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Cold Waves Accelerate the Spread of Infectious Diseases

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Key Points:

- The rapid dispersion of aerosols during cold waves hastens the transmission of infectious diseases
- Low temperatures contribute to higher risk of death during infectious disease outbreaks

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract Climate change is creating a new era of infectious disease crises, further exacerbated by extreme weather. However, the relationship between extreme weather and infectious disease remain unclear. Here, we provide a new quantitative study on the impact of cold wave on COVID-19 as an example. We found that during cold waves, extreme cold temperatures coupled with rapid aerosol transport accelerated COVID-19 outbreaks. It directly increased the number of COVID-19 cases in Beijing by 28.1% in the winter of year 2022. More urgently, cold temperatures led to a higher risk of death during infectious disease outbreaks, with a 7.07% increase in confirmed deaths and a 16.61% increase in excess mortality. Our findings emphasize the urgent need to promote a synergistic policy for responding to infectious diseases during cold wave disasters in order to minimize the risk of death among the elderly and those with underlying diseases.

Plain Language Summary The sudden drop in temperature and rapid spread of aerosols during cold waves resulted in a higher prevalence of infectious diseases. At the same time, low temperatures resulted in a higher risk of death due to infectious diseases and a variety of other factors during the epidemic.

1. Introduction

Increasing human activities have caused global climate change and ecological evolution. The resulting frequency of extreme weather events and epidemics of infectious diseases are posing a serious threat to human security and health. The occurrence of weather extremes during major outbreaks poses a huge test for public health and disaster preparedness and mitigation. With the increasing frequency of extreme weather, more than 50% of known infectious diseases in humans are becoming increasingly threatening, totaling more than 200, including malaria, cholera, and dengue fever (Mora et al., 2022). At the beginning of the coronavirus disease 2019 (COVID-19) pandemic, a total of 54 million people globally were exposed to weather-related disaster risks, and the overlap of a number of risk factors strongly challenged the resilience of social systems (Guo et al., 2020). However, there is a lack of research on the mechanisms by which extreme weather affects the spread of infectious disease outbreaks. This creates great difficulties in early warning and response to extreme weather-major epidemic complex disasters.

Cold exposure is a trigger for a wide range of diseases (Han et al., 2023). Chang et al. found a significant increase in the risk of infectious pneumonia, especially bacterial pneumonia, during cold waves (Chang et al., 2024). On one hand, cold weather conditions can prolong virus survival on surfaces and facilitate the spread of virulence factors (Dbouk & Drikakis, 2020; Mori et al., 2017; Moriyama et al., 2020). Coronaviruses, for example, can spread in cold temperatures and low humidity for up to 2 weeks (Chan et al., 2011). On the other hand, fluctuations in temperature and humidity may trigger impaired local and systemic antiviral defense mechanisms, leading to changes in respiratory epithelial cells that increase susceptibility to respiratory viruses (Deal Jr et al., 1980).

Here, we quantified the impact of weather extremes on infectious disease outbreaks using COVID-19 and cold wave extremes as examples. This will help develop strategies to contain or minimize the spread of future infectious disease outbreaks and provide a scientific basis for health policy.

2. Data and Measurement

2.1. Data Source

In this study, the COVID-19 data set is collected from the World Health Organization (WHO) (WHO, 2023). Data on COVID-19 hospitalizations, vaccinations, COVID-19 confirmed deaths, and excess mortality (count) were

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obtained from Our World In Data (Mathieu et al., 2020). The daily maximum temperature, daily minimum temperature, and daily average temperature data from surface meteorological stations in China were used to calculate the cold wave. Data from the National Meteorological Information Center. Based on previous studies, we used nitrogen dioxide (NO_2) as an indicator of the intensity of government control measures to exclude the effect of non-pharmaceutical interventions on vaccine interventions (Figure S1 in Supporting Information S1) (Lian et al., 2020, 2021). The NO_2 data were obtained from the United States Environmental Protection Agency (EPA).

