COVID-19 lockdown improved river water quality in China

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Capsule summary: River water quality improved during China's COVID-19 lockdown, but returned to normal conditions after the lockdown.

Abstract: The impacts of COVID-19 lockdowns on air quality around the world have received wide attention. In comparison, assessments of the implications for water quality are relatively rare. As the first country impacted by COVID-19, China implemented local and national lockdowns that shut down industries and businesses between January and May 2020. Based on monthly field measurements (N = 1693) and daily automonitoring (N = 65), this study analyzed the influence of the COVID-19 lockdown on river water quality in China. The results showed significant improvements in river water quality during the lockdown period but out-of-step improvements for different indicators. Reductions in ammonia nitrogen (NH_4^+-N) began relatively soon after the lockdown; chemical oxygen demand (COD) and dissolved oxygen (DO) showed improvements beginning in late January/early February and mid-March, respectively, while increases in pH were more temporally concentrated in the period from mid-March to early May. Compared to April 2019, the Water Quality Index increased at 67.4% of the stations in April 2020, with 75.9% of increases being significant. Changes in water quality parameters also varied spatially for different sites and were mainly determined by the locations and levels of economic development. After the lifting of the lockdown in June, all water quality parameters returned to pre-COVID-19 lockdown conditions. Our results clearly demonstrate the impacts of human activities on water quality and the potential for reversing ecosystem degradation by better management of wastewater discharges to replicate the beneficial impacts of the COVID-19 lockdown.

Keywords: COVID-19; lockdown; water quality; spatiotemporal variations; China

1 Introduction

The unprecedented severe acute respiratory syndrome coronavirus disease 2019 (COVID-19) has impacted ~220 countries or territories around the world (https://www.worldometers.info/coronavirus/#countries). According to the WHO COVID-19 Dashboard (https://covid19.who.int/), as of 6 August 2021, 199.5 million people have been infected with the coronavirus leading to over 4.2 million deaths worldwide. COVID-19 can spread rapidly via primary modes of transmission that include droplets, direct contact, and faecal-oral pathways (Chen et al., 2020). To slow down the diffusion of the virus, more than 170 countries have implemented localised or national lockdown measures (https://www.theigc.org/blog/a-policy-trade-off-the-impacts-of-stringent-covid-19-lockdowns/). These included shutting down industries and businesses, closing international and provincial borders, and moving education online (https://www.bbc.com/news/world-52103747).

COVID-19 lockdowns have had significant impacts on economic activities with implications for national and regional economies. COVID-19 led to an economic recession, with a projected negative global economic growth rate of -4.9% in 2020 (https://www.imf.org/en/Publications/WEO). The pandemic has also been linked to an increase in some pollutants, in particular those associated with single-use plastic items and equipment (Haque et al., 2021), considerable social tension and confusion, and negative attitudes towards public transportation (Sharifi and Khavarian-Garmsir, 2020). Conversely, positive environmental impacts of COVID-19 lockdowns have been reported by numerous studies (Braga et al., 2020; Khan et al., 2020; Paital, 2020; Saadat et al., 2020; Yunus et al., 2020). In particular, many studies across the world have suggested that COVID-19 lockdowns improved air quality by reducing nitrogen dioxide (NO_2), carbon dioxide (CO_2), and particulate matter ($PM_{2.5}$ or PM_{10}), as well as noise (Bar, 2020; Khan et al., 2020; Saadat et al., 2020; Tadano et al., 2021; Tobías et al., 2020). Sudden reductions in human activities also impacted wildlife enabling them to move into normally human-dominated zones (Bar, 2020; Khan et al., 2020; Yang et al., 2020). Paital (2020) even suggested that the COVID-19 lockdown was a self-regenerating nurture strategy of the environment in a global context.

Some studies have reported positive impacts of COVID-19 lockdowns on water quality (Khan et al., 2020; Saadat et al., 2020; Sharifi and Khavarian-Garmsir, 2020). For example, reduced discharges of industrial effluent and vessel traffic improved water transparency in Venice Lagoon, Italy (Braga et al., 2020). Yunus et al. (2020) reported that within Lake Vembanad, the longest freshwater lake in India, the concentration of suspended particulate matter decreased by an average of 15.9% during a period of lockdown in April 2020. Elsewhere in India, the impacts of lockdown have been identified in both chemical and biological water quality parameters within groundwater samples from the city of Thoothukudi (Tuticorin) (Selvam et al., 2020). However, to our knowledge, analyses of the impacts of the COVID-19 lockdown on water quality across an entire nation have not been investigated.

China was the first country to implement a COVID-19 lockdown beginning in Wuhan City on 23 January 2020 and extending across the whole country on 29 January 2020 (Table S1). Human activities, including the rapid pace of urbanization and agricultural intensification, have seriously impacted water quality throughout parts of China (Ho et al., 2019; Huang et al., 2019; Yang et al., 2013; Yu et al., 2019; Zhang et al., 2018). For example, human-induced eutrophication has exacerbated algal bloom conditions in many lakes (Ho et al., 2019) and is clearly reflected in the quantity and composition of organic matter in lakes along the Yangtze River (Liu et al., 2020a). Heavy metal pollution in China's lakes and reservoirs also displayed an increasing trend during the period 2005–2017 (Huang et al., 2019). In tackling the nation's water pollution problems, China implemented "*Detailed Rules for the Prevention and Control of Water Pollution of the People's Republic of China*" in 2000 (http://www.gov.cn/flfg/2005-08/06/content_21045.htm). These rules focus mainly on establishing wastewater discharge standards and controlling pollutant discharge to improve the quality of freshwater environments (Qin et al., 2007; Tong et al., 2017). The temporary closure of many sources of these discharges during China's COVID-19 lockdown provides a unique opportunity to investigate both the impacts of pollution reduction on water quality and the potential benefits from more stringent discharge standards.

Level I lockdown measures in China were first eased in Shanxi Province on 24 February 2020 and ended in Hubei Province, of which Wuhan is the capital, on 2 May 2020 (Table S1). Since the end of these Level I restrictions, local soft lockdowns have been enforced in response to spikes in COVID-19 cases. Based on environmental monitoring data from January to June of the years 2018–2020, this study quantifies the impacts of the COVID-19 lockdown on river water quality across China with the following specific objectives: (1) to statistically analyse the influence of the lockdown on water quality indicators; (2) to explore the possible reasons for water quality improvements; and (3) to offer policy suggestions to alleviate water pollution in the future. To the best of our knowledge, this is the first study focusing on the impacts of COVID-19 on water quality across an entire nation during and immediately after lockdown.

2 Materials and methods

2.1 Study area: China

China has a total area of 9.6 million km^2 and comprises 23 provinces, five autonomous regions, four direct-controlled municipalities, and two special administrative regions (Fig. 1, Table S1). The Heihe-Tengchong Line (or H-T Line) divides China into eastern and western halves (Fig. 1). The region to the east of this line dominates China's economic output; while it accounts for 43% of the country by area, it is home to ~94% of the country's population and contains a large proportion of the nation's cropland. Major urban/industrial conurbations, roads, and railways are also concentrated in this part of China (Yue et al., 2005). The region has been the most heavily impacted by COVID-19. Of China's 121,203 confirmed cases before 6 August 2021, more than 99% occurred in eastern China (http://www.geodata.cn/sari2020/web/index.html). Especially hard-hit provinces included Hubei, Guangdong, Henan, Zhejiang, and Hunan (Fig. 1). Consequently, China's COVID-19 lockdowns were predominantly in eastern provinces (Table S1).

