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RESEARCH ARTICLE

Analysis of the effect of temperature on tuberculosis incidence by distributed lag non-linear model in Kashgar city, China

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Abstract

The aim of this study was to explore the effect of temperature on tuberculosis (TB) incidence using the distributed lag non-linear model (DLNM) from 2017 to 2021 in Kashgar city, the region with higher TB incidence than national levels, and assist public health prevention and control measures. From January 2017 to December 2021, a total of 8730 cases of TB were reported, with the higher incidence of male than that of female. When temperature was below 1 °C, it was significantly correlated with TB incidence compared to the median observed temperature (15 °C) at lag 7, 14, and 21, and lower temperatures showed larger RR (relative risk) values. High temperature produced a protective effect on TB transmission, and higher temperature from 16 to 31 °C has lower RR. In discussion stratified by gender, the maximum RRs were achieved for both male group and female group at − 15 °C with lag 21, reporting 4.28 and 2.02, respectively. At high temperature (higher than 20 °C), the RR value of developing TB for female group was significantly larger than 1. In discussion stratified by age, the maximum RRs were achieved for all age groups (≤ 35, 36–64, ≥ 65) at − 15 °C with lag 21, reporting 3.20, 2.07, and 3.45, respectively. When the temperature was higher than 20 °C, the RR of the 36–64-year-old group and the ≥ 65-year-old group was significantly larger than 1 at lag 21, while significantly smaller than 1 for cumulative RR at lag 21, reporting 0.11, 95% confidence interval (CI) (0.01, 0.83) and 0.06, 95% CI (0.01, 0.44), respectively. In conclusion, low temperature, especially in extreme level, acts as a high-risk factor inducing TB transmission in Kashgar city. Males exhibit a significantly higher RR of developing TB at low temperature than female, as well as the elderly group in contrast to the young or middle-aged groups. High temperature has a protective effect on TB transmission in the total population, but female and middle-aged and elderly groups are also required to be alert to the delayed RR induced by it.

Keywords Tuberculosis · Temperature · Effect · DLNM · RR

Introduction

Tuberculosis (TB), as a chronic infectious disease caused by mycobacterium tuberculosis, can affect various organs of the body. According to the WHO Global TB Report 2020, TB remains the top killer of a single infectious disease to 2019, and the WHO Global TB Report 2021 estimated that the cause of death as a single source of infection ranked the second in 2020 due to the COVID-19 outbreak (WHO 2020, 2021). To achieve the goal of ending the TB epidemic by 2030, all countries have made unremitting efforts in the prevention and control of TB and achieved robust progress, which was, however, broken by a sudden outbreak of COVID-19 (McQuaid et al. 2020; Chen et al. 2020; Alene et al. 2020; Pang et al. 2020; Abdool et al. 2020; Cilloni et al. 2020; Leung et al. 2020; Bhargava and Shewade 2020). In 2020, the number of TB cases detected worldwide appeared a downward trend, with the registered cases falling

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by 18% from 7.1 million to 5.8 million, compared with 2019. In addition, the COVID-19 pandemic also resulted in a 15% decrease in the MDR/rifampicin-resistant TB patients treated, a 22% decline in patients receiving preventive treatment, and a 9% decrease in the cost of services for the diagnosis and treatment of TB prevention. Due to the disruption of basic services for TB, about 100,000 more TB deaths worldwide was estimated in 2020 (WHO 2021). For the goal of terminating TB, the prevention and control of TB still need to be strengthened in the future. According to the WHO report (WHO 2021), the number of new TB patients in China in 2020 was estimated at 842,000, with the incidence of about 59/100,000, ranking the second among 30 countries with high TB burden, leaving the arduous task of TB prevention and control in China.

Pulmonary tuberculosis is the most common form of TB. The TB is spread mainly by respiratory tract infection, involving active TB patients, sneezing, coughing, or talking loudly, which make its droplets suspended in the air and may cause TB infection if people breathe the droplets (Natarajan et al. 2020). As an infectious disease with seasonal distribution, the external environmental factors including meteorological factors play significant roles in the onset and transmission of TB. Studies have demonstrated that abnormal changes in climate can lead to significant variations in the incidence and geographical distribution of infectious diseases, accompanied with serious adverse effects on human health. Due to the diversity in the natural environment, ecological characteristics, meteorological types, population immunity, and other social factors, the impact of meteorological factors on diseases from different studies also varied (Li et al. 2021; Chen et al. 2021; Maharjan et al. 2021; Kirolos et al. 2021; Desikan et al. 2019; Onozuka and Hagihara 2015; Allen and Sheridan 2018; Feng et al. 2021; Kim et al. 2019). The incidence of TB in Kashgar city is high. Kashgar, located in the abdomen of Central Asia, is involved in the warm temperate continental arid climate zone, with long light, large annual change and daily change in temperature, less precipitation, and strong evaporation within the four seasons. Summer is hot, but the heat period is short; winter is not cold, but the low temperature period is long; spring and summer are characterized as high wind, sandstorm, and dust. The annual average temperature is 11.8 °C; the coldest month is January, with the average temperature of about −6 °C; the hottest month is July, with the average temperature of about 26 °C. Tuberculosis has developed to one of the main public health problems affecting the health of the residents in Kashgar city, China. It is very necessary to study the influence of temperature on the transmission of TB.

The study on the influence of meteorological factors on infectious diseases can provide a scientific reference for the prevention and control of infectious diseases. Some quantitative research methods, such as statistics and mathematical models, are increasingly applied in this field, with the most commonly being using infectious disease data and concurrent meteorological factors for univariate correlation analysis and multiple regression analysis. In addition, principal component regression analysis, step-wise discriminant analysis, gray association analysis, and geographic information system methods have also gradually been considered. The diversity of factors considered in mathematical modeling has developed to a critical direction in studying the influence of meteorological factors on infectious diseases, among which the distributed lag non-linear model (DLNM) has been gradually applied in recent years. In addition to the general advantages of mathematical modeling, it stands out with the advantage of dealing with the lag and persistence of the health effects of meteorological conditions (Allen and Sheridan 2018; Watson et al. 2020; Zhang et al. 2019; Iguchi et al. 2018; Liu et al. 2021; Kakarla et al. 2019). Studies have shown the relation of temperature change with the incidence of infectious diseases, reporting a nonlinear temperature-exposure–response curve and an existing lag effect. Beak et al. (2022) found that daily mean temperature and maximum temperature were negatively associated with hepatitis A in the 6-week lag. Okiring et al. (2021) found the effect of temperature on malaria incidence in Uganda was often non-linear and subject to temporal lags. Fong and Smith (2022) found that there was exposure-lag response of temperature on daily COVID-19 incidence in twelve Italian cities. Wang et al. (2022) found that there was a nonlinear lag relationship between temperature and influenza incidence and indicated that low temperature increased the risk of influenza in Lanzhou. The DLNM can simultaneously fit the nonlinear relationship of the exposure–response and the lag effect of the exposure. Chaw et al. (2022) investigated the association between climate variables and pulmonary tuberculosis (PTB) incidence using DLNM in Brunei-Muara district, Brunei Darussalam; they observed positive but delayed relationship between TB incidence and minimum temperature. Huang et al. (2020) assessed the association between ambient temperature change and the risk of TB admissions based on DLNM; the overall exposure–response curves of their study suggested that there were statistically significant associations between two temperature change metrics and the risk of TB admissions; the maximum lag-specific relative risk of TB admissions was 1.088 (95%CI: 1.012–1.171, lag 4 day) for exposing to large temperature drop (TCN = −4 °C) in winter. Xiao et al. (2018) found that temperature had the nonlinear relationship of the exposure–response and the lag effect on TB transmission; informed prevention and preparedness measures for TB can therefore be constructed on the basis of meteorological variations.

