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Effects of air pollutants and their interactive environmental factors on winter wheat yield

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ABSTRACT

Quantifying the environmental determinants influencing crop yields is essential for crop management and ensuring global food security. However, comprehensive studies on the relative importance of multiple environmental factors and their interactions on crop yields during different phenological stages are still limited. In this study, we adopted a spatial heterogeneity detection method—geographic detector (GeoDetector)—to quantify how environmental factors, i.e., air pollutants, elevation, meteorological factors, and soil conditions, as well as their interactive effects, contributed to winter wheat yield. Data collected from agrometeorological stations in Henan Province, China, from 2014 to 2017 were analyzed as a case study. Results revealed that the dominant factors impacting winter wheat yield were elevation and soil acidity (pH). The interactions between elevation and soil conditions showed the strongest explanatory power throughout the growth period. Although air pollutants had relatively low independent impacts on yield, the interactions between air pollutants and other factors had significant nonlinear impacts. Contrary to traditional studies, ozone (O_3) did not significantly impact winter wheat yield. In our study, carbon monoxide (CO) and sulfur dioxide (SO_2) were the main air pollutants affecting yield at most growth stages, and the interactions between CO and elevation, pH, soil organic matter, and SO_2 were significant. The effects of air pollutants on yield also changed across the growth stages, with the greatest impact observed from the three-leaf to tillering stages, and the weakest observed from the tillering to green-up stages. These findings improve our understanding of the relative importance of environmental factors on winter wheat yields, and have important implications for managing agricultural activities, improving crop models, and developing food security policies.

1. Introduction

Ending hunger in all its forms worldwide and achieving food security are important aims of “The 2030 Agenda for Sustainable Development,” which highlights the global sustainable development goals of the United Nations members (UN, 2015). However, this is a difficult goal to achieve. A report published by the Food and Agriculture Organization of the United Nations (FAO) shows that hunger continues to rise, reaching 821 million people—approximately 1/9 of the world’s population—in 2017 (FAO et al., 2017, 2018). The growing demand for food from a population of hungry people will affect not only regional food inventory

Abbreviations: A-M, anthesis to milk-ripe; B–H, booting to heading; CO, carbon monoxide; El, elevation; E-T, emergence to three-leaf; G-S, green-up to standing; H-A, heading to anthesis; J-B, jointing to booting; MaxT, maximum temperature; MinT, minimum temperature; M-M, milk-ripe to maturity; NO_2, nitrogen dioxide; O_3, ozone; O-G, overwintering to green-up; PM, particulate matter; Pre, precipitation; S-E, sowing to emergence; S-J, standing to jointing; SO_2, sulfur dioxide; SOM, soil organic matter; SSD, sunshine duration; Tem, temperature; TK, total potassium; TN, total nitrogen; T-O, tillering to overwintering; TP, total phosphorus; T-T, three-leaf to tillering.

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management (Duan et al., 2018; Gharaei et al., 2019a) and agricultural trade policies (Gharaei et al., 2019b, 2019c), but also global food supply chains (Giri and Bardhan, 2014; Shah et al., 2018) and the international economy (Giri and Masanta, 2018; Gharaei et al., 2019d). Although life-threatening famine is no longer an issue in China, which is the largest developing country in the world, there is still a food security crisis due to excessive dependence on imports, a large and growing population base, insufficient arable land, and serious environmental degradation (Zhao et al., 2016). In light of this threat, developing approaches to stabilize and improve food production has become a major goal of scientific research. To realize this goal, there is an urgent need to identify and quantitatively evaluate the main factors affecting crop productivity, and push for strategies to make this productivity sustainable.

Wheat is the world's most widely distributed common food crop and has the largest planting area. It feeds more than 35% of the world's population, making it vital to the issues of food chains (Hoseini Shekarabi et al., 2018; Rabbani et al., 2018) and food security (Ren et al., 2019). The relationship between wheat and its growing conditions is complex, as its growth and yield are affected by many factors and their interactions. Crop variety (Liu et al., 2009), soil (Martínez et al., 2008), climatic conditions (Schlenker and Roberts, 2009), and tillage or management techniques are generally considered to be the most important determinants of wheat yield (He et al., 2015).

However, many studies have shown that the impact of increasing air pollution on wheat production should not be underestimated. For example, an increase in the concentration of atmospheric particulate matter less than 2.5 μm in diameter ($PM_{2.5}$) has a significant negative effect on the average yield of wheat, as severe haze can reduce the surface air temperature by reducing solar radiation, which may in turn affect wheat growth (Kaiser and Qian, 2002; Zhou et al., 2018). Additionally, high ozone (O_3) concentrations near the ground also affect crop growth and reduce wheat yield (Feng et al., 2008; Feng and Kobayashi, 2009). A recent study based on air pollution monitoring data concluded that O_3 concentrations above the critical level of 40 ppb of accumulated O_3 exposure would reduce annual wheat production in China by 6% in 2015 (Feng et al., 2019). Simultaneously, the presence of nitrogen oxides in the atmosphere enable volatile organic compounds to rapidly form O_3 via photochemical reactions, which further affect wheat growth (Martins and de Fátima Andrade, 2008; Li et al., 2019). Another study demonstrated that gaseous pollutants such as carbon monoxide (CO), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and atmospheric particulate matter less than 10 μm in diameter (PM_{10}) reduced plant height, photosynthesis, and the straw and grain yield, further confirming that air pollutants have adverse impacts on wheat (Adrees et al., 2016).

Wheat requires different factors to grow during different phenological periods and, therefore, its sensitivity to environmental factors also changes across these periods (Liu et al., 2018; Xiao et al., 2018). Studying the effects of air pollutants and other environmental factors on wheat yield, using individual phenological periods as a research unit, can help us better understand the mechanisms by which air pollutants and their interactions affect wheat yield. Such studies will help scientists and managers design strategies, across growth periods, to cope with the potential adverse effects of environmental changes, especially the long-term problems of air pollution. More generally, these data will provide theoretical support for strategies that ensure sustainable development and food security; appropriate control measures can be implemented if individual air pollutants have a significant effect on wheat yield during any growth stages.

The majority of previous studies investigating the factors that contribute to the variation in wheat yield under conditions of manipulation experiments, which can be drastically different from field conditions and do not fully reflect the degree to which different environmental factors affect wheat yield. Conducting regional quantitative analyses of the associations between wheat yield and real environmental conditions can better analyze environmental impacts and provide a theoretical basis for an appropriate experimental design and the development and optimization of crop models.

