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2 **Global Source-Receptor-Relationship Database for**
3 **Integrated Tropospheric Ozone Observations from**
4 **Multiplatform Datasets in Western North America during**
5 **1994-2021**

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20 **Abstract.** Long-term atmospheric ozone observations in Western North America (WNA) provide
21 essential data for assessing tropospheric ozone trends. Backward atmospheric simulations based on
22 these observations establish the source-receptor relationships (SRRs) to improve our understanding
23 of the factors driving ozone trends across different regions, time periods, and atmospheric layers.
24 In this study, we integrated 28 years of ozone observations (1994–2021) from ozonesondes, lidar,
25 commercial aircraft, and aircraft campaigns across WNA, spanning the upper atmospheric
26 boundary layer, free troposphere, and upper troposphere (i.e., 900 to 300 hPa). We integrated the
27 multiplatform datasets using a data fusion framework to generate 553,608 gridded ozone receptors.
28 For each receptor, we use the FLEXible PARTicle (FLEXPART) dispersion model, driven by
29 ERA5 reanalysis data, to produce the SRRs calculations, providing global simulations at high
30 temporal (hourly) and spatial (1° x 1°) resolution from the surface up to 20 km above ground level.
31 This SRR database retains detailed information for each receptor, including the gridded ozone value
32 product, which enables user to illustrate and identify source contributions to various subsets of



33 ozone observations in the troposphere above WNA over nearly 3 decades at different vertical layers
34 and temporal scales, such as diurnal, daily, seasonal, intra-annual, and decadal. More generally, the
35 calculated SRRs are applicable to any study looking to evaluate origins of airmasses reaching
36 WNA. As such, this database can support source contribution analyses for other atmospheric
37 components observed over WNA, if other co-located observations have been made at the spatial
38 and temporal scales defined for some or all of the gridded ozone receptors used here.

39

40 **Short summary.** Atmospheric observations show that free tropospheric ozone has increased across
41 the Northern Hemisphere over the past three decades. The sources driving this increase remain
42 unclear. In this study, we developed a source-receptor relationship database combining harmonized
43 multiplatform ozone data and advanced atmospheric transport modeling. This database can identify
44 the emission regions responsible for ozone increases and can also be used to analyze other co-
45 observed atmospheric constituents.

46

47 **1 Introduction**

48 The IPCC Sixth Assessment Report concluded that free tropospheric (FT) ozone generally
49 increased in the Northern Hemisphere from the mid-1990s through 2016 (Gulev et al., 2021). From
50 a global perspective, Gaudel et al. (2020) reported increasing median FT ozone trends ranging from
51 1.2 ppbv/decade over the Gulf of Guinea to 5.6 ppbv/decade over Southeast Asia. Building on this
52 work, Chang et al. (2023) incorporated additional ozone data and identified a positive regional
53 trend in median FT ozone over western North America (WNA), with an increase rate of 0.7 ± 0.3
54 ppbv/decade (1994–2019). These positive trends in FT ozone raise growing concerns about their
55 radiative effects and their potential to increase surface ozone levels in WNA, where FT influence
56 is significant (e.g. Jaffe et al., 2018). Therefore, it is critical to understand the processes driving
57 changes in FT ozone.

58 Previous studies have examined key factors influencing tropospheric ozone levels over WNA,
59 including intercontinental transport of ozone from Asia (e.g., Jacob et al., 1999; Cooper et al.,
60 2010), stratospheric intrusions (e.g., Lin et al., 2012, 2015), wildfires (e.g., Jaffe et al., 2008, 2012),
61 and transport from tropical marine environments (e.g., Grant et al., 2000; Cooper et al., 2011).
62 While global-scale modeling studies suggest that increasing anthropogenic emissions contribute to
63 rising FT ozone levels (e.g., Fiore et al., 2012), detailed analyses of atmospheric transport pathways
64 and source attributions are limited. Such studies are essential to identify the drivers, such as source
65 regions, most closely associated with observed ozone increases. This gap motivated the current



66 study, which applies a Lagrangian Particle Dispersion Modeling framework in backward mode to
67 quantify source-receptor relationships (SRRs) for 553,608 ozone receptors which span altitudes
68 from 900 hPa to 300 hPa across WNA over the period 1994–2021.

69 A similar SRR framework was used by Cooper et al. (2010) to explain increased FT ozone
70 concentrations above WNA during April and May from 1995 to 2008. That study used an earlier
71 version of the European Centre for Medium-Range Weather Forecasts (ECMWF) model with a 2°
72 x 2° spatial resolution, generating SRRs up to 16 km above ground level. However, Cooper et al.
73 (2010) focused exclusively on springtime. Chang et al. (2023) demonstrated that positive FT ozone
74 trends over WNA are also present in summer and winter. Therefore, this study extends the analysis
75 of Cooper et al. (2010) by simulating SRRs across all seasons over nearly three decades (1994–
76 2021) using an updated version of the ECMWF model. The complete set of backward simulations,
77 described herein, are archived for future use. Our high-resolution Lagrangian-based product
78 provides an efficient alternative to computationally expensive chemical transport models for
79 quantifying SRRs in the FT ozone observation dataset.

80 In addition to supporting ozone research for WNA, the SRRs calculated in this study are
81 applicable to investigations of air mass origins and source contribution analyses for other
82 atmospheric components observed in the region. These SRRs can be used in studies with co-located
83 observations that align with the spatial and temporal scales defined for some or all of the gridded
84 ozone receptors used here. Further potential applications are discussed in this paper.

85 The paper is organized as follows: Section 2 describes the receptor locations used in this
86 study, followed by Section 3 which details the settings for the SRR simulations. Section 4 provides
87 illustrations and examples of the model products, and Section 5 discusses additional applications
88 of the data. Conclusions are provided in Section 6, and data set availability and formats are
89 described in Section 7.

