



Technical note: Assessment of OMI/MLS Satellite-Derived Tropospheric Ozone Product for predicting monthly ground-level ozone concentrations

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Abstract. Ground-level ozone is a hazardous air pollutant that contributes to respiratory and cardiovascular morbidity and mortality, as well as to climate change and vegetation damage. Despite its significance, global surface ozone monitoring remains spatially sparse, particularly outside of North America, Europe, and East Asia. Satellite-based products such as the Ozone Monitoring Instrument/Microwave Limb Sounder (OMI/MLS) tropospheric column ozone (TCO) dataset offer a potential solution for improving estimates of global ozone at ground level. Here we evaluate the performance of the OMI/MLS TCO product as a predictor of global ground-level ozone by comparing it to monthly average ground-based Maximum Daily 8-hour Average (MDA8) ozone measurements from the second Tropospheric Ozone Assessment Report (TOAR-II) database (2005–2022). Linear regressions were conducted globally, as well as by year, world region, concentration range, and month. A positive correlation was found between the TCO product and ground-based measurements, although that correlation was modest ($R^2 = 0.29$ over the entire period globally). Regression parameters did not vary strongly by season, region or year. Correlations were highest in May through October and highest in Europe and lowest in North America. The regression results were used with the satellite product to generate global maps of estimated ground-level ozone for each month from 2005 to 2022. While not a substitute for in situ measurements, our ground-level ozone product based on OMI/MLS TCO shows potential as an independent observational input to global data fusion methods in areas lacking ground-based monitoring.

1. Introduction

Ozone is a harmful air pollutant at ground-level that is toxic to humans and crops; simultaneously, it acts as a potent greenhouse gas in the troposphere, contributing to positive radiative forcing (Iglesias-Suarez et al., 2018). Ozone is produced photochemically through reactions of volatile organic compounds (VOCs) and nitrogen oxides (NO_x) driven by sunlight (Atkinson, 2000), with ground-level concentrations elevated due to human emissions. In comparison to stratospheric ozone, which protects Earth's surface (and inhabitants) from harmful UV radiation, ground-level ozone is known to pose a serious threat to human health due to its reactivity with lung tissue during respiratory exposure (U.S. Environmental Protection



30 Agency, 2020; Balmes, 2022). Ozone has many immediate effects including lung function impairment and inflamed airways, but has also been associated with increased mortality due to respiratory and cardiovascular effects during short and long-term exposures (Di et al., 2017; Jerrett et al., 2009; Turner et al., 2016). In 2021, long-term ozone exposure was estimated to have contributed to about 490,000 (107,000–837,000) deaths globally, which is 0.7 % (0.2–1.2 %) off all deaths in that year (Brauer et al., 2024). Additionally, ozone has been shown to contribute to climate change via radiative forcing as a greenhouse gas, and can damage plant tissue due to its chemical reactivity, leading to reduced growth and propagation (Intergovernmental Panel On Climate Change, 2021; Agathokleous et al., 2020; Emberson et al., 2018).

Motivated by the harmful effects on health and vegetation, research has attempted to better understand the global distribution of ground-level ozone. While the number of ground-level ozone monitors has grown rapidly since the 1970s, the majority of measurements are in Europe, North America, and East Asia (Fleming et al., 2018; Schultz et al., 2017). Elsewhere, ground-based monitoring stations are sparse, and this scarcity limits our understanding of ground-level ozone in regions with few monitors (e.g. South America, Africa), complicating efforts to estimate population exposure and health effects.

To bridge gaps in regions with few ground-based monitoring stations, various methods, including computer modeling, chemical reanalysis, machine learning, and geostatistical methods have been applied. Chemical reanalysis describes the assimilation of many atmospheric observations from satellites into chemical transport models to estimate historical atmospheric composition and provide a long-term record. Since they have typically not used ground observations, they are designed to estimate three-dimensional ozone, and not particularly ground-level. Current chemical reanalyses provide global estimates of several chemicals over many years, such as the Copernicus Atmosphere Monitoring Service (CAMS), with estimates from 2003 to the present at $0.75^\circ \times 0.75^\circ$ spatial resolution (Inness et al., 2019). Unlike chemical reanalysis, machine learning methods utilize ground observations as training data, integrating diverse inputs such as chemical transport model outputs, satellite data, meteorological conditions, and spatio-temporal information. These machine learning models are applied to estimate global ground-level ozone, generating high-resolution estimates of the monthly average Maximum Daily 8-hour (MDA8) ozone. (Liu et al., 2022; Sun et al., 2022).

Geostatistical methods have also been used by our group to estimate global ground-level ozone, as a sequence of methods. First, a multiple-model ensemble is calculated by weighting based on their performance across different geographic regions (Chang et al., 2019). Then the multimodel composite undergoes a spatially nonhomogeneous and nonlinear bias correction, and these ozone estimates are fused with ground observations using the Bayesian Maximum Entropy (BME) data fusion framework (Becker et al., 2023; DeLang et al., 2021). This dataset estimates ozone globally for the 6-month ozone seasonal maximum of monthly average daily maximum 8 h ozone (OSDMA8), for 1990 to 2017 at 0.1 degree resolution, and has been used in recent Global Burden of Disease studies to estimate the global impacts of exposure to ozone on human mortality (Brauer et al., 2024)



Our group recently conducted a systematic intercomparison and evaluation against observations of six global ground-level
65 ozone datasets, including three chemical reanalyses, two machine learning studies, and one geostatistical method (Wang et al.,
2025). This intercomparison found important disagreement among these datasets, with differences in global average ozone
greater than 5 ppb, as well as differences in ozone spatial distributions and long-term trends. For example, the estimated
fraction of the population in Europe exposed to greater than 50 ppb varies among datasets from 9 % to 76 %. Such differences
would have important implications for ozone health impact assessments and suggest that the global distribution of ozone
70 remains uncertain.

Satellite observations have the potential to overcome the lack of ground-level ozone measurements, as they provide nearly
continuous global coverage, including in regions lacking ground monitors. Historically, however, satellite measurements have
not been shown to accurately detect surface ozone (Gaudel et al., 2018). Ozone is not only produced in the lower troposphere,
75 but also exists at high concentrations in the upper troposphere and the stratosphere, where it is produced photochemically due
to the presence of shorter wavelength UV radiation. Ozone's vertical profile thus presents a challenge for satellites to detect
ozone near the surface. Many satellites have been shown to estimate the total ozone column well, and some satellite products
can measure tropospheric ozone, but satellites have traditionally been considered poor predictors of ground-level ozone
(Anenberg et al., 2020; Gaudel et al., 2018; Liu et al., 2010).