Geographic detector (GeoDetector) is a method of detecting spatial heterogeneity that may be suitable for understanding the relationships between multiple environmental factors and wheat yield. The core underlying hypothesis of GeoDetector is that, if explanatory variable *X* has an important influence on variable *Y*, then *Y* will show a similar spatial distribution to that of *X* (Wang et al., 2010; Wang and Hu, 2012). This technique detects the consistency of spatial distribution patterns between dependent and independent variables through spatial heterogeneity and measures the degree to which different independent variables explain dependent variables. GeoDetector is better able to determine causation than general statistical methods because it is much harder for two variables to be uniformly distributed in two dimensions than in one dimension (Wang et al., 2016). Compared with traditional statistical and spatial analysis methods, this technique can not only explain the driving factors contributing to spatial differentiation without the assumption of linearity, but also quantify the interactions between these driving factors (Wang et al., 2016; Xie et al., 2017; He et al., 2019). GeoDetector has been widely used in studies on land pollution, air pollution, and ecosystem health (Shi et al., 2018; Bai et al., 2019; He et al., 2019).

We used GeoDetector to explore the effects of environmental factors—including meteorological factors, air pollutants, and soil conditions—on winter wheat yield using data from agrometeorological stations in Henan Province, China from 2014 to 2017. The objectives of this study were to: (1) identify the key environmental factors influencing winter wheat yield, (2) determine the effects of air pollutants on winter wheat yield under real environmental conditions, and (3) analyze the effects of these factors on winter wheat yield at different growth stages. These results are expected to guide efforts toward improving food security and crop models.

2. Material and methods

2.1. Study area

Henan Province (110°21′E to 116°39′E, 31°23′N to 36°22′N) lies in the center of China and has high topography in the west and low topography in the east (Fig. 1). There were three main reasons for selecting Henan Province as the present case study area. First, Henan is China's largest grain producer, accounting for more than 20% of the country's total wheat planting area and 25% of its total wheat production (National Bureau of Statistics of China, 2016). Second, with rapid economic growth and industrial development, air pollution in Henan Province has become an increasingly serious issue in recent years (Wang et al., 2016; Zhang et al., 2020). Finally, and most importantly, there are 35 agricultural meteorological stations in the province that comprehensively monitor the growth status, phenological periods, and yield of winter wheat, thereby guaranteeing sufficient data for analysis. Therefore, Henan is a representative area for analyzing the effects of various environmental factors on winter wheat yield.

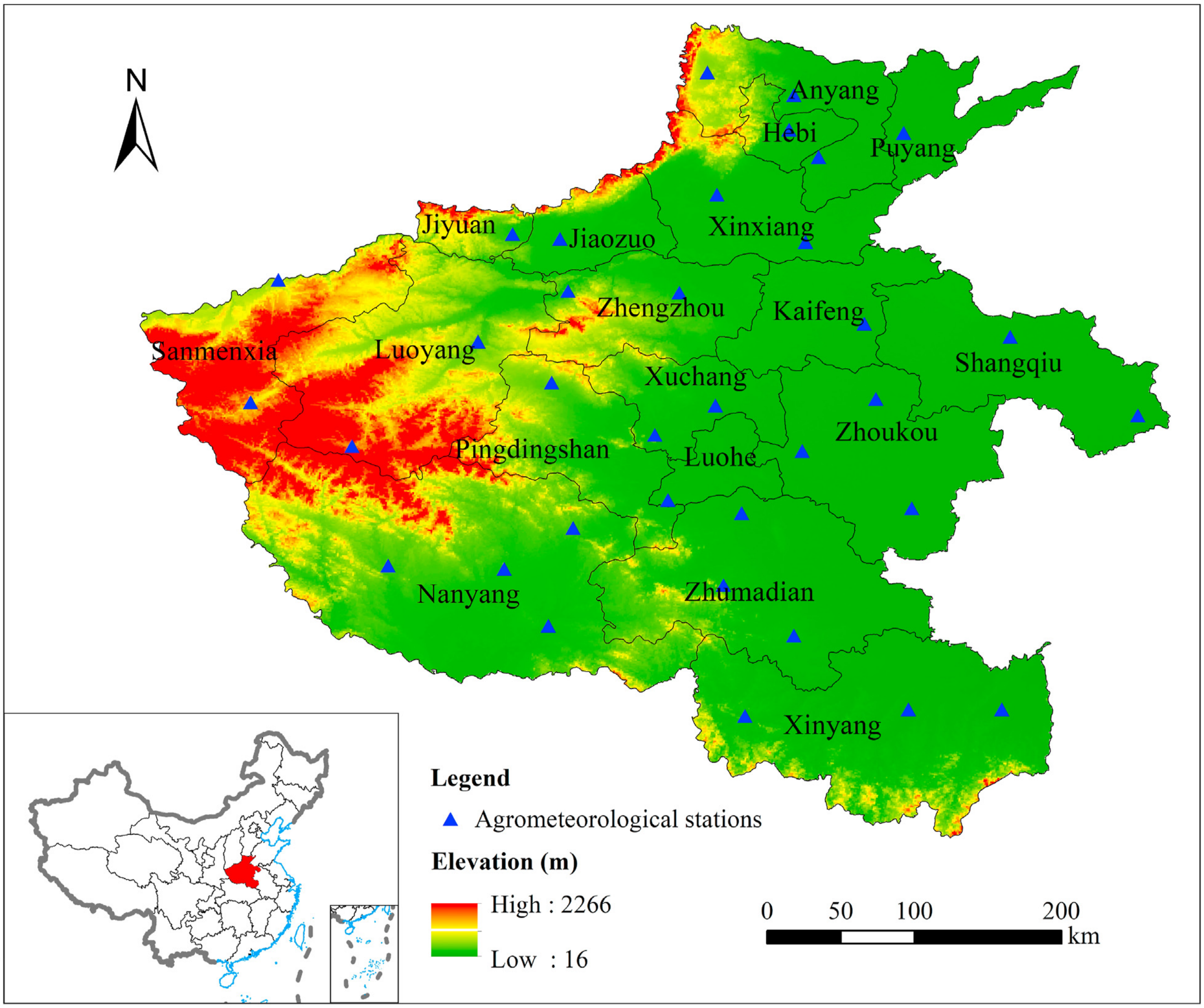

Fig. 1. Study area and spatial distribution of agrometeorological stations.

