The Effect and Attributable Risk of Daily Temperature on Category C Infectious Diarrhea in Guangdong Province, China

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Research Article

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Abstract

Previous studies have explored the effect between ambient temperature and infectious diarrhea (ID) mostly using the relative risk, which provides limited information in practical applications. There is limited study focused on the disease burden of ID caused by temperature, especially for different subgroups and cities in a multi-city setting. This study aims to estimate the effects and attributable risks of temperature on category C ID and explore potential modifiers among various cities in Guangdong. At first, the distributed lag non-linear models (DLNMs) were used to explore city-specific associations between daily mean temperature and category C ID from 2014 to 2016 in Guangdong and pooled them by applying the multivariate meta-analysis. Then, the multivariate meta-regression was further implemented to analyze the potential heterogeneity among various cities. Finally, we assessed the attributable burden of category C ID due to temperature, low (below the 5th percentile of temperature) and high temperature (above the 95th percentile of temperature) for each city and subgroup population. Comparing with the 50th percentile of daily mean temperature, adverse effects on category C ID were found when temperature was lower than 12.27℃ in Guangdong province. Some city-specific factors (longitude, urbanization rate, population density, disposable income per capita, and the number of medical technicians and beds per thousand persons) could modify the relationship of temperature-category C ID. During the study period, there were 60,505 category C ID cases (17.14% of total cases) attributable to the exposure of temperature, with the attributable fraction (AF) of low temperature (4.23%, 95% empirical confidence interval (eCI): 1.79%-5.71%) was higher than high temperature (1.34%, 95%eCI: 0.86%-1.64%). Males, people under 5 years and workers appeared to be more vulnerable to temperature, with an AF of 29.40%, 19.25%, and 21.49%, respectively. The AF varied substantially at the city level, with the largest AF of low temperature occurred in Shaoguan (9.58%, 95%eCI: 8.36%-10.09%), and that of high temperature occurred in Shenzhen (3.16%, 95%eCI: 2.70%-3.51%). Low temperature was an important risk factor for category C ID in Guangdong province, China. The exposure-response relationship could be modified by city-specific characteristics. Considering the whole population, the attributable risk of low temperature was much higher than high temperature, and males, people under 5 years and workers were vulnerable populations.

1. Introduction

Infectious diarrhea (ID) is a group of intestinal infectious diseases caused by various pathogenic microorganisms (including bacteria, viruses, and parasites) and their products, with diarrhea as the main symptom (Kelly 2019). It remains a severe public health issue, with an estimated 1.7 billion morbidities and 1.4–1.9 million diarrhea-related deaths annually in the world (Leung et al. 2016, Levy et al. 2016). In China, a total of 20,518,684 ID cases were detected during the ten years from 2004 to 2013 (Yang et al. 2017). To facilitate the management of ID, ID other than cholera, dysentery, typhoid, and paratyphoid is defined as other infectious diarrhea (OID) and classified into category C notifiable infectious diseases (Yang et al. 2017). In 2014 and 2015, 867,545 and 937,616 OID cases were reported respectively in China, with incidences ranging from 3.8 to 506.7 per 100,000 people at the provincial level (Zhang &Zhang 2017). Meanwhile, the problem is particularly acute in Guangdong province. According to the Announcement of Infectious Diseases of the Chinese Public Health Science Data Center (https://www.phsciencedata.cn/), the number of OID cases in Guangdong ranks first from 2009 to 2016 and continues to rise rapidly.

Pieces of evidence are showing that climate change can affect the distribution and survival of vectors, and the physiological functions and immune statuses of the human body to a certain extent, thereby changing the incidence of ID (Barrett et al. 2015, Wei et al. 2014). Some documents have proved that temperature is the main meteorological factor affecting the onset of ID (Tao et al. 2015). For instance, a multicity study in mainland China found that there is a M-shaped relationship between temperature and OID (Wang et al. 2021). In Jinan, China, every 5°C increase of temperature leads to a 61% increase of bacillary dysentery at lag one week, while in Guangzhou showed that low temperature can increase the count of ID (Liu et al. 2019, Wang et al. 2019). In Tamil Nadu, India, a significantly positive correlation was found between weekly average temperature and diarrhea at lag 1–3 week (Mertens et al. 2019). In Cape Town, when the lowest and highest temperature increase by 5℃, the count of ID of children increases by 15% and 6% respectively after adjusting autocorrelation with a one-week lag (Musengimana et al. 2016).

However, previous studies mostly quantified the relationship of temperature-ID via relative risk (RR). Although RR is helpful for epidemiologists to determine whether there exist connections between given factors and diseases, it can not reflect the actual effects of exposures from the public health perspective (Northridge 1995). By contrast, attributable risk assessment is a method that can comprehensively consider the exposure effect and the exposure rate to assess the population attributable burden caused by risk factors (Yang et al. 2016). It represents the proportion or number of cases that can be prevented without being exposed to the specific risk factor and provides crucial information for health policymakers to formulate interventions and allocate health resources (Cheng et al. 2017).

Several studies displayed that the association between temperature and disease may vary in different cities, which could be caused by geographic, socio-economic and other city-specific characteristics (Fu et al. 2021, Huang et al. 2015, Zhao et al. 2018). But a detailed screening of all characteristics was lacked to explore potential heterogeneity of temperature-OID in Guangdong province. Furthermore, the prevalence of infectious diarrhea is varied in different populations due to the difference in immunity and adaptability of subgroups (Qu et al. 2012), while limitied studies have compared the temperature-OID relationship and morbidity burden due to temperature among gender, age, and occupation subgroups in a multi-city setting.

To fill the above research gap, we used surveillance data of 21 prefecture-level cities to obtain the temperature-OID relationship of each subgroup in Guangdong province. We also collected geographic, socio-economic, and health resource indicators of each city to analyze the potential

heterogeneity. Finally, we estimated the disease burden for each city and subgroup to identify vulnerable regions and populations. The results will contribute to the formulation of prevention strategies and the allocation of health resources.

