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City water stress and industrial water-saving potential in stringent management of China

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Article

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City water stress and industrial water-saving potential under stringent management in China

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China's industrial water withdrawal soared in the last decades and remained high. Stringent water management policies were set to save water through improving industrial withdrawal efficiency by 20% between 2015 and 2020. Although China has a nation-wide water scarcity, scarcity at city-level has not been fully explored. Thus, it is meaningful to use sectoral data to investigate industrial water saving potential and implication for alleviating scarcity. Here, we account for water withdrawal and scarcity in 272 prefectural cities, using a 2015 data benchmark. The top 10% of low-efficiency sectors occupied 46% water use. In scenario analysis of 41 sectors across 146 water scarce cities, we assume a convergence of below-average efficiencies to the national sector-average. Results reveal overall efficiency could be increased by 20%, with 18.9 km^3 (±3.2%) water savings, equivalent to annual water demand of Australia or Hebei province in China. A minority of sectors (13%) could contribute to most (43%) water savings whilst minimizing economic perturbations. In contrast, implementing water efficiency measures in the majority of sectors would result in significant economic disruption to achieve identical savings. Water efficiency improvements should be targeted towards this minority of sectors: cloth(ing) supply-chain, chemical manufacturing, and electricity and heat supply.

Key words: industrial water saving, China, city, stringent management, water scarcity

Freshwater is an essential and global resource[1]. Over the last 50 years, China's industrial water withdrawal increased in 90% of its cities[2], and has remained at a high level above 126 km^3/yr from 2013 to 2018[3] largely due to low water-use efficiency. China used to have transnationally low efficiency partly owing to mis-management[4–7], specifically poor sectoral controls and water-saving initiatives[8]. China's response to this was to legislate for industrial water withdrawals through the so-called stringent water resources management system ("Three-Redline" regulations), introduced by the Chinese State Council in 2011[9], and aimed at saving water through improving industrial withdrawal per value-added by 20% between 2015 and 2020. More recently, China established national water-saving demonstration (sponge) cities, but specific control on both industrial water withdrawal intensities and volumes still remains poor[10].

Although nation-wide China is deficient in water[11], with a wicked problem between water demand and availability[4,12], city-level water scarcity has not been fully explored[13]. The science of water scarcity assessment has developed for the past 30 years and, as more spatial geo-data have been available, studies have adopted more integrated and multi-faceted approaches typically based on spatial resolution in grid units at the river basin scale[14,15] or global levels[16–18], rather than at administrative/territory based units such as the city level. There is only a single city-level based study in 2005 from the Ministry of Water Resources in China, which is not widely available to the public[19]. Thus far, to the best of our knowledge, an appraisal of cities and their water scarcity status is unavailable. In terms of measuring scarcity, the criticality ratio (water withdrawal to annual renewable freshwater) is a simple and classical indicator of blue water and quantitative scarcity[20,21]. It has thus far been applied at the provincial level[16,22–24], but not at the city level due to data limitations[7].

Water scarcity is typically exacerbated by unsustainable levels of water withdrawal; hence, society ought to be well placed to mitigate it by improving water use efficiency, especially by reducing water withdrawal intensities. Many studies have focused on agricultural intensification[25,26] in relation to better water management in land use[27] and irrigation[28]. However, due to lack of measured efficiency data, there remains a dearth of research especially from an industrial and sectoral perspective[29], to explore water saving potential and implication on scarcity alleviation[30] at the city level.

We first accounted for datasets on water withdrawal for 41 industrial sectors in 272 prefecture-level cities (88% of China's population), and water scarcity for all cities (343) in 2015, based on a point-sourced survey in China[31,32]. We identified cities suffering from water scarcity, and low water efficiency sectors at the city level (compared with the national average). Second, we found the most severely affected city type, and detected water scarcity and differences amongst these city-groups. Finally, in scenario analysis we assumed a convergence of below-average efficiencies to the national sector-average, to explore water saving potential amongst 41 industrial sectors and implication on water stress of Chinese cities under the constraint of the 20%-intensity-reduction. For key sectors and cities, our results help to identify priorities and optimize efforts for improving water use efficiency and facilitate more effective water management through enabling distinctive saving strategies.

