



A daily gridded dataset of nitrogen wet deposition over East Asia for 2011 to 2016 based on multisource observation-model fusion

Nan Yang^{1,2†}, Nuohang Liu^{1,2†}, Baozhu Ge^{1, *}, Zhechen He^{1,2}, Yin Zhou^{1,2}, Danhui Xu³, Zifa Wang¹

¹State Key Laboratory of Atmospheric Environment and Extreme Meteorology, Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing, 100029, China

²University of Chinese Academy of Sciences, Beijing 100049, China

³National Center for Climate Change Strategy and International Cooperation, Ministry of Ecology and Environment, Beijing, 100035, China

Correspondence author: Baozhu Ge (gebz@mail.iap.ac.cn)

†These authors contributed equally and should be considered as co-first authors.

Abstract. East Asia is a global hotspot of atmospheric nitrogen deposition, where episodic wet-deposition pulses can strongly affect ecosystem nutrient inputs and acidification. However, most datasets aggregate observations to monthly or annual scales, masking short-lived high-load deposition pulses from individual rainstorms and hindering the quantification of event-scale deposition dynamics. Here we develop a 45 km gridded daily dataset of oxidized and reduced nitrogen wet deposition over East Asia for 2011–2016. Ground-based measurements from the National Acid Deposition Monitoring Network (NADMN) and the Acid Deposition Monitoring Network in East Asia (EANET), satellite precipitation retrievals, and chemical transport simulations are integrated via a two-step framework. Precipitation adjustment constrains monthly deposition totals and reconstructs event-based daily deposition distributions, followed by measurement–model fusion to assimilate wet-deposition observations. Compared with the raw model output, the dataset reduces oxidized-nitrogen overestimation and better agreement with the observed spread of reduced-nitrogen wet deposition. Station-held-out validation shows improved identification of high-deposition days, with correct classification of the highest observed deposition quartile increasing by 12.7 and 20.8 percentage points for oxidized and reduced nitrogen, respectively. The daily dataset helps identify high-deposition periods and assess when and where short-lived nitrogen inputs occur and how much they contribute to cumulative deposition. It also supports regional nitrogen-budget analyses and model evaluation. However, uneven observational coverage and remaining errors in daily estimates warrant caution when interpreting individual events, particularly in sparsely monitored regions. The NetCDF data are available at <https://doi.org/10.57760/sciencedb.015vd> (Yang et al., 2026).

1 Introduction

As an important driver of global environmental change, atmospheric nitrogen deposition has received particular concern in East Asia because of the region's substantial anthropogenic emissions and diverse ecosystems (Crippa et al., 2023; Tan et al., 2026). Reactive nitrogen emitted from fossil-fuel combustion and agricultural activities enters terrestrial and aquatic



ecosystems through wet and dry deposition. Excessive nitrogen inputs can acidify soils, promote eutrophication, and reduce biodiversity (Bouwman et al., 2002; Chen et al., 2023; Fowler et al., 2015; Midolo et al., 2019; Vitousek et al., 1997; Zhao et al., 2017). Long-term assessments covering the past two decades have documented a transition from increasing or stable deposition to an overall decline in East Asia, particularly China, with the clearly decrease occurring in oxidized nitrogen following NO_x emission controls (Liu et al., 2024; Ma et al., 2023; Wen et al., 2020, 2024). These studies have provided an extensive observational basis for characterizing the long-term evolution of nitrogen deposition. However, existing observations and assessments are commonly aggregated at monthly or annual scales. Such temporal aggregation smooths out short-lived, high-load deposition pulses associated with individual rainstorms and typhoons, thereby limiting the characterization of event-scale deposition dynamics and their potential ecological effects (Gao et al., 2023; Zhang et al., 2022). This limitation is particularly important because extreme precipitation can deliver substantial nitrogen inputs within a short period. During the four landfalls of Super Typhoon Muifa in 2022, mean wet deposition of oxidized and reduced nitrogen over the affected regions increased to 20.4 and 66.1 times, respectively, the corresponding values near the typhoon-genesis region under comparable rainfall conditions, accompanied by an increased contribution from in-cloud scavenging (Zhang et al., 2025). Such episodic inputs may impose short-term nutrient-loading pressures on coastal ecosystems that cannot be resolved from monthly or annual deposition totals. Event-scale nitrogen deposition datasets are therefore needed to quantify these episodic inputs and support assessments of their ecological consequences.

Currently, there are several global observation networks and datasets for nitrogen deposition, including the Acid Deposition Monitoring Network in East Asia (EANET, <https://www.eanet.asia/>), the National Atmospheric Deposition Program of the United States (NADP, <http://nadp.slh.wisc.edu/>), and the European Monitoring and Evaluation Programme (EMEP, <https://www.emep.int/>). Among them, EANET is a monitoring network in East Asia launched in 2001, comprising only 54 observation sites established by 11 countries including China, South Korea, Vietnam, and Japan. To analyze the spatial heterogeneity of nitrogen deposition caused by anthropogenic emissions and complex meteorological conditions in East Asia, especially in China, more reliable deposition datasets with high spatiotemporal resolution are required. In recent years, nitrogen deposition monitoring networks have also been successively established in China, such as the National Acid Deposition Monitoring Network (NADMN), which contains wet deposition results from 320 cities across China for the period 2011–2016 (Li et al., 2019). The China Nitrogen Deposition Monitoring Network (NNDMN), established by the team of Liu Xuejun at China Agricultural University, covers nearly 60 monitoring sites during 2011–2020 (Wen et al., 2024). The Chinese Ecosystem Research Network (CERN) of the Chinese Academy of Sciences has conducted wet deposition observations at over forty typical ecosystem sites (Yu et al., 2019). However, spatiotemporal discrepancies in sampling frequency and monitoring protocols exist among these networks, making it difficult to capture short-term, high nitrogen deposition pulses driven by extreme precipitation and pollutant air mass transport.

Spatial interpolation has commonly been used to extend the representativeness of site observations. Qu et al. (2017), for example, showed that ordinary kriging effectively characterized the spatial distribution of nitrogen deposition in South China, while Liu et al. (2016) used a modified Cressman method to represent total nitrogen over the Bohai Sea. Unlike methods that



interpolate observations alone, OI combines observations with a model background. Nie et al. (2015) showed that OI reduced model–observation discrepancies and improved agreement with independent observations, and Robichaud et al. (2025) reported improvements in both the accuracy and spatial completeness of regional air-quality fields. Nevertheless, direct interpolation of station observations remains limited by sparse coverage and local representativeness, particularly in regions with complex terrain, heterogeneous emissions, and strong atmospheric transport. Chemical transport models (CTMs) partly address these limitations by explicitly representing emissions and atmospheric physical and chemical processes (Seinfeld and Pandis, 2006) and have therefore been widely used to estimate the spatiotemporal variability of nitrogen deposition (Ackerman et al., 2019; Liu et al., 2024; Zhang et al., 2012) (Ge et al., 2014). To improve the simulation of wet deposition, linear precipitation adjustment has been used to reduce wet-deposition biases associated with simulated precipitation (Appel et al., 2011; Itahashi et al., 2020, 2021; Zhang et al., 2018).

Schwede and Lear (2014) developed a hybrid observation–model framework for estimating total sulfur and nitrogen deposition across the United States. Measurement–model fusion (MMF) uses observations to constrain model biases while retaining spatially continuous model information, thereby combining the observational basis of monitoring networks with the spatial coverage of chemical transport models. Related marine applications combined ship-based aerosol nitrate and ammonium measurements with estimated deposition velocities to derive particulate nitrogen dry-deposition fluxes and evaluate model performance (Baker et al., 2017). For wet deposition specifically, Zhang et al. (2019) developed a two-step approach that first adjusted modelled deposition using observation-based precipitation fields and then corrected the remaining biases using wet deposition measurements. Fu et al., (2022) subsequently synthesised multimodel ensemble and MMF approaches, illustrated regional applications using 2010 deposition maps, and outlined priorities for global deposition mapping, including expanded observational coverage and uncertainty quantification. However, existing regional wet-deposition fusion and precipitation-adjustment applications have largely focused on monthly or annual totals (Itahashi et al., 2021; Zhang et al., 2019). These temporal aggregates obscure the timing and magnitude of short-lived, high-load nitrogen inputs associated with individual rainfall events. Here, we present a daily gridded dataset of oxidized and reduced nitrogen wet deposition across East Asia for 2011–2016, constructed from NADMN and EANET observations and NAQPMS simulations through a two-step precipitation-adjustment and measurement–model fusion approach. The dataset provides the temporal detail needed to characterise day-to-day variability and rainfall-associated high-load nitrogen inputs that are obscured by monthly or annual totals. Its principal contribution is a spatially continuous, daily-resolution data resource for event-scale nitrogen deposition assessments, evaluation of wet-deposition simulations, and integration with ecosystem observations.

2 Data

2.1 Model configuration and setup

The Nested Air Quality Prediction Modeling System (NAQPMS) is a three-dimensional Eulerian chemical transport model developed by the Institute of Atmospheric Physics, Chinese Academy of Sciences. It represents the major physical and



chemical processes governing atmospheric transport, chemical transformation, aerosols, and dry and wet deposition. NAQPMS has been applied to simulations of air pollution and atmospheric deposition across East Asia (Ge et al., 2014; Tan et al., 2023; Wang et al., 2001). The simulation domain is the same as MICS-Asia phase III (Itahashi et al., 2020), covered East Asia and adjacent regions on a Lambert conformal conic projection centred at 115° E and 44° N. It comprised 182×172 grid cells with a horizontal spacing of 45 km. The model used 20 vertical layers, with the lowest layer centred approximately 50 m above ground and seven layers within the lowest 2 km. Simulations covered 2011–2016. Boundary concentrations of NO₂, O₃, and CO were provided by the global chemical transport model MOZART v2.4. NAQPMS was run monthly, with a 5 d spin-up period preceding each monthly simulation.

The NAQPMS wet deposition module includes a grid-scale cloud scheme and a diagnostic convective cloud scheme (Ge et al., 2014). The grid-scale scheme represents resolved clouds occupying a model grid cell, whereas the diagnostic convective scheme represents subgrid-scale convection and assumes a cloud lifetime of 1 h. Both schemes account for aqueous-phase chemistry and wet scavenging; the convective scheme additionally includes subgrid-scale vertical transport. Wet scavenging comprises in-cloud and below-cloud processes. For aerosols, in-cloud scavenging represents particle uptake and removal by cloud and rain water. Below-cloud scavenging depends on precipitation intensity, aerosol particle size, raindrop size distribution, and particle–raindrop collision efficiency. Previous work has examined the effects of thermophoresis, diffusiophoresis, and electrostatic interactions on below-cloud scavenging, particularly for particles in the Greenfield-gap size range (Xu et al., 2019a). Subsequent NAQPMS studies have improved the diagnosis of convective in-cloud scavenging and used the model to investigate nitrogen wet deposition during landfalling typhoons (Liu et al., 2025; Tan et al., 2023; Zhang et al., 2022, 2025).

Anthropogenic emissions within China for 2011–2016 were obtained from the Multi-resolution Emission Inventory for China version 1.4 (MEICv1.4; Geng et al., 2024), while emissions outside China were taken from the Regional Emission Inventory in Asia (REAS; Kurokawa and Ohara, 2020). Because REAS data were unavailable after 2015, the 2015 inventory was retained outside China for the 2016 simulation. Biogenic emissions were obtained from CAMS-GLOB-BIOv3.1, which was generated with the Model of Emissions of Gases and Aerosols from Nature version 2.1 (MEGANv2.1; Guenther et al., 2012; Sindelarova et al., 2022). Biomass-burning emissions were provided by the Global Fire Emissions Database (GFED; Van Der Werf et al., 2017).

Meteorological fields for NAQPMS were generated using version 4.0 of the Weather Research and Forecasting model (WRF; Skamarock et al., 2019). The initial and lateral boundary conditions for WRF were obtained from the National Centers for Environmental Prediction Final Operational Global Analysis data, with a temporal resolution of 6 h and a horizontal resolution of $1^\circ \times 1^\circ$. The physical parameterization schemes used in WRF are summarized in Table 1. Each WRF integration covered 36 h: the first 12 h were treated as spin-up, and the final 24 h were retained as the meteorological fields for the corresponding day.



2.2 Observation data

130 Three observation networks of wet nitrogen deposition data including, NADMN, EANET, and the China National
 Environmental Monitoring Centre (CNEMC), were compiled in this study. NADMN provides daily measurements for 2011–
 2016. The network expanded after 2012, from 313 stations in 2011 to 561 stations in each year from 2012 to 2016 (Li et al.,
 2019). EANET includes seven sites in China, located mainly in Chongqing, Shaanxi, Fujian, and Guangdong, and also provides
 observations elsewhere in East Asia. CNEMC provides annual data from 291 stations across China for 2013–2016. Figure 1
 135 shows the spatial distribution of the three networks. Earlier wet-deposition assessments in China relied mainly on monthly or
 annual averages from relatively sparse sites (Tan et al., 2022; Xu et al., 2019b; Zhang et al., 2021), limiting their ability to
 resolve short-term nitrogen inputs. Daily NADMN measurements provide an observational basis for evaluating such events.
 Direct interpolation of station measurements nevertheless remains uncertain in regions with complex terrain, heterogeneous
 emissions, and sparse monitoring, particularly western China (Jia et al., 2014). Recent machine-learning approaches that
 140 combine satellite retrievals, meteorology, and emissions have improved the spatiotemporal representation of deposition (Jiang
 and Zhang, 2026; Lin et al., 2025), but they do not explicitly represent atmospheric physical and chemical processes. CTMs
 provide this process information but retain precipitation-related wet-deposition biases (Itahashi et al., 2021). Directly fusing
 wet deposition amounts without localized precipitation correction will inevitably amplify their uncertainty. We therefore
 adjusted the simulated precipitation before fusing the model background with quality-controlled observations.

