Response to Reviewer 2

Comments to the Author:

This article develops a 20m-resolution rice map for Africa by combining time-series SAR and optical data. It is a pioneering effort involving Africa, as there are few high-resolution rice maps in Africa, and it is quite a challenge to map rice at a continental scale.

RESPONSE: Thank you very much for your appreciation and detailed feedback on our study.

However, the data quality is still questionable and subject to further validation and improvement.

RESPONSE: Thanks for your comment. We acknowledge that data validation is essential and plan to integrate additional ground-truth data in future research to enhance accuracy. Further in-field validation campaigns are also considered to confirm our dataset's quality across different regions in Africa.

The Authors admitted that large areas of rainfed rice cultivation in Africa lack the distinct flooding signals typical of irrigated rice, but the methodology is based on the detection of flooding signals. How can you then map rainfed rice fields? More importantly, it does not seem the author's product can differentiate irrigated rice and rainfed rice, which is important to support rice monitoring and agricultural and climate mitigation policy development.

RESPONSE: Thanks for your comment and sorry for the confusion. Our methodology is based on comprehensive rice samples and the efficiency of supervised classification. There is no emphasis on the detection of flooding signals. We acknowledge that it is a deficiency at present and plan to address it in future work. Nonetheless, we believe that our current 20m-resolution rice map for Africa represents a valuable advancement, providing critical insights into rice distribution at a continental scale, and setting an essential foundation for rice monitoring and future research.

The authors also admitted that the main challenge is constructing a training/validation sample set. However, the method used in this study is not convincing, as there is no real "ground-truth" data.

RESPONSE: Thanks for your comment. We agree that the lack of ground-truth data is a limitation in our study. Our current approach relies on expert knowledge and statistics, but we are actively seeking partnerships to facilitate in-situ data collection in Africa, which will help us refine and validate our training/validation sets more effectively.

Line 55: so spatial distribution map is not gridded maps? This sentence is not accurate.

RESPONSE: Thanks for your comment and sorry for the confusion. It is revised in the manuscript.

Line 53-54: The existing datasets have low resolution and are all gridded datasets rather than high resolution distribution maps.

Figure 5: how do you know which are rice fields, which are wetlands, which are other land covers?

RESPONSE: Thanks for your comment and sorry for the confusion. This is confirmed by expertise of researchers referring to optical imagery and land cover dataset (WorldCover from ESA).

I have a big concern about the procedure of constructing the training/validation sample set. The first step is ok and fine, which uses some image signal to find potential rice fields, but the second step is questionable: cross-referencing the intersections of the rice grid map from CROPGRIDS and Cropland distribution maps with corresponding optical imagery. CROPGRIDS is very coarse, with each grid including multiple land covers, and I do not know how you can confirm whether a location within that grid is a rice field or not. If this works, I can simply make a map of rice fields by cross-overlaying Cropland distribution with CROPGRIDS.

RESPONSE: Thanks for your comment and sorry for the confusion. Rice fields are determined by visual interpretation on optical imagery. Cross-referencing the intersections of the rice grid map from CROPGRIDS and Cropland distribution maps serves as a validation step. The expression is revised for improved readability.

Line 199-201: Specifically, after positioning potential rice-plating areas, rice plots were identified and selected as rice samples by visual interpretation on optical imagery and further validated by cross-referencing the intersections of the rice grid map from CROPGRIDS and cropland distribution maps.

The negative samples, which are randomly sampled based on World Cover products, are also questionable. World Cover Product is subject to errors (omission and commission), how can you guarantee your samples are correct and accurate?

RESPONSE: Thanks for your comment and sorry for the confusion. Plots of other land types are also determined by visual interpretation on optical imagery. The ‘randomly sampled’ process is conducted within these plots. The expression is also revised for improved readability.

Line 208-211: In the classification experiments conducted for each country, dozens of plots for each land cover type (non-rice cropland, built-up areas, water bodies, wetlands, forests, grasslands, etc.) were uniformly selected by visual interpretation based on optical imagery and the WorldCover product. For each land cover type, 300 sample points were randomly selected within these plots as negative samples for the classifier input.

There is no demonstration/validation of the performance of the image segmentation. Shall at least use some known crop field (must include rice fields) to demonstrate the segmentation can reasonably divide different fields.

RESPONSE: Thanks for your comment and sorry for the confusion. The effect of image segmentation is presented in Fig. 8, and explained in Line 281-283. Description is added to section 3.2.1 SNIC Object oriented segmentation.

Line 232-233

The effect of segmentation is demonstrate in Fig.8.

Line 281-283

Additionally, the mean values calculated from object-based segmentation of optical imagery improved the representation of SAR image noise and fragmented plots while preserving clear boundaries.