2.2. The Modified SEIR Model

The second version of the Global Prediction System of COVID-19 Pandemic (GPCP) developed by Lanzhou University (http://covid-19.lzu.edu.cn/) was used to analyze the impact mechanism of COVID-19 (J. Huang et al., 2023, 2020). The system uses a modified version of the Susceptible-Exposed-Infected-Recovered (SEIR) epidemiological model. In the typical mathematical model of infectious diseases, one often simplify the virus-host interaction and the evolution of an epidemic into a few basic disease states (Anderson, 1991). Susceptible-infected-recovered (SIR) model partitions the population into three groups or compartments: susceptible individuals, infected individuals, and removed individuals. $S(t)$, $I(t)$, and $R(t)$ denote the sizes of these subpopulations at time t (Weiss, 2013). SIR is a compartmental model that divides the population under study into compartments and assumes the nature and time rate of migration from one partition to another, indicating that individuals move from susceptible class S to infectious class I to removed class R (Brauer, 2008). The traditional SIR model is too simple to precisely and effectively predict the trend of the disease. In the SEIR model, people at risk of infection occur in susceptible compartments. When coming into contact with an infected person from a susceptible compartment, move to an exposed compartment. When infected, transfer to the infected compartment. The patient may recover or die and will be moved to the removed compartment (Zisad et al., 2021).

The theoretical framework of modified SEIR model is based on the division of the human host population into categories containing susceptible cases (S), protected cases (P), potentially infected cases (E), infected cases (I), quarantined cases (Q), recovered cases (R), and cases of mortality (D). The sum of the seven groups is equal to the total population (N). The model makes two assumptions. First, the total population is assumed to remain constant since the population of a given country or region changes very little over a short period of time. Second, the population is assumed to be evenly mixed during the epidemic. The mortality and cure rates in the model vary over time according to the actual situation. The following equations are included in the transmission model (Peng et al., 2020).

$$\frac{dS(t)}{dt} = -\frac{\beta(t)\,I(t)\,S(t)}{N} - \alpha S(t) \tag{1}$$

$$\frac{dP(t)}{dt} = \alpha S(t) \tag{2}$$

$$\frac{dE(t)}{dt} = \frac{\beta(t)\,I(t)\,S(t)}{N} - \gamma E(t) \tag{3}$$

$$\frac{dI(t)}{dt} = \gamma E(t) - \delta I(t) \tag{4}$$

$$\frac{dQ(t)}{dt} = \delta I(t) - \lambda(t)Q(t) - \kappa(t)Q(t) \tag{5}$$

$$\frac{dR(t)}{dt} = \lambda(t)\,Q(t) \tag{6}$$

$$\frac{dD(t)}{dt} = \kappa(t)\,Q\,(t) \tag{7}$$

Where the dynamics of each group are determined by the parameters protection rate (α), infection rate (β), average latent time (γ), average quarantine time (δ), cure rate (λ), and mortality rate (κ). The parameters of the model are generated by inversion of real epidemic data. An initial value is first provided for each coefficient in the model, and the coefficients in the model are inverted in real time using coefficient optimization algorithms and the latest epidemic data. Since the parameters in the model are generated by the inversion of the actual epidemiological related data, the effects of multiple factors during the development of the epidemic are included. The simulation of pre-cold wave historical data included seasonal variation factors in regional infectious disease outbreaks and the influence of human social behavior. The simulation results represent the original outbreak trends in the absence of the cold wave. Therefore, the simulated prediction results of the historical data before the cold wave were compared and analyzed with the real data after the cold wave to quantify the effect of the cold weather event on the epidemic trend.

2.3. Cold Wave Indicator

Here, cold wave is defined as a discrete event characterized by anomalously low temperatures. These events are identified based on their deviation from a baseline climatology, established from historical temperature data. The determination of the relative threshold index was conducted using the percentile definition method, where the 10th percentile value was first defined as the extreme low temperature threshold for the station, and then the temperature data from the station were compared to the threshold and statistically analyzed to identify cold wave event (Manton et al., 2001). Thresholds are determined using data sorted for the historical period (1 January 2007-31 December 2022, encompassing a total of 15 winters (defined as the period from December of the current year to February of the following year)). Temperatures fall below these relative thresholds, based on historical reference periods, are considered for analysis. Since here we consider the rapid transport of viral particles during extreme cold temperatures, events with temperatures below the cold threshold for ≥ 1 day are classified as cold waves. Each cold wave event is characterized by distinct temporal boundaries, determined based on when temperatures cross the established thresholds, thereby providing well-defined start and end times. Cold wave events are discrete, with ≥ 2 days between cold waves.

