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 #2' s comments

We thank Referee #2 very much for such valuable comments and suggestions improving the manuscript. We learn carefully and provide preliminary answers to the comments point to point.

This paper calculated the WFCP from physical model and then analyzed the water footprints of major crops in Chine between 2001 and 2018, it is a useful topic and the analysis workflow is fine. But my major concern is about the quality of the data, I think there are data with better quality can be used as input and generate more reliable dataset for analysis. Therefore, my opinion is that the paper needs a major revision and a new version of the dataset should be generated before the analysis as the current version make no sense in scientific community.

Responses: Thank you very much for the positive words on the significance of the dataset and recognition of the workflow. We are very grateful for your kind concerns about the input data quality and related issues. We totally agree with the comments. Actually, we tested carefully the feasibility of all the well-acknowledged existing and new data to ensure the best data quality as we can. Please kindly refer to our point-to-point responses as followed.

1. Some concerns about the input dataset:

(1) Irrigated and rainfed crop areas between 2001 and 2018 is generated from the combination of MIRCA 2000 with 5 arcmin resolution and the year book data, but currently, there are actually a lot of new dataset about irrigated cropland from satellite data, for example, Zhang et.al (https://www.sciencedirect.com/science/article/abs/pii/S0022169422009830) 2022, and Zhang et.al 2022 (https://www.nature.com/articles/s41597-022-01522-z). Maybe there are still other data products, I just searched in Google and found the above two

datasets. All these irrigation data could be verified and then resampled to 5 arcmin, and used as input data. Basically, the spatial distribution of irrigation land generated from satellite are more reliable than a 15-year-old coarse resolution data and yearbook. As the irrigation cropland is the basement of all the following data generation, please keep the pace with new datasets in the geo-agricultural community.

Responses: Thank you for your comments. Prior to initiating this study, we screened the required crop planting area data based on the following criteria: distinguishing crop types, separating irrigated and rainfed areas, long-term temporal resolution, and high spatial resolution. MIRCA2000 was selected because it meets the objectives of this study. This is also the reason that the MIRCA2000 dataset is still the most widely used for crop water consumption or requirement dataset making (e.g., Hoch et al., 2023; Li et al., 2023; Ruess et al., 2022; Lutz et al., 2022; Liu et al., 2022; Chiarelli et al., 2022; Chiarelli et al., 2020; Rosa et al., 2020). In order to improving the reliability of the input land use data, the proportional scaling approach based on the MIRCA2000 dataset have been applied in numerous studies in this field (Sloat et al., 2020; Yue et al., 2022; Mialyk et al., 2022; Wang et al., 2019).

Table R1 presents the crop planting area and irrigated area data products, including those the Referee#2 recommended. Recent years have witnessed the emergence of numerous long-term and high-resolution irrigation area datasets for China, thanks to the combined application of remote sensing technology and machine learning approaches. However, these datasets do not differentiate between irrigated and rainfed cropping systems, and do not contain crop-specific planting information. These deficiencies fail to fulfill the original intentions of this study design.

Table R1. Inventory of irrigated cropland data.

Source	Spatial coverage	Temporal resolution	Spatial resolution	Crop type distinction	Planting pattern
Zhang et al., 2022	China	2000-2019	500 m	No	Only irrigated croplands
Zhang et al., 2022	China	2000	250 m	No	Only irrigated croplands
Zhu et al., 2014	China	2000	5 arcmin	No	Only irrigated croplands
GFSAD1KCD	Globe	2007-2012	1000 m	6 crops	Irrigated and rainfed croplands

GAEZ+ (Grogan et al., 2022)	Globe	2015	5 arcmin	26 crops	Irrigated and rainfed croplands
SPAM (IFPRI 2019)	Globe	2000, 2005, 2010	5 arcmin	42 crops	Irrigated and rainfed croplands
MIRCA2000 (Portmann et al., 2010)	Globe	2000	5 arcmin	26 crops	Irrigated and rainfed croplands

Global scale data compensates the aforementioned deficiencies to some extent. However, it is worth mentioning that existing global databases have certain limitations, including a limited range of crop types and intermittent time series. For instance, the SPAM dataset is only publicly available for a few specific years 2000, 2005 and 2010, and interpolation is still required to fill in the gaps. The GFSAD1KCD dataset encompasses a smaller variety of crop types.

