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Responses to Reviewer #2

The manuscript's novelty is not yet convincingly established. Several of the stated innovations appear to be incremental combinations of existing data sources and standard analytical tools rather than clearly original methodological contributions. There are multiple global ozone projections under the CMIP6 scenarios employing Climate Chemistry models as well as data-driven methods, such as Li et al., 2026; Ni et al., 2026; Ma et al., 2026; Brown et al., 2022. The current manuscript did not provide enough innovations to construct ozone concentration datasets at either global or regional scale. Meanwhile, it looks like a repetitive work of their own work which applied similar ML techniques in studying global ozone changes under the same CMIP6 scenarios (Ni et al., 2026).

Response:

We thank the reviewer for the insightful comment. We agree that several previous studies have projected or analyzed future O_3 variations using chemistry–climate models and data-driven approaches. Nevertheless, we believe our study provides important additional contributions to the community, particularly by offering a comprehensive projection of O_3 changes **across Africa under multiple scenarios** driven by climate change, along with a detailed decomposition of the associated **driving factors** and the associated **health burden** changes.

With a data-driven approach to estimate O_3 concentrations, Ma et al. (2026) selected air temperature as the sole predictor variable, and constructed a regression relationship between air temperature and O_3 using an L2 regularization function, mapping temperature to O_3 concentrations at a single target grid point. This method was then applied to two climate models to predict O_3. This study provides a ML-based approach for estimating O_3, however, uncertainties remain since the dominant meteorological factors driving O_3 variations often vary by region and season. Relying exclusively on temperature while neglecting other key variables such as solar radiation, relative humidity, and wind speed may oversimplify the complex photochemical and dynamical processes governing O_3 formation and transport.

By using three chemistry-climate model outputs (UKESM1-0-LL, GISS-E2-1-G, and MRI-ESM2-0) from the Aerosol-Chemistry Model Intercomparison Project (AerChemMIP), Brown et al. (2022) evaluated the climate-driven changes in near-surface O_3 concentrations over South America and Africa under the SSP3-7.0 scenario. This prior modelling study revealed the ozone-climate penalty over Africa, which supports several conclusions in our study with an integrated machine learning (ML) framework, although they found some disagreement of O_3 responses between models. To reduce uncertainties, our study applied climate projections from 18 global climate models under four future scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5). To make one step further, individual contributions of changing meteorological conditions and changing natural isoprene emissions under climate change are separately evaluated using sensitivity ML-based simulations, rather than simplified linear regression. In addition, the corresponding future health risks in Africa related to increasing O_3 and rising temperature are also assessed.

We appreciate that the reviewer also noticed our recent work about O_3 **bias-correction** and future predictions over **China, the United States, and Europe** (Ni et al., *ES&T*, 2026)**.** Although both these two studies used ML models, the methods are completely different. The CMIP6 multi-model and CESM2 model simulations exhibit systematic biases regarding the spatial distributions, long-term variations, and magnitudes of O_3 concentrations. To address these potential biases, Ni et al. (2026) integrated near-surface O_3 observations over China, the United States, and Europe from 2014–2020 based on a ML algorithm LightGBM to project O_3 and correct model outputs. The ML model in Ni et al. (2026) is to correct the model bias rather than to predict O_3 concentration, and the effectiveness of this method is largely constrained to regions with abundant observational data. Therefore, the ML-based bias-correction method can only be applied to China, the United States, and Europe. However, the monitoring stations are sparse and unevenly distributed in Africa, where the bias-correction method is not applicable.

In this study we project near-surface O_3 concentrations over Africa during 2020–2050 under four different scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5) based on a ML approach. The input data include GEOS-Chem simulations, climate projections from 18 global climate models, precursor emissions, and many other auxiliary datasets (land use and population). The novel method in our study lies in taking advantage of the chemical transport model in simulating O_3, and incorporating future meteorological variables from ScenarioMIP multi-model ensemble to reduce the uncertainties inherent in climate model. In addition, the climate-driven changes in biogenic isoprene emissions and meteorological conditions are individually analyzed in this study, thereby providing a comprehensive understanding the impacts of climate change on O_3 variations. Moreover, the associated impacts on mortality from changing O_3 due to increasing isoprene emissions, changing meteorological conditions and rising temperature are separately evaluated, which was rarely involved in previous studies.

We have now clarified the novelty in the manuscript, as "Compared with previous studies that relied on simplified linear regression relationships or limited numbers of chemistry-climate model outputs, our study incorporates projections from 18 global climate models under four future scenarios to better constrain uncertainties in future climate-driven O_3 changes across Africa. In addition, the individual contributions of climate-driven changes in biogenic isoprene emissions and meteorological conditions are separately evaluated through ML-based sensitivity simulations, providing a more comprehensive understanding of the impacts of climate change on O_3 variations. Furthermore, the associated mortality burdens attributable to changing O_3 concentrations due to increasing isoprene emissions and changing meteorological conditions, as well as mortality burdens linking to rising temperature are separately quantified, offering an integrated assessment of future air quality and health risks across Africa."

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