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Assessment of ecological water scarcity in China

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Abstract
The increasing water use for human activities is threatening the health of ecosystems. Most previous studies on water scarcity mainly centered on human society. In this study, we developed a new indicator, ecological water scarcity (WS\textsubscript{eco}), that considers water quantity, water quality, and environmental flow requirements. WS\textsubscript{eco} was assessed at the provincial level in China. The results show that northern China suffered more severe WS\textsubscript{eco} than southern China. In addition, the WS\textsubscript{eco} level decreased in 65% of provinces from 2016 to 2019, implying the great achievement of China’s effort in saving water and reducing pollution. The main driving factor of WS\textsubscript{eco} in most provinces was pollution rather than human water use. The findings of this study demonstrate the spatial distribution, temporal dynamics, and driving factors of WS\textsubscript{eco} in China. The results can be used to guide efforts for ecological restoration and sustainable water management in different regions.

1. Introduction

Water resources are fundamental for human beings and the environment as sufficient water supply is essential for the development of societies and health of ecosystems (Cai et al 2021, WWAP 2015, Vörösmarty et al 2018). However, with the rapid development of societies, the global water demand has increased by approximately 600% over the past 100 years (Boretti and Rosa 2019). The growing population and corresponding increase in the water demand have led to water scarcity, which has become a global issue (Mekonnen and Hoekstra 2016). This situation is prominent in China owing to the uneven geographic distribution of water resources (Du et al 2022, Wang et al 2017, Li and Qian 2018). Moreover, the over-exploitation of water resources for economic development has significantly impacted the environment (Cosgrove and Loucks 2013, Sun et al 2016).

The water demand of ecosystems should be considered when the water scarcity of a region is assessed. Alcamo and Henrichs (2002) evaluated global water scarcity using criticality ratio, which accounts for the environmental flow requirements (EFR). EFR refers to the minimum quantity and quality of water discharge that are required to maintain sustainable and functional ecosystems (Pastor et al 2014, Virkki et al 2022). Severe water stress occurs when the criticality ratio is >40%. However, the use of 40% as a threshold does not accurately reflect the different natural conditions across regions. Liu et al (2016) developed a quantity–quality-EFR water scarcity assessment framework. Based on the framework, Ma et al (2020a) conducted a national scale assessment of water scarcity with high resolution; however, the heterogeneity of environmental water demand was not accounted for, and a simple but not scientific rule was used by assuming 80% of water resources are for EFR. Although researchers have started to consider regional temporal-spatial differences in EFR, they mostly focus on water scarcity assessment at small scales (Liu et al 2016, Van Vliet et al 2017) and rarely focus on the quantification of ecological water scarcity (WS\textsubscript{eco}). Also, most previous studies ignored the water quality relevant EFR, which lead to the gap of estimation regarding water quantity and quality required by ecosystems (Quinteiro et al 2018, Liu and Zhao 2020). Liu and Zhao (2020) for the first time introduced the
concept of 3-Dimensional water scarcity and explicitly defined ecological water scarcity. However, so far, no method has been developed to assess ecological water scarcity.

In the present study, we established an indicator to quantify the ecological water scarcity in China from 2016 to 2019 at the provincial level. Moreover, we accounted for the quality and quantity heterogeneity of regional EFR. Finally, we assessed the temporal variation of WS\textsubSCRI{eco} in 2016–2019 and the impacts of human water use and pollution on WS\textsubSCRI{eco}. We also highlighted the impacts of the South–North Water Transfer Project (SNWTP) on WS\textsubSCRI{eco}. The findings of the present study can help identify the regions suffer from ecological water scarcity and the hotspots for ecological restoration and conservation.