90

91 **2 Reconciliation of multiplatform ozone observations**

92 To quantify trends and variability in free tropospheric ozone, a gridded ozone dataset was
93 generated using a data fusion technique (Chang et al., 2022, 2023). We expand the previous fused
94 dataset from Chang et al. (2023) to include observations from 900 to 300 hPa during 1994 to 2021
95 using the same statistical method. This extension, which incorporates additional tropospheric ozone
96 data spanning the upper atmospheric boundary layer, free troposphere, and upper troposphere,
97 offers a more comprehensive characterization of tropospheric ozone variability and further supports
98 the validation of previous results. By identifying and adjusting for inconsistencies due to differing



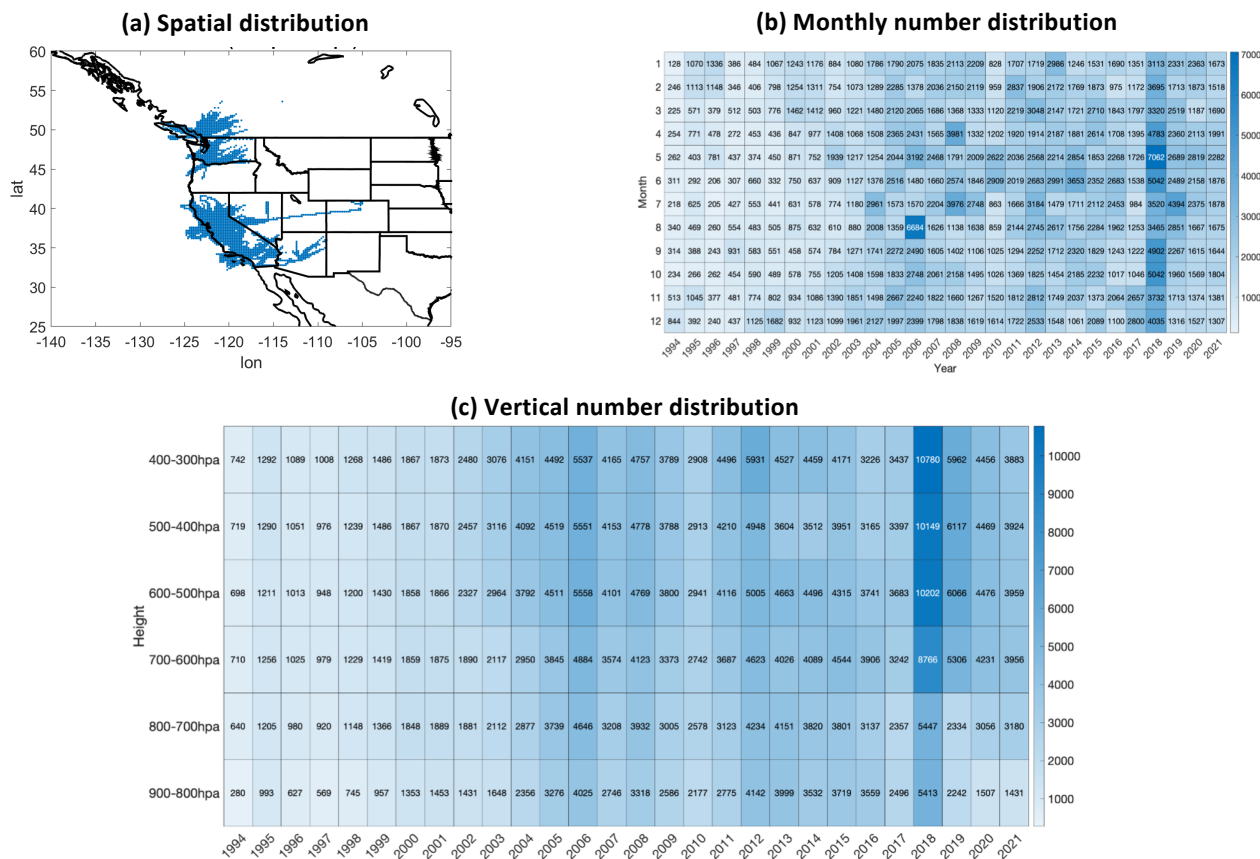
99 sampling frequencies and measurement uncertainties, this fused ozone observation product is
100 expected to be regionally representative (Chang et al., 2022, 2024). Original ozone observations
101 were obtained from various data platforms collected between 1994 and 2021, spanning altitudes
102 from 900 to 300 hPa across WNA. These observations were integrated into $0.2^\circ \times 0.2^\circ$ grid cells
103 with 10-hPa vertical intervals over the WNA region. The new gridded ozone dataset ($N = 553,608$)
104 includes time, latitude, longitude, altitude, and corresponding ozone values. Each grid cell from the
105 data fusion product is treated as a receptor to generate SRRs.

106 Specifically, the tropospheric ozone observations over WNA used in this study include: 1)
107 ozonesonde records above Edmonton (1970–2021), Kelowna (2003–2017) and Port Hardy (2018–
108 2021) from the Canadian Ozonesonde Network (Environment and Climate Change Canada, 2022),
109 and above Trinidad Head (California, 1997–2021) and Boulder (Colorado, 1967–2021) maintained
110 by the NOAA Global Monitoring Laboratory (NOAA GML, 2022), with a roughly once-per-week
111 sampling frequency; 2) lidar measurements above the Jet Propulsion Laboratory Table Mountain
112 Facility (California, 2000–2021, NASA JPL 2022), with 2–5 profiles per week; 3) commercial
113 aircraft observations operated by the IAGOS (In-Service Aircraft for a Global Observing System)
114 program since 1994 (Boulangier et al. 2022); and 4) approximately 200 flights from the NASA
115 AJAX/SNAAX field campaigns (2011–2018, Iraci et al, 2021).

