

Response to Reviewer #2

This research developed the first 20-meter global coconut maps using U-Net and Sentinel imagery. According to the results shown in the paper, the dataset can provide essential and detailed spatial distribution for global coconuts, and the accuracy is relatively high. However, it is recommended to address the mentioned points to improve the clarity, comprehensiveness, and applicability of the research.

Response: Thank you for the positive assessment of the interest in the dataset. We have now addressed your insightful comments. By doing so, the article has substantially improved. Thanks.

1. Please summarize the previous efforts and methods developed for coconut tree monitoring in the introduction section. This will help readers understand the novelty and significance of the current research.

Response: We have now included a paragraph that summarizes previous studies on coconut palm mapping and explains why our study is novel by saying that there is no global coconut palm map with such level of spatial detail (Lines 51-60):

“Sub-meter satellite data and aerial images have been used for detecting individual coconut palms (Zheng et al., 2023; Freudenberg et al., 2019; Zheng et al., 2021), delineating coconut palm canopy (De Souza and Falcão, 2020; Vermote et al., 2020), and coconut palm detection in the context of land cover classification (Burnett et al., 2019). These studies used various methodologies, including threshold-based classification, random forest using feature extraction, and more advanced techniques such as object detection and semantic segmentation using deep learning. Similar efforts have been made to map coconut palm using decametric-scale satellites such as Sentinel-1, Sentinel-2, or Landsat-7 (Lang et al., 2021; Jenifer and Natarajan, 2021; Palaniswami et al., 2006). Another study detected individual coconut palms using airborne laser scanning (Mohan et al., 2019). Despite previous efforts to map coconut palm, these studies have focused on the local and regional scale, and a global coconut palm map has not been produced yet at a high spatial resolution.”

2. Provide details of the training samples used in this study. Please present an example of one image (Sentinel-1 and -2 composite) and one corresponding per-pixel label image to illustrate the data used for training.

Response: We have now added Fig. A3, which shows four paired Sentinel composites and per-pixel label images for different coconut palm regions.