Water withdrawal and water scarcity datasets at the city level

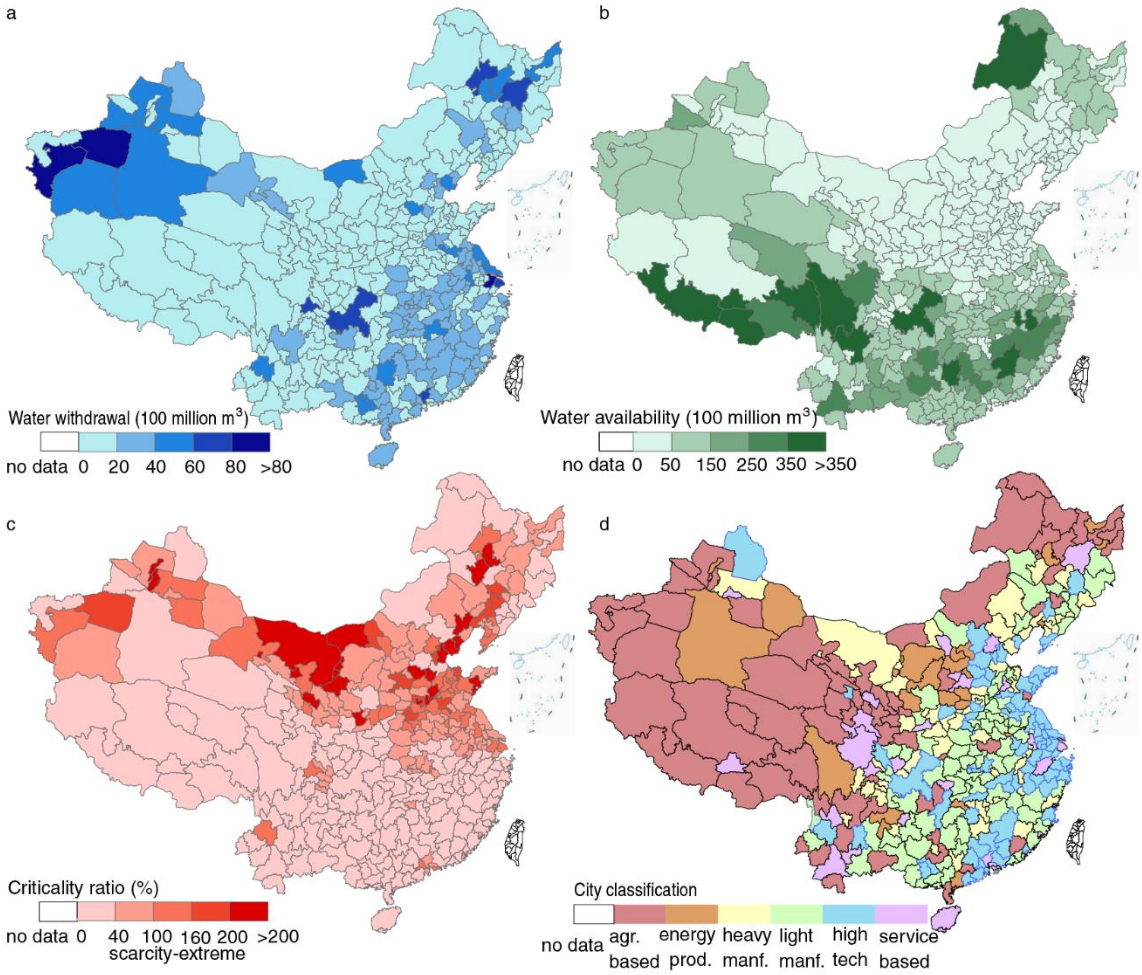

Fig. 1. Prefecture-level cities and their water situation based on 2015 data. (a) total water withdrawal, (b) water availability, (c) criticality ratio (%), and (d) six groups with predominant sector clustering. Average size of cities was 2.80 million ha; average population was 4.43 million.

We built up datasets using a general accounting framework for Chinese cities, as developed for previous work[31,32]. Drawn on the datasets, Fig. 1a represents a map of total water withdrawal at the city level. Criticality ratio was determined by dividing total water withdrawal (1a) by water availability (1b) for each city[23,33,34]. Typically an empirical threshold of 40% is regarded as water scarcity status[18,35,36], and over-100% as extreme water scarcity stress, signifying that annual water withdrawal exceeds renewable water resources[13].

Overall, 146 of 272 cities (55% of population) were found to be under water scarce conditions, a result consistent with previous studies[13]. These cities are represented by darker colors in Fig. 1(c): Guangzhou and Shenzhen (south), Shanghai, Suzhou, and Yancheng (east), Harbin (north), and Hotan (west). Notably, in contrast to an earlier study[13], we also identified some severe water-scarce areas in south China: Shenzhen (south; 108%) and Foshan (southeast; 107%). Water scarcity in China is known to already be serious, thus caution should be exercised when interpreting the south expansion of scarcity.

Sixty-nine Chinese cities (25%) were found to be under extreme water scarcity. These cities occupied 27% of the population. We identified cities in different regions experiencing extreme scarcity (Fig. 1c), for example Jiayuguan, Kelamayi and Lanzhou (northwest), Panjin (northeast), Puyang and Zhengzhou (central), and Shanghai (east). One of the adverse effects of extreme scarcity was observed in Zhengzhou, where average level of shallow groundwater decreased by 0.5 m in 2015[3]. Of 13 metropolitan areas containing over-ten-million citizens, 11 cities were constrained by water scarcity, and 6 by extreme scarcity. Median criticality ratio was 46%, varying between 0.38% in Ganzi (southwest) to over 200% in Jiayuguan (northwest). This median was six percentages exceeding the scarcity threshold of 40%.