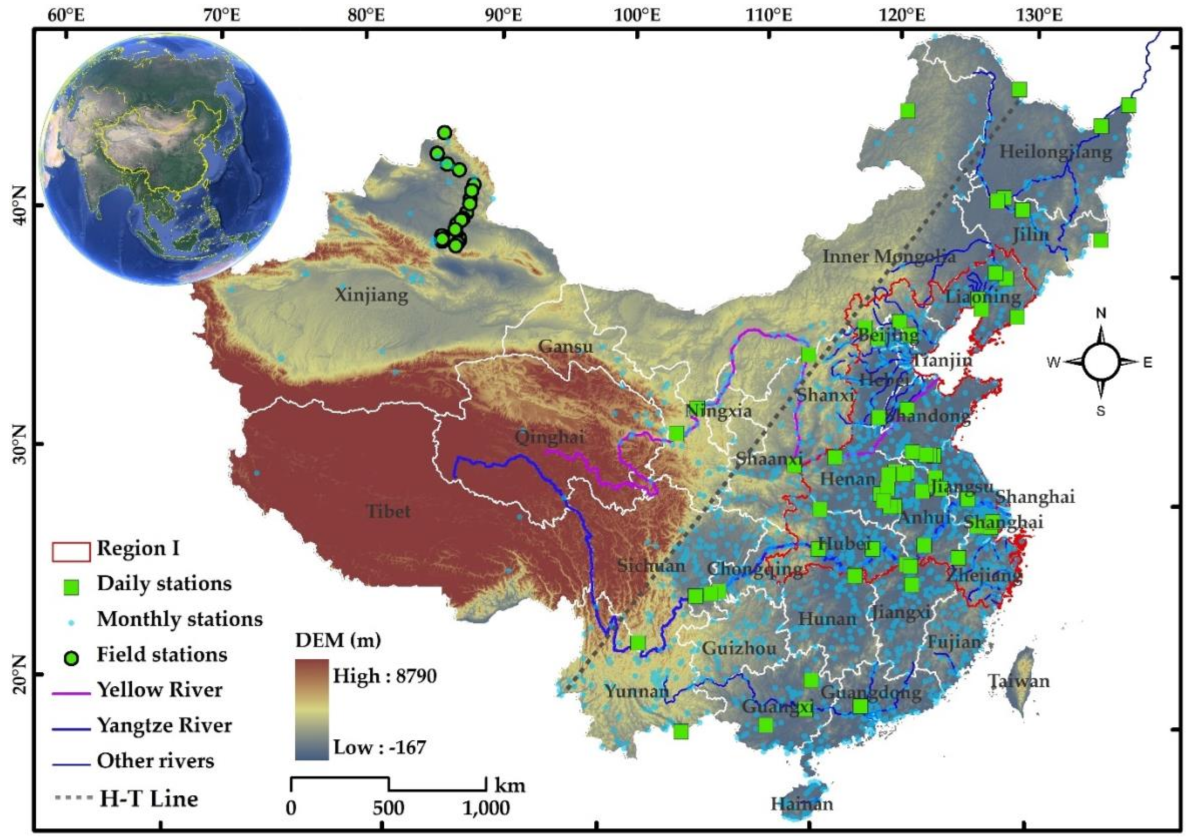

Fig. 1. The river water quality sampling sites. Region I is a relatively economically developed area in China. National and provincial boundaries were obtained from the National Geomatics Center of China (http://www.ngcc.cn/ngcc/). The inset global map was obtained from Google Earth. The Shuttle Radar Topography Mission digital elevation model (DEM) with a spatial resolution of 90 m was obtained from NASA (earthdata.nasa.gov). The H-T Line refers to a demarcation line of China's population density and economic development, with much higher values in the east (Hu, 1935).

Based on the spatial distribution of GDP across China, we divided the country into two regions (Fig. 1). Of the two, Region I is relatively economically developed, containing major urban and industrial centres, for example, the Beijing-Tianjin-Hebei Region and the Yangtze River Delta (Fig. 1). In contrast, Region II is generally characterized by relatively lower levels of economic development on the whole, with the exception of Guangdong (Fig. 1).

2.2 Monthly proportions of different water quality levels

Across China, river water quality at 1693 stations was monitored on a monthly basis by the Ministry of Ecology and Environment (Fig. 1). During each sampling period, 21 water quality parameters were collected, including concentrations of hydrogen ions (H^+ or pH), dissolved oxygen (DO), ammonia nitrogen (NH_4^+-N), and chemical oxygen demand (COD) using the potassium permanganate method (MEEPRC, 2002). Based on the values of the 21 elementary items and the environmental quality standards for surface water (Table S2), water quality levels were calculated. For a specific station, the water quality level of the worst indicator was used. In this study, monthly proportions of different water quality levels from January to June (the months immediately before, during, and after the 2020 lockdown) in 2018, 2019, and 2020 were sourced from the national surface water quality bulletin (http://www.mee.gov.cn/hjzl/shj/dbsszyb/). Data for the first two years were defined as being representative of normal conditions for comparison with those from 2020.

2.3 Daily river water quality data

Whilst 21 water quality variables were measured (Section 2.2), not all are publicly available. This study was only able to acquire daily automatic monitoring data for pH, DO, NH_4^+-N, and COD from 65 stations on rivers in eastern China (Fig. 1) from the China National Environmental Monitoring Centre (http://www.cnemc.cn/). These variables provide a good representation of water quality because they are the indicators that normally fall below the water quality standards in China. Taking April 2020 as an example, 78.3% of the monitored rivers with poor water quality were placed in this class due to high COD and NH_4^+-N, low DO, or inappropriate pH. As shown in Table S2, a water body with good ambient water quality (Level I, II, or III) was characterized by pH of 6–9, high DO (≥ 5 mg/L), low NH_4^+-N (≤ 1.0 mg/L), and low COD (≤ 6 mg/L) (MEEPRC, 2002).

We employed daily data recorded at 08:00 local time between 23 January and 22 June in 2018, 2019, and 2020. These dates cover the extent of the Chinese COVID-19 lockdown in 2020 (Table S1). The arithmetic mean values across the stations on each day of the period in each of the three years, as well as at a monthly time step, were calculated. It should be noted that missing data from some stations in some months means that inter-year comparisons of water quality parameters were based on different numbers of stations.

2.4 Multi-source data for explaining water quality variations

This study employed daily newly confirmed COVID-19 cases from the National Earth System Science Data Center (http://www.geodata.cn/) for 23 January–22 June in 2020 to track the extent of the disease and efficacy of the lockdown. Daily data were available for all of China except Taiwan, Hongkong, and Macao (Fig. 1). In order to gauge the intensity of the lockdown and explain the spatiotemporal variations in water quality, we also acquired the following multi-source data.

(1) From the National Bureau of Statistics of China (http://data.stats.gov.cn/), we obtained the total sewage discharge volume from 2000–2019, the provincial population and urban ratio in 2019, the provincial NH_4^+-N and COD discharges in 2014 (industrial, domestic, and agricultural), the provincial gross domestic product (GDP) for 2019, and the provincial cumulative growth of industrial added value data at a monthly time step (CGoIAV, %) for February–May 2020. CGoIAV refers to the change in the percent of industrial added value from January to the current month compared with the same period in the previous year (i.e., 2019).

(2) From the Ministry of Housing and Urban-Rural Development of the People's Republic of China (http://www.mohurd.gov.cn/), we obtained the daily railway transport passenger volume (persons) from January to June 2020.