2. Methods and data

2.1. Ecological water scarcity indicator

WS\textsubSCRI{eco} describes an unsustainable state in which the spatial and temporal distribution of the water quantity and quality cannot meet the ecological needs of the region. The insufficient water supply for ecosystems is mainly resulted from precipitation deficit, water overuse and pollution. The WS\textsubSCRI{eco} indicator was calculated as follows:

\[ WS_{\text{eco}} = 1 - \frac{Q}{e} = 1 - \frac{BWR - BWF - GWF}{e} \]

\[ = \frac{GWF + BWF - BWA}{e} \]  \hspace{1cm} (1)

\[ BWA = BWR - e \]  \hspace{1cm} (2)

where \( e \) (m\(^3\) yr\(^{-1}\)) is the water demand for ecosystems to maintain a healthy status; \( Q \) (m\(^3\) yr\(^{-1}\)) is the water supply for ecosystems; BWF (m\(^3\) yr\(^{-1}\)) is the blue water footprint, which equivalents to blue water consumption (Hoekstra et al. 2011); GWF (m\(^3\) yr\(^{-1}\)) is the gray water footprint and represents water pollution produced by human activities; BWR (m\(^3\) yr\(^{-1}\)) is the blue water resources; and BWA (m\(^3\) yr\(^{-1}\)) is the blue water availability.

Considering GWF = \( \max \) (GWF\(_{ij}\)):  \hspace{1cm} (3)

\[ GWF_{ij} = \frac{L_i}{C_{\text{max},i} - C_{\text{nat},i}} \]

where GWF (m\(^3\) yr\(^{-1}\)) is the amount of freshwater required to dilute pollutants; GWF\(_{ij}\) (m\(^3\) yr\(^{-1}\)) is the volume of dilution water for pollutant \( i \); \( L_i \) (kg yr\(^{-1}\)) is the load of pollutant \( i \); \( C_{\text{max},i} \) (mg l\(^{-1}\)) is the ambient water quality standard for pollutant \( i \); and \( C_{\text{nat},i} \) (mg l\(^{-1}\)) is the natural background concentration of pollutant \( i \).

When WS\textsubSCRI{eco} is larger than 0, it means water supply for ecosystems is less than \( e \), suggesting that the ecological water scarcity exists, while when WS\textsubSCRI{eco} equals to 1, it means the water supply for ecosystems equals to 0, indicating that there is no qualified water left for ecosystem. Based on the above analysis and previous studies (Liu and Zhao 2020, Ma et al. 2020a), subjectively, WS\textsubSCRI{eco} was classified into four levels: low (<0), moderate (0–0.5), significant (0.5–1.0), and severe (>1.0).

2.2. Data collection

We obtained water consumption data, blue water resources for each province from water resource bulletin (Ministry of Water Resources of China 2017, 2018, 2019, National Bureau of Statistics of China 2020) to calculate BWF and BWR. We got the pollutant loads of each province from China’s Environmental Statistical Yearbooks (National Bureau of Statistics of China 2017, 2018, 2019, 2020), including total nitrogen (TN), total phosphorus (TP), ammonia-nitrogen (NH\(_3\)-N), and chemical oxygen demand (COD). We collected all the datasets from 2016–2019 because (a) the accounting methods of pollutant load data published by the National Bureau of Statistics of China are different before 2016 and afterwards, (b) the influence of human activities is significant during this period due to the implementation of SNWTP project and the management of pollutant discharge.

Water quality requirements to calculate GWF were based on the Environmental Quality Standards for Surface Water of China (Ministry of Environmental Protection of China 2003). We selected Grade III as the ambient water quality standard because this standard meets the requirement for aquatic species, aquaculture, and swimming. The grades higher than III indicate poor water quality. According to Grade III, the ambient water quality standard (\( C_{\text{max}} \)) of COD, NH\(_3\)-N, TN, and TP was estimated as 20, 1, 1, and 0.2 mg l\(^{-1}\), respectively. Following Hoekstra et al. (2011), we assumed the natural background concentration (\( C_{\text{nat}} \)) = 0 because the lack of concentration data for above pollutants. This simplified method may cause the underestimation of GWF, however, it will not largely influence the results (Liu et al. 2016).

