Dear Editors and Reviewers,

We very much appreciate the constructive comments from the reviewers, which have helped improve our manuscript, "SEA-Rice-Ci10: High-resolution Mapping of Rice Cropping Intensity and Harvested Area Across Southeast Asia using the Integration of Sentinel-1 and Sentinel-2 Data" (MS No: essd-2024-90). Our detailed responses to the comments are included in the supplement with the following notes:

- The original review comments (in black)
- Our response on how the manuscript was revised (in red) and
- Revised paragraphs in the new manuscript (in blue)

Most or all suggestions are included in the revised manuscript. We are also submitting an annotated version of the revised manuscript.

Sincerely,

Rudiyanto, on behalf of all co-authors

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Reviewer #1:

RC1: 'Comment on essd-2024-90', Anonymous Referee #1, 25 Apr 2024

The SEA-Rice-Ci10 study devised a novel approach called the Local Unsupervised Classification with Phenological Labeling Method (LUCK-PALM). This method aimed to accurately quantify and map rice cropping intensity and harvested areas across Southeast Asia from 2020 to 2021, with a 10-meter resolution using time-series inputs from Sentinel-1 and Sentinel 2A/B imagery. The LUCK-PALM method is able to resolve the challenge due to the discrepancy in rice cropping calendar among the country and regions. Compared to agricultural statistics and existing rice maps, the study demonstrates its strength in retrieving field paddy details. The study, being open-source and featuring an open dataset, offers valuable insights into agricultural decision-making and management practices, such as methane emissions from rice cultivation, but the quality of the manuscript could be enhanced by addressing the following major and minor comments regarding methodology and content organization, etc. Please refer to the detailed feedback provided for further improvement.

Response: Thank you very much for the constructive comments. We will response to your comments per point below.

Major comments:

1. As shown in Fig.2 and Section 2.3.5, the “Google Map Very High Resolution and Street View” is the data source for exports to label rice and non-rice areas. Although examples and locations of such street view imagery are given in Fig.3, Fig.17 and Figure.S2/Table.S4, it would be good if more details about the street view collection for validations are provided. For example, how was each street view image acquired and how many validation points did the experts label in each grid or each country/province/district? Were those points selected randomly or the selection process was the same as the 2,000 random samples from each defined area?

Response: Thank you for your comments on clarifying the methodology used in this study. Our method is actually an extension of our method in our previous study, which had relatively high accuracy with a high Kappa coefficient of 0.92 for classifying rice and non-rice fields across Peninsular Malaysia, as we stated in Section 2.3, Lines 169-173. We have improved the description of the methodology especially the roles of VHRI and street view in the labelling process on section 2.3.5 Line 268 to 272. Here, we stressed that VHRI and street view images only provided information on rice and non-rice field classes, not cropping intensity. Cropping intensity is obtained from representative spectra of the cluster (Section 2.3.6).

We introduce the local unsupervised classification with phenological labelling (LUCK-PALM) method to produce a map of rice growing intensity (SEA-Rice-Ci10). This framework is the extension of our previous work (Fatchurachman et al., 2022) which used phenology-based approach by combining Sentinel-1 and Sentinel-2 time series data for mapping rice extent and cropping calendar across Peninsular Malaysia. They reported a high Kappa coefficient of 0.92 for classifying rice fields. In this extension, we included an additional index to detect soil water changes, Modified Normalized Difference Water Index (MNDWI) generated from Sentinel-2 data. The flowchart of this study is illustrated in Fig. 2, and each step is explained in the sections below:

and

Moreover, the identification of rice and non-rice fields was also assisted by overlaying the resulting cluster map on the very high-resolution image (VHRI) base map (i.e. satellite layer) in GEE and the Street View images in Google Maps. We manually checked the clusters with the VHRI and Street View images to verify the spectra profiles interpretation is correct in distinguishing rice fields from other crops (Rudiyanto et al., 2019; Zhang et al., 2020; Fatchurrachman et al., 2022).

2. The manuscript provided an assumption (line 219-220) that 25 to 30 clusters output from the unsupervised K-Means classification method would sufficiently represent the spectral data variations in each grid – with 2,000 points and 72 bands. Further explicit explanations or justifications for this assumption should be provided to offer readers a clearer understanding of its methods and enhance transferability.

