Dear the reviewers and the editor,

Manuscript ID ESSD-2024-402 entitled “20 m Africa Rice Distribution Map of 2023.”

We would like to express our sincere gratitude to the editor and the reviewers for your constructive feedback and thorough review of our manuscript. We have carefully considered all suggestions and have made the corresponding revisions to the manuscript. In addition to addressing the reviewer’s comments, we have also refined the overall language to enhance the quality of the paper, and redrawn some of the figures for greater clarity. Below, we provide detailed responses to the reviewer's comments, including clarifications where necessary. We hope these revisions address the concerns and uncertainties raised by the reviewer. In the manuscript and this file, the red parts are revisions suggested by the reviewer 1, blue parts for suggestions of reviewer 2. And the green parts are the changed contents that are intended to improve the expressions.

Sincerely,

Hong Zhang

Response to Reviewer 1

Comments to the Author:

This study presents a high-resolution rice distribution map in Africa using an innovative approach that combines time-series optical and SAR data. Given the limitations of current rice distribution products in this region, this study will provide a valuable product for monitoring rice cultivation in African. This product can contribute to assessing food security and the sustainability of rice production in African, such as the evaluation of rice yield and GHGs emission. However, there are several major comments that needed to be addressed:

RESPONSE: Thank you very much for your appreciation of our work.

1. Please provide the full form of all abbreviations when they first appear, such as SAR, to ensure clarity for readers.

RESPONSE: Thanks for pointing it out. They are revised in the manuscript.

Line 14 Synthetic Aperture Radar (SAR)

Line 60-61 Land Surface Water Index (LSWI) and Enhanced Vegetation Index (EVI)

Line 116-117 FAO (Food and Agriculture Organization of the United Nations)

Line 144-145 NDWI (Normalized Difference Water Index) and NDVI (Normalized Difference Vegetation Index)

Line 151 European Space Agency's (ESA)

Line 244 GRD (Ground Range Detected) data)

Line 264 UN (United Nations)

Line482 SDGs (Sustainable Development Goals)

2. Section 2.2.1: More details are needed on the criteria used for image screening.

RESPONSE: Thanks for your suggestion. Details are added in the manuscript.

Line 140-145

The main data sources in the study are time-series SAR data and optical data for their high temporal and spatial coverage. Specifically, the monthly average VH and VV data of Sentinel-

1 satellite for the whole year of 2023 were obtained as SAR data input on the GEE platform. Because rice is sensitive to NDWI (Normalized Difference Water Index) and NDVI (Normalized Difference Vegetation Index)(De Lima et al., 2021; Zhang et al., 2019), the monthly average B3, B4, B8, and B8A band data of Sentinel-2 satellite for the whole year of 2023 were obtained as optical data input to composite NDWI and NDVI.

3. Section 2.2.4: Is it appropriate to distinguish the distribution of single- and double-season rice in 2023 using a crop type dataset in 2017? My main concern is that the planting area of single- and double-season rice in Africa have expanded rapidly in recent years.

RESPONSE: Thanks for your comment. This could be a problem as we mention it in 4.3 and sorry for the confusion that it is not well explained in the manuscript. Explanation is added in discussion part.

Line 450-458:

Another potential problem is when comparing with statistic data, the administrative distribution data of rice planting intensity in RiceAtlas product is utilized to calculate the planting area from the paddy area of the mapping result. This dataset of year 2017 could lead to gaps between calculated planting area with actual planting area and that with statistical data since rice cultivation expands rapidly in recent years as mentioned in section 4.3. However, there is no up-to-date dataset of rice intensity in Africa. And other datasets including rice intensity in Africa like GCI (Global Cropping Intensity) from year 2001 to 2019 (Liu et al., 2021), and GCI30(Zhang et al., 2021) from year 2016 to 2018, are pixel-level datasets, which are assumed to change more than administrative-level data over time. Therefore, RiceAtlas is chosen as the rice intensity source to balance consistency and data availability. Nevertheless, more up-to-data intensity data can provide more insight into the rice planting status in Africa.

