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ORIGINAL PAPER

Important meteorological variables for statistical long-term air quality prediction in eastern China

Libo Zhang[1] · Yongqiang Liu[2] · Fengjun Zhao[2,3]

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Abstract Weather is an important factor for air quality. While there have been increasing attentions to long-term (monthly and seasonal) air pollution such as regional hazes from land-clearing fires during El Niño, the weather-air quality relationships are much less understood at long-term than short-term (daily and weekly) scales. This study is aimed to fill this gap through analyzing correlations between meteorological variables and air quality at various timescales. A regional correlation scale was defined to measure the longest time with significant correlations at a substantial large number of sites. The air quality index (API) and five meteorological variables during 2001–2012 at 40 eastern China sites were used. The results indicate that the API is correlated to precipitation negatively and air temperature positively across eastern China, and to wind, relative humidity and air pressure with spatially varied signs. The major areas with significant correlations vary with meteorological variables. The correlations are significant not only at short-term but also at long-term scales, and the important variables are different between the two types of scales. The concurrent regional correlation scales reach seasonal at $p < 0.05$ and monthly at $p < 0.001$ for wind speed and monthly at $p < 0.01$ for air temperature and relative humidity. Precipitation, which was found to be the most important variable for short-term air quality conditions, and air pressure are not important for long-term air quality. The lagged correlations are much smaller in magnitude than the concurrent correlations and their regional correction scales are at long term only for wind speed and relative humidity. It is concluded that wind speed should be considered as a primary predictor for statistical prediction of long-term air quality in a large region over eastern China. Relative humidity and temperature are also useful predictors but at less significant levels.

✉ Yongqiang Liu
yliu@fs.fed.us

1 International Center for Ecology, Meteorology and Environment, College of Applied Meteorology, Nanjing University of Information Science and Technology, Nanjing 210044, China

2 Center for Forest Disturbance Science, USDA Forest Service, 320, Green St, Athens, GA 30602, USA

3 Research Institute of Forest Ecology, Environment and Protection, Chinese Academy of Forestry, 2 Dongxiaofu, Xiangshan Road, Beijing 100091, China

1 Introduction

Weather is one of the air pollution contributors (Nidzgorska-Lencewicz and Czarnecka 2015). Atmospheric processes can lead to severe air pollution events over a large region (Wang et al. 2010). The $PM_{2.5}$ center in southern California of the USA is associated with the stagnation condition characterized by an anticyclonic system, weak wind, no precipitation, and usually high temperature (Tai et al. 2010). Weather patterns were found to be related to the orientation, gradients, and characteristic patterns of daily air quality index (AQI) in the northern Mid-Atlantic of the USA (Croft and Melendez 2009). Understanding the weather-air quality relationships would help identify the major elements, processes, and mechanisms for the formation of air pollution events and develop prediction models.

The analysis of weather-air quality relationships and their applications to air quality prediction have focused on the short term (daily and weekly) in the past decades. Short-term air quality prediction informs the public of when severe air pollution weather such as regional smog and haze would occur. The major weather conditions concerned are synoptic systems and processes such as low pressure and vertical temperature inversion (Zhang et al.

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2014). Operational short-term air quality prediction has benefited greatly from the development of dynamical regional air quality models (Byun and Schere 2006; Sofiev et al. 2006; Wang et al. 2004; Peterson et al. 2014). These models use dynamical regional weather models to predict daily air pollutant distributions through simulating atmospheric dispersion and transport, mixing and deposition, and chemical reactions.

There are increasing attentions to the long-term (monthly and seasonal) weather-air quality relationships due to more frequent and persistent air quality disasters caused by, for example, intense forest fires and agricultural residue burning during anomalous weather events such as El Niño (Marlier et al. 2013; Shi et al. 2014). About a dozen prolonged severe smog events occur in the eastern China annually, affecting long-term outdoor activities such as construction, farming, recreation, and sport events (CMA 2015). Long-term air quality prediction helps administrations evaluate the risks for frequent and persistent air pollution events and take necessary measures to minimize the impacts. The concerned weather conditions include prolonged atmospheric anomalies such as droughts and heat waves.

Long-term air quality prediction is a big challenge to research and operational communities. Dynamical weather and air quality models depend on the initial atmospheric conditions, which can affect the subsequent atmospheric processes only for a certain period, after which atmospheric energy dissipation and nonlinearity become dominant. Thus, currently dynamical models are mainly effective for short-term air quality prediction. Operational real-time air quality prediction using dynamical models is mostly for 1 to 3 days (Zhang et al. 2012).

Statistical techniques such as correlation and regression analyses, empirical orthogonal function, and artificial neural network have been widely used to analyze weather-air quality relationships (Cobourn 2007; Stadlober et al. 2008;

