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, offering valuable insights into the current state of rice production in the region. It also holds potential for applications such as modeling rice yield and greenhouse gas emissions. However, a major concern lies in the fact that rice cultivation in Africa is heavily constrained by water availability, resulting in two rice cropping systems: irrigated rice and rainfed rice. Notably, the latter accounts for up to 60% of the total rice planting area. Consequently, it is critical to distinguish the distributions of rainfed and irrigated rice, and also elaborate on the specific methods used to distinguish these systems and validate the dataset's accuracy, as accurate identification of rainfed and irrigated rice is critical for enhancing data precision and expanding its application potential.

RESPONSE: We appreciate your valuable feedback and thoughtful suggestions. We acknowledge the importance of distinguishing between rainfed and irrigated rice systems, as they are critical for enhancing the applicability of the dataset and important for understanding water use and crop management practices. Currently, the existing rice distribution datasets of Africa are all gridded maps with very limited resolution (highest at 3', ~5.5km), as listed in the table below which is difficult to meet the needs of fine-grained research and decision-making. Therefore, our research focuses on the mapping of rice areas at a high spatial resolution, especially critical in Africa where detailed agricultural data are lacking.

Table 1 Current rice distribution map of Africa

DATASET	DATA TIME	PUBLISHED TIME	RESOLUTION
SPAM2010	2010	2020	5'
GAEZ+2015	2015	2020	5'
SPAMAF2017 (Sub Sahara)	2017	2020	5'
CROPGRIDS	2023	2023	3'

During the rice sample set construction period of our experiment, we conducted an extensive review of relevant literature, news reports, and various data sources (part of them listed in Table 2) to identify regions with confirmed rice cultivation.

Table 2 References for identifying confirmed rice fields

Country	Published literature
Benin	(Loko et al., 2022)
Burkina Faso	(Barro et al., 2021)
Chad	*(Liang et al., 2017)*
Egypt	*(Mathieu, 2022)*
Kenya	*(Menge et al., 2024)*
Madagascar	*(Voahanyinirina and Elie, 2007)*

Mali	*(Diuk-Wasser et al., 2007)*
Mozambique	*(Kajisa and Vu, 2023)*
South Sudan	(Fewsnet, 2018)

Country	**Report**
Angola	https://zixun.16988.com/news/getDetail?id=666121 http://www.aape.org.cn/dwgk/zzjg/ywbm/jzgc/gzdt/201801/t20180126_6059231.html
Benin	https://big5.cctv.com/gate/big5/sannong.cntv.cn/20140408/101454.shtml https://www.yixing.gov.cn/doc/2023/08/31/1166584.shtml https://www.gov.cn/xinwen/2015-03/23/content_2837484.htm
Burkina Faso	https://nyncj.taian.gov.cn/art/2022/1/19/art_45390_10292390.html http://www.chinafarmernet.com/index.php?c=show&id=34948 https://www.imsilkroad.com/news/p/444586.html
Burundi	https://www.yidaiyilu.gov.cn/p/292811.html http://world.people.com.cn/n1/2024/0217/c1002-40178064.html
Cameroon	http://shindaya.com/info.php?cid=44&id=1376
Gambia	https://www.fmprc.gov.cn/web/gjhdq_676201/gj_676203/fz_677316/1206_677632/1206x2_677652/201911/t20191130_8019921.shtml
Ghana	https://chinabn.org/invest/t4m/rice_project_background.html
Guinea	http://gn.mofcom.gov.cn/article/ddgk/202108/20210803193151.shtml
Guinea-Bissau	http://www.focac.org/zfzs/202209/t20220909_10764764.htm http://gw.mofcom.gov.cn/article/jmxw/202312/20231203461473.shtml
Mauritania	https://m.investgo.cn/article/gb/fxbg/200306/20030600100287.html
Morocco	https://www.changzhou.gov.cn/ns_news/278135579454748

Based on this information, we verified the feasibility of the feature map (R: VHmax, G: VHmin, B: VHvariance) for fast and coarse positioning of potential rice-growing areas, 6 spots of different countries (italic lines in Table 2) are presented in the figure below. The rice fields in Egypt and Mali are irrigated, the rice fields in Mozambique are rainfed, and the other three are mixed or unknown types. In the manuscript, we explain that rice appears purple on the feature map due to a combination of low VHmin values and high VHmax and VHvariance values, which correspond to the flooding period commonly observed in rice cultivation. Although rainfed rice lacks the stable flooding period typical of irrigated rice, it often experiences temporary flooding of varying durations and depths caused by rainfall (Yamamoto et al., 2012; Kwesiga et al., 2019; Panda and Barik, 2021; Mwakyusa et al., 2023). This can be seen in the updated Fig.6, rainfed and irrigated rice region reflect similar purple coloration on the feature map. This means that our method is applicable to both irrigated and rainfed rice and can accurately find potential rice growing areas, but cannot further distinguish between irrigated and rainfed rice.

Current methods using remote sensing data to distinguish irrigated rice and rainfed rice require ground truth data for supervised classification(Vogels et al., 2019), which is not available or sufficient for the various phenology of rice in Africa. The nearest rice distribution dataset distinguishing irrigated rice and rainfed rice of Africa is SPAMAF2017(International Food Policy Research, 2020), which is modeled using statistical methods and not derived directly from remote sensing data. As a result, its spatial resolution (typically 5 arc-minutes, approximately 10 km) is too coarse to serve as a reference to distinguish irrigated rice and rainfed rice for fine-scale mapping at the 20 m resolution achieved in our study. Moreover, the accuracy of SPAMAF2017 heavily depends on underlying statistical assumptions and input data, which may not fully capture the heterogeneity of rice cropping systems across diverse African landscapes and climate. Additionally, existing irrigation datasets like the FAO's Global Map of Irrigation Areas (GMIA) or the Irrigated cropland of GADAS are also inappropriate to distinguish irrigated and rainfed rice as well for their early date and low resolution, as listed in Table 3. Therefore more in-depth research such as thorough temporal feature analysis is needed in the future to distinguish irrigated and rainfed rice at a fine spatial scale and accommodate with the heterogeneity of cropping systems across diverse African landscapes and climate.