(3) To explore potential relationships between changes in water quality during the lockdown and levels of economic development, grid-based GDP in 2010, with a spatial resolution of 1000 m, was acquired from the Global Change Research Data Publishing & Repository website (http://www.geodoi.ac.cn/).

(4) From the European Centre for Medium-Range Weather Forecasts (https://www.ecmwf.int/), we obtained total precipitation between February and May in each year between 2018 and 2020, and calculated differences between 2020 and each of the two previous years (i.e., 2020 vs. 2018 and 2020 vs. 2019).

(5) In addition, we measured NH_4^+-N concentrations of snow samples in Xinjiang Province during and before the lockdown (Fig. 1). Samplings were conducted on

20 December 2019 (N = 7), between 14 and 17 January 2020 (N = 30), and on 29 February 2020 (N = 7) to collect surface snow samples. After sampling, surface snow samples were melted and stored in a fridge (-4 ℃). In the laboratory, NH_4^+-N concentrations were measured using Nesster's reagent and N-(1-Naphthyl) ethylenediamine dihydrochloride spectrophotometry (Crosby, 1968).

2.5 Water Quality Index

The Water Quality Index (WQI), proposed by Pesce and Wunderlin (2000), has been widely applied to comprehensively evaluate water quality (Huang et al., 2019; Wu et al., 2018). In the WQI calculation, measured values of water quality parameters were normalized, and a relative weight was assigned to each environmental parameter based on its potential impact on human health (Pesce and Wunderlin, 2000; Wu et al., 2018). The WQI ranges from 0 to 100, with high values denoting good water quality. In this study, the available pH, DO, NH_4^+-N, and COD data were applied to calculate the WQI using Eq. (1).

$$\mathrm{WQI} = \frac{\sum_{i=1}^{n} C_i \times P_i}{\sum_{i=1}^{n} P_i} \qquad (1)$$

where n is the number of water quality indicators used (n = 4); C_i denotes the normalization factor, with a high value for high DO and low values for high NH_4^+-N and COD; and P_i denotes the relative weight, with different values for input indicators (Refer to Table S3 for more details about on the values of C_i and P_i).

2.6 Statistical analyses

Using SPSS 18.0 (IBM Corp, Armonk, NY, USA), linear regressions were conducted to investigate the relationships among different variables. In addition, independent-samples t-tests were used to determine whether the changes in water quality indicators in different months or years were significant. Correlation analyses with a significance level of $p < 0.05$ (2-tailed test) were reported as significant. The general linear model was used to calculate the contributions of various impact factors on water quality improvements across monitoring stations (Tong et al., 2017).

3 Results

3.1 The COVID-19 lockdown in China and its economic impacts

The COVID-19 lockdown required that people stay home, so that the daily railway transport passenger volume indicates the lockdown status. After the lockdown began on 23 January 2020, daily railway transport passenger numbers decreased dramatically from 12.08 to 2.83 million over only four days. The numbers continually declined to only 1.04 million on 19 February (Fig. 2a). Subsequently, because of the removal of lockdown restrictions in some provinces (Table S1), passenger numbers increased gradually until the end of the period (Fig. 2a). The beneficial impact of the lockdown on the spread of COVID-19 was evident in the declining numbers of newly confirmed cases in China. After peaking at 15,153 on 12 February, the daily number of new cases declined, and by 19 April, it was consistently less than 50 (Fig. 2a). On 2 May, Wuhan's emergency response level was adjusted to Level II, marking the end of COVID-19 lockdowns across China.

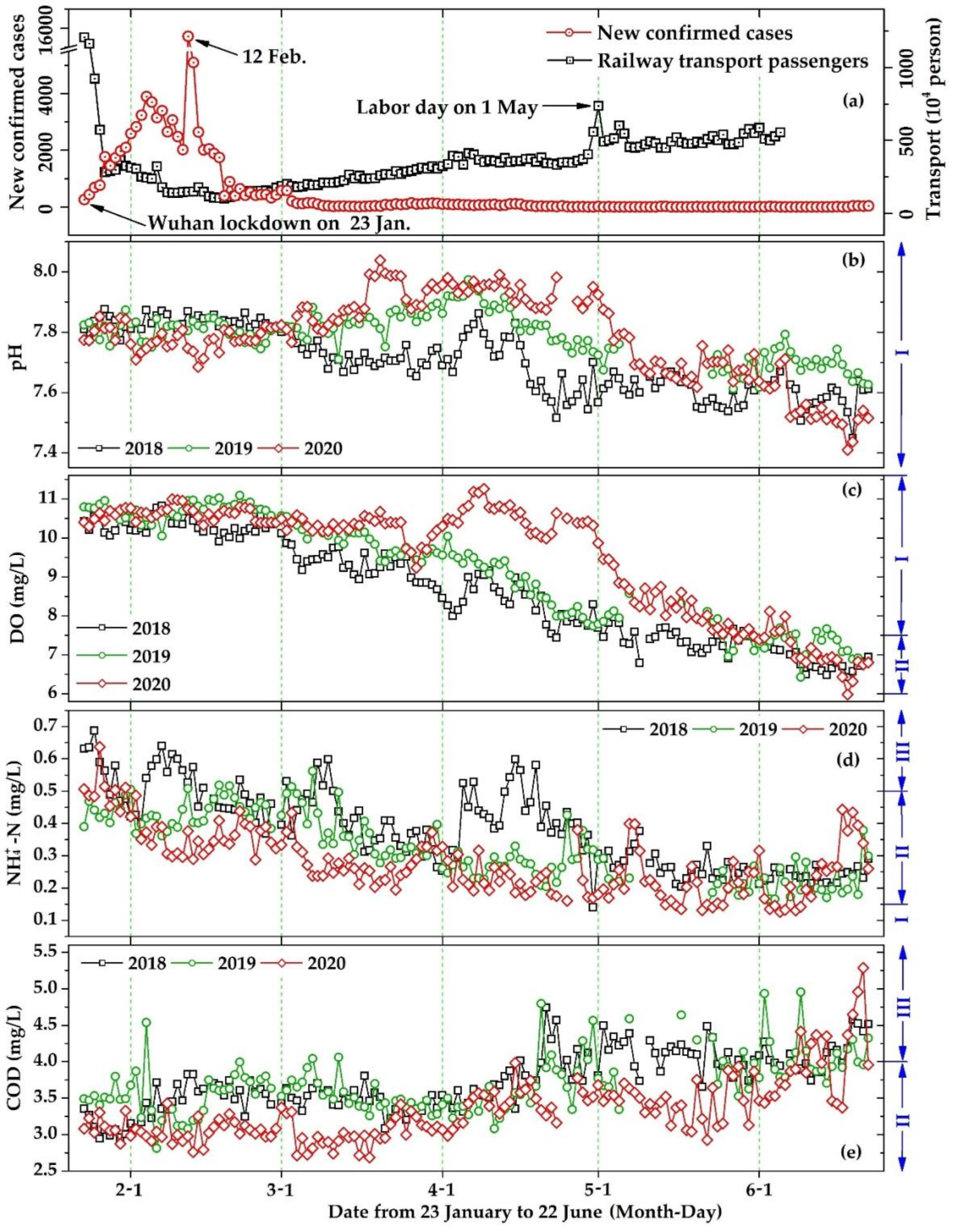

Fig. 2. Daily values of different indicators. (a) New confirmed COVID-19 cases and railway transport passenger numbers across China between 23 January and 22 June 2020. (b–e) Daily arithmetic mean values of pH, DO, NH_4^+-N, and COD derived from data for 65 monitoring sites (Fig. 1) over the same dates in 2018, 2019, and 2020. Based on the values in Table S2, the water quality standards are shown on the right axis.

