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Heat waves accelerate the spread of infectious diseases

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ABSTRACT

COVID-19 pandemic appeared summer surge in 2022 worldwide and this contradicts its seasonal fluctuations. Even as high temperature and intense ultraviolet radiation can inhibit viral activity, the number of new cases worldwide has increased to >78% in only 1 month since the summer of 2022 under unchanged virus mutation influence and control policies. Using the attribution analysis based on the theoretical infectious diseases model simulation, we found the mechanism of the severe COVID-19 outbreak in the summer of 2022 and identified the amplification effect of heat wave events on its magnitude. The results suggest that approximately 69.3% of COVID-19 cases this summer could have been avoided if there is no heat waves. The collision between the pandemic and the heatwave is not an accident. Climate change is leading to more frequent extreme climate events and an increasing number of infectious diseases, posing an urgent threat to human health and life. Therefore, public health authorities must quickly develop coordinated management plans to deal with the simultaneous occurrence of extreme climate events and infectious diseases.

1. Introduction

In the past three years, the coronavirus disease (COVID-19) pandemic has affected the lives of people worldwide (Jain et al., 2022). SARS-CoV-2 spreads like other respiratory viruses by droplets and contact, exposing the virus to external environmental conditions (Meyerowitz et al., 2021). Since COVID-19 shares a similar transmission pattern with other respiratory viruses such as seasonal influenza, it has significant associations with weather variables such as temperature, humidity, rainfall and wind speed (Flaxman et al., 2020; Mallapaty, 2021; Ma et al., 2020). Meteorological conditions, such as temperature, humidity, air pressure, ultraviolet exposure, and precipitation, might influence the survival of the virus along transmission routes, change host vulnerability, and influence the activity patterns and immune systems of individuals (Huang et al., 2022; Xu et al., 2021; Zheng et al., 2021). Understanding the impact of climate and environment on the transmission and outbreak of COVID-19 is crucial for the control and prevention of future outbreaks.

In recent years, extraordinary and unprecedented heat waves have frequently swept through North America, Europe, and China because of the presence of atmospheric circulation patterns, such as the Rossby ridge or blockings, which significantly enhance human exposure to heat waves (Luo et al., 2020; Wang et al., 2022;Xu et al., 2020; Zhou, 2022). Since the beginning of the summer of 2022, many countries have experienced intense heat waves. The Indian subcontinent has experienced an early and prolonged heat wave since March 2022 (Kumar et al., 2022). More than 25 million people in over a dozen states have been under heat warnings in the United States. The onset of summer could diminish COVID-19 transmission (Huang et al., 2020a, b). According to previous studies, the estimated viral reproduction rate is negatively correlated with temperatures >25 °C, and higher temperatures shorten the half-life of the virus (Matson et al., 2020; R Xu et al., 2021). Wu et al. demonstrated a significant negative correlation between temperature and the number of confirmed cases. Every 1 °C increase in temperature was associated with 3.08% (95%CI: 1.53–4.63%) reduction in the number of cases (Wu et al., 2020). Liu et al. showed that cold season in the Southern Hemisphere can generate an increase in total infections, whereas the warm season in the countries of the Northern Hemisphere can contribute to a decrease (X. Liu et al., 2021). Meanwhile, regions with established community outbreaks have a lower mean temperature than those without substantial community transmission (Shokouhi et al., 2020). However, since the beginning of the summer of 2022, the COVID-19 outbreak has dramatically expanded, posing a serious threat to healthcare systems.

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Epidemiological model is an important method to predict the spread of infectious diseases. It mainly predicts the spread speed, spatial range, transmission path and dynamic mechanism of infectious diseases, so as to guide the effective prevention and control of infectious diseases. In 1927, Kermack and McKendrick developed the compartmental model (susceptible infected removed, SIR model), which is now widely used, to study the Black Death in London in the 17th century and the plague in Mumbai in the 20th century (Bacaër et al., 2012). Since the establishment of SIR Model, new epidemiological models have been proposed to accelerate the research on infectious diseases, such as suspectible infective (SI) model, susceptible infected susceptible (SIS) model, suspected exposed infectious recovered (SEIR) model and so on. The SEIR model can be adapted to situations where the infected person is cured and has immunity, which is commonly used for measles, mumps, rubella, etc (Kumar et al., 2021; Lin et al., 2021). During the COVID-19 pandemic, SEIR model was also applied to predict the epidemic trend of COVID-19 (Chang et al., 2021; Huang et al., 2020a, b, 2023). The Global Prediction System for the COVID-19 Pandemic (GPCP) developed by Huang et al. was launched in May 2020 (http://covid-19.lzu.edu.cn/index.htm). The system has produced accurate COVID-19 forecasts for more than 180 countries worldwide for three consecutive years. According to previous simulation and prediction results, seasonal factors in summer can slow the spread of SARS-CoV-2. However, the number of COVID-19 cases has rapidly increased in several regions. For public protection, determining the cause of the rapid increase in COVID-19 cases in regions with high temperatures is necessary. Thus, this study aimed to elucidate the cause of the increase in COVID-19 cases in the summer of 2022.