80 Among satellite tropospheric ozone products, OMI/MLS (Levelt et al., 2006; Waters et al., 2006) has been widely used,
including to detect positive trends in tropospheric ozone in recent decades (Ziemke et al., 2019). The OMI/MLS product
combines the measurements of two instruments aboard NASA's Aura satellite to separate tropospheric ozone from the total
column. Since OMI/MLS does not have high sensitivity to ozone near the surface, it has been assumed that it is not a good
85 predictor of ground-level ozone. Still, we are not aware that the ability of OMI/MLS to predict ozone concentrations at ground
level has been analyzed systematically.

The objective of this study is to analyze the performance of the OMI/MLS tropospheric column ozone (TCO) monthly data as
a predictor of ground-level ozone. The OMI/MLS monthly satellite product is compared with ground measurements of MDA8
90 ozone, matched by location and time, to analyze correlations and linear regression parameters. We further analyze how
correlations and regression parameters vary by year, month of the year, geographic region, and between high and low observed
concentrations. We then use these regression-derived parameters to global monthly OMI/MLS observations to estimate
ground-level ozone concentrations from 2005 to 2022 based only on these satellite observations. Monthly average MDA8 is
selected as the ground-level concentration metric because it is of interest for health effects studies (Brauer et al., 2024). If
95 OMI/MLS data can be shown to predict ground-level ozone with sufficient accuracy, then they could be used in data fusion
frameworks like BME, which can include the uncertainty of predictors, to improve ground-level ozone predictions, especially
in locations lacking ground monitors.



2. Materials and methods

2.1 OMI/MLS dataset

100 The satellite data used in this study are generated by the OMI/MLS satellite instruments from the NASA Goddard Space Flight Center (Ziemke et al., 2006). OMI measures solar backscatter radiation in the visible and ultraviolet to determine the height and concentration of the ozone column, while MLS detects microwave emissions to measure stratospheric temperature and identify upper tropospheric constituents. Used in tandem, the co-located stratospheric column ozone is subtracted from total column ozone to produce global TCO observations. The instrument makes measurements daily at its overpass time of
105 approximately 1:45 PM local time, which we expect would generally agree well with the 8 h averaging time of MDA8.

From these daily raw satellite observations, gridded monthly-mean estimates of TCO in Dobson Units (DU) are created (Ziemke et al., 2006). The data are at 1° by 1° horizontal resolution with monthly values for each grid cell center from January 2005 to December 2022. This dataset was derived using newly processed OMI total ozone that uses Collection-4 L1b for
110 retrieval.

Whereas the OMI/MLS data were reported in DU, we also converted the full dataset to column average concentration in ppb using dimensional analysis, mainly to correct for differences in the tropopause height with latitude. This conversion used the monthly average tropopause pressure regridded to 1° by 1° resolution from the NCEP WMO reanalysis, and surface pressure
115 from the chemical reanalysis (TCR-2). Tropospheric column ozone (DU) was converted to a column-average ozone mixing ratio (ppbv) according to:

$$O_{3,ppbv} = 1270 \cdot \frac{TCO}{P_s - P_{trop}} \quad (1)$$

120 where TCO is tropospheric column ozone in DU, P_s is surface pressure, and P_{trop} is tropopause pressure, both in hPa.

2.2 TOAR-II dataset

The ground-level ozone measurements used for comparison in this study come primarily from the Tropospheric Ozone Assessment Report (TOAR-II) database (<https://toar-data.fz-juelich.de/gui/v2/dashboard/>, last access: 15 November 2024). TOAR is an activity led by the International Global Atmospheric Chemistry project, which aims to understand the global
125 distribution and trend of tropospheric ozone and provide data that can be used to analyze ozone's effect on health, vegetation, and climate (Schultz et al., 2017). The TOAR-II database compiles air quality monitoring data from thousands of sites in many nations. The dataset used for comparison in this study calculates monthly averages of MDA8 ozone concentration for all recorded monitoring stations through 2022.



130 Since TOAR-II observations from the United States are only available through spring 2022, the dataset was supplemented with
measurements from the US EPA Air Quality System for the remainder of 2022. We hereafter refer to this supplemented
ground-level dataset as the “TOAR-II dataset”.

2.3 Research methods

135 In general, the OMI/MLS satellite data and TOAR-II ground monitor data are compared via simple regression in which ground
station monthly averages are matched with satellite monthly averages at the center of the grid cell in which a given ground
station is located, finding the slope, intercept, squared Pearson correlation coefficient (R^2), root mean squared error (RMSE),
and mean absolute error (MAE) for the regression. The linear regression model was defined as:

$$MDA8_i = \alpha + \beta \cdot TCO_i + \varepsilon_i \quad (2)$$

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where MDA8 is the monthly average ground-level ozone concentration (ppb), TCO is the OMI/MLS tropospheric column
ozone value (DU or converted ppb), α is the intercept, β is the regression slope, and ε is the residual error term.

One single regression (for both the DU and ppb datasets) was performed that includes every monthly average in the TOAR-II
145 database that overlaps with OMI/MLS data, providing a global comparison across the entire time period. This regression also
included density analysis applied after regression, in which areas of the plot were colored to reflect their data point density.
Similar regressions were also computed for each year, grouping TOAR-II data by year, and then plotting a regression with
satellite data from that year. Regressions were also grouped by world region, including North America, Europe, East Asia, and
a single category for all other parts of the world included in the TOAR-II database. HTAP-2 regional definitions were applied
150 to analyze these geographical areas (Liang et al., 2018). Three linear regressions were performed over the low (<25 DU),
middle (25–45 DU), and high end (>45 DU) of satellite measurement values to evaluate correlations and slopes within these
ranges. Regressions were also performed for each month across all years to analyze differences in satellite performance
throughout the seasons of the year.

155 Global ground-level ozone maps were then produced by applying global OMI/MLS data as an input to the linear regression
equation to create global ground-level ozone estimates. These estimates were then plotted in their respective grid cells ($1^\circ \times$
 1°) across the globe in each month from January 2005 to December 2022.



3. Results

Table 1 shows the linear regression statistics for both the DU and converted ppb data compared to TOAR-II globally across all months and years ($N = 1,167,782$). While showing very similar regression results, the DU data has a slightly higher R^2 ($0.290 > 0.271$) and a slightly lower RMSE ($10.789 < 10.930$). Figure 1 shows these two regressions (DU and ppb) with their respective lines of best fit. The ppb data was expected to provide a slightly better estimate of ground-level ozone because it accounts for differences in tropopause height. However, the regression performance indicates that the DU dataset is a slightly better predictor of ground-level ozone. The DU dataset is focused on hereafter because of its higher correlation.

