A gridded dataset of consumptive water footprints, evaporation, transpiration, and associated benchmarks related to crop production in China during 2000-2018

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Authors' responses to Referee #3' s comments

We thank Referee #3 very much for such valuable comments and suggestions improving the manuscript. We learn carefully and provide preliminary answers to the comments point to point.

The article " A gridded dataset of consumptive water footprints, evaporation, transpiration, and associated benchmarks related to crop production in China during 2000–2018" established a gridded dataset of monthly green and blue water footprint of crop production (WFCP), evaporation and transpiration et al. based on AquaCrop model. On the whole, the paper has important research significance and much work was done, but there are some shortcomings in the paper, and it is suggested to modify.

Responses: Thank you very much for the positive words!

1. In Lines 186-187, "The statistical yearbook only has crop production statistics on the provincial level. Therefore, we calibrated crop production at the provincial scale.". The statement is not accurate. Statistics data on the city level can be found in the provincial statistical yearbook.

Responses: Thank you for your comments. You rightly pointed out that the statistical yearbooks contain crop yield data at the city level. For years and regions with more comprehensive data, it would be worthwhile to utilize higher-resolution data. We will acknowledge this limitation in the discussion section, and provide caveats on using this data product under relevant conditions. It should be noted that although provincial yearbooks include some city-level crop yield data, considering the numerous crop types involved in this study, and the division of certain crops by harvest periods (e.g. winter wheat, spring wheat, early rice, mid rice, late rice), there are indeed many instances of missing and incomplete data at the city scale. To ensure data integrity and accuracy, yield calibration was carried out at the provincial level. Such provincial calibration has been extensively applied in previous studies (Yue et al., 2022; Zhuo et al., 2016).

Although crop yield was calibrated at the provincial level, by incorporating precipitation, temperature, soil texture and other elements into the fundamental model inputs, the simulation results of this study were still able to reflect heterogeneities in the spatial distribution of crop water consumption, yield, and water footprint of crop production (WFCP) well. The meteorological and soil factors are critical factors affecting the estimation of WFCP (Zhuo et al., 2014; Tuninetti et al., 2015). We have ensured these sensitive factors meet the accuracy requirements of this study at temporal and spatial scales. We will provide unambiguous elaboration on this in the revised manuscript.

2. In your research, AquaCrop model was used to simulate crop production more than 21 crops. Wheat, corn and rice are the main food crops in China. In crop production, irrigation and fertilization are both important management measure to improve crop yield. However, only irrigation was considered. In my opinion, it is necessary to consider the effects of irrigation and fertilization on crop production in different regions when simulating crop production process using AquaCrop model.

Responses: Thank you for your comments. AquaCrop here only modeled irrigation and excluded other practices like fertilization. As you pointed out, both irrigation and fertilization are critical agronomic measures to improve crop production. It should be noted that AquaCrop was developed by the FAO as a **water-driven model**. Since the focus of this study is to assess the impacts of different water supply and irrigation practices on quantifying WFCP, irrigation practice was selected as the sole simulation factor.

The AquaCrop model adopts a semi-quantitative method to evaluate fertilizer stress. That is, it cannot directly simulate crop response to fertilizer based on plant nutritional demand and soil nutrient content (Akumaga et al., 2017). Research shows AquaCrop performs better without fertilizer stress versus with stress (Adeboye et al., 2021; Wu et al., 2022). In fact, fertilization primarily affects crop yield. By calibrating model yield output afterwards, we indirectly reflected the influence of fertilization. Moreover, due to the lack of gridded data on fertilizer types and application rates, let alone crop-specific data. So like past AquaCrop global (Mialyk et al., 2022) and national (Wang et al., 2019) studies, we assumed no nutrient stress in the simulation.

Certainly, the above assumption has limitations, which we will explain in the discussion section and call for more efforts on establishing fertilization datasets and advancing research on crop water consumption response to fertilization in future studies. When updating the WFCP database later, we will enhance model mechanisms to improve accuracy if fertilizer data becomes available.

3. As we all know, AquaCrop is a farm-scale model. In your research, the crop production at the provincial scale was calibrated and validated by statistical yearbook. I don’t think this is a good idea. It is recommended that some representative sites were selected to verify the AquaCrop parameters.

Responses: Thank you for your comments. Conservative parameters in the basic model inputs originate from the Annex, while key sensitive parameters are acquired from extensively utilized databases that considered regional differences originally. Similar to previous large-scale footprint studies (Yu et al., 2019; Li et al., 2023), model calibration focuses on the verification of evapotranspiration (ET) against high-precision remote sensing products and yield validation at administrative level. Therefore, we validated the simulated crop ET against remote sensing products over the same grids and time, which showed good consistency. For crop yield validation, on one hand it is difficult to obtain site-level measured data, and on the other hand crop yield data at the city and county levels contain missing values for the numerous crops involved. Given data consistency considerations, yield was validated at the provincial level to ensure the rationality of model parameters. We recognize this is a limitation of the study, which will be addressed in the discussion. Developing shared, high spatial resolution crop parameter databases is of paramount importance for improving relevant research.