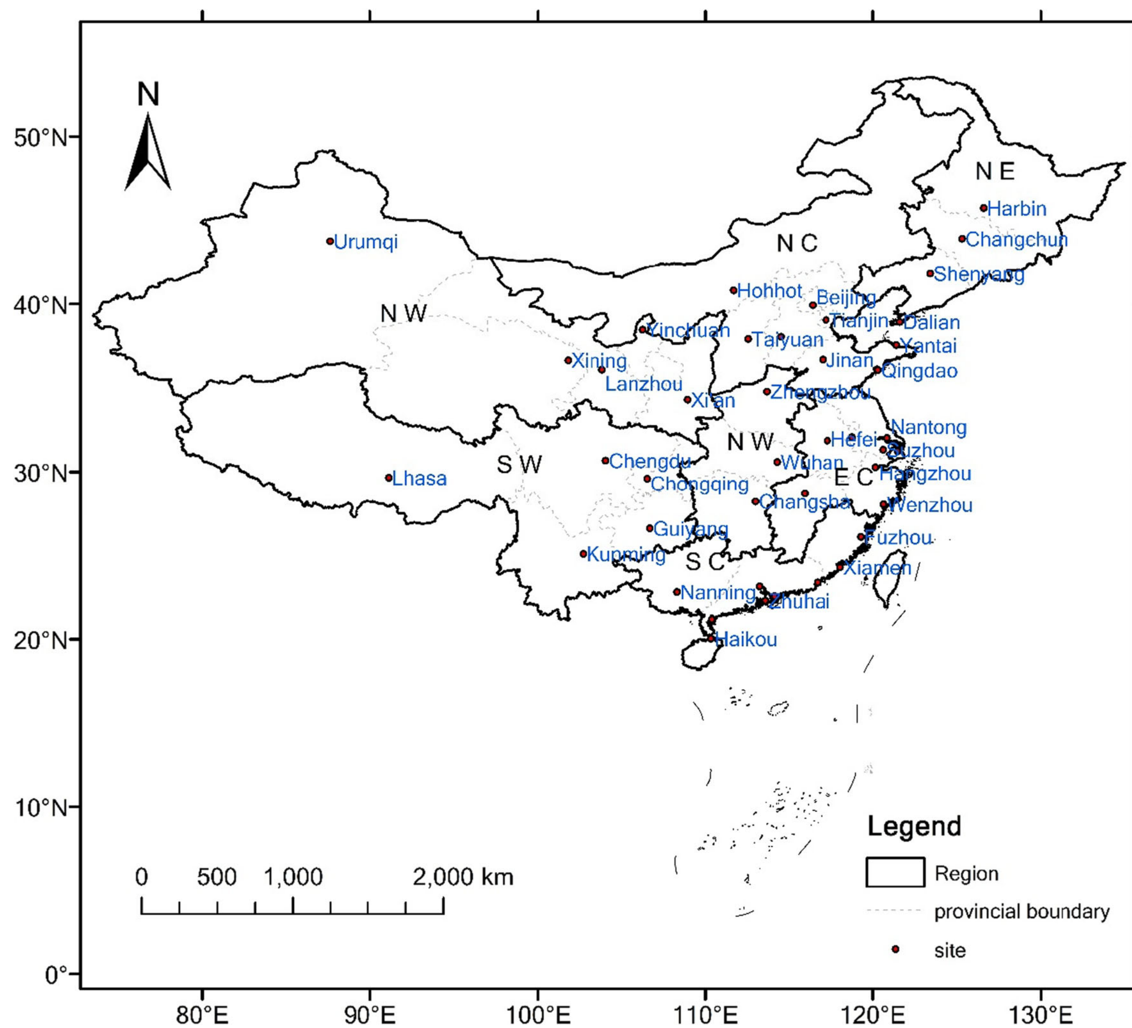

Fig. 1 The administrative divisions of Northwest (NW), North (NC), Northeast (NE), East (EC), South (SC), Central (CC), and Southwest (SW) China. The dots are the air quality measurement sites

Genc et al. 2010; Zhang et al. 2012; Deng et al. 2013; Peterson et al. 2014; Shahraiyni and Sodoudi 2016). Weather-air quality indices such as the Parameter Linking Air-quality to Meteorological conditions/haze (PLAM/h) index have been formulated to evaluate air quality based on weather conditions (Honoré et al. 2008; Kassomenos et al. 2008; Wang et al. 2013; Yang et al. 2016). Statistical relationships are also fundamental for developing statistical air quality prediction techniques. Many statistical air quality models have been developed based on short-term weather-air quality relationships (Zhang et al. 2012). Without dealing with the complex physical and chemical processes involved in dynamical models, statistical models are much more computationally efficient, which is especially important for providing long-term prediction.

However, the evidence for the long-term weather-air quality relationships is very limited. Some studies investigated the weather-air quality relationships using either daily or monthly series (Duan et al. 2008; Li 2009; Li et al. 2012, 2013) but did not calculate and compare them across short- and long-term timescales. Thus, it is not clear at how long scales their empirical relationships are statistically significant and what meteorological variables are important. This situation limits the capacity in selecting predictors in statistical prediction models for long-term air quality.

The purpose of this study is to understand the long-term weather-air quality relationships in eastern China by quantitatively estimating the longest timescales at which the relationships are statistically significant and identifying the related meteorological variables. Air pollution has escalated dramatically in the recent decades in China (UN 2001; Zhao et al. 2008; Wei et al. 2009; Li et al. 2013; Wang et al. 2013; Huang et al. 2013; Li and Wang 2013). The urban rate in China increased from 36% in 2000 to 54% in 2013 (Sheng and Yan 2014), and the number of cars per 100 urban households increased from 0.5 in 2000 to 21.5 in 2012 (NBS 2013), leading to rapid increases in air pollutant emissions. The $PM_{2.5}$ concentrations in China range from about 25 μg/m^3 in the southern coast to more than 60 μg/m^3 in northern China with a center of over 100 μg/m^3 in the Beijing mage-urban area (Rohdel and Muller 2015). In 2013, 70 out of 74 major China cities failed to meet the daily ambient air quality standards for

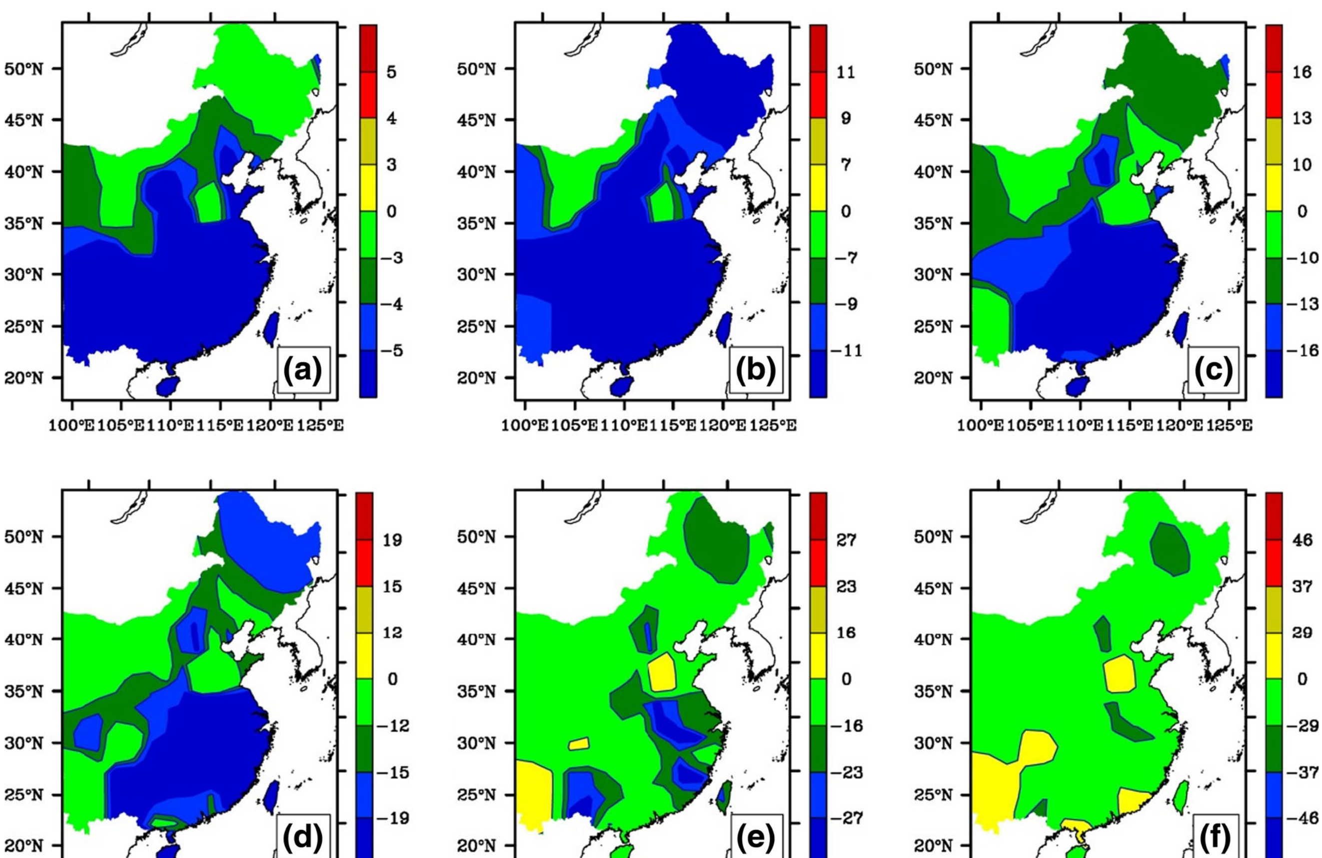

Fig. 2 Spatial distributions of concurrent correlation coefficients (%) between precipitation and API for 1-, 5-, 10-, and 15-day and 1- and 3-month series (**a**–**f**). Red and blue: highly significant ($p < 0.001$); light red and blue: intermediately significant ($p < 0.01$); yellow and green: marginally significant ($p < 0.05$)