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Table 1. Linear regression statistics for the OMI/MLS satellite (expressed as Dobson Units and converted to parts per billion) and TOAR-II ground station data over all years 2005–2022.

Unit	Slope (ppb/DU and ppb/ppb)	Intercept (ppb)	R^2	RMSE (ppb)	MAE (ppb)
<i>DU</i>	1.077	0.386	0.290	10.789	8.529
<i>ppb</i>	0.703	-2.374	0.271	10.930	8.519

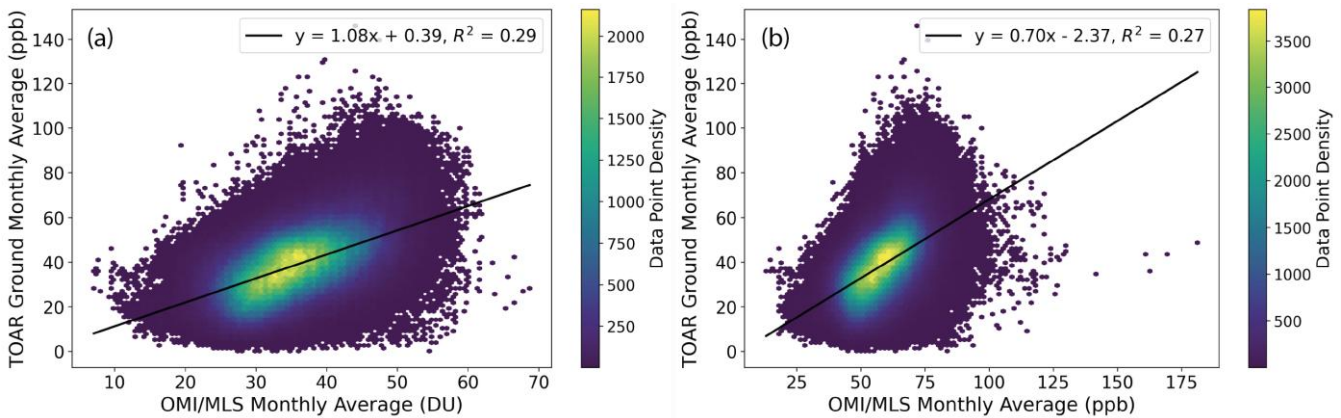


Figure 1. OMI/MLS data matched with TOAR-II ground-station data by location and month across all overlapping observations. Point density is shown by colour. (a) OMI/MLS tropospheric column ozone in Dobson units and (b) the converted column-average ozone mixing ratio.

Table 2 contains the stratified regression results for the DU data compared to TOAR-II data. The first 18 entries contain regression results for each full year of the dataset (2005–2022). Years 2007, 2005, and 2022 show the highest R^2 (0.37, 0.36, and 0.35, respectively) and have similar slopes (1.26, 1.26, 1.21 ppb/DU). Across all individual years, slopes range from 0.90 (2013) to 1.29 (2006) ppb/DU, intercepts range from -5.81 (2006) to 5.02 (2013) ppb, R^2 range from 0.23 (2013) to 0.37

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(2007), RMSE ranges from 9.87 (2013) to 11.37 (2017), MAE ranges from 7.87 (2013) to 8.92 (2017), and the number of matched ground station monthly averages (N) ranges from 45,602 (2005) to 82,556 (2018).

180 **Table 2. Linear regression statistics for DU vs. TOAR-II data grouped by year, region, satellite ozone value, and month.**

	Slope	Intercept (ppb)	R²	RMSE (ppb)	MAE (ppb)	N
<i>By year</i>						
<i>2005</i>	1.257	-5.582	0.358	10.426	8.379	45602
<i>2006</i>	1.289	-5.813	0.339	11.046	8.751	47971
<i>2007</i>	1.261	-5.330	0.367	10.299	8.227	50198
<i>2008</i>	1.250	-4.468	0.340	10.456	8.364	53549
<i>2009</i>	1.045	0.547	0.270	10.364	8.378	55526
<i>2010</i>	0.996	2.073	0.260	9.988	8.087	59705
<i>2011</i>	0.998	2.406	0.269	10.112	8.091	58189
<i>2012</i>	0.975	3.355	0.298	9.890	7.876	65407
<i>2013</i>	0.902	5.016	0.230	9.873	7.865	61720
<i>2014</i>	1.077	-0.776	0.263	11.110	8.714	64263
<i>2015</i>	1.065	-0.117	0.273	11.359	8.961	76235
<i>2016</i>	1.044	0.413	0.294	10.795	8.501	80303
<i>2017</i>	1.048	2.380	0.263	11.366	8.924	81695
<i>2018</i>	1.093	0.252	0.293	11.359	8.876	82556
<i>2019</i>	1.081	1.238	0.281	11.261	8.786	82546
<i>2020</i>	1.002	3.284	0.256	10.606	8.354	81162
<i>2021</i>	0.985	4.748	0.266	10.458	8.188	64813
<i>2022</i>	1.208	-2.321	0.352	11.107	8.755	56342
<i>By region</i>						
<i>North America</i>	0.707	16.050	0.192	9.190	7.317	259085
<i>Europe</i>	1.283	-8.215	0.318	10.245	8.240	451984
<i>East Asia</i>	1.145	-1.607	0.298	11.671	9.187	387686
<i>Rest of World</i>	0.713	10.770	0.220	10.621	8.282	69027



	Slope	Intercept (ppb)	R²	RMSE (ppb)	MAE (ppb)	N
<i>By satellite value range (DU)</i>						
<25	0.357	20.545	0.006	9.935	8.066	43199
25–45	1.167	-2.891	0.233	10.544	8.377	1030637
>45	1.058	1.129	0.036	13.119	10.047	93946
<i>By month, all years</i>						
<i>Jan</i>	-0.001	27.502	0.000	7.915	6.261	89983
<i>Feb</i>	0.030	32.318	0.000	7.894	6.269	90692
<i>Mar</i>	0.157	35.449	0.009	7.643	5.825	94531
<i>Apr</i>	0.384	33.070	0.052	8.157	6.090	100303
<i>May</i>	0.791	17.614	0.161	9.441	7.000	101661
<i>Jun</i>	0.747	16.640	0.111	11.369	8.434	101858
<i>Jul</i>	0.689	16.143	0.092	11.884	9.411	101876
<i>Aug</i>	0.653	17.526	0.082	10.985	8.754	101991
<i>Sep</i>	0.950	5.639	0.145	9.812	7.550	101502
<i>Oct</i>	1.002	0.491	0.163	8.864	6.847	99394
<i>Nov</i>	0.545	10.691	0.060	8.598	6.872	92501
<i>Dec</i>	0.174	19.909	0.008	7.974	6.306	91490

