Transmissibility of COVID-19 and its association with temperature and humidity

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RESEARCH

Transmissibility of COVID-19 and its association with temperature and humidity

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Abstract

Background: The new coronavirus disease COVID-19 outbroke in Wuhan, Hubei Province, China in December 2019, and has spread by human-to-human transmission to other areas. This study evaluated the transmissibility of the infectious disease and analyzed its association with temperature and humidity, in order to put forward suggestions on how to suppress the transmission.

Methods: In this study, we revised the reported data in Wuhan to estimate the actual number of confirmed cases. Then we used the equation derived from the Susceptible–Exposed–Infectious–Recovered (SEIR) model to calculate R_0 from January 24, 2020 to February 13, 2020 in 11 major cities in China for comparison. With the calculation results, we conducted correlation analysis and regression analysis between R_0 and temperature and humidity to see the impact of weather on the transmissibility of COVID-19.

Results: It was estimated that the cumulative number of confirmed cases had exceeded 45,000 by February 13, 2020 in Wuhan. The average R_0 in Wuhan was 2.7011, significantly higher than those in other cities ranging from 1.7762 to 2.3700. The inflection points in the cities outside Hubei Province were between January 30, 2020 and February 3, 2020, while there had not been an obvious downward trend of R_0 in Wuhan. R_0 negatively correlated with both temperature and humidity, which was significant at the 0.01 level.

Conclusions: The transmissibility of COVID-19 was strong and importance should be attached to the intervention of its transmission especially in Wuhan. According to the correlation between R_0 and weather, the spread of disease will be suppressed as the weather warms.

Keywords: COVID-19; Transmissibility; Basic reproduction number; Temperature; Humidity

Background

On December 8, 2019, the first case of unexplained pneumonia was officially reported in Wuhan, the capital of Hubei Province in China. There has been an outbreak of the new coronavirus disease (COVID-19, named by the World Health Organization on February 11, 2020) in Wuhan since December 2019, and it has spread by human-to-human transmission to other Chinese cities as well as areas outside mainland China [1]. As was reported by the National Health Commission of the People's Republic of China, the number of con-

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firmed cases had reached 63,851 by February 13, 2020 in China, including 1,380 deaths. On the same day, Hubei Province alone totally had 51,986 confirmed cases including 1,318 deaths, accounting for 81.4% and 95.5% of the whole country respectively. Among them there were 35,991 confirmed cases and 1,016 deaths in Wuhan, accounting for 69.2% and 77.1% of the number in Hubei Province respectively. The cumulative number of confirmed cases keeps rising, indicating the strong transmissibility of COVID-19, especially in Wuhan, Hubei Province. Therefore, it is of great importance to adopt reasonable indicators to assess the transmission ability of the disease, based on which effective intervention and control measures could be put forward [2, 3].

The basic reproduction number (R_0) refers to the expected number of cases generated from a single case when all people are susceptible to infection [4]. It is widely used to evaluate the transmission ability of an emerging infectious disease and determine what degree of control measures should be taken to eradicate the disease [5–8]. When $R_0 > 1$, the disease starts to spread; and when $R_0 < 1$, the disease is effectively controlled [9]. R_0 is influenced by many other factors except for the characteristics of the disease itself, such as conditions of the environment, policies of the government, people's awareness of infectious diseases and social behavior. Therefore, we can use R_0 to measure the transmissibility of COVID-19 and analyze its influencing factors, which provides data support for suggestion-proposing and decision-making.

Research on transmissible diseases like influenza [10], SARS (Severe Acute Respiratory Syndrome) [11] and MERS (Middle East Respiratory Syndrome) [12] has found that disease transmission is associated with temperature and humidity of the environment [13–18]. In terms of biological methods, influenza virus spread was found to be promoted by cold temperature and low relative humidity with the guinea pig as a model host [19]; besides, an experiment on the SARS coronavirus indicated that high temperature and high humidity suppressed the spread of the virus [20]; similarly, MERS coronavirus was more stable when temperature or humidity was lower [21]. In terms of statistical methods, case studies of SARS in four major cities in China suggested that the transmissibility had close relationship with temperature and its variation [22]; and a regression equation was derived to show how temperature, relative humidity, and wind velocity affected the transmission of SARS [23]. Thus we wonder if the spread of COVID-19 follows a similar pattern. Considering that R_0 is useful for measuring the transmission ability of infectious diseases, we conducted an effect analysis of temperature and humidity on R_0. Statistical methods such as correlation and regression were adopted for the analysis.

In summary, this paper measured the transmissibility of COVID-19 with R_0 and analyzed its correlation with temperature and humidity. First, we revised the epidemiological data in Wuhan to make R_0 more accurate. Second, we calculated R_0 and compared the average value and developing trend of R_0 in 11 cities including Wuhan. Third, we conducted correlation and regression analysis between R_0 and temperature and humidity to see the impact of weather on R_0.

Methods

Data acquisition and preprocessing

The daily accumulative number of confirmed cases and new additions is reported by the National Health Commission of the People's Republic of China as well as the health commission of each province on the official website. An R package has been developed to access the epidemiological data directly [24]. The R package was used by us to acquire the number of total cases and new additions from January 18, 2020 to February 13, 2020 in Wuhan, Hubei Province considering that

the outbreak of COVID-19 originated from Wuhan and the situation there was complex and needed much attention. Besides, we also collected the daily-reported accumulative number of confirmed cases from January 24, 2020 to February 13, 2020 in 10 Chinese major cities outside Hubei Province including Beijing, Chengdu, Chongqing, Guangzhou, Hangzhou, Hefei, Nanjing, Shanghai, Shenzhen, and Zhengzhou (listed by initials) for further calculation, estimation, and analysis.

As for Wuhan, it was estimated by Imperial College London, UK that the total number of confirmed diagnoses had reached 4,000 by January 18, 2020 [25], which was much higher than the officially reported number. So we revised the data in Wuhan to infer the actual transmissibility of the new coronavirus. There are several assumptions for the data-preprocessing procedure:

1) The first case appeared on December 8, 2019 in Wuhan and transmission started from that day on [26].
2) The cumulative number of cases $Y(t)$ by day t since the first single case followed the exponential function $Y(t) = e^{\lambda t}$ in early development [27].
3) The cumulative number of cases on January 18, 2020 was 4,000, that was, $Y(41) = 4000$ [25].
4) From February 13, 2020 on, all cases in Wuhan can be confirmed and the number of daily new cases is correct, given that the number of newly confirmed diagnoses on February 12, 2020 in Wuhan increased significantly, exceeding 10,000.