145 In terms of data preprocessing, strict quality control was applied to the aforementioned datasets to ensure their accuracy and
 completeness. Records with missing, duplicate, or anomalous data were removed to perform a completeness check.
 Specifically, if any of the three data items—precipitation amount, oxidized nitrogen concentration in precipitation, and reduced
 nitrogen concentration in precipitation—was missing for a record at a station in a given year, that record was excluded. If more
 than 20% of the records at a station were excluded, the entire station was removed. In this study, these datasets were employed
 150 in different analysis steps according to their characteristics. NADMN and EANET observations, which provide relatively
 dense spatial coverage and high temporal resolution, were fused with the gridded model output to constrain the deposition
 field. CNEMC observations were withheld from the fusion and used only for independent evaluation of the annual fused
 products.

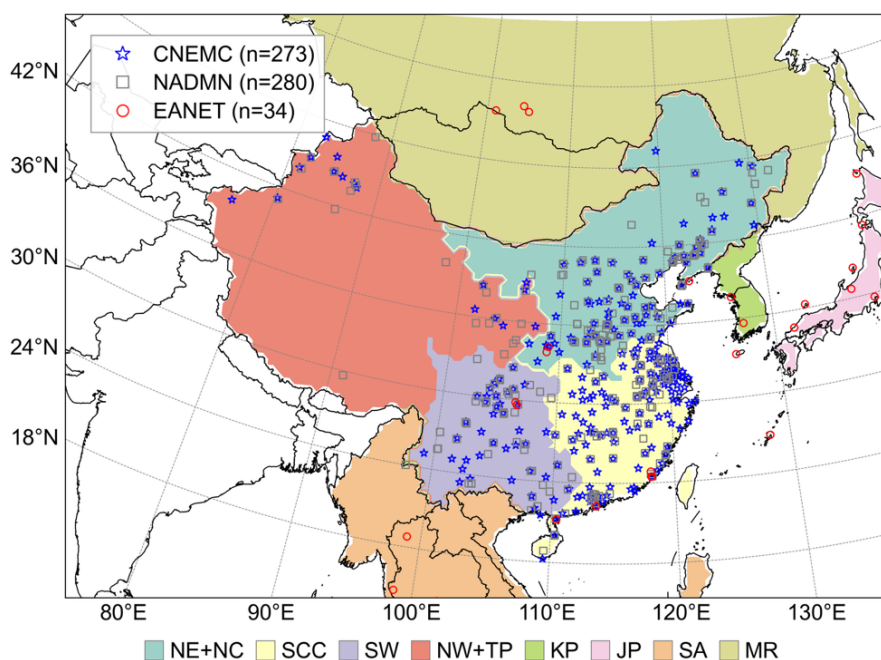


Figure 1. The dataset domain as well as the ground-based observation sites involved in this study. Marker shapes denote the data sources, and background colours denote the eight East Asian subregions used for evaluation: Northeast and North China (NE+NC), South and Central China (SCC), Southwest China (SW), Northwest China and the Tibetan Plateau (NW+TP), the Korean Peninsula (KP), Japan (JP), Southeast Asia (SA), and Mongolia and Russia (MR).

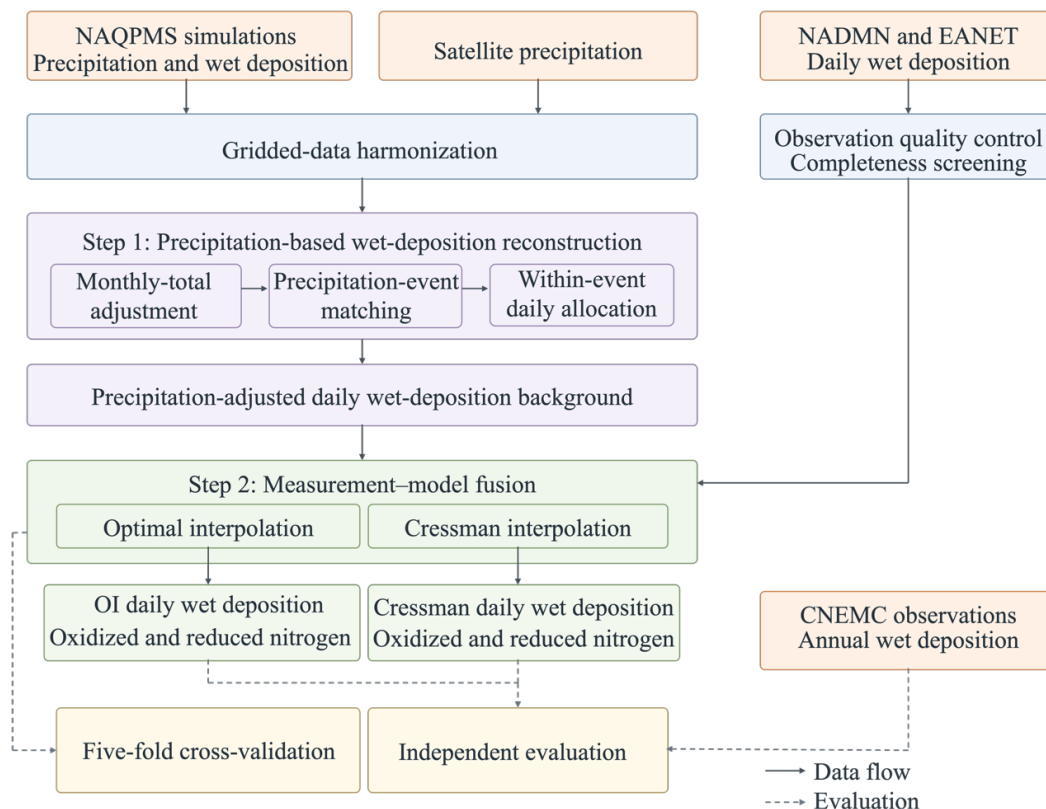
The Integrated Multi-satellite Retrievals for GPM Version 07 Final Run product (IMERG; GPM_3IMERGHH_07; Huffman et al., 2023) was used as the gridded observational precipitation dataset throughout the East Asian model domain. IMERG combines precipitation estimates from passive microwave and infrared observations at spatial and temporal resolutions of 0.1° and 30 min, respectively, and covers the full 2011–2016 study period. Half-hourly precipitation rates were converted to 30 min accumulations and aggregated to daily totals. The daily fields were then regridded to the 45 km NAQPMS grid for precipitation evaluation and daily wet-deposition reconstruction.

3 Methodology

The daily gridded nitrogen wet deposition dataset was constructed using a two-step framework comprising precipitation-based reconstruction and measurement–model fusion (Fig. 2). First, the NAQPMS daily wet-deposition background was reconstructed using IMERG precipitation through monthly-total adjustment, precipitation-event matching, and within-event daily allocation. The precipitation-adjusted background was then fused with concurrent, quality-controlled NADMN and EANET observations using Optimal interpolation (OI) and Cressman interpolation (Cressman) separately, producing daily fields of oxidized and reduced nitrogen wet deposition over East Asia for 2011–2016 at a spatial resolution of 45 km. Fusion



performance was assessed using five-fold cross-validation, while CNEMC observations, withheld from fusion, provided an independent evaluation of the annual products. Additional spatial diagnostics were calculated to characterize precipitation adjustment magnitude, distance-based observation support, and cross-validation error improvement.



175

Figure 2. Workflow for the construction and evaluation of the daily gridded nitrogen wet deposition dataset over East Asia for 2011–2016. Solid arrows indicate data flow, and dashed arrows indicate evaluation pathways. OI denotes optimal interpolation.

3.1 Precipitation adjustment

180

Systematic biases in simulated precipitation propagate directly into modelled wet deposition and therefore require correction before data fusion. Previous studies have scaled modelled wet deposition at monthly or annual resolution using the ratio of observed to modelled precipitation (Itahashi et al., 2021; Zhang et al., 2019). This approach constrains cumulative deposition but does not reconstruct its daily evolution. Direct daily scaling can also produce anomalously large values when observed and modelled precipitation events are temporally displaced or modelled precipitation approaches zero. We therefore used a three-

185 step procedure comprising monthly-total adjustment, precipitation-event matching, and within-event daily allocation. This procedure reconstructed the daily deposition sequence while conserving the adjusted monthly total. Observed and modelled



daily precipitation were first aggregated to monthly totals, and monthly modelled wet deposition was adjusted by the ratio of observed to modelled monthly precipitation:

$$W_m^{adj} = \frac{Precip_m^{obs_grid}}{Precip_m^{mod}} \times W_m^{mod} \quad (1)$$

190 Here, W_m^{adj} and W_m^{mod} denote the adjusted and original model-simulated wet deposition totals for month m , respectively; $Precip_m^{obs_grid}$ and $Precip_m^{mod}$ denote the monthly accumulated precipitation derived from the gridded observations and the WRF simulation, respectively. Both monthly precipitation totals are obtained by summing the corresponding daily precipitation amounts.

Subsequently, precipitation events are identified separately from the observed and WRF daily precipitation series. A day with
 195 daily precipitation of no less than 0.1mm d^{-1} is defined as a wet day, and consecutive wet days constitute a precipitation event. For precipitation events identified separately from the two datasets, candidate reference precipitation events are first selected within a ± 2 d time window centered on the modeled event-center date. The matching cost is then calculated as a weighted sum of four components representing differences in event-center date, duration, and accumulated precipitation, as well as the degree of date overlap, with respective weights of 0.50, 0.20, 0.20, and 0.10. A lower matching cost indicates
 200 greater similarity between the two precipitation events, and the candidate event with the minimum matching cost is selected as the best match. This process preserves the complete structure of precipitation events while reducing the influence of timing offsets in modeled precipitation on the daily allocation of wet deposition. This process preserves the complete structure of precipitation events while reducing the influence of timing offsets in modeled precipitation on the daily allocation of wet deposition. After event matching, the total wet deposition amount of all identified modeled wet deposition events in month m ,
 205 W_{me}^{mod} , is calculated. The adjusted monthly wet deposition total is then allocated among the matched events according to their proportional contributions to wet deposition in the original model:

$$W_k^{adj} = \frac{W_k^{mod}}{W_{me}^{mod}} \times W_m^{adj} \quad (2)$$

where W_k^{adj} denotes the adjusted deposition amount for the k th wet deposition event, and W_k^{mod} denotes the deposition amount of the k th modeled wet deposition event. The sum of the adjusted deposition amounts for all events is equal to the
 210 adjusted monthly wet deposition total, thereby ensuring conservation of wet deposition between the monthly and event scales. For successfully matched events, the relationship between the cumulative precipitation fraction and the cumulative wet deposition fraction is first established based on the original modeled event. The daily cumulative precipitation fractions of the observed event are then substituted into this relationship to obtain the deposition allocation coefficient for each day within the event. The adjusted daily wet deposition amount is calculated as follows:

$$215 \quad W_d^{adj} = f_d \times W_k^{adj}, \quad d \in D_k \quad (3)$$

where,



$$\sum_{d \in D_k} f_d = 1 \quad (4)$$

where W_d^{adj} denotes the adjusted wet deposition amount on day d ; f_d denotes the deposition allocation coefficient for that day within the event to which it belongs; and D_k denotes the set of dates included in the k th event. For modeled events that cannot be matched to observed events, their original occurrence dates and within-event daily allocation structures are retained. For events identified only from observations for which no corresponding process exists in the model, no additional wet deposition is generated, thereby avoiding the artificial introduction of deposition in the absence of modeled concentration information.

3.2 Measurement–model fusion

After precipitation adjustment, the daily modelled wet-deposition field was used as the background and fused with concurrent station observations. OI (Robichaud et al., 2025) and Cressman (Cressman, 1959) were applied separately to correct the gridded background using observation-minus-background departures. The general form is

$$W^{fus}(x, t) = W^{adj}(x, t) + \sum_{i=1}^{n_t} \{\lambda_i(x, t) \times [W^{obs}(x_i, t) - W^{adj}(x_i, t)]\} \quad (5)$$

Where $W^{fus}(x, t)$ and $W^{adj}(x, t)$ denote the fused wet deposition and the precipitation-adjusted modelled wet deposition at location x on day t , respectively; $W^{obs}(x_i, t)$ denotes the observed wet deposition at the i th station on day t ; $W^{adj}(x_i, t)$ denotes the wet deposition from the adjusted model background field at the location of that station; n_t is the number of valid observation stations on day t ; and $\lambda_i(x, t)$ is the fusion weight of the i th station for the target grid cell. The difference within the square brackets represents the departure of the observation from the model background.