Response: Thank you for the valuable comments. We added the justification on the sample size and number of clusters on Line 236-238. The sampling size and cluster number were based on a pre-experiment trial, considering both the result representativeness and computational time. A larger number of sample size would make the clustering inefficient and time consuming. We found that 25-30 clusters adequately represent the spectral data variations because the variation of imagery data has been reduced by applying non-crop mask as well as monthly value composite in the imagery data. As we labelled or identified each cluster, we ended up grouping similar clusters to represent rice growing patterns.

“The selection of the number of sampling points and cluster numbers was based on trial assessments that balanced the representativeness of results and computational efficiency. We found that the chosen sample size and number of clusters sufficiently capture the variations in the spectral data.”

3. The study trained local K-Means models for each grid using 2,000 randomly sampled points, and then assessed the accuracy of the produced maps with respect to agricultural statistics and existing products. However, descriptions about how the study applied the locally trained models in combination with expert knowledge to produce grid-wise maps as well as the compilation of maps into national/provincial/regency scales were missing from the manuscript. Also, as seen from the workflow of the study presented in Fig.2, the “Accuracy Assessment” was before the “Map of rice field extent and cropping intensity,” which could potentially lead to the confusion that if the accuracy assessment was conducted with the 2,000 samples each grid or with the final mapping product.

Response: Thank you for your comments. We have updated the methodology section 2.3.3 to 2.3.6 as well as flowchart in Fig 2.

