Article

Satellite-Observed Effects from Ozone Pollution and Climate Change on Growing-Season Vegetation Activity over China during 1982–2020

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Abstract: Remote sensing vegetation index data contain important information about the effects of ozone pollution, climate change and other factors on vegetation growth. However, the absence of long-term observational data on surface ozone pollution and neglected air pollution-induced effects on vegetation growth have made it difficult to conduct in-depth studies on the long-term, large-scale ozone pollution effects on vegetation health. In this study, a multiple linear regression model was developed, based on normalized difference vegetation index (NDVI) data, ozone mass mixing ratio (OMR) data at 1000 hPa, and temperature (T), precipitation (P) and surface net radiation (SSR) data during 1982–2020 to quantitatively assess the impact of ozone pollution and climate change on vegetation growth in China on growing season. The OMR data showed an increasing trend in 99.9% of regions in China over the last 39 years, and both NDVI values showed increasing trends on a spatial basis with different ozone pollution levels. Additionally, the significant correlations between NDVI and OMR, temperature and SSR indicate that vegetation activity is closely related to ozone pollution and climate change. Ozone pollution affected 12.5% of NDVI, and climate change affected 26.7% of NDVI. Furthermore, the effects from ozone pollution and climate change on forest, shrub, grass and crop vegetation were evaluated. Notably, the impact of ozone pollution on vegetation growth was 0.47 times that of climate change, indicating that the impact of ozone pollution on vegetation growth cannot be ignored. This study not only deepens the understanding of the effects of ozone pollution and climate change on vegetation growth but also provides a research framework for the large-scale monitoring of air pollution on vegetation health using remote sensing vegetation data.

Keywords: satellite-observed effects; vegetation growth; ozone pollution; climate change; long-term; China

1. Introduction

Many studies on the impact of climate change on vegetation activity not only quantitatively assess the extent of the impact of climate change on vegetation activity but also attempt to deeply understand the relationship between them [1–6], providing an important cognitive basis. However, with the deepening of research, people have gradually realized that there are many factors driving surface vegetation change (for example, human activities, air pollution, ozone pollution, etc.). Therefore, people began to focus on the effects of climate change combined with other factors (e.g., human activities) on vegetation change [2,3,7–9]. Although this has enhanced the understanding of climate change and human activity on vegetation change, it is only a crude quantitative assessment of human activity on vegetation change. However, with the rapid development of the social economy, air pollution caused by human activities has gradually attracted attention. Air pollution is becoming increasingly prominent, which not only affects human health but also affects the health and safety of surface ecosystems [8,10–13]. Some studies have also proven that climate change and air pollution are the driving forces for changes in surface...
vegetation. However, the relationship between air pollution and vegetation health has also been ignored. It is also deeply intertwined with the issue of climate change, making it increasingly difficult to study the effects of air pollution on ecosystem health. At present, the existing studies on the impact of air pollution on vegetation growth are mainly observational experiments at plot-scale or a small number of model simulation experiments (for example, focusing on ozone pollution). Although the main ozone (O\textsubscript{3}) exposure control experiments have provided the basis and theory for a deep understanding of its impact on ecosystems, there is still a lack of large-scale observation of its effects on land surface vegetation. In addition, due to the lack of long-term and large-scale surface ozone data, it is difficult to conduct large-scale and long-term studies on the impact of air pollution on ecosystem health. Therefore, there is still a lack of deep understanding of the impact of large-scale air pollution on vegetation growth. With the continuous development of remote sensing technology, remote sensing monitoring technology has achieved the characteristics of a large scale, high spatial and temporal resolution and low cost. It can record current land surface signals and provide important technical support for monitoring changes in land surface processes at the regional scale. For example, the normalized difference vegetation index (NDVI) from NOAA-AVHRR and MODIS satellite remote sensing instruments, which records land vegetation change signals, is widely used to monitor changes in terrestrial vegetation activities. In this way, it can be inferred that the signal of the impact of O\textsubscript{3} pollution on vegetation change will also be recorded in NDVI data. Hence, it is feasible to use remote sensing technology to monitor the impact of O\textsubscript{3} pollution on ecosystems on a large scale. In addition, a large number of control experiments have deepened the understanding of the mechanism of O\textsubscript{3} pollution affecting vegetation growth, but due to the limited plot-scale information provided by such experiments, this information is difficult to use to assess the impact of large-scale O\textsubscript{3} pollution on terrestrial ecosystems, and the damage degree of O\textsubscript{3} pollution to vegetation and ecosystems cannot yet be assessed. Regrettably, there is a lack of large-scale remote sensing investigations of the impact of O\textsubscript{3} pollution on terrestrial ecological processes. In short, it is necessary to urgently carry out large-scale investigations and research on the impact of O\textsubscript{3} pollution on vegetation activities in order to further understand the impact of O\textsubscript{3} pollution on ecosystems.