We further compared planting areas of 15 crop types in 2010 SPAM and our data provincially and in grids (Fig. R1 and Fig. R2). It is evident that there is a high degree of consistency between the two datasets at the provincial scale. The differences at the grid scale can be attributed to discrepancies in the identification of grid-level land use between the MIRCA2000 and SPAM datasets.

According to Fig. R3 and Fig. R4, the planting area data for sorghum, millet, barley, and sugar beets in the GAEZ+ dataset exhibit significant deviations from the values applied in this study, both at the provincial and grid scales. However, it should be emphasized that all crop planting area data in this study have been calibrated against statistical data at the provincial scale, implying an underestimation of the planting area for the mentioned crops in the GAEZ+ dataset.

Given the above analysis, we used MIRCA2000 to estimate crop planting areas by water supply and irrigation practices. Other datasets have potential but based on our screening criteria, we made assessments of available data and adopted rigorous methods to ensure the reliability of the applied data.

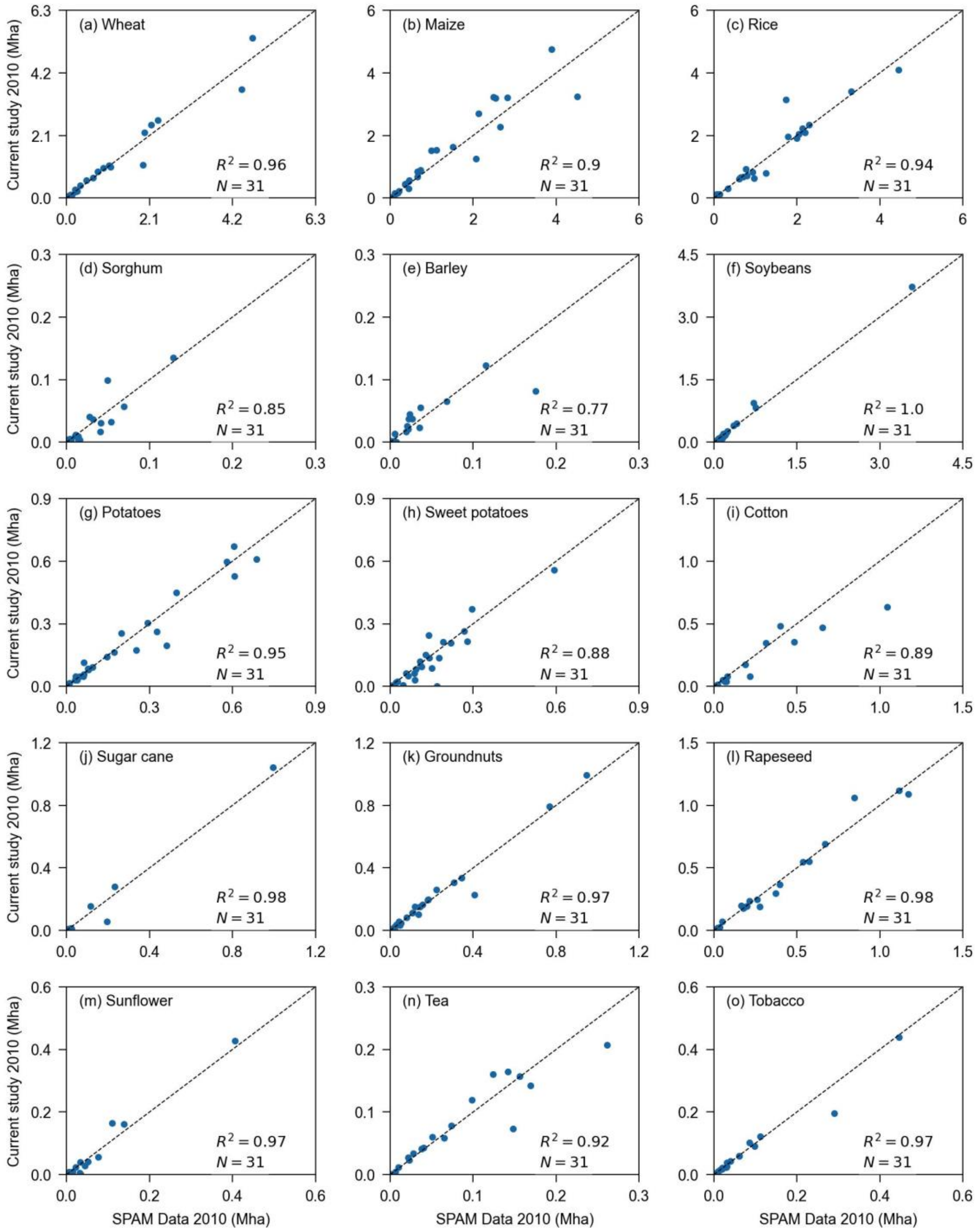

Figure R1. Comparison of the current provincial area representing land coverage with the MapSPAM2010 datasets.

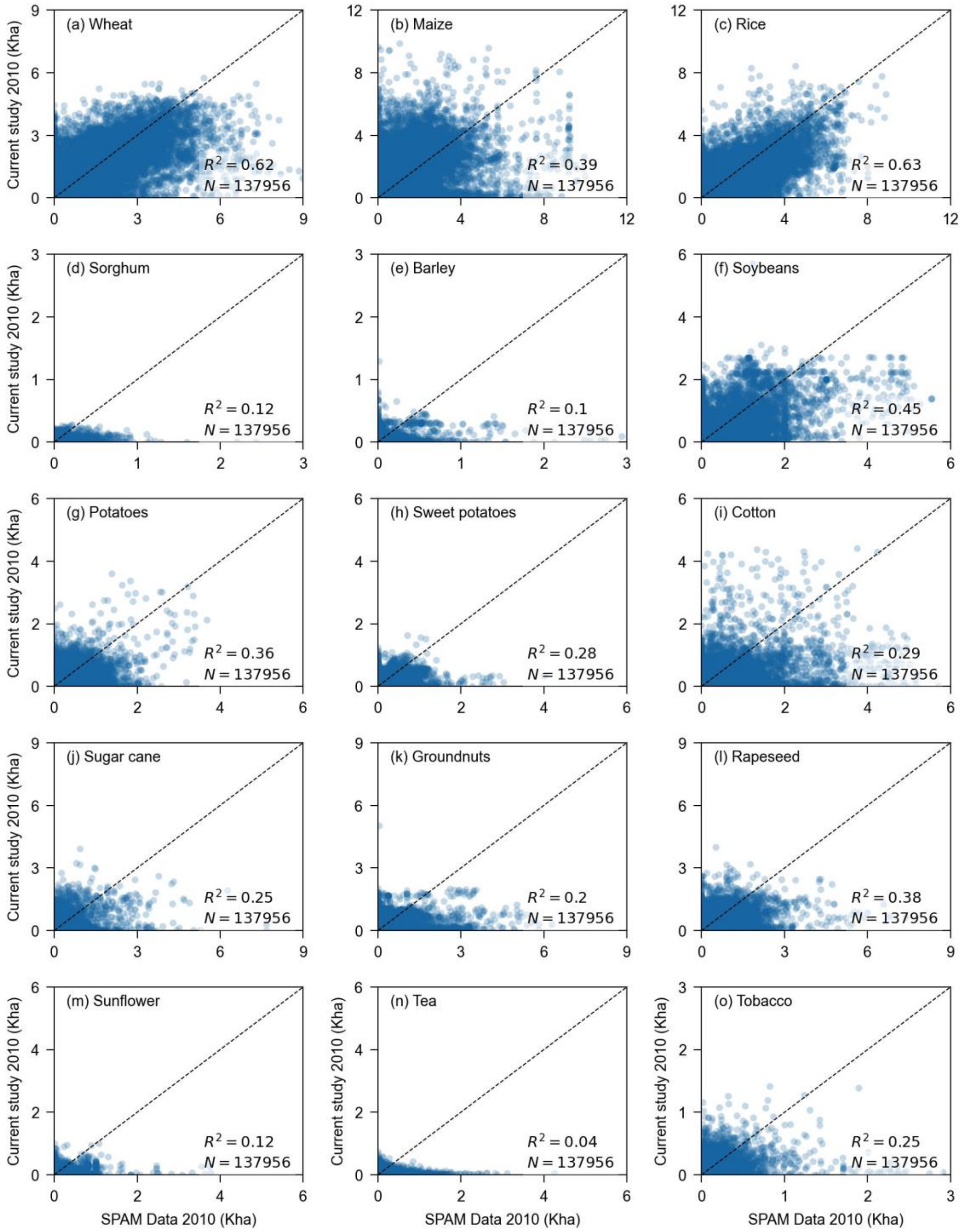

Figure R2. Comparison of the current gridded area representing land coverage with the MapSPAM2010 datasets.

