Dear reviewers   Feb.20, 2023

Manuscript ID essd-2022-392 entitled

"20 m Annual Paddy Rice Map for Mainland Southeast Asia Using Sentinel-1 SAR

Data".

We really appreciate the positive feedback of the editor and two referees and own many thanks to their reviews. We appreciate the thorough reviews provided by the editor and two referees again. We agree with these suggestions and have revised the manuscript accordingly. At the same time, in order to improve the quality of the paper, we also further modify the expression of the full text. Below is our response to his/her comments resulting in some clarification. We hope these revisions resolve the problems and uncertainties pointed out by the referee. In the manuscript and this file, the blue parts are revisions suggested by the reviewer 1, green parts for suggestions of reviewer 2. And the red parts are the changed contents that are intended to improve the expressions.

Sincerely,

Hong Zhang

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Response to Reviewer 2

Comments to the Author

As rice land mapping is significant in Northeast Asia, the authors developed a mapping method based on time-series Sentinel-1 SAR data in this area. Based on the analysis of rice backscattering characteristics in the aimed area. Based on the analysis of rice backscattering characteristics, they combined spatio-temporal statistical features with the generalization ability to rice growth patterns, together with the adoped model approaches, the 20-meter resolution rice land cover map of five countries in mainland Southeast Asia in 2019 was obtained. The methods are helpful for agricultural management in the related areas. Similar methods can be adopted to make a regional rice cover map by repeating the experiment in this paper according to subsequent data. However, I have the following suggestions or concerns that maybe helpful for the modification of the manuscript.

RESPONSE： Thank you very much for your appreciation of our work. Your suggestions have helped us a lot to improve the quality of our manuscript.

My major concerns are:

1. Is the title accurate? It is strange to call rice mapping. I would like to suggest you take into careful consideration for this. Rice land mapping? Rice land cover mapping. Anyway, rice mapping is not so suitable.

RESPONSE： Thank you very much for your suggestion.

According to your suggestion, we have made statistics on the published papers from 2017 to now (See end of the response for details). There are eight kinds of titles commonly used for extracting the area of rice plots namely "Mapping Paddy Rice", "Rice Mapping", "Mapping of Paddy Rice Extent", "Mapping Rice Fields", "Rice Planting Areas", "Detecting Rice Paddy" and "Mapping of Paddy Rice Extent".

Specifically, there are 11 papers with the title of mapping paddy rice(Wang et al., 2022; Yang et al., 2021b; Xu et al., 2021; Ni et al., 2021; Han et al., 2021; Wang et al.,

2020; Li et al., 2020; Bazzi et al., 2019; Song et al., 2018; Park et al., 2018; Lasko et al., 2018).

There are 9 papers with the title of rice map(Liu et al., 2022; Lin et al., 2022; Zhan et al., 2021; Yang et al., 2021a; Wei et al., 2021; Singha et al., 2019; Guo et al., 2019; Talema and Hailu, 2020; Zhao et al., 2021).

There are 4 papers with the title of mapping of paddy rice extent(Soh et al., 2022; Rudiyanto et al., 2019; Zhang et al., 2018; Tian et al., 2018).

There are 3 papers with the title of mapping rice fields(Son et al., 2022; Chen et al., 2020; Chang et al., 2020b).

There are 2 papers with the title of rice planting areas(Hoang-Phi et al., 2020; Stroppiana et al., 2019).

There are 2 papers with the title of detecting rice paddy(Jo et al., 2020; Crisóstomo De Castro Filho et al., 2020).

There are 2 papers with the title of mapping rice area(Stroppiana et al., 2019; Clauss et al., 2017).

There are 2 papers with the title of mapping paddy rice distribution(Wei et al., 2022; Chang et al., 2020a).

For more accurate expression, we changed the title to "20 m Annual Paddy Rice Area Map for Mainland Southeast Asia Using Sentinel-1 SAR Data". In addition, we also carefully examined the full manuscript and changed the "rice map" to "rice area map" to ensure a clear and accurate expression.

2. Section 3.2: feature extraction was not told very clearly, and affected understanding for the whole processing process for mapping. In particular, the comparison between pseudocolor image and optical image (figure 4), and the role of the optical image in cartography were not clarified.

RESPONSE: Thank you very much for your suggestion.