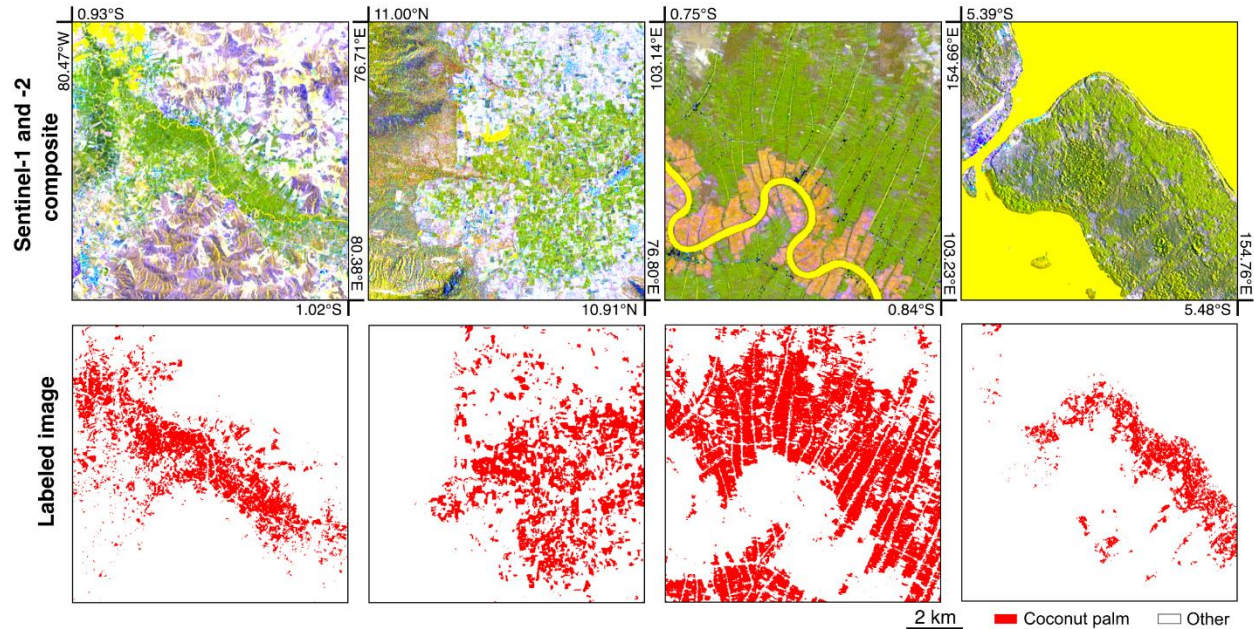


Figure A3: Example of the 10 x 10 km² images used for training the U-Net model. The training pairs included a Sentinel-1 and Sentinel-2 composite (upper panels) and the corresponding labelled image (bottom panels). The Sentinel-1 and -2 composite includes the polarization bands VV and VH, and the spectral band 11 (short-wave infrared). The classification image includes two classes: 0 (coconut palms are not present) and 1 (coconut palms are present). The panels show four different coconut-growing regions: from left to right, Manabi province (Ecuador), Tamil Nadu state (India), Jambi province (Indonesia), West Kalimantan province (Indonesia), and Bougainville (Papua New Guinea).

We included details about the training dataset in Lines 156-164:

“Semantic segmentation models require image data with a fixed size for both training and prediction. We set the size of the input images to 512 × 512 pixels, which is approximately 10 × 10 km in a 20-meter resolution image. The collection of training data consisted of digitizing polygons in regions that were identified in the bioclimatic analysis. The polygons were drawn in 146 training images (Fig. 1b) using sub-meter resolution to discriminate coconut palm plantations from other land covers. The sub-meter resolution images were the images displayed as the base layer in Google Earth. The U-Net was used for binary classification of coconut palm (digitized polygons) and the rest of land covers (image background; see Fig. A3) and, thus, the resulting layer was a binary raster, in which each pixel presented values of 0 (coconut palms are not present) and 1 (coconut palms are present).”

3. The feature differences between different crop trees (such as coconut, oil palm, mango as mentioned in the paper) should be given for better comprehension of the classification procedure.

Response: We have now extended the spectral separability analysis to the other crop trees mentioned in the main text (sago and mango plantations), which were the most problematic plantations after oil palm. We have updated Fig. A2 to include these other crop trees.

