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IMPACT OF AIR POLLUTION ON MAIZE AND WHEAT PRODUCTION

Abstract: To determine the effects of air pollution on crop yields, weather, air pollution, and maize and winter wheat yield data from 331 cities in China from 2014 to 2016 were collected and analysed. Furthermore, support vector regression and the crop growth model were applied to extrapolate the air pollution data of Beijing and Hetian and verify the relationship between air pollution and yield. Precisely, heavy air pollution usually occurred in North China, but less than moderate air pollution levels affected crop yields statistically insignificantly. Moreover, both the winter wheat and maize yields increased in moderate air pollution periods but decreased in heavy air pollution periods in 2014, 2015 and 2016. Importantly, a threshold value was necessary for the heavy air pollution periods to trigger a yield decrease. The threshold values of maize in 2015 and 2016 were 7 days and 5 days, respectively, while that of winter wheat was 10 days in both 2015 and 2016. Once the heavy air pollution periods exceeded the threshold value, both the winter wheat and maize yields decreased linearly with the periods. PM2.5 was the main air pollutant in Beijing in 2014, while PM2.5 and PM10 were the main air pollutants in Hetian in both 2015 and 2016. Regardless of whether the main air pollutant was PM2.5 or PM10, the simulated potential winter wheat yields by the crop growth model with moderate air pollution for the whole growth period were all higher than the yields under observed and heavy air pollution conditions.

Keywords: maize, wheat, air pollution, support vector regression, environment

1. Introduction

Air pollution has become the world's single largest environmental health risk [1-3]. In China, although great economic development achievements have occurred during the last four decades, the air quality has also sharply decreased [4-6]. The Ministry of Ecological Environment of China indicated that approximately 60 % of the cities in China experienced air pollution in 2012. In the last five years, many measures have been proposed to protect the atmospheric environment, and the air quality has greatly improved. However, the

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average period without air pollution in 338 cities was only 77 days in 2017. Previous studies have proven that air pollutants affect public health [7-15]. Similar to humans, crop growth characteristics also vary with environmental conditions [16]. Since the 1960s, many studies have been conducted to reveal the mechanism of crop responses to different environmental factors such as soil water, salt, and nutrition as well as agricultural management [17-21]. In addition to soil factors, weather factors also affect crop growth. For example, Long et al. [22] pointed out that increasing the CO_2 concentration from 380 ppm to 550 ppm at 25 °C would increase C_3 photosynthesis by 39 %. Fuhrer [23] indicated that elevated CO_2 levels might improve resource-use efficiency for C_3 crops and that warming could reduce positive CO_2 effects. Tubiello et al. [24] also found that relatively warmer air temperatures accelerated plant phenology, reducing dry matter accumulation and crop yields by 10 % - 40 %. Schlenker et al. [25] even proved that corn, soybean, and cotton yields increased with temperatures as high as 29 °C, 30 °C, and 32 °C, respectively, but temperatures above these values were very harmful.

Therefore, the assumption that air pollution can also impact crop growth is expected. Avnery et al. [26] proposed the potential global risk of increasing surface ozone (O_3) on soybeans, maize, and wheat in the near future (year 2030). Furthermore, Lin et al. [27] also showed that when applying the Global Burden of Disease (GBD) approach, the relative yield reduction in winter wheat, rice, and maize due to elevated O_3 levels ranged from 8.5 % - 14.0 %, 3.9 % - 15.0 %, and 2.2 % - 5.5 %, respectively, in China. Additional similar results were also found by Zhao et al. [28], Zhang et al. [29], and Feng et al. [30]. In addition to O_3, other air pollutants include atmospheric particulate matter (*APM*, e.g., PM2.5 and PM10), sulphur dioxide (SO_2), nitrogen dioxide (NO_2), and carbonic oxide (CO) [31]. In contrast to O_3, Schiferl et al. [32] found that *APM* increased 2.3 %, 11.0 %, and 3.4 % due to the production of maize, wheat, and rice, respectively, on a global scale in 2010. Moreover, [33] even pointed out that CO could improve the iron content of broccoli and maize. In addition, NO_2 is a well-known greenhouse gas that can affect air temperatures and indirectly impact crop growth [34], while SO_2 is the main cause of acid rain, which damages crops by corroding blades and acidising soils [35].

Based on the above examples, air pollutants could affect crop growth either positively (e.g., *APM* and CO) or negatively (e.g., O_3 and SO_2). However, there are still some issues surrounding this topic. First, the mechanism regarding how these air pollutants affect crop growth is still unclear. Previous studies have mainly placed emphasis on the direct toxic effects of air pollutants on crops [36, 37]. On the one hand, toxic air pollutants are usually not the main drivers of injury; on the other hand, in addition to the toxic effects of some air pollutants (e.g., SO_2 and O_3) on crops, air pollutants might also indirectly impact crop growth by changing weather factors such as radiation and temperature. Second, using crop responses to identify the occurrence of air pollution stress is also controversial. For example, Uka et al. [38] pointed out that the physiological activity of air pollution-injured crops is impaired before any external symptoms are visible, and many investigators have referred to hidden air pollution injury. Nevertheless, McLaughlin et al. [39], Grote et al. [40], and Patidar et al. [41] had the opposite opinion, i.e., that hidden air pollution injury was not a useful term, and indicated that pollutant effects could be described as acute or chronic by observing decreases in photosynthetic tissue. Third, previous studies have mainly been concerned with the relationship between specific air pollutants (e.g., SO_2 and O_3) and crop growth, while only a few studies have focused on the stress degree and stress time effects of air pollution on crop growth and yield. Importantly, van der Eerden et al.

[42], Tai et al. [43], and Emberson [44] determined that air pollution injury did not occur unless an air pollutant threshold was exceeded, and the injury had a certain magnitude and limited duration once the exposure to the pollutant ceased. Unfortunately, no clear finding has been achieved regarding this issue. Fourth, the interactive effects of different air pollutants on crop growth are also unclear. In fact, compared with other air pollutants, the relative concentrations of O_3 are usually low, while the main air pollutants in almost all cities in China are PM2.5 and PM10, especially in winter [45, 46]. Therefore, a thorough study on the effects of a range of air pollutants on crop growth is necessary. Moreover, determinations of the crop responses to the interactions of different air pollutants, especially the main air pollutants of specific cities in China, are quite scarce.

