A humidity-based exposure index representing ozone damage effects on vegetation

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Abstract

Surface ozone (O3) is detrimental to plant health. Traditional exposure indexes, such as accumulated hourly O3 concentrations over a threshold of 40 ppb (AOT40), are easy to be derived and widely used to assess O3 damage effects on vegetation. However, the regulation of environmental stresses on O3 stomatal uptake is ignored. In comparison, the dose-based indexes are much more reasonable but require complex parameterization that hinders further applications. Here, we propose a new humidity-based index (O3 RH) representing O3 damage effects on vegetation, which can be simply derived using ground-level O3 and relative humidity (RH). Compared with O3 damages to gross primary productivity (GPPd) derived from a process-based scheme over May to October in 2015–2018, the O3 RH index shows spatial correlations of 0.59 in China, 0.62 in U.S., and 0.58 (P < 0.01) in Europe, much higher than the correlations of 0.16, −0.22, and 0.24 (P < 0.01) for AOT40. Meanwhile, the O3 RH index shows temporal correlations of 0.73 in China, 0.82 in U.S., and 0.81 (P < 0.01) in Europe with GPPd, again higher than the correlations of 0.50, 0.67, and 0.79 (P < 0.01) for AOT40. Analyses of O3 RH reveal relatively stable trend of O3 vegetation damages in eastern U.S. and western Europe, despite the long-term reductions in local O3 pollution levels. Our study suggests the substitution of traditional exposure-based indexes such as AOT40 with O3 RH for more reasonable assessments of O3 ecological effects.

1. Introduction

Tropospheric ozone (O3) is a secondary air pollutant generated by photochemical reactions of nitrogen oxide (NOx = NO + NO2) and volatile organic compounds (Atkinson 2000, Kleinman 2005, Jacob and Winner 2009). Ambient surface O3 concentrations ([O3]) kept increasing by 0.5%–2% yr−1 at the middle latitudes of the Northern Hemisphere over 1970–2000 (Vingarzan 2004). Since the 1990s, [O3] decreased in rural areas in North America and Europe (on average 0.23 ppbv yr−1) but increased in urban areas worldwide (on average 0.31 ppbv yr−1) (Sicard 2020). O3 exposure (including acute exposure with high [O3] and chronic exposure) leads to foliar injury and reductions in plant productivity (Paakkonen et al. 1998, Lombardozzi et al. 2012, Yue et al. 2017, De Marco et al. 2020), which further influence the land carbon budget as well as the climate (Tian et al. 2011, Arnold et al. 2018, Gong et al. 2020).

The intensity of O3 vegetation damage depends not only on [O3], but also on environmental stresses. For example, the drought conditions with low air relative humidity (RH) and low soil-water contents
lead to closure of plants stomata, further reducing stomatal O$_3$ uptake and O$_3$ injury (Khan and Soja 2003, Hayes et al. 2012, Gao et al. 2017). The differences in carbon dioxide concentrations, and nitrogen loads may result in different vegetation responses to O$_3$ even with the same [O$_3$] (Topa et al. 2004, Thomas et al. 2006, Mishra et al. 2013). Furthermore, differences in plant function types (PFTs) as well as phenological stages also lead to different stomatal O$_3$ uptakes (Clifton et al. 2020b) and the consequent vegetation damages (Sitch et al. 2007, Anav et al. 2019). As a result, environmental stresses such as air temperature and solar radiation would indirectly regulate O$_3$ vegetation damages by influencing PFT distribution and plants phenology.

