

# Deceleration of China's human water use and its key drivers

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Edited by Peter H. Gleick, Pacific Institute for Studies in Development, Environment, and Security, Oakland, CA, and approved February 26, 2020 (received for review June 11, 2019)

Increased human water use combined with climate change have aggravated water scarcity from the regional to global scales. However, the lack of spatially detailed datasets limits our understanding of the historical water use trend and its key drivers. Here, we present a survey-based reconstruction of China's sectoral water use in 341 prefectures during 1965 to 2013. The data indicate that water use has doubled during the entire study period, yet with a widespread slowdown of the growth rates from 10.66 km<sup>3</sup>·y<sup>-2</sup> before 1975 to 6.23 km<sup>3</sup>·y<sup>-2</sup> in 1975 to 1992, and further down to 3.59 km<sup>3</sup>·y<sup>-2</sup> afterward. These decelerations were attributed to reduced water use intensities of irrigation and industry, which partly offset the increase driven by pronounced socioeconomic development (i.e., economic growth, population growth, and structural transitions) by 55% in 1975 to 1992 and 83% after 1992. Adoptions for highly efficient irrigation and industrial water recycling technologies explained most of the observed reduction of water use intensities across China. These findings challenge conventional views about an acceleration in water use in China and highlight the opposing roles of different drivers for water use projections.

water resource management | water use efficiency | water scarcity | attribution analysis | sustainable development

Water scarcity is an emerging threat to food security and socioeconomic prosperity (1–3). Increased human water use combined with climate change has aggravated the water scarcity, affecting more than 2 billion people globally (4–6). Over the last century, water use by humans has been growing more than twice of the rate of population increment (7). About 77% of this growth has occurred in developing countries (8). The water use of these countries is expected to grow substantially in the future (6, 9–11). However, our incomplete understanding of the drivers and mechanisms behind changing water use patterns makes future projections unreliable (12).

China has transitioned from an underdeveloped country to the second largest economy, but also one of the world's most water-stressed regions (13–17). To avoid the long-term water crisis, diverse water conservancy measures were developed since the 1980s (15, 18). However, how water use is responding to economic growth, structural transitions, and policy interventions over time and space is not well known. Two types of approaches

can be used for the evaluation of large-scale water use trends. The first one is to use the results from an ensemble of models to account for uncertainty in model structure, like the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) using global hydrological models (GHMs) (19). These models are driven by macroscale socioeconomic activity data (e.g., gross domestic production, population, irrigated area) and climate data to simulate water use by sector, with spatial patterns of human water withdrawals inferred from statistical downscaling (20, 21). GHMs assume simple changes of technological factors but often ignore the effect of water conservancy measures (2, 6, 8, 22, 23). The second approach consists in collecting historical

## Significance

China's rising food demand and fast economic growth increase water use and threaten water security. We present a spatially detailed survey-based reconstruction dataset of sectoral water use from 1965 to 2013 at the scale of small administrative units called prefectures. The data show that a widespread deceleration of water use in recent decades and the adoption of improved irrigation practices and industrial water recycling partly offset the increase driven by the rising water demand from economic growth and structural transition. These findings underscore the value of technological adoptions, including a determination of their potential, to help in designing targets and incentives for water scarcity mitigations.

Author contributions: F.Z. designed research; F.Z. and Y.B. performed research; F.Z., Y.B., and P.D. analyzed data; and F.Z., Y.B., P.C., P.D., Q. Tang, X.W., J.L., C.Z., J.P., Z.Y., M.G., S. Peng, C.O., X.Z., J.Z., Q. Tan, L.C., H.S., H.Y., S. Piao, H.W., and Y.W. wrote the paper.

The authors declare no competing interest.

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Data deposition: All data generated or analyzed during this study, including the NLWUD dataset, GIS files, and codes used in data analysis/figure creation, have been deposited at [https://figshare.com/articles/Zhou\\_et\\_al\\_2020\\_PNAS\\_dataset.xlsx/11545176](https://figshare.com/articles/Zhou_et_al_2020_PNAS_dataset.xlsx/11545176).

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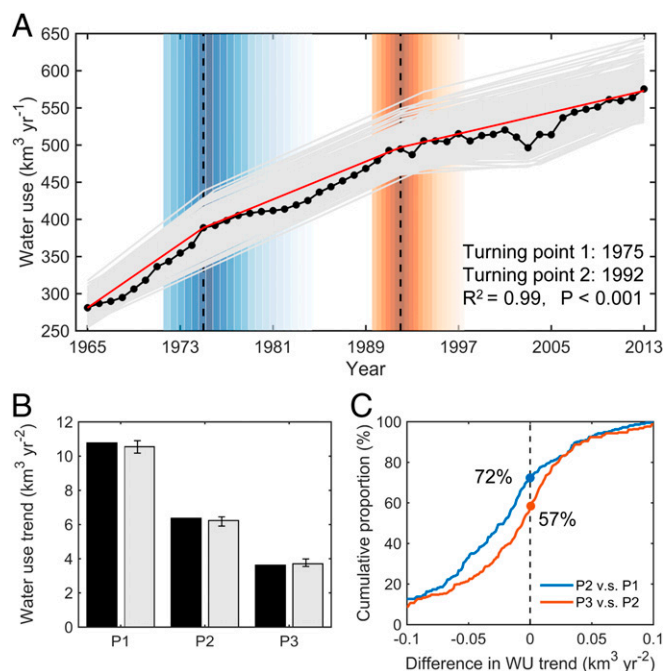
This article contains supporting information online at <https://www.pnas.org/lookup/suppl/doi:10.1073/pnas.1909902117/-DCSupplemental>.

records of water use based on surveys and statistical data. So far, water use surveys in China were analyzed either for specific sectors such as irrigation and thermoelectric power industry (24–28), or for multiple sectors but at coarse spatial resolution or during short periods (29–31).

Here, we provide a nationwide survey-based reconstruction dataset to assess the socioeconomic drivers of China's water use changes in different sectors (32). This dataset is with the spatial resolution of medium-sized administrative units known as prefectures (i.e., 341 prefectures with a median area of 13,034 km<sup>2</sup>; *SI Appendix, Methods S1 and Fig. S1*) and spans from 1965 to 2013. Data on irrigation, industrial (including thermoelectric power industry), and urban and rural water uses, which together account for more than 93% of total blue water withdrawal (33, 34), were collected separately. The rest of water use for pasture, aquaculture, and in-stream uses was excluded. We used water use from withdrawal since long-term consumption data were not readily available at the prefectural scale. We first present the spatial analysis of water use trends in China. To detect potential change in water use trends, we use a piecewise linear regression model (35). We then analyze the contributions of 14 socioeconomic drivers to water use trends at the national and prefectural scales, using modeling framework called logarithmic mean Divisia index (LMDI) (36) (*Methods*).

