



Quantifying and attributing CO emissions over Central Asia using TROPOMI and explicit observational uncertainty

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Abstract. Carbon monoxide (CO) is an important atmospheric constituent affecting both air quality and climate. Using TROPOMI CO and HCHO column retrievals within the Model-Free Inversion Estimation Framework (MFIEF), we derived daily gridded CO emission estimates over Central Asia, including Xinjiang, Kazakhstan, Kyrgyzstan, and Uzbekistan, for 2019–2024. Regional mean CO emissions decreased by 37.9 % between 2019 and 2024, with a significant seasonally adjusted trend of $-0.33 \mu\text{g m}^{-2} \text{s}^{-1} \text{yr}^{-1}$. The identified emission hotspots also weakened over the study period. Higher emissions during winter and early spring are consistent with enhanced combustion associated with residential heating and industrial activity. A perturbation-based uncertainty analysis propagates assumed observational uncertainties through the inversion and indicates that approximately 69 % of the daily grid-cell emission estimates fall outside the adopted uncertainty bounds, highlighting the potential influence of atmospheric variability, dust loading, small sources, and observational uncertainty on the reliability of grid-scale emission estimates. The spatial distribution of satellite-derived grid-scale CO emission estimates reveals differences in urban emissions relative to bottom-up inventories, indicates a moderate positive association between coal consumption and inferred CO emissions at selected industrial locations, and highlights emissions associated with persistent underground coal fires, which are not explicitly represented as a separate source category in conventional anthropogenic emission inventories. This study demonstrates the potential of MFIEF as an observation-driven approach for characterizing regional CO emission patterns and temporal variability in data-sparse regions and provides complementary information for emission-inventory development and source characterization when production and location data are not available or are out of date.

1 Introduction

Air pollution and climate change are significant environmental problems resulting from economic development, urbanization, energy consumption, and transportation (Adams et al., 2020; Bel and Holst, 2018; Liang et al., 2019). Air pollution from combustion-related emissions can adversely affect human health, atmospheric chemistry, and ecosystem stability, whereas greenhouse gas accumulation contributes

to long-term climate change and associated environmental risks. Fossil fuel combustion, particularly coal utilization, represents a major common driver of both atmospheric pollutant emissions and greenhouse gas emissions, emphasizing the importance of accurately characterizing emission sources and their temporal variations. CO is one of the lesser considered short-lived climate pollutants (Hanaoka and Masui, 2020; Khalil and Rasmussen, 1988, 1984; Szopa et al., 2021). It is a major sink of the hydroxyl radical (OH), which in turn

affects the concentrations of methane (CH_4) and ozone (O_3) (Dai et al., 2024; Patra et al., 2014; Shepherd et al., 2025; Yin et al., 2015; Zhang et al., 2006).

CO is formed due to the incomplete combustion of fossil fuels, chemical reactions when reducing iron and other minerals during extraction and processing, brick and cement production, and biomass burning (Holloway et al., 2000; Khalil and Rasmussen, 1990; Koppmann et al., 2005). In the atmosphere, CO is oxidized to carbon dioxide (CO_2) and is also produced through the oxidation of volatile organic compounds (VOCs) (Joshi et al., 2023; Koppmann et al., 2005; World Health Organization, 2021). Under unpolluted atmospheric conditions, CO concentrations can exhibit substantial seasonal variability, partly due to seasonal changes in OH abundance and atmospheric mixing (Lelieveld et al., 2016; Spivakovsky et al., 2000). In industrial areas, CO has been observed to have elevated concentration when coal consumption and overall production increase and/or combustion efficiency decreases (Munsif et al., 2021; Tian et al., 2022; Zhao et al., 2012). This includes during the winter when additional combustion is often found for residential heating and extra production occurs to meet end-of-year industrial deadlines (Batey, 1997; Li et al., 2025). Similarly, CO is observed to be elevated locally when biomass burning occurs, including wildfires, agricultural burning, and residential solid-fuel use (Lin et al., 2020; Wang et al., 2021, 2025).

Contemporary approaches to estimating CO emissions encompass several primary technical pathways, each with distinct advantages and region-specific limitations. Bottom-up inventories combine activity data (e.g., fuel consumption, industrial production, vehicle kilometers traveled) with sector-specific emission factors, as implemented in databases such as EDGAR (Crippa et al., 2020; Olivier et al., 1999) and China's Multi-resolution Emission Inventory for China (MEIC) system (Zheng et al., 2018). These inventories provide detailed sectoral and temporal information but often suffer from outdated activity data, uncertain emission factors, and incomplete representation of unregulated or diffuse sources, particularly in developing regions. Observation-constrained analyses of global NO_x and CO emission variability can provide complementary information on combustion sources that also contribute to CO_2 emissions (Wang et al., 2025). Direct atmospheric observations, obtained from ground-based networks (e.g., World Meteorological Organization Global Atmosphere Watch (WMO GAW) stations) and satellite instruments (e.g., MOPITT, TROPOMI), offer spatially consistent and temporally continuous coverage, enabling detection of large-scale pollution events such as biomass burning (Buchholz et al., 2022; Worden et al., 2013). However, retrieval uncertainties, cloud contamination, and limited sensitivity near the surface restrict their capacity for precise emission quantification. Chemical transport model (CTM) inversions (e.g., GEOS-Chem, WRF-Chem) integrate atmospheric chemistry and dynamics to optimize emissions (Jiang et al., 2015; Kopacz et al., 2010; Tang et al.,

2022), providing physically consistent estimates but requiring substantial computational resources and reliable prior inventories that are often unavailable in data-sparse regions. Isotopic analyses (Brenninkmeijer et al., 1999; Röckmann et al., 2002) can effectively distinguish anthropogenic and biogenic CO sources, yet their application is constrained by the need for high-precision laboratory measurements and limited spatial representativeness. Despite these methodological advances, CO emissions remain more uncertain than other well-monitored species such as CH_4 , NO_2 , and SO_2 (Lorente et al., 2021; Schneising et al., 2019; Wang et al., 2022; Wei et al., 2020). These challenges are particularly acute in Central Asia, where sparse monitoring, limited inventories, and heterogeneous sources – ranging from industrial activities to persistent underground coal fires – have hindered comprehensive assessments and model validation. Persistent underground coal fires in Xinjiang may begin through spontaneous oxidation of exposed coal and may also be initiated or intensified when mining exposes coal seams and fractures. Because these processes are partially related to human activity, we use the neutral term “persistent underground coal fires” and interpret them separately from regulated industrial sources.

Central Asia, as a core area of the Belt and Road Initiative, the emission control of its coal-intensive industries is crucial for regional air quality and trans-boundary pollution transport. Due to the rapid increase in coal use, industrial development, and economic growth, CO emissions are not well characterized because observational networks are sparse and emission patterns are changing rapidly (Akhmedzhanov and Karadanov, 2020; Rupakheti et al., 2021; Zeng and Shen, 2022; Zhang et al., 2011; Zhao et al., 2022). This region of the world has diverse and unique geographical and climatic conditions, environmental conditions, and development patterns, based heavily on coal and minerals (Pirajno et al., 2011; Zeng and Shen, 2022). Understanding CO emissions here is of growing importance for assessing the efficiency of coal use, especially for both non-power-generating industries and power production, in part due to the continued future growth expected in this area, and potential for addressing and formulating environmental and climate mitigation strategies (National Energy Administration, 2015; State Council, 2023).

To address these gaps, this study applies the Model-Free Inversion Estimation Framework (MFIEF), a lightweight, mass-conserving, and observation-driven modeling system designed to infer surface CO emissions from satellite retrievals of CO and HCHO without requiring complex prior inventories or computationally intensive adjoint simulations (Li et al., 2025; Lin et al., 2020). By explicitly accounting for satellite observational uncertainties, MFIEF provides a rapid and flexible means of estimating emissions at high spatial and temporal resolution, well suited for data-sparse and dynamically evolving regions such as Central Asia (Inness et al., 2022; Savenets et al., 2022). The framework enables

observation-driven characterization of the spatial and temporal variability of CO emissions and facilitates the investigation of sources that may be underrepresented in conventional inventories. Ultimately, the results contribute to improving emission inventories, informing mitigation policies, and advancing understanding of CO's role in regional air quality and climate interactions, with broader implications for carbon neutrality and sustainable development goals (Abduh et al., 2021; World Health Organization, 2021).

2 Data and Methods

2.1 Study Area

The study area spans from 35–50° N latitude and 70–100° E longitude, including Xinjiang and parts of Kazakhstan, Kyrgyzstan, Uzbekistan, Tajikistan, Afghanistan, Pakistan, and adjacent regions. The climate in this region is predominantly temperate continental, including cold and dry winters and hot and arid summers, with large diurnal and annual temperature variations. The Xinjiang area has extensive coal mining and many coal-dependent industries. The region also contains rural areas where residential solid fuel combustion and occasional biomass burning may contribute to seasonal CO variability. In addition, coal is widely used to generate power which is then exported to areas in eastern China. This leads to significant emissions of CO and other combustion byproducts. Similarly, Kazakhstan, Kyrgyzstan, and Uzbekistan also have many industries related to energy and minerals, and also play a crucial role in the regional CO emissions landscape. Figure 1 illustrates the study area together with the coal bases, steel plants, and power plants included in the source-category analysis. These facilities are located in Xinjiang and adjacent parts of Gansu and Qinghai, whereas the satellite-based inversion was conducted over the entire study domain. For the category-level temporal analysis, only steel plants and coal-fired power plants that operated continuously throughout 2019–2024 were retained, resulting in a fixed sample of 4 steel plants and 53 coal-fired power plants.

2.2 Data

2.2.1 TROPOMI

The Sentinel-5 Precursor (S5P) satellite was launched in October 2017, carrying the TROPospheric Monitoring Instrument (TROPOMI), a push-broom imaging spectrometer with a swath width of 2600 km (5.5 km × 7 km resolution at nadir), and an equator crossing time of around 13:30 local time (LT), providing global coverage once daily. CO total columns are retrieved under both clear-sky and partially cloudy-sky conditions using the CO absorption band near 2.3 µm in the shortwave infrared (SWIR). Total-column averaging kernels for clear-sky and cloudy conditions provide insights into vertical sensitivity (Borsdorff et al., 2023; Landgraf et al., 2016). In this work, the Level 3 OFFL data product from Google

Earth Engine (GEE) is filtered to ensure the quality assurance flag is above 0.5, and resampled using the Weighted Polygonal Remote Sensing Toolkit HARP (<https://stcorp.github.io/harp/doc/html/algorithms/regridding.html>, last access: 22 October 2026). The final analysis grid cell has a resolution of 0.05° × 0.05°.

