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Impact of meteorological factors on the COVID-19 transmission: A multi-city study in China

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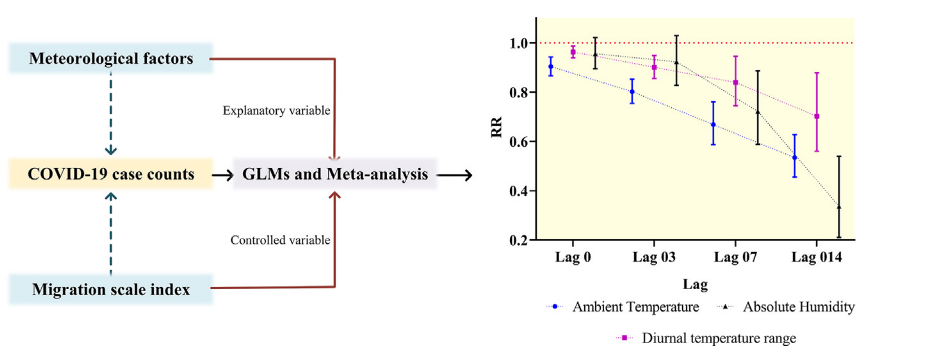
HIGHLIGHTS

- The impacts of meteorological factors on COVID-19 case counts were assessed after controlling population migration.
- The weather with low temperature, mild diurnal temperature range and low humidity likely favor the transmission of COVID-19.
- The epidemic might gradually ease partially due to rising temperatures in coming months.

GRAPHICAL ABSTRACT



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ABSTRACT

The purpose of the present study is to explore the associations between novel coronavirus disease 2019 (COVID-19) case counts and meteorological factors in 30 provincial capital cities of China. We compiled a daily dataset including confirmed case counts, ambient temperature (AT), diurnal temperature range (DTR), absolute humidity (AH) and migration scale index (MSI) for each city during the period of January 20th to March 2nd, 2020. First, we explored the associations between COVID-19 confirmed case counts, meteorological factors, and MSI using non-linear regression. Then, we conducted a two-stage analysis for 17 cities with more than 50 confirmed cases. In the first stage, generalized linear models with negative binomial distribution were fitted to estimate city-specific effects of meteorological factors on confirmed case counts. In the second stage, the meta-analysis was conducted to estimate the pooled effects. Our results showed that among 13 cities that have less than 50 confirmed cases, 9 cities locate in the Northern China with average AT below 0 °C, 12 cities had average AH below 4 g/

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Absolute humidity
Population migration

m^3, and one city (Haikou) had the highest AH (14.05 g/m^3). Those 17 cities with 50 and more cases accounted for 90.6% of all cases in our study. Each 1 °C increase in AT and DTR was related to the decline of daily confirmed case counts, and the corresponding pooled RRs were 0.80 (95% CI: 0.75, 0.85) and 0.90 (95% CI: 0.86, 0.95), respectively. For AH, the association with COVID-19 case counts were statistically significant in lag 07 and lag 014. In addition, we found the all these associations increased with accumulated time duration up to 14 days. In conclusions, meteorological factors play an independent role in the COVID-19 transmission after controlling population migration. Local weather condition with low temperature, mild diurnal temperature range and low humidity likely favor the transmission.

1. Introduction

Wuhan, the capital city of Hubei province, China, was the first major metropolitan region suffering from the coronavirus disease 2019 (COVID-19) outbreak and the epidemic center since December, 2019 (Zhou et al., 2020). COVID-19 is caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), a novel coronavirus. Due to the high contiguousness and wide spread, COVID-19 has officially been declared a pandemic by the World Health Organization (WHO) on March 11, 2020 (World Health Organization, 2020b). As of March 21th, more than 170 countries has reported this epidemic, with a total diagnosed cases of about 234,073 causing over 9000 deaths (World Health Organization, 2020b). Europe and the United States have gradually becoming the epicenter of the pandemic (World Health Organization, 2020c) and the world is facing great public health crisis from COVID-19, which is likely more severe than SARS in 2003.