The COVID-19 lockdown also shut down many industries. These closures are indicated by the negative CGoIAV values for most provinces between February and May 2020 (Fig. S1). Compared to the industrial added values in 2019 (Section 2.4), all provinces/regions across China had negative CGoIAV values in February 2020, and most were still negative in May; the mean CGoIAV was -13.5% in February, gradually rising to -2.8% in May. Most of the largest declines in CGoIAV were for provinces in eastern China. In Hubei, the province most hard-hit by COVID-19, the CGoIAV was as low as -46.2% in February, increasing to -26.2% in May (Fig. S1).

3.2 The environmental bulletin results

The environmental bulletin results showed that river water quality improved during the lockdown period in 2020 when compared to both 2018 and 2019 (Fig. 3). Moreover, improvements between February and April were more pronounced than improvements in other months. Water quality levels I, II, and III are classed as good. From 2018 to 2020, the cumulative percentage of good ambient water quality in February was 68.8%, 76.7%, and 82.7%, respectively. The corresponding values for March were 71.4%, 75.4%, and 82.2% and for April 74.1%, 75.9%, and 83.0% (Fig. 3). In contrast, improvements at the beginning (January) and end (May, Section 3.1) of China's lockdown were relatively small. The cumulative percentages of good water quality in June in each year, after the end of the national lockdown in 2020, were 72.5%, 73.1%, and 73.3%, respectively (Fig. 3).

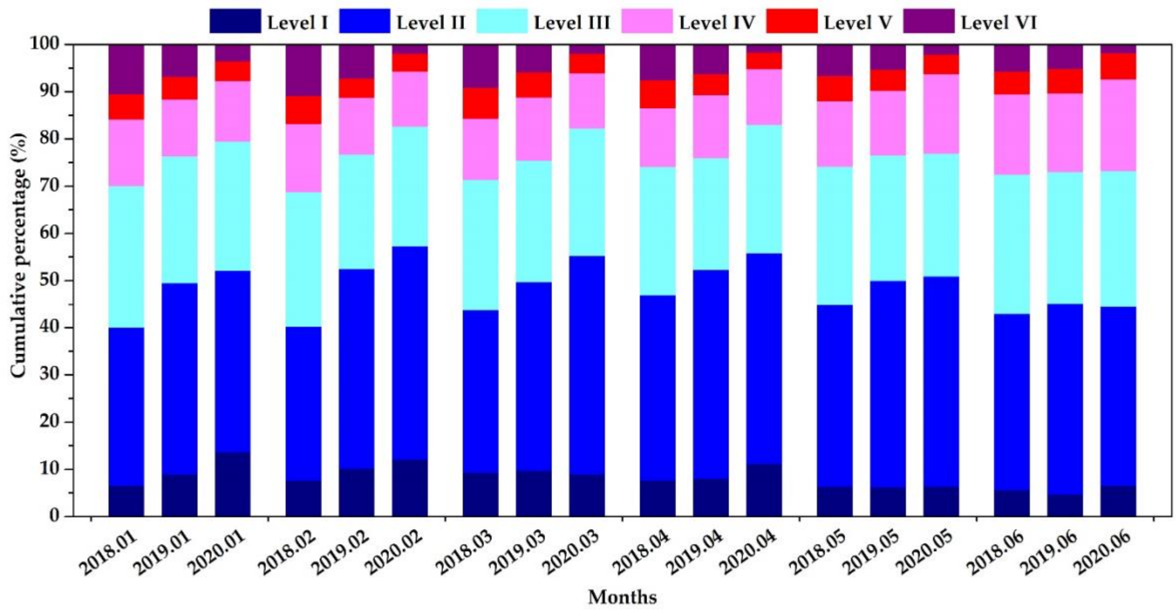

Fig. 3. Proportions of different water quality levels between January and June in 2018, 2019, and 2020. Data were sourced from the Ministry of Ecological Environment, China (Section 2.2).

3.3 Temporal variations in daily water quality

The lockdown of 2020 increased pH. In 2020, the mean pH across the 65 monitoring sites was initially similar to the corresponding values in the two previous years. It then increased and remained higher throughout March, April, and May (Figs. 2b and 4a). Compared with the values in 2018, the mean H^+ concentrations in these three months declined by 32.7%, 42.8%, and 22.1%, respectively. The corresponding figures for the comparison with 2019 indicated declines of 13.3%, 18.7%, and 4.8%. Results of the independent-samples t-test showed that the decreases in the H^+ concentration in March and April 2020 were significant, with $p < 0.01$. By the beginning of June 2020, the mean pH reached the corresponding values of the two earlier years (Fig. 2b).

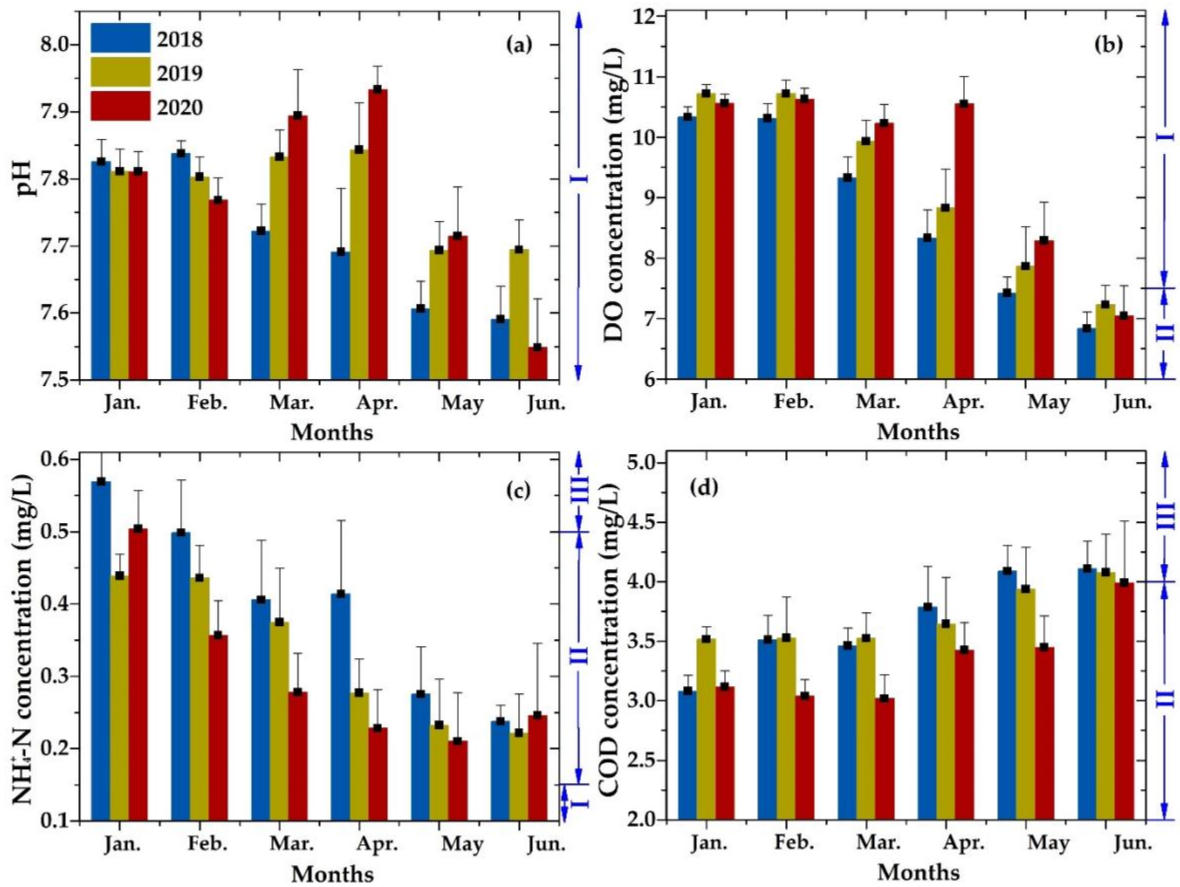

Fig. 4. Mean values of different water quality parameters in January–June 2018, 2019, and 2020: (a) pH; (b) DO; (c) NH_4^+-N; and (d) COD. The error bars indicate the standard deviations. Based on the values in Table S2, the water quality standards are shown on the right axis.