more 144 days. In 2010, the high PM pollution was linked to 1.2 million premature deaths, the fourth leading risk factor for deaths in China, comparing with 3.2 million deaths, the seventh leading risk factor for the entire world (Murray et al. 2012; WHO 2014). The roles of weather in air pollution have been studied (Kang et al. 2009; Han et al. 2009; Wang et al. 2010; Zhang et al. 2014). This study is expected to provide scientific evidence for developing statistical prediction tools for long-term air quality in eastern China, which might also have important implications for other world regions.

2 Methods

2.1 Research area

The research area is eastern China, the portion of China approximately east of 100°E (Fig. 1). This region is separated into northern China, including northeast (NE), north (NC), and eastern northwest (NW) China, and southern China, including East (EC), South (SC), Central (CC), and eastern Southwest (SW) China.

2.2 Data

The air pollution index (API) and meteorological variables were used. API was formulated using daily PM_{10}, SO_2, and NO_2. Daily API values are used to evaluate air pollution levels: 0~50 (excellent), 51~100 (good), 101~200, 201~300, and 301~500 (mild, moderate, and severe pollution). The API data have been extensively used in China (Han et al. 2007; Li 2009; Liu et al. 2011, 2016; Ren et al. 2013; Li et al. 2013; Zhu et al. 2013; Zhang et al. 2016; Tao et al. 2016), which show that annual API is larger in northern than southern China and in winter than summer. Coal combustion and dust are the major API contributors, whose emissions are the largest during winter and spring, respectively. The weather is dry and windy with frequent temperature inversion during the two seasons, leading to more severe pollutant conditions.

The API data (http://www.mep.gov.cn) started from middle 2000 in 42 key China cities, with seven more sites added later in eastern China. The daily data from January 2001 to December 2012, at 40 sites (all of the first 42 but Urumqi in NW and Lhasa in SW) were used

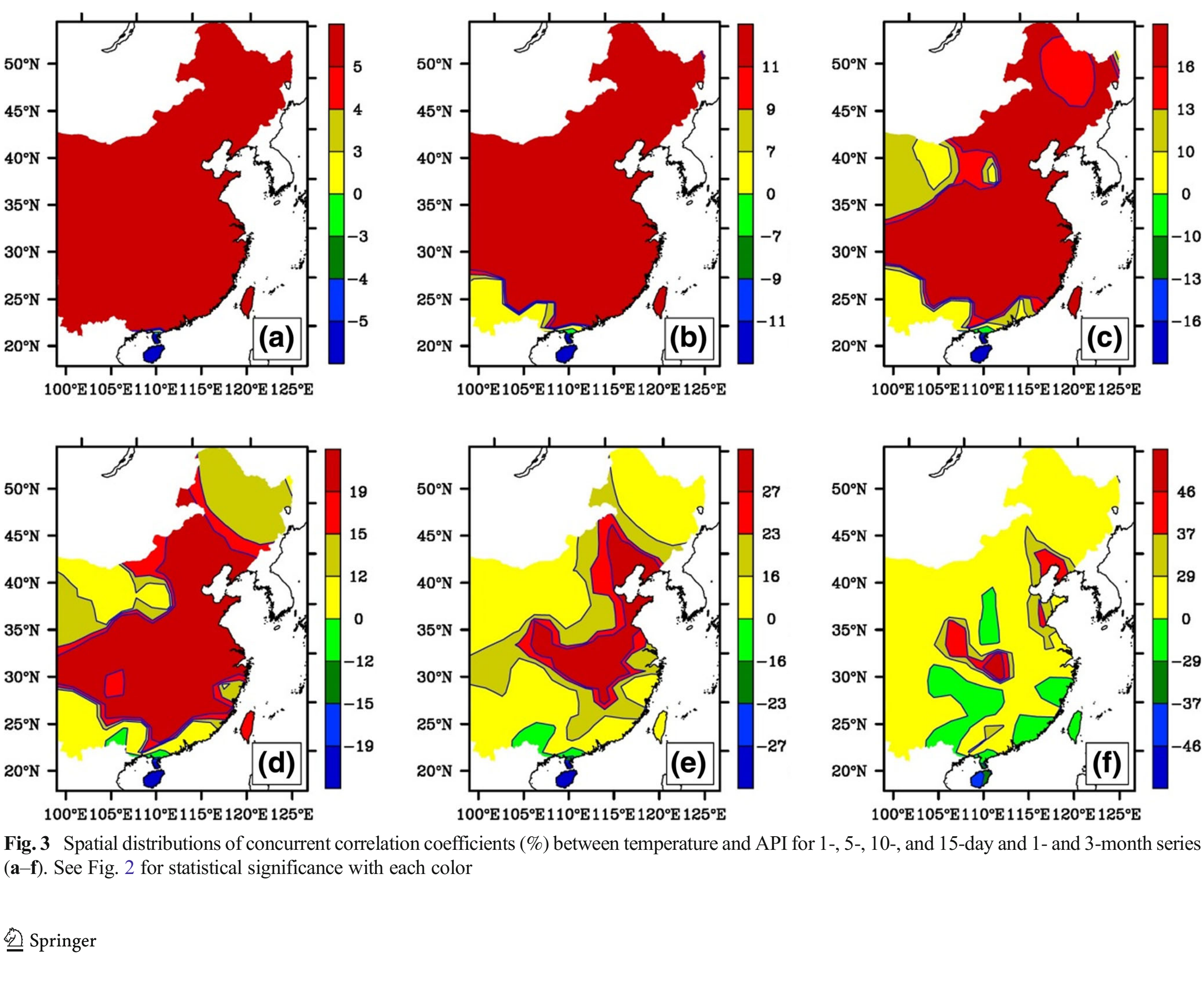

Fig. 3 Spatial distributions of concurrent correlation coefficients (%) between temperature and API for 1-, 5-, 10-, and 15-day and 1- and 3-month series (**a**–**f**). See Fig. 2 for statistical significance with each color

for this study. Western China (west of about 100° E) was not included because of very sparse measurements.

Five meteorological variables of precipitation (R), surface air temperature (T), wind speed (V), relative humidity (RH), and air pressure (P) near the air quality sites were used, which were obtained from the China Meteorological Science Data Sharing Service Network (http://cdc.nmic.cn).