In China, COVID-19 has spread in multiple major cities that have huge numbers of both inbound and outbound passengers (e.g., Beijing, Shanghai, and Guangzhou) (Wu et al., 2020). To block the quick spread of infection and control the severe epidemic, China has conducted strict measures by mobilizing and redistributing nationwide resources, shelter-in-place and quarantining all confirmed cases and close contacts. A study indicated that a series of control measures since January 23, 2020 in China reduced the COVID-19 epidemic size significantly, and the similar measures were expected to remain until the end of April 2020 (Yang et al., 2020). The current daily new COVID-19 cases in China have reached very low level. China has cumulatively reported more than 81,008 confirmed cases and over 3,255 deaths as of March 21, 2020 (National Health Commission of the People's Republic of China, 2020). Among all these effective strategies in controlling this epidemic, locking down Wuhan, a city of 11 million residents, was one of the most dramatic measures. It turned out that the limitation of population migration was effective in controlling epidemic diseases like COVID-19. However, the independent effect of meteorological factors on the transmission of COVID-19 has not been studied systemically while controlling population migration.

Previous studies showed that cold and dry weather is beneficial for the survival and spread of droplet-mediated viral diseases like

Fig. 1. Geographic patterns of COVID-19 confirmed case counts in 30 provincial capital cities of China as of March 2nd, 2020.

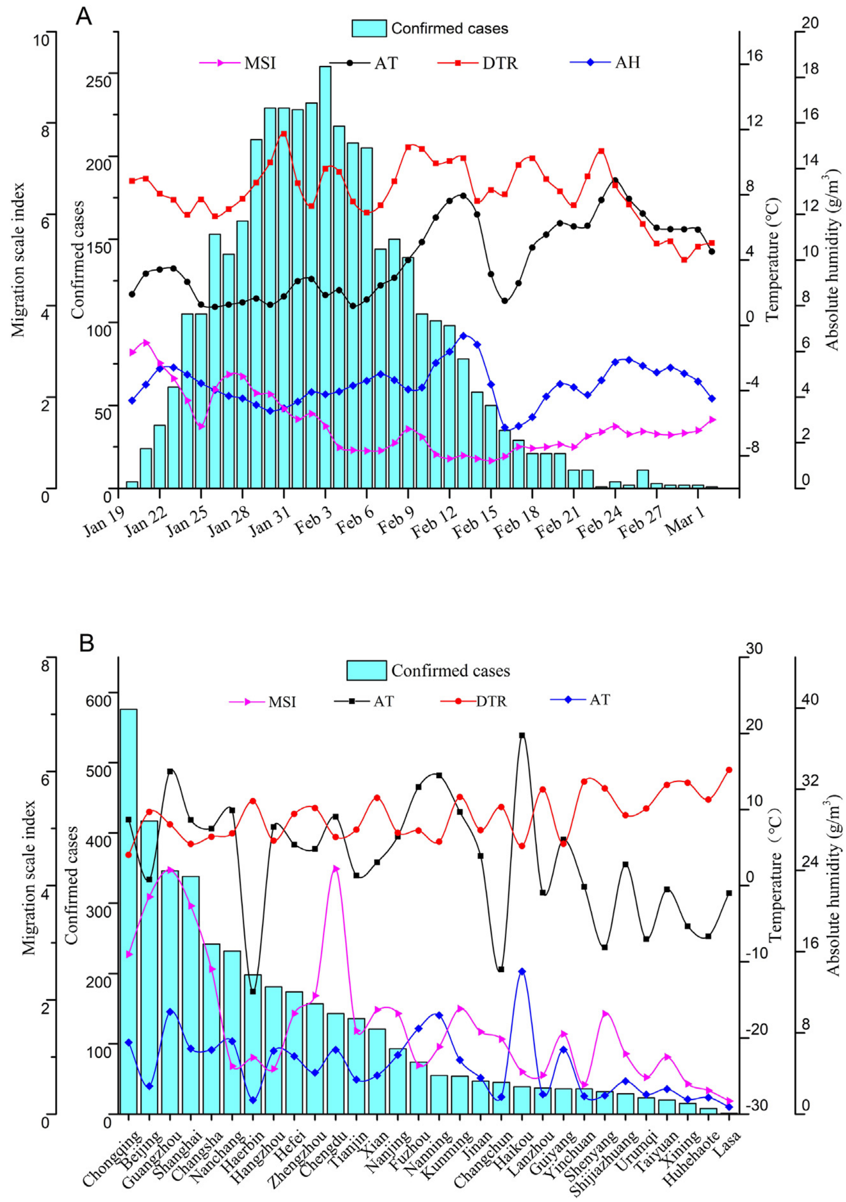

Fig. 2. Total COVID-19 case counts, average values of meteorological factors and MSI in 30 provincial capital cities of China during the period of January 20th to March 2nd 2020. Note: A: Temporal distribution; B: Regional distribution. AT: Ambient temperature; DTR: Diurnal temperature range; AH: Absolute humidity; MSI: Migration scale index.

