

We thank the reviewers for their valuable comments and suggestions to improve our manuscript. We have made revisions accordingly. The point-to-point responses are provided below in Italic. The comparison of our manuscript between this version and the previous version is also provided.

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Anonymous Referee #1:

This study explores the local and synoptic meteorological influences on summertime ozone variability in eastern China. The authors have used two different approaches, including MLR and SOM, and their MLR method includes the effects of synoptic
10 patterns. In general, I think this manuscript is well structured and the topic is suitable for ACP. The presentation quality is also very high. So I recommend publication in ACP after fixing only a few minor issues.

The reviewer's encouragement is much appreciated.

15 Minor comments.

L123. Please specify the value of d_{max} used in this study?

' d_{max} ' is specified as 1-degree distance in latitude-longitude grid. Please see Lines 132-133.

20 L283. It is worthwhile to mention the trends of anthropogenic emissions during this period. During the period of 2013-2017, the NO_x emissions have declined (Zheng et al., 2018) and the VOC emissions almost remain constant (Zheng et al., 2018; Shen et al., 2019).

Thanks. Added. See Lines 293-295.

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Line 299. The correlation of temperature with ozone is higher in the north than in the south. I guess this is because the temperature gradient along the latitude is much larger in the north than in the south. So the synoptic activities (or jet wind) in the

north can be well represented by temperature. But in the south, the marine flux into
30 the continent won't result much changes in temperature but will definitely elevate the
relative humidity. As a result, relative humidity displays much stronger correlation
with ozone in the south. However, I never found any paper that discusses about the
reason of this distinct north-south feature. Maybe the author can simply say like this.

35 The correlation of temperature with ozone is higher in the north than in the south over
eastern China (Figure 2c), which is consistent with the pattern found in the US
(Camalier et al., 2007; Shen et al., 2016).

Thanks. Revised following the reviewer's suggestions. Please see Lines 317-319.

40 Line 305. Relative humidity can also be a strong indicator of transport in the southern
China. So I won't use the words "mainly" here.

Thanks. Revised. Please see Lines 310-316.

Figure 5. I would strongly recommend using the leave-one-out cross validation to
45 avoid overfitting if the authors haven't done this.

*Thanks. We have used the leave-one-out cross validation in this revision. Please see
Lines 204-208.*

Figure 6. I don't know if there is a way to separate the effects of local meteorology
50 and synoptic patterns. They are so closely related. I would suggest deleting this figure
and also the text related.

*Thanks for the suggestion. We have deleted the comparison of the weight between
local meteorology and synoptic patterns and reserved the comparison between
different local meteorological variables in this revision.*

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Local and synoptic meteorological influences on daily variability of summertime surface ozone in eastern China

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65 Abstract

Ozone pollution in China is influenced by meteorological processes on multiple scales. Using multiple linear regression and weather classification, we statistically assess the impacts of local and synoptic meteorology on daily variability of surface ozone in eastern China in summer during 2013-2018. In this period, summertime surface ozone in eastern China (110-130°E, 20-42°N) is among the highest in the world with regional means of 73.1 and 114.7 $\mu\text{g m}^{-3}$, respectively, in daily mean and daily maximum 8-hour average. By developing a multiple linear regression (MLR) model driven by local and synoptic weather factors, we establish a quantitative linkage between the daily mean ozone concentrations and meteorology in the study region. The meteorology described by the MLR ~~model~~ can explain ~~~4643%~~ of the daily variability in summertime surface ozone across eastern China. ~~The model shows that synoptic factors contribute to ~37% of the overall meteorological effects on daily variability of surface ozone in eastern China.~~ Among local meteorological factors, relative humidity is the most influential variable in the center and south of eastern China including the Yangtze River Delta and the Pearl River Delta regions, while temperature is the most influential variable in the north covering the Beijing-Tianjin-Hebei region. To further examine the synoptic influence of weather conditions

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explicitly, six predominant synoptic weather patterns (SWPs) over eastern China in summer are objectively identified using the self-organizing map clustering technique.

85 The six SWPs are formed under the integral influence of the East Asian summer monsoon, the western Pacific subtropical high, the Meiyu front, and the typhoon activities. ~~The results show that~~ On regional mean, two SWPs bring about positive ozone anomalies ($1.1 \mu\text{g m}^{-3}$ or 1.7% and $2.7 \mu\text{g m}^{-3}$ or 4.6%, respectively), when eastern China is under a weak cyclone system or under ~~the impacts of each of~~
90 ~~the prevailing southerly wind. The impact of~~ SWPs on the daily variability of surface ozone ~~vary~~ varies largely ~~inside the study area within eastern China.~~ The maximum impact can reach $\pm 8 \mu\text{g m}^{-3}$ or $\pm 16\%$ of the daily mean ~~over~~ in some ~~subregions in eastern China~~ areas. A combination of the regression and the clustering approaches suggests a strong performance of the MLR ~~model~~ in predicting the sensitivity of
95 surface ozone in eastern China to the variation of synoptic weather. Our assessment highlights the important role of meteorology in modulating ozone pollution over China.

1 Introduction

100 Surface ozone is a major air pollutant detrimental to human health ([Jerrett et al., 2009](#)) and vegetation growth (Yue et al., 2017). Ozone exposures are estimated to be associated with ~~near~~ over ~~0.32~~ million premature deaths globally in one year (Cohen et al., 2017; Liang et al., 2018). The dominant source of surface ozone is the photochemical oxidation of volatile organic compounds (VOCs) and carbon
105 monoxide (CO) in the presence of nitrogen oxides (NO_x) (Monks et al., 2015). In the ~~past~~ recent decades, China has been suffering from severe ozone pollution, causing a worldwide concern (Verstraeten et al., 2015). High ozone concentrations exceeding China national air quality standard (200 and $160 \mu\text{g m}^{-3}$, respectively, for hourly and 8-hourly maximum values) occur frequently in major Chinese cities in the three most
110 developed regions, the Beijing-Tianjin-Hebei (BTH) region (T. Wang et al., 2006a; G.

Li et al., 2017), the Yangtze River Delta (YRD) (Shu et al., 2016, 2019), and the Pearl River Delta (PRD) (Y. Wang et al., 2017; H. Wang et al., 2018). An increasing trend of 1-3% per year in surface ozone since 2000 is observed at urban and regional background sites in the three city clusters (Y. Wang et al., 2012; Zhang et al., 2014; 115 Ma et al., 2016; Sun et al., 2016; Gao et al., 2017) and at a global baseline station in western China (Xu et al., 2016).

Surface ozone concentrations in China largely depend on emissions and meteorology (Han et al., 2018a, 2019); [Lu et al., 2019a](#)). Anthropogenic and natural 120 emissions from both native and foreign sources provide precursors for the formation of high ozone levels in China ([Ni et al., 2018](#); Han et al., 2019), while meteorology can influence surface ozone variations from instantaneous to decadal scale through its modulation of various chemical and physical processes (T. Wang et al., 2017). On a decadal scale, both observations (Zhou et al., 2013) and simulations (S. Li et al., 125 2018) show that surface ozone in southern China correlates positively to the strength of the East Asian summer monsoon (EASM).