2.4. Backward Trajectory Analysis

The Hybrid Single Particle Lagrangian Integral Trajectory (HYSPLIT) models are extensively utilized for the generation of backward trajectories of air masses from a designated starting position. These models are commonly driven by meteorological data obtained from the Global Data Assimilation System. In this study, 72-hr back trajectories were initiated at the commencement of each sampling period, and a new trajectory was initialized every hour until the conclusion of the sampling period. For the final analysis and mapping, MeteoInfoMap, a geographic information system application empowering users to visualize and analyze spatial and meteorological data in multiple formats, was employed.

3. Results

3.1. Effectiveness of Pharmacological Interventions

We take the study of the causes of the rapid peak of COVID-19 outbreak in China in the winter of 2022 as an entry point to determine the effect of extreme weather on infectious disease outbreaks. In the winter of 2022, China experienced an unusually rapid outbreak compared to other countries after the implementation of a policy to gradually liberalize COVID-19 control measures. Previous studies have found that meteorological factors and human interference may be important influences on the acceleration of outbreaks. Therefore, here we first evaluated the effectiveness of vaccine interventions in China to exclude the effect of human interference under the unblocking measure. The results showed that a rapid outbreak of COVID-19 in China in the winter of 2022 was not associated with an anthropogenic effect of vaccination. Taking the strict control period as an example, the combined impact of non-pharmaceutical and vaccine interventions in China in winter 2021 effectively enhanced protection against mutated strains (Figure 1a). At the beginning of the SARS-CoV-2 Omicron variant (B.1.1.529) outbreak, the number of new confirmed cases in Shanghai, China, was only one-tenth of that in New York State, USA, under consistent non-pharmacological control measures and vaccination rates (Figures S1–S3 in Supporting Information S1).

The results of the simulations similarly confirmed that vaccination saved 1.6 million people from infection during the outbreak. Without strict government controls, the outbreak in Hangzhou in January 2022 would have subsided around February 23 and the cumulative number of infections would have reached about 90,000 people (Figure 1b and Figure S4 in Supporting Information S1). After further undoing the impact of vaccine interventions, the

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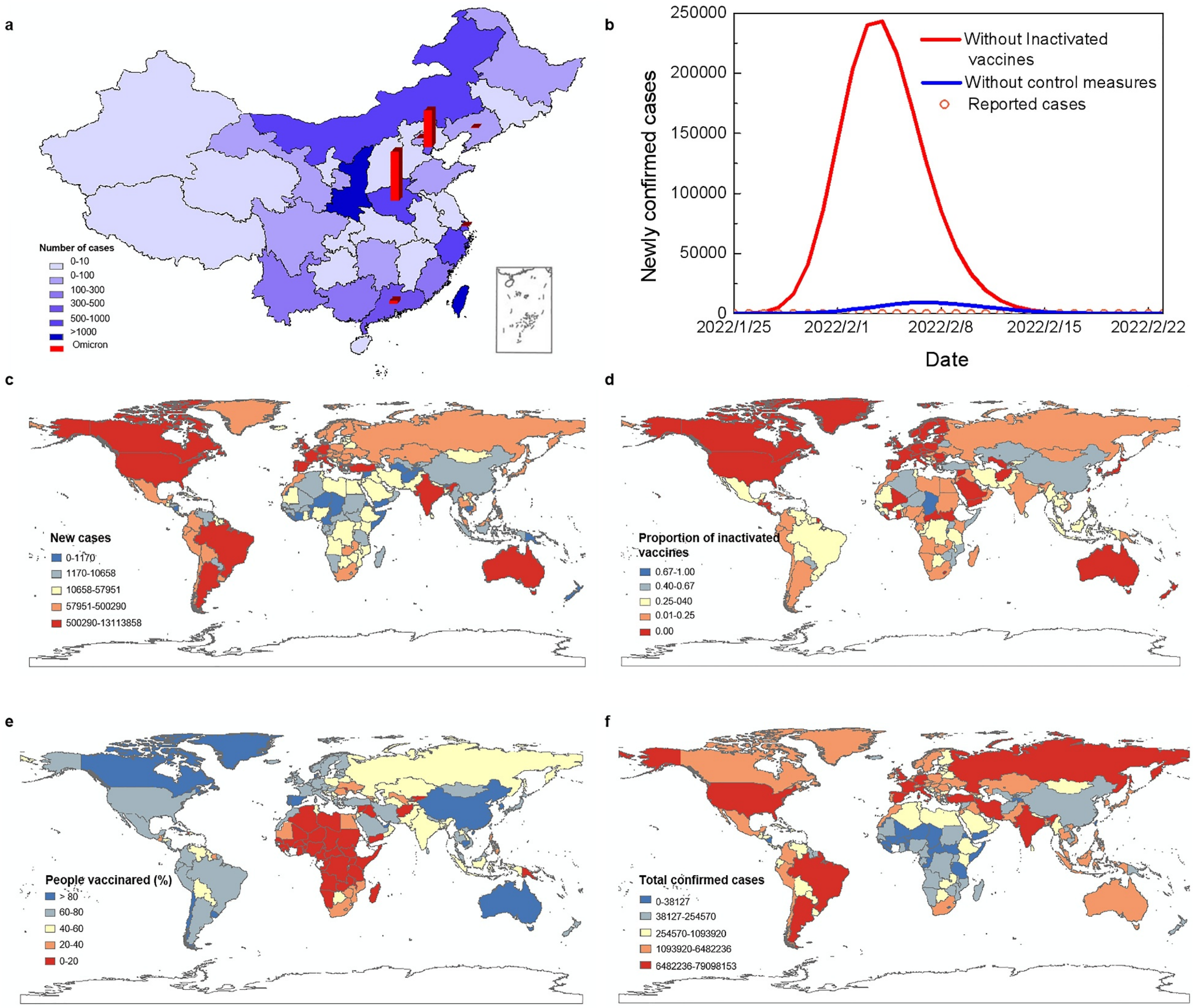