## Results

**Deceleration of China's Water Use.** National water use doubled over the period 1965 to 2013 ( $P < 0.001$ ; Fig. 1A). However, the rate



**Fig. 1.** Turning point for mean annual water use. (A) National mean annual water use during 1965 to 2013 (black dots and line). The red line is the piecewise linear fit ( $R^2 = 0.99$ ;  $P < 0.001$ ). Each gray line ( $N = 300$ ) is a piecewise linear fit for a randomly selected subset (90%) of the prefectures. The piecewise linear regression model indicates two statistically significant turning points in 1975 and 1992 (dashed lines). The shaded areas indicate the interquartile of the estimated turning points derived from 300 resampling results. (B) The water use trends before and after each of two turning points. The black and gray bars indicate the values from national mean annual water use and 300 resampling results, respectively. Error bars indicate a SD. (C) Cumulative proportion of the differences in water use trends between P2 and P1 (blue line) and between P3 and P2 (orange line). The dashed line indicates no difference between two periods.

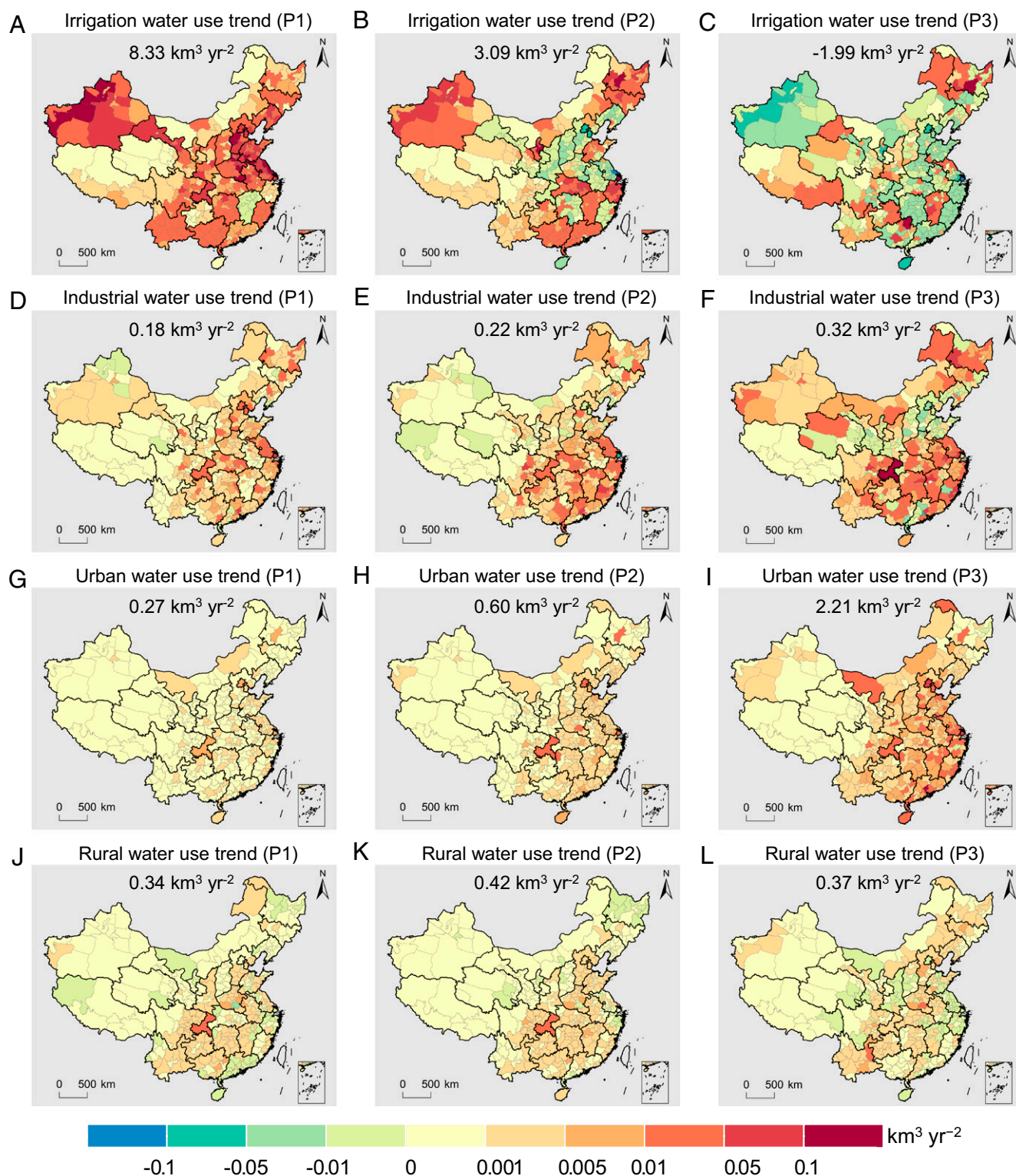
of increase slowed down, that is, a deceleration going from 10.66 km<sup>3</sup>·y<sup>-2</sup> before 1975 (period P1) to 6.23 km<sup>3</sup>·y<sup>-2</sup> in 1975 to 1992 (period P2), and further down to 3.59 km<sup>3</sup>·y<sup>-2</sup> after 1992 (period P3) (Fig. 1B). The turning points that define these periods were statistically significant at  $P < 0.001$ , with a goodness-of-fit of  $R^2 = 0.99$  (Fig. 1A). To exclude the possibility of turning points caused by large water use change over a few prefectures only, we repeated the analysis 300 times by randomly resampling 90% of the prefectures each time (gray lines in Fig. 1A) and found consistent and significant turning points in each case ( $P < 0.001$ ,  $R^2 = 0.98$  to  $0.99$ ; Fig. 1B). Spatial analyses further confirmed that the deceleration of water use in P2 and P3 was pervasive, affecting prefectures that together account for 72% and 57% of national water use (Fig. 1C), respectively. The prefectures where water use decelerated are in the most water-stressed regions during P2, but also in southeastern coastal regions during P3 (*SI Appendix, Fig. S2*).

Spatiotemporal trends of water use differ between sectors. Irrigation water use shows a clear reversal in trends from a positive value of +8.33 km<sup>3</sup>·y<sup>-2</sup> in P1 and +3.09 km<sup>3</sup>·y<sup>-2</sup> in P2 to a negative value of -1.99 km<sup>3</sup>·y<sup>-2</sup> in P3 (Fig. 2A–C). Reduced irrigation water use first occurred during P2 in the Haihe, Liaohe, and Huaihe Rivers and extended to two-thirds of the prefectures during P3. In contrast, industrial water use accelerated during the three periods, except for Beijing, Hebei, and Shandong during P3 (Fig. 2D–F). Urban water use, which corresponds to withdrawal for domestic use and service activities, also accelerated from P1 to P3, while rural water use, the water withdrawn for domestic use and livestock production, increased at a rather constant rate (Fig. 2G–I). Across those four different sectors, both industrial and urban water uses showed an obvious westward spread of positive trends, and they surpassed irrigation and rural water uses in more than one-quarter of prefectures during the 2010s (*SI Appendix, Fig. S3*). Although the difference of water use trends between three periods shows strong spatial variation, a dominant feature was the decreased irrigation water use, which occurred in 61% of the prefectures from P1 to P2 and in 45% of them from P2 to P3 (*SI Appendix, Fig. S4*).