To assess the O$_3$ risks to ecosystem functions, various damaging indexes have been proposed and applied. In general, these indexes can be classified into exposure-based or dose-based groups. The accumulated O$_3$ over a threshold of 40 ppb (AOT40) is a typical exposure-based index adopted by the Long-Range Transboundary Air Pollution (CLRTAP) Convention to assess the ecological impacts of O$_3$ (Fuhrer et al. 1997, Spranger et al. 2004). AOT40 represents the O$_3$ exposure level using a simplified formula but is insufficient to quantify O$_3$-induced vegetation damage since the influences of environmental stresses are not considered (Emberson et al. 2000, Mills et al. 2011a). Many studies found that the vegetation damage was more determined by ‘O$_3$ uptake fluxes’ entering stomata rather than O$_3$ exposure (e.g. Musselman et al. 2006, Karlsson et al. 2007, Mills et al. 2011a, Bueker et al. 2015, De Marco et al. 2020, Clifton et al. 2020b). As a result, the dose-based index such as phytotoxic ozone dose over a threshold flux of Y nmol m$^{-2}$ PLAs$^{-1}$ (POD$_Y$ and PLAs is the projected leaf area) is proposed to represent the stomatal flux of ozone. POD$_Y$ includes the influences of environmental stresses on stomata and thus describes O$_3$ damage effects more mechanistically and precisely (Mills et al. 2011b).

The key step of estimating POD$_Y$ is the calculation of stomatal conductance ($g_s$), which is generally obtained by two kinds of model: the Jarvis model (Jarvis 1976, Emberson et al. 2000, Buckley and Mott 2013) or photosynthesis-stomata ($A_{\text{net}}$-$g_s$) model (e.g. Farquhar et al. 1980, Ball et al. 1987). The Jarvis model calculate $g_s$ by multiplying PFT-specific maximum $g_{\text{max}}$ (provided by published observational data) and a series of factors representing influences of environmental stresses (including temperature, vapor pressure deficit (VPD), soil water content and solar radiation) and phenology (Spranger et al. 2004). It is effective to assess O$_3$ vegetation damages at single-site level (e.g. Bueker et al. 2012, 2013), but the complexity in calculating each factor and the difficulties in obtaining observed input data (such as photosynthetic photon flux density, soil water potential, quasilaminar resistance ($r_{\text{L}}$) and leaf surface resistance ($r_s$) limit the application of Jarvis model when upscaling to regional or global scales. The $A_{\text{net}}$-$g_s$ model derives $g_s$ by coupling photosynthesis rates based on physiological relationships (Clifton et al. 2020a). It has been widely applied in dynamic global vegetation models (DGVMs) or land-surface models (Yue and Unger 2015, Sadiq et al. 2017), making the large-scale evaluation possible but requiring proficient coding skills and high computing resources.

Because of the complexity in deriving POD$_Y$, the exposure-based indexes are still widely used to assess O$_3$ ecological effects, especially in the atmospheric chemistry community (e.g. Sicard et al. 2016, 2017, Lin et al. 2018, Lu et al. 2018, Mills et al. 2018, Feng et al. 2019), though POD$_Y$ is a better metric to assess O$_3$ ecological effects (e.g. Mills et al. 2011a, Anav et al. 2016, Shang et al. 2017). Karlsson et al. (2004) attempted to modify AOT40 as a new index named AOT30$_{\text{VPD}}$ by considering humidity impacts on $g_s$. However, the AOT30$_{\text{VPD}}$ based on subterranean clover was designed to describe the short-term visible ozone injury and thus unable to assess O$_3$ damages on ecosystem productivity (Spranger et al. 2004). In this study, we propose a new index based on DGVMs simulations with $A_{\text{net}}$-$g_s$ model to indicate the long-term O$_3$ damage effects to ecosystem productivity. The new index named O$_3$RH has two main advantages: (a) calculations of O$_3$RH are as easy as AOT40 and (b) the index can represent spatiotemporal pattern of O$_3$ damage as efficient as the dose-based method. In particular, we are not denying the advances of POD$_Y$ metric, instead we propose the simplified but comparably effective O$_3$RH index to facilitate the current assessments of O$_3$ ecological risks for atmospheric chemistry community.

