Precipitation or temperature? Nonlinear responses of particulate matter and ozone to meteorological extremes in an arid climate Postprint

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Abstract

Northern Xinjiang, an arid inland area in Northwest China,is highly vulnerable to air pollution under intensifying climate extremes, yet the relative roles of temperature and precipitation extremes remain insufficiently understood. Using multi-source datasets for 2000–2023, including China High Air Pollutants (CHAP) particulate matter 2.5 (PM2.5), particulate matter 10 (PM10), and ozone (O3) products and Expert Team on Climate Change Detection and Indices (ETCCDI) extreme climate indices derived from the European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis v5 (ERA5)-Land, together with trend detection, change-point analysis, pixel-wise Pearson correlation, and random forest(RF)modeling,we investigated the spatiotemporal evolution of major air pollutants and their responses to meteorological extremes in northern Xinjiang. PM2.5 and PM10 generally declined from 2000 to 2023, whereas O3 increased, indicating a shift from particulate-dominated pollution toward stronger photochemical pollution. Interannually, PM2.5 showed a rise–decline pattern, PM10 exhibited arise–decline–rebound pattern, and O3 increased markedly after 2015. Clear seasonal contrasts were observed, with PM2.5 peaking in winter, PM10 in spring, and O3 in summer. During the same period, northern Xinjiang exhibited a pronounced warming–drying tendency, characterized by increasing heat-related indices, decreasing cold-related indices, reduced precipitation totals and heavy-rainfall frequency, and increasing consecutive dry days. Pollutant–climate relationships showed strong spatial heterogeneity and pollutant-specific contrasts across the Urumqi–Changji–Shihezi corridor, the Ili RiverValley, and the Junggar Basin. PM2.5 responses to precipitation shifted from predominantly positive to negative, PM10 showed mainly negative associations with precipitation extremes, and O3 responses varied by subregion. Temperature-related extremes generally explained more pollutant variability than precipitation-related extremes, with PM2.5 showing the highest sensitivity. These findings highlight the coupled influences of warming, drying, emissions, and terrain-controlled transport on air quality and support region-specific, multi-pollutant strategies for coordinated climate adaptation and air pollution control in northern Xinjiang.

Full Text

Preamble

J Arid Land (2026) 18(4): 584–607 Precipitation or temperature? Nonlinear responses of particulate matter and ozone to meteorological extremes in an arid climate LI Yalong 1,2,3,4,5,6 , HU Bing , Marie Anne Eurie FORIO , CHANG Cun , QIAO Xuning NAIBI Sulei 1,2,3,5,6 , LI Tao 1,2,3,5,6 , SONG Fengjiao 1,2,3,5,6 , YANG Bin , LIU Hailong BAO Anming 1,7,11,12,13* , Peter GOETHALS 1 State Key Laboratory of Desert and Oasis Ecology, Key Laboratory of Ecological Safety and Sustainable Development in Arid Lands, Xinjiang Institute of Ecology and Geography, Chinese Academy of Sciences, Urumqi 830011, China; University of Chinese Academy of Sciences, Beijing 100049, China; Department of Animal Sciences and Aquatic Ecology, Ghent University, Ghent 9000, Belgium; Tarim University, Alaer 843300, China; Sino-Belgian Joint Laboratory of Geo-Information, Urumqi 830011, China; Sino-Belgian Joint Laboratory of Geo-Information, Ghent 9000, Belgium; Key Laboratory of Geographic Information System (GIS) & Remote Sensing (RS) Application Xinjiang Uygur Autonomous Region, Xinjiang Institute of Ecology and Geography, Chinese Academy of Sciences, Urumqi 830011, China; School of Surveying and Land Information Engineering, Henan Polytechnic University, Jiaozuo 454003, China; Research Centre of Arable Land Protection and Urban-Rural High-Quality Development of Yellow River Basin, Henan Polytechnic University, Jiaozuo 454003, China; University of Electronic Science and Technology of China, Chengdu 611731, China; Sino-Belgian Joint Laboratory for Geo-Information, Urumqi 830011, China; China-Pakistan Joint Research Center on Earth Sciences, Chinese Academy of Sciences-Higher Education Commission of Pakistan (CAS-HEC), Islamabad 45320, Pakistan; Qinghai Forestry Carbon Sequestration Service Center, Xining 810001, China

Abstract

Northern Xinjiang, an arid inland area in Northwest China, is highly vulnerable to air pollution under intensifying climate extremes, yet the relative roles of temperature and precipitation extremes remain insufficiently understood. Using multi-source datasets for 2000–2023, including China High Air Pollutants (CHAP) particulate matter 2.5 (PM), particulate matter 10 (PM), and ozone (O products and Expert Team on Climate Change Detection and Indices (ETC-

CDI) extreme climate indices derived from the European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis v5 (ERA5)-Land, together with trend detection, change-point analysis, pixel-wise Pearson correlation, and random forest (RF) modeling, we investigated the spatiotemporal evolution of major air pollutants and their responses to meteorological extremes in northern Xinjiang. PM and PM generally declined from 2000 to 2023, whereas O increased, indicating a shift from particulate-dominated pollution toward stronger photochemical pollution. Interannually, PM showed a rise–decline pattern, PM exhibited a rise–decline–rebound pattern, and O increased markedly after 2015. Clear seasonal contrasts were observed, with PM peaking in winter, PM in spring, and O in summer. During the same period, northern Xinjiang exhibited a pronounced warming–drying tendency, characterized by increasing heat-related indices, decreasing cold-related indices, reduced precipitation totals and heavy-rainfall frequency, and increasing consecutive dry days. Pollutant–climate relationships showed strong spatial heterogeneity and pollutant-specific contrasts across the Urumqi–Changji–Shihezi corridor, the Ili River

Valley, and the Junggar Basin. PM responses to precipitation shifted from predominantly positive to negative, PM showed mainly negative associations with precipitation extremes, and O responses varied by subregion. Temperature-related extremes generally explained more pollutant variability than precipitation-related extremes, with PM showing the highest sensitivity. These findings highlight the coupled influences of warming, drying, emissions, and terrain-controlled transport on air quality and support region-specific, multi-pollutant strategies for coordinated climate adaptation and air pollution control in northern Xinjiang.

