Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Is the virus-laden standing water change the transmission intensity of SARS-CoV-2 after precipitation? A framework for empirical studies

Chengyu He, Xiaoting Wang, Ailun Shui, Xiao Zhou, Shuming Liu

School of Environment, Tsinghua University, 100084, Beijing, China

ARTICLE INFO

Keywords:
Effective reproduction number
Distributed lag model
Additional-transmission routes
Response measure
Wet season

ABSTRACT

Understanding the relationship between precipitation and SARS-CoV-2 is significant for combating COVID-19 in the wet season. However, the causes for the variation of SARS-CoV-2 transmission intensity after precipitation is unclear. Starting from “the Zhengzhou event,” we found that the virus-laden standing water formed after precipitation might trigger some additional routes for SARS-CoV-2 transmission and thus change the transmission intensity of SARS-CoV-2. Then, we developed an interdisciplinary framework to examine whether the health risk related to the virus-laden standing water needs to be a concern. The framework enables the comparison of the instant and lag effects of precipitation on the transmission intensity of SARS-CoV-2 between city clusters with different formation risks of the virus-laden standing water. Based on the city-level data of China between January 01, 2020, and December 31, 2021, we conducted an empirical study. The result showed that in the cities with a high formation risk of the virus-laden standing water, heavy rain increased the instant transmission intensity of SARS-CoV-2 by 6.2% (95%CI: 4.85–10.2%), while in the other cities, precipitation was uninfluential to SARS-CoV-2 transmission, revealing that the health risk of the virus-laden standing water should not be underestimated during the COVID-19 pandemic. To reduce the relevant risk, virus-laden water control and proper disinfection are feasible response strategies.

Funding source

This study was supported by the National Natural Science Foundation of China [grant number 52091544].

1. Introduction

Meteorological factors were found to be influential in the transmission of several contagions (Dbouk and Drikakis, 2020; Fontal et al., 2021; Habeebullah et al., 2021). As a significant meteorological factor, precipitation and its relationship with SARS-CoV-2 transmission have raised broad scholarly interests since the onset of the pandemic (Alam and Sultana, 2021). Some studies provided empirical evidence for the positive relationship between the two factors (Liu et al., 2021; Wei et al., 2020), while others yielded different conclusions with the change in study regions, periods and statistical methods (Aboura, 2022; Menebo, 2020; Zhang et al., 2022). For example, Sarkodie and Owusu used the Granger causality test on the data from the top 20 countries with confirmed cases between January 22 and April 27, 2020, to examine the effect of meteorological factors on COVID-19 health outcomes. They found that a 1% increase in precipitation would respectively increase confirmed cases and deaths by 1% and 0.86% (Sarkodie, 2020). However, based on a unique granular dataset of over 1.2 million daily observations in nine countries in 2020, Ganslmeier et al. found that precipitation was not significantly associated with COVID-19 incidence through multiple linear regression (Ganslmeier et al., 2021). Noteworthily, previous empirical studies barely investigated why the transmission intensity of SARS-CoV-2 might change after precipitation. In other words, the additional transmission routes of SARS-CoV-2 triggered by precipitation are still unclear. Such unclear prior might lead to confounders failing to be controlled and generate biased estimation, partially explaining the conflicting conclusions.

“The Zhengzhou event” revealed some additional transmission routes of SARS-CoV-2 triggered by precipitation. From June 17 to June 20, 2021, Zhengzhou, the capital of Henan Province, China, suffered a record-breaking rainstorm. As it struggled to recover from the devastating disaster, the city, which had kept zero locally-transmitted cases for more than five months, reported 126 locally-transmitted cases...
between July 30 and August 15 (The Government of Henan Province, 2021). The epidemic investigation found the most reported cases related to The Sixth Peoples Hospital of Zhengzhou, a qualified hospital for COVID-19 diagnosis and treatment, where no SARS-CoV-2 leakage event ever happened before the heavy rainstorm (Yeung, 2021). However, several people living or traveling in the vicinity of the hospital were infected after the extreme event. The standing water, the water that is stagnant in open urban areas after precipitation which might be contaminated by the virus-laden fomites and sewage from the hospital, was suspected to be a significant trigger for the additional transmission routes of SARS-CoV-2 after precipitation (Ma, 2021).

Although fomites could contaminate standing water through the washing-off effects, sewage might be the major source of the infective SARS-CoV-2 in standing water (Bhowmick et al., 2020; Kataki et al., 2021; Sojobi and Zayed, 2022). Sewage is rich in human excrete, where the excrete of COVID-19 patients was confirmed to shed an amount of infective SARS-CoV-2 (Pan et al., 2020; Xiao et al., 2020). SARS-CoV-2 has been detected in the sewage of many countries, including Australia (Ahmed et al., 2020), China (Yang et al., 2022), Italy (La Rosa et al., 2020), Japan (Haramoto et al., 2020), Netherlands (Medema et al., 2020), and the United States (Sherchan et al., 2020), and found to be viable in sewage for a week (Bivins et al., 2020). On non-precipitation days, the health risk related to SARS-CoV-2 in sewage is ignorable, because sewage flows in the closed drainage pipes and people barely expose to it (Kanakoudis, 2020). However, things are different on precipitation days, especially in cities with high percentages of combined drainage pipes (Richard et al., 2004). High volumes of stormwater runoff quickly flow into the combined drainage pipes, which might mobilize the virus that settles in sewer sections under low-flow velocities on dry weather days and exceeds the capacity of the pipes. The mix of stormwater and untreated sewers might load many viruses and pathogens, thus possibly overflow from the combined drainage pipes and stagnate in the open urban (Chan et al., 2022; Kitajima et al., 2020). Then, the virus-laden standing water becomes the virus source triggering some additional routes for SARS-CoV-2 transmission, including aerosolized virus inhalation, virus-laden water ingestion, and fomite contact. Reviews of the three additional transmission routes can be found in SI 1.1 - SI 1.3.