4. Section 3.1: How was the quality of screened samples assessed, and how are these samples distributed?

RESPONSE: Thanks for your comment and sorry for the confusion. The “screening” process is part of visual interpretation. The visual interpretation is conducted referring to the intersections of the rice grid map from CROPGRIDS, cropland distribution maps, corresponding optical imagery and the fast coarse positioning feature (R: VHmax, G: VHmin, B: VHvariance), as described in section 3.1.1.

5. The accuracy of the rice distribution map highly depends on image segmentation. Please explain the reason for choosing bands such as B3, B4, B8 and B8A for image segmentation, and provided results demonstrating the image segmentation.

RESPONSE: Thanks for your comment. The reason to choose band B3, B4, B8 and B8A is added in the manuscript, as explained in response to comment 2. The effect of image segmentation is presented in Fig. 8, and explained in Line 277-280.

Line 281-282

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.

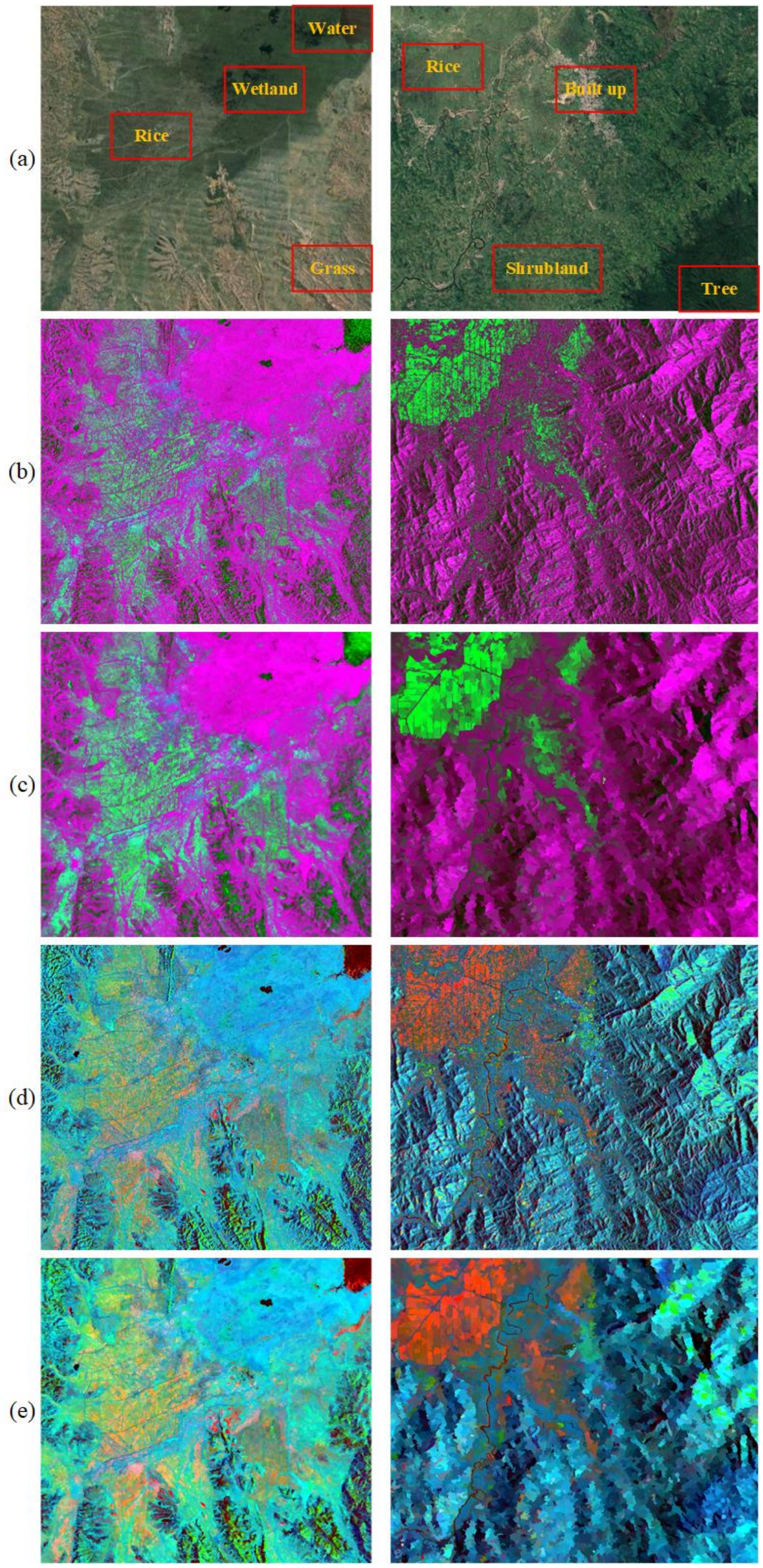


Figure 8. Example of pseudo-color composites using selected time-series SAR features: (a) optical image(From ©Google Earth) (b) pseudo-color composite 1 (R: VH_min, G: VH_variance, B: VH_mean) (c) mean values of pseudo-color composite 1 overlaid on the object-based segmentation result from NDVI time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

6. If more reliable rice samples can be obtain based on fast coarse positioning and ancillary data, is it possible to map rice distribution directly using this method? Additionally, after SAR features screening, can rice paddy be distinguished from similar elements such as wetland?