The incidence of TB is very high in Kashgar city, China; however, the influence of temperature on TB incidence remains severely under-discussed in detail. This study aimed to clarify the impact of temperature on TB incidence during 2017–2021 in Kashgar city. The results are expected to facilitate the optimization of TB-related public health policies by the local healthcare departments.

Materials and methods

The study area

Kashgar region is located in central Eurasia, northwest China and southwest of Xinjiang Uygur Autonomous Region, China (see Fig. 1), between east longitude 71.39'~79.52' and north latitude 35.28'~40.16'. Kashgar city is currently the only city in Kashgar region, with resident population of 0.7069 million in 2019.

Data collection

We conducted a retrospective time-series study of daily TB incidence and meteorological variables in Kashgar city from 2017 to 2021. Daily observations of historical meteorological conditions, including temperature, wind speed, and relative humidity in Kashgar city, were from websites (https://tianqi.2345.com/wea_history/51709.htm). Daily reported cases of TB from 2017 to 2021 in Kashgar city, including case sex and age information, were from the Kashgar regional centers for Disease Control and Prevention. The distribution of the data is listed in Table 1. The maximum daily incidence of TB was 83, and the minimum was 0. The lowest daily mean temperature was −15.4 °C, the highest was 31.4 °C, and p_{50} (50% quantile) was about 15 °C. The minimum daily humidity was 7%, and the maximum was 93%; the minimum daily wind speed was 0.4 m/s, and the maximum was 11.2 m/s. The time series of meteorological data are shown in Fig. 2. Periodic change was shown in the scatter plot of daily mean temperature: the greatest increase was in June and July, and greatest decrease in January. The time series of TB incidence are shown in Fig. 3, where the number of TB cases fluctuated greatly in June and December. A higher number of TB generally occurred in April, May, and June.

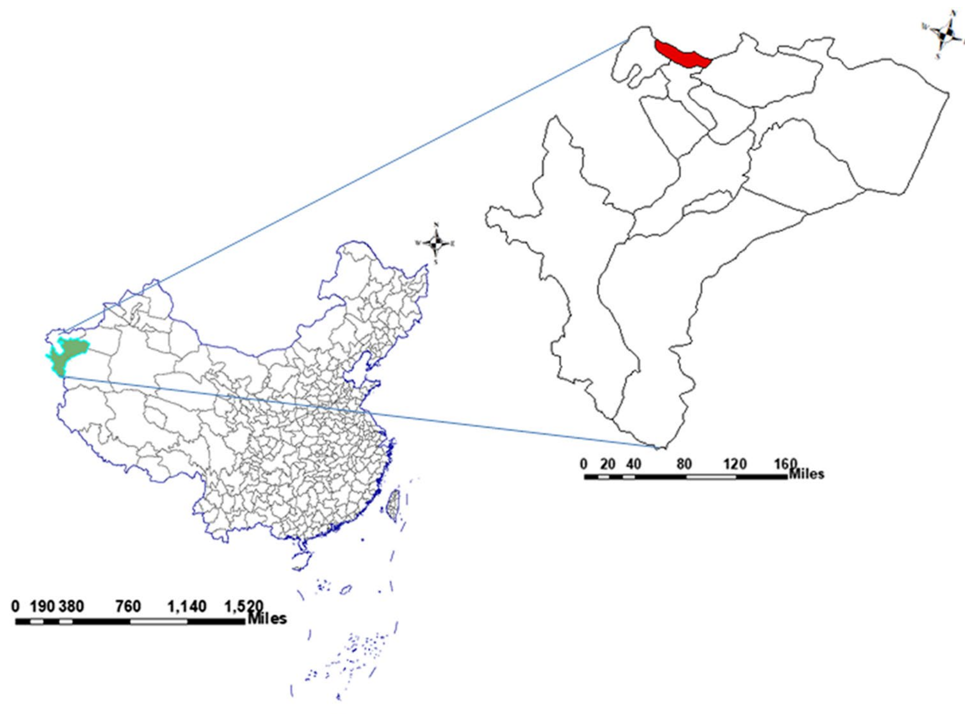

Fig. 1 Green-colored area indicates the location of Kashgar region in China, and red-colored area indicates the location of Kashgar city in Kashgar region, China. The map was created using GIS version 10.4

Table 1 Demographic characteristics of daily TB cases and characteristics of daily meteorological data in Kashgar city, 2017–2021

		Min	P_{25}	P_{50}	P_{75}	P_{95}	Max	Mean ± std
Total		0	0	0	6	22	83	4.78 ± 9.07
Gender	Male	0	0	0	3	12	62	2.55 ± 5.09
	Female	0	0	0	3	10	59	2.21 ± 4.81
Age	≤ 35	0	0	0	1	5	27	1.06 ± 2.29
	36–64	0	0	0	2	8	60	1.78 ± 3.87
	≥ 65	0	0	0	3	11	49	2.18 ± 4.37
Temperature		− 15.4	2.3	14.7	22.5	27.4	31.4	12.58 ± 11.33
Humidity		7	31	42	57	76	93	44.16 ± 17.09
Wind speed		0.4	1.7	2.2	2.9	4.8	11.2	2.47 ± 1.20

std, standard deviation; *Total*, the number of daily TB cases, regardless of gender and age