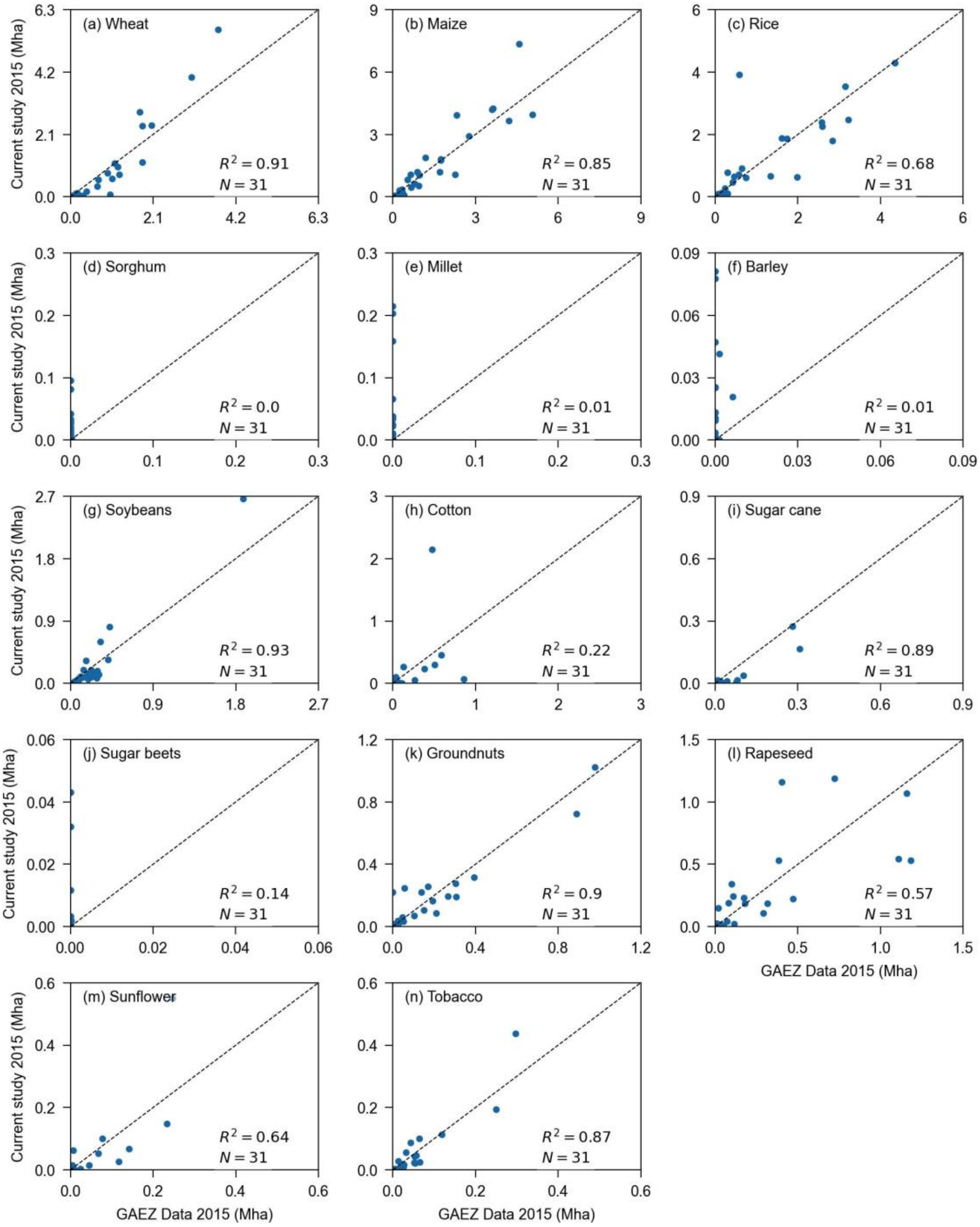

Figure R3. Comparison of the current provincial area representing land coverage with the GAEZ+2015 datasets.