2. Materials and Methods

2.1. Data source

In this study, we used statistical dynamics and epidemiological modeling methods to identify the possible mechanisms of the outbreak during the summer of 2022. We assessed future trends in heat waves and their health impacts. The results are helpful for developing epidemic prevention plans to allow for the rational allocation of medical resources. Data on global COVID-19 confirmed cases were obtained from the COVID-19 Data Repository of the Center for Systems Science and Engineering at Johns Hopkins University (https://github.com/CSSEGISandData/COVID-19). Population mobility data were obtained from Google COVID-19 Community Mobility Reports (https://www.google.com/covid19/mobility/). The data include movement trends over time by geography across different categories of places such as retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residential areas. It should be noted that the data may not be comprehensive enough as it is difficult to follow each individual in detail. But in this study, it is more of an analysis of trends and influencing mechanisms. We used population movement data to analyze possible reasons for spikes in the number of cases during heat waves, and thus this data was useful and sufficient for our study. In addition, this data source has been cited in several articles (Saha et al., 2020; Zhu et al., 2020; Wellenius et al., 2021). The data were also used in our previous publication (Huang et al., 2022). Traceable data of the impacts of heat wave on pathogenic human diseases are available at https://camilo-mora.github.io/Diseases/(Mora et al., 2022). The data based on a systematic search for empirical examples about the impacts of ten climatic hazards sensitive to greenhouse gas emissions on each known human pathogenic disease (Mora et al., 2022). The data of human West Nile virus (WNV) infections were obtained from: https://www.ecdc.europa.eu/en/west-nile-virus-infection.WNV infection is a zoonotic disease transmitted by mosquitoes that is endemic in Europe, affecting countries in Western, Southern and Eastern Europe. Because the virus is mosquito-borne, the effects of climate change and extreme weather conditions are likely to contribute to WNV transmission by increasing mosquito survival, reproduction and biting rates, increasing pathogen replication in mosquitoes, and prolonging the disease transmission season (Epstein, 2001; Paz, 2015).

Heat wave data were obtained from the National Centers for Environmental Prediction (NCEP)/National Center for Atmospheric Research (NCAR) re-analysis of 2-m surface temperature field data (http://www.psl.noaa.gov/data/gridded/data.ncep.reanalysis.html). The NCEP/NCAR re-analysis 1 project used a state-of-the-art analysis/forecast system to perform data assimilation using past data from 1948 to the present. Average historical data were selected from the daily average 2-m ground temperature in June yearly from 1981 to 2010. The original data were Gaussian gridded data, which were interpolated into regular gridded data with a resolution of $1^\circ \times 1^\circ$. The source and processing methods for the test data were consistent with those for the historical average state data.

The temperature data for the four future climate scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5) in CMIP6 were obtained from ten Earth system models (ACCESS-CM2, ACCESS-ESM1-5, BCC-CSM2-MR, CanESM5, CESM2-WACCM, CMCC-CM2-SR5, CMCC-ESM2, MPI-ESM1-2-HR, NorESM2-LM, TaiESM1). To reduce the variation in simulated data between different models, all model temperature data were selected from the r1i1p1f1 series on a daily basis, and all data were interpolated to a spatial resolution of $1^\circ \times 1^\circ$.

2.2. Heat wave indicator

Here, we define a heat wave as a prolonged discrete anomalously high-temperature event that can be described by its duration, intensity, evolution rate, and spatial extent. A heat wave event must be defined relative to the baseline climatology, with temperatures above the 90th percentile threshold based on a 30-year historical baseline period. These thresholds vary with time and spatial location. Three days was used as a balance to achieve a relatively uniform global count under the current climate conditions. Events with temperatures exceeding the 90th percentile threshold for ≥ 3 days were considered heat waves. Heat-wave events are discrete, with well-defined start and end times. An interval between an event of ≤ 2 days and a subsequent event of ≥ 3 days was considered a continuous event.

The climatological mean (T_m) was calculated over a reference period, to which all values were relative, where j is the day of the year, y_s and y_e are the start and end of the climatological base period, respectively, and T is the daily temperature on day (d) of year (y).

$$T_m(j) = \sum\nolimits_{y=y_s}^{y_e} \tag{1}$$

$$\sum\nolimits_{d=j-3}^{j+3} \frac{T(y,d)}{11(y_e - y_s + 1)} \tag{2}$$

In calculating the threshold (T%) for the heat wave, P_{90} is the 90th percentile, and $X = \{T\ (y,\ d)\ |\ y_s \leq y \leq y_e,\ j - 3 \leq d \leq j + 3\}$.

$$T_{90}(j) = P_{90}(X) \tag{3}$$

The start and end of the heat wave (t_s, t_e) were calculated as t_s: $T(t) > T_{90}$ (j) and $T\ (t - 1) < T_{90}(j)$ and t_e: $T(t) < T_{90}$ (j) and $T\ (t - 1) > T_{90}(j)$. $t_e - t_e \geq 3$, respectively, where gap was ≤ 2 days.