The daily variation of surface ozone in China is sensitive to synoptic weather systems, as illustrated by studies for BTH (Zhang et al., 2012; Huang et al., 2015), 130 YRD (Shu et al., 2016, 2019), PRD (Zhang et al., 2013; Jiang et al., 2015), and other regions of China (Tan et al., 2018). Frontal systems can drive the transboundary transport of ozone in northern China (Ding et al., 2015; Dufour et al., ~~2016~~2015). Downdrafts in the periphery circulation of a typhoon system can strongly enhance surface ozone before the typhoon landing in eastern or southern China (Jiang et al., 135 2015; Shu et al., 2016). Zhao and Wang (2017) suggested that a stronger western Pacific subtropical high (WPSH) can lead to lower surface ozone concentration over southern China and higher one over northern China in summer. Moreover, surface ozone concentrations also vary with mesoscale weather systems in hours (Hu et al.,

2018), such as the mountain-valley circulation (T. Wang et al., 2006b) and the land-sea breezes (H. Wang et al., 2018). Despite ~~the valuable~~these discussed mechanisms ~~of~~on how weather systems ~~mentioned above influences~~influence ozone concentrations in China ~~reported by previous studies, quantified ozone anomalies resulted from these~~, there is a lack of quantitative assessments on the influences of these weather systems are lacked on ozone pollution.

Weather systems ~~at~~on different scales bring about different changes in local meteorological variables ~~and thus surface ozone through their impacts on, which, in turn, impact~~ chemistry and physical processes ~~that modulate surface ozone concentrations~~. However, the relative importance of ~~various~~local meteorological factors to surface ozone ~~concentrations in~~in different regions of China are still unclear. Previous studies suggested the importance of temperature, relative humidity, and winds to surface ozone in different regions (Lou et al., 2015; Pu et al., 2017; Zhan et al., 2018). The key influential meteorological factors vary from ~~cities~~region to ~~cities in China~~region (Gong et al., 2018; Chen et al., 2019). In general, high ozone episodes commonly appear under weak wind, high temperature, low humidity, and clear conditions ~~;~~ (Bloomfield et al., 1996; Zanis et al., 2000, 2011; Ordóñez et al., 2005). These weather conditions can enhance stagnation and production of ozone (Camalier et al., 2007; Shen et al., 2017a). Variations of these local meteorological variables depend on the dominant weather systems (Davis et al., 1998; Han et al., 2018b; Leung et al., 2018).

To have a comprehensive and quantitative understanding of how weather influences ozone pollution in China is the primary motivation of this study, in which, we aim to quantify the impacts of meteorology, specifically the dominant synoptic weather systems and the key local meteorological variables, on daily variations of surface ozone in eastern China, including ~~the~~ three representative megacity clusters, BTH,

YRD, and PRD. Surface ozone in China was not regularly and systematically monitored until 2012 when real-time hourly ozone data were available online from China Ministry of Ecology and Environment (MEE) (<http://www.mee.gov.cn/>) (T. Wang et al., 2017). ~~Owing to the limitation of in situ measurement, there is a lack of a long-term assessment on the synoptic influence on ozone pollution.~~

~~The~~In this study, the ground ozone observations from MEE covering 2013-2018 period are used. First, we characterize the seasonal variations of surface ozone in eastern China and the interannual changes during 2013-2018 in summer (June-August), which is the season of interest in this study. Second, we search for a linkage between the daily variation of surface ozone and the local and synoptic meteorological factors statistically and develop a multiple linear regression (MLR) model based on the linkage. Third, we examine the sensitivity of daily surface ozone to the variation in synoptic weather systems. Considering the complexity of the synoptic meteorology in eastern China (Ding et al., 2017; Han et al., 2018b), we employ an objective clustering technique, the self-organizing map (SOM), to identify the predominant synoptic weather patterns (SWPs). In the following sections, we introduce the data and methods in section 2. The seasonal and interannual variations of surface ozone in eastern China are characterized in section 3. Section 4 illustrates the linkage between ozone variability and meteorology on both local and synoptic scales, while section 5 describes sensitivity of surface ozone to various typical SWPs over the entire eastern China. Finally, we discuss our results and draw conclusions in section 6.

2 Data and methods

2.1 Surface ozone observations and meteorological data

Hourly surface ozone measurements from the MEE observation network averaged over the stations in each city were used in the study. The measurements were

195 downloaded from <http://beijingair.sinaapp.com/>, which were previously archived at
200 <http://pm25.in>, a mirror of data from the official MEE publishing platform
(<http://106.37.208.233:20035/>). The network covers 63 cities in eastern China (110-
130°E, 20-42°N) in 2013, increasing to 118 in 2014 and 185 during 2015-2018.
Locations of the 185 cities are shown in Figure 1, including 13, 26, and 9 cities,
respectively, in BTH, YRD, and PRD. The unit of ozone concentrations in the original
records and in this study is ‘ $\mu\text{g m}^{-3}$ ’, with a conversion factor of $1 \mu\text{g m}^{-3} = 0.47 \text{ ppbv}$
at 273 K and 1013.25 hPa.

The National Centers for Environmental Prediction (NCEP) Final (FNL)
205 Operational global analysis data during the same period were acquired from
<https://rda.ucar.edu/datasets/ds083.2/>. The data are available on $1^\circ \times 1^\circ$ latitude grids
every 6 hours ~~for~~at the surface and at 26 layers from 1000 to 10 hPa. We made daily
averaged pollution and meteorological data in summer from 2013 to 2018. The ozone-
weather relationship is examined using the daily mean data, unless stated otherwise.

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Using an inverse-distance weighting (Tai et al., 2010), we interpolated the daily
citypollution measurements from the cities onto the FNL grid (1° latitude and $\times 1^\circ$
longitude) to produce continuous gridded data. Ozone at each FNL grid was
calculated with a weighted average of the concentration in the cities within a search
215 distance (d_{max}) from that grid, following the equation:

$$z_j = \frac{\sum_{i=1}^{n_j} (1/d_{i,j})^k z_i}{\sum_{i=1}^{n_j} (1/d_{i,j})^k} \quad (1)$$

where z_j is the calculated ozone at grid j , z_i is the observed ozone in city i , $d_{i,j}$ is the
distance between city i and the center of grid j , n_j is the number of the cities within
 d_{max} from grid j ($d_{i,j} \leq d_{max}$), k is a parameter measuring the influence of distance on
220 the target grid. We used 2 for k , and 1-degree distance in latitude-longitude grid for
 d_{max} in the interpolation. The generated gridded ozone data cover most of the
mainland in eastern China (Figure 1c). The measurements interpolated to the grids

were used in this study, unless stated otherwise.