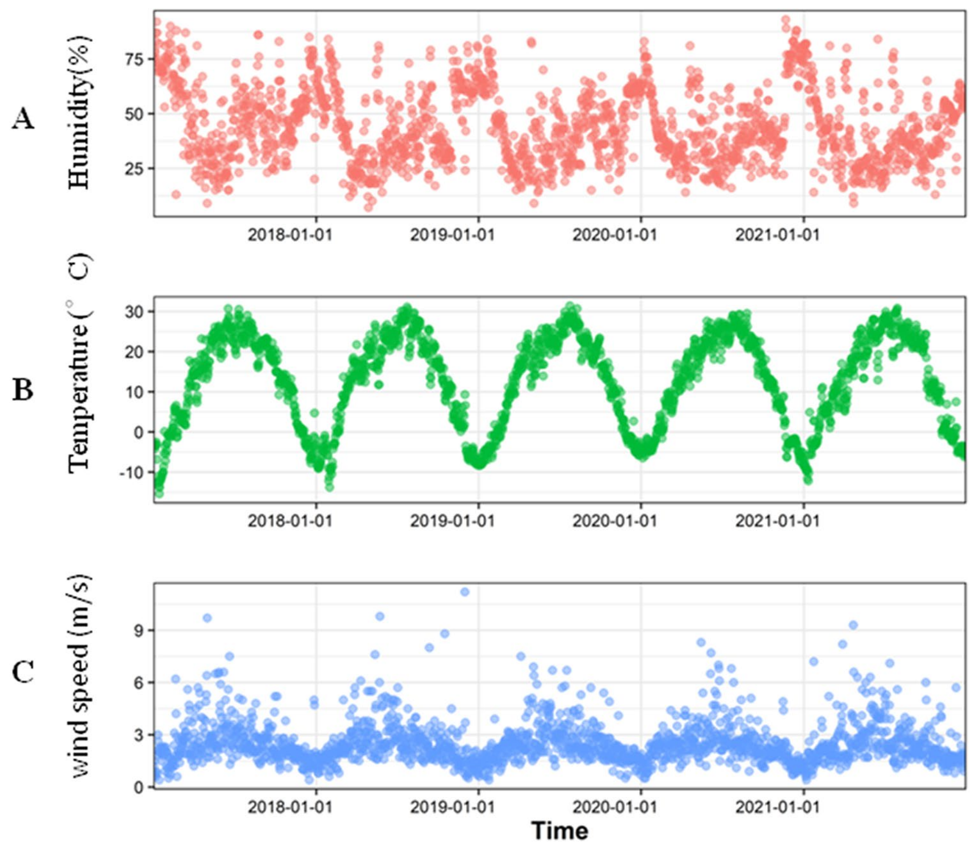

Fig. 2 Time trends of meteorological factors in Kashgar city, 2017–2021. **A** Relative humidity (%). **B** Mean temperature (°C). **C** Wind speed (m/s)

Model descriptions

We performed a basic statistical analysis of the time series of TB cases and meteorological data and constructed the DLNM model based on these data. The daily incidence of TB is a small probability event, its distribution is similar to Possion distribution, and the number of daily incidence of TB was excessively discrete. Therefore, the quasi-Poisson distribution was adopted in the DLNM model in our study. The mean temperature as a "cross-basis" form was included to estimate the effect of temperature on the number of TB cases from 2 dimensions: variable level and lag time. The "cross-basis" form is as follows:

The logarithm of the expected values Y_t at the day t is dependent. Y_t denoted the daily TB incidence on day t. α was the intercept, and $temp_{t,l}$ is the cross-basis matrix produced by the DLNM. The temperature exposure-reaction dimension takes natural cubic splines as the basis function, and the exposure-lag effect dimension takes polynomial as the basis function. The ns is the natural cubic spline function, and the *df* is the degree of freedom, and poly is the polynomial function. The AIC (Akaike information criterion) is applied to select the *df* of day to control long-term trends, humidity, and wind speed (Lu et al. 2020). Based on the AICs, we chose *df* = 3 for ns to the climatic factors mentioned above.

$$temp_{t,l} = crossbasis\left(temperature, lag = 21,\ \text{argvar} = list\left(fun = {}^{\varepsilon}ns^{\varepsilon}, knots = round(median(temperature))\right)\right),\ \text{arg}\ \ lag = list\left(fun = {}^{\varepsilon}poly^{\varepsilon}, df = 4\right)$$

In this study, the lag effect of 3 weeks was analyzed on the TB incidence; the maximum lag was set to 21 days in the model. The "cross-basis" of the daily mean temperature was used as the independent variable, while controlling the influence of humidity, wind speed, time trend, and week effect, which were incorporated into the model. The model formula is:

We chose *df* = 7 every year for ns to long-term trends. Dow_t was the day of the week on day t, which was a categorical variable (1, 2, 3… 7).

All the statistical analyses were performed using SPSS 25 and R software program, version 4.1.3. Based on the generalized linear model (glm) model, the "DLNM" package was used to

$$Log\left[E\left(Y_t\right)\right] = \alpha + \beta\left(temp_{t,l}\right) + ns\left(humidity_t, df = 3\right) + ns\left(windspeed_t, df = 3\right) + ns(time, df = 7^{*}5) + \gamma Dow_t$$

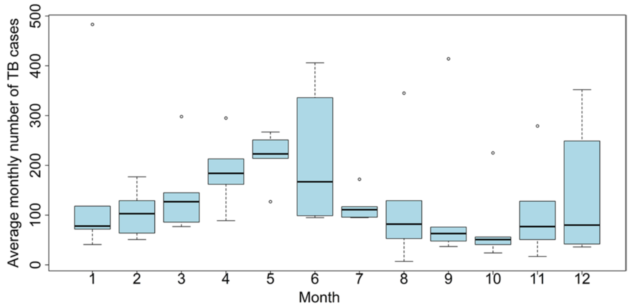

Fig. 3 Average monthly distribution of TB incidences in Kashgar city, 2017–2021

analyze the nonlinear and lag effects of the risk factors. Relative risk (RR) and cumulative relative risk (cumRR) were estimated by the "crosspred" function, and the plot function visualized some results. $p < 0.05$ was deemed as statistically significant. The map figure was created using GIS version 10.4.