RESPONSE: Thanks for your comment. Reliable samples are essential in rice mapping when supervised classification is involved. So it is possible to map rice distribution directly using this method if there are more reliable rice samples. In fact, the fast coarse positioning strategy is proposed to tackle the problem of lacking reliable rice samples of Africa.

As for the second question, it is hard to distinguish rice paddy from similar elements such as wetland. Actually, we conducted experiments to perform unsupervised classification using the same SAR features hoping to distinguish rice paddy from other ground objects even generate rice samples automatically, but the result was not ideal. Therefore the sample construction still relies on visual interpretation. The fast coarse positioning strategy improves the efficiency of visual interpretation greatly.

7. The structure of the methods is confusing, and the description of the methodology is unclear. This section required further improved.

RESPONSE: Thanks for your comment. This section is rewritten.

The flowchart is refined. “SAMPLE SET MAKING” is changed into “SAMPLE SET CONSTRUCTION”, and “Fast Coarse Location” is changed into “Fast Coarse Positioning”

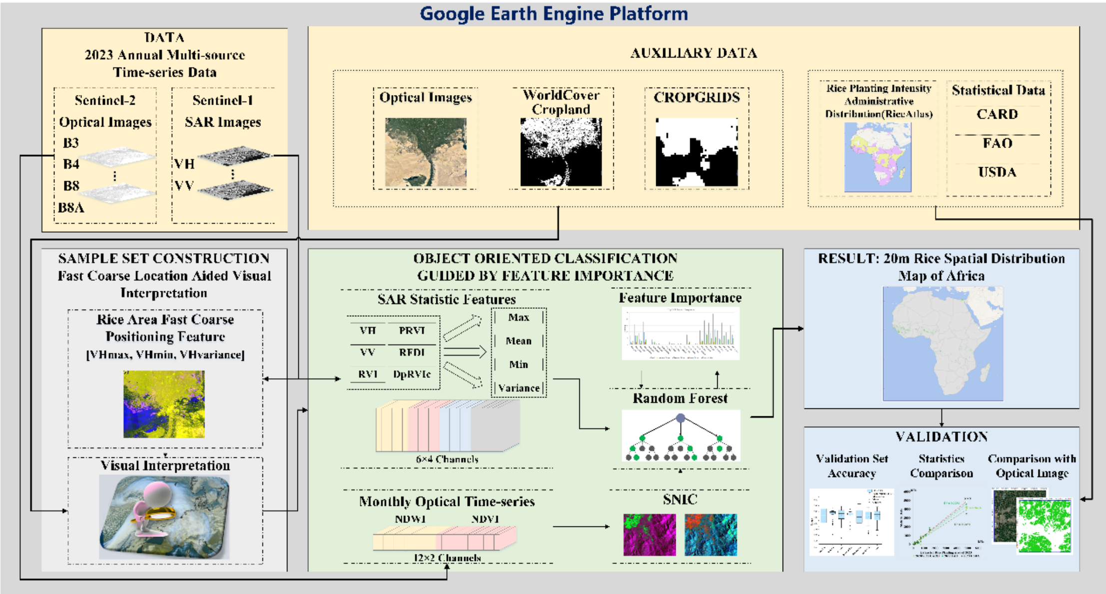


Figure 4. **Flowchart of the proposed rice mapping method (Optical images are from ©GoogleEarth)**

Line 171-185:

The workflow for mapping the spatial distribution of rice in Africa at a 20-meter resolution is depicted in Fig. 4. The study adopts a multi-source time-series data approach combined with a supervised classifier to achieve large-scale, high-resolution mapping of rice distribution in Africa. The workflow is primarily divided into two main stages: sample set construction and object-based classification guided by feature importance.