225 2.2 Development of a prediction model of surface ozone

MLR is an effective and widely-used way to describe the relationship between meteorology and air quality and thus to help prediction of air quality (Shen et al., 2015; Otero et al., 2016; K. Li et al., 2019). MLR establishes a linear function between a scalar response and the explanatory variables. In this study, we applied a
230 stepwise MLR ~~model~~ to quantitatively correlate daily surface ozone ~~in eastern China~~ and meteorology in summer. Considering the combined effect of meteorology at various scales, we used both local meteorological variables and synoptic circulation factors as predictors following Shen et al. (2017b), who showed that, comparing with regression models only considering local meteorology, adding the synoptic factors in
235 a MLR can significantly improve the model performance. The MLR ~~model~~ takes the following form:

$$\hat{Y} = b + \sum_{i=1}^{K_1} \alpha_i X_i + \sum_{j=1}^{K_2} \beta_j S_j \quad (2)$$

where \hat{Y} is the predicted value of surface ozone, b is the intercept term, X_i is the local meteorological variables with a total number of K_1 , S_j is the synoptic meteorological
240 factors with a total number of K_2 , and α_i and β_j are the regression coefficients. We used 10 local meteorological variables ($K_1=10$), ~~i.e., including~~ relative humidity at 2 m (RH2m), cloud fraction (CF), temperature at 2 m (T2m), planetary boundary layer height (PBLH), zonal wind at 850 hPa (U850), meridional wind at 850 hPa (V850), vertical wind at 850 hPa (W850), wind speed at 850 hPa (WS850), geopotential
245 height at 850 hPa (HGT850), and sea level pressure (SLP), all of which were identified significantly ($p < 0.05$) correlated to the daily variations of surface ozone in part of eastern China, as shown in Figure 2. Cloud fraction retrievals at $1^\circ \times 1^\circ$ grids were from the spaceborne Atmospheric Infrared Sounder (AIRS) instrument (AIRS3STD daily product, <https://disc.gsfc.nasa.gov/>). The other 9 local meteorology
250 were from FNL data (section 2.1). We computed the anomalies of meteorological

variables and ozone on a given day by taking the difference between the value of a given meteorological variable (or ozone) on that day and the mean value of the meteorological variable (or ozone) in that month. Thus, all the data were detrended and the influences of meteorology on the ozone variability on longer time scales (trends, and annual and seasonal variations) were generally removed. Any anomaly of a variable (or ozone) divided by its corresponding monthly mean is referred as relative anomaly of that variable (or ozone) with a unit of %.

WeFor S_j in equation (2), we also usedidentified two synoptic factors generatedfromthrough the singular value decomposition (SVD) of the spatial correlations between surface ozone and local meteorological variables in eastern China (Shen et al., 2017b). The SVD approach effectively extracted representative signals from the spatial distribution of the correlation coefficients. The extracted information was then used to characterize the spatial patterns of the meteorological variables aton a synoptic scale by inverting SVD. For each of the FNL grids in eastern China, we constructed the synoptic circulation factors as follows. First, we calculated the correlation coefficients between daily mean surface ozone at thatagiven grid and each of the 10 meteorological variables at all the grids in eastern China in summer during 2013-2018. For example, the correlations for the grid of Nanjing are shown in Figure S1, which indicates that surface ozone in Nanjing is correlated to the meteorology in the surrounding regions. We made a matrix A that consists of the correlation coefficients for that grid with elements of 21 (numbers of grids in longitude) \times 23 (numbers of grids in latitude) \times 10 (numbers of the local meteorological variables). Second, to fit the decomposition, we aligned the dimension of longitude-latitude into one column and reshaped matrix A into a 483 (longitude \times latitude) \times 10 two-dimensional matrix F . The SVD decomposed F used the equation:

$$F=ULV^T \quad (3)$$

where U is 483 \times 10 matrix, L is a 10 \times 10 diagonal matrix with non-negative numbers

on the diagonal, V is also a 10×10 matrix. The columns of the three transformations
 280 together characterize SVD modes, with 10 modes in total. Each column of U
 represents the spatial weights of the SVD mode and each column of V represents the
 variable weights in the SVD mode. The spatial and variable weights of the first two
 SVD modes for the Nanjing grid are shown in Figure S2. The pattern of the spatial
 weight of the first SVD mode for the Nanjing grid (Figure S2a) is similar to the
 285 pattern of the correlations between surface ozone and relative humidity (Figure S1a)
 and cloud fraction (Figure S1b). The first SVD mode is more correlated to relative
 humidity and cloud fraction than other variables (Figure S2b). Therefore, the first
 SVD mode for the Nanjing grid is related to chemical processes of ozone. In contrast,
 the second SVD mode for the Nanjing grid is more related to transport than chemical
 290 processes (Figure S2d). Third, we assigned the anomalies of the daily mean values of
 the 10 local meteorological variables in eastern China to a 552 (days in summer of
 2013-2018) $\times 21$ (longitude) $\times 23$ (latitude) $\times 10$ (meteorology) four-dimensional matrix
 M . At each grid, we normalized the time series of each variable to zero mean and unit
 standard deviation. Then, the magnitude of each SVD mode for every day t was
 295 calculated by inverting SVD:

$$S_{k,t} = U_k^T M_t V_k \quad (4)$$

where U_k and V_k ~~respectively~~ are the k^{th} columns of U and V , respectively. $S_{k,t}$ is a
 scalar depicting the magnitude of the k^{th} SVD mode. $S_{k,t}$ refers to a newly produced
 meteorological field ~~and reflects that represents~~ the influence of synoptic ~~factors~~
 300 ~~related to meteorology on~~ ozone variability. We implemented the procedure at every-
~~FNL~~ grid in eastern China. The first two SVD modes can generally explain 55-85% of
 the total variance. They can respectively reflect the dynamical or thermal
 characteristics ~~in the of~~ synoptic meteorology (Shen et al., 2017b). Therefore, we
 applied the primary two SVD modes in the MLR ~~model~~ ($K_2=2$).

305 We used the leave-one-out cross validation to avoid overfitting of the MLR for each

310 grid. Data during the study period (summer over 2013-2018) included 552-day observations. Each time, one observation in the time series was reserved as the test set and the remaining ones were used as the training set. The process was repeated until all observations had been predicted. Every observation was to be a test set once and a training set 551 times.

We measured the relative importance of each of the meteorological variables to ozone by its relative contributions to the total explained variance of the MLR ~~model~~.

315 The weight of each predictor (w_i) was calculated from the normalized MLR coefficient (z_k):

$$w_i = \frac{z_k^2}{\sum_{k=1}^{12} z_k^2} \quad (5)$$

where z_k is:

$$z_k = \frac{s_k}{s_y} c_k \quad (6)$$

320 and ~~12 is~~ the number of all the predictors is 12, including 10 local and 2 synoptic meteorological factors (section 2.2). c_k is the regression coefficient, referring to α_i or β_j in equation (2). s_k is the standard deviation of a predictor, i.e., X_i or S_j in equation (2). s_y is the standard deviation of the observed daily surface ozone.

325 **2.3 Classification of the synoptic weather patterns**

Weather classification is a well-established tool to characterize atmospheric processes at on multiple scales and further to study air pollution-weather relationship (Han et al., 2018b). The methods for weather classification can be generally categorized into three groups: subjective, mixed, and objective, depending on the automatic degree during the classification process (Huth et al., 2008). The methods can also be categorized in 330 more detail according to the basic features of each classification algorithm (Philipp et al., 2014). Depending on the study domain and research objectives, different meteorological variables including geopotential height, mean sea level pressure, and

zonal and meridional winds are used for the classification.

