) Partial dependence plots of the SHAP value against the two most important factors in (a). (e), (f) As in (b) and (c), but for the two most important factors in (d). (h), (i) As in (b) and (c), but for the two most important factors in (g). SHAP > 0 (SHAP < 0) indicates that the corresponding driving factor has a positive (negative) contribution to the prediction. The dark pink line is the fitted line. The dark pink shaded area denotes the 95% confidence interval of the mean estimate, while the light pink shaded area means the 95% prediction interval.

Although the primary influencing factors differ among regions, certain commonalities remain evident. The results demonstrated that these 13 driving factors exhibit generally consistent relationships with EMFLX across the five regions. Specifically, NDVI, LAI, and soil moisture were negatively correlated with EMFLX, whereas temperature, near-surface wind speed, and wind850hPa exhibited positive correlations (Fig. 9). Additionally, the impact of near-surface wind speed consistently surpassed that of wind850hPa across these regions, highlighting the predominant role of near-surface wind speed in modulating dust activity (Fig. 9), which was also demonstrated in other researches (Wu et al. 2022; Zhou et al. 2024).

Based on the dominant factors and their effects in each region, we further analyzed the possible causes of dust variations across regions. For the GUR region, the EMFLX were mainly influenced by climate factors (Fig. 7a). In recent years, this region has experienced a warming and humidification trend, with a notable rise in temperature and comparatively high soil moisture (Figs. 10a,b,e,f), creating favorable conditions for vegetation growth (Huang et al. 2011; Zhang et al. 2021, 2022). The improvement in surface conditions and a significant decline in wind speed (Fig. 11) have led to the reduction in EMFLX in this region (Fig. 2a). Wind and climate factors exerted comparable influence in the TAK region (Fig. 7d). A notable increase in wind speed (Fig. 11) and rising temperatures (Fig. 10b) have