2. Methods

2.1. Study site

Guangdong province (latitude 20°09'-25°31'N and longitude 109°45'-117°20'E) is located in southern China. It contains 21 prefecture-level cities with a total population of 109.99 million at the end of 2016 (https://data.cnki.net/area/Yearbook/). Guangdong province features a subtropical monsoon climate, with sufficient light, heat, and precipitation resources each year (Wang et al. 2019). The position of Guangdong is presented in Fig. 1.

2.2. Data collection

Daily reported OID cases in Guangdong province from 1 January 2014 to 31 December 2016 were obtained from the Chinese Center for Disease Control and Prevention (China CDC). All OID cases were diagnosed according to the criterion (WS 271–2007) published by the Ministry of Health of the People's Republic of China in 2007 (Wang et al. 2021). Based on the Law of National Communicable Diseases Control, OID cases must be reported within 24h via the Internet-based National Notifiable Infectious Disease Reporting Information System (NIDRIS) once diagnosed (Deng et al. 2015). The reported information consists of age, gender, occupation, onset date, and the administrative code of residence.

Daily meteorological data, including mean temperature, wind speed, relative humidity, and accumulated precipitation were collected from fixed monitoring stations of Guangdong, provided by China Meteorological Data Sharing Service System (http://data.cma.gov.cn/). If cities had more than one weather station, we chose the one nearest to the city center. The missing meteorological data were interpolated with the average value of the five adjacent days.

We also collected city-specific characteristics between 2014 to 2016 including geographic factors (i.e., latitude and longitude), demographic characteristics (i.e., population density, urbanization rate, and primary school students per thousand persons), economic indicators (i.e., GDP and disposable income per capita), and health resource information (i.e., the number of medical technicians and beds per thousand persons) from the Guangdong Statistical Yearbook (Zhao et al. 2021). More details were given in Table A1.

2.3. Statistical analysis

We applied a two-stage time-series analysis. In the first stage, taking the median temperature of all cities as the reference, distributed lag non-linear models (DLNM) with a quasi-Poisson distribution were used to estimate the associations of temperature-OID for 21 cities. DLNM could simultaneously describe the delayed and non-linear effects of a specific exposure, which has been confirmed applying well in environmental epidemiology (Gasparrini et al. 2015). The model was:

$$\log\left[E\left(Y_t\right)\right] = \beta + cb\left(Temperature_{t,l}\right) + ns\left(Humidity, 3\right) + ns\left(Precipitation3\right) + ns\left(Wind, 3\right) + ns(time, 7 \times 3) + lag(res, 1)$$

Where $E\left(Y_t\right)$ represents the expected number of OID on day *t*, β is the intercept; $cb\left(Temperature_{t,l}\right)$ denotes a cross-basis function to fit both delayed and non-linear effects of temperature. The maximum lag days *l* were set to 35 according to previous research (Liu et al. 2018). The $ns\left(Humidity, 3\right) + ns\left(Precipitation, 3\right) + ns\left(Wind, 3\right)$ were enrolled to adjust confounding of other meteorological variables, and the $ns(time, 7 \times 3)$ was designed to control seasonality and long-term trends (Liu et al. 2020). The lagged residual error $lag(res, 1)$ was incorporated to control autocorrelation.

In the second stage, a multivariate meta-analysis was adopted to pool the city-specific effects to obtain the overall cumulative and lag effects of temperature-OID in Guangdong (Gasparrini et al. 2012). Then, the meta-regression was applied to analyze the possible city-specific modifiers, and the multivariate extensions of I^2 statistics and Cochran *Q* test were chosen to assess the residual heterogeneity (Gasparrini &Armstrong 2013). The goodness of meta-regression was evaluated by the Akaike information criterion (AIC) and Bayesian information criterion (BIC). Finally, the attributable risks (including attributable fraction, AF; and attributable number, AN) of temperatures on OID for each city and subgroup were calculated by applying the “forward perspective” within the framework of DLNM. The Monte Carlo simulation was applied to calculate 95% empirical confidence interval (eCI) as an evaluation indicator of attributable risk (Gasparrini &Leone 2014).

To identify vulnerable groups (defined by the largest AF), the whole population was stratified by gender (males and females), age (0–5, 6–19 and ≥ 20 years), and occupation (scattered and nursery children, housekeeping and unemployed, students, farmers, workers, and others consisting of teachers, herders, medical staffs and so on). Furthermore, defining the temperature below 5th as low temperature and higher than 95th as high temperature in this study will conductive to better identify sensitive subgroups and cities.

The robustness of the model was evaluated by changing the maximum lag days (25, 30, 35, and 40), altering the 3–5 *df* for meteorological factors and 7–10 *df* for time variable, and controlling the first-order lagged residual errors or not. R 4.0.3 with packages of “dlnm” and “mvmeta” was conducted all analyses. $P < 0.05$ (two-sided) was considered statistically significant.

3. Results

3.1. Description of meteorological and OID data

From 2014 to 2016, a total of 353,061 OID cases were notified in the 21 cities of Guangdong province, of which 58.28% were males and 41.72% were females, with the sex ratio was 1.40:1 (Table 1). In terms of age, the majority of people under 5 years accounted for 72.70%. Scattered and nursery children were the main group for occupation patients, with a proportion of 74.10%.

The OID case counts varied across the 21 cities in Guangdong. Shenzhen, Guangzhou, and Jiangmen ranked the top three, reaching about 40% of the total number of cases (Fig. 1, Table A2). The time-series curve of OID and temperature showed opposite trends (Fig. 2). During the study period, the average daily mean temperature, relative humidity, precipitation, and wind speed were 22.70 °C, 79.14 %, 5.38 mm, and 2.12 m/s, respectively. More descriptive information was presented in Table A2.

