Response to Comments of Referee #1:

This manuscript developed a gridded dataset of monthly industrial water withdrawal (IWW) for China, spanning a 56-year period from 1965 to 2020 at a spatial resolution of 0.1° and 0.25°. While the dataset covers a wide range of time, the spatial precision appears to be high. However, I have some concerns regarding the spatialization method used in the study. I think the method has too many uncertainties and strong assumptions, and the use of some definitions of industrial water is unclear. Therefore, I suggest that you make the following modifications to your manuscript to address these concerns:

Response: Thank you for taking your time to review our study and provide feedback and comments. We appreciate your concerns regarding the spatialization method for industrial water withdrawal. Although far from perfect, we feel that using industrial enterprise data for spatialization has clear advantages compared to other spatial proxies such as population or nightlights, as the former is directly connected to industrial production processes in which water is withdrawn and consumed. In the revision, we performed more validations for the data and revised texts to clarify and discuss the assumptions and uncertainty in the methodology and data.

1. **The authors need to make the abstract more concise and focused. Instead of mentioning hydrology and geographical sustainability in a broad sense, the relevance of the dataset to specific research areas or applications should be emphasized.**

Response: Thank you for the comments.

We modified this part to be more specific, and the revised texts are shown below:

"The CIWW dataset, together with its methodology and auxiliary data, is useful for water resource management and hydrological models."

2. **Line35-45. The author lists the spatialization methods of sectoral IWW, but does not demonstrate the shortcomings of the current methods. The low accuracy of dataset is mentioned, but how the author judges the low accuracy of these datasets is not clear.**

Response: Thank you for the comments.

The shortcomings in current methods are the spatial proxies and the global statistical data used for downscaling, resulting in lower accuracy for regional applications. Firstly, the spatialization of IWW in manufacturing and mining relies on spatial proxies such as population density, urban or industrial area (e.g., Water GAP model 2.2 (Wada et al., 2016); Huang et al., 2018) (Table R1). These are only indirect factors related to IWW but not the factor that is directly relevant to industrial production processes that consume water (i.e., enterprise-level production). Moreover, they cannot separate different industrial sectors whose water use efficiency could be substantially different. Secondly, almost all existing IWW datasets are global datasets, which means they used national-level IWW statistical data downscaled to derive gridded data (Hejazi et al., 2014; Water GAP model2.2 (Wada et al., 2016); Huang et al., 2018)(Table R1), without incorporating information at sub-regional levels (e.g., provincial statistics). Therefore, global datasets are sufficient in revealing the global general pattern but may have poor performance for specific regions like China which keeps it from being used for localized studies (Liu et al., 2019). Besides, some IWW datasets are only estimated by water intake from electricity, omitting manufacturing and mining water withdrawal (e.g., H08 model (Wada et al., 2016)).

In the revision, we added more explanation for method introduction.

Table R1 Method and data sources ofIWW spatial mapping in previous studies

Sector	Method for Spatialization	Data sources	References
Total IWW	Downscaled only by demographic data	National data from World Resources Institute (country level)	WWDR-II Annual Industrial water withdrawal
	Downscaled by demographic data, socio-economic, and geographical data	FAO AQUASTAT database (country level)	Hanasaki et al., 2008a
	Downscaled by urban area data		Otaki et al., 2008
Total IWW only containing Electricity	Electricity production * Unit Water Demand Then downscaled by demographic data	Statistical data on Electricity production (country level)	H08 model (Wada et al., 2016)
	Electricity production * Unit Water Demand Then downscaled by demographic data, socio-economic, and geographical data		Water GAP model 2.0 (Alcamo et al., 2007)
Electricity	Thermal electricity production * Unit Water Demand (point level) Then summed up to grid	Statistical data on Electricity production (Point level)	KASIM model (Koch and Vögele, 2009) Water GAP model 2.2 (Wada et al., 2016) Huang et al., 2018
Manufacturing and mining	Downscaled only by demographic data	Statistical data (country level)	Water GAP model 2.2 (Wada et al., 2016) Huang et al., 2018
	Total industrial water withdrawal - water withdrawal by electricity, omitting the mining water withdrawal	FAO AQUASTAT database (country level)	Hejazi et al., 2014

3. **line65-70. The rationale for the need for long-term and high-resolution IWW data in China requires further clarification. The reasons mentioned in the manuscript, such as water conflicts caused by increased water demand and water resource management are too broad and do not provide a specific explanation for the need of such data.**

Response: Thank you for the comments.