influenza (Lowen et al., 2007; Shaman and Kohn, 2009; Li, 2011). The SARS epidemic was gradually faded with the warming weather coming, and was basically ended in July, 2003 (Tan et al., 2005; Wang et al., 2006; Cao et al., 2016), suggesting that the temperature and its variations might have affected the SARS outbreak. Some studies have suggested that the climate change might have contributed to various infectious diseases emergence and spread (Lofgren et al., 2007; Gale et al., 2010; Stott, 2016), including the SARS and COVID-19. In Korea, researchers found that the risk of influenza incidence was significantly increased with low daily temperature and low/high relative humidity (RH), but a positively correlated with diurnal temperature range (DTR) (Park et al., 2020). Absolute humidity (AH) had significant correlations with influenza viral survival and transmission rates (Shaman et al., 2010; Shaman et al., 2011). One important feature of COVID-19 epidemic is that the countries currently suffering most from the disease are most located in the regions with low temperature. Therefore, meteorological factors, such as ambient temperature (AT) and humidity, might play an important role in the spread of the disease.

Many factors might influence the COVID-19 epidemic, including social and political factors, geographical factors, climatic factors, etc. (Casadevall, 2020; Wu et al., 2020). When only considering the temperature in single-factor model in the higher-temperature group, every 1 °C increase in the minimum temperature leads to a decrease of the cumulative number of COVID-19 cases by 0.86 (Wang et al., 2020). Luo etc. reported that weather was related to the spread of COVID-19, but the increase of temperature may not necessarily lead to declines in case counts without the implementation of extensive public health interventions (Luo et al., 2020). In another study, researchers estimated that the weather variables explain 18% of the variation in disease doubling time, and the remaining 82% may be related to containment measures, general health policies, population density, transportation or cultural aspects (Oliveiros et al., 2020). Because of the human to human transmission, the migration should be considered when evaluate the effects of meteorological factors over COVID-19 transmission. However, to

Table 1
Summary of statistics for total confirmed COVID-19 case counts, MSI and meteorological factors in 30 cities during the period of January 20th to March 2nd, 2020.[a]

Cities	Counts of confirmed cases	Migration scale index	Daily average temperature (°C)	Diurnal temperature range (°C)	Absolute humidity (g/m^3)
Chongqing	576	2.80 ± 2.80	8.67 ± 1.83	4.03 ± 2.36	7.06 ± 1.15
Beijing	417	3.80 ± 3.80	0.80 ± 2.92	9.69 ± 4.54	2.75 ± 2.02
Guangzhou	346	4.27 ± 4.27	15.01 ± 3.50	8.04 ± 5.96	10.07 ± 3.33
Shanghai	338	3.64 ± 3.64	8.62 ± 2.92	5.47 ± 4.20	6.45 ± 2.18
Changsha	242	2.54 ± 2.54	7.49 ± 3.34	6.42 ± 2.47	6.33 ± 3.11
Nanchang	232	0.84 ± 0.84	9.88 ± 3.81	6.85 ± 0.77	7.17 ± 3.18
Haerbin	198	0.99 ± 0.99	−13.90 ± 5.68	11.08 ± 0.98	1.39 ± 0.89
Hangzhou	181	0.79 ± 0.79	7.72 ± 2.38	5.91 ± 2.64	6.23 ± 2.20
Hefei	174	1.76 ± 1.76	5.37 ± 3.12	9.42 ± 1.11	5.70 ± 3.54
Zhengzhou	157	2.08 ± 2.08	4.82 ± 2.73	10.20 ± 2.52	4.08 ± 2.34
Chengdu	143	4.29 ± 4.29	9.03 ± 1.75	6.39 ± 5.88	6.33 ± 1.21
Tianjin	136	1.46 ± 1.46	1.33 ± 2.96	7.35 ± 1.24	3.39 ± 2.12
Xian	121	1.83 ± 1.83	3.07 ± 2.21	11.53 ± 2.39	3.81 ± 2.02
Nanjing	93	1.76 ± 1.76	6.46 ± 2.37	6.95 ± 2.45	5.82 ± 2.99
Fuzhou	74	0.85 ± 0.85	12.94 ± 3.29	7.23 ± 0.90	8.42 ± 3.89
Nanning	55	1.18 ± 1.18	14.47 ± 3.84	5.77 ± 1.33	9.73 ± 3.77
Kunming	54	1.84 ± 1.84	9.69 ± 2.36	11.63 ± 2.83	5.34 ± 2.94
Jinan	47	1.44 ± 1.44	3.91 ± 3.28	7.28 ± 1.44	3.57 ± 3.76
Changchun	45	1.31 ± 1.31	−11.01 ± 5.92	10.32 ± 1.72	1.68 ± 1.12
Haikou	39	0.74 ± 0.74	19.73 ± 3.30	5.20 ± 0.70	14.05 ± 3.14
Lanzhou	37	0.68 ± 0.68	−0.92 ± 2.05	12.62 ± 0.86	1.95 ± 0.54
Guiyang	36	1.40 ± 1.40	6.04 ± 3.90	5.48 ± 1.32	6.35 ± 3.58
Yinchuan	36	0.52 ± 0.52	−0.15 ± 3.95	13.64 ± 0.98	1.76 ± 0.64
Shenyang	32	1.76 ± 1.76	−8.80 ± 4.36	12.77 ± 1.15	1.83 ± 0.89
Shijiazhuang	29	1.06 ± 1.06	2.77 ± 3.05	9.25 ± 1.71	3.24 ± 0.95
Urumqi	23	0.64 ± 0.64	−7.02 ± 3.77	10.12 ± 0.00	1.92 ± 0.23
Taiyuan	20	1.00 ± 1.00	−0.52 ± 2.30	13.24 ± 1.42	2.46 ± 0.67
Xining	15	0.53 ± 0.53	−5.30 ± 0.90	13.51 ± 0.65	1.45 ± 0.40
Huhehaote	8	0.41 ± 0.41	−6.65 ± 3.71	11.30 ± 0.34	1.63 ± 0.39
Lhasa	1	0.23 ± 0.23	−0.98 ± 0.55	15.20 ± 0.47	0.70 ± 0.10
Average	130.17 ± 138.60	1.62 ± 1.14	3.44 ± 7.97	9.13 ± 3.04	4.75 ± 3.14

