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Supplementary appendix

This appendix formed part of the original submission and has been peer reviewed. We post it as supplied by the authors.

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The 2021 Chinese Report of The Lancet Countdown on Health and Climate Change

Appendix

Important notes about the indicator structure

The indicator system of the current report was reorganized to better reflect the health profiles of climate change in China and to keep consistent with the global report, the mapping to the indicators in 2020 were provided in **Table 1**. Among the 27 indicators presented in the current report, 3 were newly introduced (indicator 2.2.3 Urban green space, indicator 5.1.2 newspaper coverage of climate change and health, indicator 5.4 government engagement of health and climate change), 19 were inherited from the last year's report where 2 are combined by old indicators, and 5 were introduced from last year's appendix to this year's main text given the sufficient development and improvement.

Table 1 Indicator list for Lancet Countdown China Report 2021 and mapping to 2020 report

2021 report	2020 source	2020 indicator
1.1.1 heat-related mortality	maintext	1.1.2
1.1.2 change in labour capacity	maintext	1.1.3
1.2.1 wildfires	maintext	1.2.1
1.2.2 flood and drought	appendix	1.2.3
1.3 climate-sensitive infectious diseases	maintext	1.3
2.1.1 national level adaptation planning and assessment	maintext	2.1
2.1.2 city-level climate change risk assessments	appendix	2.1.3
2.2.1 detection, preparedness, and response to health emergencies	maintext	2.2.1
2.2.2 air conditioning - benefits and harms	maintext	2.2.2
2.2.3 Urban green space	New	#N/A
2.3 climate information services for health	appendix	2.3
3.1 energy system and health	maintext	3.1
3.2 clean household energy	maintext	3.2
3.3 air pollution, energy, and transport	maintext	3.3+3.4
3.4 food, agriculture, and health	appendix	3.5
4.1.1 costs of heat-related mortality	maintext	4.1.1
4.1.2 economic costs of heat-related labor productivity loss	maintext	4.1.2
4.1.3 economic costs of air pollution	maintext	4.1.3
4.1.4 economic losses due to climate-related extreme events	appendix	4.1.4
4.2.1 investment in new coal, low-carbon energy and energy efficiency	maintext	4.2.1
4.2.2 employment in low-carbon and high-carbon industries	maintext	4.2.2
4.2.3 net value of fossil fuel subsidies and carbon prices	maintext	4.2.3+4.2.4
5.1.1 media coverage of health and climate change on Weibo	maintext	5.1

5.1.2 Newspaper coverage of health and climate change	New	#N/A
5.2 individual engagement in health and climate change	maintext	5.2
5.3 Coverage of health and climate change in scientific journals	maintext	5.3
5.4 Government engagement in health and climate change	New	#N/A

Section 1: Climate change impacts, exposures, and vulnerability

Indicator 1.1: Health and heat

Indicator 1.1.1: Heatwave-related mortality

Methods

The methodology for this indicator was similar to the methods in the 2020 China Lancet Countdown report[1]. The heatwave definition and the rationale of choosing this definition has been described in details in the indicator 1.1.3 (exposure of vulnerable populations to heatwaves) in this appendix. In short, the heatwave event was defined as a period of three or more days where the daily maximum temperature was higher than the reference (the 92.5th percentile of daily maximum temperature over the warm season (May 1st to Sep 30th) between 2007 and 2013) at a given location, which was chosen among different heatwave definitions to best capture the health effects of heat events in China[2,3]. The days of heatwave were defined as the number of days within the heatwave event. The deaths attributable to heatwave (DAHW) are calculated. The method is as follows:

$$\boldsymbol{DAHW_{y,p} = Pop_{y,p} \times Mort_{y,p} \times HW_{y,p} \times AF_{y,p}}$$

Where $Pop_{y,p}$ refers to the grid cell-level population size in year y and in grid p. $Mort_{y,p}$ is the baseline daily non-accidental mortality rate. $HW_{y,p}$ is the grid cell-level heatwave days in a specific year. $AF_{y,p}$ is the attributable fraction (AF), which is calculated as:

$$\boldsymbol{AF = (RR - 1)/RR}$$

Where relative risks (RR) represent the increase in the risk of mortality resulting from heatwave compared with non-heatwave. The exposure-response relationship between heatwave and mortality in different provinces (autonomous regions) is represented by the related capital cities in mainland China[3], and the relationship is assumed to be consistent during the study period. Then gridded annual deaths number of heatwaves from 2000 to 2020 could be calculated by the above formulas, and summed to gain provincial and national DAHW. We limit our research to the warm season.

Data

1. Original RR values are derived from Yang et al[3]. Based on the general trend that risks are homogeneous in the same climate region and higher in the north of China than that in the south[4], provincial relative risks are combined by climate zones (eg. Semi-arid monsoon climate, subtropical monsoon climate, arid continental climate and plateau climate.)
2. Non-accidental mortality rates ($\boldsymbol{Mort_{y,p}}$), as well as population structure data at province levels are derived from China Statistical Yearbook[5].
3. Gridded climate data was from the European Centre for Medium-Range Weather Forecasts (ECMWF), ERA5 project

4. Population data was from the Chambers (2020) hybrid gridded demographic data for the world.[6]

Caveats

The main caveats of this indicator are the limited number of exposure-response functions for such a big country like China and that the effects of heatwave on mortality were assumed to be constant without considering population adaptation.

The selection of the most appropriate heatwave definition remains controversial [7]. We chose heatwave definitions among different definitions to best capture the health effects of heat events in China [2,3]. The detailed chosen progress could be found in the 2020 China Lancet Countdown report appendix [1].

Also, the mortalities considered in this indicator were non-accidental. Accidental injuries have been proved to be statistically related to changing climate, and might be included if appropriate data or method are available[8].

Future Form of Indicator

One possible improvement of this indicator would be to calculate the mortality for different age groups, gender, and diseases.

Additional Findings

Among the provinces, heatwave-related deaths were highest in Guangdong (2113 deaths) followed by Liaoning (1366) and Guangxi (1130), which accounted for 14.5%, 9.4%, 7.8% of total deaths in China in 2020. Guangdong and Guangxi provinces are located in South China, while Liaoning is located in Northeast China.

Table 2: Average annual deaths per heatwave in China from 2000 to 2020

Year	Deaths per heatwave
2000	1.9
2001	1.9
2002	2.5
2003	3.9
2004	2.6
2005	2.9
2006	2.2
2007	2.8
2008	1.2
2009	2.9
2010	2.2
2011	1.9
2012	2.7
2013	3.5
2014	2.1
2015	2.3
2016	2.6
2017	3.4
2018	2.5
2019	3.0

2020 1.8

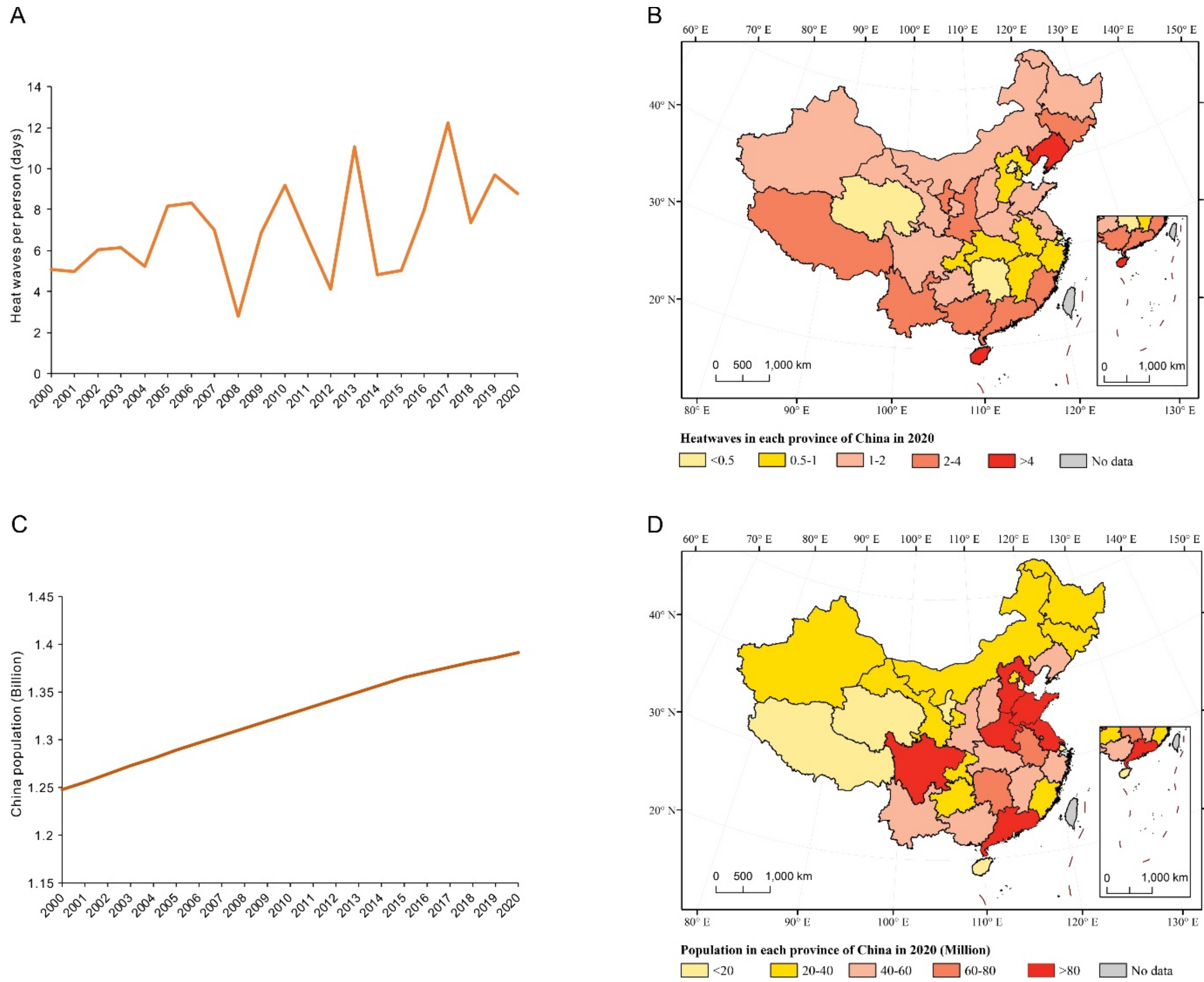

***Figure 1*: Heatwave exposures and population in China**

(A) Annual heatwave exposures per person from 2000 to 2020. (B) Heatwave exposure in each province in China in 2020. (C) Population in China from 2000 to 2020. (D) Population in each province of China in 2020.

Indicator 1.1.2: Change in labour capacity

Methods

The methodology for this indicator has been improved from the 2020 China Lancet Countdown report appendix. In the previous Chinese Lancet Countdown report, we assumed all workers working indoor which underestimate the heatwave exposures during work, and only estimated work hours lost (WHL) in three sectors (primary, secondary and terdiary), using the daily mean and maximum WBGT approximately estimating hourly WBGT. In the 2021 report, we considered the ratio of workers working outdoors, and directly estimate the hourly WBGT by collecting high-resolution climate data. We showed WHL in four sectors (agriculture, construction, manufacturing, service), following the sectors analysed in the Global Lancet Countdown report.

Firstly, wet bulb globe temperature was estimated based on gridded (0.5° * 0.5°) climate data. We calculated the hourly WBGT in the shade (WBGT_shade) using temperature and dew point temperature, and calculated the hourly WBGT in the sun (WBGT_sun) using temperature, dew point temperature, solar radiation and wind speed. The detailed iteration calculation method is described in Kjellstrom et al.[9]

Secondly, the fraction of work hours lost (WHL) in each industry was estimated based on the loss function between WBGT and WHL. The loss function was from Watts et al[10] and showed as:

$$loss\ fraction = \frac{1}{2}\left(1 + \mathrm{ERF}\left(\frac{\mathrm{WBGT_{hour}} - \mathrm{Prod_{mean}}}{\mathrm{Prod_{sd}} * \sqrt{2}}\right)\right)$$

$\mathrm{WBGT_{hour}}$ is the hourly WBGT_shade or WBGT_sun estimated in the first step. $\mathrm{Prod_{mean}}$ and $\mathrm{Prod_{sd}}$ are the fixed parameters for laborers working with different activity levels (***Table 3***). In this study, labour was divided into engaging in agriculture, construction, manufacturing and service. We assumed labor in agriculture and construction working at a metabolic rate of 400W, manufacturing at 300W and service at 200W. As the agriculture and construction sectors require mainly outdoor work, while service and manufacturing require mainly indoor work. Therefore, we used the WBGT sun to calculate the hourly work time loss in agriculture and construction, and WBGT_shade in manufacturing and service. (***Table 4***)

Thirdly, we assumed a laborer works 8 hours a day (typically from 8 am to 5 pm with an hour break from 12 am to 1 pm for Chinese workers), and 8 hours is the legal working time stipulated by the Labor Law of China. We counted the gridded number of annual losses by summing the hourly work time loss in the second step, and then multiply by the girded annual number of workers to obtain the WHL in different sectors. The total WHL was estimated by summing WHL in all four industries.

Table 3: Input values for labor loss fraction

Metabolic rate	$\mathrm{Prod_{mean}}$	$\mathrm{Prod_{sd}}$
200W	35.53	3.94
300W	33.49	3.94
400W	32.47	4.16

W: watts

Data

1. Gridded climate data was from the European Centre for Medium-Range Weather Forecasts (ECMWF), ERA5 project .[11]
2. Population data was from the hybrid gridded demographic data for the world. [6]
3. Data on the percentage of people working in each industry was from 2020 Statistical Yearbook of China.[5]

Caveats

The loss function was used to estimate WHL globally. However, whether the function is appropriate for estimating WHL at the provincial level of China is still unknown. In the future, the function should be tested and checked. Besides, the results of WHL in 2020 may be biased due to the occurrence of COVID-19. Parts of workers in different positions may stop working (e.g., tourism) or work overtime (e.g., medical staff) in this special year. As the difficulty in data on the number of workers whose working time affected by COVID-19, we did not consider the impact of the epidemic in the report.

Future form of indicator

This indicator will be updated to show the number and percentage of workers whose productivity were seriously affected by extreme temperature.

Additional Information

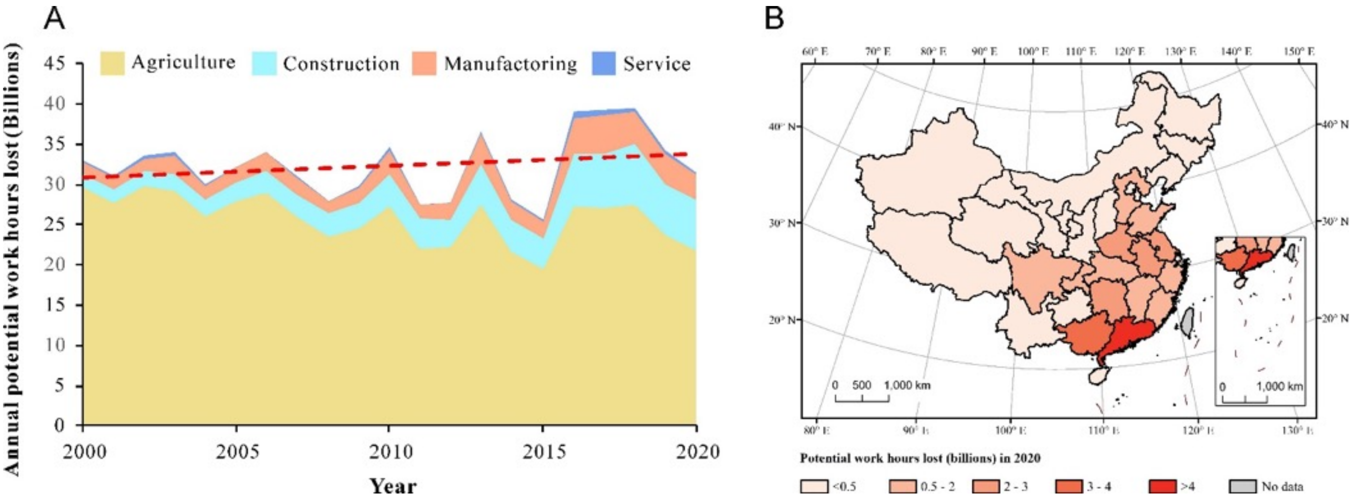

Figure 2: **Heat-related work hours lost in China.**

(A) Annual potential work hours lost due to heat in each sector from 2000 to 2020. (B) Potential work hours lost (billions) in 2020.

Table 4: The total WHL and average WHL for each person employed in four industries from 2000 to 2020 in China (Unit in total loss: billion hours; Unit in each person's loss: hours)

Year	agriculture			construction			manufacturing			Service	
	Total	Each person		Total	Each person		Total	Each person		Total	Each person
2000	29.5	84.7		1.8	89.2		1.4	11.6		0.1	0.4
2001	27.8	79.5		1.6	81.7		1.5	11.9		0.1	0.7
2002	29.8	85.3		1.9	89.1		1.6	12.5		0.2	1.3
2003	29.2	84.8		2.1	93.4		2.3	18.4		0.4	2.3
2004	26.1	77.4		2.1	86.4		1.7	12.3		0.1	0.5
2005	27.8	84.4		2.4	93.4		1.8	12.6		0.1	0.4
2006	29.0	89.7		2.8	103.3		2.1	14.4		0.1	0.6
2007	25.9	81.4		2.8	98.5		2.2	13.8		0.1	0.6
2008	23.5	75.5		2.9	92.7		1.6	9.4		0.0	0.2
2009	24.6	80.1		3.1	92.7		2.0	11.7		0.1	0.3
2010	27.4	90.2		4.0	108.3		3.0	17		0.4	1.4
2011	22.1	74.7		3.7	90.3		1.7	9.8		0.1	0.3
2012	22.2	75.7		3.5	90.1		2.1	11		0.1	0.2
2013	27.4	95.4		5.2	122.5		3.7	19.7		0.3	1
2014	21.6	76.6		4.0	88.2		2.4	12.6		0.2	0.6
2015	19.4	70.2		3.8	83.6		2.2	11.3		0.1	0.3
2016	27.3	100.4		6.5	128.9		4.5	23.8		0.8	2.6

2017	27.1	101.4		6.8	135		4.6	25.2		0.7	2.3
2018	27.5	105.9		7.5	138.5		4.1	23		0.3	1.1
2019	23.7	93.2		6.4	118.1		3.6	20.3		0.6	1.7
2020	21.7	87.2		6.3	117.3		3.2	18.2		0.3	0.9

Indicator 1.1.3: Exposure of vulnerable populations to heatwaves

Methods

The methodology for this indicator is similar to the methodology described in the 2020 global Lancet Countdown report appendix, but the definition of heatwave in the China report is different from the global report. Besides, in this year's report, we want to build the linkage between heat exposures and socioeconomic vulnerabilities, so we disaggregated heatwave exposures in developed and less-developed counties, and defined people living in less-developed counties as vulnerable populations.

There are over 2800 counties in China, and the average population size and area are around 0.5 million people and 3000 square kilometers respectively. The socioeconomic inequalities within counties are generally small but are large between counties. Therefore, county-level population and income data are widely used in inequality studies in China. And here we define people living in poor counties as vulnerable counties. Less-developed counties are extracted from the official list of China's poor counties in 2014 published by the government. According to the list, there are 832 poor counties in China. Developed counties are all the counties that are not in the list. The county-level averaged and per capita number of heatwave exposure days of the vulnerable and not vulnerable population was calculated at each corresponding grid. Less-developed and developed county-level and country level exposure were computed by averaging over corresponding cell data. The heatwave exposure from 1986 to 2005 was averaged to be the baseline data. For each year from 2000 to 2020, the change in heatwave exposures relative to the baseline was assessed.

Defining heatwave remains a highly controversial topic.[3] An extremely strict heatwave definition (e.g., at least four consecutive days with daily maximum temperature ≥ 99th percentile) may underestimate the heat-related deaths and could not protect the public health efficiently because moderate heatwave (e.g., at least two consecutive days with daily maximum temperature ≥ 90th percentile) may have already caused considerable number of deaths, while a loose heatwave definition may activate the heatwave early warning too early and too frequently, and cause inconvenience to the public and waste health resources.

To determine which heatwave definition could best capture the health impact of heatwave in China, Yang et al. compared the goodness of model fits among 15 heatwave definitions in 31 capital cities of China using the Akaike Information Criterion for quasi-Poisson (QAIC).[4] Finally, they found that heatwave definition as at least 3 consecutive days with daily maximum temperature ≥ 92.5th percentile performed the best model fit at the national scale, as the Q-AIC under this definition was much smaller than others. Therefore, although different from the global definition, we believe this definition is the best and most appropriate one to estimate the health impact of heatwave at the national level for China.

Similar to the previous year, our study only adopted the warm season (i.e., 1 May to 30 September) ambient temperature in heatwaves on population health analyses, because only using the warm season data can effectively remove the confounding effect of cold temperature, and also adjust the effect of moderate hot temperature to avoiding the overestimation of the risk of heatwave.[3, 5]

The gridded 92.5th percentile of daily maximum temperature was calculated for 1986 - 2005 with a resolution of 0.5°. For each year from 2000 to 2020, the number of heatwave events and total days of heatwaves per year was calculated according to the definition.

The 92.5th percentile of daily maximum temperature over the warm season (May 1st to Sep 30th) between 1986 and 2005 was computed as reference baseline, and a heatwave event was defined as a period of three or more days where the daily maximum temperature was higher than the reference baseline at a given grid. The days of heatwave were defined as the number of days within the heatwave event.

Data

1. Climate data was taken from European Centre for Medium-Range Weather Forecasts (ECMWF), ERA5 project.[1]
2. Population data from the hybrid gridded demographic data for the world was taken from Chambers (2020).[2]
3. GDP data was taken from 2000-2020 China Statistical Yearbook[5].
4. Less-developed counties were taken from the list of China's poor counties in 2014[12].

Caveats

This year, we considered vulnerable population based on socioeconomic status. The definition of vulnerable population (living in less-developed provinces) includes all ages, but does not include all vulnerable groups that are in poor health status and so on. As described in the global Lancet Countdown 2020 report, there may be some inconsistencies with the population data due to the use of two distinct data sources.

Future Form of Indicator

Future indicator may define vulnerable population based on socioeconomic status, healthcare accessibility (e.g., number of hospital beds per unit number of people).

Additional Information

Compared with baseline (1986-2005), a county-level average of 3.36 additional heatwave exposure days was recorded in China in the year 2020, slightly less than that of 2019. Heatwave days per person were 3.21, 2.49, and 3.52 for national average, less-developed and developed counties, however, top 30 counties with extremely high heat wave exposure were less-developed. Populations in less-developed counties are at higher risks of heatwave exposures.

Heat and heatwave exposure may be more fatal for people in poor or less-developed areas, attributing to a relative short of healthcare, and a more hostile living environment.[13,14]
This indicator tracks the county-level averaged and per capita number of heatwave days that people exposed in the whole country, as well as in developed and less-developed areas from 2000 to 2020.

Additional county-level averaged heatwave exposures in China in year 2020 decreased from 9.54 to 3.36 days compared to the previous year. However, high heat wave exposure per capita was mainly concentrated in counties of less-developed provinces Yunnan, Hainan and Guangxi in 2020, with the top eight counties being over 58 days. Heatwave exposures may aggravate the social vulnerability of less-developed areas, and amplify the gap between developed and less-developed areas.

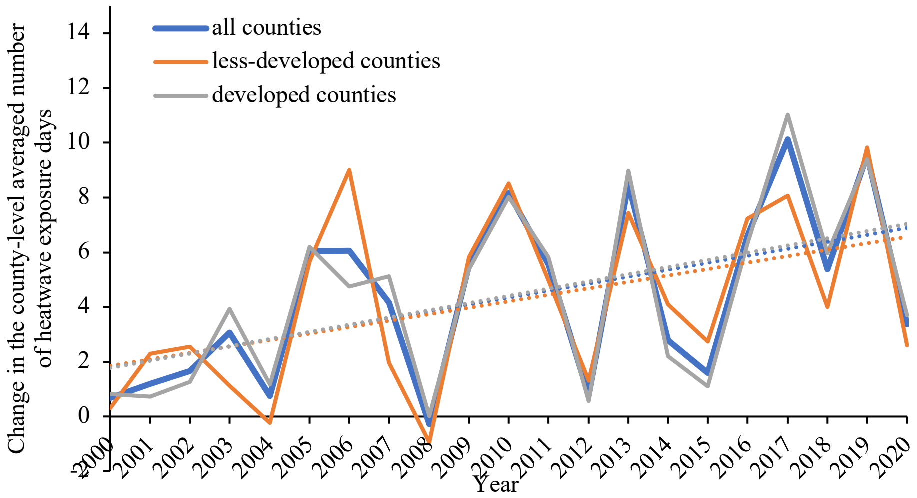

***Figure 3*: Change in the county-level averaged number of heatwave exposure days for people in China, living in developed and less-developed areas from 2000 to 2020, relative to the 1986–2005 average.**

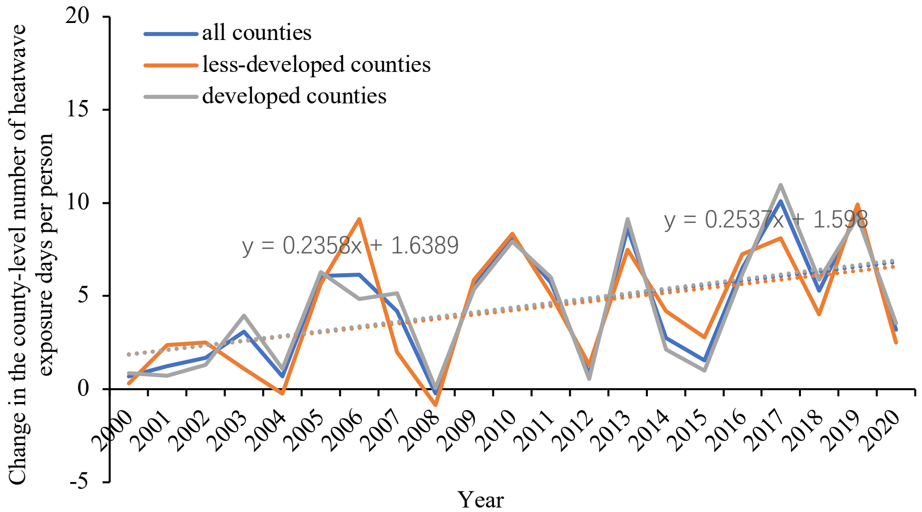

***Figure 4*: Change in the county-level number of heatwave exposure days for each person in China, living in developed and less-developed areas from 2000-2020, relative to the 1986–2005 average.**

Indicator 1.1.4: Health and exposure to warming

Methods

This indicator remains the same to the methodology described in the 2021 global Lancet Countdown report and 2020 China Lancet Countdown report[1]. Monthly averaged summer temperature (June, July and August) was obtained from the ERA5 reanalysis data set and population count data from a hybrid gridded demographic data. Both are gridded data with horizontal grid of 0.5°. Population-weighted temperature and area-weighted temperature were calculated every year from 1986 to 2020 for every province and the entire country. Changes in population-weighted and area-weighted temperatures were calculated every year from 2000 to 2020 with 1986-2005 as the baseline. Area-weighted temperature was calculated by averaging temperature records at every grid inside a province/for the entire country. Population-weighted temperature was calculated in a similar method with weights proportional to population count.

Data

1. Climate data was taken from European Centre for Medium-Range Weather Forecasts (ECMWF), ERA5 project.[11]

2. Population data is from a hybrid gridded demographic data for the world, created by Chambers (2020).[3]

Caveats

The horizontal resolution of temperature data is too coarse to reflect warming trend at local level. Localized temperature data are preferred.

Future Form of Indicator

Future version may consider using localized reanalysis data set, instead of the global reanalysis data set.

Additional Information

The country-wide population-weighted temperature rose by 0.57°C in 2020 compared with the 1986-2005 baseline, with a slight decrease compared to 2016-2019 (***Figure 5***). Province-level changes in annual average population-weighted temperature in 2020 relative to the 1986-2005 average are presented in ***Figure 6***. Regions with profound warming were in South of the Yangtze River and Northeast China, such as Zhejiang, Jiangxi, Hunan, Fujian, Liaoning, and Jilin Province. Although the population density is high in the North and East China, such as Shandong, Henan, Shanxi, and Anhui provinces, they witness less population-weighted temperature rise. The spatial distribution in 2020 was quite different from that in 2019 and 2018, which the northern and eastern regions experienced much higher population-weighted temperature rise than the South China.

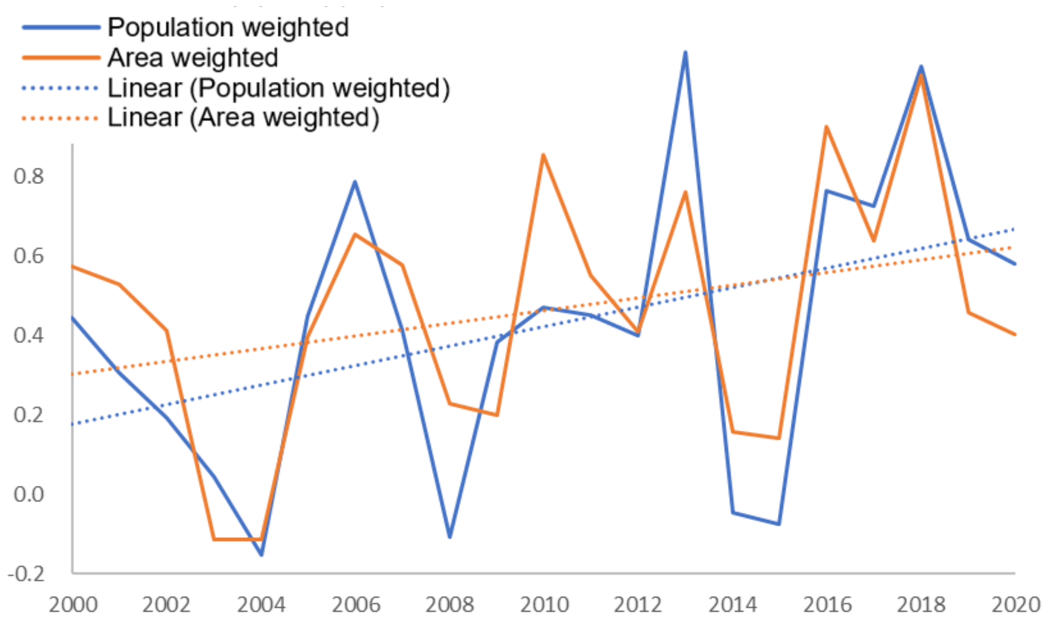

Figure 5: Mean summer warming relative to the 1986–2005 average in China

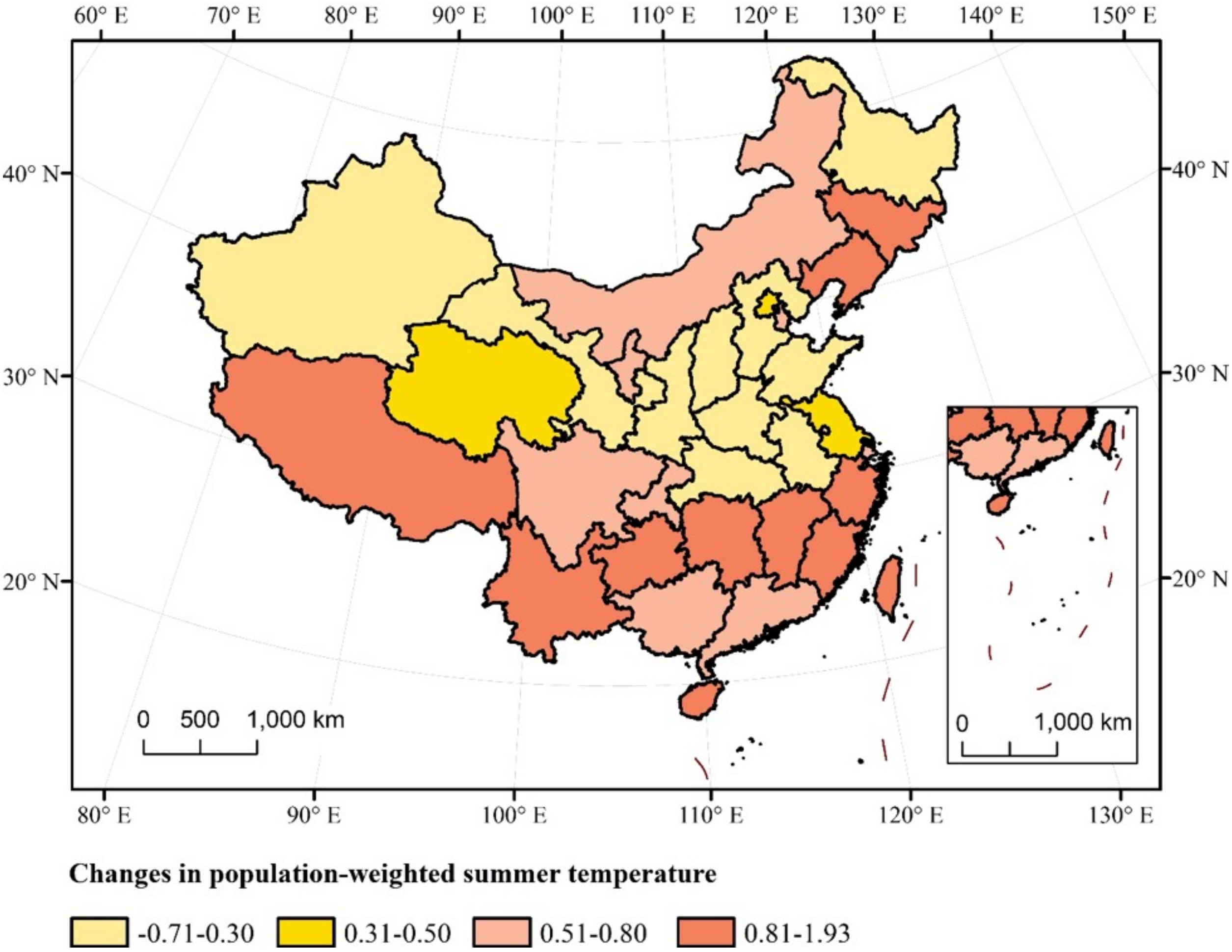

Figure 6: Change in population-weighted summer temperature in 2020, relative to the 1986-2005 average

Indicator 1.1.5: Vulnerability to extremes of heat

Methods

The methodology for this indicator has been improved from the 2020 China Lancet Countdown report appendix [1], which incorporates a new sub-indicator indicates the socio-economic level of population. This indicator displays a heat vulnerability index derived from (1) the proportion of the population over 65 years, (2) the prevalence of chronic disease among population over 65 years, (3) the proportion of the population living in urban areas, (4) the number of air conditioners owned per 100 urban households at year-end, (5) the green covered area as % of built-up area and (6) the per capita gross regional product, using the equation below:

$$HV_i = \frac{(pop65_i + popurban_i + disease_i - AC_i - green_i - GDP_i)}{6}$$

in which, HV_i refers to the heat vulnerability index in province *i*; *$pop65_i$* refers to the proportion of population over 65 years in province *i*; *$popurban_i$* refers to the proportion of the population living in urban areas in province *i*; *$disease_i$* is the chronic disease prevalence among population over 65 years in province *i*; *AC_i* is the air conditioner ownership per

100 urban household in province i; $green_i$ is the percentage of green covered area in province i; GDP_i is the per capita gross regional product in province i. Increased urbanization may exacerbate heat island effect and therefore the health effect of heat [15], while expanding green area and installing air conditioners are treated as adaptation measures of this [16,17]. A higher GDP indicates a better socio-economic development, which can mitigate the adverse health effects to heat [18,19].

The index was normalized to provide ranges between 0 and 100. The higher value of the index, the higher the vulnerability to heat exposure is. The index displays aggregated trends by regions for the period 2000 to 2019. The Cox-Stuart trend test was used to examine the significance of trend with years.

Data

1. The prevalence of chronic disease among population over 65 years was extracted from National Health Service Survey (NHSS) Report published by Statistical Information Center of National Health Commission. (http://www.nhc.gov.cn/mohwsbwstjxxzx/).

2. The other data related to the heat vulnerability index (proportion of the population over 65 years, proportion of the population living in urban areas, air conditioner owned per 100 urban households at year-end, green covered area as % of built-up area (%), the per capita gross regional product) was extracted from China Statistical Yearbook compiled by National Bureau of Statistics from 2001 to 2020.[20]

Caveats

The caveats of this indicator would mainly be in four aspects.

First, the prevalence of chronic disease among population over 65 years is not available at the provincial level. Second, the index does not include the existence of heat early warning systems. Third, a linear regression model was used to handle with the missing value in some sub-indicators, leading to some bias. Fourth, adjustment of survey method used by National Bureau of Statistics during the study period may cause fluctuation of the data to some extent.

Future Form of Indicator

In the future, we would consider including more sub-indicators to better reflect various aspects of vulnerability to heat. E.g., number of beds in medical institutions per 10,000 populations, which could reflect the level of local health services to some extent and be related to the mitigation of the vulnerability to extremes of heat.

Additional Information

The national average vulnerability to extremes of heat basically remained unchanged in 2019 compared to 2018, after a fluctuation due to the interaction of aging population, urbanization and economic development during this period. Northeast China remains the most vulnerable area, followed by Northwest China, Southwest China**.** Vulnerability seems to have reached a plateau in most regions of China since 2015 ***(Figure** 7*). However, vulnerability in South Central China continued to decrease by 3.71% in 2019 compared to 2015, because of the rapid popularization of air conditioners. The vulnerability in most of provinces increased lot since 2000, of which the increases in Guangdong, Heilongjiang, Shanghai, Yunnan and Hebei were above 10% (***Figure 8***).

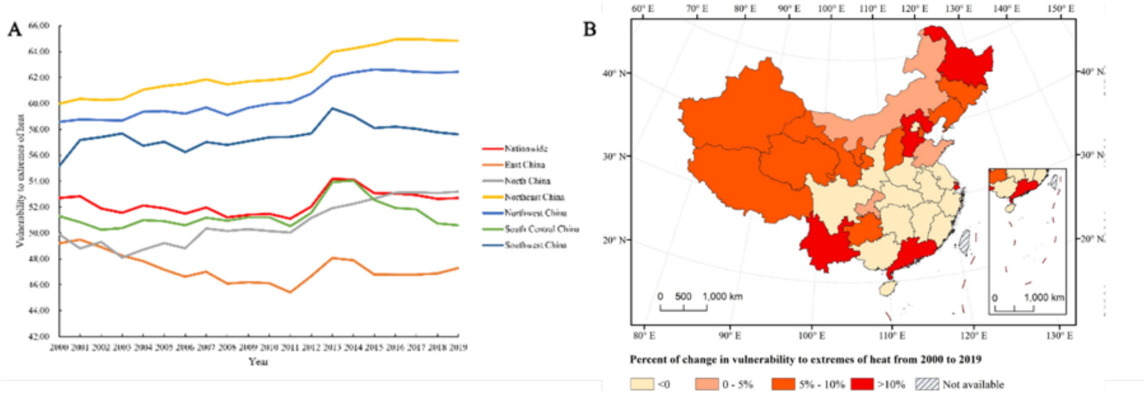

Figure 7: Vulnerability to extremes of heat in China. (A) Trend in different regions from 2000 to 2019. (B) Percent of change in vulnerability to extremes of heat from 2000 to 2019 at province-level

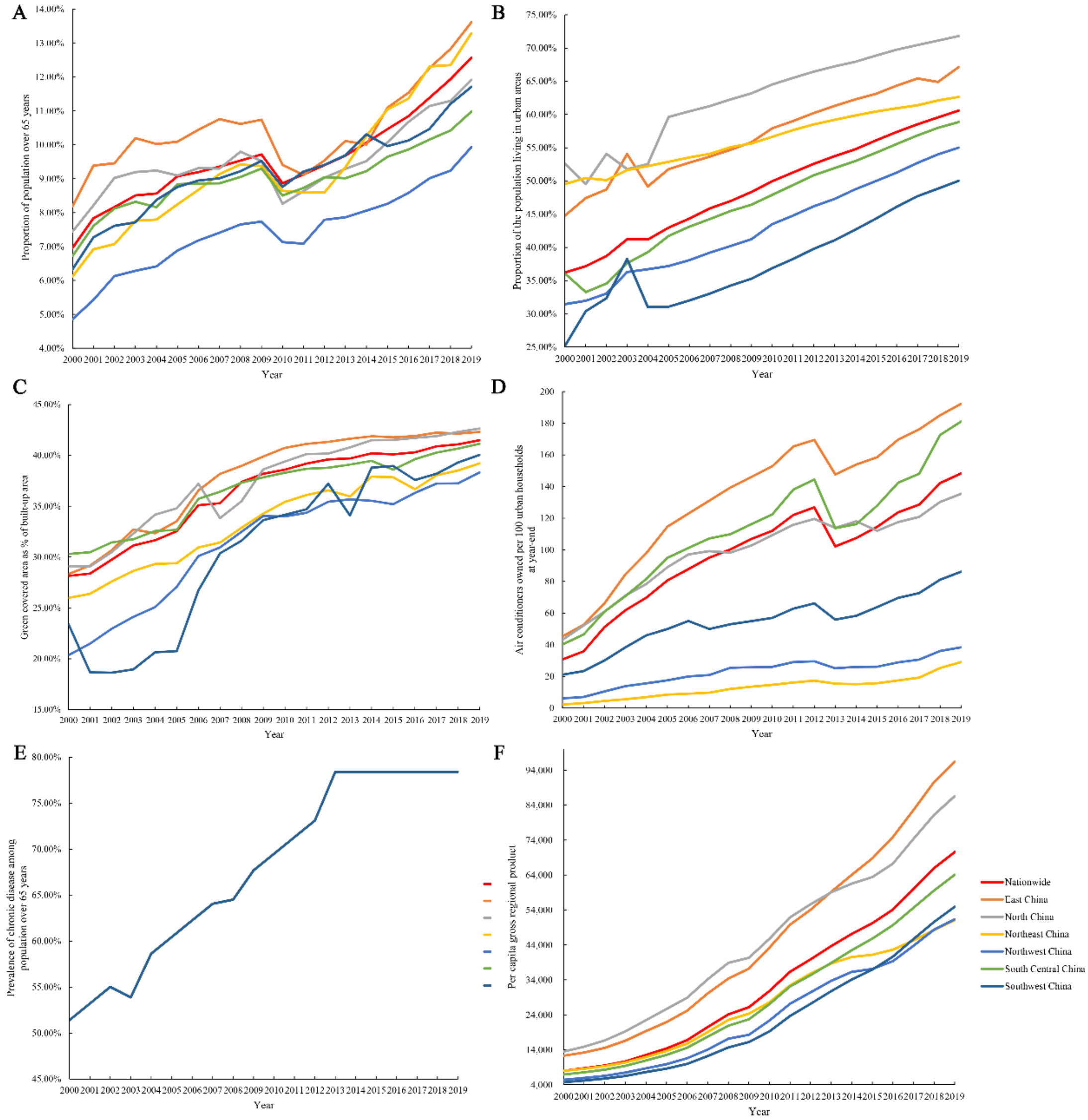

Figure 8: Trend of (A) Proportion of the population over 65 years, (B) Proportion of the population living in urban areas, (C) Green covered area as % of built-up area (%), (D) Air conditioner owned per 100 urban households at year-end, (E) The prevalence of chronic disease among population over 65 years, (F) The per

capita gross regional product in China from 2000 to 2019.
The sudden decline in proportion of population over 65 years around 2011, air conditioner ownership in China around 2013 was due to the change in statistical approach from data source.

Indicator 1.2: Health and extreme weather events

Indicator 1.2.1: Wildfires

Methods

This indicator has been improved from the 2020 China Lancet Countdown report to assess the impacts of wildfires on health from two perspectives: model-based risks (average number of days people that are exposed to very high or extremely high risk of wildfire annually) and satellite-observed exposure (the change in population exposure to wildfires). The methodology we used are the same as the 2020 Global Lancet Countdown report.
Five-year GPW population (2000, 2005, 2010, 2015, and 2020) with a spatial resolution of 0.5' was linearly interpolated for each year from 2001 to 2020, and a copy was re-gridded to 0.25° with conservative methods to align with the spatial resolution of Fire danger index (FDI) data[21]. The Global Artificial Impervious Areas (GAIA) data[22], which tracks the development of impervious areas from 1985-2018 using the full archive of 30-m resolution Landsat images, are reclassified to generate a mask of wildfire surface (impervious area excluded) for population.
The change in model-based risks is represented as the change in the average annual number of days that people are exposed to high fire danger. The detailed method is identical to the 2020 global Lancet Countdown report[10]. **Provided by ECMWF ERA5 atmospheric reanalysis, the model-based risks identify meteorological conditions that would cause flames to spread out of control, which is classified into 6 classes based on the numerical value: very low, low, medium, high, very high and extreme.** The indicator was calculated by:

$$RPD_y = Pop_y \times \sum FR_{d,pixel}$$

Where RPD_y refers to yearly person-days exposed to high fire risk (FDI≥5) in a specified year y, and Pop_y refers to the population from gridded population data in year y. $FR_{d,pixel}$ refers to a high fire risk count located within a population data *pixel* in a unique day d of year y. Fire risk pixels were aggregated yearly from 2001 to 2020 and spatially joined with global population data on 0.25° grids.
Satellite-observed exposure is represented in terms of the average annual number of days people were exposed to active fire. The combustion NASA Near Real-Time MODIS Active Fire Detections Products (MCD14DL) [23]were used as fire point data. The indicator was calculated by:

$$CPD_y = Pop_y \times \sum FP_{d,pixel}$$

Where CPD_y refers to person-days exposed to wildfire in a specified year y, and Pop_y refers to the population from gridded population data in a specified year y. $FP_{d,pixel}$ refers to a fire point count located within a population data pixel in a unique day d of year y. Active fire pixels were aggregated yearly from 2001 to 2020 and spatially joined with global population data on 0.25° grids.

Data

1. Fire danger indices (FDI) data from Copernicus Emergency Management Service for the European Forest Fire Information System (EFFIS).[21]
2. NASA Near Real-Time MODIS Active Fire Detections Products (MCD14DL) from 2001 to 2019 were used as fire point data, this contains both Terra (from November 2000) and Aqua (from July 2002) pixels in the same annual file.[23]

3. Population data from NASA Socioeconomic Data and Applications Center (SEDAC) Gridded Population of the World (GPWv4.11).
4. Annual maps of global artificial impervious area (GAIA) between 1985 and 2018, as urban-area population mask.[22]
5. China Boundary data, in CGCS_2000 geographic coordinate system, from National Geomatics Center of China (http://www.ngcc.cn/ngcc/).
6. The definition of 6 classes of wildfire risks are obtained through the fire danger forecast module of EFFIS (https://effis.jrc.ec.europa.eu/about-effis/technical-background/fire-danger-forecast).

Caveats

Due to limited observational capabilities, this indicator doesn't explicitly quantify and model the human exposure to wildfire smoke, which is associated with respiratory morbidity and with growing evidence supporting an association with all-cause mortality.[24]

Additionally, FDI data couldn't capture all the changes of the summer monsoon and fire season temperature in China under the context of climate change.

Future Form of Indicator

Sub-province (city-level) estimates will be reported to better represent the populations at risk.

Additional Information

Overall, the model-based-risks were decreasing slightly over the past two decades and the fluctuations are very little. Our modeling results are only affected by two types of the factors: wind speed and soil moisture which affect fire speed, and vegetation abundance which provide fuel for fire burning. Therefore, the slight decrease of model-based risks cannot be attribute to adaptation improvement or climate change.

On the contrary, the satellite-observed exposures were rising partially due to warming climate. In the areas where the exposures were risking, the population did not show a significant downward trend and the increase was due to an increase in fire spots. We checked with the departments of forestry, and the data provided affirmed that the number of wildfires increased. Through literature review, we concluded that three factors contribute to the wildfire exposure increase. First, the warming climate has led to an increase in wildfire season temperature, which is positively correlated with the frequency of fires in northern and western China. Second, the frequency of fires has increased due to the shortening of the summer rainy season in the monsoon climate. Third, the long-term policy of fighting all forest fires has led to a large accumulation of flammable combustible material in some areas of the forest, which is prone to high intensity fires and large fires. Fires in the Daxing'anling forest area have a long average burn time and are more likely to burn over a large area.

We recommend that the alternative fuel-reduction treatments before fire season would be an ideal way to reduce the potential fire exposure damage.