Duration (D) was defined as the consecutive period of time that temperature exceeds the threshold.

$$D = t_e - t_s \tag{4}$$

Intensity (i_{max}, i_{mean}, i_{var}): i_{max} and i_{mean} represent the highest temperature anomaly value and mean temperature anomaly during the heat wave, respectively, and i_{var} is the variation in the intensity of the heat wave over the duration

$$i_{max} = \max\ (T(t) - T_m(j)) \tag{5}$$

$$i_{mean} = \overline{T(t) - T_m(j)} \tag{6}$$

$$i_{var} = \sigma T(t) \tag{7}$$

2.3. Model simulation

The second version of the Global Prediction System for the COVID-19 Pandemic (GPCP, v2) developed by Lanzhou University was used to simulate and predict the epidemic trend based on a modified version of the suspected, exposed, infectious, and recovered (SEIR) epidemiological model (Huang et al., 2020a, b). Based on real-time epidemic data, the GPCP can reliably predict the daily and seasonal number of new COVID-19 cases worldwide. Currently, the system has successfully predicted COVID-19 pandemics in more than 180 countries with an average accuracy of 82.7%. In addition, the system provided the basis for prediction and decision-making of several regional COVID-19 pandemics in China, with an average accuracy of 89.3%. The prediction results based on the past three years confirmed that the core dynamic mechanism of the current model could reflect the changing trend of the epidemic. The first version of the model used a modified SIR Epidemic model, which incorporated real global epidemic data and considered the effects of meteorological factors and quarantine measures on COVID-19 transmission (Huang et al., 2020a, b). The second version of the system uses a more sophisticated SEIR model (Huang et al., 2023). The modified model added protected (P) and quarantined (Q) cases compared to the conventional SEIR model. This takes into account individual self-protection measures, isolating the impact of numbers, and separating deaths from recoveries, which results in more accurate simulations and predictions. In addition, the system introduced the latest epidemic data in real time, and used the improved least square method to invert the model coefficients, so that the simulation results were more in line with the epidemic development law in different regions. In this version, we considered the impact of the time of community closure and self-isolation on the development of the epidemic. At the same time, the EEMD-ARMA method was used to modify the prediction results to obtain better prediction effect.

The original theoretical framework was based on the division of the human host population into susceptible, infected but not yet infectious (exposed), infectious, and recovered individuals. The susceptible (S) refers to people who are not sick but are vulnerable to infection after coming into contact with the infected person. In the case of immune evasion of the virus, almost all populations are at risk of infection when exposed to the virus, even at high vaccine coverage. The exposed (E) refers to people who have been in contact with an infected person but are not contagious. The infective (I) represents the people with infectious capacity. The recovered (R) are those who recovered or died from the disease. Omicron has a limited immune period, so R can be changed to S and then become infected. The model contains the following equations:

$$\frac{dS(t)}{dt} = -\frac{\beta I(t)S(t)}{N} \tag{8}$$

$$\frac{dE(t)}{dt} = \frac{\beta I(t)S(t)}{N} - \gamma E(t) \tag{9}$$

$$\frac{dI(t)}{dt} = \gamma E(t) - (\lambda + \kappa)I(t) \tag{10}$$

$$\frac{dR(t)}{dt} = (\lambda + \kappa)I(t) \tag{11}$$

The second version of the COVID-19 Pandemic Global Forecasting System uses a more sophisticated SEIR model. Based on the original model, the human host population was divided into seven categories, including susceptible cases (S), protected cases (P), potentially infected cases (E, infected cases in a latent period), infected cases (I, infected cases that have not been quarantined), quarantined cases (Q, confirmed and quarantined cases), recovered cases (R), and cases of mortality (D). The model contains the following equations:

$$\frac{dS(t)}{dt} = -\frac{\beta(t)I(t)S(t)}{N} - \alpha S(t) \tag{12}$$

$$\frac{dP(t)}{dt} = \alpha S(t) \tag{13}$$

$$\frac{dE(t)}{dt} = \frac{\beta(t)I(t)S(t)}{N} - \gamma E(t) \tag{14}$$

$$\frac{dI(t)}{dt} = \gamma E(t) - \delta I(t) \tag{15}$$

$$\frac{dQ(t)}{dt} = \delta I(t) - \lambda(t)Q(t) - \kappa(t)Q(t) \tag{16}$$

$$\frac{dR(t)}{dt} = \lambda(t)Q(t) \tag{17}$$

$$\frac{dD(t)}{dt} = \kappa(t)Q\ (t) \tag{18}$$

The dynamics of each population group are governed 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 protection rate α represents social distance. When $\alpha > 0$, individuals were passed from group S to group P, indicating that a social distance measure was taken. The infection rate β represents the average susceptible number of effective contacts per patient per day. The average latent time $1/\gamma$ represents the time between infection and the onset of symptoms. Infected persons transmit the virus to others at a rate δ before entering the isolation phase. λ is the recovery rate of the patients. κ is the mortality rate. The parameters of the model were obtained from actual epidemic data inversion (Huang et al., 2021). To simulate the original development trend of the epidemic in the absence of heat waves, we selected the number of confirmed cases before each heat wave to retrieve the original parameters. The entire simulation process includes data collection, basic coefficient inversion and assimilation, simulation and prediction. After determining the basic coefficients of the model, the COVID-19 historical data before the heat wave will be fitted. By running the model with the already-inverted basic coefficients, daily prediction results for a single country or region were obtained. The simulation results were compared with reported data to quantify the impact of heat waves on the epidemic.

