Review #1:

General Comment: This manuscript developed a high spatial resolution (4km) rice yield dataset from 1995 to 2015, covering major rice growing seasons and regions in Asia. Overall, this dataset would be a good complement to current rice yield products due to its high spatiotemporal resolution. I have the following questions or suggestions, which may help improve the manuscript clarity.

Response to general comment:

We are grateful for anonymous referee #1's recognition of this study's importance. We carefully revised our manuscript and provided a point-by-point response below. We have addressed all points raised in the revised manuscript.

Note: The individual comments (shown in black) are listed below including our responses (shown in blue) and revised parts in the manuscript (shown in *red and italic font*). Line numbers (shown in **blue and bold font**) that we mention in this comment refer to our revised manuscript with all markup version.

Comment 1: The authors used the GLASS AVHRR LAI data to extract key crop phenological indicators for training, including planting, heading, and harvesting dates. However, since rice fields in Asia are very fragmented and the spatial resolution of GLASS LAI data (i.e., 0.05 deg) is not fine enough to capture pure rice LAI information, there should be mixed-pixel problems. How did the authors deal with these problems? In addition, I would say the extracted planting and harvesting dates are more of indicators of the early rapid growth and senescence stages rather the real planting and harvesting dates. The authors should clarify these conceptual differences to avoid possible confusions.

Response to comment 1:

Thank you very much for your comments and suggestions.

Yes, mixed-pixed problems could impact accurately retrieving crop information. We agree with you that the problems could affect the extraction of LAI information. Fortunately, some efforts can reduce the mixed-pixel influence in some degree such as our efforts. Firstly, GLASS LAI product has the highest accuracy and the lowest uncertainty compared with other available LAI products (Xiao et al., 2016; Liang et al., 2021). Secondly, we used annual paddy rice of 500 m as base maps which can reduce the influence of other land cover types by capturing the dynamic temporal variation of rice distribution **(Lines 124-125)**. Moreover, only pixels with LAI value within or equal to average ± two times standard deviation were selected to identify rice growing information for the reduction the interference of abnormal values **(Lines 211-212)**. Finally, we filtered out a fraction of pixels where the rice growing information couldn't be detected by inflection-based and threshold-based methods (details in Sect. 2.3.1). These measures helped us to reduce the influence caused by mixed-pixel problems. The accuracy of phenological information used in this study was satisfactory enough ($R^2 > 0.8$) for the main rice-cropping seasons according to Zhang et al. (2022). Nevertheless, we further discussed the relevant uncertainties in Sect. 4.3.1 **(Lines 436-439)**.

Thank you for pointing out these conceptual differences of the phenological information. The extracted planting dates were the transplanting dates which located in the early rapid growth stage (Mandal et al., 2018). For harvesting dates, they referred to the occurrence of leaf senescence at maturity period (Ogawa et al., 2021; Ni et al., 2021; Zhou et al., 2019). These two dates are truly indicated the early rapid growth and senescence stages. However, these extraction rules were thought as transplanting and maturity dates detection according to most previous studies (Luo et al., 2020; Niu et al., 2022). To avoid ambiguity, we replaced planting with transplanting and harvesting with maturity according to relevant researches (Dong and Xiao, 2016;). Correspondingly, the figure of LAI extraction in Fig. 2 Step1 was also revised.

References:

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Zhang, J., Wu, H., Zhang, Z., Zhang, L., Luo, Y., Han, J., and Tao, F.: Asian Rice Calendar Dynamics Detected by Remote Sensing and Their Climate Drivers, Remote Sens., 13, https://doi.org/10.3390/rs14174189, 2022.

Zhou, G., Liu, X., and Liu, M.: Assimilating remote sensing phenological information into the WOFOST model for rice growth simulation, Remote Sens., 11, 268, 2019.

Comment 2: The authors used the Pearson correlation analysis to identify those predictors with a significant correlation with rice yield at each administrative unit for training (Lines 218-220). I'm curious if the authors trained the model in each administrative unit and then combined all the training results to get the rice yields for the entire Asian region. More explanations about the experimental implementations should be given. Meanwhile, how do the authors deal with the multicollinearity problems of these predictors? There is a significant correlation between the different predictors in Table S3. In addition, I found very limited information on hyper-parameters in the supplementary material, the authors may want to provide detailed information of those parameters in each optimal model (e.g., how many hidden layers, node numbers, and max-depth, etc). Furthermore, in Line 295, detailed information on the trained 27 optimal models should also be give (maybe present in the supplementary material).