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SOM, an artificial neural network method with unsupervised learning (Kohonen, 1990; Michaelides et al., 2007), is widely used in cluster analysis in atmospheric sciences (Jiang et al., 2017; Liao et al., 2018; Stauffer et al., 2018) because of its superiorities over other algorithms (Liu et al., 2006; Jensen et al., 2012). SOM performs a nonlinear projection from the input data space to a two-dimensional array of nodes objectively. Each node is representative of the input data. SOM allows missing values in the input data and can effectively visualize the relationships between different output nodes (Hewitson and Crane, 2002).

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The FNL geopotential height fields (section 2.1) at 850 hPa can well capture the synoptic circulation variations over eastern China (Han et al., 2018b). In this study, we used geopotential height at 850 hPa in 2013-2018 as the input for SOM. Each of the SOM output nodes corresponds to a cluster of SWPs. Finally, we identified six predominant SWPs over eastern China in summer. All days in summer of 2013-2018 were included in the clustering results.

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3 Seasonal and interannual variations of surface ozone in eastern China

Figure 3 and Figure 4, respectively, show the seasonal and interannual variations of the regional mean surface ozone concentrations in eastern China and the three subregions (BTH, YRD, and PRD) during 2013-2018. Among n cities with air quality monitoring in a given region, if ozone levels exceed the national air quality standard in m cities, we defined the ratio of m to n as the regional exceedance probability of ozone (Figure 3c). Higher regional exceedance probability implies ozone pollution over wider surface areas in that region. Primary pollutant (Figure 3d) is defined in the Air Quality Index (AQI) system, in which, AQI for an individual air pollutant is calculated based on the concentrations of ~~the~~that pollutant. When the individual AQI

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of a pollutant on a day is both above 50 and the largest among all the pollutants ~~on~~
that ~~day this~~ pollutant is defined as the primary pollutant on that day.

365 On ~~the~~ regional average, the seasonality of daily mean ozone is similar to that of
daily maximum 8-hour average (MDA8) ozone in eastern China, as well as in the
three subregions (BTH, YRD, and PRD) (Figures 3a and 3b). In BTH, both daily
mean and MDA8 have a unimodal seasonal pattern and peak in June, being 99.5 and
158.4 $\mu\text{g m}^{-3}$, respectively. The extremely high ozone in June leads to a simultaneous
370 seasonal maximum in both probability of the regional exceedance (46.9% of the cities
with ozone measurements in BTH) and primary pollutant (68.7% of the days in June)
(Figures 3c and 3d). The seasonal peak of surface ozone in BTH mainly results from
enhanced photochemistry due to stronger solar radiation and lower humidity (Hou et
al., 2014). Surface ozone over YRD reaches a seasonal maximum in May (82.6 and
375 127.7 $\mu\text{g m}^{-3}$, respectively, for daily mean and MDA8 ozone), earlier than that over
BTH. While the seasonal peak over PRD occurs the latest in October (71.5 and 118.1
 $\mu\text{g m}^{-3}$, respectively, for daily mean and MDA8 ozone). Although ~~the~~ temperature is
higher in summer than in the other seasons, the EASM brings more cloudy weather,
stronger convection, and clearer air from the oceans, weakening the production and
380 accumulation of surface ozone over YRD and PRD (Hou et al., 2015; S. Li et al.,
2018). The pre-monsoon and post-monsoon peak of surface ozone were also found in
YRD and PRD, respectively (He et al., 2008; T. Wang et al., 2009).

On ~~the~~ regional and seasonal ~~average~~averages, daily mean and MDA8 ozone over
385 eastern China in summer are 73.1 and 114.7 $\mu\text{g m}^{-3}$, respectively. Among the three
~~city clusters~~subregions, summertime surface ozone is highest in BTH (88.3 and 143.7
 $\mu\text{g m}^{-3}$, respectively, for daily mean and MDA8 ozone), second highest in YRD (72.9
and 114.7 $\mu\text{g m}^{-3}$), and lowest in PRD (51.0 and 91.9 $\mu\text{g m}^{-3}$) (Figures 3a and 3b).
These regional differences among the three ~~city clusters~~subregions appear similar to

390 these in the Ozone Monitoring Instrument (OMI) tropospheric column ozone (Figure
1). The regional exceedance probability of ozone over eastern China reaches 17.7% in
summer, accompanied with a high percentage (45.6%) of ozone being the primary
pollutant. Among the three subregions, BTH has the highest regional exceedance
probability of ozone (35.1%) and ~~the~~ probability of ozone being the primary pollutant
395 ~~(55.8%) are largest in BTH.%).~~

A rapid increasing trend in summertime surface ozone over China after 2012 was
observed in recent studies (Lu et al., 2018; Silver et al., 2018; Shen et al., ~~2019~~2019a;
K. Li et al., 2019). We examine the regional mean ~~trend~~trends over eastern China in
400 daily, daytime (7:00-18:00), and nighttime (19:00-6:00) means (Figure 4). Significant
~~(p<0.05)~~ summer increasing trends (p<0.05) of approximately 3-6 $\mu\text{g m}^{-3}$ or 4-8% per
year are found over eastern China, BTH, and YRD during 2013-2018, while the
increasing trend over PRD during the period is insignificant ($p>0.05$). Silver et al.
(2018) found the annual mean MDA8 ozone ~~has~~ increased significantly ($p<0.05$) at
405 ~~around~~ ~50% of the over 1000 stations across China from 2015 to 2017, with a
median rate of 4.6 $\mu\text{g m}^{-3} \text{ year}^{-1}$. The increasing trend over eastern China was also
captured by the OMI satellite records of tropospheric ozone, reported by Shen et al.
(~~2019~~2019a). The absolute increasing trend (in ~~a unit of~~ $\mu\text{g m}^{-3}$) in daytime is higher
than that in nighttime, whereas the relative increasing trend (in ~~a unit of~~ %) in daytime
410 is lower than that in nighttime (Figures 4e-4h vs. Figures 4i-4l). The increasing ozone
trend over China may result from both meteorology and anthropogenic emissions.
During 2013-2017, the anthropogenic emissions of NO_x in China declined (Zheng et
al., 2018) but the anthropogenic emissions of VOCs changed little (Zheng et al., 2018;
Shen et al., 2019b). K. Li et al. (2019) suggested the ~40% decrease of fine particulate
415 matter ($\text{PM}_{2.5}$) is the primary reason for the increasing trend of surface ozone in
summer during 2013-2017, as the aerosol sink of hydroperoxy radicals was weakened
and thus ozone production was enhanced. Figure 44b demonstrates a strong increase

in summertime surface ozone over BTH from 2016 to 2017, which is probably related to the hot extremes in 2017 (Herring et al., 2019). The sudden decline in summertime surface ozone over PRD from 2016 to 2017 (Figure 4d) is likely associated with the extremely heavy precipitation in 2017 (Herring et al., 2019).