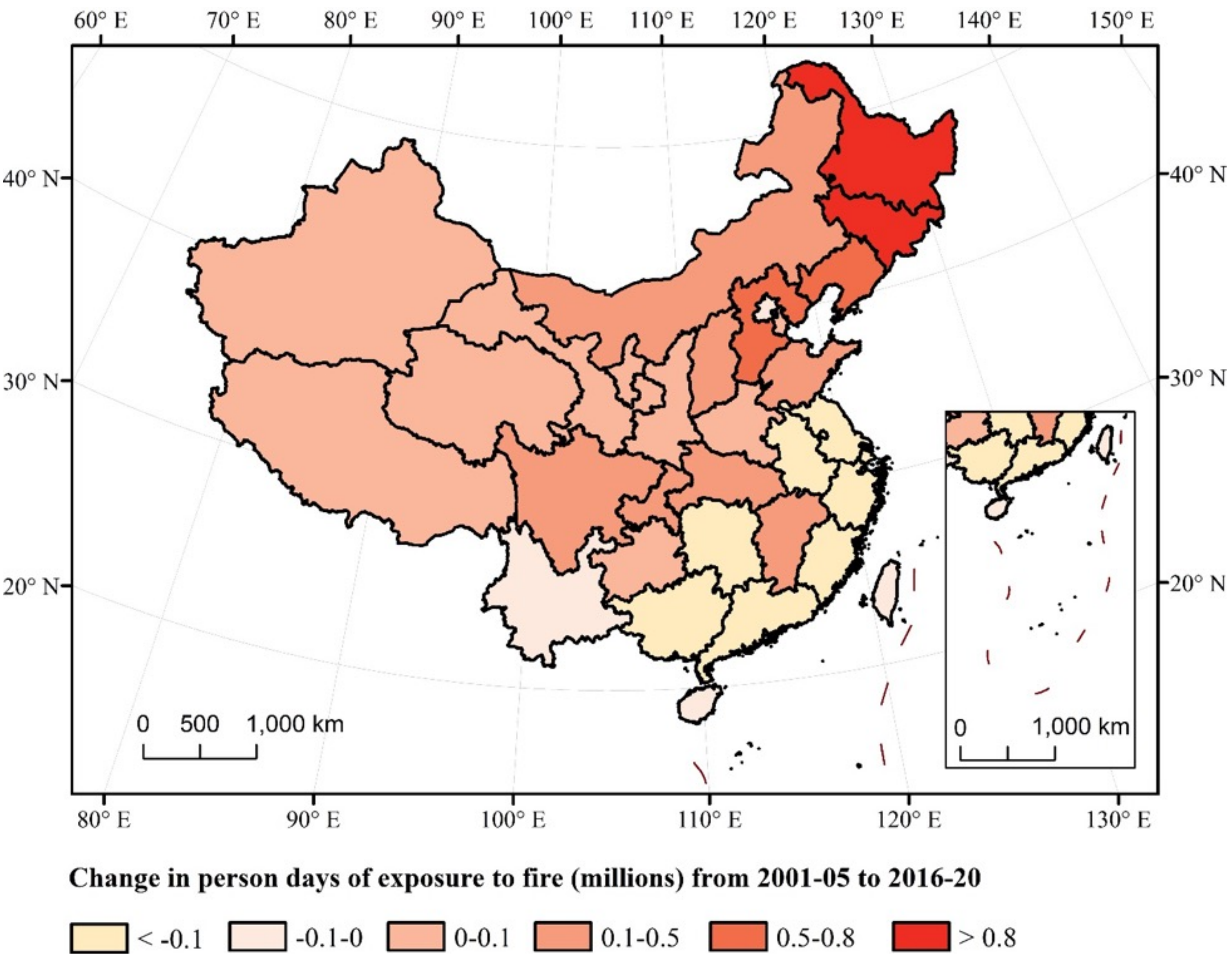

Figure 9**: Change in satellite-observed exposure to wildfires across China from 2001-2005 to 2016-2020.**

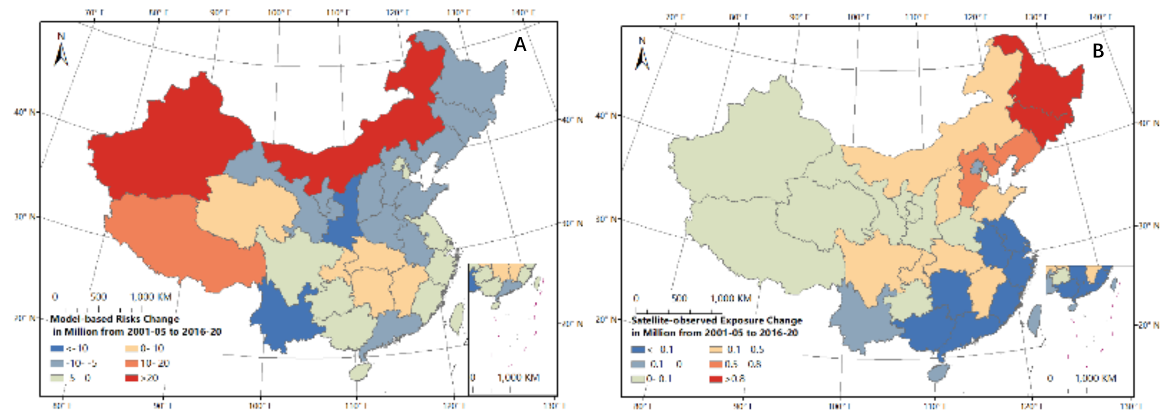

Figure 10**: Model-based risks (A), satellite-observed exposure (B) change in provinces from 2001-04 to 2016-19**

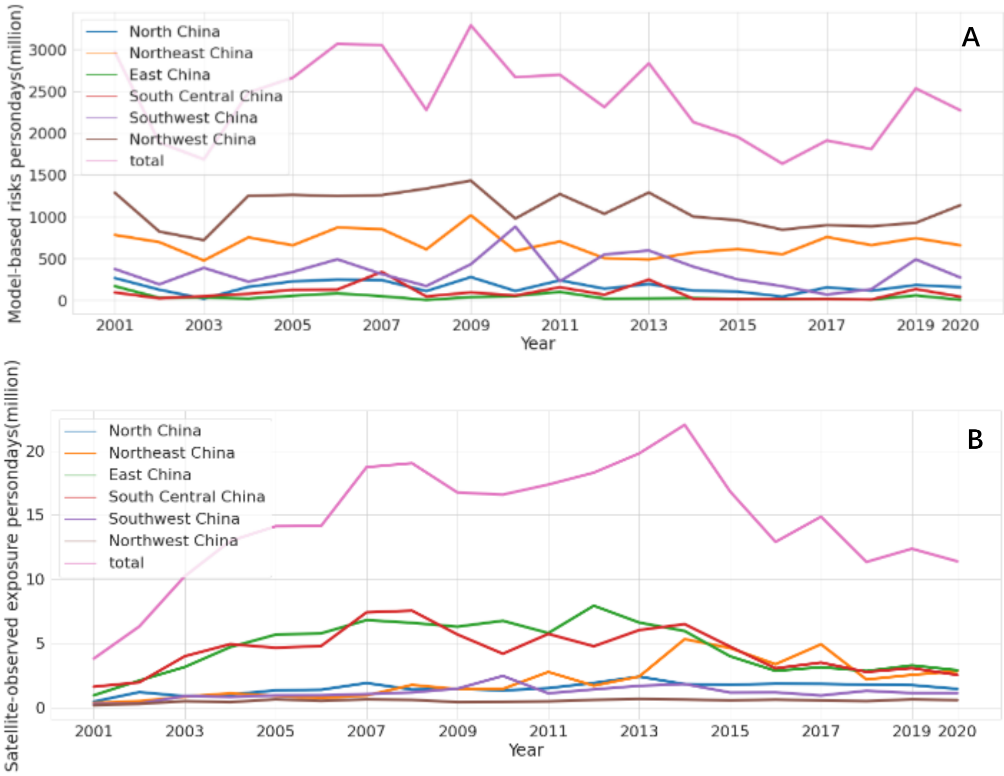

Figure 11: **National and regional trend in model-based risks (A), satellite-observed exposure(B).**

Indicator 1.2.2: Flood and drought

Methods

The methodology for this indicator has been improved from the 2020 China Lancet Countdown report appendix by replacing the frequency and intensity-focused EM-DAT international disaster database to damage-focused Yearbook of Meteorological Disasters in China. Damage data on flood and drought is taken from Yearbook of Meteorological Disasters in China, which has been published since 2004 by China Meteorological Press. The time scale of the damage data is from 2004 to 2018. The intensity and frequencies of flood and drought were available in last year's China Lancet Countdown report[1]. Compared to the reference period (1980-1999), the number of flood disasters has increased significantly from 2000 to 2019, while there was no significant change in the number of drought in 2000-2019, with no severe drought between 2018 and 2019.

In Yearbook of Meteorological Disasters in China, flood refers to the local or regional rainstorm, which leads to flood, debris flow, landslide and other geological disasters, causing affected agricultural area of more than 50,000 hectares, or deaths toll of more than 10 people, or a direct economic loss of more than 100 million yuan. Drought is defined as a kind of meteorological disaster that the precipitation is obviously less than that in the same period of the year due to less or no rain in a period. In this context, drought lasting for more than 20 days in a province or an area of more than 50,000 square kilometers, causing more than 100,000 hectares of the agricultural affected area, or making it difficult for more than 100,000 people to use domestic water or production water, is recorded. The definitions and criteria of flood and drought in EM-DAT database used in last year's report and Yearbook of Meteorological Disasters in China used in this year's report were summarized in Table 5.

Table 5 The definition and criteria of flood and drought in EM-DAT database and Yearbook of Meteorological Disasters in China

EM-DAT	Yearbook of Meteorological Disasters in China
· Flood: Flood is defined as hydrological flood, including riverine flood (the overflow of water from a stream channel onto normally dry land in the floodplain), coastal flood (higher-than-normal levels along the coast and in lakes or reservoirs) and flash flood (ponding of water at or near the point where the rain fell). · Drought: Drought refers to climatological drought, which is an extended period of unusually low precipitation that produces a shortage of water for people, animals and plants. At least one of the following criteria must be fulfilled in order for an event to be entered into the database: (1) 10 or more people deaths; (2) 100 or more people affected/injured/homeless; (3) Declaration by the country of a state of emergency and/or an appeal for international assistance.	· Flood: A local or regional rainstorm process occurs in an area, causing floods or other geological disasters such as mudslides and landslides. And at least one of the following criteria must be fulfilled: (1) 50,000 hectares or more of agricultural area affected; (2) 10 or more people deaths; (3) Direct economic losses of 100 million yuan or more. · Drought: A drought event lasting more than 20 days in a province or an area of at least 50,000 km^2. And at least one of the following criteria must be fulfilled: (1) 100,000 hectares or more of agricultural area affected; (2) 100,000 or more people have difficulty in water for living and production.

We track the number of people affected by flood and drought at both the national and provincial levels as the main indices. Moreover, the population killed by flood and the population difficulty in drinking water by drought are also counted. Hence, the cluster of vulnerable areas and provinces could be identified. The Mann-Kendall trend test is used to explore the potential time trend of these indices. Only statistically significant (at 0.05 significance level) linear trends over time are shown in the figures.

Data

1. Affected data in China (excluding Hong Kong, Macao and Taiwan) are from Yearbook of Meteorological Disaster in China (2004-2019) published by China Meteorological Press.[25]

Caveats

First, due to the two-year lag of Yearbook of Meteorological Disasters in China, we are unable to obtain and analyze the latest data after 2018.

Second, this measure ignores the longer causal chains involving the interactions of weather, climate, disasters, health and health services.

Finally, the data on the population exposed to natural disasters was not available, which may be another important indicator.

Future form of indicator

Future efforts will include a comparison of estimates of those exposed with those affected. Additionally, it will also explore the impact of replacing the number of people killed with the number requiring assistance.

Additional information

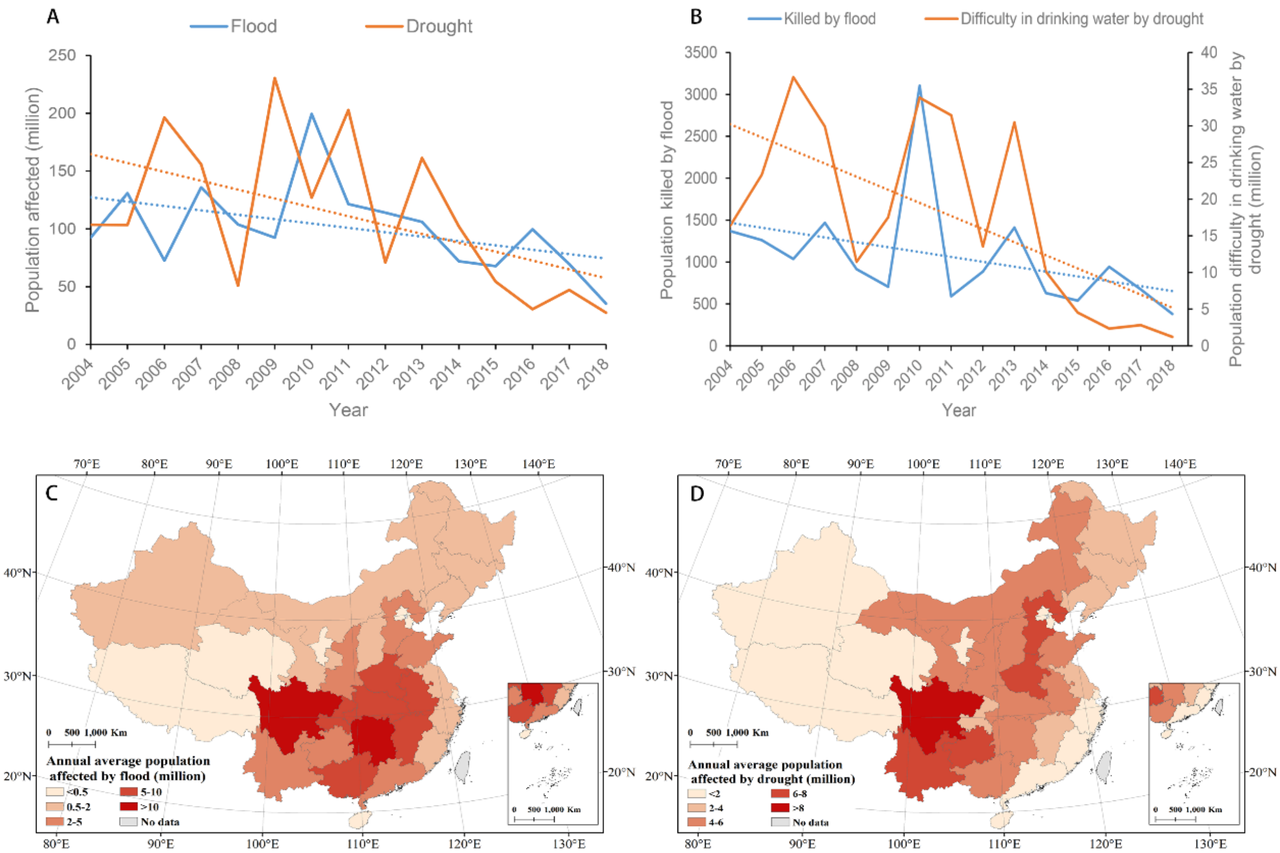

Figure 12: **Health damage caused by floods and droughts**

(A) Trend of population affected by floods and droughts (2004-2018). (B) Trend of population killed by floods and difficulty in drinking water due to droughts. (C) Annual average population affected by floods from 2004 to 2018 by province. (D) Annual average population affected by droughts from 2004 to 2018 by province.

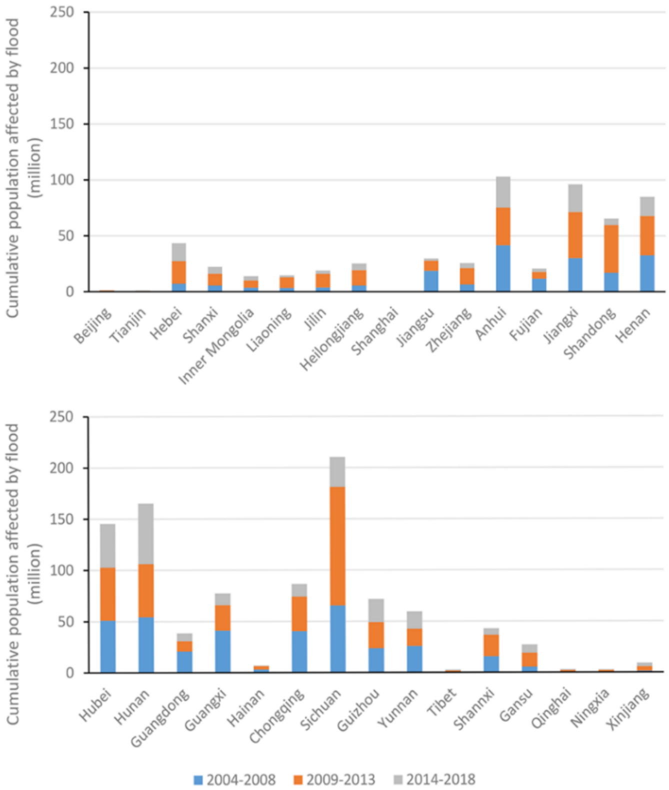

***Figure 13*: Cumulative population affected by flood in provinces of China, from 2004 to 2018.**

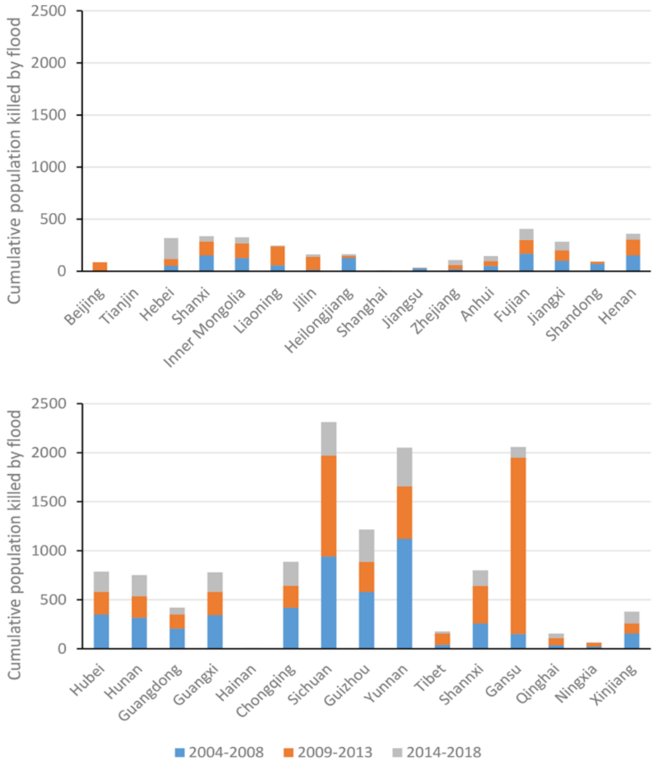

***Figure 14*: Cumulative population killed by flood in provinces of China, from 2004 to 2018.**

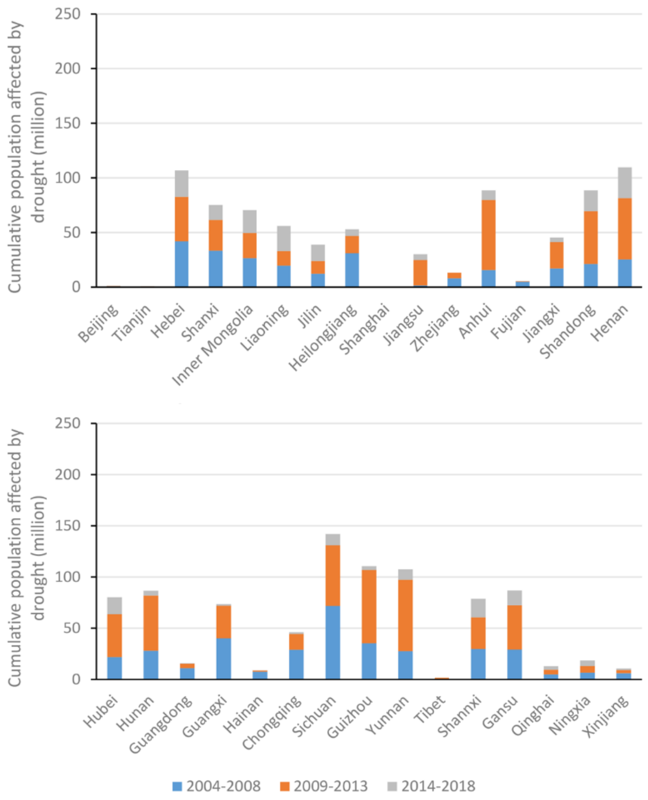

***Figure 15*: Cumulative population affected by drought in provinces of China, from 2004 to 2018.**

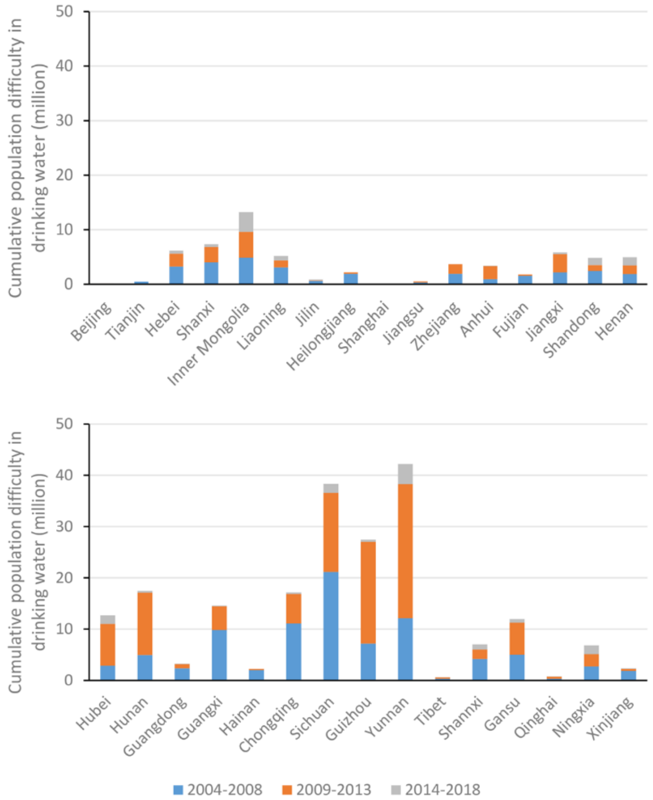

***Figure 16*: Cumulative population difficulty in drinking water in provinces of China, from 2004 to 2018.**

Table 6: **National damages caused by flood and drought.**

Year	Affected by flood (million)	Killed by flood	Affected by drought (million)	Difficulty in drinking water (million)
2004	92.451	1370	103.679	16.359
2005	130.858	1260	103.420	23.336
2006	72.608	1036	196.285	36.648
2007	135.826	1467	155.754	29.904
2008	103.724	915	50.824	11.458
2009	92.457	704	230.386	17.506
2010	199.354	3104	127.042	33.842
2011	121.378	591	202.710	31.451
2012	113.924	887	70.843	13.563
2013	105.885	1411	161.158	30.468
2014	72.001	631	101.947	10.125
2015	67.775	540	54.365	4.542
2016	99.549	942	30.572	2.346
2017	69.512	674	47.170	2.812
2018	35.262	380	27.427	1.217

Table 7: **Cumulative population affected by flood (million) in provinces of China, from 2004 to 2018.**

Province	2004-2008	2009-2013	2014-2018	Total
Beijing	0.097	1.002	0.259	1.358
Tianjin	0.053	0.640	0.144	0.837
Hebei	7.083	20.283	15.880	43.246
Shanxi	5.389	10.734	6.139	22.262
Inner Mongolia	3.398	6.624	3.712	13.734
Liaoning	3.208	9.431	1.857	14.496
Jilin	3.618	12.291	2.857	18.766
Heilongjiang	5.481	13.719	5.884	25.084
Shanghai	0.049	0.094	0.017	0.160
Jiangsu	18.549	9.048	2.070	29.667
Zhejiang	6.490	14.495	4.544	25.529
Anhui	41.455	33.611	27.811	102.877
Fujian	11.606	6.044	2.936	20.586
Jiangxi	29.993	41.182	24.730	95.905
Shandong	16.919	42.703	5.674	65.296
Henan	32.457	35.150	17.115	84.722
Hubei	51.029	51.721	42.652	145.402
Hunan	54.336	51.707	59.032	165.075
Guangdong	20.748	10.005	7.684	38.437
Guangxi	41.171	24.842	11.373	77.386
Hainan	2.934	3.612	0.431	6.977

Chongqing	40.313	33.884	12.218	86.415
Sichuan	65.523	115.688	29.195	210.406
Guizhou	23.561	25.489	22.713	71.763
Yunnan	25.772	16.748	16.925	59.445
Tibet	0.740	0.906	0.852	2.498
Shannxi	15.503	21.071	6.312	42.886
Gansu	5.380	13.612	8.080	27.072
Qinghai	0.687	1.147	0.954	2.788
Ningxia	0.651	1.265	0.582	2.498
Xinjiang	1.276	4.243	3.467	8.986

***Table 8*: Cumulative population affected by drought (million) in provinces of China, from 2004 to 2018.**

Province	2004-2008	2009-2013	2014-2018	Total
Beijing	0.803	0.146	0.190	1.139
Tianjin	0.652	0.013	0	0.665
Hebei	41.948	40.710	24.292	106.950
Shanxi	33.341	28.092	13.813	75.246
Inner Mongolia	26.538	23.027	20.854	70.419
Liaoning	19.643	13.312	22.927	55.882
Jilin	12.224	11.730	14.814	38.768
Heilongjiang	30.919	15.921	6.126	52.966
Shanghai	0	0	0	0
Jiangsu	1.458	23.360	5.270	30.088
Zhejiang	8.093	5.084	0	13.177
Anhui	15.672	64.023	8.691	88.386
Fujian	4.898	0.500	0.143	5.541
Jiangxi	17.038	24.153	4.039	45.230
Shandong	21.184	48.184	19.192	88.560
Henan	25.354	55.952	28.319	109.625
Hubei	21.949	41.732	16.508	80.189
Hunan	28.090	53.868	4.746	86.704
Guangdong	11.149	4.145	0.479	15.773
Guangxi	40.278	31.762	1.479	73.519
Hainan	7.738	0.895	0.112	8.745
Chongqing	28.998	15.550	1.666	46.214
Sichuan	71.754	59.306	10.915	141.975
Guizhou	35.369	71.478	3.678	110.525
Yunnan	27.719	69.445	10.482	107.646
Tibet	0.617	1.022	0.149	1.788
Shannxi	29.725	30.989	17.932	78.646
Gansu	29.258	43.170	14.431	86.859
Qinghai	4.902	4.759	3.394	13.055

Ningxia	6.546	6.784	5.247	18.577
Xinjiang	6.106	3.027	1.593	10.726

Indicator 1.2.3: Cyclones

Methods

This indicator has been improved from four aspects. First, the 2020 China Lancet Countdown report only provided the landing information of Tropical Cyclones (TCs), and did not consider the tracks and the scopes of the impacts after landing. In this year's report, the buffer analysis were used to simulate the affect areas of TCs. Second, we evaluate the impacts of TCs at city levels this year. Third, compared with the occurrences of TCs in the 2020 China Lancet Countdown report, we used a TC Affected Index to provide the exposure density information, which is better to show the intensity of exposure at certain area. Finally, based on the buffer analysis evaluating the affected areas, the population exposed to TCs were calculated at provincial levels.

In this indicator, data that indicate exposure and impacts dimensions from two databases were used to estimate the effects of tropical cyclones (TC) in China. Based on maximum average wind speeds near the bottom center of TC given by China Meteorological Administration (CMA), 6 different grades could be included in the dataset: (1) tropical depression(10.8-17.1m/s); (2) tropical storm(17.2-24.4m/s); (3) severe tropical storm(24.5-32.6m/s); (4) typhoon(32.7-41.4m/s); (5) severe typhoon(41.5-50.9m/s); (6) super typhoon(≥51m/s). Exposure data from 1981 to 2016 are from the satellite retrieve TC sizes provided by CMA Tropical Cyclone Data Centre, given the information on center location, intensity, size, and extent of the destructive winds[26]. For impact dimension caused by TC, a hybrid gridded dataset of demographic data for the world from1981 to 2016, given as 5-year population bands at a 0.5-degree grid resolution, was used to calculate the exposed population in China.[6]

The wind forces up to Beaufort scale forces 7(13.9-17.1m/s) are defined as exposed regions. Buffer analysis were used to calculate the exposure areas of TC. The annual *TC Affected Index*, showing hotspot of TC on the spatial-temporal distribution, which contains both occurrences and exposed area information, was used to represent the city-level-exposure, and were calculated as follows:

$$\text{TC Affected Index } = \frac{The\ cumulative\ areas\ of\ TC\ exposure\ at\ city\ level}{The\ total\ areas\ of\ the\ city} \times 100\%$$

Based on the buffer analysis, using the grid raster dataset, the annual exposed population at provincial level was summed. Considering the sensitivity to TC, children less than 15 years old and adults aged over 65 were defined as the vulnerable population.

The *student t*-test is used to compare the difference between the *TC Affected Index* from 2000 to 2016 and the baseline of the reference period (1981-1999) when the data satisfy the normality test, otherwise, the *Mann-Whitney U* test would be used[27]. With this method, the exposed and vulnerable population changes could also be identified by comparing with the baseline on temporal scales.

Data

1. Exposure data, by estimating tropical cyclone size in the northwestern Pacific from geostationary satellite infrared images, from 1981 to 2016 are from the CMA Tropical Cyclone Database provided by CMA Tropical Cyclone Data Centre[26]. (http://tcdata.typhoon.org.cn/tcsize.html)
2. Exposed and vulnerable population data affected by TC in China origin from Hybrid gridded demographic data for the world, 1981-2016[28]. (https://zenodo.org/record/3768003)

Caveats

The caveats of this indicator would mainly be in two aspects.
1. The buffer analysis was based on the tracks of TC given per 6 hours, using rough radii of TC, not show the wind rose map, which provided multi wind directions and more precise radii information, probably leading to underestimating the exposure and impacts of TC.
2. The spatial relationships and clusters of TC exposures and the impacts are not included.

Future form of indicator

1. The finer and more precise data on spatial-temporal resolution of TC sizes will be used.
2. The spatial and cluster analysis would be used to identify the hotspot and spatial point patterns of TC exposures and impacts on human health.

Additional Information

Located at the northwestern Pacific, the hotspots of tropical cyclones (TC) genesis, China suffers a lot from the impacts of TC. Compared with the baseline (1981–1999), the tracks of TC have been moving northwards[26,29-32]. In previous years, Guangdong and Hainan were considered as the most affected provinces. While in recent years, the affected areas and intensities in Fujian are increasing, but decreasing in Guangdong and Hainan. The population exposed in these provinces have significantly increased. (***Figure 17***). According to media reports, in 2020, the northeast China were suffered three TCs hits in a half month[33,34], which is rarely seen in history.

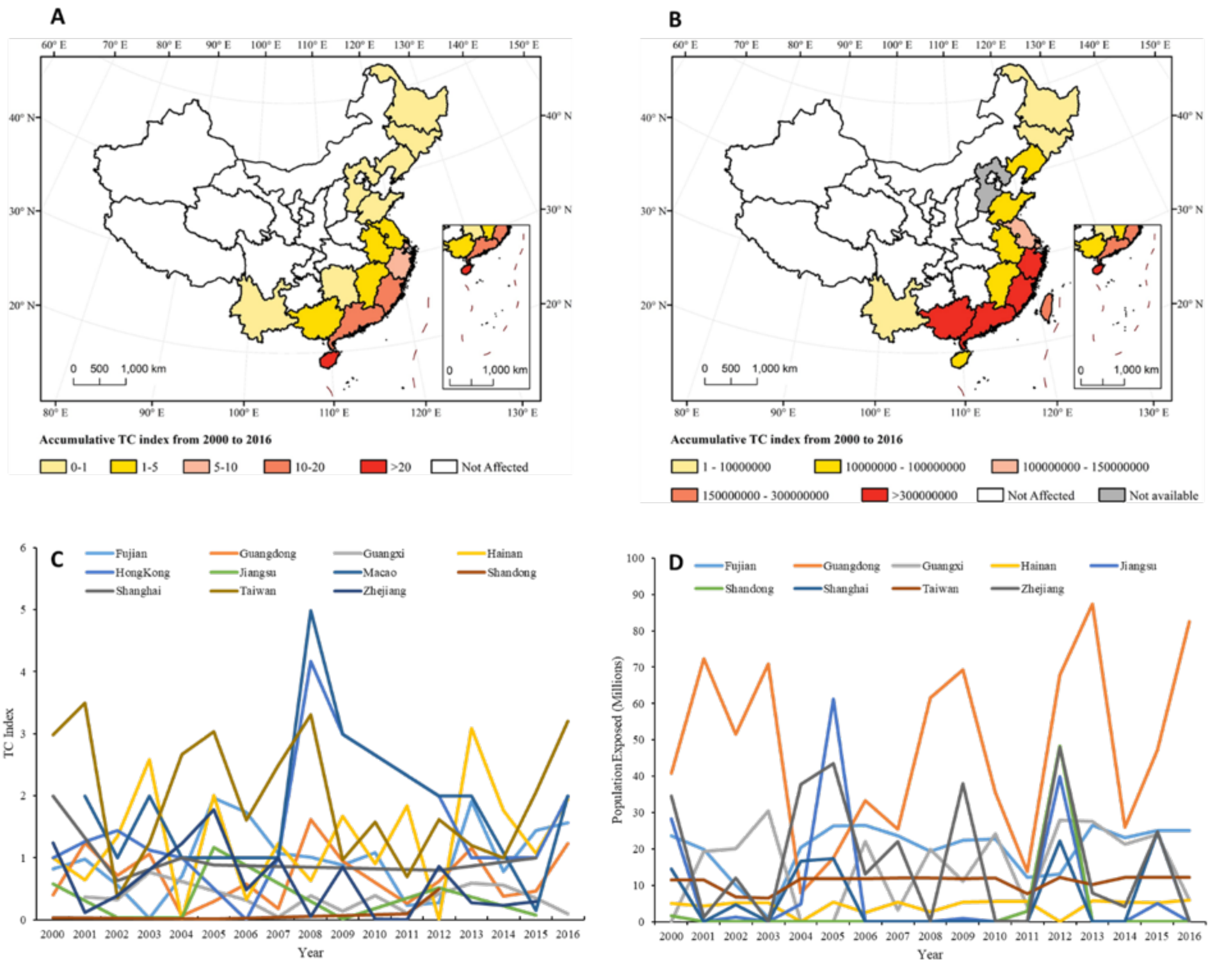

Figure 17: **The spatiotemporal distribution of the exposure and impacts on tropical cyclone (A) Accumulative TC Index from 2000 to 2016. (B) Accumulative TC Exposed Population from 2000 to 2016. (C) TC Index in Main Costal Provinces from 2000 to 2016. (D) TC Exposed Population in Main Costal Provinces from 2000 to 2016.**

Cities such as Fuzhou, Putian, Quanzhou and Xiamen are more vulnerable in Mainland China, compared with baseline, TC affected index for these cities are significantly increased. *Mean TC Index Changes* and *Mean TC Exposed Area Changes* were calculated as follow:

$$\begin{aligned}&\boldsymbol{Mean\ TC\ Index\ Changes}\\&\quad = \boldsymbol{Mean\ TC\ Index\ from\ 2000\ to\ 2016 - Mean\ TC\ Index\ from\ 1981\ to\ 1999}\end{aligned}$$

$$\begin{aligned}&\boldsymbol{Mean\ TC\ Exposed\ Area\ Change}\\&\quad = \boldsymbol{Mean\ TC\ Exposed\ Area\ from\ 2000\ to\ 2016}\\&\quad - \boldsymbol{Mean\ TC\ Exposed\ Area\ from\ 1981\ to\ 1999}\end{aligned}$$

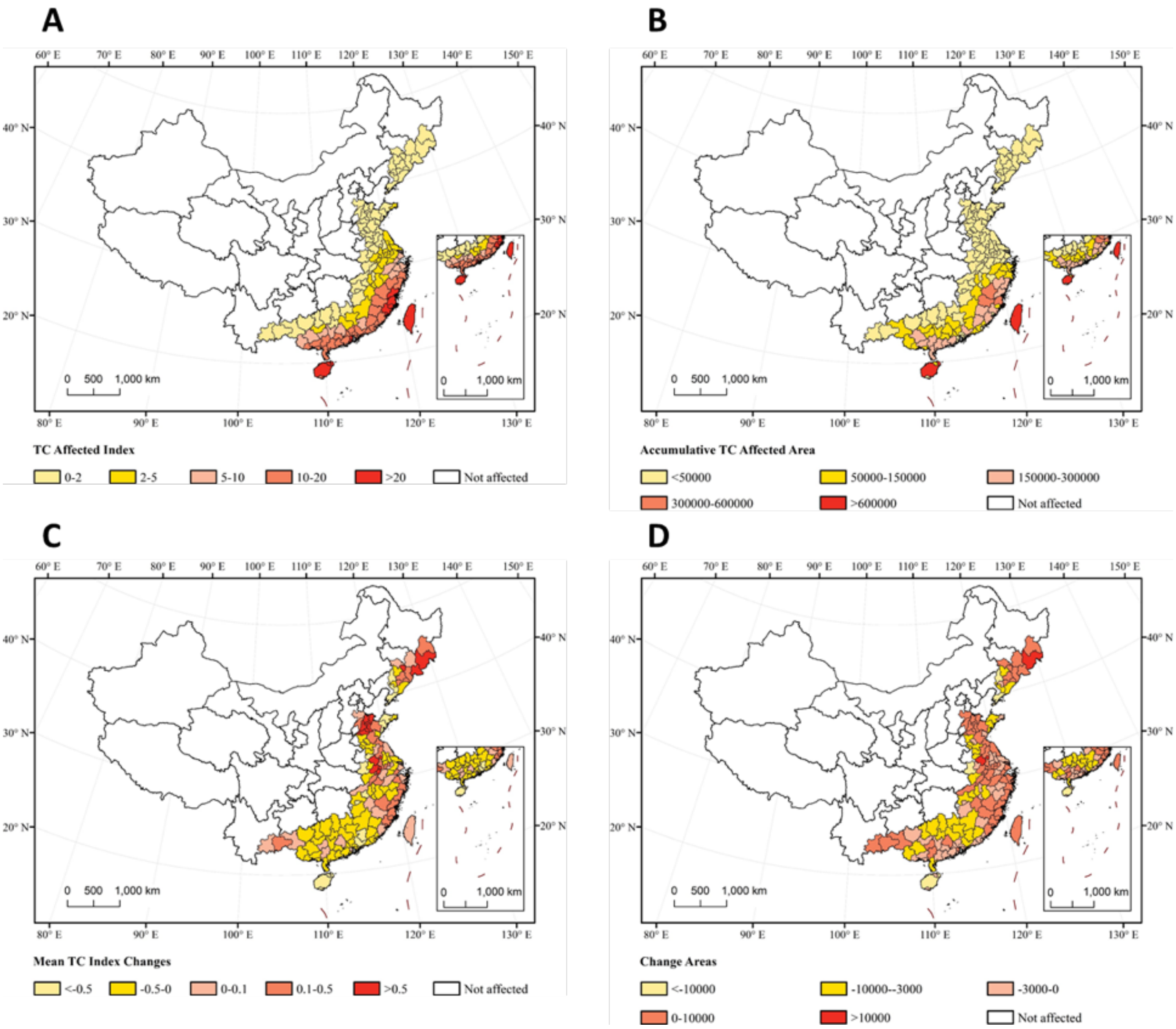

***Figure 18*: The spatial distribution of the exposure and impacts on tropical cyclone at city level (A) Accumulative TC Index from 2000 to 2016 at city level. (B) Accumulative TC Affected Areas from 2000 to 2016. (C) Mean TC Index Changes Compared with Baseline (compared between mean TC Index from 1981 to 1999 and this Index from 2000 to 2016). (D) Mean TC Exposed Area Changes Compared with Baseline.**

Table 9 Accumulative TC Exposure Information from 2000 to 2016 at City Levels

NO	Name	TC_Affected_Area(km^2)	TC_Index
1	Cangzhou	22.6761	0.0016
2	Shenyang	35.9360	0.0028
3	Dalian	3026.0879	0.2368
4	Anshan	4757.9647	0.5185
5	Fushun	15683.7604	1.3941
6	Benxi	14152.0759	1.6769
7	Dandong	26062.2429	1.7786
8	Liaoyang	2418.8616	0.5181
9	Tieling	3889.2823	0.3002
10	Jilin	2371.2121	0.0864
11	Siping	15.4769	0.0011
12	Liaoyuan	4026.3487	0.7817
13	Tonghua	19510.8732	1.2565
14	Baishan	20393.0166	1.1710
15	Yanbian	27117.1510	0.6259
16	Mudanjiang	4851.3170	0.1259
17	Shanghai	39568.2757	6.3213
18	Nanjing	15900.2727	2.4111
19	Wuxi	16535.9953	3.5584
20	Xuzhou	4690.3814	0.4173
21	Changzhou	13079.5490	3.0053
22	Suzhou	41722.1945	4.9261
23	Nantong	32094.7374	3.7420
24	Lianyungang	14716.0598	1.9873
25	Huaian	18023.0714	1.8029
26	Yancheng	39194.7576	2.6276
27	Yangzhou	12696.9392	1.9199
28	Zhenjiang	8410.1762	2.1983
29	Taizhou	14971.1125	2.5863
30	Suqian	13171.0069	1.5348
31	Hangzhou	94964.6338	5.6433
32	Ningbo	77895.5300	9.0923
33	Wenzhou	166679.2902	14.6844
34	Jiaxing	28825.4143	7.1782
35	Huzhou	26801.0059	4.6030
36	Shaoxing	70010.8373	8.7347
37	Jinhua	89667.8621	8.1999
38	Quzhou	43184.3117	4.8758
39	Zhoushan	9629.8094	7.8627
40	Taizhou	109168.5399	11.6748
41	Lishui	183356.8959	10.6408

42	Hefei	5836.3839	0.8302
43	Wuhu	9704.3847	2.8917
44	Bengbu	649.0226	0.1089
45	Maanshan	5197.3287	2.9980
46	Tongling	2184.3625	2.1066
47	Anqing	3527.4119	0.2287
48	Huangshan	34265.8791	3.4968
49	Chuzhou	22176.8394	1.6450
50	Suzhou	403.3274	0.0406
51	Chaohu	20939.1417	2.2186
52	Luan	257.9249	0.0140
53	Chizhou	15642.0962	1.8452
54	Xuancheng	43827.6126	3.5825
55	Fuzhou	302156.1999	26.3233
56	Xiamen	34386.3723	22.0938
57	Butian	92778.6391	24.6972
58	Sanming	315662.8462	13.6911
59	Quanzhou	252741.3678	23.1016
60	Zhangzhou	247778.6871	19.7684
61	Nanping	331301.5559	12.5750
62	Longyan	230824.4424	12.0683
63	Ningde	269537.0547	20.6281
64	Nanchang	902.4995	0.1218
65	Jingdezhen	5323.9751	1.0103
66	Jiujiang	3034.7671	0.1610
67	Xinyu	617.1161	0.1927
68	Yingtan	9883.6352	2.8013
69	Ganzhou	142327.8881	3.6034
70	Jian	23452.3561	0.9251
71	Yichun	467.9414	0.0250
72	Fuzhou	80917.3893	4.2849
73	Shangrao	60745.3041	2.6618
74	Jinan	6853.6318	0.8524
75	Qingdao	1944.4116	0.1795
76	Zibo	6028.2289	1.0004
77	Zaozhuang	2555.2676	0.5625
78	Dongying	3607.7898	0.5288
79	Yantai	7111.8378	0.5261
80	Weifang	11328.6208	0.7206
81	Jining	3122.5640	0.2802
82	Taian	5022.0882	0.6538
83	Weihai	13503.3942	2.4838
84	Rizhao	6220.2088	1.1834

85	Laiwu	2187.5567	1.0003
86	Linyi	18470.2332	1.0761
87	Dezhou	4277.9505	0.4153
88	Binzhou	7419.2444	0.8620
89	Chenzhou	285.4044	0.0147
90	Yongzhou	1041.2693	0.0465
91	Guangzhou	89353.2773	12.4126
92	Shaoguan	45475.8182	2.4651
93	Shenzhen	33344.8483	17.8484
94	Zhuhai	31669.5134	20.8018
95	Shantou	37857.2868	17.9135
96	Foshan	52996.2766	13.7331
97	Jiangmen	183067.3387	19.5092
98	Zhanjiang	242990.2021	19.8692
99	Maoming	191597.6219	16.8238
100	Zhaoqing	120312.4521	8.0615
101	Huizhou	153383.7104	13.5406
102	Meizhou	166906.4198	10.5373
103	Shanwei	74635.0572	15.4996
104	Heyuan	139338.6048	8.9010
105	Yangjiang	151149.0561	19.3651
106	Qingyuan	73144.2396	3.8564
107	Dongguan	38954.5653	16.1891
108	Zhongshan	33265.3795	20.2971
109	Chaozhou	56419.9676	18.0993
110	Jieyang	80808.2398	15.4503
111	Yunfu	108660.2086	13.9211
112	Nanning	196777.1702	8.8936
113	Liuzhou	4252.0302	0.2286
114	Guilin	101.7787	0.0037
115	Wuzhou	73360.0656	5.8310
116	Beihai	59293.4011	17.6448
117	Fangchenggang	88457.9487	14.9296
118	Qinzhou	158452.7225	14.9200
119	Guigang	87813.8822	8.2474
120	Yulin	178626.4744	13.8727
121	Baise	62468.6304	1.7200
122	Hezhou	18938.3149	1.6203
123	Hechi	31186.5936	0.9312
124	Laibin	59832.5257	4.4700
125	Chongzuo	137282.6466	7.8469
126	Haikou	56499.1312	25.9283
127	Sanya	31165.5633	16.9006

128	Hainanshengxiadanwei	660868.9150	22.0816
129	Honghe	6111.7668	0.1901
130	Wenshan	27951.6233	0.8864
131	Taiwan	1216381.7550	33.5154
132	Hongkong	21243.1265	19.9678
133	Macao	477.6350	21.0998

Children and the old are more vulnerability to TC exposures. **Table 10**,**Table 11** and **Table 12** show the sensitive population and total population affected by TC.

Table 10 Children Less than 15 Years Old Exposed to TC at Provincial Level

NO	Province	Mean_1981_1999	Mean_2000_2016	Difference
1	Anhui	3619465	1414046	-2205419
2	Fujian	3197424	3362016	164592
3	Guangdong	10481765	9029980	-1451785
4	Guangxi	5575022	4566310	-1008712
5	Guizhou	222485	0	-222485
6	Hainan	1115519	1070335	-45183
7	Heilongjiang	0	11940	11940
8	Henan	1745641	0	-1745641
9	Hubei	917400	0	-917400
10	Hunan	574351	0	-574351
11	Jiangsu	5548354	2807326	-2741029
12	Jiangxi	2300313	1382246	-918068
13	Jilin	94477	283167	188690
14	Liaoning	3677758	724015	-2953743
15	Shandong	3272564	2682454	-590110
16	Shanghai	1312732	1539081	226348
17	Taiwan	2387124	1906090	-481033
18	Yunnan	315283	555574	240291
19	Zhejiang	5283203	2999567	-2283636

Table 11 Adults Aged Over 65 Exposed to TC at Provincial Level

NO	Province	Mean_1981_1999	Mean_2000_2016	Difference
1	Anhui	1384780	986525	-398255
2	Fujian	763126	1618655	855530
3	Guangdong	2031078	3342052	1310974
4	Guangxi	939888	1666582	726694
5	Guizhou	39948	0	-39948
6	Hainan	212020	422224	210204
7	Heilongjiang	0	5094	5094
8	Henan	315498	0	-315498
9	Hubei	244029	0	-244029
10	Hunan	124209	0	-124209

11	Jiangsu	2113855	2073536	-40319
12	Jiangxi	370882	445484	74602
13	Jilin	40848	208833	167985
14	Liaoning	1584453	647119	-937334
15	Shandong	1096510	1799896	703387
16	Shanghai	679440	1673181	993740
17	Taiwan	595678	1177623	581946
18	Yunnan	50759	196158	145399
19	Zhejiang	1725744	1894705	168960

Table 12 Total Population exposed to TC at Provincial Level

NO	Province	Mean_1981_1999	Mean_2000_2016	Difference
1	Anhui	14959532	9433262	-5526270
2	Fujian	13177984	20079750	6901766
3	Guangdong	40928927	47714204	6785277
4	Guangxi	16652926	18688362	2035436
5	Guizhou	617557	0	-617557
6	Hainan	3631407	5002136	1370730
7	Heilongjiang	0	66270	66270
8	Henan	5421861	0	-5421861
9	Hubei	3495913	0	-3495913
10	Hunan	1905853	0	-1905853
11	Jiangsu	28163871	20229738	-7934133
12	Jiangxi	7075880	5788869	-1287010
13	Jilin	562076	2294870	1732794
14	Liaoning	19690811	6096703	-13594108
15	Shandong	13618490	17608972	3990483
16	Shanghai	9176404	16717861	7541457
17	Taiwan	8707649	10971642	2263993
18	Yunnan	977805	2450909	1473104
19	Zhejiang	25052119	20546810	-4505310

Indicator 1.3: Climate-sensitive infectious diseases

Methods

The methodology for this indicator has been improved from the 2020 China Lancet Countdown report appendix by replacing GBD DALY data with China CDC data source. This indicator focuses on dengue – a notable climate-sensitive vector-borne infectious disease in China. There are three sub-indicators – the climate suitability for *Aedes aegypti and Aedes albopictus,* the vulnerability index to dengue, and the disease burden for dengue in China. Compared to the national level climate suitability assessment, this year's report has dived into the provincial level results.

The climate suitability *Aedes aegypti and Aedes albopictus* is represented by vectorial capacity (VC), which expresses the average daily number of subsequent cases in a susceptible population resulting from one infected case. It is affected by climatic and environmental factors such as land-use type, temperature and rainfall. The VC was calculated according to the method provided by Rocklöv et al.(2019)[35] and Liu-Helmersson et al. (2014)[36]. It takes into account interaction among host, vector and virus. VC is expressed as:

$$VC = ma^2 b_m p^n / -\ln p$$

Where a is the average vector biting rate, b_m is the probability of vector infection and transmission of virus to its saliva, p is the daily survival probability, n is the duration of the extrinsic incubation period-(EIP) , and m is set to 1 assuming female vector and human population as in Watts et al.(2019).[37] Detailed model description and explanation, as well as the relationship between daily temperature with these parameters can be found in Rocklöv et al. (2019).[35] In this study, the time unit is 1 day, and each vector parameter depends on the temperature. The parameter value comes from the literature, usually from experimental data, as described in Liu-Helmersson et al. (2014).[36] The trend of VC time series was analyzed by Mann Kendall trend test. The time unit is 1 year. A two-tailed $p < 0.05$ was considered statistically significant.

The dengue vulnerability index was calculated by dividing VC with average International Health Regulation (IHR) core capacity. The average of IHR core capacity scores is the percentage of attributes of 13 core capacities that have been attained at a specific point in time (presented on an annual basis). It measures the ability to detect, assess, report, inform and deal with public health emergencies.

The 13 core capacities of IHR are: (1) National legislation, policy and financing; (2) Coordination and National Focal Point communications; (3) Surveillance; (4) Response; (5) Preparedness; (6) Risk communication; (7) Human resources; (8) Laboratory; (9) Points of entry; (10) Zoonotic events; (11) Food safety; (12) Chemical events; (13) Radionuclear emergencies.

$$\text{Vulnerability} = \frac{\text{VC}}{\text{Average IHR core capacity score}}$$

Considering the limitation of the availability of provincial-level IHR score in China, we replace the average IHR core capacity score with average provincial comprehensive health emergencies management index reported in indicator 2.2.1 in this report. The index developed in indicator 2.2.1 in this report considers 20 indicators covering three aspects (risk exposure and preparedness, detection and response, and resource support and social participation), which is similar to the assessment framework of IHR. This index was then calibrated with correction coefficient of the provincial health emergency management index which was set according to literature with the eastern provinces as the baseline, the central and western provinces multiplied by 0.951 and 1.0024 respectively.

Then, the estimated vulnerability of provincial-level from 2010-2019 is calculated by the following formula:

$$\text{Estimated vulnerability} = \frac{\text{VC}}{\substack{\text{Average provincial comprehensive health emergencies} \\ \text{management index}}}$$

And, the average provincial comprehensive health emergencies management index, 2010-2019 is calculated by the following formula:

$$\text{Average provincial comprehensive health emergencies management index, 2010} - 2019$$
$$= \left(\frac{\text{average comprehensive health emergencies management ability score in China in 2019}}{\text{average IHR score in China in 2019}}\right)$$
$$\times (\text{average IHR score in China, 2010} - 2019) \times \text{Correction efficient}$$

The national Disability-Adjusted Life Years (DALYs) for dengue fever between 2005 and 2019 are calculated based on the method provided by Xu et al. (2020) which is updated based on the technical basis for DALYs of the World Health Organization (Murray, 1994). The national trends are presented as all-age DALY rates per 1,000,000 individuals over the period.

$$\text{DALY} = \int_{a}^{a+l} D\left[KCxe^{-\beta x} + (1-K)\right]e^{-r(x-a)}\,dx$$

Time lived at different ages has been valued using an exponential function of the form $Cxe^{-\beta x}$. A continuous discounting function of the form $e^{-r(x-a)}$ has been used where *r* is the discount rate and *a* is the age of onset. *D* is the disability weight (or 1 for premature mortality). K is an age-weighting modifier. The solution of the definite integral from the age of onset *a* to a+L where *L* is the duration of disability or time lost due to premature mortality gives us the DALY formula for an individual：

$$\text{DALY} = \frac{KDCe^{-\beta a}}{(\beta+r)^2}\left[e^{-(\beta+r)(l)}\big(1+(\beta+r)(l+a)\big) - (1+(\beta+r)a)\right] + \frac{D(1-K)}{r}(1-e^{-rl})$$

Where *D* is the disability weight (or 1 for premature mortality), *r* is the discount rate, *C* is the age-weighting correction constant, β is the parameter from the age-weighting function, *a* is the age of onset, and *L* is the duration of disability or time lost due to premature mortality. In the specific form used for calculating DALYs, *r* equals 0.03, β equals 0.04, and *C* equals 0.1658 (Murray, 1994)[38]. K equals 1. *L* is set as 14 days and *D* equals 0.81 for dengue based on Endy et al. (2007)[39], Shepard et al. (2013)[40], and Guidelines for clinical diagnosis and treatment of dengue fever in China (2018)[41].

Data

1. Monthly average daily temperature data with the resolution 0.25° from 2004-2019 were from Library for Climate Studies of Chinese Meteorological Administration.[42]
2. The spatio-temporal distributions of *Aedes aegypti* and *Ae. albopictus* in China were from the China CDC.[43]
3. The IHR core capacity scores from 2010 to 2019 in China were downloaded from WHO website.[44]
4. The provincial comprehensive health emergencies management index in 2019 is from Indicator 2.2.1 of this report.
5. The correction coefficients of provincial health emergency management index were set according to a reference.[45]
6. The incidence and mortality data of dengue fever come from the infectious disease information monitoring system of the China CDC.