**Drivers of Water Use Trends.** We attempted to quantify the relative contributions of 14 socioeconomic drivers to total water use trends (6 sector size indicators, 2 structure-related indicators, and 6 intensity-related indicators; Table 1 and *SI Appendix, Fig. S5*). Virtual water use through intersectoral transfer and interregional/international trade was not attributed, due to the lack of multiregional input–output tables at the prefectural scale (37, 38). Overall, our findings suggest that total water use trends in China resulted primarily from the opposite effects of increased socioeconomic activities and improved water use efficiencies. The decelerations of water use were jointly driven by reduced water use intensities (hereafter “WUIs”) of irrigation and industry, which partly offset the increase due to socioeconomic development (i.e., economic growth, population growth, and economic structural change) by a relative amount of 55% in P2 and 83% in P3 (Fig. 3).

Before 1975, the expansion of irrigated areas was the main driver of the widespread increase of national water use, amounting to 25.7% (Fig. 3). The second most important driver was industrial growth, measured by the industrial gross value added of products (GVA), which elevated national water use by 8.5% mainly in maritime prefectures and central China (*SI Appendix, Fig. S6*). Changes in other indicators associated with sector size, i.e., urban and rural population, service growth, and livestock population, had negligible impacts on national water use. Decomposition of structural changes in both irrigation and industrial sectors corresponded to increase water use by 5.0%, primarily due to the increased water uses for growing rice in





**Fig. 2.** Spatial pattern of sectoral water use trends during P1 (1965 to 1975) (A, D, G, and J), P2 (1975 to 1992) (B, E, H, and K), and P3 (1992 to 2013) (C, F, I, and L). In order to quantify the trends, we performed linear least-squares regression analysis using water use as the dependent variable and year as the independent variable.

south and wheat in north China as well as thermoelectric power industry in east China (*SI Appendix, Fig. S7*).

Between 1975 and 1992 in the period P2, industrial growth was the dominant factor for water use increase across the whole

country in 55% of prefectures (Fig. 3 and *SI Appendix, Fig. S8*). This factor alone pushed water use upward by 43.8%, primarily in east China. The effect of irrigated area expansion in P2 was two-thirds smaller than that in the previously analyzed period,

Table 1. A list of 14 socioeconomic drivers to water use trends

Sector	Driver	Note
Irrigation water use	Changes in irrigated area	Area of cropland actually under irrigation
	Shift in crop mix	Crop mix is measured as the proportion of each of the five crops* to total irrigated area
Industrial water use	Change in per-area WUI	WUI is defined as water use per unit of irrigated area for each type of crop
	Changes in industrial GVA	Industrial GVA is adjusted to the value at 2010 prices to remove the effect of inflation over time
Urban water use	Shift in industrial structure	Industrial structure is measured as the proportion of each of the 11 industries† to total industrial GVA
	Change in per-GVA WUI	WUI is defined as water use per unit of GVA of products for each type of industry
	Changes in urban population	Population living in urban regions
	Change in per-capita WUI	WUI is defined as water use per capita of urban population
Rural water use	Changes in service GVA	Same as the adjustment for industrial GVA
	Change in per-GVA WUI	WUI is defined as the water use per unit of GVA of service activities
	Changes in rural population	Population living in rural regions
	Change in per-capita WUI	WUI is defined as water use per capita of rural population
	Changes in livestock population	Livestock population is measured as the commodity calories of seven types of animal‡
	Change in per-calorie WUI	WUI is defined as water use per unit of livestock commodity calories

GVA, gross value added; WUI, water use intensity.  
\*Wheat, maize, rice, vegetables and fruits, and other crops.  
†Thermal electricity, mining, cement, electronics, machinery, metallurgy, petrochemicals, textile, paper making, food processing, and other industries.  
‡Swine, sheep, poultries, cattle, donkeys, horses, and mules.

which dominated the increased water use mainly in northeast China and northern Xinjiang (SI Appendix, Fig. S8). Shift in crop mix contributed marginally to the increased total water use, while industrial structural transition contributed another 3.5% following the continuous growth of thermoelectric power industry (SI Appendix, Fig. S7). The decrease of industrial WUI

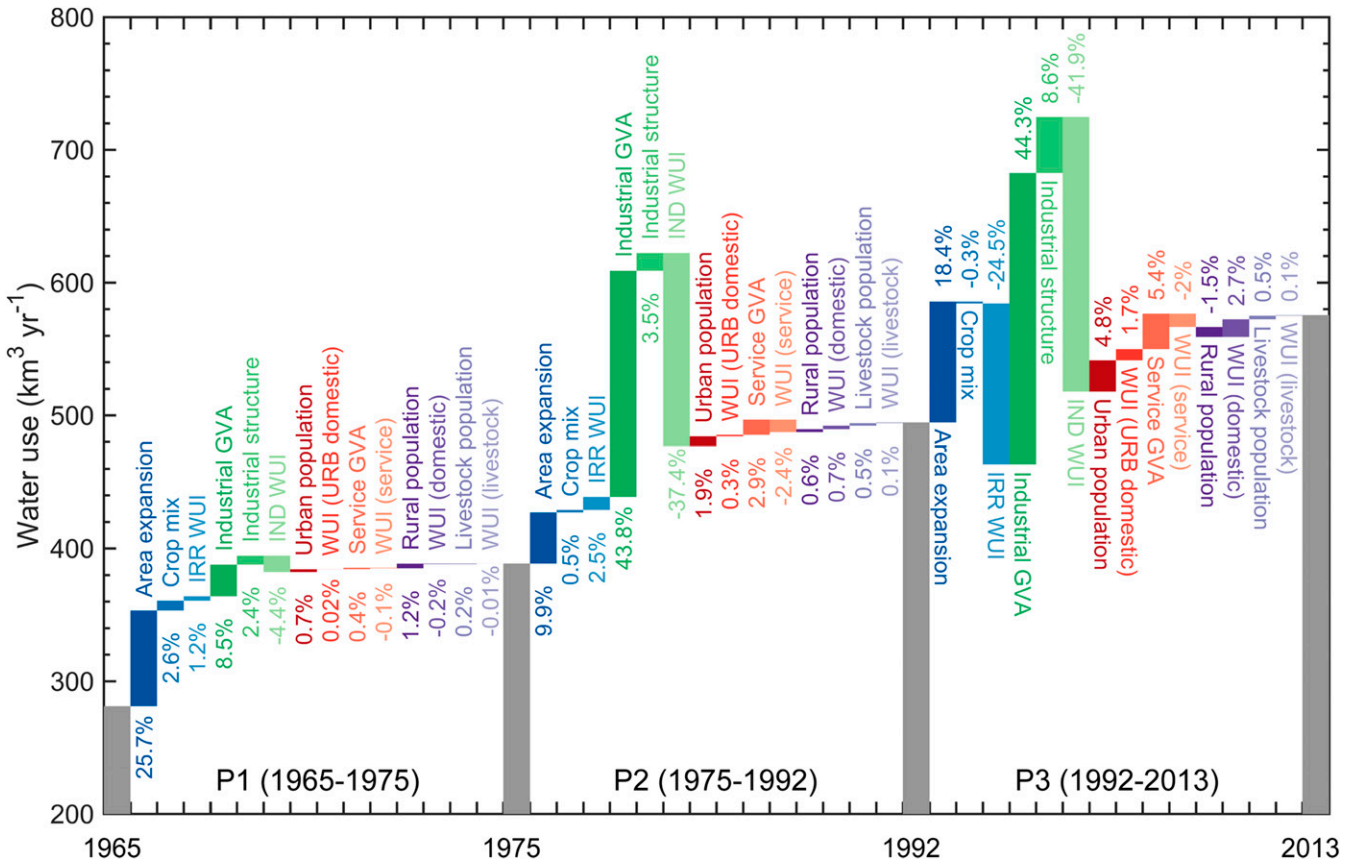


Fig. 3. Contribution of 14 socioeconomic drivers to the change in total water use during P1 (1965 to 1975), P2 (1975 to 1992), and P3 (1992 to 2013). The length of each bar reflects the contribution of each driver to water use change during the corresponding period, whereas the value below the bar indicates its contribution proportion. The effects of 14 drivers were listed by same order during three periods: irrigation (blue), industrial (green), urban (red), and rural (purple) sectors. Attribution of water use by sector or at the annual scale can be found in SI Appendix, Fig. S5. WUI stands for water use intensity, and the definition of the other factors can be found in Table 1.