4 Meteorological drivers for summertime surface ozone in eastern China

Meteorological factors can individually or integrally modulate surface ozone concentration through their impacts on relevant chemical, dynamical, and thermal processes in the atmosphere. Figure 2 shows a simple way to examine the overall effect of each of the meteorological variables statistically by correlating surface ozone with a selected set- of local meteorological variables during 2013-2018 summer.

Among all the meteorological variables, relative humidity shows the highest correlation with surface ozone in eastern China on regional mean- ($r=-0.39$). Relative humidity can influence ozone through various processes. Atmospheric water vapor can directly influence ozone concentrations by HO_x (HO_x=OH+H+peroxy radicals) chemistry in complicated ways (Zanis et al., 2002; Jacob et al., 2009; Lu et al., 2019b). Moreover, a higher relative humidity is usually associated with more fractions of clouds, which can slow the photochemical production of surface ozone. Higher relative humidity may also somewhat be linked with larger atmospheric instability, favoring the dispersion of surface ozone (Camalier et al., 2007). The correlation map of cloud fraction is similar to that of relative humidity (Figures 2a and 2b). The correlation of temperature with ozone is higher in the north than in the south over eastern China (Figure 2c), which ~~may due~~ is similar to lower humidity in the north. pattern found in the eastern United States (Camalier et al., 2007; Shen et al., 2016). Meridional wind at 850 hPa is ~~positively~~ positively correlated to surface ozone positively in the north but negatively in the most areas of the south (Figure 2f). In summer, the south-westerly monsoon wind prevails over eastern China (Figure S3). Higher meridional wind brings clean and humid marine air to the south, while it transports

ozone and its precursors from the south to the north. All the meteorological variables are not independent with each other. ~~For example, relative humidity is strongly correlated with cloud fraction. A higher relative humidity is usually associated with more fractions of clouds, which can slow the photochemical production of surface ozone. The impacts of relative humidity on surface ozone are mainly through the chemical processes. In addition, higher relative humidity may somewhat be linked with larger atmospheric instability, favoring the dispersion of surface ozone (Camalier et al., 2007).~~ Overall, the meteorological variables that are related to photochemistry processes (relative humidity, cloud fraction, and temperature) have more significant correlation than transport-related variables (zonal, meridional, and vertical winds and wind speed) (Figure 2), implying greater effects of chemical process than physical transport. S. Li et al. (2018) also suggested the chemical process is the uppermost factor controlling surface ozone levels over eastern China in summer.

Combining the effects of different meteorological variables, we applied the MLR ~~model (section 2.2)~~ using predictors of both local and synoptic factors (~~section 2.2~~) to simulate summertime daily surface ozone in eastern China. The MLR ~~model~~ was ~~developed using the observation data in 2013-2017 and~~ evaluated ~~with observation data in 2018, using the leave-one-out cross validation to avoid overfitting.~~ The MLR ~~model~~ performs strongly as it can explain ~~3014~~-65% variations in the observed surface ozone concentrations ~~in 2013-2017~~, yielding a regional mean coefficient of determination (R^2) of ~~4643~~% (Figure ~~5e~~).~~5a~~). ~~The mean absolute error (MAE) and the root mean square error (RMSE) of regional mean ozone anomalies in eastern China between observations and predictions by the MLR are 12.0 and 7.1 $\mu\text{g m}^{-3}$, respectively (Figure 6a).~~ Geographically, the model performs better in the south ($R^2=0.5251$ in YRD and $R^2=0.5449$ in PRD) than in the north ($R^2=0.4442$ in BTH) (Figure ~~5e~~). ~~In the validation period, the model also shows strong performance ($R^2=0.38$ in eastern China) (Figure 5d). Moreover, we simulated surface ozone-~~

475 ~~considering~~5a). Compared with the simulation that only ~~considers~~ the local
meteorological variables (Figure 5a) and only the synoptic factors (Figure 5b) in the
MLR ~~model~~. Compared with the two simulations (Figures 5a and 5b),² the model
performance is overall improved in ~~areas in~~ eastern China when both local and
synoptic ~~meteorological~~ factors are considered (Figure 5eFigures 5a vs. 5b). Shen et
al. (2017b) found that, compared with ~~the~~ MLR ~~model describing that describes~~
480 monthly PM_{2.5} in the United States ~~driven by only the~~using local
~~meteorology~~meteorological factors, the inclusion of ~~the~~synoptic ~~meteorological~~
factors in the MLR ~~model~~increases R² from 34% to 43%. ~~In addition, we~~ We also
conducted the stepwise MLR ~~model~~ using local and synoptic meteorology without
detrending the input data. The results show that meteorology can explain ~~39~~18% of
485 the increasing trend in the regional mean of summertime surface ozone over eastern
China from 2013 to 2018, and the explained variance is ~~23%, 53~~16%, 41%, and
~~57~~44% for BTH, YRD, and PRD, respectively (Figure ~~S3~~S4).

490 We applied the MLR ~~model~~ to identify the dominant meteorological drivers for
ozone variability (section 2.2). ~~Synoptic factors diagnosed by SVD are the most~~
~~pronounced drivers in ~45% areas of eastern China and contribute to 30–60% of the~~
~~meteorological effects on surface ozone over these locations (Figure 6b). The regional~~
~~mean contributions of the synoptic factors are 37% over eastern China and 41% over~~
~~BTH, YRD, and PRD (Figure 6b). Among the local meteorology, relative humidity is~~
495 dominant over ~~~48~~51% areas of eastern China, mainly in the central and the southern
regions including YRD and PRD (Figure 6e). ~~Relative humidity is estimated to~~
~~account for ~30% of the meteorological impacts on daily surface ozone variation in~~
~~YRD and PRD on the regional scale (Figures 7c and 7d), although at~~5c), ~~although on~~
a city scale in PRD, Zhao et al. (2016) suggested that sea level pressure is the most
500 significant variable for MDA8 ozone in Hong Kong. Air temperature is the most
important local meteorological variable in ~~~15~~17% areas of eastern China,

specifically in the north including BTH (Figure 6e). ~~Temperature is estimated to account for 20% of the meteorological impact in BTH (Figure 7b5c).~~ The importance of temperature to surface ozone over BTH was also suggested by Chen et al. (2019).

505 Previous studies found that temperature and relative humidity showed pronounced impact on ozone in the north and south of the eastern ~~US~~ United States, respectively (Camalier et al., 2007; Porter et al., 2015). The difference of the most influential variables between the south and north in eastern China is similar to that in the eastern United States. In Europe, Otero et al. (2016) suggested that temperature is the most
510 important local meteorological driver over a major part of Europe. On regional average, the second most important meteorological variable for the daily surface ozone variation in eastern China, BTH, YRD, and PRD is temperature, relative humidity, geopotential height at 850 hPa, sea level pressure, and meridional wind at 850 hPa, respectively (Figure 76).