Remote sensing vegetation index data contain more important surface change information, such as the effects of ozone pollution, climate change and other factors on vegetation growth. However, information on air pollution, which is closely related to vegetation growth, has been ignored. Therefore, ozone mass mixing ratio (OMR) data at 1000 hPa from the ECMWF Reanalysis v5 (ERA5) data set from 1982 to 2020 were used to characterize long-term surface ozone pollution. Combined with NDVI data, temperature (T), precipitation (P) and surface net radiation (SSR) data from the last 39 years (1982–2020), a multiple linear regression model was developed. Finally, the effects of ozone pollution and climate change on terrestrial vegetation growth in China during the growing season (April to October) were quantitatively assessed.

2. Methodologies
2.1. Datasets
2.1.1. Normalized Difference Vegetation Index (NDVI)

NDVI is an important parameter for characterizing land surface vegetation change and has been widely used to investigate the impact of climate change or human activities on vegetation activities. Therefore, we used NDVI as a key indicator of long-term vegetation change in China to quantitatively assess the impact of ozone pollution and climate change on terrestrial vegetation activity in China. We used the Climate Data Record (CDR) of NDVI Data with a spatial resolution of 0.5\degree \times 0.5\degree and a temporal resolution of 1 day from 1982 to 2020 to characterize the variation characteristics of terrestrial vegetation activities in China. The data set (from https://www.ncei.noaa.gov/products/climate-data-records/normalized-difference-vegetation-index, accessed on 23 October 2021) is...
a consistent, long-term record of global surface vegetation coverage activity based on remotely sensed observations. Firstly, we averaged the data of the first 15 days and the last 15 days of each month and then reconstructed the monthly NDVI data of China during the growing season (April to October) from 1982 to 2020 using the maximum value composite (MVC) method [26]. To accurately detect the variation in NDVI, all NDVI were multiplied by 100 to amplify the variation of small signals.

2.1.2. Ozone Mass Mixing Ratio (OMR) Data

Due to the lack of long-term continuously observed data on surface ozone pollution, it is difficult to quantitatively assess the impact of ozone pollution on surface vegetation change on a long-term time scale. For this reason, the monthly average OMR at 1000 hPa from 1982 to 2020 was used to describe the ozone pollution status near the ground surface. OMR is the (dimensionless) ratio of the mass of ozone to the mass of dry air per cubic meter and this ratio represents the ponderal mixture of these two gaseous substances, OMR is used to analyze the atmospheric composition ERA5 products (from https://cds.climate.copernicus.eu/#!/search?text=ERA5&type=dataset, accessed on 23 October 2021), and its spatial resolution is 0.25° × 0.25°. We reconstructed the data with a spatial resolution of 0.05° × 0.05° during the 1982–2020 growing seasons using the CDO (Climate Data Operator, Version 1.9.9, from https://code.mpimet.mpg.de/projects/cdo, accessed on 23 October 2021) software interpolation. To accurately detect the variation in OMR, all OMR were multiplied by 1 × 10⁹ to amplify the variation of small signals.

2.1.3. Climate Elements Data

For quantitative assessment of the impacts of climate change on growing season vegetation activity in China, we use the temperature (T) and surface net radiation (SSR) from the ERA5 data set (from https://cds.climate.copernicus.eu/#!/search?text=ERA5&type=dataset, accessed on 23 October 2021), with a spatial resolution of 0.25° × 0.25°. We also use the precipitation (P) from CRU TS v. 4.05 data set [27] (https://crudata.uea.ac.uk/cru/data/hrg/, accessed on 23 October 2021), with a spatial resolution of 0.5 d × 0.5 d. Finally, the data sets of temperature, precipitation and surface net radiation with a spatial resolution of 0.05° × 0.05° during the 1982–2020 growing seasons were reconstructed by using CDO software interpolation.