was more pronounced in P2 than in P1, mitigating the increase of total water use by 37.4% (Fig. 3). Irrigation WUI began to decrease only in the drier region of north China (*SI Appendix, Fig. S8*). Approximately 65% of the effect of irrigated area expansion and industrial growth on the increase of water use was offset by reduced WUIs of irrigation and industry.

Since 1992 in the period P3, all sector size indicators except rural population have contributed to water use growth (Fig. 3). The most important drivers were industrial growth (accounting for 44.3% of the increase of total water use) and irrigation area expansion (18.4%). Industrial structural transition resulted in national water use increase by 8.6% mainly in the Yangtze River (*SI Appendix, Fig. S9*). The shift in crop mix continued to exert as a negligible factor (−0.3%) because the effect of changes in crop types compensated for each other across different regions. For example, the change in rice cultivation drove water use down in south China but up in northeast China (*SI Appendix, Fig. S7*). During the period P3, the reduced WUI of irrigation and industry totally offset the positive influence of irrigated area expansion and industrial growth on water use trends at national scale (Fig. 3) and in 54% of the prefectures.

**Causes of the Decline in Irrigation WUI.** The reduced irrigation WUI can be linked to the decline in potential irrigation requirement (PIRR) or irrigation water availability (AIRR) (7, 39–42), but also to the improvement in irrigation efficiency (43). We first compared the spatial patterns of observed irrigation WUI trends with PIRR trends simulated by GHM models (*SI Appendix, Fig. S10*). Our results indicate that, in provinces and times of decreasing WUI, PIRR may be the main factor of a decrease of WUI only in the Sichuan Basin and a part of the North China Plain (*SI Appendix, Fig. S10*). We then analyzed the relationship between actual irrigation water consumption ( $IWC = \text{irrigation water} \times \text{consumption-to-withdrawal ratio}$ ) and PIRR at the provincial scale in 1971 to 2013 (*SI Appendix, Fig. S11*), each of which was divided by AIRR following a Budyko-type framework of water consumption (44). AIRR is defined as renewable freshwater minus flood water and water with higher priority than irrigation (*Methods*). We find that AIRR potentially acted as a limiting factor mainly for the drier northern China, where nearly all available irrigation water was actually used (i.e.,  $IWC/AIRR$  stabilizing around one) and irrigated agriculture was over-developed ( $PIRR/AIRR \geq 1$ ). Together, these results hint that improved irrigation efficiency might be the main driver of nationwide decrease in irrigation WUI, and also that emerging limitations of AIRR could play a role in the push for improved irrigation efficiency.

Unfortunately, there is no observation on irrigation efficiency at prefectural level, or even at provincial level for China. To circumvent this problem, we used information of the irrigated area with adoption of water-conserving irrigation (WCI) technology as a proxy for irrigation efficiency. Two elements support this idea: a correlation between irrigation efficiency and WCI in China obtained using diverse sources of data (*SI Appendix, Fig. S12*), and one study based on a long-term survey in north China (1995 to 2007), which showed that technological adoption delivered the benefit of reduced irrigation WUI (45). To disentangle the contributions of PIRR, AIRR, and WCI, we used diagnostic models that were calibrated well at the provincial scale over the period after 1975 (*Methods* and *SI Appendix, Fig. S13A*). The models explained the decreasing irrigation WUI by technological adoption, which is consistent with Huang et al. (45). Studies in other countries, however, suggested an opposite relationship (46, 47), i.e., water-conserving technological adoption leading to an increase in intensive farming and thereby an increase in irrigation WUI. The first reason for inconsistent results could be that intensive farming such as high planting density and more sequential cropping had already been well developed

in many prefectures of China (48). The second reason may be found in the nature of land institution in China (45, 49). Indeed, additional intensification requiring a change in irrigation infrastructure has been difficult to be adopted due to the high fixed costs for small fields (~0.14 ha averaged in China) allocated to farmers (45, 50, 51).

According to our diagnostic models (*Methods*), technological adoption could explain most of the reduced irrigation WUI in China and in many provinces during P3, but not during P2 when WCI was too low to have substantial effect on irrigation water use (9.3% of national irrigated area in 1992) (Fig. 4 *A* and *B*). Other factors that were not explained by the model seem to be nonnegligible (Fig. 4 *A* and *B*), including farmers' behavior (52). Farmers were skilled at adjusting their adaptation behavior in response to the changes in local climate (53), water availability (54, 55), market condition (56), and irrigation subsidies (57), which eventually influence irrigation. Despite these potential effects in China, how and to what extent farmers' behavior can determine irrigation WUI changes still remain elusive and require more investigation.

**Causes of the Decline in Industrial WUI.** Industrial WUI depends on freshwater demand, the amount of water evaporated, and on-site water recycling from each facility. From water balance considerations, we developed another suite of diagnostic models to quantify the contributions from water evaporation and recycling to the decline in industrial WUI during P2 and P3 (*Methods*). Our results suggest that the models were capable of reproducing the interannual variations of WUI in multiple provinces (*SI Appendix, Fig. S13B*). Results in Fig. 4 *C* and *D* indicate that better industrial water recycling accounted for the most of the reduced industrial WUI in both P2 and P3, which generally has offset the positive effects of increased water evaporation.