2.3 Correlations at various timescales

The elements of the original daily data were averaged over five periods of 5, 10, 15, 1 month, and 3 months to form additional time series. The periods together with the original 1-day period were regarded as timescales, which are denoted as 1d, 5d, 10d, 15d, 1m, and 3m. Each series was deseasonalized by averaging a specific element of the series over 12 years and then subtracting the average from this element. Considering the relatively large interannual variability with the daily series, the deseasonalized daily series element was obtained by subtracting the 5-day instead of 1-day average.

Correlation coefficients between API and one of the meteorological variables (MET = R, T, V, RH, or P), r_k(MET, t), were calculated for each timescale t. $k = 0$ for the concurrent correlation with no time lag or $k = 1$ for lagged correlation with the API lagging MET by one series interval. Although concurrent correlations reflect the instant impacts of weather to understand the processes and mechanisms of air pollutions, they also can provide useful information for prediction, as discussed later. Lagged correlations reflect the subsequent impacts of weather on air quality, which are traditionally used to find predictors of statistical air quality models.

Statistical significance of correlations was tested at three significance (SIG) levels of $p \leq 0.001$, 0.01, and 0.05. The correlations meeting the corresponding critical values are regarded as highly (HS), intermediately (IS), and marginally (MS) significant, respectively.

2.4 Regional correlation scales

$r_k(MET, t)$ measures correlations at individual sites. To find those meteorological variables with statistical long-term

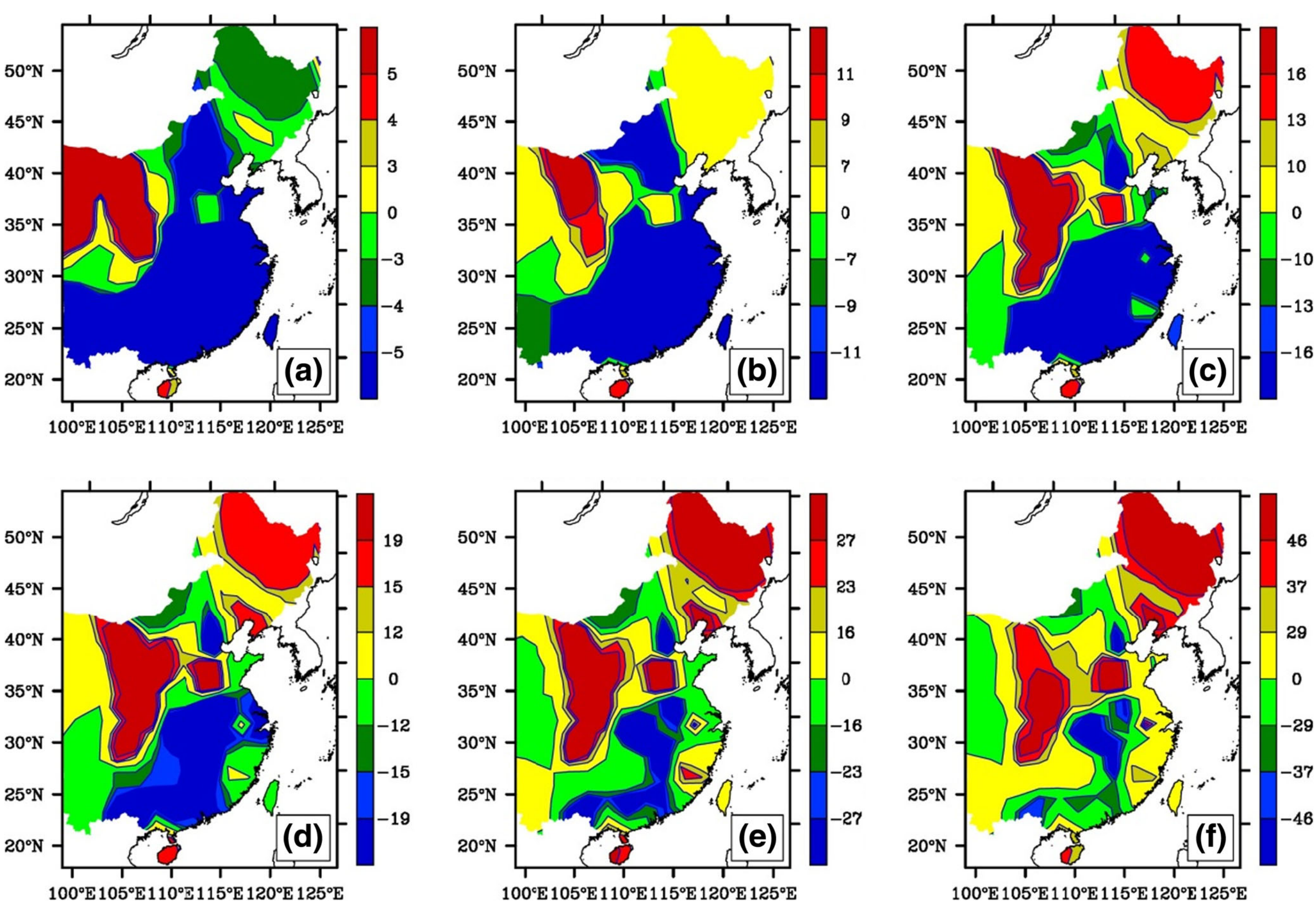

Fig. 4 Spatial distributions of concurrent correlation coefficients (%) between wind speed and API for 1-, 5-, 10-, and 15-day and 1- and 3-month series (**a**–**f**). See Fig. 2 for statistical significance with each color

correlations at a certain number of sites, a regional correlation scale, $t_{reg,k}(MET, SIG, N)$, was defined. The scale is the largest t value for $r_k(MET, t)$ at the SIG level at N or more sites. $t_{reg,k}$ is inversely proportional to the SIG level. Selection of N is arbitrary. A larger N means a larger region but normally a shorter $t_{reg,k}$. In this study, we used a value so that $N/N_o = 1/3$, where N_o is the number of measurement sites. This ratio is comparable to the math constant, e, which has been extensively used to measure the attenuation rate of a dynamic system (e.g., Liu and Avissar 1999). The corresponding number was N= 14.

3 Results

3.1 Spatial patterns of concurrent correlations

$r_0(R, t)$ is negative across eastern China, except at a few sites for the 1m and 3m series (Fig. 2), meaning that air pollution becomes more severe with decreasing rainfall. The areas with significant correlations remain large until 15d, especially in southern China. $r_0(R, 1\text{m})$ is HS or IS at a few sites, while $r_0(R, 3\text{m})$ is not significant at HS or IS everywhere. Note that the inverse distance weighting (IDW) method (Li and Heap 2008) was used to interpolate the correlation results at the 40 sites to the regularly distributed grid points when illustrating the spatial patterns.