2.2. Methods

2.2.1. Determination of Ozone Pollution Zones

First, we calculated the minimum values of OMR data for each year from 1982 to 2020 in China and then obtained the minimum values as the background value (OMR₀) of ozone mass ratio in China, which was calculated by Formula (1).

\[
OMR_0 = \text{Minimum}\left\{\text{Minimum}\{OMR_{y,ij}\}\right\}
\]

In the above formula, y is the year and ij is the lattice point of row i and column j in the region of China.

Referring to the Chinese EPA’s (Environmental Protection Agency) classification method of ozone pollution in China, the classification threshold value increased by approximately 55%. The value of OMR₀ is the threshold value of primary ozone pollution in the growing season, and the level of ozone pollution in China in the growing season is then determined (see Table 1 for details).

2.2.2. Principal Component Analysis (PCA)

Principal component analysis (PCA) is an important factor analysis method and a multivariate statistical analysis method based on unsupervised learning [28–30]. We used the PCA function in Origin 2018 software to detect meteorological factors and air pollution factors that affect vegetation growth.
3. Results

Figure 1. The technical schematic diagram of this study.

2.2.3. Methods for Quantitatively Assessing the Effects of Ozone Pollution and Climate Change on Vegetation Change

The multiple linear regression method has been widely used to detect the impact of climate change and human activities on vegetation growth [31,32]. Therefore, we use a multiple linear regression method to quantitatively assess the impact of ozone pollution and climate change on terrestrial vegetation change in China. The calculation formula is as follows:

\[
\partial \text{NDVI}_{\text{predict}} = \frac{\partial \text{NDVI}}{\partial O} \partial O + \frac{\partial \text{NDVI}}{\partial T} \partial T + \frac{\partial \text{NDVI}}{\partial P} \partial P + \frac{\partial \text{NDVI}}{\partial S} \partial S + \epsilon, \tag{2}
\]

\[
I_{\text{climate}} = \frac{\partial \text{NDVI}}{\partial T} \partial T + \frac{\partial \text{NDVI}}{\partial P} \partial P + \frac{\partial \text{NDVI}}{\partial S} \partial S \times 100\%, \tag{3}
\]

\[
I_{\text{ozone}} = \frac{\partial \text{NDVI}}{\partial \text{NDVI}_{\text{obs}}} \times 100\% \tag{4}
\]

In Equations (2) and (3), \(\frac{\partial \text{NDVI}}{\partial O}, \frac{\partial \text{NDVI}}{\partial T}, \frac{\partial \text{NDVI}}{\partial P}\) and \(\frac{\partial \text{NDVI}}{\partial S}\) are partial regression coefficients in Equation (2) and refer to the impacts of ozone pollution (\(I_{\text{ozone}}\)) and climate change (\(I_{\text{climate}}\)) on vegetation growth. O, T, P and S are OMR, temperature, precipitation and SSR, respectively. \(\text{NDVI}_{\text{predict}}\) and \(\text{NDVI}_{\text{obs}}\) are predictive and remote sensing observational NDVI values, respectively. \(\epsilon\) is the residual item.

Figure 1 briefly summarizes the method of this study.

### Table 1. Grades of OMR during growth seasons over 1982–2020.

| Regions | Value | Grades | Thresholds |
|---------|-------|--------|-----------|
| R1      | OMR0–650 | Good   | ≤OMR0 + OMR0 × 55% |
| R2      | 650–700 | Moderate | ≤OMR0 + OMR0 × 67% |
| R3      | 700–750 | Unhealthy | ≤OMR0 + OMR0 × 79% |
| R4      | 750–800 | Very Unhealthy | ≤OMR0 + OMR0 × 90% |
| R5      | >800  | Hazardous | ≥OMR0 + OMR0 × 90% |

Note: OMR0 = 420 (kg/kg). The OMR were multiplied by \(1 \times 10^7\) to amplify the variation of small signals.
3. Results
3.1. Spatiotemporal Characteristics of Ozone at 1000 hPa during 1982–2020

