Enhanced drought resistance of vegetation growth in cities due to urban heat, CO$_2$ domes and O$_3$ troughs

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Abstract

Sustained increase in atmospheric CO$_2$ is strongly coupled with rising temperature and persistent droughts. While elevated CO$_2$ promotes photosynthesis and growth of vegetation, drier and warmer climate can potentially negate this benefit, complicating the prediction of future terrestrial carbon dynamics. Manipulative studies such as free air CO$_2$ enrichment (FACE) experiments have been useful for studying the joint effect of global change factors on vegetation growth; however, their results do not easily transfer to natural ecosystems partly due to their short-duration nature and limited consideration of climatic gradients and potential confounding factors, such as O$_3$. Urban environments serve as a useful small-scale analogy of future climate at least in reference to CO$_2$ and temperature enhancements. Here, we develop a data-driven approach using urban environments as test beds for revealing the joint effect of changing temperature and CO$_2$ on vegetation response to drought. Using 75 urban-rural paired plots from three climate zones over the conterminous United States (CONUS), we find vegetation in urban areas exhibits a much stronger resistance to drought than in rural areas. Statistical analysis suggests the drought resistance enhancement of urban vegetation across CONUS is attributed to rising temperature (with a partial correlation coefficient of 0.36) and CO$_2$ (with a partial correlation coefficient of 0.31) and reduced O$_3$ concentration (with a partial correlation coefficient of $-0.12$) in cities. The controlling factor(s) responsible for urban-rural differences in drought resistance of vegetation vary across climate regions, such as surface O$_3$ gradients in the arid climate, and surface CO$_2$ and O$_3$ gradients in the temperate and continental climates. Thus, our study provides new observational insights on the impacts of competing factors on vegetation growth at a large scale, and ultimately, helps reduce uncertainties in understanding terrestrial carbon dynamics.

1. Introduction

Terrestrial ecosystems assimilate ca. 30% of anthropogenic carbon dioxide (CO$_2$) emissions (Friedlingstein et al 2020) and have been a substantial carbon sink over the past six decades (Ballantyne et al 2012, Keenan and Williams 2018, Morecroft et al 2019). Increasing land carbon uptake has been partly attributed to enhanced vegetation growth in response to rising atmospheric CO$_2$ concentrations (Schimel et al...
2015, Zhu et al 2016), known as the CO₂ fertilization effect. However, sustained global warming, coupled with extreme climate events such as droughts, have the potential to offset this CO₂ fertilization benefit, causing depressions in vegetation productivity and even a net release of CO₂ into the atmosphere (Lewis et al 2011, Choat et al 2018). Therefore, revealing the interactive and competing effects of altered temperature (∆T) and CO₂ (∆CO₂) on the response of vegetation growth and productivity to drought (D; hereafter denoted as ∆T | ∆CO₂ | D effects) is critical for understanding terrestrial carbon cycle dynamics and for informing reliable mitigation and adaption plans for climate change (Reichstein et al 2013, Brodribb et al 2020).

Examining the ∆T | ∆CO₂ | D effects on vegetation growth is generally challenging although there have been some manipulative experiments (Apgaua et al 2019, Birami et al 2020). With controlled experiments, there are uncertainties in translating experimental results into ecologically realistic predictions of how vegetation will respond to ∆T and ∆CO₂ under drought (Dusenge et al 2019, Brodribb et al 2020) at a large scale. In addition, the limited coverage of species and environmental conditions in manipulated experiments may result in inconclusive findings (Duan et al 2013, Birami et al 2020). For instance, ozone (O₃) exposure can induce reductions in vegetation growth (Gregg et al 2003, Ainsworth et al 2012) but is often overlooked in manipulative experiments. While large-scale free air CO₂ enrichment (FACE) and open top chambers experiments may allow exposure of vegetation to, besides rising CO₂, various stress factors such as drought and elevated temperature simultaneously (Ainsworth and Long 2021), such facilities are typically costly to maintain in the long term (Calfapietra et al 2010). It is also difficult in imposing more than two global change factors in these manipulative experiments. As such, there is a dearth of consistent long-term observations for advancing our knowledge of the interactive and combined effect of ∆T | ∆CO₂ | D effects on vegetation growth. For example, stomatal closure in response to drought can result in low leaf intercellular CO₂ and an enhanced sensitivity of photosynthetic rate to rising atmospheric CO₂, i.e. ‘the low intercellular CO₂ effect’, thus leading to relatively larger carbon uptake under drought and elevated atmospheric CO₂ (Kelly et al 2016). This beneficial effect was demonstrated using two Eucalyptus species in short-term experiments where leaf area index remained unchanged while long-term acclimation to drought counteracted this benefit (Kelly et al 2016, Jiang et al 2021).

