

Quantifying Multi-pollutant Co-exposure via Deep Learning-Based Simultaneous Prediction Using Geostationary Satellite Data

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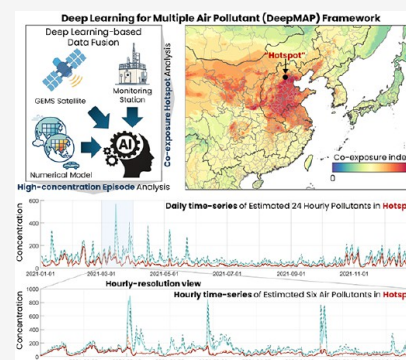
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ABSTRACT: Simultaneous prediction of multiple air pollutants is essential for quantifying human co-exposure and evaluating the health impacts of pollutant mixtures. However, spatial and temporal gaps in geostationary satellite observations, chemical transport models, and ground-based monitoring networks hinder accurate hourly assessments of multi-pollutant dynamics. Here, we present Deep Learning for Multiple Air Pollutant analysis (DeepMAP), a deep learning framework that simultaneously predicts six major air pollutants—PM₁₀, PM_{2.5}, O₃, NO₂, CO, and SO₂—at hourly resolution. DeepMAP demonstrated robust performance across multiple pollutants and generalized well to unseen regions. The framework accurately captured dynamic high-concentration co-pollution episodes during March 2021, with normalized RMSE values below 0.36 for all pollutants. DeepMAP revealed that PM₁₀–PM_{2.5} co-exceedance was the most frequent across East Asia (91 days/year), followed by PM₁₀–PM_{2.5}–NO₂ (42), PM_{2.5}–O₃ (18), and PM₁₀–PM_{2.5}–O₃ (12). Hotspots for PM₁₀–PM_{2.5}–NO₂–O₃ co-exceedance were identified over the North China Plain, East China, and South Korea, where the regional annual totals reached 24, 19, and 15 days, respectively. A novel co-exposure index further identified three distinct hotspot regions where the contribution of NO₂ was approximately twice that observed elsewhere. Our findings provide a high-resolution, data-driven framework for characterizing multi-pollutant co-exposure and identifying regional priorities for air quality management and public health protection.

KEYWORDS: multi-task learning, deep learning, co-exposure, air pollution, geostationary satellite



1. INTRODUCTION

Air pollution exposure is inherently multi-pollutant, as the air we breathe is a complex mixture of pollutants—particulate matter (PM₁₀ and PM_{2.5}), nitrogen dioxide (NO₂), ozone (O₃), carbon monoxide (CO), and sulfur dioxide (SO₂). Although the 2021 World Health Organization (WHO) air quality guidelines addressed these six major pollutants, they do not explicitly consider the combined or synergistic health effects of pollutant mixtures.¹ Growing epidemiological evidence shows that multi-pollutant co-exposure amplifies adverse health outcomes—ranging from cardiovascular and metabolic disorders to renal, immune, and respiratory diseases—beyond the effects of single pollutants.^{2–8} Quantifying the health and exposure risks associated with such mixtures is therefore critical. Equally important is identifying regional and continental-scale co-exposure hotspots to support early warnings, policy interventions, and progress toward global sustainability goals.^{8,9}

Ground-based monitoring networks provide direct measurements of surface-level pollutant concentrations but remain spatially sparse and unevenly distributed, hindering large-scale assessments. Even in regions with relatively dense networks—such as China, South Korea, and Japan—temporal data gaps are frequent, often reading to incomplete multi-pollutant records. Addressing these discontinuities is challenging, as they arise

from abrupt spatial (e.g., mountainous or desert terrain), temporal (e.g., monsoon onset or wind shift events), and chemical (e.g., pollutant-specific emission changes) transitions that are difficult to model or interpolate accurately.¹⁰

Satellite remote sensing offers a promising alternative to ground-based measurements by providing spatially extensive observations of aerosol optical depth (AOD) and key trace gases (e.g., NO₂ and O₃).^{11–15} Recent advancements in geostationary sensors—Geostationary Environment Monitoring Spectrometer (GEMS) over East Asia—represent a major leap toward continuous hourly air quality monitoring, offering finer temporal resolution than polar-orbiting satellites, which typically provide only one or two observations per day. Yet, substantial limitations persist: optical sensors cannot penetrate clouds, leading to large spatiotemporal gaps, with our analysis showing that only 7.4–21.6% of hourly GEMS pixels are usable annually (Figure S1).

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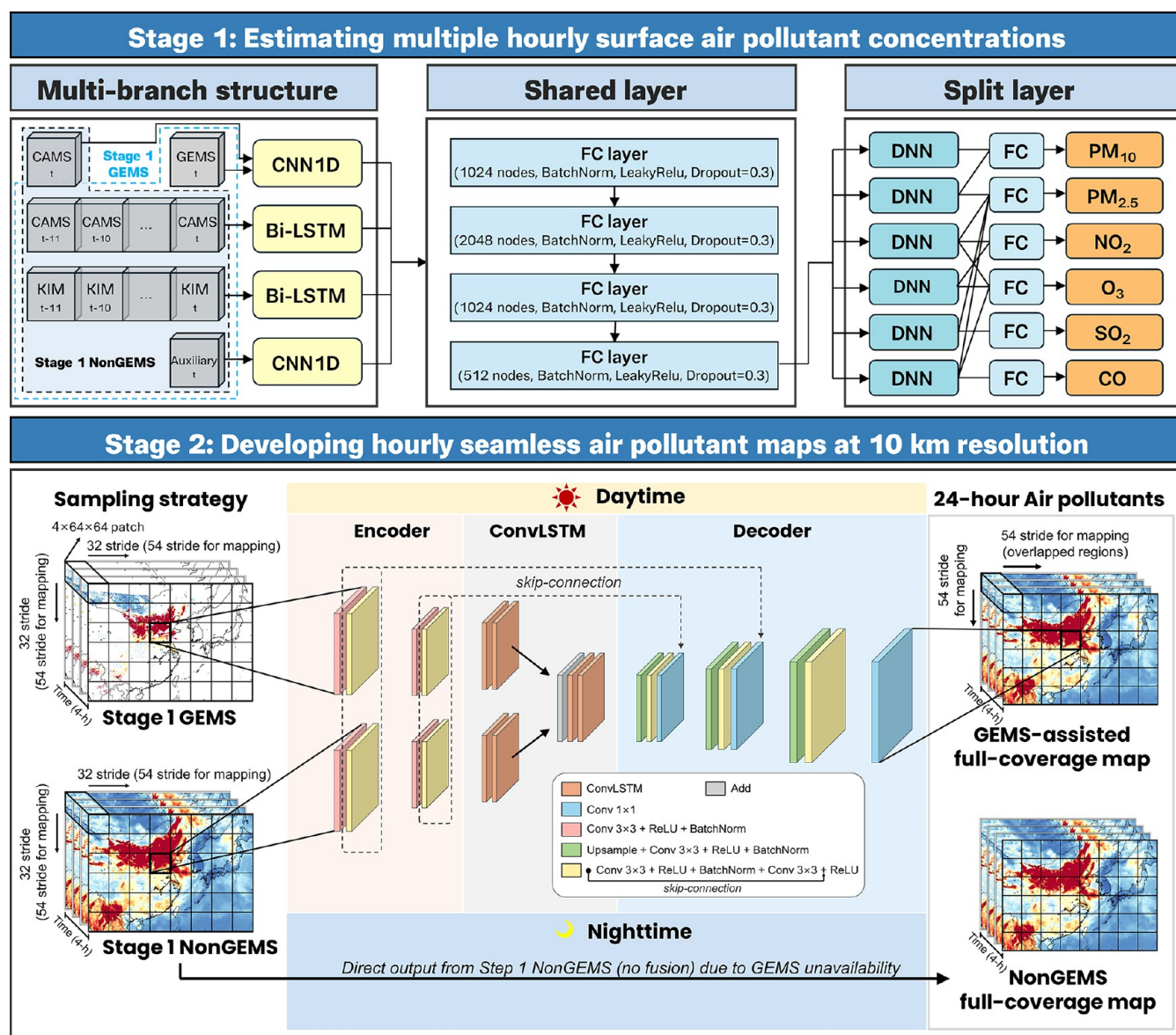


Figure 1. Flowchart of the proposed DeepMAP framework. DeepMAP comprises Stage 1 and Stage 2 to produce detailed, full-coverage maps of six air pollutants (PM_{10} , $\text{PM}_{2.5}$, NO_2 , O_3 , CO , and SO_2) in East Asia. Stage 1 estimates multiple surface air pollutant concentrations using multi-branch, shared, and split-layer structures. FC denotes fully connected layers. Stage 2 generates GEMS-assisted full coverage via ResNet-ConvLSTM fusion and provides nighttime coverage directly from Stage 1 NonGEMS when GEMS observations are unavailable.

These missing data hinder the detection of short-term pollution episodes and evaluation of associated health risks.^{16,17}

Chemical transport models (CTMs) simulate pollutant dynamics by representing atmospheric physical and chemical processes at sub-hourly scales.^{18,19} However, their accuracy is constrained by coarse emission inventories, uncertain boundary conditions, and limited assimilation of ground-based data.^{18–21} High computational costs and coarse resolutions further limit their ability to resolve fine-scale pollution variability, while many inventories assume “typical day” conditions that overlook true day-to-day emission fluctuations.

Recent advances in deep learning, combined with in situ measurements, high spatiotemporal resolution remote sensing imagery, CTM outputs, and meteorological data,^{17,22,23} offer powerful solutions to these challenges. Deep learning models can integrate heterogeneous data sources, bridge observational gaps, and improve the spatiotemporal fidelity of exposure

assessment. Nevertheless, major obstacles remain. Persistent cloud-induced missing data and uncertainty in imputed AOD^{16,24} continue to degrade model accuracy, and most existing approaches estimate a single pollutant at a time. This single-target design not only increases computational burden but also neglects interactions among pollutants driven by shared meteorological and chemical processes.^{22,25,26} A recent study in Oakland, California, addressed multi-pollutant estimation through data assimilation rather than deep learning.²⁷ Moreover, most existing research still relies on daily composites from polar-orbiting satellites, which miss key diurnal peaks in pollutant levels due to limited overpasses and cloud cover, leading to systematic underestimation of short-term exposures.^{28,29}

In contrast, geostationary satellites enable continuous, hourly monitoring that captures diurnal pollutant dynamics. Building on this capability, we developed Deep Learning for Multiple Air Pollutant analysis (DeepMAP)—a framework for generating

hourly, spatially continuous ground-level concentration maps for six pollutants (PM_{10} , $\text{PM}_{2.5}$, NO_2 , O_3 , SO_2 , and CO) at 10-km spatial resolution. By integrating GEMS observations with CTM outputs, meteorological data, and ground-based measurements, DeepMAP provides a unified, data-driven approach for assessing both short- and long-term exceedances relative to the 2021 WHO guidelines. We further quantify the alarming multi-pollutant composition of co-exposure and identify sub-regional hotspots near major emission sources, revealing that substantial populations across East Asia experience recurrent multi-pollutant co-exceedances each year.

2. MATERIALS AND METHODS

2.1. Data Collection

This study focuses on severe air pollution events across East Asia during January 2021 to December 2023, a period following the launch of the GEMS satellite, which enables hourly monitoring of aerosols and trace gases (Figure S2). To realistically capture dynamic atmospheric conditions, we integrated diverse open-source datasets into DeepMAP, including GEMS (<https://nesc.nier.go.kr>, last access: 19 January 2024),³⁰ Copernicus Atmosphere Monitoring Service (CAMS) forecast (<https://ads.atmosphere.copernicus.eu/datasets/cams-global-atmospheric-composition-forecasts>, last access: 25 January 2024),³¹ the Korean Integrated Model (KIM) (<https://apihub.kma.go.kr>, last access: 19 January 2024),³² and land cover-related variables, including normalized difference vegetation index (<https://search.earthdata.nasa.gov>, last access: 17 February 2024), digital elevation model (<https://earthexplorer.usgs.gov>, last access: 29 August 2023), built-up surface (<https://ghsl.jrc.ec.europa.eu/download.php>, last access: 28 November 2023), population density (<https://www.earthdata.nasa.gov/data/projects/gpw/>, last access: 3 June 2021), and road density (<https://www.globio.info/download-grip-dataset/>, last access: 3 June 2021).^{33–36}

Surface-level concentrations of six pollutants— PM_{10} , $\text{PM}_{2.5}$, NO_2 , O_3 , CO , and SO_2 —were obtained from 1837, 74, 665, and 725 ground stations in mainland China (<http://beijingair.sinaapp.com>, last access: 21 February 2024), Taiwan (<https://airtw.moeenv.gov.tw>, last access: 9 May 2024), South Korea (<https://www.airkorea.or.kr/>, last access: 20 May 2024), and Japan (<https://soramame.env.go.jp>, last access: 18 February 2024), respectively (Table S1).

To ensure data consistency, all datasets were regridded to a fixed 10-km GEMS Level-3 (L3) grid. This static grid was chosen because GEMS-derived variables—our primary inputs—exhibit time-varying pixel geometries across four scan modes (Half East, Half Korea, Full Central, and Full West). Bilinear interpolation was applied to input variables with similar or finer resolution (i.e., GEMS, KIM, and auxiliary variables), while spline interpolation was used for coarser datasets (i.e., CAMS data and the lowest GEMS O_3 profile) to improve continuity and reduce block artifacts. Ground-based observations located within the same output grid were averaged using inverse distance weighting.

Meteorological variables from KIM, provided at 3-h intervals, were linearly interpolated to hourly resolution. The interpolated results showed strong agreement with in-situ measurements from the NOAA Integrated Surface Database (Figure S3). All data were temporally aligned to ground-based observation times (e.g., GEMS measurements between 13:45 and 14:15 were aligned to 14:00). Detailed variable descriptions and preprocessing steps are summarized in Text A and Tables S1–S2.

2.2. Modeling Framework

DeepMAP consists of two stages designed to produce spatially continuous, high-resolution maps of multiple air pollutants:

Stage 1: Ground-level pollutant retrieval using two complementary models—one with (GEMS model) and one without (NonGEMS model) GEMS inputs

Stage 2: Spatiotemporal fusion of two Stage 1 outputs to achieve full-coverage, hourly maps (Figure 1).

The Stage 1 GEMS model captures detailed spatial heterogeneity (3.5 km $\times$ 8 km and 7 km $\times$ 8 km pixel sizes) but suffers from data gaps caused by cloud cover. Conversely, the NonGEMS model, which excludes GEMS inputs, provides continuous 24-h predictions but with coarser spatial representation. To manage the large size of the NonGEMS dataset, we applied stratified random subsampling by pollutant and month for each station-interpolated pixel. For each month, we computed mean and standard deviation (SD) of each target pollutant and randomly sampled 1% from each of three concentration strata—below (mean + SD), between (mean + SD) and (mean + 2SD), and above (mean + 2SD). Consequently, a total of 2,065,740 samples were retained from the original 35,126,733 samples, corresponding to an overall retention rate of approximately 6% (Table S3).

Stages 1 and 2 are trained independently (i.e., decoupled training strategy). Stage 2 integrates the outputs from both Stage 1 models to produce a full diurnal cycle: a ResNet-ConvLSTM-based fusion of daytime GEMS-assisted outputs and nighttime NonGEMS estimates. This approach exploits the spatial richness of GEMS during daytime and the temporal continuity of NonGEMS at night.

2.3. Multi-task Learning for Simultaneous Prediction

Simultaneous retrieval of six air pollutants (i.e., PM_{10} , $\text{PM}_{2.5}$, NO_2 , O_3 , CO , and SO_2) was performed using a multi-task learning framework. Compared with single-task models, this approach improves performance by 1) exploiting shared information across pollutants; 2) leveraging inter-task dependencies; and 3) reducing model complexity through shared representations.

For both the GEMS and NonGEMS scenarios, the multi-task approach consistently outperformed single-pollutant models, yielding R^2 improvements of 0.03 (PM_{10}), 0.01 (NO_2), 0.03 (CO), and 0.11 (SO_2) under clear-sky conditions, and 0.02, 0.01, 0.03, and 0.08, respectively, under all sky conditions (Tables S4 and S5).

Each model features a multi-branch architecture with shared, split, and physics-informed concatenate layers. The multi-branch design combines bi-LSTM and 1D CNN modules to exploit complementary data characteristics—temporal continuity in numerical models (i.e., KIM and CAMS) and spatial details in satellite inputs (i.e., GEMS and auxiliary variables). The Bi-LSTM sequence length was optimized at 12 h (out of 6, 12, 18, and 24 h tested), which yielded the best performance with the highest R^2 and lowest nRMSE across all pollutants (Figure S4). In the NonGEMS model, 1D CNN replaced GEMS variables with CAMS fields to account for data availability (see Supporting Information B.1 for model details).

Remarkably, the proposed multi-branch structure not only surpassed the non-multi-branch structure suggested by Yang et al. (2023a) but also exceeded the performance of an earlier multi-output random forest model proposed by Yang et al. (2023b) (Table S6).^{37,38}

Shared layers captured cross-pollutant relationships through fully connected networks, while split layers were specialized in pollutant-specific features. The physics-informed concatenation layer selectively incorporates inputs from chemically relevant species, reflecting precursor-driven chemical regimes (e.g., oxidation capacity and secondary aerosol formation), following Vafaieikia et al. (2020) and Yang et al. (2023a).^{37,39} Further, integrated physically constrained tasks,^{37,39} such as ensuring $\text{PM}_{2.5} < \text{PM}_{10}$, minimized the following loss function:

$$\text{loss} = \frac{1}{n \times 6} \sum_{i=1}^n \sum_{j=1}^6 (y_{j,\text{pred}} - y_{j,\text{obs}})^2 + \lambda \sum_{i=1}^n \text{ReLU}(y_{\text{PM}_{10},\text{pred}} - y_{\text{PM}_{2.5},\text{pred}}) \quad (1)$$

where j denotes pollutant index, n is the total sample count, and λ is the weight for the constraint item, set to 10^{-5} referring to Yang et al. (2023a).³⁷

Training was conducted for 500 and 400 epochs (learning rate = 0.001, batch size = 512) using 2.07 million (GEMS) and 1.76 million (NonGEMS) samples, respectively. The total training time was

Table 1. Model Performance Evaluation^a

Air pollutant	PM ₁₀			PM _{2.5}			NO ₂		
Time	All	Day	Night	All	Day	Night	All	Day	Night
R ²	0.77	0.79	0.76	0.77	0.78	0.77	0.61	0.63	0.59
slope	1.10	1.11	1.09	1.12	1.12	1.12	1.07	1.03	1.08
RMSE	25.0	23.5	25.8	13.6	12.4	14.2	6.2	4.88	6.81
nRMSE	0.52	0.51	0.53	0.52	0.51	0.52	0.49	0.46	0.50
mean obs	47.8	45.9	48.7	26.3	24.5	27.2	12.7	10.7	13.7
Air pollutant	O ₃			CO			SO ₂		
Time	All	Day	Night	All	Day	Night	All	Day	Night
R ²	0.76	0.81	0.71	0.51	0.52	0.50	0.25	0.30	0.22
slope	1.12	1.12	1.12	1.10	1.17	1.07	1.02	1.03	1.01
RMSE	10.4	10.0	10.5	0.21	0.21	0.21	2.22	2.26	2.20
nRMSE	0.32	0.26	0.36	0.42	0.43	0.42	0.79	0.75	0.80
mean obs	32.5	39.1	28.9	4.90	4.81	4.95	2.8	3.0	2.7

^aSeparate test results of the DeepMAP (Stage 2), where all metrics were calculated against unseen ground-based measurements for all-day, daytime, and nighttime periods during 2021–2023. RMSE units of PM₁₀, PM_{2.5}, NO₂, O₃, CO, and SO₂ are μg/m³, μg/m³, ppb, ppb, ppm, and ppb, respectively. The mean observed concentrations for each pollutant are also reported to aid interpretation of the normalized error metrics.

approximately 22 h, and generation of one hourly six-pollutant map required <1 min.

2.4. GEMS-Assisted Full-Coverage Reconstruction

The Stage 2 model features an end-to-end trainable ConvLSTM-ResNet architecture designed to reconstruct detailed spatiotemporal pollutant distributions from incomplete or coarse inputs. The ConvLSTM layers capture dynamic dependencies, while ResNet encoders—decoders efficiently learn spatial context through residual connections. Previous studies have demonstrated its ability to effectively simulate time series and capture fine spatial contextual features, particularly atmospheric and ocean dynamics.^{40,41} Separate ConvLSTM streams for the two Stage 1 outputs are merged into higher ConvLSTM layers, enabling latent interaction between GEMS and NonGEMS features. The ResNet encoder—decoder is structured in a U-Net configuration with skip connections to preserve fine spatial details during reconstruction. See [Supporting Information B.2](#) for specific details of Stage 2.

Due to GPU memory constraints, training was performed on 64 × 64 pixel patches, which were later mosaicked into full-domain outputs (300 × 512 pixels). During training, image patches were extracted using a stride of 32 pixels to increase the sample diversity. During inference, a larger stride of 54 pixels (i.e., 10-pixel overlap) was applied to reduce boundary artifacts. Only samples for which all 4-h patches contained more than 30% valid GEMS coverage were retained, ensuring reliable learning of Stage 1 GEMS-derived spatial pattern. Each pollutant model was trained for 300 epochs (learning rate = 1 × 10^{−4}, batch size = 500), requiring approximately 4.9 h per model, while generating a 4-h map sequence took only 20 s. The key software packages, version, and computing environment used in Stages 1 and 2 are summarized in [Table S7](#).

2.5. Model Evaluation

Model performance for Stage 1 was evaluated using both an independent test and spatial 10-fold cross-validation (SPCV). For the independent test, 163 grid cells encompassing 369 stations (10% stratified by country) were reserved and consistently used in Stage 2 evaluations. The remaining 90% (1,475 pixels derived from 2,935 stations) were randomly divided into 10 subsets for SPCV, each serving once as validation and nine times as training data.

To evaluate Stage 2, which performs spatial fusion of Stage 1 outputs, we additionally tested model performance over unseen areas using two masking strategies: 1) cloud masks (2:00 to 5:00 UTC) to emulate real cloud-covered regions by considering the varying hourly GEMS scan modes, and 2) square masks (128 × 128 patches, approximately 1280 × 1280 km²) to assess performance under widespread pollution events. Two representative days per month (72 total) were selected across the 2021–2023 period.

2.6. Exposure Assessment Using WHO Guidelines

To evaluate short- and long-term exposure risk, we applied the 2021 WHO air quality guidelines.^{8,42,43} Hourly DeepMAP outputs were averaged to produce daily maps [for O₃, the maximum daily 8-h average (MDA8)], and then aggregated into annual means [for O₃, the peak season (April–September)].