Additional Information

Total VC in most of the provinces in China has increased since 2004. *Ae. Albopictus* only existed in 25 provincial-level administration divisions (PLADs) of China, and *Ae.aegypti* only existed in Guangdong, Hainan and Yunnan, according to spatio-temporal distributions of *Aedes aegypti* and *Ae. albopictus* in China provided by China CDC. Means of total VC in Guangdong and Hainan were the highest, and means of total VC in provinces in southwestern border and southeastern coastal areas were relatively higher (***Figure 19***). Total VC in Guangdong, Yunnan and Hainan all showed upward trends in 2004-2019 were 15.0%, 24.7% and 43.6%, respectively. (***Figure 20***)

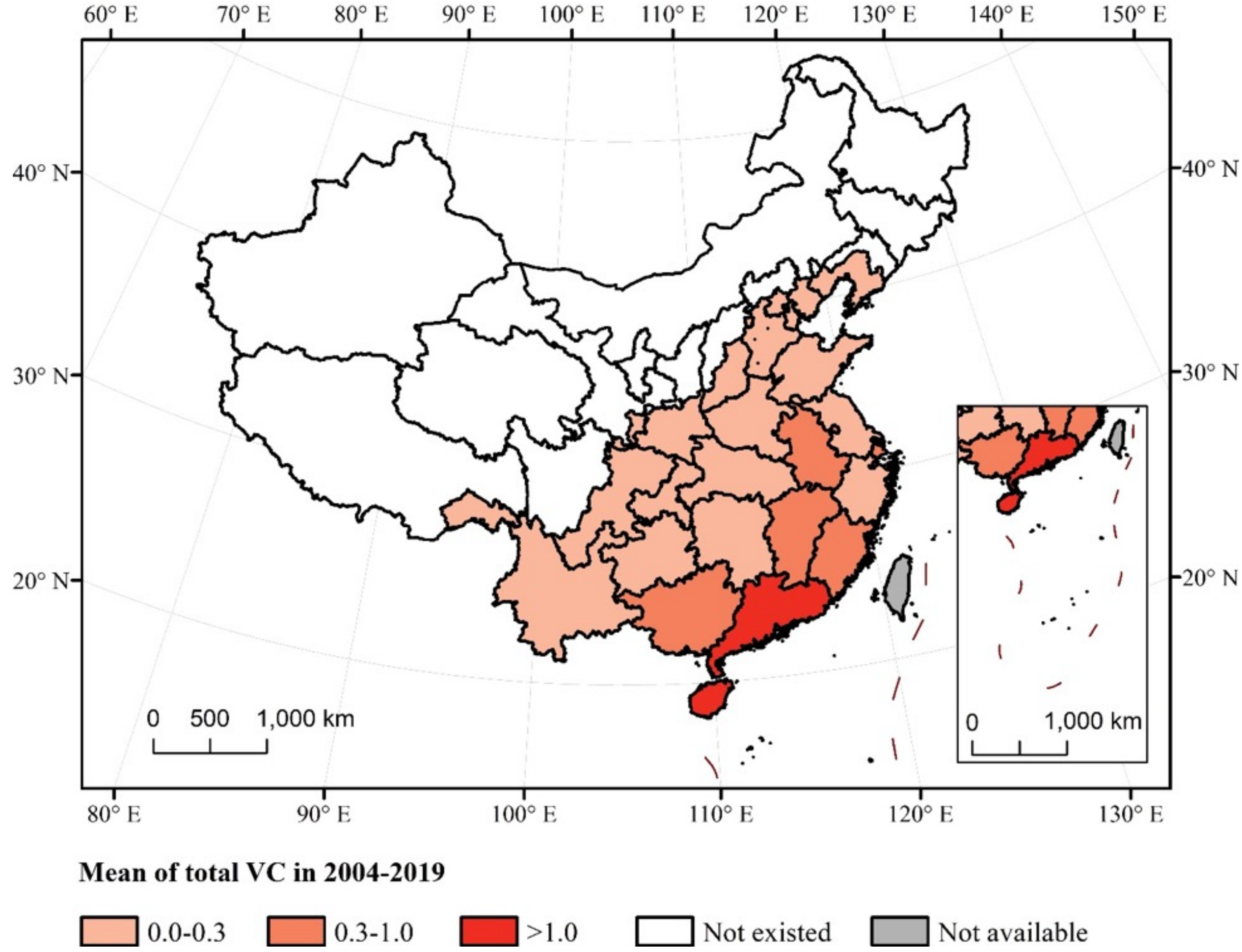

Figure 19**:Mean of total VC in China in 2004-2019.**

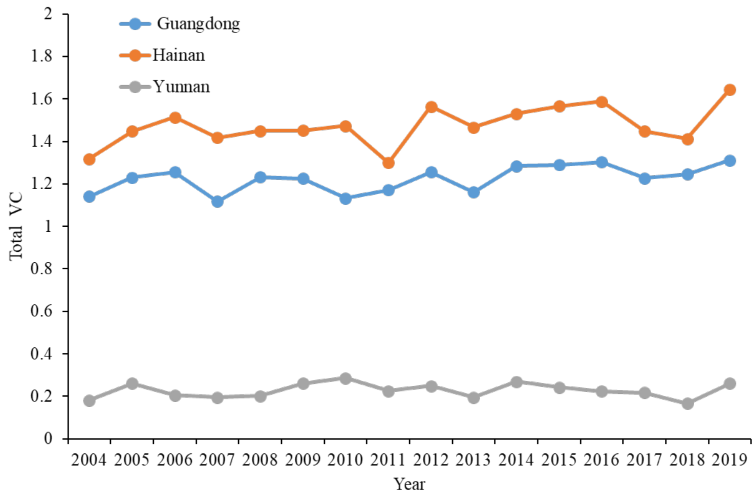

***Figure 20*: Total VC in 3 PLADs, China, 2004-2019.**

Dengue vulnerability index in 14 single *Ae. albopictus* distribution PLADs show an increasing trend from 2010-2019. These PLADs include Anhui, Beijing, Gansu, Hebei, Henan, Hubei, Hunan, Jiangsu, Liaoning, Shaanxi, Shandong, Shanxi, Sichuan, Tianjin, respectively. In contrast, dengue vulnerability index in 5 single *Ae. albopictus* distribution PLADs including Chongqing, Fujian, Jiangxi, Shanghai and Zhejiang show a decreasing trend, and no obvious change of this index in 3 PLADs including Tibet, Guangxi, and Guizhou, respectively, during this period.

Compared with the DF vulnerability index in 2010, it increased slightly in 2 PLADs with both *Ae. aegypti* and *Ae. albopictus* distribution, including Guangdong (8.39%), Hainan (4.42%), and decreased in Yunnan (14.63%), respectively (**Table 13**).

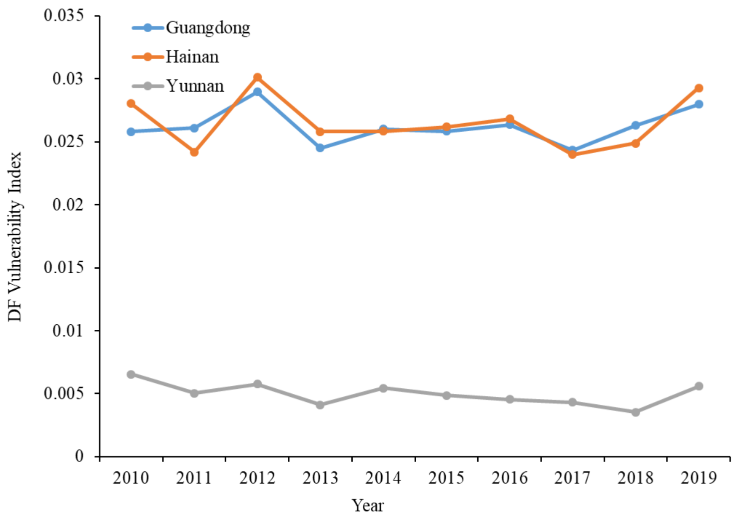

Figure *21*: Dengue vulnerability index in 3 PLADs with both *Ae. aegypti* and *Ae. albopictus* distribution, China, 2010-2019.

The VC Mean show a decreasing trend in Shanghai and Zhejiang, no change of that in Tibet and Gansu, and an increasing trend of that in other 21 PLADs in 2019, compared with that in 2004 (**Figure *22***).

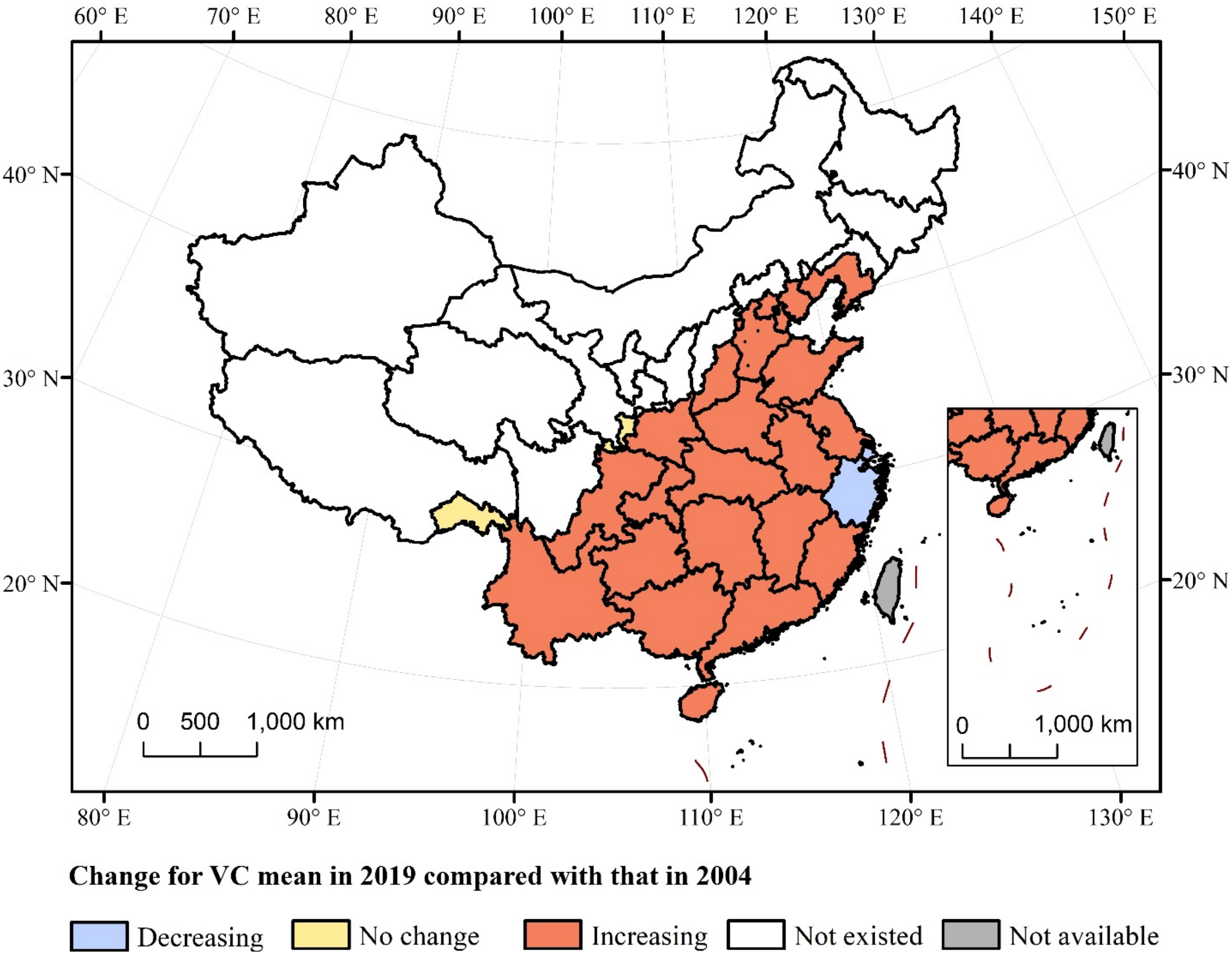

Figure *22*: Change for VC mean in 2019 compared with that in 2004

Table 13: Provincial-vulnerability index of dengue fever between 2010 and 2019 in China

No	PLADs	District	Vulnerability index									
			2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
1	Beijing	Eastern	0.002032	0.001805	0.001642	0.001603	0.001714	0.00138	0.001734	0.001654	0.002332	0.001885
2	Tianjin	Eastern	0.004572	0.004821	0.004771	0.004604	0.00472	0.004503	0.004856	0.005516	0.006122	0.005997
3	Hebei	Eastern	0.003185	0.002935	0.002685	0.002875	0.002614	0.00243	0.002663	0.003074	0.00383	0.003174
4	Shanxi	Central	0.001847	0.001137	0.001136	0.001673	0.000576	0.000929	0.001104	0.001355	0.002111	0.001953
5	Liaoning	Eastern	0.002111	0.001628	0.001533	0.002239	0.00206	0.00156	0.002113	0.002306	0.002761	0.002157
6	Shanghai	Eastern	0.005548	0.005237	0.005434	0.004531	0.00397	0.004102	0.005011	0.004599	0.006005	0.004797
7	Jiangsu	Eastern	0.004552	0.003723	0.004654	0.004038	0.003247	0.003217	0.004047	0.004145	0.004847	0.004155
8	Zhejiang	Eastern	0.005023	0.004842	0.004755	0.005433	0.003921	0.00331	0.004749	0.004951	0.005408	0.00439
9	Anhui	Central	0.006194	0.005661	0.00671	0.006334	0.004714	0.004708	0.005528	0.005681	0.006736	0.006405
10	Fujian	Eastern	0.005823	0.005604	0.005571	0.005565	0.005636	0.004534	0.005902	0.005714	0.005761	0.005516
11	Jiangxi	Central	0.007927	0.007673	0.007754	0.007963	0.007225	0.006447	0.007407	0.007263	0.008347	0.007754
12	Shandong	Eastern	0.003918	0.003281	0.003993	0.004225	0.003181	0.003393	0.003817	0.004251	0.004558	0.004583
13	Henan	Central	0.004442	0.004227	0.005295	0.006204	0.003938	0.003667	0.004884	0.005084	0.005676	0.005927
14	Hubei	Central	0.004806	0.003807	0.004816	0.005322	0.00333	0.003348	0.004721	0.00438	0.005353	0.005144
15	Hunan	Central	0.007565	0.007175	0.007767	0.008372	0.005724	0.005891	0.00705	0.007237	0.008199	0.007522

16	Guangdong	Eastern	0.025817	0.026099	0.028973	0.024501	0.026005	0.025842	0.026375	0.024334	0.026307	0.027983
17	Guangxi	Eastern	0.007855	0.00799	0.008987	0.007195	0.008358	0.0079	0.008685	0.007269	0.007533	0.008172
18	Hainan	Eastern	0.02805	0.024183	0.03012	0.025827	0.025849	0.026189	0.026833	0.023984	0.024878	0.029289
19	Chongqing	Western	0.003716	0.003754	0.003208	0.004272	0.002663	0.002031	0.003638	0.003524	0.003665	0.003121
20	Sichuan	Western	0.00131	0.001759	0.001284	0.00199	0.001026	0.001261	0.001914	0.001534	0.001819	0.001515
21	Guizhou	Western	0.001767	0.002218	0.001497	0.00243	0.001893	0.001353	0.002078	0.001871	0.002065	0.001936
22	Yunnan	Western	0.006556	0.005044	0.005754	0.004119	0.005455	0.004869	0.004536	0.004316	0.003542	0.005597
23	Tibet	Western	0	0	0	0	0	0	0	0	0	0
24	Shaanxi	Western	0.000973	0.000436	0.001363	0.001631	0.000746	0.000816	0.00172	0.001394	0.001409	0.000883
25	Gansu	Western	0	0	0	0	0	0	0.000358	0.000387	0	0

***Table* 14: National all-age DALY rate between 2005 and 2019 for dengue in China**

Year	All-age DALY rate (per 1 000 000)
2005	0.03
2006	0.03
2007	0.02
2008	0.01
2009	0.01
2010	0.01
2011	0.02
2012	0.02
2013	0.14
2014	1.35
2015	0.11
2016	0.06
2017	0.19
2018	0.17
2019	0.66

Caveats

Overall, VC should be improved by a more sophisticated model in the future. In addition, lacking data concerning IHR core capacities score in each province of China is another major caveat.

Future Form of Indicator

In future reports, VC can be calculated considering more climatic, environmental and social factors according to different mosquito virus serotypes. New information about data, method and spatial-temporal scale, etc. can be investigated further.

In addition, the DF vulnerability index of the provinces with *Ae. aegypti* and *Ae. albopicuts* distribution can be calculated if we can obtain more index to estimate the precise comprehensive health emergencies management index at the provincial level.

Section 2: Adaptation, planning, and resilience for health

Indicator 2.1: Adaptation planning and assessment

Indicator 2.1.1: National level adaptation planning and assessment

Methods

The methodology for this indicator has been improved from the 2020 China Lancet Countdown report appendix. A mixed approach, including qualitative analysis of national government documents and national assessment reports related to climate change response and a nation-wide China Health and Climate Change Survey for quantitative analysis, was applied for this indicator this year. Both document review and quantitative survey will continue to be conducted annually.

Government documents were searched on the websites of the State Council of PRC, the National Development and Reform Commission, the National Health Commission of PRC *etc.*, and search covered keywords related to climate change, health, adaptation, vulnerabilities, and response *etc*. All the documents were read through and relevant contents/sections related to climate change and health adaptations were mainly reviewed to qualitatively summarize the national planning findings. The following national government documents were identified as highly relevant:

- The People's Republic of China. China's National Plan in Response to Climate Change (in Chinese). 2007[46].
- China's National Development and Reform Commission and eight other ministries. China's National Climate Change Adaptation Strategy (in Chinese). 2013[47].
- China's National Development and Reform Commission. China's National Climate Change Planning (2014-2020) (in Chinese). 2014[48].

National reports and documents on assessments of climate change impacts, vulnerability, and adaptation for health released since the year 2000 were also systematically searched. The series of reports, "Climate and Environmental Evolution in China", "The National Assessment Report on Climate Change", and "Green Book of Climate Change-Annual Report on Actions to Address Climate Change" were mainly reviewed to qualitatively summarize the national assessment findings.

The quantitative data for this indicator included a voluntary national online survey, the China Health and Climate Change Survey (the English version of the questionnaire is available in the following part), which was designed by referring to 2018 WHO Health and Climate Change Country Survey.[49].The survey items related to adaptation assessment mainly include assessment of health impacts, vulnerability, and adaptation, impacts of assessment results on health services policy etc. In the WHO survey, impacts, vulnerability and adaptation assessments for health is a single assessment, not three separate assessments. However, in our survey we differentiated three stages to get more detailed information on progress in each province. Otherwise, some of the respondents might report no assessments completed even if they actually finished one or two stages of the assessments.

Focus group discussions and key informant consultations were operated to ensure the validation of the questionnaire. The survey was sent to the provincial Centers for Diseases Control and Prevention in all 31 provinces/regions/municipalities in mainland China in early March 2021, and 30 of them completed the survey.

The English version of the questionnaire is shown as follows.

2021 China health and climate change survey

Dear Sir/Madam: Hello!

I am an investigator of the project "Climate change and human health in China". This research was conducted by the National Health Commission. We sincerely invite you to participate in this survey. The purpose of this survey is to track and understand the adaptation policies, measures and assessment of climate change health risks in China, and summarize the progress, problems and challenges for climate change and health at China's national and provincial level, so as to provide reference for future policy formulation, implementation and climate change health adaptation.

Your truthful answers are very important to our research. The information you provide will be completely confidential. The completion and submission of this questionnaire indicates that you have informed consent to this survey.

Thank you again for your cooperation.

Basic information of participants：

Name:_________________

Affiliation: _____________

Tel: _____________

Email: _____________

Part One: Adaptation Planning

1. **Has your province implemented policies or measures to address climate change health risks at the provincial level?**
   A. Yes
   B. No
   C. Under development
   D. Unknown

If you answer "Yes", please answer 1.1 to 1.3

1.1 In which year did the policy measures implemented begin? <u>(please fill in N if not clear)</u>?
( );

In which year was it most recently updated? (please fill in N if not clear)? ();

Note: Please list the names of the policy or measures implemented at the provincial level below. (<u>please fill in the key words briefly, if not clear, please fill in N</u>);

____

1.2 Have the progress of the implementation of relevant policies and measures been monitored?
A. Yes
B. No
C. Unknown

1.3 Is there any government funding to support the implementation of climate change and health-related policies and measures?

A. All of them

B. Most of them

C. Very few of them

D. None

E. Unknown

2. **Have a memorandum or strategic cooperation agreement with the Meteorological Department been signed to clarify the specific responsibilities for responding to climate change and health?**
   A. Yes
   B. No
   C. Unknown

If you answer "Yes", please answer 2.1

2.1 Have the meteorological departments provided meteorological information services to health departments or institutions?

A. Yes

B. No

C. Unknown

If you answer "Yes", please answer the following questions

2.1.1 Which meteorological information related to health has been provided?

() Temperature

() Precipitation

() Humidity

() Wind

() Disaster weather events (typhoon, sandstorm, etc.)

() Air quality

() Ultraviolet

() Others_____________

2.1.2 Did health departments or institutions use the meteorological information for decision-making?

A. Yes

B. No

C. Unknown

3. **What do you think are the main challenges in addressing the health risks of climate change? (Select up to 5 items)**
   A. Insufficient attention from the government
   B. Insufficient scientific understanding of the health risks of climate change
   C. Lack of a clear responsible agency or lead department
   D. Lack of multi-sectoral cooperation mechanism
   E. Lack of government funding support
   F. Lack of health manpower security
   G. Insufficient level of primary medical care

H. Lack of complete monitoring data and information system
I. Lack of risk monitoring, prediction and assessment technology
J. Others________

Part Two: Climate change and health impact, vulnerability and adaptation assessment

1. Has a scientific assessment of the health impacts of climate change been conducted?

A. Province-wide
B. A few cities
C. No
D. Unknown

**Health impact assessment refers to the assessment of the adverse effects of climate change or extreme events on health. For example, assessing the effects of high temperature or heat wave exposure on cardiovascular disease mortality or morbidity.*

If you answer "Province-wide" or "A few cities", please answer the following questions:

1.1 In which year(s) was the assessment conducted? ();

Note: Please list the name of the most recent report below (you can briefly fill in the key words of the report, if not clear, please fill in N).

____

1.2 Which climate sensitive diseases or health outcomes have been involved in the most recent assessment? (Multiple choice)

A. Vector-borne diseases
B. Water-borne or food-borne diseases
C. Respiratory or cardiovascular morbidity or mortality
D. Heatwave related morbidity or mortality
E. Extreme events (flooding, typhoon, etc.) related injury or deaths
F. Malnutrition and food safety
G. Women and children health
H. Mental health
I. Occupational health and labor capacity
J. Others（Please specify: ____________________）

1.3 Has the most recent assessment involved projections of health impacts of climate change?

A. Yes
B. No
C. Unknown

2. Has a scientific assessment of health vulnerability to climate change been conducted?

A. Province-wide
B. A few cities
C. No
D. Unknown

** Assessment of health vulnerability refers to assessing which individuals or groups are more vulnerable to climate change and extreme weathers because of their own physiological and demographic susceptibility, or the disadvantaged conditions such as their geographical location and social circumstances in which they live. For example, to assess whether the effects of heat wave exposure on cardiovascular disease mortality are different between men and women, as well as urban and rural areas, and which subgroups are more vulnerable.*

3. Has a scientific assessment of health adaptation to climate change been conducted?

A. Province-wide
B. A few cities
C. No
D. Unknown

**The assessment of health adaptation includes the assessment of the planning, implementation, effectiveness of adaptation policies or measures responding to climate change and extreme weathers. For example, to assess whether the health-related heat early warning systems are initiated in a vulnerable area, and if the implementing of the system has reduced cardiovascular disease mortality attributable to heat waves.*

If you answer "Province-wide" or "A few cities" for the above questions 1-3, please answer questions 4-5:

4. Did the results of the assessment result in the development of new or revision of existing health policies and/or programs?

A. Strongly
B. Somewhat/Moderately
C. Minimally
D. No
E. Unknown

5. Did the results of the assessment influence the allocation of human and financial resources within the health departments to address health risks of climate change?

A. Strongly
B. Somewhat/Moderately
C. Minimally
D. No
E. Unknown

6. Have more attentions been paid to climate change in the health-related works because of the COVID-19 pandemic?

A. Yes

B. No

C. Unknown

If you answer "Yes", please answer the following questions:

6.1 Specifically, in which health-related works where climate change has been paid more attention

____

Data

1. National reports and documents on adaptation planning and assessment of climate change impacts, vulnerability,

and adaptation to health were retrieved from government websites or databases as described above.

2. Data on provincial adaptation planning and assessment for health were obtained from the nationwide online voluntary survey targeted on provincial CDCs conducted by Sun Yat-sen University in early March, 2021.

Caveats

The national online survey related to climate change and health adaptations was conducted in China for the second time in 2021. All provinces of mainland China, except Tibet, have participated in this survey. It was completed by the provincial Centers for Diseases Control and Prevention in the provinces/regions/municipalities in mainland China, which might only reflect the adaptation plans from local governments' perspectives.

Future Form of Indicator

National reports and documents on climate change and adaptation plans for health will continue to be searched and reviewed annually. The China Health and Climate Change Survey will also be conducted annually and will continue to be the primary source of data to track this indicator 2.1.1. The survey tool could be improved in the future, in terms of the stricter validation of the detailed response.

Additional Information

The Central Government of China issued the National Plan in Response to Climate Change in 2007, which mentions the health impacts of climate change.[46] In 2013, the National Development and Reform Commission (NDRC) and eight other ministries jointly published the National Climate Change Adaptation Strategy, with a section entitled "Human Health", proposing to improve the health and epidemic prevention system, to provide public weather-health information services.[47] In 2014, the NDRC further implemented the National Climate Change Planning (2014-2020), emphasizing the improvement of population adaptability under climate change.[48]

In recent years, the national reports on climate change had involved health as a part of the assessment. Health had been included as a section of a chapter in the report of "Climate and Environmental Evolution in China: 2012"[50] and "The Third National Assessment Report on Climate Change"[51] in 2015, respectively.

Of the 30 provinces surveyed, six provinces (Guangdong, Hunan, Yunnan, Sichuan, Shanghai, and Jiangxi) reported that they have formulated health and climate change adaptation plans or measures at the provincial level. However, only Guangdong and Hunan have provided more details on the adaptation plans or measures, including the name of relevant government document and the year of implementation. In 2014 and 2017, Guangdong province issued the "12th Five Year Plan of Guangdong Province to Address Climate Change" and the "13th Five Year Plan of Guangdong Province to Address Climate Change", respectively. In 2018, Hunan province issued a series of policies and measures, such as the "Work Plan for Green Energy Conservation in Hunan Province". Six provinces (Fujian, Henan, Jiangsu, Gansu, Tianjin, and Heilongjiang) reported that they were making relevant adaptation plans (***Figure 24***). In this survey, although six provinces (Hunan, Jiangsu, Yunnan, Shanghai, Jiangxi, and Heilongjiang) indicated that provincial health departments and meteorological departments are carrying out close cooperation in health and climate change adaptation plans and strategies, and therefore the meteorological departments have provided meteorological information to health departments. However, only three provinces (Yunnan, Shanghai, and Jiangxi) have used the meteorological information to guide decision-making in the field of health (***Figure 25)***. The survey found that the lack of multi-sectoral cooperation mechanism (73%), the lack of perfect monitoring data and information system (63%), the lack of government funding support (63%), the lack of clear responsible agencies or leading departments (57%) are the main challenges to deal with the health risks of climate change (***Figure 26)***.

In terms of adaptation assessment of health risks to climate change, three provinces (Guangdong, Shanghai, and Jiangxi) reported the province-wide comprehensive assessment of health impact, vulnerability, and adaptation to climate change had been done (***Figure** 27)*. Respiratory or cardiovascular disease mortality and morbidity, and the health effects of heat waves were the most assessed climate-sensitive health outcomes (***Figure** 28)*. However, only two provinces (Shanghai and Jiangxi) thought their assessment findings had a strong influence on health policy-making. In terms of the allocation of human and financial resources, only three provinces (Sichuan, Shanghai, and Jiangxi) indicated the assessment findings had a strong influence (***Figure** 29)*.

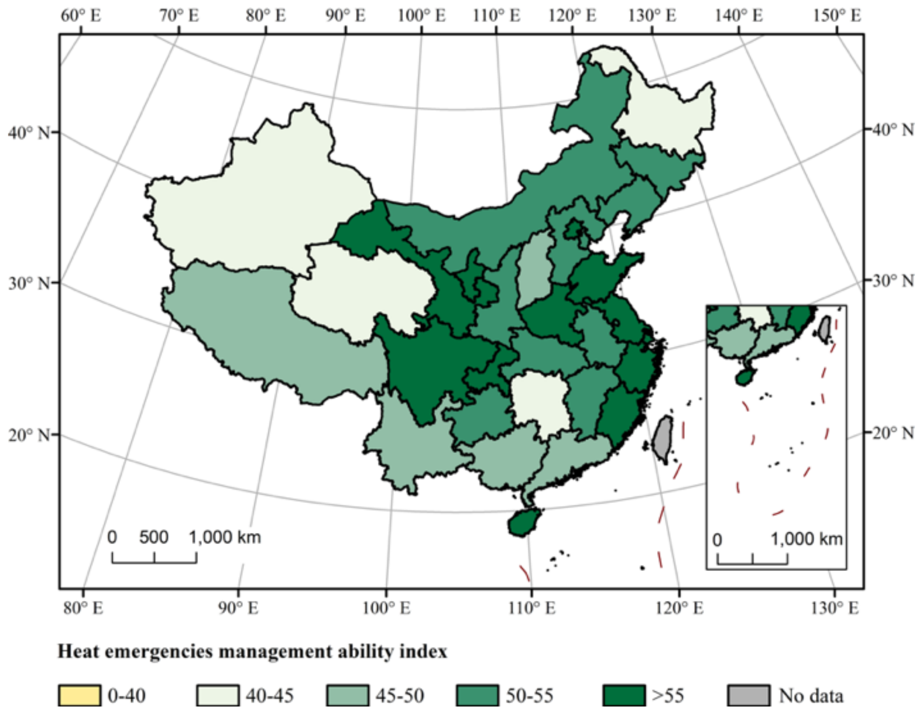

***Figure 23*: Comprehensive index measuring health emergencies management ability in different provinces in China in 2019**

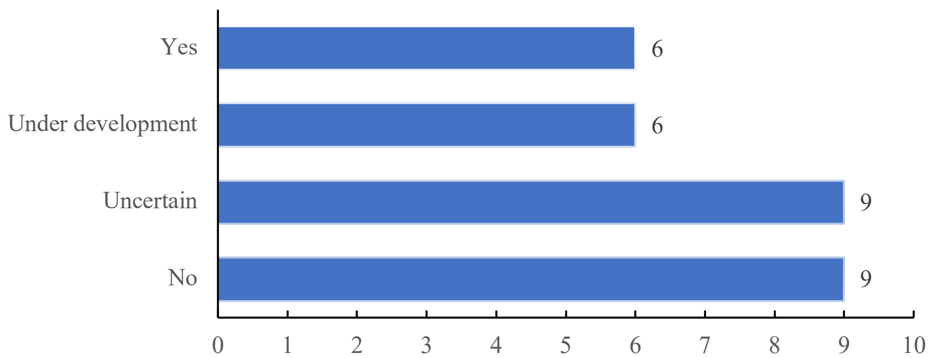

***Figure 24:* Number of provinces declared policies implementation to deal with the health risks of climate change**

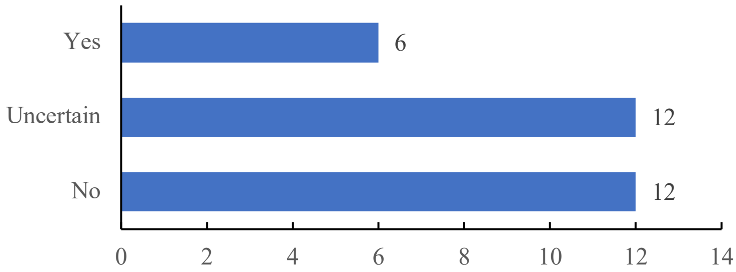

Figure 25: **Number of provinces declared health department collaborating with the meteorological department to tackle the health risks of climate change**

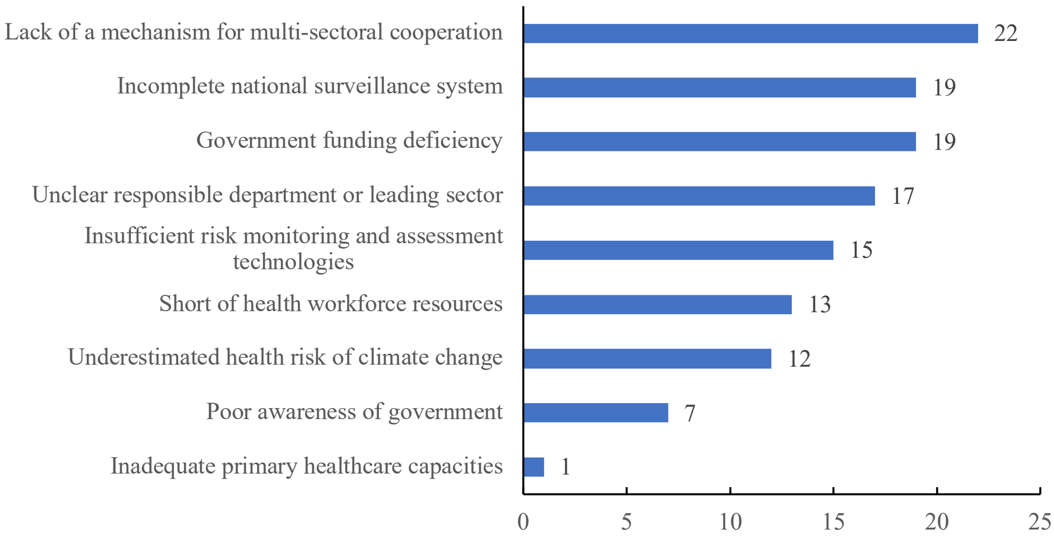

Figure 26: **The main challenges in addressing the health risks of climate change**

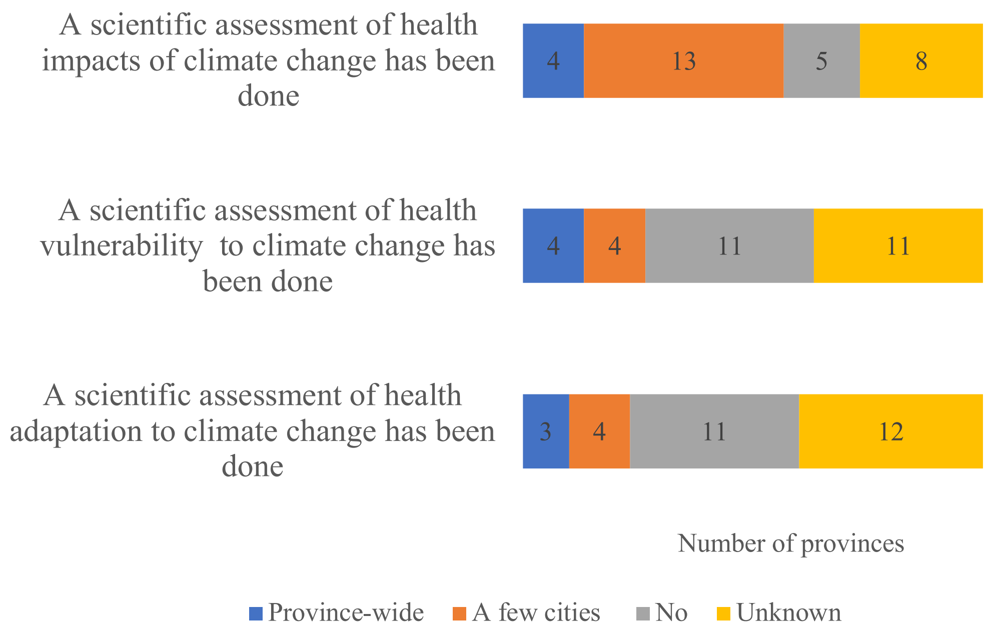

Figure 27: **Number of provinces with a scientific assessment of climate change impacts, vulnerability, and adaptation for health**

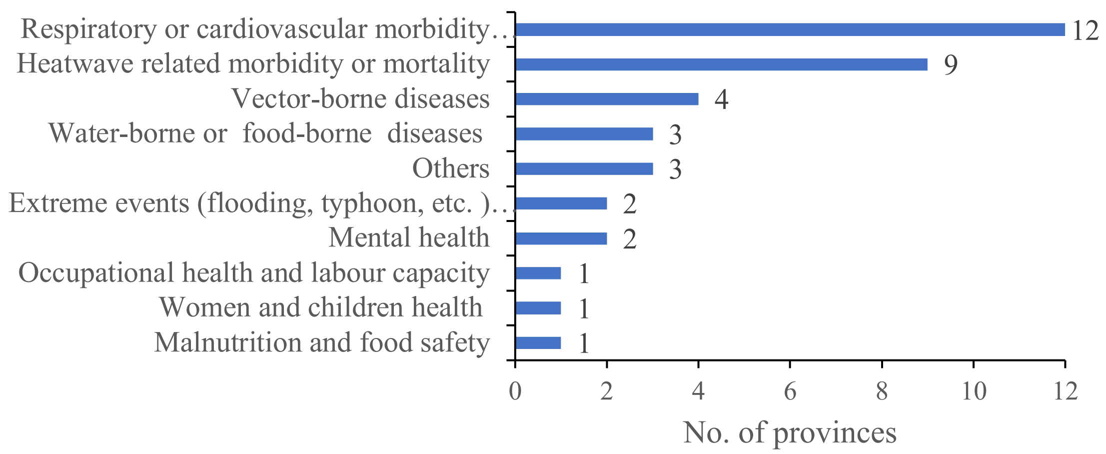

Figure 28: **The assessed climate sensitive diseases and health outcomes**

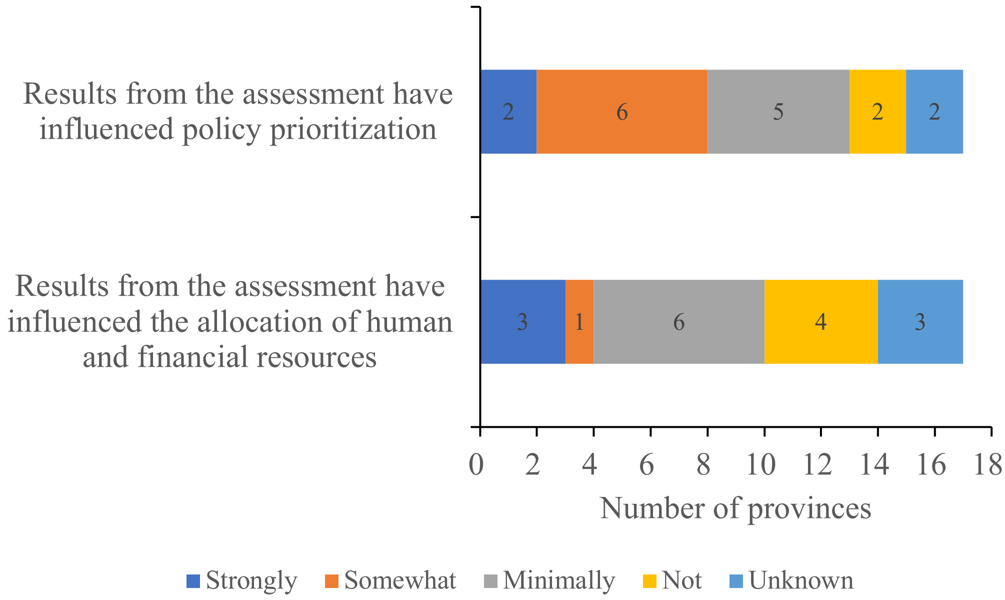

Figure 29: **The impacts of assessment findings on the policy prioritization and the allocation of human and financial resources (Seventeen provinces conducted assessment)**

Indicator 2.1.2: City-level climate change risk assessments

Methods

Two sub-indicators were developed to measure the indicator.

The first is the proportion of cities that have undertaken or are undertaking climate change risk or vulnerability assessments based on the CDP Annual Cities Survey. In 2019, 12 Chinese cities with 2 in mainland China reported questions about climate change risk or vulnerability assessments. In 2020, it increased to 17 Chinese cities with 9 in mainland China.

The second is the proportion of provinces with one or more cities that have conducted or are conducting climate change risk or vulnerability assessments. A new annual survey targeting provincial meteorological departments has been launched for the China report since this year. Provincial meteorological departments in mainland China are invited to participate in the survey to report the progress of city-level climate change risk or vulnerability assessments in their provinces. The English version of the questionnaire is available in the method part of indicator 2.3 in appendix. All the 31 provinces in mainland China responded to the survey with city-level meteorological departments in seven capital or major cities representing their corresponding provinces. The related information of Hong Kong and Taiwan is based on the CDP Annual Cities Survey, since Hong Kong and major cities in Taiwan participated in it. The information of Macao is based on The People's Republic of China Third National Communication on Climate Change. The part of basic information of Macao SAR on addressing climate change shows the information of climate change impact assessment undertaken by the Macao SAR Government.

Data

1. CDP Annual Cities Survey[52]
2. Provincial Survey on the Progress in Climate Change Risk Assessment and Climate Information Services for Health targeted on provincial meteorological departments (The English version of the questionnaire is available in the method part of indicator 2.3 in appendix).
3. The People's Republic of China Third National Communication on Climate Change[53]

Caveats

Only a small portion of Chinese cities participated in the CDP Annual Cities Survey. It made the first sub-indicator lack representativeness, though more cities in mainland China participated in 2020 than in 2019.

The new survey targeting provincial meteorological departments is established on the collaborative relationships between the authors and the provincial meteorological departments rather than an official top-down mode.

Although for most provinces, the provincial meteorological bureaus were surveyed, for several provinces, the meteorological bureaus of the capital or major cities were surveyed instead due to the lack of contact with the corresponding provincial meteorological bureaus.

The authors tried best to look for people in charge of climate change assessment and adaptation in the meteorological departments to answer the questions, but it is unlikely to ensure that the actual respondents completely grasp the progress of city-level climate change risk assessments in their provinces.

Future Form of Indicator

The author team of the China report of the Lancet Countdown on health and climate change will seek for chances of official surveys led by the central government at the provincial level and even at the city level in the future and enrich the questionnaire content to investigate more details about the city-level climate change risk or vulnerability assessments, especially in terms of how climate change impacts health outcomes and health services.

Additional Information

According to the CDP (Carbon Disclosure Project) Cities Annual Survey[52], in 2020, 14 of 17 cities surveyed with 6 of 9 in mainland China reported that they had undertaken or were undertaking climate change risk assessments, better than 2019 (1 of 2 in mainland China). Since this year, a survey targeting provincial meteorological departments has been launched for the annual report, meteorological departments from all 31 provinces in mainland China responded to the survey, with 12 provinces claimed to have one or more cities that have completed or are undertaking risks or vulnerability assessments. Combined the results from CDP and our survey together, 18 of 34 provinces had one or more cities that had completed or were undertaking risk or vulnerability assessments (***Figure 30***). The city level assessments concentrated in the southeast.

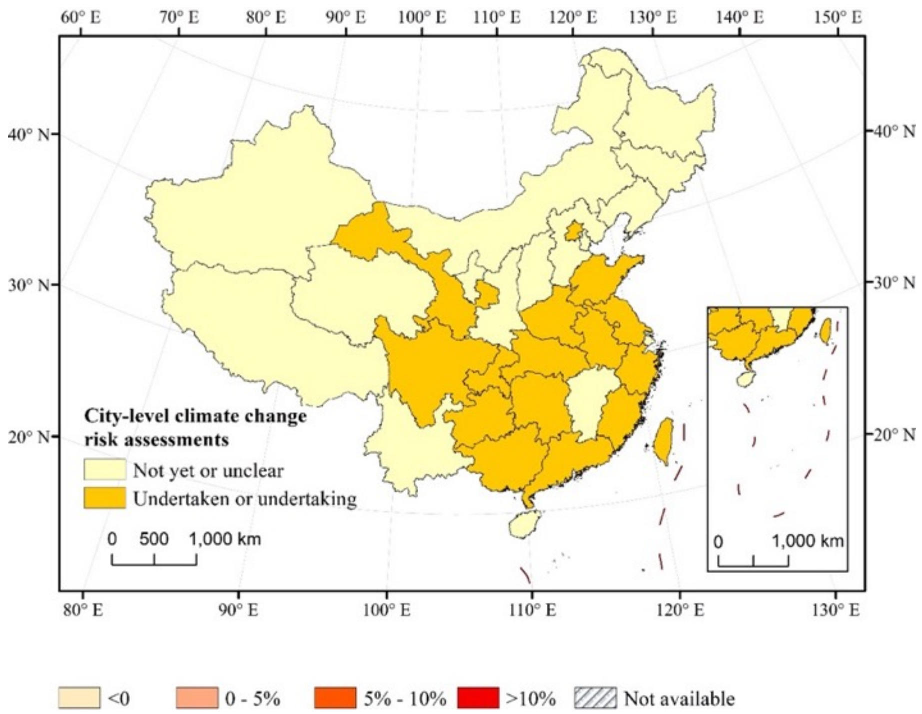

Figure 30: **Provinces with one or more cities that have completed or undertaking risk or vulnerability assessments**

The 18 provinces that had city-level risk or vulnerability assessments completed or being undertaken include Anhui, Beijing, Chongqing, Fujian, Gansu, Guangdong, Guangxi, Guizhou, Henan, Hong Kong, Hubei, Hunan, Jiangsu, Macao, Shandong, Sichuan, Taiwan and Zhejiang.

Table 15: The results of city-level climate change risk assessments based on the CDP Cities Survey 2020

Has a climate change risk or vulnerability assessment been undertaken for your city?	Cities	Province
Yes	Fuzhou	Fujian
	Hangzhou	Zhejiang
	Hong Kong	Hong Kong
	Kaohsiung	Taiwan
	New Taipei	Taiwan
	Pingtung	Taiwan
	Qingdao	Shandong
	Taichung	Taiwan
	Tainan	Taiwan
	Taipei	Taiwan
	Taoyuan	Taiwan
	Zhenjiang	Jiangsu
In progress	Chengdu	Sichuan
	Wuhan	Hubei
Not intending to undertake	Guangzhou	Guangdong

	Nanjing	Jiangsu
	Shenzhen	Guangdong

Table 16: The results of city-level climate change risk assessments based on our survey from provincial meteorological departments in 2020

Has a climate change risk or vulnerability assessment been undertaken for any city in your province?	Province	City
Undertaken	Beijing	Beijing
	Gansu	Wuwei
	Guangxi	Baise
	Guizhou	Guiyang
	Hubei	Wuhan
	Zhejiang	Hangzhou
Undertaking	Anhui	Hefei
	Chongqing	
	Guangdong	
	Henan	
	Hunan	
	Sichuan	

Indicator 2.2: Adaptation delivery and implementation

Indicator 2.2.1: Detection, preparedness, and response to health emergencies

Methods

The methodology for this indicator has been improved from the 2020 China Lancet Countdown report appendix. First, the third-level indicator RE&P 1.5 changed from Number of port entry and exit personnel into Number of entry overnight tourists, which was considered to be more closely related to health risk exposure. Second, the indicator RS&SP 2.2 was changed into number of private non-enterprises in the health sector, instead of social organisations, due to the update of statistic scale of China Civil Affairs' Statistics Yearbook, which has been compiled by the Ministry of Civil Affairs of the PRC since 1990. Furthermore, a time-series analysis between two consecutive years was made. Considering the renewing of the index, data source and weights, it would be invalid to compare directly the scores regarding health emergencies management in 2019 with those in 2018. A linear revising process was applied to modify the 2019 results into the same criteria with the 2018 index system. And if there are further updates of the index system due to data availability (which will be quite slight to ensure the stability of index system), such revision process will ensure the comparability of results between different years.

The system includes three dimensions: risk exposure and preparedness, detection and response, resource support and social participation. The index applies to public health emergencies, covering disease outbreaks, mass illness of unknown origin, serious food and occupational poisoning and other emergencies that jeopardise public health, including the climate-sensitive diseases and medical rescue caused by climate-related extreme events. The three dimensions are divided into six second-level indicators and 20 third-level indicators. The indicators of the index system are listed as follows.

Table 17: The indicators of the provincial comprehensive health emergencies management ability index system

First-level Indicators	Second-level Indicators	Third-level Indicators
Risk Exposure and Preparedness(RE&P): the degree of risk faced by the provinces in the health environment and the work done about emergency preparedness.	RE&P 1: Health emergency environmental risks: the health risks due to population mobility and risk management of the provinces.	RE&P 1.1: Proportion of cities identifies as National Health Cities
		RE&P 1.2: Urban population density
		RE&P 1.3: Percentage of migrant population
		RE&P 1.4: Passenger traffic volume
		RE&P 1.5: Number of entry overnight tourists
	RE&P 2: Health emergency preparedness: the health emergency preparedness of the provinces, in terms of emergency planning, emergency space, and fiscal investment.	RE&P 2.1: Completeness of emergency planning for public health emergencies
		RE&P 2.2: Construction space for emergency facilities
		RE&P 2.3: Percentage of medical and health expenditure out of total government public expenditure
Detection and Response(D&R): the ability for infectious diseases detection and early warming of the provinces, and the health emergency response ability from the perspective of results.	D&R 1: Health emergency detection and early warning: the ability for infectious diseases detection and early warming of the provinces from the perspective of information construction.	D&R 1.1: Construction of Infectious Disease Surveillance Reporting Systems
		D&R 1.2: Availability rate of 4G mobile phone
	D&R 2: Health emergency response: • the management and response to infectious diseases of the provinces.	D&R 2.1: Incidence of category A and B infectious diseases
		D&R 2.2: Death rate of category A and B infectious diseases
Resource Support and Social Participation(RS&SP): the ability to guarantee medical services and the degree of participation of social forces in health care of the provinces.	RS&SP 1: Medical service and resource support: the condition of medical resources and material supplies of the provinces.	RS&SP 1.1: Number of hospitals per 1,000 population
		RS&SP 1.2: Number of primary health care institutions per 1,000 population
		RS&SP 1.3: Number of practicing and assistant doctors per 1,000 population
		RS&SP 1.4: Number of registered nurses per 1,000 population
		RS&SP 1.5: Number of beds in medical and health institutions per 1,000 population
		RS&SP 1.6: Production capacity of pharmaceutical manufacturing industry
	RS&SP 2: Health emergency social participation: the participation of stakeholders in health emergencies.	RS&SP 2.1: Percentage of registered volunteers
		RS&SP 2.2: Number of private non-enterprises in the health sector

The contents and calculation methods of the indicators are described as follows.

- *RE&P 1.1: Proportion of cities identified as National Health Cities*: This indicator is measured by the ratio of the number of National Health Cities in one province to the total number of cities in the province. The National Health City is a national selection carried out every year by Bureau of Disease Control and Prevention, National Health Commission of the PRC. The list of National Health Cities was obtained from the website of National Health Commission of the PRC. The amount of cities was obtained from China Statistical Yearbook.
- *RE&P 1.2: Urban population density*: Urban population density is relevant to the risk of disease spread. It was obtained from China Urban and Rural Construction Statistical Yearbook.
- *RE&P 1.3: Percentage of migrant population*: The percentage of migrant population reflects the risk level of imported infectious diseases and affect community resilience to emergencies. It was obtained from Migrant Population Data Platform, which is an online database provided by Migrant Population Service Center, National Health Commission of the PRC.

- *RE&P 1.4: Passenger traffic volume*: This indicator is measured by the domestic passenger traffic volume per year via one province, including railway, highway and waterway. It's also an indicator reflects the risk level of imported infectious diseases. The data were obtained from China Statistical Yearbook.
- *RE&P 1.5: Number of entry overnight tourists:* This indicator is measured by the number of international entry overnight tourists per year via one province. It also reflects the risk level of imported infectious diseases. The data were obtained from China Statistical Yearbook.

- *RE&P 2.1: Completeness of emergency planning for public health emergencies*: This indicator is measured by text analysis to provincial emergency planning for public health emergencies. The results are graded into 0-5 points. The criteria of text analysis include definition of emergencies at different levels, reporting standards, responsibilities and tasks of different departments, mechanisms of emergency response. The text of provincial emergency planning for public health emergencies was obtained from website of general office of provincial government.
- *RE&P 2.2: Construction space for emergency facilities*: The redundancy of construction space for emergency facilities is important when severe epidemic outbreaks. This indicator is measured by the area of urban construction land for municipal utilities per 10,000 population. The data of area of urban construction land for municipal utilities was obtained from China Urban and Rural Construction Statistical Yearbook. The data of population was obtained from China Statistical Yearbook.
- *RE&P 2.3: Percentage of medical and health expenditure out of total government public expenditure*: Fiscal investment is a fundamental work in health emergency preparedness. The data were obtained from China Statistical Yearbook.

- *D&R 1.1: Construction of Infectious Disease Surveillance Reporting Systems*: Infectious Disease Surveillance Reporting System is a national major project in the field of health emergency response. The system plays an important role in detection, surveillance and rapid reporting to infectious diseases. This indicator is measured by the percentage of counties covered by the system in one province. The data is collected by Chinese Center for Disease Control and Prevention.
- *D&R 1.2: Availability rate of 4G mobile phone*: This indicator is measured by the percentage of population who own a 4G mobile phone. It is a key indicator that reflects the accessibility of warming information. The data were obtained from China Information Almanac.

- *D&R 2.1: Incidence of category A and B infectious diseases*: This indicator is one of the most common used indicators in health emergency response assessment. The infectious diseases are divided into Category A, B and C based on the Law of the People's Republic of China on the Prevention and Treatment of Infectious Diseases[54]. Category A and B infectious diseases are the diseases prevalent and cause casualties easily. The data were obtained from China Health Statistics Yearbook.
- *D&R 2.2: Death rate of category A and B infectious diseases*: This indicator is another one of the most common used indicators in health emergency response assessment. The data were obtained from China Health Statistics Yearbook.