Here, we approach the interactive effects of environmental drivers on vegetation growth and productivity along an urban–rural gradient (Calfapietra et al 2015) from 2001 to 2018 in the conterminous United States (CONUS). This urban plant physiology concept advocates the use of urban-rural gradients as a test bed and as a cost-efficient means for plant physiological studies since cities are experiencing conditions, such as temperature and CO₂ enhancements, decades ahead of projected change for natural ecosystems (Zhao et al 2016, Wang et al 2019). In addition, global climate change has exacerbated drought in both frequency and severity in urban and its neighboring rural regions (Güneralp et al 2015, Vicente-Serrano et al 2020), posing tremendous pressure on urban-rural ecosystems (Zhang et al 2019). With the long-term monitoring of drought conditions (Dai 2013, 2021), urban-rural contrasts in environmental conditions such as surface O₃ gradient (∆O₃, typically higher O₃ concentrations in rural regions) can be exploited to reveal the response of vegetation growth and productivity to multiple altered environmental factors under drought. In this study, we analyze 75 urban-rural pairs of various sizes among three climatic zones (arid, temperate, and continental climate zones; figures 2, S1, and table S1 (available online at stacks.iop.org/ERL/16/124052/mmedia)) for revealing environmental drivers under-lying ecosystem response to drought. The monthly enhanced vegetation index (EVI, 1 km) (Huete et al 2002) was used as a proxy for natural (non-crop) vegetation growth and productivity during the growing season, i.e. June, July, and August (JJA). EVI values were spatially averaged for urban and rural extents individually over pixels of plant functional types (PFTs) commonly identified in each urban–rural pair. We utilized a linear mixed-effects model to remove variation in EVI induced by climate variables such as solar radiation so that response of vegetation growth to drought and non-drought conditions could be inferred from EVI anomalies (i.e. observations—linear model predictions, denoted as EVIₜ). Drought resistance of vegetation growth (ΔEVIₜ) was computed as the difference in EVIₜ between drought and non-drought conditions for each urban–rural pair. The objectives of this study are to reveal the urban–rural differences in drought resistance of vegetation growth (hereafter denoted as dEVIₜ) and to understand the underlying drivers (e.g. irrigation) of such differences across the CONUS, particularly the role of ∆T, ∆O₃, and ∆CO₂, in explaining the observed dEVIₜ at a large scale.

2. Data and methods

2.1. Data for vegetation, weather, and drought
The monthly MODIS EVI Version 6 (MOD13 A3; https://lpdaac.usgs.gov/products/mod13a3v006/) data at 1 km were used as a proxy for vegetation growth and productivity. We only analyzed EVI derived during the growing season, i.e. JJA, between 2001 and 2018, because of the high-water demand from vegetation partly attributed to higher temperatures in summer relative to other seasons. The EVI product is computed from surface reflectance that
has been corrected for molecular scattering, ozone absorption, and aerosols. The EVI values are considered a better indicator than normalized difference vegetation index to characterize vegetation status in urban areas since EVI has improved sensitivity in high biomass regions and is less sensitive to canopy background signal and atmospheric influences (Huete et al 2002). In this study, urban extent and its rural counterpart each has a total of 54 observations, i.e. 18 (years) * 3 (months). Urban and rural extents were delineated using the yearly MODIS Land Cover Type (MCD12Q1); https://lpdaac.usgs.gov/products/mcd12q1v006/). Version 6 product (Sulla-Menashe et al 2019) (see details in supplementary document, Section-Delineation of urban and rural extents).