During the sample set construction phase, visual interpretation is conducted referring to ESA WorldCover cropland data, CROPGRIDS rice grid map, and optical image, with statistical features from VH time-series aiding in the fast coarse positioning of potential rice-growing regions.

During the classification phase, classification experiments were conducted in every country separately. Object-based segmentation is first performed on optical images to obtain super-pixel results, which helps mitigate the effects of speckle in SAR imagery, enhances classification accuracy, and better captures the complex spatial patterns of rice fields. The mean values of SAR data (VH, VV) and various radar vegetation indices derived from SAR data within these super-pixels are then used as input features. A random forest classifier is applied to train the model, which gives ranks of the importance of the input features. The most important features of different sub-regions of Africa are selected for a subsequent classification to produce the rice paddy distribution map. Finally, accuracy validation is conducted using statistical data and validation datasets.

3.1 Sample set construction: fast coarse positioning aided visual interpretation

8. The figures and tables need better organization. For instance, there are overlaps between Table5 and Fig7, and some figures, such as fig.12, are missing horizontal or vertical axes.

RESPONSE: Thanks for pointing it out. They are revised in the manuscript.

The overlap between Table5 and Fig7 is deleted.

Fig. 12 is refined.

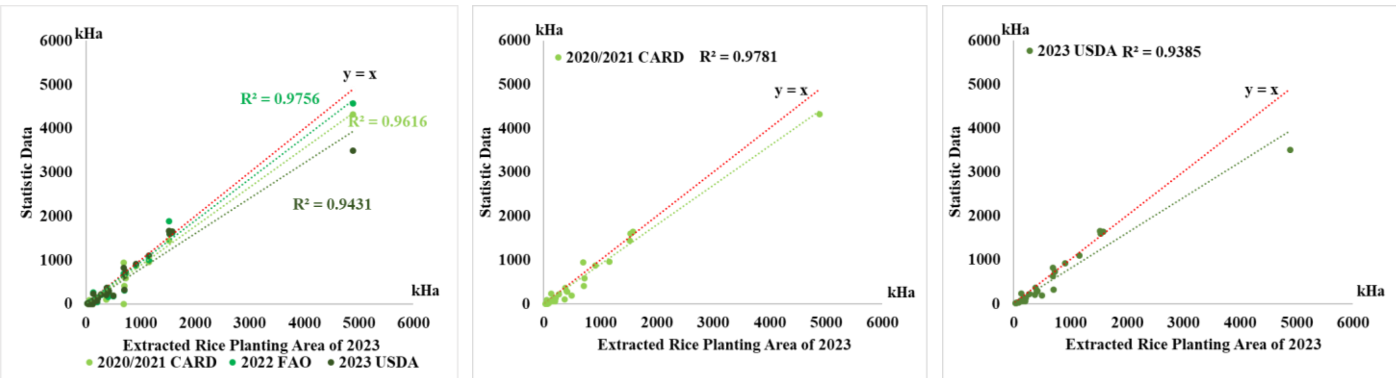


Figure 12. The linear fitting results between the 2023 rice planting area derived from this study and the existing statistical data, with mapping results as the x-axis and existing statistical data as the y-axis. The red dashed line represents the y = x line. (a) fitting results for all 34 countries, (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.

Legends of Fig.15 are modified.