To clearly investigate the spatial distribution characteristics of 1000 hPa ozone in the 1982–2020 growing seasons, we used the method of determining ozone pollution zones (see Section 2.2.1) and the spatial OMR data at 1000 hPa. China is divided into the regions R1, R2, R3, R4 and R5 with different levels of ozone pollution (see Figure 2). Figure 2a shows a decreasing trend of OMR from north to south. The high value center of OMR is located in the R5 region of Northwest China, and the low value center is located in the R1 region of southern China. The average OMR value of R5 is approximately 1.34 times higher than that of R1, 5.3% higher than that of R4, and 1.13 times higher than that of R3. The OMR values of R5 and R4 are approximately 7.6% and 1.8% higher than the national average (768.9), respectively. In addition, R5 and R4 cover an area of approximately 73% of the national area. The OMR is higher in northern China. The change rate (slope) of OMR in most areas of China were greater than zero during 1982–2020, which indicates that OMR is increasing. In addition, the increase rate (slope > 0) of OMR in Northwest China was higher than 1.5. OMR showed a decreasing trend (slope < 0) in South China. According to the trend of OMR nationwide (Figure 3a), OMR increased significantly at a rate of 1.51a⁻¹ from 1982 to 2020 (r = 0.6, p < 0.001). From the perspective of zoning, Figure 3b–f shows that OMR in the R1–R5 region has exhibited an increasing trend in the past 39 years (the increase rate from southeast to northwest varies from 0.53 to 2.08a⁻¹), and the R2–R5 region has exhibited a significant increase (significant at the 99% confidence level). The values in R1 increased at a rate of 0.53a⁻¹. Taken together, these results show that ozone pollution in China has tended to worsen over the past 39 years.

Figure 2. (a) The spatial distribution of OMR in the growing season from 1982 to 2020 and (b) the spatial distribution of the rate of OMR change. The colored lines from south to north refer to the contour lines of OMR values of 650, 700, 750 and 800 kg/kg, respectively. The author used the software of ArcGIS 10.5 to produce the figure.
3.2. Spatiotemporal Characteristics of NDVI during 1982–2020

We also investigated the spatial and temporal variation characteristics of regional NDVI in China during the growing season from 1982 to 2020 (Figures 4 and 5). Figure 4a shows that an increasing trend from north to south in the nationally averaged NDVI during 1982–2020 occurs, which is contrary to the change trend of OMR. For example, the NDVI value of the R5 zone with the highest level of OMR is 0.21 ± 0.11, and that of the R1 zone with the lowest level of OMR is 0.51 ± 0.06. As shown in Figure 4b, the change rate (slope) of NDVI in 79.95% of the total vegetation cover area in China during 1982–2020 was greater than 0, indicating that at a national scale, vegetation activity in China showed an increasing trend. According to the change trend of national NDVI (Figure 5a), from 1982 to 2020, the national NDVI increased significantly at the rate of 0.97a⁻¹ (r = 0.81, p < 0.001). The increasing rates (slopes) of NDVI in the R1, R2, R3, R4 and R5 zones were 1.57a⁻¹ (r = 0.70, p < 0.001), 1.67a⁻¹ (r = 0.76, p < 0.001), 1.33a⁻¹ (r = 0.77, p < 0.001), 1.18a⁻¹ (r = 0.85, p < 0.001) and 0.37a⁻¹ (r = 0.55, p < 0.001), respectively. In conclusion, the vegetation activity in China has mainly been enhanced in the past 39 years.

It is worth noting that Figures 4 and 5 depict that the NDVI shows an increasing trend from 1982 to 2020 despite the aggravation of ozone pollution. This indicates that it
is difficult to directly obtain information on the inhibition of vegetation growth by ozone pollution from the vegetation activity records observed by remote sensing.