HCHO is a volatile organic compound (VOC), and is important due to its being both directly emitted into the atmosphere by combustion, industrial activities, traffic, and fires; as well as being produced due to the chemical decay of heavier VOCs. Since the atmospheric lifetime of HCHO is much shorter than that of CO, the loading of HCHO scales linearly with the rate of in-situ production of CO (Cohen and Prinn, 2011), with the decay mostly due to OH and photolysis, and as such is sensitive to the weather, climate, water availability, aerosols, and other complex atmospheric factors (Anderson et al., 2021; Dienhart et al., 2021; Lui et al., 2017). The column loading of HCHO is also successfully retrieved by TROPOMI, although TROPOMI is less sensitive to HCHO than to CO (Landgraf et al., 2024; Romahn et al., 2022). In this work, concurrent HCHO and CO total-column observations at the same time and location are used, allowing for consistency between the retrieved species. In this study, Level-3 HCHO data from GEE are used and resampled by HARP to a resolution of 0.05° × 0.05°. These data can be downloaded from <https://disc.gsfc.nasa.gov/datasets> (last access: 22 October 2026).

2.2.2 Wind

European Centre for Medium-Range Weather Forecasts Reanalysis v5 (ERA5) data is a widely used reanalysis dataset providing high-resolution climate data, covering multiple meteorological parameters and variables (Hersbach et al., 2020). This study employs wind field products averaged at 05:00 and 06:00 Coordinated Universal Time (UTC) under the monthly mean surface pressure field. The 05:00 and 06:00 UTC times correspond to the TROPOMI observation window over the study region. More details can be found at <https://cds.climate.copernicus.eu/datasets/reanalysis-era5-pressure-levels> (last access: 22 October 2026).

2.2.3 EDGAR

The Emissions Database for Global Atmospheric Research (EDGAR) emissions database (Olivier et al., 1999) provides monthly bottom-up emissions for CO, and other species. This study used monthly sectoral CO emissions from EDGAR version 8.1 at a spatial resolution of 0.1° × 0.1° and resampled the data to the 0.05° × 0.05° MFIEF grid for spatial comparison. The included sectors comprise the power industry, industrial combustion, buildings, transport, agriculture, fuel exploitation, industrial processes, and waste management. EDGAR represents anthropogenic emissions esti-

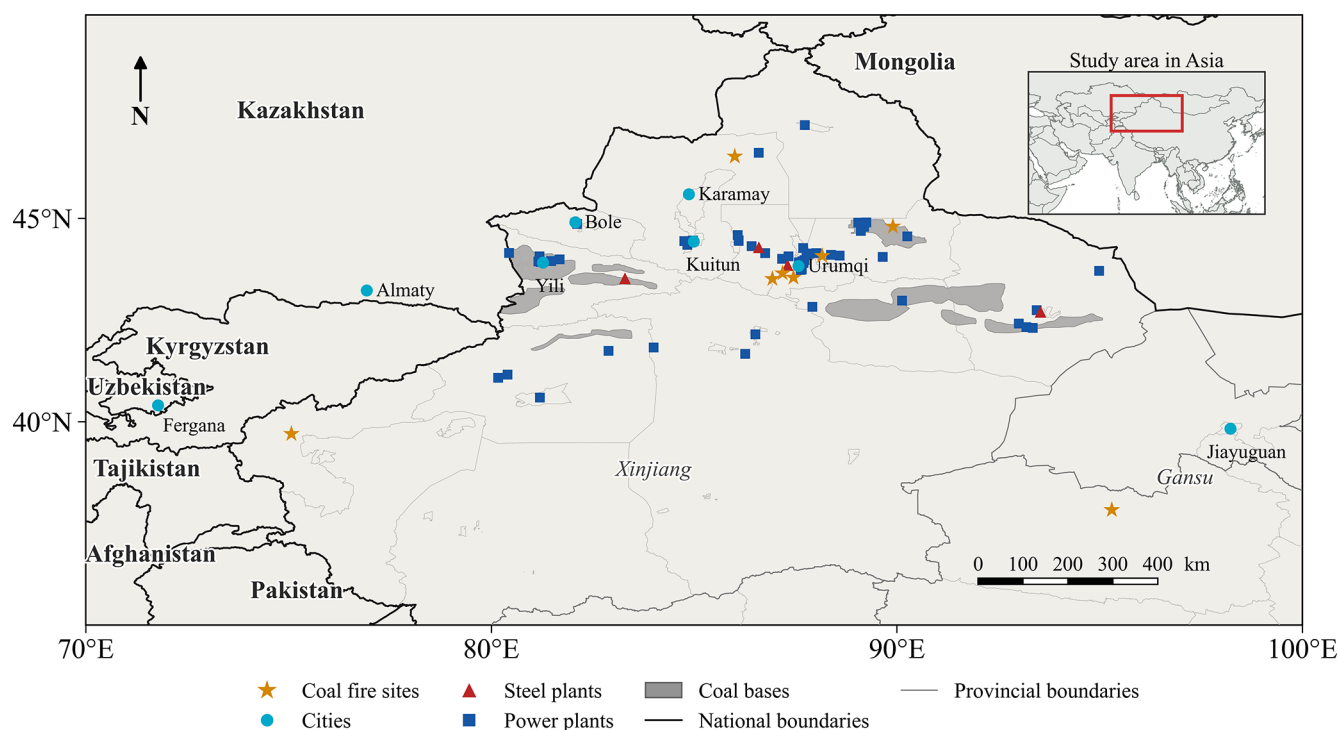


Figure 1. Study area (35–50° N, 70–100° E). The mapped coal bases and industrial facilities provide geographic context for the source-category analysis and are located in Xinjiang and adjacent parts of Gansu and Qinghai. For the 2019–2024 category-level statistics, only continuously operating facilities were retained, comprising 4 steel plants and 53 coal-fired power plants.

mated from activity data, emission factors, and spatial allocation proxies, whereas MFIEF derives grid-scale emission signals from satellite observations without explicitly separating anthropogenic and non-industrial sources. No explicit uncertainty bounds are provided with the data, although studies show it can range from 20 % up to 150 % depending on the species and location, on grids which have a source (i.e., the value is not zero or empty) (McDuffie et al., 2020). The data can be accessed at <https://edgar.jrc.ec.europa.eu/> (last access: 22 October 2026).

2.2.4 AAOD

The Multi-angle Imaging Spectro Radiometer (MISR), aboard NASA's Terra satellite, is a pioneering instrument designed to characterize Earth's atmosphere and surface through simultaneous observation at nine distinct viewing angles. A key advanced product derived from MISR data is the Absorption Aerosol Optical Depth (AAOD). This parameter quantitatively estimates the fractional optical thickness of absorbing aerosols, primarily caused by light-absorbing species such as black carbon and mineral dust, and is relevant to trace gas inversions including CO and HCHO which are based on atmospheric absorption. The L3 AAOD data product used in this paper has a resolution of 0.25° and is resampled to the common 0.05° grid cell only to align the datasets; this resampling does not add spatial information. The data

can be searched from <https://disc.gsfc.nasa.gov/datasets> (last access: 22 October 2026) (Liu et al., 2025).

2.3 Research Methods

The MFIEF is utilized to estimate CO emissions (Li et al., 2023; Qin et al., 2023). Equation (1) takes into account factors such as CO column changes, chemical decay and production, and transport, and relies on retrieved data from TROPOMI CO and HCHO to approximate the weighting coefficients (α_i) of the underlying partial differential equations that govern the transformation between CO and its driving factors, using the same equations used by world-leading chemical transport models (Cohen and Prinn, 2011). Specifically, emissions cause CO to increase, acting as a source term, while chemical reactions and mixing between in-plume and out of plume regions may lead to the loss or gain of CO, and are represented by a first order linearization of differential equations acting upon and by the CO concentration. The transport of CO is also an important factor, affected by both pressure-induced and advective processes, with the advective term representing the horizontal movement of CO due to wind, and the pressure-induced transport term accounting for the convergence or divergence of the atmosphere itself, accounting for the gain or loss due to non-uniform winds across the concentration and emissions gradients. As such, the transport terms can either increase or decrease the CO column in

a given location depending on the direction and magnitude of the flow (Li et al., 2025; Lu et al., 2025a), which account for topography, land–sea breezes, variable weather systems, and more simplified atmospheric conditions in which there is a substantial concentration gradient due to strong variation in emissions sources in space, with a non-uniform wind field. Combining these terms yields the CO emissions Eq. (1), where:

$$E_{\text{CO}} = \frac{dV_{\text{CO}}}{dt} + \alpha_2 \cdot V_{\text{CO}} + \alpha_3 \cdot \nabla(\mathbf{u} \cdot V_{\text{CO}}) - \alpha_4 \cdot V_{\text{HCHO}} \quad (1)$$

V_{CO} represents the TROPOMI CO column loading after conversion to units of ($\mu\text{g m}^{-2}$). $\alpha_2 \cdot V_{\text{CO}}$ represents the sink of CO with α_2 (s^{-1}) as the inverse CO lifetime. $\alpha_4 \cdot V_{\text{HCHO}}$ represents CO production, with α_4 (s^{-1}) as the inverse HCHO lifetime. $\nabla(\mathbf{u} \cdot V_{\text{CO}})$ represents the daily zonal and meridional dispersion of CO with a unit of ($\mu\text{g m}^{-2} \text{s}^{-1}$), and α_3 (m^{-1}) represents the transport distance. This mass conservation equation for CO provides a framework for understanding and quantifying the changes in CO columns in the atmosphere, considering the various processes that influence its distribution, following Li et al. (2025).

The emission, production, and transport terms of Eq. (1) are initialized, TROPOMI observations and their retrieved uncertainties, meteorological data, and either an initial a priori emissions dataset, or our own previously inverted emissions dataset in the case of multiple iterations. The fitting is based on multiple least squares regression for each grid cell on a month-by-month basis, reflecting the differences in albedo, elevation, land-surface use, emissions type, and differences in confounding variables on each pixel specifically grouping all daily data from TROPOMI and the ECMWF reanalysis where they all occur. This process provides sufficient data to compute the weighting terms α_i , while also accounting for the changes in land-surface, atmosphere, and other factors. In the case where a pixel in any given month either does not have enough data or produces a fit with a p value larger than 0.05, the values of the model are set to NaN on that grid cell during that month. To ensure physically realistic and mathematically consistent values for the coefficients α_2 , α_3 , and α_4 , physical cutoffs are applied. Any value that is not positive ($\alpha > 0$) is set to NaN.

Equation (1) is then used to calculate estimates of CO emissions across all grid cells. To estimate the maximum probability density of the coefficients during the corresponding grid cell-by-grid cell and month-by-month basis, the solution distribution of α within the valid range (from the 10th percentile to the 90th percentile of the Probability Density Function (PDF)) is sampled 1000 times per grid cell. The mean value of this distribution is assigned as the day's average emission in that grid cell, and its standard deviation was used to characterize parameter-induced variability in the estimated CO emissions. This process allows us to estimate the coefficients and their uncertainties, taking into account the available data and the physical constraints on the parameters,

providing a more robust and accurate representation of the CO mass conservation equation in the study region.

For the calculation of CO emissions, grid-cell filtering based on the distribution of retrieved values is required following the method established by (Zheng et al., 2026). Random errors are expected to cluster around zero and to produce approximately symmetric positive and negative values. For each grid cell, we identify the most negative retrieved emission value, $-\theta \mu\text{g m}^{-2} \text{s}^{-1}$, and define a symmetric interval from $-\theta$ to $\theta \mu\text{g m}^{-2} \text{s}^{-1}$. Values within this interval are treated as being dominated by retrieval noise rather than a resolvable positive emission signal and are excluded. This screening reduces the influence of grid cells for which the inversion cannot distinguish a true positive emission signal from the effects of observational noise.