The main objectives of this study are to determine the effect of air pollution on crop yields and explore the abovementioned unknowns. Specifically, with collected weather, air pollutant (PM2.5, PM10, SO_2, NO_2, O_3, and CO), and crop yield data (Section 2), we first analyse the spatial distribution of air pollution in China from 2014 to 2016 (Section 3.1). Second, maize and winter wheat are used as indicator crops to quantitatively describe the relationships among stress degree and stress time of air pollution and crop yield (Section 3.2). Then, the main air pollutants in typical cities are detected, and support vector regression (*SVR*) is applied together with a crop growth model (world food studies, WOFOST) to extend the air pollution data (Sections 3.3 and 3.4) and preliminarily quantify the negative and positive effects of air pollutants on crop yields (Sections 4 and 5).

2. Materials and methods

2.1. Data collection

Air pollution data were obtained from the data centre of the Ministry of Ecological Environment, China (http://datacenter.mep.gov.cn). Data on six air pollutants, including ambient fine particulate matter (PM2.5 [$\mu g \cdot m^{-3}$]), inhalable particulate matter (PM10 [$\mu g \cdot m^{-3}$]), SO_2 [$\mu g \cdot m^{-3}$], N_2O [$\mu g \cdot m^{-3}$], CO [$mg \cdot m^{-3}$] and O_3 [$\mu g \cdot m^{-3}$], and the air quality indices, *AQI* of 111, 331, and 331 cities in 2014, 2015, and 2016, respectively, were collected. All air pollution data were initially six hour mean values that were then averaged to obtain daily mean values. Winter wheat and maize are the two main cereal crops in northern China, where the degree of air pollution is relatively more serious than that in southern China. For the maize yield, data from 36, 49, and 41 cities in 2014, 2015, and 2016, respectively, were collected in this study. For the winter wheat yield, data from 27, 67, and 67 cities in 2014, 2015, and 2016, respectively, were collected. In addition, based on literature searches, we found that the maize growth period mainly varied from April to October among the target cities. However, except for August and September, winter wheat was grown in the fields the whole year. The yields were obtained from the statistical yearbooks of each city by downloading the data from the China National Knowledge Infrastructure (CNKI, http://www.cnki.net). In addition, we also collected the winter wheat and maize yields in two typical areas (Beijing and Xinjiang; see Section 2.2) from 1998 to 2016 from the database of the National Statistics Bureau, China (http://data.stats.gov.cn).

Importantly, there were usually several air pollution monitoring stations in each city; therefore, the data from all stations were averaged to represent the air quality of a specific city. Similarly, the statistical yield of a specific city was the average of all fields in that city.

Climate data were obtained from the China standard meteorological data website (CSMD, http://data.cma.cn). The meteorological data included precipitation [mm], net

surface solar radiation, R_n [MJ·m^{-2}], incident solar radiation, R_s [MJ·m^{-2}], average air temperature, T_{mean} [°C], maximum air temperature, T_{max} [°C], minimum air temperature, T_{min} [°C], vapour pressure [kPa], relative humidity *RH* [%], and wind speed [m·s^{-1}]. Climate data of 331 cities from 1980 to 2017 in China were obtained previously, but very little of the climate data matched the air pollution and crop yield data, which were limited by the available time periods. In addition, the above data in this study might have some measurement errors while our study ignore the issue.

2.2. Analysis framework

The framework of the study is shown in Figure 1. First, we analysed the spatial distribution of air pollution data and established the relationship between the air pollution data and the crop yield. Second, we selected two typical cities (Beijing and Hetian) and crops (winter wheat and maize) to analyse the main air pollutants in these cities during crop growth periods. Beijing was selected because whole air pollution data were available for 2014. Hetian was selected because it was one of the most air polluted cities in China in 2015 and 2016 and winter wheat and maize are also planted in large areas. Third, *SVR* was used to mimic the meteorological factors of the two typical cities under different air pollution degrees based on the main air pollutants. Fourth, WOFOST was used to simulate the winter wheat and maize yields under the observed weather conditions and air pollution scenarios (mimicked by *SVR*) in both potential and water stress conditions. Finally, the effects of air pollution on crop yield were analysed from the measurements and modelled results.

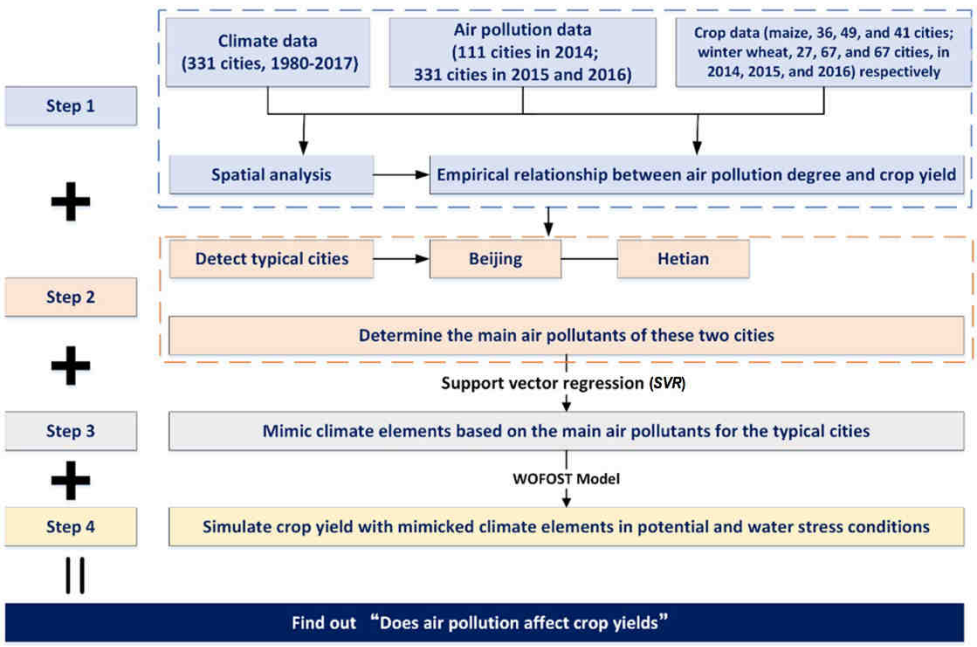


Fig. 1. Framework of the study

2.3. *SVR*

One important purpose of our study was to analyse the effects of the air pollution degree on crop yields by crop modelling. *SVR* was used to mimic the meteorological factors (except precipitation) from the air pollution data. A brief description of *SVR* is presented hereafter. *SVR* is one category of support vector machine (*SVM*) techniques and can be summarised in three steps. The first step is to define two datasets: one set for learning and one set for testing. Second, users need to select an appropriate kernel function and an optimal model for training the input dataset (learning dataset). Third, the testing dataset is used for cross-validation. In our study, the Gaussian function was used as the kernel function $k(x_i, x)$ (Eq. (1)) to map the sample space of a high-dimensional feature space (Hilbert space) and transform nonlinear into linear regression data by defining the optimal hyperplane [47]:

$$k\left(x_i, x\right) = \exp\left(-\frac{\left\|x_i - x\right\|^2}{\sigma^2}\right) \tag{1}$$

where x_i is the i^{th} support vector and σ is the kernel width ($\sigma > 0$).