Based on those assumptions, the data-revising procedure in Wuhan is as follows:

1) According to assumption 2 and 3, the exponential growth rate is estimated as $\lambda = ln[Y(41)]/41$.
2) According to assumption 2 and 3, the number of new additions on January 18, 2020 equals $Y(41) - Y(40) = 4000 - e^{\lambda * 40} = 733$.
3) According to assumption 4, the number of new additions on February 13, 2020 is 2,997, which is consistent with the officially reported number.
4) According to assumption 2, the daily number of new additions $y(t)$ can be calculated by

$$\begin{aligned} y(t) &= Y(t) - Y(t-1) \\ &= e^{\lambda t} - e^{\lambda(t-1)} \\ &= e^{\lambda t}(1 - e^{-\lambda}). \end{aligned} \tag{1}$$

Thus

$$ln[y(t)] = ln(1 - e^{-\lambda}) + \lambda t. \tag{2}$$

So the relationship between $ln[y(t)]$ and t is linear. Replace $ln(1-e^{-\lambda})$ with a and λ with b in Equation (2), and the coefficients a and b of the linear equation can be determined by substituting $y(41) = 733$ and $y(67) = 2997$ into the equation respectively.
5) The number of new additions each day from January 19, 2020 to February 12, 2020 can be calculated through the equation $y(t) = e^{a+bt}$, where a and b are the coefficients obtained in procedure 4.
6) With the daily number of new additions known, the daily cumulative number of cases from January 19, 2020 to February 13, 2020 can be calculated by $Y(t) = Y(t-1) + y(t), t = 42, 43, ..., 67$.

As for other cities outside Hubei Province, it is assumed that the officially reported data is accurate. Based on the relationship $ln[Y(t)] = \lambda t$, we performed logarithmic fitting between the cumulative number of diagnoses and time and inferred that transmission started on December 27, 2019 outside Hubei Province.

Calculation of the basic reproduction number

The basic reproduction number indicates the average number of people infected by a patient during the infectious period in the absence of control interventions [4]. It is also denoted R_0, which measures transmissibility of infectious diseases. There are several ways to

estimate R_0, including formula derivation [28, 29] and model fitting [30–32].

We describe the transmission pattern of COVID-19 with the Susceptible–Exposed–Infectious–Recovered (SEIR) model. In the exposed stage, an individual infection is not able to infect others. The duration of the exposed stage T_E is also called the latent period. While in the infectious stage with a duration of T_I, an infected person does infect susceptible people. Assuming that the cumulative number of confirmed diagnoses increases exponentially in the early stages of an epidemic, the relationship between the basic reproduction number R_0 and the exponential growth rate λ can be written as [33]

$$R_0 = (1 + \lambda T_E)(1 + \lambda T_I). \quad (3)$$

The serial interval T_g is the sum of T_E and T_I. Let $f = T_E/T_g$ be the ratio of the latent period to the serial interval, and then the basic reproduction number can be expressed as [27]

$$\begin{aligned} R_0 &= 1 + \lambda(T_E + T_I) + \lambda^2 T_E T_I \\ &= 1 + \lambda T_g + \lambda^2 T_E(T_g - T_E) \\ &= 1 + \lambda T_g + \lambda^2 f T_g(T_g - f T_g) \\ &= 1 + \lambda T_g + f(1 - f)(\lambda T_g)^2. \quad (4) \end{aligned}$$

The exponential growth rate is $\lambda = ln[Y(t)]/t$, where t is the number of days required to generate the cumulative number of $Y(t)$ cases from the first case. According to the research on the first 425 patients with confirmed COVID-19, the mean latent period T_E = 5.2 (days) and the mean serial interval T_g = 7.5 (days) [34]. Adopting these values, we can calculate the ratio of the latent period to the serial interval by $f = T_E/T_g = 5.2/7.5 = 0.6933$.

Correlation and regression analysis between R_0 and weather

Correlation analysis measures the strength of the linear correlation between two variables and expresses it with appropriate statistical indicators [35]. It is a commonly used statistical method to study the relationship between variables [36]. Regression analysis determines the quantitative relationship between two variables in statistics [37]. Among all kinds of regression methods, linear regression establishes the relationship between the dependent variable Y and the independent variable X with a linear equation $Y = a + bX$ [38]. There are two coefficients in the equation, a as the intercept and b as the slope. We performed correlation analysis and linear regression between R_0 and weather with the statistical analysis software IBM SPSS Statistics 25. The procedure is listed below.

1) We collected the data of the daily average temperature and humidity from January 24, 2020 to February 13, 2020 in four Chinese major cities which were Beijing (the capital of China), Shanghai (the municipality of China), Guangzhou (the capital of Guangdong Province) and Chengdu (the capital of Sichuan Province).
2) We imported the data of temperature and humidity together with R_0 into the SPSS software and added cities as the classification label.
3) Through correlation analysis, the Pearson correlation coefficients between R_0 and temperature and humidity were calculated respectively.
4) Through regression analysis, the intercept a and the slope b of the linear equation were estimated with R_0 as the dependent variable Y and temperature or humidity as the independent variable X.
5) We split the data by the city label and repeated procedure 3 and 4 for each city separately.

Results

Comparisons of transmission among different cities

Fig. 1 presents the comparison between officially reported data and revised data in Wuhan with important points marked on it. The estimated number of cumulative cases was higher than the official number every day, and it had reached 46,933 by February 13, 2020, which was 1.3 times that of the official number 35,991. The unusual high peak of new cases on February 12, 2020 was smoothed by revision.

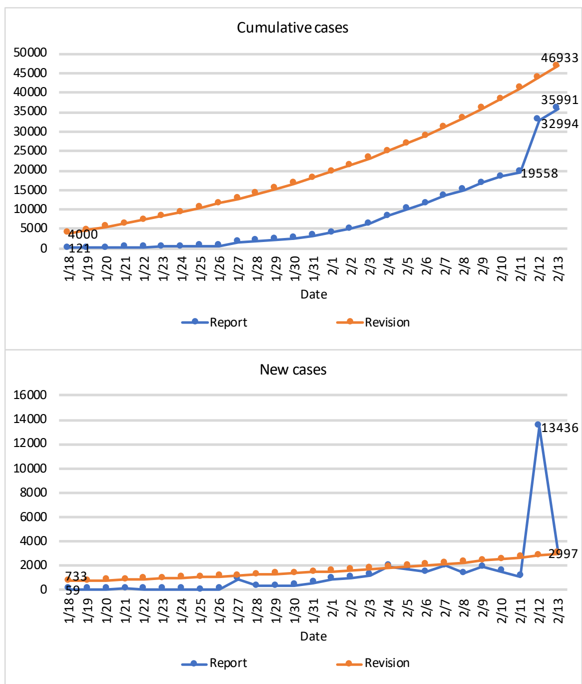

Figure 1 . Comparisons between reported and revised data in Wuhan.