Keywords

extreme climate events; air pollution dynamics; climate-pollution coupling; ozone formation mechanisms; gas-particle transformation; random forest Citation:

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1 Introduction

In recent decades, the accelerating pace of global industrialization has deteriorated air pollution, posing a growing threat to public health and ecological security (Goforth and Nock, 2022; Hobbs, 2002; Jin et al., 2024; Brustad et al., 2025; Zhao et al., 2025; Zou et al., 2025) . Extensive evidence indicates that both short- and long-term exposure to air pollutants significantly increase the incidence and mortality rates of respiratory and cardiovascular diseases. Key pollutants such as fine particulate matter (particulate matter 2.5 (PM)), inhalable particulate matter (particulate matter 10 (PM)), and ozone (O) are associated with human health and environmental issues such as cardiopulmonary diseases, cancer, acid rain, reduced visibility, and crop yield losses, and are therefore prioritized in both national and international air quality standards (Müller et al., 2022; Yang et al., 2023; Chen and Zhang, 2024; Li et al., 2024; Chen et al., 2025a; Liu et al., 2025a; Liu et al., 2025b; Wang et al., 2025a; Zhang et al., 2025a) Meanwhile, global climate change is amplifying the frequency, intensity, and duration of extreme weather events, presenting profound challenges to both human society and natural systems (Qiao et al., 2024; Kramer and Minet, 2025; Zhou et al., 2025) . Extremes such as heatwaves, drought, and intense precipitation can strongly regulate the spatiotemporal distribution of air pollutants by altering atmospheric chemistry, boundary-layer dynamics, and removal processes (Zhang et al., 2021; Hammer et al., 2023; Huang et al., 2025; Wang et al., 2025b) Importantly, the effects of extreme temperature and precipitation on particulate matter and O frequently nonlinear and sometimes bidirectional. For example, high temperatures can enhance photochemical activity and atmospheric oxidizing capacity, thereby promoting O formation and secondary aerosol production, yet high temperatures may also reduce near-surface pollutant accumulation through a deeper planetary boundary layer or the volatilization of semi-volatile components such as ammonium nitrate. Precipitation can efficiently remove particles via wet scavenging (washout effect), but under weak rainfall and high-humidity conditions it may enhance PM via aqueous-phase reactions and hygroscopic growth (Li et al., 2023; Ryalls et al., 2024; Guan and Zhang, 2025; Lü et al., 2025; Zhang et al., 2025a, Zhang et al., 2025b) Furthermore, precipitation can modify solar radiation and temperature, indirectly influencing photochemistry and further complicating climate-pollution interactions (Wang et al., 2024; Camacho-Caballero et al., 2025; Xu et al., 2025) . These processes suggest that understanding air pollution under extremes requires not only identifying "whether" relationships exist, but also quantifying "how strongly" different types of extremes matter and "whether" thresholds or regime shifts occur.

Arid and semi-arid areas are particularly sensitive to climate extremes because of scarce precipitation, strong radiative forcing, and pronounced seasonal temperature contrasts, which together shape distinctive meteorology–emission coupling and pollutant formation pathways.

Northern Xinjiang, located in the arid to semi-arid continental interior of Eurasia, features a dry climate, limited precipitation, and large seasonal and diurnal temperature variations (Guo et al., 2025; Qu et al., 2025; Zhao et al., 2026) . Its complex terrain, together with diverse emission sources—spring dust storms, wintertime residential heating, industrial activities, agricultural emissions, and vehicular exhaust—produces pollutant characteristics that differ markedly from those in eastern China (Chen et al., 2025b; Hu et al., 2025) . Recent warming and drying trends, accompanied by more frequent extreme events, further increase the uncertainty of air quality outcomes and raise the urgency of clarifying climate–pollution linkages in this region (Bi et al., 2025; Li et al., 2025; Wang et al., 2025c) Despite growing interest in air pollution–meteorology interactions, several gaps remain for arid areas. First, existing studies often examine temperature-related extremes (e.g., heatwaves) and precipitation-related extremes (e.g., drought or heavy rainfall) separately, making it difficult to provide a head-to-head assessment of their relative importance. Second, many investigations focus on a single pollutant and/or a limited season, whereas arid areas frequently exhibit strong seasonal regime contrasts (e.g., wintertime accumulation and heating-related particulate pollution versus warm-season photochemical O production and dust-related processes). Third, nonlinear and threshold-like responses are frequently hypothesized but are not consistently evaluated across space and time, especially when long-term and spatially continuous pollutant data are lacking (Duan et al., 2025; Yuan et al., 2025) . These limitations hinder a clear answer to the key question implied by our title: Do precipitation extremes or temperature extremes play a more dominant role in shaping air pollution in an arid climate?

To address these gaps, this study integrates multi-source datasets from 2000 to 2023, including air pollutant fields from the China High Air Pollutants (CHAP) product and standardized extreme climate indices derived from the Expert Team on Climate Change Detection and Indices (ETCCDI) framework, to examine the spatiotemporal evolution of PM , and O and their relationships with meteorological extremes in northern Xinjiang. Specifically, we aim to: (1) characterize the long-term trends and spatial patterns of key pollutants and extreme climate indices; (2) explore how pollutant–extreme associations vary across seasons and subregions (e.g., urban corridors versus ecological zones); and (3) assess whether these associations exhibit nonlinear features under extreme conditions. By organizing the analysis around precipitation- and temperature-related extremes within the same study area, this work is intended to improve understanding of climate–pollution interactions in arid environments and to support climate-adaptive strategies for air quality management.

2.1 Study area

Northern Xinjiang (43°25′–49°10′N, 79°30′–91°20′E; approximately 4.50$×$10), north of the Tianshan Mountains region of Xinjiang Uygur Autonomous Region (hereinafter referred to as Xinjiang), China, encompasses major cities such as Urumqi, Karamay, Yining, Altay, Tacheng, Changji, and Bortala. The region is characterized by a mid-temperate continental arid to semi-arid climate. Winters are cold and summers are hot, with large diurnal and seasonal temperature ranges. Precipitation is generally low, whereas sunshine duration is long and solar radiation is strong, resulting in high evaporative demand. Mean annual temperature is generally about 5.0–8.0°C, and annual precipitation is spatially

Figure 1

Figure 1: Figure 1

heterogeneous but mostly low, with wetter mountain–valley areas and much drier basin interiors.