4. Whether the parameters are consistent in AquaCrop model under different irrigation methods?

Responses: Thank you for your comments. As stated in the AquaCrop model user manual, different irrigation practices are distinguished by the parameter of surface wetness fraction, while other parameters remain consistent (Raes et al., 2018). This irrigation practices differentiation approach is commonly used before (Pereira et al., 2015; Wang et al., 2019; Chibarabada et al., 2020; Li et al., 2022; Yue et al., 2022).

Specifically, as elaborated in Section 2.2.3, Different irrigation practices indirectly affect water consumption during the growth period due to differences in the fraction of the surface wetted (fw) by each method. where the fw-values used for furrow, sprinkler, and micro-irrigation were 80%, 100%, and 40%, respectively.

5. Lines 391-392. The crop parameters do not vary with simulation time and space. It is inaccurate for the whole Country to use only one set of crop parameters to simulate crop yield. In my opinion, different crop parameters should be used for each province.

Responses: Thank you for your comments. Due to inappropriate narration, our description of crop parameters in the manuscript has caused severe misunderstanding during your review. In fact, strict regional differences were considered during the initial screening of the 21 crop parameters. First, the 31 provinces were divided into 8 major regions at the provincial level (Table R1). According to the regional classification results, we adjusted the crop types and planting date parameters. Based on planting and irrigation practices, we tuned the crop rooting depth.

Table R1. Regional classification.

Region	Provinces	Regional classification
North	Beijing, Tianjin, Shanxi	Temperate
Northeast	Inner Mongolia, Liaoning, Jilin, Heilongjiang	Continental temperate & temperate
Huang-huai-hai	Hebei, Henan, Shandong, Anhui	Temperate
Northwest	Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang	Continantal temperate & plateau and Mountain
Southeast	Shanghai, Zhejiang, Fujian	Sub-tropics
East	Jiangsu, Hubei, Hunan, Jiangxi	Sub-tropics
South	Guangdong, Guangxi, Hainan	Sub-tropics & tropics
Southwest	Chongqing, Sichuan, Guizhou, Yunan, Tibet	Sub-tropics

In our previous research (Li et al., 2022), ten input variables or model parameters were selected, including reference evapotranspiration (ET_o), crop transpiration coefficient (KcTr), planting date (PD), soil evaporation coefficient (KE), maximum canopy cover (MCC), precipitation (PR), canopy decline coefficient (CDC), planting density of the crop (DC), reference harvest index (HI_0), and normalised water productivity (WP*). The results showed that water footprint of crop production (WFCP) is generally more sensitive to **KcTr** and **PD** among the model parameters.

In the Annex of the Reference manual for the AquaCrop (Raes et al., 2018), default values of crop parameters for the 12 crops covered in this study are given, including crop phenology, crop transpiration, biomass production and yield formation, and stresses, totaling 41 parameters. Furthermore, these parameters are further classified based on crop sensitivity as conservative generally applicable (including **KcTr**), conservative for a given species but can or may be cultivar specific, dependent on environment and/or management and cultivar specific. The conservative parameters are generally applicable and remain unchanged across a wide spectrum of conditions, including different climatic and geographic locations, crop cultivars and genotypes, as well as variable soil moisture stress statuses. Once calibrated, these identical parameters would be utilized without further modification.

Regarding the other sensitive parameter **PD**, the phenology dataset generated by Luo et al. (2020) only included three major crops wheat, rice and maize. As indicated on the website of China Meteorological Data Service Center, the “Ten-day Values Dataset of Crop Growth and Development and Soil Moisture Content” they published has not gone through quality control and is of average quality. In this study, we primarily used the phenology data published by Chen et al. (1995) as model input, because this dataset has been widely applied and its reliability has been validated (Long et al., 2010; Cao et al., 2014; Ding et al., 2020).

Table R2. The proportions of crop water consumption in stages L2 and L3 for various crops.