2. Methods

2.1. The Yale Interactive terrestrial Biosphere (YIBs) model

The YIBs model includes nine PFTs and can dynamically simulate vegetation biophysical processes, including leaf photosynthesis ($A_{\text{tot}}$), respiration, transpiration, phenology, and carbon allocation at the global scale (Yue and Unger 2015). Stomatal conductance ($g_s$) is dependent on $A_{\text{tot}}$ following the Ball–Berry scheme (Farquhar et al. 1980, Ball et al. 1987):

$$g_s = m \frac{(A_{\text{tot}} - R_d) \times \text{RH}}{C_i} + b,$$  

(1)

where $R_d$ is the respiration rate, RH and $C_i$ indicate the RH and CO$_2$ concentration at the leaf surface, respectively. $m$ and $b$ are PFT-dependent parameters regulating stomatal conductance (see details in Yue and Unger (2015) and Gong et al. (2020)). Previous studies have extensively validated YIBs-simulated gross primary productivity (GPP) and showed reasonable seasonality compared to site-level observations (correlation coefficients larger than 0.8) with
biases ranging from −19% to 7% depending on different PFTs (Yue and Unger 2015). In this study, we perform global simulations using the YIBs model with resolution of 1° × 1° over 2015–2018. Meteorological fields from Version 2 of Modern Era Retrospective-analysis for Research and Application (MERRA2) (Molod et al 2015) and observed O3 (section 2.4) are used to drive the model.

2.2. O3 damage scheme in YIBs
The O3 damage ratio ($F$) to the original photosynthesis is calculated as a linear function of stomatal O3 uptake fluxes ($F_{O3}$) (Sitch et al 2007):

$$F = a \times \max \left[ F_{O3} - F_{O3,crit}, 0 \right],$$

(2)

where the PFT-specific parameters $a$ and $F_{O3,crit}$ are derived from observations (Sitch et al 2007, Yue and Unger 2015). The parameter $a$ has two sets of values representing varied sensitivities from low to high (see details in Sitch et al (2007) and Gong et al (2020)). $F_{O3}$ is calculated by the following formula:

$$F_{O3} = \frac{[O_3]}{R_a + \frac{k_{O3}}{g_c}}$$

(3)

where $[O_3]$ is the ambient O3 concentration and $R_a$ is the aerodynamic resistance. $k_{O3}$ is set as 1.67 to represent the ratio of leaf resistance for O3 to leaf resistance for water vapor. The stomatal conductance $g_c$ is derived from equation (1). Evaluations showed that this scheme was able to simulate reasonable GPP-O3 and $g_c$-O3 relationships for various PFTs (Yue et al 2016, Yue and Unger 2018).

2.3. Definition of O3 damaging indexes
Three widely used indexes, including maximum daily 8 h (MDA8) $[O_3]$, AOT40, and POD1, are compared for O3 vegetation damage:

$$AOT40_d = \sum_{h=8}^{20} \max \left[ [O_3]_{d,h} - 40, 0 \right]$$

(4)

$$POD1_d = \sum_{h=1}^{24} \max \left( (F_{O3})_{d,h} - 1.0 \right) \times 3600$$

(5)

where $[O_3]_{d,h}$ is the observed O3 concentrations (ppbv) at $h$ hour (local time) on $d$ day, and $(F_{O3})_{d,h}$ is the simulated stomatal O3 uptake fluxes (nmol m$^{-2}$ s$^{-1}$). The O3 flux threshold in POD1 is selected as 1 nmol m$^{-2}$ s$^{-1}$ following the recommendation by CLRTAP (2017) since it provides the strongest relationships (maximum $R^2$) between O3 flux and vegetation damages (Bueker et al 2015). To account for the dependence of O3 damage on $[O_3]$ and $g_c$ (equation (3)), the latter of which is related to RH (equation (1)), we propose a new RH-based O3 damage index $O3_{RH}$ as follows:

$$O3_{RH} = f(O_3) \times f(RH)$$

where the $f(O_3)$ and $f(RH)$ are expressed following the thresholds described in section 3.3:

$$f(O_3) = \max \left( 0, \text{MDA8}[O_3]_{d} - 20 \right)$$

(7)

$$f(RH) = \max \left( 0, \min \left( RH_d - 40\%, 40\% \right) \right)$$

(8)

where RH$_d$ is the daily-mean RH (%) and MDA8 $[O_3]_{d}$ (ppbv) is the MDA8 value on $d$ day, respectively. The reason why RH is selected as the key environmental factor is that multi-linear regressions show that RH plays much more dominant roles than temperature and radiation in accounting for O3 damages (see section 3.1). The thresholds of MDA8 $[O_3] = 20$ ppbv and RH$_d = 40\%$ are selected because grid-by-grid analyses show that O3-induced GPP damages are very limited below those thresholds (see section 3.3).

2.4. O3 observations
We use hourly surface O3 data from the monitoring network in China, the U.S., and Europe (figure S1 available online at stacks.iop.org/ERL/16/044030/mmedia)). These regions cover a dominant fraction of land areas suffering severe O3 pollution and the consequent vegetation damages (Lu et al 2018, Unger et al 2020). The site-level $[O_3]$ over 2015–2018 are interpolated into 1° × 1° grids with missing values for grids without observational sites. The hourly O3 data since 1980 in the U.S. and since 1990 in the Europe are further used to examine the trends of different metrics.

2.5. Multi-linear regression method
To evaluate the key environmental factors that influence O3 vegetation damages, we derive the multi-linear regressions between the daily O3-induced GPP damages (GPP$_d$, calculated by YIBs model) and the most related factors, including MDA8 $[O_3]$ from observations, and daily-mean temperature ($T$), RH and direct solar radiation (PAR) from MERRA2 reanalyzed data at each 1° × 1° grid:

$$GPP_d = b_0 + b_1 \times \text{MDA8}[O_3] + b_2 \times T + b_3 \times RH$$

$$+ b_4 \times \text{PAR}$$

(9)

For each coefficient $b$ ($b_1$, $b_2$, $b_3$ and $b_4$), the statistical significances ($P$ values) are examined by t-test. Finally, the factor with the minimum $P$ value is determined as the key factor at each grid.

3. Results
3.1. Key factors determine O3 vegetation damage
Following the multi-linear regression method, figure 1 shows the key factors that dominate O3-induced GPP damages in China, the U.S. and Europe over May to October in 2015–2018. In almost all
1° × 1° grids, O3 vegetation damages are dominated by the ambient [O3] or RH. Specifically, RH is more important in regions with dry climate (such as northern China, western U.S. and the Mediterranean littoral), while the MDA8 [O3] drives GPP damages more in wet regions (such as southern China, eastern U.S. and the Atlantic coast in Europe). It should be noted that T and PAR are able to influence gs and O3 stomatal uptake via determining photosynthesis rates in the Ball–Berry model, but these two factors are not dominating O3-induced GPP damages based on the multi-linear regressions. As a result, we focus only on the two key factors (MDA8 [O3] and RH) in the following analysis.

3.2. A review of O3 vegetation damage with water stress

We explore the impacts of drought on O3 vegetation damage from literature (table S1), which includes experiments for specific PFTs under four different conditions: (a) well-watered (WW) condition with low O3 exposure (generally charcoal-filtered air); (b) WW condition with high O3 exposure (generally ambient air or mixture of ambient air with O3 from an O3 generator); (c) reduced-water (RW) condition with low O3 exposure, and (d) RW condition with high O3 exposure. Generally, almost all observational studies showed that O3 was more detrimental to vegetation under WW condition than RW condition. The alleviated O3 damage is related to RW-induced closure of stomata that limits O3 uptake. These experiments further reveal the alleviation effect of drought on O3 vegetation damages, which is missing in the traditional O3 exposure indexes (such as AOT40).