116 The observational methods that produced the ozone data set have varying levels of
117 accuracy (Tarasick et al., 2019), however, according to the well-known concept of error analysis
118 (Taylor and Thompson, 1982), the random nature of the relatively small measurement errors is not
119 expected to impact our ability to detect long-term ozone trends. For example, a sensitivity analysis
120 of tropospheric ozone trends, accounting for varying levels of measurement uncertainty (e.g.,
121 adding 10% or 20% random uncertainty to each data point), was conducted by Gaudel et al. (2024).
122 The results indicate that when the dataset time period is sufficiently long, the observed trends
123 remain consistent. In other words, despite the fact that the greater data uncertainty resulted in higher
124 trend uncertainty, trends can still be detectable under large random uncertainty (i.e., 20%). It should
125 be noted that the modern ozone instrumental measurement uncertainty is typically much lower than
126 the imposed uncertainty used in the above sensitivity analysis (Tarasick et al., 2019). Similarly,
127 Van Malderen et al. (2025) assessed the impact of measurement uncertainties on ozone
128 observations in the free troposphere, assuming 2.5% for lidar, 5.5% for ozonesondes, and 5.5% for
129 IAGOS. The impacts were minor compared to analyses that assumed no measurement uncertainty.
130 Therefore, we consider this data fusion product, which integrates large datasets from multiple
131 platforms spanning nearly three decades, to be robust for ozone trend analysis over WNA.



132



133

134 **Figure 1: The distribution of defined data receptors from the data fusion product: (a) spatial**
 135 **pattern over WNA, (b) number of receptors by month of year across 28 years, (c) number of**
 136 **receptors divided by vertical layers with 100 hPa intervals across 28 years.**

137

138 Figure 1 shows the distribution of the data fusion product across WNA, along with monthly
 139 and vertical layer counts of receptors. For each receptor location, we conducted backward
 140 simulations of historical air mass dispersion and transport processes covering up to 15 days on a
 141 global scale. We retained all detailed simulation outputs for each receptor to allow users to select
 142 specific receptors as needed. Additional details are provided in the following sections.

143



144 **3 Configuration of the SRR product**

145 In this study, we developed the model product using a commonly-used Lagrangian Particle
146 Dispersion Model, FLEXPART ("FLEXible PARTicle dispersion model", v10.4, Pisso et al.,
147 2019), driven by ECMWF reanalysis v5 (ERA5) data (Hersbach et al., 2020). This product is
148 another key component of our SRR database and provides crucial support for understanding source
149 contributions to the overall representative tropospheric ozone trends observed over the WNA
150 region.

151 Specifically, the ERA5 reanalysis data has high spatial and temporal resolutions on the
152 global scale, that is $0.25^\circ \times 0.25^\circ$ spatial and hourly temporal resolution, and 137 vertical levels.
153 The overall uncertainty estimates of ERA5 have been described by Hersbach et al. (2020) using
154 ensemble spread and comparisons with observations. Their analysis, for example, showed that the
155 global mean differences between the nine ensemble members and the control member for
156 temperature, relative humidity, and the u-component of wind at the 500 hPa level were 0.006 K,
157 0.3%, and $0.4 \text{ cm}\cdot\text{s}^{-1}$, respectively for the year 2018. They showed that the magnitude of the
158 ensemble spread is closely related to the quality of the observing system, and also demonstrated
159 that ERA5 has a significant improvement over its previous generation (ERA-Interim). In an
160 independent study, a cross-comparison among three widely used reanalysis datasets, including
161 ERA5, was conducted by Wu et al. (2024). Their study indicated that, when compared to limited
162 observations from field campaigns, the reanalysis datasets exhibited mean wind vector differences
163 ranging from 2 to $4.5 \text{ m}\cdot\text{s}^{-1}$, with ERA5 showing the closest agreement with observations. Many
164 other studies have evaluated ERA5 from different perspectives, consistently highlighting its strong
165 performance. These findings further reinforce the reliability of our source-receptor database.

166 FLEXPART is a Lagrangian particle dispersion model (LPDM) with the ability to study global
167 transport in both forward and backward modes. In this study, we used the backward mode of
168 FLEXPART to calculate SRRs describing the sensitivity of a receptor to a source (e.g. Seibert and
169 Frank 2004). We released 10,000 trajectory particles from each receptor and simulated their
170 backward 4D SRR fields. Stohl et al. (1998) simulated the long-range dispersion of tracer gases
171 using FLEXPART v2.0 based on three large-scale tracer experiments. They compared the model
172 results with tracer gas measurements from various locations and found that the model performed
173 very well under fair meteorological conditions but was less accurate in the presence of fronts.
174 Additionally, they mentioned that the coarse resolution of the meteorological inputs at that time
175 limited the implementation of vertical wind fields, restricting potential improvements in model
176 performance. Forster et al. (2007) evaluated FLEXPART v6.2 in terms of its convective transport



177 performance, finding good agreement at higher altitudes above the atmospheric boundary layer
178 when convection was included in the model. At the time, they emphasized the need for tropospheric
179 profile measurements. Furthermore, they compared forward and backward simulations and found
180 only minor differences, which could be tolerated given the large overall uncertainties of convective
181 parameterizations. Pisso et al. (2019) provided detailed descriptions of FLEXPART v10.4,
182 including references to evaluations of several model components, such as the convection scheme
183 and aerosol lifetime estimation. More recently, Bekel et al. (2024) evaluated and compared
184 FLEXPART v11 and v10.4. While v11 introduces improvements, many key features of v10.4 and
185 v11 exhibit comparable performance. Overall, in LPDMs, the meteorological driver plays a crucial
186 role in determining the level LPDM performance, while differences among various LPDMs remain
187 small (Hegarty et al., 2013). Based on the results from a wide range of studies, we consider
188 FLEXPART-ERA5 to be one of the best current options for establishing our SRRs database.