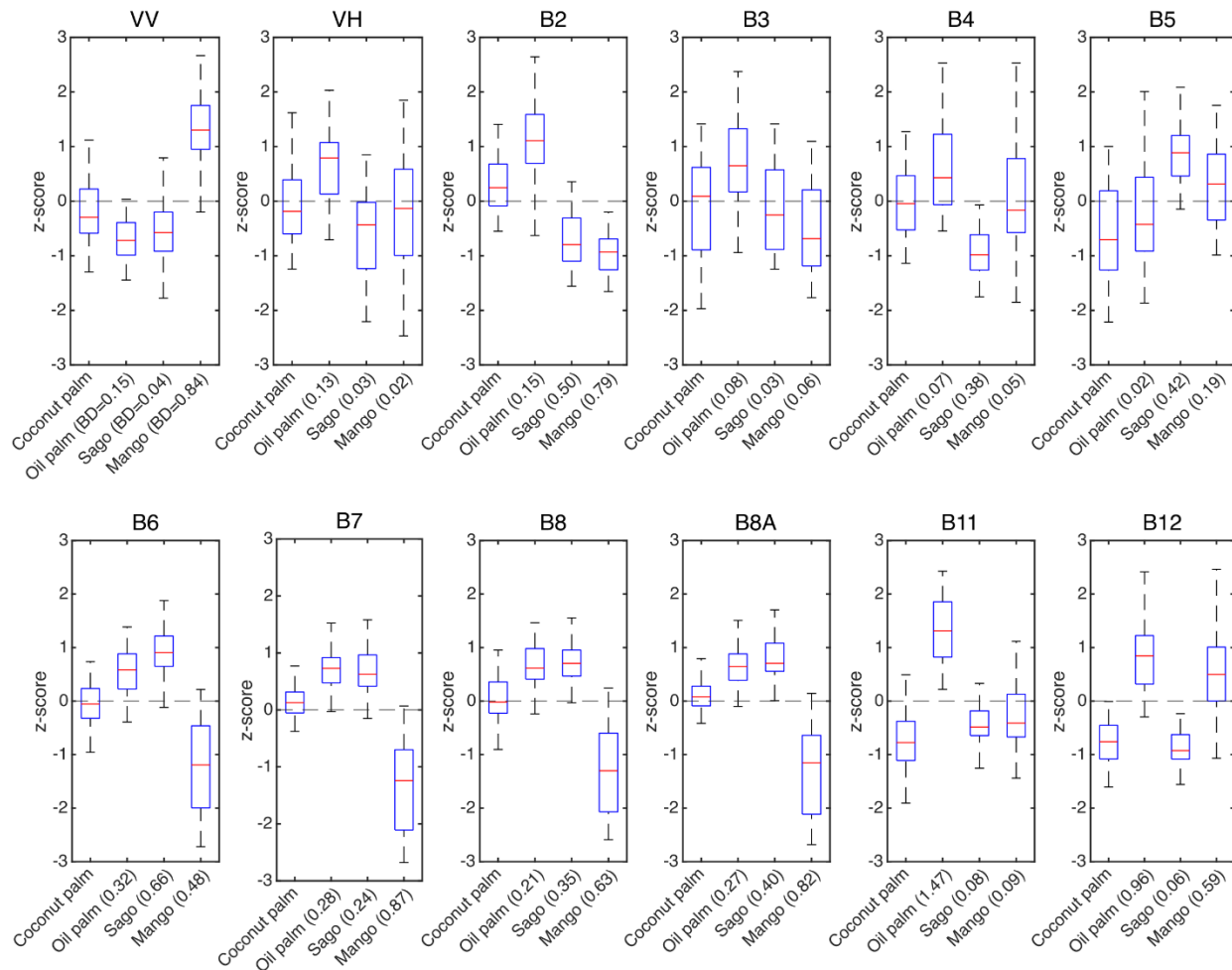


Figure A2: Spectral and backscatter separability between coconut palm and oil palm, sago, and mango plantations. The overlap between distributions was estimated for the VV and VH bands in Sentinel-1 and for the 10- and 20-meter bands in Sentinel-2. The separability was measured in terms of Bhattacharyya distance (BD) between distributions of coconut palm and oil palm points. The Bhattacharyya distance is displayed in parenthesis in the x-axis. The higher the Bhattacharyya distance the lower the overlap between the two distributions.

4. Is it possible to investigate the correlation between the mapping results and FAO statistics on a country level (besides the three countries shown in Table 2)? This analysis will strengthen the validity and reliability of the mapping results.

Response: The manuscript now includes Fig. A9, which depicts the FAO statistics and the coconut palm mapped area on a country level. We have now used this figure to emphasize that our map depicts closed-canopy coconut palm, while sparse coconut palm is mostly omitted. The high rate of omission in sparse coconut palm likely explains the gap between FAO statistics and our product:

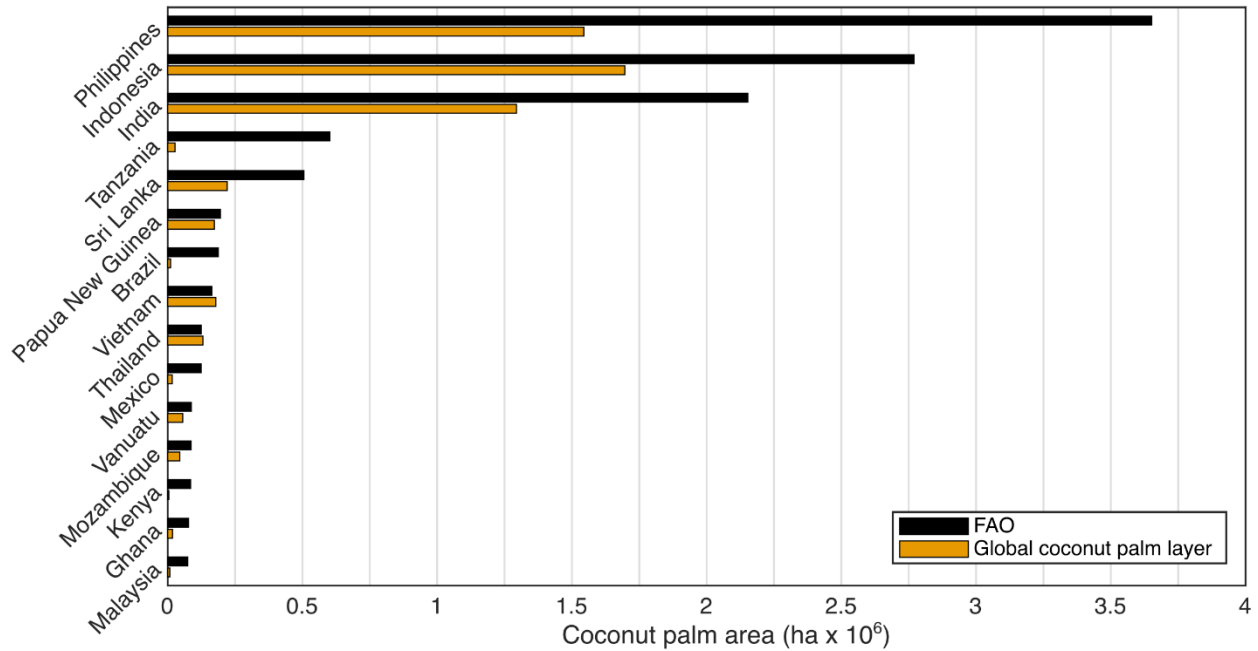


Fig. A9: Coconut palm area mapped using Sentinel-1 and Sentinel-2 and coconut palm harvested area from FAO for the top 15 coconut-producing countries in 2020.

5. Compare different semantic segmentation models or explain why U-Net was chosen as the final model for mapping. Additionally, discuss the potential use of other deep learning models, and elaborate on why semantic segmentation models were preferred.

Response: We have included the justification for using a semantic segmentation model (U-Net model) in Lines 152-153:

“Semantic segmentation is well suited for mapping plantations, such as coconut palm, since it can automatically capture the spatial and contextual information in the image and, as a result, less effort is required compared to feature engineering in standard machine learning (Ma et al., 2019). Such contextual information includes the shape of the plantation or texture patterns within the plantation.”

Also, we have elaborated on the potential use of other deep learning techniques and explained why semantic segmentation was preferred in our study (Lines 329-335 in the Discussion section):

“Object detection using deep learning applied to very high-resolution images (<1 meter), such as those obtained by DigitalGlobe or Planet, offers great potential for the detection of individual coconut palms (De Souza and Falcão, 2020; Vermote et al., 2020; Freudenberg et al., 2019). This approach could be used to detect coconut palm plantations with incomplete canopy closure and coconut palms that are scattered across the land. In our study, the decametric resolution of Sentinel-1 and Sentinel-2 images made the use of object detection techniques unfeasible. Object detection using deep learning and sub-meter images could

complement our closed-canopy coconut palm layer and could also be useful for mapping different palm trees, including coconut palm, oil palm, and sago palm.”