Gridded daily weather data are from the Daymet Version 4 product (Thornton et al 2020) (available at ORNL DAAC https://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=1840), including minimum temperature (\(T_{\text{min}}\)), maximum temperature (\(T_{\text{max}}\)), precipitation (Pr), shortwave radiation (srad), and day length (dayl) at a spatial resolution of 1 km. The product is derived from daily meteorological observations recorded at weather stations in the North America and has undergone strict cross-validation and quality controls (Thornton et al 2021). srad and dayl were summarized into one variable as daily total radiation (Srad = srad * dayl). The daily weather variables were aggregated to monthly mean values from JJA between 2001 and 2018. Monthly PDSI dataset (Dai 2021) from the National Center for Atmospheric Research Climate Data Guide (https://climatedataguide.ucar.edu/climate-data/palmer-drought-severity-index-pdsi) is used to define dry to wet conditions for each urban-rural pair. PDSI is computed based on information associated with antecedent and current moisture supply (i.e. precipitation) and demand (i.e. potential evapotranspiration as a function of air temperature). It is a standardized metric with values typically ranging from −4 to 4 though further extreme values may be possible. The gridded product has a spatial resolution of 2.5° and thus each single urban-rural pair share one PDSI value. The single PDSI value can help understand the background drought conditions. We followed the NOAA Climate Prediction Center (www.cpc.ncep.noaa.gov/products/monitoring_and_data/drought.shtml) to define the drought conditions based on PDSI. Here a PDSI value less than −2 means that urban-rural pairs experience a drought condition and a value larger than 0 but less than 2 means that urban-rural pairs undergo a non-drought condition.

2.2. Drought response of vegetation growth and productivity

Prior to the quantification of drought response of vegetation growth and productivity, common PFTs were identified (further details related to identification of common PFTs can be found in supplementary section 2). Albeit the isolation of common PFTs within urban-rural pairs, EVI signals at 1 km still suffer background spectral contaminations from impervious surfaces or other non-vegetation pixels, resulting in smaller EVI values in urban extents compared to those in rural areas (Zhao et al 2016) with exceptions for urban-rural pairs in semi-arid and arid regions (Georgescu et al 2011) (figure S3). In addition, urban-rural differences in background climate can exert an impact on vegetation growth (i.e. EVI values).

Thus, direct comparisons in EVI between urban and rural areas (e.g. urban EVI minus rural EVI) under drought conditions (PDSI < −2) cannot facilitate revealing differences in drought response of vegetation growth and productivity between urban and rural areas. Here, a linear mixed-effects model was used to help define drought response of vegetation growth and productivity since the model did not have a strong requirement for data distribution (i.e. independent variables may not be necessarily normally distributed, Schiepleth et al 2020)).

First, we conducted a panel analysis to remove variation in EVI induced by weather variables including \(T_{\text{min}}, T_{\text{max}}, \text{Pr}, \text{srad}\) using equation (1) for all urban and all rural areas individually (thus urban-rural difference in climate variables can be accounted for):

\[
y_{i,t} = \alpha_1 t + \alpha_2 T_{\text{min}} + \alpha_3 T_{\text{max}} + \alpha_4 \text{srad} + \alpha_5 \text{Pr} + \epsilon_{i,t}
\]