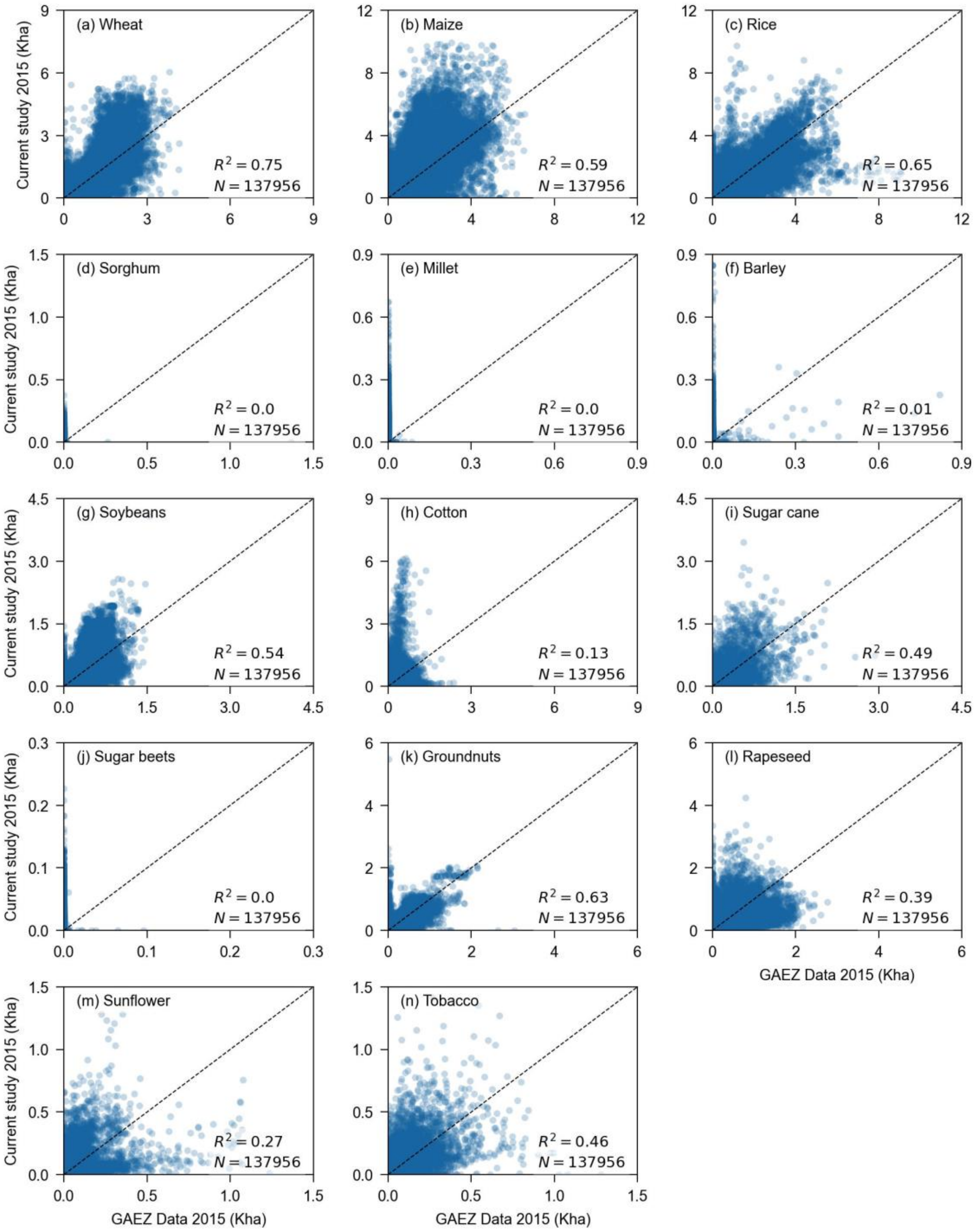

Figure R4. Comparison of the current gridded area representing land coverage with the GAEZ+2015 datasets.