2.2. Data sources

The data on winter wheat in this study—including data from the 13 key phenological stages (Table S1) and the average yield per square meter in 2014–2017—were collected at the 35 agrometeorological stations operated by the Henan Provincial and China Meteorological Administrations (Fig. 1). To comprehensively analyze the influence of environmental factors on winter wheat yield during each growth period, we divided the data into the following 12 phenological periods: sowing to emergence (S-E), emergence to three-leaf (E-T), three-leaf to tillering (T-T), tillering to overwintering (T-O), overwintering to green-up (O-G), green-up to standing (G-S), standing to jointing (S-J), jointing to booting (J-B), booting to heading (B–H), heading to anthesis (H-A), anthesis to milk-ripe (A-M), and milk-ripe to maturity (M-M).

Given that elevation, meteorological factors, air pollutants, and soil conditions have previously been shown to affect wheat growth, we integrated these variables in the present analysis (Table S2). The elevation (El) of each station and daily meteorological data—mean temperature at 2-m above the ground (Tem), maximum and minimum temperature at 2-m above the ground (MaxT and MinT), precipitation (Pre), sunshine duration (SSD)—during the study period were also obtained from the China Meteorological Administration. Data from the following daily air pollutant variables were obtained from the China National Environmental Monitoring Center after checking for data quality: CO, $PM_{2.5}$, PM_{10}, SO_2, NO_2, and O_3. Soil factors—pH, soil organic matter (SOM), total nitrogen (TN), total phosphorus (TP), and total potassium (TK)—were obtained from the Soil Database of China for Land Surface Modeling (30 arc-seconds) (Wei et al., 2013). This dataset has high spatial accuracy and includes many soil physical and chemical properties that accurately represent the real soil conditions in China. Based on the extent of the winter wheat root system, datasets at 0–0.829 m deep were selected to represent the soil factors for winter wheat growth (Qiu et al., 2013).

Since the annual winter wheat growth duration and phenological period varied at different stations (Table S3), we extracted the data for environmental variables strictly according to each phenological period of winter wheat recorded by each agrometeorological station. The daily meteorological and air pollutant data were derived from an average of 24 h of data. For X days in a period, X measurements of daily mean data are included in the calculation for this period. This meant we could ensure the proper correlation for each period between environmental factors and crop yield although the environmental factor data included in the analysis were segmented. To ensure the authenticity of the data, we deleted the missing records (23 items) of the green-up and standing periods from some stations for individual years.

2.3. GeoDetector

GeoDetector is a technique proposed by Wang et al. (2010) for detecting spatial heterogeneity and revealing its driving factors. It consists of four modules: a factor detector, a risk detector, an interaction detector, and an ecological detector. In this study, the factor and interaction detectors were used to determine the strength at which different environmental factors influenced winter wheat yield. The explanatory power between variable X (elevation, meteorological factors, soil, and air pollutants) and Y (winter wheat yield) was measured by the q statistic, which is defined as follows:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} = 1 - \frac{ssw}{sst}$$

$$SSW = \sum_{h=1}^{L} N_h \sigma_h^2, SST = N\sigma^2$$

where $h(1, \ldots \ldots, L)$ is the number of strata for environmental factors; N_h and N represent the total number of subjects in stratum h and the entire region, respectively; σ_h^2 and σ^2 denote the variance of stratum h and the entire region, respectively; SSW is the within sum-of-squares; and SST is the total sum-of-squares. The q value is within $[0, 1]$, meaning that factor X explains $q \times 100\%$ of the winter wheat yield, and a larger q value indicates a stronger explanatory power of X on yield. In extreme cases, if the spatial distribution of Y is completely determined by a factor X, then the q value is 1, whereas a q value of 0 indicates that factor X has no relationship with Y.

The interaction detector was used to quantify the interaction between two environmental variables on wheat yield; it assessed whether the explanatory power of the dependent variable Y would increase or decrease when interacting with evaluation factors $X1$ and $X2$, or whether the influence of these factors on Y was independent. The interaction detector calculated the q value $[q(X1 \cap X2)]$ of a two-factor interaction based on the factor detector. The interaction relationship was then divided into five categories after comparing $q(X1)$, $q(X2)$, and $q(X1 \cap X2)$ (Table 1).

According to the data requirements of GeoDetector, the input variables must be discrete (Wang et al., 2016). The main data classification methods used by GeoDetector include expert experience, equal interval stratification, K-means, natural breaks, and quantiles (Ren et al., 2016; Ding et al., 2019; Liang and Li, 2019; Zhu et al., 2019). In this study, the q statistic was used as the evaluation index to compare the effects of these classification methods (Wang and Xu, 2017). Finally, all of the variables were distributed into eight categories based on the quantiles classification method using ArcGIS software (https://www.esri.com).

Table 1
Five categories of interaction between two factors.

Judgement basis	Interaction effect
$q(X1 \cap X2) < \text{Min}(q(X1), q(X2))$	Weaken, nonlinear
$\text{Min}(q(X1), q(X2)) < q(X1 \cap X2) < \text{Max}(q(X1), q(X2))$	Weaken, univariate
$q(X1 \cap X2) > \text{Max}(q(X1), q(X2))$	Enhance, bivariate
$q(X1 \cap X2) = q(X1) + q(X2)$	Independent
$q(X1 \cap X2) > q(X1) + q(X2)$	Enhance, nonlinear

Notes: suppose $q(X1) = 0.2$ and $q(X2) = 0.4$. If $q(X1 \cap X2) = 0.1, 0.3, 0.5, 0.6$, or 0.7, the interaction between x1 and x2 is “Weaken, nonlinear”, “Weaken, univariate”, “Enhance, bivariate”, “Independent”, or “Enhance, nonlinear”, respectively.

3. Results

3.1. Impacts of environmental factors on winter wheat yield

The effects of individual factors on winter wheat yield were determined based on q values (Fig. 2 and Table S4). The effects of each environmental factor varied across the 12 growth periods. Overall, El and soil pH were the most dominant factors ($q > 0.327$) throughout all stages, followed by other soil factors, meteorological conditions, and air pollutants. In particular, there was substantial variation in the impacts of these driving factors on winter wheat yield among the 12 stages.