In the learning process, users need to solve the quadratic optimization problem given in Eqs. (2) and (3):

$$\min\left\{\frac{1}{2}\|W\|2 + C\sum_{i=1}^{n}\left(\xi_i + \xi^*\right)\right\} \tag{2}$$

$$st.\begin{cases} y_i - \left(W \cdot x_i\right) - b \le \varepsilon + \xi_i \\ \left(W \cdot x_i\right) + b - y_i \le \varepsilon + \xi^* \end{cases} \tag{3}$$

where ε is defined as an insensitive function, and the error between the simulated and observed values can be ignored if the error is less than ε. Slack variables, ξ and ξ^*, are used to measure the deviation degree of the sample data that are out of the insensitive channel (2ε). A penalty factor, C, is introduced to modify the sample data that deviated from the insensitive channel. W and b are normal vectors and intercepts for the hyperplane, respectively, n is the number of learning samples, and y_i is the value of the learning objective function.

In our study, the input data were data on the six air pollutants (PM2.5, PM10, SO_2, NO_2, O_3, and CO), and the output data were data on the five meteorological factors (R_s, T_{max}, T_{min}, vapour pressure, and wind speed). The six air pollutants were used together to precisely mimic the eight meteorological factors individually using *SVR*. For each *SVR* simulation, 2/3 of the data pairs were used for *SVR* learning, and the other 1/3 were used for the testing process. *SVR* was conducted in the R package "e1071" [48]. More details on *SVR* can be found in Benkedjouh et al. [49], Zhang et al. [50], and Smola et al. [51]. Four climate scenarios were precisely mimicked in our study. First, 100 was added to the daily PM2.5 and PM10 values to imitate all days that exceeded a moderate air pollution level (denoted PM2.5 + 100 and PM10 + 100, respectively). Second, 300 was added to the daily PM2.5 and PM10 values to imitate all days that exceeded a heavy air pollution level (denoted PM2.5+300 and PM10+300, respectively). We modified PM2.5 and PM10 because they were the two main air pollutants in our studied cities (Section 3.2).

2.4. Description of the WOFOST model

WOFOST is a generic crop simulation model that can simulate the plant growth and physiological development processes of a crop from emergence through maturity at daily time steps. The model can simulate crop growth in three modes. More precisely, considering no limitations about the drivers of crop growth, such as temperature, solar radiation, atmosphere CO_2 concentration and agriculture management, the model can simulate the potential growth of crops. The other two modes are the water-limited mode and the nutrient-limited mode. In the water-limited mode, WOFOST considers water availability as the factor limiting crop growth. In the nutrient-limited mode, three macro nutrients (nitrogen, phosphorus, and potassium) can be considered limiting factors. In WOFOST, dry matter accumulation is estimated from the radiation energy intercepted by the canopy and the rate of gross CO_2 assimilation. The daily gross CO_2 assimilation estimation is obtained by integrating assimilation rates by leaf layer and by day. The assimilated CO_2 is used for two purposes. A portion of the CO_2 is used for the maintenance of respiration, and the other portion is partitioned between different plant organs (leaves, stems, storage organs, and roots) based on a pre-defined partitioning fraction for these organs. In the water-limited and nutrient-limited modes, WOFOST uses the ratio of actual to potential transpiration as a reduction coefficient for gross assimilation.

In this study, WOFOST was used to simulate maize and winter wheat in Beijing and Hetian, respectively. By reviewing the statistical yearbooks of these two cities, the sowing and maturity dates for maize were May 1st and September 21st, respectively. For winter wheat, the sowing and maturity dates were October 1st and June 15th, respectively. The cultivars of maize and winter wheat were “Grain maize 201” and “Winter wheat 104”, respectively, and all the crop parameters were set to default values in WOFOST. The measured climate data and four climate scenarios (PM2.5 + 100, PM10 + 100, PM2.5 + 300, PM10 + 300) were modelled under water stress and potential conditions by WOFOST.

2.5. Statistical evaluation

The relative root mean square error (*RRMSE*, Eq. (4)) and correlation coefficient (*R*, Eq. (5)) were used to evaluate the accuracy of the simulation:

$$RRMSE = \sqrt{\sum_{i=1}^{n} \frac{\left(Y_i^{mea} - Y_i^{sim}\right)^2}{n}} / Y_{\text{ave}}^{mea} \tag{4}$$

$$R = \frac{\sum_{i=1}^{n}\left(Y_i^{mea} - Y_{\text{ave}}^{mea}\right)\left(Y_i^{sim} - Y_{ave}^{sim}\right)}{\sqrt{\sum_{i=1}^{n}\left(Y_i^{mea} - Y_{ave}^{mea}\right)^2}\sqrt{\sum_{i=1}^{n}\left(Y_i^{sim} - Y_{ave}^{sim}\right)^2}} \tag{5}$$

where n is the number of samples, Y_i^{mea} is the i^{th} measurement, Y_i^{sim} is the i^{th} simulation, and Y_{ave}^{mea} and Y_{ave}^{sim} are the means of the measurements and simulations, respectively.

3. Results

3.1. Spatial distribution of air pollution days

Moderate or above-moderate air pollution levels occurred in 96 cities, while the total number of recorded cities was only 111 in 2014. Moreover, more than 65.6 % of the 96 cities had a heavy degree of air pollution in 2014. Moderate or heavy air pollution levels mainly occurred in North China, such as Xinjiang and Hebei Provinces. For example, there were 35 and 28 days with moderate and heavy air pollution levels, respectively, in Bayingolin, Xinjiang, in 2014. Furthermore, Xingtai in Hebei suffered the longest air pollution duration in 2014, which had 40 and 36 days of moderate and heavy air pollution levels, respectively. In addition, Beijing, the capital city, also had 29 and 15 days of moderate and heavy air pollution levels, respectively, in 2014. Compared with the whole year in 2014, a similar number of days with air pollution during the wheat growth period in almost all cities was found, indicating good air quality in August and September. The air quality was much better during the maize growth periods than during the wheat growth period. Except for Bayingolin, which had 18 days of heavy air pollution, all other cities had less than 6 days of heavy air pollution.