3. Results

3.1. Global distribution of heat waves and epidemics

An unusual increase in the incidence of COVID-19 has been observed in the summer of 2022. The outbreak entered a global surge after a mutation on June 19, 2022 (reliability standard 0.05) (Fig. 1a). The number of new cases worldwide has increased to >78% in 1 month. In Italy, the number of new cases in the summer was approximately 13.8 times higher than that in the same period of 2021 and 623.6 times higher than that in 2020 (Fig. 1b). We observed that this outbreak was consistent with the global distribution of summer heat waves. The frequent occurrence of extreme heat events may be an important reason for COVID-19 outbreaks in some countries in the summer of 2022. A significant increase occurred during the heat waves in most regions (Fig. 1c). In Campania, Italy, a 181.2% increase in new cases was recorded during a heat wave. In France, the number of new prominent cases increased by >114.5%. In Asia, South America, North America, and Oceania, the number of cases also increased by an average of approximately 121.5% in the heat wave-hit regions. More worryingly,

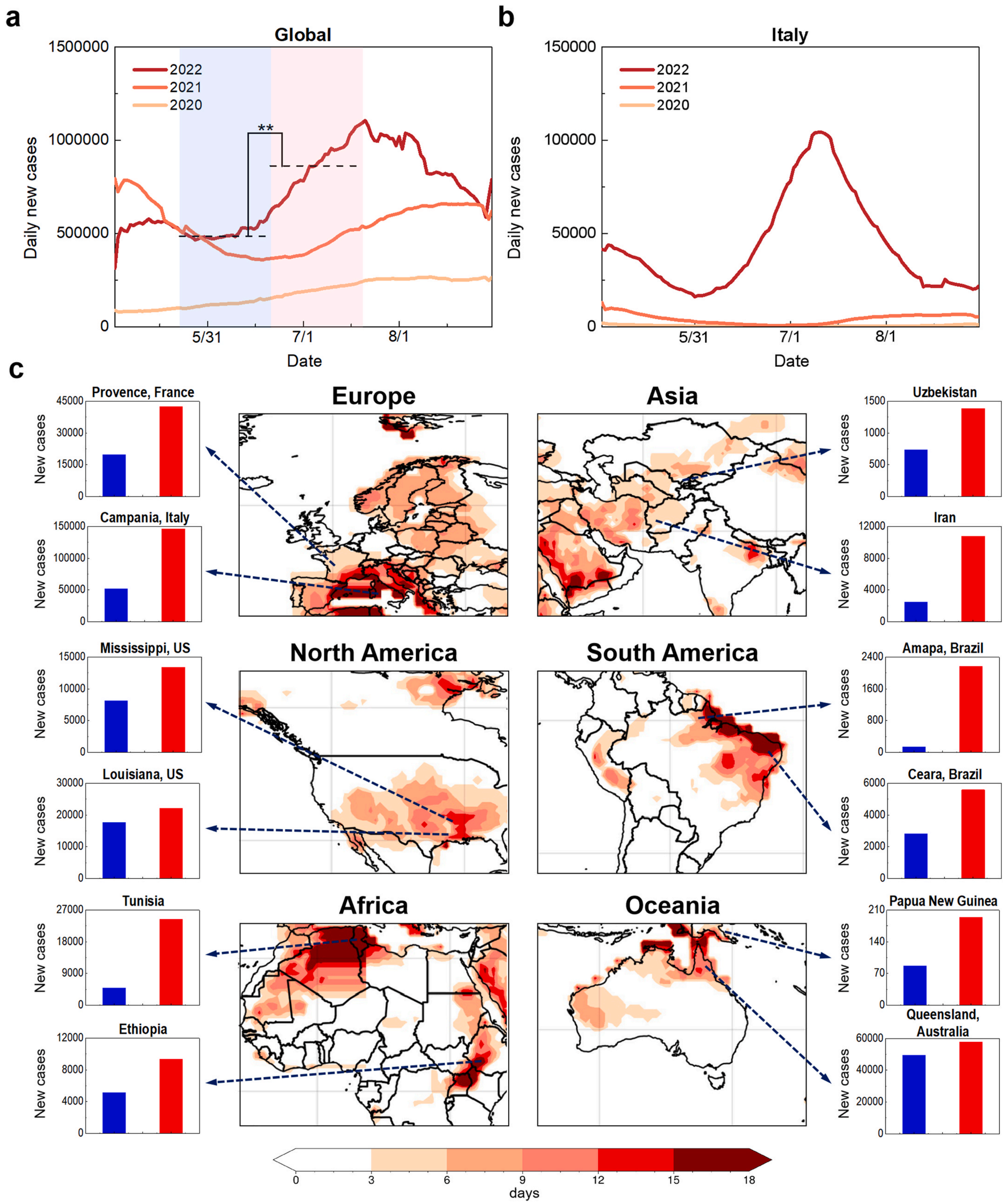

Fig. 1. **Relationship between heat waves and the epidemic. (a)** Time-series curve of the number of new confirmed cases globally (2020–2022). The line indicates the 7-day moving average of the number of new confirmed cases. The black dashed line is the 30-day average. **(b)** Time series curve of the number of new confirmed cases in Italy (2020–2022). **(c)** Spatial distribution of global heat waves and confirmed cases. The blue column represents the number of new confirmed cases 14 days before a local heat wave event, and the red column represents the number of new confirmed cases 14 days after the heat wave event.

Africa, Tunisia, and Ethiopia recorded an average increase of approximately 298.4% in new cases, which could further increase the vulnerability of low-income urban dwellers to heat (Marcotullio et al., 2021).