Figure 1. Impact of vaccine interventions on early Omicron outbreaks in China. (a) Spatial distribution of newly confirmed cases in China at the beginning of the Omicron outbreak. (b) Simulation of the epidemic in Hangzhou, China. (c) Spatial distribution of newly confirmed cases. (d) Spatial distribution of the proportion of inactivated vaccines licensed. (e) Spatial distribution of vaccination rates. (f) Spatial distribution of cumulative number of confirmed cases.

cumulative number of infections would exceed 1.7 million as of February 23rd. In addition, globally, the number of newly confirmed COVID-19 cases is highly consistent with the distribution of inactivated vaccine licensing ratios. It is not significantly correlated with the distribution of cumulative number of cases and vaccination rates (Figures 1c–1f). Thus, vaccine interventions in China after deregulation are effective. After human interference was ruled out, the influence of meteorological factors took center stage in this unusually rapid outbreak.

3.2. Impact of Cold Wave on Infectious Disease During Rigorous Interventions

During winter, extreme low temperatures is a critical meteorological factor influencing the spread and outbreak of infectious diseases. Here, we first analyze the impact of cold waves on infectious disease outbreaks, using the COVID-19 prevention and control period in China as an example. During the period of stringent government control, multiple small-scale transmissions occurred in Heilongjiang Province, China, 75.0% of which occurred during the fall and winter seasons. The time series curves showed that the outbreak trend in Heilongjiang was highly consistent with the peak in Russia in fall and winter, with no significant correlation in summer (Figure 2a). Newly confirmed cases increased by 233.33% and 2755.56% within 14 days after the two cold waves in Heilongjiang. In Heihe and Suihua, several outbreaks of COVID-19 have still not identified the source of infection. The backward trajectory analysis results revealed that the local area was subjected to rapid aerosol delivery from