[a] To account for the latent period of COVID-19, for each city, averaged meteorological parameters were calculated during the period of 20th to March 2nd, 2020.

our knowledge, previous studies have not controlled the population migration to examine independent effects of weather conditions on the COVID-19 transmission.

In this study, we first explored non-linear relation between COVID-19 case counts and meteorological factors. Then we used generalized linear models to examine the associations between meteorological factors and COVID-19 daily case counts in 30 provincial capitals except for Wuhan in China while controlling the population migration.

2. Methods

2.1. Data collection

Since the COVID-19 condition was much more complicated compared with other provinces due to government interventions in Hubei, like Wuhan lockdown and mass screening, we chosen to study the relationship in 30 capital cities of China. We obtained daily officially reported confirmed case counts from the Health Commission of the 30 capital cities except Wuhan during the period January 20th to March 2nd 2020 (Fig. 1). The daily meteorological data, including hourly temperature and RH, were obtained from Shanghai Meteorological Bureau and Data Center of Ministry of Ecology from January 5th to March 2nd 2020. Meanwhile, migration scale index (MSI) of the 30 cities was collected from the website of Baidu Migration (https://qianxi.baidu.com/?from=mappc). MSI reflects the population scale of moving in, and MSI of cities can be comparable. The daily average AT and DTR were calculated based on hourly data. AH was calculated according to the method used in the previous study which was measured by vapor pressure (g/m^3) (Shaman et al., 2011; Davis et al., 2016; Liu et al., 2018).

2.2. Statistical analysis

A descriptive analysis was performed to explore the city-specific characteristics of confirmed case counts, AT, DTR, AH and MSI of these 30 cities. For each city, average meteorological data were calculated based on the period of January 20th to March 2nd, 2020 to account for the lag effect and the latent period of COVID-19. Then, a second order polynomial non-linear regression models were fitted between total COVID-19 confirmed case counts and AT, DTR, AH, MSI.

We characterize the disease transmission and case distribution in the 13 cities with less than 50 confirmed cases. Then, a two-stage analysis was conducted for the other 17 cities with more than 50 cases in each city. In the first stage, because of the clustering characteristics of the disease, we adopted generalized linear models with negative binomial distribution to estimate city-specific effects. The analyses were performed with R software version 3.3.2, and the “MASS” package (MASS: Support functions and datasets for venables and Ripley's MASS, 2019) was used to fitting models. The fitted formulas were as follows:

$$\mathrm{Log}\ E\,(Y_t) = \alpha + \beta_1 AT + ns\,(RH, 3) + \beta_2 MSI \qquad (1)$$