Industrial water withdrawal in China has been increasing, accounting for 20% of human water withdrawal, and shows substantial spatial variations. The gridded data of IWW are needed to characterize such changes for research and application purposes. However, the currently available gridded datasets of IWW in China are those from global data which typically have poor performance at fine scales due to their methodology and data sources. This is our motivation to specifically develop a gridded long-term IWW dataset in China with significant improvements in methodology and data sources compared to existing data to address the data gap.

With the gridded long-term IWW dataset in China, users can not only explore long-term changes of IWW, the tendency and effects of human water demand-supply in industrial activities at the local scale, and then provide recommendations on regional adjustment of industrial structure and water resources management; but also can be used as the reference and validation data applied to the model, with process-based models to gain an in-depth understanding of hydrological processes (Addor et al., 2020).

In the revision, we added a more detailed description on the reasons for the need for long-term and high-resolution IWW data in China.

4. Why should this sentence be placed here alone?

Response: Thank you for pointing out this issue.

We want to emphasize that the data variable in this dataset is industrial water withdrawal rather than industrial water consumption. We have moved the sentence to the beginning of the introduction:

“Industrial water withdrawal (IWW, the amount of water abstracted from freshwater sources for industrial rather than water consumption) accounted for approximately 19% of human water withdrawal globally, which is the second largest sector of human water use following irrigation.”

5. In this manuscript, industrial water withdrawal and industrial water use are considered to have the same meaning. Nevertheless, the two definitions are different, and industrial water use also includes industrial reuse water consumption.

Response: Thank you for the comments.

We apologize for the confusion regarding the definitions. The statistical IWW data from 2003 to 2020 were from the China National Water Resources Bulletin. The issue is that in China National Water Resources Bulletin (in Chinese), water withdrawal is called "water use" (in Chinese). However, according to its definition, it is defined as the annual amount of water withdrawal for industrial production activities, including primary production, auxiliary production, and ancillary production, excluding recycled water. Thus, the literal "water use" actually means "water withdrawal". We use the term "water withdrawal" when describing the data sources to avoid this confusion.

To avoid confusion between the concepts of water withdrawal and water use, we replace water use with water withdrawal in Section 2.1.4 and add the definition as follows:

"Long-time statistical IWW data were required to produce IWW data for the past four decades.

Provincial surveyed data on IWW in China from the National Water Resources Bulletin (http://www.mwr.gov.cn/sj/tjgb/szygb/, last access: 3 May 2022) from 2003 to 2020 were used. To further extend the time series to the earlier period, the IWW by (Zhou et al., 2020) (referred to as 'Zhou2020 data' hereafter) from 1965 to 2002 was used by summing up the prefecture data to the provincial level. The definition in the National Water Resources Bulletin is the annual amount of water withdrawal for industrial production activities, including primary production, auxiliary production, and ancillary production, excluding recycled water, which is consistent with Zhou2020 data (Zhou et al., 2020) and IWW in our study. Thus, we used them to obtain complete statistical records of IWW from 1965 to 2020 in China."

6. **I think the spatialization method used has a lot of uncertainties. The authors assume the industrial water use efficiency was the same for all industrial enterprises in the same province and the same subsector. A province contains large, medium and small enterprises, and their water use coefficients must be different.**

Response: Thank you for the comments and we totally agree. In reality, the water use efficiency of a given enterprise could be different from other enterprises even for the same subsector, due to investment, technology, revenue, scale, and so on. It is reasonable to expect that enterprises of different sizes tend to have different water use efficiencies, and it is possible that larger companies may have higher water use efficiency than smaller ones. However, the problem is that currently we do not have data to provide specific information about the enterprise sizes and their water use efficiencies. If we arbitrarily introduce this scaling relationship without actual data, this would bring new uncertainty to spatial distribution. In the future, when such data becomes available, incorporating this information could better estimate enterprise-level IWW. We added a discussion on this matter in the revision.