The calculation results of the basic reproduction number R_0 from January 24, 2020 to February 13, 2020 in 11 Chinese major cities are shown in Fig. 2. The values with the label "Wuhan" were calculated using the officially reported number of cases, while those with "Wuhan (revised)" were calculated using the revised number of cases. In this way, the broken line of "Wuhan" reflects the changing trend of R_0, and the one of "Wuhan (revised)" reflects the value size of R_0. It is assumed that the cumulative number of confirmed cases reported officially in cities outside Hubei Province is accurate, so the broken lines of the other 10 cities represent not only trends but also actual values.

As can be seen from Fig. 2, R_0 in Wuhan is significantly higher than those in cities outside Hubei Province. Besides, R_0 in cities outside Hubei Province has begun to decrease, while R_0 in Wuhan does not show a significant downward trend.

For a more detailed analysis, the average basic reproduction number of the 21 days in each city and the date of the inflection point are presented in Table 1. The cities are listed by the average R_0 from high to low. The inflection point refers to the day after which R_0 shows a downward trend.

Table 1 The average R_0 and the inflection point of each city (listed by the average R_0)

City	Average R_0	Inflection point
Wuhan	2.7011	None
Chongqing	2.3700	1/30
Beijing	2.2545	2/2
Shenzhen	2.2193	2/3
Shanghai	2.2191	2/1
Guangzhou	2.1711	2/1
Hangzhou	2.0598	1/31
Chengdu	2.0024	1/30
Zhengzhou	1.9774	2/3
Hefei	1.9501	2/2
Nanjing	1.7762	2/2

Table 1 suggests that the average R_0 in Wuhan far exceeds those in other cities, which is 0.33 higher than that in Chongqing, the city which ranks second. It should be noted that the average R_0 in Wuhan is calculated with the revised data to better fit the real value. In fact, the average basic reproduction number calculated with the officially reported data is also much higher than those in other cities, which is 2.3978.

The inflection points of cities outside Hubei Province range from January 30 to February 3, indicating that the control measures on transmission have worked since late January or early February. Although R_0 in

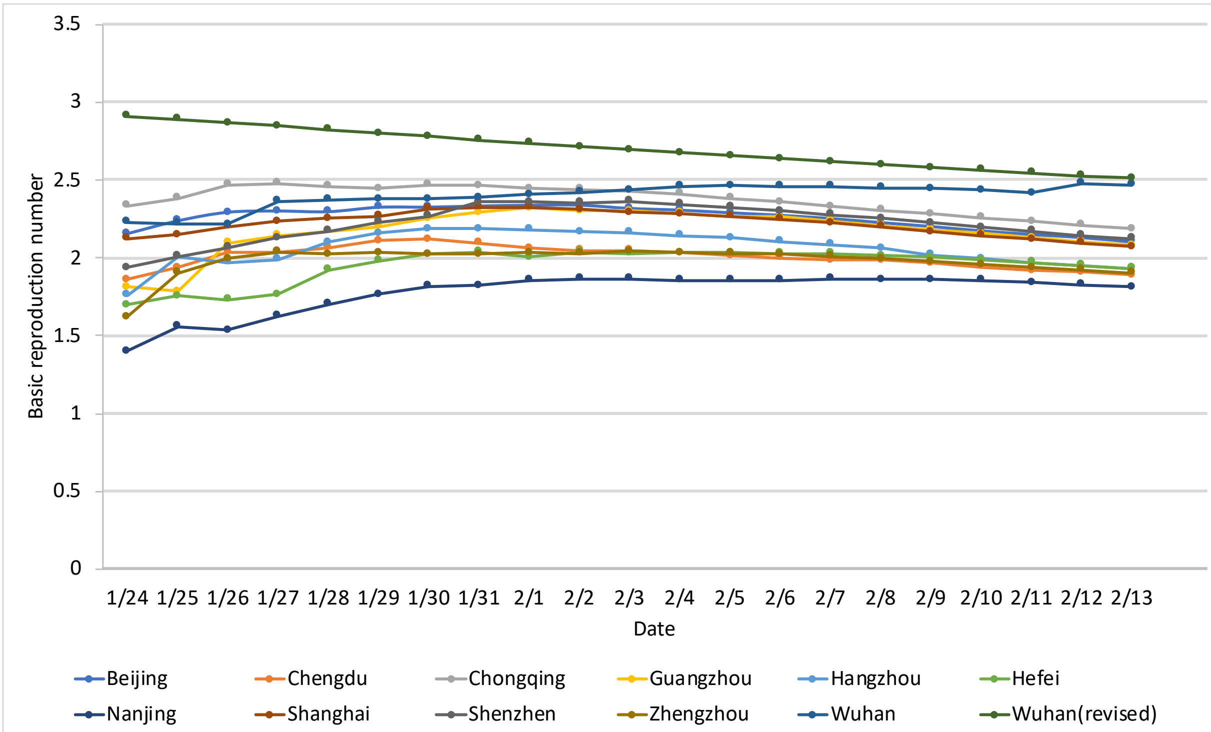

Figure 2 . Calculation results of the basic reproduction number.

Wuhan reaches a peak on February 12, it cannot be determined that February 12 is the inflection point. Because since that day, Hubei Province has included the number of clinically diagnosed cases into the number of confirmed cases. The modification of the diagnostic criteria leads to a sudden increase of newly confirmed patients, which explains why R_0 is particularly high on February 12. The inflection point of Wuhan has not appeared, so the situation in Hubei remains grim.

Correlation between R_0 and temperature

Table 2 shows the Pearson correlation coefficients and significance between R_0 and temperature. The row of "Summary" suggests that calculated as a whole, the correlation between R_0 and temperature is statistically significant at the 0.01 level. The correlation coefficient is -0.459, so R_0 and temperature have a negative correlation, which means that R_0 decreases as the temperature increases. The higher the temperature, the lower the transmission capability. As for the analysis of each city, R_0 negatively correlates with temperature in Shanghai and Chengdu, correlation significant at the 0.01 level. Correlation is not significant in Beijing, and Guangzhou.