Table 3 Dataset with irrigation information

DATASET	**DATA TIME**	**RESOLUTION**	**COVERAGE**
GMIA	2013	5’	Global
SPAMAF2017 (Sub Sahara)	2017	5’	Africa
GADAS Irrigated cropland	2019	0.5°~5’	Global

Thank you once again for your valuable suggestions regarding this study. In our subsequent work, we will leverage the findings of this study and incorporate more detailed survey data to delve deeper into the distribution patterns of rain-fed and irrigated rice in Africa, thereby providing stronger scientific support for food security and water resource management in the continent.

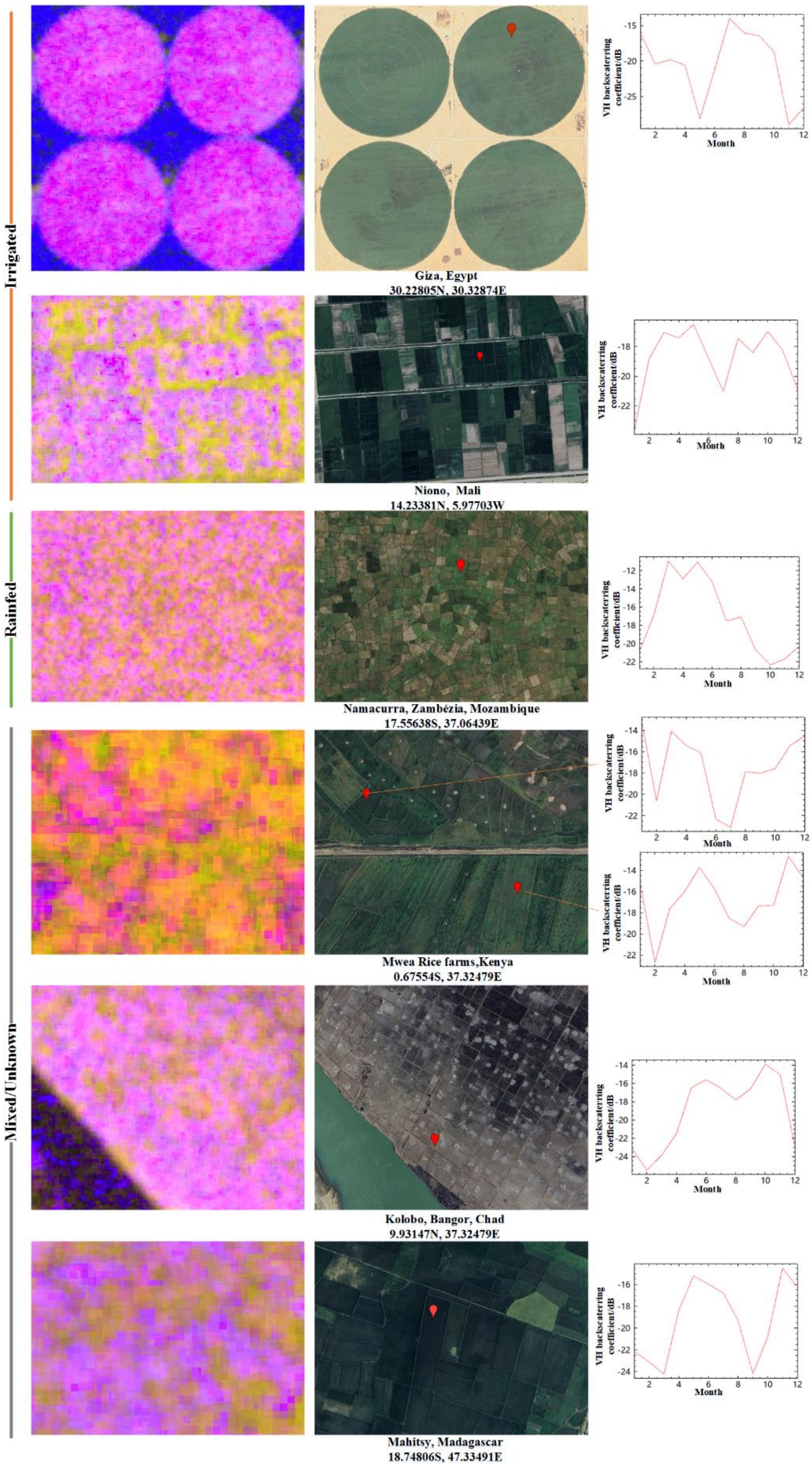


Figure 6. Examples of rice fields (a) Pseudo-color composite image (R: VHmax, G: VHmin, B: VHvariance) (b) Optical image (c) VH backscattering coefficient time series curve of the point marked in (b)

Page 13, Line 218-233:

Generally, the rice plots have these features on optical images: (1) circular irrigation fields or fields with internal blocks or strips to retain water, especially near water, rivers, lakes, etc. (2) very uniform greenness and texture during the growing season. If the features are not clear enough, the time series curve of VH data would be examined for obvious fluctuations since the backscatter of VH polarized data of rice has a clear drop during the flooding period. Fig. 6 presents some examples of rice fields and the VH backscattering coefficient time series of the red-marked point. The field in Egypt is an example of the typical circular irrigated rice paddy during the growing season that can be located refer to the literature(Mathieu, 2022). The fields in Mali are in the irrigated region around Niono(Diuk-Wasser et al., 2007). The fields in Mozambique are an example of rainfed rice paddy during the growing season that can be located referring to the literature(Kajisa and Vu, 2023). The fields in Kenya are in the concentrated rice planting area in Mwea and can be located from (Menge et al., 2024), which are examples of rice fields with internal blocks or strips. The fields in Chad are part of the China-aided Bongor Rice Demonstration Base in Chad, which is an example of rice fields in the non-growing season (Liang et al., 2017). The fields in Madagascar are in Mahitsy where rice cultivation has a long history(Voahanyinirina and Elie, 2007). The corresponding pseudo-color composite feature map in Fig.6 also proves the effectiveness of the fast coarse positioning method.