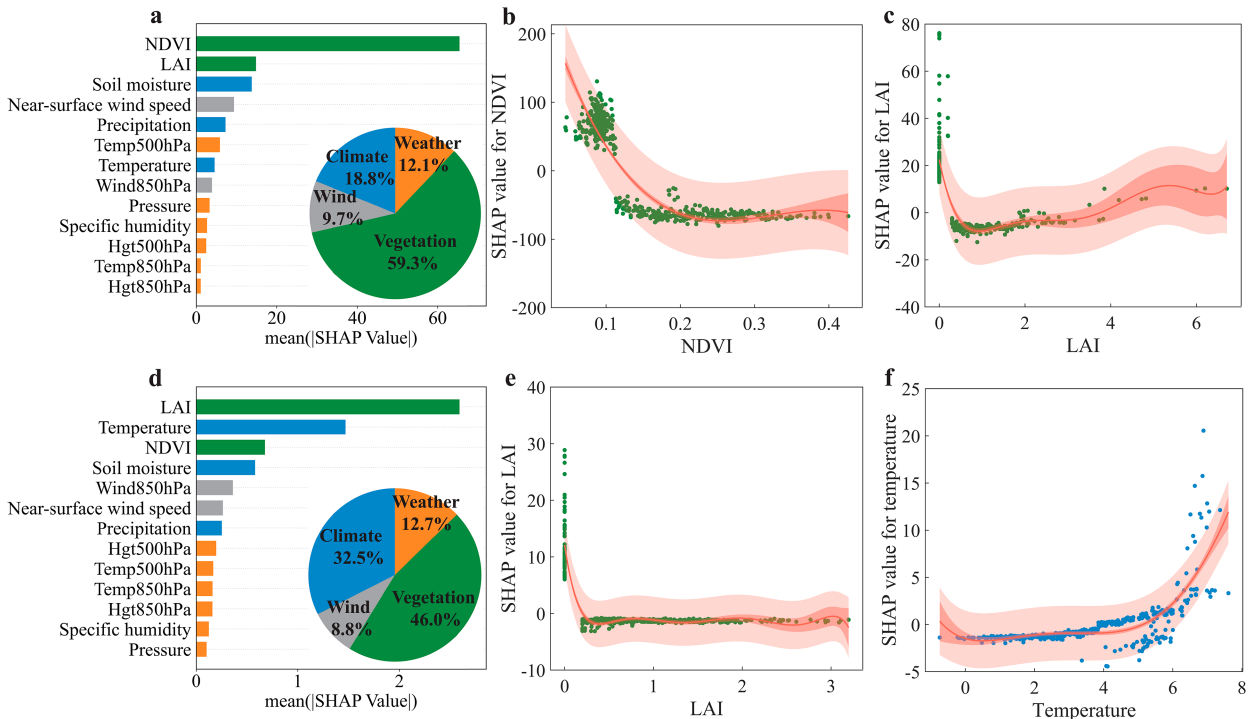


FIG. 8. Drivers of EMFLX ($\text{mg m}^{-2} \text{ day}^{-1}$) variations in regions undergoing vegetation changes. The importance of driving factors arranged in descending order in (a) BAD and (d) MON regions. The importance of each variable is evaluated based on its mean [SHAP] value. Inset pie charts display the contributions of vegetation, weather, climate, and wind factors. (b),(c) Partial dependence plots of the SHAP value against the two most important factors in (a). (e),(f) As in (b) and (c), but for the two most important factors in (d). SHAP > 0 (SHAP < 0) indicates that the corresponding driving factor has a positive (negative) contribution to the prediction. The dark pink line is the fitted line. The dark pink shaded area denotes the 95% confidence interval of the mean estimate, while the light pink shaded area means the 95% prediction interval.

contributed to the intensification of EMFLX in this area (Fig. 2a). The GOB region was also predominantly influenced by climate factors (Fig. 7g). This region exhibited a strong warming trend, with temperature increased exceeding 2.0°C in some areas (Fig. 10b). Meanwhile, persistently low precipitation led to severe drought and a significant decline in soil moisture (Fig. 10d), which was consistent with previous researches (Hessl et al. 2018; Han et al. 2021). Combined with increasing wind speeds (Fig. 11), these factors collectively resulted in a notable rise of EMFLX (Fig. 2a).

However, vegetation factors played a dominant role in EMFLX variations (Figs. 8a,d) in regions where vegetation cover increased (e.g., BAD region) or decreased (e.g., MON region). In the BAD region, the overall vegetation has been increased (Fig. 4). On one hand, increased vegetation (Fig. 4) and rising soil moisture (Fig. 10) alter the physical and chemical properties of the soil, thereby enhancing soil stability (Bronick and Lal 2005; Yang et al. 2017). On the other hand, it reduces wind speed by increasing the surface roughness (Dupont et al. 2014; Mayaud et al. 2016). Both effects contribute to a substantial reduction in EMFLX (Fig. 2a). In the MON region, the vegetation cover has been worsening (Fig. 4). Vegetation degradation has led to diminished soil stability and decreased surface roughness (Bronick and Lal 2005; Dupont et al. 2014; Mayaud et al. 2016; Yang et al. 2017), ultimately

resulting in the increased EMFLX (Fig. 2a). Meanwhile, significant increases in temperature and wind speed (Figs. 10 and 11) in this region have further promoted the intensification of EMFLX.

Overall, these results highlighted the distinct driving mechanisms of dust activity among the five regions. To better understand the overall dust variations across East Asia, it was necessary to consider the combined effects of these regions using a weighted averaging approach. In summary, the EMFLX in East Asia exhibited an increasing trend (Fig. 2b). This trend was mainly governed by climate factors (32.9%), followed by wind factors (25.0%) and weather factors (24.1%). Vegetation factors exerted the weakest influence, contributing only 18.0% to the overall EMFLX. The dust variations across East Asia were mainly dominated by the TAK and GOB regions (Table 1). In recent years, these two regions have experienced a pronounced warming and drying trend, characterized by rising temperatures (Fig. 10b), decreasing soil moisture (Fig. 10f), and persistently low precipitation (Fig. 10d). These climatic changes, accompanied by the strengthening of wind speed, jointly drove the intensification of dust activity across East Asia. However, the weakening of dust activity in the BAD and GUR regions has partially offset the enhancement effect in the other regions, resulting in a relatively moderate overall increasing trend of dust activity across East Asia.