189 In summary, we expect that the uncertainties associated with the multiplatform-fusion ozone
190 product are primarily aleatoric (i.e. random), a concept well understood in statistical error analysis
191 (Taylor and Thompson, 1982). The uncertainties associated with the FLEXPART-ERA5-based
192 SRRs, which are separate from the random errors associated with the multiplatform-fusion ozone
193 products, are also aleatoric and not systematically biased. A scientific application for integrating
194 our native SRR database (combining the multiplatform-fusion ozone product and FLEXPART-
195 ERA5-based SRRs) at longer time scale (i.e. monthly and yearly) with a focus on different ozone
196 level percentiles, which could further reduce errors, has been conducted by Ryoo et al. (in
197 preparation).

198 Our SRR product spans a 28-year period from 1994 to 2021, with native hourly temporal
199 resolution and $1^\circ \times 1^\circ$ spatial resolution globally. We output 5 layers of SRRs from the surface up
200 to 20 km to support the investigation of the different source regions associated with different
201 altitudes and to understand their source contributions. The 5 layers include surface to 300 m a.g.l.,
202 300 m to 3 km a.g.l., 3 km to 8 km a.g.l., 8 km to 13 km a.g.l., and 13 km to 20 km a.g.l. We used
203 the default FLEXPART schemes such as the Gaussian approximation of boundary layer turbulence
204 and the Emanuel-based convection parameterization (Stohl et al., 2005). ERA5 provided
205 meteorological variable inputs. We used Flex_extract v7.1.2 (Tipka et al. 2020) to extract ERA5
206 global products for the FLEXPART simulations. The output unit of the SRR field is $\text{s m}^3 \text{kg}^{-1}$,
207 which represents the residence time weighted by the volume of air mass. FLEXPART offers several
208 unit options. The primary consideration in selecting this specific unit is to facilitate users in



209 quantifying source contributions by region or atmospheric layer when linking our SRRs with
210 emission rates, in addition to conducting residence time analysis.

211 This SRR database was implemented on NASA High End Computing (HEC) Pleiades
212 Broadwell Nodes. The operational framework was set up on a monthly batch configuration,
213 processing all receptors within a given month in one FLEXPART-ERA5 run using a single
214 processor. Overall, the Lagrangian model framework used here is computationally efficient. Most
215 individual runs required less than 100 hours to complete. Excluding the time required for
216 downloading ERA5 data, approximately one month was needed to generate this comprehensive set
217 of products.

218 The output field structure of the SRR product is a five-dimensional matrix (SRR
219 (receptor,lat,long,height,time)). Details of the receptor information are stored into a separate file,
220 as described in Section 2. Latitude and longitude are represented in $1^\circ \times 1^\circ$ grid cells, and heights
221 denote the five vertical layers as previously described. The time dimension extends from the
222 observational receptors back 15 days with hourly outputs. Retaining detailed information allows
223 users to customize the five-dimensional data to select specific receptors, geographic regions,
224 vertical layers, or backward time intervals up to 15 days. Examples are provided in the next two
225 sections.

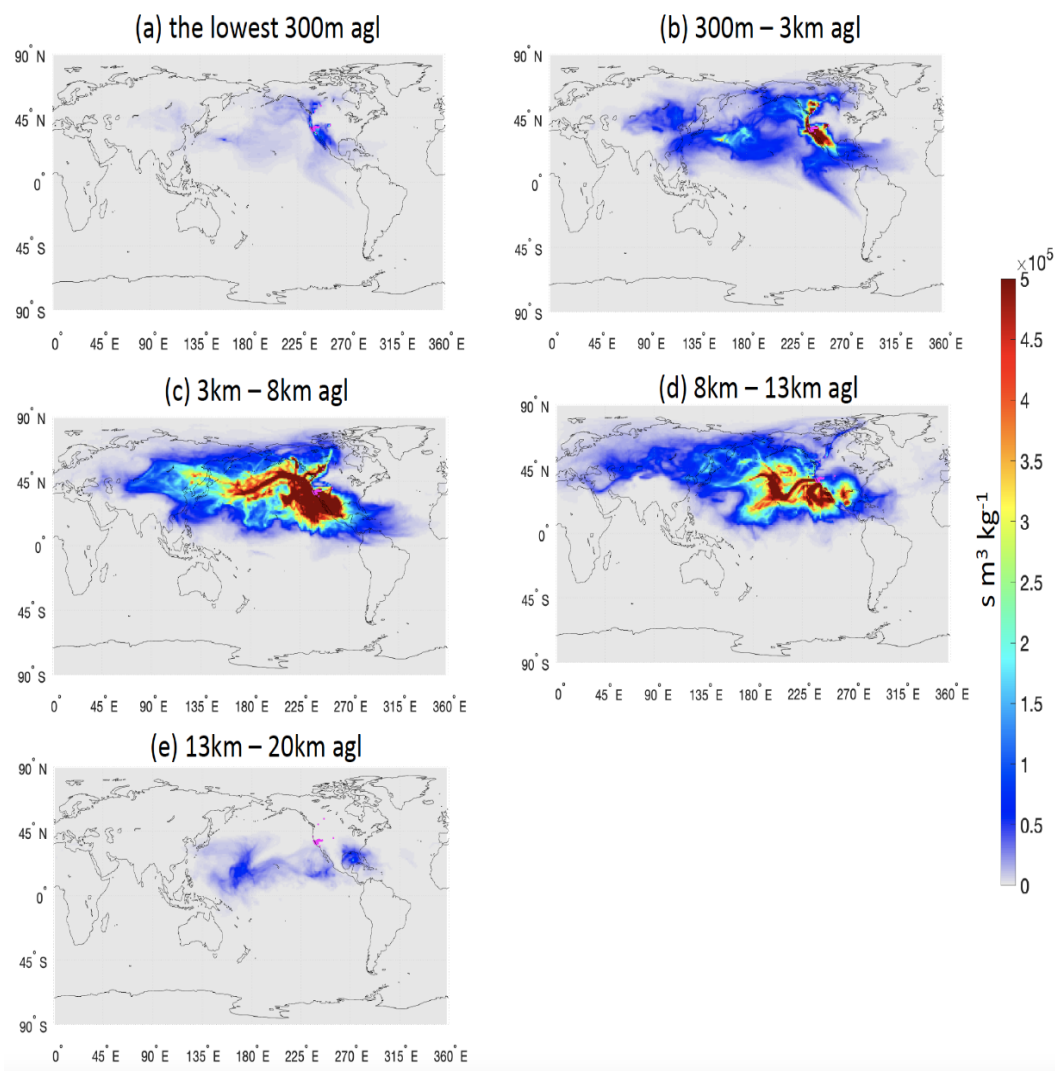
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227 **4 Product illustration**