2.4 Propagation of observational uncertainty into CO emission estimates

The accuracy and precision targets for TROPOMI total CO column prior to launch were 15 % and 10 % respectively (Landgraf et al., 2016; Martínez-Alonso et al., 2020; Veefkind et al., 2012). There hasn't been enough research on specific issues which impact the column retrievals of CO and HCHO including aerosol loadings and microphysical properties, cloud cover under low cloud conditions, changes in surface reflectivity from pixel to pixel, and the initial CO and CH₄ data, which could result in greater uncertainty than what has been mentioned (Hu et al., 2024; Lu et al., 2024). The uncertainty in TROPOMI CO total column has implications for CO emission calculations. First, emission calculation relies on accurate and precise CO column concentration data. Second, since emissions estimation requires the use of a non-linear gradient operator (Lu et al., 2025b; Zheng et al., 2026), uncertainty in the spatial domain plays an additional role. Consequently, if small perturbations within the observational uncertainty range lead to relatively large changes in inverted emissions, this indicates that the computed emission estimates may be strongly affected by noise (Beekmann and Derognat, 2003; Rao, 2005; Reilly et al., 1987). In such instances, the emissions cannot be regarded as stable; thus, their reliability is questionable. This makes it difficult to assess the robustness of the inverted emissions and may reduce confidence in the retrieved emission estimates. Accordingly, this study propagates the assumed observational uncertainties through MFIEF and quantifies the corresponding range of variation in the inverted emissions and allows for a more robust product.

Random perturbations were applied to both the retrieved CO and HCHO column data within conservative retrieval uncertainty bounds. The perturbations were randomly added to (or subtracted from) the observed data and a bootstrap resampling was performed to sufficiently sample the perturbation space. Specifically, each data point of CO column and HCHO column retrieved from TROPOMI, on a daily and gridded

basis, was randomly perturbed within $\pm 10\%$ of its original value. In addition to point-wise perturbations, the non-linear influence on spatial gradients was also evaluated. For example, given two neighboring grid cells, if there is an overlapping portion of the data range after the random $\pm 10\%$ perturbations are applied, the direction of the computed gradient, and therefore the emissions may shift. In these cases, the resulting gradient becomes unstable, and therefore the emissions estimate is also not likely trustworthy. The calculated changes define the emission uncertainty range associated with propagation of the perturbed observational inputs. Specifically, the relative emission response was calculated by Eq. (2):

$$E_{\text{resp}} = \frac{E_{\text{CO}(\pm)} - E_{\text{CO}}}{E_{\text{CO}}} \quad (2)$$

$E_{\text{CO}(\pm)}$ denotes the newly calculated CO emission, E_{CO} denotes the initial CO emission, E_{resp} denotes the change of CO emission result, i.e., the observational contribution to emission uncertainty. The distribution of these responses quantifies the observational contribution to emission uncertainty, and forms a minimum of the total top-down emissions uncertainty. Grid cells exhibiting responses larger than the adopted threshold are classified as exceeding this uncertainty range and are excluded from the final emission product, following Zheng et al. (2026). The CO emission calculation and uncertainty-screening workflow is summarized in Fig. 2.

2.5 Statistical trend analysis

Regional means were calculated from daily spatial means. To quantify the temporal trend in regional CO emissions, we fitted an ordinary least-squares regression to the monthly mean emission series from January 2019–December 2024. The model included continuous time, expressed in years since January 2019, and calendar-month fixed effects to account for seasonality:

$$E_t = \beta_0 + \beta_1 T_t + \sum_{m=2}^{12} \gamma_m M_{m,t} + \epsilon_t \quad (3)$$

where E_t is the regional monthly mean CO emission flux, T_t is the time elapsed since January 2019, and $M_{m,t}$ represents calendar-month indicator variables. Heteroskedasticity- and autocorrelation-consistent standard errors with a maximum lag of 12 months were used to account for serial correlation in the monthly series. As a non-parametric robustness test, we also applied the seasonal Mann–Kendall test with a period of 12 months and calculated the corresponding seasonal Sen's slope. Statistical significance was evaluated at the 0.05 level. The regression used all 72 monthly observations. The percentage change between the 2019 and 2024 annual means was reported as a descriptive endpoint comparison and was not interpreted as the regression slope. Trend coefficients are reported with 95 % confidence intervals.

3 Results

3.1 Spatiotemporal Distribution of CO Observations

Figure 3a presents the spatial distribution of the average TROPOMI CO total column from 2019–2024 across the study area, revealing a domain-wide mean of $1.54 \times 10^{18} \text{ molec.cm}^{-2}$. The concentration is predominantly influenced by anthropogenic activities, with elevated values ($> 2.0 \times 10^{18} \text{ molec.cm}^{-2}$) located in, around, and downwind of major urban and industrial centers such as Urumqi, Fergana, Almaty, Jiayuguan, and the Zhundong Coalfield. In contrast, natural areas like the Tianshan and Altai Mountains exhibit lower concentrations, averaging around $1.0 \times 10^{18} \text{ molec.cm}^{-2}$. Moderately high CO levels are also observed in the desert regions of central Xinjiang, likely due to enhanced photochemical production from VOCs under intense ultraviolet radiation. Elevated CO is also found in parts of northwestern Kazakhstan, where biomass burning and residential solid fuel combustion may contribute to seasonal variations in the regional background CO, particularly during the heating season. The statistical distribution of the CO total column, shown in Fig. 3b, deviates from a normal distribution and is distinctly bimodal, with the 25th and 75th percentiles for the entire period calculated at 1.23 and $1.83 \times 10^{18} \text{ molec.cm}^{-2}$, respectively. Analysis of interannual variability shows that the highest CO levels occurred in 2021, with an annual mean of $1.59 \times 10^{18} \text{ molec.cm}^{-2}$, particularly in high-value zones. Conversely, 2022 marked the lowest concentrations across both high- and low-value zones, with the mean dropping to $1.44 \times 10^{18} \text{ molec.cm}^{-2}$. The values subsequently rebounded to an intermediate level in 2023 ($1.52 \times 10^{18} \text{ molec.cm}^{-2}$), followed by a further increase in 2024 ($1.56 \times 10^{18} \text{ molec.cm}^{-2}$). This is consistent with findings indicating that the general air pollution policies implemented by China are driving CO (Li et al., 2025; Liu et al., 2024) more than lockdowns related to COVID-19 (Fan et al., 2021; Zheng et al., 2021).

Figure 4 presents the available daily CO total columns from 2019–2024 in the $0.05^\circ \times 0.05^\circ$ resampled grid cells containing the Wugonggou underground coal-fire site (44.075° N , 88.156° E), the center of Urumqi (43.825° N , 87.575° E), Xinjiang Daan Special Steel (42.700° N , 93.542° E), and Shenhua Guoneng Hami Power Station (42.411° N , 93.009° E). Each time series represents one selected grid cell. The mean CO total columns at these four locations were 1.96 , 2.17 , 2.25 , and $2.05 \times 10^{18} \text{ molec.cm}^{-2}$, respectively. All locations generally exhibited higher values in winter and lower values in summer, reflecting the combined effects of seasonal emissions, atmospheric transport, boundary-layer mixing, and faster CO oxidation associated with higher OH abundance in summer (Liu et al., 2022; Sun et al., 2023; Yang et al., 2021). The Wugonggou grid cell exhibited weaker seasonality, with a monthly amplitude of $0.32 \times 10^{18} \text{ molec.cm}^{-2}$, compared with $0.71 - 0.77 \times$

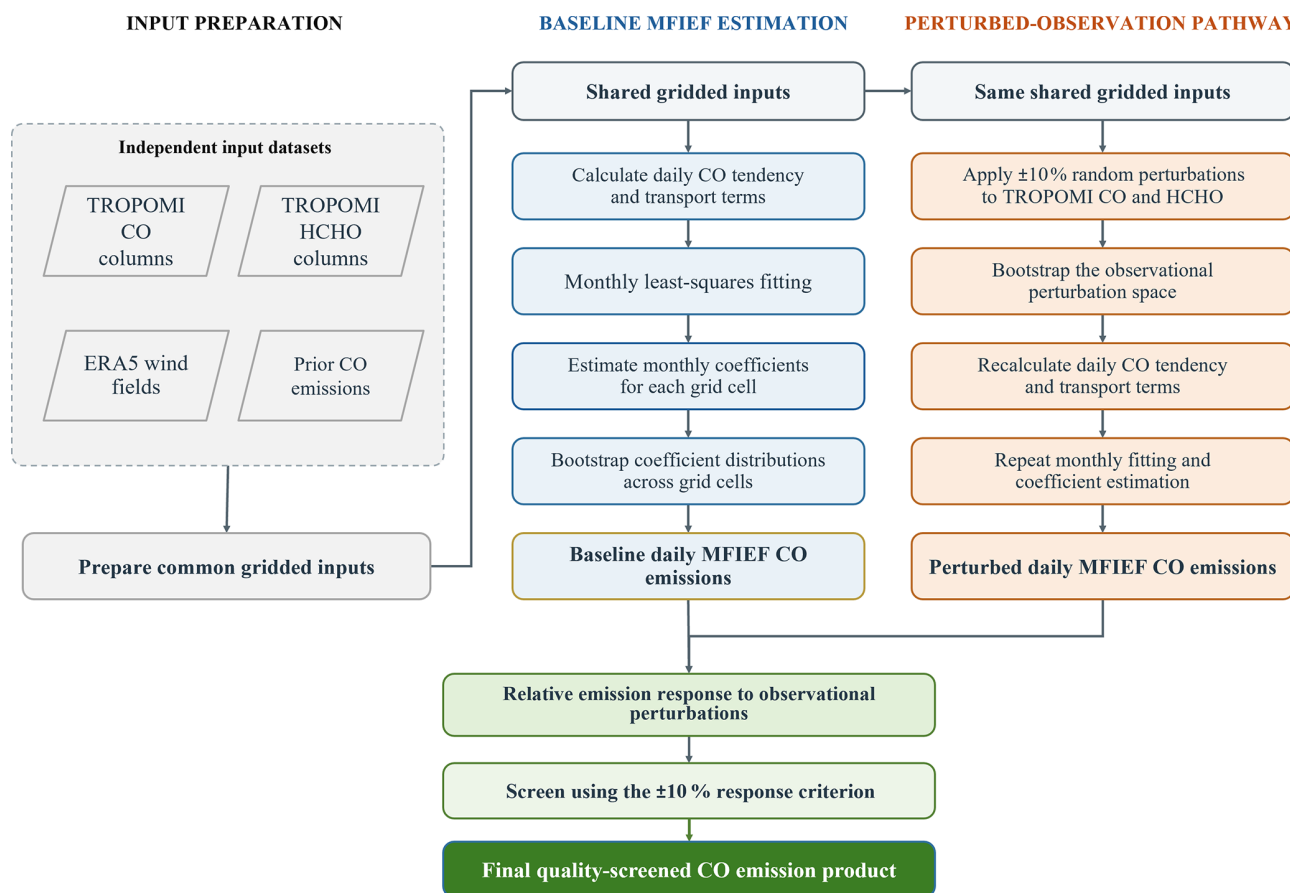


Figure 2. Workflow of MFIEF-based CO emission estimation and uncertainty-propagation analysis based on $\pm 10\%$ perturbations of TROPOMI CO and HCHO observations.