where \(y_{i,t}\) refers to EVI observations for city \(i\) in month \(t\) (June, July, or August) between 2001 and 2018, \(\alpha_1\) captures the EVI trend over the study period among cities, \(\alpha_2, \alpha_3, \alpha_4, \alpha_5\) defines the sensitivity of EVI to \(T_{\text{min}}, T_{\text{max}}, \text{srad}, \text{and Pr}\), respectively, \((1/\text{City}_i)\) accounts for the random effect without intercept among cities (each city as a group), and \(\epsilon\) is the error term. The component \((1/\text{City}_i)\) can account for variations that do not change with climate variables, e.g. variations in EVI attributed to spatial variations of soil quality and impervious surface fractions among different cities and rural counterparts, respectively. Although each urban-rural pair shares one PDSI value extracted from the monthly PDSI dataset, there may be still differences in drought conditions between urban and rural regions. The weather variables including \(T_{\text{min}}, T_{\text{max}}, \text{and Pr}\) in equation (1) can help account for such differences in drought conditions between urban and rural regions that may not be captured by the monthly PDSI dataset. Baseline models without weather variables or random effects were also tested; however, both Akaike
2.3. Urban-rural differences in environmental variables

To help explain the observed discrepancies in drought response of vegetation growth and productivity between urban and rural areas, variables associated with CO$_2$ and O$_3$ concentrations and mean temperature ($T_m$) were used. The mean temperatures for urban and rural extents individually were computed using $T_{\min}$ and $T_{\max}$ provided by the gridded Daymet product following equation (3):

$$T_{m,l} = \frac{T_{\max,l} + T_{\min,l}}{2}$$

where $l$ refers to either urban or rural extents. CO$_2$ concentrations within urban and rural extents were derived from the bias-corrected column-average dry air mole fraction of CO$_2$ ($X_{CO_2}$) from Orbiting Carbon Observatory (Eldering et al 2017) (OCO-2, spatial resolution 1.3$^\circ$2.25 km$^2$). The $X_{CO_2}$ dataset was obtained from the reprocessed OCO-2 Lite files Version 10 r (available at https://disc.gsfc.nasa.gov/datasets) and has a retrieval accuracy of approximately 1 ppm. Although $X_{CO_2}$ is not a direct measurement of surface CO$_2$ concentration, the $X_{CO_2}$ dataset well characterizes the urban CO$_2$ dome (if any) at the city level (Kort et al 2012, Fu et al 2019) and urban-rural gradients in $X_{CO_2}$ have a linear relationship with surface CO$_2$ gradients (Wang et al 2019). Since the dataset is only available from 2014 and has large gaps in both spatial and temporal domains, the mean $X_{CO_2}$ values were computed for urban and rural extents individually using all observations available within the urban or rural extents (i.e. $X_{CO_2}$ values...
between 2015 and 2019). Thus, we did not further differentiate variation in urban-rural $X_{CO_2}$ gradients among JJA.

The ozone data were obtained using the hourly EPA’s Air Quality Data (www.epa.gov/outdoor-air-quality-data) collected at outdoor monitors across the United States. Hourly O$_3$ data from each station within either an urban or rural polygon were aggregated to a monthly scale and then further averaged over all stations within that region (urban or rural). However, only around one-third of urban-rural pairs (24 of 75 urban-rural pairs) had valid monthly mean O$_3$ observations from 2001 to 2018, resulting in large data gaps for analysis. Thus, daily L2 total column O$_3$ data between 2004 and 2018 derived from the Ozone Monitoring Instrument (OMI) (Dobber et al. 2006) onboard the Aura satellite (available at https://disc.gsfc.nasa.gov/datasets) were also used to facilitate surface-level O$_3$ estimations. The satellite-based O$_3$ data were gridded at 0.25$^\circ$ by 0.25$^\circ$ and retrieved using the enhanced TOMS version-8 algorithm applied to the ultraviolet radiance data at 317.5 and 331.2 nm with a bias less than 3% (Balis et al. 2007). We did not use the satellite-based O$_3$ data directly for analysis in this study since the satellite O$_3$ dataset contained the total ozone column data. A regression analysis suggested that there was a statistically significant linear relationship between urban-rural differences in total column O$_3$ and surface O$_3$ gradients (equation (4)) (based on 24 urban-rural pairs, as shown in figure S5(C), with all three months of data considered). Thus, the regression equation was used to convert satellite-based monthly mean O$_3$ differences between urban and rural areas to surface urban-rural differences in O$_3$. Behind this conversion, it was assumed that O$_3$ concentration was relatively stable over years for each month (either from satellite- or station-based observations). This assumption was evidenced by figures S5(A) and (B) showing that the ratio between standard deviation and mean of the O$_3$ concentration was relatively small (2%–10%) over years for each month within urban or rural extents.