More importantly, we discovered that countries hit by heat waves in 2021 experienced summer COVID-19 peaks for the second consecutive year. For countries that were not affected by heat waves in 2021, summer heat waves in 2022 with high intensity resulted in the first local summer outbreaks. Therefore, with the increase and expansion of heat waves, extreme weather events and major infectious diseases may occur in many countries. In particular, in areas with high population density and high mobility, the damage will be more severe, even causing a global catastrophe.

3.2. *Influence mechanism of heat waves on the epidemic*

The temperature anomaly contributed to the rapid increase in cases during the heat waves. As the temperature anomalies increased, the number of cases also increased (Fig. 2a). The correlation coefficient R between the two sets of data reached 0.72, and passed the significance test of 0.01, so the surge in the number of cases after the heat wave was significantly correlated with the change in temperature. Previous studies have demonstrated that heat has a profound influence on viral load, virulence, host defense, and physiological resilience. High temperatures can inhibit viral activity, and intense ultraviolet irradiation can accelerate the half-life of viral aerosols (Dabisch et al., 2021). Thus, the main link between heat and the acceleration of the pandemic may be guided by changes in perceptions of public risk. Interventions to prevent heat-related illnesses and death, such as leaving home to cool down in public places, shopping malls or gardens, and seeking ambulatory medical care, contradict public health advice on strict social distancing for curbing the spread of COVID-19. It is worth noting that, as the growth and fluctuation of the number of cases are affected by various natural environmental factors and uncertainties of human activities, R^2 may be relatively low. However, some objective rules can be obtained from the results of our analysis. Based on published research on factors affecting COVID-19, the R^2 in this study is within the range that can be interpreted (Saputra et al., 2021; Rashed et al., 2020; Huang et al., 2022; Kodera et al., 2020) .

Our results further supported this hypothesis. Statistics of population movement data indicated that the number of people shopping increased significantly by 89.1% after the beginning of the heat wave event, while parks, traffic, work, and homes all demonstrated a small negative growth (Fig. 2b). In malls, large gatherings and physical contact lead to significant increases in contact rates and susceptible supply that directly trigger super-spreader events and subsequent COVID-19 disasters (Fig. 2c). Additionally, ventilation flow from air conditioners can result in complex flow patterns, and local recirculation flows in confined spaces can substantially increase infection risks (H. Liu, 2021). Returning aerosols from air conditioning/ventilation systems due to limited filtration efficiency can also cause aerosol exposure of individuals adjacent to ventilation outlets (Pan et al., 2022).

Thus, seasonal regulation of COVID-19 evolution under unexpected natural crises is limited. COVID-19 risk perception is weakened during heat waves, reducing compliance with COVID-19 prevention measures. Social distancing and space use restrictions may hamper efforts to provide cooling protection, and social and healthcare systems are likely to

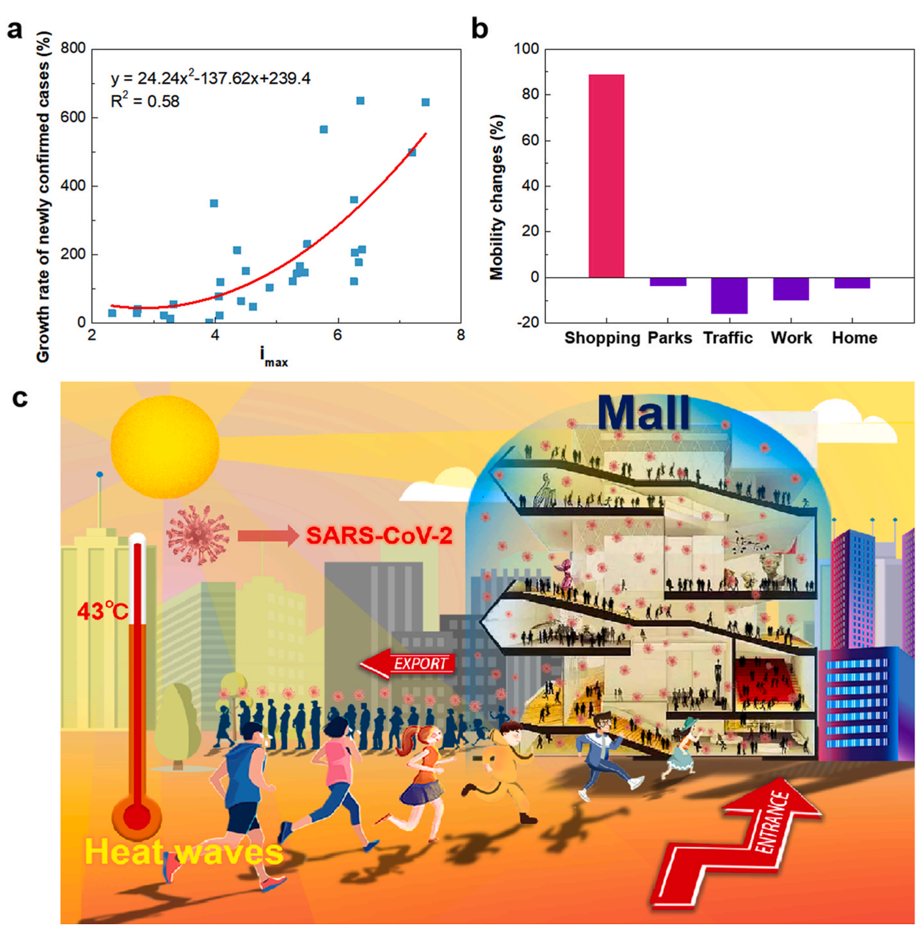

Fig. 2. Influence mechanism of heat waves on the epidemic. (a) Relationship between growth rate of confirmed cases and maximum temperature anomaly. The blue dots indicate the rate of 14-day increase in cases since the heat wave. **(b)** Changes in population movements after heat waves. The columns represent the growth rate of population movement five days after a heat wave event. **(c)** The impact process of heat wave events on the epidemic.