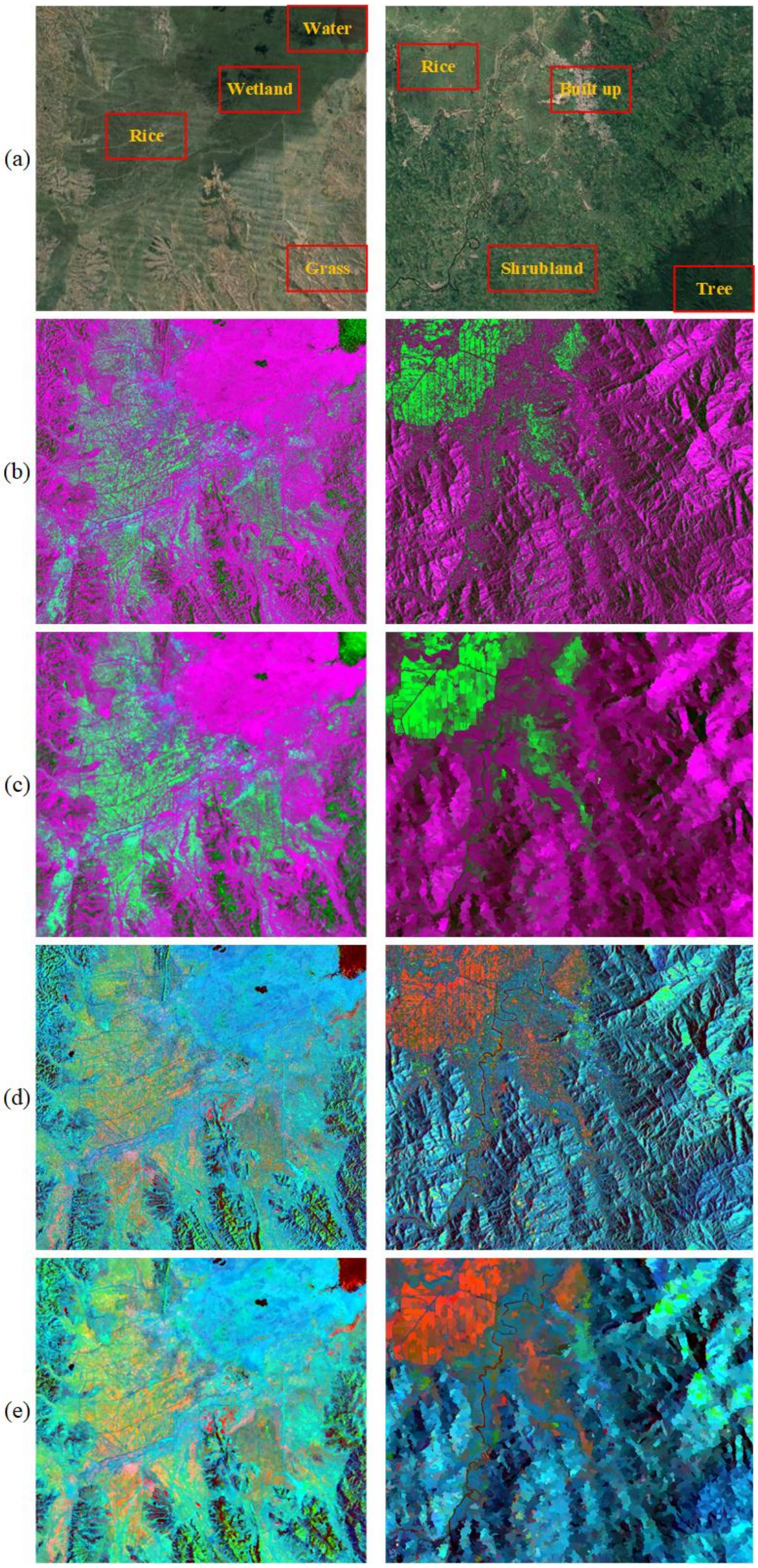


Figure 8. Example of pseudo-color composites using selected time-series SAR features: (a) optical image(From ©Google Earth) (b) pseudo-color composite 1 (R: VH_min, G: VH_variance, B: VH_mean) (c) mean values of pseudo-color composite 1 overlaid on the object-based segmentation result from NDVI time series (d) pseudo-color composite 2 (R: VV_variance, G: VV_mean, B: PRVI_mean); (e) mean values of pseudo-color composite 2 overlaid on the object-based segmentation result from NDVI time series.

The division between single-season and double-season rice fields based on crop calendar from riceAltas is too simple. I hope the authors can do better based on time series inundation/phenological data. riceAltas's crop calendar is country/county-based and we know there is much variation within a country and county.

RESPONSE: Thanks for your suggestion. We acknowledge that it could be a deficiency. We utilized the intensity data mainly to compare with statistics and get a general knowledge of rice cultivation in Africa. More thorough research with precise phenology information would be conducted based on current result. As for RiceAtlas, we chose it for its better stability in time than pixel-level intensity datasets.

