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Epidemiological characteristics of RSV in pediatric inpatients with lower respiratory tract infections in Suzhou and their correlation with meteorology and atmospheric pollutants

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Abstract

Background Lower respiratory infections are the leading cause of illness and death in children under 5, primarily due to respiratory syncytial virus(RSV). Climate and pollution influence disease and pathogen prevalence. This study investigates the correlation between meteorological factors, atmospheric pollutants, and RSV infections in children, aiming to implement effective clinical measures and reduce RSV risk in children by enhancing the environment.

Methods This study included patients with lower respiratory tract infections who were hospitalized in the Department of Respiratory Medicine at Children's Hospital of Soochow University from January 2006 to December 2019 as the research subjects. This study analyzed detection rates across different ages, genders, and seasons, while also examining the relationship of RSV infection between meteorological factors and atmospheric pollutants. RSV was detected using direct immunofluorescence, and an LS-SVM prediction model with lag nonlinear curves was established in conjunction with meteorological data. In this model, monthly average temperature, atmospheric pollutant levels, and average monthly wind speed were used as predictive variables for construction and prediction. A distributed lag nonlinear model (DLNM) was developed, which included the creation of a lag nonlinear curve by integrating meteorological data.

Results A total of 19,637 pediatric cases of lower respiratory tract infections were included in this study. The detection rate of RSV over 14 years averaged 14.9% (2934/19637). The male-to-female ratios for positive detection was 1.2:1. The primary detection season for RSV is winter, with a detection rate of 33.7%. The prevalence of RSV was correlated with climatic factors and atmospheric pollution. Utilizing the monthly average temperature, monthly average wind speed, and levels of atmospheric pollutants as the predictive factors in LS-SVM for model construction

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and prediction, a DLNM identified that the relative risk (RR) of RSV infection fluctuated with changes in the temperature and wind speed.

Conclusion RSV has the highest detection rate in infants and is often detected during winter.The influence of meteorological factors and atmospheric pollutants on RSV infection rates cannot be overlooked, with observation of a lag effect.

Keywords Lower respiratory tract infection, RSV, Children, Climatic factors, Atmospheric pollution

Background

Lower respiratory tract infections are the main cause of morbidity and mortality in children less than 5 years of age. In 2015, an estimated 900,000 children less than the age of 5 years died from lower respiratory tract infections, with 80% of these deaths occurring in children aged from 1 to 59 months [1, 2]. Viruses are the predominant etiological agents causing lower respiratory tract infections in children, respiratory syncytial virus (RSV) has the highest detection rate among them. The burden of viral infections is greater in developing countries than in developed nations as the mortality rate due to viruses or related lower respiratory tract infections is several times higher in developing countries than in developed ones [3, 4].Geographical variations lead to regional differences in climate, with factors like temperature, daily temperature range, sunlight duration, wind speed, humidity, and rainfall influencing pathogen prevalence [5, 6]. Climate change and atmospheric pollution also play roles in disease occurrence and pathogen circulation.

Thus, the objective of this study was to examine the effect of meteorological factors on the epidemiological trends of lower respiratory tract RSV infections. Further, this study aims to provide a theoretical foundation for future development of effective clinical management and intervention strategies based on research into RSV, climatic factors, and atmospheric pollution, emphasizing the importance of improving environmental conditions to reduce the risk of respiratory tract infections in children.

Methods

Study design and study population

A retrospective analysis was performed in pediatric patients with acute lower respiratory tract infections admitted to the Respiratory Department of the Affiliated Children's Hospital of Soochow University between January 1, 2006, and December 31, 2019.

Clinical data and meteorological information

Clinical data from pediatric inpatients at the Respiratory Medicine Department of Children's Hospital of Soochow University.The meteorological data is provided by the Suzhou Meteorological Bureau, with the location of the meteorological observation station at longitude 120°38' East and latitude 31°17' North.

Eligibility criteria

Inclusion criteria

We enrolled pediatric patients aged 1–14 with lower respiratory tract infections [1], lasting less than a month, and possessing complete medical records.

Exclusion criteria

Patients with immunodeficiency, severe congenital heart disease, congenital airway malformations, primary ciliary dyskinesia, cystic fibrosis, pulmonary tuberculosis, chromosomal abnormalities, neuromuscular diseases, or any other underlying diseases were excluded. Cases in which the same child was readmitted within an interval of less than one month between two hospital stays were also excluded.

Detection of viral antigens

Respiratory syncytial virus (RSV) antigens in nasopharyngeal secretions was detected using direct immunofluorescence assay (reagents sourced from the US company Chemicon).Throughout the entire research process, the detection and sampling protocols remained consistent with no changes made.

Lower respiratory tract infections

Lower respiratory tract infections included bronchiolitis, bronchopneumonia, lobar or segmental pneumonia, interstitial pneumonia, and bronchial asthma with infection, as defined by the standard diagnostic criteria [1].

Meteorological data collection

The meteorological data were provided by the Suzhou Meteorological Bureau, with the geographical coordinates of the meteorological observation station at 120°38' east longitude and 31°17' north latitude. The data included monthly average relative humidity (%), monthly total sunshine duration (h), monthly average temperature (℃), monthly average wind speed (m/s), and monthly total rainfall (mm) for the entire year from 2006 to 2019. The monthly average temperature, wind speed, and relative humidity were calculated as the sum of daily meteorological monitoring data for each month divided by the number of days in that month, while the monthly total sunshine duration and monthly total rainfall represented the sum of daily meteorological monitoring data within one month. The daily average relative humidity was monitored by a DHC2-type humidity sensor, and it represented the average value of hourly observations. The daily average temperature was the statistical average of hourly observation data, and the daily average wind speed was based on the wind speed averages taken every 10 min.

Stepwise Linear Regression Analysis of Environmental Factors and Positive Pathogen Detection Rates, and Establishment of the Least Squares Support Vector Machine (LS-SVM) Prediction Model Based on Environmental Factors (Meteorological Factors and Atmospheric Pollutants).