$10^{18} \text{ molec. cm}^{-2}$ at the other three locations. This weaker variation is consistent with the relatively persistent nature of underground coal combustion and the weaker influence of seasonally varying urban and industrial activities in the surrounding area.

3.2 Spatiotemporal Distribution of CO Emissions

To distinguish dust-dominated regions from other aerosol types, we utilized the AAOD ratio between 443 and 880 nm. Mineral dust typically exhibits stronger absorption at shorter wavelengths due to its iron oxide content, leading to higher $\text{AAOD}_{443}/\text{AAOD}_{880}$ ratios, whereas other aerosols like black carbon show less spectral dependence. A higher ratio thus suggests a greater contribution of dust to total absorption. Based on this spectral behavior, we selected a threshold of $\text{AAOD}_{443}/\text{AAOD}_{880} > 4.5$ to identify and mask dust-dominated areas, thereby minimizing potential biases in CO emission estimates associated with dust contamination. Grid cells exceeding this threshold were excluded, effectively removing spurious emission signals caused by enhanced atmospheric absorption and scattering from absorbing aerosols which impact the retrieval of CO and HCHO. As shown

in Fig. 5a, the spatial distribution of AAOD ratios highlights extensive dust-affected areas, primarily in the desert and arid parts of western China and southern Kazakhstan. This screening process resulted in the exclusion of approximately 14 % of the study area, underscoring the importance of aerosol correction in satellite-based emission inversion.

To quantify emission uncertainty associated with observational inputs, we varied the total column concentrations of CO and HCHO within ranges of $\pm 10\%$ and $\pm 20\%$, representing the adopted TROPOMI retrieval uncertainty ranges. Grid-cell estimates were retained when the relative change in emissions remained within the corresponding uncertainty bound. As illustrated in Fig. 5b, under the $\pm 10\%$ and $\pm 20\%$ perturbation thresholds, 31.3 % and 33.7 % of grid cells, respectively, remained within the corresponding uncertainty bound over the 6-year period. Figure 5b shows how the emission estimates change as observational uncertainty propagates through the inversion, with estimates falling within the corresponding bounds retained. Furthermore, Fig. 5c shows the number of days with reliable emissions after applying the $\pm 10\%$ filter, with a spatial average of approximately 135 valid days per grid cell. The results indicate that stricter

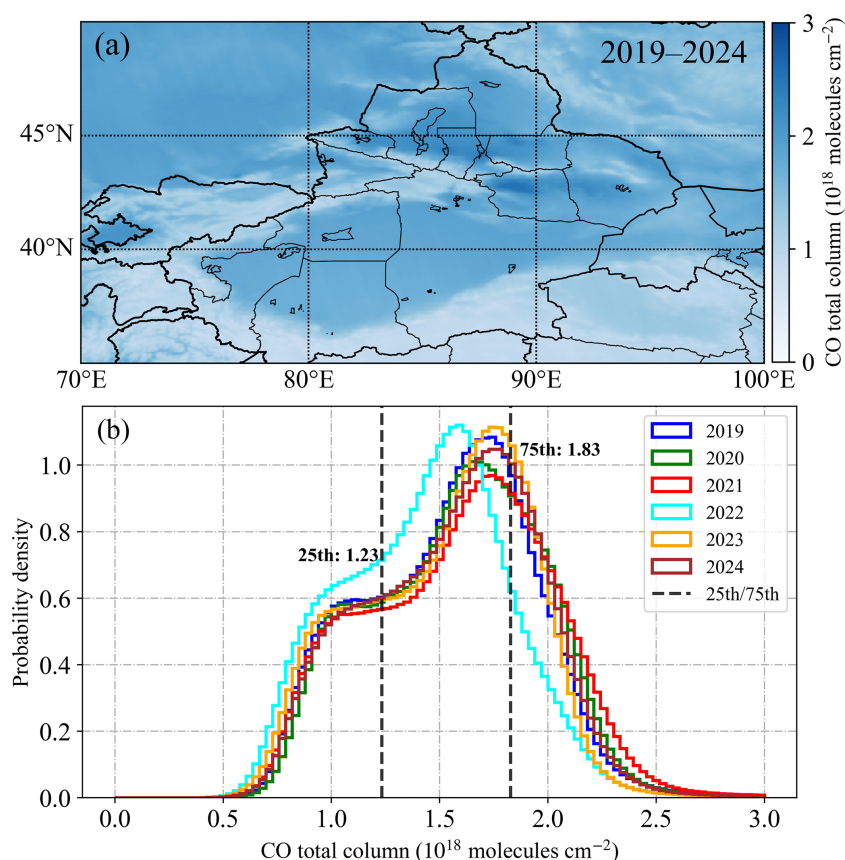


Figure 3. Spatial and statistical distributions of TROPOMI CO total columns over the study area during 2019–2024. **(a)** Mean spatial distribution over the 6-year period. **(b)** Annual probability density distributions of CO total-column values over the study area.

observational-uncertainty filtering leads to a gradual reduction in retained emission estimates, quantifying how input-column uncertainty affects the inversion outcomes. This is an important point, since many papers calculating emissions using satellites have assumed that reducing uncertainty leads to a more precise end result (Estrada et al., 2025; Shen et al., 2023), whereas this result demonstrates that both very high and very low emissions results are both impacted by observational noise.

Following application of the $\pm 10\%$ observational-uncertainty filter, the spatial distribution of the MFIEF-derived emissions broadly corresponds to the major features of the CO total column distribution. Figure 6 summarizes the annual spatial distributions, probability density distributions, and spatial variability of the derived emissions from 2019–2024. Regional mean emissions and the mean intensity of the identified hotspot regions decreased over the study period, while the emission distributions shifted toward lower values.

Regional mean CO emissions decreased from $4.93 \mu\text{g m}^{-2} \text{s}^{-1}$ in 2019 to $3.06 \mu\text{g m}^{-2} \text{s}^{-1}$ in 2024, corresponding to a 37.9 % endpoint reduction. The seasonally adjusted trend was $-0.33 \mu\text{g m}^{-2} \text{s}^{-1} \text{yr}^{-1}$ (95 % confidence

interval: -0.52 to $-0.15 \mu\text{g m}^{-2} \text{s}^{-1} \text{yr}^{-1}$; HAC-adjusted $p < 0.001$). A seasonal Mann–Kendall test independently supported the decreasing trend: $-0.20 \mu\text{g m}^{-2} \text{s}^{-1} \text{yr}^{-1}$ ($p < 0.001$). This overall trend toward lower emissions is further reflected in the evolution of emission hotspots, which we defined as regions where the emission flux exceeded twice the study area’s mean ($6.72 \mu\text{g m}^{-2} \text{s}^{-1}$). A total of 11 such hotspots were identified, primarily situated between 39.83 – 46.58°N and 81.08 – 98.23°E . Their average intensity decreased markedly from $9.51 \mu\text{g m}^{-2} \text{s}^{-1}$ in 2019 to $5.63 \mu\text{g m}^{-2} \text{s}^{-1}$ in 2024, representing a total reduction of 40.8 % or an average annual decrease of $0.68 \mu\text{g m}^{-2} \text{s}^{-1} \text{yr}^{-1}$. The PDFs of the emissions (Fig. 6b) provide further evidence of this systematic reduction, showing a distinct leftward shift toward lower values. The distribution peak decreased from $3.34 \mu\text{g m}^{-2} \text{s}^{-1}$ in 2019 to $2.85 \mu\text{g m}^{-2} \text{s}^{-1}$ in 2024. Concurrently, the PDFs of the standard deviations (Fig. 6c) indicate a significant weakening of spatial heterogeneity, with the peak value dropping from $1.66 \mu\text{g m}^{-2} \text{s}^{-1}$ to below $1.30 \mu\text{g m}^{-2} \text{s}^{-1}$. In summary, the results depicted in Fig. 6 clearly highlight a marked downward trend in CO emissions between 2019 and 2024, characterized by reduced hotspot intensity, a

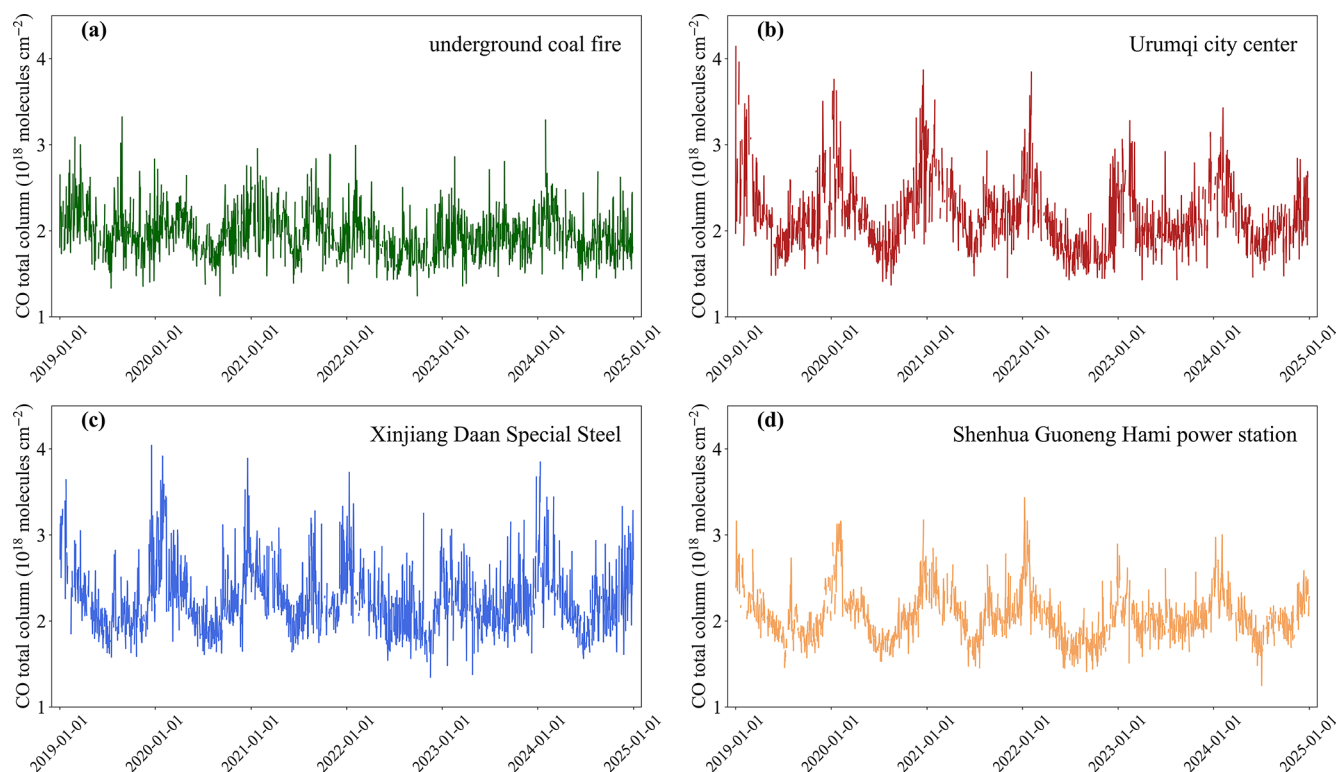


Figure 4. Time series of TROPOMI CO total columns in the $0.05^{\circ} \times 0.05^{\circ}$ grid cells containing (a) the Wugonggou underground coal-fire site, (b) the center of Urumqi, (c) Xinjiang Daan Special Steel, and (d) Shenhua Guoneng Hami Power Station during 2019–2024.

systematic shift of the emission distribution to lower values, and reduced spatial variability. These observed changes may reflect the combined effects of emission-control policies, industrial restructuring, energy use, meteorology, sampling, and non-industrial sources; their individual contributions cannot be separated here. Together, these results indicate a statistically significant regional decline, reduced hotspot intensity, and weaker spatial variability over the study period.