The above inferences show that the virus-laden standing water, the trigger for some additional transmission routes, might be a significant reason for the variation of SARS-CoV-2 transmission intensity after precipitation. However, to our knowledge, few empirical studies considered the impacts. Through qualitative analysis, Han and He suggested that urban flood events and the often-accompanied sewage overflows would pose renewed risks of virus spread and might jeopardize previous efforts for COVID-19 mitigation (Han and He, 2021). However, they did not obtain conclusive findings from their preliminary analysis about the relationship between flood events and spikes of COVID-19 cases in seven United States areas with a combined sewer system. The conclusion of Chan et al. support the viewpoint of Han and He. They found that COVID-19 incidence is higher in areas with combined sewer systems, heavy precipitation, and high percentages of impervious surfaces by fitting a quasi-Poisson regression model on the monthly data from the United States between February 2020 and July 2021 (Chan et al., 2022). Understanding the health risk of virus-laden standing water during the COVID-19 pandemic is significant for combatting the disease in the wet season. However, the two empirical studies are based on the data from the United States; the regional empirical evidence is insufficient for a clear understanding of the problem. Thus, more empirical studies are needed.

To support more empirical studies for understanding whether the health risk related to virus-laden standing water needs to be concerned during the COVID-19 pandemic, this study develops a framework to quantify the instant and lag effects of precipitation on the variation of SARS-CoV-2 transmission intensity in cities with different formation risks of the virus-laden standing water. Compared with previous studies, the framework has three improvements. First, the framework preliminarily characterizes the formation risk of the virus-laden standing water in cities. Second, the framework does not use the widely adopted proxies for SARS-CoV-2 transmission: daily reports cases and incidence, while introducing the time-varying reproduction number to reveal the real-time transmission intensity of SARS-CoV-2. Such improvement reduces the estimation bias attributable to the uncertain time lag between SARS-CoV-2 infection and report (Carducci et al., 2020; van Doremalen, 2020).
et al., 2020). Third, based on the prior that SARS-CoV-2 is viable in sewage and fomites for several days, the framework highlighted the lag effects of precipitation on SARS-CoV-2 transmission. Based on the framework, we conducted an empirical study using the city-level data of China between January 01, 2020, and December 31, 2021.

2. Method

Fig. 1 visualizes the developed framework. Details of each part are stated as follows.

2.1. City cluster

To differ the formation risk the virus-laden standing water after precipitation, cities are grouped based on four indicators in the framework, including (i) the sewer density in built areas, (ii) the green-land rate in built areas, (iii) the rate of combined drainage pipes in drainage pipes (it would be stated as CSS rate in following parts for concise), (iv) the population density. The sewer density in built areas is the proxy for the capacity of the urban drainage system. The green-land rate in built areas is the proxy for the permeability of cities adopting the green-land rate yet permeable areas rate to represent the permeability of cities is due to the data availability. CSS rate characterizes the risk of sewage overflow on precipitation days, calculated by dividing the length of the combined drainage pipes over the total length of the drainage pipe for rainstorms.

The reasons for the indicator chosen are stated as follows. Poor drainage ability and large impermeable surfaces would increase the speed and volume of stormwater runoff that flows into the combined drainage pipes (Clark, 2018). Facing the high speed and volume of stormwater runoff, cities with a high rate of combined drainage pipes would have a greater risk for combined sewage overflow (Li, 2015; Richard et al., 2004). Unfortunately, poor drainage ability and large impermeable surfaces also enable the stagnation of the combined sewage overflow in open urban areas. Meanwhile, the impacts of the virus-laden standing water would be greater in populated cities since more population means a greater risk of exposure and secondary transmission. Thus, if the additional transmission routes related to the virus-laden standing water after precipitation deserve to be a concern, the effects of precipitation on the SARS-CoV-2 transmission would be different in cities with different drainage abilities, population density, CSS rate, and population density.

The method used for city clustering is Partitioning around medoids (PAM), a technique for partitioning cluster analysis (Kauffman and Rousseeuw, 1990). Compared to K-means, the other popular partitioning cluster approach, PAM is more robust to outliers because PAM identifies clusters by the most representative observation rather than the centroid. Conceptually, the PAM algorithm consists of three steps:

1. PAM would select K observations randomly as medoids of clusters.
2. PAM would calculate the distances of observations to the selected medoids, assign observations to the closest medoid and calculate the total cost for the present medoids (i.e., the sum of the distances of each observation from its medoid).
3. PAM would swap the present medoids by the randomly selected point (not medoid), repeat the reassignment process, and calculate the total cost. The new one would replace the present medoid when the total cost is smaller, and the replacement process will break until the medoids do not change.

As the four indicators vary in range, we standardize the indicators to a mean of 0 and a standard deviation of 1. The clustering numbers are identified as two by plotting the within-groups sums of squares against the number of clusters extracted.

2.2. The time-varying reproduction number

Previous studies usually adopted daily confirmed cases or incidences as the proxy for SARS-CoV-2 transmission in the relationship examination of precipitation and COVID-19 (Aboura, 2022; Sarkodie, 2020; Zhang et al., 2022). However, because of the incubation period and reporting delay, a patient would be reported as a confirmed case after an uncertain time lag since he/she was infected with SARS-CoV-2 (Alvarez et al., 2021; Trauer et al., 2021). Thus, the estimated effects of precipitation on SARS-CoV-2 transmission might be biased when daily confirmed cases or incidences are adopted (Ranan-Eliya et al., 2021). Here, we introduce an indicator to reveal the real-time transmission intensity of SARS-CoV-2: the time-varying reproduction number ($R_t$). $R_t$ is defined as the expected number of secondary infections caused by a primary case infected at time $t$ (Alvarez et al., 2021; Bickel et al., 2000) and has been widely adopted in previous studies to examine the effect of non-pharmaceutical interventions on SARS-CoV-2 transmission (Flaxman et al., 2020; Yang et al., 2021). We adopt the Bayesian Discrete Renewal Model proposed by (Cori et al., 2013) for $R_t$ estimation; the model could directly estimate $R_t$ from the observations of the daily reported cases, as shown in Eq. (1)-Eq. (3):

$$ P_{m,t} = \frac{N_m}{N_m - \sum_{i=1}^{t-1} I_i} $$

(1)

$$ R_{m,t} = \frac{P_{m,t} I_{m,t}}{\sum_{i=1}^{t-1} I_{m,i} R_{m,i}} $$

(2)

$$ g \sim \Gamma(3.64, 3.08) $$

(3)

where $P_{m,t}$ is the population adjustment factor for city $m$ on day $t$, showing the population saturation of susceptible;

$N_m$ is the population size of city $m$, which is assumed constant during the study period;

$$ \sum_{i=1}^{t-1} I_i $$ is the accumulative cases from the pandemic start day to day $t$;

$R_{m,t}$ is the time-varying reproduction number of city $m$ on day $t$;

$I_{m,t}$ is the number of cases infected in city $m$ on day $t$;

$g_{t-s}$ is the infectivity of individuals who have been infected for $t-s$ days; according to periods studies, $g_{t-s}$ could be characterized by the distribution of generation time (i.e., the time from the infection of a primary case to infection of the cases the individual generates); here, we adopted the estimation of (Ganyani et al., 2020);

$$ \sum_{i=0}^{t-1} I_{g_{t-s}} $$ is the total infectiousness of infected individuals on day $t$.