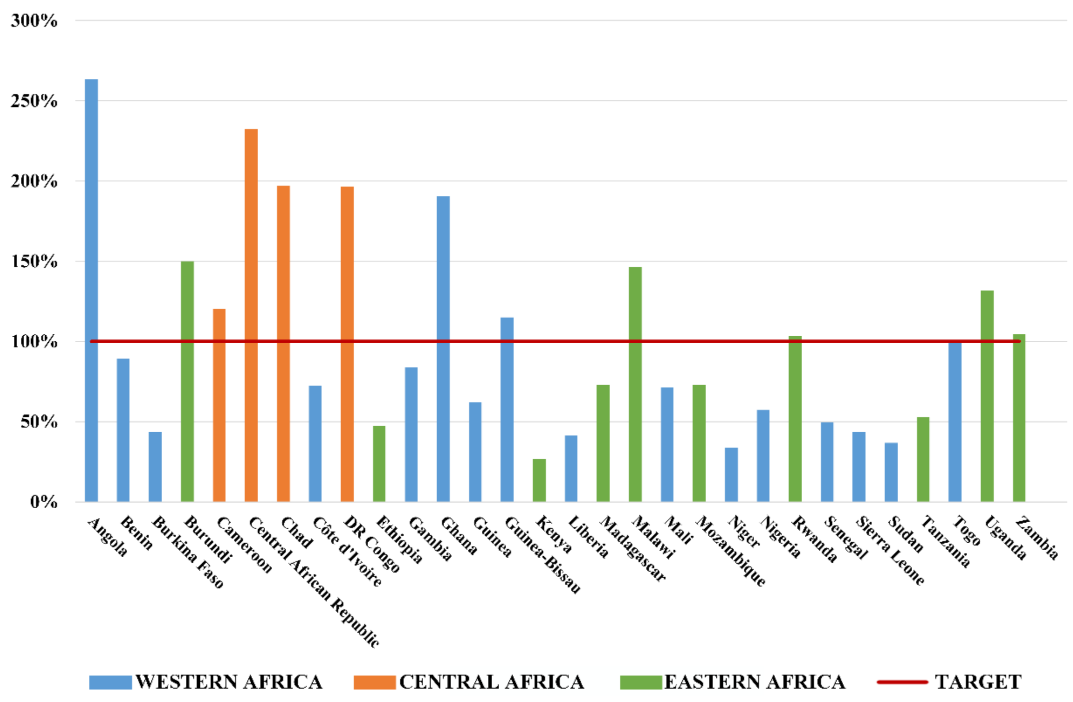


Figure 15. Comparison of current rice planting areas and 2030 targets for CARD countries

9. The discussion section should be strengthened, especially by comparing the methods in this study with those used in other studies, and the implications of the rice distribution map for Africa should also be emphasized further.

RESPONSE: Thanks for your thorough suggestion. This part is revised accordingly.

Line 430-470:

5.1 Strengths and limitations

To produce large-scale, high-resolution rice distribution maps across Africa, this study proposed a method effectively combining Sentinel-1 SAR and Sentinel-2 optical imagery, addressing key challenges in sample collection and classification. By leveraging time-series statistical features from Sentinel-1 VH data for initial fast coarse positioning of potential rice-planting areas and complementing this with visual interpretation using auxiliary datasets, the study efficiently generates reliable samples. During the classification phase, the approach integrates object-based segmentation results from Sentinel-2 optical time-series data with feature importance guided Random Forest classification results from Sentinel-1 SAR time-series data. This combination enhances the precision of rice paddy boundaries and reduces noise in heterogeneous landscapes, showing a significant improvement than pixel based method. Additionally, the proposed method requires no phenology information, allowing for a more adaptable mapping process across diverse rice-growing regions like Africa, avoiding the inaccuracies that arise from seasonal variability and diverse planting practices, which are common challenges in phenology-based methods. Collectively, these strengths underscore the method's robustness, efficiency, and scalability, positioning it as a reliable tool for high-resolution agricultural monitoring across Africa.

Despite these strengths, the study acknowledges limitations related to the SNIC algorithm, particularly in the calibration of key parameters—seed distance and neighbourhood size, which affects the size and definition of segmented objects. In this study, it was primarily achieved through a process of trial and visual inspection. While this method provided a practical solution within the context of this research, the robustness of the method needs to be further strengthened. Future research should focus on developing more systematic approaches to parameter optimization. This could involve the use of automated tuning algorithms or machine learning techniques that adjust parameters dynamically based on the characteristics of the input data, thereby improving the accuracy, consistency, and scalability of the segmentation process.