Response to comment 2:

Thanks very much for your constructive comment.

We trained the optimal models in each case (one specific rice-cropping period, including all administrative units in the country. Such training case contains many administrative units which are at the minimum administrative division scale with available rice yield records from 1995 to 2015. The gridded predictors selected in these cases were input into the optimal models to produce the gridded rice yield and all the gridded rice yield were combined to get the AsiaRiceYield4km dataset. We agreed with you that more experimental implementations should be given, thus we added more details in the revised manuscript Sect. 2.3.2 **(Lines 226-229)** and one new paragraph named *(5) Gridded rice yield estimation* in Sect. 2.3.3 **(Lines 296-299)**. Besides, Figure 2 was adjusted correspondingly.

Multicollinearity problems can affect the performance of regression models (Ma and Cheng, 2016; Yang et al., 2022), but machine learning (ML) can overcome this problem in some degree (Feng et al., 2016; Zhao et al., 2019; Guo et al., 2021; Chan et al., 2022). ML can capture non-linear relationships and handle the interactions among predictors (Breiman, 2001; Shalev-Shwartz and Ben-David, 2014; Leng and Hall, 2020). Specifically, both random forest (RF) and extreme gradient boosting (XGBoost) are tree-based algorithms which can inherently immune to multicollinearity problems (Guo et al., 2021). Besides, the bagging process in RF and bootstrapping process in XGBoost can also mitigate multicollinearity effects according to Ma and Cheng (2016) and Ma (2020).

For hyper-parameters, we followed your suggestions to add hyper-parameter spaces in the revised supplement. Besides, more details about the defined space and the optimal set of values were listed in the supplement (Table S4 and S5) and the Python library details of ML algorithms were also presented **(Lines 34-36 and 37-39 in the supplement)**.

References:

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Zhao, X., Yu, B., Liu, Y., Chen, Z., Li, Q., Wang, C., and Wu, J.: Estimation of poverty using random forest regression with multi-source data: A case study in Bangladesh, Remote Sens., 11, 375, 2019.

Comment 3: The authors compared their dataset with observations via scatter plots (Figure 5). This is good. However, it would be better if the authors can additionally provide comparisons of the interannual variations in rice yield for each rice system (e.g., single, double early and later) in each country (there should be some survey data). The performance of your dataset in capturing interannual variations in rice yield is important.

Response to comment 3:

Thanks very much for your constructive comment.

We agree with you that the comparison of interannual variation is essentially important for rice yield dataset. Here, we added interannual comparison between AsiaRiceYield4km and observed yields for all countries. The results showed that our dataset has good consistency with the observed yield for all rice growing seasons. This comparison result analysis was added to the revised *Section 3.2 Comparing AsiaRiceYield4km products* in the manuscript **(Lines 338 to 345)**.

Comment 4. The authors used cumulative values of predictors (e.g., LAI and PDSI) in different phenological periods (e.g., vegetative and reproductive) to train models. However, these cumulative information has no actual physiological significance. Meanwhile, considering that crop phenological dates (e.g., planting and harvesting) vary from year to year, it would be better to use the average value of these predictors over each phenological periods for training (i.e., more comparable across years).

Response to comment 4:

We did select eight cumulative growing predictors (CGP) during annual rice phenological stage, including leaf area index (LAI) and seven climate variables. LAI can indicate the vegetational variation in rice growing status and biomass. Therefore, we believe the cumulated LAI predictors have the actual physiological significance as many previous studies confirmed. Meanwhile, the cumulative climate predictors represent weather conditions during rice growing period which have no physiological significance, the same for the cumulative climate ones.

Nevertheless, we still followed you to replace predictors from CGP category with average values in some cases to validate the estimate results. According to Fig. C1, difference of R^2 and *RMSE* for the three cases is 0-0.2 and 7-59 kg/ha, respectively. The predictors from average values had the similar impact on rice yield estimation with those from CGP. Such comparison results are attributed to the good consistency between CGPs and their related averages. Moreover, compared with the monthly resolution of weather predictors, the small change (±10 days per decade, Zhang et al., 2022) of temporal variation of rice phenological dates do not significantly affect the results. Therefore, we still used cumulative values for rice yield prediction.