3.3. Relationships among GPP damages, MDA8 [O3], and RH

The four year simulations show large GPP reductions are predicted in southeastern China, eastern U.S., and central Europe (figures 2(a)–(c)). However, these hotspots of GPP damages do not overlap with the maximum MDA8 [O3] centers, which are located in north China, western U.S., and southern Europe, respectively (figures 2(d)–(f)). The dry climate facilitates O3 production but leads closure of plants stomata, further inhibiting O3 uptake and bringing quite low GPP damages. The spatial inconsistency between [O3] and GPP damages makes the low and even negative spatial correlation coefficients of −0.12 ~ 0.21 between GPP reductions and [O3]. Similarly, the correlations between GPP reductions and AOT40 are as low as −0.22–0.24 at these regions (figures 2(g)–(i)), suggesting that AOT40 fails in depicting reasonable spatial pattern of O3 vegetation damages.

Fumigation experiments in section 3.2 show that moist conditions enhance O3 vegetation damages. However, the relationships among [O3], humidity, and the resultant vegetation damages are rather complex. Here, we use RH as an indicator of drought conditions and analyze the relationships among GPP reductions, MDA8 [O3], and RH over all the grids throughout the four year simulations (figure 3). Large GPP reductions occur at the conditions with high MDA8 [O3] and RH, though the frequency of such days/grids is limited considering increased RH is correspondent to reduced [O3] (figure 3). Previous studies also revealed that high air humidity could dampen net O3 production rates and consequently reduce ambient [O3] (Wang et al. 2017, Gong and Liao 2019). As a result, to depict O3-induced GPP reductions, the connections between [O3] and RH should be considered. Furthermore, GPP damages are moderate if MDA8 [O3] is lower than 20 ppbv (figure 3) or RH is lower than 40%. For the conditions of 40% < RH < 80%, GPP damages become more severe with increased RH, indicating that the stomatal opening plays an important role. However, the effects of [O3] reduction by increasing RH overwhelm stomata opening if RH >80%, leading to low [O3] and the consequent low GPP damages at very wet conditions.

Figure 1. Key factors driving the O3 vegetation damages in (a) China, (b) the U.S. and (c) Europe over May to October in 2015–2018 by multi-linear regressions. The daily samples of GPP damages (%), MDA8 [O3] and meteorological parameters (RH, T and PAR) are from YIBs model simulations, ground-level observations and MERRA2 reanalyzed data, respectively. The factor at each grid with the minimum P value is taken as the key factor.
3.4. Development and evaluation of O$_3$RH index

Based on the above analyses, we propose the humidity-based index O$_3$RH calculated with a dose-based perspective using the instantaneous MDA8 [O$_3$] and RH (section 2.3). The O$_3$ damage effects on vegetation are considered trivial if [O$_3$] is lower than 20 ppbv or RH is lower than 40%. Above those thresholds, O$_3$-induced GPP reductions are dependent on both daytime [O$_3$] and g, (equation (3)), the latter of which is positively correlated with RH (equation (1)). For the wet conditions with RH $>$80%, GPP damages are mainly influenced by [O$_3$], which decreases with increasing RH (figure 3).

Figures 2(j)–(o) shows the spatial patterns of O$_3$RH averaged over May to October in 2015–2018. The correlation coefficients between GPP damages and O$_3$RH range from 0.58 to 0.62 over China, the U.S and Europe, suggesting that the new index O$_3$RH significantly enhances the spatial representation of GPP damages compared to the traditional dose-based AOT40 (correlation coefficients ranging from $-0.22$ to 0.24). In general, O$_3$RH reflects the hotspots of O$_3$-induced damages located in wet regions with relatively high O$_3$ concentrations, such as southeastern China, eastern U.S., and central Europe. However, the O$_3$RH index ignores varied O$_3$ sensitivities among