Stepwise linear regression analysis

To investigate the relationship between environmental factors (including meteorological factors and atmospheric pollutants) and the positive detection rates of pathogens, a stepwise linear regression analysis was conducted. The positive pathogen detection rate is defined as the percentage of positive cases of Respiratory Syncytial Virus (RSV) relative to the total number of samples tested, multiplied by 100%. This analysis identified key environmental risk factors that significantly influence pathogen detection rates. These risk factors were subsequently used as predictor variables in the predictive modeling process.

Least squares support vector machine (LS-SVM)

Support Vector Machine (SVM), developed by Vladimir Vapnik and his colleagues at Bell Labs in 1995, is a supervised learning technique based on the principle of Structural Risk Minimization (SRM). SVM models are particularly effective for handling dynamic, non-linear, and complex time series data, making them highly suitable for tasks such as signal processing, pattern recognition, and non-linear regression.

Building on the foundation of SVM, Least Squares Support Vector Machine (LS-SVM) was proposed by Suykens and Vandewalle in 1999 [7]. LS-SVM is primarily used to approximate the precise non-linear relationship between input and output variables, effectively addressing non-linear classification and regression problems [8]. Compared to traditional SVM, LS-SVM offers lower computational complexity, reduced time consumption, and higher accuracy [9]. Research has demonstrated that LS-SVM outperforms ARIMA models and BP neural network models in predicting disease incidence rates [7]. Additionally, LS-SVM excels in handling missing data compared to traditional methods such as deletion, mean imputation, and nearest neighbor imputation.Therefore, LS-SVM was chosen as the predictive model for this study on the trends of pathogen prevalence.

Application of LS-SVM in pathogen prevalence prediction

In this study, risk factors identified via stepwise linear regression were used as predictors. Data were imported into MATLAB, and the LS-SVM algorithm was applied to construct the prediction model. Model performance was evaluated using the coefficient of determination (R^2) and root mean square error (RMSE). R^2 reflects the goodness of fit between observed and predicted data, while RMSE indicates prediction deviation. Consistently high R^2 and low RMSE values in the RSV prediction model demonstrate its reliability and accuracy.

Distributed lag non-linear models based on environmental factors

To further analyze the impact of environmental factors on RSV infection, distributed lag non-linear models (DLNMs) were established based on the predictor factors derived from the stepwise linear regression analysis. Cross-basis matrices were constructed for meteorological data, with RSV-positive infections as the dependent variable. A quasi-Poisson link function was used for fitting the model.

The DLNM package in R software was utilized to assess the attributable risk of predictor factors on the RSV-positive infection rate. The exposure-lag-response relationship was calculated using the DLNM framework. Based on quasi-likelihood for Akaike's information criterion (Q-AIC), the degree of freedom for months was set at 12. The DLNM model was constructed using the dlnm package in conjunction with the splines package. Graphical representations were used to describe the relationships between meteorological factors and RSV, as well as the lag effects. The median values of meteorological factors were used as references to calculate the cumulative relative risk (RR) values at various lag times for different ranges of meteorological factors.

Predictive factors: inclusion of monthly average temperature and monthly average wind speed

Based on the results of the stepwise regression analysis, two key environmental factors—monthly average temperature and monthly average wind speed—were identified as significant predictors of RSV infection. These factors were incorporated into the LS-SVM model as predictor variables for constructing and predicting RSV trends. The inclusion of these variables enhanced the model's ability to capture the complex relationships between environmental conditions and pathogen prevalence.

Statistical analysis

Statistical data analysis was conducted using SPSS 25.0 software package. For the analysis of categorical data, the variability in inter-group rates was evaluated using the chi-square test. If the conditions were not satisfied, the Fisher's exact probability method was employed. A P-value < 0.05 indicated a statistically significant difference. For continuous data, a normality test and homogeneity of variance test were performed. Normally distributed data were represented as mean ± standard deviation (± s), while non-normally distributed data were represented using the median (M) and percentile (P25; P75). The comparison of means between groups was performed using the Duncan test.

For verifying correlation coefficients, if the data met the assumption of normal distribution, Pearson correlation analysis was used. If the assumption was violated, Spearman non-parametric test was applied. Interaction analyses among RSV, meteorological factors, as well as variable selection of independent variables, were conducted using stepwise regression analysis. A correlation coefficient ® was interpreted as follows: $0 < |r| \le 0.2$ indicated weak correlation, $0.2 < |r| \le 0.5$ indicated low correlation, $0.5 < |r| \le 0.8$ indicated significant correlation, and $0.8 < |r| < 1$ indicated high correlation. A P-value < 0.05 denoted a statistically significant difference. For epidemiological time series forecasting, MATLAB (version 2021a) software was utilized to build predictive models and plots using the LS-SVM algorithm. For non-distributed lag models, the DLNM package in R software (version 4.1.0) was utilized for fitting. Graphs were generated by using GraphPad Prism software, version 9.3.1.

Results

Grouping

Lower respiratory tract infections in children were categorized according to age, gender, season, and pathogen. Age ranges from 28 days to 14 years were divided into the following four groups: infant group (≤ 1 year), toddler group (> 1– ≤ 3 years), preschool group (> 3– ≤ 6 years), and school-age group (> 6 years).The RSV detection rates across different age groups were as follows: 2,242 cases (21.9%) in infants, 515 cases (10.9%) in toddler group, 147 cases (4.7%) in preschool group, and 30 cases (1.9%) in school-age group. The detection rate was highest in infants, with the differences being statistically significant (P < 0.05). In terms of gender, children were categorized into the following two groups: male children were found in 12,062 cases (61.4%), while female children were found in 7575 cases (38.6%), with a male-to-female ratio of 1.6:1. Seasonal classification included the following four groups: spring (March to May) showing 4928 cases (25.1%), summer (June to August) showing 5042 cases (25.7%), autumn (September to November) showing 4831 cases (24.6%), and winter (December to February of the following year) showing 4836 cases (24.6%).

Distribution of RSV in genders and ages

Among male pediatric patients, 1,923 out of 12,062 cases tested positive for RSV, accounting for 15.95% of the total male inpatient population. Among female pediatric patients, 1,011 out of 7,575 cases tested positive for RSV, accounting for 13.35% of the total female inpatient population (P < 0.05). The male-to-female ratios for positive detection were 1.2:1 for RSV. The RSV detection rate was highest in infancy group at 21.9% (2,242/10,251), and it decreased with increasing age as follow: toddler group10.9%(515/4,725), preschool group 4.7%(147/3,104), and school-age group 1.9% (30/1,557), showing significant differences ($\chi^2 = 909.97$, $P < 0.001$).