Figure 7 presents the monthly regional mean CO emissions and the mean number of valid emission-estimate days per grid cell from January 2019–December 2024. A valid day is defined as a day for which a grid cell retains an emission estimate after the quality and perturbation-response screening described above; the plotted valid-day metric is the spatial mean of this monthly count across the study domain. Overall, CO emissions exhibited a clear downward trend, decreasing from an exceptionally high level of $9.25 \mu\text{g m}^{-2} \text{s}^{-1}$ in January 2019 to around $2.5\text{--}3.0 \mu\text{g m}^{-2} \text{s}^{-1}$ after 2022, with occasional wintertime rebounds (e.g., $5.07 \mu\text{g m}^{-2} \text{s}^{-1}$ in December 2023). Seasonal fluctuations are evident, with higher emissions generally observed in winter and early spring, and lower values during late spring and summer, consistent with stronger heating-related combustion sources during colder times, annual production cycle which ends on Chinese New Year varying from mid-January through mid-

February. The number of valid observational days shows substantial variability, ranging from fewer than 2 d per month (e.g., July 2020 and August 2022–2024) to more than 5 d per month (December 2021). The valid-day series is presented only as a sampling diagnostic and is not interpreted as a physical driver of emission variability.

Figure 8 illustrates the temporal evolution of gridded CO emissions at four representative locations: the Wugonggou underground coal-fire site, Urumqi city center, Xinjiang Daan special steel plant, and Shenhua Guoneng Hami coal-fired power plant. Because the inversion is performed at a spatial resolution of $0.05^{\circ} \times 0.05^{\circ}$, these estimates represent the net emissions from all sources within the corresponding grid cell rather than emissions from an individual facility. Over 2019–2024, the mean emission fluxes were $4.50 \mu\text{g m}^{-2} \text{s}^{-1}$ at Wugonggou, $4.75 \mu\text{g m}^{-2} \text{s}^{-1}$ in central Urumqi, $5.77 \mu\text{g m}^{-2} \text{s}^{-1}$ at the selected steel-plant grid cell, and $4.43 \mu\text{g m}^{-2} \text{s}^{-1}$ at the selected coal-fired power-plant grid cell. The largest observed emission values generally occurred near the beginning of the study period, followed by a pronounced weakening of high-emission episodes. At Wugonggou, for example, the maximum daily emission flux of $14.0 \mu\text{g m}^{-2} \text{s}^{-1}$ occurred in December 2019, while the maximum observed values in subsequent years declined to 9.98, 7.65, 5.09, 5.42, and $4.97 \mu\text{g m}^{-2} \text{s}^{-1}$ from 2020–2024, respectively. Its annual mean similarly decreased from

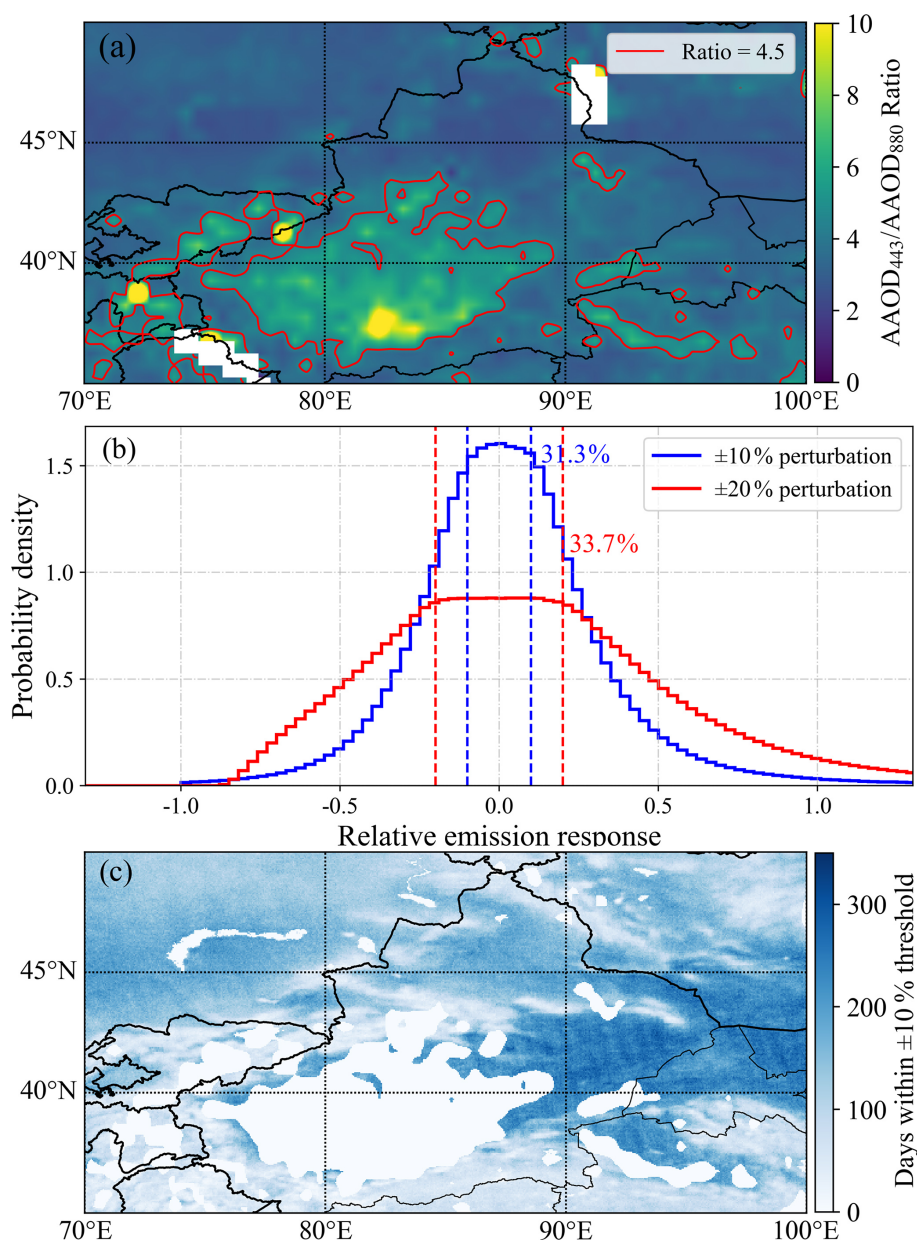


Figure 5. (a) Spatial distribution of the mean AAOD₄₄₃/AAOD₈₈₀ ratio during 2019–2024. Grid cells with ratios greater than 4.5 were identified as dust-dominated areas and excluded from the subsequent CO emission inversion. (b) Probability density distributions of the relative emission changes resulting from $\pm 10\%$ and $\pm 20\%$ perturbations in the TROPOMI CO and HCHO total-column inputs. The blue and red dashed lines indicate corresponding uncertainty bounds of ± 0.1 and ± 0.2 , respectively. The annotated percentages represent the proportions of estimates remaining within the corresponding uncertainty bounds. (c) Number of valid retrievals after $\pm 10\%$ observational-uncertainty filtering.

$6.38 \mu\text{g m}^{-2} \text{s}^{-1}$ in 2019 to $3.03 \mu\text{g m}^{-2} \text{s}^{-1}$ in 2024. The temporal evolution further indicates that the long-term reduction was particularly evident in the weakening of wintertime high-emission episodes, whereas changes during the remaining months were weaker and less monotonic. Similar attenuation of high-emission episodes was observed in the Urumqi and power-plant grid cells, while the steel-plant grid showed a smaller overall reduction. However, wintertime sampling

was sparse in some years, and these seasonal differences should therefore be interpreted as descriptive temporal patterns rather than independent trends. Moreover, the causes of the observed changes cannot be uniquely separated among changes in source activity, emission-control measures, atmospheric transport and chemical loss, and temporal sampling. In particular, Wugonggou is an uncontrolled underground coal-fire source rather than an engineered industrial stack,