3.3. Relationships between Vegetation Activity and Ozone and Climate Elements

Many studies on the impact of climate change on vegetation growth have shown that the vegetation change recorded by remote sensing observations contains the signal of climate change [2,5,7]. In Section 3.2, the results suggested that the effects of ozone pollution on vegetation activity cannot be directly identified from the vegetation change records observed by remote sensing. Therefore, we used principal component analysis to explore the potential relationships among NDVI, OMR, T, P and SSR (Figures 6 and 7 and Table 2). In Figure 6, the angles between NDVI and OMR, T and SSR are small, which indicates that there are high correlations between NDVI and OMR, T and SSR (see Table 2), which means that the growth of vegetation is closely related to the changes in surface ozone (O$_3$), T, P and SSR. For example, in Figure 6a, the correlation coefficients between the national average NDVI and OMR, T and SSR are 0.54, 0.68 and 0.67, respectively. In addition, the variance percentage information of different regions in Figure 7 shows that OMR, T, P and SSR all contribute to the change in NDVI, but the contributions of meteorological elements and ozone pollution to the change in NDVI variance are different in different pollution zones. Table 2 also shows that there are significant differences in the correlations between NDVI, OMR and meteorological elements in different pollution zones. For example, in R5, the region with the most severe ozone pollution (Figure 6b), NDVI was significantly correlated with temperature ($r = 0.43$, $p < 0.01$), but in R2, R3 and R4, NDVI was also significantly correlated with OMR and SSR, with correlation coefficients greater than 0.41 ($p = 0.01$). The above results indicate that vegetation activity (represented by NDVI) during the growing season is closely related to ozone pollution and climate change. Therefore, in Sections 3.4 and 3.5, we used the method described in Section 2.2.3 to evaluate the effects from ozone pollution and climate change on growing season vegetation activity over 1982–2020.

![Figure 4](image-url)

**Figure 4.** (a) Spatial distribution of multiyear average NDVI during 1982–2020 and (b) spatial distribution of the rate of NDVI change. The colored lines from south to north refer to the contour lines of OMR values of 650, 700, 750 and 800 kg/kg, respectively. The author used the software of ArcGIS 10.5 to produce the figure.
Figure 5. Annual variation in NDVI in different regions during 1982–2020. To accurately detect the variation in NDVI, all NDVI were multiplied by 100 to amplify the variation of small signals. (a) is annual variation in NDVI over China. (b–f) are annual variation in NDVI over ozone pollution region of R1, R2, R3, R4 and R5, respectively.
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Figure 6. Relationships between NDVI and OMR (O3 refers to OMR) and climate elements (T, P, SSR) during 1982–2020. The graphs are based on PCA results. (a) presents relationships over China. (b-f) are relationships over ozone pollution region of R1, R2, R3, R4 and R5, respectively.

Figure 7. Comparison of the percentage of variance of NDVI, OMR and meteorological elements.

Table 2. Correlation coefficients between NDVI and OMR and meteorological elements.

| Regions | OMR | T   | P   | SSR |
|---------|-----|-----|-----|-----|
| China   | 0.54*| 0.68*| 0.19| 0.67*|
| R1      | 0.37 | 0.35 | 0.19| 0.59*|
| R2      | 0.44*| 0.48*| −0.03| 0.68*|
| R3      | 0.44*| 0.52*| −0.04| 0.63*|
| R4      | 0.49*| 0.71*| 0.04| 0.56*|
| R5      | 0.34 | 0.43*| 0.25| 0.25 |

Note: * indicates a significant correlation at the 99% significance level (\( p < 0.01 \)).

3.4. Effect of Ozone Pollution on Vegetation Activity

Based on Formula (4), we quantitatively assessed the effects of ozone pollution on vegetation activity in China during the 1982–2020 growing seasons (Figure 8). Figure 8 shows that \( Iozone \) presents a decreasing trend from northwest to southeast, which is generally consistent with the spatial variation trend of OMR (Figure 2). For example, Northwest China has high \( Iozone \) values, while East China is covered by low \( Iozone \) values (0–6%). Most areas north of 30 degrees north latitude have an \( Iozone \) greater than 9%. According to the statistical results of pollution zones (Table 3), the national average \( Iozone \) is 12.5% ± 6.5%. Only the \( Iozone \) of R5 is higher than the national average, and its value is 15.8% ± 5.5%. According to the statistics of different vegetation types, the effect percentages of forest, shrub and farmland are 12.1%, 12.0% and 11.7%, respectively, which are lower than the national average by approximately 2.9%, 4.2% and 6.6%, respectively. The results show...
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| R3      | 0.44 * | 0.52 * | −0.04 | 0.63 * |
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3.4. Effect of Ozone Pollution on Vegetation Activity