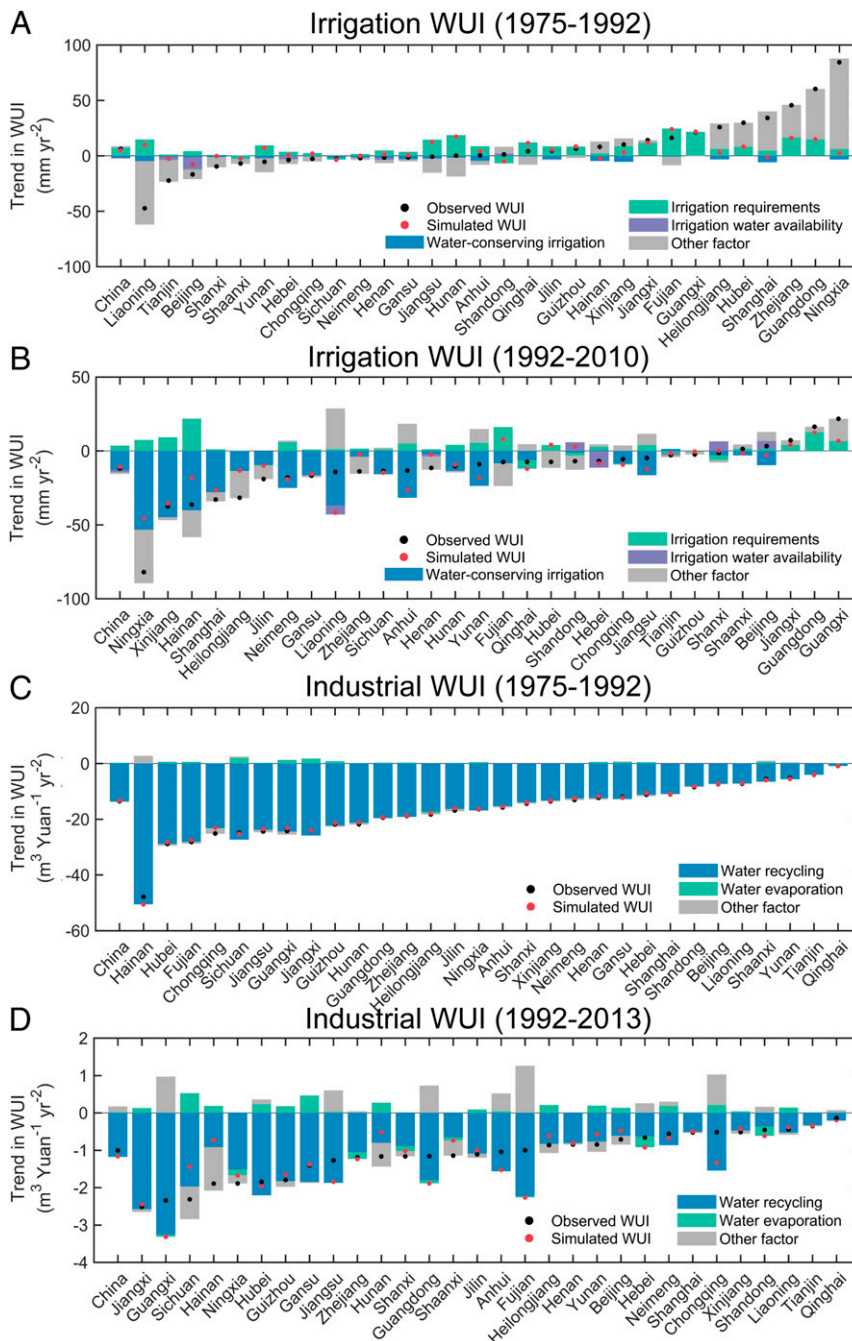
Other factors, such as the changes in the installed capacity and cooling technology type (25), might also contribute to the industrial WUI reduction particularly in the recent two decades (Fig. 4 *C* and *D*). For example, larger thermoelectric power facilities have a lower unit freshwater demand and a lower WUI, mainly due to a higher thermal efficiency (58). Similar results can be found for air- or seawater-cooling technologies that began to be widely used in China since 2008 compared to recirculating cooling (59). However, relevant data were not accessible at the prefectural scale for our study period. We also found that other factors, e.g., the growth of water-intensive products (e.g., food and beverages), were positively correlated to the industrial WUI increase in water-abundant regions (e.g., Guangxi, Guangdong, Fujian, Chongqing, Anhui; Fig. 4 *C* and *D*).

## Discussion

Our study provides evidence of the deceleration of human water use across China and attempts to identify its key drivers. The deceleration was driven by decreased WUIs of irrigation and industry. Without the improvement of WUIs from adoption of WCI technologies and industrial water recycling, China's freshwater withdrawals would have been 1.8 times larger than the actual water use during the period 1975 to 2013.

Technological adoptions came along with policy interventions in China (*SI Appendix, Fig. S14*), although a causal relationship with policies cannot be established. Before 1975, irrigation infrastructure investment was a key priority to increase agricultural production, resulting in an increase of irrigated areas from less than 30 to 43% of all croplands (56). At that time, improvement in demand-side management was not targeted, and irrigation WUI across the nation slightly increased, that is, irrigation became less efficient (*SI Appendix, Fig. S14*). Between 1975 and 1992, industry infrastructure investment boosted GVA by ~13 times and caused a higher water demand. The first water volume quota system imposed in 1986 for more than 200 industrial





**Fig. 4.** Causes of WUI trend in different periods. (A) Irrigation WUI in 1975 to 1992. (B) Irrigation WUI in 1992 to 2010. (C) Industrial WUI in 1975 to 1992. (D) Industrial WUI in 1992 to 2013. Note different order of provinces in x axes. The analyses were conducted for the whole country and for 30 provinces in 1975 to 2010 for irrigation WUI and in 1975 to 2013 for industrial WUI, as the technological adoption data before 1975, irrigation requirement (PIRR) data after 2010, or in Tibet, Hong Kong, Macau, and Taiwan or at the prefectural scale were not accessible.

products (60) incentivized industries to degrade WUI through industrial water recycling, which increased from 25% in 1986 to 42% in 1992 (*SI Appendix, Fig. S14*). In contrast, over the same period, the increase of irrigated areas stagnated or even reversed primarily in south China due to declined investment (56).

Continued water withdrawals became increasingly difficult as marginal cost increase and negative externalities (e.g., water quality deterioration) grew (61). To support faster socioeconomic development and the growing food demand after 1992, many water conservancy measures were taken, including the nationwide integrated agricultural development programs, the construction of large-scale

irrigation districts, and the adoption of a water volume quota system for 193 crops (*SI Appendix, Fig. S14*). These policy interventions pushed the adoption of WCI technologies to increase from 9.3% of cropland areas in 1992 to 51.4% in 2013, leading to the decreased irrigation WUI shown in Fig. 3. For the industrial sector, after 1998, increasing-block tariffs were enforced in most of prefectures (60). Such water-pricing reform, alongside industrial wastewater discharge standards (62), doubled the ratio of industrial water recycling (88% at present; *SI Appendix, Fig. S14*). After 2000, direct caps on water withdrawal and minimum environmental flow requirements have been progressively established in the drier catchments of north

China, e.g., Yellow (63), Heihe (64), and Tarim (65), further limiting total water use.

The growth of China's water use is very likely to continue to slow down, as the latest policy interventions (e.g., the national water conservancy action plan [2019 to 2035]) provide a more stringent constraint to approach a peak of water withdrawal ( $700 \text{ km}^3 \cdot \text{y}^{-1}$  in 2035). However, uncertainties and potential future water scarcity will come from three aspects. First, China's land institution is undergoing a rapid transition toward large-scale farming through the farmland transfer system issued in 2014 (66), alongside the adoption of WCI planned to cover 75% of irrigated area in 2030 (*SI Appendix, Fig. S14*). These ongoing transitions may feedback on farmers to expand irrigated areas or shift to water-intensive crops, which could offset the savings due to future improvement of irrigation efficiency, in line with previous findings in other contexts (46, 47). Such rebound effects occurred in 1992 to 2013 in the Songhuajiang and Heihe Rivers where farm size is approximately three times larger than the national average (*SI Appendix, Fig. S15*). Second, our results indicate that the westward development of the industrial sector has worsened water scarcity in many arid and semiarid regions. High industrial water recycling has already been adopted in these regions (>88%) except in Xinjiang, so that the potential for further water conservation would be limited. Without a stronger enforcement of capping water withdrawal, the industrial sector may become the most important driver continuing to increase water use. Last, China is urbanizing at an unprecedented rate, which promotes economic growth and increases household wealth (13). The increasing per-capita income, alongside generalized tap water accessibility, will stimulate a more water-intensive lifestyle and thereby domestic water use (67). Future policies to underpin water targets in the United Nations Sustainable Development Goals framework will be crucial to address the challenge of decoupling water use from socioeconomic development in China.