As shown in Fig. 2(a), the q values for elevation and meteorological factors ranged between 0.001 and 0.462; El had the highest q value, followed by Tem, MinT, MaxT, SSD, and Pre. The significance test (Table S4) indicated that El had significant effects ($p < 0.01$) on winter wheat yield across all growth stages, and temperature (Tem, MinT, and MaxT) had a significant effect during the sowing to tillering periods. The explanatory power for El ($q > 0.333$) was highest during the growth periods identified in the significance test, followed by Tem ($q > 0.128$), MinT ($q > 0.127$), and MaxT ($q > 0.063$). Although other meteorological factors also showed significant impacts on the winter wheat yield in some growth stages, the q values were relatively low (<0.020), suggesting that these factors could not effectively explain yield.

All five soil factors had significant influences on winter wheat yield (Table S4). The pH ($q = 0.389$) had the largest mean q value for all 12 stages, followed by TP ($q = 0.292$), TN ($q = 0.277$), SOM ($q = 0.252$), and TK ($q = 0.200$). The pH was the dominant factor during all growth stages except during the T-T stage. The effects of pH and TN on yield at the T-T stage were clearly lower, whereas the explanatory power of SOM and TP increased greatly. From the overwintering to standing periods, the effects of SOM and TN exceeded those of TP, becoming the most important soil factors, followed by pH.

Of the six air pollutants, CO had a significant effect throughout the growth period and SO_2 was influential during sowing to tillering and green-up to milk-ripe, indicating that they are the major air pollutants affecting winter wheat yield. NO_2 and O_3, the second level of air pollutants, had significant effects on yield in some periods. PM had the smallest effects on yield: although they were significant in several stages, except for the T-T stage, the q values at those stages were relatively low ($q < 0.015$). An obvious variation in the influence of air pollutants was that CO had the greatest q value during the S-E stage and from the tillering to maturity periods, followed by SO_2, but the opposite pattern was observed during the E-T and T-T periods. According to the significance test, the only period in the 12 growth stages where all pollutants had a significant impact on winter wheat yield was during the T-T stage, with the greatest effect of SO_2 ($q = 0.099$), followed by NO_2 ($q = 0.038$), CO ($q = 0.033$), $PM_{2.5}$ ($q = 0.027$), O_3 ($q = 0.019$), and PM_{10} ($q = 0.017$). These results suggest that winter wheat is most susceptible to air pollutants during the T-T stage.

3.2. Interactions among influencing factors

The interaction between any two environmental factors basically showed nonlinear effects on enhancement (Table S5). The interaction between soil factors and elevation and the interactions between individual soil factors had the greatest explanatory power for winter wheat yield in the study area, with q values above 0.600. The interaction between El and TN during H-A had the highest q value (0.823). El and pH combined with other soil factors best explained the variation in winter wheat yield. Although no single air pollutant had strong explanatory power, the interactions among

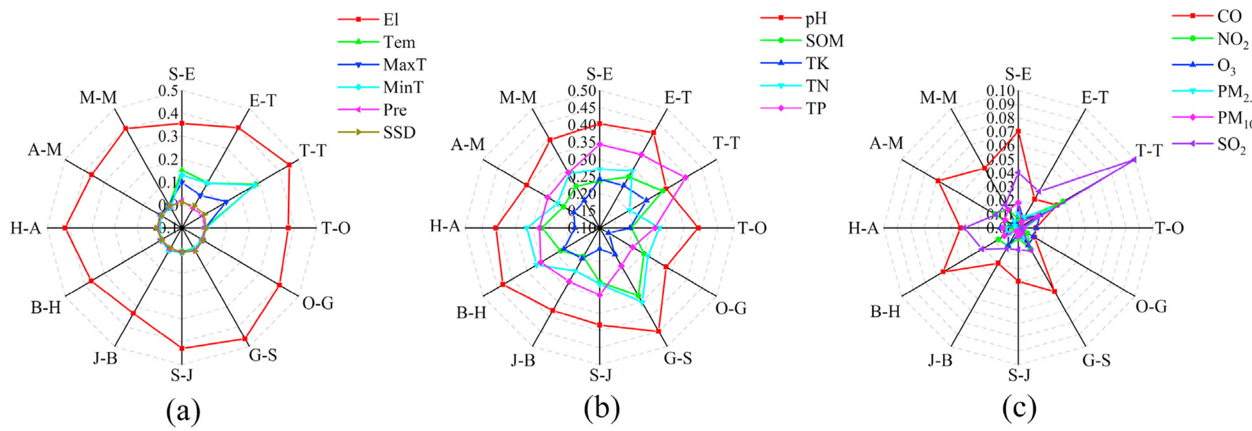

Fig. 2. Explanatory power (q values) of the effect of environmental factors (a. elevation and meteorological factors, b. soil factors, and c. air pollutants) on winter wheat yield over the 12 growth stages.

these pollutants and other environmental factors may have had. Therefore, we examined the effects of the top 10 pairs of air pollutants and other environmental factors, as well as the interactions among all air pollutants, on winter wheat yield.

3.2.1. Interactions between air pollutants and elevation and meteorological factors

The interactions between air pollutants and elevation and meteorological factors were still largely dominated by El and CO, and the top six interactions across the 12 growth stages were all associated with El (Fig. 3). The q value for CO∩El was the highest across all stages, indicating that the interaction between these factors was the strongest during all growth periods. The interactions among CO, SO_2, NO_2, O_3, and El had the greatest effects except during the jointing to anthesis periods and M-M stages, at which point the interaction between PM and El became stronger. Nonlinear increases were clearest for the interactions between CO and EL, even during the two periods (T-O and O-G) in which individual air pollutants had the weakest effect on winter wheat yield. It is worth noting that the interaction between PM_{10} and El had a greater influence during the H-A and M-M periods, second only to CO∩El, even though the single-factor effects of PM_{10} were relatively weak ($q < 0.015$) during these two periods.