Regression results are also shown for these datasets grouped by world region across all months and years, including North America, Europe, East Asia, and all other stations not included in these regions. Ground stations in Europe showed the highest R² with satellite observations (0.32). The regression over European countries yielded a slope of 1.28 ppb/DU and intercept of -8.22 ppb. The regression in East Asia showed the next highest R² (0.30), with a slope of 1.15 ppb/DU and intercept of -1.61 ppb. The regression in North America yielded the lowest R² of 0.19 with a slope of 0.71 ppb/DU and intercept of 16.05 ppb. Regression outside of these regions yielded a R² of 0.22, a slope of 0.71 ppb/DU and intercept of 10.77 ppb. The regional regression over Europe included the most matched ground station measurements (451984) followed by East Asia (387686), North America (259085), and the rest of the world (69027).

The regression results for the low, middle, and high ranges of the satellite dataset are also included. The correlation between satellite measurements between 0–25 DU and their matching ground-level observations was the lowest of any bin (R²: 0.006) and the slope in this region was 0.36 ppb/DU. The correlation in the 25–45 DU range was the highest of the three (R²: 0.23), with a slope of 1.17 ppb/DU. The R² in the upper range (>45 DU) was also small (0.04) with a slope of 1.06. Figure 2 shows these 3 regressions plotted over the entire dataset.

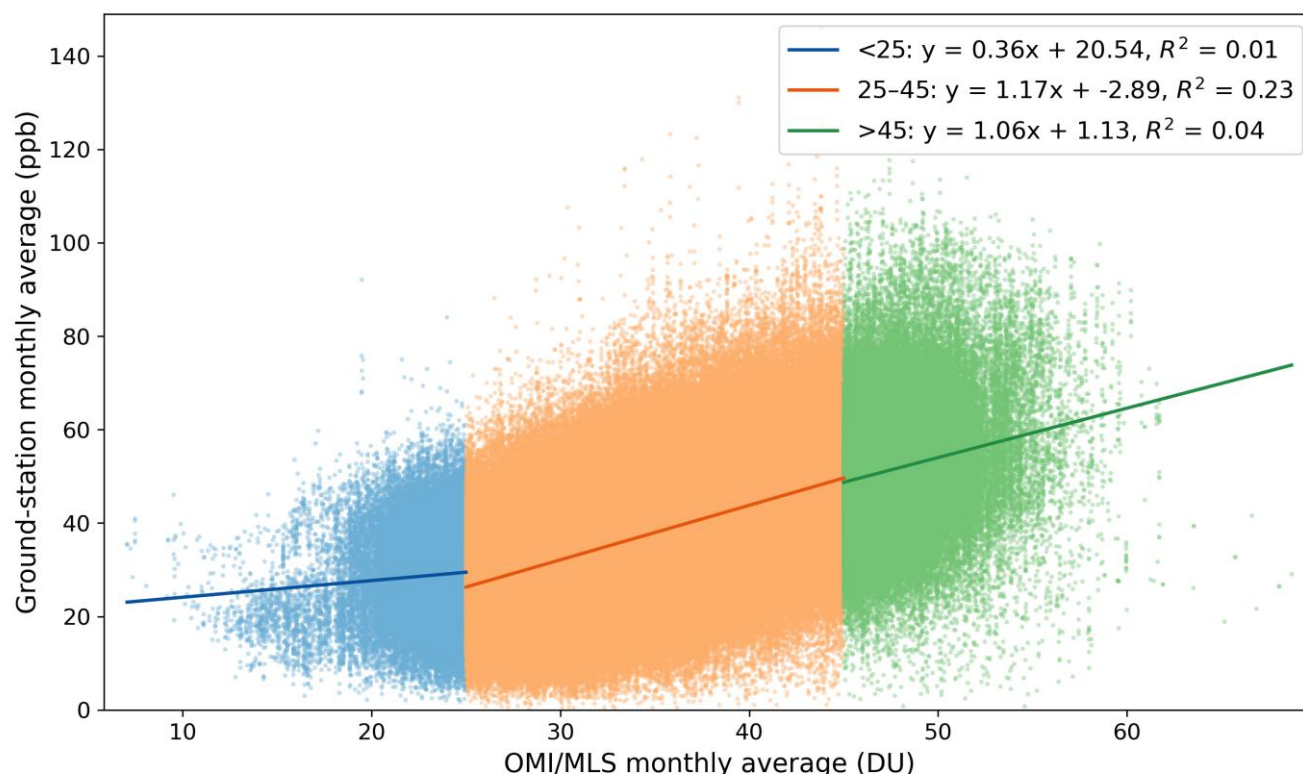


Figure 2. OMI/MLS tropospheric column ozone in Dobson units compared with TOAR-II observations, with separate linear regressions for low (<25 DU), middle (25–45 DU), and high (>45 DU) satellite values.

200 The final 12 entries of Table 2 contain regression statistics for these data grouped by month across all years (i.e. every observation made in a given month over all years in the dataset). October, May, and September show the highest R^2 (0.16, 0.16, and 0.15, respectively). These months also show the three highest slopes (1.00, 0.791, and 0.95) of any month. The summer months in the Northern Hemisphere (NH) have the three next highest R^2 (June: 0.11, July: 0.09, and August: 0.08). The R^2 for winter months in the NH (Dec, Jan, Feb) are some of the lowest of any of the regressions (0.0081, 0.0000, and 205 0.0003 respectively). The slopes for these months (range -0.001 to 0.174 ppb/DU) are lower than the other months.

While there is variability in the Table 2 results by year, region, value range, and month, results are not so different from the results in Table 1 to justify a different regression based upon these variables. Therefore, the global regression results in Table 1 are applied to estimate global ground-level ozone.