In 2015, air pollution data in 331 cities were recorded, and moderate and heavy air pollution occurred in 237 and 125 cities, respectively. The region with heavy air pollution levels was also North China, especially Xinjiang and Hebei Provinces, which was similar to the 2014 findings. However, the air quality in Bayingolin and Xingtai improved in 2015. More precisely, Bayingolin had 22 days and 14 days of moderate and heavy air pollution, respectively, in 2015, which was 37.1 % and 50 % lower, respectively, than the numbers in 2014. Similarly, the periods of moderate and heavy air pollution in Xingtai were only 29 and 23 days in 2015 respectively. The city with the most serious air pollution was Hetian in 2015, which had 69 days of heavy air pollution. Another city, Kashi, in Xinjiang also suffered from heavy air pollution in 2015. Although the heavy air pollution period of Kashi was shorter than that of Hetian, the moderate air pollution period was as long as 99 days. In addition, only 13 days of heavy air pollution were recorded in Beijing in 2015. Similar to the 2014 results, the number of days with air pollution during the wheat growth period was comparable with the number during the whole year, while better air quality was also found during the maize growth period in 2015. For instance, the number of cities with moderate and heavy air pollution remained 237 and 125 during the wheat growth period. However, only 26 cities experienced heavy air pollution during the maize growth period. Moreover, except for Xinjiang, there were less than 4 days of heavy air pollution in all other cities during the maize growth period.

In 2016, there were 232 and 104 cities with moderate and heavy air pollution, respectively, and there were 331 cities in total. The air pollution degree distribution in 2016 was similar to that in 2015. Specifically, Hetian and Kashi in Xinjiang were also the 2 cities suffering from the longest heavy air pollution period. The heavy air pollution periods in Hetian and Kashi were 63 and 60 days, respectively, while the moderate air pollution periods of these two cities were 43 and 80 days, respectively. In addition, there were 28 days and 7 days with moderate and heavy air pollution, respectively, in Beijing; compared with the previous year, the number decreased by 3 and 5 days, respectively. The air pollution conditions in the wheat and maize growth periods were also similar in 2014 and 2015, and Hetian was also the city with the longest heavy air pollution duration in both the wheat (63 days) and maize (32 days) growth periods.

3.2. Crop yield and air pollution

Both the maize and winter wheat yield slightly increased each year. The average maize yield was 6067 kg/ha, 6398 kg/ha, and 6674 kg/ha in 2014, 2015, and 2016, respectively, and the average winter wheat yield in the three years was 5616 kg/ha, 5784 kg/ha, and 5815 kg/ha, respectively (Fig. 2a). However, the annual and inter-annual crop yield distributions were also uniform. For example, the maize yield ranges in the three years were 5831 kg/ha, 9556 kg/ha, and 4294 kg/ha, respectively. For winter wheat, the ranges were 3352 kg/ha, 5071 kg/ha, and 4738 kg/ha, respectively (Fig. 2b). Moreover, in Xinjiang, which had the heaviest degree of air pollution, the average maize and winter wheat yields from 1998 to 2016 were 6996 kg/ha and 5294 kg/ha, while the ranges were only 1043 kg/ha and 911 kg/ha, respectively. However, compared with Xinjiang, the yield ranges of maize and winter wheat in Beijing increased 17.9 % and 124.3 %, respectively, while the air pollution condition was much better in Beijing than in Xinjiang in 2014 (Fig. 2b).

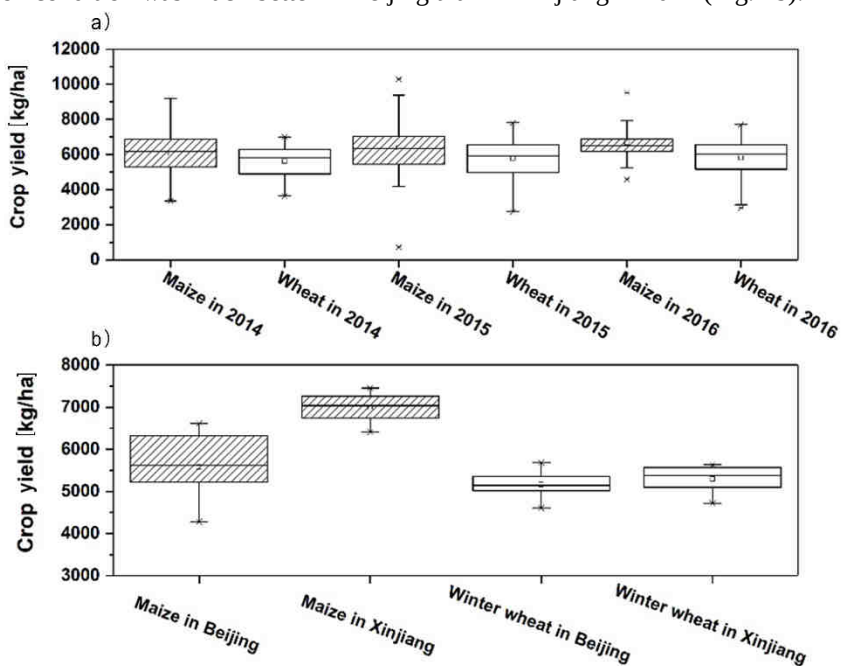


Fig. 2. Maize and winter wheat yield distributions in different cities and years. a) The crop yields of different cities in 2014, 2015 and 2016, b) The maize and winter wheat yields in Beijing and Xinjiang from 1998 to 2016. The horizontal line in each box is the median, the ends of each box are the lower hinge (25th percentile, Q1) and the upper hinge (75th percentile, Q3), and the whiskers extend to 1.5 times the difference between Q3 and Q1. Outliers beyond the whiskers are indicated by a cross

The relationships among the air pollution periods and the maize and wheat yields are indicated in Figure 3. In 2014, although no significant correlation was found between the maize yield and moderate air pollution periods, a slight increase was detected for the maize yield with the number of moderate air pollution days (Fig. 3a). Similarly, the winter wheat yields, which were greater or less than 5200 kg/ha, also increased with the number of

moderate air pollution days during the growth periods (Fig. 3c). However, heavy air pollution reduced both the maize and winter wheat yields when the heavy air pollution lasted beyond a threshold value. For instance, the winter wheat yield decreased linearly with the number of heavy air pollution days (R^2 = 0.67) when the heavy air pollution lasted more than 6 days (Fig. 3d). Similar phenomena were also found in 2015 and 2016. More precisely, both the maize and winter wheat yields slightly increased with the number of moderate air pollution days during the growth periods (Fig. 3e, g, i, and k). The R^2 values between the maize and winter wheat yields and the number of moderate air pollution days in 2015 and 2016 were 0.03, 0.11, and 0.10, 0.05, respectively. Heavy air pollution also reduced the crop yields, and the threshold values of maize in 2015 and 2016 were 7 days (Fig. 3f) and 5 days (Fig. 3i), respectively, while the threshold value of winter wheat was 10 days in both 2015 and 2016 (Fig. 3h, l).