- *RS&SP 1.1: Number of hospitals per 1,000 population*: Hospitals are the major place for health emergency medical treatment. The data were obtained from China Health Statistics Yearbook.
- *RS&SP 1.2: Number of primary health care institutions per 1,000 population*: Primary health care institutions are the major place for early medical treatment and disease prevention. The data were obtained from China Health Statistics Yearbook.
- *RS&SP 1.3: Number of practicing and assistant doctors per 1,000 population*: The number of doctors reflects the ability of treatment for health emergency. The data were obtained from China Health Statistics Yearbook.

- *RS&SP 1.4: Number of registered nurses per 1,000 population*: The number of nurses reflects the ability of nursing for health emergency. The data were obtained from China Health Statistics Yearbook.
- *RS&SP 1.5: Number of beds in medical and health institutions per 1,000 population*: The number of beds in medical and health institutions reflects the admission capacity for health emergency. The data were obtained from China Health Statistics Yearbook.
- *RS&SP 1.6: Production capacity of pharmaceutical manufacturing industry*: The production capacity of pharmaceutical manufacturing industry is important for medical material supplies when severe epidemic outbreaks. This indicator is measured by the annual gross domestic product of pharmaceutical manufacturing industry per 10,000 population. The data of annual gross domestic product of pharmaceutical manufacturing industry were obtained from China Industry Statistics Yearbook.

- *RS&SP 2.1: Percentage of registered volunteers*: Volunteer participation assists the response to health emergency, and it also reflects residents' resilience to health emergency. The data were obtained from the Website of China Volunteer Service, an online platform provided by Ministry of Civil Affairs of the PRC.
- *RS&SP 2.2: Number of private non-enterprises in health sector*: Social organisations play important roles in the process of heath emergency response. This indicator is measured by the number of private non-enterprises in health sector in one province (in natural logarithm). These data were obtained from China Civil Affairs' Statistics Yearbook.

To integrate these indictors into an index, we determine weights for all the indicators. We assume the six second-level indicators take equal weights for the index and determine the relative weights of the third-level indicators under the same second-level indicators by Entropy Weigh method (EWM).

The calculation steps of EWM are as follows.

a) Min-Max Normalization.

$$\varphi_{ij}^{'} = \begin{cases} \dfrac{\varphi_{ij} - min\left\{\varphi_{1j}, \varphi_{2j}, \dots, \varphi_{nj}\right\}}{max\left\{\varphi_{1j}, \varphi_{2j}, \dots, \varphi_{nj}\right\} - min\left\{\varphi_{1j}, \varphi_{2j}, \dots, \varphi_{nj}\right\}} & (for\ positive\ indicators) \\ \dfrac{max\left\{\varphi_{1j}, \varphi_{2j}, \dots, \varphi_{nj}\right\} - \varphi_{ij}}{max\left\{\varphi_{1j}, \varphi_{2j}, \dots, \varphi_{nj}\right\} - min\left\{\varphi_{1j}, \varphi_{2j}, \dots, \varphi_{nj}\right\}} & (for\ negative\ indicators) \end{cases}$$

φ_{ij} is the original data of the jth third-level indicator of the ith province, n is the amount of provinces. A positive indicator is an indicator that larger value means better result, while a negative indicator is an indicator that larger value means worse result.

b) Calculate the proportion of normalised sample value.

$$p_{ij} = \frac{\varphi_{ij}^{'}}{\sum_{i=1}^{n} \varphi_{ij}^{'}}\ (j = 1, 2, \dots m)$$

m is the amount of the third-level indicators under the same second-level indicator.

c) Calculate the entropy of indicators.

$$e_j = -\frac{1}{\ln n}\sum_{i=1}^{n} p_{ij} \ln\left(p_{ij}\right)\ (j = 1, 2, \dots m)$$

e_j is the entropy of the jth third-level indicator.

d) Calculate the entropy redundancy of indicators.

$$d_j = 1 - e_j$$

d_j is the entropy redundancy of the jth third-level indicator.

e) Determine the relative weights of indicators.

$$w_j = \frac{d_j}{\sum_{j=1}^{m} d_j} \ (j = 1, 2, \dots m)$$

The relative weights of third-level indicators are shown below.

Table 18: Relative weights of third-level indicators under the same second-level indicator

First-level Indicators	Second-level Indicators	Third-level Indicators	Relative weights
Risk Exposure and Preparedness(RE&P)	RE&P 1: Health emergency environmental risks	RE&P 1.1: Proportion of cities identifies as National Health Cities	0.469
		RE&P 1.2: Urban population density	0.192
		RE&P 1.3: Percentage of migrant population	0.139
		RE&P 1.4: Passenger traffic volume	0.152
		RE&P 1.5: Number of entry overnight tourists	0.048
	RE&P 2: Health emergency preparedness	RE&P 2.1: Completeness of emergency planning for public health emergencies	0.261
		RE&P 2.2: Construction space for emergency facilities	0.475
		RE&P 2.3: Percentage of medical and health expenditure out of total government public expenditure	0.264
Detection and Response(D&R)	D&R 1: Health emergency detection and early warning	D&R 1.1: Construction of Infectious Disease Surveillance Reporting System	0.319
		D&R 1.2: Availability rate of 4G mobile phone	0.681
	D&R 2: Health emergency response	D&R 2.1: Incidence of category A and B infectious diseases	0.549
		D&R 2.2: Death rate of category A and B infectious diseases	0.451
Resource Support and Social Participation(RS&SP)	RS&SP 1: Medical service and resource support	RS&SP 1.1: Number of hospitals per 1,000 population	0.153
		RS&SP 1.2: Number of primary health care institutions per 1,000 population	0.139
		RS&SP 1.3: Number of practicing and assistant doctors per 1,000 population	0.175
		RS&SP 1.4: Number of registered nurses per 1,000 population	0.070
		RS&SP 1.5: Number of beds in medical and health institutions per 1,000 population	0.127
		RS&SP 1.6: Production capacity of pharmaceutical manufacturing industry	0.336
	RS&SP 2: Health emergency social participation	RS&SP 2.1: Percentage of registered volunteers	0.752
		RS&SP 2.2: Number of private non-enterprises in the health sector	0.248

The index results about 2 specific years follow different index system and relative weights. To integrate the evaluation criterion and make time-series analysis, the original 2019 index results (s_{22}), were linearly transformed, on the basis of 2018 standard, into 2019 revised results (s_{21}).

$$s_{21} = a\, s_{22} + b$$

s_{21} is comparable with s_{11}, which is the index results in 2018.
The procedure is described as follows.

a) Calculate the average score of 2019 in both original and revised standards.

$s_{22,avg}$. is the average of original index results of every province in 2019.

$s_{21,avg}$ is the score that can be obtained in 2018 with the average level of 2019. For every single third-level indicator existed in both systems, for example the jth third-level indicator, calculate

$$\varphi_{avg,j} = \frac{\sum_{i=1}^{n} \varphi_{ij}}{n}$$

and for the ones that were not included in the 2019 index system, the $\varphi_{avg,j}$ uses data from 2018 as an alternative.

b) Compare and fit the original results in 2018 and 2019.

It is assumed that the relative distributions of provincial indexes are similar in two years, so that s_{11} and s_{22} have linear relationship as

$$s_{11} = a' s_{22} + b'$$
$$a \approx a'$$

Fit the original results of two years and get the estimated value of a as 0.9084.

c) Calculate the constant b.

$$b = s_{21,avg} - a\, s_{22,avg}$$

d) Calculate s_{21}.

A total of 3 columns of index scores are involved, and it is important to make a clear distinction. s_{11}, or the 2018 (original) index result as below in Table 18, is the score of 2018 measured in 2018 reference frame. s_{22}, or the 2019 original index result, is the score of 2019 measured in 2019 reference frame. Due to the EWM methodology, these two reference frames do not give a same original score for the same development level in two different years. Thus s_{21}, or the 2019 revised index result, is created to help make comparison. It means the index score of 2019 in 2018 reference frame, and all the time-series analyses are made between 2019 revised index result and 2018 (original) index result.

Data

Unless otherwise specified, the most recent version of data available is used in this study.

1. The list of *2018-2020 National Health Cities* is obtained from the website of National Health Commission of the PRC (http://www.nhc.gov.cn/).
2. Data for total cities, population, passenger traffic volume (including railway, highway and waterway), number of entry overnight tourists, and percentage of medical and health expenditure in government public expenditure are taken from the China Statistical Yearbook. The most recent available version is China Statistical Yearbook 2020[55], which contains the data of every province in 2019.
3. The data on urban population density and area of urban construction land for municipal utilities are based on China Urban and Rural Construction Statistical Yearbook. The most recent available version is China Urban and Rural Construction Statistical Yearbook 2019,[56] which contains the data of every province in 2019.
4. The data on the percentage of migrant population are based on the website of Migrant Population Data Platform (http://www.chinaldrk.org.cn/wjw/#/home). The most recent available data are based on the Sixth National Census of China.
5. The text of provincial emergency planning for public health emergencies is taken from the websites of the general office of every provincial government.

6. The percentage of counties covered by Infectious Disease Surveillance Reporting System is collected by Chinese Center for Disease Control and Prevention.
7. The data on the percentage of population available to a 4G mobile phone are based on China Information Almanac. The most recent available version is China Information Almanac 2019-2020,[57] which contains the data of every province in 2018.
8. The data on the incidence of category A and B infectious diseases, the death rate of category A and B infectious diseases, the number of hospitals, the number of primary health care institutions number of practicing and assistant doctors, the number of registered nurses and number of beds in medical and health institutions are based on China Health Statistics Yearbook 2020[58]. The most recent available version contains the data of every province in 2019.
9. The data on annual gross domestic product of pharmaceutical manufacturing industry are based on China Industry Statistical Yearbook. The most recent available version is 2020 China Industry Statistical Yearbook[59], which contains the data of every province in 2019.
10. The data of percentage of registered volunteers are based on the Website of China Volunteer Service (https://npo.chinavolunteer.cn). The data we use in this study were obtained on 2021-03-08.
11. The data on the number of private non-enterprises in the health sector are taken from the China Civil Affairs' Statistics Yearbook. The most recent available version is China Civil Affairs' Statistics Yearbook 2020,[60] which contains the data of every province in 2019.

Caveats

In this study, the data of most third-level indicators are based on 2019. But limited by the availability of data, the data of some third-level indicators are based on 2018. The indicator RE&P 1.3 is based on data from 2010. The 2019 revised index result is an approximate estimate, according to the linear transformation above. It is assumed that the provincial average score and provincial distribution will not change too much in merely one year.

Future Form of Indicator

Firstly, a Time-Series Analysis between 2 years has been done and a methodology for analysis of a longer time span could be developed in the future. By putting the 2018 reference frame as a standard, the original result of every future year can be translated into the certain criterion. Secondly, in 2021, the latest Five-Year Plan of hygiene and health will be updated and released, reporting the summary of the past and the outlook for the future. More indicators about comprehensive health emergencies management assessment could be considered. Finally, all the data we adopt in this year are collected by official government and could be updated in the next years.

Additional Information

The index results of comprehensive health emergencies management ability are listed below. The results present regional differences and take the order of North China, East China, Northeast China, Southwest China, South Central China, and Northwest China, from higher to lower. The average index result of provinces in the above 6 regions are 57.23, 56.27, 52.18, 51.21, 50.65, and 50.07 respectively.

Table 19: Index results and rank of provincial comprehensive health emergencies management ability in 2018 and 2019

Region	Index result (2019 original)	Index result (2019 revised)	Rank (2019)	Index result (2018)	Rank (2018)
North China	58.84	57.23	1	50.33	2

Northeast China	53.04	52.18	3	48.21	3
East China	57.73	56.27	2	55.24	1
South Central China	51.27	50.65	5	45.46	4
Southwest China	51.91	51.21	4	42.15	6
Northwest China	50.60	50.07	6	44.82	5

To clarify the major driving force of score improvement, we quantified the increment (or decrement) of average index score caused by each third-level indicator (***Figure 31***). The indicators with largest contributions include RS&SP 2.1, D&R 1.2, RE&P 2.2, RS&SP 1.3, and RS&SP 1.5, which reflects the improvements in completeness of emergency planning for public health emergencies and construction space for emergency facilities, and how population distribution and mobility changes in a way impeding infectious disease spread. Apart from the improvement in absolute value of indicators, weight change and distribution of indicator values also contributed to the improvement of the scores. In the EWM method we used to integrate scores from different indicators, when the inter-provincial differences are narrowed of an indicator, the weight of this indicator decreases. Therefore, the narrowing gap between provinces in some low-score indicators also contributed to the improvement of the overall score.

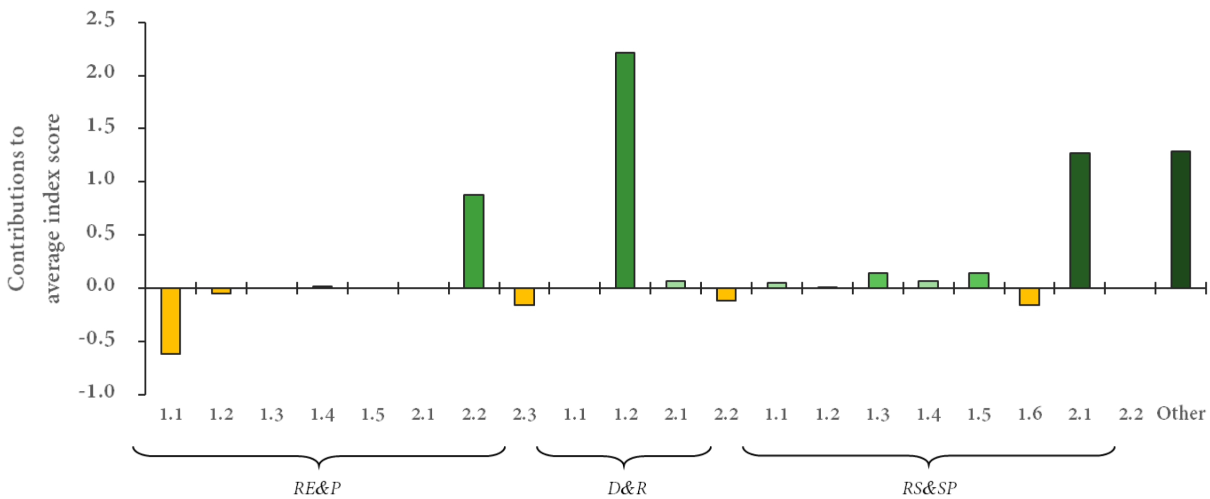

***Figure 31*: The increment (or decrement) of average index score for health emergencies management caused by third-level indicators**

Indicator 2.2.2: Air conditioning - benefits and harms

Methods

The methodology for this indicator has been improved from the 2020 China Lancet Countdown report appendix. First, we introduced a new indicator air conditioner inventory to measure the ownership of air conditioners in China across regions. Second, we expanded the accounting scope of carbon emission produced when using air conditioners by replacing last year's data source by IEA's source, which is consistent with the global report.

In terms of the calculation of prevented fraction of heatwave-related mortality due to air conditioning, the method is consistent with *the 2020 China report of the Lancet Countdown on health and climate change*[1] and *the 2020 report of* *the Lancet Countdown on health and climate change: responding to converging crises*[10]. Thus, the formula for prevented fraction is:

$$\text{Prevented Fraction} = P_{ac}(1 - RR_{ac}) = P_{ac}(1 - 0.24) = P_{ac}(0.76)$$

Where P_{ac} is the proportion of the population having household air conditioning, compared with a scenario of complete absence of household air conditioning; RR_{ac} is the relative risk of death during a heatwave or hot weather among persons who have household air conditioning compared with persons who do not have household air conditioning, which is consistent with the parameter used in in the 2020 global Lancet Countdown report.

Data

In this study, the Chinese air conditioner inventory was calculated at both national and provincial level. Furthermore, the air conditioner inventories between urban and rural households were compared. These analyses are new compared to the last year. The data were derived based on China Statistical Yearbook 2001-2020 from National Bureau of Statistics.

The P_{ac} in China has been calculated in the supplementary appendix of *the 2020 report of the Lancet Countdown on health and climate change: responding to converging crises*[10]based on the data from International Energy Agency (IEA). Thus, the Chinese result of P_{ac} in each year was directly adopted in this study.

In terms of the CO_2 emissions from air conditioning, the Chinese data in each year was from IEA. It should be noted that the object and data source of this part in this report is different from that in *the 2020 China report of the Lancet Countdown on health and climate change*[1]. Last year, we chose energy consumption and CO_2 emission only from Chinese urban household air conditioning as indicators. The data was from the Annual Report on China Building Energy Efficiency by the Building Energy Conservation Research Center in Tsinghua University. However, in this year, we choose CO_2 emission caused by air conditioning from all areas (including both urban and rural areas) and all types of buildings (including both commercial and household use) as the indicator, which is consistent with the global report. Thus, the latter covers a wider range than the former.

Caveats

The calculation of prevented fraction of heatwave-related mortality due to air conditioning cannot been reconciled with the calculation of heatwave-related mortality (Indicator 1.1.2) yet, because of different definitions and values of RR.

In the indicator of heatwave-related mortality, RR represents the increase in the risk of mortality resulting from heatwave compared with non-heatwave and its value is generally above 1. However, in this indicator, RR represents the relative risk among persons who have air conditioning compared with persons who do not have air conditioning, which is estimated to be 0.24. Furthermore, these two types of RR are not simply reciprocal relationship. Therefore, these two indicators cannot fit each other.

Additional Information

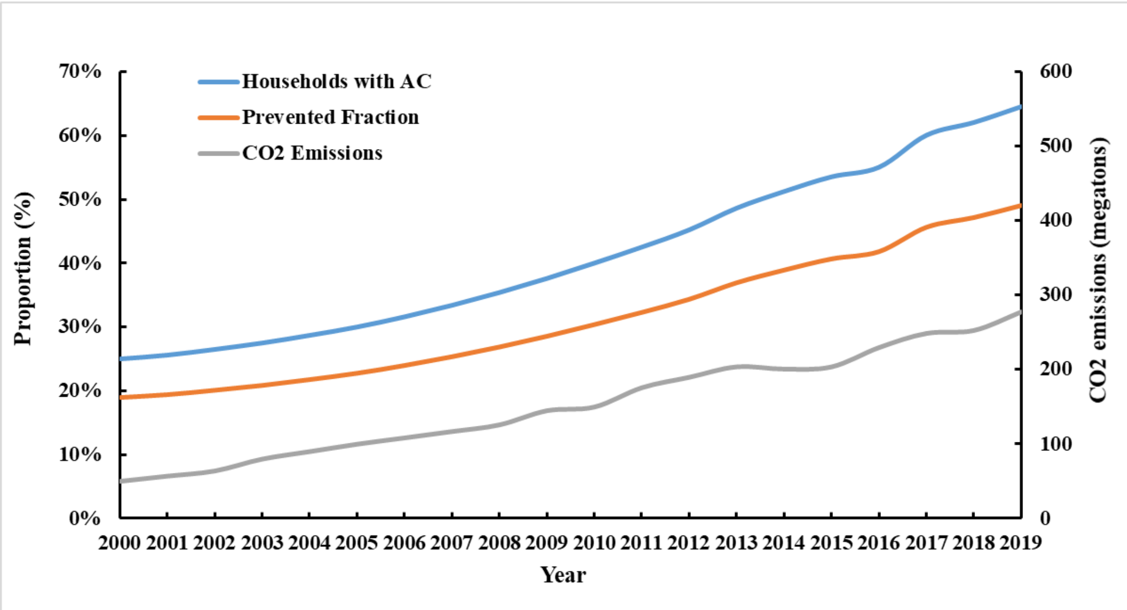

***Figure 32*: Prevented fraction of heatwave-related mortality caused by household air-conditioning use and energy consumption of urban household air-conditioning in China.**

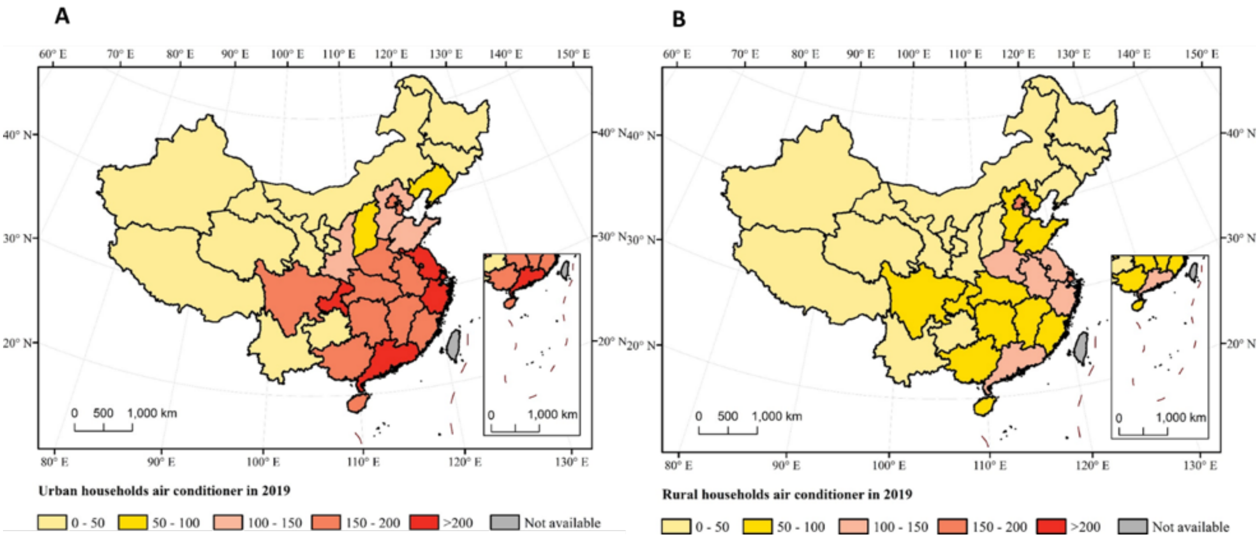

***Figure 33* : Chinese Provincial Air Conditioner Inventories of Per Hundred Households in 2019 (Data Source: National Bureau of Statistics)**
(A) Urban households air conditioner inventories per hundred households in 2019. (B) Rrban households air conditioner inventories per hundred households in 2019.

Indicator 2.2.3: Urban green space

Methods

This is a new indicator in this year's report to use population-weighted NDVI to measure urban greeness. Normalized

Difference Vegetation Index (NDVI), calculated as the ratio between the difference in the surface reflectance intensities of the red (around 0.66 μm) and infrared radiation (around 0.86 μm) divided by the sum of their intensities, is a most commonly used metrics to monitor vegetation on a global and local scale. NDVI is associated with the fraction of solar radiation absorbed by plants during photosynthesis. Ranging in value between -1 and 1, a large positive NDVI value is typically associated with a high density of green vegetation and thus indicates a higher greenness level. We used NDVI images from the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor at a 250-meter resolution to estimate greenness level. MOD13Q1 data is processed in 16-day periods by compiling the best available pixel value over the 16 days. We used cloud masks to remove cloud pixels for retaining best-quality information about vegetation. All MOD13Q1 images from the year 2010 to 2020 were acquired. For each year, one NDVI median layer was computed from the MODIS NDVI time series stack to represent the average greenness condition by finding the median value of the time series profile on a pixel basis. The median value is used instead of the mean to remove the potential outliers. To more accurately estimate the effects of greenness on communities, a population weighted NDVI layer was computed by multiplying NDVI median by the population density.

Based on the eleven-population weighted NDVI layers, the mean greenness condition for each province was calculated by summing up all weighted values encompassed by all city boundaries within that province, and dividing by the sum of the weights. All the MODIS data processing was performed on the Google Earth Engine cloud computing platform. For a more effective indication of provinces' greenness level, we categorized NDVI values using the following table:

***Table 20*: Categorization of greenness level by NDVI value[10]:**

Greenness level	Categorization	NDVI range
Exceptionally low	1	<0.19
Very low	2	0.2-0.29
Low	3	0.3-0.39
Moderate	4	0.4-0.49
High	5	0.5-0.59
Very high	6	0.6-0.69
Exceptionally high	7	>0.7

Data

1. MODIS NDVI products were obtained from MOD13Q1 V6 Terra VI 16-day global 250m[61]
2. City boundaries were collected from the Global Rural–Urban Mapping Project (GRUMP) urban extent polygons.[62,63]
3. Population data was acquired from the Gridded population data of the world Version 4.11 (GPWv4)[64].

Caveats

NDVI is a continuous measurement that provides information for each pixel on the landscape, including non-vegetated lands (e.g., impervious surfaces). We did not exclude the non-vegetated areas for calculating each province's mean NDVI considering the following reasons. First of all, although, non-vegetated lands can be removed using MODIS Land Cover Type product (MCD12Q1), the 500-meter resolution is much coarser than the NDVI layer. Considering that urban green spaces are typically highly fragmented and presented in irregular and small patches. A coarse resolution mapping produce can not capture the complete distribution of small-size patches, thus causing underestimation of urban spaces. Second, the accuracy is estimated to be 73.6% globally as evaluated by the science team[65] and the accuracy in China is lower due to landscape complexity and deficient training samples as reported by a third party team.[66] Third, most non-vegetated lands typically have less seasonal or inter-annual changes. By taking the median value of the year-round data, the inter-annual changes for those pixels would be even less. Therefore, the annual NDVI trend can reflect the changes in vegetation.

Future form of the Indicator

In the next year's report, we will adapt a to-be-released new global land cover product iMap that is developed based on state-of-the-art cloud computing, artificial intelligence, virtual constellations, and spatio-temporal reconstruction and fusion.[67] iMap is the first set of global daily 30 meter seamless data cubes for 1985-2020 and the accuracy is reported 10% higher than existing ones by checking against a third-part validation set. Because of its high spatial resolution (30 meter) and high temporal frequency (daily), we will be able to summarize the total green space area more accurately. Moreover, we can characterize the landscape patterns of green spaces at the intra-urban scale, which are more effective indicators for health-related issues, such as long-term air quality trend,[68] physical activities,[69] and urban heat island.[70]

Additional information

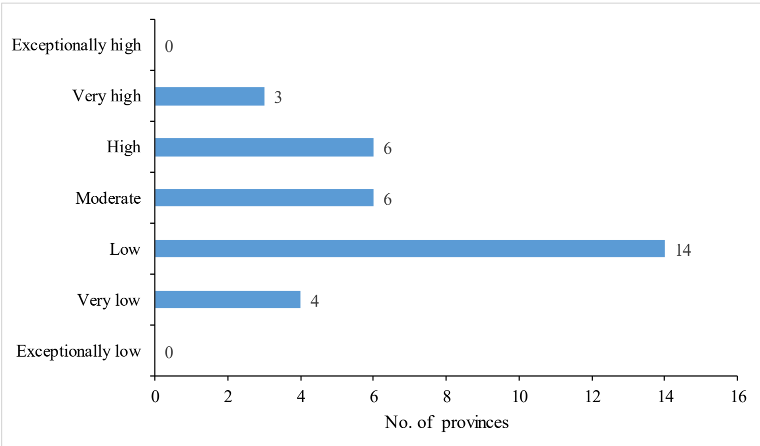

Figure 34: The number of provinces by greenness level in year 2020.

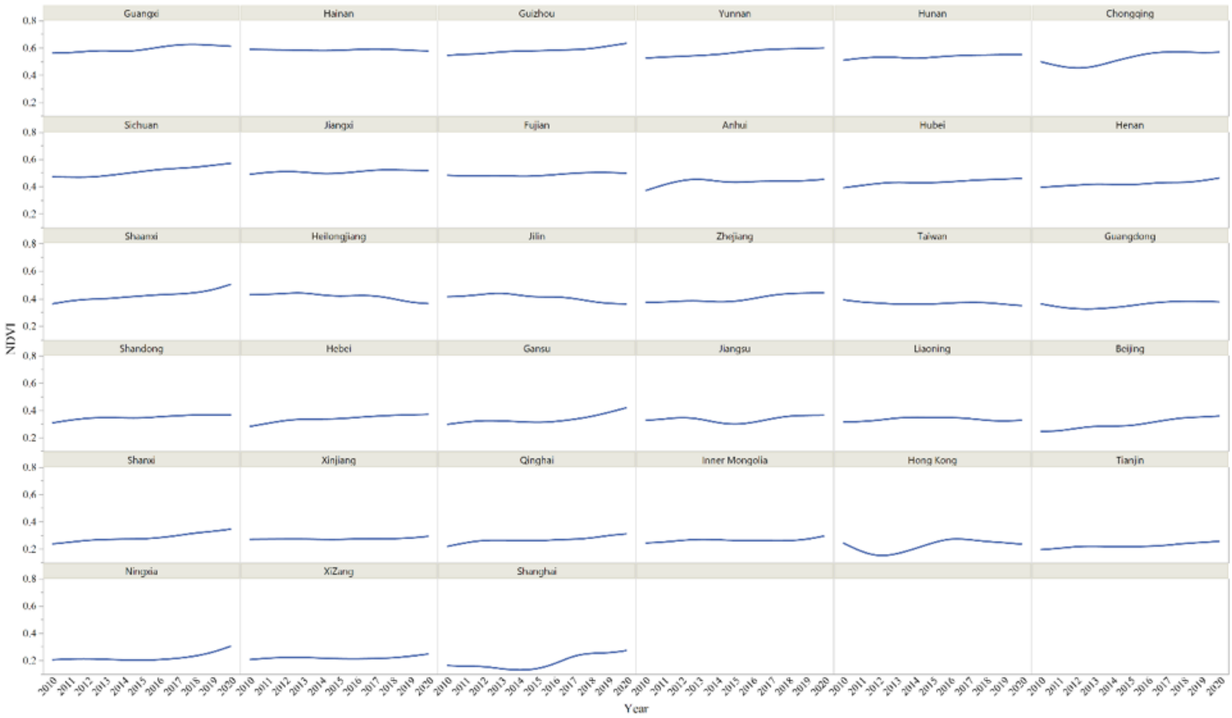

Figure 35: The NDVI trend for each province over the past decade (year 2010-2020).

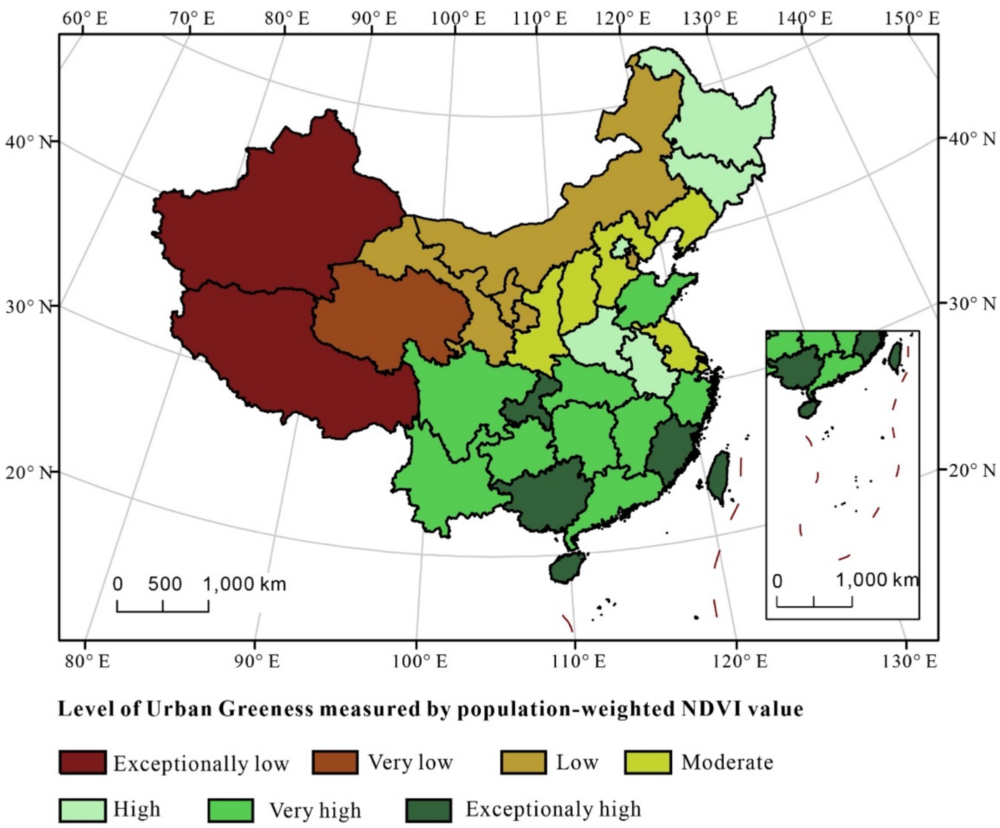

Figure 36: **Population-weighted urban greenness level of different provinces in 2020**

Indicator 2.3: Climate information services for health

Methods

The methodology for this indicator has been improved from the 2020 China Lancet Countdown report appendix by adding data obtained through questionnaire that targeted the provincial CMAs. This indicator is measured from two aspects at the provincial scale. The first is whether provincial meteorological departments provide the public health sector with climate and weather information / products, following the relevant question in the Country Profile Database Integrated questionnaire of the World Meteorological Organization (WMO), and if yes, what specific information such as temperature, precipitation, humidity, wind, hazard events, air quality and ultraviolet has been provided. The second is whether meteorological information has been used to support decision-making for health in provinces.

As mentioned in indicator 2.1.2, a new annual survey targeting provincial meteorological departments has been launched for the China report since this year. Provincial meteorological departments in mainland China are invited to participate in the survey to report the two aspects in their provinces.

The English translation of the survey questionnaire is attached as follows:

Provincial Survey on the Progress in
Climate Change Risk Assessment and Climate Information Services for Health

We are sincerely inviting you to participate in this survey, which aims to track the process of city-level climate change assessment and climate information services for health in provinces in China and support the decision-making for health adaptation to climate change. The results of the survey will be involved into the 2021 China report of the Lancet Countdown on health and climate change.

By filling and submitting this questionnaire you are indicating that you consent to this survey. Your cooperation is appreciated.

Your organization: ______________________

Section 1 City-level climate change risk or vulnerability assessment

Is there any **city** in your province having undertaken a climate change risk or vulnerability assessment? Please select one of the following options:

- o Yes
- o In process
- o Intending to undertake in the next 2 years
- o Not intending to undertake
- o Do not know

If you select "Yes", please provide the following information on the assessment(s).
(If there is more than one city having undertaken its assessment, please provide the information for each city.)

City 1:
(1) City: ________________________
(2) In which year was the related study or report published? __________________
(3) Title of the study/report: ________________________

City 2:
(1) City: ________________________
(2) In which year was the related study or report published? __________________
(3) Title of the study/report: ________________________

Section 2 Climate information services for health

1. Does the provincial meteorological department provide the public health sector with climate products/information?
    - o Yes
    - o No
    - o Do not know

    If you select "Yes", please select which product(s)/information has been provided?
    - o Temperature
    - o Precipitation
    - o Humidity
    - o Wind
    - o Hazard events
    - o Air quality
    - o Ultraviolet
    - o Other information: ________________________

- Relevant product(s): ________________________

2. Is climate information involved into decision-making in the public health sector in your province?
   - Yes
   - No
   - Do not know

Data

1. Provincial Survey on Climate Change Assessment and Information Services

Caveats

The new survey targeting provincial meteorological departments is established on the collaborative relationships between the authors and the provincial meteorological departments rather than an official top-down mode.

Though for most provinces, the provincial meteorological bureaus were surveyed, but for several provinces, the meteorological bureaus of the capital or major cities were surveyed instead due to the lack of contact with the corresponding provincial meteorological bureaus.

Compared with meteorological departments, public-health departments like the Centers for Disease Control and Prevention are supposed to better know whether and how meteorological information is used to support decision-making for health in their provinces.

Future Form of Indicator

The author team of the China report of the Lancet Countdown on health and climate change will seek for chances of official surveys led by the central government at the provincial level and even at the city level targeting both the meteorological and public-health departments in the future and enrich the questionnaire content to investigate more details about climate information services for health.

Additional Information

Based on the survey results, the 21 provinces whose meteorological departments provided meteorological information or products to the public health sector included Anhui, Beijing, Chongqing, Fujian, Gansu, Guangdong, Guangxi, Guizhou, Hainan, Hebei, Heilongjiang, Henan, Hebei, Hunan, Jiangxi, Liaoning, Qinghai, Shandong, Shanghai, Tianjin and Tibet. The 10 provinces reported that meteorological information was used to support public health-related decision-making included Beijing, Chongqing, Fujian, Guangxi, Hainan, Henan, Hubei, Jiangxi, Qinghai and Shanghai. Figure 37 shows the number of provinces whose meteorological departments provided each category of meteorological information to the public health sector.

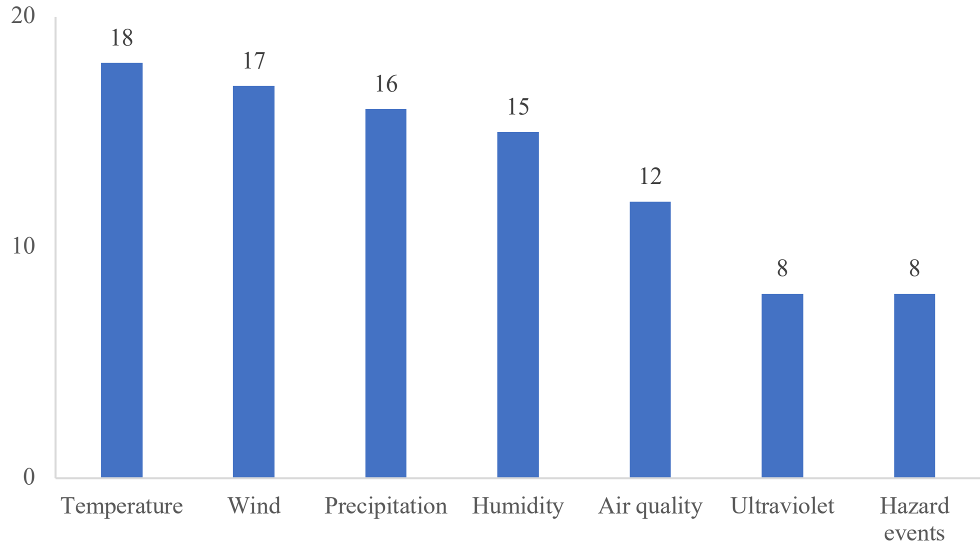

Figure 37: **The number of provinces whose meteorological departments provided each category of meteorological information to the public health sector**

Section 3: Mitigation actions and health co-benefits

Indicator 3.1 Energy system and health

Indicator 3.1.1 Carbon intensity of the energy system

Methods

The methodology for this indicator remains similar to that described in the 2020 China Lancet Countdown report appendix.

This indicator contains two components:

1. Carbon intensity (CI) of the energy system, both at national (2000-2020) and regional (six regions) (2000-2020) scales, in $kgCO_2$/US$; and
2. China national CO_2 emissions from energy combustion by fuel and industrial process (mainly cement), in $MtCO_2$ (2000-2020).

The technical definition of CI is the kilogram (kg) of CO_2 emitted for each unit (US$) of Gross Domestic Product (GDP). The rationale for the indicator choice is that carbon intensity of the economic system will provide information on the level of fossil fuel use, which has associated air pollution impacts. Higher intensity values indicate a more fossil dominated economic system, and one that is likely to have a higher coal share. As countries pursue climate mitigation goals, the carbon intensity is likely to reduce with benefits for air pollution. The indicator is calculated based on total CO_2 emissions from fossil fuel divided by GDP. GDP reflects the economic development status in an area/country.

The national and provincial CO_2 emissions from 2000 to 2018 (30 provinces excluding Tibet) are calculated by sectoral approach[2-4] .Due to the lack of energy balance data in 2019 and 2020, the projection of national CO_2 emissions in 2019 and 2020 was based on national CIs in 2019 and 2020, which are published by National Statistical Communique[71,72]. CO_2 emissions of 30 provinces in 2019 and 2020 are calculated by extrapolating from their carbon emission in 2018 and their GDP growth rates in 2019 and 2020, relative to their GDP in 2018.

$$CI_t = {CO_2}_t / GDP_t$$

Where *t* represents year; $CO2_t$ denotes CO_2 emission in *t*; GDP_t represents the GDP in *t* which is adjusted by the constant price in 2015 and the present GDP value and GDP index in *t*, which are collected from China Statistical Yearbook[73].

The sectoral approach is applied to calculate carbon emissions of China and China's provinces from 2000 to 2018 in this study. We didn't adopt reference approach to do carbon emissions calculations (in our 2020 China Lancet Countdown, reference approach was applied) because compared to the reference approach, carbon emissions calculated by the sectoral approach are 1% to 7% lower and these results by the sectoral approach are more accurate[1,74]. The sectoral approach can be generally formulated as:

$$CE_i = AD_i \times EF_i$$

Where CE_i refers to CO_2 emissions from type *i* included in types of fossil fuels and cement, AD_i refers to the activity data of the type *i*, and EF_i refers to the emission factor of the type *i*.

Daily CO_2 emissions of China in 2019 and 2020 was taken from the Carbon Monitor (https://carbonmonitor.org/), and then recalibrated by the total amount of national emissions from our calculation.

Data

1. Energy balance tables are taken from China Energy Statistical Yearbook 2001-2020[75];
2. The daily CO_2 emissions of China in 2019 and 2020 is taken from the Carbon Monitor

(https://carbonmonitor.org/).

Caveats

Due to a lack of latest data from Chinese Energy statistical data for 2019 and 2020, in our paper, national carbon emissions of 2019 and 2020 projected by annual growth rates of national CI may not be accurate. And daily national carbon emissions projection of 2019 and 2020 by the Carbon Monitor is based on assumption of changes of social and economic activities, which can create bias from the real emissions. Provincial carbon emissions of 2019 and 2020 was projected by provincial GDP growth rates, which can also create bias.

Future Form of Indicator

This indicator for the national level and provinces will need to be updated to provide the data for the most recent years.

Additional Information

In a nutshell, the CIs of six regions are in the decreasing trend, with the Southwest deceasing the largest (-60.8%) and the Northwest decreasing the smallest (-31.2%).

The CIs in the Northwest and Northeast are higher and in the Eastern region is lower. Compared to 2019, the CI of the Southwest and Northwest in 2020 increased by 0.07% and 0.2%, respectively, while other four regions' CIs dropped by around 1.51% to 1.53%, which potentially indicates more carbon-intensive economic development mode in the Southwest and Northwest. For carbon emissions, the East region's carbon emissions dominated among six regions from 2004 to 2020 (*Figure 38*), but it had the lowest CI among six regions from 2000 to 2017. Contrary to the East region, the Northwest's carbon emissions were the lowest annually, but its CI was the almost the top one per year among six regions. Thus, it shows that carbon emissions from every unit of GDP output in the East region is lower than those from the Northwest, representing a greener economy. But decarbonizing continuously the energy structure and improving the energy efficiencies of economic sectors should still be further prioritized in the East. It also denotes that northwest China has lower carbon emissions with higher CI, which relies on carbon-intensive economy. Under the COVID-19 with the extreme global economy recession, (increased the lowest among six regions), northwest China has showed its economy downwards. Therefore, it is vital for the Northwest area to change the economy structure, develop greener economic sectors and use more clean and renewable energy, etc.

Six regions' CO_2 emissions increased at high paces from 2000 to 2013, reaching the peak during the period around 2013, and since around 2018, they have started to rise up (*Figure 39*). In 2020, CO2 emissions of the North, Northeast, East, South, Southwest, and Northwest regions were 400.8 Mt CO_2, 387.6 Mt CO_2, 425.8 Mt CO_2, 308.2 Mt CO_2, 230.0 Mt CO_2, and 206.5 Mt CO_2, respectively, increasing by 1.4%, -0.2%, 1.7%, 0.2%, 5.3%, and 0.8% compared to 2019.

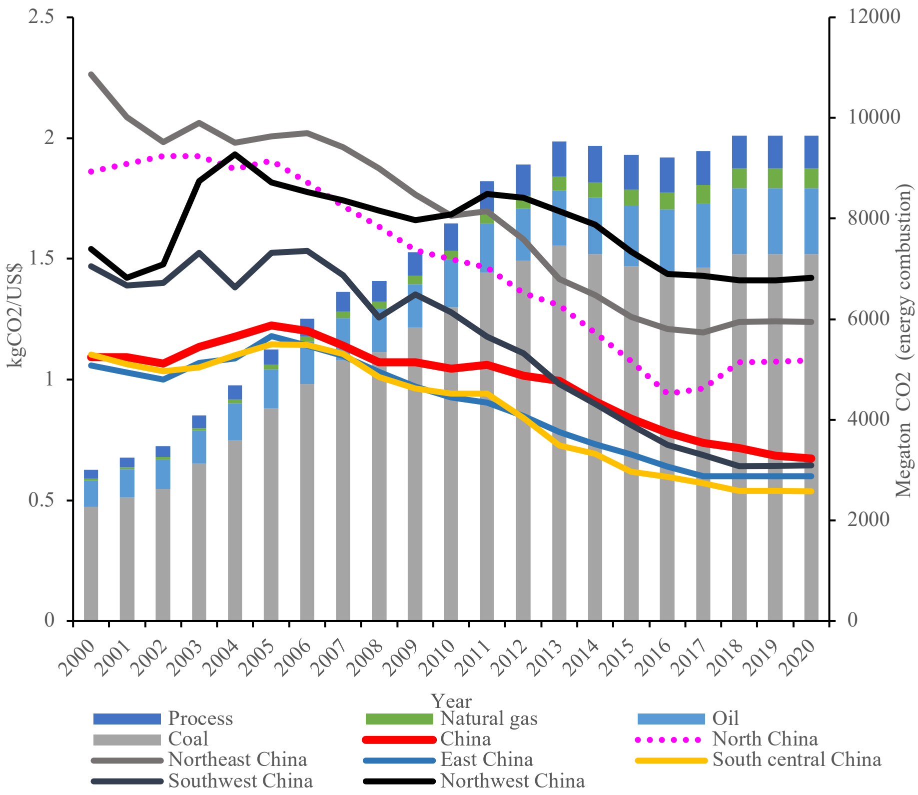

Figure 38: **Carbon intensity of GDP for China and six regions in China**

GDP=Gross Domestic Product. CO_2=carbon dioxide. Carbon intensity trends are shown by a trend line (primary axis) and CO_2 emissions by stacked bars (secondary axis).

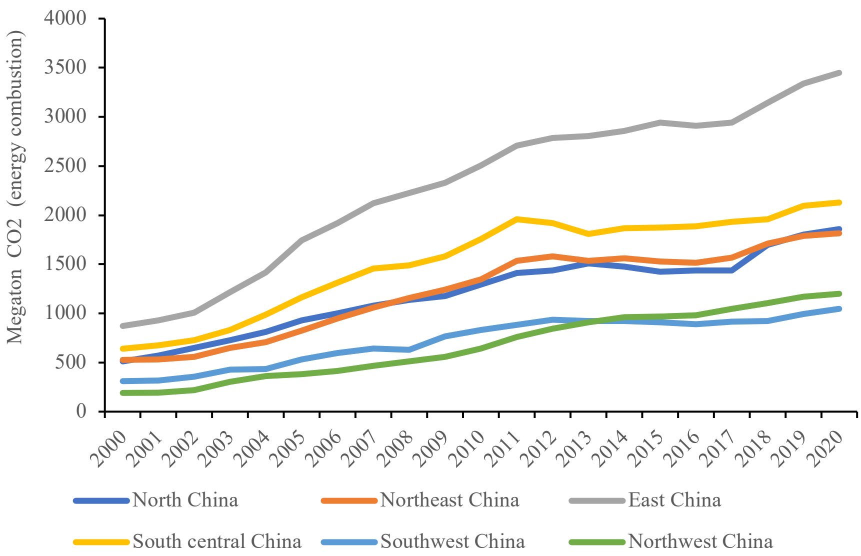

Figure 39: CO_2 emissions of six regions in China from 2000 to 2020

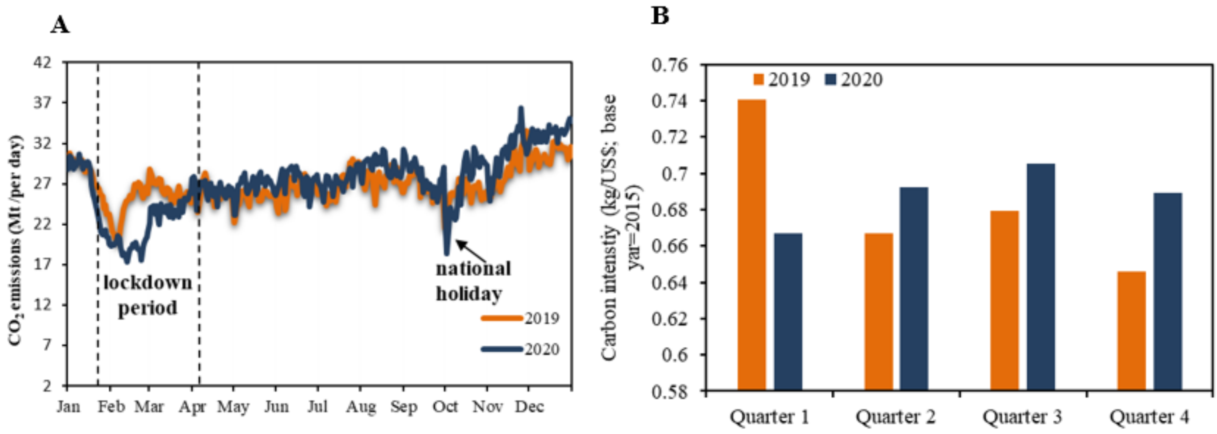

***Figure 40.* Chinese CO_2 emissions and its carbon intensity between 2019 and 2020**

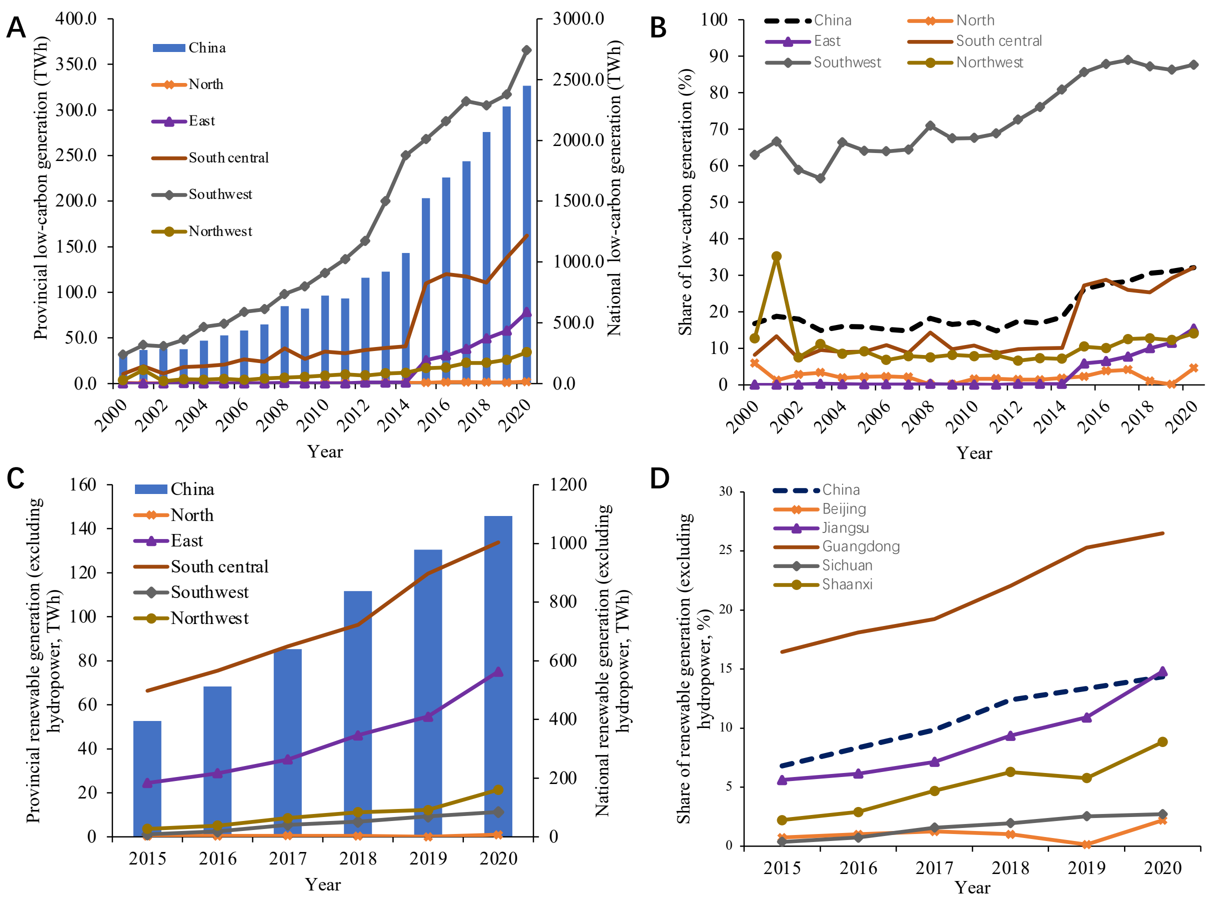

***Figure 41*: Renewable and low-carbon emission electricity generation by region (A-C and province D)**

(A) Electricity generated from low-carbon sources. (B) Share of electricity generated from low-carbon sources. (C) Electricity generated from renewable sources (excluding hydropower). (D)

Share of electricity generated from renewable sources (excluding hydropower). TWh=terawatt hours.