Fig. 1(a), (b) and (c) show a mismatch in distribution between water use and availability at the city level. This uneven distribution results in water resources being commonly over-exploited in northern China. For example, several hotspots (with large water withdrawals) in northwest China, such as Hotan, Kuerle and Bayannur, have criticality ratios exceeding 100%. This indicates that environmental flow[37–39] is largely reduced for natural runoff and ecosystem survival. Fig. 1(d) shows city classifications and their intuitive spatial distribution. We classified cities into six groups, namely: agriculture-based, energy production, heavy manufacturing, light manufacturing, high-tech and service-based cities, using a clustering based methodology[40].

Discrepancies in water withdrawal and water scarcity between cities

When constrained by severe water scarcity, one might expect industries in water scarce cities to adopt water saving technologies, hence their industrial water withdrawal intensities should be lower than comparable industries in water sufficient areas. In other words, water scarcity should force local industries to be front-runners in water use efficiency. Nevertheless, a few water scarce cities (Fig. 2(a)) such as Qiqihar (north), Yingkou (east), Wuhai (west) and Puyang (central), had water intensities which were much higher than in cities abundant in water resources. Although China has set intensity reduction targets in stringent management since 2011, reducing intensities of sectors in water-scarce cities should therefore be prioritized. Awareness of industrial water savings should be given greater focus in these sectors in water scarce cities to prevent the situation to get worse. For example, cities such as Wuhai, Hegang, Puyang, and Qitaihe, had water intensities which were still high, yet they were all included in the 69 cities known to be over-exploiting resources, as released by the Chinese government in 2018[41].

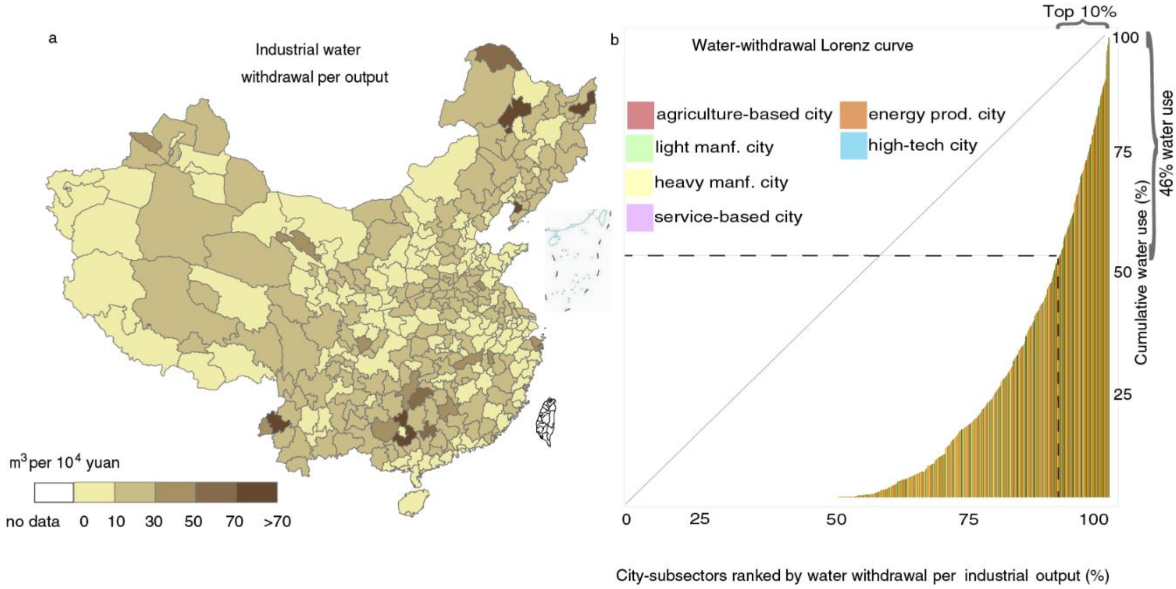

Fig. 2. Discrepancies in water withdrawal intensities across cities; (a) spatial distributions of overall industrial intensities across cities; and (b) water-withdrawal Lorenz curve depicted by different intensities of a total of 41×272=11,152 city-sector combinations from six groups. (Different city groups are represented by their corresponding color, as the same below.)