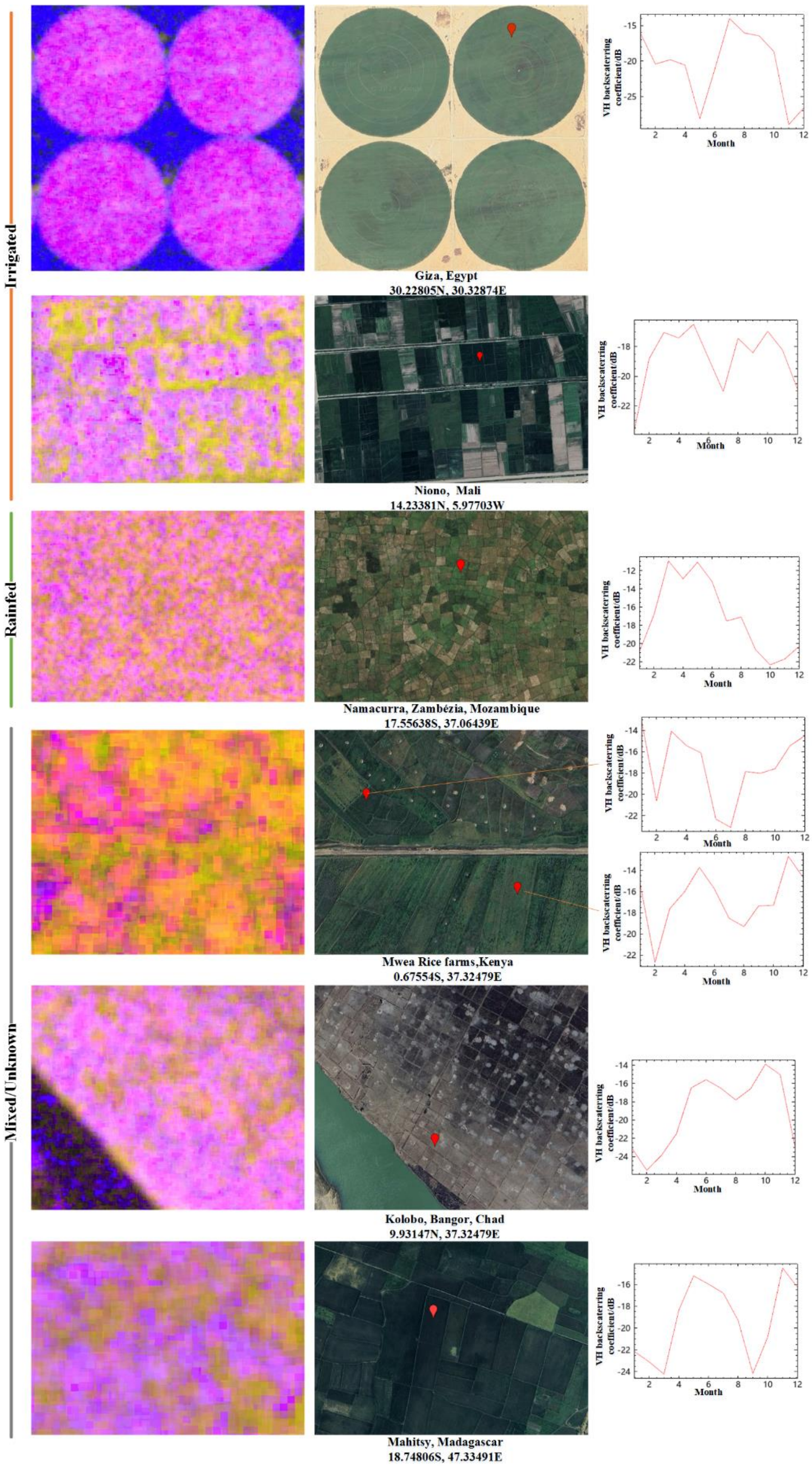


Figure 6. Examples of rice fields (a) Pseudo-color composite image (R: VHmax, G: VHmin, B: VHvariance) (b) Optical image (c) VH backscattering coefficient time series curve of the point marked in (b)

Response to Reviewer 2

RESPONSE: We are grateful for your detailed comments and constructive suggestions. Below, we provide a point-by-point response:

Comments to the Author:

Rainfed and Irrigated Paddies:

While the authors acknowledge the deficiency in the response, the issue remains unaddressed. Although the authors claim that "there is no emphasis on the detection of flooding signals," the methodology heavily relies on detecting irrigation or flooding signals. For example, the statistical features suggested by Sun et al. (designed for irrigated paddies) are used for constructing samples, and most important features identified by the RF models are SAR backscattering-based, which are primarily used to detect flooding signals.

To address this, here are some actionable suggestions:

Clarify whether the product is intended to map (a) only irrigated paddies or (b) both irrigated and rainfed paddies.

If (a), justify why the methodology works exclusively for irrigated paddies and discuss the implications and limitations of omitting rainfed paddies.

If (b), justify how the methodology accommodates both types of paddies and whether they can be differentiated or mapped as a single class.

RESPONSE: Thanks for your valuable feedback and thoughtful suggestions.

Our product is (b), intended to map both irrigated and rainfed paddies as one class.

The statistical features suggested by Sun et al. are effective in Southeast Asia where the rice systems are dominated by rainfed lowland rice and irrigated lowland rice, which is mentioned in the literature. So the feature can capture the character of both irrigated and rainfed rice. This makes sense because though rainfed rice lacks the stable flooding period characteristic of irrigated rice, experiencing temporary floods of different durations and depths is a common phenomenon, typically caused by rainfall(Yamamoto et al., 2012; Kwesiga et al., 2019; Panda and Barik, 2021; Mwakyusa et al., 2023). Additionally, while the RF model utilizes SAR backscattering features, these features capture broader hydrological and phenological signals rather than focusing exclusively on flooding signals. Therefore it is able to map them as a class. This explanation is also added to the manuscript.

Page 10, Line 192-207:

Sun used the statistical features (max, min, variance) of VH time-series data for pseudo-color composite in rice mapping in Southeast Asia as input features for rice extraction (Sun et al., 2023), In the pseudo-color feature map (R: VH_{max}, G: VH_{min}, B: $VH_{variance}$), rice appears purple because VH_{min} is small, while VH_{max} and $VH_{variance}$ are larger mainly caused by the drop of VH backscattering during flooding period. This is true with both irrigated rice and rainfed rice in Southeast Asia in the literature. In the experiment, it was found that rice in Africa also exhibits similar behaviour, as shown in Fig. 5, for it is a common phenomenon for rainfed rice to experience temporary floods of different durations and depths caused by rainfall though not the same with the stable flooding period of irrigated rice (Yamamoto et al., 2012; Kwesiga et al., 2019; Panda and Barik, 2021; Mwakyusa et al., 2023). And it can be seen from Fig.5 that the rice planting region stands out distinctly in the feature map, making it easy to locate the general rice planting region. But it cannot be completely distinguished from ground objects like wetlands for their similarity in the feature map. Therefore, the feature map was only used for fast coarse positioning and preliminary screening of rice regions. Specific examples of selected rice fields are presented in Fig. 6.