Indicator 3.1.2 Coal phase-out

Methods

The methods for this indicator are identical to the 2020 China Lancet Countdown report. Two sub-indicators are used here: (1) Total primary energy supply from coal in China and by province (in EJ units); and (2) share of coal in total primary energy supply.

The indicator on primary energy coal supply is an aggregation of all coal types used across all sectors from annual editions of Energy Statistical Yearbook of China. The data is available for the period 2000-2020 at the national level, and for the period 2000-2017 for each province.

Data

The data for this indicator is taken from annual edition of Energy Statistical Yearbook of China.

Caveats

These indicators provide a proxy for air quality emissions associated with the combustion of coal. Further work is required to convert coal use by sector and type into emissions of different air quality pollutants.

Future Form of Indicator

In the future, this indicator set could be developed to also estimate the actual air pollutant emissions associated with coal use. This will require sectoral use, coal type (both of which are available) and appropriate emission factors.

Additional Information

The phase-out of coal is an important first step to mitigate climate change and avoid premature death. Concerningly, although overall coal share in China's energy mix continued to decline, national coal use for energy increased by 0.66% from 2019 to 2020 [76], surpassing its 2014 peak.

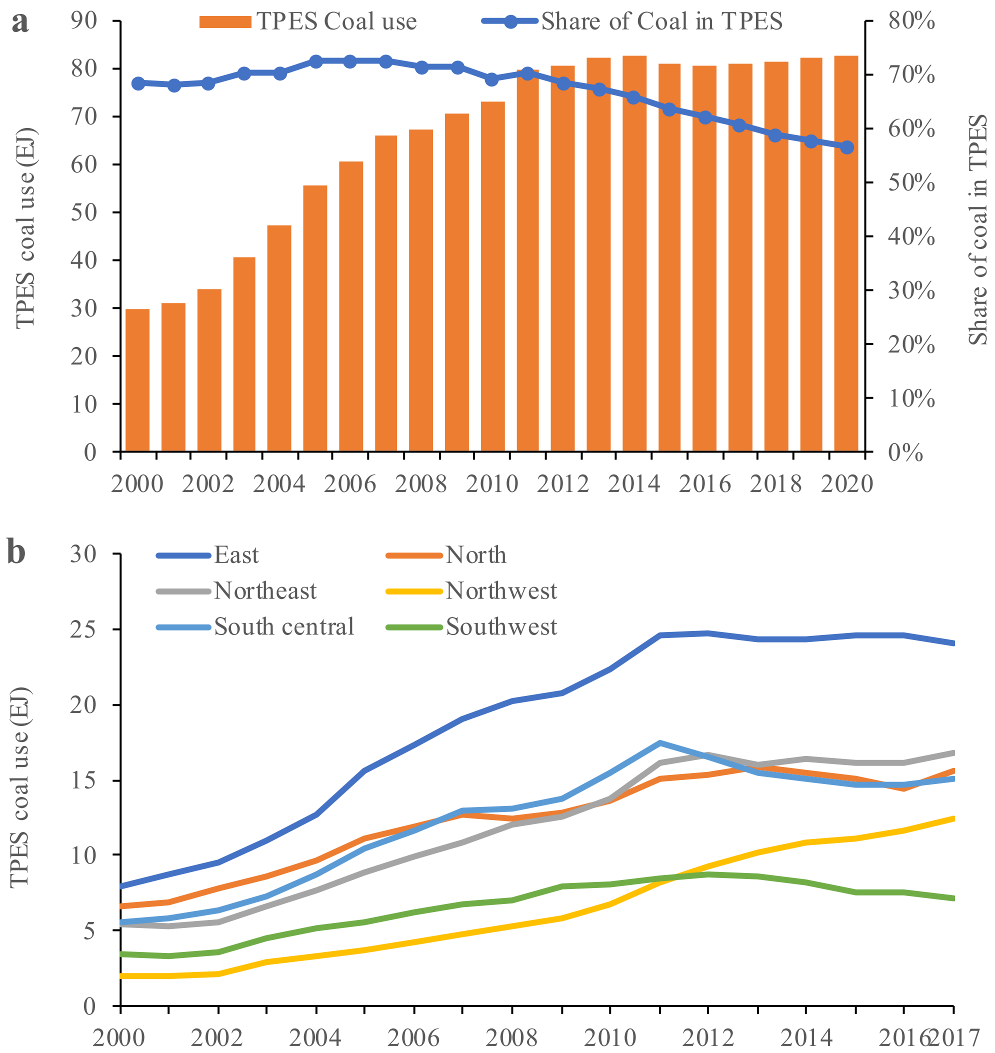

Figure 42: **National and regional Total Primary Energy Supply (TPES) from coal. (A) TPES from coal and the proportion in TPES in China (2000-2020); (B) TPES from coal in six regions (2000-2018).**

Table 21: Coal consumption by province, 2010-2018

Unit: PJ

Province	2010	2011	2012	2013	2014	2015	2016	2017	2018
Beijing	551.5	495.3	475.2	422.7	363.5	243.9	177.4	102.7	57.8
Tianjin	1006.2	1101.5	1109.0	1105.0	1052.4	950.1	885.5	811.3	801.8
Hebei	5749.3	6445.8	6564.5	6628.2	6203.7	6058.7	5883.4	5739.3	6191.1
Shanxi	6251.7	7008.3	7232.7	7669.2	7868.3	7769.4	7456.6	8989.2	10238.4
Inner Mongolia	5652.8	7260.5	7665.8	7309.0	7633.5	7640.6	7677.3	8079.3	9233.9
Liaoning	3539.5	3779.3	3813.8	3795.8	3768.5	3629.1	3546.9	3681.6	3745.6
Jilin	2006.0	2310.0	2320.0	2179.9	2172.7	2052.6	1971.3	1958.2	1789.3

Heilongjiang	2557.9	2763.2	2923.3	2777.2	2846.0	2811.9	2937.9	3028.8	2797.2
Shanghai	1229.9	1285.7	1193.8	1189.3	1024.8	989.8	968.3	958.3	924.8
Jiangsu	4835.7	5728.2	5811.5	5850.0	5633.7	5695.8	5871.4	5572.4	5315.3
Zhejiang	2920.2	3093.1	3008.9	2964.4	2893.9	2894.2	2919.9	2985.5	2966.5
Anhui	2800.0	3043.3	3078.0	3279.2	3304.7	3280.5	3292.5	3367.0	3488.0
Fujian	1470.8	1824.1	1776.2	1691.1	1716.2	1603.5	1429.0	1579.0	1790.5
Jiangxi	1307.5	1462.8	1423.9	1518.6	1565.2	1611.5	1594.6	1624.7	1648.0
Shandong	7814.0	8147.4	8422.1	7888.4	8281.6	8567.3	8569.9	7989.1	8853.3
Henan	5453.1	5939.6	5283.6	5245.5	5076.3	4965.4	4862.1	4745.4	4672.1
Hubei	2819.7	3308.5	3307.2	2546.9	2488.5	2463.0	2446.2	2465.3	2322.2
Hunan	2370.3	2722.6	2529.6	2349.5	2281.6	2332.4	2395.5	2596.7	2285.0
Guangdong	3345.9	3859.9	3691.4	3581.0	3561.5	3472.3	3377.6	3594.7	3570.6
Guangxi	1299.3	1472.2	1520.6	1537.4	1422.7	1265.8	1364.4	1384.4	1535.5
Hainan	135.5	170.6	194.9	211.2	213.2	224.4	212.5	230.1	243.2
Chongqing	1339.1	1504.9	1413.0	1213.0	1276.0	1265.9	1187.8	1182.0	1073.1
Sichuan	2411.6	2397.7	2485.2	2444.7	2312.2	1944.5	1856.7	1644.5	1568.1
Guizhou	2283.4	2529.8	2790.0	2857.5	2745.9	2686.5	2855.9	2807.1	2512.1
Yunnan	1957.1	2023.0	2061.9	2047.9	1815.9	1614.6	1561.9	1509.6	1548.6
Shaanxi	2436.3	2787.9	3302.0	3610.6	3846.6	3846.2	4117.7	4201.2	4057.7
Gansu	1128.2	1319.4	1372.8	1369.3	1405.9	1372.6	1335.0	1331.5	1426.6
Qinghai	266.0	315.7	389.1	434.0	380.3	315.7	410.8	365.7	343.0
Ningxia	1206.8	1663.6	1686.2	1786.3	1854.1	1864.6	1813.9	2314.8	2659.2
Xinjiang	1696.9	2039.9	2517.9	2973.7	3367.8	3633.9	3974.2	4264.1	4558.5

Note: (1) data for Tibet is not available. (2) Due to statistical difference, provincial sum does not equal to national total.

Indicator 3.1.3: Low-carbon emission electricity

Methods

The methods for this indicator are identical to the 2020 China Lancet Countdown report. Two sub-indicators are used here, and presented in two ways:

1. Total low carbon electricity generation, in absolute terms (TWh) and as a percentage share of total electricity generated (to include solar, wind and nuclear and hydropower); and
2. Total renewable generation (excluding hydro), in TWh, and as a percentage share of total electricity generated.

The increase in the use of low carbon and renewable energy for electricity generation will push other fossil fuels, such as coal, out of the mix over time, resulting in an improvement in air quality, with benefits to health. The indicator of renewable electricity (excluding hydro) has been used to allow for the racking of rapidly emergent renewable technologies. For both indicators, electricity generation, rather than capacity, has been chosen as a metric as the electricity generated from these technologies is what actually displaces fossil-based generation.

Due to lack of provincial data on electricity generation , six provinces who have the highest GDP in 2020[73] in their region were selected to represent their region (Beijing for North; Liaoning for Northeast; Jiangsu for East; Guangdong for South central; Sichuan for Southwest; Shaanxi for Northwest) . The data is taken from the China energy balance tables (EBTs)[77]. The absolute level indicators are total gross generated electricity aggregated from the relevant technologies. The share indicators are estimated as the low carbon or renewable generation as a percentage of total generation.

Data

The data is taken from the China EBTs[77] and China Electricity Council (https://cec.org.cn/index.html)..

Caveats

1. Solar, wind and nuclear generation were only recorded since 2015 by the National Bureau Statistics of China. And the data of wind and solar generation in provincial level in 2018 is lacking.

2. This indicator set does not provide information on the air pollutant emissions displaced due to the increasing share of renewable generation.

Future Form of Indicator

Detailed data of provinces should be updated to get the accurate regional results.

Additional Information

From 2000 to 2014, the only low-carbon electricity in China is the hydropower, which accounts for a large share of low-carbon electricity (57.1% ~74.09%) than renewable energy from 2015 to 2019 but descends during this period. The national share of renewable energy increased annually. In 2020, renewable energy increased by 11.82% while hydropower increased by 4.09%. The power from wind and solar increased by 15% and 17% respectively, relative to 2019 and low-carbon electricity in 2020 already accounted for 32% of China's total power generation. In North China, the renewable electricity has increased by 25% compared with last year (2020), while the South Central only increased by 5%. Southern region (i.e., Southwest, and South central) generated more hydropower than northern provinces. It is mainly because that there are more rivers, better favorable and preferable terrain and more humid climate in the southern area of China than northern area. However, it should be note that in the Northeast China, its hydropower is still abundant.

The shares of renewable energy in Northeast and South central were higher than national average level, but they had different shares of types of renewable energy mainly due to their resource endowment and socioeconomic development level. There was 57.2%, 33.9% and 8.9 % of renewable energy from nuclear, wind and solar generation, respectively in Liaoning in 2020; while there were 86.8%, 7.7% and 5.5 % of renewable energy from nuclear, wind and solar generation, respectively in Guangdong in 2020.

In 2020, low-carbon electricity nationally accounted for 32.12% of total China electricity generation). As costs continue to fall, solar generation continues to grow at remarkable rates of around 16.7 % per year but still only accounts for 3.42 % of total generation. Among 6 provinces of China, Inner Mongolia produces the most solar power, 11.9 TWh in 2020[77]. The Northwest China is the area that provides the most solar power in China due to proper and suitable natural environment for solar generation.

The detailed data of different sources of electricity generation in China and other six regions see **Table 22- Table 28.**

Table 22: Different sources of electricity generation in China (TWh)

Year	Hydropower	Nuclear	Wind	Solar	Thermal power	Low carbon generation	Renewable generation	Total generation
2000	222.4	0.0	0.0	0.0	1088.5	222.4	0.0	1328.7
2001	277.4	0.0	0.0	0.0	1176.8	277.4	0.0	1480.8
2002	288.0	0.0	0.0	0.0	1328.8	288.0	0.0	1602.4
2003	283.7	0.0	0.0	0.0	1580.4	283.7	0.0	1910.6
2004	353.5	0.0	0.0	0.0	1795.6	353.5	0.0	2203.3
2005	397.0	0.0	0.0	0.0	2047.3	397.0	0.0	2500.1
2006	435.8	0.0	0.0	0.0	2369.6	435.8	0.0	2865.9
2007	485.3	0.0	0.0	0.0	2722.9	485.3	0.0	3281.6
2008	637.0	0.0	0.0	0.0	2707.2	637.0	0.0	3495.8
2009	615.6	0.0	0.0	0.0	2982.8	615.6	0.0	3714.7
2010	722.2	0.0	0.0	0.0	3331.9	722.2	0.0	4207.0
2011	698.9	0.0	0.0	0.0	3833.7	698.9	0.0	4712.9
2012	872.1	0.0	0.0	0.0	3892.8	872.1	0.0	4987.7
2013	920.3	0.0	0.0	0.0	4247.0	920.3	0.0	5431.6
2014	1072.9	0.0	0.0	0.0	4400.1	1072.9	0.0	5794.3
2015	1130.3	170.8	185.8	38.8	4284.2	1525.6	395.3	5814.9
2016	1184.0	213.3	237.1	61.6	4437.1	1696.0	511.9	6133.0
2017	1189.8	248.1	295.0	96.7	4662.7	1829.6	639.8	6451.1
2018	1232.1	295.0	365.8	176.9	4924.9	2069.8	837.7	6769.2

2019	1301.9	348.7	405.7	223.8	5045.0	2280.1	978.2	7325.3
2020	1355.2	366.2	466.5	261.1	5174.3	2449.0	1093.8	7623.6

Table 23: Different sources of electricity generation in Beijing (representing North China) (TWh)

Year	Hydropower	Nuclear	Wind	Solar	Thermal power	Low carbon generation	Renewable generation	Total generation
2000	0.9	0.0	0.0	0.0	13.7	0.9	0.0	14.5
2001	0.2	0.0	0.0	0.0	13.0	0.2	0.0	13.3
2002	0.4	0.0	0.0	0.0	13.6	0.4	0.0	14.2
2003	0.7	0.0	0.0	0.0	18.6	0.7	0.0	19.2
2004	0.4	0.0	0.0	0.0	19.8	0.4	0.0	20.4
2005	0.5	0.0	0.0	0.0	21.0	0.5	0.0	21.3
2006	0.5	0.0	0.0	0.0	20.7	0.5	0.0	21.5
2007	0.5	0.0	0.0	0.0	22.3	0.5	0.0	22.8
2008	0.0	0.0	0.0	0.0	24.3	0.0	0.0	24.3
2009	0.0	0.0	0.0	0.0	24.1	0.0	0.0	24.3
2010	0.4	0.0	0.0	0.0	26.2	0.4	0.0	26.9
2011	0.4	0.0	0.0	0.0	25.6	0.4	0.0	26.3
2012	0.4	0.0	0.0	0.0	28.3	0.4	0.0	29.1
2013	0.5	0.0	0.0	0.0	32.8	0.5	0.0	33.6
2014	0.7	0.0	0.0	0.0	35.9	0.7	0.0	36.9
2015	0.7	0.0	0.3	0.1	41.1	1.0	0.3	42.1
2016	1.2	0.0	0.3	0.1	41.8	1.7	0.4	43.4
2017	1.1	0.0	0.3	0.1	37.2	1.6	0.5	38.8
2018	1.0	0.0	0.4	0.1	42.3	1.4	0.4	43.7
2019	1.0	0.0	0.0	0.1	42.1	1.1	0.1	43.1
2020	1.1	0.0	0.4	0.6	43.4	2.1	1.0	45.5

Table 24: Different sources of electricity generation in Liaoning (representing Northeast China) (TWh)

Year	Hydropower	Nuclear	Wind	Solar	Thermal power	Low carbon generation	Renewable generation	Total generation
2000	1.5	0.0	0.0	0.0	62.8	1.5	0.0	64.6
2001	2.3	0.0	0.0	0.0	63.9	2.3	0.0	66.2
2002	1.4	0.0	0.0	0.0	70.9	1.4	0.0	72.5
2003	2.3	0.0	0.0	0.0	81.2	2.3	0.0	83.7
2004	3.9	0.0	0.0	0.0	83.4	3.9	0.0	87.5

2005	5.7	0.0	0.0	0.0	84.5	5.7	0.0	90.4
2006	4.7	0.0	0.0	0.0	96.3	4.7	0.0	101.5
2007	4.4	0.0	0.0	0.0	106.5	4.4	0.0	111.5
2008	3.9	0.0	0.0	0.0	108.5	3.9	0.0	113.8
2009	2.9	0.0	0.0	0.0	111.7	2.9	0.0	116.3
2010	4.4	0.0	0.0	0.0	120.4	4.4	0.0	129.5
2011	3.2	0.0	0.0	0.0	126.0	3.2	0.0	137.0
2012	3.8	0.0	0.0	0.0	130.4	3.8	0.0	144.1
2013	6.1	0.0	0.0	0.0	133.4	6.1	0.0	155.4
2014	4.2	0.0	0.0	0.0	137.0	4.2	0.0	165.6
2015	3.2	14.5	11.2	0.1	135.8	29.0	25.8	166.5
2016	4.7	20.0	12.9	0.3	140.0	37.9	33.2	177.9
2017	3.5	23.6	14.4	0.6	140.9	42.0	38.6	182.9
2018	2.8	28.4	16.5	1.0	141.1	48.7	45.9	189.8
2019	2.8	32.7	15.3	1.4	147.4	52.2	49.4	199.6
2020	5.7	32.7	19.4	5.1	141.0	62.9	57.2	203.9

Table 25: Different sources of electricity generation in Jiangsu (representing East China) (TWh)

Year	Hydropower	Nuclear	Wind	Solar	Thermal power	Low carbon generation	Renewable generation	Total generation
2000	0.0	0.0	0.0	0.0	91.0	0.0	0.0	91.0
2001	0.0	0.0	0.0	0.0	98.6	0.0	0.0	98.7
2002	0.1	0.0	0.0	0.0	111.6	0.1	0.0	111.7
2003	0.4	0.0	0.0	0.0	133.3	0.4	0.0	133.7
2004	0.3	0.0	0.0	0.0	155.1	0.3	0.0	155.5
2005	0.3	0.0	0.0	0.0	211.4	0.3	0.0	212.0
2006	0.3	0.0	0.0	0.0	251.3	0.3	0.0	253.6
2007	0.3	0.0	0.0	0.0	257.7	0.3	0.0	267.5
2008	0.7	0.0	0.0	0.0	263.1	0.7	0.0	281.5
2009	0.2	0.0	0.0	0.0	276.2	0.2	0.0	292.8
2010	0.3	0.0	0.0	0.0	316.6	0.3	0.0	335.9
2011	0.2	0.0	0.0	0.0	356.3	0.2	0.0	376.3
2012	1.1	0.0	0.0	0.0	377.9	1.1	0.0	400.1
2013	1.1	0.0	0.0	0.0	409.9	1.1	0.0	432.1
2014	1.2	0.0	0.0	0.0	409.4	1.2	0.0	434.6
2015	1.2	16.6	5.9	1.9	410.4	25.6	24.5	436.1
2016	1.7	15.4	9.4	4.1	440.3	30.6	28.9	470.9

2017	2.9	17.3	11.7	6.2	453.0	38.0	35.1	491.5
2018	3.3	24.2	17.3	4.6	447.7	49.4	46.1	493.4
2019	3.3	32.9	15.9	5.9	443.9	57.9	54.7	501.5
2020	3.2	35.5	22.9	16.7	429.0	78.3	75.1	507.3

Table 26: Different sources of electricity generation in Guangdong (representing South Central China) (TWh)

Year	Hydropower	Nuclear	Wind	Solar	Thermal power	Low carbon generation	Renewable generation	Total generation
2000	10.6	0.0	0.0	0.0	103.9	10.6	0.0	129.3
2001	19.0	0.0	0.0	0.0	107.5	19.0	0.0	141.8
2002	10.9	0.0	0.0	0.0	121.0	10.9	0.0	152.6
2003	18.0	0.0	0.0	0.0	139.9	18.0	0.0	188.3
2004	19.2	0.0	0.0	0.0	166.1	19.2	0.0	214.1
2005	20.8	0.0	0.0	0.0	176.5	20.8	0.0	227.9
2006	26.8	0.0	0.0	0.0	188.4	26.8	0.0	246.6
2007	24.1	0.0	0.0	0.0	218.7	24.1	0.0	273.2
2008	38.8	0.0	0.0	0.0	196.9	38.8	0.0	271.6
2009	26.9	0.0	0.0	0.0	215.8	26.9	0.0	275.8
2010	34.9	0.0	0.0	0.0	248.8	34.9	0.0	323.7
2011	33.1	0.0	0.0	0.0	301.8	33.1	0.0	380.2
2012	36.7	0.0	0.0	0.0	288.1	36.7	0.0	376.4
2013	38.9	0.0	0.0	0.0	297.3	38.9	0.0	387.5
2014	40.7	0.0	0.0	0.0	301.9	40.7	0.0	401.3
2015	43.7	60.6	5.5	0.2	293.4	110.0	66.4	403.5
2016	44.3	70.3	4.7	0.4	297.2	119.9	75.5	417.0
2017	30.8	80.0	5.5	1.1	332.9	117.3	86.5	450.3
2018	14.7	89.2	6.3	0.8	326.0	111.0	96.3	437.0
2019	18.5	110.2	6.9	2.5	334.6	138.0	119.5	472.6
2020	28.5	116.1	10.3	7.4	342.6	162.3	133.8	504.9

Table 27: Different sources of electricity generation in Sichuan (representing Southwest China) (TWh)

Year	Hydropower	Nuclear	Wind	Solar	Thermal power	Low carbon generation	Renewable generation	Total generation
2000	31.5	0.0	0.0	0.0	18.5	31.5	0.0	50.0
2001	42.2	0.0	0.0	0.0	20.9	42.2	0.0	63.3

2002	41.0	0.0	0.0	0.0	28.6	41.0	0.0	69.6
2003	48.0	0.0	0.0	0.0	36.8	48.0	0.0	84.9
2004	62.1	0.0	0.0	0.0	31.4	62.1	0.0	93.4
2005	65.3	0.0	0.0	0.0	36.5	65.3	0.0	101.9
2006	78.5	0.0	0.0	0.0	44.2	78.5	0.0	122.7
2007	81.4	0.0	0.0	0.0	44.9	81.4	0.0	126.3
2008	98.1	0.0	0.0	0.0	40.1	98.1	0.0	138.3
2009	106.5	0.0	0.0	0.0	51.3	106.5	0.0	157.9
2010	121.3	0.0	0.0	0.0	57.0	121.3	0.0	179.5
2011	136.4	0.0	0.0	0.0	60.9	136.4	0.0	198.1
2012	156.2	0.0	0.0	0.0	58.8	156.2	0.0	215.1
2013	200.2	0.0	0.0	0.0	62.8	200.2	0.0	263.1
2014	250.1	0.0	0.0	0.0	59.0	250.1	0.0	309.5
2015	266.8	0.0	1.0	0.1	45.0	267.9	1.1	313.0
2016	285.2	0.0	1.8	0.6	39.8	287.6	2.4	327.4
2017	304.1	0.0	3.8	1.7	38.4	309.6	5.5	348.0
2018	298.2	0.0	5.5	1.4	44.8	305.1	6.9	349.9
2019	307.6	0.0	7.3	2.0	50.3	316.8	9.3	367.1
2020	354.1	0.0	8.6	2.7	51.3	365.4	11.3	416.7

Table 28: Different sources of electricity generation in Shaanxi (representing Northwest China) (TWh)

Year	Hydropower	Nuclear	Wind	Solar	Thermal power	Low carbon generation	Renewable generation	Total generation
2000	3.5	0.0	0.0	0.0	23.7	3.5	0.0	27.2
2001	14.9	0.0	0.0	0.0	27.5	14.9	0.0	42.4
2002	2.6	0.0	0.0	0.0	31.8	2.6	0.0	34.4
2003	4.7	0.0	0.0	0.0	37.3	4.7	0.0	41.9
2004	4.2	0.0	0.0	0.0	45.6	4.2	0.0	49.8
2005	5.1	0.0	0.0	0.0	49.6	5.1	0.0	54.9
2006	4.0	0.0	0.0	0.0	54.5	4.0	0.0	58.5
2007	5.5	0.0	0.0	0.0	65.1	5.5	0.0	70.7
2008	6.4	0.0	0.0	0.0	78.7	6.4	0.0	85.3
2009	7.5	0.0	0.0	0.0	83.4	7.5	0.0	90.9
2010	8.7	0.0	0.0	0.0	102.5	8.7	0.0	111.2
2011	10.0	0.0	0.0	0.0	112.2	10.0	0.0	122.2
2012	8.9	0.0	0.0	0.0	125.2	8.9	0.0	134.2

2013	11.1	0.0	0.0	0.0	139.2	11.1	0.0	151.2
2014	11.7	0.0	0.0	0.0	149.1	11.7	0.0	163.0
2015	13.4	0.0	2.8	0.8	145.2	17.0	3.6	162.3
2016	12.5	0.0	3.7	1.3	158.1	17.6	5.1	175.7
2017	14.2	0.0	5.1	3.4	158.6	22.7	8.5	181.4
2018	11.5	0.0	7.2	4.0	156.7	22.7	11.2	178.2
2019	13.7	0.0	7.1	5.2	185.9	26.0	12.2	211.9
2020	12.8	0.0	9.5	11.9	208.4	34.2	21.4	242.6

Indicator 3.2: Clean household energy

Methods

This indicator is modelled with household investigation data compiled by National Bureau of Statistics.

The clean energy is defined as the energy with low emissions.[78] Compared to the methods used in the 2020 Report, two major differences are as follows. The new report compared the rising tendency of energy consumption between rural and urban areas, and discussed the policy impact by literature review.

Data

1. The per capita household energy consumption data is from the China Statistical Yearbook 2001-2020.
2. The renewable energy usage data of rural areas is from the China Rural Statistical Yearbook 2001-2020.
3. The total per capita household energy consumption data is from UNEP.

Caveats

The caveats of this indicator would mainly be in two aspects. First, the types of renewable energy sources are limited. For example, wind energy, hydro energy and tidal energy are not included. More recent and adequate data may reveal different results especially in 2020 due to the impact of COVID-2019. Second, regional difference should not be neglected considering the difference of climate and economics.

Additional Information

The use of inefficient fuels for cooking alone is estimated to cause over 4 million deaths annually in the world, mainly among women and children.[78] Increasing the proportion of clean energy use could benefit health and reduce greenhouse gas emissions.[79] This indicator reports on household energy consumption using data compiled by the National Bureau of Statistics. Per capita household energy consumption has increased significantly, by 229% from 3.9GJ in 2000 to 12.7 GJ in 2018. While the urban per capita household energy was 2.4 times than that in rural areas in 2000s, the latter increased rapidly and reached the same level in 2016. The per capita coal consumption, reported as the preferred energy source as the substitution of biomass for rural residents,[80] had reduced 17.9% in 2018 while liquefied petroleum gas consumption stopped increasing. Electrification is believed to be the major access to household energy structure transition in the future,[81] while clean coal technologies, meeting the low emissions demand, should also be paid more attention as the temporary substitution plan.[80] However, most coal consumption was still with high pollution, and thus the total coal consumption had reduced in the past few years. The rural centralized residence policy could promote clean energy popularization.[82]

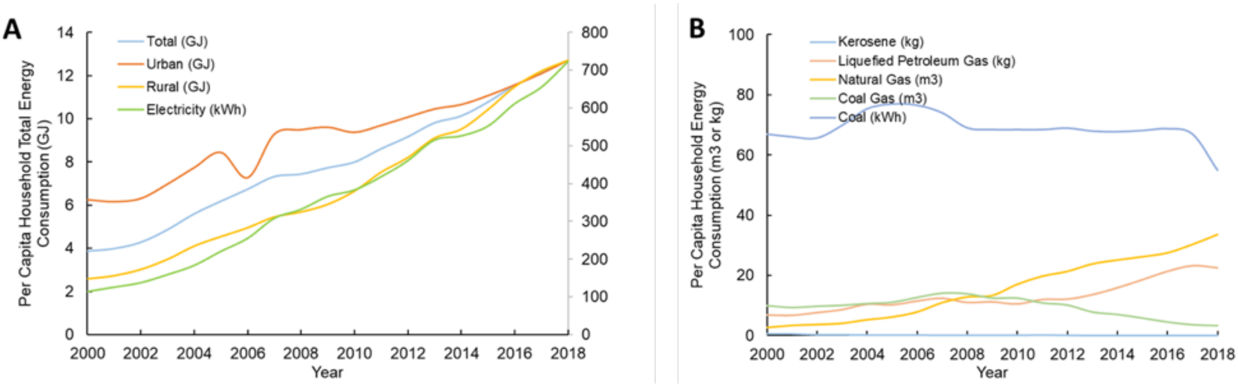

Figure 43: **Development of Household Energy Consumption in China**

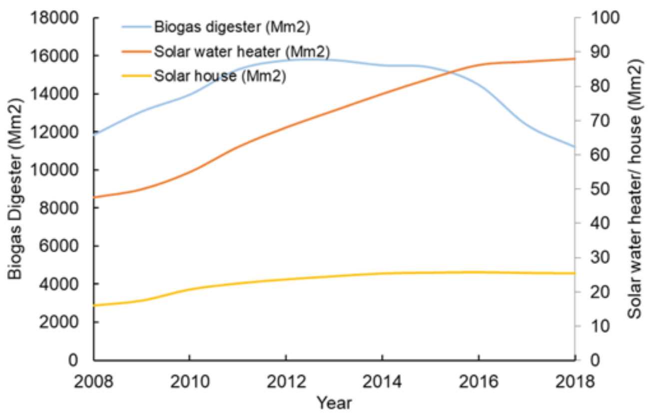

Figure 44: **Development of Renewable Energy Consumption in Rural China**

Indicator 3.3: Air pollution, energy, and transport

Indicator 3.3.1: Exposure to air pollution in cities

Methods

This indicator reports the trends of annual air pollutant concentrations in China's cities based on monitoring data. The distribution of city-specific annual average $PM_{2.5}$ and annual daily maximum 8-hour average ozone concentrations is illustrated based on the monitoring data involving 366 cities during 2015-2020 in China. The level of surface ozone pollution is first introduced in this year's report. The methodology for this indicator remains similar to that described in the 2020 China Lancet Countdown report appendix.

Data

Data of daily 24-hour average $PM_{2.5}$ and daily maximum 8-hour average (DMA8) ozone concentrations of 366 China's cities were collected from the Data Center of Ministry of Ecology and Environment of China.[83] Following 'Technical Regulation for Ambient Air Quality Assessment' (HJ 633-2013) published by the former Ministry of Environmental Protection of China, the city-specific annual average $PM_{2.5}$ concentration is calculated by arithmetic mean of daily 24-hour average $PM_{2.5}$ concentrations, and the value of the 90th percentile of DMA8 is set to be the annual daily maximum 8-hour average (ADMA8) ozone concentration.[84]

Caveats

Due to the adjustment of administrative divisions, the monitoring data of 2015-2019 involved 367 cities, while those of 2020 only contained 366 cities (excluding Laiwu, which was incorporated into Jinan in 2019). The records of Laiwu during 2015-2019 were eliminated for consistency.

Future Form of Indicator

Given the worsening surface ozone pollution, there is an urgent need for a comprehensive assessment of the detrimental effects on human health attributable to ozone pollution exposure.[85,86] The follow-up study on this indicator may focus on health impacts estimates on city-level to provide insights for city-specific air pollution control.

Additional Information

Table 29: Statistics for annual average $PM_{2.5}$ concentrations of 366 China's cities.

Year	Minimum ($\mu g/m^3$)	Median ($\mu g/m^3$)	Maximum ($\mu g/m^3$)	Number of cities with annual average $PM_{2.5}$ concentration >35$\mu g/m^3$
2015	10	49	118	290
2016	11	45	157	268
2017	10	42	100	260
2018	8	38	116	219
2019	7	36	110	192
2020	6	32	113	151

Table 30: Statistics for ADMA8 ozone concentrations of 366 China's cities.

Year	Minimum ($\mu g/m^3$)	Median ($\mu g/m^3$)	Maximum ($\mu g/m^3$)	Number of cities with ADMA8 ozone concentration >100$\mu g/m^3$
2015	58	136	203	338

2016	50	139	224	342
2017	78	147	219	358
2018	74	148	215	360
2019	82	147	208	357
2020	89	138	194	355

Indicator 3.3.2: Deaths attributable to ambient air pollution by sector

Methods

This indicator quantifies the number of deaths attributable to long-term ambient fine particulate matter ($PM_{2\cdot5}$) exposure by sectorial sources for each province in China. The greenhouse gas-air pollution interactions and synergies (GAINS) model is used to quantify the sectorial contribution to ambient $PM_{2\cdot5}$.[81] Data from the International Energy Agency (IEA) World Energy Outlook 2020 and the data of Chinese statistical yearbook in 2020 and China energy statistical yearbook 2019 are integrated into GAINS to develop the provincial air pollution emission inventory by fuels and sectors.

Atmospheric chemistry and dispersion coefficients with the European Monitoring and Evaluation Programme (EMEP) Chemistry Transport Model are used to simulate the changes in ambient $PM_{2\cdot5}$ with varying emissions.[82] We also made a validation between ambient annual PM2·5 concentration of the GAINS and the official data that released by Chinese government.

Deaths attributable to total ambient $PM_{2\cdot5}$ by provinces and sectors in China are calculated using the integrated exposure-response functions (IERs) employed by the WHO (2016) assessment on the disease burden from long-term exposure to ambient air pollution,[83] which relies on cause-specific mortality relative risk (RR) functions and requires the application to a higher range of annual average concentrations in the study area.

The concentration-response (C-R) functions and relative risks [Eq. (1)] were based on the IERs from the GBD 2019 across the full range of $PM_{2\cdot5}$ concentrations. $RR_{IER}(z)$ represents the relative risks in the $PM_{2\cdot5}$ exposure concentration of C (in micrograms per meter cubed); C_0 represents the counterfactual concentration below which it is assumed there is no additional risk. For very large C, $RR_{IER}(z)$ approximates 1+α. A power of $PM_{2\cdot5}$, δ, was included here to predict risk over a very large range of concentrations.

$$RR_{IER}(Z)=\begin{cases} 1, \text{ for } C < C_0 \\ 1+\alpha\{1-\exp[-\gamma(C-C_0)^{\delta}]\}, \text{ for } C \geq C_0 \end{cases} \quad (1)$$

We adopted a calculation approach [Eq. (2)] developed for the GBD 2019 to estimate $PM_{2.5}$-related mortality in each province, and the following seven endpoints are included in our estimation: ischemic heart disease (IHD), chronic obstructive pulmonary disease (COPD), lung cancer (LC), diabetes, preterm birth (PTB), and stroke in adults, and acute lower respiratory infections (ALRI) in children less than 5 years old. For IHD and stroke, the RR is different between age strata, and for COPD and LC, the RR in the same exposure concentration is the same for the entire group of adults (aged 25 or more). We estimated the attributable deaths $M_{i,j}$ of each province (and of each age stratum for IHD and stroke) and disease endpoint j attributable to ambient $PM_{2\cdot5}$ for Province i.

$$M_{i,j}=P_i\times\hat{I}_j\times(RR_j(C_i)-1),\ \text{where}\quad \hat{I}_j=\frac{I_j}{RR_j} \qquad (2)$$

$\hat{I}_j$ represents the hypothetical "underlying incidence" (i.e., cause-specific mortality rate) that would remain if $PM_{2\cdot5}$ concentrations were reduced to the theoretical minimum risk concentration. Here, P_i is the population of province i, I_j is the reported regional average annual disease incidence (mortality) rate for endpoint j, C_i represents the annual-average $PM_{2\cdot5}$ concentration in county i, RR_j (C_i) is the relative risk for end point j at concentration C_i, and RR_j represents the average population-weighted relative risk for end point j.

Data

1. Emissions data was taken from the IEA World Energy Outlook 2020, the Chinese statistical yearbook in 2020, and the China energy statistical yearbook 2019.
2. Provincial air pollution emission inventory by fuels and sectors was from GAINS model;
3. Provincial demographic and mortality data was from Chinese statistical yearbook in 2015 and 2019;
4. Baseline mortality data was obtained from Zhou et al.[85] and the results of GBD 2019 studies;
5. The RR value and estimated parameters were from GBD 2019.

Caveats

There are three key caveats of this indicator. Firstly, the annual mean $PM_{2\cdot5}$ concentration for each province was calculated from GAINS model, the health effects related to air pollution are calculated based on provincial concentration rather than grid data. Second, compared with the previous report of only five common diseases included in IER data, this year's report added diabetes and preterm birth, which improved the accuracy of calculation. Finally, $PM_{2\cdot5}$ from various sources used the same C-R function and RR, so the estimated results may deviate from the actual situation to some extent.

Indicator 3.3.3: Sustainable and healthy transport

Methods

The methods of this indicator are identical to the 2020 China Lancet Countdown report. This indicator shows the changes in emission intensity of road transport, as well as the average emission per vehicle, of 4 major pollutants (CO, HC, NOx, PM_{10}), from 2000 to 2019 for China, and total emission intensity of road transport for all provinces from 2010 to 2019, where data is available. Emissions intensity is calculated through the ratio of vehicular emissions to vehicle ownership.

Data

The data from China Vehicle Environmental Management Annual Reports and the National Bureau Statistics of China 2020[87,88].

1. Emission data is from China Vehicle Environmental Management Annual Reports (2009-2020).
2. Vehicle ownership data is from National Bureau of Statistics of China (2000-2019).

Caveats

Firstly, data used did not include low-speed vehicle or motorcycles, so it does not consider all emissions from vehicles. Secondly, this indicator does not currently measure greenhouse gas emissions intensity, so whilst it is an indicator of the health co-benefits of mitigation (through the reduction in road transport-related air pollutants), it does not currently measure mitigation directly. Thirdly, this indicator does not consider other health co-benefits of mitigation in the transport sector, such as the health benefits resulting from increased physical activity related to walking and cycling. Finally, provincial emission data is not available before 2010.

Additional Information

We use the emission intensity of road transport, calculated by the ratio of emission and vehicle ownership, to determine the average emission for the whole fleet including green-car. The emission intensities of carbon monoxide (CO), hydrocarbon (HC), nitrogen oxide (NO_x) and particulate matter (PM) have dropped stably since 2000 and over 90% as of 2018. In 2018, the Ministry of Ecology and Environment released the final regulation for the China VI emission standard for new heavy-duty vehicles, this world's most stringent HDV emission standard was gradually implementing in China, In the same year, the promulgation of the "Three-year Action Plan for Promoting the Adjustment of Transport Structure (2018-2020)" and other such plans also accelerate the transport structure transition. By the end of 2019, the total emission of four pollutants from vehicles nationwide was 16.038 million tons, declined by 60% year over year (y-o-y). Except for NO_x, the emission intensities for CO, HC and NO_x reduced by 76%, 50% and 84% y-o-y, reflecting the effectiveness of mobile source emission control. In 2019, the number of green-car (including plug-in hybrid electric vehicles, battery electric vehicles and fuel cell electric vehicles) reached 3.81 million, an increase of more than 1 million for two consecutive years, showing a rapid growth trend. The traffic activities were greatly limited in lockdown period under the impact of COVID-19[89] in 2020, which resulted in a large decline in transport emission especially in NO_x[90], the annual transport emission is predicted to decrease further in 2020. Moreover, as the number of civilian vehicles continue to grow to 281.9 million[91], the emission intensity of road transport would hit a new low in 2020.

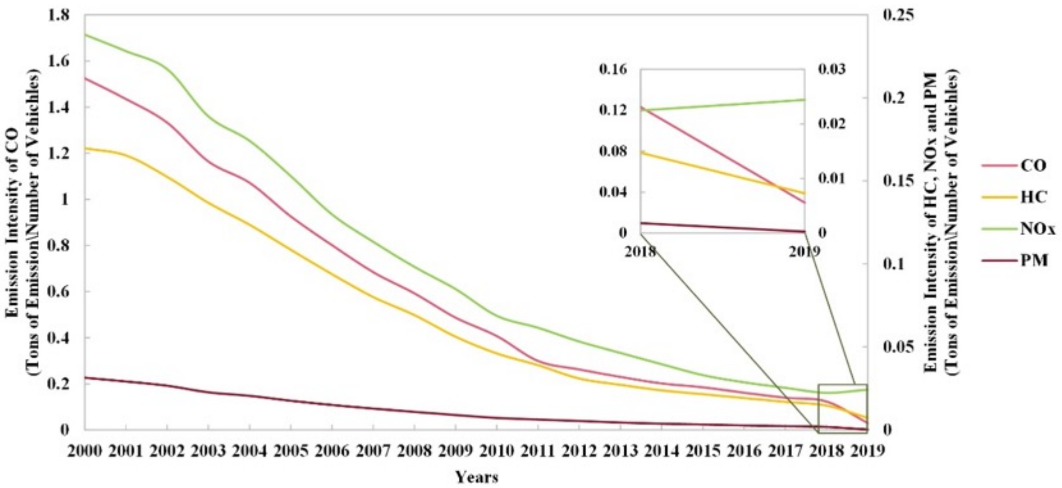

Figure 45: **The air pollution emissions intensity of road transport in China from 2000 to 2019 for CO, HC, NO_x and PM.**

Indicator 3.4: Food, agriculture, and health

Methods

The methods of this indicator are identical to the 2020 China Lancet Countdown report. At the national level, emissions from livestock and crop production in China (area code 351) were obtained from the FAOSTAT from 2000-2018. At the provincial level, emissions of 30 provinces in China mainland in 2018 were calculated, taking data from the China Statistical Yearbook. For livestock, methane emissions from enteric fermentation and manure management are calculated by multiplying livestock numbers and emission factors per head, nitrous oxide emissions from manure management and manure left on pasture are calculated by multiplying manure excreta and emission factors per kilogram of manure nitrogen. The following livestock are included: ruminant including buffaloes, camels, cattle (dairy), cattle (non-dairy), goats, and sheep, and non-ruminant including chicken (broilers), chicken (layers), ducks, swine (market), swine (breeding), asses, horses, mules, and turkeys.

For crops, methane emission from rice cultivation is calculated by multiplying rice area and emission factors per hectare. Nitrous oxide emissions from fertilizer (synthetic fertilizer and manure) and crop residues applied to soil are calculated by multiplying the nitrogen content of fertilizer or crop residue returning to field and emission factors per kilogram of nitrogen. Emissions from crop residue burning are calculated by multiplying the dry biomass of crop residue for burning and emissions factors per kilogram of dry biomass.

Data

1. At provincial level, crop production, sown area of rice and synthetic fertilizer use for crop emission calculation, and livestock number for livestock emission calculation were obtained from China Statistical Yearbook 2019 and China Rural Statistic Yearbook 2019.
2. Emission factors for crop residue, enteric fermentation, manure management, and manure left on pasture were obtained FAOSTAT (calculated data).
3. Crop residue biomass was calculated by multiplying grain production and a straw/grain ratio obtained from Gu et al. (2015).[92]

4. Emission factors for straw burning were derived from Zhang et al. (2017)[93] and Zhang et al. (2008)[94]. Animal excreta were calculated according to the Technical Guidelines for Compiling the Inventory of Atmospheric Ammonia Emission.[95]
5. The percentage of manure applied to soil was derived from Ma et al. (2012).[96]

Caveats

The sum of provincial emissions calculated differ from national emission obtained from FAOSTAT, because some parameters are missing in FAOSTAT for the calculation of provincial emissions, or China specific data derived from literature. The sum of provincial emissions from livestock was 5% lower than livestock emissions for China obtained from FAOSTAT, mainly due to a relatively underestimation of emissions from manure left on pasture. In calculating manure nitrogen left on pastures by grazing livestock, China's five main pastoral areas: Inner Mongolia, Gansu, Qinghai, Tibet, and Xinjiang were classified as grazing systems according to Bai et al. (2013),[97] while other provinces were assumed to have no grazing systems due to data availability. This classification leads to a relatively underestimation of livestock manure left on pasture. The sum of provincial emissions from crop production was 17% higher than crop emissions for China obtained from FAOSTAT, mainly due to a relatively overestimation of emissions from burning of crop residues. In calculating emissions from burning of crop residues, we used emission factors derived from Zhang et al. (2008),[94] who simulated the open burning of crop residues in China by a custom-designed combustion and test device. The emission of CO_2e per kilogram dry matter of burned crop residues was 17-28 times higher than that from FAOSTAT calculated data using IPCC Tier 1 method.

Additional Information

Headline finding: During 2000-2018 total CO_2e emissions from livestock have decreased by 7%, while emissions from crop production increased by 17% during 2000 -2018.

CO_2e emissions from Chinese livestock had decreased by 7% during 2000-2018 mainly due to the reduction of non-dairy cattle population. However, non-dairy cattle are still the largest contributor to total emissions, account for 27% in 2018 **(Figure 46**). Inner Mongolia, Sichuan, Yunnan and Xinjiang together account for 31% of total livestock emissions in China, because of large ruminants populations **(Figure 47**). During the same period, emissions from crop production increased by 17% mainly due to the growing synthetic fertilizer use. Synthetic fertilizer alone accounts for nearly half of total crop emissions. Henan, Heilongjiang, Hunan, and Guangxi together contribute 27% to national total emissions from crop production. The environmental impact of synthetic fertilizer has been taken seriously by China government. Without initiated the "Zero Growth in Chemical Fertilizer Use" plan in 2015[98], the chemical fertilizer use and CO_2e emissions from crop production would have increased by 18% and 9% respectively in 2018. Total agricultural CO_2e emissions in 2018 had increased by less than 1% compared with 2000, and can be completely offset by annual CO_2 sequestration of China's forest according to the afforestation target of China's NDCs on climate change.

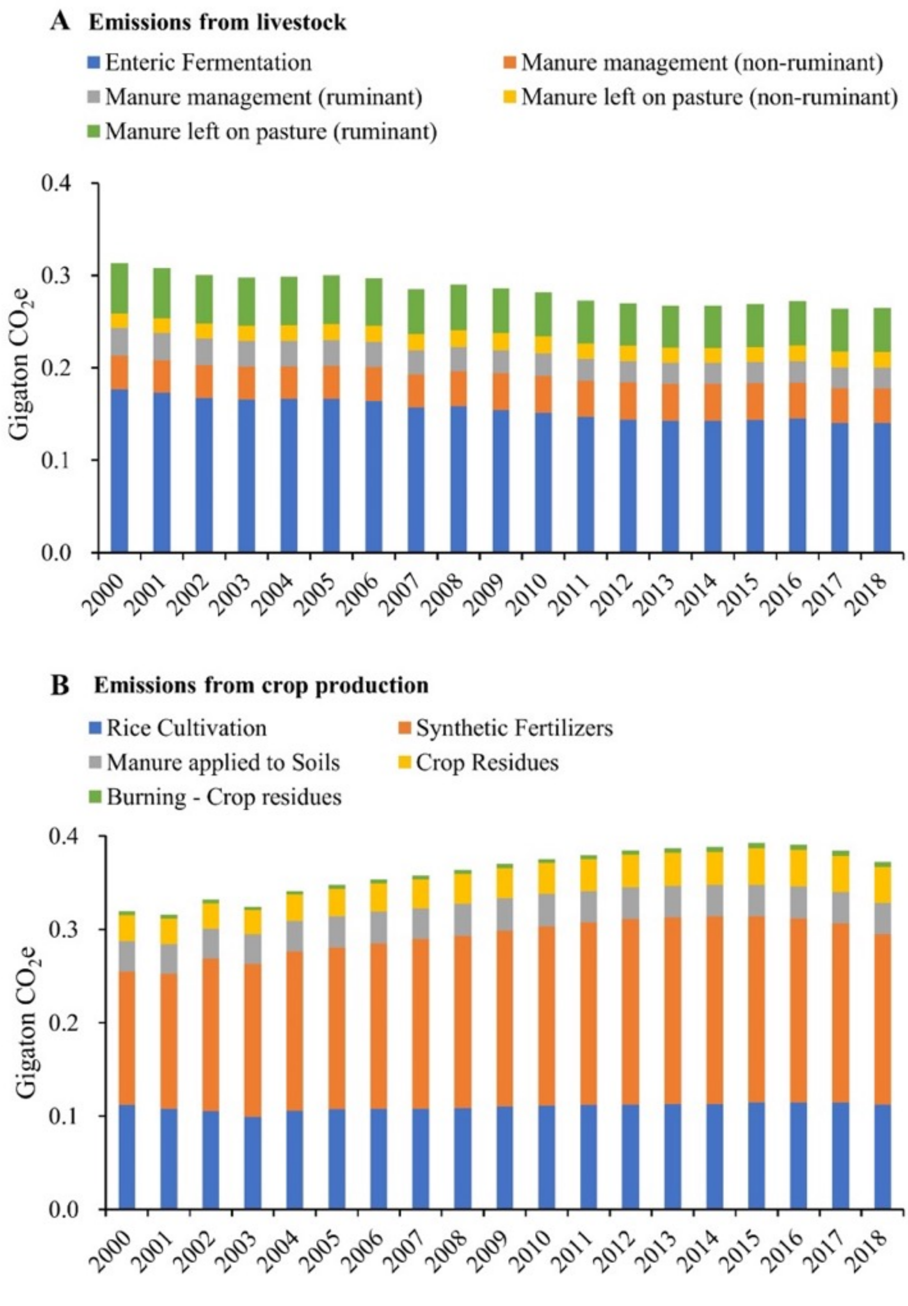

***Figure 46*: Crop production and livestock emissions from 2000 to 2018**

(A) CO_2e emissions from livestock. (B) CO_2e emissions from crop production. CO_2e=carbon dioxide equivalent.

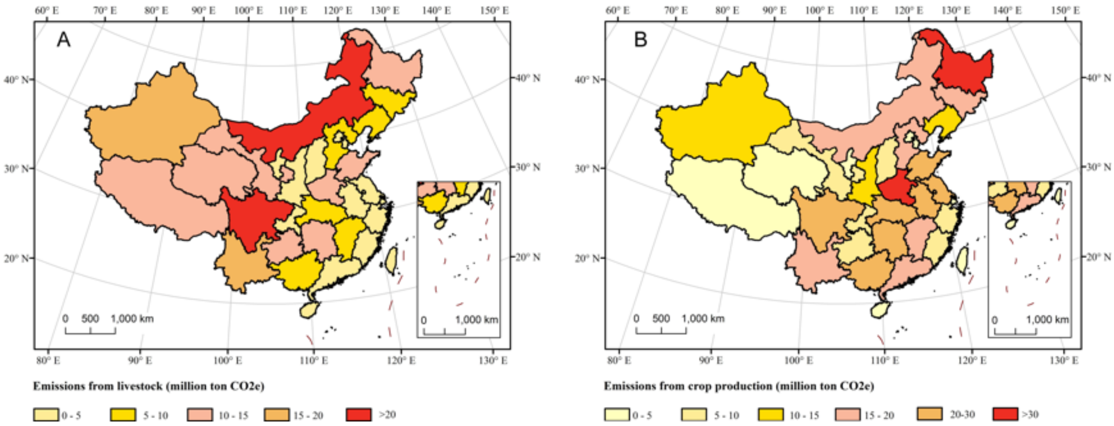

Figure 47**: Provincial CO_2e emissions by agricultural production and livestock sectors in 2018**

(A) CO_2e emissions from livestock. (B) CO_2e emissions from crop production. CO_2e=carbon dioxide equivalent.

The overall emissions from livestock have decreased by 7% from 2000 to 2018. Enteric fermentation (53) has the highest contribution to total livestock emissions in 2018, followed by manure left on pasture of ruminants (18%), manure management of non-ruminants (14%), manure management of ruminants (9%), and manure left on pasture of non-ruminants (7%). The emissions from enteric fermentation, manure management of ruminants and manure left on pasture of ruminants have decreased by 21%, 26% and 13% respectively from 2000 to 2018, whereas the emission from manure management of non-ruminants and manure left on pasture of non-ruminants have increased by 5% and 11% respectively.