In section 3.2 feature extraction, firstly, the variation characteristics of VH polarization time series backscatter coefficients of four typical land cover types (rice, water, settlement and non-rice vegetation) in the study area were analyzed. It can be

seen that the time steps of each growing season for the selected Rice 1- Rice 4 were inconsistent. This makes the backscatter coefficient curves of the rice growth cycle more diverse and does not allow us to summarize a generalized model of rice evolution. Therefore, it will be difficult to accomplish the rice extraction task using a direct reliance on the fixed relationship between phenology and time.

Through a large number of comparative experiments and analysis, and in combination with our previous research work (Xu et al., 2021), three time series statistical features were selected to describe the most significant SAR features in the rice growth process for rice mapping in the study area. Finally, the pseudo-color image synthesized by three time-series statistical features is compared with the optical image to show that rice and other landcovers in the feature map have obvious differentiation.

The optical image in Figure 4 is mainly used for reference. In the pseudo-color feature map, rice has significantly different characteristics from other landcovers s (water, settlements and non-rice vegetation). In order to prove the accuracy of the landcovers selected, we selected the corresponding optical image for comparison.

The optical image plays an auxiliary role in the process of rice mapping, and is not used as the input of rice extraction model together with pseudo-color feature map. First of all, optical image was used to judge landcovers to assist in sample preparation in 3.3: training and validation sets. Secondly, optical image was used as the contrast of landcovers in the feature map in section 3.2: feature extraction. Finally, the rice extraction results were compared with optical images to illustrate the accuracy of the results in section 4: results.

I have also some minor points as the following:

1. Abstract section: I am wondering what was the complex growth patterns for rice in tropical and subtropical regions. Since this is too vagur, would you please tell in details?

RESPONSE: Thank you very much for your suggestion. Sorry that the inaccurate word has troubled you. We referred to relevant literature and changed the "growth pattern" to "cultivation pattern" or "planning pattern" in the manuscript. The rice planting pattern

(or cultivation pattern) is a planting attempt on land that regulates the layout and sequence of planting for a certain period. For example，there are three patterns of rice planting pattern:(1) paddy-paddy-paddy, (2) paddy-paddy-fallow, (3) paddy-fallow-paddy.

The climate of Southeast Asia is suitable for the growth of rice all year round. There is no strict restriction on the planting time of rice. The planting time of rice in the whole region is not uniform, and the growing stages of rice in different regions are not synchronized. It is difficult to describe the cultivation of rice with a unified phenological information. Therefore, in this paper "complexity" refers to the diversity of rice planting patterns, especially for the entire land mass of Southeast Asian countries, which makes it difficult to establish a representative rice crop pattern. In this paper we attempt to establish a method for rice area extraction based on SAR data analysis, rather than relying more on ancillary data, such as complex phenological characteristics of various regions, or huge amounts of ground survey information.

2. Introduction section: United Nation's sustainable development goals and the significances of food are not the most important for this manuscript, so please have some cut at this to make it short, and focus on the mapping methods and the advances in this field, and be noted that this is data manuscript.

RESPONSE： Thank you very much for your suggestion. We have adjusted this part according to your suggestion to make it more concise.

Page 1，line 25

Sustainable development Goal 2 "Zero Hunger" was set by the United Nations in 2015(Desa, 2016). The dual pressure of population and environment threatens the sustainability of global food security (Faostat, 2010; Godfray et al., 2010). Rice feeds more than half of the world's population as a staple food and is a major crop for world food security (Kuenzer and Knauer, 2012). Asia is the largest rice-producing region in the world (Chen et al., 2012), and Southeast Asia accounts for 40% of global rice exports (Yuan et al., 2022). High-precision rice planting area maps are the basis for

monitoring rice growth and forecasting yields, the cornerstone for the government, planners and policymakers to formulate reasonable policies, and the guarantee of global food security (Mosleh et al., 2015; Laborte et al., 2017; Clauss et al., 2018; Jin et al., 2018; Yu et al., 2020; Hoang-Phi et al., 2021).

3. Line 37, line 40-41, and also line 45-47: references were in wrong format or not suitable. Please also check many other places expressed like this.

RESPONSE: Thank you very much for your suggestion. We added the missing part of the reference in line 37, deleted one reference in line 40-41, and adjusted the position of one reference in line 45-47 in the original manuscript. Moreover, we also checked and revised the references to ensure correct formatting and complete content.

Page 2, line 41

…Luo et al. and Wei et al. used Landsat time-series data to produce 1 km and 30 m resolution rice datasets for China, respectively (Luo et al., 2020; Wei et al., 2022)….