Co-exposure is defined as simultaneous exposure to ≥2 pollutants and is evaluated using both short-term (co-exceedance days) and long-term (co-exposure index) metrics. Regional co-exposure was quantified using population-weighted concentrations, computed by multiplying grid-level pollutant values by population counts and dividing by the total population. Thresholds for short-term exposure were defined for all six pollutants, while long-term thresholds were applied to four (PM₁₀, PM_{2.5}, NO₂, and O₃) ([Table S8](#)). According to the 2021 WHO guidelines, the increased risks were suggested by assuming a linear hazard ratio, based on relative risks derived from systematic reviews and meta-analyses. Details of the thresholds, the corresponding increased risk, and references are provided in [Table S9](#). All concentrations were converted to consistent units: NO₂, O₃, and SO₂ from μg/m³ to ppb by dividing by 1.88, 1.96, and 2.62, respectively, and CO from mg/m³ to ppm by multiplying by 0.873.

2.6.1. Short-Term Exposure. Co-exceedance days were defined when ≥ 2 pollutants exceeded WHO thresholds in the same pixel and day.⁸ Regions with >3 co-exceedance days per year were designated “hotspots” according to WHO suggestions.

2.6.2. Long-Term Exposure. A co-exposure index was developed by grading annual mean concentrations of the four pollutants (PM₁₀, PM_{2.5}, NO₂, and O₃) according to WHO long-term thresholds, ranging from the Long-term Air Quality Guideline (L-AQG) to Interim Target 1 (L-IT1), with higher grades indicating increasing air pollution severity ([Table S8](#)):

$$\text{Co-exposure index} = \frac{1}{4}(w_{i,\text{PM}_{10}} + w_{i,\text{PM}_{2.5}} + w_{i,\text{NO}_2} + w_{i,\text{O}_3}) \quad (2)$$

where $w_{i,p}$ denotes the normalized grade for pollutant p . For PM₁₀ and PM_{2.5}, grades were 0, 0.2, 0.4, 0.6, 0.8, and 1 based on their respective L-AQG and L-IT1–L-IT4 (e.g., 0 for below L-AQG; 0.2 for above L-AQG; 0.4, 0.6, and 0.8 from L-IT4 to L-IT2; and 1 for ≥ L-IT1). For NO₂, four levels (0.25, 0.50, 0.75, and 1) were used; for O₃, three levels (0.33, 0.66, and 1) were used. Grades ranged from 0–1, with larger values indicating higher pollution severity relative to the WHO long-term guideline levels. This index enables an integrated assessment of chronic exposure to multiple pollutants, providing a unified framework for identifying co-exposure hotspots across East Asia.

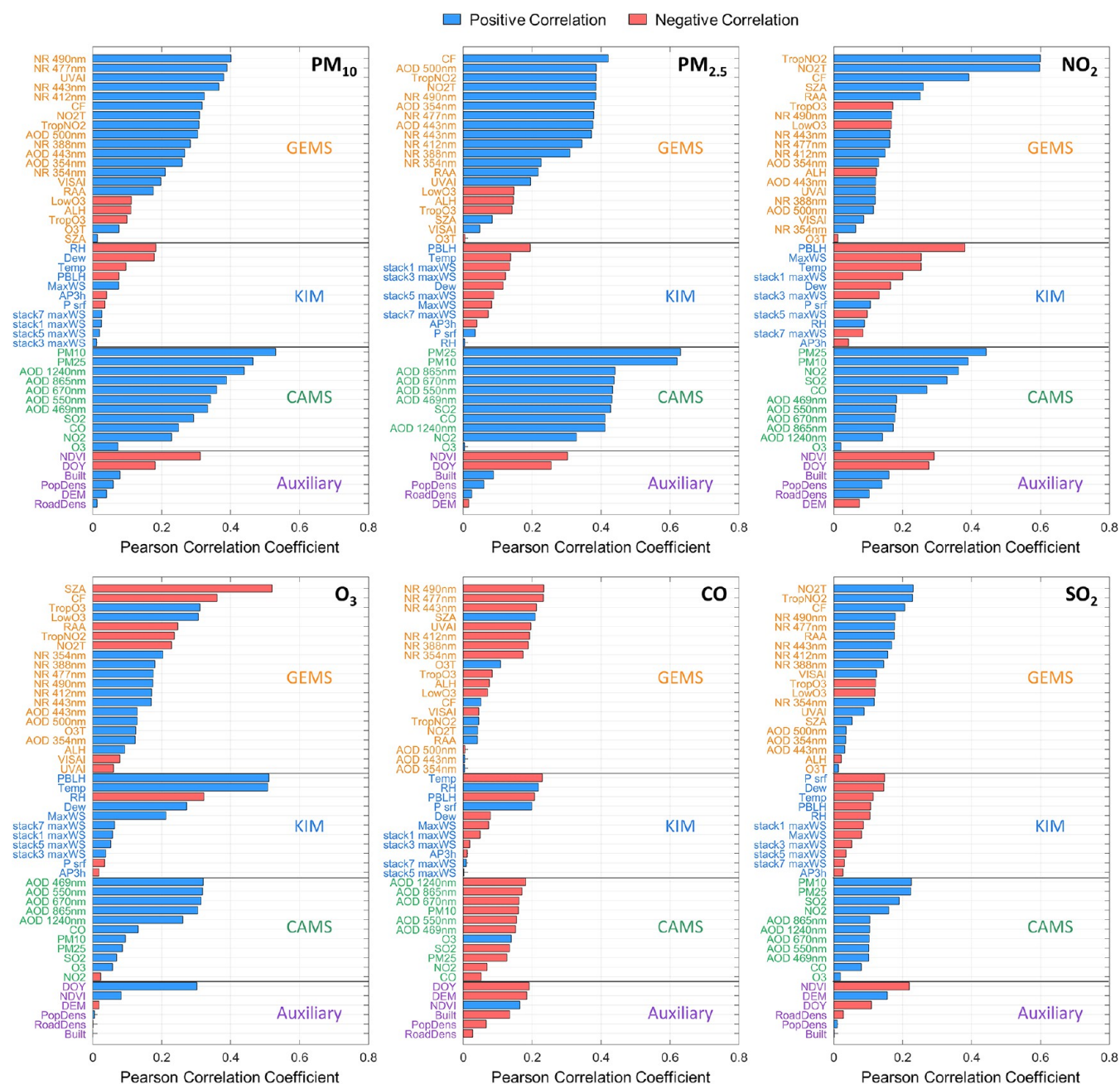


Figure 2. Bar plots of Pearson correlation coefficients between all input variables of Stage 1 GEMS model and the six target variables (PM_{10} , $\text{PM}_{2.5}$, NO_2 , O_3 , CO , and SO_2) computed from daytime samples at ground-based monitoring sites during the entire study period (2021–2023). Positive and negative correlations are shown in blue and red, respectively.

3. RESULTS

3.1. Model Performance Evaluation

DeepMAP accurately estimated hourly concentrations of six air pollutants across East Asia during 2021–2023 (Table 1). In spatial predictive validation using an independent 24-h test set, explained variances (R^2) reached 0.77, 0.77, 0.61, 0.76, and 0.51, with RMSEs of $25.0 \mu\text{g}/\text{m}^3$, $13.6 \mu\text{g}/\text{m}^3$, 6.2 ppb, 10.4 ppb, and 0.21 ppm for PM_{10} , $\text{PM}_{2.5}$, NO_2 , O_3 , and CO , respectively; normalized RMSE (nRMSE) (i.e., RMSE divided by the mean concentration) were 0.52, 0.52, 0.49, 0.32, and 0.42, respectively. Daytime and nighttime skill was broadly comparable, but daytime performance was consistently stronger (higher R^2 and lower nRMSE) across all pollutants, under-

scoring the value of daytime GEMS inputs. SO_2 exhibited lower R^2 values of 0.25 and 0.30 over 24-h time and daytime, respectively, likely reflecting weaker linear relationships with key predictors (e.g., KIM dew-point temperature (−0.20) and GEMS NO_2 total column density (0.23) in both Stage 1 NonGEMS and GEMS models (Figure 2 and Table S10).

The Stage 1 GEMS model (multi-task, satellite-assisted; herein, the GEMS-based input of DeepMAP) exhibited strong spatial generalization in SPCV, with $R^2 = 0.87, 0.84, 0.73, 0.90$, and 0.53 and nRMSE = 0.35, 0.36, 0.37, 0.16, and 0.44 for PM_{10} , $\text{PM}_{2.5}$, NO_2 , O_3 , and CO , respectively (Table S11). The NonGEMS model (24-h, no satellite inputs) performed lower but remained robust ($R^2 = 0.74, 0.75, 0.58, 0.75$, and 0.45;

Table 2. Model Performance Comparison with Previous Studies for SPCV (i.e., Out-of-Station-Based Cross-Validation)^a

Metric	CHAP (daily)		TAP (daily)		DeepMAP (daily)		DeepMAP (hourly)	
	R ²	RMSE (nRMSE)	R ²	RMSE (nRMSE)	R ²	RMSE (nRMSE)	R ²	RMSE (nRMSE)
PM ₁₀	0.82	27.1 μg/m ³	-	-	0.89	15.0 μg/m ³ (0.33)	0.77	24.9 μg/m ³ (0.52)
PM _{2.5}	*0.86–0.90	*10.0–18.4 μg/m ³	0.69–0.83	14.6–26.4 μg/m ³	0.88	9.0 μg/m ³ (0.35)	0.77	13.5 μg/m ³ (0.52)
NO ₂	0.68	6.2 ppb (0.35)	-	-	0.74	4.1 ppb (0.33)	0.61	6.2 ppb (0.49)
O ₃	0.80	10.8 ppb	0.84	-	0.81	9.6 ppb (0.21)	0.76	10.3 ppb (0.32)
CO	0.61	0.37 ppm (0.42)	-	-	0.66	0.15 ppm (0.30)	0.51	0.21 ppm (0.42)
SO ₂	0.70	5.5 ppb (0.71)	-	-	0.46	1.4 ppb (0.50)	0.25	2.2 ppb (0.79)

^a* indicates no mention of a specific CV method. The reviewed papers include PM₁₀, PM_{2.5}, NO₂, O₃, CO, and SO₂ results from the China High Air Pollutants (CHAP) dataset^{44–48} and PM_{2.5} and O₃ results from the Tracking Air Pollution (TAP) dataset.^{49,50}

nRMSE = 0.53, 0.51, 0.51, 0.32, and 0.44), enabling full-coverage estimates in unseen areas.

Because SPCV and separate test results were consistent, we emphasize separate test results under clear, cloudy, and all-sky conditions (Table S11). Under clear-sky conditions, DeepMAP achieved strong performance, with R² = 0.87, 0.84, 0.75, 0.90, 0.56, and 0.40 for PM₁₀, PM_{2.5}, NO₂, O₃, CO, and SO₂, respectively, leveraging satellite information from Stage-1 GEMS (Table S12). As valid cloud-free coverage increased, DeepMAP consistently outperformed Stage 1 NonGEMS, highlighting the added value of satellite-based information (i.e., Stage 1 GEMS) (Figure S5). DeepMAP also maintained superior performance under cloudy conditions (Table S12). Moreover, analyses during high-concentration seasons and for annual averages indicate that satellite-derived spatial gradients improve the representation of regional-scale enhancements (Figures S6–S9). Importantly, in regions lacking satellite retrievals, DeepMAP reproduced the spatial structures of the Stage 1 GEMS model—achieving higher R² values and lower nRMSE than Stage 1 NonGEMS—demonstrating fusion rather than simple merging (Figures S10 and S11).

Overall, DeepMAP performance improved with increasing population density and co-exposure index, but decreased with elevation for PM₁₀, PM_{2.5}, NO₂, CO, and SO₂. In contrast, O₃ exhibited consistently low and stable nRMSE across all stratification schemes (Figures S12–S14). In addition, daily-scale performance was comparable to, or exceeded, recent daily models in unseen regions (Table 2; 44–50). Hourly performance, as expected, was modestly lower than the daily averages but captured diurnal variability. DeepMAP also outperformed CAMS forecast and reanalysis at 1–3 h scales for all six pollutants (Table S13). Even for SO₂, DeepMAP's R² (0.23 and 0.22) and nRMSE (4.76 and 6.80) surpassed CAMS forecast and reanalysis.

3.2. Spatiotemporal Analysis of a High-Concentration Episode

DeepMAP produced gapless, hourly 10-km maps for a severe air pollution episode spanning 27–29 March 2021 (Figures 3 and 4). Unlike the patchy clear-sky coverage of the Stage-1 GEMS retrievals (Figure S15), DeepMAP delivered 100% spatial coverage for 24 h. Time-series validation at unseen stations within major hotspots—Beijing-Tianjin-Hebei (BTH), Yangtze River Delta (YRD), and Seoul Metropolitan Area (SMA)—showed strong agreement with ground measurements (Figure 3 and Figures S16–S17). In BTH, hourly R² reached 0.84, 0.88, 0.83, 0.88, 0.80, and 0.47 with nRMSE of 0.36, 0.30, 0.24, 0.30, 0.23, and 0.32 for PM₁₀, PM_{2.5}, NO₂, O₃, CO, and SO₂, respectively. Performance in YRD and SMA was similarly strong

(overall nRMSE < 0.21 and 0.25, respectively) (Figures S16 and S17).

On 27–28 March, DeepMAP captured anthropogenic-driven pollution in BTH—elevated PM_{2.5}/PM₁₀ ratios (fine aerosol) and high PM_{2.5}, NO₂, CO, and SO₂ (Figures 4 and S18). On 29 March, low PM_{2.5}/PM₁₀ ratios (dust-dominant aerosol) prevailed from Mongolia to South Korea, indicating trans-boundary transport. Along the dust pathway, strong SE winds, higher PBLH, and lower RH (relative to surroundings) from 10:00 UTC 27 March to 1:00 UTC 29 March favored elevated PM₁₀ and PM_{2.5} concentrations.^{51,52} DeepMAP tracked the dust front hourly, showing increases at the southeastern edge and decreases along the northwestern edge relative to the prior hour (Figure S18).

Morning conditions in BTH, YRD, and SMA featured high NO₂/CO/SO₂ and low O₃, consistent with local emissions and lower PBLH/temperature; late afternoon reversed this pattern (low NO₂, high O₃) under higher PBLH/temperature.^{53,54} These results demonstrate DeepMAP's ability to resolve seamless diurnal cycles and associated meteorological drivers.

3.3. Short-Term Multi-pollutant Co-exceedances

Using WHO short-term guidelines (S-AQG/S-ITs), nearly all East Asian cities failed to meet the S-AQG for two or more air pollutants (Figures 5 and S19). Among 520 cities, 83%, 92%, 55%, and 85% exceeded S-AQG for PM₁₀, PM_{2.5}, NO₂, and O₃, respectively, for at least 30 days annually (Figure S19). Even at looser thresholds (S-IT 1), exceedances remained substantial: 21% (PM₁₀), 27% (PM_{2.5}), and 3% (O₃) experienced >7 days yr⁻¹ above S-IT 1. In contrast, SO₂ exceeded S-AQG on <7 days in only 1% of cities, and CO did not exceed its S-AQG in any city (Figure S19), indicating relatively lower regional burdens for these two pollutants.

Co-exceedances were widespread (Figure 5). PM₁₀-PM_{2.5} co-exceedance was most frequent in East Asia (91 days), followed by PM₁₀-PM_{2.5}-NO₂ (42), PM_{2.5}-O₃ (18), and PM₁₀-PM_{2.5}-O₃ (12). Only 1 day exhibited simultaneous exceedance of all four pollutants (PM₁₀-PM_{2.5}-NO₂-O₃). However, North China Plain, East China, and South Korea recorded 24, 19, and 15 four-pollutant days, mainly in March, April, and October (19, 16, and 13 days), likely reflecting winter heating carryover, spring dust, and autumnal ozone formation under ample sunlight and stable high-pressure systems.^{55,56}

Between October and March, Northeast China, North China Plain, and East China experienced 52, 120, and 77 days (approximately 14%–30% of the year) with simultaneous PM₁₀-PM_{2.5}-NO₂ exceedances; from May to September, these regions recorded 42, 117, and 71 days of PM_{2.5}-O₃ co-exceedance. Hebei, Shandong, and Henan provinces emerged as persistent

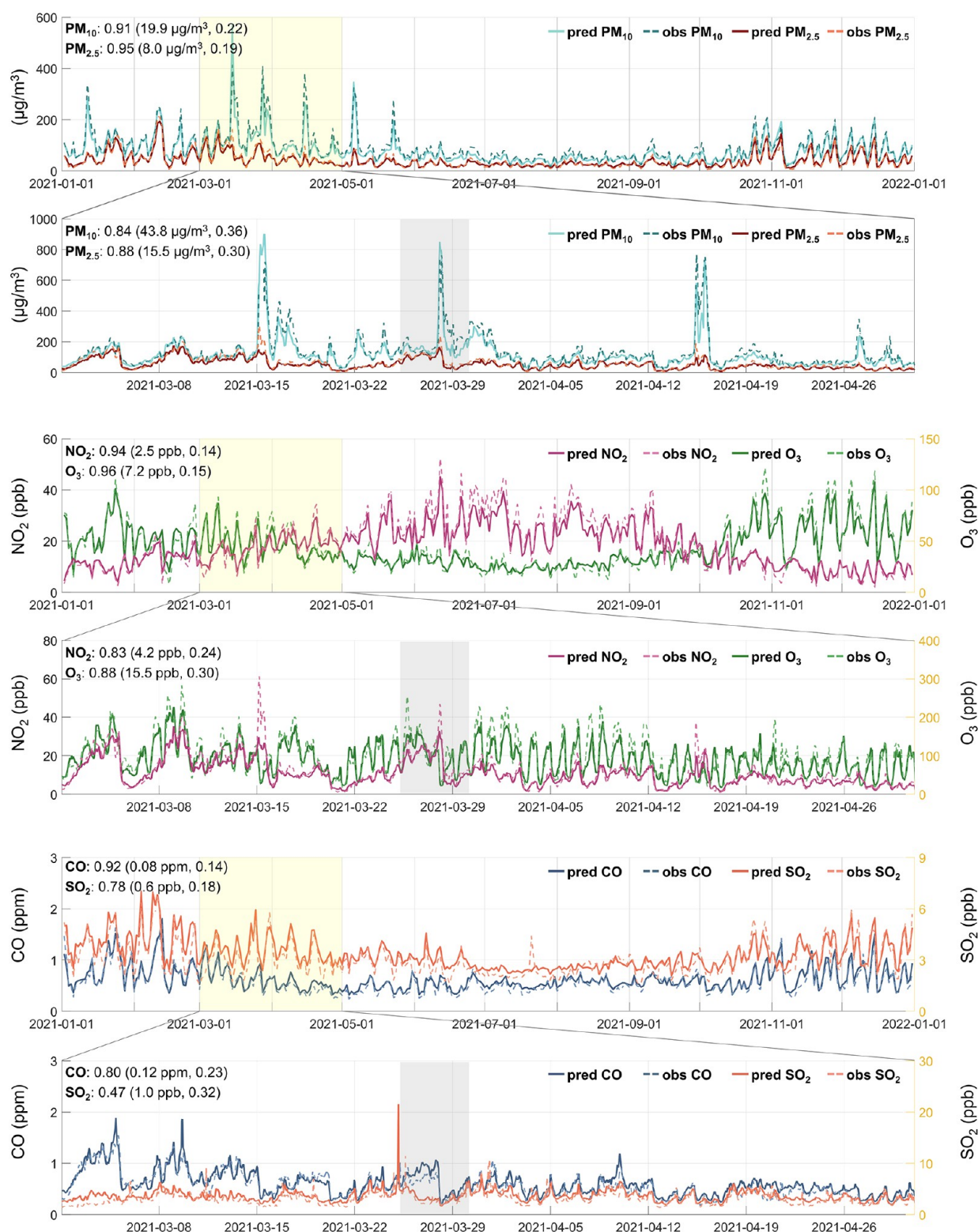


Figure 3. Daily and hourly time series of multiple air pollutants in BTH (unseen stations). Time-series validation results at unseen stations are shown on a daily scale in 2021 and on an hourly scale from March to April 2021 for the key hotspot region, BTH. To represent overall trends, hourly concentrations from seven unseen stations within the BTH region were averaged. Statistical metrics (R^2 , RMSE, and nRMSE) are displayed in the upper-left corner of each panel.

hotspots. In South Korea, NO₂ dominated: 63 days with PM_{2.5}-

NO₂ co-exceedance and 23 days with NO₂-only exceedance.

3.4. Long-Term Multi-pollutant Co-exposure

A co-exposure index (0–1) based on WHO long-term thresholds for PM₁₀, PM_{2.5}, NO₂, and O₃ (Section 2.6) reveals granular patterns of chronic multi-pollutant risk across East Asia

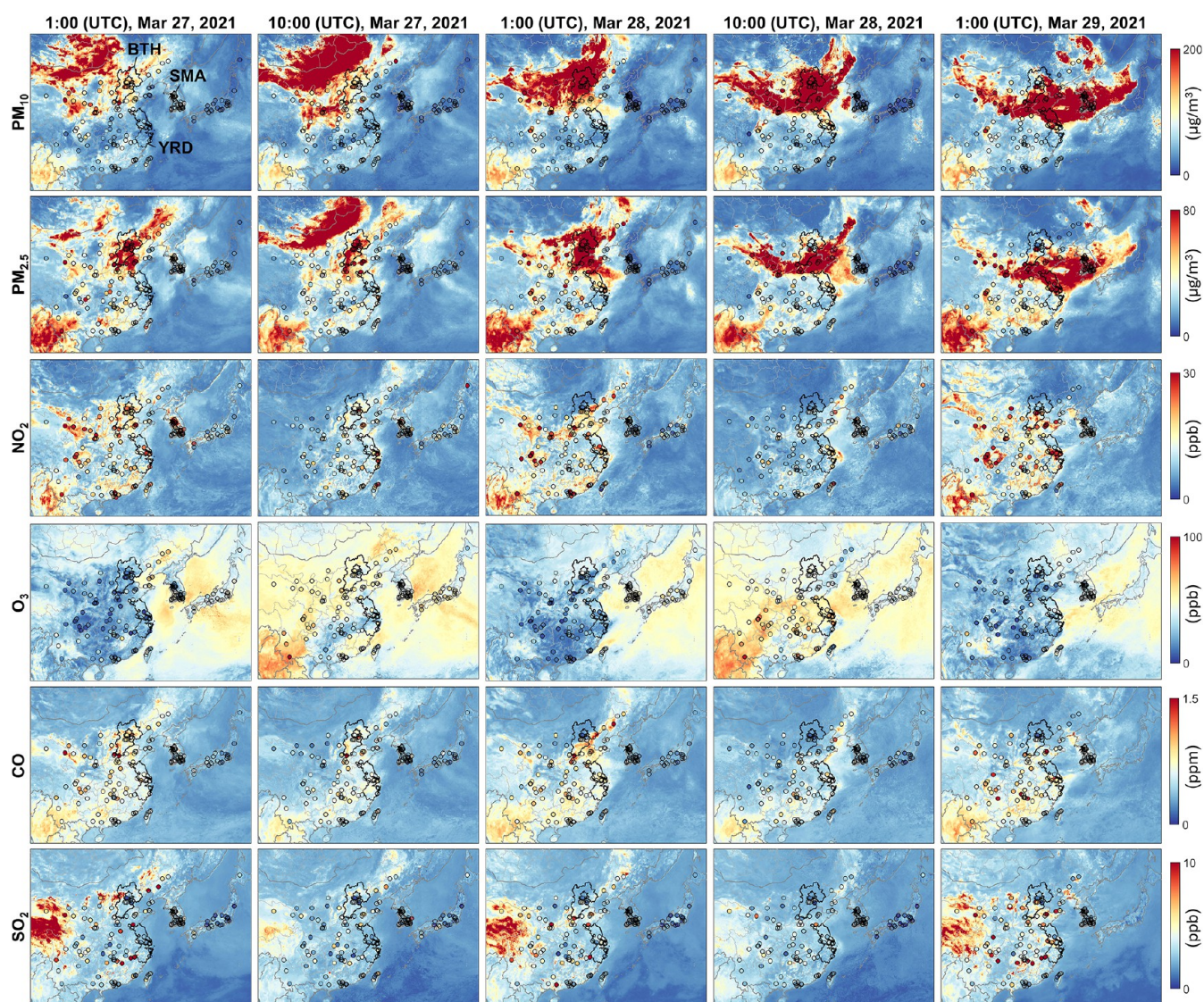


Figure 4. Hourly gapless 10-km maps (PM_{10} , $\text{PM}_{2.5}$, NO_2 , O_3 , CO , and SO_2), March 27–29, 2021. DeepMAP-derived hourly concentration maps of multiple air pollutants at a 10-km spatial resolution over East Asia during the high-concentration episode from March 27–29, 2021. From top to bottom, the maps show PM_{10} , $\text{PM}_{2.5}$, NO_2 , O_3 , CO , and SO_2 . The colored scatters indicate the observed surface-level concentrations of the six pollutants measured at unseen ground-based stations. The bold boundaries indicate the major regions, including BTH, YRD, and SMA regions, in East Asia.