515

5 Synoptic impacts on summertime surface ozone in eastern China

In the last section, we have shown that both local and synoptic meteorological factors are important ~~for~~to surface ozone variations in eastern China. The synoptic factors used there were extracted via an inverting SVD process and do not stand for specific
520 weather systems. In this section, we ~~will~~ further ~~show~~invest how ~~the specified~~different synoptic weather systems influence surface ozone in eastern China by looking into the typical SWPs. Atmospheric circulations over eastern China in summer are largely regulated by the evolution of the components of EASM, for instance, the ~~western~~ Pacific subtropical high (WPSH), WPSH, the subtropical westerly jet, the Meiyu front,
525 and the Southwest Vortex (Ding and Chan, 2005). Among these systems, the WPSH can largely modulate the seasonal migration of the rain belt over eastern China. Typhoon is also an influential weather system, especially on the southeast coastal regions. The main features of the synoptic circulations over eastern China during 2013-2018 can be represented by six predominant SWPs (Figures ~~8-13~~7-12), which

530 were identified by an objective approach, SOM (section 2.3). The occurrence
frequency of these SWPs is shown in Figures [8-137-12](#). We name the six SWPs by
their dominant weather systems or prevailing wind, including Pattern 1 featured
southwesterly wind (P1 or PSW), Pattern 2 featured Southerly wind (P2 or PS),
Pattern 3 featured Northeast Cold Vortex (P3 or PNECV), Pattern 4 featured a weak
535 cyclone (P4 or PWC), Pattern 5 featured strong WPSH (P5 or PSWPSH), and Pattern
6 featured typhoon systems (P6 or PTC) (Table 1).

To compare the differences of meteorological conditions among the six SWPs, we
calculated the daily EASM index (EASMI) and WPSH index (WPSHI) representing
540 the strength of EASM and WPSH respectively. The two indexes were normalized to
zero mean and unit standard deviation. The averaged anomalies of the normalized
indexes under each SWP are shown in Figures [8-137-12](#) and Table 1. The EASMI is a
shear vorticity index defined as the difference of the regional mean zonal wind at 850
hPa between 5-15°N, 90-130°E and 22.5-32.5°N, 110-140°E in B. Wang and Fan
545 (1999) recommended by B. Wang et al. (2008). The WPSHI is defined by the
accumulative enhancement of geopotential height above the WPSH characteristic
isoline (5880 gpm at 500 hPa) averaged over the area north to 10°N. The WPSHI is
adopted by the National Climate Center in China (<https://cmdp.ncc-cma.net>) in the
monitoring and diagnosis of the atmospheric circulation. Using the WPSHI, Zhao and
550 Wang (2017) found a significant correlation between the WPSH and the first
empirical orthogonal function (EOF) pattern of surface ozone in China. Moreover, we
used the averaged anomalies of the meteorological variables in a SWP to describe that
SWP. We used the averaged ozone anomaly (in $\mu\text{g m}^{-3}$) (Figures [8-137-12](#)) and the
averaged relative ozone anomaly (the ozone anomaly divided by the monthly ozone
555 mean, in %) ([Table 1 and Figure 14S5](#)) under a SWP to assess the influence of that
SWP on ozone (Han et al., 2018b). Furthermore, a common index for air stagnation
(Horton et al., 2012) is used to assess the impact of air stagnation on surface ozone.

560 For each FNL grid, when the daily average wind speed at 10 m, daily average wind speed at 500 hPa, and the daily total precipitation on a day are respectively less than 3.2 m s⁻¹, 13 m s⁻¹, and 1 mm, the day is considered as a stagnant day ~~for~~at that grid.

The National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center (CPC) precipitation data

(<https://www.esrl.noaa.gov/psd/data/gridded/data.cpc.globalprecip.html>) were used in the calculation of the air stagnation index.

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The characteristics of the six SWPs and their impacts on surface ozone are briefly summarized in Table 1. PSW (P1) is the most common circulation pattern occurring in 25% days of summer during 2013-2019 (Figure [8b7b](#)). Characterized with weak EASM conditions, PSW is dominated by an anomalous anticyclone located in the southeast of eastern China (Figure [8e7e](#)). In PSW, the enhanced meridional wind brings clear marine air to the south of eastern China (Figure [8j7j](#)), where the meridional wind is significantly correlated to surface ozone (Figure 2f). The enhanced zonal wind from the anomalous anticyclonic circulation (Figure [8e7e](#)) increases the ozone export from the south of eastern China (Yang et al., 2014). The negative anomalies of temperature (Figure [8g7g](#)), and positive anomalies of relative humidity (Figure [8f7f](#)) and cloud fraction (Figure [8h7h](#)) in the south are all unfavorable for photochemical processes. In consequence, PSW reduces ozone levels in the south (Figure [8e7c](#)) by enhancing the dispersion and suppressing the production of ozone. Negative anomalies of -1.5 (-2.4%) and -6.6 µg m⁻³ (-13%) in the regional mean ozone are ~~respectively~~ observed over YRD and PRD (~~Figures 8e, respectively (Figure 7c and 14aTable 1)~~). In contrast, the lower cloud fraction (Figure [8h7h](#)) and higher temperature (Figure [8g7g](#)) in the north stimulate ozone production. Surface ozone over BTH increases by 3.4 µg m⁻³ (3.6%) from the regional mean in PSW (~~Figures 8eFigure 7c and 14aTable 1~~).

585

PS (P2) is the second frequent SWP (Figure 9b8b), characterized with strong EASM and weak WPSH (Figure 9a). In 8a). Under PS, the FNL meteorological data illustrates show frequent stagnation events (Figure 9181), low humidity (Figure 9f8f), and low cloud fraction (Figure 8h) over most of eastern China. In contrast to PSW, the zonal wind has negative anomalies (Figure 9e8e) in PS, reducing ozone export from the south of eastern China. Overall, an increase of $1.1 \mu\text{g m}^{-3}$ (1.7%) in the regional mean ozone concentrations is resulted in eastern China is observed in under PS (Figures 9eFigure 8c and 14bTable 1).

PNECV (P3) is a typical pattern for Meiyu, an important climate phenomenon over the middle and lower reaches of the Yangtze River during from early June to mid-July (Figure 10a,9a). PNECV is characterized by persistent rainfall (Ding and Chan, 2005). Under a combined effect of the Northeast Cold Vortex and the WPSH, Meiyu front forms and maintains over YRD (He et al., 2007). Meiyu in PNECV increases relative humidity (Figure 10f9f) and decreases air stagnation (Figure 10i9i) over YRD. Consequently, PNECV reduces surface ozone concentrations by $1.3 \mu\text{g m}^{-3}$ (1.7%) over YRD (Figures 10eFigure 9c and 14eTable 1). Meantime, more sunny days with high temperature (Figure 10g9g) and low moisture (Figure 10f9f) occur in the north to YRD, affected by the northwesterly and downward airflows from the Northeast Cold Vortex (Figure 10a9a). As a result, positive ozone anomalies are observed in the regions north of YRD (Figure 10e9c).