Page 2, line 46

…Xiao et al., Gumma et al. and Bridhikitti et al. produced low- and medium-resolution rice area maps for several South and Southeast Asian countries using MODIS data at the 500 m spatial resolution, respectively (Xiao et al., 2006; Gumma et al., 2011a; Gumma et al., 2011b; Bridhikitti and Overcamp, 2012; Gumma et al., 2014). Nelson and Gumma extracted the 500 m spatial resolution general rice extent map in Asia from 2000 to 2012 using MODIS data (Nelson and Gumma, 2015) ….

4. Line 68-70: what was the difference between the two categories? The information in the second category can also include phenological information. So, confusing as far as this expression is concerned.

RESPONSE: Thank you very much for your comment.

Although both methods may have phenological information, the role of phenological information is different. In the first method, phenological information

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plays a major role. It is necessary to manually use the growing phenological calendar to identify the phenological periods of rice in the time series data or to make phenological indicators based on phenological information.

The second method is to directly input the time series data into the machine learning model, relying on the model to learn the rice information in the time series data, while the phenology information only plays an auxiliary role in the early stage of the study. Compared with the phenology-based method, this method is less dependent on human.

5. Line 70-74: Please refer to relevant literature, the expression of crop phenology should be regulated.

RESPONSE: Thank you very much for your suggestion. We use more accurate words for better reading.

Page 3, line 74

…The phenology-based approach refers to the extraction of rice by defining phenological indicators or identifying rice growing stages by combining the time-series data covering the rice growth cycle and the analysis of rice phenological calendar (Nelson et al., 2014; Chen et al., 2016; Nguyen and Wagner, 2017; Liu et al., 2018; Xin et al., 2020; Ni et al., 2021). The growing stages such as transplanting, heading and maturity are most often used to extract rice. Shew et al. combined vegetation indices extracted from Landsat time-series data with a rule-based algorithm for growing stages to map a 30 m dry season rice map of Bangladesh from 2014 to 2018 (Shew and Ghosh, 2019) ….

6. Line 106: the editing was careless: see line 106 "inSoutheast Asia".

RESPONSE: Thank you very much for your suggestion. We corrected this editorial error.

Page 4, line 111

Therefore, in this study, to meet the requirements of high-precision rice area mapping in Southeast Asia....

7. Due to the limited information in table 1, I suggest make it supplement.

RESPONSE： Thank you very much for your suggestion. We adjusted table 1 to shorten the space it occupies. Other tables have been revised to give a more attractive and concise presentation

Page 6, line 163

Table 1. List of Sentinel-1 SAR data in 2019 used in this study

Country	Satellite	Orbit-Frame	Number of images	Country	Satellite	Orbit-Frame	Number of images	Country	Satellite	Orbit-Frame	Number of images
Experimental Data											
Myanmar	S1A	41-44	31	Thailand	S1B	62-1	29	Vietnam	S1A	55-31	31
		41-50	31			62-2	29			55-37	31
		41-55	31			62-3	29			55-42	31
		41-60	31			62-4	29			55-47	31
		41-65	31			62-5	29			55-62	31
		41-70	31			62-20	27			55-67	31
	S1A	70-1217	31		S1A	62-21	27			55-72	31
		70-1222	31			62-22	26	Laos	S1A	26-44	31
		70-1227	31			62-23	24			26-49	31
		70-1232	31			62-24	25			26-54	31
		70-1237	31		S1B	91-1	32			26-59	31
		70-1242	31			91-2	32			26-64	31
		70-1247	31			91-3	32			26-69	31
		70-1252	31			91-4	32		S1A	99-1240	30
		70-1257	31		S1A	135-16	23			99-1245	30
		70-1262	31			135-17	23			99-1250	30
		70-1267	31			135-18	23		S1A	128-44	30
	S1A	143-46	30			135-19	23			128-49	30
		143-51	30		S1B	164-1	32			128-54	30
		143-56	30			164-2	32			128-59	30
		143-61	30			164-3	32			128-64	30
		143-66	30			164-4	32	Cambodia	S1A	26-29	28
		143-71	30			164-5	32		S1B	26-32	30
		143-76	30		S1A	164-20	13			26-38	30
	S1A	172-1248	28		S1A	172-17	31			26-43	30
		172-1253	28			172-18	31		S1A	99-1220	30
		172-1258	28	Vietnam	S1A	26-23	28			99-1225	30
		172-1263	28			26-34	31		S1B	99-31	31
		172-1268	28		S1A	128-29	30		S1A	128-34	30
		172-1273	28			128-69	30			128-39	30
Training Dataset											
Thailand	S1A	99-16	29								