3.2. Cumulative effects and lag effects of temperature on OID

Fig. 3 showed the cumulative effects of temperature-OID, with an approximate L-shaped exposure-response curve over 35 lag days. The adverse effect of the whole population emerged when temperature was lower than 12.27℃. An inverted V-shaped curve was presented for the lag effect of low temperature, with RR started to be larger than 1 at lag9, and reached the maximum at lag20 (RR=1.046, 95% CI: 1.035-1.058) (Fig. A1).

The accumulative risks of different subgroups were presented in Fig. 3. Compared with the total population, males and females showed similar risks under low temperatures. In terms of age, the cumulative RR of low temperature for people aged 6-19 years was higher than that for people under 5 years (RR=1.073, 95% CI: 1.044-1.103 versus RR=1.026, 95% CI: 1.014-1.038). For patients with different occupations, the effects of scattered and nursery children and students were significant in low temperatures, with the cumulative RR of 1.026 (95%CI: 1.015-1.038) and 1.093 (95%CI: 1.045-1.143), respectively. Furthermore, the results showed that high temperature only had adverse effects on people under 5 years and scattered and nursery children. More details were given in Table A3.

3.3. Analysis of multivariate meta-regression

The results of multivariate meta-regression (intercept-only model) displayed that the residual heterogeneity was significant (Q=2,574.5, p <0.001), but the heterogeneity attributed to the actual difference among 21 cities was high, with I^2 statistics of 97.67% (Table 2). Several city-specific characteristics could explain partial residual heterogeneity, including longitude, population density, urbanization rate, disposable income per capita, and the number of medical technicians and beds per thousand persons.

Based on the significant city-specific characteristics in Table 2, the temperature-OID associations were predicted and reported for the 5th and 95th percentiles of modifiers in Fig. 4. In high-longitude cities, the effects of medium-low temperature (7℃ to 24℃) on OID were significantly enhanced. The high temperature was associated with greater effects on OID among cities with high urbanization rate, high population density, and high disposable income per capita. Besides, we found that cities equipped with better health resources (i.e., more medical technicians and beds) had higher risks of OID at low temperatures.

3.4. Attributable risk assessment

During the study period, 60,505 OID cases (17.14% of the total OID case counts) were attributable to daily mean temperature, and the AF of low temperature (4.23%, 95%eCI: 1.79%-5.71%) was higher than that of high temperature (1.34%, 95%eCI: 0.86%-1.64%) (Table 3). The attributable risk varied substantially at the city level, Shenzhen and Dongguan had fairly high AN, with the numbers were 27,133 and 8,783, respectively. Ranked first of the AF in low temperature was Shaoguan (9.58%, 95%eCI: 8.36%-10.09%) and in high temperature was Shenzhen (3.16%, 95%eCI: 2.70%-3.51%).

Fig. 5 illustrated the AF of temperature (low and high) in different subgroups. Males, people under 5 years and workers appeared to be more vulnerable to temperature, with AF of 29.40%, 19.25%, and 21.49%, respectively. There were some variations for vulnerable groups under different temperature conditions, males, people under 5 years, and scattered and nursery children in low temperature while males, people under 5 years, and workers in high temperature (Table A4).

3.5. Sensitivity analyses

After changing the *df* for meteorological factors and time variable, the maximum lag days, and controlling the autocorrelation or not, the pooled temperature-OID curves changed little, indicating that the model had good robustness (Fig. A2-8).

4. Discussion

The emergence and re-emergence of sensitive diseases related to climate change will affect the already overloaded medical system. A previous study indicated that the incidence of OID is increasing at an annual rate of 6.6% in China (Yang et al. 2017). Therefore, it is essential to explore the climate-OID relationships and search for modifiable risk factors (i.e., modifiers among cities) within this association. In this study, the relationships and attributable risks were analyzed between daily mean temperature and OID in Guangdong and potential effect modifiers were identified among 21

cities. To our knowledge, this is the first study that conducted a comprehensive attributable risk assessment to identify vulnerable groups and regions for OID and explored potential effect modifiers in Guangdong province. Our research will provide decision-makers with valuable information to formulate and improve prevention strategies for targeted populations and regions.

This study detected that low temperature had an adverse effect on OID incidence, which is similar to the findings in Guangzhou city, the capital of Guangdong province (Wang et al. 2019). The mechanism by which low temperature exerted adverse effects may involve both pathogens and hosts. From the perspective of pathogens, according to seasonal characteristics of different pathogens, OID can be classified into two main categories, including viral diarrhea (rotavirus and norovirus) prevalent in winter and bacterial diarrhea (Campylobacter jejuni, Escherichia coli, Salmonella, Vibrio parahaemolyticus) prevalent in summer and autumn (Fang et al. 2019). We found that viral diarrhea accounted for 91.64% of all biology-tested OID cases according to the reported data of Guangdong from 2014 to 2016. Rotavirus and norovirus are more suitable for growth and reproduction under a low-temperature environment (Carlton et al. 2016). For example, a study pointed out that norovirus presents the strongest transmission ability at 8°C (Gao et al. 2020). Besides, a meta-analysis found that the annual incidence of rotavirus infection increases by 1.3% when the monthly average temperature decreases by 1℃ (Jagai et al. 2012). Furthermore, evidence from laboratory studies displayed that low temperature could increase the reproduction of viruses and reduce the decay rate in the environment, thereby prolonging the survival time of viruses on the surface of contaminated objects and aquatic environments (Bozkurt et al. 2015). From the perspective of the host, people who live in subtropical zones are more vulnerable to cold and prefer to stay indoors during cold weather, which increases the probability of contacting with infected people and contaminated objects (Wang et al. 2018).