228 Figure 2 illustrates maps of SRRs summed up at a monthly scale for all ozone receptors. Pink
229 dots mark receptor locations during this month, and the SRR fields represent the influence function
230 values integrated across each vertical layer. Areas with higher values indicate greater source
231 sensitivities to influencing the ozone values observed over WNA. Since ozone receptors are
232 primarily located within the FT, high values are concentrated with the FT from 3-13 km above
233 ground level, with additional influences seen from the lowest 300 m layer and the highest layer
234 (13-20 km). By preserving the FLEXPART outputs in these five vertical layers, studies addressing
235 a wide variety of processes and emission sectors can be devised using this model product. For
236 example, aviation influences are expected in the 8-13 km layer (Ryoo et al., in preparation).



237



238

239 **Figure 2: Monthly influences can be studied with this dataset. Aggregated SRRs of FT ozone**
240 **over WNA during July 2016 are shown for sources located in (a) the near-surface layer (0 –**
241 **300 m a.g.l.); (b) boundary layer (300-3000 m a.g.l.); (c) a middle tropospheric layer (3 – 8 km**
242 **a.g.l.); (d) an upper tropospheric layer (8 – 13 km a.g.l.); and (e) a stratospheric layer (13 – 20**
243 **km a.g.l.). The pink dots represent the geospatial locations of all receptors available during**
244 **July 2016.**



245

246 The SRR datasets retain detailed high-resolution information, which, when integrated over
247 multiple years or decades, enables more robust statistical analyses to understand transport patterns.
248 For instance, we present an example of SRR patterns aggregated over a 28-year period across
249 various altitudes from two distinct receptor subsets: those associated with the lowest (cleanest)
250 ozone levels (left column) and those with higher ozone levels (right column) (Figure 3). SRRs are
251 aggregated monthly across various altitudes for cases when ozone values at the receptors are at
252 their low and high percentiles, compared to those over the mid-year period (2004–2014). A more
253 detailed statistical framework is outlined in Ryoo et al. (in preparation) to minimize the influence
254 of varying numbers of receptors across months and years. All subsequent SRR illustrations given
255 here are generated using the same algorithm applied in Figure 3. These visualizations allow us to
256 compare the SRR patterns across the Northern Hemisphere during winter over the time period. The
257 results demonstrate that this SRR product provides a valuable tool for examining how atmospheric
258 transport patterns vary by altitude and across different subsets of in situ ozone observations over
259 WNA.