Also, the distribution coefficient of monthly water shortage regards the whole country as a whole, without considering the differences among provinces.

Response： Yes, there are indeed regional differences in the seasonality of IWW. Figure R1 shows the monthly variations of production output across provinces for different industrial sectors, and we can see most of them follow some differences in different provinces (e.g., for electricity and manufacturing sectors). However, at the provincial level, the seasonal fluctuations may exhibit unreasonable or chaotic patterns that are hard to explain, such as manufacturing and mining sectors of Hainan, Guangxi province. For example, Tibet's fraction of manufacturing production in January and February was too low, under 0.025. The exact reasons are unclear, but they could be caused by statistical/random errors in the data. Therefore, we used each subsector's national mean monthly variations to allocate IWW instead of using provincial-level seasonal variations which are problematic in certain places. This choice would not affect much the seasonality of the final IWW because the seasonality of different sectors plays a dominant role in determining the seasonality of IWW for a province (Reynaud, 2003; Sathre et al., 2022). In the revised manuscript, we added Figure R1 as Figure 3C and a more detailed discussion on seasonal variations among provinces.

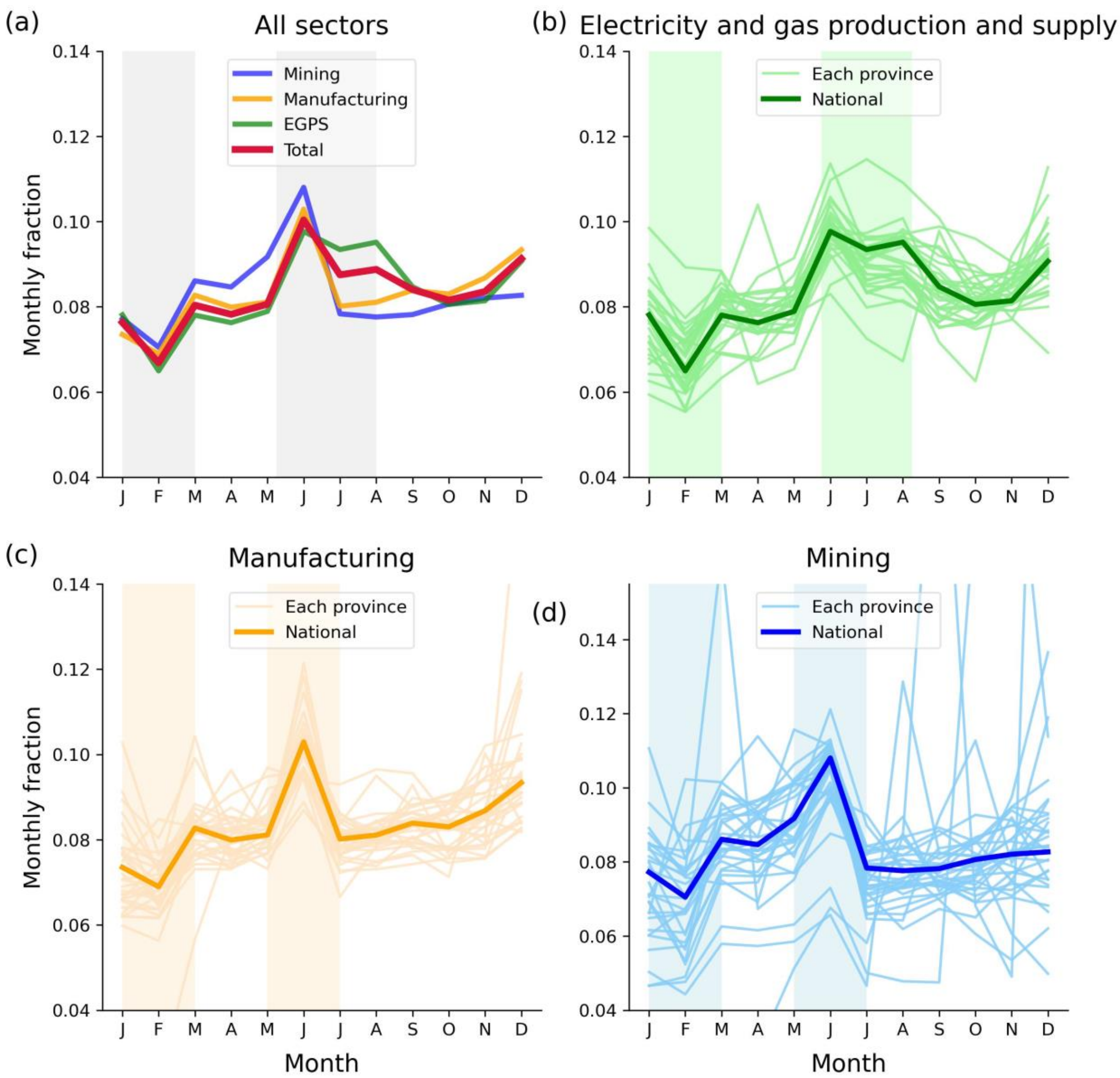

Figure R1. The seasonal variations of the national total IWW (a) and provincial IWW for separate industrial sectors, including electricity and gas production and supply (EGPS) (b), manufacturing (c), and mining sectors (d). The seasonal variations were the fraction of monthly IWW to the annual total during 2006-2010. The thick lines stand for water withdrawal of sectors, and the thin color lines stand for provinces. Shadows represent the seasons with peak and low water withdrawal of a year.

Moreover, the manuscript used the water use efficiency of enterprises in 2008 for the spatialization of IWW from 1965 to 2020. Can the coefficient of 2008 represent the period from 1965 to 2020?