Table 2 Correlation analysis between R_0 and temperature

	Pearson correlation	Sig. (2-tailed)	N
Summary	-.459**	.000	84
Beijing	-.429	.052	21
Shanghai	-.735**	.000	21
Guangzhou	-.410	.065	21
Chengdu	-.732**	.000	21

**. Correlation is significant at the 0.01 level (2-tailed).

Linear regression was performed on the whole data as well as the data in Shanghai and Chengdu which showed a significant correlation. Table 3 presents the linear regression results. Replace a and b in the equation $Y = a + bX$ with the corresponding actual values in Table 3, and correlation between R_0 (corre-

sponding to Y) and temperature (corresponding to X) can be expressed more precisely. For example, the linear regression equation of Shanghai is written as $Y = 2.424 - 0.026X$. It can be inferred from $b < 0$ that R_0 negatively correlates with temperature in Shanghai, which is consistent with the correlation analysis result above.

Table 3 Linear regression analysis of temperature to R_0

	Intercept a	Slope b
Summary	2.240	-.010
Shanghai	2.424	-.026
Chengdu	2.259	-.026

We plotted every pair of temperature and R_0 in a city or the whole data on the scatter figure to make correlation more intuitive, which was presented in Fig. 3. The regression lines followed the corresponding linear regression equations.

Correlation between R_0 and humidity

The Pearson correlation coefficients and significance between R_0 and humidity are presented in Table 4. According to the first row, the correlation between R_0 and humidity is statistically significant at the 0.01 level in general. The correlation coefficient is -0.391, indicating that R_0 decreases as the humidity increases. As for the analysis of each city, R_0 negatively correlates with humidity in Beijing and Shanghai, which is significant at the 0.01 level. While the correlation is significantly positive in Chengdu at the 0.01 level, which implies that the transmission ability and humidity have consistent trends there. Correlation is not significant in Guangzhou.

The correlation was significant in Beijing, Shanghai, and Chengdu, and thus we conducted linear regression on the data of the three cities as well as the summary of all cities. The linear regression results are presented in Table 5. Replace a and b in the equation $Y = a + bX$ with the corresponding actual values in Table 5, and the correlation between R_0 (corresponding to Y) and

Table 4 Correlation analysis between R_0 and humidity

	Pearson correlation	Sig. (2-tailed)	N
Summary	-.391**	.000	84
Beijing	-.568**	.007	21
Shanghai	-.722**	.000	21
Guangzhou	-.363	.106	21
Chengdu	.619**	.003	21

**. Correlation is significant at the 0.01 level (2-tailed).

humidity (corresponding to X) can be expressed with a quantitative method.

Table 5 Linear regression analysis of humidity to R_0

	Intercept a	Slope b
Summary	2.415	-.004
Beijing	2.417	-.003
Shanghai	2.542	-.004
Chengdu	1.651	.005

Fig. 4 presents the scatters of humidity and R_0 pairs in a city or the whole data. The regression lines of the scatters show the changing trend of R_0 with humidity.

Discussion

Sensitivity analysis of R_0

To analyze the sensitivity of R_0 to the three key parameters in Equation (4): $R_0 = 1 + \lambda T_g + f(1-f)(\lambda T_g)^2$, we differentiated R_0 to λ, T_g and f respectively:

$$\frac{\partial R_0}{\partial \lambda} = T_g + 2f(1-f)\lambda T_g^2, \quad (5)$$

$$\frac{\partial R_0}{\partial T_g} = \lambda + 2f(1-f)\lambda^2 T_g, \quad (6)$$

$$\frac{\partial R_0}{\partial f} = (1-2f)(\lambda T_g)^2. \quad (7)$$

Substitute the variables with $\lambda = 0.1372$ (which is the average λ from January 24 to February 13 in Beijing), $T_g = 7.5$ and $f = 0.6933$, and the specific values can be calculated:

$$R_0 = 2.2541, \quad (8)$$

$$\frac{\partial R_0}{\partial \lambda} = 10.7820, \quad (9)$$

$$\frac{\partial R_0}{\partial T_g} = 0.1972, \quad (10)$$

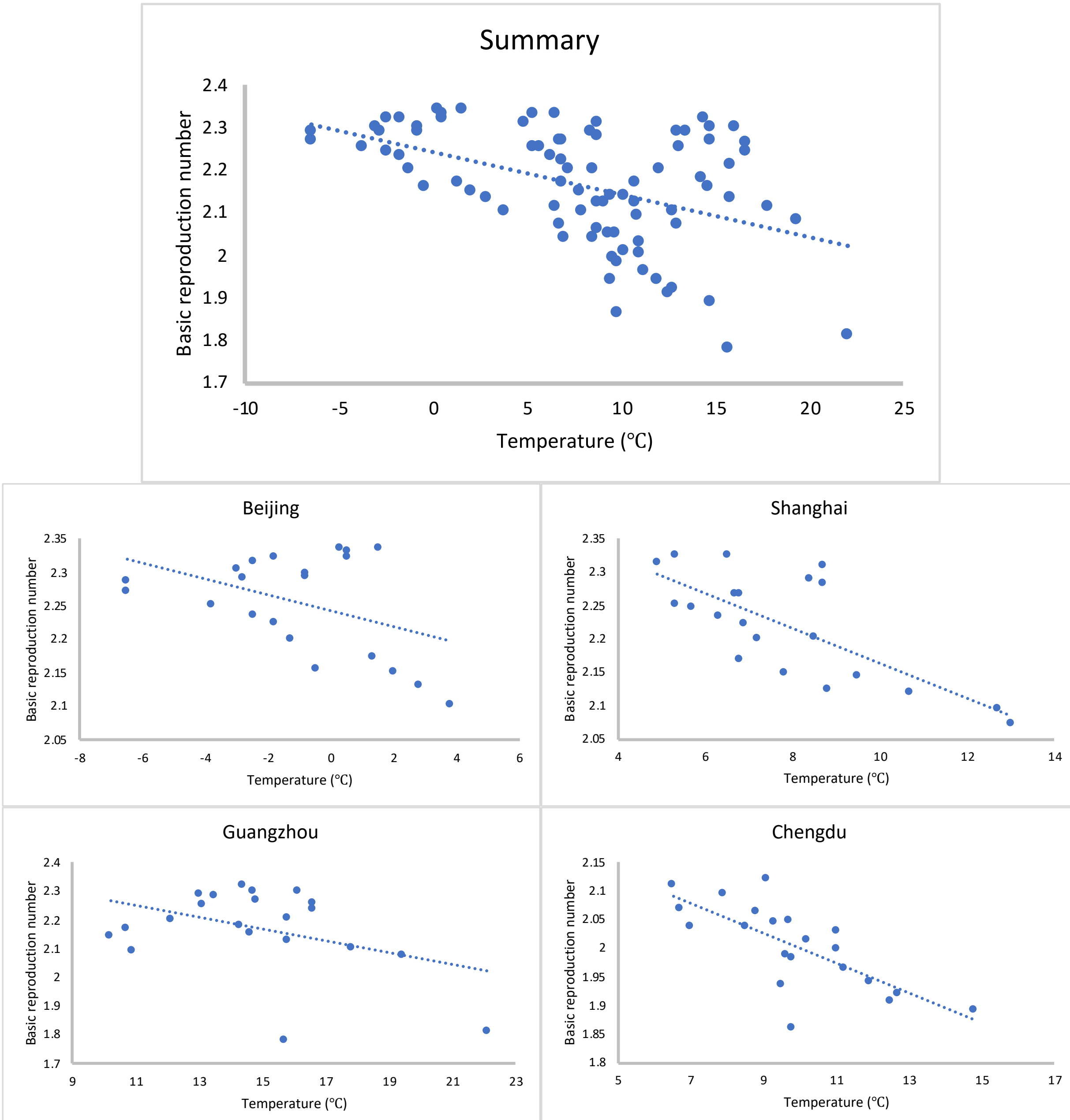

Figure 3 . Scatter plot of temperature and basic reproduction number.

$$\frac{\partial R_0}{\partial f} = -0.4093. \quad (11)$$

The sensitivity of the basic reproduction number R_0 to the exponential growth rate λ, the serial interval T_g and the latent period ratio f can be estimated according to the range of variables and the scale of partial derivatives. When the variables fluctuate within a small range around the given value, R_0 increases as λ or T_g increases and decreases as f increases. λ, T_g and f range at the scales of 10^{-2}, 10^{0} and 10^{-1} respectively. And the scales of their partial derivatives are 10^{1}, 10^{-1} and 10^{-1}. Thus the fluctuation scales of R_0 are 10^{-1}, 10^{-1} and 10^{-2} corresponding to λ, T_g and

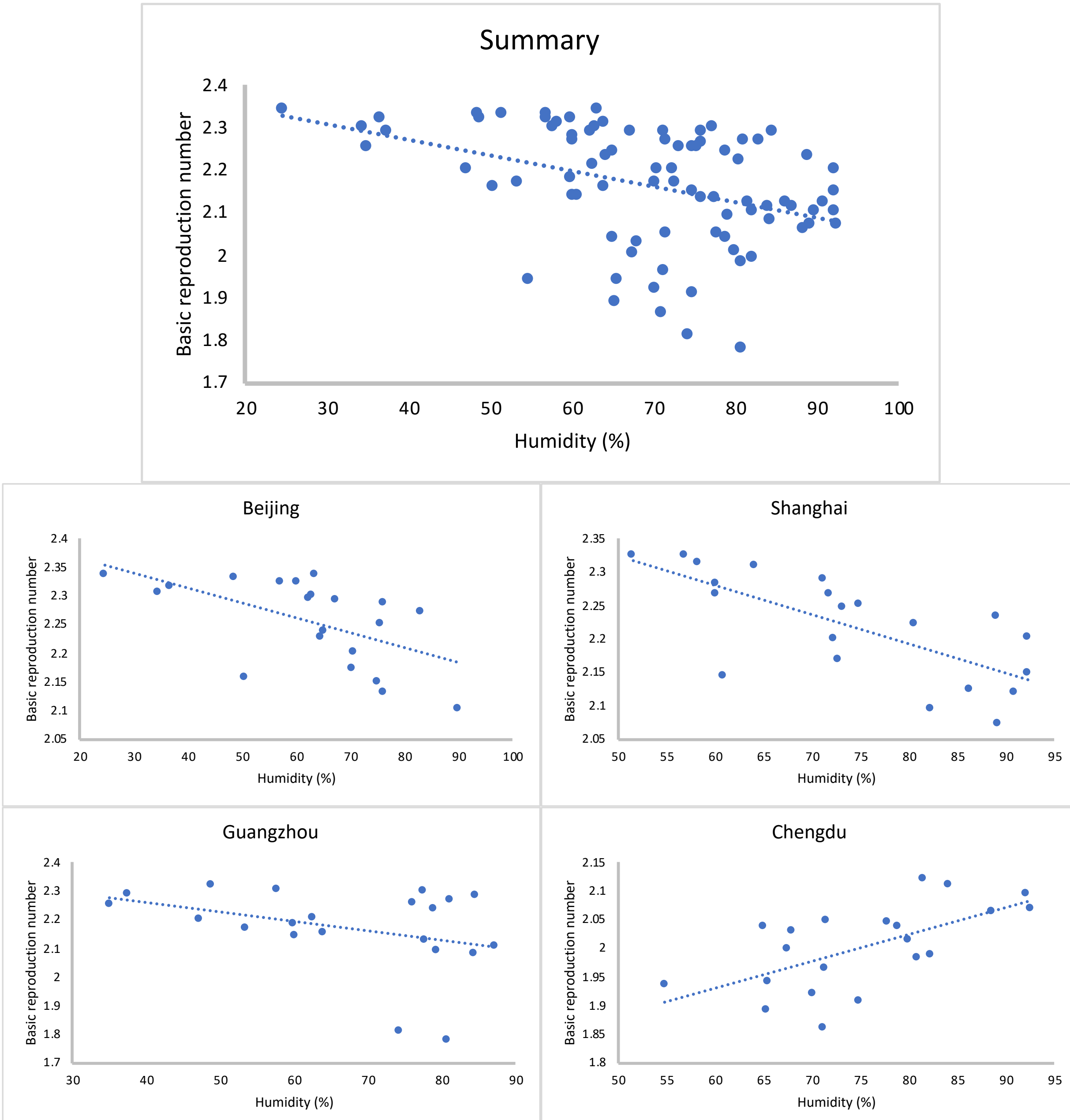

Figure 4 . Scatter plot of humidity and basic reproduction number.

f, which implies that R_0 is more sensitive to λ and T_g than f. The accuracy of parameters or variables is important for the estimation of the basic reproduction number. As the research on COVID-19 progresses, we can get more precise data and better describe the transmission pattern of the new coronavirus. But the calculation in this paper still makes sense, considering that we focus on relative values instead of absolute values of R_0 in comparison and correlation analysis. Results are reasonable as long as we use the consistent equation and parameters to calculate R_0. By comparison, we can see that the control of COVID-19 is es-

pecially urgent in Wuhan and people in other cities should also attach importance to inhibiting the spread of the disease. The vigilance cannot languish until R_0 drops below 1.