(Figure 6), closely aligning with short-term co-exposure hotspots (Figure 5). Spatial autocorrelation was strong (Moran's $I = 0.73$, $p < 0.001$). The North China Plain and East China exhibited the highest co-exposure index values (0.88 and 0.64), respectively. In the North China Plain, annual means exceeded L-IT1 for PM_{10} , $\text{PM}_{2.5}$, and O_3 and L-IT2 for NO_2 , indicating substantial potential for chronic health impacts. East China and South Korea also showed elevated co-exposure (≈ 0.53), driven primarily by NO_2 levels ≈ 0.07 above the East Asian mean, consistent with dense population and built-up land cover (Figure S20). Japan displayed NO_2 and O_3 exposure comparable to regional levels, suggesting the continued need for NO_2 and O_3 controls, while PM exposures remained relatively low.

Linking hotspots to sources, we analyzed spatial associations with 11 sectors from the Emission Database for Global Atmospheric Research of the European Commission. Power generation and industry showed the strongest positive

association ($R = 0.56$), with the highest spatially adjusted coefficient ($\beta = 0.036$) and the lowest spatial dependence ($\rho = 0.51$) after accounting for spatial autocorrelation (Table S14). Solid waste incineration and agricultural burning ($R = 0.54$; $\beta = 0.035$; $\rho = 0.52$), and road transport ($R = 0.51$; $\beta = 0.032$; $\rho = 0.55$) followed. Refining power generation with the Global Power Plant Database (11 fuel types), coal-fired capacity exhibited the strongest and statistically significant spatial correlation ($R = 0.53$; $\beta = 0.033$; $\rho = 0.53$), implicating coal combustion as the dominant driver of regional co-exposure hotspots (Table S15).

4. DISCUSSION

4.1. Hourly Monitoring Protocol and Modeling Approach

We developed DeepMAP, a deep learning-based framework that estimates hourly concentrations of multiple air pollutants by fusing satellite observations, CTM outputs, and auxiliary predictors. Prior efforts have largely targeted single pollutant

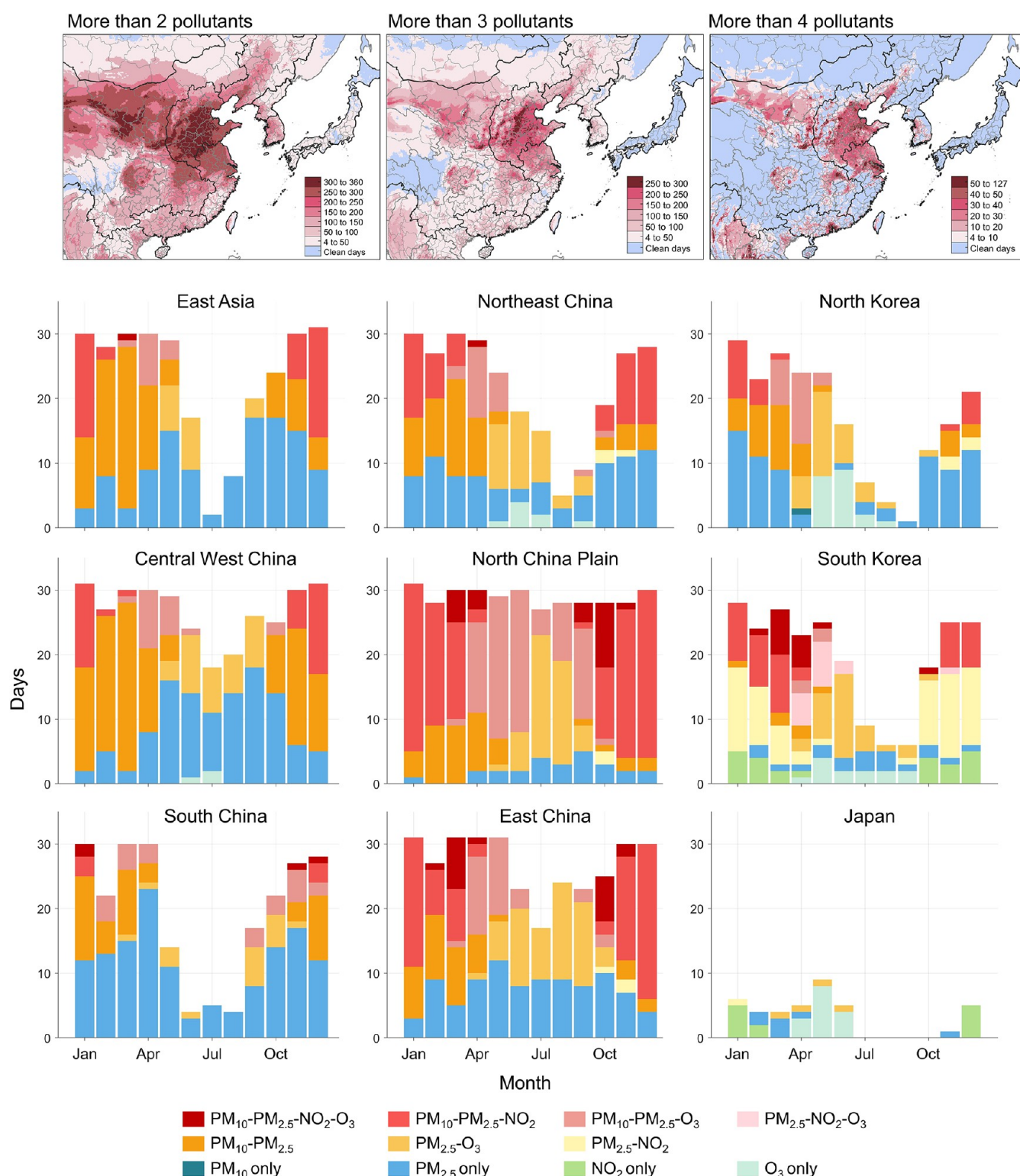


Figure 5. Annual mean co-exceedance days (2021–2023) and monthly composition by sub-region using population-weighted concentrations. Co-exceedance days for multiple air pollutants, averaged annually during 2021–2023, exceeding the WHO S-AQG for each pollutant. The composition of monthly co-exceedance days is calculated using population-weighted concentration averaged over Northeast China, Central West China, North China Plain, South China, East China, North Korea, South Korea, and Japan.

or pairs (e.g., $\text{PM}_{2.5}\text{-O}_3$ and $\text{PM}_{10}\text{-PM}_{2.5}$) and specific emission hotspots (e.g., BTH, YRD, and inland China) and have typically operated at a daily cadence.^{25,26,44–50} As a result, they have been limited in probing inter-pollutant interactions and broader applications. By contrast, DeepMAP generates spatially

continuous, sub-national maps of six pollutants at hourly resolution through three complementary architectures—multi-task, multi-branch, and ConvLSTM-ResNet—that jointly capture nonlinear temporal-spatial dependencies. This design enables seamless gap-filled monitoring, even when satellite

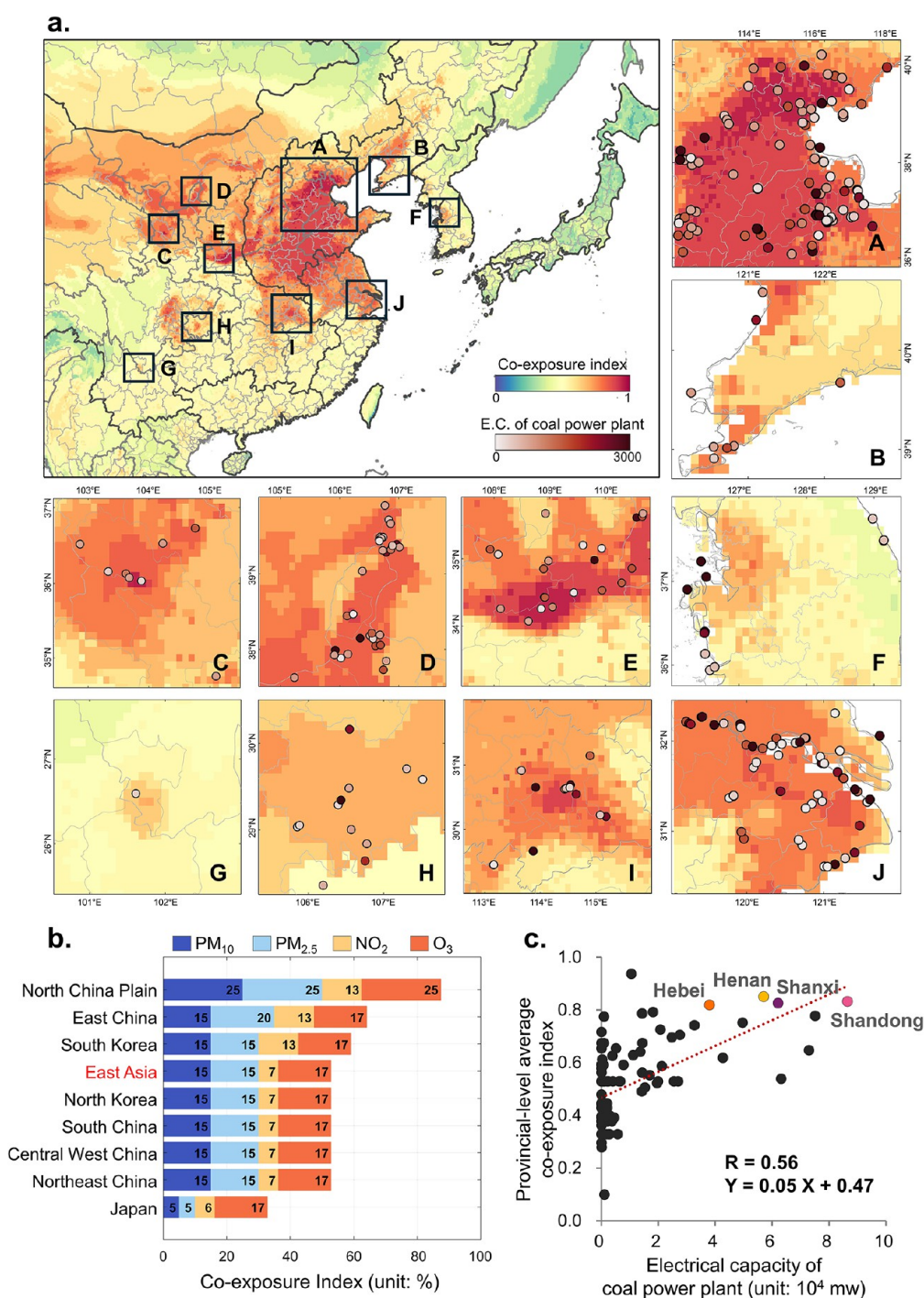


Figure 6. Spatial map for long-term co-exposure to air pollutants and their relationship with coal power plants. (a) Long-term co-exposure index (WHO L-AQG to L-ITs); summary statistics in Table S16; inset highlights severe clusters and coal power plant locations/capacity. (b) Index composition by sub-region (relative contributions of PM₁₀, PM_{2.5}, NO₂, and O₃). (c) Provincial co-exposure index versus coal power plant capacity. Individual pollutant exposure maps are provided in Figure S21.

inputs are missing. The resulting fields reveal evolving dust sources and delineate areas of pronounced short- and long-term co-exposure.

DeepMAP is well suited to diagnose hourly variability arising from both natural and anthropogenic drivers. Our analysis highlights frequent high-concentration episodes in China and transboundary transport into South Korea.^{57,58} As Gu and Yim (2016) emphasized, the public health burden of transboundary pollution can rival that of major behavioral risk factors,⁵⁷

underscoring the need for coordinated national and regional policies. Beyond land, sparse coastal monitoring has historically necessitated CTMs for marine applications; yet DeepMAP outperformed CAMS at unseen shoreline stations (Table S17), suggesting value for deposition-driven marine ecosystem studies involving oxidized and reduced nitrogen.^{59,60}

4.2. Quantifying Exposure to Multiple Air Pollutants

Despite recent regional improvements in air quality,^{61,62} we find pronounced spatial inequities in multi-pollutant exposure across

520 regions in 11 East Asian countries (2021–2023). Long-standing industrial hubs—Hebei, Shandong, and Henan—stand out as persistent clusters, reflecting heavy-industry footprints (e.g., steel and cement) and investment patterns prioritizing local economic output.^{63,64} Ongoing “dual-carbon” actions in China—electrification, expansion of renewables, and capacity controls—aim at peaking carbon by 2030 and neutrality by 2060.⁶⁵ DeepMAP’s granular co-exposure maps support multi-pollutant mitigation strategies under these policies beyond what is captured by traditional air quality indices.

Control strategies should address the joint adverse associations of PM_{2.5} (as the main contributor) with co-occurring pollutants such as PM₁₀, NO₂, and O₃. Recent multi-pollutant epidemiological studies have reported monotonically increasing exposure–response relationships for non-accidental and cause-specific mortality under joint exposure to multiple pollutants.^{2,66–68} For example, Huang et al. (2023) developed a weighted environmental risk score (WERS) integrating PM_{2.5}, NO₂, and O₃ and reported hazard ratios of 1.186 (95% confidence interval: 1.118–1.259), 1.248 (1.042–1.496), and 1.173 (1.083–1.270) for non-accidental, cardiovascular disease, and cancer mortality, respectively, per SD increase in WERS.⁶⁶ It should be noted, however, that the epidemiological estimates of Huang et al. (2023) were derived from long-term annual mean exposures, whereas DeepMAP generates hourly concentrations aggregated to diverse temporal scales. Due to these conceptual and methodological differences in exposure metrics (e.g., WERS), direct numerical comparisons with previous cohort studies should be interpreted with caution.

Although the co-exposure index proposed here does not aim to infer synergistic or antagonistic health effects, the resulting spatially resolved diagnostics identify priority areas and pollutant combinations (including ≥ 2 co-occurring species) that warrant season- and region-specific interventions. In practice, dominant pollutant mixtures vary substantially across months and regions; effective policy design should therefore be composition-aware rather than pollutant-agnostic.

4.3. Limitations and Future Directions

Performance for SO₂ was comparatively lower, likely reflecting the dominance of sparse point-source emissions and weak column-surface coupling, which constrain the ability of gridded predictors to represent surface SO₂ variability.^{69,70} Incorporating physics-guided features—e.g., point-source plume indicators and boundary-layer dynamics—may improve realism. In addition, the SPCV results should be interpreted as conservative estimates, as relatively higher nRMSE values are observed in regions with sparse air quality monitoring (Figure S22). Future work could explicitly account for spatial autocorrelation in air quality fields within station-sparse regions and evaluate more expressive spatiotemporal learning frameworks (e.g., SimVP and diffusion models) to further enhance spatial detail.⁷¹ Although DeepMAP provides day–night fields, nighttime skill is constrained by the absence of GEMS; integrating geostationary thermal imagery (e.g., Himawari brightness temperatures) could strengthen nocturnal estimates.⁷²

Two additional caveats warrant mention. First, our exposure assessment assumes uniform exposure within each grid, ignoring human mobility and time-activity patterns (indoors vs outdoors). Second, although WHO air quality thresholds provide a harmonized public health benchmark for cross-regional exposure assessment, health risk estimation based on these thresholds does not yet account for heterogeneity in population

vulnerability (e.g., age, socioeconomic status) or region-specific concentration–response functions. Nevertheless, mitigation efforts in the identified hotspots are expected to yield substantial risk reductions. Future analyses should integrate vulnerability-weighted population surfaces, subgroup-specific response functions, and—where data permit—extend the record prior to 2021 to examine long-term trends in multi-pollutant co-exceedances and their public health impacts.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at <https://pubs.acs.org/doi/10.1021/acs.est.5c15772>.

Additional descriptions of the study area, datasets, preprocessing, and model configurations; sensitivity analyses of input sequence length, cloud cover, and distances between training and separate test stations; extended model validation results stratified by geographic region, terrain, pollution level, and coastal proximity; supplementary spatial and temporal distributions of hourly patterns and seasonal and annual Stage 1 and Stage 2 air pollutant estimates and their differences; and additional analyses of co-exposure indices and emission source-based statistical relationships (PDF)

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Notes

The authors declare no competing financial interest.

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NOTE ADDED AFTER ASAP PUBLICATION

Due to a production error, the version of this paper that was published ASAP March 20, 2026, included an error in the Conflict of Interest statement. 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, and the corrected version was posted March 23, 2026.



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Supporting Information of

Quantifying multi-pollutant co-exposure via deep learning-based simultaneous prediction using geostationary satellite data

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Summary: 50 Pages, Text A and B, 22 Supplementary Figures, and 17 Supplementary Tables

Supplementary Text

A Supplement: Dataset

A.1 GEMS satellite data

The present study proposes a framework for generating seamless spatial distributions of multi-air pollutants over the spatial coverage of the GEMS satellite sensor, launched in February 2020 (1). GEMS is the first geostationary satellite sensor with UV-visible hyperspectral channels to monitor aerosols and gaseous substances across East Asia, where air pollution is severe. GEMS observes air quality with multiple scanning modes (i.e., Half East, Half Korea, Full Central, and Full West) up to 10 times a day (08:00–17:00, South Korea’s local time) at a nominal spatial resolution of $3.5 \text{ km} \times 8 \text{ km}$.

This study used various types of aerosol information and viewing geometry to examine the association between ground-based air pollutants and scattering and absorbing aerosols in the model: AOD at 354, 443, 500 nm, aerosol layer height, aerosol index, solar zenith angle, and relative azimuth angle. Considering the difference in spectral absorption intensities for each air pollutant, normalized radiance data at six wavelengths (354, 388, 412, 443, 477, and 490 nm) were used. To represent the wide spatial distribution of gaseous substances, we used the tropospheric and total vertical column density (VCD) products of NO_2 and O_3 . For quality assurance of the GEMS products, this study applied the “good” flag in the VCD NO_2 product and used four filtering steps recommended as good quality in the O_3 profile product (i.e., $\text{ProcessingQualityFlag} = 0$, $\text{RootMeanSquareErrorOfFit} < 3$, $\text{EffectiveCloudFractionUV} < 0.8$, and $\text{SolarZenithAngle} < 70$).

A.2 CAMS CTM data

CAMS forecasts were used to obtain spatially continuous atmospheric information. Among several operational CTMs, CAMS forecasts were selected because they provide hourly total column density of air pollutants and aerosols at a relatively fine-scale spatial resolution (40 km),

covering the entire study area. CAMS forecasts produce atmospheric information using a 4D-VAR data assimilation process, which combines a previous forecast with satellite observations of AOD and various air pollutants for the initial condition. CAMS provides a five-day forecast of global atmospheric composition twice a day at 00:00 and 12:00 (UTC). We used 11 atmospheric variables from CAMS at the announcement time closest to the corresponding time when estimating air pollutants: AOD at 469, 550, 670, 865, and 1240 nm, and the total column density of PM₁₀, PM_{2.5}, NO₂, O₃, CO, and SO₂.

A.3 KIM numerical model data

The study used the KIM to reflect the meteorological conditions for air pollutant estimation. KIM is a numerical weather forecasting model operated by the Korea Meteorological Administration (KMA) (2). The KIM system provides approximately 50 forecast products, assimilating various measurement data with the initial condition based on an advanced hybrid 4D ensemble variation. The KIM products have a detailed horizontal spatial resolution of 12 km at a global scale and 90 layers (~ 80 km) in the vertical direction, updated every 6 h at 00:00, 06:00, 12:00, and 18:00 UTC. This study used seven meteorological variables from the KIM products of the 18:00 UTC forecast field, which is close to the GEMS observing time. We selected the input variables based on previous studies (3, 4). Additionally, the accumulated maximum wind speed data for the past 1, 3, 5, and 7 d were calculated using maximum wind speed information to reflect the long-term dispersion of air pollutants⁴.

B Supplement: Model Framework

B.1 Details in a multi-tasking learning approach

The bi-LSTM model, a type of LSTM, is designed to handle sequential information in both forward and backward orientations from input data. This technique utilizes dual LSTM layers to

process forward and backward sequences concurrently, enabling it to grasp the context from both previous and upcoming time steps. Bi-LSTM has gained widespread adoption by providing a deeper understanding of the input sequence, outperforming traditional time series-based deep learning approaches in environmental fields (5–7).

A 1D CNN is a variant of the vanilla CNN that enables the extraction of various features using multiple one-dimensional filters. Compared to standard fully connected neural networks, 1D CNNs extract local features through convolutional operations using a sliding window technique. This technique allows the network to focus on local details and effectively extract relevant information. Thus, 1D CNNs are commonly used for collecting features from one-dimensional data in various applications, such as speech recognition and sensor data processing (6–7). In the present study, we utilized this structure to extract the spatial features associated with air quality and its sources.