The estimation method for the numbers of the daily confirmed cases is shown in Eq. (4)-Eq. (9):

$$ C_{m,t} \sim \text{Negative binomial}(c_{m,t}, \frac{g_{t-s}}{\psi_2}) $$

(4)

$$ c_{m,t} = \sum_{i=t-0}^{t-1} I_{m,i} C_{m,t-i} $$

(5)

$$ \psi_2 \sim \mathcal{N}(0.5) $$

(6)

$$ \pi \sim \mathcal{Gamma}(5.1, 0.86) $$

(7)

$$ \pi_1 \sim \mathcal{Gamma}(1.62, 0.064) $$

(8)

$$ \psi_2 \sim \mathcal{Gamma}(1.62, 0.064) $$

(9)

where $C_{m,t}$ is the estimation for the reported cases (including symptomatic and asymptomatic cases) in city $m$ on day $t$;
\( c_{m,t} \) is the expected number of the reported cases in city \( m \) on day \( t \); \( y_{m,t} \) is a positive half normal distribution for characterizing the variance of the negative binominal distribution; \( \pi \) is the distribution of times from infection to report, which is assumed as the convolution of an infection-to-onset distribution and an onset-to-report distribution; \( \pi_1 \) is distribution of times from infection to onset, following (Walker et al., 2020); \( \pi_2 \) is distribution of times from onset to report, following the estimation of (Lauer et al., 2020).

Following (Abbott et al., 2020; Flaxman et al., 2020), the prior of \( R_0 \) is set to be
\[
R_{0,0} \sim \text{Gamma}(3.28, 2) \tag{10}
\]

The models for different cities are separately ran and fitted by Markov Chain Monte Carlo (2000 iterations under 4 Markov Chains).

In addition, we adopt the most popular accuracy measures for times-series forecasts to show the accuracy of our estimations on the daily report cases. Such measuring could reveal the reliability of our \( R_t \) estimation to some extent, because \( R_t \) plays a significant role in daily report cases estimation in our model. The adopted measures are root-mean-square error (RMSE) and Nash-Sutcliffe model efficiency (NSE), as shown in Eq. (11)-Eq. (12). NSE compares the performances of a model with the model that only uses the mean of the observed data (Guo et al., 2018). The model is more accurate when its corresponding NSE is closer to 1.

\[
\text{RMSE}_{m} = \sqrt{\frac{1}{T} \sum_{t=1}^{T} (C_{m,t} - \bar{C}_{m})^2} \tag{11}
\]

\[
\text{NSE}_{m} = 1 - \frac{\sum_{t=1}^{T} (C_{m,t} - \bar{C}_{m})^2}{\sum_{t=1}^{T} (C_{m,t} - \bar{C}_{m})^2} \tag{12}
\]

where \( C_{m,t} \) is the observation number of the daily confirmed cases of city \( m \) on day \( t \); \( \bar{C}_{m} \) is the average daily confirmed cases of city \( m \) between day 1 and day \( T \).

### 2.3. Instant and lag effects

SARS-CoV-2 was found to be viable in water and foamy for several days (Bivins et al., 2020). In the other words, the additional transmission routes triggered by precipitation might be risky for several days. Thus, the log distributed lag model, an econometric model is integrated in the framework to estimate the instant and lag effect of precipitation on the variation of SARS-CoV-2 transmission intensity. In our models, the daily cumulative precipitations of cities are classified into five levels according to The Participation Grade in China (GB/T 28,592–2012) (State Administration for Market Regulation, 2012). Drizzle (daily cumulative precipitation less than 10 mm) and no precipitation are set as level 0, as they could barely trigger the above-described transmission routes related to virus-laden water. Moderate rain (the 24 h of participation between 10 mm and 25 mm) is set as level 1. Heavy rain (the 24 h of participation between 25 mm and 50 mm) is set as level 2. Rainsnstrom (the 24 h of participation between 25 mm and 50 mm) is set as level 3. Heavy rainstorm (the 24 h of participation greater than 100 mm) is set as level 4. Temperature, humidity, policy stringency, and the individual effects of cities are chosen as confounders for adjusting the effect estimations (Grigby-Toussaint, 2022). R ratio, the ratio of \( R_t \) over \( R_{t-1} \), is adopted as the dependent variable of the log distributed lag model, since the effects of precipitation on SARS-CoV-2 transmission are expected to be relative to its original level (Li et al., 2021). An R ratio greater than 1 reveals an increase in transmission intensity, but an R ratio lower than 1 reveals a decrease in transmission intensity. The final model is shown in Eq. (13):

\[
\log( \text{RR}_{m,c,t} ) = \alpha_c + \sum_{k=1}^{4} \sum_{i=0}^{6} \beta_{m,c,k}^{i,t} x_{m,c,k}^{i,t} + \sum_{i=1}^{4} \gamma_{c,i} z_{c,i} + a_{m.c} I_{m,c} \tag{13}
\]

where \( \text{RR}_{m,c,t} \) represents the R ratio of cluster \( c \) city \( m \) on day \( t \); \( \alpha_{c} \) represents the baseline of R ratio for cluster \( c \) cities in the absence of impacts of precipitation and all the confounders; \( \beta_{m,c,k}^{i,t} \) Represents the s days lag effects of precipitation at level k for cluster \( c \) city \( m \); \( x_{m,c,k}^{i,t} \) is the binary indicator of whether the precipitation of cluster \( c \) city \( m \) on day \( t \)-s is at level k; \( \gamma_{c,i} \) represents the effects of confounder \( i \) for cities of cluster \( c \); \( z_{c,i} \) represents the value of confounder \( i \) for cluster \( c \) city \( m \) on day \( t \); \( a_{m,c} \) represents the individual effect of cluster \( c \) city \( m \); \( I_{m,c} \) is the binary indicator of whether is the city \( m \).