It is noteworthy that high temperature caused adverse effects only in people under 5 years, and scattered and nursery children. Several studies have shown that a relatively smaller peak often appears in summer (Fang et al. 2019). It is mainly caused by bacteria because high temperature may promote the regeneration of bacteria and then increase the intake of food contaminated by bacteria (Kovats et al. 2004, Liu et al. 2020). Therefore, the mechanism of susceptibility of people under 5 years and scattered and nursery children may involve an immature immune system and bad hygiene habits, which can promote bacterial infection (Xu et al. 2013).

The results of multivariate meta-regression showed that some modifiers could explain partial residual heterogeneity among 21 cities. We found high longitude strengthened the association between medium-low temperature and OID. To explore the mechanism of the modification effect of longitude, we further studied the topography of Guangdong. Since the mountains in the southeast of Meizhou block a lot of water vapor from the South China Sea, it appears that high longitude regions have a lower relative humidity (77.5% in Meizhou to 82.7% in Zhanjiang) (Liao et al. 2014). Lower relative humidity improves the survival rate and survival time of rotavirus, and the infectivity of rotavirus will rapidly lose when relative humidity reaches 80% (Hashizume et al. 2008).

In cities with high urbanization rate and high population density, the relative risk of high temperature on OID was significantly increased. In the past decades, a substantial part of rural people and migrant workers have entered cities, leading to the increase of urbanization rates and population densities. Crowded population will increase disease transmission via direct or indirect contact (Hao et al. 2019). Moreover, people living in urban villages with poor sanitary conditions were more likely to be infected with OID (Zhang et al. 2016).

The result of effect modification analysis for disposable income per capita showed that cities with high disposable income have a higher OID risk in high temperature. It may be due to the higher outpatient rate at a greater level of economic development (Qian et al. 2017). In addition, we also found that low temperature could amplify the risks of OID in cities having better medical resources. This is likely because that people living in these areas tend to have a higher level of hygiene awareness, and they might incline to seek medical treatment when they had the symptoms of OID.

In this study, the attributable risk of the males was much greater than that of the females, which might be due to the gender differences in immune levels, behavioral patterns, and occupational exposures (Anteneh et al. 2017, Sevilimedu et al. 2016). The exact mechanisms are not clear and require further research. For age subgroups, the OID burden of people under 5 years was higher, which further confirms that people under 5 years are the main group who suffer from diarrhea worldwide (Das et al. 2014, Heaney et al. 2019). For occupation subgroups, the burden of workers far exceeded that of other subpopulations, which is likely that workers are more susceptible to OID due to worse living and sanitary conditions. We also found that the cumulative effects of temperature-OID in low temperature and high temperature for students, farmers, workers, and others were not significant, but the AFs were significant. The possible speculation of these results was due to their relatively small dataset, which led to the unstable fit of the effect estimates (Gasparrini et al. 2015).

The RR of temperature-OID we explored was small because the exposure of population to temperature is broad and inconspicuous; therefore it may not be a priority when formulating prevention strategies. However, attributable risk assessment can take account of both the adverse effect of temperature and the exposure level of population, so it could show the actual adverse effect of temperature and identify vulnerable populations (Yang et al. 2016). For instance, although the effect of temperature-OID for males was not prominent in our study, we found that they have higher attributable risks from a public health perspective.

Several limitations should be acknowledged. Firstly, our research was limited to only one province, so the conclusion might not be suitable for other geographic regions. Secondly, due to the lack of information on the pathogenic composition, we could not explore the effect of temperature on

different types of pathogens. Thirdly, our meteorological data were collected from fixed weather monitoring stations, which may lead to measurement biases compared with the actual exposure level of individuals.

5. Conclusions

In conclusion, this study demonstrated that low temperature could increase the incidence of OID, and the associations varied slightly in different subgroups. City-specific characteristics can explain partial heterogeneity among different cities. Furthermore, we found that males, people under 5 years and workers were the vulnerable groups. Therefore, corresponding prevention strategies should be actively taken to reduce the burden of OID.

Declarations

Ethics approval and consent to participate

Ethical approval for analysis of this de-identified data was granted by the Ethics Review Committee, School of Public Health, Shandong University (20120501).

Availability of data and materials

The authors do not have permission to share data.

Consent for publication

There is no conflict of interest that exists in this manuscript, and it is approved by all authors.

Competing interests

All the authors declared no conflict of interests.

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Authorship contributions statement

HQ: Conceptualization, Methodology, Software, Formal analysis, Data Curation, Writing – Original Draft, Visualization. **GQ:** Methodology, Writing – Review & Editing. **ZR:** Methodology, Data Curation, Writing – Review & Editing. **WHT:** Resources, Writing – Review & Editing. **LH:** Writing – Review & Editing. **JBF:** Conceptualization, Validation, Resources, Writing – Review & Editing, Supervision, Project administration, Funding acquisition. All authors read and approved the final manuscript.

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Tables

Table 1

Distribution of OID cases in Guangdong province, 2014–2016

Group	Cases of OID (N)	Percentage (%)
Total	353,061	
Gender		
Male	205,776	58.28
Female	147,285	41.72
Age (years)		
≤5	256,685	72.70
6-19	22,690	6.43
≥20	73,686	20.87
Occupation		
Scattered and nursery children	261,608	74.10
Housekeeping and Unemployed	16,742	4.74
Students	17,391	4.92
Farmers	20,615	5.84
Workers	25,937	7.35
Others	10,768	3.05