The urban-rural differences in environmental variables ($\Delta E$) including $T_m$, $X_{CO_2}$, $CO_2$, and O$_3$ were calculated using equation (4):

$$\Delta E = E_u - E_r$$  (4)

where $E$ indicates the variable $T_m$, $CO_2$, or O$_3$, $E_u$ is the mean value in the urban extent, and $E_r$ refers to the mean value in the rural region. To determine the main factors in controlling differences in drought response of vegetation growth and productivity, the partial correlations of $\Delta x_a$ with latitude, longitude, urban size, mean monthly temperature, $\Delta T_m$, $\Delta CO_2$, and $\Delta O_3$ were computed. We binned urban-rural differences in $T_m$, $X_{CO_2}$, and O$_3$ every 0.1 $^\circ$C, 0.1 ppm, and 0.1 ppbv to reduce stochastic error and data uncertainties. $\Delta T$, $\Delta CO_2$, $\Delta O_3$ were also binned every 0.5 $^\circ$C, 0.5 ppm, and 0.5 ppbv; however, the new binning strategy would not change the significant linear slopes as shown in figures 4(A)–(C).

3. Results

Drought resistance of vegetation growth and productivity in urban areas was stronger than drought resistance in rural areas based on analysis of monthly EVI from 2001 to 2018 (figure 2). Statistically significant differences (p-value < 0.05) were observed in $\Delta EVI_a$ between urban and rural areas except for urban-rural pairs in early summer in arid climate (figure 2). For all selected urban-rural pairs, on average, $\Delta EVI_a$ in urban areas, was less negative than that in rural areas regardless of months within the growing season (JJA) (figure 2(B)). These negative $\Delta EVI_a$ values are expected since $\Delta EVI_a$ refers to the difference in EVI$_a$ between drought and non-drought conditions and mean EVI$_a$ under drought is smaller than that under non-drought conditions (figure S4(B)). A less negative value in $\Delta EVI_a$ suggests a stronger ability to resist dampening effects of drought on vegetation growth. More specifically, mean $\Delta EVI_a$ in urban areas was $-0.0435$, $-0.0261$, and $-0.0174$, and in rural areas, was $-0.0779$, $-0.0535$, and $-0.0316$, for JJA, respectively (figure 2(B)). Intuitively, it may be reasonable to assume that the less negative mean $\Delta EVI_a$ value in urban areas stems from the fact that urban areas typically, except those in arid climate, exhibited a smaller EVI compared to rural regions in each month (JJA) (figure S3). The observed smaller EVI in urban areas in temperate and continental climate zones partly results from the coarse resolution of vegetated pixels (1 km) that suffer signal contaminations from underlying impervious surfaces (i.e. dampening effect of impervious surfaces on EVI). This mixed signal effects (or spectral mixture of vegetation and impervious surfaces within a pixel) can further propagate to EVI$_a$ and $\Delta EVI_a$ calculations, causing smaller standard deviations in EVI$_a$ (figure S4) and $\Delta EVI_a$ in urban regions compared to rural regions (figure 2). However, such an intuitive explanation should not be a concern since the $\Delta EVI_a$ was computed as the difference in EVI$_a$ between drought and non-drought conditions for urban and rural extents individually (see the section 2 for further details), i.e. we did not compare EVI$_a$ under drought conditions in urban areas with EVI$_a$ under drought conditions in rural areas directly.