$r_0(T, t)$ (Fig. 3) shows similar spatial distributions and changes with timescale to $r_0(R, t)$ but with opposite sign, meaning that air pollution becomes more severe with increasing temperature. $r_0(T, t)$ has higher significant level, HS in almost entire eastern China for 1d–15d. $r_0(T, 1\text{m})$ is HS or IS in parts of CC, EC, and NC. $r_0(T, 3\text{m})$ is significant at a few sites.

Unlike $r_0(R, t)$ and $r_0(T, t)$, $r_0(V, t)$ (Fig. 4) has varied signs across eastern China. Negative $r_0(V, 1\text{d})$ spreads over entire region except eastern NW and western NC. This area decreases in size with increasing timescale. $r_0(R, 1\text{m})$ and $r_0(R, 3\text{m})$ are HS at many sites.

Similar to $r_0(V, t)$, $r_0(RH, t)$ (Fig. 5) has varied signs and is significant at 1m and 3m scales. $r_0(RH, 1\text{d})$ and $r_0(RH, 5\text{d})$ are negative across eastern China except in NC and NE. Positive values occur in southern China for longer scales. $r_0(RH, 10\text{d})$ and $r_0(RH, 15\text{d})$ are HS in a majority of the region.

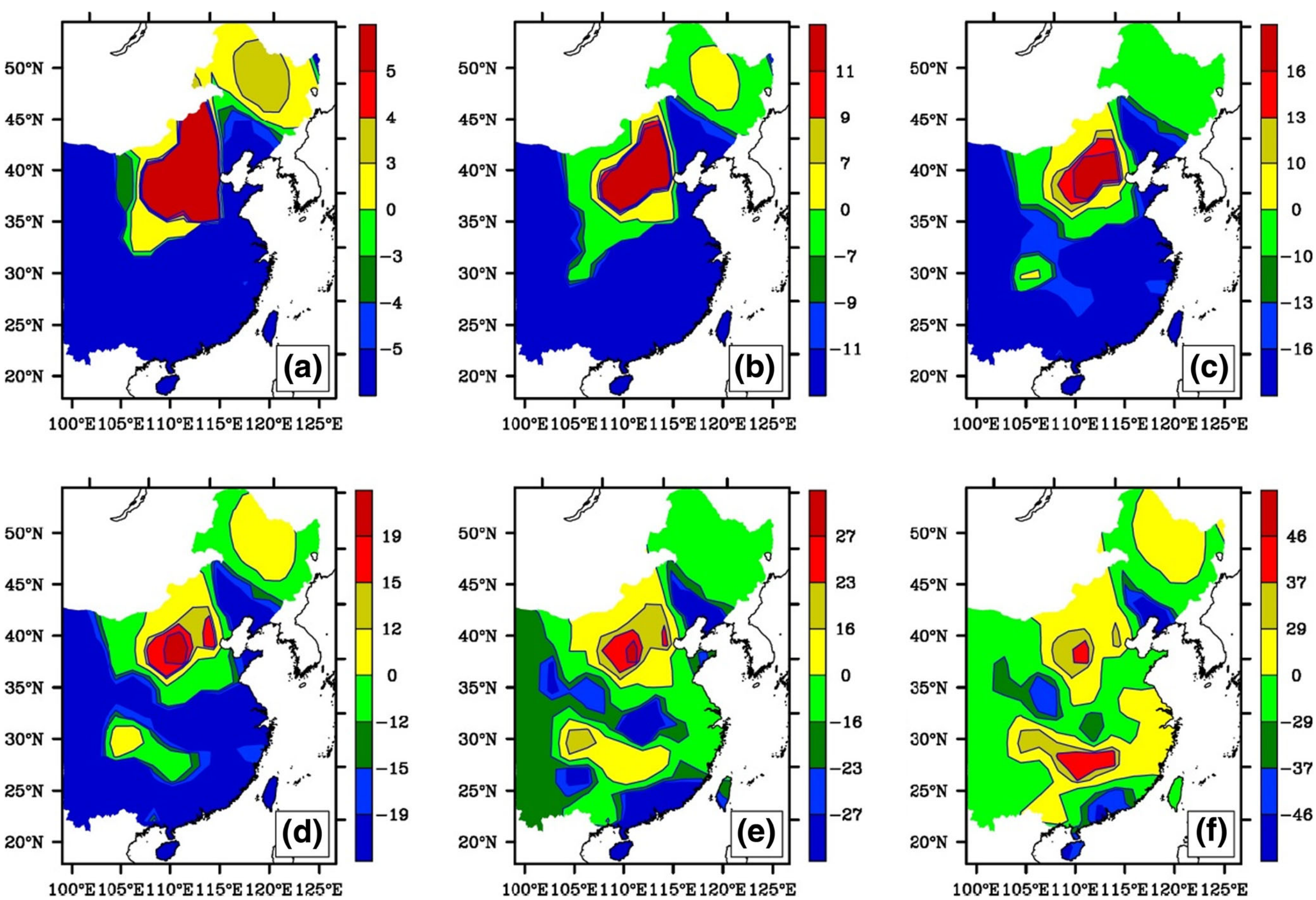

Fig. 5 Spatial distributions of concurrent correlation coefficients (%) between relative humidity and API for 1-, 5-, 10-, and 15-day and 1- and 3-month series (**a**–**f**). See Fig. 2 for statistical significance with each color