Results

Epidemiological characteristics

A total of 8730 cases of TB were reported in Kashgar city from January 1, 2017, to December 31, 2021, with 4663 male cases and 4029 female cases. The TB incidence was higher in the elderly, in which the ≥65-year-old group accounted for 46% of the total group. In this period, the daily mean temperature, daily humidity, and daily wind speed in Kashgar city showed seasonal changes (see Fig. 1), with a relative high temperature and high wind speed while low humidity from May to August. The temperature and wind speed around January every year were low, while the humidity was high. The correlation between meteorological factors and the incidence of TB in each group was analyzed by Spearman correlation analysis (see Table 2), reporting significant correlation between meteorological factors and different groups of TB cases. The correlation coefficient of daily mean temperature with daily mean relative humidity and daily average mean wind speed was −0.612 and 0.597, respectively. Considering the correlation of the wind speed and humidity with the number of TB patients and the daily mean temperature, we involved the daily mean relative humidity and daily mean wind speed into the DLNM model when analyzing the effect of mean temperature on the incidence of TB as confounding factors.

Effect of the daily average temperature on the TB incidence

According to the analysis of DLNM model, the temperature effect on the TB incidence in Kashgar city from 2017 to 2021 showed non-linear relationships for the total

Table 2 Spearman's correlation coefficients between meteorological factors and the incidence of TB in different groups

	Temperature	Humidity	Wind speed	Total	Male	Female	0–35	36–64
Humidity	−0.612**							
Wind speed	0.597**	−0.590**						
Total	0.072**	−0.067**	0.075**					
Male	0.083**	−0.083**	0.083**	0.942**				
Female	0.064**	−0.066**	0.078**	0.941**	0.846**			
≤35	0.088**	−0.082**	0.077**	0.830**	0.796**	0.789**		
36–64	0.062**	−0.053*	0.070**	0.811**	0.782**	0.791**	0.665**	
≥65	0.055*	−0.059*	0.068**	0.938**	0.901**	0.908**	0.782**	0.744**

* $p < 0.05$, ** $p < 0.01$

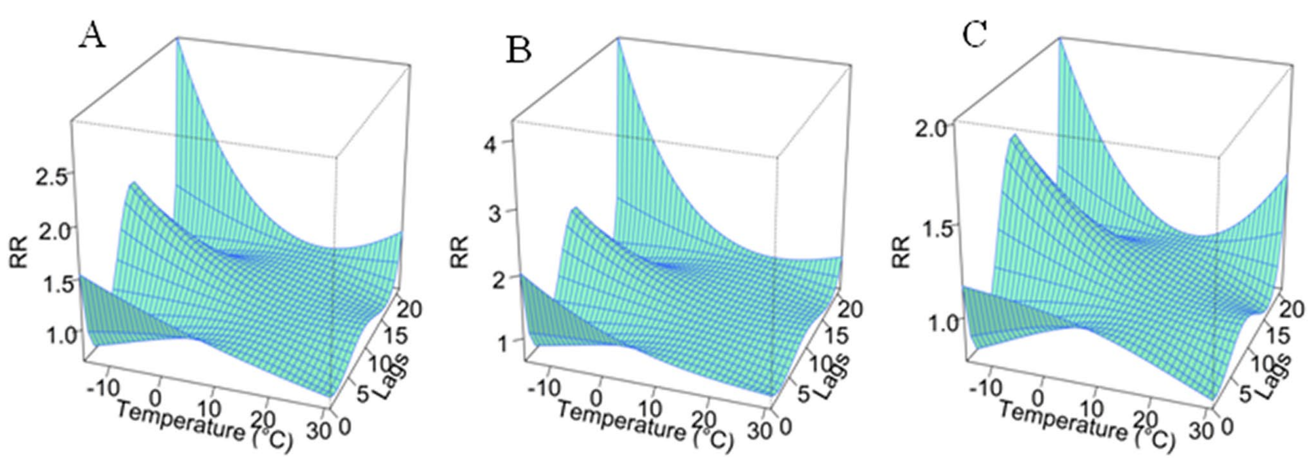

Fig. 4 Three-dimensional plots of different temperature lag effects stratified by gender. **A** Total. **B** Male. **C** Female

population, different gender stratification (see Fig. 4), and different age stratification (see Fig. 5). The median of temperature was 14.7 °C, and 15 °C was defined as the reference. The highest RR in each group appeared at − 15 °C with lag 21 days, and the highest RR values were 2.96 in total population, 2.02 in female group, 4.28 in male group, 3.20 in ≤ 35-year-old group, 2.07 in 36–64 years group, and 3.45 in ≥ 65 years group. Figures 6 and 7 depicted contour maps of different temperature lag effects, where blue area represents RR less than 1 and red area represents RR greater than 1. The redder the area, the greater the RR, indicating a higher risk of TB onset.

Figures 6 and 7 showed the RR-lag relationship at different temperatures. RR referred to the multiple of TB cases at a given temperature, as compared with the reference value − 15 °C. In each group, the RR of low temperature was higher at lag around 10 days and reached its maximum at lag 21 days. High temperature brought about a protective effect on TB transmission for most groups, resulting in an increased RR only for female group and for 36–64-year-old group at lag 20.

We studied the effect of temperature of different lag days on TB incidence in different population, setting 15 °C (50th percentile) as the threshold value of temperature, performing a detailed analysis of the effect of temperature on TB incidence at lag 7, 14, and 21 days. As Figs. 8 and 9 show, for total group and different subgroups, low temperature (≤ 15 °C) has resulted in an increased RR, while higher temperature from 20 to 31 °C reported lower RR compared to the median observed temperature (15 °C) at lags 7 and 14. However, for temperature at lag 21 days, low temperature still maintained

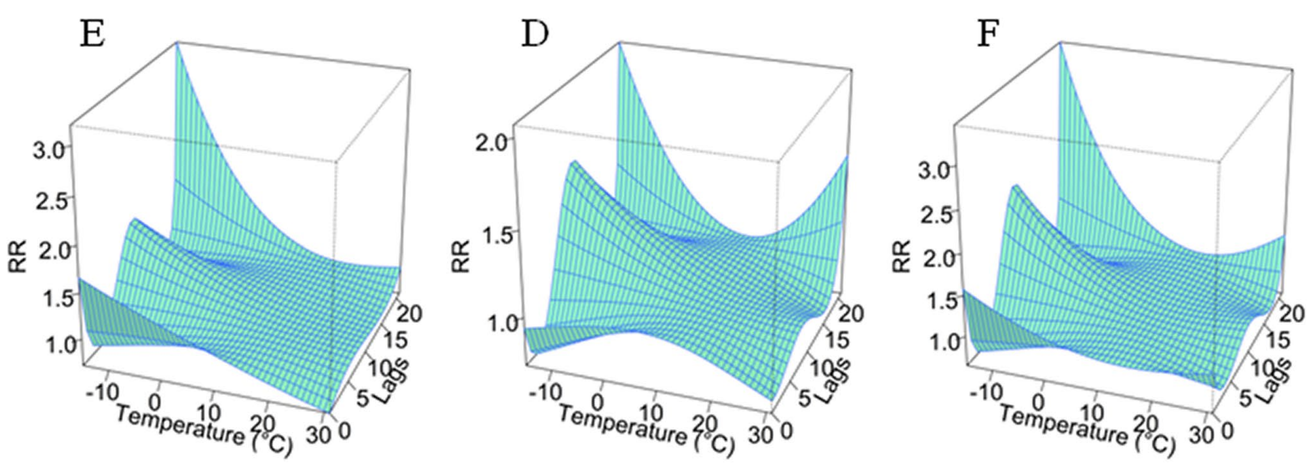

Fig. 5 Three-dimensional plots of different temperature lag effects stratified by age. **D** ≤ 35. **E** 36–64. **F** ≥ 65