In OI, the fusion weights in Eq. (5) are determined from the statistical characteristics of the model background and observation errors. The weight matrix is expressed as follows:

$$K = BH^T(HBH^T + R)^{-1} \quad (6)$$

where K is the OI weight matrix, whose elements correspond to the fusion weights in Eq. (5); H is the observation operator that maps the model grid values to the observation-site locations; B and R are the model background-error covariance matrix and the observation-error covariance matrix, respectively; and the superscripts T and -1 denote matrix transposition and matrix inversion, respectively. The background-error covariance between locations u and v , B_{uv} , is calculated as:

$$B_{uv} = \sigma_b^2 \times \exp\left(-\frac{d_{uv}}{L}\right), \quad R = \sigma_o^2 I = q \times \sigma_b^2 I \quad (7)$$

Where d_{uv} is the horizontal distance between the two locations; L is the background-error correlation length; σ_b^2 and σ_o^2 are the background-error variance and observation-error variance, respectively; q is the ratio of the observation-error variance to the background-error variance; and I is the identity matrix. Observation errors at different stations are assumed to be mutually independent.



245 This study employs the Hollingsworth–Lönnberg method to estimate the background and observation errors from the spatial statistical structure of the innovations (Hollingsworth and Lönnberg, 1986; Nie et al., 2015). First, the covariance of the innovations between different station pairs is calculated as a function of separation distance, and its spatial decay relationship is fitted. The background-error variance σ_b^2 and correlation length L are determined from the fitted curve. The observation-error variance σ_o^2 is then estimated as the difference between the total innovation variance and the background-error variance, after which the error-variance ratio q is calculated. Because the error characteristics vary among years and nitrogen forms, L and q are estimated separately for oxidized and reduced nitrogen in each year (Table S2). Therefore, the OI weights depend jointly on station distance, the spatial correlation of the background errors, and the relative magnitudes of the observation and model-background errors.

In Cressman, the weights are determined according to the distance between each station and the target grid cell. The distance-based weight and normalized weight for the i th station are expressed, respectively, as follows:

$$w_i(x) = \begin{cases} \frac{R_c^2 - d_i^2(x)}{R_c^2 + d_i^2(x)} & , \quad d_i(x) < R_c \\ 0 & , \quad d_i(x) \geq R_c \end{cases} \quad (8)$$

where $d_i(x)$ is the horizontal distance between the i th station and the target grid cell x ; R_c is the Cressman radius of influence; and $w_i(x)$ is the corresponding distance-based weight. The fusion weights in Eq. (5) are expressed in normalized form, i.e., $\lambda_i = \frac{w_i}{\sum_j w_j}$, where the subscript j is the summation index used to sum the weights of all valid stations within the radius of influence on day t . When no valid observations are available within the radius of influence, the fused result remains equal to the precipitation-adjusted model background value.

The radius of influence R_c was determined through sensitivity tests, with candidate values of 45, 60, 75, 90, 105, 120, and 135 km. First, the spatial coverage under each radius was calculated as the proportion of grid cells in the study domain for which at least one valid observation station was located within the radius of influence, with 70 % specified as the minimum coverage requirement. The fusion performance was then compared across candidate radii, with the evaluation results presented in Table S3.. The results show that both oxidized and reduced nitrogen achieve the best overall performance at $R_c = 90$ km. Therefore, 90 km was ultimately adopted as the Cressman radius of influence for both oxidized and reduced nitrogen wet deposition.

3.3 Validation methods and evaluation criteria

Previous studies have used binary classification to distinguish precipitation and non-precipitation days. Accuracy, the false alarm ratio, and the Heidke skill score have been used to assess the ability of precipitation products to reproduce occurrence and associated uncertainty (AghaKouchak and Mehran, 2013; Dong et al., 2020; Hu et al., 2025). Following this approach, daily nitrogen wet deposition was classified as occurring or not occurring. The Heidke skill score, accuracy, and false alarm ratio were then used to compare how well the model background and fused products reproduced daily deposition occurrence.



$$HSS = \frac{2(TP \times TN - FP \times FN)}{(TP + FN)(FN + TN) + (TP + FP)(FP + TN)} \quad (9)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (10)$$

$$FAR = \frac{FP}{TP + FP} \quad (11)$$

Here, true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) describe the correspondence between daily observations and fused (or modeled) data in terms of nitrogen wet deposition occurrence. For each station–year combination, the 1st percentile of positive observed daily wet deposition values is used as the binary classification threshold, and the same threshold is applied to the observed, modeled, and fused time series. Values above the threshold are assigned a value of 1, indicating deposition occurrence, whereas values less than or equal to the threshold are assigned a value of 0, indicating that the criterion for deposition occurrence is not met. Based on this classification, the Heidke skill score (HSS) is used to measure classification skill after accounting for random agreement, accuracy is used to characterize the overall ability to distinguish between deposition and no-deposition conditions, and the false alarm ratio (FAR) is defined as the proportion of cases in which deposition is predicted but not observed among all cases predicted as deposition occurrences.

Because nitrogen wet deposition varies strongly across East Asia, the 25th, 50th, and 75th percentiles of positive observed daily deposition were calculated separately for oxidized and reduced nitrogen. Daily deposition was classified into four magnitude categories: low, moderate, high, and very high. The observation-derived thresholds were applied consistently to the model background and held-out five-fold cross-validation results to evaluate changes in magnitude-classification performance after fusion.

The fused products were evaluated using annual station-wise five-fold cross-validation with complete station holdout, together with independent observations. Because the availability and spatial distribution of valid monitoring stations varied among years, the five-fold grouping was performed separately for each year. Monitoring stations were used as the grouping unit, and the valid stations in each year were divided into five subsets with similar numbers of stations and spatially balanced distributions. In each iteration, all daily observations from the stations in one fold were completely withheld for validation, while the remaining four folds were used for data fusion. The predictions from the five held-out folds were then recombined to form a complete annual out-of-fold dataset. Finally, the annual out-of-fold datasets from 2011–2016 were concatenated, without refitting across years, to calculate the pooled daily, monthly, and annual statistics. Monthly and annual values were obtained by aggregating the held-out daily predictions for each station. CNEMC observations, which were not used in fusion, provided an independent evaluation of the annual products. Performance was quantified using the correlation coefficient (R), root mean square error (RMSE), mean absolute error (MAE), and normalized mean error (NME):

$$R = \frac{\sum_{i=1}^N (MF_i - MF_m)(Obs_i - Obs_m)}{[\sum_{i=1}^N (MF_i - MF_m)^2 \sum_{i=1}^N (Obs_i - Obs_m)^2]^{\frac{1}{2}}} \quad (12)$$



$$MSE = \left[\frac{1}{N} \sum_{i=1}^N (MF_i - Obs_i)^2 \right]^{\frac{1}{2}} \quad (13)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |MF_i - Obs_i| \quad (14)$$

305 where N is the number of samples, MF_i and Obs_i represent the modelled value (or fused result) and the observed value for the i -th sample, respectively, and MF_m and Obs_m denote the mean of the model-simulated values (or fused results) and the mean of the observed values, respectively.

3.4 Spatial diagnostics of adjustment, observation support, and validation improvement

310 Precipitation adjustment magnitude, distance-based observation support, and cross-validation error improvement were used to characterize the spatial characteristics of the daily oxidized and reduced nitrogen wet deposition products during 2011–2016 (Fig. 10). The precipitation adjustment magnitude was defined as the mean absolute daily difference between the original and precipitation-adjusted model estimates:

$$A_P(x) = \frac{1}{N_P(x)} \sum_{t \in \mathcal{T}_P(x)} |W^{\text{adj}}(x, t) - W^{\text{mod}}(x, t)| \quad (15)$$

315 where $W^{\text{mod}}(x, t)$ and $W^{\text{adj}}(x, t)$ denote the original and precipitation-adjusted daily wet deposition at grid cell x on day t , respectively; $\mathcal{T}_P(x)$ is the set of dates on which both estimates are valid; and $N_P(x)$ is the number of these paired days during 2011–2016. Valid zero-deposition days were retained. This diagnostic is expressed in $\text{kg N ha}^{-1} \text{d}^{-1}$ and describes the magnitude of the daily changes introduced by precipitation adjustment.

320 Distance-based observation support was calculated using the exponential distance function in Eq. (7). For each grid cell and day with valid observations, the maximum distance factor among the concurrently valid observation sites was obtained as follows:

$$h(x, t) = \max_{i \in \mathcal{O}_t} \left\{ \exp \left[-\frac{d(x, x_i)}{L_t} \right] \right\} \quad (16)$$

325 where $\mathcal{O}_t$ is the set of stations with valid observations and precipitation-adjusted background values on day t ; $d(x, x_i)$ is the horizontal distance between the target grid cell and station i ; and L_t is the correlation length estimated for the corresponding year and nitrogen form. Valid zero-deposition observations were included. The daily distance factor was set to zero when no valid observations were available. The daily factors were then averaged over valid product days:

$$H(x) = \frac{1}{N_H(x)} \sum_{t \in \mathcal{T}_H(x)} h(x, t) \quad (17)$$

where $\mathcal{T}_H(x)$ is the set of dates with valid OI product values during 2011–2016, and $N_H(x)$ is the number of these days. Days without valid observations were assigned zero and retained in the average, while missing product days were excluded. The



index ranges from 0 to 1, with higher values indicating closer and more frequently available observations. This diagnostic
 summarizes distance-based support; the full OI weights are determined using Eqs. (6)–(7).

At each monitoring location, normalized cross-validation error improvement was calculated as follows:

$$S_i = \frac{MAE_i^{mod} - MAE_i^{fus}}{MAE_i^{mod} + MAE_i^{fus}} \quad (18)$$

where MAE_i^{mod} and MAE_i^{fus} are the mean absolute errors of the original model estimates and the held-out OI predictions,
 respectively, calculated using Eq. (14). Observations, original model estimates, and held-out predictions were matched on the
 same valid dates. Daily errors were pooled across the available years at each monitoring location before calculating the mean
 absolute errors and the improvement index. The index ranges from -1 to 1 : positive values indicate lower errors after fusion,
 zero indicates equal errors, and negative values indicate increased errors. When both mean absolute errors were zero, the index
 was assigned zero; locations without paired valid samples were excluded. Because the original model was used as the reference,
 the comparison represents the combined effect of precipitation adjustment and OI. Cross-validation error improvement was
 shown at monitoring locations, while precipitation adjustment magnitude and observation support were mapped on the 45 km
 grid.

4 Results and discussion

4.1 Evaluation of simulated nitrogen wet deposition

NAQPMS performance was evaluated against site-based observations at spatial and temporal scales. Figure 3 compares the
 2011–2016 mean annual spatial distributions of simulated oxidized and reduced nitrogen wet deposition and the corresponding
 fusion results obtained using OI with station observations. The model reproduced the broad pattern of higher deposition in
 southern and eastern China and lower deposition in northwestern China. Oxidized nitrogen was overestimated at many sites
 in central and eastern China (Fig. 3a). OI reduced this overestimation at some sites and improved agreement with observations
 while retaining the overall spatial pattern (Fig. 3b). Reduced nitrogen biases varied more strongly by region. Simulations
 underestimated deposition at some sites in eastern China and overestimated it at some sites in southwestern China (Fig. 3c).
 The fused results showed closer agreement with observations, although biases remained at several sites (Fig. 3d).

Figure S2 compares monthly oxidized and reduced nitrogen wet deposition from observations and model simulations during
 2011–2016. Both observations and simulations showed higher deposition in summer and lower deposition in winter. Oxidized
 nitrogen was overestimated in most months, particularly in summer, whereas winter biases were smaller. Some summer peaks
 of reduced nitrogen were underestimated during 2011–2013 and in 2016, while overestimation occurred in some summer
 months of 2014 and 2015. Part of the wet deposition bias was associated with simulated precipitation: summer precipitation
 peaks were overestimated in some years, consistent with the summer overestimation of oxidized nitrogen deposition (Fig. S1).



Precipitation adjustment reduced the annual wet deposition errors for both nitrogen forms and provided an improved background field for subsequent observation-based fusion.

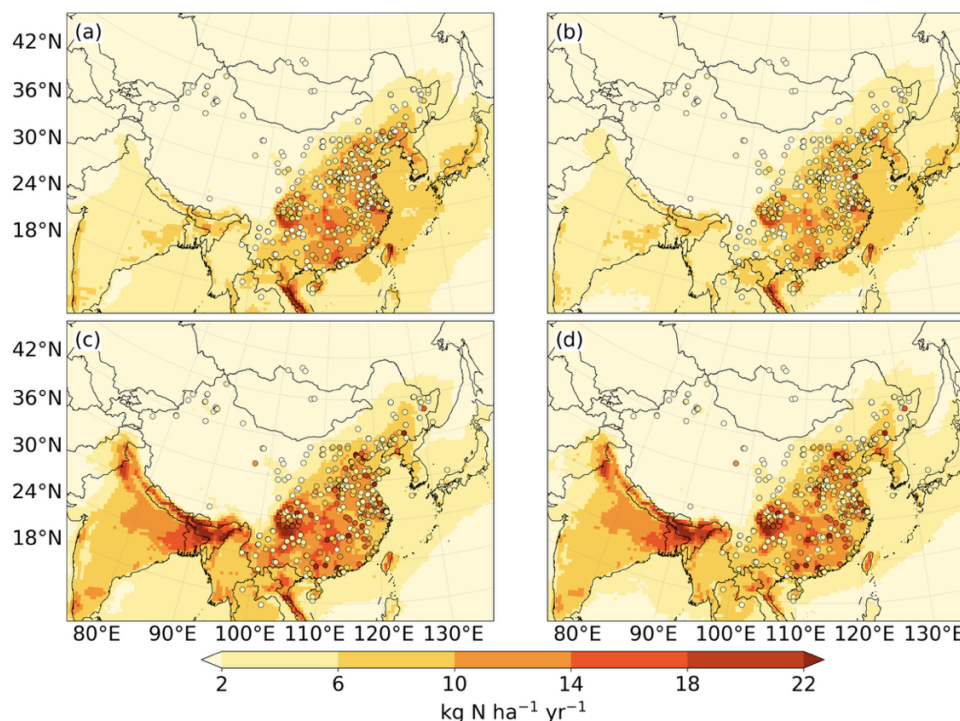


Figure 3. Spatial distributions of mean annual nitrogen wet deposition over East Asia during 2011–2016: (a, b) oxidized nitrogen and (c, d) reduced nitrogen. The left panels (a, c) show model simulations, with station observations represented by colored circles; the right panels (b, d) show the OI products. Mean annual deposition is calculated from annual totals, with station observations averaged over their available years. Gridded fields and station observations share the same color scale ($\text{kg N ha}^{-1} \text{ yr}^{-1}$).