Crop	Proportion	Crop	Proportion
Spring wheat	75.8%±0.8%	Cotton	79.5%±1.0%
Winter wheat	87.8%±0.6%	Sugar cane	87.7%±1.4%
Spring maize	88.6%±0.5%	Sugar beets	89.3%±0.7%
Summer maize	73.8%±1.3%	Groundnuts	90.4%±0.6%
Early rice	78.7%±0.8%	Spring rapeseed	73.1%±1.8%
Mid rice	80.4%±1.0%	Winter rapeseed	77.8%±2.2%
Late rice	86.3%±0.4%	Sunflower	80.6%±0.6%
Sorghum	77.2%±1.6%	Tomatoes	73.6%±1.3%
Millet	77.4%±0.9%	Apple	86.8%±0.5%
Spring barley	77.0%±1.4%	Tea	85.0%±0.7%
Winter barley	85.2%±0.9%	Tobacco	83.3%±0.5%
Soybeans	69.9%±1.4%	Cabbage	76.3%±1.4%
Potatoes	71.7%±1.1%	Grapes	73.2%±1.4%
Sweet potatoes	66.6%±1.0%		

In this study for example, the proportions of crop water consumption in the crop development (L2) and mid-season (L3) stages for various crops are shown in Table R2, with more than 13 crops having L2 and L3 water consumption proportions over 80%. As shown in Table R3, when PD varies ±10 days, the change in WFCP is within 4%. When PD varies ±20 days, the change in WFCP is within 8.5%. The impact of PD on WFCP estimation is acceptable, because the crop water consumption during the growing season is mainly concentrated in L2 and L3 stages. In these processes, crop water consumption increases substantially with the rise of canopy cover and crop growth demand. Therefore, based on the parameter adjustments that have been implemented at the provincial level, minor shifts in PD forward or backward have relatively small influences on WFCP.

Table R3. Sensitivity analysis of water footprint of crop production to planting date.

Crop	-20 days	-15 days	-10 days	-5 days	5 days	10 days	15 days	20 days
Wheat (297 sites)	-5.9%	-4.5%	-3.0%	-1.4%	2.0%	3.9%	5.6%	7.5%
Maize (304 sites)	-0.4%	0.0%	0.2%	0.3%	0.2%	-0.1%	-0.6%	-1.5%
Rice (480 sites)	0.4%	0.5%	0.5%	0.4%	-0.5%	-1.1%	-2.3%	-3.6%
Soybean (299 sites)	6.3%	5.0%	3.5%	1.8%	-1.9%	-4.0%	-6.2%	-8.5%

We obtained these key parameters like reference harvest index, crop growth stages, and maximum root depth for this study by referring to the literature (Allen et al., 1998; Vanuytrecht et al., 2014; Xie et al., 2011; Zhang and Zhu, 1990; Hoekstra and Chapagain, 2006). These data have been validated to be reliable and applicable in large-scale studies. Due to data limitations, the remaining parameters such as maximum canopy cover, canopy cover decline coefficient, canopy growth coefficient were assigned the mean values within the reference range provided in the Annex. Although this approach may overlook certain potential variations, the use of mean values generally captures the central tendency of the data.

In summary, unlike small-scale studies at site level that emphasize region-specific measured parameters for model simulation, large regional-scale studies often adopt literature-recommended parameter values during data collection, with greater focus on regional variability and wide adaptability of the parameters. (Hoekstra and Wiedmann 2014; Davis et al., 2017; Mekonnen and Hoekstra 2020; Lutz et al., 2022; Halpern et al., 2022; Liu et al., 2022; Chiarelli et al., 2022; Demay et al., 2023). It was neither practical nor feasible to calibrate crop parameters individually for each grid given the constraints of available data. Nevertheless, we have made every effort to ensure the reliability of the model input parameters within the existing limitations. We will add more elaboration on this issue in the discussion section of the revised manuscript. It should be reemphasized that the WFCP database generated in this study is updatable annually. Should higher-resolution crop parameter products become available in future, we will update the existing WFCP database accordingly.

6. The discussion needs to be rewritten. The results of this study can be compared with those of others, and the reasons for the similarities and differences can be analyzed. For example, in section 4.1, it is inadequate just compared with the evapotranspiration result with SEBAL model, which is a single-source model. In your research, evaporation and transpiration has been estimated. It will be more meaningful to verify evaporation and transpiration based on the two-source model.

Responses: Thank you for your comments. In the revised manuscript, we will compare our simulation results with those from other two-source models, and elucidate the underlying reasons for the discrepancies between the simulation results.

Minor questions:

1. In Line 40, what's the mean of "CWASI".

Responses: Thank you for your comments. We sincerely apologize for the inconvenience caused to your review work due to the use of abbreviations. "CWASI" refers to the abbreviation for the virtual water and water footprint dataset created by Tamea et al. (2021) in Line 40. In the revised manuscript, we will rewrite this sentence to avoid confusion.

2. In Lines 130, 135 et al., no spaces before "where …".

Responses: Thank you for your comments. We will carefully check the entire manuscript and add spaces before all instances of "where", in order to ensure formatting accuracy and consistency. In the revised manuscript, we will pay particular attention to this issue to avoid similar oversights from recurring.

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