3.2.2. Interactions between air pollutants and soil factors

The interaction between soil factors and air pollutants had a significant effect on winter wheat yield, and the q values for the top 10 pairs of interacting factors during all growth stages exceeded 0.320 (Fig. 4). There were two main explanations for this: a) these effects were driven by individual soil factors with high explanatory power, such as pH for most of stages and TP for the T-T stage; or b) some air pollutants interacted with soil factors in a significant nonlinear manner. For example, the interactions of CO, NO_2, and SO_2 with SOM showed the clearest nonlinear increases, especially during the S-E, T-T, A-M, and M-M stages. Also, although CO had a stronger explanatory power than SO_2 and NO_2, the interactions of NO_2 and SO_2 with pH were larger than that of CO with pH during the S-E stage. CO∩pH was the most important interaction affecting winter wheat yield in the T-O and green-up to milk-ripe periods, whereas the effect of the interaction between CO and SOM exceeded that of CO∩pH during the M-M stage. The interactions between SO_2 and pH, TP, and SOM had the greatest explanatory power in the E-T, T-T, and O-G stages, respectively. It is worth noting that no interactions between air pollutants and TK were observed, except for a significant interaction between SO_2 and TK during the T-T stage. In general, the interactions between CO, NO_2, and SO_2 and soil factors had the greatest explanatory power.

3.2.3. Interactions between air pollutants

Although individual air pollutants did not have strong explanatory power on the variation in winter wheat yield, interactions between various pollutants showed clear nonlinear increases in effect size, especially during the T-T and S-E periods, with average q values above 0.100 (Fig. 5). In particular, the interactions between CO and SO_2 with other factors showed the greatest effects, with significantly higher q values than those of other interaction types. The interaction between CO and SO_2 had clear effects during many growth periods, with q values for the S-E, T-T, B—H, H-A, and M-M stages all exceeding 0.150. The strongest interaction was CO∩SO_2 ($q = 0.191$) during the H-A stage, followed by NO_2∩SO_2 ($q = 0.177$) and CO∩SO_2 ($q = 0.172$) during the T-T stage. The interactions of O_3, the pollutant that is generally the focus of research, with SO_2 during the T-T stage and CO during booting to anthesis stage increased significantly, even if the individual effect of O_3 on winter wheat yield was not significant in those stages. During the T-O and O-G stages, the interactions among air pollution factors showed similar results to those observed in single-factor analyses, with low q values of <0.050, indicating that the effects of pollutants on winter wheat yield were minimal during these two stages.

4. Discussion

In this study, we quantified the effects of elevation, meteorological factors, soil factors, and air pollutants as well as their interactions on winter wheat yield using the GeoDetector method. The relative importance of various factors and their interactions were identified at different wheat growth stages, with implications for not only agricultural management and crop models, but also the kinds of pollutants that should be curbed to protect this vital crop.

Overall, our results showed that elevation and soil pH were the major determinants of winter wheat yield and displayed strong interactive effects with other environmental factors (e.g., TN, TP, SOM, CO, and SO_2). These results are consistent with the general notion previously established in literature that soil and meteorological conditions are the main factors affecting crop growth (Martínez et al., 2008; Liu et al., 2009; Scanlan et al., 2017). Numerous studies have revealed a relationship between elevation and soil conditions as well as climate characteristics, confirming that elevation is not only related to variations in soil pH, soil temperature, fertility, and depth, but also to variations in precipitation,

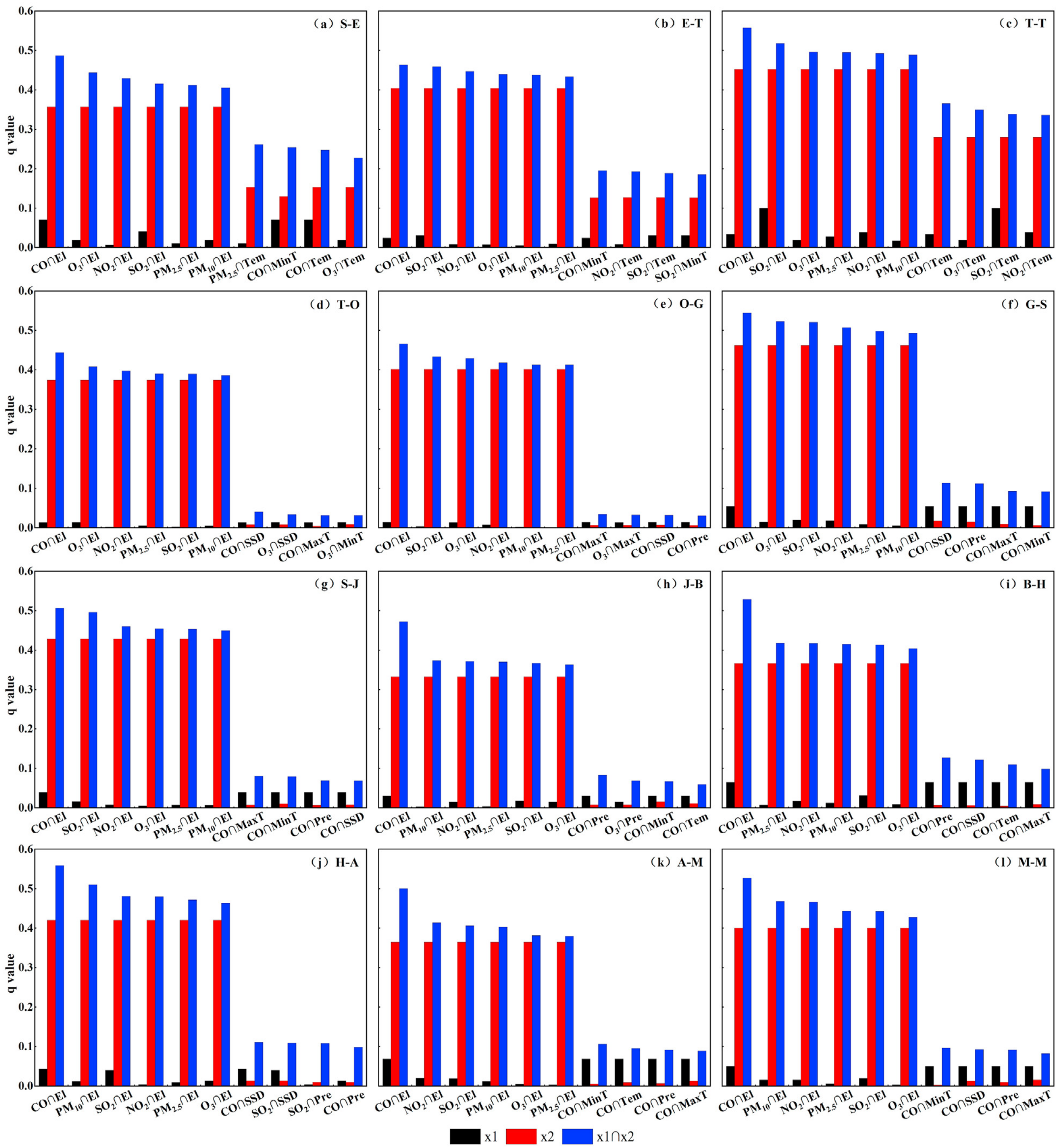

Fig. 3. Interactive effects of air pollutants and meteorological factors on winter wheat yield over the 12 growth stages (a–l).

light, air temperature, and other climatic factors (Tan et al., 2004; Sasaki and Kurihara, 2008; Deng et al., 2015). Therefore, we conclude that elevation—which influences winter wheat growth via regional climate characteristics and soil conditions, especially air and soil temperature—is the most important overall factor affecting yield.