As regional climate largely controls the types of ecosystems, we further grouped urban-rural pairs into three main climate zones based on Köppen-Geiger scheme (Beck et al. 2018), including arid, temperate, and continental climates. The drought resistance of vegetation growth within each climate zone is shown in figures 2(C)–(E). The separate analysis
Among climate zones and months shows consistent findings that urban vegetation exhibits stronger ability to resist drought impacts than rural vegetation though the urban-rural differences in vegetation drought resistance varies (figures 2(C)–(E)). In the arid zone, on average, ΔEVIa (urban-rural differences in drought resistance of vegetation growth) was 0.0047 and 0.0135 for July and August (p-value < 0.01), respectively while there was no difference in ΔEVIa for June (p-value > 0.01). Compared to the arid zone, the temperate and continental climate zones in general showed a much higher value for ΔEVIa in June and July. For example, the mean ΔEVIa in July for urban-rural pairs under the continental climate was 0.0133 and under the temperate climate was 0.0177, much higher than 0.0047 for urban-rural pairs from the arid zone. For mean ΔEVIa in August, urban-rural pairs from the temperate zone exhibited the largest value (0.0148), followed by those from the arid (0.0135) and continental (0.017) climate zones.

We next explored the potential effects of several drivers underlying urban-rural discrepancies in drought resistance of vegetation growth, including urban-rural differences in monthly mean temperature (ΔT), CO₂ (ΔCO₂), and O₃ (ΔO₃), city size (Size), the latitude and longitude of a city (Lat and Lon, in case spatial location would be a factor), and background monthly mean temperature (Tₘ). To find the main factors controlling ΔEVIa, partial correlation coefficients (partial CC) between ΔEVIa and potential drivers were computed for all selected urban-rural pairs from all three climate zones (figure 3(A)) as well as separately for arid (figure 3(B)), temperate (figure 3(C)), and continental climates (figure 3(D)). The main factors in controlling ΔEVIa across the conterminous U.S. were ΔT (partial CC of 0.36), ΔCO₂ (0.31), and ΔO₃ (−0.12) as seen in figure 3(A). Significant linear relations were also observed for the associations of ΔT, ΔCO₂, ΔO₃ and ΔEVIa from binned observations (figure 4) that were adopted to reduce stochastic error and data uncertainties in the analysis. The main controlling factors for ΔEVIa in each climate zone were different among three climate backgrounds. For example, the most influential variable was ΔO₃ in the arid zone (partial CC of 0.37, figure 3(B)), while in the temperate zone, the main drivers influencing ΔEVIa were ΔCO₂ (partial CC of 0.22), ΔO₃ (partial CC of −0.18), and Tₘ (partial CC of −0.15) (figure 3(C)). In the continental zone (figure 3(D)), ΔCO₂, followed by ΔO₃ was the main factor in affecting ΔEVIa. Overall, ΔT was identified as a main driver for ΔEVIa over the CONUS.
but not in each climate zone. Further explanations for this finding were presented in the discussion section.