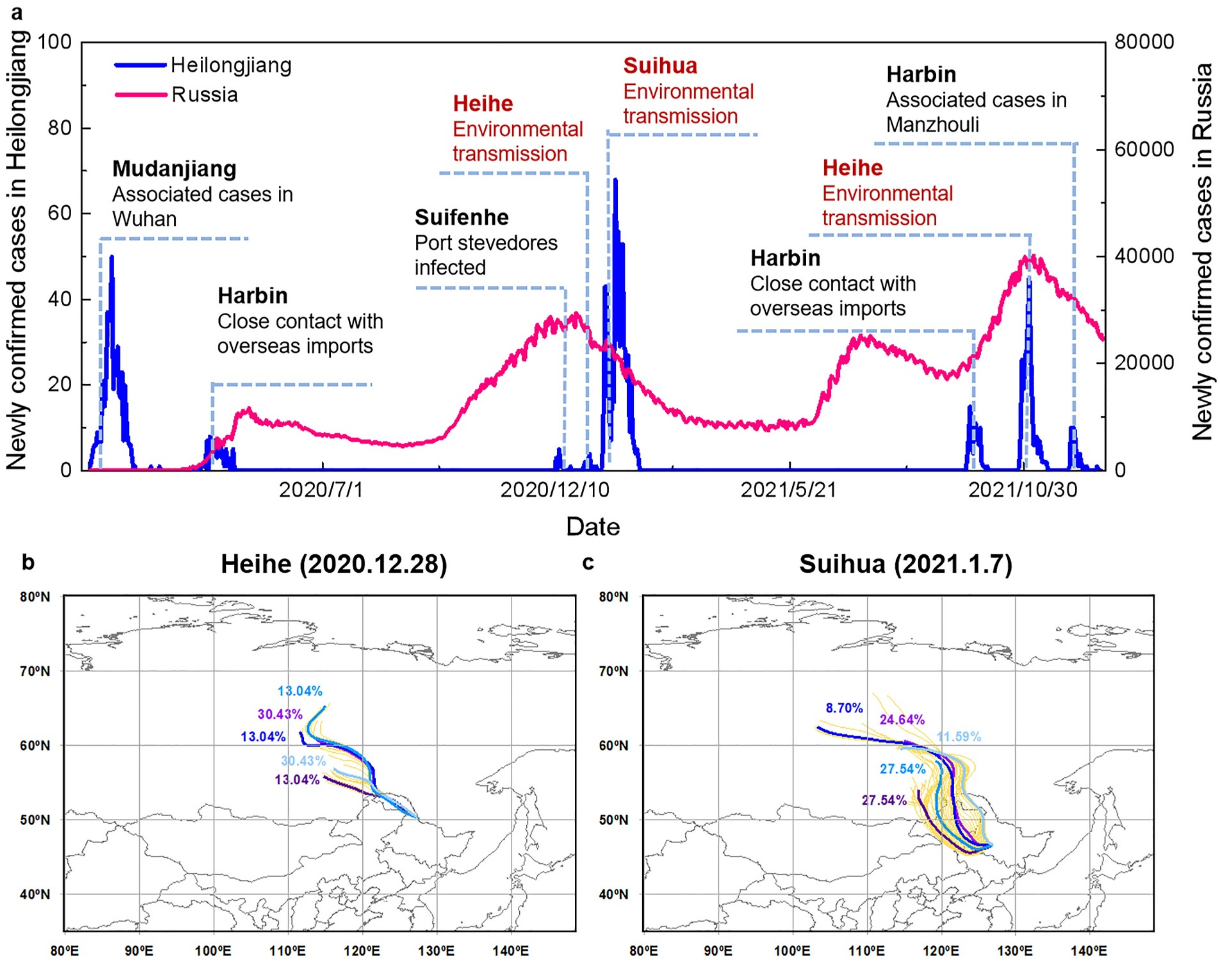

Figure 2. Source analysis of COVID-19 outbreak in Heilongjiang Province during strict control period. (a) Comparison of COVID-19 time series between Heilongjiang Province and Russia. (b–c) Backward trajectory analysis during small-scale COVID-19 outbreaks in Heihe and Suihua, Heilongjiang Province.

Russia during the cold waves (Figures 2b and 2c). The initial timing of the small local outbreak coincided with a rapid drop in temperatures. The virus traceability results further confirmed the homology of the infected strain with the Russian strain, and the timing of the outbreaks similarly coincided with the peak period in Russia.

Aerosols are multiphase systems in the atmosphere containing suspended solid and liquid particles that can act as vectors for the transmission of viruses (Audi et al., 2020). Although the atmospheric processes that aerosol particles undergo after their release from the body may, to some extent, cause severe damage to biomass, low temperatures can increase the stability of viruses by, for example, enhancing the lipid ordering of the viral envelope (Polozov et al., 2008). This enhances the ability of the virus to remain protected for longer periods of time in vitro, allowing the virus to keep alive for increased time periods, thereby increasing the infection risk. For example, the half-life of the Severe acute respiratory syndrome corona virus 2 (SARS-CoV-2) was 22 hr longer at 10°C than at 27°C (Morris et al., 2021). Thus, low temperatures and rapid cold air movement during the cold wave facilitate the distinct spread of viral aerosols. It has been demonstrated that pathogens can spread over long distances in the environment by aerosol airborne transmission, which is more likely to occur in winter (Pöhlker et al., 2023; Tellier, 2022).