4.2 Cross-validation of the fused products

Five-fold cross-validation was used to evaluate improvements in nitrogen wet deposition estimates achieved by OI and Cressman, while multiyear mean spatial differences were further examined to characterize the bias correction patterns of the two methods. Figure 4 presents the spatial distributions of the multiyear mean observed-minus-modelled (OmM), observed-minus-fused (OmF), and fused-minus-modelled (FmM) differences for OI, with the corresponding Cressman results shown in Fig. S3. Before fusion, oxidized nitrogen wet deposition was substantially overestimated at several sites in North China and other regions ($\text{OmM} < -2.5 \text{ kg N ha}^{-1}$), whereas reduced nitrogen wet deposition was underestimated at some sites along the eastern coast ($\text{OmM} > 2.5 \text{ kg N ha}^{-1}$). After fusion, both methods substantially reduced the multiyear mean biases at most sites, particularly in central and eastern China, where the monitoring network is relatively dense. The OmF differences for OI were close to zero at most sites, indicating improved agreement between the fused estimates and observations. Cressman showed



similar improvements, with even smaller multiyear mean biases at some sites. The spatial distributions of FmM revealed broadly consistent correction directions for the two methods, both producing negative adjustments over parts of central and eastern China, consistent with the overestimation by the original model in these regions. In comparison, OI produced a more spatially continuous and smoother adjustment field at the regional scale. Nevertheless, residual biases remained at several sites in Sichuan, Chongqing, Jiangsu, Guangdong, and Anhui. The substantial differences in wet deposition among neighbouring sites in these areas (Fig. S4) limited the ability of the two methods to capture local spatial gradients in wet deposition.

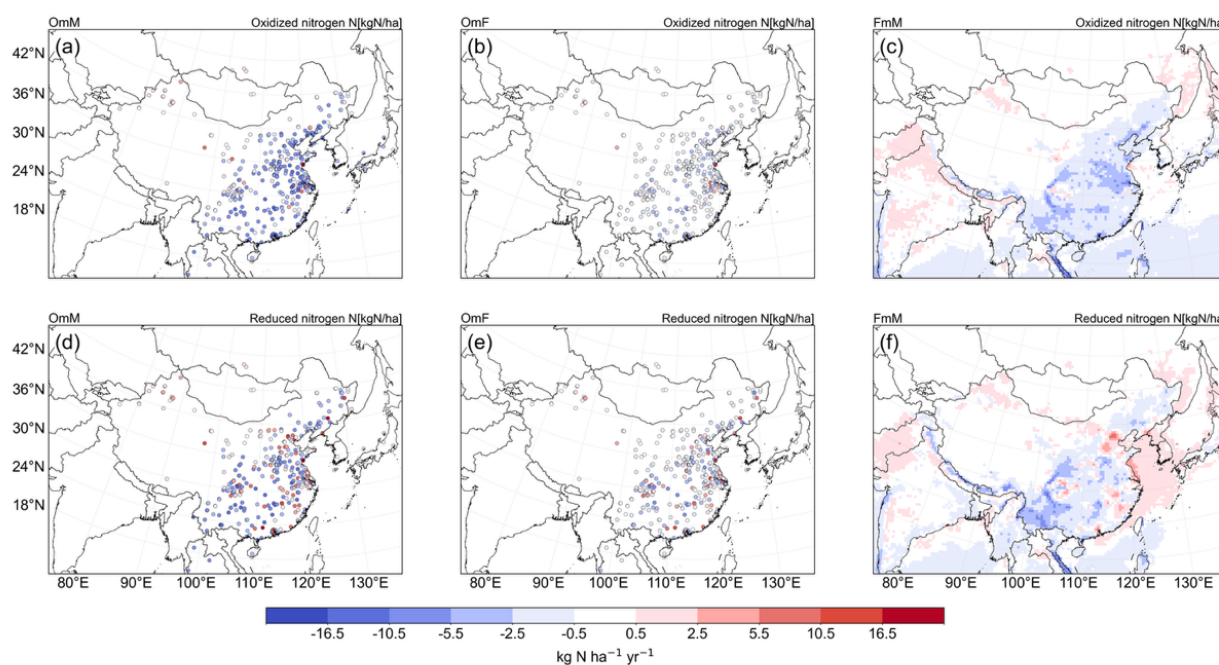


Figure 4. Spatial distributions of the six-year mean OmM (left column), OmF (middle column), and FmM (right column) for oxidized and reduced nitrogen wet deposition ($\text{kg N ha}^{-1} \text{yr}^{-1}$) over East Asia based on OI fusion.

Figure 5 shows the monthly variation in the MAE of oxidized and reduced nitrogen wet deposition across eight subregions of East Asia for the model simulations and the OI and Cressman results obtained through five-fold cross-validation. Overall, the MAE of the model simulations exhibited a seasonal pattern characterized by higher values in summer and lower values in winter, while both fusion methods reduced the MAE in most regions and months. For oxidized nitrogen wet deposition, the MAE decreased from $0.41 \text{ kg N ha}^{-1} \text{month}^{-1}$ before fusion to 0.31 and $0.32 \text{ kg N ha}^{-1} \text{month}^{-1}$ after OI and Cressman, respectively, corresponding to reductions of 24.83% and 22.74%. For reduced nitrogen wet deposition, the MAE decreased from 0.46 to 0.38 and $0.40 \text{ kg N ha}^{-1} \text{month}^{-1}$, corresponding to reductions of 17.43% and 12.67%, respectively. These results indicate that OI performed better in terms of both overall error reduction and consistency across regions. Among the different subregions, the most pronounced improvements occurred in South Korea and North Korea, where the 12-month mean MAE of oxidized nitrogen decreased by 48.43% and 49.93% after OI and Cressman, respectively, while that of reduced nitrogen



395 decreased by 28.95% and 24.76%, respectively. In contrast, the improvement in reduced nitrogen wet deposition was relatively limited in Central and Southern China, where the 12-month mean MAE decreased by 16.74% and 8.08% after OI and Cressman, respectively. This may primarily be attributable to the large spatial variability in reduced nitrogen wet deposition among neighboring monitoring stations in this region (Fig. S4), which makes it difficult for the fusion methods to effectively capture local variations in deposition. Overall, OI produced larger reductions in the MAE of both nitrogen forms and showed relatively
 400 stable performance across regions. Cressman also reduced simulation errors in most regions, but the magnitude of improvement exhibited more pronounced regional differences.

Beyond the general long-term assessment, evaluating the performance of the fused data across different temporal scales is also important for assessing their ability to characterize daily variations and monthly and annual accumulation patterns. Table 1 summarizes the station-based five-fold cross-validation results for the model simulations, OI, and Cressman at daily, monthly,
 405 and annual scales from 2011 to 2016. At the daily scale, the R values between modeled and observed oxidized nitrogen (reduced nitrogen) wet deposition were only 0.16 (0.17). After OI and Cressman, the corresponding values increased to 0.41 (0.47) and 0.39 (0.42), respectively. Correspondingly, the RMSE decreased from 0.12 (0.15) kg N ha⁻¹ d⁻¹ to 0.10 (0.12) and 0.10 (0.13) kg N ha⁻¹ d⁻¹, respectively, while the MAE decreased from 0.03 to 0.02 kg N ha⁻¹ d⁻¹. These results demonstrate that both fusion methods improved the ability to reproduce daily wet deposition amounts and their temporal variations, with
 410 OI producing a more pronounced improvement for reduced nitrogen. Nevertheless, the daily R values remained below 0.50 after fusion, indicating that the accurate characterization of daily wet deposition remains challenging because of the influence of precipitation processes and local variations in nitrogen deposition.

As the data were aggregated from the daily to the monthly scale, the agreement with observations further improved for both nitrogen forms. The R values for modeled oxidized nitrogen (reduced nitrogen) were 0.41 (0.45), increasing to 0.54 (0.63)
 415 after OI and 0.51 (0.58) after Cressman. Correspondingly, the RMSE decreased from 0.93 (1.10) kg N ha⁻¹ month⁻¹ to 0.76 (0.90) and 0.82 (1.06) kg N ha⁻¹ month⁻¹, respectively. At the annual scale, the R values for oxidized nitrogen (reduced nitrogen) reached 0.53 (0.61) after OI, exceeding those obtained with Cressman [0.47 (0.54)] and the model simulations [0.44 (0.46)]. The RMSE and MAE also decreased from 6.24 (6.34) and 4.95 (4.69) kg N ha⁻¹ yr⁻¹ in the model simulations to 4.86 (5.73) and 3.47 (4.00) kg N ha⁻¹ yr⁻¹ after OI, respectively. Cressman also improved annual oxidized nitrogen deposition. However,
 420 the annual RMSE for reduced nitrogen increased from 6.34 to 6.60 kg N ha⁻¹ yr⁻¹, although its R and MAE still improved, indicating that relatively large deposition biases may remain for some station–year combinations. Overall, both fusion methods improved the agreement between nitrogen wet deposition and observations across different temporal scales. However, OI consistently produced higher R values and lower RMSE and MAE values at all scales, indicating more stable improvements. Meanwhile, the fused data characterized monthly and annual cumulative deposition patterns more effectively than daily
 425 variations. Substantial uncertainty remains in the model representation of wet deposition events driven by short-term weather processes, highlighting the need for further evaluation and optimization using observations with higher temporal resolution.

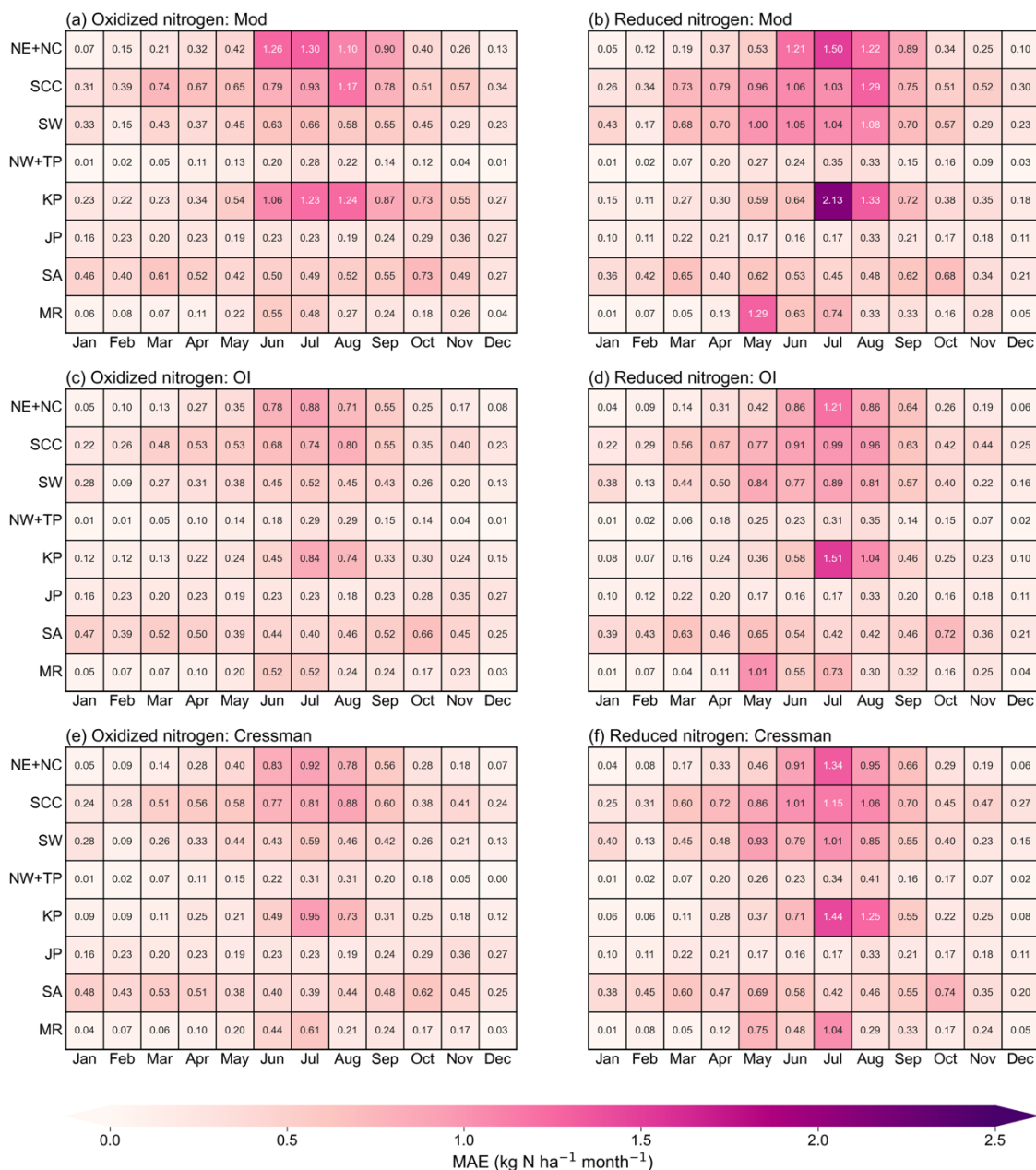


Figure 5. Monthly MAEs of oxidized (left columns) and reduced nitrogen (right columns) wet deposition before and after data fusion over the East Asian subregions based on five-fold cross-validation. (a, b) Model simulations, (c, d) OI fusion and (e, f) Cressman fusion. Units: kg N ha⁻¹ month⁻¹.