A disproportionately small fraction of sectors at the city level contributed to large industrial water withdrawals. Thus sectors of low-efficiencies across cities should be well targeted to save water. We ranked a total of 41×272=11,152 city-sector combinations by order of water intensity from low to high and then calculated share of cumulative water withdrawal accordingly. We depicted these shares relative to shares of cumulative numbers of sectors and obtained a water-withdrawal Lorenz curve (Fig. 2b). The curve indicates that the top 10% of high-intensity sectors account for 46% of water withdrawal, as a disproportionate fraction. Such high-intensity water users were mostly found in small and developing cities, with representative industries such as papermaking and product manufacturing in Chenzhou (central), Lincang (southwest) and Qiqihar (northeast); liquor, beverage and tea manufacturing in Jingdezhen (mid-east), Anqing (mid-south) and Wuzhou (southwest); and electricity and hot water supply in Changde (mid-south).

We compared water scarcity occurrence amongst different city-groups. The most-severely affected were found in the high-tech group (Fig. 3); 38 cities over the 40% criticality-ratio (water scarce) and 20 above 100% (extremely scarce). These are the highest in their corresponding tier, indicating economic growth limitations subject to water resources constraints. Notably, population in high-tech cities accounts for 33% of the total, and are commonly affected from severe water scarcity. Heavy- and light-manufacturing cities were also ranked, following high-tech cities. These water scarce cities with sectors of low water withdrawal efficiencies should be targeted.

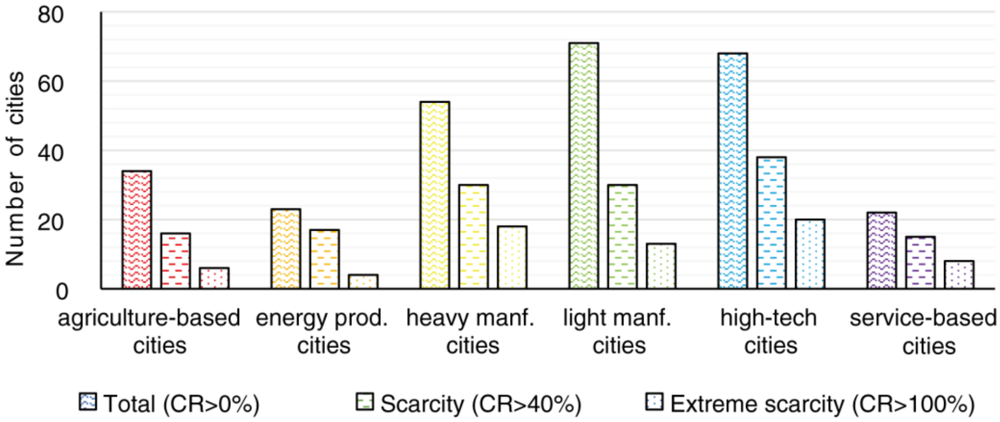

Fig. 3. Statistics of city numbers in different criticality-ratio categories.

Industrial water saving potential based on efficiency improvement

Industrial sectors in 272 cities were investigated for two reasons: first, there were special regulations for industrial water withdrawal intensity in the redline policy; a number of cities were even required to implement the most up-to-date technologies or regulatory standards for water savings during industrial production. Second, the 41 industrial sectors we considered in total (see appendix III details) showed high heterogeneity in water use and saving potential[32].

For scenario analysis in individual of 41 industrial sectors, we substituted above-average water intensities with average ones, by assuming technical progress in water use efficiency. Scenario A was for all 272 cities and B was for the 146 water-stressed cities. Water saving strategies are more stringent in A than B. If water withdrawal intensity of a sector in a city was lower than the national sector-average, we left water intensity as it was. This would help maintain a stable technological and economic structure whilst improving efficiency; If intensity of a sector was higher than the national sector-average, but it occurred in a city with no water stress (criticality ratio less than 40%), we did not substitute it either;

Only for sectors that both had above-average intensities and were located in water-stressed cities, we did substitute intensities with national sector-averages. In fact, technology is a vital factor underpinning different intensities in the same sector. For example, in Suzhou, electricity and hot water supply consumed as much as 5.3 km^3 p.a. (64% of total water use) due to once-through cooling technology (water-intensive) accounting for 99% in thermal plants. Conversion of these plants to circulating cooling technologies, would result in large water savings. In contrast, food or general machinery manufacturing in Dongguan and Hanzhong, which stood out as high-efficiency exemplars, should be set as demonstration sites for peers in the same sector.

For all 272 cities, we estimated 41.91 km^3 (±4.45%) water could be saved. This amount equates to 7% of total water use for the whole of China, and is more than total industrial water consumption (31 km^3), twice the water demand of Australia or Hebei province of China in 2015[42], and almost 2,000 times the water storage capacity of the West Lake in Hangzhou, China. A relatively small fraction (27%) of 11,152 city-sector combinations contributed to large water savings (39%) of total industrial water withdrawals. Fig. 4(a) illustrates sectors towards right-hand side of x-axis could contribute approximately 10% water savings, whilst those on the left could contribute a 0.2% reduction.