$$\mathrm{Log}\ E\,(Y_t) = \alpha + \beta_1 DTR + ns\,(RH, 3) + \beta_2 MSI \qquad (2)$$

$$\mathrm{Log}\ E\,(Y_t) = \alpha + \beta_1 AH + \beta_2 MSI \qquad (3)$$

where t is the day of the observation; $E(Y_t)$ is the expected number of daily confirmed cases on day t; α is the intercept; β is the regression coefficient. Considering the lag effects and the average latent period of COVID-19, 3-day moving average RH and 3-day moving average MSI were controlled in the models when exploring the effects of AT (1) and DTR (2). As a meteorological factor, natural cubic splines (ns) with 3 *df* was used for controlling RH. Considering the collinearity, only three-day moving average MSI were controlled in the models (3) when dealing with AH. Because of the lag effects, we evaluated the associations in lag 0, lag 03, lag 07 and lag 014 between daily confirmed case counts and these meteorological factors for each city.

In the second stage of the analysis, we conducted a random effects meta-analysis to pool estimates across city-specific associations. The meta-analysis was performed based on STATA/SE 11.0 (StataCorp LLC, USA).

All results were expressed as the relative risk (RR) in daily confirmed case counts with 95% confidence intervals (95% CI) relative to a fixed change (1 °C or 1 g/m^3) of each factor. Statistical significance was set at *p*-value < 0.05.

3. Results

3.1. Descriptive analysis

As of March 2nd, 2020, a total of 3,905 cases were officially reported in 30 provincial capital cities in China. Among these cities, 17 cities had more than 50 confirmed cases, accounting for 90.6% of all cases in this study. During our study period, the daily MSI, AT, DTR and AH for these 30 cities were 1.62 ± 1.14, (3.44 ± 7.97) °C, (9.13 ± 3.04) °C and (4.76 ± 3.14) g/m^3. Strong regional differences were observed for meteorological factors and MSI.

Among the 13 cities that have less than 50 cases, 9 cities located in the Northern China with average AT below 0 °C, 12 cities had average AH below 4 g/m^3 and one city (Haikou) had the highest AH (14.05 g/m^3) (Figs. 1, 2 and Table 1). The MSI in these 13 cities were relatively lower than the remaining 17 cities that have more than 50 cases (Fig. 2).

3.2. Temporal and regional characteristics of COVID-19 transmission

The nonlinear regression analysis results (Fig. 3) suggest brief distribution characteristics between confirmed case counts and AT, DTR, AH, MSI. We found an obvious trend association between AT and the confirmed case counts, it seemed that the confirmed case number increased with temperature increasing in the range of −20 °C–20 °C. Like that, similar trend was also found between confirmed case counts and MSI. Well, we found there was an arched shape for the relationship between confirmed case counts and period-average AH, as there were more confirmed cases at the AH of around 6 g/m^3. However, the regression model showed that the confirmed cases counts declined with the increase of DTR in the range of 5 °C–15 °C.

3.3. AT, DTR and AH negatively related to the increase of COVID-19 transmission

Concerning the small sample size in those 13 cities, the fitted city-specific generalized linear models and meta-analysis were only conducted for the 17 cities with 50 and more cases to explore the associations between COVID-19 case counts and meteorological factors (Fig. 4). In city-specific analysis, significant negative associations were found in 9 cities (Beijing, Tianjin, Zhengzhou, Hangzhou, Shanghai, Xian, Nanchang, Fuzhou and Guangzhou) in lag 03. In meta-analysis, the pooled results showed that each 1 °C increase in AT was related to the decline of daily confirmed COVID-19 case counts, the corresponding overall RR was 0.80 (95% CI: 0.75, 0.85) (Fig. 4A). Each 1 °C increase in DTR was associated with decreased patients in lag 03 and the pooled RR was 0.90 (95% CI: 0.86, 0.95). In the city level, it was significant for Hangzhou, Nanchang, Fuzhou, Chengdu and Zhengzhou in lag 03 (Fig. 4B). As showed in Fig. 4C, AH had significant negative effects on confirmed case counts for 4 cities, including Guangzhou, Hangzhou, Nanchang, and Nanjing. Meta-analysis showed that each 1 g/m^3 increase in AH was significantly associated with reduced confirmed case