![Figure 2](image-url)
different plant species, leading to lower spatial consistency between O$_3$RH and GPP damages than that between POD$_1$ and GPP damages (figures 2(i)–(l)). Figure S2 examines the temporal correlations between simulated GPP damages and different metrics over three selected regions (shown in figures 2(a)–(c)). The exposure-based metrics like MDA8 [O$_3$] and AOT40 perform best in western Europe (40°–55° N, 0°–20° E) with correlation coefficients of 0.8 and 0.79. However, these indexes show medium correlations (0.65 and 0.67) over eastern U.S. (30°–45° N, 75°–95° W), and poor correlations (0.41 and 0.50) in eastern China (22°–42° N, 110°–120° E). It reveals that the traditional exposure-based index AOT40, which is originally proposed to evaluate the O$_3$ ecological effects over Europe (Fuhrer \textit{et al.} 1997), should be used with cautions over regions outside Europe due to the missing of regulations by water stress. As a comparison, the new O$_3$RH index shows regionally consistent high temporal correlation coefficients (0.73–0.82) with local GPP damages, highlighting the importance of water stress in regulating O$_3$-induced vegetation damages.

3.5. Application of the O$_3$RH index

With the O$_3$RH index, we expect to estimate O$_3$-induced GPP damages as reasonable as DGVM simulations. Figure S3 compares the O$_3$RH with GPP percentage damages (GPP$_d$ (%)) over May to October simulated by YIBs model over China, the U.S and Europe. Over these regions, high R$^2$ from 0.60 to 0.75 are predicted between O$_3$RH and GPP$_d$ (table S2). Such correlations are much higher than the R$^2$ of 0.24–0.47 between AOT40 and GPP$_d$, indicating the improvement of O$_3$RH in describing the O$_3$ ecological effects. We further calculate the linear regression between O$_3$RH and GPP$_d$ (%) as follows:

$$GPP_d(\%) = 0.65 \times O_3RH - 0.92.$$ (10)

The average slope of 0.65 is accompanied by a range of uncertainties from 0.51 to 0.77 for different years at different regions (table S2).

We further examine the long-term trends of O$_3$-induced GPP damages with different metrics based on site-level observations (figure 4). Surface MDA8 [O$_3$] significantly reduces by 0.142 ppbv yr$^{-1}$ in eastern U.S. from 1980 to 2018 and 0.086 ppbv yr$^{-1}$ in western Europe from 1990 to 2017 (figure 4(a)). The trends of AOT40 show consistent and significant changes as that of MDA8 [O$_3$], with reductions in eastern U.S. and western Europe but enhancement in China (figure 4(b)). However, trends of O$_3$RH are moderate and insignificant for both eastern U.S. and western Europe (figure 4(c)), in part attributed to the positive trends in RH (not shown). As a result, estimates based on O$_3$RH suggest that declining [O$_3$] failed to bring expected lower O$_3$ vegetation damages in these two regions. Such conclusion is consistent with regional studies using observations (Ronan \textit{et al.} 2020) and DGVMs (Yue \textit{et al.} 2016).

\begin{figure}
\centering
\includegraphics[width=\textwidth]{figure3.png}
\caption{Relationships among the ambient O$_3$ concentrations, RH, and the percentage of GPP damages. All the daily samples from the 1° × 1° grids in figure 2 are collected and aggregated into different bins of O$_3$ concentrations and RH. For each bin, the average GPP damages is shown as filled patches and the number of samples is shown as colored contours.}
\end{figure}
4. Discussions

In this study, we proposed a new humidity-based index \( O_3 \)RH to simplify the calculation of \( O_3 \) vegetation damage but with comparable accuracy to dose-based indexes or simulations by DGVMs. The \( O_3 \)RH index provides a bridge between atmospheric chemistry community and ecological science community by considering the key environmental factors that influencing \( O_3 \) vegetation damages. With the help of \( O_3 \)RH, it becomes possible to assess reasonable regional or global \( O_3 \)-induced vegetation damages only by normal ground-level \( O_3 \) and meteorological observations without expensive and complex experiments. For policy makers, \( O_3 \)RH is a more scientific and reliable index to evaluate \( O_3 \) ecological effects relative to the traditional exposure indexes.