The deceleration of water use revealed by our dataset partly challenges the results from GHMs. The multi-GHM ensemble from ISIMIP suggests an acceleration of total water use across China over the period 1971 to 2010 (*SI Appendix, Fig. S16A*). This ensemble also does not reproduce the observed spatial pattern of water use trends across China (*SI Appendix, Fig. S16B–G*). One reason for this bias may be that technological change factors were prescribed as temporally or spatially constant (9, 43) without consideration of policy interventions and actual technological adoption. Another limitation of GHM is that socioeconomic activities data used to drive them over China were simply disaggregated from national-scale statistics (7, 9). To improve model drivers, the survey-based reconstruction dataset of water use presented in this study is valuable, and should be extended to other regions. The empirical linkages between WUI changes and technological adoptions identified in this study may be also used for designing more realistic future water withdrawal scenarios (8, 19), with the ultimate goal to improve GHMs for assessing water use targets and water scarcity mitigation (12). Future work to quantify technological change factors triggered by ongoing policies is needed to help reduce the uncertainty of water use projections. In addition to modeling future water use from the demand side, integrating supply and demand to represent the feedbacks of emerging water scarcity on future investments in water-demanding sectors should be attempted by coupling GHMs with economic models.

## Materials and Methods

**Definitions.** The definition of human water use in this study is in line with that from Food and Agriculture Organization AQUASTAT. Water use is the annual quantity of water withdrawn from surface or groundwater resources for the irrigation, industrial, urban, and rural water use sectors (17). This definition is consistent with the nationally coordinated surveys of water use in China (33). 1) Irrigation water use is the annual quantity of water withdrawn for irrigation including the losses during conveyance and field application, but it

does not include water used for irrigated pasture or aquaculture. 2) Industrial water use is the annual quantity of water withdrawn for industrial purposes, including self-supplied industries and industries connected to the public supply network. 3) Urban water use is the annual quantity of water withdrawn by the public supply network for the direct use of urban residents, including urban domestic water use and water use for the service sector, but it does not include in-stream uses such as recreation, navigation, or inland fisheries. 4) Rural water use is the annual quantity of water withdrawn by the public supply network for the direct use of rural residents, including rural domestic water use and water use for livestock drinking and cleaning.

The size effects refer to the production, GVA, population, or quantity of socioeconomic activity that consumes water withdrawn from surface or groundwater resources. In this study, "size indicators" correspond to five types of socioeconomic activity: 1) irrigated area is the area of cropland under irrigation; 2) GVA of industrial or service sectors is the value of outputs minus the value of intermediate consumptions in monetary value at constant 2010 China yuan (CNY) prices; 3) urban population is the population living in urban regions, including urban residents registered with an urban residential permit ("hukou") and rural residents who have migrated to urban regions regardless of whether or not they have obtained an urban hukou (68); 4) rural population is the population living in rural regions; 5) livestock commodity calories are defined as the product of livestock population, animal-specific average weight per head, and animal-specific energy content per fresh weight produced, with coefficients obtained from Bennetzen et al. (69).

WUI is defined as water use per unit of size indicator. 1) Irrigation WUI is defined as water use per unit of irrigated area for each type of crop. 2) Industrial WUI is defined as water use per unit of GVA of products for each type of industry. 3) Service WUI is defined as the water use per unit of GVA of service activities, and it is grouped under urban domestic sector. 4) Livestock WUI is defined as water use per unit of livestock commodity calories produced, and it is grouped under the rural domestic sector. 5) The rest of urban WUI and of rural WUI, mainly water used by households, are defined as water use per capita of urban and rural population, respectively. These definitions of WUI are consistent with previous studies (7, 23), except for thermoelectric power industry when WUI is defined as water use per unit of electricity production (23). However, prefectural-scale data of electricity production are unavailable for the study period.

The structure effect is defined as the combined effect of the different economic activities, such as crop mix (i.e., each crop's proportion of the total irrigated area) and industrial structure [i.e., each industry's proportion of total industrial GVA (70)].

**Datasets.** To evaluate the drivers of regional water use trends, we reconstructed a new National Long-term Water Use Dataset of China (NLWUD). The NLWUD includes water use and related size indicators used to calculate WUI for the four sectors in 341 prefectures during the period 1965 to 2013. The definition and distribution of prefectures can be found in *SI Appendix, Method S1 and Fig. S1*. In addition, irrigation data were further separated into five crop types (wheat, maize, rice, vegetables and fruits, and other crops), and industrial data were separated into 11 subsectors (thermal electricity, mining, cement, electronics, machinery, metallurgy, petrochemicals, textile, paper making, food processing, and other industries). See *SI Appendix, Table S2* for the classification of crop types and industrial subsectors. The data for urban and rural sectors are separated into four subsectors, namely, urban households (mainly drinking, washing, and sanitation water) and the tertiary service subsector part of the urban sector, rural households and livestock production subsector part of the rural sector.

The data of water use by subsector and prefecture were obtained from two nationally coordinated surveys: the first and second National Water Resources Assessment Programs for the period 1965 to 2000 and the Water Resources Bulletins of 31 provinces for the rest of the period 2001 to 2013. Both of these surveys were led by the Ministry of Water Resources and had an identical survey methodology including definition, survey unit, sector classification, field survey or measurements, and quality assurance. See detailed survey methodology in *SI Appendix, Method S2*. China experienced an extensive shift of prefectural boundaries during the past five decades, and these changes have resulted in discontinuities in the spatial data. We therefore harmonized the temporal evolution of water use to the 2013 administrative map of China, based on the history of boundary and name changes given by the Ministry of Civil Affairs of China. The detailed information of the harmonization process can be found in *SI Appendix, Method S3*.

The data related to size indicators were acquired mainly from the other nationally coordinated surveys or databases. First, urban and rural populations

by prefecture were obtained from the dataset of "geospatial distribution of population in China" for the period 1980 to 2013, and extended to the rest of the period 1965 to 1979 using a regression approach (68). Second, industrial GVA by subsector and prefecture were obtained from the China Industry Economy Yearbook covering the period 1965 to 2013, led by the National Bureau of Statistics. We adjusted the GVA to remove the effect of inflation and expressed the value at 2010 prices. Third, the other prefectural-scale data such as irrigation area by crop, GVA of service sector (constant 2010 CNY), and livestock population by animal were obtained from the statistical yearbooks of China's 31 provinces, given by the provincial statistics registers. Finally, WUIs were calculated for each of the subsectors and prefectures. It should be noted that the reconstructed datasets contain some uncertainties but should not affect our findings unduly. More detailed discussion can be found in *SI Appendix, Method S4*.