Ruminants have the highest emissions of all livestock emissions in 2018 (75% of total). The emissions are from non-dairy cattle (32%), followed by goats and sheep (22%), buffalo (17%) and dairy cattle (4%). Emissions from non-ruminants come from pigs (16%), poultry (8%) and others (1%). A decrease in stock of non-dairy cattle by 42% is the main reason for livestock emission reduction from 2000 to 2018, while the stock of dairy cattle, goats and sheep, buffaloes, swine, and poultry increased by 15%, 8%, 20%, 2%, and 43% respectively (***Figure 48***). The overall emissions from crop production have increased by 17% from 2000 to 2018. Synthetic fertilizer (49%) has the highest contribution to total crop emissions in 2018, followed by rice cultivation (30%), crop residues (10%), manure applied to soil (9%) and crop residues burning (1%). The majority of the increase in emissions from 2000 to 2018 is attributed to synthetic fertilizer and crop residues which contributes 75% and 19% to total increase in crop emissions. From 2000 to 2015, China's chemical fertilizer use increased by 45%. In 2015, China made a plan of Zero Growth in Chemical Fertilizer Use by 2020. [98] Since 2015, China's chemical fertilizer use has begun to decline (***Figure 49***).

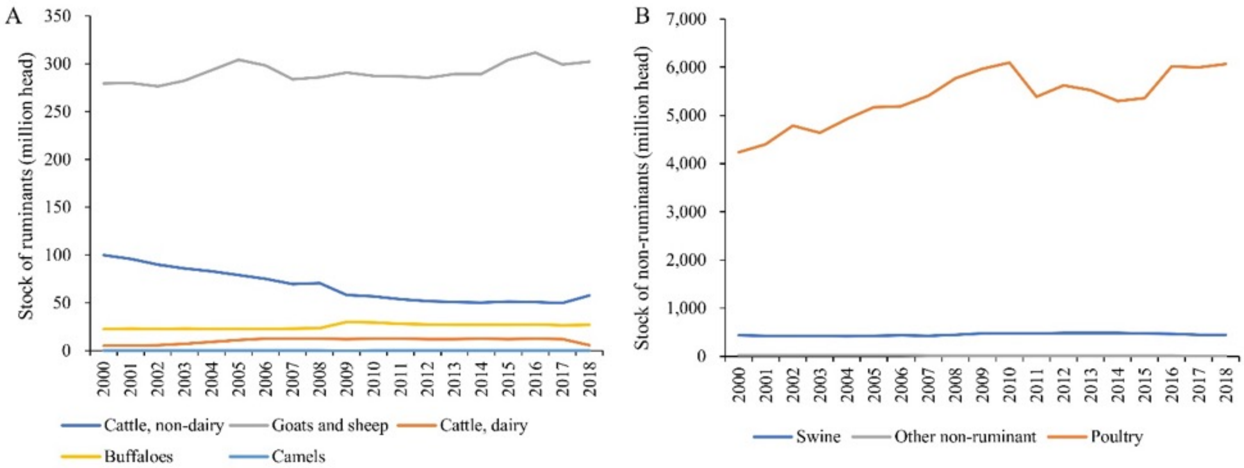

Figure 48: **China's livestock number during 2000 to 2018**

(A) Stock of ruminant animals. (B) Stock of non-ruminant animals.

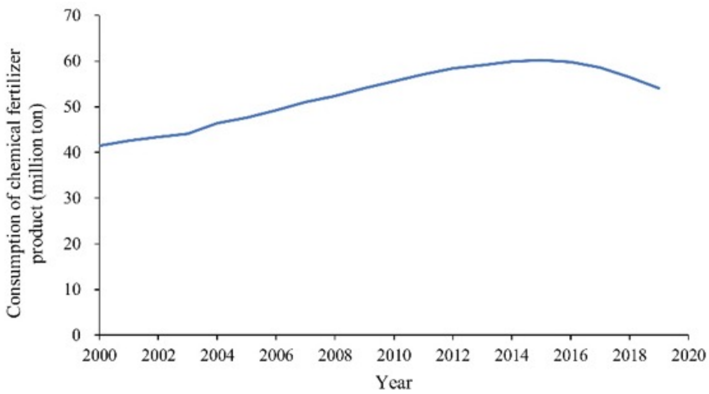

Figure 49: **China's consumption of chemical fertilizer products during 2000 to 2019**

Section 4: Economics and finance

Indicator 4.1: health and economic costs of climate change and benefits from its mitigation

Indicator 4.1.1: costs of heatwave-related mortality

Methods

Methods

Because a value of statistical life (VSL) relies highly on estimates of 'willingness to pay' by individuals, the economic calculation method based on VSLs are better at evaluating the costs from individual perspective, and cannot fully reflect the real impacts on the economic system. Therefore, different from the 2020 report which estimated the monetized value of heatwave-related mortality through value of a statistical life, this year's indicator was updated to unify the methodologies in indicator 4.1 and evaluated the economic costs of heatwave-related mortality of working-age people. We used an Input-Output (IO) model (detail description of this method can be found in Xia's work[99]) to capture the direct and indirect costs.

Using the heatwave-related working age mortality data provided by WG1 as the input, we used the Chinese IO tables available for eight years (2002, 2005, 2007, 2010, 2012, 2015, 2017, 2018) for national economic costs analysis. Assuming a fixed input-output relationship in 2018, 2019 and 2020, the evaluation on national level was extended to 2020. We used a multi-regional IO table in 2017 for provincial analysis.

For direct losses for each sector, we assumed the heatwave-related working age mortality rate equals to the direct loss rate of industrial value added because labor is a major input for industrial production. The direct loss was then put in assessing model to estimate the overall economic cost for each year. Comparing the overall and direct losses gives the estimated indirect losses resulting from inter-dependence relationship among sectors and regions.

Data

1. Heatwave-related working age mortality data is provided by WG1;
2. The Chinese IO tables for eight years came from the website of the National Bureau of Statistics of China[100].
3. The Chinese multi-regional IO table for 2017 is obtained from the CEADs dataset[101].

Caveats

The caveats of this indicator would mainly be in four aspects.

First, non-working age population (the elderly) don't take part in economic activity, therefore they are not considered in IO analysis framework, and the results only shows the economic costs of working-age population deaths from heat. Second, the input-output analysis framework has assumed no market-based price adjustment and substitution of inputs, which implies the costs may be overestimated. Third, due to data available, the analysis is only performed at specific years with accessible IO tables. Fourth, the impact of COVID-19 on heatwave-related mortality as well as the impact of COVID-19 on the economic costs of heatwave-related mortality are not studied due to lack of data.

Additional information

Table 31: National direct and indirect economic losses from heatwave-related mortality (US$ million, $2015)

Years	Primary		Secondary		Tertiary	
	Direct losses	Indirect losses	Direct losses	Indirect losses	Direct losses	Indirect losses
2002	2.33	1.68	7.73	19.00	7.03	6.20
2005	2.75	1.94	10.78	32.00	8.67	9.03
2007	1.93	1.36	9.03	29.76	6.91	6.01

2010	3.27	2.32	13.53	48.95	15.76	17.20
2012	1.43	1.01	6.66	22.39	6.56	5.67
2015	2.07	1.45	9.12	34.79	11.21	9.90
2017	4.42	3.01	22.44	68.98	28.67	24.77
2018	2.79	1.76	14.86	44.89	19.99	37.58
2019	3.78	2.44	20.41	62.66	28.70	24.83
2020	2.85	1.75	14.11	44.16	20.34	17.53

Table 32: Provincial economic loss in 2017 (US$ million, $2015)

Provinces	Economic loss	Provinces	Economic loss	Provinces	Economic loss
Beijing	4.16	Tianjin	5.22	Hebei	9.37
Shanxi	2.96	Inner Mongolia	6.75	Liaoning	9.11
Jilin	4.04	Heilongjiang	3.88	Shanghai	2.12
Jiangsu	9.00	Zhejiang	4.86	Anhui	2.62
Fujian	3.28	Jiangxi	3.67	Shandong	23.22
Henan	15.17	Hubei	2.86	Hunan	4.06
Guangdong	5.23	Guangxi	1.21	Hainan	0.40
Chongqing	5.30	Sichuan	0.97	Guizhou	2.01
Yunnan	2.44	Tibet	0.09	Shaanxi	8.77
Gansu	4.75	Qinghai	0.11	Ningxia	1.06
Xinjiang	3.32				

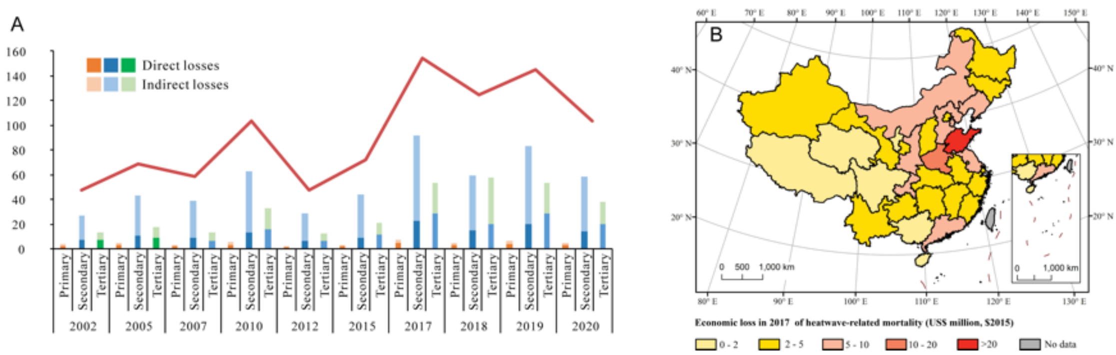

Figure 50: **Economic costs of heatwave-related mortality (US$ million, 2015).**

a. National direct and indirect economic losses; b. Provincial economic loss in 2017

Indicator 4.1.2: Economic costs of heat-related labour productivity loss

Methods

The methodology for this indicator remains similar to that described in the 2020 China Lancet Countdown report appendix. Despite similarity in the assessment process with Indicator 4.1.1, this indicator highlights the economic costs resulting from potential heat-related labour productivity losses reported in indicator 1.1.3. Please refer to Indicator 4.1.1 for a detailed description of the method used for this indicator.

Data

1. The Chinese national IO tables between 2007 and 2018 are obtained from the website of the National Bureau of Statistics of China. [100] The Chinese multi-regional IO table for 2017 is obtained from the CEADs dataset. [101,102]

   The calculations are first performed on the national scale using the Chinese national IO tables for the past decade 2011-2020, and then on the provincial scale using the Chinese Multiregional IO table in 2017. On the national scale, we add the analysis of 2018-2020 with the recent release of the 2018 national IO table, compared to the China's report of the previous year. As the national IO tables are only available for 2010, 2012, 2015, 2017, and 2018, we use the table of the closest year to approximate the years without IO tables after scaling the table to the GDPs of those years. We recalculate the national costs between 2007-2017 to reflect the updates of results of Indicator 1.1.3. On the provincial scale, we perform a multi-regional analysis for a more recent year 2017 with the newly released multi-regional IO table from the CEADs dataset. All the IO tables used in this analysis are converted from current LCU prices into constant US$ in 2015. The economy is divided into 20 production sectors in each IO table, as listed in the right column of **Table 33**.

2. Data on heat-related labour productivity loss is provided by WG1 responsible for Indicator 1.1.3. It is calculated as percentage losses of annual working hours in four major sectors, including agricultural, construction, manufacturing, and services sectors, on both the national and provincial scales. We categorize the 20 sectors in the IO tables into the four major sectors (**Table 33**) and assume that sectors within the same categories share the same levels of heat-related labour productivity loss.

Table 33: Sector concordance.

Agriculture	Agriculture
Manufacture	Mining
	Foods and Tobacco
	Textiles
	Timbers and Furniture
	Paper and Printing
	Petroleum, Coking, Nuclear Fuel

	Chemicals
	Nonmetallic Mineral Products
	Metal Products
	Ordinary Machinery
	Transport Equipment
	Electrical Equipment
	Electronic Equipment
	Other Manufacturing Industry
	Electricity, Gas, Water
Construction	Construction
	Transport
Services	Wholesale, Retail, Catering
	Other Services

3. Chinese GDP are from the World Bank Development Indicator Database.[103]
   We use this GDP to calibrate the IO tables adopted in the analysis.

Caveats

See Indicator 1.1.3, for caveats related to the calculation of heat-related labour productivity loss.

The current report employs a supply-driven IO model that fixes the input proportions between different kinds of productive factors. This means that producers do not seek for substitutive factor inputs when labourers become less productive due to heat-related labour productivity loss. The model also excludes the possibility of price adjustment, such as rising wages, to encourage labourer's production enthusiasm. Such rigidity decides that the model is better suitable for a short-term analysis. Therefore, the indirect economic cost is estimated during a single year with heat stress.

Future Form of Indicator

In the future, this indicator will be updated to more recent years with well-established Chinese IO tables both on the national and multi-provincial scales.

Additional Information

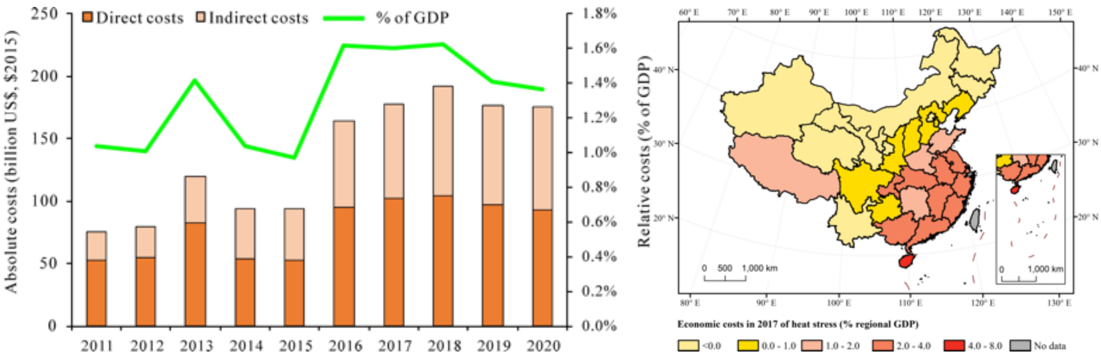

Figure 51: **Economic costs of heat-related labour productivity loss.**

(A) National-level results, by year, in billions of 2015 US$; (B) Provincial-level results in 2017, relative to provincial GDP.

Note: Negative values indicate economic gains from inter-provincial dependencies.

Table 34: Chinese economic costs from heat-related labour productivity loss by year. The absolute costs are given in billions of US$ at 2015 prices, and the relative costs are given as percentages of China's GDP.

Years	Direct costs	Indirect costs	% of GDP
2011	53.0	22.1	1.03%
2012	54.8	24.4	1.01%
2013	82.3	37.2	1.41%
2014	53.7	40.5	1.04%
2015	52.6	41.7	0.97%
2016	94.8	69.2	1.61%
2017	101.8	75.7	1.60%
2018	104.0	88.5	1.62%
2019	97.4	78.6	1.41%
2020	93.0	82.2	1.36%

Table 35: Chinese economic costs at the provincial level, in percent of regional GDP, from heat-related labour productivity loss in 2017.

Provinces	Direct costs	Indirect costs	Total costs
Beijing	0.08%	-0.17%	-0.09%
Tianjin	0.33%	0.44%	0.77%
Hebei	0.58%	0.30%	0.88%
Shanxi	0.07%	-0.04%	0.02%
Inner Mongolia	0.04%	-0.19%	-0.16%
Liaoning	0.22%	0.09%	0.31%

Jilin	0.09%	-0.25%	-0.16%
Heilongjiang	0.09%	-0.16%	-0.06%
Shanghai	1.17%	2.61%	3.78%
Jiangsu	1.43%	1.16%	2.59%
Zhejiang	1.33%	1.35%	2.68%
Anhui	1.49%	0.96%	2.44%
Fujian	1.17%	1.12%	2.30%
Jiangxi	1.80%	1.37%	3.17%
Shandong	0.70%	0.36%	1.06%
Henan	0.97%	0.37%	1.33%
Hubei	1.35%	0.79%	2.14%
Hunan	1.17%	0.65%	1.83%
Guangdong	1.45%	1.78%	3.23%
Guangxi	2.10%	1.39%	3.49%
Hainan	3.25%	3.50%	6.75%
Chongqing	1.00%	1.30%	2.29%
Sichuan	0.61%	0.27%	0.88%
Guizhou	0.24%	-0.01%	0.23%
Yunnan	0.07%	-0.24%	-0.17%
Tibet	0.65%	0.62%	1.28%
Shaanxi	0.23%	-0.06%	0.18%
Gansu	0.01%	-0.22%	-0.21%
Qinghai	0.00%	-0.16%	-0.16%
Ningxia	0.01%	-0.30%	-0.29%
Xinjiang	0.05%	-0.27%	-0.21%
Macao	Null	Null	Null
Hong Kong	Null	Null	Null
Taiwan	Null	Null	Null
Total	0.94%	0.77%	1.71%

Indicator 4.1.3: Economic costs of air pollution-related premature deaths

Methods

This indicator measures the direct and indirect economic costs of $PM_{2.5}$-related premature deaths. Compared with the previous year, we used the same model as in Indicator 4.1.1 and update the results to year 2019.

The main calculation procedures are as follows:

1. The calculations are first performed on the national scale for two years 2015 and 2019 using the national IO tables, and then on the provincial scale for year 2015 using the multi-regional IO table. We scale the national table of 2018 up to 2019 according to GDP growth to approximate the Chinese economy in 2019. This is because that the IO table of 2019 is not available at the time of writing. All the IO tables used in this indicator are converted from current LCU prices into constant US$ in 2015.
2. The percentage losses of labor productivity in the three industries (i.e., primary, secondary, and tertiary) are derived from the sectoral results of $PM_{2.5}$-related premature deaths in Indicator 3.3, using the same method as the previous China's report.[1]
3. Then we input the relative labor losses into the assessing model same as Indicator 4.1.2 to calculate the direct and indirect economic costs of $PM_{2.5}$-related premature deaths.

Data

1. The Chinese national IO tables of 2015 and 2018 are obtained from the website of the National Bureau of Statistics of China. [100] The Chinese multi-regional IO table for 2015 is obtained from the CEADs dataset.[101]
2. Data on premature mortality from ambient PM2.5 pollution is provided by WG3 responsible for Indicator 3.3.
3. The provincial labor force by industry is sorted from Chinese provincial statistical yearbooks.
4. The all-cause mortalities by province and age group are collected from the sixth national population census of China.[104]

Caveats

See Indicator 3.3, for caveats related to the calculation of premature mortality due to ambient $PM_{2.5}$ pollution.

The morbidity rates of $PM_{2.5}$ pollution, which could entail larger economic costs, are not incorporated in this indicator. However, this could be supplemented by comparing the results with previous work that considers both $PM_{2.5}$-related mortality and morbidity rates.[105,106] The comparison would deliver more comprehensive information on the economic costs of $PM_{2.5}$ pollution. The industrial labour losses are not derived directly from the sectoral results of $PM_{2.5}$-related deaths, as deaths attributed to a certain sector (e.g., the transport sector), do not necessarily mean deaths taking place within that sector. The breakdown of labour losses into the three industries is weighted-proportional to the regional employment in those industries. For example, it is assumed that most $PM_{2.5}$-related labour deaths attributed to the agricultural sector fall into the primary industry, while those attributed to the transport sector belong mainly to the secondary and tertiary industries.

Therefore, the primary industry is given more weight when proportionally disaggregating the labour deaths with agricultural causes into the three industries, while the secondary and tertiary industries are given more weights for those attributed to the transport sector. The report employs a supply-driven IO model that fixes the input proportions between different kinds of productive factors. This means that producers do not seek for substitutive factor inputs when labour employment decreases due to $PM_{2.5}$-related mortality. The model also excludes the possibility of market-based price adjustment, such as rising wages, to encourage the working enthusiasm of the remaining laborers. Such rigidity decides that the $PM_{2.5}$-related economic cost is estimated on the short-term scale with constant economic conditions. Finally, this indicator considers the economic costs of mortality related to people's ability to work, however it does not consider the monetary value people place on life (i.e., VSL).

Future Form of Indicator

An ideal form of this indicator would reflect economic costs resulting from both mortality and morbidity rates of $PM_{2.5}$ pollution. This can be developed in future iterations of this indicator. The provincial-level results will be updated to 2017 in future when data on $PM_{2.5}$-related premature deaths covers that year.

Additional Information

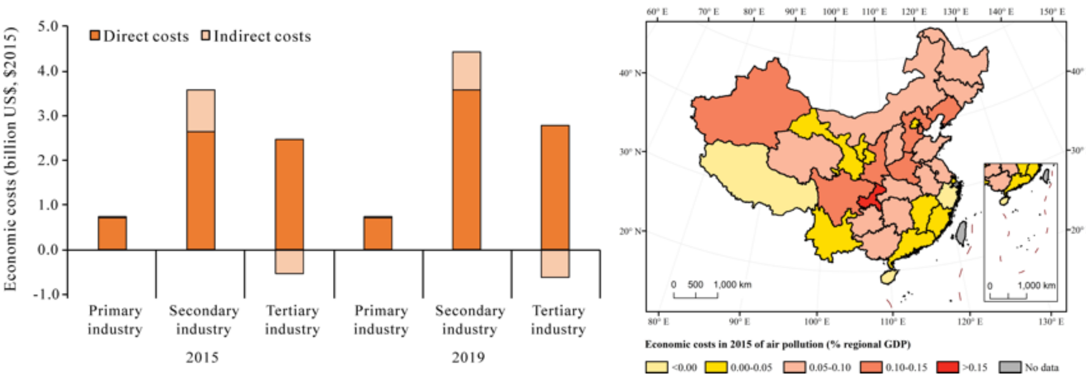

Figure 52: **Economic costs of $PM_{2.5}$-related premature deaths. (A) National-level results, by year and industry, in billions of 2015 US$; (B) Provincial-level results in 2015, relative to provincial GDP.**

Note: Negative values indicate economic gains from inter-provincial dependencies.

Table 36: Chinese direct and indirect economic costs, in billions of US$ at 2015 prices, from $PM_{2.5}$-related premature deaths by year and industry.

Years	Direct costs			Indirect costs		
	Primary	Secondary	Tertiary	Primary	Secondary	Tertiary

	industry	industry	industry	industry	industry	industry
2015	0.70	2.66	2.48	0.03	0.92	-0.54
2019	0.70	3.57	2.79	0.05	0.87	-0.63

Table 37: Chinese economic costs at the provincial level, in percent of regional GDP, from $PM_{2.5}$-related premature deaths in 2015.

Provinces	Direct costs	Indirect costs	Total costs
Beijing	0.045%	0.003%	0.048%
Tianjin	0.072%	0.033%	0.105%
Hebei	0.109%	0.029%	0.139%
Shanxi	0.079%	0.021%	0.099%
Inner Mongolia	0.054%	-0.002%	0.052%
Liaoning	0.085%	0.031%	0.116%
Jilin	0.068%	0.012%	0.080%
Heilongjiang	0.057%	0.001%	0.058%
Shanghai	0.030%	0.008%	0.039%
Jiangsu	0.048%	0.006%	0.053%
Zhejiang	0.024%	-0.026%	-0.002%
Anhui	0.060%	0.016%	0.076%
Fujian	0.019%	-0.003%	0.016%
Jiangxi	0.040%	-0.003%	0.037%
Shandong	0.063%	0.014%	0.077%
Henan	0.080%	0.026%	0.106%
Hubei	0.082%	0.015%	0.097%
Hunan	0.070%	0.015%	0.085%
Guangdong	0.024%	-0.004%	0.020%
Guangxi	0.048%	0.008%	0.056%
Hainan	0.018%	-0.025%	-0.007%
Chongqing	0.119%	0.070%	0.189%
Sichuan	0.114%	0.027%	0.141%
Guizhou	0.055%	0.005%	0.060%
Yunnan	0.023%	-0.020%	0.003%
Tibet	0.000%	-0.012%	-0.012%
Shaanxi	0.111%	0.031%	0.143%
Gansu	0.044%	-0.008%	0.036%
Qinghai	0.053%	0.000%	0.053%
Ningxia	0.042%	0.001%	0.044%
Xinjiang	0.099%	0.012%	0.111%

Macao	Null	Null	Null
Hong Kong	Null	Null	Null
Taiwan	Null	Null	Null
Total	0.059%	0.010%	0.069%

Indicator 4.1.4: Economic losses due to climate-related extreme events

Methods

This indicator measures both the direct and indirect economic losses of climate-related extreme events, including droughts, floods, hailstorms, thunderstorms, cyclones, blizzards and extreme low temperatures, as in the Indicator 1.2. Direct losses are the physical or tangible damage due to these events, while indirect losses or footprint refer to the subsequent losses, including business interruption losses of affected economic sectors, and the spread of losses towards other initially non-affected economic sectors, and the costs of recovery processes. The methodology for this indicator has been improved from the 2020 China Lancet Countdown report appendix.

This year we improve on our indirect economic footprint assessment model, which is an extension of the Adaptive Regional Input-Output (ARIO) model, by considering dynamic inventory adjustment and substitution between suppliers from different regions.[107,108] This has overcome some rigidity of the traditional IO models, while maintaining its simplicity. A full description of the model is provided in Guan, Wang [107]. We also adopt a new dataset from the Yearbook of Meteorological Disasters in China[109], which reports national physical/direct damage 2-3 times more than Munich Re in the 2020 report[1].

Our disaster impact model includes four main modules, that is, an initial shock module, a production module, an allocation and recovery module, and a demand module.

Initial shock module. This module describes the initial or direct damage of extreme events to physical assets, including both industrial and residential capital. Industrial capital is productive capital that is invested in production. Residential capital is not involved in production processes, but its restoration after a disaster would compete resources with that of industrial capital, and therefore affect the recovery of production. The damaged capital is recovered by the post-flood reconstruction activities. The capital held by firms of sector i or households in region r at time t is expressed as:

$$K_{ir}(t) = K_{ir}(t-1) - K_{ir}^{D}(t) + K_{ir}^{REC}(t-1), \tag{1}$$

and $$K_{res,r}\left(t\right)=K_{res,r}\left(t-1\right)-K_{res,r}^{D}\left(t\right)+K_{res,r}^{REC}\left(t-1\right). \tag{2}$$

Here $K_{ir}\left(t\right)$ and $K_{res,r}\left(t\right)$ are the surviving capital stock held by industrial sector i and the residential sector in region r at time t, respectively. $K_{ir}^{D}\left(t\right)$ and $K_{res,r}^{D}\left(t\right)$ refer to the amount of capital damaged/destroyed by the extreme event. $K_{ir}^{REC}\left(t-1\right)$ and $K_{res,r}^{REC}\left(t-1\right)$ represent the recovered capital at the end of period $t-1$ (see allocation and recovery module).

We use $\gamma_{ir}^{K}\left(t\right)$ to denote the percentage reduction in productive capital of sector i in region r at time t, relative to the pre-disaster level, in the aftermaths of the extreme event. It is calculated as:

$$\gamma_{ir}^{K}\left(t\right)=\frac{\bar{K}_{ir}-K_{ir}\left(t\right)}{\bar{K}_{ir}}. \tag{3}$$

Here $\bar{K}_{ir}$ is the capital stock of sector i in region r in the pre-disaster equilibrium.

Production module. The production module is used to characterize production processes. Firms in a sector rent capital and employ labour to process natural resources and intermediate inputs produced by other sectors into a specific product. In the traditional IO modelling, different types of inputs are used in fixed proportions in production, which follows the Leontief production function.[110] In other words, products cannot be substituted in the traditional IO modelling, which may lead to overestimation of the economic losses.[111] Recently Guan, Wang [107] incorporated the possibility of cross-regional substitution in their analysis where products of a sector in a region are substitutable by the products of the same sector from other regions. The production process for each sector can be then expressed as follows:

$$x_{ir}=\min\left\{\text{for all } j,\ \frac{z_{j,ir}}{a_{j,ir}};\ \text{for all } k,\ \frac{va_{k,ir}}{b_{k,ir}}\right\}. \tag{4}$$

Here x_{ir} demotes the output of sector i in region r in monetary values. $z_{j,ir}$ are the intermediate input made by sector j from all regions and used in the production of sector i in region r. $va_{k,ir}$ are the value-added/primary input k (i.e., capital and labour) used by this sector. $a_{j,ir}$ and $b_{k,ir}$ are the input coefficients which indicate the amount of intermediate input j and primary input k required to produce one unit of product i in region r, respectively, as below:

$$a_{j,ir} = \frac{\overline{z}_{i,ir}}{\overline{x}_{ir}}, \tag{5}$$

and

$$b_{k,ir} = \frac{\overline{va}_{k,ir}}{\overline{x}_{ir}}. \tag{6}$$

Here the overbars indicate the values of variables in the pre-disaster equilibrium state, which can be obtained from the IO tables. Equation (4) is a Leontief-type production function as mentioned above. It does not allow substitution between different types of inputs, as economic agents do not have enough time to adjust other inputs to replace temporary shortages. However, we still allow for the substitution between products of the same sector from different regions. As in Equations (4)-(6), we do not distinguish between intermediate product j from different regions, considering products of the same sector from different regions are completely mutual substitutable, and therefore $z_{j,ir} = \sum_s z_{js,ir}$.

In an equilibrium state, producers use intermediate products and primary inputs to produce goods and services to satisfy demand from their clients. However, after an extreme event, output will decrease due to the capital and inventory constraints. Note that we do not consider labour constraint here due to the lack of relevant data.

First, the capital productive capacity of sector i in region r following the extreme event, $x_{ir}^{K}(t)$, is constrained by the proportion of the available capital relative to the pre-disaster level. This assumption is embodied in the essence of the IO model, which is hard-coded through the Leontief-type production function and its restricted substitution. That is, as capital and labour are considered perfectly complementary as well as the main factors of production, and the full employment of those factors in the economy is also assumed, we assume that damage in capital assets is directly or linearly related with production level and therefore, value added level. Then, the remaining productive capacity of the industrial capital at each production period is defined as below:

$$x_{ir}^{K}(t) = \left(1-\gamma_{ir}^{K}(t)\right) * \overline{x}_{ir}. \tag{7}$$

Here $\gamma_{ir}^{K}(t)$ is the proportion of capital damaged by the extreme event, as calculated in Equation (3).

Second, insufficient inventory of intermediate products will create a bottleneck for production activities. The potential production level, $x_{ir}^{j}\left(t\right)$, that the inventory of the intermediate product j can support is:

$$x_{ir}^{j}\left(t\right)=\frac{S_{ir}^{j}\left(t-1\right)}{a_{j,ir}}. \tag{8}$$

Here $S_{ir}^{j}\left(t-1\right)$ refers to the amount of intermediate product j held by sector i in region r at the end of the time $t-1$.

Considering both constraints, the maximum production capacity, $x_{ir}^{\max}\left(t\right)$, of sector i in region r can be expressed as:

$$x_{ir}^{\max}\left(t\right)=\min\left\{x_{ir}^{K}\left(t\right);\ \text{for all } j,\ x_{ir}^{j}\left(t\right)\right\}. \tag{9}$$

The actual production of sector i in region r depends on both its maximum production capacity and the total orders it expects to receive from the clients, as below:

$$x_{ir}^{a}\left(t\right)=\min\left\{x_{ir}^{\max}\left(t\right),\ TD_{ir}\left(t-1\right)\right\}. \tag{10}$$

Here we assume that the firm always expects to receive the same quantities of orders as the previous period, that is, $TD_{ir}\left(t-1\right)$ (see demand module).

Therefore, the inventory of product j held by the sector i in region r will be consumed during the production process. We use $S_{ir}^{j,used}\left(t\right)$ to denote the amount of intermediate product j used in the production of sector i in region r at time t, as below:

$$S_{ir}^{j,used}\left(t\right)=a_{j,ir}*x_{ir}^{a}\left(t\right). \tag{11}$$

Allocation and recovery module. This module mainly describes how suppliers allocate products to their clients and how damaged capital and production capacity are recovered. In the aftermath of an extreme event, the supply of a sector, including domestic products and imports, will not be able to fulfil all the orders of its clients due to production constraints. In this analysis we use a prioritized-proportional rationing scheme to model the resource allocation process during the disequilibrium period. We assume that the firm first allocates its products to address the intermediate demand and then proportionally allocates the remaining products to other categories of demands. This assumption is based on the observation that business-to-business relationships are stronger than business-to-client relationships and therefore should be prioritized.[112,113]

First, products of sector i in region r is allocated to sector j in region s in quantities, $FRC_{js}^{ir}(t)$, as below:

$$FRC_{js}^{ir}(t)=\begin{cases}\dfrac{FOD_{js}^{ir}(t-1)}{\sum_s\sum_j FOD_{js}^{ir}(t-1)}*\left[x_{ir}^{a}(t)+\overline{im}_{ir}\right], & if\ x_{ir}^{a}(t)+\overline{im}_{ir}<\sum_s\sum_j FOD_{js}^{ir}(t-1)\\ FOD_{js}^{ir}(t-1), & if\ x_{ir}^{a}(t)+\overline{im}_{ir}\geq\sum_s\sum_j FOD_{js}^{ir}(t-1)\end{cases}. \quad (12)$$

Here $FOD_{js}^{ir}(t-1)$ refers to the orders issued by firms of sector j in region s to its suppliers of sector i in region r at time $t-1$. If the total supply, that is, the actual output plus imports, of sector i in region r is small than its expected total orders from downstream sectors, $\sum_s\sum_j FOD_{js}^{ir}(t-1)$, it will allocate all its products to the business clients in proportion to the orders. Otherwise, it will allocate just enough products to satisfy the expected intermediate demand. We assume that the imports of a sector are not significantly affected by the extreme event and remain stable at the pre-disaster level, $\overline{im}_{ir}$.

The remaining products of sector i in region r, after satisfying the intermediate demand, at time step t, is equal to:

$$x_{ir}^{rem}(t)=x_{ir}^{a}(t)+\overline{im}_{ir}-\sum_s\sum_j FRC_{js}^{ir}(t). \quad (13)$$

Then, the remaining products will be proportionally allocated to the final demand and reconstruction demand. The final demand mainly consists of four types, that is, household consumption, government expenditure, fixed capital formation and exports. The reconstruction demand refers to the demand for capital goods to restore both the industrial and residential capital damaged by the extreme events. The quantities of products of sector i in region r allocated to the k th type of final demand in region h, $HRC_{kh}^{ir}(t)$, are expressed as follows:

$$HRC_{kh}^{ir}(t)=\frac{HOD_{kh}^{ir}(t-1)}{\sum_k\sum_h HOD_{kh}^{ir}(t-1)+\sum_j\sum_s ROD_{js}^{ir}(t-1)+\sum_h ROD_{res,h}^{ir}(t-1)}*x_{ir}^{rem}(t). \quad (14)$$

Here $HOD_{kh}^{ir}(t-1)$ refers to the orders issued by the k th type of final users in region h to its suppliers of sector i in region r at time $t-1$. $ROD_{js}^{ir}(t-1)$ and $ROD_{res,h}^{ir}(t-1)$ are the orders issued to support the reconstruction of damaged capital of sector j in region s and of the residential sector in region h, respectively.

Similarly, the quantities of products of sector i in region r allocated to the reconstruction demand of industrial capital of sector j in region s, $RRC_{js}^{ir}(t)$, and residential capital of the residential sector in region h, $RRC_{res,h}^{ir}(t)$, are as follows:

$$RRC_{js}^{ir}(t)=\frac{ROD_{js}^{ir}(t-1)}{\sum_k\sum_h HOD_{kh}^{ir}(t-1)+\sum_j\sum_s ROD_{js}^{ir}(t-1)+\sum_h ROD_{res,h}^{ir}(t-1)}*x_{ir}^{rem}(t), \tag{15}$$

and $$RRC_{res,h}^{ir}(t)=\frac{ROD_{res,h}^{ir}(t-1)}{\sum_k\sum_h HOD_{kh}^{ir}(t-1)+\sum_j\sum_s ROD_{js}^{ir}(t-1)+\sum_h ROD_{res,h}^{ir}(t-1)}*x_{ir}^{rem}(t). \tag{16}$$

Then, sector j in region s receives intermediates from all regions to restore its inventories of product i at time step t, as below:

$$S_{js}^{i,restored}(t)=\sum_r FRC_{js}^{ir}(t). \tag{17}$$

Therefore, the quantities of intermediates i held by sector j in region s at the end of period t are as below:

$$S_{js}^{i}(t)=S_{js}^{i}(t-1)-S_{js}^{i,used}(t)+S_{js}^{i,restored}(t). \tag{18}$$

Similarly, the recovered capital of sector j in region s and the residential sector in region h at the end of period t are equal to,

$$K_{js}^{REC}(t)=\sum_i\sum_r RRC_{js}^{ir}(t), \tag{19}$$

and

$$K_{res,h}^{REC}(t)=\sum_i\sum_r RRC_{res,h}^{ir}(t). \tag{20}$$

Demand module. At the end of each period downstream clients issue orders to their suppliers according to their production, consumption and reconstruction plans for the next period. When a product comes from multiple suppliers, the orders are redistributed among suppliers from different regions according to their production capacities.

A firm issues orders to its suppliers because of the need to restore its intermediate product inventory. We assume that the firm of sector j in region s has a specific targeted inventory level of product i, $S_{js}^{i,G}(t)$, equal to a given number of days, n_{js}^{i}, of intermediate consumption of product i, based on its maximum production capacity at time step t, which is calculated as below:

$$S_{js}^{i,G}(t) = n_{js}^{i} * a_{i,js} * x_{js}^{\max}(t). \tag{21}$$

To fill the gap between the targeted and the actual inventory levels of intermediate product i, the firm of sector j in region s will allocate its orders among the suppliers of product i in different regions based on their production capacities. Then the order issued by the firm of sector j in region s to its supplier of sector i in region r is equal to,

$$FOD_{js}^{ir}(t) = \begin{cases} \left(S_{js}^{i,G}(t) - S_{js}^{i}(t)\right) * \dfrac{\overline{FOD}_{js}^{ir} * x_{ir}^{a}(t)}{\sum_{r} \overline{FOD}_{js}^{ir} * x_{ir}^{a}(t)}, & if\ S_{js}^{i,G}(t) > S_{js}^{i}(t) \\ 0 & if\ S_{js}^{i,G}(t) \le S_{js}^{i}(t) \end{cases}. \tag{22}$$

Here $\overline{FOD}_{js}^{ir}$ is the intermediate demand of sector j in region s for inputs of sector i in region r at the pre-disaster level.

Similarly, final users (i.e., domestic households, governments, investors, and foreign consumers) allocate orders among their suppliers from different regions based on their demand and the production capacities of their suppliers. The k th type of final demand in region h for product i at time t is obtained by adding up the demand from different regions, as below:

$$HD_{kh}^{i}(t) = \sum_{r} \overline{hd}_{kh}^{ir}. \tag{23}$$

Here $\overline{hd}_{kh}^{ir}$ is the k th type of final demand in region h for product i in region r at the pre-disaster equilibrium. We assume that various types of final demand do not shift significantly in the short run after the extreme event.

Then, the orders issued by the k th type of final users of region h to the suppliers of product i

in region r is as below:

$$HOD_{kh}^{ir}\left(t\right)=HD_{kh}^{i}\left(t\right)*\frac{\overline{hd}_{kh}^{ir}*x_{ir}^{a}\left(t\right)}{\sum_{r}\overline{hd}_{kh}^{ir}*x_{ir}^{a}\left(t\right)}. \tag{24}$$

Finally, a firm or a household also issues orders to its suppliers because of the reconstruction demand to recover its capital damaged by the extreme event. We assume that the firm of sector j in region s and the household in region h set their targeted level of capital stock at the pre-disaster level, $\bar{K}_{js}$ and $\bar{K}_{res,h}$, respectively. We use the capital matrix coefficients, d_{s}^{ir}, to express the quantities of product i in region r that are invested in one unit of capital formation in region s. We assume that different sectors in the same region share the same capital matrix coefficients. Therefore, the total demand for product i to support reconstruction of sector j in region s and the residential sector in region h at time step t, $RD_{js}^{i}\left(t\right)$ and $RD_{res,h}^{i}\left(t\right)$, are calculated as below:

$$RD_{js}^{i}\left(t\right)=\sum_{r}\left(\bar{K}_{js}-K_{js}\left(t\right)\right)*d_{s}^{ir}, \tag{25}$$

and

$$RD_{res,h}^{i}\left(t\right)=\sum_{r}\left(\bar{K}_{res,h}-K_{res,h}\left(t\right)\right)*d_{h}^{ir}. \tag{26}$$

Here $K_{js}\left(t\right)$ and $K_{res,h}\left(t\right)$ are the capital stock held by sector j in region s and the residential sector in region h at time t, respectively, which are derived from Equation (1) and (2).

Then the orders issued by the reconstruction activities of sector j in region s and the residential sector in region h to the suppliers of product i in region r are as below:

$$ROD_{js}^{ir}\left(t\right)=RD_{js}^{i}\left(t\right)*\frac{x_{ir}^{a}\left(t\right)}{\sum_{r}x_{ir}^{a}\left(t\right)}, \tag{27}$$

and

$$ROD_{res,h}^{ir}\left(t\right)=RD_{res,h}^{i}\left(t\right)*\frac{x_{ir}^{a}\left(t\right)}{\sum_{r}x_{ir}^{a}\left(t\right)}. \tag{28}$$

Therefore, the total orders received by sector i in region r are,

$$TD_{ir}\left(t\right)=\sum_{s}\sum_{j}FOD_{js}^{ir}\left(t\right)+\sum_{k}\sum_{h}HOD_{kh}^{ir}\left(t\right)+\sum_{s}\sum_{j}ROD_{js}^{ir}\left(t\right)+\sum_{h}ROD_{res,h}^{ir}\left(t\right). \tag{29}$$

Economic losses/footprint. At each time step, the economic agents on the supply and demand sides go through the above production, allocation and recovery and demand adjustment procedures. This discrete-time dynamic procedure can reproduce the economic equilibrium and simulate the propagation of exogenous shocks in the economic network. During a climate-related extreme event, if the supply of a sector is constrained by capital damage, this will have two effects. On the one hand, the decrease in output of this sector means that the orders of its clients cannot be fulfilled. This will result in a decrease in inventory of these clients, which will constrain their production. This is the so-called forward or downstream effect. By contrast, less output in this sector also means less use of intermediate products from its suppliers. This will reduce the production level of its suppliers. This is the so-called backward or upstream effect.

We define the physical damage from the extreme event as the direct economic losses, while the value-added decrease of all sectors in the economic network triggered by capital constraints as the indirect economic losses. The impacts of the exogenous shocks continuously propagate through the supply chain, from one sector to another and one region to another, leaving footprint in the economic network. We use the concept, disaster footprint, as a vivid expression of the overall economic impacts of a disastrous extreme event. The direct and indirect economic footprint of the event are calculated as below:

$$DirectFootprint = \sum_t \sum_i \sum_r \left(K_{ir}^D(t) + K_{res,r}^D(t) \right), \tag{30}$$

and

$$IndirectFootprint = \sum_t \sum_i \sum_r \left(\overline{va}_{ir} - va_{ir}(t) \right). \tag{31}$$

Here $va_{ir}(t)$ is the value-added of sector i in region r at time t, which is equal to the value of output minus the value of intermediate input used to produce that output, as below:

$$va_{ir}(t) = x_{ir}^a(t) - \sum_s \sum_j a_{js,ir} * x_{ir}^a(t). \tag{32}$$

Here $a_{js,ir}$ is the input coefficient that indicates the amount of input from sector j in region s required to produce one unit of output of sector i in region r. It can be drawn from the IO tables.

Data

1. Data on physical or direct damage is sourced from the Yearbook of Meteorological Disasters in China.[109]

   These series of yearbooks, which are published by China Meteorological Administration, record direct damage of five categories of climate-related extreme events (i.e., droughts, floods, hailstorms and thunderstorms, cyclones, blizzards and extreme low temperatures) in China on both the national and provincial scales from 2003 to 2018. On the national scale, they report direct damage 2-3 times higher than Munich Re, the data source of the 2020 China's report.

The annual direct damage due to climate-related extreme events is first broken down into three industrial sectors (i.e., primary, secondary and tertiary industries) and a residential sector, according to the proportions based on empirical evidence of China's historical events between 1961-1990, and damages of the three industrial sectors are further disaggregated into 20 subsectors (see **Table 33** in Indicator 4.1.2) in proportion to their value added.

The annual direct damage of each sector is then divided into five months (from May to September), as the summer seasons are considered as highly risky with climate-related extreme events.

2. The Chinese national IO tables between 2009-2018 are obtained from the website of the National Bureau of Statistics of China. The Chinese multi-regional IO table for 2017 is obtained from the CEADs dataset. [101,102]

   The calculations are first performed on the national scale using the Chinese national IO tables between 2009-2018, and then on the provincial scale using the Chinese Multiregional IO table in 2017. As the national IO tables are only available for 2010, 2012, 2015, 2017, and 2018, we use the table of the closest year to approximate the years without IO tables after scaling the table to the GDPs of those years. All the IO tables used in this analysis are converted from current LCU prices into constant US$ in 2015.

3. Chinese GDP are from the World Bank Development Indicator Database.[103]

   We use this GDP to calibrate the IO tables adopted in the analysis.

Caveats

The model does not consider productivity losses of labours, another key productive factor, resulting from climate-related extreme events, as such data is not available at present. However, empirical evidence shows that compared to the percentage losses of capital, the relative losses of labour are usually much lower, so that they have little effect on the modelling results.

The model assumes that the imports and final demand remain unchanged after an extreme event, we mainly focus on the propagation effects initiated by capital damage due to the event.

Future Form of Indicator

In the future, this indicator will be developed to incorporate the compound effect of COVID-19 when damage data is updated to 2020.

Additional Information

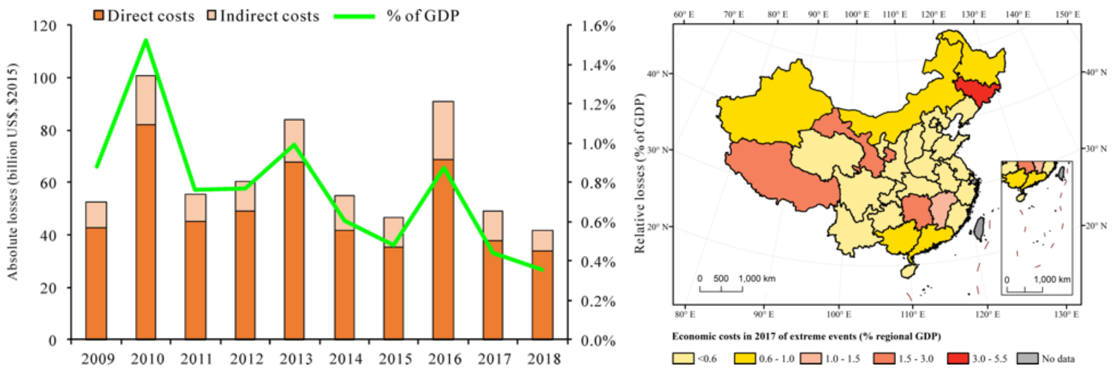

Figure 53: **Economic losses due to climate-related extreme events.**

(A) National-level results, by year, in billions of 2015 US$; (B) Provincial-level results in 2017, relative to provincial GDP.

Note: Negative values indicate economic gains from the stimulus effects of post-disaster reconstruction and inter-provincial substitution.

With improvements on methodology this year, the results show that $1 of direct damage triggers $0.23-0.32 of indirect economic loss nationwide between 2009-2018, lower than $0.32-0.36 as in the 2020 report.

Table 38: Chinese direct and indirect losses, in billions of US$ at 2015 prices, from climate-related extreme events by year and industry.

	Direct losses				Indirect losses			
Years	Primary industry	Second industry	Tertiary industry	Residential sector	Primary industry	Second industry	Tertiary industry	Residential sector
2009	2.8	7.9	7.9	24.3	5.4	1.0	3.4	0.0
2010	5.3	15.2	15.0	46.5	10.4	1.9	6.5	0.0
2011	2.9	8.4	8.3	25.6	5.7	1.0	3.6	0.0
2012	3.1	9.0	9.0	27.7	6.7	1.4	3.5	0.0
2013	4.4	12.6	12.4	38.5	9.4	1.9	4.8	0.0
2014	2.7	7.7	7.7	23.7	7.5	2.6	3.3	0.0
2015	2.3	6.5	6.5	20.0	6.3	2.2	2.8	0.0
2016	4.4	12.8	12.6	39.1	12.4	4.2	5.4	0.0
2017	2.4	7.0	7.0	21.6	6.4	2.1	2.4	0.0
2018	2.2	6.2	6.2	19.1	5.0	1.1	2.1	0.0

Table 39: Chinese economic losses at the provincial level, in percent of regional GDP, from climate-related extreme events in 2017.

Provinces	Direct costs	Indirect costs	Total costs
Beijing	0.00%	-0.01%	-0.01%
Tianjin	0.00%	-0.04%	-0.04%
Hebei	0.14%	0.00%	0.14%
Shanxi	0.36%	0.03%	0.39%
Inner Mongolia	0.81%	0.18%	0.99%
Liaoning	0.47%	0.02%	0.49%
Jilin	2.76%	0.43%	3.18%
Heilongjiang	0.34%	0.66%	0.99%
Shanghai	0.00%	-0.05%	-0.05%
Jiangsu	0.01%	-0.03%	-0.02%
Zhejiang	0.09%	0.01%	0.10%
Anhui	0.07%	0.14%	0.22%
Fujian	0.05%	0.04%	0.10%
Jiangxi	0.59%	0.46%	1.05%
Shandong	0.12%	0.01%	0.13%
Henan	0.13%	0.17%	0.31%
Hubei	0.43%	0.16%	0.59%
Hunan	1.79%	1.03%	2.81%
Guangdong	0.37%	0.33%	0.70%
Guangxi	0.53%	0.21%	0.74%
Hainan	0.09%	-0.25%	-0.16%
Chongqing	0.13%	-0.02%	0.11%
Sichuan	0.19%	0.03%	0.22%
Guizhou	0.42%	0.05%	0.47%
Yunnan	0.44%	0.09%	0.53%
Tibet	1.19%	0.48%	1.66%
Shaanxi	0.74%	0.13%	0.87%
Gansu	1.14%	0.37%	1.51%
Qinghai	0.65%	-0.12%	0.52%
Ningxia	0.37%	0.08%	0.45%
Xinjiang	0.32%	0.35%	0.67%
Macao	Null	Null	Null
Hong Kong	Null	Null	Null
Taiwan	Null	Null	Null

Total	0.34%	0.15%	0.49%

Indicator 4.2: Investing in a low-carbon economy

Indicator 4.2.1: Investment in new coal capacity and low-carbon energy and energy efficiency

Methods

In this China Lancet Countdown report, data was presented as 'overnight' investment, in which all capital spending on a new plant is assigned to the year in which the plant became operational. It is different from the 2020 global Lancet Countdown report which used a different approach and considered 'ongoing' capital spending, with investment in a new plant spread evenly from the year new construction begins, to the year it becomes operational.
The data for this indicator is from the Wind Economic database.[114] Wind is a comprehensive and paid database which massively combines macro and sectoral data. It is commonly used for financial and macro analysis. Four categories of energy investment (fossil, nuclear, hydro, and wind) are from Wind Economic database. Investment of Solar PV has been derived from new power generation facilities (Wind Economic database) and unit investment. Investment of Biomass remain the same as data in 2019 global Lancet Countdown report. Six categories of energy investment are defined:

• Fossil-fired power – investment in fixed capital information and constructing power generation facilities of coal-, gas-, and oil-fired electricity.
• Nuclear –investment in fixed capital information and constructing power generation facilities of nuclear electricity.
• Hydro power – investment in fixed capital information and constructing power generation facilities of hydroelectricity.
• Wind power – investment in fixed capital information and constructing power generation facilities of wind electricity.
• Solar PV – investment in fixed capital information and constructing power generation facilities of solar electricity.
• Biomass – investment in fixed capital information and constructing power generation facilities of biomass electricity.
• Grid – investment in fixed capital information of constructing overall power grid.

There are two types of investments for each kind of energy in the power sector. One is the investment in fixed capital formation, which is a general term for the workload of constructing and purchasing fixed assets and the expenses related to it in a certain period (type 1). The other is investment in new power generation facilities (type 2,Table 40). Considering the data continuity, especially the availability of data in 2019-2020, only the latter type of investment was analyzed in this indicator.

In 2020 report, we also include data of new power generation facilities in country and provincial level for fossil, nuclear, hydro, wind and solar PV from Wind Economic database (Table 41). However, provincial investment is not available from public access. Thus, to analyze provincial investment of low-carbon energy, we had to process country-level energy investment data and new capacity of power generation facilities to obtain unit investment for each category of energy from 2008 to 2020, and then we further calculated to have provincial investment of energy.