Table 2

Multivariate meta-regression models for meta-predictors

Meta-predictors	Cochran *Q* test			I^2 (%)	Model fits		Wald test		
	Q	*df*	*P*		AIC	BIC	Stat	*df*	*p*
Intercept only	2,574.5	60	<0.001	97.67	238.5	257.8			
City-specific factors									
Latitude	2,427.5	57	<0.001	97.65	242.8	268.5	1.7	3	0.634
Longitude	2,396.0	57	<0.001	97.62	235.5	261.2	10.7	3	0.013
Population density	1,970.1	57	<0.001	97.11	236.9	262.6	12.0	3	0.007
Urbanization rate	1,849.1	57	<0.001	96.92	238.9	264.6	7.9	3	0.049
Primary school student	2,517.8	57	<0.001	97.74	243.5	269.2	1.1	3	0.788
Disposable income	2,197.1	57	<0.001	97.41	238.1	263.8	8.3	3	0.040
GDP per capita	2,212.0	57	<0.001	97.42	238.9	264.6	6.9	3	0.075
Medical technician	2,343.3	57	<0.001	97.57	233.8	259.5	13.6	3	0.004
Medical bed	2,487.0	57	<0.001	97.71	235.7	261.4	10.3	3	0.016

Table 3

Attributable risk of temperature in Guangdong province, 2014–2016

City	Attributable number (AN, N)			Attributable fraction (AF, %)		
	Overall Tem	Low Tem	High Tem	Overall Tem	Low Tem	High Tem
Chaozhou	487	101	21	36.48(19.31,46.42)	7.55(2.84,9.09)	1.61(-0.79,2.85)
Dongguan	8,783	1,407	648	39.57(31.45,45.51)	6.34(5.35,6.97)	2.92(2.49,3.24)
Foshan	5,298	546	416	26.39(9.7,37.65)	2.72(-0.99,4.95)	2.07(1.38,2.54)
Guangzhou	7,546	1,997	268	21.62(7.17,31.99)	5.72(4.26,6.62)	0.77(-0.42,1.58)
Heyuan	1,087	226	31	41.82(31.53,48.82)	8.69(7.78,9.13)	1.19(-0.86,2.34)
Huizhou	1,599	419	62	23.06(3.55,36.26)	6.04(2.84,7.91)	0.89(-0.28,1.63)
Jiangmen	1,837	670	66	8.19(-10.24,21.4)	2.99(-0.09,4.85)	0.29(-1.14,1.32)
Jieyang	2,836	738	20	30.32(19.78,38.19)	7.89(6.30,8.86)	0.22(-1.36,1.31)
Maoming	-2,041	-6	-132	-26.46(-71.78,1.52)	-0.07(-10.25,5.48)	-1.71(-4.6,0.22)
Meizhou	6,274	1,713	503	23.94(11.68,32.85)	6.54(5.32,7.32)	1.92(0.8,2.75)
Qingyuan	-7,393	-598	189	-41.93(-84.82,-12.36)	-3.39(-10.22,0.81)	1.07(-0.18,1.94)
Shantou	1,493	323	11	9.82(-3.42,19.63)	2.13(-0.88,4.05)	0.07(-1.38,1.16)
Shanwei	1,846	508	-97	25.61(16.87,32.26)	7.04(5.14,8.15)	-1.35(-2.92,-0.11)
Shaoguan	1,753	462	-41	36.35(13.41,49.51)	9.58(8.36,10.09)	-0.85(-6.99,1.82)
Shenzhen	27,133	4,147	2,462	34.77(25.29,41.78)	5.31(4.07,6.12)	3.16(2.7,3.51)
Yangjiang	-4,924	-469	-64	-28.66(-60.1,-6.39)	-2.73(-8.47,0.85)	-0.37(-2.06,0.87)
Yunfu	1,071	203	63	41.67(20.55,52.82)	7.89(4.06,9.52)	2.45(1.76,2.77)
Zhanjiang	-125	-45	34	-3.02(-31.96,15.07)	-1.08(-8.86,3)	0.82(-1.18,2.16)
Zhaoqing	-5,007	215	-229	-26.92(-54.8,-6.97)	1.16(-2.52,3.52)	-1.23(-2.69,-0.14)
Zhongshan	5,081	1,035	362	30.37(19.44,38.24)	6.18(4.68,7.03)	2.16(0.8,3.08)
Zhuhai	5,868	1,348	128	34.14(28.11,39.13)	7.84(7.38,8.14)	0.75(-0.52,1.71)
Total	60,505	14,940	4,722	17.14(2.83,26.32)	4.23(1.79,5.71)	1.34(0.86,1.64)

Note: Tem, temperature.