However, the \( O_3 \)RH is also confronted with various sources of uncertainties. First, the index adopts MDA8 [\( O_3 \)] and daily RH, thus ignoring the impacts of diurnal variations on \( O_3 \) vegetation damages. Also, some studies assessed \( O_3 \) vegetation damages by accumulated \( O_3 \) metrics (e.g. Bueker et al. 2015, Lombardozzi et al. 2015), leading higher vegetation damages at the end of growth season. Such effects cannot be represented by the instantaneous daily \( O_3 \)RH index. Second, air humidity instead of soil moisture is applied in the parameterization, because...
observations of soil moisture are much more difficult than RH. Many studies have shown the important roles of soil water content in regulating stomatal activities (Hayes et al 2012, De Marco et al 2016, Cionni et al 2017). Although the soil moisture and air RH show high temporal correlations (figure S4), it remains unclear how the differences between RH and soil water stress may influence the accuracy of index. Third, the varied sensitivities of different PFTs to O3 are not considered in O3-RH. Observations show that plants have different sensitivities to the same dose of stomatal O3 fluxes (Sitch et al 2007, Bueker et al 2013). Omissions of PFT-specific characteristics may result in biases of predicted vegetation damages.

The calibration and validation of O3-RH are dependent on the a process-based DGVM (YIBs) and a semi-mechanistic O3 vegetation damages Sitch et al (2007) scheme in this study. The model dependence may also bring uncertainties. For example, the 1° × 1° resolution remains too coarse to reflect the high spatial variability of [O3] and meteorological factors. Furthermore, Sitch et al (2007) scheme derives GPP damages by the instantaneous F03. However, some studies also reported the sluggish effects that stomata lost functions under O3 exposure (Paoletti and Grulke 2010, Hoshika et al 2014, Lombardozzi et al 2015), which is difficult to be represented in Sitch et al (2007) scheme. The extraordinary high correlations between GPP damages and POD3 (figures 2(j)–(l)) are also attributed to the F03 dependent scheme even though most filed experiments show correlations coefficients between vegetation damages and POD3 generally lower than 0.8 (Bueker et al 2015, Convention et al 2017).

Despite these uncertainties, we demonstrate that the O3-RH index is a simplified but effective way to assess regional O3 vegetation damages. We suggest the substitution of traditional AOT40 with O3-RH to account for the regulation by water stress. Analyses using O3-RH show that O3 vegetation damages continue increasing in China and remain stable in eastern U.S. and western Europe during the past several years and decades. Such trends pose a long-lasting threat by surface O3 to global ecosystems.

5. Conclusion

To overcome the poor spatiotemporal representations of traditional O3 exposure indexes and disadvantages of dose-based indexes in complex and skilled calculations, a new humidity-based index O3-RH was proposed in this study to better assess the O3 ecological effects. We firstly selected RH and [O3] as the key factors determining the magnitudes of O3-induced vegetation damages by multi-linear regressions, and then explored the relationships among [O3], RH and GPP damages with the help of YIBs model. The simulation as well as field experiments from literature both supported that moist conditions enhance O3 vegetation damages. Based on these analyses, O3-RH was proposed and evaluated, which showed better spatiotemporal variation of O3-induced GPP reductions than the AOT 40 index. Applications of O3-RH index show that the decline of [O3] over the past several decades cannot relieve O3 vegetation damages in eastern U.S and western Europe. Meanwhile, the fast increases of surface [O3] boost damages to vegetation in China. Our results showed that O3-RH was able to be calculated as easy as exposure-based indexes (not dependent on any expensive observations or numerical models) and had similar spatiotemporal representation of O3 damage as dose-based method, which greatly facilitated the assessment of O3 vegetation damages, especially for policy makers and researchers without ecological backgrounds.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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Conflict of interest

The authors declare no competing financial interest.

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