This region includes the Urumqi–Changji–Shihezi Economic Belt, the most densely populated and industrialized corridor along the northern slope of the Tianshan Mountains, where emissions from urban activity and energy use are concentrated (Fig. 1

). It also contains the Ili River Valley, a westward-opening intermontane valley characterized by relatively higher precipitation and strong cross-border airflow exchange, making it a key transport pathway and a comparatively

strong "self-cleaning" subregion. As a mid-latitude arid–semi-arid area, the semi-enclosed Junggar Basin—bordered by the Altai and Tianshan mountains and linked to Central Asia via the Alataw Pass and Ili River Valley—shapes pollutant dispersion and extreme weather through: (1) winter cold-air pooling and inversions that trap pollutants; (2) westerly corridors transporting dust and external pollutants; and (3) orographic precipitation on the Tianshan' s northern slopes that drives wet deposition. This coupled topography–climate system provides an ideal setting to study pollution–extreme climate feedbacks.

Elevation (a) and remote sensing image (b) of northern Xinjiang. DEM, digital elevation model.

2.2.1 Air pollutant data

developed by the research team at the University of Maryland, the USA and released by the National Xizang Plateau Center 6168e75d-93ab-4e4a-b7ff-33152e49d0bf) et al., 2020, 2021) . CHAP integrates satellite remote sensing, ground observations, atmospheric reanalysis, and emission-related information.

Machine-learning-based fusion and gap filling are used to generate spatially continuous near-surface pollutant fields over China. CHAP provides gridded concentrations at 1 km resolution for 2000–2023, with products available at daily, monthly, and annual scales. The dataset includes PM , and NO among others.

This study used CHAP PM , and O to examine pollutant patterns and their associations with climate extremes in northern Xinjiang from 2000 to 2023. Because the ETCCDI indices were analyzed on an annual basis, we aligned all pollutant metrics to the same annual scale.

Annual PM , and O values were obtained primarily from the CHAP annual product; when annual layers were unavailable for specific pixels/years, we computed annual means from monthly products. To ensure adequate temporal coverage, annual means were calculated only when at least 10 valid months were available in a given year; otherwise, the annual value for that pixel was treated as missing.

Extreme climate data Meteorological variables were obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF Reanalysis v5 (ERA5)-Land for 2000–2023, including 2 m air temperature and total precipitation at the surface (nalysis-era5-land). We used temperature and precipitation to derive extreme climate indices following the ETCCDI definitions (Table 1). ERA5-Land provides sub-daily meteorological fields at a relatively fine spatial resolution (approximately 0.1°) and hourly temporal frequency.

Daily maximum temperature (TX) and daily minimum temperature (TN) were derived from hourly 2 m temperature, and daily precipitation totals were derived from accumulated precipitation fields.

List of the Expert Team on Climate Change Detection and Indices (ETCCDI) core climate indices Classification Indicator name Definition

Annual (1 st January to 31 st December in NH or 1 st July to 30 th June of next year in SH) count between first span of at least 6 d with TG>5.0°C and first span after 1 st July (1 st January in SH) of 6 d with TG<5.0°C

Growing season length Extreme temperature Cold spell duration indicator Annual count of days with at least 6 consecutive days when TN<10 percentile Warm spell duration indicator Annual count of days with at least 6 consecutive days when TX>90 percentile Diurnal temperature range Monthly mean difference between TX and RX1day Maximum 1-day precipitation amount Monthly maximum 1-day precipitation RX5day Maximum 5-day precipitation amount Monthly maximum consecutive 5-day precipitation Consecutive dry days Maximum number of consecutive days with RR<1.0 mm Extreme precipitation Consecutive wet days Maximum number of consecutive days with RR$ 1.0*mmSimpledailyintensityindexAnnualtotalprecipitationdividedbythenumberofwetdays(definedasP*
Note: TN, daily minimum temperature; TX, daily maximum temperature; NH, Northern Hemisphere; SH, Southern Hemisphere; TG, daily mean temperature.

PRCP denotes the daily precipitation amount used as the input precipitation variable, and RR represents the daily precipitation amount in ETCCDI formula notation.

3 Methods

3.1 Temporal consistency and spatial harmonization All analyses were conducted at the annual scale over 2000–2023. Annual ETCCDI indices were computed from ERA5-Land daily series using the RClimDex-based implementation. Annual pollutant concentrations (PM , and O) were obtained from the CHAP annual product and/or aggregated from monthly products as annual means. We used annual mean O to maintain temporal consistency with the annual ETCCDI indices and the annual-scale analyses in this study.

We noted that annual averaging may smooth warm-season O episodes; therefore, O -climate relationships are interpreted as long-term co-variability rather than event-scale behavior.

CHAP pollutant fields are provided at 1 km resolution, whereas ERA5-Land is coarser. To support pixel-wise analyses, we harmonized all datasets to a common grid. Specifically, we first projected all layers to a consistent coordinate reference system (Universal Transverse Mercator (UTM) for Xinjiang) and then resampled them to a 1 km grid using bilinear interpolation. This resampling was performed for grid alignment and does not increase the intrinsic information content of the original reanalysis data.

3.2 Trend and change-point analysis

We quantified long-term trends and potential abrupt shifts in annual pollutant concentrations (PM , and O) and annual ETCCDI indices using the Theil-Sen slope estimator, the Mann-Kendall (M-K) significance test, and the M-K mutation test. These methods are robust to non-normality and outliers and are widely used for environmental time series analysis. 3.3 Pollutant–extreme associations and modeling We examined spatial heterogeneity in pollutant–extreme relationships using pixel-wise correlation analyses between annual pollutant series and annual ETCCDI indices during 2000–2023.

Specifically, the correlation maps represent pixel-wise temporal Pearson correlations. For each 1 km pixel, Pearson' s was calculated between the annual pollutant time series (annual mean PM and O) and the annual ETCCDI index time series over 2000–2023 (=24). To reduce the potential influence of shared long-term trends, we conducted a robustness check by repeating the correlations on detrended annual anomalies (removing a linear trend from each pixel-wise time series prior to correlation); the main spatial patterns were generally consistent. These maps were used to identify regions where pollutant variability is more strongly associated with temperature-related versus precipitation-related extremes.