B.2 Details in the developed model for detailed full-coverage air pollutant maps

ConvLSTM is an effective structure that combines the advantages of CNN and LSTM to capture both time-series patterns and spatial information. This model includes the memory cells and three gates of LSTM but overcomes the major limitations of LSTM, namely the loss of spatial information, through its space-time structure. Owing to these advantages, ConvLSTM has been used for remote sensing studies and has shown promising results (8–9).

To improve the generalization of the full-coverage model, the overall loss function (Eq (3)) is composed of equally weighted structure and content loss terms, consisting of mean absolute error (MAE) (Eq (4)) and the structural similarity index measure (SSIM) (Eq (5)). SSIM is a popular error term used to evaluate models based on the structural similarities of a prediction. This

combination of multiple loss terms ensures consistency in structure and content between the predicted and reference images, respectively. To better reflect the detailed spatial patterns of the Stage 1 GEMS model, we randomly erased 32×32 patches from a map of the Stage 1 GEMS model and added loss terms ($MSE_{clear_{masked}}, 1 - SSIM_{clear_{masked}}$) between the erased and the predicted images (Eq (3)).

To further preserve fine-scale spatial structures in the reconstructed maps, we introduced an edge-aware gradient loss based on the Sobel operator. Specifically, spatial gradients for both the predicted and reference images were computed using Sobel filters, and a gradient consistency loss was imposed to align the predicted gradients with those of the reference images (Eq (7)). This term helps maintain sharp transitions and spatial boundaries that are often smoothed when optimizing solely with pixel-wise losses.

In addition, an edge-weighted reconstruction loss was applied to emphasize regions with prominent spatial gradients. The weighting factor was derived from the normalized gradient magnitude of the reference images, ensuring that pixels near edges contribute more strongly to the total loss (Eq (6) – (8)).

Because the clear and cloudy reference maps may exhibit discrepancies in certain regions, we further introduced a discrepancy-aware attenuation weight (Eq (9)). This term reduces the influence of edge-based losses in regions where the clear and cloud targets differ substantially, thereby preventing the model from overfitting to inconsistent spatial signals.

$$Loss_{base} = MAE_{clear} + MAE_{clear_{masked}} + MAE_{cloudy} + (1 - SSIM_{clear}) + (1 - SSIM_{clear_{masked}}) + (1 - SSIM_{cloudy}) \quad (3)$$

$$MAE = \sum_{j=1}^n |\hat{y}_j - y_j| \quad (4)$$

$$SSIM = \frac{(2\mu_{\hat{y}}\mu_y + C_1)(2\sigma_{\hat{y}y} + C_2)}{(\mu_{\hat{y}}^2 + \mu_y^2 + C_1)(\sigma_{\hat{y}}^2 + \sigma_y^2 + C_2)} \quad (5)$$

$$Loss_{edge} = \frac{1}{n} \sum_{j=1}^n w_j^{clear} |\hat{y}_j - y_j^{clear}| + \frac{1}{n} \sum_{j=1}^n w_j^{cloudy} |\hat{y}_j - y_j^{cloudy}| \quad (6)$$

$$Loss_{gradient} = \frac{1}{n} \sum_{j=1}^n w_j^{clear} |\nabla \hat{y}_j - \nabla y_j^{clear}| + \frac{1}{n} \sum_{j=1}^n w_j^{cloudy} |\nabla \hat{y}_j - \nabla y_j^{cloudy}| \quad (7)$$

$$w_j^{clear} = \frac{|\nabla y_j^{clear}|}{mean(|\nabla y_j^{clear}|)} \times Mask_{clear} \times w_{discrepancy} \quad (8a)$$

$$w_j^{cloudy} = \frac{|\nabla y_j^{cloudy}|}{mean(|\nabla y_j^{cloudy}|)} \times Mask_{cloudy} \times w_{discrepancy} \quad (8b)$$

$$w_{discrepancy} = Sigmoid\left(-(|y_j^{clear} - y_j^{cloudy}| - median(|y_j^{clear} - y_j^{cloudy}|)) \times \frac{1}{20}\right) \quad (9)$$

$$Loss_{total} = Loss_{base} + \lambda_{edge} \times Loss_{edge} + \lambda_{gradient} \times Loss_{gradient} \quad (10)$$

where $\hat{y}$ is the predicted value (full-coverage results), y is the reference value (Stage 1 GEMS, masked Stage 1 GEMS, Stage 1 NonGEMS), n is the sample size, μ and σ are the average and variance, respectively, and C_1 and C_2 are the constants that stabilize the denominator. $Mask_{clear}$

indicates the cloud-free region, whereas Mask_{cloudy} represents the region covered by clouds. ∇y denotes the spatial gradient computed using the Sobel operator. λ_{edge} and $\lambda_{gradient}$ denote weighting coefficients controlling the contributions of the edge (0.2) and gradient (0.1) losses, respectively.

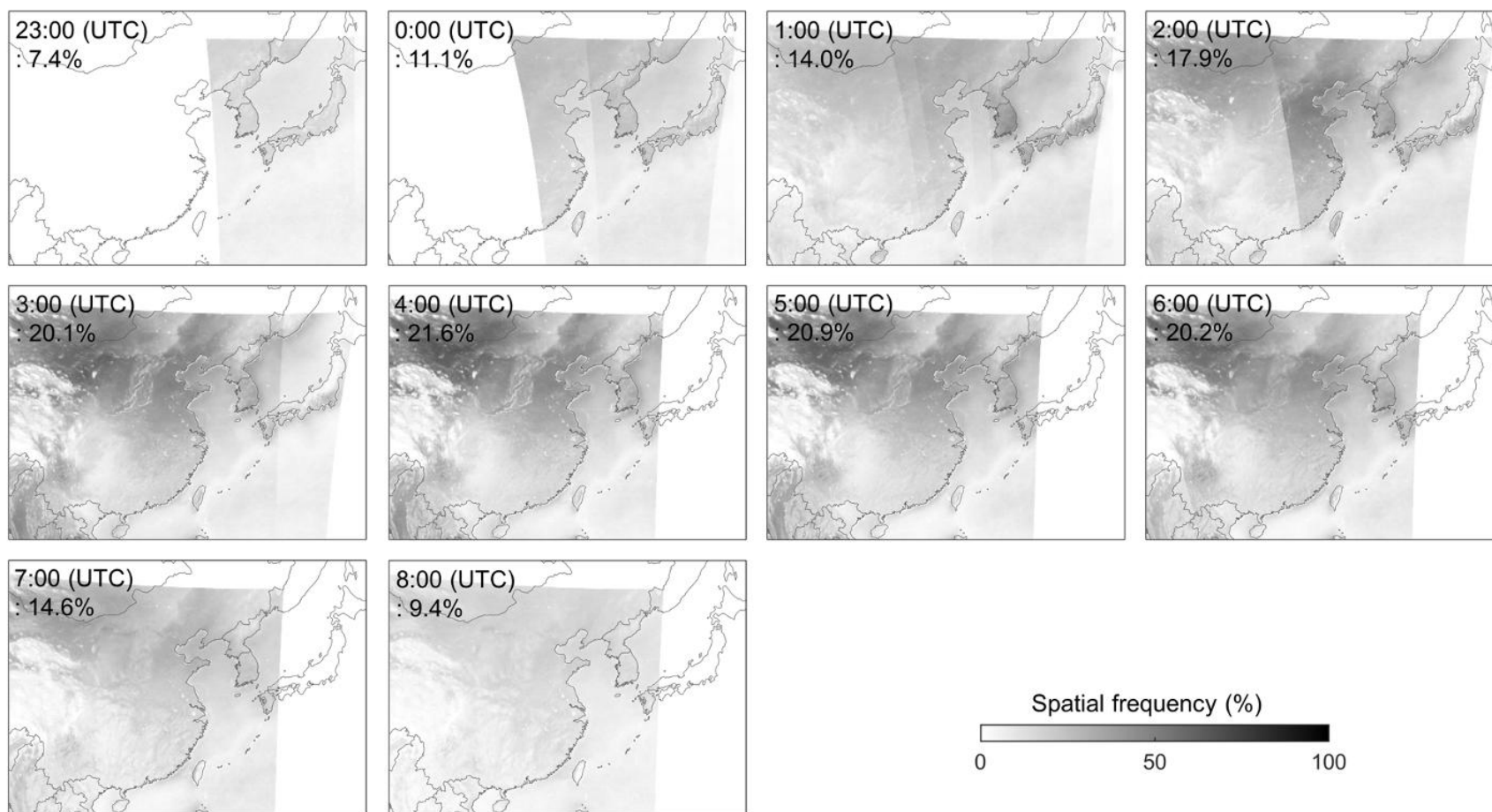


Fig. S1 Hourly spatial frequency of Stage 1 GEMS outputs during 2021–2023.

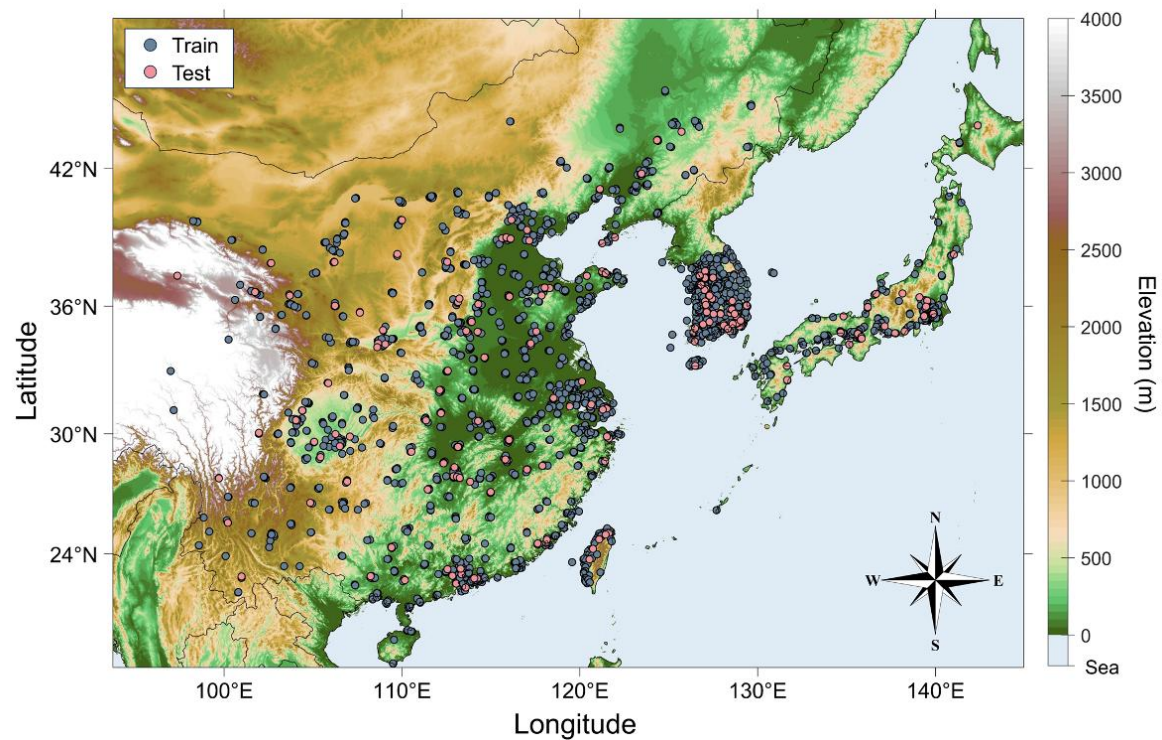


Fig. S2 Study area with ground observation stations in East Asia. The background image represents the elevation (m) derived from SRTM DEM. Blue indicates the sites used for training and spatial 10-fold validation, and pink dots indicate a separate test set (10% of the total stations).

Table S1. Summary of input and target variables of Stage 1 GEMS and NonGEMS models and Stage 2 model for estimating multiple ground-level air pollutants.

Data category	Variables	Abbreviation	Spatial Resolution	Temporal Resolution
Stage 1 - Input data				
GEMS	Aerosol Optical Depth 354, 443, Aerosol Layer Height	AOD 354, 443, 500 nm ALH	3.5 km × 8 km aerosol	6–10 times
	Normalized Radiance 354, 388, 412, 433, Ultraviolet Aerosol Index	NR 354, 388, 412, 433, 477, 550 nm UVAI		
	Visible Aerosol Index	VISAI		
	Aerosol Layer Height	ALH		
	Cloud Fraction	CF		
	Relative Azimuth Angle	RAA		
	Solar Azimuth Angle	SAA		
	NO ₂ Vertical Column Density (total and troposphere)	NO2T TropNO2	7 km × 8 km gaseous	
	O ₃ Vertical Column Density	O3T		
	O ₃ Profile (the lowest layer)	LowO3	28 km × 32 km gaseous	
CAMS global atmospheric composition forecast	Aerosol Optical Depth 469, 550, 670, 865, 1240 nm	AOD 469, 550, 670, 865, 1240 nm_CAMS	40 km × 40 km	hourly
	PM ₁₀	PM ₁₀ _CAMS		
	PM _{2.5}	PM _{2.5} _CAMS		
	total column NO ₂	NO ₂ _CAMS		
	total column O ₃	O ₃ _CAMS		
	total column CO	CO_CAMS		

	total column SO ₂	SO ₂ _CAM5		
KIM	Temperature	Temp	12 km × 12 km	3-hour
	Dewpoint	Dew		
	Temperature			
	Relative Humidity	RH		
	Surface Pressure	Psrf		
	Planetary Boundary Layer	PBLH		
	Wind speed (gust) (3-hour	MaxWS		
	Stack 3-hour precipitation	AP3h		
	Accumulated maximum wind	stack1, 3, 5, 7_maxWS		
VIIRS	Normalized Difference	NDVI	1 km × 1 km	16-day
SRTM	Digital Elevation Model	DEM	90 m	-
GHSL	Built-up ratio	Built	1 km × 1 km	5 year
GPWv4	Population Density	PopDens	30 arc	5 year
GLOBIO	Road Density	RoadDens	8 km × 8 km	-
-	Day of Year	DOY	-	-

Stage 1 - Target data

AirKorea (South Korea)				
BMEMC (China)	PM ₁₀ , PM _{2.5} , NO ₂ , O ₃ , SO ₂ , CO	PM ₁₀ , PM _{2.5} , NO ₂ , O ₃ , SO ₂ , CO	Point-based format	hourly
MOENV (Taiwan)				
NIES (Japan)				

Stage 2 – Input data

Stage 1 GEMS estimation maps	Stage 1 GEMS	Hourly
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Stage 1 NonGEMS estimation maps	PM ₁₀ , PM _{2.5} , NO ₂ , O ₃ , SO ₂ , CO	Stage 1 NonGEMS	10 km (cropped 64×64 pixels)	(4-h interval)
Stage 2 – Output data				
-	PM ₁₀ , PM _{2.5} , NO ₂ , O ₃ , SO ₂ , CO	Stage 2	10 km (64×64 pixels)	Hourly (4-h interval)

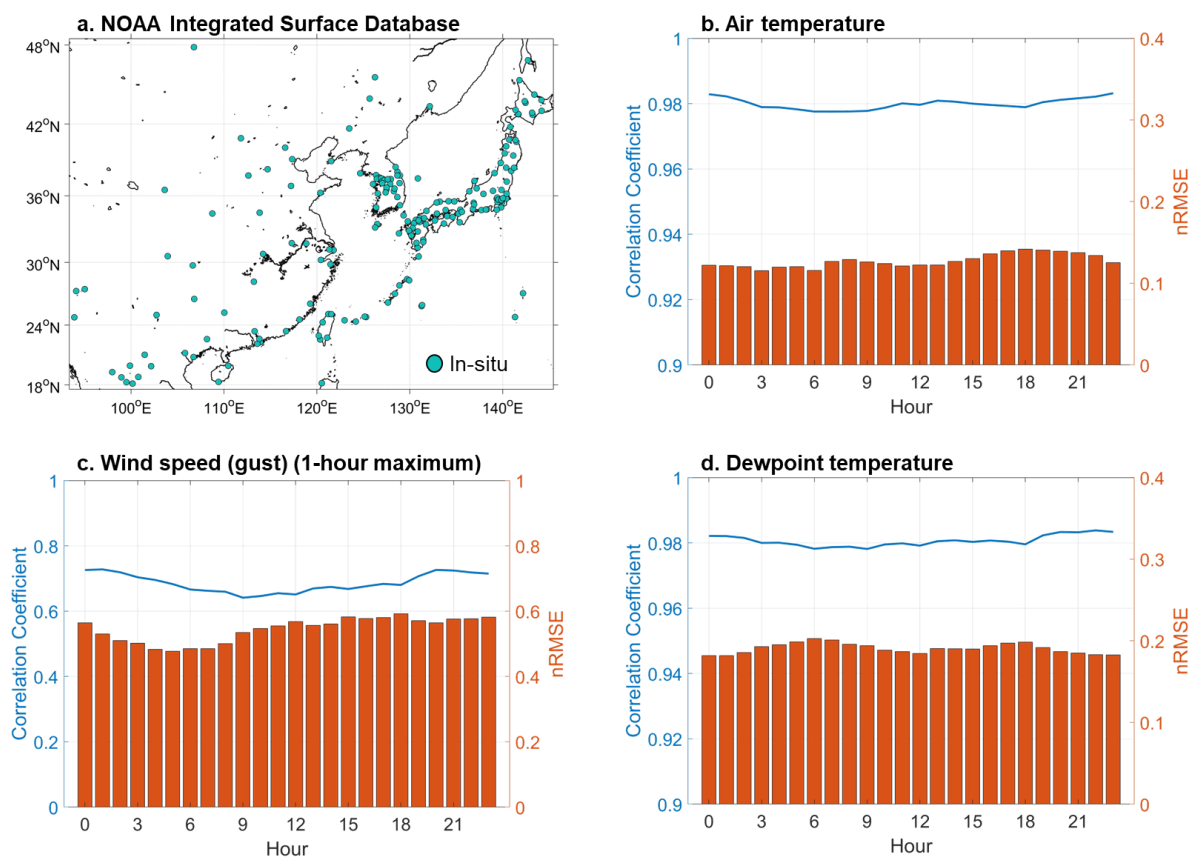


Fig. S3 (a) Spatial distribution of in-situ observation sites from the Integrated Surface Database (ISD), a global dataset that provides hourly and synoptic surface observations provided by NOAA (www.ncei.noaa.gov/products/land-based-station/integrated-surface-database). (b–d) Bar and line graphs for the evaluation of time interpolation for KIM-derived air temperature, dewpoint temperature, and wind speed (gust) using ISD observations during 2021. Since wind speed (gust) is not directly available in ISD, we indirectly validated the interpolated wind speed (gust) using the available hourly wind speed.

Table S2. Summary of the preprocessing method of input and target variables

Data source	Spatial preprocessing	Temporal preprocessing
GEMS (only O ₃ profile)	Bilinear interpolation (Spline interpolation)	-
KIM	Bilinear interpolation	Linear interpolation
CAMS	Spline interpolation	-
VIIRS	Bilinear interpolation	-
SRTM	Bilinear interpolation	-
GHSL	Bilinear interpolation	
GPWv4	Line Density function (ArcGIS)	
GLOBIO	Bilinear interpolation	

Table S3. Sample sizes before and after stratified random subsampling by pollutant and month for each air pollutant. Low, medium, and high ranges indicate below (mean + standard deviation [SD]), between (mean + SD) and (mean + 2SD), and above (mean + 2SD), respectively.

	Range	Before subsamples	After subsamples	Retention (%)
PM ₁₀	low	30,509,175	1,786,231	5.9
	medium	3,236,652	193,138	6.0
	high	1,380,906	86,371	6.3
	total	35,126,733	2,065,740	5.9
PM _{2.5}	low	30,112,688	1,761,187	5.8
	medium	3,513,649	210,297	6.0
	high	1,500,396	94,256	6.3
	total	35,126,733	2,065,740	5.9
NO ₂	low	29,884,101	1,750,544	5.9
	medium	3,653,555	217,789	6.0
	high	1,589,077	97,407	6.1
	total	35,126,733	2,065,740	5.9
O ₃	low	29,371,286	1,726,477	5.9
	medium	4,584,389	269,374	5.9
	high	1,171,058	69,889	6.0
	total	35,126,733	2,065,740	5.9
CO	low	30,079,837	1,753,928	5.8
	medium	3,742,429	219,447	5.9
	high	1,304,467	92,365	7.1
	total	35,126,733	2,065,740	5.9
SO ₂	low	30,964,008	1,815,956	5.9
	medium	2,868,629	170,086	5.9
	high	1,294,096	79,698	6.2
	total	35,126,733	2,065,740	5.9

Table S4. Statistics from the separate test for the proposed case (Stage 1 GEMS), which include GEMS products, and the single-target estimation model (Single), which are developed separately for each of the six air pollutants using the same multi-branch and shared structures using the equivalent input dataset (sample size= 186,828).

Air pollutants	PM₁₀ (μg/m³)		PM_{2.5} (μg/m³)		NO₂ (ppb)		O₃ (ppb)		CO (ppm)		SO₂ (ppb)	
	Stage 1 GEMS	Single	Stage 1 GEMS	Single	Stage 1 GEMS	Single	Stage 1 GEMS	Single	Stage 1 GEMS	Single	Stage 1 GEMS	Single
R²	0.88	0.85	0.86	0.86	0.76	0.75	0.90	0.91	0.57	0.54	0.42	0.31
RMSE	23.6	25.5	10.9	10.8	4.5	4.6	7.2	6.9	0.21	0.22	2.5	2.7
nRMSE	0.35	0.38	0.34	0.34	0.34	0.35	0.16	0.15	0.41	0.42	0.64	0.70
MBE	-1.3	-2.1	-1.3	-1.2	-0.5	-0.4	0.1	-0.1	-0.02	-0.02	-0.2	-0.3
nMBE	-0.02	-0.03	-0.04	-0.04	-0.04	-0.03	0.00	0.00	-0.03	-0.03	-0.05	-0.06

Table S5. Statistics from the separate test for the proposed case (Stage 1 NonGEMS), which excludes GEMS products, and the single-target estimation model (Single), which are developed separately for each of the six air pollutants using the same multi-branch and shared structures using the equivalent input dataset (sample size = 232,230).