We have not included a comparison of semantic segmentation models. Following the recommendations in *The aims & scope* of the journal, ‘any comparison to other methods is beyond the scope of regular articles.’

6. Incorporate the coconut-producing regions obtained based on the literature review and SPAM. It might be useful to overlay these regions with the coconut locations shown in Figure 1a to demonstrate their spatial distribution.

Response: The manuscript now includes Fig. A1, which depicts the coconut palm layer in the SPAM dataset. Most of the coconut-producing regions obtained in the literature review depict general administrative regions (districts, provinces, states, etc.). We consider that a map showing these administrative boundaries would not be very informative for the reader. Instead of displaying the administrative boundaries, we believe that the points extracted from these regions (illustrated in Fig. 1a) are more informative and meaningful.

We opted to display the SPAM layer and the point dataset (Fig. 1a) in separate figures. Overlaying one on top of the other would obscure either layer.

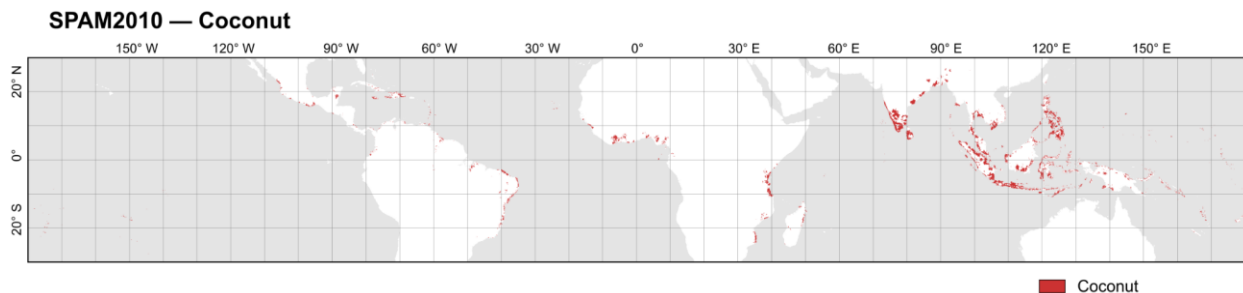


Figure A1: Coconut palm map extracted from the Spatial Production Allocation Model for 2010 (SPAM2010). This layer represents areas where the extent of coconut palm plantations exceeds 50 hectares within each ~ 9 km² pixel off the SMAP dataset.

7. As this study took the semantic segmentation model as the mapping network, it may be helpful to provide pixel-level validation results in addition to the accuracy obtained from validation points, as it will provide a more comprehensive evaluation of the model's performance and its ability to accurately delineate coconut tree boundaries.

Response: We have now included the probability layer as an auxiliary data to the global coconut palm layer. We have explained the probability layer in the Methods section (Lines 164-166):

“In addition, we generated a probability layer using the second-last layers of the convolutional neural network. Rather than probability layers, the second-last layers represent a confidence score (ranging from 0 to 100) for each class prediction. The probability layer we provide corresponds to the second-last layer of the class ‘coconut’.”

We have also added a new figure (Fig. A8) showcasing the probability layer.