### 2.4. Data acquisition and filtration

Data for this study are fourfold. First, the daily cumulative precipitations at the city-level, covering 371 cities in China from January 1, 2020, to December 31, 2021 (\( n = 271,572 \)), are gathered from a database with real-time metrology factors reports for cities in mainland China (https://airwise.hjhj-e.com/). The dataset containing 371 cities yet not 687 cities (i.e., the number of cities in China published by the Urban and Rural Construction Statistical Yearbook, 2020) is due to the data merge of the prefecture- and the county-level cities. In detail, there are 301 prefecture-level cities and 386 county-level cities in China, but many county-level cities are governed by the near prefecture-level city. In statistical data, the county-level cities would be merged into the corresponding prefecture-level city, causing fewer cities in the relevant dataset than in the officially announced cities. Second, the daily confirmed cases of COVID-19 in the city-level, covering 425 cities in China from January 1, 2020, to December 31, 2021 (\( n = 211,467 \)), are obtained from a website for real-time reports of COVID-19 confirmed cases in China’s cities (https://3g.dxy.cn/newh5/view/pneumonia). As missing data widely exist in the dataset, we assume the lacked data are zero. Similarly, data merge between county- and prefecture-level cities also is a significant reason for containing 425 cities in the data set yet not 687 cities. In addition, some cities that never reported any COVID-19 confirmed cases between 2020 and 2021, such as Sansha in Hainan Province and Dongying in Shandong Province, were excluded from the dataset. Noteworthy, different merge criteria among county- and prefecture-level cities result in the different number of cities in the first and the second datasets. Thus, we adjusted both datasets into the 301 prefecture-level cities before further data process. The third is the covariates for the log distributed lag model, including temperature, humidity, and policy stringency index. The daily temperature and humidity are gathered from (https://airwise.hjhj-e.com/) with the same spatial and temporal covers as the precipitation data; the policy stringency indexes are gathered from OxCGRT (https://www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker), a database for tracking and comparing government responses over COVID-19 around the world. The policy stringency index is the integration of 21 indicators, covering policies in terms of contaminant, closure, economic response, and health system (Zha et al., 2022). The policy stringency index ranges from 0 to 100 and increases when the policy portfolio becomes more stringent. As OxCGRT does not include the city-level data for mainland China, we assume the policy stringency index for all cities in a province is same as the provincial policy stringency index. The fourth is the data for city clustering (i.e., population density, sewer density, green-land rate in built areas, and the rate of combined drainage pipes in precipitation drainage pipes); the data for
292 China’s cities in 2020 are gathered from EPSDATA (https://www.epsnet.com.cn/index.html#/Index), a comprehensive information service platform.

Because of the huge inconsistency among above four data sets, we filter the gathered data before the effect examination by following criteria. First, cities that lack one dimension data of the above four were omitted. Second, data beyond the range of April 1, 2020–November 1, 2020, and April 1, 2021–November 1, 2021 are excluded, because most precipitation in China concentrate between April and October; however, 96.71% of COVID-19 confirmed cases in mainland China between January 1, 2020, and December 31, 2021, were reported between January 1, 2020, and April 1, 2021. Such imbalanced data might cause bias estimation. Third, reliable $R_t$ estimation is the basis for revealing the effect of precipitation on the transmission of SARS-CoV-2. However, $R_t$ estimated by the Bayesian Discrete Renewal Model (Section 2.2) is usually unreliable when the number of the daily reported confirmed cases is small (Wang et al., 2020). To decrease the bias triggered by inaccurate $R_t$, cities with less than 100 reported cases during the two periods (i.e., April 01, 2020–November 01, 2020 and April 01, 2020–November 01, 2020) are excluded. Finally, 15 cities (i.e., Beijing, Chengdu, Foshan, Urumqi, Guangzhou, Harbin, Nanjing, Putian, Shanghai, Shenzhen, Tianjin, Wuhan, Xiamen, Yangzhou, Zhengzhou) are kept for further analysis. Future empirical studies could include more cities when more observations are available. Noteworthily, precipitation cannot impact the virus transmission when no virus exists in a city. To exclude bias in this term, we conduct wave extractions before the effect examination. In detail, the days with ignorable $R_t$ and zero confirmed cases for more than 14 days are excluded. The study is based on R Studio Version 1.2.1.

### 3. Results and discussion

260 cities (omitting 32 cities with lack values) in China are grouped into two clusters by PAM, where 132 cities belong to Cluster 1 and 128 cities belong to Cluster 2. As for the 15 cities selected for further analysis, four are Cluster 1 cities, and the others are Cluster 2 cities (Table 1).

### 3.1. $R_t$ and daily confirmed cases

21 waves during the study periods are included for effects

| Cluster | Index                        | Cities                          |
|---------|------------------------------|---------------------------------|
| Cluster 1 | Shanghai, Urumqi, Zhengzhou, Harbin |
| Cluster 2 | Foshan, Guangzhou, Nanjing, Putian, Shenzhen, Tianjin, Xiamen, Wuhan, Yangzhou, Beijing, Chengdu |

![Fig. 2](image-url) The notched box plots of the population density, the sewer density, the green-land rate, and the CSS rate by different city clusters. The jittered grey points show the actual observations of cities; the rug plots at the left sides of each subplot indicate the general spread of the population density, the sewer density, the green-land rate, and the CSS rate of cities in China. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)
In detail, 6 waves occurred in Cluster 1 cities are selected (Fig. 3), including 4 short waves (i.e., C1-1, C1-2, C1-5, and C1-6 in Table 2, lasting for 43–82 days long) and 2 long waves (C1-3, C1-4 in Table 2, lasting for 213 days). 15 waves occurred in Cluster 2 cities are selected (Fig. 4), including 6 short waves (C2-10, C2-11, C2-12, C2-13, C2-14, C2-15 in Table 2, lasting for 61–75 days long) and 9 long waves (C2-1, C2-2, C2-3, C2-4, C2-5, C2-6, C2-7, C2-8, C2-9 in Table 2, lasting for 159–213 days long).