Air pollutants	PM₁₀ (μg/m³)		PM_{2.5} (μg/m³)		NO₂ (ppb)		O₃ (ppb)		CO (ppm)		SO₂ (ppb)	
Model	Stage 1 NonGEMS	Single	Stage 1 NonGEMS	Single	Stage 1 NonGEMS	Single	Stage 1 NonGEMS	Single	Stage 1 NonGEMS	Single	Stage 1 NonGEMS	Single
R²	0.76	0.74	0.78	0.78	0.60	0.59	0.76	0.78	0.49	0.46	0.24	0.16
RMSE	26.1	26.6	13.2	12.9	6.3	6.3	10.6	9.7	0.21	0.22	2.2	2.4
nRMSE	0.54	0.55	0.5	0.49	0.49	0.5	0.33	0.3	0.43	0.44	0.79	0.83
MBE	-1.7	-1.5	-1.3	-1.2	-0.4	-0.7	-1.4	0.2	-0.01	0	-0.1	-0.1
nMBE	-0.04	-0.03	-0.05	-0.05	-0.03	-0.06	-0.04	0.01	-0.03	0	-0.04	-0.05

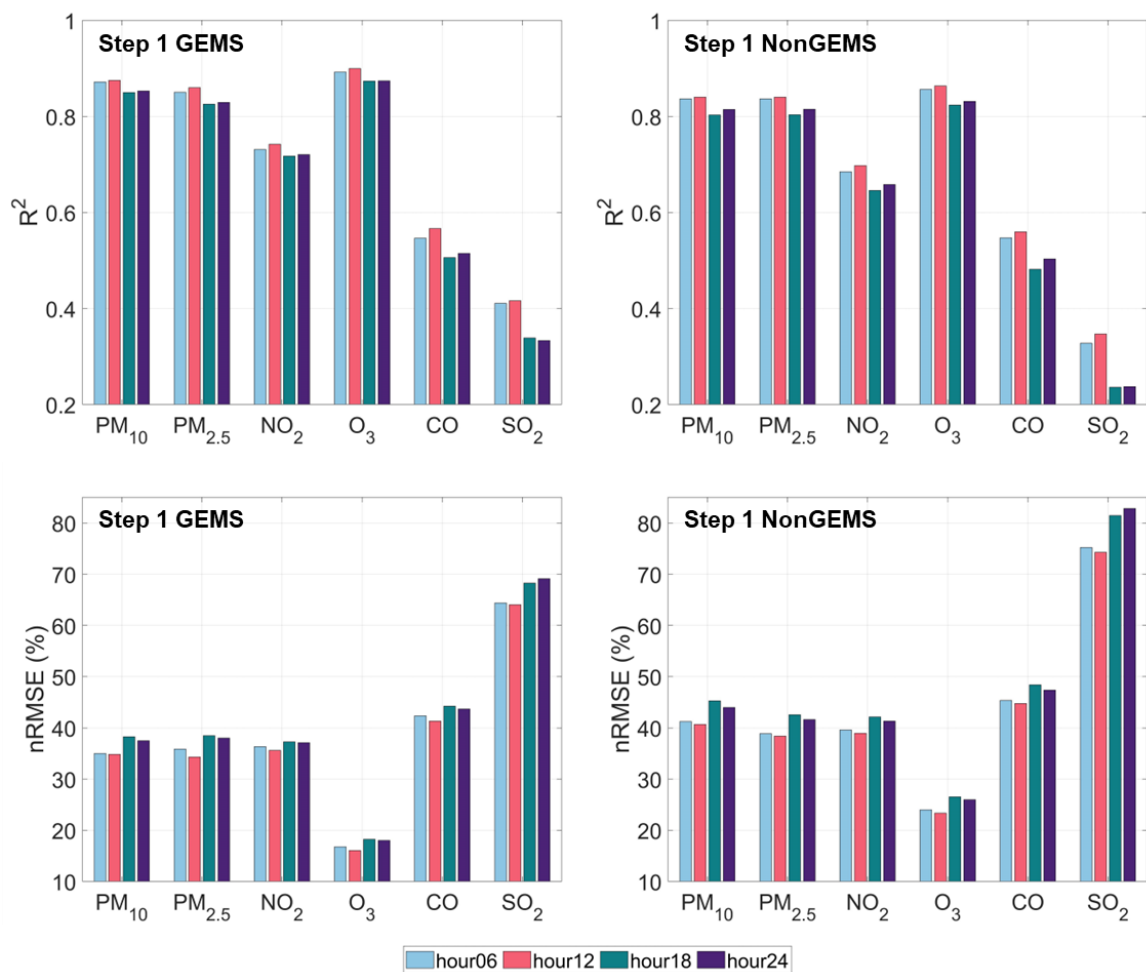


Fig. S4 Comparison of Stage 1 model results for four input sequence lengths (6, 12, 18, and 24 h) using a Bi-LSTM. Here, we calculated results using the daytime dataset to compare Stage 1 GEMS and NonGEMS models.

Table S6. Statistics from the separate test for the proposed structure (Stage 1 GEMS), which include GEMS products, the same proposed structure without multibranch structures (No-Multibranch) and Multioutput random forest (MultiRF), which are suggested by Yang et al. (2023a) and Yang et al. (2023b) (10, 11), respectively, using the equivalent input dataset (sample size = 188,279).

Air pollutants	PM ₁₀ (µg/m ³)			PM _{2.5} (µg/m ³)			NO ₂ (ppb)		
	Stage 1 GEMS	No- Multibranch	MultiRF	Stage 1 GEMS	No- Multibranch	MultiRF	Stage 1 GEMS	No- Multibranch	MultiRF
R²	0.87	0.86	0.82	0.86	0.84	0.81	0.74	0.73	0.70
RMSE	23.5	24.2	28.9	10.8	11.4	12.8	4.8	4.9	5.2
nRMSE	0.35	0.36	0.43	0.34	0.36	0.41	0.36	0.37	0.39
MBE	-1.4	-1.5	-0.3	-1.3	-0.4	-0.3	-0.6	-0.2	-0.4
nMBE	-0.02	-0.02	0.00	-0.04	-0.01	-0.01	-0.05	-0.02	-0.03
Air pollutants	O ₃ (ppb)			CO (ppm)			SO ₂ (ppb)		
	Stage 1 GEMS	No- Multibranch	MultiRF	Stage 1 GEMS	No- Multibranch	MultiRF	Stage 1 GEMS	No- Multibranch	MultiRF
R²	0.90	0.88	0.87	0.57	0.53	0.51	0.42	0.36	0.37
RMSE	7.3	7.9	8.8	0.2	0.2	0.2	2.5	2.7	2.6
nRMSE	0.16	0.17	0.19	0.41	0.43	0.45	0.64	0.68	0.67
MBE	0.1	0.0	-0.2	0.0	0.0	0.0	-0.2	-0.3	0.1
nMBE	0.00	0.00	0.00	-0.03	-0.01	0.01	-0.05	-0.08	0.02

Table S7. Main software and environment for modeling DeepMAP framework.

Main software / environment	Version
Operating system	Ubuntu 22.04.2 LTS
GPU	NVIDIA GeForce RTX 3090 Ti
CUDA version	12.2
Python version	3.8.10
numpy	1.22.4
pandas	2.0.3
scikit-learn	1.1.3
torch	2.4.1
torchvision	0.19.1

Table S8. 2021 WHO guidelines for long- and short-term exposure to six air pollutants. conc. represents the concentration of each air pollutant, while increased risk indicates the percentage increase in mortality risk as pollutant concentrations rise to their respective thresholds from baseline level. L-AQG and L-IT denote the Long-term Air Quality Guideline and Interim Target defined by the WHO guidelines, while S-AQG and S-IT indicate the corresponding short-term thresholds.

Period	Level		PM ₁₀ µg/m ³	PM _{2.5} µg/m ³	NO ₂ ppb	O ₃ ppb	CO ppm	SO ₂ ppb
Annual (O ₃ for peak- season)	L-AQG	conc.	15	5	5	31	-	-
		increased risk (%)	baseline					
	L-IT4	conc.	20	10				
		increased risk (%)	2	4	-	-	-	-
	L-IT3	conc.	30	15	11			
		increased risk (%)	6	8	3	-	-	-
	L-IT2	conc.	50	25	16	36		
		increased risk (%)	14	16	6	2	-	-
	L-IT1	conc.	70	35	21	51		
		increased risk (%)	22	24	9	8	-	-
Daily average (O ₃ for MDA)	S-AQG	conc.	45	15	13	51	3	15
		increased risk (%)	baseline					
	S-IT4	conc.	50	25				
		increased risk (%)	0.2	1	-	-	-	-
	S-IT3	conc.	75	37.5				-
		increased risk (%)	1	1	-	-	-	
	S-IT2	conc.	100	50	27	61		19
		risk	2	2	2	1	-	1
	S-IT1	conc.	150	75	64	82	6	48
		increased risk (%)	4	4	7	3	6	5

Table S9. Relative risk (RR) and corresponding references (12–16), as reported by WHO 2021 for short and long-term exposure to six air pollutants (PM₁₀, PM_{2.5}, NO₂, O₃, SO₂, and CO).

Air pollutant	Short-term		Long-term	
	RR (cause)	Reference	RR (cause)	Reference
PM ₁₀	1.0041 (all-cause mortality)	Orellano et al (2020)	1.04 (all-cause non-accidental mortality)	Chen and Hoek (2020)
PM _{2.5}	1.0065 (all-cause mortality)	Orellano et al (2020)	1.08 (all-cause non-accidental mortality)	Chen and Hoek (2020)
NO ₂	1.0072 (all-cause mortality)	Orellano et al (2020)	1.02 (all-cause mortality)	Huangfu and Atkinson (2020)
O ₃	1.0043 (all-cause mortality)	Orellano et al (2020)	1.01 (all-cause mortality)	Huangfu and Atkinson (2020)
SO ₂	1.0059 (all-cause mortality)	Orellano et al (2021)	-	-
CO	1.019 (hospital admission due to myocardial infarction)	Lee et al (2020)	-	-

Table S10. Pearson correlation coefficients between all input variables of Stage 1 NonGEMS model and the six target variables (PM₁₀, PM_{2.5}, NO₂, O₃, CO, and SO₂) computed from 24-hour samples at ground-based monitoring sites during the entire study period (2021–2023).

Air pollutant	PM₁₀	PM_{2.5}	NO₂	O₃	SO₂	CO
PM ₁₀ CAMS	0.50	0.60	0.43	-0.04	0.18	0.43
PM _{2.5} CAMS	0.46	0.61	0.45	-0.07	0.17	0.45
AOD 1240 nm CAMS	0.36	0.36	0.09	0.16	0.06	0.21
SO ₂ CAMS	0.35	0.46	0.35	0.00	0.15	0.34
AOD 865 nm CAMS	0.30	0.36	0.09	0.16	0.04	0.23
AOD 670 nm CAMS	0.29	0.36	0.09	0.16	0.04	0.24
AOD 550 nm CAMS	0.28	0.37	0.09	0.16	0.04	0.24
AOD 469 nm CAMS	0.28	0.37	0.10	0.17	0.04	0.24
CO CAMS	0.24	0.41	0.21	0.01	0.03	0.32
NO ₂ CAMS	0.18	0.26	0.33	-0.09	0.05	0.23
O ₃ CAMS	0.11	0.04	0.06	0.13	0.08	-0.03
Built	0.04	0.05	0.15	-0.01	-0.04	0.04
PopDens	0.03	0.04	0.12	-0.02	-0.01	0.06
DEM	0.03	-0.01	-0.06	-0.01	0.14	0.06
RoadDens	0.01	0.01	0.10	-0.02	-0.04	0.02
stack7 maxWS	-0.01	-0.10	-0.07	0.13	-0.03	-0.13
P_srf	-0.01	0.04	0.10	-0.02	-0.13	-0.04
MaxWS	-0.02	-0.14	-0.26	0.32	-0.07	-0.18
stack5 maxWS	-0.02	-0.12	-0.09	0.12	-0.03	-0.14
stack3 maxWS	-0.04	-0.15	-0.12	0.11	-0.05	-0.16
stack1 maxWS	-0.04	-0.18	-0.20	0.13	-0.07	-0.19
PBLH	-0.07	-0.16	-0.32	0.52	-0.03	-0.17
NDVI	-0.09	-0.09	-0.11	0.01	-0.05	-0.04
AP3h	-0.11	-0.10	-0.08	-0.02	-0.06	-0.04
Temp	-0.20	-0.25	-0.30	0.37	-0.14	-0.18
RH	-0.22	-0.03	-0.02	-0.40	-0.17	0.03
DOY	-0.27	-0.34	-0.32	0.24	-0.12	-0.23
Dew	-0.28	-0.24	-0.27	0.16	-0.20	-0.14

Table S11. Model performance evaluation of Stage 1 GEMS and NonGEMS models. Average and standard deviation of model accuracies (R^2 and nRMSE) from 11 folds, including 10-fold SPCV and a separate test.

Air Pollutant		PM ₁₀	PM _{2.5}	NO ₂	O ₃	CO	SO ₂
Stage 1 GEMS model							
SPCV+Separate test Average (STD)	R^2	0.87	0.84	0.73	0.90	0.53	0.34
		(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.07)
	nRMSE	0.35	0.36	0.37	0.16	0.44	0.80
		(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.10)
Separate test	R^2	0.87	0.86	0.74	0.90	0.57	0.42
	nRMSE	0.35	0.34	0.36	0.16	0.41	0.64
Stage 1 NonGEMS model							
SPCV+Separate test Average (STD)	R^2	0.74	0.75	0.58	0.75	0.45	0.20
		(0.02)	(0.02)	(0.02)	(0.01)	(0.03)	(0.03)
	nRMSE	0.53	0.51	0.51	0.32	0.44	0.88
		(0.03)	(0.01)	(0.02)	(0.01)	(0.03)	(0.07)
Separate test	R^2	0.76	0.78	0.60	0.76	0.49	0.24
	nRMSE	0.54	0.50	0.49	0.33	0.43	0.79

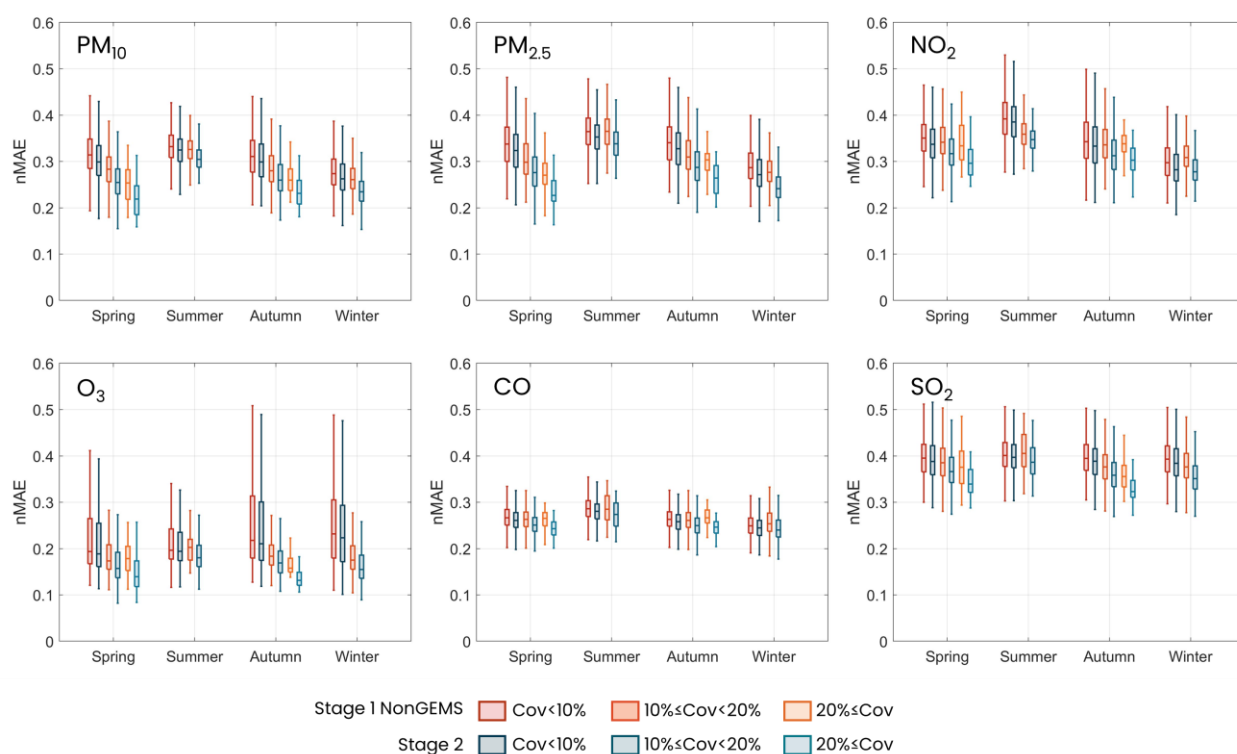


Fig. S5 Model accuracy of Stage 2 and Stage 1 GEMS stratified by GEMS-derived cloud cover in Spring, Summer, Autumn, and Winter during 2021–2023: valid coverage below 10%, between 10% and 20%, and above 20%. The normalized mean absolute error (nMAE) was calculated using unseen ground-based stations under full-coverage conditions. Owing to extensive missing values in summer and limited daytime observations in winter, cases with valid coverage exceeding 20% are not available for these seasons.

Table S12. Separate test results of Stage 1 models (GEMS and NonGEMS) and Stage 2 (i.e., our final model, DeepMAP), evaluated under cloud-free and cloudy conditions during daytime (i.e., hours with available GEMS products) with unseen ground-based measurements. For comparability, performance metrics (e.g., R^2 , RMSE, and nRMSE) are calculated using only coincident daytime samples.

	Condition	Model	N	R^2	RMSE	nRMSE
PM ₁₀	cloud-free	Stage 1 GEMS	210,446	0.86	24.7	0.36
		Stage 1 NonGEMS	210,446	0.76	32.8	0.48
		DeepMAP	210,446	0.87	24.0	0.35
	cloud	Stage 1 NonGEMS	1210,058	0.74	23.8	0.57
		DeepMAP	1210,058	0.76	23.4	0.56
PM _{2.5}	cloud-free	Stage 1 GEMS	209,667	0.83	12.6	0.39
		Stage 1 NonGEMS	209,667	0.74	15.9	0.49
		DeepMAP	209,667	0.84	12.3	0.38
	cloud	Stage 1 NonGEMS	1,205,255	0.74	12.5	0.54
		DeepMAP	1,205,255	0.75	12.4	0.54
NO ₂	cloud-free	Stage 1 GEMS	211,126	0.75	4.6	0.35
		Stage 1 NonGEMS	211,126	0.62	5.7	0.43
		DeepMAP	211,126	0.75	4.6	0.35
	cloud	Stage 1 NonGEMS	1,213,206	0.58	5.0	0.49
		DeepMAP	1,213,206	0.59	4.9	0.48
O ₃	cloud-free	Stage 1 GEMS	211,403	0.90	7.4	0.16
		Stage 1 NonGEMS	211,403	0.84	10.6	0.23
		DeepMAP	211,403	0.90	7.4	0.16
	cloud	Stage 1 NonGEMS	1,212,878	0.78	10.4	0.28
		DeepMAP	1,212,878	0.79	10.4	0.27
CO	cloud-free	Stage 1 GEMS	211,102	0.55	0.22	0.42
		Stage 1 NonGEMS	211,102	0.44	0.25	0.47
		DeepMAP	211,102	0.56	0.22	0.43
	cloud	Stage 1 NonGEMS	1,208,320	0.50	0.20	0.43
		DeepMAP	1,208,320	0.51	0.20	0.43
SO ₂	cloud-free	Stage 1 GEMS	211,120	0.40	2.6	0.65
		Stage 1 NonGEMS	211,120	0.25	2.9	0.74
		DeepMAP	211,120	0.40	2.6	0.65
	cloud	Stage 1 NonGEMS	1,212,143	0.21	2.2	0.80
		DeepMAP	1,212,143	0.25	2.2	0.78

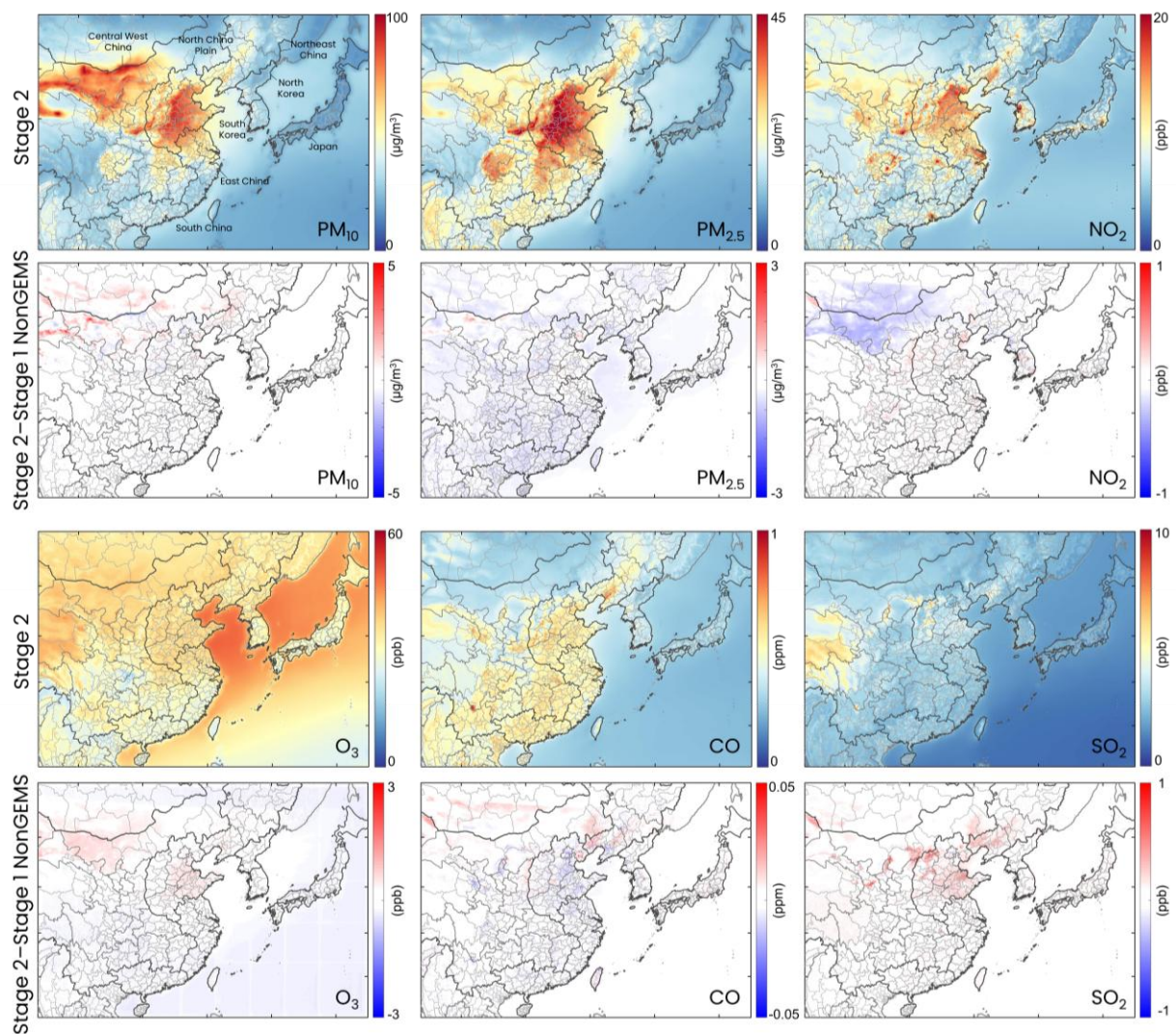


Fig. S6 Annual mean concentrations of Stage 2 (top panels) and differences between Stage 2 and Stage 1 NonGEMS (bottom panels) averaged over 2021–2023 for PM₁₀, PM_{2.5}, NO₂, O₃, CO, and SO₂. Difference maps represent Stage 2 minus Stage 1 NonGEMS.