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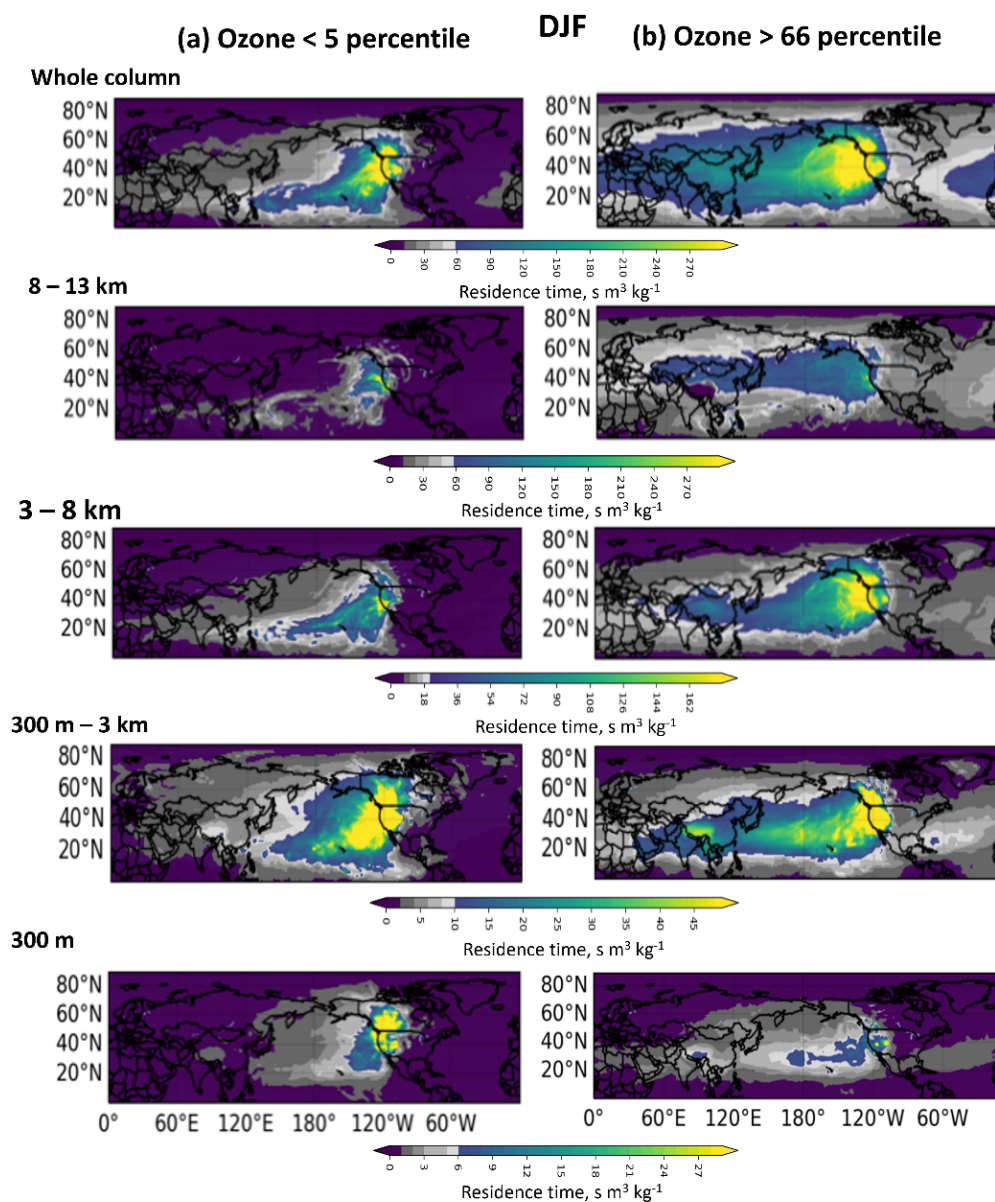
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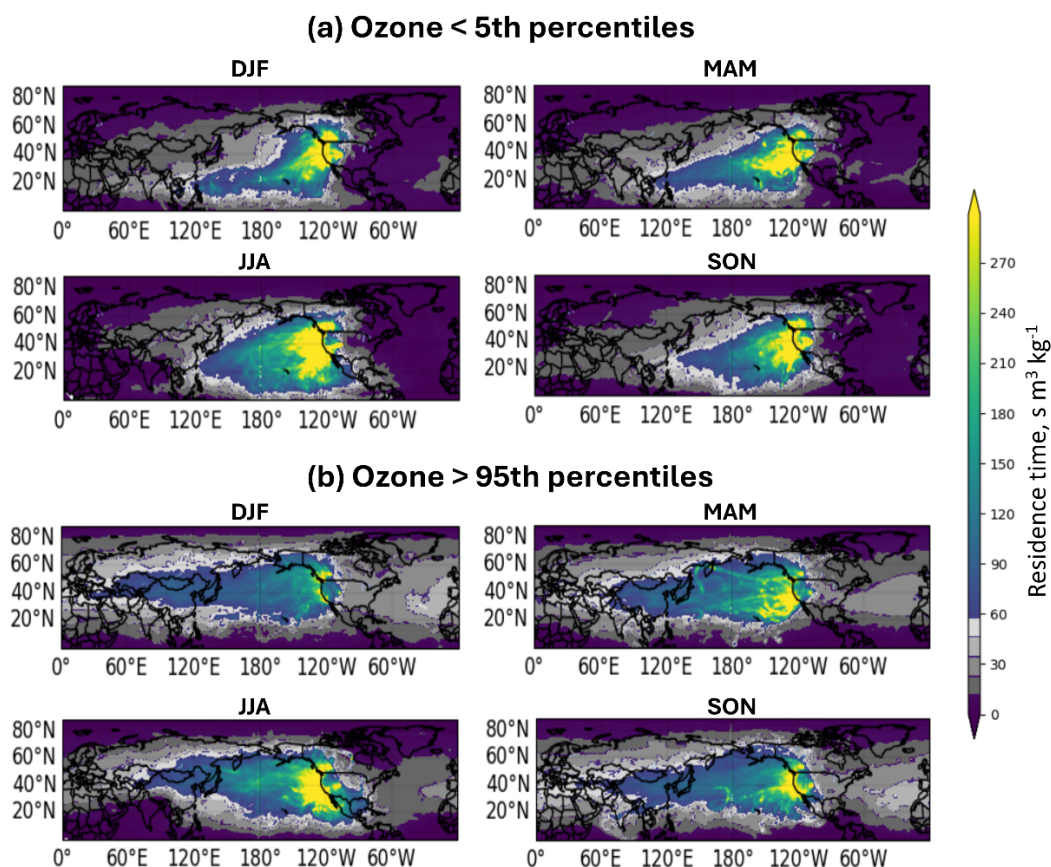


266

267 **Figure 3: Sensitivity of two FT ozone categories (< 5th percentile in panel (a) and > 66th**
268 **percentile in panel (b)) are shown as a function of altitude during wintertime. Air parcels**
269 **reaching WNA with very different amounts of ozone have origins in different regions of the**
270 **Pacific and Asia.**



271 Our dataset of backward simulations can also be used to illustrate atmospheric transport
272 pathways as a function of season. Figure 4 shows an example of aggregated analysis of the seasonal
273 patterns at all altitudes for the entire 28-year period. A consistent feature across all seasons is the
274 significant influence from the western North Pacific Ocean. However, panel (a) shows that the
275 latitudinal extent of source locations for the cleanest parcels (ozone < 5th percentile) varies with
276 season. Transport from the tropical North Pacific Ocean dominates in winter, but the influence
277 widens in spring and ultimately includes broader mid-latitude regions during summer. In contrast,
278 panel (b) shows that the air parcels containing the largest amounts of ozone (> 95th percentile)
279 show some modest seasonal variation in longitudinal extent but originate from a wide range of
280 latitudes in all seasons.