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Table 2. Data information used in the study

Data type	Data product or country name	Year	Resolution	Description of use	Data access	Last access (dd/mm/yyyy)
SAR imagery	Sentinel-1	2019	20*22 m (rg*az)	The backscatter characteristics extraction	https://search.asf.alaska.edu/#/	11/10/2022
DEM	Shuttle Radar Topography Mission (SRTM) 3sec	2000	90m	Terrain correction	https://search.earthdata.nasa.gov/search?q=SRTM	11/10/2022
Land cover data	ESA WorldCover 2020	2020	10 m	Generation of water and woodland masks	https://esa-worldcover.org/en	11/10/2022
Available rice area map	Vietnam-wide annual land use/land cover datasets (VLUCD)	2019	30 m	Spatial consistency assessment	https://www.eorc.jaxa.jp/ALOS/en/dataset/lulc/lulc_vnm_v2109_e.htm	11/10/2022
	Rice data of Asia from IRRI (IRRI Rice Data)	2000 to 2012	500 m	Spatial consistency assessment	https://www.irri.org/mapping	11/10/2022
Statistical yearbook	Vietnam	2019	Province scale	Precision verification	https://www.gso.gov.vn/en/homepage/	11/10/2022
	Cambodia	2019	Province scale	Precision verification	http://nis.gov.kh/index.php/km/	11/10/2022
	Laos	2019	Province scale	Precision verification	https://www.lsb.gov.la/en/home/	11/10/2022
	Thailand	2019	Province scale	Precision verification	http://www.nso.go.th/sites/2014en	11/10/2022
	Myanmar	2019	State scale	Precision verification	https://www.mopf.gov.mm/en/page/planning/central-statistical-organization-cso/752	11/10/2022

Table 3. Information of validation sample set

Class	Number of plots	Number of pixels
Rice	1913	2,128,431
Non-rice	2032	2,188,477

Table 4. Accuracy of the rice area map based on the validation set

Class	Accuracy	Precision	Recall	Kappa
Rice	92.20%	92.45%	90.26%	0.8425

Table 5. Statistics, other rice maps and the extracted rice area for five Southeast Asian countries

Country	Statistics of rice cultivation area ($\times 10^{\wedge 6}$ ha)	IRRI rice data ($\times 10^{\wedge 6}$ ha)	Statistics of paddy land area ($\times 10^{\wedge 6}$ ha)	VLUCD ($\times 10^{\wedge 6}$ ha)	Extracted rice cultivation area ($\times 10^{\wedge 6}$ ha)
Thailand	10.9442	12.7198	-	-	12.8508
Cambodia	3.2638	3.0740	-	-	2.8215
Myanmar	6.9209	6.4575	-	-	5.5390
Laos	0.8435	0.9856	-	-	0.8458
Vietnam	7.4695	6.1527	4.1205	3.8210	3.3270

8. Section 2.2.2: the agricultural statistical yearbooks may have great uncertainty, which may affect its credibility. Please discuss uncertainties it brought.

RESPONSE: Thank you very much for your suggestion. We discussed the uncertainty of statistical data in the second paragraph of section 5 of the manuscript. In addition to statistical data, we also evaluate the precision of rice extraction results from various rice products at the national and provincial levels to prove the accuracy of the extraction results as much as possible.

Page 21, line 407

…A possible reason is that the statistical cycle is not strictly aligned with the data collection cycle. The rice area extracted in this study is the total area of all fields that have been planted with rice in a year. Most agricultural statistics record the total area of rice planted in different growing seasons on an annual basis or even from one month of one year to the next. In addition, the statistical methods may cause errors in the statistics. The well-organized rice growing seasons were mainly considered in all statistics, and the random and irregular planting behavior of individual farmers was inevitably ignored. Considering the data collection conditions and statistical errors, it is understandable that the extracted rice maps differ from the official statistics...

9. Section 3.1: it was told the Sentinel-1 time-series data were preprocessed by using SNAP software, but you omitted the mechanism for conducting such events, and did not mention the how to determine the authority of the software.

RESPONSE: Thank you very much for your suggestion. We have explained this section in detail.

Page 8, line 189

The Sentinle-1 time-series data were preprocessed using the Sentinel Application Platform (SNAP) (Filipponi, 2019). The SNAP is a common architecture for all Sentinel Toolboxes. ESA/ESRIN is providing the SNAP user tool free of charge to the Earth Observation Community.