Epidemiological characteristics of RSV infections

The average annual detection rate of RSV over a period of 14 years was 14.94%(2934/19637).RSV peaked in winter, which was significantly higher than that in the other seasons (χ2 = 2150.4, $P < 0.001$). RSV peaked in January, February, and December, with the detection rate decreasing from January to June and reaching its lowest point in June. Then, the detection rate increased gradually from July to December, with the highest rate in December for the entire year (Fig. 1).

The relationship between climatic factors and viral pathogens in the Suzhou region

Overview of meteorological factors in the Suzhou region

From 2006 to 2019, the monthly average temperature in Suzhou was 17.5 ± 8.6 °C, the average relative humidity was 71.2 ± 6.0%, the total monthly rainfall was 100.8 ± 74.1 mm, the total monthly sunshine duration was 145.1 ± 48.5 h, and the average monthly wind speed was 2.3 ± 0.5 m/s.

Monthly distribution of meteorological factors in the Suzhou region The temperature in Suzhou exhibited an increasing trend from January to July and August, with July and August representing the peak temperatures, followed by a decline, consistent with the natural seasonal pattern. The relative humidity remained relatively high throughout the year, with minor differences between months, and June showed the highest relative humidity. The total monthly rainfall peaked in June, likely associated with the plum rain season in Suzhou. The total monthly sunshine duration was longer in April, May, July, and August compared to the other months, while the sunshine duration was noticeably shortened in June due to the increased rainy days during the plum rain season. The average monthly wind speed showed minimal variation

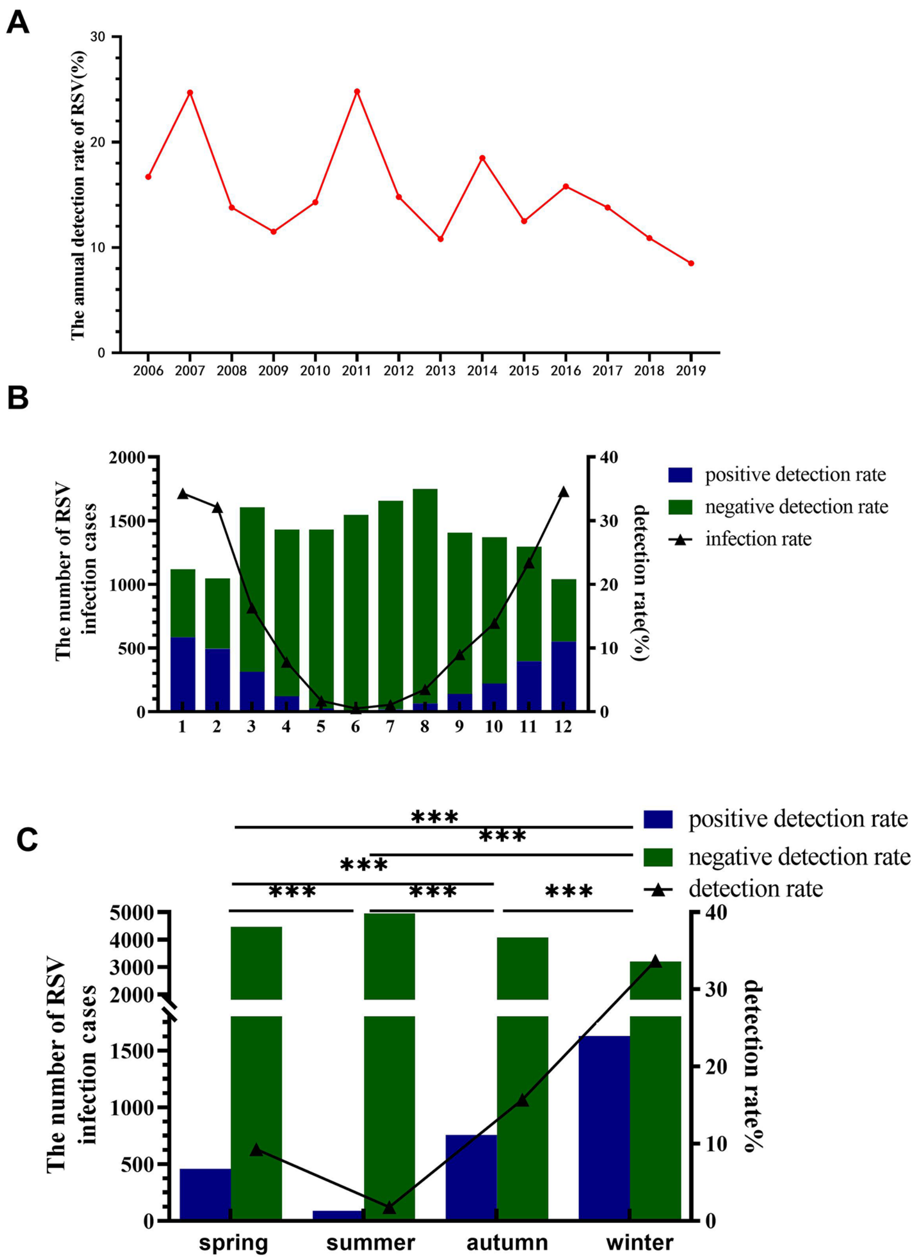

Fig. 1 Epidemiological Characteristics of RSV Infections. (**A**) The Annual Detection Rate of RSV. (**B**) Monthly Number of Detected RSV Cases and Detection Rate. (**C**) Number of Detected RSV Cases and Detection Rate in Different Seasons

across months, with slightly faster speeds from March to August compared to the other months (Fig. 2A).

Seasonal distribution of meteorological factors in the Suzhou region The average temperature in Suzhou varied across the four seasons, with the highest temperature in summer and the lowest temperature in winter, reflecting the subtropical monsoon climate of Suzhou and demonstrating distinct seasonal changes. The relative humidity was highest in summer and lowest in spring. The total monthly rainfall was highest in summer, with minor differences in rainfall between the other seasons. The total monthly sunshine duration was significantly longer in spring and summer than in autumn and winter, with winter having the shortest duration. The average wind speed was higher in spring and summer compared to autumn and winter, with minimal difference in the wind speed between spring and summer or between autumn and winter (Fig. 2B).