**Trend Analysis.** We apply piecewise linear regression to detect where the slope of a linear function changes, and to fit multiple linear models to each section of the water use (WU) time series. For a time series of WU, a continuous piecewise linear regression model with multiple turning points ( $Y_i$ ) can be described as follows:

$$WU = \begin{cases} \alpha_0 + \alpha_1 t + \varepsilon, & t \leq Y_1 \\ \alpha_0 + \alpha_1 t + \sum_{i=1}^{l-1} \alpha_{i+1} (t - Y_i) + \varepsilon, & t \in (Y_i, Y_{i+1}] \\ \alpha_0 + \alpha_1 t + \sum_{i=1}^l \alpha_{i+1} (t - Y_i) + \varepsilon, & t > Y_l \end{cases}, \quad [1]$$

where  $t$  is year,  $\alpha_0$ ,  $\alpha_1$ , and  $\alpha_{i+1}$  are regression coefficients, and  $\varepsilon$  is the residual of the regression. The slope of water use is  $\alpha_1$  before the year  $Y_1$ ,  $\sum_{i=1}^l \alpha_i$  with the period from  $Y_i$  to  $Y_{i+1}$ , and  $\sum_{i=1}^{l+1} \alpha_i$  after the  $Y_l$ . Least-squares error technique is applied to fit the model to the observations to determine  $Y_i$  and  $\alpha_i$  ( $i = 0$  to  $l + 1$ ). To avoid linear regression in a period with too few years, we confine each period to be not less than a decade. The necessity of introducing turning points is tested statistically with the  $t$  test under the null hypothesis that  $\alpha_i$  ( $i = 2$  to  $l + 1$ ) are not different from zero. The diagnostic statistics for the regression also include the goodness-of-fit ( $R^2$ ), the  $P$  value for the whole model, and the  $P$  values for the trends of each section. We consider  $P < 0.01$  as significant. Finally, two turning points (i.e., 1975 and 1992) were detected national water use.

**Decomposition Analysis.** We apply the LMDI (36, 69, 70) in our decomposition analysis. The LMDI analysis compares a set of socioeconomic drivers between the base and final year of a given period (i.e., before 1975, between 1975 and 1992, and after 1992), and explores the effects of these drivers on the change in water use by sector and prefecture. It is important to note that the approach does not allow one to immediately understand the mechanisms at work, as it is a decomposition of effects (also referred to as "driving" factors), and not a causal model. However, the quantification of the effects is an important step toward modeling and projections of water use.

Few studies have applied the LMDI to water-related analysis (25, 71). There are many ways to decompose sectoral water use for different purposes. See *SI Appendix, Method S5* for the detailed description and justification of the decomposition forms (23, 25, 72). We decompose water use at national or prefectural scale as follows:

$$WU = \sum_i \sum_j (WU_{ij}), \quad [2a]$$

where

$$WU_1 = \sum_j \left( A \times \frac{A_j}{A} \times \frac{WU_{1j}}{A_j} \right) = \sum_j A \times a_j \times u_{1j}, \quad [2b]$$

$$WU_2 = \sum_j \left( P \times \frac{P_j}{P} \times \frac{WU_{2j}}{P_j} \right) = \sum_j P \times p_j \times u_{2j}, \quad [2c]$$

$$WU_3 = \sum_j \left( T_j \times \frac{WU_{3j}}{T_j} \right) = \sum_j T_j \times u_{3j}, \quad [2d]$$

$$WU_4 = \sum_j \left( L_j \times \frac{WU_{4j}}{L_j} \right) = \sum_j L_j \times u_{4j}, \quad [2e]$$

and  $WU_{ij}$  is water use in subsector  $j$  of sector  $i$ . Sectors  $i = 1$  to 4 correspond

to irrigation, industrial, urban, and rural sectors, respectively.  $A_j$  is the irrigated area for crop  $j$ , where  $j = 1$  to 5 represents different types of crop.  $P_j$  is the industrial GVA of subsector  $j$ , where  $j = 1$  to 11 represents different industries. According to Eq. 2b, irrigation water use is decomposed into three factors: total irrigated area  $A$ , proportion of each of the five crops in total irrigated area to measure crop mix effects  $a_j = A_j/A$ , and  $u_{1j} = WU_{1j}/A_j$ , the irrigation WUI of crop  $j$ , representing the water used per unit of irrigated area. According to Eq. 2c, industrial water use is also decomposed into three factors: the total industrial GVA  $P$ , the proportion of each of the 11 industries to total industrial GVA to represent the industrial structure effects  $p_j = P_j/P$ , and the industrial WUI of subsector  $u_{2j} = WU_{2j}/P_j$  that is equal to the water withdrawal per inflation-adjusted unit of industrial GVA. According to Eq. 2d, urban water use is decomposed into two factors for each of the subsectors:  $T_j$  corresponds to urban population for  $j = 1$  and GVA of service activities for  $j = 2$  and  $u_{3j} = WU_{3j}/T_j$  is urban WUI, equal to the water withdrawn per capita of the urban population or per inflation-adjusted unit of service activities GVA. According to Eq. 2e, rural water use is decomposed into two factors for each of the subsectors:  $L_j$  refers to the rural population for  $j = 1$  and to livestock population (measured as livestock commodity calories summed from seven types of animal [i.e., swine, sheep, poultry, cattle, donkeys, horses, and mules]) for  $j = 2$  and  $u_{4j} = WU_{4j}/L_j$  is the rural WUI, equal to the water used per capita of rural population or per unit of livestock commodity calories.

Using the LMDI decomposition, the change of water use of sector  $i$  in the year  $t$  compared to the year  $t - 1$  is computed as follows:

$$\Delta WU = WU^t - WU^{t-1} = \sum_i \Delta WU_i, \quad [3a]$$

where

$$\Delta WU_1 = \sum_j w_{1j} \ln \left( \frac{A^t}{A^{t-1}} \right) + \sum_j w_{1j} \ln \left( \frac{a_j^t}{a_j^{t-1}} \right) + \sum_j w_{1j} \ln \left( \frac{u_{1j}^t}{u_{1j}^{t-1}} \right) \quad [3b]$$

$$= \Delta WU_A + \Delta WU_a + \Delta WU_{u1},$$

$$\Delta WU_2 = \sum_j w_{2j} \ln \left( \frac{P^t}{P^{t-1}} \right) + \sum_j w_{2j} \ln \left( \frac{p_j^t}{p_j^{t-1}} \right) + \sum_j w_{2j} \ln \left( \frac{u_{2j}^t}{u_{2j}^{t-1}} \right) \quad [3c]$$

$$= \Delta WU_P + \Delta WU_p + \Delta WU_{u2},$$

$$\Delta WU_3 = w_{3,1} \ln \left( \frac{T_1^t}{T_1^{t-1}} \right) + w_{3,2} \ln \left( \frac{T_2^t}{T_2^{t-1}} \right) + w_{3,1} \ln \left( \frac{u_{3,1}^t}{u_{3,1}^{t-1}} \right) + w_{3,2} \ln \left( \frac{u_{3,2}^t}{u_{3,2}^{t-1}} \right) \\ = \Delta WU_{T1} + \Delta WU_{T2} + \Delta WU_{u3,1} + \Delta WU_{u3,2}, \quad [3d]$$