Based on Formula (4), we quantitatively assessed the effects of ozone pollution on vegetation activity in China during the 1982–2020 growing seasons (Figure 8). Figure 8 shows that $I_{ozone}$ presents a decreasing trend from northwest to southeast, which is generally consistent with the spatial variation trend of OMR (Figure 2). For example, Northwest China has high $I_{ozone}$ values, while East China is covered by low $I_{ozone}$ values (0–6%). Most areas north of 30 degrees north latitude have an $I_{ozone}$ greater than 9%. According to the statistical results of pollution zones (Table 3), the national average $I_{ozone}$ is 12.5% ± 6.5%. Only the $I_{ozone}$ of R5 is higher than the national average, and its value is 15.8% ± 5.5%. According to the statistics of different vegetation types, the effect percentages of forest, shrub and farmland are 12.1%, 12.0% and 11.7%, respectively, which are lower than the national average by approximately 2.9%, 4.2% and 6.6%, respectively. The results show that the R5 zone with the highest level of ozone pollution has the greatest impact on vegetation activities. Moreover, grass is the vegetation type strongly affected by ozone pollution, and crop is weakly affected by ozone pollution.

Figure 8. The spatial distribution of effects ($I_{ozone}$) from ozone pollution on vegetation activity in the growing season from 1982 to 2020. The colored lines from south to north refer to the contour lines of OMR values of 650, 700, 750 and 800 kg/kg, respectively. The author used the software of ArcGIS 10.5 to produce the figure.
Table 3. Effects of ozone pollution ($I_{\text{ozone}}$) on vegetation growth in China. The unit is %.

| Regions | Forest Mean | SD | Shrub Mean | SD | Grass Mean | SD | Crop Mean | SD | Average Mean | SD |
|---------|-------------|----|------------|----|------------|----|------------|----|-------------|----|
| R1      | 11.2        | 6.7 | 10.6       | 6.5 | 11.6       | 6.4 | 9.4        | 6.2 | 10.8        | 6.6 |
| R2      | 12.3        | 6.7 | 12.8       | 6.8 | 13.4       | 6.5 | 12.3       | 6.8 | 12.6        | 6.7 |
| R3      | 10.9        | 7.0 | 9.0        | 6.8 | 12.6       | 6.8 | 10.0       | 6.9 | 11.0        | 7.0 |
| R4      | 10.19       | 6.5 | 11.7       | 6.4 | 13.9       | 6.4 | 11.6       | 6.8 | 12.4        | 6.7 |
| R5      | 16.29       | 5.29| 15.7       | 5.6 | 15.4       | 5.7 | 15.0       | 6.1 | 15.8        | 5.5 |

Note: the values were calculated by Formula (4). ‘SD’ is a standard deviation.

3.5. Effect of Climate Changes on Vegetation Activity

Based on Formula (3), we quantitatively assessed the impact of climate change on vegetation activity in China during the growing season from 1982–2020 (Figure 9). Figure 8 shows that $I_{\text{climate}}$ presents a decreasing trend from northwest to southeast, which is similar to the spatial variation trend of $I_{\text{ozone}}$ (Figure 8). For example, the $I_{\text{climate}}$ in most areas of Northwest China is greater than 30%, and East China is covered by low $I_{\text{climate}}$ values (0–20%). $I_{\text{climate}}$ is greater than 30% in most areas north of 30 degrees north latitude. According to the statistical results of pollution zones (Table 4), the national average $I_{\text{climate}}$ value is 26.7% ± 20.7%. For different vegetation types, the effect percentages of shrub, forest and crop are 26.2%, 26.1% and 25.4%, respectively, which are lower than the national averages by approximately 2.1%, 2.5% and 5.1%, respectively. These results present that the impact of climate change on vegetation activity increases from south to north (which is consistent with the north–south trend of ozone pollution), grass is strongly affected by climate change, crop is weakly affected by climate change and the impact of climate change on shrub is greater than that on forest.