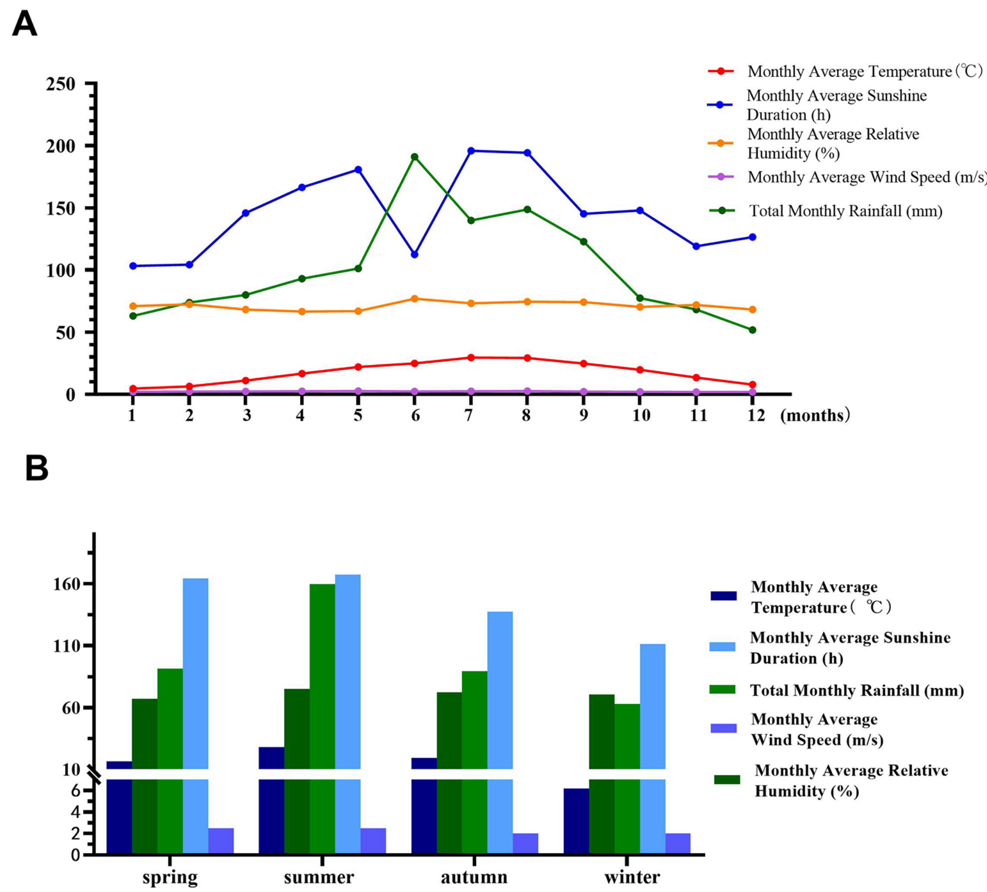

Fig. 2 Monthly and Seasonal Distribution of Meteorological Factors in the Suzhou Region. (**A**) Monthly Distribution of Meteorological Factors in the Suzhou Region. (**B**) Seasonal Distribution of Meteorological Factors in the Suzhou Region

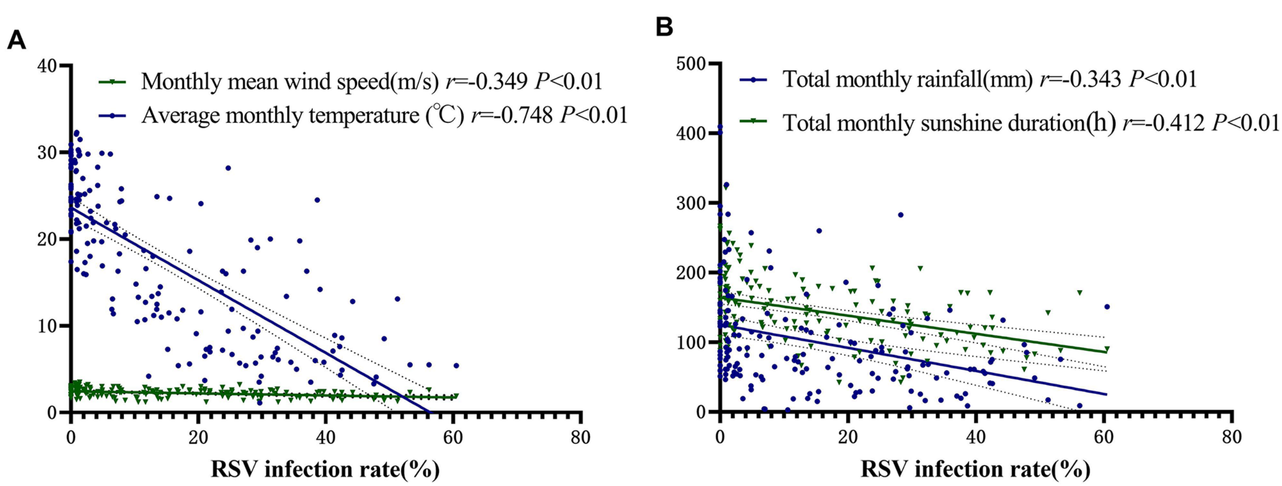

Fig. 3 Analysis of the Correlation Between RSV and Meteorology. (**A**) Correlation of RSV Infection Rate with Monthly Average Wind Speed and Temperature. (**B**) Correlation of RSV Infection Rate with Total monthly rainfall and sunshine duration

Analysis of the correlation between RSV and meteorology

RSV was significantly negatively correlated with the average monthly temperature, and it showed a low negative correlation with total monthly rainfall, monthly sunshine duration, and average monthly wind speed (Fig. 3).