Furthermore, large contributors arose from fewer sectors at the city level, as shown in 4(b) (above the dotted line), whilst it was less effective to tap saving potential for sectors in the lower section (below the dotted line). Typically, there will be more than a single sector affected in most cities. Jiang (2009)[43] recommended exploration of cost-effective and long-term saving options by considering perturbations caused to economy. Here we hypothesized that the fewer individual sectors substituted, the less economic perturbation would result. Interestingly, a minority of sectors could save most water whilst affecting fewer cities. This seems a win-win opportunity. Instead, most sectors needed to disturb more economy to achieve the same saving. From an industrial water usage perspective, we therefore recommended water saving initiatives in five key sectors which potentially contributed half the available water savings: electricity and hot water supply (13.0%), chemical material and product manufacturing (10.6%), cloth (textile) manufacturing (9.4%), papermaking and products manufacturing (9.0%), and clothing (apparel, footwear and hats) manufacturing (7.8%). Requiring all industrial sectors to improve water efficiency does not therefore represent an optimal policy choice. This finding also applies to

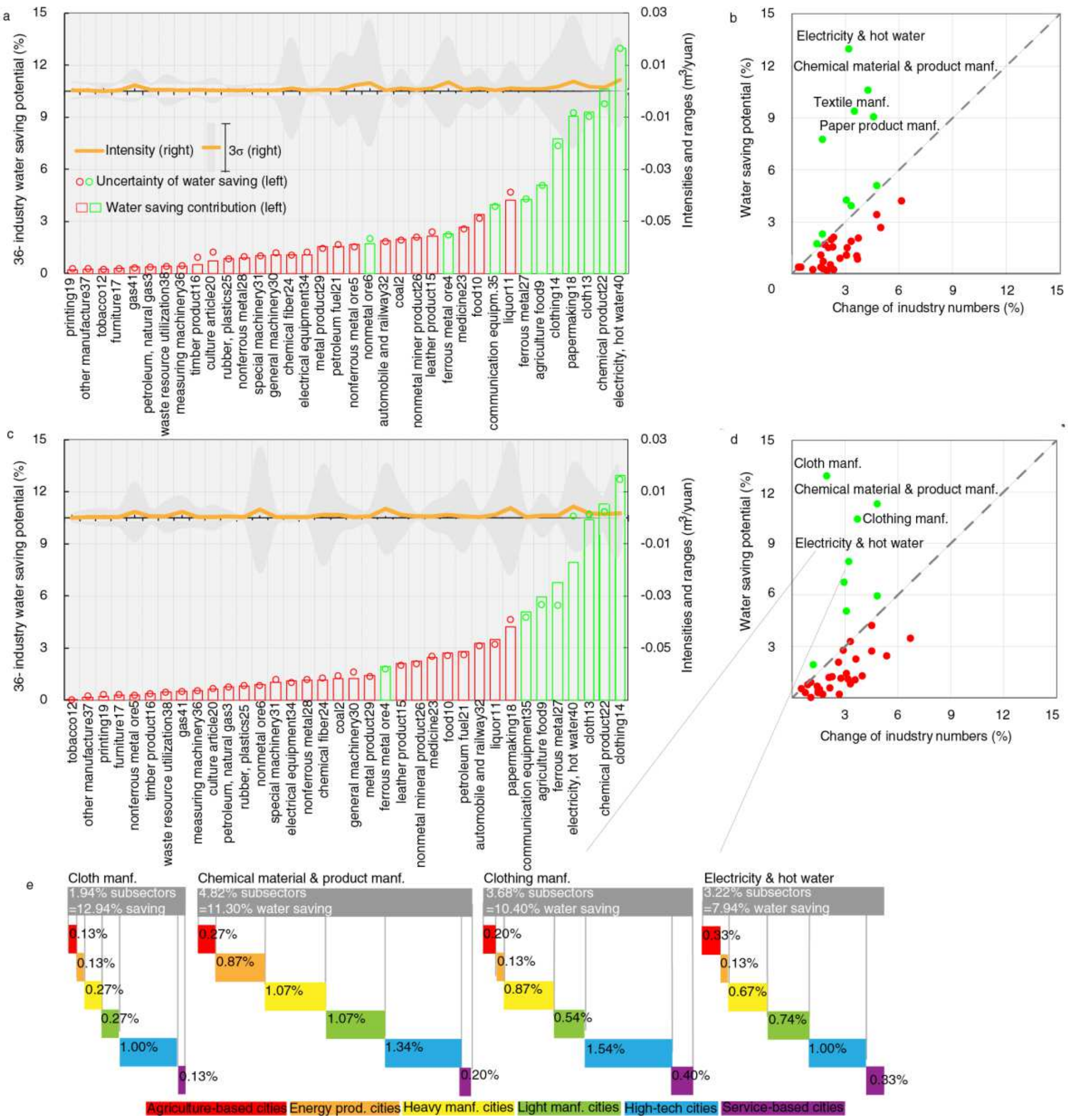

Fig. 4. Water saving potential and withdrawal intensity in each sector; (a) and (b) for Scenario A, and (c), (d) and (e) for B. Grey shading indicates empirical distribution range of intensities in each sector. Upper and lower boundaries were calculated by the three-standard-deviation method. (e) shows the top four water-saving sectors and their structure within different city-groups. For brevity, we listed a product and a code in each sector; 2-8 represent mining and processing, 9-39 are manufacturing, and 40-42 are production and supply of electricity, gas and hot water. For full names and descriptions please refer to appendix III. We excluded sectors of small contributions.

water scarce cities (Scenario B, Fig. 4(c) and (d)). In 4(a) and (c), uncertainty arose from treatment of high-intensity sectors during the survey, considering considerable heterogeneity of water use technology across cities for the same sector. For Jing-Jin-Ji agglomeration 0.96 km^3 (±9.8%) water could be saved.

In the 146 water scarce cities, reducing high water intensities in a relatively small fraction (13%) of 11,152 city-sector combinations would result in large water saving (18%) of total industrial water withdrawals. A level of 18.9 km^3 (±3.2%) of water would be saved. This equates to annual water demand of Australia or Hebei province of China, and almost 1,000 times the West Lake capacity. For individual city-groups, water savings would reach 7.90 km^3 for high-tech cities, 4.17 km^3 for heavy manufacturing cities, 3.40 km^3 for service-based cities, 2.71 km^3 for light manufacturing cities, 0.7 km^3 for energy production cities, and 0.62 km^3 for agriculture-based cities. For individual cities, water savings ranged from 118,700 m^3 in Beijing, to 2.0 km^3 in Guangzhou. We hypothesized industrial value-added levels remained unchanged, in which case water withdrawal per value added would decrease by 20%, equating to the 2015-20 efficiency target in the stringent management. At identical water availability levels, criticality-ratio reduction ranged from 0.72% in Dongguan to 62% in Lanzhou. A small number of cities would be alleviated below the scarcity threshold (40%) and shake off water scarcity, for example Jilin city (northeast), Jincheng (northwest), Yulin and Tongchuan (west), and Xiangtan (mid-south). Heavy-manufacturing cities would be alleviated by 11% on average to sub extreme-scarcity level. At the national level, although the situation would remain severe, mean water scarcity level of 146 cities would fall by six percentage points from 95% to 89%.

