

1 **Reply to the comments from the editor (Jens-Uwe Grooß):**

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3 Editor Review of the Manuscript "Stratospheric ozone trends and attribution over 1984-2020  
4 using ordinary and regularised multivariate regression models" by Li et al.

5 As one of the reviewers of this manuscript did not commit a review and the other review was  
6 quite positive, I decided to base the decision of this manuscript on only one regular review  
7 and this editor review. Although I am not an expert on regression methods, I find the paper  
8 written clearly and understandable. Especially, the uncertainties of the derived ozone trends  
9 depending on the regression methods seem important to me. Also the depiction of the  
10 contribution of the natural processes to ozone changes is described well.

11 I would, however, suggest some more discussion of the results: To me it is not clear, in how  
12 far the shown differences in regression methods are now explaining the discrepancy in the  
13 lower stratosphere that was first pointed out by Ball et al. (2020). Besides the variability  
14 induced by the regression method, is there a model improvement with respect to the  
15 Multi-model-mean shown by Ball et al.? Or is this only the difference between free running  
16 CCMs and the CTM shown here. What can be learned from the machine-learning results  
17 (ML-TOMCAT)? Does the similarity with SWOOSH suggest that the basic mechanisms are  
18 well understood or would you expect this similarity as it is constructed by machine-learning  
19 using the observations? Why are the trends in the tropics so different between the two  
20 re-analyses? Is this due to the vertical velocities?

21 Therefore I suggest minor revisions to include this discussion, that would potentially bring the  
22 shown results better into the context of the present literature.

23  
24 **Reply:** We thank the editor for his useful comments and suggestions about more discussion of  
25 the results, which have helped to improve the manuscript. The editor's comments are given  
26 below in black text, followed by our point-by-point responses in blue text.

27  
28 (1) how far the shown differences in regression methods are now explaining the discrepancy  
29 in the lower stratosphere that was first pointed out by Ball et al. (2020).

30  
31 **Reply:** Indeed, regression model methodologies do play some role in the trend estimation.  
32 Ball et al. (2020) used dynamical linear regression model (DLM) that attempts to determine  
33 time varying trends. Basically, DLM takes into account the temporal relationship between the  
34 dependent and independent variables, whereas OLS-type models assume that temporal  
35 relationship between dependent and independent variables is not important. So, to some  
36 extent somewhat larger negative trends shown in the study of Ball et al. (2020) are most  
37 probably due to the regression methodology adopted in their study. On the other hand, even  
38 with OLS/Ridge regression, models used here also show negative (though smaller in  
39 magnitude) in the lower stratosphere and exact causes for those trends are still not well  
40 understood. Although many recent studies (e.g., Chipperfield et al., 2018, Dietermüller et al.,  
41 2021, Li et al., 2022) attribute negative ozone trends in the lower stratosphere to dynamical  
42 changes, usage of reanalysis forcings (ERA1, ERA5, MERRA) are also not consistent, adding  
43 uncertainty in our understanding about the dynamical changes (e.g. Davis et al., 2023).

45 We have added some discussion about the differences in regression methods and comparison  
46 with the previous results (e.g. Ball et al., 2020) about the lower stratospheric ozone trends in  
47 the revised manuscript: "Negative trends with larger uncertainties are observed in the lower  
48 stratosphere, which are most pronounced in the tropics ( $-6.1 \pm 12.0$  % per decade at 100 hPa),  
49 followed by the decrease at NH mid-latitudes ( $-1.6 \pm 3.2$  % per decade at 100 hPa). The largest  
50 difference between OLS and Ridge regression methods occurs in the tropical lowermost  
51 stratosphere with a difference of  $\sim 9$  % per decade at 100 hPa (but with larger  
52 uncertainties  $>10$  % per decade for both regression methods), followed by the NH  
53 mid-latitudes with  $>2$  % per decade difference at 100 hPa ( $\sim 3$  % per decade uncertainties).  
54 Note that, despite the large differences between OLS and Ridge-based trends, they are still  
55 within the uncertainties of the individual trends. The observed ozone decreases in the lower  
56 stratosphere are similar to recent records (e.g. Ball et al., 2019; 2020; Godin-Beekmann et al.,  
57 2022), which could be explained by the increased tropical upwelling and mid-latitude mixing  
58 (Wargan et al., 2018; Ball et al., 2020; Orbe et al., 2020; Davis et al., 2023). Nevertheless, the  
59 modelled lower stratospheric trends do not match those derived from observations." (Lines  
60 295-304)

61 "Compared to the trend estimates from simulation ERA5 in Figure 3, the ML-TOMCAT data  
62 set shows more consistent results with the SWOOSH data, with negative ozone trends in the  
63 tropical and NH mid-latitude lower stratosphere. Largest differences between SWOOSH- and  
64 ML-TOMCAT-based ozone trends appear in the SH mid-latitude lower stratosphere where  
65 ML-TOMCAT shows positive trends, and in the tropical mid- and lower stratosphere with  
66 close to zero trends near 60 hPa (although these trends have large uncertainties). On the other  
67 hand, trends from model simulation ERA5 show largest inconsistencies with respect to  
68 SWOOSH-based trends in the lower stratosphere. Simulation ERA5 shows positive trends for  
69 all three latitude bands that are more pronounced in the SH mid-latitudes ( $5.4 \pm 2.0$  % per  
70 decade at 100 hPa for Ridge regression). These differences between satellite-based datasets  
71 and model simulation suggest there are still large uncertainties in the lower stratosphere  
72 where dynamical processes dominate (Dietmüller et al., 2021; Li et al., 2022). Ball et al.  
73 (2020) reported significant discrepancies in observation-model lower stratospheric ozone  
74 trends by using various satellite-based data sets and chemistry-climate models (CCMs).  
75 Although the inconsistencies vary with various datasets and fit methods (Dietmüller et al.,  
76 2021; Bogner et al., 2022), models generally do not reproduce the observations and the reason  
77 remains an open question." (Lines 305-319)

78  
79 (2) Besides the variability induced by the regression method, is there a model improvement  
80 with respect to the Multi-model-mean (MMM) shown by Ball et al.? Or is this only the  
81 difference between free running CCMs and the CTM shown here.