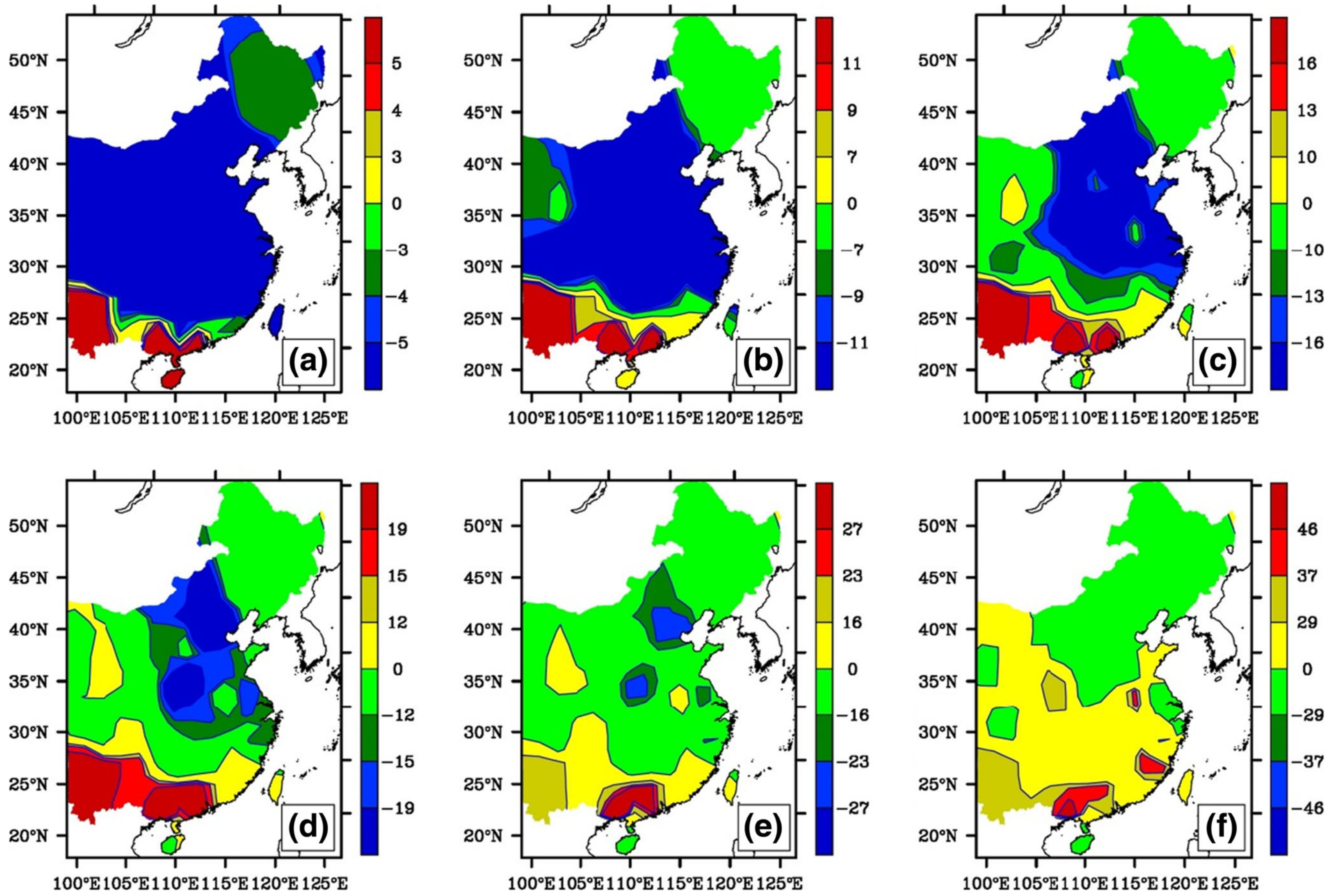

Fig. 6 Spatial distributions of concurrent correlation coefficients (%) between air pressure and API for 1-, 5-, 10-, and 15-day and 1- and 3-month series (**a**–**f**). See Fig. 2 for statistical significance with each color

$r_0(P, t)$ (Fig. 6) is negative in northern China and parts of southern China and positive mainly in the southern coast. The positive area expands northward with increasing timescale. The correlations are mostly HS until 15d.

3.2 Spatial patterns of lagged correlations

r_1(MET, t) has similar spatial patterns and signs to r_0(MET, t) but with much smaller magnitude for most variables. $r_1(R, t)$, for example, is insignificant for all timescales. The magnitude decreases more rapidly with timescale for most variables. An exception is $r_1(V, t)$, which is HS even at 1m and 3m scales at many sites (Fig. 7). The area of positive values is larger in $r_1(V, t)$ than $r_0(V, t)$.

3.3 Regional correlation scales

The number of sites with HS correlations does not decrease considerably until t = 1m for most variables (Fig. 8). For example, the number for R is 28 for 1d, 32 for 5d (the only case among all variables that the number increases from 1d to 5d series), 20 for 10d, and 15 for 15d. It then drops dramatically to four for 1m and zero for 3m series. However, no substantial drops after the 15-day series are found for V. The value declines steadily or changes little from 1d to 3m, which are 30, 24, 22, 14, 16, and 10.

While the regional correlation scales are at short term (≤ 15d) for R and P at any significant level, and for T and RH at HS, they reach long term, 1m for V at the HS level and for T and RH at the IS level, and 3m for V at MS.

The regional lagged correction scales are at the long term only for V and RH (Fig. 9), 1m for V at HS, and 3m for V at IS and for RH at MS.

4 Discussion

The weather-air quality relationships in China depend on meteorological variables (Han et al. 2009; Zhang et al. 2014). This study shows two types of variables with different spatial patterns. The first type includes precipitation and temperature, each showing a same correlation sign across China, negatively with precipitation significant at large timescales mainly in SC, and positively with temperature significant at large timescales