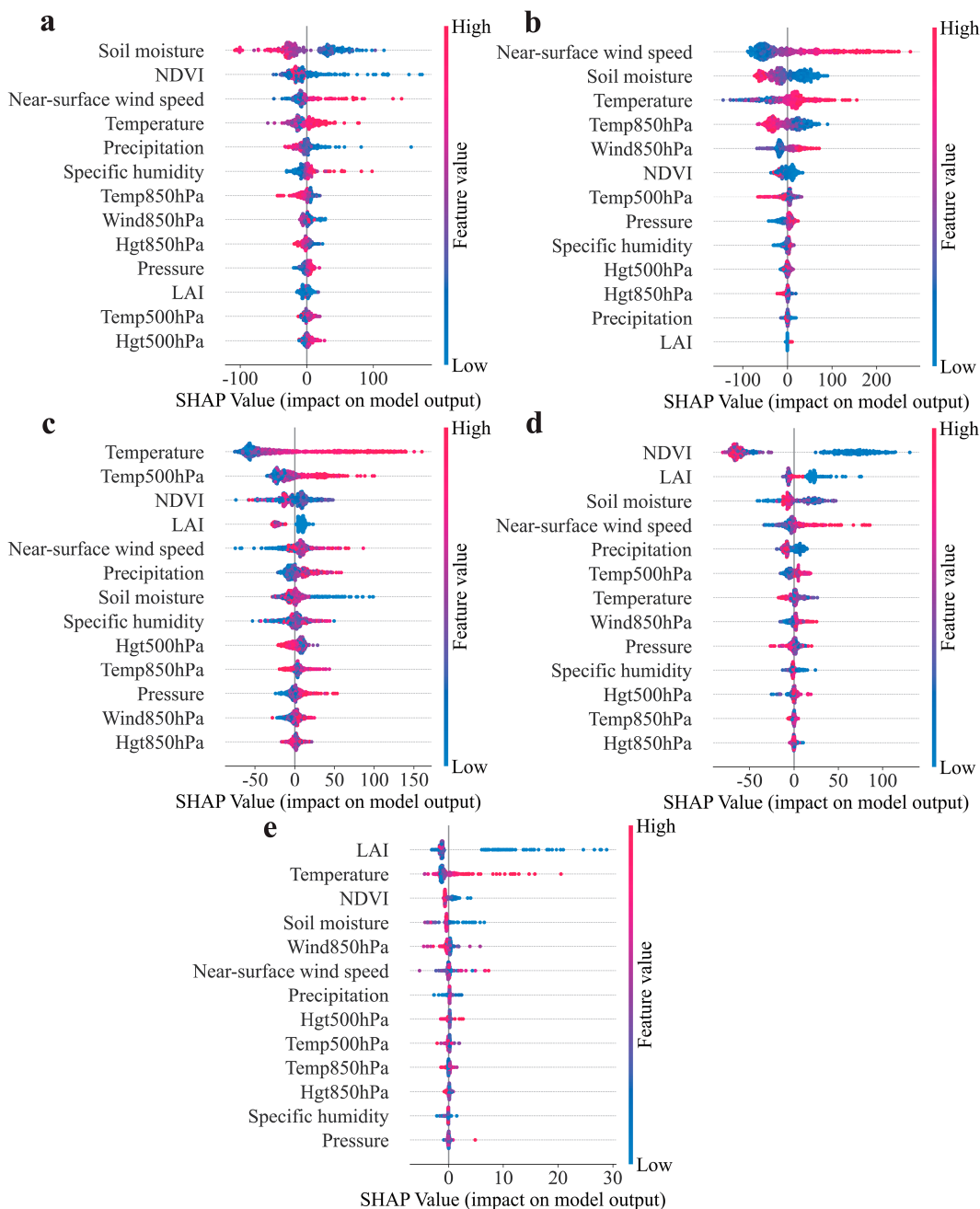


FIG. 9. The influence of 13 driving factors. The roles of 13 driving factors in (a) the GUR region, (b) the TAK region, (c) the GOB region, (d) the BAD region, and (e) the MON region. The color of the scatter represents the magnitude of feature values. SHAP > 0 (SHAP < 0) indicates that the corresponding driver factor has a positive (negative) contribution to the prediction.

Notably, the contribution of vegetation factor to dust variations across the East Asia was relatively low, markedly lower than its influence in the BAD and MON regions. This phenomenon may be related to the low vegetation cover in the major dust source regions of East Asia, where the overall vegetation density was lower than in the BAD and MON regions.