Figure 9. The spatial distribution of the effects ($I_{\text{climate}}$) of climate change on vegetation activity in the growing season from 1982 to 2020. The colored lines from south to north refer to the contour lines of OMR values of 650, 700, 750 and 800 kg/kg, respectively. The author used the software of ArcGIS 10.5 to produce the figure.
Table 4. Impacts of climate change \( (I_{\text{climate}}) \) on terrestrial vegetation growth in China. The unit is %.

| Regions | Forest Mean | Forest SD | Shrub Mean | Shrub SD | Grass Mean | Grass SD | Crop Mean | Crop SD | Average Mean | Average SD |
|---------|-------------|-----------|------------|----------|------------|----------|-----------|---------|--------------|------------|
| R1      | 22.9        | 19.5      | 21.5       | 18.3     | 26.0       | 20.5     | 19.7      | 16.9    | 22.3         | 19.0       |
| R2      | 23.5        | 19.7      | 23.6       | 19.8     | 30.80      | 21.9     | 23.9      | 19.4    | 24.9         | 20.30      |
| R3      | 27.0        | 20.8      | 23.9       | 19.8     | 28.0       | 20.9     | 25.4      | 21.3    | 26.6         | 21.00      |
| R4      | 24.2        | 19.6      | 30.0       | 20.4     | 29.40      | 21.6     | 26.7      | 21.3    | 27.5         | 21.2       |
| R5      | 32.7        | 21.7      | 31.7       | 21.7     | 31.90      | 21.8     | 31.1      | 21.4    | 32.3         | 21.9       |

Note: the values were calculated by Formula (3). ‘SD’ is a standard deviation.

4. Discussion

Remote sensing vegetation index data records not only have the advantage of large-scale observations of the dynamics of surface vegetation but also record important information, such as the effects of ozone pollution, climate change and other factors on vegetation growth. Based on this important understanding, we attempted to develop a numerical model to further evaluate the impacts of ozone pollution and climate change on vegetation growth at the national scale by using long-term remote sensing vegetation index (NDVI) data. The two main objectives of this study are to use multiple linear regression techniques to isolate the signal of the impact of ozone pollution and climate change on vegetation growth from long-term continuous observation of remote sensing vegetation data and to then quantitatively assess their impacts on growing-season vegetation growth.

4.1. The Evaluated Effects from Ozone Pollution and Climate Change on Vegetation Growth

In this study, combining long-term continuous (1982–2020) remote sensing NDVI data with ERA5 reanalysis near-surface OMR data and meteorological element data, we quantitatively evaluated the effects of ozone pollution and climate change on vegetation activity during the growing season in China. Due to the different mechanisms of ozone pollution and climate change on vegetation growth, and the lack of high temporal resolution of ozone data, it is difficult to evaluate the cumulative effects of toxicity of vegetation exposure and the negative effects on vegetation growth. Therefore, it is difficult to obtain direct remote sensing observation evidence of these effects. It was also difficult to directly isolate the ozone pollution-induced effect signal on vegetation growth from NDVI records. Because both the increasing trends in OMR and NDVI present in different ozone pollution regions during the 1982–2020 growing seasons (April to October). To this end, we developed a new mathematical method of a multiple linear regression model to indirectly evaluate their effect on vegetation growth during the growing season. The estimated result of this study is that ozone pollution affects 12.49% of vegetation change in China during the growing season. This result is close to that of other studies. For example, at the national scale, ozone pollution reduces the net primary productivity (NPP) of terrestrial ecosystems in China by 10–18% [33]. The results indirectly demonstrate that a long-term remote sensing vegetation index can be used to quantitatively assess the impact of air pollution on terrestrial vegetation growth and that the assessment results are effective.

Additionally, we estimated the impact of climate change on vegetation activity during the growing season to be 26.7%, which is lower than the 60.6% (impact on NPP) assessed by Ge et al. [2]. This is because their methods ignored the important role of air pollution and CO₂ fertilizer promotion, thus amplifying the impact of climate change on NPP. In terms of vegetation types, both ozone pollution and climate change have a greater impact on grassland growth (the sum of the two is 42.6%) and a smaller impact on crop (the sum of the two is 37.01%). The low impact on crop is because manual management measures (e.g., fertilization, watering, etc.) partly compensate for the negative impacts caused by ozone pollution and climate change [34].

In short, the effects of ozone pollution on vegetation growth and the growth of terrestrial vegetation in China during the growing season should not be ignored. In this study, a linear regression model, climate elements, OMR and remote sensing vegetation...
data were used to indirectly assess the impact of ozone pollution on terrestrial surface vegetation growth, providing a method for monitoring the impact of ozone pollution on terrestrial ecosystems based on remote sensing technology. The results also serve to increase scientists’ understanding of the impact of the second largest air pollutant on ecosystems, helping to improve the understanding of the threat of ozone pollution to the ecological security of the land surface.