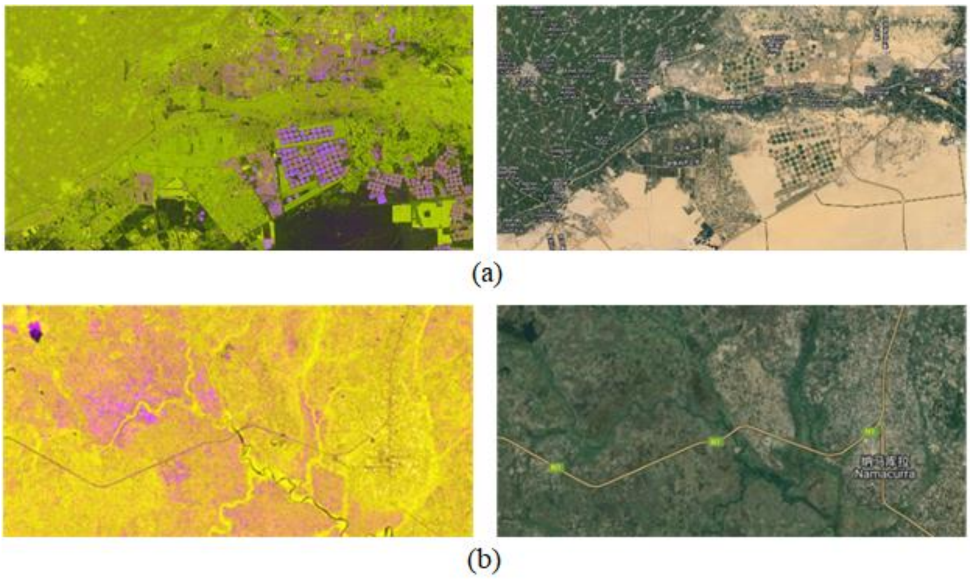


Figure 5. Pseudo-color composite image (R: VH_{max}, G: VH_{min}, B: $VH_{variance}$) used for fast coarse positioning, and corresponding optical image in Africa (From ©Google Earth) (a) irrigated region in Egypt(Mathieu, 2022) (b) rainfed lowland region in Mozambique(Kajisa and Vu, 2023). Examples of rice fields selected from these areas of Egypt and Mozambique are presented in Fig. 6.

Visual Interpretation on Optical Imagery for Rice Location Sampling:
Simply relying on the expertise of researchers for visual interpretation is not sufficiently convincing. While differentiating broad categories like forests, water bodies, and built-up areas from cropland may be straightforward, distinguishing specific cropland types—such as rice versus wheat—can be challenging due to their similar color and texture.
Please clarify the unique color, texture features, or contextual information used to visually identify rice paddies.
Provide concrete examples demonstrating this interpretation.
Include validation with real ground truth data to support these interpretations.
I also recommend publishing the training and validation samples alongside the final rice

paddy maps. This will enable users to assess the quality of both the maps and the samples.

RESPONSE: Thanks for your detailed suggestion.

To distinguish rice from other crops, the fast coarse positioning feature based on the pseudo color image (R: VHmax, G: VHmin, B: VHvariance) is used to provide a reference for rice sample construction. Due to the unique feature of reduced backscattering coefficient caused by the flooding period of rice, it appears purple in the feature map, while other crops without a flooding period do not appear purple like rice. This provides an important basis for identifying rice. Figure (1) is an example of rice and non-rice crops with their pseudo-color image and optical image in Egypt. The irrigated rice is on the left and the non-rice crop is on the upper and right part. Their colors in the pseudo-color image are very different from each other.

Rice fields usually bear rather uniform greenness and texture during the growing season: Figure (2) (a). And they are usually near water like rivers, lakes, etc.: Figure (2) (b). Besides, they tend to have internal blocks or strips to retain water: Figure (2) (c) and (d).

These criteria are also added to the manuscript. A figure with more representative rice fields is added to demonstrate the criteria (Figure 6), which can be located from other published literature. And the temporal VH backscattering curves of marked points are provided to prove these fields are indeed rice fields.

We fully recognize the importance of data sharing. After further validation and optimization, we plan to publicly release the training and validation samples to serve as a reference for other researchers.