To further quantify the contributions of different extreme indices and capture potential nonlinear relationships, we applied random forest (RF) regression. RF models were used to relate annual pollutant concentrations to temperature- and precipitation-related ETCCDI indices, leveraging RF' s ability to model nonlinear effects and interactions.

M-K significance test The M-K significance test follows the -test. The null hypothesis is that equals zero in the Theil-Sen trend analysis, and no monotonic trend exists in the time series (Li et al., 2023).

$= = + = - \sum\sum$, (1)

$- > \quad - = - = \quad <$

where denote the values of the time series at the observations, respectively; is the total number of observations in the time series; and is a statistic that obeys the standard normal distribution. Under the null hypothesis, the expected value of is 0, and the variance of denoted as), is calculated as follows (Nanditha et al., 2024): var( ) where denotes the number of groups with the same value in samples; and denotes the number of repetitions.

The corresponding -values for different statistic intervals in the M-K statistics formula are (Nanditha et al., 2024):

$- \quad > \quad = = \quad + <$

var( ) . (4) var( )

, the null hypothesis is rejected, proving that there is a monotonic trend in the time series. Specifically, when 1.96≤ <2.58, there is a monotonic trend and significant change at <0.05 level; when $ $2.58, there is a monotonic trend and highly significant change at <0.01 level; and when <1.96, there is no significant change. A positive indicates a monotonic increasing trend, whereas a negative indicates a monotonic decreasing trend.

M-K mutation test For a time series) with samples, if the corresponding value at the step is greater than the corresponding value at the step, the number of values is accumulated to construct the order sequence . The cumulative statistic was calculated as follows (Li et al., 2023):

$= = = \quad \sum$, (5)

, (6) where 2, 3, ···, denotes the time step or sample position in the sequence; and represents the number of previous observations that 1, 2, ···, -1) are smaller than The mean) and variance) of the order column are calculated as (Li et al., 2023): , (7)

(1)(2 5) var( ) 72 k n n n S − + = . (8)

Under the assumption that the time series is random, the standardized forward sequential statistic UF was calculated as follows (Qiao et al., 2024):

$- = =$. (9)

-series is inverted to obtain a new time series . This process is repeated to obtain UB = -UF , where UB -1, ···, 1. Given a significance level (generally =0.05, = $±$1.96). indicates a significant trend change. UF >0 indicates an upward trend, and vice versa. The intersection of UF and UB represents the mutation point. If the mutation point is at the significance level, the corresponding year is proven to be the mutation start time.

Pearson correlation calculation The Pearson correlation coefficient was used to quantify the interannual association between air pollutants and extreme climate indices. In this study, pixel-wise temporal Pearson correlations were calculated between annual mean pollutant concentrations (PM , and O) and annual ETCCDI indices over northern Xinjiang during 2000–2023. Because both pollutant concentrations and extreme climate indices were analyzed at the annual scale, all variables were first temporally harmonized to ensure comparability. For each 1 km pixel, the correlation coefficient was computed from 24 annual observations (=24), and the resulting correlation maps were used to identify spatial heterogeneity in pollutant responses to temperature-related and precipitation-related extremes. These analyses provided the basis for comparing whether pollutant variability was more strongly associated with thermal extremes or hydrological extremes across different subregions of northern Xinjiang.

$- - =$

, (10)

where is the Pearson correlation coefficient between variables represents the value of the variable in the year; represents the annual average value of the variable represents the value of the variable in the year; represents the annual average value of the variable ; and represents the number of years (Qiao et al., 2024).

4.1 Air pollution trends

4.1.1 Spatial distribution characteristics From 2000 to 2023, PM and PM exhibited broadly similar spatial patterns, with persistent hotspots in the Urumqi-Changji–Shihezi Economic Belt and the eastern Junggar industrial hub, especially around the Zhundong Industrial Park (Figs. 2 and 3). During 2000-2014, pollutant levels in these areas frequently exceeded national limits, with annual PM >50 μg/m (locally>70) and PM often close to 100 μg/m . After 2014, concentrations generally declined and high-value areas contracted, consistent with strengthened emission control measures. In contrast, Altay Prefecture and northern Tacheng Prefecture maintained comparatively low PM and PM levels (typically<35 μg/m), likely reflecting weaker anthropogenic emissions and their distance from major dust-source regions. showed an opposite spatial pattern to particulate pollution before 2015, with lower values in the industrial belts and higher values in cleaner mountainous and northern areas (Fig. 4 [FIGURE:4]). This contrast is consistent with reduced photochemical O production under heavy aerosol loading.

Since 2016, O however, rose sharply, with most regions, exceeding 100 μg/m annually, indicating a growing photochemical pollution risk across northern Xinjiang. , and O in northern Xinjiang during 2000-2023. Overall, PM and PM displayed widespread declining trends, whereas O showed a broad increase, suggesting a transition in the dominant pollution pattern. PM decreased by -0.53 μg/(m a) on average, with pronounced reductions in Altay Prefecture, Tacheng Prefecture, Ili Kazak Autonomous Prefecture, and Bortala Spatial distribution of annual mean particulate matter 2.5 (PM) concentrations in northern Xinjiang from 2000 to 2023. (a), 2000; (b), 2001; (c), 2002; (d), 2003; (e), 2004; (f), 2005; (g), 2006; (h), 2007; (i), 2008; (j), 2009; (k), 2010; (l), 2011; (m), 2012; (n), 2013; (o), 2014; (p), 2015; (q), 2016; (r), 2017; (s), 2018; (t), 2019; (u), 2020; (v), 2021; (w), 2022; (x), 2023.

Figure 5

Figure 2: Figure 5

White areas indicate missing data and were excluded from analysis.