(2) The crop phenology for the major crop need to be further specific. For example, the winter wheat, the planting date of winter wheat is Oct 15, and all winter wheat are assumed to have the same phenology characters. But this is not the situation in practice, and the phenology of winter have significant difference even in North China Plain with different sowing, emergence and dormancy date. It is essential to use more detailed

phenology data as input.

Responses: Thank you for your comments. As you rightly pointed out, we recognize the significance of planting date (PD). Currently, there are some phenology datasets for major Chinese crops. The dataset generated by Luo et al. (2020), which only encompasses 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. Here we mainly used phenology data published by Chen et al. (1995) for model input since it is widely used and its reliability is validated (Long et al., 2010; Cao et al., 2014; Ding et al., 2020).

We discussed the effects of inputs like PD on water footprint of crop production (WFCP) estimation in the discussion, "The effect of PD differed for each crop, and advancing or delaying it exposed crops to completely different rain and heat conditions .... in future research, attention to the collection and organisation of basic data can play a positive role in the improvement of the model mechanism and accuracy of the output." As shown in Table R2, our previous study conducted a sensitivity analysis of WFCP to PD at the site scale. The results indicated that when PD shifts ±10 days, the change in WFCP remains within 4%. With PD shifts of ±20 days, the variation in WFCP is under 8.5% (Li et al., 2022).

Table R2. 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%

Sources: Li et al., (2022).

In short, PD's effect on WFCP estimation is acceptable since crop water use is primarily concentrated in crop development (L2) and mid-season (L3) stages. In this study for instance, with over 13 crops having L2 and L3 water consumption proportions exceeding 80% (Fig. R5). Therefore, minor shifts in PD forward or backward have relatively small influences on WFCP.

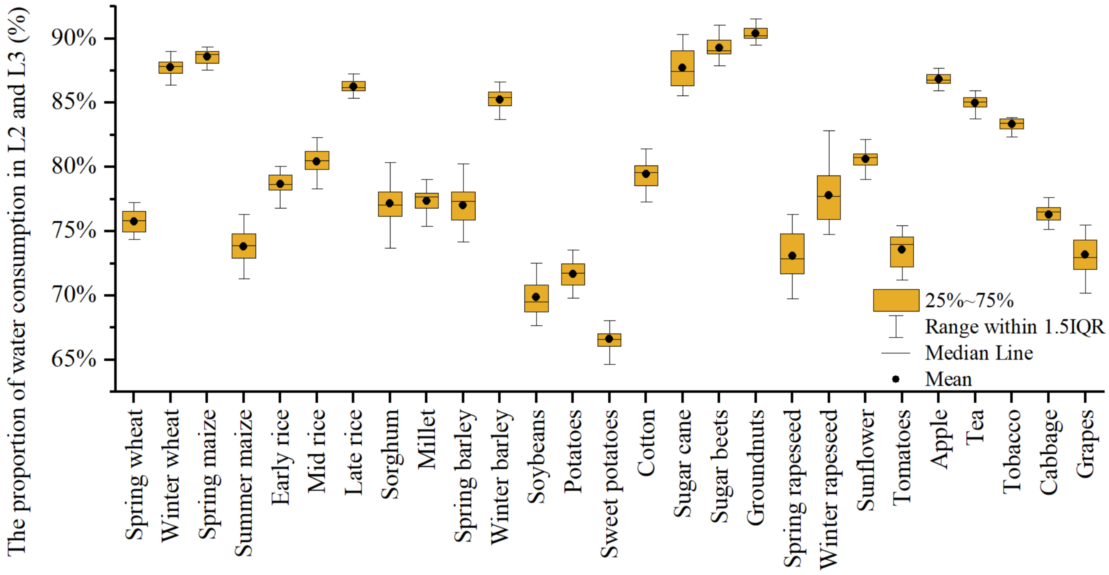

Figure R5. The proportions of crop water consumption in stages L2 and L3 for various crops.