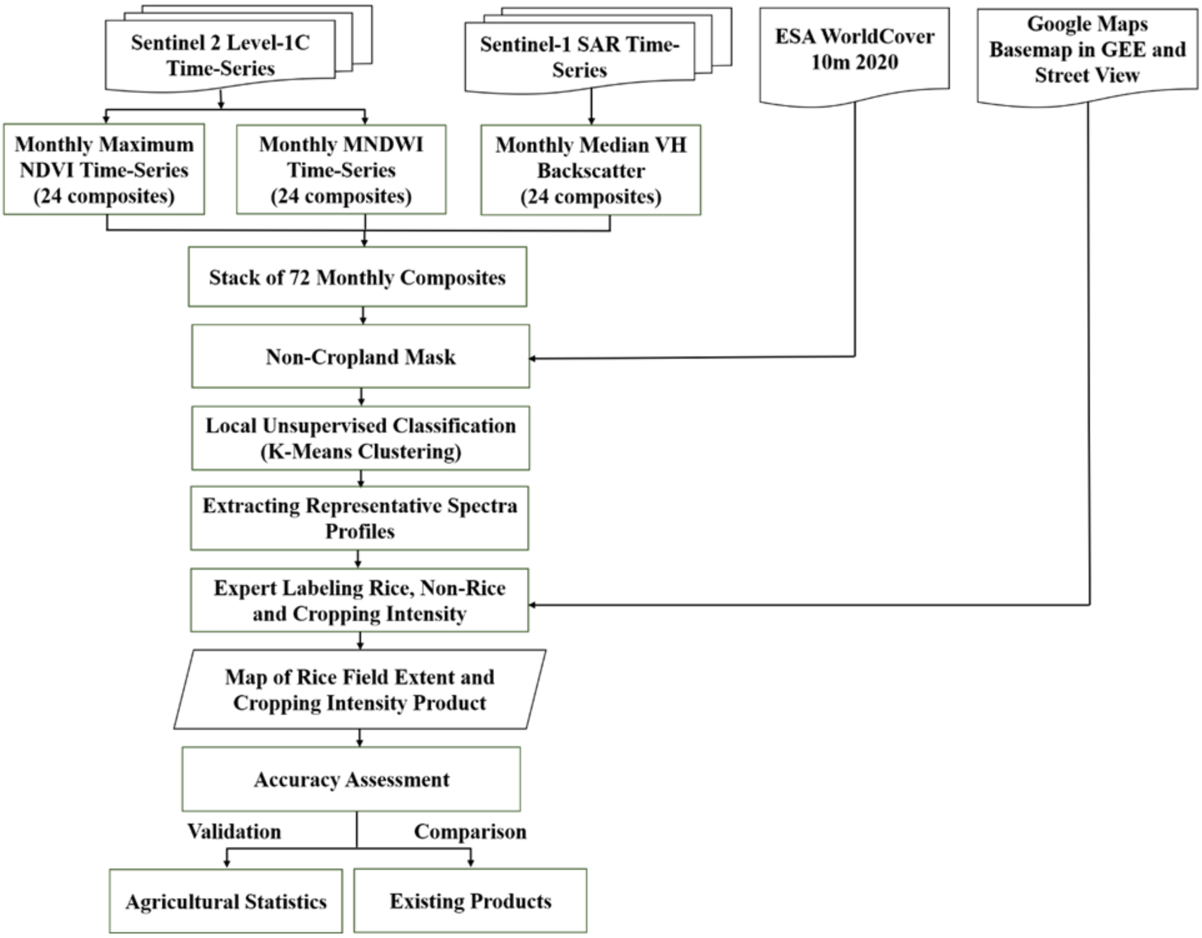


Figure 2: Workflow of LUCK-PALM for mapping rice extent and cropping intensity using combined Sentinel-1 and Sentinel-2 time-series data.

2.3.4. Extracting representative spectra profiles

To identify rice or non-rice groups, it is essential to obtain representative spectra of VH backscatter, NDVI, and MNDWI for each cluster generated by the K-means algorithm. To extract these representative spectra for each cluster, we randomly sampled 2,000 points within the defined area (i.e., for each grid) using the “sample ()” function in GEE and then computed the spatial median of each cluster using the "ee.Reducer.median()" function in GEE (Rudiyanto et al., 2019; Fatchurrachman et al., 2022). Figure 3 illustrates examples of representative spectral profiles of VH backscatter, NDVI, and MNDWI for clusters representing rice fields, water bodies, trees, and built-up areas.

2.3.5 Expert labelling for identifying paddy rice fields and non-rice fields

Based on the representative spectra profiles, expert labelling was conducted by visually inspecting each spectrum to identify clusters associated with rice fields and non-rice fields. Rice fields have a unique time series spectra profile in which the VH backscatter and NDVI values fluctuate seasonally and differ from other non-crop land uses (e.g., water, built-up, trees) as shown in Fig. 3. Spectral time series of non-cropping areas were relatively constant. The NDVI and VH backscatter coefficients of paddy rice change as it grows and matures. During rice transplanting or flooding phase, NDVI and VH backscatter coefficients have the lowest value while MNDWI reaches a maximum peak. The NDVI and VH backscatter coefficients rise after transplanting as the paddy rice grows and develops a peak at the heading stage (Davitt et al. 2020; Zhang et al., 2020b; Huang et al., 2023). After the rice harvest, the NDVI and VH backscatter coefficients decrease (Ramadhani et al., 2020; Fatchurrachman et al., 2022).

Next, we also differentiated between rice field and other crops. In Southeast Asian countries, rice is cultivated parallel with other crops such as sugarcane (Thailand, Indonesia, Philippines) and cassava (Thailand). Figure 4a shows an example of NDVI profiles to distinguish between rice and sugarcane and cassava in Thailand. The length of one season of rice is around 4 months for irrigated rice fields and around 7 months for rainfed rice fields, while both sugarcane and cassava have a longer season of around 10 months. In Indonesia, cash crops like maize and water melon are planted in rice fields during the dry season as reported by Rudiyanto et al. (2019). The NDVI and MNDWI profiles for a double rice cropping system followed by a cash crop is shown in Fig 4b. Rice season can be distinguished by examining the MNDWI signal peak during transplanting, which is higher in rice fields (0.01) compared to other crops (-0.20) due to standing water.

Moreover, the identification of rice and non-rice fields was also assisted by overlaying the resulting cluster map on the very high-resolution image (VHRI) base map (i.e. satellite layer) in GEE and the Street View images in Google Maps. We manually checked the clusters with the VHRI and Street View images to verify the spectra profiles interpretation is correct in distinguishing rice fields from other crops (Rudiyanto et al., 2019; Zhang et al., 2020; Fatchurrachman et al., 2022).