$$\Delta WU_4 = w_{4,1} \ln \left( \frac{L_1^t}{L_1^{t-1}} \right) + w_{4,2} \ln \left( \frac{L_2^t}{L_2^{t-1}} \right) + w_{4,1} \ln \left( \frac{u_{4,1}^t}{u_{4,1}^{t-1}} \right) + w_{4,2} \ln \left( \frac{u_{4,2}^t}{u_{4,2}^{t-1}} \right) \\ = \Delta WU_{L1} + \Delta WU_{L2} + \Delta WU_{u4,1} + \Delta WU_{u4,2}, \quad [3e]$$

and  $w_{ij} = (WU_{ij}^t - WU_{ij}^{t-1}) / (\ln WU_{ij}^t - \ln WU_{ij}^{t-1})$  is a weighting factor called the logarithmic mean weight (36).  $\Delta WU_A$ ,  $\Delta WU_a$ ,  $\Delta WU_{u1}$ ,  $\Delta WU_P$ ,  $\Delta WU_p$ ,  $\Delta WU_{u2}$ ,  $\Delta WU_{T1}$ ,  $\Delta WU_{T2}$ ,  $\Delta WU_{u3,1}$ ,  $\Delta WU_{u3,2}$ ,  $\Delta WU_{L1}$ ,  $\Delta WU_{L2}$ ,  $\Delta WU_{u4,1}$ , and  $\Delta WU_{u4,2}$  are WU changes corresponding to change in irrigation area, shift in crop mix, change in irrigation WUI, change in industrial GVA, shift in industrial structure, change in industrial WUI, change in urban population, change in GVA of service activities, change in urban domestic WUI, change in service sector WUI, change in rural population, change in livestock population, change in rural WUI, and change in livestock WUI, respectively.

**Contribution Analysis.** Following the experiences from the GHMs (7, 39–42), we first developed diagnostic models to identify different driving factors for the interannual variations in WUIs of irrigation and industry. These analyses were conducted for the whole country and for 30 provinces in 1975 to 2010 for irrigation WUI and in 1975 to 2013 for industrial WUI, as the technological adoption data before 1975, PIRR data after 2010, or in Tibet, Hong Kong, Macau, and Taiwan or at the prefectural scale were not accessible. We then used least-squares error technique to fit the model to the whole time series considering the total variances. Finally, we conducted scenario simulations using the models to isolate the contributions of changes in different driving factors to WUI trends. The first scenario is a control simulation with all driving factors varied over study periods. The second scenario is a simulation with each of technological change factors fixed at the starting year levels (i.e., 1975 and 1992).



Irrigation WUI is modeled as the ratio of PIRR to irrigation efficiency (IE), limited by freshwater availability allocated to irrigation sector (AIRR) as well (9, 43, 72, 73):

$$WUI = \min\left\{\frac{PIRR}{IE}, AIRR\right\}, \quad [4a]$$

where

$$AIRR = RFR(1 - \eta) - (u_2 + u_3), \quad [4b]$$

$$1/IE = a \cdot WCI + b, \quad [4c]$$

and PIRR is derived from an ensemble of six GHMs (i.e., DBH, H08, LPJmL, PCR-GLOBWB, WaterGAP2, VIC) of ISIMIP (7, 39–42). AIRR is defined as renewable freshwater resources (local, upstream import, and transboundary transfer; RFR) minus both of flood water ( $\eta \cdot RFR$ ) and industrial and domestic water uses ( $u_2 + u_3$ ), because flood water is unavailable for human use and  $u_2 + u_3$  have a high supply reliability (e.g., >95%). Data of RFR,  $\eta$ ,  $u_2$ , and  $u_3$  are obtained from the first and second National Water Resources Assessment Programs. IE is more difficult to quantify over time and space (74, 75). WCI, defined as the ratio between the area equipped for WCI and total irrigated area, was taken as a proxy for the variation of IE, as IE is correlated with WCI at the national level (SI Appendix, Fig. S12). Even if the relationship is only a correlation, and not a causality, we can still use the relationship to determine the irrigation efficiency corresponding to a given level of WCI. Data for WCI were obtained from the China Water Conservancy Yearbook and the China Statistics Yearbook.

Industrial WUI can be described by a simple water balance model, assuming that demand is always satisfied, that evaporation happens before recycling, and that recycling repeats finitely for the whole productive process. We note  $WU_2$ , the quantity of freshwater withdrawn for industries. A part is evaporated ( $\nu$ ), a part is recycled ( $\tau$ ), and the evaporation and recycling processes are repeated  $N$  times ( $>1$ ). Freshwater demand ( $D$ ) is the sum of first water withdrawal and multiple recycled water inputs, i.e.,  $D = WU_2 \cdot \sum_{n=0}^N [(1 - \nu)\tau]^n$ . The summation can be simply rewritten as  $[1 - (1 - \nu)\tau]^{-1} - \beta$  according to the

mathematics of geometric series, because the absolute value of  $(1 - \nu)\tau$  is much smaller than 1. Thus, industrial WUI ( $=WU_2/GVA$ ) is then derived as follows:

$$WUI = \frac{D}{GVA} \cdot \frac{1}{[1 - (1 - \nu)\tau]^{-1} - \beta}, \quad [5]$$

where  $D/GVA$  is per unit freshwater demand and  $\beta$  is a constant to be calibrated. Data for  $\nu$  and  $\tau$  for different provinces during 1975 to 2013 were obtained from the China Urban Construction Statistics Yearbook, but data for  $D/GVA$ , whose effect is represented within model residual, is not publicly available.

**Data Availability.** All data generated or analyzed during this study, including NLWUD dataset, GIS files, and codes used in data analysis/figure creation, are publicly available online at [https://figshare.com/articles/Zhou\\_et\\_al\\_2020\\_PNAS\\_dataset\\_xlsx/11545176](https://figshare.com/articles/Zhou_et_al_2020_PNAS_dataset_xlsx/11545176). Simulated data of PIRR (as “pirrww”) under “historical” scenario, actual irrigation water use (as “airrww”), industrial water use (as “amanww”), and domestic water use (as “adomww”) in 1971 to 2010 are available in the ISIMIP2a at <https://www.isimip.org/gettingstarted/data-access/>. The programs used to generate all of the results are MATLAB (R2016b) and ArcGIS (10.4).

**ACKNOWLEDGMENTS.** We acknowledge the editors and three anonymous reviewers for improving the manuscript. This study was supported by the National Natural Science Foundation of China (Grant 41561134016) and the National Key Research and Development Program of China (Grant 2016YFD0800501). P. Ciais, C. Ottle, P. Dumas, and J. Polcher acknowledge the support from the CHINA-TREND-STREAM French national project (Grant ANR-15-CE01-011) and the “Investissements d’avenir” program (Grant ANR-16-CONV-0003 [CLAND]). J.L. acknowledges support from the National Natural Science Foundation of China (Grant 41625001). Q. Tang acknowledges support from the National Natural Science Foundation of China (Grant 41730645). We acknowledge the Ministry of Water Resources and the National Bureau of Statistics, who are responsible for the long-term water use and socioeconomic activity datasets, respectively. We also acknowledge the ISIMIP, which provides GHM modeling results.

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