To evaluate \( e \), we obtained simulated discharge data (0.5–degree resolution grid) from the Inter-Sectoral Impact Model Intercomparison Project 2b (Frieler et al. 2017). We used pre-industrial (1801–1860) discharge data (Virkki et al. 2022) to represent the natural flows (Richter et al. 2003) because the data represent a period during which the environment was not substantially altered by human activities. To control the uncertainties using single global hydrological model (GHM) with single general circulation model (GCM) (Liu et al. 2017b), we obtained 16 datasets from four different GHMs including H08 (Hanasaki et al. 2018), LPJmL (Sitch et al. 2003), PCRaster global water balance (PCR-GLOBWB) (Sutanudjaja et al. 2018), and Water – Global Assessment and Prognosis (WaterGAP2) (Schmied et al. 2016). Each GHM is forced using meteorological data from four GCMs (GFDL-ESM2M, HadGEM2-ES,...
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IPSLS-CM5A-LR, and MIROC5) and the climate drivers were all extracted from the Coupled Model Intercomparison Project Phase 5.

2.3. Calculation of e

\[ e = P\% \times \text{BWR} \]  
\[ P\% = \frac{\text{EFR}}{\text{MAF}} \]

\( e \) (m\(^3\) yr\(^{-1}\)) is calculated as \( P\% \) of BWR (m\(^3\) yr\(^{-1}\)), which means water demand for ecosystems accounts for \( P\% \) of BWR. \( P\% \) is the proportion of annual EFR (m\(^3\) s\(^{-1}\)) in mean annual flow (MAF (m\(^3\) s\(^{-1}\))), and it represents the percentage of the minimum flow requirement to maintain functional ecosystems in annual flow. Based on the equations above, we firstly calculated the EFR and it dived into three steps as followed in figure 1.

For the first step, we converted the 0.5-degree grid-scale daily discharge data to second-order basin-scale monthly discharge data and 0.5-degree grid-scale annual discharge data. It is worth noting that in China, there are 80 s-order basins and were divided based on primary tributaries of the major rivers in ten first-order river basins. We selected the second-order basin-scale because it is the highest level of river network that can be rasterized into 0.5-degree resolution grid. Secondly, for the second-order basin-scale discharge dataset, we used five methods, namely the Tennant method (Tennant 1976), Tessmann method (Tessmann 1980), Smakhtin method (Smakhtin et al 2004), variable monthly flow method (Pastor et al 2014), and the Q90/Q50 method (Pastor et al 2014) to calculate the EFRs. For the Tennant method, the ecological status was divided into eight classifications and we selected the standard required to maintain a ‘good’ level of habitat quality, which was the minimum flow required to sustain a healthy ecosystem. This is consistent with the ecological goal of the other four methods. We transformed the median of 80 results from monthly to annual and calculated the mean annual discharge in 60 years. Additionally, we calculated discharge weight of each grid in the province according to grid-scale mean annual discharge data. Finally, we transformed annual EFRs from second-order basin scale to provincial scale according to the discharge weight.

We calculated MAF at provincial scale based on the same methods as calculating EFR. Then, we obtained the \( P\% \) of each province according to equation (5). The minimum and maximum \( P\% \) of each province was 21% and 43%, respectively. The results of \( P\% \) are much less than the percentage of common used for evaluating water demand for ecosystems in water scarcity assessment (Hoekstra et al 2012, Ma et al 2020a), which may result from using hydrological methods to take flow regime into consideration in EFR calculation; while it is similar to Liu et al (2016), \( P\% \) was assumed as 26% in Huangqihai River Basin of Neimeng province in
China, which may be due to the use of Tennant method in both studies. Based on the results, $e$ was calculated using equation (4).

2.4. Smooth the climate variability

Human activities and climate variability both can affect $W_{\text{eco}}$. To understand the impact of human water use and pollution on $W_{\text{eco}}$, we need to smooth the impact of climate variability. Therefore, instead of using BWR of a specific year, we used the four-year average BWR to calculate $W_{\text{eco}}$ in different years. The method of controlling variables can ensure the BWR is consistent under different BWF and GWF changes. The regions where $W_{\text{eco}}$ changes were mostly attributed to GWF changes. The areas where $W_{\text{eco}}$ increased between 2016 and 2019 of the provinces (figure 3(c)). Heilongjiang presented the most significant decline (−12%) and Guizhou presented the most significant increase (31%). The BWF decreased, remained nearly unchanged, and increased in 39%, 22%, and 39% of the provinces (figure 3(e)). Shanghai presented the most significant decline (−29%) and Guizhou presented the most significant increase (15%). Comparing figures 3(c)–(e), the areas where $W_{\text{eco}}$ decreased, evident GWF decline was observed, whereas BWF changes presented minor impacts on $W_{\text{eco}}$. This might have occurred because GWF was substantially larger than BWF in most areas. Therefore, $W_{\text{eco}}$ changes were mostly attributed to GWF changes. The regions where $W_{\text{eco}}$ declined in figure 3(c) nearly all suffered from $W_{\text{eco}}$ in figure 2, which indicates that $W_{\text{eco}}$ improved in $W_{\text{eco}}$ regions. Conversely, although Guizhou was under low $W_{\text{eco}}$ in 2016–2019, its GWF and BWF increased between 2016 and 2019.