The steps were as follows: (1) Orbit correction: This operation refines the inaccurate orbit state vectors provided in the metadata of a SAR product with the precise orbit files which are available days to weeks after the generation of the product;(2) Thermal noise removal: Because SAR are contaminated by additive thermal noise, this step is introduced to mitigate thermal noise effects;(3) Radiometric calibration: This process provides the image in which the pixel values can be directly related to the radar backscatter of the image;(4) Coregistration: This step co-registers multitemporal intensity images; (5) Terrain correction: This process converts SAR data from the slant or ground range projection to geographic coordinate projection and corrects the distortion effects that occurred during the acquisition (overlay, shading);(6) Multitemporal speckle noise filtering: This operation reduces speckles, which degrade the quality of the image and make interpretation of features more difficult;(7) Converting values to decibels: This step convers the multitemporal intensity map to sigma 0 (σ^0) on the decibel (dB) scale using a logarithmic transformation. The final σ^0 images with 20 m resolution in the WGS84 geographic coordinate system were obtained.

10. Section 3.4: similar to above problem, the reason for choosing U-Net model was not introduced and affected the reliability of your processing results.

RESPONSE: Thank you very much for your suggestion. We modified section 3.4 and Figure 5.

Page 13, line 274

In this paper，high-precision rice area mapping was accomplished using U-Net model. U-Net is a classical semantic segmentation model widely used in biomedical image segmentation and remote sensing (Wei et al., 2019; Xu et al., 2021; Lin et al., 2022). It outputs semantically labeled pixel-by-pixel images corresponding to the input image while extracting high-level semantic features, so that the spatial details of the input image can be maintained (Ronneberger et al., 2015). SAR images cover a large spatial area, which include multiple ground objects with complex and rich semantic

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information; rice fields are spatially characterized by continuous and large distribution. Therefore, U-Net is used to fully combine the spatial and semantic information in SAR images to achieve high-precision rice area extraction.

The structure of U-Net model is shown in Figure 5. U-Net consists of encoder (contracting path) and decoder (expansive path). The encoder is used for feature extraction, and the decoder is used to restore the size of the input image. U-Net has 23 convolutional layers, including eighteen 3×3 convolutional layers, four 2×2 convolutional layers and one 1×1 convolutional layer. The encoder part consists of five downsampling units, where each unit consists of two 3×3 convolutional layers and a 2×2 max-pool layer. The output of the downsampling unit is input to the next downsampling unit by max-pooling. The decoder contains four upsampling units, each of which consists of two 3×3 convolutional layers and a 2×2 deconvolutional layer. In the final stage of the decoder, the feature vector of the last upsampling unitis converted into a probability mapping by the 1×1 convolutional layer. The dimension of the probability mapping is 2 and the pixel value indicates the probability that the pixel belongs to rice and non-rice.

Meanwhile, thanks to the U-shaped structure and skip connection, each downsampling is cascaded with the corresponding upsampling, and this fusion of features at different scales is greatly helpful for upsampling to recover pixels. Specifically, the shallow downsampling multiplier is small and the feature map has more detailed rice spatial distribution features (low-level spatial features). While the deep downsampling multiplier is large and the information is heavily condensed with large spatial loss. But the high-level semantic features obtained from deep downsampling help in the determination of rice regions. When the high-level and low-level features are fused, it helps to improve the segmentation accuracy.

To solve the problem of uneven data distribution, we added a batch normalization (BN) layer (Ioffe and Szegedy, 2015) before each convolutional layer. The BN layer allows the input data to follow the same distribution to achieve regularization of the model.
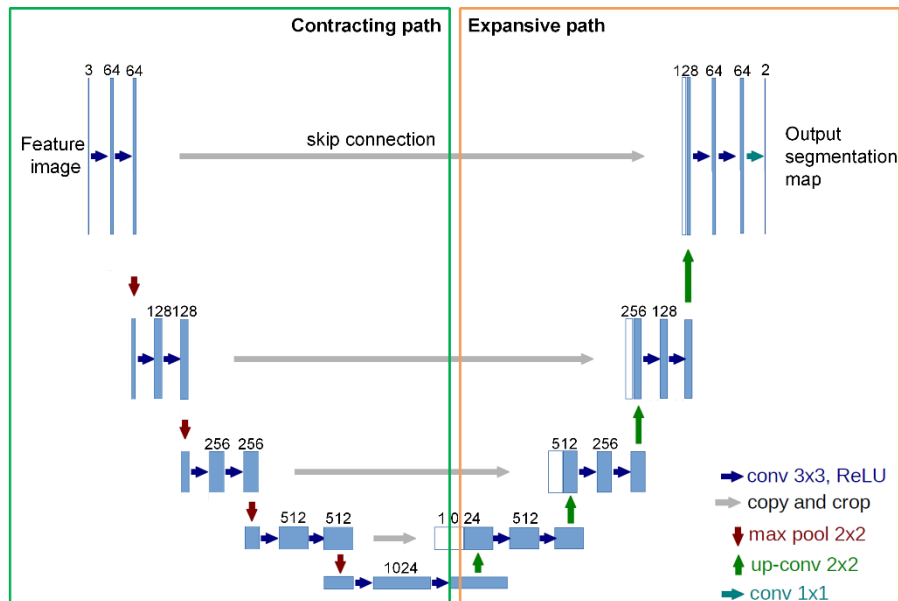
Figure 5. Structure of the U-Net model.