6. Conclusions and discussion

Our results demonstrated that northwestern China and southern Mongolia were hotspots of dust activity in East Asia (Fig. 1), which was consistent with previous studies (Zhao et al. 2006; Wang et al. 2021). We further revealed that the regions with significant decreases in dust activity were mainly located in western Inner Mongolia, China, and northern

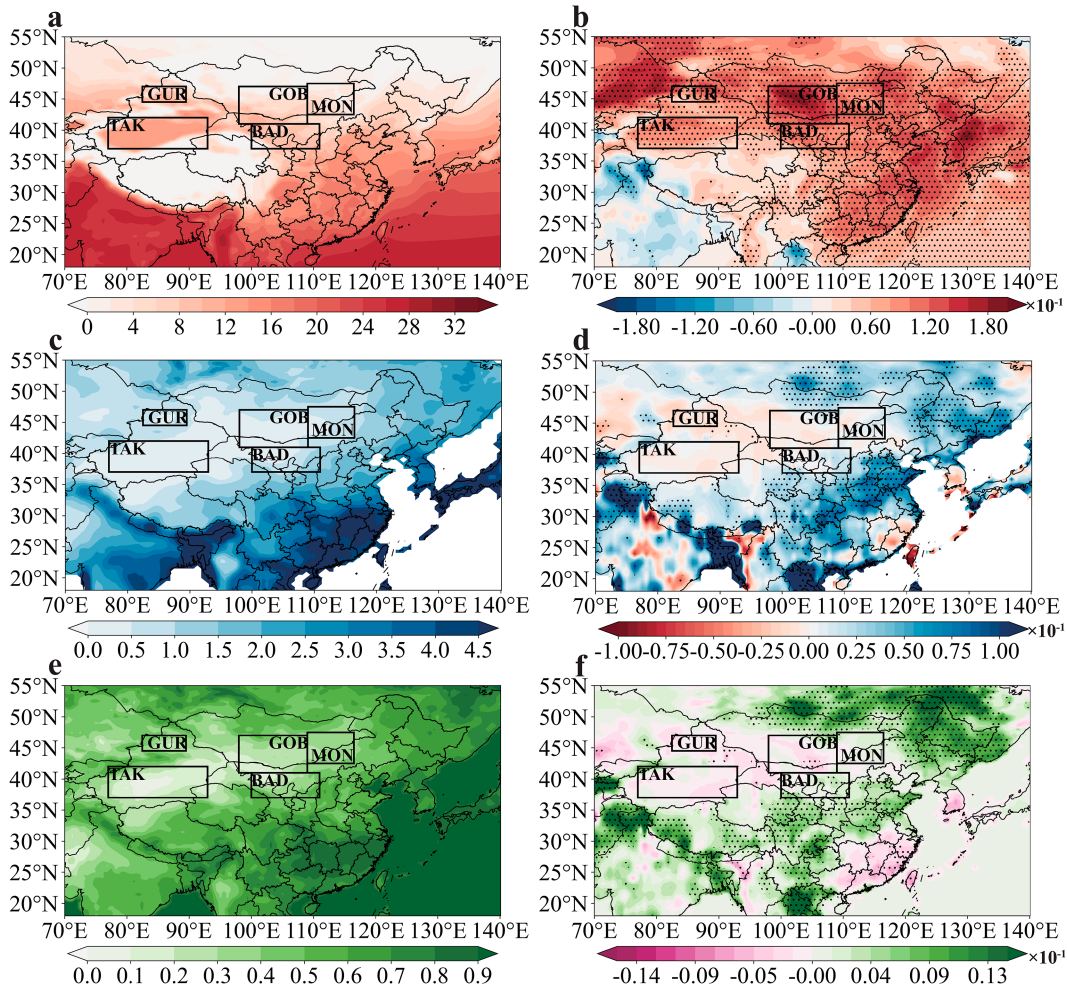


FIG. 10. Distribution and trends of climate factors. (a) The average value of temperature ($^{\circ}\text{C}$). (b) Linear trends of temperature ($^{\circ}\text{C yr}^{-1}$) and their spatial distribution of significance. (c) The average value of precipitation (mm day^{-1}). (d) Linear trends of precipitation ($\text{mm day}^{-1} \text{yr}^{-1}$) and their spatial distribution of significance. (e) The average value of soil moisture (dimensionless). (f) Linear trends of soil moisture and their spatial distribution of significance. The black dots mean passing the 90% significance test.