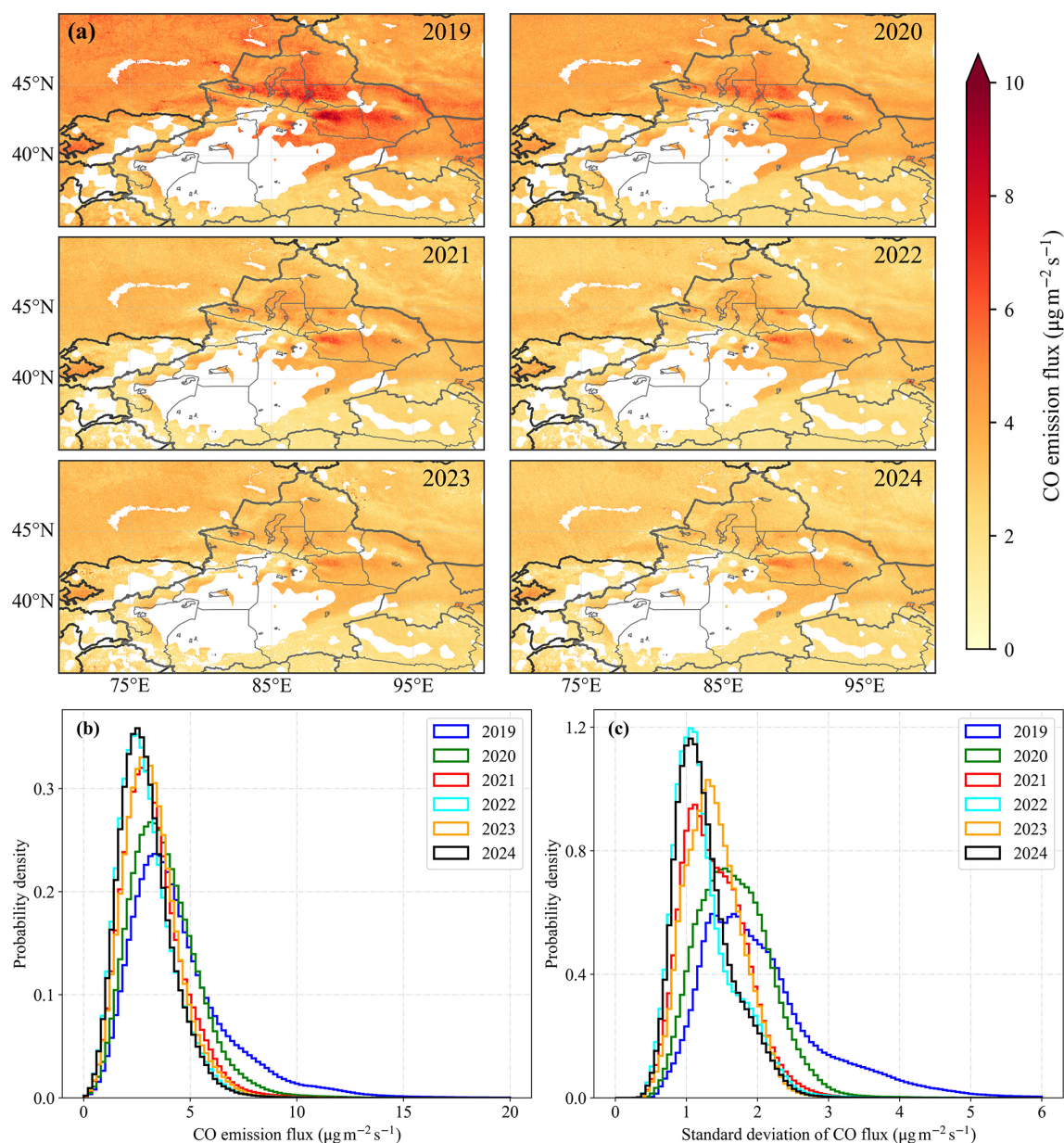


Figure 6. Annual characteristics of MFIEF-derived CO emissions from 2019–2024. **(a)** Annual mean CO emission flux; grid cells with fewer than 10 valid emission-estimate days in a year are shown as missing values. **(b)** Probability density distributions of annual mean CO emission fluxes. **(c)** Probability density distributions of the interannual standard deviation of CO emission fluxes. Emission-flux units are $\mu\text{g m}^{-2} \text{s}^{-1}$.

and its temporal evolution should not be interpreted in terms of the same emission-control mechanisms as the urban and industrial grid cells.

Table 1 includes industrial facilities that operated continuously throughout 2019–2024. The screened sample contains 53 coal-fired power plants and 4 steel plants; the city-center and underground coal-fire categories each contain 8 locations. Based on grid-scale estimates from this fixed sample, mean emissions decreased from $6.47\text{--}3.74 \mu\text{g m}^{-2} \text{s}^{-1}$ at city-center locations (42.2 %), from $7.09\text{--}4.18 \mu\text{g m}^{-2} \text{s}^{-1}$

at underground coal fire locations (41.0 %), from $6.22\text{--}4.08 \mu\text{g m}^{-2} \text{s}^{-1}$ at steel-plant locations (34.4 %), and from $4.94\text{--}3.02 \mu\text{g m}^{-2} \text{s}^{-1}$ at coal-fired power-plant locations (38.9 %) between 2019 and 2024. The 90th-percentile values also decreased, including from $11.00\text{--}6.58 \mu\text{g m}^{-2} \text{s}^{-1}$ at steel-plant locations and from $8.20\text{--}4.69 \mu\text{g m}^{-2} \text{s}^{-1}$ at coal-fired power-plant locations.

Figure 9 compares estimated coal consumption with satellite-derived grid-scale CO emissions for 11 selected coal-fired power plants in 2023. Coal consumption ranged

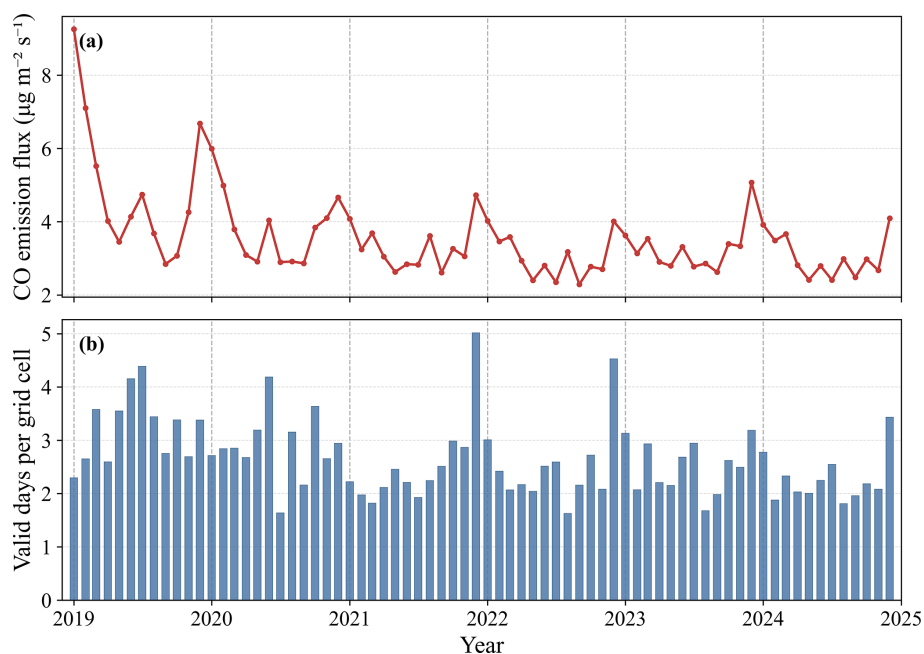


Figure 7. Monthly mean CO emission flux and temporal sampling coverage over the study region from January 2019–December 2024. **(a)** Spatially averaged monthly CO emission flux derived from grid cells satisfying the observational-quality criteria. **(b)** Mean number of valid observation days per grid cell per month, averaged over all grid cells in the study region, including grid cells with no valid observations in a given month. The valid-day series is shown as a diagnostic of temporal sampling coverage rather than as an explanatory driver of emission variability.

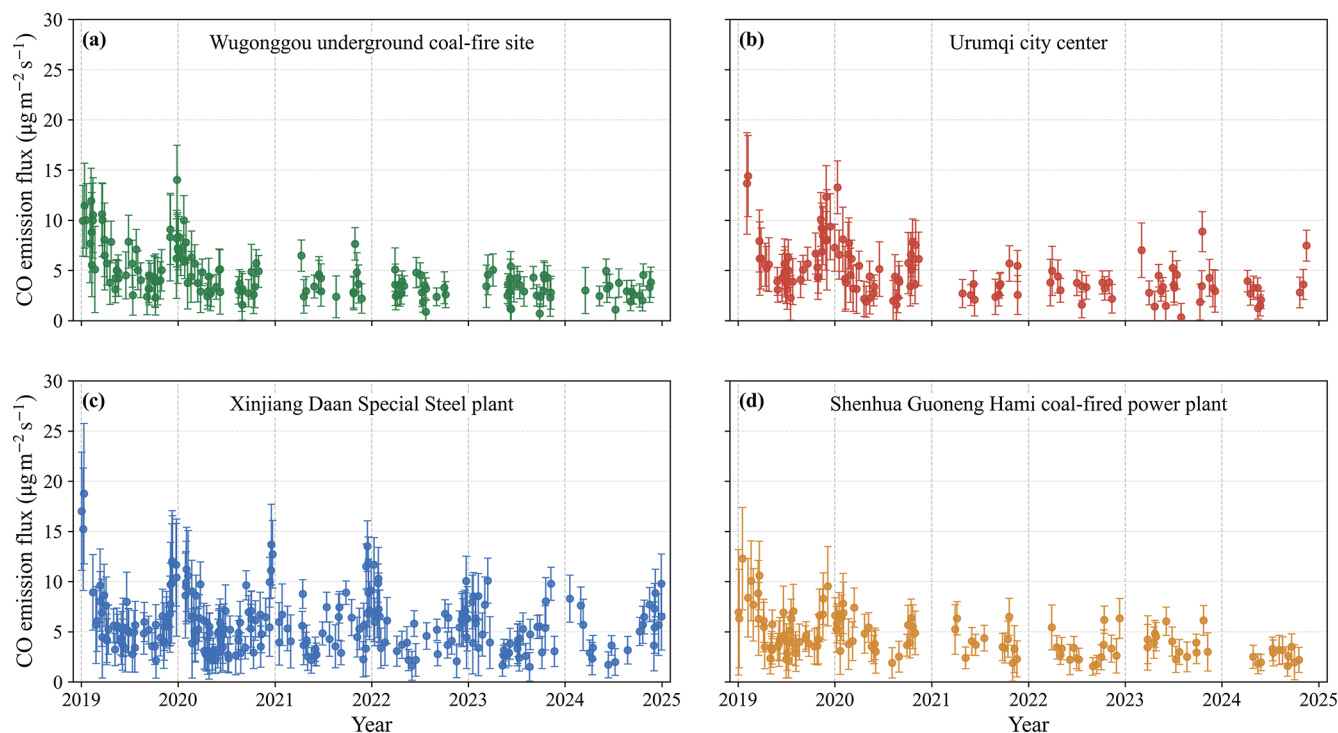


Figure 8. Temporal variations in MFIEF-derived CO emission fluxes at four representative locations from January 2019–December 2024: **(a)** the Wugonggou underground coal-fire site, **(b)** Urumqi city center, **(c)** the Xinjiang Daan Special Steel plant, and **(d)** the Shenhua Guoneng Hami coal-fired power plant. Markers represent the mean emission fluxes, and error bars indicate ± 1 standard deviation. The values were extracted from the 0.05° grid cell containing each location.

Table 1. Annual statistics of grid-scale CO emission fluxes for selected source categories from 2019–2024. Steel-plant and power-plant samples include only facilities operating continuously across all 6 years (unit: $\mu\text{g m}^{-2} \text{s}^{-1}$).

Type	Number of locations	Year	Mean $\pm$ SD	10th	20th	50th	80th	90th	Annual change
City Center	8	2019	6.47 ± 2.93	2.73	3.43	5.30	9.47	12.03	
		2020	5.26 ± 2.20	2.45	3.09	4.76	7.08	9.08	−19 %
		2021	4.35 ± 1.75	2.16	2.72	4.01	5.74	7.11	−17 %
		2022	3.95 ± 1.59	1.94	2.44	3.57	5.21	6.32	−9 %
		2023	3.92 ± 1.65	2.07	2.65	3.80	5.09	6.01	−1 %
		2024	3.74 ± 1.53	1.96	2.38	3.40	4.96	6.08	−5 %
Coal fire site	8	2019	7.09 ± 3.00	3.35	4.06	5.81	9.93	12.27	
		2020	5.41 ± 2.23	2.69	3.04	5.07	6.87	9.74	−24 %
		2021	4.84 ± 1.76	2.31	3.15	4.33	6.45	7.34	−10 %
		2022	4.54 ± 1.74	1.92	2.58	4.10	6.41	6.82	−6 %
		2023	4.30 ± 1.76	2.08	2.62	3.82	5.91	7.68	−5 %
		2024	4.18 ± 1.71	1.73	2.18	3.99	5.70	7.22	−3 %
Steel plants	4	2019	6.22 ± 2.77	2.61	3.56	5.36	8.89	11.00	
		2020	4.96 ± 2.07	2.24	2.95	4.34	6.62	8.37	−20 %
		2021	4.33 ± 1.77	2.25	2.71	3.79	5.54	7.48	−13 %
		2022	4.33 ± 1.56	1.74	2.18	3.41	5.59	8.11	0 %
		2023	4.23 ± 1.68	1.96	2.51	3.84	5.78	7.16	−2 %
		2024	4.08 ± 1.47	1.89	2.48	3.49	5.28	6.58	−4 %
Power plants	53	2019	4.94 ± 2.18	2.34	2.80	4.33	6.85	8.20	
		2020	4.10 ± 1.78	2.01	2.43	3.80	5.43	6.69	−17 %
		2021	3.32 ± 1.38	1.79	2.20	3.10	4.30	5.17	−19 %
		2022	2.99 ± 1.25	1.37	1.80	2.81	4.01	4.69	−10 %
		2023	3.13 ± 1.33	1.51	2.09	2.92	4.26	4.64	5 %
		2024	3.02 ± 1.21	1.53	1.91	2.88	4.02	4.69	−4 %

SD: standard deviation.

from approximately $57\text{--}206 \text{ kt coal yr}^{-1}$, while the mean grid-scale CO emissions ranged from approximately $2.8 \times 10^3\text{--}4.0 \times 10^3 \text{ tCOyr}^{-1}$. A moderate positive association was observed between coal consumption and the inferred CO emissions ($r = 0.59$, $p = 0.058$, $N = 11$; Fig. 9a), indicating that plants with higher coal consumption generally tended to be located in grid cells with higher inferred emissions. However, the relationship did not reach the conventional significance level of $p < 0.05$. The relatively broad 25th–75th percentile ranges also indicate substantial temporal variability in the grid-scale emission estimates.