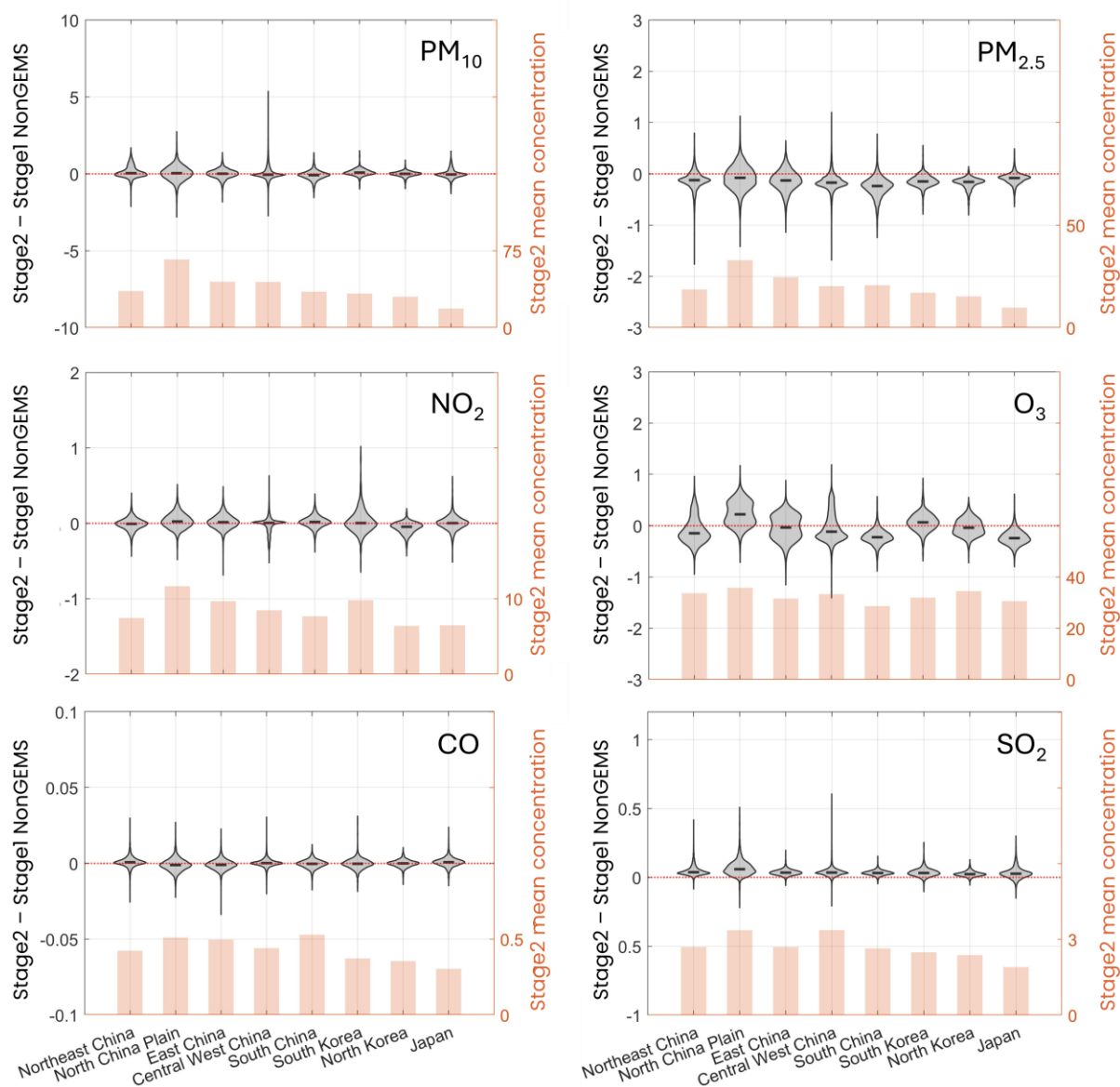


Fig. S7 Violin plots of differences between annual mean concentrations of Stage 2 and Stage 1 NonGEMS (Stage 2 – Stage 1 NonGEMS), averaged over 2021–2023, for PM₁₀, PM_{2.5}, NO₂, O₃, CO, and SO₂ at provincial level. Orange bar graphs indicate the corresponding provincial mean concentrations of Stage 2.

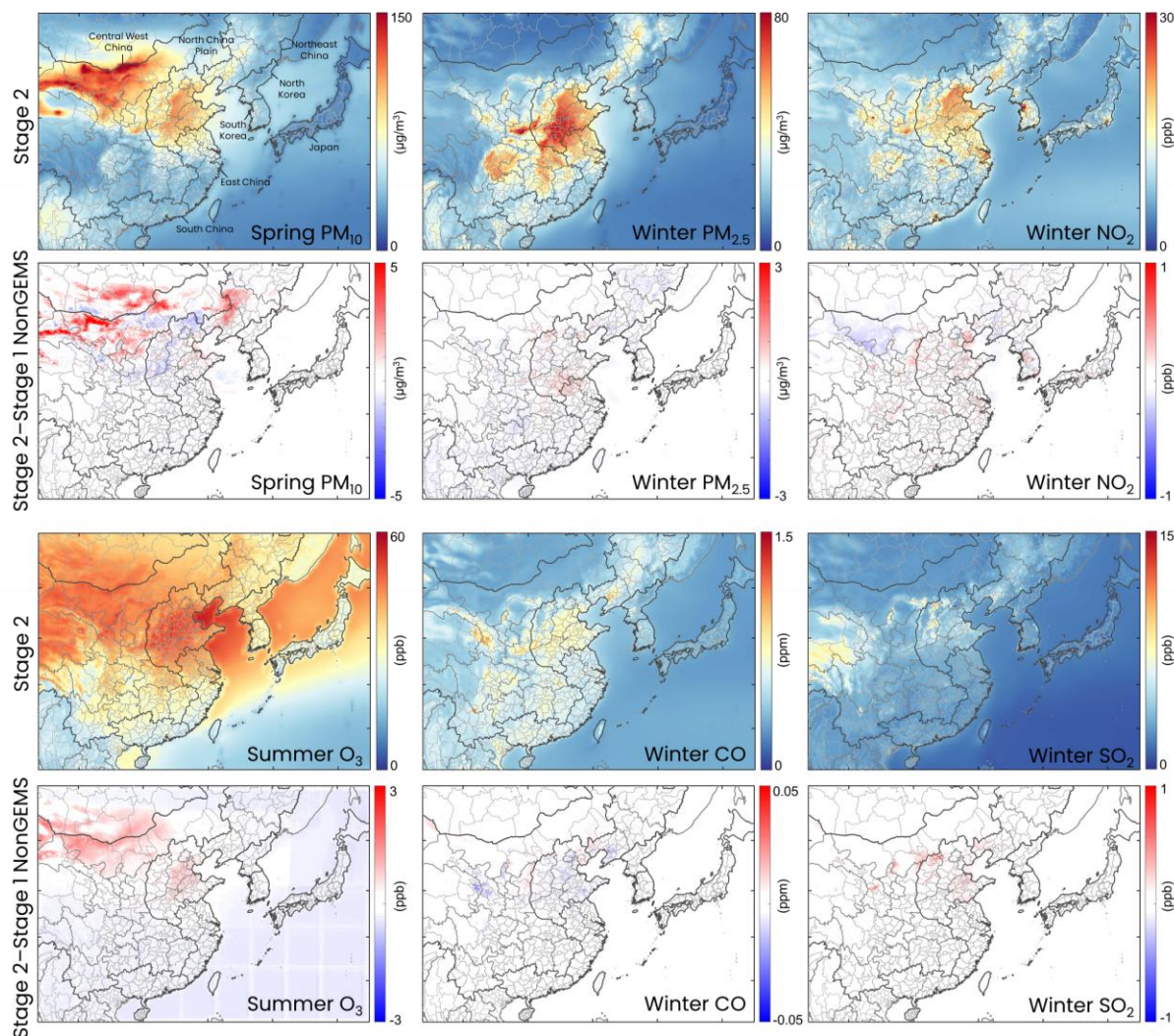


Fig. S8 High-concentration seasonal mean concentrations of Stage 2 (top panels) and differences between Stage 2 and Stage 1 NonGEMS (bottom panels) averaged over 2021–2023 for PM₁₀, PM_{2.5}, NO₂, O₃, CO, and SO₂. PM₁₀ is shown for spring; PM_{2.5}, NO₂, CO, and SO₂ for winter; and O₃ for summer, corresponding to the high-concentration season of each pollutant. Difference maps represent Stage 2 minus Stage 1 NonGEMS.

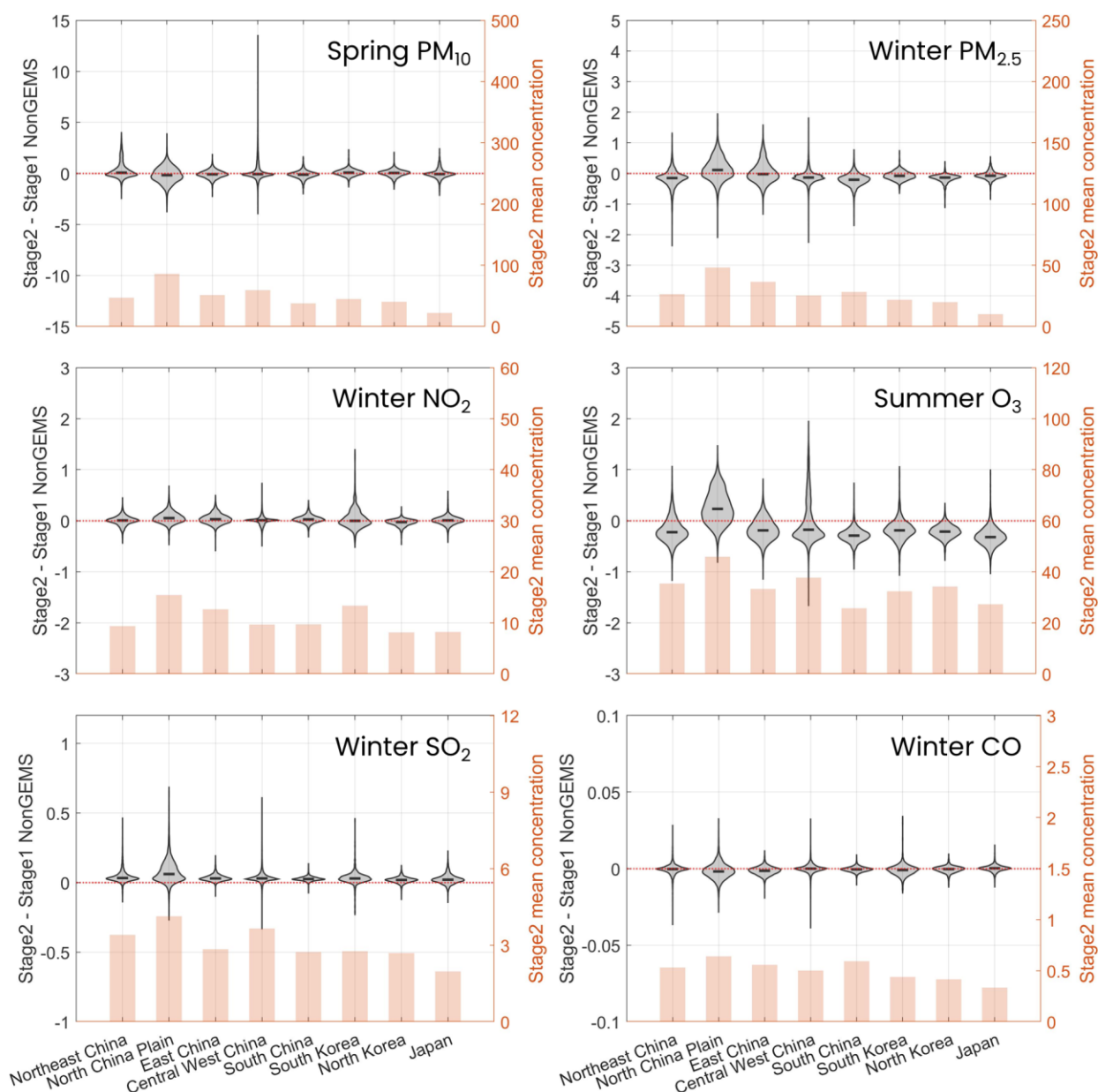


Fig. S9 Violin plots of differences between high-concentration seasonal mean concentrations of Stage 2 and Stage 1 NonGEMS (Stage 2 – Stage 1 NonGEMS), averaged over 2021–2023, for PM₁₀, PM_{2.5}, NO₂, O₃, CO, and SO₂ at the provincial level. Orange bar graphs indicate the corresponding provincial mean concentrations of Stage 2. PM₁₀ is shown for spring; PM_{2.5}, NO₂, CO, and SO₂ for winter; and O₃ for summer, corresponding to the high-concentration season of each pollutant.

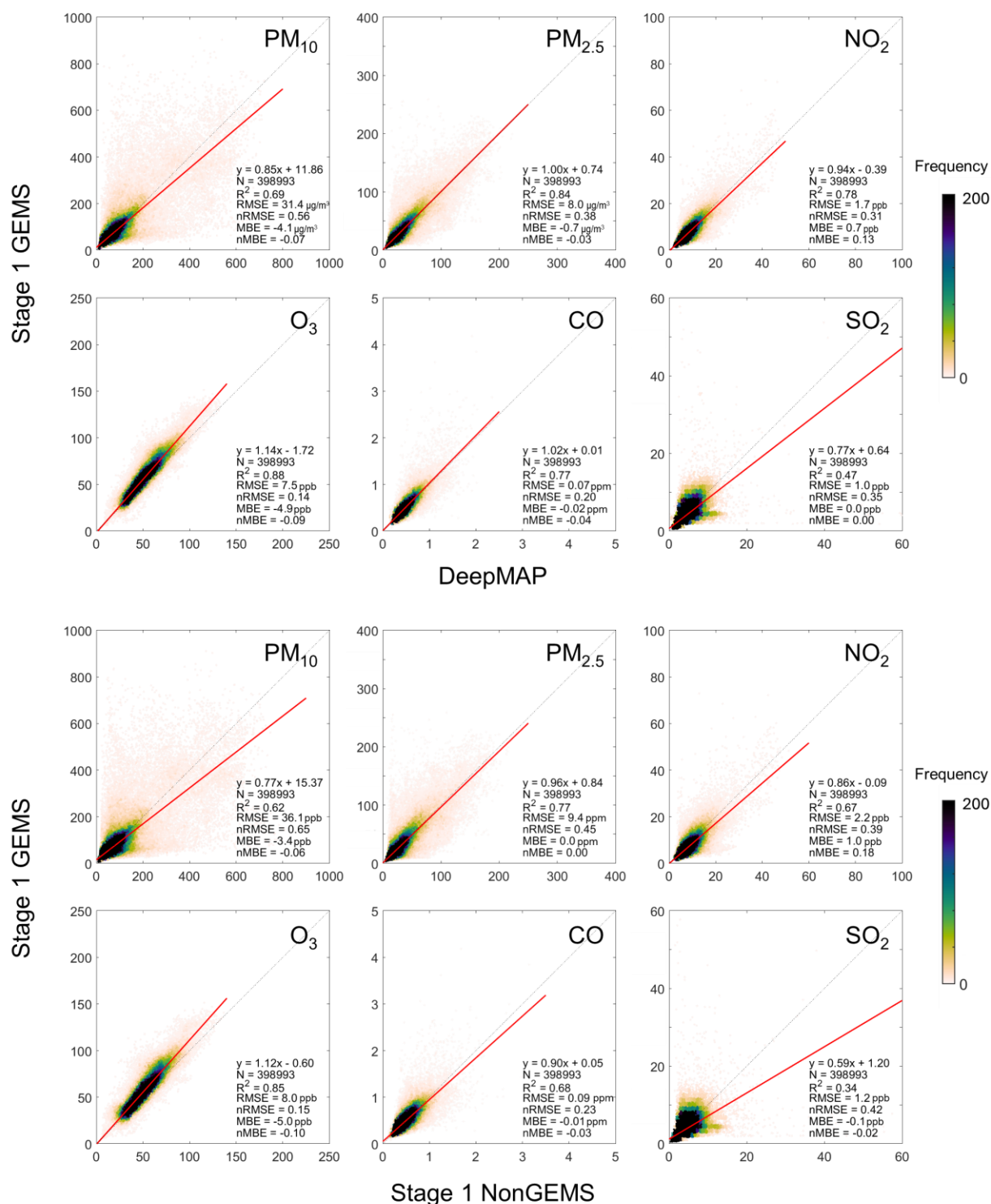


Fig. S10 Scatterplots of spatial validation using additional cloud mask (applying cloud mask at 2:00 UTC to that at 5:00 UTC) between the Stage 1 GEMS and DeepMAP models; between the Stage 1 GEMS and NonGEMS models, separately.

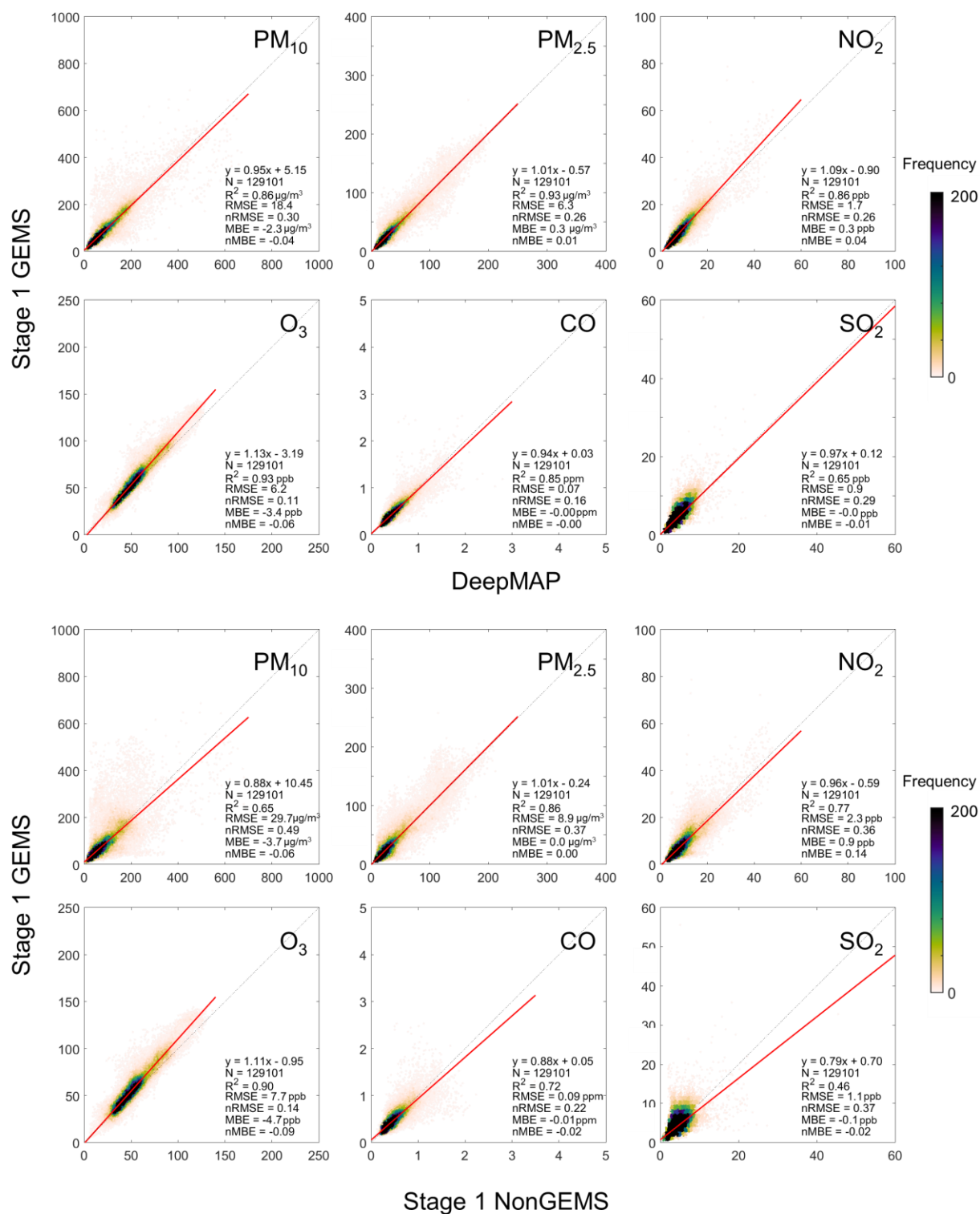


Fig. S11 Scatterplots of spatial validation using square mask (128 pixels $\times$ 128 pixels) at 5:00 UTC between the Stage 1 GEMS and DeepMAP models; between the Stage 1 GEMS and NonGEMS models, separately.

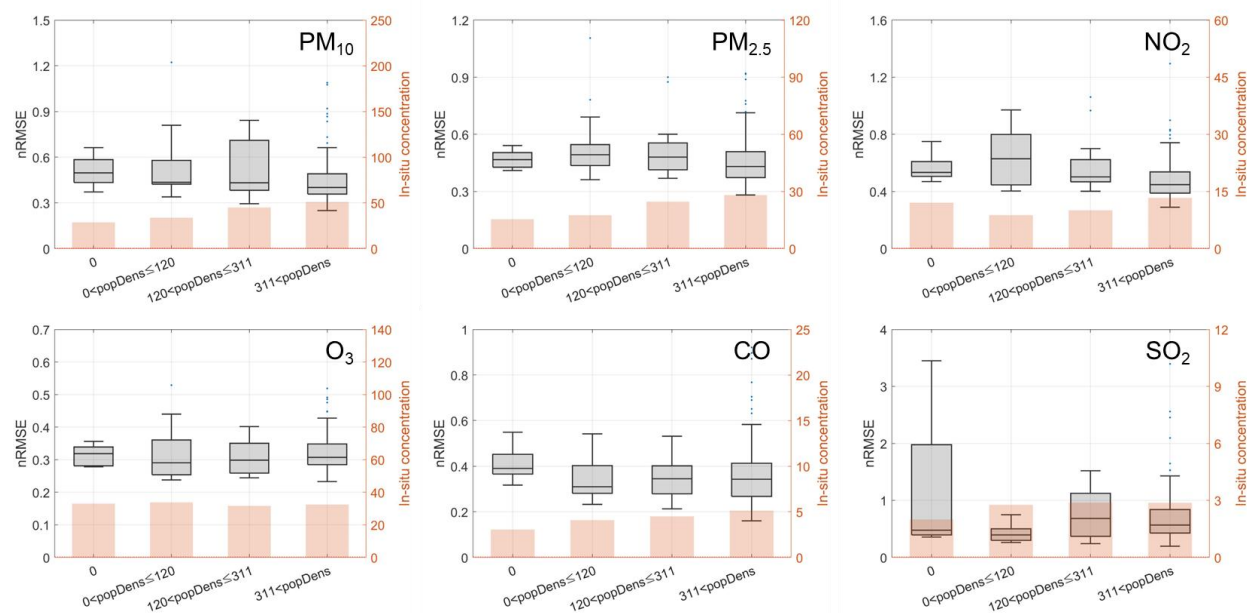


Fig. S12 Boxplots of nRMSE values evaluated at separate test stations, overlaid with bar charts showing the average concentrations from ground-based measurements. Stations were grouped according to population density into four categories: population density = 0, 0 < population density ≤ 120, 120 < population density ≤ 311, and population density > 311. Population density is defined as the number of people per 1 km² grid cell.