Effects of temperature and humidity on the transmission of COVID-19

The Pearson correlation coefficient between temperature and humidity is 0.212 ($P > 0.05$), so the two weather indicators do not significantly correlate with each other. Therefore, the effects of temperature and humidity on R_0 are independent and can be analyzed separately.

The overall correlation between R_0 and temperature or humidity is significantly negative, implying that raising the temperature and humidity properly contributes to controlling the transmission of COVID-19, which is consistent with the results of the biological and statistical research on other infectious diseases. It could be explained in several aspects. First, in terms of biological characteristics, a lot of research has confirmed that viruses are less active at high temperature and high humidity [17, 39, 40]. Second, in terms of the transmission media, viruses spread as droplets or aerosols, which maintain large particle sizes at high humidity and thus can settle rapidly or be blocked by masks, nasal cavity, etc [41]. Third, in terms of human immunity, high temperature and high humidity protect the immune organs and benefit people's health. To sum up, relatively high temperature and humidity is good for suppressing the spread of COVID-19, which is especially important in hospitals and other public places where people gather.

As for the correlation in each city, R_0 negatively correlates with both temperature and humidity in Shanghai; R_0 negatively correlates with humidity in Beijing, while the correlation with temperature is not significant; R_0 negatively correlates with temperature in Chengdu, while the correlation with humidity is positive; R_0 correlates with neither temperature nor humidity in Guangzhou. The deviation of the results may be due to several factors. First, there is a lack of data, since there are only 21 groups of data in correlation analysis of each city. As time goes by, we will be able to collect data over a longer period and the results may be more significant. Second, consuming that COVID-19 outbroke in winter, people's activity and virus transmission mainly occur indoors. Beijing is north of Qinling Mountains-Huaihe River Line in China and there is central heating indoors. So the room temperature is actually higher than the outdoor temperature, which may also affect the results. Third, the effect of weather on COVID-19 is complicated. The joint distribution between weather and potential confounders such as policies, medical condition, and health awareness should be taken into account. Nevertheless, we promote a constructive idea of using R_0 as the measurement of the transmissibility and analyzing the relationship between R_0 and weather with statistical methods, and put forward valuable suggestions on the adjustment of temperature and humidity.

Conclusions

In this paper, we calculated and compared the basic reproduction number of COVID-19 in different cities, and analyzed its association with temperature and humidity. First, we revised the daily number of new cases and cumulative cases in Wuhan and estimated that the real number of cumulative cases was 1.3 times that of the officially reported number on February 13, 2020. Second, we calculated R_0 from January 24, 2020 to February 13, 2020 in 11 major cities in China, and found out that R_0 in Wuhan was significantly higher than those in other cities. Besides, the inflection point was around February 1, 2020 in cities outside Hubei Province, while the inflection point had not appeared in Wuhan. Third, we conducted correlation analysis and linear regression between R_0 and two weather in-

dicators, the results of which implied that R_0 negatively correlated with temperature and humidity. Consequently, the spread of COVID-19 is most violent in Wuhan, Hubei Province, and effective action should be taken to control the transmission. As the weather warms, the transmissibility is predicted to be reduced.

Abbreviations

COVID-19: Corona Virus Disease 2019; R_0: Basic reproduction number; SARS: Severe acute respiratory syndrome; MERS: Middle east respiratory syndrome; SEIR: Susceptible–Exposed–Infectious–Recovered

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Author's contributions

HZ conceived the study. XG and YZ collected the data. XG analyzed the data and drafted the manuscript. XG and HZ interpreted the results. XG, HZ and YZ revised the manuscript. All authors read the approved the final manuscript.

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Availability of data and materials

Not applicable.