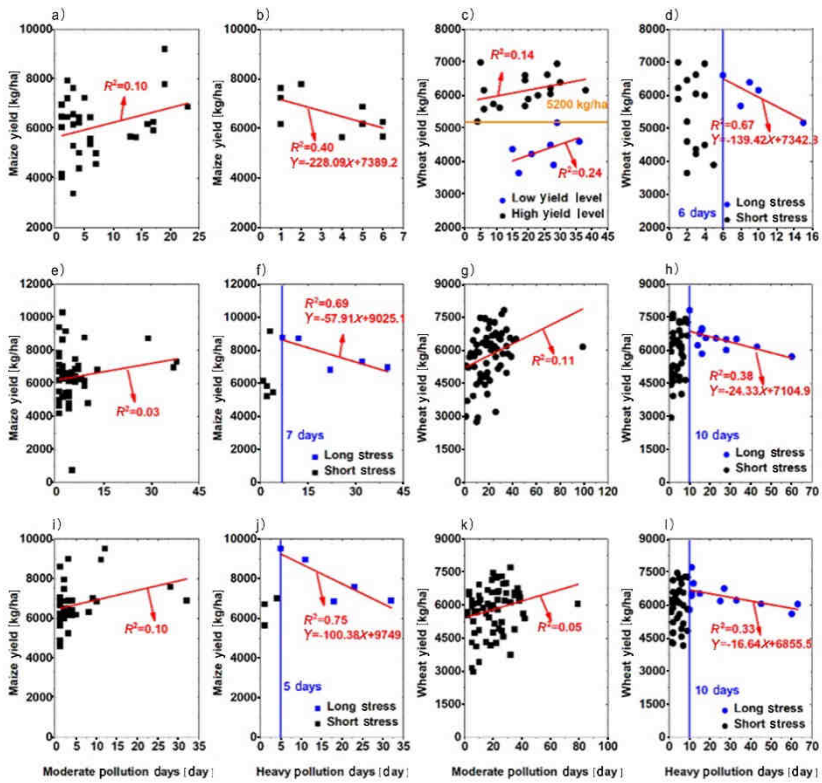


Fig. 3. Relationships between air pollution periods and crop yields. Subplots a) - d) are the maize and winter wheat yield with the number of moderate and heavy air pollution days in Beijing in 2014; e) - h) are the maize and winter wheat yield with the number of moderate and heavy air pollution days in Hetian in 2015; and i) - l) are the maize and winter wheat yields with the number of days with moderate and heavy air pollution in Hetian in 2016

The occurrence times of air pollution in Beijing and Hetian are shown in Figure 4. The main air pollutant in Beijing in 2014 was PM2.5, and heavy air pollution mainly

occurred in winter (Fig. 4a and b). In contrast to Beijing, Hetian suffered from heavy air pollution for the whole year in both 2015 and 2016. Moreover, there were fewer days with air pollution from September to December than in other periods. In addition to PM2.5, PM10 was also a main air pollutant in Hetian in both 2015 and 2016. Specifically, regarding the main air pollutants, PM2.5 and PM10, there were 5 and 64 days, respectively, in 2015 with heavy air pollution in Hetian, while there were 9 and 51 days, respectively, in 2016 (Fig. 4c-h).

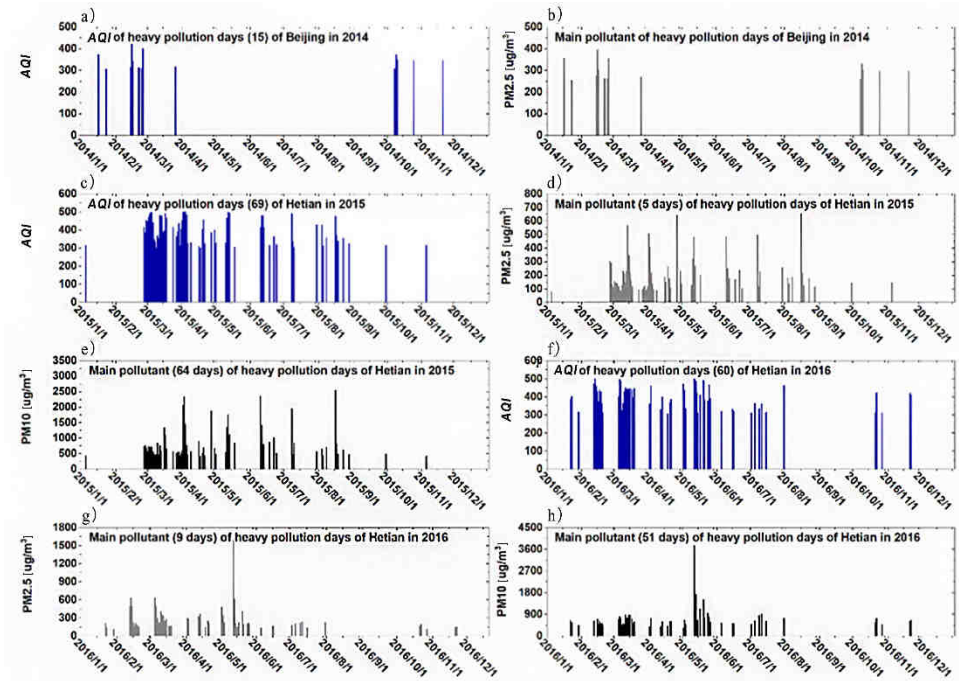


Fig. 4. The occurrence time of air pollution and the main air pollutants in Beijing and Hetian. Subplots a), b) are the conditions in Beijing in 2014; c) - e) are the conditions of Hetian in 2015; and f) - h) are the conditions in Hetian in 2016

3.3. *SVR*

Basic meteorological data, such as the R_s, T_{min}, T_{max}, vapour pressure, and wind speed, of Beijing and Hetian in 2014, 2015, and 2016 were predicted from the air pollutants using *SVR* (Fig. 5). In the learning process, *SVR* obtained high accuracy for all 5 meteorological factor predictions for Beijing in 2014 and Hetian in 2016. More precisely, the *R* values of the 5 meteorological factor predictions for Beijing in 2014 ranged from 0.716 to 0.988, and the largest *RRMSE* was only 13.9 % (Table 1). For Hetian in 2016, the smallest *R* value and largest *RRMSE* of the 5 meteorological factors were 0.778 % and 20.1 %, respectively.