3.4. Impacts of the SNWTP on $W_{\text{eco}}$

To alleviate the water shortage in the north, the well-known SNWTP plans to deliver 44.3 billion m$^3$ of water annually from the south to the arid north through three routes: the Middle, Eastern, and Western Routes (Webber et al 2017). However, the Western Route have not been implemented yet, so in this study, we discussed the impacts of the Middle Route and the Eastern Route.

In the Middle Route, water-receiving areas included Henan, Hebei, Tianjin, and Beijing, whereas the water-supply area Hubei is. In the Eastern Route, water-receiving area is Shandong, and Jiangsu is the water-supply area. In all water-receiving areas, GWF was substantially larger than BWA, and BWF was larger than BWA in some years (figure 4). Therefore, the $W_{\text{eco}}$ in these regions was affected by both the scare BWA and severe pollution. For water-supply...
Figure 2. Average ecological water scarcity ($W_{eco}$) at the provincial level in 2016–2019.

areas, BWF was substantially less than BWA while GWF was relatively large. Jiangsu was under severe $W_{eco}$ in 2016–2019, and Hubei was under severe $W_{eco}$ in 2019 due to the climate-induced decrease in BWA.

The SNWTP played an important role in mitigating water pressure in water-receiving areas, especially in Tianjin and Beijing (figure 5(a)). In 2019, the total BWR in Tianjin was 2.1 billion m$^3$, of which 1.3 billion m$^3$ was attributed from the SNWTP (Ministry of Water Resources of China 2020). Furthermore, the water supplied from Hubei and Jiangsu to the SNWTP gradually increased (figure 5(b)). Figures 5(c) and (d) show the impacts of SNWTP on the $W_{eco}$ of the above areas and $W_{eco}^*$ is the $W_{eco}$ excluding SNWTP. As shown in figure 5(c), SNWTP significantly affected the $W_{eco}$ reduction in some receiving areas, especially in Tianjin and Beijing, where the average $W_{eco}$ decreased by 21.6 and 9.0 compared with the average $W_{eco}$, respectively, while in Shandong and Henan, the $W_{eco}$ decrease was not obvious. In dry years (figure 5(a)), the decline in water resources led to a more significant impact of the SNWTP on $W_{eco}$, especially in Tianjin in 2019, where $W_{eco}$ decreased by 42.1 compared with $W_{eco}^*$ (figure 5(c)). In contrast, the average $W_{eco}$ increase was only 0.1 in water supply areas (figure 5(d)).

4. Discussion

4.1 Assessment of ecological water scarcity and driving factors in China

As is shown in table 1, large value of GWF and insufficient BWR (compared to BWF) were the two main issues that leads to $W_{eco}$. For example, in Ningxia, GWF and BWF were much larger than BWA, leading to severe $W_{eco}$. The highest BWF and GWF occurred in Xinjiang and Guangdong, respectively, while the lowest BWF and GWF was in Shanghai and Xizang, respectively. According to table 1, $W_{eco}$ can be summarized into four types (table 2).

Areas under Type 1 included Hebei and Ningxia; and they were under severe $W_{eco}$. Their BWF and GWF were both substantially larger than their BWA. Therefore, water-saving measures and pollution control are crucial to mitigate $W_{eco}$ in those areas.

Type 2 comprised Xinjiang and Neimeng, and the $W_{eco}$ of them was significant and moderate, respectively. The sum of BWF and GWF were both substantially larger than their BWA. Therefore, water-saving measures and pollution control are crucial to mitigate $W_{eco}$, especially in Tianjin in 2019, where $W_{eco}$ decreased by 42.1 compared with $W_{eco}^*$ (figure 5(c)). In contrast, the average $W_{eco}$ increase was only 0.1 in water supply areas (figure 5(d)).