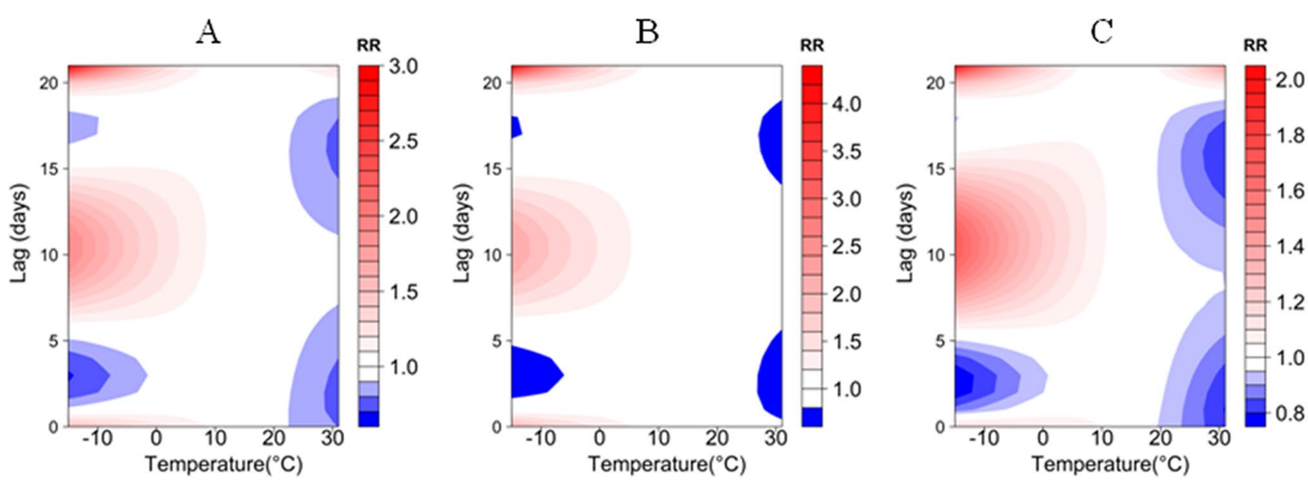

Fig. 6 Contour plots of the combined effect of time lags and mean temperature on the incidence RR of TB stratified by gender. **A** Total. **B** Male. **C** Female

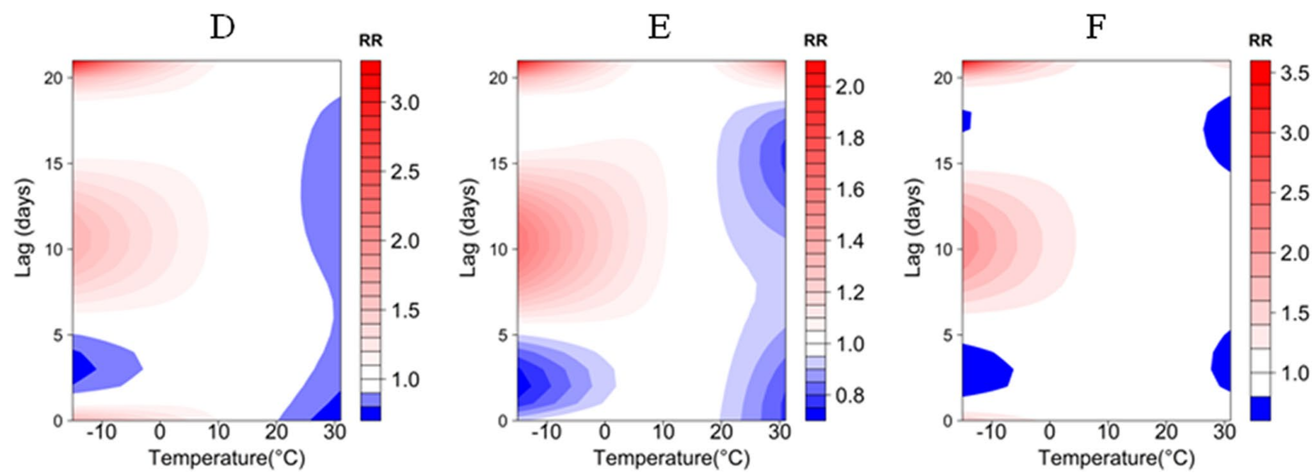

Fig. 7 Contour plots of the combined effect of time lags and mean temperature on the incidence RR of TB stratified by age. **D** ≤ 35. **E** 36–64. **F** ≥ 65

a risk factor of TB, similar to lag 7 days and 14 days, while high temperature at lag 21 days on the effect of TB incidence reported difference from that of the other lag days, except for ≤ 35 group; the risk of TB increased in line with the temperature in all groups, especially for the female group and the group of 35–64 years old, with a significant increase in risk.

We studied the cumulative lag effects of different temperatures (– 15 °C, – 5 °C, 5 °C, 25 °C, 30 °C) at different lag days (lag 3, lag 7, lag 14, lag 21) on the TB incidence, listing the results stratified by gender in Table 3. For the total population, male and female groups in the temperature below 15 °C, e.g., – 15 °C, – 5 °C, and 5 °C, the cumulative risk increased in line with the lag days, with the largest cumulative RR at lag 21. Compared with the three groups above, the highest RR of the cold effect of TB was reported in the male group, with the cumulative RR reaching 64.46 at the temperature of – 15 °C with a lag of 14 days, and 268.09 at the temperature of – 15 °C with a lag of 21 days; the risk of cold effect in the female group was minimal. When the temperature exceeded 15 °C, e.g., 25 °C and 30 °C, the protective effect of the hot effect on the TB incidence increased in line with the lag period, which, for the male group, was the greatest, with the cumulative RR of 0.02, 95% CI (0.00, 0.11) at the temperature of 30 °C with a 21-day lag. As shown in Table 4, the cumulative RR of each age group was the largest at – 15 °C with lag 21 days, and the lag effect of temperature on the TB incidence varied among different age groups. The cumulative cold effect was greatest in the ≥ 65-year-old group, reaching 146.18 at – 15 °C with 21 days lag, which was much higher than that in the 36–64-year-old group. Cumulative hot effects, e.g., at 25 °C and 30 °C, were protective factors of TB transmission at each lag period.