Previous studies have demonstrated that temperature substantially influenced wheat growth (Jesse et al., 2015; Zhao et al., 2016), which is consistent with our results. Nevertheless, we have provided further insight into the phenological stages at which temperature influenced the wheat growth process, revealing that temperature had the greatest effect on wheat yield during the first three growth stages. Water resources are often considered important for crop growth and yield (Li et al., 2015; Pirttioja et al., 2015; Fronzek et al., 2017). However, precipitation did not significantly affect wheat yield at any point in the growth process in this study. This can be explained by the use of groundwater or surface water irrigation when water sources are insufficient. Wheat cultivation had more artificial interventions at the agrometeorological stations than it would in normal farmlands. Thus, the use of artificial irrigation on wheat during water shortages may have masked the influence of natural precipitation on wheat yield.

The negative effects of air pollution on agricultural systems have received increasing research attention, especially in China, owing to

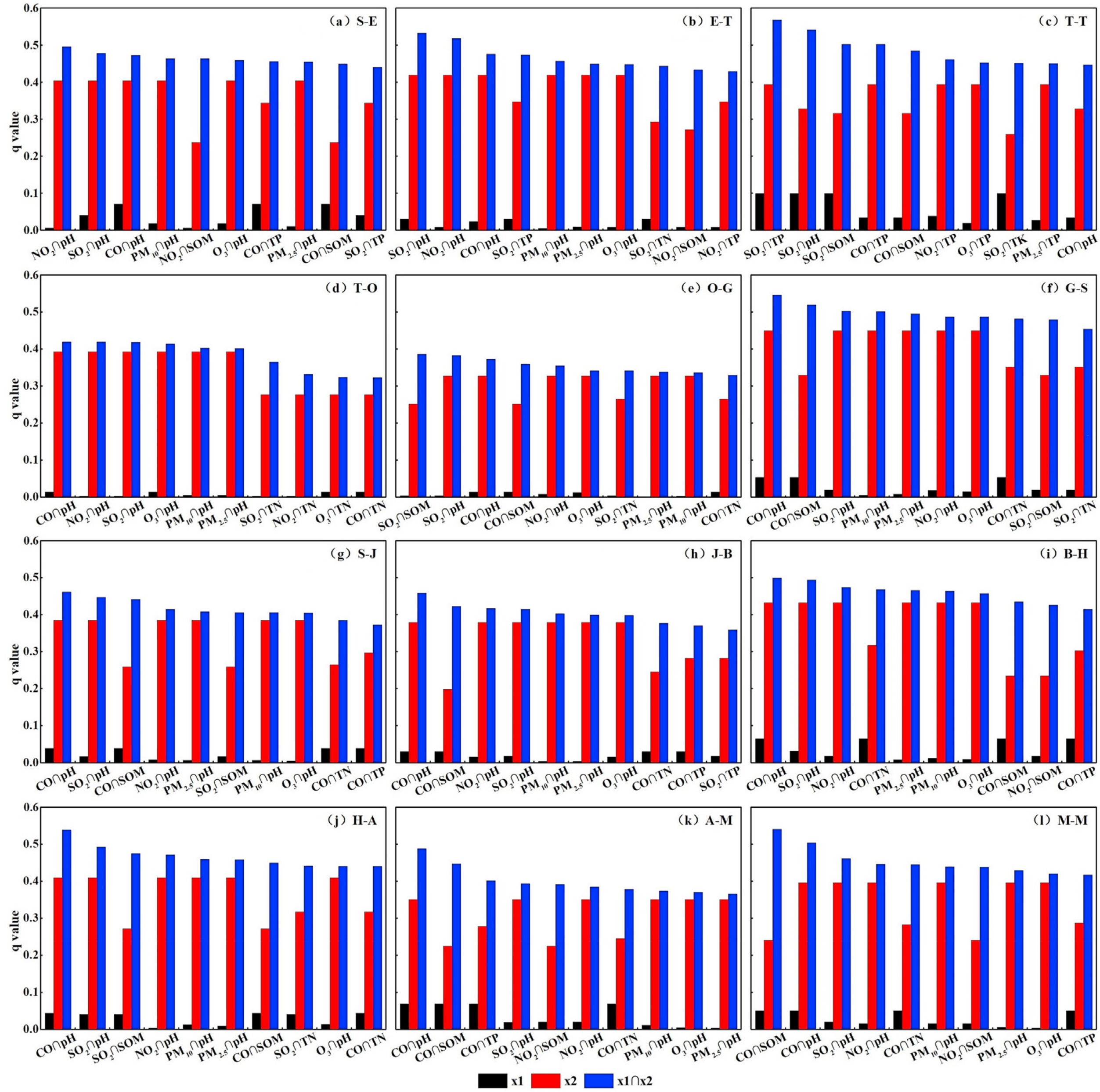

Fig. 4. Interactive effects of air pollutants and soil factors on winter wheat yield during the 12 growth stages (a–l).