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

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Figures

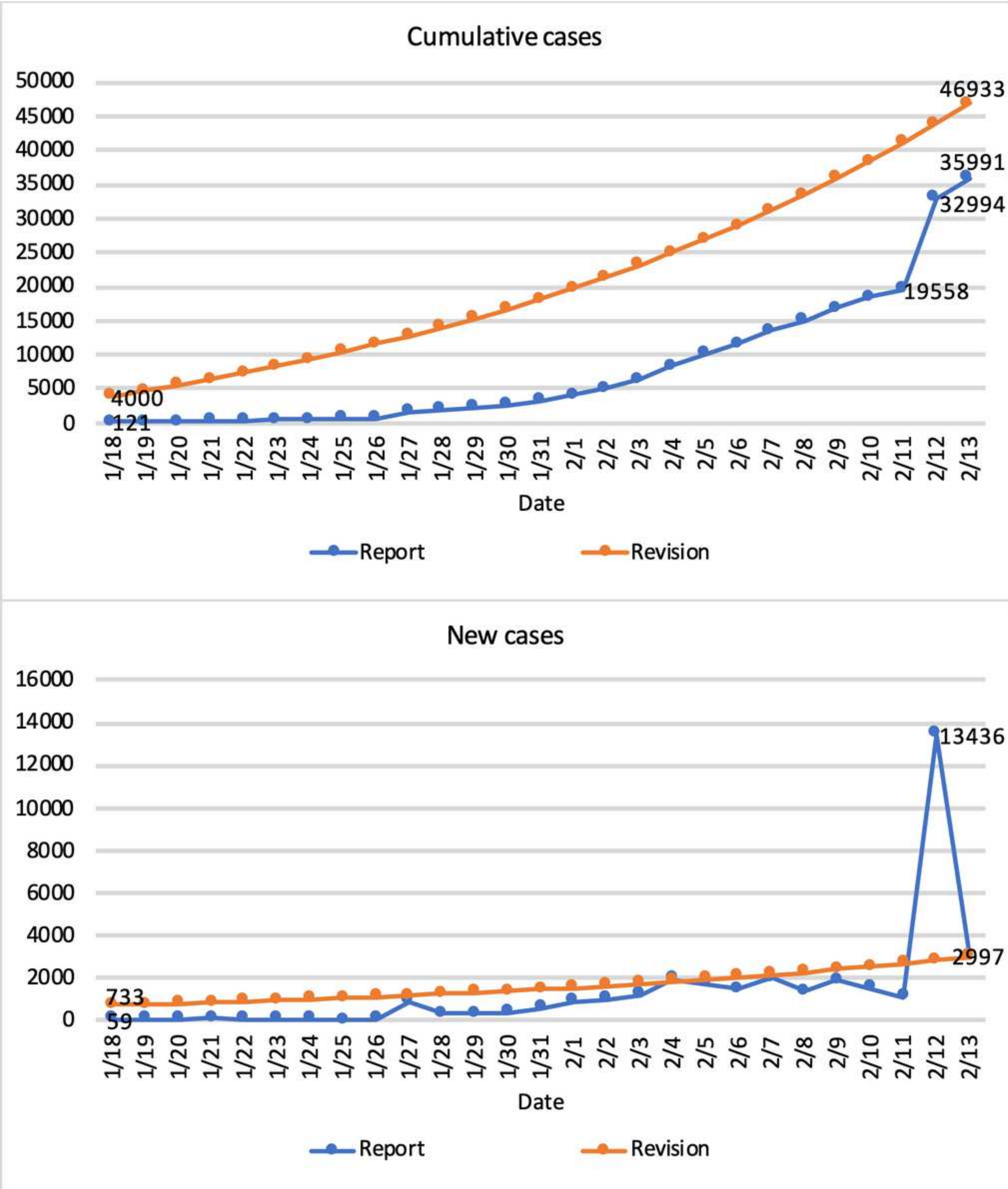

Figure 1

Comparisons between reported and revised data in Wuhan.

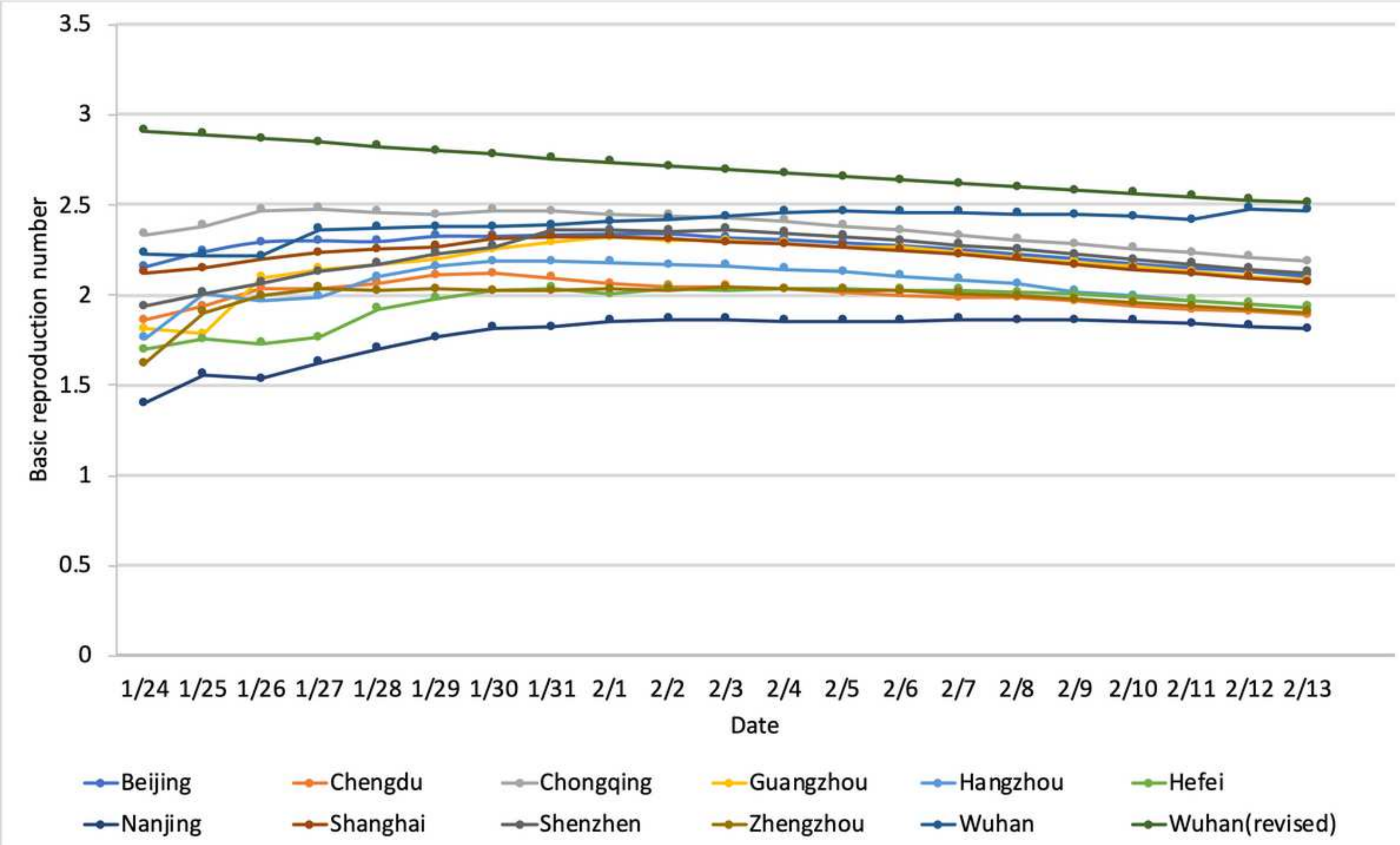

Figure 2

Calculation results of the basic reproduction number.