281 **Figure 4: Seasonal sensitivity of residence time of parcels containing (a) the cleanest FT ozone**
282 **level (< 5th percentile) and (b) the highest FT ozone level (> 95th percentile) over WNA during**



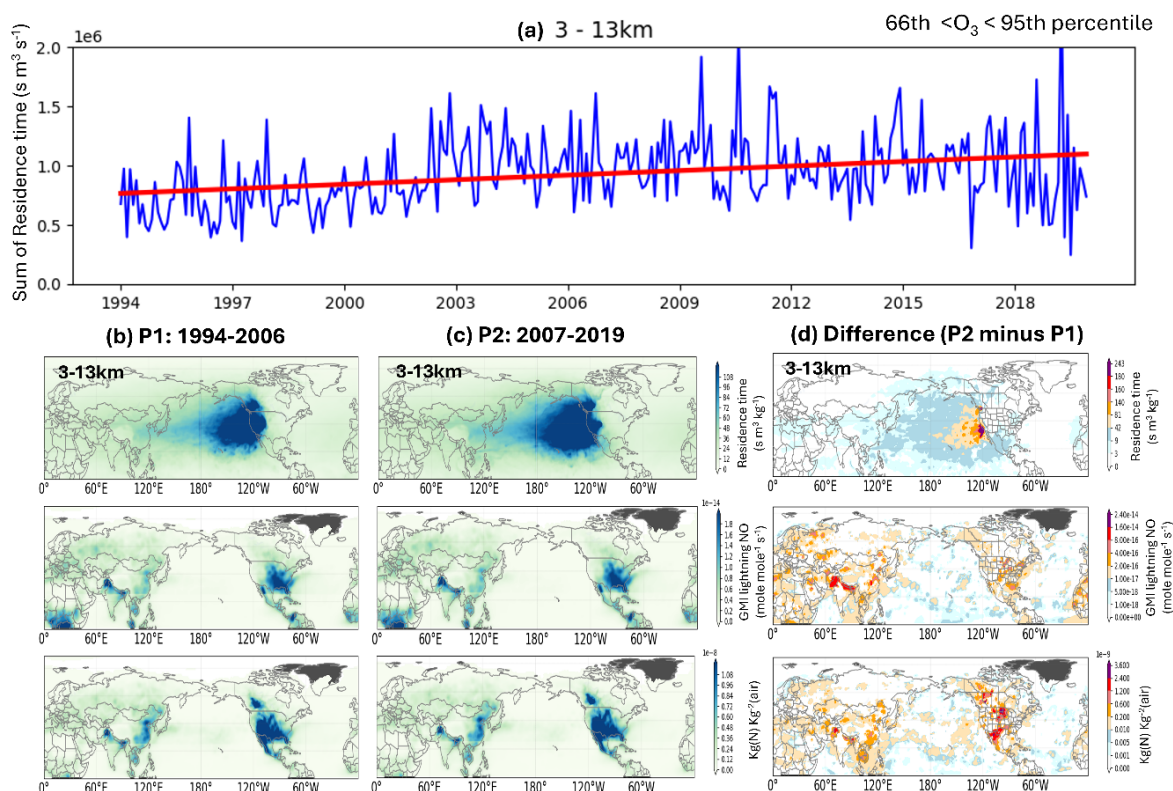
283 **the complete 28-year dataset, including winter (DJF), spring (MAM), summer (JJA), and fall**
284 **(SON).**

285

286 **5 Discussion and additional applications**

287 The SRR database supports atmospheric transport studies, such as examining airmass
288 influences across seasons, altitudes, and ozone mixing ratios (Section 4). Additionally, the 28-year
289 SRR dataset offers the potential for correlation analyses with climate indices, providing valuable
290 insights into the impacts of climate change on atmospheric transport and, consequently, FT ozone
291 levels over WNA (Ryoo et al., in preparation).

292 SRRs can also be linearly convolved with gridded emission source fields to explore the
293 contributions of both anthropogenic and natural sources to ozone formation. For example, lightning
294 nitrogen oxides (NO_x) are a natural source of ozone formation. By convolving the SRR fields with
295 the lightning NO_x source rate, we can identify specific lightning regions that contribute to FT ozone
296 levels over WNA. Figure 5 illustrates a related analysis. An increasing trend of SRRs across
297 altitudes from 3 to 13 km, associated with the 66th to 95th percentiles of WNA ozone receptor
298 levels, is shown in Figure 5 (a). To clarify whether lightning NO_x sources align with the SRRs and
299 whether the increased SRRs bring more lightning-related ozone formation to the downwind WNA
300 FT ozone levels, we calculate the global lightning NO_x flux rate using the Global Modeling
301 Initiative (GMI) model (e.g., Bey et al., 2001; Kinnison et al., 2001). We compare the SRR fields
302 with the lightning NO_x flux rate fields over the Northern Hemisphere for the periods 1994–2006
303 and 2007–2019 (middle row of Figure 5 (b and c)). Additionally, we computed a field of SRR
304 multiplied by the lightning NO_x flux rate to focus on the influence of source regions on the 66th to
305 95th percentiles of WNA ozone levels (bottom row of Figure 5 (b) and (c)). Changes in this field
306 between the two periods are shown (Figure 5 (d)), with higher values indicating regions where
307 lightning activity may contribute to WNA ozone levels in terms of both magnitude and variation.
308 Further detailed scientific analysis is warranted.