The lockdown had an apparent impact of increasing DO. At the beginning of February in both 2018 and 2019, DO began to decline, which continued until the end of June. In contrast, in 2020, DO remained high, albeit with some large fluctuations, until the end of April (Fig. 2c). On average, DO was 9.7% and 26.6% higher in March and April 2020, respectively, compared to the average values in 2018. The corresponding figures when comparing 2020 with 2019 were 3.0% and 19.5% (Fig. 4b). Increases in DO in March, April, and May 2020 were significant, with $p < 0.05$. From the end of April 2020, DO declined rapidly and reached normal level by June.

The lockdown reduced NH_4^+-N. At the beginning of the lockdown in January 2020, NH_4^+-N was, on average, similar to the mean values in both 2018 and 2019 (Fig. 2d). Then, throughout the lockdown from February to April 2020, the mean NH_4^+-N concentrations fell below those in 2018 (2019) by an average of 28.5%, 31.5%, and 44.9% (18.2%, 25.8%, and 17.6%), respectively (Fig. 4c). The decreases in NH_4^+-N in February, March, and April 2020 were significant, with $p < 0.01$. In May and early June 2020, although the lockdown had ended, the mean NH_4^+-N was still lower than the averages in 2018 and 2019, and it then increased towards the end of the month (Fig. 2d).

The lockdown also appeared to have reduced COD. This was initially evident shortly after the beginning of the lockdown (Fig. 2e). On average, COD during February and March 2020 was 13.4% and 12.8% lower, respectively, compared to the same months in 2018. The corresponding declines from 2019 were 13.8% and 14.4% (Fig. 4d). Although COD increased from the beginning of April, the average values were still lower than in the previous years, especially in May (Fig. 2e). Decreases in COD in February, March, April, and May 2020 were significant, with $p < 0.01$. By late June 2020, after the end of the lockdown, COD was of a similar magnitude to the corresponding values in the two previous years.

In sum, the responses of the different water quality indicators to the COVID-19 lockdown were out-of-step. During China's lockdown, DO (NH_4^+-N, COD) showed improvements beginning in mid-March (early February, late January) (Fig. 2) and ending late May (mid-June, early June), respectively, while changes in pH were more temporally concentrated in the period from mid-March to early May.

3.4 Spatial variations in changes in daily water quality

Changes across the four water quality parameters during China's COVID-19 lockdown were concentrated during the period of February–May but were out-of-step (Section 3.3). In order to investigate spatial variations of changes in water quality, the mean values of the four parameters at each of the 65 monitoring sites during different periods (H^+: March–April; DO: March–May; NH_4^+-N: February–April; COD: February–May) in 2020 were compared with the corresponding values in 2018 and 2019. This revealed spatial differences in the magnitude of the changes across different monitoring sites, as discussed below.

Across the 47 sites with available data, the mean pH in March–April 2020 was higher than that in 2018 at 30 sites and lower at the remaining 17 sites (Fig. 5a). Changes in the H^+ concentration ranged from -91.6% to 322.1%. When compared to 2019, the mean March–April pH at the 47 sites with data was higher in 2020 at 25 sites (lower at the remaining 22 sites) (Fig. 5b). Both increases and decreases in the H^+ concentration occurred, with an overall range between -96.2% and 419.7%. More sites in northern China experienced large increases in H^+ concentration, and the magnitude of H^+ change showed a significant increase with the latitude of the monitoring site ($p < 0.05$, 2-tailed test); compared to 2018 and 2019, both the Pearson's r values were 0.38 (Fig. S2).

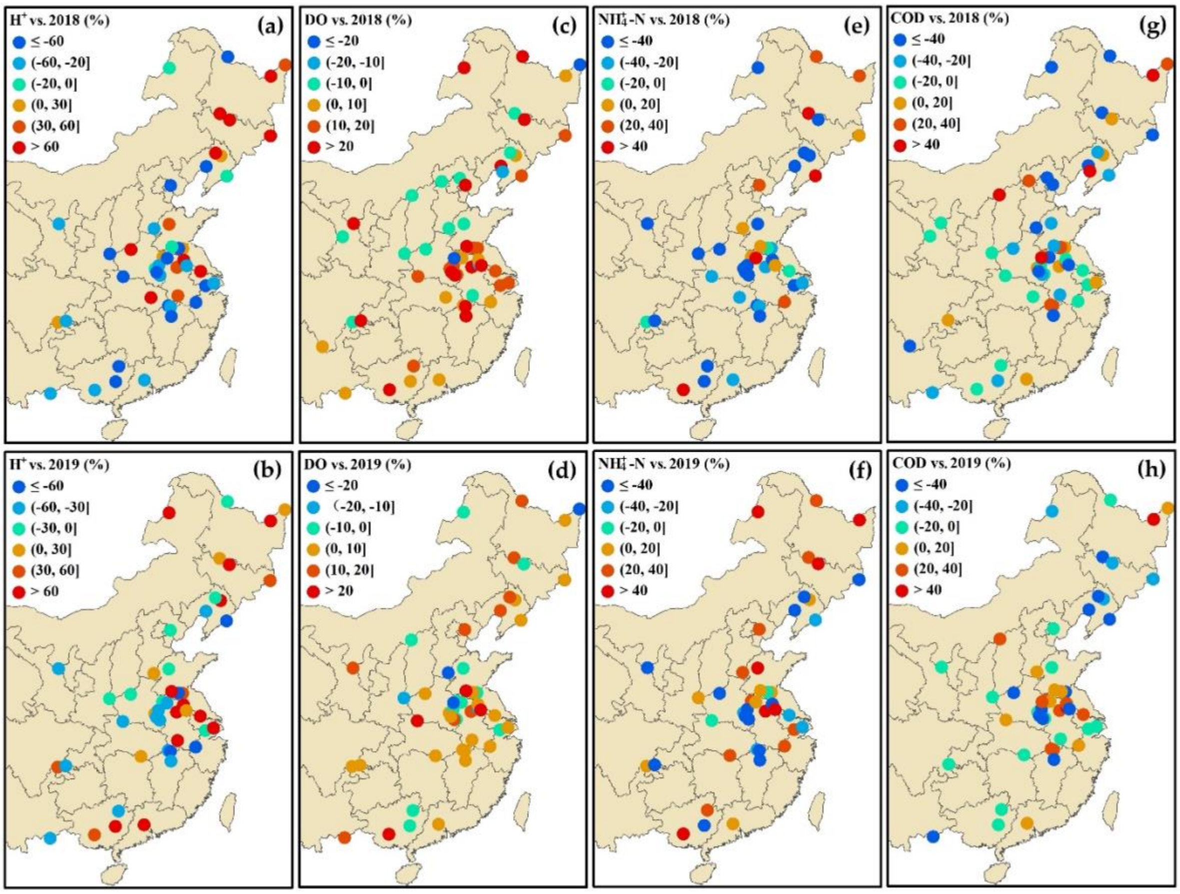

Fig. 5. Mean percentage changes in the four water quality parameters across monitoring sites in eastern China during different periods of 2020 and the same months in 2018 and 2019, respectively: (a–b) are for H^+ during March–April; (c–d) are for DO during March–May; (e–f) are for NH_4^+-N during February–April; (g–h) are for COD during February–May. Base maps show the province boundaries in China (Fig. 1).