The relationship between atmospheric pollutants and RSV in the Suzhou area

Overview of atmospheric pollutants in the Suzhou area

The main atmospheric pollutants in the Suzhou area were Sulfur Dioxide(SO_2), nitrogen oxides (measured as NO_2), particulate matter (PM10), Carbon Monoxide(CO), Ozone(O_3), and fine particulate matter (PM2.5). Their average concentrations from 2006 to 2019 over the 14-year period were as follows:

SO_2: 27.3 ± 13.9 μg/m^3, NO2: 49.3 ± 12.2 μg/m^3, PM10: 82.4 ± 24.7 μg/m^3, CO: 0.8 ± 0.2 mg/m^3, O_3: 97.9 ± 32.4 μg/m^3, and PM2.5: 52.0 ± 22.4 μg/m^3. The Air Quality Index (AQI) is the index for environmental air quality. AQI represents the quantitative severity of the primary pollutant and is derived from the Air Quality Sub-Index calculated for various air pollutants at the same time, with the AQI being taken as the value of the primary pollutant. In China the AQI is divided into six levels: Level I is excellent (0 ~ 50), Level II is good (51 ~ 100), Level III is light pollution (101 ~ 150), Level IV is moderate pollution (151 ~ 200), Level V is severe pollution (201 ~ 300), and Level VI is severe pollution (greater than 300).The average AQI over the 14- year period was 90.6 ± 19.8.

Annual variation of atmospheric pollutants According to the "Environmental Air Quality Standards" (GB3095-2012), the annual changes in atmospheric pollutants in the Suzhou area were as follows: NO_2: Except for the year 2006 when the concentration was relatively low and did not surpass the annual average secondary concentration limit value, in other years, it surpassed the annual average secondary concentration limit value.

PM2.5: It surpassed the annual average secondary concentration limit value in all years. PM10: From 2006 to November 2016, it surpassed the annual average secondary concentration limit value, but from 2017, the annual average concentration of PM10 decreased below the secondary concentration limit value. SO_2: From 2006 to October 2015, it surpassed the annual average primary concentration limit value, but from 2016, the annual average concentration of SO_2 decreased below the primary concentration limit value. O_3: In 2017 and 2018, it surpassed the average primary concentration limit value but it did not surpass the annual average secondary concentration limit value; and in other years, it did not surpass the annual average primary concentration limit value. CO: Throughout the monitoring period, it did not surpass the average primary concentration limit value. AQI: Only in 2013, the air quality was rated as mild pollution, while in the other years, the air quality was rated as good. Overall, the average concentrations of SO_2, CO, PM10, PM2.5, and AQI showed a clear decreasing trend year by year. The average concentration of NO_2 remained relatively high without a significant decreasing trend. The O_3 concentration over the years also did not show a significant decreasing trend (Fig. 4A).

Monthly variation of atmospheric pollutants In the monthly distribution trends of atmospheric pollutants, the average concentrations of SO_2, NO_2, PM10, and PM2.5 were higher at the beginning and end of the year over the years, while the corresponding concentrations were lowest in the middle of the year. In contrast, the monthly average concentration of O_3 was higher in the middle of the year and lower at the beginning and end of the year. Specifically, SO_2 had higher average concentrations in January and December compared to the other months; NO_2 showed higher monthly average concentrations in November and December, and lower concentrations in July and August; PM10 showed notably increased concentrations in January, November, and December compared to the other months; PM2.5 showed higher average concentrations in January and December; and CO showed minimal monthly concentration variation throughout the year. Unlike the other atmospheric pollutants, O_3 gradually reached its peak in the middle of the year. The AQI was higher from December to January of the following year, with relatively consistent values in the other months. From 2013 to 2017, the monthly average AQI reached light pollution levels in January and December, with occasional instances of moderate pollution in December 2013, while pollution levels remained generally good in the other months. From 2018 to 2019, the AQI consistently remained at a good level without any instances of light pollution (Fig. 4B).

Correlation analysis between RSV and atmospheric pollutants

RSV showed a significant positive correlation with NO_2, CO, and PM2.5, and a significant negative correlation with O_3. It had a low positive correlation with SO_2, PM10, and AQI. (Fig. 5).

Stepwise linear regression analysis of environmental factors and positive pathogen detection rates

The regression equation for RSV included the monthly average temperature as a predictor. For every increase of 1 °C in the temperature, the detection rates of RSV decreased by 1.267% respectively. The regression equation for RSV also included the monthly average wind speed, showing that for every decrease of 1 m/s in wind speed, the detection rates of RSV increased by 3.387% respectively (Table 1).

The LS-SVM prediction model based on environmental factors (meteorological factors)

The R2 values were found to be high and the RMSE values were low in the prediction models for RSV, suggesting that modeling predictions based on the corresponding predictor variables were reliable.