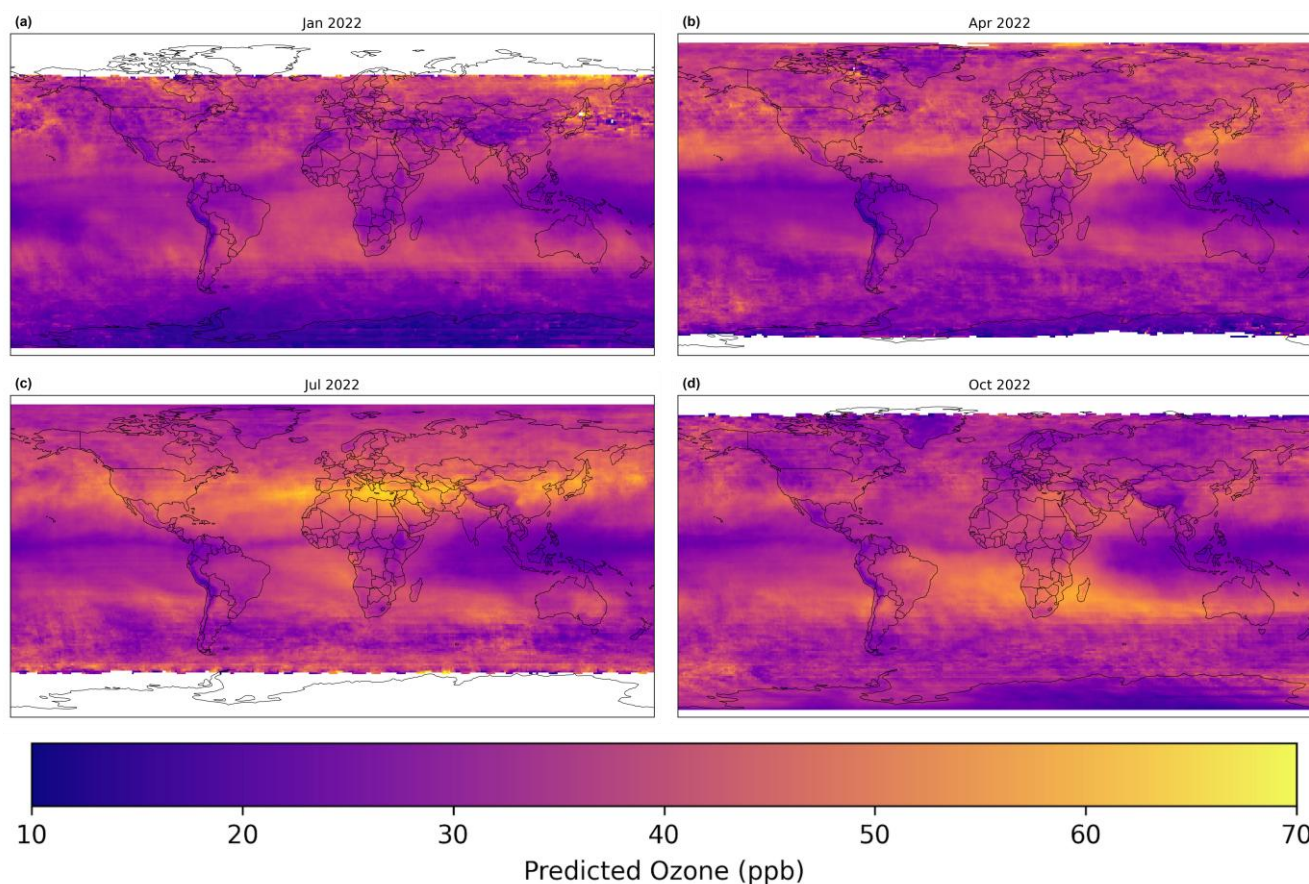


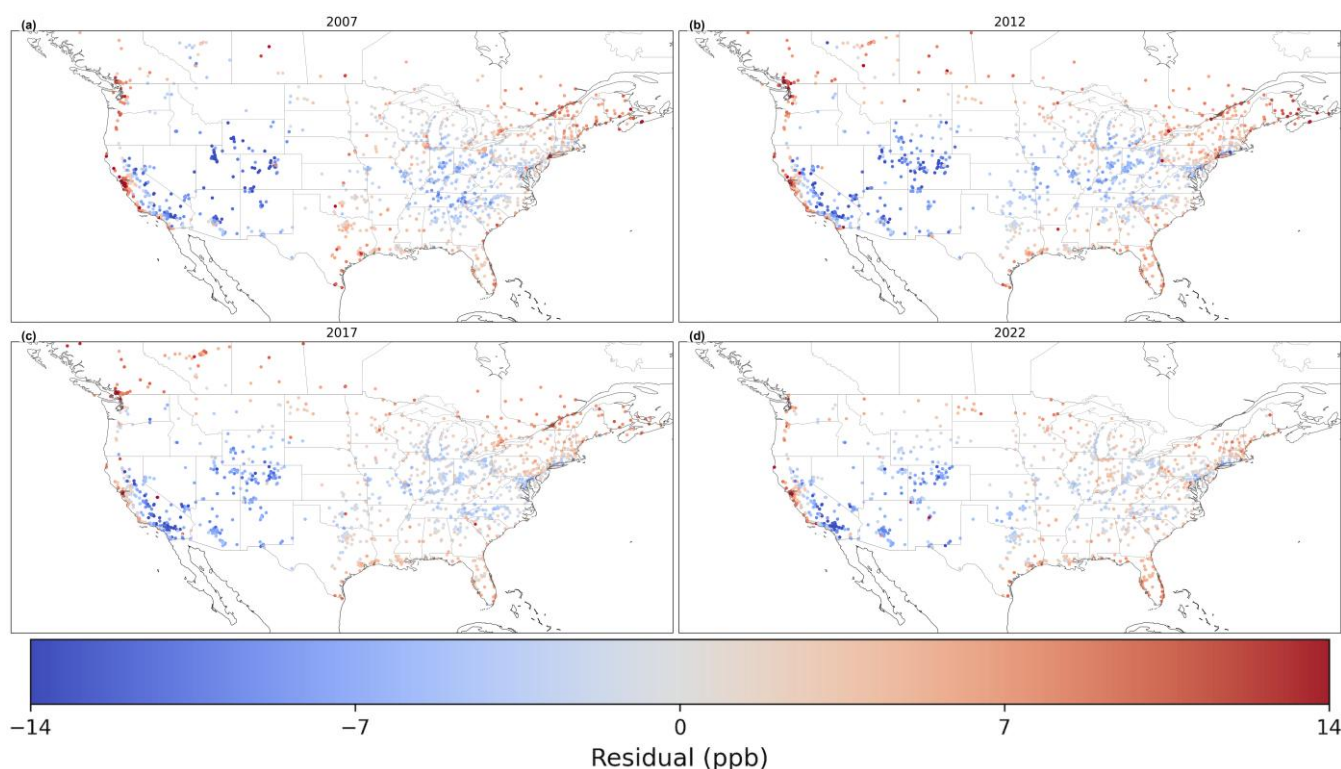
Figure 3. Estimated global ground-level ozone for (a) January, (b) April, (c) July, and (d) October 2022, derived from OMI/MLS tropospheric column ozone and the global linear regression with TOAR-II observations. A very small number of predicted ozone values were below 10 ppb or greater than 70 ppb. Country boundaries are from Natural Earth, 1:110 million Admin 0 Countries.