Discussion

Kashgar has the higher incidence of TB than the national average level in China. For many years, a lot of manpower and material resources have been invested in the prevention and treatment of TB in Kashgar city, reducing the TB incidence in the past 2 years. However, for reaching the target of ending TB by 2030, there still remains a long way to go, as the task of TB prevention and control in Kashgar city is still arduous.

The relationship of local meteorological variables with TB incidence is complex, as the effect is not only determined in the current period but also influenced by preceding time points to some extent (Rao et al. 2016; Zhang et al. 2015; Xu et al. 2020; Wang et al. 2021). Nonlinearity and lag effects require to be considered when exploring the effect of temperature on TB transmission. In view of the advantages of DLNM in analyzing such problems, it was applied for analysis in this study.

To explore the relationship between local daily mean temperature and TB incidences, a quasi-Poisson time series combined with DLNM was utilized. The results reported the low temperature as a high-risk factor for TB transmission, as the RR value reached the highest at extreme cold temperatures (– 15 °C) with a lag of 21 days. At the same lag days, the lower the temperature, the higher the risk of TB transmission, which was consistent with previous studies. Li et al. (2021) found that average temperature was negatively associated with the risk of TB in Jiangsu province of China. Onozuka and Hagihara (2015) found that the occurrence of extreme cold temperature events resulted in a significant increase in the number

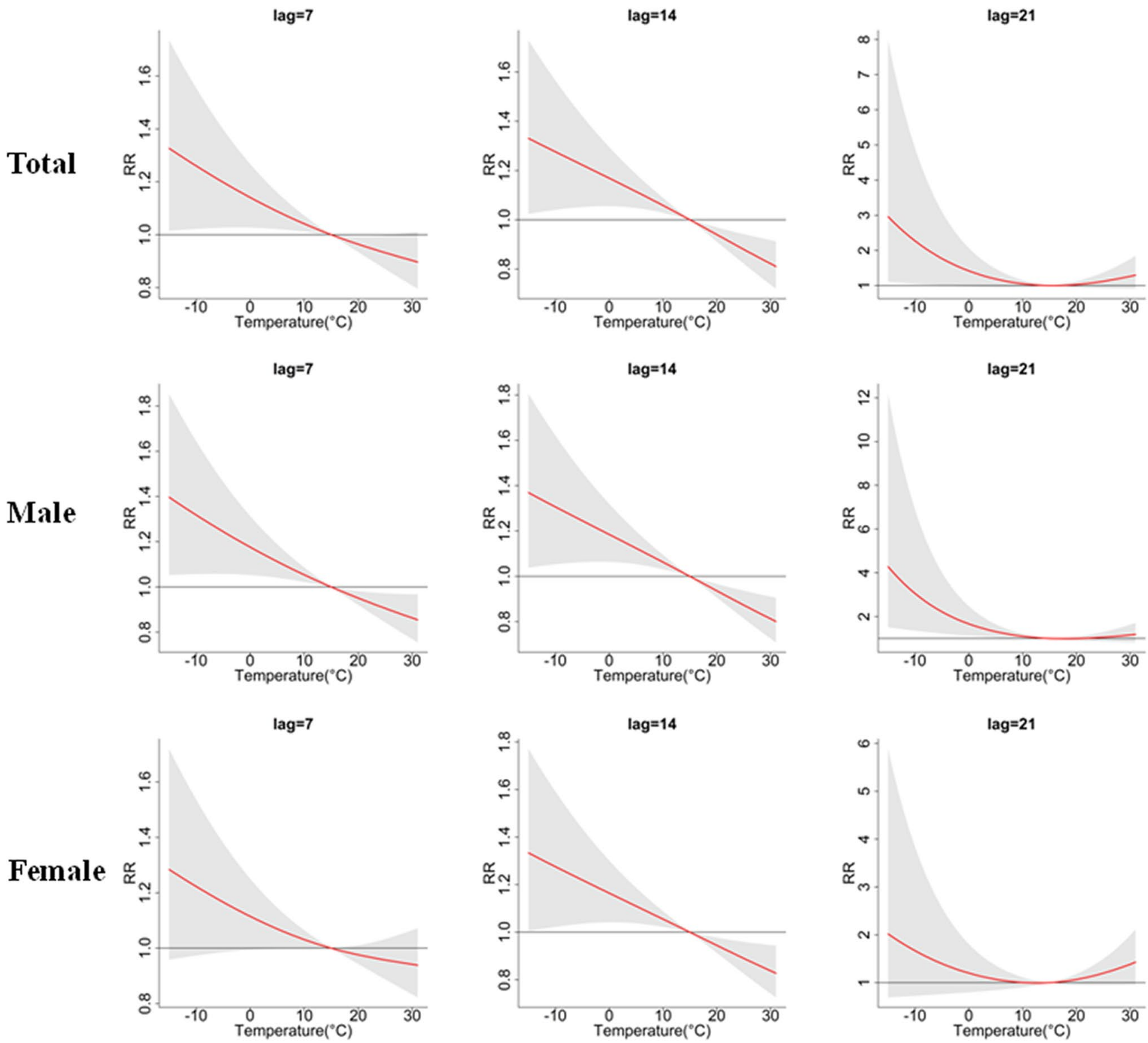

Fig. 8 The lag-specific effect at different values of the temperature on the incidence of TB stratified by gender in Kashgar city during 2017–2021, with reference at 15 °C. The graphs also show 95% CI

of TB cases (RR 1.23, 95% CI 1.05–1.45). Rao et al. (2016) found that areas with low temperature tended to have higher TB incidences in Qinghai province of China. Based on the total population data analysis, we found that high temperature produced a protective effect on TB transmission in Kashgar city, which was consistent with some studies; Chen et al. (2021) found that extreme high temperature has significantly decreased the risk of PTB at the provincial levels. However, some literatures also reported high temperature as a risk factor of TB transmission; for example, Onozuka and Hagihara (2015) revealed that the occurrence of extreme heat temperature events resulted in a significant increase in the number of TB cases in Fukuoka, Japan, which seems to vary from place to place as the effect on TB incidence.