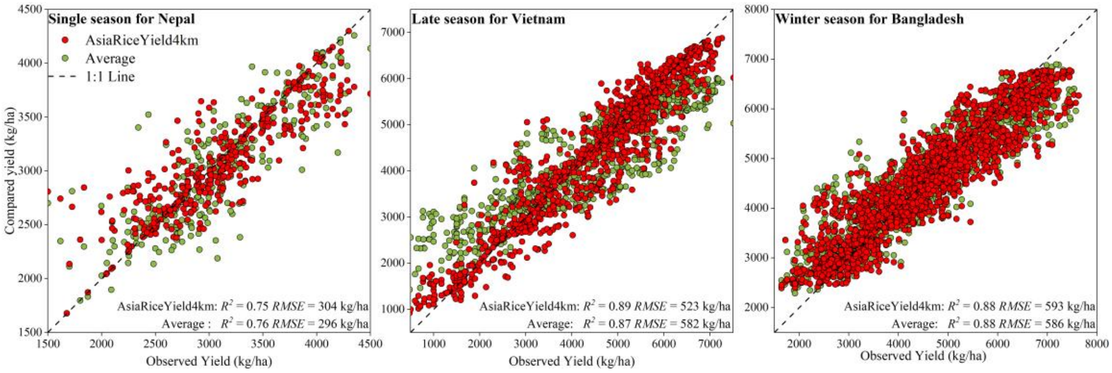


Fig. C1: The accuracy of AsiaRiceYield4km and the average.

Reference:

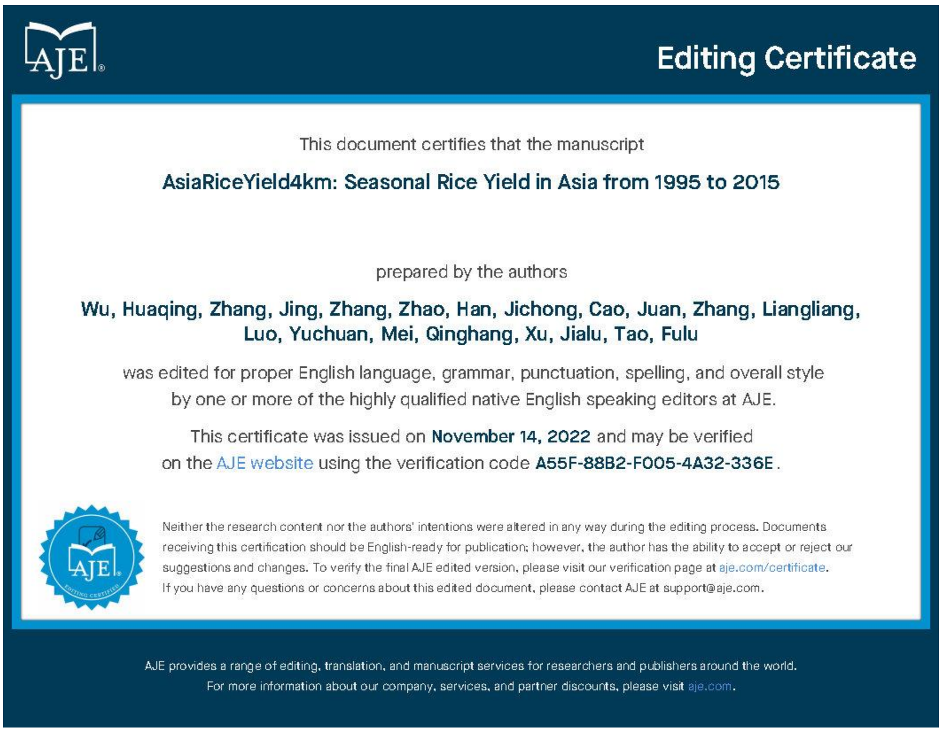
Zhang, J., Wu, H., Zhang, Z., Zhang, L., Luo, Y., Han, J., and Tao, F.: Asian Rice Calendar Dynamics Detected by Remote Sensing and Their Climate Drivers, Remote Sens., 13, https://doi.org/10.3390/rs14174189, 2022.

Comment 5: I would suggest that the authors get editing help from someone with full professional proficiency in English, as the current manuscript has substantial language issues. I pointed out some, but not all.

Response to comment 5:

Thanks very much for your suggestions.