4. Discussion and conclusions

We found urban ecosystems were more resistant to drought compared to their rural counterparts regardless of climate zones across CONUS. However, the main variables that contribute to such urban-rural differences in drought resistance of vegetation growth varies among climate zones. In general, surface temperature gradient ($\Delta T$) was the most influential factor ($p$-value < 0.01, figure 2(A)) at the continental scale that consists of various ecosystems. Higher temperature in urban areas in relative to rural areas, observed for most of the selected urban-rural pairs (figure S6), likely leads to an earlier start but later end of the growing season and thus a longer growing season (Li et al. 2017, Wang et al. 2019), resulting in enhanced vegetation growth prevalent in urban areas (Zhao et al. 2016) (while still a lower EVI value compared to rural areas due to the dampening effect from impervious surfaces). Thus, when the very same drought occurred in both urban and rural areas, the enhanced vegetation growth attributed to higher temperatures in urban areas exhibited a better ability/chance to endure/survive drought stress. In addition, plants growing in warmer/drier urban environments may already have had (screened before planting) or developed traits that allow them to better cope with drought stress (Anderegg and HilleRisLambers 2016). However, $\Delta T$ was not the controlling factor driving the urban-rural contrast of vegetation drought resistance within individual climate zones as shown in figure 3 partly due to the much less variation of $\Delta T$ in each climate zone (figure S7). Specifically, as shown in figure S7, vegetation growth in arid or semi-arid cities in general exhibits a much stronger drought resistance compared to that in the other two climate zones despite a wide range of $\Delta T$ from $-2.0$ °C to $3.5$ °C. Even though urban-rural difference in drought resistance varies from $-0.10$ to $0.11$ within temperate or continental climate regions, in a similar magnitude of variation in arid climate, there is a much smaller variation of $\Delta T$. Thus, the urban-rural temperature gradient is not strong enough to cause such considerable differences in vegetation growth. The stronger drought resistance of vegetation (mainly shrub and grass) growth in cities from the arid zone
Figure 4. The relationship between urban-rural differences in drought resistance of vegetation growth (dEVI<sub>a</sub>) and main controlling factors, i.e. \(\Delta T\), \(\Delta CO_2\), \(\Delta O_3\) (A)–(C), identified over the CONUS. \(\Delta T\), \(\Delta CO_2\), \(\Delta O_3\) were binned every 0.1 °C, 0.1 ppm, and 0.1 ppbv. The solid line refers to a statistically significant slope and the shaded area shows the 95% confidence intervals. The number of samples (dEVI<sub>a</sub> in three months from 75 cities) before binning is 840 (for \(\Delta T\) and \(\Delta O_3\)) and each dot in the scatter plots represents a bin. \(\Delta CO_2\) was computed based on \(X_{CO_2}\) averaged between 2014 and 2018 for urban and rural extents individually due to data gaps in both spatial and temporal domains. Thus, the number of samples for \(\Delta CO_2\) is smaller than those of \(\Delta T\) and \(\Delta O_3\).

was mainly related to vegetation growth in rural areas exposed to higher ozone concentration (figure S8). Higher ozone concentration in rural areas than in cities (Gregg et al 2003), could cause more reduction in photosynthesis and vegetation growth in rural areas (Ainsworth et al 2012), which accounted for the negative relationship between surface O<sub>3</sub> gradients and urban-rural differences in drought resistance of vegetation growth (figures 3 and 4(C)). In addition, urban-rural difference in drought resistance of vegetation growth in the temperate zone is also sensitive to background monthly mean temperature \(T_m\). Since the selected urban-rural pairs from the temperate climate zone exhibits the highest background monthly mean temperature (figure S9), this result emphasizes possible temperature stress on vegetation growth, particularly in urban areas, given relatively stable temperature gradients for urban-rural pairs from the temperate zone (figure S7).

Surface CO<sub>2</sub> gradient is identified as another important factor, in addition to surface temperature and O<sub>3</sub> gradients, responsible for the observed urban-rural discrepancies in drought resistance of vegetation growth. The surface CO<sub>2</sub> gradient is represented by the satellite-based \(X_{CO_2}\) gradient since there is a positive, linear relationship between the two (with a scale factor of \(~25\) (Wang et al 2019). This satellite-based CO<sub>2</sub> gradient dataset (figure S10) shows that a greater difference in CO<sub>2</sub> concentration between urban and rural areas could result in a much stronger urban-rural difference in drought resistance of vegetation growth, particularly under temperate and continental climates (figures 3(A), (C), (D) and 4(B)). This conclusion is consistent with previous studies that emphasize the beneficial effect of atmospheric CO<sub>2</sub> enhancement on vegetation growth under drought conditions by stimulating photosynthesis (Ainsworth and Rogers 2007) or by increasing the water use efficiency of plants (Keenan et al 2013). However, the beneficial effect of CO<sub>2</sub> on urban-rural contrast in drought resistance is observed in temperate and continental zones rather than in arid zones even though urban-rural pairs from the arid zone typically showed the largest CO<sub>2</sub> gradient (figure S11). The insensitivity of drought impact on vegetation growth to CO<sub>2</sub> gradients in the arid zone, relative to
other two climate zones, may result from other more limiting factors such as nutrient deficiency (Wang et al. 2020) or stomatal closure in response to rising CO$_2$ at the cost of enhanced growth (Frank et al. 2015) in urban regions from the arid zone. Drought in the water-limited region is often more severe (as indicated in figure S12), and it is also possible that such drought condition completely overwhelms the beneficial effects of elevated CO$_2$ on vegetation growth.