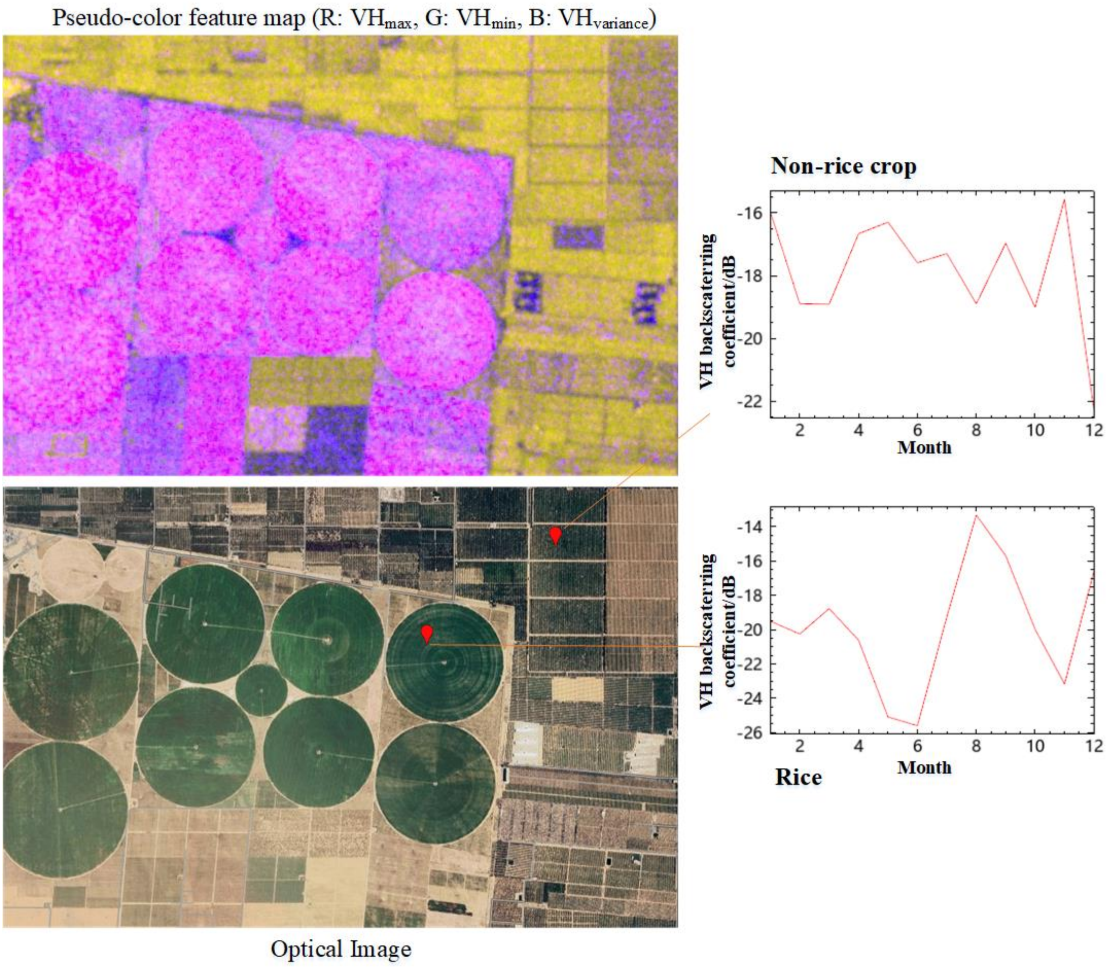
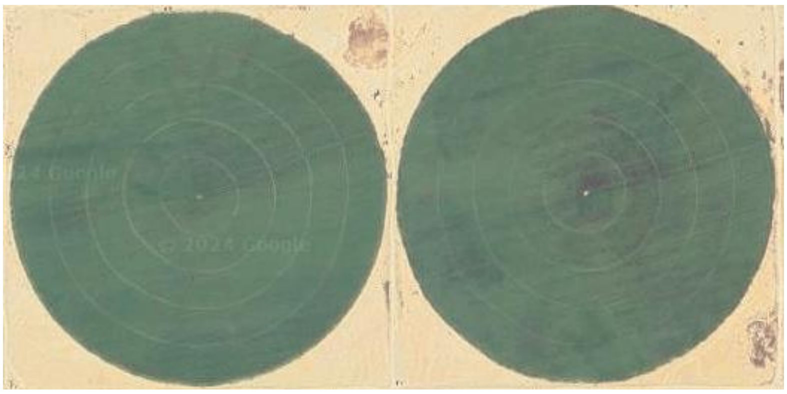


Figure (1) Comparison of rice and non-rice crops on feature map and VH backscattering coefficient curve



(a)

(b)

(c)

(d)

Figure (2) Examples of visual interpretation criteria (a) uniform greenness and texture during growing season (b) near water like rivers, lakes, etc. (c) internal strips, (d) internal blocks.

Page 11, Line 218-233:

Generally, the rice plots have these features on optical images: (1) circular irrigation fields or fields with internal blocks or strips to retain water, especially near water, rivers, lakes, etc. (2) very uniform greenness and texture during the growing season. If the features are not clear enough, the time series curve of VH data would be examined for obvious fluctuations since the backscatter of VH polarized data of rice has a clear drop during the flooding period. Fig. 6 presents some examples of rice fields and the VH backscattering coefficient time series of the red-marked point. The field in Egypt is an example of the typical circular irrigated rice paddy during the growing season that can be located refer to the literature(Mathieu, 2022). The fields in Mali are in the irrigated region around Niono(Diuk-Wasser et al., 2007). The fields in Mozambique are an example of rainfed rice paddy during the growing season that can be located referring to the literature(Kajisa and Vu, 2023). The fields in Kenya are in the concentrated rice planting area in Mwea and can be located from (Menge et al., 2024), which are examples of rice fields with internal blocks or strips. The fields in Chad are part of the China-aided Bongor Rice Demonstration Base in Chad, which is an example of rice fields in the non-growing season (Liang et al., 2017). The fields in Madagascar are in Mahitsy where rice cultivation has a long history(Voahanyinirina and Elie, 2007). The corresponding pseudo-color composite feature map in Fig.6 also proves the effectiveness of the fast coarse positioning method.