The grid-scale CO emission-to-coal-consumption ratio, calculated as the satellite-derived CO emission from the $0.05^\circ \times 0.05^\circ$ grid cell containing each power plant divided by the reported coal consumption of that plant, ranged from approximately $14\text{--}53 \text{ g CO kg}^{-1} \text{ coal}$. This ratio is used only as a comparative metric rather than a facility-specific emission factor, because the satellite-derived emissions represent the combined emissions from all sources within the corresponding grid cell rather than actual stack emissions. The ratio showed a strong inverse relationship with coal consumption ($r = -0.93$, $p < 0.001$, $N = 11$; Fig. 9b). However, because coal consumption is included in the denomina-

tor, the relationship is partly affected by mathematical coupling. Contributions from other sources within the grid cell may further influence the ratio, particularly for plants with lower coal consumption.

4 Discussion

Figure 10 compares the spatial distributions of the MFIEF-derived grid-scale CO emission estimates and EDGAR anthropogenic CO emissions for their overlapping period from 2019–2022. Datasets show relatively high emissions in major urban and industrialized regions in northern Xinjiang, as well as in some regions of Kazakhstan, which may have high CO emissions due to industrial activities, transportation and home heating. In contrast, low emission values are mainly found in remote areas of Xinjiang, such as steppes, deserts, and mountainous regions, as well as in some sparsely populated and less industrialized regions of Kazakhstan. Overall, the geographical distribution of CO emissions shows obvious unevenness, with the emission intensity in urban and industrial areas being significantly higher than that in the surrounding rural and natural areas, especially in the urban centers in northern Xinjiang and some industrial areas in Kaza-

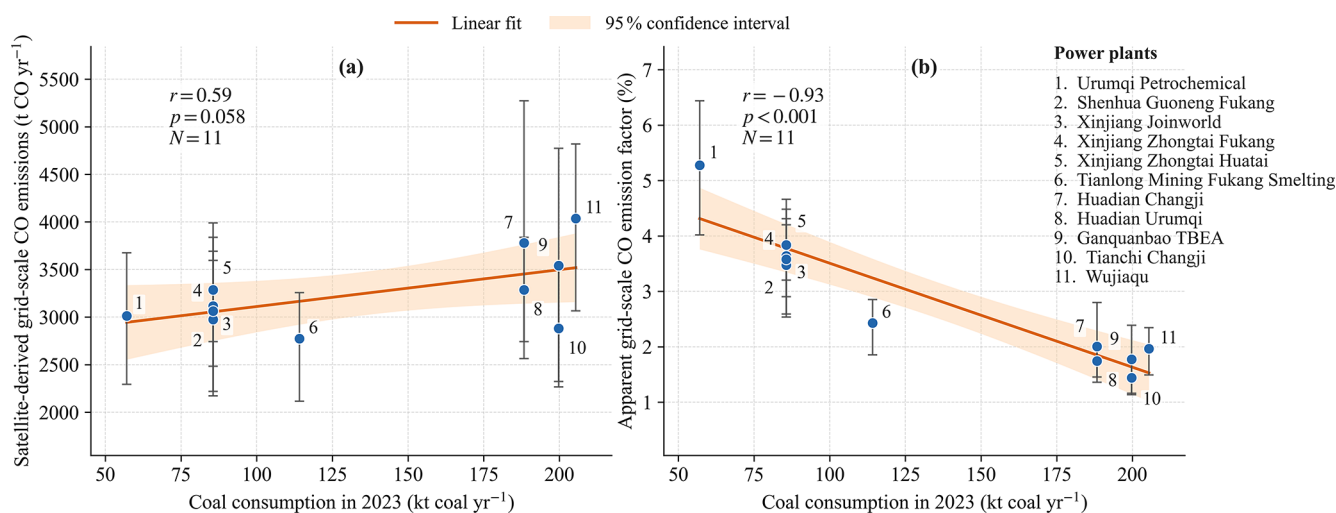


Figure 9. Relationship between satellite-derived CO emissions and coal consumption at selected coal-fired power plants. **(a)** Comparison between annual coal consumption and MFIEF-derived CO emissions for individual power-plant grid cells. **(b)** Relationship between coal consumption and the grid-scale CO emission-to-coal-consumption ratio. Circles and vertical error bars represent the means and 25th–75th percentile ranges, respectively.

khstan, where high emissions may be related to the local level of economic development, the structure of energy consumption, and the industrial layout. This broad spatial correspondence indicates that both approaches capture several major anthropogenic emission regions. Nevertheless, local differences are evident around individual urban and industrial areas, reflecting actual differences between the bottom-up and top-down approaches in the observational record in terms of source, spatial allocation, and temporal sampling.

Figure 10b shows the grid-cell difference calculated as MFIEF minus EDGAR for the common analysis period. The MFIEF-derived fluxes are higher than the EDGAR anthropogenic emissions across most of the study domain, whereas urban centers such as Urumqi and Almaty show locally lower MFIEF values, with differences reaching approximately $-5 \mu\text{g m}^{-2} \text{s}^{-1}$. Madrazo et al. (2018) compared local Cuban emission inventories with EDGAR for CO emissions and mentioned that EDGAR overestimates the stationary source emission factors by a factor of three, while Li et al. (2025) indicates that both EDGAR and MEIC estimates of well-established urban areas and large factories overestimate CO emissions in Shanxi, while newer and smaller urban sources are underestimated or missing. The distributions of the grid-cell differences are shown in Fig. 10c. Across 2019–2022, differences are positive across most matched grid cells. The annual mean and median differences decrease from 3.95 and $3.64 \mu\text{g m}^{-2} \text{s}^{-1}$ in 2019 to 2.50 and $2.43 \mu\text{g m}^{-2} \text{s}^{-1}$ in 2022, respectively, while the distribution peak shifts from 3.20– $2.20 \mu\text{g m}^{-2} \text{s}^{-1}$. These statistics characterize the numerical differences between the datasets. EDGAR estimates anthropogenic emissions using sector-specific activity data and emission factors on a monthly

time scale and locates them based on a priori information, whereas MFIEF derives a grid-scale signal constrained by atmospheric observations. These differences may arise from additional or missing emission sources, inaccuracies in the spatial allocation of sources, or differences between actual emissions and bottom-up estimates. Differences in atmospheric transport, satellite sampling and retrievals, and inversion assumptions including chemistry, physics, and long-range-transport may all contribute to the observed variability and uncertainty in the top-down estimate. For additional magnitude context, Wang et al. (2025) reported observation-constrained CO emission fluxes ranging approximately from $0\text{--}30 \mu\text{g m}^{-2} \text{s}^{-1}$, with values in relatively clean regions generally below $6 \mu\text{g m}^{-2} \text{s}^{-1}$. The regional mean fluxes obtained in this study ranged from $3.06\text{--}4.93 \mu\text{g m}^{-2} \text{s}^{-1}$, with peak values exceeding $10 \mu\text{g m}^{-2} \text{s}^{-1}$, and therefore are of a comparable order of magnitude and spread. This numerical comparison provides a broad reference for the inferred emission magnitudes.

Figure 11 compares MFIEF-derived grid-scale CO emission fluxes with EDGAR anthropogenic CO emissions at selected coal-fire sites and urban centers. At the four persistent underground coal-fire sites, MFIEF identifies enhanced CO emissions, whereas EDGAR shows limited emissions in the corresponding grid cells. This difference is expected because persistent underground coal fires are not explicitly represented as an independent source category in EDGAR and may therefore be absent or only indirectly represented within existing anthropogenic sectors. At the selected urban locations, the differences between MFIEF and EDGAR were strongly site dependent. The mean EDGAR emissions at Urumqi and Almaty were approximately 2.0 and 2.4