Xinjiang, China, while the areas with increasing dust activity were concentrated in southern and eastern Mongolia, as well as southern Xinjiang of China (Fig. 2a). This spatial interannual change pattern aligns with earlier findings (Wang et al. 2021; Mu and Fiedler 2025). Based on this spatial pattern, we quantified the contributions of these regions to dust activity across East Asia and identified the TAK region as the predominant contributor, consistent with Chen et al. (2017). Notably, despite regional disparities in long-term trends, a widespread increase in dust activity has been observed since 2020 (Figs. 2b and 3a), consistent with recent studies (Chen et al. 2023; Tan et al. 2025). Moreover, dust activity exhibited large seasonal variation, with spring identified as the peak period (Fig. 3b). This phenomenon may be related to the frequent occurrence of cold air outbreaks and Mongolian cyclones during the spring season (Wu et al. 2016; Mu and Fiedler 2025).

We found that recent changes in dust activity have been closely associated with evolving trends of vegetation cover

changes. Across East Asia, dust activity mainly occurred in bare land areas. In regions experiencing vegetation increase, dust activity decreased significantly, while dust activity increased markedly in areas with vegetation degradation (Figs. 2a and 4). Meanwhile, dust activity has increased significantly since 2020 in East Asia (Fig. 2b), coinciding with a slight deterioration in vegetation cover during the same period (Figs. 5a,c). These findings highlight a pronounced inverse relationship between dust activity and vegetation cover across East Asia, emphasizing the critical modulatory influence of vegetation dynamics on regional dust emissions, which is consistent with previous studies (Mao et al. 2013; Zhao et al. 2025). Our findings revealed marked regional differences in dust activity and their dominant driving factors under varying vegetation conditions. In persistently bare land areas (GUR, TAK, and GOB regions), the vegetation factor was not the primary driver of dust variations (Figs. 7a,d,g). Conversely, the aforementioned regions were primarily influenced by climate factors and wind factors, which is consistent

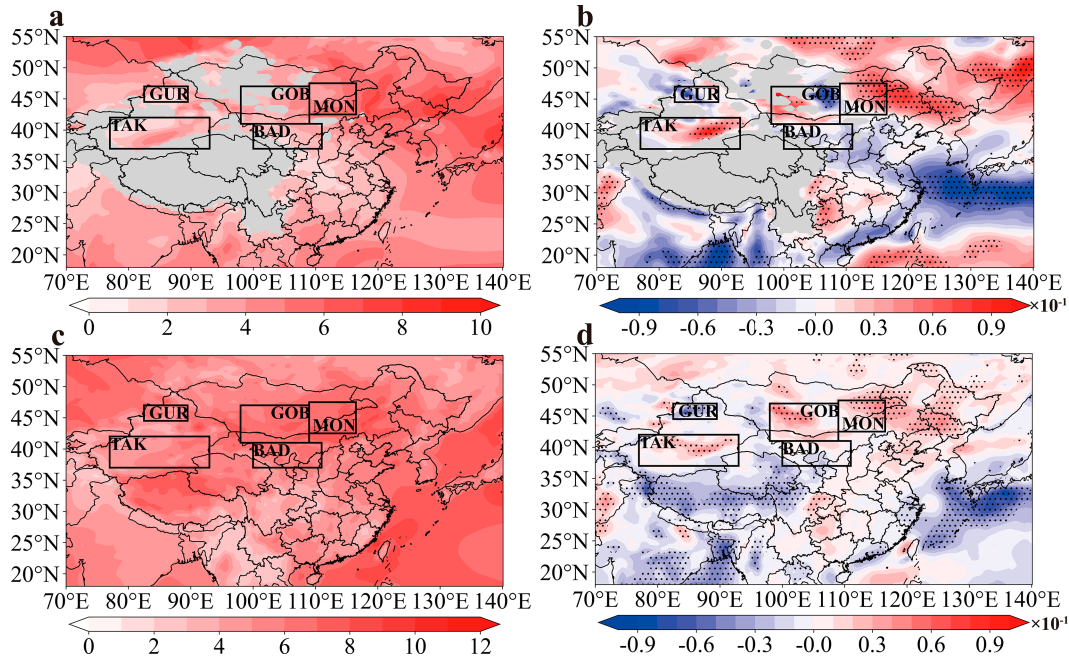


FIG. 11. Distribution and trends of wind factors. (a) The average value of wind850hPa (m s^{-1}). (b) Linear trends of wind850hPa ($\text{m s}^{-1} \text{yr}^{-1}$) and their spatial distribution of significance. (c) The average value of near-surface wind speed (m s^{-1}). (d) Linear trends of near-surface wind speed ($\text{m s}^{-1} \text{yr}^{-1}$) and their spatial distribution of significance. The black dots mean passing the 90% significance test.