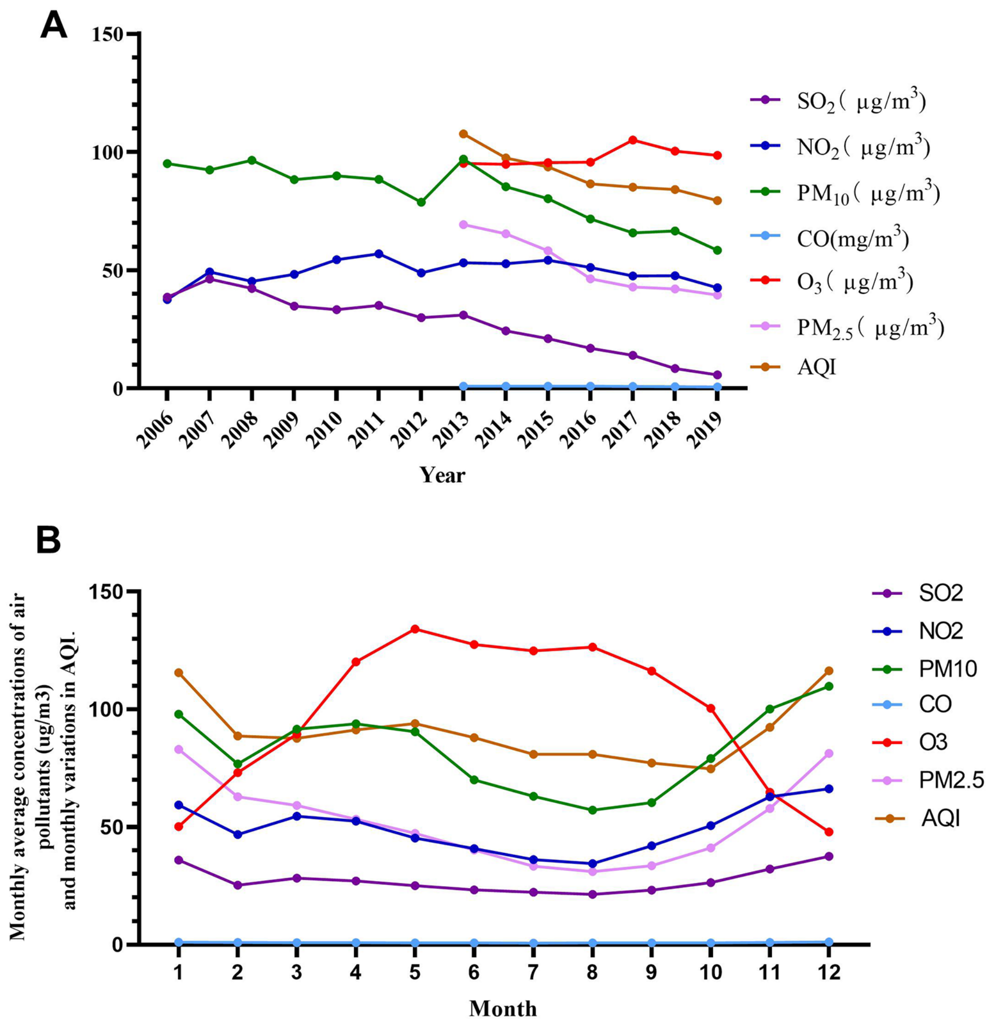

Fig. 4 Annual and Monthly Variation of Atmospheric Pollutants. AQI： Air Quality Index. (**A**) Annual Average Concentrations of Atmospheric Pollutants and AQI Index in Suzhou Region. (**B**) Monthly Average Concentrations of Atmospheric Pollutants and AQI Index in Suzhou Region

Predictive factor: the monthly average temperature

In accordance with the results of the stepwise regression equation, the monthly average temperature was paired with monthly average wind speed and SO_2 concentration as bivariate predictor variables and introduced into the prediction models for RSV, respectively.

For the RSV prediction model, the monthly average temperature and wind speed were included as predictor variables, resulting in a model parameter of R2 = 0.750 (RMSE = 5.524).

Predictive factor: the monthly average wind speed

According to the results of the stepwise regression equation, the monthly average temperature and wind speed were combined as bivariate predictor variables and jointly entered into the prediction model for RSV. The monthly average temperature and wind speed were used as predictor variables for the RSV prediction model, resulting in a model parameter of R2 = 0.750 (RMSE = 5.524).

Distributed lag non-linear models based on environmental factors (meteorological factors and atmospheric pollutants)

In the analysis of the non-linear model of lagged distribution of RSV infections and temperature, the relative risk (RR) varied with temperature changes. Two-dimensional and three-dimensional correlation plots at different temperatures and lag times revealed a non-linear relationship between temperature and RSV positive infection counts at different lag times. It was found that the high temperature effect appeared late and lasted for a short period, while the low temperature effect appeared early and lasted longer. From the RR value changes in the two-dimensional correlation plot, it was observed that the low temperature effect was greater than the high temperature effect (Supplementary Fig. 1 A1-2).

Cumulative lag effect plots for the months of January to March showed that using the median average temperature of 17℃ as a reference, the RR values were higher