309 **Figure 5: (a) SRRs within the 3 - 13 km layers as a function of time for receptors containing**
 310 **ozone amounts between the 66th and 95th percentile. (b) and (c) SRRs for two time periods**
 311 **(1994-2006 and 2007-2019) (top row); average lightning NOx concentrations, weighted by**
 312 **area and time over the Northern Hemisphere, as estimated by the GMI system (middle row);**
 313 **multiplication of top and middle row highlights areas of greatest potential influence (bottom**
 314 **row). (d) Differences between panels (b) and (c).**

315

316 By integrating gridded lightning NOx emissions with SRRs, users can better distinguish
 317 contributions from various geospatial locations. A similar approach, focusing on the impact of
 318 aircraft NOx emissions on FT ozone formation over WNA, is discussed in Ryoo et al. (in
 319 preparation). Another potential application involves linking fire-related trace gases (e.g., carbon
 320 monoxide (CO)) with SRRs to assess the influence of the changes of fire events on FT ozone levels
 321 over WNA.



322 It is important to note that the analysis described above does not account for chemical
323 reactions (e.g., formation or loss processes). Instead, these analyses simply provide an initial
324 indication of regions likely contributing to ozone formation in WNA. Ozone formed locally in
325 regions with high NO_x levels or during transport could be delivered to our ozone receptor locations,
326 and therefore, higher SRR-weighted NO_x emissions are indicative of regions with a potentially
327 significant impact on FT ozone over WNA. While uncertainties remain, this approach provides a
328 rapid and effective means to identify regions associated with FT ozone formation over WNA and
329 to analyze how changes in source regions contribute to variations in downwind FT ozone levels.

330 The SRR product in our archived database extends beyond ozone research, supporting
331 transport and source attribution analyses for other atmospheric components observed over WNA at
332 the spatial and temporal scales defined by the ozone receptor grids. For instance, IAGOS profiles
333 (Section 2) have included CO measurements since 2001, and AJAX missions (Section 2) have
334 collocated methane (CH₄) observations. Additionally, all ozone observations are paired with co-
335 located water vapor measurements. For example, we can use the SRR database to understand
336 decadal-scale changes in the source regions of moisture over western North America, such as
337 variability in atmospheric rivers.

338 Moreover, measurements not directly linked to the ozone observation platforms used in
339 this study (Section 2) but aligned with the spatial and temporal framework defined by the ozone
340 receptors, such as dust-related aerosol measurements in the FT over WNA, can also leverage the
341 SRR database to analyze the transport and origin of diverse atmospheric constituents.

342

343 **6 Summary**

344 Using the statistical technique established by Chang et al. (2022), we integrated and
345 reconciled a gridded ozone database from various ozone observing platforms, covering 900 to 300
346 hPa, primarily focused on the free-tropospheric and upper tropospheric layers, for nearly three
347 decades (1994–2021). In conjunction with this fused dataset, we conducted backward simulations
348 using the Lagrangian-based transport model FLEXPART to calculate source-receptor relationships
349 (SRRs) for each gridded ozone data point. The FLEXPART model is an offline model driven by
350 ERA-5 reanalysis data. FLEXPART-ERA5 is designed to deliver the SRR product at high temporal
351 and spatial resolution on a global scale, with the available SRR information up to 15 days prior.

352 This SRR database, which combines the multiplatform-fusion ozone product and
353 FLEXPART-ERA5-based SRRs, was developed specifically to support multi-decadal analyses of
354 airmasses containing a range of ozone values to advance the understanding of ongoing changes in



355 FT ozone, as most recently identified in Chang et al. (2023). It also supports the analysis of
356 increased FT ozone trends across a range from synoptic dynamics to mesoscale processes in
357 relation to various climate indicators (Ryoo et al., in preparation).

358 Our archived product includes both the Western North America (WNA) fused ozone data and
359 SRR modeling output, providing a powerful resource for understanding atmospheric transport and
360 emission source contributions to FT ozone levels over WNA under various scenarios. This product
361 also holds potential for investigating other aspects of atmospheric components which are relevant
362 to the receptor grid chosen here.

363

364 **7 Data and Code availability and File format**

365 The model outputs, associated receptor data, and post-processing scripts will ultimately be
366 available at NASA's DAAC/ASDC (<https://asdc.larc.nasa.gov/project/WNA-BackTraj>). For
367 immediate needs during the review process, a representative subset of our data has been uploaded
368 to the Zenodo repository (Cui et al., 2024). Specifically, the gridded receptor details are stored in a
369 CSV file that includes columns for the year, month, day, hour, latitude, longitude, pressure, and
370 corresponding ozone values. As outlined in Section 3, FLEXPART model outputs from each
371 monthly batch run are stored in separate monthly folders in binary format. The 28 years of binary
372 files occupy approximately 4 TB of storage. Post-processing scripts to read these binary files in
373 various programming languages are available at <https://www.flexpart.eu/wiki/FpOutput>.
374 Additionally, we have attached a MATLAB script with other archived files. For example, Ryoo et
375 al. (in preparation) used this MATLAB script to convert binary files to NetCDF format and to
376 reduce the domain from global to the Northern Hemisphere for further analysis. That 1° x 1°
377 monthly output for the Northern Hemisphere is also archived at the same location.

378

379 **Competing interests:**

380 The authors declare that they have no conflict of interest.

381

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