In our model, $R_t$ is a significant basis for estimating the daily confirmed cases. Accurate estimation of the daily confirmed cases could thus reveal the reliability of the $R_t$ estimation to some extent. Table 2 shows indicators for measuring the accuracy of daily confirmed case estimations in different selected waves. It could find that RMSE and NSE are both higher in the short waves which have concentrated daily confirmed cases. For the 10 short waves, NSE ranges between 0.894 and 0.988, with the average at 0.934; RMSE ranges between 0.402 and 2.969, with the average at 1.630. For the 11 long waves, NSE ranges between 0.811 and 0.917, with the average at 0.840; RMSE ranges between 0.496 and 1.717, with the average at 0.821. The reasons for the differences are twofold. First, RMSE measures absolute error while NSE measures relative error. The variances of the daily reported cases in short waves are much higher than those in long waves. For example, the peak for the daily reported cases in short waves could reach 111 (wave C1-5), while the daily reported cases in long waves barely surpass 20. Second, the long waves usually show in big cities with active commerce, high population mobility and stringent interventions (e.g., Guangzhou, Chengdu, Shanghai, and Tianjin). In such complicate situation, the curves for daily confirmed cases in these cities are inconsistent with the natural epidemic development curve.

As for $R_t$, two results could be observed. First, the variations of $R_t$ are around half-month ahead of the case reports. Taking wave C2-10 as an example, $R_t$ of the wave peaks on September 2, 2021, while the daily report cases peaks on September 15, 2021. The main reason for the difference is the time lag induced by the incubation period and the report delay. Second, $R_t$ usually shows a significant variance in the waves with concentrated daily confirmed cases, yet a slight variance in the waves with scattered daily confirmed cases. For example, in the short wave of Beijing, $R_t$ ranges between 0.511 and 0.861, while in the long wave of Beijing, $R_t$ ranges between 0.758 and 1.601. The results make sense. First, the variances of the daily confirmed cases in short waves are more significant, as we state above. Second, according to the definition of $R_t$, the ratio between the secondary infections and the
primary case would spike when the number of the primary case is small.

3.2. The instant and lag effects of precipitation

Table 3 and Table 4 describe the data for examining the instant and lag effects of precipitation on the SARS-COV-2 transmission intensity, where precipitation is the independent variable; R ratio is the dependent variable; humidity, temperature, and policy stringency index are covariants. Generally speaking, average values for the considered variables in different clusters are approximately the same. However, the
maximum and the median value of precipitation for the data of Cluster 1 cities are much higher than that of Cluster 2 cities, as the extreme precipitation event that occurred in Zhengzhou, 2021 is included in the data of Cluster 1 cities. In addition, the minimal humidity and temperature for the data of the two clusters show notable differences.

Fig. 5 shows the trends of the R ratio for the cities from different clusters over a week after the moderate rain, the heavy rain, the rainstorm, and the heavy rainstorm. It could find that moderate rain barely impacts the R ratio of Cluster 1 cities (the left part of Fig. 5). However, heavy rain would significantly increase the immediacy transmission intensity in Cluster 1 cities by 6.2% (95%CI: 4.85%–10.2%). In addition, the R ratio of Cluster 1 cities would respectively be 1.049 (95%CI: 1.234) at 0 days, 1.188, 1.051 (95%CI: 0.877–1.259), and 1.032 (95%CI: 0.863–1.234) at 0 days, 2 days and 4 days after a heavy rainstorm. Although the relevant coefficients are statistically insignificant, we think the possibility that heavy rainstorms as an accelerator for the virus transmission should not be underestimated in Cluster 1 cities, since the data scale for the heavy rainstorm, an extreme event, is too small to generate reliable estimation. We think different conclusions might be drawn on a bigger data set. As for Cluster 2 cities (the right part of Fig. 5), it could observe that the R ratios in the corresponding four subfigures are approximate to horizontal lines. It suggests precipitation is uninformative to the virus transmission intensity in Cluster 2 cities. The fitted coefficients for the models of the two cluster cities can be found in Table S1 and Table S2. Although the differences between the effects of precipitation on the variation of SARS-CoV-2 transmission intensity in different city clusters are not huge, the results still reveal that the risk of the additional transmission routes triggered by precipitation should not be underestimated. In addition, it is worth noting that China has continuously conducted strict disinfection during the COVID-19 pandemic. This measure would reduce the risk of the virus-laden standing water. Thus, empirical evidence based on data from countries with different disinfection requirements is needed.

4. Policy implication

Preparing for health risk triggered by the virus-laden standing water is necessary for cities, not only for combating COVID-19 but also for combating waterborne epidemics. In our view, two strategies are feasible, including virus-laden standing water control and proper disinfection.

Reducing virus-laden standing water after precipitation could fundamentally control the relevant health risk. In detail, drainage ability enhancement and combined sewer system upgrade are both feasible measures. For drainage ability, most drainage systems in urban areas, especially those aged drainage systems in the central area of metropolises, do not have enough capacity to handle the heavy surface runoff (Katihvhu et al., 2022). Taking China as an example, the latest vision of The Outdoor Drainage Design Criterion (GB50014-2021) requires the recurrence period of torrential rain in the urban drainage pipes is 5–10 years for the crucial regions in big cities (i.e., cities with more than 1 million people). However, Beijing, China’s capital city, still uses the drainage system far from reaching the criterion. The city has 66% and 21% of drainage pipes whose recurrence periods are designed at one year and 3–5 years, respectively (Ren, 2022). Sustainable water system design is a widely adopted strategy for enhancing the drainage ability of

---

**Table 3**

Descriptive statistics for waves of Cluster 1 cities (n = 682).

|                | Min  | 1st Qu | Median | Mean  | 3rd Qu | Max   |
|----------------|------|--------|--------|-------|--------|-------|
| Precipitation  | 0.000| 0.000  | 0.094  | 5.655 | 2.975  | 471.600 |
| Humidity       | 31.87| 62.00  | 74.00  | 72.73 | 85.00  | 100.00 |
| Temperature    | -7.64| 17.40  | 22.74  | 21.23 | 27.02  | 32.96  |
| Stringency Index| 32.41| 44.44  | 56.48  | 57.19 | 65.74  | 87.96  |
| R ratio        | 0.6099| 0.9844| 1.0003 | 0.9799| 1.0063 | 1.2683 |

**Table 4**

Descriptive statistics for waves of Cluster 2 cities (n = 2173).