Spatial distribution of annual mean particulate matter 10 (PM) concentrations in northern Xinjiang from 2000 to 2023. (a), 2000; (b), 2001; (c), 2002; (d), 2003; (e), 2004; (f), 2005; (g), 2006; (h), 2007; (i), 2008; (j), 2009; (k), 2010; (l), 2011; (m), 2012; (n), 2013; (o), 2014; (p), 2015; (q), 2016; (r), 2017; (s), 2018; (t), 2019; (u), 2020; (v), 2021; (w), 2022; (x), 2023.

White areas indicate missing data and were excluded from analysis.

Spatial distribution of annual mean ozone (O) concentrations in northern Xinjiang from 2000 to 2023. (a), 2000; (b), 2001; (c), 2002; (d), 2003; (e), 2004; (f), 2005; (g), 2006; (h), 2007; (i), 2008; (j), 2009; (k), 2010; (l), 2011; (m), 2012; (n), 2013; (o), 2014; (p), 2015; (q), 2016; (r), 2017; (s), 2018; (t), 2019; (u), 2020; (v), 2021; (w), 2022; (x), 2023. White areas indicate missing data and were excluded from analysis.

Mongolian Autonomous Prefecture, while slight localized increases occurred in the Urumqi–Changji–Shihezi Economic Belt and the Zhundong Industrial Park. PM declined more rapidly (-0.84 μg/(m a)), particularly in the Ili River Valley and southern Altay Prefecture. This spatial pattern is consistent with a weakening influence of dust-related particles on PM ; however, because dust emissions and specific dust-control actions were not quantified in this study, the interpretation should be considered indicative rather than confirmatory. In contrast, O increased by +0.47 μg/(m a), with the strongest upward trends in the Urumqi–Changji–Shihezi Economic Belt, northwestern Tacheng Prefecture, northern Ili Kazak Autonomous Prefecture, and many areas exhibiting statistically significant trends (Fig. 5

).

Spatial distribution of Theil-Sen slope (a–c) and Mann-Kendall (M-K) significance (d–f) for PM and O in northern Xinjiang from 2000 to 2023 Interannual and seasonal trends in air pollution variability From 2000 to 2023, air pollution in northern Xinjiang underwent substantial changes (Fig. 6 [FIGURE:6]).

Annual mean PM showed a "rise–decline" pattern, increasing from 36 μg/m in 2000 to 40 in 2011 and then decreasing to 23 μg/m by 2023 (Fig. 6a1). Annual mean PM exhibited a "rise–decline–rebound" pattern, peaking at 91 μg/m in 2012, declining to 57 μg/m in 2020, and rebounding to 62 μg/m in 2023 (Fig. 6a2). In contrast, annual mean O remained around 82 before 2015 and then increased to 101 μg/m by 2023 (Fig. 6a3). M-K mutation tests identified breakpoints in 2020, 2019, and 2019 for PM , and O , respectively (Fig. 6b1–b3). All pollutants exhibited clear seasonal cycles (Fig. 6c1–c3): PM peaked in winter, peaked in spring, and O peaked in summer. Over time, winter PM peaks weakened after 2015 and reached a minimum of 45 μg/m in the winter of 2023, whereas summer O peaks strengthened after 2016 and exceeded 130 μg/m by 2023, indicating an increasing prominence of photochemical pollution (Fig. 6d).

In summary, northern Xinjiang' s air pollution profile has shifted from particulate matter dominance to photochemical O pollution: PM and PM levels have generally declined, while has intensified. This trend highlighted the need to pivot air quality management from "particulate matter reduction" toward "O control" .

4.2.1 Trends in extreme precipitation

From 2000 to 2023, most precipitation-related extreme indices in northern Xinjiang showed an overall decline, indicating reduced precipitation amount, weakened intensity, and fewer heavy-rainfall events (Fig. 7 [FIGURE:7]). Annual total wet day precipitation (PRCPTOT) decreased from 444.8 mm (2000) to 329.6 mm (2023). Heavy and very heavy precipitation also declined markedly (to be specific, very wet days (R95P) decreased from 107.3 to 42.6 mm, and extremely wet days (R99P) dropped from 44.1 to 8.5 mm from 2000 to 2023). Consistently, maximum 1-day precipitation amount (RX1day) and maximum 5-day precipitation amount (RX5day) decreased to 14.6 and 31.3 mm, respectively, and rainfall frequency weakened (number of moderate precipitation days (R5MM) decreased from 29.0 to 21.8 d, and number of heavy precipitation days (R10MM) from 10.20 to 6.70 d from 2000 to 2023). In contrast, drought conditions intensified, with consecutive dry days (CDD) increasing from 34.8 d (2000) to a peak of 55.90 d (2013) and remaining high at 48.30 d in 2023.

Interannual (a1 a3 and b1 b3), seasonal (c1 c3), and monthly (d) variation characteristics of $PM_{2\cdot5}$, PM_{10}, and O_3 in northern Xinjiang from 2000 to 2023. In panels b1 UF and UB represent the forward and backward sequential statistics of the M-K mutation test, respectively; and in panels c1–c3, IQR represents the interquartile range.

Spatially, higher precipitation metrics were concentrated along the Tianshan Mountains (e.g., higher consecutive wet days (CWD) and more frequent moderate-to-heavy rainfall), whereas western Tacheng Prefecture and northern Karamay City exhibited much larger CDD values, indicating stronger drought persistence (Fig. 8 [FIGURE:8]). Theil-Sen and M-K results suggested widespread decreases in PRCPTOT and rainfall-frequency indices (e.g., R5MM and R10MM), particularly across eastern Tianshan Mountains northern slope, including Urumqi–Changji–Shihezi corridor. An increasing CDD trend was evident in parts of the eastern Junggar Basin, while the Altay Mountains showed a weak increasing tendency in precipitation-related indices, although not statistically significant.

Trends in extreme temperature From 2000 to 2023, temperature-related extreme indices in northern Xinjiang consistently indicated warming and a lengthening

Figure 10

Figure 3: Figure 10

of warm conditions (Fig. 9 [FIGURE:9]). Heat-related indices (growing season length (GSL), summer days (SU), warm nights (TN90P), tropical nights (TR), warm days (TX90P), and warm spell duration indicator (WSDI)) increased overall, with SU and WSDI

Linear trends of extreme precipitation indices. (a), consecutive dry days (CDD); (b), consecutive wet days (CWD); (c), annual total wet day precipitation (PRCPTOT); (d), number of moderate precipitation days (R5MM); (e), number of heavy precipitation days (R10MM); (f), very wet days (R95P); (g), extremely wet days (R99P); (h), maximum 1-day precipitation amount (RX1day); (i), maximum 5-day precipitation amount (RX5day); (j), simple daily intensity index (SDII).