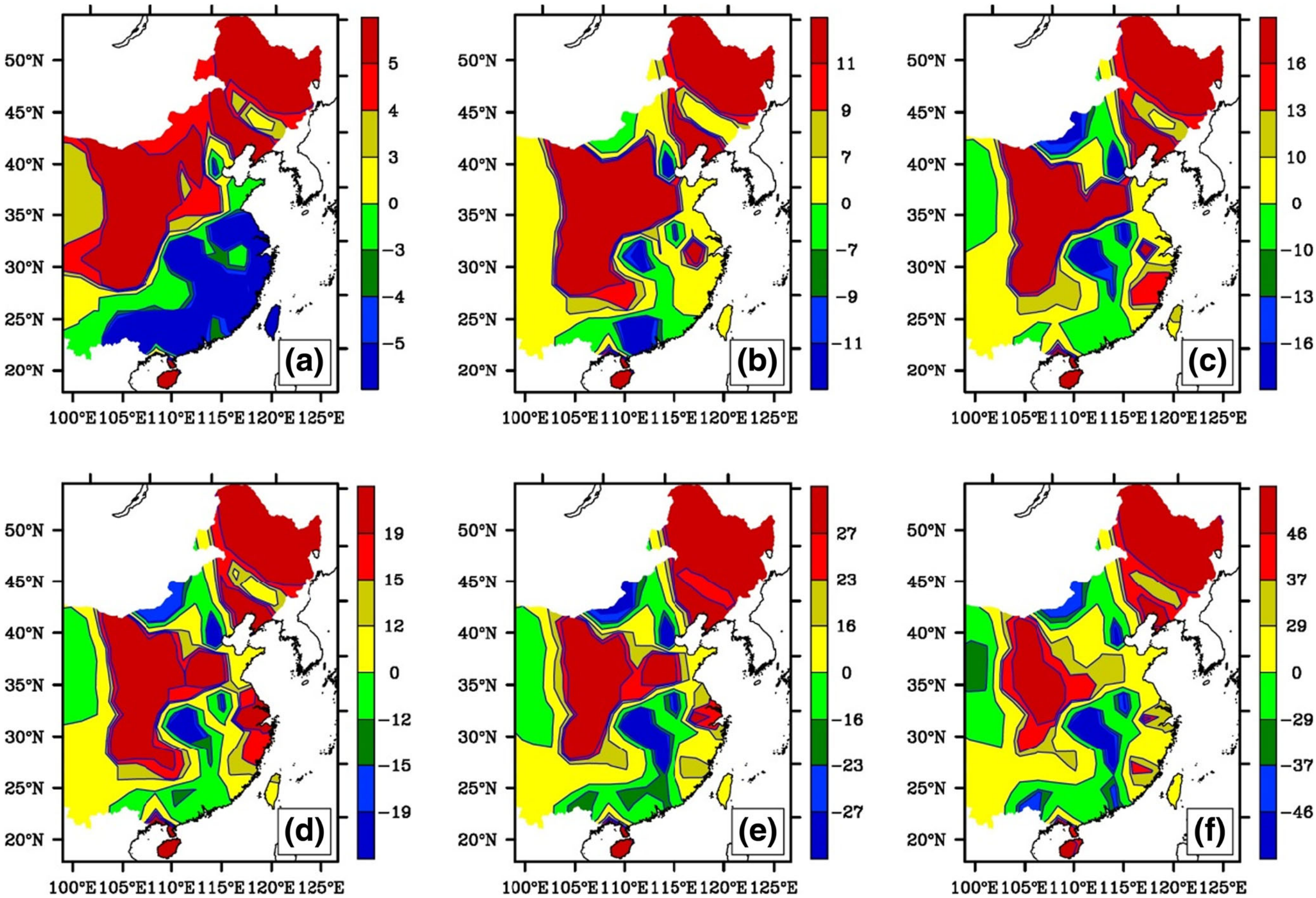

Fig. 7 Spatial distributions of lagged correlation coefficients (%) between wind speed and API for 1-, 5-, 10-, and 15-day and 1- and 3-month series (**a**–**f**). See Fig. 2 for statistical significance with each color

mainly in EC and NC. The signs basically agree with the previous studies (Duan et al. 2008; Li 2009; Li et al. 2012, 2013; Deng et al. 2013). Rainfall can wash out air pollutants through wet deposition. Sands from dust storms and urban construction sites are one of the major PM_{10} sources in northern China. Warmer temperature lifts more dust particles from the ground construction or desert into the air, though the atmospheric planetary boundary layer becomes less stable with higher surface temperature, and therefore, it leads to more vertical transport of ground air pollutants at urban sites.

The second type shows spatially varied correlation signs with other variables. The daily correlations are positive in western NW and negative in other regions for wind speed. Higher wind speed in northwestern China lifts more dust particles from the ground to the air, which is a major PM_{10} source during spring, but leads to larger transport and dispersion from highly air polluted urban to less polluted rural in eastern China (Tian et al. 2005; Ren et al. 2005; Han et al. 2007; Li et al. 2014). The daily correlations are mostly negative except in NC and NE for relative humidity. Relative humidity is a ratio of actual to saturated water vapor pressure values, which are basically proportional to precipitation and air temperature, respectively. The positive correlations for precipitation explain the overall negative correlations for relative humidity, while positive correlations for temperature, especially in northern China, explain the positive correlations for relative humidity in this region. The daily correlations are mostly negative except in the southern coastal area for air pressure. Kang et al. (2009) found that the atmosphere was controlled by a stable high-pressure system after passage of a cold front with rainfall, strong wind, and low air pollution level, and air pressure was then reduced gradually and air pollutants accumulated with PM_{10} reached the highest level when a stable low air pressure system prevailed.

For short-term air quality, Deng et al. (2013) found that precipitation is the most important meteorological variable, followed by wind speed, humidity, and temperature. This study also finds large correlations with short-term air quality for precipitation. However, for long-term air quality, this study indicates that wind speed rather than precipitation becomes most important, followed by humidity and temperature, while precipitation is no more a factor.

Our study used deseasonalized time series. The correlation coefficients with daily series are consistent with those from a

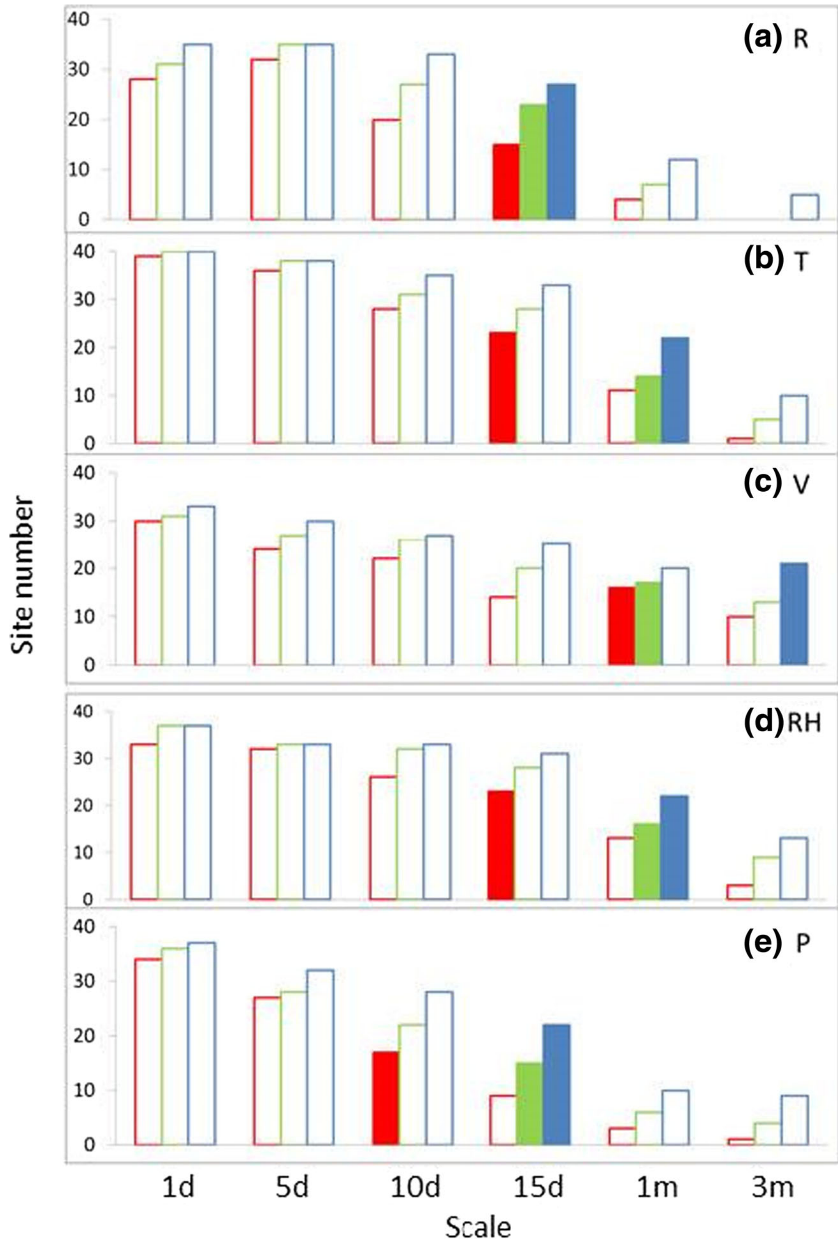

Fig. 8 Site number with significant concurrent correlations between API and precipitation (**a**), air temperature (**b**), wind speed (**c**), water vapor pressure (**d**), and air pressure (**e**). The red, green, and blue bars are significant at $p < 0.001$, 0.01, and 0.05. The filled bars are regional correlation scales

similar study also using deseasonalized meteorological variables over 11 years in the contiguous USA (Tai et al. 2010). The correlation signs for air temperature and pressure, however, are opposite to some studies using original data series. Wang (2008) and Deng et al. (2013), using original daily series of 3-year and 12-year periods, respectively, at multiple sites across China, and Zhou et al. (2014), using original monthly series during 2000–2010 at three NC sites, found negative API correlations with air temperature and positive with air pressure. This is simply because the API is higher in winter and lower in summer, while precipitation and air temperature are lower and air pressure is higher in winter and opposite in summer. The original data series usually lead to higher correlation magnitude. The daily correlations for precipitation from Deng et al. (2013) were between − 0.2 and − 0.4 at a majority of sites, while the correlations in this study with the seasonal cycle removed are only about − 0.1. The monthly correlations for precipitation from Zhou et al. (2014) were − 0.43, − 0.37, and − 0.41 at the examined three sites. The values are reduced to − 0.25, − 0.02, and − 0.14 in our study using the data with the seasonal cycles removed. (But we got pretty close values of − 0.40, − 0.36, and − 0.40 if also using the original data.)