3.3. Impact of Cold Wave on Infectious Disease After Relaxation of Interventions

We further analyzed the impact of the cold waves on infectious diseases using the trend of outbreaks during the COVID-19 relaxation of control measures in China as an example. The results of the backward trajectory analysis indicated that rapid aerosol transport from Hebei under the influence of the cold wave accelerated the outbreak in

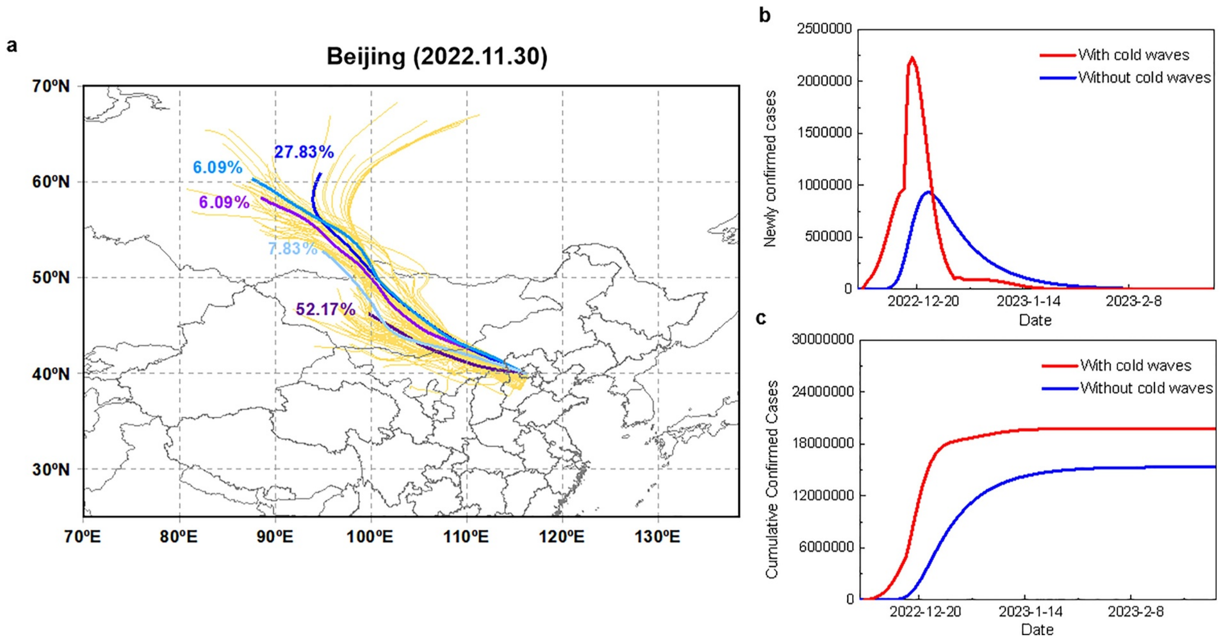

Figure 3. Source analysis of COVID-19 outbreaks in Beijing during deregulation. (a) Backward trajectory analysis during the cold wave in Beijing. (b) Simulation analysis of the number of newly confirmed cases in Beijing. (c) Simulation analysis of the cumulative number of confirmed cases in Beijing.

Beijing (Figure 3a). The results of the attribution analysis showed that the peak number of new cases in Beijing under the influence of the cold wave was about 2.23 million (Figures 3b and 3c). The cumulative infection is about 19.75 million, accounting for about 90.2% of the total population of Beijing. Without the influence of the cold wave, the trend of the COVID-19 epidemic would be more gentle, and the peak of new cases is expected to arrive around 23 December 2022, with a maximum of about 930,000 people. The cumulative number of infections is about 15.42 million, about 70.4% of the total population. Therefore, the impact of the cold wave may have contributed to an increase of about 28.1% in the number of confirmed cases of COVID-19 outbreaks in the first wave after the gradual relaxation of outbreak control policies in Beijing, resulting in an increase of 19.8% in the percentage of the cumulative number of infections in the total population of Beijing.

In addition to cold wave extremes that can exacerbate the rapid spread of viral aerosols, people would also have lower immunity during cold weather, thus potentially susceptible to viral infection. Cold air causes vasoconstriction of the respiratory tract, which leads to a weakened immune system (Eccles, 2002; Giesbrecht, 1995). Fluctuations in temperature and humidity may also result in alterations to respiratory epithelial cells, thereby increasing susceptibility to infection. Dry, cold air makes the nasal mucosa susceptible to small ruptures, which creates opportunities for viral invasion (Deal Jr et al., 1980). In addition, people tend to stay indoors and close the windows potentially during cold waves. These two factors will increase the risk of infections and also the number of people to be infected. Studies have shown that COVID-19 can be airborne in poorly ventilated or poorly recirculated indoor environments (Yao et al., 2020). Small infectious droplets and particles can remain suspended in the air for minutes to hours and spread away from the source. In indoor environments, SARS-CoV-2 RNA was detected even 57 days after exposure (Liu et al., 2021).