Despite the identified main variables, factors such as landscape configuration/composition, atmospheric deposition (e.g., nitrogen and phosphorus), and management practices may also affect the observed discrepancies in drought resistance of vegetation growth between urban and rural areas. For example, urban landscape configuration and composition has been related to surface temperature gradients between urban and rural areas (Connors et al. 2013, Estoque et al. 2017), thus either strengthening or accentuating the effect of temperature gradients on difference in drought resistance between urban and rural vegetation growth. As urban areas typically have a higher atmospheric nitrogen and phosphorus deposition (Decina et al. 2018), this may lessen nutrient restrictions on vegetation growth, thus contributing positively to the observed differences in drought resistance of vegetation growth between urban and rural areas. Human practices such as urban irrigation, however, may be a factor weakening the conclusion made towards the main factors driving the urban-rural differences in drought resistance of vegetation growth. Thus, we repeated the analysis by excluding some urban-rural pairs from the arid zone where irrigation typically was most pronounced and led to ‘the oasis effect’ (Georgescu et al. 2011), i.e. higher EVI in cities than in rural areas (figure S3). Further analysis of urban-rural pairs from the three climate zones suggests that the main factors controlling the urban-rural differences in drought resistance of vegetation growth are still gradients of temperature and CO$_2$ and O$_3$ concentrations but with a smaller partial CC (figures S13 and 3(A)). Thus, although urban irrigation contributed positively to the observed urban-rural contrasts in drought resistance of vegetation growth, such a factor alone could not explain all the observed variances associated with drought resistance. Even under strong irrigation for cities in the arid zone, surface O$_3$ gradient was still identified as the main driver for observed discrepancies in drought resistance of vegetation growth between urban and rural areas (figure 3(B)). As such, there is strong evidence in attributing the observed discrepancies in drought resistance of vegetation growth between urban and rural areas to factors including temperature, CO$_2$, and O$_3$ gradients. Urban-rural gradients in wind speed and humidity were also accounted for in the analysis (figure S15). The results suggested the controlling factor for the urban-rural differences in drought resistance would still be temperature, CO$_2$, and O$_3$ gradients (figure S15).

Benefiting from long-term satellite and station-based datasets, our study provides a data driven approach for revealing the impacts of competing and interactive environmental factors on response of vegetation growth to drought at a large scale. This approach advocates the urban plant physiology concept by utilizing urban-rural contrasts in environmental conditions, such as altered temperature gradients and O$_3$ concentration. The substantial differences in environmental conditions along urban-rural gradients can provide a ‘natural laboratory’ that is more widely accessible, compared to manipulative environments, to the scientific community to understand ecosystem traits under a changing climate. With projected increase in temperature and atmospheric CO$_2$ in the future, we can also select only urban-rural pairs with positive values in ∆T and ∆CO$_2$ for analysis. In this case, it is found that the mean urban-rural difference in drought resistance of vegetation growth becomes positive, i.e. 0.0389 for June, 0.0294 for July, and 0.0201 for August (figure S14). Thus, the novel aspect of this study is to provide a more general assessment of vegetation responses to environmental factors across different regions, and ultimately, to reduce uncertainties in quantifying terrestrial carbon dynamics.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

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Conflict of interest

The authors declare no conflicts of interest relevant to this study.

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