Look at Table 8: if assume these survey statistics are right, your estimate overestimates a lot for many countries such as Angola, Burundi, Cameroon, Cameroon, and the Gambia, suggesting possible large commission errors. The high R2 score in Figure 12 can only suggest that your product generally captured the continental-scale distribution pattern, and does not directly approve a high-quality high-resolution map.

RESPONSE: Thanks for your comment. We acknowledge that there might be some overestimation in certain countries. The causes of these discrepancies are analyzed in section 4.3, Line 358-368. We agree that high R^2 score does not fully validate the high-resolution map quality for the lack of sub country level statistics, but it demonstrate the general reliability of our result. And the accuracy is further analyzed is section 4.4.

Line 363-373:

These discrepancies may be attributed to several factors. In developing countries in Africa, data collection and reporting systems are often incomplete and inconsistent, leading to major gaps in the accuracy of reported rice cultivation areas. The issue is further compounded by the dominance of smallholder farming systems, where individual farm sizes are smaller and scattered, making them even harder to track and report on accurately. This often results in underreporting or outdated figures in official statistics. Additionally, rice cultivation in these regions has undergone rapid changes in recent years, with some areas seeing significant increases in planting that aren't being fully captured by traditional reporting methods. Although multiple auxiliary datasets were integrated when constructing rice sample set for this study, the process still heavily relied on expert knowledge. This is particularly challenging in countries with limited rice cultivation, where rice fields are more difficult to identify, leading to sample errors that directly affect mapping accuracy. Moreover, the rice intensity distribution information used to estimate planting areas was published in 2017 and may not fully capture the present situation in 2023, contributing to discrepancies between the mapped data and reported cultivation areas.

Even based on the current accuracy assessment, many countries still have over accuracy ~69.76%, which is too low to accept based on the current technology of rice-paddy mapping.

RESPONSE: Thanks for your comment and sorry for the confusion. There is only one country with OA(overall accuracy) under 70% (South Sudan), 4 countries between 70% and 80% (Niger, Zambia, Angola, and Sudan). All these countries have small area of rice, posing extra challenge to sample set construction, hence the relatively lower OA in these countries. This can be improved by future field survey in Africa. This explanation is also added to section 4.4.

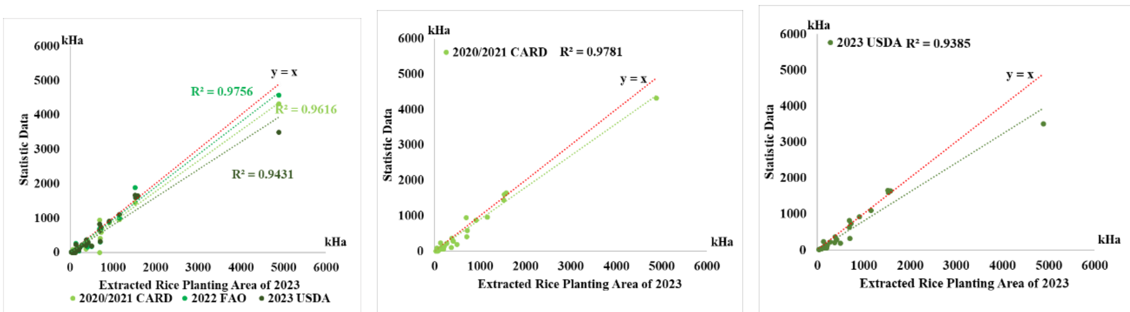
Line 396-401

Overall Accuracy (OA):

The overall accuracy (OA) ranges from 69.76% in South Sudan to 94.17% in Guinea, with a mean of around 86.30%. Of all countries in study site, one country has OA under 70% (South Sudan), 4 countries between 70% and 80% (Niger, Zambia, Angola, and Sudan). All these countries have small area of rice, posing extra challenge to sample set construction, hence the relatively lower OA in these countries. But countries with extensive rice cultivation, such as Ghana and Senegal, show OAs above 90%, reflecting the model's robustness in regions with more homogeneous and concentrated rice production.

Line 406-409

Outliers and Challenges: The box plot (Fig.12) analysis reveals stable and consistent performance across most countries, with median values clustering between 85% and 90%. However, outliers such as South Sudan, Angola, and Niger show lower accuracy scores, mainly caused by lack of sufficient rice samples, suggesting that additional refinement is needed for these regions.



(a) (b) (c)

Figure 12. The linear fitting results between the 2023 rice planting area derived from this study and the existing statistical data, with mapping results as the x-axis and existing statistical data as the y-axis. The red dashed line represents the y = x line. (a) fitting results for all 34 countries, (b) fitting results for 30 countries after excluding those with missing data from the CARD dataset (c) fitting results for 27 countries after excluding those with missing data from the USDA dataset.