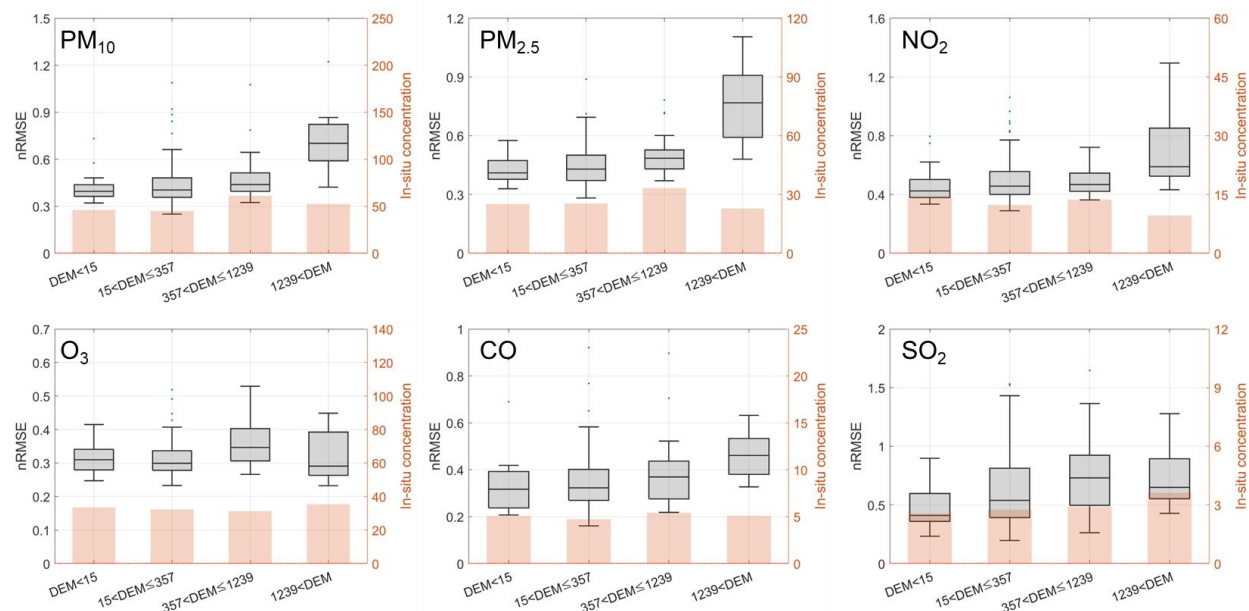


Fig. S13 Boxplots of nRMSE values evaluated at separate test stations, overlaid with bar charts showing the average concentrations from ground-based measurements. Stations were grouped according to digital elevation model (DEM, unit: meter) into four categories: $DEM \leq 15$ m, $15 < DEM \leq 357$ m, $357 < DEM \leq 1,239$ m, and $DEM > 1,239, 357$ m.

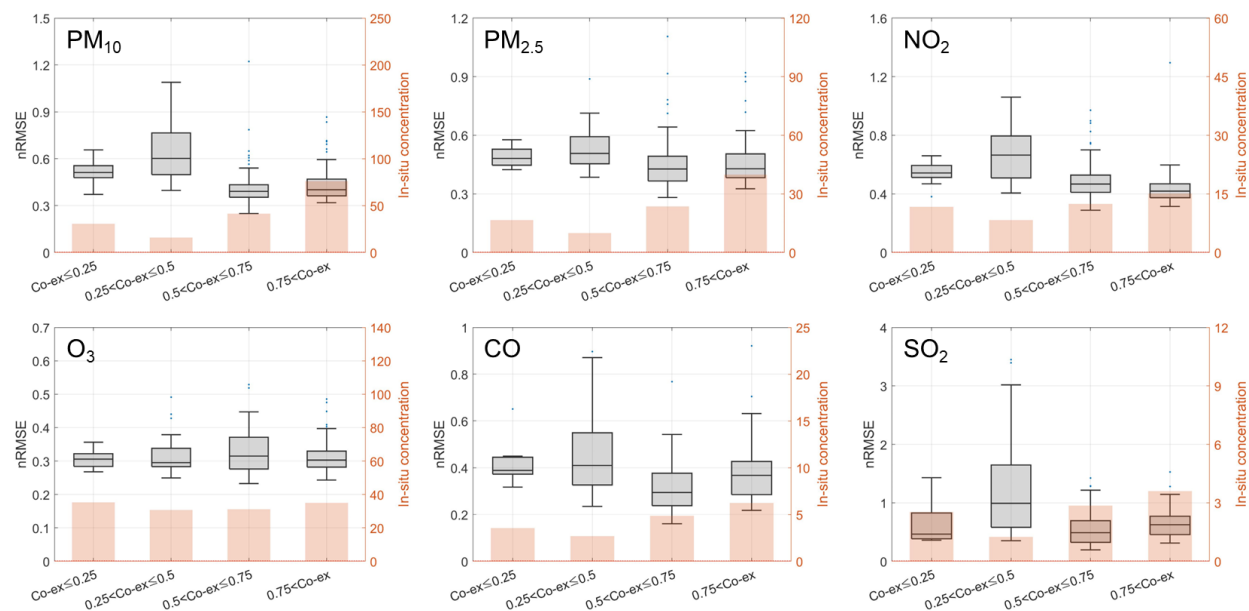


Fig. S14 Boxplots of nRMSE values evaluated at separate test stations, overlaid with bar charts showing the average concentrations from ground-based measurements. Stations were grouped according to the proposed co-exposure index into four categories: co-exposure index ≤ 0.25 , $0.25 < \text{co-exposure index} \leq 0.5$, $0.5 < \text{co-exposure index} \leq 0.75$, and co-exposure index > 0.75 .

Table S13. Statistics from the separate test for DeepMAP, CAMS forecast, and CAMS reanalysis in a separate test using unseen ground-based measurements.

Air pollutants	PM ₁₀ (µg/m ³)			PM _{2.5} (µg/m ³)			NO ₂ (ppb)		
	DeepMAP	CAMS forecast	CAMS reanalysis	DeepMAP	CAMS forecast	CAMS reanalysis	DeepMAP	CAMS forecast	CAMS reanalysis
R²	0.77	0.26	0.24	0.77	0.37	0.30	0.61	0.24	0.26
RMSE	24.9	46.8	116.5	13.5	25.9	86.4	6.2	13.7	16.1
nRMSE	0.52	0.98	2.44	0.51	0.99	3.29	0.49	1.08	1.27
MBE	-1.26	1.1	60.4	-0.98	6.0	50.8	-0.40	4.4	6.2
nMBE	-0.03	0.02	1.26	-0.04	0.23	1.93	-0.03	0.35	0.49
N	4,067,250	4,070,921	1,356,486	4,054,647	4,058,294	1,352,327	4,080,872	1,360,677	1,360,677
Air pollutants	O ₃ (ppb)			CO (ppm)			SO ₂ (ppb)		
	DeepMAP	CAMS forecast	CAMS reanalysis	DeepMAP	CAMS forecast	CAMS reanalysis	DeepMAP	CAMS forecast	CAMS reanalysis
R²	0.76	0.47	0.48	0.51	0.11	0.20	0.25	0.02	0.03
RMSE	10.3	17.2	18.5	0.21	0.56	0.70	2.2	15.7	21.4
nRMSE	0.32	0.53	0.57	0.42	1.14	1.36	0.79	5.55	7.59
MBE	-1.19	-3.9	-2.7	-0.01	-0.07	0.15	-0.1	7.1	12.0
nMBE	-0.04	-0.12	-0.08	-0.02	-0.15	0.30	-0.03	2.51	4.25
N	4,068,984	1,357,666	1,357,666	4,065,703	1,356,077	1,356,077	4,079,407	1,360,515	1,360,515

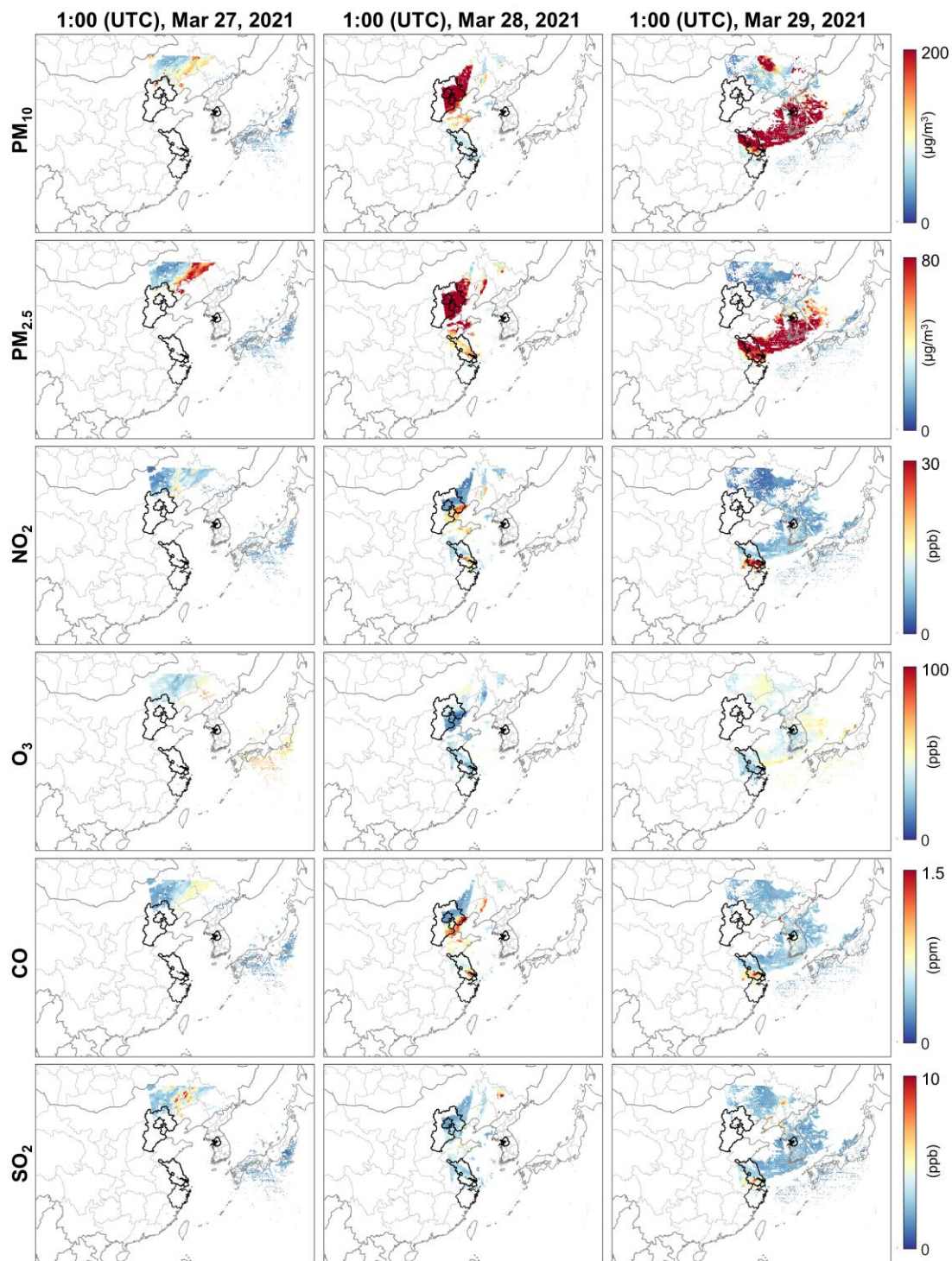


Fig. S15 Conventional satellite-based retrieval-derived (Stage 1 GEMS) hourly concentration maps of multiple air pollutants at a 10-km spatial resolution over East Asia during the high-concentration episode from May 27–29, 2021.

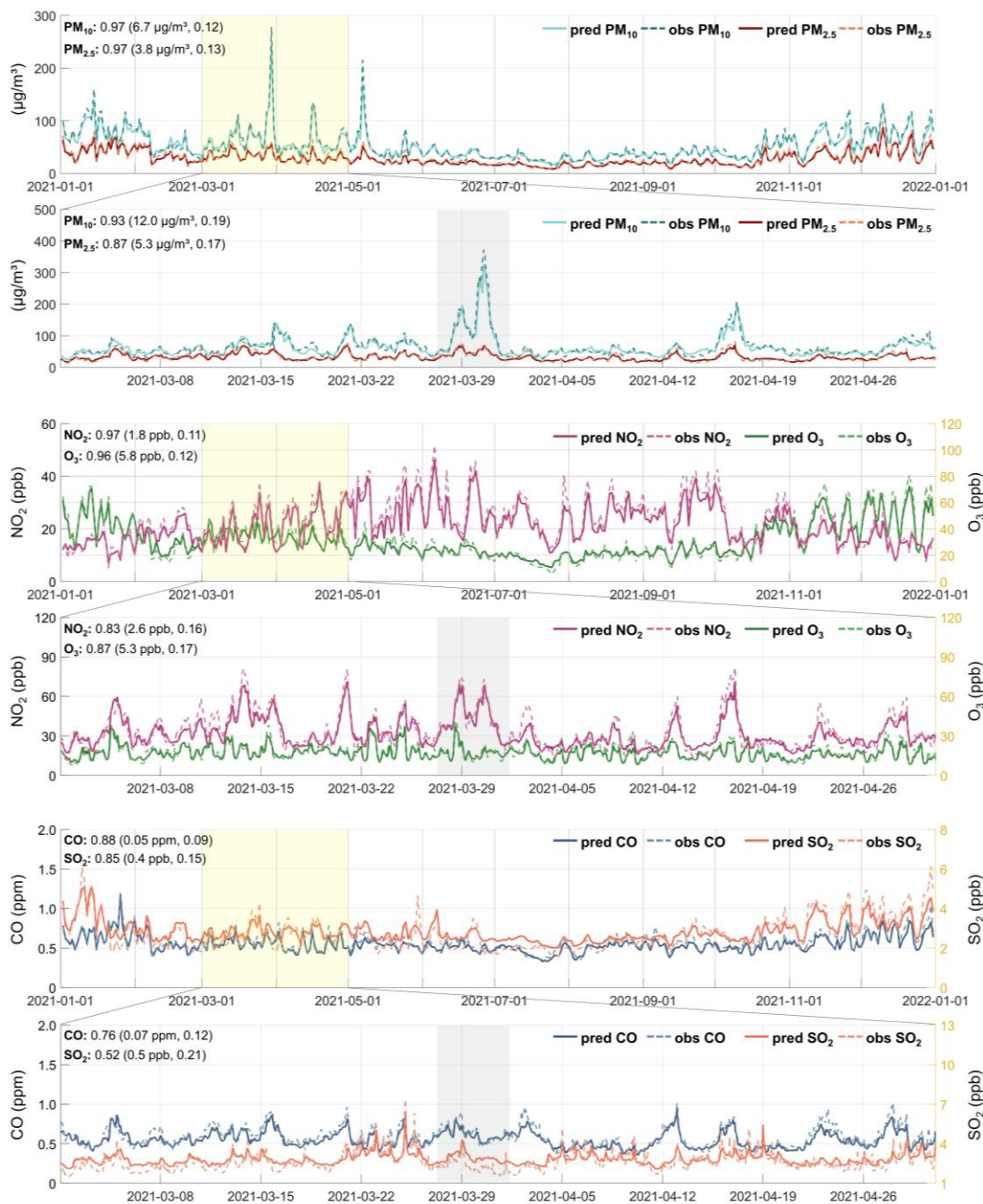


Fig. S16 Time-series validation results at unseen stations are shown on a daily scale in 2021 and on an hourly scale from March to April 2021 for the key hotspot region, YRD. To represent overall trends, hourly concentrations from 20 unseen stations within the YRD region were averaged. Statistic metrics (R^2 , RMSE, and nRMSE) are displayed in the upper-left corner of each panel.

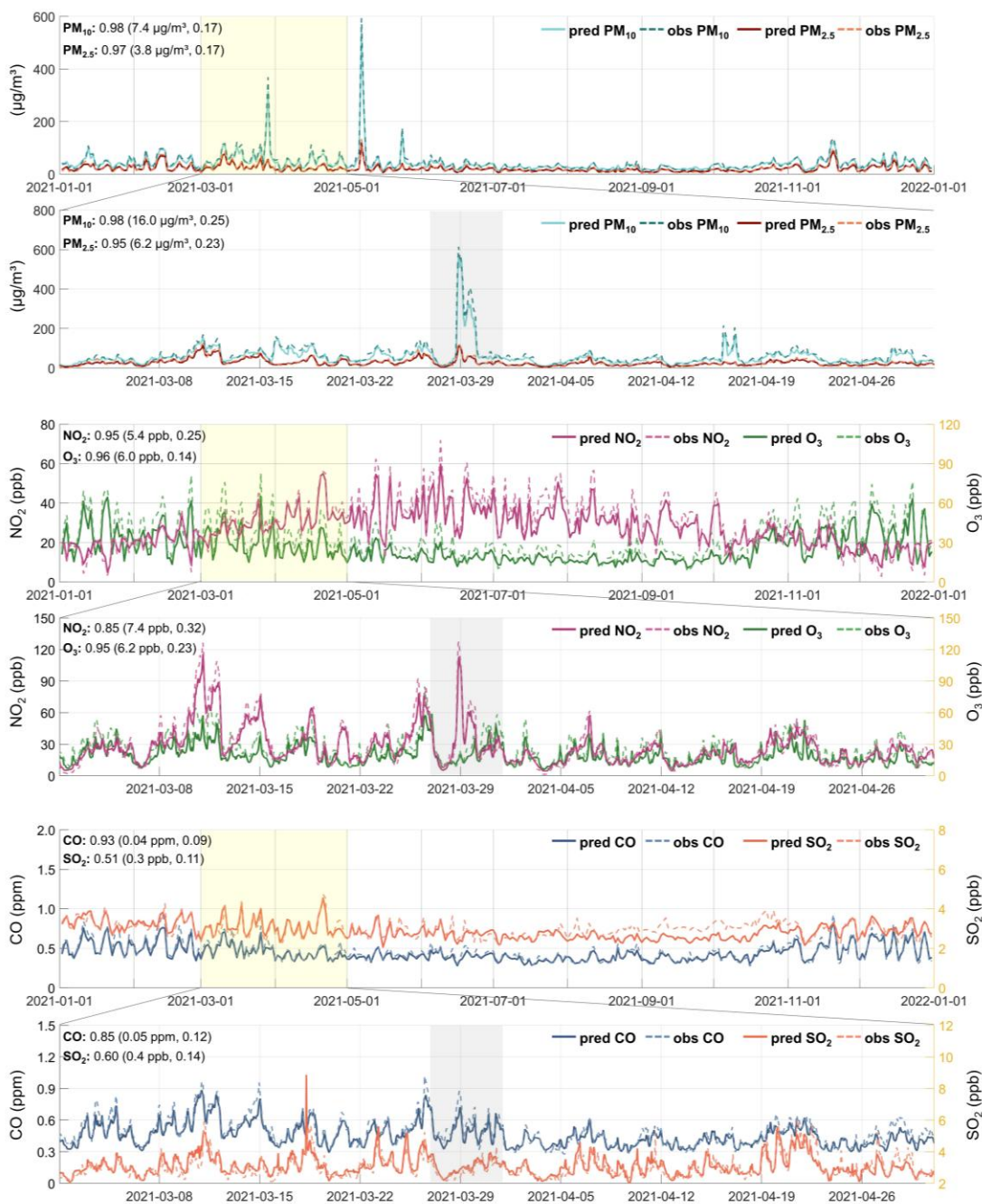


Fig. S17 Time-series validation results at unseen stations are shown on a daily scale in 2021 and on an hourly scale from March to April 2021 for the key hotspot region, SMA. To represent overall trends, hourly concentrations from 27 unseen stations within the SMA region were averaged. Statistic metrics (R^2 , RMSE, and nRMSE) are displayed in the upper-left corner of each panel.