Spatial distribution of mean values (a1–a10), Theil-Sen slope (b1–b10), and M-K significance test results (c1–c10) of extreme precipitation indices

Linear trends of extreme temperature indices. (a), cold spell duration indicator (CSDI); (b), diurnal temperature range (DTR); (c), frost days (FD); (d), growing season length (GSL); (e), ice days (ID); (f), summer days (SU); (g), cool nights (TN10P); (h), warm nights (TN90P); (i), tropical nights (TR); (j), cool days (TX10P); (k), warm days (TX90P); (l), warm spell duration indicator (WSDI). showing the strongest upward trends (0.39 and 0.35 d/a, respectively). SU increased from 61.30 to 80.70 d, and WSDI increased from 5.10 to 19.20 d. Warm-day frequency (TX90P) increased from 11.80 to 19.30 d, while warm-night frequency (TN90P) increased from 13.00 to 20.60 d.

Cold-related indices generally declined. Frost days (FD) decreased at -0.27 d/a (from 189.10 to 180.60 d). Cool days (TX10P) and cool nights (TN10P) also showed significant downward trends (-0.13 and -0.12 d/a, respectively), whereas ice days (ID) exhibited only a weak decrease.

Spatially, higher SU values were concentrated in the Junggar Basin and lower values occurred in high-elevation mountainous regions (Fig. 10

). Increases in WSDI were most evident in the Urumqi–Changji–Shihezi corridor and the Ili River Valley. TX90P and TN90P showed broadly similar spatial patterns, with higher values in Urumqi City, Ili Kazak Autonomous Prefecture, and northwestern Tacheng Prefecture. Figure 10 further highlights these hotspots, with pronounced increases in TR, TN90P, and WSDI in the Urumqi–Changji–Shihezi corridor and marked increases in TX90P, SU, diurnal temperature range (DTR), and WSDI in the Ili River Valley.

From 2000 to 2023, northern Xinjiang exhibited a clear warming-drying tendency. Heat-related indices (e.g., SU, WSDI, TX90P, and TR) increased,

Figure 11

Figure 4: Figure 11

whereas cold-related indices (e.g., FD, TX10P, and TN10P) declined, indicating more frequent and persistent high-temperature extremes.

Spatial distribution of mean values (a1–a12), Theil-Sen slope (b1–b12), and M-K significance test results (c1–c12) of extreme temperature indices In parallel, precipitation totals and heavy-precipitation frequency decreased, while CDD increased, suggesting enhanced drought conditions. Hot–dry extremes were most pronounced in the Urumqi–Changji–Shihezi corridor and the Ili River Valley. 4.3 Atmospheric pollution responses to extreme climate

4.3.1 Spatial patterns of correlation

Figures. 11 and 12 present pixel-wise temporal Pearson correlations computed from annual time series (2000–2023; =24) between annual mean pollutants and annual ETCCDI indices.

Pixel-level correlation analysis based on annual time series (2000–2023) revealed strong spatial heterogeneity in the response of PM , and O to extreme precipitation in northern Xinjiang (Fig. 11

). Precipitation generally showed positive correlations with particulates in the Ili River Valley, the Urumqi–Changji–Shihezi Economic Belt, and northwestern Tacheng Prefecture, likely due to humidity-driven secondary aerosol formation, long-range transport, and wet–dry–resuspension of dust, while prolonged dry spells (CDD) in southern Altay Prefecture further favored particle accumulation. O responses were region-specific: in northern Altay Prefecture and parts of the Ili Kazak Autonomous Prefecture, strong precipitation events increased O via post-rain clear skies, enhanced photochemistry, and biogenic volatility organic compounds (VOCs) emissions; in contrast, in the industrialized Urumqi–Changji–Shihezi area, they suppressed O through scavenging, reduced radiation, and unfavorable thermodynamic conditions.

These

results

highlighted pollutant-specific, region-dependent, mechanism-diverse linkages between extreme precipitation and air quality, reflecting a complex nonlinear coupling of pollution and climate.

Heat-related indices (e.g., TX90P, SU, TR, and WSDI) were generally associated with higher and PM in the Urumqi–Changji–Shihezi Economic Belt, the Junggar East zone, and parts of the Ili Kazak Autonomous Prefecture, especially low-elevation valley and basin-margin areas, whereas the relationships were weaker in high-altitude zones (Fig. 12 [FIGURE:12]). Cold-related indices often showed the opposite pattern: they reduced particulates in Beitun and Karamay cities but increased them in Tacheng Prefecture, Ili Kazak Autonomous Prefecture, and Urumqi–Changji–Shihezi Economic Belt due to heating emissions and inversion effects. O correlations were more complex—high-temperature indices boosted O in industrial belts, basin margins, and western Ili

Atmospheric pollution–extreme precipitation index spatial correlation patterns. (a1–a10), PM (b1–b10), PM ; (c1–c10), O . Pixel-wise Pearson correlation coefficients ( ) are computed from annual time series (2000–2023; =24). Statistical significance can be assessed using a two-sided -test for Pearson' s <0.05 level; thus, weak correlations should be interpreted cautiously.

Atmospheric pollution–extreme temperature index spatial correlation patterns. (a1–a12), PM (b1–b12), PM ; (c1–c12), O . Pixel-wise Pearson correlation coefficients ( ) are computed from annual time series (2000–2023; =24). Statistical significance can be assessed using a two-sided -test for Pearson' s <0.05 level; thus, weak correlations should be interpreted cautiously.

River Vally via intensified VOC–nitrous oxides (NO) photochemistry, with TR notably raising nighttime precursors; in contrast, mountain and plateau fringes showed weak or negative correlations between O and heat-related indices owing to low emissions and good ventilation.

Cold indices generally suppressed O through reduced photochemistry and radiation. These patterns indicated pollutant-specific, region-dependent, and mechanism-diverse responses to thermal extremes.