Mean March–May DO was higher in 2020 than in 2018 at 41 of the 57 sites with data (lower at the remaining 16 sites) (Fig. 5c). Most of the sites located in southeast China experienced increased DO. Overall differences in the DO concentration across all sites ranged from -30.3% to 54.7%. Compared to 2019, the mean March–May DO was higher in 2020 at 33 of the 51 sites with data, with differences varying between -29.3% and 44.6% (Fig. 5d). There was, however, no clear spatial pattern of increases or decreases across the sites (Table 1).

Table 1 Impact factors on the percentage changes in the four water quality indicators across monitoring sites (H^+: March–April; DO: March–May; NH_4^+-N: February–April; COD: February–May). r denotes the Pearson correlation coefficient, and symbol "*" denotes p < 0.05. The contribution was calculated using the general linear model (Section 2.6).

Index	Factors	2020 vs. 2018 (%)				2020 vs. 2019 (%)			
		H^+	DO	NH_4^+-N	COD	H^+	DO	NH_4^+-N	COD
Pearson's r	Longitude	0.38*	-0.06	0.34*	0.20	-0.24	-0.14	0.28	-0.09
	Latitude	0.38*	-0.04	0.09	0.05	0.38*	-0.11	0.25	-0.12
	GDP	0.27	-0.22	0.03	0.04	-0.18	0.08	0.09	-0.07
	DEM	-0.06	0.00	-0.37*	-0.16	0.05	0.07	-0.16	0.10
	Rainfall	-0.13	0.01	0.08	-0.07	0.07	-0.05	0.12	-0.19
Contribution (%)	Longitude	14.12	0.30	28.26	43.33	19.34	0.35	6.83	13.32
	Latitude	1.98	0.24	23.07	13.71	8.54	3.54	16.56	34.80
	GDP	65.17	66.54	5.63	13.54	42.73	13.66	24.46	1.48
	DEM	0.32	0.27	7.21	2.92	6.02	0.01	12.85	26.31
	Rainfall	8.08	1.78	23.34	10.20	15.01	15.67	20.52	6.50
	Others	10.33	30.87	12.49	16.3	8.36	66.77	18.78	17.59

The mean NH_4^+-N concentrations in February–April were lower in 2020 than those in 2018 at 31 of the 45 sites with data (higher at 14 sites) (Fig. 5e). The magnitude of the differences ranged between -326.8% and 54.1%. There was a positive relationship between the change in NH_4^+-N and site longitude (r = 0.34 and p < 0.05) (Table 1), with only one site in southern China experiencing increases (Fig. 5e). of the 44 sites with data, 21 experienced lower February–April mean NH_4^+-N in 2020 when compared to 2019, with the range of differences equalling -141.7% to 63.3% (Fig. 5f). The change magnitude in NH_4^+-N was also correlated with the site longitude, with r = 0.28 and p = 0.06 (Table 1).

Across the 56 sites with data for mean COD in February–May for both 2018 and 2020, reductions in 2020 were recorded at 36 sites (increases at 19 sites) (Fig. 5g). The changes between these two years at different sites ranged between -251.2% and 54.0%. Declines between 2019 and 2020 were also dominant (30 of the 49 sites with data in both years; increases at the remaining 19). Across the 49 sites, changes in the mean COD ranged between -140.0% and 47.2% (Fig. 5h). With a majority of sites experiencing declines in 2020 when compared to both 2018 and 2019, those sites with increased COD were concentrated in the developed Region I (Figs. 1 and 5).

3.5 Spatiotemporal variations in WQI

The mean WQI values across all stations also showed that China's lockdown improved river water quality throughout the country (Fig. 6). When compared to 2018, monthly mean WQI values were higher in all months from January to June 2020 (Fig. 6a). Similarly, comparisons between 2020 and 2019 show higher WQI values in February, and in particular March, April, and May (Fig. 6a).

Since pH, DO, NH_4^+-N, and COD values showed significant improvements in March and April 2020 (Section 3.3), we explored the changes in WQI values across different stations in these two months. Compared to March 2018 (2019), 68.1% (66.0%) of stations had higher WQI values in March 2020, with 78.1% (77.4%) being significant (t-test, Figs. 6b–c). Compared to April 2018 (2019), the WQI values increased at 84.1% (67.4%) stations in April 2020, with 81.1% (75.9%) being significant (t-test, Figs. 6d–e). The comprehensive WQI showed greater improvements in water quality during China's lockdown than the results indicated by a single water quality parameter (Sections 3.3 and 3.4).