Monthly global ground-level estimates of monthly average MDA8 use satellite data in each grid cell as an input to the linear regression equation (Table 1). Figure 3 illustrates the global ground-level ozone estimates predicted using the linear regression between the OMI/MLS DU dataset and the TOAR-II dataset. 2022 was selected for Fig. 3 because it is the most recent year included in the dataset; other years are shown in Figure S1.

Figure 3 shows differences in monthly ground-level ozone across both hemispheres that follow expected patterns. In January 2022, ground-level ozone was relatively low in the NH compared to other months. SH concentrations are slightly higher in January 2022 than April 2022. In April 2022, NH concentrations showed a significant increase. Ground-level ozone reached yearly maximums in the NH by July 2022, with high concentration bands across the Middle East, China, Europe, and the United States. Ozone levels also increased in the SH in July 2022, with less-pronounced hotspots over Eastern Australia and Argentina. In October 2022, concentrations in the NH dropped while concentrations in the SH rose to yearly maximums with particular increases over Argentina, Brazil, and South Africa. Across different months in Fig. 3, ground-level ozone remains

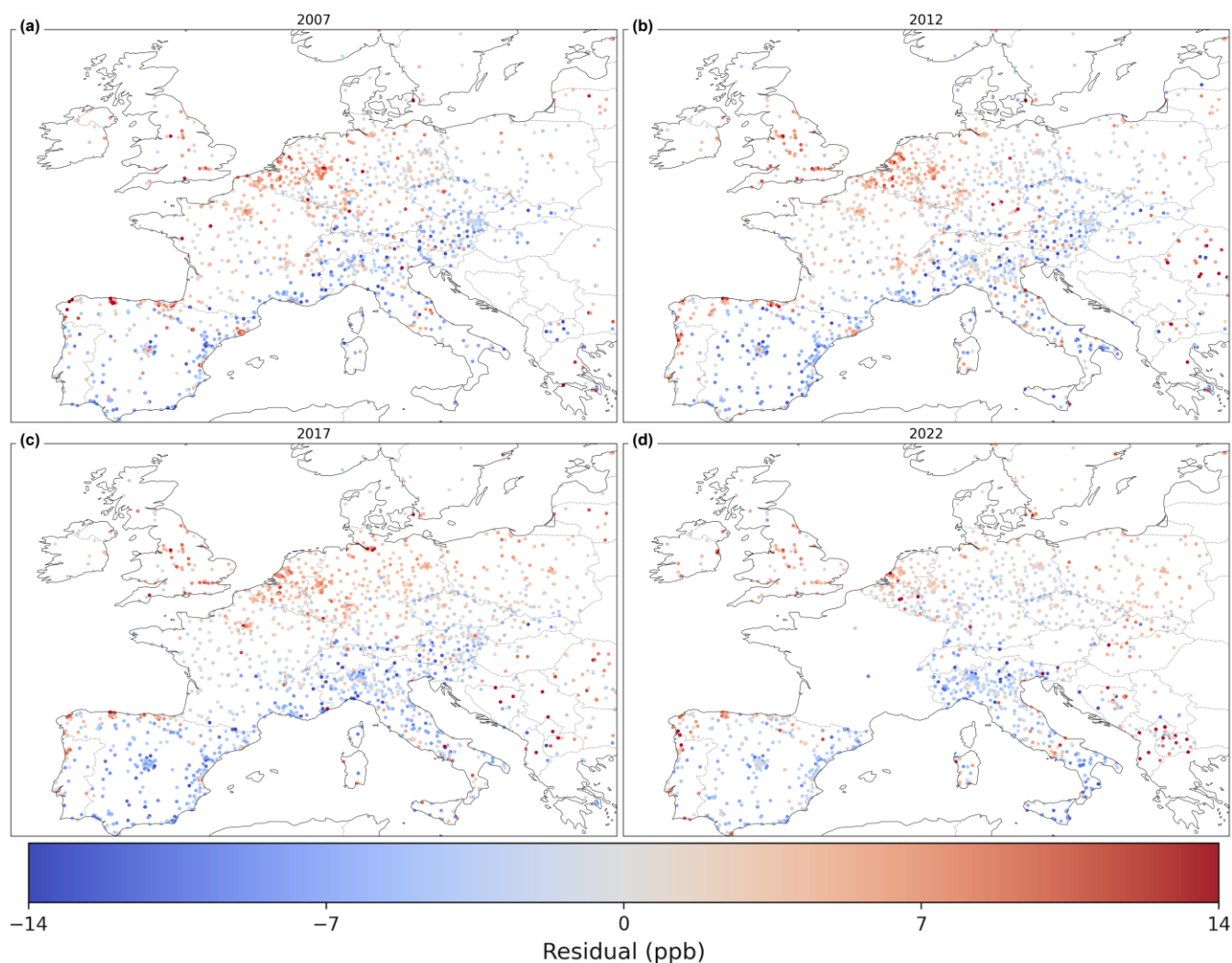


low near the equator relative to the bands in the Northern and Southern Hemispheres. These patterns were visible across other years as well (Figure S2).