its dual status as a major agricultural country and a region with serious air pollution (Yang and Liu, 2015; Sun et al., 2017). The combined effects of human activities and meteorological conditions on air pollution further emphasize the importance of prevention and control in China; accordingly, quantifying the impacts on crop growth has become a focus of recent research (Zhang et al., 2018). Studies of the effects of air pollution on crops typically assess different pollutant concentrations in open-top chambers and free air concentration enrichment environments (Zhu et al., 2011; Wang et al., 2012). In addition, dose-response relationships based on manipulation experiments have been applied to assess the regional impact of air pollution on crop yield (Wang et al., 2012; Feng et al., 2019). However, these experiments do not capture true open-air conditions and, thus, do not fully reflect the impact of air pollution on crops. In view of this limitation, we believe that the application of both statistical models and mechanistic experiments is an effective way to obtain accurate results. Although statistical models cannot clarify the mechanisms underlying observed effects or establish causality between factors, they can provide guidance or a theoretical basis for research based on observed correlations. However, few studies have analyzed the effects of air pollution on grain yield based on statistical models or spatial correlation analyses (Zhou et al., 2018). Although the GeoDetector method cannot clearly identify the positive or negative effects that environmental factors have on wheat yield, it provides more convincing indicators than those do general statistics, as it considers spatial heterogeneity between variables (Wang et al., 2016; Wang and Xu, 2017). In addition, a previous study found that the larger the q value, the higher the correlation, and vice versa (Wang et al., 2020). Therefore, these results were helpful in identifying the key environmental factors affecting wheat yield and providing a reliable theoretical basis for targeted agricultural experiments.

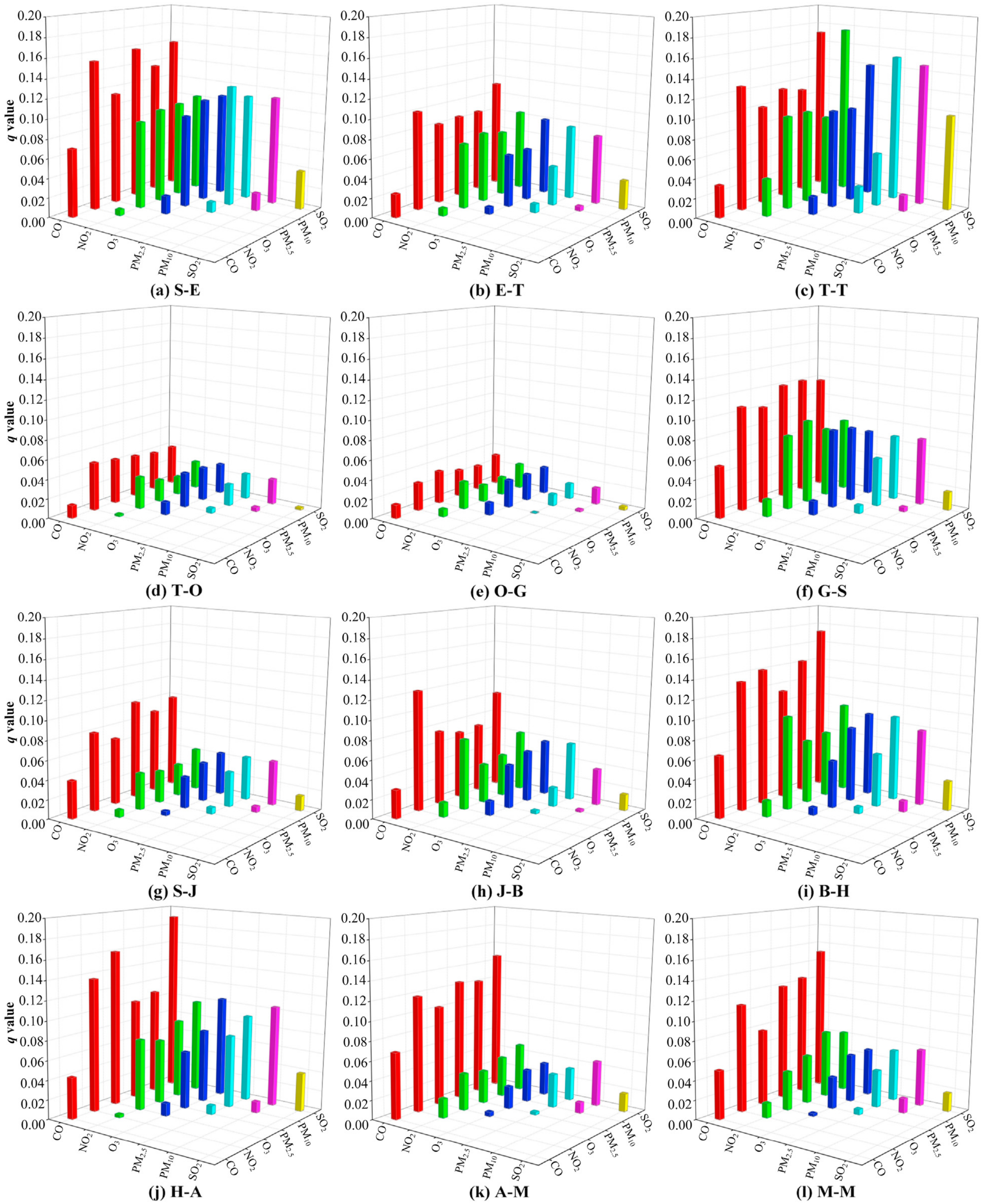

Fig. 5. Interactive effects between air pollutants on winter wheat yield across the 12 growth stages (a–l).

Although we found the explanatory power of individual air pollutants to be lower than that of soil, elevation, and meteorological factors, their interactions with soil properties, meteorological factors, and other air pollutants clearly influenced winter wheat yield to different degrees depending on the growth stage. The interaction between soil factors and air pollution was the clearest—especially during the S-E, T-T, A-M, and M-M stages—and the interaction between CO, NO_2, SO_2, and SOM showed significant nonlinear enhancement. More quantitative experiments on the interaction between soil and pollutants during these periods may help improve wheat fertilization practices. The interaction between CO, NO_2, SO_2, and El had a significant effect on all the growth stages, whereas PM∩El increased significantly during the J-B, B–H, H-A, and M-M stages, and had the highest impact on yield after CO∩El. Controlling dust and reducing motor vehicle emissions during these stages may be an effective measure for reducing the degree of winter wheat damage. Acid rain is another environmental pollutant that is of concern. In this study, the effect of SO_2∩Pre showed a significant nonlinear enhancement across the entire growth cycle—especially during the S-E and H-A stages (Table S5)—indicating that acid rain would also have an impact on winter wheat yield. However, the effect of acid rain on winter wheat yield in our study region was minor as acid rain in China mostly occurs in the region south of the Yangtze River (Tang et al., 2010).