Another potential problem is when comparing with statistic data, the administrative distribution data of rice planting intensity in RiceAtlas product is utilized to calculate the planting area from the paddy area of the mapping result. This dataset of year 2017 could lead to gaps between calculated planting area with actual planting area and that with statistical data since rice cultivation expands rapidly in recent years as mentioned in section 4.3. However, there is no up-to-date dataset of rice intensity in Africa. And other datasets including rice intensity in Africa like GCI (Global Cropping Intensity) from year 2001 to 2019 (Liu et al., 2021), and GCI30 from year 2016 to 2018, are pixel-level datasets, which are assumed to change more than administrative-level data over time. Therefore, RiceAtlas is chosen as the rice intensity source to balance consistency and data availability. Nevertheless, more up-to-data intensity data can provide more insight into the rice planting status in Africa.

5.2 Enlightenment and implications

The experiment result highlights regional variations in the importance of specific features for rice mapping across Africa. Despite these variations, temporal statistical features from SAR data—particularly VH, VV, and PRVI—consistently demonstrated their utility in capturing the temporal dynamics of rice cultivation. By further exploring and experimenting with these temporal SAR features, future studies could refine rice detection models to be more sensitive to regional differences and temporal changes in Africa. This could involve integrating these features with additional data sources, such as optical imagery or other environmental variables, to create more robust and comprehensive mapping models.

The rice distribution map generated in this study has significant implications for agricultural monitoring and food security across Africa. By providing an accurate baseline for rice distribution, this study supports government and research initiatives focused on food resource management, land use planning, and climate impact assessments. Unlike current rice mapping studies in Africa, which have been constrained by limited spatial resolution and are primarily represented as gridded data, this approach offers a reliable, scalable framework that aligns with Africa's need for consistent agricultural data.

10. Some references are incorrect, such as those in lines 61 and 189, and should be corrected.

RESPONSE: Thanks for pointing it out. Style of all references is revised in the manuscript.

Reference

de Lima, I. P., Jorge, R. G., and de Lima, J. L. P.: Remote sensing monitoring of rice fields: Towards assessing water saving irrigation management practices, Frontiers in Remote Sensing, 2, 762093, 2021.
Liu, X., Zheng, J., Yu, L., Hao, P., Chen, B., Xin, Q., Fu, H., and Gong, P.: Annual dynamic dataset of global cropping intensity from 2001 to 2019, Scientific Data, 8, 283, 10.1038/s41597-021-01065-9, 2021.
Zhang, B., Liu, X., Liu, M., and Meng, Y.: Detection of Rice Phenological Variations under Heavy Metal Stress by Means of Blended Landsat and MODIS Image Time Series, Remote Sensing, 11, 13, 2019.
Zhang, M., Wu, B., Zeng, H., He, G., Liu, C., Tao, S., Zhang, Q., Nabil, M., Tian, F., and Bofana, J.: GCI30: A global dataset of 30-m cropping intensity using multisource remote sensing imagery, Earth System Science Data Discussions, 2021, 1-22, 2021.

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.