435

Table 1. Evaluation of model simulations and fusion results for oxidized and reduced nitrogen wet deposition at daily, monthly, and annual scales during 2011–2016. n denotes the number of valid observation–estimate pairs, R is the Pearson correlation coefficient, RMSE is the root mean square error, and MAE is the mean absolute error. The units of RMSE and MAE are $\text{kg N ha}^{-1} \text{d}^{-1}$, $\text{kg N ha}^{-1} \text{month}^{-1}$, and $\text{kg N ha}^{-1} \text{yr}^{-1}$ at the daily, monthly, and annual scales, respectively.

Oxidized nitrogen	Temporal scale	Method	n	R	RMSE	MAE
	Daily	Mod	567369	0.16	0.12	0.03
		OI	567369	0.41	0.10	0.02
		Cressman	567369	0.39	0.10	0.02
	Monthly	Mod	18636	0.41	0.93	0.54
		OI	18636	0.54	0.76	0.40
		Cressman	18636	0.51	0.82	0.42
	Yearly	Mod	1553	0.44	6.24	4.95
		OI	1553	0.53	4.86	3.47
		Cressman	1553	0.47	5.44	3.77
Temporal scale	Method	n	R	RMSE	MAE	
Reduced nitrogen	Daily	Mod	567369	0.17	0.15	0.03
		OI	567369	0.47	0.12	0.02
		Cressman	567369	0.42	0.13	0.02
	Monthly	Mod	18636	0.45	1.10	0.59
		OI	18636	0.63	0.90	0.47
		Cressman	18636	0.58	1.06	0.52
	Yearly	Mod	1553	0.46	6.34	4.69
		OI	1553	0.61	5.73	4.00
		Cressman	1553	0.54	6.60	4.44

4.3 Categorical evaluation of daily wet-deposition occurrence and magnitude

440

Figure 6 presents the regional five-fold cross-validation results derived from NADMN and EANET observations for OI; the corresponding Cressman results are shown in Fig. S4. Both methods improved the classification of daily wet-deposition occurrence. For oxidized nitrogen (reduced nitrogen), Cressman increased the Heidke skill score (HSS) from 0.28 (0.27) to 0.40 (0.42), increased accuracy from 0.80 (0.81) to 0.84 (0.85), and reduced the false alarm ratio (FAR) from 0.71 (0.70) to 0.58 (0.57). OI increased the HSS to 0.37 (0.39) and kept the accuracy to 0.83, while reducing the FAR to 0.62 (0.61). Cressman produced larger mean improvements, but its station-level metric distributions were wider in some regions. OI produced smaller



mean improvements in several regions but more concentrated distributions. Method performance should therefore be evaluated
 445 in terms of both the mean improvement and its consistency among sites.

Accuracy was generally higher within China than in most other East Asian regions, indicating better discrimination between
 deposition and non-deposition days where monitoring was denser. Table 2 shows that the evaluation sample was much larger
 within China than in the Korean Peninsula, Japan, Southeast Asia, Mongolia, and Russia. Metrics for the latter regions were
 therefore more sensitive to individual sites. Northwest China and the Tibetan Plateau had the largest spatial coefficient of
 450 variation for oxidized nitrogen deposition (1.442), and this combination of sparse monitoring and strong heterogeneity
 produced relatively low HSS values and broad metric distributions. By contrast, the Korean Peninsula had a lower coefficient
 of variation despite its smaller sample size, allowing observation increments to be transferred more consistently among
 neighbouring sites. The Cressman results nevertheless remained widely dispersed in this region, indicating that their larger
 average improvement was not uniform across stations. Regional fusion performance therefore depended on station coverage,
 455 spatial heterogeneity, and the response of each interpolation method to local observation increments.

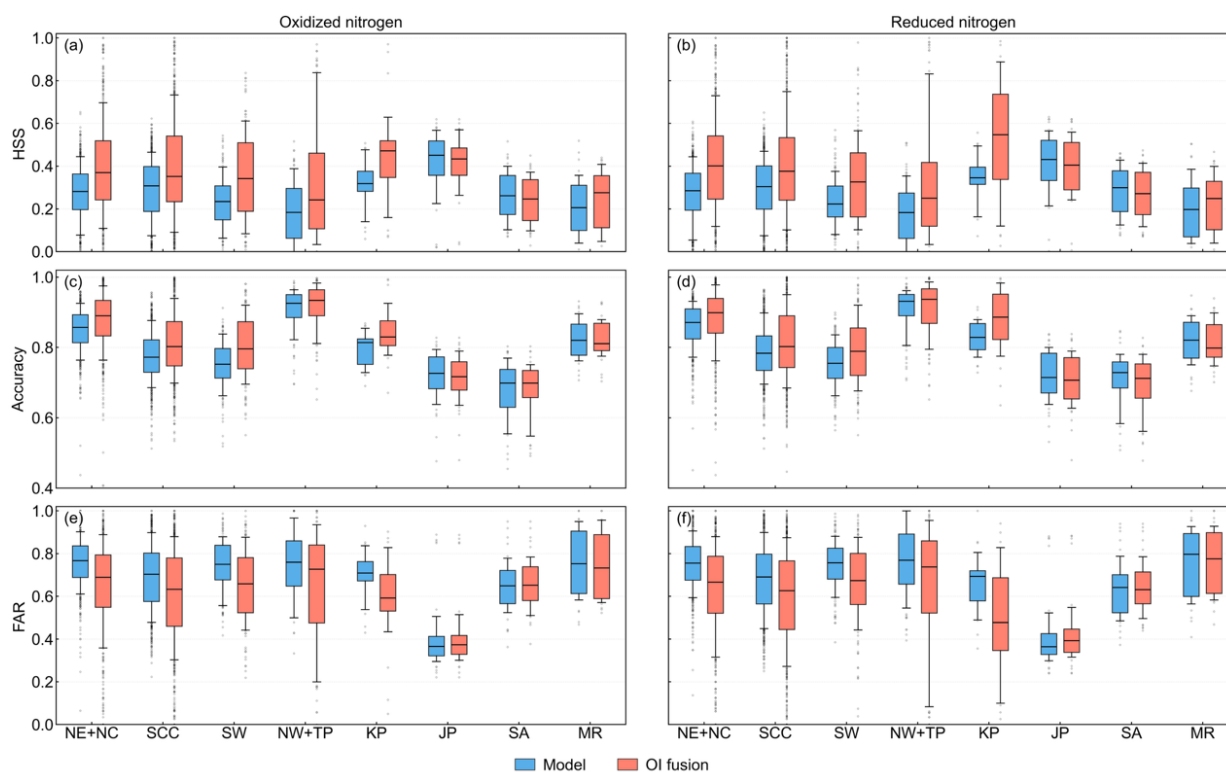


**Figure 6. Regional evaluation of oxidized and reduced nitrogen wet-deposition occurrence before and after OI across
 eight East Asian regions. Panels (a–f) present the Heidke skill score (HSS), accuracy, and false alarm ratio (FAR) for
 the original model simulations and OI fusion results. Boxplots show the distributions of station–year evaluation metrics
 460 obtained from fivefold cross-validation.**



Daily deposition was classified into low, moderate, high, and very high categories using the quartiles of the observed distributions. Held-out five-fold cross-validation results were then used to evaluate magnitude classification (Fig. 7). For oxidized nitrogen, exact classification rates of 19.87 %–34.03 % for the model increased to 26.81 %–44.75 % after OI and 25.18 %–43.95 % after Cressman. The largest gains occurred in the very-high category, with increases of 12.74 and 11.94 percentage points, respectively. For reduced nitrogen, model classification rates of 19.02 %–43.47 % increased to 30.12 %–52.88 % after OI and 27.03 %–44.45 % after Cressman. In the very-high category, the corresponding improvements were 20.80 and 21.84 percentage points. OI generally produced the higher classification rates because its error-covariance-based weights propagated observation increments smoothly over larger spatial scales. Cressman applied local corrections within a fixed radius, which could either overextend or insufficiently propagate individual increments.

Table 2. Regional variability in observed oxidized and reduced nitrogen wet deposition. Here, n denotes the number of valid station–year records during 2011–2016. Mean and Std are the arithmetic mean and sample standard deviation, respectively, of the station-specific annual mean daily wet deposition. CV is the coefficient of variation (Std/Mean). Records from the same station in different years are counted separately.

Oxidized nitrogen	n	Mean	Std	CV
NE+NC	583	0.012	0.012	0.953
SCC	372	0.018	0.015	0.872
SW	271	0.015	0.015	0.961
NW+TP	103	0.004	0.006	1.442
KP	29	0.012	0.008	0.635
JP	13	0.008	0.002	0.202
SA	48	0.011	0.010	0.906
MR	25	0.002	0.002	0.964
Reduced nitrogen	n	Mean	Std	CV
NE+NC	583	0.019	0.017	0.896
SCC	372	0.026	0.020	0.780
SW	271	0.027	0.023	0.860
NW+TP	103	0.005	0.006	1.074
KP	29	0.028	0.013	0.451
JP	13	0.009	0.003	0.345
SA	48	0.023	0.018	0.781
MR	25	0.004	0.003	0.946

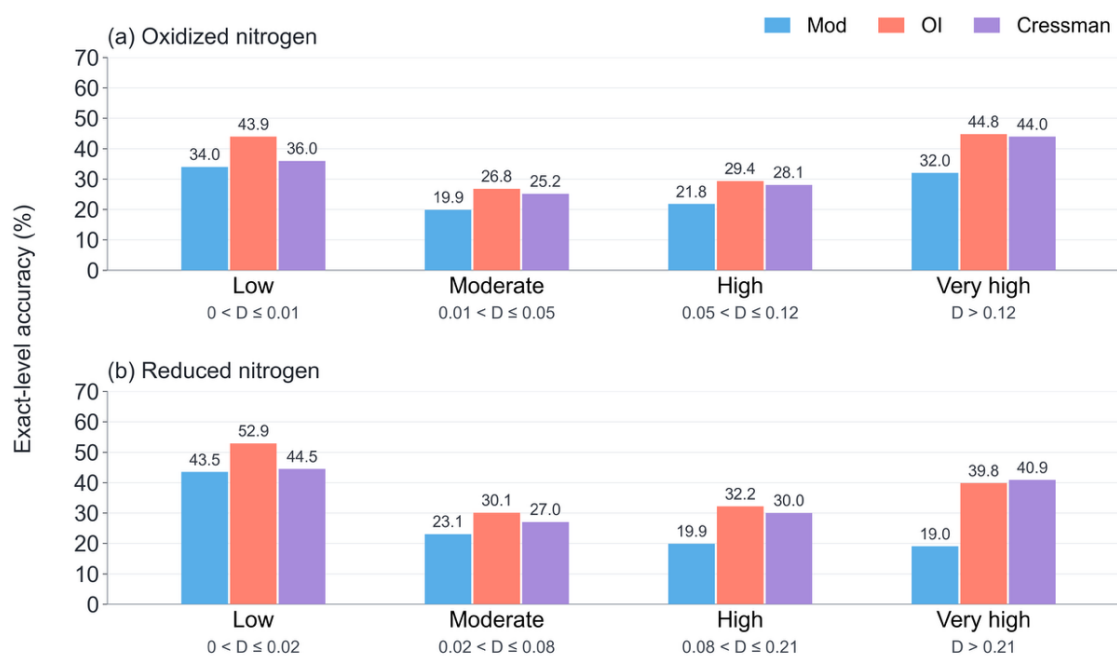


Figure 7. Exact classification rates for the low, moderate, high, and very high daily wet-deposition categories for oxidized (a) and reduced (b) nitrogen in the model, OI, and Cressman products.