with previous research (Tai et al. 2021; Wu et al. 2022; Zhou et al. 2024). Specifically, the GUR region was mainly influenced by climate factors (42.4%) (Fig. 7a). In the TAK region, wind and climate factors exerted comparable influence (37.8% and 31.5%) (Fig. 7d). The GOB region was also predominantly influenced by climate factors (44.5%) (Fig. 7g). However, vegetation factors played a dominant role in dust variations (Figs. 8a,d) in regions where vegetation cover increased (e.g., BAD region) or decreased (e.g., MON region). Notably, the contribution of vegetation dynamics to dust activity in these two regions (contribution $> 45\%$) was significantly higher than that in previous studies (Wu et al. 2022; Zhou et al. 2024; Zhao et al. 2025), which may be attributed to the subregional quantification approach employed in our analysis.

These distinct regional patterns of dust activity and their driving mechanisms collectively shaped the overall dust variations regime in East Asia. In the whole of East Asia, climate factors emerged as the primary drivers of dust variations, whereas vegetation exerted the weakest influence, which is broadly consistent with previous studies (Wu et al. 2022; Zhou et al. 2024). This result could be largely attributed to the dominant role of the TAK region in East Asia (Table 1). As a result, the influences of driving factors in regions with relatively low contributions to total dust variations were largely diminished in the overall analysis. This suggested that large-scale analyses might overlook important regional heterogeneities. Therefore, our findings highlight the importance of subregional assessments, especially when evaluating the contribution of vegetation to dust variations, as vegetation conditions varied greatly among regions.

The observed decline in dust activity in the BAD region illustrates the potential of vegetation recovery in suppressing dust activity. Since the late 1970s, multiple large-scale ecological restoration programs have been implemented by the Chinese government, such as the Three-North Shelter Forest Program and the Natural Forest Conservation Program (Bryan et al. 2018). These programs have played a significant role in vegetation recovery across China (Fig. 4), as confirmed by numerous studies (Zhang et al. 2016; Liu et al. 2020; Song et al. 2022). In recent years, vegetation recovery has been identified as a crucial factor contributing to the decline in dust activity in China (Tan and Li 2015; Wang et al. 2021), accounting for approximately 59.3% (Fig. 8a).

In recent years, the desert regions of Mongolia have remained bare land (Fig. 4). These regions have experienced persistent temperature rise and low precipitation, resulting in severe drought conditions (Fig. 10), which was demonstrated by previous study (Hessl et al. 2018; Han et al. 2021). With further increases in wind speed (Fig. 11), dust activity has become exceptionally active, as demonstrated in the GOB region. Moreover, similar to the U.S. Great Plains in the 1930s, Mongolia has undergone slight vegetation degradation in its vegetated regions (Fig. 4). This phenomenon has been driven not only by climate change, including rising temperatures and persistently low precipitation, but also by intensive human activities, such as overgrazing and coal mining (Piao et al. 2017; Han et al. 2021). In recent years, severe drought caused by rising temperatures and persistently low precipitation, along with accelerating vegetation degradation in Mongolia (Han et al. 2021), closely resembles the climate and vegetation degradation conditions observed

in the United States during the 1930s (Donat et al. 2016; Lee and Gill 2015). The combined effects of these climate changes and accelerating vegetation degradation may contribute to a sustained increase in dust activity in Mongolia, as evidenced in the MON region. Given the striking similarities between current climate and vegetation cover changes trends in Mongolia and those observed in the United States during the 1930s Dust Bowl period, urgent and proactive interventions are crucial to avert a similar ecological catastrophe.

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Data availability statement. All datasets used in this study are publicly available. MERRA-2 data are available at <https://disc.sci.gsfc.nasa.gov/datasets/>. MOD13C2 data are available at <https://lpdaac.usgs.gov/products/mcd15a3hv006/>. MCD15A3H data are available at <https://lpdaac.usgs.gov/products/mcd15a3hv006/>.

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