The manuscript was carefully revised with the help of professional editors of AJE (https://www.aje.cn/?_ga=2.249467463.1174155384.1668480853-862469041.1668480853, last accessed: 15 November 2022). The editing certificate was as follows: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AsiaRiceYield4km: Seasonal Rice Yield in Asia from 1995 to 2015

prepared by the authors

Wu, Huaqing, Zhang, Jing, Zhang, Zhao, Han, Jichong, Cao, Juan, Zhang, Liangliang, Luo, Yuchuan, Mei, Qinghang, Xu, Jialu, Tao, Fulu

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Figure C2: Editing certificate for the manuscript.

Other concerns:

Comment 6: Line 72: When you say prediction, it is more of a future period than a historical period.

Response to comment 6:

Thank you. We realized that it is inappropriate to use rice yield prediction for a historical period dataset. We change “prediction” to “estimation” and “predicted” to “estimated” throughout the manuscript.

Comment 7: Line 112: Change “i.e., ” to “e.g., ”

Response to comment 7:

Corrected as suggested. The same errors were also corrected in **Line 434**.

Comment 8: Line 113: Change “Philippines” to “China”: the season number of 12 and 13 should belong to China.

Response to comment 8:

Thank you, we apologized for our carelessness. We have made this correction to the manuscript.

Comment 9: Line 117: Change “are” to “were”.

Response to comment 9:

Corrected as suggested.

Comment 10: Line 275: Have you tried any other proportions (e.g., 0.6/0.2/0.2) to examine the robustness of your datasets, trained models and evaluation results?

Response to comment 10:

According to your suggestion, we have tried different proportion strategies for ML models (Table C1). For the two dataset division strategies, we used R^2 and *RMSE* of training, validation, testing and estimation result for accuracy comparison. For the two division strategies, the results showed similar accuracy. It suggested that our datasets, trained models and evaluation results were robustness.

Table C1: Accuracy of rice yield estimation for different proportion strategies.

Case	Division strategy	R^2 (%)				RSME (kg/ha)			
		Training	Validation	Testing	Estimation	Training	Validation	Testing	Estimation
Single season for Republic of Korea	0.6/0.2/0.2	99	69	67	79	22	232	219	190
	0.56/0.24/0.2	99	68	64	80	25	226	232	186
Early season for Thailand	0.6/0.2/0.2	99	83	70	85	37	322	412	303
	0.56/0.24/0.2	99	83	71	84	39	326	409	314
Autumn season for Vietnam	0.6/0.2/0.2	99	77	84	64	53	510	332	633
	0.56/0.24/0.2	99	77	83	65	67	536	353	618

Comment 11: Figure 3: What does the legend mean? I didn't see any difference in the color of these dots.

Response to comment 11:
For Fig. 3, the legend referred to the training accuracy (R^2 and *RMSE*). We are sorry that the previous legend range is too large (R^2: 0 - 1; *RMSE*: 0 - 1000kg/ha), resulting in no differences for estimated models. We have adjusted the legend range to: R^2 from 0.9 to 1 and *RMSE* from 0 to 500kg/ha, as the training R^2 was over 0.9 and the training *RMSE* was lower than 400 kg/ha for all optimal models (**Line 316-322**).

Comment 12: Section 3.2: I would suggest moving this section to the end of "3 Results". Meanwhile, you should add additional analysis of temporal variations.

Response to comment 12:
Thanks very much for your constructive comment. We have moved Sect. 3.2 to the end of Sect. 3 and adjusted the title to *3.4 The spatiotemporal spatial characterizations of AsiaRiceYield4km*. The analysis of temporal variations for rice yield was also added (**Lines 381-387**).

Comment 13: Line 417: Add using: by "using" multi-source

Response to comment 13:
Corrected as suggested.

Comment 147: Table S1: names of the local administrative unit presents the specific… -> names of the local administrative unit represent the specific…

Response to comment 14:
Corrected as suggested.

Comment 15: Table S2: Provide the full names of these abbreviations in the footnotes.

Response to comment 15:
The full names have been added.

Comment 16 : Table S3: What do you mean in these rows:

The sum of for whole growing period
The sum of for vegetative stage
The sum of for reproductive stage
The maximum for whole growing period

Response to comment 16:
We feel sorry for our carelessness. Variable "wind speed" was missing. Thanks to your kind reminder, we have revised and simplified them in Table S3. These rows were:
Sum of wind speed for whole growing period

Sum of wind speed for vegetative period
Sum of wind speed for reproductive period
Maximum wind speed