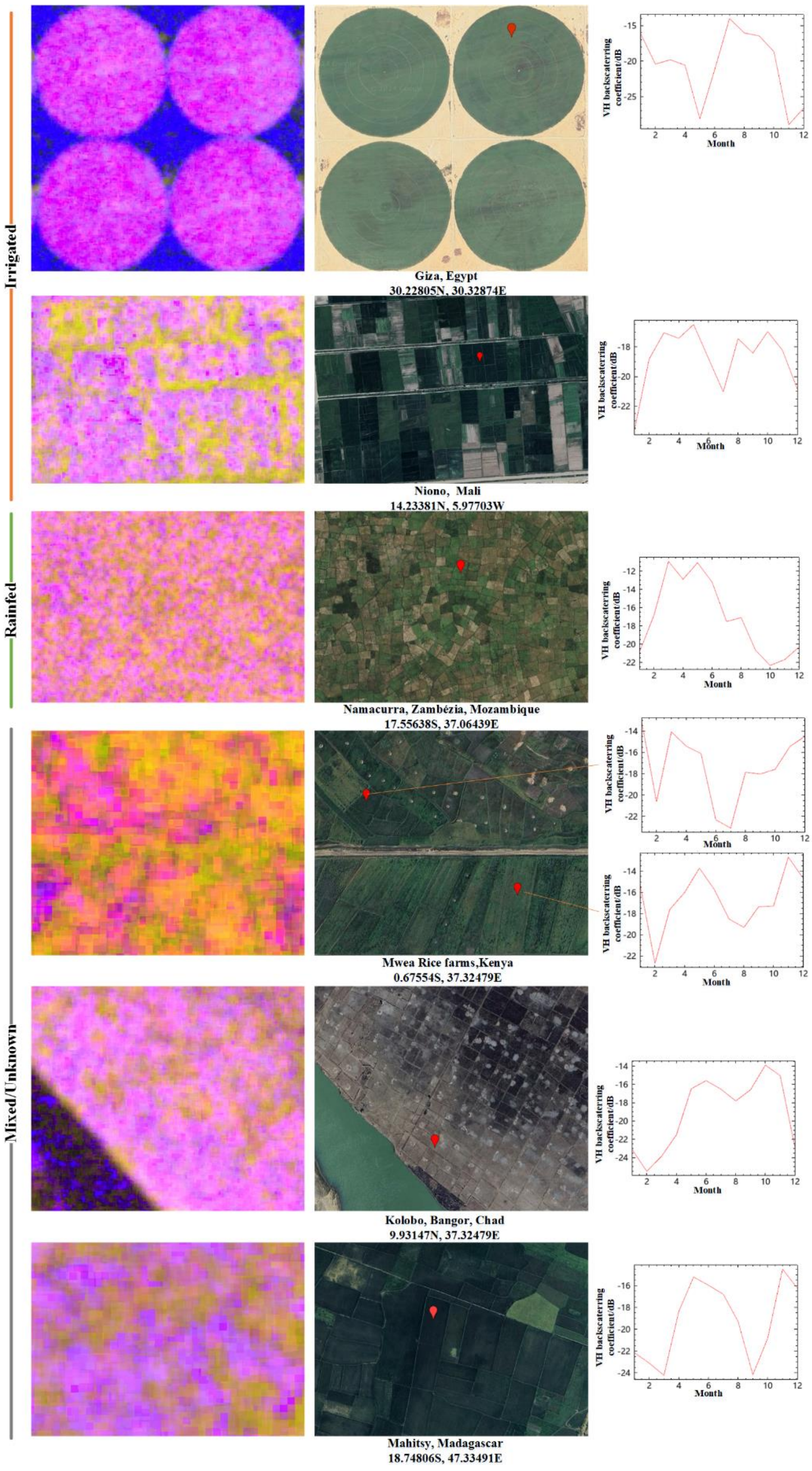


Figure 6. Examples of rice fields (a) Pseudo-color composite image (R: VHmax, G: VHmin, B: VHvariance) (b) Optical image (c) VH backscattering coefficient time series curve of the point marked in (b)

Cross-Validation with CROPGRIDS and Cropland Distribution Maps:
The use of CROPGRIDS and Cropland Distribution maps for validation does not appear logically sound. CROPGRIDS provides coarse grid-level estimates of rice paddy percentages without validating specific locations. Similarly, Cropland Distribution maps can confirm a sample is cropland but cannot verify whether it is rice or not. As such, these validations do not provide meaningful additional insights.
RESPONSE: Thanks for your comment and sorry for the confusion caused by expression. The fast coarse positioning feature is first used to locate potential rice paddy. Then we focus on the area where CROPGRIDS has high value. The higher the CROPGRIDS value is, the more rice area in the grid, and the easier we could find rice fields in this area. The cropland distribution map is used to further narrow it down. Finally, it is confirmed by visual interpretation on the optical imagery. Corrections are made to the manuscript.

Page 12, Line 211-214:
Specifically, the process begins with positioning potential rice-planting areas using the fast coarse positioning feature. The intersection of the high-value rice grid map from CROPGRIDS and the cropland distribution map is then utilized to further narrow down these areas. Finally, rice plots are selected and confirmed as rice samples through visual interpretation of optical imagery.

Segmentation:
While I agree with the advantages of object-oriented classification methods, Figure 8 is too vague to illustrate the effectiveness of segmentation. The image resembles a pixel-based approach and does not highlight individual objects.
I suggest including a few zoomed-in comparisons of segmented fields with manually delineated fields from very high-resolution imagery.
This would better demonstrate that the segmentation can accurately delineate individual fields or, at the very least, avoid segmenting objects across different field types or classes.
RESPONSE: Thanks for your suggestion. We updated Figure 9(original Fig. 8) to include zoomed-in comparisons of the classification feature before and after segmentation. The boundary of fields can be seen in the optical image. And in the pseudo-color image, the main field ridges are well preserved. It can be seen in pseudo-color composite 1 rice fields present as light green while non-rice fields present as purple. In pseudo-color composite 2 rice fields present as red/orange while non-rice fields present as green. The contrast colors of rice and non-rice fields in the pseudo-color composite of the selected feature also demonstrate the effectiveness of feature selection and classification. Descriptions are also added to the manuscript.

Page 17, Line 305-313:
Fig. 9 illustrates an example of selected features, focusing on an area southwest of Lake Alaotra in Madagascar. The classification features used in the supervised classification for this region include six features specific to East Africa: VH_mean, PRVI_mean, VV_mean, VH_variance, VH_min, and VV_variance. These features were combined into two groups for pseudo-color composites, where clear

distinctions between rice fields and other land cover types, including wetlands and grasslands that are prone to misclassification, can be observed. Zoomed-in images are provided in the third column. The contrast of rice and non-rice fields, the field ridges, and the consistency with optical images can be observed clearly. This demonstrates that the selected features effectively differentiate rice from other land cover types, enabling accurate spatial mapping of rice distribution. 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.

(a)
(b)
(c)
(d)
(e)