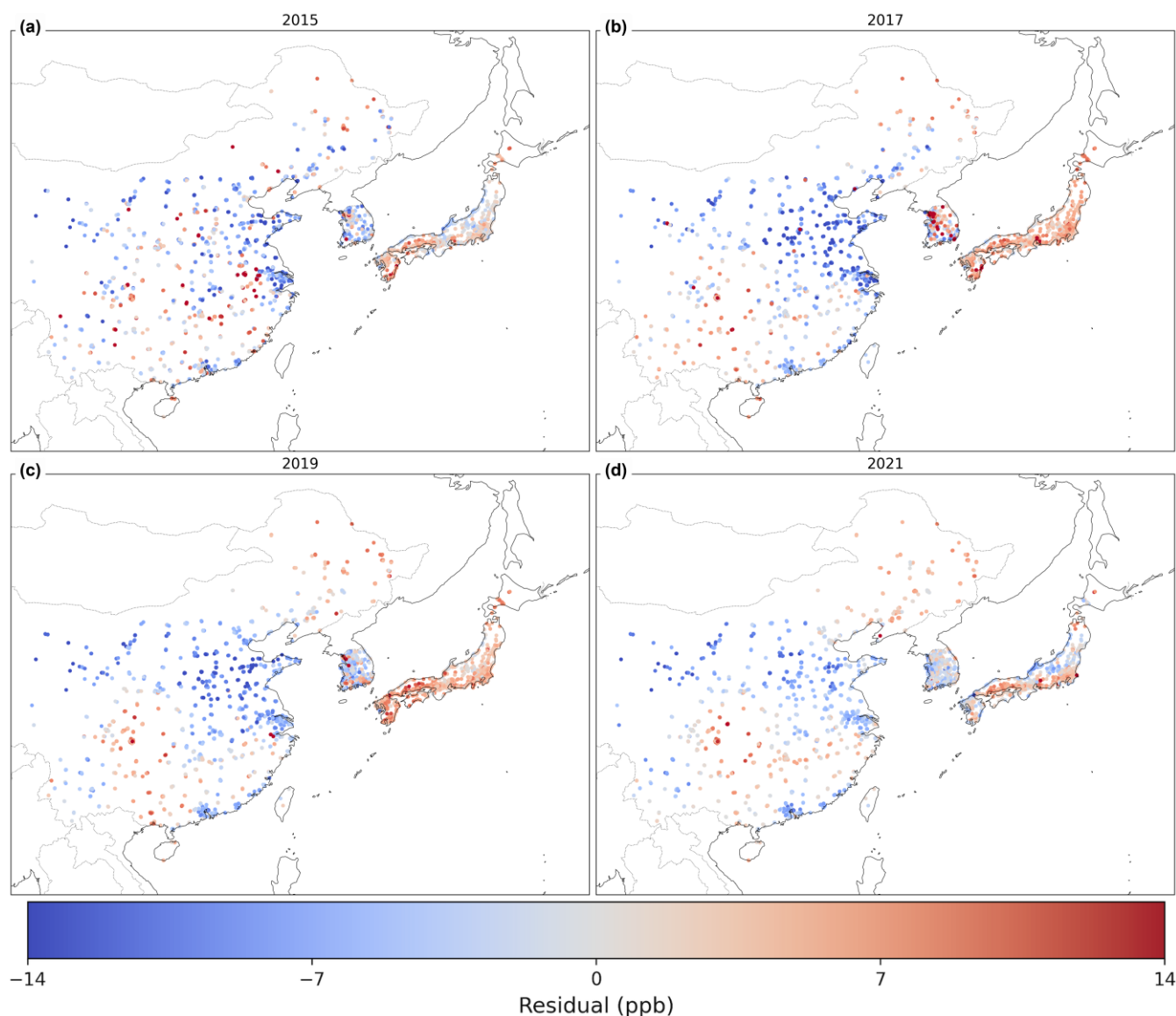
230 **Figure 4. Residual maps (satellite-based prediction minus observed) for North America in (a) 2007, (b) 2012, (c) 2017, and (d) 2022 for ground-level MDA8 ozone averaged over all months in each year. Blue points reflect an underprediction, and red points an overprediction, of measured ground-level ozone. Country boundaries are from Natural Earth, 1:110 million Admin 0 Countries.**

Figure 4 contains maps of yearly residuals for selected years in North America. Yearly averages were used to calculate residuals (satellite-based prediction minus observed) rather than monthly averages. These maps were created to identify any regional trends, especially in North America where regression performance was lower than other world regions. While more detailed analysis should be performed to elucidate satellite performance in particular regions, there are a few apparent visible trends. Across all years, there is a significant underprediction of ground-level ozone across the California Central Valley and in Southern California. Underprediction is also seen over other Western states such as Colorado, Wyoming, Utah, Arizona, and New Mexico. A general overprediction is visible at stations near the San Francisco Bay. These figures also show a general overprediction of ground-level ozone in the Northwestern US and in Canada near the US border. Patterns in the Eastern US are less pronounced, but in general we see overpredictions across the Southeast coast (Texas, Louisiana, and Florida) and in the Northeast. Residual maps for each year are available in Figure S2



245 **Figure 5. Residual maps (satellite-based prediction minus observed) for Europe in (a) 2007, (b) 2012, (c) 2017, and (d) 2022 for ground-level MDA8 ozone averaged over all months in each year. Blue points reflect an underprediction, and red points an overprediction, of measured ground-level ozone. Country boundaries are from Natural Earth, 1:110 million Admin 0 Countries.**

Figure 5 contains maps of yearly residuals in Europe. Despite the higher performance over Europe, there are still visible trends in the residual figures. In general, we see underprediction along the Mediterranean coast and in Southern regions (Spain, Italy, 250 Austria, Southern France), although these patterns are less absolute than in the US. We see a general band of overprediction across Northern countries (the United Kingdom, Belgium, Germany, Northern France).



255 **Figure 6. Residual maps (satellite-based prediction minus observed) for East Asia in (a) 2015, (b) 2017, (c) 2019, and (d) 2021 for ground-level MDA8 ozone averaged over all months in each year. Blue points reflect an underprediction, and red points an overprediction, of measured ground-level ozone. Country boundaries are from Natural Earth, 1:110 million Admin 0 Countries.**

Figure 6 contains maps of yearly residuals in East Asia. Because Chinese data are not included in the TOAR-II dataset until 2014, more recent years were selected compared to Figs. 4 and 5. Despite East Asia's relatively strong performance, there are still visible residual trends. In general, we see strong underpredictions in Northern Central China and along China's Southeast
 260 coast. There are overpredictions in the Northeast Heilongjiang region, especially in later years. There is more variance in Central China, but we observe more overprediction on average. Residuals are varied in Japan, but in general we see strong



bands of overprediction, especially in Southern regions and along the Pacific coast. There are not consistent patterns visible in South Korea across many years.

4. Discussion

265 The linear regression results show a positive correlation between the OMI/MLS $1^\circ \times 1^\circ$ DU dataset and TOAR-II ground-level observations. While the R^2 between the two datasets is not strong enough to support using satellite data in place of other estimates of ground-level ozone, this study shows that OMI/MLS measurements correlate weakly with ground-level measurements. Based on the correlation between the OMI/MLS and TOAR-II datasets, the OMI/MLS-derived product estimated here could be considered as an input to global ground-level ozone data fusion, potentially providing information in
 270 important regions with a lack of monitors. Data fusion methods such as BME can weight input data based on their estimated uncertainty and can thus give low weight to the OMI/MLS-derived data where the data are less reliable. Applying the linear fit equation to the satellite data may provide insightful estimates of global ground-level ozone, particularly in regions of the world with sparse ozone monitoring stations.