Table 1

Statistical indices of support vector regression (*SVR*) predictions

Process	City/year	Beijing/2014		Hetian/2015		Hetian/2016	
	Factor	***R*** **[-]**	***RRMSE*** **[%]**	***R*** **[-]**	***RRMSE*** **[%]**	***R*** **[-]**	***RRMSE*** **[%]**
Learning	R_s	0.966	13.90	0.737	23.70	0.897	19.60
	T_{min}	0.967	—	0.843	—	0.958	—
	T_{max}	0.988	12.20	0.811	24.90	0.942	20.10
	Pressure	0.929	0.30	0.577	0.50	0.778	0.50
	Wind speed	0.716	12.20	0.754	20.40	0.815	19.10
Testing	R_s	0.813	23.20	0.158	29.20	0.698	33.30
	T_{min}	0.936	—	0.637	—	0.973	—
	T_{max}	0.936	21.20	0.4	17.40	0.968	14.80
	Pressure	0.812	0.40	0.49	0.60	0.925	0.40
	Wind speed	0.636	14.70	0.709	22.00	0.858	17.80

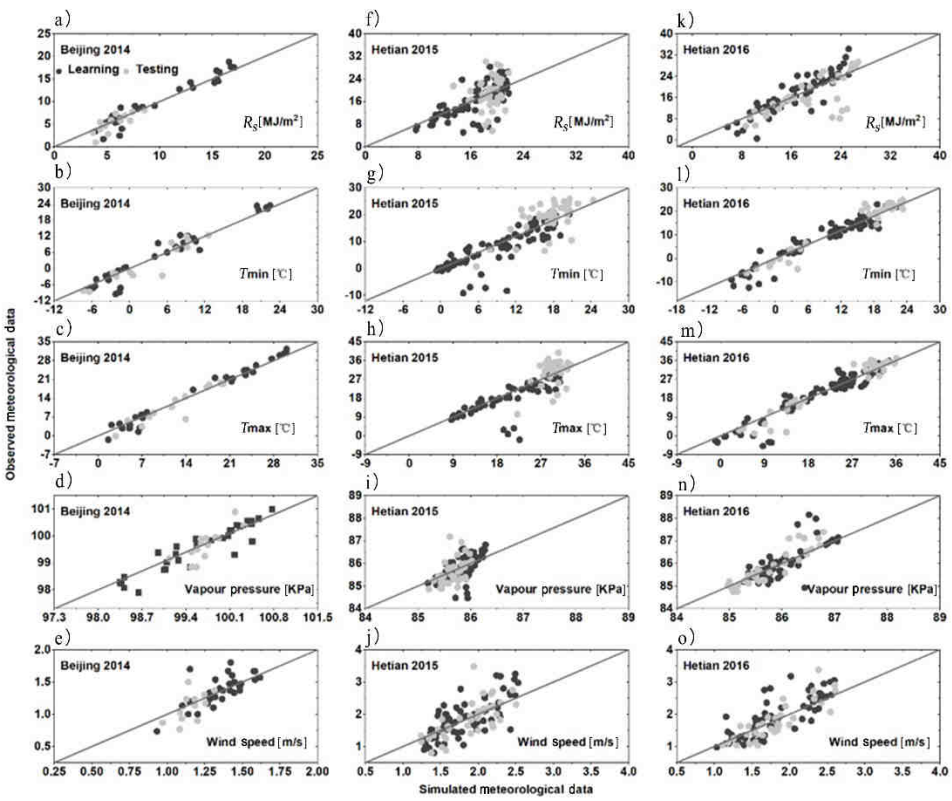


Fig. 5. Predictions of radiation R_s, minimum T_{min} and maximum T_{max} temperature, vapour pressure, and wind speed in Beijing and Hetian in 2014, 2015, and 2016 from the air pollutants by support vector regression (*SVR*). Dark points indicate the learning process, and grey points indicate the testing process

However, the prediction accuracy for Hetian was slightly lower in 2015 than in 2014 and 2016. The *R* of the vapour pressure simulation was only 0.577, but the *RRMSE* was

0.5 %, which also indicates an acceptable prediction accuracy. Similar phenomena were also found in the testing process; the prediction accuracy was higher for Beijing in 2014 and Hetian in 2016 than for Hetian in 2015. For example, the R value of Rs for Hetian in 2015 was only 0.158, but in 2014 and 2016, the R values were 0.813 and 0.698, respectively. However, the *RRMSE* of the 5 meteorological factors for Hetian in 2015 were all still lower than 30 % (Table 1).

3.4. Simulated crop yield in WOFOST

In the potential conditions, the simulated maize and winter wheat yields using the observed weather data and default parameters in WOFOST were 5152 kg/ha and 5123 kg/ha, respectively. The simulated maize yield increased to 7689 kg/ha and decreased to 1984 kg/ha when PM2.5 was regarded as the main air pollutant to mimic the moderate and heavy air pollution for the whole crop growth period (Fig. 6a). However, the simulated winter wheat yield decreased to 4873 kg/ha and 3753 kg/ha in the mimicked moderate and heavy air pollution conditions, respectively, by increasing the PM2.5. In contrast, when PM10 was the main air pollutant, the simulated winter wheat yield increased 27.4 % and decreased 6.1 % in the mimicked moderate and heavy air pollution conditions, respectively, while the simulated maize yield was 4294 kg/ha for both air pollution conditions.

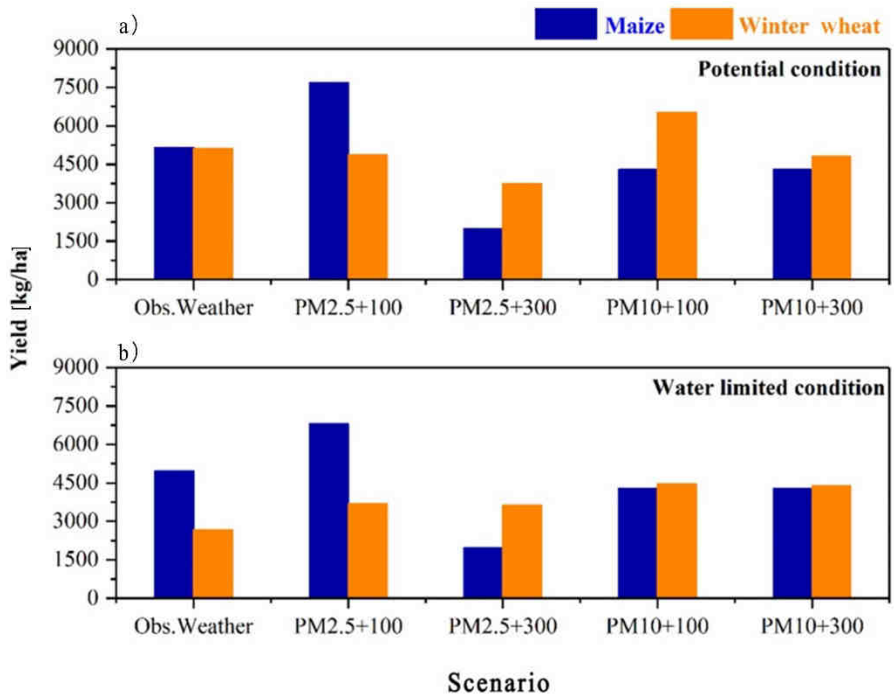


Fig. 6. Simulated maize and winter wheat yields under potential a) and water-limited b) conditions with observed weather data and mimicked moderate and heavy air pollution data by regarding PM2.5 and PM10 as the main air pollutants.