Notably, in contrast to conventional understanding, electricity and hot water supply was not the largest contributor to water savings. Manufacturing of clothing, chemical materials and products, and textile would bring greater savings. The largest potential was in the cloth-clothing supply chain, including from cotton to intermediate products (yarn, cloth and other materials), and from yarn etc. to final clothing products such as apparels, footwears, hats, masks, and trims. This finding is supported by a previous study[44], and could be useful in water saving management for relevant industrial committees.

We also decomposed structure of the important 13% sector fraction into different cities and groups, and identified four sectors (Fig. 4(d)) which contributed to half of total water savings; cloth(ing) supply chain, chemical material and product manufacturing, and electricity and hot water supply. Fig. 4(e) shows proportions of affected sectors from individual city-groups, respectively. For example, cloth manufacturing contributed to 12.94% (~2.37 km^3) of water saving in total, yet these sectors accounted for just 1.94% overall at the city level. These subsectors and cities should be prioritized. A list is provided in appendix IV.

Most severely scarce city-groups were effectively pinned down, such as high-tech, heavy- and light-manufacturing cities. These city-groups basically hold the top three places for efficiency improvements. For example, proportions of affected cities (sectors) in heavy-manufacturing and high-tech cities were all highest; 78% (37%) and 56% (26%) respectively. Proportions of water-saving contributions from individual city-groups were also checked and consistent (upon request). Thus, we were able to reliably and robustly validate discussion on substitution.

Of course, realization of water intensity reductions is likely to be different[29] from our rather crude scenario analyses; technologies between sectors and cities vary, and we must consider institutional as well as technical interventions. In fact, China's water saving potential in this regard is significant, with opportunities for factories and enterprises to adopt or advance efficient water-use equipment from their respective sector in the global environment. The main improvements we would recommend are in water recirculation (wet tower) in power generation, for example abstraction per kWh could be improved from 168 liters to 5 liters[45]. Alternatively, we would encourage sectoral water abstraction and use rights, and incentives such as trade and other subsidies for water-saving sectors and cities[46] through water management contracts[47]. Regularly updated indices for leading-edge enterprises and high water efficiency manufactured products should be promoted by water efficiency labels[48] and national awards. Finally, online/real-time monitoring on water withdrawal of key sectors at the city level through roll-out of smart meters should be considered[22].