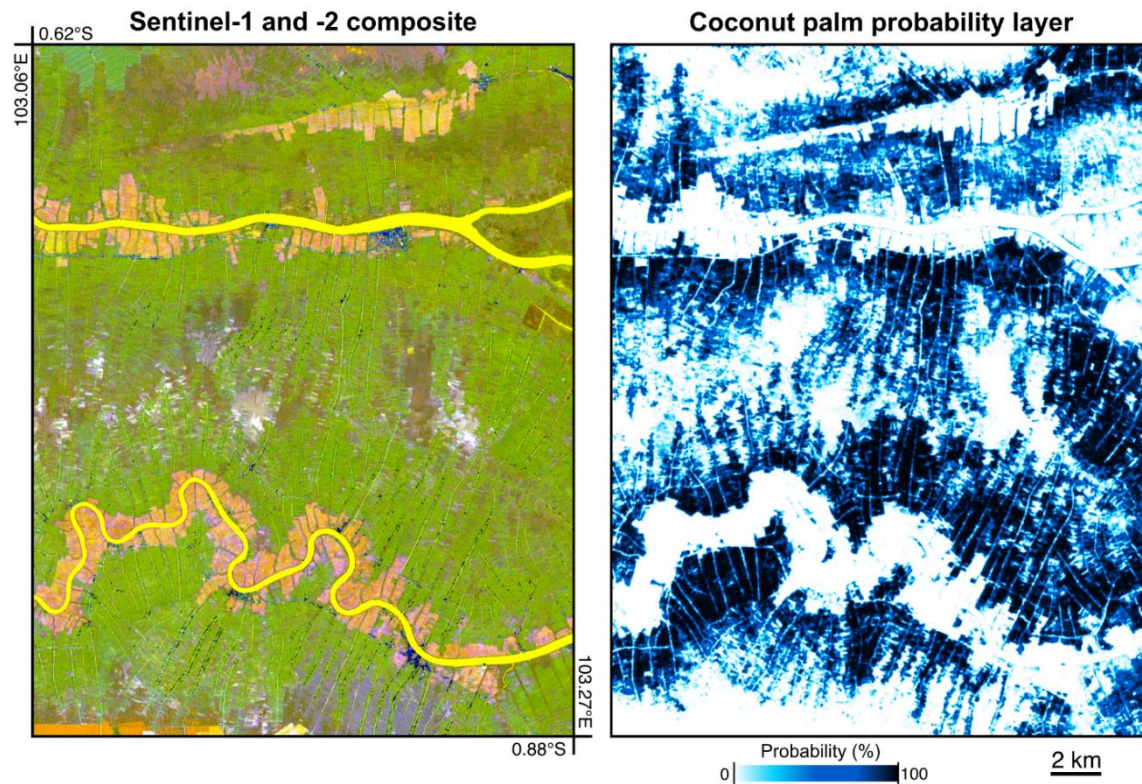


Figure A8: Sentinel-1 and Sentinel-2 annual composite (left panel) and probability layer (right panel) produced with the U-Net model in Riau province (Indonesia). The Sentinel-1 and -2 composite includes the polarization bands VV and VH, and the spectral band 11 (short-wave infrared). The probability layer represents a score that indicates the confidence level of the classification model in predicting the presence of coconut palm.

8. Is it possible to classify the coconut to Sparse, Dense open-canopy and Closed-canopy? It will provide more detailed mapping results, and give the readers opportunity to choose the product they need, just like the previous global oil palm product the authors developed, which provide the smallholder oil palms and industrial oil palm plantations.

Response: Unfortunately, it is not possible to produce a comprehensive map of sparse, dense open-canopy and closed-canopy with the methodology presented in this study and using Sentinel-1 and Sentinel-2. We have mentioned, however, that the potential use of the probability layer could be used as a proxy for coconut palm density (Lines 316-317):

“We also generated a probability layer that provides a score indicating the confidence level of the model output. This probability layer could serve as a proxy for coconut palm density.”

Please note that a similar issue occurred for the global oil palm plantation in our previous study (Descals et al., 2019). We successfully trained a model that distinguished between smallholders and industrial oil palm plantations. However, the model’s output was accurate only if the plantation presented a closed canopy.

Descals, A., Wich, S., Meijaard, E., Gaveau, D. L., Peedell, S., & Szantoi, Z. (2021). High-resolution global map of smallholder and industrial closed-canopy oil palm plantations. *Earth System Science Data*, 13(3), 1211-1231.