Data

1. Energy investment data, listed by wind, hydro, nuclear, fossil and overall power grid, is taken from the Wind Economic database.[114]
2. New power generation facilities data in country and provincial-level, listed by fossil, nuclear, hydro, wind and solar PV, is taken from Wind Economic database.
3. Biomass data is taken from the China National Renewable Energy Center (CNREC) Renewable Energy Outlook 2019.[115]
4. Values presented are in US$ 2020 billion, based on the value of RMB in 2015 and the exchange rate according to National Bureau of Statistics of China. [116]

Caveats

Renewable energy investment here mainly includes centralized project but excludes investment in decentralized facilities. In the original dataset, there are two types of investment dataset. Type 1 is investment in fixed capital formation, and Type 2 is investment in new power generation facilities. Type 1 doesn’t include solar PV and is only available up to 2017. Type 2 is more comprehensive and includes data until 2020, however, it doesn’t include other facilities related to renewable energy power generation and distribution. It is worth noting that type 2 is part of type 1 and investment in constructing power generation facilities could partially represents the future use of this energy. Furthermore, we also used data from China’s Renewable Energy Outlook 2019[115] for biomass, however data for 2020 is currently not available.

Data on the recent investments in energy efficiency improvement is not available. Meanwhile, low-carbon energy may also include sectors other than power generation, although data is not available.

Future Form of Indicator

Further datasets containing data on investments in energy efficiency and low-carbon energy in sectors other than power generation will be explored.

Additional Information

Table 40. Investment in power sector construction from 2008 to 2020 (US$ billion)

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Fossil	31.67	29.33	26.24	19.78	17.05	15.48	18.61	18.64	17.59	13.27	11.77	11.19	7.94
Hydro	16.02	16.48	15.07	16.94	21.07	20.78	15.32	12.65	9.7	9.62	10.21	13.33	15.47
Nuclear	6.22	11.1	11.91	13.33	13.35	10.16	8.66	9.06	7.92	7.02	6.62	7.19	5.43
Wind	9.95	14.86	19.09	15.75	10.33	10.52	14.88	19.24	14.56	10.53	9.73	22.6	37.61
Solar PV		0.04	0.25	2.39	1.28	13.2	9.39	14.38	32.62	41.28	27.11	11.71	17.31
Biomass										4	6.28	8.33	
Grid	54.71	74.19	63.53	64.44	62.37	65.04	67.06	74.50	85.50	82.72	81.53	71.61	75.6
Total	63.86	71.8	72.55	68.2	63.08	70.13	66.86	73.97	82.39	85.73	71.72	74.34	83.76

[Notes: originally derived from Wind Economic database and China Renewable Energy Outlook 2019[115]]

Table 41. New power generation facilities from 2008 to 2020

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Fossil	65.55	65.86	58.31	62.41	52.36	36.50	47.91	64.00	48.36	45.78	41.19	44.23	56.37
Hydro	21.48	21.06	16.43	12.83	16.76	29.93	21.80	16.08	11.74	12.88	8.54	4.45	13.23
Nuclear	0.00	0.00	1.74	1.75	0.66	2.21	5.47	7.24	7.20	2.18	8.84	4.09	1.12
Wind	4.99	9.73	14.57	15.28	12.96	14.06	21.01	29.61	18.73	19.52	21.00	25.72	71.67
Solar PV	0.00	0.03	0.20	1.96	1.07	11.30	8.25	12.82	34.59	53.38	44.73	26.52	48.20
Biomass					0.50	4.35	0.90	0.91	1.83	2.74	3.05	4.73	5.43

Table 42. Provincial level data of investment in power sector construction in 2020. (US$ billion)

Province	New coal	Renewable energy
Anhui	0.09	2.71
Beijing	0.02	0.07
Fujian	0.25	1.35
Gansu	0.29	0.75
Guangdong	1.04	2.57
Guangxi	0.03	3.15
Guizhou	0.01	0.93
Hainan	0.14	0.3
Hebei	0.51	5.94
Henan	0.35	4.23
Heilongjiang	0.25	0.58
Hubei	0.26	1.51
Hunan	0.01	1.7
Jilin	0.01	1.22
Jiangsu	0.24	3.37

Jiangxi	0.36	1.75
Liaoning	0.14	1.49
Inner Mongolia	0.6	4.95
Ningxia	0.19	2.56
Qinghai	0	3.71
Shandong	0.88	5.21
Shanxi	0.4	4.57
Shaanxi	0.82	2.65
Shanghai	0	0.01
Sichuan	0.05	5.36
Tianjin	0.13	0.25
Tibet		0.98
Xinjiang	0.57	3.56
Yunnan	0.01	4.13
Zhejiang	0.3	1.99
Chongqing	0.02	0.2

[Notes: originally derived from Wind Economic database]

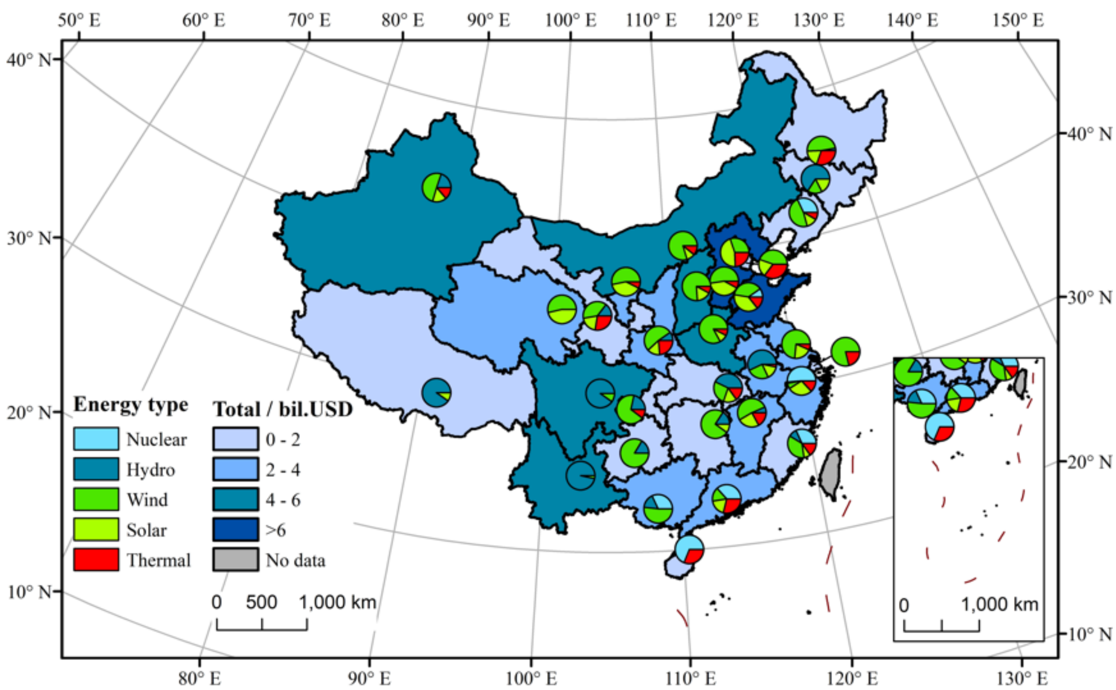

Figure 54: **Investment in power sector construction in 2020**

Indicator 4.2.2: Employment in low-carbon and high-carbon industries

Methods

This indicator presents China's direct employment in fossil fuel extraction industries, including coal mining, oil and gas exploration and extraction, as well as direct and indirect employment in renewable energy. The methodology for this indicator remains the same as in the 2020 China Lancet Countdown report.

The data for this indicator is sourced from IRENA Renewable Energy and Jobs Annual Review 2020[117] (renewables) and CEIC Data (2012-2020)[118] (fossil fuel extraction), National Bureau of Statistics of China[119].

Renewable industries included are:

- Hydropower
- Solar energy
- Wind energy;
- Bioenergy;
- Other technologies.

Bioenergy includes liquid biofuels, soil biomass and biogas. Solar energy includes solar heating/cooling; solar photovoltaic and concentrated solar power, 'Other technologies' includes geothermal energy, ground-based heat pumps, municipal and industrial waste, and ocean energy. Fossil fuel extraction includes coal mining, oil and gas exploration and production. Fossil fuel extraction values include direct employment, whereas renewable energy jobs include direct and indirect employment (e.g., equipment manufacturing), except for large hydropower (direct employment only).

Due to an improvement in data collection and estimation methodology, employment values reported for other technologies are unavailable in some years.

Data

1. Data on renewable energy employment is sourced from IRENA Renewable Energy and Jobs Annual Review 2020.[117]
2. Data on employment in fossil fuel extraction is from CEIC Data (2012-2020)[118], National Bureau of Statistics of China[119]

Caveats

The caveats of this indicator can be described in three aspects. Provincial level data is not available for most recent years and employment in low-carbon industries data is only available from 2012. Both direct and indirect employment in renewable industries is counted, whereas only direct employment in fossil fuel extraction is considered for employment in fossil fuel industries.

Future Form of Indicator

An ideal future form of this indicator would track both direct and indirect employment from the renewables and fossil fuel extraction industries, along with the provincial level distribution in their change over time.

Additional Information

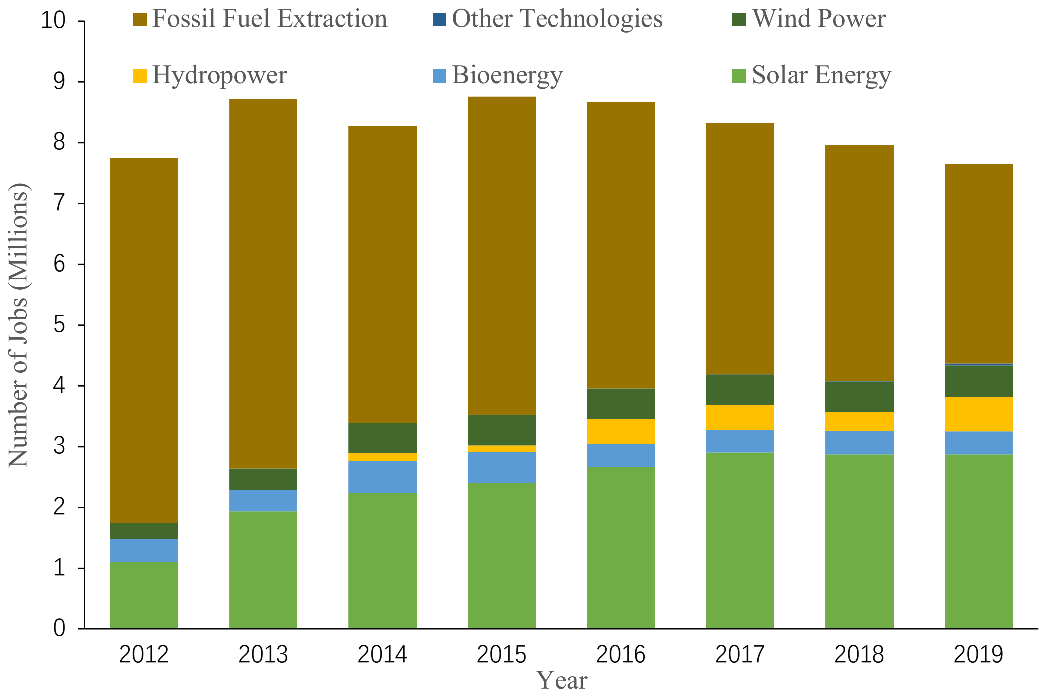

Figure 55: **Employment in renewable energy and fossil-fuel extraction sectors**

Table 43: China employment in renewable energy and fossil-fuel extraction sectors (Million Jobs)

	2012	2013	2014	2015	2016	2017	2018	2019
Solar Energy	1.1	1.93	2.241	2.395	2.663	2.897	2.875	2.87
Bioenergy	0.38	0.354	0.521	0.521	0.376	0.376	0.382	0.384
Hydropower	0	0	0.126	0.1	0.407	0.407	0.308	0.561
Wind Power	0.267	0.356	0.502	0.507	0.509	0.51	0.51	0.518
Other Technologies	0	0	0	0	0	0.002	0.003	0.028
Fossil Fuel Extraction	5.996	6.072	4.884	5.238	4.72	4.13	3.881	3.294

Indicator 4.2.3: net value of fossil fuel subsidies and carbon prices

Methods

The methodology for this indicator is the same as described in the 2020 global and China Lancet Countdown report appendix[10]. The data for fossil fuel consumption subsidies is taken from the IEA [120], which is calculated based on the price-gap approach. As the most commonly applied methodology for quantifying consumption subsidies, the price-gap approach compares average end-user price paid by consumers with reference prices that reflect full cost of supply. Therefore, the price gap equals to the amount by which an end-use price falls short of the reference price, indicating the presence of a subsidy. Prices are presented in real 2019 US$. The data required for the price-gap calculations are extensive. Original data and a detailed description of the calculation methodology can be obtained from the IEA[120].

Data for coverage and strength of carbon pricing, including general information and daily real-time prices, are from the World Bank Carbon Pricing Dashboard and the websites of carbon pilot markets in China. Price data period is from 2014 to 2020 for eight pilot markets, including Beijing, Shanghai, Guangdong, Tianjin, Hubei, Chongqing, Fujian, and Shenzhen. Annual weighted average prices are calculated from daily price data for these eight pilot markets. GHG coverage data is presented as the proportions of 2012 global (53,937 MtCO2e), national and jurisdiction's anthropogenic GHG emissions are based on emission data from EDGAR (Emissions Database for Global Atmospheric Research) as well as the coverage calculations from World Bank Carbon Pricing Dashboard. Here the "proportion of jurisdiction's GHG emissions covered" is calculated by dividing the covered quantity of emissions of carbon markets by the total GHG emissions in the corresponding administrative region. For example, when calculating the emission coverage of regional pilots, then the "jurisdiction's emission" is the sum of all GHG emissions in these pilot regions. Here data is presented for 2019.

Data

1. IEA, Fossil-fuel consumption subsidies by country [120];
2. Data on carbon prices is taken from the World Bank Carbon Pricing Dashboard;[121]
3. GHG emissions data is taken from EDGAR.[122]

Caveats

Coal consumption subsidies for all the years during 2010 to 2019, and gas consumption subsidies for some years are unavailable, due to the lack of consistent data. Moreover, values do not include the economic value of the unpriced negative externalities.

The instruments experience some overlap in emission coverage with China's national ETS. The time series plot shows the annual average prices of carbon in eight Chinese pilot carbon markets (Table 45). All these markets open in the year 2013 or later, and the prices are somewhat fluctuant. Generally, the prices are relatively low, especially compared to the prices of carbon pricing initiatives in other countries, which are typically above US$15 and could also be as high as more than US$100 (Sweden carbon tax). Currently, the prices of these pilots are probably unable to support the climate target "well below 2°C" as literatures show that the required carbon price might be US$40-80 by 2020.

Future Form of Indicator

1. The consistent inclusion of production and consumption subsidies for all fuels, especially coal, available on an annual basis.
2. Along with that of carbon pricing data, to create a 'net carbon price' indicator.

Additional Information

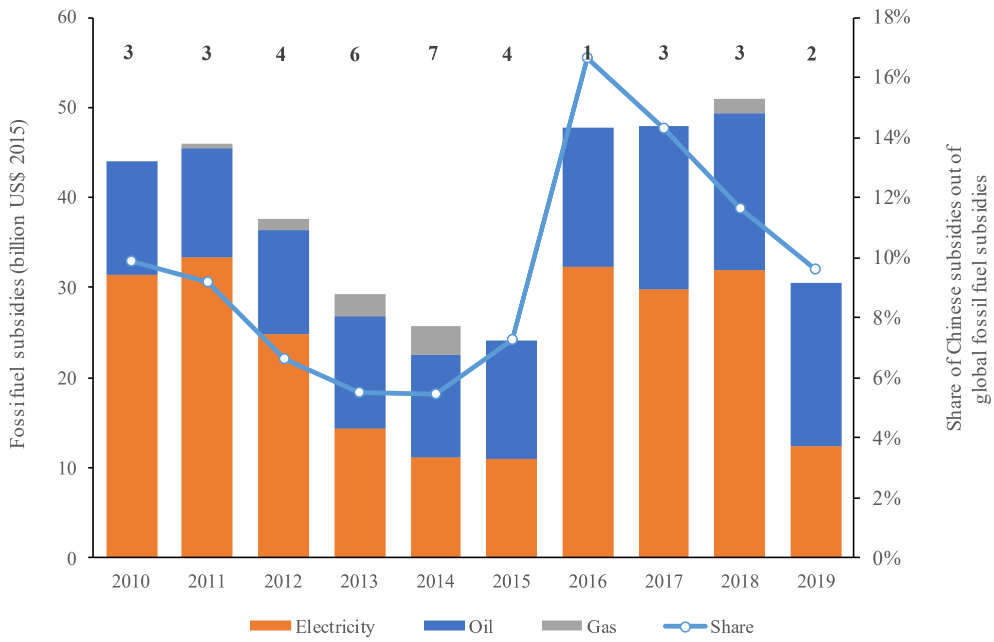

Figure 56: **Fossil fuel and electricity consumption subsidies in China, 2010-2019**

Note: The number on top of each bar represents the rank of fossil fuel subsidy of China in the world on the corresponding year.

Table 44: Fossil fuel consumption subsidies in China, 2010-2019 (million real 2019 US$)

Year	Oil	Electricity	Gas	Coal	Total
2010	12,519.1	31,416.2	-	-	43,935.3
2011	12,060.1	33,386.4	558.6	-	46,005.1
2012	11,677.5	24,785.2	1,122.3	-	37,585.0
2013	12,353.7	14,361.1	2,483.9	-	29,198.7
2014	11,417.9	11,080.4	3,186.1	-	25,684.4
2015	13,121.2	10,961.9	-	-	24,083.1
2016	15,439.7	32,300.4	-	-	47,740.1
2017	18,069.4	29,892.5	-	-	47,961.9
2018	17,519.5	31,880.9	1,549.1	-	50,949.5
2019	18,091.6	12,389.5	-	-	30,481.0

Table 45: Carbon prices in eight pilot markets in China, US$ /tCO2

Name of the initiative	2013	2014	2015	2016	2017	2018	2019	2020
Beijing pilot ETS		8.52	8.21	8.40	7.94	9.48	11.38	12.63
Chongqing pilot ETS		5.00	3.91	1.26	0.24	3.84	0.56	3.84

Fujian pilot ETS					5.56	3.20	1.546	2.51
Guangdong pilot ETS		10.08	5.49	1.39	2.02	2.33	2.97	3.95
Hubei pilot ETS		3.41	4.18	2.21	1.91	2.33	4.20	3.95
Shanghai pilot ETS		6.42	4.73	1.38	4.90	6.23	4.56	5.80
Shenzhen pilot ETS	4.77	12.99	5.98	5.90	5.76	6.76	0.56	3.40
Tianjin pilot ETS		5.69	4.21	2.30	1.32	1.36	2.11	3.27

Section 5: Public and political engagement

Indicator 5.1: Media coverage of health and climate change

Indicator 5.1.1: Coverage of health and climate change on Weibo

Method

The methodology for this indicator has been improved from the 2020 China Lancet Countdown report appendix by expand the social media accounts tracked. This year, we selected the same Chinese social media platform as the last year's report, *Weibo* (https://weibo.com/), which is the leading social media in China with large number of users and broad[123].

7 social accounts were included this year, including official media such as @人民日报(People's Daily), @新华社(Xinhuanet), commercial media such as @新京报(The Beijing News), @澎湃新闻(The Paper), and professional media @健康时报(Health Times), @中国科学报(China Science Daily) and (中国气象报) China Meteorological News. Among them, three are the accounts used in last year's report, including @People's Daily, @The Beijing News, and @China Science Daily; four are newly added, including @Xinhuanet, @Health Times, @The Paper, and @ China Meteorological News. Two accounts used in last year's report were excluded from this year's analysis, including @Caixin and @Health News, the former no longer post information since later 2020, while the latter had abnormal data fluctuations.

Key words used for the topics of Climate Change, and Health are shown in Table 46.

Table 46 Keywords for the health and climate change search in Weibo

Climate change-related keywords		Health-related keywords	
Chinese	English	Chinese	English
气候变化	Climate change	疟疾	Malaria
全球变暖	Global warming	腹泻	Diarrhea/ Scour
温室	Greenhouse	感染	Infected
极端天气	Extreme weather	肺炎	Pneumonia
全球环境变化	Global environment change	流行病	Epidemic
低碳	Low carbon	公共卫生	Public health
可再生能源	Renewable energy	卫生	Hygiene
碳排放	Carbon Production	发病	Disease outbreak
二氧化碳排放	Carbon dioxide emissions	营养	Nutrition
气候污染	Air pollution	精神障碍	Mental disorders
气候	Climate	发育	Puberty growth
全球升温	Global warming	传染	Infection
再生能源	Renewable energy	疾患	Disease

CO2 排放	CO2 emissions	症	Symptom
温室气体	Greenhouse gas	瘟疫	Epidemic
极端气候	Extreme weather	流感	Flu
高温	High temperature	流行感冒	Influenza
变暖	Warming	治疗	Treatment
排放	Emission	保健	Health care
环境变化	Environmental change	健康	Health
升温	Warming	死亡	Death
全球温升	Global warming	精神疾病	Mental disease
热浪	Heat wave	精神病	Mental illness
暴雨	Rainstorm	登革热	Dengue
气温	Temperature	饥饿	Hunger/ Famine/ Starvation
洪水	Flooding	粮食	Food
洪灾	Inundation	有害	Harmful
气候反常	Abnormal climate	皮肤病	Dermatosis
野火	Wildfire	风湿	Rheumatism
山火	Forest fire	呼吸系统疾病	Respiratory diseases
雪灾	Snowstorm	人类健康	Human health
低温	Low temperature	人体健康	Physical health
年代际	Interdecadal	身体健康	Body health
冰雪	Ice and snow	心脏病	Heart disease
可持续发展	Sustainable development	糖尿病	Diabetes
海洋酸化	Ocean acidification	疾病	Illnesses
静稳	Stagnant	热死	Heat death
		口罩	Face mask
		防护	Protection

We used four steps to filter the posts to ensure that they are related to our target topics.

Step 1: Crawling all the climate change posts from 2010 to 2020 on Weibo
With a python-based crawler, all qualified posts published by seven Weibo accounts @People's Daily, @The Beijing News, @China Science Daily, @HealthTimes, @The Paper, @Xinhuanet, @China Meteorological News were collected from January, 2010 to December, 2020. 37 climate change related keywords were used, which is in accordance with the new climate change keywords used in the study of *Media coverage of health and climate change for People's Daily in China*[124]. The keywords are presented in the column of "Climate Change" in Table 46.

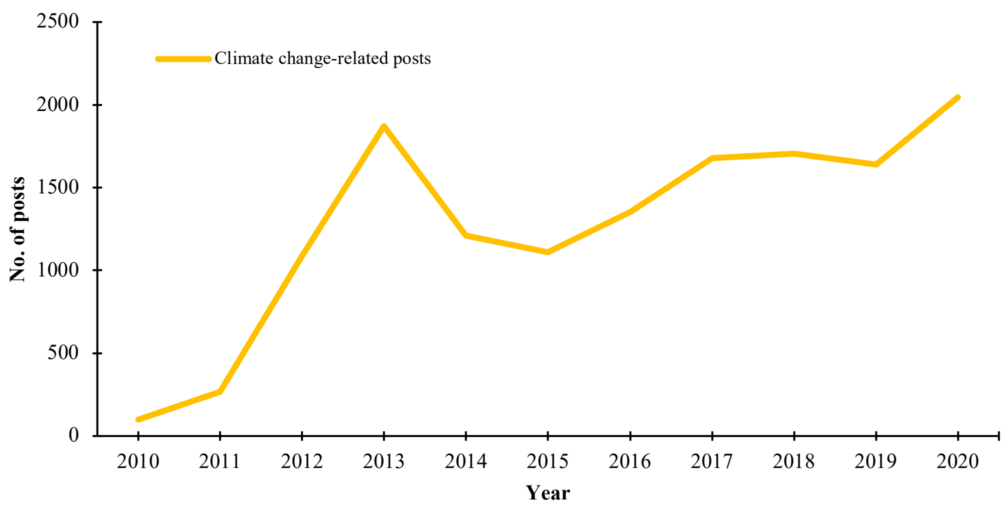

Figure 57 Coverage of climate change on Weibo between 2010 and 2020

Step 2: Searching for health-related posts

We then checked whether these climate-related posts are health-related by search health-related key works (**Table 46**) in in the posts. Our choice of health keyword list followed previous research of Media coverage of health and climate change for People's Daily in China [124]. If a post contains at least 1 health-related word and word frequency ratio in the whole post is greater than 0.01, this post is regarded as relevant to health topics.

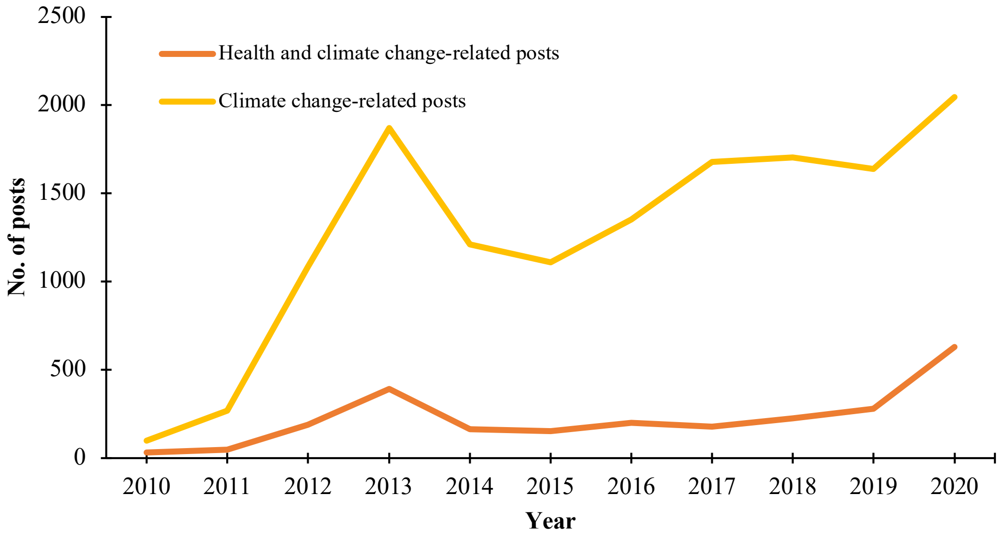

Figure 58 Coverage of climate change and health and climate change on Weibo between 2010 and 2020

Step 3: Data validation by systematic sampling and manual screening

The validity of health and climate posts was checked through manual screening. 427 posts out of 630 posts from all 7 accounts in 2020 were valid, and the resulting positive rate was 0.67. 685 posts out of 1192 posts from four newly added accounts between 2010-2019 were valid, and the resulting positive rate was 0.57.

The validity of climate-related posts was checked through systematic sampling, because the number of posts is too large for manual screening. 135 posts (or 2%) were selected from 6784 posts as a sample between 2010-2019 from four newly added accounts. And then the validation of the 135 samples were tested through manual screening, where 113 posts were valid with a positive rate at 0.84. 91 posts were selected from 2046 posts as a sample in 2020 from seven accounts. And the validation of the 91 posts were tested, where 71 posts were valid with a positive rate at 0.78.

Step 4: Searching for COVID-19 related posts.

Step 4: With a python-based crawler, all qualified posts published by seven Weibo accounts from January, 2010 to December, 2020. Nine COVID-19 related keywords were used (Table 47).

Table 47 Keywords for the COVID-19 search in Weibo

Keywords for the COVID-19 search in Weibo	English translation of these keywords
	COVID Coronavirus Corona
新冠*（新冠病毒，新冠病毒肺炎，新冠疫情，新冠病毒肺炎疫情） 新型冠状病毒	COVID* coronavirus
疫情 冠状病毒 SARS COVID*（COVID-19，COVID 19，COVID19） Coronavirus SARS-CoV-2	COVID-19 COVID 19 COVID19 Coronavirus SARS-CoV-2 2019 novel coronavirus (for picking up very early occurrences)

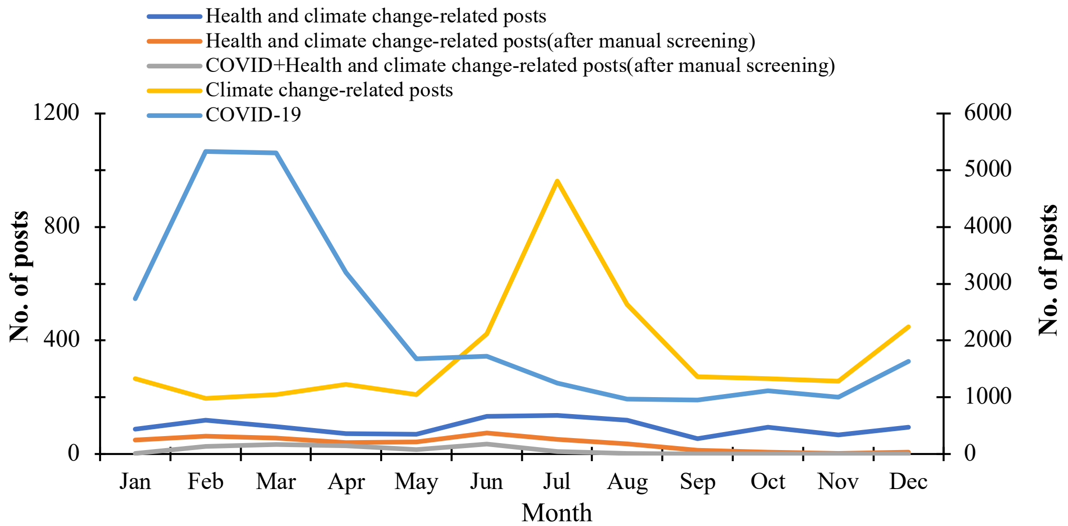

Figure 59 Coverage of climate change, health and climate change and COVID-19 on seven social media accounts on Weibo in 2020.

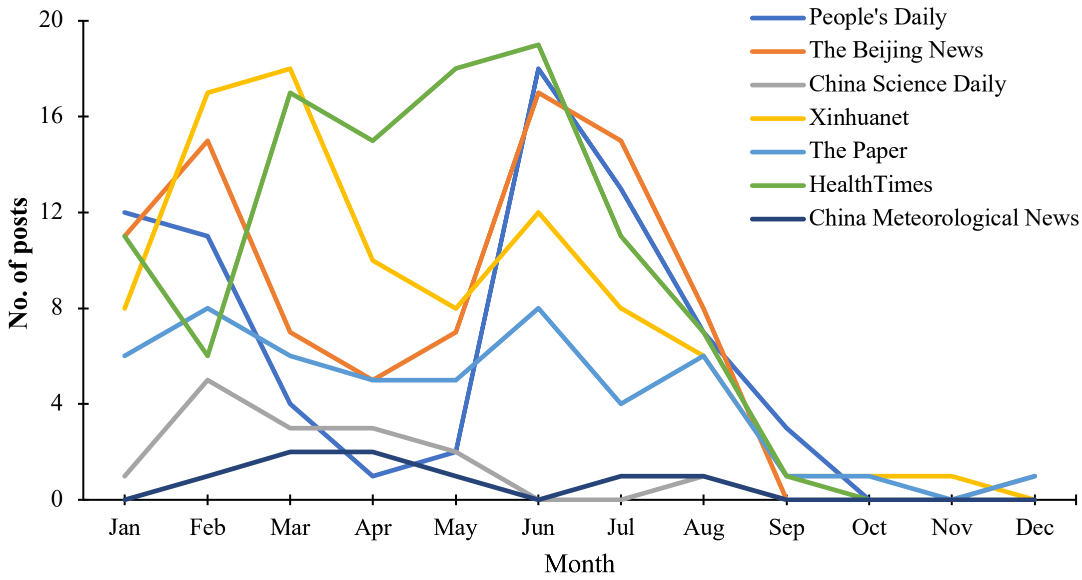

Figure 60 Coverage of health and climate change of seven social media accounts on Weibo in 2020

Data

1. Posts published by Weibo accounts @People's Daily, @The Beijing News, and @China Science Daily, @Xinhuanet, @Health Times, @The Paper, and @ China Meteorological News were collected from January, 2010 to December, 2020;
2. Choice of keywords in accordance to previous research of media coverage of health and climate change for People's Daily in China in the global Lancet Countdown report.[1]

Additional Information

Across the 2010-2020 period, there was an average of 1074 posts per year discussing climate change, in which about 12.2% or 131 posts (after manual screening) per year were related to human health. In 2020, there were about 26889 posts published on COVID-19 and only 149 posts relating to both COVID-19 and health.

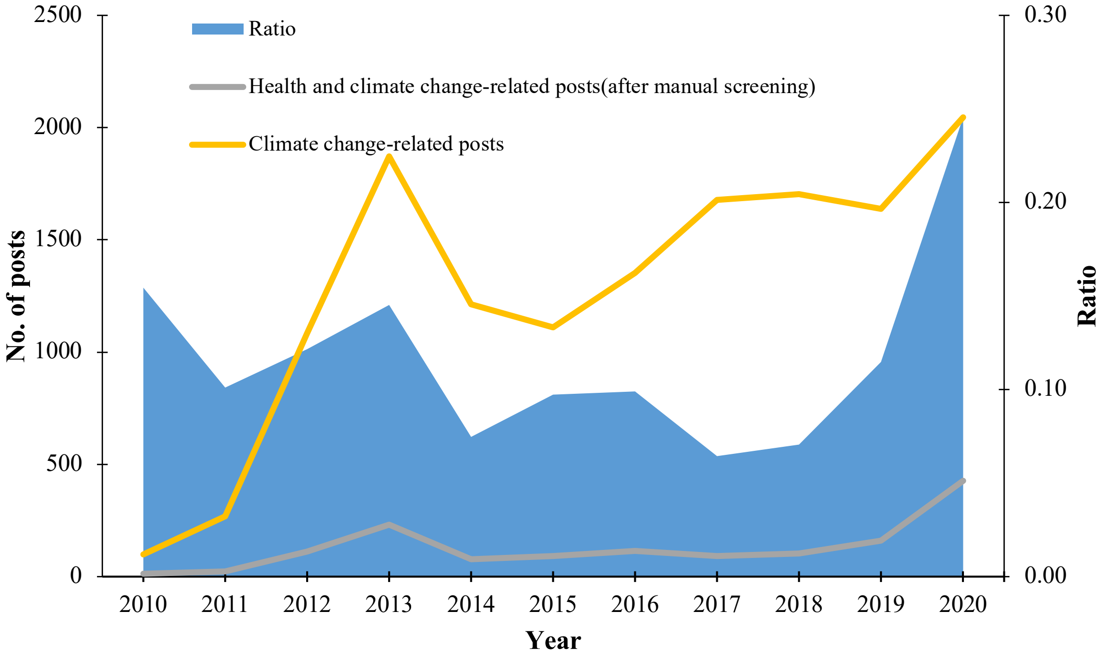

Figure 61: **Coverage of health and climate change on Weibo after screening between 2010 and 2020.**

Caveats

The keywords used in this research are obtained from the study of Media coverage of health and climate change for People's Daily in China after manual screen, which is a traditional media. Therefore, the keywords should be more in line with the characteristics of social media in the future research.

Indicator 5.1.2: Newspaper coverage of health and climate change in China

Methods

This is a newly introduced indicator this year to track the media coverage from traditional media. Despite the boom in new media and audience segmentations nowadays, newspaper still played a crucial role in public agenda setting and was an important channel of public engagement[125]. For the 2021 Lancet Countdown Report, we selected the most influential newspaper in each of the 34 provinces to track their coverage on climate and health. Newspaper articles from January 2008 to December 2020 were searched and downloaded by using professional search function of three newspaper databases, CNKI, WiseNews or Duxiu. To keep data consistency and comparability between indicators, the keywords used for climate change and health are the same as the keywords used in indicator 5.1.1 (**Table 46**).

Firstly, climate change related keywords in accordance with the keywords in the 2020 global Lancet Countdown report, were used to track news articles of climate change. The keywords used are the same as indicator 5.1.1, and are presented in the first column of Table 46. The keywords in the first column of Table 46 are identical to last year's keywords to ensure comparability between indicators. The result is shown in **Figure 62**.

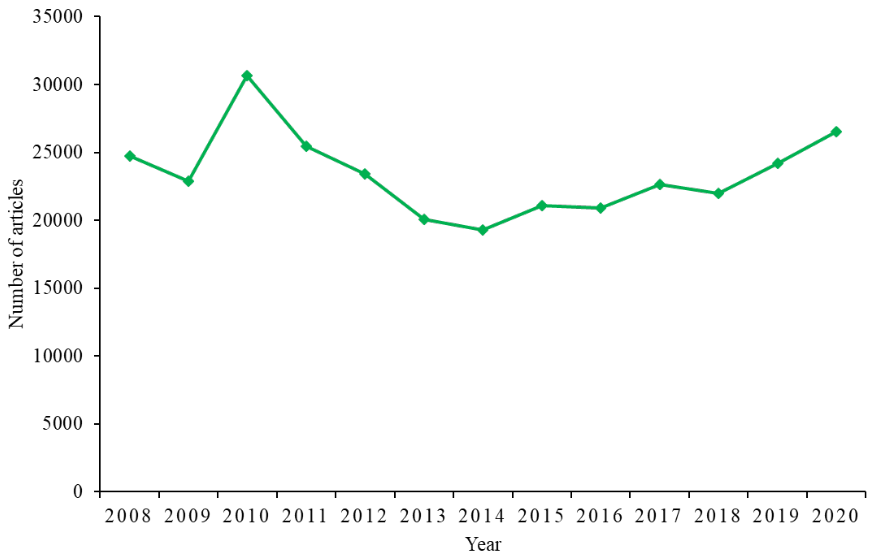

Figure 62 Number of articles identified in Chinese newspapers by searching the keywords from topic Climate Change

Secondly, combine the key words which related to climate change and health which are presented in the column of "Climate Change" and "Health" in Table 46. In the newspaper databases, the retrieval function was set as "keywords" and the relationship between the two groups of keywords as "and". The relevant articles published from 2008 to 2020 were retrieved respectively. The keywords presented in the second column of Table 46.

Thirdly, machine filtration was conducted based on the parameter setting regarding newspaper coverage in the global Lancet Countdown report. The threshold of score for each article is set to be 10, meaning the times of appearance of the keywords from both climate change and health in one article should be no less than 10. The threshold of ratio for each article is set to be no less than 1%, meaning in every 100 characters in the article, there should be no less than 1 keyword. The results before and after machine filtration are presented in **Figure 63**.

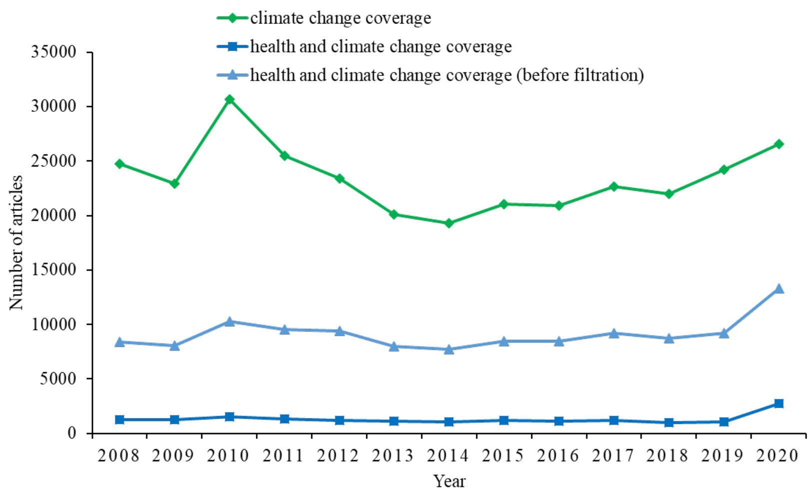

Figure 63: **Numbers of all articles for climate change only (green line), for both health and climate change before machine filtration (light blue line), and for both health and climate change after machine filtration (blue line)**

Finally, with special attention paid to COVID-19 pandemic in 2020, COVID-19 keywords were used to search COVID-19 related articles within the newspaper coverage of health and climate change. The keywords(Table 48) which are in accordance to the 2021 global report, are slightly different from the keywords used in indicator 5.1.1.

Table 48 Keywords for the COVID-19 search in Chinese newspapers

Keywords for the COVID-19	English translation
COVID 新冠*（新冠病毒，新冠病毒肺炎，新冠疫情，新冠病毒肺炎疫情）	COVID Coronavirus Corona
COVID* 新型冠状病毒	COVID* coronavirus
COVID-19 COVID 19 COVID19 Coronavirus 冠状病毒 新冠肺炎 新冠疫情	COVID-19 COVID 19 COVID19 Coronavirus SARS-CoV-2 2019 novel coronavirus (for picking up very early occurrences)

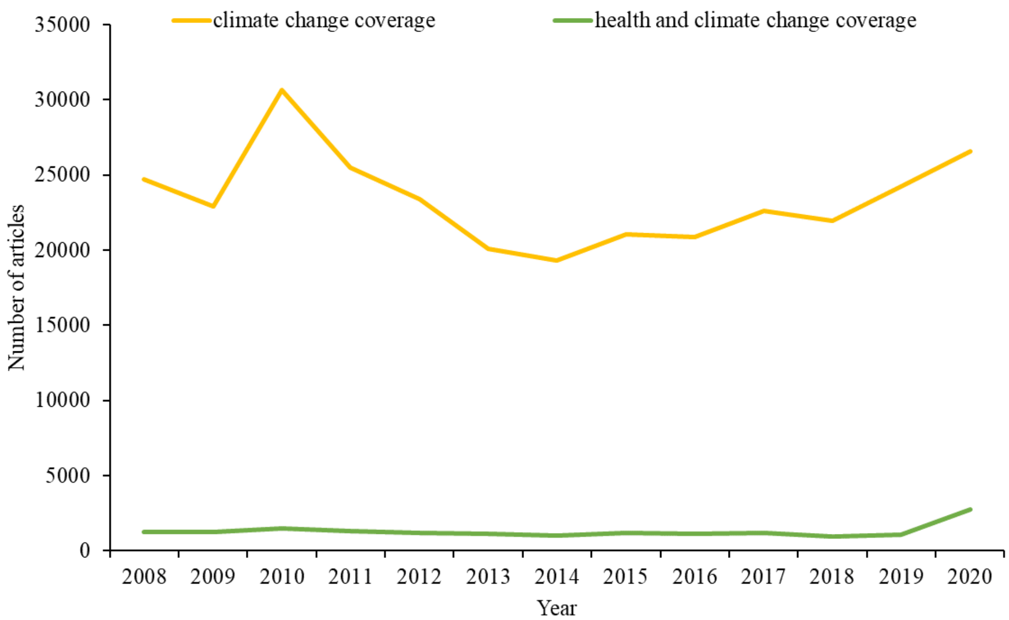

Figure 64: **Coverage of climate change and health and climate change in Chinese newspapers from 2008 to 2020**

Data

1. All the articles from 2008 to 2020 published on Chinese provincial newspapers (retrieved from CNKI, WiseNews, and Duxiu Database)[125];

2. Choice of keywords in accordance to previous research of media coverage of health and climate change for People's Daily in China in the global Lancet Countdown report[37].

Caveats

Firstly, the most influential provincial newspaper in each province or administrative division was selected, while there might be more than one influential newspaper in some province or administrative division. Therefore, this indicator only reflected the media coverage of the selected newspapers which do not cover all newspapers in China.

Secondly, multiple newspaper databases were used to retrieve newspapers for data analyses, which may affect the comparability and consistency. CNKI, WiseNews and Duxiu as three main newspaper databases were used to retrieve newspaper data, since there is no single database include all the newspapers across the 2008-2020 period. As for the three databases, the search function and format are not the same, which can affect the data retrieval and analysis of newspaper coverage.

Thirdly, provincial newspapers were used for data analyses, but national newspapers, such as People's Daily, as well as professional newspapers like China Meteorological News are not included. Analyses of provincial newspapers show provincial difference in newspaper coverage of health and climate change, while it is still possible to miss some coverage provided by national and professional newspapers.

Future Form of Indicator

In the future, the indicator of the media coverage of health and climate change based on newspaper data will continue to be a primary data source to track this indicator. In future, both national newspaper such as People's Daily and provincial newspapers can be included to reflect national and local media coverage of health and climate change.

Indicator 5.2: Individual engagement in health and climate change

Methods

Same as the analysis of the 2020 China Lancet Countdown report[1], this indicator uses the individuals' search preferences to reflect the public engagement for health and climate change. The analysis is based on the search queries identified by keyword matching from Baidu. As a popular Chinese search engine, Baidu takes up the majority of market share (78.41% of China market in 2020 according to StatCounter[126]) of search engines in China over the past decade. We also conduct an analysis of individual engagement of different demographic groups. All data is anonymized and no queries can be associated with an individual. In order to capture search queries related to health and climate change, a set of keywords are designed by this team of researchers which is the same with the report in the 2020 China report[1]. The queries are identified as health queries, climate change keyword and health &climate change co-queries, if they contain a minimum of one health keyword (**Table 49**), at least one climate change keyword (**Table 50**), and contain both health and climate change keywords, respectively.

Table 49 Health-related keywords for the Baidu search

Health-related keywords in Chinese	**Health-related keywords in English**
健康	Healthy
疾病	Disease
养生	Health preservation
保健	Healthcare
公共卫生	Public health
疟疾	Malaria
死亡率	Mortality
营养	Nutrition
营养不良	Malnutrition
脱水	dehydration
发病	Morbidity
发病率	Morbidity
发育迟缓	Stunting
传染病	Communicable disease
慢性病	Chronic disease
高血压	Hypertension
肿瘤	Tumour
中风	Apoplexy
心脏病	Heart disease
肺炎	Pneumonia

癌症	Cancer
肺癌	Lung cancer
肝癌	Liver cancer
糖尿病	diabetes
肥胖	Obesity
身体超重	Overweight
非传染性疾病	Non-communicable diseases
流行病	Epidemic
流行病学	Epidemiology
腹泻	Diarrhoea
SARS	SARS
非典型肺炎	Atypical pneumonia
严重急性呼吸综合征	Severe acute respiratory syndrome (SARS)
重症急性呼吸综合症	Severe acute respiratory syndrome (SARS)
麻疹	Measles
早产	Premature
流产	Abortion
抑郁障碍	Depressive disorder
抑郁症	Depression
心理障碍	Psychological disorders
心理问题	Psychological problems
心理疾病	Mental illness
精神障碍	Mental disorders
精神病	Mental disease
精神疾病	Mental illness
精神健康	Mental health

Table 50 Climate change-related keywords

Climate change-related keywords in Chinese	**Climate change-related keywords in English**
气候变化	Climate change
气候变暖	Climate warming
全球变暖	Global warming
全球暖化	Global warming
全球温度升高	Global temperature rise
全球气温升高	Global temperature rise
地球温度升高	The rise of the earth's temperature
海平面上升	Sea level rise
冰川融化	Glacial melting

温室效应	Greenhouse effect
温室气体排放	Greenhouse gas emissions
碳排放	Carbon emission
二氧化碳排放	CO2 emission
碳减排	Carbon emission reduction
二氧化碳减排	Carbon dioxide reduction
温室气体减排	Greenhouse gas emission reduction
极端天气	Extreme weather
全球环境变化	Global environmental change
气候变异	Climate variability

Table 51 COVID-19 keywords

COVID-19 keywords in Chinese	**COVID-19 keywords in English**
新冠肺炎	novel coronavirus pneumonia
新型冠状肺炎	New type of coronary pneumonia
发生在武汉的肺炎	Pneumonia in Wuhan
出现在武汉的病毒	Viruses in Wuhan
新型冠状病毒	Novel coronavirus
新冠病毒	Novel coronavirus
COVID	COVID

The climate change query proportion was calculated by using the number of identified climate change queries to divide the total number of queries in the same fixed time interval. The formula of query proportion can be formulated as:

$$climate\ change\ query\ proportion\ = \frac{number\ of\ identified\ climate\ change\ queries}{number\ of\ total\ queries}$$

$$\frac{Health\ \&\ climate\ change\ co-queries}{Climate\ change\ queries} = \frac{number\ of\ identified\ health\&climate\ change\ co-queries}{number\ of\ iddentified\ climate\ change\ queries}$$

$$\frac{Health\ \&\ climate\ change\ co-queries}{Health\ queries} = \frac{number\ of\ identified\ health\&climate\ change\ co-queries}{number\ of\ identified\ health\ queries}$$

To identify the COVID-19 queries, a set of keywords was also developed by this team of researchers, (Table 51). Queries with at least one COVID-19 keyword were identified as COVID-19 queries. The queries in which appeared keywords from both (i) COVID-19, and (ii) climate change was identified as COVID19&climate change co-queries. Note that the COVID-19 is formally named in 12th February 2020 by WHO. In order to reflect the search queries of COVID-19 in Jan. 2020, we also include the *Viruses in Wuhan* and *Pneumonia in Wuhan* as keywords. The formula for calculating COVID19 query proportion and COVID19&climate change co-query proportion is:

$$COVID19\ query\ proportion\ = \frac{number\ of\ identified\ \text{COVID19}\ queries}{number\ of\ total\ queries}$$

$$COVID19\&climate\ change\ co-query\ proportion = \frac{number\ of\ identified\ \text{COVID19\&climate change}\ co-queries}{number\ of\ total\ queries}$$

The designed indicator was also calculated in provincial level and demographic group level to visualize the geographical and demographical distribution of query proportion in China. All the queries were searched within the recent year (from 1st Jan. 2020 to 31th Dec. 2020). For each demographic group (like the users with different education and income levels) in China, the climate change query proportion and health query proportion were calculated with the number of identified health or climate change queries of this demographic group as numerator, and with the number of total queries of this demographic group as denominator. Similarly, for each province in China, the query proportion were calculated with the number of identified queries in this province as numerator, and with the number of total queries in this province as denominator. None of the queries of this study can be associated with a particular individual.

Data

The search query data were based on search query logs from search engine provided by Baidu Inc. All the analytics of this indicator are conducted on Baidu' servers by researchers from Baidu. Each query record only contained the query, the submission time, the submission city and a few of demographical properties indicated by the submission user without of any identity information of the user. The demographical properties of users were determined through a deep learning user profiling prediction platform within Baidu using big data like user query, location and other data. Any of original search logs are being processed and used with respect to Baidu's privacy policy (https://www.baidu.com/duty/yinsiquan.html).

Caveats

First of all, the search query data of Baidu in China do not cover all population groups in China. Some population groups do not actively use the search engine such as the elderly, children and less educated people. Therefore, this indicator only reflected the individual engagement that is biased towards attention from typical internet users.

Second, the analysis of the demographical groups will be affected by the prediction accuracy of Baidu's deep learning-based user profiling prediction platform. Though such profiling prediction platform has achieved high-level prediction accuracy with many enterprise applications in the company, it does not have 100% prediction accuracy. According to statistics, the accuracy of education level label is 81%, the one of the income level is 70%, and the one of gender label is about 89%.

Third, the coverage of keywords has an influence on the final results. All the queries were identified by keywords which have been enumerated with the best effort. However, it is still possible to miss some keywords to identify the related queries.

Future Form of Indicator

In the future, the indicator of the individual engagement based on search engine data will continue to be a primary data source to track this indicator. In future, some analysis about the co-query of climate change and some specific diseases can be conducted to reflect different concerns between the climate change and health.

Additional Information

Table 52 Queries (per hundred thousand) related to health and climate change in 2017-2020

Year	2017	2018	2019	2020
$\frac{\# \ of \ climate \ change \ queries}{\# \ of \ total \ queries}$	0.793	1.018	0.921	1.427
$\frac{Health \ \& \ climate \ change \ co-queries}{Climate \ change \ queries}$	204.8	146.3	203.4	363.3
$\frac{Health \ \& \ climate \ change \ co-queries}{Health \ queries}$	0.396	0.359	0.467	0.607

There is a notable rising trend from 2019 to 2020 for individual engagement in health and climate change. While the proportion of queries related to climate change continued to increase in the past four years, the queries for health and climate change are still seldom co-searched by users. However, there is a clear rising trend from 2019 to 2020: the climate change queries of 2020 increased by 54.9% than the ones of

2019, and the health & climate change co-queries of 2020 increased by 78.6%. A possible reason for such increase is that the COVID-19 pandemic makes more individuals pay attention to the relations between climate change and public health, since previous studies have suggested that climate change might contribute to the emergence of various infectious diseases[127-129]. However, there is no conclusive evidence of a direct connection between climate change and the COVID-19 pandemic.