In summary, we have reported water withdrawal and scarcity accounting for 272 Chinese cities, using a 2015 data benchmark. The top 10% of low-efficiency sectors made up 46% industrial water use. In scenario analysis of 41 sectors across 146 water-scarce cities, through efficiency improvements by 20% and satisfying the stringent management policy, 18.9 km^3 (±3.2%) water saving would be realized.

Yet, here we recommend water saving potential in a handful of sectors, as these sectors identified to contribute to half of total water savings amongst 41 sectors. Focusing on these sectors makes sense in terms of producing water saving returns, whilst minimizing potential economic disruption across the industrial base. China may therefore target key sectors and cities in stringent water management, rather than requiring all industries and cities to be involved in water saving.

Methods

City-level industrial water withdrawal data sources. Industrial total water withdrawal and water-withdrawal per value added were compiled from water resources bulletins at provincial and city levels. Industrial water withdrawal is a newly withdrawn water amount[3]. This variable may depict pressure on available water resources from domestic economic activities more accurately since it excludes reused water.

Industrial water withdrawal intensities for individual sectors in each city were derived from the China High Resolution Emission Gridded Dataset[31], in which a key survey of spot-sites covered 162,000 enterprises, across 41 industrial sectors for all 343 prefecture-level cities (including leagues, regions and autonomous prefectures) in China. Sectoral industrial outputs were sourced from statistical yearbook for each city.

We applied the general accounting framework used in previous work, and built up city-level and territory-based industrial water withdrawal data for individual sector and city, according to IPCC administrative boundary (scope 1)[49]. For method validation please refer to detailed discussion in previous paper[32] and Turner et al. (2010) [50]. Of 343 cities, only 272 cities' data were available for sectoral accounting datasets, and 343 were further accounted for total blue-water withdrawal, availability and quantitative blue-water scarcity status.

Clusters for city classification. Cluster analysis usually refers to magnitudes of a series of pre-provision indicators (or variables) for specific datasets[51]. In the result, difference within a group would be significantly small, whilst relatively large between groups i.e., clusters represent variables with similar attributes[52,53]. Beyond administrative or provincial territories, city-level studies[54,55] concerning resource use across industries have utilized Shan et al. methodology[40] to classify Chinese cities into different groups (a k-mean cluster analysis). We used a similar treatment (employing proportions of industrial output) and supplemented with an agriculture-based grouping, to Shan et al. method. Agriculture-based cities occupied greater proportions of farming, forestry, animal husbandry, and fisheries in their GDP than other cities. We thought six groups represented different economic development stages by assuming a development time lag. For example, representatives of service-based cities were the so-called first-tier cities, including Beijing, Shanghai, Guangzhou, Shenzhen, as well as provincial capitals such as Wuhan and Nanjing. These were typified as wealthy and industrialized economies, as demonstrated by average per capita GDP of 132,302 Yuan. This ranked 1st in all six groups, and was more than twice that of energy production cities. Service-based cities were assumed to take leading position for industrialization process in all Chinese cities.

Fig. 1 in the Appendix shows top-/bottom-ten sectors for water withdrawal efficiency and GDP statistics in six groups. Some low-efficiency and large water-users should be targeted to save water. Examples of energy production cities include Daqing, Panjin, Changzhi and Liupanshui. Although the top and bottom ten for water withdrawal intensity were amongst the smallest, this group appeared vulnerable since some cities such as Wuhai, Panjin, Hegang, Huozhou, and Qitaihe, have exhausted energy and water resources. High-tech cities followed, of which examples included Dalian, Nanchang, and Shaoguan. In heavy manufacturing cities, water withdrawal intensities were complex: these were amongst the largest, for example Panzhihua, Sanmenxia, Anshan and Handan, and most withdrawal efficiency varied across a large range. Service-based city water withdrawal intensities were not high. Furthermore, some cities were featured through cluster sectors with large water-use, such as Changchun (heavy manufacturing: special purpose machinery), Suzhou (high-tech manufacturing: communications equipment), and Yangzhou (heavy manufacturing: chemical materials and products). These sectors could learn from their peers within the same group.

Application of criticality ratio as an indicator for water scarcity. The criticality ratio (%) was applied to measure annual water scarcity[23], i.e.:

$$Criticality\ Ratio_i = Water\ withdrawal_i / Water\ availability_i \quad (1)$$

where i represents a city (one ratio number for one city); water withdrawal was the total amount from including farming, forestry, animal husbandry, fisheries, industry, construction, service, household, and ecosystem and environment preservation; and water availability included surface water and groundwater. There are mainly three indicators in the current study: net runoff, natural streamflow, and natural streamflow minus consumptive use from upstream human activities[13]. We adopted the natural-streamflow measure and obtained relevant data from water resources bulletins for the cities, referring to Zhao et al. (2019)[56]. Basically produced from domestic precipitation, it is calculated through surface water plus groundwater minus double measurements. In 2015, China's precipitation (and water availability) was 2.8% (0.9%) more than, but close to, its average values through multiple years (1957-2000, with statistics)[3]. Criticality ratio takes into consideration environmental flows[39,57] and connects with water quality and biodiversity[58]. The higher the ratio is, the more stress is placed on available water resources from withdrawal, and the greater the probability of water scarcity occurrence[35].