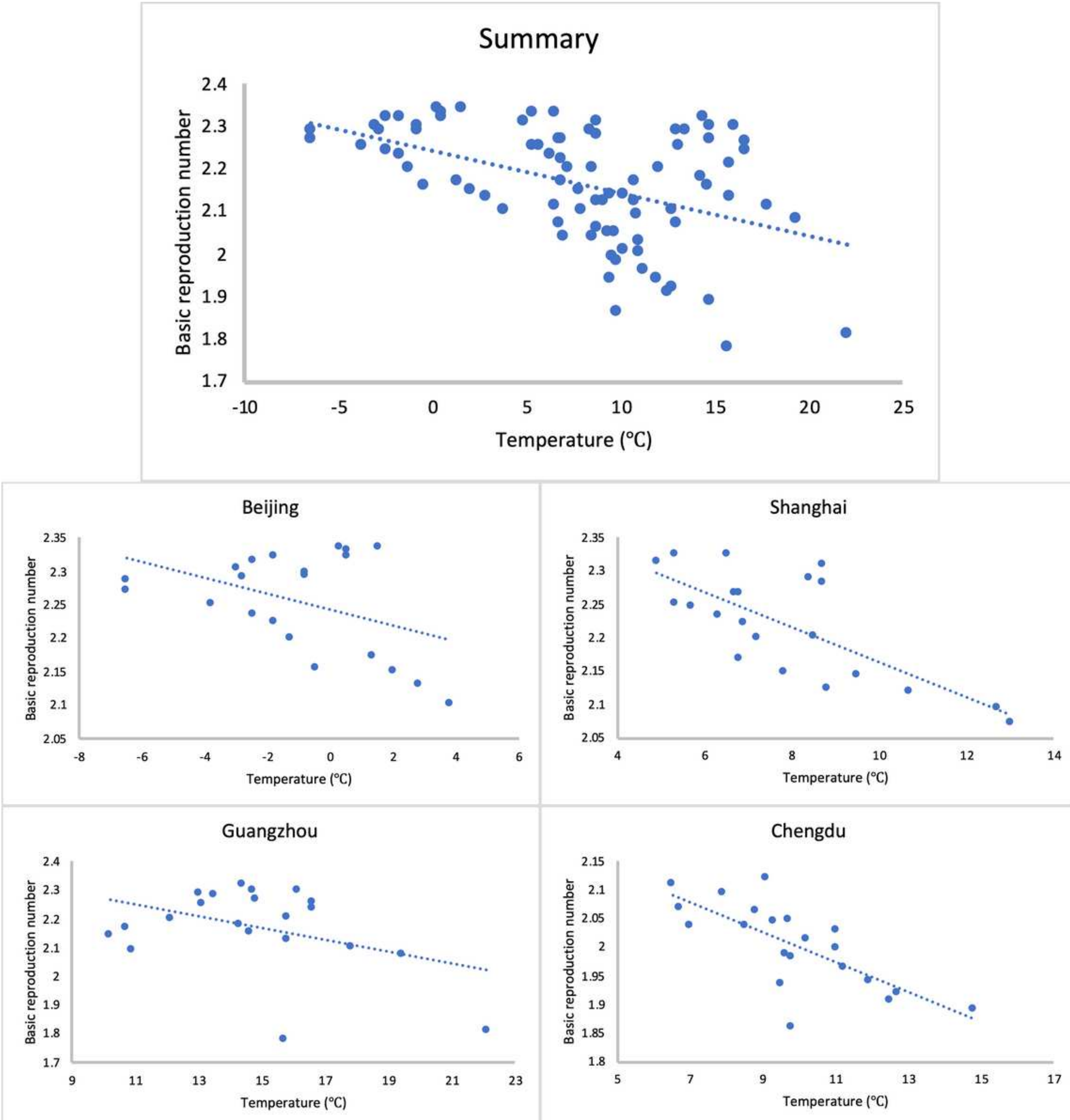

Figure 3

Scatter plot of temperature and basic reproduction number.

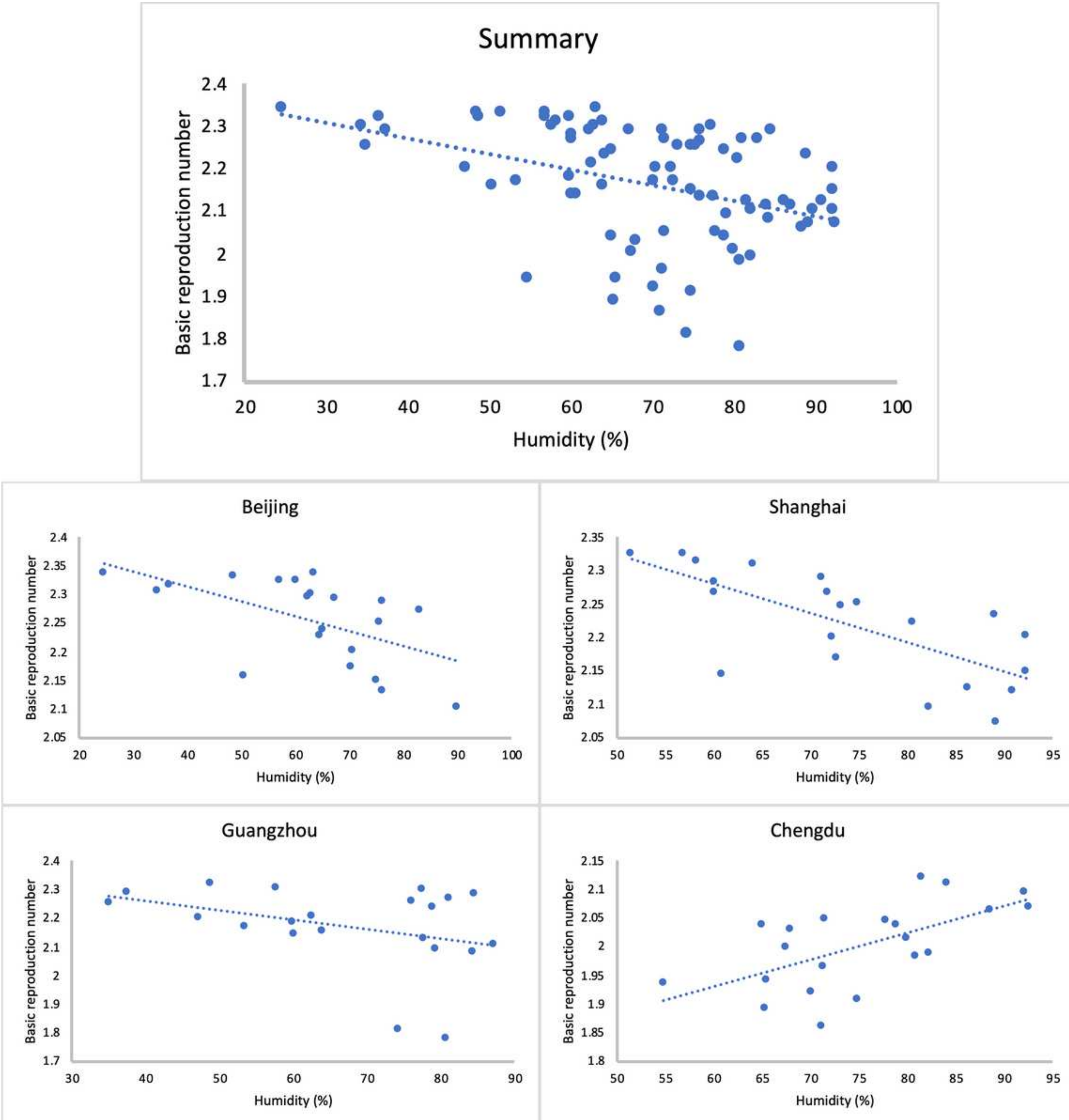

Figure 4

Scatter plot of humidity and basic reproduction number.