11. Section 7, the conclusion section: the expression were not suitable, since you should tell the most important findings for the rice land mapping technology in this work, but not the evaluation and remark on that.

RESPONSE: Thank you very much for your suggestion. We revised the conclusion according to your suggestion.

Page 22, line 440

Ending hunger and malnutrition is essential, and rice plays a critical role. Satellite-based remote sensing offers the most practical means of monitoring rice cultivation in mainland Southeast Asia. Questions remain, however, as to appropriate timing, number of satellite observations, spatial resolution of satellite imagery, and effective data processing methods for rice distribution and production information.

To perform large-scale rice area mapping in tropical and subtropical regions, an efficient rice area mapping method based on time series SAR features and a deep learning model is proposed. A 20-meter spatial resolution rice area map of mainland Southeast Asia was produced using the 2019 Sentinel-1 time series data and the proposed rice area mapping method. The accuracy of the proposed method on the validation sample set was 92.20%. Our rice area maps correlated significantly with

statistical data and were consistent with other rice area maps. These results demonstrate the advantages of the proposed method for rice area mapping with complex cropping patterns. The rice maps we produced will provide data support for agricultural resource studies, such as yield prediction and agricultural management.

References

Bazzi, H., Baghdadi, N., El Hajj, M., Zribi, M., Minh, D. H. T., Ndikumana, E., Courault, D., and Belhouchette, H.: Mapping Paddy Rice Using Sentinel-1 SAR Time Series in Camargue, France, Remote Sensing, 11, 10.3390/rs11070887, 2019.

Chang, L., Chen, Y.-T., Chan, Y.-L., and Wu, M.-C.: A Novel Feature for Detection of Rice Field Distribution Using Time Series SAR Data, IGARSS 2020 - 2020 IEEE International Geoscience and Remote Sensing Symposium, 10.1109/igarss39084.2020.9323278, 2020a.

Chang, L., Chen, Y.-T., Wang, J.-H., and Chang, Y.-L.: Rice-Field Mapping with Sentinel-1A SAR Time-Series Data, Remote Sensing, 13, 10.3390/rs13010103, 2020b.

Chen, N., Yu, L., Zhang, X., Shen, Y., Zeng, L., Hu, Q., and Niyogi, D.: Mapping Paddy Rice Fields by Combining Multi-Temporal Vegetation Index and Synthetic Aperture Radar Remote Sensing Data Using Google Earth Engine Machine Learning Platform, Remote Sensing, 12, 10.3390/rs12182992, 2020.

Clauss, K., Ottinger, M., and Kuenzer, C.: Mapping rice areas with Sentinel-1 time series and superpixel segmentation, International Journal of Remote Sensing, 39, 1399-1420, 10.1080/01431161.2017.1404162, 2017.

Crisóstomo de Castro Filho, H., Abílio de Carvalho Júnior, O., Ferreira de Carvalho, O. L., Pozzobon de Bem, P., dos Santos de Moura, R., Olino de Albuquerque, A., Rosa Silva, C., Guimarães Ferreira, P. H., Fontes Guimarães, R., and Trancoso Gomes, R. A.: Rice Crop Detection Using LSTM, Bi-LSTM, and Machine Learning Models from Sentinel-1 Time Series, Remote Sensing, 12, 10.3390/rs12162655, 2020.

Guo, Y., Jia, X., Paull, D., and Benediktsson, J. A.: Nomination-favoured opinion pool for optical-SAR-synergistic rice mapping in face of weakened flooding signals, ISPRS Journal of Photogrammetry and Remote Sensing, 155, 187-205, 10.1016/j.isprsjprs.2019.07.008, 2019.