9. Include zoomed-in regions that contain both coconut trees and oil palms (or other plantations) to illustrate the model's capability to accurately extract coconuts from other tree types. This may help to address the statement made by the authors: "The separability analysis revealed a low separability between coconut and oil palm in the VV and VH bands."

Response: We have now included Fig. A6, which illustrates zoomed-in regions that grow coconut palm and other plantations (oil palm, mango, and sago). Thanks for the suggestion.

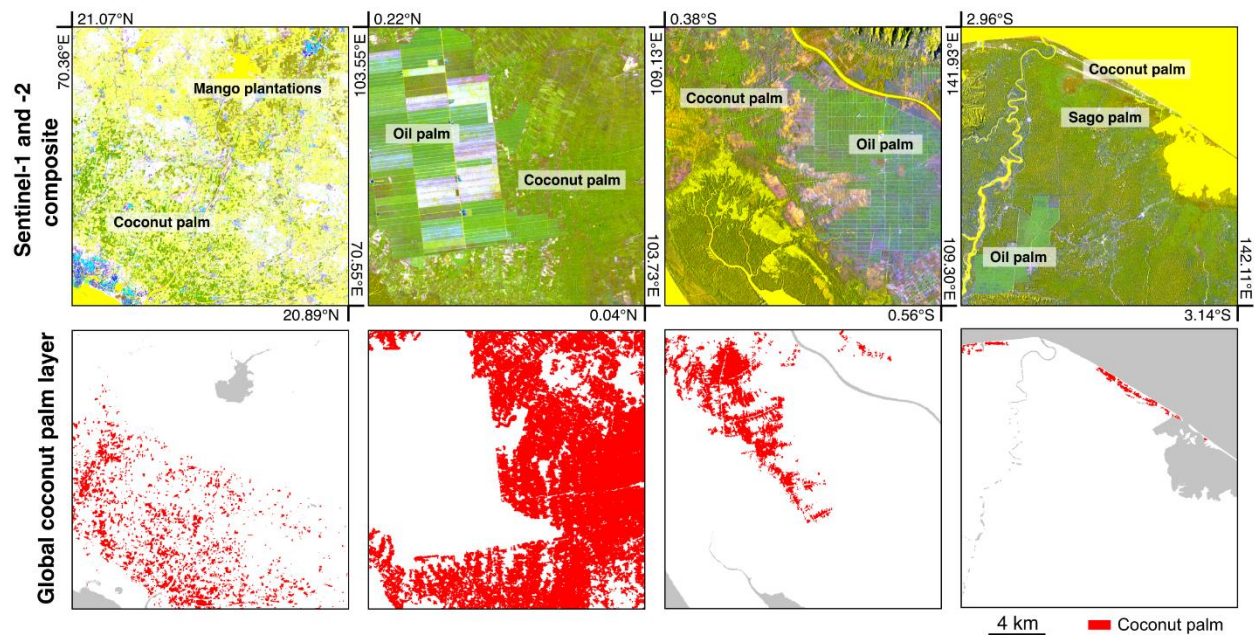


Figure A6: Classification of Sentinel-1 and Sentinel-2 annual composites in regions with the presence of other crops that exhibit similarities to coconut palm in the Sentinel composites. The Sentinel-1 and -2 composite (upper panels) includes the polarization bands VV and VH, and the spectral band 11 (short-wave infrared). The regions are, from left to right, Gujarat state (India), Riau province (Indonesia), West Kalimantan province (Indonesia), and Sandaun Province (Papua New Guinea). The classification image (bottom panels) shows the coconut palm plantations in red.

10. Provide the uncertainty map of the classification results to help users better understand and utilize the dataset shared in this research.

Response: The probability layer has been now included as an auxiliary data to the classification layer. The layer was uploaded to Google Earth Engine to facilitate user access. We have included a figure showing the probability layer and have included an explanation of this new layer (see response to point 7). Thanks for the suggestion. We hope the probability layer enables users to have a better understanding and use of the dataset.