275 We find only small differences in performance between the OMI/MLS DU dataset and ppb dataset, with the DU dataset performing slightly better (Table 1). When converting to concentration (ppb), there is a correction for the tropopause height with latitude, season and location. We expected this converted dataset (ppb) to perform better than the raw DU dataset given these corrections, but it did not. The concentration dataset should be further analyzed, particularly in specific world regions as it may reduce regional error, but the better overall performance of the DU dataset was preferred for this study. The finding that
 280 the slope when using the ppb data is less than one reflects the vertical distribution of ozone in the troposphere, with higher concentrations aloft.

Given the objective to analyze the use of satellite data as an input to global ground-level ozone data fusion, the moderate R^2 (0.22) between OMI/MLS data and TOAR-II data in world regions outside of North America (0.19), Europe (0.32), and East
 285 Asia (0.30) is promising, providing some support for the use of satellite data in regions with low monitor density.

Ground-level ozone is typically highest in June, July and August in temperate regions of the NH, where most monitoring stations in the TOAR-II database are located. Ozone concentrations are also high in the months before and after the summer in both hemispheres, particularly in their respective springs. These surrounding months (October, May, and September)
 290 showed the three highest R^2 followed by June, July, and August. The OMI/MLS TCO measurements may be expected to perform better in these months because the higher ground-level concentrations may account for a higher fraction of the TCO. However, our analysis finds that this dataset estimates ground-level concentrations most accurately in the late spring and early autumn months in the NH. The winter months of the NH showed the worst performance which was expected.



295 The regression results in Table 2 do not show a clear reason to use a different regression line for different years, months, or
 world regions. While some individual years have better regression performance than the aggregated data, most yearly R^2 are
 very similar to or less than the aggregated coefficient. Regression results across Europe and East Asia are slightly better than
 across the globe, but North America and other regions perform worse. As has been discussed, the performance by month is
 significantly worse than the aggregate. The results in Fig. 2 further support the overall regression results, as the slopes do not
 300 vary substantially with the magnitude of ozone. The differences in performance across different categories, particularly world
 region, are worth investigating further, but there is not substantial evidence against using the global aggregate regression. Users
 interested in particular years, months or regions could use the linear regression results to better estimate ozone for their
 particular applications, but we chose to use the global results for all years and months as the best estimate of ozone over the
 entire record.

305 Our satellite-derived estimates of global ground-level ozone are subject to errors from the satellite measurements, and do not
 distinguish between areas or months with different ozone vertical profiles. Other studies have begun to use satellite ozone
 measurements and correct them based on vertical ozone profiles from a computer model and from measured ozonesonde
 profiles to estimate ground-level ozone (Colombi et al., 2021), but this has not been done previously on a global scale.

310 While it is worth recognizing the limitations of this study, particularly the relatively weak correlation between OMI/MLS and
 TOAR-II data, the general patterns evident in the monthly global ozone maps included in Fig. 3 are promising. These maps
 capture expected patterns in ground-level ozone in the two Hemispheres. In particular, we expect ground-level ozone
 concentrations to be highest during the summer months and lowest during the winter months. This pattern is clearly visible in
 315 the NH with a gradual rise from January to July, and then a gradual decline from July to October and the following winter.
 The SH is generally less polluted and experiences lower ground-level ozone concentrations than the NH. SH concentrations
 in 2022 are a bit less evident, but there is a visible increase from the winter (July) to the spring (October). The maps also
 identify regions that are known to have high ozone, including the Middle East, East Asia, South Africa, and California in their
 respective spring and summer seasons. The relatively low concentrations of ground-level ozone near the equator are also
 320 expected because of the high humidity, which fuels the formation of HO_x radicals that destroy ground-level ozone.

Further exploration of the seasonal and regional results is important for future work to better understand differences in satellite
 performance as a predictor of ground-level concentrations, particularly to elucidate the relatively poor performance in North
 America. While the residual analysis performed in this study is not sufficient to explain the poor performance in North
 325 America, it is clear that there are consistent patterns of overprediction/underprediction in specific regions such as California.
 Understanding drivers of performance in North America will inform satellite use in other parts of the world as an observational
 input.



5. Conclusions

This study finds the OMI/MLS TCO data product to be a useful tool in the estimation of global ground-level ozone. While this
330 satellite data is certainly not a perfect predictor of ground-level ozone, it shows an R^2 of 0.29 over all ground monitoring
stations globally over many years and follows expected regional patterns. This study produced global maps using a linear
regression of OMI/MLS data and ground measurements to produce estimates of monthly ground-level ozone from Jan 2005
to December 2022. These maps are limited in using simple linear regressions to convert OMI/MLS TCO monthly data to
ground-level concentrations, and do not compare with observations as well as other available global datasets (Wang et al.,
335 2025). Therefore, we caution against using our ozone dataset directly, but suggest that they can be considered as inputs for
global data fusion methods to estimate ground-level ozone; these particular data may be valuable because they are based on
observations that are independent from ground measurements and computer models.

Code and data availability

Observational ozone data are publicly available from the TOAR-II data portal (<https://toar-data.org/>, last access: 26 June 2026)
340 (Schröder et al., 2021). Additional U.S. ozone observations for 2022 were obtained from the U.S. EPA Air Quality System
(AQS), available through the EPA AirData portal (<https://www.epa.gov/outdoor-air-quality-data>, last access: 26 June 2026).
The OMI/MLS tropospheric column ozone dataset is publicly available from the NASA Goddard Space Flight Center cloud-
slicing archive (https://acd-ext.gsfc.nasa.gov/Data_services/cloud_slice/, last access: 26 June 2026). TCR-2 surface pressure
data are publicly available at <https://doi.org/10.5067/NN87W53OVGUS> (Miyazaki, 2024). Monthly WMO tropopause
345 pressure data derived from NCEP reanalysis products are available from the NASA Goddard Space Flight Center atmospheric
data archive (<https://acd-ext.gsfc.nasa.gov/anonftp/acd/atmos/ziemke/>, last access: 26 June 2026). The derived monthly global
surface ozone estimates generated in this study will be uploaded to a publicly available permanent repository (zenodo) before
the final paper is accepted.

Author contributions

350 This research was conceived by JS and JJW. HW, JZ, and JS provided ozone concentration datasets and supporting data
resources. HW and JS provided TOAR-II observational data. Data analyses, statistical modeling, figure generation, and
numerical results were produced by JS with input from MLS and JJW. JJW supervised the project. JS and JJW wrote the
manuscript, and all authors provided edits and comments on drafts.



Competing interests

- 355 At least one of the (co-)authors is a member of the editorial board of *Atmospheric Chemistry and Physics*. The authors declare that they have no conflict of interest.

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