3.4. Mechanisms of Cold Wave Impact and Risk of Mortality

Outbreaks of respiratory infectious diseases are facilitated by changes in human activities during cold snaps (indoor congregation, closed doors and windows), rapid transmission of viral aerosols over long distances, and reduced human immunity. In a future of extreme weather disasters and infectious diseases, there is an urgent need for comprehensive, long-term public health measures to respond to the imminent threat posed by multiple hazards (Figure 4a). More urgently, the drop in temperature will not only have an impact on the infection rate of infectious diseases, but will also lead to a more severe burden of infectious disease-related deaths. In order to exclude the additional mortality risk associated with deregulation policies, here we further analyze the mortality risk

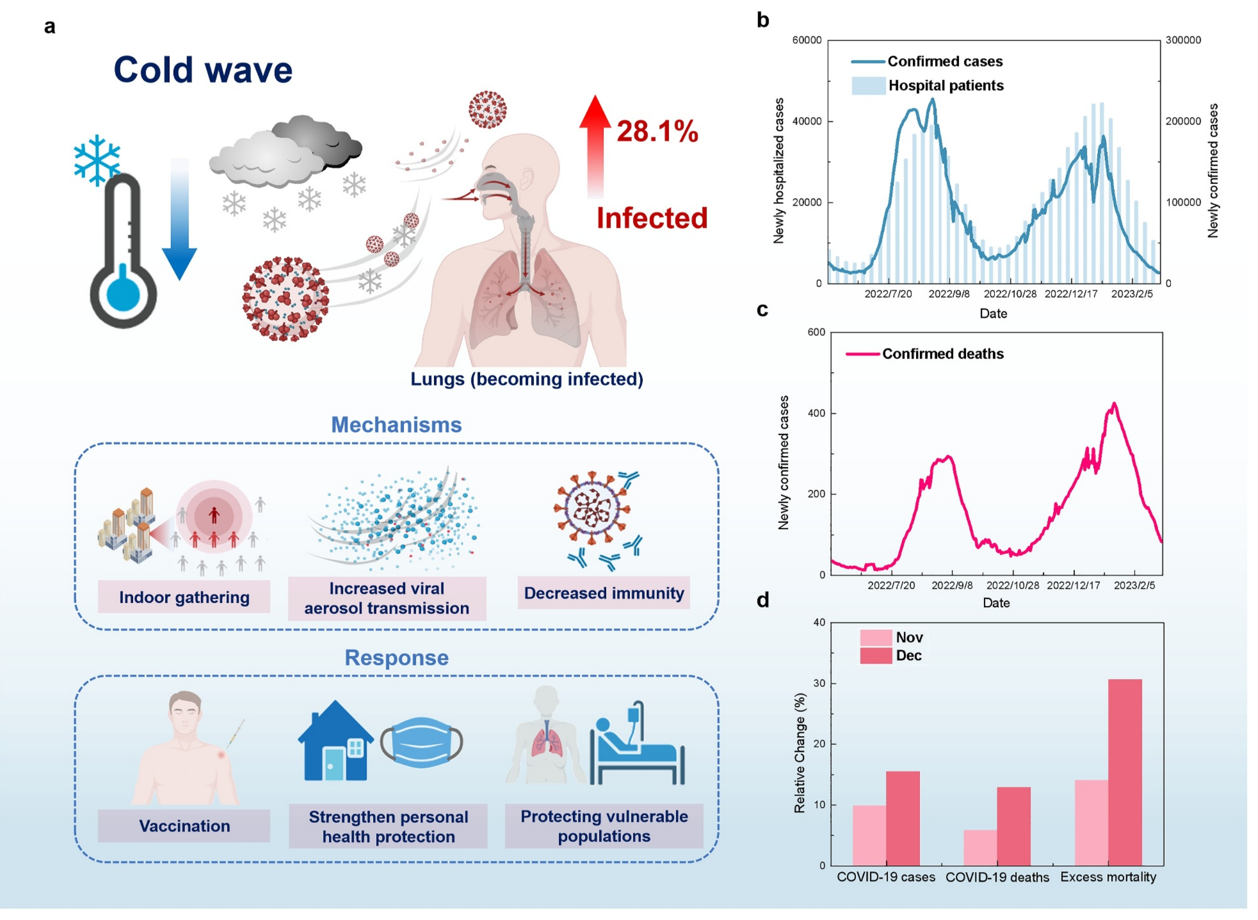

Figure 4. A framework for the impact of cold waves on infectious diseases and risk of mortality. (a) A framing of the impact of cold waves on infectious diseases. (b) Time series of the number of hospital patients and newly confirmed cases. (c) Time series of the number of newly confirmed deaths. (d) Growth rate of cases, deaths and excess mortality.

associated with cold waves on infectious diseases, using Japan as an example. Compared to the summer, the number of new confirmed cases of COVID-19 decreased by approximately 13.7% in the winter of 2022. However, hospitalizations and deaths increased by 65.3% and 157.1%, respectively (Figures 4b and 4c). Compared to November, the number of new confirmed cases and deaths increased by 5.65% and 7.07% respectively in December (Figure 4d).

In addition, low temperatures resulted in higher excess mortality rates (increase of about 16.61%) (Figure 4d). This means that during a multi-hazard period where a cold wave coincides with infectious diseases, there may be a greater risk of deaths from overlapping diseases, such as cardiovascular and cerebrovascular diseases and cancer. For example, the double stacking of influenza and COVID-19 may pose a higher health threat in winter (Park et al., 2020). The winter of 2022 in Japan experienced the most severe influenza since the COVID-19 outbreak (Figure S5 in Supporting Information S1). In China, there has been a noteworthy surge in various infectious diseases since the winter of 2022. Especially in December 2023, the number of people with influenza increased by 120.79% compared to November and even more than 5,000% compared to the same period in 2022, which is an urgent danger signal (Figure S6 in Supporting Information S1).

4. Conclusion and Discussion