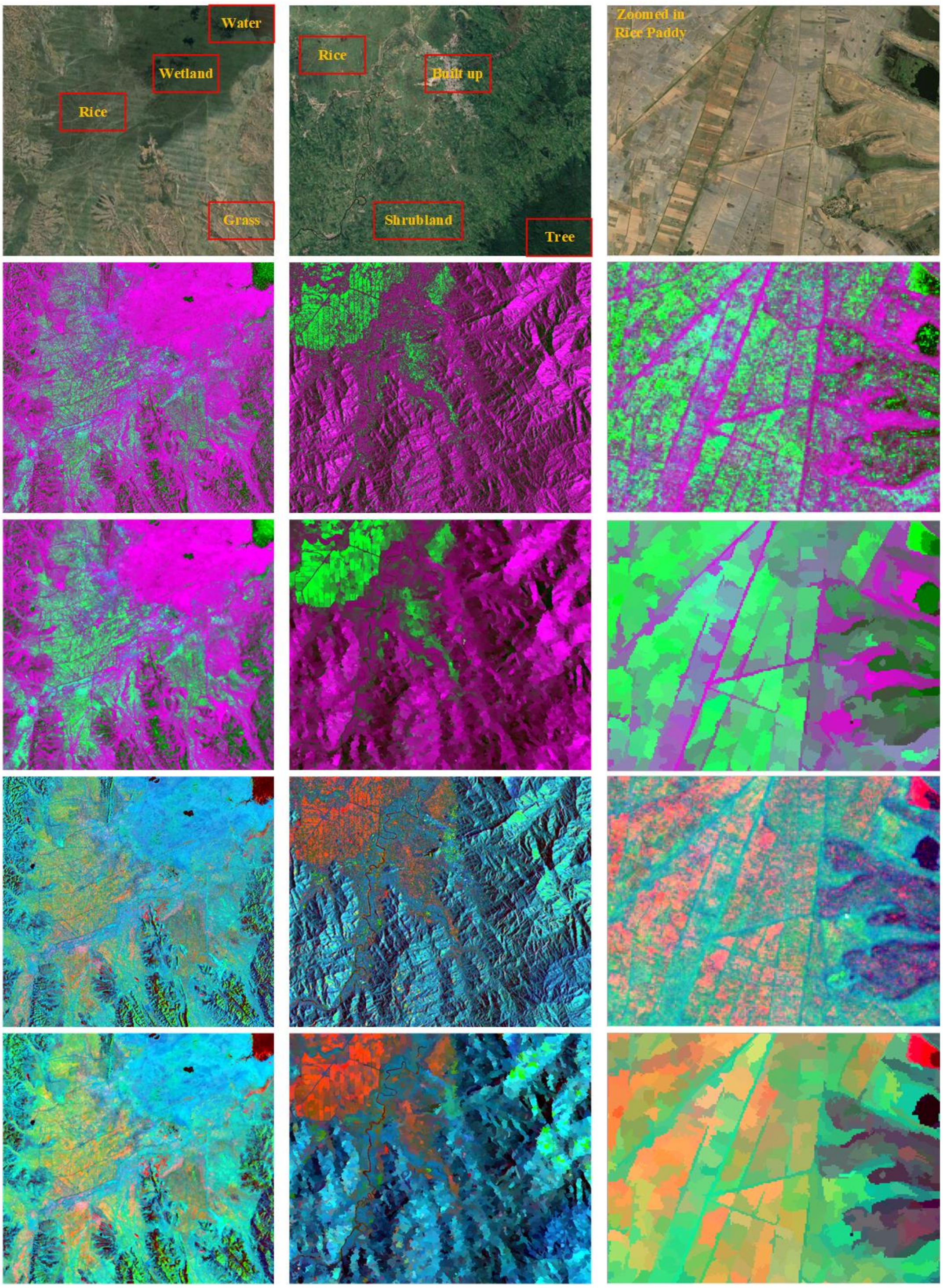


Figure 9. Example of pseudo-color composites using selected time-series SAR features: (a) optical image(From ©Google Earth) (b) pseudo-color composite 1 (R: VH_min, G: VH_variance, B: VH_mean) (c) mean values of pseudo-color composite 1 overlaid on the object-based segmentation result from NDVI time 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.

Single-Season vs. Double-Season Rice Paddies:

Although the authors acknowledge this as a potential deficiency, the concern remains unresolved. If no improvement can be made in this aspect, I recommend excluding this part to avoid delivering potentially misleading information. Future studies could address this issue using pixel-based or object-based classification methods informed by remote sensing signals.

RESPONSE: Thanks for your suggestion. We have thoroughly considered your suggestion and decided to delete the relative parts. Currently, the intensity information is only used to calculate the planting area to fit with statistics data to demonstrate the effectiveness of our method. The order of Section 2.2.4 and Section 2.2.5 is changed. Corrections are made in Section 2.2.5, Section 4.2, and Section 4.3 accordingly.

Page 8-9, Line158-172:

2.2.4 Statistical data

Three kinds of statistical data were used in the study, as shown in Table 2.

Table 2. Statistical data on rice area used in the study

Statistical Data	Data Time	Retrieve Time
USDA(United States Department of Agriculture): Rice planting/harvesting area in African countries (Usda, 2023)	2023	2024/02
FAO(Food and Agriculture Organization of the United Nations): Rice harvesting area in African countries (Fao, 2022)	2022	2024/03
CARD(COALITION for African Rice Development): Rice planting/harvesting area in CARD countries (Card, 2022)	2020/2021	2024/05

2.2.5 Administrative distribution data of rice planting intensity

In the comparison stage with statistical data, the administrative distribution data of rice planting intensity in RiceAtlas (Fig. 3) product (Laborte et al., 2017) were used to map the rice paddy area in the mapping results to planting/harvesting area to compare with statistical data since the area data they provide are all planting/harvesting area other than paddy area. The areas without single/double season information were defaulted to planting single-season rice.

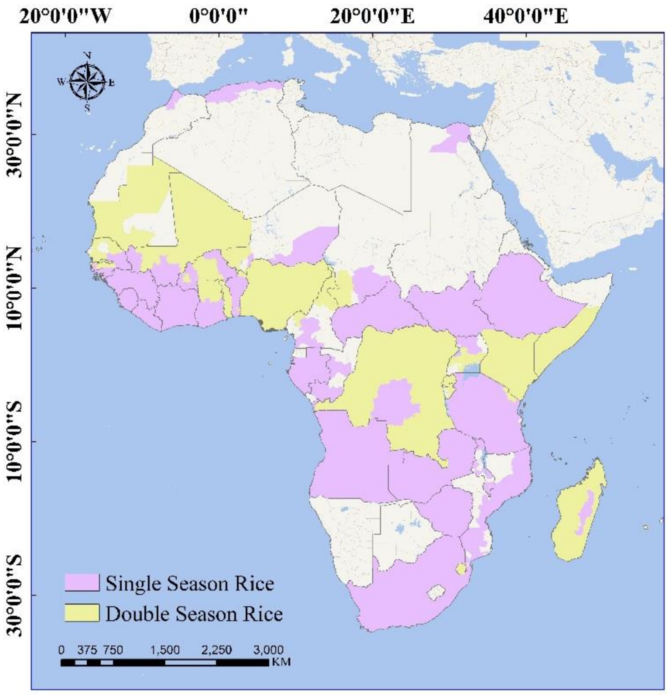


Figure 3. Administrative distribution map of rice intensity from RiceAtlas

To calculate the planting area, the paddy area is first derived from the mapping result. Then paddy area is allocated to the single season paddy area and the double season area according to the rice intensity map. Where

$$\text{Paddy Area} = \text{Single Season Paddy Area} + \text{Double Season Paddy Area} \quad (1)$$

Then the planting area is calculated using:

$$\text{Planting Area} = \text{Single Season Paddy Area} + 2 * \text{Double Season Paddy Area} \quad (2)$$

Page 20-23, Line 326-351:

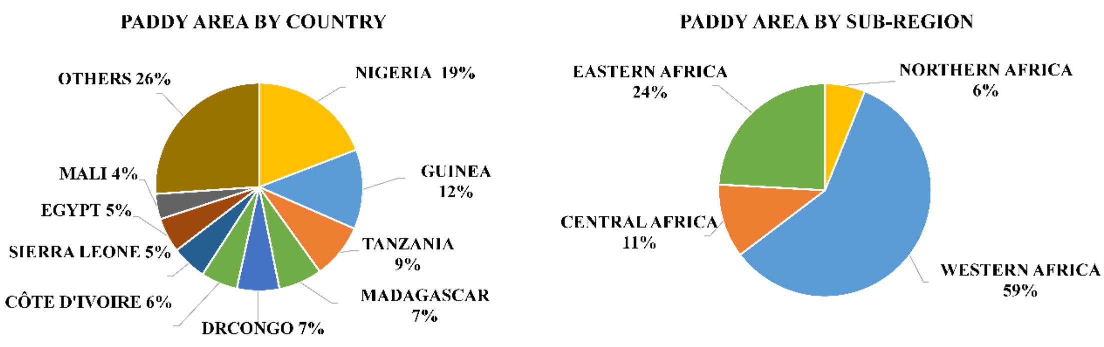
Table 5. Country-level statistics of rice paddy area in Africa based on the 20m spatial distribution map for 2023.

No.	Country	Paddy Area/Ha	No.	Country	Paddy Area/Ha
1	Angola	30375	18	Madagascar	865405
2	Benin	149095	19	Malawi	120866
3	Burkina Faso	205356	20	Mali	502970
4	Burundi	53626	21	Mauritania	63672
5	Cameroon	210191	22	Morocco	40454

6	Central African Republic	70545	23	Mozambique	415471
7	Chad	283113	24	Niger	45410
8	Côte d'Ivoire	727320	25	Nigeria	2446413
9	Democratic Republic of the Congo	841988	26	Rwanda	30984
10	Egypt	689114	27	Senegal	202077
11	Ethiopia	155157	28	Sierra Leone	694314
12	Gambia	103316	29	South Sudan	48605
13	Ghana	355311	30	Sudan	52553
14	Guinea	1580359	31	Togo	97076
15	Guinea-Bissau	178277	32	Uganda	199103
16	Kenya	29610	33	United Republic of Tanzania	1088377
17	Liberia	135214	34	Zambia	83916

Table 5 presents the country-level statistics of rice paddy area in Africa based on the 20m spatial distribution map for 2023.

The total rice paddy area across Africa in 2023 is approximately 12,795,631 hectares. Among the countries, three have rice areas exceeding 1 million hectares: Nigeria, Guinea, and Tanzania. Six countries fall within the range of 500,000 to 1 million hectares: Madagascar, the Democratic Republic of Congo (DRC), Côte d'Ivoire, Sierra Leone, Egypt, and Mali. Thirteen countries have rice areas between 100,000 and 500,000 hectares: Mozambique, Ghana, Chad, Cameroon, Burkina Faso, Senegal, Uganda, Guinea-Bissau, Ethiopia, Benin, Liberia, Malawi, and Gambia. Lastly, twelve countries have rice areas between 50,000 and 100,000 hectares: Togo, Zambia, Central African Republic, Mauritania, Burundi, Sudan, South Sudan, Niger, Morocco, Kenya, Rwanda, and Angola. The proportion of rice area by country is illustrated in Fig. 11(a).



(a) (b)

Figure 11. The proportions of rice paddy area in Africa (a) by country (others: aggregate of countries with areas less than 500,000 hectares). (b) by sub-region

Fig. 11(b) shows the distribution of rice area by sub-region in Africa. It can be seen that rice planting is primarily concentrated in Western Africa, followed by Eastern Africa and Central Africa, with the least in Northern Africa. The specific distribution of major production areas is detailed in Table 6.

Table 6. Distribution of Major Rice-Producing Regions in Africa

	Northern Africa
Egypt	Predominantly located in the Nile Delta and the Faiyum Oasis.
	Western Africa
Nigeria	Concentrated along the western side of the Kainji Reservoir, as well as along the Niger, Benue, Sokoto, and other rivers and their tributaries.
Guinea	Mainly distributed in the coastal plains of the Boffa region in the west, the plains of the Koundara region in the northwest, and along the Niger and Sankarani rivers and their tributaries in the east.
Mali	Primarily located along the Niger River and its tributaries in the central and eastern regions.
Sierra Leone	Concentrated in the western plains.
Côte d'Ivoire	Mainly found along the Bandama River in the northwest, the Bafing region in the west, and the northern areas.
	Central Africa

Democratic Republic of the Congo	Predominantly located near Kinshasa and around Lake Mukamba.
Eastern Africa	
Tanzania	Concentrated in the Mapogoro and Itambaleo regions, the southern areas of Lake Victoria, southern Morogoro, and the Kilimanjaro region.
Madagascar	Mainly distributed in the western regions of Lake Alaotra, southwestern areas, and the Ankililoaka region.

4.3 Comparison of rice area and statistical data

Table 7 presents the statistical data of rice planting areas for 34 African countries with more than 5,000 hectares of rice area, listed in alphabetical order. The first column shows the rice planting/harvest area reported by the Coalition for African Rice Development (CARD) for its member countries in 2020/2021. The second column provides the 2022 rice harvest area data from FAO. The third column shows the 2023 rice planting/harvest area reported by USDA. The fourth column presents the 2023 rice planting area derived from this study using the rice intensity data of RiceAtlas. All area units are in hectares.

Low Accuracy in Certain Countries:
The authors attribute low accuracy in some countries to the small size of rice paddies, which limits the construction of sufficient training samples. However, based on the described sample construction process (via visual interpretation), it does not appear overly difficult to increase the number of samples.
Why not expand the sample size to enhance accuracy in these countries? This would significantly improve the overall quality of the data product.
RESPONSE: Thanks for your comment and sorry for the confusion. When the rice paddy area of a country is too small compared to the total land area, the rice plots we can locate are very limited since wetland is similar to rice paddies in the feature map, which has far larger area causing rice paddies to look like scattered noise. Future improvements in algorithm and usage of more auxiliary data are both needed to improve the mapping quality in these countries. Explanations are added to the manuscript.

Page 26, Line402-410:

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 the 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 areas of rice, posing extra challenges to sample set construction. When the rice paddy area of a country is too small compared to the total land area, the rice plots we can locate are very limited since wetlands are similar to rice paddies in the feature map, which has far larger area causing rice paddies to look like scattered noise, 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.

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