4.2. Limitations and Future Perspectives

However, the method of quantitative assessment is limited. In fact, vegetation changes are affected by many different factors. For example, the anthropogenic activities (such as afforestation, emissions, land use changes) also affect vegetation growth. Yet, the interactive effects between climate change and ozone pollution on vegetation change are difficult to evaluate. The combined effects from climate change and ozone pollution on vegetation growth are also ignored, because ozone formation is strongly correlated with temperature [35]. Additionally, the combined effects will reduce global crop production in the future climate change and ozone air pollution scenarios [36]. Furthermore, long-term and continuous OMR data at 1000 hPa from ERA5 do not represent real ground-level ozone concentrations, which also affects the uncertainty of the estimation of this study. Additionally, by affecting photosynthesis processes, the intake of ozone into the vegetation also induces growing-season vegetation growth. Of course, this effect evaluation requires ozone observations with higher temporal resolution (e.g., hourly) to support the investigation.

Furthermore, this paper indirectly assessed the impact of ozone pollution on vegetation growth based on limited data and could not deeply consider the delayed impact of ozone pollution on vegetation growth. At the same time, ignoring the uncertainty of the spatial and temporal accuracy of the data will increase the uncertainty of the evaluation results. In addition, particularly since vegetation growth processes are not linear, a non-linear effect from air pollution and climate change on vegetation changes may exist. The linear model cannot thoroughly describe the effect mechanism of ozone pollution on the vegetation growth process, and the land surface physical process model with high temporal resolution coupled with the air pollution model still needs to be further explored. Finally, whether exposure to ozone in the early stage will make vegetation produce stress resistance and lead to a decrease in the influence of vegetation in the face of more serious pollution in the later stage remains to be further studied.

In the future, global warming and ozone pollution will continue to be one of the important climate change and environmental issues that people pay attention to. Quantitative assessment of the impacts of ozone pollution and climate change on vegetation activities will help nurture a deeper understand of the mechanism of the impacts of ozone pollution and climate change on terrestrial vegetation.

5. Conclusions

Serious ozone pollution and climate change affect vegetation growth. However, due to the lack of long-term continuous observation of surface ozone data and the neglect of the signal of ozone influence on vegetation growth in remote sensing vegetation data, there is a lack of deep understanding of the impact of large-scale and long-term ozone pollution on vegetation health. Therefore, we take 1000 hPa OMR data in ERA5 reanalysis data as an index to approximately depict the surface ozone status, considering the impact of climate change on vegetation growth, and use NDVI data from the past 39 years (1982–2020) to develop a multiple linear regression model. The effects of ozone pollution and climate change on terrestrial vegetation growth in China during the growing season (April to October) were quantitatively assessed. We found that OMR increased in 99.9% of regions in China during the past 39 years, and there were five regions (R1, R2, R3, R4 and R5) with severe ozone pollution from southeast to northwest. In addition, NDVI showed an increasing trend in approximately 79.9% of the regions in China, and NDVI in all five
regions showed a significant increasing trend. In addition, the significant correlations between NDVI and OMR, temperature and SSR indicate that terrestrial vegetation activity in China is closely related to ozone pollution and climate change. Finally, it was found that 12.5% of NDVI changes in the growing season were affected by ozone pollution and 26.7% by climate change. The analysis of the impact of ozone on the NDVI of different ecosystems showed that the grassland was most affected by ozone pollution ($I_{\text{ozone}}$ was approximately 13.4%), and the values for forest, shrub and farmland were 12.1%, 12.0% and 11.7%, respectively. At the same time, grass was the most affected ecosystem type ($I_{\text{climate}}$ was approximately 29.2%), and the values for shrub, forest and crop were 26.2%, 26.1% and 25.4%, respectively. In conclusion, the impact of ozone pollution on vegetation growth in China is 0.47 times that of climate change, and the impact of ozone pollution on vegetation growth cannot be ignored. It is worth noting that this study not only deepens the understanding of the effects of ozone pollution and climate change on vegetation growth but also provides a research framework for the large-scale monitoring of air pollution on vegetation health using remote sensing vegetation data.

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