This study demonstrates an amplifying effect of cold weather on infectious diseases outbreak and health threats. The quantification of the effects of extreme weather on epidemics and the analysis of the mechanisms of impact will help to rapidly develop prevention and control programs for infectious diseases during extreme weather and to minimize the risk of mortality in the elderly and in populations with underlying diseases. This has important practical implications for controlling infections, preventing outbreaks and superspreading events, and implementing societal behaviors to control pandemics (Callaway, 2021; Tian et al., 2020; Tian & Stenseth, 2019). In addition, in this work, we use an improved SEIR model to attribute the effects of the cold wave on COVID-19. The simulation results incorporate the effects of a variety of factors such as population aggregation, seasonal variations, etc. However, a further distinction between indoor and outdoor transmission of the virus has not yet been made. This is an important direction for future research on the mechanisms by which changes in the climate environment affect infectious diseases.

Currently, climate change is leading to an increasing frequency of extreme weather (Otto, 2016). In addition to affecting food production and global energy supply, global infectious disease prevention and control will certainly face a more complex and severe situation.This will bring unpredictable risk challenges to vulnerable populations. COVID-19 is not an isolated example. Strengthening evidence-based research on the interrelated factors of climate change and SARS-CoV-2-like virus transmission dynamics is critical (Yao et al., 2020). It can help to develop proactive response policies to address environmental conditions that contribute to the accelerated spread of respiratory infectious diseases. In summary, climate change-induced health outcomes have become a hot issue in the interdisciplinary field of meteorology and medicine (C. Huang et al., 2011). Therefore integrated strategies to prevent future COVID-19-like epidemics need to be designed from a climate and environmental perspective. Future control programs for emerging and major infectious diseases need to be integrated from multiple perspectives of biology, public health, sustainability science, atmospheric science and environmental science.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

COVID-19 case data are available from the World Health Organization (WHO, 2023). The COVID-19 hospitalizations, vaccinations, confirmed deaths, and excess mortality (counts) data were obtained from Our World In Data (Mathieu et al., 2020). Temperature data are available from the China Surface Basic Meteorological Observation Data set provided by the National Meteorological Science Data Center of the China Meteorological Data Network (NMC, 2023) Individuals can access it by registering with their real names. The NO_2 data were obtained from the United States Environmental Protection Agency (EPA, 2023).

Acknowledgments

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