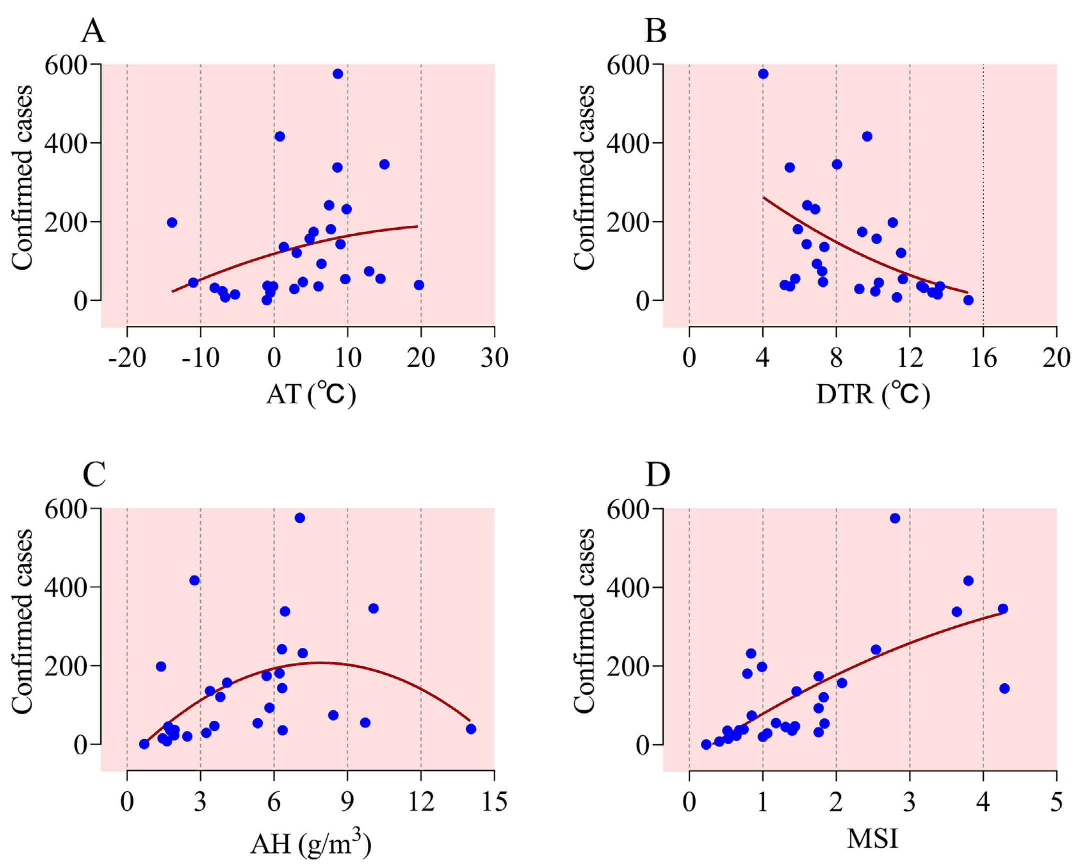

Fig. 3. Associations between COVID-19 confirmed case counts and meteorological factors, MSI in 30 provincial capital cities of China. Note: (A) AT, Curve formula: Y = 118.5 + 5.552 ∗ X-0.1022 ∗ X^2, R^2 = 0.08776; (B) DTR, Curve formula: Y = 408.5–40.24 ∗ X + 0.9651∗ X^2, R^2 = 0.2379; (C) AH, Curve formula: Y = –40.20 + 62.59∗ X-3.957 ∗ X^2, R^2 = 0.2291; (D) MSI: Y = –38.21 + 125.7 ∗ X-8.973 ∗ X^2, R^2 = 0.4953. The brown lines in figures represent second order polynomial curves. The blue dots represent the 30 cities. AT: Ambient temperature; DTR: Diurnal temperature range; AH: Absolute humidity; MSI: Migration scale index. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