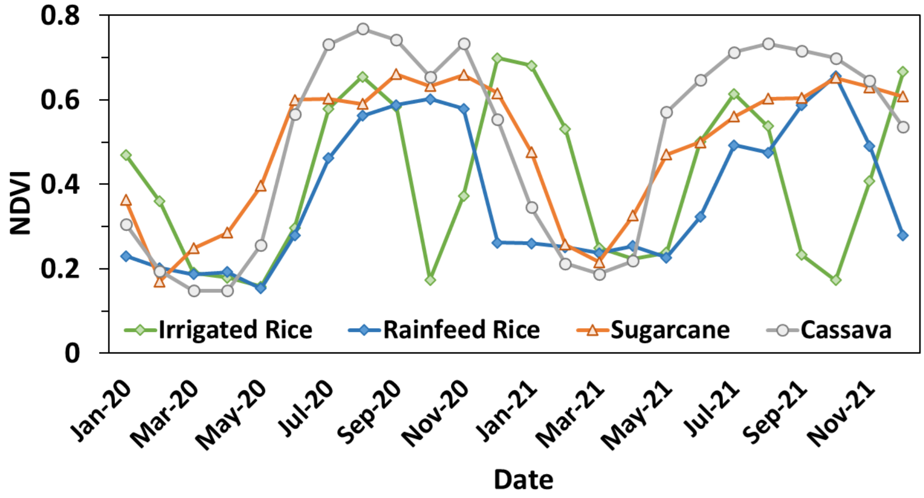
2.3.6 Expert labelling for identifying paddy rice cropping intensity

After identifying clusters as rice fields, we determined their cropping intensity based on the number of NDVI peaks (i.e., the number of rice seasons). Figure 5 illustrates the standard NDVI temporal profile for different paddy rice planting systems (single, double, and triple) on Java Island, Indonesia. In this labeling process, we manually labeled each cluster using the “remap()” function in GEE. We assigned the integer 0 to the non-rice class, and 1, 2, and 3 to single, double, and triple rice cropping intensities, respectively. After that the results were exported in the GeoTIFF raster file format. From these results, the total growing area and harvested area were calculated by the following formulas, respectively:

Total growing area = growing area with single season + growing area with double season + growing area with triple season (1)

Total harvested area = growing area with single season + (2 x growing area with double season) + (3 x growing area with triple season (2)

(a)



(b)