Therefore, these provinces should focus on reducing water consumption and pollution from the agricultural sector.
Figure 3. Temporal changes in 2016–2019: (a) $W_{eco}$ at the provincial level. (b) $W_{eco}$ changes between 2016 and 2019, and (c) $W_{eco}$ changes using four-year average BWR. (d) BWF change ratio between 2016 and 2019, and (e) GWF change ratio.

Most provinces suffering from $W_{eco}$ were classified into Type 3, such as in Guangdong and Hubei. The GWF could directly lead to $W_{eco}$ even though BWF was substantially less than BWA, GWF almost equaled to BWA. Therefore, regions under Type 3 should focus on pollution control.

Theoretically, there exists the Type 4. However, in reality, it is very rare that GWF less than BWA, and this situation did not occur in our study areas as well. The above analysis indicates that most areas suffering from $W_{eco}$ in northern China was caused by severe pollution and scarce BWR, and pollution played a primarily role. This finding is consistent with the result of Zhao et al. (2021), who reported that GWF plays an important role in water scarce provinces in northern China. Furthermore, our analysis demonstrates that in most regions the $W_{eco}$ relieved from 2016 to 2019 primarily due to the declining GWF. This trend is consistent with the findings of Ma et al. (2020b), who reported that pollution discharges reduced in 2003–2017.

4.2. Implications of ecological water scarcity

The $W_{eco}$ indicator provides a theoretical method to assess regional $W_{eco}$ considering the EFR demand for quantity and quality to sustain ecosystems. This indicator can be applied to provide more accurate results for water scarcity assessments in various scenarios, as well as in different temporal and spatial scales for diachronic and synchronic studies. Moreover, we
Figure 4. Temporal changes in the BWF, GWF, BWA, and WS\textsubscript{eco} of regions in the Middle and Eastern Route (2016–2019).

Figure 5. Temporal change of WS\textsubscript{eco} and BWR in water-receiving and water-supply areas. (a) BWR and water from SNWTP in water-receiving areas. (b) BWR and water to SNWTP in water-supply areas. (c) impacts of SNWTP on the WS\textsubscript{eco} in water-receiving areas (WS\textsubscript{eco}∗ = WS\textsubscript{eco} excluding SNWTP), and (d) in water-supply areas.
Table 1. Average BWA, BWF, GWF, and $WS_{eco}$ at provincial level in 2016–2019 (100 million m$^3$/Dimensionless).

| Province   | BWA  | BWF  | GWF  | $WS_{eco}$ |
|------------|------|------|------|------------|
| Ningxia    | 7.6  | 35.2 | 138.8| 40.2       |
| Tianjin    | 19.1 | 17.9 | 118.0| 21.0       |
| Shanghai   | 26.4 | 16.2 | 289.1| 14.9       |
| Hebei      | 135.0| 136.0| 497.7| 14.5       |
| Beijing    | 37.9 | 20.9 | 157.1| 11.1       |
| Shandong   | 168.4| 136.3| 742.4| 9.0        |
| Shantung   | 85.8 | 58.9 | 274.2| 7.2        |
| Jiangsu    | 254.3| 243.5| 931.6| 6.4        |
| Henan      | 210.6| 130.9| 654.6| 5.3        |
| Liaoning   | 176.6| 87.3 | 420.5| 4.7        |
| Shanxi     | 254.0| 55.4 | 278.6| 0.7        |
| Anhui      | 493.8| 133.8| 473.6| 0.5        |
| Hubei      | 565.9| 125.6| 530.7| 0.5        |
| Xinjiang   | 643.4| 387.3| 387  | 0.4        |
| Gansu      | 184.5| 76.2 | 139.6| 0.4        |
| Neimeng    | 263.3| 127.0| 162.6| 0.2        |
| Guangdong  | 1375.0|160.7|1300.6|0.2        |
| Hebei      | 705.1| 96.7 | 577.4|−0.01       |
| Heilongjiang| 595.8|180.6|325.7 |−0.1        |
| Fujian     | 822.3| 67.9 | 530.7|−0.3        |
| Chongqing  | 331.1| 42.8 | 202.7|−0.3        |
| Jilin      | 299.3| 65.6 | 164.2|−0.4        |
| Hunan      | 1090.2|134.4|559.8 |−0.5        |
| Jiangxi    | 1079.2|115.2|484.1 |−0.6        |
| Sichuan    | 1602.9|139.3|684.1 |−0.8        |
| Guizhou    | 632.0| 55.0 | 250.6|−0.8        |
| Hainan     | 243.2| 20.7 | 99.0 |−0.8        |
| Guangxi    | 1424.3|132.2|448.3 |−1.2        |
| Yunnan     | 1305.2|94.9 |246.0 |−1.4        |
| Qinghai    | 444.3| 16.3 | 81.7 |−1.4        |
| Xizang     | 3106.7|26.2 |29.7 |−2.0        |