4.4 Comparison with the independent CNEMC dataset

To evaluate the reliability of the fused dataset against independent observations, CNEMC observations for 2013–2016, which were not used in fusion, were used to evaluate the annual statistical distributions of the model, OI, and Cressman products (Fig. 8). For oxidized nitrogen, the observed mean and standard deviation were 5.62 and 4.27 kg N ha⁻¹ yr⁻¹, respectively, compared with 9.41 and 4.00 kg N ha⁻¹ yr⁻¹ in the model. The model error was therefore dominated by systematic overestimation, accompanied by a modest underrepresentation of variability. OI reduced the mean to 7.60 kg N ha⁻¹ yr⁻¹, although the standard deviation decreased to 3.68 kg N ha⁻¹ yr⁻¹. Cressman produced a comparable mean correction (7.49 kg N ha⁻¹ yr⁻¹) and a standard deviation closer to the observations (4.17 kg N ha⁻¹ yr⁻¹). For reduced nitrogen, the observed mean and standard deviation were 9.16 and 6.68 kg N ha⁻¹ yr⁻¹, respectively. The model reproduced the mean (9.46 kg N ha⁻¹ yr⁻¹) but underestimated the standard deviation (3.89 kg N ha⁻¹ yr⁻¹). OI retained a similar mean (9.56 kg N ha⁻¹ yr⁻¹) and increased the standard deviation to 4.45 kg N ha⁻¹ yr⁻¹. Cressman restored more of the observed variability (standard deviation of 5.86 kg N ha⁻¹ yr⁻¹) but increased the mean to 10.03 kg N ha⁻¹ yr⁻¹. Thus, OI provided a better balance between correcting the oxidized-nitrogen mean bias and maintaining a stable reduced-nitrogen mean, whereas Cressman represented local dispersion more strongly at the cost of a larger positive mean bias.



These statistical characteristics are closely related to the model resolution and the weighting structures of the two fusion methods. The model background field uses a 45 km grid, and the associated spatial averaging weakens local differences at the station scale, resulting in a more concentrated distribution of modeled values and an underestimated standard deviation. The pronounced overestimation of mean oxidized nitrogen reflects the combined effects of errors in emission inputs, precipitation processes, and wet-scavenging calculations within the model background field. OI determines the propagation weights of observation increments jointly from the background-error and observation-error covariance matrices, such that the analysis retains a certain proportion of the model background information. This weighting structure prevents excessive corrections driven by local observation increments and therefore maintains a stable mean for reduced nitrogen. However, it also retains the smooth spatial characteristics of the model background field, limiting the complete recovery of the oxidized nitrogen standard deviation to the observed level. In contrast, Cressman directly propagates observation increments within a fixed radius of influence and responds more strongly to local high and low values, thereby more fully restoring the sample dispersion. When positive increments dominate within the radius of influence, however, this local correction also increases the mean deposition amount.

Overall, the fusion-based corrections addressed the dominant model errors differently for the two nitrogen forms. For oxidized nitrogen, they primarily reduced the systematic overestimation by the model; for reduced nitrogen, they compensated for the model's underestimation of the observed variability while maintaining a generally reasonable mean magnitude. Although OI did not produce standard deviations that were consistently closest to the observations, it achieved a more balanced performance among correcting the mean oxidized nitrogen deposition, maintaining the overall magnitude of reduced nitrogen deposition, and ensuring the stability of the fused results. This indicates that the observational information incorporated into the fusion can effectively correct deterministic biases in the model background field and restore part of the variability attenuated by grid averaging and spatial smoothing. The CNEMC observations were not used in the fusion, yet the fused results remained in good agreement with them in terms of key statistical characteristics, demonstrating the reliability of the OI results when evaluated against an independent monitoring network and across datasets. Together with the preceding validation results for different temporal scales, interannual variations, and seasonal variations, these findings show that the fusion-based correction enhances the ability of the dataset to reproduce the magnitudes and variability of both forms of nitrogen wet deposition, providing a multiscale, continuous, and stable data foundation for regional nitrogen-cycle analysis and assessments of the ecological effects of nitrogen deposition.

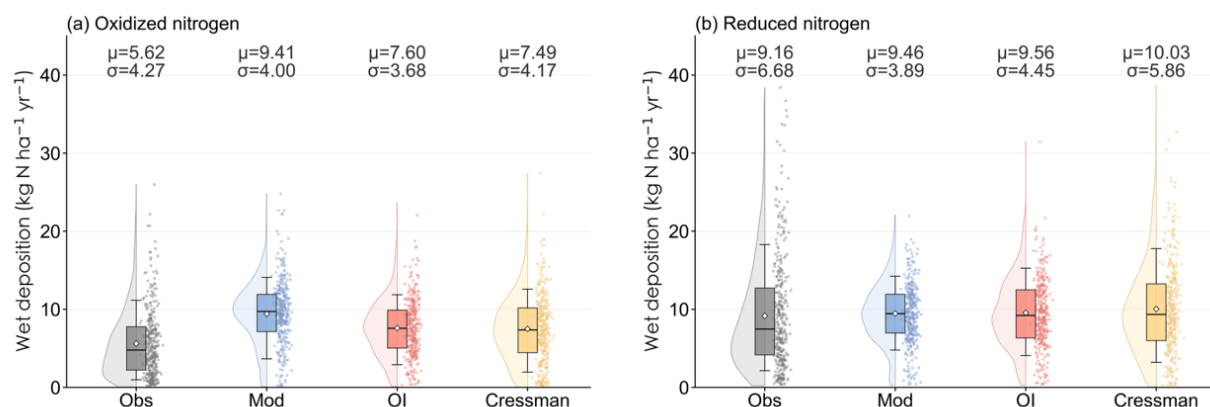


Figure 8. Paired raincloud plots of annual oxidized and reduced nitrogen wet deposition from the CNEMC dataset. (a) CNEMC oxidized nitrogen and (b) CNEMC reduced nitrogen. Black, blue, and red (yellow) represent the observations, model simulations, and fused results, respectively. The half-violin plots show the distributions, and the box plots indicate the quantiles.

4.5 Uncertainty and limitations

Precipitation adjustment and measurement-model fusion improved estimates of oxidized and reduced nitrogen wet deposition, but uncertainty remains in the observations, precipitation reconstruction, model background, fusion methods, and spatial coverage. Cross-validation assesses reconstruction performance for the available monitoring network, while the independent CNEMC comparison provides a further evaluation at the annual scale. Neither evaluation directly verifies deposition fluxes in every 45 km grid cell. The gridded values are regional estimates with spatially varying observational constraints, rather than direct grid-scale measurements.

Ground-based observations were screened for completeness and subjected to quality control, but combining records from multiple monitoring networks can leave residual uncertainty. Stations measure local precipitation chemistry, whereas each 45 km grid cell covers an area with heterogeneous emissions, terrain, precipitation, and atmospheric transport. This point-to-grid representativeness difference matters most where deposition varies sharply between nearby stations. Monitoring coverage is also uneven across East Asia. Figure 9 summarizes precipitation adjustment magnitude, distance-based observation support, and cross-validation error improvement for the daily product during 2011 to 2016. Mean precipitation adjustment magnitudes varied spatially for both nitrogen forms (Fig. 9a, d). Adjustments were generally larger in central and southern China and smaller in northern and northwestern China. Reduced nitrogen also showed pronounced adjustments along the southwestern margin of the displayed domain. These patterns describe how strongly precipitation adjustment changed the deposition estimates, rather than where it demonstrably reduced errors.

Distance-based observation support had similar spatial patterns for the two nitrogen forms (Fig. 9b, e). Support was more extensive and relatively continuous in central and eastern China, but elsewhere it was largely concentrated around monitoring



sites. Northwest China and the Tibetan Plateau had weaker support, apart from localized areas around individual stations. Substantial precipitation adjustments also occurred in some areas with weak deposition-observation support. Precipitation information thus helped reconstruct the background field beyond the areas constrained by local deposition observations. At many monitored locations in China, the mean absolute error of daily deposition was lower after precipitation adjustment and OI than in the original model (Fig. 9c, f). Improvements varied among sites, with small changes at some stations and increased errors at others. Because the comparison uses the original model as its reference, it evaluates the combined effect of precipitation adjustment and OI, not their separate contributions. Relatively extensive observation support and error reductions at many sites support analyses of regional daily variability in central and eastern China. However, neither distance-based support nor station-level error improvement quantifies uncertainty in unmonitored grid cells.

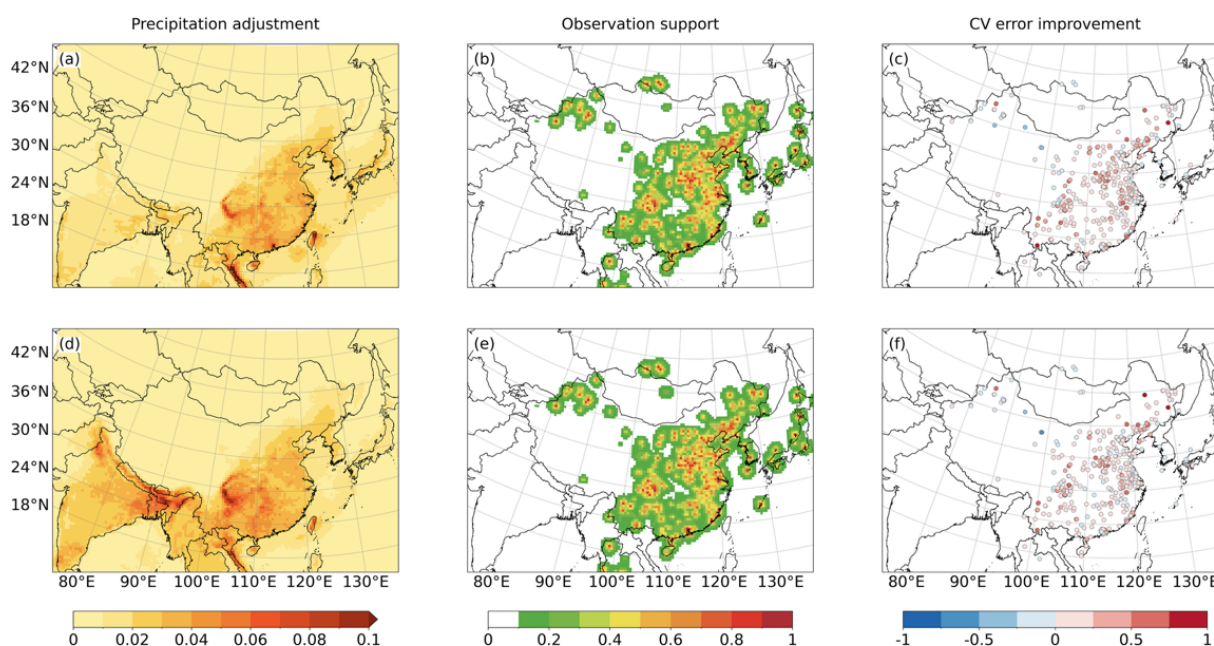


Figure 9. Spatial distributions of precipitation adjustment magnitude (a, d; $\text{kg N ha}^{-1} \text{d}^{-1}$), distance-based observation support (b, e), and normalized cross-validation MAE improvement (c, f; circles) for oxidized (a–c) and reduced (d–f) nitrogen wet deposition during 2011–2016.

Precipitation retrieval and event matching introduce further uncertainty. IMERG retrieval errors are of particular concern over complex terrain and during convective or weak rainfall. Regridding the 0.1° precipitation product to the 45 km model grid further smooths local precipitation structures. The adjustment method constrains monthly wet deposition totals and redistributes deposition among matched precipitation events, avoiding unstable daily scaling when modeled rainfall is small or displaced in time. It cannot fully correct errors in precipitation intensity, event duration, or location. Observed precipitation events without a modeled counterpart do not generate additional deposition because the corresponding modeled atmospheric concentrations are unavailable. Deposition associated with these missed events may therefore remain underestimated.



Precipitation adjustment also leaves uncertainties in emissions, atmospheric transport, chemical transformation, and wet-scavenging mechanisms in the NAQPMS background field uncorrected. Validation reveals a further limitation at the daily scale. Correlations remained below 0.50 after fusion, despite improvements over the model background, while agreement increased at monthly and annual scales. The product therefore represents accumulated deposition more reliably than the exact timing and magnitude of individual daily events. The annual RMSE for reduced nitrogen from Cressman exceeded that of the model background, showing that local fusion corrections do not necessarily improve annual estimates and can increase errors for some station-year combinations.

The dataset is best suited to examining regional daily variability and monthly and annual accumulation, identifying candidate periods of high deposition, and evaluating regional-scale model simulations. Individual grid cells, isolated daily extremes, complex terrain, and areas far from monitoring stations require greater caution. At 45 km resolution, the daily product cannot resolve subdaily precipitation processes, local station-scale gradients, or cloud-scale scavenging mechanisms. OI is recommended as the primary product because it provides more balanced error reduction and regional stability. The Cressman product offers a complementary estimate of sensitivity to the fusion method.

5 Conclusions

This study developed a daily gridded dataset of oxidized and reduced nitrogen wet deposition over East Asia for 2011–2016 at a spatial resolution of 45 km. The dataset was constructed using a two-step framework that combined precipitation-based reconstruction of NAQPMS simulations with measurement–model fusion. Satellite precipitation was used to constrain monthly deposition totals and reconstruct daily deposition within precipitation events, while NADMN and EANET observations were incorporated through OI and Cressman. The resulting products were evaluated using station-wise five-fold cross-validation and independent CNEMC observations.