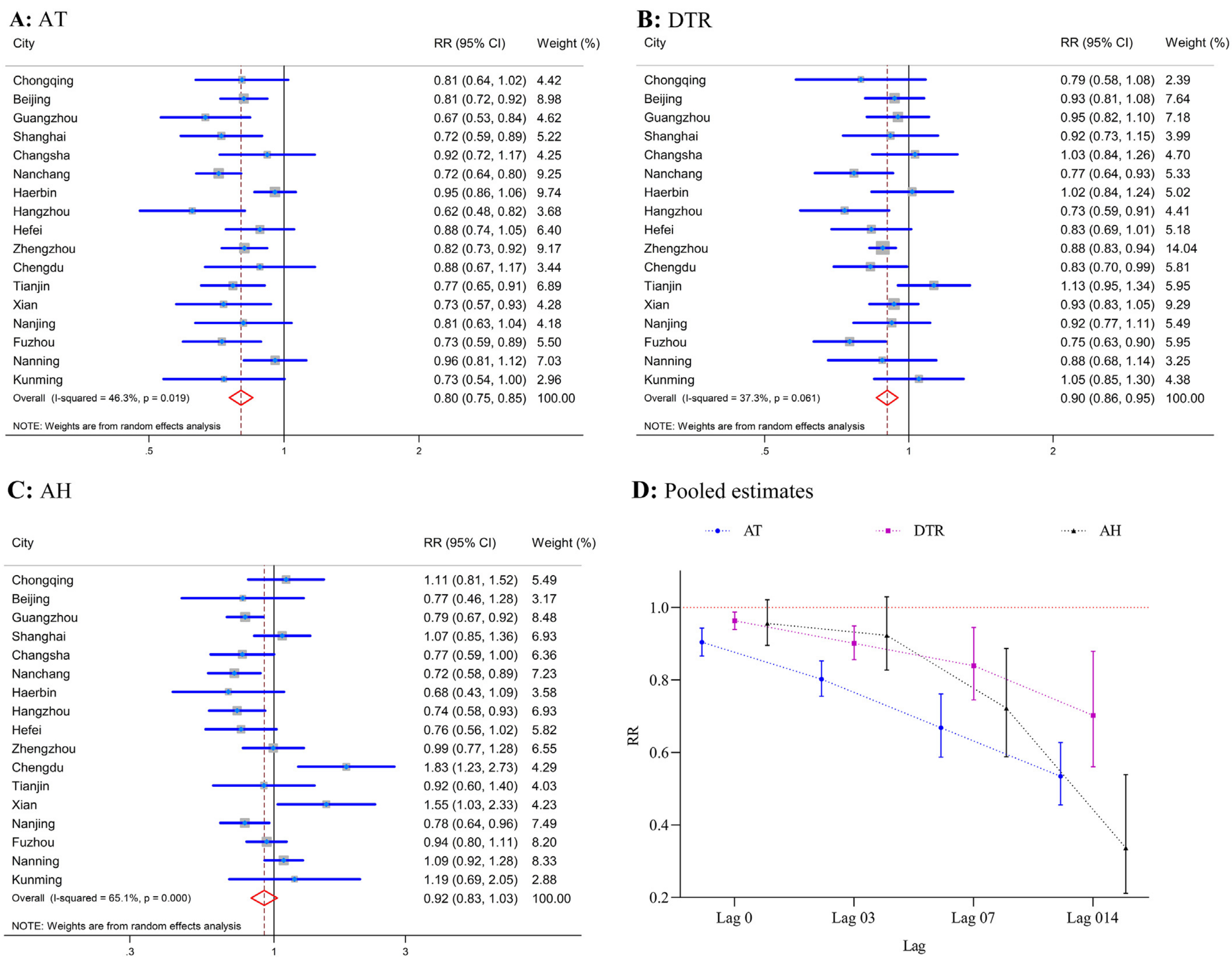

Fig.ure 4. Meta-analysis for effects of meteorological factors on COVID-19 case counts in 17cities during the period of January 20th to March 2nd 2020. Note: (A) AT; (B) DTR; (C) AH; (D) Pooled estimates in lag 0, lag 03, lag 07 and lag 014. The associations of COVID-19 case counts with AT, AH and DTR in each city was evaluated by fitting generalized linear models respectively (Lag 03). The meta-analysis was conducted to combine the city-specific results. AT: Ambient Temperature; DTR: Diurnal Temperature Range; AH, Absolute Humidity.

counts for 17 cities cities in lag 07, lag 014 and the combined RR was 0.72 (95% CI: 0.59, 0.89) and 0.33 (95% CI: 0.21, 0.54).

Fig. 4D showed associations between confirmed case counts and AT, DTR and AH in lag 0, lag 03, lag 07 and lag 014. The pooled effects of AT, DTR and AH became stronger with the increase of cumulative lag days.

4. Discussions

As of March 2nd, China has reported 80, 302 COVID-19 cases. This is the first study to examine the impact of meteorological factors on COVID-19 after controlling population migration. Our results indicated that COVID-19 transmission may be affected by meteorological factors, and a weather with low temperature, mild diurnal temperature range and low humidity likely favor its transmission.