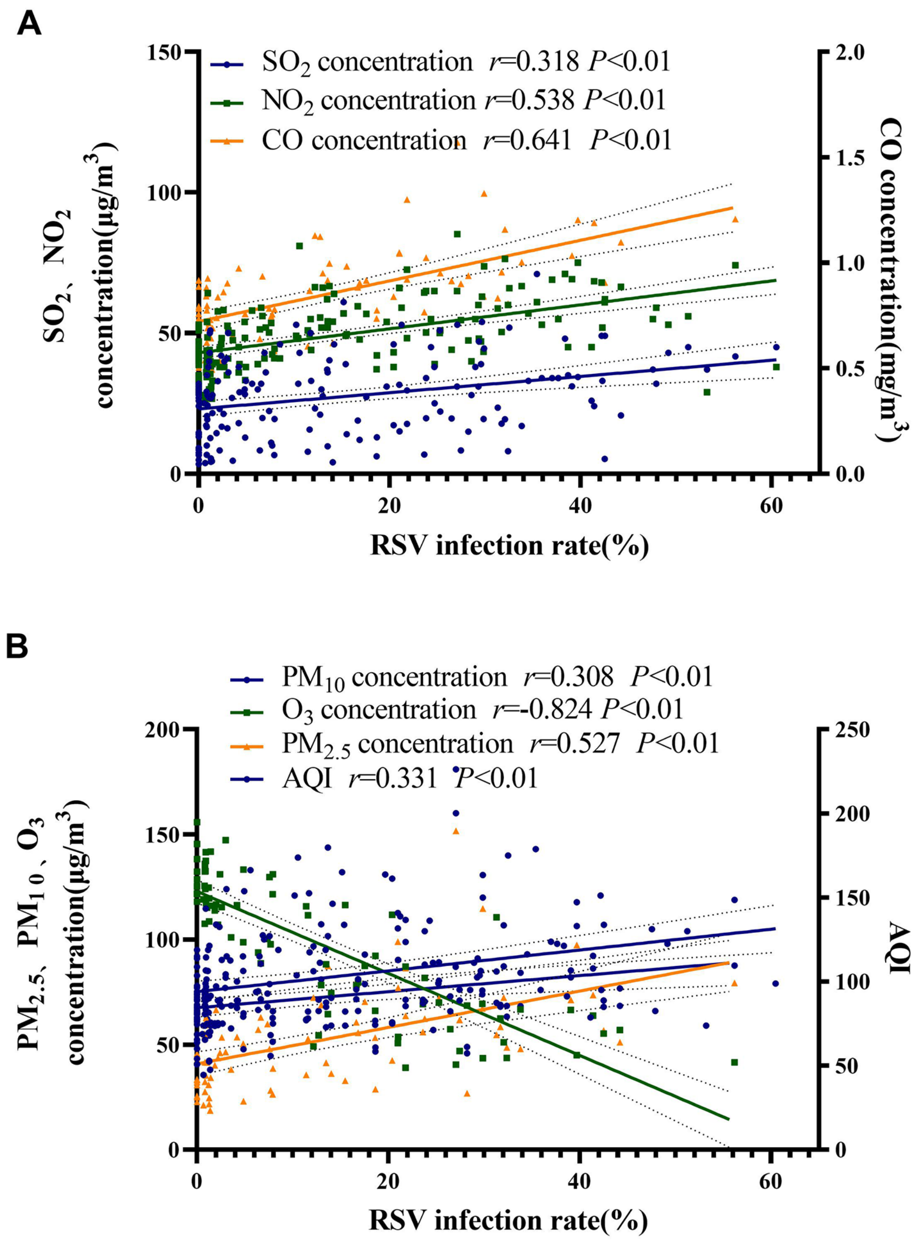

Fig. 5 Correlation Analysis between RSV and Atmospheric Pollutants. (**A**) Correlation Analysis of RSV Infection Rate with Atmospheric Pollutants SO2, NO2 and CO. (**B**) Correlation Analysis of RSV Infection Rate with PM2.5, PM10, O3 Concentrations and AQI

Table 1 Regression equation for the monthly average temperature and pathogen detection rate

Pathogen	Stepwise Linear Regression Equation	Predictor Variable
RSV	$Y = 44.523 - 1.267 \times_1 - 3.387 \times_2$	X1 represents the average monthly temperature X2 represents the average monthly wind speed

The regression equation for RSV included the monthly average temperature as a predictor. For every increase of 1 °C in the temperature, the detection rates of RSV decreased by 1.267% respectively. The regression equation for RSV also included the monthly average wind speed, showing that for every decrease of 1 m/s in wind speed, the detection rates of RSV increased by 3.387% and 0.633%, respectively (Table 1)

at low temperatures, indicating a significant sustained lag effect. As the temperature rose, the RR gradually decreased; the cumulative RR was higher at lower temperatures, and the risk gradually decreased as the temperature increased (Supplementary Fig. 1 A3).

In the analysis of the non-linear lagged distribution model of RSV positive infections with wind speed, the RR varied with changes in the wind speed. Two-dimensional and three-dimensional correlation plots at different wind speeds and lag times revealed a non-linear relationship between wind speed and RSV positive infection counts at different lag times. From the images(Supplementary

Fig. 1 B1), it was observed that relative to the reference wind speed (2.3 m/s), when the wind speed ranged from 2.1 to 2.9 m/s, the RR was slightly higher, indicating that wind speeds within this range had some impact on RSV positive infection counts. However, the RR gradually diminished with an increasing lag time, with a lag duration of approximately 0 to 22 days. When the wind speed was less than 1.9 m/s relative to the reference wind speed, the initial RR was low but it increased with longer lag times. Wind speeds greater than 2.9 m/s had a minimal impact on RSV positive infection counts. From the RR value changes in the two-dimensional correlation plot, it was evident that the effect of low wind speeds was greater than that of high wind speeds (Supplementary Fig. 1 B1-2).

The cumulative lag effect plot for 1–3 months showed that as the lag time ranged from 0 to 3 months, the cumulative effect of wind speed exhibited a trend of an initial increase and then a decrease with an increasing wind speed (Supplementary Fig. 1 B3).

Discussion

Urbanization is an important carrier of socio-economic development, and the acceleration of urbanization processes usually promotes improvement at the industrial, medical, and educational levels. However, the damage to health caused by air pollution due to urbanization may, in some cases, offset the benefits of urbanization. Atmospheric pollutants, especially inhalable particulate matter, serve as the primary environmental risk affecting our health, with almost 90% of the world's population breathing air that exceeds the upper limits set by the World Health Organization [10]. From 1990 to 2017, the number of deaths in the African region due to air pollution increased by 60% [11]. The Institute for Health Metrics and Evaluation at the University of Washington estimated that approximately 4.3% of the reduction in disability-adjusted life years in children under 5 years due to lower respiratory infections is attributed to the decrease in air pollution [12]. RSV causing lower respiratory tract infections spread through the air, which is a major route of infection and disease transmission, while changes in the air quality and infectiousness of pathogens, antibiotic resistance, and virulence of pathogens have resulted in various public health issues.

Suzhou is located in the Northern Hemisphere and belongs to the subtropical monsoon climate zone, with distinct temperature differences and seasons. The relative humidity is slightly higher in summer, less distinct in autumn and winter, and lowest in spring, corresponding to the total precipitation trend, although the relative humidity fluctuations between seasons are relatively small. Since China's Ministry of Environmental Protection issued the new "Ambient Air Quality Standards" in 2012, air pollutants in the Suzhou region have decreased, especially PM10, PM2.5, AQI, and SO2, which have shown a significant annual decline since 2013, indicating that environmental pollution control measures in the Suzhou region have been effective. High temperatures can increase the risk of respiratory diseases, leading to death and hospitalization from air pollution [13]. Exposure to air pollutants containing heavy metals, polycyclic aromatic hydrocarbons, and toxic chemicals derived from cigarette smoke can have many negative effects on various systems of the body. Climate change can influence health, and air pollutants affected by climatic factors can further impact the body [10]. A positive correlation has been found between exposure to air pollutants and the risk of infection with novel coronavirus as well as the severity of COVID-19 [14, 15]. Researchers, such as Anwar [16], suggested that an increase in PM2.5 by one unit can lead to an approximate 14.5% increase in mortality in children aged under 5 years. Short-term exposure to PM2.5 can alter the microbial colonization of the oral mucosa, increase airway inflammation, and decrease lung function [5]. O3 can cause systemic oxidative stress and inflammation, with a greater impact on the elderly and children with asthma. Prolonged high concentrations of O3 increase the risk of sepsis-related mortality, with the strongest association found in pneumonia patients. The short-term effects of O3 are associated with social mortality rates [17, 18]. Overall, while the incidence of epidemics largely depends on the initial exponential growth phase, favorable environmental conditions can influence transmission [19]. This study found a certain correlation between meteorological factors, air pollutants, and infections and epidemics caused by RSV.