We further performed some analysis stratified by gender and age, finding the increased effect of low temperature on the risk of TB transmission in both male and female groups, showing significantly higher sensitivity and cumulative effect in male group than in female group, which is consistent with the study of Feng et al. (2021). High temperature brings about a protective effect on TB transmission in male group, while for female group, temperature exceeding 20 °C with a lag 21 days could be a risk factor for TB transmission

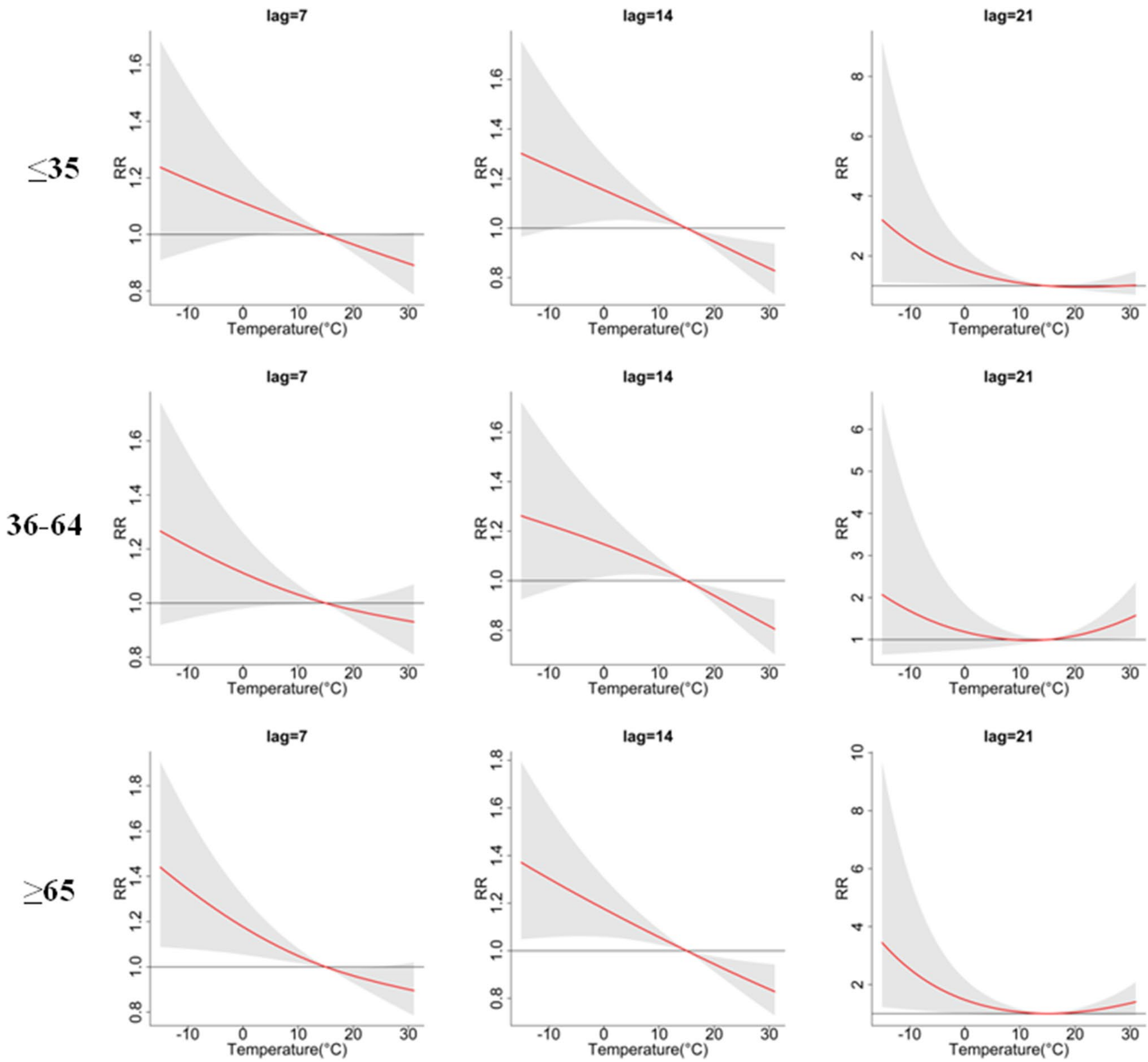

Fig. 9 The lag-specific effect at different values of the temperature on the incidence of TB stratified by age in Kashgar city during 2017–2021, with reference at 15 °C (50th percentile). The graphs also show 95% CI

(see Fig. 7 and Table 3). The age-stratified analysis reported that the incidence of TB was higher in the ≥ 65-year-old group in Kashgar city, which may be related to the low immunity of the elderly, and accompanied with the higher sensitivity to low temperature and the cumulative lag effect than that in ≤ 35 and 36–64 groups, which was consistent with the study of Feng et al. (2021) (Feng et al. (2021) found that the elders (age > 65 years) were at the greatest risk to extreme temperatures and the response were very acute). High temperature did not serve as a risk factor for TB transmission in ≤ 35 group, but it did for the other groups at lag 21. As Fig. 6 shows, when the temperature exceeds 20 °C with a lag of 21 days, the RR values for the TB incidence were all higher than 1, which might be related to the difference in the sensitivity to high temperature of different age groups. The inconsistency of the stratified analysis results might also be influenced by the local living habits, working conditions, and living environment in Kashgar city.