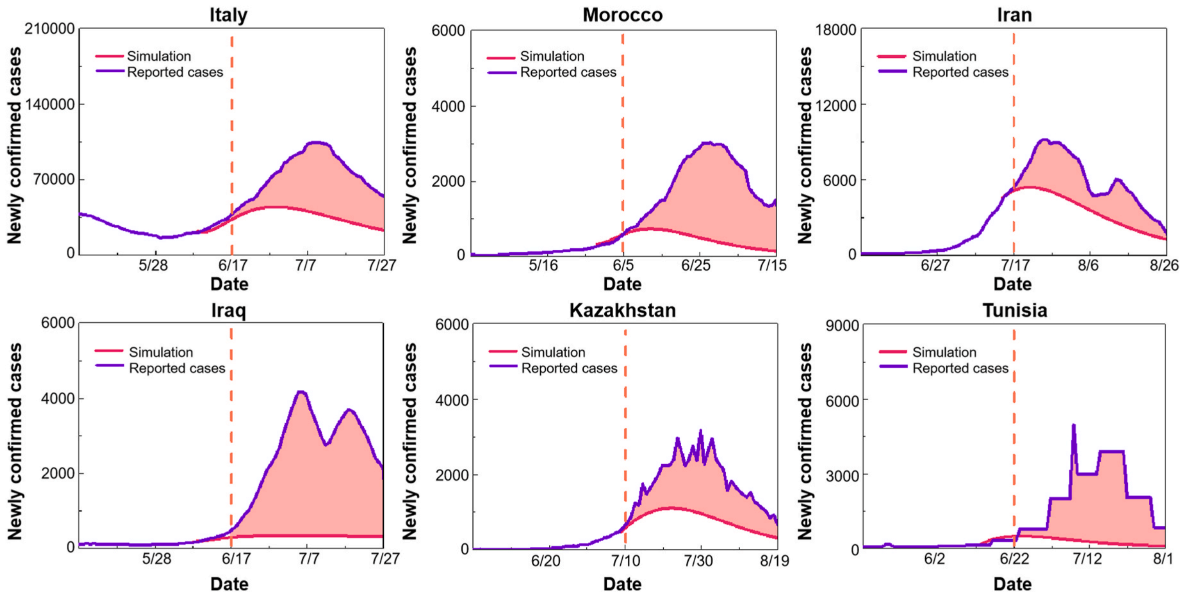

Fig. 3. Attribution analysis of the influence of heat waves on the epidemic. (a–f) Simulation results for countries severely affected by heat waves. The purple line represents the 7-day sliding average of the number of reported cases. The red line indicates the number of new confirmed cases in a simulated scenario without a heat wave. The red shading indicates the increase in cases due to heat waves.

be overwhelmed. COVID-19 disease has not completely disappeared and continues to mutate. The frequency of a variety of emerging infectious diseases continues to rise worldwide. Summer heat waves pose an imminent challenge to the coordinated management of public health.

3.3. Attribution analysis of the impact of heat wave on the epidemic

We further provide an attribution analysis for the 2022 summer outbreak based on the second version of the Global Prediction System for the COVID-19 Pandemic (GPCP, v2; details in the Materials and Methods) (Huang et al., 2020a, b) (Fig. 3). Simulations demonstrate that by September 1, 2022, approximately 69.3% of the cases could have been avoided without heat waves. In Italy, without the impact of the heat wave, the cumulative number of confirmed cases during the summer was only approximately 1.6 million, with a peak of 44,808 new cases per day. Unfortunately, with natural disasters and the pandemic, Italy reported over 4.4 million confirmed cases in summer 2022. The number of new cases per day has exceeded 140,000, which has caused severe public health challenges and serious threats to the lives and health of the local people.

The timing of the heat wave onset and the initial number of cases greatly influenced the contribution of the heat waves to the outbreak. In regions with high initial case counts and late onset of heat waves, such as Italy and Iran, heat waves increased the number of cases by approximately 108.8% on average, which contributed to approximately 47.7% of new cases. The accelerating effects of heat waves need to be urgently addressed to prevent catastrophic outbreaks beyond the public health capacity in these regions. In regions with low initial case counts, heat waves contributed to approximately 80.0% of the new cases. This is conducive to implementing precise and timely measures to reduce the risk of severe acute respiratory syndrome coronavirus 2 (SARS-Cov-2) infection before heat waves occur. Therefore, early and effective COVID-19 interventions can mitigate the negative impact of heat waves by reducing the initial number of infections before they occur. This will help relieve the burden of the healthcare system and its related socio-economic consequences.