Both methods also improved the classification of daily wet-deposition occurrence and magnitude. For oxidized nitrogen (reduced nitrogen), OI increased HSS to 0.37 (0.39) and accuracy to 0.83 (0.83), while reducing FAR to 0.62 (0.61). The corresponding values for Cressman were 0.40 (0.42), 0.84 (0.85), and 0.58 (0.57). Cressman produced larger average improvements in occurrence classification, whereas OI generally showed less dispersed metric distributions in several regions. Both methods improved classification across the four deposition-magnitude categories. For the very-high category, classification rates increased by 12.74% and 20.80% percentage points after OI and by 11.94% and 21.84% percentage points after Cressman for oxidized and reduced nitrogen, respectively. These improvements support the use of the products to identify candidate high-deposition periods, while substantial differences among stations remain.

Independent comparison with CNEMC observations supported the improvements at the annual scale. For oxidized nitrogen, OI and Cressman reduced the model mean from 9.41 to 7.60 and 7.49 kg N ha⁻¹ yr⁻¹, respectively, bringing it closer to the observed mean of 5.62 kg N ha⁻¹ yr⁻¹. For reduced nitrogen, both methods partly restored the observed variability underestimated by the model. The standard deviation increased from 3.89 kg N ha⁻¹ yr⁻¹ in the model to 4.45 and 5.86 kg N



595 $\text{ha}^{-1} \text{yr}^{-1}$ after OI and Cressman, respectively, compared with $6.68 \text{ kg N ha}^{-1} \text{yr}^{-1}$ in the observations. Cressman reproduced more of the observed dispersion but increased the mean reduced nitrogen deposition, whereas OI maintained a mean closer to the observations. Together with the cross-validation results, this comparison supports OI as the primary product and Cressman as a complementary estimate of sensitivity to the fusion method.

The spatial diagnostics further showed that precipitation adjustment and observational support varied across the domain. Larger
 600 precipitation adjustments occurred mainly in central and southern China, while distance-based observation support was more extensive and continuous in central and eastern China. Daily cross-validation errors decreased at many monitored locations, although improvements varied among sites and errors increased at some locations. These diagnostics clarify the spatial differences in background reconstruction and observational support; they do not provide a direct estimate of accuracy for every grid cell.

605 The dataset provides an observation-constrained resource for examining regional daily wet-deposition variability, monthly and annual accumulation, and high-deposition periods, as well as evaluating regional model simulations. Its application should account for uneven monitoring coverage, point-to-grid representativeness differences, and remaining uncertainty in daily event timing and magnitude. Interpretation of isolated daily extremes and estimates in sparsely monitored or complex-terrain regions requires particular care. Further improvements should focus on expanding observations, refining precipitation-event
 610 reconstruction, and evaluating high-deposition events using independent measurements with sufficient temporal resolution.

Code and data availability

The daily gridded dataset of oxidized and reduced nitrogen wet deposition over East Asia presented in this study covers the period from 1 January 2011 to 31 December 2016. The dataset has a daily temporal resolution and is provided on the native NAQPMS Lambert conformal conic grid (182×172 grid cells) with a horizontal spacing of 45 km. It contains observation-
 615 constrained daily wet deposition estimates for both nitrogen forms generated using optimal interpolation (OI). The dataset is organized into six annual NetCDF files, each containing daily oxidized and reduced nitrogen wet deposition fields. The complete dataset is freely available from the Science Data Bank (ScienceDB) at <https://doi.org/10.57760/sciencedb.015vd> under the Creative Commons Attribution 4.0 International (CC BY 4.0) licence (Yang et al., 2026).

Author contributions

620 BG, NL, and ZW designed the overall research direction; NL and DX performed simulations using the NAQPMS model; NY, NL, ZH, and YZ processed the observational and model data; NY, NL, and BG determined the data fusion method; and NY wrote the manuscript. All co-authors contributed to this work.



Competing interests

The authors declare that they have no conflict of interest.

625 Disclaimer

Copernicus Publications remains neutral with regard to jurisdictional claims made in the text, published maps, institutional affiliations, or any other geographical representation in this paper. While Copernicus Publications makes every effort to include appropriate place names, the final responsibility lies with the authors. Views expressed in the text are those of the authors and do not necessarily reflect the views of the publisher.

630 Acknowledgements

We acknowledge the National Acid Deposition Monitoring Network (NADMN), the China National Environmental Monitoring Centre (CNEMC), and the Acid Deposition Monitoring Network in East Asia (EANET) for the nitrogen wet deposition observations used in this study.

Financial support

635 This research has been supported by the National Natural Science Foundation of China (grant nos. 42122049 and 42377104).

References

- Ackerman, D., Millet, D. B., and Chen, X.: Global estimates of inorganic nitrogen deposition across four decades, *Global Biogeochem. Cycles*, 33, 100–107, <https://doi.org/10.1029/2018GB005990>, 2019.
- AghaKouchak, A. and Mehran, A.: Extended contingency table: Performance metrics for satellite observations and climate
640 model simulations, *Water Resour. Res.*, 49, 7144–7149, <https://doi.org/10.1002/wrcr.20498>, 2013.
- Appel, K. W., Foley, K. M., Bash, J. O., Pinder, R. W., Dennis, R. L., Allen, D. J., and Pickering, K.: A multi-resolution assessment of the Community Multiscale Air Quality (CMAQ) model v4.7 wet deposition estimates for 2002–2006, *Geosci. Model Dev.*, 4, 357–371, <https://doi.org/10.5194/gmd-4-357-2011>, 2011.
- Baker, A. R., Kanakidou, M., Altieri, K. E., Daskalakis, N., Okin, G. S., Myriokefalitakis, S., Dentener, F., Uematsu, M., Sarin,
645 M. M., Duce, R. A., Galloway, J. N., Keene, W. C., Singh, A., Zamora, L., Lamarque, J.-F., Hsu, S.-C., Rohekar, S. S., and Prospero, J. M.: Observation- and model-based estimates of particulate dry nitrogen deposition to the oceans, *Atmos. Chem. Phys.*, 17, 8189–8210, <https://doi.org/10.5194/acp-17-8189-2017>, 2017.



- Bouwman, A. F., van Vuuren, D. P., Derwent, R. G., and Posch, M.: A global analysis of acidification and eutrophication of terrestrial ecosystems, *Water, Air, Soil Pollut.*, 141, 349–382, <https://doi.org/10.1023/A:1021398008726>, 2002.
- 650 Chen, C., Xiao, W., and Chen, H. Y. H.: Mapping global soil acidification under N deposition, *Glob. Change Biol.*, 29, 4652–4661, <https://doi.org/10.1111/gcb.16813>, 2023.
- Cressman, G. P.: An operational objective analysis system, *Mon. Weather Rev.*, 87, 367–374, [https://doi.org/10.1175/1520-0493\(1959\)087%3C0367:AOOAS%3E2.0.CO;2](https://doi.org/10.1175/1520-0493(1959)087%3C0367:AOOAS%3E2.0.CO;2), 1959.
- Crippa, M., Guizzardi, D., Butler, T., Keating, T., Wu, R., Kaminski, J., Kuenen, J., Kurokawa, J., Chatani, S., Morikawa, T.,
 655 Pouliot, G., Racine, J., Moran, M. D., Klimont, Z., Manseau, P. M., Mashayekhi, R., Henderson, B. H., Smith, S. J., Suchyta, H., Muntean, M., Solazzo, E., Banja, M., Schaaf, E., Pagani, F., Woo, J.-H., Kim, J., Monforti-Ferrario, F., Pisoni, E., Zhang, J., Niemi, D., Sassi, M., Ansari, T., and Foley, K.: The HTAP_v3 emission mosaic: merging regional and global monthly emissions (2000–2018) to support air quality modelling and policies, *Earth Syst. Sci. Data*, 15, 2667–2694, <https://doi.org/10.5194/essd-15-2667-2023>, 2023.
- 660 Dong, J., Crow, W. T., and Reichle, R.: Improving rain/no-rain detection skill by merging precipitation estimates from different sources, *J. Hydrometeorol.*, 21, 2419–2429, <https://doi.org/10.1175/JHM-D-20-0097.1>, 2020.
- Fowler, D., Steadman, C. E., Stevenson, D., Coyle, M., Rees, R. M., Skiba, U. M., Sutton, M. A., Cape, J. N., Dore, A. J., Vieno, M., Simpson, D., Zaehle, S., Stocker, B. D., Rinaldi, M., Facchini, M. C., Flechard, C. R., Nemitz, E., Twigg, M., Erisman, J. W., Butterbach-Bahl, K., and Galloway, J. N.: Effects of global change during the 21st century on the nitrogen
 665 cycle, *Atmos. Chem. Phys.*, 15, 13849–13893, <https://doi.org/10.5194/acp-15-13849-2015>, 2015.
- Fu, J. S., Carmichael, G. R., Dentener, F., Aas, W., Andersson, C., Barrie, L. A., Cole, A., Galy-Lacaux, C., Geddes, J., Itahashi, S., Kanakidou, M., Labrador, L., Paulot, F., Schwede, D., Tan, J., and Vet, R.: Improving estimates of sulfur, nitrogen, and ozone total deposition through multi-model and measurement-model fusion approaches, *Environ. Sci. Technol.*, 56, 2134–2142, <https://doi.org/10.1021/acs.est.1c05929>, 2022.
- 670 Gao, W., Yang, X., Zhang, Y., Zhao, T., Shi, B., Yang, T., Ma, J., Xu, W., Wu, Y., and Sun, W.: Suppression of methane uptake by precipitation pulses and long-term nitrogen addition in a semi-arid meadow steppe in northeast China, *Front. Plant Sci.*, 13, 1071511, <https://doi.org/10.3389/fpls.2022.1071511>, 2023.
- Ge, B. Z., Wang, Z. F., Xu, X. B., Wu, J. B., Yu, X. L., and Li, J.: Wet deposition of acidifying substances in different regions of China and the rest of East Asia: modeling with updated NAQPMS, *Environ. Pollut.*, 187, 10–21, <https://doi.org/10.1016/j.envpol.2013.12.014>, 2014.
- 675 Geng, G., Liu, Y., Liu, Y., Liu, S., Cheng, J., Yan, L., Wu, N., Hu, H., Tong, D., Zheng, B., Yin, Z., He, K., and Zhang, Q.: Efficacy of China’s clean air actions to tackle PM_{2.5} pollution between 2013 and 2020, *Nat. Geosci.*, 17, 987–994, <https://doi.org/10.1038/s41561-024-01540-z>, 2024.
- Guenther, A. B., Jiang, X., Heald, C. L., Sakulyanontvittaya, T., Duhl, T., Emmons, L. K., and Wang, X.: The Model of Emissions of Gases and Aerosols from Nature version 2.1 (MEGAN2.1): an extended and updated framework for modeling
 680 biogenic emissions, *Geosci. Model Dev.*, 5, 1471–1492, <https://doi.org/10.5194/gmd-5-1471-2012>, 2012.



- Hollingsworth, A. and Lönnberg, P.: The statistical structure of short-range forecast errors as determined from radiosonde data. Part I: the wind field, *Tellus A: Dyn. Meteorol. Oceanogr.*, 38, 111–136, <https://doi.org/10.3402/tellusa.v38i2.11707>, 1986.
- Hu, J., Miao, C., Su, J., Zhang, Q., Gou, J., and Sun, Q.: An upgraded high-precision gridded precipitation dataset for the Chinese mainland considering spatial autocorrelation and covariates, *Earth Syst. Sci. Data*, 17, 3987–4004, <https://doi.org/10.5194/essd-17-3987-2025>, 2025.
- Huffman, G. J., Stocker, E. F., Bolvin, D. T., Nelkin, E. J., and Tan, J.: GPM IMERG Final Precipitation L3 Half Hourly 0.1 degree x 0.1 degree V07, Goddard Earth Sciences Data and Information Services Center (GES DISC) [dataset], <https://doi.org/10.5067/GPM/IMERG/3B-HH/07>, 2023.
- Itahashi, S., Ge, B., Sato, K., Fu, J. S., Wang, X., Yamaji, K., Nagashima, T., Li, J., Kajino, M., Liao, H., Zhang, M., Wang, Z., Li, M., Kurokawa, J., Carmichael, G. R., and Wang, Z.: MICS-Asia III: overview of model intercomparison and evaluation of acid deposition over Asia, *Atmos. Chem. Phys.*, 20, 2667–2693, <https://doi.org/10.5194/acp-20-2667-2020>, 2020.
- Itahashi, S., Ge, B., Sato, K., Wang, Z., Kurokawa, J., Tan, J., Huang, K., Fu, J. S., Wang, X., Yamaji, K., Nagashima, T., Li, J., Kajino, M., Carmichael, G. R., and Wang, Z.: Insights into seasonal variation of wet deposition over southeast Asia via precipitation adjustment from the findings of MICS-Asia III, *Atmos. Chem. Phys.*, 21, 8709–8734, <https://doi.org/10.5194/acp-21-8709-2021>, 2021.
- Jia, Y., Yu, G., He, N., Zhan, X., Fang, H., Sheng, W., Zuo, Y., Zhang, D., and Wang, Q.: Spatial and decadal variations in inorganic nitrogen wet deposition in China induced by human activity, *Sci. Rep.*, 4, 3763, <https://doi.org/10.1038/srep03763>, 2014.
- Jiang, Y. and Zhang, X.: Estimating daily wet nitrate deposition across China considering under-cloud and in-cloud scavenging effects from satellite observations, *IEEE Trans. Geosci. Remote Sens.*, 64, 1–10, <https://doi.org/10.1109/TGRS.2026.3663637>, 2026.
- Kurokawa, J. and Ohara, T.: Long-term historical trends in air pollutant emissions in Asia: Regional Emission inventory in ASia (REAS) version 3, *Atmos. Chem. Phys.*, 20, 12761–12793, <https://doi.org/10.5194/acp-20-12761-2020>, 2020.
- Li, R., Cui, L., Zhao, Y., Zhang, Z., Sun, T., Li, J., Zhou, W., Meng, Y., Huang, K., and Fu, H.: Wet deposition of inorganic ions in 320 cities across China: spatio-temporal variation, source apportionment, and dominant factors, *Atmos. Chem. Phys.*, 19, 11043–11070, <https://doi.org/10.5194/acp-19-11043-2019>, 2019.
- Lin, R., Liao, W., Liu, H., Yang, L., Chen, W., and Wang, X.: Integrating machine learning with causal inference to improve prediction of ammonium wet deposition in the Pearl River Delta, *Sustainability*, 17, 1970, <https://doi.org/10.3390/su17051970>, 2025.
- Liu, L., Wen, Z., Liu, S., Zhang, X., and Liu, X.: Decline in atmospheric nitrogen deposition in China between 2010 and 2020, *Nat. Geosci.*, 17, 733–736, <https://doi.org/10.1038/s41561-024-01484-4>, 2024.
- Liu, N., Ge, B., Su, X., Chen, X., Wild, O., Zhang, Y., Wang, Z., and Wang, Z.: High-resolution convective wet scavenging simulations: a case study of the Fukushima Daiichi nuclear power plant accident, *J. Geophys. Res.: Atmos.*, 130, e2024JD043202, <https://doi.org/10.1029/2024JD043202>, 2025.