Our findings on the impact of meteorological conditions over the transmission of COVID-19 are consistent with previous studies on the transmission of SARS or other infectious diseases (Tan et al., 2005; Lin et al., 2006; Liu et al., 2018; Park et al., 2020). Some studies suggested that global climate change might be accompanied by the changes to the outbreak of infectious diseases (Bezirtzoglou et al., 2011; Anwar et al., 2019; Casadevall, 2020). As we know, viruses are completely dependent on their hosts for replication and survival. It is possible that as virus has adapted to gradually higher global AT, some new and previously unknown infectious diseases are likely to emerge and spread (Casadevall, 2020), such as SARS-CoV and Ebola virus, and poses a threat to human health. The emergence and spread of novel coronavirus since December 2019 might be related to the ongoing climate change. In winter and spring, a decrease in resistance to respiratory diseases in a colder environment for population might be easier to accelerate the spread velocity. Lin etc. showed that in days with a lower air temperature during the epidemic, the risk of increased daily incidence of SARS was 18.18-fold (95% CI: 5.6, 58.8) higher than in days with a higher temperature (Lin et al., 2006). Tan etc. found a close association between temperature, its variations and the SARS outbreak in the four cities in China, suggesting that SARS more likely outbreaks in spring (Tan et al., 2005). Consistent with these results, we also found that each 1 °C increase in AT was related to the decline of daily confirmed case counts, the corresponding overall RR was 0.80 (95% CI: 0.75, 0.85). In addition, Lambrechts etc. has found that a large DTR might impede dengue virus infection of the mosquito midgut and reduce transmission risks compared to a small DTR or constant temperature. Intensity of dengue virus transmission can be influenced by the specific combination of mean and range in temperature fluctuations (Lambrechts et al., 2011). In our study, each 1 °C increase in DTR was associated with decreased patients in lag 03 and the pooled RR was 0.90 (95% CI: 0.86, 0.95). This suggests that novel coronavirus might be also more suited to survive in an environment with small DTR or constant temperature.

AH is an indicator describing the mass of water vapor per volume of air (g/m^3). Shaman et al. found that 50% of influenza virus transmission variability and 90% of influenza virus survival variability could be explained by AH variation, whereas, only 12% and 36% could be explained by relative humidity (Shaman and Kohn, 2009), and the epidemic influenza typically peaks in the winter when low AH maximizes R0 (Shaman et al., 2011). A previous study found that AH was one of most important weather parameters in predicting heat-related mortality among a spectrum of weather parameters (Zhang et al., 2014). These studies indicated that AH may be a better indicator of humidity in acute health effects. The COVID-19 outbreak in China happened in winter and early spring with lower AH. Our results indicated that there might exist an optimum low humidity for COVID-19 to spread. Because those 12 cities with AH below 4 g/m^3 confirmed fewer case counts than other cities. For the 17 cities with more than 50 cases, results showed that every 1 g/m^3 increase in AH was significantly associated with declined confirmed case counts in lag 07, lag 014 and the combined RR was 0.72 (95% CI: 0.59, 0.89) and 0.33 (95% CI: 0.21, 0.54). Consistent with our results, Liu et al. has explored the effects of AH on H7N9 infection risks in China and found significantly higher effects of low AH on risks of H7N9 infection (Liu et al., 2018). Possible explanation is that low AH might increase the stability of coronavirus and favor its transmission like influenza did (Lowen et al., 2007). Our results are somewhat different from a previous study about early COVID-19 outbreak, which reported that the changes in temperature and humidity as spring and summer months arriving might not lead to decline of confirmed case counts without the implementation of extensive public health interventions (Luo et al., 2020). Although public health control measures play a major role in controlling pandemic like COVID-19, our results indicate an independent role of weather conditions on the transmission. Unlike this study, we used data over a longer period and controlled the population migration in our models. Therefore, we are optimistic that this epidemic will be faded to a large degree in the coming warmer season with the enforcement of public health interventions in China.

As we know, the COVID-19 in China firstly confirmed in Wuhan and a considerable proportion of confirmed cases in other cities of China were imported from Wuhan, which may confuse the relation of meteorological environment and COVID-19. However, we controlled its effect with MSI and estimated a significant association between the meteorological environment and COVID-19 transmission. The most important environmental implication is that, AT, DTR and AH are critical factor for COVID-19 transmission, which also deserve to be better studied in other regions during this pandemic.

In conclusions, our study implicates that meteorological factors play an independent role in the COVID-19 transmission. A weather with low temperature, mild diurnal temperature range and low humidity favors the transmission. This study indicates that the epidemic might gradually ease as a result of rising temperatures in coming months as well as the implementation of public health control measures.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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