Under water stress condition, the simulated maize yield in different air pollution conditions with the two main air pollutants was similar to that under the potential condition. Furthermore, the simulated winter wheat yield with heavy air pollution was lower than that with moderate air pollution regardless of whether the main air pollutant was PM2.5 or PM10. However, the simulated winter wheat yield with heavy air pollution was even higher than the yield with the observed weather data (Fig. 6b). For example, the simulated winter wheat yields with heavy air pollution were 3635 kg/ha and 4379 kg/ha when PM2.5 and PM10 were the main air pollutants, respectively, which increased 26.5 % and 63.9 % compared with the yield obtained with the observed weather data.

4. Discussion

Previous studies have mainly pointed out that air pollution reduces crop yields [52]. For example, Wahid et al. [53] found reductions of 42 % and 37 % in the grain yields of two cultivars of rice due to air pollution. Agrawal et al. [54] indicated that heavy air pollution decreased yields by 73 %, 25 %, and 20 % for mung, wheat, and mustard, respectively. Burney et al. [55] suggested that the wheat yields in India in 2010 were as much as 36 % lower than the yields in 1980 due to air pollution. The results of all these studies were similar to our findings under heavy air pollution conditions. However, the difference was the air pollution period. Our study indicated that short-term air pollution, even heavy air pollution, had no noticeable relationship with the crop yields ($p > 0.05$). Only after a period of heavy air pollution did the crop yields linearly decrease. More precisely, the threshold periods of maize in 2015 and 2016 were 7 days and 5 days, respectively, while that of winter wheat was 10 days in both 2015 and 2016, respectively (Fig. 3). This phenomenon was similar to the effects of many other environmental stresses on crop growth [56-60]. For instance, Helms et al. [61] found that soybean seedling emergence was seriously affected only when water stress lasted 12 days. Campos et al. [62] even indicated that after 23 days of water stress, rewatering caused the gradual recovery of linear electron flow and CO_2 assimilation. The reason for yield reductions with heavy air pollution might be because the air pollutant affected the weather conditions, which then had indirect effects on crop growth [63]. Fan et al. [64] proposed a relationship between daily global diffuse solar radiation and the concentrations of PM2.5 and O_3 [65], Yang et al. [66], and Khodakarami et al. [67] also pointed out that anthropogenic alterations of pollutant loads in the atmosphere (e.g. PM2.5, PM10, NO_2, and O_3) resulted in the attenuation of surface solar radiation due to the scattering and absorbing of solar radiation.

Table 2

Crop coefficients of winter wheat and maize in different growth stages in Xinjiang Province

Name	Growth stage	Month	Crop coefficient
Winter wheat	Initial	9, 10, 11, 12, 1, 2, 3	0.4
	Fast growth	4, 5	0.8
	Middle period	6, 7	1.2
	Late period	8	0.785
Maize	Initial	4	0.4
	Fast growth	5, 6	0.85
	Middle period	7	1.3
	Late period	8	0.885

However, an interesting phenomenon in our study was that the yields of both maize and winter wheat were even higher with moderate air pollution than with light or no air pollution (Fig. 3). The possible reason might be that the air pollutants reduced the surface vapour evaporation, which decreased the heat dissipation and especially benefited crop growth in winter. Taking Hetian as an example to support this possible reason, the potential evapotranspiration (*ETP*) was calculated by the Penman-Monteith equation and crop coefficients (Table 2) from the Food and Agriculture Organization of the United Nations (FAO) [68]. The *ETP* values of winter wheat and maize with moderate air pollution in Hetian were all higher than the values with light and heavy air pollution conditions from April to July in 2015 and from April to May in 2016 (Fig. 7), which was in accordance with the WOFOST simulations (Fig. 6).

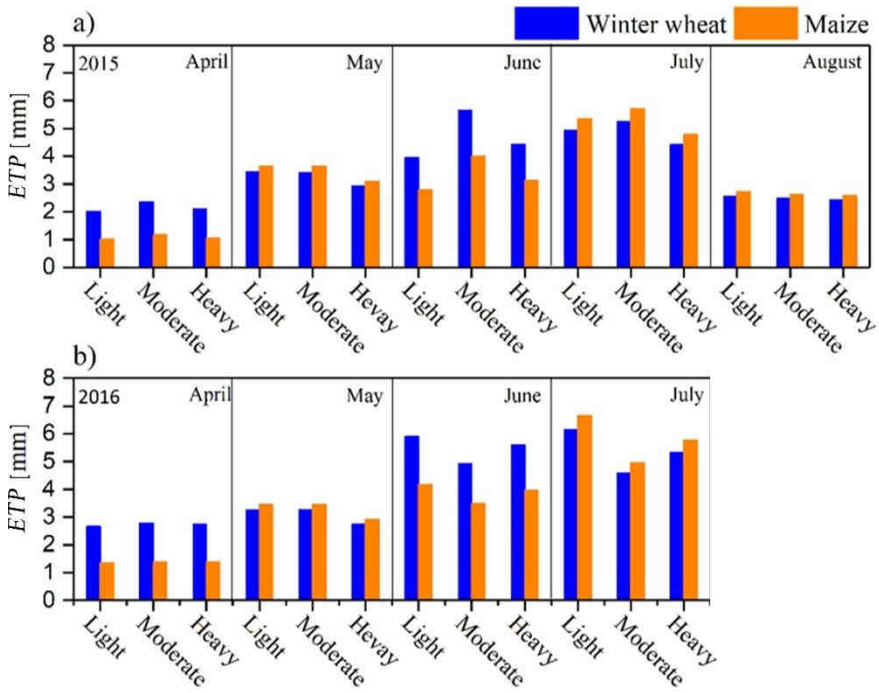


Fig. 7. Potential evapotranspiration, *ETP* values calculated by the Penman-Monteith equation and crop coefficients from the Food and Agriculture Organization of the United Nations (FAO) under different air pollution degrees in 2015 and 2016, respectively, in Hetian, Xinjiang Provinces