We used water use efficiency and the resulting spatial-seasonal patterns of IWW in 2008 to downscale IWW in other years from 1965 to 2020, serving as a time-invariant pattern for downscaling. First, we made this choice mainly because of the data constraint since no data were available to calculate subsector water use efficiency for years other than 2008. This practice is not ideal but is justifiable given the data limit and the practices adopted in other studies. Developing long-time series gridded data of IWW based on either a time-invariant pattern (e.g., H08, WaterGAP3, and PCR-GLOBAL) or patterns with decadal updates (e.g., Huang et al., 2018; Dong et al., 2022) for downscaling can be found in previous studies (Table R2). Second, industrial water use efficiency generally improved over time with the development of technology. This means that the temporal improvement in water use efficiency is likely to apply for all enterprises (Chen et al., 2019), while the spatial differences in water use efficiency of a given year are still determined by the spatial distribution of economic conditions which remain relatively stable over the years. The changes in total IWW from statistical IWW data could reflect the influence of long-term factors. For the above reasons, we chose the approach to develop the long-term gridded IWW data.

The dataset developed based on the time-invariant pattern 2008 should be reasonably well for the recent ~20 years but may contain larger biases for earlier years. We added this vital point to the manuscript to make the users aware of this issue so that they can choose the period of the data for their specific needs and accuracy considerations. In the revised manuscript, we added a more detailed discussion on using a time-invariant spatial pattern for long years IWW downscaling.

Table R2 Spatial pattern used for long-term data extension in previous studies

Spatial pattern	**Long-term data**	**Used for**	**Reference**
NASA Back Marble night-time light intensity map in 2012-2016	1980-2016	Model (VIC-5)	Droppers et al., 2020
Distribution of urban population in 2009	1950-2010	Model (WaterGAP3)	Flörke et al., 2013
Global population distribution map and national boundary information in 2005	1970-2010	Model (H08)	Hanasaki et al., 2008
Global IWW map in 2000	1960-2001	Model (PCR-GLOBWB)	Wada et al., 2011a, b
Linear Interpolation based on GDP dataset in 1990, 2000 and 2010, same as 1990 before 1990	1971-2010	Model (CLHMS, the Coupled Land Surface-Hydrologic Model System)	Dong et al., 2022
Global population density maps with decadal updates (1980, 1990, 1995, 2000, 2005)	1970-2010	Water Dataset	Huang et al., 2018

Reference

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