|                | Min  | 1st Qu | Median | Mean  | 3rd Qu | Max   |
|----------------|------|--------|--------|-------|--------|-------|
| Precipitation  | 0.000| 0.000  | 0.0572 | 5.651 | 3.482  | 194.200 |
| Humidity       | 16.21| 68.00  | 74.00  | 73.73 | 84.00  | 100.00 |
| Temperature    | 7.30 | 22.54  | 26.22  | 24.97 | 28.70  | 33.80  |
| Stringency Index| 35.19| 46.30  | 47.22  | 51.63 | 57.87  | 81.94  |
| R ratio        | 0.5348| 0.9943| 0.9997 | 0.9927| 1.0041 | 1.4430 |

---

**Fig. 5.** The instant and lag effects of precipitation on the variation of SARS-CoV-2 transmission intensity. R ratio reveals the change of the transmission intensity. Numbers k (range between 0 and 6) on the horizontal axis shows k days after a precipitation event; k = 0 represents the instant effect of a precipitation event on the variation of SARS-CoV-2 transmission intensity; k = 6 represents the lag effect of a precipitation event on the variation of SARS-CoV-2 transmission intensity after 6 days. Moderate rain represents the daily cumulative participation ranging between 10 mm and 25 mm; heavy rain represents the daily cumulative participation ranging between 25 mm and 50 mm; rainstorm represents the daily cumulative participation ranging between 50 mm and 100 mm; heavy rainstorm represents the daily cumulative participation greater than 100 mm. The black line with points shows the estimations for the instant and lag effects; the corresponding dark and light colors respectively show the 50% and 95% credible interval. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)
cities (e.g., sponge city in China and low impact development in the United States and Canada), which includes several decentralized source control measures, like green roofs, vegetation ditch, and rainfall gardens to increase rainfall infiltration and reduce runoff generation (François et al., 2021; Zhu et al., 2021). Unfortunately, sustainable water system design is efficient for small tributary areas but hard to handle the long-time extreme rainfall (Feng, 2019; Guo, 2017). Thus, optimizing the urban sewer system still need to be highlighted. Emerging technologies, like the Internet of Things and Big Data, could be integrated into the urban sewer system to diagnose the system bottlenecks and further support system optimization (Yin et al., 2021).

Besides drainage ability enhancement, the combined sewer system upgrade could also reduce the formation risk of the virus-laden standing water. Although the combined sewer system has been separated in many regions, the improvement of the system still has a long way to go. For example, China planned to separate a quarter of the combined drainage pipeline in cities and prefectures from 2016 to 2020 (Ministry of Housing and Urban-Rural Development, 2016). At the national level, the percentage of the combined drainage pipeline of the total drainage pipelines decreased from 18.8% in 2015 to 12.6% in 2020, achieving the goal set in 2016 (Ministry of Housing and Urban-Rural Development, 2020). However, several problems will be found if we go further to the provincial level. Taking the rich provinces (i.e., Guangdong, Zhejiang, Jiangsu) in east China as an example, Guangdong has the longest urban drainage pipelines (i.e., 122,541 km), while it relies more on the combined drainage pipelines than the other two provinces. Combined drainage pipes in Jiangsu and Zhejiang respectively account for 9.02% and 4.85% of urban drainage pipes, while the value in Guangdong is 18.42% (Fig. 6). Noteworthily, the population density of Guangdong is respectively 1.75 and 1.86 times that in Jiangsu and Zhejiang; meanwhile, the frequency of heavy rainstorms in Guangdong is respectively 7.38 and 6.08 times that in Jiangsu and Zhejiang between 2000 and 2020 (Fig. S2). Considering the health risk related to the virus-laden standing water, Guangdong is urgent to accelerate its pace in combined sewer system separation compared with Zhejiang and Jiangsu. The pace for combined sewer system separation should consider the regional risk to public health.

Proper disinfection against the environment and fomite could help cut the additional transmission routes triggered by the virus-laden standing water (University of Minnesota Extension, 2018). Although WHO does not identify the outdoor environment, such as streets and sidewalks, as the main routes for COVID-19 spread, the empirical evidence from China shows that thorough disinfection is necessary when the outdoor environment is soaked by the sewage overflow after precipitation, especially in the cities with a large number of COVID-19 confirmed cases (WHO, 2020). Noteworthily, over-disinfection should be avoided since the disinfection by-products also threaten human health (Ruecker et al., 2017).

5. Conclusions

COVID-19 presents unprecedented challenges to urban risk management in the wet season. This study preliminary explored the causes for the variation of SARS-CoV-2 transmission intensity after precipitation. Starting from “the Zhengzhou event,” we found that the virus-laden water that is stagnant in open urban areas after precipitation (i.e., the virus-laden standing water) might trigger some additional routes for SARS-CoV-2 transmission. To understand whether the health risk related to virus-laden standing water needs to be concerned during the COVID-19 pandemic, we developed an interdisciplinary framework that integrates models from Data Mining, Epidemiology, Bayesian Statistics, and Econometrics to support relevant empirical studies. Using the framework, we conducted an empirical study based on the city-level data in China between January 01, 2020, and December 31, 2021. We found that heavy rain would increase the instant transmission intensity of SARS-CoV-2 by 6.2% (95%CI: 4.85–10.2%) in cities with a high formation risk of the virus-laden standing water, while in the other cities, it is uninfluential. Such difference suggests that the health risk of the virus-laden standing water should not be underestimated. Based on this finding, we discussed the response measures regarding virus-laden water control and proper disinfection to reduce the relevant risk.

Author contribution

Chengyu He: Conceptualization, Methodology, Investigation, Writing original draft. Xiaoting Wang: Writing - review & editing, Visualization. Aliun Shui: Investigation, Visualization. Xiao Zhou: Writing - review & editing, Shuming Liu: Conceptualization, Writing - review & editing, Supervision, Funding acquisition.

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.

Data availability

Data will be made available on request.
Acknowledgments
This study was supported by the National Natural Science Foundation of China [grant number 52091544].

Appendix A. Supplementary data
Supplementary data to this article can be found online at https://doi.org/10.1016/j.envres.2022.114127.