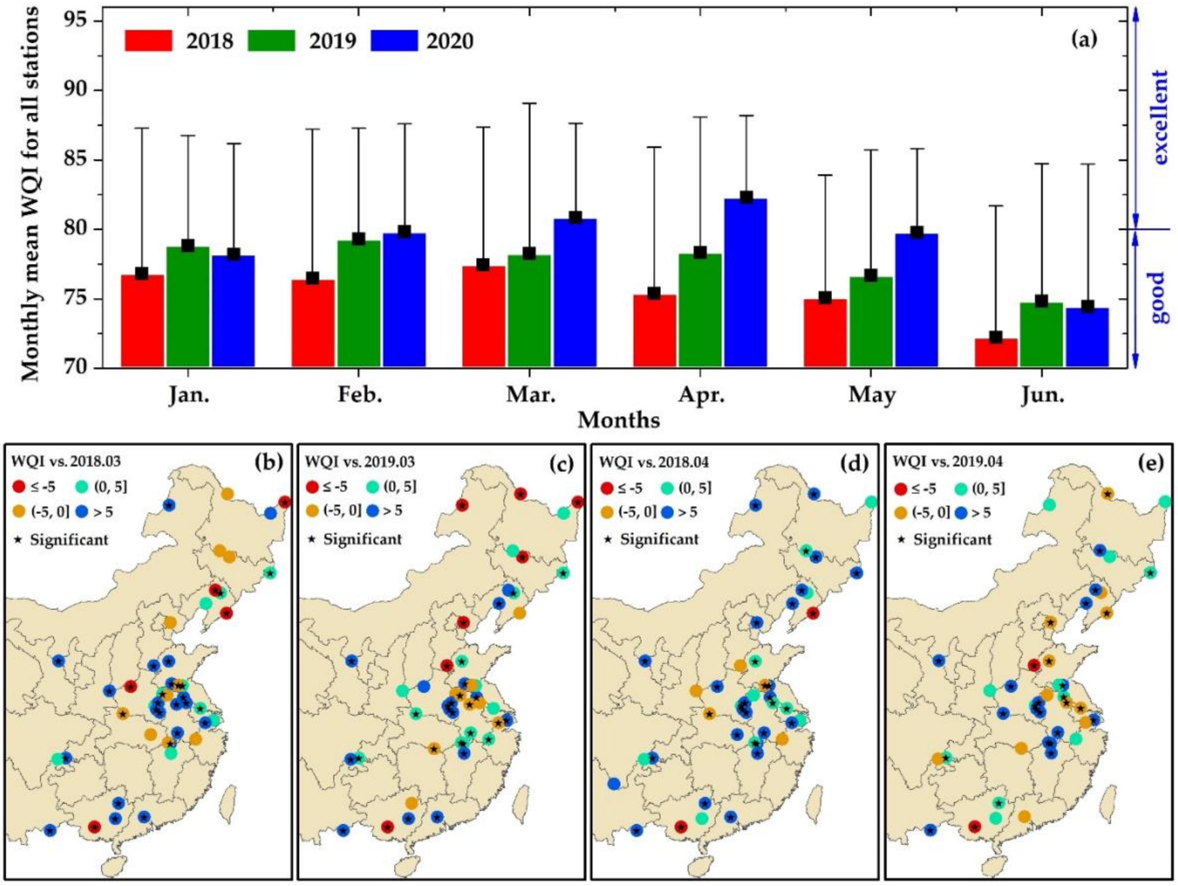

Fig. 6. Comparisons of monthly mean WQI in 2020 to those in 2018 and 2019. (a) Monthly mean WQI values across all stations. The water quality standard is shown on the right axis: WQI ⩾ 80, excellent; 61–80, good; 30–60, acceptable; and WQI < 30, poor (Chang et al., 2020). (b–e) are the comparisons of values in March and April 2020 to the corresponding months in 2018 and 2019, respectively.

3.6 Relationships between precipitation and water quality changes

Precipitation varied from year to year during each of the years between 2018 and 2020. Across the monitoring stations, precipitation from February to May 2020 was generally lower than in 2018 but higher than in 2019. Compared to 2018, the total precipitation during these months differed by between -66% and 166%, with an average of -6.42%. When compared to 2019, the differences ranged from -73% to 113%, with an average of 10.06%.

Precipitation variations did not show obvious impacts on water quality improvements. When compared to both 2018 and 2019, there were no significant relationships between differences in precipitation and water quality across the different monitoring stations (Table 1). Compared to 2018, precipitation variation explained only 8.1%, 1.8%, 23.3, and 10.2% of the improvements in H^+, DO, NH_4^+-N, and COD, respectively. When compared to 2019, the corresponding values were 15.0%, 15.7%, 20.5%, and 6.5%, respectively (Table 1).

4 Discussion

4.1 Possible reasons for water quality improvements

Human activities have had significant impacts on water quality in China. The country's rapid economic development has placed considerable pressure on aquatic environments, with results including widespread deterioration in water quality (Duan et al., 2009; Huang et al., 2019; Tong et al., 2017; Yang et al., 2012). For example, the annual volume of sewage discharged to China's aquatic systems increased from 33.18×10^9 m^3 in 2000 to 55.46×10^9 m^3 in 2019. To improve water quality, the Chinese government has since 2000 implemented major strategies for alleviating water pollution (Huang et al., 2019; Qin et al., 2007; Tong et al., 2017; Yang, 2014). China's COVID-19 lockdown resulted in a unique period during which the intensity of many human activities was reduced, with beneficial implications for water quality.

The COVID-19 lockdown improved river water quality by reducing industrial sewage discharges. Industrial activities are important sources of NH_4^+-N and COD to China's rivers (Shon et al., 2006; Zhang et al., 2015); across different provinces, 1.2–47.5% of NH_4^+-N and 3.3–45.6% of COD were sourced from this group of human activities (Fig. S3). The COVID-19 lockdown shut down many industries, as indicated by the negative CGoIAV values, and required people to stay home resulting in the low railway transport passenger volume (Section 3.1). With the exception of Hubei Province, CGoIAV in May was significantly negatively related to COVID-19 cases percent, with r = -0.53 and p < 0.05 (Fig. S1). In contrast, agricultural discharges to streams and rivers, that include fertiliser and pesticide residues, were less likely to have been impacted by the COVID-19 lockdown. Compared to 2019, agricultural sown area and total output in China in 2020 increased, albeit by relatively small amounts (0.6% and 0.9%, respectively; http://www.gov.cn/xinwen/2020-12/10/content_5568623.htm).

Improved air quality might also have beneficial impacts on improving water quality. Many studies have suggested that the COVID-19 lockdown reduced atmospheric pollution (Bauwens et al., 2020; Shi and Brasseur, 2020; Wang and Su, 2020). Atmospheric deposition is an important source of water nutrients, which can further increase COD by enhancing primary production (Pandey et al., 2014). Although the COVID-19 lockdown had limited impacts on the relatively small economic activities in western China (Xinjiang, Qinghai, and Tibet) (Fig. S1), the available data suggested improving air quality (Wang and Su, 2020) did lead to some improvements in water quality within this part of China. Mean NH_4^+-N of *in-situ* snow samples in January 2020 (0.9 mg/L) was close to that in December 2019 (0.87 mg/L) (Fig. S4a). However, it declined to 0.48 mg/L in February 2020, with reductions of 45.3% and 46.9% from December 2019 and January 2020, respectively. The largest decline at an individual site was 81.4%, and the average across the five sites with lower NH_4^+-N concentrations was 62.7% (Fig. S4b).

The water quality improvements across different monitoring sites were mainly determined by the site locations and the levels of economic development. For example, the longitude, latitude, and GDP together contributed 81.3%, 67.1%, 57.0%, and 70.1% to the changes between 2020 and 2018 in H^+, DO, NH_4^+-N, and COD, respectively (Table 1). The severity of COVID-19 lockdown, as indicated by the number of confirmed cases, was mainly located in the east (Fig. S1), whilst the north dominated the area experiencing the largest improvements in air quality (Wang and Su, 2020). Compared to both 2018 and 2019, improvements in water quality between February and April 2020 were generally greater in the developed Region I than those in the undeveloped Region II (Text S1). For example, when compared April 2020 to the same month in 2019, mean improvements in DO, NH_4^+-N, and COD in Regions I and II were 22.6% vs. 14.8%, 25.1% vs. 3.7%, and 8.4% vs. 4.5%, respectively (Table S4).

4.2 Policy suggestions to alleviate water pollution

The investigation of water quality improvements during China's COVID-19 lockdown provides opportunities to review approaches to improve river water quality under both the special circumstances experiences in 2020 and normal socio-economic conditions. Some policy suggestions are given below.

First, location-specific pollutant discharge reduction strategies are required to target water quality problems. (1) More attention should be paid to the reduction of pollutant discharges in densely populated areas. Within provinces in Region I, which have a much higher population density (Fig. 7a), river water per unit area received more NH_4^+-N and COD from human activities compared to other provinces in the less densely population Region II (Fig. 7c–d). Improvements in water quality in Region I were therefore more significant during the lockdown (Text S1). Moreover, an increasing proportion of people across China now live in cities. In Beijing and Shanghai, the urban ratios exceeded 85% in 2019 (Fig. 7b). Therefore, reducing pollutant discharges within rapidly urbanising regions should be a priority. (2) Different provinces should adopt alternative pollution reduction strategies that reflect their levels of development and the magnitude of pollution problems that they face. Although industrial and domestic activities are the major sewage sources, their discharge ratio varies greatly by province: for NH_4^+-N discharge in 2014, the ratio ranged from 27.5% in Heilongjiang to 86.3% in Yunnan; for COD discharge in 2014, the ratio ranged from 55.6% in Shandong to 93.1% in Shanghai (Fig. S3).