In addition to considering fixed planting dates and crop duration, we conducted a sensitivity analysis of the effect of growing degree days (GDD) on the quantification of WFCP (Zhuo et al., 2014). The GDD measures heat units during crop growth, greatly improves the accuracy of expressing and predicting crop phenological cycles compared to other methods like calendar year or days (McMaster and Wilhelm, 1997). The results indicated that when wheat PD was shifted 30 days earlier than the reference date, yield and WFCP decreased by 0.25% and 0.3% respectively. When rice planting was delayed by 30 days, yield and WFCP reduced by 0.2% and 9.3% respectively. Therefore, under constant GDD, yield and WFCP showed low sensitivity to changes in crop PD.

We will incorporate additional elaboration regarding the sensitivity analysis of WFCP to crop phenology in the discussion section. Moreover, we will highlight aspects that require attention when applying the data from this study to specific crops and local regions. Should higher-resolution crop phenology characters products become available in future, we will update the existing WFCP database accordingly.

1. Data comparison

Figure 9, Please include RMSE in the Figure, when analyzing quantitative results, RMSE is more commonly used to evaluate overestimation and underestimation. Although it seems the value of R square is good here, I found the number of high ET value is small, this indicates the high R square value in this Figure do not make sense either, Please include more high ET-value pixels in the analysis.

Responses: Thank you for your comments. As suggested, the RMSE will be added in the revised figure. The lack of high ET values in Figure 9 is attributed to the preliminary screening applied when selecting data for comparison in this study. As described in Section 2.3.2 of the manuscript: Because of the spatially fragmented nature of crop cultivation, we conducted remote sensing validation according to the Chinese Agricultural Cropping System to reduce the interference of non-agricultural land with the validation results. We selected grids in which the sum of planted areas was greater than 5 kha (> 50% of a single grid) and greater than 10 kha (>100% of a single grid) for single- and multi-crop regions, respectively. In terms of the time span, 19 of the 21 crops studied experienced growth periods from April to August; therefore, these five months were set as the validation interval in terms of total evapotranspiration.

1. Separation of E and T

The separation of E and T can not be verified because there is no validation data. Please address this in discussion section, pay attention to include the uncertainty analysis of E and T separation.

Responses: Thank you for your comments. We will supplement this part in the discussion section of the revised manuscript. The preliminary plan is to compare the results of this study with existing public databases of E/ET proportions at the same spatiotemporal scales, in order to validate the reliability of the separated E and T results obtained in this study.

Line 183, Can you show the map of humid (AI > 0.5) and arid (AI < 0.5) zones?

Responses: Thank you for your comments. We sincerely apologize for the confusion caused by the unclear illustration, which inconvenienced your review. The climate zones are defined as the ratio of rainfall to reference evapotranspiration, where humid (AI > 0.5) and arid (AI < 0.5) zones are delineated. In Figure 6, we differentiated the arid and humid zones with wine red boundary lines, and the specific locations of arid and humid areas can be found in Figure 6a. We will improve this part in the revised manuscript.

Line 194, What remote sensing data have you used for comparison?

Responses: Thank you for your comments. We sincerely apologize for the oversight on our part, which caused inconvenience to your review. The Section 2.3.2 corresponding to Line 194 refers to the comparison between the ET products generated by the SEBAL model and the results of this study over the same spatiotemporal extent. We will supplement elaboration on this part in the revised manuscript.

Line 316~319, I think the two factors addressed here do not make sense as the data used in the analysis have significant shortage, please use your new version to compare.

Responses: Thank you for your comments. In previous responses, we have provided elaborate accounts of the screening process for model data such as crop parameters, which will be supplemented in the manuscript. Prior to the simulation, we conducted rigorous screening and reliability validation of the input data based on principles of accuracy and representativeness, using the currently optimal available data. We recognize that the accuracy of all model studies, including AquaCrop, is contingent on model mechanisms and input data. Therefore, laying emphasis on collection and collation of fundamental data in future studies will play a positive role in improving model mechanisms and output precision.

It should be noted that the WATNEEDS dataset compared with this study in Lines 316-319 represents crop water requirements, while WFCP in this study refers to crop water consumption during the growing period, as has been elaborated in Lines 51-52 of the Introduction. Therefore, we think the two factors addressed here are valid, that the primary factors leading to discrepancies between the datasets are the differences in simulation mechanisms (crop water requirements vs. crop water consumption) and irrigation practices (whether distinguishing irrigation practices). We will clarify such information in the revision, to avoid any confusions to readers.

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