Han, J., Zhang, Z., Luo, Y., Cao, J., Zhang, L., Cheng, F., Zhuang, H., Zhang, J., and Tao, F.: NESEA-Rice10: high-resolution annual paddy rice maps for Northeast and Southeast Asia from 2017 to 2019, Earth System Science Data, 13, 5969-5986, 10.5194/essd-13-5969-2021, 2021.

Hoang-Phi, P., Lam-Dao, N., Pham-Van, C., Chau-Nguyen-Xuan, Q., Nguyen-Van-Anh, V., Gummadi, S., and Le-Van, T.: Sentinel-1 SAR Time Series-Based Assessment of the Impact of Severe Salinity Intrusion Events on Spatiotemporal Changes in Distribution of Rice Planting Areas in Coastal Provinces of the Mekong Delta, Vietnam,

Remote Sensing, 12, 10.3390/rs12193196, 2020.

Jo, H.-W., Lee, S., Park, E., Lim, C.-H., Song, C., Lee, H., Ko, Y., Cha, S., Yoon, H., and Lee, W.-K.: Deep Learning Applications on Multitemporal SAR (Sentinel-1) Image Classification Using Confined Labeled Data: The Case of Detecting Rice Paddy in South Korea, IEEE Transactions on Geoscience and Remote Sensing, 58, 7589-7601, 10.1109/tgrs.2020.2981671, 2020.

Lasko, K., Vadrevu, K. P., Tran, V. T., and Justice, C.: Mapping Double and Single Crop Paddy Rice With Sentinel-1A at Varying Spatial Scales and Polarizations in Hanoi, Vietnam, IEEE J Sel Top Appl Earth Obs Remote Sens, 11, 498-512, 10.1109/JSTARS.2017.2784784, 2018.

Li, H., Fu, D., Huang, C., Su, F., Liu, Q., Liu, G., and Wu, S.: An Approach to High-Resolution Rice Paddy Mapping Using Time-Series Sentinel-1 SAR Data in the Mun River Basin, Thailand, Remote Sensing, 12, 10.3390/rs12233959, 2020.

Lin, Z., Zhong, R., Xiong, X., Guo, C., Xu, J., Zhu, Y., Xu, J., Ying, Y., Ting, K. C., Huang, J., and Lin, T.: Large-Scale Rice Mapping Using Multi-Task Spatiotemporal Deep Learning and Sentinel-1 SAR Time Series, Remote Sensing, 14, 10.3390/rs14030699, 2022.

Liu, R., Zhang, G., Dong, J., Zhou, Y., You, N., He, Y., and Xiao, X.: Evaluating Effects of Medium-Resolution Optical Data Availability on Phenology-Based Rice Mapping in China, Remote Sensing, 14, 10.3390/rs14133134, 2022.

Ni, R., Tian, J., Li, X., Yin, D., Li, J., Gong, H., Zhang, J., Zhu, L., and Wu, D.: An enhanced pixel-based phenological feature for accurate paddy rice mapping with Sentinel-2 imagery in Google Earth Engine, ISPRS Journal of Photogrammetry and Remote Sensing, 178, 282-296, 10.1016/j.isprsjprs.2021.06.018, 2021.

Park, S., Im, J., Park, S., Yoo, C., Han, H., and Rhee, J.: Classification and Mapping of Paddy Rice by Combining Landsat and SAR Time Series Data, Remote Sensing, 10, 10.3390/rs10030447, 2018.

Rudiyanto, Minasny, Shah, Soh, Arif, and Setiawan: Automated Near-Real-Time Mapping and Monitoring of Rice Extent, Cropping Patterns, and Growth Stages in Southeast Asia Using Sentinel-1 Time Series on a Google Earth Engine Platform, Remote Sensing, 11, 10.3390/rs11141666, 2019.

Singha, M., Dong, J., Zhang, G., and Xiao, X.: High resolution paddy rice maps in cloud-prone Bangladesh and Northeast India using Sentinel-1 data, Sci Data, 6, 26, 10.1038/s41597-019-0036-3, 2019.

Soh, N. C., Shah, R. M., Giap, S. G. E., Setiawan, B. I., and Minasny, B.: High-Resolution Mapping of Paddy Rice Extent and Growth Stages across Peninsular Malaysia Using a Fusion of Sentinel-1 and 2 Time Series Data in Google Earth Engine, Remote Sensing, 14, 1875, 10.3390/rs14081875, 2022.