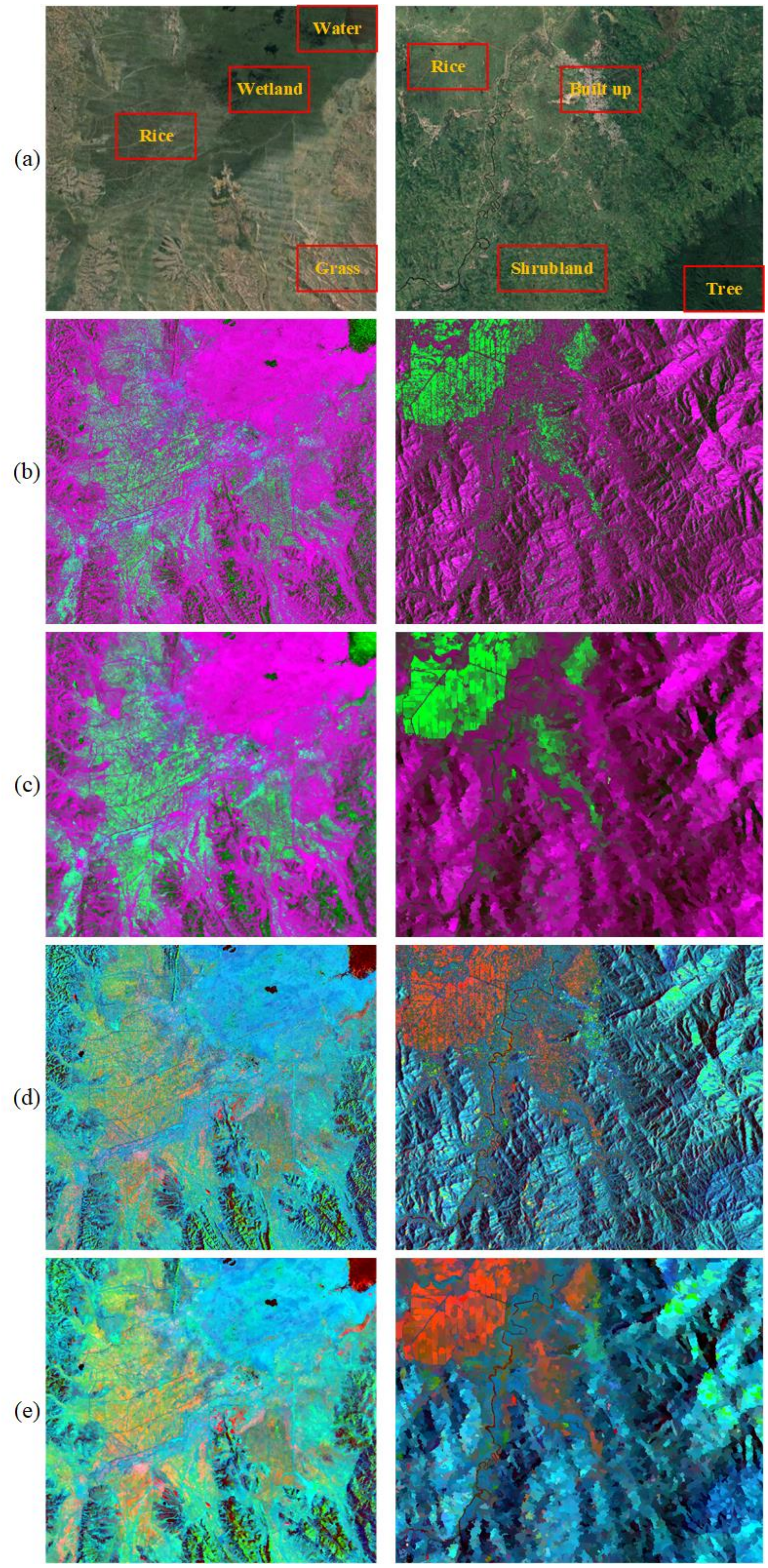


Figure 8. Example of pseudo-color composites using selected time-series SAR features: (a) optical image(From ©Google Earth) (b) pseudo-color composite 1 (R: VH_min, G: VH_variance, B: VH_mean) (c) mean values of pseudo-color composite 1 overlaid on the object-based segmentation result from NDVI time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

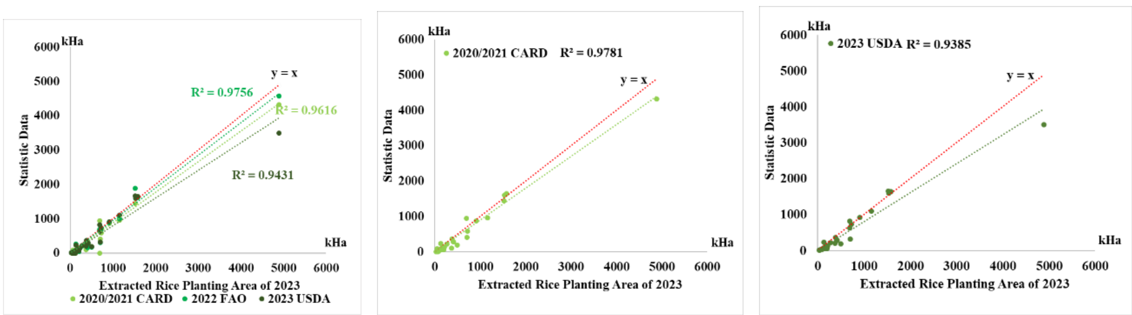
Line 396-401

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.