References
Abbott, Sam, Hellewell, Joel, Thompson, Robin N., Sherratt, Katharine, Gibbs, Hamish P., Bose, Niko L., Monday, James D., Meakin, Sophie, Dougherty, Emma L., Chun, June Young, Chan, Yung-Wai Desmond, Finger, Flavio, Campbell, Paul, Endo, Akira, Carl, A., Pearson, B., Gima, Amy, Russell, Tim, Flasche, Stefan, Kucharski, Adam J., Eggo, Rosalind M., Funk, Sebastian 2020. Estimating the time-varying reproduction number of SARS-CoV-2 using national and subnational case data. Wellcome Open Res. 5, 112. https://doi.org/10.12688/wellcomeopenres.16006.

Ahounou, Sofiane, 2022. The influence of climate factors and government interventions on the covid-19 pandemic: evidence from 134 countries. Environ. Res. 208 https://doi.org/10.1016/j.envres.2021.112484.

Ahmed, Warish, Angel, Nicola, Edson, Janette, Bibby, Kyle, Funk, Sebastian 2020. Persistence of SARS-CoV-2 in wastewater in Australia: a proof of existing literature. Environ. Chell. 5, 10.2166/aqua.2020.000.

Bickel, P., Diggle, P., Fienberg, S., Krickeberg, K., Olkin, I., Zeger, S., 2000. SARS-CoV-2: a modelling study across 131 countries. Lancet Infect. Dis. 21 (2), 193–199. https://doi.org/10.1016/S1473-3099(20)30052-5.

Bril, V., Pont, A., Coghe, P., Schraepen, F., 2021. Haitians willingness to invest in rainwater infrastructure. J. Water Supply Res. Technol. - Aqua 70 (8), 1287–1300. https://doi.org/10.2166/aqua.2020.000.

C. He et al. Environmental Research 215 (2022) 114127

Choi, Deok Joong, Blumberg, Berndt, 2019. Presence of SARS-coronavirus-2 RNA in sewage and correlation with reported confirmed cases: estimation and application. Ann. Intern. Med. 172 (9), 677–685. https://doi.org/10.2166/aqua.2020.000.

Dwivedi, Sanjai K., 2021. Concerns and strategies for wastewater treatment during the COVID-19 pandemic to stop plausible transmission. Resour. Conserv. Recycl. 164, 106566. https://doi.org/10.1016/j.resconrec.2021.106566.

Han, Jie, He, Shanshan, 2021. Urban flooding events pose risks of virus spread during the novel coronavirus (COVID-19) pandemic. Sci. Total Environ. 755 https://doi.org/10.1016/j.scitotenv.2021.140452.

Haramoto, Eiji, Malla, Bikash, Thakali, Ocean, Kitajima, Masaki, 2020. First environmental surveillance for the presence of SARS-CoV-2 RNA in wastewater and river water in Japan. Sci. Total Environ. 737, 140405 https://doi.org/10.1016/j.scitotenv.2020.140452.

Hara, M., Kuroda, S., Kato, Y., Umebayashi, R., Watanabe, Y., Okada, M., Kitajima, Masaaki, 2020. First report of the daily reproduction number of COVID-19 by inverting the renewal equation using the wastewater surveillance of COVID-19 in the community. Sci. Total Environ. 728, 138764 https://doi.org/10.1016/j.scitotenv.2020.138764.

Haramoto, Eiji, Malla, Bikash, Thakali, Ocean, Kitajima, Masaki, 2020. Persistence of SARS-CoV-2 RNA in sewage and river water in Japan. Sci. Total Environ. 737, 140405 https://doi.org/10.1016/j.scitotenv.2020.140452.

Hara, M., Kuroda, S., Kato, Y., Umebayashi, R., Watanabe, Y., Okada, M., Kitajima, Masaaki, 2020. First report of the daily reproduction number of COVID-19 by inverting the renewal equation using the wastewater surveillance of COVID-19 in the community. Sci. Total Environ. 728, 138764 https://doi.org/10.1016/j.scitotenv.2020.138764.

He, C. et al. NEJM2004973. https://doi.org/10.1056/NEJMc2004973.

Hara, M., Kuroda, S., Kato, Y., Umebayashi, R., Watanabe, Y., Okada, M., Kitajima, Masaaki, 2020. Persistence of SARS-CoV-2 RNA in sewage and river water in Japan. Sci. Total Environ. 737, 140405 https://doi.org/10.1016/j.scitotenv.2020.140452.

Hara, M., Kuroda, S., Kato, Y., Umebayashi, R., Watanabe, Y., Okada, M., Kitajima, Masaaki, 2020. Persistence of SARS-CoV-2 RNA in sewage and river water in Japan. Sci. Total Environ. 737, 140405 https://doi.org/10.1016/j.scitotenv.2020.140452.

Hara, M., Kuroda, S., Kato, Y., Umebayashi, R., Watanabe, Y., Okada, M., Kitajima, Masaaki, 2020. Persistence of SARS-CoV-2 RNA in sewage and river water in Japan. Sci. Total Environ. 737, 140405 https://doi.org/10.1016/j.scitotenv.2020.140452.
Pan, Yang, Zhang, Daitao, Yang, Peng, Leo, L., Poon, M., Wang, Guanyi, 2020. Viral load of SARS-CoV-2 in clinical samples. Lancet Infect. Dis. 20 (4), 411–412. https://doi.org/10.1016/S1473-3099(20)30113-4.

Raman-Eliya, Prasan, Ravindra, Wijemunjie, Nilmini, Gunawardana, J.R.N.A., Amarasinghe, Sarasi N., Sivagnanam, Ishwari, Fonseka, Sachini, Kapuge, Yasodhara, Sigera, Chathurani P., 2021. Increased intensity of PCR testing confirmed covid-19 transmission within countries during the first pandemic wave. Health Aff. 40 (1), 70–81. https://doi.org/10.1377/hlthaff.2020.01409.

Ren, Shan, 2022. Beijing Urban Flooding Model Will Be Compiled (In Chinese) Beijing Daily.

Richard, Field, Sullivan, Daniel, Tafari Anthony, N., 2004. Management of Combined Sewer Overflows. CRC Press LLC. LEWIS PUBLISHERS.

La Rosa, Giuseppina, Iaconelli, Marcello, Mancini, Pamela, †, Giuny Bonannino Ferraro, Veneri, Carolina, Bonadonna, Lucia, Lucentini, Luca, Salfredini, Elisabetta, 2020. First detection of SARS-CoV-2 in untreated wastewaters in Italy. Sci. Total Environ. 736, 139652 https://doi.org/10.1016/j.scitotenv.2020.139652.