3.4. Future heat wave trends and health risks

Extreme heat events will continue to intensify throughout the summer season worldwide (Fig. 4a). A systematic examination of regional and global observed heat wave trends using key heat wave indicators revealed that the heat wave frequency exhibited the most rapid and significant changes in almost all regions (Pan et al., 2022). These changes were more pronounced at higher radiation levels. Global warming is expected to persist as CO_2 emissions continue to rise. Heat waves will become more frequent and intense and last longer. Many parts of the world will have hot weather in excess of 40 °C in summer of 2060 (Fig. 4b). Without more aggressive emission reductions, many people living in the tropics will be exposed to dangerous heat index values on most days of the year by 2100 (Vargas et al., 2022).

Heat-related health threats are projected to increase further as climate change progresses. In addition to the increased risk of death from cardiovascular, cerebrovascular, and respiratory conditions owing to extreme heat exposure, climate change could undermine eradication efforts for the global burden of infectious disease transmission (Ebi et al., 2021). Most infectious diseases confronted by humanity worldwide have been at some point aggravated by climatic hazards, including heat waves (Fig. 4c). In Europe, there has been a significant increase in the number of West Nile virus infections. Italy, in particular, saw 10 times more cases in the summer of 2022 than in 2021, which could also be linked to heat waves (Fig. 4d). Changing environmental conditions are increasing the suitability for the transmission of water-borne, air-borne, food-borne, and vector-borne pathogens (The Lancet Infectious Diseases, 2021). Climate change is leading to closer and more widespread contact between wildlife and humans, thereby promoting the occurrence and spread of new infectious diseases (Carlson et al., 2022). Large zoonotic disease outbreaks have already occurred in tropical Africa and Southeast Asia, and the risk will likely converge in other parts of the world under the impact of climate change (Gandy, 2022). This will inevitably lead to global pandemics that humanity cannot afford.

4. Conclusions and discussion

The influence of seasonal factors on the epidemic may partly explain some of the pandemic waves in different countries, and can significantly mitigate the epidemic risk profile. However, our study adds to the evidence that the impact of weather on transmission risk makes it difficult to quell outbreaks alone. The combination of social and meteorological factors plays a role in the coronavirus outbreak because this public