For individual air pollutants, the effects of CO, SO_2, and NO_2 on winter wheat yield appear to be greater than those of O_3, providing a basis for future research. These results are reasonable given that the O_3 concentration shows clear seasonal fluctuation, and the growing season of winter wheat does not coincide with the peak period of O_3 pollution. Experiments manipulating O_3 concentration may overestimate the influence of this factor on winter wheat yield (Zhang and Zhang, 2019). Importantly, the consideration of the wheat phenophase could identify more practical results and provide theoretical support to prevent and control air pollution and develop strategies for food security.

In general, crop models (e.g., CERES-Wheat, APSIM, WOFOST) are typically developed based on semi-empirical and semi-parametric methods, using data from a large number of manipulation experiments to consider the influence of weather, soil, variety, and management measures (Keating et al., 2003; De Wit and Van Diepen, 2007; Iglesias and Rosensweig, 2009; Hoogenboom et al., 2019). However, crop models that consider the mechanisms by which air pollution factors influence crops are still limited. Our results confirmed that air pollutants influenced winter wheat yield through the effects of single factors and interactions with other factors, which varied spatially and with the growth period. These results provide a theoretical basis for further studies evaluating the mechanisms underlying crop growth, designs for manipulation experiments, and the improvement of crop models. For instance, the same air pollution scenario can be established during the different growth periods of winter wheat to explore and quantify the determinants of growth and yields. Moreover, different air pollution scenarios can be applied during the T-T stage to explore threshold parameter values, with the goal of reducing the degree of damage to crops. However, to effectively apply these results to improve crop models, it is not sufficient to rely on statistical models alone, and a large number of comprehensive experiments are still needed to improve and verify the reliability of the models.

This study did have some limitations. First, although the monitoring data for winter wheat growth from agrometeorological stations provided reliable information, the data for soil parameters were incomplete and data from supporting air quality monitoring stations were insufficient. Second, a few stations may have some limiting factors that are not included in our study—such as if there is frost damage for one day during a critical growing phase, meaning wheat yield might be much lower while our results would not reflect this issue. Third, wheat varieties differ as different regions choose the most suitable crop varieties according to their local environment. We did not take into account the differences between wheat varieties, and this may inevitably have lead to some variation in our results. In addition, the growth conditions for crops involve a highly integrated anthropogenic and natural system, and thus various factors such as pest species and field management methods may have affected the results. However, GeoDetector has proved effective in previous studies and our use of credible monitoring data and inclusion of the main factors affecting the growth system of crops made our data robust. We, therefore, believe that the study limitations do not negate the reliability of our results. In general, the present findings provide new insights into the impacts of environmental factors on winter wheat and offer scientific support for the development of food security policies in China.

5. Conclusions and policy implications

This study explored the influence of multiple environmental factors on winter wheat yield using quantitative analysis with the GeoDetector method. The results revealed that elevation and soil pH were the two most dominant factors, with discrepant influences from these factors on winter wheat yield at different growth stages. The interactions between air pollutants and all factors were significantly more powerful in explaining the variation in winter wheat yield than the influence of single factors. The main air pollutants affecting winter wheat yield during most growth stages were CO and SO_2, although their effects were greatest during the T-T stage. These findings not only contribute to our understanding of the relative importance of influencing factors on the yield of winter wheat, but also provide practical strategies for agricultural activities, crop models optimization, and the formulation of food security policy.

Wheat is the most important food crop in the world, and it plays a critical role in globe food security. Hence, a series of measures should be implemented to reduce the damage to wheat yield from air pollution. First, breeding efforts should consider the effects of air pollution on wheat to genetically increase its resistance to air pollution. Second, leaf protectants may be an effective way to guard against the damage from air pollutants to wheat plants, especially if they are sprayed extensively during the growth period when wheat is susceptible to air pollution (e.g. T-T stage). Third, and most feasibly, because wheat is planted over large areas and its varieties change in different planting regions, preventing and controlling air pollution in farmland is another important way to reduce the damage to wheat yield. Based upon our findings, the Chinese government should implement the stricter measures to protect air quality and winter wheat production, as follows. a) Strengthen air pollution prevention and control measures in major food producing areas, e.g., technological innovations for heavy polluting enterprises or new energy-saving and emission reduction mechanisms, that combine incentives with constraints, should be created to reduce emission intensities. b) Knowledge of measures to prevent and control air and soil pollution should be disseminated to farmers. For example, it is necessary to put an end to the burning of agricultural straw and the discharge of wastewater, waste gas, and other pollutants onto farmland. c) Stricter prevention and control measures should be implemented during the phenological periods in which crops are significantly affected by air pollution. For example, actions for traffic control and periodic closure of heavy polluting enterprises should be implemented in order to reduce CO and SO_2 emissions during the periods when they have the largest impact, such as stages S-E, T-T, B–H, and H-A. During the T-T stage, in which crops are more susceptible to air pollution, the control of industrial emission sources should be strengthened, and multiple measures should be taken to reduce the levels of SO_2 and other air pollutants. Most importantly, refined farmland soil attributes should be investigated, as soil is the most important factor affecting crop yield; this will provide more accurate data for studying the interaction between air pollution and soil factors.

Future studies should focus on the effects of CO and SO_2 and their interactions with other environmental factors on wheat yield. In addition, the impact of air pollution on crop quality, as important as crop yield, should be examined by researchers. More systematic experiments considering multiple air pollutants during different phenological periods will help to reveal the mechanisms of air pollution on crops. This will allow farmers not only to understand exactly what is affecting their crops, but also to make informed choices about what to grow. At the same time, crop models should be improved by taking into account the impacts of air pollution. The coupling of air quality models with crop models may be an important research direction in the future. This will provide scientific support for targeted air pollution control in agricultural areas and regional food security assessment work.

CRediT authorship contribution statement

Tianning Zhang: Conceptualization, Methodology, Software, Validation, Formal analysis, Writing – original draft, Resources, Visualization. **Hongquan Song:** Conceptualization, Methodology, Software, Data curation, Writing – review & editing, Funding acquisition. **Boyan Zhou:** Methodology, Investigation, Resources, Data curation. **Lei Wang:** Software, Resources, Data curation. **An Yang:** Resources, Data curation. **Tuanhui Wang:** Methodology, Resources. **Haijiang Kong:** Validation, Resources. **Youmin Chen:** Methodology, Software. **Shenghui Zhou:** Methodology, Software. **Shenglei Fu:** Formal analysis, Investigation, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2021.127230.

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