PWC (P4) features the weakest WPSH, when a weak extratropical cyclone locates over the east of the mainland China (Figure 11a10a). The extratropical cyclone is probably formed by the an eastward movement of the Southwest Vortex or the a transition from a typhoon. Pushed by the cyclone, the WPSH retreats (Y. Li et al., 2018). The weak pressure gradient over the mainland of eastern China (Figure 11a10a) in PWC results in more stable weather conditions. The anomalies of the

615 meteorological variables in PWC show opposite spatial patterns to those in PSW
(Figure 87 vs Figure 110). With the favorable meteorological conditions except
temperature, PWC enhances ozone over the south, with PWC statistically increased
regional mean values of ozone by 5.2 $\mu\text{g m}^{-3}$ (7.5%) over YRD and 6.7 $\mu\text{g m}^{-3}$ (11.8%)
over PRD (Figures 11eFigure 10c and 14eTable 1). Mean negative ozone anomalies
of -4.8 $\mu\text{g m}^{-3}$ (-5.1%) are observed over BTH in PWC (Figure 10c and Table 1).

620 PSWPSH (P5) occurs in late summer (Figure 12a11b), when Meiyu breaks in the
Yangtze River and the rain belt jumpshifts to North China (Ding and Chan, 2005). In
PSWPSH, the WPSH is the strongest and extends westward the mostly (Figure
12a11a). Thus, relative humidity is lower than the seasonal mean over YRD and
625 higher than the seasonal mean over BTH (Figure 12f11f). Meantime, stable weather
conditions occur more frequently over YRD (Figure 12i11i). Therefore, ozone
accumulates over YRD in PSWPSH with a regional mean enhancement of 1.8 $\mu\text{g m}^{-3}$
(2.5%) (Figures 12eFigure 11c and 14eTable 1). Surface ozone decreases by 0.8
(1.4%) and 5.0 $\mu\text{g m}^{-3}$ (8.9%)), respectively, over BTH and PRD under this SWP
630 (Figures 12eFigure 11c and 14eTable 1).

PTC (P6) is a typical typhoon weather pattern that is over the southeast coast of the
mainland China (Figure 13a12a). Forced by a typhoon system, the WPSH in PTC
migrates further north than under the other SWPs. The typhoon system brings clear
635 and moist marine air to coastal citiesareas in eastern China, reducing surface ozone by
6.8 $\mu\text{g m}^{-3}$ (9.2%) over YRD (Figures 13eFigure 12c and 14fTable 1). Shu et al.
(2017) identified that SWPs like PTC can lead to clean $\text{PM}_{2.5}$ episodes in YRD.
However, the cyclonic circulation enhances ozone transport from the central part of
eastern China to the downwind regions in the south including PRD. The collective
640 effect of higher temperature, lower humidity, and heavier downdrafts, PTC increases
surface ozone in PRD by 7.9 $\mu\text{g m}^{-3}$ (15.5%) (Figures 13eFigure 12c and 14fTable 1).

Lam et al. (2018) found ozone increases by $16.8 \mu\text{g m}^{-3}$ at urban stations in Hong Kong of PRD, when the synoptic circulation controlling PRD is featured typhoon in the vicinity of Taiwan, similar to PTC. They also suggested that this SWP is associated with the interannual variations of ozone pollution in Hong Kong.

We further compared the SWPs analysis with that from the MLR ~~model~~ discussed in section 4. We evaluate the performance of the MLR ~~model~~ under the six SWPs based on the predicted (Figures ~~7d~~, 8d, 9d, 10d, ~~11d~~, 12d, and 13d) and observed (Figures ~~7c~~, 8c, 9c, 10c, 11c, ~~12e~~, and ~~13e12c~~) ozone anomalies. The comparison shows that the ozone anomalies predicted by the MLR have spatial variations and magnitudes similar to those in the observations under each of the SWPs. The MAE of averaged ozone anomalies under each of the SWPs ranges $1.0\text{-}2.2 \mu\text{g m}^{-3}$, and the RMSE ranges $1.4\text{-}2.8 \mu\text{g m}^{-3}$ (Table S1). The MLR ~~model~~ can well capture the ozone anomalies under the six predominant SWPs (Figures ~~8-137-12~~). For example, the negative ozone anomaly over PRD under PSW (~~P1~~)-featured weak EASM (Figures ~~8e7c~~ vs. ~~8d7d~~), the negative ozone anomaly over YRD under PNECV (~~P3~~)-featured Meiyu (Figures ~~10e9c~~ vs. ~~10d9d~~), and the positive ozone anomaly over PRD ~~caused by~~ under PTC (~~P6~~)-featured typhoon (Figures ~~13e12c~~ vs. ~~13d12d~~). Since the MLR-~~model~~ only considers the meteorological influence on surface ozone, the consistency between the regression and the clustering results suggests that the mean observed ozone anomalies under a SWP can adequately reflect the sensitivity response of daily ozone variation to meteorology. The noise of day-to-day variations of chemistry and emissions in the surface ozone data can be largely removed by long-term average of ozone anomalies under a SWP from the big data set of surface ozone (Han et al., 2018b).

~~6-Discussion and conclusions~~

In addition, we applied the MLR to reveal the most important local meteorological

670 factor for daily ozone variability under each of the six SWPs (Figure S6). The MLR
was conducted under each of the SWPs with the same procedures in the full summer.
The most important meteorological variable for ozone over some areas in eastern
China may vary with the prevailing SWP (Figure S6). The dominant driver in PRD is
675 meridional wind at 850 hPa under PSW, PS, and PSWPSH, demonstrating the
significant influences of marine air inflow. Controlled by the typhoon system, the
most important factor over some coastal areas is zonal wind at 850 hPa under PTC.

6 Summary

Meteorology can influence surface ozone variability on different time scales, from
680 long-term trends to sub-daily scale variations. Based on surface ozone observations ~~in~~
~~eastern China~~ during 2013-2018 from MEE, we characterized the seasonal and
interannual variations of surface ozone in eastern China. The measurements show that
surface ozone pollution in the study region is severest in summer and the severity
goes is in a rapid increasing trend during the study period. We then focused on the
685 meteorological influence on the daily variability of summertime surface ozone in
eastern China. We took daily anomalies of meteorological and ozone values to remove
the variabilities on scales longer ~~time scales than daily variations~~ in these datasets. We
estimated the local and synoptic meteorological impacts on daily variability of surface
ozone using a MLR ~~model~~ and a SOM clustering technique. ~~Synoptic~~ The MLR is
690 driven by local meteorological variables and synoptic weather factors identified by
the SVD analysis ~~were combined with local meteorological variables to drive the~~
~~MLR model. The regression model.~~

The MLR suggests that on regional average, meteorology can explain 4643%
695 variations in the summertime daily surface ozone in eastern China, with an explained
variance of up to 65% over some locations (Figure 5e5a). The regression model ~~also~~
shows that meteorology contributes to 3918% of the increasing trend in the regional

mean of summertime surface ozone over eastern China from 2013 to 2018. Exploiting the MLR, we also identified the key meteorological variables that are mostly responsible for daily variations of summertime surface ozone in eastern China during 2013-2018. Among the local meteorological variables, relative humidity is the foremost over most areas in the center and south of eastern China including YRD and PRD, while temperature is the foremost in the north including BTH (Figure 5c).