Figures

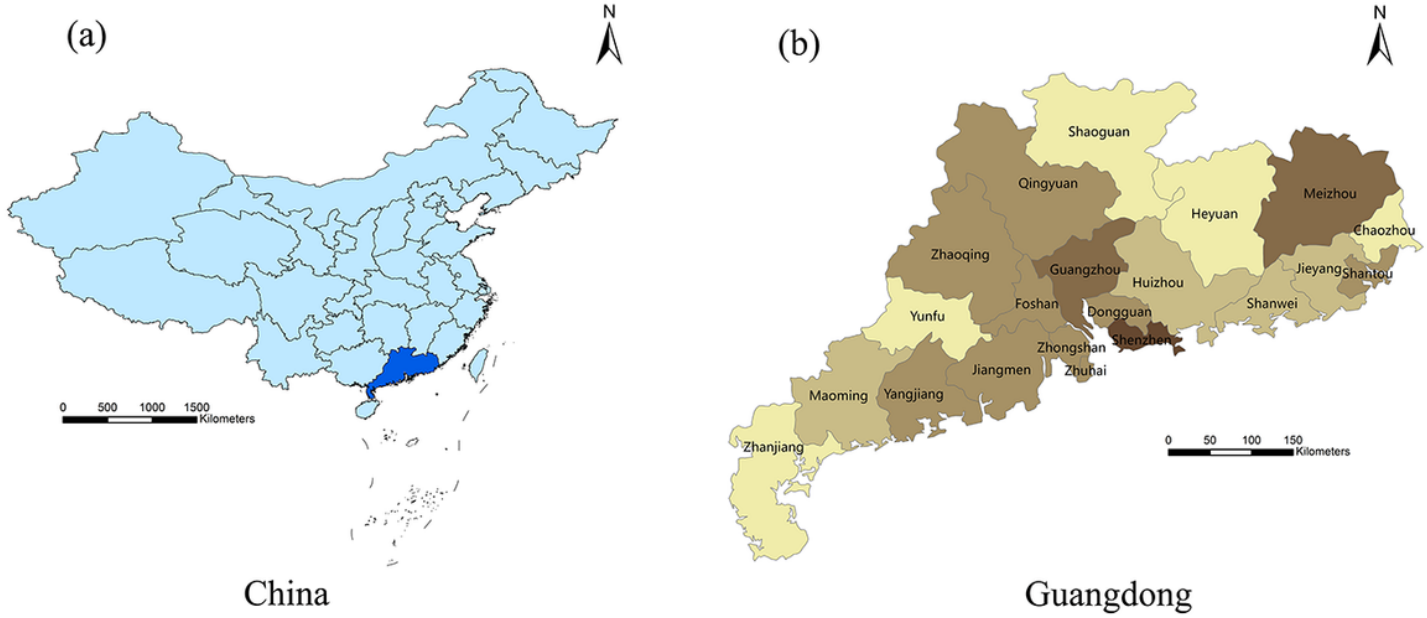

Figure 1

Location of Guangdong province in China (a) and the distribution of OID cases in 21 prefecture-level cities (b)