However, the highest *ETP* values of winter wheat and maize in April 2015 and from June to July 2016 were found under light air pollution conditions. There might be two reasons for this phenomenon. First, heavy air pollution also had direct effects on the crop yields that might be beyond the indirect effects due to climate [55]. Amundson et al. [69] pointed out that both nitric oxide and NO_2 could either be toxic or be metabolised by crops. However, the authors also indicated that nitrogen oxides are less phytotoxic than SO_2 and O_3. Wang et al. [70] reported that crops would decrease their photosynthetic uptake of CO_2 and increase respiration and thus generate acute hazards (e.g., necrotic spots on leaf

surfaces, leaves withering off) at high concentrations of SO_2. Choi et al. [71] found that even at low SO_2 concentrations, extensive crop tissue damage also occurred due to the formation of sulphate. This negative effect of O_3 arises from the disturbance of the equilibrium between production and the scavenging of reactive oxygen species (ROS) within crop tissues, and Telesnicki et al. [72] found that O_3 reduced the antioxidant potential in crops and had no effect on lipid peroxidation in plants. Second, the toxic effects of air pollutants would have complex interactions with other environmental stresses, such as the stresses of water, nutrients, salinity, and heavy metals. For example, Wang et al. [73] found that SO_2 could alleviate cadmium toxicity in the roots of foxtail millet seedlings. In our study, compared with the potential conditions, the simulated maize yield under water stress decreased by 3.5 %. After considering heavy air pollution, the maize yield further decreased 56.7 % and 13.6 % when PM2.5 and PM10 were regarded as the main air pollutants, respectively. However, based on the empirical equations from Figure 3, heavy air pollution for the whole growing period inhibited maize growth.

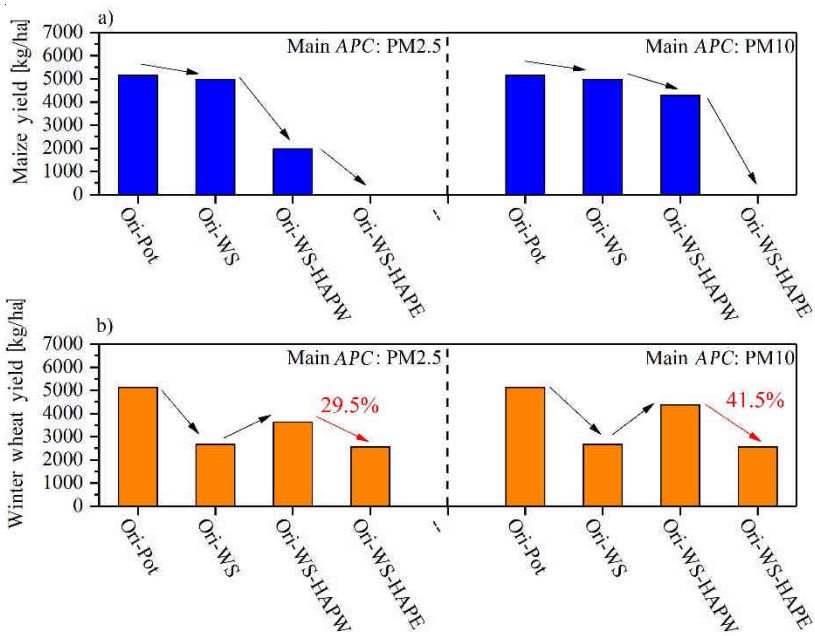


Fig. 8. Simulated crop yields with different weather conditions by the WOFOST model: a) Maize and b) winter wheat. *APC* represents the air pollution component. Ori-Pot represents the observed weather data in potential conditions. Ori-WS represents the observed weather data in the water stress condition. Ori-WS-HAPW represents the mimicked weather data considering heavy air pollution for the whole crop growth period using support vector regression (*SVR*). Ori-WS-HAPE represents the mimicked weather data considering heavy air pollution for the whole crop growth period using the empirical equations from Figure 3

Moreover, compared with the WOFOST simulations, the empirical equations (Fig. 3) also further decreased the winter wheat yield by 29.5 % (PM2.5) and 41.5 % (PM10) (Fig. 8), which also proved the toxicity and interactions between air pollution and other

environmental stresses on crop growth. However, the simulated winter wheat yield under water stress was higher with heavy air pollution (Ori-WS-HAPW) in the WOFOST model (Fig. 8b), which might be an unreasonable benefit of air pollution (e.g. lower heat dissipation). We think this result reflects both the complex coupling effects between heavy air pollution and water stress and the limitations of the WOFOST model.

Therefore, although the present study first quantificationally relates air pollution to crop yield, there are still some shortcomings that need further study. First, the empirical equations for the relationships between yield reduction and the heavy air pollution period were deduced with limited data, and the results still need further verification on a longer time scale for more crops. Second, an *AQI* was used for classifying the levels of air pollution, which is common in many studies [74-79]. Nevertheless, some studies have indicated that *AQI*, which were proposed initially for human health considerations, represent only primary air pollutants [80-84]. Therefore, further studies should focus on the appropriateness of *AQI* for crop health. Third, our present work proved the toxicity of air pollutants, but whether these assessments can accurately determine toxic impacts remains unclear. Moreover, the *SVR* prediction could also have introduced some errors, and more measured data are needed to further verify the *SVR* simulations. In addition, the mechanism of the interactions between air pollution and other environmental stresses for crop growth remains unknown. More exactly, previous studies proved that crop growth could be affected by both water and salt stresses and their interactions [19, 62]. However, very few studies focused on the interactions between air pollution and water stress or salt stress while these issues are highly likely to exist, especially in arid or semi-arid regions.

5. Conclusion

In this study, we analysed weather, air pollution, and maize and winter wheat yield data from 331 cities in China from 2014 to 2016 to prove that air pollution could affect crop yields. More precisely, both the winter wheat and maize yields decreased during heavy air pollution periods in 2014, 2015 and 2016 when the heavy air pollution period was longer than a threshold value. The threshold values of maize in 2015 and 2016 were 7 days and 5 days, respectively, while that of winter wheat was 10 days in both 2015 and 2016. Linearly empirical equations between the heavy air pollution periods and the crop yields were also established. Interestingly, short-term air pollution had almost no effect on the crop yield, while moderate air pollution might increase the crop yield. *SVR* was applied to mimic weather data under different air pollution conditions, and WOFOST was used to simulate the winter wheat and maize yields under air pollution in potential and water stress conditions. The simulation results were in accordance with the statistical analysis of the observed data and further revealed the direct (toxicity) and indirect (by affecting the weather) ways by which air pollution affects crop yields. The WOFOST simulations also proved the occurrence of complex interactions between air pollution and other environmental stresses. In the future research, experiments in the phytotron are necessary to consider the interactions between air pollutions and other environmental factors such as water, salt, and nutrients. In addition, the effects of different components of air pollutions on crop growth also need more attentions in the future.

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