In addition to Fig. 3, we further found there appeared to be discrepancies in criticality ratio in different city-types, indicating frequency and severity of water scarcity occurrence, referring to Veldkamp et al. (2016)[59]. For energy production cities (Appendix Fig. 2), frequency seemed relatively higher, but not as severe when compared to heavy manufacturing group. Trendline curve peaked at 50%, exceeding the 40% definition for water scarcity. In other words, most cities appeared to be distributed to the right of scarcity threshold. Reassuringly, there appeared to be relatively few instances of cities occurring in the extreme scarcity region (i.e. >100%).

In contrast, heavy manufacturing cities had lower frequencies of water scarcity occurrence, but once over the 40% threshold it tended to be more severe. The peak in the frequency trendline appeared at approximately 10-15% i.e., most cities tended to be distributed in a narrow band to the left of scarcity threshold. However, there was a greater, more even spread of samples above the extreme scarcity threshold, with a slight frequency approximately 5% for each distance, so the trendline tended to decrease gradually. Examples were Jiayuguan (3507%, northwest), Shizuishan (962%, northwest), Baiyin (489%, northwest), Tangshan (290%, north), Alashan (287%, northwest), Dongying (200%, east) and Baotou (189%, north). This small subset (approximately 13%) of cities in this group mainly influenced our findings for water scarcity in heavy manufacturing cities.

According to discrepancies of scarcity occurrence in different city-types, we also considered distinct water saving strategies. For heavy manufacturing cities, policy focus should therefore be on a small number of scarce cities at this stage. By comparison, for energy production cities, policy makers should focus on a greater number of cities. For agriculture-based and light-manufacturing cities, given their relatively lower GDP per capita, balance between economic development and water saving needs to be better coordinated in decision-making.

Uncertainty analysis. We also clustered cities based on economic shares of GDP for primary, secondary and tertiary industries, then classified cities into three groups for sensitivity analysis. We found only minor differences between ratios of cities at individual water scarcity levels, from the groups using proportions of industrial output. Specifically, for agriculture-based cities, the >40% and >100% criticality ratios accounted for 46% and 17% respectively; for industry-based cities they were 54% and

25%; whilst for service-based cities they were 67% and 35%. Although clusters were based on different indexes, we found no significant differences in water-scarcity distribution and status. We also verified water withdrawal per GDP of agriculture-based cities of 211m^3 per 10^4 Yuan, which was close to the magnitude of representative agriculture province such as Heilongjiang at 210 in 2015[60]. Finally, for individual city groups we validated median and average criticality ratios and water intensities; these results as well as significance tests for our group classification are available upon request.

Besides, we may over-estimate criticality ratio, considering water withdrawal statistics do include those from reservoirs and upstream rivers, while water availability data do not include these parts. We were unable to incorporate these data into water availability generally due to statistical incongruence between cities. Thus, our results could suffer from an upward bias in some cities. In future, we will supplement these data by combining hydrological simulations[59,61,62]. In summary, verifications suggest our city clusters are unbiased, and the results are robust and credible.

Limitations and future work

Our study collated and accounted results for a single year and did not consider fluctuations in inter-annual precipitation and withdrawal, due to data availability. Variation of water availability for individual cities should be considered in future work since we have observed significant fluctuation, for example a decrease of approximately 60% in Qingdao, Zaozhuang, Laiwu and Linyi cities in 2016, due to reduced precipitation in dry years. This further work will not only reduce uncertainty of water scarcity status, but also explore temporal insights into understanding of water scarcity and allow for more time-series and statistical-significance testing.

Water quality-induced scarcity[16,63,64] has not been included in this paper due to lack of data for water temperature and salinity, nutrient and other pollutants. Besides, the extent to which water savings could be driven by water stress needs quantitative analysis.

At this stage our study is also limited by data availability for agriculture; we do not find sufficient irrigation efficiency data for subdivided crops or lands in individual cities, in order to project water saving potential for agriculture. For industrial sectors, it is better to use value-added to substitute output to assess efficiency, especially when such sectoral value-added data will be accessible in the future.

Finally, we only considered direct water savings for isolated sectors. It is only partially feasible to assume a smooth knowledge transfer of water efficiency experience from wealthier cities to poorer ones, for example technology progress for saving water. Consumption-based water accounting considers water saving throughout the entire supply chains, which would be practical in future work.

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