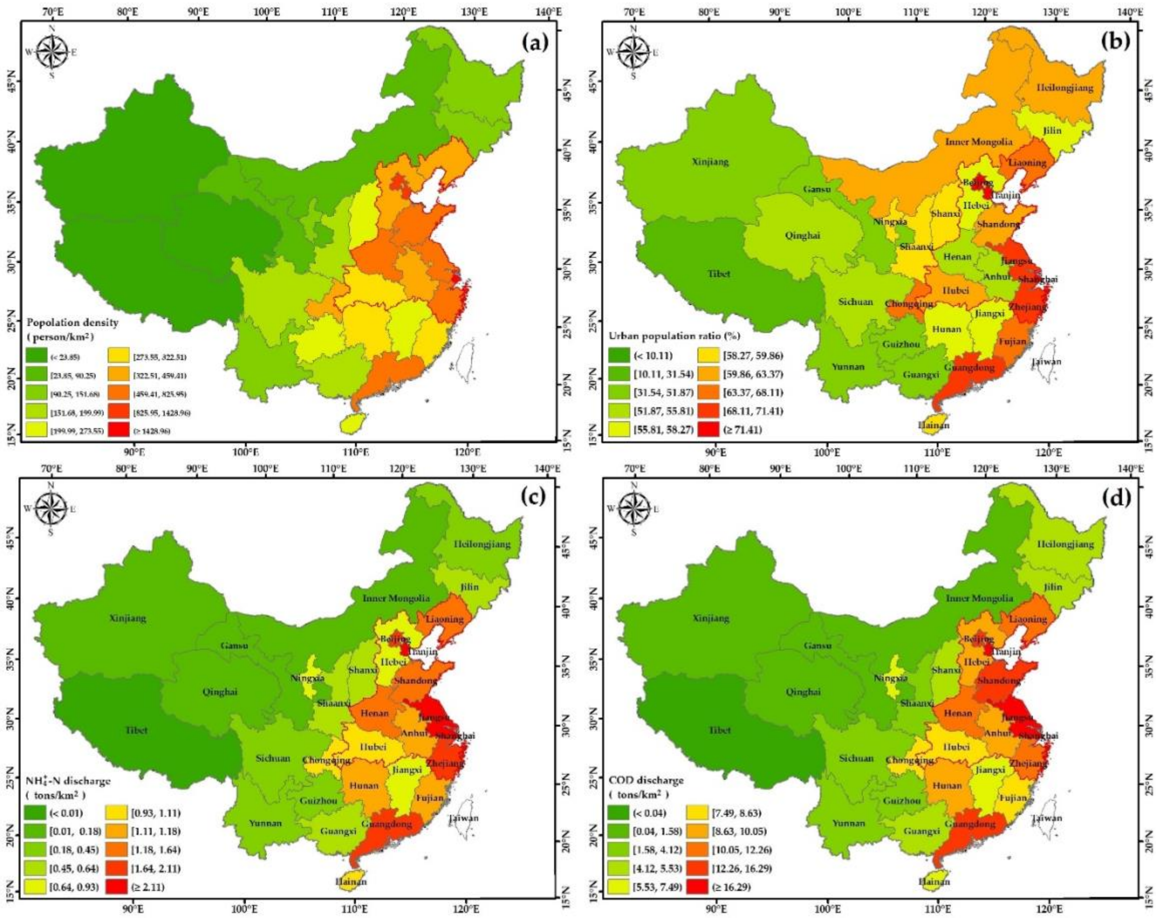

Fig. 7. Statistical data from the National Bureau of Statistics. (a) The provincial population density in 2019; (b) urban population ratio in different provinces in 2019; (c–d) NH_4^+-N and COD discharges per square kilometre in different provinces in 2014.

Second, pollutant reduction strategies should be sustained. Although the responses of different water quality indicators to pollutant reduction during the COVID-19 lockdown were out-of-step, pH, DO, NH_4^+-N, and COD returned to normal levels after the lockdown in June 2020 (Section 3.3). Explanations for the relatively quick return to these levels include the fact that some provinces ended their lockdowns before May, in some cases as early as late February (Table S1). Another reason is that the economy rebounded rapidly, leading to the discharge of large volumes of wastewater as lockdowns were lifted. CGoIAV across China as a whole was -13.5% in February 2020, but increased to -1.3% in June. By December of the same year, CGoIAV was positive at 2.8% (https://data.stats.gov.cn/). Government policies aimed at reducing pollutant discharges therefore require sustained, year-round efforts so as to alleviate water pollution in a long term.

The different water quality indicators employed in this study are interrelated. For example, from January to June 2020, the daily mean COD across all stations showed a significant negative linear relationship to both DO (r = -0.51, $p < 0.01$) and pH (r = -0.65, $p < 0.01$). Organic matter remineralization under conditions of high COD leads to reductions in DO and increased production of CO_2 (Wang et al., 2018). CO_2 dissolves in water to form carbonic acid, which lowers the water pH. Given these inter-relationships, comprehensive control of the discharges of all pollutants is required.

4.3 Limitations and future work

More water quality monitoring and pollutant reduction data would enable further insights into the impacts of the COVID-19 lockdown on river water quality in China. First, in addition to the 21 elementary items in Table S2, water temperature, total nitrogen, and *E. coli* would have, in particular, been valuable (MEEPRC, 2002). Second, some specific pollutants related to the COVID-19 epidemic were not considered, and data are generally scarce. The pandemic has resulted in the pollution of single-use plastic items and equipment in aquatic environments (Haque et al., 2021), and future research should seek to establish the immediate and longer-term implications of this increasing pollution source. The COVID-19 virus has also been detected in wastewater (Sherchan et al., 2020), and concerns have been raised regarding the potential for transmission of the virus via this source (Carducci et al., 2020; Liu et al., 2020b). Again, this should be considered as a priority research area no least given its potential public health consequences.

Accurate investigations that include consideration of the site-scale data and sewage volumes are required to further quantitatively assess the impacts of the COVID-19 lockdown on river water quality at different sites. This is a common limitation of published studies on the impacts of COVID-19 lockdowns on environmental improvement (Braga et al., 2020; Lal et al., 2020; Saadat et al., 2020). First, the mean values of water quality indicators across all stations indicated improvements (Section 3.2), although some stations showed water quality deterioration (COD at a station in Shandong Province for example; Fig. S5). In addition, water quality indicators at some stations fluctuated much more than at others (Figs. S5 and S6), which might reflect the influence of local changes in wastewater discharges or precipitation resulting changes in river discharge. For example, the sudden rise and subsequent decline in COD in June 2020 (Fig. S6) on sites along the Yangtze River is most likely to be the result of summer flooding (Zhou et al., 2021).

5 Conclusions

The COVID-19 lockdown led to a general improvement in river water quality in China. During the lockdown period of February–May 2020, the mean pH and DO in the most of the rivers included within this study increased. Conversely, the dominant trend was for a decline in NH_4^+-N and COD concentrations. Changes across the four water quality parameters investigated in detail were concentrated during the period of February–May but were out-of-step. Moreover, changes in these water quality parameters at different sites varied according to spatial location and economic development. After China's lockdown, water quality returned to levels experienced in the two previous years that were not subject to lockdown. These results demonstrate the influence of human activities on China's water quality and the potential for addressing the nation's water quality problems by reducing wastewater discharges. Sustained and targeted strategies will, however, be required if the short-term improvements in China's river water quality exhibited during the unprecedented conditions in 2020 are to be replicated in the long term.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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