In this study, we applied the 5-year daily incidence data of TB in Kashgar city for analysis, providing a large and representative sample size. We stratified the data by age and gender to analyze the effect of daily mean temperature on TB transmission, which facilitated specific interventions for sensitive populations. The complex associations identified

Table 3 Accumulate relative risk (RR) estimated with 95% CI of the effect of different temperatures (– 15 °C, – 5 °C, 5 °C, 25 °C, 30 °C) on TB incidence stratified by gender at different lag days in Kashgar city, China, in 2017–2021

Group	Temperature (°C)	lag3 (95%CI)	lag7 (95%CI)	lag14 (95%CI)	lag21 (95%CI)
Total	– 15	0.71 (0.11, 4.47)	0.66 (0.09, 4.92)	26.33 (1.76, 393.09)	85.98 (3.01, 2454.2)
	– 5	0.99 (0.33, 2.95)	1.08 (0.33, 3.51)	10.26 (2.06, 51.14)	23.48 (3.15, 174.96)
	5	1.18 (0.73, 1.88)	1.35 (0.81, 2.24)	3.57 (1.76, 7.28)	5.57 (2.25, 13.79)
	25	0.56 (0.34, 0.92)	0.39 (0.22, 0.7)	0.21 (0.09, 0.50)	0.13 (0.04, 0.39)
	30	0.38 (0.18, 0.84)	0.21 (0.08, 0.53)	0.09 (0.02, 0.36)	0.04 (0.01, 0.25)
Male	– 15	0.9 (0.13, 6.34)	0.79 (0.09, 6.56)	64.46 (3.78, 1098.76)	268.09 (7.96, 9028.48)
	– 5	1.16 (0.37, 3.67)	1.27 (0.36, 4.43)	18.48 (3.43, 99.73)	53.05 (6.45, 436.71)
	5	1.26 (0.77, 2.07)	1.52 (0.89, 2.60)	4.77 (2.26, 10.05)	8.73 (3.37, 22.58)
	25	0.53 (0.32, 0.88)	0.31 (0.17, 0.58)	0.16 (0.07, 0.39)	0.07 (0.02, 0.23)
	30	0.35 (0.16, 0.79)	0.15 (0.06, 0.40)	0.06 (0.01, 0.25)	0.02 (0.00, 0.11)
Female	– 15	0.59 (0.08, 4.37)	0.65 (0.07, 5.75)	14.42 (0.73, 283.06)	43.93 (1.09, 1769.44)
	– 5	0.86 (0.26, 2.84)	0.99 (0.27, 3.56)	6.57 (1.12, 38.4)	13.28 (1.46, 121.02)
	5	1.08 (0.65, 1.81)	1.22 (0.7, 2.12)	2.77 (1.27, 6.03)	3.82 (1.41, 10.35)
	25	0.63 (0.37, 1.08)	0.49 (0.26, 0.94)	0.3 (0.12, 0.76)	0.23 (0.07, 0.8)
	30	0.46 (0.19, 1.08)	0.31 (0.11, 0.87)	0.16 (0.03, 0.7)	0.11 (0.02, 0.79)

Table 4 Accumulate relative risk (RR) estimated with 95% CI of the effect of different temperatures (– 15 °C, – 5 °C, 5 °C, 25 °C, 30 °C) on TB incidence stratified by age at different lag days in Kashgar city, China, in 2017–2021

Group	Temperature (°C)	lag3 (95%CI)	lag7 (95%CI)	lag14 (95%CI)	lag21 (95%CI)
≤ 35	– 15	1.04 (0.13, 8.33)	0.94 (0.09, 9.74)	19.56 (0.81, 472.85)	132.47 (2.55, 6875.87)
	– 5	1.22 (0.36, 4.17)	1.26 (0.32, 4.94)	8.7 (1.35, 55.99)	30 (2.96, 303.81)
	5	1.26 (0.75, 2.12)	1.38 (0.78, 2.44)	3.37 (1.53, 7.42)	6.09 (2.26, 16.43)
	25	0.57 (0.34, 0.96)	0.43 (0.24, 0.79)	0.21 (0.09, 0.50)	0.13 (0.04, 0.39)
	30	0.4 (0.18, 0.91)	0.25 (0.1, 0.67)	0.09 (0.02, 0.36)	0.04 (0.01, 0.26)
36–64	– 15	0.38 (0.04, 3.31)	0.41 (0.04, 4.34)	6.35 (0.26, 155.17)	19.37 (0.37, 1021.09)
	– 5	0.68 (0.19, 2.44)	0.77 (0.19, 3.07)	4.29 (0.65, 28.48)	8.39 (0.78, 89.93)
	5	1.00 (0.58, 1.73)	1.12 (0.62, 2.03)	2.44 (1.06, 5.62)	3.24 (1.12, 9.4)
	25	0.62 (0.35, 1.11)	0.49 (0.25, 0.96)	0.27 (0.1, 0.72)	0.23 (0.06, 0.85)
	30	0.44 (0.18, 1.11)	0.3 (0.1, 0.88)	0.13 (0.03, 0.62)	0.11 (0.01, 0.83)
≥ 65	– 15	0.6 (0.08, 4.43)	0.62 (0.07, 5.23)	50.24 (2.87, 879.62)	146.18 (4.17, 5123.9)
	– 5	0.84 (0.26, 2.74)	0.99 (0.28, 3.49)	13.14 (2.39, 72.33)	29.72 (3.52, 250.72)
	5	1.03 (0.62, 1.72)	1.25 (0.72, 2.17)	3.53 (1.64, 7.57)	5.74 (2.17, 15.19)
	25	0.72 (0.42, 1.23)	0.45 (0.23, 0.86)	0.3 (0.12, 0.78)	0.15 (0.04, 0.54)
	30	0.57 (0.24, 1.34)	0.26 (0.09, 0.75)	0.17 (0.04, 0.77)	0.06 (0.01, 0.44)

are valuable for designing strategies for early warning, prevention, and control of TB epidemics. Our study also has some limitations, for example, the number of TB cases may be affected by other confounders in addition to the meteorological factors in study, such as air pollutant variables and living habits, and due to residents' range of activities or other reasons, the current exposure measurement may not reflect the actual situation of individual exposure. Based on our results, in-depth studies should be continued, such as considering air pollutant variables and living habits on the effect of TB transmission.

Conclusions

It is the first work to study the effect of temperature on the TB incidence based on a DLNM model in Kashgar city, China. Our study provides quantitative evidence that that low temperature, especially extreme low temperature, could increase the risk of TB transmission, accompanied with a long-time lag effect. According to our findings, the RR of low temperature was higher in male group and ≥ 65 years, of which both are suggested to be careful of low temperature as the cause of risk of TB transmission. High temperature, especially extremely high temperature, has a long-term lag effect risk for female groups and the age group over 35 years, and both are suggested to be careful of high temperature protection, so as to reduce the risk of TB infection.

Author contribution Yanling Zheng: conceptualization, methodology, formal analysis, investigation, resources, writing—original draft, writing—review and editing, and visualization. Xiaowang Peng and Mawlanjan Emam: conceptualization, investigation, resources, data curation, and visualization. Dongmei Lu, Maozai Tian, and Kai Wang: investigation and visualization.

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Data availability Daily observations of historical meteorological conditions were from websites (https://tianqi.2345.com/wea_history/51709.htm). Daily reported cases of TB are available from the corresponding author (Xiaowang Peng, 410,388,299@qq.com) on reasonable request.

Declarations

Ethical approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

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