82  
83 Reply: The TOMCAT 3-D off-line chemical transport model (CTM) shown here is forced  
84 with meteorological fields from ECMWF ERA5 reanalyses (Hersbach et al., 2020) with a  
85 coherent historical assimilation of observations and full stratospheric chemistry scheme to  
86 reproduce the behaviour of ozone as closely as possible.

87

88 Objectively, there is no model improvement with respect to the Multi-model-mean (MMM)  
89 shown by Ball et al. (2020). The inconsistencies in observation-model lower stratospheric  
90 ozone trends shown in this study show some differences with those in previous study (Ball et  
91 al., 2020), which results from the difference between free-running CCMs and the CTM shown  
92 here. As replied above, we have added some discussion about the discrepancy of the ozone  
93 trends in the lower stratosphere.

94  
95 (3) What can be learned from the machine-learning results (ML-TOMCAT)? Does the  
96 similarity with SWOOSH suggest that the basic mechanisms are well understood or would  
97 you expect this similarity as it is constructed by machine-learning using the observations?

98  
99 Reply: The ML-TOMCAT data set we use here is a long-term chemically (and dynamically)  
100 consistent, satellite-data-based global gap-free stratospheric ozone profile data generated by  
101 applying a supervised machine-learning (ML) algorithm to the random-forest (RF) regression  
102 analysis (Dhomse et al., 2021).

103  
104 The similarity or better agreement with SWOOSH is not surprising, as also mentioned by the  
105 reviewer (Dr Mark Weber), since satellite corrections used for ML-TOMCAT are derived  
106 from the same MLS data which are also part of SWOOSH, i.e. using 20 years of UARS-MLS  
107 (1991–1998) and AURA-MLS (2005–2016) measurements as a training period. However, it is  
108 also important that for the non-MLS time period, SWOOSH relies on limited (~30 profiles  
109 per day) observations from SAGE II and HALOE solar occultation instruments. So, monthly  
110 zonal means in SWOOSH data would have a limited set of observations but ML-TOMCAT  
111 would have means from all the model grid points. Dhomse et al. (2021) have demonstrated  
112 that ML-TOMCAT ozone concentrations are well within uncertainties of the observational  
113 data sets at almost all stratospheric levels, and there are significant improvements compared  
114 to the TOMCAT 3-D chemical transport model. Here we aim to illustrate that even with a  
115 limited set of denser observations to construct machine-learning based data, it still shows  
116 remarkable consistency with purely satellite measurement-based data in terms of ozone  
117 trends.

118  
119 We have also added some sentences and comments about the similarity/agreement of the  
120 ML-TOMCAT data set with SWOOSH in the revised manuscript, e.g. "Comparing the  
121 ML-TOMCAT-based trend estimates with the ERA5-forced model simulation, we find  
122 ML-TOMCAT shows significant improvements with much better consistency with the  
123 SWOOSH data set, despite the ML-TOMCAT training period overlapping with SWOOSH  
124 only for the Microwave Limb Sounder (MLS) measurement period." (abstract, Lines 44-46)  
125 & "The better agreement between ML-TOMCAT and SWOOSH, due to satellite corrections  
126 derived from the same MLS measurements, show some improvements in this  
127 machine-learning based data set compared to TOMCAT chemical transport model." (Lines  
128 306-308).

129  
130 (4) Why are the trends in the tropics so different between the two re-analyses? Is this due to  
131 the vertical velocities?

132

133 Reply: Due to the differences existed between ERA5 and ERA-Interim reanalyses (e.g.  
134 vertical and horizontal resolutions, radiative transfer models and measurements assimilated,  
135 and changes in number and type of observations adopted), the differences of the trends in the  
136 tropics between the two re-analyses can be attributed to many reasons, including the different  
137 vertical velocities.

138

139 A detailed comparison between the model simulations forced by two re-analyses (ERA-Interim and  
140 ERA5), including the difference of the stratospheric ozone profiles trends, has been reported  
141 in Li et al. (2022). From the discussion about the differences in age-of-air (AoA) tracer  
142 between two simulations, there exist some fundamental differences in the representation of  
143 Brewer-Dobson circulations between two reanalysis data sets.

144

145 As for TOMCAT setup, simulation ERA5 shows improvements in the TCO biases in the  
146 tropics compared to simulation ERA-Interim. A possible explanation is that the finer vertical  
147 resolution in ERA5 alters vertical transport pathways that are critical for controlling ozone  
148 concentration as, within a few kilometres in the stratosphere, the ozone lifetime changes from  
149 days to a few years. Besides, simulation ERA5 shows increasing AoA trends in the whole  
150 stratosphere, while simulation ERA-Interim shows a hemispheric dipole trend pattern with increasing  
151 AoA in the NH and decreasing trend in the SH lower stratosphere.

152

153 As differences between TOMCAT simulation forced with ERA-Interim and ERA5 are already  
154 discussed in Li et al., (2022), the reviewer (Dr Mark Weber) suggested to omit results and  
155 discussion of ERA-Interim. Hence, all the related comparison between the two model simulations has  
156 been removed from the revised manuscript.

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