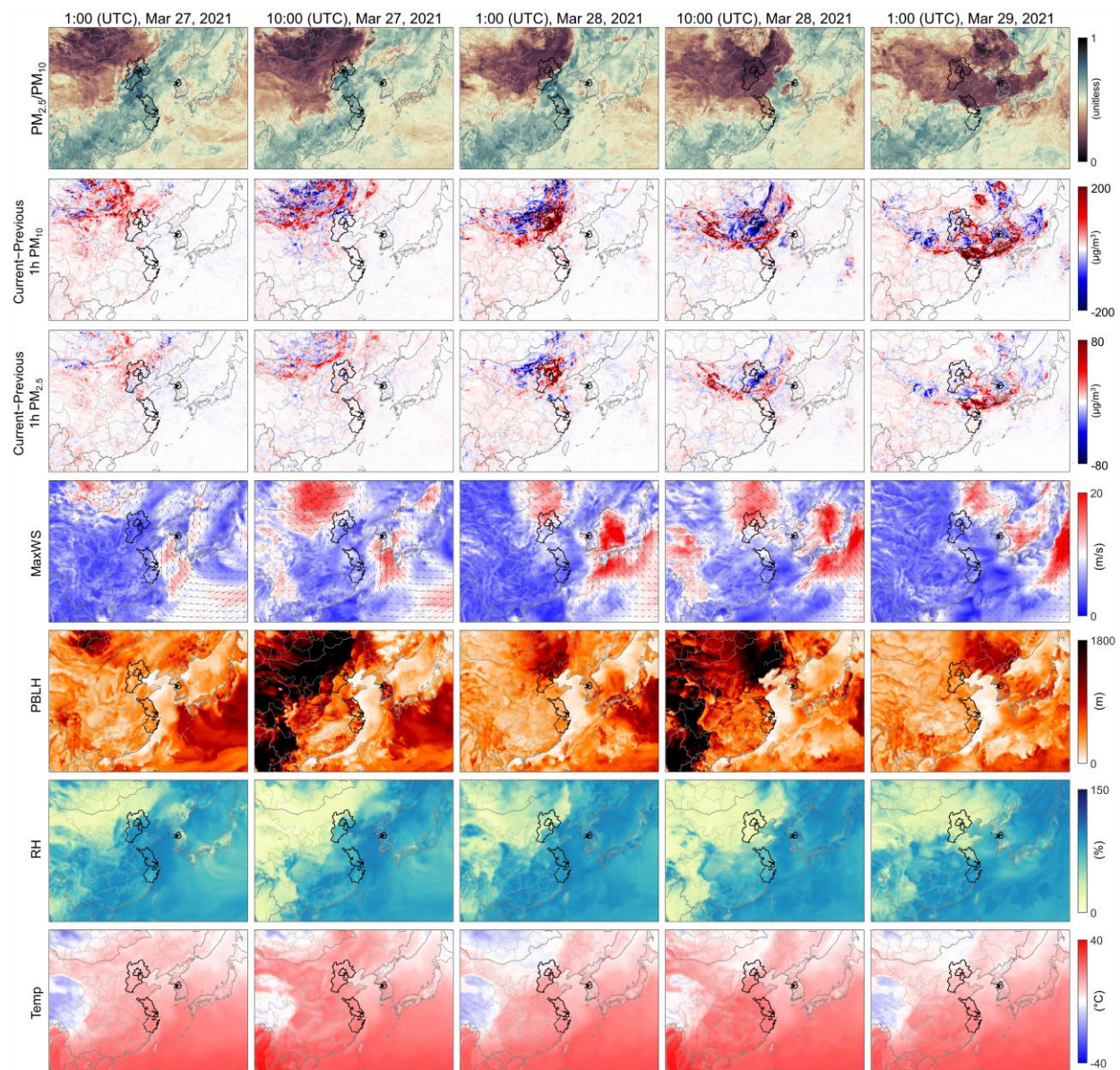


Fig. S18 Spatial patterns of $\text{PM}_{2.5}$ to PM_{10} ratio, hourly difference maps of PM_{10} and $\text{PM}_{2.5}$ (current hour minus the previous hour), and the hourly distribution of maximum wind speed (3-hour maximum), planetary boundary layer height (PBLH), relative humidity (RH), and air temperature (Temp) from top to bottom. The bold boundaries indicate the major regions of East Asia, including BTH, YRD, and SMA. Wind directions are included by arrows in the MaxWS panels.

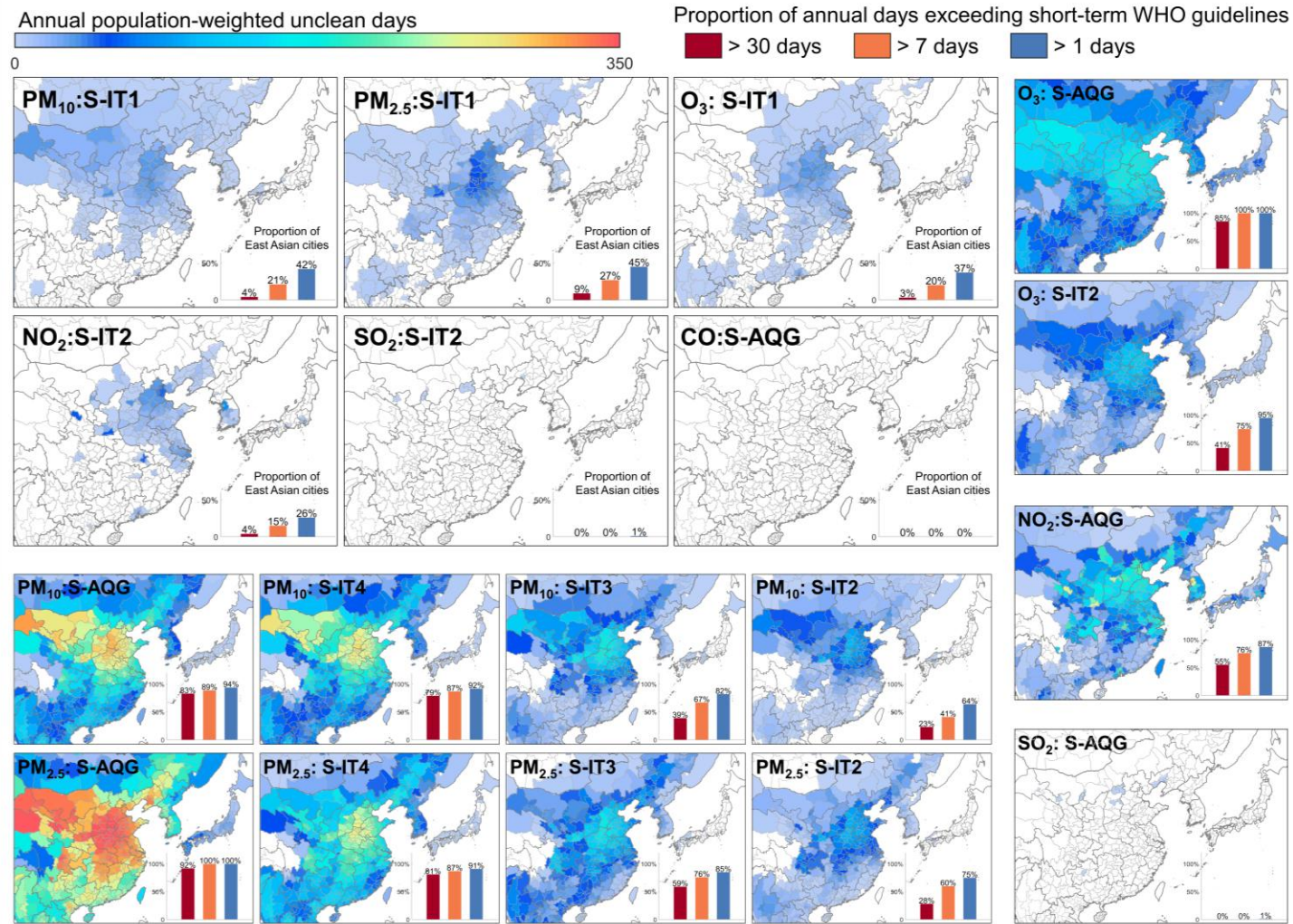


Fig. S19 Annual unclean days for short-term air pollutants in East Asia. Daily risk exposure to ambient PM₁₀, PM_{2.5}, NO₂, O₃, SO₂, and CO pollution. The spatial distributions represent the population-weighted annual number of unclean days exceeding the WHO-recommended S-AQG and S-ITs during 2021–2023. The bar charts illustrate the proportions of 520 East Asian cities experiencing population-weighted unclean days exceeding 1 day, 7 days, and 30 days annually (unit:%).

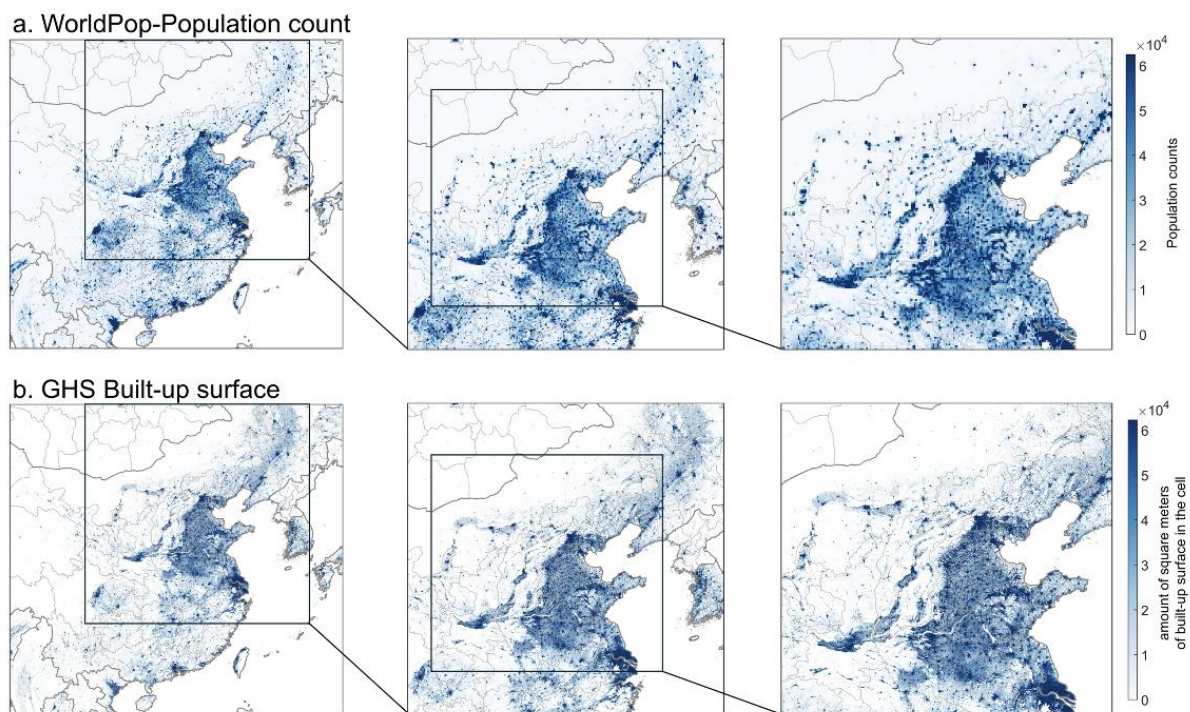


Fig. S20 Spatial distribution of population counts from WorldPop (a) and built-up surface counts from GHS (b).

Table S14. Spatial analysis results between a co-exposure index and 11 types of emission sources from the recent 2022 Emission Database for Global Atmospheric Research (EDGAR v8.1) of the European Commission (https://edgar.jrc.ec.europa.eu/emissions_data_and_maps). Emissions (unit: tons) were aggregated at the provincial level across East Asia prior to the correlation analysis. Spatial analysis based on the spatial lag model was conducted for each emission source, calculating beta (β), rho (ρ), and Pseudo R^2 . β represents the spatially adjusted influence of each emission source on the co-exposure index, whereas ρ indicates the degree of spatial dependence among neighboring regions. We reported significance levels as $p < 0.05$ (as *), $p < 0.01$ (as **), and $p < 0.001$ (as ***).

Types of EDGAR emission sources	Pearson R	β (Spatial Lag)	ρ	Pseudo R^2
Combustion in power generation and in industry	0.56***	0.036***	0.51***	0.65
Solid waste incineration and agricultural waste burning	0.54***	0.035***	0.52***	0.64
Combustion in residential and other combustion (transformation industry and oil refineries)	0.51***	0.032***	0.55***	0.64
Road transportation	0.48***	0.031***	0.54***	0.63
Glass production	0.42***	0.024***	0.56***	0.62
Cement production	0.40***	0.022***	0.57***	0.62
Large-scale gold production	0.38***	0.019**	0.57***	0.61
Iron and steel production	0.30***	0.017**	0.59***	0.61
Production of Zn, Cu, Pb, and Hg	0.26***	0.012*	0.59***	0.60
Chlor-alkali industry, mercury cell technology	0.09	0.005	0.61***	0.60
Artisanal and small-scale gold production	0.03	0.001	0.61***	0.60

Table S15. Spatial analysis results between the co-exposure index and 11 types of power generation sources from the Global Power Plant Database (version 1.3.0) (<https://datasets.wri.org/datasets/global-power-plant-database/>). Power plant capacities (unit: MW) were aggregated to the provincial level across East Asia. Spatial lag model was applied to each emission source to estimate the regression coefficient (β), spatial dependence (ρ), and model fit (Pseudo R^2). β represents the spatially adjusted influence of each emission source on the co-exposure index, whereas ρ indicates the degree of spatial dependence among neighboring regions. We reported significance levels as $p < 0.05$ (as *), $p < 0.01$ (as **), and $p < 0.001$ (as ***).

Types of power plant emission sources	Pearson R	β (Spatial Lag)	ρ	Pseudo R^2
Coal	0.53***	0.033***	0.53***	0.64
Solar	0.38***	0.022***	0.57***	0.62
Wind	0.34***	0.017**	0.58***	0.61
Gas	0.16*	0.015**	0.60***	0.61
Hydro	0.16*	0.007	0.60***	0.60
Biomass	0.09	0.005	0.61***	0.60
Wave and Tidal	0.09	0.005	0.61***	0.60
Waste	0.07	0.002	0.61***	0.60
Nuclear	-0.05	-0.001	0.61***	0.60
Oil	-0.18*	-0.006	0.60***	0.60
Geothermal	-0.19**	-0.006	0.60***	0.60

Table S16. Statistic metrics of a co-exposure index as presented in Fig. 6. The table summarizes the average, standard deviation (STD), maximum, and minimum values of the co-exposure index at the provincial level. Additionally, it provides the number and percentage of provinces and populations exceeding two thresholds: a co-exposure index of 0.8 at the city level and the average co-exposure index (0.49).

Metrics/Statistic at provincial level	Average	STD	Max	Min	# of provinces (% of total provinces)	# of population (% of total population)
Total	0.49	0.13	0.94	0.10	202	1,164,012,860
Statistical Metrics (> 0.8 at city level)	0.85	0.04	0.94	0.82	5 (2.5%)	226,907,045 (19.5%)
Statistical Metrics (≥ 0.50 at city level)	0.59	0.09	0.94	0.51	101 (50.0%)	1,044,167,019 (89.7%)

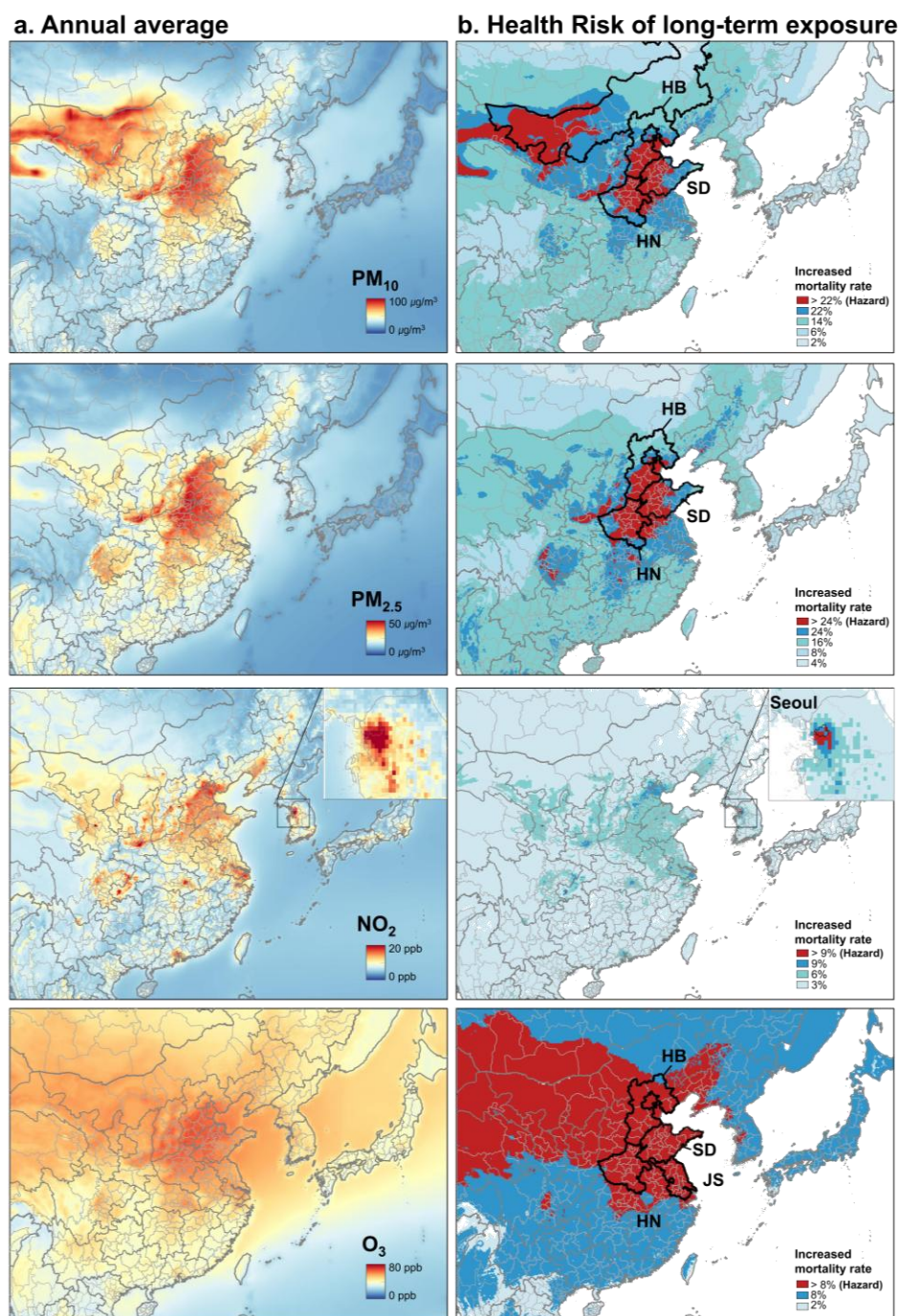


Fig. S21 Spatial distributions of air pollutants and their long-term exposure health impact in East Asia. (a) Annual average concentrations of PM₁₀, PM_{2.5}, and NO₂, and the peak-season (April–September) average for O₃ during 2021–2023 are shown. (b) Corresponding health impact distributions were calculated according to WHO guidelines for long-term exposure, using annual and peak-season averages.

Table S17. Statistical metrics for the DeepMAP, CAMS forecast, and CAMS reanalysis in separate test stations along the coastline. The analysis includes 60 separate test stations located within 1 km of the coastline in the entire study area.

Air pollutants		PM ₁₀ (µg/m ³)		PM _{2.5} (µg/m ³)			NO ₂ (ppb)		
Model	DeepMAP	CAMS-Forecast	CAMS-Reanalysis	DeepMAP	CAMS-Forecast	CAMS-Reanalysis	DeepMAP	CAMS-Forecast	CAMS-Reanalysis
R ²	0.80	0.27	0.15	0.75	0.37	0.23	0.55	0.25	0.30
RMSE	15.1	30.5	78.0	8.0	16.4	57.1	6.6	13.2	14.0
nRMSE	0.52	1.04	2.67	0.51	1.04	3.61	0.55	1.10	1.17
MBE	0.4	3.8	35.3	-0.2	5.6	30.2	-0.8	3.8	2.1
nMBE	0.01	0.13	1.21	-0.02	0.35	1.91	-0.07	0.32	0.17
N	398795	399118	132952	396264	396578	132140	399314	133089	133089
Air pollutants		O ₃ (ppb)		CO (ppm)			SO ₂ (ppb)		
Model	DeepMAP	CAMS-Forecast	CAMS-Reanalysis	DeepMAP	CAMS-Forecast	CAMS-Reanalysis	DeepMAP	CAMS-Forecast	CAMS-Reanalysis
R ²	0.69	0.41	0.38	0.40	0.19	0.15	0.26	0.04	0.05
RMSE	10.1	16.0	17.0	1.67	0.24	0.40	1.4	10.8	14.0
nRMSE	0.30	0.48	0.51	0.51	0.73	1.20	0.65	5.17	6.74
MBE	-2.2	-3.9	1.3	0.48	-0.04	0.05	0.1	4.7	7.0
nMBE	-0.06	-0.12	0.04	0.14	-0.13	0.15	0.05	2.27	3.36
N	397727	132950	132950	392642	130914	130914	398073	132804	132804

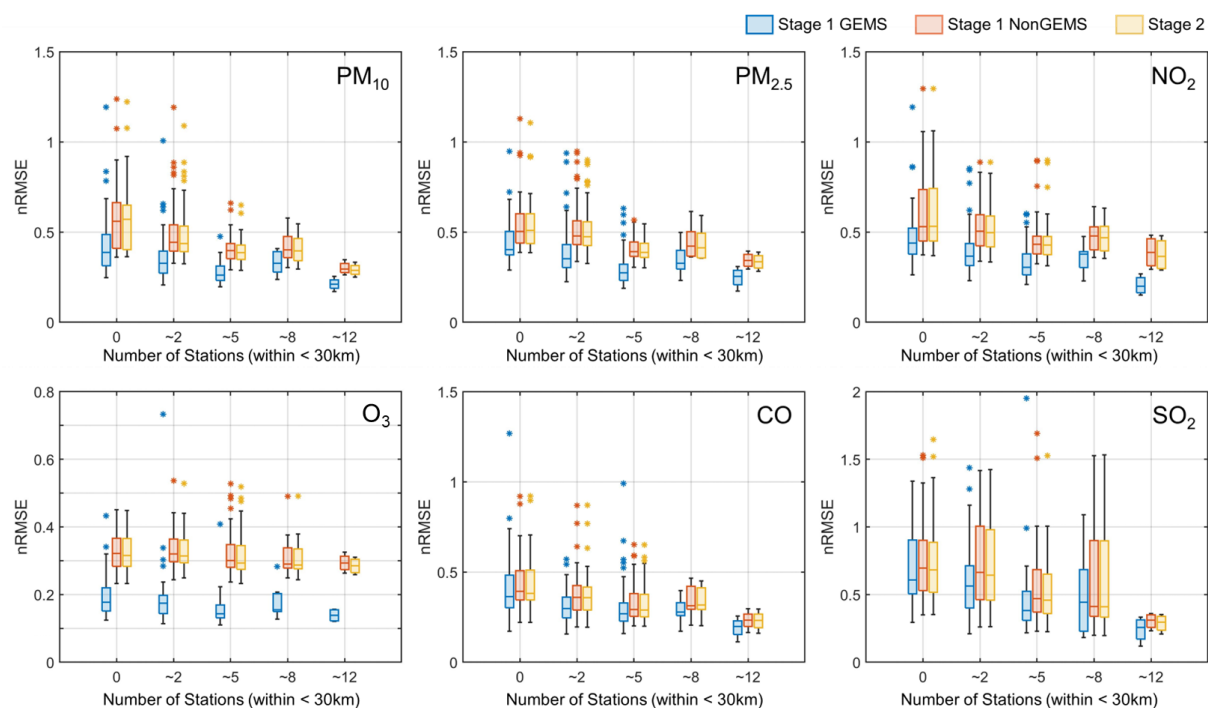


Fig. S22 Model performance (nRMSE) of independent test stations stratified by the number of nearby monitoring stations within 30 km. The thresholds of 2, 5, 8, and 12 stations correspond to the 25th, 50th, 75th, and 100th percentiles of the distribution of surrounding station counts across all test stations. Boxplots show the distribution of nRMSE calculated for each independent test station.

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