Son, N.-T., Chen, C.-F., Chen, C.-R., Cheng, Y.-S., Toscano, P., Syu, C.-H., Guo, H.-Y., Chen, S.-L., Liu, T.-S., and Zhang, Y.-T.: Exploiting Sentinel-1 data and machine learning–based random forest for collectively mapping rice fields in Taiwan, Applied Geomatics, 1-15, 10.1007/s12518-022-00440-4, 2022.

Song, P., Mansaray, L. R., Huang, J., and Huang, W.: Mapping paddy rice agriculture over China using AMSR-E time series data, ISPRS Journal of Photogrammetry and

Remote Sensing, 144, 469-482, 10.1016/j.isprsjprs.2018.08.015, 2018.

Stroppiana, D., Boschetti, M., Azar, R., Barbieri, M., Collivignarelli, F., Gatti, L., Fontanelli, G., Busetto, L., and Holecz, F.: In-season early mapping of rice area and flooding dynamics from optical and SAR satellite data, European Journal of Remote Sensing, 52, 206-220, 10.1080/22797254.2019.1581583, 2019.

Talema, T. and Hailu, B. T.: Mapping rice crop using sentinels (1 SAR and 2 MSI) images in tropical area: A case study in Fogera wereda, Ethiopia, Remote Sensing Applications: Society and Environment, 18, 10.1016/j.rsase.2020.100290, 2020.

Tian, H., Wu, M., Wang, L., and Niu, Z.: Mapping Early, Middle and Late Rice Extent Using Sentinel-1A and Landsat-8 Data in the Poyang Lake Plain, China, Sensors (Basel), 18, 10.3390/s18010185, 2018.

Wang, M., Wang, J., and Chen, L.: Mapping Paddy Rice Using Weakly Supervised Long Short-Term Memory Network with Time Series Sentinel Optical and SAR Images, Agriculture, 10, 10.3390/agriculture10100483, 2020.

Wang, M., Wang, J., Chen, L., and Du, Z.: Mapping paddy rice and rice phenology with Sentinel-1 SAR time series using a unified dynamic programming framework, Open Geosciences, 14, 414-428, doi:10.1515/geo-2022-0369, 2022.

Wei, J., Cui, Y., Luo, W., and Luo, Y.: Mapping Paddy Rice Distribution and Cropping Intensity in China from 2014 to 2019 with Landsat Images, Effective Flood Signals, and Google Earth Engine, Remote Sensing, 14, 759, 10.3390/rs14030759, 2022.

Wei, P., Chai, D., Lin, T., Tang, C., Du, M., and Huang, J.: Large-scale rice mapping under different years based on time-series Sentinel-1 images using deep semantic segmentation model, ISPRS Journal of Photogrammetry and Remote Sensing, 174, 198-214, 10.1016/j.isprsjprs.2021.02.011, 2021.

Xu, L., Zhang, H., Wang, C., Wei, S., Zhang, B., Wu, F., and Tang, Y.: Paddy Rice Mapping in Thailand Using Time-Series Sentinel-1 Data and Deep Learning Model, Remote Sensing, 13, 3994, 10.3390/rs13193994, 2021.

Yang, L., Wang, L., Abubakar, G. A., and Huang, J.: High-Resolution Rice Mapping Based on SNIC Segmentation and Multi-Source Remote Sensing Images, Remote Sensing, 13, 10.3390/rs13061148, 2021a.

Yang, L., Huang, R., Huang, J., Lin, T., Wang, L., Mijiti, R., Wei, P., Tang, C., Shao, J., Li, Q., and Du, X.: Semantic Segmentation Based on Temporal Features: Learning of Temporal-Spatial Information From Time-Series SAR Images for Paddy Rice Mapping, IEEE Transactions on Geoscience and Remote Sensing, 1-16, 10.1109/tgrs.2021.3099522, 2021b.

Zhan, P., Zhu, W., and Li, N.: An automated rice mapping method based on flooding signals in synthetic aperture radar time series, Remote Sensing of Environment, 252, 10.1016/j.rse.2020.112112, 2021.

Zhang, X., Wu, B., Ponce-Campos, G., Zhang, M., Chang, S., and Tian, F.: Mapping up-to-Date Paddy Rice Extent at 10 M Resolution in China through the Integration of Optical and Synthetic Aperture Radar Images, Remote Sensing, 10, 10.3390/rs10081200, 2018.

Zhao, R., Li, Y., and Ma, M.: Mapping Paddy Rice with Satellite Remote Sensing: A Review, Sustainability, 13, 10.3390/su13020503, 2021.