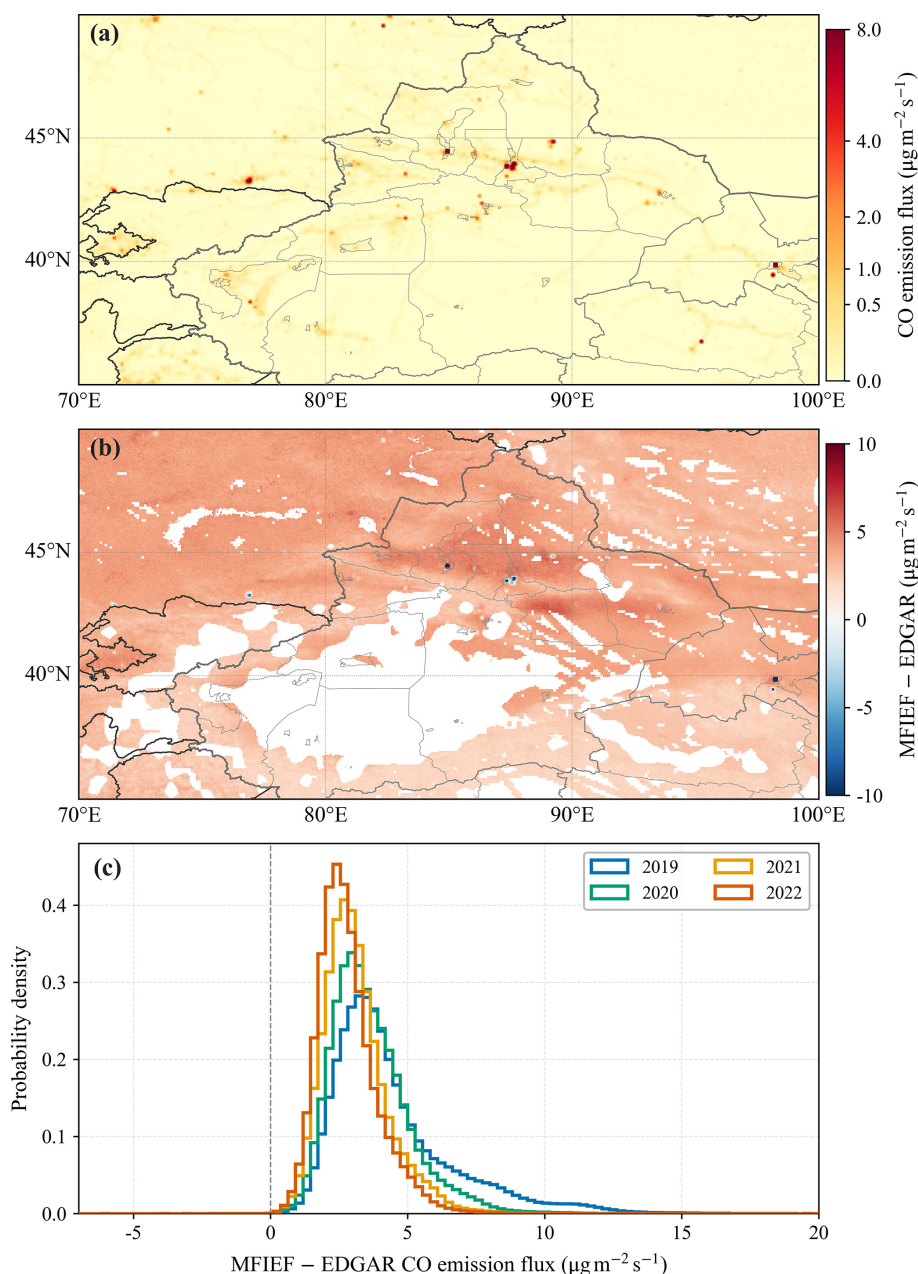


Figure 10. Comparison of CO emission estimates from MFIEF and EDGAR during their overlapping period from 2019–2022. **(a)** Mean EDGAR anthropogenic CO emission flux. **(b)** Mean grid-cell difference calculated as MFIEF minus EDGAR. Positive values indicate larger MFIEF-derived fluxes, whereas negative values indicate larger EDGAR emissions. **(c)** Probability density distributions of the monthly grid-cell differences. The differences reflect the distinct source coverage, spatial allocation, temporal representation, and estimation methods of MFIEF and EDGAR.

times higher than the corresponding MFIEF estimates, respectively, whereas the discrepancy was much larger at Jiayuguan, where EDGAR emissions were approximately 63 times higher. The two datasets also exhibited distinct temporal characteristics. For example, at Jiayuguan, the inter-month variability of MFIEF monthly emissions was substantially larger than that of EDGAR (coefficient of variation: 41.5 % versus 3.7 %). Moreover, daily MFIEF estimates

showed considerable within-month variability, with median intra-month coefficients of variation of approximately 22 %–35 % across the selected urban sites. These differences indicate that discrepancies between bottom-up inventories and satellite-derived estimates are associated not only with emission magnitude but also with differences in spatial allocation and prescribed temporal profiles of emission sources.

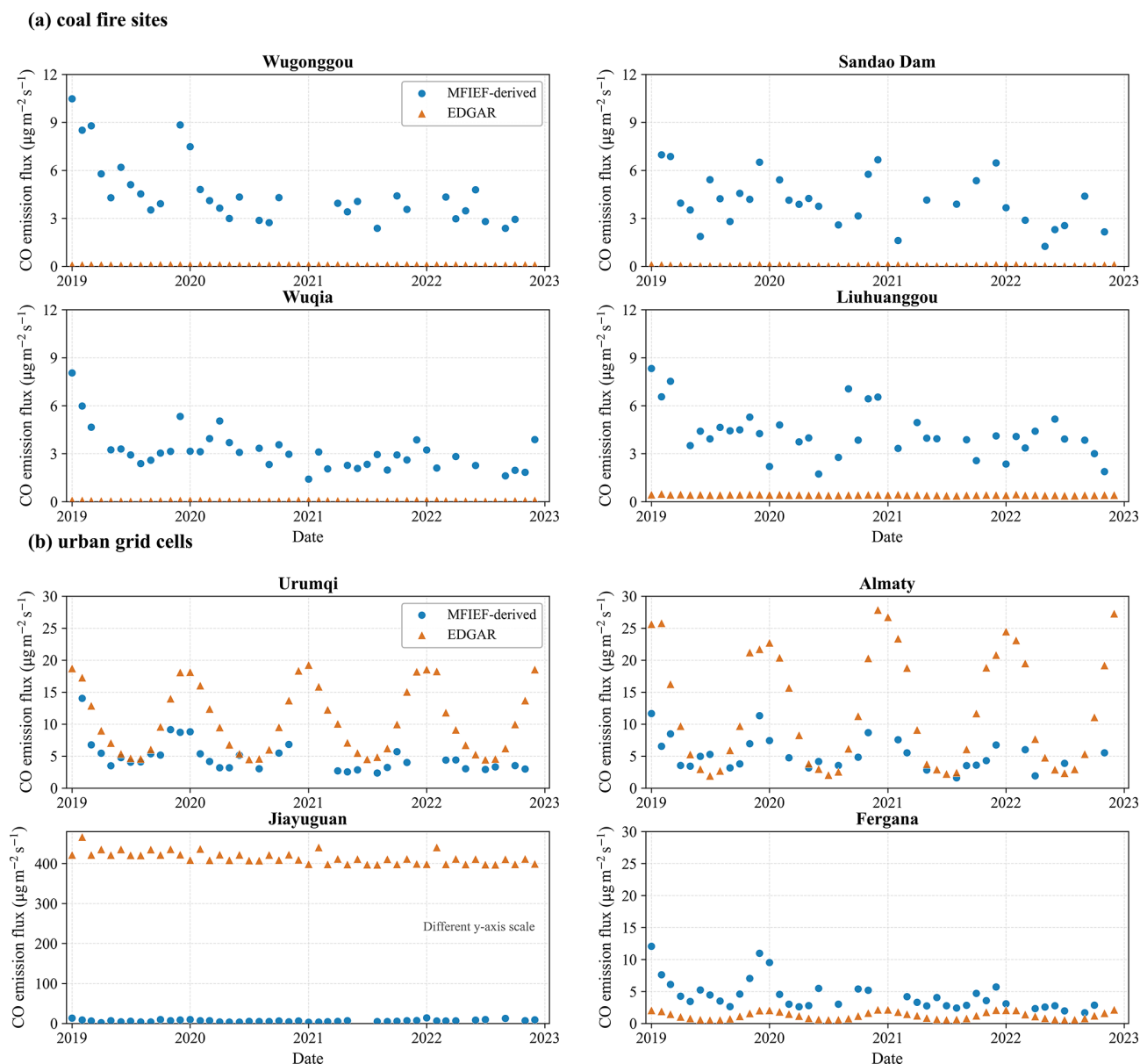


Figure 11. Comparison of MFIEF-derived grid-scale CO emission fluxes and EDGAR anthropogenic CO emissions at selected locations. **(a)** Persistent underground coal-fire sites, which are not explicitly represented as a separate source category in EDGAR. **(b)** Selected urban centers. MFIEF-derived emissions are presented as monthly means, with vertical bars indicating the within-month variability (standard deviation) of daily estimates, whereas EDGAR values represent monthly inventory estimates. The comparison illustrates differences in source coverage and temporal representation between the two datasets.

5 Conclusion

In this study, we applied the Model-Free Inversion Estimation Framework to derive gridded CO emission estimates over Central Asia using TROPOMI CO and HCHO total-column retrievals together with meteorological reanalysis data. Propagating observational uncertainty through the inversion quantifies the corresponding range of derived emissions and identifies the grid cells where the estimates meet the adopted stability criteria.

Regional mean CO emissions decreased from $4.93 \mu\text{g m}^{-2} \text{s}^{-1}$ in 2019 to $3.06 \mu\text{g m}^{-2} \text{s}^{-1}$ in 2024, corresponding to a 37.9 % endpoint reduction. The regional decline remains significant after accounting for seasonality. The identified emission hotspots weakened over the study period. Higher emissions during winter and early spring were observed at several urban and industrial locations. These temporal patterns may reflect a combination of changes in industrial activity, residential heating, energy use, emission-control measures, meteorological conditions, satel-

lite sampling, and persistent underground coal-fire activity. Interestingly, peak emissions at the underground coal-fire sites occurred 1 year later than those at the industrial and urban sites, further suggesting that underground coal fires exhibit distinct temporal behavior and may be inadequately represented in conventional bottom-up emission inventories. Together, these changes characterize the principal regional evolution of CO emissions during 2019–2024.

These findings demonstrate the value of observation-driven inversion for regional emission characterization. The uncertainty analysis quantifies the observational contribution to emission uncertainty and identifies grid-cell estimates that do not meet the adopted stability criteria. The retained estimates provide complementary constraints on regional emission patterns and source environments, particularly for characterizing emerging, spatially variable, and temporally dynamic emission sources that may be inadequately represented in conventional inventories. Future applications to other satellite-retrieved species will require species-specific evaluation of retrieval sensitivity, chemistry, transport, and independent validation data.

Several limitations should be considered when interpreting the MFIEF-derived CO emissions. First, independent ground-based or facility-level CO emission measurements with spatial and temporal coverage comparable to the satellite-derived estimates are unavailable across the study region. The comparisons with EDGAR and reported coal consumption provide contextual assessments of spatial correspondence and physical plausibility. Second, the derived emissions remain sensitive to uncertainties in the satellite CO and HCHO retrievals, meteorological fields, temporal sampling, and the assumptions used to separate transport, chemical production, and surface emissions. In particular, vertical transport can alter the relationship between surface CO concentrations and satellite-observed column loadings (Wang et al., 2026). Third, the grid-scale emission flux estimated for an industrial facility includes the combined influence of sources within the corresponding grid cell. The present results are most appropriate for characterizing broad spatial patterns and relative temporal variability at the grid scale. Future integration of ground-based observations, facility-level measurements, aircraft or UAV observations, and multi-species satellite measurements would provide additional constraints on emission magnitude and source attribution.

Data availability. The authors would like to thank the TROPOMI, ERA-5, and EDGAR products for making their data available. The satellite CO and HCHO datasets used in this study are available at <https://disc.gsfc.nasa.gov/datasets> (last access: 22 October 2026). The ERA-5 reanalysis product is available at <https://doi.org/10.24381/cds.bd0915c6> (Hersbach et al., 2023). The EDGAR product can be accessed from <https://edgar.jrc.ec.europa.eu/> (last access: 22 October 2026). The data that support the

findings of this study are openly available at the following DOI: <https://doi.org/10.6084/m9.figshare.28462817> (Feng, 2025).

Author contributions. This work was conceptualized by JBC and YF. The methods were developed by JBC and KQ. XL and LL provided insights on methodology. Visualizations were made by YF and JBC. Writing of the original draft was done by YF and JBC. Writing at the review and editing stages were done by XL, LL, SW, ZL, LW, JL and JBC.

Competing interests. The authors have the following competing interests: Jason Blake Cohen is a member of the editorial board of Atmospheric Chemistry and Physics.

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