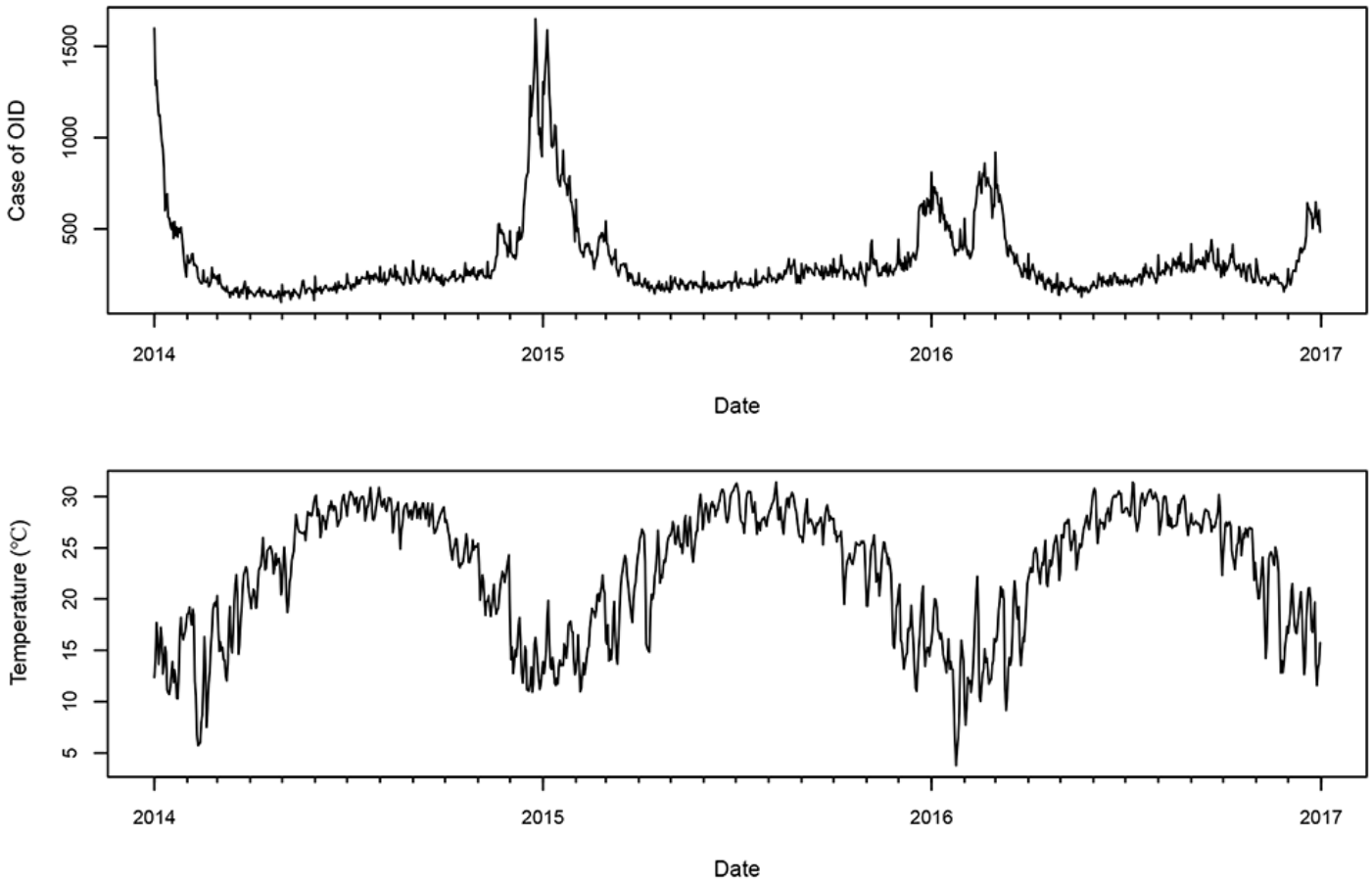

Figure 2

Time series curve of daily OID and mean temperature in Guangdong, 2014–2016

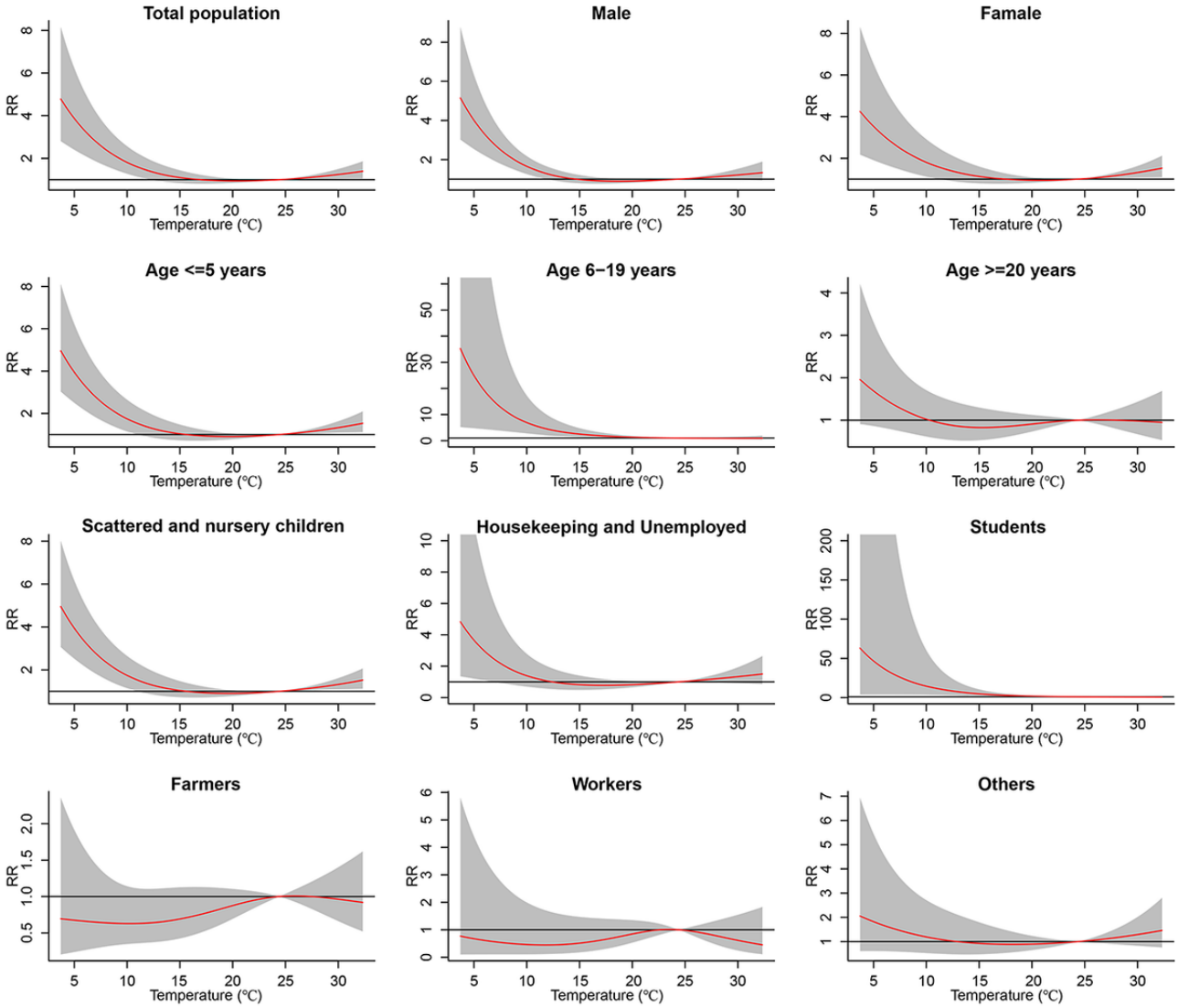

Figure 3

Pooled cumulative effects in total population and gender, age, and occupation subgroups