The API mainly considers PM_{10} concentrations. China started to monitor $PM_{2.5}$, O_3, and CO in 2012, which together with the air pollutants included in the API are used to formulate the AQI, a better air quality index than the API, because $PM_{2.5}$ and O_3 are more closely related to

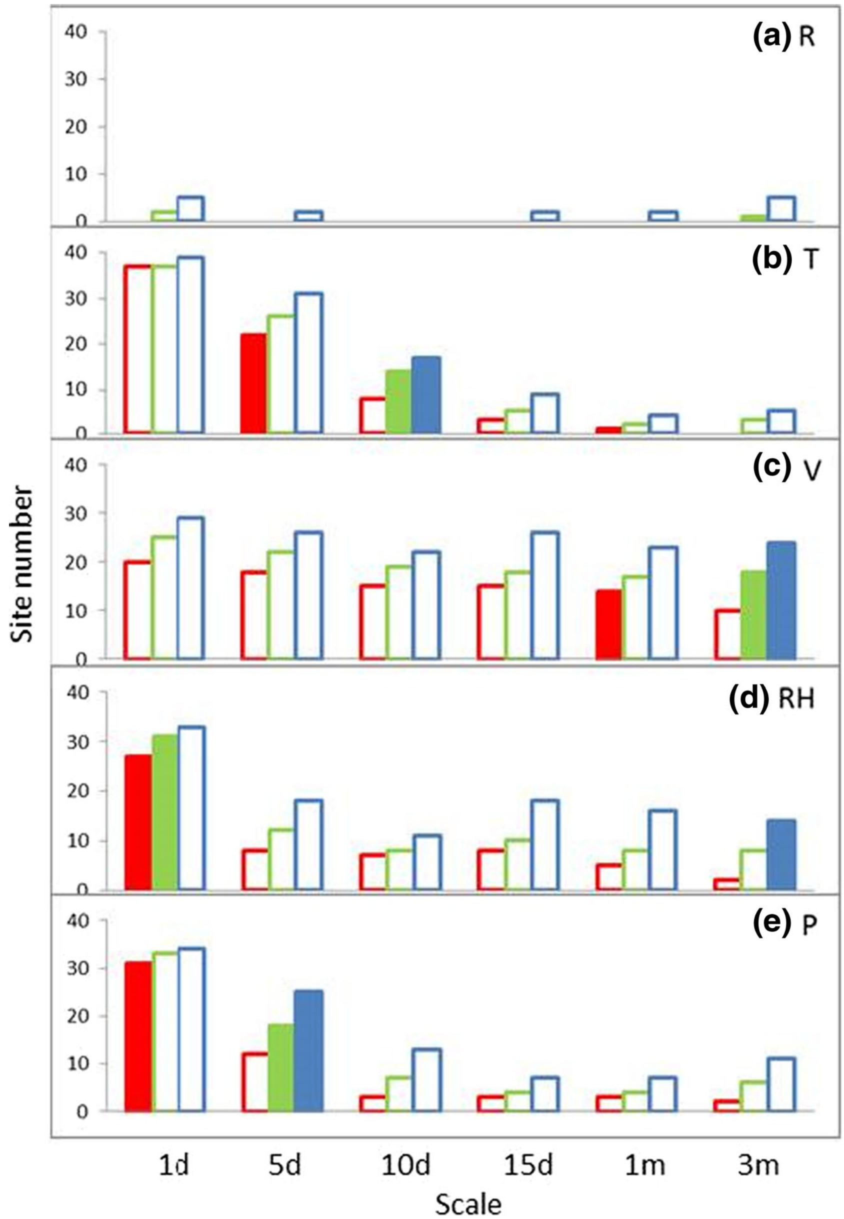

Fig. 9 Site number with significant lagged correlations between API and precipitation (**a**), air temperature (**b**), wind speed (**c**), water vapor pressure (**d**), and air pressure (**e**). The three bars for each scale are significant at $p < 0.001$, 0.01, and 0.05. The filled bars are regional correlation scales

regional smog and haze. Some differences are expected between the two indices in their correlations with weather. For example, wind speed and air temperature are positively correlated with PM_{10} in the regions with large dust concentrations, but could be negatively with $PM_{2.5}$ due to strong horizontal and vertical transport and dispersion of fine particles by wind. The AQI data have been used in short-term weather-air quality correlation analyses (Chen et al. 2015). They should be valuable for long-term analyses in the future when long data series become available. Also, weather-air quality relationships over time periods beyond seasonal scale could exist under external forcing such as El Niño and climate change (Jacob and Winner 2009; Marlier et al. 2013), which were not analyzed in this study due to limited length of data series.

5 Conclusions

It can be concluded based on the weather-air quality relationships obtained from this study that meteorological conditions are valuable for statistical air quality prediction not only at short-term (daily and weekly) but also at long-term (monthly and seasonal) scales in many eastern China regions. Wind speed is the most important variable for statistical prediction of long-term air quality over a large area. Temperature and relative humidity are also useful variables at less significant levels. The major areas with significant long-term correlations are different among the three variables. On the other hand, precipitation, which was found in previous studies as the most important factor for short-term air quality in China, and air pressure are not important for long-term air quality prediction.

Long-term air quality prediction could be made through two approaches. One is based on the lagged correlations. This is actually the technique often used to conduct, for example, statistical weather prediction. This approach relates meteorological elements as predictors, which are available at current time from observations, to air quality as a dependent variable or predict and at a future time. However, only wind speed and relative humidity among the analyzed meteorological variables have significant long-term relationships with subsequent air quality in a large region. The other approach is based on the concurrent weather-air quality relationships. To predict air quality at a future time, weather conditions at the same are used, which are available from operational weather forecast provided in many world regions including China (bcc.cma.gov.cn/channel.php?channelId=63). Besides detailed short-term meteorological conditions, the forecast products also include monthly and seasonal outlook. One problem is that the outlook usually only includes temperature and precipitation, while wind speed, which is the most important variable for statistical long-term air quality prediction, is often not available.

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