RSV was negatively correlated with the air temperature, with a higher detection rate of RSV observed in colder temperatures. Therefore, RSV was more commonly detected in winter when the temperatures were lower, consistent with research findings obtained both domestically and internationally [20, 21]. This study found that the RSV detection rate decreased by 1.267% for every 1 °C increase in temperature, while it increased with every 1 m/s decrease in wind speed. In Suzhou, the average temperature and wind speed during winter were the lowest among all seasons, further providing climatic evidence for the high RSV infection rate in winter. This may be attributed to the fact that RSV, being an enveloped virus, exhibits higher stability and longer survival at low temperatures [22, 23]. Additionally, lower external temperatures can cause vasoconstriction of the respiratory mucosa and suppress the body's immune system, increasing susceptibility to viral infections [24]. The increased infection rate associated with reduced wind speed may be attributed to slower viral dispersion, prolonged viral residence time within a confined space, and enhanced host exposure to the virus, thereby elevating the likelihood of infection [25].Additionally, this study revealed that RSV infection rates were significantly positively correlated with NO2, CO, and PM2.5, but significantly negatively correlated with O3. Air pollutant data from Suzhou indicated that the concentrations of NO2, CO, and PM2.5 were markedly higher in winter, while O3 levels were significantly lower. Therefore, atmospheric pollution should be considered an important contributing factor to the increased RSV infection rate.Exposure to atmospheric pollutants such as PM2.5, NO2, and CO may alter microbial colonization in the oral mucosa, increase airway inflammation, and reduce lung function, thereby leading to an elevated infection rate [5, 11]. Therefore, the influence of climatic factors and atmospheric pollution on RSV infection rates cannot be overlooked. Moreover, the cold environment forces people to gather indoors in confined spaces, which facilitates aerosol transmission of the virus.

The impact of temperature on the distribution of RSV was also observed in a DLNM. When the lag time was short, the RR decreased with an increase in the temperature. However, as the lag time extended, the RR showed a bimodal trend of an initial decrease and then an increase with the temperature. This study found that when the temperature was below the reference temperature of 17℃, the cumulative RR significantly increased with a longer lag time. This indicates that temperature has a clear lagged and cumulative effect on RSV, consistent with both domestic and international literatures [22, 26]. The prevalence of RSV was not only correlated with the temperature but it was also negatively correlated with the wind speed, which is in line with research findings obtained from both domestic and international sources [27, 28]. The stepwise linear regression equation showed that for every 1 m/s decrease in the wind speed, the detection rate of RSV increased by 3.387%. In DLNM, compared to the reference wind speed of 2.3 m/s, at lower wind speeds, there was a more pronounced lag and cumulative effect; at wind speeds between 2.1 and 2.9 m/s, an immediate effect was observed, with a lag effect lasting around 22 days, and the RR showed an initial increase followed by a decreasing trend. The cumulative RR effect gradually increased with a longer lag time when the wind speed was below 2.3 m/s. This suggests that there is a significant lag effect of the wind speed on RSV, with a relatively small cumulative effect. This may be due to the fact that RSV is more likely to colonize in the respiratory epithelial cells under lower wind speeds over time, and relative to the reference wind speed, RSV is more likely to be immediately transmitted at wind speeds between 2.1 and 2.9 m/s.

Conclusion

In summary, our 14-year study reveals that atmospheric pollutants in Suzhou, including SO2, NO2, PM10, PM2.5, and O3, consistently exceeded national standards. While annual averages of SO2, PM10, and PM2.5 have declined, NO2 and O3 remain elevated, with seasonal variations influenced by temperature, humidity, rainfall, sunlight, and wind. Our analysis identifies immediate and lag effects of meteorological factors and air pollutants on RSV infection, guiding potential pathogen impact assessments and informing vaccination and pollution control strategies. Employing DLNM and LS-SVM, we achieved accurate predictions, highlighting the feasibility of clinical forecasting based on predictive factors.

Abbreviations

AQI	Air Quality Index
CDC	Centers for Disease Control
cDNA	complementary Deoxyribonucleic Acid
CO	Carbonic Oxide
DLNM	Distributed Lag Non-linear Model
DNA	Deoxyribonucleic Acid
ELISA	Enzyme-Linked Immunosorbent Assay
HDI	Human Development Index
LS-SVM	Least Square Support Vector Machine
mRNA	Messager Ribonucleic Acid
PBS	Phosphate Buffer Saline
PCR	Polymerase Chain Reaction
Q-AIC	Quasi-likelihood for Akaike's Information Criterion
RMSE	Root Mean Square Error
RNA	Ribonucleic Acid
RNasin	Ribonuclease Inhibitor
RSV	Respiratory Syncytial Virus
RT-PCR	Reverse-Transcription Polymerase Chain Reaction
WHO	World Health Organization

Supplementary Information

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Supplementary Material 1. Distributed Lag Non-linear Models Based on Environmental Factors. RR： relative risk，3D： Three-dimensional，2D： two - dimensional. **Supplementary Figure A1**. Correlation of RR with the Monthly Average Temperature in a 3D Regarding the Lag Time. **Supplementary Figure A2**. Correlation of RR with the Monthly Average Temperature in a 2D Regarding the Lag Time. **Supplementary Figure A3**. Cumulative Lag Effect of Temperature on RSV. **Supplementary Figure B1**. Correlation of RR with Monthly Average Wind Speed in a 3D Considering the Lag Time. **Supplementary Figure B2**. Correlation of RR with Monthly Average Wind Speed in a 2D Considering the Lag Time. **Supplementary Figure B3**. Cumulative Lag Effect of Wind Speed on RSV

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Author contributions

Zhengrong Chen and Chuangli Hao designed the study. Heting Dong, Yanxia Zou, Mengyao Yan statistical analysis of all data and wrote the manuscript. Huiming Sun, Jiawei Chen, Yongdong Yan and Canhong Zhu compiled the collected data. All authors read and approved the final manuscript.

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Data availability
Data and material are available and stored in Children`s Hospital of Soochow University.

Declarations

Ethics approval and consent to participate
This study was performed after Ethics committee of Children`s Hospital of Soochow University approval was obtained(NO.2021CS191).This study is a retrospective study and the need for consent to participate was waived by Ethics committee of Children`s Hospital of Soochow University.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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