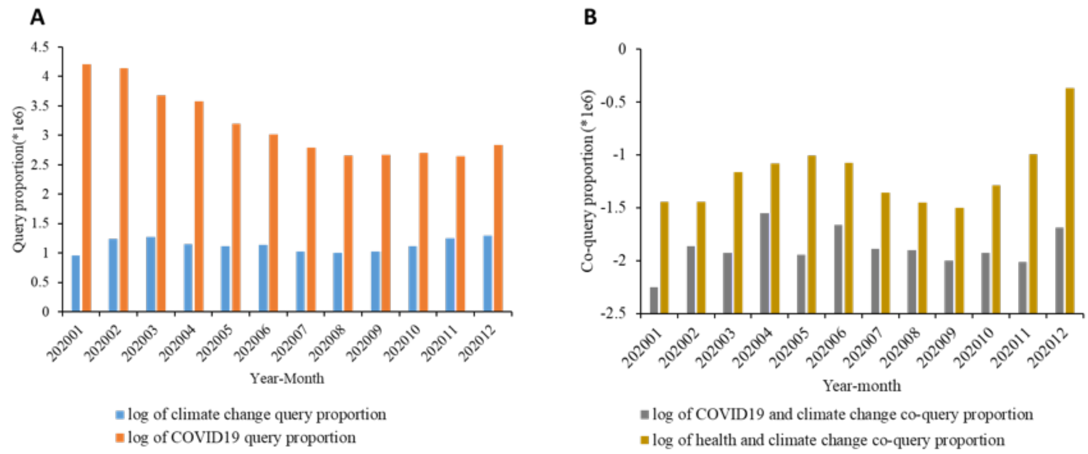

Figure 65 **:Queries (per million) from month to month in 2020 of climate change, COVID-19, COVID-19&climate change, and health &climate change (per million). Note that the Y- axes are logarithmic axes (with base 10).**

(A) Query proportion of climate change and COVID-19; (B) Query proportion of COVID-19&climate change and health & climate change.

Figure 65 shows the query proportion from month to month in 2020 of climate change, COVID-19, COVID-19&climate change, and health & climate change. As we can see from *Figure 65* (a), the query proportion of COVID-19 had two peaks at the beginning (January) and the ending (December) of 2020. The reason for appearing peak in Dec. 2020 is that a few of new COVID-19 infections raised worries about a second wave of outbreak in China. Whereas, the peaks of query proportion of climate change is in Mar. 2020 and Dec. 2020, which indicates that the COVID-19 pandemic may draw more individual attention about the climate change challenge of our earth. *Figure 65* (b) future illustrates the co-query proportion of COVID-19&climate change co-query and health & climate change co-query. Different from *Figure 65* (a), the first peaks of such co-query proportions appeared in the second quarter of 2020 which have a time lag with the first peak of COVID-19 queries. In particular, the first peak of COVID19&climate change query proportion appeared in April 2020, but the first peak of health & climate change query proportion appeared one-month latter (in May 2020), which seems that more and more people paid attention to the relations between health and climate change after realizing or hearing the possible relation between COVID-19 and climate change.

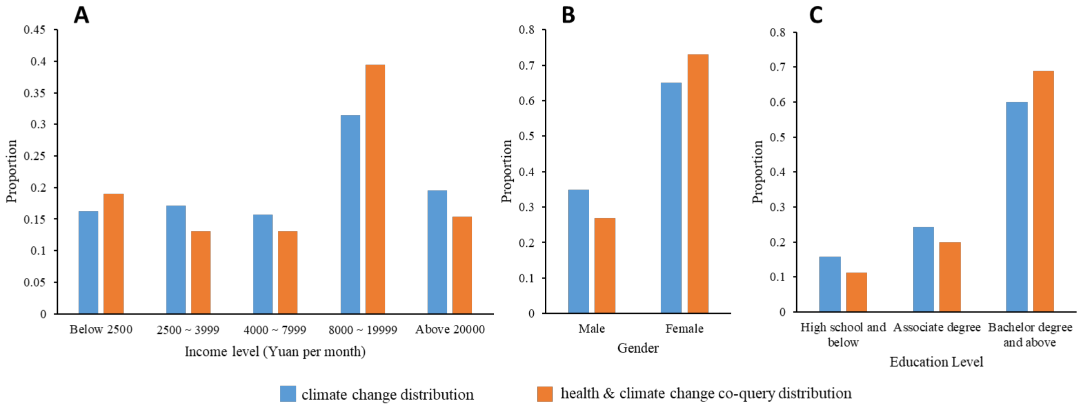

Figure 66: **The distribution of the proportion of the queries related to climate change and health & climate change query of demographic groups in China in 2020. (Note that the figures show the histogram distribution of the queries per person with a partial demographical property. The sum of the distribution on each demographical group (with the same color) equals to one. For example, the climate change queries of male and female in figure (b) equals to one.)**
(A) Distribution by income level; (B)Distribution by gender; (C)Distribution by Education.

Analysis on different demographical groups showed that female people and people with tertiary education have higher number of climate change queries and health &climate change co-queries. As shown in Figure 66 , the number of climate change queries per female person was 186.52% of the one of per male person. Meanwhile, the number of health & climate change co-query per female person was 270.47% of the one of per male person. The people with high education level also paid more attention to climate change and health & climate change. The number of health & climate change queries per person with bachelor degree or above was 381.25% and 247.94% of the person with high school or below degree and associate degree, respectively. However, there was no clear trend of such individual engagement for different income level groups.

Figure 67 illustrates that the arid areas in Northern and Western China have a more substantial proportion of climate change queries, indicating more people engaging in the climate change concern than other areas in China. In particular, as the same with the analysis of 2019[1], Tibet is still one of the top areas which had more people engaging in the climate change, which indirectly witnessed the increasing effects of climate change on the world's third pole.

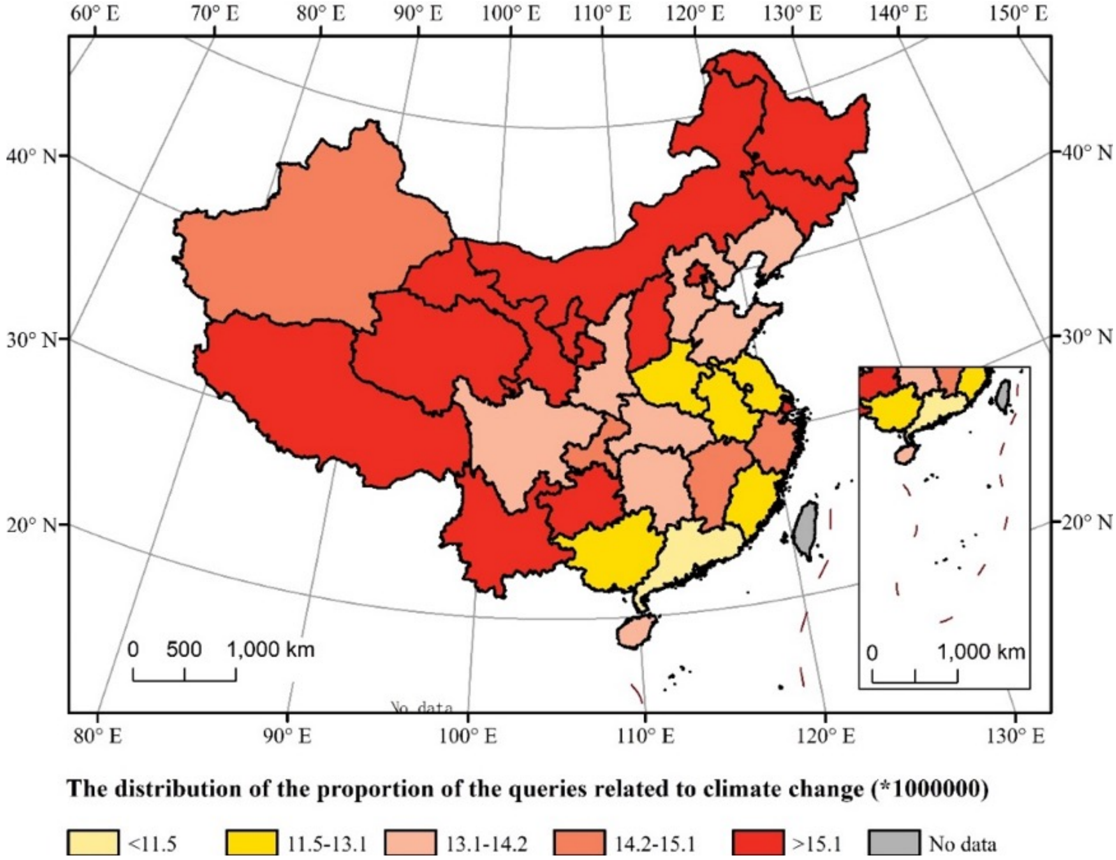

Figure 67 The distribution of the proportion of the queries related to climate change in different provinces in China in 2020

Indicator 5.3: Coverage of health and climate change in scientific journals

Methods

The methodology for this indicator remains similar to that described in the 2020 China Lancet Countdown report appendix. The inclusion of climate-related terms and their co-occurrence with health terms in scientific publications was tracked using a bibliometric search in both Ovid Medline (including Medline In-Process & Other Non-Indexed Citations for those citations not indexed) and Ovid Embase databases. Following a search unrestricted by geographical location, results for China were specifically filtered through Endnote.

The Ovid Embase and Ovid Medline databases were selected due to their coverage of health, medical and biomedical sciences, with content that is predominantly journal articles. Where Medline is predominantly health and biomedicine, Embase has a greater pharmaceutical focus, all of which are relevant to health and climate change. Both databases are updated online daily and can thus provide the annual data (with a 31 December cut-off each year) needed for the indicator. These databases also function through the sophisticated Ovid interface and allow access to the comprehensive indexing systems and thesaurus of Medical Subject Headings (MeSH) for Medline and Emtree for Embase.

Also considered for use were Science Direct and the Web of Science suite of databases, but, with broad subject coverage, these would not enable the necessary search precision.

By screening the retrieved articles between 2007 and 2020, those articles that contained both health and climate change terms in their title or abstract, but do not make any meaningful link between them, were excluded. A meaningful link here means some association between climate change and an aspect of health. This link may be the focus of the article or tangential to it. As an example, climate change may be mentioned at the end of an abstract, where it is noted the health topic that is the focus of the article (e.g., dengue fever distribution) is expected to worsen or change under climate change scenarios.

Data were extracted using search filters that function via Boolean operators (AND, OR, NOT) (see below for final search strategies). For purposes of consistency and efficiency of analysis, the majority of each search filter is designed to produce results with the search terms in either the title or abstract. Indeed, indexing is also likely to be poorly assigned or inconsistently assigned to references. The search filter is designed to retrieve all relevant results (high sensitivity) while keeping irrelevant results, and therefore effort on the part of the researchers, to a minimum (high precision).

To identify articles where associations are made between climate change and health, the filter was split into two facets, one for climate change and one for health. Terms that made up the filter were derived using both subjective and objective methods. Subjective methods included utilising terms already known by the research team, as well as those appearing in previous iterations of the Lancet Countdown. Objective methods included the use of online word frequency software (Writewords). Articles looking at health and climate change were run through this software, which organises the words or phrases in order of frequency, allowing relevant terms to be extracted.

The iteration for the 2021 Lancet Countdown report adopted a revised methodology to improve accuracy. Where previous analyses included articles with article keywords depicting a relationship between health and climate change, the 2021 Lancet Countdown analysis does not. Though the numbers provided are lower than previous years, this provides more accuracy and granularity.

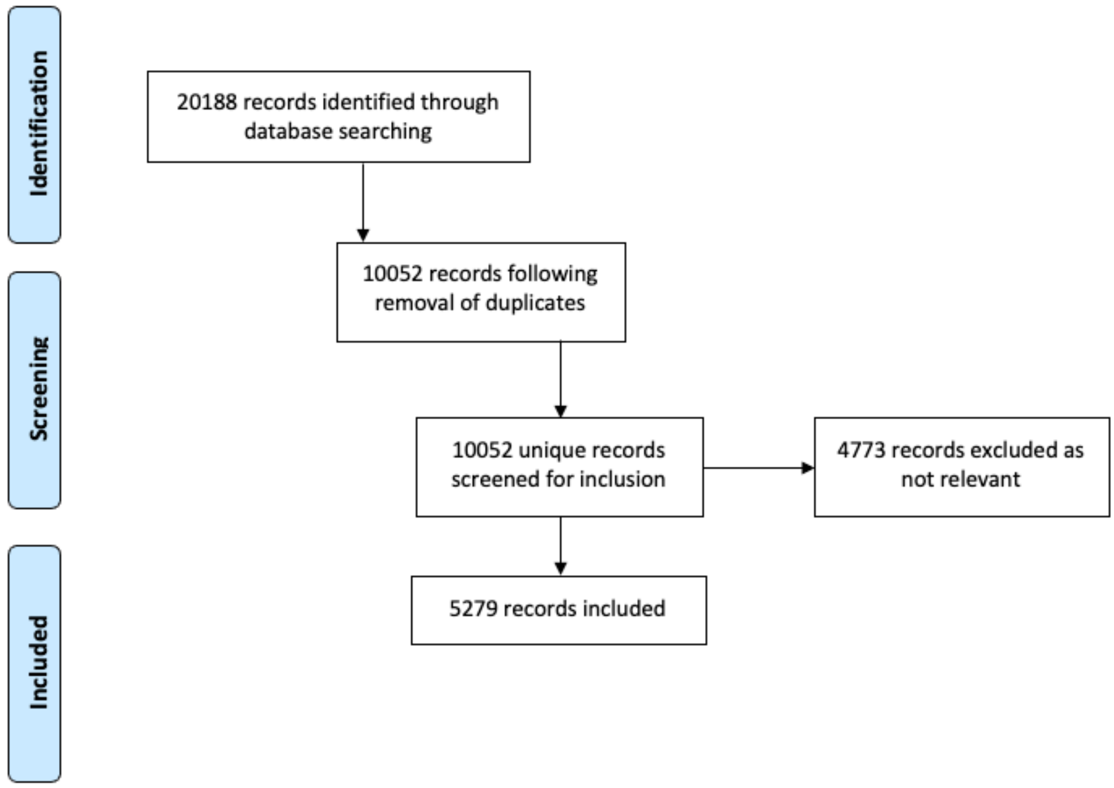

Figure 68. PRISMA flow diagram showing steps of selection process.

Numbers indicate the article count retained at each step of the process. With the applied search terms more than 20,000 scientific articles on health and climate change were identified for the period of 2007-2020. After the screening process, only 26.1% (n=5279) were retained and found to be relevant.

Following screening, precision was established by calculating the number of relevant records retrieved, divided by the total number of unique records retrieved. The development of the search strategy was repeated, and all of the necessary stages leading up to this point, until precision was established at over 50% for each database.

With an acceptable level of precision established for each database, the data were coded and organised in Endnote, Excel and R. In addition to the indicator enhancements outlined above, the method used to identify the location of the first author was improved, resulting in greater accuracy. As the results for China are filtered by this variable, there are differences between the results outlined here and those in previous iterations of the report.

Table 53. Search terms

Medline		**Medline (In-Process & Other Non-Indexed Citations)**		**Embase**	
1	carbon footprint*.ti,ab.	**1**	(climat* adj3 chang*).ti,ab.	**1**	(climat* adj3 chang*).ti,ab.
2	carbon	**2**	climate variability.ti,ab.	**2**	Climate Change/

	footprint/				
3	(climat* adj3 chang*).ti,ab..	**3**	(climat* adj3 warming).ti,ab.	**3**	Greenhouse Effect/
4	climat* cris?s.ti,ab.	**4**	global warming.ti,ab.	**4**	greenhouse gas*.ti,ab.
5	climat* variability.ti,ab.	**5**	greenhouse effect*.ti,ab.	**5**	global warming.ti,ab.
6	climat* warming.ti,ab.	**6**	green house effect*.ti,ab.	**6**	Carbon Footprint/
7	exp Climate Change/	**7**	greenhouse gas*.ti,ab.	**7**	Greenhouse Gas/
8	GHG*.ti,ab.	**8**	(greenhouse adj2 emission*).ti,ab.	**8**	(greenhouse adj2 emission*).ti,ab.
9	global warming.ti,ab.	**9**	climat* model*.ti,ab.	**9**	(climat* adj3 warming).ti,ab.
10	greenhouse effect*.ti,ab.	**10**	climat* scenario*.ti,ab.	**10**	GHG*.ti,ab.
11	greenhouse effect/	**11**	green house emission*.ti,ab.	**11**	climat* model*.ti,ab.
12	greenhouse emission*.ti,ab.	**12**	GHG*.ti,ab.	**12**	climat* variability.ti,ab.
13	greenhouse gas*.ti,ab.	**13**	carbon footprint*.ti,ab.	**13**	carbon footprint*.ti,ab.
14	Greenhouse Gases/	**14**	climate induced.ti,ab.	**14**	climat* scenario*.ti,ab.
15	climate induced.ti,ab.	**15**	climat* cris?s.ti,ab.	**15**	greenhouse effect*.ti,ab.
16	climat* scenario*.ti,ab.	**16**	health.ti.	**16**	climate induced.ti,ab.
17	climat* model*.ti,ab.	**17**	disease*.ti.	**17**	climat* cris?s.ti,ab.
18	exp Health/	**18**	infectious.ti.	**18**	Ep.fs.
19	Global Health/	**19**	mortality.ti.	**19**	exp Malignant neoplasm/
20	health status/	**20**	healthy.ti.	**20**	exp skin disease/
21	health status disparities/	**21**	mental.ti.	**21**	exp lung disease/

22	exp disease/	**22**	malaria.ti.	**22**	diabetes mellitus/
23	exp virus diseases/	**23**	dengue.ti.	**23**	Disease association/
24	exp viruses/ and human*.ab.	**24**	respiratory.ti.	**24**	Western blotting/
25	exp Communicable Diseases/	**25**	infection*.ti.	**25**	etiology/
26	Infection/	**26**	wellbeing.ti.	**26**	immunology/
27	aedes/	**27**	well being.ti.	**27**	Infection/
28	water/ps	**28**	outbreak*.ti.	**28**	Death/
29	allergens/	**29**	zika.ti.	**29**	Cardiovascular disease/
30	exp Disease Outbreaks/	**30**	undernutrition.ti.	**30**	Fever/
31	exp Mortality/	**31**	influenza.ti.	**31**	health/
32	mo.fs.	**32**	hospitali?ation*.ti.	**32**	Mental disease/
33	exp Malaria/	**33**	epidemic.ti.	**33**	Epidemiology/
34	exp disease transmission, infectious/	**34**	ecohealth.ti.	**34**	Cerebrovascular accident/
35	exp Neoplasms/	**35**	ebola.ti.	**35**	hospital admission/
36	exp Heat Stress Disorders/	**36**	death.ti.	**36**	anemia/
37	exp Fever/	**37**	kills.ti.	**37**	Chronic disease/
38	exp Metabolic Diseases/	**38**	cholera.ti.	**38**	public health/
39	exp Death/	**39**	foodborne.ti.	**39**	cancer risk/
40	exp Skin/re	**40**	epidemics.ti.	**40**	Virus infection/
41	exp Environmental Illness/	**41**	endemic.ti.	**41**	kidney failure/
42	Community-Acquired Infections/	**42**	pandemic.ti.	**42**	Mental health/
43	exp Mental Disorders/	**43**	syndrome.ti.	**43**	Neurologic disease/

44	Environmental Exposure/ae	**44**	asthma.ti.	**44**	Health status/
45	nutrition disorders/	**45**	illness*.ti.	**45**	exp Birth weight/
46	child nutrition disorders/	**46**	morbidity.ti.	**46**	Human immunodeficiency virus/
47	exp Rickettsiaceae/	**47**	cancer.ti.	**47**	exp zoonosis/
48	exp infant nutrition disorders/	**48**	malnutrition.ti.	**48**	prophylaxis/
49	exp malnutrition/	**49**	mental health.ti.	**49**	Disease transmission/
50	exp wasting syndrome/	**50**	mental disorder*.ti.	**50**	Gastrointestinal disease/
51	exp encephalitis/	**51**	(global adj2 nutrition*).ti.	**51**	Infection risk/
52	salmonella infections/	**52**	(population adj2 nutrition*).ti.	**52**	Mental stress/
53	Helminthiasis/	**53**	(security adj2 nutrition*).ti.	**53**	antivirus agent/
54	food contamination/	**54**	(insecurity adj2 nutrition*).ti.	**54**	exp allergen/
55	zoonoses/	**55**	(global adj2 food adj2 (supply or production)).ti.	**55**	Childhood disease/
56	Noncommunicable Diseases/	**56**	(security adj2 food).ti.	**56**	immunogenicity/
57	health.ti.	**57**	(insecurity adj2 food).ti.	**57**	malnutrition/
58	disease*.ti.	**58**	lyme disease.ti.	**58**	Pregnancy outcome/
59	infectious.ti.	**59**	Chikungunya.ti.	**59**	exp *malaria/
60	mortality.ti.	**60**	Hantavirus.ti.	**60**	Health hazard/
61	healthy.ti.	**61**	West Nile disease.ti.	**61**	Life expectancy/
62	mental.ti.	**62**	west nile fever.ti.	**62**	Child development/
63	mental.ti.	**63**	global disease*.ab.	**63**	dermatology/
64	malaria.ti.	**64**	global health.ab.	**64**	hygiene/
65	malaria.ti.	**65**	well being.ab.	**65**	virus detection/
66	dengue.ti.	**66**	wellbeing.ab.	**66**	genotoxicity/
67	respiratory.ti.	**67**	human health.ab.	**67**	Allergic rhinitis/

68	infection*.ti.	**68**	vector borne disease*.ab.	**68**	women's health/
69	wellbeing.ti.	**69**	health implication*.ab.	**69**	exp leishmania/
70	well being.ti.	**70**	public health.ab.	**70**	encephalitis/
71	outbreak*.ti.	**71**	health consequence*.ab.	**71**	Child health/
72	zika.ti.	**72**	mental health.ab.	**72**	Communicable disease/
73	undernutrition.ti.	**73**	reproductive health.ab.	**73**	virus vector/
74	influenza.ti.	**74**	health adaptation.ab.	**74**	infant mortality/
75	hospitali?ation.ti.	**75**	(mortality adj2 morbidity).ab.	**75**	Health disparity/
76	epidemic.ti.	**76**	infectious disease*.ab.	**76**	Psychological well being/
77	ecohealth.ti.	**77**	health outcomes.ab.	**77**	Reproductive health/
78	ebola.ti.	**78**	health vulnerability.ab.	**78**	Tropical medicine/
79	death.ti.	**79**	(health adj2 impact*).ab.	**79**	Vulnerable population/
80	kills.ti.	**80**	(health adj2 threat*).ab.	**80**	Allergic disease/
81	cholera.ti.	**81**	(burden adj2 disease*).ab.	**81**	Maternal welfare/
82	foodborne.ti.	**82**	(population adj2 health).ab.	**82**	Toxoplasma gondii/
83	epidemics.ti.	**83**	(health adj2 effect*).ab.	**83**	Disease burden/
84	endemic.ti.	**84**	(health adj2 risk*).ab.	**84**	Childhood mortality/
85	pandemic.ti.	**85**	(health adj2 benefit*).ab.	**85**	Dengue virus/
86	syndrome.ti.	**86**	(health adj2 co-benefit*).ab.	**86**	Infectious agent/
87	asthma.ti.	**87**	mental disorder*.ab.	**87**	respiratory tract allergy/
88	illness*.ti.	**88**	Noncommunicable Disease*.ab.	**88**	enterovirus/
89	morbidity.ti.	**89**	malaria.ab.	**89**	anopheles/
90	cancer.ti.	**90**	syndrome.ab.	**90**	pollen allergy/
91	malnutrition.ti.	**91**	(tree or trees or soil).ti.	**91**	campylobacter/
92	mental health*.ti.	**92**	(people or human* or public health or men or women or children or patients or students).af.	**92**	exp Heat injury/
93	(global adj2 nutrition*).ti.	**93**	(editorial or letter or comment).pt.	**93**	Global health/
94	(population adj2	**94**	or/1-15	**94**	Non communicable disease/

	nutrition*).ti.				
95	(security adj2 nutrition*).ti.	**95**	or/16-90	**95**	norovirus/
96	(insecurity adj2 nutrition*).ti.	**96**	94 and 95	**96**	Ebola hemorrhagic/
97	(global adj2 food adj2 (supply or production)).ti.	**97**	96 not 91	**97**	Health impact assessment/
98	(security adj2 food).ti.	**98**	97 and 92	**98**	Yellow fever/
99	(insecurity adj2 food).ti.	**99**	limit 98 to yr="2007 - 2019"	**99**	leptospira/
100	Chikungunya.ti.	**100**	limit 99 to abstracts	**100**	chikungunya/
101	Hantavirus.ti.	**101**	100 not 93	**101**	Arbovirus/
102	West Nile virus.ti.			**102**	tick-borne disease/
103	west nile fever.ti.			**103**	Food insecurity/
104	global disease*.ab.			**104**	Premature mortality/
105	global health.ab.			**105**	Trihalomethanes/
106	well being.ab.			**106**	population health/
107	wellbeing.ab.			**107**	Japanese encephalitis/
108	human health.ab.			**108**	Crimean-Congo hemorrhagic fever/
109	vector borne disease*.ab.			**109**	urban health/
110	health implication*.ab.			**110**	disease*.ti.
111	public health.ab.			**111**	cancer.ti.

112	health consequence*. ab.			**112**	health.ti.
113	mental health.ab.			**113**	infection*.ti.
114	reproductive health.ab.			**114**	mortality.ti.
115	health adaptation.ab.			**115**	respiratory.ti.
116	(mortality adj2 morbidity).ab.			**116**	death.ti.
117	infectious disease*.ab.			**117**	healthy.ti.
118	syndrome.ab.			**118**	mental.ti.
119	health outcomes.ab.			**119**	asthma.ti.
120	health vulnerability.a b.			**120**	influenza.ti.
121	(health adj2 impact*).ab.			**121**	illness*.ti.
122	(health adj2 threat*).ab.			**122**	malaria.ti.
123	(burden adj2 disease*).ab.			**123**	infectious.ti.
124	(population adj2 health).ab.			**124**	outbreak*.ti.
125	(health adj2 effect*).ab.			**125**	hospitali?ation*.ti.
126	(health adj2 risk*).ab.			**126**	epidemic.ti.
127	(health adj2 benefit).ab.			**127**	dengue.ti.
128	(health adj2 co- benefit*).ab.			**128**	endemic.ti.
129	mental			**129**	well being.ti.

	disorder*.ab.				
130	Noncommunicable Disease*.ab.			**130**	pandemic.ti.
131	malaria.ab.			**131**	cholera.ti.
132	mycotoxins/ not food contamination/			**132**	ebola.ti.
133	respiratory tract diseases/			**133**	zika.ti.
134	Aspergillus/			**134**	west nile virus.ti.
135	Candida/			**135**	epidemics.ti.
136	exp candida/			**136**	wellbeing.ti.
137	exp aspergillus/			**137**	Hantavirus.ti.
138	Disease Susceptibility/			**138**	(insecurity adj2 food).ti.
139	encephalitis/			**139**	kills.ti.
140	HIV infections/			**140**	(global adj2 food adj2 (supply or production)).ti.
141	bacterial infection/			**141**	flavivirus.ti.
142	or/1-17			**142**	(global adj2 nutrition*).ti.
143	or/18-131			**143**	(security adj2 nutrition*).ti.
144	or/18-141			**144**	ecohealth.ti.
145	(tree or trees).ti.			**145**	(security adj2 food).ti.
146	soil.ti.			**146**	(mortality adj2 morbidity).ab.
147	exp animals/ not humans.sh.			**147**	public health.ab.
148	142 and 143			**148**	mental health.ab.
149	142 and 144			**149**	infectious disease*.ab.
150	148 not 145			**150**	well being.ab.
151	150 not 146			**151**	malaria.ab.
152	151 not 147			**152**	health outcomes.ab.

153	149 not 145			**153**	(health adj2 effect*).ab.
154	153 not 146			**154**	human health.ab.
155	154 not 147			**155**	mental disorder*.ab.
156	155 NOT 152			**156**	(burden adj2 disease*).ab.
157	limit 152 to yr="2007 - Current"			**157**	(health adj2 impact*).ab.
158	limit 155 to yr="2007 - Current"			**158**	wellbeing.ab.
159	(editorial or letter or comment).pt.			**159**	global health.ab.
160	157 not 159			**160**	gastroenteritis.ab.
161	158 not 159			**161**	(population adj2 health).ab.
				162	reproductive health.ab.
				163	(health adj2 threat*).ab.
				164	health consequence*.ab.
				165	health implication*.ab.
				166	flavivirus.ab.
				167	aeroallergens.ab.
				168	vector borne disease*.ab.
				169	(health adj2 co-benefit*).ab.
				170	health adaptation.ab.
				171	or/1-17
				172	or/18-170
				173	(tree or trees).ti.
				174	soil.ti.
				175	(exp animal/ or nonhuman/) not exp human/
				176	or/172-174
				177	171 and 172
				178	177 not 176
				179	limit 178 to yr="2007 -2019"
				180	limit 179 to abstracts

Data

1. Scientific journal articles on health and climate change were searched in the national database, CNKI (https://www.cnki.net/).
2. Articles in scientific journals were searched in the Ovid Embase and Ovid Medline databases. The bibliometric search worked with specific inclusion and exclusion criteria that were applied to capture only the most relevant literature. This includes peer-reviewed scientific articles on health and climate change in English, with no direct restriction to country or population applied. All peer-reviewed articles, originating from Chinese institutions, and reporting the findings of original qualitative and quantitative studies will be included, together with reviews, editorials, viewpoints, letters or comments.

Caveats

The methodology provided here enables a quantitative appraisal of the research question. The quality of the data and the specifics of its content are not assessed by the indicator team. However, with the outputs all published in peer-reviewed journals, there is a de facto check on quality. For this reason, the indicator does not cover grey literature.

Future form of the indicator

There remains scope to formulate add-ons to the indicator, for example focusing on trends in scientific coverage of particular climate-sensitive health outcomes.

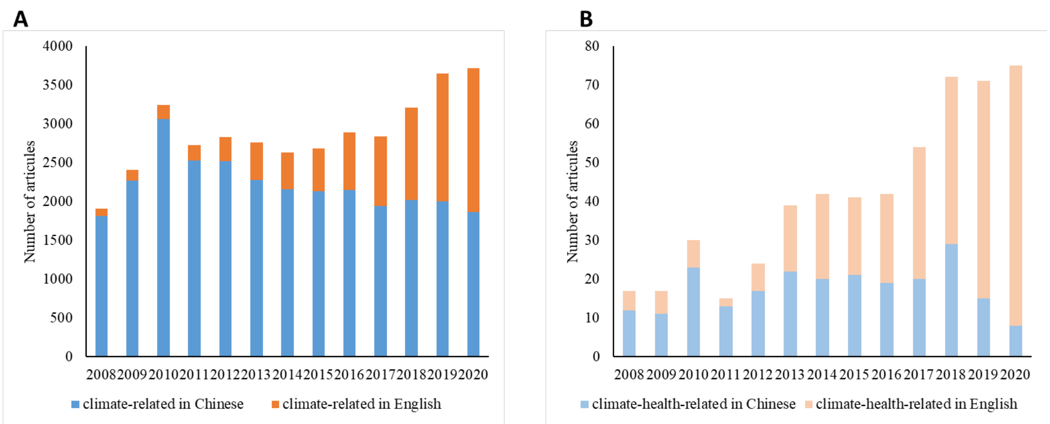

Figure 69: **Annual coverage of climate change and health and climate change- related articles from Chinese scholars (2008-2020)**

(A) Climate change related articles from Chinese scholars (2008-2020); (B) Climate change and health-related articles from Chinese scholars (2008-2020)

Indicator 5.4: Health and climate change in the Chinese government

Methods

Indicator 5.4 is a newly added indicator to track governmental engagement in health and climate change. Articles and attached policy files (word or pdf) from four government official websites were examined, including China Meteorological Administration, National Development and Reform Commission, National Health Commission of the People's Republic of China, Ministry of Ecology and Environment of the people's Republic of China, which represent the meteorological sector, economics and development sector, public health sector, and environmental protection sector respectively.

Key words for the searching on topic of Climate Change and Health were shown in Table 54.

Table 54 Keywords for the search in Chinese government website

Keywords for the health and climate change search in the government search		English translation of these Chinese keywords	
气候相关词汇	健康相关词汇	Key words for "Climate Change"	Key words for "Health"
气候变化	健康	Climate* change*	Health
全球变暖	疾病	Global warming	Disease
温室效应	非传染性疾病 传染病	Greenhouse effect	Non-Communicable, NCD, Communicable
温室气体排放 温室气体减排 二氧化碳（碳）减排		Greenhouse gas emission* Carbon emissions*	
干旱	流行病学	Drought	Epidemiology
野火	生活方式	Bushfire	Lifestyle
热带气旋	死亡	Tropical cyclone	Mortality
热浪	营养	Heatwave	Nutrition
	营养不良		Malnutrition
	脱水		Dehydration
	发病		Morbidity
	移民		Migration
	精神疾病		Mental disorders
	协同效益（应）		Co-Benefits

Three steps are used to collect and validate the climate change and health related articles on the official websites.

Step 1: Crawling all the climate change articles from 2008 to 2020 on four governmental websites

With a python-based crawler, all qualified articles published by four Chinese government official websites from January, 2008 to December, 2020 were collected. 11 climate change related keywords were used in the column of "Climate Change" in Table 1, which is in accordance with the new climate change keywords used in the *MJA-Lancet Countdown on health and climate change: Australian policy inaction threatens lives*. The keywords are presented in the column of “Climate Change” in Table 54.

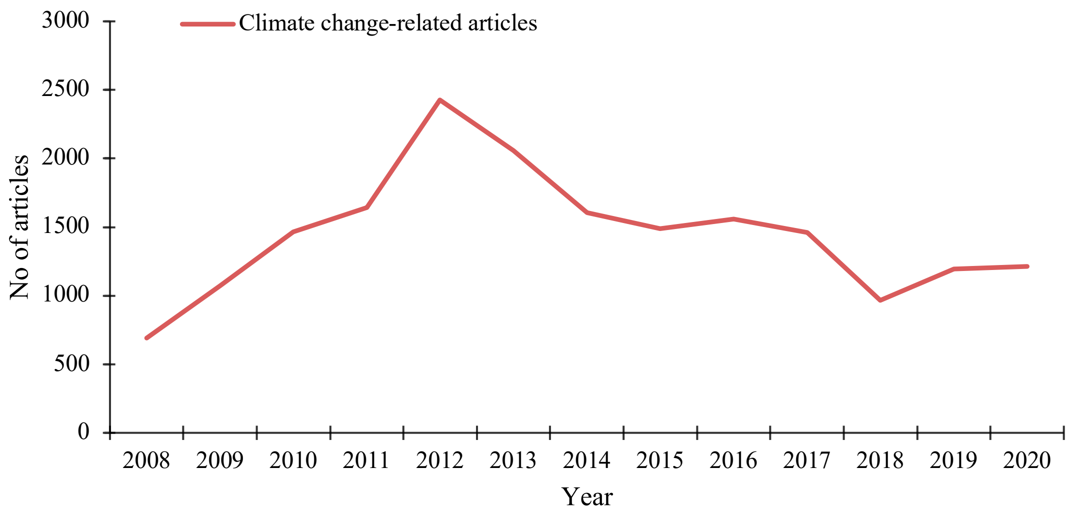

Figure 70 Coverage of climate change articles on Chinese government websites between 2008 and 2020.

Step 2: Searching for health-related articles

We then checked whether these climate-related articles are health-related by search health-related key works (**Table 54**) in in the posts. Our choice of health keyword list followed previous research of Media coverage of health and climate change for People’s Daily in China [124]. If a post contains at least 1 health-related word and word frequency ratio in the whole post is greater than 0.01, this post is regarded as relevant to health topics. The results are shown in Figure 71.

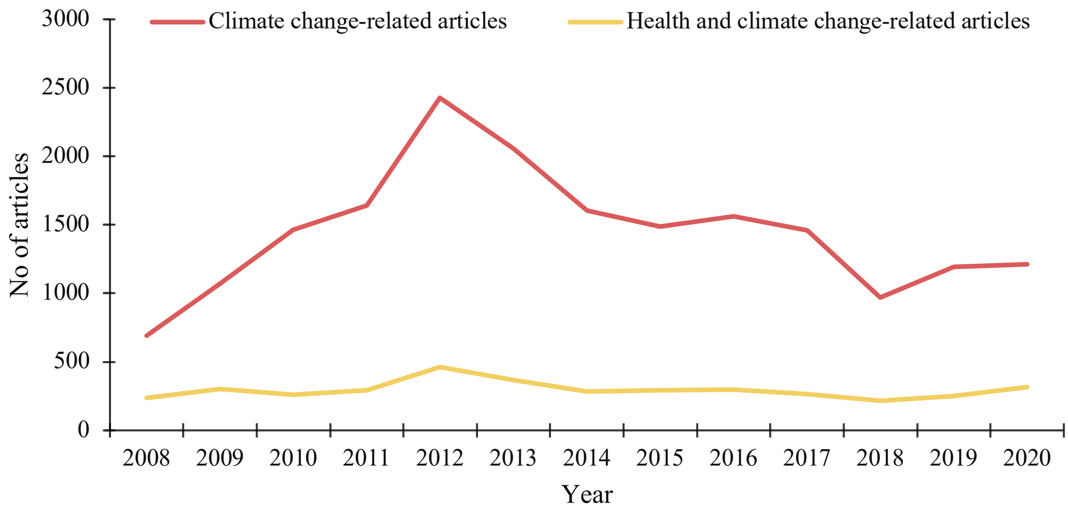

Figure 71 Coverage of climate change and climate change — health mentioned together on Chinese government websites between 2008 and 2020

Step 3: Systematic sampling and manual screening was added to test the false positive rate

We add manual screening process to test the data of health and climate change related articles to exclude the articles which showed the keywords but irrelevant to both health and climate change. As a result of manual screening， 781 (or 20%) was selected from a total number of 3838 articles by four government official websites regarded as both health and climate change articles. Manual screening on the 781 articles shows a false positive rate of 0.20. Systematic sampling again was used to test the false positive rate of climate change related articles. 189 articles (or 1%) were selected from 18842 as a sample between 2008-2020 of four government official websites. Manual screening on the 189 articles shows a false positive rate was 0.14.

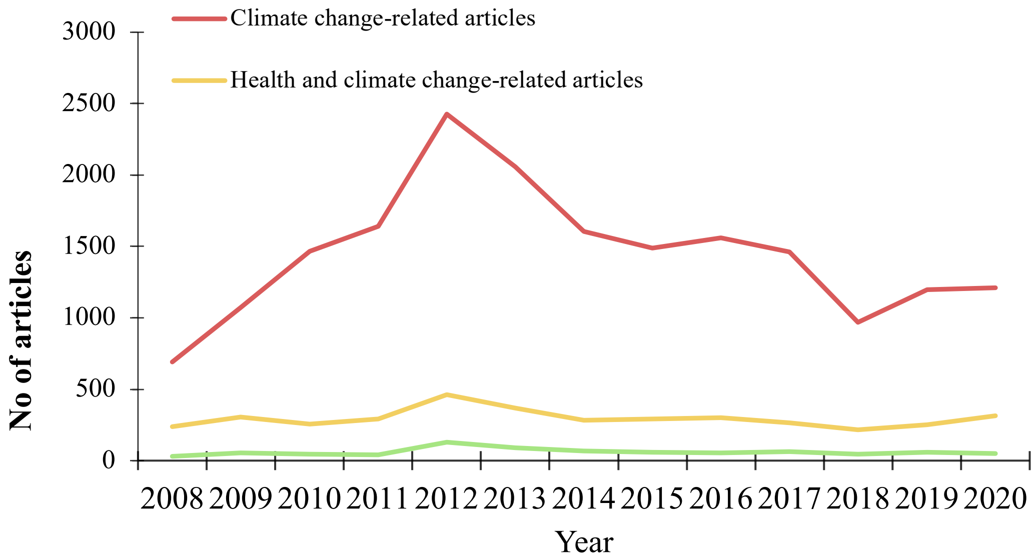

Figure 72 Coverage of climate change and climate change-health mentioned together(after systematic sampling and manual screening)on Chinese government websites between 2008 and 2020.

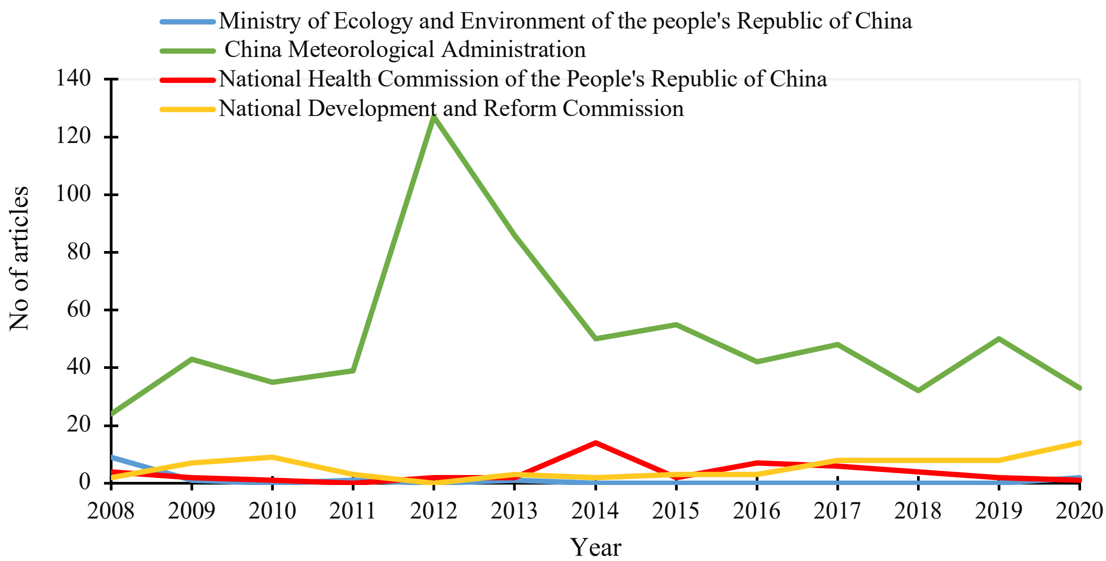

Figure 73 Coverage of climate change and health mentioned together on different Chinese government website between 2008 and 2020

Data

Across the 2008-2020 period, there was an average of 1449 articles per year discussing climate change, in which about 4.5% or 65 articles (after manual screening) per year were related to human health. China Meteorological Administration has more 10 times articles than other 3 government official websites with the number of average years of climate change and health related articles.

Additional Information

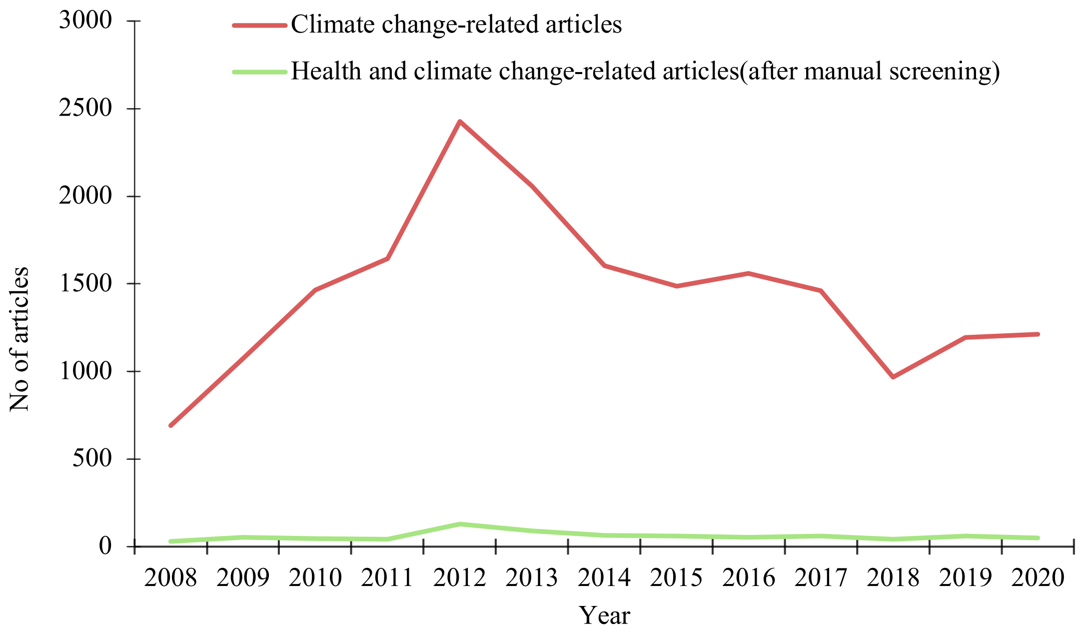

Figure 74: **Annual Coverage of Health and climate change-related articles on four Chinese government websites between 2008 and 2020**

Caveats
The data we obtained from governmental websites only partially represent governmental engagement, because for one thing, not all policy files will be uploaded on their official website, for another, the information online cannot fully reflect their efforts offline.

Future Form of Indicator
In order to further improve the accuracy and relevance of the research samples, keywords can be adjusted according to the Chinese context in the future.

Additional information to Figure 7 in the main text

Table 55: Description of impacts indicators used in figure 7

Indicator	Meaning	Baseline period	Baseline value	Latest year	standardization
Heatwave-related mortality	The number of heatwave-related mortality in China	1986-2005	7564.00	2020	$$yearly\ score = \frac{year\ value}{baseline\ value}$$
Costs of heatwave-related mortality	The economic costs of heatwave-related mortality in China (billion 2015 USD)	2002	43.00	2020	
Labor productivity	The annual heat-related work hours	2015	25.54	2020	

loss	loss in China (billion working hours)				
Costs of labor productivity loss	The economic costs of heatwave-related labor productivity loss in China (billion 2015 USD)	2011	75.08	2020	
Number of flood	\	1986-2005	6.25	2019	
Number of drought	\	1986-2005	1.05	2019	
Climate suitability for dengue fever	VC	2004	0.25	2019	
Exposure of wildfire	Satellite-observed exposure (person·day)	2001-2004	8337784.50	2020	

Table 56: Description of response indicators used in figure 7

indicator	Original data	worst case value	worst case year	target value	target meaning	standardization
Health emergency management	National average health emergency score	0	\	100	Full score in health emergency management	yearly score $= \frac{original\ data - worst\ case\ value}{target\ value - worst\ case\ value}$
Adaptation planning	Number of mainland provinces having health adaptation plan	0	\	31	All provinces have adaptation planning	
Reduction of Carbon intensity	Carbon Intensity	1.22389	2005	0	Carbon Neutrality	
Coal phase-out	Share of Coal in TPES	0.725	2007	0	Total Coal Phase-out	
Low-carbon electricity	share of low-carbon electricity generation in total	0.147874	2007	1	100% Low-carbon electricity	

	electricity generation					
Clean household energy use	Share of electricity in total household energy consumption	0.221352	2000	1	100% Electrification in household energy consumption	
Reduction of urban air pollution	Number of cities reaching WHO interm-1 target of $PM_{2.5}$ concentrations ($10\mu g/m^3$)	0	\	1	Air qualities in all cities in China meet the WHO interm-1 target (35ug/m3)	
Fossil Fuel Subsidies	Fossil fuel subsidies value	50.94952	2018	0	Zero fossil fuel subsidies	

Comparison of between 2021 report and 2020 report

Table 57: indicator value comparison between report in 2021 and 2020

Indicator	sub indicator	Year in 2021 report	Value in 2021 report	Year in 2020 report	Value In 2020 report	whether increase from last report	unit
1.1.1 heat-related mortality		2020	14543.65	2019	21219.24	decrease	
1.1.2 change in labour capacity		2020	31.51351	2019	34.2767	decreae	billion working hours
1.2.1 wildfires						decrease	
	risk	2020	2273.651	2019	2535.878	decrease	millions persondays
	exposure	2020	11.38895	2019	12.36957	decrease	millions persondays
1.2.2 flood and drought							
	population affected by flood	2018	35.262	2017	69.512	decrease	millions

	number of flood	2019	6	2018	8	decrease	
	population affected by drought	2018	27.427	2017	47.17	decrease	millions
	number of drought	2019	0	2018	0	\	
1.3 climate-sensitive infectious diseases							
	VC	2019	0.31503	2018	0.318676	decrease	
	disease burden for dengue fever	2019	0.66	2018	0.17	increase	
2.1 Adaptation planning and assessment		2019	6	2020	3	improve	number of provinces with health adaptation plans
2.2.1 detection, preparedness, and response to health emergencies		2019	53.4	2018	48.1	improve	
2.2.2 air conditioning - benefits and harms		2019				increase	
	air conditioner inventory	2019	115.6	2018	109.3	increase	
	air conditioner-related carbon emission	2018	253	2017	249	increase	Mt
	air conditioner-prevented heatwave-related mortality	2018	47%	2017	46%	increase	fraction prevented
2.2.3 Urban green space		2020	9	2019	9	improve	number of provinces with high/exceptionally

							high urban greenness
2.3 climate information services for health		2020	21	\			number of provinces with information sharing
3.1 energy system and health						improve	
	carbon intensity	2020		2019		decrease	
	coal phase-out	2020		2019		increase	
	low carbon electricity	2020		2019		increase	
3.2 clean household energy						worse	
	household consumption	2020	15.39	2019	13.74	increase	Total (GJ per person)
	electricity share	2020	35.18	2019	35.53	decrease	%
3.3 air pollution, energy, and transport		2020	174	2019	215	improve	number of cities meeting WHO interm target-1 (35ug/m3)
4.1.1 costs of heat-related mortality		2020	176	2019	212	decrease	billion 2015 USD
4.1.2 economic costs of heat-related labor productivity loss		2020	175.2	2019	176	decrease	billion 2015 USD
4.1.3 economic costs of air pollution		2019	4.37	2015	3.88	increase	billion 2015 USD
4.1.4 economic losses due to climate-related extreme events		2018	41.9	2017	49	decrease	billion 2015 USD
4.2.1 investment in new coal, low-carbon energy and energy efficiency		2020	75.82	2018	63.15	improve	billion 2015 USD
4.2.2 employment in low-carbon and high-carbon		2018	1.05076	2017	1.015012	improve	ratio of renewable energy

industries							employment to fossil fuel extraction employment
	RE employment	2020	4.361	2019	4.078	increase	
	fossil fuel extraction employment	2020	3.257	2019	3.294	decrease	
4.2.3 net value of fossil fuel subsidies and carbon prices						improve	
	share of fossil fuel subsidies	2019	9.6	2018	11.64	decrease	%
	carbon prices	2020		2019		increase	
5.1.1 media coverage of health and climate change on Weibo		2020	427	2019	160	improve	number of articles related to climate-health
5.1.2 Newspaper coverage of health and climate change		2020	2766	2019	1072	improve	number of articles related to climate-health
5.2 individual engagement in health and climate change		2020	363.3	2019	203.4	improve	Queries (per hundred thousand) related to health and climate change, #climate-health/#climate
5.3 Coverage of health and climate change in scientific journals		2020	75	2019	71	improve	number of articles published by Chinese scholars in Chinese and English
5.4 Government engagement in health and climate change		2020	48	2019	60	worse	number of articles related to climate-health on government websites

The value of all 5 indicators in section 1, which tracked health impacts, decreased from the previous year, except for the significant increase in disease burden of dengue fever (sub-indicator for indicator 1.3). And the resulting economic costs were also decreasing, causing the value of 4 indicators that tracked economic costs of health impacts related to climate change, except for the economic costs of air pollution. However, this does not imply that the health threats from climate change were alleviating in China. In fact, all the impacts were still much higher than their historical baseline, signaling the continuous health threats from climate change. Among the 16 indicators that tracked response to health risks related to climate change, situations depicted in 12 indicators were improving, 2 were worsening (indicator 3.2 clean household energy and indicator 5.4 government engagement), 1 were mixed (indicator 2.2.2 air conditioning - benefits and harms) and 1 with no previous data to compare (indicator 2.3 climate information service for health).

Table 58: policy recommendation comparison between report in 2021 and 2020

Policy Recommendations in 2020 Report	Policy Recommendation in 2021 Report
1. Enhance inter-departmental cooperation. 2. Strengthen health emergency preparedness. 3. Support research and raise awareness 4. Increase climate mitigation. 5. Ensure the recovery from COVID-19 protects health now, and in the future.	1. Promote systematic thinking in the related departments and further strengthen multi-departmental cooperation. 2. Extend the assessment of health impacts of climate change and make national and region-specific adaptation plans accordingly. 3. Strengthen China's climate mitigation actions and ensure health is included in China's pathway to achieve carbon neutrality. 4. Raise awareness on the climate-health linkages at all levels.

In this year's report, we provide more detailed and tailored policy recommendations than those in last year's report. For instance, we emphasize the significance of inter-departmental cooperation in both reports with no specific policy actions are recommended in last year's report and detailed policy recommendations for health sector and climate and development-related sector in this year's report.

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