Ruecker, A., Uzun, H., Karafili, T., Tsui, M.T.K., Chow, A.T., 2017. Disinfection byproduct precursor dynamics and water treatability during an extreme flooding event in a coastal blackwater river in southeastern United States. Chemosphere 188, 90–98. https://doi.org/10.1016/j.chemosphere.2017.08.122.

Sarkodie, Samuel Asumadu, Owusu, Phebe Asantewaa, 2020. Impact of meteorological factors on COVID-19 pandemic: evidence from top 20 countries with confirmed cases. Environ. Res. 191 https://doi.org/10.1016/j.envres.2020.110101.

Sherchan, Samendra P., Shahin, Shahira, Ward, Lauren M., Tandukar, Sarmila, Tiong, G. Aw, Schmitz, Bradley, Ahmed, Warish, Kitajima, Masaaki, 2020. First detection of SARS-CoV-2 RNA in wastewater in north America: a study in Louisiana, USA. Sci. Total Environ. 743, 140621 https://doi.org/10.1016/j.scitotenv.2020.140621.

Sojphi, Adebayo Olutunbosun, Zayed, Tarek, 2022. Impact of sewer overflow on public health: a comprehensive scientometric analysis and systematic review. Environ. Res. 203 (June 2021), 111609 https://doi.org/10.1016/j.envres.2021.111609.

State Administration for Market Regulation, 2012. Grade of Participation.

Walker, Patrick G.T., Whittaker, Charles, Watson, Oliver J., Baguelin, Marc, 2018. Cleaning up after a Flood. https://Extension.Unmn.Edu/Flooding/Cleaning-after-Flood.

Trauer, James M., Lydeamore, Michael J., Dalton, Gregory W., David Pilcher, Sojobi, Adebayo Olatunbosun, Zayed, Tarek, 2022. Impact of sewer overflow on public health: a comprehensive scientometric analysis and systematic review. Environ. Res. 203 (June 2021), 111609 https://doi.org/10.1016/j.envres.2021.111609.

Sarkodie, Samuel Asumadu, Owusu, Phebe Asantewaa, 2020. Impact of meteorological factors on COVID-19 pandemic: evidence from top 20 countries with confirmed cases. Environ. Res. 191 https://doi.org/10.1016/j.envres.2020.110101.

Shen, Zhong, 2020. The impact of COVID-19 and strategies for mitigation and suppression in low- and middle-income countries. Science.

Wei, Ji, Te, Liu, Yun Xia, Zhu, Yu Chen, Qian, Jie, Ye, Run Ze, Li, Chun Yu, Ji, Xiao Kang, Li, Hong Kai, Chang, Qi, Wang, Ying, Fan, Yang, Zhou, Yu Hao, Yan, Ran, Cui, Xiao Ming, Liu, Yuan Li, Jia, Na, Li, Shi Xue, Li, Xiu Jun, Xue, Fu Zhong, Zhao, Lin, Cao, Wu Chun, 2020. Impacts of transportation and meteorological factors on the transmission of COVID-19. Int. J. Hyg Environ Health. 230 https://doi.org/10.1016/j.ijheh.2020.1103610.

Who, 2020. Modes of Transmission of Virus Causing COVID-19: Implications for IPC Precaution Recommendations. https://Who.Int/News-Room/Commentary/Detail/Modes-of-Transmission-of-Virus-Causing-Covid-19-Implications-for-Ipc-Precaution-Recommendations.

Xie, Pei, Sun, Jing, Xu, Yonghao, Li, Fang, Huang, Xiaofang, Li, Heying, Zhao, Jingxian, Huang, Sicheng, Zhao, Jincun, 2020. Infectious SARS-CoV-2 in feces of patient with severe COVID-19. Emerg. Infect. Dis. 26 (8), 1920–1922. https://doi.org/10.3201/cid2608.200681.

Yang, Bingyi, Huang, Angkana T., García-Carreras, Bernardo, Hart, William E., Staid, Andrea, Matt, D., Hitchings, T., Lee, Elizabeth C., Howe, Chandlee J., Grantz, Kyra H., Amy, Wesolowski, Lemaire, Joseph Chadi, Rattigan, Susan, Moreno, Carlos, Borgert, Brooke A., Dale, Celeste, Quigley, Nicole, Cummings, Andrew, McLenn, Alizee, LeMonaco, Kaelene, Schlossberg, Sarah, Barron-Kraus, Drew, Harrison, Shrock, Khoury, Stephanie, Indra, Meenal, Yau, Hung Leong, Cummings, Ben, Giannas, Peter, McLean, Martha Grace, Hubbard, Ken, Saunders, Camazia, Weldon, Caroline, Phillips, Caroline, Rosenbaum, David, Tabla, Dianelys, Leslier, Justin, Laird, Carl D., Cummings, Derek A.T., 2021. Effect of specific non-pharmaceutical intervention policies on SARS-CoV-2 transmission in the counties of the United States. Nat. Commun. 12 (1) https://doi.org/10.1038/s41467-021-23865-8.

Yao, Shoulin, Qian, Dong, Li, Siqi, Zhao, Cheng, Kang, Xiao Feng, Ren, Doheng, Xu, Chenyang, Lia, Xianhong, Lin, Peng, Sun, Lingli, Zhao, Jianhong, Yang, Jiao, Han, Taoli, Liu, Yanchen, Qian, Yi, Liu, Yi, Huang, Xia, Qi, Jiashui, 2022. Persistence of SARS-CoV-2 RNA in wastewater after the end of the COVID-19 epidemics. J. Hazard Mater. 429 (January), 128358 https://doi.org/10.1016/j.jhazmat.2022.128358.

Yeung, Jessie, 2021. Death Toll from China Floods Jumps to 302, as Covid Outbreak Complicates Recovery. https://Www.Cnn.Com/2021/08/03/China/China-Zhengzhou-Flood-Deaths-Covid-Intl-Hnk/Index.Html.

Zhu, Shiyao, Li, Dezhi, Huang, Guanying, Gyan Chhipi-Shrestha, Kh Md Nahiduzzaman, Zhang, Xinxuan, Maggioni, Viviana, Paul, Houser, Yuan, Xue, Meiwen, 2022. The impact of COVID-19 and strategies for mitigation and suppression in low- and middle-income countries. Science.