4.3.2 Interannual variation of correlations The relationship between extreme precipitation and PM showed a phased shift from predominantly positive to predominantly negative correlations. This pattern is consistent with a transition from a period when a coal-dominated energy structure and higher precursor availability may have favored humidity-related secondary aerosol formation to a period when wet deposition more strongly contributes to particle removal. PM maintained a stable negative correlation with most precipitation indices, indicating the long-term stability of precipitation' s scavenging effect on coarse particles. In contrast, O has generally shown a positive correlation with extreme precipitation, a pattern particularly evident in 2020, possibly due to the synergistic effect of strong sunlight and enhanced biogenic emissions following rainfall (Fig. 13 [FIGURE:13]).

Heatmap of correlations between air pollutants and extreme climate indices For thermal extremes, warm indices (e.g., SU, GSL, TR, and TN90P) were generally positively correlated with particulate matter pollutants, suggesting that high temperatures contribute to elevated particle concentrations. Cold indices (e.g., FD, ID, CSDI, TN10P, and TX10P) tended to be negatively correlated with particulate matter, indicating that low temperatures reduce dust-raising activities and weaken pollution accumulation. Interestingly, the correlation between and temperature indices was opposite to that of particulate matter: warm indices were often negatively correlated with O , while cold indices were positively correlated.

RF analysis further revealed that extreme temperature indices generally have higher importance scores than extreme precipitation indices in explaining pollutant variability. PM showed greater sensitivity to climate extremes than PM , with this sensitivity being most pronounced in 2010, when extreme climate indices had the strongest explanatory power for all pollutants (Fig.

Extreme temperature–pollution relationships in northern Xinjiang were generally stronger than those with precipitation, and the RF results suggested potential nonlinearity in the temperature effects. PM and O showed distinct temperature sensitivities, although the specific response-curve shapes (e.g., U/inverted-U) require dedicated diagnostics to confirm. In contrast, precipitation–pollution linkages complex region-specific, including moisture-related modulation in the Urumqi–Changji–Shihezi Economic Belt and the Ili River Valley. Interannual variability intensified and peaked around 2020, likely reflecting the combined

influence of emission-control policies, energy-structure adjustments, and background climate conditions.

Random forest (RF) importance of air pollutants in relation to extreme climate indices in northern Xinjiang from 2000 to 2023. (a), 2000; (b), 2005; (c), 2010; (d), 2015; (e), 2020; (f), 2023.

Spatially, particulate matter responses to temperature extremes manifested as (1) a "low-temperature–high-pollution" coupling in winter urban agglomerations, and (2) elevated risk in arid basins under "high-temperature–dust" synergy. O responses included: (1) strong "high-temperature–O" coupling in industrial clusters, (2) cross-border valley impacts from biogenic emissions and transboundary transport, and (3) enhanced photochemical efficiency in arid basins. Collectively, these patterns indicated that pollutant responses to extreme climate arise from the coupled effects of emission source changes, meteorological modulation, and ecological regulation, underscoring the high sensitivity and heterogeneity of multi-pollutant–climate interactions in arid inland areas.

5 Discussion

5.1 Pollutant-specific regimes and dominant controls in northern Xinjiang Northern Xinjiang exhibits distinct pollutant regimes shaped by the joint effects of emissions, transport, and meteorological constraints. The conceptual summaries (Figs. 15 and 16) highlight that particulate matter reflects both anthropogenic contributions and dust-related influences, whereas O behaves primarily as a secondary pollutant sensitive to thermal–radiative conditions (Singh and Gautam, 2022; Daisley et al., 2025; Jia et al., 2025) . Importantly, because this study does not explicitly analyze precursor species (e.g., NO , and VOCs) or emissions, the discussion below focuses on interpreting the observed spatial–temporal patterns in PM and O and their co-variability with climate extremes, rather than making quantitative attribution to specific chemical pathways.

Schematic diagram of particulate matter sources. SO , sulfur dioxide; NH , ammonia; NO , nitrogen oxides; VOCs, volatile organic compounds; UV, ultraviolet radiation; H , sulfuric acid; HNO , nitric acid; , organic peroxy radicals; SOA, secondary organic aerosol; NH , ammonium nitrate; (NH ammonium sulfate. and photochemical reaction processes. NO, nitric oxide; O, atomic oxygen; NO , nitrogen dioxide; O , molecular oxygen. 5.2 Extreme climate as a modulator of air pollution: evidence from spatial associations The spatial association patterns with precipitation-related extremes (Fig. 11) showed pronounced heterogeneity and contrasting signs across subregions. For PM and PM , wetness and heavy-precipitation metrics were positively associated with particle variability in parts of the

western/northwestern sector, whereas other areas exhibited weak or negative associations. This indicated that precipitation variability did not produce a uniform air-quality response and likely interacted with regional background conditions (e.g., transport pathways, emission intensity, and surface properties) (Qiao et al., 2024; Wang et al., 2025b; Zhang et al., 2025a; Zhou et al., 2025).

Because precursor concentrations and emission changes were not explicitly constrained here, the mechanistic interpretations were presented as plausible pathways consistent with the observed patterns, rather than definitive chemical attribution. O exhibited stronger spatial contrasts than particulates (Figs. 11 and 12): positive associations with heavy-precipitation metrics were more evident in northern–northeastern mountainous areas, whereas negative-to-weak associations were more common across the central basin and the Urumqi–Changji–Shihezi area. These opposite signs suggested that precipitation-related changes in radiation and mixing can affect O differently across emission and chemical environments, and therefore a single mechanism cannot explain the full regional pattern (Ryalls et al., 2024; Luo et al., 2025; Qu et al., 2025). 5.3 Temperature–precipitation climate envelopes of pollutants To further elucidate the combined effects of temperature and precipitation on pollutant concentrations in northern Xinjiang, we conducted a temperature–precipitation climate-envelope analysis using pooled annual observations from 2000 to 2023. Annual mean temperature, annual cumulative precipitation, and annual mean concentrations of PM , and O were spatially matched, and 5000 point-year samples were randomly selected for visualization in Figure 17 [FIGURE:17]. For visualization, pollutant concentrations were classified into low, medium, and high groups using quantile-based thresholds derived from the pooled multi-year samples, with the 33 and 67 percentiles used as the cut points to separate the lower, middle, and upper thirds of the concentration distributions. The corresponding cut points were 25 and 40 μg/m for PM , 70 and 100 μg/m for PM , and 105 and 110 μg/m for O The results showed distinct pollutant-specific climate envelopes. High PM concentrations were mainly concentrated under relatively cool and dry conditions, indicating pollutant accumulation under weak dispersion and anthropogenic influence (Fig. 17a). High PM concentrations were more common under warmer and drier conditions, consistent with enhanced dust mobilization in arid basin areas (Fig. 17b). O reached its highest values under warm and relatively dry conditions, reflecting enhanced photochemical production under higher temperature and stronger solar radiation (Fig. 17c). Overall, these results indicated that pollutant responses to combined temperature–precipitation conditions are nonlinear, spatially heterogeneous, and pollutant-specific.