~~Exploiting the MLR model, we also identified the key meteorological variables that are mostly responsible for variations of summertime surface ozone in eastern China during 2013-2018. On regional average, the synoptic circulation factors constructed by the SVD analysis were estimated to contribute to 37% of the meteorological impact over eastern China and 41% over BTH, YRD, and PRD (Figure 6b). Among the local meteorological variables, relative humidity is the foremost over most locations in the center and south of eastern China including YRD and PRD, while temperature is more important in the north including BTH (Figure 6c).~~

We assessed the impacts of the dominant synoptic weather systems on surface ozone using cluster analysis. Employing the SOM, the summer synoptic circulations over eastern China during 2013-2018 were objectively classified into six predominant SWPs (Figures 8-137-12). The six SWPs control the variations of the key meteorological variables and thus impact the transport and production of ozone regionally. Among the six SWPs, the SWP (PS) featured southerly wind, strong EASM and weak WPSH (Figure 8), and the SWP (PWC) featured a weak extratropical cyclone and the weakest WPSH (Figure 10) tend to increase the regional mean surface ozone in eastern China. In contrast, the other four SWPs (namely, PSW, PNECV, PSWPSH, and PTC) tend to reduce regional mean surface ozone in eastern China (Figures 7, 9, 11, and 12). As the predominant meteorological controlling variables of surface ozone vary greatly in space (Figures 2 and 65), strong differences

are found in surface ozone concentrations under every SWP between northern and southern parts of eastern China or between eastern and western parts of eastern China (Figures 8-14). ~~Daily~~ 7-12). Under the dominant SWP, daily mean surface ozone over in some ~~regions in~~ areas of eastern China can ~~maximally~~ increase or decrease maximally by $8 \mu\text{g m}^{-3}$ or 16% ~~impacted by~~ of the ~~dominant SWP~~ mean (Table 1).

Among the six SWPs, the SWP (PS) featured southerly wind, strong EASM and weak WPSH (Figure 9a), and the SWP (PWC) featured a weak extratropical cyclone and the weakest WPSH (Figure 11a) tend to increase the regional mean surface ozone in eastern China (Figures 9c and 11c). For specific regions in eastern China, PS and PWC statistically enhance ozone in YRD and PRD. However, mean negative ozone anomalies are observed over some locations in PS and PWC, such as BTH in PWC.

In contrast, the other four SWPs (namely, PSW, PNECV, PSWPSH, and PTC) tend to reduce regional mean surface ozone in eastern China. PSW is a SWP featured southeasterly wind and weak EASM (Figure 8a) and it leads to overall ozone reduction in the south of eastern China including YRD and PRD (Figure 8c). When eastern China is influenced by the Northeast Cold Vortex, the WPSH, and the Meiyu front (Figure 10a), PNECV tends to reduce ozone over YRD (Figure 10c). Whereas, ozone likely increases over some subregions in eastern China in the four SWPs. PSWPSH featured the strongest and the most extensive WPSH (Figure 12a) can enhance ozone over YRD, although it may reduce regional mean ozone over eastern China (Figure 12c). When the atmospheric circulation is controlled by the typhoon systems with their centers around Taiwan, southeast to the mainland of China (Figure 13a), PTC reduces ozone in YRD, while enhances ozone in PRD (Figure 13c).

This study provides some new insights on the relationship between meteorology and air pollution, by untangling the complex response of surface ozone to different

SWPs and local meteorological variables. The most significant meteorological variables for surface ozone in eastern China were identified regionally, which was rarely investigated by previous studies (Gong et al., 2018; Zhan et al., 2018; Chen et al., 2019). Extending from previous studies, we quantified ozone anomalies in eastern China resulting from the prominent synoptic weather systems such as the WPSH (Shu et al., 2016; Zhao and Wang, 2017), the extratropical cyclones (Zhang et al., 2013; Liao et al., 2017), the Meiyu front, and typhoon (Jiang et al., 2015; Lam et al., 2018). These systems are important drivers for variations of air pollutants over eastern China (Ding et al., 2017). The ~~relationship between weather and ozone is examined in one specific season, summer. Averaged mean~~ ozone anomalies under a SWP in ~~a relatively long term (six years over 2013-2018) was were~~ used to represent the ozone sensitivity to that SWP. This method ~~is also applicable for a full year, as it~~ can remove the seasonal differences in the pollutant concentrations ~~of pollution~~ and the frequency of SWPs (Han et al., 2018b). No consideration of seasonal differences in ~~ozone pollutant~~ concentrations and meteorology can lead to biases in addressing daily variations of a pollutant (e.g. Zhang et al., 2013, 2016; Liao et al., 2017).

In this study, the developed MLR and cluster techniques can well describe the meteorological impacts on the surface ozone variation in eastern China. Both regression and clustering analyses show strong performance, so they can be effective tools for air quality forecast. ~~Many previous studies have reported the significance of local meteorology to the prediction of daily ozone in China (Zhao et al., 2016), however, few have included the meteorology at a synoptic scale. Here, we emphasized the synoptic role in the meteorological effects on surface ozone. The constructed synoptic factors by the SVD analysis can be a useful predictor for short-term forecast of surface ozone. Regarding the time scale, this study focused on the day-to-day variations of surface ozone. Investigating the meteorological influences on a shorter time scale, such as diurnal variations, should be one of the directions for~~

785 ~~future work. The regression and clustering approaches can also be applied to project~~
~~the potential effects of climate change on ozone variations in the future (Shen et al.,~~
~~2017b). In the MLR regression analysis, we focused on the meteorological effects~~
~~without direct consideration of variations in emissions, assuming emissions in a~~
~~season are more or less constant.~~Here, we emphasize the importance of synoptic
meteorology to the daily variations of surface ozone. The constructed synoptic factors
by the SVD analysis can be a useful predictor for forecasting such daily variations. As
ozone responses nonlinearly to variations in meteorology, emissions, and chemistry
790 (Wu et al., 2009), the developed MLR ~~model~~ cannot fully ~~describe the importance of~~
~~meteorology to surface ozone~~ predict daily ozone variations yet. Therefore, ~~future~~
~~work is needed to address the~~ the nonlinearity issue. need to be addressed in the
future. Future work can also be conducted on the sensitivity of the diurnal ozone
variation to meteorology and on the impact of climate change on future surface ozone
795 levels regionally and globally (Shen et al., 2017b).

Data availability

Surface ozone measurements were obtained from the public website of MEE
(<http://beijingair.sinaapp.com/>). The FNL meteorological data were acquired from
800 NCEP (<https://rda.ucar.edu/datasets/ds083.2/>). The OMI tropospheric column ozone
monthly data were from NASA Goddard Space Flight Center
(https://acdext.gsfc.nasa.gov/Data_services/cloud_slice/).

Author contributions

805 H. Han designed the study and performed the research. H. Han and L. Shu analyzed
the data and developed the model. H. Han and J. Liu wrote the manuscript with inputs
from L. Shu, T. Wang, and H. Yuan.

Competing interests

810 The authors declare that they have no conflict of interest.

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