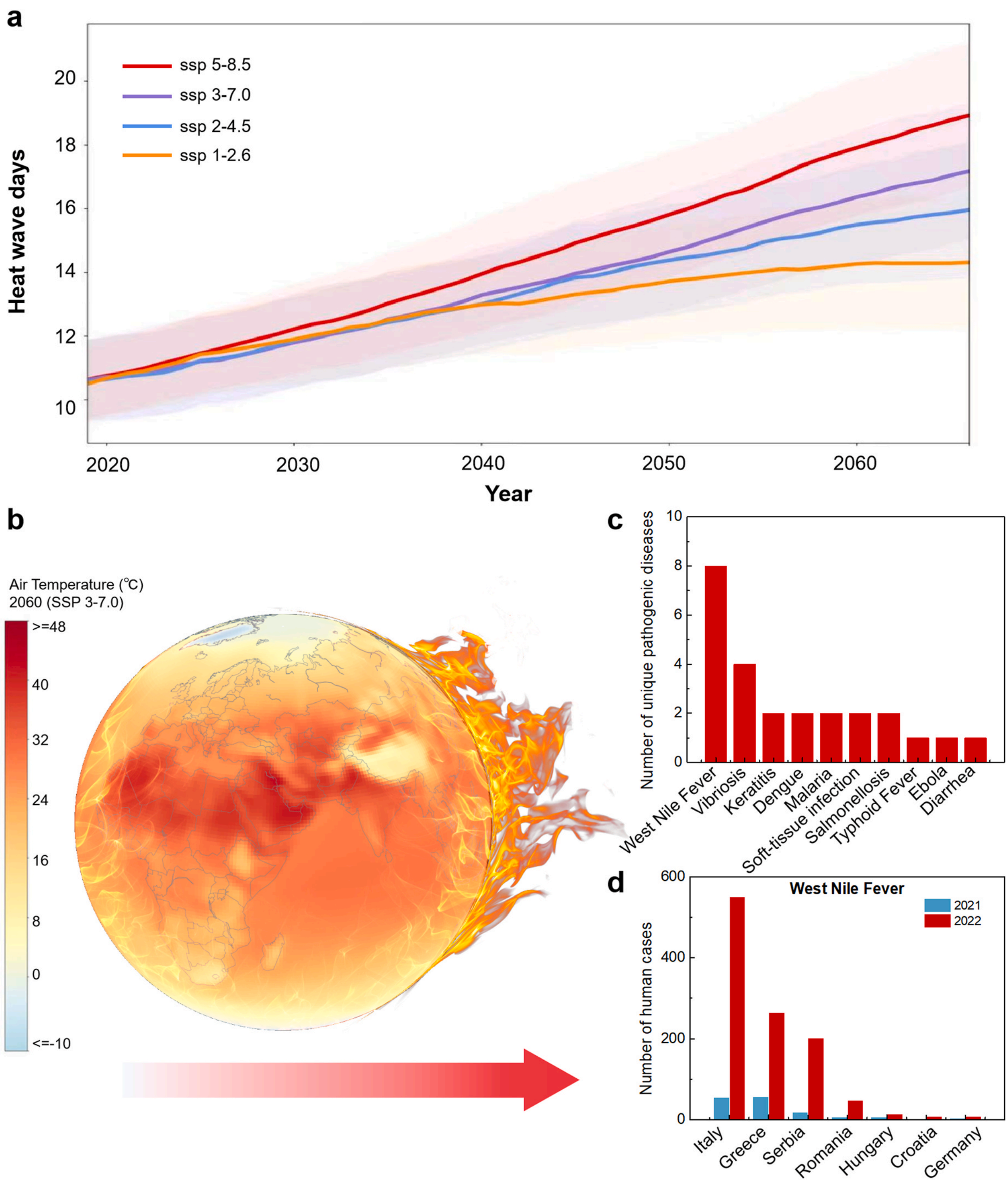

Fig. 4. Trends and health hazards of heat waves. (a) Prediction of the trend of heat waves in the future. The curves demonstrate the results of the multi-model ensemble, and the shadows indicate the range of 2 times the standard deviation between the models. **(b)** Global temperature distribution in summer 2060. **(c)** The impacts of heat wave on pathogenic human diseases. The bar is proportional to the number of unique pathogenic diseases. **(d)** Comparative analysis of West Nile virus infections in Europe. The blue and red bars represent 2021 and 2022, respectively.

health problem is too complex to be explained by climatic conditions alone. Quarantine plans, social distancing, number of residents per household, immigration control plans, and personal hygiene conditions are some of the confounding variables interfering with the spread of the novel coronavirus (Yip et al., 2007). Research exploring the impact of meteorological factors such as temperature and humidity on the global spread of infectious diseases requires synergies between the implementation of government policies and awareness of personal protection, especially in vulnerable countries. Non-pharmaceutical interventions (NPIs) can reduce the frequency and duration of contact, thereby reducing the number of nodes for viral replication (Oraby et al., 2021). During the pandemic, NPIs, including social/physical distancing, wearing of masks, case isolation and workplace closure, should be adhered to, while drug interventions are intensified (Sun et al., 2021). The summer season should have been taken advantage of for reducing transmission to contain the pandemic rather than worsening the disaster by human activities.

Moreover, under the current pandemic, climate change needs urgent attention, which is now creating a dangerous new era for the spread of infectious diseases, making outbreaks more widespread and serious, and can be a source of significant and sudden risks. Changing environmental conditions are increasing the suitability for the transmission of pathogens and the risk of trans-species viral transmission (Danovaro et al., 2011; Devaux et al., 2019). The combination of this heat wave with COVID-19 was not an accident. Extreme heat events are becoming a permanent feature of the summer season worldwide. Hot ambient conditions and the associated heat stress can increase the mortality and morbidity risks of various diseases (Ebi et al., 2021). In addition to heat waves, during extreme weather events such as forest fires, heavy precipitation, floods, and storms, the usual assistance and rescue measures complicate personal protection against SARS-CoV-2 infection, leading to an additional burden on the overall healthcare system (Chan et al., 2022; Huang et al., 2022; Sannigrahi et al., 2022). Similar to COVID-19, climate change is a global problem, and its destructiveness has never been more urgent. Therefore, a coordinated response from policymakers, businesses, and wider community is an urgent need.

The GPCP-2 prediction system used in this paper combines statistical methods with improved epidemiological models. We introduced an improved inverting coefficients method into the model to improve the goodness of fit of the model (Huang et al., 2023). Thus, simulations during heat waves have included elements of seasonal variation in regional COVID-19 outbreaks and the effects of human social behaviour. At present, there are some other factors that cause errors in model prediction, and the prediction accuracy of the model can be increased by model improvement. The main influencing factors include the impact of population movement, data quality, data accuracy, economic factors, environmental transmission of the virus, and the triggering and accelerating effects of unexpected events such as extreme weather events. For the impact of sudden natural disasters such as heat wave, more in-depth mechanism research and the introduction of model simulation parameterization scheme are needed in the future. In the future, under the influence of multiple disasters of extreme weather disasters and infectious diseases, it is necessary to combine the epidemiological model with the climate model through multidisciplinary integration. This will further improve the accuracy of epidemic prediction, make early warning of disasters in advance, and provide a basis for the formulation of multi-disaster response policies.

Our prediction method can also be applied to other infectious diseases. For example, we recently made a predication for the number of new cases of monkeypox worldwide (Zhang et al., 2022). Monkeypox can be transmitted to humans from humans, rodents, primates and other animals. Monkeypox is spread through direct contact with the body fluids of an infected person or objects contaminated with the virus. Similar to COVID-19, it can also be transmitted by respiratory droplets. By introducing the latest epidemic data in real time and using the improved least square method to invert the latest model coefficients, the subsequent epidemic development can be predicted. The GPCP used the COVID-19 prediction model to predict and simulate the transmission and vaccination scenarios of monkeypox. The existing prediction results can be found on our official website http://covid-19.lzu.edu.cn/index.htm.

Credit author statement

J. Huang designed this study. X. Lian, J. Huang and H. Li, contributed to the data analysis and manuscript writing. All of the authors contributed to the discussion and interpretation of the manuscript. All of the authors reviewed the manuscript.

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

The data supporting the findings of this study are available within the article.

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