- Liu, Y., Yu, J., Shen, Y., and Lv, X.: A modified interpolation method for surface total nitrogen in the Bohai Sea, *J. Atmos. Oceanic Technol.*, 33, 1509–1517, <https://doi.org/10.1175/JTECH-D-15-0250.1>, 2016.
- Ma, M., Zheng, B., Xu, W., Cao, J., Zhou, K., and Zhao, Y.: Trend and interannual variations of reactive nitrogen deposition in China during 2008–2017 and the roles of anthropogenic emissions and meteorological conditions, *J. Geophys. Res.: Atmos.*, 128, e2022JD037489, <https://doi.org/10.1029/2022JD037489>, 2023.
- Midolo, G., Alkemade, R., Schipper, A. M., Benítez-López, A., Perring, M. P., and De Vries, W.: Impacts of nitrogen addition on plant species richness and abundance: a global meta-analysis, *Global Ecol. Biogeogr.*, 28, 398–413, <https://doi.org/10.1111/geb.12856>, 2019.
- Nie, S., Luo, Y., Wu, T., Shi, X., and Wang, Z.: A merging scheme for constructing daily precipitation analyses based on objective bias-correction and error estimation techniques, *J. Geophys. Res.: Atmos.*, 120, 8671–8692, <https://doi.org/10.1002/2015JD023347>, 2015.
- Qu, L., Xiao, H., Zheng, N., Zhang, Z., and Xu, Y.: Comparison of four methods for spatial interpolation of estimated atmospheric nitrogen deposition in South China, *Environ. Sci. Pollut. Res.*, 24, 2578–2588, <https://doi.org/10.1007/s11356-016-7995-0>, 2017.
- Robichaud, A., Cole, A., Cheng, I., Cathcart, H., Feng, J., and Hou, A.: Data fusion of modelled and-measured deposition in the U.S. and Canada, part I: description of methodology and validation of wet deposition of sulfur and nitrogen, *Atmos. Environ.*, 347, 121074, <https://doi.org/10.1016/j.atmosenv.2025.121074>, 2025.
- Schwede, D. B. and Lear, G. G.: A novel hybrid approach for estimating total deposition in the United States, *Atmos. Environ.*, 92, 207–220, <https://doi.org/10.1016/j.atmosenv.2014.04.008>, 2014.
- Seinfeld, J. H. and Pandis, S. N.: *Atmospheric chemistry and physics: from air pollution to climate change*, 2nd ed., John Wiley & Sons, Hoboken, NJ, USA, 1203 pp., ISBN 9780471720188, 2006.
- Sindelarova, K., Markova, J., Simpson, D., Huszar, P., Karlicky, J., Darras, S., and Granier, C.: High-resolution biogenic global emission inventory for the time period 2000–2019 for air quality modelling, *Earth Syst. Sci. Data*, 14, 251–270, <https://doi.org/10.5194/essd-14-251-2022>, 2022.
- Skamarock, W. C., Klemp, J. B., Dudhia, J., Gill, D. O., Liu, Z., Berner, J., Wang, W., Powers, J. G., Duda, M. G., Barker, D. M., and Huang, X.-Y.: A Description of the Advanced Research WRF Version 4, NCAR/TN-556+STR, National Center for Atmospheric Research, Boulder, Colorado, USA, <https://doi.org/10.5065/1dfh-6p97>, 2019.
- Tan, J., Su, H., Itahashi, S., Tao, W., Wang, S., Li, R., Fu, H., Huang, K., Fu, J. S., and Cheng, Y.: Quantifying the wet deposition of reactive nitrogen over China: synthesis of observations and models, *Sci. Total Environ.*, 851, 158007, <https://doi.org/10.1016/j.scitotenv.2022.158007>, 2022.
- Tan, J., Zhang, Y., Liu, X., Lam, Y. F., Latif, M. T., Manomaiphiboon, K., Fu, J. S., Ooi, M. C. G., Huang, L., Wang, Y., Chen, H., Zhang, K., Mu, Q., and Li, L.: Data driven analysis on changing patterns of reactive nitrogen deposition in East and Southeast Asia, *Atmos. Environ.*, 374, 121962, <https://doi.org/10.1016/j.atmosenv.2026.121962>, 2026.



- Tan, Q., Ge, B., Itahashi, S., Gan, L., Zhang, Y., Xie, S., Liu, Y., Xu, D., Chen, X., Wu, L., Pan, X., Wang, W., Wu, J., Li, J.,
 750 Wang, J., Xu, X., Fu, J. S., and Wang, Z.: Unexpected high contribution of in-cloud wet scavenging to nitrogen deposition
 induced by pumping effect of typhoon landfall in China, *Environ. Res. Commun.*, 5, 021005, <https://doi.org/10.1088/2515-7620/acb90b>, 2023.
- Vitousek, P. M., Aber, J. D., Howarth, R. W., Likens, G. E., Matson, P. A., Schindler, D. W., Schlesinger, W. H., and Tilman,
 755 D. G.: Human alteration of the global nitrogen cycle: sources and consequences, *Ecol. Appl.*, 7, 737–750,
[https://doi.org/10.1890/1051-0761\(1997\)007%5B0737:HAOTGN%5D2.0.CO;2](https://doi.org/10.1890/1051-0761(1997)007%5B0737:HAOTGN%5D2.0.CO;2), 1997.
- Wang, Z., Maeda, T., Hayashi, M., Hsiao, L.-F., and Liu, K.-Y.: A nested air quality prediction modeling system for urban
 and regional scales: application for high-ozone episode in Taiwan, *Water, Air, Soil Pollut.*, 130, 391–396,
<https://doi.org/10.1023/A:1013833217916>, 2001.
- Wen, Z., Xu, W., Li, Q., Han, M., Tang, A., Zhang, Y., Luo, X., Shen, J., Wang, W., Li, K., Pan, Y., Zhang, L., Li, W., Collett,
 760 J. L., Zhong, B., Wang, X., Goulding, K., Zhang, F., and Liu, X.: Changes of nitrogen deposition in China from 1980 to 2018,
Environ. Int., 144, 106022, <https://doi.org/10.1016/j.envint.2020.106022>, 2020.
- Wen, Z., Ma, X., Xu, W., Si, R., Liu, L., Ma, M., Zhao, Y., Tang, A., Zhang, Y., Wang, K., Zhang, Y., Shen, J., Zhang, L.,
 Zhao, Y., Zhang, F., Goulding, K., and Liu, X.: Combined short-term and long-term emission controls improve air quality
 sustainably in China, *Nat. Commun.*, 15, 5169, <https://doi.org/10.1038/s41467-024-49539-9>, 2024.
- 765 van der Werf, G. R., Randerson, J. T., Giglio, L., van Leeuwen, T. T., Chen, Y., Rogers, B. M., Mu, M., van Marle, M. J. E.,
 Morton, D. C., Collatz, G. J., Yokelson, R. J., and Kasibhatla, P. S.: Global fire emissions estimates during 1997–2016, *Earth
 Syst. Sci. Data*, 9, 697–720, <https://doi.org/10.5194/essd-9-697-2017>, 2017.
- Xu, D., Ge, B., Chen, X., Sun, Y., Cheng, N., Li, M., Pan, X., Ma, Z., Pan, Y., and Wang, Z.: Multi-method determination of
 the below-cloud wet scavenging coefficients of aerosols in Beijing, China, *Atmos. Chem. Phys.*, 19, 15569–15581,
 770 <https://doi.org/10.5194/acp-19-15569-2019>, 2019a.
- Xu, W., Zhang, L., and Liu, X.: A database of atmospheric nitrogen concentration and deposition from the nationwide
 monitoring network in China, *Sci. Data*, 6, 51, <https://doi.org/10.1038/s41597-019-0061-2>, 2019b.
- Yang, N., Liu, N., Ge, B., He, Z., Zhou, Y., Xu, D., and Wang, Z.: A daily gridded dataset of nitrogen wet deposition over
 East Asia for 2011 to 2016 based on multisource observation-model fusion (V1), *Science Data Bank [dataset]*,
 775 <https://doi.org/10.57760/sciencedb.015vd>, 2026.
- Yu, G., Jia, Y., He, N., Zhu, J., Chen, Z., Wang, Q., Piao, S., Liu, X., He, H., Guo, X., Wen, Z., Li, P., Ding, G., and Goulding,
 K.: Stabilization of atmospheric nitrogen deposition in China over the past decade, *Nat. Geosci.*, 12, 424–429,
<https://doi.org/10.1038/s41561-019-0352-4>, 2019.
- Zhang, L., Jacob, D. J., Knipping, E. M., Kumar, N., Munger, J. W., Carouge, C. C., van Donkelaar, A., Wang, Y. X., and
 780 Chen, D.: Nitrogen deposition to the United States: distribution, sources, and processes, *Atmos. Chem. Phys.*, 12, 4539–4554,
<https://doi.org/10.5194/acp-12-4539-2012>, 2012.



- Zhang, Q., Li, Y., Wang, M., Wang, K., Meng, F., Liu, L., Zhao, Y., Ma, L., Zhu, Q., Xu, W., and Zhang, F.: Atmospheric nitrogen deposition: a review of quantification methods and its spatial pattern derived from the global monitoring networks, *Ecotoxicol. Environ. Saf.*, 216, 112180, <https://doi.org/10.1016/j.ecoenv.2021.112180>, 2021.
- 785 Zhang, Y., Mathur, R., Bash, J. O., Hogrefe, C., Xing, J., and Roselle, S. J.: Long-term trends in total inorganic nitrogen and sulfur deposition in the US from 1990 to 2010, *Atmos. Chem. Phys.*, 18, 9091–9106, <https://doi.org/10.5194/acp-18-9091-2018>, 2018.
- Zhang, Y., Foley, K. M., Schwede, D. B., Bash, J. O., Pinto, J. P., and Dennis, R. L.: A measurement-model fusion approach for improved wet deposition maps and trends, *J. Geophys. Res.: Atmos.*, 124, 4237–4251, <https://doi.org/10.1029/2018JD029051>, 2019.
- 790 Zhang, Y., Su, X., Ge, B., Xu, X., Tan, Q., Chen, G., Xu, D., Chen, X., Wu, L., Gao, M., Pan, X., Guo, J., Liu, X., Fu, J. S., and Wang, Z.: Enhanced wet deposition of nitrogen induced by a landfalling typhoon over East Asia: implications for the marine eco-environment, *Environ. Sci. Technol. Lett.*, 9, 1014–1021, <https://doi.org/10.1021/acs.estlett.2c00762>, 2022.
- Zhang, Y., Ge, B., Chen, G., Wang, D., Li, F., Fu, J. S., Liu, X., and Wang, Z.: Consecutive wet deposition of nitrogen along half of China's coastal cities induced by Super Typhoon Muifa (2022) with multiple landfalls, *J. Environ. Sci.*, 156, 126–138, <https://doi.org/10.1016/j.jes.2024.11.004>, 2025.
- 795 Zhao, Y., Zhang, L., Chen, Y., Liu, X., Xu, W., Pan, Y., and Duan, L.: Atmospheric nitrogen deposition to China: a model analysis on nitrogen budget and critical load exceedance, *Atmos. Environ.*, 153, 32–40, <https://doi.org/10.1016/j.atmosenv.2017.01.018>, 2017.

800

805

810