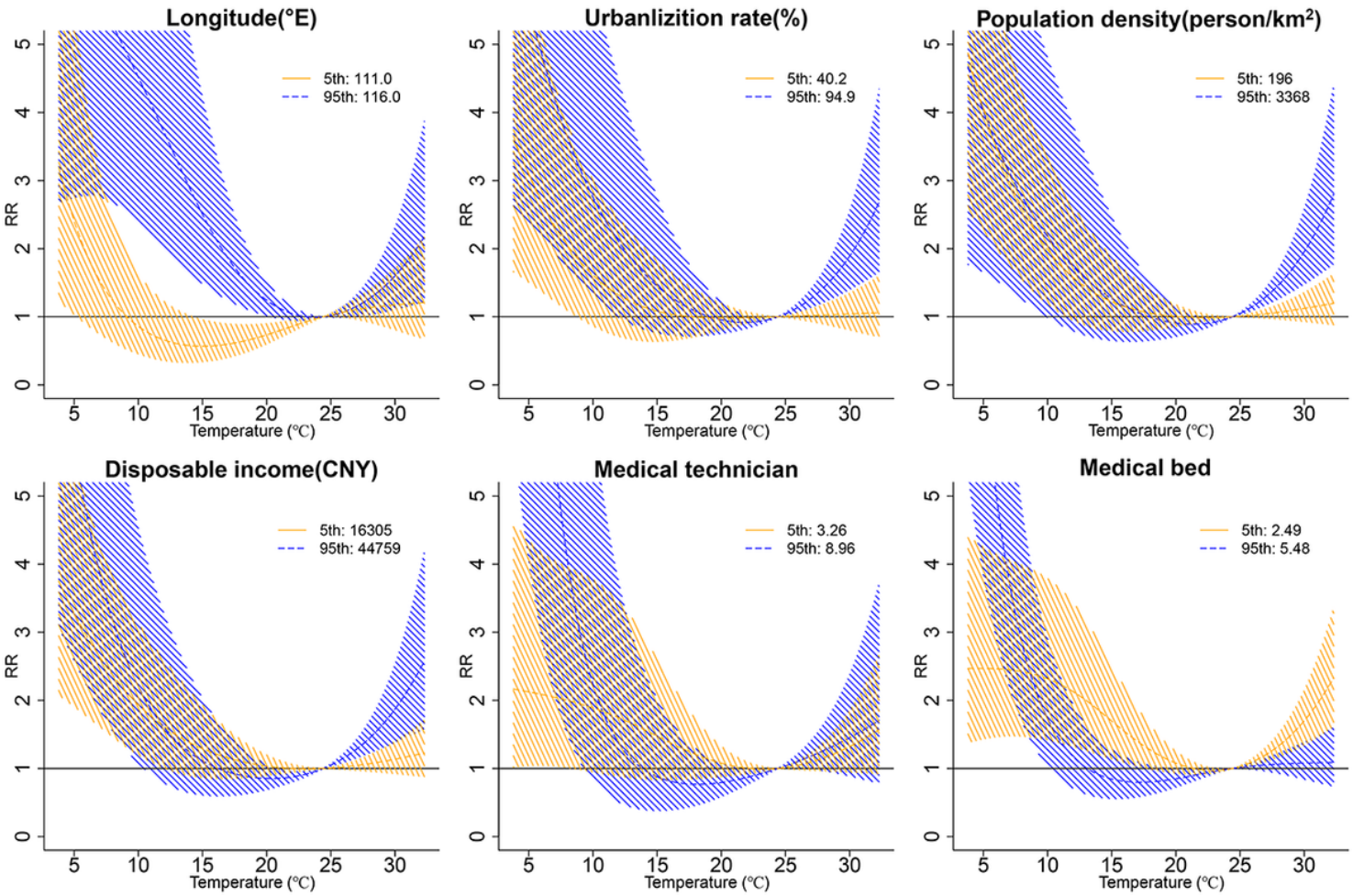

Figure 4

Predicted temperature-OID relationships for the 5th (yellow line) and 95th (blue line) percentiles of the significant modifiers. Reference: the 50th percentile of temperature

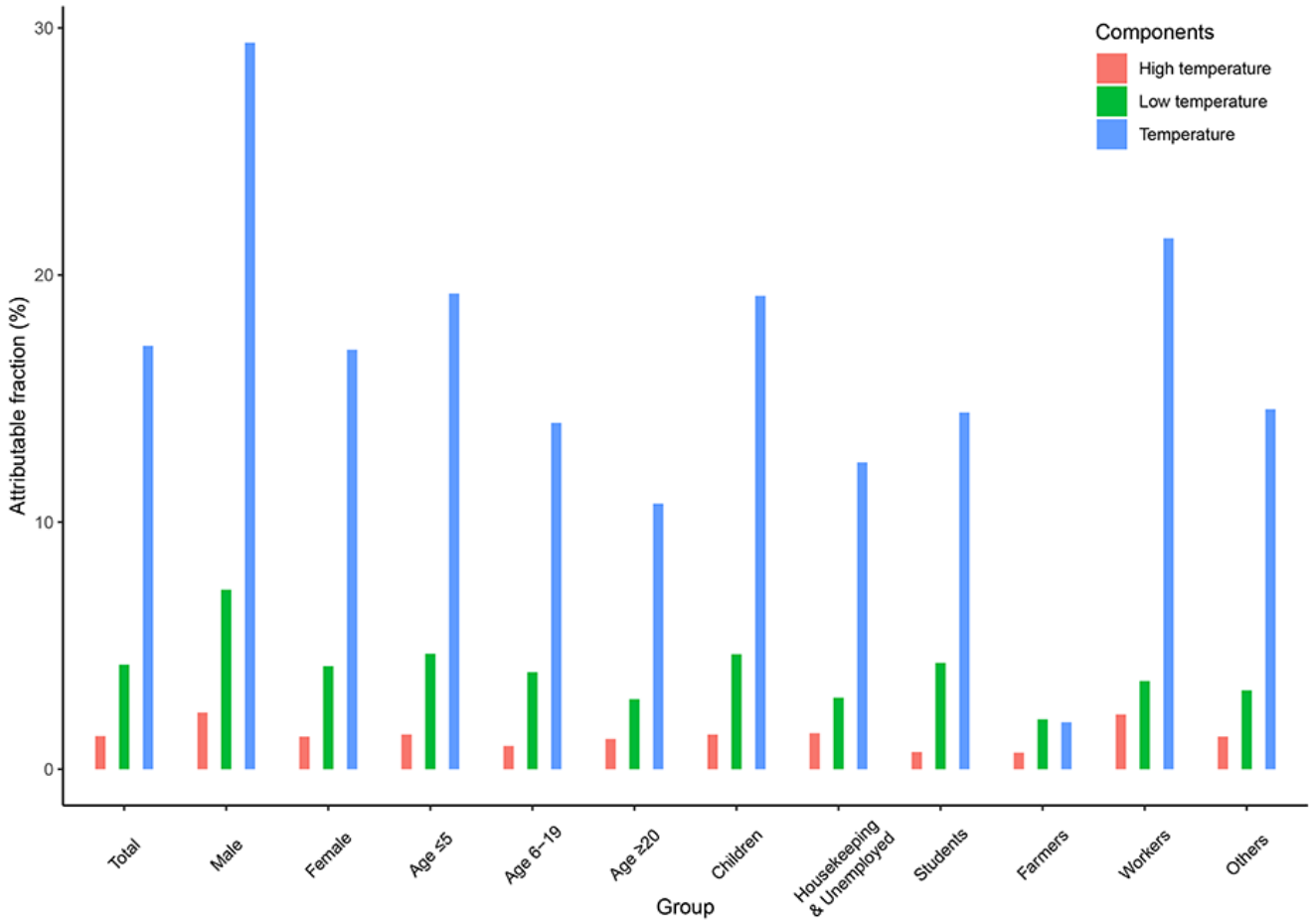

Figure 5

The estimated attributable risks for gender, age, and occupation subgroups

Supplementary Files

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