Table 2. Types of $WS_{eco}$.

| Condition                          | Description                                                                 | Provinces                                                                 |
|------------------------------------|-----------------------------------------------------------------------------|---------------------------------------------------------------------------|
| Type 1 BWF > BWA; GWF > BWA        | BWF and GWF both are leading cause to $WS_{eco}$                             | Hebei, Ningxia                                                           |
| Type 2 BWF < BWA; GWF < BWA; BWF + GWF > BWA | The sum of BWF and GWF is the leading cause to $WS_{eco}$                  | Xinjiang, Neimeng                                                       |
| Type 3 BWF < BWA; GWF $\cong$ BWA or GWF > BWA | Pollution is the leading cause to $WS_{eco}$                               | Tianjin, Shanghai, Beijing, Shandong, Shanxi, Jiangsu, Henan, Liaoning, SHandxi, Gansu, Anhui, Hubei, Zhejiang, Guangdong |
| Type 4 BWF > BWA; GWF < BWA         | Water consumption is the leading cause to $WS_{eco}$                        |                                                                           |

can recognize the possible reasons contributing to $WS_{eco}$ such as water resources overuse, excessive pollution discharge, or natural factor (decrease of BWA).

The main driving factor to $WS_{eco}$ in most provinces was GWF. Increasingly human activities aggravate the untreated sewage, impacting the environment negatively and leading to higher levels of $WS_{eco}$. Therefore, it is urgent to reduce the pollution on $WS_{eco}$. In addition, the uneven distribution of BWR leads to severe $WS_{eco}$ in the north of China, and SNWTP plays a role in relieving water stress in northern China to some extent. Besides, in water-stressed regions, it is necessary to promote water-saving irrigation and optimizing the agricultural production structure. Finally, non-point pollution sources should be addressed (Sun et al 2012).

4.3 Limitations
This study also presents a few limitations. First, the GWF calculation did not consider self-purification capacity of water body, which will lead to overevaluation. Second, for a few provinces, water consumption data were not available during 2016–2019, and we estimated the water consumption through average
water consumption ratios and water withdrawal. Moreover, the time series of this study was relatively short and the analysis of temporal variation of $W_{Sco}$ was relatively insufficient. Future studies should consider these limitations and obtain improved results.

5. Conclusions

This study provides a new perspective for the assessment of ecological water scarcity and offers a comprehensive assessment at provincial scale during 2016–2019 in China. The results show that $W_{Sco}$ presents regional heterogeneity. In northern China, most areas suffered from severe $W_{Sco}$, whereas the southwest regions showed low $W_{Sco}$. Moreover, from 2016 to 2019, $W_{Sco}$ of most regions in China decreased. Furthermore, the primary reason affecting the $W_{Sco}$ is pollution. Therefore, the main conclusions of this study are (a) in most areas, pollution might affect $W_{Sco}$ more than human water use; (b) $W_{Sco}$ can be alleviated by reducing pollution and restoring ecosystems; and (c) water management projects such as the SNWTP might help mitigate water scarcity. Therefore, future water policies should focus on reducing pollution and implementing water management policies based on the local water scarcity situation to achieve sustainable development.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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Conflict of interest

The authors declare that they have no conflict of interest.

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