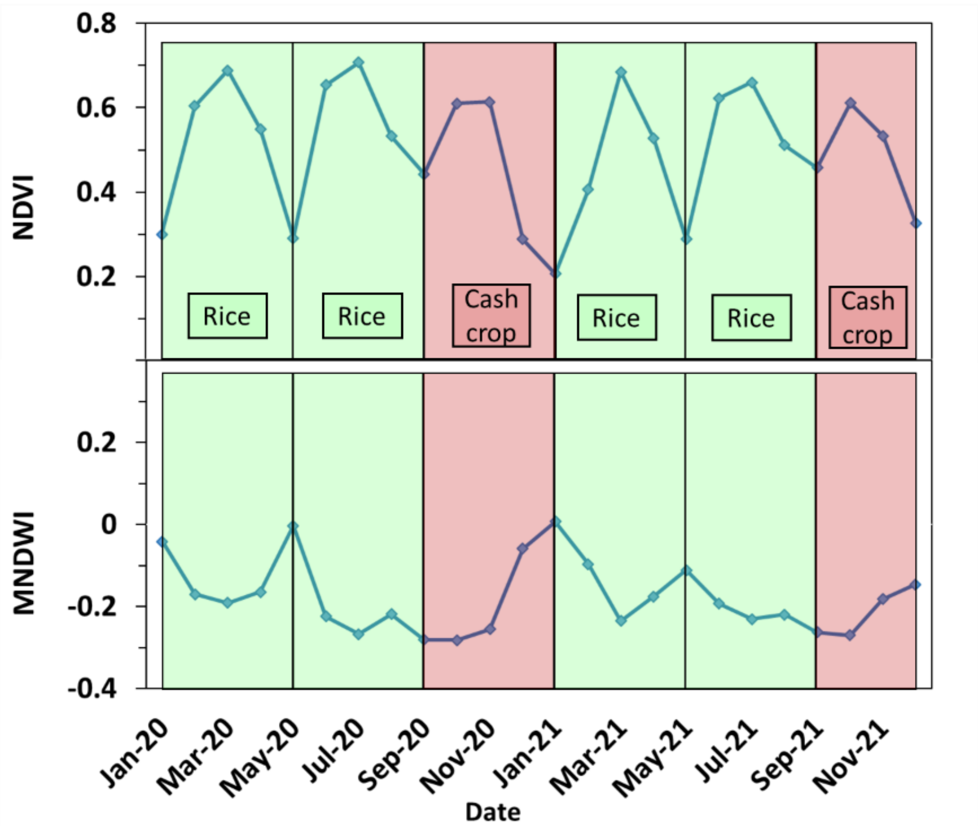


Figure 4. Representative spectra profiles for (a) NDVI of rice and other crops (sugarcane and cassava) and (b) NDVI and MNDWI for double rice season followed by cash crops

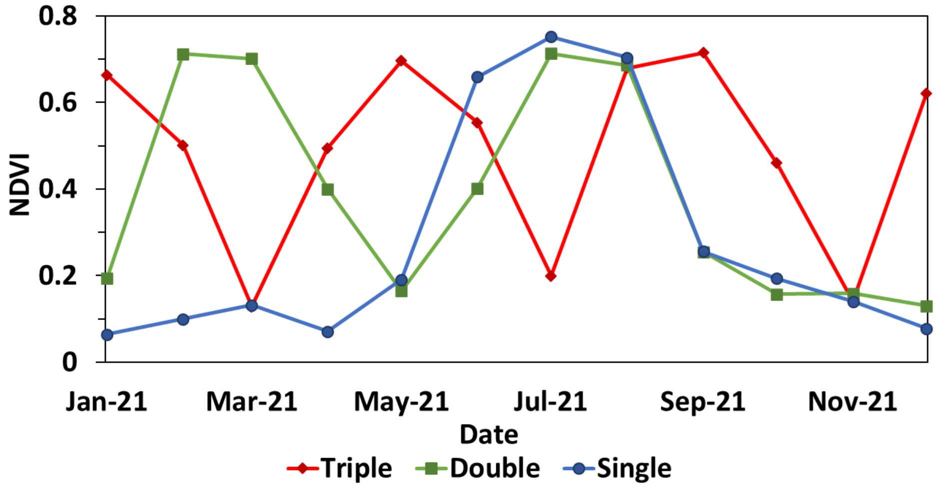


Figure 5. Representative spectra profiles of NDVI for single (blue lines), double (green lines) and triple (red lines) rice cropping intensities.

4. The methods presented in the manuscript featured the workflow from Sentinel time series to rice / non-rice crop mapping (in terms of spatial distribution), but it appears that descriptions about how the authors retrieve the cropping intensity of rice (from time series-based spectral profiles?) were less elaborated in methods.

Response: Thank you for your suggestion, we further elaborated how to determine rice cropping intensity. We have added it in the new section 2.3.6.

Minor comments:

1. In Fig.2, it is good to be concise in workflow illustrations, but how high is “Google Maps Very High Resolution” presented here? Also, the capitalization styles of words in Fig.2. could be more consistent.

Response: Thank you. Now we have revised using consistent words in Fig 2. Roles of are explained section 2.3.5 Line 268 to 272.

2. In Section 2.3.2 (line 192-195), what is the difference between using different landcovers from the WorldCover dataset to “filter out” non-croplands and using waterbody, tree, and built-up layers from the same dataset to “mask” non-cropland areas? The goal to facilitate computation and processing, as well as improving model performance is clear here, but the description of this step could be clearer.

Response: Thank you for your clarification. It is the same meaning as “masking”. Thus to avoid redundancy, we removed “Waterbody, tree, and build-up layers from the WorldCover dataset were employed to mask non-cropland areas in Southeast Asia.”

3. 3 appears to be coarser than other figures provided in the manuscript in terms of resolution.

Response: The resolution of Figure 3 has been improved.

4. 18 could have legends and classification accuracy and/or coefficients of determinant labeled on the map for each region.

Response: R^2 and RMSE from relationship between map products and statistical data for harvested area were added in Figure 18. We note that the harvested area for 20mRice-MSEAsia and NESEA-Rice 10m in these regions was calculated from the growing area with a single season (see Eq (2) in section 2.3.6), as rice fields in these regions have a single cropping intensity.

5. Line 642 has a typo: “penological mapping.”

Response: Thank you, we have revised it Line 707.

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