Together, Figure 17 indicates pollutant-specific "preferred" climate envelopes rather than a single monotonic response, while Figure 18 [FIGURE:18] summarizes the key pathways linking climate, dispersion, and transformation/removal processes. (1) Summer (hot–high-radiation–arid): these conditions tend to coincide with higher O favor photochemical activity, while aridity enhances dust resuspension and elevates PM especially in basins and dust-prone areas. Episodic rainfall can rapidly reduce concentrations via wet deposition. (2) Winter (cold–inversion-prone–humid): stagnant conditions suppress dispersion and are associated with enhanced PM accumulation; wintertime emissions (e.g., heating-related activity) likely contribute, although emissions are not quantified here. (3) River valleys (e.g., Ili River Vally): frequent summer precipitation strengthens atmospheric "self-cleaning", making pollutant levels more sensitive to precipitation variability.

Overall, air pollution in northern Xinjiang is modulated by the combined effects of temperature and precipitation, with strong spatiotemporal heterogeneity; this suggests value in coordinated climate–air-quality management, especially under increasing extremes.

5.4 Limitations and prospects

This study primarily quantifies statistical co-variability between climate extremes and at the annual scale and therefore does not establish causality. A key limitation is

Temperature–precipitation climate envelopes of PM (a), PM (b), and O (c) in northern Xinjiang.

Scatter points represent 5000 randomly selected point-year samples from pooled annual observations during 2000–2023. Pollutant concentrations were classified into low, medium, and high groups using tertile-based thresholds derived from the pooled multi-year samples, where 33 and 67 denote the 33 and 67 percentiles of each pollutant distribution, respectively. Marginal histograms indicate the frequency distributions along the temperature and precipitation axes.

Pollution sources, transformation, and climate impacts. P, precipitation; Pc_R, photochemical reaction; PBLH, planetary boundary layer height; T, temperature; UHI, urban heat island effect.

that precursor species (e.g., NO , and VOCs) and emissions were not explicitly analyzed, which constrains mechanistic attribution for secondary aerosol formation and O photochemistry and limits the separation of emission-driven versus meteorology-driven effects. Moreover, ETCCDI indices were derived from ERA5-Land without local station-based validation or bias correction, and meteorological fields were projected/resampled to 1 km for spatial alignment, which may introduce uncertainty over complex terrain. For O , satellite-based near-surface products generally carry higher uncertainty than particulate matter, and the use of annual means may underrepresent warm-season peaks and episodic pollution events; thus, O –climate relationships here should be interpreted as long-term associations rather than event-scale responses. Finally, while RF identifies influential predictors, it does not determine the functional form of predictor–response relationships; therefore, any inferred nonlinear shapes should be interpreted cautiously and verified using response-curve diagnostics in future work.

Future work should integrate precursor constraints (e.g., NO –VOC sensitivity), emission inventories, and process-based chemical transport modeling, such as Weather Research and Forecasting model coupled with Chemistry (WRF-Chem) and Community Multiscale Air Quality model (CMAQ), complemented by more season-focused and event-scale analyses, to better quantify the processes underlying the observed regional contrasts (Li et al., 2023)

6 Conclusions

Based on atmospheric pollution and extreme climate index data from 2000–2023 in northern Xinjiang, this study systematically analyzed the spatiotemporal evolution patterns of three pollutants (PM , and O), revealing their coupling relationships and changing trends with extreme precipitation and extreme temperature. The main conclusions are as follows: (1) Atmospheric pollutants exhibit staged variation patterns and PM rose before 2011, then declined markedly, with shifts around 2020 and 2018, respectively, reflecting policy impacts. O continued to increase, especially after 2015, indicating more complex control challenges. (2) Extreme climate events tend toward "warmer and drier" conditions Warm-related temperature indices increased and cold-related ones decreased, showing a clear warming trend. Extreme precipitation declined, while continuous dry days rose, suggesting heightened drought risk. (3) Pollution–climate response relationships show marked regional differences and non-linear patterns Precipitation and temperature exerted bidirectional effects on pollutant concentrations. PM correlations with extreme precipitation shifted from positive to negative due to changes in source structure and enhanced wet deposition, while PM generally showed negative correlations except for positive cases in the Ili River Valley. O –precipitation responses varied regionally, with both positive and negative effects. Extreme temperatures produced a U-shaped response for PM an inverted U-shaped response for O . Spatially, particulates were dominated by winter "low-temperature–high-pollution" coupling in urban clusters and "high-temperature–dust synergy" in arid basins. O patterns reflected strong "high-temperature–O" coupling in industrial clusters, biogenic plus cross-border transport effects in valley regions, and rising photochemical efficiency in arid basins. (4) Response intensity and contribution differ among pollutants RF analysis indicated that extreme temperature indices generally explained pollutant variability better than extreme precipitation indices, with PM showing the highest sensitivity, followed by , and PM being relatively less sensitive.

Northern Xinjiang is undergoing a clear “warming and drying”trend that strongly shapes air pollutant patterns. And pollution–climate couplings show marked spatial and pollutant-specific differences, requiring targeted management to achieve coordinated pollution control and climate adaptation.

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

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Figure 21

Figure 5: Figure 21

Figure 24

Figure 6: Figure 24

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Figures

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Figure 28

Figure 7: Figure 28